River: machine learning for streaming data in Python

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Abstract

River is a machine learning library for dynamic data streams and continual learning. It provides multiple state-of-the-art learning methods, data generators/transformers, performance metrics and evaluators for different stream learning problems. It is the result from the merger of the two most popular packages for stream learning in Python: Creme and scikit-multiflow. River introduces a revamped architecture based on the lessons learnt from the seminal packages. River’s ambition is to be the go-to library for doing machine learning on streaming data. Additionally, this open source package brings under the same umbrella a large community of practitioners and researchers. The source code is available at https://github.com/online-ml/river.

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**Keywords:** Stream learning, online learning, data stream, concept drift, supervised learning, unsupervised learning, Python.

1. Introduction

In machine learning, the conventional approach is to process data in batches or chunks. Batch learning models assume that all the data is available at once. When a new batch of data is available, said models have to be retrained from scratch. The assumption of data availability is a hard constraint for the application of machine learning in multiple real-world applications where data is continuously generated. Additionally, storing historical data requires dedicated storage and processing resources which in some cases might be impractical, e.g. storing the network logs from a data center. A different approach is to treat data as a stream, in other words, as an infinite sequence of items; data is not stored and models continuously learn one data sample at a time (Bifet et al., 2018).

**Creme** (Halford et al., 2019) and **scikit-multiflow** (Montiel et al., 2018) are two open-source libraries to perform machine learning in the stream setting. These original libraries started as independent projects with the same goal, to provide to the community the tools to advance the state of streaming machine learning and promote its usage on real-world applications. **River** is the merger of these projects, combining the strengths of both projects while leveraging the lessons learnt from their development. **River** is mainly written in Python, with some core elements written in Cython (Behnel et al., 2011) for performance.

Supported applications of **river** are generally as diverse as those found in traditional batch settings, including: classification, regression, clustering and representation learning, multi-label and multi-output learning, forecasting, and anomaly detection.

2. Architecture

Machine learning models in **river** are extended classes of specialized **mixins** depending on the learning task, e.g. classification, regression, clustering, etc. This ensures compatibility across the library and eases the extension/modification of existing models and the creation of new models compatible with **river**.

All predictive models perform two core functions: learn and predict. Learning takes place in the **learn_one** method (updates the internal state of the model). Depending on the learning task, models provide predictions via the **predict_one** (classification, regression, and clustering), **predict_proba_one** (classification), and **score_one** (anomaly detection) methods. Note that **river** also contains transformers, which are stateful objects that transform an input via a **transform_one** method.

In the following example, we show a complete machine learning task (learning, prediction and performance measurement) easily implemented in a couple of lines of code:

```python
>>> from river import evaluate
>>> from river import metrics
>>> from river import synth
>>> from river import tree
```
```python
>>> stream = synth.Waveform(seed=42).take(1000)
>>> model = tree.HoeffdingTreeClassifier()
>>> metric = metrics.Accuracy()

>>> evaluate.progressive_val_score(stream, model, metric)
Accuracy: 77.58%
```

### 2.1 Why dictionaries?

The de facto container for *multidimensional*, homogeneous arrays of fixed-size items in Python is the `numpy.ndarray` (van der Walt et al., 2011). However, in the stream setting, data is available one sample at a time. Dictionaries are an efficient way to store *one-dimensional* data with $O(1)$ lookup and insertion (Gorelick and Ozsvaldl, 2020). Additional advantages of dictionaries include:

- Accessing data by name rather than by position is convenient from a user perspective.
- The ability to store different data types. For instance, the categories of a nominal feature can be encoded as strings alongside numeric features.
- The flexibility to handle new features that might appear in the stream (feature evolution) and sparse data.

River provides an efficient Cython-based extension of dictionary structures that supports operations commonly applied to unidimensional arrays. These operations include, for instance, the four basic algebraic operations, exponentiation, and the dot product.

### 2.2 Pipelines

Pipelines are an integral part of River. They are a convenient and elegant way to “chain” a sequence of operations and warrant reproducibility. A pipeline is essentially a list of estimators that are applied in sequence. The only requirement is that the first $n - 1$ steps are transformers. The last step can be a regressor, a classifier, a clusterer, a transformer, etc. For example, some models such as logistic regression are sensitive to the scale of the data. A best practice is to scale the data before feeding it to a linear model. We can chain the scaler transformer with a logistic regression model via a `|` (pipe) operator as follows:

```python
>>> from river import linear_model
>>> from river import preprocessing

>>> model = (preprocessing.StandardScaler() |
...          linear_model.LogisticRegression())
```

1. The actual performance of this operations can be affected by the size of the data to store. We assume that samples from a data stream are relatively small.
2.3 Instance-incremental and batch-incremental

Instance-incremental methods update their internal state one sample at a time. Another approach is to use mini-batches of data, known as batch-incremental learning. River offers some limited support for batch-incremental methods. Mixins include dedicated methods to process data in mini-batches, designated by the suffix \_many instead of \_one, e.g. \texttt{learn\_one()} – \texttt{learn\_many()}. These methods expect \texttt{pandas.DataFrame} (pandas development team, 2020) as input data, a flexible data structure with labeled axes. This in turn allows a uniform interface for both instance-incremental and batch-incremental learning.

3. Benchmark

We benchmark the implementation of 3 ml algorithms\(^2\): Gaussian Naive Bayes (GNB), Logistic Regression (LR), and Hoeffding Tree (HT). Table 1 shows similar accuracy for all models. Table 2 shows the processing time (learn and predict) for the same models where river models perform at least as fast but overall faster than the rest. Tests are performed on the Elec2 dataset (Harries and Wales, 1999) which has 45312 samples with 8 numerical features. Reported processing time is the average of running the experiment 7 times on a system with a 2.4 GHz Quad-Core Intel Core i5 processor and 16GB of RAM. Additional benchmarks for other ml tasks and packages are available in the project’s repository\(^3\).

4. Summary

River has been developed to satisfy the evolving needs of a major machine learning community – learning from data streams. The architecture has been designed for both flexibility and ease of use, with the goal of supporting successful use in diverse domains, including in industrial applications as well as in academic research. On benchmark tests performs at least as well as related (but more limited) methods.

\(^2\) These are incremental-learning models. \texttt{scikit-learn} has many other batch-learning models available. On the other hand, \texttt{river} includes incremental-learning methods available in \texttt{Creme} and \texttt{scikit-multiflow}.

\(^3\) https://github.com/online-ml/river/tree/master/benchmarks
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