Automatic acceleration of Numpy applications on GPUs and multicore CPUs

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Abstract

Frameworks like Numpy are a popular choice for application developers from varied fields such as image processing to bio-informatics to machine learning. Numpy is often used to develop prototypes or for deployment since it provides efficient implementation for operations involving arrays. Such an approach requires every operation to be executed eagerly. The result of each operation needs to be stored in memory which increases the memory footprint of the application. It also increases the bandwidth requirements since all uses must read from this memory. We propose an approach that records the sequence of Numpy operations for deferred execution. When the values of an array are needed, for example when the values are stored to disk or displayed on screen, the sequence of operations required to compute these value are compiled into a function and executed. This removes the need to store/load intermediates in slow memory, resulting in better performance. In cases where the library implementation is more efficient (like matrix-matrix multiply), those are used instead. The approach also allows us to seamlessly target both multicore CPUs and NVIDIA GPUs, thereby porting the Numpy application to these architectures without changing the user program. The benefit of the approach is evaluated by targeting computation samples from various domains and on average on order of magnitude performance improvement over Numpy is observed.

Keywords  Numpy, GPUs, Machine Learning

1 Introduction

Numpy [14] has long been the default module for developing applications in Python that rely on array-based data structures. Image processing, deep learning, bio-informatics are just a few domains where Python and Numpy are used to either develop prototypes or applications that are deployed for public use. The main reason for this is that Numpy provides efficient implementation for operations involving arrays. At the same time, Numpy has several limitations. Firstly, efficient implementations are provided for CPU execution, i.e., there is no off the shelf method to execute the Numpy operation on the GPU. A majority of the operations provided by Numpy, like numpy.add or numpy.subtract are embarrassingly parallel, i.e., The same computation is executed independently on each element of the array. Such a computation pattern matches well with the GPU execution model which requires the use of lots of parallel threads with minimal communication for efficient execution. For more complex operations like np.dot, which implements matrix-matrix and matrix-vector multiplications, existing libraries provide efficient implementation on GPUs. For example, cuBLAS [4] provides efficient GEMM implementation for NVIDIA GPUs. Yet, there is no mechanism in Numpy to leverage these libraries.

A second limitation comes from the fact that Numpy is a library. Each operation provided by Numpy is implemented through a dedicated function. For example, consider the snippet shown in Listing 1. The four multiplications and two additions are done eagerly with intermediate result (which in itself is an array), stored in memory. These are read again during its subsequent uses. Since the actual computation is simple, the entire execution is bandwidth bound. As the arrays get larger, streaming the array from memory multiple times results in poor performance. The overhead of memory allocation and deallocation of temporary arrays further worsens the situation.

In this paper, we propose a framework called Grumpy, that employs an alternative approach that addresses both of these issues. Instead of performing each operation eagerly, we build a representation of the operations seen so far. This is done by providing a python module called grumpy that can be used instead of numpy. It provides the same operations as numpy and can be used as a drop-in replacement for it. When the result of the operation is needed (due to the print operation, for example), we use a JIT compiler to generate code for all the operations seen so far and execute it as a single function.

This approach has the following advantages

• There is no need to explicitly store the intermediate results in memory. For example, for Listing 1, the generated function directly computes the value of z without storing the values of all the intermediate arrays in memory.

Listing 1. Numpy implementation of simple arithmetic ops

```python
import numpy as np
x = np.array([10, 20], np.int32)
y = np.array([20], np.int32)
z = x*x + 2*x*y + y*y
print(z)
```
• Since the JIT compiler can see more of the computation than individual operations, traditional compiler optimizations can now be applied to generate a more efficient function.

• The JIT compiler can generate native code to target multiple architectures. By using the embarrassingly parallel nature of the array operations in numpy, we can automatically generate code and run the computation either on GPUs (specifically NVIDIA GPUs) or on multi-core CPUs.

In general, it is not always efficient to do all evaluation lazily, or to generated code for all operations using a JIT compiler. For example, consider the snippet in Listing 2 which representative of MNIST computation from Deep Learning domain. It contains operations such as transpose and matrix-vector multiplies. Instead of generating code using a JIT compiler, it is more efficient to use tuned implementations provided by libraries such as LAPACK [1] or cuBLAS [4]. To account for this Grumpy recognizes computations that are better offloaded to efficient library implementation, while generating optimized fused kernels for the rest of the computation.

The rest of the paper is organized as follows. Section 2 describes the internal representation used to describe the computation, and how this is used to offload parts of the computation to a library while the rest of the computation is JIT compiled. Section 3 describes the code-generation process within the JIT compiler. Section 4 evaluates the performance improvements from using this approach on a few benchmarks. Section 5 describes other frameworks that have similar goals and describes the advantages/disadvantages of the Grumpy compared with these frameworks.

2 Fusion of operations in the DAG

To move from an eager evaluation approach to a lazy evaluation approach we need a representation of the computation seen so far. A Directed Acyclic Graph, $G = (V, E)$ is a natural abstraction to represent the sequence of operations to be evaluated, and the data dependencies between them. A node $n \in V$ represent the result of an operation, which is in general an $n$-dimensional tensor. An edge $e \in E$ represents the use of the tensor produced by the source node in the target node. The leaves of the graph represent inputs to the computation. The root is the result of the computation. It is not required to store the intermediates in memory, but it is required to produce the output in memory. Similar to numpy, the size of the tensor represented by each node, and the data type of the tensor elements are computed automatically while the DAG is built based on the semantics of each operation. Figure 1 shows the DAG that represents the computation in Listing 1. output is the result of the computation and is therefore the root. $W, a$ and $b$ are inputs to the computation and are the leaves of the DAG.

The nodes in the graph can be used to represent any mathematical operation ranging from addition, subtraction of arrays to more complex operations like,

• BLAS computations such as matrix-vector multiply or matrix-matrix multiply
• Reduction and scan along multiple (or all) dimension of the array.
• Reads and writes of portion of array through slicing operations.
• Index and layout transformation operations like reshape and multi-dimensional transpose operations.

to name a few. The semantics of all operations match the semantics of the corresponding numpy operations, including aspects like broadcast [2] for pointwise operations. Note that we do not need to account for branching constructs like if-then-else or loops. Since Python is an interpreted language, only the operations executed are seen by the Grumpy module, and needs to be represented in the DAG.

Each node in the graph has three attributes

• operation: Represents the operations being represented by the node
• data: Contains the values in the $n$-dimensional tensor that would be generated after the operation represented by this node is executed.
• is_materialized : A boolean attribute that signifies if the data has been computed and stored in memory or not.

At the start of the computation, only the inputs nodes have the data field non-empty and represents the values in the arrays that are inputs to the computation. The is_materialized field is also true only for the inputs. As more operations are

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**Listing 2. Simple MNIST in Numpy**

```python
import numpy as np
W = np.array([[10, 200], np.float32])
a = np.array([200], np.float32)
b = np.array([10], np.float32)
x = np.transpose(W).dot(max(a, 0)) + b;
output = 1.0 / (1.0 + np.exp(-x));
print(output);
```
for (int j = 0; j < 20; j++)
    for (int i = 0; i < 10; i++)
        z[i][j] = x[i][j] * x[i][j] + 2 * x[i][j] * y[j] + y[j] * y[j];

void fused_example(const int &x[10][20], const int &y[20], int &z[10][20]) {
    for (int i = 0; i < 10; i++)
        for (int j = 0; j < 20; j++)
            z[i][j] = x[i][j] * x[i][j] + 2 * x[i][j] * y[j] + y[j] * y[j];
}

When such an operation is encountered, the DAG is built to capture the semantics of the operations specified for lazy evaluation. The is_materialized field is set to false for these nodes and the data field is empty. If the result of a particular node is needed (through a print or other similar operations), the DAG is traversed backwards to find all the operations needed to evaluate the result. On encountering a materialized node (one with the is_materialized field set to true), none of its predecessors are visited as part of the traversal. At the end of the traversal, all visited nodes form a subgraph, which itself is a DAG where the leaves, and only the leaves, are materialized. This subDAG is passed to the JIT compiler that compiles the graph into a single fused function, which accepts the input arrays as arguments, and the generates the array containing the result of the operation at the root. Listing 3 is representative of the code generated for the subDAG rooted at $z$ with leaves $x$ and $y$ in Figure 1. Note that the generated code correctly implements the broadcast semantics of multiplying arrays $x$ and $y$. Details of code-generation are presented in Section 3.

The JIT compiler in Grumpy compiles this code to execute on a multi-core CPU or NVIDIA GPU. On execution, the result of the output is stored in memory. The attribute data of this node is associated with these result array stored in memory, and the node is set as been materialized. Since Python is an interpreted language, at this point it is not known how the values computed for this node will be used. Marking the node as materialized ensures that other nodes which depend on this node will use the value computed in memory, instead of recomputing these values.

As mentioned in Section 1, for some computations (like the matrix-vector multiply in Listing 2) it is better to fall back to more efficient library implementation than to have the JIT compiler generate code for such operations. To enable this, when such an operation is encountered, all the operands to this operation are materialized. This is done since all the operands would have been computed and stored in memory, for use within the library function invoked to compute the result of the operation. On return from the library call, the node corresponding to the operation is marked as materialized so that all uses of this node will use the values generated from the library call.

To illustrate the above mechanism, consider the DAG for the MNIST example from Listing 2 shown in Figure 2. The operation for node matvec is better handled by cuBLAS for GPU execution, by invoking the relevant gemv API calls. Before invoking the function, the values of the matrix and the vector (which are the operands to matvec) need to be materialized. The value of $max$ is computed by generating a function to implement the max function, JIT-compiling it and executing it. cuBLAS also provides a version of gemv computation where the input matrix is stored as transpose. This is recognized by Grumpy, and it proceeds to materialize the operand of the transpose. Since this is the array $W$ that is already materialized, there is nothing to do here. On return from the cuBLAS function, the matvec node is marked as materialized. The rest of the operations to compute the output can be fused into a single function with matvec and $b$ being inputs to the function.

The algorithm used to split an input DAG into a list of sub-graphs, each of which is to be either JIT compiled and executed or handed off to a library is shown in Algorithm 1. The sub-graphs are to be executed in the order specified by this list. It uses two helper functions to create the sub-graphs, materialize_node and materialize_pred_of_node.

materialize_node is a function that checks if a node has to be materialized based on the properties of the operation. Some of the cases where this function returns true are listed below.

- When the operation is better handled through use of libraries, like cuBLAS.
- When the operation is not embarrassingly parallel, like reductions or scans (along one or many dimensions of the array). These operations require inter-thread communication. When executed in parallel, fusing these operations with their successors would either need an explicit synchronization between threads or these computations have to be executed redundantly in all the threads. Not
Algorithm 1: create_subgraph(rootNodes, graphList, visited)

```
begin
newGraph = φ;
candidates = φ;
if root ∈ visited then
    candidates = push(root);
visited = visited ∪ root;
set_materialized(node);
while ¬ is_empty(candidates) do
    node = candidates.pop();
    newGraph.nodes = newGraph.nodes ∪ node;
    if ¬ is_materialized(node) then
        if materialize_node(node) then
            create_subgraph(node, graphList, visited);
        foreach pred ∈ predecessors(node) do
            if pred ∈ visited then
                if materialize_pred_of_node(pred, node) then
                    create_subgraph(pred, graphList, visited);
                newGraph.nodes = newGraph.nodes ∪ pred;
            else if ¬ is_materialized(pred) then
                visited = visited ∪ pred;
                candidates.push(pred);
            else if pred ∉ newGraph.nodes then
                newVisited = φ;
                create_subgraph(pred, graphList, newVisited);
            newGraph.edges = newGraph.edges ∪ [node, pred];
        graphList.append(newGraph);
```

all hardware have effective mechanism to do the former (for example on NVIDIA GPUs it is not always possible to synchronize threads across all thread blocks) and the latter is not efficient.

materialize_pred_of_node is a function that returns true if a predecessors of a node has to be materialized. This function returns true for cases where the node represents an operation that is to be executed by a library. Since the operands of the library have to be computed and stored in memory before the library call, this step is required. Note that sometimes it is better to not materialize the immediate predecessor. For example, for an matrix-matrix multiply or a matrix-vector multiply, if the predecessor is a transpose, cuBLAS provides methods that allow the input to be transposed before the computation is performed. In this case it is better to materialize the predecessor of the transpose. This detail is omitted from the Algorithm 1 for sake of clarity.

Another aspect of algorithm to note is in lines 23. If a node encountered has been visited during the subgraph creation, but does not belong to the current subgraph, then it is a node that belongs to a subgraph that was created earlier. One way to handle this is to include all the nodes in the sub-DAG rooted at this node into the current subgraph. This would mean the computation represent by this sub-DAG is replicated in all subgraphs that use the result of this node. An alternative approach is to materialize this node so that it becomes a leaf to all subgraphs that use this node. This is the approach used in Grumpy.

To control JIT compilation overhead, when the size of the subDAG rooted at each node reaches a threshold it is JIT compiled. The heuristics used here are outside the scope of this paper.

### 3 Code Generation for fused operations

The JIT compiler used within Grumpy is based on LambdalJIT [10]. It is an LLVM based compiler that can generate code to execute either on the multicore CPU or on the GPU. Its supports code generation for three primitive operations: map, map-reduce and map-scan. This section provides details of the code-generation process.

#### 3.1 Map operations

Map operations are a natural representation of computations where the same operations is to be performed on a different elements of an array. These operations can be done in parallel without any need for synchronization. For example, consider the code in Listing 3 that implements the computation represented by the DAG in Figure 1. This computation can be viewed as executing the function example_pt_fn shown in Listing 4 over a 2D orthogonal iteration space. Given this function (refered to as point function) and the iteration space dimensions, the JIT compiler will generate code that partitions this iteration space to either

- CPU threads on multicore CPUs with each thread executing a block of this iteration space, or
- GPU with each thread executing one point in this iteration space

In general the code-generator accepts a point function and an n-Dimensional iteration space to generate the code for the parallel execution of the map operation. It is expected that the first n arguments of point function are integers that represent the point in the iteration space being executed.

To generate the point function for a subgraph found in Algorithm 1, the code generation starts from the root of the subgraph. The shape of the result tensor (i.e., the result of
the operation represented by the root node) gives the dimensionality and shape of the iteration space to be used in the generated code. The first \( n \) arguments of the point function also represent the index into the result tensor where the value computed by the point function is to be stored. These indices are translated into indices for predecessors, and so on till the leaves of the subgraph are reached. The index expression at the leaves are used to reads inputs to the subgraph (Algorithm 1 ensures that the leaves are materialized). For example, consider a subgraph with a transpose operation of a 2D tensor as the root. Say, the first two arguments of the point function are \( i \) and \( j \), i.e., the point function computes the value of element \((i, j)\). Then the indices to use for the predecessor would be \((j, i)\). The index expression translation needs to account for broadcast semantics, slicing, and other index transformation operations. The point function generated and the shape of the root node are passed to a routine that generates code for map operation. This function, when invoked, executes the computation represented by the subgraph.

### 3.2 Map-Reduce and Map-Scan operations

The map-reduce operations represents the computation where elements of a tensor are combined to produce a single value using an associative and commutative operation (we assume floating point operations satisfy both within some error bounds). For example, the numpy. sum() operation, which is a reduction with sum operator over all axis of the input array fits such an abstraction. To generate code for such computations, the code generators takes two functions as inputs. First, a binary operation that takes two values of the same type and combines them using an associative and commutative operation to generate a result of the same type. The second is a map function, similar to the function describes in Section 3.1, but instead of void return type it returns a value that is of the same type as the arguments of the binary operation. The map function is used to produce all the elements that are to be combined using the binary operator to produce a single final result value. For example, the Listing 5 shows the map function, ip_map and the binary operator, ip_reduce to be used to implement an inner-product of two 1-D vectors \( a \) and \( b \). The map operations first performs the element wise multiplication of the two vectors to generate the values that are to be combined using + operation to get the final result.

When the subgraph to be JIT compiled has a root which represents a reduction value to generate a single value, it first generates the binary function based on the reduction operation being used. It then generates the point function for the map in a process similar to the one described in Section 3.1. The dimensionality of the map function is same as that of the operand of the root node, since its the result of the operand that are the values to be combined during the reduction operation represented by the root. The shape of the operand to the root node, the map function and the binary operation is used to the map-reduce code for the desired target.

On CPU the iteration space for the map operation is split amongst the threads in a blocked fashion. The result of the map operation are then combined using the binary operator to get a value per thread. The values generated for each thread is then combined using the binary operator to get the final result.

On the GPU, the iteration space of the map operation is distributed amongst threads, with one point per thread. The result generated from threads in a thread block are combined in shared memory to a single value. The result from each thread block is written out to global memory. A separate kernel is used to do the final reduction of these values to get the final result. Note that for this kernel does not use the map operation. It only uses the binary operation to combine these values.

For cases where the root of the subgraph that is to be JIT compiled is a scan operation, a map-scan primitive is used. It requires the same map point function and binary operator as above. Further details about the mechanism to compute the map-scan in parallel on the CPU and GPU are not relevant to this paper. For further details about the scan algorithm generated please refer to the work-efficient parallel scan algorithm described here [8].

### 4 Experimental Results

The Grumpy framework described in Sections 2 and 3 is deployed as a python module, called grumpy that implements the same interface as Numpy. The goal is that the only change a user has to make is to import this module instead of numpy. While we would like handle all the numpy methods within Grumpy, it is a daunting task due to sheer number of methods that Numpy supports. To ensure we achieve the desired deployment model we ensure that grumpy and numpy modules interact seamlessly. Internally, the grumpy module intercepts operation sequence that can handled by the framework and passes it on to the core Grumpy libraries. For the unhandled operations, it is forwarded to the numpy module. We describe briefly few aspects of this mechanism.

### Listing 5. Map and Reduce function used to generate the map-reduce function that computes the inner product of two 1-D vectors

```c
float ip_map(int i, float *a, float *b) {
    return a[i] * b[i];
}

float ip_reduce(float a, float b) {
    return a + b;
}
```
for i in range(iterations):
    center = grid[1:-1, 1:-1]
    north = grid[0:-2, 1:-1]
    east = grid[1:-1, 2:]
    south = grid[2:, 1:-1]
    for i in range(iterations):
        center[:, i] = 0.2 * (center + north + east + west + south)
    return grid

4.1 grumpy - numpy Interoperability

The grumpy python module provides an ndarray object similar to the one that is provided by numpy. This object has the same methods, attributes, etc. as Numpy version of the same object. While it is not implemented this way, it can be thought of as a derived object of the numpy.ndarray. An instance of the grumpy.ndarray object represents a node in the DAG internal representation in Grumpy. To be able to inter-operate with numpy seamlessly, we have to ensure that each method provided by grumpy knows how to handle input arguments being numpy arrays. These typically form the leaves of the sequence of operations that are then evaluated lazily using Grumpy, and therefore act as inputs to the computation. If an unsupported operation is encountered (which would include print methods), before falling back to numpy, the nodes that correspond to the arrays being passed to the fallback routine need to be materialized. This triggers the materialization process, and the result is forwarded to the numpy methods as a numpy array.

4.2 Performance gains on multi-core CPUs and GPU

For the rest of the section we discuss some of the benchmarks that were targeted using this approach. We picked six benchmarks from different fields for evaluation. Black-Scholes is a widely used computation in financial application domain. KMeans is a basic clustering algorithm from statistical analysis domain. Jacobi stencil represents a stencil computation used in many simulation applications. Listing 6 so the numpy implementation used for the baseline. The fourth application is from deep-learning domain and is an RNN training sample. The Grumpy JIT-Compiler was implemented in LLVM-3.8. On the CPU, we can use LLVM to JIT-Compile to x86 code. On the GPU LLVM produces PTX [6] instructions, that are similar to assembly instructions. The CUDA [5] driver can compile the PTX to the machine instructions. We use CUDA-9.0 for our experiments. To support GPU execution, inputs to the kernel to be executed are automatically copied onto the device and the results are copied back to the host. Our implementation does not implement any specific CPU or GPU optimization to reduce the complexity of handling multiple backends. For example, we do not use vectorization for CPUs. We do not make use of fast shared memory on GPUs to improve performance. As a result the main benefit from using Grumpy would be only through fusion or through use of specialized libraries for certain operations.

Figure 3 shows the performance improvements over Numpy execution when using Grumpy. For each individual figure the speedup over Numpy when using 1, 2 and 4 CPU threads are shown (these lines use values from the left side y-axis). The figure also shows the speed up when executing the computation using a GP 100 (using the value from the right side y-axis). The performance numbers include the overhead of JIT compilation. It is expected that for small problem sizes, the overhead of JIT compilation dominates. As a result it should be expected that Grumpy would be considerably slower than Numpy. As problem size increases and the computation time dominates the overall execution time, the performance benefits of fusion in Grumpy as well as the ability to execute the computation in parallel on CPUs or to offload to GPUs starts showing dividends. We present below an analysis of the performance improvements on each of these benchmarks.

Black-Scholes (Figure 3a) is a computation that contain a lot of point-wise operations which could be completely fused. For small problem sizes, the JIT compilation overhead dominates, but for large problem sizes, Grumpy provides as much as 76x speed up over Numpy. No hand tuned kernels from libraries are needed for executing this computation. KMeans computation is inherently poorly suited for the GPU execution model due to irregular accesses to the input data during clustering. For this computation as well, there are no computations offloaded to libraries. Due to these factors, the GPU performance (Figure 3b) is not as drastic from Grumpy. Interestingly, for large problem sizes, the multi-core CPU performance shows good improvement, both due to fusion and parallelism.

The Jacobian stencil computation shows that Grumpy is able to fuse the computation into a single kernel even when slicing. The generated code is what one would have written in a low-language like CUDA. An interesting point to note is that slicing in Numpy doesn’t create a new array, but a view of the same buffer. That is the main reason behind almost no improvement on CPU from fusion. Further, being bandwidth bound, parallelism doesn’t help as much on the CPU. GPU performance still shows about 6 times improvement over Numpy.

The RNN training sample has a lot of dot products, and very few sequences of point functions. This results in the compilation overhead having a major impact on the performance. Consequently, Grumpy obtains a speed up of just 2.5 times over Numpy when running on GPUs. On CPUs no improvement is seen. One issue here is specific to the current implementation. Grumpy doesn’t use BLAS libraries for CPUs. Instead it uses a rudimentary matrix-matrix multiply kernel which is not optimized for cache or to use vector instruction units on CPUs. Since matrix-matrix multiplies...
form a major portion of the computation, this implementation deficiency hurts the speed up achieved with Grumpy on CPUs.

Another interesting metric to look at is the performance benefit when the JIT compilation overhead is not accounted for. This would be an estimate of the benefit from fusion and library usage when compared to Numpy. For each of the benchmark, Figure 4 shows the speed up over Numpy when the JIT compilation overhead is not included in the overall execution time for Grumpy. In general, one would expect that for small problem sizes the JIT compilation overhead is large, and this is shown to be the case. The JIT overhead seems to affect RNN (Figure 4d) the most due to high startup cost, and many small kernels compiled.

5 Related Work

Previous works have targeted a similar approach. Bohrium [9] offers similar support for accelerating Numpy frameworks on CPU and GPUs. It effectively supports lazy evaluation by use of a GPU Vector Engine that aggregates operations into a single CUDA kernel. This effectively implements lazy evaluation, but does not seem to have a DAG IR that can allow further optimizations like CSE at the level of array expressions. While such operations are not currently implemented in Grumpy, having an explicit DAG IR opens the possibility to do more complex optimization on array expressions.

ArrayFire [15] provides a similar interface to array computing as Numpy and targets multiple architectures as well. Since it doesn’t support Numpy directly, any Numpy application would have to be manually ported to this framework. CuPy [7] is listed as a drop-in replacement of Numpy, but fusion is only possible through user defined functions through special API. Theano [13] with PyCUDA provides a similar interface. Unlike these frameworks, Grumpy and Bohrium are true drop-in replacement for Numpy that automatically generate fused kernels for element-wise operations.

There have also been previous work that support a similar execution model specifically for Deep Learning applications. XLA [3] is a compiler framework within Tensorflow that intercepts operations in Tensorflow to build a graph representation of the operation sequence and JIT compiles them. These meta operations are then inserted back into the TensorFlow graph for execution. While it addresses many of the similar concerns, the focus of this work has mainly been...
Deep-Learning applications. NNVM [11] is a compiler framework similar to XLA for MxNET. PyTorch [12] has recently added a JIT compilation support as well. Being specific to deep-learning the space of computations supported by these are not as general as application written in Numpy.

6 Future Work

In this paper we have discussed Grumpy, a drop-in replacement for Numpy that can automatically build a representation of operations specified in a Numpy application. This representation is then used to fuse operations and execute them either on multicore CPUs or GPUs. For operations where a hand-tuned implementation is available these are used automatically. While the performance evaluation shown in Section 4 show considerable promise, there are several bottlenecks that need to be addressed.

The main bottleneck is the cost of JIT compilation. Strategies that hide this cost need to be incorporated into Grumpy. One way to do this is through pipelining. The entire computation is not executed as a single fused function in Grumpy, but rather a sequence of functions. It is possible to overlap the compilation with the execution of these functions.

The generated code could also be made more efficient. The Grumpy generated code doesn’t employ machine specific optimization like use of vector instructions on CPUs or shared memory on GPUs. On CPUs, Grumpy doesn’t make use of efficient BLAS libraries either.

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