Scikit-Multiflow: A Multi-output Streaming Framework

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Abstract

scikit-multiflow is a multi-output/multi-label and stream data mining framework for the Python programming language. Conceived to serve as a platform to encourage democratization of stream learning research, it provides multiple state of the art methods for stream learning, stream generators and evaluators. scikit-multiflow builds upon popular open source frameworks including scikit-learn, MOA and MEKA. Development follows the FOSS principles and quality is enforced by complying with PEP8 guidelines and using continuous integration and automatic testing. The source code is publicly available at https://github.com/scikit-multiflow/scikit-multiflow.

Keywords: Machine Learning, Stream Data, Multi-output, Drift Detection, Python

1. Introduction

Recent years have witnessed the proliferation of Free and Open Source Software (FOSS) in the research community. Specifically, in the field of Machine Learning, researchers have benefited from the availability of different frameworks that provide tools for faster development, allow replicability and reproducibility of results and foster collaboration.

scikit-learn (Pedregosa et al., 2011) is the most popular open source software machine learning library for the Python programming language. It features various classification, regression and clustering algorithms including support vector machines, random forest, gradient boosting, k-means and DBSCAN, and is designed to inter-operate with the Python numerical and scientific packages NumPy and SciPy.

MOA (Bifet et al., 2010) is the most popular open source framework for data stream mining, with a very active growing community. It includes a collection of machine learning al-
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algorithms (classification, regression, clustering, outlier detection, concept drift detection and recommender systems) and tools for evaluation. Related to the WEKA project (Hall et al., 2009), MOA is also written in Java, while scaling to more demanding problems.

The MEKA project (Read et al., 2016) provides an open source implementation of methods for multi-label learning and evaluation. In multi-label classification, the aim is to predict multiple output variables for each input instance. This different from the ‘standard’ case (binary, or multi-class classification) which involves only a single target variable.

Following the FOSS principles, we introduce scikit-multiflow, a multi-output/multi-label and data stream framework for the Python programming language. scikit-multiflow is inspired in the popular frameworks scikit-learn, MOA and MEKA.

As a multi-output streaming framework, scikit-multiflow serves as a bridge between research communities that have flourished around the aforementioned popular frameworks, providing a common ground where they can thrive. scikit-multiflow assists on the democratization of Stream Learning by bringing this research field closer to the Machine Learning community, given the increasing popularity of the Python programming language. The objective is two-folded: First, fill the void for a stream learning framework in Python, which can interact with available tools such as scikit-learn and extends the set of available state-of-the-

Table 1: Available methods. Methodologies on the left, and frameworks on the right of the vertical bar.

| Methodologies | Java | Python |
|---------------|------|--------|
| Classification | Regression | Single-Output | Multi-Label | Multi-Output | Drift Detection |
| kNN | ✓ | ✓ | ✓ | ✓ | ✓ |
| kNN + ADWIN | ✓ | ✓ | ✓ | ✓ | ✓ |
| SAM kNN | ✓ | ✓ | ✓ | ✓ | ✓ |
| Hoeffding Tree | ✓ | ✓ | ✓ | ✓ | ✓ |
| Hoeffding Adaptive Tree | ✓ | ✓ | ✓ | ✓ | ✓ |
| Adaptive Random Forest | ✓ | ✓ | ✓ | ✓ | ✓ |
| Oza Bagging | ✓ | ✓ | ✓ | ✓ | ✓ |
| Leverage Bagging | ✓ | ✓ | ✓ | ✓ | ✓ |
| Multi-output Learner | ✓ | ✓ | ✓ | ✓ | ✓ |
| SGD | ✓ | ✓ | ✓ | ✓ | ✓ |
| Naive Bayes | ✓ | ✓ | ✓ | ✓ | ✓ |
| MLP | ✓ | ✓ | ✓ | ✓ | ✓ |
| ADWIN | ✓ | ✓ | ✓ | ✓ | ✓ |
| DDM | ✓ | ✓ | ✓ | ✓ | ✓ |
| EDDM | ✓ | ✓ | ✓ | ✓ | ✓ |
| Page Hinkley | ✓ | ✓ | ✓ | ✓ | ✓ |

| Reference | |
|-----------|------|
| Bishop (2006) | |
| Bifet et al. (2018) | |
| Losing et al. (2017) | |
| Hulten et al. (2001) | |
| Bifet et al. (2018) | |
| Gomes et al. (2017) | |
| Oza (2005) | |
| Bifet et al. (2018) | |
| Bishop (2006) | |
| Bishop (2006) | |
| Bishop (2006) | |
| Bishop (2006) | |
| Bifet et al. (2018) | |
| Gama et al. (2004) | |
| Bifet et al. (2018) | |
| Page (1954) | |

* Depending on the base learner.
† We have only listed incremental methods for data-streams; MEKA and scikit-learn have many other batch-learning models available. MEKA in particular, has many problem-transformation methods which may be incremental depending on the base learner (it is able to use those from the MOA framework).
art methods on this platform. Second, provide a set of tools to facilitate the development of stream learning research.

It is important to notice that scikit-multiflow complements scikit-learn, whose primary focus is batch learning, expanding the set of free and open source tools for Stream Learning. In addition, scikit-multiflow can be used within Jupyter Notebooks, a popular interface in the Data Science community. Special focus in the design of scikit-multiflow is to make it friendly to new users and familiar to experienced ones.

scikit-multiflow contains stream generators, learners, change detectors and evaluation methods. Stream generators include: Multi label, Random-RBF, Random-RBF with drift, Random Tree Regression, SEA and Waveform. Learners and change detectors are listed in Table 1. Available evaluators are prequential and hold-out.

2. Notation and background

Consider a continuous stream of data $A = \{(\vec{x}_t, y_t)\}_{t = 1, \ldots, T}$ where $T \to \infty$. $\vec{x}_t$ is a feature vector and $y_t$ the corresponding target where $y$ is continuous in the case of regression and discrete for classification. The objective is to predict the target $y$ for an unknown $\vec{x}$. Two classes are considered in binary classification, $y \in \{0, 1\}$, while $K > 2$ labels are used in multi-label classification, $y \in \{1, \ldots, K\}$. For both binary and multi-label classification only one class is assigned per instance. On the other hand, in multi-output learning $y$ is a targets vector and $\vec{x}_t$ can be assigned multiple-targets at the same time.

Different to batch learning, where all data is available for training $\text{train}(X, y)$; in stream learning, training is performed incrementally as new data is available $\text{train}(\vec{x}_i, y_i)$. Performance $P$ of a given model is measured according to some loss function that evaluates the difference between the set of expected labels $Y$ and the predicted ones $\hat{Y}$. Hold-out evaluation is a popular performance evaluation method for batch and stream settings, where tests are performed in a separate test set. Prequential-evaluation or interleaved-test-then-train evaluation, is a popular performance evaluation method for the stream setting only, where tests are performed on new data before using it to train the model.

3. Architecture

The StreamModel class is the base class in scikit-multiflow. It contains the following abstract methods:

- **fit** — Trains a model in a batch fashion. Works as a an interface to batch methods that implement a fit() functions such as scikit-learn methods.
- **partial_fit** — Incrementally trains a stream model.
- **predict** — Predicts the target’s value in supervised learning methods.
- **predict_proba** — Calculates the probability of a sample pertaining to a given class in classification problems.

An StreamModel object interacts with two other objects: an Stream object and (optionally) an StreamEvaluator object. The Stream object provides a continuous flow of data on request. The StreamEvaluator performs multiple tasks: query the stream for data, train and test the model on the incoming data and continuously tracks the model’s performance.
The sequence to train a Stream Model and track its performance using prequential evaluation in scikit-multiflow is outlined in Figure 1.

4. Development

scikit-multiflow is distributed under the BSD License. Development follows the FOSS principles and includes:

- A webpage including documentation: https://scikit-multiflow.github.io/.
- A web platform for users: https://goo.gl/AyPsMj
- Version control via git. The source code is publicly available at https://github.com/scikit-multiflow/scikit-multiflow
- Package deployment and software quality are enforced via continuous integration and automatic testing, https://travis-ci.org/scikit-multiflow/scikit-multiflow
- A user guide: https://scikit-multiflow.github.io/scikit-multiflow/user-guide

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