A Python Toolbox to Tackle the Curse of Imbalanced Datasets in Machine Learning

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Abstract

`imbalanced-learn` is an open-source python toolbox aiming at providing a wide range of methods to cope with the problem of imbalanced dataset frequently encountered in machine learning and pattern recognition. The implemented state-of-the-art methods can be categorized into 4 groups: (i) under-sampling, (ii) over-sampling, (iii) combination of over- and under-sampling, and (iv) ensemble learning methods. The proposed toolbox only depends on `numpy`, `scipy`, and `scikit-learn` and is distributed under MIT license. Furthermore, it is fully compatible with `scikit-learn` and is part of the `scikit-learn-contrib` supported project. Documentation, unit tests as well as integration tests are provided to ease usage and contribution. The toolbox is publicly available in GitHub `https://github.com/scikit-learn-contrib/imbalanced-learn`.

Keywords: Imbalanced Dataset, Over-Sampling, Under-Sampling, Ensemble Learning, Machine Learning, Python.

1. Introduction

Real world datasets commonly show the particularity to have a number of samples of a given class under-represented compared to other classes. This imbalance gives rise to the "class imbalance" problem (Prati et al., 2009) (or "curse of imbalanced datasets") which is the problem of learning a concept from the class that has a small number of samples.

The class imbalance problem has been encountered in multiple areas such as telecommunication managements, bioinformatics, fraud detection, and medical diagnosis, and has been considered one of the top 10 problems in data mining and pattern recognition (Yang and Wu, 2006; Rastgoo et al., 2016). Imbalanced data substantially compromises the learning process, since most of the standard machine learning algorithms expect balanced class distribution or an equal misclassification cost (He and Garcia, 2009). For this reason, sev-

eral approaches have been specifically proposed to handle such datasets. Such standalone methods have been implemented mainly in R language (Torgo, 2010; Kuhn, 2015; Dal Pozzolo et al., 2013). Up to our knowledge, however, there is no python toolbox allowing such processing while cutting edge machine learning toolboxes are available (Pedregosa et al., 2011; Sonnenburg et al., 2010).

In this paper, we present the `imbalanced-learn` API, *a python toolbox to tackle the curse of imbalanced datasets in machine learning.* The following sections present the project vision, a snapshot of the API, an overview of the implemented methods, and finally, the conclusion of this paper, including future functionalities for the `imbalanced-learn` API.

2. Project management

Quality insurance In order to ensure code quality, a set of unit tests is provided leading to a coverage of 99 % for the release 0.1.8 of the toolbox. Furthermore, the code consistency is ensured by following `PEP8` standards and each new contribution is automatically checked through landscape, which provides metrics related to code quality.

Continuous integration To allow user and developer to either use or contribute to this toolbox, Travis CI is used to easily integrate new code and ensure back-compatibility.

Community-based development All the development is performed in a collaborative manner. Tools such as git, GitHub, and gitter are used to ease collaborative programming, issue tracking, code integration, and idea discussions.

Documentation A consistent API documentation is provided using `sphinx` and `numpydoc`. An additional installation guide and examples are also provided and centralized on GitHub[1].

Project relevance At the edition time, the repository is visited no less than $2,000$ per week, attracting about 300 unique visitors per week. Additionally, the toolbox is supported by `scikit-learn` through the `scikit-learn-contrib` projects.

3. Implementation design

```
1  from sklearn.datasets import make_classification
2  from sklearn.decomposition import PCA
3  from imblearn.over_sampling import SMOTE
4
5  # Generate the dataset
6  X, y = make_classification(n_classes=2, weights=[0.1, 0.9],
7                             n_features=20, n_samples=5000)
8
9  # Apply the SMOTE over-sampling
10 sm = SMOTE(ratio='auto', kind='regular')
11 X_resampled, y_resampled = sm.fit_sample(X, y)
```

Listing 1: Code snippet to over-sample a dataset using SMOTE.

The implementation relies on `numpy`, `scipy`, and `scikit-learn`. Each sampler class implements three main methods inspired from the `scikit-learn` API: (i) `fit` computes the parameter values which are later needed to resample the data into a balanced set; (ii)

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1. `https://github.com/scikit-learn-contrib/imbalanced-learn`

`sample` performs the sampling and returns the data with the desired balancing ratio; and (iii) `fit_sample` is equivalent to calling the method `fit` followed by the method `sample`. A class `Pipeline` is inherited from `scikit-learn` toolbox to automatically combine `samplers`, `transformers`, and `estimators`.

4. Implemented methods

The `imbalanced-learn` toolbox provides four different strategies to tackle the problem of imbalanced dataset: (i) under-sampling, (ii) over-sampling, (iii) a combination of both, and (iv) ensemble learning. The following subsections give an overview of the techniques implemented.

4.1 Notation and background

Let χ an imbalanced dataset with χ_{min} and χ_{maj} being the subset of samples belonging to the minority and majority class, respectively. The balancing ratio of the dataset χ is defined as:

$$r_\chi = \frac{|\chi_{min}|}{|\chi_{maj}|} \; , \tag{1}$$

where $|\cdot|$ denotes the cardinality of a set. The balancing process is equivalent to resample χ into a new dataset χ_{res} such that $r_\chi > r_{\chi_{res}}$.

4.2 Under-sampling

Under-sampling refers to the process of reducing the number of samples in χ_{maj}. The implemented methods can be categorized into 2 groups: (i) fixed under-sampling and (ii) cleaning under-sampling.

Fixed under-sampling refer to the methods which perform under-sampling to obtain the appropriate balancing ratio $r_{\chi_{res}}$. The implemented methods perform the under-sampling based on different criteria such as: (i) random selection, (ii) clustering, (iii) nearest neighbours rule (i.e., `NearMiss` (Mani and Zhang, 2003)), and (iv) classification accuracy (i.e., `instance hardness threshold` (Smith et al., 2014)).

In the contrary to the previous methods, *cleaning under-sampling* do not allow to reach specifically the balancing ratio $r_{\chi_{res}}$, but rather clean the feature space based on some empirical criteria. These criteria are derived from the nearest neighbours rule, namely: (i) `condensed nearest neighbours` (Hart, 1968), (ii) `edited nearest neighbours` (Wilson, 1972), (iii) `one-sided selection` (Kubat et al., 1997), (iv) `neighbourhood cleaning rule` (Laurikkala, 2001), and (v) `Tomek links` (Tomek, 1976).

4.3 Over-sampling

In the contrary to under-sampling, data balancing can be performed by over-sampling such that new samples are generated in χ_{min} to reach the balancing ratio $r_{\chi_{res}}$. Two methods are currently available: (i) `Random over-sampling` is performed by randomly replicating the samples of χ_{min} to obtain the appropriate balancing ratio $r_{\chi_{res}}$ and `SMOTE` which randomly generate new samples between tuple of nearest neighbours of χ_{min} (Chawla et al., 2002).

Different variants of this algorithm have been proposed: `SMOTE borderline 1 & 2` (Han et al., 2005) and `SMOTE SVM` (Nguyen et al., 2011).

4.4 Combination of over- and under-sampling

`SMOTE` over-sampling can lead to over-fitting which can be avoided by applying cleaning under-sampling methods (Prati et al., 2009). In that regard, Batista et al. (2003) combined `SMOTE` either with `Tomek links` or `edited nearest neighbours`.

4.5 Ensemble learning

Under-sampling methods imply that samples of the majority class are lost during the balancing procedure. Ensemble methods offer an alternative to use most of the samples. In fact, an ensemble of balanced sets is created and used to later train any classifier. Two methods are available to build such ensemble proposed by Liu et al. (2009): `EasyEnsemble` and `BalanceCascade`. The former is based on iteratively applying the `random under-sampling` method to build several sets, each of them with a desired balancing ratio $r_{\chi_{res}}$. The latter differs such that a classifier is used at each iteration to determine the class of the randomly selected samples. Misclassified samples are kept and propagated in the next subset.

5. Future plans and conclusion

In this paper, we shortly presented the foundations of the `imbalanced-learn` toolbox vision and API. As avenues for future works, additional methods based on prototype/instance selection, generation, and reduction will be added as well as additional user guides.

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