



**University College Dublin**

**School Of Mathematics and Statistics**

**COMPARISON AND EVALUATION OF DIFFERENT  
MACHINE LEARNING METHODS AT PREDICTING  
CREDIT CARD DEFAULT**

By

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## **Abstract**

(the spacing is set to 1.5)

no more than 250 words for the abstract

- a description of the research question/knowledge gap what we know and what we don't know
- how your research has attempted to fill this gap
- a brief description of the methods
- brief results
- key conclusions that put the research into a larger context

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# 1 Introduction

A credit card is a financial instrument issued by banks and other financial institutions with a pre-set credit limit allowing customers to make cashless transactions. Each month or at different intervals, a statement is issued by the credit card provider with details of spending history, the interest charged, balance, and payment deadlines.

As of May 2022, there were 1.5 million active credit cards in circulation in Ireland with daily spending exceeding €1 million.<sup>1</sup> Further to that, according to research conducted by the Central Statistics Office in 2018, 12.7% of all households have credit card debt but is 21.0% for households with two adults and one to three children under 18.<sup>2</sup>

A default event concerning a credit card occurs if a customer does not pay the amount due within 120 days of their latest statement date. However, the deadline can depend on the issuing institution. The most significant risk to lenders is a large and unexpected number of customers failing to meet their credit repayment obligations. This is known as credit default risk. Credit default prediction is central to managing risk in a consumer lending business. Financial institutions are legally obligated to create models that predict credit defaults. Credit card default prediction is based on historical data of credit card customers. The use of models to predict and analyse credit card customer default behaviour is a typical classification problem. These models advise the banks capital requirements, which ensure that the bank can absorb losses brought about by a significant increase in credit defaults. Credit default prediction also allows lenders to optimize lending decisions, which leads to a better customer experience and sound business economics. Current models exist to help manage risk but is it possible to create better models that outperform those currently in use? Given that banking portfolios can be worth billions, even marginal improvements in preventing and reducing defaults can be considered significant.

The big data paradigm has revolutionised the banking industry, changing the way financial institutions operate. Developments in technology has revolutionized the customer experience and has also granted access to a ever-growing volume of structured and unstructured information. Institutions can leverage this new information in many ways including predicting credit default. There have been advances in Machine Learning (ML) techniques such as representation learning methods e.g. Neural Networks, ensemble learning methods such as Random Forest and linear separating methods e.g. Support Vector Machines. These models have yet to be widely deployed because of their opaque nature i.e. Black-Box methods. From a regulation perspective, transparency and explainability are necessary when deploying credit default prediction models in practice. However, they may still provide value to financial institutions and may in the future be accepted as valid, clear and sound methods for predicting credit card default.

The aim of this project is to apply a range of advanced machine learning techniques to predict credit card default using the historical data of credit card customers. The following report describes the process undertaken to compare a number of models. Beginning with an industrial size dataset, cleansing and formatting the data before using it to train, tune and evaluate the chosen models based on the historical data of credit card customers.

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<sup>1</sup><https://www.centralbank.ie/statistics/data-and-analysis/credit-and-debit-card-statistics/daily-credit-and-debit-card-statistics>

<sup>2</sup><https://www.cso.ie/en/releasesandpublications/ep/p-hfcs/householdfinanceandconsumptionsurvey2018/debtandcredit/>

## 2 Review of Literature

There have been numerous articles and papers within the scope of using ML methods to predict credit default, this includes the prediction for credit card default.

### 2.1 Taiwan Data

Studies examining credit card default have been concentrated, mainly using the data used originally used as part of Yeh & hui Lien (2009) . This data is currently freely available as the Default credit card clients Data Set on the UC Irvine Machine Learning Repository.<sup>3</sup> This data, collected in October 2005, is from a cash and credit card issuing bank in Taiwan, the targets were credit card holders of the bank. Among the total 30,000 observations, 22.12% are the cardholders who defaulted on payment. This research employed a binary variable, default payment (Yes = 1, No = 0), as the response variable. This data uses 23 variables as explanatory variables including a mix of personal information(age,gender,marital status and education level), amount of credit given, historical bill statements, and historical payment information.

This initial study, Yeh & hui Lien (2009), compared six classification algorithms - K-nearest neighbour, Logistic regression, Discriminant analysis Nave Bayesian classifier, Artificial Neural Networks, Classification Trees. In the classification accuracy, the results show that there are little differences in error amongst the six methods. The generated probability of default by the Artificial Neural Network most closely resembled the actual probability of default. The actual probability of default was estimated using a novel “Sorting Smoothing Method”.

Other research on predicting credit card default is subsequent years utilised this data to train and evaluate model. The following is a sample of articles available, applying a wide variety of Machine Learning methods to this classification problem.

Another study, (Neema & Soibam 2017), took a similar approach in choice of methods but attempted to predict the best possible cost-effective outcome from the risk management perspective. Again, K-Nearest Neighbour Logistic Regression, Classification Trees and Discriminant Analysis were evaluated but also Naive Bayes and Random Forest classifiers were included. This was evaluated using a cost function which gave a higher cost to defaulters classified not correctly as they are the minority in the data. Defaulted payments can prove more costly to a bank rather than potential customers wrongly identified as a potential default case. It was concluded that original data with Random Forest algorithm is the best in terms of a good balance on cost versus accuracy.

Yang & Zhang (2018) introduces two new methods used to predict credit card default. Support Vector Machine (SVM) involves using a kernel function to map the predictor data into a high-dimensional feature space where the outcome classes are easily separable. XGBoost and LightGBM, forms of gradient boosted trees algorithm were used, as well as previously tried methods - Logistic Regression and Neural Networks. LightGBM and XGBoost were both deemed to have the

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<sup>3</sup><https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients>

best performance in the prediction of categorical response variables.

While other studies have used Neural Networks in predicting credit card defaults, the models used have been vague and little detail has been given on architecture or tuning of the model. Chou & Lo (2018), trialled a range of Networks, experimenting with two to five layers with number of processing units of 64, 32, 16 units. Neural Networks with three layers and 64 units recorded the highest accuracy of all configurations.

Due to a lack of credit card specific data pertaining to defaulting on payment, all available studies which predict credit card default utilise the Taiwan data which is both region specific, dated over 15 years and obtained at a time when credit card issuers in Taiwan faced a credit card debt crisis.<sup>4</sup>

## 2.2 Other Literature

In the scope of predicting defaults on other forms of credit such as mortgages, research has also been conducted using data collected by the Central Bank of Ireland, comprising four separate portfolios of over 300,000 owner-occupier mortgage loans of Irish lenders, Fitzpatrick & Mues (2016). It was found that boosted regression trees provided the best classification algorithms for mortgage default prediction.

A 2019 research thesis, Egan (2021), examined a number of high-performing methods in predicting credit default on a Home Credit dataset<sup>5</sup>. Home Credit is an international non-bank financial institution that specializes in lending to people with little or no credit history. This study examined methods that could be deemed explainable - - which consisted of a number of tree-based ensemble methods. The top performing model was deemed to be XGBoost, a form of gradient boosted trees algorithm.

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<sup>4</sup><https://sevenpillarsinstitute.org/case-studies/taiwans-credit-card-crisis/>

<sup>5</sup><https://www.kaggle.com/c/home-credit-default-risk>



## 3 Data

### 3.1 Underlying Data

Data used for this project was obtained from the Kaggle website which is a crowd-sourced platform and community to train and challenge data scientists to solve complex data science, machine learning and predictive analytics problems.<sup>6</sup> One of Kaggles main features is it's competition platform.<sup>7</sup> Kaggle allows users to organise and host competitions, these range from commercially-purposed prediction problems to more experimental research competitions. They give entrants the opportunity to grow their data science skills and compete for prizes and gives hosts a outlet to tackle a tough business problem by turning it into a competition and allowing Kaggles user base of 10 million to provide potential solutions to the problem.

Access to the data through this route requires registering with Kaggle and joining the American Express - Default Prediction competition.<sup>8</sup> American Express is a globally integrated payments company. The largest payment card issuer in the world, they provide customers with access to products, insights, and experiences that enrich lives and build business success.<sup>9</sup> This competition provides an industrial scale data set to build a machine learning model to predict credit card default using time-series behavioural data and anonymised customer profile information over the period of March 2017 to March 2018. The target binary variable i.e. default is calculated by observing 18 months performance window after the latest credit card statement, and if the customer does not pay due amount in 120 days after their latest statement date it is considered a default event.

### 3.2 Data Structure

#### 3.2.1 train\_labels.csv

A list of unique customer identifiers `customer_ID` with the target label `target` indicating a default event with `target = 1` indicating a default, `target = 0` indicating no default. There are 458913 observations in this data meaning 458913 unique AMEX customers. 74.1% of customers in the data did not default on payment while 25.9% did

#### 3.2.2 train\_data.csv

This is a tabular data set corresponding to the training data, consisting of 190 features. It contains multiple statement dates per `customer_ID`, each observation corresponds to a monthly statement for a customer. The data is ordered firstly by `customer_ID`, corresponding with the `train_labels.csv` file and secondly ordered chronologically by statement date. The dataset contains aggregated profile

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<sup>6</sup><https://www.kaggle.com/getting-started/44916>

<sup>7</sup><https://www.kaggle.com/docs/competitions>

<sup>8</sup><https://www.kaggle.com/competitions/amex-default-prediction/data>

<sup>9</sup><https://about.americanexpress.com/our-company/our-business/our-business/default.aspx>

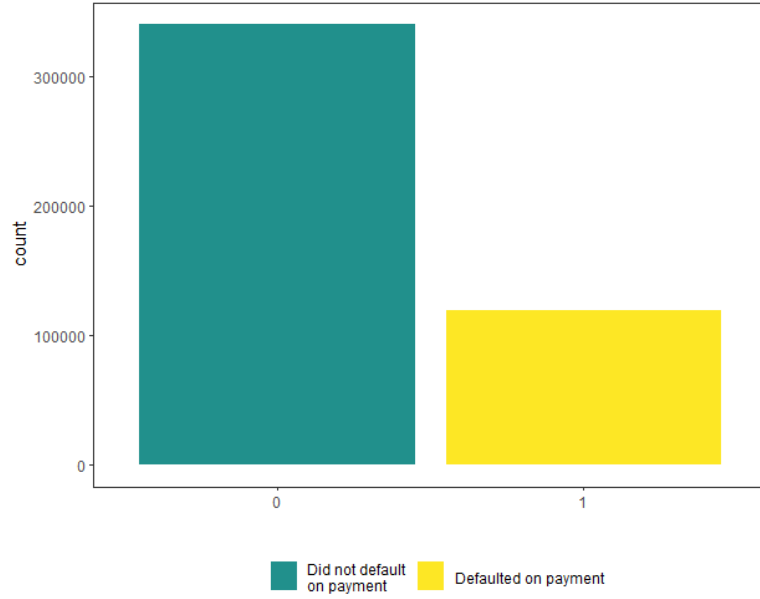


Figure 1: Breakdown of defaults in training data

features for each customer at each statement date. There are 177 numeric features which are anonymised and normalized, and fall into the following general categories:

Table 1: Variable Categories

Variable Name	Category
D_*	Delinquency variables
S_*	Spend variables
P_*	Payment variables
B_*	Balance variables
R_*	Risk variables

There are 11 categorical variables - B\_30, B\_38, D\_114, D\_116, D\_117, D\_120, D\_126, D\_63, D\_64, D\_66 and D\_68.

The remaining two unaccounted for features are the variable S\_2 which contains the date of the statement and customer\_ID which can be used to match to the target label.

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Table 2: First five rows and columns from train\_data.csv

customer_ID	S_2	P_2	D_39
0000099d6bd597052cdcda90ffabf56573fe9d7c79be5fbac11a8ed792feb62a	2017-03-09	0.9384687	0.001733339
0000099d6bd597052cdcda90ffabf56573fe9d7c79be5fbac11a8ed792feb62a	2017-04-07	0.9366646	0.005775443
0000099d6bd597052cdcda90ffabf56573fe9d7c79be5fbac11a8ed792feb62a	2017-05-28	0.9541803	0.091505397
0000099d6bd597052cdcda90ffabf56573fe9d7c79be5fbac11a8ed792feb62a	2017-06-13	0.9603836	0.002455224
0000099d6bd597052cdcda90ffabf56573fe9d7c79be5fbac11a8ed792feb62a	2017-07-16	0.9472484	0.002483014

### 3.2.3 test\_data.csv

924621 unique values

**3.2.4** sample\_submission.csv

**3.3** Data Engineering

**3.4** Data Cleaning

## 4 Methods

### 4.1 Random Forest (RF)

Random Forests, Breiman (2001), are a very powerful ensemble classification method. The method uses classification trees and bootstrapping extensively. Ensemble learning is an aggregation of predictions made by multiple classifiers with the goal of improving accuracy. A random forest is a random collection of classification trees estimated on random subsets of the data.

A Classification Tree is an iterative process of splitting the data into partitions based on values of the observations, and then splitting it up further on each of the branches.

The classifier is trained in order to produce pure buckets, minimising the entropy or spread of the target variable in each bucket. The majority value of the target variable in a bucket is then used for predictions. The main disadvantage is that Classification Trees suffer from over-fitting and bias and using a single Classification Tree would present an over simplistic model.

In a Random Forest, each Classification Tree is grown independently, and each individual Classification Tree has an equal vote as to what the outcome is. Random forests provide an improvement by means of a small tweak that reduces the dependence among the trees. The main idea is to use only a random subset of the predictor variables at each split of the classification tree fitting step, this is generally taken as  $\sqrt{N}$  where  $N$  is the number of features but can be specified by the user. If we build classifiers on subsets of the variables, then they will behave more independently than if we build them on all of the data. This increases diversity and averaging results across independent classifiers will be more stable than averaging results on dependent ones.

The main parameter of the Random Forests to be tuned is the number of Classification Trees used and is tuned to prevent overfitting and improve efficiency.

### 4.2 Support Vector Machines (SVM)

Support Vector Machines, Boser et al. (1992) and Cortes & Vapnik (1995), are based on linear classifiers, where a linear combination of input features and parameters is employed to define the plane of maximum separation between classes

using a kernel function to map the data  $X$  of the input space into a high-dimensional feature space

A support vector classifier seeks to maximize the distance between the classes

inseparable in the original space can be linearly classified in the high-dimensional space.

### 4.3 Deep Neural Network (DNN)

## 5 Results

## 6 Discussion

### 6.1 Context of Results

### 6.2 Future Research

introduce dynamic element? Recurrent Neural Network (Hsu et al. 2019)

cost function?

## 7 Conclusion

## 8 Bibliography

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## 9 Appendices

### 9.1 Appendix A: additional tables

Insert content for additional tables here.

## 9.2 Appendix B: additional figures

Insert content for additional figures here.

### 9.3 Appendix C: code

Insert code (if any) used during your dissertation work here.

## 10 Abbreviations

Table 3: List of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
AMEX	American Express
DNN	Deep Neural Network
ML	Machine Learning
NN	Neural Network
RF	Random Forest
SVM	Support Vector Machines