PySAD: A Streaming Anomaly Detection Framework in Python

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Abstract

PySAD is an open-source python framework for anomaly detection on streaming data. PySAD serves various state-of-the-art methods for streaming anomaly detection. The framework provides a complete set of tools to design anomaly detection experiments ranging from projectors to probability calibrators. PySAD builds upon popular open-source frameworks such as PyOD and scikit-learn. We enforce software quality by enforcing compliance with PEP8 guidelines, functional testing and using continuous integration. The source code is publicly available on github.com/selimfirat/pysad.

Keywords: Anomaly detection, outlier detection, streaming data, online, sequential, data mining, machine learning, python.

1. Introduction

Anomaly detection on streaming data has attracted a significant attention in recent years due to its real-life applications such as surveillance systems (Yuan et al., 2014) and network intrusion detection (Kloft and Laskov, 2010). We introduce a framework for anomaly detection on data streams, for which methods can only access instances as they arrive, unlike batch setting where model can access all the data (Henzinger et al., 1998). Streaming methods can efficiently handle limited memory and processing time requirements of real-life applications. These methods only store and process an instance or a small window of recent instances. In recent years, various Free and Open Source Software (FOSS) has been developed for both anomaly detection and streaming data. However, these software packages either lack focus on anomaly detection or designed for batch data. We categorize the existing frameworks as (i) streaming frameworks and (ii) anomaly detection frameworks. The focus of streaming frameworks is not only anomaly detection but also other machine learning tasks on streaming data such as classification and regression. Hence, they have limited number of specialized streaming anomaly detection methods due to need to maintain different methods for other tasks concurrently. We particularly concentrate on streaming anomaly detection and introduce a compherensive framework since these methods can be easily adapted to real-life applications due to their nature with high-speed and bounded memory (Gaber, 2012).

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We introduce a streaming anomaly detection framework in Python (PySAD), which is currently the only framework with focus on streaming anomaly detection. PySAD provides several different well-known state of the art methods for anomaly detection on streaming data. PySAD serves models that are specifically designed for both univariate and multivariate data. Furthermore, one can experiment via PySAD in supervised, semi-supervised and unsupervised setting. PySAD builds upon existing open-source libraries such as PyOD (Zhao et al., 2019) and scikit-learn (Pedregosa et al., 2011). PySAD contains stream simulators, evaluators, preprocessors, statistic trackers, postprocessors, probability calibrators and more. In addition to streaming models, PySAD provides integrations for batch anomaly detectors of the PyOD (Zhao et al., 2019) so that they can be used in the streaming setting.

2. Streaming Anomaly Detection and PySAD

A streaming anomaly detection model \mathcal{M} receives stream of data $\mathcal{D} = \{(\boldsymbol{x}_t, y_t) \mid t = 1, 2, ...\}$, where $\boldsymbol{x}_t \in \mathbb{R}^m$ is a column vector with the input dimension m and y_t is defined as:

$$y_t = \begin{cases} 1, & \text{if } \mathbf{x}_t \text{ is anomalous,} \\ 0, & \text{else.} \end{cases}$$

Note that y_t is not required for unsupervised models. In streaming anomaly detection, a model receives the data as new instances (x_t, y_t) and either stores the instance for a limited time and memory or directly trains itself, unlike batch models, where a batch model can access all the data \mathcal{D} with a finite number of instances during training.

```
from pysad.evaluation.metrics import AUROCMetric
1
     from pysad.models.loda import LODA
2
     from pysad.utils.data import Data
4
     model = LODA()
5
     metric = AUROCMetric()
6
     streaming_data = Data().get_iterator("arrhythmia.mat")
7
     for x, y_true in streaming_data:
9
         anomaly_score = model.fit_score_partial(x)
10
11
         metric.update(y_true, anomaly_score)
12
13
     print(f"Area under ROC metric is {metric.get()}.")
14
```

Listing 1: Example usage of LODA model in PySAD framework.

To describe a model in our API, we define $X = \begin{bmatrix} x_1 & \dots & x_n \end{bmatrix}$ and $y = \begin{bmatrix} y_1 & \dots & y_n \end{bmatrix}^T$ for any $n \in \mathbb{Z}^+$. All models in PySAD extends BaseModel that provides the following interface:

• fit_partial(x_t, y_t): Trains the model using instance (x_t, y_t), at time t.

- score_partial(x_t): Returns the anomaly score for x_t .
- fit_score_partial(x_t, y_t): Runs fit_partial(x_t, y_t) and returns score_partial(x_t).
- fit(X, y): Calls fit_partial(x_t , y_t) for $t = 1, ..., n \in \mathbb{Z}^+$ in order.
- score(X): Returns $\left[\text{score_partial}(x_1) \quad ... \quad \text{score_partial}(x_n)\right]^T$.
- fit_score(X, y): Returns [fit_score_partial(x_1, y_1) ... fit_score_partial(x_n, y_n)]^T. Listing 1 presents an example usage of a PySAD model. One can add a new model to PySAD via only by defining fit_partial and score_partial and extending BaseModel. Other details of for contributing the framework is available at Developer Documentation. All programming interfaces are available at API reference. Figure 1 shows the usage of

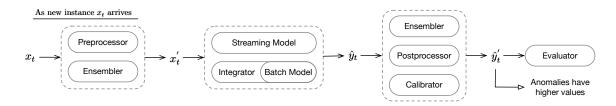


Figure 1: The usage of components in PySAD as a pipeline.

components in PySAD framework. The framework provides a complete set of tools for anomaly detection on streaming data. The components are modular so that they can be combined to create a pipeline. Preprocessors, e.g., unit norm scaler, transform x_t without changing its dimensions. Projectors projects given input to a (possibly) lower dimensional space in streaming setting so that models can better discriminate anomalies. Given instance x_t , a model predicts its label y_t as \hat{y}_t . Ensemblers combine scores of an instance from multiple models into a score. Postprocessors transform a score into another score, e.g., applying exponentially smoothed average to the scores improves the streaming anomaly detection performance (Hundman et al., 2018). Probability calibrators converts target score into the probability of being anomalous using techniques such as Gaussian tail fitting (Ahmad et al., 2017) or conformal prediction (Ishimtsev et al., 2017).

3. Comparison with Related Software

Jubat.us (Hido et al., 2013) has only Local Outlier Factor method (Breunig et al., 2000), which is developed in C++ language. MOA has 6 different models that are older than 6 years and written in Java (Bifet et al., 2010). The rest of the related frameworks and ours are developed in and for Python language. Creme (Halford et al., 2019) and skmultiflow (Montiel et al., 2018) have only Half Space Trees method (Tan et al., 2011). Alibi-detect has only Spectral Residual method (Ren et al., 2019) for univariate data and Mahalanobis Distance method (Le and Ho, 2005) for categorical data. The frameworks focused on anomaly detection, which are currently PyOD (Zhao et al., 2019) and ADTK (Wen, 2020) only target anomaly detection on batch data, whereas our PySAD framework targets anomaly detection on streaming data. Although PyOD and ADTK contains several different models for batch data, they do

^{1.} They do not have proper citations. We have found their age via commit history.

not have any specialized model for streaming data, whereas all of PySAD methods are for the streaming data. Table 1 presents the comparison of our PySAD framework with the aforementioned existing frameworks.

	creme	jubat.us	adtk	pyod	skmultiflow	alibi-detect	moa	pysad
Language	Python	C++	Python	Python	Python	Python	Java	Python
# of Models*	1	1	0	0	1	2	6	16
Streaming	~	V	X	X	✓	✓	~	~
Transformers	~	V	~	X	✓	×	~	~
Projectors	~	X	×	×	×	×	~	/
Ensemblers	~	X	~	~	✓	×	~	/
Calibrators	×	X	×	×	×	X	X	~

^{*} The number of models for streaming data.

Current versions: creme (0.6.1), jubat.us (1.1.1), adtk (0.6.2), pyod (0.8.1), skmultiflow (0.5.3), alibi-detect (0.4.1), moa (2020.07), pysad (0.1.1).

Table 1: Comparison with existing frameworks for streaming data and anomaly detection.

As a streaming anomaly detection framework, the PySAD framework complements the streaming frameworks and anomaly detection frameworks whose primary focus is batch learning. The PySAD makes various models easily accessible to research community. Uniquely, the PySAD contains unsupervised probability calibrators to convert anomaly scores into probabilities. The raw anomaly scores are usually not interpretable in a probabilistic manner and cannot be directly converted into decision of anomalousness (Safin and Burnaev, 2017).

4. Development and Architecture

PySAD framework is distributed under BSD License 2.0. PySAD does not depend on any proprietary software. The development of PySAD framework favors the FOSS principles and encompasses the followings:

- Collaborative Development We host PySAD via Github, which allow collaboration between developers through a version control system and an issue tracking system. The source code is publicly available at github.com/selimfirat/pysad.
- Continuous Integration For software quality, we enforce continuos integration with functional testing on Linux, Windows and MacOS platforms via Azure Pipelines.
- Quality Standards The source code obey PEP8 standard of Python. We enforce more than 95% test coverage and 100% documentation coverage.

We describe the required open-source dependencies of PySAD as follows. We use numpy package for linear algebra operations and data structures (Walt et al., 2011). We employ scikit-learn for utility and projection methods (Pedregosa et al., 2011). We use scipy for optimization and efficient linear algebra operations (Virtanen et al., 2020). We utilize PyOD, an anomaly detection package that offers a rich set of anomaly detectors for batch data, to provide ensemblers and for streaming isolation forest model implementation (Zhao et al., 2019). Moreover, we provide integration methods of the PyOD's batch detectors to the streaming data.

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