Mortgage Loan Predictor

By Alex Martin

Poll

How many people would like to buy a house/or already own a house?

The Situation

Owning a home is highly aspirational and a key life milestone:

- Financial stability.
- Potential property value appreciation.
- Stability.
- Free from the whims of landlords.
- Fosters a stronger sense of community.
- Offers financial security for future generations.
- A base to build from.
- And many more...

The Problem

“What do I have to do to get a mortgage?”

- Mortgage approval process is a ‘black-box’
- Denied applications show on your credit report for a year.

A Solution?

- Develop a mortgage prediction app that allows users to determine potential approval before submitting official applications.
- This will help prevent users from making unnecessary applications that could harm their chances of obtaining a mortgage in the future.
- Provide users with reasons for the decision so they know what they need to improve on in the future.

Methodology

- Data Collection
- Data Wrangling
- EDA
- Predictive Analysis
- Predictor App

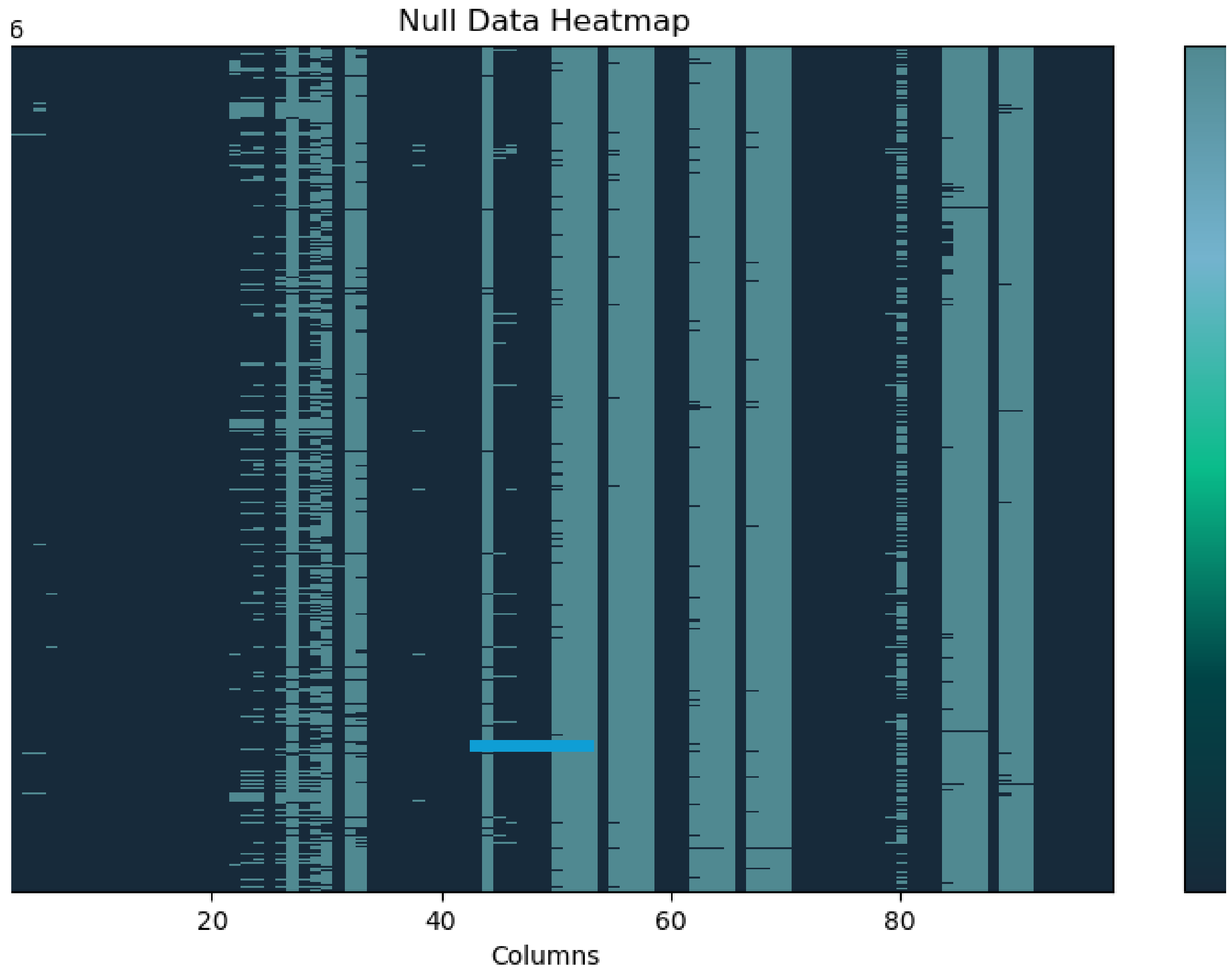
Data Collection

- https://ffiec.cfpb.gov/data-browser/data/2022?category=states

Data Wrangling

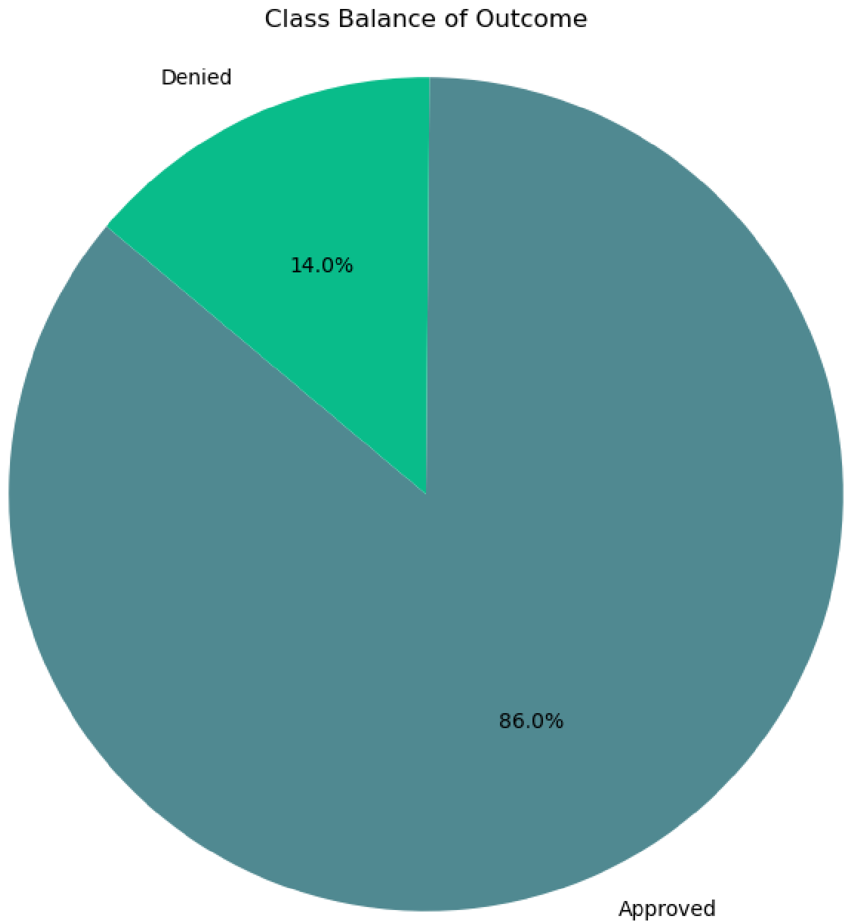
Dimension	Count
Row	5,081,179
Columns	99

Exemption	Count
‘Exempt’	942,042
1111	1,756,100
8888	8,547



Exploratory Data Analysis

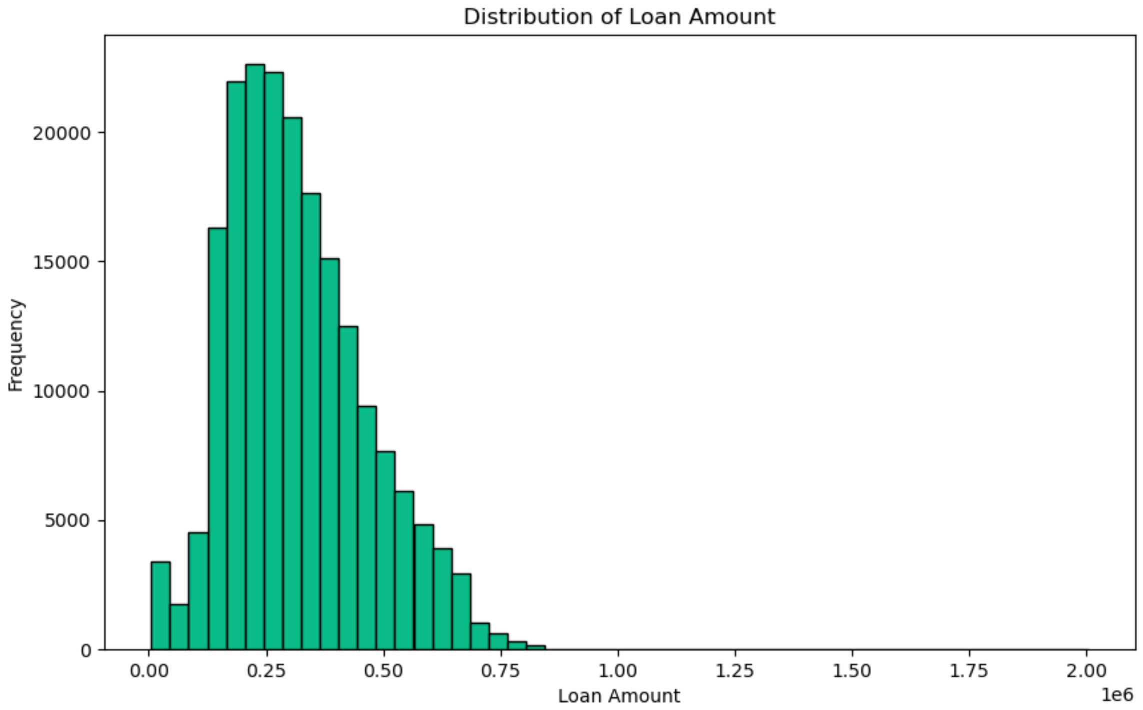
Approved v. Denied

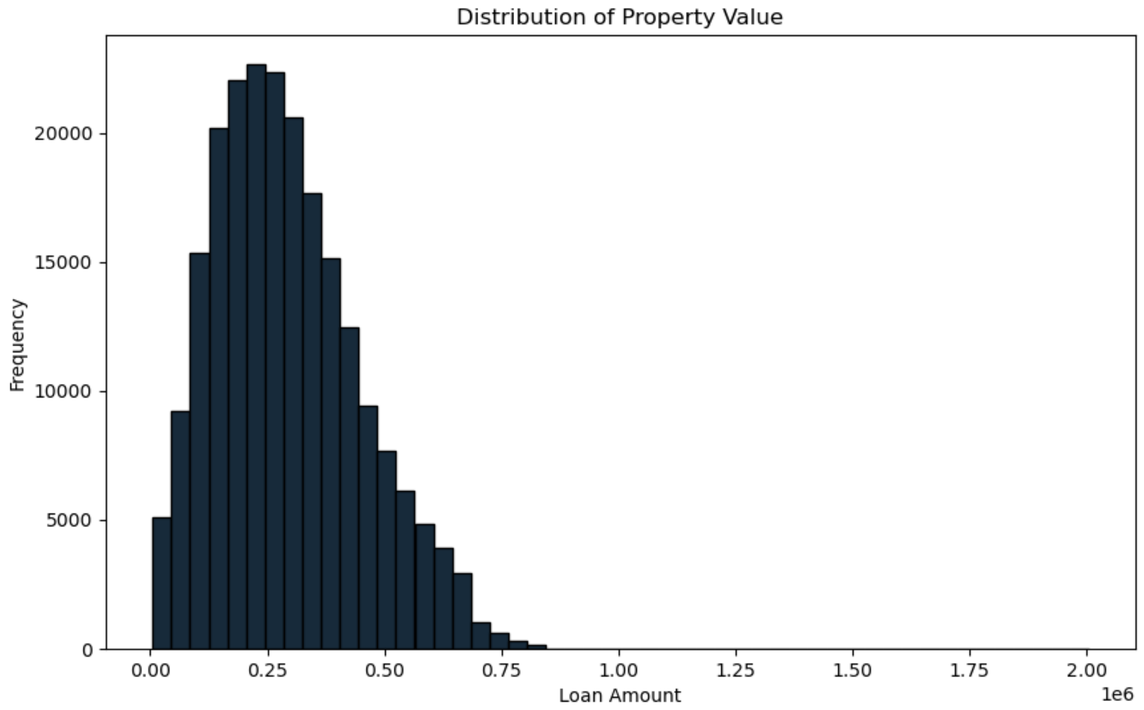


- 86% of Mortgage loans were approved
- 14% of Mortgage loans were denied
- Large class imbalance in the dataset

Outcome	Count
Approved	4,362,232
Denied	713,641

Data Distribution



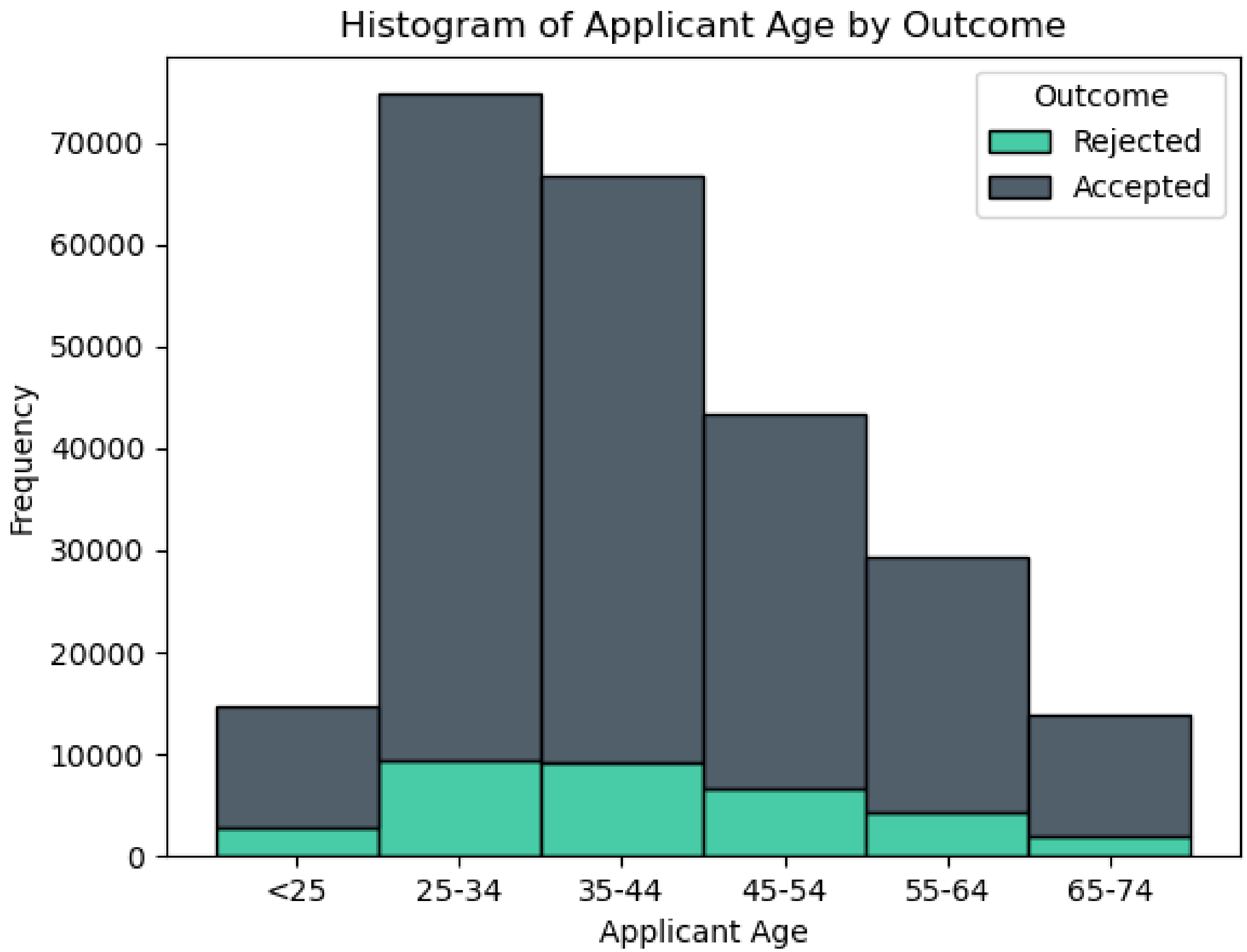


Median loan amount: $285,000
Mean loan amount: $382,0000
Mode loan amount: $205,000

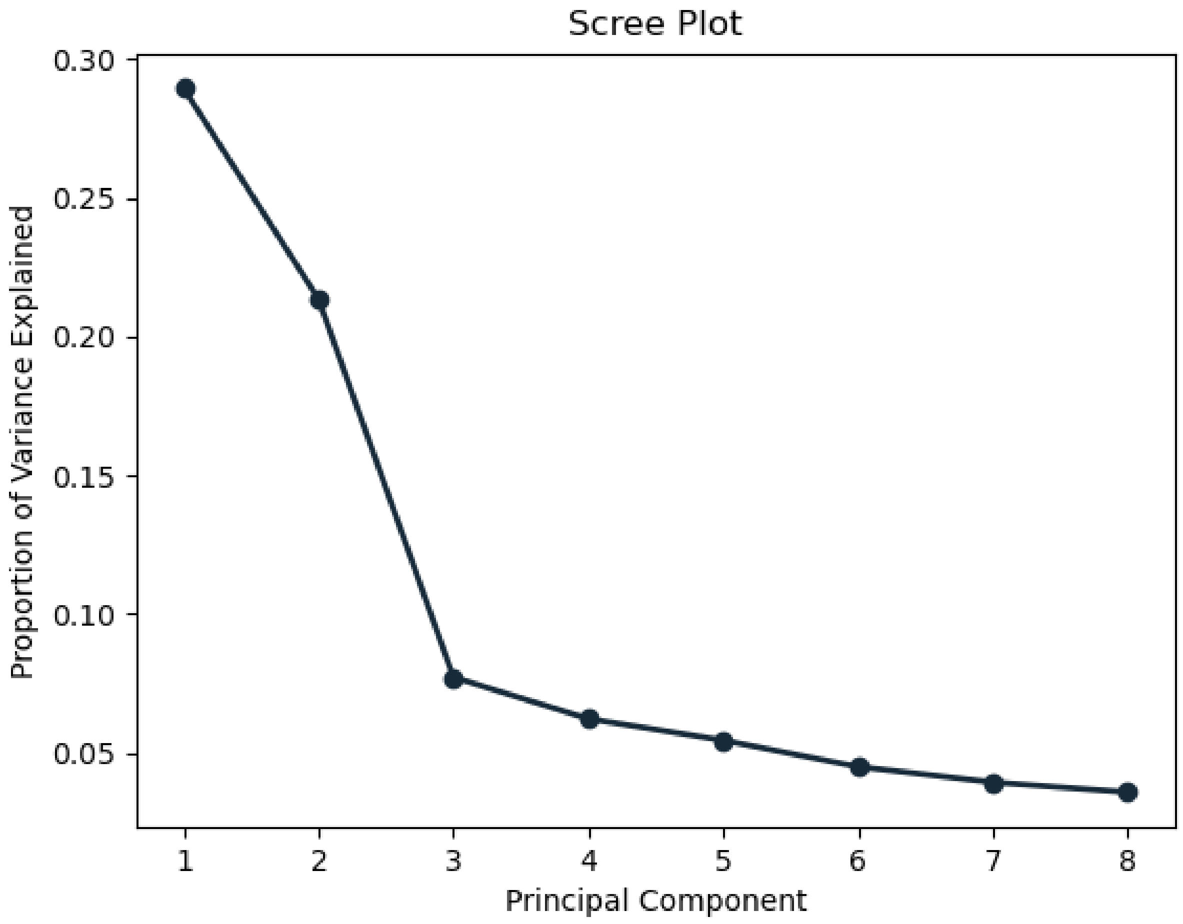
Median loan amount: $355,000
Mean loan amount: $522,0000
Mode property value: $255,000

Mortgage Application by Age

- The most common age to apply for a mortgage in between 25-34.
- Rejection and Acceptance follow the same pattern
- There is no age discrimination for mortgage applicants.



Principle Component Analysis



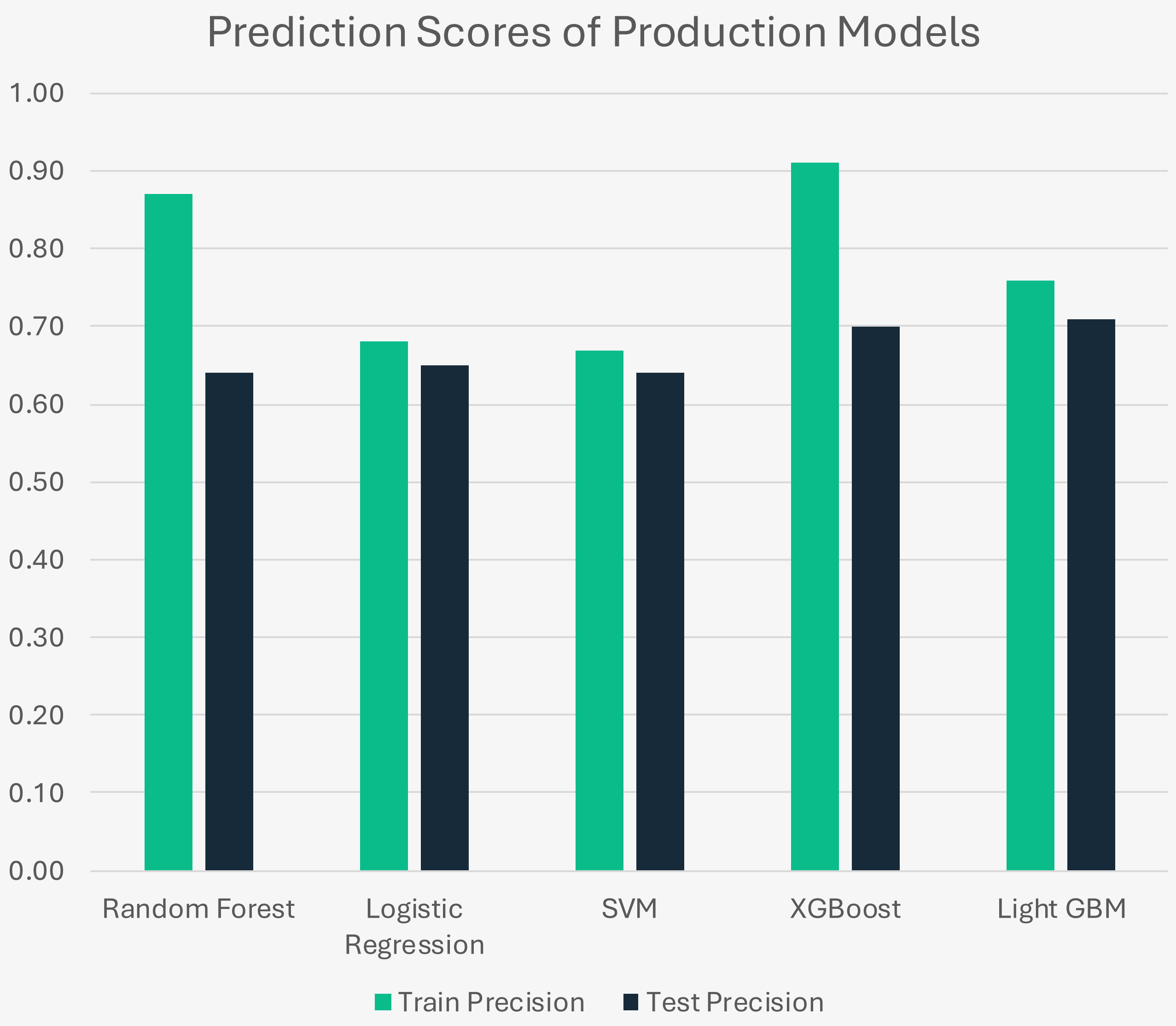
Principal Component	Proportion of Variance Explained	Cumulative Proportion of Variance Explained
PC1	0.289	0.289
PC2	0.214	0.503
PC3	0.077	0.58
PC4	0.062	0.643
PC5	0.055	0.697
PC6	0.045	0.742
PC7	0.039	0.782
PC8	0.036	0.818

Modelling

Measuring model performance

- Precision, Recall, F1 score and ROC-AUC to measure the performance.

- **Precision** measures the accuracy of positive predictions.
    - This is important in my model as a false positive would mean giving someone a prediction of approval for a mortgage and then getting denied.
    - This would be the worst outcome for my model as customers could damage their credit cores with failed applications.
    - Furthermore, it would undermine customer trust in the model/function.



Modelling

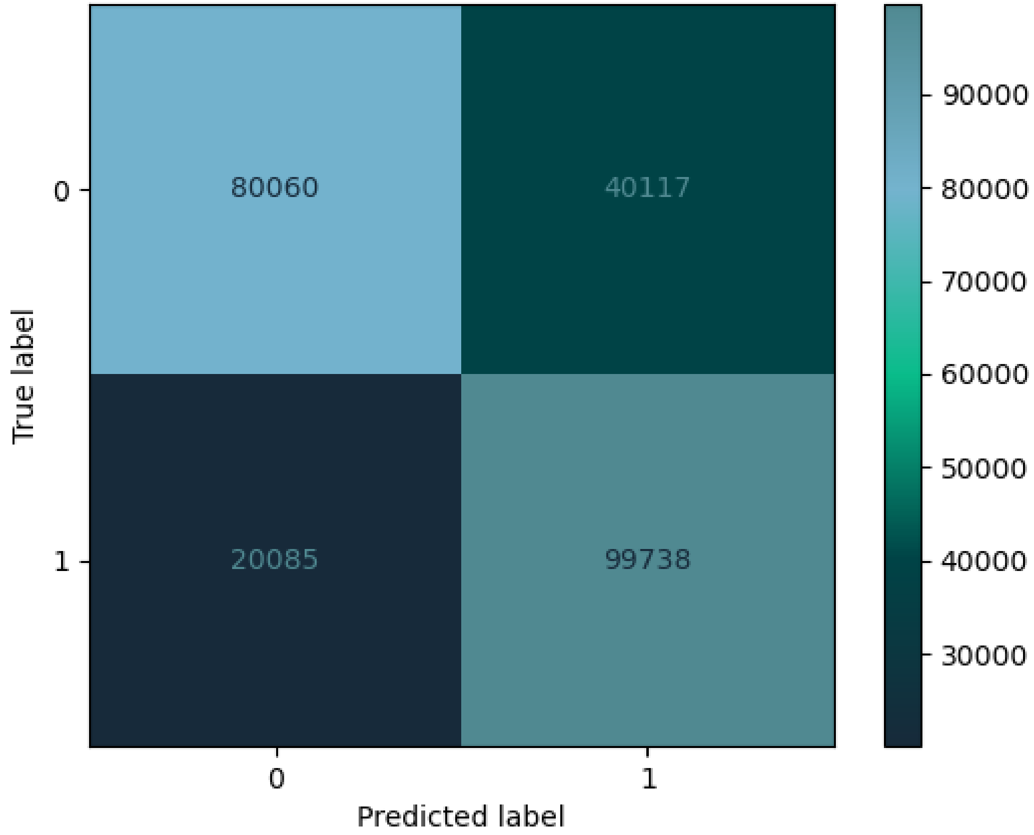
The are the supervised learning classification models tested:

- Random Forest
- Logistic Regression
- Support Vector Machine
- eXtreme Gradient Boosting
- Light Gradient Boosting Machine

Model Selection- LightGBM

- Gradient Boosting:
  - Builds models in a sequential manner where each new model corrects errors made by the previous ones.
- Leaf-wise Growth:
  - Unlike traditional boosting methods that grow trees level-wise, LightGBM grows trees leaf-wise. This means it splits the leaf with the maximum loss reduction, leading to a more complex and potentially more accurate model.
- Histogram-based Algorithm:
  - LightGBM uses a histogram-based algorithm to bucket continuous feature values into discrete bins, significantly speeding up the training process and reducing memory usage.

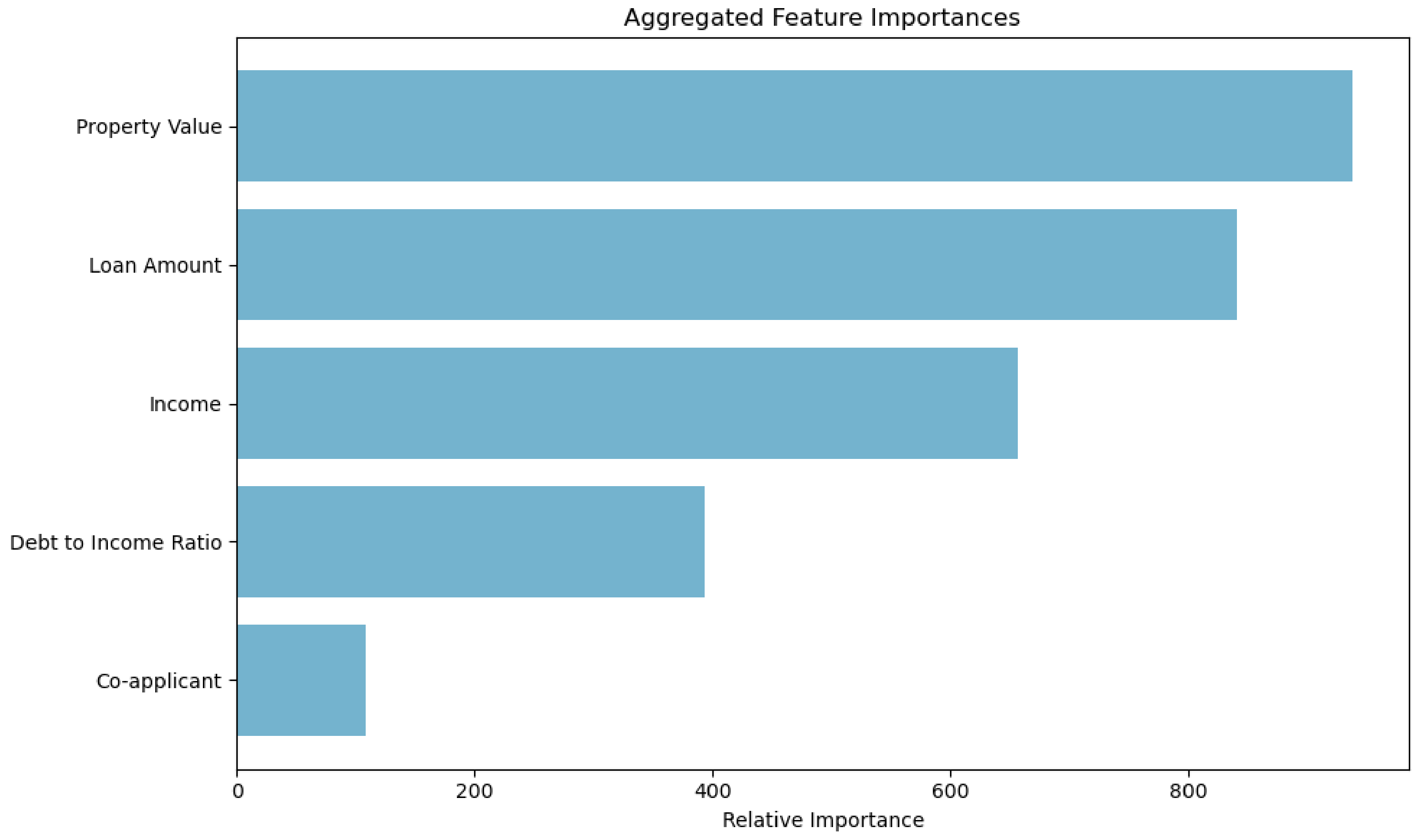
Performance Evaluation



	Precision	Recall	f1-score
0	0.80	0.67	0.73
1	0.71	0.83	0.77
Accuracy			0.75
Macro - Avg	0.76	0.75	0.75
Weighted - Avg	0.76	0.75	0.75

Model Transparency

- Model transparency is of utmost importance for this app
- Enables customers to understand the factors that made the decision.
- Property Value and Loan Amount have the largest effect on likelihood of mortgage approval.



Demo time…

Future Developments

- More time cleaning the data.
- Computational power for more model tuning.
- UK data.
- Information on macro lending decisions.


Thank you for your time
Any questions?