ECS 171 Project Report
Group 3

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1 Introduction

Modern life is dominated by companies knowing what you do. From your Instagram posts to your credit card statement, corporations love to collect your data. This data can not only used for business analysis or targeted advertising, but also for credit scores. This one number can determine whether you can get a loan, buy a house, or even get a job. Companies have a vested interest in making sure that this number is both accurate and hard to predict. If people learned how to game the system, it could lead to a loss of trust in the system. However, this also means that the system could be biased against certain groups of people.

In order to effectively minimize credit risk, it is important to conduct a reasonable evaluation of personal credit. A machine learning model that can give lenders a credit rating based on a vast collection of borrower's personal information and historical records is necessary. They may even extend beyond data that is traditionally used, analyzing social media posts to get a sense of a person's lifestyle beyond their financial history. This could lead to more accurate credit scores, but it could also lead to more bias and discrimination.

In the future, it may be the case that credit scores are calculated by machine learning models. While potentially being more accurate, this could introduce many of the problems with bias and positive feedback loops that we see in other machine learning models. Therefore, it is important to understand how these models work and how they can be improved. It may also be important to provide tools to help people better understand what factors affect their credit score the most, and how they could improve their credit score.

Our goal is to take small steps towards this future by training models to predict credit scores based on a dataset of personal information and historical records. We will also analyze the results of these models to determine which factors are most important in determining credit score. Finally, we will discuss how these models could be improved and how they could be used in the future. Our hope is that our work will help people better understand how credit scores are calculated and how they can be improved.

2 Literature Review

In recent years, Machine Learning Models have gained popularity in the financial industry for their accuracy in predicting trends with large, complex data. To keep up with the increasing demand for more sophisticated fraud detection software, anti-money laundering systems, and risk detection programs, many big credit institutions have decided to deploy various ML models.

In a study conducted by Vidovic et. al, ML algorithms were used to predict PD, the probability of default, which is a major component in risk assessment. Using annual financial data from private companies, attributes that are relevant in the calculation of PD, such as profitability, leverage, efficiency, Country Risk Score (CRS), and Industry Risk Score (IRS), were identified. They compared the performance of various models, such as Altman Z-score, Logistic Regression, SVM, Naive Bayes, and Decisions Trees, on data from private companies, and used ROC and AUC curves to determine performance statistics. Through this, they were able to determine that both logistic regression and decision tree models proved to have high accuracy at predicting PD values in the given dataset, with logistic regression achieving an accuracy rate of 93.1% in-sample and 93.6% for out-sample and decision trees achieving an accuracy rate of 99.8% in-sample and 94.8% out-sample.

The results of this study were able to demonstrate the potential of ML models in predicting elements of credit risk scores. However, the researchers involved in this study also highlight the limitations of both their study, as well as ML models in predicting credit risk. They mention that the current dataset solely consists of values from private companies, and in the future, these models would have to be tested on larger and more diverse datasets. In addition, they acknowledge the fact that the larger datasets can contain a lot of noise, which could result in false predictions, and thus state that the correct precautions must be taken to account for this.

3 Data

3.1 Data Source

We chose to use the German Credit Data Set from the UCI Machine Learning Repository. This dataset contains 1000 instances of credit applicants, each with 20 attributes. The attributes are a mix of numerical and categorical data. The dataset also contains a binary label indicating whether the applicant is a good or bad credit risk. The dataset was originally collected by Professor Dr. Hans Hofmann of the University of Hamburg. The dataset was donated to the UCI Machine Learning Repository in 1994. The dataset can be found at this link.

3.2 Data Preprocessing

We had several key problems to overcome with our data processing. The first was that the data was primarily categorical, and used special encodings to represent the categories. We thus had to take steps to convert this categorical data using either numeric or one-hot encoding.

3.2.1 Numeric Encoding

For many variables, such as employment history or amount of savings, it makes sense to provide an inherent numerical scale to the model. It pre-biases the models to expect these variables to be a range that has a definite positive and negative direction. It does not necessarily imply a correlation with the credit score, but it does provide a more intuitive way for the model to understand the data.

3.2.2 One-Hot Encoding

For other variables, however, we had no choice but to use one-hot encoding. For example, a person's sex and marital status. These variables have no inherent numerical scale, so we chose to use one-hot encoding to represent them. For one variable, the purpose of the loan, we did not choose to use this encoding scheme. This was because there were 10 possible values, and this would have added greatly to the dimensionality of the data. Instead, we found that splitting the dataset into 10 separate problems based on the purpose of the loan was a better solution. This was not entirely foolproof, as we did have issues with some datasets being prohibitively small, but we will discuss this more in later sections.

4 Models

We chose to make three models for this project:

- Logistic Regression
- Random Forest
- Neural Network (Multilayer Perceptron)

4.1 Logistic Regression

We chose to use logistic regression as one of our models because it is a simple model that is easy to interpret. It is also a good baseline model to compare our other models to.

Parameter	Values
C	0.001, 0.01, 0.1, 1, 10, 100
penalty	l1, l2
solver	liblinear, saga
fit_intercept	True, False
tol	1e-3, 1e-4, 1e-5

Table 1: Hyperparameters for Logistic Regression

Purpose	C, penalty, solver, tol
Business	0.01, l2, liblinear, 1e-3
New Car	1, l2, saga, 1e-4
Used Car	0.1, l2, saga, 1e-3
Education	0.001, l2, liblinear, 1e-3
Furniture	0.1, l2, liblinear, 1e-3
Radio/TV	1, l1, liblinear, 1e-3
Repairs	0.001, l1, liblinear, 1e-3

Table 2: Best Hyperparameters for Logistic Regression

4.1.1 Hyperparameter Tuning

We tuned our hyperparameters according to Table 1.

The best hyperparameters for each of the models we made are shown in Table 2. `fit_intercept` was always true in the best results, so it was excluded from the table.

4.1.2 Results

Because of the decision to split the dataset into separate training tasks, we have separate models. The final results of these models are shown in Table 3. These results are overall quite good, with the worst accuracy being

Purpose	Accuracy	MSE
Business	0.750	0.250
New Car	0.702	0.298
Used Car	0.952	0.048
Education	0.600	0.400
Furniture	0.730	0.270
Radio/TV	0.839	0.161
Repairs	0.800	0.200

Table 3: Results for Logistic Regression

Parameter	Values
n_estimators	50, 100, 150, 300
min_samples_split	2, 5, 10
min_samples_leaf	1, 2, 3
criterion	gini

Table 4: Hyperparameters for Random Forest

60% and the worst MSE being 0.4. However, it is important to note that several of the datasets were quite small, and this caused issues for several other models that were even too small to be trained. This is a problem that we will discuss in later sections.

4.2 Random Forest

4.2.1 Hyperparameter Tuning

We tuned our hyperparameters according to Table 4. The best hyperparameters for each of the models we made are shown in Table 5. `'gini'` was always the best criterion, so it was excluded from the table.

Purpose	estimators, split, leaf
Appliance	50, 5, 1
Business	300, 5, 2
New Car	50, 2, 3
Used Car	100, 2, 1
Education	50, 2, 3
Furniture	300, 2, 2
Other	50, 2, 1
Radio/TV	150, 5, 1
Repairs	50, 2, 2

Table 5: Best Hyperparameters for Random Forest

Purpose	Accuracy	MSE
Appliance	0.667	0.333
Business	0.750	0.250
New Car	0.809	0.191
Used Car	0.904	0.095
Education	0.500	0.500
Furniture	0.702	0.297
Other	0.333	0.667
Radio/TV	0.768	0.232
Repairs	0.400	0.600

Table 6: Results for Random Forest

4.2.2 Results

We recorded the accuracy and MSE for each of the models we made. These results are shown in Table 6.

4.3 Neural Network (Multilayer Perceptron)

Neural networks, in particular simple perceptron models seemed ideal for the type of data we selected. We had a relatively small set of inputs, and a single binary output.

We tried a variety of different hyperparameters with varying activation functions and number of hidden layers. After rigorous testing, we have only achieved a model with the greatest accuracy of around 75%. Different activation functions such as sigmoid and relu produced similar results. It seems like increasing the number of hidden layers decreased the overall accuracy of model. The best model had 2 hidden layers and used the sigmoid function. We will discuss later why our accuracy is so low, even with extensive training and hyperparameter tuning.

4.3.1 Training

TODO: add graphs here showing the accuracy and loss of the model over time

4.3.2 Hyperparameter Tuning

TODO: NN hyperparameters

4.3.3 Results

5 Conclusion and Overview

5.1 Comparing Models

5.2 Overall Sucess

5.3 Looking Forward and Improvements