

# CREDIT CARD FRAUD DETECTION REPORT

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## ABSTRACT

Now a days cyber crimes have been increased. The problem we are dealing is finding a credit card transaction is fraudulent or not using machine learning. This is binary classification problem solved using 3 layered neural networks.

Exploratory Data Analysis, Data Preprocessing, Modeling, Evaluation tasks are performed for the data.

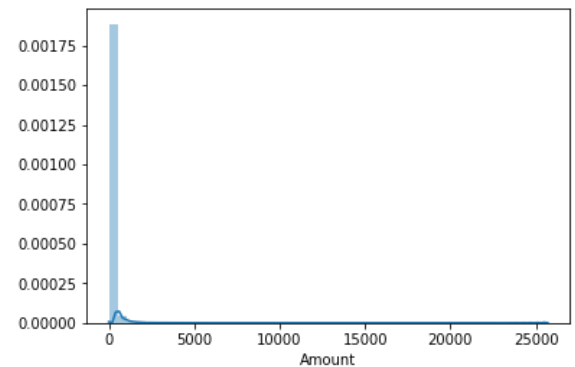
## INTRODUCTION

Dataset:

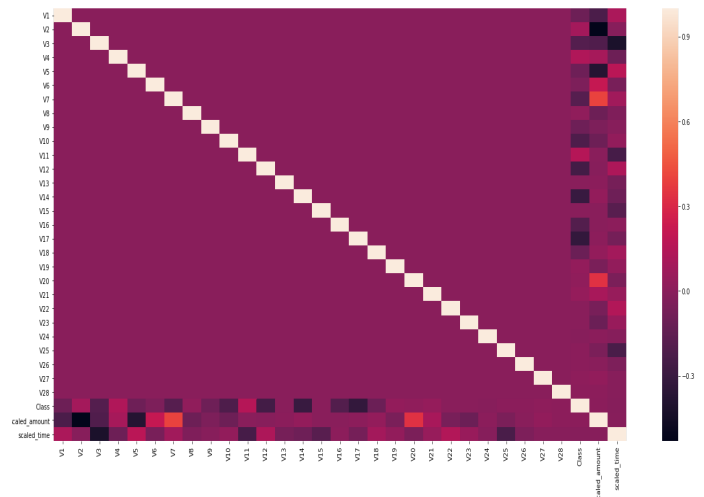
- The dataset is of size 284807 rows with 30 independent variables and 1 target variable.
- The data set contains 285315 non fraud cases and 492 fraud cases.

## EXPLORATORY DATA ANALYSIS

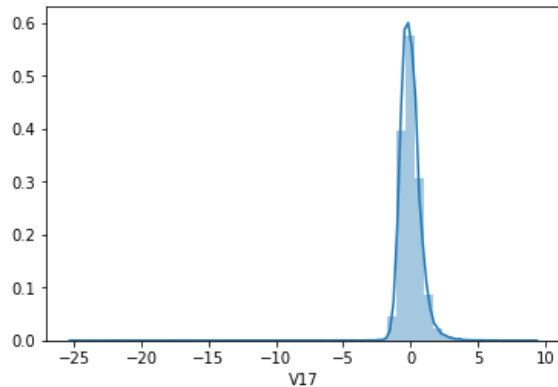
- Distribution of Amount of Transaction



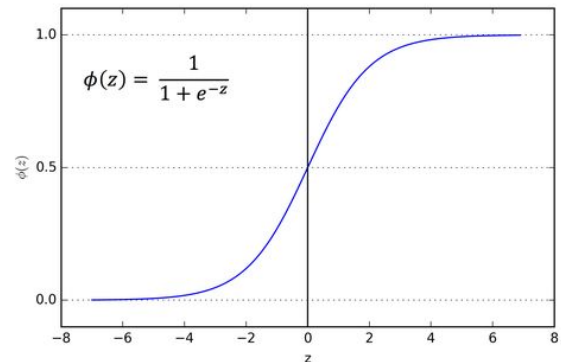
- Normalization of the Data
- Correlation between the variables



Distribution of one of the important variable

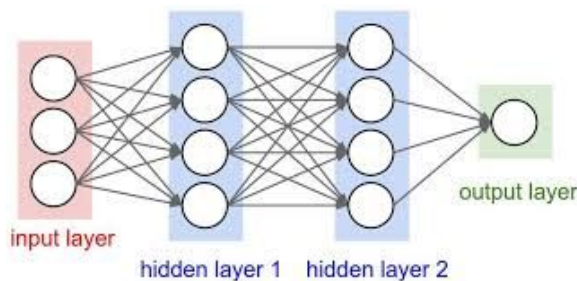


and 1. Probability above 0.5 as one class and below 0.5 as other.



## MODELING

- The Dataset is split into (80-20) train and test sets.
- Create a three layered neural network with nodes [10 -5 -1]
- Input dimension is 30 (No of features)



- Layers are Dense(fully connected)
- At the output Sigmoid Activation function is used. It gives probability between 0

- Adam Optimization function is used for updating weights through backpropagation

For each Parameter  $w^j$   
(j subscript dropped for clarity)

$$\nu_t = \beta_1 * \nu_{t-1} + (1 - \beta_1) * g_t$$

$$s_t = \beta_2 * s_{t-1} + (1 - \beta_2) * g_t^2$$

$$\Delta \omega_t = -\eta \frac{\nu_t}{\sqrt{s_t + \epsilon}} * g_t$$

$$\omega_{t+1} = \omega_t + \Delta \omega_t$$

$\eta$  : Initial Learning rate

$g_t$  : Gradient at time  $t$  along  $\omega^j$

$\nu_t$  : Exponential Average of gradients along  $\omega_j$

$s_t$  : Exponential Average of squares of gradients along  $\omega_j$

$\beta_1, \beta_2$  : Hyperparameters

## EVALUATION METRICS

used or classification problems

- Confusion Matrix:

		Prediction outcome		
		positive	negative	
Actual value	positive	<i>TP</i>	<i>FN</i>	<i>TP + FN</i>
	negative	<i>FP</i>	<i>TN</i>	<i>FP + TN</i>
		<i>TP + FP</i>	<i>FN + TN</i>	

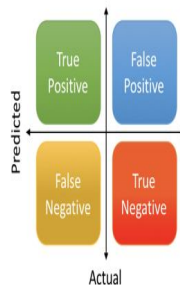
```
target_names = ['class 0', 'class 1']
print(classification_report(y_test, y_pred, target_names=target_names))
```

	precision	recall	f1-score	support
class 0	1.00	1.00	1.00	56864
class 1	0.00	0.00	0.00	98
accuracy			1.00	56962
macro avg	0.50	0.50	0.50	56962
weighted avg	1.00	1.00	1.00	56962

$$\text{Precision} = \frac{\text{True Positive}}{\text{Actual Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{Predicted Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total}}$$



## CONCLUSION

From the above results the three layered neural network model performed well for the data in both train and test set with satisfying results.

- F1 score :

$$\frac{2 * (\text{Precision} * \text{Recall})}{(\text{precision} + \text{Recall})}$$

(precision + Recall)

## RESULTS

Training Accuracy : 99.944 %

Test Accuracy : 99.827%

Hence there is no overfitting and no under fitting.

