Predicting the Likelihood of a Loan Application being approved

T. Hastings Reeves

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Data Science Intensive Capstone Project, May 2021 Cohort

Thanks to Springboard Mentor: AJ Sanchez, PH.D., President of Exodus Software Services, INC.

Dream Housing Finance Company

Current process of approval for loan applications:

 \circ Weigh specific criteria found in the application

Approve or deny loan request, individually.

Understanding the problem

Loan Application

- Key Factors
 - o Loan ID
 - Gender
 - Married
 - Education
 - o Income
 - Loan Amount
 - o Loan Term
 - Property Area

Individual review

Credit History,
 Applicant and
 Co-Applicant
 Income, and Loan
 Amount are key
 variables in helping
 loan officers weigh
 the criteria.

Approval or Denial

- Based on individual loan application.
- Case by case basis, from beginning of process to end.
- Time-consuming.

Project objective:

Utilize machine learning to expedite the beginning level decision making process for loan approval.

Data Acquisition & Wrangling

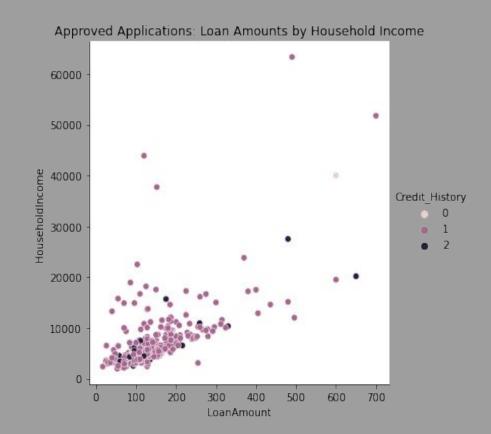
The data was supplied by Dream Housing Finance Company:

- 614 loan applications
- 13 categories of information
- Target: Loan Approval

Data Exploration:

Credit History:

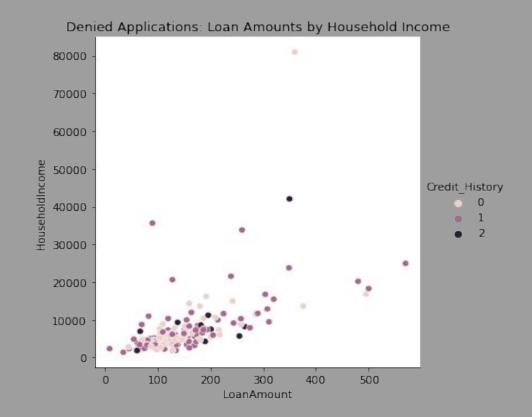
- Very few applications that were approved did not meet the Credit History Requirement.
- Some earners' income at \$40,000/month did not meet the Credit History Requirements but was approved.



Data Exploration:

Credit History:

- The majority of the applications did not meet the Credit History Requirements were denied.
- One earners' income was \$80,000/month, yet they did not meet the Credit History Requirement, and were denied.



Machine Learning Baseline Model

- Type: Supervised Learning
- Binary Classification: 1 for Approved, 0 for Denied
- Imbalanced data: Nearly a 3:1 ratio from Class 1 to Class 0.
- Tools: Scikit Learn and imblearn
- Algorithm: Logistic Regression

Modeling Steps:

Pre-Processing:	 Train/Test split at 70/30, with stratify condition set to 'y'. pd.get_dummies for label encoding 				
Performance Metrics:	Accuracy ReportClassification Report, AUC and ROC				
Resampling:	 Random Undersampling, Random Oversampling, SMOTE Baseline Model, Random Forest, Decision Tree 				
Best Models:	Random Forest-SMOTE, Logistic Regression-SMOTE				

MODEL:	Recall: Minority	Precision: Minority	F1: Minorit y	Recall: Majority	Precision: Majority	F1: Majorit y	AUC
Baseline Model: Logistic Regression(Training data)	0.42	0.87	0.56	0.97	0.79	0.87	0.744
Logistic Regression: Random Oversampling	0.55	0.27	0.36	0.31	0.6	0.41	0.738
Logistic Regression: Random Undersampling	0.6	0.49	0.54	0.71	0.8	0.75	0.741
**Logistic Regression: SMOTE	0.53	0.55	0.54	0.8	0.79	0.8	0.745
**Random Forest: Random Oversampling	0.53	0.65	0.58	0.87	0.8	0.83	0.744
Random Forest: Random Undersampling	0.62	0.52	0.57	0.74	0.81	0.77	0.738
*Random Forest: SMOTE	0.53	0.66	0.59	0.87	0.8	0.84	0.749
Decision Tree: Random Oversampling	0.55	0.55	0.55	0.8	0.8	0.8	0.674
Decision Tree: Random Undersampling	0.55	0.39	0.46	0.61	0.75	0.67	0.579
Decision Tree: SMOTE	0.55	0.52	0.54	0.77	0.79	0.78	0.662

Model Comparisons

- *Best Model
- **High Performing
 Models
- Baseline Model uses training data due to overfitting on Test set CR.

Loan Application Approval Or Denial

Findings

While we were not able to conclusively classify 1 or 0 we can set parameters to determine 4 sets of categories to group loans into:

- 1. **Definitely Approved**
- 2. Tentatively Approved
- 3. Tentatively Denied
- 4. Definitely Denied

Future Work:

- Ensemble Methods utilizing
 Logistic Regression and
 Random Forest.
- 2. Clustering Algorithm to develop new insights.
- 3. Creating and finding evaluating the performance of multiple Random Undersampled models.