



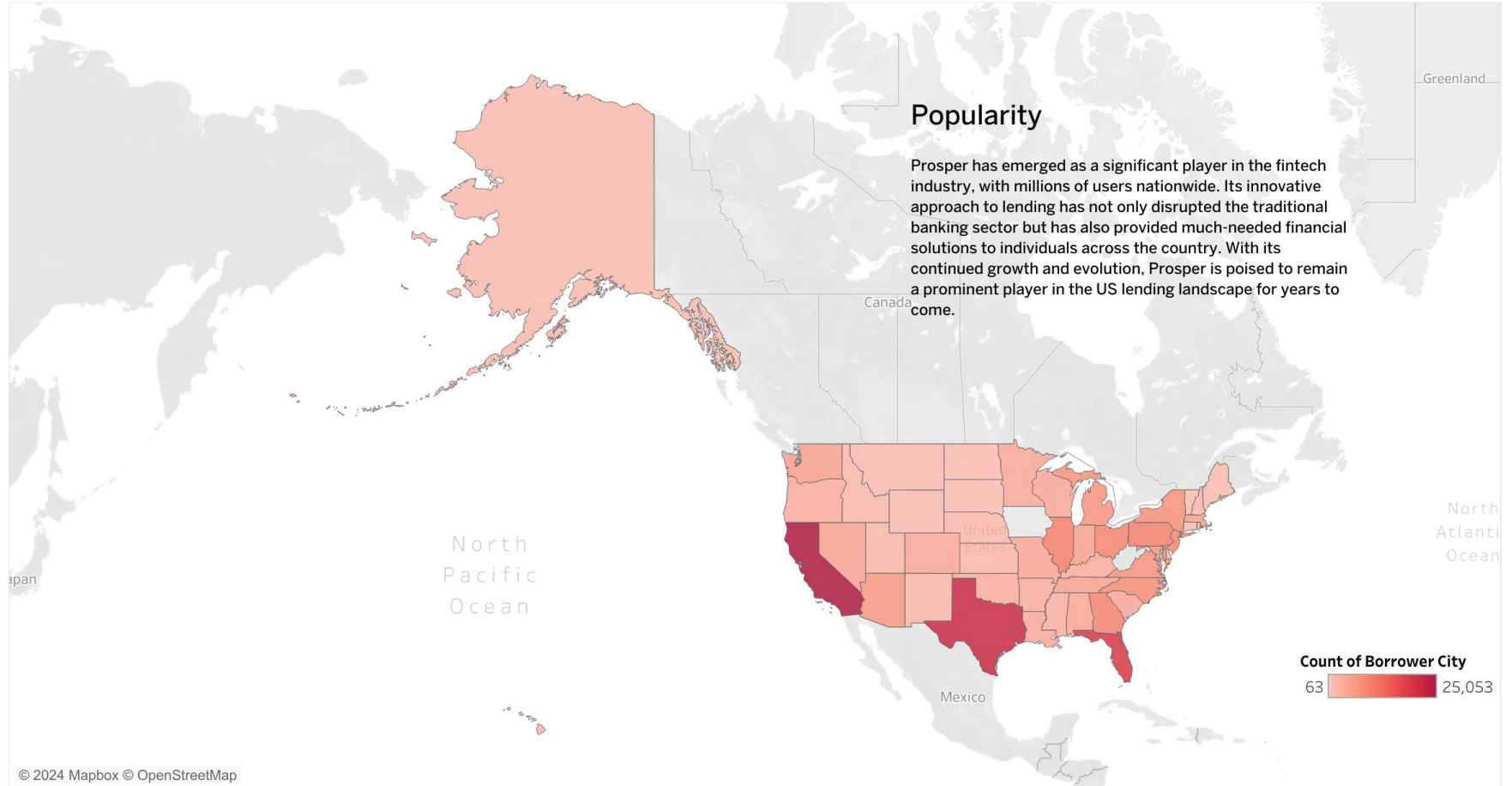
A tool for financial freedom.

WHAT IS PROSPER?

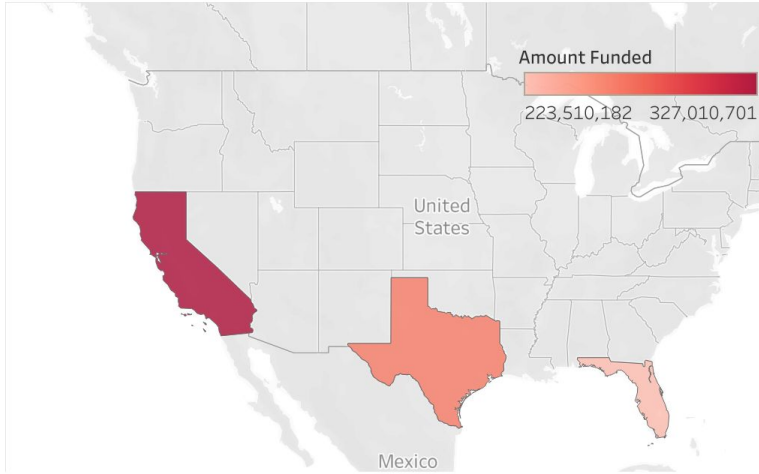
Prosper is a leading peer-to-peer lending platform, has seen a steady rise in popularity across the United States in recent years. Founded in 2005, the platform has provided individuals with an alternative to traditional banking by facilitating loans directly between borrowers and investors.

Popularity

Prosper has emerged as a significant player in the fintech industry, with millions of users nationwide. Its innovative approach to lending has not only disrupted the traditional banking sector but has also provided much-needed financial solutions to individuals across the country. With its continued growth and evolution, Prosper is poised to remain a prominent player in the US lending landscape for years to come.



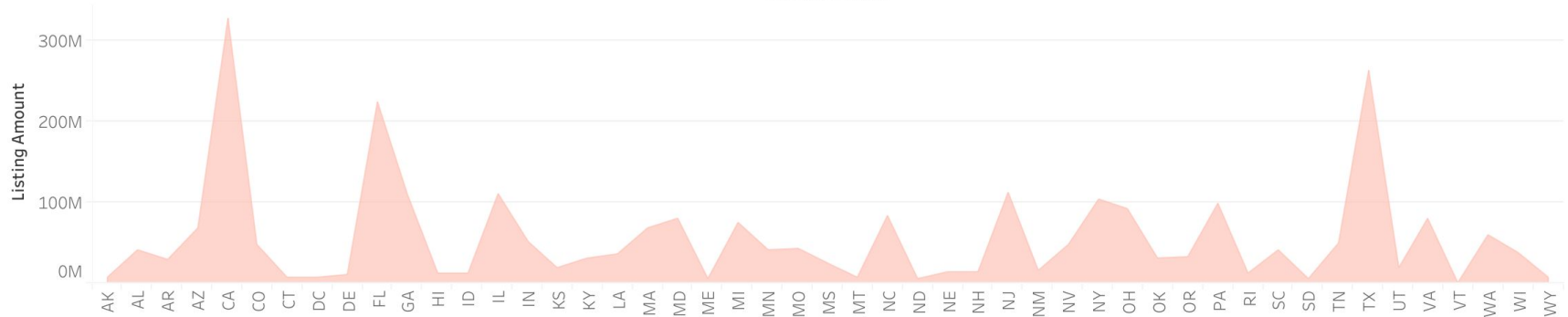
U.S States with the highest usage.

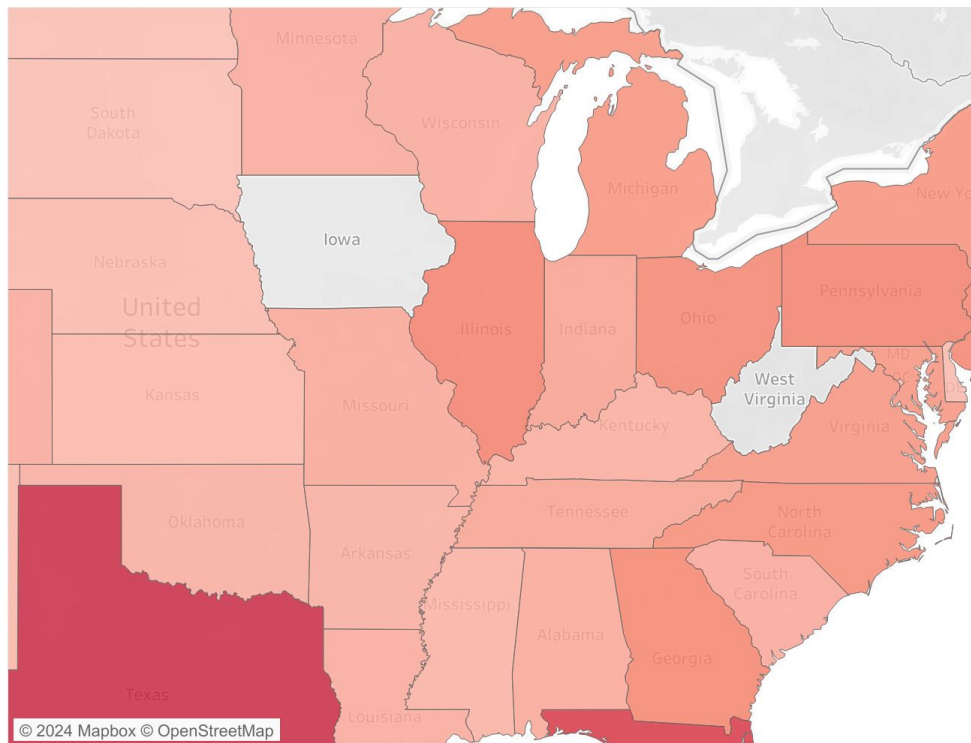


STATES OF MOST POPULARITY

Prosper has experienced significant popularity in key states like Texas, Florida, and California, reflecting its nationwide appeal. In Texas, where financial innovation is embraced, Prosper's user-friendly platform and efficient loan processing have resonated strongly with residents seeking diverse financial solutions. In Florida, a state known for its entrepreneurial spirit, Prosper's peer-to-peer lending model has attracted both borrowers and investors looking to capitalize on opportunities. Meanwhile, in California, a hub of tech-savvy consumers, Prosper's innovative approach to lending has garnered widespread attention, driving its popularity among a diverse demographic.

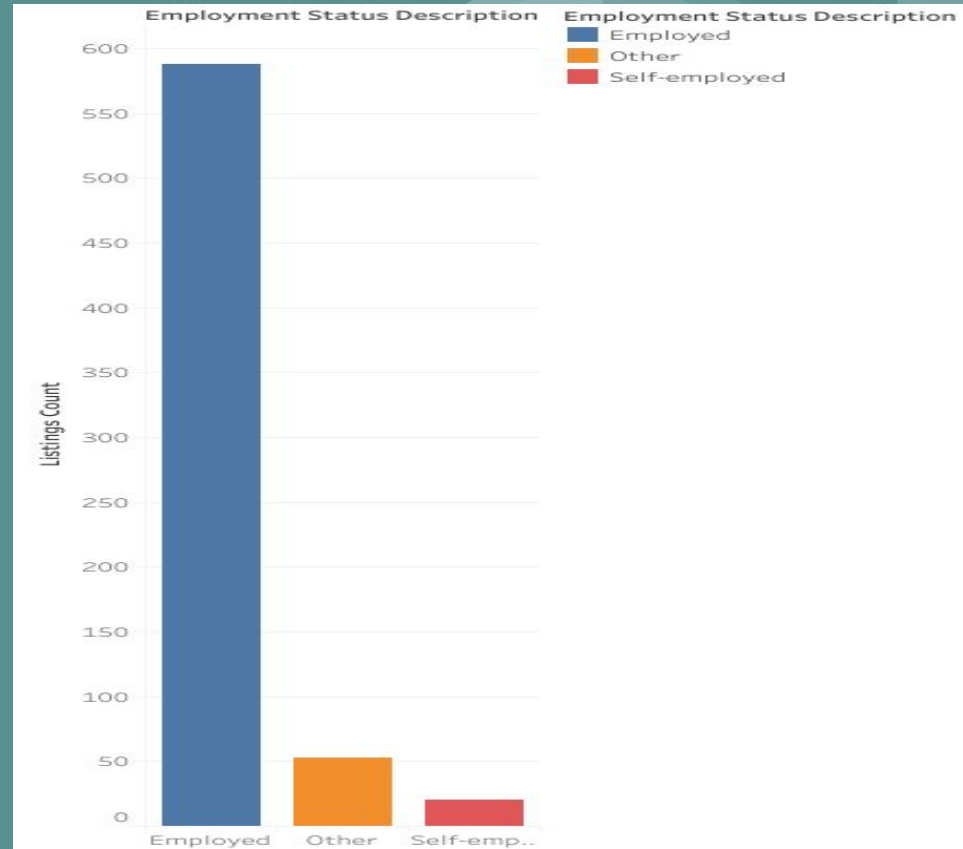
Borrower State



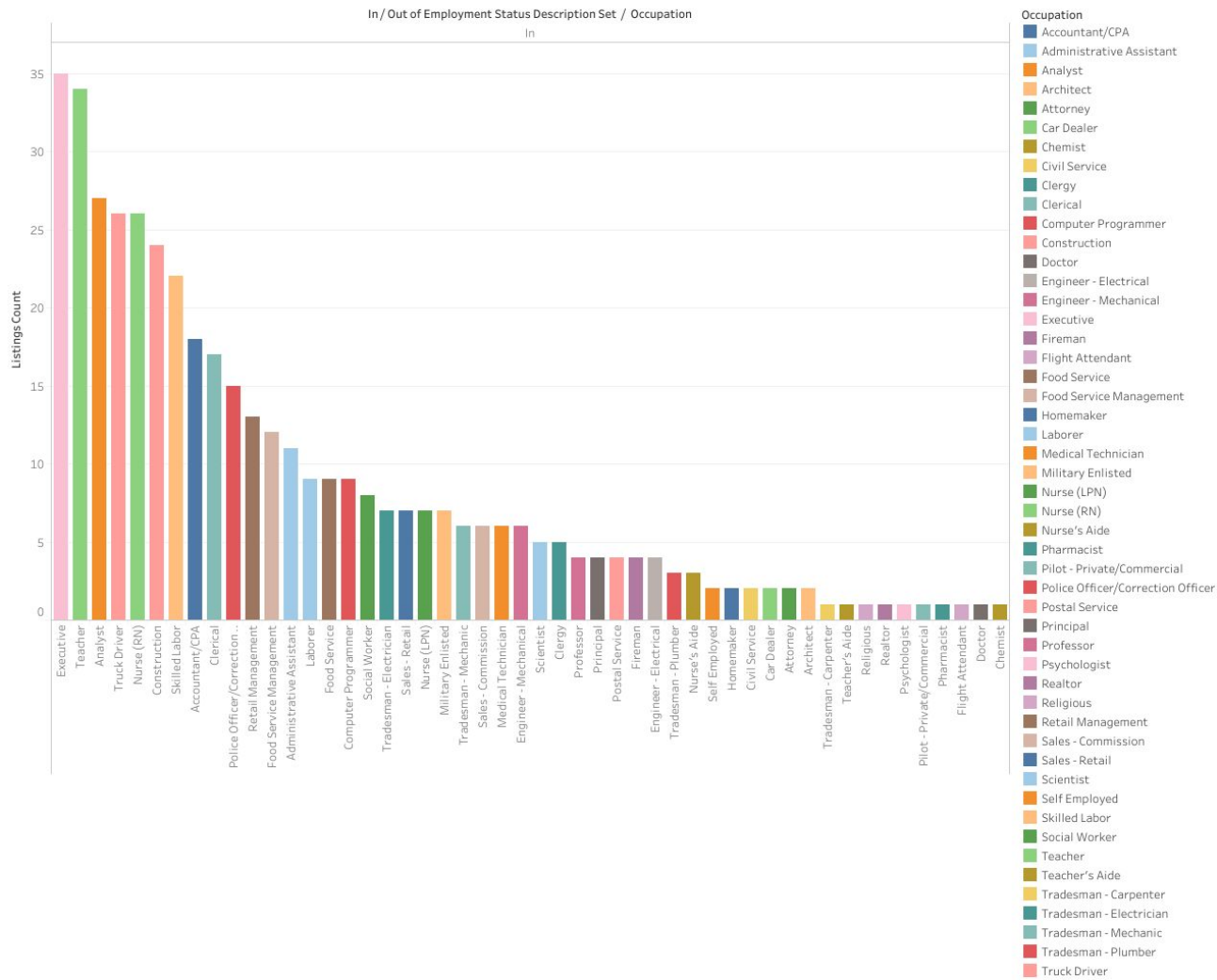


Prosper's unavailability in Iowa and West Virginia stems from regulatory restrictions specific to those states. Each state has its own set of regulations governing peer-to-peer lending platforms like Prosper. In the case of Iowa and West Virginia, the regulatory environment may present challenges or barriers that make it difficult for Prosper to operate within those states. These regulations could include licensing requirements, interest rate caps, or other compliance measures that Prosper may find prohibitive or impractical to meet. As a result, Prosper has made the decision to refrain from offering its services in Iowa and West Virginia, ensuring compliance with state laws while focusing on serving borrowers in other regions where it can operate effectively within regulatory frameworks.

A high majority of borrowers are actually employed while a few being self-employed



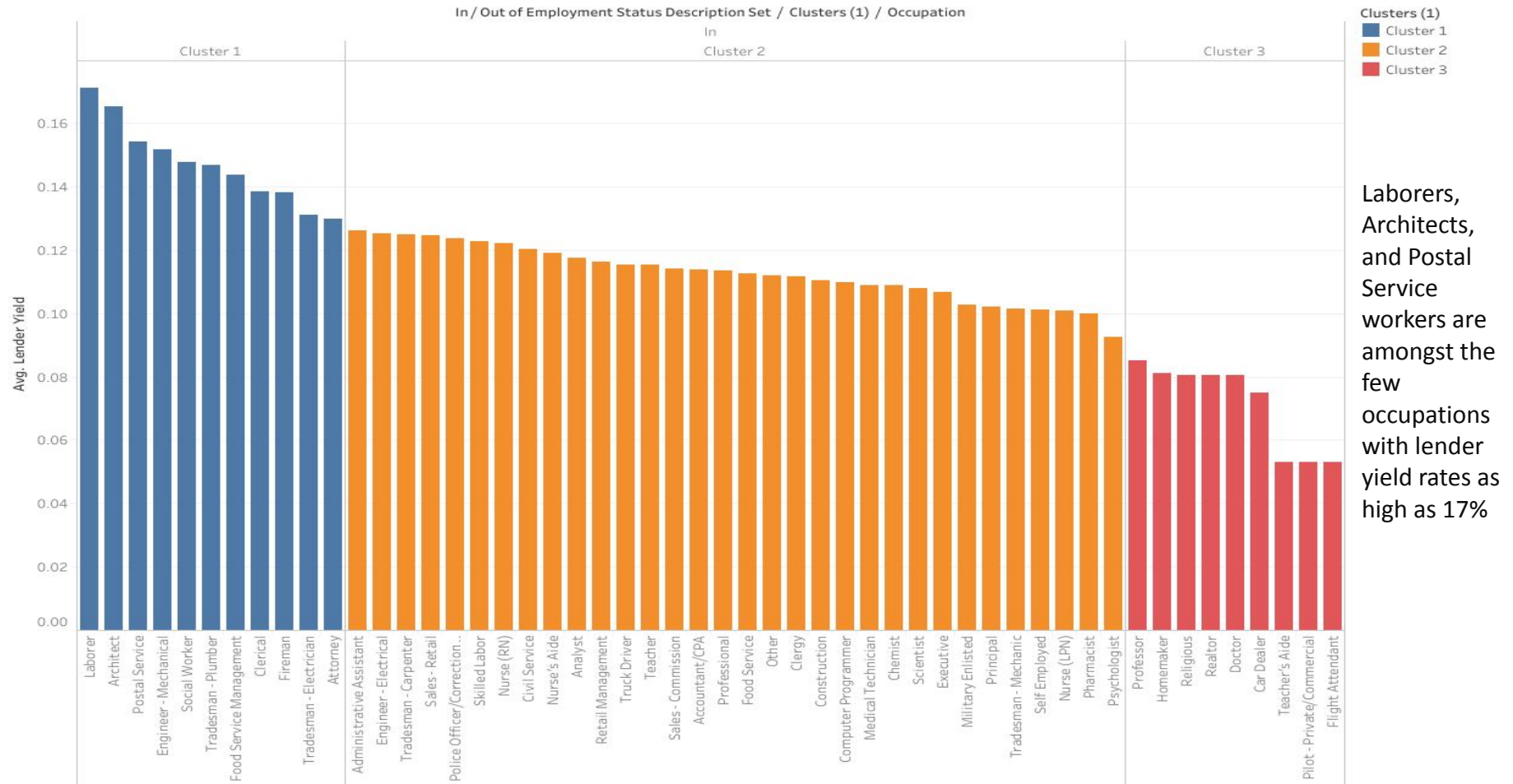
Occupational Distribution of Loan Listings



Executives borrowed a whopping \$766,900 in total.

Deep diving more into the employed borrowers, the top three borrowers based off of their occupations are Executives, Teachers, and Analysts.

Occupational Lender Yield Rates

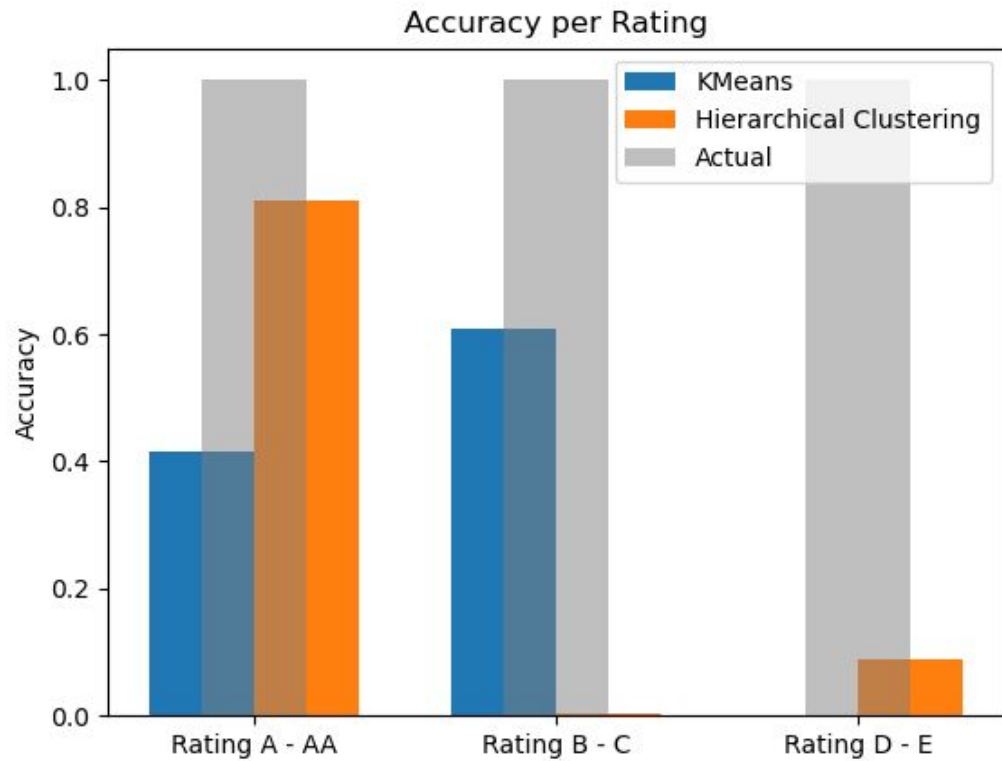


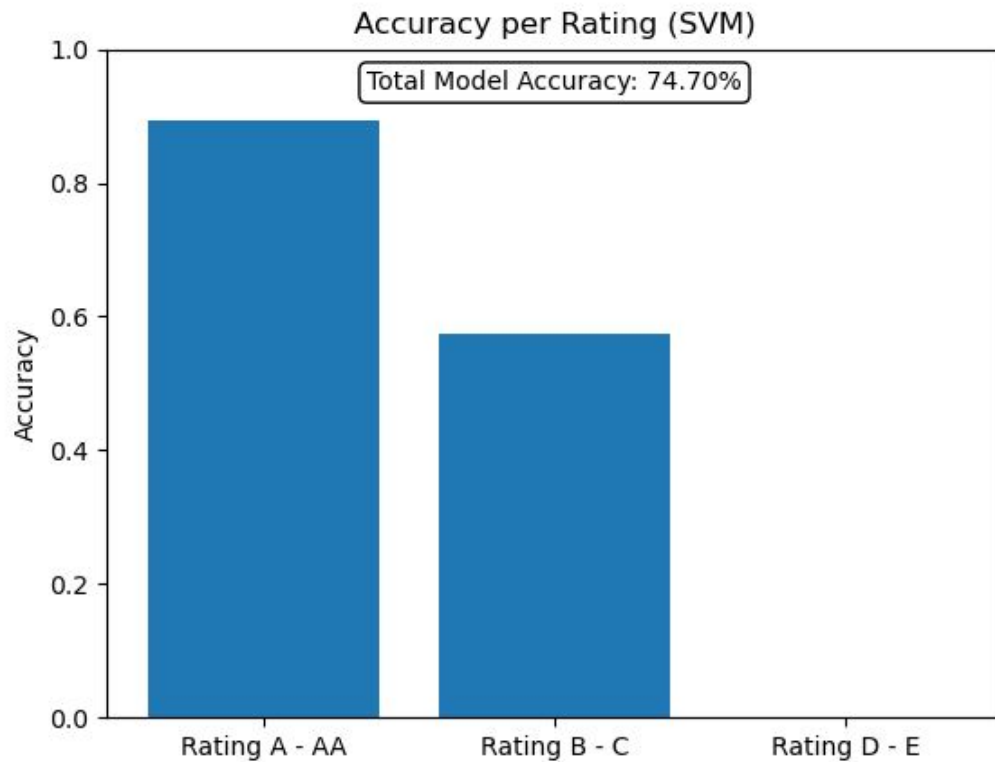


Data Cleaning/DB Setup

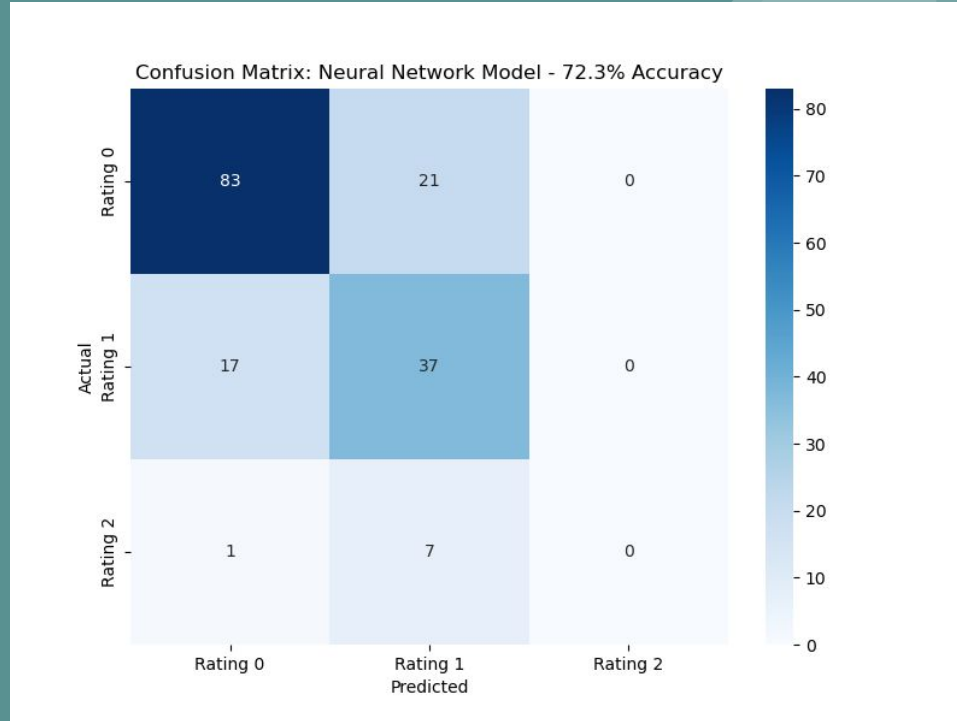
- In the data cleaning process, we transformed a raw dataset with over 200,000 rows of data into a refined one with 661 entries. Using the pandas library, we selected relevant columns and dropped any rows with missing values.
- In order to manage our data, we created an SQL database using PostgreSQL.
- To establish a connection between our python environment and the database, we took advantage of the SQLAlchemy library. Utilizing the `create_engine` function, we configured the engine to interface with our database. Using the Pandas library, we were able to extract the dataset into a pandas dataframe for further analysis.







The following confusion matrix table describes the performance of the classification model on a set of test data for which the true values are known, based on the provided data on ratings 0, 1, and 2.



Rating 0 = Safe Loans

Rating 1 = Moderate Loans

Rating 2 = Risky Loans

Pre Optimization:

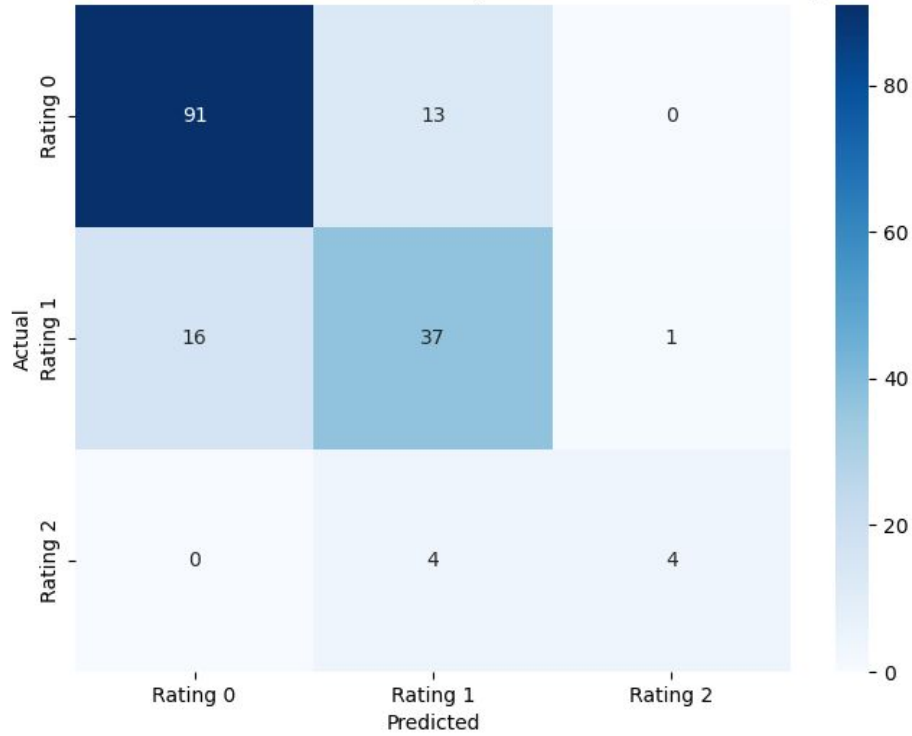
The accuracy of the neural network model on the test data was approximately 72.3%.

Rating 0 = Safe Loans

Rating 1 = Moderate Loans

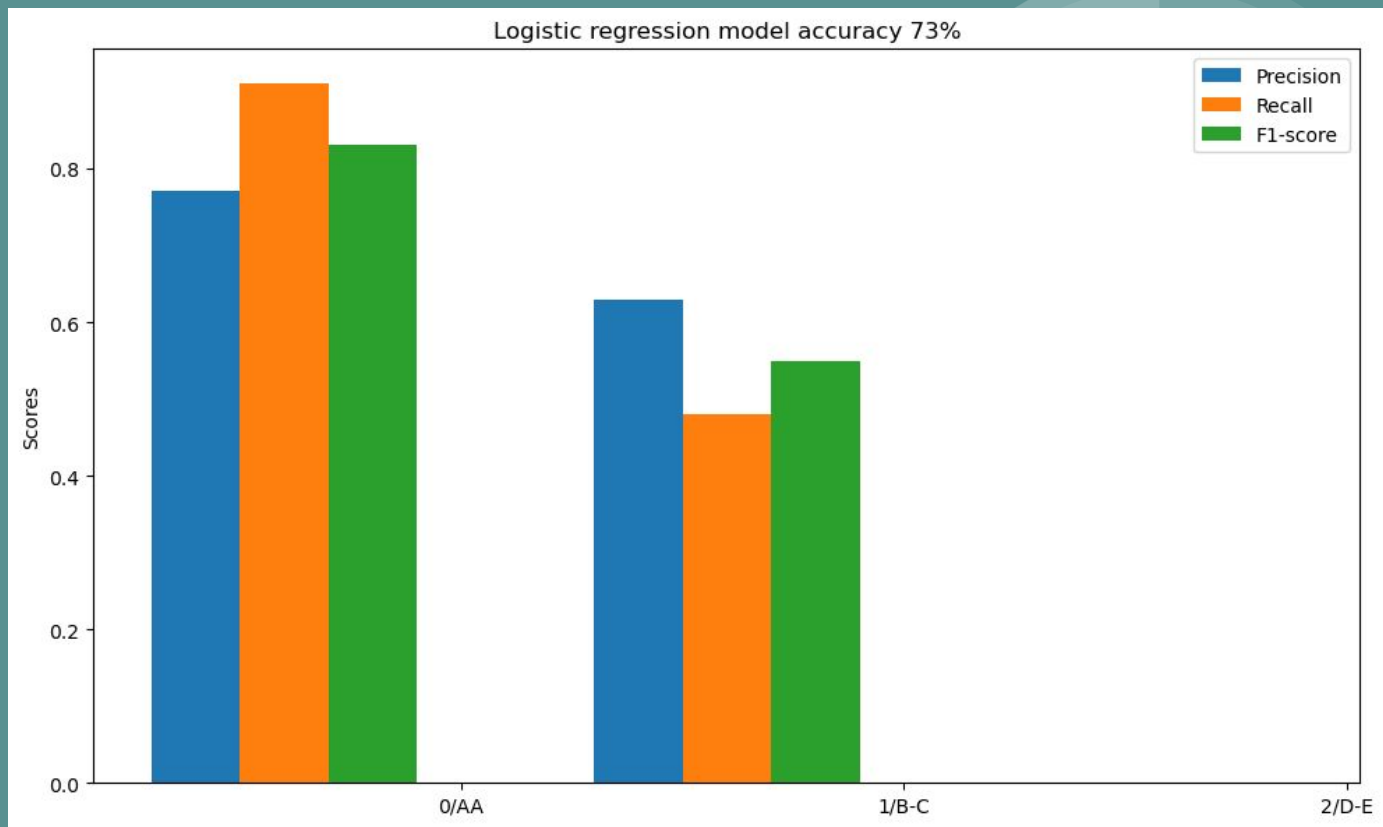
Rating 2 = Risky Loans

Confusion Matrix: Neural Network Optimization - 79.5% Accuracy



Post Optimization:

After adding an additional hidden layer to the model, the accuracy improved to approximately 79.5%.



Limitations:

- The predictive models showed limited accuracy in forecasting high-risk loans compared to those with low to moderate risk.
- One of the limitations of our dataset was having fewer rows of data for the high risk listings.

