A New Over-sample Method Based on Distribution Density

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***Abstract*—A new method was proposed for leaning from the imbalanced dataset based the samples distribution density in this paper. In the proposed scheme, a model of samples distribution density was designed, followed by the improved smote progress SDD-SMOTE where we smoted the minority samples according to the samples distribution density. Cross-validation results show that proposed SDD-SMOTE method to some extent improves the minority prediction in both the recall and the precision metrics.**

***Index Terms*—imbalanced dataset; knowledge discovery; over sample; distribution density**

I. Introduction

Artificial intelligence techniques have been used in many real-world domains such as the scientific area, the business studies, the Internet mining and other applications. Learning from the imbalanced datasets are one of the popular domains of these applications [1], [2], [3], [4],[5]. When instances are inherently rare or hard to predict, the imbalanced data problem occurs.

In the classification problem field, the scenario of imbalanced data sets appears when the number of samples that represent the different classes is very different among them [6]. Class-imbalanced problems widely exist in the fields of medical diagnosis, fraud detection, network intrusion detection, science and engineering problems, and so on. A two-class data set is said to be imbalanced when one of the classes (the minority one) is heavily under-represented with regard to the other class (the majority one) [7][8][9]. This challenge comes from the fact that classifiers tend to predict the majority class in the presence of class imbalance. However, it is usually the minority class we are most interested. As a result, addressing and solving imbalanced data problem is very critical for improving classification performance for the total dataset.

In this paper, we propose a novel scheme to solve the imbalanced data problem, a new over-sample method based on distribution density(SDD-SMOTE). The main part of our proposed scheme is the distribution density of samples (SDD) method. SDD-SMOTE builds a classifier by smote from a revised dataset from the original one according to the distribution density of samples.

This paper is organized as follows: in Section 2, we present related works. We present our SDD-SMOTE technique and overall SDD-SMOTE scheme in Section 3. Assessment metrics for imbalanced learning are reviewed in Section 4, which provides various suggested methods that are used to compare and evaluate the performance of different imbalanced learning algorithms. And then we show our empirical experiments and evaluate the results with other concerned method dealing with the imbalanced problem. Considering how learning from imbalanced data is a relatively new topic in data mining and knowledge discovery community, in Section 5, we present a detailed discussion on the opportunities and challenges for future research.

II. The State-of-the-Art Solutions for Imbalanced Learning

A. Random Oversampling Technology

The main idea of random oversampling follow naturally from its description by adding a set S’ sampled only from the minority, i.e., the trained dataset includes such two parts as the original dataset plus the random

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oversampled samples from the minority class. This provides a mechanism for varying the degree of class distribution balance to any desired level. The oversampling method is simple to both understand and visualize, thus we refrain from providing any specific examples of its functionality[10].

Solberg considered the problem of imbalanced data sets in oil slick classification from SAR imagery. To better deal with this imbalance problem, he over-sampled (with replacement)100 samples from the oil slick, and then he randomly sampled 100 samples from the non oil slick class to create a new dataset with equal probabilities. He learned a classifier tree on this balanced data set and achieved a 14% error rate on the oil slicks in a leave-one-out method for error estimation; on the look alikes he achieved an error rate of 4%[11].

However, oversampling often involves making exact copies of samples which may lead to over-fitting [12].

B. SMOTE Method

To better address and solve the leaning problem from the imbalanced dataset, a combination of synthetic minority oversampling technique (SMOTE), a particular oversampling technique for the minority class, along with random undersampling for the majority class has been proposed in[6]. In this paper it is argued that regular oversampling by simple replication of minority cases affects the decision regions in feature space and may tend to overfitting, thus it is necessary to use sophisticated techniques in order to increase the number of samples in the minority classes [13]. The SMOTE algorithm is described as follows:

```
Algorithm SMOTE(T, N, k)
Input: Number of minority class samples $T$; Amount of SMOTE $N$%; Number of nearest neighbors $k$
Output: $(N/100)* T$ synthetic minority class samples
(* If N is less than 100%, randomize the minority class samples as only a random percent of them will be SMOTEd. *)
if $N <100$
    then Randomize the $T$ minority class samples
    $T = (N/100) * T$
    $N = 100$
endif
$N = (int)(N/100)$( * The amount of SMOTE is assumed to be in integral multiples of 100. * )
$k$ = Number of nearest neighbors
$numattrs$ = Number of attributes
$Sample$[ ][ ]: array for original minority class samples
$newindex$: keeps a count of number of synthetic samples generated, initialized to 0
$Synthetic$[ ][ ]: array for synthetic samples
for $i \leftarrow 1$ to $T$
    Compute $k$ nearest neighbors for $i$, and save the indices in the $nnarray$
    Populate($N$, $i$, $nnarray$)
endfor
Populate(N, i, nnarray) (* Function to generate the synthetic samples. * )
while $N \geq 0$
    Choose a random number between 1 and $k$, call it $nn$. This step chooses one of the $k$ nearest neighbors of $i$.
    for $attr \leftarrow 1$ to $numattrs$
        Compute: $dif = Sample[nnarray[nn]][attr] - Sample[i][attr]$
        Compute: $gap$ = random number between 0 and 1
        $Synthetic[newindex][attr] = Sample[i][attr] + gap * dif$
    endfor
    $newindex$++
    $N = N - 1$
endwhile
return (* End of Populate. * )
End.
```

The *SMOTE* algorithm has shown better performance the the ordinary methods in many situations [12-13].

C. Advanced SMOTE Method

The SMOTE algorithm generates synthetic minority samples to over-sample the minority class. For every minority sammple, its k (which is set to 5 in SMOTE) nearest neighbors of the same class are calculated, then some samples are randomly selected from them according to the over-sampling rate. After that, new synthetic examples are generated along the line between the minority example and its selected nearest neighbors.

The SMOTE algorithm was modified several times, trying to generate more positive samples. Han proposed a Borderline-SMOTE algorithm [14] to improve the SMOTE method. Borderline-SMOTE copy only positive samples close to the decision boundary feature space, and these samples are the most likely to be misclassified. Experiments show that, Borderline-SMOTE obtained better classification performance the pure SMOTE. Alexander Liu proposed a generative oversampling technology [15], learning new data points from the data points and shows good performance in the text classification data set.

Jia Li and Jun-Ling Yu integrated the over-sampling method of Random-SMOTE (R-S), which is based on SMOTE method, in imbalanced data mining[16]. They used the R-S method to increase the number of the minority randomly in the minority sample space until it is almost equal to the majority in data mining tasks. 5 UCI imbalanced data sets are balanced with the integrated data mining process. Log it algorithm is used for classification with these data sets. The result shows that the integrated use of R-S in data mining can improve the performance of the classifier significantly.

SMOTEBoost algorithm [17] combines SMOTE technique and the standard boosting procedure. It utilizes SMOTE for improving the accuracy over the minority class and utilizes boosting not to sacrifice accuracy over the entire data set. Wang et al. [18] propose an adaptive over-sampling technique based on data density (ASMOBD), which can adaptively synthesize different number of new samples around each minority sample according to its level of learning difficulty. Gao et al. [19] propose probability density function estimation based over-sampling approach for two-class imbalanced classification problems.

III. THE SDD-SMOTE IMPLEMENTATION

According to common sense, the bigger a sample distribution density is, the more other samples around it. For most classifiers, e.g., the decision tree classifier, they will produce more leaf nodes when it tends to over-fitting. Based on this, a new method of SDD-SMOTE algorithm based on sample distribution density (SDD) is proposed here. More details are described as follows.

The distance d_{xy} between sample x and y is defined as formula 1:

$$d_{xy} = 1 - \frac{\sum_{i=1}^{l} w_{x_i} \cdot w_{y_i}}{\sqrt{\sum_{i=1}^{l} (w_{x_i})^2 \cdot \sum_{i=1}^{l} (w_{y_i})^2}} \tag{1}$$

Where l is the length of the features of the samples, w_{x_i} and w_{y_j} are the weights of the *jth* feature of the sample x and y.

Definition 1. For $\forall x \in \Omega'$, if $y_i \in \Omega'$ is the *ith* nearest neighbor of sample x, the density matrix constructed by x and its k neighbors can be described as $DM=(d_{ij})_{t*k}$

Where k is the number of the neighbors of sample x ,t is the number of the total samples, and $1 \le i \le k$, then we get

$$z_i = \sum_{j=1}^{k} \frac{1}{d_{ij}} \tag{2}$$

Then we normalized z_i ,

$$density(z_i) = \frac{z_i}{\sum_{i=1}^{n'} z_i} \tag{3}$$

And we further calculate the SMOTEed samples for every sample x

$$SMOTEfactor(x_i) = \lceil (1 - density(x_i)) * k \rceil \tag{4}$$

Now we can implement the SDD-SMOTE algorithm. More details are described as follows:

```
Algorithm SDD-SMOTE(T $SMOTEfactor(x_i)$ , k)
Input: Number of minority class samples T; Amount of SMOTE $SMOTEfactor(x_i)$ ; Number of nearest neighbors k
Output: ( $SMOTEfactor(x_i)$ )* T synthetic minority class samples
（1） k = Number of nearest neighbors
（2） numattrs = Number of attributes
（3） Sample[ ][ ]: array for original minority class samples
（4） newindex: keeps a count of number of synthetic samples generated, initialized to 0
（5） Synthetic[ ][ ]: array for synthetic samples
（6） for i ← 1 to T
（7） Compute k nearest neighbors for i, and save the indices in the nnarray
（8） Populate(N, i, nnarray)
（9） endfor
Populate( $SMOTEfactor(x_i)$ , i, nnarray) (* Function to generate the synthetic samples. * )
（10） while $SMOTEfactor(x_i) \ge 0$
（11） Choose a random number between 1 and k, call it nn. This step chooses one of the k nearest neighbors of i.
（12） for attr ← 1 to numattrs
（13） Compute: dif = Sample[nnarray[nn]][attr] − Sample[i][attr]
（14） Compute: gap = random number between 0 and 1
（15） Synthetic[newindex][attr] = Sample[i][attr] + gap * dif
（16） endfor
（17） newindex++
（18） $SMOTEfactor(x_i)$ = $SMOTEfactor(x_i)$ − 1
（19） endwhile
（20） return (* End of Populate. * )
End.
```

IV. EXPERIMENTS AND RESULTS

A. Datasets

All experiments implemented in this paper are written in matlab. Standard pre-processing is performed on great majority of the raw data. The SVMlight [20] package is used as an implementation of SVM. When we implemented the experiments, we chose a variety of UCI datasets with different imbalanced ratio, samples size and attribute number of these samples described as Table 1.

TABLE I.
DESCRIPTION OF UCI DATA SETS

Data Set	Attributes	Concept/ Counter -concept	Positive samples	Negative samples	Imbalance ratio
German	20	Bad/Good	300	700	2.33
Vehicle	18	Van/Remainder	199	647	3.25
Satimage	38	4/Remainder	626	5809	9.28
Nursery	8	Not-recom/Remainder	328	12632	38.51

B. Performance Measures

To evaluate the utility of the various feature selection methods, we use the *F-measure*, a measure that combines precision and recall. *Precision* is defined as the ratio of correct categorization of documents into categories to the total number of attempted classifications, namely,

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \qquad (5)$$

Recall is defined as the ratio of correct classifications of documents into categories to the total number of labeled data in the testing set, namely,

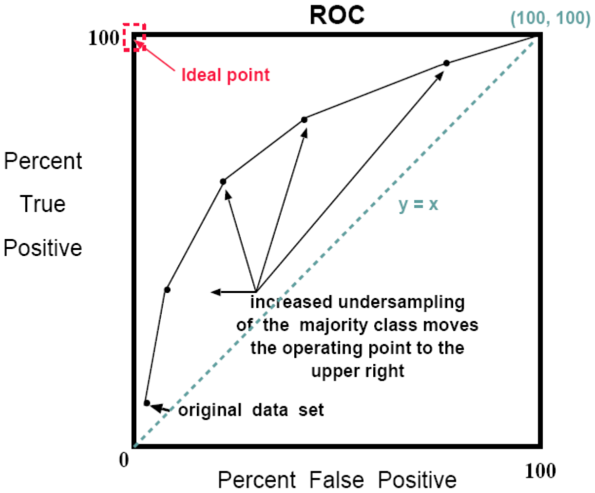
$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \qquad (6)$$

F - measure is defined as the harmonic mean of precision and recall. Hence, a good classifier is assumed to have a high *F - measure* , which indicates that the classifier performs well with respect to both precision and recall, namely,

$$F\text{ - }measure = \frac{2 * Precision * Recall}{Precision + Recall} \qquad (7)$$

$$G\text{ - }mean = \sqrt{\frac{TP}{TP+FN} * \frac{TN}{TN+FP}} \qquad (8)$$

Kubat and Matwin electively under-sampled the instances in the majority class while keeping the original instances in the minority class. They have used the geometric mean as a performance measure for the classifier, which can be related to a single point on the ROC curve. The minority examples were divided into four categories: some noise overlapping the positive class decision region, borderline samples, redundant samples and safe samples[4].



Figur1. ROC curve

C. Performance Results

- Performance with the size of the selected features
  To evaluate the performance of the SDD-SMOTE algorithm, we firstly carry out the experiments with the different size of the selected features for the 4 UCI data sets with conspicuous discrimination in imbalance ratio and data distribution. For each of the 4 datasets, results are averaged over ten standard 10-fold cross validation (CV) experiments and we employ the SVM classifier. In each fold nine out of ten samples are selected to be training set, and the left one out of five samples is testing set. This process repeats 10 times so that all samples are selected in both training set and testing set.
  Experimental results are shown as described in figure 2 to figure 5.
- The results show that such performance measures as *Precision, Recall* and *F - measure* of the SDD-SMOTE algorithm are well illustrated in figure 2 to figure 5 with different size of the selected features in the German, Vehicle, Satimage and the Nursery data sets.

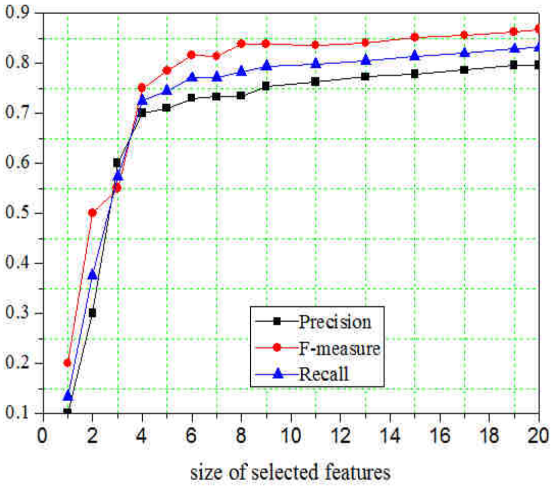


Figure 2. Result from the German dataset

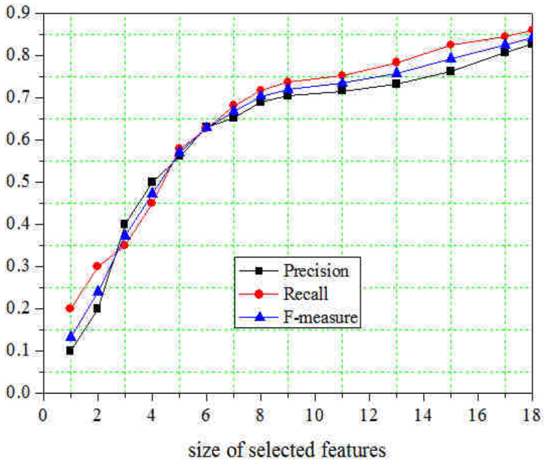


Figure 3. Result from the Vehicle dataset

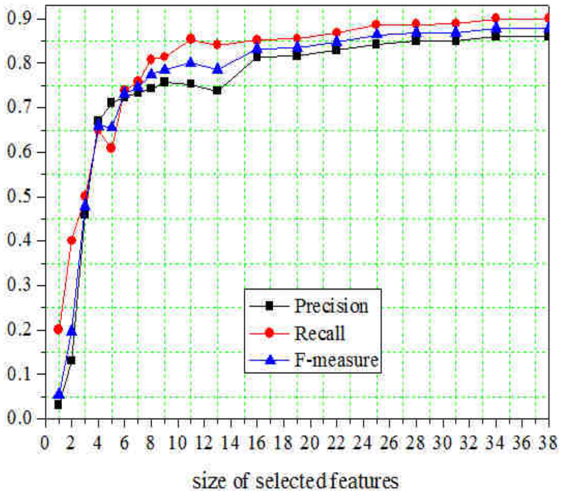


Figure 4. Result from the Satimage dataset

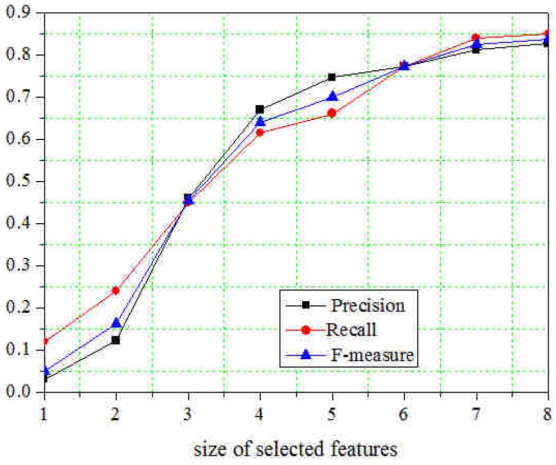


Figure 5. Result from the Nursery dataset

- Effect of noise to performance

  To better test the SDD-SMOTE performance, we employed the different noise ratio as reference [21] in the four datasets Vehicle、German、Nursery and Satimage. We implied the four different noise ratio $\gamma=0\%$, $\gamma=5\%$, $\gamma=10\%$ and $\gamma=15\%$, the SVM as the base classifier, ten standard 10-fold cross validation, and the *F-measure* as the performance measure. CV results are described as follows:

TABLE II.
CV RESULT ON THE GERMAN DATASET

Noise rate	Algorithm/Classifier	SDD-SMOTE	ROR	SMOTE	RUR
γ=0%	SVM	2-2-6	3- 3- 4	3- 2- 5	2- 4-4
	RUR	2- 4- 4	4- 2- 4	2- 3- 5	
	SMOTE	3- 3- 4	5- 3- 2		
	ROR	2- 4- 4			
γ=5%	SVM	2-1-7	2- 3- 5	2- 2- 6	2- 4-4
	RUR	2- 4- 4	4- 2- 4	2- 3- 5	
	SMOTE	3- 2- 5	5- 4- 1		
	ROR	2- 2- 5			

γ=10%	SVM	1-2-7	2- 2- 6	2- 1- 7	2- 2-6
	RUR	2- 3- 5	3- 4- 3	2- 2- 6	
	SMOTE	3- 3- 4	5- 3- 2		
	ROR	2- 1- 7			
γ=15%	SVM	0-1-9	2- 1- 7	1- 2- 7	2- 2-6
	RUR	1- 5- 4	4- 2- 4	2- 2- 6	
	SMOTE	3- 2- 5	6- 3- 1		
	ROR	0- 3- 7			

TABLE III.
CV RESULT ON THE VEHICLE DATASET

Noise rate	Algorithm/Classifier	SDD-*SMOTE*	ROR	SMOTE	RUR
γ=0%	SVM	2-1-7	3- 2- 5	3- 3- 4	3- 2-5
	RUR	3- 1- 6	4- 2- 4	2- 4- 4	
	SMOTE	4- 1- 5	5- 3- 2		
	ROR	3- 2- 5			
γ=5%	SVM	2-0-8	2- 3- 5	2- 2- 6	2- 4-4
	RUR	2- 3- 5	4- 2- 4	2- 3- 5	
	SMOTE	3- 2- 5	6- 3- 1		
	ROR	2- 3- 5			
γ=10%	SVM	1-1-8	2- 3- 5	2- 2- 6	2- 3-5
	RUR	2- 3- 5	3- 4- 3	2- 2- 6	
	SMOTE	3- 3- 4	5- 3- 2		
	ROR	2- 3- 5			
γ=15%	SVM	1-0-9	2- 1- 7	2- 0- 8	2- 1-7
	RUR	2- 2- 6	3- 3- 4	2- 2- 6	
	SMOTE	3- 3- 4	6- 3- 1		
	ROR	0- 2- 8			

TABLE IV.
CV RESULT ON THE SATIMAGE DATASET

Noise rate	Algorithm/Classifier	SDD-*SMOTE*	ROR	SMOTE	RUR
γ=0%	SVM	4-1-5	3- 5- 2	3- 4- 3	2- 5-3
	RUR	3- 3- 4	3- 3- 4	3- 4- 3	
	SMOTE	3- 4- 3	2- 5- 3		
	ROR	2- 5- 3			

γ=5%	SVM	3-2-5	3- 3- 4	3- 2- 5	2- 6-2
	RUR	3- 3- 4	3- 2- 5	2- 4- 4	
	SMOTE	3- 3- 4	3- 4- 3		
	ROR	3- 3- 4			
γ=10%	SVM	2-2-6	3- 3- 4	2- 3- 5	2- 4-4
	RUR	3- 2- 5	4- 2- 4	2- 4- 4	
	SMOTE	3- 3- 4	4- 2- 4		
	ROR	3- 2- 5			
γ=15%	SVM	2-2-6	2- 3- 5	1- 2- 7	2- 4-4
	RUR	2- 4- 4	4- 2- 4	2- 3- 5	
	SMOTE	4- 2- 4	5- 3- 2		
	ROR	2- 1- 7			

From table 1 to table 4 we can find the CV results of SDD-SMOTE and other algorithms. Every number, e.g., 2-2-6 in the first place of the table 2, represents the times of performance results of the SVM and the SDD-SMOT, i.e., in the ten standard 10-fold cross validation, the performance times of the SVM better than the SDD-SMOTE is 2, equal to the SDD-SMOTE is 2, and worse than the SDD-SMOTE is 6. We can get the conclusion that the SDD-SMOTE shows better performance in all the four UCI data sets with different noise rate.

V. Conclusion and Future Work

In this paper, we described our SDD-SMOTE learning method based on distribution density to solve the imbalanced data problem. Since some classes are not trained well when data are imbalanced, the imbalanced data cause serious performance degradation for the classification. To better address this issue, the SDD-SMOTE smoted special samples according to their distribution density.

Our method of SDD-SMOTE works to cause the classifier to build larger decision regions that contain nearby minority class points. The same reasons may be applicable to why SDD-SMOTE performs better than SVM, RUR, ROR and pure SMOTE. SDD-SMOTE provides density based minority class samples to learn from, thus allowing a learner to carve broader decision regions, leading to more coverage of the minority class.

To verify the effectiveness of our SDD-SMOTE, we experiment with for real-world UCI data sets with different feature sizes, and the empirical results show that the SDD-SMOTE performs better than concerned methods. We expect that our SDD-SMOTE can be applied to other real-world data mining applications, where we suffer from the imbalanced data problem.

Future work may consider additional learners, e.g., different variations of SVM or neural network classifiers. SDD-SMOTE can also be compared to cost-sensitive learning in future work. Alternative measures of classifier performance can also be analyzed. Future work should also consider employing the SDD-SMOTE in the context of multi-class and one-class learning[22] even in the more complex environment[23].

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