A New Improved Boosting for Imbalanced Data Classification

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Abstract. As one of the most important component of artificial intelligence, machine learning is getting more and more attention. AdaBoost, a classic machine learning algorithm, is widely used. However, when faced with imbalanced data classification, AdaBoost’s recognition rate of minority samples is low due to ignoring class imbalance. In many cases, minority samples are of high value. For this shortage, combining the theory of margin and cost-sensitive idea, a new Boosting algorithm called CMBoost is proposed based on cost-sensitive margin statistical characteristics, which is firstly through optimizing margin statistical characteristics to improve formal algorithm and then extended by cost-sensitive. Experimental results on the UCI dataset show that the CMBoost algorithm is superior to AdaBoost for imbalanced data classification problem.

1. Introduction
In recent years, imbalanced data classification has become a hot topic in the field of data mining and machine learning. Imbalanced dataset refer to the number of samples of one class in the dataset far less than the number of other classes, in which the majority of classes are called negative classes, while the minority is called positive class. The problem of classification of imbalanced dataset exists in people's real life and industrial production. For example, E-mail filtering, fraud detection, medical diagnosis, DNA microarray data analysis, software defect prediction, etc. In these applications, the classification accuracy of positive class is often more important. Therefore, to improve the classification accuracy of positive class has become the focus of research on imbalanced dataset. AdaBoost is a kind of strong learning algorithm to improve the weak learning algorithm performance, which has been applied to various fields of pattern recognition successfully. The original AdaBoost algorithm treats both positive and negative samples equally and is not suitable for imbalanced data classification. Cost-sensitive AdaBoost introduces classification cost into AdaBoost algorithm, which can be used for imbalanced data classification. One of them is weighting method, which modifies the weight of Boosting update steps and is simple implementation, but lacks of theoretical support. Another one is the loss function method, which directly minimizes the expectation of cost sensitive loss. The algorithm is highly theoretical, but the realization is complex, which requires numerical method to solve.

In this paper, a new Boosting algorithm called CMBoost is proposed based on cost-sensitive margin statistical characteristics. Firstly, on the basis of generalization error bound based on the margin distribution, it is proposed to reduce the generalization error by optimizing the statistical characteristics of the margin, and then extend it with cost sensitivity, so that the algorithm can adapt to the imbalanced data. Experimental results on the UCI dataset show that the CMBoost algorithm is superior to the AdaBoost algorithm.
2. AdaBoost

The AdaBoost\cite{10} algorithm was firstly proposed for bi-class classification. The algorithm takes as input a training set \{(x_i, y_i)\} where with the sample \(x_i\) is an attribute value vector as a realization of the attribute set \(X = \{X_1, X_2, \ldots, X_n\}\), and class label \(y\) assumes a value in \(Y\), with two classes, assuming that \(Y = \{-1, 1\}\). AdaBoost calls a given base learning algorithm repeatedly in a series of rounds \(t = 1, 2, \ldots, M\). The weight of the \(t^{th}\) training sample on the iteration \(t\) is denoted by \(D_t\).

Initially, all weights are set equally. The weight of the \(t^{th}\) base classifier \(h_t\) is the weight assigned to \(h_t\).

The base learner’s task is to come up with a base classifier \(h_t : X \rightarrow Y\) based on the distribution \(D_t\) to minimize the classification error. Once the base classifier \(h_t\) has been trained, AdaBoost chooses a parameter \(\alpha_t \in \mathbb{R}\) which measures the performance of the classification \(h_t\). The data distribution \(D_t\) is then updated. The final classification criterion \(F\) is a weighted majority vote of the \(M\) base classifiers

\[ F(x) = \sum_{t=1}^{M} \alpha_t h_t(x) \]

where \(\alpha_t\) is the weight assigned to \(h_t\).

3. CMBoost algorithm

We use \(\Pr\) to refer as the probability with respect to \(D\) and \(E[\cdot]\) to denote the expected values. Let \(H\) be a base classifier space and \(C(H)\) denote the convex hull of \(H\). A voting classifier \(f \in C(H)\) is of the following form

\[ f = \sum \alpha_i h_i \quad \text{with} \quad \sum \alpha_i = 1 \quad \text{and} \quad \alpha_i \geq 0 \]  

(1)

For an example \((x, y)\), the margin with respect to the voting classifier \(f = \sum \alpha_i h_i\) is defined as \(yf(x)\) or \(\rho\), in other words

\[ yf(x) = \rho = \sum_{\iota: y \neq h_{\iota}(x)} \alpha_i - \sum_{\iota: y \neq h_{\iota}(x)} \alpha_i \]  

(2)

Schapire\cite{11} derived the generalization error bounds based on the margin distribution, as shown in Theorem 1

Theorem 1: \(D_n\) is made up of \(N\) training samples which are selected randomly from a distribution \(\text{Dist}_{\text{tr}}\) on the training set \(X \times Y\). Assuming that the base classifier space \(H\) is limited and \(\delta > 0\), for all \(\theta > 0\), every voting classifier \(f \in C(H)\) satisfies the following bound with probability at least \(1 - \delta\)

\[ \Pr_{D_n}[yf(x) < 0] \leq \Pr_{\text{Dist}_{\text{tr}}}[yf(x) \leq \theta] + O\left(\frac{1}{N\ln N}\left(\ln N\ln|H| + \ln \frac{1}{\delta}\right)^{\frac{1}{2}}\right) \]  

(3)

As we can see, the generalization error bounds relate to the margin distribution, but how do we get a good margin distribution? We know that statistical characteristics are good tools for describing distributions. Therefore, on the basis of bounds of margin in the past, the generalization error bounds derived from literature\cite{12} reveal the relationship between them and the statistical characteristics of margin, as shown in Theorem 2:

Theorem 2: \(D_n\) is made up of \(N(N > 5)\) training samples which are selected randomly from a distribution \(\text{Dist}_{\text{tr}}\) on the training set \(X \times Y\). For all \(\delta > 0\), every voting classifier \(f \in C(H)\) satisfies the following bound with probability at least \(1 - \delta\):

\[ \Pr_{D_n}[yf(x) < 0] \leq \frac{1}{N^m} + \inf_{\theta > 0} \left\{ \Pr_{\text{Dist}_{\text{tr}}}[yf(x) < \theta] \right\} + \frac{3\sqrt{N}}{N^{2/3}} + \frac{7\mu}{3N} + \sqrt{\frac{3\mu}{N}} \Gamma(\theta) \]  

(4)
where
\[
\mu = 144 \ln m \ln(2|H| / \delta^2) + \ln(2|H| / \delta)
\]
\[
\Gamma(\theta) = \Pr[\gamma f(x) < \theta | \Pr[\gamma f(x) \geq 2\theta / 3]]
\]
(5)

In the theorem, \(E[y f(x)]\) is the margin mean and \(\Gamma(\theta)\) reflects the size of the margin variance. It can be seen that the margin statistical characteristics of training sample set directly affect the size of generalization error. When the size of the training sample set and the complexity of the base classifier are fixed, if the margin mean gets larger and the margin variance gets smaller at the same time, the generalization error will get smaller. Therefore, the algorithm performance is improved by maximizing the margin mean and minimizing the margin variance. If \(m_{\text{ave}}\) is the margin mean, \(m_{\text{var}}\) is the margin variance and \(\lambda_1 > 0, \lambda_2 > 0\) are weighing coefficient, we can construct the margin statistical characteristics \(m_{\text{ave}} = \lambda_1 m_{\text{ave}} - \lambda_2 m_{\text{var}}\)
(6)

Then the improved AdaBoost algorithm is represented by the following formula:
\[
\min \ m_{\text{ave}}
\]

s.t. \(\alpha \geq 0, \Gamma \alpha = D\)
(7)

where
\[
m_{\text{ave}} = \frac{1}{N} \sum_{i=1}^{N} \rho_i
\]
(8)
\[
m_{\text{var}} = \frac{1}{N-1} \sum_{i=1}^{N} (\rho_i - \mu)^2
\]
(9)

We have
\[
m_{\text{ave}} = \lambda_1 m_{\text{ave}} - \lambda_2 m_{\text{var}}
\]
\[
= \lambda_1 \frac{1}{N} \sum_{i=1}^{N} (\rho_i - \mu)^2 - \lambda_2 \frac{1}{N} \sum_{i=1}^{N} \rho_i
\]
(10)

Defining
\[
A = \begin{bmatrix}
1 & c & \cdots & c \\
c & 1 & \cdots & c \\
\vdots & \vdots & \ddots & \vdots \\
c & c & \cdots & 1
\end{bmatrix}_{N \times N}, \quad c = \frac{-1}{N-1}
\]
(11)

\[
\lambda = \frac{\lambda_2}{2N\lambda_1}
\]
(12)
\[
\rho = [\rho_1; \rho_2; \cdots; \rho_N]
\]
(13)

We get
\[
m_{\text{ave}} = 2\lambda_1 \left(\frac{1}{2} \rho^T A \rho + \lambda^T \rho\right)
\]
(14)

Then we can rewrite (7) as
\[
\min \ \frac{1}{2} \rho^T A \rho + \lambda^T \rho
\]

s.t. \(\alpha \geq 0, \Gamma \alpha = D\)
\[
\rho_i = y_i h_i \alpha, \forall i = 1, 2, \cdots, N.
\]
(15)

where
\[ h_i = [h_i(x_1); h_i(x_2); \ldots; h_i(x_d)] \] (16)
\[ \alpha = [\alpha_1; \alpha_2; \ldots; \alpha_d] \] (17)

As \( x^T A x \geq \theta \) is always holds for any real non-zero vector \( x \), so \( A \) is positive semidefinite matrix.

In the training sample set, the size of the positive sample set \( L^+ \) is \( n^+ \) and the size of the negative sample set \( L^- \) is \( n^- \), then the imbalance degree of the sample set is \( r = n^- / n^+ \). Suppose the weight of each sample when calculating the margin mean is \( k_i \) and the cost sensitive parameter is \( c \), then

\[ d_i = \begin{cases} 1 + c r_i \ln \frac{r_i}{c r_i}, & i \in L^- \\ 1 + c \ln \frac{1}{r_i}, & i \in L^+ \end{cases} \] (18)
\[ k_i = \begin{cases} 1 + c r_i \ln \frac{r_i}{c r_i}, & i \in L^- \\ 1 + c r_i \ln \frac{r_i}{c r_i}, & i \in L^+ \end{cases} \] (19)

We have cost-sensitive margin mean
\[ cmg_{av} = \frac{1}{N} \sum_{i=1}^{N} d_i \rho_i \] (20)
and cost-sensitive margin variance
\[ cmg_{av} = \frac{1}{N-1} \sum_{i \neq j} (k_i \rho_i - k_j \rho_j)^2 \] (21)

Then we can construct the cost-sensitive margin statistical characteristics:
\[ cmg_w = \lambda cmg_{av} - \lambda \rho \sum_{i=1}^{N} d_i \rho_i \] (22)

Defining
\[ K = \text{diag}(k_1, k_2, \ldots, k_N) \] (23)
\[ B = K^T A K \] (24)
\[ d = [d_1, d_2, \ldots, d_N] \] (25)
\[ \lambda = -\frac{\lambda}{2N \lambda} d \] (26)

Then
\[ cmg_w = 2 \lambda \left( \frac{1}{2} \rho^T B \rho + \lambda \rho \right) \] (27)

Then the CMBoost algorithm is represented by the following formula:
\[
\min_{\alpha, \rho} \frac{1}{2} \rho^T B \rho + \lambda \rho \\
\text{s.t. } \alpha \geq 0, \ 1^T \alpha = D \\
\rho_i = y_i h_i^T \alpha, \forall i = 1, 2, \ldots, N.
\] (28)
As $x^T B x \geq 0$ is always holds for $x^T A x \geq 0$, then $B$ is positive semidefinite matrix. So (28) is a convex quadratic problem. Because the $H$ is unknown, we can’t solve the problem by usual QP solvers. As in LPBoost\cite{13}, column generation can be used to attack this problem. Then we apply column generation to this problem.

The Lagrangian of (28) is

$$L(\alpha, \rho, u, r, q) = \frac{1}{2} \rho^T B \rho + \lambda^T \rho + r(\alpha^T - D)$$

$$-q^T \alpha + \sum_{i=1}^{N} u_i [r_i - y_i h_i(\alpha)]$$

The infimum of $L$ is

$$\inf_{\rho} L = \inf_{\rho} \left[ \frac{1}{2} \rho^T B \rho + (u + \lambda)^T \rho \right]$$

$$+ \inf_{\alpha} \left[ (r^T q^T - \sum_{i=1}^{N} u_i y_i h_i(\alpha)) - Dr \right]$$

For finite infimum, must hold. So we have

$$\sum_{i=1}^{N} u_i y_i h_i(\alpha) \leq r^T$$

For the first term in $L$

$$\frac{\partial}{\partial \rho} \left[ \frac{1}{2} \rho^T B \rho + (u + \lambda)^T \rho \right] = 0, \forall i$$

This results in $\rho = -B^{-1}(u + \lambda)$, and the infimum is

$$-\frac{1}{2} (u + \lambda)^T B^{-1}(u + \lambda)$$

Through putting the results together, the dual is

$$\max_{\rho} -\frac{1}{2} (u + \lambda)^T B^{-1}(u + \lambda) - Dr$$

$$\text{s.t.} \sum_{i=1}^{N} u_i y_i h_i(\alpha) \leq r^T$$

We can reformulate (28) as

$$\min_{\rho} \frac{1}{2} (u + \lambda)^T B^{-1}(u + \lambda) + r,$$

$$\text{s.t.} \sum_{i=1}^{N} u_i y_i h_i(\alpha) \leq r^T$$

To speed up the convergence, we add the most violated constraint by solving the following problem:

$$h(\alpha) = \arg \max_{h(x)} \sum_{i=1}^{N} u_i y_i h(x_i)$$

4. Evaluation method

In traditional classification learning, classification accuracy is generally used as the evaluation criterion. However, for imbalanced dataset, it is unreasonable to use classification accuracy to evaluate the performance of classifiers. Therefore, for imbalanced data, many scholars propose evaluation methods such as F-measure\cite{14} and G-mean\cite{15}, most of which are based on the confusion matrix (see Table 1). In Table 1, TP and TN respectively represent the number of positive and negative samples of the correct classification, while FP and FN respectively represent the number of positive and negative samples of the wrong classification.
Table 1. Confusion matrix for bi-class problem

|                  | Be classified into positive class | Be classified into negative class |
|------------------|-----------------------------------|----------------------------------|
| True positive class | TP                                | FN                               |
| True negative class | FP                                | TN                               |

F-measure is an evaluation criterion for imbalanced data classification problem, which is defined as follows:

\[
F\text{-measure} = \frac{(1 + \beta^2) \times \text{Recall} \times \text{Precision}}{\beta^2 \times \text{Recall} + \text{Precision}}
\]  

(36)

\[
\text{Recall} = \frac{TP}{TP + FN}, \quad \text{Precision} = \frac{TP}{TP + FP}
\]  

(37)

Only when the recall and precision are both large, F-measure will be large. Therefore, it is reasonable to evaluate the classification performance of classifiers for positive class.

G-mean is an evaluation criterion for the overall classification performance, which is defined as follows:

\[
G\text{-mean} = \sqrt{\text{Positive Accurary} \times \text{Negative Accurary}}
\]  

(38)

\[
\text{Positive Accurary} = \text{Recall} = \frac{TP}{TP + FN}
\]  

(39)

\[
\text{Negative Accurary} = \frac{TN}{TN + FP}
\]  

(40)

G-mean is to maximize the accuracy of two classes while maintaining the balance of the classification accuracy of positive and negative class. In this article, F-measure is used to evaluated the classification performance of the positive class, while G-mean is used to evaluated the overall classification performance.

5. Experiment and analysis

To test the effectiveness of the proposed method, several UCI dataset are selected. For data containing multiple classes, one of them is taken as positive and the rest as negative. The information of UCI dataset is given in Table 2. The dataset is divided into two halves. One half is training sample set and the other is test sample set. F-measure and G-mean are used to evaluate the performance of AdaBoost and CMBoost which is shown in Table 3.

Table 2. Information of UCI dataset

| Dataset | Total size | Positive class size | Negative class size | Imbalance degree |
|---------|------------|---------------------|---------------------|------------------|
| heart   | 303        | 139                 | 164                 | 1.18             |
| sonar   | 208        | 97                  | 111                 | 1.14             |
| vehicle | 846        | 212                 | 634                 | 2.99             |
| wine    | 178        | 59                  | 119                 | 2.02             |
| wpbc    | 198        | 47                  | 151                 | 3.21             |
| segment | 2310       | 330                 | 1980                | 6.00             |
| vote    | 435        | 168                 | 267                 | 1.59             |
Table 3. Algorithm performance comparison

| Dataset | Algorithm | F-measure | G-mean |
|---------|-----------|-----------|--------|
| heart   | AdaBoost  | 0.78      | 0.81   |
|         | CMBoost   | 0.82      | 0.83   |
| sonar   | AdaBoost  | 0.74      | 0.76   |
|         | CMBoost   | 0.78      | 0.82   |
| vehicle | AdaBoost  | 0.26      | 0.41   |
|         | CMBoost   | 0.42      | 0.68   |
| wine    | AdaBoost  | 0.94      | 0.96   |
|         | CMBoost   | 0.94      | 0.95   |
| wpbc    | AdaBoost  | 0.77      | 0.44   |
|         | CMBoost   | 0.86      | 0.59   |
| segment | AdaBoost  | 0.43      | 0.74   |
|         | CMBoost   | 0.58      | 0.86   |
| vote    | AdaBoost  | 0.93      | 0.95   |
|         | CMBoost   | 0.94      | 0.95   |

From Table 3, first of all, we can see that the mean F-measure of CMBoost is 7% larger than that of AdaBoost, while the mean G-mean of CMBoost is 8.8% larger than that of AdaBoost. Besides, for almost balanced dataset like heart, sonar, vote, AdaBoost performs very well. While for imbalanced dataset like vehicle, segment, the performance of AdaBoost is bad. The CMBoost has more enhancements on the imbalanced dataset than the balanced dataset.

6. Conclusion

Many domains are affected by the problem of class imbalance. It can be challenging to construct a classifier that effectively identifies the examples of the positive class. Several techniques have been proposed for dealing with the problem of class imbalance. In this paper, we have proposed a new algorithm, called CMBoost, for alleviating the problem of class imbalance. We compare the performance of CMBoost with AdaBoost from UCI dataset, finding that CMBoost performs better when compared to AdaBoost, especially for imbalanced dataset.

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