

CREDIT CARD FRAUD DETECTION

Thesis submitted in partial fulfillment of the
requirements for

Postgraduate diploma in data science

By

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Examiner 1

Examiner 2

Signature:

Signature:

Name:

Name:



CERTIFICATE

This is to certify that the project titled

CREDIT CARD FRAUD DETECTION

Is a bonafide record of the work done by

Jothi Prakash Anandan

Reg no: 17125760069

In partial fulfillment of the requirements for the award of **Postgraduate Diploma in data science** under Manipal University, Manipal and the same has not been submitted elsewhere for any kind of certification/recognition.

Ramakrishna Ganesan

Faculty

Manipal Prolearn

Manipal University

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I would like to express my sincere gratitude to the Director of Manipal global academy of data science, **Dr. Ramesh Babu** for having given me the opportunity to work on the project titled “**Credit card fraud detection**”.

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This project helped me research and learn important aspects of how credit defaults happen and also helped me sharpen my data analysis skills by working on this real business case.

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3. ABSTRACT

In this project, machine learning, network analysis and UI building tools and techniques were used to analyze credit defaulting from credit card transactions in September 2013 by European cardholders. The dataset has been collected and analyzed during a research collaboration of Worldline and the Machine Learning Group (<http://mlg.ulb.ac.be>) of ULB (Université Libre de Bruxelles) on big data mining and fraud detection.

This dataset presents transactions that occurred in two days, where we have 492 frauds out of 284,807 transactions. The dataset is highly unbalanced, the positive class (frauds) account for 0.172% of all transactions.

It contains only numerical input variables which are the result of a PCA transformation. Unfortunately, due to confidentiality issues, they cannot provide the original features and more background information about the data. Features V1, V2, ... V28 are the principal components obtained with PCA, the only features which have not been transformed with PCA are 'Time' and 'Amount'. Feature 'Time' contains the seconds elapsed between each transaction and the first transaction in the dataset. The feature 'Amount' is the transaction Amount, this feature can be used for example-dependant cost-sensitive learning. Feature 'Class' is the response variable and it takes value 1 in case of fraud and 0 otherwise.

Further, various machine learning and visualization techniques were leveraged on the data to find defaults.

4. INTRODUCTION

a. Motivation

The health of the credit card industry is best measured not by the number of people with cards, but rather the number who pay their bills. Bad payment habits begin by nicking you with more fees and lower credit scores, and, in advanced cases, can lead to the loss of a vehicle or home, garnishment, and bankruptcy.

Credit card defaults, after a lengthy decline, are starting to tick up slightly.

Delinquencies in bank cards rose in the third quarter of 2016, but remain near historical lows, according to the American Bankers Association's Consumer Credit Delinquency Bulletin.

Bank card delinquencies increased 26 basis points to 2.74 percent of all accounts in the third quarter, but remain well below their 15-year average of 3.68 percent. The ABA report defines a delinquency as a late payment that is 30 days or more overdue.⁴

The trend looks similar when examining accounts that have been overdue for three months. TransUnion's Industry Insights Report found that the credit card delinquency rate reached 1.79 percent in Q4 2016, an increase of 12.6 percent from 1.59 percent in Q4 2015. The credit card delinquency rate remains more than a full point below its peak in Q4 2009 (2.97 percent).

b. Project scope

The scope of the project is somewhat restricted by the missing sensitive data. The PCA data might be useful for prediction but the high dimensional credit history data is really necessary in order to produce quality visualizations which are missing in the selected dataset.

The customer name, a date with an exact time of transfer, location, device used for money transfer are some of the crucial information necessary for clustering/segmenting the data and the number of defaults is very low and the unbalanced data might have some impact in the prediction and insights extracted.

To balance out the data and make the predictions and visuals in a justified manner t-SNE is used. To extract maximum insight variable importance is carried out in random forest algorithm. The Gini index will give us the idea of which dimensional data has the highest impact on the defaults.

c. Project focus

All the banks are having losses due to illegal or defaulted transactions that happen using their network and they are trying to predict/classify a transaction to be worthy or defaulting. There are heavy losses due to illegal transactions and some of them are mentioned below.

1. Estimates created by the Attorney-General's Department show that identity crime costs Australia upwards of \$1.6 billion each year, with the majority of about \$900 million being lost by individuals through credit card fraud, identity theft, and scams.
2. In 2015, the Minister for Justice and Minister Assisting the Prime Minister for Counter-Terrorism, Michael Keenan, released the report Identity Crime and Misuse in Australia 2013-14.
3. This report estimated that the total direct and indirect cost of identity crime was closer to \$2 billion, which includes the direct and indirect losses experienced by government agencies and individuals, and the cost of identity crimes recorded by police.

To classify/predict the defaultable transaction is the target objective.

5. PROJECT DESCRIPTION

a. Business/Data understanding:

The dataset has been collected and analyzed during a research collaboration of Worldline and the Machine Learning Group (<http://mlg.ulb.ac.be>) of ULB (Université Libre de Bruxelles) on big data mining and fraud detection.

It contains only numerical input variables which are the result of a PCA transformation. Unfortunately, due to confidentiality issues, they cannot provide the original features and more background information about the data. Features V1, V2, ... V28 are the principal components obtained with PCA, the only features which have not been transformed with PCA are 'Time' and 'Amount'. Feature 'Time' contains the seconds elapsed between each transaction and the first transaction in the dataset. The feature 'Amount' is the transaction Amount, this feature can be used for example-dependant cost-sensitive learning. Feature 'Class' is the response variable and it takes value 1 in case of fraud and 0 otherwise.

b. Data limitations:

This dataset presents transactions that occurred in two days, where we have 492 frauds out of 284,807 transactions. The dataset is highly unbalanced, the positive class (frauds) account for 0.172% of all transactions.

c. Dataset understanding

Column	Description	Type
Time	Number of seconds elapsed between each transaction (over two days)	Numeric
V1	-	Numeric
V2	-	Numeric
V3	-	Numeric
V4	-	Numeric
V5	-	Numeric
V6	-	Numeric
V7	-	Numeric
V8	-	Numeric
V9	-	Numeric
V10	-	Numeric
V11	-	Numeric
V12	-	Numeric
V13	-	Numeric
V14	-	Numeric
V15	-	Numeric
V16	-	Numeric
V17	-	Numeric
V18	-	Numeric
V19	-	Numeric
V20	-	Numeric
V21	-	Numeric
V22	-	Numeric
V23	-	Numeric
V24	-	Numeric
V25	-	Numeric
V26	-	Numeric
V27	-	Numeric
V28	-	Numeric
abc	-	Numeric
Amount	Amount of money for this transaction	Numeric
Class	Fraud or Not-Fraud	Boolean

d. Business objective

This project has been broken down into 3 subparts and objectives

1. Identify the important variables which led to the default.
2. Exploratory data analysis to be implemented as graphs and UI based decisions for efficient and user-friendly exploration and comparison of correlation.
3. Prediction of default using machine learning algorithms.

6. TOOLS AND TECHNOLOGIES

Exploratory data analysis & machine learning

1. RStudio
2. T-SNE
3. Random forest algorithm

RStudio

RStudio is a free and open-source integrated development environment (IDE) for R, a programming language for statistical computing and graphics. RStudio was founded by JJ Allaire, creator of the programming language ColdFusion. Hadley Wickham is the Chief Scientist at RStudio.

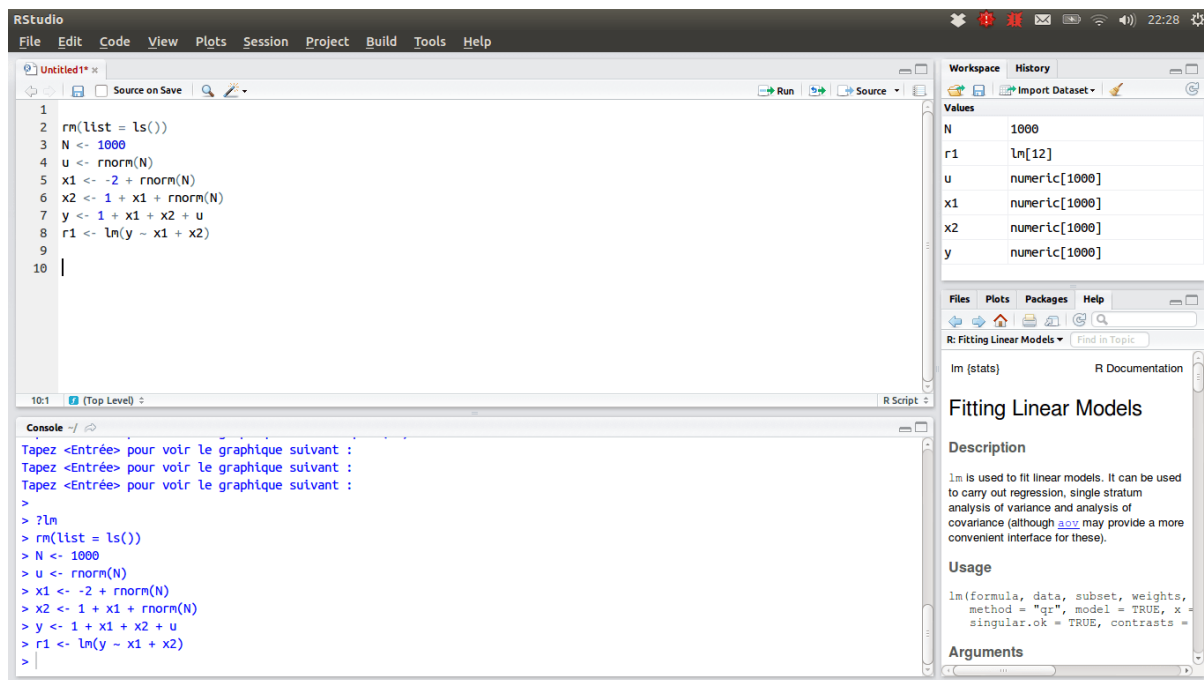
RStudio is available in two editions: RStudio Desktop, where the program is run locally as a regular desktop application; and RStudio Server, which allows accessing RStudio using a web browser while it is running on a remote Linux server. Prepackaged distributions of RStudio Desktop are available for Windows, macOS, and Linux.

RStudio is available in open source and commercial editions and runs on the desktop (Windows, macOS, and Linux) or in a browser connected to RStudio Server or RStudio Server Pro (Debian, Ubuntu, Red Hat Linux, CentOS, OpenSUSE and SLES).

RStudio is written in the C++ programming language and uses the Qt framework for its graphical user interface.

Work on RStudio started around December 2010, and the first public beta version (v0.92) was officially announced in February 2011. Version 1.0 was released on 1 November 2016. Version 1.1 was released on 9 October 2017.

Credit card fraud detection



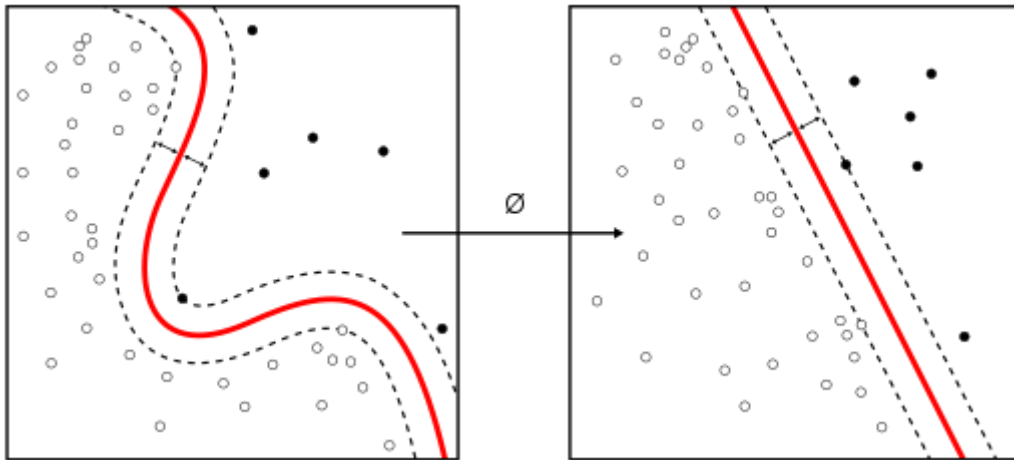
t-SNE

t-distributed stochastic neighbor embedding (t-SNE) is a machine learning algorithm for visualization developed by Laurens van der Maaten and Geoffrey Hinton. It is a nonlinear dimensionality reduction technique well-suited for embedding high-dimensional data for visualization in a low-dimensional space of two or three dimensions. Specifically, it models each high-dimensional object by a two- or three-dimensional point in such a way that similar objects are modeled by nearby points and dissimilar objects are modeled by distant points with high probability.

The t-SNE algorithm comprises two main stages. First, t-SNE constructs a probability distribution over pairs of high-dimensional objects in such a way that similar objects have a high probability of being picked, whilst dissimilar points have an extremely small probability of being picked. Second, t-SNE defines a similar probability distribution over the points in the low-dimensional map, and it minimizes the Kullback–Leibler divergence between the two distributions with respect to the locations of the points in the map. Note that whilst the original algorithm uses the Euclidean distance between objects as the base of its similarity metric, this should be changed as appropriate.

t-SNE has been used for visualization in a wide range of applications, including computer security research, music analysis, cancer research, bioinformatics, and biomedical signal processing. It is often used to visualize high-level representations learned by an artificial neural network.

While t-SNE plots often seem to display clusters, the use of t-SNE for clustering has been shown to be unreliable, as t-SNE does not preserve distances. Even data coming from a single Gaussian can appear to be "clustered" in a t-SNE visualization.



Random forest algorithm

Random forests or random decision forests are an ensemble learning method for classification, regression, and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or means prediction (regression) of the individual trees. Random decision forests correct for decision trees' habit of overfitting to their training set.

The first algorithm for random decision forests was created by Tin Kam Ho using the random subspace method, which, in Ho's formulation, is a way to implement the "stochastic discrimination" approach to the classification proposed by Eugene Kleinberg.

An extension of the algorithm was developed by Leo Breiman and Adele Cutler, and "Random Forests" is their trademark. The extension combines Breiman's "bagging" idea and random selection of features introduced first by Ho and later independently by Amit and Geman in order to construct a collection of decision trees with controlled variance.

