Investing in Peer2Peer Lending

Section 1
Team Gamma 1

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Agenda

1. Big Question
2. Cleaning and Imputing the data
3. Accepted/Rejected Model
4. Loan Default Model
5. Investment Financial
6. Recommendations and Implications

Big Question: Where should Dr. D invest his money?

Goal: Maximize $10,000,000 investment with respect to key factors

Key Factors:

- Loan defaulting
- Return/value of loan
- Time of loan
- Possibility of delay in payment

How:

→ Identify predictive features for loan approval and status
→ Evaluate the financial outcomes for default
→ Determine how to value a loan based on desired risk

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Find common feature variables and impute null and NaN values in accepted data

Compared the feature variables between the accepted and rejected data and found 9 features that will match between the two datasets

ACCEPTED DATA

1. 'Loan_amnt' → Drop values with missing loan amount
2. 'Issue_d' → Drop values with no date
3. 'Purpose' → Impute missing values with 'Other'
4. 'Fico_range_low'
5. 'Fico_range_high'
6. 'Dti' → Impute missing value with mean DTI
7. 'Addr_state'
8. 'Emp_length'
9. 'Policy_code'

- ❑ Feature engineer a binary 'accepted' score
- ❑ Calculate a risk score by averaging the high and low FICO score

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Finish cleaning and imputing rejected data and combine accepted and rejected dataframes of common features

Compared the feature variables between the accepted and rejected data and found **9 features** that will match between the two datasets

ACCEPTED DATA
+
REJECTED DATA

1. 'Loan_amnt'
2. 'Issue_d'
3. Purpose
4. 'Fico_range_low'
5. 'Fico_range_high'
6. 'Dti'
7. 'Addr_state'
8. 'Emp_length'
9. 'Policy_code'

Combined data frame of ACCEPTED and REJECTED data has 9 common feature variables plus **'Accepted?'** and **'Risk_Score'** engineered variables

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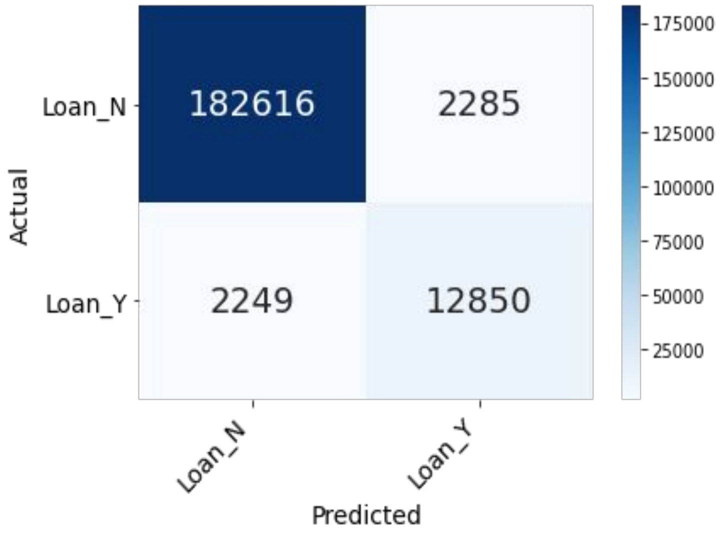
jupyter

Accepted/Rejected Model for prediction

Results: This model has an accuracy of 0.9773 in predicting whether a loan is accepted/rejected. It scores highly for recall and precision.

- ❑ Read in all concatenated data from drive
- ❑ Take a random sample and clean data, dfSample
- ❑ One-hot encode data
- ❑ Utilize train_test_split
- ❑ Implement **Random Forest**
- ❑ Evaluate model accuracy via Confusion Matrix



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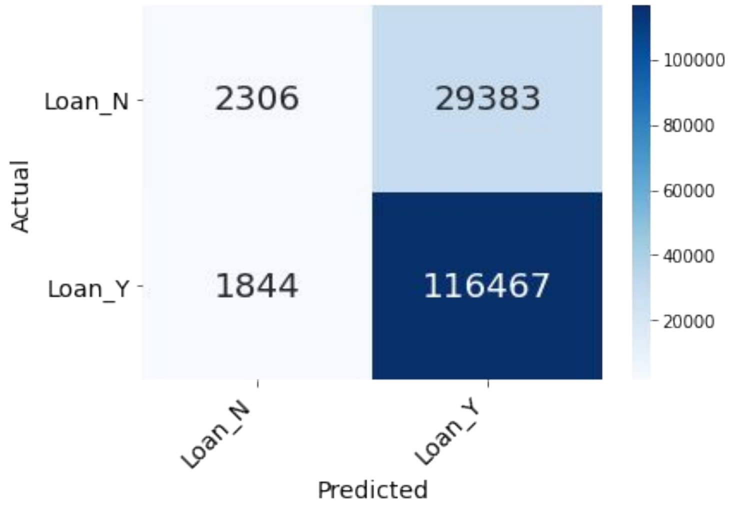
Based off accepted/rejected model, we created a model for predicting loan defaults

Results: This model has an accuracy of 0.79182 in predicting whether a loan will default through logistic regression

- Take smaller sample of accepted data to Colab crashed / more manageable
- Scale features (Standard Scaler)
- One-hot encode data
- Utilize train__test__split
- Implement **logistic regression**
- Evaluate model accuracy via Confusion Matrix



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Calculating ROI based on the logistic regression model

$$\underline{\textbf{Simplified ROI of a loan}} = \left[\frac{\text{Monthly installment} \times \text{Term Length (36 or 60 months)}}{\text{Total loan amount}} \right] - 1$$

ROI of a loan considering the risk of default = Simplified ROI of a loan x Chance of Default from Logistic Regression

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Assuming an initial investment of $10M, Dr. D can average over $1.01M in profit (over 3 years) from investing in Lending Club

Investing in Lending Club

ROI: 10.16% three-year rate

Implications:

- ❑ Higher level of risk (A-F)
- ❑ Higher level of return
- ❑ ROI is normalized to 3 month horizon
- ❑ Return on $10M =
  - ❑ ~$1,016,000

VS

Investing in Treasury Bonds

ROI: 3.44%* three-year rate

Implications:

- ❑ Stable return
- ❑ Guaranteed by government
- ❑ Return on $10M =
  - ❑ ~$344,000

*ROI of three-year treasury rate based upon historic value, not current rate

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