Correspondence

SVMs Modeling for Highly Imbalanced Classification

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***Abstract*—Traditional classification algorithms can be limited in their performance on highly unbalanced data sets. A popular stream of work for countering the problem of class imbalance has been the application of a sundry of sampling strategies. In this correspondence, we focus on designing modifications to support vector machines (SVMs) to appropriately tackle the problem of class imbalance. We incorporate different "rebalance" heuristics in SVM modeling, including cost-sensitive learning, and over- and undersampling. These SVM-based strategies are compared with various state-of-the-art approaches on a variety of data sets by using various metrics, including *G*-mean, area under the receiver operating characteristic curve, *F*-measure, and area under the precision/recall curve. We show that we are able to surpass or match the previously known best algorithms on each data set. In particular, of the four SVM variations considered in this correspondence, the novel *granular SVMs–repetitive undersampling* algorithm (GSVM-RU) is the best in terms of both effectiveness and efficiency. GSVM-RU is effective, as it can minimize the negative effect of information loss while maximizing the positive effect of data cleaning in the undersampling process. GSVM-RU is efficient by extracting much less support vectors and, hence, greatly speeding up SVM prediction.**

***Index Terms*—Computational intelligence, cost-sensitive learning, granular computing, highly imbalanced classification, oversampling, support vector machines (SVMs), undersampling.**

I. Introduction

Mining highly unbalanced data sets, particularly in a cost-sensitive environment, is among the leading challenges for knowledge discovery and data mining [1], [2]. The class imbalance problem arises when the class of interest is relatively rare as compared with other class(es). Without the loss of generality, we will assume that the positive class (or class of interest) is the minority class, and the negative class is the majority class. Various applications demonstrate this characteristic of high class imbalance, such as bioinformatics, e-business, information security, and national security. For example, in the medical domain, the disease may be rarer than normal cases; in business, the defaults may be rarer than good customers, etc. For our work on the Secure Computing TrustedSource network reputation system (http://www.trustedsource.org), we have to address the high imbalance toward malicious IP addresses. In addition, rapid classification is paramount as most malicious machines are only active for a brief period of time [3].

Sampling strategies, such as over- and undersampling, are extremely popular in tackling the problem of class imbalance, i.e., either the minority class is oversampled, the majority class is undersampled, or some combination of the two is deployed. In this correspondence, we focus on learning support vector machines (SVMs) with different sampling techniques. We focus on comparing the methodologies on the aspects of *effectiveness and efficiency*. While effectiveness and efficiency can be application dependent, in this correspondence, we define them as follows.

Definition 1: Effectiveness means the ability of a model to accurately classify unknown samples, in terms of some metric.

Definition 2: Efficiency means the speed to use a model to classify unknown samples.

SVM embodies the structural-risk-minimization principle to minimize an upper bound on the expected risk [4], [5]. Considering that structural risk is a reasonable tradeoff between the training error and the modeling complication, the SVM has a superior generalization capability. Geometrically, the SVM modeling algorithm works by constructing a separating hyperplane with the maximal margin. Compared with other standard classifiers, SVM is more accurate on moderately imbalanced data. The reason is that only SVs are used for classification and many majority samples far from the decision boundary can be removed without affecting the classification [6]. However, an SVM classifier can be sensitive to high class imbalance, resulting in a drop in the classification performance on the positive class. It is prone to generating a classifier that has a strong estimation bias toward the majority class, resulting in a large number of false negatives [6], [7].

There have been some recent works in improving the classification performance of SVMs on unbalanced data sets [6]–[8]. However, they do not address efficiency very well, and depending on the strategy for countering imbalance, they can take a longer time for classification than a standard SVM. In addition, SVM can be slow for classification on large data sets [9]–[11]. The speed of the SVM classification depends on the number of SVs. For a new sample X, $K(X, SV)$, the similarity between X and SV is calculated for each SV. Then, it is classified using the sum of these kernel values and a bias. One method to speed up the SVM classification is by decreasing the number of SVs.

We previously presented a preliminary version of the *granular SVMs–repetitive undersampling* (GSVM-RU) algorithm [12]. A variant of this GSVM technique has been successfully integrated into Secure Computing's TrustedSource reputation system for providing real-time collaborative sharing of global intelligence about the latest e-mail threats [3]. However, it remains unclear how GSVM-RU performs compared with other state-of-the-art algorithms. Therefore, we present an exhaustive empirical study on benchmark data sets.

In this correspondence, we also theoretically extend GSVM-RU based on the information-loss-minimization principle and design a new "combine" aggregation method. Furthermore, we revise it as a highly effective and efficient SVM modeling technique by explicitly executing granulation and aggregation by turns and, hence, avoiding extracting too many negative granules. As a prior-knowledge-guided repetitive undersampling strategy to "rebalance" the data set at hand, GSVM-RU can improve classification performance by the following: 1) extracting informative samples that are essential for classification and 2) eliminating a large amount of redundant, or even noisy, samples. Aside from GSVM-RU, we also propose three other SVM modeling methods that overweight the minority class, oversample the minority class, or undersample the majority class. These SVM modeling

Manuscript received August 9, 2007; revised February 21, 2008 and June 21, 2008. First published December 9, 2008; current version published January 15, 2009. This paper was recommended by Associate Editor E. Santos.

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Digital Object Identifier 10.1109/TSMCB.2008.2002909

TABLE I
CONFUSION MATRIX

	predicted positives	predicted negatives
real positives	TP	FN
real negatives	FP	TN

methods are compared favorably with previous works in 25 groups of experiments.

The rest of this correspondence is organized as follows. Background knowledge is briefly reviewed in Section II. Section III presents GSVM-RU and three other SVM modeling algorithms with different "rebalance" techniques. Section IV compares these four algorithms with state-of-the-art approaches on seven highly imbalanced data sets under different metrics. Finally, Section V concludes this correspondence.

II. BACKGROUND

A. Metrics for Imbalanced Classification

Many metrics have been used for effectiveness evaluation on imbalanced classification. All of them are based on the confusion matrix as shown in Table I. With highly skewed data distribution, the overall accuracy metric at (1) is no longer sufficient. For example, a naive classifier that predicts all samples as negative has high accuracy. However, it is totally useless in detecting rare positive samples. To deal with class imbalance, two kinds of metrics have been proposed

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}. \quad (1)$$

To obtain an optimal balanced classification ability, sensitivity at (2) and specificity at (3) are usually adopted to separately monitor the classification performance on two classes. Notice that sensitivity is also called true positive rate or positive class accuracy, while specificity is also called true negative rate or negative class accuracy. Based on these two metrics, G-mean was proposed at (4), which is the geometric mean of sensitivity and specificity [13]. Furthermore, an area under a receiver operating characteristic curve (AUC-ROC) can also indicate a balanced classification ability between sensitivity and specificity as a function of varying a classification threshold [14]

$$\text{sensitivity} = \text{TP}/(\text{TP} + \text{FN}) \quad (2)$$

$$\text{specificity} = \text{TN}/(\text{TN} + \text{FP}) \quad (3)$$

$$G\text{-Mean} = \sqrt{\text{sensitivity} * \text{specificity}}. \quad (4)$$

On the other hand, sometimes, we are interested in the highly effective detection ability for only one class. For example, for a credit-card-fraud-detection problem, the target is detecting fraudulent transactions. For diagnosing a rare disease, what we are particularly interested in is finding patients with this disease. For such problems, another pair of metrics, precision at (5) and recall at (6), is often adopted. Notice that recall is the same as sensitivity. F-measure at (7) is used to integrate precision and recall into a single metric for the convenience of modeling [15]. Similar to AUC-ROC, an area under precision/recall curve (AUC-PR) can be used to indicate the detection ability of a classifier between precision and recall as a function of varying a decision threshold [16]

$$\text{precision} = \text{TP}/(\text{TP} + \text{FP}) \quad (5)$$

$$\text{recall} = \text{TP}/(\text{TP} + \text{FN}) \quad (6)$$

$$F\text{-Measure} = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}}. \quad (7)$$

In this correspondence, the *perf* code, which is available at http://kodiak.cs.cornell.edu/kddcup/software.html, is utilized to calculate all of the four metrics.

B. Previous Methods for Imbalanced Classification

Many methods have been proposed for imbalanced classification, and some good results have been reported [2]. These methods can be categorized into the following three different categories: cost-sensitive learning, oversampling the minority class, or undersampling the majority class. Interested readers may refer to [17] for a good survey. However, different measures have been used by different authors, which make comparisons difficult.

Recently, several new models have been reported in the literature with good classification performance on imbalanced data. Hong *et al.* [18] proposed a classifier-construction approach based on orthogonal forward selection, which precisely aims at high effectiveness and efficiency. Huang *et al.* [19], [20] proposed a biased minimax probability machine, which offers an elegant and systematic way to incorporate a certain bias for the minority class by directly controlling the lower bound of the real accuracy.

Previous research that aims to improve the effectiveness of SVM on imbalanced classification includes the following. Vilariño *et al.* [22] used a Synthetic Minority Oversampling TEchnique (SMOTE) [21] oversampling and also a random undersampling for SVM modeling on an imbalanced intestinal-contraction-detection task. Raskutti and Kowalczyk [8] demonstrated that a one-class SVM that learned only from the minority class can sometimes perform better than an SVM modeled from two classes. Akbani *et al.* [6] proposed the SMOTE with Different Costs algorithm (SDC). SDC conducts SMOTE oversampling on the minority class with different error costs. As a result, the decision boundary can be far away from the minority class. Wu and Chang [7] proposed the kernel boundary alignment algorithm (KBA) that adjusts the boundary toward the majority class by modifying the kernel matrix.

Vilariño *et al.* [22] worked on only one data set. One-class SVM actually performs worse in many cases compared with a standard two-class SVM [8]. SDC or KBA improves the classification effectiveness on a two-class SVM. However, they are not efficient and, hence, are difficult to scale to very large data sets. Wu and Chang [7] reported that KBA usually takes a longer time for classification than SVM. SDC is also slower than the standard SVM modeling because oversampling increases the number of SVs. Unfortunately, SVM itself is already very slow on large data sets [9]–[11].

This correspondence contrasts with the previous works as follows.

1) Most prior works evaluate classification performance only on one or two metrics mentioned earlier. We present a broader experimental study on all four metrics.
2) Most previous works use decision trees as the basic classifier [1]. While there are some recent papers on SVM for imbalanced classification [6]–[8], [22], the application of SVM is still not completely explored, particularly the realm of undersampling of SVs. Because SVM decides the class of a sample based only on SVs, which are training samples close to the decision boundary, the modeling effectiveness and efficiency may be improved for the imbalanced classification by exploring the SV-based undersampling.

III. GSVM-RU ALGORITHM

Granular computing represents information in the form of some aggregates (called information granules) such as subsets, subspaces, classes, or clusters of a universe. It then solves the targeted problem

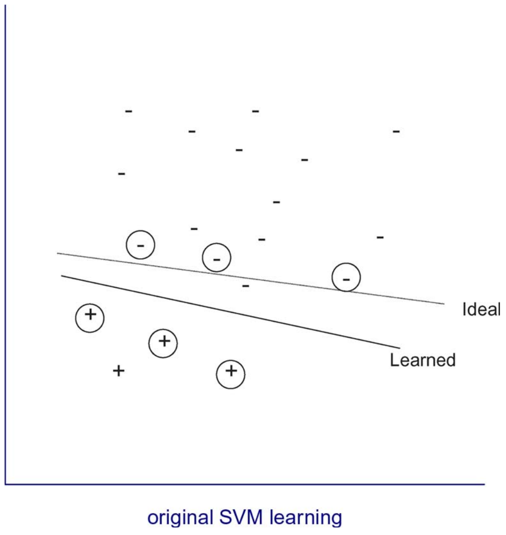


Fig. 1. Original SVM modeling. The circled points denote SVs.

in each information granule [23]. There are two principles in granular computing. The first principle is divide-and-conquer—to split a huge problem into a sequence of granules (granule split). The second principle is data cleaning—to define the suitable size for one granule to comprehend the problem at hand without getting buried in unnecessary details (granule shrink). As opposed to traditional data-oriented numeric computing, granular computing is knowledge oriented [24]. By embedding prior knowledge or prior assumptions into the granulation process for data modeling, a better classification can be obtained. A granular computing-based learning framework called GSVM was proposed in our previous work [25]. GSVM combines the principles from statistical learning and granular computing theories in a systematic and formal way. GSVM extracts a sequence of information granules, with granule split and/or shrink, and then builds SVMs on some of these granules if necessary. The main potential advantages of GSVM are the following.

1) GSVM is more sensitive to the inherent data distribution by establishing a tradeoff between the local significance of a subset of data and the global correlation among different subsets of data or between the information loss and the data cleaning. Hence, GSVM may improve the classification effectiveness.
2) GSVM may speed up the classification process by eliminating redundant data locally. As a result, it is more efficient and scalable on huge data sets.

Based on GSVM, we propose a GSVM-RU algorithm that is specifically designed for highly imbalanced classification.

A. GSVM-RU

SVM assumes that only SVs are informative to classification and other samples can be safely removed. However, for a highly imbalanced classification, the majority class pushes the ideal decision boundary toward the minority class [6], [7]. As shown in Fig. 1, (circled minus signs) negative SVs that are close to the learned boundary may not be the most informative or even noisy. Some informative samples may hide behind them. To find these informative samples, we can conduct cost-sensitive learning or oversampling. However, these two "rebalance" strategies increase the number of SVs (Figs. 2 and 3) and, hence, slow down the classification process.

To improve efficiency, it is natural to decrease the size of the training data set. In this sense, undersampling is, by nature, more suitable than other approaches for modeling an SVM for imbalanced classification.

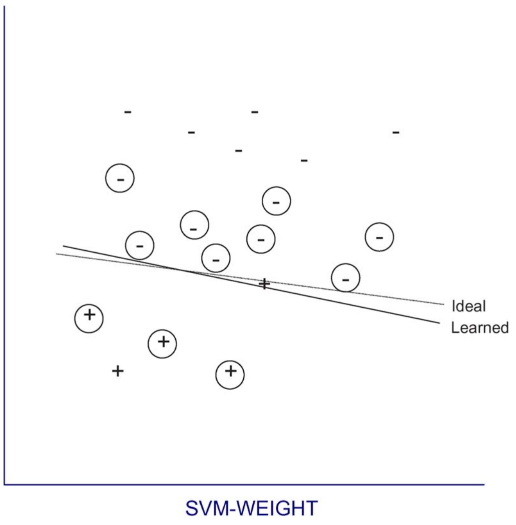


Fig. 2. SVM-WEIGHT modeling. The circled points denote SVs.

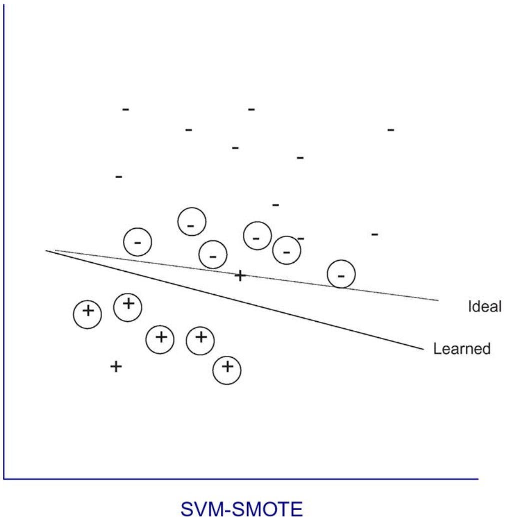


Fig. 3. SVM-SMOTE modeling. The circled points denote SVs.

However, the elimination of some samples from the training data set may have two effects.

1) Information loss: Due to the elimination of informative or useful samples, classification effectiveness is deteriorated.
2) Data cleaning: Because of the elimination of irrelevant, redundant, or even noisy samples, classification effectiveness is improved.

For a highly imbalanced data set, there may be many redundant or noisy negative samples. Random undersampling is a common undersampling approach for rebalancing the data set to achieve better data distribution. However, random undersampling suffers from information loss. As Fig. 4 shows, although random undersampling pushes the learned boundary close to the ideal boundary, the cues about the orientation of the ideal boundary may be lost [6].

GSVM-RU is targeted to directly utilize SVM itself for undersampling. The idea is based on the well-known fact about SVM—only SVs are necessary, and other samples can be safely removed without affecting the classification. This fact motivates us to explore the possibility of utilizing SVM for data cleaning/undersampling.

However, due to the highly skewed data distribution, the SVM modeled on the original training data set is prone to classify every sample as negative. As a result, a single SVM cannot guarantee to

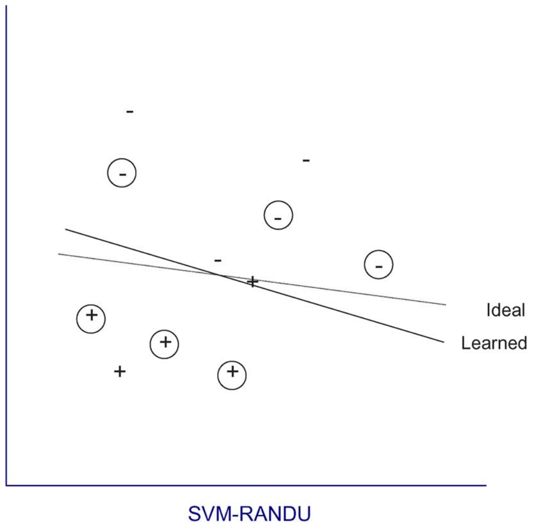


Fig. 4. SVM-RANDU modeling. The circled points denote SVs.

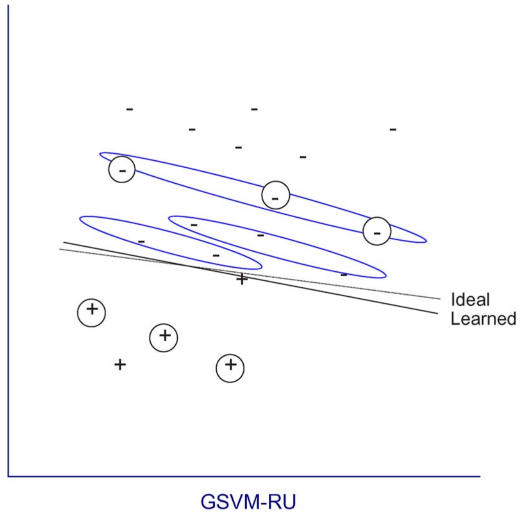


Fig. 5. GSVM-RU modeling. The circled points denote SVs.

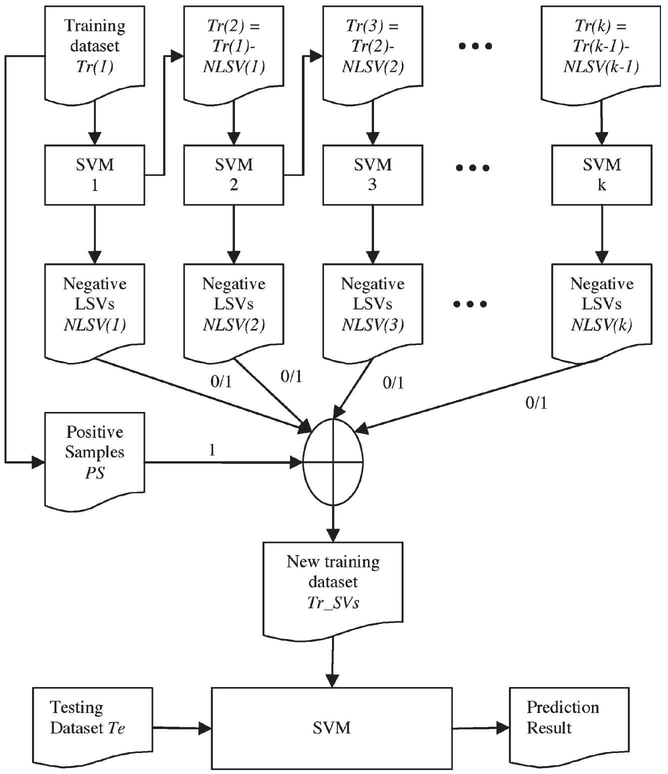


Fig. 6. Basic idea of GSVM-RU.

extract all informative samples as SVs. Fortunately, it seems reasonable to assume that a single SVM can extract a part of, although not all, informative samples. Under this assumption, multiple information granules with different informative samples can be formed by the following granulation operations. First, we assume that all positive samples are informative in order to form a positive information granule. Second, negative samples extracted by an SVM as SVs are also possibly informative so that they form a negative information granule. Here, we call these negative samples negative local support vectors (NLSVs). Then, these NLSVs are removed from the original training data set to generate a smaller training data set, on which a new SVM is modeled to extract another group of NLSVs. This process is repeated several times to form multiple negative information granules. After that, all other negative samples still remaining in the training data set are simply discarded.

An aggregation operation is then executed to selectively aggregate the samples in these negative information granules with all positive samples to complete the undersampling process. Finally, an SVM is modeled on the aggregated data set for classification. As shown in Fig. 5, considering that only a part of the NLSVs (and the negative samples very far from the decision area) is removed from the original data set, the GSVM-RU undersampling can still give good cues about the orientation of the ideal boundary and, hence, can overcome the shortcoming of random undersampling, as mentioned earlier. Fig. 6 shows the idea of the GSVM-RU.

For the SVM modeling, GSVM-RU adds another hyperparameter Gr, which is the number of negative granules. To implement GSVM-RU as a utilizable algorithm, there are two related problems.

1) How many negative information granules should be formed?
2) How will the samples in these information granules be aggregated?

It seems safe to extract more granules to reduce information loss. However, information contributed by two different granules may be redundant or even noisy to each other. Hence, lesser granules may decrease this redundancy or noise from the final aggregation data set. In general, if Gr granules are extracted, we have 2^{Gr} different combinations to build the final aggregation data set. It is extremely expensive to try all of these combinations.

For simplicity and efficiency, in this correspondence, we revise the preliminary GSVM-RU algorithm [12] and propose running granulation and aggregation in turns. First, the aggregation data set is initialized to consist of only positive samples. Furthermore, the best classification performance is initialized as the performance of the naive classifier that classifies every sample as negative. When a new negative granule is extracted, the corresponding NLSVs are immediately aggregated into the aggregation data set. An SVM is then modeled on this new aggregation data set. If the classification performance is improved, we continue to the next phase to extract another granule; otherwise, the repetitive undersampling process is stopped, and the classifier in the previous phase will be saved for future classification.

In [12], we proposed the "discard" operation for aggregation. When a new negative granule is extracted, only negative samples in the latest granule are aggregated into the new aggregation data set, and all samples in the old negative granules are discarded. This operation is based on the "boundary push" assumption. If the old NLSVs are

TABLE II
CHARACTERISTICS OF DATA SETS

Dataset	# of Samples	# of Positive samples (%)	# of Features	Validation Method
Oil	937	41 (4.38%)	49	10-fold CV
Mammography	11183	260 (2.32%)	6	10-fold CV
Satimage	6435	626 (9.73%)	36	10-fold CV
Abalone (19 vs. other)	4177	32 (0.77%)	8	6:1 or 7:3 partition
Abalone (9 vs. 18)	731	42 (5.75%)	8	10-fold CV
Yeast (ME2 vs. other)	1484	51 (3.44%)	8	6:1 partition
Yeast (CYT vs. POX)	483	20 (4.14%)	8	10-fold CV

discarded, the decision boundary is expected to be closer to the ideal one. The repetitive undersampling process is stopped when the new extracted granule alone cannot further improve the classification performance.

However, the "discard" operation is not always suitable because it removes all previous negative granules which are likely to be informative. In this correspondence, we design a new "combine" aggregation operation. When a new granule is extracted, it is combined with all old granules to form a new aggregation data set. The assumption is that not all informative samples can be extracted as NLSVs in one granule. As a result, this operation is expected to reduce information loss by extracting NLSVs multiple times. The repetitive undersampling process is stopped when the new extracted granule cannot further improve the classification performance if joined with the previous aggregation data set.

The choice of which aggregation operation is better is data and, also, metric dependent. For efficiency, we run both of them only when the second negative granule is extracted. The winner will be used for the following aggregation. All SVMs modeled in the repetitive process use the same kernel and parameters, which are tuned with grid search [26]. With such a repetitive undersampling process, a clear knowledge-oriented data-cleaning strategy is implemented.

B. Three Other SVM Modeling Algorithms

In this correspondence, we investigate three other "rebalance" techniques on SVM modeling for an exhaustive comparison study.

1) SVM-WEIGHT: SVM-WEIGHT implements cost-sensitive learning for SVM modeling. The basic idea is to assign a larger penalty value to false negatives (FNs) than false positives (FPs) [6], [27], [28]. Although the idea is straightforward and has been implemented in LIBSVM [26], there is no systematic experimental report yet to evaluate the performance of this idea on highly imbalanced classification. Without the loss of generality, the cost for an FP is always one. The cost for an FN is usually suggested to be the ratio of negative samples over the positive samples. However, our experiments show that it is not always optimal. Hence, we add one parameter Rw into this algorithm. If there are Np and Nn positive and negative samples, respectively, the FN cost should be $Nn/(Rw * Np)$. The optimal value of Rw is decided by the grid search.

2) SVM-SMOTE: SVM-SMOTE adopts the SMOTE algorithm [21] to generate more pseudopositive samples and then builds an SVM on the oversampling data set [6]. SVM-SMOTE also introduces one parameter Ro. If there are Np positive samples, we should add $Ro * Np$ pseudopositive samples into the original training data set. The optimal value of Ro is decided by the grid search.

3) SVM-RANDU: SVM-RANDU randomly selects a few negative samples and then builds an SVM on the undersampling data set [6]. Random undersampling was studied in [1], [13]. SVM-RANDU has an unknown parameter Ru. If there are Np positive samples, we should randomly select $Ru * Np$ negative samples from the original training data set. The optimal value of Ru is decided by the grid search.

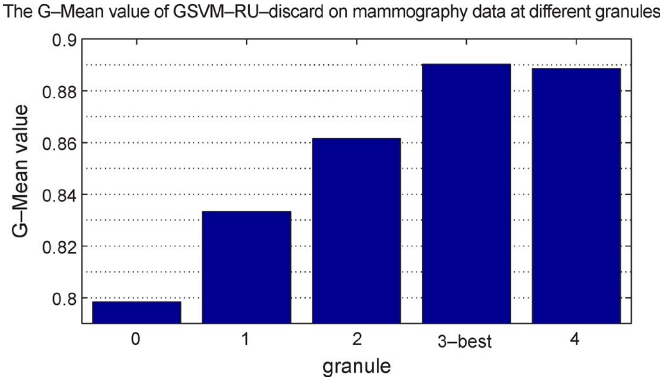


Fig. 7. G-mean values of GSVM-RU modeling with "discard" operation on mammography data.

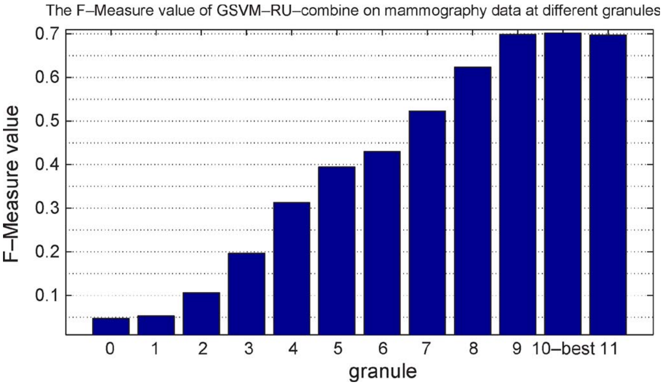


Fig. 8. F-measure values of GSVM-RU modeling with "combine" operation on mammography data.

C. Time Complexity

On highly imbalanced data, an SVM typically needs $O((Np + Nn)^3)$ time for training in the worst case [5]. SVM-RANDU takes $O((Np + Np * Ru)^3)$, which is faster than SVM because, typically, $Np * Ru \ll Nn$. SVM-SMOTE, takes $O((Np * (Ro + 1) + Nn)^3)$, which is slower than SVM because it increases the size of the training data set. SVM-WEIGHT seems to take the same $O((Np + Nn)^3)$ time as SVM. However, overweighting typically makes it harder for SVM learning to converge, and hence, it usually takes a longer time than SVM without overweighting. GSVM-RU takes $O(Gr * (Np + Nn)^3)$ because we need to model an SVM for each granule extraction. However, the later modeling steps are faster because the previous negative SVs (which are "hard" samples for classification) have been removed.

At the prediction phase, if an SVM has Ns SVs and there are Nu unknown samples for prediction, it takes $O(Ns * Nu)$ time for prediction. Our experiments demonstrate that GSVM-RU and SVM-RANDU extract significantly less SVs and, hence, are more efficient.

TABLE III
EFFECTIVENESS OF CLASSIFICATION

dataset	metric	validation	previous best	GSVM-RU	best in this work
Oil	G-Mean	10-fold CV	**87.4** (WRF [29])	84.9 (D)	84.9 (GSVM-RU)
Mam	G-Mean	10-fold CV	86.7 (BRF [29])	**89.0** (D)	**90.5** (SVM-RANDU)
Sat	G-Mean	10-fold CV	88.1 (AdaCost [30])	**89.9** (D)	**90.6** (SVM-WEIGHT)
A(9-18)	G-Mean	10-fold CV	74.1 (CSB2 [30])	**86.5** (D)	**86.5** (GSVM-RU)
Y(C-P)	G-Mean	10-fold CV	**80.9** (AdaCost [30])	79.8 (D)	79.9 (SVM-WEIGHT)
A(19)	G-Mean	7 times 6:1	57.8 (KBA [7])	**81.1** (D)	**81.5** (SVM-WEIGHT)
A(19)	G-Mean	7 times 7:3	80.6 (DEC [6])	**81.9** (D)	**84.5** (SVM-WEIGHT)
Y(ME2)	G-Mean	7 times 6:1	82.2 (KBA [7])	**87.8** (D)	**87.8** (GSVM-RU)
Oil	AUC-ROC	10-fold CV	85.4 (SMOTE [21])	**93.8** (D)	**94.2** (SVM-SMOTE)
Mam	AUC-ROC	10-fold CV	93.3 (SMOTE [21])	**93.9** (D)	**94.8** (SVM-RANDU)
Sat	AUC-ROC	10-fold CV	89.8 (SMOTE [21])	**95.1** (D)	**96.2** (SVM-WEIGHT)
A(9-18)	AUC-ROC	10-fold CV	N/A	93.6 (D)	94.1 (SVM-SMOTE)
Y(C-P)	AUC-ROC	10-fold CV	N/A	84.5 (D)	84.5 (GSVM-RU)
A(19)	AUC-ROC	7 times 6:1	**87.4** (KBA [7])	86.2 (D)	86.6 (SVM-WEIGHT)
Y(ME2)	AUC-ROC	7 times 6:1	**95.2** (KBA [7])	92.8 (D)	93.6 (SVM-RANDU)
Oil	F-Measure	10-fold CV	55.0 (DataBoost-IM [30])	**64.1** (D)	**66.7** (SVM-WEIGHT)
Mam	F-Measure	10-fold CV	**71.3** (WRF [29])	70.2 (C)	70.2 (GSVM-RU)
Sat	F-Measure	10-fold CV	**70.2** (SMOTE-Boost [31])	69.1 (C)	69.7 (SVM-SMOTE)
A(9-18)	F-Measure	10-fold CV	45.0 (DataBoost-IM [30])	**60.4** (D)	**64.7** (SVM-SMOTE)
Y(C-P)	F-Measure	10-fold CV	58.0 (DataBoost-IM [30])	**68.8** (D)	**68.8** (ALL)
Oil	AUC-PR	10-fold CV	N/A	58.8 (D)	61.1 (SVM-WEIGHT)
Mam	AUC-PR	10-fold CV	N/A	64.3 (C)	68.4 (SVM-SMOTE)
Sat	AUC-PR	10-fold CV	N/A	74.4 (C)	75.4 (SVM-SMOTE)
A(9-18)	AUC-PR	10-fold CV	N/A	65.5 (D)	66.6 (SVM-WEIGHT)
Y(C-P)	AUC-PR	10-fold CV	N/A	62.9 (D)	62.9 (GSVM-RU)

IV. EMPIRICAL STUDIES

The experiments are conducted on a machine with a Centrino 1.6-MHz CPU and 1024-MB memory. The software is based on the OSU SVM Classifier Matlab Toolbox, which is available at http://sourceforge.net/projects/svm/ and implements a Matlab interface to LIBSVM [26].

A. Data Sets

Seven data sets, collected from related works, are used in our empirical studies. As shown in Table II, all of them are highly imbalanced, as less than 10% of the samples are positive. There are also significant variations of the data size (from several hundreds to over tens of thousands) and the number of features (from 6 to 49).

For each data set, the performance is evaluated with the following four metrics: G-mean, AUC-ROC, F-measure, and AUC-PR.

The classification performance is estimated with different training/testing heuristics. For five of the seven data sets, ten-fold cross validation is used. For Abalone (19 versus other) and Yeast (ME2 versus other) data sets, it is estimated by averaging on a seven times random partition, with a training/testing ratio of 6 : 1 or 7 : 3. Basically, if a training/testing heuristic was used for a data set in previous works, we also use it for comparison.

For each fold or each training/testing process, the data is normalized first so that each input feature has zero mean and one standard deviation on the training data set; then, classification algorithms are executed on the normalized training data set, and the model parameters are optimized by the grid search.

The modeling process is carried out separately for each of the four metrics. SVM-SMOTE and SVM-RANDU are executed ten times, and the average performance ± standard deviation is reported. SVM-WEIGHT and GSVM-RU are executed only once because they are stable in the sense that the performance is never modified among multiple runs if parameters are fixed.

In the following, only high-level comparisons between GSVM-RU and other approaches are reported. Readers can access detailed comparison results on each data set at http://tinman.cs.gsu.edu/~cscyntx/gsvm-ru/imbalance-result.pdf.

B. How GSVM-RU Improves Classification

With limited space, the mammography data set is used as one example to show how GSVM-RU works to improve classification. We obtain similar performance gains on other data sets.

With G-mean for evaluation, the best validation performance is observed when the "discard" aggregation operation is adopted and the fourth granule is used as the final aggregation data set (i.e., the first three granules are discarded). The result indicates that the first assumption (the decision boundary is pushed toward the minority class) is reasonable here. When the NLSVs in the old granules are discarded, the decision boundary gradually goes back to the "ideal" one, and thus, classification performance is improved (Fig. 7). After the fifth granule is extracted, too many informative samples are discarded so that the classification performance deteriorates. Hence, the repetitive undersampling process is stopped.

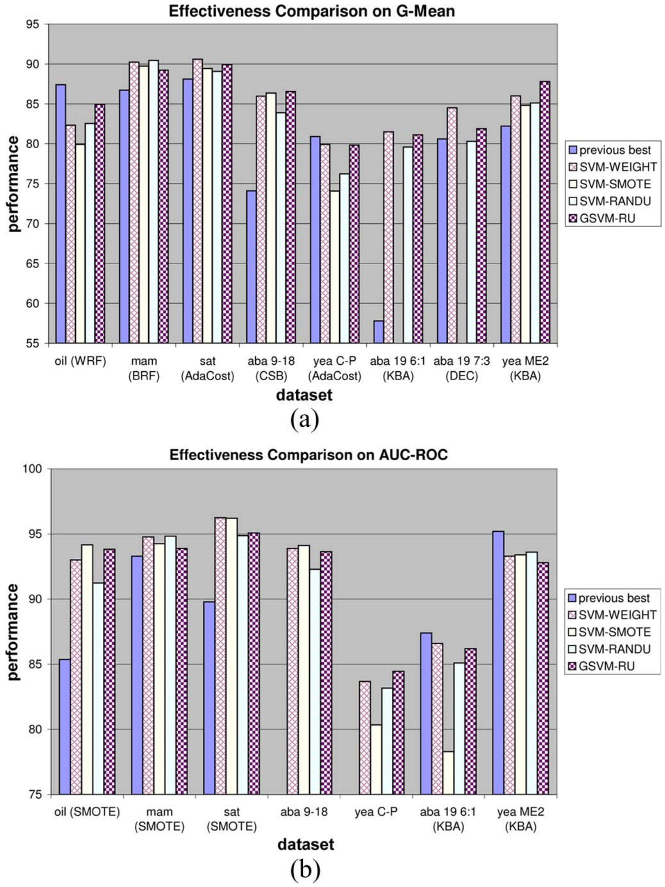
With F-measure for evaluation, the best validation performance is observed when the "combine" aggregation operation is adopted and the first 11 granules are combined to form the final aggregation data set. The result indicates that the second assumption (a part but not all of the informative samples can be extracted in one granule) is reasonable in this case. When more and more informative samples are combined into the aggregated data set, information loss is lesser so that a more accurate classification can be obtained (Fig. 8). However, when the 12th granule is extracted and combined into the aggregation data set, the validation performance cannot be further improved. The reason is that the new extracted samples are too far from the "ideal" boundary so that they are prone to be redundant or irrelevant rather than informative. Hence, the repetitive undersampling process is stopped.

C. GSVM-RU Versus Previous Best Approaches

Twenty-five groups of experiments are conducted with 25 different data set/metric combinations (Table III). Of them, 18 groups are available for effectiveness comparison with previous studies. For 12 groups, GSVM-RU outperforms the previous best approach. For six other groups, the performance of GSVM-RU is very close to the previous best result.

TABLE IV
AVERAGE PERFORMANCE OF PREVIOUS BEST APPROACHES AND GSVM-RU ON 18 EXPERIMENTS

	previous best	GSVM-RU
G-Mean/8	79.7	85.2
AUC-ROC/5	90.2	92.4
F-Measure/5	59.9	66.5



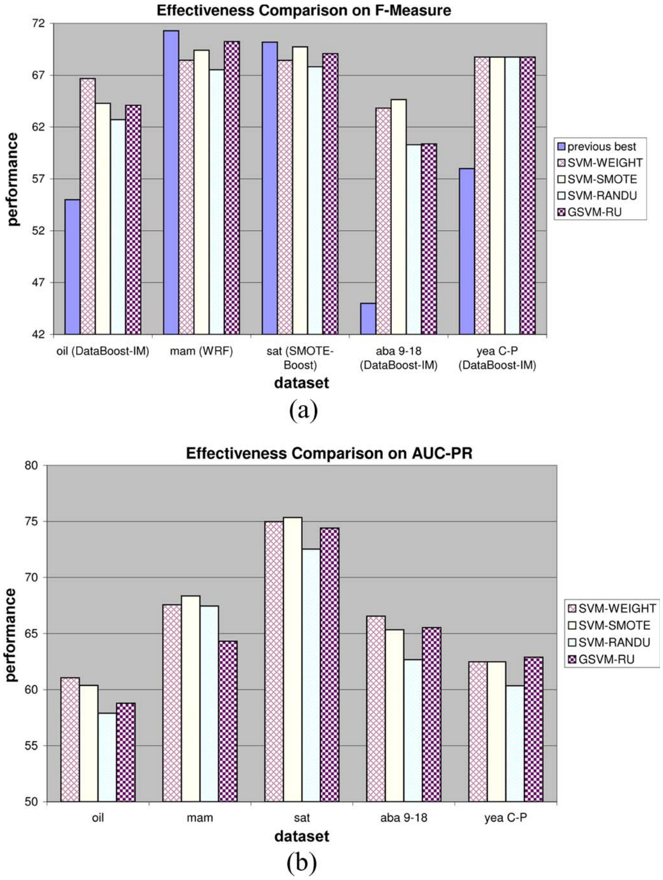
(a)

(b)

Fig. 9. (a) G-mean analysis. (b) AUC-ROC analysis.

Table IV reports the average performance on G-mean, AUC-ROC, and F-measure metrics on the 18 groups of experiments. GSVM-RU demonstrates better average performance than previous best approaches on all three metrics.

Figs. 9(a) and 10(b) show comparison results on the four metrics. In each figure, the performance of the previous best approach, SVM-WEIGHT, SVM-SMOTE, SVM-RANDU, and GSVM-RU is reported for each available data set. The value on the horizontal axis is formatted as *data name (previous best approach name)*. If there is no previous result, only data name is reported. It can be clearly seen that GSVM-RU and the other three SVM modeling algorithms are able to surpass or match the previously known best algorithms on each of the 18 data set/metric combinations, i.e., we effectively compare these SVM modeling techniques against the best known approaches under the same experimental conditions. Notice that in Fig. 9(a), the G-mean value of SVM-SMOTE is zero for the Abalone data set (19 versus other) with both 7 times 6 : 1 splitting or 7 times 7 : 3 splitting. Moreover, notice that there are no "previous best" results in Fig. 10(b) because no previous research has been conducted for AUC-PR analysis on these data sets.



(a)

(b)

Fig. 10. (a) F-measure analysis. (b) AUC-PR analysis.

D. GSVM-RU Versus Other Three SVM Modeling Algorithms

Table V reports the average performance of four SVM modeling algorithms over the 25 groups of experiments. SVM-WEIGHT demonstrates almost the same effectiveness as GSVM-RU with all four metrics. However, GSVM-RU extracts only 181 SVs, which means that GSVM-RU is more than four times faster than SVM-WEIGHT (with 794 SVs) for classification.

SVM-SMOTE demonstrates a similar effectiveness on AUC-ROC, F-measure, and AUC-PR to GSVM-RU. However, it is worse on G-mean. The reason is that it achieves zero G-mean value on the extremely imbalanced Abalone (19 versus other) data set. SVM-SMOTE is also much slower, with 655 SVs for classification. Moreover, SVM-SMOTE is unstable because of the randomness of the oversampling process.

SVM-RANDU is slightly faster than GSVM-RU for prediction by extracting only 143 SVs. However, SVM-RANDU is slightly less effective than GSVM-RU with all four metrics. Moreover, SVM-RANDU is unstable because of the randomness of the undersampling process.

V. CONCLUSION

In this correspondence, we have implemented and rigorously evaluated four SVM modeling techniques, including one novel method of undersampling SVs. We compare these four algorithms with state-of-the-art approaches on seven highly imbalanced data sets under four metrics (G-mean, AUC-ROC, F-measure, and AUC-PR). The comparative approaches consist of the best known technique on the corresponding data sets. To our knowledge, this is the first work to conduct an exhaustive comparative study with all four metrics and the

TABLE V
AVERAGE PERFORMANCE OF FOUR SVM MODELING ALGORITHMS ON 25 EXPERIMENTS

	SVM-WEIGHT	SVM-SMOTE	SVM-RANDU	GSVM-RU
G-Mean/8	85.1	63.0	83.4	85.2
AUC-ROC/7	91.6	90.1	90.7	91.4
F-Measure/5	67.2	67.4	65.4	66.5
AUC-PR/5	66.5	66.4	64.2	65.2
Efficiency/25 (#SVs)	794	655	143	181
Stability	YES	NO	NO	YES

variations in SVM modeling. Hence, we expect that this correspondence can be helpful for future research works for comparison study on these benchmark highly imbalanced data sets.

Specifically, the GSVM-RU algorithm implements a guided repetitive undersampling strategy to "rebalance" the data set at hand. GSVM-RU is effective due to the following: 1) extraction of informative samples that are essential for classification and 2) elimination of a large amount of redundant, or even noisy, samples. As shown in Table III, GSVM-RU outperforms the previous best approach in 12 groups of experiments and performs very close to the previous best approach in six other groups of experiments.

In most cases, GSVM-RU achieves the optimal performance with the "discard" operation. This demonstrates that the "boundary push" assumption seems to be true for many highly imbalanced data sets. Considering its efficiency, the "discard" operation is also suggested as the first aggregation operation to try for GSVM-RU modeling. However, the optimal performance is observed with the "combine" operation on the mammography and the satimage data sets for F-measure and AUC-PR metrics. This suggests that the "information loss" assumption may be more suitable for some highly imbalanced data sets, particularly with F-measure and AUC-PR metrics.

We have also systematically investigated the effect of overweighting the minority class on SVM modeling. The idea, named SVM-WEIGHT, seems to be naive at first glance and, hence, is ignored in previous research works. However, our experiments show that it is actually highly effective. Although SVM-WEIGHT is not efficient compared with GSVM-RU, considering that the former extracts more SVs, it can be the first SVM modeling method of choice if the available data set is not very large.

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