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Python Module Index ........................................... 215
- **JAX** = XLA + Autograd
- **SymJAX** = JAX + symbolic programming + deep Learning

**XLA** is a compiler that optimizes a computational graph by fusing multiple kernels into one preventing intermediate computation, reducing memory operations and increasing performances.

**JAX** is a python interface that provides a Numpy-like software on top of XLA and providing just-in-time compilation as well as advanced automatic differentiations.

**SymJAX** is a symbolic programming version of JAX simplifying graph input, output and updates and providing additional functionalities for general machine learning and deep learning applications. From an user perspective SymJAX appears to Theano with fast graph optimization/compilation and broad hardware support, along with Lasagne-like deep learning functionalities.

This is an under development research project, not an official product, expect bugs and sharp edges; please help by trying it out, reporting bugs.
1.1 Installation

This installation is restricted to GPU support only.

1.1.1 Installation with pip

1. Install all GPU divers and compilers (cuda, cudnn, and GPU drivers).
2. Install jax following Jax Installation. Here is a minimal instruction to install the GPU version

```bash
$ PYTHON_VERSION=cp37  # alternatives: cp35, cp36, cp37, cp38
$ CUDA_VERSION=cuda92  # alternatives: cuda92, cuda100, cuda101, cuda102
$ PLATFORM=linux_x86_64  # alternatives: linux_x86_64
$ BASE_URL='https://storage.googleapis.com/jax-releases'
$ pip install --upgrade $BASE_URL/$CUDA_VERSION jaxlib-0.1.38-$PYTHON_→VERSION-none-$PLATFORM.whl
```

3. Install SymJAX with

```bash
$ pip install symjax
```

1.1.2 Manual installation

1. Clone this repository with

```bash
$ git clone https://github.com/RandallBalestriero/SymJAX
```

2. Install.

```bash
$ cd SymJAX
$ pip install -r requirements.txt
$ pip install .
```
1.2 Examples

1.2.1 Multivariate Gaussian

```python
import sys
sys.path.insert(0, "./")

import symjax as sj
import symjax.tensor as T
import matplotlib.pyplot as plt
import matplotlib
matplotlib.use('Agg')

##### 2D GAUSSIAN EXAMPLE

t = T.linspace(-5, 5, 5)
x, y = T.meshgrid(t, t)
X = T.stack([x.flatten(), y.flatten()], 1)
p = T.pdfs.multivariate_normal.pdf(X, T.zeros(2), T.eye(2))
p = p.reshape((5, 5)).round(2)

print(p)
# Tensor(Op=round_, shape=(5, 5), dtype=float32)
# lazy evaluation (not compiled nor optimized)

print(p.get())
# [[0. 0. 0. 0. 0.]
# [0. 0.01 0. 0. 0.]
# [0. 0.01 0.16 0.01 0.]
# [0. 0. 0.01 0. 0.]
# [0. 0. 0. 0. 0.]]

# create the function which internally compiles and optimizes
# the function does not take any arguments and only outputs the
# computed tensor p
f = sj.function(outputs=p)
print(f())
# [[0. 0. 0. 0. 0.]
# [0. 0.01 0. 0. 0.]
# [0. 0.01 0.16 0.01 0.]
# [0. 0. 0.01 0. 0.]
# [0. 0. 0. 0. 0.]]
```

1.2.2 Stochastic Gradient Descent

```python
import sys
sys.path.insert(0, "./")

import symjax
import symjax.tensor as T

# create our variable to be optimized
mu = T.Variable(T.random.normal(()))
```

(continues on next page)
# create our cost
cost = T.exp(-(mu-1)**2)

# get the gradient, notice that it is itself a tensor that can then
# be manipulated as well
g = symjax.gradients(cost, mu)
print(g)

# (Tensor: shape=(), dtype=float32)

# create the compiled function that will compute the cost and apply
# the update onto the variable
f = symjax.function(outputs=cost, updates={mu:mu-0.2*g})

for i in range(10):
    print(f())

# 0.008471076
# 0.008201109
# 0.007946267
# 0.007705368
# 0.0074773384
# 0.007261208
# 0.0070561105
# 0.006861261
# 0.006675923
# 0.006499458

### 1.2.3 CIFAR-10 Classification

```python
import sys
sys.path.insert(0, "..")
import symjax.tensor as T
import symjax as sj
import numpy as np

# load the dataset
images_train, labels_train, images_test, labels_test = sj.datasets.cifar10.load()

# some renormalization
images_train /= images_train.max((1, 2, 3), keepdims=True)
images_test /= images_test.max((1, 2, 3), keepdims=True)

# create the network
BATCH_SIZE = 32
inputs = T.Placeholder((BATCH_SIZE,) + images_train.shape[1:], 'float32')
outputs = T.Placeholder((BATCH_SIZE,), 'int32')
deterministic = T.Placeholder((1,), 'bool')

layer = [sj.layers.RandomCrop(inputs, crop_shape=(3, 32, 32),
                              padding=[[0, 0], [4, 4], [4, 4]],
                              deterministic=deterministic)]
layer.append(sj.layers.Conv2D(layer[-1], (32, 3, 3, 3)))
```

(continues on next page)
layer.append(sj.layers.BatchNormalization(layer[-1], [0, 2, 3],
   deterministic))
layer.append(sj.layers.Activation(layer[-1], T.relu))
layer.append(sj.layers.Pool2D(layer[-1], (2, 2)))
layer.append(sj.layers.Conv2D(layer[-1], (64, 32, 3, 3)))
layer.append(sj.layers.BatchNormalization(layer[-1], [0, 2, 3],
   deterministic))
layer.append(sj.layers.Activation(layer[-1], T.relu))
layer.append(sj.layers.Pool2D(layer[-1], (2, 2)))
layer.append(sj.layers.Dense(layer[-1], 128))
layer.append(sj.layers.BatchNormalization(layer[-1], [0],
   deterministic))
layer.append(sj.layers.Activation(layer[-1], T.relu))
layer.append(sj.layers.Dense(layer[-1], 10))

# each layer is itself a tensor which represents its output and thus
# any tensor operation can be used on the layer instance, for example
for l in layer:
   print(l.shape)
   # (32, 3, 32, 32)
   # (32, 32, 30, 30)
   # (32, 32, 30, 30)
   # (32, 32, 15, 15)
   # (32, 64, 13, 13)
   # (32, 64, 13, 13)
   # (32, 64, 6, 6)
   # (32, 128)
   # (32, 128)
   # (32, 10)

loss = sj.losses.sparse_crossentropy_logits(outputs, layer[-1]).mean()
accuracy = sj.losses.accuracy(outputs, layer[-1])
params = sum([lay.variables() for lay in layer], [])
lr=sj.schedules.PiecewiseConstant(0.005, {50: 0.001, 75: 0.0005})
opt = sj.optimizers.Adam(loss, params, lr)

for l in layer:
   opt.updates.update(l.updates)

test = sj.function(inputs, outputs, deterministic,
   outputs=[loss, accuracy])

train = sj.function(inputs, outputs, deterministic,
   outputs=[loss, accuracy], updates=opt.updates)

for epoch in range(100):
   L = list()
   for x, y in sj.utils.batchify(images_test, labels_test, batch_size=BATCH_SIZE,
L.append(test(x, y, 1))
print('Test Loss and Accu:', np.mean(L, 0))
L = list()
for x, y in sj.utils.batchify(images_train, labels_train, 
    batch_size=BATCH_SIZE, option='random_see_all'):
    L.append(train(x, y, 0))
print('Train Loss and Accu', np.mean(L, 0))
lr.update()
2.1 General

2.1.1 symjax

`class function (*classargs, outputs=[], updates=None, device=None, backend=None, default_value=None)`

Generate a user function that compiles a computational graph.

Based on given inputs, outputs and update policy of variables. This function internally jit compile the underlying jax computational graph for performances and thus should be favored to the get method of tensors.

Parameters

- **classargs** *(trailing tuple)* – the inputs to the function to be compiled. The tuple should contain all the placeholders that are roots of any output given of the function and update values
- **outputs** *(List (optional))* – the outputs of the function, if a single element, it can be given as a standalone and not a list
- **updates** *(Dict (optional))* – the dictionary of updates as per `{var:new_value}` for any variable of the graph
- **device** – ??
- **backend** *(‘cpu’ or ‘gpu’)* – the backend to use to run the function on
- **default_value** *(not implemented)* – not implemented

Returns the user frontend function that takes the specified inputs, returns the specified outputs and perform internally the updates

Return type `callable`

Examples

```python
>>> import jaxonn
>>> import jaxonn.tensor as T
>>> x = T.ones((4, 4))
>>> xs = x.sum() + 1
>>> f = jaxonn.function(outputs=x)
>>> print(f())  # returns 17
```
```python
>>> w = T.Variable(0., name='w')
>>> increment = jaxonn.function(updates={w: w + 1})
>>> for i in range(10):
...     increment()
>>> print(w.value)  # returns 10
```

Gradients (scalar, variables)
Compute the gradients of a scalar w.r.t to a given list of variables.

Parameters
- **scalar** (symjax.tensor.base.Tensor) – the variable to differentiate
- **variables** (List or Tuple) – the variables used to compute the derivative.

Returns gradients – the sequency of gradients ordered as given in the input variables

Return type Tuple

Jacobians (tensor, variables, mode='forward')
Compute the jacobians of a tensor w.r.t to a given list of variables.

The tensor needs not to be a vector, but will be treated as such. For example if tensor.shape is (10, 3, 3) and a variable shape if (10, 10) the resulting jacobian has shape (10, 3, 3, 10, 10). It is possible to specify the mode forward or backward. For tall jacobians, forward is faster and vice-versa.

Parameters
- **vector** (Tensor) – the variable to differentiate
- **variables** (List or Tuple) – the variables used to compute the derivative.

Returns jacobians – the sequency of gradients ordered as given in the input variables

Return type Tuple

2.1.2 symjax.tensor

Implements the NumPy API, using the primitives in jax.lax. As SymJAX follows the JAX restrictions, not all NumPy functions are present.

- Notably, since JAX arrays are immutable, NumPy APIs that mutate arrays in-place cannot be implemented in JAX. However, often JAX is able to provide a alternative API that is purely functional. For example, instead of in-place array updates (x[i] = y), JAX provides an alternative pure indexed update function jax.ops.index_update().
- NumPy is very aggressive at promoting values to float64 type. JAX sometimes is less aggressive about type promotion.

Finally, since SymJAX uses jit-compilation, any function that returns data-dependent output shapes are incompatible and thus not implemented. In fact, The XLA compiler requires that shapes of arrays be known at compile time. While it would be possible to provide. Thus an implementation of an API such as numpy.nonzero(), we would be unable to JIT-compile it because the shape of its output depends on the contents of the input data.

Not every function in NumPy is implemented; contributions are welcome!
Control Flow

**cond** *(predicate, true_predicate, true_fun, false_predicate, false_fun)*

*Predicate should be a boolean tensor with shape ()*  True_input is the input passed to true_fn that will give the output if the predicate evaluates to True, and conversely for False...

LAX-backend implementation of `cond()`.

**scan** *(fn, init, xs, constants=(), length=None)*

Scan a function over leading array axes while carrying along state.

The type signature in brief is

```python
scan :: (c -> a -> (c, b)) -> c -> [a] -> (c, [b])
```

where we use `[t]` here to denote the type `t` with an additional leading axis. That is, if `t` is an array type then `[t]` represents the type with an additional leading axis, and if `t` is a pytree (container) type with array leaves then `[t]` represents the type with the same pytree structure and corresponding leaves each with an additional leading axis.

When `a` is an array type or None, and `b` is an array type, the semantics of `scan` are given roughly by this Python implementation:

```python
def scan(f, init, xs, length=None):
    if xs is None:
        xs = [None] * length
    carry = init
    ys = []
    for x in xs:
        carry, y = f(carry, x)
        ys.append(y)
    return carry, np.stack(ys)
```

Unlike that Python version, both `a` and `b` may be arbitrary pytree types, and so multiple arrays can be scanned over at once and produce multiple output arrays. (None is actually an empty pytree.)

Also unlike that Python version, `scan` is a JAX primitive and is lowered to a single XLA While HLO. That makes it useful for reducing compilation times for jit-compiled functions, since native Python loop constructs in an @jit function are unrolled, leading to large XLA computations.

Finally, the loop-carried value `carry` must hold a fixed shape and dtype across all iterations (and not just be consistent up to NumPy rank/shape broadcasting and dtype promotion rules, for example). In other words, the type `c` in the type signature above represents an array with a fixed shape and dtype (or a nested tuple/list/dict container data structure with a fixed structure and arrays with fixed shape and dtype at the leaves).

**Parameters**

- **f** – a Python function to be scanned of type `c -> a -> (c, b)`, meaning that `f` accepts two arguments where the first is a value of the loop carry and the second is a slice of `xs` along its leading axis, and that `f` returns a pair where the first element represents a new value for the loop carry and the second represents a slice of the output.

- **init** – an initial loop carry value of type `c`, which can be a scalar, array, or any pytree (nested Python tuple/list/dict) thereof, representing the initial loop carry value. This value must have the same structure as the first element of the pair returned by `f`.

- **xs** – the value of type `[a]` over which to scan along the leading axis, where `[a]` can be an array or any pytree (nested Python tuple/list/dict) thereof with consistent leading axis sizes.
• **length** – optional integer specifying the number of loop iterations, which must agree with
  the sizes of leading axes of the arrays in `xs` (but can be used to perform scans where no
  input `xs` are needed).

**Returns** A pair of type `(c, [b])` where the first element represents the final loop carry value and
the second element represents the stacked outputs of the second output of `f` when scanned over
the leading axis of the inputs.

## Index Operations

### `index_update(x, idx, y)`

Pure equivalent of `x[idx] = y`.

LAX-backend implementation of `index_update()`. ADDITIONOriginal docstring below.

Returns the value of `x` that would result from the

**NumPy-style indexed assignment::** `x[idx] = y`

Note the `index_update` operator is pure; `x` itself is not modified, instead the new value that `x` would
have taken is returned.

Unlike NumPy’s `x[idx] = y`, if multiple indices refer to the same location it is undefined which
update is chosen; JAX may choose the order of updates arbitrarily and nondeterministically (e.g., due
to concurrent updates on some hardware platforms).

**Args:** `x`: an array with the values to be updated. `idx`: a Numpy-style index, consisting of `None`,
integers, `slice` objects,
  ellipses, ndarrays with integer dtypes, or a tuple of the above. A convenient syntactic
  sugar for forming indices is via the `jax.ops.index` object.

  `y`: the array of updates. `y` must be broadcastable to the shape of the `array` that would be re-
  turned by `x[idx]`.

**Returns:** An array.

```python
>>> x = jax.numpy.ones((5, 6))
>>> jax.ops.index_update(x, jax.ops.index[::2, 3:], 6.)
array([[1., 1., 1., 6., 6., 6.],
       [1., 1., 1., 1., 1., 1.],
       [1., 1., 1., 6., 6., 6.],
       [1., 1., 1., 1., 1., 1.],
       [1., 1., 1., 6., 6., 6.]], dtype=float32)
```

### `index_add(x, idx, y)`

Pure equivalent of `x[idx] += y`.

LAX-backend implementation of `index_add()`. ADDITIONOriginal docstring below.

Returns the value of `x` that would result from the

**NumPy-style indexed assignment::** `x[idx] += y`

Note the `index_add` operator is pure; `x` itself is not modified, instead the new value that `x` would have
taken is returned.

Unlike the NumPy code `x[idx] += y`, if multiple indices refer to the same location the updates
will be summed. (NumPy would only apply the last update, rather than summing the updates.)
order in which conflicting updates are applied is implementation-defined and may be nondeterministic (e.g., due to concurrency on some hardware platforms).

**Args:**
x: an array with the values to be updated. idx: a Numpy-style index, consisting of None, integers, slice objects, ellipses, ndarrays with integer dtypes, or a tuple of the above. A convenient syntactic sugar for forming indices is via the `jax.ops.index` object.

**y:** the array of updates. *y* must be broadcastable to the shape of the array that would be returned by `x[idx].`

**Returns:**
An array.

```python
>>> x = jax.numpy.ones((5, 6))
>>> jax.ops.index_add(x, jax.ops.index[2:4, 3:], 6.)
array([[1., 1., 1., 1., 1., 1.],
       [1., 1., 1., 1., 1., 1.],
       [1., 1., 1., 7., 7., 7.],
       [1., 1., 1., 7., 7., 7.],
       [1., 1., 1., 1., 1., 1.]], dtype=float32)
```

**index_max** (x, idx, y)
Pure equivalent of `x[idx] = maximum(x[idx], y).`

LAX-backend implementation of `index_max()`. ADDITIONOriginal docstring below.

```
Returns the value of x that would result from the NumPy-style indexed assignment::
x[idx] = maximum(x[idx], y)
```

Note the `index_max` operator is pure; x itself is not modified, instead the new value that x would have taken is returned.

Unlike the NumPy code `x[idx] = maximum(x[idx], y),` if multiple indices refer to the same location the final value will be the overall max. (NumPy would only look at the last update, rather than all of the updates.)

**Args:**
x: an array with the values to be updated. idx: a Numpy-style index, consisting of None, integers, slice objects, ellipses, ndarrays with integer dtypes, or a tuple of the above. A convenient syntactic sugar for forming indices is via the `jax.ops.index` object.

**y:** the array of updates. *y* must be broadcastable to the shape of the array that would be returned by `x[idx].`

**Returns:**
An array.

```python
>>> x = jax.numpy.ones((5, 6))
>>> jax.ops.index_max(x, jax.ops.index[2:4, 3:], 6.)
array([[1., 1., 1., 1., 1., 1.],
       [1., 1., 1., 1., 1., 1.],
       [1., 1., 1., 6., 6., 6.],
       [1., 1., 1., 6., 6., 6.],
       [1., 1., 1., 1., 1., 1.]], dtype=float32)
```

**index_min** (x, idx, y)
Pure equivalent of `x[idx] = minimum(x[idx], y).`
LAX-backend implementation of `index_min()`. ADDITIONAL Original docstring below.

Returns the value of \( x \) that would result from the

**NumPy-style indexed assignment**: \( x[\text{idx}] = \text{minimum}(x[\text{idx}], y) \)

Note the `index_min` operator is pure; \( x \) itself is not modified, instead the new value that \( x \) would have taken is returned.

Unlike the NumPy code \( x[\text{idx}] = \text{minimum}(x[\text{idx}], y) \), if multiple indices refer to the same location the final value will be the overall min. (NumPy would only look at the last update, rather than all of the updates.)

**Args**: \( x \): an array with the values to be updated. \( \text{idx} \): a Numpy-style index, consisting of `None`, integers, `slice` objects, ellipses, ndarrays with integer dtypes, or a tuple of the above. A convenient syntactic sugar for forming indices is via the `jax.ops.index` object.

\( y \): the array of updates. \( y \) must be broadcastable to the shape of the \( x[\text{idx}] \) array that would be returned by \( x[\text{idx}] \).

**Returns**: An array.

```python
g = jax.numpy.ones((5, 6))
g = jax.ops.index_minimum(g, jax.ops.index[2:4, 3:], 0.)
```

### Numpy Like

**hat_1D** \((x, t_{\text{left}}, t_{\text{center}}, t_{\text{right}})\)

Hat basis function in 1-D

Hat function, continuous piecewise linear

**Parameters**

- \( x \) *(array-like)* – the sampled input space
- \( t_{\text{left}} \) *(scalar)* – the position of the left knot
- \( t_{\text{center}} \) *(scalar)* – the position of the center knot
- \( t_{\text{right}} \) *(scalar)* – the position of the right knot

**Returns** output – same shape as \( x \) with applied hat function

**Return type** array

**one_hot** \((i, N, \text{dtype}='\text{float32}')\)

Create a one-hot encoding of \( x \) of size \( k \).
Other

**abs** (x)
Calculate the absolute value element-wise.

LAX-backend implementation of `absolute()`. ADDITION
Original docstring below.

LAX-backend implementation of `absolute()`. Original docstring below.

```python
absolute(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

np.abs is a shorthand for this function.

**Returns absolute** — An ndarray containing the absolute value of each element in x. For complex input, a + ib, the absolute value is \(\sqrt{a^2 + b^2}\). This is a scalar if x is a scalar.

**Return type**  ndarray

### Examples

```python
>>> x = np.array([-1.2, 1.2])
>>> np.abs(x)
array([ 1.2, 1.2])
```

Plot the function over \([-10, 10]\):

```python
>>> import matplotlib.pyplot as plt
>>> x = np.linspace(start=-10, stop=10, num=101)
>>> plt.plot(x, np.abs(x))
>>> plt.show()
```

Plot the function over the complex plane:

```python
>>> xx = x + 1j * x[:, np.newaxis]
>>> plt.imshow(np.abs(xx), extent=[-10, 10, -10, 10], cmap='gray')
>>> plt.show()
```

abs(x)
Calculate the absolute value element-wise.

LAX-backend implementation of `absolute()`. ADDITION
Original docstring below.

LAX-backend implementation of `absolute()`. Original docstring below.

```python
absolute(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

np.abs is a shorthand for this function.

**Returns absolute** — An ndarray containing the absolute value of each element in x. For complex input, a + ib, the absolute value is \(\sqrt{a^2 + b^2}\). This is a scalar if x is a scalar.

**Return type**  ndarray

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Examples

```python
>>> x = np.array([-1.2, 1.2])
>>> np.absolute(x)
array([1.2, 1.2])
>>> np.absolute(1.2 + 1j)
1.5620499351813308
```

Plot the function over [-10, 10]:

```python
>>> import matplotlib.pyplot as plt

>>> x = np.linspace(start=-10, stop=10, num=101)
>>> plt.plot(x, np.absolute(x))
>>> plt.show()
```

Plot the function over the complex plane:

```python
>>> xx = x + 1j * x[:, np.newaxis]
>>> plt.imshow(np.abs(xx), extent=[-10, 10, -10, 10], cmap='gray')
>>> plt.show()
```

add (x1, x2)

Add arguments element-wise.

LAX-backend implementation of `add()`. ADDITION

Original docstring below.

```
Parameters:

- x1, x2: Input arrays to be added element-wise.

Returns:

- add: The sum of x1 and x2, element-wise. This is a scalar if both x1 and x2 are scalars.

Return type:

- ndarray or scalar

Notes

Equivalent to `x1 + x2` in terms of array broadcasting.

Examples

```python
>>> np.add(1.0, 4.0)
5.0
>>> x1 = np.arange(9.0).reshape((3, 3))
>>> x2 = np.arange(3.0)
>>> np.add(x1, x2)
array([[0., 2., 4.],
       [3., 5., 7.],
       [6., 8., 10.]])
```
```

all (a, axis=None, dtype=None, out=None, keepdims=False)

Test whether all array elements along a given axis evaluate to True.

LAX-backend implementation of `all()`. ADDITION

Original docstring below.

```
Parameters:

- a: Input array.
- axis: Axis along which the reduction is performed. If `None`, the product over all the dimensions is performed.
- dtype: The data type of the returned array and of the accumulator in which the elements are summed. By default, the accumulator data type is the same as the input array.
- out: Optional output array for the result.
- keepdims: If `True`, the axes that are reduced are left in the result as dimensions with size one.

Returns:

- result: A boolean array representing whether all elements along the specified axis evaluate to True.

Examples

```python
>>> np.all([1, 2, 3, 4])
True
>>> np.all([1, 2, 3, 4, 5], axis=0)
array([1, 2, 3, 4, 5], dtype=bool)
```
```
**Returns all** – A new boolean or array is returned unless `out` is specified, in which case a reference to `out` is returned.

**Return type**  ndarray, bool

See also:

- `ndarray.all()` equivalent method
- `any()` Test whether any element along a given axis evaluates to True.

**Notes**

Not a Number (NaN), positive infinity and negative infinity evaluate to `True` because these are not equal to zero.

**Examples**

```python
got = np.all([[True, False], [True, True]])
got
```

```python
got = np.all([[True, False], [True, True]], axis=0)
got
```

```python
got = np.all([-1, 4, 5])
got
```

```python
got = np.all([1.0, np.nan])
got
```

```python
z = np.all([-1, 4, 5], out=o)
io, id(o), z
```

**allclose** (`a, b, rtol=1e-05, atol=1e-08`)

Returns True if two arrays are element-wise equal within a tolerance.

LAX-backend implementation of `allclose()`. ADDITIONOriginal docstring below.

The tolerance values are positive, typically very small numbers. The relative difference \((rtol \times abs(b))\) and the absolute difference \(atol\) are added together to compare against the absolute difference between \(a\) and \(b\).

NaNs are treated as equal if they are in the same place and if `equal_nan=True`. Infs are treated as equal if they are in the same place and of the same sign in both arrays.

**Returns allclose** – Returns True if the two arrays are equal within the given tolerance; False otherwise.

**Return type**  bool

See also:

- `isclose()`, `all()`, `any()`, `equal()`
Notes

If the following equation is element-wise True, then allclose returns True.

\[
\text{absolute}(a - b) \leq (\text{atol} + \text{rtol} \times \text{absolute}(b))
\]

The above equation is not symmetric in \(a\) and \(b\), so that allclose\((a, b)\) might be different from allclose\((b, a)\) in some rare cases.

The comparison of \(a\) and \(b\) uses standard broadcasting, which means that \(a\) and \(b\) need not have the same shape in order for allclose\((a, b)\) to evaluate to True. The same is true for \textit{equal} but not \textit{array_equal}.

Examples

```python
>>> np.allclose([1.0, 1e-7], [1.00001e10, 1e-8])
False
>>> np.allclose([1.0, 1e-8], [1.00001e10, 1e-9])
True
>>> np.allclose([1.0, 1e-8], [1.0001e10, 1e-9])
False
>>> np.allclose([1.0, np.nan], [1.0, np.nan])
False
>>> np.allclose([1.0, np.nan], [1.0, np.nan], equal_nan=True)
True
```

`alltrue(a, axis=None, dtype=None, out=None, keepdims=False)`

Test whether all array elements along a given axis evaluate to True.

LAX-backend implementation of \texttt{all}(). ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{all}(). Original docstring below.

Returns all – A new boolean or array is returned unless \texttt{out} is specified, in which case a reference to \texttt{out} is returned.

Return type ndarray, bool

See also:

\texttt{ndarray.all()} equivalent method

\texttt{any()} Test whether any element along a given axis evaluates to True.

Notes

Not a Number (NaN), positive infinity and negative infinity evaluate to \textit{True} because these are not equal to zero.

Examples

```python
>>> np.all([[True, False], [True, True]])
False
>>> np.all([[True, False], [True, True]], axis=0)
array([[ True, False]])
```
```python
>>> np.all([-1, 4, 5])
True

>>> np.all([1.0, np.nan])
True

>>> o=np.array(False)
>>> z=np.all([-1, 4, 5], out=o)
>>> id(z), id(o), z
(28293632, 28293632, array(True)) # may vary
```

**amax** (*a*, *axis=None*, *dtype=None*, *out=None*, *keepdims=False*)

Return the maximum of an array or maximum along an axis.

LAX-backend implementation of `amax()`. Original docstring below.

LAX-backend implementation of `amax()`. Original docstring below.

Returns **amax** – Maximum of *a*. If *axis* is None, the result is a scalar value. If *axis* is given, the result is an array of dimension *a*.ndim – 1.

Return type

ndarray or scalar

See also:

*amin* The minimum value of an array along a given axis, propagating any NaNs.

*nanmax* The maximum value of an array along a given axis, ignoring any NaNs.

*maximum* Element-wise maximum of two arrays, propagating any NaNs.

*fmax* Element-wise maximum of two arrays, ignoring any NaNs.

*argmax* Return the indices of the maximum values.

*nanmin*, *minimum*, *fmin*

Notes

NaN values are propagated, that is if at least one item is NaN, the corresponding max value will be NaN as well. To ignore NaN values (MATLAB behavior), please use nanmax.

Don’t use `amax` for element-wise comparison of 2 arrays; when *a*.shape[0] is 2, `maximum(a[0], a[1])` is faster than `amax(a, axis=0)`.

Examples

```python
>>> a = np.arange(4).reshape((2,2))
>>> a
array([[0, 1],
       [2, 3]])
>>> np.amax(a)   # Maximum of the flattened array
3
>>> np.amax(a, axis=0)   # Maxima along the first axis
array([2, 3])
>>> np.amax(a, axis=1)   # Maxima along the second axis
array([1, 3])
```

(continues on next page)
You can use an initial value to compute the maximum of an empty slice, or to initialize it to a different value:

```
>>> np.max([-50], [10], axis=-1, initial=0)
array([ 0, 10])
```

Notice that the initial value is used as one of the elements for which the maximum is determined, unlike for the default argument Python’s `max` function, which is only used for empty iterables.

```
>>> np.max([5], initial=6)
6
>>> max([5], default=6)
5
```

## amin

```
amin(a, axis=None, dtype=None, out=None, keepdims=False)
```

Return the minimum of an array or minimum along an axis.

LAX-backend implementation of `amin()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `amin()`. Original docstring below.

| Returns | amin | Minimum of a. If `axis` is None, the result is a scalar value. If `axis` is given, the result is an array of dimension `a.ndim - 1`. |
|---------|------|---------------------------------------------------------------------------|

| Return type | ndarray or scalar |

See also:

- `amax()` The maximum value of an array along a given axis, propagating any NaNs.
- `nanmin()` The minimum value of an array along a given axis, ignoring any NaNs.
- `minimum()` Element-wise minimum of two arrays, propagating any NaNs.
- `fmin()` Element-wise minimum of two arrays, ignoring any NaNs.
- `argmin()` Return the indices of the minimum values.

- `nanmax()`, `maximum()`, `fmax()`
**Notes**

NaN values are propagated, that is if at least one item is NaN, the corresponding min value will be NaN as well. To ignore NaN values (MATLAB behavior), please use `nanmin`.

Don’t use `amin` for element-wise comparison of 2 arrays; when `a.shape[0]` is 2, `minimum(a[0], a[1])` is faster than `amin(a, axis=0)`.

**Examples**

```python
def example_code:
    a = np.arange(4).reshape((2,2))
    a
    # Minimum of the flattened array
    np.amin(a)
    # Minima along the first axis
    np.amin(a, axis=0)
    # Minima along the second axis
    np.amin(a, axis=1)
    np.amin(a, where=[False, True], initial=10, axis=0)
    np.array([[0, 1],
               [2, 3]])
    np.array([-50, 10])
    np.array([-50, 0])
```

>>> `b = np.arange(5, dtype=float)`

Notice that the initial value is used as one of the elements for which the minimum is determined, unlike for the default argument Python’s `min` function, which is only used for empty iterables.

Notice that this isn’t the same as Python’s `default` argument.

```python
def example_code:
    b
    # Minimum of the flattened array
    np.amin(b)
    # Minima along the first axis
    np.amin(b, axis=0)
    # Minima along the second axis
    np.amin(b, axis=1)
    np.amin(b, where=~np.isnan(b), initial=10)
    np.nanmin(b)
    np.array([-50, 10])
    np.array([-50, 0])
```

**angle(z)**

Return the angle of the complex argument.

LAX-backend implementation of `angle()`. ADDITION

LAX-backend implementation of `angle()`. Original docstring below.

**Returns**

- angle – The counterclockwise angle from the positive real axis on the complex plane in the range (-\(\pi\), \(\pi\)], with dtype as numpy.float64.

.. versionchanged:: 1.16.0 This function works on subclasses of ndarray like `ma.array`.
Return type  ndarray or scalar

See also:

arctan2(), absolute()

Examples

```python
>>> np.angle([1.0, 1.0j, 1+1j])  # in radians
array([ 0. , 1.57079633, 0.78539816]) # may vary
>>> np.angle(1+1j, deg=True)  # in degrees
45.0
```

any (a, axis=None, dtype=None, out=None, keepdims=False)
Test whether any array element along a given axis evaluates to True.

LAX-backend implementation of any(). ADDITIONOriginal docstring below.

LAX-backend implementation of any(). Original docstring below.

Returns single boolean unless axis is not None

Returns any – A new boolean or ndarray is returned unless out is specified, in which case a reference to out is returned.

Return type  bool or ndarray

See also:

daarray.any() equivalent method

all()  Test whether all elements along a given axis evaluate to True.

Notes
Not a Number (NaN), positive infinity and negative infinity evaluate to True because these are not equal to zero.

Examples

```python
>>> np.any([[True, False], [True, True]])
True

>>> np.any([[True, False], [False, False]], axis=0)
array([ True, False])

>>> np.any([-1, 0, 5])
True

>>> np.any(np.nan)
True

>>> o=np.array(False)
>>> z=np.any([-1, 4, 5], out=o)
>>> z, o
(array(True), array(True))
```

(continues on next page)
append \( (\text{arr}, \text{values}, \text{axis}=\text{None}) \)

Append values to the end of an array.

LAX-backend implementation of \( \text{append}() \). ADDITIONOriginal docstring below.

LAX-backend implementation of \( \text{append}() \). Original docstring below.

**Returns** append  – A copy of \( \text{arr} \) with \( \text{values} \) appended to \( \text{axis} \). Note that \( \text{append} \) does not occur in-place: a new array is allocated and filled. If \( \text{axis} \) is None, \( \text{out} \) is a flattened array.

**Return type**  \( \text{ndarray} \)

See also:

- **insert()** Insert elements into an array.
- **delete()** Delete elements from an array.

**Examples**

```python
>>> np.append([1, 2, 3], [[4, 5, 6], [7, 8, 9]])
array([1, 2, 3, ..., 7, 8, 9])
```

When \( \text{axis} \) is specified, \( \text{values} \) must have the correct shape.

```python
>>> np.append([[1, 2, 3], [4, 5, 6]], [[7, 8, 9]], axis=0)
array([[1, 2, 3],
       [4, 5, 6],
       [7, 8, 9]])
```

>>> np.append([[1, 2, 3], [4, 5, 6]], [[7, 8, 9]], axis=0)
Traceback (most recent call last):
  ...
ValueError: all the input arrays must have same number of dimensions
```

**arange** \( (\text{start}, \text{stop} = \text{None}, \text{step} = \text{None}, \text{dtype} = \text{None}) \)

Return evenly spaced values within a given interval.

LAX-backend implementation of \( \text{arange}() \). ADDITIONOriginal docstring below.

LAX-backend implementation of \( \text{arange}() \). Original docstring below.

\[ \text{arange}([\text{start}], \text{stop}, \text{step}, \text{dtype} = \text{None}) \]

Values are generated within the half-open interval \( [\text{start}, \text{stop}) \) (in other words, the interval including \( \text{start} \) but excluding \( \text{stop} \)). For integer arguments the function is equivalent to the Python built-in \text{range} function, but returns an ndarray rather than a list.

When using a non-integer step, such as 0.1, the results will often not be consistent. It is better to use \text{numpy.linspace} for these cases.

**Returns**
**arange** [ndarray] Array of evenly spaced values.

For floating point arguments, the length of the result is `ceil((stop - start)/step)`. Because of floating point overflow, this rule may result in the last element of `out` being greater than `stop`.

numpy.linspace : Evenly spaced numbers with careful handling of endpoints. numpy.ogrid: Arrays of evenly spaced numbers in N-dimensions. numpy.mgrid: Grid-shaped arrays of evenly spaced numbers in N-dimensions.

```python
>>> np.arange(3)
array([0, 1, 2])
>>> np.arange(3.0)
array([ 0., 1., 2.])
>>> np.arange(3,7)
array([3, 4, 5, 6])
>>> np.arange(3,7,2)
array([3, 5])
```

**arccos**

Trigonometric inverse cosine, element-wise.

LAX-backend implementation of `arccos()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `arccos()`. Original docstring below.

arccos(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

The inverse of `cos` so that, if `y = cos(x)`, then `x = arccos(y)`.

**Returns**

- **angle** – The angle of the ray intersecting the unit circle at the given x-coordinate in radians [0, pi]. This is a scalar if `x` is a scalar.

- **Return type** ndarray

**See also:**

cos(), arctan(), arcsin(), emath.arccos()

**Notes**

`arccos` is a multivalued function: for each `x` there are infinitely many numbers `z` such that `cos(z) = x`. The convention is to return the angle `z` whose real part lies in [0, pi].

For real-valued input data types, `arccos` always returns real output. For each value that cannot be expressed as a real number or infinity, it yields `nan` and sets the `invalid` floating point error flag.

For complex-valued input, `arccos` is a complex analytic function that has branch cuts [-inf, -1] and [1, inf] and is continuous from above on the former and from below on the latter.

The inverse `cos` is also known as `acos` or `cos^-1`. 
References

M. Abramowitz and I.A. Stegun, “Handbook of Mathematical Functions”, 10th printing, 1964, pp. 79. http://www.math.sfu.ca/~cbm/aands/

Examples

We expect the arccos of 1 to be 0, and of -1 to be pi:

```python
>>> np.arccos([1, -1])
array([ 0. ,  3.14159265])
```

Plot arccos:

```python
>>> import matplotlib.pyplot as plt
>>> x = np.linspace(-1, 1, num=100)
>>> plt.plot(x, np.arccos(x))
>>> plt.axis('tight')
>>> plt.show()
```

arccosh(x)

Inverse hyperbolic cosine, element-wise.

LAX-backend implementation of `arccosh()`. ADDITION

Original docstring below.

LAX-backend implementation of `arccosh()`. Original docstring below.

arccosh(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns arccosh – Array of the same shape as x. This is a scalar if x is a scalar.

Return type : ndarray

See also:

cosh(), arcsinh(), sinh(), arctanh(), tanh()

Notes

`arccosh` is a multivalued function: for each x there are infinitely many numbers z such that \( \cosh(z) = x \). The convention is to return the z whose imaginary part lies in \([-\pi, \pi]\) and the real part in \([0, \infty]\).

For real-valued input data types, `arccosh` always returns real output. For each value that cannot be expressed as a real number or infinity, it yields `nan` and sets the `invalid` floating point error flag.

For complex-valued input, `arccosh` is a complex analytical function that has a branch cut \([-\infty, 1]\) and is continuous from above on it.
References

Examples

```python
>>> np.arccosh([np.e, 10.0])
array([ 1.65745445, 2.99322285])
>>> np.arccosh(1)
0.0
```

arcsin\(x\)

Inverse sine, element-wise.

LAX-backend implementation of :func:`arcsin`. ADDITIONOriginal docstring below.

LAX-backend implementation of :func:`arcsin`. Original docstring below.

```python
arcsin(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

Returns angle 

The inverse sine of each element in \(x\), in radians and in the closed interval \([-\pi/2, \pi/2]\). This is a scalar if \(x\) is a scalar.

Return type

ndarray

See also:

\(\sin()\), \(\cos()\), \(\arccos()\), \(\tan()\), \(\arctan()\), \(\arctan2()\), \(\text{emath.arcsin()}\)

Notes

\(\arcsin\) is a multivalued function: for each \(x\) there are infinitely many numbers \(z\) such that \(\sin(z) = x\). The convention is to return the angle \(z\) whose real part lies in \([-\pi/2, \pi/2]\).

For real-valued input data types, \(\arcsin\) always returns real output. For each value that cannot be expressed as a real number or infinity, it yields \(\text{nan}\) and sets the \text{invalid} floating point error flag.

For complex-valued input, \(\arcsin\) is a complex analytic function that has, by convention, the branch cuts \([-\text{inf}, -1]\) and \([1, \text{inf}]\) and is continuous from above on the former and from below on the latter.

The inverse sine is also known as \(\text{asin}\) or \(\sin^{-1}\).

References

Abramowitz, M. and Stegun, I. A., *Handbook of Mathematical Functions*, 10th printing, New York: Dover, 1964, pp. 79ff. http://www.math.sfu.ca/~cbm/aands/

Examples

```python
>>> np.arcsin(1)    # pi/2
1.5707963267948966
>>> np.arcsin(-1)   # -pi/2
-1.5707963267948966
>>> np.arcsin(0)
0.0
```
\textbf{\texttt{arcsinh}(x)}

Inverse hyperbolic sine element-wise.

LAX-backend implementation of \texttt{arcsinh()}. ADDITION Original docstring below.

LAX-backend implementation of \texttt{arcsinh()}. Original docstring below.

\texttt{arcsinh(x, l, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])}

\textbf{Returns out} – Array of the same shape as \(x\). This is a scalar if \(x\) is a scalar.

\textbf{Return type} ndarray or scalar

\textbf{Notes}

\texttt{arcsinh} is a multivalued function: for each \(x\) there are infinitely many numbers \(z\) such that \(\sinh(z) = x\). The convention is to return the \(z\) whose imaginary part lies in \([-\pi/2, \pi/2]\).

For real-valued input data types, \texttt{arcsinh} always returns real output. For each value that cannot be expressed as a real number or infinity, it returns \texttt{nan} and sets the \texttt{invalid} floating point error flag.

For complex-valued input, \texttt{arccos} is a complex analytical function that has branch cuts \([1j, \infty j]\) and \([-1j, -\infty j]\) and is continuous from the right on the former and from the left on the latter.

The inverse hyperbolic sine is also known as \texttt{asinh} or \(\sinh^{-1}\).

\textbf{References}

\textbf{Examples}

\begin{verbatim}
>>> np.arcsinh(np.array([np.e, 10.0]))
array([ 1.72538256, 2.99822295])
\end{verbatim}

\textbf{\texttt{arctan}(x)}

Trigonometric inverse tangent, element-wise.

LAX-backend implementation of \texttt{arctan()}. ADDITION Original docstring below.

LAX-backend implementation of \texttt{arctan()}. Original docstring below.

\texttt{arctan(x, l, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])}

The inverse of tan, so that if \(y = \tan(x)\) then \(x = \arctan(y)\).

\textbf{Returns out} – Out has the same shape as \(x\). Its real part is in \([-\pi/2, \pi/2]\) \((\arctan(+/-\infty) \text{ returns } +/-\pi/2)\). This is a scalar if \(x\) is a scalar.

\textbf{Return type} ndarray or scalar

\textbf{See also:}

\texttt{arctan2()} The “four quadrant” \texttt{arctan} of the angle formed by \((x, y)\) and the positive \(x\)-axis.

\texttt{angle()} Argument of complex values.
Notes

\(arctan\) is a multi-valued function: for each \(x\) there are infinitely many numbers \(z\) such that \(\tan(z) = x\). The convention is to return the angle \(z\) whose real part lies in \([-\pi/2, \pi/2]\).

For real-valued input data types, \(arctan\) always returns real output. For each value that cannot be expressed as a real number or infinity, it yields \(nan\) and sets the \(invalid\) floating point error flag.

For complex-valued input, \(arctan\) is a complex analytic function that has \([ij, \infty j]\) and \([-ij, -\infty j]\) as branch cuts, and is continuous from the left on the former and from the right on the latter.

The inverse tangent is also known as \(atan\) or \(\tan^{-1}\).

References

Abramowitz, M. and Stegun, I. A., *Handbook of Mathematical Functions*, 10th printing, New York: Dover, 1964, pp. 79. [http://www.math.sfu.ca/~cbm/aands/](http://www.math.sfu.ca/~cbm/aands/)

Examples

We expect the \(arctan\) of 0 to be 0, and of 1 to be \(\pi/4\):

```python
>>> np.arctan([0, 1])
array([0.        , 0.78539816])
```

```python
>>> np.pi/4
0.78539816339744828
```

Plot \(arctan\):

```python
>>> import matplotlib.pyplot as plt
>>> x = np.linspace(-10, 10)
>>> plt.plot(x, np.arctan(x))
>>> plt.axis('tight')
>>> plt.show()
```

\(arctan2(x_1, x_2)\)

Element-wise arc tangent of \(x_1/x_2\) choosing the quadrant correctly.

LAX-backend implementation of \(arctan2()\). ADDITIONAL Original docstring below.

LAX-backend implementation of \(arctan2()\). Original docstring below.

arctan2\((x_1, x_2, /, out=None, *\), where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

The quadrant (i.e., branch) is chosen so that \(arctan2(x_1, x_2)\) is the signed angle in radians between the ray ending at the origin and passing through the point \((1,0)\), and the ray ending at the origin and passing through the point \((x_2, x_1)\). (Note the role reversal: the “\(y\)-coordinate” is the first function parameter, the “\(x\)-coordinate” is the second.) By IEEE convention, this function is defined for \(x_2 = +/-0\) and for either or both of \(x_1\) and \(x_2 = +/-\infty\) (see Notes for specific values).

This function is not defined for complex-valued arguments; for the so-called argument of complex values, use \(angle\).

**Returns**

\(angle\) – Array of angles in radians, in the range \([-\pi, \pi]\). This is a scalar if both \(x_1\) and \(x_2\) are scalars.
Return type  ndarray

See also:

arctan(), tan(), angle()

Notes

arctan2 is identical to the atan2 function of the underlying C library. The following special values are defined in the C standard: [1].

| x1  | x2  | arctan2(x1,x2) |
|-----|-----|----------------|
| +/-0| +0  | +/- 0          |
| +/-0| -0  | +/- pi         |
| > 0 | +/-inf| +0 / +pi     |
| < 0 | +/-inf| -0 / -pi      |
| +/-inf| +inf| +/- (pi/4)   |
| +/-inf| -inf| +/- (3*pi/4) |

Note that +0 and -0 are distinct floating point numbers, as are +inf and -inf.

References

Examples

Consider four points in different quadrants:

```python
>>> x = np.array([-1, +1, +1, -1])
>>> y = np.array([-1, -1, +1, +1])
>>> np.arctan2(y, x) * 180 / np.pi
array([-135., -45., 45., 135.])
```

Note the order of the parameters. arctan2 is defined also when x2 = 0 and at several other special points, obtaining values in the range [-pi, pi]:

```python
>>> np.arctan2([-1, -1], [0, 0])
array([ 1.57079633, -1.57079633])
>>> np.arctan2([-0, 0, np.inf], [+0, -0, np.inf])
array([ 0. , 3.14159265, 0.78539816])
```

arctanh(x)

Inverse hyperbolic tangent element-wise.

LAX-backend implementation of arctan(). ADDITIONOriginal docstring below.

LAX-backend implementation of arctan(). Original docstring below.

arctanh(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns out – Array of the same shape as x. This is a scalar if x is a scalar.

Return type  ndarray or scalar

See also:

emath.arctanh()
Notes

\( \text{arctanh} \) is a multivalued function: for each \( x \) there are infinitely many numbers \( z \) such that \( \tanh(z) = x \). The convention is to return the \( z \) whose imaginary part lies in \([-\pi/2, \pi/2]\).

For real-valued input data types, \( \text{arctanh} \) always returns real output. For each value that cannot be expressed as a real number or infinity, it yields \( \text{nan} \) and sets the \text{invalid} floating point error flag.

For complex-valued input, \( \text{arctanh} \) is a complex analytical function that has branch cuts \([-1, -\infty]\) and \([1, \infty]\) and is continuous from above on the former and from below on the latter.

The inverse hyperbolic tangent is also known as \( \text{atanh} \) or \( \tanh^{-1} \).

References

Examples

```python
>>> np.arctanh([0, -0.5])
array([ 0. , -0.54930614])
```

\texttt{argmax}(\( a, \text{axis}=\text{None} \))

Returns the indices of the maximum values along an axis.

LAX-backend implementation of \texttt{argmax()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{argmax()}. Original docstring below.

\textbf{Returns index array} – Array of indices into the array. It has the same shape as \( a.\text{shape} \) with the dimension along \( \text{axis} \) removed.

\textbf{Return type} \ ndarray of ints

See also:

\texttt{ndarray.argmax()}, \texttt{argmin()}

\texttt{amax()} \ The maximum value along a given axis.

\texttt{unravel_index()} \ Convert a flat index into an index tuple.

\texttt{take\_along\_axis()} \ Apply \texttt{np.expand_dims(index\_array, \text{axis})} from \texttt{argmax} to an array as if by calling \texttt{max}.

Notes

In case of multiple occurrences of the maximum values, the indices corresponding to the first occurrence are returned.

Examples

```python
>>> a = np.arange(6).reshape(2,3) + 10
>>> a
array([[10, 11, 12],
       [13, 14, 15]])
>>> np.argmax(a)
5
>>> np.argmax(a, axis=0)
```

(continues on next page)
Indexes of the maximal elements of a N-dimensional array:

```python
>>> np.argmax(a, axis=1)
array([2, 2])
```

Indexes of the maximal elements of a N-dimensional array:

```python
>>> ind = np.unravel_index(np.argmax(a, axis=None), a.shape)
>>> ind
(1, 2)
>>> a[ind]
15
```

```python
>>> b = np.arange(6)
>>> b[1] = 5
>>> b
array([0, 5, 2, 3, 4, 5])
```

```python
>>> np.argmax(b)  # Only the first occurrence is returned.
1
```

```python
>>> x = np.array([[4, 2, 3], [1, 0, 3]])
>>> index_array = np.argmax(x, axis=-1)
>>> np.take_along_axis(x, np.expand_dims(index_array, axis=-1), axis=-1)
array([[4],
       [3]])
```

```python
>>> np.take_along_axis(x, np.expand_dims(index_array, axis=-1), axis=-1).ravel()
array([4, 3])
```

`argmin(a, axis=None)`

Returns the indices of the minimum values along an axis.

LAX-backend implementation of `argmin()`. Original docstring below.

LAX-backend implementation of `argmin()`. Original docstring below.

Returns `index_array` – Array of indices into the array. It has the same shape as `a.shape` with the dimension along `axis` removed.

Return type `ndarray of ints`

See also:

- `ndarray.argmin()`, `argmax()`
- `amin()` The minimum value along a given axis.
- `unravel_index()` Convert a flat index into an index tuple.
- `take_along_axis()` Apply `np.expand_dims(index_array, axis)` from argmin to an array as if by calling min.
Notes

In case of multiple occurrences of the minimum values, the indices corresponding to the first occurrence are returned.

Examples

```python
>>> a = np.arange(6).reshape(2,3) + 10
>>> a
array([[10, 11, 12],
       [13, 14, 15]])
>>> np.argmin(a)
0
>>> np.argmin(a, axis=0)
array([0, 0, 0])
>>> np.argmin(a, axis=1)
array([0, 0])
```

Indices of the minimum elements of a N-dimensional array:

```python
>>> ind = np.unravel_index(np.argmin(a, axis=None), a.shape)
>>> ind
(0, 0)
```

```python
>>> x = np.array([[4,2,3], [1,0,3]])
>>> index_array = np.argmin(x, axis=-1)
>>> # Same as np.min(x, axis=-1, keepdims=True)
>>> np.take_along_axis(x, np.expand_dims(index_array, axis=-1), axis=-1)
array([[2],
       [0]])
>>> # Same as np.max(x, axis=-1)
>>> np.take_along_axis(x, np.expand_dims(index_array, axis=-1), axis=-1)....
```

`argsort(a, axis=-1, kind='quicksort', order=None)`

Returns the indices that would sort an array.

LAX-backend implementation of `argsort()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `argsort()`. Original docstring below.

Perform an indirect sort along the given axis using the algorithm specified by the `kind` keyword. It returns an array of indices of the same shape as `a` that index data along the given axis in sorted order.

**Returns** `index_array` – Array of indices that sort `a` along the specified `axis`. If `a` is one-dimensional, `a[index_array]` yields a sorted `a`. More generally, `np.take_along_axis(a, index_array, axis=axis)` always yields the sorted `a`, irrespective of dimensionality.
Return type  ndarray, int

See also:

- `sort()`  Describes sorting algorithms used.
- `lexsort()`  Indirect stable sort with multiple keys.
- `ndarray.sort()`  Inplace sort.
- `argpartition()`  Indirect partial sort.
- `take_along_axis()`  Apply `index_array` from argsort to an array as if by calling sort.

Notes

See `sort` for notes on the different sorting algorithms.

As of NumPy 1.4.0 `argsort` works with real/complex arrays containing nan values. The enhanced sort order is documented in `sort`.

Examples

One dimensional array:

```python
g = np.array([3, 1, 2])
g.argsort()  # [1, 2, 0]
```

Two-dimensional array:

```python
g = np.array([[0, 3], [2, 2]])
g.argsort(axis=0)  # [[0, 1], [1, 0]]
g.argsort(axis=1)  # [[0, 1], [0, 1]]
```

Indices of the sorted elements of a N-dimensional array:

```python
g = np.array([0, 1, 2, 3, 4])
g.argsort()  # [4, 1, 2, 3, 0]
```
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```python
>>> x[ind]  # same as np.sort(x, axis=None)
array([0, 2, 2, 3])
```

Sorting with keys:

```python
>>> x = np.array([[1, 0], [0, 1]], dtype=[('x', '<i4'), ('y', '<i4')])
>>> x
array([[1, 0],
       [0, 1]],
       dtype=[('x', '<i4'), ('y', '<i4')])
```

```python
>>> np.argsort(x, order=('x','y'))
array([1, 0])
```

```python
>>> np.argsort(x, order=('y','x'))
array([0, 1])
```

`around(a, decimals=0)`

Round an array to the given number of decimals.

LAX-backend implementation of `round_()`. ADDITIONOriginal docstring below.

LA

`asarray(a, dtype=None, order=None)`

Convert the input to an array.

LAX-backend implementation of `asarray()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `asarray()`. Original docstring below.

Parameters

- **dtype (data-type, optional)** – By default, the data-type is inferred from the input data.

Returns

- **out** – Array interpretation of `a`. No copy is performed if the input is already an ndarray with matching dtype and order. If `a` is a subclass of ndarray, a base class ndarray is returned.

Return type

ndarray

See also:

- `asanyarray()` Similar function which passes through subclasses.
- `ascontiguousarray()` Convert input to a contiguous array.
- `asarray()` Convert input to a floating point ndarray.
- `asfortranarray()` Convert input to an ndarray with column-major memory order.
- `asarray_chkfinite()` Similar function which checks input for NaNs and Infs.
- `fromiter()` Create an array from an iterator.
- `fromfunction()` Construct an array by executing a function on grid positions.
Examples

Convert a list into an array:

```python
>>> a = [1, 2]
>>> np.asarray(a)
array([1, 2])
```

Existing arrays are not copied:

```python
>>> a = np.array([1, 2])
>>> np.asarray(a) is a
True
```

If `dtype` is set, array is copied only if `dtype` does not match:

```python
>>> a = np.array([1, 2], dtype=np.float32)
>>> np.asarray(a, dtype=np.float32) is a
True
>>> np.asarray(a, dtype=np.float64) is a
False
```

Contrary to `asanyarray`, ndarray subclasses are not passed through:

```python
>>> issubclass(np.recarray, np.ndarray)
True
>>> a = np.array([(1.0, 2), (3.0, 4)], dtype='f4,i4').view(np.recarray)
>>> np.asarray(a)
False
>>> np.asanyarray(a)
True
```

**atleast_1d(**arys**)

Convert inputs to arrays with at least one dimension.

LAX-backend implementation of `atleast_1d()`.

Original docstring below.

Scalar inputs are converted to 1-dimensional arrays, whilst higher-dimensional inputs are preserved.

Returns

`ret [ndarray]` An array, or list of arrays, each with `a.ndim >= 1`. Copies are made only if necessary.

`atleast_2d`, `atleast_3d`

```python
>>> np.atleast_1d(1.0)
array([1.])
>>> x = np.arange(9.0).reshape(3,3)
>>> np.atleast_1d(x)
array([[ 0.,  1.,  2.],
       [ 3.,  4.,  5.],
       [ 6.,  7.,  8.]])
```

```python
>>> np.atleast_1d(x) is x
True
```
atleast_2d(*arys)
  View inputs as arrays with at least two dimensions.
  LAX-backend implementation of atleast_2d().
  Original docstring below.

  Parameters
  *arys (array, list of arrays) - Input data to be converted to arrays with
    at least two dimensions.

  Returns
  res, res2, … (ndarray) - An array, or list of arrays, each with
    ndim >= 2. Copies are avoided where possible, and views with two or more
    dimensions are returned.

  atleast_1d, atleast_3d

atleast_3d(*arys)
  View inputs as arrays with at least three dimensions.
  LAX-backend implementation of atleast_3d().
  Original docstring below.

  Parameters
  *arys (array, list of arrays) - Input data to be converted to arrays with
    at least three dimensions.

  Returns
  res1, res2, … (ndarray) - An array, or list of arrays, each with
    ndim >= 3. Copies are avoided where possible, and views with three or more
    dimensions are returned. For example, an 1-D array of shape (N,) becomes a
    view of shape (1, N, 1), and a 2-D array of shape
    (M, N) becomes a view of shape (M, N, 1).

  atleast_1d, atleast_2d
>>> x = np.arange(12.0).reshape(4,3)
>>> np.atleast_3d(x).shape
(4, 3, 1)
>>> np.atleast_3d(x).base is x.base  # x is a reshape, so not base itself
True

>>> for arr in np.atleast_3d([1, 2], [[1, 2]], [[[1, 2]]]):
...    print(arr, arr.shape)
...
[[[1]
 [2]]] (1, 2, 1)
[[[1]
 [2]]] (1, 2, 1)
[[[1 2]]] (1, 1, 2)

bitwise_and\((x1, x2)\)
Compute the bit-wise AND of two arrays element-wise.

LAX-backend implementation of `bitwise_and()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `bitwise_and()`. Original docstring below.

```
bitwise_and(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

Computes the bit-wise AND of the underlying binary representation of the integers in the input arrays. This ufunc implements the C/Python operator &.

Returns out – Result. This is a scalar if both x1 and x2 are scalars.

Return type ndarray or scalar

See also:
logical_and(), bitwise_or(), bitwise_xor()

binary_repr() Return the binary representation of the input number as a string.

Examples

The number 13 is represented by 00001101. Likewise, 17 is represented by 00010001. The bit-wise AND of 13 and 17 is therefore 00000000, or 1:

```
>>> np.bitwise_and(13, 17)
1
>>> np.bitwise_and(14, 13)
12
>>> np.bitwise_and([11,7], [4,25])
array([0, 1])
```
array([ 2,  4, 16])

>>> np.bitwise_and([True, True], [False, True])
array([False, True])

bitwise_not (x)
Compute bit-wise inversion, or bit-wise NOT, element-wise.
LAX-backend implementation of invert(). ADDITION
Original docstring below.

LAX-backend implementation of invert(). Original docstring below.
invert(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Computes the bit-wise NOT of the underlying binary representation of the integers in the input arrays. This
ufunc implements the C/Python operator  ~.

For signed integer inputs, the two’s complement is returned. In a two’s-complement system negative numbers
are represented by the two’s complement of the absolute value. This is the most common method of representing
signed integers on computers [1]_. A N-bit two’s-complement system can represent every integer in the range
\(-2^{N-1}\) to \(+2^{N-1} - 1\).

Returns out – Result. This is a scalar if x is a scalar.

Return type ndarray or scalar

See also:

bitwise_and(), bitwise_or(), bitwise_xor(), logical_not()
binary_repr() Return the binary representation of the input number as a string.

Notes

bitwise_not is an alias for invert:

>>> np.bitwise_not is np.invert
True

References

Examples

We’ve seen that 13 is represented by 00001101. The invert or bit-wise NOT of 13 is then:

>>> x = np.invert(np.array(13, dtype=np.uint8))
>>> x
242
>>> np.binary_repr(x, width=8)
'11110010'

The result depends on the bit-width:

>>> x = np.invert(np.array(13, dtype=np.uint16))
>>> x
65522

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When using signed integer types the result is the two’s complement of the result for the unsigned type:

```python
>>> np.invert(np.array([13], dtype=np.int8))
array([-14], dtype=int8)
>>> np.binary_repr(-14, width=8)
'11110010'
```

Booleans are accepted as well:

```python
>>> np.invert(np.array([True, False]))
array([False, True])
```

**bitwise_or(x1, x2)**

Compute the bit-wise OR of two arrays element-wise.

LAX-backend implementation of `bitwise_or()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `bitwise_or()`. Original docstring below.

`bitwise_or(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])`

Computes the bit-wise OR of the underlying binary representation of the integers in the input arrays. This ufunc implements the C/Python operator `|`.

- **Returns out** – Result. This is a scalar if both `x1` and `x2` are scalars.
- **Return type** `ndarray` or scalar

**See also:**

`logical_or()`, `bitwise_and()`, `bitwise_xor()`,

`binary_repr()` Return the binary representation of the input number as a string.

**Examples**

The number 13 has the binary representation 00001101. Likewise, 16 is represented by 00010000. The bit-wise OR of 13 and 16 is then 00011101, or 29:

```python
>>> np.bitwise_or(13, 16)
29
>>> np.binary_repr(29)
'11101'
```

```python
>>> np.bitwise_or(32, 2)
34
>>> np.bitwise_or([33, 4], 1)
array([33,  5])
>>> np.bitwise_or([33, 4], [1, 2])
array([33,  6])
```

```python
>>> np.bitwise_or(np.array([2, 5, 255]), np.array([4, 4, 4]))
array([ 6,  5, 255])
```
```python
>>> np.array([2, 5, 255]) | np.array([4, 4, 4])
array([ 6, 5, 255])
>>> np.bitwise_or(np.array([2, 5, 255, 2147483647], dtype=np.int32),
... np.array([4, 4, 4, 2147483647], dtype=np.int32))
array([ 6, 5, 255, 2147483647])
>>> np.bitwise_or([True, True], [False, True])
array([ True, True])
```

**bitwise_xor** *(x1, x2)*

Compute the bit-wise XOR of two arrays element-wise.

LAX-backend implementation of `bitwise_xor()`. ADDITION

Original docstring below.

LAX-backend implementation of `bitwise_xor()`. Original docstring below.

LAX-backend implementation of `bitwise_xor()`. ADDITION

`bitwise_xor(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])`

Computes the bit-wise XOR of the underlying binary representation of the integers in the input arrays. This ufunc implements the C/Python operator `^`.

**Returns**

`out` – Result. This is a scalar if both `x1` and `x2` are scalars.

**Return type**

ndarray or scalar

**See also:**

- `logical_xor()`, `bitwise_and()`, `bitwise_or()`
- `binary_repr()` — Return the binary representation of the input number as a string.

**Examples**

The number 13 is represented by `00001101`. Likewise, 17 is represented by `00010001`. The bit-wise XOR of 13 and 17 is therefore `00011100`, or 28:

```python
>>> np.bitwise_xor(13, 17)
28
>>> np.binary_repr(28)
'11100'
```

```python
>>> np.bitwise_xor(31, 5)
26
>>> np.bitwise_xor([31,3], 5)
array([26, 6])
```

```python
>>> np.bitwise_xor([31,3], [5,6])
array([26, 5])
>>> np.bitwise_xor([True, True], [False, True])
array([ True, False])
```

**block** *(arrays)*

Assemble an nd-array from nested lists of blocks.

LAX-backend implementation of `block()`. ADDITION

Original docstring below.

LAX-backend implementation of `block()`. Original docstring below.
Blocks in the innermost lists are concatenated (see `concatenate`) along the last dimension (-1), then these are concatenated along the second-last dimension (-2), and so on until the outermost list is reached.

Blocks can be of any dimension, but will not be broadcasted using the normal rules. Instead, leading axes of size 1 are inserted, to make `block.ndim` the same for all blocks. This is primarily useful for working with scalars, and means that code like `np.block([v, 1])` is valid, where `v.ndim == 1`.

When the nested list is two levels deep, this allows block matrices to be constructed from their components.

New in version 1.13.0.

Returns

- **block_array** – The array assembled from the given blocks.

  The dimensionality of the output is equal to the greatest of:
  * the dimensionality of all the inputs
  * the depth to which the input list is nested

Return type **ndarray**

Raises **ValueError** –

- If list depths are mismatched - for instance, `[[a, b], c]` is illegal, and should be spelt `[[a, b], [c]]`
- If lists are empty - for instance, `[[a, b], []]

See also:

- `concatenate()` – Join a sequence of arrays together.
- `stack()` – Stack arrays in sequence along a new dimension.
- `hstack()` – Stack arrays in sequence horizontally (column wise).
- `vstack()` – Stack arrays in sequence vertically (row wise).
- `dstack()` – Stack arrays in sequence depth wise (along third dimension).
- `vsplit()` – Split array into a list of multiple sub-arrays vertically.

Notes

When called with only scalars, `np.block` is equivalent to an `ndarray` call. So `np.block([[1, 2], [3, 4]])` is equivalent to `np.array([[1, 2], [3, 4]])`.

This function does not enforce that the blocks lie on a fixed grid. `np.block([[a, b], [c, d]])` is not restricted to arrays of the form:

```
AAAAbb
AAAbb
cccDD
```

But is also allowed to produce, for some `a`, `b`, `c`, `d`:

```
AAAAbb
AAAbb
cDDDD
```

Since concatenation happens along the last axis first, `block` is _not_ capable of producing the following directly:

```
AAAAbb
cccb
cccDD
```

See also:
Matlab’s “square bracket stacking”, \([A, B, \ldots; p, q, \ldots]\), is equivalent to `np.block([[A, B, \ldots], [p, q, \ldots]])`.

### Examples

The most common use of this function is to build a block matrix

```python
>>> A = np.eye(2) * 2
>>> B = np.eye(3) * 3
>>> np.block([[A, np.zeros((2, 3))], [np.ones((3, 2)), B]])
array([[ 2.,  0.,  0.,  0.,  0.],
       [ 0.,  2.,  0.,  0.,  0.],
       [ 1.,  1.,  3.,  0.,  0.],
       [ 1.,  1.,  0.,  3.,  0.],
       [ 1.,  1.,  0.,  0.,  3.]])
```

With a list of depth 1, `block` can be used as `hstack`

```python
>>> np.block([1, 2, 3])  # hstack([1, 2, 3])
array([1, 2, 3])
```

```python
>>> a = np.array([1, 2, 3])
>>> b = np.array([2, 3, 4])
>>> np.block([a, b])  # hstack([a, b])
array([ 1,  2,  3,  2,  3,  4, 10])
```

```python
>>> A = np.ones((2, 2), int)
>>> B = 2 * A
>>> np.block([A, B])  # hstack([A, B])
array([[ 1,  1,  2,  2],
       [ 1,  1,  2,  2]])
```

With a list of depth 2, `block` can be used in place of `vstack`:

```python
>>> a = np.array([1, 2, 3])
>>> b = np.array([2, 3, 4])
>>> np.block([[a], [b]])  # vstack([a, b])
array([[1, 2, 3],
       [2, 3, 4]])
```

```python
>>> A = np.ones((2, 2), int)
>>> B = 2 * A
>>> np.block([[A], [B]])  # vstack([A, B])
array([[ 1,  1],
       [ 2,  2],
       [ 2,  2]])
```

It can also be used in places of `atleast_1d` and `atleast_2d`

```python
>>> a = np.array(0)
>>> b = np.array([1])
```
can_cast()

Returns True if cast between data types can occur according to the casting rule. If from is a scalar or array scalar, also returns True if the scalar value can be cast without overflow or truncation to an integer.

LAX-backend implementation of can_cast().

```
can_cast(from_, to, casting='safe')
```

Returns

out [bool] True if cast can occur according to the casting rule.

Changed in version 1.17.0: Casting between a simple data type and a structured one is possible only for “unsafe” casting. Casting to multiple fields is allowed, but casting from multiple fields is not.

Changed in version 1.9.0: Casting from numeric to string types in ‘safe’ casting mode requires that the string dtype length is long enough to store the maximum integer/float value converted.

dtype, result_type

Basic examples

```
>>> np.can_cast(np.int32, np.int64)
True
>>> np.can_cast(np.float64, complex)
True
>>> np.can_cast(complex, float)
False
```

```
>>> np.can_cast('i8', 'f8')
True
>>> np.can_cast('i8', 'f4')
False
>>> np.can_cast('i4', 'S4')
False
```

Casting scalars

```
>>> np.can_cast(100, 'i1')
True
>>> np.can_cast(150, 'i1')
False
>>> np.can_cast(150, 'u1')
True
```
```python
>>> np.can_cast(3.5e100, np.float32)
False
>>> np.can_cast(1000.0, np.float32)
True
```

Array scalar checks the value, array does not

```python
>>> np.can_cast(np.array(1000.0), np.float32)
True
>>> np.can_cast(np.array([1000.0]), np.float32)
False
```

Using the casting rules

```python
>>> np.can_cast('i8', 'i8', 'no')
True
>>> np.can_cast('<i8', '>i8', 'no')
False
>>> np.can_cast('<i8', '>i8', 'equiv')
True
>>> np.can_cast('<i4', '>i8', 'equiv')
False
>>> np.can_cast('<i4', '>i8', 'safe')
True
>>> np.can_cast('<i8', '>u4', 'safe')
False
>>> np.can_cast('<i8', '>u4', 'same_kind')
True
>>> np.can_cast('<i8', '>u4', 'unsafe')
True
```

**cei**l \((x)\)

Return the ceiling of the input, element-wise.

LAX-backend implementation of `ceil()`. ADDITION

LAX-backend implementation of `ceil()`. Original docstring below.

ceil(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

The ceiling of the scalar \(x\) is the smallest integer \(i\), such that \(i \geq x\). It is often denoted as \([x]\).

**Returns**

\(y\) – The ceiling of each element in \(x\), with float dtype. This is a scalar if \(x\) is a scalar.

**Return type** ndarray or scalar

See also:

`floor()`, `trunc()`, `rint()`
Examples

```python
>>> a = np.array([-1.7, -1.5, -0.2, 0.2, 1.5, 1.7, 2.0])
>>> np.ceil(a)
array([-1., -1., -0., 1., 2., 2., 2.])
```

**clip** *(a, a_min=None, a_max=None)*

Clip (limit) the values in an array.

LAX-backend implementation of `clip()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `clip()`. Original docstring below.

Given an interval, values outside the interval are clipped to the interval edges. For example, if an interval of [0, 1] is specified, values smaller than 0 become 0, and values larger than 1 become 1.

Equivalent to but faster than `np.maximum(a_min, np.minimum(a, a_max))`. No check is performed to ensure `a_min < a_max`.

**Returns** clipped_array – An array with the elements of `a`, but where values < `a_min` are replaced with `a_min`, and those > `a_max` with `a_max`.

**Return type** `ndarray`

See also:

`ufuncs-output-type()`

Examples

```python
>>> a = np.arange(10)
>>> np.clip(a, 1, 8)
array([1, 1, 2, 3, 4, 5, 6, 7, 8, 8])
```

```python
>>> a = np.arange(10)
>>> np.clip(a, [3, 4, 1, 1, 1, 4, 4, 4, 4, 4], 8)
array([3, 4, 2, 3, 4, 5, 6, 7, 8, 8])
```

**column_stack** *(tup)*

Stack 1-D arrays as columns into a 2-D array.

LAX-backend implementation of `column_stack()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `column_stack()`. Original docstring below.

Take a sequence of 1-D arrays and stack them as columns to make a single 2-D array. 2-D arrays are stacked as-is, just like with `hstack`. 1-D arrays are turned into 2-D columns first.

**Returns** stacked – The array formed by stacking the given arrays.

**Return type** 2-D array

See also:

`stack()`, `hstack()`, `vstack()`, `concatenate()`
Examples

```python
>>> a = np.array((1, 2, 3))
>>> b = np.array((2, 3, 4))
>>> np.column_stack((a, b))
array([[1, 2],
       [2, 3],
       [3, 4]])
```

**concatenate** *(arrays, axis=0)*

Join a sequence of arrays along an existing axis.

LAX-backend implementation of `concatenate()`. ADDITION

Original docstring below.

LAX-backend implementation of `concatenate()`. Original docstring below.

```python
concatenate((a1, a2, ...), axis=0, out=None)

Returns

res [ndarray] The concatenated array.

ma.concatenate : Concatenate function that preserves input masks. array_split : Split an array into multiple sub-arrays of equal or near-equal size.

split : Split array into a list of multiple sub-arrays of equal size. hstack : Stack arrays in sequence horizontally (column wise) vsplit : Split array into multiple sub-arrays vertically (row wise) dstack : Stack array into multiple sub-arrays along the 3rd axis (depth). stack : Stack a sequence of arrays along a new axis. hstack : Stack arrays in sequence horizontally (column wise) vstack : Stack arrays in sequence vertically (row wise) dstack : Stack arrays in sequence depth wise (along third dimension) block : Assemble arrays from blocks.

When one or more of the arrays to be concatenated is a MaskedArray, this function will return a MaskedArray object instead of an ndarray, but the input masks are not preserved. In cases where a MaskedArray is expected as input, use the ma.concatenate function from the masked array module instead.

```python
>>> a = np.array([[1, 2], [3, 4]])
>>> b = np.array([[5, 6]])
>>> np.concatenate((a, b), axis=0)
array([[1, 2],
       [3, 4],
       [5, 6]])
>>> np.concatenate((a, b.T), axis=1)
array([[1, 2, 5],
       [3, 4, 6]])
>>> np.concatenate((a, b), axis=None)
array([1, 2, 3, 4, 5, 6])
```

This function will not preserve masking of MaskedArray inputs.

```python
>>> a = np.ma.arange(3)
>>> a[1] = np.ma.masked
>>> b = np.arange(2, 5)
>>> a
masked_array(data=[0, --, 2],
             mask=[False, True, False],
```
```python
>>> b
array([2, 3, 4])
>>> np.concatenate([a, b])
masked_array(data=[0, 1, 2, 2, 3, 4],
    mask=False,
    fill_value=999999)
>>> np.ma.concatenate([a, b])
masked_array(data=[0, --, 2, 2, 3, 4],
    mask=[False, True, False, False, False, False],
    fill_value=999999)
```

`np.conj(x)`

Return the complex conjugate, element-wise.

LAX-backend implementation of `conjugate()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `conjugate()`. Original docstring below.

```
conjugate(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

The complex conjugate of a complex number is obtained by changing the sign of its imaginary part.

**Returns**
- `y` – The complex conjugate of `x`, with same dtype as `y`. This is a scalar if `x` is a scalar.

**Return type**
`ndarray`

**Notes**

`np.conj` is an alias for `np.conjugate`:

```python
>>> np.conj is np.conjugate
True
```

**Examples**

```python
>>> np.conjugate(1+2j)
(1-2j)
```

```python
>>> x = np.eye(2) + 1j * np.eye(2)
>>> np.conjugate(x)
array([[ 1.-1.j, 0.-0.j],
       [ 0.-0.j, 1.-1.j]])
```

`np.conjugate(x)`

Return the complex conjugate, element-wise.

LAX-backend implementation of `conjugate()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `conjugate()`. Original docstring below.

```
conjugate(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

The complex conjugate of a complex number is obtained by changing the sign of its imaginary part.
Returns y – The complex conjugate of x, with same dtype as y. This is a scalar if x is a scalar.

Return type ndarray

Notes

conj is an alias for conjugate:

```python
>>> np.conj is np.conjugate
True
```

Examples

```python
>>> np.conjugate(1+2j)
(1-2j)
```

```python
>>> x = np.eye(2) + 1j * np.eye(2)
>>> np.conjugate(x)
array([[ 1.-1.j,  0.-0.j],
       [ 0.-0.j,  1.-1.j]])
```

corrcoef (x, y=None, rowvar=True)

Return Pearson product-moment correlation coefficients.

LAX-backend implementation of corrcoef(). ADDITIONOriginal docstring below.

LAX-backend implementation of corrcoef(). Original docstring below.

Please refer to the documentation for cov for more detail. The relationship between the correlation coefficient matrix, R, and the covariance matrix, C, is

\[ R_{ij} = \frac{C_{ij}}{\sqrt{C_{ii} * C_{jj}}} \]

The values of R are between -1 and 1, inclusive.

Returns R – The correlation coefficient matrix of the variables.

Return type ndarray

See also:

cov() Covariance matrix

Notes

Due to floating point rounding the resulting array may not be Hermitian, the diagonal elements may not be 1, and the elements may not satisfy the inequality abs(a) <= 1. The real and imaginary parts are clipped to the interval [-1, 1] in an attempt to improve on that situation but is not much help in the complex case.

This function accepts but discards arguments bias and ddof. This is for backwards compatibility with previous versions of this function. These arguments had no effect on the return values of the function and can be safely ignored in this and previous versions of numpy.
cos(x)
Cosine element-wise.
LAX-backend implementation of `cos()`. ADDITIONOriginal docstring below.
LAX-backend implementation of `cos()`. Original docstring below.
cos(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns y – The corresponding cosine values. This is a scalar if x is a scalar.

Return type  ndarray

Notes
If out is provided, the function writes the result into it, and returns a reference to out. (See Examples)

References
M. Abramowitz and I. A. Stegun, Handbook of Mathematical Functions. New York, NY: Dover, 1972.

Examples

```python
>>> np.cos(np.array([0, np.pi/2, np.pi]))
array([ 1.00000000e+00, 6.12303177e-17, -1.00000000e+00])

>>> # Example of providing the optional output parameter
>>> out1 = np.array([0], dtype='d')
>>> out2 = np.cos([0.1], out1)
>>> out2 is out1
True

>>> # Example of ValueError due to provision of shape mis-matched `out`
>>> np.cos(np.zeros((3,3)),np.zeros((2,2)))
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
ValueError: operands could not be broadcast together with shapes (3,3) (2,2)
```

cosh(x)
Hyperbolic cosine, element-wise.
LAX-backend implementation of `cosh()`. ADDITIONOriginal docstring below.
LAX-backend implementation of `cosh()`. Original docstring below.
cosh(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Equivalent to \( \frac{1}{2} \ast (\exp(x) + \exp(-x)) \) and \( \cos(1j\ast x) \).

Returns out – Output array of same shape as x. This is a scalar if x is a scalar.

Return type  ndarray or scalar
Examples

```python
>>> np.cosh(0)
1.0
```

The hyperbolic cosine describes the shape of a hanging cable:

```python
>>> import matplotlib.pyplot as plt
>>> x = np.linspace(-4, 4, 1000)
>>> plt.plot(x, np.cosh(x))
>>> plt.show()
```

count_nonzero(a, axis=None)

Counts the number of non-zero values in the array `a`.

LAX-backend implementation of `count_nonzero()`. Original docstring below.

The word “non-zero” is in reference to the Python 2.x built-in method `__nonzero__()` (renamed `__bool__()` in Python 3.x) of Python objects that tests an object’s “truthfulness”. For example, any number is considered truthful if it is nonzero, whereas any string is considered truthful if it is not the empty string. Thus, this function (recursively) counts how many elements in `a` (and in sub-arrays thereof) have their `__nonzero__()` or `__bool__()` method evaluated to `True`.

**Returns**

- `count` – Number of non-zero values in the array along a given axis. Otherwise, the total number of non-zero values in the array is returned.

**Return type**

int or array of int

See also:

nonzero() Return the coordinates of all the non-zero values.

Examples

```python
>>> np.count_nonzero(np.eye(4))
4
>>> np.count_nonzero([[0,1,7,0],[3,0,0,2,19]])
5
```  

cov (m, y=None, rowvar=True, bias=False, ddof=None, fweights=None, aweights=None)

Estimate a covariance matrix, given data and weights.

LAX-backend implementation of `cov()`. Original docstring below.

Covariance indicates the level to which two variables vary together. If we examine N-dimensional samples, $X = [x_1, x_2, ..., x_N]^T$, then the covariance matrix element $C_{ij}$ is the covariance of $x_i$ and $x_j$. The element $C_{ii}$ is the variance of $x_i$.

See the notes for an outline of the algorithm.

**Returns**

- `out` – The covariance matrix of the variables.
**Return type**  ndarray

See also:

`corrcoef()`  Normalized covariance matrix

**Notes**

Assume that the observations are in the columns of the observation array `m` and let `f = fweights` and `a = aweights` for brevity. The steps to compute the weighted covariance are as follows:

```python
>>> m = np.arange(10, dtype=np.float64)
>>> f = np.arange(10) * 2
>>> a = np.arange(10) ** 2.
>>> ddof = 1
>>> w = f * a
>>> v1 = np.sum(w)
>>> v2 = np.sum(w * a)
>>> m -= np.sum(m * w, axis=None, keepdims=True) / v1
>>> cov = np.dot(m * w, m.T) * v1 / (v1**2 - ddof * v2)
```

Note that when `a == 1`, the normalization factor `v1 / (v1**2 - ddof * v2)` goes over to `1 / (np.sum(f) - ddof)` as it should.

**Examples**

Consider two variables, `x_0` and `x_1`, which correlate perfectly, but in opposite directions:

```python
>>> x = np.array([[0, 2], [1, 1], [2, 0]]).T
>>> x
array([[0, 1, 2],
       [2, 1, 0]])
```

Note how `x_0` increases while `x_1` decreases. The covariance matrix shows this clearly:

```python
>>> np.cov(x)
array([[ 1., -1.],
       [-1., 1.]])
```

Note that element `C_{0,1}`, which shows the correlation between `x_0` and `x_1`, is negative.

Further, note how `x` and `y` are combined:

```python
>>> x = [-2.1, -1, 4.3]
>>> y = [3, 1.1, 0.12]
>>> X = np.stack((x, y), axis=0)
>>> np.cov(X)
array([[11.71 , -4.286 ],
       [-4.286 , 2.144133]])
```

```python
>>> np.cov(x, y)
array([[11.71 , -4.286 ],
       [-4.286 , 2.144133]])
```

```python
>>> np.cov(x)
array(11.71)
```

**cross** `(a, b, axisa=-1, axisb=-1, axisc=-1, axis=None)`

Return the cross product of two (arrays of) vectors.

2.1. General
LAX-backend implementation of `cross()`. ADDITION Original docstring below.

The cross product of \(a\) and \(b\) in \(\mathbb{R}^3\) is a vector perpendicular to both \(a\) and \(b\). If \(a\) and \(b\) are arrays of vectors, the vectors are defined by the last axis of \(a\) and \(b\) by default, and these axes can have dimensions 2 or 3. Where the dimension of either \(a\) or \(b\) is 2, the third component of the input vector is assumed to be zero and the cross product calculated accordingly. In cases where both input vectors have dimension 2, the z-component of the cross product is returned.

**Returns** \(c\) – Vector cross product(s).

**Return type** ndarray

**Raises** `ValueError` – When the dimension of the vector(s) in \(a\) and/or \(b\) does not equal 2 or 3.

**See also:**

- `inner()` Inner product
- `outer()` Outer product.
- `ix_()` Construct index arrays.

**Notes**

New in version 1.9.0.

Supports full broadcasting of the inputs.

**Examples**

Vector cross-product.

```python
>>> x = [1, 2, 3]
>>> y = [4, 5, 6]
>>> np.cross(x, y)
array([-3, 6, -3])
```

One vector with dimension 2.

```python
>>> x = [1, 2]
>>> y = [4, 5, 6]
>>> np.cross(x, y)
array([12, -6, -3])
```

Equivalently:

```python
>>> x = [1, 2, 0]
>>> y = [4, 5, 6]
>>> np.cross(x, y)
array([12, -6, -3])
```

Both vectors with dimension 2.

```python
>>> x = [1, 2]
>>> y = [4, 5]
>>> np.cross(x, y)
array(-3)
```
Multiple vector cross-products. Note that the direction of the cross product vector is defined by the right-hand rule.

```python
>>> x = np.array([[1,2,3], [4,5,6]])
>>> y = np.array([[4,5,6], [1,2,3]])
>>> np.cross(x, y)
array([[-3, 6, -3],
       [ 3, -6,  3]])
```

The orientation of $c$ can be changed using the `axis` keyword.

```python
>>> np.cross(x, y, axis=0)
array([[-3, 3],
       [ 6, -6],
       [-3, 3]])
```

Change the vector definition of $x$ and $y$ using `axisa` and `axisb`.

```python
>>> x = np.array([[1,2,3], [4,5,6], [7, 8, 9]])
>>> y = np.array([[7, 8, 9], [4,5,6], [1,2,3]])
>>> np.cross(x, y)
array([[-6, 12, -6],
       [ 0,  0,  0],
       [ 6, -12,  6]])
```

```python
>>> np.cross(x, y, axisa=0, axisb=0)
array([[-24, 48, -24],
       [-30, 60, -30],
       [-36, 72, -36]])
```

cumsum(a, axis=None, dtype=None)

Return the cumulative sum of the elements along a given axis.

LAX-backend implementation of `cumsum()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `cumsum()`. Original docstring below.

Parameters

dtype (dtype, optional) – Type of the returned array and of the accumulator in which the elements are summed. If dtype is not specified, it defaults to the dtype of a, unless a has an integer dtype with a precision less than that of the default platform integer. In that case, the default platform integer is used.

Returns

cumsum_along_axis – A new array holding the result is returned unless out is specified, in which case a reference to out is returned. The result has the same size as a, and the same shape as a if axis is not None or a is a 1-d array.

Return type

ndarray.

See also:

sum() Sum array elements.

trapz() Integration of array values using the composite trapezoidal rule.

diff() Calculate the n-th discrete difference along given axis.
Notes

Arithmetic is modular when using integer types, and no error is raised on overflow.

Examples

```python
>>> a = np.array([[1,2,3], [4,5,6]])
>>> a
array([[1, 2, 3],
       [4, 5, 6]])
>>> np.cumsum(a)
array([ 1, 3, 6, 10, 15, 21])
>>> np.cumsum(a, dtype=float)  # specifies type of output value(s)
array([ 1., 3., 6., 10., 15., 21.])
>>> np.cumsum(a,axis=0)        # sum over rows for each of the 3 columns
array([[1, 2, 3],
       [5, 7, 9]])
>>> np.cumsum(a,axis=1)        # sum over columns for each of the 2 rows
array([[ 1, 3, 6],
       [ 4, 9, 15]])
```

cumprod

Return the cumulative product of elements along a given axis.

LAX-backend implementation of `cumprod()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `cumprod()`. Original docstring below.

Parameters
dtype (dtype, optional) – Type of the returned array, as well as of the accumulator in which the elements are multiplied. If dtype is not specified, it defaults to the dtype of a, unless a has an integer dtype with a precision less than that of the default platform integer. In that case, the default platform integer is used instead.

Returns
cumprod – A new array holding the result is returned unless out is specified, in which case a reference to out is returned.

Return type
ndarray

See also:
ufuncs-output-type()

Notes

Arithmetic is modular when using integer types, and no error is raised on overflow.
Examples

```python
>>> a = np.array([1, 2, 3])
>>> np.cumprod(a)  # intermediate results 1, 1*2
...                # total product 1*2*3 = 6
array([1, 2, 6])
>>> a = np.array([[1, 2, 3], [4, 5, 6]])
>>> np.cumprod(a, dtype=float)  # specify type of output
array([1., 2., 6., 24., 120., 720.])
```

The cumulative product for each column (i.e., over the rows) of `a`:  
```python
>>> np.cumprod(a, axis=0)
array([[1, 2, 3],
       [4, 10, 18]])
```

The cumulative product for each row (i.e. over the columns) of `a`:  
```python
>>> np.cumprod(a, axis=1)
array([[1, 2, 6],
       [4, 20, 120]])
```

cumprod `(a, axis=None, dtype=None)`

Return the cumulative product of elements along a given axis.

LAX-backend implementation of `cumprod()`. ADDITIONAL Original docstring below.

LAX-backend implementation of `cumprod()`. Original docstring below.

Parameters `dtype` *(dtype, optional)* – Type of the returned array, as well as of the accumulator in which the elements are multiplied. If `dtype` is not specified, it defaults to the dtype of `a`, unless `a` has an integer `dtype` with a precision less than that of the default platform integer. In that case, the default platform integer is used instead.

Returns `cumprod` – A new array holding the result is returned unless `out` is specified, in which case a reference to out is returned.

Return type `ndarray`

See also:

ufuncs-output-type()

Notes

Arithmetic is modular when using integer types, and no error is raised on overflow.

Examples

```python
>>> a = np.array([1, 2, 3])
>>> np.cumprod(a)  # intermediate results 1, 1*2
...                # total product 1*2*3 = 6
array([1, 2, 6])
>>> a = np.array([[1, 2, 3], [4, 5, 6]])
>>> np.cumprod(a, dtype=float)  # specify type of output
array([1., 2., 6., 24., 120., 720.])
```

The cumulative product for each column (i.e., over the rows) of `a`: 

```python
>>> np.cumprod(a, axis=0)
array([[ 1,  2,  3],
       [ 4, 10, 18]])
```

The cumulative product for each row (i.e. over the columns) of `a`:

```python
>>> np.cumprod(a, axis=1)
array([[ 1,  2,  6],
       [ 4, 20, 120]])
```

deg2rad(x)

Convert angles from degrees to radians.

LAX-backend implementation of `deg2rad()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `deg2rad()`. Original docstring below.

```
deg2rad(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

**Returns** y – The corresponding angle in radians. This is a scalar if `x` is a scalar.

**Return type** ndarray

See also:

- `rad2deg()` Convert angles from radians to degrees.
- `unwrap()` Remove large jumps in angle by wrapping.

**Notes**

New in version 1.3.0.

deg2rad(x) is `x * \pi / 180`.

**Examples**

```python
>>> np.deg2rad(180)
3.1415926535897931
```

degrees(x)

Convert angles from radians to degrees.

LAX-backend implementation of `rad2deg()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `rad2deg()`. Original docstring below.

```
rad2deg(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

**Returns** y – The corresponding angle in degrees. This is a scalar if `x` is a scalar.

**Return type** ndarray

See also:

- `deg2rad()` Convert angles from degrees to radians.
- `unwrap()` Remove large jumps in angle by wrapping.
Notes

New in version 1.3.0.

`rad2deg(x)` is `180 * x / pi`.

Examples

```python
>>> np.rad2deg(np.pi/2)
90.0
```

diag(v, k=0)

Extract a diagonal or construct a diagonal array.

LAX-backend implementation of `diag()`.

LAX-backend implementation of `diag()`. Original docstring below.

See the more detailed documentation for `numpy.diagonal` if you use this function to extract a diagonal and wish to write to the resulting array; whether it returns a copy or a view depends on what version of numpy you are using.

Returns out – The extracted diagonal or constructed diagonal array.

Return type ndarray

See also:

`diagonal()` Return specified diagonals.

`diagflat()` Create a 2-D array with the flattened input as a diagonal.

`trace()` Sum along diagonals.

`triu()` Upper triangle of an array.

`tril()` Lower triangle of an array.

Examples

```python
>>> x = np.arange(9).reshape((3,3))
>>> x
array([[0, 1, 2],
       [3, 4, 5],
       [6, 7, 8]])

>>> np.diag(x)
array([0, 4, 8])

>>> np.diag(x, k=1)
array([1, 5])

>>> np.diag(x, k=-1)
array([3, 7])

>>> np.diag(np.diag(x))
array([[0, 0, 0],
       [0, 4, 0],
       [0, 0, 8]])
```
**diag_indices** \((n, ndim=2)\)

Return the indices to access the main diagonal of an array.

LAX-backend implementation of `diag_indices()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `diag_indices()`. Original docstring below.

This returns a tuple of indices that can be used to access the main diagonal of an array \(a\) with \(a.ndim \geq 2\) dimensions and shape \((n, n, \ldots, n)\). For \(a.ndim = 2\) this is the usual diagonal, for \(a.ndim > 2\) this is the set of indices to access \(a[i, i, \ldots, i]\) for \(i = [0..n-1]\).

**Parameters**

- **diagonal**

```python
np.diag_indices(a, offset=0, axis1=0, axis2=1)
```

Return specified diagonals.

LAX-backend implementation of `diagonal()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `diagonal()`. Original docstring below.

If \(a\) is 2-D, returns the diagonal of \(a\) with the given offset, i.e., the collection of elements of the form \(a[i, i+offset]\). If \(a\) has more than two dimensions, then the axes specified by `axis1` and `axis2` are used to determine the 2-D sub-array whose diagonal is returned. The shape of the resulting array can be determined by removing `axis1` and `axis2` and appending an index to the right equal to the size of the resulting diagonals.

In versions of NumPy prior to 1.7, this function always returned a new, independent array containing a copy of the values in the diagonal.

In NumPy 1.7 and 1.8, it continues to return a copy of the diagonal, but depending on this fact is deprecated. Writing to the resulting array continues to work as it used to, but a FutureWarning is issued.

Starting in NumPy 1.9 it returns a read-only view on the original array. Attempting to write to the resulting array will produce an error.

In some future release, it will return a read/write view and writing to the returned array will alter your original array. The returned array will have the same type as the input array.

If you don’t write to the array returned by this function, then you can just ignore all of the above.

If you depend on the current behavior, then we suggest copying the returned array explicitly, i.e., use `np.diagonal(a).copy()` instead of just `np.diagonal(a)`. This will work with both past and future versions of NumPy.

**Returns**

```python
array_of_diagonals
```

- **array_of_diagonals** – If \(a\) is 2-D, then a 1-D array containing the diagonal and of the same type as \(a\) is returned unless \(a\) is a matrix, in which case a 1-D array rather than a (2-D) matrix is returned in order to maintain backward compatibility.

  If \(a.ndim > 2\), then the dimensions specified by `axis1` and `axis2` are removed, and a new axis inserted at the end corresponding to the diagonal.

**Return type**

`ndarray`

**Raises**

**ValueError** – If the dimension of \(a\) is less than 2.

**See also**

- `diag()` MATLAB work-a-like for 1-D and 2-D arrays.
- `diagflat()` Create diagonal arrays.
- `trace()` Sum along diagonals.
## Examples

```python
>>> a = np.arange(4).reshape(2,2)
>>> a
array([[0, 1],
       [2, 3]])

>>> a.diagonal()
array([0, 3])

>>> a.diagonal(1)
array([1])
```

A 3-D example:

```python
>>> a = np.arange(8).reshape(2,2,2); a
array([[[0, 1],
        [2, 3]],
       [[4, 5],
        [6, 7]]])

>>> a.diagonal(0, # Main diagonals of two arrays created by skipping
    ... 0, # across the outer(left)-most axis last and
    ... 1) # the "middle" (row) axis first.
array([[0, 6],
       [1, 7]])
```

The sub-arrays whose main diagonals we just obtained; note that each corresponds to fixing the right-most
(column) axis, and that the diagonals are “packed” in rows.

```python
>>> a[:,:,0] # main diagonal is [0 6]
array([[0, 2],
       [4, 6]])

>>> a[:,:,1] # main diagonal is [1 7]
array([[1, 3],
       [5, 7]])
```

The anti-diagonal can be obtained by reversing the order of elements using either `numpy.flipud` or `numpy.fliplr`.

```python
>>> a = np.arange(9).reshape(3, 3)
>>> a
array([[0, 1, 2],
       [3, 4, 5],
       [6, 7, 8]])

>>> np.fliplr(a).diagonal() # Horizontal flip
array([2, 4, 6])

>>> np.flipud(a).diagonal() # Vertical flip
array([6, 4, 2])
```

Note that the order in which the diagonal is retrieved varies depending on the flip function.

### `divide(x1, x2)`

Returns a true division of the inputs, element-wise.

LAX-backend implementation of `true_divide()`. ADDITION

```
true_divide(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

Instead of the Python traditional ‘floor division’, this returns a true division. True division adjusts the output
type to present the best answer, regardless of input types.

### 2.1. General
**Returns out** – This is a scalar if both \( x_1 \) and \( x_2 \) are scalars.

**Return type** ndarray or scalar

**Notes**

The floor division operator \( // \) was added in Python 2.2 making \( // \) and \( / \) equivalent operators. The default floor division operation of \( / \) can be replaced by true division with `from __future__ import division`.

In Python 3.0, \( // \) is the floor division operator and \( / \) the true division operator. The `true_divide(x1, x2)` function is equivalent to true division in Python.

**Examples**

```python
>>> x = np.arange(5)
>>> np.true_divide(x, 4)
array([ 0. , 0.25, 0.5 , 0.75, 1. ])
```

```python
>>> x//4
array([0, 0, 0, 0, 1])
```

```python
>>> from __future__ import division
>>> x/4
array([ 0. , 0.25, 0.5 , 0.75, 1. ])
>>> x//4
array([0, 0, 0, 0, 1])
```

divmod \((x_1, x_2)\)

Return element-wise quotient and remainder simultaneously.

LAX-backend implementation of `divmod()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `divmod()`. Original docstring below.

divmod(x1, x2[, out1, out2], / [, out=(None, None)], *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

New in version 1.13.0.

np.divmod(x, y) is equivalent to \((x // y, x \% y)\), but faster because it avoids redundant work. It is used to implement the Python built-in function `divmod` on NumPy arrays.

**Returns**

- **out1** (ndarray) – Element-wise quotient resulting from floor division. This is a scalar if both \( x_1 \) and \( x_2 \) are scalars.

- **out2** (ndarray) – Element-wise remainder from floor division. This is a scalar if both \( x_1 \) and \( x_2 \) are scalars.

**See also:**

- `floor_divide()` Equivalent to Python’s `//` operator.

- `remainder()` Equivalent to Python’s `%` operator.

- `modf()` Equivalent to `divmod(x, 1)` for positive \( x \) with the return values switched.
Examples

```python
>>> np.divmod(np.arange(5), 3)
(array([0, 0, 0, 1, 1]), array([0, 1, 2, 0, 1]))
```

**dot** *(a, b, precision=None)*

Dot product of two arrays. Specifically,

LAX-backend implementation of `dot()`. ADDITION

LAX-backend implementation of `dot()`. In addition to the original NumPy arguments listed below, also supports `precision` for extra control over matrix-multiplication precision on supported devices. See `jax.lax.dot()` for details.

Original docstring below.

```python
dot(a, b, out=None)
```

- If both `a` and `b` are 1-D arrays, it is inner product of vectors (without complex conjugation).
- If both `a` and `b` are 2-D arrays, it is matrix multiplication, but using `matmul` or `a @ b` is preferred.
- If either `a` or `b` is 0-D (scalar), it is equivalent to `multiply` and using `numpy.multiply(a, b)` or `a * b` is preferred.
- If `a` is an N-D array and `b` is a 1-D array, it is a sum product over the last axis of `a` and `b`.
- If `a` is an N-D array and `b` is an M-D array (where `M>=2`), it is a sum product over the last axis of `a` and the second-to-last axis of `b`:

  ```python
dot(a, b)[i,j,k,m] = sum(a[i,j, :] * b[k,:, m])
```

Returns

`output` [ndarray] Returns the dot product of `a` and `b`. If `a` and `b` are both scalars or both 1-D arrays then a scalar is returned; otherwise an array is returned. If `out` is given, then it is returned.

`ValueError` If the last dimension of `a` is not the same size as the second-to-last dimension of `b`.

vdot : Complex-conjugating dot product. tensordot : Sum products over arbitrary axes. einsum : Einstein summation convention. matmul : '@' operator as method with out parameter.

```python
>>> np.dot(3, 4)
12
```

Neither argument is complex-conjugated:

```python
>>> np.dot([2j, 3j], [2j, 3j])
(-13+0j)
```

For 2-D arrays it is the matrix product:

```python
>>> a = [[1, 0], [0, 1]]
>>> b = [[4, 1], [2, 2]]
>>> np.dot(a, b)
```

(continues on next page)
```python
array([[4, 1],
       [2, 2]])
```

```python
>>> a = np.arange(3*4*5*6).reshape((3,4,5,6))
>>> b = np.arange(3*4*5*6[::-1].reshape((5,4,6,3))
>>> np.dot(a, b)[2,3,2,1,2,2]
499128
>>> sum(a[2,3,2,1] * b[1,2,:,2])
499128
```

dsplits (ary, indices_or_sections)
Split array into multiple sub-arrays along the 3rd axis (depth).

LAX-backend implementation of dsplit(). ADDITIONOriginal docstring below.

La

dstack (tup)
Stack arrays in sequence depth wise (along third axis).

LAX-backend implementation of dstack(). ADDITIONOriginal docstring below.

LAX-backend implementation of dstack(). Original docstring below.

This is equivalent to concatenation along the third axis after 2-D arrays of shape (M,N) have been reshaped to (M,1,1) and 1-D arrays of shape (1,N) have been reshaped to (1,1,N). Rebuilds arrays divided by dsplit.

This function makes most sense for arrays with up to 3 dimensions. For instance, for pixel-data with a height (first axis), width (second axis), and r/g/b channels (third axis). The functions concatenate, stack and block provide more general stacking and concatenation operations.

Returns stacked – The array formed by stacking the given arrays, will be at least 3-D.

Return type ndarray

See also:

stack () Join a sequence of arrays along a new axis.
nvstack () Stack along first axis.
hstack () Stack along second axis.
concatenate () Join a sequence of arrays along an existing axis.

dsplit () Split array along third axis.

Examples

```python
>>> a = np.array((1,2,3))
>>> b = np.array((2,3,4))
>>> np.dstack((a,b))
array([[1, 2],
       [2, 3],
       [3, 4]])
```
\begin{verbatim}
>>> a = np.array([[1],[2],[3]])
>>> b = np.array([[2],[3],[4]])
>>> np.dstack((a,b))
array([[1, 2],
       [2, 3],
       [3, 4]])
\end{verbatim}

einsum(*operands, **kwargs)

Evaluates the Einstein summation convention on the operands.

LAX-backend implementation of einsum(). ADDITIONOriginal docstring below.

LAX-backend implementation of einsum(). In addition to the original NumPy arguments listed below, also supports precision for extra control over matrix-multiplication precision on supported devices. See jax.lax.dot() for details.

Original docstring below.

einsum(subscripts, *operands, out=None, dtype=None, order='K', casting='safe', optimize=False)

Using the Einstein summation convention, many common multi-dimensional, linear algebraic array operations can be represented in a simple fashion. In \textit{implicit} mode einsum computes these values.

In \textit{explicit} mode, einsum provides further flexibility to compute other array operations that might not be considered classical Einstein summation operations, by disabling, or forcing summation over specified subscript labels.

See the notes and examples for clarification.

Returns

output [ndarray] The calculation based on the Einstein summation convention.

einsum_path, dot, inner, outer, tensordot, linalg.multi_dot

New in version 1.6.0.

The Einstein summation convention can be used to compute many multi-dimensional, linear algebraic array operations. einsum provides a succinct way of representing these.

A non-exhaustive list of these operations, which can be computed by einsum, is shown below along with examples:

- Trace of an array, \texttt{numpy.trace()}.
- Return a diagonal, \texttt{numpy.diag()}.
- Array axis summations, \texttt{numpy.sum()}.
- Transpositions and permutations, \texttt{numpy.transpose()}.
- Matrix multiplication and dot product, \texttt{numpy.matmul()} \texttt{numpy.dot()}.
- Vector inner and outer products, \texttt{numpy.inner()} \texttt{numpy.outer()}.
- Broadcasting, element-wise and scalar multiplication, \texttt{numpy.multiply()}.
- Tensor contractions, \texttt{numpy.tensordot()}.
- Chained array operations, in efficient calculation order, \texttt{numpy.einsum_path()}.\end{verbatim}
The subscripts string is a comma-separated list of subscript labels, where each label refers to a dimension of the corresponding operand. Whenever a label is repeated it is summed, so np.einsum('i,i', a, b) is equivalent to np.inner(a, b). If a label appears only once, it is not summed, so np.einsum('i', a) produces a view of a with no changes. A further example np.einsum('ij,jk', a, b) describes traditional matrix multiplication and is equivalent to np.matmul(a, b). Repeated subscript labels in one operand take the diagonal. For example, np.einsum('ii', a) is equivalent to np.trace(a).

In *implicit mode*, the chosen subscripts are important since the axes of the output are reordered alphabetically. This means that np.einsum('ij', a) doesn’t affect a 2D array, while np.einsum('ji', a) takes its transpose. Additionally, np.einsum('ij,jk', a, b) returns a matrix multiplication, while, np.einsum('ij,jh', a, b) returns the transpose of the multiplication since subscript ‘h’ precedes subscript ‘i’.

In *explicit mode* the output can be directly controlled by specifying output subscript labels. This requires the identifier ‘->’ as well as the list of output subscript labels. This feature increases the flexibility of the function since summing can be disabled or forced when required. The call np.einsum('i->', a) is like np.sum(a, axis=-1), and np.einsum('ii->i', a) is like np.diag(a). The difference is that einsum does not allow broadcasting by default. Additionally, np.einsum('ij,jh->ih', a, b) directly specifies the order of the output subscript labels and therefore returns matrix multiplication, unlike the example above in implicit mode.

To enable and control broadcasting, use an ellipsis. Default NumPy-style broadcasting is done by adding an ellipsis to the left of each term, like np.einsum('...ii->...i', a). To take the trace along the first and last axes, you can do np.einsum('i...i', a), or to do a matrix-matrix product with the left-most indices instead of rightmost, one can do np.einsum('ij...,jk...->ik...', a, b).

When there is only one operand, no axes are summed, and no output parameter is provided, a view into the operand is returned instead of a new array. Thus, taking the diagonal as np.einsum('ii->i', a) produces a view (changed in version 1.10.0).

einsum also provides an alternative way to provide the subscripts and operands as einsum(op0, sublist0, op1, sublist1, ..., [sublistout]). If the output shape is not provided in this format einsum will be calculated in implicit mode, otherwise it will be performed explicitly. The examples below have corresponding einsum calls with the two parameter methods.

New in version 1.10.0.

Views returned from einsum are now writeable whenever the input array is writeable. For example, np.einsum('ijk...->kji...', a) will now have the same effect as np.swapaxes(a, 0, 2) and np.einsum('ii->i', a) will return a writeable view of the diagonal of a 2D array.

New in version 1.12.0.

Added the optimize argument which will optimize the contraction order of an einsum expression. For a contraction with three or more operands this can greatly increase the computational efficiency at the cost of a larger memory footprint during computation.

Typically a ‘greedy’ algorithm is applied which empirical tests have shown returns the optimal path in the majority of cases. In some cases ‘optimal’ will return the superlative path through a more expensive, exhaustive search. For iterative calculations it may be advisable to calculate the optimal path once and reuse that path by supplying it as an argument. An example is given below.

See numpy.einsum_path() for more details.
```python
>>> a = np.arange(25).reshape(5,5)
>>> b = np.arange(5)
>>> c = np.arange(6).reshape(2,3)

Trace of a matrix:

```python
>>> np.einsum('ii', a)
60
>>> np.einsum(a, [0,0])
60
>>> np.trace(a)
60

Extract the diagonal (requires explicit form):

```python
>>> np.einsum('ii->i', a)
array([ 0, 6, 12, 18, 24])
>>> np.einsum(a, [0,0], [0])
array([ 0, 6, 12, 18, 24])
>>> np.diag(a)
array([ 0, 6, 12, 18, 24])

Sum over an axis (requires explicit form):

```python
>>> np.einsum('ij->i', a)
array([ 10, 35, 60, 85, 110])
>>> np.einsum(a, [0,1], [0])
array([ 10, 35, 60, 85, 110])
>>> np.sum(a, axis=1)
array([ 10, 35, 60, 85, 110])

For higher dimensional arrays summing a single axis can be done with ellipsis:

```python
>>> np.einsum('...j->...', a)
array([ 10, 35, 60, 85, 110])
>>> np.einsum(a, [Ellipsis,1], [Ellipsis])
array([ 10, 35, 60, 85, 110])

Compute a matrix transpose, or reorder any number of axes:

```python
>>> np.einsum('ji', c)
array([[0, 3],
       [1, 4],
       [2, 5]])
>>> np.einsum('ij->ji', c)
array([[0, 3],
       [1, 4],
       [2, 5]])
>>> np.einsum(c, [1,0])
array([[0, 3],
       [1, 4],
       [2, 5]])
>>> np.transpose(c)
array([[0, 3],
       [1, 4],
       [2, 5]])
```

Vector inner products:
Matrix vector multiplication:

```python
>>> np.einsum('ij,j', a, b)
array([[ 30,  80, 130, 180, 230]])
>>> np.einsum(a, [0,1], b, [1])
array([[ 30,  80, 130, 180, 230]])
>>> np.dot(a, b)
array([[ 30,  80, 130, 180, 230]])
>>> np.einsum('...j,j', a, b)
array([[ 30,  80, 130, 180, 230]])
```

Broadcasting and scalar multiplication:

```python
>>> np.einsum('..., ...', 3, c)
array([[ 0,  3,  6],
       [ 9, 12, 15]])
>>> np.einsum(',ij', 3, c)
array([[ 0,  3,  6],
       [ 9, 12, 15]])
>>> np.einsum(3, [Ellipsis], c, [Ellipsis])
array([[ 0,  3,  6],
       [ 9, 12, 15]])
>>> np.multiply(3, c)
array([[ 0,  3,  6],
       [ 9, 12, 15]])
```

Vector outer product:

```python
>>> np.einsum('i,j', np.arange(2)+1, b)
array([[0, 1, 2, 3, 4],
       [0, 2, 4, 6, 8]])
>>> np.einsum(np.arange(2)+1, [0], b, [1])
array([[0, 1, 2, 3, 4],
       [0, 2, 4, 6, 8]])
>>> np.outer(np.arange(2)+1, b)
array([[0, 1, 2, 3, 4],
       [0, 2, 4, 6, 8]])
```

Tensor contraction:

```python
>>> a = np.arange(60.).reshape(3,4,5)
>>> b = np.arange(24.).reshape(4,3,2)
>>> np.einsum('ijk,jil->kl', a, b)
array([[4400., 4730.],
       [4532., 4874.],
       [4664., 5018.],
       [4796., 5162.],
       [4928., 5306.]])
>>> np.einsum(a, [0,1,2], b, [1,0,3], [2,3])
array([[4400., 4730.],
       [4532., 4874.],
       [4664., 5018.],
       [4796., 5162.],
       [4928., 5306.]])
```
Writeable returned arrays (since version 1.10.0):

```python
>>> a = np.zeros((3, 3))
>>> np.einsum('ii->i', a)[1] = 1
>>> a
array([[1., 0., 0.],
       [0., 1., 0.],
       [0., 0., 1.]])
```

Example of ellipsis use:

```python
>>> a = np.arange(6).reshape((3, 2))
>>> b = np.arange(12).reshape((4, 3))
>>> np.einsum('ki,jk->ij', a, b)
array([[10, 28, 46, 64],
       [13, 40, 67, 94]])

>>> np.einsum('ki,...k->i...', a, b)
array([[10, 28, 46, 64],
       [13, 40, 67, 94]])

>>> np.einsum('k...,jk', a, b)
array([[10, 28, 46, 64],
       [13, 40, 67, 94]])
```

Chained array operations. For more complicated contractions, speed ups might be achieved by repeatedly computing a ‘greedy’ path or pre-computing the ‘optimal’ path and repeatedly applying it, using an `einsum_path` insertion (since version 1.12.0). Performance improvements can be particularly significant with larger arrays:

```python
>>> a = np.ones(64).reshape(2,4,8)

Basic einsum: ~1520ms (benchmarked on 3.1GHz Intel i5.)
```

```python
>>> for iteration in range(500):
...    _ = np.einsum('ijk,ilm,njm,nlk,abc->', a, a, a, a, a)
```

Sub-optimal einsum (due to repeated path calculation time): ~330ms

```python
>>> for iteration in range(500):
...    _ = np.einsum('ijk,ilm,njm,nlk,abc->', a, a, a, a, optimize='optimal')
```

Greedy einsum (faster optimal path approximation): ~160ms

```python
>>> for iteration in range(500):
...    _ = np.einsum('ijk,ilm,njm,nlk,abc->', a, a, a, a, optimize='greedy')
```
Optimal *einsum* (best usage pattern in some use cases): ~110ms

```python
>>> path = np.einsum_path('ijk,ilm,njm,nlk,abc->', a, a, a, a, a, optimize='optimal')[0]
>>> for iteration in range(500):
...     _ = np.einsum('ijk,ilm,njm,nlk,abc->', a, a, a, a, a, optimize=path)
```

### `equal(x1, x2)`

Return `(x1 == x2)` element-wise.

LAX-backend implementation of `equal()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `equal()`. Original docstring below.

`equal(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])`

**Returns** `out` – Output array, element-wise comparison of `x1` and `x2`. Typically of type bool, unless `dtype=object` is passed. This is a scalar if both `x1` and `x2` are scalars.

**Return type** `ndarray` or scalar

See also:

- `not_equal()`
- `greater_equal()`
- `less_equal()`
- `greater()`
- `less()`

### Examples

```python
>>> np.equal([0, 1, 3], np.arange(3))
array([ True,  True, False])
```

What is compared are values, not types. So an int (1) and an array of length one can evaluate as True:

```python
>>> np.equal(1, np.ones(1))
array([ True])
```

### `empty(shape, dtype=None)`

Return a new array of given shape and type, filled with zeros.

LAX-backend implementation of `zeros()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `zeros()`. Original docstring below.

`zeros(shape, dtype=float, order='C')`

**Returns**

- `out` [ndarray] Array of zeros with the given shape, dtype, and order.

`zeros_like`: Return an array of zeros with shape and type of input. `empty`: Return a new uninitialized array. `ones`: Return a new array setting values to one. `full`: Return a new array of given shape filled with value.

```python
>>> np.zeros(5)
array([ 0., 0., 0., 0., 0.])
```
empty_like(x, dtype=None)
Return an array of zeros with the same shape and type as a given array.
LAX-backend implementation of zeros_like(). ADDITIONOriginal docstring below.
LAX-backend implementation of zeros_like(). Original docstring below.

Parameters **dtype** *(data-type, optional)* – Overrides the data type of the result.

Returns **out** – Array of zeros with the same shape and type as a.

Return type **ndarray**

See also:
empty_like() Return an empty array with shape and type of input.
ones_like() Return an array of ones with shape and type of input.
full_like() Return a new array with shape of input filled with value.
zeros() Return a new array setting values to zero.

Examples

```
>>> x = np.arange(6)
>>> x = x.reshape((2, 3))
>>> x
array([[0, 1, 2],
       [3, 4, 5]])
>>> np.zeros_like(x)
array([[0, 0, 0],
       [0, 0, 0]])
```

```
>>> y = np.arange(3, dtype=float)
>>> y
array([0., 1., 2.])
>>> np.zeros_like(y)
array([0., 0., 0.])
```
exp(x)
Calculate the exponential of all elements in the input array.
LAX-backend implementation of exp(). ADDITIONOriginal docstring below.
LAX-backend implementation of exp(). ADDITIONOriginal docstring below.
exp(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, ex-tobj])

**Returns** out – Output array, element-wise exponential of x. This is a scalar if x is a scalar.

**Return type** ndarray or scalar

See also:
expm1() Calculate exp(x) - 1 for all elements in the array.
exp2() Calculate 2**x for all elements in the array.

**Notes**
The irrational number \( e \) is also known as Euler’s number. It is approximately 2.718281, and is the base of the natural logarithm, \( \ln \) (this means that, if \( x = \ln y = \log_e y \), then \( e^x = y \). For real input, \( \exp(x) \) is always positive.

For complex arguments, \( x = a + ib \), we can write \( e^x = e^a e^{ib} \). The first term, \( e^a \), is already known (it is the real argument, described above). The second term, \( e^{ib} \), is \( \cos b + i \sin b \), a function with magnitude 1 and a periodic phase.

**References**

**Examples**
Plot the magnitude and phase of \( \exp(x) \) in the complex plane:

```python
>>> import matplotlib.pyplot as plt

>>> x = np.linspace(-2*np.pi, 2*np.pi, 100)
>>> xx = x + 1j * x[:, np.newaxis]  # a + ib over complex plane
>>> out = np.exp(xx)

>>> plt.subplot(121)
>>> plt.imshow(np.abs(out),  
... extent=[-2*np.pi, 2*np.pi, -2*np.pi, 2*np.pi], cmap='gray')
>>> plt.title('Magnitude of exp(x)')

>>> plt.subplot(122)
>>> plt.imshow(np.angle(out),  
... extent=[-2*np.pi, 2*np.pi, -2*np.pi, 2*np.pi], cmap='hsv')
>>> plt.title('Phase (angle) of exp(x)')
```

exp2(x)
Calculate 2**p for all p in the input array.
LAX-backend implementation of exp2(). ADDITIONOriginal docstring below.
LAX-backend implementation of \texttt{exp2()}. Original docstring below.

\begin{verbatim}
exp2(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

    Returns out – Element-wise $2^x$. This is a scalar if $x$ is a scalar.

    Return type ndarray or scalar
\end{verbatim}

\textbf{See also:}

\texttt{power()}

\textbf{Notes}

New in version 1.3.0.

\textbf{Examples}

\begin{verbatim}
>>> np.exp2([2, 3])
a
array([ 4., 8.])
\end{verbatim}

\texttt{expand_dims(a, axis)}

Expand the shape of an array.

LAX-backend implementation of \texttt{expand_dims()}. ADDITIONOriginal docstring below.

\begin{verbatim}
insert a new axis that will appear at the axis position in the expanded array shape.

    Returns result – View of a with the number of dimensions increased.

    Return type ndarray
\end{verbatim}

\textbf{See also:}

\texttt{squeeze() The inverse operation, removing singleton dimensions}

\texttt{reshape() Insert, remove, and combine dimensions, and resize existing ones}

doc.indexing(), \texttt{atleast_1d()}, \texttt{atleast_2d()}, \texttt{atleast_3d()}

\textbf{Examples}

\begin{verbatim}
>>> x = np.array([1, 2])
>>> x.shape
(2,)

The following is equivalent to \texttt{x[np.newaxis, :]} or \texttt{x[np.newaxis]}:

\begin{verbatim}
>>> y = np.expand_dims(x, axis=0)
>>> y
array([[1, 2]])
>>> y.shape
(1, 2)
\end{verbatim}

The following is equivalent to \texttt{x[:, np.newaxis]}:

\end{verbatim}
```python
>>> y = np.expand_dims(x, axis=1)
>>> y
array([[1],
       [2]])
>>> y.shape
(2, 1)

axis may also be a tuple:

>>> y = np.expand_dims(x, axis=(0, 1))
>>> y
array([[1, 2]])

>>> y = np.expand_dims(x, axis=(2, 0))
>>> y
array([[1],
       [2]])

Note that some examples may use None instead of np.newaxis. These are the same objects:

```python
>>> np.newaxis
is None
True
```

**expm1**

Calculate \( \exp(x) - 1 \) for all elements in the array.

LAX-backend implementation of `expm1()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `expm1()`. Original docstring below.

expm1(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns out – Element-wise exponential minus one: out = \( \exp(x) - 1 \). This is a scalar if x is a scalar.

Return type  ndarray or scalar

See also:

**log1p**  \( \log(1 + x) \), the inverse of expm1.

Notes

This function provides greater precision than \( \exp(x) - 1 \) for small values of x.

Examples

The true value of \( \exp(1e-10) - 1 \) is 1.00000000005e-10 to about 32 significant digits. This example shows the superiority of expm1 in this case.

```python
>>> np.expm1(1e-10)
1.00000000005e-10
>>> np.exp(1e-10) - 1
1.000000082740371e-10
```
**eye** (*N*, *M=None*, *k=0*, *dtype=None*)

Return a 2-D array with ones on the diagonal and zeros elsewhere.

LAX-backend implementation of `eye()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `eye()`. Original docstring below.

- **Parameters**
  - `dtype` *(data-type, optional)*
    - **Returns**
      - `I` – An array where all elements are equal to zero, except for the *k*-th diagonal, whose values are equal to one.

- **Return type**
  - `ndarray of shape (N,M)`

See also:

- `identity()` (almost) equivalent function
- `diag()` diagonal 2-D array from a 1-D array specified by the user.

**Examples**

```python
>>> np.eye(2, dtype=int)
array([[1, 0],
       [0, 1]])

>>> np.eye(3, k=1)
array([[0., 1., 0.],
       [0., 0., 1.],
       [0., 0., 0.]])
```

**fabs** *(x)*

Compute the absolute values element-wise.

LAX-backend implementation of `fabs()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `fabs()`. Original docstring below.

`fabs(x, l, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])`

This function returns the absolute values (positive magnitude) of the data in *x*. Complex values are not handled, use `absolute` to find the absolute values of complex data.

- **Returns**
  - `y` – The absolute values of *x*, the returned values are always floats. This is a scalar if *x* is a scalar.

- **Return type**
  - `ndarray or scalar`

See also:

- `absolute()` Absolute values including complex types.
Examples

```python
>>> np.fabs(-1)
1.0
>>> np.fabs([-1.2, 1.2])
array([ 1.2,  1.2])
```

flip ($m$, axis=None)

Reverse the order of elements in an array along the given axis.

LAX-backend implementation of `flip()`. ADDITION

LAX-backend implementation of `flip()`. Original docstring below.

The shape of the array is preserved, but the elements are reordered.

New in version 1.12.0.

Returns out – A view of $m$ with the entries of axis reversed. Since a view is returned, this operation is done in constant time.

Return type array_like

See also:

flipud() Flip an array vertically (axis=0).

fliplr() Flip an array horizontally (axis=1).

Notes

Flip(m, 0) is equivalent to flipud(m).

flip(m, 1) is equivalent to fliplr(m).

flip(m, n) corresponds to m[...,::-1,...] with ::-1 at position n.

flip(m) corresponds to m[::−1,::−1,...] with ::−1 at all positions.

flip(m, (0, 1)) corresponds to m[::-1,::-1,...] with ::−1 at position 0 and position 1.

Examples

```python
>>> A = np.arange(8).reshape((2,2,2))
>>> A
array([[[0, 1],
        [2, 3]],
       [[4, 5],
        [6, 7]]])
>>> np.flip(A, 0)
array([[[4, 5],
        [6, 7]],
       [[0, 1],
        [2, 3]]])
>>> np.flip(A, 1)
array([[[2, 3],
        [0, 1]],
       [[6, 7],
        [4, 5]]])
```
>>> np.flip(A)
array([[7, 6],
      [5, 4],
      [3, 2],
      [1, 0]])
>>> np.flip(A, (0, 2))
array([[5, 4],
      [7, 6],
      [1, 0],
      [3, 2]])
>>> A = np.random.randn(3,4,5)
>>> np.all(np.flip(A,2) == A[:,:,::-1,...])
True

flipud(m)
Flip array in the up/down direction.

LAX-backend implementation of flipud(). Original docstring below.

LAX-backend implementation of flipud(). Original docstring below.

Flip the entries in each row in the up/down direction. Columns are preserved, but appear in a different order than before.

Returns f – A view of m with the columns reversed. Since a view is returned, this operation is \(O(1)\).

Return type ndarray

See also:

flipud() Flip array in the up/down direction.

rot90() Rotate array counterclockwise.

Notes

Equivalent to m[::,-1]. Requires the array to be at least 2-D.

Examples

```python
>>> A = np.diag([1.,2.,3.])
>>> A
array([[1., 0., 0.],
       [0., 2., 0.],
       [0., 0., 3.]])
>>> np.flipud(A)
array([[0., 0., 1.],
       [0., 2., 0.],
       [3., 0., 0.]])
```

```python
>>> A = np.random.randn(2,3,5)
>>> np.all(np.flipud(A) == A[:,:,::-1,...])
True
```

flipud(m)
Flip array in the up/down direction.
LAX-backend implementation of `flipud()`. Original docstring below.

Flip the entries in each column in the up/down direction. Rows are preserved, but appear in a different order than before.

**Returns out** – A view of \( m \) with the rows reversed. Since a view is returned, this operation is \( \mathcal{O}(1) \).

**Return type** array_like

**See also:**

`fliplr()` Flip array in the left/right direction.

`rot90()` Rotate array counterclockwise.

**Notes**

Equivalent to \( m[:,::-1,...] \). Does not require the array to be two-dimensional.

**Examples**

```python
>>> A = np.diag([1.0, 2, 3])
>>> A
array([[1., 0., 0.],
       [0., 2., 0.],
       [0., 0., 3.]])
>>> np.flipud(A)
array([[0., 0., 3.],
       [0., 2., 0.],
       [1., 0., 0.]])
```

```python
>>> A = np.random.randn(2,3,5)
>>> np.all(np.flipud(A) == A[::-1,...])
True
```

```python
>>> np.flipud([1,2])
array([2, 1])
```

**float_power\((x1, x2)\)**

First array elements raised to powers from second array, element-wise.

LAX-backend implementation of `float_power()`. Original docstring below.

LAX-backend implementation of `float_power()`. Original docstring below.

`float_power(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])`

Raise each base in \( x1 \) to the positionally-corresponding power in \( x2 \). \( x1 \) and \( x2 \) must be broadcastable to the same shape. This differs from the power function in that integers, float16, and float32 are promoted to floats with a minimum precision of float64 so that the result is always inexact. The intent is that the function will return a usable result for negative powers and seldom overflow for positive powers.

New in version 1.12.0.

**Returns y** – The bases in \( x1 \) raised to the exponents in \( x2 \). This is a scalar if both \( x1 \) and \( x2 \) are scalars.
Return type: ndarray

See also:

power()  power function that preserves type

Examples

Cube each element in a list.

```
>>> x1 = range(6)
>>> x1
[0, 1, 2, 3, 4, 5]
>>> np.float_power(x1, 3)
array([ 0., 1., 8., 27., 64., 125.])
```

Raise the bases to different exponents.

```
>>> x2 = [1.0, 2.0, 3.0, 3.0, 2.0, 1.0]
>>> np.float_power(x1, x2)
array([ 0., 1., 8., 27., 16., 5.])
```

The effect of broadcasting.

```
>>> x2 = np.array([[1, 2, 3, 3, 2, 1], [1, 2, 3, 3, 2, 1]])
>>> x2
array([[1, 2, 3, 3, 2, 1],
       [1, 2, 3, 3, 2, 1]])
>>> np.float_power(x1, x2)
array([[ 0., 1., 8., 27., 16., 5.],
       [ 0., 1., 8., 27., 16., 5.]])
```

floor(x)

Return the floor of the input, element-wise.

LAX-backend implementation of `floor()`. Original docstring below.

LAX-backend implementation of `floor()`. Original docstring below.

floor(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

The floor of the scalar x is the largest integer i, such that i <= x. It is often denoted as \lfloor x\rfloor.

Returns y – The floor of each element in x. This is a scalar if x is a scalar.

Return type: ndarray or scalar

See also:

ceil(), trunc(), rint()
Notes

Some spreadsheet programs calculate the “floor-towards-zero”, in other words \(\text{floor}(-2.5) == -2\). NumPy instead uses the definition of \(\text{floor}\) where \(\text{floor}(-2.5) == -3\).

Examples

```python
>>> a = np.array([-1.7, -1.5, -0.2, 0.2, 1.5, 1.7, 2.0])
>>> np.floor(a)
a = array([-2., -2., -1., 0., 1., 1., 2.])
```

**\(\text{floor}\_\text{divide}(x1, x2)\)**

Return the largest integer smaller or equal to the division of the inputs. It is equivalent to the Python `//` operator and pairs with the Python `% (remainder)`, function so that \(a = a \mod b + b \times (a \div b)\) up to roundoff.

LAX-backend implementation of `\text{floor}\_\text{divide}(\). ADDITIONALOriginal docstring below.

LAX-backend implementation of `\text{floor}\_\text{divide}(\). Original docstring below.

floor\_divide(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns \(y = \text{floor}(x1/x2)\) This is a scalar if both \(x1\) and \(x2\) are scalars.

Return type `ndarray`

See also:

`remainder()` Remainder complementary to floor\_divide.

`divmod()` Simultaneous floor division and remainder.

`divide()` Standard division.

`floor()` Round a number to the nearest integer toward minus infinity.

`ceil()` Round a number to the nearest integer toward infinity.

Examples

```python
>>> np.floor\_divide(7,3)
2
>>> np.floor\_divide([1., 2., 3., 4.], 2.5)
a = array([0., 0., 1., 1.])
```

**\(\text{fmod}(x1, x2)\)**

Return the element-wise remainder of division.

LAX-backend implementation of `\text{fmod}(\)`. ADDITIONALOriginal docstring below.

LAX-backend implementation of `\text{fmod}(\)`. Original docstring below.

fmod(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

This is the NumPy implementation of the C library function fmod, the remainder has the same sign as the dividend \(x1\). It is equivalent to the Matlab(TM) `rem` function and should not be confused with the Python modulus operator \(x1 \mod x2\).

Returns \(y –\) The remainder of the division of \(x1\) by \(x2\). This is a scalar if both \(x1\) and \(x2\) are scalars.
Return type  array_like

See also:

\texttt{remainder()}  Equivalent to the Python $\%$ operator.
\texttt{divide()}

Notes

The result of the modulo operation for negative dividend and divisors is bound by conventions. For \texttt{fmod}, the sign of result is the sign of the dividend, while for \texttt{remainder} the sign of the result is the sign of the divisor. The \texttt{fmod} function is equivalent to the Matlab(TM) \texttt{rem} function.

Examples

\begin{verbatim}
>>> np.fmod([-3, -2, -1, 1, 2, 3], 2)
array([-1, 0, -1, 1, 0, 1])
>>> np.remainder([-3, -2, -1, 1, 2, 3], 2)
array([1, 0, 1, 1, 0, 1])
>>> np.fmod([5, 3], [2, 2.])
array([1., 1.])
>>> a = np.arange(-3, 3).reshape(3, 2)
>>> a
array([[-3, -2],
       [-1,  0],
       [ 1,  2]])
>>> np.fmod(a, [2,2])
array([[-1,  0],
       [-1,  0],
       [ 1,  0]])
\end{verbatim}

\texttt{full}(\texttt{shape}, \texttt{fill\_value}, \texttt{dtype=}\texttt{None})

Return a new array of given shape and type, filled with \texttt{fill\_value}.

LAX-backend implementation of \texttt{full()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{full()}. Original docstring below.

Parameters

- \texttt{shape} (int or sequence of ints) – Shape of the new array, e.g., (2, 3) or 2.
- \texttt{dtype} (data-type, optional) –

The desired data-type for the array The default, None, means \texttt{np.array(fill\_value).dtype}.

Returns \texttt{out} – Array of \texttt{fill\_value} with the given shape, dtype, and order.

Return type  ndarray

See also:

\texttt{full\_like()}  Return a new array with shape of input filled with value.
\texttt{empty()}  Return a new uninitialized array.
ones()  Return a new array setting values to one.

zeros()  Return a new array setting values to zero.

Examples

```python
>>> np.full((2, 2), np.inf)
array([[inf, inf],
       [inf, inf]])
```

full_like(a, fill_value, dtype=None)
Return a full array with the same shape and type as a given array.

LAX-backend implementation of `full_like()`.

Parameters

- `dtype` (data-type, optional) – Overrides the data type of the result.
- `out` – Array of `fill_value` with the same shape and type as `a`.
- `ndarray`

See also:

empty_like()  Return an empty array with shape and type of input.

ones_like()  Return an array of ones with shape and type of input.

zeros_like()  Return an array of zeros with shape and type of input.

full()  Return a new array of given shape filled with value.

Examples

```python
>>> x = np.arange(6, dtype=int)
>>> np.full_like(x, 1)
array([1, 1, 1, 1, 1, 1])
>>> np.full_like(x, 0.1)
array([0.1, 0.1, 0.1, 0.1, 0.1, 0.1])
>>> np.full_like(x, np.nan, dtype=np.double)
array([nan, nan, nan, nan, nan, nan])
```

gcd(x1, x2)
Returns the greatest common divisor of |x1| and |x2|

LAX-backend implementation of `gcd()`.

Examples

```python
>>> y = np.arange(6, dtype=np.double)
>>> np.full_like(y, 0.1)
array([0.1, 0.1, 0.1, 0.1, 0.1, 0.1])
```
gcd(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns y – The greatest common divisor of the absolute value of the inputs This is a scalar if both x1 and x2 are scalars.

Return type ndarray or scalar

See also:

lcm() The lowest common multiple

Examples

```python
gcd(12, 20)
4
>>> np.gcd.reduce([15, 25, 35])
5
>>> np.gcd(np.arange(6), 20)
aarray([20, 1, 2, 1, 4, 5])
```

geomspace (start, stop, num=50, endpoint=True, dtype=None, axis=0)
Return numbers spaced evenly on a log scale (a geometric progression).

LAX-backend implementation of `geomspace()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `geomspace()`. Original docstring below.

This is similar to `logspace`, but with endpoints specified directly. Each output sample is a constant multiple of the previous.

Changed in version 1.16.0: Non-scalar `start` and `stop` are now supported.

Parameters
dtype (`dtype`) – The type of the output array. If `dtype` is not given, infer the data type from the other input arguments.

Returns samples – `num` samples, equally spaced on a log scale.

Return type ndarray

See also:

logspace() Similar to geomspace, but with endpoints specified using log and base.

linspace() Similar to geomspace, but with arithmetic instead of geometric progression.

arange() Similar to linspace, with the step size specified instead of the number of samples.

Notes

If the inputs or dtype are complex, the output will follow a logarithmic spiral in the complex plane. (There are an infinite number of spirals passing through two points; the output will follow the shortest such path.)
Examples

```python
>>> np.geomspace(1, 1000, num=4)
array([ 1.,  10., 100., 1000.])
>>> np.geomspace(1, 1000, num=3, endpoint=False)
array([ 1. , 31.6227766 , 1000. ])
>>> np.geomspace(1, 1000, num=4, endpoint=False)
array([ 1. , 5.62341325, 31.6227766 , 177.827941 ])
```

Note that the above may not produce exact integers:

```python
>>> np.geomspace(1, 256, num=9, dtype=int)
array([1 , 2 , 4 , 8 , 16 , 32 , 64 , 127 , 256])
```

Negative, decreasing, and complex inputs are allowed:

```python
>>> np.geomspace(1000, 1, num=4)
array([1000., 100., 10., 1.])
>>> np.geomspace(-1000, -1, num=4)
array([-1000., -100., -10., -1.])
>>> np.geomspace(1j, 1000j, num=4)  # Straight line
array([0. +1.j, 0. +10.j, 0. +100.j, 0.+1000.j])
>>> np.geomspace(-1+0j, 1+0j, num=5)  # Circle
array([-1.00000000e+00+1.22464680e-16j, -7.07106781e-01+7.07106781e-01j,
        6.12323400e-17+1.00000000e+00j, 7.07106781e-01+7.07106781e-01j,
       1.00000000e+00+0.00000000e+00j])
```

Graphical illustration of endpoint parameter:

```python
>>> import matplotlib.pyplot as plt
>>> N = 10
>>> y = np.zeros(N)
>>> plt.semilogx(np.geomspace(1, 1000, N, endpoint=True), y + 1, 'o')
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.semilogx(np.geomspace(1, 1000, N, endpoint=False), y + 2, 'o')
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.axis([0.5, 2000, 0, 3])
[0.5, 2000, 0, 3]
>>> plt.grid(True, color='0.7', linestyle='-', which='both', axis='both')
>>> plt.show()
```

greater(x1, x2)

Return the truth value of (x1 > x2) element-wise.

LAX-backend implementation of `greater()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `greater()`. Original docstring below.

greater(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns out – Output array, element-wise comparison of x1 and x2. Typically of type bool, unless dtype=object is passed. This is a scalar if both x1 and x2 are scalars.

Return type ndarray or scalar
See also:

greater_equal(), less(), less_equal(), equal(), not_equal()

Examples

```python
>>> np.greater([4,2],[2,2])
array([ True, False])
```

If the inputs are ndarrays, then np.greater is equivalent to ‘>’.

```python
>>> a = np.array([4,2])
>>> b = np.array([2,2])
>>> a > b
array([ True, False])
```

**greater_equal**(x1, x2)

Return the truth value of (x1 >= x2) element-wise.

LAX-backend implementation of `greater_equal`. ADDITION

```
LAX-backend implementation of `greater_equal`. Original docstring below.

greater_equal(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

Returns out – Output array, element-wise comparison of x1 and x2. Typically of type bool, unless
dtype=object is passed. This is a scalar if both x1 and x2 are scalars.

Return type bool or ndarray of bool

See also:

greater(), less(), less_equal(), equal(), not_equal()

Examples

```python
>>> np.greater_equal([4, 2, 1], [2, 2, 2])
array([ True, True, False])
```

**heaviside**(x1, x2)

Compute the Heaviside step function.

LAX-backend implementation of `heaviside(). ADDITION

```
LAX-backend implementation of `heaviside(). Original docstring below.

heaviside(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

The Heaviside step function is defined as:

\[
\text{heaviside}(x1, x2) = \begin{cases} 
0 & \text{if } x1 < 0 \\
x2 & \text{if } x1 = 0 \\
1 & \text{if } x1 > 0
\end{cases}
\]

where x2 is often taken to be 0.5, but 0 and 1 are also sometimes used.

Returns out – The output array, element-wise Heaviside step function of x1. This is a scalar if both
x1 and x2 are scalars.
Return type  ndarray or scalar

Notes

New in version 1.13.0.

References

Examples

```python
>>> np.heaviside([-1.5, 0, 2.0], 0.5)
array([ 0. , 0.5, 1. ])
>>> np.heaviside([-1.5, 0, 2.0], 1)
array([ 0., 1., 1.])
```

hsplit (ary, indices_or_sections)  
Split an array into multiple sub-arrays horizontally (column-wise).

LAX-backend implementation of hsplit(). ADDITIONOriginal docstring below.

LA

hstack (tup)  
Stack arrays in sequence horizontally (column wise).

LAX-backend implementation of hstack(). ADDITIONOriginal docstring below.

LAX-backend implementation of hstack(). Original docstring below.

This is equivalent to concatenation along the second axis, except for 1-D arrays where it concatenates along the first axis. Rebuilds arrays divided by hsplit.

This function makes most sense for arrays with up to 3 dimensions. For instance, for pixel-data with a height (first axis), width (second axis), and r/g/b channels (third axis). The functions concatenate, stack and block provide more general stacking and concatenation operations.

Returns stacked – The array formed by stacking the given arrays.

Return type  ndarray

See also:

stack()  Join a sequence of arrays along a new axis.

vstack()  Stack arrays in sequence vertically (row wise).

dstack()  Stack arrays in sequence depth wise (along third axis).

concatenate()  Join a sequence of arrays along an existing axis.

hsplit()  Split array along second axis.

block()  Assemble arrays from blocks.
Examples

```python
>>> a = np.array((1, 2, 3))
>>> b = np.array((2, 3, 4))
>>> np.hstack((a, b))
array([1, 2, 3, 2, 3, 4])
>>> a = np.array([[1], [2], [3]])
>>> b = np.array([[2], [3], [4]])
>>> np.hstack((a, b))
array([[1, 2],
       [2, 3],
       [3, 4]])
```

**identity** *(n, dtype=None)*

Return the identity array.

LAX-backend implementation of `identity()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `identity()`. Original docstring below.

The identity array is a square array with ones on the main diagonal.

**Parameters**

- **dtype** *(data-type, optional)* – Data-type of the output. Defaults to `float`.

**Returns**

- **out** – `n x n` array with its main diagonal set to one, and all other elements 0.

**Return type**

`ndarray`

Examples

```python
>>> np.identity(3)
array([[1., 0., 0.],
       [0., 1., 0.],
       [0., 0., 1.]])
```

**imag** *(val)*

Return the imaginary part of the complex argument.

LAX-backend implementation of `imag()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `imag()`. Original docstring below.

**Returns**

- **out** – The imaginary component of the complex argument. If `val` is real, the type of `val` is used for the output. If `val` has complex elements, the returned type is float.

**Return type**

`ndarray` or scalar

See also:

`real()`, `angle()`, `real_if_close()`
Examples

```python
>>> a = np.array([1+2j, 3+4j, 5+6j])
>>> a.imag
array([2., 4., 6.])
>>> a.imag = np.array([8, 10, 12])
>>> a
array([1. +8.j, 3.+10.j, 5.+12.j])
>>> np.imag(1 + 1j)
1.0
```
A multidimensional example:

```python
>>> a = np.arange(24).reshape((2,3,4))
>>> b = np.arange(4)
>>> np.inner(a, b)
array([[ 14,  38,  62],
       [ 86, 110, 134]])
```

An example where \(b\) is a scalar:

```python
>>> np.inner(np.eye(2), 7)
array([[ 7.,  0.],
       [ 0.,  7.]])
```

```python
isclose(a, b, rtol=1e-05, atol=1e-08, equal_nan=False)
```

Returns a boolean array where two arrays are element-wise equal within a tolerance.

Warning: The default \(atol\) is not appropriate for comparing numbers that are much smaller than one (see Notes).

Returns \(y\) – Returns a boolean array of where \(a\) and \(b\) are equal within the given tolerance. If both \(a\) and \(b\) are scalars, returns a single boolean value.

Return type array_like

See also:

allclose()

Notes

New in version 1.7.0.

For finite values, isclose uses the following equation to test whether two floating point values are equivalent.

\[
\text{absolute}(a - b) <= (atol + rtol \times \text{absolute}(b))
\]

Unlike the built-in \texttt{math.isclose}, the above equation is not symmetric in \(a\) and \(b\) – it assumes \(b\) is the reference value – so that isclose\((a, \ b)\) might be different from isclose\((b, \ a)\). Furthermore, the default value of atol is not zero, and is used to determine what small values should be considered close to zero. The default value is appropriate for expected values of order unity: if the expected values are significantly smaller than one, it can result in false positives. \(atol\) should be carefully selected for the use case at hand. A zero value for \(atol\) will result in \texttt{False} if either \(a\) or \(b\) is zero.
Examples

```python
>>> np.isclose([1e10, 1e-7], [1.00001e10, 1e-8])
array([ True, False])

>>> np.isclose([1e10, 1e-8], [1.00001e10, 1e-9])
array([ True, True])

>>> np.isclose([1e10, 1e-8], [1.0001e10, 1e-9])
array([False, True])

>>> np.isclose([1.0, np.nan], [1.0, np.nan])
array([ True, False])

>>> np.isclose([1.0, np.nan], [1.0, np.nan], equal_nan=True)
array([ True, True])

>>> np.isclose([1e-8, 1e-7], [0.0, 0.0])
array([ True, False])

>>> np.isclose([1e-100, 1e-7], [0.0, 0.0], atol=0.0)
array([False, False])

>>> np.isclose([1e-10, 1e-10], [1e-20, 0.0], atol=0.0)
array([ True, True])
```

**isclose**

Returns a bool array, where True if input element is complex.

LAX-backend implementation of `isclose()`. ADDITION
Original docstring below.

LAX-backend implementation of `isclose()`. Original docstring below.

What is tested is whether the input has a non-zero imaginary part, not if the input type is complex.

**Returns out** – Output array.

**Return type** ndarray of bools

**See also:**

`isreal()`

`iscomplexobj()` Return True if x is a complex type or an array of complex numbers.

Examples

```python
>>> np.isclose([1+1j, 1+0j, 4.5, 3, 2, 2j])
array([ True, False, False, False, False, True])
```

**iscomplex**

Returns a bool array, where True if input element is complex.

LAX-backend implementation of `iscomplex()`. ADDITION
Original docstring below.

LAX-backend implementation of `iscomplex()`. Original docstring below.

What is tested is whether the input has a non-zero imaginary part, not if the input type is complex.

**Returns out** – Output array.

**Return type** ndarray of bools

**See also:**

`isreal()`

`iscomplexobj()` Return True if x is a complex type or an array of complex numbers.

Examples

```python
>>> np.iscomplex([1+1j, 1+0j, 4.5, 3, 2, 2j])
array([ True, False, False, False, False, True])
```

**isfinite**

Test element-wise for finiteness (not infinity or not Not a Number).

LAX-backend implementation of `isfinite()`. ADDITION
Original docstring below.

LAX-backend implementation of `isfinite()`. Original docstring below.

isfinite(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

The result is returned as a boolean array.

**Returns y** – True where x is not positive infinity, negative infinity, or NaN; false otherwise. This is a scalar if x is a scalar.

**Return type** ndarray, bool
See also:

isinf(), isneginf(), isposinf(), isnan()

Notes

Not a Number, positive infinity and negative infinity are considered to be non-finite.

NumPy uses the IEEE Standard for Binary Floating-Point for Arithmetic (IEEE 754). This means that Not a Number is not equivalent to infinity. Also that positive infinity is not equivalent to negative infinity. But infinity is equivalent to positive infinity. Errors result if the second argument is also supplied when x is a scalar input, or if first and second arguments have different shapes.

Examples

```python
>>> np.isfinite(1)
True
>>> np.isfinite(0)
True
>>> np.isfinite(np.nan)
False
>>> np.isfinite(np.inf)
False
>>> np.isfinite(np.NINF)
False
>>> np.isfinite([np.log(-1.),1.,np.log(0)])
array([False, True, False])
```

```python
>>> x = np.array([-np.inf, 0., np.inf])
>>> y = np.array([2, 2, 2])
>>> np.isfinite(x, y)
array([0, 1, 0])
>>> y
array([0, 1, 0])
```

isinf(x)

Test element-wise for positive or negative infinity.

LAX-backend implementation of isinf(). ADDITIONOriginal docstring below.

LAX-backend implementation of isinf(). Original docstring below.

isinf(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns a boolean array of the same shape as x, True where x == +/-inf, otherwise False.

Returns y – True where x is positive or negative infinity, false otherwise. This is a scalar if x is a scalar.

Return type bool (scalar) or boolean ndarray

See also:

isneginf(), isposinf(), isnan(), isfinite()
Notes

NumPy uses the IEEE Standard for Binary Floating-Point for Arithmetic (IEEE 754).
Errors result if the second argument is supplied when the first argument is a scalar, or if the first and second
arguments have different shapes.

Examples

```python
>>> np.isinf(np.inf)
True
>>> np.isinf(np.nan)
False
>>> np.isinf(np.NINF)
True
>>> np.isinf([np.inf, -np.inf, 1.0, np.nan])
array([ True,  True, False, False])
```

```python
>>> x = np.array([-np.inf, 0., np.inf])
>>> y = np.array([2, 2, 2])
>>> np.isinf(x, y)
array([1, 0, 1])
>>> y
array([1, 0, 1])
```

isnan(x)
Test element-wise for NaN and return result as a boolean array.
LAX-backend implementation of isnan(). ADDITIONOriginal docstring below.
LAX-backend implementation of isnan(). Original docstring below.
isnan(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns y – True where x is NaN, false otherwise. This is a scalar if x is a scalar.

Return type ndarray or bool

See also:
isinf(), isneginf(), isposinf(), isfinite(), isnat()

Notes

NumPy uses the IEEE Standard for Binary Floating-Point for Arithmetic (IEEE 754). This means that Not a
Number is not equivalent to infinity.
### isreal(x)
Returns a bool array, where True if input element is real.
LAX-backend implementation of `isreal()`. ADDITIONOriginal docstring below.
LAX-backend implementation of `isreal()`. Original docstring below.
If element has complex type with zero complex part, the return value for that element is True.

- **Returns out** – Boolean array of same shape as `x`.
- **Return type** `ndarray, bool`

### Examples
```python
>>> np.isreal([1+1j, 1+0j, 4.5, 3, 2, 2j])
array([False, True, True, True, True, False])
```

### isscalar(num)
Returns True if the type of `element` is a scalar type.
LAX-backend implementation of `isscalar()`. ADDITIONOriginal docstring below.
LAX-backend implementation of `isscalar()`. Original docstring below.

- **Returns val** – True if `element` is a scalar type, False if it is not.
- **Return type** `bool`

### Examples
```python
>>> np.isscalar([1+1j, 1+0j, 4.5, 3, 2, 2j])
array([False, True, True, True, True, False])
```

### Notes
If you need a stricter way to identify a `numerical` scalar, use `isinstance(x, numbers.Number)`, as that returns `False` for most non-numerical elements such as strings.

In most cases `np.ndim(x) == 0` should be used instead of this function, as that will also return true for 0d arrays. This is how numpy overloads functions in the style of the `dx` arguments to `gradient` and the `bins` argument to `histogram`. Some key differences:
|                  | isscalar(x) | np.ndim(x) == 0 |
|------------------|-------------|-----------------|
| PEP 3141 numeric objects (including builtins) | True        | True            |
| builtin string and buffer objects               | True        | True            |
| other builtin objects, like `pathlib.Path`, `Exception`, the result of `re.compile` | False       | True            |
| third-party objects like `matplotlib.figure.Figure` | False       | True            |
| zero-dimensional numpy arrays                    | False       | True            |
| other numpy arrays                                | False       | False           |
| `list`, `tuple`, and other sequence objects       | False       | False           |

### Examples

```python
global x

>>> np.isscalar(3.1)
True
>>> np.isscalar(np.array(3.1))
False
>>> np.isscalar([3.1])
False
>>> np.isscalar(False)
True
>>> np.isscalar('numpy')
True
```

NumPy supports PEP 3141 numbers:

```python
global x

>>> from fractions import Fraction
>>> np.isscalar(Fraction(5, 17))
True
>>> from numbers import Number
>>> np.isscalar(Number())
True
```

### ix_(*args)

Construct an open mesh from multiple sequences.

LAX-backend implementation of `ix_()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `ix_()`. Original docstring below.

This function takes N 1-D sequences and returns N outputs with N dimensions each, such that the shape is 1 in all but one dimension and the dimension with the non-unit shape value cycles through all N dimensions.

Using `ix_` one can quickly construct index arrays that will index the cross product. `a[np.ix_([1,3],[2,5])]` returns the array `[[a[1,2] a[1,5]], [a[3,2] a[3,5]]].`

**Parameters** `args` (*N* 1-D sequences) — Each sequence should be of integer or boolean type. Boolean sequences will be interpreted as boolean masks for the corresponding dimension (equivalent to passing in `np.nonzero(boolean_sequence)`).

**Returns** `out` — *N* arrays with *N* dimensions each, with *N* the number of input sequences. Together these arrays form an open mesh.

**Return type** tuple of ndarrays

See also:

`ogrid()`, `mgrid()`, `meshgrid()`
**Examples**

```python
>>> a = np.arange(10).reshape(2, 5)
>>> a
array([[0, 1, 2, 3, 4],
       [5, 6, 7, 8, 9]])

>>> ixgrid = np.ix_([0, 1], [2, 4])
>>> ixgrid
(array([[0],
        [1]]), array([[2, 4]]))

>>> ixgrid[0].shape, ixgrid[1].shape
((2, 1), (1, 2))

>>> a[ixgrid]
array([[2, 4],
       [7, 9]])

>>> ixgrid = np.ix_(True, True, [2, 4])

>>> a[ixgrid]
array([[2, 4],
       [7, 9]])

>>> ixgrid = np.ix_(True, True, False, False, True, False, True)

>>> a[ixgrid]
array([[2, 4],
       [7, 9]])
```

**kron** *(a, b)*  
Kronecker product of two arrays.

LAX-backend implementation of `kron()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `kron()`. Original docstring below.

Computes the Kronecker product, a composite array made of blocks of the second array scaled by the first.

**Returns** out

**Return type** ndarray

**See also:**

`outer()` The outer product

**Notes**

The function assumes that the number of dimensions of `a` and `b` are the same, if necessary prepending the smallest with ones. If `a.shape = (r0,r1,...,rN)` and `b.shape = (s0,s1,...,sN)`, the Kronecker product has shape `(r0*s0, r1*s1, ..., rN*sN)`. The elements are products of elements from `a` and `b`, organized explicitly by:

\[
\text{kron}(a,b)[k_0,k_1,...,k_N] = a[i_0,i_1,...,i_N] \times b[j_0,j_1,...,j_N]
\]

where:

\[
kt = it \times st + jt, \quad t = 0, \ldots, N
\]

In the common 2-D case (N=1), the block structure can be visualized:
Examples

```python
>>> np.kron([1,10,100], [5,6,7])
array([ 5, 6, 7, ..., 500, 600, 700])
>>> np.kron([5,6,7], [1,10,100])
array([ 5, 50, 500, ..., 7, 70, 700])
>>> np.kron(np.eye(2), np.ones((2,2)))
array([[1., 1., 0., 0.],
       [1., 1., 0., 0.],
       [0., 0., 1., 1.],
       [0., 0., 1., 1.]])
```

```python
>>> a = np.arange(100).reshape((2,5,2,5))
>>> b = np.arange(24).reshape((2,3,4))
>>> c = np.kron(a,b)
>>> c.shape
(2, 10, 6, 20)
>>> I = (1,3,0,2)
>>> J = (0,2,1)
>>> J1 = (0,) + J  # extend to ndim=4
>>> S1 = (1,) + b.shape
>>> K = tuple(np.array(I) * np.array(S1) + np.array(J1))
>>> c[K] == a[I]*b[J]
True
```

**lcm** *(x1, x2)*

Returns the lowest common multiple of |x1| and |x2|

LAX-backend implementation of `lcm()`.

**Original docstring below.**

LAX-backend implementation of `lcm()`.

```python
lcm(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

**Returns** y – The lowest common multiple of the absolute value of the inputs. This is a scalar if both x1 and x2 are scalars.

**Return type** ndarray or scalar

**See also:**

`gcd()` The greatest common divisor
Examples

```python
>>> np.lcm(12, 20)
60
>>> np.lcm.reduce([3, 12, 20])
60
>>> np.lcm.reduce([40, 12, 20])
120
>>> np.lcm(np.arange(6), 20)
array([0, 20, 20, 60, 20, 20])
```

**left_shift** *(x1, x2)*
Shift the bits of an integer to the left.

LAX-backend implementation of `left_shift()`. ADDITIONS
Original docstring below.

LAX-backend implementation of `left_shift()`. Original docstring below.

```python
left_shift(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

Bits are shifted to the left by appending `x2` 0s at the right of `x1`. Since the internal representation of numbers is in binary format, this operation is equivalent to multiplying `x1` by `2**x2`.

Returns **out** -- Return `x1` with bits shifted `x2` times to the left. This is a scalar if both `x1` and `x2` are scalars.

**Return type** array of integer type

See also:

**right_shift()** Shift the bits of an integer to the right.

**binary_repr()** Return the binary representation of the input number as a string.

Examples

```python
>>> np.binary_repr(5)
'101'
>>> np.left_shift(5, 2)
20
>>> np.binary_repr(20)
'10100'
>>> np.left_shift(5, [1,2,3])
array([10, 20, 40])
```

**less**(x1, x2)
Return the truth value of `(x1 < x2)` element-wise.

LAX-backend implementation of `less()`. ADDITION
Original docstring below.

LAX-backend implementation of `less()`. Original docstring below.

```
less(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

Returns **out** -- Output array, element-wise comparison of `x1` and `x2`. Typically of type bool, unless `dtype=object` is passed. This is a scalar if both `x1` and `x2` are scalars.
Return type  ndarray or scalar

See also:

greater(), less_equal(), greater_equal(), equal(), not_equal()

Examples

```python
>>> np.less([1, 2], [2, 2])
array([ True, False])
```

**less_equal**(x1, x2)

Return the truth value of (x1 <= x2) element-wise.

LAX-backend implementation of `less_equal()`. ADDITION Original docstring below.

LAX-backend implementation of `less_equal()`. Original docstring below.

```python
less_equal(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

Returns out – Output array, element-wise comparison of x1 and x2. Typically of type bool, unless dtype=object is passed. This is a scalar if both x1 and x2 are scalars.

Return type  ndarray or scalar

See also:

greater(), less(), greater_equal(), equal(), not_equal()

Examples

```python
>>> np.less_equal([4, 2, 1], [2, 2, 2])
array([False, True, True])
```

**linspace**(start, stop, num=50, endpoint=True, retstep=False, dtype=None, axis=0)

Return evenly spaced numbers over a specified interval.

LAX-backend implementation of `linspace()`. ADDITION Original docstring below.

LAX-backend implementation of `linspace()`. Original docstring below.

Returns num evenly spaced samples, calculated over the interval [start, stop]. The endpoint of the interval can optionally be excluded.

Changed in version 1.16.0: Non-scalar start and stop are now supported.

Parameters dtype (dtype, optional) – The type of the output array. If dtype is not given, infer the data type from the other input arguments.

Returns

- samples (ndarray) – There are num equally spaced samples in the closed interval [start, stop] or the half-open interval [start, stop) (depending on whether endpoint is True or False).
- step (float, optional) – Only returned if retstep is True

Size of spacing between samples.

See also:
**arange**() Similar to **linspace**, but uses a step size (instead of the number of samples).

**geomspace**() Similar to **linspace**, but with numbers spaced evenly on a log scale (a geometric progression).

**logspace**() Similar to **geomspace**, but with the end points specified as logarithms.

**Examples**

```python
>>> np.linspace(2.0, 3.0, num=5)
array([2. , 2.25, 2.5 , 2.75, 3. ])
>>> np.linspace(2.0, 3.0, num=5, endpoint=False)
array([2. , 2.2, 2.4, 2.6, 2.8])
>>> np.linspace(2.0, 3.0, num=5, retstep=True)
(array([2. , 2.25, 2.5 , 2.75, 3. ]), 0.25)
```

Graphical illustration:

```python
>>> import matplotlib.pyplot as plt
>>> N = 8
>>> y = np.zeros(N)
>>> x1 = np.linspace(0, 10, N, endpoint=True)
>>> x2 = np.linspace(0, 10, N, endpoint=False)
>>> plt.plot(x1, y, 'o')
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.plot(x2, y + 0.5, 'o')
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.ylim([-0.5, 1])
(-0.5, 1)
>>> plt.show()
```

**log**(x)

Natural logarithm, element-wise.

LAX-backend implementation of **log**(). ADDITION: Original docstring below.

LAX-backend implementation of **log**(). Original docstring below.

log(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

The natural logarithm log is the inverse of the exponential function, so that log(exp(x)) = x. The natural logarithm is logarithm in base e.

**Returns** y - The natural logarithm of x, element-wise. This is a scalar if x is a scalar.

**Return type** ndarray

See also:

log10, log2, log1p, emath.log()
Notes

Logarithm is a multivalued function: for each \( x \) there is an infinite number of \( z \) such that \( \exp(z) = x \). The convention is to return the \( z \) whose imaginary part lies in \([-\pi, \pi]\).

For real-valued input data types, \( \log \) always returns real output. For each value that cannot be expressed as a real number or infinity, it yields \( \text{nan} \) and sets the \text{invalid} floating point error flag.

For complex-valued input, \( \log \) is a complex analytical function that has a branch cut \([-\infty, 0]\) and is continuous from above on it. \( \log \) handles the floating-point negative zero as an infinitesimal negative number, conforming to the C99 standard.

References

Examples

```python
>>> np.log([1, np.e, np.e**2, 0])
array([ 0., 1., 2., -Inf])
```

\( \log_{10}(x) \)

Return the base 10 logarithm of the input array, element-wise.

LAX-backend implementation of \( \log_{10}() \). ADDITIONAL docstring below.

LAX-backend implementation of \( \log_{10}() \). Original docstring below.

\[
\log_{10}(x, /, \text{out}=\text{None}, *, \text{where}=\text{True}, \text{casting}=\text{same_kind}, \text{order}=\text{K}, \text{dtype}=\text{None}, \text{subok}=\text{True}, \text{signature}, \text{extobj})
\]

**Returns**

\( y \) – The logarithm to the base 10 of \( x \), element-wise. \( \text{NaNs} \) are returned where \( x \) is negative. This is a scalar if \( x \) is a scalar.

**Return type**

\( \text{ndarray} \)

See also:

\( \text{emath.log10()} \)

Notes

Logarithm is a multivalued function: for each \( x \) there is an infinite number of \( z \) such that \( 10^{z} = x \). The convention is to return the \( z \) whose imaginary part lies in \([-\pi, \pi]\).

For real-valued input data types, \( \log_{10} \) always returns real output. For each value that cannot be expressed as a real number or infinity, it yields \( \text{nan} \) and sets the \text{invalid} floating point error flag.

For complex-valued input, \( \log_{10} \) is a complex analytical function that has a branch cut \([-\infty, 0]\) and is continuous from above on it. \( \log_{10} \) handles the floating-point negative zero as an infinitesimal negative number, conforming to the C99 standard.
log1p (x)
Return the natural logarithm of one plus the input array, element-wise.
LAX-backend implementation of log1p(). ADDITIONOriginal docstring below.
LAX-backend implementation of log1p(). Original docstring below.

log1p(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
Calculates log(1 + x).

Returns y – Natural logarithm of 1 + x, element-wise. This is a scalar if x is a scalar.

Return type
ndarray

See also:
expm1() \( \exp(x) - 1 \), the inverse of log1p.

Notes
For real-valued input, log1p is accurate also for x so small that \( 1 + x \approx 1 \) in floating-point accuracy.
Logarithm is a multivalued function: for each x there is an infinite number of \( z \) such that \( \exp(z) = 1 + x \). The convention is to return the \( z \) whose imaginary part lies in \([-\pi, \pi]\).

For real-valued input data types, log1p always returns real output. For each value that cannot be expressed as a real number or infinity, it yields nan and sets the invalid floating point error flag.

For complex-valued input, log1p is a complex analytical function that has a branch cut \([-\infty, -1]\) and is continuous from above on it. log1p handles the floating-point negative zero as an infinitesimal negative number, conforming to the C99 standard.

References

Examples

```python
>>> np.log1p(1e-99)
1e-99
>>> np.log(1 + 1e-99)
0.0
```

log2 (x)
Base-2 logarithm of x.
LAX-backend implementation of log2(). ADDITIONOriginal docstring below.
LAX-backend implementation of log2(). Original docstring below.

log2(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

2.1. General
Returns y – Base-2 logarithm of $x$. This is a scalar if $x$ is a scalar.

Return type  ndarray

See also:
$log()$, $log10()$, $log1p()$, emath.log2()

Notes

New in version 1.3.0.

Logarithm is a multivalued function: for each $x$ there is an infinite number of $z$ such that $2^z = x$. The convention is to return the $z$ whose imaginary part lies in $[-\pi, \pi]$.

For real-valued input data types, $\log2$ always returns real output. For each value that cannot be expressed as a real number or infinity, it yields $\text{nan}$ and sets the $\text{invalid}$ floating point error flag.

For complex-valued input, $\log2$ is a complex analytical function that has a branch cut $[-\infty, 0]$ and is continuous from above on it. $\log2$ handles the floating-point negative zero as an infinitesimal negative number, conforming to the C99 standard.

Examples

```python
code x = np.array([0, 1, 2, 2**4])
code np.log2(x)
array([-Inf,  0.,  1.,  4.])
```

```python
code xi = np.array([0+1.j, 1, 2+0.j, 4.j])
code np.log2(xi)
array([ 0.+2.26618007j, 0.+0.j , 1.+0.j , 2.+2.26618007j])
```

logical_and(*args)
Compute the truth value of $x_1$ AND $x_2$ element-wise.

LAX-backend implementation of $\text{logical_and}()$. ADDITIONOriginal docstring below.

LAX-backend implementation of $\text{logical_and}()$. Original docstring below.

logical_and($x_1$, $x_2$, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns y – Boolean result of the logical AND operation applied to the elements of $x_1$ and $x_2$; the shape is determined by broadcasting. This is a scalar if both $x_1$ and $x_2$ are scalars.

Return type  ndarray or bool

See also:
$logical_or()$, $logical_not()$, $logical_xor()$, $bitwise_and()$
Examples

```python
>>> np.logical_and(True, False)
False
>>> np.logical_and([True, False], [False, False])
array([[False, False]])
```

```python
>>> x = np.arange(5)
>>> np.logical_and(x>1, x<4)
array([False, False,  True,  True, False])
```

**logical_not (**args**)

Compute the truth value of NOT x element-wise.

LAX-backend implementation of `logical_not`. ADDITIONAL Original docstring below.

LAX-backend implementation of `logical_not`. Original docstring below.

`logical_not(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])`

- Returns `y` – Boolean result with the same shape as `x` of the NOT operation on elements of `x`. This is a scalar if `x` is a scalar.

- **Return type** bool or ndarray of bool

---

**See also:**

`logical_and()`, `logical_or()`, `logical_xor()`

---

Examples

```python
>>> np.logical_not(3)
False
>>> np.logical_not([True, False, 0, 1])
array([False,  True,  True, False])
```

```python
>>> x = np.arange(5)
>>> np.logical_not(x<3)
array([False, False, False,  True,  True])
```

**logical_or (**args**)

Compute the truth value of x1 OR x2 element-wise.

LAX-backend implementation of `logical_or`. ADDITIONAL Original docstring below.

LAX-backend implementation of `logical_or`. Original docstring below.

`logical_or(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])`

- Returns `y` – Boolean result of the logical OR operation applied to the elements of `x1` and `x2`; the shape is determined by broadcasting. This is a scalar if both `x1` and `x2` are scalars.

- **Return type** ndarray or bool

---

**See also:**

`logical_and()`, `logical_not()`, `logical_xor()`, `bitwise_or()`
Examples

```python
>>> np.logical_or(True, False)
True
>>> np.logical_or([True, False], [False, False])
array([ True, False])
```

```python
>>> x = np.arange(5)
>>> np.logical_or(x < 1, x > 3)
array([ True, False, False, False, True])
```

**logical_xor(***args**)
Compute the truth value of x1 XOR x2, element-wise.

LAX-backend implementation of `logical_xor`. Original docstring below.

LAX-backend implementation of `logical_xor`. Original docstring below.

```python
logical_xor(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

Returns y – Boolean result of the logical XOR operation applied to the elements of x1 and x2; the shape is determined by broadcasting. This is a scalar if both x1 and x2 are scalars.

**Return type** bool or ndarray of bool

**See also:**
`logical_and`, `logical_or`, `logical_not`, `bitwise_xor`

Examples

```python
>>> np.logical_xor(True, False)
True
>>> np.logical_xor([True, True, False, False], [True, False, True, False])
array([False, True, True, False])
```

```python
>>> x = np.arange(5)
>>> np.logical_xor(x < 1, x > 3)
array([ True, False, False, False, True])
```

Simple example showing support of broadcasting

```python
>>> np.logical_xor(0, np.eye(2))
array([[ True, False],
       [False, True]])
```

**logspace**(start, stop, num=50, endpoint=True, base=10.0, dtype=None, axis=0)
Return numbers spaced evenly on a log scale.

LAX-backend implementation of `logspace`. Original docstring below.

LAX-backend implementation of `logspace`. Original docstring below.

In linear space, the sequence starts at base ** start (base to the power of start) and ends with base ** stop (see endpoint below).

Changed in version 1.16.0: Non-scalar start and stop are now supported.
Parameters `dtype (dtype)` – The type of the output array. If `dtype` is not given, infer the data type from the other input arguments.

Returns `samples` – `num` samples, equally spaced on a log scale.

Return type `ndarray`

See also:

`arange()` Similar to `linspace`, with the step size specified instead of the number of samples. Note that, when used with a float endpoint, the endpoint may or may not be included.

`linspace()` Similar to `logspace`, but with the samples uniformly distributed in linear space, instead of log space.

`geomspace()` Similar to `logspace`, but with endpoints specified directly.

Notes

Logspace is equivalent to the code

```python
>>> y = np.linspace(start, stop, num=num, endpoint=endpoint)
... >>> power(base, y).astype(dtype)
...```

Examples

```python
>>> np.logspace(2.0, 3.0, num=4)
array([ 100. , 215.443469 , 464.15888336, 1000. ])
>>> np.logspace(2.0, 3.0, num=4, endpoint=False)
array([100. , 177.827941 , 316.22776602, 562.34132519])
>>> np.logspace(2.0, 3.0, num=4, base=2.0)
array([4. , 5.0396842 , 6.34960421, 8. ])
```

Graphical illustration:

```python
>>> import matplotlib.pyplot as plt

>>> N = 10
>>> x1 = np.logspace(0.1, 1, N, endpoint=True)
>>> x2 = np.logspace(0.1, 1, N, endpoint=False)
>>> y = np.zeros(N)
>>> plt.plot(x1, y, 'o')
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.plot(x2, y + 0.5, 'o')
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.ylim([-0.5, 1])
(-0.5, 1)
>>> plt.show()
```

`matmul (a, b, precision=None)`

Matrix product of two arrays.

LAX-backend implementation of `matmul ()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `matmul ()`. In addition to the original NumPy arguments listed below, also supports `precision` for extra control over matrix-multiplication precision on supported devices. See `jax.lax.dot ()` for details.
Original docstring below.

```
matmul(x1, x2, /, out=None, *, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```  
**Returns** y – The matrix product of the inputs. This is a scalar only when both x1, x2 are 1-d vectors.

**Return type** ndarray

**Raises** ValueError – If the last dimension of a is not the same size as the second-to-last dimension of b.

If a scalar value is passed in.

**See also:**

- `vdot()` Complex-conjugating dot product.
- `tensordot()` Sum products over arbitrary axes.
- `einsum()` Einstein summation convention.
- `dot()` alternative matrix product with different broadcasting rules.

**Notes**

The behavior depends on the arguments in the following way.

- If both arguments are 2-D they are multiplied like conventional matrices.
- If either argument is N-D, N > 2, it is treated as a stack of matrices residing in the last two indexes and broadcast accordingly.
- If the first argument is 1-D, it is promoted to a matrix by prepending a 1 to its dimensions. After matrix multiplication the prepended 1 is removed.
- If the second argument is 1-D, it is promoted to a matrix by appending a 1 to its dimensions. After matrix multiplication the appended 1 is removed.

`matmul` differs from `dot` in two important ways:

- Multiplication by scalars is not allowed, use * instead.
- Stacks of matrices are broadcast together as if the matrices were elements, respecting the signature \((n, k), (k, m) \to (n, m)\):

```python
>>> a = np.ones([9, 5, 7, 4])
>>> c = np.ones([9, 5, 4, 3])
>>> np.dot(a, c).shape
(9, 5, 7, 9, 5, 3)
>>> np.matmul(a, c).shape
(9, 5, 7, 3)
>>> # n is 7, k is 4, m is 3
```

The `matmul` function implements the semantics of the `@` operator introduced in Python 3.5 following PEP465.
Examples

For 2-D arrays it is the matrix product:

```python
>>> a = np.array([[1, 0],
...                [0, 1]])
>>> b = np.array([[4, 1],
...                [2, 2]])
>>> np.matmul(a, b)
array([[4, 1],
       [2, 2]])
```

For 2-D mixed with 1-D, the result is the usual.

```python
>>> a = np.array([[1, 0],
...                [0, 1]])
>>> b = np.array([1, 2])
>>> np.matmul(a, b)
array([1, 2])
>>> np.matmul(b, a)
array([1, 2])
```

Broadcasting is conventional for stacks of arrays

```python
>>> a = np.arange(2 * 2 * 4).reshape((2, 2, 4))
>>> b = np.arange(2 * 2 * 4).reshape((2, 4, 2))
>>> np.matmul(a,b).shape
(2, 2, 2)
>>> np.matmul(a, b)[0, 1, 1]
98
>>> sum(a[0, 1, :] * b[0 , :, 1])
98
```

Vector, vector returns the scalar inner product, but neither argument is complex-conjugated:

```python
>>> np.matmul([2j, 3j], [2j, 3j])
(-13+0j)
```

Scalar multiplication raises an error.

```python
>>> np.matmul([1,2], 3)
Traceback (most recent call last):
...
ValueError: matmul: Input operand 1 does not have enough dimensions ...
```

New in version 1.10.0.

```python
max (a, axis=None, dtype=None, out=None, keepdims=False)  
Return the maximum of an array or maximum along an axis.
```

LAX-backend implementation of `amax()`.

LAX-backend implementation of `amax()`. Original docstring below.

```
Returns amax – Maximum of a. If axis is None, the result is a scalar value. If axis is given, the result is an array of dimension a.ndim - 1.

Return type ndarray or scalar

See also:
```
**amin()**  The minimum value of an array along a given axis, propagating any NaNs.

**nanmax()**  The maximum value of an array along a given axis, ignoring any NaNs.

**maximum()**  Element-wise maximum of two arrays, propagating any NaNs.

**fmax()**  Element-wise maximum of two arrays, ignoring any NaNs.

**argmax()**  Return the indices of the maximum values.

**nanmin(), minimum(), fmin()**

### Notes

NaN values are propagated, that is if at least one item is NaN, the corresponding max value will be NaN as well. To ignore NaN values (MATLAB behavior), please use nanmax.

Don’t use *amax* for element-wise comparison of 2 arrays; when *a.shape[0]* is 2, *maximum(a[0], a[1])* is faster than *amax(a, axis=0)*.

### Examples

```python
>>> a = np.arange(4).reshape((2,2))
>>> a
array([[0, 1],
       [2, 3]])
>>> np.amax(a)  # Maximum of the flattened array
3
>>> np.amax(a, axis=0)  # Maxima along the first axis
array([2, 3])
>>> np.amax(a, axis=1)  # Maxima along the second axis
array([1, 3])
>>> np.amax(a, where=[False, True], initial=-1, axis=0)
array([-1, 3])
```

You can use an initial value to compute the maximum of an empty slice, or to initialize it to a different value:

```python
>>> np.max([[-50], [10]], axis=-1, initial=0)
array([ 0, 10])
```

Notice that the initial value is used as one of the elements for which the maximum is determined, unlike for the default argument Python’s *max* function, which is only used for empty iterables.

```python
>>> np.max([5], initial=6)
6
>>> max([5], default=6)
5
```
**maximum**(*x1*, *x2*)

Element-wise maximum of array elements.

LAX-backend implementation of `maximum()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `maximum()`. Original docstring below.

```
maximum(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

Compare two arrays and returns a new array containing the element-wise maxima. If one of the elements being compared is a NaN, then that element is returned. If both elements are NaNs then the first is returned. The latter distinction is important for complex NaNs, which are defined as at least one of the real or imaginary parts being a NaN. The net effect is that NaNs are propagated.

Returns

- **y** – The maximum of *x1* and *x2*, element-wise. This is a scalar if both *x1* and *x2* are scalars.

- **Return type** ndarray or scalar

See also:

- `minimum()` Element-wise minimum of two arrays, propagates NaNs.
- `fmax()` Element-wise maximum of two arrays, ignores NaNs.
- `amax()` The maximum value of an array along a given axis, propagates NaNs.
- `nanmax()` The maximum value of an array along a given axis, ignores NaNs.
- `fmin()`, `amin()`, `nanmin()`

Notes

The maximum is equivalent to `np.where(x1 >= x2, x1, x2)` when neither *x1* nor *x2* are nans, but it is faster and does proper broadcasting.

Examples

```
>>> np.maximum([2, 3, 4], [1, 5, 2])
array([2, 5, 4])
```

```
>>> np.maximum(np.eye(2), [0.5, 2]) # broadcasting
array([[ 1. ,  2. ],
       [ 0.5,  2. ]])
```

```
>>> np.maximum([np.nan, 0, np.nan], [0, np.nan, np.nan])
array([ NaN, 0. , NaN])
>>> np.maximum(np.Inf, 1)
inf
```

**mean**(*a*, *axis=None*, *dtype=None*, *out=None*, *keepdims=False*)

Compute the arithmetic mean along the specified axis.

LAX-backend implementation of `mean()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `mean()`. Original docstring below.

Returns the average of the array elements. The average is taken over the flattened array by default, otherwise over the specified axis. float64 intermediate and return values are used for integer inputs.
Parameters **dtype** (*data-type, optional*)– Type to use in computing the mean. For integer inputs, the default is *float64*; for floating point inputs, it is the same as the input dtype.

**Returns** m – If *out=None*, returns a new array containing the mean values, otherwise a reference to the output array is returned.

**Return type** ndarray, see dtype parameter above

See also:

*average()*  Weighted average

*std(), var(), nanmean(), nanstd(), nanvar()*

**Notes**

The arithmetic mean is the sum of the elements along the axis divided by the number of elements.

Note that for floating-point input, the mean is computed using the same precision the input has. Depending on the input data, this can cause the results to be inaccurate, especially for *float32* (see example below). Specifying a higher-precision accumulator using the *dtype* keyword can alleviate this issue.

By default, *float16* results are computed using *float32* intermediates for extra precision.

**Examples**

```python
>>> a = np.array([[1, 2], [3, 4]])
>>> np.mean(a)
2.5
>>> np.mean(a, axis=0)
array([2., 3.])
>>> np.mean(a, axis=1)
array([1.5, 3.5])
```

In single precision, *mean* can be inaccurate:

```python
>>> a = np.zeros((2, 512*512), dtype=np.float32)
>>> a[0, :] = 1.0
>>> a[1, :] = 0.1
>>> np.mean(a)
0.54999924
```

Computing the mean in *float64* is more accurate:

```python
>>> np.mean(a, dtype=np.float64)
0.55000000074505806 # may vary
```

**median** (*a, axis=None, out=None, overwrite_input=False, keepdims=False*)

Compute the median along the specified axis.

LAX-backend implementation of *median*. ADDITIONOriginal docstring below.

LAX-backend implementation of *median*. Original docstring below.

Returns the median of the array elements.
**Returns median** – A new array holding the result. If the input contains integers or floats smaller than `float64`, then the output data-type is `np.float64`. Otherwise, the data-type of the output is the same as that of the input. If `out` is specified, that array is returned instead.

**Return type** ndarray

**See also:** `mean()`, `percentile()`

**Notes**

Given a vector \( V \) of length \( N \), the median of \( V \) is the middle value of a sorted copy of \( V \), \( V_{\text{sorted}} \) - i.e., \( V_{\text{sorted}}[(N-1)/2] \), when \( N \) is odd, and the average of the two middle values of \( V_{\text{sorted}} \) when \( N \) is even.

**Examples**

```python
>>> a = np.array([[10, 7, 4], [3, 2, 1]])
>>> a
array([[10,  7,  4],
       [ 3,  2,  1]])
>>> np.median(a)
3.5
>>> np.median(a, axis=0)
array([6.5, 4.5, 2.5])
>>> np.median(a, axis=1)
array([7., 2.])
>>> m = np.median(a, axis=0)
>>> out = np.zeros_like(m)
>>> np.median(a, axis=0, out=m)
array([6.5, 4.5, 2.5])
>>> m
array([6.5, 4.5, 2.5])
>>> b = a.copy()
>>> np.median(b, axis=1, overwrite_input=True)
array([7., 2.])
>>> assert not np.all(a==b)
>>> b = a.copy()
>>> np.median(b, axis=None, overwrite_input=True)
3.5
>>> assert not np.all(a==b)
```

### meshgrid(*args, **kwargs)

Return coordinate matrices from coordinate vectors.

LAX-backend implementation of `meshgrid()`. ADDITION: Original docstring below.

LAX-backend implementation of `meshgrid()`. Original docstring below.

Make N-D coordinate arrays for vectorized evaluations of N-D scalar/vector fields over N-D grids, given one-dimensional coordinate arrays \( x_1, x_2, \ldots, x_n \).

Changed in version 1.9: 1-D and 0-D cases are allowed.

**Returns** \( X_1, X_2, \ldots, X_N \) – For vectors \( x_1, x_2, \ldots, 'x_n' \) with lengths \( N_i=len(x_i) \), return \( (N_1, \quad N_2, \quad N_3, \ldots N_n) \) shaped arrays if indexing='ij' or \( (N_2, \quad N_1, \quad N_3, \ldots N_n) \) shaped arrays.
if indexing='xy' with the elements of \( x_i \) repeated to fill the matrix along the first dimension for \( x_1 \), the second for \( x_2 \) and so on.

**Return type**  ndarray

**Notes**

This function supports both indexing conventions through the indexing keyword argument. Giving the string ‘ij’ returns a meshgrid with matrix indexing, while ‘xy’ returns a meshgrid with Cartesian indexing. In the 2-D case with inputs of length M and N, the outputs are of shape (N, M) for ‘xy’ indexing and (M, N) for ‘ij’ indexing. In the 3-D case with inputs of length M, N and P, outputs are of shape (N, M, P) for ‘xy’ indexing and (M, N, P) for ‘ij’ indexing. The difference is illustrated by the following code snippet:

```python
xv, yv = np.meshgrid(x, y, sparse=False, indexing='ij')
for i in range(nx):
    for j in range(ny):
        # treat xv[i,j], yv[i,j]

xv, yv = np.meshgrid(x, y, sparse=False, indexing='xy')
for i in range(nx):
    for j in range(ny):
        # treat xv[j,i], yv[j,i]
```

In the 1-D and 0-D case, the indexing and sparse keywords have no effect.

**See also:**

*index_tricks.mgrid()*  Construct a multi-dimensional “meshgrid” using indexing notation.

*index_tricks.ogrid()*  Construct an open multi-dimensional “meshgrid” using indexing notation.

**Examples**

```python
>>> nx, ny = (3, 2)
>>> x = np.linspace(0, 1, nx)
>>> y = np.linspace(0, 1, ny)
>>> xv, yv = np.meshgrid(x, y)
>>> xv
array([[0. , 0.5, 1. ],
       [0. , 0.5, 1. ]])
>>> yv
array([[0., 0., 0.],
       [1., 1., 1.]]
>>> xv, yv = np.meshgrid(x, y, sparse=True)  # make sparse output arrays
>>> xv
array([[0. , 0.5, 1. ]])
>>> yv
array([[0.],
       [1.]]
```

*meshgrid* is very useful to evaluate functions on a grid.

```python
>>> import matplotlib.pyplot as plt
>>> x = np.arange(-5, 5, 0.1)
>>> y = np.arange(-5, 5, 0.1)
>>> xx, yy = np.meshgrid(x, y, sparse=True)
```

(continues on next page)
```
>>> z = np.sin(xx**2 + yy**2) / (xx**2 + yy**2)
>>> h = plt.contourf(x,y,z)
>>> plt.show()
```

\[ \text{min}(a, \text{axis}={\text{None}}, \text{dtype}={\text{None}}, \text{out}={\text{None}}, \text{keepdims}={\text{False}}) \]

Return the minimum of an array or minimum along an axis.

LAX-backend implementation of :func:`amin()`. ADDITIONOriginal docstring below.

LAX-backend implementation of :func:`amin()`. Original docstring below.

- **Returns** amin – Minimum of a. If axis is None, the result is a scalar value. If axis is given, the result is an array of dimension a.ndim - 1.
- **Return type** ndarray or scalar

See also:

- **amax()** The maximum value of an array along a given axis, propagating any NaNs.
- **nanmin()** The minimum value of an array along a given axis, ignoring any NaNs.
- **minimum()** Element-wise minimum of two arrays, propagating any NaNs.
- **fmin()** Element-wise minimum of two arrays, ignoring any NaNs.
- **argmin()** Return the indices of the minimum values.

\[ \text{nanmax()}, \text{maximum()}, \text{fmax()} \]

Notes

NaN values are propagated, that is if at least one item is NaN, the corresponding min value will be NaN as well. To ignore NaN values (MATLAB behavior), please use nanmin.

Don’t use amin for element-wise comparison of 2 arrays; when a.shape[0] is 2, minimum(a[0], a[1]) is faster than amin(a, axis=0).

Examples

```
>>> a = np.arange(4).reshape((2,2))
>>> a
array([[0, 1],
       [2, 3]])
>>> np.amin(a)  # Minimum of the flattened array
0
>>> np.amin(a, axis=0)  # Minima along the first axis
array([0, 1])
>>> np.amin(a, axis=1)  # Minima along the second axis
array([0, 2])
>>> np.amin(a, where=[False, True], initial=10, axis=0)
array([10, 1])
```

```
>>> b = np.arange(5, dtype=float)
>>> b[2] = np.NaN
>>> np.amin(b)
```

(continues on next page)
```python
nan
>>> np.amin(b, where=~np.isnan(b), initial=10)
0.0
>>> np.nanmin(b)
0.0

>>> np.min([[-50], [10]], axis=-1, initial=0)
array([-50, 0])

Notice that the initial value is used as one of the elements for which the minimum is determined, unlike for the default argument Python's max function, which is only used for empty iterables.

Notice that this isn't the same as Python's default argument.

```python
>>> np.min([6], initial=5)
5
>>> min([6], default=5)
6
```

minimum(x1, x2)
Element-wise minimum of array elements.

LAX-backend implementation of minimum(). ADDITIONOriginal docstring below.

LAX-backend implementation of minimum(). Original docstring below.

minimum(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Compare two arrays and returns a new array containing the element-wise minima. If one of the elements being compared is a NaN, then that element is returned. If both elements are NaNs then the first is returned. The latter distinction is important for complex NaNs, which are defined as at least one of the real or imaginary parts being a NaN. The net effect is that NaNs are propagated.

**Returns** y – The minimum of x1 and x2, element-wise. This is a scalar if both x1 and x2 are scalars.

**Return type** ndarray or scalar

**See also:**

maximum() Element-wise maximum of two arrays, propagates NaNs.

fmin() Element-wise minimum of two arrays, ignores NaNs.

amin() The minimum value of an array along a given axis, propagates NaNs.

nanmin() The minimum value of an array along a given axis, ignores NaNs.

fmax(), amax(), nanmax()
Notes

The minimum is equivalent to `np.where(x1 <= x2, x1, x2)` when neither `x1` nor `x2` are NaNs, but it is faster and does proper broadcasting.

Examples

```python
>>> np.minimum([2, 3, 4], [1, 5, 2])
array([1, 3, 2])

>>> np.minimum(np.eye(2), [0.5, 2])  # broadcasting
array([[ 0.5,  0.],
       [ 0. ,  1. ]])

>>> np minimum([np.nan, 0, np.nan], [0, np.nan, np.nan])
array([nan, nan, nan])

>>> np.minimum(-np.Inf, 1)
-inf
```

mod(x1, x2)
Return element-wise remainder of division.

LAX-backend implementation of `remainder()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `remainder()`. Original docstring below.

```python
remainder(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

Computes the remainder complementary to the `floor_divide` function. It is equivalent to the Python modulus operator``x1 % x2`` and has the same sign as the divisor `x2`. The MATLAB function equivalent to `np.remainder` is `mod`.

**Warning:** This should not be confused with:
- Python 3.7’s `math.remainder` and C’s `remainder`, which computes the IEEE remainder, which are the complement to `round(x1 / x2)`. 
- The MATLAB `rem` function and or the C `%` operator which is the complement to `int(x1 / x2)`.

**Returns** `y` – The element-wise remainder of the quotient `floor_divide(x1, x2)`. This is a scalar if both `x1` and `x2` are scalars.

**Return type** `ndarray`

See also:
- `floor_divide()` Equivalent of Python `//` operator.
- `divmod()` Simultaneous floor division and remainder.
- `fmod()` Equivalent of the MATLAB `rem` function.
- `divide()`, `floor()`
Notes

Returns 0 when \( x_2 \) is 0 and both \( x_1 \) and \( x_2 \) are (arrays of) integers. \( \text{mod} \) is an alias of \( \text{remainder} \).

Examples

```python
>>> np.remainder([4, 7], [2, 3])
array([0, 1])
>>> np.remainder(np.arange(7), 5)
array([0, 1, 2, 3, 4, 0, 1])
```

\textbf{moveaxis (a, source, destination)}

Move axes of an array to new positions.

LAX-backend implementation of \texttt{moveaxis()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{moveaxis()}. Original docstring below.

Other axes remain in their original order.

New in version 1.11.0.

**Returns result** – Array with moved axes. This array is a view of the input array.

**Return type** \( \text{np.ndarray} \)

See also:

- \texttt{transpose()} Permute the dimensions of an array.
- \texttt{swapaxes()} Interchange two axes of an array.

Examples

```python
>>> x = np.zeros((3, 4, 5))
>>> np.moveaxis(x, 0, -1).shape
(4, 5, 3)
>>> np.moveaxis(x, -1, 0).shape
(5, 3, 4)
```

These all achieve the same result:

```python
>>> np.transpose(x).shape
(5, 4, 3)
>>> np.swapaxes(x, 0, -1).shape
(5, 4, 3)
>>> np.moveaxis(x, [0, 1], [-1, -2]).shape
(5, 4, 3)
>>> np.moveaxis(x, [0, 1, 2], [-1, -2, -3]).shape
(5, 4, 3)
```

\textbf{multiply (x1, x2)}

Multiply arguments element-wise.

LAX-backend implementation of \texttt{multiply()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{multiply()}. Original docstring below.
multiply(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns y – The product of x1 and x2, element-wise. This is a scalar if both x1 and x2 are scalars.

Return type ndarray

Notes

Equivalent to x1 * x2 in terms of array broadcasting.

Examples

```python
>>> np.multiply(2.0, 4.0)
8.0
```

```python
>>> x1 = np.arange(9.0).reshape((3, 3))
>>> x2 = np.arange(3.0)
>>> np.multiply(x1, x2)
array([[ 0.,  1.,  4.],
       [ 0.,  4., 10.],
       [ 0.,  7., 16.]])
```

nan_to_num(x, copy=True)

Replace NaN with zero and infinity with large finite numbers (default behaviour) or with the numbers defined by the user using the nan, posinf and/or neginf keywords.

LAX-backend implementation of nan_to_num(). ADDITIONOriginal docstring below.

LAX-backend implementation of nan_to_num(). Original docstring below.

If x is inexact, NaN is replaced by zero or by the user defined value in nan keyword, infinity is replaced by the largest finite floating point values representable by x.dtype or by the user defined value in posinf keyword and -infinity is replaced by the most negative finite floating point values representable by x.dtype or by the user defined value in neginf keyword.

For complex dtypes, the above is applied to each of the real and imaginary components of x separately.

If x is not inexact, then no replacements are made.

Returns out – x, with the non-finite values replaced. If copy is False, this may be x itself.

Return type ndarray

See also:

isinf() Shows which elements are positive or negative infinity.

isneginf() Shows which elements are negative infinity.

isposinf() Shows which elements are positive infinity.

isnan() Shows which elements are Not a Number (NaN).

isfinite() Shows which elements are finite (not NaN, not infinity)
Notes

NumPy uses the IEEE Standard for Binary Floating-Point for Arithmetic (IEEE 754). This means that Not a Number is not equivalent to infinity.

Examples

```python
>>> np.nan_to_num(np.inf)
1.7976931348623157e+308
>>> np.nan_to_num(-np.inf)
-1.7976931348623157e+308
>>> np.nan_to_num(np.nan)
0.0
>>> x = np.array([np.inf, -np.inf, np.nan, -128, 128])
>>> np.nan_to_num(x)
array([ 1.79769313e+308, -1.79769313e+308, 0.00000000e+000, # may vary
       -1.28000000e+002, 1.28000000e+002])
>>> np.nan_to_num(x, nan=-9999, posinf=33333333, neginf=33333333)
array([ 3.33333333e+007, 3.33333333e+007, -9.9990000e+03,
       -1.28000000e+02, 1.28000000e+02])
>>> y = np.array([complex(np.inf, np.nan), np.nan, complex(np.nan, np.inf)])
array([ 1.79769313e+308, -1.79769313e+308, 0.00000000e+000, # may vary
       -1.28000000e+002, 1.28000000e+002])
>>> np.nan_to_num(y)
array([1.79769313e+308+0.00000000e+000j, # may vary
       0.00000000e+000+0.00000000e+000j,
       0.00000000e+000+1.79769313e+308j])
>>> np.nan_to_num(y, nan=111111, posinf=222222)
array([2.222222+111111.j, 111111. +0.j, 111111.+222222.j])
```

**nancumprod** *(a, axis=None, dtype=None)*

Return the cumulative product of array elements over a given axis treating Not a Numbers (NaNs) as one. The cumulative product does not change when NaNs are encountered and leading NaNs are replaced by ones.

LAX-backend implementation of `nancumprod()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `nancumprod()`. Original docstring below.

Ones are returned for slices that are all-NaN or empty.

New in version 1.12.0.

**Parameters**

- **dtype**(dtype, optional) – Type of the returned array, as well as of the accumulator in which the elements are multiplied. If `dtype` is not specified, it defaults to the dtype of `a`, unless `a` has an integer dtype with a precision less than that of the default platform integer. In that case, the default platform integer is used instead.

**Returns**

- **nancumprod** – A new array holding the result is returned unless `out` is specified, in which case it is returned.

**Return type**

- ndarray

See also:

- `numpy.cumprod()` Cumulative product across array propagating NaNs.
- `isnan()` Show which elements are NaN.
Examples

```python
>>> np.nancumprod(1)
array([1])
>>> np.nancumprod([1])
array([1])
>>> np.nancumprod([1, np.nan])
array([1., 1.])
>>> a = np.array([[1, 2], [3, np.nan]])
>>> np.nancumprod(a)
array([1., 2., 6., 6.])
>>> np.nancumprod(a, axis=0)
array([[1., 2.],
       [3., 2.]])
>>> np.nancumprod(a, axis=1)
array([[1., 2.],
       [3., 3.]])
```

```
nancumsum(a, axis=None, dtype=None)
Return the cumulative sum of array elements over a given axis treating Not a Numbers (NaNs) as zero. The cumulative sum does not change when NaNs are encountered and leading NaNs are replaced by zeros.
LAX-backend implementation of nancumsum(). ADDITIONOriginal docstring below.
LAX-backend implementation of nancumsum(). Original docstring below.
Zeros are returned for slices that are all-NaN or empty.
New in version 1.12.0.

Parameters
dtype (dtype, optional) – Type of the returned array and of the accumulator in which the elements are summed. If dtype is not specified, it defaults to the dtype of a, unless a has an integer dtype with a precision less than that of the default platform integer. In that case, the default platform integer is used.

Returns nancumsum – A new array holding the result is returned unless out is specified, in which it is returned. The result has the same size as a, and the same shape as a if axis is not None or a is a 1-d array.

Return type ndarray.

See also:
numpy.cumsum() Cumulative sum across array propagating NaNs.
isnan() Show which elements are NaN.
```

Examples

```python
>>> np.nancumsum(1)
array([1])
>>> np.nancumsum([1])
array([1])
>>> np.nancumsum([1, np.nan])
array([1., 1.])
>>> a = np.array([[1, 2], [3, np.nan]])
>>> np.nancumsum(a)
(continues on next page)
```
```python
array([1., 3., 6., 6.])
>>> np.nancumsum(a, axis=0)
array([[1., 2.],
       [4., 2.]])
>>> np.nancumsum(a, axis=1)
array([[1., 3.],
       [3., 3.]])
```

**nanmax** *(a, axis=None, out=None, keepdims=False, **kwargs)*

Return the maximum of an array or maximum along an axis, ignoring any NaNs. When all-NaN slices are encountered a `RuntimeWarning` is raised and NaN is returned for that slice.

LAX-backend implementation of `nanmax()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `nanmax()`. Original docstring below.

**Returns** nanmax – An array with the same shape as `a`, with the specified axis removed. If `a` is a 0-d array, or if axis is None, an ndarray scalar is returned. The same dtype as `a` is returned.

**Return type** ndarray

**See also:**

`nanmin()` The minimum value of an array along a given axis, ignoring any NaNs.

`amax()` The maximum value of an array along a given axis, propagating any NaNs.

`fmax()` Element-wise maximum of two arrays, ignoring any NaNs.

`maximum()` Element-wise maximum of two arrays, propagating any NaNs.

`isnan()` Shows which elements are Not a Number (NaN).

`isfinite()` Shows which elements are neither NaN nor infinity.

`amin()`, `fmin()`, `minimum()`

**Notes**

NumPy uses the IEEE Standard for Binary Floating-Point for Arithmetic (IEEE 754). This means that Not a Number is not equivalent to infinity. Positive infinity is treated as a very large number and negative infinity is treated as a very small (i.e. negative) number.

If the input has a integer type the function is equivalent to `np.max`.

**Examples**

```python
>>> a = np.array([[1, 2], [3, np.nan]])
>>> np.nanmax(a)
3.0
>>> np.nanmax(a, axis=0)
array([3., 2.])
>>> np.nanmax(a, axis=1)
array([3., 3.])
```

When positive infinity and negative infinity are present:
np.nanmax([1, 2, np.nan, np.NINF])
2.0
np.nanmax([1, 2, np.nan, np.inf])
inf

nanmin (a, axis=None, out=None, keepdims=False, **kwargs)

Return minimum of an array or minimum along an axis, ignoring any NaNs. When all-NaN slices are en-
countered a RuntimeWarning is raised and Nan is returned for that slice.

LAX-backend implementation of nanmin(). ADDITIONOriginal docstring below.
LAX-backend implementation of nanmin(). Original docstring below.

Returns nanmin – An array with the same shape as a, with the specified axis removed. If a is a 0-d 
array, or if axis is None, an ndarray scalar is returned. The same dtype as a is returned.

Return type ndarray

See also:

nanmax() The maximum value of an array along a given axis, ignoring any NaNs.
amin() The minimum value of an array along a given axis, propagating any NaNs.
fmin() Element-wise minimum of two arrays, ignoring any NaNs.
minimum() Element-wise minimum of two arrays, propagating any NaNs.
isnan() Shows which elements are Not a Number (NaN).
isfinite() Shows which elements are neither NaN nor infinity.
amax(), fmax(), maximum()

Notes

NumPy uses the IEEE Standard for Binary Floating-Point for Arithmetic (IEEE 754). This means that Not a 
Number is not equivalent to infinity. Positive infinity is treated as a very large number and negative infinity is 
treated as a very small (i.e. negative) number.

If the input has a integer type the function is equivalent to np.min.

Examples

>>> a = np.array([[1, 2], [3, np.nan]])
>>> np.nanmin(a)
1.0
>>> np.nanmin(a, axis=0)
array([1., 2.])
>>> np.nanmin(a, axis=1)
array([1., 3.])

When positive infinity and negative infinity are present:

>>> np.nanmin([1, 2, np.nan, np.inf])
1.0
>>> np.nanmin([1, 2, np.nan, np.NINF])
-inf

2.1. General
**nanprod** *(a, axis=None, out=None, keepdims=False, **kwargs)*

Return the product of array elements over a given axis treating Not a Numbers (NaNs) as ones.

LAX-backend implementation of `nanprod()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `nanprod()`. Original docstring below.

One is returned for slices that are all-NaN or empty.

New in version 1.10.0.

Returns **nanprod** – A new array holding the result is returned unless `out` is specified, in which case it is returned.

Return type *ndarray*

See also:

`numpy.prod()` Product across array propagating NaNs.

`isnan()` Show which elements are NaN.

**Examples**

```python
g = np.nanprod(1)
g
# 1

e = np.nanprod([1])
e
# 1

e = np.nanprod([1, np.nan])
e
# 1.0

e = a = np.array([[1, 2], [3, np.nan]])
e
# 6.0

e = np.nanprod(a)
e
# 6.0

e = np.nanprod(a, axis=0)
e
# array([3., 2.])
```

**nansum** *(a, axis=None, out=None, keepdims=False, **kwargs)*

Return the sum of array elements over a given axis treating Not a Numbers (NaNs) as zero.

LAX-backend implementation of `nansum()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `nansum()`. Original docstring below.

In NumPy versions <= 1.9.0 Nan is returned for slices that are all-NaN or empty. In later versions zero is returned.

Returns **nansum** – A new array holding the result is returned unless `out` is specified, in which it is returned. The result has the same size as `a`, and the same shape as `a` if `axis` is not None or `a` is a 1-d array.

Return type *ndarray*

See also:

`numpy.sum()` Sum across array propagating NaNs.

`isnan()` Show which elements are NaN.

`isfinite()` Show which elements are not NaN or +/-inf.
Notes

If both positive and negative infinity are present, the sum will be Not A Number (NaN).

Examples

```python
>>> np.nansum(1)
1
>>> np.nansum([1])
1
>>> np.nansum([1, np.nan])
1.0
>>> a = np.array([[1, 1], [1, np.nan]])
>>> np.nansum(a)
3.0
>>> np.nansum(a, axis=0)
array([2., 1.])
>>> np.nansum([1, np.nan, np.inf])
inf
>>> np.nansum([1, np.nan, np.NINF])
-inf
>>> from numpy.testing import suppress_warnings
>>> with suppress_warnings() as sup:
...     sup.filter(RuntimeWarning)
...     np.nansum([1, np.nan, np.inf, -np.inf])  # both +/- infinity present
nan
```

```python
nonzero(a)
```

Return the indices of the elements that are non-zero.

LAX-backend implementation of nonzero(). ADDITIONOriginal docstring below.

LAX-backend implementation of nonzero(). At present, JAX does not support JIT-compilation of jax.numpy.nonzero() because its output shape is data-dependent.

Original docstring below.

Returns a tuple of arrays, one for each dimension of a, containing the indices of the non-zero elements in that dimension. The values in a are always tested and returned in row-major, C-style order.

To group the indices by element, rather than dimension, use argwhere, which returns a row for each non-zero element.

Note: When called on a zero-d array or scalar, nonzero(a) is treated as nonzero(atleast1d(a)).

Deprecated since version 1.17.0: Use atleast1d explicitly if this behavior is deliberate.

Returns tuple_of_arrays – Indices of elements that are non-zero.

Return type tuple

See also:

flatnonzero() Return indices that are non-zero in the flattened version of the input array.

ndarray.nonzero() Equivalent ndarray method.

count_nonzero() Counts the number of non-zero elements in the input array.
Notes

While the nonzero values can be obtained with `a[nonzero(a)]`, it is recommended to use `x[x. astype(bool)]` or `x[x != 0]` instead, which will correctly handle 0-d arrays.

Examples

```python
>>> x = np.array([[3, 0, 0], [0, 4, 0], [5, 6, 0]])
>>> x
array([[3, 0, 0],
       [0, 4, 0],
       [5, 6, 0]])
>>> np.nonzero(x)
(array([0, 1, 2, 2]), array([0, 1, 0, 1]))
```

```python
>>> x[np.nonzero(x)]
array([3, 4, 5, 6])
```

```python
>>> np.transpose(np.nonzero(x))
array([[0, 0],
       [1, 1],
       [2, 0],
       [2, 1]])
```

A common use for `nonzero` is to find the indices of an array, where a condition is True. Given an array `a`, the condition `a > 3` is a boolean array and since False is interpreted as 0, `np.nonzero(a > 3)` yields the indices of the `a` where the condition is true.

```python
>>> a = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])
>>> a > 3
array([[False, False, False],
       [ True, True, True],
       [ True, True, True]])
>>> np.nonzero(a > 3)
(array([1, 1, 1, 2, 2, 2]), array([0, 1, 2, 0, 1, 2]))
```

Using this result to index `a` is equivalent to using the mask directly:

```python
>>> a[np.nonzero(a > 3)]
array([4, 5, 6, 7, 8, 9])
```

```python
>>> a[a > 3]  # prefer this spelling
array([4, 5, 6, 7, 8, 9])
```

`nonzero` can also be called as a method of the array.

```python
>>> (a > 3).nonzero()
(array([1, 1, 1, 2, 2, 2]), array([0, 1, 2, 0, 1, 2]))
```

`not_equal(x1, x2)`

Return `(x1 != x2)` element-wise.

LAX-backend implementation of `not_equal()`. ADDITION

Original docstring below.

LAX-backend implementation of `not_equal()`. Original docstring below.

```python
not_equal(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```
Returns out – Output array, element-wise comparison of x1 and x2. Typically of type bool, unless dtype=object is passed. This is a scalar if both x1 and x2 are scalars.

Return type ndarray or scalar

See also: equal(), greater(), greater_equal(), less(), less_equal()

Examples

```python
>>> np.not_equal([1.,2.], [1., 3.])
array([False, True])
>>> np.not_equal([1, 2], [[1, 3],[1, 4]])
array([[False, True],
       [False, True]])
```

ones (shape, dtype=None)

Return a new array of given shape and type, filled with ones.

LAX-backend implementation of ones(). ADDITIONOriginal docstring below.

LAX-backend implementation of ones(). Original docstring below.

Parameters

- shape (int or sequence of ints) – Shape of the new array, e.g., (2, 3) or 2.
- dtype (data-type, optional) – The desired data-type for the array, e.g., numpy.int8. Default is numpy.float64.

Returns out – Array of ones with the given shape, dtype, and order.

Return type ndarray

See also:

ones_like() Return an array of ones with shape and type of input.
empty() Return a new uninitialized array.
zeros() Return a new array setting values to zero.
full() Return a new array of given shape filled with value.

Examples

```python
>>> np.ones(5)
array([1., 1., 1., 1., 1.])

>>> np.ones((5,), dtype=int)
array([1, 1, 1, 1, 1])

>>> np.ones((2, 1))
array([[1.],
       [1.]])
```
```python
>>> s = (2, 2)
>>> np.ones(s)
array([[1., 1.],
       [1., 1.]])
```

### ones_like(x, dtype=None)

Return an array of ones with the same shape and type as a given array.

LAX-backend implementation of `ones_like()`. Original docstring below.

LAX-backend implementation of `ones_like()`. Original docstring below.

**Parameters**
- **dtype** *(data-type, optional)* - Overrides the data type of the result.

**Returns**
- **out** - Array of ones with the same shape and type as `a`.

**Return type**
- **ndarray**

### Examples

```python
>>> x = np.arange(6)
>>> x = x.reshape((2, 3))
array([[0, 1, 2],
       [3, 4, 5]])
>>> np.ones_like(x)
array([[1., 1., 1.],
       [1., 1., 1.]])
```

```python
>>> y = np.arange(3, dtype=float)
>>> y
array([0., 1., 2.])
>>> np.ones_like(y)
array([1., 1., 1.])
```

### outer(a, b, out=None)

Compute the outer product of two vectors.

LAX-backend implementation of `outer()`. Original docstring below.

LAX-backend implementation of `outer()`. Original docstring below.

Given two vectors, `a = [a0, a1, ..., aM]` and `b = [b0, b1, ..., bN]`, the outer product [1] is:

```
[[a0*b0   a0*b1   ...   a0*bN]
 [a1*b0   .       .       .]
 [ ...       .       .       .]
 [aM*b0   aM*b1   ...   aM*bN]]
```
**Returns** `out` - `out[i, j] = a[i] * b[j]`

**Return type** `(M, N)` ndarray

**See also:**

`inner()`

`einsum()` `einsum('i,j->ij', a.ravel(), b.ravel())` is the equivalent.

`ufunc.outer()` A generalization to N dimensions and other operations. `np.multiply.outer(a.ravel(), b.ravel())` is the equivalent.

**References**

**Examples**

Make a (very coarse) grid for computing a Mandelbrot set:

```python
>>> rl = np.outer(np.ones((5,)), np.linspace(-2, 2, 5))
>>> rl
array([[-2., -1.,  0.,  1.,  2.],
       [-2., -1.,  0.,  1.,  2.],
       [-2., -1.,  0.,  1.,  2.],
       [-2., -1.,  0.,  1.,  2.],
       [-2., -1.,  0.,  1.,  2.]])
>>> im = np.outer(1j*np.linspace(2, -2, 5), np.ones((5,)))
>>> im
array([[ 0.+2.j,  0.+2.j,  0.+2.j,  0.+2.j,  0.+2.j],
       [ 0.+1.j,  0.+1.j,  0.+1.j,  0.+1.j,  0.+1.j],
       [ 0.+0.j,  0.+0.j,  0.+0.j,  0.+0.j,  0.+0.j],
       [ 0.-1.j,  0.-1.j,  0.-1.j,  0.-1.j,  0.-1.j],
       [ 0.-2.j,  0.-2.j,  0.-2.j,  0.-2.j,  0.-2.j]])
>>> grid = rl + im
>>> grid
array([[-2.+2.j, -1.+2.j,  0.+2.j,  1.+2.j,  2.+2.j],
       [-2.+1.j, -1.+1.j,  0.+1.j,  1.+1.j,  2.+1.j],
       [-2.+0.j, -1.+0.j,  0.+0.j,  1.+0.j,  2.+0.j],
       [-2.-1.j, -1.-1.j,  0.-1.j,  1.-1.j,  2.-1.j],
       [-2.-2.j, -1.-2.j,  0.-2.j,  1.-2.j,  2.-2.j]])
```

An example using a “vector” of letters:

```python
>>> x = np.array(['a', 'b', 'c'], dtype=object)
>>> np.outer(x, [1, 2, 3])
array([[['a', 'aa', 'aaa'],
       ['b', 'bb', 'bbb'],
       ['c', 'cc', 'ccc']],
      dtype=object)
```

**pad** *(array, pad_width, mode='constant', constant_values=0)*

Pad an array.

LAX-backend implementation of `pad()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `pad()`. Original docstring below.

**Returns** `pad` – Padded array of rank equal to `array` with shape increased according to `pad_width`.

**Return type** `ndarray`
Notes

New in version 1.7.0.

For an array with rank greater than 1, some of the padding of later axes is calculated from padding of previous axes. This is easiest to think about with a rank 2 array where the corners of the padded array are calculated by using padded values from the first axis.

The padding function, if used, should modify a rank 1 array in-place. It has the following signature:

```
def padding_func(vector, iaxis_pad_width, iaxis, kwargs)
```

where

- **vector** [ndarray] A rank 1 array already padded with zeros. Padded values are `vector[:iaxis_pad_width[0]]` and `vector[-iaxis_pad_width[1]:]`.
- **iaxis_pad_width** [tuple] A 2-tuple of ints, `iaxis_pad_width[0]` represents the number of values padded at the beginning of `vector` where `iaxis_pad_width[1]` represents the number of values padded at the end of `vector`.
- **iaxis** [int] The axis currently being calculated.
- **kwargs** [dict] Any keyword arguments the function requires.

Examples

```python
>>> a = [1, 2, 3, 4, 5]
>>> np.pad(a, (2, 3), 'constant', constant_values=(4, 6))
array([4, 4, 1, ..., 6, 6, 6])

>>> np.pad(a, (2, 3), 'edge')
array([1, 1, 1, ..., 5, 5, 5])

>>> np.pad(a, (2, 3), 'linear_ramp', end_values=(5, -4))
array([ 5, 3, 1, 2, 3, 4, 5, 2, -1, -4])

>>> np.pad(a, (2,), 'maximum')
array([5, 5, 1, 2, 3, 4, 5, 5, 5])

>>> np.pad(a, (2,), 'mean')
array([3, 3, 1, 2, 3, 4, 5, 3, 3])

>>> np.pad(a, (2,), 'median')
array([3, 3, 1, 2, 3, 4, 5, 3, 3])

>>> a = [[1, 2], [3, 4]]
>>> np.pad(a, ((3, 2), (2, 3)), 'minimum')
array([[1, 1, 1, 2, 1, 1, 1],
       [1, 1, 1, 2, 1, 1, 1],
       [1, 1, 1, 2, 1, 1, 1],
       [3, 3, 4, 3, 3, 3],
       [1, 1, 1, 2, 1, 1],
       [1, 1, 1, 2, 1, 1]])
```
% numpy example

```python
>>> a = [1, 2, 3, 4, 5]
>>> np.pad(a, (2, 3), 'reflect')
array([3, 2, 1, 2, 3, 4, 5, 4, 3, 2])

>>> np.pad(a, (2, 3), 'reflect', reflect_type='odd')
array([-1, 0, 1, 2, 3, 4, 5, 6, 7, 8])

>>> np.pad(a, (2, 3), 'symmetric')
array([2, 1, 1, 2, 3, 4, 5, 5, 4, 3])

>>> np.pad(a, (2, 3), 'symmetric', reflect_type='odd')
array([0, 1, 1, 2, 3, 4, 5, 6, 7, 8])

>>> np.pad(a, (2, 3), 'wrap')
array([4, 5, 1, 2, 3, 4, 5, 1, 2, 3])

>>> def pad_with(vector, pad_width, iaxis, kwargs):
...     pad_value = kwargs.get('padder', 10)
...     vector[:pad_width[0]] = pad_value
...     vector[-pad_width[1]:] = pad_value

>>> a = np.arange(6)
>>> a = a.reshape((2, 3))

>>> np.pad(a, 2, pad_with)
array([[10, 10, 10, 10, 10, 10, 10],
       [10, 10, 10, 10, 10, 10, 10],
       [10, 10, 0, 1, 2, 10, 10],
       [10, 10, 3, 4, 5, 10, 10],
       [10, 10, 10, 10, 10, 10, 10],
       [10, 10, 10, 10, 10, 10, 10]])

>>> np.pad(a, 2, pad_with, padder=100)
array([[100, 100, 100, 100, 100, 100, 100],
       [100, 100, 100, 100, 100, 100, 100],
       [100, 100, 0, 1, 2, 100, 100],
       [100, 100, 3, 4, 5, 100, 100],
       [100, 100, 100, 100, 100, 100, 100],
       [100, 100, 100, 100, 100, 100, 100]])
```

### percentile

```python
percentile(a, q, axis=None, out=None, overwrite_input=False, interpolation='linear', keepdims=False)
```

Compute the q-th percentile of the data along the specified axis.

LAX-backend implementation of `percentile()`. Original docstring below.

LAX-backend implementation of `percentile()`. Original docstring below.

Returns the q-th percentile(s) of the array elements.

**Returns** `percentile` – If `q` is a single percentile and `axis=None`, then the result is a scalar. If multiple percentiles are given, first axis of the result corresponds to the percentiles. The other axes are the axes that remain after the reduction of `a`. If the input contains integers or floats smaller than `float64`, the output data-type is `float64`. Otherwise, the output data-type is the same as that of the input. If `out` is specified, that array is returned instead.

**Return type** scalar or ndarray

**See also:**

- `mean()`
- `median()` equivalent to `percentile(..., 50)`

---

**2.1. General**

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**Notes**

Given a vector \( V \) of length \( N \), the \( q \)-th percentile of \( V \) is the value \( q/100 \) of the way from the minimum to the maximum in a sorted copy of \( V \). The values and distances of the two nearest neighbors as well as the interpolation parameter will determine the percentile if the normalized ranking does not match the location of \( q \) exactly. This function is the same as the median if \( q=50 \), the same as the minimum if \( q=0 \) and the same as the maximum if \( q=100 \).

**Examples**

```python
>>> a = np.array([[10, 7, 4], [3, 2, 1]])
>>> a
array([[10,  7,  4],
       [ 3,  2,  1]])
>>> np.percentile(a, 50)
3.5
>>> np.percentile(a, 50, axis=0)
array([6.5, 4.5, 2.5])
>>> np.percentile(a, 50, axis=1)
array([7., 2.])
>>> np.percentile(a, 50, axis=1, keepdims=True)
array([[7.],
       [2.]])
```

```python
>>> m = np.percentile(a, 50, axis=0)
>>> out = np.zeros_like(m)
>>> np.percentile(a, 50, axis=0, out=out)
array([6.5, 4.5, 2.5])
>>> m
array([6.5, 4.5, 2.5])
```

```python
>>> b = a.copy()
>>> np.percentile(b, 50, axis=1, overwrite_input=True)
array([7., 2.])
>>> assert not np.all(a == b)
```

The different types of interpolation can be visualized graphically:

**polyval** \((p, x)\)

Evaluate a polynomial at specific values.

LAX-backend implementation of ` polyval()`. ADDITIONOriginal docstring below.

LAX-backend implementation of ` polyval()`. Original docstring below.

If \( p \) is of length \( N \), this function returns the value:

\[
p[0] \cdot x^{(N-1)} + p[1] \cdot x^{(N-2)} + \ldots + p[N-2] \cdot x + p[N-1]
\]

If \( x \) is a sequence, then \( p(x) \) is returned for each element of \( x \). If \( x \) is another polynomial then the composite polynomial \( p(x(t)) \) is returned.

- **Returns** values – If \( x \) is a poly1d instance, the result is the composition of the two polynomials, i.e., \( x \) is “substituted” in \( p \) and the simplified result is returned. In addition, the type of \( x \) - array_like
Interpolation methods for list: [0 1 2 3]

- linear
- higher
- lower
- nearest
- midpoint
or poly1d - governs the type of the output: x array_like => values array_like, x a poly1d object => values is also.

Return type  ndarray or poly1d

See also:

poly1d()  A polynomial class.

Notes

Horner’s scheme [1]_ is used to evaluate the polynomial. Even so, for polynomials of high degree the values may be inaccurate due to rounding errors. Use carefully.

If x is a subtype of ndarray the return value will be of the same type.

References

Examples

```python
>>> np.polyval([3,0,1], 5)  # 3 * 5**2 + 0 * 5**1 + 1
76
>>> np.polyval([3,0,1], np.poly1d(5))
poly1d([76.])
>>> np.polyval(np.poly1d([3,0,1]), 5)
76
>>> np.polyval(np.poly1d([3,0,1]), np.poly1d(5))
poly1d([76.])
```

**power(x1, x2)**

First array elements raised to powers from second array, element-wise.

LAX-backend implementation of `power()`. ADDITION: Original docstring below.

LAX-backend implementation of `power()`. Original docstring below.

power(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Raise each base in x1 to the positionally-corresponding power in x2. x1 and x2 must be broadcastable to the same shape. Note that an integer type raised to a negative integer power will raise a ValueError.

Returns y – The bases in x1 raised to the exponents in x2. This is a scalar if both x1 and x2 are scalars.

Return type  ndarray

See also:

* float_power()  power function that promotes integers to float
Examples

Cube each element in a list.

```python
>>> x1 = range(6)
>>> x1
[0, 1, 2, 3, 4, 5]
>>> np.power(x1, 3)
array([ 0,  1,  8, 27, 64, 125])
```

Raise the bases to different exponents.

```python
>>> x2 = [1.0, 2.0, 3.0, 3.0, 2.0, 1.0]
>>> np.power(x1, x2)
array([ 0.,  1.,  8., 27., 16.,  5.])
```

The effect of broadcasting.

```python
>>> x2 = np.array([[1, 2, 3, 3, 2, 1], [1, 2, 3, 3, 2, 1]])
>>> x2
array([[1, 2, 3, 3, 2, 1],
       [1, 2, 3, 3, 2, 1]])
>>> np.power(x1, x2)
array([[ 0,  1,  8, 27, 16,  5],
       [ 0,  1,  8, 27, 16,  5]])
```

**positive**(x)

Numerical positive, element-wise.

LAX-backend implementation of `positive()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `positive()`. Original docstring below.

```python
positive(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

New in version 1.13.0.

Returns **y** – Returned array or scalar: y = +x. This is a scalar if x is a scalar.

Return type ndarrays or scalar

Notes

Equivalent to `x.copy()`, but only defined for types that support arithmetic.

**prod**(a, axis=None, dtype=None, out=None, keepdims=False)

Return the product of array elements over a given axis.

LAX-backend implementation of `prod()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `prod()`. Original docstring below.

Parameters **dtype**(dtype, optional) – The type of the returned array, as well as of the accumulator in which the elements are multiplied. The dtype of a is used by default unless a has an integer dtype of less precision than the default platform integer. In that case, if a is signed then the platform integer is used while if a is unsigned then an unsigned integer of the same precision as the platform integer is used.

Returns **product_along_axis** – An array shaped as a but with the specified axis removed. Returns a reference to out if specified.

2.1. General
Return type: ndarray, see dtype parameter above.

See also:

ndarray.prod() equivalent method

ufuncs-output-type()

Notes

Arithmetic is modular when using integer types, and no error is raised on overflow. That means that, on a 32-bit platform:

```python
>>> x = np.array([536870910, 536870910, 536870910, 536870910])
>>> np.prod(x)
16 # may vary
```

The product of an empty array is the neutral element 1:

```python
>>> np.prod([])
1.0
```

Examples

By default, calculate the product of all elements:

```python
>>> np.prod([1., 2.])
2.0
```

Even when the input array is two-dimensional:

```python
>>> np.prod([[1., 2.], [3., 4.]])
24.0
```

But we can also specify the axis over which to multiply:

```python
>>> np.prod([[1., 2.], [3., 4.]], axis=1)
array([ 2., 12.])
```

Or select specific elements to include:

```python
>>> np.prod([1., np.nan, 3.], where=[True, False, True])
3.0
```

If the type of x is unsigned, then the output type is the unsigned platform integer:

```python
>>> x = np.array([1, 2, 3], dtype=np.uint8)
>>> np.prod(x).dtype == np.uint
True
```

If x is of a signed integer type, then the output type is the default platform integer:

```python
>>> x = np.array([1, 2, 3], dtype=np.int8)
>>> np.prod(x).dtype == int
True
```
You can also start the product with a value other than one:

```python
>>> np.prod([1, 2], initial=5)
10
```

**product** *(a, axis=None, dtype=None, out=None, keepdims=False)*

Return the product of array elements over a given axis.

LAX-backend implementation of `prod()` Original docstring below.

LAX-backend implementation of `prod()`. Original docstring below.

**Parameters**

- **dtype** *(dtype, optional)* – The type of the returned array, as well as of the accumulator in which the elements are multiplied. The dtype of *a* is used by default unless *a* has an integer dtype of less precision than the default platform integer. In that case, if *a* is signed then the platform integer is used while if *a* is unsigned then an unsigned integer of the same precision as the platform integer is used.

**Returns**

- **product_along_axis** – An array shaped as *a* but with the specified axis removed. Returns a reference to *out* if specified.

**See also:**

- `ndarray.prod()` equivalent method
- `ufuncs-output-type()`

**Notes**

Arithmetic is modular when using integer types, and no error is raised on overflow. That means that, on a 32-bit platform:

```python
>>> x = np.array([536870910, 536870910, 536870910, 536870910])
>>> np.prod(x)
16 # may vary
```

The product of an empty array is the neutral element 1:

```python
>>> np.prod([])
1.0
```

**Examples**

By default, calculate the product of all elements:

```python
>>> np.prod([1., 2.])
2.0
```

Even when the input array is two-dimensional:

```python
>>> np.prod([[1., 2.], [3., 4.]])
24.0
```

But we can also specify the axis over which to multiply:
>>> np.prod([[1.,2.],[3.,4.]], axis=1)
array([ 2., 12.])

Or select specific elements to include:

>>> np.prod([1., np.nan, 3.], where=[True, False, True])
3.0

If the type of x is unsigned, then the output type is the unsigned platform integer:

```python
>>> x = np.array([1, 2, 3], dtype=np.uint8)
>>> np.prod(x).dtype == np.uint
True
```

If x is of a signed integer type, then the output type is the default platform integer:

```python
>>> x = np.array([1, 2, 3], dtype=np.int8)
>>> np.prod(x).dtype == int
True
```

You can also start the product with a value other than one:

```python
>>> np.prod([1, 2], initial=5)
10
```

`promote_types(a, b)`

Returns the type to which a binary operation should cast its arguments.

LAX-backend implementation of `promote_types()`. ADDITIONOriginal docstring below.

Returns: A numpy.dtype object.

`quantile(a, q, axis=None, out=None, overwrite_input=False, interpolation='linear', keepdims=False)`

Compute the q-th quantile of the data along the specified axis.

New in version 1.15.0.

LAX-backend implementation of `quantile()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `quantile()`. Original docstring below.

**Returns** quantile – If q is a single quantile and axis=None, then the result is a scalar. If multiple quantiles are given, first axis of the result corresponds to the quantiles. The other axes are the axes that remain after the reduction of a. If the input contains integers or floats smaller than float64, the output data-type is float64. Otherwise, the output data-type is the same as that of the input. If out is specified, that array is returned instead.

**Return type** scalar or ndarray

See also:

`mean()`

`percentile()` equivalent to quantile, but with q in the range [0, 100].

`median()` equivalent to quantile(..., 0.5)

`nanquantile()`
**Notes**

Given a vector $V$ of length $N$, the $q$-th quantile of $V$ is the value $q$ of the way from the minimum to the maximum in a sorted copy of $V$. The values and distances of the two nearest neighbors as well as the interpolation parameter will determine the quantile if the normalized ranking does not match the location of $q$ exactly. This function is the same as the median if $q=0.5$, the same as the minimum if $q=0.0$ and the same as the maximum if $q=1.0$.

**Examples**

```python
code
>>> a = np.array([[10, 7, 4], [3, 2, 1]])
>>> a
array([[10,  7,  4],
       [ 3,  2,  1]])
>>> np.quantile(a, 0.5)
3.5
>>> np.quantile(a, 0.5, axis=0)
array([6.5, 4.5, 2.5])
>>> np.quantile(a, 0.5, axis=1)
array([7., 2.])
>>> np.quantile(a, 0.5, axis=1, keepdims=True)
array([[7.],
       [2.]])
>>> m = np.quantile(a, 0.5, axis=0)
>>> out = np.zeros_like(m)
>>> np.quantile(a, 0.5, axis=0, out=out)
array([6.5, 4.5, 2.5])
>>> m
array([6.5, 4.5, 2.5])
>>> b = a.copy()
>>> np.quantile(b, 0.5, axis=1, overwrite_input=True)
array([7., 2.])
>>> assert not np.all(a == b)
```

`rad2deg(x)`

Convert angles from radians to degrees.

LAX-backend implementation of `rad2deg()`. ADDITION

LAX-backend implementation of `rad2deg()`. Original docstring below.

`rad2deg(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])`

**Returns** $y$ – The corresponding angle in degrees. This is a scalar if $x$ is a scalar.

**Return type** ndarray

See also:

`deg2rad()` Convert angles from degrees to radians.

`unwrap()` Remove large jumps in angle by wrapping.
Notes

New in version 1.3.0.

\[
\text{rad2deg}(x) = 180 \times \frac{x}{\pi}.
\]

Examples

```python
g>>> np.rad2deg(np.pi/2)
90.0
```

\textbf{radians} \((x)\)

Convert angles from degrees to radians.

LAX-backend implementation of \texttt{deg2rad()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{deg2rad()}. Original docstring below.

\texttt{deg2rad(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])}

\textbf{Returns} \(y\) – The corresponding angle in radians. This is a scalar if \(x\) is a scalar.

\textbf{Return type} \ ndarray

\textbf{See also:}

\texttt{rad2deg()} \ Convert angles from radians to degrees.

\texttt{unwrap()} \ Remove large jumps in angle by wrapping.

Notes

New in version 1.3.0.

\[
\text{deg2rad}(x) = x \times \frac{\pi}{180}.
\]

Examples

```python
g>>> np.deg2rad(180)
3.1415926535897931
```

\textbf{ravel} \((a, order='C')\)

Return a contiguous flattened array.

LAX-backend implementation of \texttt{ravel()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{ravel()}. Original docstring below.

A 1-D array, containing the elements of the input, is returned. A copy is made only if needed.

As of NumPy 1.10, the returned array will have the same type as the input array. (for example, a masked array will be returned for a masked array input)

\textbf{Returns} \(y\) – \(y\) is an array of the same subtype as \(a\), with shape \((a.size,)\). Note that matrices are special cased for backward compatibility, if \(a\) is a matrix, then \(y\) is a 1-D ndarray.

\textbf{Return type} \ ndarray_like

\textbf{See also:}
**ndarray.flat()** 1-D iterator over an array.

**ndarray.flatten()** 1-D array copy of the elements of an array in row-major order.

**ndarray.reshape()** Change the shape of an array without changing its data.

**Notes**

In row-major, C-style order, in two dimensions, the row index varies the slowest, and the column index the quickest. This can be generalized to multiple dimensions, where row-major order implies that the index along the first axis varies slowest, and the index along the last quickest. The opposite holds for column-major, Fortran-style index ordering.

When a view is desired in as many cases as possible, `arr.reshape(-1)` may be preferable.

**Examples**

It is equivalent to `reshape(-1, order=order)`.

```python
>>> x = np.array([[1, 2, 3], [4, 5, 6]])
>>> np.ravel(x)
array([1, 2, 3, 4, 5, 6])

>>> x.reshape(-1)
array([1, 2, 3, 4, 5, 6])

>>> np.ravel(x, order='F')
array([1, 4, 2, 5, 3, 6])
```

When `order` is 'A', it will preserve the array's 'C' or 'F' ordering:

```python
>>> np.ravel(x.T)
array([1, 4, 2, 5, 3, 6])
>>> np.ravel(x.T, order='A')
array([1, 2, 3, 4, 5, 6])
```

When `order` is 'K', it will preserve orderings that are neither 'C' nor 'F', but won't reverse axes:

```python
>>> a = np.arange(3)[::-1]; a
array([2, 1, 0])
>>> a.ravel(order='C')
array([2, 1, 0])
>>> a.ravel(order='K')
array([2, 1, 0])
```

```python
>>> a = np.arange(12).reshape(2,3,2).swapaxes(1,2); a
array([[ 0,  2,  4],
       [ 1,  3,  5],
       [ 6,  8, 10],
       [ 7,  9, 11]])
>>> a.ravel(order='C')
array([ 0,  2,  4,  1,  3,  5,  6,  8, 10,  7,  9, 11])
>>> a.ravel(order='K')
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
```
**real**(val)

Return the real part of the complex argument.

LAX-backend implementation of `real()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `real()`. Original docstring below.

**Returns out** - The real component of the complex argument. If `val` is real, the type of `val` is used for the output. If `val` has complex elements, the returned type is float.

**Return type** ndarray or scalar

See also:

`real_if_close()`, `imag()`, `angle()`

**Examples**

```python
>>> a = np.array([1+2j, 3+4j, 5+6j])
>>> a.real
array([1., 3., 5.])
>>> a.real = 9
>>> a
array([9.+2.j, 9.+4.j, 9.+6.j])
>>> a.real = np.array([9, 8, 7])
>>> a
array([9.+2.j, 8.+4.j, 7.+6.j])
>>> np.real(1 + 1j)
1.0
```

**remainder**(x1, x2)

Return element-wise remainder of division.

LAX-backend implementation of `remainder()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `remainder()`. Original docstring below.

remainder(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Computes the remainder complementary to the `floor_divide` function. It is equivalent to the Python modulus operator `x1 % x2` and has the same sign as the divisor `x2`. The MATLAB function equivalent to `np.remainder` is `mod`.

**Warning:** This should not be confused with:

- Python 3.7’s `math.remainder` and C’s `remainder`, which computes the IEEE remainder, which are the complement to `round(x1 / x2)`.
- The MATLAB `rem` function and or the C `%` operator which is the complement to `int(x1 / x2)`.  

**Returns y** – The element-wise remainder of the quotient `floor_divide(x1, x2)`. This is a scalar if both `x1` and `x2` are scalars.

**Return type** ndarray

See also:

`floor_divide()` Equivalent of Python `//` operator.
\texttt{divmod()}  Simultaneous floor division and remainder.

\texttt{fmod()}  Equivalent of the MATLAB \texttt{rem} function.

\texttt{divide()}, \texttt{floor()}

\textbf{Notes}

Returns 0 when \(x2\) is 0 and both \(x1\) and \(x2\) are (arrays of) integers. \texttt{mod} is an alias of \texttt{remainder}.

\textbf{Examples}

\begin{verbatim}
>>> np.remainder([4, 7], [2, 3])
array([0, 1])
>>> np.remainder(np.arange(7), 5)
array([0, 1, 2, 3, 4, 0, 1])
\end{verbatim}

\textbf{repeat} \((a, \text{repeats}, \text{axis=None})\)

Repeat elements of an array.

LAX-backend implementation of \texttt{repeat()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{repeat()}. Original docstring below.

\textbf{Returns repeated array} – Output array which has the same shape as \(a\), except along the given axis.

\textbf{Return type}  \texttt{ndarray}

\textbf{See also:}

\texttt{tile()}  Tile an array.

\textbf{Examples}

\begin{verbatim}
>>> np.repeat(3, 4)
array([3, 3, 3, 3])
>>> x = np.array([[1,2],[3,4]])
>>> np.repeat(x, 2)
array([[1, 1, 2, 2, 3, 3, 4, 4]])
>>> np.repeat(x, 3, axis=1)
array([[1, 1, 1, 2, 2, 2],
       [3, 3, 3, 4, 4, 4]])
>>> np.repeat(x, [1, 2], axis=0)
array([[1, 2],
       [3, 4],
       [3, 4]])
\end{verbatim}

\textbf{reshape} \((a, \text{newshape}, \text{order='C'})\)

Gives a new shape to an array without changing its data.

LAX-backend implementation of \texttt{reshape()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{reshape()}. Original docstring below.

\textbf{Returns reshaped array} – This will be a new view object if possible; otherwise, it will be a copy. Note there is no guarantee of the \textit{memory layout} (C- or Fortran- contiguous) of the returned array.
Return type  ndarray

See also:

ndarray.reshape()  Equivalent method.

Notes

It is not always possible to change the shape of an array without copying the data. If you want an error to be raised when the data is copied, you should assign the new shape to the shape attribute of the array:

```python
>>> a = np.zeros((10, 2))
# A transpose makes the array non-contiguous
>>> b = a.T
# Taking a view makes it possible to modify the shape without modifying
# the initial object.
>>> c = b.view()
>>> c.shape = (20)
Traceback (most recent call last):
...  
AttributeError: incompatible shape for a non-contiguous array
```

The order keyword gives the index ordering both for fetching the values from `a`, and then placing the values into the output array. For example, let’s say you have an array:

```python
>>> a = np.arange(6).reshape((3, 2))
>>> a
array([[0, 1],
       [2, 3],
       [4, 5]])
```

You can think of reshaping as first raveling the array (using the given index order), then inserting the elements from the raveled array into the new array using the same kind of index ordering as was used for the raveling.

```python
>>> np.reshape(a, (2, 3))  # C-like index ordering
array([[0, 1, 2],
       [3, 4, 5]])
>>> np.reshape(np.ravel(a), (2, 3))  # equivalent to C ravel then C reshape
array([[0, 1, 2],
       [3, 4, 5]])
>>> np.reshape(a, (2, 3), order='F')  # Fortran-like index ordering
array([[0, 4, 3],
       [2, 1, 5]])
>>> np.reshape(np.ravel(a, order='F'), (2, 3), order='F')
array([[0, 4, 3],
       [2, 1, 5]])
```
Examples

```python
>>> a = np.array([[1, 2, 3], [4, 5, 6]])
>>> np.reshape(a, 6)
array([1, 2, 3, 4, 5, 6])
>>> np.reshape(a, 6, order='F')
array([1, 4, 2, 5, 3, 6])

>>> np.reshape(a, (3,-1))  # the unspecified value is inferred to be 2
array([[1, 2],
       [3, 4],
       [5, 6]])
```

`roll(a, shift, axis=None)`

Roll array elements along a given axis.

LAX-backend implementation of `roll()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `roll()`. Original docstring below.

Elements that roll beyond the last position are re-introduced at the first.

Returns `res` – Output array, with the same shape as `a`.

Return type `ndarray`

See also:

`rollaxis()` Roll the specified axis backwards, until it lies in a given position.

Notes

New in version 1.12.0.

Supports rolling over multiple dimensions simultaneously.

Examples

```python
>>> x = np.arange(10)
>>> np.roll(x, 2)
array([8, 9, 0, 1, 2, 3, 4, 5, 6, 7])
>>> np.roll(x, -2)
array([2, 3, 4, 5, 6, 7, 8, 9, 0, 1])
```

```python
>>> x2 = np.reshape(x, (2,5))
>>> np.roll(x2, 1)
array([[9, 0, 1, 2, 3],
       [4, 5, 6, 7, 8]])
>>> np.roll(x2, -1)
array([[1, 2, 3, 4, 5],
       [6, 7, 8, 9, 0]])
>>> np.roll(x2, 1, axis=0)
array([[5, 6, 7, 8, 9],
       [0, 1, 2, 3, 4]]
```

(continues on next page)
```python
>>> np.roll(x2, -1, axis=0)
array([[5, 6, 7, 8, 9],
       [0, 1, 2, 3, 4]])
>>> np.roll(x2, 1, axis=1)
array([[4, 0, 1, 2, 3],
       [9, 5, 6, 7, 8]])
>>> np.roll(x2, -1, axis=1)
array([[1, 2, 3, 4, 0],
       [6, 7, 8, 9, 5]])
```

**rot90**

`rot90(m, k=1, axes=(0, 1))`

Rotate an array by 90 degrees in the plane specified by axes.

LAX-backend implementation of `rot90()`. ADDITION Original docstring below.

LAX-backend implementation of `rot90()`. Original docstring below.

Rotation direction is from the first towards the second axis.

Returns `y` – A rotated view of `m`.

Return type `ndarray`

See also:

- `flip()` Reverse the order of elements in an array along the given axis.
- `fliplr()` Flip an array horizontally.
- `flipud()` Flip an array vertically.

Notes

`rot90(m, k=1, axes=(1, 0))` is the reverse of `rot90(m, k=1, axes=(0, 1))` `rot90(m, k=1, axes=(1, 0))` is equivalent to `rot90(m, k=-1, axes=(0, 1))`.

Examples

```python
>>> m = np.array([[1,2],[3,4]], int)
>>> m
array([[1, 2],
       [3, 4]])
>>> np.rot90(m)
array([[2, 0],
       [4, 1]])
>>> np.rot90(m, 2)
array([[0, 2],
       [1, 3]])
>>> m = np.arange(8).reshape((2,2,2))
>>> np.rot90(m, 1, (2,1))
array([[[0, 2],
        [5, 7]],
       [[4, 6]]])
```
**round** \((a, \text{decimals}=0)\)
Round an array to the given number of decimals.
LAX-backend implementation of `round_()`. ADDITIONOriginal docstring below.

**row_stack** \((\text{tup})\)
Stack arrays in sequence vertically (row wise).
LAX-backend implementation of `vstack()`. ADDITIONOriginal docstring below.

This is equivalent to concatenation along the first axis after 1-D arrays of shape \((N,)\) have been reshaped to \((I, N)\). Rebuilds arrays divided by `vsplit`.

This function makes most sense for arrays with up to 3 dimensions. For instance, for pixel-data with a height (first axis), width (second axis), and r/g/b channels (third axis). The functions `concatenate`, `stack` and `block` provide more general stacking and concatenation operations.

**Returns stacked** – The array formed by stacking the given arrays, will be at least 2-D.

**Return type** ndarray

See also:

- `stack()` Join a sequence of arrays along a new axis.
- `hstack()` Stack arrays in sequence horizontally (column wise).
- `dstack()` Stack arrays in sequence depth wise (along third dimension).
- `concatenate()` Join a sequence of arrays along an existing axis.
- `vsplit()` Split array into a list of multiple sub-arrays vertically.
- `block()` Assemble arrays from blocks.

**Examples**

```python
>>> a = np.array([1, 2, 3])
>>> b = np.array([2, 3, 4])
>>> np.vstack((a, b))
array([[1, 2, 3],
       [2, 3, 4]])
```

```python
>>> a = np.array([[1], [2], [3]])
>>> b = np.array([[2], [3], [4]])
>>> np.vstack((a, b))
array([[1],
       [2],
       [3],
       [2],
       [3],
       [4]])
```

**sign** \((x)\)
Returns an element-wise indication of the sign of a number.
LAX-backend implementation of `sign()`. ADDITIONOriginal docstring below.
LAX-backend implementation of `sign()`. Original docstring below.

```python
sign(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

The `sign` function returns -1 if $x < 0$, 0 if $x == 0$, 1 if $x > 0$. nan is returned for nan inputs.

For complex inputs, the `sign` function returns $\text{sign}(x\text{.real}) + 0j$ if $x\text{.real} != 0$ else $\text{sign}(x\text{.imag}) + 0j$.

complex(nan, 0) is returned for complex nan inputs.

**Returns**
- `y` – The sign of $x$. This is a scalar if $x$ is a scalar.
- **Return type** `ndarray`

**Notes**

There is more than one definition of sign in common use for complex numbers. The definition used here is equivalent to $x/\sqrt{x^*x}$ which is different from a common alternative, $x/|x|$.

**Examples**

```python
>>> np.sign([-5., 4.5])
array([-1., 1.])
>>> np.sign(0)
0
>>> np.sign(5-2j)
(1+0j)
```

`signbit(x)`

Returns element-wise True where signbit is set (less than zero).

LAX-backend implementation of `signbit()`. ADDITION

```python
signbit(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

**Returns**
- `result` – Output array, or reference to `out` if that was supplied. This is a scalar if $x$ is a scalar.
- **Return type** `ndarray` of `bool`

**Examples**

```python
>>> np.signbit(-1.2)
True
>>> np.signbit(np.array([1, -2.3, 2.1]))
array([False,  True, False])
```

`sin(x)`

Trigonometric sine, element-wise.

LAX-backend implementation of `sin()`. ADDITION

```python
sin(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

LAX-backend implementation of `sin()`. Original docstring below.
sin(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns y – The sine of each element of x. This is a scalar if x is a scalar.

Return type array_like

See also:
arcsin(), sinh(), cos()

Notes

The sine is one of the fundamental functions of trigonometry (the mathematical study of triangles). Consider a circle of radius 1 centered on the origin. A ray comes in from the +x axis, makes an angle at the origin (measured counter-clockwise from that axis), and departs from the origin. The y coordinate of the outgoing ray’s intersection with the unit circle is the sine of that angle. It ranges from -1 for \( x = 3\pi/2 \) to +1 for \( \pi/2 \). The function has zeroes where the angle is a multiple of \( \pi \). Sines of angles between \( \pi \) and \( 2\pi \) are negative. The numerous properties of the sine and related functions are included in any standard trigonometry text.

Examples

Print sine of one angle:

```python
>>> np.sin(np.pi/2.)
1.0
```

Print sines of an array of angles given in degrees:

```python
>>> np.sin(np.array((0., 30., 45., 60., 90.)) * np.pi / 180. )
array([ 0. , 0.5 , 0.70710678, 0.8660254 , 1. ])
```

Plot the sine function:

```python
>>> import matplotlib.pyplot as plt
>>> x = np.linspace(-np.pi, np.pi, 201)
>>> plt.plot(x, np.sin(x))
>>> plt.xlabel('Angle [rad]')
>>> plt.ylabel('sin(x)')
>>> plt.axis('tight')
>>> plt.show()
```

sinc(x)

Return the sinc function.

LAX-backend implementation of sinc(). ADDITIONOriginal docstring below.

LAX-backend implementation of sinc(). Original docstring below.

The sinc function is \( \sin(\pi x)/(\pi x) \).

Returns

out [ndarray] sinc(x), which has the same shape as the input.

sinc(0) is the limit value 1.

The name sinc is short for “sine cardinal” or “sinus cardinalis”.
The sinc function is used in various signal processing applications, including in anti-aliasing, in the construction of a Lanczos resampling filter, and in interpolation.

For bandlimited interpolation of discrete-time signals, the ideal interpolation kernel is proportional to the sinc function.

```python
>>> import matplotlib.pyplot as plt
>>> x = np.linspace(-4, 4, 41)
>>> np.sinc(x)
array([-3.89804309e-17, -4.92362781e-02, -8.40918587e-02, # may →
    -8.90384387e-02, -5.84680802e-02, 3.89804309e-17,
    6.68206631e-02, 1.16434881e-01, 1.26137788e-01,
    8.50444803e-02, -3.89804309e-17, -1.03943254e-01,
    -1.89206682e-01, -2.16236208e-01, -1.55914881e-01,
    3.89804309e-17, 2.33872321e-01, 5.04551152e-01,
    7.56826729e-01, 9.35489284e-01, 1.000000000e+00,
    9.35489284e-01, 7.56826729e-01, 5.04551152e-01,
    2.33872321e-01, 3.89804309e-17, -1.55914881e-01,
    -2.16236208e-01, -1.89206682e-01, -1.03943254e-01,
    -3.89804309e-17, 8.50444803e-02, 1.26137788e-01,
    1.16434881e-01, 6.68206631e-02, 3.89804309e-17,
    -5.84680802e-02, -8.90384387e-02, -8.40918587e-02,
    -4.92362781e-02, -3.89804309e-17])
>>> plt.plot(x, np.sinc(x))
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.title("Sinc Function")
Text(0.5, 1.0, 'Sinc Function')
>>> plt.ylabel("Amplitude")
Text(0, 0.5, 'Amplitude')
>>> plt.xlabel("X")
Text(0.5, 0, 'X')
>>> plt.show()
```

\[
\text{sinc}(x)
\]

Hyperbolic sine, element-wise.

LAX-backend implementation of `\text{sinc}(\cdot)`.

```
Equivalent to \( 1/2 \times (\exp(x) - \exp(-x)) \) or \(-1j \times \sin(1j \times x)\).

Returns

\( y \) – The corresponding hyperbolic sine values. This is a scalar if \( x \) is a scalar.

Return type

\( \text{ndarray} \)
Notes

If `out` is provided, the function writes the result into it, and returns a reference to `out`. (See Examples)

References

M. Abramowitz and I. A. Stegun, Handbook of Mathematical Functions. New York, NY: Dover, 1972, pg. 83.

Examples

```python
>>> np.sinh(0)
0.0
>>> np.sinh(np.pi*1j/2)
1j
>>> np.sinh(np.pi*1j)  # (exact value is 0)
1.2246063538223773e-016j
>>> # Discrepancy due to vagaries of floating point arithmetic.

>>> # Example of providing the optional output parameter
>>> out1 = np.array([0], dtype='d')
>>> out2 = np.sinh([0.1], out1)
>>> out2 is out1
True

>>> # Example of ValueError due to provision of shape mis-matched `out`
>>> np.sinh(np.zeros((3,3)),np.zeros((2,2)))
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
ValueError: operands could not be broadcast together with shapes (3,3) (2,2)
```

`sort (a, axis=-1, kind='quicksort', order=None)`

Return a sorted copy of an array.

LAX-backend implementation of `sort ()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `sort ()`. Original docstring below.

Returns `sorted_array` – Array of the same type and shape as `a`.

Return type `ndarray`

See also:

`ndarray.sort ()` Method to sort an array in-place.

`argsort ()` Indirect sort.

`lexsort ()` Indirect stable sort on multiple keys.

`searchsorted ()` Find elements in a sorted array.

`partition ()` Partial sort.
Notes

The various sorting algorithms are characterized by their average speed, worst case performance, work space size, and whether they are stable. A stable sort keeps items with the same key in the same relative order. The four algorithms implemented in NumPy have the following properties:

| kind      | speed | worst case  | work space | stable |
|-----------|-------|-------------|------------|--------|
| ‘quicksort’ | 1     | O(n^2)      | 0          | no     |
| ‘heapsort’  | 3     | O(n * log(n)) | 0         | no     |
| ‘mergesort’ | 2     | O(n * log(n)) | ~n/2      | yes    |
| ‘timsort’   | 2     | O(n * log(n)) | ~n/2      | yes    |

Note: The datatype determines which of ‘mergesort’ or ‘timsort’ is actually used, even if ‘mergesort’ is specified. User selection at a finer scale is not currently available.

All the sort algorithms make temporary copies of the data when sorting along any but the last axis. Consequently, sorting along the last axis is faster and uses less space than sorting along any other axis.

The sort order for complex numbers is lexicographic. If both the real and imaginary parts are non-nan then the order is determined by the real parts except when they are equal, in which case the order is determined by the imaginary parts.

Previous to numpy 1.4.0 sorting real and complex arrays containing nan values led to undefined behaviour. In numpy versions >= 1.4.0 nan values are sorted to the end. The extended sort order is:

- Real: [R, nan]
- Complex: [R + Rj, R + nanj, nan + Rj, nan + nanj]

where R is a non-nan real value. Complex values with the same nan placements are sorted according to the non-nan part if it exists. Non-nan values are sorted as before.

New in version 1.12.0.

quicksort has been changed to introsort. When sorting does not make enough progress it switches to heapsort. This implementation makes quicksort O(n * log(n)) in the worst case.

‘stable’ automatically chooses the best stable sorting algorithm for the data type being sorted. It, along with ‘mergesort’ is currently mapped to timsort or radix sort depending on the data type. API forward compatibility currently limits the ability to select the implementation and it is hardwired for the different data types.

New in version 1.17.0.

Timsort is added for better performance on already or nearly sorted data. On random data timsort is almost identical to mergesort. It is now used for stable sort while quicksort is still the default sort if none is chosen. For timsort details, refer to CPython listsort.txt. ‘mergesort’ and ‘stable’ are mapped to radix sort for integer data types. Radix sort is an O(n) sort instead of O(n log n).

Changed in version 1.17.0.

NaT now sorts to the end of arrays for consistency with NaN.
Examples

```python
>>> a = np.array([[1,4],[3,1]])
```
```
>>> np.sort(a)            # sort along the last axis
array([[1, 4],
       [3, 1]])
```
```
>>> np.sort(a, axis=None) # sort the flattened array
array([1, 1, 3, 4])
```
```
>>> np.sort(a, axis=0)    # sort along the first axis
array([[1, 1],
       [3, 4]])
```

Use the `order` keyword to specify a field to use when sorting a structured array:

```python
>>> dtype = [('name', 'S10'), ('height', float), ('age', int)]
```
```
>>> values = [('Arthur', 1.8, 41), ('Lancelot', 1.9, 38), ...
          ('Galahad', 1.7, 38)]
```
```
>>> a = np.array(values, dtype=dtype) # create a structured array
>>> np.sort(a, order='height')
array([('Galahad', 1.7, 38), ('Arthur', 1.8, 41),
      ('Lancelot', 1.8999999999999999, 38)],
     dtype=[('name', '|S10'), ('height', '<f8'), ('age', '<i4')])
```

Sort by age, then height if ages are equal:

```python
>>> np.sort(a, order=['age', 'height'])
array([('Galahad', 1.7, 38), ('Lancelot', 1.8999999999999999, 38),
      ('Arthur', 1.8, 41)],
     dtype=[('name', '|S10'), ('height', '<f8'), ('age', '<i4')])
```

**split** *(ary, indices_or_sections, axis=0)*

Split an array into multiple sub-arrays as views into *ary*.

LAX-backend implementation of `split()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `split()`. Original docstring below.

Returns sub-arrays – A list of sub-arrays as views into *ary*.

Return type list of ndarrays

Raises ValueError – If *indices_or_sections* is given as an integer, but a split does not result in equal division.

See also:

- `array_split()` Split an array into multiple sub-arrays of equal or near-equal size. Does not raise an exception if an equal division cannot be made.
- `hsplit()` Split array into multiple sub-arrays horizontally (column-wise).
- `vsplit()` Split array into multiple sub-arrays vertically (row wise).
- `dsplit()` Split array into multiple sub-arrays along the 3rd axis (depth).
- `concatenate()` Join a sequence of arrays along an existing axis.
- `stack()` Join a sequence of arrays along a new axis.
- `hstack()` Stack arrays in sequence horizontally (column wise).
- `vstack()` Stack arrays in sequence vertically (row wise).
**dstack()** Stack arrays in sequence depth wise (along third dimension).

**Examples**

```python
>>> x = np.arange(9.0)
>>> np.split(x, 3)
[array([0., 1., 2.]), array([3., 4., 5.]), array([6., 7., 8.])]
```

```python
>>> x = np.arange(8.0)
>>> np.split(x, [3, 5, 6, 10])
[array([0., 1., 2.]),
 array([3., 4.]),
 array([5.]),
 array([6., 7.]),
 array([], dtype=float64)]
```

**sqrt**

Return the non-negative square-root of an array, element-wise.

LAX-backend implementation of `sqrt()`. ADDITION: Original docstring below.

LAX-backend implementation of `sqrt()`. Original docstring below.

```python
sqrt(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
```

Returns an array of the same shape as `x`, containing the positive square-root of each element in `x`. If any element in `x` is complex, a complex array is returned (and the square-roots of negative reals are calculated). If all of the elements in `x` are real, so is `y`, with negative elements returning `nan`. If `out` was provided, `y` is a reference to it. This is a scalar if `x` is a scalar.

**Return type** ndarray

See also: [lib.scimath.sqrt()](#) A version which returns complex numbers when given negative reals.

**Notes**

`sqrt` has—consistent with common convention—as its branch cut the real “interval” [−∞, 0), and is continuous from above on it. A branch cut is a curve in the complex plane across which a given complex function fails to be continuous.

**Examples**

```python
>>> np.sqrt([1,4,9])
array([ 1., 2., 3.])
```

```python
>>> np.sqrt([4, -1, -3+4J])
array([ 2.+0.j, 0.+1.j, 1.+2.j])
```

```python
>>> np.sqrt([4, -1, np.inf])
array([ 2., nan, inf])
```
**square**<br>Return the element-wise square of the input.<br><br>LAX-backend implementation of `square()`. ADDITIONOriginal docstring below.<br><br>LAX-backend implementation of `square()`. Original docstring below.<br><br>`square(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])`<br><br>Returns `out` – Element-wise $x^2$, of the same shape and dtype as $x$. This is a scalar if $x$ is a scalar.<br><br>Return type ndarray or scalar<br><br>See also:<br><br>numpy.linalg.matrix_power(), `sqrt()`, `power()`<br><br>**Examples**<br><br>`>>> np.square([-1j, 1])`<br><br>array([-1.-0.j, 1.+0.j])

**squeeze**<br>Remove single-dimensional entries from the shape of an array.<br><br>LAX-backend implementation of `squeeze()`. ADDITIONOriginal docstring below.<br><br>LAX-backend implementation of `squeeze()`. Original docstring below.<br><br>Returns `squeezed` – The input array, but with all or a subset of the dimensions of length 1 removed. This is always $a$ itself or a view into $a$.<br><br>Return type ndarray<br><br>Raises ValueError – If `axis` is not None, and an axis being squeezed is not of length 1<br><br>See also:<br><br>`expand_dims()` The inverse operation, adding singleton dimensions<br>`reshape()` Insert, remove, and combine dimensions, and resize existing ones<br><br>**Examples**<br><br>`>>> x = np.array([[0], [1], [2]])`<br>`>>> x.shape`<br>(1, 3, 1)<br>`>>> np.squeeze(x).shape`<br>(3,)<br>`>>> np.squeeze(x, axis=0).shape`<br>(3, 1)<br>`>>> np.squeeze(x, axis=1).shape`<br>(1, 3)
stack (arrays, axis=0)
Join a sequence of arrays along a new axis.

LAX-backend implementation of stack(). Original docstring below.

The axis parameter specifies the index of the new axis in the dimensions of the result. For example, if axis=0 it will be the first dimension and if axis=-1 it will be the last dimension.

New in version 1.10.0.

Returns stacked – The stacked array has one more dimension than the input arrays.

Return type ndarray

See also:
concatenate() Join a sequence of arrays along an existing axis.
split() Split array into a list of multiple sub-arrays of equal size.
block() Assemble arrays from blocks.

Examples

```python
>>> arrays = [np.random.randn(3, 4) for _ in range(10)]
>>> np.stack(arrays, axis=0).shape
(10, 3, 4)

>>> np.stack(arrays, axis=1).shape
(3, 10, 4)

>>> np.stack(arrays, axis=2).shape
(3, 4, 10)

>>> a = np.array([1, 2, 3])
>>> b = np.array([2, 3, 4])
>>> np.stack((a, b))
array([[1, 2, 3],
       [2, 3, 4]])

>>> np.stack((a, b), axis=-1)
array([[1, 2],
       [2, 3],
       [3, 4]])
```

std (a, axis=None, dtype=None, out=None, ddof=0, keepdims=False)
Compute the standard deviation along the specified axis.

LAX-backend implementation of std(). Original docstring below.

Returns the standard deviation, a measure of the spread of a distribution, of the array elements. The standard deviation is computed for the flattened array by default, otherwise over the specified axis.

Parameters dtype (dtype, optional) – Type to use in computing the standard deviation. For arrays of integer type the default is float64, for arrays of float types it is the same as the array type.
Returns **standard_deviation** – If `out` is None, return a new array containing the standard deviation, otherwise return a reference to the output array.

**Return type**  ndarray, see dtype parameter above.

**See also:** `var()`, `mean()`, `nanmean()`, `nanstd()`, `nanvar()`, `ufuncs-output-type()`

**Notes**

The standard deviation is the square root of the average of the squared deviations from the mean, i.e., \( \text{std} = \sqrt{\text{mean}(\text{abs}(x - x.\text{mean()} )**2)} \).

The average squared deviation is normally calculated as \( x.\text{sum()} / N \), where \( N = \text{len}(x) \). If, however, \( \text{ddof} \) is specified, the divisor \( N - \text{ddof} \) is used instead. In standard statistical practice, \( \text{ddof}=1 \) provides an unbiased estimator of the variance of the infinite population. \( \text{ddof}=0 \) provides a maximum likelihood estimate of the variance for normally distributed variables. The standard deviation computed in this function is the square root of the estimated variance, so even with \( \text{ddof}=1 \), it will not be an unbiased estimate of the standard deviation per se.

Note that, for complex numbers, \( \text{std} \) takes the absolute value before squaring, so that the result is always real and nonnegative.

For floating-point input, the \( \text{std} \) is computed using the same precision the input has. Depending on the input data, this can cause the results to be inaccurate, especially for float32 (see example below). Specifying a higher-accuracy accumulator using the `dtype` keyword can alleviate this issue.

**Examples**

```python
>>> a = np.array([[1, 2], [3, 4]])
>>> np.std(a)
1.1180339887498949 # may vary
>>> np.std(a, axis=0)
adarray([1., 1.])
>>> np.std(a, axis=1)
adarray([0.5, 0.5])
```

In single precision, `std()` can be inaccurate:

```python
>>> a = np.zeros((2, 512*512), dtype=np.float32)
>>> a[0, :] = 1.0
>>> a[1, :] = 0.1
>>> np.std(a)
0.45000005
```

Computing the standard deviation in float64 is more accurate:

```python
>>> np.std(a, dtype=np.float64)
0.44999999925494177 # may vary
```

**subtract** \((x1, x2)\)

Subtract arguments, element-wise.

LAX-backend implementation of `subtract()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `subtract()`. Original docstring below.
subtract(x1, x2, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Returns y – The difference of x1 and x2, element-wise. This is a scalar if both x1 and x2 are scalars.

Return type  ndarray

Notes
Equivalent to x1 - x2 in terms of array broadcasting.

Examples

```python
>>> np.subtract(1.0, 4.0)
-3.0

>>> x1 = np.arange(9.0).reshape((3, 3))
>>> x2 = np.arange(3.0)
>>> np.subtract(x1, x2)
array([[ 0.,  0.,  0.],
       [ 3.,  3.,  3.],
       [ 6.,  6.,  6.]])
```

sum(a, axis=None, dtype=None, out=None, keepdims=False)
Sum of array elements over a given axis.

LAX-backend implementation of sum(). ADDITIONOriginal docstring below.

LAX-backend implementation of sum(). Original docstring below.

Parameters  dtype(dtype, optional) – The type of the returned array and of the accumulator in which the elements are summed. The dtype of a is used by default unless a has an integer dtype of less precision than the default platform integer. In that case, if a is signed then the platform integer is used while if a is unsigned then an unsigned integer of the same precision as the platform integer is used.

Returns  sum_along_axis – An array with the same shape as a, with the specified axis removed. If a is a 0-d array, or if axis is None, a scalar is returned. If an output array is specified, a reference to out is returned.

Return type  ndarray

See also:

ndarray.sum()  Equivalent method.
add.reduce()  Equivalent functionality of add.
cumsum()  Cumulative sum of array elements.
trapz()  Integration of array values using the composite trapezoidal rule.

mean(), average()
Notes

Arithmetic is modular when using integer types, and no error is raised on overflow.

The sum of an empty array is the neutral element 0:

```python
>>> np.sum([])
0.0
```

For floating point numbers the numerical precision of sum (and np.add.reduce) is in general limited by directly adding each number individually to the result causing rounding errors in every step. However, often numpy will use a numerically better approach (partial pairwise summation) leading to improved precision in many use-cases. This improved precision is always provided when no axis is given. When axis is given, it will depend on which axis is summed. Technically, to provide the best speed possible, the improved precision is only used when the summation is along the fast axis in memory. Note that the exact precision may vary depending on other parameters. In contrast to NumPy, Python’s math.fsum function uses a slower but more precise approach to summation. Especially when summing a large number of lower precision floating point numbers, such as float32, numerical errors can become significant. In such cases it can be advisable to use dtype="float64" to use a higher precision for the output.

Examples

```python
>>> np.sum([0.5, 1.5])
2.0
>>> np.sum([0.5, 0.7, 0.2, 1.5], dtype=np.int32)
1
>>> np.sum([[0, 1], [0, 5]])
6
>>> np.sum([[0, 1], [0, 5]], axis=0)
array([0, 6])
>>> np.sum([[0, 1], [0, 5]], axis=1)
array([1, 5])
>>> np.sum([[0, 1], [np.nan, 5]], where=[False, True], axis=1)
array([1., 5.])
```

If the accumulator is too small, overflow occurs:

```python
>>> np.ones(128, dtype=np.int8).sum(dtype=np.int8)
-128
```

You can also start the sum with a value other than zero:

```python
>>> np.sum([10], initial=5)
15
```

**swapaxes** (a, axis1, axis2)

Interchange two axes of an array.

LAX-backend implementation of swapaxes(). ADDITIONOriginal docstring below.

LAX-backend implementation of swapaxes(). Original docstring below.

**Returns** a_swapped – For NumPy >= 1.10.0, if a is an ndarray, then a view of a is returned; otherwise a new array is created. For earlier NumPy versions a view of a is returned only if the order of the axes is changed, otherwise the input array is returned.

**Return type** ndarray
Examples

```python
>>> x = np.array([[1,2,3]])
>>> np.swapaxes(x,0,1)
array([[1],
       [2],
       [3]])

>>> x = np.array([[[0,1],[2,3]],[[4,5],[6,7]]])
>>> x
array([[0, 1],
       [2, 3],
       [4, 5],
       [6, 7]])

>>> np.swapaxes(x,0,2)
array([[0, 4],
       [2, 6],
       [1, 5],
       [3, 7]])
```

take (a, indices, axis=None, out=None, mode=None)
Take elements from an array along an axis.

LAX-backend implementation of `take()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `take()`. Original docstring below.

When axis is not None, this function does the same thing as “fancy” indexing (indexing arrays using arrays); however, it can be easier to use if you need elements along a given axis. A call such as `np.take(arr, indices, axis=3)` is equivalent to `arr[:,:,:,indices,...]`.

Explained without fancy indexing, this is equivalent to the following use of `ndindex`, which sets each of `ii`, `jj`, and `kk` to a tuple of indices:

```python
Ni, Nk = a.shape[:axis], a.shape[axis+1:]
Nj = indices.shape
for ii in ndindex(Ni):
    for jj in ndindex(Nj):
        for kk in ndindex(Nk):
            out[ii + jj + kk] = a[ii + (indices[jj],) + kk]
```

Returns out – The returned array has the same type as `a`.

Return type ndarray (Ni..., Nj..., Nk...)

See also:

compress() Take elements using a boolean mask
ndarray.take() equivalent method
take_along_axis() Take elements by matching the array and the index arrays
Notes

By eliminating the inner loop in the description above, and using \texttt{s\_} to build simple slice objects, \texttt{take} can be expressed in terms of applying fancy indexing to each 1-d slice:

\begin{verbatim}
Ni, Nk = a.shape[:axis], a.shape[axis+1:]
for ii in ndindex(Ni):
    for kk in ndindex(Nj):
        out[ii + s\_[\ldots] + kk] = a[ii + s\_[\ldots] + kk][indices]
\end{verbatim}

For this reason, it is equivalent to (but faster than) the following use of \texttt{apply\_along\_axis}:

\begin{verbatim}
out = np.apply\_along\_axis(lambda a\_1d: a\_1d[indices], axis, a)
\end{verbatim}

Examples

\begin{verbatim}
>>> a = [4, 3, 5, 7, 6, 8]
>>> indices = [0, 1, 4]
>>> np.take(a, indices)
array([4, 3, 6])
\end{verbatim}

In this example if \texttt{a} is an ndarray, “fancy” indexing can be used.

\begin{verbatim}
>>> a = np.array(a)
>>> a[indices]
array([4, 3, 6])
\end{verbatim}

If \texttt{indices} is not one dimensional, the output also has these dimensions.

\begin{verbatim}
>>> np.take(a, [[0, 1], [2, 3]])
array([[4, 3],
       [5, 7]])
\end{verbatim}

\texttt{take\_along\_axis}(\texttt{arr}, \texttt{indices}, \texttt{axis})
Take values from the input array by matching 1d index and data slices.

LAX-backend implementation of \texttt{take\_along\_axis()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{take\_along\_axis()}. Original docstring below.

This iterates over matching 1d slices oriented along the specified axis in the index and data arrays, and uses the former to look up values in the latter. These slices can be different lengths.

Functions returning an index along an axis, like \texttt{argsort} and \texttt{argpartition}, produce suitable indices for this function.

New in version 1.15.0.

Returns

\texttt{out: ndarray (Ni\ldots, J, Nk\ldots)} The indexed result.

This is equivalent to (but faster than) the following use of \texttt{ndindex} and \texttt{s\_}, which sets each of \texttt{ii} and \texttt{kk} to a tuple of indices:
Ni, M, Nk = a.shape[:axis], a.shape[axis], a.shape[axis+1:]
J = indices.shape[axis]  # Need not equal M
out = np.empty(Ni + (J,) + Nk)
for ii in ndindex(Ni):
    for kk in ndindex(Nk):
        a_1d = a[ii + s[:], + kk]
        indices_1d = indices[ii + s[:], + kk]
        out_1d = out[ii + s[:], + kk]
        for j in range(J):
            out_1d[j] = a_1d[indices_1d[j]]

Equivalently, eliminating the inner loop, the last two lines would be:

```python
out_1d[:] = a_1d[indices_1d]
```

take : Take along an axis, using the same indices for every 1d slice
put_along_axis : Put values into the destination array by matching 1d index and data slices

For this sample array

```python
>>> a = np.array([[10, 30, 20], [60, 40, 50]])
```
\textbf{tan}(x)

Compute tangent element-wise.

LAX-backend implementation of \texttt{tan()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{tan()}. Original docstring below.

tan(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

Equivalent to \texttt{np.sin(x)/np.cos(x)} element-wise.

\textbf{Returns}

- \texttt{y} – The corresponding tangent values. This is a scalar if \texttt{x} is a scalar.

\textbf{Return type}

\texttt{ndarray}

\textbf{Notes}

If \texttt{out} is provided, the function writes the result into it, and returns a reference to \texttt{out}. (See Examples)

\textbf{References}

M. Abramowitz and I. A. Stegun, Handbook of Mathematical Functions. New York, NY: Dover, 1972.

\textbf{Examples}

\begin{verbatim}
>>> from math import pi
>>> np.tan(np.array([-pi,pi/2,pi]))
array([-1.22460635e-16, 1.63317787e+16, -1.22460635e-16])

>>> # Example of providing the optional output parameter illustrating
>>> # that what is returned is a reference to said parameter
>>> out1 = np.array([0], dtype='d')
>>> out2 = np.cos([0.1], out1)
>>> out2 is out1
True

>>> # Example of ValueError due to provision of shape mis-matched 'out'
>>> np.cos(np.zeros((3,3)),np.zeros((2,2)))
Traceback (most recent call last):
  File "<stdin>"", line 1, in <module>
ValueError: operands could not be broadcast together with shapes (3,3) (2,2)
\end{verbatim}

\textbf{tanh}(x)

Compute hyperbolic tangent element-wise.

LAX-backend implementation of \texttt{tanh()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{tanh()}. Original docstring below.

tanh(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
Equivalent to np.sinh(x)/np.cosh(x) or -1j * np.tan(1j*x).

Returns y – The corresponding hyperbolic tangent values. This is a scalar if x is a scalar.

Return type ndarray

Notes

If out is provided, the function writes the result into it, and returns a reference to out. (See Examples)

References

Examples

```python
>>> np.tanh((0, np.pi*1j, np.pi*1j/2))
array([ 0. +0.00000000e+00j, 0. -1.22460635e-16j, 0. +1.63317787e+16j])
```

```python
>>> # Example of providing the optional output parameter illustrating
>>> # that what is returned is a reference to said parameter
>>> out1 = np.array([0], dtype='d')
>>> out2 = np.tanh([0.1], out1)
>>> out2 is out1
True
```

```python
>>> # Example of ValueError due to provision of shape mis-matched 'out'
>>> np.tanh(np.zeros((3,3)),np.zeros((2,2)))
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
ValueError: operands could not be broadcast together with shapes (3,3) (2,2)
```

tensordot (a, b, axes=2, precision=None)

Compute tensor dot product along specified axes.

LAX-backend implementation of tensordot(). ADDITIONOriginal docstring below.

LAX-backend implementation of tensordot(). In addition to the original NumPy arguments listed below, also supports precision for extra control over matrix-multiplication precision on supported devices. See jax.lax.dot() for details.

Original docstring below.

Given two tensors, a and b, and an array_like object containing two array_like objects, (a_axes, b_axes), sum the products of a’s and b’s elements (components) over the axes specified by a_axes and b_axes. The third argument can be a single non-negative integer_like scalar, N; if it is such, then the last N dimensions of a and the first N dimensions of b are summed over.

Returns output – The tensor dot product of the input.

Return type ndarray

See also:

dot(), einsum()
Notes

Three common use cases are:

- \( \text{axes} = 0 \): tensor product \( a \otimes b \)
- \( \text{axes} = 1 \): tensor dot product \( a \cdot b \)
- \( \text{axes} = 2 \): (default) tensor double contraction \( a : b \)

When \( \text{axes} \) is \text{integer_like}, the sequence for evaluation will be: first the -Nth axis in \( a \) and 0th axis in \( b \), and the -1th axis in \( a \) and Nth axis in \( b \) last.

When there is more than one axis to sum over - and they are not the last (first) axes of \( a (b) \) - the argument \( \text{axes} \) should consist of two sequences of the same length, with the first axis to sum over given first in both sequences, the second axis second, and so forth.

The shape of the result consists of the non-contracted axes of the first tensor, followed by the non-contracted axes of the second.

Examples

A “traditional” example:

```python
>>> a = np.arange(60.).reshape(3,4,5)
>>> b = np.arange(24.).reshape(4,3,2)
>>> c = np.tensordot(a,b, axes=(1,0),([1,0],[0,1]))
>>> c.shape
(5, 2)
>>> c
array([[4400., 4730.],
       [4532., 4874.],
       [4664., 5018.],
       [4796., 5162.],
       [4928., 5306.]])
>>> # A slower but equivalent way of computing the same...
>>> d = np.zeros((5,2))
>>> for i in range(5):
...     for j in range(2):
...         for k in range(3):
...             for n in range(4):
...                 d[i,j] += a[k,n,i] * b[n,k,j]
>>> c == d
array([[ True,  True],
       [ True,  True],
       [ True,  True],
       [ True,  True],
       [ True,  True]])
```

An extended example taking advantage of the overloading of + and *:

```python
>>> a = np.array(range(1, 9))
>>> a.shape = (2, 2)
>>> A = np.array((['a', 'b', 'c', 'd'], dtype=object))
>>> A.shape = (2, 2)
>>> a; A
array([[1, 2],
       [3, 4]],
       dtype=object)
```
array([[5, 6],
       [7, 8]]),
dtype=object)

>>> np.tensordot(a, A) # third argument default is 2 for double-contraction
array(['abbcddddd', 'aaaaabbbbbccccccccddddd'], dtype=object)

>>> np.tensordot(a, A, 1)
array([['acc', 'bdd'],
       ['aaacc', 'bbddddd']],
       [['aaaaacc', 'bbbdddddd'],
        ['aaaaaaacc', 'bbbbddddddd']]), dtype=object)

>>> np.tensordot(a, A, 0) # tensor product (result too long to incl.)
array([['a', 'b'],
       ['c', 'd'],
       ...
...

>>> np.tensordot(a, A, (0, 1))
array([['abbccddd', 'aaaaabbbbbccccccccddddd'],
       ['aabbccc', 'bbddddd']]), dtype=object)

>>> np.tensordot(a, A, (2, 1))
array([['abb', 'cdd'],
       ['aaabb', 'ccddd']],
       [['aaaaabb', 'ccddd'],
        ['aaaaaaabb', 'ccccddd']]), dtype=object)

>>> np.tensordot(a, A, ((0, 1), (0, 1)))
array(['abbcddddd', 'aaaaabbbbbccccccccddddd'], dtype=object)

>>> np.tensordot(a, A, ((2, 1), (1, 0)))
array(['acccbbddd', 'aaaaaccbbbbccccccccddddd'], dtype=object)

**tile** *(a, reps)*
Construct an array by repeating A the number of times given by reps.

LAX-backend implementation of *tile*. ADDITIONOriginal docstring below.

LAX-backend implementation of *tile*. Original docstring below.

If *reps* has length *d*, the result will have dimension of \( \max(d, A.\text{ndim}) \).

If \(A.\text{ndim} < d\), \(A\) is promoted to be \(d\)-dimensional by prepending new axes. So a shape (3,) array is promoted to (1, 3) for 2-D replication, or shape (1, 1, 3) for 3-D replication. If this is not the desired behavior, promote \(A\) to \(d\)-dimensions manually before calling this function.

If \(A.\text{ndim} > d\), *reps* is promoted to \(A.\text{ndim}\) by pre-pending 1’s to it. Thus for an \(A\) of shape (2, 3, 4, 5), a *reps* of (2, 2) is treated as (1, 1, 2, 2).

Note : Although tile may be used for broadcasting, it is strongly recommended to use numpy’s broadcasting operations and functions.

**Returns**
\(c\) – The tiled output array.
Return type  ndarray

See also:

repeat()  Repeat elements of an array.

broadcast_to()  Broadcast an array to a new shape

Examples

```python
got = np.array([[0, 1, 2], [0, 1, 2]])
out = np.tile(got, (2, 2))
array([[0, 1, 2, 0, 1, 2],
       [0, 1, 2, 0, 1, 2]])
```

```python
c = np.array([1,2,3,4])
out = np.tile(c, (4,1))
array([[1, 2, 3, 4],
       [1, 2, 3, 4],
       [1, 2, 3, 4],
       [1, 2, 3, 4]])
```

```
trace(a, offset=0, axis1=0, axis2=1, dtype=None, out=None)
```

Return the sum along diagonals of the array.

LAX-backend implementation of `trace()`. Original docstring below.

LAX-backend implementation of `trace()`. Original docstring below.

If `a` is 2-D, the sum along its diagonal with the given offset is returned, i.e., the sum of elements `a[i, i+offset]` for all `i`.

If `a` has more than two dimensions, then the axes specified by `axis1` and `axis2` are used to determine the 2-D sub-arrays whose traces are returned. The shape of the resulting array is the same as that of `a` with `axis1` and `axis2` removed.

**Parameters**

- **dtype** *(dtype, optional)*  – Determines the data-type of the returned array and of the accumulator where the elements are summed. If `dtype` has the value `None` and `a` is of integer type of precision less than the default integer precision, then the default integer precision is used. Otherwise, the precision is the same as that of `a`.

**Returns**

- **sum_along_diagonals**  – If `a` is 2-D, the sum along the diagonal is returned. If `a` has larger dimensions, then an array of sums along diagonals is returned.
Return type
ndarray

See also:
diag(), diagonal(), diagflat()

Examples

```python
>>> np.trace(np.eye(3))
3.0
>>> a = np.arange(8).reshape((2,2,2))
>>> np.trace(a)
array([[6, 8]])
```

```
>>> a = np.arange(24).reshape((2,2,2,3))
>>> np.trace(a).shape
(2, 3)
```

transpose(\(a, axes=None\))
Permute the dimensions of an array.

LAX-backend implementation of transpose(). ADDITIONOriginal docstring below.

LAX-backend implementation of transpose(). Original docstring below.

Returns \(p - a\) with its axes permuted. A view is returned whenever possible.

Return type
ndarray

See also:
moveaxis(), argsort()

Notes

Use transpose(\(a, argsort(axes)\)) to invert the transposition of tensors when using the \(axes\) keyword argument.

Transposing a 1-D array returns an unchanged view of the original array.

Examples

```python
>>> x = np.arange(4).reshape((2,2))
>>> x
array([[0, 1],
       [2, 3]])
```

```
>>> np.transpose(x)
array([[0, 2],
       [1, 3]])
```

```
>>> x = np.ones((1, 2, 3))
>>> np.transpose(x, (1, 0, 2)).shape
(2, 1, 3)
```
**tri** (*N*, *M=None*, *k=0*, *dtype=None*)

An array with ones at and below the given diagonal and zeros elsewhere.

LAX-backend implementation of `tri()`. Original docstring below.

Parameters

- **dtype** (*dtype*, **optional**) – Data type of the returned array. The default is float.

Returns **tri** – Array with its lower triangle filled with ones and zero elsewhere; in other words

\[ T[i,j] == 1 \text{ for } j \leq i + k, \text{ 0 otherwise.} \]

Return type

`ndarray` of shape (*N*, *M*)

**Examples**

```python
>>> np.tri(3, 5, 2, dtype=int)
array([[1, 1, 1, 0, 0],
       [1, 1, 1, 1, 0],
       [1, 1, 1, 1, 1]])
```

```python
>>> np.tri(3, 5, -1)
array([[0., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 1., 0., 0., 0.]])
```

**tril** (*m*, *k=0*)

Lower triangle of an array.

LAX-backend implementation of `tril()`. Original docstring below.

Parameters

- **k** (*int*, **optional**) – The diagonal above which to zero elements. Default is 0, representing the main diagonal.

Returns **tril** – Lower triangle of `m`, of same shape and data-type as `m`.

Return type

`ndarray`, shape (*M*, *N*)

See also:

- **triu()** same thing, only for the upper triangle

**Examples**

```python
>>> np.tril([[1,2,3],[4,5,6],[7,8,9],[10,11,12]], -1)
array([[0., 0., 0.],
       [4., 0., 0.],
       [7., 8., 0.],
       [10., 11., 12.]])
```

**tril_indices** (*args, **kwargs*)

Return the indices for the lower-triangle of an (*n*, *m*) array.

LAX-backend implementation of `tril_indices()`. Original docstring below.

Parameters

- **args** (*optional*)
- **kwargs** (*optional*)

Returns **tril_indices** – Indices of the lower-triangle of an (*n*, *m*) array.

Return type

`tuple` of (*N*, *M*)

**Examples**

```python
```
Returns

**inds** [tuple of arrays] The indices for the triangle. The returned tuple contains two arrays, each with the indices along one dimension of the array.

triu_indices : similar function, for upper-triangular. mask_indices : generic function accepting an arbitrary mask function. tril, triu

New in version 1.4.0.

Compute two different sets of indices to access 4x4 arrays, one for the lower triangular part starting at the main diagonal, and one starting two diagonals further right:

```python
>>> il1 = np.tril_indices(4)
>>> il2 = np.tril_indices(4, 2)
```

Here is how they can be used with a sample array:

```python
>>> a = np.arange(16).reshape(4, 4)
>>> a
array([[ 0, 1, 2, 3],
       [ 4, 5, 6, 7],
       [ 8, 9, 10, 11],
       [12, 13, 14, 15]])
```

Both for indexing:

```python
>>> a[il1]
array([ 0, 4, 5, ..., 13, 14, 15])
```

And for assigning values:

```python
>>> a[il1] = -1
>>> a
array([[ -1,  1,  2,  3],
       [ -1, -1,  6,  7],
       [ -1, -1, -1, 11],
       [ -1, -1, -1, -1]])
```

These cover almost the whole array (two diagonals right of the main one):

```python
>>> a[il2] = -10
>>> a
array([[-10, -10, -10,  3],
       [-10, -10, -10, -10],
       [-10, -10, -10, -10],
       [-10, -10, -10, -10]])
```

**triu** *(m, k=0)*

Upper triangle of an array.

LAX-backend implementation of **triu()**. ADDITIONOriginal docstring below.

**triu_indices** *(args, **kwargs)*

Return the indices for the upper-triangle of an (n, m) array.

LAX-backend implementation of **triu_indices()**. ADDITIONOriginal docstring below.

LAX-backend implementation of **triu_indices()**. Original docstring below.
Returns

 inds  [tuple, shape(2) of ndarrays, shape(n)] The indices for the triangle. The returned tuple contains two arrays, each with the indices along one dimension of the array. Can be used to slice a ndarray of shape(n, n).

tril_indices : similar function, for lower-triangular. mask_indices : generic function accepting an arbitrary mask function. triu, tril

New in version 1.4.0.

Compute two different sets of indices to access 4x4 arrays, one for the upper triangular part starting at the main diagonal, and one starting two diagonals further right:

```python
>>> iu1 = np.triu_indices(4)
>>> iu2 = np.triu_indices(4, 2)
```

Here is how they can be used with a sample array:

```python
>>> a = np.arange(16).reshape(4, 4)
>>> a
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11],
       [12, 13, 14, 15]])
```

Both for indexing:

```python
>>> a[iu1]
array([ 0,  1,  2, ..., 10, 11, 15])
```

And for assigning values:

```python
>>> a[iu1] = -1
>>> a
array([[ -1, -1, -1, -1],
       [ 4, -1, -1, -1],
       [ 8,  9, -1, -1],
       [12, 13, 14, -1]])
```

These cover only a small part of the whole array (two diagonals right of the main one):

```python
>>> a[iu2] = -10
>>> a
array([[ -1, -1, -10, -10],
       [ 4, -1, -1, -10],
       [ 8,  9, -1, -1],
       [12, 13, 14, -1]])
```

true_divide(x1, x2)

Returns a true division of the inputs, element-wise.

LAX-backend implementation of true_divide(). ADDITIONOriginal docstring below.

LAX-backend implementation of true_divide(). Original docstring below.

true_divide(x1, x2, /, out=None, * , where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])
Instead of the Python traditional ‘floor division’, this returns a true division. True division adjusts the output type to present the best answer, regardless of input types.

- **Returns out** – This is a scalar if both x1 and x2 are scalars.
- **Return type** ndarray or scalar

**Notes**

The floor division operator `//` was added in Python 2.2 making `//` and `/` equivalent operators. The default floor division operation of `/` can be replaced by true division with `from __future__ import division`.

In Python 3.0, `//` is the floor division operator and `/` the true division operator. The `true_divide(x1, x2)` function is equivalent to true division in Python.

**Examples**

```python
>>> x = np.arange(5)
>>> np.true_divide(x, 4)
array([ 0. , 0.25, 0.5 , 0.75, 1. ])
>>> x//4
array([0, 0, 0, 0, 1])
>>> from __future__ import division
>>> x/4
array([ 0. , 0.25, 0.5 , 0.75, 1. ])
>>> x//4
array([0, 0, 0, 0, 1])
```

**var(a, axis=None, dtype=None, out=None, ddof=0, keepdims=False)**

Compute the variance along the specified axis.

LAX-backend implementation of `var()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `var()`. Original docstring below.

Returns the variance of the array elements, a measure of the spread of a distribution. The variance is computed for the flattened array by default, otherwise over the specified axis.

- **Parameters**
  - `dtype (data-type, optional)` – Type to use in computing the variance. For arrays of integer type the default is `float64`; for arrays of float types it is the same as the array type.

- **Returns**
  - `variance` – If `out=None`, returns a new array containing the variance; otherwise, a reference to the output array is returned.

- **Return type** ndarray, see `dtype` parameter above

**See also:**

`std()`, `mean()`, `nanmean()`, `nanstd()`, `nanvar()`, `ufuncs-output-type()`
Notes

The variance is the average of the squared deviations from the mean, i.e., \( \text{var} = \text{mean}(\text{abs}(x - x. \text{mean}())**2) \).

The mean is normally calculated as \( x.\text{sum}() \div N \), where \( N = \text{len}(x) \). If, however, \( \text{ddof} \) is specified, the divisor \( N - \text{ddof} \) is used instead. In standard statistical practice, \( \text{ddof}=1 \) provides an unbiased estimator of the variance of a hypothetical infinite population. \( \text{ddof}=0 \) provides a maximum likelihood estimate of the variance for normally distributed variables.

Note that for complex numbers, the absolute value is taken before squaring, so that the result is always real and nonnegative.

For floating-point input, the variance is computed using the same precision the input has. Depending on the input data, this can cause the results to be inaccurate, especially for \( \text{float32} \) (see example below). Specifying a higher-accuracy accumulator using the \( \text{dtype} \) keyword can alleviate this issue.

Examples

```python
>>> a = np.array([[1, 2], [3, 4]])
>>> np.var(a)
1.25
>>> np.var(a, axis=0)
array([1., 1.])
>>> np.var(a, axis=1)
array([0.25, 0.25])
```

In single precision, var() can be inaccurate:

```python
>>> a = np.zeros((2, 512*512), dtype=np.float32)
>>> a[0, :] = 1.0
>>> a[1, :] = 0.1
>>> np.var(a)
0.20250003
```

Computing the variance in float64 is more accurate:

```python
>>> np.var(a, dtype=np.float64)
0.20249999932944759 # may vary
>>> ((1-0.55)**2 + (0.1-0.55)**2)/2
0.2025
```

**vdot** \((a, b, \text{precision}=\text{None})\)

Return the dot product of two vectors.

LAX-backend implementation of \( \text{vdot()} \). ADDITIONOriginal docstring below.

LAX-backend implementation of \( \text{vdot()} \). In addition to the original NumPy arguments listed below, also supports \( \text{precision} \) for extra control over matrix-multiplication precision on supported devices. See \( \text{jax. lax.dot()} \) for details.

Original docstring below.

\( \text{vdot(a, b)} \)

The \( \text{vdot(a, b)} \) function handles complex numbers differently than \( \text{dot(a, b)} \). If the first argument is complex the complex conjugate of the first argument is used for the calculation of the dot product.
Note that \texttt{vdot} handles multidimensional arrays differently than \texttt{dot}: it does \textit{not} perform a matrix product, but flattens input arguments to 1-D vectors first. Consequently, it should only be used for vectors.

**Returns**

- \textbf{output} \ [ndarray] Dot product of \(a\) and \(b\). Can be an int, float, or complex depending on the types of \(a\) and \(b\).

- \textbf{dot} \ [Return the dot product without using the complex conjugate of the] first argument.

```
>>> a = np.array([1+2j, 3+4j])
>>> b = np.array([5+6j, 7+8j])
>>> np.vdot(a, b)
(70-8j)
>>> np.vdot(b, a)
(70+8j)
```

Note that higher-dimensional arrays are flattened!

```
>>> a = np.array([[1, 4], [5, 6]])
>>> b = np.array([[4, 1], [2, 2]])
>>> np.vdot(a, b)
30
>>> np.vdot(b, a)
30
>>> 1*4 + 4*1 + 5*2 + 6*2
30
```

\textbf{vsplit (ary, indices_or_sections)}

Split an array into multiple sub-arrays vertically (row-wise).

LAX-backend implementation of \texttt{vsplit()}. ADDITIONOriginal docstring below.

\textbf{vstack (tup)}

Stack arrays in sequence vertically (row wise).

LAX-backend implementation of \texttt{vstack()}. ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{vstack()}. Original docstring below.

This is equivalent to concatenation along the first axis after 1-D arrays of shape \((N,)\) have been reshaped to \((1,N)\). Rebuilds arrays divided by \texttt{vsplit}.

This function makes most sense for arrays with up to 3 dimensions. For instance, for pixel-data with a height (first axis), width (second axis), and r/g/b channels (third axis). The functions \texttt{concatenate}, \texttt{stack} and \texttt{block} provide more general stacking and concatenation operations.

**Returns** \textbf{stacked} – The array formed by stacking the given arrays, will be at least 2-D.

**Return type** \texttt{ndarray}

See also:

- \texttt{stack()} Join a sequence of arrays along a new axis.
- \texttt{hstack()} Stack arrays in sequence horizontally (column wise).
- \texttt{dstack()} Stack arrays in sequence depth wise (along third dimension).
**concatenate()** Join a sequence of arrays along an existing axis.

**vsplit()** Split array into a list of multiple sub-arrays vertically.

**block()** Assemble arrays from blocks.

### Examples

```python
>>> a = np.array([1, 2, 3])
>>> b = np.array([2, 3, 4])
>>> np.vstack((a, b))
array([[1, 2, 3],
       [2, 3, 4]])

>>> a = np.array([[1], [2], [3]])
>>> b = np.array([[2], [3], [4]])
>>> np.vstack((a, b))
array([[1],
       [2],
       [3],
       [2],
       [3],
       [4]])
```

**zeros**(shape, dtype=None)
Return a new array of given shape and type, filled with zeros.

LAX-backend implementation of `zeros()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `zeros()`. Original docstring below.

zeros(shape, dtype=float, order='C')

Returns

- out : [ndarray] Array of zeros with the given shape, dtype, and order.
- zeros_like : Return an array of zeros with shape and type of input.
- empty : Return a new uninitialized array.
- ones : Return a new array setting values to one.
- full : Return a new array of given shape filled with value.

```python
>>> np.zeros(5)
array([ 0.,  0.,  0.,  0.,  0.])

>>> np.zeros((5,), dtype=int)
array([0, 0, 0, 0, 0])

>>> np.zeros((2, 1))
array([[ 0.],
       [ 0.]])

>>> s = (2,2)
>>> np.zeros(s)
array([[ 0.,  0.],
       [ 0.,  0.]])
```
zeros_like(x, dtype=None)
Return an array of zeros with the same shape and type as a given array.

LAX-backend implementation of zeros_like(). ADDITIONOriginal docstring below.

LAX-backend implementation of zeros_like(). Original docstring below.

Parameters
dtype (data-type, optional) – Overrides the data type of the result.

Returns
default – Array of zeros with the same shape and type as a.

Return type
ndarray

See also:
empty_like() Return an empty array with shape and type of input.
ones_like() Return an array of ones with shape and type of input.
full_like() Return a new array with shape of input filled with value.
zeros() Return a new array setting values to zero.

Examples

>>> x = np.arange(6)
>>> x = x.reshape((2, 3))
>>> x
array([[0, 1, 2],
       [3, 4, 5]])
>>> np.zeros_like(x)
array([[0, 0, 0],
       [0, 0, 0]])

>>> y = np.arange(3, dtype=float)
>>> y
array([0., 1., 2.])
>>> np.zeros_like(y)
array([0., 0., 0.])

2.1.3 symjax.tensor.pdfs

Multivariate Normal

class multivariate_normal

logpdf(mean, cov)
Log of the multivariate normal probability density function.

Parameters
x (array_like) –

Returns
pdf – Log of the probability density function evaluated at x
Return type: ndarray

**pdf** *(mean, cov)*

Multivariate normal probability density function.

:param x: Quantiles, with the last axis of x denoting the components.
:type x: array_like

Returns **pdf** – Probability density function evaluated at x

Return type: ndarray

## 2.1.4 symjax.tensor.signal

### Apodization Windows

| Function      | Description                           |
|---------------|---------------------------------------|
| `blackman(M)` | Return the Blackman window.           |
| `bartlett(M)` | Return the Bartlett window.           |
| `hamming(M)`  | Return the Hamming window.            |
| `hanning(M)`  | Return the Hanning window.            |
| `kaiser(M, beta)` | Return the Kaiser window.            |

### Fourier Transforms

| Function      | Description                           |
|---------------|---------------------------------------|
| `fft(a[, n, axis, norm])` | Compute the one-dimensional discrete Fourier Transform. |
| `ifft(a[, n, axis, norm])` | Compute the one-dimensional inverse discrete Fourier Transform. |
| `fft2(a[, s, axes, norm])` | Compute the 2-dimensional discrete Fourier Transform. |
| `ifft2(a[, s, axes, norm])` | Compute the 2-dimensional inverse discrete Fourier Transform. |
| `fftn(a[, s, axes, norm])` | Compute the N-dimensional discrete Fourier Transform. |
| `ifftn(a[, s, axes, norm])` | Compute the N-dimensional inverse discrete Fourier Transform. |
| `rfft(a[, n, axis, norm])` | Compute the one-dimensional discrete Fourier Transform for real input. |
| `irfft(a[, n, axis, norm])` | Compute the inverse of the n-point DFT for real input. |
| `rfft2(a[, s, axes, norm])` | Compute the 2-dimensional FFT of a real array. |
| `irfft2(a[, s, axes, norm])` | Compute the 2-dimensional inverse FFT of a real array. |
| `rfftn(a[, s, axes, norm])` | Compute the N-dimensional discrete Fourier Transform for real input. |
| `irfftn(a[, s, axes, norm])` | Compute the inverse of the N-dimensional FFT of real input. |
| `fftfreq(n[, d])` | Return the Discrete Fourier Transform sample frequencies. |
| `rfftfreq(n[, d])` | Return the Discrete Fourier Transform sample frequencies |
### Additional Time-Frequency Representations

| Function          | Description                                                                 |
|-------------------|-----------------------------------------------------------------------------|
| `mfcc(signal, window, hop, n_filter, ...)` | [https://librosa.github.io/librosa/_modules/librosa/feature/spectral.html#mfcc](https://librosa.github.io/librosa/_modules/librosa/feature/spectral.html#mfcc) |
| `dct(signal[, axes])` | [https://dsp.stackexchange.com/questions/2807/fast-cosine-transform-via-fft](https://dsp.stackexchange.com/questions/2807/fast-cosine-transform-via-fft) |
| `wvd(signal, window, hop, L[, apod, mode])` | the time should be the last dimension return the analytical signal |

### Detailed Descriptions

**blackman** *(M)*  
Return the Blackman window.  
LAX-backend implementation of `blackman()`.  

The Blackman window is a taper formed by using the first three terms of a summation of cosines. It was designed to have close to the minimal leakage possible. It is close to optimal, only slightly worse than a Kaiser window.  

**Returns**  
- `out` – The window, with the maximum value normalized to one (the value one appears only if the number of samples is odd).  

**Return type**  
.ndarray  

**See also**  
`bartlett()`, `hamming()`, `hanning()`, `kaiser()`  

**Notes**  
The Blackman window is defined as  

\[ w(n) = 0.42 - 0.5 \cos(2\pi n/M) + 0.08 \cos(4\pi n/M) \]  

Most references to the Blackman window come from the signal processing literature, where it is used as one of many windowing functions for smoothing values. It is also known as an apodization (which means “removing the foot”, i.e. smoothing discontinuities at the beginning and end of the sampled signal) or tapering function. It is known as a “near optimal” tapering function, almost as good (by some measures) as the kaiser window.  

**References**  
Blackman, R.B. and Tukey, J.W., (1958) The measurement of power spectra, Dover Publications, New York.  
Oppenheim, A.V., and R.W. Schafer. Discrete-Time Signal Processing. Upper Saddle River, NJ: Prentice-Hall, 1999, pp. 468-471.
Examples

```python
>>> import matplotlib.pyplot as plt
>>> np.blackman(12)
array([-1.38777878e-17,  3.26064346e-02,  1.59903635e-01, # may vary
     4.14397981e-01,  7.36045180e-01,  9.67046769e-01,
     9.67046769e-01,  7.36045180e-01,  4.14397981e-01,
     1.59903635e-01,  3.26064346e-02, -1.38777878e-17])
```

Plot the window and the frequency response:

```python
>>> from numpy.fft import fft, fftshift
>>> window = np.blackman(51)
>>> plt.plot(window)
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.title("Blackman window")
Text(0.5, 1.0, 'Blackman window')
>>> plt.ylabel("Amplitude")
Text(0, 0.5, 'Amplitude')
>>> plt.xlabel("Sample")
Text(0.5, 0, 'Sample')
>>> plt.show()

>>> plt.figure()
<Figure size 640x480 with 0 Axes>
>>> A = fft(window, 2048) / 25.5
>>> mag = np.abs(fftshift(A))
>>> freq = np.linspace(-0.5, 0.5, len(A))
>>> with np.errstate(divide='ignore', invalid='ignore'):
...     response = 20 * np.log10(mag)
...     response = np.clip(response, -100, 100)
...     plt.plot(freq, response)
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.title("Frequency response of Blackman window")
Text(0.5, 1.0, 'Frequency response of Blackman window')
>>> plt.ylabel("Magnitude [dB]")
Text(0, 0.5, 'Magnitude [dB]')
>>> plt.xlabel("Normalized frequency [cycles per sample]")
Text(0.5, 0, 'Normalized frequency [cycles per sample]')
>>> _ = plt.axis('tight')
>>> plt.show()
```

**bartlett** *(M)*

Return the Bartlett window.

LAX-backend implementation of `bartlett()`. ADDITIONAL Original docstring below.

The Bartlett window is very similar to a triangular window, except that the end points are at zero. It is often used in signal processing for tapering a signal, without generating too much ripple in the frequency domain.

**Returns out** – The triangular window, with the maximum value normalized to one (the value one appears only if the number of samples is odd), with the first and last samples equal to zero.

**Return type** array

See also:

`blackman()`, `hamming()`, `hanning()`, `kaiser()`
Notes

The Bartlett window is defined as

\[ w(n) = \frac{2}{M - 1} \left( \frac{M - 1}{2} - \left| n - \frac{M - 1}{2} \right| \right) \]

Most references to the Bartlett window come from the signal processing literature, where it is used as one of many windowing functions for smoothing values. Note that convolution with this window produces linear interpolation. It is also known as an apodization (which means "removing the foot", i.e. smoothing discontinuities at the beginning and end of the sampled signal) or tapering function. The Fourier transform of the Bartlett is the product of two sinc functions. Note the excellent discussion in Kanasewich.

References

Examples

```python
>>> import matplotlib.pyplot as plt
>>> np.bartlett(12)
array([ 0.        , 0.18181818, 0.36363636, 0.54545455, 0.72727273, # may vary
        0.90909091, 0.90909091, 0.72727273, 0.54545455, 0.36363636,
        0.18181818, 0.        ])
Plot the window and its frequency response (requires SciPy and matplotlib):

```
hamming\((M)\)

Return the Hamming window.

LAX-backend implementation of hamming(). ADDITIONOriginal docstring below.

The Hamming window is a taper formed by using a weighted cosine.

**Returns out** – The window, with the maximum value normalized to one (the value one appears only if the number of samples is odd).

**Return type** ndarray

See also:

bartlett(), blackman(), hanning(), kaiser()

**Notes**

The Hamming window is defined as

\[
w(n) = 0.54 - 0.46 \cos\left(\frac{2\pi n}{M - 1}\right) \quad 0 \leq n \leq M - 1
\]

The Hamming was named for R. W. Hamming, an associate of J. W. Tukey and is described in Blackman and Tukey. It was recommended for smoothing the truncated autocovariance function in the time domain. Most references to the Hamming window come from the signal processing literature, where it is used as one of many windowing functions for smoothing values. It is also known as an apodization (which means “removing the foot”, i.e. smoothing discontinuities at the beginning and end of the sampled signal) or tapering function.

**References**

**Examples**

```python
>>> np.hamming(12)
array([ 0.08 , 0.15302337, 0.34890909, 0.60546483, 0.84123594, # may vary
0.98136677, 0.98136677, 0.84123594, 0.60546483, 0.34890909,
0.15302337, 0.08 ])
```

Plot the window and the frequency response:

```python
>>> import matplotlib.pyplot as plt
>>> from numpy.fft import fft, fftshift
>>> window = np.hamming(51)
>>> plt.plot(window)
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.title("Hamming window")
Text(0.5, 1.0, 'Hamming window')
>>> plt.ylabel("Amplitude")
Text(0, 0.5, 'Amplitude')
>>> plt.xlabel("Sample")
Text(0.5, 0, 'Sample')
>>> plt.show()
```

```python
>>> pl.figure()
<Figure size 640x480 with 0 Axes>
>>> A = fft(window, 2048) / 25.5
```

(continues on next page)
```python
>>> mag = np.abs(fftshift(A))
>>> freq = np.linspace(-0.5, 0.5, len(A))
>>> response = 20 * np.log10(mag)
>>> response = np.clip(response, -100, 100)
>>> plt.plot(freq, response)
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.title("Frequency response of Hamming window")
Text(0.5, 1.0, 'Frequency response of Hamming window')
>>> plt.ylabel("Magnitude [dB]")
Text(0, 0.5, 'Magnitude [dB]')
>>> plt.xlabel("Normalized frequency [cycles per sample]")
Text(0.5, 0, 'Normalized frequency [cycles per sample]')
>>> plt.axis('tight')
...
>>> plt.show()
```

**hanning(M)**

Return the Hanning window.

LAX-backend implementation of `hanning()`. ADDITIONOriginal docstring below.

The Hanning window is a taper formed by using a weighted cosine.

Returns out – The window, with the maximum value normalized to one (the value one appears only if M is odd).

Return type ndarray, shape(M,)

See also:

`bartlett()`, `blackman()`, `hamming()`, `kaiser()`

Notes

The Hanning window is defined as

\[ w(n) = 0.5 - 0.5\cos \left( \frac{2\pi n}{M-1} \right) \quad 0 \leq n \leq M-1 \]

The Hanning was named for Julius von Hann, an Austrian meteorologist. It is also known as the Cosine Bell. Some authors prefer that it be called a Hann window, to help avoid confusion with the very similar Hamming window.

Most references to the Hanning window come from the signal processing literature, where it is used as one of many windowing functions for smoothing values. It is also known as an apodization (which means “removing the foot”, i.e. smoothing discontinuities at the beginning and end of the sampled signal) or tapering function.

References

Examples

```python
>>> np.hanning(12)
array([0. , 0.07937323, 0.29229249, 0.57115742, 0.82743037,
       0.97974649, 0.97974649, 0.82743037, 0.57115742, 0.29229249,
       0.07937323, 0.29229249])
```

Plot the window and its frequency response:
>>> import matplotlib.pyplot as plt
>>> from numpy.fft import fft, fftshift

>>> window = np.hanning(51)
>>> plt.plot(window)
[<matplotlib.lines.Line2D object at 0x...>]

>>> plt.title("Hann window")
Text(0.5, 1.0, 'Hann window')

>>> plt.ylabel("Amplitude")
Text(0, 0.5, 'Amplitude')

>>> plt.xlabel("Sample")
Text(0.5, 0, 'Sample')

>>> plt.show()

>>> plt.figure()
<Figure size 640x480 with 0 Axes>

>>> A = fft(window, 2048) / 25.5

>>> mag = np.abs(fftshift(A))

>>> freq = np.linspace(-0.5, 0.5, len(A))

>>> with np.errstate(divide='ignore', invalid='ignore'):
...
    response = 20 * np.log10(mag)

>>> response = np.clip(response, -100, 100)

>>> plt.plot(freq, response)
[<matplotlib.lines.Line2D object at 0x...>]

>>> plt.title("Frequency response of the Hann window")
Text(0.5, 1.0, 'Frequency response of the Hann window')

>>> plt.ylabel("Magnitude [dB]")
Text(0, 0.5, 'Magnitude [dB]')

>>> plt.xlabel("Normalized frequency [cycles per sample]")
Text(0.5, 0, 'Normalized frequency [cycles per sample]')

>>> plt.axis('tight')
...

>>> plt.show()
Notes

The Kaiser window is defined as

\[ w(n) = I_0 \left( \beta \sqrt{1 - \frac{4n^2}{(M-1)^2}} \right) / I_0(\beta) \]

with

\[ -\frac{M-1}{2} \leq n \leq \frac{M-1}{2}, \]

where \( I_0 \) is the modified zeroth-order Bessel function.

The Kaiser was named for Jim Kaiser, who discovered a simple approximation to the DPSS window based on Bessel functions. The Kaiser window is a very good approximation to the Digital Prolate Spheroidal Sequence, or Slepian window, which is the transform which maximizes the energy in the main lobe of the window relative to total energy.

The Kaiser can approximate many other windows by varying the beta parameter.

| beta | Window shape       |
|------|-------------------|
| 0    | Rectangular       |
| 5    | Similar to a Hamming |
| 6    | Similar to a Hanning |
| 8.6  | Similar to a Blackman |

A beta value of 14 is probably a good starting point. Note that as beta gets large, the window narrows, and so the number of samples needs to be large enough to sample the increasingly narrow spike, otherwise NaNs will get returned.

Most references to the Kaiser window come from the signal processing literature, where it is used as one of many windowing functions for smoothing values. It is also known as an apodization (which means “removing the foot”, i.e. smoothing discontinuities at the beginning and end of the sampled signal) or tapering function.

References

Examples

```python
>>> import matplotlib.pyplot as plt
>>> np.kaiser(12, 14)
aarray([7.72686684e-06, 3.46009194e-03, 4.65001899e-02, # may vary
        2.2973120e-01, 5.99835316e-01, 9.45674898e-01,
        9.45674898e-01, 5.99835316e-01, 2.2973120e-01,
        4.65200189e-02, 3.46009194e-03, 7.72686684e-06])
```

Plot the window and the frequency response:

```python
>>> from numpy.fft import fft, fftshift
>>> window = np.kaiser(51, 14)
>>> plt.plot(window)
[<matplotlib.lines.Line2D object at 0x...>]
>>> plt.title("Kaiser window")
Text(0.5, 1.0, 'Kaiser window')
>>> plt.ylabel("Amplitude")
```

(continues on next page)
>>> plt.xlabel("Sample")
Text(0.5, 0, 'Sample')

>>> plt.show()

>>> plt.figure()
<Figure size 640x480 with 0 Axes>

>>> A = fft(window, 2048) / 25.5
>>> mag = np.abs(fftshift(A))
>>> freq = np.linspace(-0.5, 0.5, len(A))
>>> response = 20 * np.log10(mag)
>>> response = np.clip(response, -100, 100)

>>> plt.plot(freq, response)
[<matplotlib.lines.Line2D object at 0x...>]

>>> plt.title("Frequency response of Kaiser window")
Text(0.5, 1.0, 'Frequency response of Kaiser window')

>>> plt.ylabel("Magnitude [dB]")
Text(0, 0.5, 'Magnitude [dB]')

>>> plt.xlabel("Normalized frequency [cycles per sample]"
Text(0.5, 0, 'Normalized frequency [cycles per sample]')

>>> plt.axis('tight')
(-0.5, 0.5, -100.0, ...) # may vary

>>> plt.show()

fft (a, n=None, axis=-1, norm=None)
Compute the one-dimensional discrete Fourier Transform.

LAX-backend implementation of fft(). ADDITIONOriginal docstring below.

LAX-backend implementation of fft(). Original docstring below.

This function computes the one-dimensional n-point discrete Fourier Transform (DFT) with the efficient Fast
Fourier Transform (FFT) algorithm [CT].

Returns out – The truncated or zero-padded input, transformed along the axis indicated by axis, or
the last one if axis is not specified.

Return type complex ndarray

Raises IndexError – if axes is larger than the last axis of a.

See also:

numpy.fft() for definition of the DFT and conventions used.

ifft() The inverse of fft.

fft2() The two-dimensional FFT.

fftn() The n-dimensional FFT.
rfftn() The n-dimensional FFT of real input.

fftfreq() Frequency bins for given FFT parameters.
Notes

FFT (Fast Fourier Transform) refers to a way the discrete Fourier Transform (DFT) can be calculated efficiently, by using symmetries in the calculated terms. The symmetry is highest when $n$ is a power of 2, and the transform is therefore most efficient for these sizes.

The DFT is defined, with the conventions used in this implementation, in the documentation for the `numpy.fft` module.

References

Examples

```python
>>> np.fft.fft(np.exp(2j * np.pi * np.arange(8) / 8))
array([-2.33486982e-16+1.14423775e-17j, 8.00000000e+00-1.25557246e-15j,
       2.33486982e-16+2.33486982e-16j, 0.00000000e+00+5.20784380e-16j,
      -1.14423775e-17+2.33486982e-16j, 0.00000000e+00+1.14423775e-17j,
       1.14423775e-17+1.14423775e-17j, 0.00000000e+00+1.14423775e-17j])
```

In this example, real input has an FFT which is Hermitian, i.e., symmetric in the real part and anti-symmetric in the imaginary part, as described in the `numpy.fft` documentation:

```python
>>> import matplotlib.pyplot as plt
>>> t = np.arange(256)
>>> sp = np.fft.fft(np.sin(t))
>>> freq = np.fft.fftfreq(t.shape[-1])
>>> plt.plot(freq, sp.real, freq, sp.imag)
<matplotlib.lines.Line2D object at 0x...
...>
>>> plt.show()
```

`ifft` ($a$, $n$=None, $axis$=-1, $norm$=None)

Compute the one-dimensional inverse discrete Fourier Transform.

LAX-backend implementation of `ifft()`. ADDITION

Original docstring below.

LAX-backend implementation of `ifft()`. Original docstring below.

This function computes the inverse of the one-dimensional $n$-point discrete Fourier transform computed by `fft`. In other words, `ifft(fft(a)) == a` to within numerical accuracy. For a general description of the algorithm and definitions, see `numpy.fft`.

The input should be ordered in the same way as is returned by `fft`, i.e.,

- $a[0]$ should contain the zero frequency term,
- $a[1:n//2]$ should contain the positive-frequency terms,
- $a[n//2 + 1:]$ should contain the negative-frequency terms, in increasing order starting from the most negative frequency.

For an even number of input points, $A[n//2]$ represents the sum of the values at the positive and negative Nyquist frequencies, as the two are aliased together. See `numpy.fft` for details.

**Returns out** – The truncated or zero-padded input, transformed along the axis indicated by $axis$, or the last one if $axis$ is not specified.

**Return type** complex ndarray

**Raises IndexError** – If $axes$ is larger than the last axis of $a$. 

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See also:

```python
calculaiton.
```

numpy.fft()  An introduction, with definitions and general explanations.

fft()  The one-dimensional (forward) FFT, of which ifft is the inverse

ifft2()  The two-dimensional inverse FFT.

ifftn()  The n-dimensional inverse FFT.

Notes

If the input parameter `n` is larger than the size of the input, the input is padded by appending zeros at the end. Even though this is the common approach, it might lead to surprising results. If a different padding is desired, it must be performed before calling ifft.

Examples

```python
calculaiton.
```

```python
calculaiton.
```

fft2(a, s=None, axes=(-2, -1, norm=None)

Compute the 2-dimensional discrete Fourier Transform

LAX-backend implementation of fft2(). ADDITION

LAX-backend implementation of fft2(). Original docstring below.

This function computes the `n`-dimensional discrete Fourier Transform over any axes in an `M`-dimensional array by means of the Fast Fourier Transform (FFT). By default, the transform is computed over the last two axes of the input array, i.e., a 2-dimensional FFT.

Returns out – The truncated or zero-padded input, transformed along the axes indicated by axes, or the last two axes if axes is not given.

Return type complex ndarray

Raises

- ValueError – If `s` and axes have different length, or axes not given and len(s) != 2.
- IndexError – If an element of axes is larger than than the number of axes of a.

See also:

```python
calculaiton.
```

2.1. General

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*ifft2()* The inverse two-dimensional FFT.

*fft()* The one-dimensional FFT.

*fftn()* The $n$-dimensional FFT.

*ffts**ift()** Shifts zero-frequency terms to the center of the array. For two-dimensional input, swaps first and third quadrants, and second and fourth quadrants.

**Notes**

*ff2* is just *fftn* with a different default for *axes*.

The output, analogously to *fft*, contains the term for zero frequency in the low-order corner of the transformed axes, the positive frequency terms in the first half of these axes, the term for the Nyquist frequency in the middle of the axes and the negative frequency terms in the second half of the axes, in order of decreasingly negative frequency.

See *fftn* for details and a plotting example, and *numpy.fft* for definitions and conventions used.

**Examples**

```python
>>> a = np.mgrid[:5, :5][0]
>>> np.fft.fft2(a)
array([[ 50. +0.j , 0. +0.j , 0. +0.j , # may vary
        0. +0.j , 0. +0.j ],
       [-12.5+17.20477401j, 0. +0.j , 0. +0.j ,
        0. +0.j , 0. +0.j ],
       [-12.5 +4.0614962j , 0. +0.j , 0. +0.j ,
        0. +0.j , 0. +0.j ],
       [-12.5 -4.0614962j , 0. +0.j , 0. +0.j ,
        0. +0.j , 0. +0.j ],
       [-12.5-17.20477401j, 0. +0.j , 0. +0.j ,
        0. +0.j , 0. +0.j ]])
```

**ifft2**($a, s=None, axes=(-2, -1), norm=None)

Compute the 2-dimensional inverse discrete Fourier Transform.

LAX-backend implementation of *ifft2*. ADDITIONOriginal docstring below.

LAX-backend implementation of *ifft2*. Original docstring below.

This function computes the inverse of the 2-dimensional discrete Fourier Transform over any number of axes in an M-dimensional array by means of the Fast Fourier Transform (FIT). In other words, *ifft2*(*fft2*($a$)) == $a$ to within numerical accuracy. By default, the inverse transform is computed over the last two axes of the input array.

The input, analogously to *fft*, should be ordered in the same way as is returned by *fft2*, i.e. it should have the term for zero frequency in the low-order corner of the two axes, the positive frequency terms in the first half of these axes, the term for the Nyquist frequency in the middle of the axes and the negative frequency terms in the second half of both axes, in order of decreasingly negative frequency.

**Returns out** – The truncated or zero-padded input, transformed along the axes indicated by *axes*, or the last two axes if *axes* is not given.

**Return type** complex ndarray

**Raises**

- **ValueError** – If $s$ and *axes* have different length, or *axes* not given and \( \text{len}(s) \neq 2 \).
- **IndexError** – If an element of `axes` is larger than than the number of axes of `a`.

See also:

```python
numpy.fft() Overall view of discrete Fourier transforms, with definitions and conventions used.
fft2() The forward 2-dimensional FFT, of which ifft2 is the inverse.
ifftn() The inverse of the n-dimensional FFT.
fft() The one-dimensional FFT.
ifft() The one-dimensional inverse FFT.
```

### Notes

`ifft2` is just `ifftn` with a different default for `axes`.

See `ifftn` for details and a plotting example, and `numpy.fft` for definition and conventions used.

Zero-padding, analogously with `ifft`, is performed by appending zeros to the input along the specified dimension. Although this is the common approach, it might lead to surprising results. If another form of zero padding is desired, it must be performed before `ifft2` is called.

### Examples

```python
>>> a = 4 * np.eye(4)
>>> np.fft.ifft2(a)
array([[1.+0.j, 0.+0.j, 0.+0.j, 0.+0.j], # may vary
       [0.+0.j, 0.+0.j, 0.+0.j, 1.+0.j],
       [0.+0.j, 0.+0.j, 1.+0.j, 0.+0.j],
       [0.+0.j, 1.+0.j, 0.+0.j, 0.+0.j]])
```

```python
fftn(a, s=None, axes=None, norm=None)
```

Compute the N-dimensional discrete Fourier Transform.

LAX-backend implementation of `fftn()`. ADDITIONOriginal docstring below.

LAX-backend implementation of `fftn()`. Original docstring below.

This function computes the N-dimensional discrete Fourier Transform over any number of axes in an M-dimensional array by means of the Fast Fourier Transform (FFT).

**Returns**

- `out` – The truncated or zero-padded input, transformed along the axes indicated by `axes`, or by a combination of `s` and `a`, as explained in the parameters section above.

**Return type** complex ndarray

**Raises**

- **ValueError** – If `s` and `axes` have different length.

- **IndexError** – If an element of `axes` is larger than than the number of axes of `a`.

See also:

```python
numpy.fft() Overall view of discrete Fourier transforms, with definitions and conventions used.
ifftn() The inverse of fftn, the inverse n-dimensional FFT.
fft() The one-dimensional FFT, with definitions and conventions used.
```
**rfftn()**  The \(n\)-dimensional FFT of real input.

**fft2()**  The two-dimensional FFT.

**fftshift()**  Shifts zero-frequency terms to centre of array

**Notes**

The output, analogously to \texttt{fft}, contains the term for zero frequency in the low-order corner of all axes, the positive frequency terms in the first half of all axes, the term for the Nyquist frequency in the middle of all axes and the negative frequency terms in the second half of all axes, in order of decreasingly negative frequency.

See \texttt{numpy.fft} for details, definitions and conventions used.

**Examples**

```python
>>> a = np.mgrid[:3, :3, :3][0]
>>> np.fft.fftn(a, axes=(1, 2))
array([[ 0.+0.j, 0.+0.j, 0.+0.j],  # may vary
        [ 0.+0.j, 0.+0.j, 0.+0.j],
        [ 9.+0.j, 0.+0.j, 0.+0.j],
        [ 0.+0.j, 0.+0.j, 0.+0.j],
        [18.+0.j, 0.+0.j, 0.+0.j],
        [ 0.+0.j, 0.+0.j, 0.+0.j],
        [ 0.+0.j, 0.+0.j, 0.+0.j]],)
```

```python
>>> np.fft.fftn(a, (2, 2), axes=(0, 1))
array([[ 2.+0.j, 2.+0.j, 2.+0.j],  # may vary
        [ 0.+0.j, 0.+0.j, 0.+0.j],
        [-2.+0.j, -2.+0.j, -2.+0.j],
        [ 0.+0.j, 0.+0.j, 0.+0.j]],)
```

```python
>>> import matplotlib.pyplot as plt
>>> [X, Y] = np.meshgrid(2 * np.pi * np.arange(200) / 12,
...                     2 * np.pi * np.arange(200) / 34)
>>> S = np.sin(X) + np.cos(Y) + np.random.uniform(0, 1, X.shape)
>>> FS = np.fft.fftn(S)
>>> plt.imshow(np.log(np.abs(np.fft.fftshift(FS))**2))
<matplotlib.image.AxesImage object at 0x...>
>>> plt.show()
```

**ifftn**  \((a, \texttt{s=None}, \texttt{axes=None}, \texttt{norm=None})\)

Compute the \(N\)-dimensional inverse discrete Fourier Transform.

LAX-backend implementation of \texttt{ifftn}(). ADDITIONOriginal docstring below.

LAX-backend implementation of \texttt{ifftn}(). Original docstring below.

This function computes the inverse of the \(N\)-dimensional discrete Fourier Transform over any number of axes in an \(M\)-dimensional array by means of the Fast Fourier Transform (FFT). In other words, \texttt{ifftn(fft(a)) == a} to within numerical accuracy. For a description of the definitions and conventions used, see \texttt{numpy.fft}.

The input, analogously to \texttt{ifft}, should be ordered in the same way as is returned by \texttt{fft}, i.e. it should have the term for zero frequency in all axes in the low-order corner, the positive frequency terms in the first half of all axes, the term for the Nyquist frequency in the middle of all axes and the negative frequency terms in the second half of all axes, in order of decreasingly negative frequency.
Returns out – The truncated or zero-padded input, transformed along the axes indicated by axes, or by a combination of s or a, as explained in the parameters section above.

Return type complex ndarray

Raises

- ValueError – If s and axes have different length.
- IndexError – If an element of axes is larger than the number of axes of a.

See also:

numpy.fft() Overall view of discrete Fourier transforms, with definitions and conventions used.

fftn() The forward n-dimensional FFT, of which ifftn is the inverse.

ifft() The one-dimensional inverse FFT.

ifft2() The two-dimensional inverse FFT.

ifftshift() Undoes fftshift, shifts zero-frequency terms to beginning of array.

Notes

See numpy.fft for definitions and conventions used.

Zero-padding, analogously with ifft, is performed by appending zeros to the input along the specified dimension. Although this is the common approach, it might lead to surprising results. If another form of zero padding is desired, it must be performed before ifftn is called.

Examples

```python
>>> a = np.eye(4)
>>> np.fft.ifftn(np.fft.fftn(a, axes=(0,)), axes=(1,))
array([[1.+0.j, 0.+0.j, 0.+0.j, 0.+0.j], # may vary
       [0.+0.j, 1.+0.j, 0.+0.j, 0.+0.j],
       [0.+0.j, 0.+0.j, 1.+0.j, 0.+0.j],
       [0.+0.j, 0.+0.j, 0.+0.j, 1.+0.j]])
```

Create and plot an image with band-limited frequency content:

```python
>>> import matplotlib.pyplot as plt
>>> n = np.zeros((200,200), dtype=complex)
>>> n[60:80, 20:40] = np.exp(1j*np.random.uniform(0, 2*np.pi, (20, 20)))
>>> im = np.fft.ifftn(n).real
>>> plt.imshow(im)
<matplotlib.image.AxesImage object at 0x...>
>>> plt.show()
```

rfft (a, n=None, axis=-1, norm=None)

Compute the one-dimensional discrete Fourier Transform for real input.

LAX-backend implementation of rfft(). ADDITIONOriginal docstring below.

LAX-backend implementation of rfft(). Original docstring below.

This function computes the one-dimensional n-point discrete Fourier Transform (DFT) of a real-valued array by means of an efficient algorithm called the Fast Fourier Transform (FFT).
Returns out – The truncated or zero-padded input, transformed along the axis indicated by axis, or the last one if axis is not specified. If n is even, the length of the transformed axis is \((n/2)+1\). If n is odd, the length is \((n+1)/2\).

Return type complex ndarray

Raises IndexError – If axis is larger than the last axis of a.

See also:

numpy.fft() For definition of the DFT and conventions used.

irfft() The inverse of rfft.

fft() The one-dimensional FFT of general (complex) input.

fftn() The n-dimensional FFT.

rfftn() The n-dimensional FFT of real input.

Notes

When the DFT is computed for purely real input, the output is Hermitian-symmetric, i.e. the negative frequency terms are just the complex conjugates of the corresponding positive-frequency terms, and the negative-frequency terms are therefore redundant. This function does not compute the negative frequency terms, and the length of the transformed axis of the output is therefore \(n//2 + 1\).

When \(A = rfft(a)\) and fs is the sampling frequency, \(A[0]\) contains the zero-frequency term 0*fs, which is real due to Hermitian symmetry.

If \(n\) is even, \(A[-1]\) contains the term representing both positive and negative Nyquist frequency (+fs/2 and -fs/2), and must also be purely real. If \(n\) is odd, there is no term at fs/2; \(A[-1]\) contains the largest positive frequency (fs/2*(n-1)/n), and is complex in the general case.

If the input \(a\) contains an imaginary part, it is silently discarded.

Examples

```python
>>> np.fft.fft([0, 1, 0, 0])
array([ 1.+0.j, 0.-1.j, -1.+0.j, 0.+1.j]) # may vary
>>> np.fft.rfft([0, 1, 0, 0])
array([ 1.+0.j, 0.-1.j, -1.+0.j]) # may vary
```

Notice how the final element of the \(fft\) output is the complex conjugate of the second element, for real input. For \(rfft\), this symmetry is exploited to compute only the non-negative frequency terms.

irfft(a, n=None, axis=-1, norm=None)

Compute the inverse of the n-point DFT for real input.

LAX-backend implementation of \(irfft()\). ADDITIONOriginal docstring below.

LAX-backend implementation of \(irfft()\). Original docstring below.

This function computes the inverse of the one-dimensional n-point discrete Fourier Transform of real input computed by \(rfft\). In other words, \(irfft(rfft(a), len(a)) == a\) to within numerical accuracy. (See Notes below for why \(len(a)\) is necessary here.)

The input is expected to be in the form returned by \(rfft\), i.e. the real zero-frequency term followed by the complex positive frequency terms in order of increasing frequency. Since the discrete Fourier Transform of real input is
Hermitian-symmetric, the negative frequency terms are taken to be the complex conjugates of the corresponding positive frequency terms.

**Returns out** – The truncated or zero-padded input, transformed along the axis indicated by `axis`, or the last one if `axis` is not specified. The length of the transformed axis is `n`, or, if `n` is not given, $2 \times (m-1)$ where `m` is the length of the transformed axis of the input. To get an odd number of output points, `n` must be specified.

**Return type** `ndarray`

**Raises** `IndexError` – If `axis` is larger than the last axis of `a`.

See also:

- `numpy.fft()` For definition of the DFT and conventions used.
- `rfft()` The one-dimensional FFT of real input, of which `irfft` is inverse.
- `fft()` The one-dimensional FFT.
- `irfft2()` The inverse of the two-dimensional FFT of real input.
- `irfftn()` The inverse of the `n`-dimensional FFT of real input.

**Notes**

Returns the real valued `n`-point inverse discrete Fourier transform of `a`, where `a` contains the non-negative frequency terms of a Hermitian-symmetric sequence. `n` is the length of the result, not the input.

If you specify an `n` such that `a` must be zero-padded or truncated, the extra/removed values will be added/removed at high frequencies. One can thus resample a series to `m` points via Fourier interpolation by:

$$a_{\text{resamp}} = \text{irfft}(\text{rfft}(a), m).$$

The correct interpretation of the hermitian input depends on the length of the original data, as given by `n`. This is because each input shape could correspond to either an odd or even length signal. By default, `irfft` assumes an even output length which puts the last entry at the Nyquist frequency; aliasing with its symmetric counterpart. By Hermitian symmetry, the value is thus treated as purely real. To avoid losing information, the correct length of the real input **must** be given.

**Examples**

```python
>>> np.fft.ifft([1, -1j, -1, 1j])
array([0.+0.j, 1.+0.j, 0.+0.j, 0.+0.j])  # may vary
>>> np.fft.irfft([1, -1j, -1])
array([0., 1., 0., 0.])
```

Notice how the last term in the input to the ordinary `ifft` is the complex conjugate of the second term, and the output has zero imaginary part everywhere. When calling `irfft`, the negative frequencies are not specified, and the output array is purely real.

**rfft2** (`a`, `s=None`, `axes=(-2, -1)`, `norm=None`)

Compute the 2-dimensional FFT of a real array.

LAX-backend implementation of `rfft2()`. ADDITION: Original docstring below.

LAX-backend implementation of `rfft2()`. Original docstring below.

**Returns out** – The result of the real 2-D FFT.

**Return type** `ndarray`
See also:

\texttt{rfftn()}  Compute the N-dimensional discrete Fourier Transform for real input.

Notes

This is really just \texttt{rfftn} with different default behavior. For more details see \texttt{rfftn}.

\texttt{irfft2}(a, s=\texttt{None}, axes=(-2, -1), norm=\texttt{None})  
\hspace{1em} Compute the 2-dimensional inverse FFT of a real array.
\hspace{1em} LAX-backend implementation of \texttt{irfft2()}. ADDITIONOriginal docstring below.
\hspace{1em} LAX-backend implementation of \texttt{irfft2()}. Original docstring below.
\hspace{1em} \textbf{Returns} \ \texttt{out} \ – \ The result of the inverse real 2-D FFT.
\hspace{1em} \textbf{Return type} \ ndarray

See also:

\texttt{irfftn()}  Compute the inverse of the N-dimensional FFT of real input.

Notes

This is really \texttt{irfftn} with different defaults. For more details see \texttt{irfftn}.

\texttt{rfftn}(a, s=\texttt{None}, axes=\texttt{None}, norm=\texttt{None})  
\hspace{1em} Compute the N-dimensional discrete Fourier Transform for real input.
\hspace{1em} LAX-backend implementation of \texttt{rfftn()}. ADDITIONOriginal docstring below.
\hspace{1em} LAX-backend implementation of \texttt{rfftn()}. Original docstring below.
\hspace{1em} This function computes the N-dimensional discrete Fourier Transform over any number of axes in an M-dimensional real array by means of the Fast Fourier Transform (FFT). By default, all axes are transformed, with the real transform performed over the last axis, while the remaining transforms are complex.
\hspace{1em} \textbf{Returns} \ \texttt{out} \ – \ The truncated or zero-padded input, transformed along the axes indicated by \texttt{axes}, or by a combination of \texttt{s} and \texttt{a}, as explained in the parameters section above. The length of the last axis transformed will be \texttt{s[-1]}//2+1, while the remaining transformed axes will have lengths according to \texttt{s}, or unchanged from the input.
\hspace{1em} \textbf{Return type} \ complex ndarray

\textbf{Raises}

- \texttt{ValueError} \ – \ If \texttt{s} and \texttt{axes} have different length.
- \texttt{IndexError} \ – \ If an element of \texttt{axes} is larger than than the number of axes of \texttt{a}.

See also:

\texttt{irfftn()}  The inverse of \texttt{rfftn}, i.e. the inverse of the n-dimensional FFT of real input.
\texttt{fft()}  The one-dimensional FFT, with definitions and conventions used.
\texttt{rfft()}  The one-dimensional FFT of real input.
\texttt{fftn()}  The n-dimensional FFT.
\texttt{rfft2()}  The two-dimensional FFT of real input.
Notes

The transform for real input is performed over the last transformation axis, as by `rfft`, then the transform over the remaining axes is performed as by `fftn`. The order of the output is as for `rfft` for the final transformation axis, and as for `fftn` for the remaining transformation axes.

See `fft` for details, definitions and conventions used.

Examples

```python
>>> a = np.ones((2, 2, 2))
>>> np.fft.rfftn(a)
array([[8.+0.j, 0.+0.j], # may vary
       [0.+0.j, 0.+0.j]],
       [[0.+0.j, 0.+0.j],
        [0.+0.j, 0.+0.j]])
```

```python
>>> np.fft.rfftn(a, axes=(2, 0))
array([[4.+0.j, 0.+0.j], # may vary
       [4.+0.j, 0.+0.j]],
       [[0.+0.j, 0.+0.j],
        [0.+0.j, 0.+0.j]])
```

`irfftn(a, s=None, axes=None, norm=None)`

Compute the inverse of the N-dimensional FFT of real input.

LAX-backend implementation of `irfftn()`. ADDITION Original docstring below.

LAX-backend implementation of `irfftn()`. Original docstring below.

This function computes the inverse of the N-dimensional discrete Fourier Transform for real input over any number of axes in an M-dimensional array by means of the Fast Fourier Transform (FFT). In other words, `irfftn(rfftn(a), a.shape) == a` to within numerical accuracy. (The `a.shape` is necessary like `len(a)` is for `irfft`, and for the same reason.)

The input should be ordered in the same way as is returned by `rfftn`, i.e. as for `irfft` for the final transformation axis, and as for `fftn` along all the other axes.

Returns `out` – The truncated or zero-padded input, transformed along the axes indicated by `axes`, or by a combination of `s` or `a`, as explained in the parameters section above. The length of each transformed axis is as given by the corresponding element of `s`, or the length of the input in every axis except for the last one if `s` is not given. In the final transformed axis the length of the output when `s` is not given is `2 * (m-1)` where `m` is the length of the final transformed axis of the input.

To get an odd number of output points in the final axis, `s` must be specified.

Return type `ndarray`

Raises

- `ValueError` – If `s` and `axes` have different length.
- `IndexError` – If an element of `axes` is larger than than the number of axes of `a`.

See also:

- `rfftn()` The forward n-dimensional FFT of real input, of which `ifftn` is the inverse.
- `fft()` The one-dimensional FFT, with definitions and conventions used.
- `irfft()` The inverse of the one-dimensional FFT of real input.
irfft2() The inverse of the two-dimensional FFT of real input.

Notes

See fft for definitions and conventions used.
See rfft for definitions and conventions used for real input.

The correct interpretation of the hermitian input depends on the shape of the original data, as given by s. This is because each input shape could correspond to either an odd or even length signal. By default, irfftn assumes an even output length which puts the last entry at the Nyquist frequency; aliasing with its symmetric counterpart. When performing the final complex to real transform, the last value is thus treated as purely real. To avoid losing information, the correct shape of the real input must be given.

Examples

```python
>>> a = np.zeros((3, 2, 2))
>>> a[0, 0, 0] = 3 * 2 * 2
>>> np.fft.irfftn(a)
array([[[1., 1.],
        [1., 1.]],
       [[1., 1.],
        [1., 1.]],
       [[1., 1.],
        [1., 1.]]])
```

fftfreq(n, d=1.0)
Return the Discrete Fourier Transform sample frequencies.

LAX-backend implementation of fftfreq(). ADDITIONOriginal docstring below.

LAX-backend implementation of fftfreq(). Original docstring below.

The returned float array f contains the frequency bin centers in cycles per unit of the sample spacing (with zero at the start). For instance, if the sample spacing is in seconds, then the frequency unit is cycles/second.

Given a window length n and a sample spacing d:

```
f = [0, 1, ..., n/2-1, -n/2, ..., -1] / (d*n) if n is even
f = [0, 1, ..., (n-1)/2, -(n-1)/2, ..., -1] / (d*n) if n is odd
```

Returns f – Array of length n containing the sample frequencies.

Return type ndarray

Examples

```python
>>> signal = np.array([-2, 8, 6, 4, 1, 0, 3, 5], dtype=float)
>>> fourier = np.fft.fft(signal)
>>> n = signal.size
>>> timestep = 0.1
>>> freq = np.fft.fftfreq(n, d=timestep)
>>> freq
array([-3.7, -2.5, -1.2, -0.1, 0.1, 1.2, 2.5, 3.7])
```

rfftfreq(n, d=1.0)
Return the Discrete Fourier Transform sample frequencies (for usage with rfft, irfft).
LAX-backend implementation of \textit{rfftfreq()}. ADDITIONOriginal docstring below.
LAX-backend implementation of \textit{rfftfreq()}. Original docstring below.

The returned float array \( f \) contains the frequency bin centers in cycles per unit of the sample spacing (with zero at the start). For instance, if the sample spacing is in seconds, then the frequency unit is cycles/second.

Given a window length \( n \) and a sample spacing \( d \):

\[
\begin{align*}
\text{if } n \text{ is even} \\
& f = [0, 1, \ldots, n/2-1, n/2] / (d \times n) \\
\text{if } n \text{ is odd} \\
& f = [0, 1, \ldots, (n-1)/2-1, (n-1)/2] / (d \times n)
\end{align*}
\]

Unlike \textit{fftfreq} (but like \textit{scipy.fftpack.rfftfreq}) the Nyquist frequency component is considered to be positive.

\textbf{Returns} \( f \) – Array of length \( n/2 + 1 \) containing the sample frequencies.

\textbf{Return type} \ ndarray

\textbf{Examples}

\begin{verbatim}
>>> signal = np.array([-2, 8, 6, 4, 1, 0, 3, 5, -3, 4], dtype=float)
>>> fourier = np.fft.rfft(signal)
>>> n = signal.size
>>> sample_rate = 100
>>> freq = np.fft.fftfreq(n, d=1./sample_rate)
>>> freq
array([ 0., 10., 20., ..., -30., -20., -10.])
>>> freq = np.fft.rfftfreq(n, d=1./sample_rate)
>>> freq
array([ 0., 10., 20., 30., 40., 50.])
\end{verbatim}

\textbf{mfcc} \( \text{(signal, window, hop, n_filter, low_freq, high_freq, nyquist, n_mfcc, nfft=None, mode='valid', apod=<function hanning>)} \)
https://librosa.github.io/librosa/_modules/librosa/feature/spectral.html#mfcc

\textbf{dct} \( \text{(signal, axes=-1)} \)
https://dsp.stackexchange.com/questions/2807/fast-cosine-transform-via-fft

\textbf{wvd} \( \text{(signal, window, hop, L, apod=<function hanning>, mode='valid')} \)

\textbf{hilbert_transform} \( \text{(signal)} \)
the time should be the last dimension return the analytical signal

\textbf{2.1.5} \textbf{symjax.tensor.random}

\begin{verbatim}
bernoulli(key[, p, shape]) Sample Bernoulli random values with given shape and mean.
beta(key, a, b[, shape, dtype]) Sample Beta random values with given shape and float dtype.
cauchy(key[, shape, dtype]) Sample Cauchy random values with given shape and float dtype.
dirichlet(key, alpha[, shape, dtype]) Sample Dirichlet random values with given shape and float dtype.
\end{verbatim}

continues on next page
Table 4 – continued from previous page

| Function          | Description                                                                 |
|-------------------|-----------------------------------------------------------------------------|
| `gamma`           | Sample Gamma random values with given shape and float dtype.                |
| `gumbel`          | Sample Gumbel random values with given shape and float dtype.               |
| `laplace`         | Sample Laplace random values with given shape and float dtype.              |
| `logit`           | Logit ufunc for ndarrays.                                                   |
| `multivariate_normal` | Sample multivariate normal random values with given mean and covariance. |
| `normal`          | Sample standard normal random values with given shape and float dtype.      |
| `pareto`          | Sample Pareto random values with given shape and float dtype.               |
| `randint`         | Sample uniform random values in [minval, maxval) with given shape/dtype.    |
| `shuffle`         | Shuffle the elements of an array uniformly at random along an axis.         |
| `truncated_normal`| Sample truncated standard normal random values with given shape and dtype.  |
| `uniform`         | Sample uniform random values in [minval, maxval) with given shape/dtype.    |

Detailed Description

**bernoulli**

```
(key: jax.numpy.lax_numpy.ndarray, p: jax.numpy.lax_numpy.ndarray = 0.5, shape: Optional[Sequence[int]] = None) → jax.numpy.lax_numpy.ndarray
```

Sample Bernoulli random values with given shape and mean.

LAX-backend implementation of `bernoulli()`. ADDITIONOriginal docstring below.

Returns: A random array with boolean dtype and shape given by `shape` if `shape` is not None, or else `p.shape`.

**beta**

```
(key: jax.numpy.lax_numpy.ndarray, a: Union[float, jax.numpy.lax_numpy.ndarray], b: Union[float, jax.numpy.lax_numpy.ndarray], shape: Optional[Sequence[int]] = None, dtype: numpy.dtype = <class 'numpy.float64'>) → jax.numpy.lax_numpy.ndarray
```

Sample Beta random values with given shape and float dtype.

LAX-backend implementation of `beta()`. ADDITIONOriginal docstring below.

Returns: A random array with the specified dtype and shape given by `shape` if `shape` is not None, or else by broadcasting `a` and `b`.

**cauchy**

```
(key, shape=(), dtype=<class 'numpy.float64'>)
```

Sample Cauchy random values with given shape and float dtype.

LAX-backend implementation of `cauchy()`. ADDITIONOriginal docstring below.

Returns: A random array with the specified shape and dtype.

**dirichlet**

```
(key, alpha, shape=None, dtype=<class 'numpy.float64'>)
```

Sample Dirichlet random values with given shape and float dtype.

LAX-backend implementation of `dirichlet()`. ADDITIONOriginal docstring below.

Returns: A random array with the specified dtype and shape given by `shape + (alpha.shape[-1],)` if `shape` is not None, or else `alpha.shape`. 

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**gamma** *(key, a, shape=None, dtype=<class 'numpy.float64'>)*
Sample Gamma random values with given shape and float dtype.
LAX-backend implementation of `gamma()`. ADDITIONOriginal docstring below.

Returns: A random array with the specified dtype and with shape given by `shape` if `shape` is not None, or else by `a.shape`.

**gumbel** *(key, shape=(), dtype=<class 'numpy.float64'>)*
Sample Gumbel random values with given shape and float dtype.
LAX-backend implementation of `gumbel()`. ADDITIONOriginal docstring below.

Returns: A random array with the specified shape and dtype.

**laplace** *(key, shape=(), dtype=<class 'numpy.float64'>)*
Sample Laplace random values with given shape and float dtype.
LAX-backend implementation of `laplace()`. ADDITIONOriginal docstring below.

Returns: A random array with the specified shape and dtype.

**logit** *(x)*
Logit ufunc for ndarrays.
LAX-backend implementation of `logit()`. ADDITIONOriginal docstring below.
LAX-backend implementation of `logit()`. Original docstring below.

logit(x, /, out=None, *, where=True, casting='same_kind', order='K', dtype=None, subok=True[, signature, extobj])

logit(x)
The logit function is defined as logit(p) = log(p/(1-p)). Note that logit(0) = -inf, logit(1) = inf, and logit(p) for p<0 or p>1 yields nan.

Returns out – An ndarray of the same shape as x. Its entries are logit of the corresponding entry of x.

Return type ndarray

See also:
`expit()`

Notes
As a ufunc logit takes a number of optional keyword arguments. For more information see ufuncs
New in version 0.10.0.

Examples

```python
>>> from scipy.special import logit, expit

>>> logit([0, 0.25, 0.5, 0.75, 1])
array([-inf, -1.09861229, 0., 1.09861229, inf])

expit is the inverse of logit:
```
```python
>>> expit(logit([0.1, 0.75, 0.999]))
array([ 0.1 , 0.75 , 0.999])
```

Plot logit(x) for x in [0, 1]:

```python
>>> import matplotlib.pyplot as plt
>>> x = np.linspace(0, 1, 501)
>>> y = logit(x)
>>> plt.plot(x, y)
>>> plt.grid()
>>> plt.ylim(-6, 6)
>>> plt.xlabel('x')
>>> plt.title('logit(x)')
>>> plt.show()
```

`multivariate_normal(key: jax.numpy.lax_numpy.ndarray, mean: jax.numpy.lax_numpy.ndarray, cov: jax.numpy.lax_numpy.ndarray, shape: Optional[Sequence[int]] = None, dtype: numpy.dtype = <class 'numpy.float64'>) -> jax.numpy.lax_numpy.ndarray`

Sample multivariate normal random values with given mean and covariance.

LAX-backend implementation of `multivariate_normal()`. ADDITIONOriginal docstring below.

Returns: A random array with the specified dtype and shape given by `shape + mean.shape[-1:]` if `shape` is not `None`, or else `broadcast_shapes(mean.shape[:-1], cov.shape[:-2]) + mean.shape[-1:]`.

`normal(key: jax.numpy.lax_numpy.ndarray, shape: Sequence[int] = (), dtype: numpy.dtype = <class 'numpy.float64'>) -> jax.numpy.lax_numpy.ndarray`

Sample standard normal random values with given shape and float dtype.

LAX-backend implementation of `normal()`. ADDITIONOriginal docstring below.

Returns: A random array with the specified shape and dtype.

`pareto(key, b, shape=None, dtype=<class 'numpy.float64'>)`

Sample Pareto random values with given shape and float dtype.

LAX-backend implementation of `pareto()`. ADDITIONOriginal docstring below.

Returns: A random array with the specified dtype and with shape given by `shape` if `shape` is not `None`, or else by `b.shape`.

`randint(key: jax.numpy.lax_numpy.ndarray, shape: Sequence[int], minval: Union[int, jax.numpy.lax_numpy.ndarray], maxval: Union[int, jax.numpy.lax_numpy.ndarray], dtype: numpy.dtype = <class 'numpy.int64'>) -> jax.numpy.lax_numpy.ndarray`

Sample uniform random values in `[minval, maxval)` with given shape/dtype.

LAX-backend implementation of `randint()`. ADDITIONOriginal docstring below.

Returns: A random array with the specified shape and dtype.

`shuffle(key: jax.numpy.lax_numpy.ndarray, x: jax.numpy.lax_numpy.ndarray, axis: int = 0) -> jax.numpy.lax_numpy.ndarray`

Shuffle the elements of an array uniformly at random along an axis.

LAX-backend implementation of `shuffle()`. ADDITIONOriginal docstring below.

Returns: A shuffled version of `x`.

`truncated_normal(key: jax.numpy.lax_numpy.ndarray, lower: Union[float, jax.numpy.lax_numpy.ndarray], upper: Union[float, jax.numpy.lax_numpy.ndarray], shape: Optional[Sequence[int]] = None, dtype: numpy.dtype = <class 'numpy.float64'>) -> jax.numpy.lax_numpy.ndarray`

Sample truncated normal random values with given shape and float dtype.

LAX-backend implementation of `truncated_normal()`. ADDITIONOriginal docstring below.

Returns: A random array with the specified dtype and with shape given by `shape` if `shape` is not `None`, or else by `lower.shape`.
Sample truncated standard normal random values with given shape and dtype.

LAX-backend implementation of truncated_normal(). ADDITIONOriginal docstring below.

Returns: A random array with the specified dtype and shape given by shape if shape is not None, or else by broadcasting lower and upper.

uniform(key: jax.numpy.lax_numpy.ndarray, shape: Sequence[int] = (), dtype: numpy.dtype = <class 'numpy.float64'>, minval: Union[float, jax.numpy.lax_numpy.ndarray] = 0.0, maxval: Union[float, jax.numpy.lax_numpy.ndarray] = 1.0) → jax.numpy.lax_numpy.ndarray

Sample uniform random values in [minval, maxval) with given shape/dtype.

Returns: A random array with the specified shape and dtype.

2.1.6 symjax.utils

utils

alias of symjax.utils

2.2 Deep Learning

2.2.1 symjax.datasets

Images

| symjax.datasets.mnist | Grayscale digit classification. |
|----------------------|---------------------------------|
| symjax.datasets.fashionmnist | Grayscale image classification |
| symjax.datasets.dsprites | Greyscale image classification and disentanglement |
| symjax.datasets.svhn | Street number classification. |
| symjax.datasets.cifar10 | Image classification. |
| symjax.datasets.cifar100 | Image classification. |
| symjax.datasets.ibeans | Plant images classification. |
| symjax.datasets.cassava | Plant images classification. |
| symjax.datasets.stl10 | Image classification with extra unlabeled images. |
| symjax.datasets.tinyimagenet | Tiny Imagenet has 200 classes. |

Audio

| symjax.datasets.audiomnist | Digit recognition |
|---------------------------|------------------|
| symjax.datasets.esc | ESC-10/50: Environmental Sound Classification |
| symjax.datasets.warblr | Binary audio classification, presence or absence of a bird. |
| symjax.datasets.gtzan | Music genre classification |
| symjax.datasets.dclde | Music instrument classification |
| symjax.datasets.irmas | Singer/technique/vowel of singing voices |
| symjax.datasets.vocalset | |

continues on next page
Table 6 – continued from previous page

| Dataset Name                                      | Description                                                                 |
|---------------------------------------------------|------------------------------------------------------------------------------|
| `symjax.datasets.freefield1010`                   | Audio binary classification, presence or absence of bird songs.              |
| `symjax.datasets.birdvox_70k`                     | A dataset for avian flight call detection in half-second clips.              |
| `symjax.datasets.birdvox_dcase_20k`               | Binary bird detection classification.                                        |

**Detailed description (Image)**

**class mnist**

Grayscale digit classification.

The MNIST database of handwritten digits, available from this page, has a training set of 60,000 examples, and a test set of 10,000 examples. It is a subset of a larger set available from NIST. The digits have been size-normalized and centered in a fixed-size image. It is a good database for people who want to try learning techniques and pattern recognition methods on real-world data while spending minimal efforts on preprocessing and formatting.

**static download**(path)**

Download the MNIST dataset and store the result into the given path

**Parameters** path (str) – the path where the downloaded files will be stored. If the directory does not exist, it is created.

**static load**(path=None)

**Parameters** path (str (optional)) – default ($DATASET_PATH), the path to look for the data and where the data will be downloaded if not present

**Returns**

- `train_images` (array)
- `train_labels` (array)
- `valid_images` (array)
- `valid_labels` (array)
- `test_images` (array)
- `test_labels` (array)

**class fashionmnist**

Grayscale image classification.

Zalando’s article image classification. Fashion-MNIST is a dataset of Zalando’s article images consisting of a training set of 60,000 examples and a test set of 10,000 examples. Each example is a 28x28 grayscale image, associated with a label from 10 classes. We intend Fashion-MNIST to serve as a direct drop-in replacement for the original MNIST dataset for benchmarking machine learning algorithms. It shares the same image size and structure of training and testing splits.

**download()**

Download the fashion-MNIST dataset and store the result into the given path

**Parameters** path (str) – the path where the downloaded files will be stored. If the directory does not exist, it is created.

**load()**

**Parameters** path (str (optional)) – default ($DATASET_PATH), the path to look for the data and where the data will be downloaded if not present.
Returns

- **train_images** (array)
- **train_labels** (array)
- **test_images** (array)
- **test_labels** (array)

**class dsprites**
greyscale image classification and disentanglement

This dataset consists of 737,280 images of 2D shapes, procedurally generated from 5 ground truth independent latent factors, controlling the shape, scale, rotation and position of a sprite. This data can be used to assess the disentanglement properties of unsupervised learning methods.

dSprites is a dataset of 2D shapes procedurally generated from 6 ground truth independent latent factors. These factors are color, shape, scale, rotation, x and y positions of a sprite.

All possible combinations of these latents are present exactly once, generating $N = 737280$ total images.

**download()**
Download the MNIST dataset and store the result into the given path

**Parameters**

- **path** (str) – the path where the downloaded files will be stored. If the directory does not exist, it is created.

**load()**

**Parameters**

- **path** (str (optional)) – default ($DATASET\_PATH$), the path to look for the data and where the data will be downloaded if not present

**Returns**

- **images** (array)
- **latent** (array)
- **classes** (array)

**class svhn**
Street number classification.

The SVHN dataset is a real-world image dataset for developing machine learning and object recognition algorithms with minimal requirement on data preprocessing and formatting. It can be seen as similar in flavor to MNIST (e.g., the images are of small cropped digits), but incorporates an order of magnitude more labeled data (over 600,000 digit images) and comes from a significantly harder, unsolved, real world problem (recognizing digits and numbers in natural scene images). SVHN is obtained from house numbers in Google Street View images.

**download()**
Download the SVHN dataset and store the result into the given path

**Parameters**

- **path** (str) – the path where the downloaded files will be stored. If the directory does not exist, it is created.

**load()**

**Parameters**

- **path** (str (optional)) – default $DATASET\_PATH$, the path to look for the data and where the data will be downloaded if not present

**Returns**

- **train_images** (array)
class cifar10
Image classification.

The CIFAR-10 dataset was collected by Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton. It consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images. The dataset is divided into five training batches and one test batch, each with 10000 images. The test batch contains exactly 1000 randomly selected images from each class. The training batches contain the remaining images in random order, but some training batches may contain more images from one class than another. Between them, the training batches contain exactly 5000 images from each class.

download()
Download the MNIST dataset and store the result into the given path

    Parameters path (str) – the path where the downloaded files will be stored. If the directory does not exist, it is created.

load()

    Parameters path (str (optional)) – default ($DATASET_PATH), the path to look for the data and where the data will be downloaded if not present

Returns

- train_images (array)
- train_labels (array)
- test_images (array)
- test_labels (array)

class cifar100
Image classification.

The CIFAR-100 dataset is just like the CIFAR-10, except it has 100 classes containing 600 images each. There are 500 training images and 100 testing images per class. The 100 classes in the CIFAR-100 are grouped into 20 superclasses. Each image comes with a “fine” label (the class to which it belongs) and a “coarse” label (the superclass to which it belongs).

download()
Download the CIFAR100 dataset and store the result into the given path

    Parameters path (str) – the path where the downloaded files will be stored. If the directory does not exist, it is created.

class ibeans
Plant images classification.

This dataset is of leaf images taken in the field in different districts in Uganda by the Makerere AI lab in collaboration with the National Crops Resources Research Institute (NaCRRI), the national body in charge of research in agriculture in Uganda.

The goal is to build a robust machine learning model that is able to distinguish between diseases in the Bean plants. Beans are an important cereal food crop for Africa grown by many small-holder farmers - they are a significant source of proteins for school-age going children in East Africa.

The data is of leaf images representing 3 classes: the healthy class of images, and two disease classes including Angular Leaf Spot and Bean Rust diseases. The model should be able to distinguish between these 3 classes
with high accuracy. The end goal is to build a robust, model that can be deployed on a mobile device and used in the field by a farmer.

The data includes leaf images taken in the field. The figure above depicts examples of the types of images per class. Images were taken from the field/garden a basic smartphone.

The images were then annotated by experts from NaCRII who determined for each image which disease was manifested. The experts were part of the data collection team and images were annotated directly during the data collection process in the field.

Class Examples Healthy class 428 Angular Leaf Spot 432 Bean Rust 436 Total: 1,296

Data Released 20-January-2020 License MIT Credits Makerere AI Lab

```
static download(path)
    Download the ibeans dataset and store the result into the given path
    Parameters path (str) – the path where the downloaded files will be stored. If the directory does not exist, it is created.

static load(path=None)
    Parameters path (str (optional)) – default ($DATASET_PATH), the path to look for the data and where the data will be downloaded if not present

Returns

• train_images (array)
• train_labels (array)
• valid_images (array)
• valid_labels (array)
• test_images (array)
• test_labels (array)
```

class cassava

Plant images classification.

The data consists of two folders, a training folder that contains 5 subfolders that contain the respective images for the different 5 classes and a test folder containing test images.

Participants are to train their models using the images in the training folder and provide a submission file like the sample provided which contains the image name exactly matching the image name in the test folder and the corresponding class prediction with labels corresponding to the disease categories, cmd, healthy, cgm, cbd, cbb.

Please cite this paper if you use the dataset for your project: https://arxiv.org/pdf/1908.02900.pdf

```
static download(path)
    Download the cassava dataset and store the result into the given path
    Parameters path (str) – the path where the downloaded files will be stored. If the directory does not exist, it is created.

static load(path=None)
    Parameters path (str (optional)) – default ($DATASET_PATH), the path to look for the data and where the data will be downloaded if not present

Returns

• train_images (array)
```
symjax, Release 0.0.1

- **train_labels** *(array)*
- **valid_images** *(array)*
- **valid_labels** *(array)*
- **test_images** *(array)*
- **test_labels** *(array)*

**class stl10**

Image classification with extra unlabeled images.

The STL-10 dataset is an image recognition dataset for developing unsupervised feature learning, deep learning, self-taught learning algorithms. It is inspired by the CIFAR-10 dataset but with some modifications. In particular, each class has fewer labeled training examples than in CIFAR-10, but a very large set of unlabeled examples is provided to learn image models prior to supervised training. The primary challenge is to make use of the unlabeled data (which comes from a similar but different distribution from the labeled data) to build a useful prior. We also expect that the higher resolution of this dataset (96x96) will make it a challenging benchmark for developing more scalable unsupervised learning methods.

**static load**(path=None)

load the data

**Parameters**

- **path** *(str (optional)) – the path to look for the data and where it will be downloaded if not present*

**Returns**

- **train_images** *(array) – the training images*
- **train_labels** *(array) – the training labels*
- **test_images** *(array) – the test images*
- **test_labels** *(array) – the test labels*
- **extra_images** *(array) – the unlabeled additional images*

**class tinyimagenet**

Tiny ImageNet has 200 classes. Each class has 500 training images, 50 validation images, and 50 test images. We have released the training and validation sets with images and annotations. We provide both class labels and bounding boxes as annotations; however, you are asked only to predict the class label of each image without localizing the objects. The test set is released without labels. You can download the whole tiny ImageNet dataset here.

**Detailed description (Audio)**

**class audiomnist**

**digit recognition**  [https://github.com/soerenab/AudioMNIST](https://github.com/soerenab/AudioMNIST)

A simple audio/speech dataset consisting of recordings of spoken digits in wav files at 8kHz. The recordings are trimmed so that they have near minimal silence at the beginnings and ends.

FSDD is an open dataset, which means it will grow over time as data is contributed. In order to enable reproducibility and accurate citation the dataset is versioned using Zenodo DOI as well as git tags.

**Current status**

- 4 speakers 2,000 recordings (50 of each digit per speaker) English pronunciations
class esc
ESC-10/50: Environmental Sound Classification
https://github.com/karolpiczak/ESC-50#download
The ESC-50 dataset is a labeled collection of 2000 environmental audio recordings suitable for benchmarking methods of environmental sound classification.
The dataset consists of 5-second-long recordings organized into 50 semantical classes (with 40 examples per class) loosely arranged into 5 major categories:

- Animals
- Natural soundscape & water sounds
- Human, non-speech sounds
- Interior/domestic sounds
- Exterior/urban noises

Clips in this dataset have been manually extracted from public field recordings gathered by the Freesound.org project. The dataset has been prearranged into 5 folds for comparable cross-validation, making sure that fragments from the same original source file are contained in a single fold.

load()
ESC 50.
https://github.com/karolpiczak/ESC-50#download

Parameters
- path (str (optional)) – default $DATASET_path, the path to look for the data and where the data will be downloaded if not present

Returns
- wavs (array) – the wavs as a numpy array (matrix) with first dimension the data and second dimension time
- fine_labels (array) – the labels of the final classes (50 different ones) as a integer vector
- coarse_labels (array) – the labels of the classes big category (5 of them)
- folds (array) – the fold as an integer from 1 to 5 specifying how to split the data one should not split a fold into train and test so as it would make the same recording (but different subparts) be present in train and test, biasing optimistically the results.
- esc10 (array) – the boolean vector specifying if the corresponding datum (wav, label, . . . ) is in the ESC-10 dataset or not. That is, to load the ESC-10 dataset simply load ESC-50 and use this boolean vector to extract only the ESC-10 data.

class warblr
Binary audio classification, presence or absence of a bird.
Warblr comes from a UK bird-sound crowdsourcing research spinout called Warblr. From this initiative we have 10,000 ten-second smartphone audio recordings from around the UK. The audio totals around 44 hours duration. The audio will be published by Warblr under a Creative Commons licence. The audio covers a wide distribution of UK locations and environments, and includes weather noise, traffic noise, human speech and even human bird imitations. It is directly representative of the data that is collected from a mobile crowdsourcing initiative.

download()
Download the data

load()
Load the data given a path

class gtzan
music genre classification
This dataset was used for the well known paper in genre classification “Musical genre classification of audio signals” by G. Tzanetakis and P. Cook in IEEE Transactions on Audio and Speech Processing 2002.
Unfortunately the database was collected gradually and very early on in my research so I have no titles (and obviously no copyright permission etc). The files were collected in 2000-2001 from a variety of sources including personal CDs, radio, microphone recordings, in order to represent a variety of recording conditions. Nevertheless I have been providing it to researchers upon request mainly for comparison purposes etc. Please contact George Tzanetakis (gtzan@cs.uvic.ca) if you intend to publish experimental results using this dataset.

There are some practical and conceptual issues with this dataset, described in “The GTZAN dataset: Its contents, its faults, their effects on evaluation, and its future use” by B. Sturm on arXiv 2013.

dclde
alias of symjax.datasets.dclde

class irmas
music instrument classification

ref https://zenodo.org/record/1290750#.WzCwSRyxXMU

This dataset includes musical audio excerpts with annotations of the predominant instrument(s) present. It was used for the evaluation in the following article:

Bosch, J. J., Janer, J., Fuhrmann, F., & Herrera, P. “A Comparison of Sound Segregation Techniques for Predominant Instrument Recognition in Musical Audio Signals”, in Proc. ISMIR (pp. 559-564), 2012

Please Acknowledge IRMAS in Academic Research

IRMAS is intended to be used for training and testing methods for the automatic recognition of predominant instruments in musical audio. The instruments considered are: cello, clarinet, flute, acoustic guitar, electric guitar, organ, piano, saxophone, trumpet, violin, and human singing voice. This dataset is derived from the one compiled by Ferdinand Fuhrmann in his PhD thesis, with the difference that we provide audio data in stereo format, the annotations in the testing dataset are limited to specific pitched instruments, and there is a different amount and length of excerpts.

class vocalset
singer/technique/vowel of singing voices

source: https://zenodo.org/record/1442513#.W7OaFBNKjx4

We present VocalSet, a singing voice dataset consisting of 10.1 hours of monophonic recorded audio of professional singers demonstrating both standard and extended vocal techniques on all 5 vowels. Existing singing voice datasets aim to capture a focused subset of singing voice characteristics, and generally consist of just a few singers. VocalSet contains recordings from 20 different singers (9 male, 11 female) and a range of voice types. VocalSet aims to improve the state of existing singing voice datasets and singing voice research by capturing not only a range of vowels, but also a diverse set of voices on many different vocal techniques, sung in contexts of scales, arpeggios, long tones, and excerpts.

load()

Parameters path (str (optional)) – a string where to load the data and download if not present

Returns

• singers (list) – the list of singers as strings, 11 males and 9 females as in male1, male2, ...
• genders (list) – the list of genders of the singers as in male, male, female, ...
• vowels (list) – the vowels being pronounced
• data (list) – the list of waveforms, not all equal length

class freefield1010
Audio binary classification, presence or absence of bird songs. freefield1010. is a collection of over 7,000
excerpts from field recordings around the world, gathered by the FreeSound project, and then standardised for research. This collection is very diverse in location and environment, and for the BAD Challenge we have newly annotated it for the presence/absence of birds.

**class birdvox_70k**

a dataset for avian flight call detection in half-second clips

Version 1.0, April 2018.

Created By

Vincent Lostanlen (1, 2, 3), Justin Salamon (2, 3), Andrew Farnsworth (1), Steve Kelling (1), and Juan Pablo Bello (2, 3).

(1): Cornell Lab of Ornithology (CLO) (2): Center for Urban Science and Progress, New York University (3): Music and Audio Research Lab, New York University

https://wp.nyu.edu/birdvox

Description

The BirdVox-70k dataset contains 70k half-second clips from 6 audio recordings in the BirdVox-full-night dataset, each about ten hours in duration. These recordings come from ROBIN autonomous recording units, placed near Ithaca, NY, USA during the fall 2015. They were captured on the night of September 23rd, 2015, by six different sensors, originally numbered 1, 2, 3, 5, 7, and 10.

Andrew Farnsworth used the Raven software to pinpoint every avian flight call in time and frequency. He found 35402 flight calls in total. He estimates that about 25 different species of passerines (thrushes, warblers, and sparrows) are present in this recording. Species are not labeled in BirdVox-70k, but it is possible to tell apart thrushes from warblers and sparrows by looking at the center frequencies of their calls. The annotation process took 102 hours.

The dataset can be used, among other things, for the research, development and testing of bioacoustic classification models, including the reproduction of the results reported in [1].

For details on the hardware of ROBIN recording units, we refer the reader to [2].

[1] V. Lostanlen, J. Salamon, A. Farnsworth, S. Kelling, J. Bello. BirdVox-full-night: a dataset and benchmark for avian flight call detection. Proc. IEEE ICASSP, 2018.

[2] J. Salamon, J. P. Bello, A. Farnsworth, M. Robbins, S. Keen, H. Klinck, and S. Kelling. Towards the Automatic Classification of Avian Flight Calls for Bioacoustic Monitoring. PLoS One, 2016.

@inproceedings{lostanlen2018icassp, title = {BirdVox-full-night: a dataset and benchmark for avian flight call detection}, author = {Lostanlen, Vincent and Salamon, Justin and Farnsworth, Andrew and Kelling, Steve and Bello, Juan Pablo}, booktitle = {Proc. IEEE ICASSP}, year = {2018}, published = {IEEE}, venue = {Calgary, Canada}, month = {April}, }

**static download(path)**

Download the BirdVox dataset and store the result into the given path

**Parameters**

- **path (str)** – the path where the downloaded files will be stored. If the directory does not exist, it is created.

**static load(path=None)**

- **Parameters**

  - **path (str (optional))** – default ($DATASET_PATH$), the path to look for the data and where the data will be downloaded if not present

**Returns**

- **wave (array(70804, 12000))** – the waveforms in the time amplitude domain

- **labels (array(70804,))** – binary values representing the presence or not of an avian
class birdvox_dcase_20k

Binary bird detection classification

Dataset is 16.5Go compressed.

BirdVox-DCASE-20k: a dataset for bird audio detection in 10-second clips

Version 2.0, March 2018.

Created By

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(1): Cornell Lab of Ornithology (CLO) (2): Center for Urban Science and Progress, New York University (3): Music and Audio Research Lab, New York University

https://wp.nyu.edu/birdvox

Description

The BirdVox-DCASE-20k dataset contains 20,000 ten-second audio recordings. These recordings come from ROBIN autonomous recording units, placed near Ithaca, NY, USA during the fall 2015. They were captured on the night of September 23rd, 2015, by six different sensors, originally numbered 1, 2, 3, 5, 7, and 10.

Out of these 20,000 recording, 10,017 (50.09%) contain at least one bird vocalization (either song, call, or chatter).

The dataset is a derivative work of the BirdVox-full-night dataset [1], containing almost as much data but formatted into ten-second excerpts rather than ten-hour full night recordings.

In addition, the BirdVox-DCASE-20k dataset is provided as a development set in the context of the “Bird Audio Detection” challenge, organized by DCASE (Detection and Classification of Acoustic Scenes and Events) and the IEEE Signal Processing Society.

The dataset can be used, among other things, for the development and evaluation of bioacoustic classification models.

We refer the reader to [1] for details on the distribution of the data and [2] for details on the hardware of ROBIN recording units.

[1] V. Lostanlen, J. Salamon, A. Farnsworth, S. Kelling, J.P. Bello. “BirdVox-full-night: a dataset and benchmark for avian flight call detection”, Proc. IEEE ICASSP, 2018.

[2] J. Salamon, J. P. Bello, A. Farnsworth, M. Robbins, S. Keen, H. Klinck, and S. Kelling. Towards the Automatic Classification of Avian Flight Calls for Bioacoustic Monitoring. PLoS One, 2016.

Data Files

The wav folder contains the recordings as WAV files, sampled at 44,1 kHz, with a single channel (mono). The original sample rate was 24 kHz.

The name of each wav file is a random 128-bit UUID (Universal Unique IDentifier) string, which is randomized with respect to the origin of the recording in BirdVox-full-night, both in terms of time (UTC hour at the start of the excerpt) and space (location of the sensor).

The origin of each 10-second excerpt is known by the challenge organizers, but not disclosed to the participants.

Please Acknowledge BirdVox-DCASE-20k in Academic Research

When BirdVox-70k is used for academic research, we would highly appreciate it if scientific publications of works partly based on this dataset cite the following publication:
V. Lostanlen, J. Salamon, A. Farnsworth, S. Kelling, J. Bello. “BirdVox-full-night: a dataset and benchmark for avian flight call detection”, Proc. IEEE ICASSP, 2018.

The creation of this dataset was supported by NSF grants 1125098 (BIRDCAST) and 1633259 (BIRDVOX), a Google Faculty Award, the Leon Levy Foundation, and two anonymous donors.

```python
static download(path)
    Download the Birdvox dataset and store the result into the given path

    Parameters path (str) – the path where the downloaded files will be stored. If the directory does not exist, it is created.

static load(path=None)
    Parameters path (str (optional)) – default ($DATASET_PATH), the path to look for the data and where the data will be downloaded if not present

    Returns

    • wavs (array) – the waveforms in the time amplitude domain
    • labels (array) – binary values representing the presence or not of an avian
    • recording (array) – the file number from which the sample has been extracted
```

2.2.2 symjax.initializers

initializers
alias of symjax.initializers
glorot (shape, gain=1, distribution=<function normal>)
    Glorot weight initialization. This is also known as Xavier initialization [1].

    Parameters

    • initializer (lasagne.init.Initializer) – Initializer used to sample the weights, must accept std in its constructor to sample from a distribution with a given standard deviation.

    • gain (float or 'relu') – Scaling factor for the weights. Set this to 1.0 for linear and sigmoid units, to ‘relu’ or sqrt(2) for rectified linear units, and to sqrt(2/(1+alpha**2)) for leaky rectified linear units with leakiness alpha. Other transfer functions may need different factors.

    • c01b (bool) – For a lasagne.layers.cuda_convnet.Conv2DCLayer constructed with dimshuffle=False, c01b must be set to True to compute the correct fan-in and fan-out.
For a `DenseLayer`, if `gain='relu'` and `initializer=Uniform`, the weights are initialized as

\[
a &= \sqrt{\frac{12}{\text{fan\_in} + \text{fan\_out}}} \\
W &\sim U[-a, a]
\]

If `gain=1` and `initializer=Normal`, the weights are initialized as

\[
\sigma &= \sqrt{\frac{2}{\text{fan\_in} + \text{fan\_out}}} \\
W &\sim N(0, \sigma)
\]

He weight initialization. Weights are initialized with a standard deviation of  
\[
\sigma = \text{gain} \sqrt{\frac{1}{\text{fan\_in}}} \quad \text{[1]}
\]

**Parameters**

- `initializer` (`lasagne.init.Initializer`) – Initializer used to sample the weights, must accept `std` in its constructor to sample from a distribution with a given standard deviation.
- `gain` (`float or 'relu'`) – Scaling factor for the weights. Set this to `1.0` for linear and sigmoid units, to `relu` or `sqrt(2)` for rectified linear units, and to `sqrt(2/(1+alpha**2))` for leaky rectified linear units with leakiness `alpha`. Other transfer functions may need different factors.
- `c01b` (`bool`) – For a `lasagne.layers.cuda_convnet.Conv2DCCLayer` constructed with `dimshuffle=False`, `c01b` must be set to True to compute the correct fan-in and fan-out.

**References**

See also:

- `HeNormal()` Shortcut with Gaussian initializer.
- `HeUniform()` Shortcut with uniform initializer.

`normal(shape, mean=0.0, std=1.0)`

Sample initial weights from the Gaussian distribution. Initial weight parameters are sampled from \(N(\text{mean}, \text{std})\).

**Parameters**

- `std` (`float`) – Std of initial parameters.
- `mean` (`float`) – Mean of initial parameters.

`uniform(shape, range=0.01, std=None, mean=0.0)`

Sample initial weights from the uniform distribution. Parameters are sampled from \(U(a, b)\).

**Parameters**

- `range` (`float or tuple`) – When `std` is None then `range` determines `a, b`. If `range` is a float the weights are sampled from \(U(-\text{range}, \text{range})\). If `range` is a tuple the weights are sampled from \(U(\text{range}[0], \text{range}[1])\).
• **std** *(float or None)* – If std is a float then the weights are sampled from \(U(\text{mean} - \sqrt{3} \times \text{std}, \text{mean} + \sqrt{3} \times \text{std})\).

• **mean** *(float)* – see std for description.

### 2.2.3 `symjax.layers`

#### Renormalization

| `BatchNormalization(input_or_shape, axis, ...)` | batch-normalization layer |

#### Data Augmentation

| `RandomCrop(input_or_shape, crop_shape, ...)` | random crop selection form the input |
| `RandomFlip(input_or_shape, p, axis, ..., [seed])` | random axis flip on the input |
| `Dropout(input_or_shape, p, deterministic[, seed])` | binary mask onto the input |

#### Convolution

| `Conv1D(input_or_shape, n_filters, filter_length)` | 1-D (time) convolution |
| `Conv2D(input_or_shape, n_filters, filter_shape)` | 2-D (spatial) convolution |

#### Pooling

| `Pool1D(input_or_shape, pool_shape[, ...])` | 2-D (spatial) pooling |
| `Pool2D(input_or_shape, pool_shape[, ...])` | 2-D (spatial) pooling |

#### Utilities

| `forward(input, layers)` | perform a forward path in the layers given an input |

### 2.2.4 `symjax.optimizers`

*optimizers*

alias of `symjax.optimizers`

**class** `Adam` *(grads_or_loss, learning_rate, beta1=0.9, beta2=0.999, epsilon=1e-06, params=None)*

Adaptive Gradient Based Optimization with renormalization

**Parameters**

• **grads_or_loss** *(scalar tensor or list of gradients)* – either the loss (scalar of Tensor type) to be differentiated or the list of gradients already computed and possibly altered manually (such as clipping)

• **params** *(list of parameters to update)* – if grads_or_loss is al list then it
should be ordered w.r.t. the given parameters

- **learning_rate** (*constant or Tensor*) – the learning rate use to update the parameters
- **beta1** (*constant or Tensor*) – the value of the exponential moving average of the average of the gradients through time (updates)
- **beta2** (*constant or Tensor*) – the value of the exponential moving average of the variance of the gradients through time

**updates**
Type  list of updates

**variables**
Type  list of variables

**class NesterovMomentum** *(grads_or_loss, learning_rate, momentum, params=None)*
Nesterov momentum Optimization

   Parameters

   - **grads_or_loss** (*scalar tensor or list of gradients*) – either the loss (scalar of Tensor type) to be differentiated or the list of gradients already computed and possibly altered manually (such as clipping)
   - **params** (*list of parameters to update*) – if grads_or_loss is a list then it should be ordered w.r.t. the given parameters
   - **learning_rate** (*constant or Tensor*) – the learning rate use to update the parameters

   **updates**
Type  list of updates

   **variables**
Type  list of variables

**class SGD** *(grads_or_loss, learning_rate, params=None)*
Gradient Descent Optimization

   Parameters

   - **grads_or_loss** (*scalar tensor or list of gradients*) – either the loss (scalar of Tensor type) to be differentiated or the list of gradients already computed and possibly altered manually (such as clipping)
   - **params** (*list of parameters to update*) – if grads_or_loss is a list then it should be ordered w.r.t. the given parameters
   - **learning_rate** (*constant or Tensor*) – the learning rate use to update the parameters

   **updates**
Type  list of updates

   **variables**
Type  list of variables
• genindex
• modindex
• search
[CT] Cooley, James W., and John W. Tukey, 1965, “An algorithm for the machine calculation of complex Fourier series,” Math. Comput. 19: 297-301.
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