Analysing-Credit-Risk-on-European-Peer-to-Peer-lending-platform-Bondora

The main purposes of this analysis are to summarize the characteristics of variables that can affect the loan status and to get some ideas about the relationships among variables.

Introduction

Peer-to-peer (P2P) lending is a form of online micro-financing that has been growing as an alternative to traditional credit financing. P2P lending allows individuals to lend or borrow directly from each other without financial intermediaries, through an internet based platform

Understanding the Dataset

The Dataset is from Bondora, a P2P lending platform in Europe. The retrieved data is a pool of both defaulted and non-defaulted loans from the time period between 1st March 2009 and 27th January 2020. The data comprises of demographic and financial information of borrowers, and loan transactions. The total is 134, 000 loan application with 112 variables.

Feature	Description
ActiveLateCategory	When a loan is in Principal Debt then it will be categorized by Principal Debt days
ActiveLateLastPaymentCategory	Shows how many days has passed since last payment and categorised if it is overdue
ActiveScheduleFirstPaymentReached	Whether the first payment date has been reached according to the active schedule
Age	The age of the borrower when signing the loan application
Amount	Amount the borrower received on the Primary Market. This is the principal balance of your purchase from Secondary Market
AmountOfPreviousLoansBeforeLoan	Value of previous loans
AppliedAmount	The amount borrower applied for originally
AuctionBidNumber	Unique bid number which is accompanied by Auction number
AuctionId	A unique number given to all auctions
AuctionName	Name of the Auction, in newer loans it is defined by the purpose of the loan
AuctionNumber	Unique auction number which is accompanied by Bid number

Feature	Description
BidPrincipal	On Primary Market BidPrincipal is the amount you made your bid on. On Secondary Market BidPrincipal is the purchase price
BidsApi	The amount of investment offers made via Api
BidsManual	The amount of investment offers made manually
BidsPortfolioManager	The amount of investment offers made by Portfolio Managers
BoughtFromResale_Date	The time when the investment was purchased from the Secondary Market
City	City of the borrower
ContractEndDate	The date when the loan contract ended
Country	Residency of the borrower
County	County of the borrower
CreditScoreEeMini	1000 No previous payments problems 900 Payments problems finished 24-36 months ago 800 Payments problems finished 12-24 months ago 700 Payments problems finished 6-12 months ago 600 Payment problems finished < 6 months ago 500 Active payment problems
CreditScoreEsEquifaxRisk	Generic score for the loan applicants that do not have active past due operations in ASNEF; a measure of the probability of default one year ahead; the score is given on a 6-grade scale: AAA (“Very low”), AA (“Low”), A (“Average”), B (“Average High”), C (“High”), D (“Very High”).
CreditScoreEsMicroL	A score that is specifically designed for risk classifying subprime borrowers (defined by Equifax as borrowers that do not have access to bank loans); a measure of the probability of default one month ahead; the score is given on a 10-grade scale, from the best score to the worst: M1, M2, M3, M4, M5, M6, M7, M8, M9, M10.
CreditScoreFiAsiakasTietoRiskGrade	Credit Scoring model for Finnish Asiakastieto RL1 Very low risk 01-20 RL2 Low risk 21-40 RL3

Feature	Description
	Average risk 41-60 RL4 Big risk 61-80 RL5 Huge risk 81-100
CurrentDebtDaysPrimary	How long the loan has been in Principal Debt
CurrentDebtDaysSecondary	How long the loan has been in Interest Debt
DateOfBirth	The date of the borrower's birth
DebtOccuredOn	The date when Principal Debt occurred
DebtOccuredOnForSecondary	The date when Interest Debt occurred
DebtToIncome	Ratio of borrower's monthly gross income that goes toward paying loans
DefaultDate	The date when loan went into defaulted state and collection process was started
DesiredDiscountRate	Investment being sold at a discount or premium
EAD1	Exposure at default, outstanding principal at default
EAD2	Exposure at default, loan amount less all payments prior to default
Education	1 Primary education 2 Basic education 3 Vocational education 4 Secondary education 5 Higher education
EL_V0	Expected loss calculated by the specified version of Rating model
EL_V1	Expected loss calculated by the specified version of Rating model
EL_V2	Expected loss calculated by the specified version of Rating model
EmploymentDurationCurrentEmployer	Employment time with the current employer
EmploymentPosition	Employment position with the current employer
EmploymentStatus	1 Unemployed 2 Partially employed 3 Fully employed 4 Self-employed 5 Entrepreneur 6 Retiree
ExistingLiabilities	Borrower's number of existing liabilities
ExpectedLoss	Expected Loss calculated by the current Rating model

Feature	Description
ExpectedReturn	Expected Return calculated by the current Rating model
FirstPaymentDate	First payment date according to initial loan schedule
FreeCash	Discretionary income after monthly liabilities
Gender	0 Male 1 Woman 2 Undefined
GracePeriodEnd	Date of the end of Grace period
GracePeriodStart	Date of the beginning of Grace period
HomeOwnershipType	0 Homeless 1 Owner 2 Living with parents 3 Tenant, pre-furnished property 4 Tenant, unfurnished property 5 Council house 6 Joint tenant 7 Joint ownership 8 Mortgage 9 Owner with encumbrance 10 Other
IncomeFromChildSupport	Borrower's income from alimony payments
IncomeFromFamilyAllowance	Borrower's income from child support
IncomeFromLeavePay	Borrower's income from paternity leave
IncomeFromPension	Borrower's income from pension
IncomeFromPrincipalEmployer	Borrower's income from its employer
IncomeFromSocialWelfare	Borrower's income from social support
IncomeOther	Borrower's income from other sources
IncomeTotal	Borrower's total income
Interest	Maximum interest rate accepted in the loan application
InterestAndPenaltyBalance	Unpaid interest and penalties
InterestAndPenaltyDebtServicingCost	Service cost related to the recovery of the debt based on the interest and penalties of the investment
InterestAndPenaltyPaymentsMade	Note owner received loan transfers earned interest, penalties total amount
InterestAndPenaltyWriteOffs	Interest that was written off on the investment
InterestLateAmount	Interest debt amount
InterestRecovery	Interest recovered due to collection process from in debt loans

Feature	Description
LanguageCode	1 Estonian 2 English 3 Russian 4 Finnish 5 German 6 Spanish 9 Slovakian
LastPaymentOn	The date of the current last payment received from the borrower
LiabilitiesTotal	Total monthly liabilities
ListedOnUTC	Date when the loan application appeared on Primary Market
LoanDate	Date when the loan was issued
LoanDuration	Current loan duration in months
LoanId	A unique ID given to all loan applications
LoanNumber	A unique number given to all loan applications
LoanStatusActiveFrom	How long the current status has been active
LossGivenDefault	Gives the percentage of outstanding exposure at the time of default that an investor is likely to lose if a loan actually defaults. This means the proportion of funds lost for the investor after all expected recovery and accounting for the time value of the money recovered. In general, LGD parameter is intended to be estimated based on the historical recoveries. However, in new markets where limited experience does not allow us more precise loss given default estimates, a LGD of 90% is assumed.
MaritalStatus	1 Married 2 Cohabitant 3 Single 4 Divorced 5 Widow
MaturityDate_Last	Loan maturity date according to the current payment schedule
MaturityDate_Original	Loan maturity date according to the original loan schedule
ModelVersion	The version of the Rating model used for issuing the Bondora Rating
MonthlyPayment	Estimated amount the borrower has to pay every month
MonthlyPaymentDay	The day of the month the loan payments are scheduled for The actual date is adjusted for weekends and bank holidays (e.g. if 10th is

Feature	Description
	Sunday then the payment will be made on the 11th in that month)
NewCreditCustomer	Did the customer have prior credit history in Bondora 0 Customer had at least 3 months of credit history in Bondora 1 No prior credit history in Bondora
NextPaymentDate	According to schedule the next date for borrower to make their payment
NextPaymentNr	According to schedule the number of the next payment
NextPaymentSum	According to schedule the amount of the next payment
NoOfPreviousLoansBeforeLoan	Number of previous loans
note_id	A unique ID given to the investments
NoteLoanLateChargesPaid	The amount of late charges the note has received
NoteLoanTransfersInterestAmount	The amount of interest the note has received
NoteLoanTransfersMainAmount	The amount of principal the note has received
NrOfDependants	Number of children or other dependants
NrOfScheduledPayments	According to schedule the count of scheduled payments
OccupationArea	1 Other 2 Mining 3 Processing 4 Energy 5 Utilities 6 Construction 7 Retail and wholesale 8 Transport and warehousing 9 Hospitality and catering 10 Info and telecom 11 Finance and insurance 12 Real-estate 13 Research 14 Administrative 15 Civil service & military 16 Education 17 Healthcare and social help 18 Art and entertainment 19 Agriculture, forestry and fishing
OnSaleSince	Time when the investment was added to Secondary Market
PenaltyLateAmount	Late charges debt amount
PlannedInterestPostDefault	The amount of interest that was planned to be received after the default occurred
PlannedInterestTillDate	According to active schedule the amount of interest the investment should have received

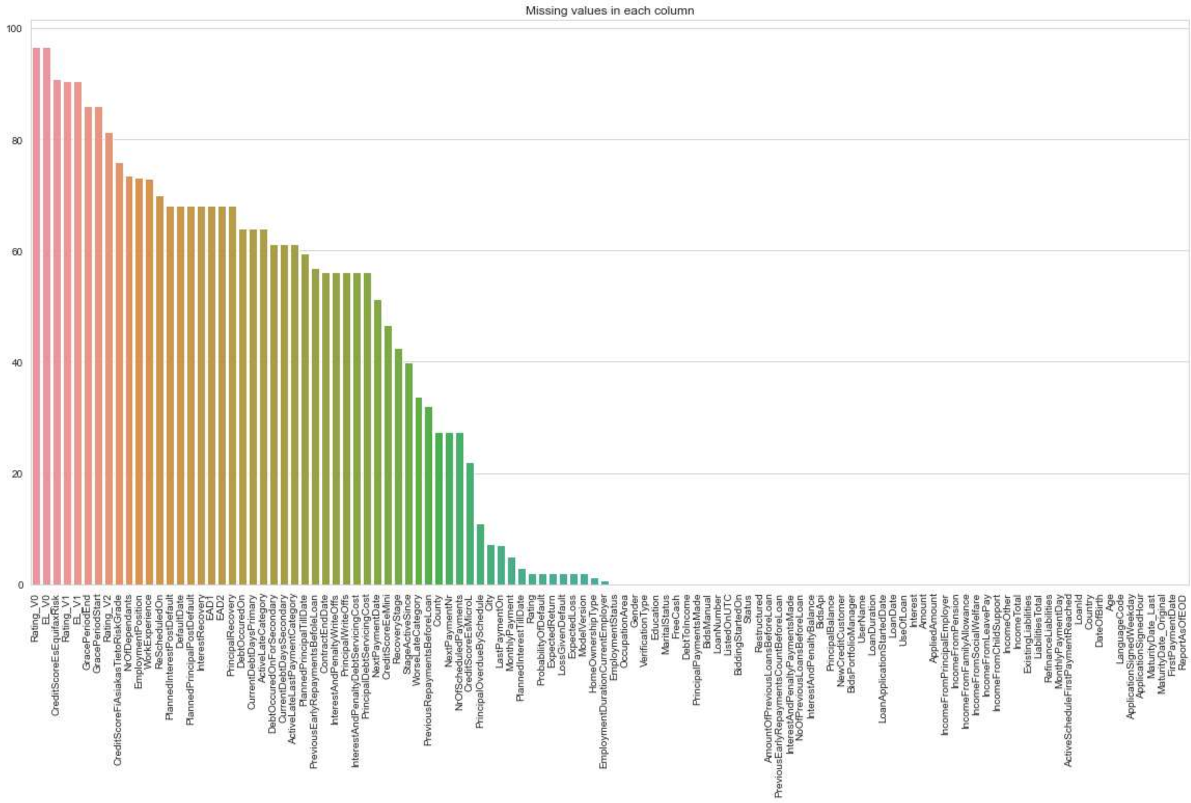
Feature	Description
PlannedPrincipalPostDefault	The amount of principal that was planned to be received after the default occurred
PlannedPrincipalTillDate	According to active schedule the amount of principal the investment should have received
PreviousEarlyRepaymentsBeforeLoan	How much was the early repayment amount before the loan
PreviousEarlyRepaymentsCountBeforeLoan	How many times the borrower had repaid early
PreviousRepaymentsBeforeLoan	How much the borrower had repaid before the loan
PrincipalBalance	Principal that still needs to be paid by the borrower
PrincipalDebtServicingCost	Service cost related to the recovery of the debt based on the principal of the investment
PrincipalLateAmount	Principal debt amount
PrincipalOverdueBySchedule	According to the current schedule, principal that is overdue
PrincipalPaymentsMade	Note owner received loan transfers principal amount
PrincipalRecovery	Principal recovered due to collection process from in debt loans
PrincipalWriteOffs	Principal that was written off on the investment
ProbabilityOfDefault	Probability of Default, refers to a loan's probability of default within one year horizon.
PurchasePrice	Investment amount or secondary market purchase price
Rating	Bondora Rating issued by the Rating model
Rating_V0	Bondora Rating issued by version 0 of the Rating model
Rating_V1	Bondora Rating issued by version 1 of the Rating model
Rating_V2	Bondora Rating issued by version 2 of the Rating model
RecoveryStage	Current stage according to the recovery model 1 Collection 2 Recovery 3 Write Off
RefinanceLiabilities	The total amount of liabilities after refinancing

Feature	Description
ReScheduledOn	The date when the a new schedule was assigned to the borrower
Restructured	The original maturity date of the loan has been increased by more than 60 days
SoldInResale_Date	The date when the investment was sold on Secondary market
SoldInResale_Price	The price of the investment that was sold on Secondary market
SoldInResale_Principal	The principal remaining of the investment that was sold on Secondary market
StageActiveSince	How long the current recovery stage has been active
Status	The current status of the loan application
UseOfLoan	0 Loan consolidation 1 Real estate 2 Home improvement 3 Business 4 Education 5 Travel 6 Vehicle 7 Other 8 Health 101 Working capital financing 102 Purchase of machinery equipment 103 Renovation of real estate 104 Accounts receivable financing 105 Acquisition of means of transport 106 Construction finance 107 Acquisition of stocks 108 Acquisition of real estate 109 Guaranteeing obligation 110 Other business All codes in format 1XX are for business loans that are not supported since October 2012
UserName	The user name generated by the system for the borrower
VerificationType	Method used for loan application data verification 0 Not set 1 Income unverified 2 Income unverified, cross-referenced by phone 3 Income verified 4 Income and expenses verified
WorkExperience	Borrower's overall work experience in years
WorseLateCategory	Displays the last longest period of days when the loan was in Principal Debt
XIRR	XIRR (extended internal rate of return) is a methodology to calculate the net return using the loan issued date and amount, loan repayment dates and amounts and the

Feature	Description
	principal balance according to the original repayment date. All overdue principal payments are written off immediately. No provisions for future losses are made & only received (not accrued or scheduled) interest payments are taken into account.

Data Pre-processing

The data is pre-processed by removing the variables that are not relevant to the analysis, and by dealing with missing values. for the missing values, the variables with more than 40% missing values are removed, and the rest are imputed by the mean or mode value of the variable.



Then for categorical variables, we removed the irrelevant values that could happen during the data collection process, and then try to prepare the data to be used in the analysis with higher integrity and correctness.

In addition, the Default Status variable was defined in this process where we created a column for the default status of each loan application. The default status is defined as 1 if the loan is defaulted, and 0 if the loan is not defaulted.

The shape of the dataset after pre-processing is **(77394, 42)** including the target variable which is Default Status.

Exploratory Data Analysis (EDA)

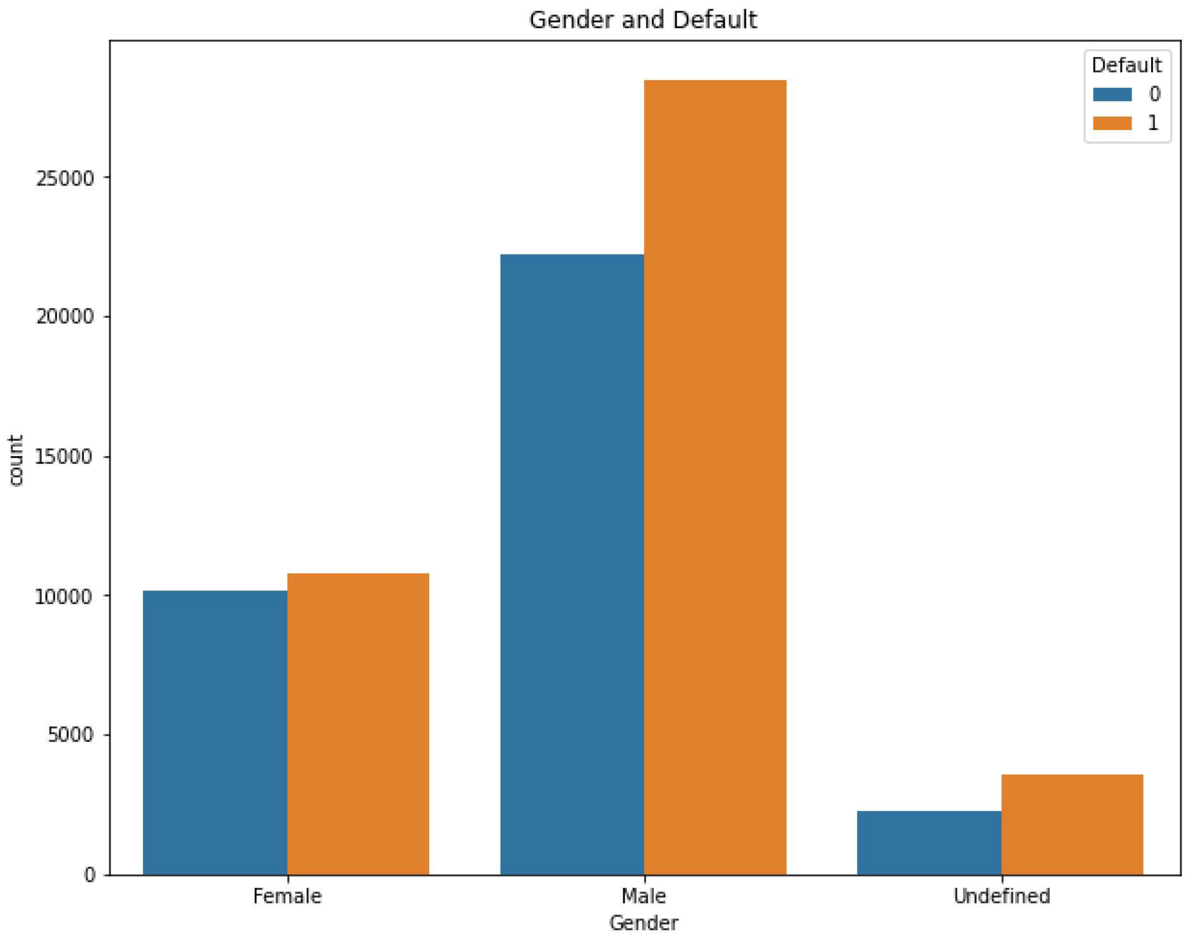
The EDA is done to understand the data and to get some ideas about the relationships among variables. The EDA is done by using the univariate and bivariate analysis. The univariate analysis is done by using the descriptive statistics and the visualization. The bivariate analysis is done by using the visualization.

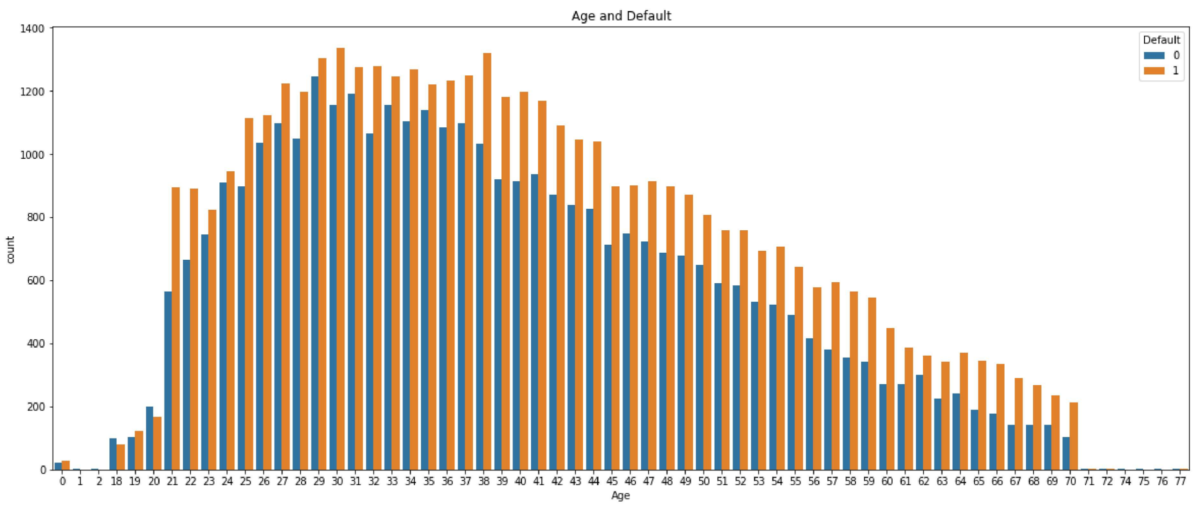
We found many correlation between the variables and tried to identify and visualize the relationships among variables. The relationships are visualized by using the scatter plot, box plot, and bar plot.

All the insights and findings from the EDA can be found in the file the EDA NoteBook.

These are some of the insights and findings from the EDA:

- The Gender Distribution in the dataset is **66% Male** and **34% Female**.
- The Age Distribution in the dataset is **68% between 25 and 44 years old**.
- check the following plots for more insights about the Age and Gender Distribution in the dataset.





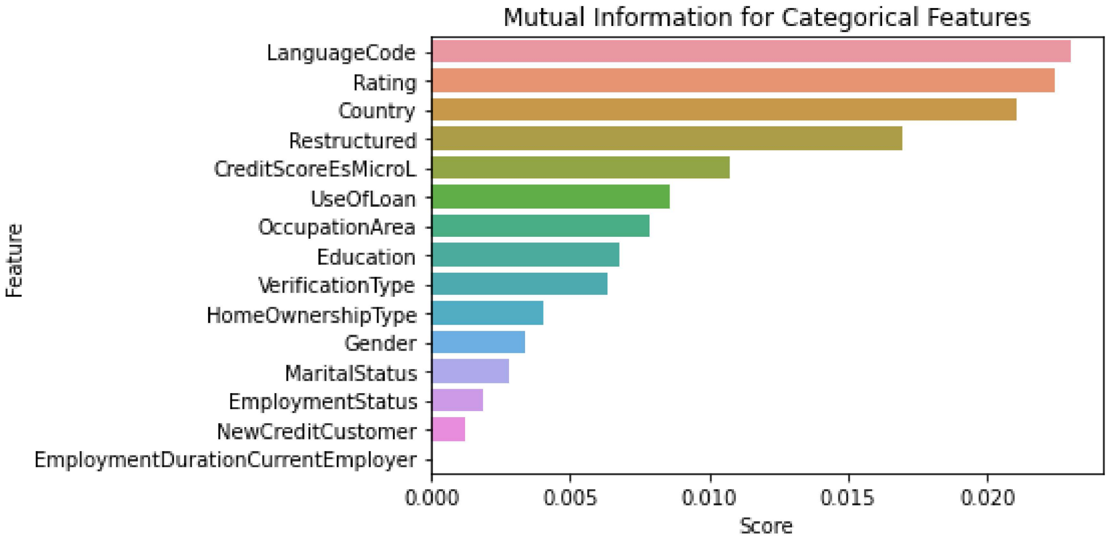
Feature Engineering and Selection

The feature engineering and selection is done to prepare the data for the machine learning model. The feature engineering is done by removing the outliers in the dataset and by applying the method of Mutual Information to select the most relevant features. Then according to the results of EDA we tested some new variables that could be useful for the analysis. and finally we applied the method of Principal Component Analysis (PCA) to reduce the dimensionality of the data.

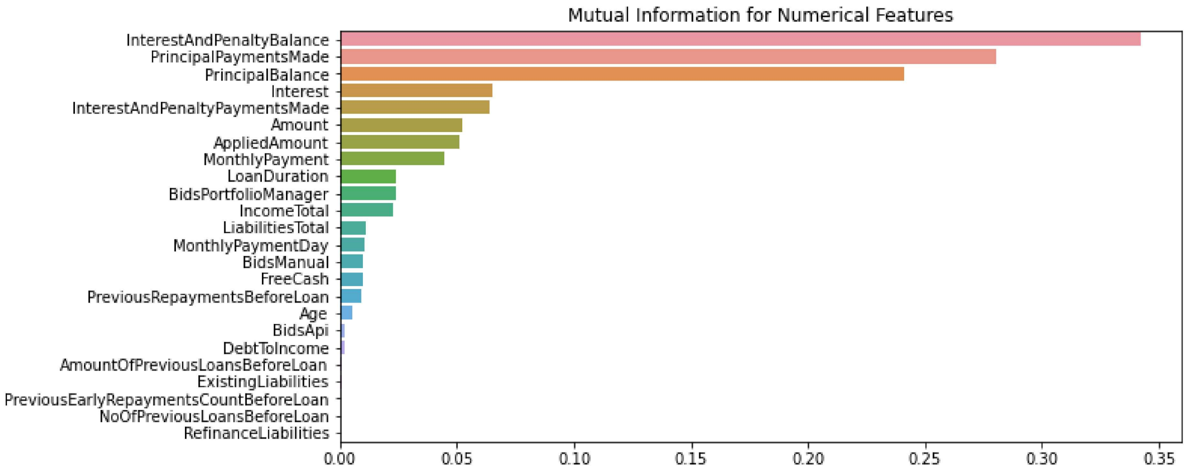
The feature engineering and selection is done by using the following methods:

- Mutual Information (MI) and the result is as follows:

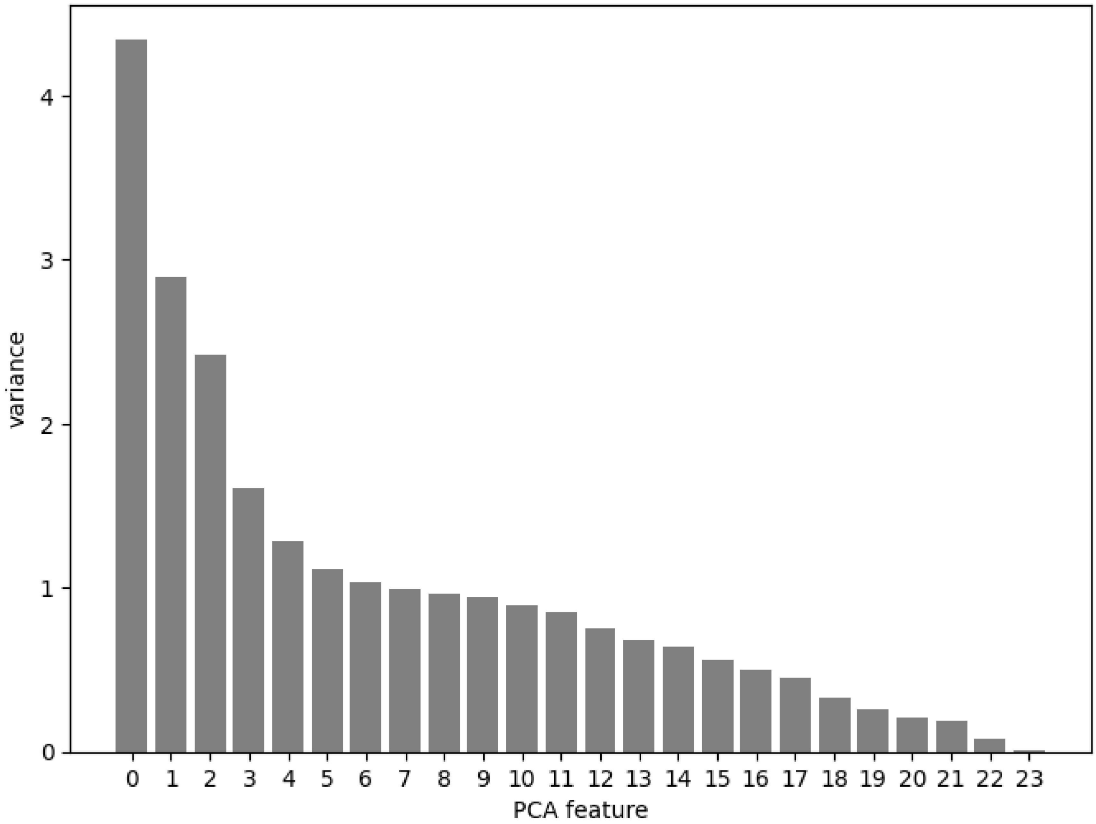
For Category Variables:



For Numeric Variables:



- Principal Component Analysis (PCA) and the explained variance is as follows:



Machine Learning Model

Classification Model

The first target variable is the Default Status, which is a binary variable. The classification model is used to predict the Default Status of the loan application. The classification model is done by using the Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting Classifier. All models were evaluated by using the accuracy, precision, recall, F1 score and confusion matrix. Then we selected the best model with the highest accuracy and applied the model to the test data.

The selected model was: **Logistic Regression** with the accuracy of **88.57 %**

Regression Model

As part of the credit risk analysis, predicting the default state of the loan is just one part of the analysis. There are other factors that the credit risk depends on. In our analysis, we created the target variables that has an impact on the credit score. These Targets are:

- Equated Monthly Instalment (EMI)
- Eligible Loan Amount (ELA)
- Preferred Rate of Interest (PROI)

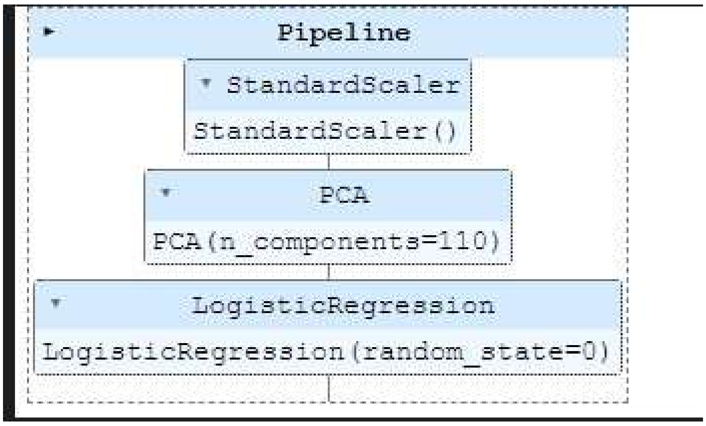
Then we create a model to predict these targets using Regression Model. The regression model is done by using the Linear Regression, Ridge Regression, Random Forest Regressor, and Gradient Boosting Regressor. All models were evaluated by using the R2 score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Then we selected the best model with the highest R2 score and applied the model to the test data.

The selected model was: **Ridge Regression** with the R2 score of **89.07 %**

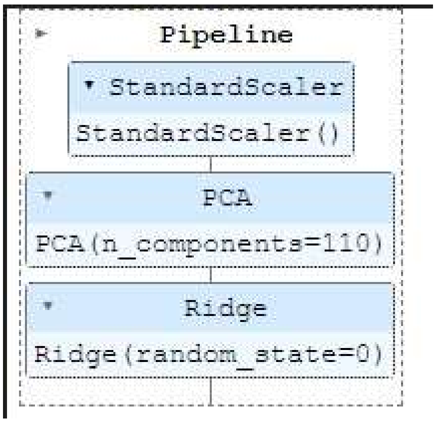
Pipeline

The pipeline is done by using the Pipeline from sklearn. The pipeline is done by using the Standard Scaler, PCA, and the selected model. The pipeline is done for both classification and regression model.

The pipeline for the classification model is as follows:



The pipeline for the regression model is as follows:



These pipelines are used to predict the Default Status, EMI, ELA, and PROI. They were deployed in the web application using the Flask framework with pickle to save the model.

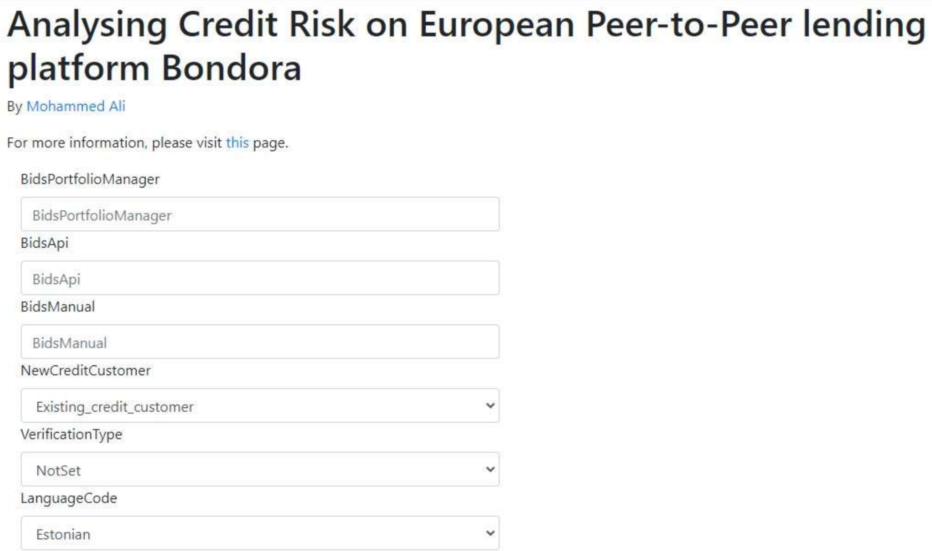
Deployment

The deployment is done by using the Flask framework. The web application is deployed in the Heroku platform. The web application is done by using the HTML, CSS, and JavaScript. The web application is done by using the Bootstrap framework. The web application is done by using the Flask framework with pickle to save the model.

There are two pages in the web application:

- One page to let the user enter the required data to predict the Default Status, EMI, ELA, and PROI.
- The other page to show the result of the prediction.

Here is the link to the web application: https://credit-risk-analysis.herokuapp.com/ Here is a screenshot of the web application:



Result and Conclusion

The final result is a web application that predicts the parameters required to calculate the credit score of a given loan application and investors can use this web application to predict the credit score of a loan application before investing in it, this will help investors to make a better decision and to reduce the risk of investing in a loan application that will be defaulted.

Credit

This project was done as a part of Data Analytics and Machine Learning Internship at Technocolabs.

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