IMBENS: Ensemble Class-imbalanced Learning in Python

Zhining Liu\textsuperscript{1}\textsuperscript{*}
Jian Kang\textsuperscript{1}
Hanghang Tong\textsuperscript{1}
Yi Chang\textsuperscript{2}
\textsuperscript{1} University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA
\textsuperscript{2} Jilin University, Changchun, Jilin 130012, China

Abstract

imbalanced-ensemble, abbreviated as imbens, is an open-source Python toolbox for leveraging the power of ensemble learning to address the class imbalance problem. It provides standard implementations of popular ensemble imbalanced learning (EIL) methods with extended features and utility functions. These ensemble methods include resampling-based, e.g., under/over-sampling, and reweighting-based, e.g., cost-sensitive learning. Beyond the implementation, we empower EIL algorithms with new functionalities like customizable resampling scheduler and verbose logging, thus enabling more flexible training and evaluating strategies. The package was developed under a simple, well-documented API design that follows scikit-learn for increased ease of use. imbens is released under the MIT open-source license and can be installed from Python Package Index (PyPI) or https://github.com/ZhiningLiu1998/imbalanced-ensemble.

Keywords: Ensemble Learning, Class-imbalance, Machine Learning, Python

1 Introduction

Class imbalance, also known as the long-tail problem, is the fact that the classes are not represented equally in a classification problem. Such issue widely exists in many real-world applications, such as click-through rate prediction (click/ignore), medical diagnosis (patient/non-patient), financial fraud detection (fraud/normal transaction), and network intrusion detection (malicious/normal request), etc (Haixiang et al., 2017). Imbalanced data often leads to degraded predictive performance of many standard machine learning algorithms since they assume a balanced class distribution and are directly optimized for global accuracy (He and Garcia, 2008; He and Ma, 2013). Imbalanced learning (IL) aims to tackle the class imbalance problem, i.e., learn an unbiased model from imbalanced data.

Most of the commonly used IL methods are based on resampling and reweighting, which are also the primary interest of existing open-source IL packages such as imblearn (Lemaitre et al., 2017) and smote-variants (Kovács, 2019). Beyond them, ensemble imbalanced learning (EIL) improves typical IL methods by combining the results of multiple independent resampling/reweighting and reducing variance (Galar et al., 2012). Recent studies have shown that EIL solutions are highly competitive and gaining increasing popularity in real-world applications (Haixiang et al., 2017; Dong et al., 2020). However, despite the success of EIL, only a handful of methods are available in existing open-source packages, while many

\textsuperscript{*}. Work initialized while at Jilin University.
### Table 1: Ensemble imbalanced learning methods implemented in imbens.

| Method                        | Solution Type | Ensemble Type | Multi-core |
|-------------------------------|---------------|---------------|------------|
| SELF_PACED_ENSEMBLE (Liu et al., 2020) | ✓ | ✓ | ✓ | Iterative |
| BALANCECASCADE (Liu et al., 2009) | ✓ | ✓ | ✓ | Iterative |
| BALANCED_RANDOM_FOREST (Chen et al., 2004) | ✓ | ✓ | ✓ | Parallel |
| EASY_ENSEMBLE (Liu et al., 2009) | ✓ | ✓ | ✓ | Parallel |
| RUSBOOST (Seiffert et al., 2010) | ✓ | ✓ | ✓ | Iterative |
| UNDER_BAGGING (Barandela et al., 2003) | ✓ | ✓ | ✓ | Parallel |
| OVERBOOST (Galar et al., 2012) | ✓ | ✓ | ✓ | Iterative |
| SMOTEBOOST (Chawla et al., 2003) | ✓ | ✓ | ✓ | Iterative |
| kMEANS_SMOTEBOOST (Chawla et al., 2003) | ✓ | ✓ | ✓ | Iterative |
| OVER_BAGGING (Wang and Yao, 2009) | ✓ | ✓ | ✓ | Parallel |
| SMOTE_BAGGING (Wang and Yao, 2009) | ✓ | ✓ | ✓ | Parallel |
| ADA_COST (Fan et al., 1999) | ✓ | ✓ | ✓ | Iterative |
| ADA_UCOST (Shawe-Taylor and Karakoulas, 1999) | ✓ | ✓ | ✓ | Iterative |
| ASYMBOOST (Viola and Jones, 2001) | ✓ | ✓ | ✓ | Iterative |

* Abbreviations: under-sampling (US), over-sampling (OS), reweighting (RW), imbln, svs.

To fill this gap, we present the imbalanced-ensemble (imbens) Python toolbox to better leverage the power of ensemble learning to address the class imbalance problem. Currently (version 0.2.0), imbens have implemented 14 popular EIL methods that based on different imbalance handling strategies (e.g., under/over-sampling and reweighting) and ensemble manners (e.g., boosting and bagging), as summarized in Table 1. These methods are implemented with high-level abstractions based on the taxonomy in Table 1, and new algorithms can be easily implemented by taking advantage of inheritance and polymorphism. imbens also provides a number of practical features and utilities for better training, evaluating, and comparing different EIL models. Altogether, imbens is an extensible open-source library for researchers and engineers to handle real-world imbalance learning problems, as well as to develop and benchmark new EIL methods under a standard unified API design.

## 2 Project Features

**Quality assurance.** This project follows the PEP8 standard. In order to ensure code quality, a standard set of unit tests is provided leading to a coverage of 96% for the release 0.2.0 of the toolbox. To allow both the user and the developer to either use or contribute to this toolbox, CircleCI is used to easily integrate new code and ensure back-compatibility.

**Documentation.** All EIL methods implemented in imbens share a unified API design similar to scikit-learn (Pedregosa et al., 2011). Detailed documentation is developed using sphinx and numpydoc and rendered using ReadtheDocs¹, including comprehensive API references, installation guideline, and code usage examples.

¹. https://imbalanced-ensemble.readthedocs.io
Table 2: Additional key parameters of the `fit` method in `imbens`.

**Functionalities.** `imbens` provides a number of extended features to ease the usage of EIL algorithms in practice. With a few parameters, users can easily customize the sampling scheduler/cost-matrix and logging information/granularity, thus gaining more precise training and verbose logging control. Additionally, a set of utility functions and modules are provided to evaluate, compare, and benchmark different EIL algorithms.

**Openness.** `imbens` is distributed under the MIT license. The code repository is hosted on GitHub to facilitate collaboration and documented contribution guidelines are provided. At the time of this writing, five contributors have participated in the form of bug reports/fixes.

**Project relevance.** `imbens` has been used/included in multiple open-source projects such as Auto_ViML, featurewiz, and awesome-machine-learning. At the edition time, the GitHub repository has received 180+ stars and its PyPI downloads exceed 1,000 per month.

3 Library Design and Implementation

The `imbens` package relies on `numpy`, `pandas`, `scipy`, and `scikit-learn`. We use `joblib` to implement multi-core execution for supported algorithms. Inspired by `scikit-learn`’s API design (Buitinck et al., 2013), all EIL algorithms inherit from a base class and share the same interface: (i) `fit` builds an ensemble classifier from the class-imbalanced training set \((X, Y)\); (ii) `predict` returns the predicted class labels corresponding to the given input samples; and (iii) `predict.proba` gives predicted class probabilities instead of labels. Additionally, inspired by `imblearn`’s API design (Lemaitre et al., 2017) and the taxonomy in Table 1, we decouple the implementation of imbalance handling and ensemble training in `imbens`. For example, all resampling + boosting EIL models (e.g., RUSBoost, SMOTEBoost) inherit the `ResampleBoostClassifier`, only with different samplers (e.g., `RandomUnderSampler`, `SMOTE`) from the `imbens.samplers` module. New models can be easily implemented within this framework by taking advantage of inheritance and polymorphism.

All EIL models take two key parameters for initialization: `estimator` and `n_estimators`. The former can be any `scikit-learn`-style classifier instance, and the latter is an integer that specifies the size of the ensemble. To enable more precise control and monitoring of the EIL training process, the `fit` function takes several additional keyword arguments. `target_label`, `n_target_samples` and `balancing_schedule` can be used to dynamically adjust the sampling strategy during training, and `cost_matrix` allows the user to specify the misclassification cost for each class. Besides, `eval_datasets`, `eval_metrics`, and `train_verbose` control the content and granularity of the ensemble training log. Table 2 summarizes the data type, availability, and semantics of these keyword arguments.
Additionally, `imbens` provides a set of utility functions (`generate_imbalance_data`, `evaluate_print`, etc.) in the `imbens.utils` and `imbens.visualizer` modules. With these utilities, Users can easily create synthetic imbalanced datasets, test EIL models, and (visually) evaluate and compare multiple EIL models. Code Snippet 1 is a demo showcasing how the deployment, evaluation, and visualization of EIL models can be conveniently conducted using the `imbens` API. Figure 1 shows examples of evaluating various EIL models on multiple datasets and metrics using the `ImbalancedEnsembleVisualizer`.

```python
>>> from imbens import ensemble, datasets, utils, visualizer

>>> X_train, X_test, y_train, y_test = datasets.generate_imbalance_data(
    ... n_samples=200, weights=[.9,.1], test_size=.5) # prepare data

>>> clf = ensemble.SelfPacedEnsembleClassifier()  # initialize ensemble
>>> clf.fit(X_train, y_train)

>>> y_test_pred = clf.predict(X_test)  # predict labels

>>> utils.evaluate_print(y_test, y_test_pred, "SPE")  # performance evaluation
SPE balanced Acc: 0.972| macro Fscore: 0.886| macro Gmean: 0.972

>>> vis = visualizer.ImbalancedEnsembleVisualizer()  # initialize visualizer
>>> vis.fit({'SPE': clf})

>>> vis.performance_lineplot()  # performance visualization

>>> vis.confusion_matrix_heatmap()  # prediction visualization
```

Code Snippet 1: Demo of `imbens` API with the `SelfPacedEnsembleClassifier` classifier.

Figure 1: Examples of using `ImbalancedEnsembleVisualizer` for visualization.

### 4 Conclusion and future plans

In this paper, we present `imbens`, a comprehensive Python toolbox for out-of-the-box ensemble class-imbalanced learning. As avenues for future work, we plan to include additional ensemble imbalanced learning methods that are based on evolutionary algorithm/meta-learning/hybrid-sampling, as well as more detailed examples, user guides and tutorials.

2. More examples can be found in the `imbens` documentation.
Acknowledgments and Disclosure of Funding

The authors would like to thank (i) Zhepei Wei, Erxin Yu, Qiang Huang, Kai Guo, Boyang Yu, Zhaonian Cai, Hangting Ye from Jilin University, (ii) Wei Cao, Jiang Bian from Microsoft Research, (iii) Pengfei Wei from ByteDance Singapore, and (iv) Jing Jiang from University of Technology Sydney, for their valuable suggestions and comments during the development of this project.

References

R. Barandela, R. M. Valdovinos, and J. S. Sánche. New applications of ensembles of classifiers. *Pattern Analysis & Applications*, 6(3):245–256, 2003.

L. Buitinck, G. Louppe, M. Blondel, F. Pedregosa, A. Mueller, O. Grisel, V. Niculae, P. Prettenhofer, A. Gramfort, J. Grobler, R. Layton, J. VanderPlas, A. Joly, B. Holt, and G. Varoquaux. API design for machine learning software: experiences from the scikit-learn project. In *ECML PKDD Workshop: Languages for Data Mining and Machine Learning*, pages 108–122, 2013.

N. V. Chawla, A. Lazarevic, L. O. Hall, and K. W. Bowyer. Smoteboost: Improving prediction of the minority class in boosting. In *European conference on principles of data mining and knowledge discovery*, pages 107–119. Springer, 2003.

C. Chen, A. Liaw, L. Breiman, et al. Using random forest to learn imbalanced data. *University of California, Berkeley*, 110(1-12):24, 2004.

X. Dong, Z. Yu, W. Cao, Y. Shi, and Q. Ma. A survey on ensemble learning. *Frontiers of Computer Science*, 14:241–258, 2020.

W. Fan, S. J. Stolfo, J. Zhang, and P. K. Chan. Adacost: misclassification cost-sensitive boosting. In *Icml*, volume 99, pages 97–105. Citeseer, 1999.

M. Galar, A. Fernandez, E. Barrenechea, H. Bustince, and F. Herrera. A review on ensembles for the class imbalance problem: bagging-, boosting-, and hybrid-based approaches. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 42(4):463–484, 2012.

G. Haixiang, L. Yijing, J. Shang, G. Mingyun, H. Yuanyue, and G. Bing. Learning from class-imbalanced data: Review of methods and applications. *Expert Systems with Applications*, 73:220–239, 2017.

H. He and E. A. Garcia. Learning from imbalanced data. *IEEE Transactions on Knowledge & Data Engineering*, (9):1263–1284, 2008.

H. He and Y. Ma. *Imbalanced learning: foundations, algorithms, and applications*. John Wiley & Sons, 2013.

G. Kovács. Smote-variants: A python implementation of 85 minority oversampling techniques. *Neurocomputing*, 366:352–354, 2019.
G. Lemaître, F. Nogueira, and 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):1–5, 2017. URL http://jmlr.org/papers/v18/16-365.html.

X.-Y. Liu, J. Wu, and Z.-H. Zhou. Exploratory undersampling for class-imbalance learning. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 39(2):539–550, 2009.

Z. Liu, W. Cao, Z. Gao, J. Bian, H. Chen, Y. Chang, and T.-Y. Liu. Self-paced ensemble for highly imbalanced massive data classification. In *2020 IEEE 36th International Conference on Data Engineering (ICDE)*, pages 841–852. IEEE, 2020.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, et al. Scikit-learn: Machine learning in python. *Journal of machine learning research*, 12(Oct):2825–2830, 2011.

C. Seiffert, T. M. Khoshgoftaar, J. Van Hulse, and A. Napolitano. Rusboost: A hybrid approach to alleviating class imbalance. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 40(1):185–197, 2010.

G. K. J. Shawe-Taylor and G. Karakoulas. Optimizing classifiers for imbalanced training sets. *Advances in neural information processing systems*, 11(11):253, 1999.

P. Viola and M. Jones. Fast and robust classification using asymmetric adaboost and a detector cascade. *Advances in Neural Information Processing System*, 14, 2001.

S. Wang and X. Yao. Diversity analysis on imbalanced data sets by using ensemble models. In *2009 IEEE Symposium on Computational Intelligence and Data Mining*, pages 324–331. IEEE, 2009.