stream-learn — open-source Python library for difficult data stream batch analysis

P. Ksieniewicz, P. Zyblewski

Wrocław University of Science and Technology
Department of Systems and Computer Networks
wys. Wyspińskiego 27, 50-370 Wrocław

Abstract

STREAM-LEARN is a Python package compatible with scikit-learn and developed for the drifting and imbalanced data stream analysis. Its main component is a stream generator, which allows to produce a synthetic data stream that may incorporate each of the three main concept drift types (i.e. sudden, gradual and incremental drift) in their recurring or non-recurring versions. The package allows conducting experiments following established evaluation methodologies (i.e. Test-Then-Train and Prequential). In addition, estimators adapted for data stream classification have been implemented, including both simple classifiers and state-of-art chunk-based and online classifier ensembles. To improve computational efficiency, package utilises its own implementations of prediction metrics for imbalanced binary classification tasks.

Keywords: Data stream, Concept drift, Imbalanced data, Dynamic class imbalance

1. Motivation and significance

Pattern recognition research increasingly goes beyond the usual pattern of building classification models on stationary data sets and focuses on data stream processing where class distributions, and hence also decision boundaries, may change over time [1]. Such phenomenon is called the concept drift [2] and causes the need to either update existing models or to replace them with completely new ones, depending on the characteristics of the changes taking place in the class distribution.

A completely different, but equally important issue is the imbalanced data classification [3]. In such problems, the prior class probabilities are uneven, and classic recognition models tend to have prediction bias towards the majority class. In the case of data streams, this issue may be further
aggravated by dynamically changing the imbalance ratio over time, where, even without concept drift, consecutive models will indicate changes in the decision boundary. Despite the fact that real data streams often have a high and dynamically changing imbalance ratio, the number of scientific works combining the research trends of data streams classification and the skewed class distribution data analysis is still relatively small.

Research conducted in the "Imbalanced data stream classification algorithm" project, aiming to deal with aforementioned problems, created a demand for a software that (i) allows generating data streams with various properties (types of concept drift, static and dynamic imbalance ratio) in (ii) class distributions based on quantitative features and for (iii) proper evaluation of the proposed classification algorithms solving this kind of problems. An additional requirement was the compatibility with the estimators available in the scikit-learn package [1], being both an extremely popular research standard-software containing a huge amount of community-verified pattern recognition methods, as well as the API scheme for such libraries as imbalanced-learn [5], used to solve imbalanced classification problems or DESlib [6], used for dynamic classifier and ensemble selection.

The authors of the scikit-learn package indicate in documentation the possibility of processing stream data (which is also highlighted in the interfaces of some estimators that allow updating models using the partial-fit method), but warn about the low efficiency of this type of approach when using online learning methods. This is due to the scripting nature of the Python language, which is much more efficient at handling matrix operations (due to the numpy package) than the nested loops being typical for low and middle-level languages.

The current solution for data stream processing using scikit-learn interfaces is the scikit-multiflow module [7]. It implements many of the methods present in the MOA [8] package (a standard environment for data streams analysis in Java that uses WEKA [9] interfaces), along with the evaluation methods. However, employing general processing idea from MOA software implies also the computationally inefficient paradigm of online processing over batch processing, where models do not receive individual samples, but their aggregated sets called data chunks.

The stream-learn module in the Python language in accordance with the scikit-learn API is the intended solution (i.e. batch-oriented data stream processing) to the problems mentioned above. As a base, it implements a data stream generator, based on the Madelon [10] model used to generate

---

1Section 8.1.1.3. Incremental learning: https://scikit-learn.org/stable/modules/computing.html
static data in scikit-learn and allows the development of both stationary and dynamic data streams, containing both concept and prior class probabilities drifts. It is supplemented with exemplary, simple stream classifiers (Accumulated Samples Classifier and Sample Weighted Meta Estimator), which may be used as the boilerplate for the users’ solutions, and state-of-art classifier ensembles (SEA [11], OnlineBagging [12], OOB [13], UOB [13] and WAE [14]). The package also implements evaluation metrics that are more computationally effective than those available in scikit-learn and imbalanced-learn. The element wrapping-up the package and allowing for conducting experiments is a pair of evaluators: Test-Then-Train [15] and Prequential [16], in their batch variants.

The stream-learn package is currently being developed at the Department of Systems and Computer Networks, Wrocław University of Science and Technology, surprisingly being also the place of its authors employment. It is used in scientific research related to the imbalanced data streams classification. The articles created so far deal with topics such as the use of preprocessing in the incremental methods of imbalanced data stream classification [17], the use of active learning techniques to reduce the number of patterns in streams [18] and exploring the possibilities of improving the classification of imbalanced data streams using the dynamic ensemble selection (DES) [19] [20].

2. Software description

2.1. Software Architecture

The stream-learn package is organised in five modules, responsible for (i) data streams, (ii) evaluation methods, (iii) classification algorithms, (iv) classifier ensembles and (v) evaluation metrics. A general diagram of the project architecture is shown in Figure 1.

The streams module contains the ARFF file parser class, which is the standard format for serialising both real data streams and those generated, for example, by the MOA software, as well as the StreamGenerator class responsible for generating synthetic data streams. A more detailed description of the module can be found in Section 3.

The evaluators module contains classes responsible for two main prediction measures estimation techniques on data streams, namely Test-Then-Train and Prequential, in their batch-based versions. The former one is based on separate windows known as data chunks, while the latter uses a sliding window as a forgetting mechanism. Both techniques, in each step, reevaluate existing classifiers.
Estimators can be found in the classifiers and ensembles modules, which contain the classifiers and state-of-art classifier ensembles adapted for data stream classification, which can be used with implemented evaluators. A complete list of estimators includes:

- **Classifiers:**
  - *Accumulated Samples Classifier* – in each step concatenates all observed data chunks and fits the model on all encountered samples.
  - *Sample Weighted Meta Estimator* – extends the partial-fit method of a given model by adding parameter allowing for weighting samples during classifier update.

- **Classifier ensembles:**
  - *SEA* – *Streaming Ensemble Algorithm* [11], trains a new base model on each incoming data chunk and adds it to the classifier pool but removes the worst model if the pool size is exceeded.
  - *OnlineBagging* [12] – uses the Poisson($\lambda = 1$) distribution to update each base classifier with the appearance of a new instance.
  - OOB and UOB [13] – integrate resampling based on the $\lambda$ value with Online Bagging.
— WAE [14] — modifies the Accuracy Weighted Ensemble (AWE) [21] by changing the weights calculation and classifier selection methods.

The metrics module implements a wide range of evaluation measures for imbalanced binary classification [22]. The decision to prepare a new implementation was made due to the low computational efficiency of the metrics contained in existing packages. Module includes recall [23], precision [23], $f_\beta$ score [24], $f_1$ score [25], balanced accuracy score [26, 27] and two different definitions of geometric mean score [28, 29].

2.2. Processing example

The package structure will be much more transparent to the user after becoming familiar with the minimum processing example included in the following subsection.

2.2.1. Preparing experiments

In order to conduct experiments, a declaration of four elements is necessary. The first is the estimator, which must be compatible with the scikit-learn API and, in addition, implement the `partial_fit()` method, allowing to re-fit the already built model. In the example, the standard Gaussian Naive Bayes algorithm will be used:

```python
1 from sklearn.naive_bayes import GaussianNB
clf = GaussianNB()
Listing 1: Declaring classifier for stream processing.
```

The next element is the data stream that will be analysed in processing. For the example purposes, it is a synthetic stream consisting of 100 chunks and precisely one concept drift. It will be prepared using the `StreamGenerator` class of the `streams` submodule:

```python
3 from strlearn.streams import StreamGenerator
4 stream = StreamGenerator(n_chunks=100, n_drifts=1)
Listing 2: Generating a stream for processing.
```

The third requirement of the experiment is to specify the metrics used in the evaluation of the methods. In the example it is the accuracy score metric available in scikit-learn package and the precision from the metrics submodule:

```python
5 from sklearn.metrics import accuracy_score
6 from strlearn.metrics import precision
7 metrics = [accuracy_score, precision]
Listing 3: Declaring metrics for evaluation.
```
The last necessary element of processing is the evaluator, i.e. the method of conducting the experiment. In the example the Test-Then-Train paradigm, implemented in evaluators submodule is chosen. It is important to note, that it is needed to provide the metrics used later in processing at the point of initialising the evaluator. In the case of none metrics given, it will use default pair of accuracy and balanced accuracy scores:

```python
from strlearn.evaluators import TestThenTrain
evaluator = TestThenTrain(metrics)
```

Listing 4: Declaring evaluation method and pointing the metrics.

### 2.2.2. Processing and understanding results

Once all processing requirements have been met, the evaluation may be conducted. Calling the evaluator’s process method, fed with given stream and classifier starts the evaluation:

```python
evaluator.process(stream, clf)
```

Listing 5: Running the experiment.

The obtained results are stored in the scores attribute of the evaluator. Printing the example’s scores shows a three-dimensional numpy array with dimensions $(1, 99, 2)$:

- The first dimension is the index of a classifier submitted for processing. In the above example, only one model was used, but it is also possible to pass a tuple or a list of classifiers that will be processed in parallel.

- The second dimension specifies the instance of evaluation, which in the case of Test-Then-Train methodology directly means the index of the processed chunk (skipping the first chunk, which cannot be tested due to the lack of a model in the beginning of processing).

- The third dimension points the consecutive metric used in the processing.

Using this knowledge, it is finally possible to illustrate the results of a simple, exemplary experiment in the form of a plot illustrated in Figure 2.

### 3. Data stream generation

A key element of the stream-learn package is a generator that allows to prepare a replicable (according to the given seed) classification dataset with class distribution changing over the course of a stream, with base concepts
build on a default class distributions for the scikit-learn package from the make_classification() function. These types of distributions try to reproduce the rules for generating the Madelon set [10]. The StreamGenerator is capable of preparing any variation of the data stream known in the general taxonomy of data streams.

3.1. Stationary stream

The simplest variation of data streams are stationary streams. They contain one basic concept, static for the whole course of the processing. Chunks differ from each other in terms of the patterns inside, but the decision boundaries of the models built on them should not be statistically different. This type of a stream may be generated with a clean generator call, without any additional parameters. Such a stream is illustrated in the Figure 3 which contains the series of scatter plots for a two-dimensional stationary stream with the binary problem.

What is important, contrary to a typical call to make_classification(), the n_samples parameter, determining the number of patterns in the set, is not specified here, but instead two new attributes of a data stream are provided:

- n_chunks — to determine the number of chunks in a data stream.
• `chunk_size` — to determine the number of patterns in each data chunk.

Additionally, data streams may contain noise which, while not considered as a concept drift, provides additional challenge during the data stream analysis and classifiers should be robust to it. The `StreamGenerator` class implements noise by inverting the class labels of a given percentage of incoming instances in the data stream. This percentage can be defined by a `y_flip` parameter, like in standard scikit-learn dataset generation call. If a single float is given as the parameter value, the percentage of noise refers to combined instances from all the classes, while if a tuple of floats is specified, the noise occurs within each class separately using the given percentages.

3.2. Streams containing concept drifts

The most commonly studied nature of data streams is their variability in time. Responsible for this is the phenomenon of the concept drift, described in the introduction to this article. The stream-learn package tries to meet the need to synthesise all the basic variations of this phenomenon (i.e. sudden, gradual and incremental drifts).

3.2.1. Sudden (Abrupt) drift

This type of a drift occurs when the concept from which the data stream is generated is suddenly replaced by another one. Concept probabilities used by the `StreamGenerator` class are created based on sigmoid function, which is generated using `concept_sigmoid_spacing` parameter, which determines the function shape and how sudden the change of concept is. The higher the value, the more sudden the drift becomes. Here, this parameter takes the default value of 999, which allows for a generation of sigmoid function simulating an abrupt change in the data stream. Illustration of the sudden drift is presented in the Figure 4a.

3.2.2. Gradual drift

Unlike sudden drifts, gradual ones are associated with a slower change rate, which can be noticed during a longer observation of the data stream. This kind of drift refers to the transition phase where the probability of getting instances from the first concept decreases while the probability of sampling from the next concept increases. The `StreamGenerator` class simulates gradual drift by comparing the concept probabilities with the generated random noise and, depending on the result, selecting which concept is active at a given time. Illustration of the gradual drift is presented in the Figure 4b.
3.2.3. Incremental (Step-wise) drift

The incremental drift happens when a series of barely noticeable changes in the concept used to generate the data stream occurs, in opposite of gradual drift, which is mixing samples from different concepts without changing them. Due to this, the drift may be identified only after some time. The severity of changes, and hence the speed of transition of one concept into another is, like in previous example, described by the concept_sigmoid_spacing parameter. Illustration of the incremental drift is presented in the Figure 4c.

3.2.4. Recurrent drift

The cyclic repetition of class distributions is a completely different property of concept drifts. If after another drift, the concept earlier present in the stream returns, we are dealing with a recurrent drift. We can get this kind of data stream by setting the recurring flag in the generator. Illustration of the recurrent drift is presented in the Figure 5a.

3.2.5. Non-recurring drift

The default mode of consecutive concept occurrences is a non-recurring drift, where in each concept drift a completely new, previously unseen class
distribution is synthesised. Illustration of the non-recurring drift is presented in the Figure 5b.

(a) Data stream with recurring drift.

(b) Data stream with non-recurring drift.

Figure 5: Changes in class distribution under recurring and non-recurring concept drift.

3.3. Class imbalance

Another area of data stream properties, different from a concept drift phenomenon, is the prior probability of problem classes. By default, a balanced stream is generated, i.e. one in which patterns of all classes are present in a similar number, like the stationary stream presented in Figure 2.

3.3.1. Stationary imbalanced stream

The basic type of problem in which we are dealing with disturbed class distribution is a stationary imbalanced stream, where the classes maintain a predetermined proportion in each chunk of data stream. To acquire this type of a stream, one should pass the list to the weights parameter of the generator (i) consisting of as many elements as the classes in the problem and (ii) adding up to one. Illustration of the stationary imbalanced stream is presented in the Figure 6a.

3.3.2. Dynamically imbalanced stream

A less common type of imbalanced data, impossible to obtain in static datasets, is data imbalanced dynamically. In this case, the class distribution is not constant throughout the course of a stream, but changes over time, similar to changing the concept presence in gradual streams. To get this type of a data stream, a tuple of three numeric values is passed to the weights parameter of the generator:
- the number of cycles of distribution changes.
- `concept_sigmoid_spacing` parameter, deciding about the dynamics of changes on the same principle as in *gradual* and *incremental drifts*.
- range within which oscillation is to take place.

Illustration of the *dynamically imbalanced stream* is presented in the Figure 6b.

![Figure 6a: Statically imbalanced data stream.](image)

![Figure 6b: Dynamically imbalanced data stream.](image)

![Figure 6c: Dynamically Imbalanced Stream with Concept Oscillation (DISCO).](image)

Figure 6: Changes in class distribution under dynamically changing prior class probabilities (a,b) and concept drift paired with dynamic imbalance (c).

### 3.4. Mixing drift properties

Of course, when generating data streams, we do not have to limit ourselves to just one modification of their properties. One may easily prepare a stream with many drifts, any dynamics of changes, a selected type of drift and a diverse, dynamic imbalanced ratio. The last example of a data stream is such proposition, namely, DISCO (*Dynamically Imbalanced Stream with Concept Oscillation*). Illustration of the DISCO stream is presented in the Figure 6c.
4. Impact

The stream-learn library allows to conduct research on the new algorithms for batch processing of data streams. Previous work employing it in a scientific process has already shown that it may be successfully used to verify the effectiveness of new methods against already established state-of-art solutions implemented in accordance with the scikit-learn library. The most important area of research possible with its use is classification of data streams containing concept drifts and/or dynamic class imbalance. Thanks to the precise, replicable and user-friendly stream generation procedure, it also allows for a wide spectrum of drift detection analyses, depending not only on types of drifts, but also on the dynamics of their changes. Finally, it also implements online bagging methods (UOB, OOB), which, to the knowledge of the authors, have not yet had open and stable implementation.

5. Conclusions

The stream-learn package is a user-friendly and open source Python library for difficult data stream classification. It allows generating streams with different characteristics, containing various types of concept drift and class-imbalance levels, including the possibility of drift in prior class probabilities. Additional modules allow conducting experiments on data streams using well-known estimation methodologies, implemented classifiers and classifier ensembles (some not present in any other Python package). Its main idea is to let the user to immediately familiarize with the data stream classification task.

The package has already been tested in the research process of preparing several scientific articles and it is an ideal tool for users who care about the simplicity of processing, ease of the use and integration with the scikit-learn machine learning library.

Acknowledgements

This work was supported by the Polish National Science Centre under the grant No. 2017/27/B/ST6/01325 as well as by the statutory funds of the Department of Systems and Computer Networks, Faculty of Electronics, Wroclaw University of Science and Technology.

References

[1] J. Gama, P. P. Rodrigues, An overview on mining data streams, in: Foundations of Computational, Intelligence Volume 6, Springer, 2009, pp. 29–45.
[2] B. Krawczyk, L. Minku, J. Gama, J. Stefanowski, M. Wozniak, Ensemble learning for data stream analysis: A survey, Information Fusion 37 (2017) 132–156. doi:10.1016/j.inffus.2017.02.004.

[3] B. Krawczyk, Learning from imbalanced data: open challenges and future directions, Progress in Artificial Intelligence 5 (4) (2016) 221–232.

[4] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, E. Duchesnay, Scikit-learn: Machine learning in Python, Journal of Machine Learning Research 12 (2011) 2825–2830.

[5] G. Lemaître, F. Nogueira, C. K. Aridas, Imbalanced-learn: A python toolbox to tackle the curse of imbalanced datasets in machine learning, Journal of Machine Learning Research 18 (17) (2017) 1–5.

[6] R. M. O. Cruz, L. G. Hafemann, R. Sabourin, G. D. C. Cavalcanti, DESlib: A Dynamic ensemble selection library in Python, arXiv preprint arXiv:1802.04967 (2018).

[7] J. Montiel, J. Read, A. Bifet, T. Abdessalem, Scikit-multiflow: A multi-output streaming framework, Journal of Machine Learning Research 19 (72) (2018) 1–5.

[8] A. Bifet, G. Holmes, R. Kirkby, B. Pfahringer, MOA: massive online analysis, J. Mach. Learn. Res. 11 (2010) 1601–1604.

[9] Appendix b - the weka workbench, in: I. H. Witten, E. Frank, M. A. Hall, C. J. Pal (Eds.), Data Mining (Fourth Edition), fourth edition Edition, Morgan Kaufmann, 2017, pp. 553 – 571.

[10] I. Guyon, Design of experiments of the nips 2003 variable selection benchmark, in: NIPS 2003 workshop on feature extraction and feature selection, 2003.

[11] N. Street, Y. Kim, A streaming ensemble algorithm (sea) for large-scale classification, Proceedings of the 7Th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (2001) 377–382.

[12] N. C. Oza, Online bagging and boosting, in: 2005 IEEE International Conference on Systems, Man and Cybernetics, Vol. 3, 2005, pp. 2340–2345 Vol. 3.
[13] S. Wang, L. L. Minku, X. Yao, Resampling-based ensemble methods for online class imbalance learning, IEEE Transactions on Knowledge and Data Engineering 27 (5) (2015) 1356–1368.

[14] M. Woźniak, A. Kasprzak, P. Cal, Weighted aging classifier ensemble for the incremental drifted data streams, in: H. L. Larsen, M. J. Martin-Bautista, M. A. Vila, T. Andreasen, H. Christiansen (Eds.), Flexible Query Answering Systems, Springer Berlin Heidelberg, Berlin, Heidelberg, 2013, pp. 579–588.

[15] J. Gama, Knowledge Discovery from Data Streams, 1st Edition, Chapman & Hall/CRC, 2010.

[16] J. Gama, R. Sebastião, P. P. Rodrigues, On evaluating stream learning algorithms, Machine Learning 90 (3) (2013) 317–346.

[17] B. Gulowaty, P. Ksieniewicz, Smote algorithm variations in balancing data streams, in: H. Yin, D. Camacho, P. Tino, A. J. Tallón-Ballesteros, R. Menezes, R. Allmendinger (Eds.), Intelligent Data Engineering and Automated Learning – IDEAL 2019, Springer International Publishing, Cham, 2019, pp. 305–312.

[18] P. Ksieniewicz, M. Woźniak, B. Cyganek, A. Kasprzak, K. Walkowiak, Data stream classification using active learned neural networks, Neurocomputing 353 (2019) 74 – 82, recent Advancements in Hybrid Artificial Intelligence Systems.

[19] P. Zyblewski, P. Ksieniewicz, M. Woźniak, Classifier selection for highly imbalanced data streams with minority driven ensemble, in: L. Rutkowski, R. Scherer, M. Korytkowski, W. Pedrycz, R. Tadeusiewicz, J. M. Zurada (Eds.), Artificial Intelligence and Soft Computing, Springer International Publishing, Cham, 2019, pp. 626–635.

[20] P. Zyblewski, R. Sabourin, M. Woźniak, Data preprocessing and dynamic ensemble selection for imbalanced data stream classification, in: The European Conference on Machine Learning ECML19, IoT Stream for Data Driven Predictive Maintenance workshop proceedings [Article in Press].

[21] H. Wang, W. Fan, P. S. Yu, J. Han, Mining concept-drifting data streams using ensemble classifiers, in: Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD ’03, ACM, New York, NY, USA, 2003, pp. 226–235.
[22] Visual-based analysis of classification measures and their properties for class imbalanced problems, Information Sciences 462 (2018) 242 – 261.

[23] D. Powers, Ailab, Evaluation: From precision, recall and f-measure to roc, informedness, markedness & correlation, J. Mach. Learn. Technol 2 (2011) 2229–3981.

[24] R. A. Baeza-Yates, B. Ribeiro-Neto, Modern Information Retrieval, Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA, 1999.

[25] Y. Sasaki, The truth of the f-measure, Teach Tutor Mater (01 2007).

[26] K. H. Brodersen, C. S. Ong, K. E. Stephan, J. M. Buhmann, The balanced accuracy and its posterior distribution, in: Proceedings of the 2010 20th International Conference on Pattern Recognition, ICPR ’10, IEEE Computer Society, Washington, DC, USA, 2010, pp. 3121–3124.

[27] J. D. Kelleher, B. M. Namee, A. D’Arcy, Fundamentals of Machine Learning for Predictive Data Analytics: Algorithms, Worked Examples, and Case Studies, The MIT Press, 2015.

[28] R. Barandela, J. Sánchez, V. García, E. Rangel, Strategies for learning in class imbalance problems, Pattern Recognition 36 (2003) 849–851.

[29] M. Kubat, S. Matwin, Addressing the curse of imbalanced training sets: One-sided selection, in: ICML, 1997.

Required Metadata

Current code version
| Nr. | Code metadata description                                      | Please fill in this column |
|-----|-----------------------------------------------------------------|-----------------------------|
| C1  | Current code version                                            | 0.8.5                       |
| C2  | Permanent link to code/repository used for this code version    | `https://github.com/w4k2/stream-learn` |
| C3  | Legal Code License                                              | GPL-3.0                     |
| C4  | Code versioning system used                                     | git                         |
| C5  | Software code languages, tools, and services used               | python                      |
| C6  | Compilation requirements, operating environments & dependencies  |                             |
| C7  | If available Link to developer documentation/manual            | `https://w4k2.github.io/stream-learn/` |
| C8  | Support email for questions                                     | `pawel.zyblewski@pwr.edu.pl` |