Loan Approval Screener

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Phase 3 Project

Outline

Business Problem

Summary

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Business Problem

Banks want an easy way
to screen
loan applications.

Make strong inferences with
data from prior applications
about likelihood of approval.

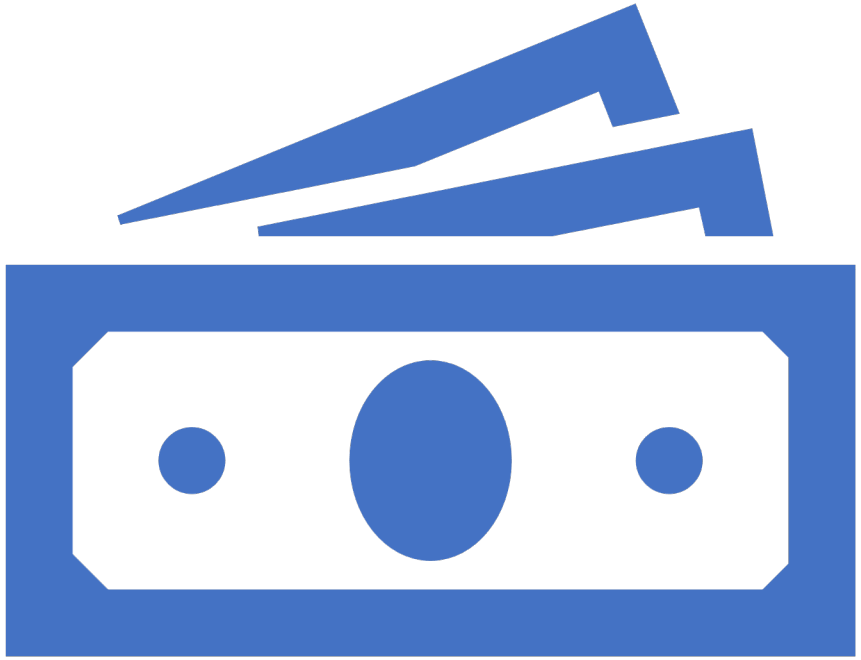
Business Opportunity

- Reduce human-hours for banks
  - Use model to select applications that are highly likely to be approved.
- Improve pipeline for customer experience by automating questions and providing likelihood of approval for customer.

Data - Overview

Loan Application Data

- 307,511 Applications
- 122 Features
  - Type of Loan:
    - 90% Cash Loans
    - 10% Revolving Loans
  - Application Results:
    - 8% Approved
    - 92% Rejected



Data Manipulation

- Class Imbalance Issues:
  - Improve balance of Approval/Refusal ratio
  - Used under-sampling and over-sampling techniques to improve balance
- Replaced missing numerical and categorical data with mean and mode, respectively.
- 100 % of data from 39 features and 1 target feature used for model.

Data Manipulation, continued
Improving Class Balance

- Initial data set had an 8% prevalence of Loan Approval.
  - Ideally, a classification model will have a 50% prevalence of each class.

Solutions for class imbalance:

- Under-sample Majority Class (Loan Rejection)
  - Randomly selected 40,000 applications that were rejected.
- Over-sample Minority Class (Loan Approval)
  - Used Synthetic Minority Oversampling (SMOTE) to increase loan approvals from 24,825 values to 40,000 values.

Feature Selection

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Optimal number of features : 63
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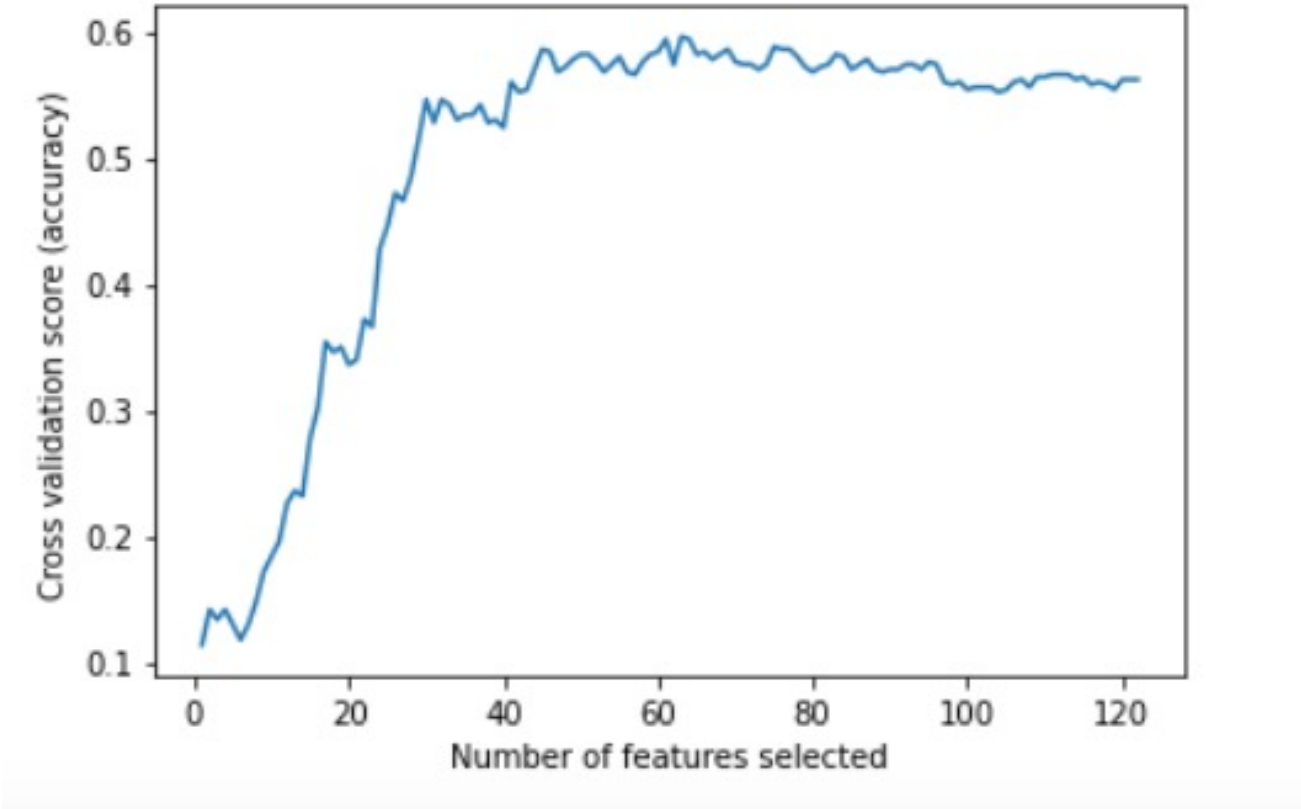
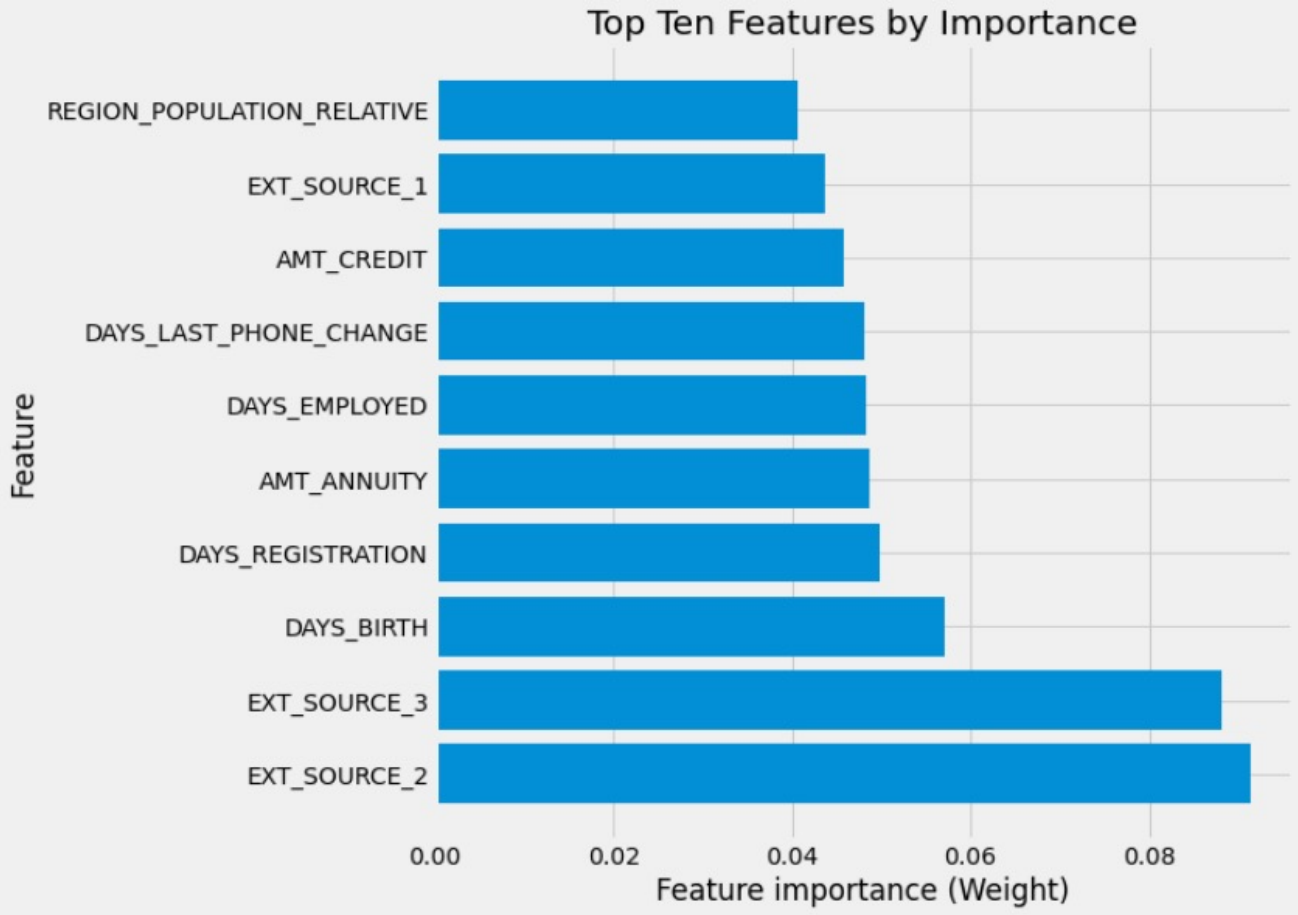


- Optimal number of features to include was 63.
- I chose 39 features, and after encoding the categorical features, the final models included 61 columns.
- I would have added more features, but I was limited in computational power on my machine.

Feature Importance



- Top Ten Features by importance in the 6th Random Forest Model.
- Top singular model produced
- EXT_SOURCE not defined, but could be a form of credit score.
- Important to note these features so they are included on future loan applications:
  - Birth Date
  - Employment start date
  - Amount of Credit Available
  - Common Annuities

Methods

- Classification Modeling
  - Main Models:
    - Random Forest
    - Gradient Boost
    - Voting Classifier
- Optimize for Loan Approval, or True Positive Rate
  - Value high True Negative Rate, as well.
  - Best scores for True Positive Rate valued because that means the model will have a high likelihood of flagging a
- Identify features with most influence on Loan Approval

Final Model Methods

- Voting Classifier
  - Used 3 models:
    - Top Random Forest optimized for True Positive Rate
    - Top Random Forest optimized for True Negative Rate
    - Top Gradient Boost Model optimized for True Positive Rate
  - Combination of these models yielded better results than any one of the models alone.
    - This is called an ensemble model and optimizes the best parts of each model.
    - 2x heavier weight was applied to the top Random Forest model for True Positive Rate

Results of Best Model

- 84% True Positive Rate
  - 84/100 applications that were approved, were flagged for approval by model
    - Maintained a 40% True Negative Rate, which means many applications can be successfully filtered out.

- Model as a Screener:
  - 84% of applications that are approved, will be recommended for viewing by a person.
  - 31% of applications can be filtered out, with an 84% chance that they would have been rejected.

Conclusions

- This model could save banks time and money by accurately filtering loan applications.
  - Could reduce applications read by people by over 30%
  - 84% likely that approved loans will be recommended for review by a person
    - Makes loan officer’s job simpler and faster.

- Top features for banks to follow in this model:
  - Birth Date
  - Employment start date
  - Amount of Credit Available
  - Common Annuities

Further Studies Recommended

- Gather data on more relevant features
  - Credit Score
  - Cash and Invested Savings
  - Retirement Savings
  - Debt to Income Ratio
- Test model on other samples of market data
  - Iterate and improve model for these samples or market segments
- Improve pipeline for loans by developing digital questionnaire
  - Attain data inexpensively – directly from consumer
  - Tailor questions to garner data from most relevant features