***Abstract*—Imbalanced data classification problem has always been a popular topic in the field of machine learning research. In order to balance the samples between majority and minority class. Oversampling algorithm is used to synthesize new minority class samples, but it could bring in noise. Pointing to the noise problems, this paper proposed a denoising autoencoder neural network (DAE) algorithm which can not only oversample minority class sample through misclassification cost, but it can denoise and classify the sampled dataset. Through experiments, compared with the denoising autoencoder neural network (DAE) with oversampling process and traditional fully connected neural networks, the results showed the proposed algorithm improves the classification accuracy of minority class of imbalanced datasets.**

***Keywords*—imbalanced data; oversampling; Anomaly detection using autoencoder neural network; classification**

I. Introduction

The most prominent form of payment is a credit card. Credit card is a small thin plastic or fiber card that contains information about the person such as picture or service to his linked account charges for which will be debited regularly. Now a day's card information is read by ATM's, swiping machines, store readers, bank and online transaction. Each card as a unique card number which is very important, its security is mainly relies on physical security of the card and also privacy of the credit card number.

Credit card fraud is regarded as an illegal activity in which anyone tries to use the physical card information without the consent and knowledge of the cardholder. Credit card can be dealt in two ways: one is online fraud that can be detected through mobile phone, internet, web, shopping and other is offline fraud that detects the card which is stolen by using their personal details [3]. Credit card fraud is one of the malicious activities that occur in an online transaction. Generally, credit card fraud refers to the unauthorized access of credit or debit card for making payments. These are simply the fraudulent source of funds used in different transactions.

According to Federal Trade Commission (2020, 2021). Just in USA alone credit card fraud went up 44.7% from 2019 to 2020. It makes the credit card second most common type of identity theft reported. Fraud is at an alarming rate with the emergence of technologies causing huge financial loss.

This is a very relevant problem that demands the attention of machine learning and data science communities where the solution to this problem can be automated. This problem is particularly challenging from the perspective of learning, as it is characterized by various factors such as class imbalance.

The banking fraud can't be completely but at least we can prevent from happening and its occurrence to certain level using machine learning techniques and Deep learning techniques. In

this paper, we compare performance of different algorithms to Deep learning mode like Autoencoders.

II. Literature Review

Zarrabi et.al[1] . Deep Auto encoder is proposed by the author that serves as a best extraction of the details of the features from the fraud transaction occurred in the credit card. For the class mark problems, softmax tools used here by the author. For classifying a form of fraud an AutoEncoder is used here which maps the data into a high-dimensional space. Deep learning can be said as one of the most effective methods for detecting the credit card fraud. To understand the dynamic distribution of the data in the networks types becomes difficult to understand. For extraction the best features of data with a high amount of precision and low variance the networks via Deep Auto encoder was used.

K.Ratna Sree Vall et .al [2]. Supervised learning, provided the unexpected input example of the associate degree, and is designed to perform predictions. The supervised methods used in this paper are, Random Forest, Logistic Regression, Naive Bayes and a boosting technique (AdaBoost) to enhance the classification algorithm. AdaBoost or Adaptive Boosting is a boosting method, which provides us with a single "strong classifier" with the combination of multiple "weak classifiers". It was therefore concluded here that compared to logistic regression and even the Naïve Bayes techniques with a boosting technique, the random forest classifier is stronger.

Francis Cheon Dong Hee Lee Han Seon Joo Ook Lee et.al[3] Deep learning hybrid based approach is suggested by the author using LSTM and Bi-LST network.

John and Naaz et.al[4] used local outlier factor and Isolation Forest to get the higher accuracy and they obtained the accuracy of 97% by outlier factor and 76% by Isolation Forest.

Rinky D. Patel and Dheeraj Kumar Singh et.al[5] discuss about class imbalance and how to handle it and also discuss how to work on large dataset. The implemented work was

overcome these challenges.

III. Dataset

Our dataset is from Kaggle, and the dataset is available from https://www.kaggle.com/mlg-ulb/creditcardfraud[7]. The dataset is from transactions of a European bank in September 2013 that are CSV format. It contains 492 (0.17%) fraud transactions and 284,807 (99.83%) genuine transactions. Due to privacy and confidentiality many background information is not provided only PCA transformed data is given. Only time and amount are not transformed to PCA all other given values v1, v2, v3 . . . .. v28 are PCA transformed numeric values .The dataset is composed of 31 numerical features and V1, V2... V28 are from the Principal Component Analysis (PCA). Among the features, "Time" represents the time between the first transaction and other transactions. "Amount" indicates the total amount of transactions from the credit card. The target column is the "Class" that contains only 1 representing fraud transactions, and 0 for genuine transactions. Therefore, the binary classification should be conducted for treating the dataset

Fig-1:Showing Imbalance of data in percentage

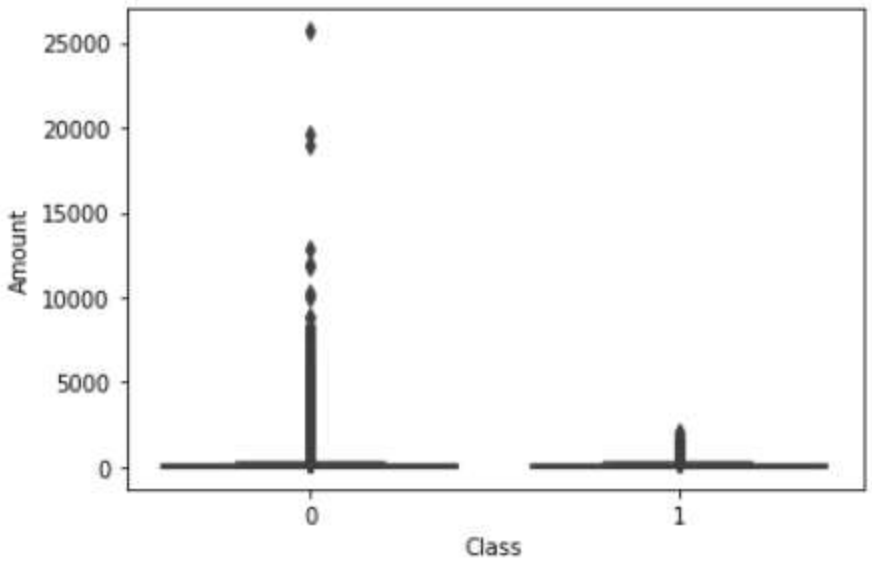
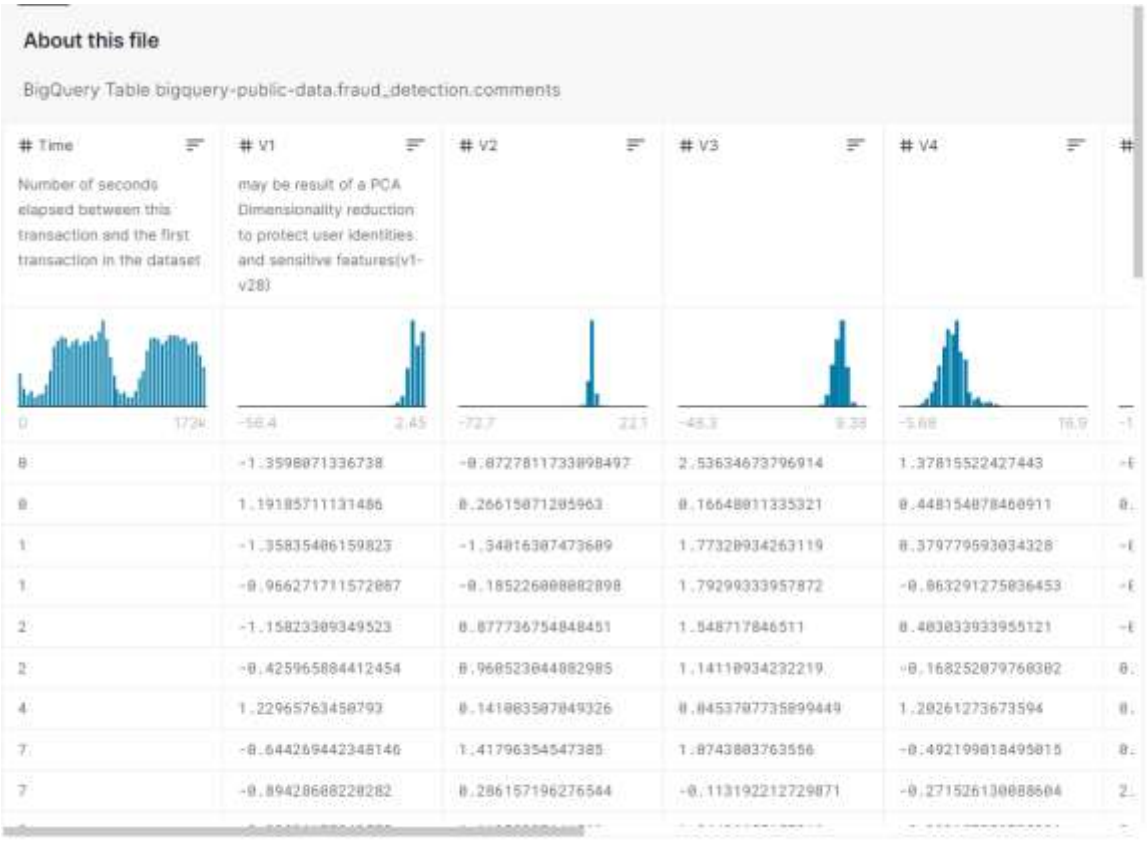


Fig-2: Showing Imbalance of class with respect with Amount



About this file

BigQuery Table bigquery-public-data.fraud_detection.comments

# Time Number of seconds elapsed between this transaction and the first transaction in the dataset	# V1 may be result of a PCA Dimensionality reduction to protect user identities and sensitive features(v1-v28)	# V2	# V3	# V4	#
0	-1.3598071336738	-0.0727811733098497	2.53634673796914	1.37815522427443	-(
0	1.19185711131486	0.26615071205963	0.16648011335321	0.448154078460911	0.
1	-1.35835406159823	-1.34016307473609	1.77320934263119	0.379779593034328	-(
1	-0.966271711572087	-0.185226008082898	1.79299333957872	-0.863291275036453	-(
2	-1.15823309349523	0.877736754848451	1.548717846511	0.403033933955121	-(
2	-0.425965884412454	0.960523044082985	1.14110934232219	-0.168252079760302	0.
4	1.22965763450793	0.141083507849326	0.0453707735899449	1.20261273673594	0.
7	-0.644269442348146	1.41796354547385	1.8743803763556	-0.492199018495015	0.
7	-0.89428688228282	0.286157196276544	-0.113192212729871	-0.271526130088604	2.

Fig-3 : Showing dataset page from Kaggle

IV. Background

4.1 Supervise learning methods

Logistic Regression->Logistics Regression is less inclined to the overfitting, but it can overfit in high-dimensional datasets. We can consider regularization techniques to avoid overfitting. Any big outliers will be transform into the range of 0 and 1. Its help mainly to solve classifications problem and supply us the knowledge whether the event is happening or not.
RandomForestClassifier ->A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting.

tree algorithms, used for ranking, classification and many other machine learning tasks

KNN ->. It is a supervised machine learning algorithm. The algorithm can be used to solve both classification and regression problem statements. The number of nearest neighbours to a new unknown variable that has to be predicted or classified is denoted by the symbol 'K

GaussianNB ->In this classification method, the probability of an object associated, with a particular category or class with certain feature is learned. Naive Bayes algorithm can fit model fast and provide high accuracy when applied to big data and need less training.

4.2 Anomaly detection methods

Isolation Forest ->Isolation Forest is an unsupervised anomaly detection learning algorithm that operates on the concept of isolating anomalies. The Isolation Forest algorithm aims to make it easier to separate anomalous instances in a dataset from the rest of the sample (isolate), relative to usual points. The algorithm recursively creates partitions in the sample in order to isolate a data point by randomly selecting an attribute and then randomly selecting a split value for an attribute between the minimum and maximum values permitted for that attribute.

Autoencoders ->Autoencoder has a structure of feed-forward neural network that consists of the same input and out dimension. Autoencoder simply copies the input to the output .

Setting a limitation to the neural network can make this simple neural network more complicated. Representative constraint is to limit the number of neurons between n input and output. This constraint has two advantages. Firstly, it would prevent autoencoders from simply copying inputs to the output. Secondly, it would learn how to represent data more effectively. This simple autoencoder is defined as an under complete autoencoder, which is a symbolic model of the autoencoder. The autoencoder incorporates two separate parts,

which are the encoder and decoder. The encoder converts inputs into inner representations. The decoder transforms inner representations into outputs

Layer (type)	Output Shape	Param #
dense_10 (Dense)	(None, 100)	3000
dense_11 (Dense)	(None, 50)	5050
dense_12 (Dense)	(None, 25)	1275
dense_13 (Dense)	(None, 12)	312
dense_14 (Dense)	(None, 6)	78
dense_15 (Dense)	(None, 12)	84
dense_16 (Dense)	(None, 25)	325
dense_17 (Dense)	(None, 50)	1300
dense_18 (Dense)	(None, 100)	5100
dense_19 (Dense)	(None, 29)	2929

Total params: 19,453
Trainable params: 19,453
Non-trainable params: 0

Fig-4: Architecture of the model used

V. Result and Experiment analysis

A comparison table was prepared to compere different machine learning and deep learning model. We calculated precision, recall, ROC curve and accuracy with the help of inbuilt models present in Sklearn like accuracy and AUC_Score.

Accuracy : It represents the fraction of the total number of transactions that have been detected correctly (fraudulent and nonfraudulent).

Precision: Precision represents precise/accuracy of model. Precision is a good measure to determine when the cost of false positive is high.

Recall: Recall calculates how many of the Actual Positives our model capture through labeling it as Positive (True Positive). It should be the model metric that we use our best model when there is high cost associated with False Negative.

ROC curve: It stands for Receiver Operating Characteristic (ROC) curve. In this, for different cut-off points, the true positive rate (Sensitivity)is plotted in function of the false positive rate (100-Specificity). If the ROC curve is closer to the upper left corner, then the overall accuracy of the test will be high. The area under the ROC curve (AUC) is a measure that parameter can distinguish between two groups (fraudulent/nonfraudulent)

Reconstruction error:

The training of autoencoder neural network is to optimize reconstruction error using the given samples. The cost function of autoencoder neural network defined in the project is

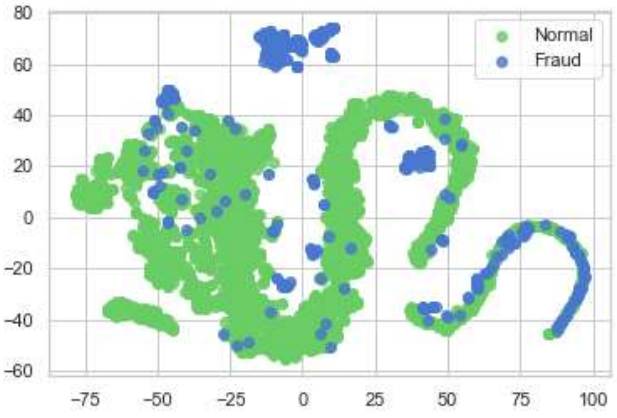


Fig-> Applying T-sne on 4000 sample

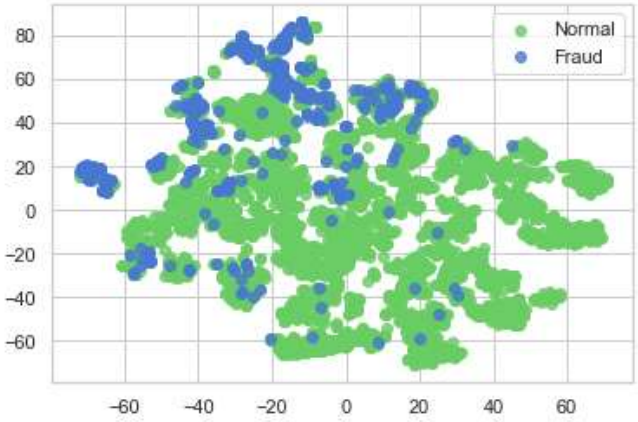


Fig-6-> Applying T-sne over reconstructed

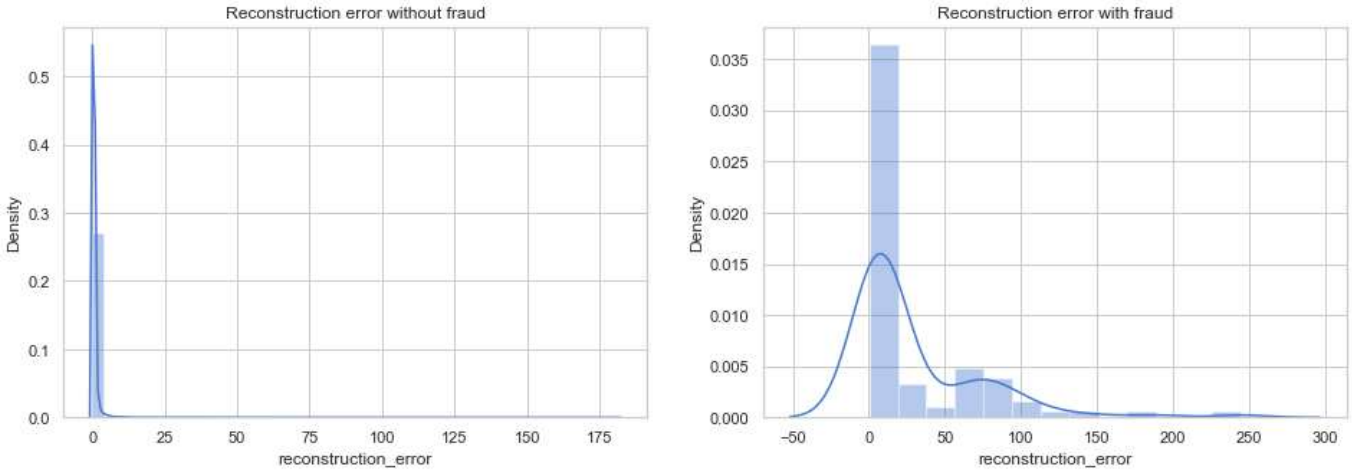


Fig-7->Reconstruction error after passing the whole dataset through autoencoder

Results comparison

The performance of the algorithm must be closely compared with other algorithm to classify between fraudulent and non fraudulent data. Comparison with standard classification algorithms like Logistic Regression, Naïve Bayes and KNN has been done.

Table 1 : Comparison of Algorithms

Algorithm	Accuracy	Precision	Recall	Auc_ROC_Score
Logistic Regression(Imbalanced)	0.999	0.875	0.670	0.835
Logistic Regression(balanced)	0.973	0.053	0.904	0.938
Naïve bayes(imbalanced)	0.977	0.057	0.829	0.903
Naïve bayes(balanced)	0.973	0.051	0.851	0.912
KNN(imbalanced)	0.999	0.986	0.776	0.888
KNN(balanced)	0.997	0.405	0.872	0.935
RandomForest	0	0.285	0.282	0.640
AutoEncoder(thr>2)	0.955	0.032	0.867	0.911
AutoEncoder(thr>3)	0.973	0.049	0.785	0.879

VI. Conclusion and Future Scope

The credit card fraud detection methods have gained popularity in the past decade with the evolution of statistical models, machine learning algorithms, data mining techniques. The fraud transaction prediction has 2 phases which are feature extraction and classification. Within the first phase, the feature extraction technique is applied and within the second phase, classification is applied for fraud transaction detection, Fraud transaction detection is that the major issue of prediction because of a frequent and enormous number of transactions. During this comparative research study, we tried to analyze the dataset through various graphs and also tried to detect fraud using some classification algorithms and make comparative analysis.

As we can see from the data above simple algorithm like Logistic Regression performs same as compared to much dense Deep learning model like AutoEncoder. And even after balancing the imbalance between classes performance of various algorithms only improve by a little margin.

More surprising thing is that Logstic Regression take very less time to train compared to Deep AutoEncoder but both have almost similar result.

Also even when trained on Non-fraud dataset only , Anomaly detection techniques like RandomForest and AutoEncoder can detect anomaly. Supervised Learning method LogisticRegression and anomaly detecting using autoencoder both has similar AUC_Score.

In future Deep learning models like LSTM, BiLSTM , And unsupervised learning methods like clustering or even a combination of both could be use but more importantly a balanced dataset could be used to properly measure their performance.

VII. References

1. Zarrabi, H. Kazemi, “Using deep networks for fraud detection in the credit card transactions, “IEEE 4th International Conference In Knowledge-Based Engineering and Innovation (KBEI), pp. 0630-0633, 2017
2. Khyati Chaudhary, Jyoti Yadav, Bhawna Mallick, “A review of Fraud Detection Techniques: Credit Card”, International Journal of Computer Application, Volume 45- No.1 2012.
3. MIN JONG CHEON, 2DONG HEE LEE, 3HAN SEON JOO, OOK LEE, “DEEP LEARNING BASED HYBRID APPROACH OF DETECTING FRAUDULENT TRANSACTIONS” Journal of Theoretical and Applied Information Technology 31st August 2021. Vol.99. No 16
4. Credit Card Fraud Detection Based on Transaction Behaviour -by John Richard D. Kho, Larry A. Vea” published by Proc. of the 2017 IEEE Region 10 Conference (TENCON), Malaysia, November 5-8, 2017 [2] CLIFTO
5. Rinky D. Patel and Dheeraj Kumar Singh, “Credit Card Fraud Detection & Prevention of Fraud Using Genetic Algorithm”, published by International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-2, Issue-6, January 2013.
6. Aditya Saini, Swarna Deep Sarkar, Shadab Ahmed, SP Maniraj “ Credit Card Fraud Detection using Machine Learning and Data Science”, International Journal of Engineering Research & Technology, ISSN: 2278-0181, Vol. 8 Issue 09, September-2019
7. https://www.kaggle.com/mlg-ulb/creditcardfraud

   report link https://github.com/shaaguunz/college_project_2/tree/main/INT248