Benchmark time series data sets for PyTorch – the torchtime package

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Abstract

The development of models for Electronic Health Record data is an area of active research featuring a small number of public benchmark data sets. Researchers typically write custom data processing code but this hinders reproducibility and can introduce errors. The Python package torchtime provides reproducible implementations of commonly used PhysioNet and UEA & UCR time series classification repository data sets for PyTorch. Features are provided for working with irregularly sampled and partially observed time series of unequal length. It aims to simplify access to PhysioNet data and enable fair comparisons of models in this exciting area of research.

1 Why torchtime?

The development and benchmarking of models for time series that are irregularly sampled, partially observed and of unequal length is an area of active research. An important application is Electronic Health Record (EHR) data which feature challenging patterns of missingness and sources of bias including informative observation [1]. Access to EHR data is tightly controlled and there are a small number of public data sets. Each year, the major machine learning conferences include a number of papers using PhysioNet [2] challenge and MIMIC [3, 4] EHR data. In addition, resources such as the UEA & UCR time series classification repository [5] provide data sets across a range of domains that are useful for demonstrating model generality and in ablation studies.

Current best practice for reproducibility and the fair comparison of models [6] is to make available all the data and code supporting results, including any code used to prepare data for modelling. Data processing approaches vary, often for good reason. However, the repetition of writing broadly similar data classes is wasteful and can introduce errors.

The Python package torchtime addresses these issues by providing implementations of commonly used data sets for PyTorch. It simplifies access to PhysioNet and UEA & UCR repository data, removing the need for researchers to write their own data classes and enabling better research by providing reproducible implementations to level the model development and benchmarking playing field.

∗Equal contribution.
For example, controlling the level of missingness in a data set.
Within reason, as medical data can often not be made available due to its sensitive nature.

Preprint. Work in progress.
1.1 Related work

sktime [7] prepares UEA & UCR time series classification repository data sets for use in Python and medical_ts_datasets⁴ [8] prepares PhysioNet data for TensorFlow. torchtime builds on this work by providing PyTorch users with finer control of data splits, missing data simulation/imputation and the ability to append observational masks and time delta channels. The authors are unaware of a comprehensive Python package that prepares PhysioNet and other common benchmark time series classification data sets for PyTorch.

1.2 Paper structure

Section 2 demonstrates how torchtime simplifies the training of a basic RNN model on PhysioNet 2012 challenge data. Section 3 provides introductory material and section 4 covers torchtime usage in detail including code examples. Sections 5 and 6 provide additional information on working with missing data and sequences of unequal length. The appendices include further detail on the implementation, the API and the PhysioNet 2012 challenge data.

2 Introduction: torchtime in action

The following example fits the GRU-Simple model [9] to PhysioNet 2012 challenge data. GRU-Simple is a Gated Recurrent Unit (GRU) with an observational mask and the time since last observation (the "time delta") appended to input data.

```python
import numpy as np
import torch
import torch.nn as nn
from sklearn.metrics import roc_auc_score
from torch.utils.data import DataLoader
from torchtime.collate import packed_sequence
from torchtime.data import PhysioNet2012

BATCH_SIZE = 128
LEARNING_RATE = 1e-3
HIDDEN_SIZE = 64
N_EPOCHS = 250
SEED = 293120

device = "cuda" if torch.cuda.is_available() else "cpu"
device = torch.device(device)
torch.manual_seed(SEED)

physionet2012 = PhysioNet2012(
    split="train",
    train_prop=2/3,
    impute="forward",  # use forward imputation as in Che et al, 2018
time=False,
    mask=True,
    delta=True,
    seed=SEED,
)
```

Data is loaded using the torchtime.data.PhysioNet2012 class. The mask and delta arguments add an observational mask and time delta. As PhysioNet 2012 challenge data are sequences of unequal length, the torchtime.collate.pack_padded collate function is used to return training batches as PyTorch PackedSequence objects.

⁴https://github.com/ExpectationMax/medical_ts_datasets
train_loader = DataLoader(
    physionet2012, collate_fn=packed_sequence, batch_size=BATCH_SIZE
)

Note that random seeds are set in the data class (line 23) to ensure reproducibility of the training and validation data sets and in PyTorch (line 15) for reproducible model training.

GRU-Simple is used in a binary classification context by passing the final hidden state of the GRU to a fully connected linear layer with sigmoid activation, as the aim is to train a model to predict the probability of in-hospital death.

class GRUSimpleBinaryClassifier(nn.Module):
    def __init__(self, input_size, hidden_size):
        super(GRUSimpleBinaryClassifier, self).__init__()
        self.gru = nn.GRU(
            input_size=input_size,
            hidden_size=hidden_size,
            batch_first=True,
        )
        self.linear = nn.Linear(in_features=hidden_size, out_features=1)

    def forward(self, x, hx=None):
        _, h_n = self.gru(x, hx)
        return torch.sigmoid(self.linear(h_n).squeeze(0))

The PhysioNet 2012 challenge data has 45 channels. For the GRU-Simple model, an observational mask and time delta is added for each channel resulting in $45 \times 3 = 135$ input channels.

model = GRUSimpleBinaryClassifier(
    input_size=135,
    hidden_size=HIDDEN_SIZE,
).to(device)

The model is trained using the Adam optimiser and binary cross-entropy loss for 250 epochs. Predictions are made on the training data after each epoch and the area under the ROC curve is recorded.

optimizer = torch.optim.Adam(model.parameters(), lr=LEARNING_RATE)
loss_function = nn.BCELoss()

auc = np.full(N_EPOCHS, np.nan)
for epoch in range(N_EPOCHS):
    # Train model in batches
    for batch in train_loader:
        X = batch["X"].to(device)
        y = batch["y"][data.unsqueezes(1)].to(device)
        optimizer.zero_grad()
        pred = model(X)
        loss = loss_function(pred, y)
        loss.backward()
        optimizer.step()
    model.eval()

5One time channel, 37 time series channels and seven fixed variables: age, gender, height and type of ICU unit (one-hot encoded giving four channels).
No attempt was made to tune hyper-parameters or optimise performance in this simple example, however the best model during training returns an AUC of 79.5% on the validation data. The performance over five randomly generated seeds is (80.4 ± 1.2)%. This performance is consistent with the (80.8 ± 1.1)% reported in Horn et al. [8] despite different data splits, hyper-parameters and other model design choices.

3 Background information

torchtime is available from the Python Package Index. Installation instructions and documentation can be found at the project website, https://philipdarke.com/torchtime.

3.1 Supported data sets

All data sets in the UEA & UCR time series classification repository [5] and two PhysioNet repository [2] data sets are supported:

- Predicting Mortality of ICU Patients: The PhysioNet/Computing in Cardiology Challenge 2012 [10]
- Early Prediction of Sepsis from Clinical Data: The PhysioNet/Computing in Cardiology Challenge 2019 [11]

In addition, a binary prediction variant of the PhysioNet 2019 challenge is provided. As in Kidger et al. [12], the first 72 hours of data are used to predict whether the patient develops sepsis at any point during hospitalisation.

3.2 Batch first convention

torchtime uses the “batch first” convention under which data tensors are of shape 

\[ (n, s, c) \]

where \( n \) is number of batches, \( s \) sequence length, and \( c \) number of channels. Recurrent Neural Network models in PyTorch typically have a `batch_first` argument which should be set to True when using torchtime data sets.

3.3 Training and validation splits

All UEA & UCR repository data are provided in separate training and validation files in varying proportions. PhysioNet challenges are provided in two/three equal sized sets. torchtime combines all data and takes samples to create training, validation and, if applicable, test data sets in the proportions specified by the user.

3.4 Reproducibility

Stratified sampling and missing data simulation are non-deterministic, however data sets are reproduced for a given random seed and care is taken to maintain this behaviour across releases. For

6293120, 339980, 555902, 711053 and 977556. You may not be able to replicate these results due to hardware differences.

7https://physionet.org/content/challenge-2012/1.0.0/

8https://physionet.org/content/challenge-2019/1.0.0/

9Note that Kidger et al. [12] appear to take the first 72 rows of data rather than 72 hours as in torchtime.
completely reproducible results, all other non-deterministic behaviour should be controlled including batch generation and parameter initialisation. See https://pytorch.org/docs/stable/notes/randomness.html for guidance.

4 Using torchtime

Each data set in the torchtime.data module has a consistent API with attributes X, y and length:

- X are the time series data in a tensor of shape \((n, s, c)\) where \(n\) is the number of sequences, \(s\) the (longest) sequence length and \(c\) the number of channels. By default, the first channel is a time stamp and subsequent channels are as provided in the source data.\(^{10}\)
- y are target labels. These typically have shape \((n, l)\) where \(l\) is the number of classes.\(^{11}\)
- length are the length of each sequence in a tensor of shape \((n)\).

4.1 Creating a data set

There are two required arguments, split and train_prop. UEA & UCL repository data sets also require the dataset argument. See https://www.timeseriesclassification.com/dataset.php for a list of data sets.

split The split argument determines whether training, validation or, if applicable, test data are returned by the X, y and length attributes. The primary use of split is to specify the data returned when using a DataLoader (see 4.2). Data splits can also be accessed explicitly by appending _train, _val or _test to the attribute. For example, X_train returns training time series and y_val returns validation labels regardless of split.

train_prop Training and validation data sets are created by default. The train_prop argument sets the proportion of data allocated to training (see example 4.1). To create a training/validation/test split, also specify the proportion of data in the validation set using the val_prop argument (see example 4.2). Data splits are formed using stratified sampling.

```python
from torchtime.data import PhysioNet2012
physionet2012 = PhysioNet2012(
    split="train",
    train_prop=0.7,
)
```

Example 4.1: PhysioNet 2012 challenge data with a 70/30% training/validation split. The val_prop argument is not required.

4.2 Using DataLoaders

Data sets are typically passed to a PyTorch DataLoader for model training. torchtime.data classes return batches as a dictionary of tensors X, y and length. The split argument determines whether training, validation or, if applicable, test data are returned when using a DataLoader.

It is recommended to use one instance of a torchtime.data class for a data set. If DataLoaders are required for validation and/or test splits, an efficient approach is to pass the validation/test data to TensorDataset as in example 4.3. This avoids holding multiple complete copies of the data set in memory.

\(^{10}\)See appendix C for PhysioNet 2012 challenge channel order.

\(^{11}\)An exception is the PhysioNet 2019 challenge where a binary target is provided at each time point i.e. a tensor of shape \((n, s)\).
from torchtime.data import UEA

arrowhead = UEA(
    dataset="ArrowHead",
    split="train",
    train_prop=0.7,
    val_prop=0.2,
    seed=123,  # to reproduce example
)

Accessing data with the X, y and length attributes:

```python
>>> arrowhead.X  # shape (148, 251, 2)
tensor([[[ 0.0000, -1.8010],
            [ 1.0000, -1.7989],
            [ 2.0000, -1.7784],
            ...
            [248.0000, -1.7965],
            [249.0000, -1.7985],
            [250.0000, -1.8010]],
         ...
         [[ 0.0000, -2.4343],
          [ 1.0000, -2.4315],
          [ 2.0000, -2.3426],
          ...
          [248.0000, -2.4596],
          [249.0000, -2.4922],
          [250.0000, -2.4644]])

>>> arrowhead.y  # shape (148, 3)
tensor([[0., 0., 1.],
         ...
         [0., 0., 1.]]))

>>> arrowhead.length  # shape (148)
tensor([251, ... 251])
```

Example 4.2: The UEA & UCR repository data set ArrowHead with a 70/20/10% training/validation/test split (note both train_prop and val_prop must be specified). ArrowHead is a univariate time series presented as a supervised classification problem with three classes. There are 148 sequences in the training data, each with 251 observations and two data channels (a time stamp/index followed by the time series).
from torchtime.data import UEA
from torch.utils.data import DataLoader, TensorDataset

# Data set
arrowhead = UEA(
    dataset="ArrowHead",
    split="train",
    train_prop=0.7,
    val_prop=0.2,
    seed=123,  # to reproduce example
)

# Training data (see line 6)
train_dataloader = DataLoader(arrowhead, batch_size=32)

# Validation data
val_data = TensorDataset(
    arrowhead.X_val,
    arrowhead.y_val,
    arrowhead.length_val,
)
val_dataloader = DataLoader(val_data, batch_size=32)

# Test data
test_data = TensorDataset(
    arrowhead.X_test,
    arrowhead.y_test,
    arrowhead.length_test,
)
test_dataloader = DataLoader(test_data, batch_size=32)

Using the DataLoaders to iterate through batches:

```python
>>> train_batch = next(iter(train_dataloader))
>>> train_batch["X"].shape
torch.Size([32, 251, 2])  # sequences are 251 long with 2 channels

>>> val_batch = next(iter(val_dataloader))
>>> val_batch[1].shape
torch.Size([32, 3])  # labels have 3 classes

>>> test_batch = next(iter(test_dataloader))
>>> test_batch[2].shape
torch.Size([32])  # length of each sequence
```

Alternatively, to access full validation/test data:

```python
>>> arrowhead.X_val.shape
torch.Size([42, 251, 2])  # 42 sequences in validation data

>>> arrowhead.y_test.shape
torch.Size([21, 3])  # 21 sequences in test data
```

Example 4.3: An efficient strategy to generate iterable DataLoaders for training, validation and test data splits. Note that train_dataloader returns batches as a named dictionary, but val_dataloader and test_dataloader return a list [X, y, length]. Alternatively, the full training/test data can be accessed using the X/y/length_val and X/y/length_test attributes.
4.3 Other options

See Appendix B for the full API. In summary:

- Arguments are provided to impute and, for UEA & UCR data sets, simulate missing data. See 5.2 and 5.3 for more information.
- By default, a time stamp is appended to time series data as the first channel. This can be removed by setting the `time` argument to `False`. Additional arguments are provided to add missing data masks and time delta channels, see 5.1.
- The boolean argument `standardise` standardises the time series. The training data mean $\mu_t$ and standard deviation $\sigma_t$ are calculated for each channel $c$ and the transform $(x_c - \mu_t^c)/\sigma_t^c$ applied to the training, validation and, if applicable, test data. By default, data is not standardised.
- Data splits are formed by stratified sampling. The `seed` argument can be set to return reproducible splits. By default, no seed is set.
- When a data set is first initialised, data are downloaded, processed and cached in the `.torchtime` directory. By default the cache is placed the project root but this can be changed using the `path` argument, for example to share a cache across projects. Set the `overwrite_cache` argument to `True` to refresh the cache.

5 Working with missing data

5.1 Observational masks and time delta channels

Patterns of missingness can be informative in some applications. For example, a doctor may be more likely to order a particular diagnostic test if they believe a patient has a medical condition. The presence or absence of this test result provides information about patient health in addition to its value.

Missing data/observational masks can be used to inform models of missing data. These are appended by setting the `mask` argument to `True`.

```python
from torchtime.data import UEA

char_traj = UEA(
    dataset="CharacterTrajectories",
    split="train",
    train_prop=0.7,
    missing=[0.8, 0.2, 0.5], # simulate missing data
    mask=True, # add observational mask channels
    seed=456, # to reproduce example
)
```

Example sequence (first five observations):

```text
>>> char_traj.X[0, 0:5]
tensor([[ 0.0000,  nan,  0.1640,  0.6631,  0.0000,  1.0000,  1.0000],
        [ 1.0000, -0.0678,  0.2123,  nan,   1.0000,  1.0000,  0.0000],
        [ 2.0000, -0.1190,  0.2448,  nan,   1.0000,  1.0000,  0.0000],
        [ 3.0000,  nan,    nan,  1.0139,  0.0000,  0.0000,  1.0000],
        [ 4.0000,  nan,  0.2550,  nan,   0.0000,  1.0000,  0.0000]])
```

Example 5.1: Simulated missing data for the UEA & UCR repository data set CharacterTrajectories (see 5.3). The final three channels are an observational mask where 1.0 indicates data were recorded.
Some models require the time since the previous observation (the time delta $\delta$), for example GRU-D [9]. This is added using the delta argument. See Che et al. [9] for implementation details.

The time, mask and delta arguments can be combined as required. The channel order is always time stamp, time series data, missing data mask then time delta.

```python
>>> char_traj.X[0, 0:5]
tensor([[ 0.0000,  nan,  0.1640,  0.6631,  0.0000,  0.0000,  0.0000],
        [ 1.0000, -0.0678,  0.2123,  nan,  1.0000,  1.0000,  1.0000],
        [ 2.0000, -0.1190,  0.2448,  nan,  1.0000,  1.0000,  2.0000],
        [ 3.0000,  nan,  1.0139,  1.0000,  1.0000,  3.0000],
        [ 4.0000,  nan,  0.2550,  nan,  2.0000,  2.0000,  1.0000]])
```

Example 5.2: The final three channels are time deltas $\delta_t,c$ for the UEA class in example 5.1 with delta=True (rather than mask). The second time series channel is observed at times 2 and 4 therefore $\delta_{4,1}$ is 2 i.e. two time units since last observation. Note that $\delta_{0,c} = 0 \forall c \in X$ by definition.

5.2 Imputation

Off-the-shelf deep learning models are unable to handle missing values. A simple strategy to overcome this limitation is to impute missing values, and torchtime supports “zero”, mean, forward and custom imputation functions using the impute argument. Imputation has no impact on the observational mask or time delta channels.

- Under zero imputation, missing data are replaced with the value zero.
- Under mean imputation, missing data are replaced with the training data channel mean.
- Under forward imputation, missing values are replaced with the previous channel observation. Note that this approach does not impute initial missing values, therefore these are replaced with the corresponding channel mean in the training data.
- Alternatively a custom imputation function can be passed to impute. This must accept the arguments $X$ (time series), $y$ (labels), fill (the training data means/modes for each channel, see 5.2.1) and select (the channels to impute). It must return tensors $X$ and $y$ post imputation.

The mean and forward imputation implementations ensure that knowledge of the time series at times $t > i$ is not used when imputing values at time $i$. This is required when developing models that make online predictions.

5.2.1 Handling categorical variables

Mean imputation is unsuitable for categorical variables. The channel indices of categorical variables should be passed to the categorical argument to impute values with the training data channel mode rather than the mean. This is also required for forward imputation to appropriately impute initial missing values. The calculated channel mean/mode can be overridden using the channel_means argument, for example to impute missing data with a fixed value.

5.3 Simulating missing data for UEA & UCR repository data sets

Data sets in the UEA & UCR repository are typically regularly sampled and fully observed. To aid model development, missing data can be simulated in these data using the missing argument. Data are dropped at random and replaced with NaNs.

5.3.1 Regularly sampled data with missing time points

If missing is a single value, data are dropped across all channels. This simulates regularly sampled data where some time points are not recorded for example dropped data over a network.
from torchtime.data import UEA

char_traj = UEA(
    dataset="CharacterTrajectories",
    split="train",
    train_prop=0.7,
    missing=0.5,  # 50% missing
    seed=123,  # to reproduce example
)

dataloader = DataLoader(char_traj, batch_size=32)

Example sequence (first five observations):

```python
>>> char_traj.X[0, 0:5]
tensor([[ 0.0000, -0.1849, 0.1978, 0.3263],
        [ 1.0000, nan, nan, nan],
        [ 2.0000, -0.3744, 0.2511, 0.4260],
        [ 3.0000, nan, nan, nan],
        [ 4.0000, nan, nan, nan]])
```

Example 5.3: Simulated missing data for the UEA & UCR repository data set CharacterTrajectories. Note that each time point is either fully observed or missing.

5.3.2 Regularly sampled data with partial observation

Alternatively, data can be dropped independently for each channel by passing a list representing the proportion missing for each channel. This simulates regularly sampled data with partial observation, i.e. not all channels are recorded at each time point.

```python
>>> char_traj.X[0, 0:5]
tensor([[ 0.0000, nan, 0.1978, 0.3263],
        [ 1.0000, nan, 0.2399, nan],
        [ 2.0000, nan, 0.2511, nan],
        [ 3.0000, nan, nan, 0.4016],
        [ 4.0000, nan, nan, 0.3410]])
```

Example 5.4: Simulated missing data for the UEA class in example 5.3 with missing=[0.8, 0.2, 0.5]. Note that each time point has a varying number of observations.

6 Sequences of unequal length

PhysioNet and some\textsuperscript{12} UEA & UCR data sets feature sequences of unequal length. Tensors must be of regular shape, therefore sequences are padded\textsuperscript{13} to the length of the longest sequence with NaNs. The length of each sequence before padding is available using the length attribute.

Data sets of variable length can be efficiently represented in PyTorch using a PackedSequence object. These are formed using torch.nn.utils.rnn.pack_padded_sequence() which by default expects the input batch to be sorted in descending length. Two collate functions are provided to support the use of PackedSequence objects in models:

\textsuperscript{12}For example CharacterTrajectories.

\textsuperscript{13}Padding is carried out at data set level to reduce the data processing required at batch generation. This increases memory usage if $\max(s_b) \ll \max(s_d)$ where $s_b$ and $s_d$ are sequence lengths for the batch and data set respectively.
• `torchtime.collate.sort_by_length()` sorts each batch by descending length.
• `torchtime.collate.packed_sequence()` returns X and y as a PackedSequence object.

Custom collate functions should be passed to the `collate_fn` argument of a DataLoader.

7 Conclusion

`torchtime` is a Python package providing PhysioNet challenge and UEA & UCR repository data sets for use in PyTorch. Flexible data splits, missing data imputation, observational masks and time delta channels are supported. In addition, missing data can be simulated for UEA & UCR repository data sets. `torchtime` is well documented and open source under the MIT license.

Our aim is to support model development and benchmarking for complex time series data with a focus on Electronic Health Records. The longer term intention is to provide PyTorch implementations of relevant deep learning models. Feedback and suggestions for additional data sets, features or models are welcome.

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`torchtime` uses some of the data processing ideas in Kidger et al. [12] and Che et al. [9].

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Contributions

Philip Darke conceptualised the work, developed `torchtime`, drafted the manuscript and is the guarantor. Paolo Missier and Jaume Bacardit supervised the work. All authors critically revised the manuscript and approved the final version.

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A Implementation

A.1 Package structure

The `torchtime.data` module contains the following classes that inherit from the PyTorch `torch.utils.data.Dataset` abstract class and can be passed to a DataLoader:

- `torchtime.data.PhysioNet2012`
- `torchtime.data.PhysioNet2019`
- `torchtime.data.PhysioNet2019Binary`
- `torchtime.data.UEA`

The `torchtime.collate` module provides collate functions for working with sequences of unequal lengths and the `torchtime.impute` module provides helper functions for data imputation. Full API documentation is available at https://philipdarke.com/torchtime.

A.2 High-level approach

When creating an instance of a data class:

1. `torchtime` checks if the data set has been cached and, if so, loads and validates it by checking SHA256 checksums.
2. If no cache is available, the checksum test fails or the argument `overwrite_data` is set, data is downloaded, processed and combined to create a master data set. The tensors $X$, $y$ and $\text{length}$ as defined in section 4 are cached in the `.torchtime` directory.
3. Missing data is simulated if applicable.
4. Time stamp, observational mask and time delta channels are appended as required.
5. Training, validation and test data splits are formed using stratified sampling.
6. Data is standardised if specified.
7. Missing data is imputed if specified.
8. The attributes $X$, $y$ and $\text{length}$ are set to the data split specified by the `split` argument.

Data format varies across PhysioNet challenges but EHR data are typically provided as a separate text file for each participant. `torchtime` downloads all data from PhysioNet and iterates through each file to extract the time series data. The 2012 challenge requires additional processing as the data is in a “long” format, channels are not provided in order (see appendix C) and the indicator $-1$ is used for missing data.

For UEA & UCR repository data, a similar approach to `sktime` [7] is used to download and extract the time series from the repository.

A.3 Defining a new data set

A data class is defined by inheriting the private class `torchtime.data._TimeSeriesDataset` and overloading the `get_data` method. `get_data` must download and process the data set and return the tensors $X$, $y$ and $\text{length}$ for the full data. The `torchtime.utils` module contains private helper functions to simplify the task.

A.4 Development and quality control

The primary dependencies are PyTorch [13], `sktime` [7] for extracting time series from `.ts` files and `scikit-learn` [14] for stratified sampling. Python Poetry was used for packaging.

To validate data integrity, the SHA256 is checked when a data set is loaded from cache. This prevents the accidental use of an invalid data set. To aid code quality, a comprehensive suite of unit tests are run to test core functionality and ensure reproducibility of data sets when making changes to the code base.
torchtime is open source software under the MIT license and code is available at https://github.com/philipdarke/torchtime.

A.5 Results

The experiments in this manuscript were carried out on a machine running Ubuntu 22.04.4 LTS with a single NVIDIA RTX 3070 GPU and using torchtime v0.5.0.

B API

B.1 Required arguments
dataset The data set to return. String. **UEA & UCR data sets only**.
split The data split returned by attributes X, y and length. String: “train”, “val” (validation) or “test”.
train_prop The proportion of data in the training set. Float.

B.2 Optional arguments
val_prop The proportion of data in the validation set. Float.
missing The proportion of data to drop at random (see 5.3). If missing is a single value, data are dropped from all channels. To drop data independently from each channel, pass the proportion missing for each channel in a list. **Float or list of floats (default 0.0). UEA & UCR data sets only**.
impute The method used to impute missing data (see 5.2). Function or string: “none”, “zero”, “mean” or “forward” (default “none”).
categorical Channel indices of categorical variables. Only required if imputing data. **List of integers. UEA & UCR data sets only**.
channel_means Override the calculated channel mean/mode, for example \{1:4.5, 3:7.2\} overrides channels 1 and 3 with the values 4.5 and 7.2 respectively. Only used if imputing data. **Dictionary with integer keys and values (default \{\}). UEA & UCR data sets only**.
time Append a time stamp as the first channel. **Boolean (default True)**.
mask Append an observational mask for each channel. **Boolean (default False)**.
delta Append the time since previous observation for each channel. **Boolean (default False)**.
standardise Standarise the time series. **Boolean (default False)**.
overwrite_cache Refresh the cached dataset. **Boolean (default False)**.
path Path to the .torchtime cache directory. **String (default "." i.e. the project root directory)**.
seed Random seed for reproducibility. **Integer (default "none")**.

C PhysioNet 2012

C.1 Time series channels

Data channels are in the following order:

| Channel | Description |
|---------|-------------|
| 0. Mins | Minutes since ICU admission. Derived from the PhysioNet time stamp. |
| 1. Albumin | Albumin (g/dL). |
| 2. ALP | Alkaline phosphatase (IU/L). |
| 3. ALT | Alanine transaminase (IU/L). |
| 4. AST | Aspartate transaminase (IU/L). |
| 5. Bilirubin | Bilirubin (mg/dL). |
| 6. BUN | Blood urea nitrogen (mg/dL). |
7. **Cholesterol**  Cholesterol (mg/dL).
8. **Creatinine**  Serum creatinine (mg/dL).
9. **DiasABP**  Invasive diastolic arterial blood pressure (mmHg).
10. **FiO2**  Fractional inspired O\(_2\) (0-1).
11. **GCS**  Glasgow Coma Score (3-15).
12. **Glucose**  Serum glucose (mg/dL).
13. **HCO3**  Serum bicarbonate (mmol/L).
14. **HCT**  Hematocrit (%).
15. **HR**  Heart rate (bpm).
16. **K**  Serum potassium (mEq/L).
17. **Lactate**  Lactate (mmol/L).
18. **Mg**  Serum magnesium (mmol/L).
19. **MAP**  Invasive mean arterial blood pressure (mmHg).
20. **MechVent**  Mechanical ventilation respiration (0:false, or 1:true).
21. **Na**  Serum sodium (mEq/L).
22. **NDiasABP**  Non-invasive diastolic arterial blood pressure (mmHg).
23. **NIMAP**  Non-invasive mean arterial blood pressure (mmHg).
24. **NI SysABP**  Non-invasive systolic arterial blood pressure (mmHg).
25. **PaCO2**  Partial pressure of arterial CO\(_2\) (mmHg).
26. **PaO2**  Partial pressure of arterial O\(_2\) (mmHg).
27. **pH**  Arterial pH (0-14).
28. **Platelets**  Platelets (cells/nL).
29. **RespRate**  Respiration rate (bpm).
30. **SaO2**  O\(_2\) saturation in hemoglobin (%).
31. **SysABP**  Invasive systolic arterial blood pressure (mmHg).
32. **Temp**  Temperature (°C).
33. **TroponinI**  Troponin-I (µg/L). Note this is labelled TropI in the PhysioNet data dictionary.
34. **TroponinT**  Troponin-T (µg/L). Note this is labelled TropT in the PhysioNet data dictionary.
35. **Urine**  Urine output (mL).
36. **WBC**  White blood cell count (cells/nL).
37. **Weight**  Weight (kg).
38. **Age**  Age (years) at ICU admission.
39. **Gender**  Gender (0: female, or 1: male).
40. **Height**  Height (cm) at ICU admission.
41. **ICUType1**  Type of ICU unit (1: Coronary Care Unit).
42. **ICUType2**  Type of ICU unit (2: Cardiac Surgery Recovery Unit).
43. **ICUType3**  Type of ICU unit (3: Medical ICU).
44. **ICUType4**  Type of ICU unit (4: Surgical ICU).

Channels 38 to 41 do not vary with time. Channels 11 (GCS) and 27 (pH) are assumed to be ordinal and are imputed using the same method as a continuous variable. Variable 20 (MechVent) has value NaN (the majority of values) or 1. It is assumed that value 1 indicates mechanical ventilation and NaN indicates either missing data or no mechanical ventilation. Accordingly, the channel mode is assumed to be zero. Channels 41 to 44 are the one-hot encoded PhysioNet variable ICUType.

**C.2 Outcome**

The outcome is the **In-hospital death** field (0: survivor, or 1: died in hospital).