Over-sampling Algorithm Based on in imbalanced Classification

Abstract

The problem of imbalanced classification is that in the classification problem, different classes of samples differ in the sample size, distribution and the classification cost. In the traditional classification algorithms, however, it is assumed that the samples are evenly distributed, resulting in the poor recognition of the samples of interest. In order to improve the accuracy of the minority class samples, scholars have proposed many approaches including data-level and algorithm-level methods. Data-level algorithms are used as an optional part of preprocessing and have a wider range of applications, which has led to a lot of attention. Oversampling, the algorithm uses various methods to increase the minority class samples in the training set, increases the recognition rate of the minority class samples. However, these oversampling methods are too coarse to improve the classification effect of the minority class samples, because they can’t make full use of the information in the original samples, but increase the training time because of adding extra samples. In this paper, we propose to use the distribution information of the minority class samples, use the variational auto-encoder to fit the probability distribution function of them, and reasonably expand the minority class sample set. The experimental results prove the effectiveness of the proposed algorithm.

Keywords: imbalanced classification; generative model; variational auto-encoder;

Introduction

The classification problem is a very important part of machine learning, and it is also the first step for artificial intelligence to understand human life. At present, most classifiers assume that the samples of different classes are evenly distributed, and the classification cost is the same. However, in reality, the data people are more concerned about is often scarce, such as the detection of credit card fraud and medical disease diagnosis. In the diagnosis of medical data, most of the results are normal while only a small proportion of the results are diagnosed as diseases, which indicates the even distribution in different classes samples. Second, if healthy people are misdiagnosed as diseases, they can be removed by other inspection methods, errors do not cause very serious accidents, but if the disease is diagnosed as healthy, it may cause the patient to miss the best treatment time and cause serious consequences. This is the second feature of the imbalanced classification problems: different classes of misclassification costs are inconsistent. At the same time, if samples are classified as diseases as much as possible because they are afraid to miss the disease samples, it will cause a huge waste of medical resources and intensify conflicts between doctors and patients. Therefore, it is not feasible to determine all samples as positive, and the best way is to try to separate these two results as correct as possible. Due to the scarcity of the minority class samples and perusing the global accuracy, the classifier pays less attention to the minority class, so the recognition effect of it is not good. Imbalanced classification problems arise in many fields, such as bioinformatics [9, 11], remote sensing image recognition [4], and privacy protection in cybersecurity [5]. The imbalanced problems cover widely and have a very important practical significance.

The traditional solutions to the imbalanced problems are divided into two parts: the algorithm-level algorithms and the data-level algorithms. The algorithm-level algorithms mainly focus on the different misclassification costs, and the algorithm level is mostly based on cost-sensitive method, that is, misclassification costs are different in different classes, such as improved neural network [12]: it uses the approximation of F1 value of the minority class as the cost function; the bagging algorithm[8] continues to enhance the misclassified the minority class samples, and improve the recognition rate of the minority class samples; structured SVM [10] uses the F1 value of the minority class samples as the optimization function, and thus has a better performance in the classification of the minority class samples.

Introduction

The data-level algorithms focus on the first feature of the imbalanced classification problem, which mainly adjusts the distribution of data through data resampling to reduce the impact of imbalanced classification. As for the different classes of sampled samples, it can be divided into over-sampling, under-sampling and combinations of the both. Over-sampling refers to the process of increasing the of training times of the minority class samples that are easier to be ignored in the training process. The common methods of oversampling include repeating the known samples, SMOTE[1] for Linear Interpolation of Samples, etc. Oversampling can effectively improve the classification performance of the minority class, and simply copying samples does not add additional information. However, SMOTE's method of random interpolation is too random and lacks typicality. Under-sampling [9] refers to remove the majority class samples for obfuscation classification, which can quickly reach equilibrium, but may take a risk of losing valuable samples.

The oversampling method can be divided into random sampling and information sampling.

Random sampling means sampling directly using samples, which includes simple repetition [11], linear interpolation [12], nonlinear interpolation [13], etc.; SMOTE [12], as a classic oversampling algorithm, interpolates linearly in the minority class samples will increase the amount of information and rationality of synthesized samples in random oversampling, which improves the classification effect. Border-line-smote [14], on the basis of SMOTE, has filtered the minority class samples that needed to be interpolated, and in order to reduce the risk of overfitting, it mainly interpolates linearly in boundary samples. The above oversampling methods only consider the influence of the sample size on the classification effect and the local sample distribution, instead of considering the overall distribution of the sample.

Sampling with information [15] uses the distribution information in the sample to fit its probability distribution function and sample it according to the modeling content. Chen[2] proposed normal distribution based on oversampling approach and this approach use the probability of minority class to model and oversampling, whose experimental results are better than SMOTE and random oversampling. Different scholars have proposed oversampling algorithms based on various distributions, such as the Gaussian distribution[2, 13], Weibull distribution [6], etc. Due to the distribution information, these algorithms have made greater progress than random interpolation method. However, the problems are also obvious: assume the sample obeys some prior distribution such as normal distribution, we can use EM to calculate the parameters of the distribution. If the distribution meets this hypothesis, it will get better results, otherwise, if the distribution disobeys the hypothesis, not only the improvement is limited, but also the true distribution of the sample is hard to get. Because of these above situations, it is inconsistent in their effect on the distribution of different datasets.

Data level processing is of great matter in imbalanced classification. In spite of the consistency in the importance of practical problems, it will have a positive effect on the final classification results.

Since the factors that affect the datasets classification include not only the sample size, but also the sample distribution, while the current oversampling methods only use direct replication or simple linear interpolation to generate data, which do not make full use of information of distribution and not guarantee the rationality of the interpolation sample. Therefore, in this paper, we propose a vae model to expand the minority class samples.

Our method aims at the difficulty in classifying the minority class in imbalanced datasets, and according to the distribution relationship between samples, we use vae which generates data well in a neural network to increase minority instances, and the experimental results prove the effectiveness of the algorithm.

We propose this algorithm to use vae to model the distribution of minority class sample. To our knowledge, first, the output dimension of the neural network is not limited so it can generate data of any dimension; second, the strong fitting ability of the neural network can simulate any distribution function without any prior knowledge in advance.

Therefore, in order to resolve the imbalanced problem, we use this model to oversampling the minority class samples.

We organize the paper as follows. Section 2 describes relevant work of this paper. Section 3 presents our algorithm and analyze it. Section 4 introduces the basic data sets and show our experimental results. Section 5 concludes the paper.

# Related work

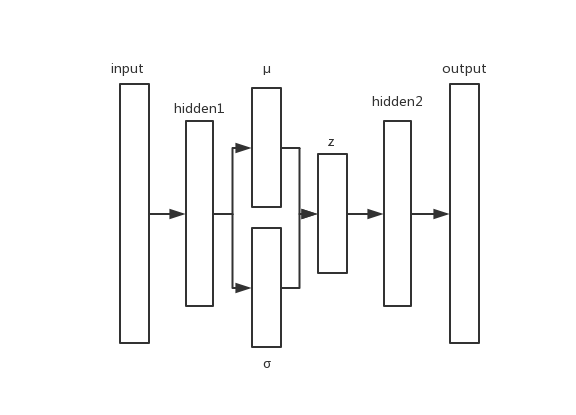
The neural network proposed in the paper is used to fit the probability distribution function of minority class data due to the strong ability of fitting. Therefore, it is possible to avoid the inconsistency between hypothesis and original distribution, and to improve the quality of the generated samples and to elevation the effect of classification.

Vae(variational auto-encoder)

In 2003, KM[3] proposed vae: add variational inference to auto-encoder and use parameterization trick to make the variational inference combined with stochastic gradient descent. The overall structure of vae network is in the form of encoder-decoder, while it assumes the hidden variables to be a normal distribution. And this feature, which is easy to sample and the final probability distribution function is uncertain, coincides with the characteristics of distribution-based oversampling.

In vae, we assume the variables are determined by the hidden compression code z, the encoder can map z to visible form, which makes z obey a particular distribution (such as Gaussian distribution, etc.). Knowing the possibility distribution function and its mapping function, we can sample z and encode z, to get new x to generate infinite sample theoretically. Therefore, in this paper, the vae structure is used to fit the minority samples’ distribution and the model is sampled to solve the oversampling problem of the minority samples.

The structure of vae as shown below:



Assume z is a latent variable, and its distribution function is, we can use Bayesian conditional probability formula to calculate:

However, in z's prior distribution, most of z cannot generate reliable samples, that is tends to 0, so is tends to 0. To simplify the calculation, only need to be calculated. Considering the z with larger P(X|z), which is represented by form the encoder, but only considering this part of z cannot generate samples that are not in original data. So we need to assume the distribution of and complete the error through the decoder.

Assuming generates the distribution , we use KL divergence to calculate the difference between the real distribution and the assumption:

Definition of KL divergence:

The above equation shows that if pq is closer, KL divergence will tend to 0. And the objective function of vae model is

Apply Bayes rule to, we can get both and

Apply the into it

Note that X is fixed, and Q can be any distribution, not just a distribution which does a good job at mapping X to the z’s to produce X. since we’re interested in inferring P(X), it makes sense to construct a Q which does depend on X, and in particular, one which makes small:

Because is fixed, the minimum will transform to maximize vthe alue of right side of the equation, and is the probability of X decoded by z. It is calculated as the cross-entropy or mean-squared error of the original sample. The latter can be regarded as the difference between the assumption and the distribution of z in the encoder.

# Method

In this paper, based on the distribution of oversampling for the imbalanced classification problem, a generation model using vae is proposed: in order to improve the classification effect, we use vae to sample the hidden space z and generate the synthetic minority class samples. The network structure is shown in Figure 1. Since the original vae is applied to image generation, the synthesis results can be naturally visualized. However, the sequence data is used directly in this article and it requires some improvement:

There might have discrete features in the sequence data, while the features generated by the stochastic gradient descent must be continuously differentiable, so this part of the feature must be filtered before vae training. Use 1NN to classify the generated samples and combine the continuous features with the discrete features of the nearest original sample into a new composite sample;

Due to the sample size is too small to determine reliably whether the feature is discrete, we assume that it is a discrete feature if it appears less than 2. In fact, it is useless in classification if the feature has only one value in each sample.

The mathematical description of the method is as follows:Given training dataset ， is the sample of d dimension, is the labels represent negative and positive. We use P and N to represents a positive class sample subset and a negative class sample subset, where P contains positive samples, N contains negative samples, and .

During the training of the vae model, feature appears in Jth dimension in training set needs statistics first to exclude discrete features, the formula is shown as bellow:

，

If , the feature in column j is discrete, otherwise, the feature is continuous. Divide the features in the dataset into continuous and discrete features in order and take out the continuous features as the final training set.

Train a vae model with and randomly sample it, assume is synthetic a sample:

is the final synthetic sample, and is the final training set.

算法架构Algorithm Architecture

|  |
| --- |
| Algorithm 1：VAEOS：VAE-based oversampling approach to imbalanced learning. |
| Input: : dataset with N samples, consisting of positive samples in P and negative samples in N  Output: Classifier H trained with dataset after the oversampling algorithm  Procedure:   1. Divide X into training dataset and testing dataset 2. Data preprocessing according to formula () 3. Compute for each feature in , decide each discrete feature and continuous feature 4. Decide according to formula 5. Use to train a model and randomly sample with the corresponding model 6. Synthesize the according to formula 7. Train a classifier H with |

# Experiment

Dataset description

In this paper, all datasets are select from UCI Machine Learning Repository, and some of them are multi-label datasets, so we select one class as the minority class and the remaining samples as majority class.

Table 1 dataset description

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Index | Dataset | 样本总数 | 属性数 | 少数类 | 不平衡率 |
| 1 | breast-w | 699 | 9 | 241 | 1.90 |
| 2 | vehicle | 846 | 18 | 199 | 3.25 |
| 3 | segment-challenge | 1500 | 19 | 205 | 6.32 |
| 4 | Diabetes | 768 | 8 | 268 | 1.87 |
| 5 | Ionosphere | 351 | 34 | 126 | 1.79 |
| 6 | Sonar | 208 | 60 | 97 | 1.14 |

Data preprocess

There are missing values in the datasets, in order to ensure the integrity of the datasets, we use the most frequent value as a supplement. For datasets whose attribute values are not within a certain range, we use normalization to scale it, the formula is shown as below:

Then

Evaluation indicators base on confusion matrix

In traditional classification method, global accuracy is used as the evaluation indicator, while in the imbalanced problem, using this indicator will make the classifier insensitive to the minority class for the number of positive class is less. In extreme conditions, assume the dataset only contain 1% minority class, if the classifier decides all samples as majority class, the accuracy still can reach 99%, however, the recognition rate of the minority class samples is 0. Therefore, the traditional classification algorithm will make the minority class easily divided into majority class, which results in low recognition rate. In binary classification, the confusion matrix is often used to evaluate the performance of the classifier, which is defined as follows:

表2 二分类问题的混淆矩阵

|  |  |  |
| --- | --- | --- |
|  | Positive prediction | Negative prediction |
| Positive class | True positive(TP) | False negative(FN) |
| Negative class | False positive(FP) | True negative(TN) |

Among them, TP is the number of correct predictions that an instance is positive. TN is the number of incorrect predictions that an instance is positive, FN is the number of incorrect of predictions that an instance negative, and FP is the number of correct predictions that an instance is negative. There are some new evaluation metrics based on confusion matrix to calculate the accuracy and recall of imbalance data such as F-value, G-mean and AUC[7].

In paper [14], it explained AUC is not reliable in the extreme conditions, so it only uses F-value and gmean to analyze the classification in the experiment.

F-value id the evaluation matric of accuracy and recall, and it biased to the performance of minority class, the definition is as follows:

Then and , the value of is [0,+∞].

And in this experiment, we choose for F-value is the average between recall and accuracy.

Gmean is the geometric mean of the classification accuracy of minority class and majority class, then:

Only when the precision of minority class and precision of majority are high at the same time, gmean will be maximum.

**Algorithm and parameters cooperation**

In this paper, we compare different oversampling algorithms such as NDO-sampling[7] and random interpolation algorithm SMOTE. The classifier is unified with naïve Bayes to reduce the impact of classifier’s parameters on classification. In order to ensure the data distribution is more consistent with the original one, minority class and majority class should be fragmented simultaneously in cross-validation. To reduce the impact of the randomness on the results of the comparison, each algorithm calculates the average of 10 times with 10-fold cross-validation.

|  |  |  |  |
| --- | --- | --- | --- |
| 算法 | 本文方法 | NDO | SMOTE |
| 参数 | Vae：5层  Hidden1:[]  Hidden2:[]  Hidden3:[]  Encoder和decoder为对称结构 | Same with paper [7] | k=5 |

Experiment result

不同算法的对比

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 100% | | | 200% | | | 300% | | |
|  | VAE | NDO | SMOTE | VAE | NDO | SMOTE | VAE | NDO | SMOTE |
| breast-w | 94.22 | **94.38** | **94.38** | **94.99** | 94.38 | 94.38 | **94.99** | 94.38 | 94.38 |
| vehicle | 58.07 | 55.66 | 56.26 | 58.75 | 56.63 | 56.45 | 59.36 | 56.27 | 56.45 |
| segment-challenge | 66.49 | 65.47 | 62.44 | 69.56 | 66.55 | 61.15 | 70.86 | 61.90 | 61.15 |
| Diabetes | 65.88 | 65.93 | 66.27 | 65.50 | 66.74 | 66.33 | 64.98 | 65.59 | 66.33 |
| Ionosphere | 87.02 | 82.34 | 80.54 | 87.62 | 82.63 | 82.71 | 86.20 | 81.44 | 82.71 |
| Sonar | 58.34 | 71.85 | 70.40 | 43.66 | 73.90 | 70.41 | 32.21 | 73.89 | 70.43 |

不同算法的对比

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 100% | | | 200% | | | 300% | | |
|  | VAE | NDO | SMOTE | VAE | NDO | SMOTE | VAE | NDO | SMOTE |
| breast-w | 96.77 | **96.89** | **96.89** | 97.22 | 96.89 | 96.89 | 97.21 | 96.89 | 96.89 |
| vehicle | 74.40 | 72.06 | 72.35 | 76.43 | 71.98 | 71.87 | 78.22 | 71.73 | 71.90 |
| segment-challenge | 91.54 | 91.79 | 89.69 | 92.81 | 92.22 | 89.41 | 93.30 | 92.47 | 89.03 |
| Diabetes | 79.85 | 79.73 | 80.25 | 78.19 | 77.78 | 76.71 | 77.86 | 74.95 | 74.48 |
| Ionosphere | 93.53 | 89.62 | 87.79 | 93.98 | 89.84 | 88.56 | 93.49 | 90.07 | 89.45 |
| Sonar | 61.33 | 63.77 | 64.67 | 62.05 | 65.13 | 65.03 | 66.13 | 65.02 | 65.39 |

不同算法的对比

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 100% | | | 200% | | | 300% | | |
|  | VAE | NDO | SMOTE | VAE | NDO | SMOTE | VAE | NDO | SMOTE |
| breast-w | 96.04 | 96.35 | 96.35 | 96.47 | 96.35 | 96.35 | 96.45 | 96.35 | 96.35 |
| vehicle | 75.00 | 72.71 | 73.27 | 75.79 | 73.50 | 73.18 | 76.31 | 73.30 | 73.34 |
| segment-challenge | 90.60 | 89.55 | 88.91 | 91.47 | 89.23 | 89.36 | 91.78 | 89.41 | 89.01 |
| Diabetes | 73.43 | 73.57 | 73.84 | 72.92 | 74.07 | 73.01 | 72.48 | 73.24 | 73.03 |
| Ionosphere | 88.83 | 86.47 | 85.32 | 89.08 | 86.66 | 85.99 | 87.81 | 86.86 | 86.98 |
| Sonar | 58.48 | 67.31 | 67.37 | 49.97 | 68.81 | 67.59 | 40.20 | 68.73 | 67.81 |

过采样率同结果的关系

The result shown in the table indicate that vae performs better in generating samples than NDO and SMOTE when the number of oversampling is the same. In the meanwhile, compared with the traditional oversampling algorithms which sacrifice some majority class to ensure the classification performance of minority, the proposed method can generate more reasonable samples, so it can guarantee the rational distribution of synthetic samples and improve the overall classification performance。

# Conclusion

In this paper, we use a genetive model to replace the traditional oversampling mechanism in order to make full use of the information in the dataset. The experiment results prove the effectiveness of the proposed method, but in the procedure of sampling, it is still too rough to guarantee the generated samples’ impact on the classifiers, and our next expansion work is to add a screening mechanism for generated samples to overcome this drawback.

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