CCT College Dublin

Assessment Cover Page

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Declaration

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| --- |
| By submitting this assessment, I confirm that I have read the CCT policy on Academic Misconduct and understand the implications of submitting work that is not my own or does not appropriately reference material taken from a third party or other source. I declare it to be my own work and that all material from third parties has been appropriately referenced. I further confirm that this work has not previously been submitted for assessment by myself or someone else in CCT College Dublin or any other higher education institution. |

Prediction for lending loans

Word count: 2,969 words

## Table of contents

[Table of contents 3](#_w2b5qc91shel)

[List of Figures 4](#_qu0qt0jsoamm)

[Introduction 5](#_37041gfy3b00)

[Business understanding 5](#_f27wby1pvcsx)

[Hypothesis 6](#_hnim1g2ex6fw)

[General goal 6](#_661oi4dtxqam)

[Success criteria/indicators 6](#_ibmk5ux239dh)

[Technologies 6](#_5poayr8hwgn)

[Libraries 6](#_e3jm6rp2sitl)

[Models 7](#_6ady5g2ljeva)

[Datasets and source 7](#_597mabpt9cn9)

[Descriptive statistics 11](#_sai3ymlwptfj)

[Data preparation 15](#_qekc2b3jdv3b)

[Model implementation 21](#_d7gklkhanrn7)

[Deployment 22](#_13tpygmpw3nl)

[Challenges 23](#_y7n4pc94gqui)

[Results and analysis 23](#_mab4aegwkzyj)

[Conclusion 25](#_nsqnf26gn17b)

[Reference list 26](#_3z44o5wi77sr)

## List of Figures

[Figure 1: Libraries and models 7](#_xrqck0vrnn1s)

[Figure 2: Read CSV 8](#_himytwo15w93)

[Figure 3: See all the attributes 8](#_z3di9jcynqes)

[Figure 4: Check null values 9](#_ycldsb202ld3)

[Figure 5: Totals of null values 9](#_t3sefk9nauhh)

[Figure 6: Remove null values 10](#_4yu8waw9xi69)

[Figure 7: Check data types 10](#_52bekna2rd2p)

[Figure 8: Descriptive table of datasets 11](#_h9jh7dfiq5ym)

[Figure 9: Percentage of approved and denied loan 11](#_khvemvc7uvug)

[Figure 10: Females vs Males income 12](#_bx16pxf28hjs)

[Figure 11: Loan status vs Education 12](#_nctg842ftxzn)

[Figure 12: Loan status vs Married 13](#_kycv42dx77q5)

[Figure 13: Loan amount frequency 14](#_ak5qcbt0uq9r)

[Figure 14: Loan amount frequency vs Loan Status 14](#_875zgd35vnuy)

[Figure 15: Loan status by Dependents 15](#_wv67ug7wdml5)

[Figure 16: Data types for the datasets 15](#_q2ynb1m8t9sb)

[Figure 17: Data normalization 16](#_hromfdg7dhm4)

[Figure 18: Drop independent variable from the dataset 16](#_gfobsb34hn79)

[Figure 19: Libraries and models 17](#_a7t0s45qtjqb)

[Figure 20: Check datatypes and change object data to float 18](#_nzdyvc82v180)

[Figure 21: Frequency of all variables 19](#_u0wsqbrdnrcg)

[Figure 22: Heatmap for all variables and correlations 19](#_uf27cmjympa1)

[Figure 23: Association between variables 20](#_ev0dju3z9b8r)

[Figure 24: Concad method 21](#_oao0287p03e0)

[Figure 25: Split dependent variable and independent variables 21](#_t5xcf3u9amhy)

[Figure 26: Decision tree classification 21](#_dyuwjhj64mfy)

[Figure 27: Linear regression, mean squared error 22](#_dpzwmdm5ejb1)

[Figure 28: Random forest regressor 22](#_4csz0jcmd5kf)

[Figure 29: Saving Linear regression model in .pkl format 22](#_281wdnpttb15)

[Figure 30: Linear regression deployed model 23](#_aq5w8durvhgb)

[Figure 31: Coefficient magnitudes 24](#_q2fjlispjprj)

[Figure 32: Additional features 24](#_50hyjtme80ik)

[Figure 33: Ascending order of coefficients magnitudes 25](#_x7il7d13iq83)

## Introduction

Our team was given a task to research a subject that caught our attention and create a business plan around it. We need to create a hypothesis or a set of questions, then come up with solutions. We all agree after a few discussions that loan defaulting in financial services is an interesting topic. We know there had been a lot of data gathered on this subject and thought there would be some solid datasets available for us to analyse and make predictions. We come up with the concept of identifying potential loan defaulters. After some searching, we discovered the loan defaulter datasets on Kaggle. We will evaluate which feature affect the decision making and loan lending.

(Lee and Lee, 2018) state that there are different types of borrowers - individuals, partnerships, companies, clubs and societies, trusts and others. The datasets we work on is subjected to individuals’ application.

According to (Lee and Lee, 2018), a credit score is computed dependent on a person’s current and past credit history and the likelihood that the person will meet the debt obligations. Lenders use the credit scores in order to decide whether the loan request satisfies the eligibility criteria, what the charged interest rate should be and the cap of the credit limit.The score is calculated on numerous factors and the key components are:

* history of payments made for several accounts, including credit cards and mortgages loans - 35%;
* credit occurrences like lawsuits, insolvencies, and county court judgments(30%);
* The number of new credit accounts and credit cards impacts negatively on the credit score, because the borrower can not afford paying back the loan(15%);

We will review if the research done by (Lee and Lee, 2018) matches with the outcome from the datasets analysis.

## Business understanding

We have used Cross-Industry Standard Process for Data Mining (CRISP) methodology for this project and our main objective is to reduce the risk of lending to borrowers who are likely to default on their loan.

The dataset consists of borrowers whose loan status is approved or rejected. We will evaluate all the variables in the datasets and determine which ones have the highest impact on the decision to approve or decline a loan. The data mining process will involve data preparation, such as cleaning the dataset from NaN or missing values, data normalization, analyse the relationships between the variables, train and test the datasets with a couple of models such as Decision Tree Classifier, Linear Regression, Random Forest Classifier, neighbors Classifier and based on the results make a conclusion, which model is the best performing one. In order to produce this project plan, we have used Ghantt chart with timeline on when each task should be completed by.

## Hypothesis

We will identify if the bank is at risk by lending money to their clients and prove the hypothesis that Credit History feature has the highest impact on predicting the decision for loan approval.

## General goal

The primary objective of this project is to identify loan defaulters from a database of customers. We aim to utilize regression, classification and prediction techniques in this report. This may allow us to make predictions on loan defaulters.

## Success criteria/indicators

Success of this project would be determined by finding a correlation between the individual customer circumstances and a proclivity to default on a loan. To achieve the best predictions and results with higher accuracy, we will use machine learning models and algorithms such as linear regression, random forest algorithms and others to predict the outcome. We would hope one of these algorithms would provide us with test results in excess of 98%.

## Technologies

The programming language of choice is Python. We use Jupyter Notebook in order to work on the datasets.

## Libraries

We use the following libraries:

* Numpy
* Pandas
* Matplotlib.pyplot
* Seaborn

*For preprocessing data we use:*

* Label Encoder
* MinMaxScaler
* StandardScaler

*Training and testing the data:*

* import train\_test\_split

*Evaluating the model:*

* Metrics
* Accuracy\_score

## Models

* Decision Tree Classifier
* Linear Regression
* Random Forest regressor

## Datasets and source

The datasets which we use for this project are called ‘Home Loan Approval’ and the source is from Kaggle (Konapure, 2023). This datasets are owned by a finance company, which lends loans to people who want to buy properties in rural, semi-urban and urban area. They need to automate the approval process by segmenting the customers’ eligibility.

### Figure 1: Libraries and models

Pandas package for Python was used to analyse and handle the datasets. This library is suitable and efficient in handling data (Müller and Guido, 2017).

NumPy is the numerical package for Python, is also utilized.

We select the seaborn library for data visualization, which generates fascinating and practical statistical visualizations like heatmaps, bar charts, pie charts, scatter plots, and others. As an alternate library for producing high-quality graphs and charts, Matplotlib is also imported.

We have two types of datasets. One CSV is used to train data and one CSV is used to test data, so we can evaluate the success of the trained data.

### Figure 2: Read CSV

We use loan = pd.read\_csv(‘loan\_train.csv) code and load the datasets into pandas dataframe and we name it ‘loan’. The CSV files are in the same directory as the Jupyter notebook that contains this code.

We run loan.head() to display the first 5 rows and all columns, so we can quickly check what kind of data we work with. The attributes in this dataset are categorical Loan\_ID, Gender, Married, Dependents, Education, Self\_Employed, Credit\_History, Property\_Area, Loan\_Status and numerical attributes - ApplicantIncome, CoapplicantIncome, LoanAmount and Loan\_Amount\_Term.

### Figure 3: See all the attributes

It is a common issue to handle missing value in a dataset and we will use **isnull** method in order to identify them (Harrison, 2019).

### Figure 4: Check null values

This dataset is not high-dimensional one as we have only 11 attributes to analyse. We should exclude Loan status, because it is dependent variable in this data mining process and Loan ID, because it doesn’t have impact on the analysis.

Since it will be inefficent to review the rows and columns individually, we can use sum the missing values.

### Figure 5: Totals of null values

Another method used when treating datasets for missing values is impute values. For example, for 'Loan amount' we can take into account an average value, the same applies for the other columns such as 'Loan amount term' or 'Credit history'. It is important that we handle the data as accurately as possible, so we use the method **dropna** instead and we'll remove rows where columns contain null values.

### Figure 6: Remove null values

After cleaning the datasets, we reduced the rows from 614 to 480.

### Figure 7: Check data types

The data consists of different types : object = 8, float = 4, int = 1.

## Descriptive statistics

### Figure 8: Descriptive table of datasets

loan.describe() method provides quick statistical data for the numerical columns. We need to check approved loans vs rejected loans and 69.2% of the loan applications are approved, whereas 30.8% of the applications are rejected.

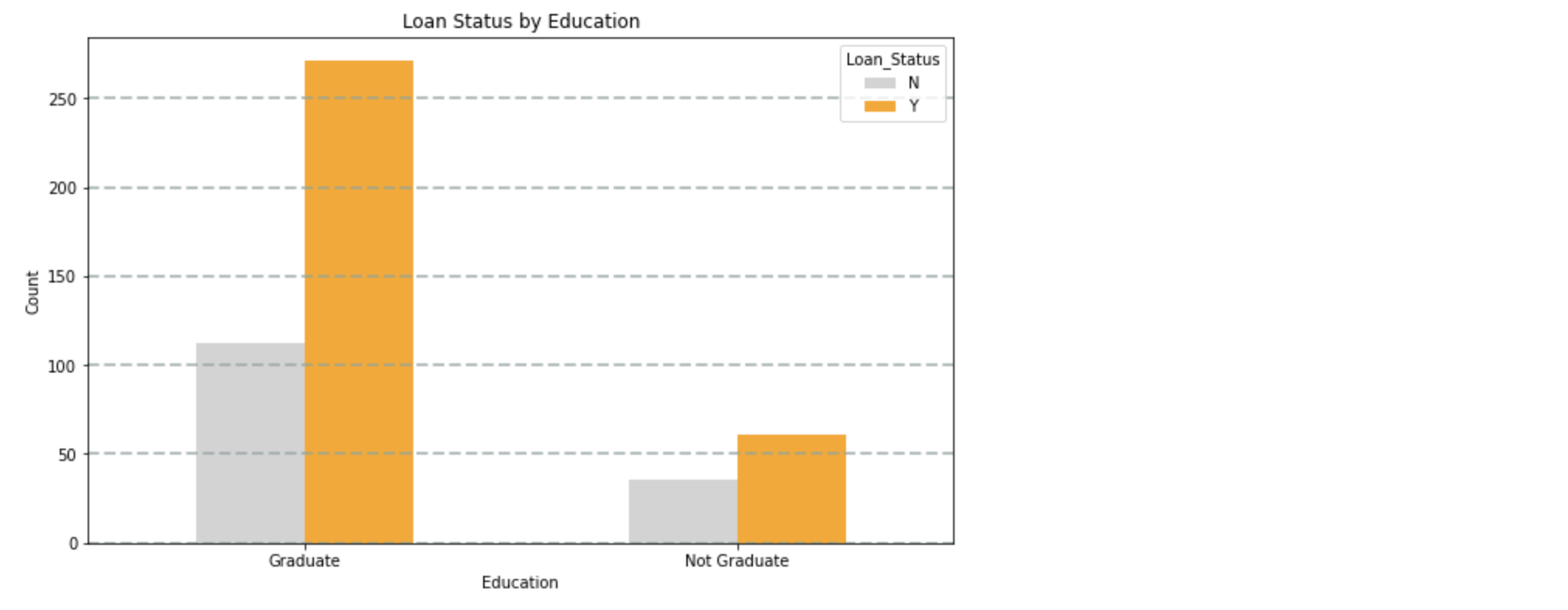
### Figure 9: Percentage of approved and denied loan

We used matplotlib library in order to visualize the above chart where we have done comparison of Males' vs Females' income. The chart shows that males have a better income than females.

### Figure 10: Females vs Males income

We created the same chart and compared two variables: 'Loan status' vs 'Education'.





### Figure 11: Loan status vs Education

The above data is with categorical variables ('Education') and ('Loan Status').We compare the two variables, so we can see that there is an apparent relationship between the education vs approval of the loan application. The same observations are with married couples, where we can see that Married couples are more likely to receive loan approval.



### Figure 12: Loan status vs Married



### Figure 13: Loan amount frequency

We are examining the data distribution of the variable 'Loan amount' in order to find out how frequently each value of this variable occurs and we have also included a piece of code which gives us an idea of what is the minimum, median and maximum value.

We also created a swarm plot, which shows that there are a lot of approved application for the lower loan amounts from the range of 100k to 200k.

### Figure 14: Loan amount frequency vs Loan Status

We compared the variable ‘Dependents’ vs ‘Loan status’. More than 175 approved loan applications belong to individuals with no children.



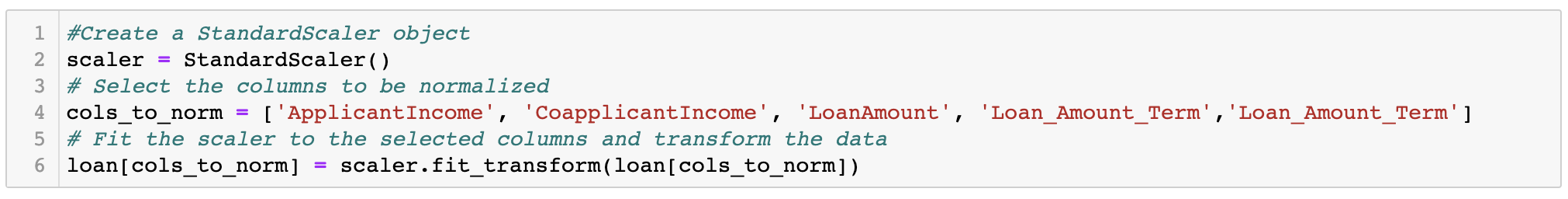
### Figure 15: Loan status by Dependents

## Data preparation

### Figure 16: Data types for the datasets

The above code displays numerical and categorical columns in this dataset.

We need to run Lable Encoder from sklearn libary in order to convert categorical string data into integer data. All the values are converted to zeros and ones - ‘Yes’ = 1, ‘No’ = 0, Property\_Area with values ‘Rural’ = 0, ‘Semi-urban’=1, ‘Urban’=2.

Figure 16: Data normalization with Standard scaler

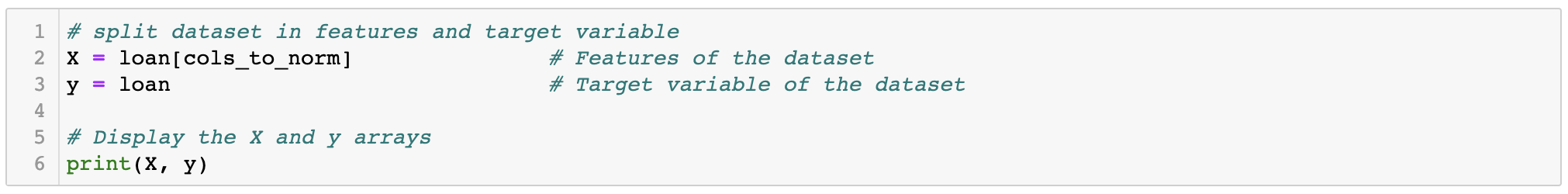
### Figure 17: Data normalization

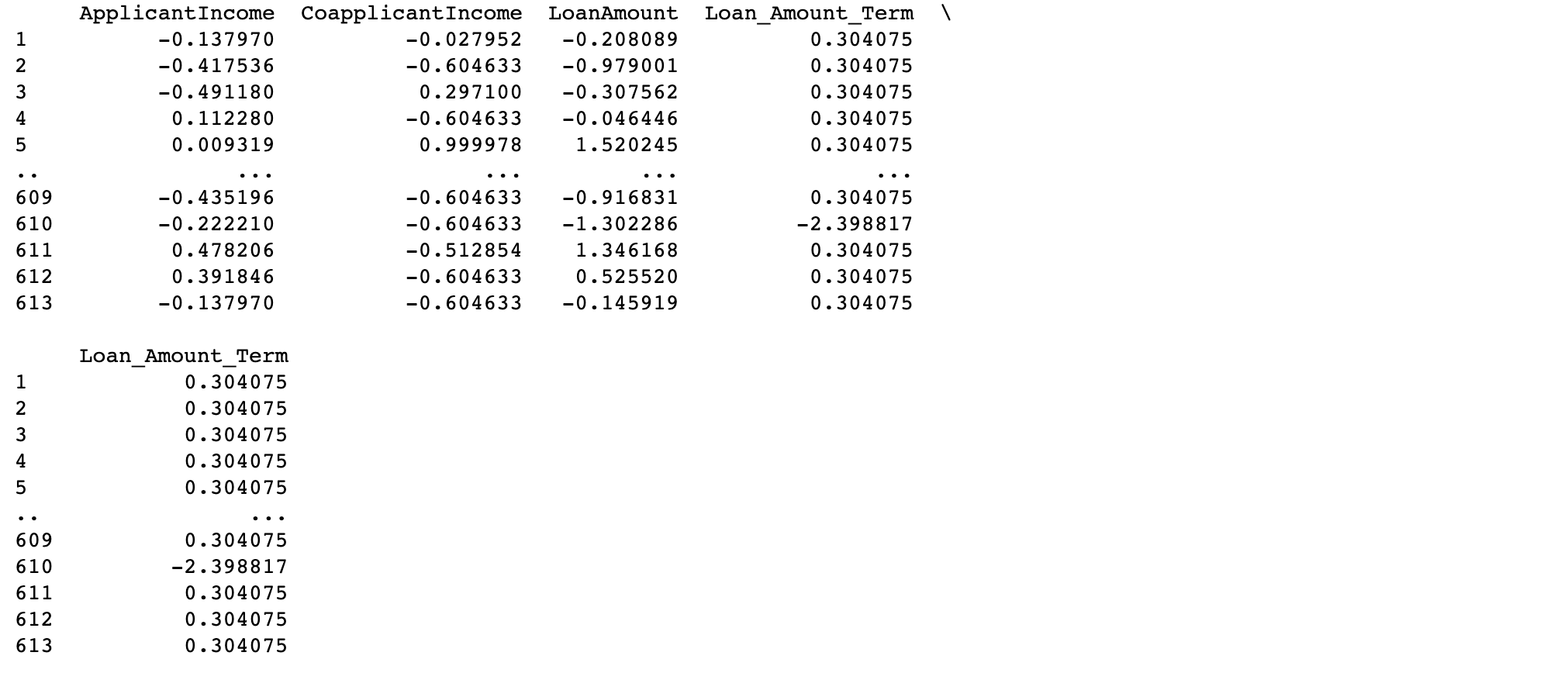
A crucial step in pre-prosessing data for a machine learning model is feature scaling. Since machine learning model sees only numbers, if the spectrum of numbers is quite broad from tens to thousands, the assumption will be that the higher ranging numbers have a superiority (Roy, 2020). This is why we apply it across the columns Applicant Income, Coapplicant Income and Loan amount.

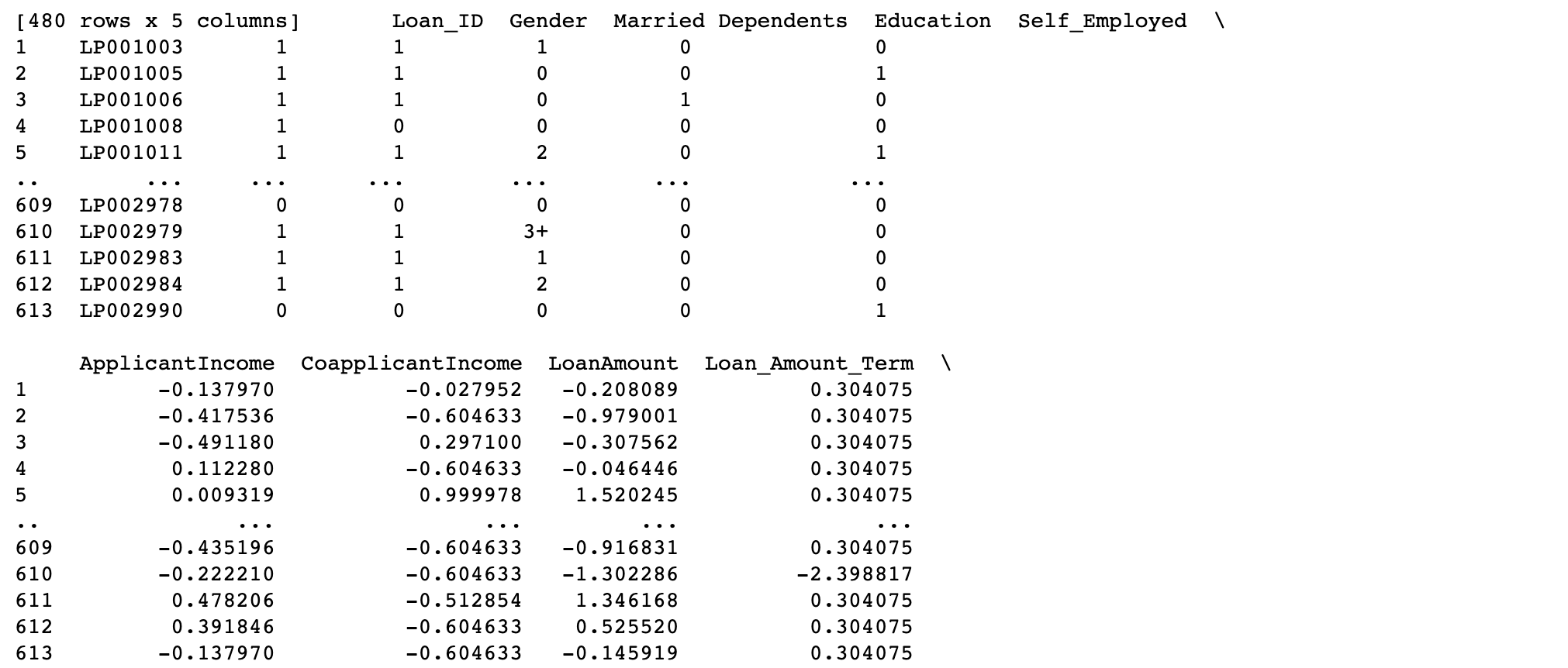
### Figure 18: Drop independent variable from the dataset

In order to evaluate the machine learning performance, we use the X and y as dependent and independent variables. The model will identify the relationship between the features in X and the target variable.

In addition to the above code, we need to define the X dependent variables as cols\_to\_norm.

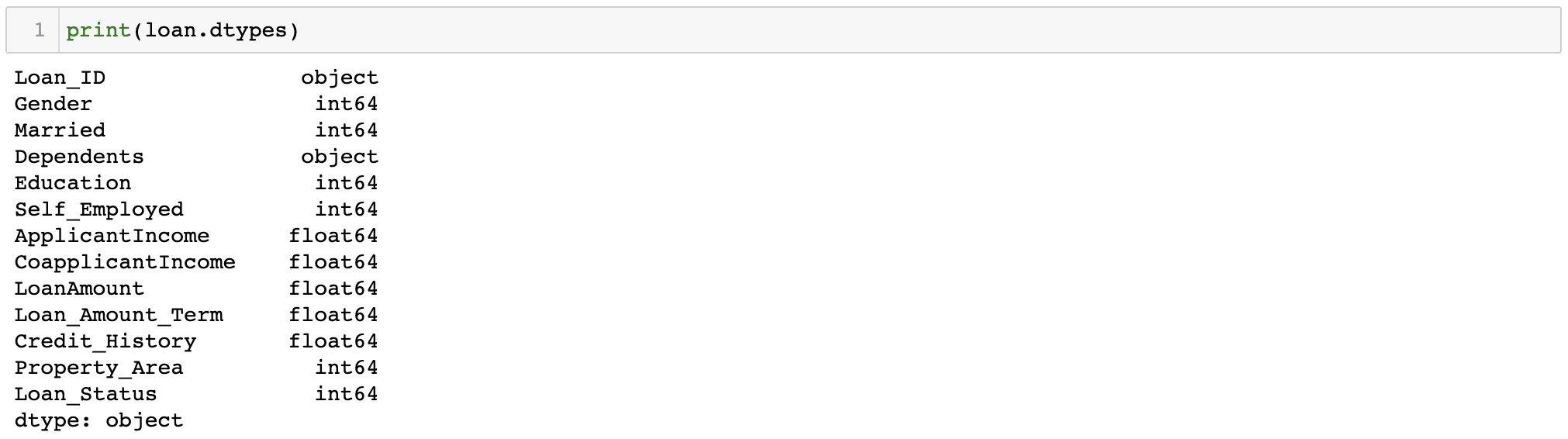






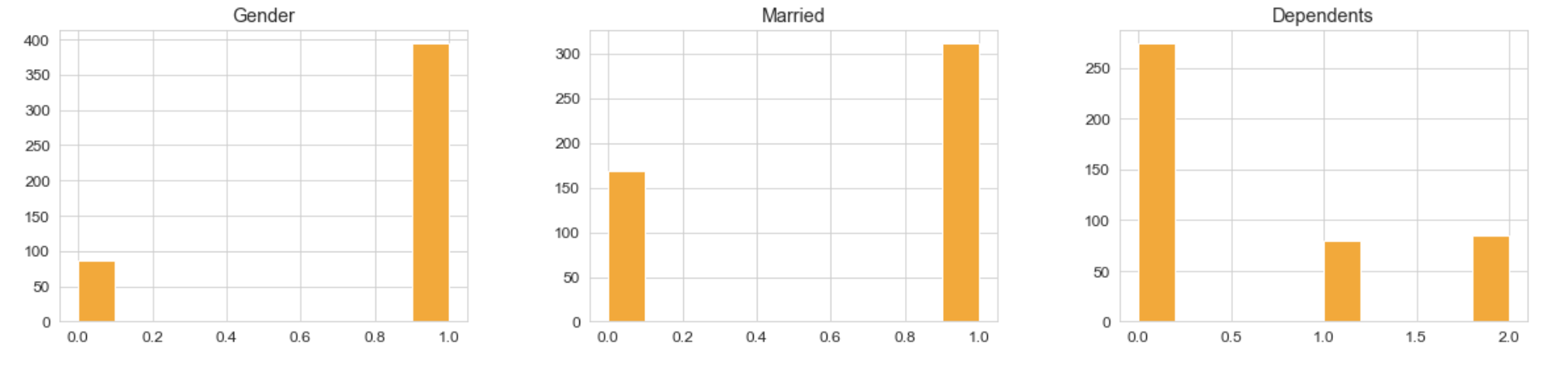
### Figure 19: Libraries and models

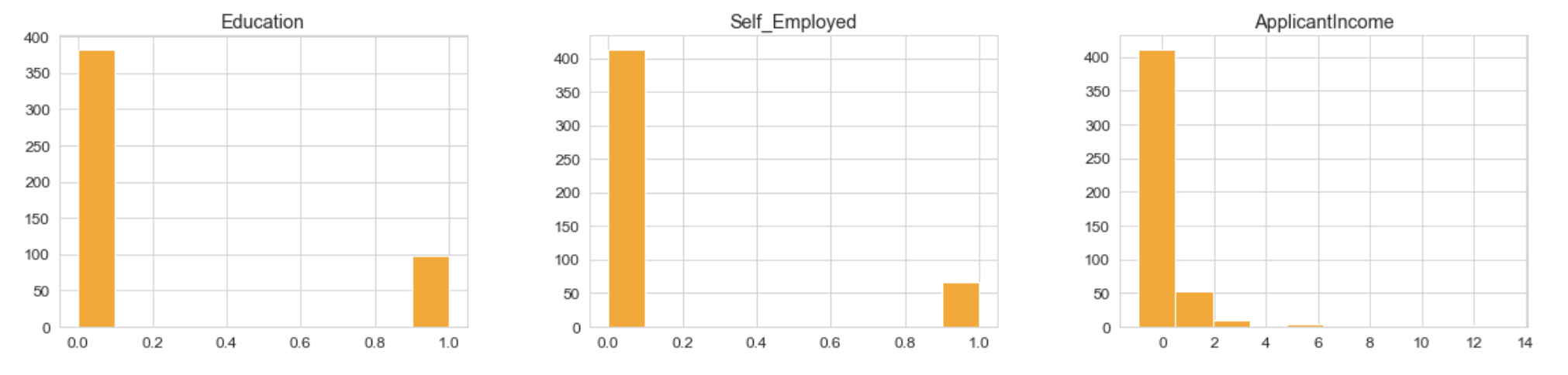
After checking again the data types, there is one more column to convert and it is ‘Dependents’.

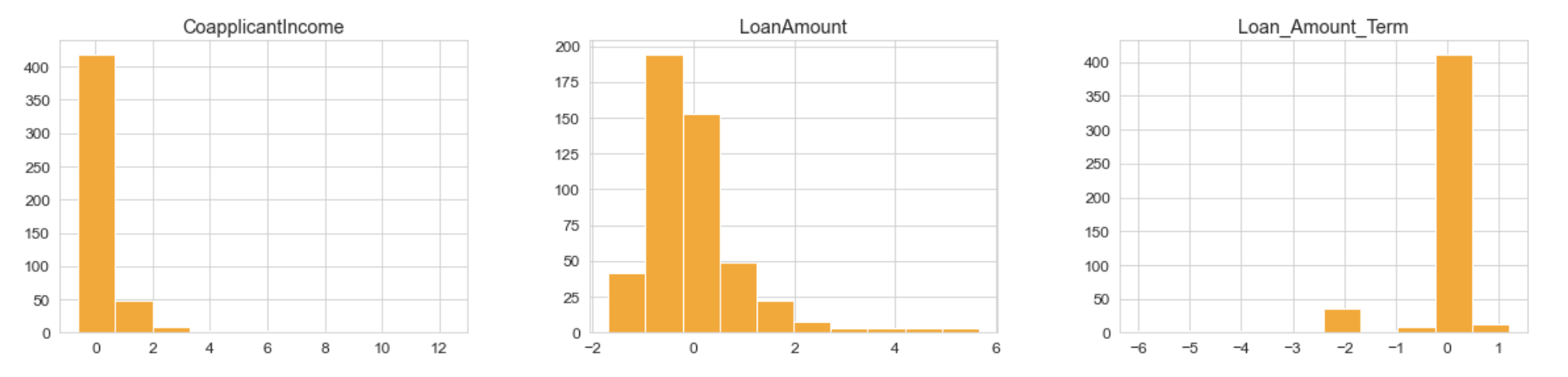


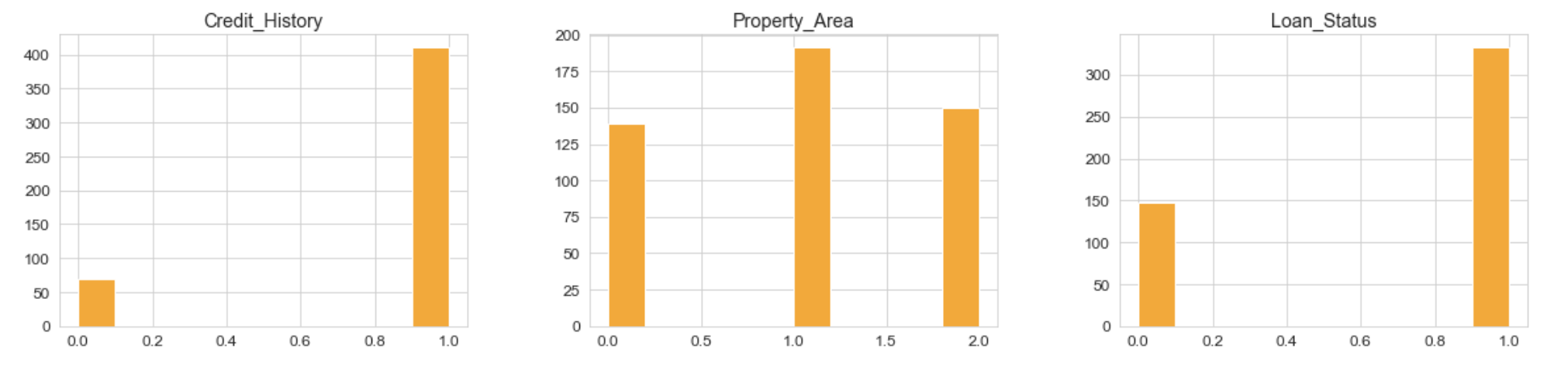
### Figure 20: Check datatypes and change object data to float

Since the data is normalised and cleaned for missing values it is essential to check the frequence of all variables.









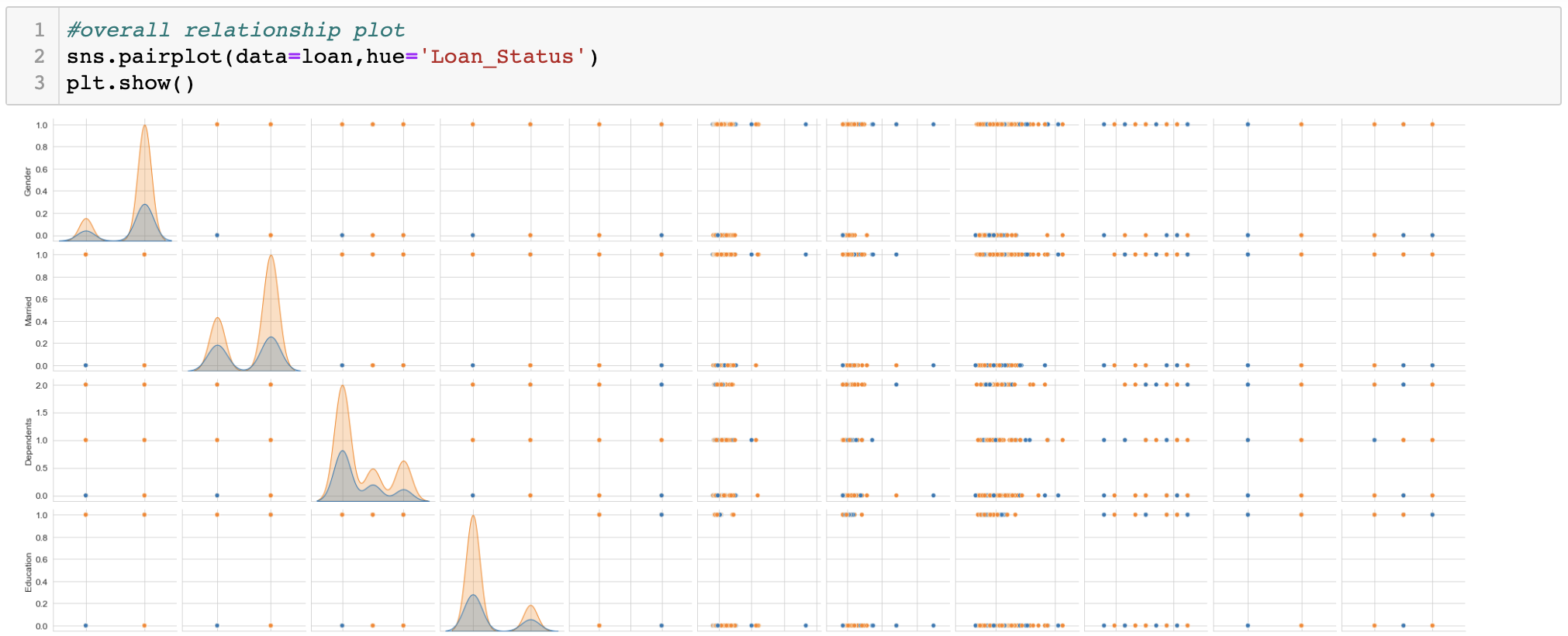
### Figure 21: Frequency of all variables

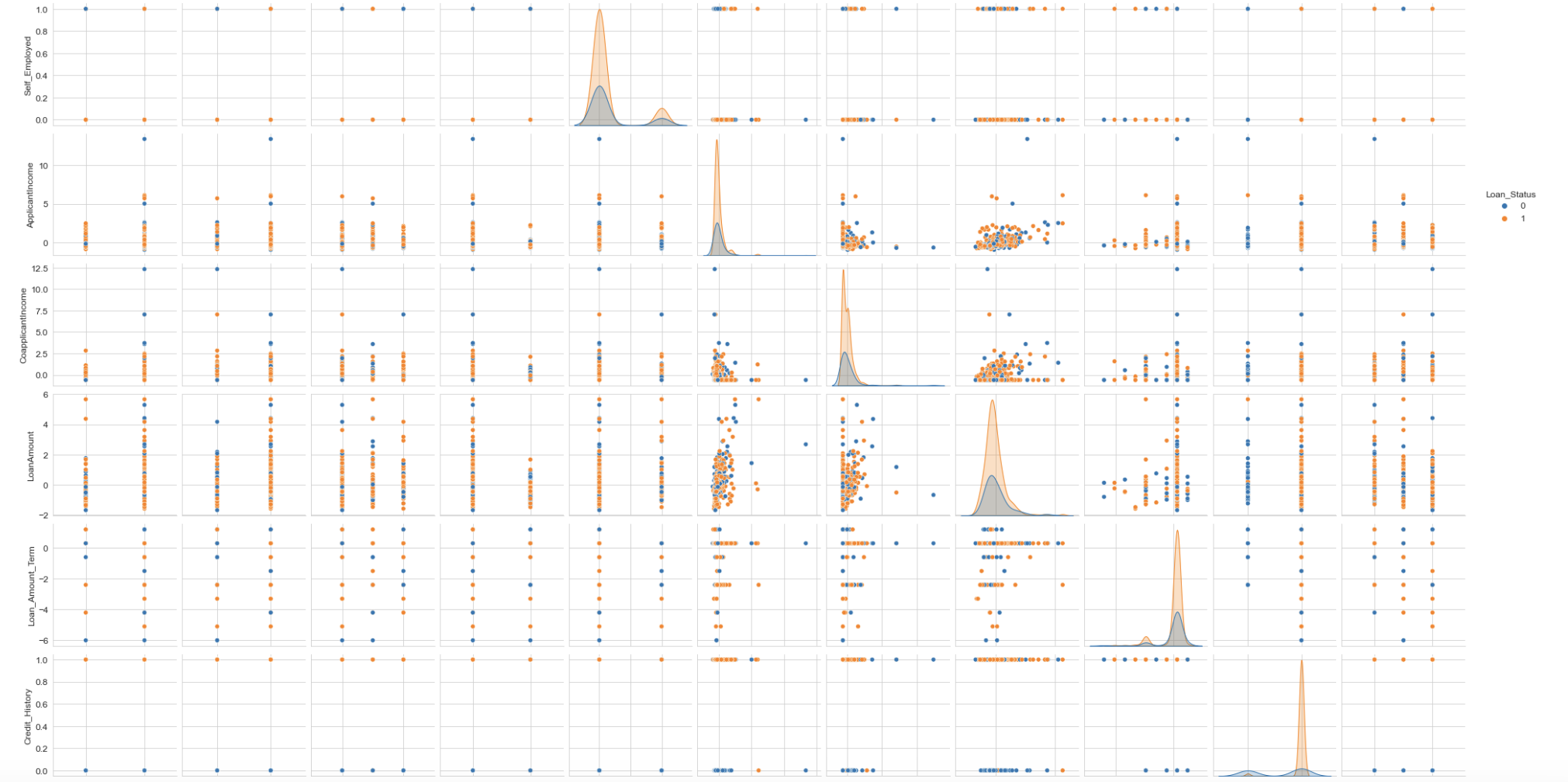
We run the following code to identify the correlations between variables.

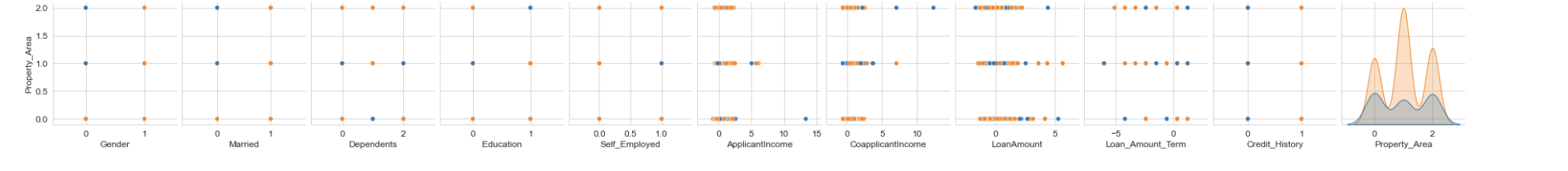
### Figure 22: Heatmap for all variables and correlations

The heatmap shows that there is 53% correlation between Loan\_status and Credit\_history and 52% correlation between ApplicantIncome and LoanAmount.

The below plot diagrams are produced with Seaborn library. The variables are coloured according to the target variable Loan\_status. The resulting plot displays all the relationships between variables in the dataset ‘loan’.

1





### Figure 23: Association between variables

By analysing the scatter plot and histograms, we can identify that there is a strong positive correlation between the approval of the loan amount and the credit history. The scatter plots showcase that males receive more loan approvals than females. Married couples get more approved applications than single individuals. If there is a mortgage application, the property area matters, as there are more approvals for semi-urban areas. Applicants who don’t have children or are not self-employed are more likely to receive loan approval. The most strongly associated independent variables to the target variable are ‘ApplicantIncome’, ‘Loan amount’, ‘CoApplicantIncome’ and ‘Credit\_History’. These numerical variables are appropriate for prediction of the independent variable ‘y’ = ‘Loan\_Status’.

## Model implementation

When we start splitting the data into training and testing and then run the code for DecisionTreeClassifier, we get errors that our data still contains NAN or missing values. We run pandas ‘concad’ method by combining the dependent and independent variables back again and after cleaning the data, the number of rows reduce to 439.

### Figure 24: Concad method

### Figure 25: Split dependent variable and independent variables

Our independent variables are Credit History, Applicant Income, Coapplicant Income, Loan Amount, Loan amount term. Dependent variable is Loan status.

We split the data into ‘train’ and ‘test’ again. We run the code for Decision Tree Classifier and we receive model accuracy 0.71 score.

### Figure 26: Decision tree classification

This accuracy score is not good enough, because this would mean that 29% of the applications could be misqualified. Money could be lended to applicants, who can not afford paying back the loan and this could be a financial risk for the bank. We did a test with just four features: 'Married', 'Education', 'LoanAmount' and 'Credit\_History'. The percentage went down to 60%.

We also run code for Linear regression model and we get a score of 0.14 mean squared error.

### Figure 27: Linear regression, mean squared error

The lower the value of mean squared error is, the better. The result is satisfying. We test other models to see if we get a better score.

### Figure 28: Random forest regressor

Random Forest Regressor model is with high mean squared error and low R-squared error. The model is performing poor judging by the results.

We also test the K-neighbours Classifiers and we received an accuracy score of 75%.

We save Linear regression in .pkl format so we can deploy and evaluate the models with new data.

### Figure 29: Saving Linear regression model in .pkl format

## 

## Deployment

We have a separate file loan\_test datasets, which was used for deploying the Linear regression model. These datasets were with lesser number of rows and this time we didn’t want to use the drapna method, but instead we imputed the missing values with means. We also used LabelEncoder and StandardScaller. We added a column Loan\_status and we removed column Loan\_ID. Since the number of the columns from the test data matches with the number of columns with the training dataset, we could deploy the model. It made predictions that some of the instances are 98% predicted accurately.

### Figure 30: Linear regression deployed model

## Challenges

We followed best practices for remote collaboration, using Google Meet to facilitate meetings once weekly. We also utilised Google Docs to share documents, allowing us all to collaborate on the document. We followed CRISP methodology for working on the project, which was easy to follow.

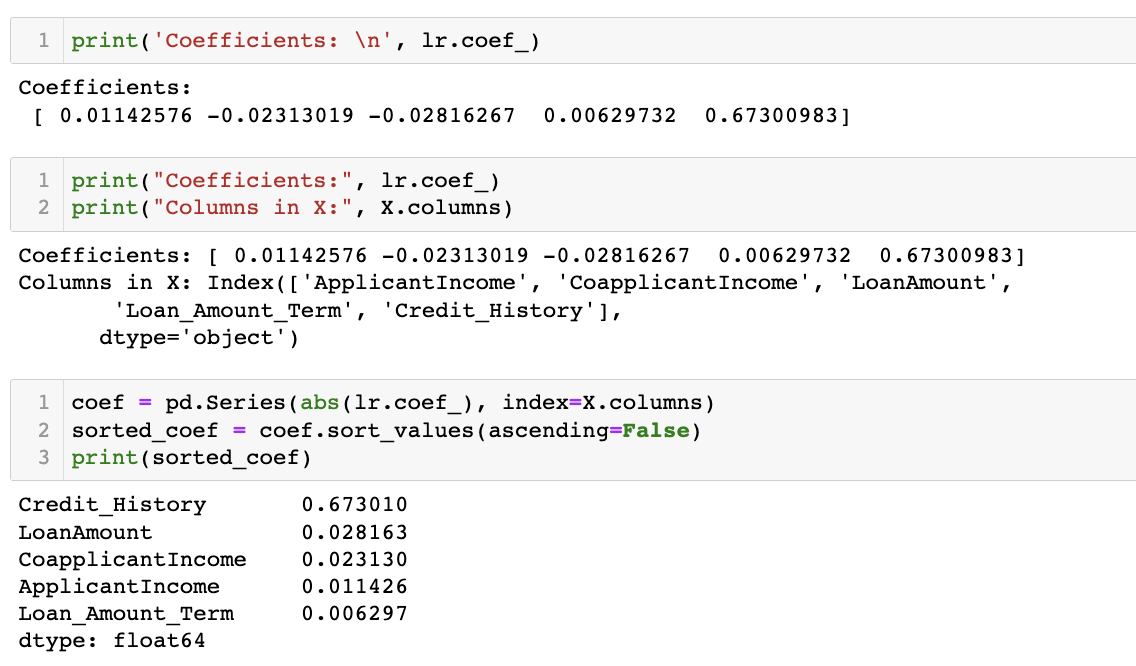
When we implemented the machine learning model, we received errors that there are still null values present. We repeated the process of cleaning the null values. The same applies for string data in column ‘Dependents’, where we treated the data with values 3+ and we needed to convert to integer. We had to repeat the steps.

It was challenging to implement the **deployment** of the machine learning model. We treated the new test data in a slightly different manner, where we imputed the missing values with ‘mean’ and also added a column ‘Loan\_Status’, as it was missing in the file. Even though we had all the libraries in place, we received an error that .pkl file is missing. After a couple of attempts, we managed to successfully deploy the Linear regression model and we received results that some of the instances are predicted with 98% accuracy.

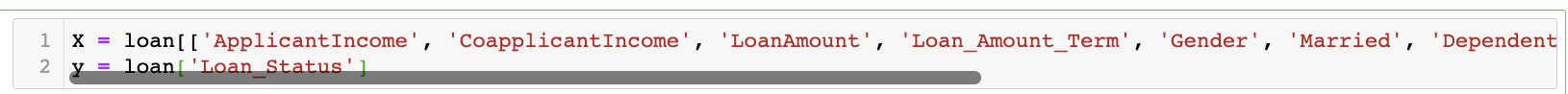
We outlined the feature importance for the best performing model and it has proven to be correct based on the research done by others in this area. We can not be fully confident that our data has been pre-processed with suitable methods or metrics, thus leading the outcome with biased results, however we used recommended approaches and accomplished satisfactory results.

## Results and analysis

Since the best performing score is for Linear regression model, we implemented coefficient magnitudes sorting values, based on the features we initially selected and we received the score as follows: Credit history 0.673, Loan amount 0.028, CoApplicant income 0.023, Applicant income 0.011 and Loan amount Term 0.006. We wanted to avoid biases and we added all of the attributes as features in this analysis and the outcome was slightly different.



### Figure 31: Coefficient magnitudes



### Figure 32: Additional features

The model was tested with all of the features present in the datasets Loan and ‘Credit history’ stands out with its feature importance.



### Figure 33: Ascending order of coefficients magnitudes

The highest ranking is Credit history, followed by the marriage status of the applicants and the request loan amount. The results from this dataset analysis confirm the findings of (Lee and Lee, 2018) that Credit history impacts the decision to lend loans.

It is important to highlight that Heatmap displayed the same results, where we noticed high correlation between Loan status and Credit history. This feature also influence on the requested loan amount, where in the event that the applicant doesn’t have credit history, there is a higher likelihood of rejection of the loan application and if the applicant has credit history, there is a higher likelihood of approval of the loan application.

We believe that these datasets are missing key applicant’s information. For instance, if the applicant is owning already a home or renting as the asset owning can affect the individual’s financial capacity.

Overall, we are content with the results and the outcome is sufficient and proves the hypothesis.

## Conclusion

Using a large dataset, this project has demonstrated how machine learning techniques can be applied effectively to predict loan defaults. After carefully inspecting and preparing the data, which included handling missing values, encoding categorical variables, and normalizing numerical features, we began our analysis.

We tested the predictive power of several machine learning models, including Linear Regression, Decision Trees, and Random Forests. We evaluated and compared these models using various metrics in a methodical manner. We were able to improve the performance of our linear regression classifier by using feature selection approaches, and it proved that credit history is the most significant predictor for approving loans to applicants. Other factors that influence the decision to lend loans include marital status. Individuals who are married are more likely to get their applications approved because, in case one of the individuals defaults on the loan, the partner can support and continue paying the due credit. Education also has an effect on the decision, and it appears to be the third most important feature.

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