Survey of resampling techniques for improving classification performance in unbalanced datasets

Ajinkya More (ajinkya@umich.edu)

ABSTRACT

A number of classification problems need to deal with data imbalance between classes. Often it is desired to have a high recall on the minority class while maintaining a high precision on the majority class. In this paper, we review a number of resampling techniques proposed in literature to handle unbalanced datasets and study their effect on classification performance.

1. INTRODUCTION

Classification problems often suffer from data imbalance across classes. This is the case when the size of examples from one class is significantly higher or lower relative to the other classes. For many such problems it is desirable to build classifiers with good performance on the minority class. Using out of the box classifiers for such problems may lead to suboptimal results with respect to this objective.

In this paper we study several techniques for boosting classification performance in the presence of data imbalance. We begin with examples of some domains where unbalanced datasets is the norm.

1.1 Examples

1.1.1 Fraud detection

Detecting fraud in online transactions is a problem of significant monetary impact. The number of fraudulent transactions is typically a small fraction of all transactions and hence this problem is often cited as a protypical data imbalance problem. In many cases, a fraud detection system will flag potentially fraudulent transactions to be reviewed manually by an analyst. Given the financial implication of green lighting a fraudulent transaction, it is desirable to have a classifier that can achieve near perfect recall on the fraudulent class at the expense of lower precision, especially in the case when the cost of manual review is much smaller.

1.1.2 Product categorization

E-commerce retailers categorize their product catalog into functional groups to aid search retrieval. There is substaintial variation in the number of items belonging to each category. For instance, there are only a few iPhone models while the number of iPhone accessories (e.g. cases, chargers, stylii, etc) is several hundred fold more. There is bound to be a significant amount of overlap in the description and images of items from these two categories. An automatic product categorization system can potentially confuse between the two classes. If the retailer is optimizing for revenue, it will be better to ensure all iPhones are categorized correctly at the risk of classifying a few iPhone accessories as iPhones.

1.1.3 Disease diagonsis

For any given disease, the fraction of healthy people outnumber those affected with it. In case of rare diseases, it is a tautology to say that the dataset is highly imbalanced. If an automated classification system is used to predict the presence of the disease (likely followed by an expert evaluation), it is extremely important to have recall on the disease class to be as close to 1 as possible. In this particular case, even high precision on the minority class is essential since a significant amount of expert analysis may be needed for avoiding false positive disease prediction on healthy people.

2. NOTATION AND METRICS

Let us fix some notation to use in the remainder of the paper. We will compare several methods for handling unbalanced datsets via a case study on a synthetic two class dataset. Let us denote the majority class by L and the minority class by S. By these symbols, we will refer to both the sets representing these classes as well as the respective class labels. Denote by r = |S|/|L| the ratio of the size of the minority class to the majority class. Let the training set be denote by T.

We will compare various techniques with respect to their effect on the recall on the minority class S and the precision on the majority class L. This is motivated by applications to problems with the following characteristics:

- 1. A large number of instances need to be evaluated.
- 2. The minority class is present in a small fraction of the instances.
- 3. Only instances flagged as minority class (by an automated classification system) will be reviewed manually.
- 4. The cost of manual review is significantly lower relative to the cost of a missed detection of the minority class.

This may in case in problems such as fraud detection, identifying imminent hardware or software failures in large computer networks, identifying product issues from online reviews, etc.

3. DATASET

We compare the performance of the various methods on a synthetic dataset. We generate the dataset using the make_classification function from the Python library scikitlearn. We use the following parameters:

- 1. $n_{samples} = 10000$ (number of data points)
- 2. $n_{classes} = 2$ (number of classes)

- 3. weights = [0.1, 0.9] (fraction of sizes of each class)
- 4. class_sep = 1.2 (the amount separation between the clusters defining the two classes)
- 5. n_features = 5 (number of features)
- 6. n_informative = 3 (number of informative features)
- 7. $n_{redundant} = 1$ (number of redundant features)
- 8. $n_clusters_per_class = 1$

For ease of visualization, we perform dimensionality reduction via principal component analysis and pick the first two principal components to form our dataset. A scatterplot for the original dataset is shown below.



4. METHOD COMPARISON

In this section we explore several methods for handling the data imbalance. We split our dataset as 70% training and 30% test. We perform 5-fold cross validation on the training set to select the best parameters and report the results on the test set. The results were obtained using python libraries scikit-learn and imbalanced-learn.

4.1 Baseline

We obtain baseline results using logistic regression where we perform 5-fold cross validation to search for the best regularization parameter and the penalty type $(l_1 \text{ or } l_2)$. The classification boundary on the training set is shown below.



The performance on the test set is as follows.

precision on L	recall on S
0.90	0.12

4.2 Weighted loss function

One technique for handling class imbalance, is to use a weighted loss function. In order to boost performance on the minority class, the penalty for misclassifying minority class examples can be increased. For example the loss function for logistic regression is

$$-\sum_{j\in\mathcal{C}}\sum_{y_i=j}ln(P(y_i=j|x_i;\theta))$$

where C is the set of classes, (x_i, y_i) is an input-label pair in the training set and θ is the set of parameters. A weighted loss function may be obtained as [8]

$$-\Sigma_{j\in\mathcal{C}}\Sigma_{y_i=j}w_jln(P(y_i=j|x_i;\theta)$$

In scikit-learn, this can be done for supported classifiers using the 'class_weight' parameter. Setting this parameter to 'balanced', weights inversely proportional to the class sizes are used to multiply the loss function.

The resulting decision boundary and the performance on the test set are shown below.



precision on L	recall on S
0.98	0.89

4.3 Undersampling methods

4.3.1 Random undersampling of majority class

A simple undersampling technique is uniformly random undersampling of the majority class. This can potentially lead to loss of information about the majority class. However, in cases where each example of the majority class is near other examples of the same class, this method might yield good results.



We perform random undersampling of L in order to achieve a value of r = 0.5. Fitting a logistic regression classifier to this resampled dataset, we get the following performance.

	L	S
Before resampling	6320	680
After resampling	1360	680



4.3.2 NearMiss-1

The NearMiss family of methods [11] perform undersampling of points in the majority class based on their distance to other points in the same class. We discuss the 3 variants proposed in the paper here.

In NearMiss-1, those points from L are retained whose mean distance to the k nearest points in S is lowest, where k is a tunable hyperparameter.



We show below the result of using NearMiss-1 with k = 3.





precision on L	recall on S
0.92	0.32

4.3.3 NearMiss-2

In contrast to NearMiss-1, NearMiss-2 keeps those points from L whose mean distance to the k farthest points in S is lowest.



We show below the result of using NearMiss-2 with k = 3.







4.4 NearMiss-3

The final NearMiss variant, NearMiss-3 selects k nearest neighbors in L for every point in S. In this case, the undersampling ratio is directly controlled by k and is not separately tuned.



We show below the result of using NearMiss-3 with k = 3.

	L	S
Before resampling	6320	680
After resampling	964	680



precision on L	recall on S
0.91	0.20

4.4.1 Condensed Nearest Neighbor (CNN)

In CNN undersampling [4], the goal is to choose a subset U of the training set T such that for every point in T its nearest neighbor in U is of the same class. U can be grown iteratively as follows:

- 1. Select a random point from T and set $U = \{p\}$.
- 2. Scan T-U and add to U the first point found whose
- nearest neighbor in U is of a different class
- 3. Repeat step 2 until U is maximal

Undersampling via CNN can be slower compared to other methods since it requires many passes over the training data. Further, because of the randomness involved in the selection of points at each iteration, the subset selected can vary significantly.



A variant of CNN is to only undersample L *i.e.* retain all points from S but retain only those points in L that belong to U. We show performance below using this variant.

	L	S
Before resampling	6320	680
After resampling	882	680



precision on L	recall on S
0.93	0.39

4.4.2 Edited Nearest Neighbor (ENN)

In ENN [14], undersampling of the majority class is done by removing points whose class label differs from a majority of its k nearest neighbors.



The following results were obtained by employing ENN with k = 5.





4.4.3 Repeated Edited Nearest Neighbor

In Repeated Edited Nearest Neighbor, the ENN algorithm is applied successively until ENN can remove no further points.





4.4.4 Tomek Link Removal

A pair of examples is called a Tomek link if they belong to different classes and are each other's nearest neighbors [13]. Undersampling can be done by removing all tomek links from the dataset. An alternate method is to only remove the majority class samples that are part of a Tomek link.



We show the performance of the latter technique below.

	L	S
Before resampling	6320	680
After resampling	6051	680





4.5 Oversampling methods

At the other end of the spectrum are methods oversampling points from the minority class. We explore a few such methods in this section.

4.5.1 Random oversampling of minority class

Points from the minority class may be oversampled with replacement. This method is prone to overfitting. We consider the result of oversampling of S to achieve r = 0.5.

	L	S
Before resampling	6320	680
After resampling	6320	3160



precision on L	recall on S
0.97	0.76

4.5.2 SMOTE

A more sophisticated means for oversampling is Synthetic Minority Oversampling Technique (SMOTE) which is outlined below [1].

For each point p in S:

- 1. Compute its k nearest neighbors in S.
- 2. Randomly choose $r \leq k$ of the neighbors (with replacement).
- 3. Choose a random point along the lines joining p and each of the r selected neighbors.
- 4. Add these synthetic points to the dataset with class S.

We show below the results of applying SMOTE with k = 5 in order to achieve r = 0.5.







precision on L	recall on S
0.97	0.77

4.5.3 Borderline-SMOTE1

There are two enhancements of SMOTE, termed borderline SMOTE [3], which may yield better performance than vanilla SMOTE.

For each point p in S:

- 1. Compute its *m* nearest neighbors in *T*. Call this set M_p and let $m' = |M_p \cap L|$.
- 2. If m' = m, p is a noisy example. Ignore p and continue to the next point.
- 3. If $0 \le m' \le \frac{m}{2}$, p is safe. Ignore p and continue to the next point.
- 4. If $\frac{m}{2} \leq m' \leq m$, add p to the set DANGER.

For each point d in DANGER, apply the SMOTE algorithm to generate synthetic examples.

We apply Borderline-SMOTE1 with k = 5 in order to achieve r = 0.5.





4.5.4 Borderline-SMOTE2

Borderline-SMOTE2 is similar to Borderline-SMOTE1 except in the last step, new synthetic examples are created along the line joining points in DANGER to either their nearest neighbors in S or their nearest neighbors in L. In the latter case, the synthetic points are chosen such that they are closer to the original point.

We apply Borderline-SMOTE2 with k = 5 in order to achieve r = 0.5.



4.6 Combination methods

Performing a combination of oversampling and undersampling can often yield better results than either in isolation. We discuss two particular combinations here.

4.6.1 SMOTE + Tomek Link Removal

We show the result of performing SMOTE with k = 5 and r = 0.5 followed by Tomek link removal.

	L	S
Before resampling	6320	680
After resampling	6050	3160



precision on L	recall on S	
0.97	0.80	

4.6.2 SMOTE + ENN

The following result is obtained by performing SMOTE with k = 5 and r = 0.5 followed by ENN with k = 5.

	L	S
Before resampling	6320	680
After resampling	4894	3160



precision on L	recall on S	
0.97	0.92	

4.7 Ensemble methods

4.7.1 EasyEnsemble

In EasyEnsemble [10] a sequence of classifiers are built by resampling the majority class. The algorithm is outlined below.

1. For i = 1, ..., N:

- (a) Randomly sample a subset L_i of L such that $|L_i| = |S|$.
 - (b) Learn an AdaBoost ensemble using L_i and S

$$F_i(x) = sgn(\sum_{j=1}^{n_i} w_{ij} f_{ij}(x) - b_i)$$

2. Combine the above classifiers into a meta-ensemble

$$F(x) = sgn(\sum_{i=1}^{N} (\sum_{j=1}^{n_i} w_{ij} f_{ij}(x) - b_i))$$

precision on L	recall on S
0.98	0.88

4.7.2 BalanceCascade

BalanceCascade [10] is similar to EasyEnsemble except the classifier created in each iteration influences the selection of points in the next iteration.

- 1. Set $t = r^{\frac{1}{N-1}}$
- 2. For i = 1, ..., N:
 - (a) Randomly sample a subset L_i of L such that $|L_i| = |S|$.
 - (b) Learn an AdaBoost ensemble using ${\cal L}_i$ and ${\cal S}$

 $F_i(x) = sgn(\sum_{j=1}^{n_i} w_{ij} f_{ij}(x) - b_i)$

- (c) Tune b_i such that the false positive rate for F_i is t.
- 3. Undersample L to remove points correctly classified by F_i .
- 4. Combine the above classifiers into a meta-ensemble

$$F(x) = sgn(\sum_{i=1}^{N} (\sum_{j=1}^{n_i} w_{ij} f_{ij}(x) - b_i))$$

precision on L	recall on S	
0.99	0.91	

5. CONCLUSION

In this paper we discussed some resampling techniques to improve classification performance on the minority class in the presence of data imbalance. We presented the performance of several methods on a synthetic dataset in terms of precision on the majority class and recall on the minority class.

The methods discussed in this paper are by no means an exhaustive list. Several other techqniues have been proposed in literature which have had success in handling data imbalance. Some of these include One side selection [9], ADASYN [5], SVM SMOTE [12], SMOTEBoost [2], Cluster-Based Oversampling [7], Kernel-based methods and active learning [6].

On our synthetic dataset, with respect to our chosen metric, the methods SMOTE+ENN in combination with a logistic regression classifier and BalanceCascade give the best performance. However, depending on the data distribution, the presence of within class imbalance in addition to between class imbalance and the choice of classifier used on resampled datasets, other methods may yield better results.

6. **REFERENCES**

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