Solving the Imbalanced Class Problem in Software Defect Prediction Using GANS

S.Kaliraj, Aman Jaiswal

Abstract: Prediction of software defects is a highly researched and important domain for cost-saving advantage in software development. Different methods of classification using attributes of static code were used to predict defects in software. However, the defective instances count is very minimal compared to the count of non-defective instances and this leads to imbalanced data, where the ratio of data class is not equal. For such data, conventional machine learning techniques give poor results. While there are different strategies to address this issue, normal oversampling methods are different versions of the SMOTE algorithm. These approaches are based on local information, instead of the complete distribution of minority class. GANs is used to approximate the true data distribution of minority class data used for software defect prediction.

Index Terms: Class imbalanced, Software defects, Gans.

I. INTRODUCTION

The available data for current software defect prediction is imbalanced, the project's goal is to resolve the problem of imbalanced class distribution in the dataset available for the early fault prediction model based on machine learning. Prediction of software defects is a highly researched and important domain for cost-saving advantage in software development. Different methods of classification using attributes of static code were used to predict defects. However, the defective instances count is very minimal compared to the count of non-defective instances and this leads to imbalanced data. For such data, conventional machine learning techniques give poor results. While there are different strategies to address this issue, normal oversampling methods are different versions of the SMOTE algorithm. These approaches are based on local information, instead of the complete distribution of minority class. GANs is used to approximate the true data distribution of minority class data used for early software defect prediction. The data thus generated is compared with the data generated from other techniques like random-oversampling, smote and adasyn.

II. LITERATURE SURVEY

Bruce Christianson, David Bowes, Yi Sun, mainly due to the lack of data cleaning and removal of Software prediction experiments conducted with the help of NASA's Metrics Data Program may have had erroneous findings[20]. This is Repeated data points in training and testing data published by the IEEE Society in April 2011. The inference that can be made of this is that the NASA dataset requires a lot of pre-processing before machine learning can be used.

Another literature survey led us to the finding that Imbalanced data is very commonly found in the real world software data and must be taken into account when predicting defects. This was published in Model Software Defects as Anomalies in October 2017[13]. It shows that the majority of data available for fault prediction is imbalanced, i.e., the minority class instances are very less than the majority class instances and this creates an imbalanced dataset for training a model.

The survey of another paper that deals with generating data using Generative Adversarial Networks gave us the results that shows that cGAN can perform better than other forms of classifiers. It can be concluded that The cGAN extension of the GAN framework can be used for minority class oversampling[17].

The survey of another paper that deals with an improved approach for SDA based defect prediction gave us the overview that class imbalance heavily affects the performance of prediction[9].

III. SURVEYED TECHNIQUES

RANDOM OVER SAMPLING:

This technique randomly selects data points from the original data set and then replicates the data points that represent the minority data points.

Fig.1 Random over sampling.

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The replicated data points are then copied into the training dataset. The fig.1 shows an image that shows minority class represented by blue dots being replicated. Random oversampling is implemented in our project using imblearn python library for rapid development and testing.

SMOTE: Synthetic Minority Over-sampling Technique
In this technique, the majority class is not taken into account instead of the minority class is taken into consideration. The synthetic dataset is created by taking each minority point and k nearest elements and a synthetic element is created at the halfway of the instance and its nearest neighbor.

Fig.2 SMOTE.
Smote is able to generate synthetic data in between the line that represents the minority class samples. Figure 2 shows synthetic instances being inserted in the intermediate space between the line joining two minority points. The imblearn library takes care of any noisy samples that may be generated due to unclear separation between majority and minority class clusters. This is done by border-lining the instances of both the classes and using this border to distinguish between the majority and minority classes.

ADASYN: It allows to generate adaptively the minority samples according to their distribution. The amount of synthetic data generated is more for the minority instances that are harder to learn and less instances are generated for data points that are easier to learn like majority class instances.

IV. PROPOSED TECHNIQUES
Why GAN?
Generative adversarial networks is relatively a new technology than compared to other forms of oversampling methods mentioned in the paper. The majority of application of Gans have been limited to the field of computer vision and other image related applications. It has been used to generate image samples. The training data for such models have been from the image domain and also the output have been from the image domain. An effectively trained Gan is able to generate hyper-realistic images that have never existed before. The aim of the paper is to exploit this property of the generative adversarial neural networks and create realistic data for minority class and thus use this data for training a prediction model.

GANS: The paper aims to evaluate the generators ability to effectively generate synthetic datasets for the minority class instances. The structure of Gans can be seen in the figure 3. It consists of two separate networks commonly called as generator and discriminator. The job of the generator is to generate artificial samples and the job of discriminator is to identify with a good enough accuracy that the generated samples are real or fake. A network is said to be trained if it becomes difficult for the discriminator to tell the difference between real and generated data, i.e., the probability according to discriminator of the data being fake or real comes close to 0.50. The process of training the network is initiated by generating a random noise from latent space to serve as an input to the generator. The generator then generates an output according to the structure and weights of the generator. The project deals with tabular data rather than image data which is common for gans. The output is randomly inputed into the discriminator therefore the discriminator is unaware if the inputed data is generated data or real data. This process can be seen in the form of a switch in fig(3) before the discriminator. The discriminator then output the probability of the inputed data being real. This is done by setting the output layer of the discriminator network as a sigmoidal function. The output of the discriminator is simultaneously used by the generator for modification of weights and discriminator for fine-tuning. This process goes on until the discriminator is unable to determine if the inputed data is real or fake. In our case the data is our processed data i.e. 2 PCA components and a label.

Fig.3 GAN EVALUATION CRITERIA:
The Gans performance to be used as an oversampler is evaluated and then matched that of with Random oversampling, Smote and Adasyn. Total accuracy is not an appropriate way to measure accuracy for imbalanced dataset therefore we use f-measure to compare different techniques.

\[
F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}
\]
F-Measure is a good way to measure the accuracy of a model trained on imbalanced dataset. It takes into account both the precision and recall to gather the result.

V. MODELS

The above figure (4) describes the integration testing process in our paper. The model is trained from different dataset available after applying each oversampling method separately. These models are then used to predict the defective instances in unseen data and then compared. The Prediction model for identifying the defective instances in the MDP dataset is a simple 3 layer neural network with one input layer, one hidden layer and one output layer. The original dataset contains 22 features. Considering the complete set of 22 features is very resource intensive and may not always lead to a better result. Therefore the 22 features are reduced to 2 features with the help of principal component analysis.

VI. RESULT

As seen in fig(6) the dataset is split into two sets training set and validation set. The ratio of the sets is kept as .10 for improving the training process as much possible. The training set is used to train the model and the validation set is used for validation. The validation set is kept completely isolated during the training process. After the model is trained the validation set is used to calculate the performance of the model which in our case is the F-measure for comparing all the over-sampling techniques. The accuracy and loss is plotted for Smote, Random oversampling and GANs. The formulas used for result evaluation is given in fig(7).

Accuracy = \frac{tp + tn}{tp + tn + fp + fn}

Precision = \frac{tp}{tp + fp}

Recall = \frac{tp}{tp + fn}

Recall = \frac{tn}{tn + fp}

These formulas are used to calculate the accuracy, precision, recall, and F-measure.

The evaluation process must be without bias hence only kc1 dataset is used to evaluate the performance of each method. Confusion matrix is calculated for each technique. fig(8) shows the confusion matrix structure.

The confusion matrix shown in fig(8) is used to show the number of true positives, false positives, false negatives and true negatives.
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Table.1 Confusion Matrix for various algorithms.

| RANDOM OVERSAMPLING | Predicted | Predicted |
|----------------------|-----------|-----------|
| Actual               | Non-Defective | Defective |
| Non-Defective        | 206       | 119       |
| Detective            | 19        | 88        |

| SMOTE | Predicted | Predicted |
|-------|-----------|-----------|
| Actual| Non-Defective | Defective |
| Non-Defective | 303 | 112 |
| Detective | 19 | 86 |

| ADASYN | Predicted | Predicted |
|--------|-----------|-----------|
| Actual| Non-Defective | Defective |
| Non-Defective | 262 | 153 |
| Detective | 14 | 93 |

| GANS | Predicted | Predicted |
|------|-----------|-----------|
| Actual| Non-Defective | Defective |
| Non-Defective | 253 | 152 |
| Detective | 14 | 93 |

Table.2 Precision, Recall, F1-score and Support

|                | Precision | Recall | F1-score | Support |
|----------------|-----------|--------|----------|---------|
| Non-Defective  | 0.95      | 0.71   | 0.81     | 413     |
| Defective      | 0.43      | 0.82   | 0.56     | 107     |
| Non-Defective  | 0.84      | 0.73   | 0.82     | 415     |
| Defective      | 0.44      | 0.82   | 0.57     | 107     |
| Non-Defective  | 0.95      | 0.63   | 0.76     | 415     |
| Defective      | 0.38      | 0.87   | 0.53     | 107     |

The results are derived from the confusion matrix by the calculation of f- measure score shown in table(2).Results can be visualized through the loss and accuracy graph. The x-axis of loss graph shows the number of epochs and y axis - shows amount the loss. In the accuracy graph the y-axis shows the accuracy.

The Smote methods shows the highest f1- measure initially, though the Gans method is able to produce high quality and correlated data. It is seen that for the over sampling NASA MDP data set, the Random over sampler method works better than ADASYN.

VII. CONCLUSION AND FUTURE WORK

The results show that GAN has the ability to perform better compared to the other methods if modeled and trained properly. The improvement in the results is due to the ability of the gan to model the true distribution of training data if given enough training time and resources. This is in contrast to the other oversampling methods where adaptive method is applied to generate minority class instances in the input space of safe areas. Training Gans require a lot of effort and time compared to other methods but once the training process is complete generation of synthetic instances is rapid and fast. The various other types of gan also be used for oversampling like WGAN. In this paper we dealt with tabular data which is not traditional for training Gans, some method can be found to transfer this data in the image domain and then train the image data with Gan. This method may provide interesting results. Future work can be done by altering the structure of generator or discriminator, which can improve the results. Implementation of the WGAN may give the paper's suggested better results. Newer models can be made that takes into consideration that the training data for minority instances is generated by gans, which can be used to optimize the prediction model which takes such training data.
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