Credit card fraud detection using Machine Learning Techniques: A Comparative Analysis

Flow of Talk

- Introduction
- Experimental Set Up and Methods
- Performance Evaluation and Results
- Conclusion
- References

Introduction

Fraud can be defined as criminal deception with intent of acquiring financial gain.

- **Credit Card Fraud**
  - **Inner Card Fraud:** Done by using false identity
  - **External Card Fraud:** Done by using stolen credit card
- **How Frauds are Recognized**
  - **Location**: Purchase made from different location
  - **Items you buy**: If you deviate from your regular buying pattern or time
  - **Frequency**: Make a large number of transactions in short period of time
  - **Amount**: Suddenly if the costly items are purchased

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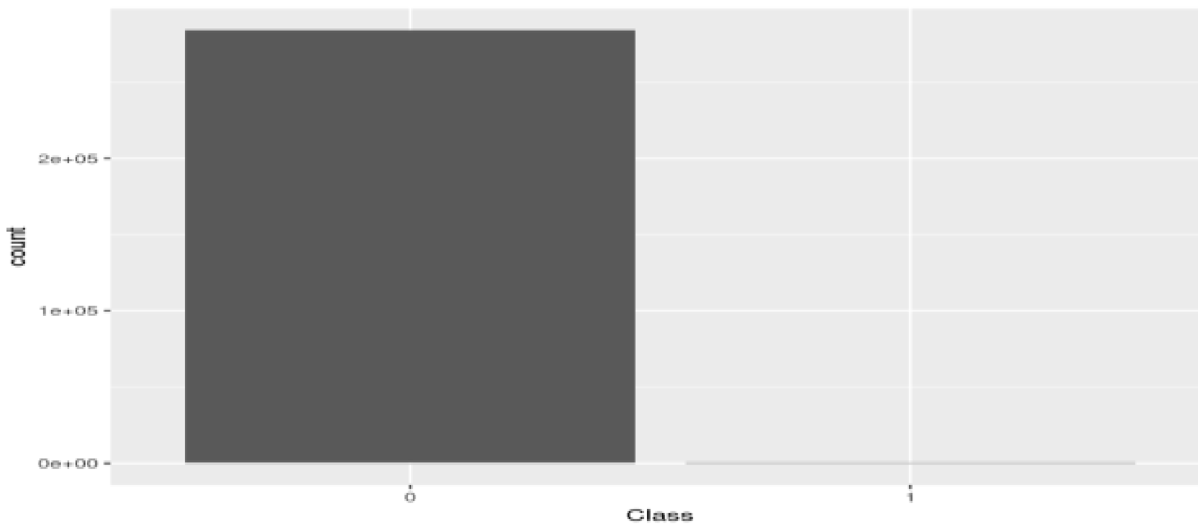
Challenges:

- ➢The data is highly skewed.
- ➢Normal Machine Learning algorithms would give 99%+ Accuracy.
- ➢But we can get 99.8% accuracy even if we classify all Frauds as Legitimate.



Authentic **Fraud**

Fig 1. Highly Unbalanced data

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- **Feature (Variables) Selection**
  - Transaction statistics
  - Regional statistics
  - Merchant type statistics
  - Time based amount statistics
  - Time based number of transaction statistics
- **Credit Card Fraud Detection**
  - **Supervised:** Models are estimated based on samples of fraudulent and legitimate transactions to classify new transactions as fraud or legitimate.
  - **Unsupervised:** The outliers' transactions are considered as potential instance of fraud.
- **Comparative Study**

Experimental Set Up and Methods

- **Dataset**
  - Sourced from ULB Machine Learning Group
  - Consisting 2,84,807 transactions , 0.172% fraud cases
  - Highly Unbalanced and Skewed towards fraud class
- **Resampling Methods**
  - The resampling methods are used to adjust the class distribution of the data as the minority class is not equally represented.
  - There are three methods to perform resampling :
    - Oversampling
    - Undersampling
    - Hybrid Sampling

Contd…

- **SMOTE :**
  - SMOTE stands for Synthetic Minority Oversampling Technique.
  - This is a statistical technique to increase the number samples in the minority class in the dataset to make it balanced.
  - It works by generating new instances of data from existing data by taking feature space of each target class and its nearest neighbours.
  - But it is effective upto 6 to 7 parameters.
- **Hybrid Sampling of data:**
  - It is done by stepwise addition and subtraction of data points interpolat [illegible] overfitting threshold

$$PC_{new} = \sum_{i=1}^{n} PC + i$$

$$NC_{new} = \sum_{i=1}^{n} NC - i$$

$$n = \mathrm{mod}((NC/PC)/2)$$

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- **Naïve Bayes Classifier**
  - **A simple classifier model that is:**
    - Based on the Bayes theorem and Conditional Probability
    - Chooses decision based on highest probability
    - Allows prior knowledge and logic
    - Uses Supervised Learning
  - **Conditional Probability:**
    - Conditional probability is a measure of the probability of an event given that another event has already occurred.
  - **Bayes Theorem:**
    - $P(H|E)= P(E|H)\, P(H)/ P(E)$
    - P(H) is the probability of hypothesis H being true.
    - P(E) is the probability of the evidence(regardless of the hypothesis).
    - P(E|H) is the probability of the evidence given that hypothesis is true.
    - P(H|E) is the probability of the hypothesis given that the evidence is there.

Contd..

- **Naïve Bayes Classifier**

$$P(c_i \mid f_k) = \frac{P(f_k \mid c_i)^* P(c_i)}{P(f_k)}$$

$$P(f_k \mid c_i) = \prod_{i=1}^{n} P(f_k|c_i) k = 1, \ldots, n; i = 1, 2$$

- Bayesian classification rule

$$If\ P(c_1|f_k) > P(c_2|f_k)\ then\ the\ classification\ is\ C_1$$
$$If\ P(c_1|f_k) < P(c_2|f_k)\ then\ the\ classification\ is\ C_2$$

Contd…

- **k-Nearest Neighbour Classifier**
  - K - Nearest neighbors is a lazy learning instance based classification(regression) algorithm which is widely implemented in both supervised and unsupervised learning techniques.
  - It is lazy Learner as it doesn't learn from a discriminative function from training data but memorizes training dataset.
  - This technique implements classification by considering majority of vote among the “k” closest points to the unlabeled data point.
  - It uses three types of functions for distance calculation
    - Euclidian
    - Manhattan
    - Minkowski

Contd…

- **k-Nearest Neighbour Classifier**

$$D_{ij} = \sqrt{\sum_{k=1}^{n}(X_{ik} - X_{jk})^2} \quad \mathrm{k} = 1, 2, \ldots, \mathrm{n}$$

Formula to calculate Euclidean distance

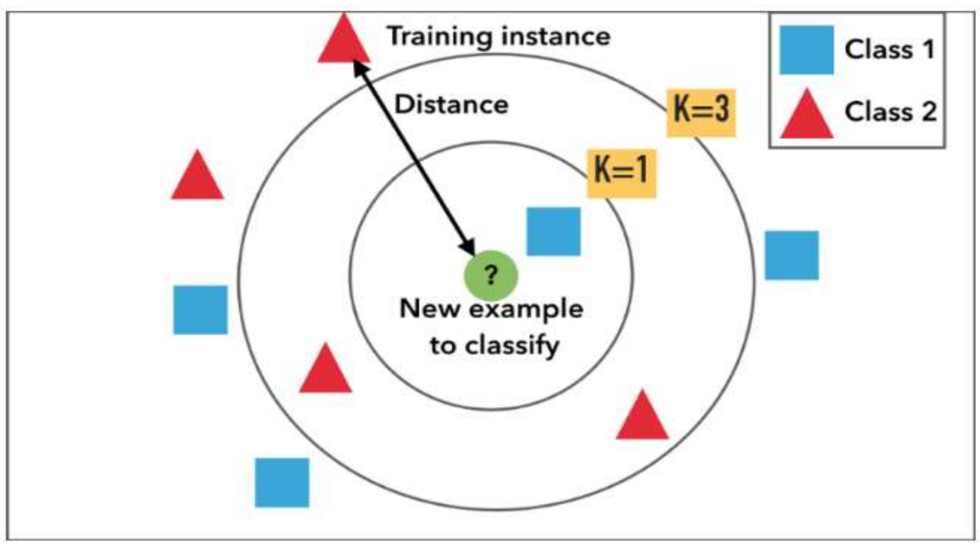

Fig 2. Example of k-NN classification

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- **Logistic Regression Classifier:**
  - Logistic Regression is a statistical method for analyzing a dataset in which there are one or more independent variables that determine an outcome. The outcome is measured with a dichotomous variable, where there are only two possible outcomes.
  - The goal of logistic regression is to find the best fitting model to describe the relationship between the dichotomous characteristic of interest, and a set of independent variables.
  - Logistic Regression generates the coefficients of a formula to predict a Logit Transformation of the probability of presence of the characteristic of interest.

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- **Logistic Regression Classifier**

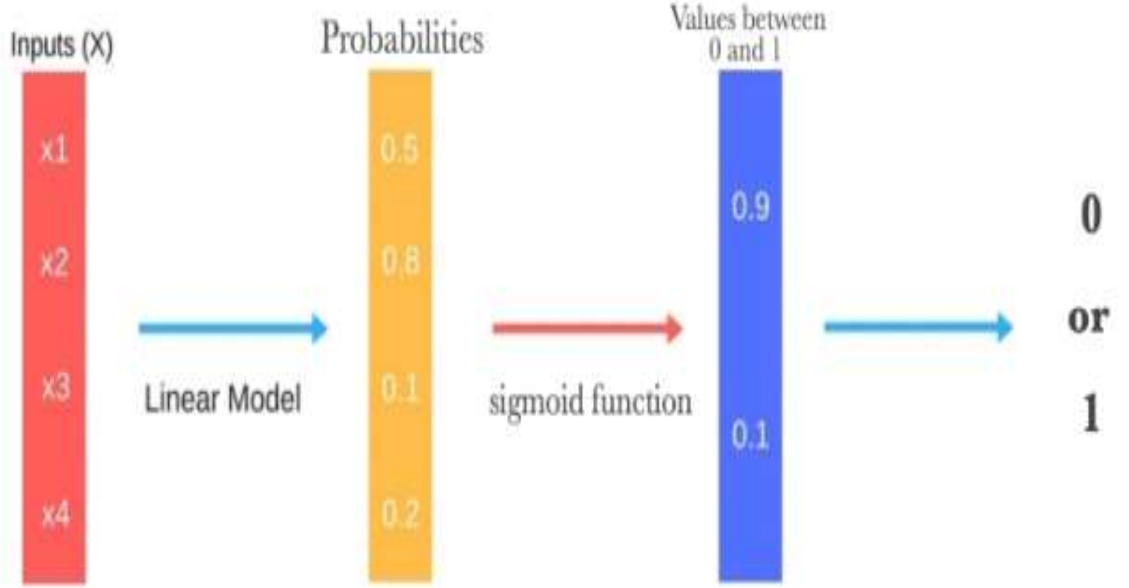

Fig.3 Working of Logistic Regression Model

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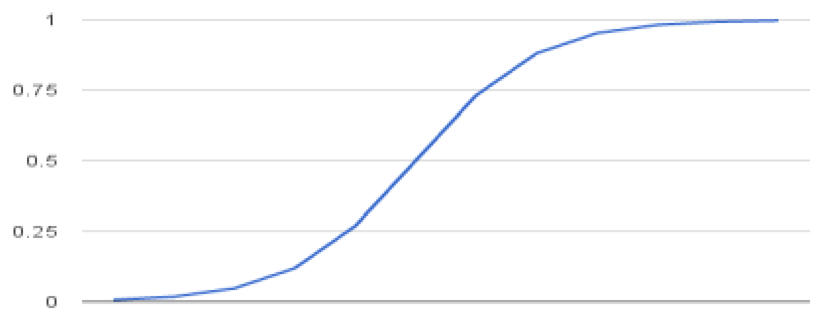

Fig.4 Sigmoid Function

Sigmoid Function:

- A sigmoid function is a mathematical function having a characteristic "S"-shaped curve or sigmoid curve.
- A sigmoid function is a bounded, differentiable, real function that is defined for all real input values and has a non-negative derivative at each point.

$$\sigma(x) = \frac{1}{(1+\ell^{-x})}$$

$$x = w_0 z_0 + w_1 z_1 + \ldots + w_n z_n$$

Performance Evaluation and Results

- Four metrics used in evaluation
  - True Positive Rate(TPR)
  - True Negative Rate (TNR)
  - False Positive Rate (FPR)
  - False Negative Rate (FNR)

$$TPR = \frac{TP}{P}$$

$$TNR = \frac{TN}{N}$$

$$FPR = \frac{FP}{N}$$

$$FNR = \frac{FN}{P}$$

Contd …

- **Performance of naïve bayes, k-nearest neighbour and logistic regression classifiers are evaluated based on :**
  - Accuracy
  - Sensitivity
  - Specificity
  - Precision
  - Matthews Correlation Coefficient (MCC)
  - Balanced Classification Rate(BCR)

Contd…

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{FP + TN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$MCC = \frac{(TP{*}TN) - (FP{*}FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

$$BCR = {}^{1}/_{2} \, {*} \left(\frac{TP}{P} + \frac{TN}{N} \right)$$

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- **Comparative Performance**

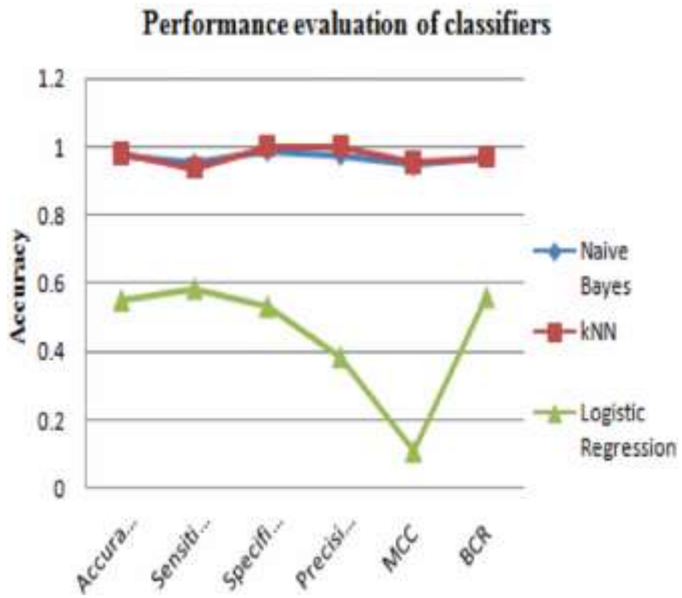

Figure 4
Performance evaluation chart for naive bayes, knn and logistic regression
*mcc = matthews correlation coefficient
*bcr = balanced classification rate

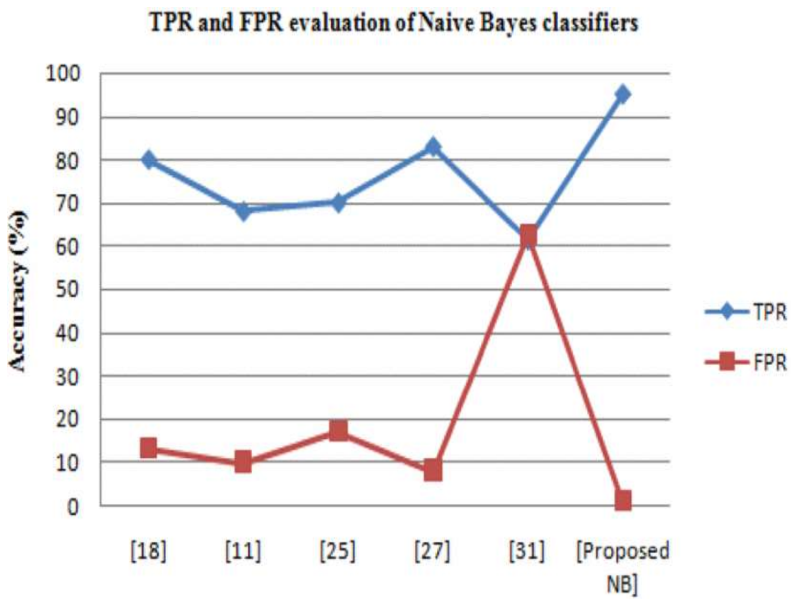

Figure 5
TPR and FPR evaluation of naïve bayes classifiers
*TPR = true positive rate
*fpr = false positive rate
*proposed NB = proposed naïve bayes classifier

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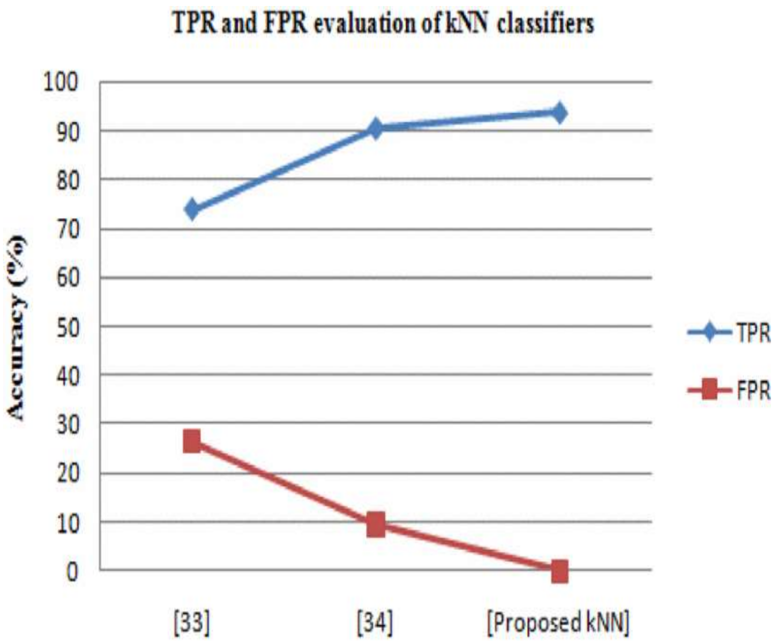

Figure 6
TPR and FPR evaluation of k-nearest neighbour classifiers
*TPR = true positive rate
*fpr = false positive rate
*proposed knn = proposed k-nearest neighbor classifier

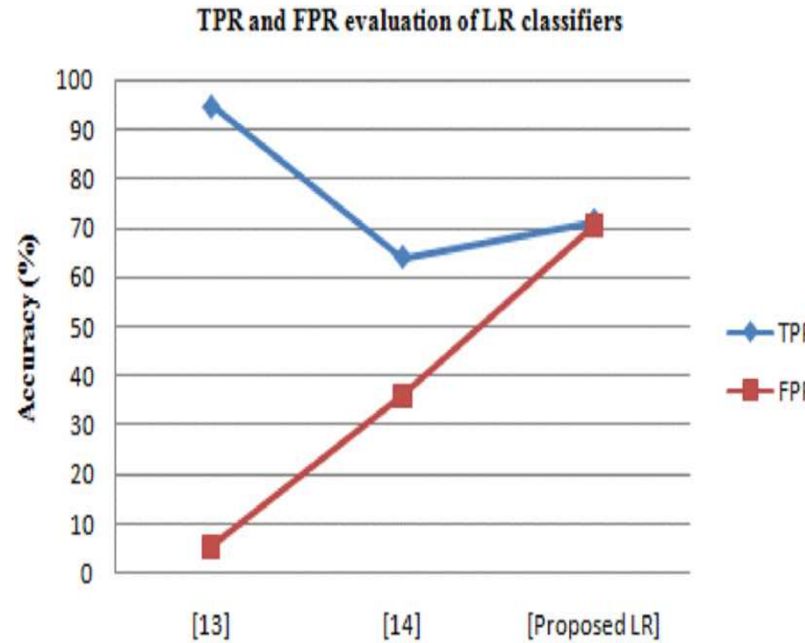

Figure 7
TPR and FPR evaluation of logistic regression classifiers
*TPR = true positive rate
*fpr = false positive rate
*proposed LR = proposed logistic rgression classifier

Conclusion

- Three classifiers based on different machine learning techniques (Naïve Bayes, K-nearest neighbours and Logistic Regression) are trained on real life of credit card transactions data and their performances on credit card fraud detection evaluated and compared based on several relevant metrics.
- The highly imbalanced dataset is sampled in a hybrid approach where the positive class is oversampled and the negative class under-sampled, achieving two sets of data distributions.
- The performances of the three classifiers are examined on the two sets of data distributions using accuracy, sensitivity, specificity, precision, balanced classification rate and Matthews Correlation coefficient metrics.
- Results from the experiment shows that the kNN shows significant performance for all metrics evaluated except for accuracy in the 10:90 data distribution.

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Thank you