PREDICTING FUNDING TIME FOR MICRO-LOANS

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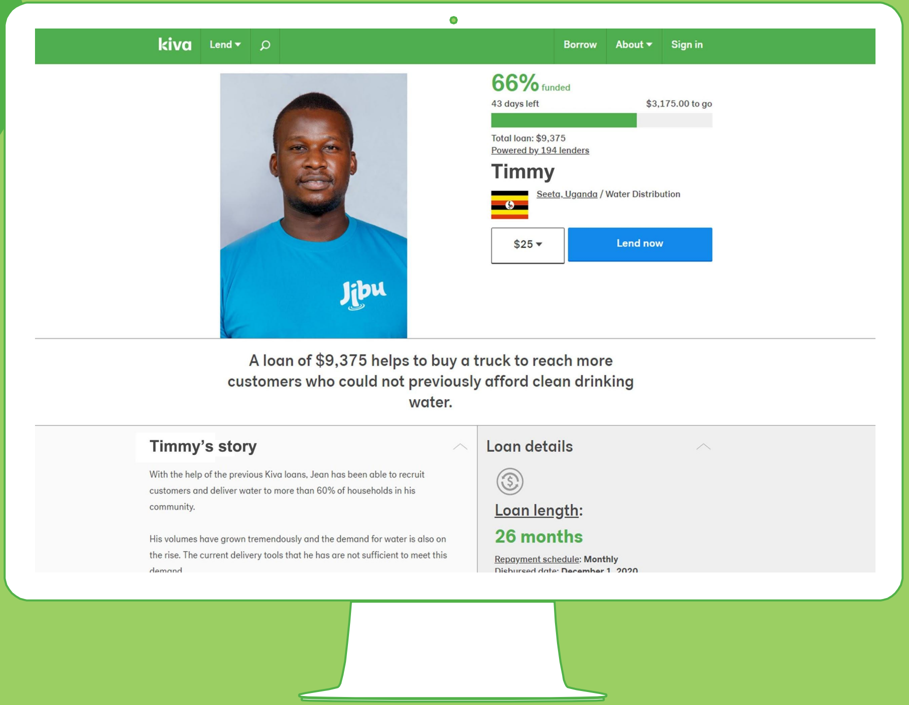
Problem Statement

PREDICTING FUNDING TIME FOR MICRO-LOANS

Microlending is a form of peer-to-peer financing that has seen continued expansion over the past couple of decades. Microloans are most commonly granted to impoverished borrowers who typically lack collateral.

Kiva.org is an internet-based microlending platform that was founded in 2005. Since Kiva's inception, they have processed almost 2 million loans via their platform in over 75 countries. Similar to other microcredit organizations, Kiva promotes a 95.8% repayment rate and over 1.9 million lenders.

While most of the loans processed through Kiva's site are $500 or less, there are many factors which may affect the time to funding besides just the loan amount. **Kiva has reached out to us to help them build a predictive model which will ultimately be implemented as a tool for borrowers. We have been tasked to build a predictor that will help borrowers estimate the total time required to fund a loan.**



Kiva.org

This screenshot shows what a typical borrower page looks like. Borrowers fill out a profile including items such as some personal information, country, activity the loan will be used for, loan information, etc.

$1.5 billion

In loans

1.9 million

Lenders

95.8%

Repayment rate

1.
Data Discovery and Cleaning

Data Discovery

- Data “snapshot” from Kiva
- 1.96 M loans from 2006 - August 2020
- 1.85 M funded loans from 99 countries

Data Cleaning

Trimmed Columns

First, we trimmed the unnecessary columns to reduce our dataset size; We also dropped all loans with no ‘raised time’.

Funding Status

Next, we dropped loan statuses of ‘expired’, ‘refunded’, and ‘fundraising’, only keeping ‘funded’ loans.

Date Calculation

We then calculated the total time to raise the loan and manipulated the date time information to calculate ‘hours to fund’.

Images / Videos

We coded all image and video IDs to just represent whether an image or video was included.

Mapping Genders

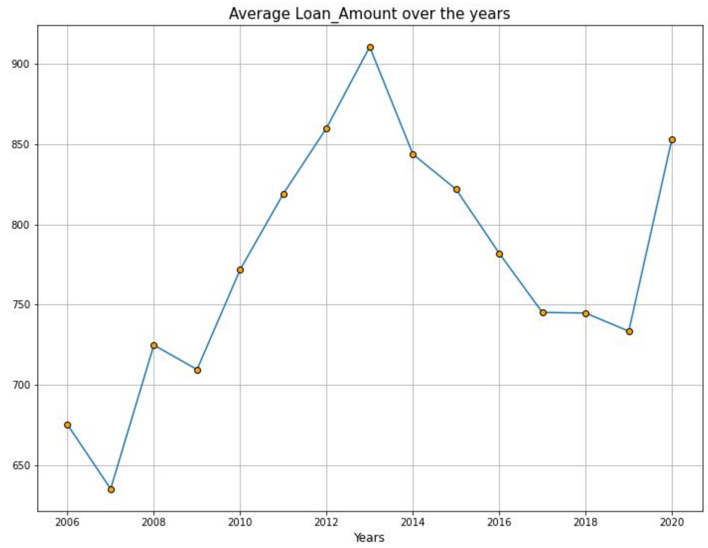
Genders were mapped to a single character; individual females and males were mapped to ‘F’ and ‘M’, respectively; multiple borrowers were mapped to ‘G’.

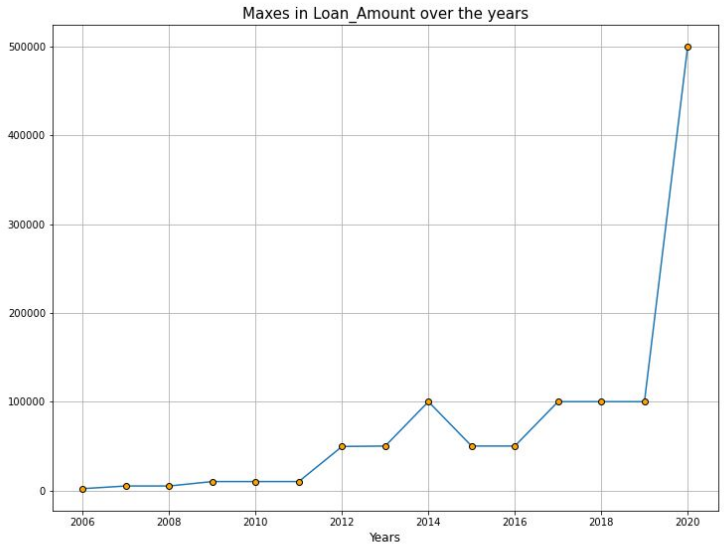
Dropping Columns

Any remaining columns that were no longer needed or used were drop to limit the dataset file size.

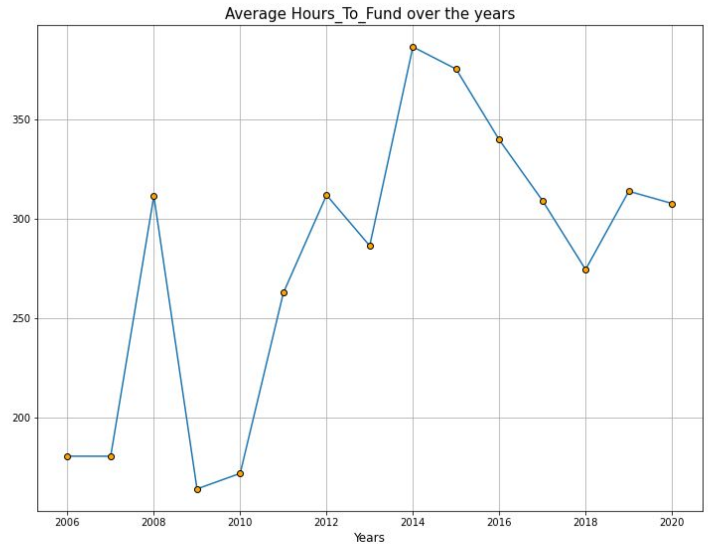
2.
Exploratory Data Analysis

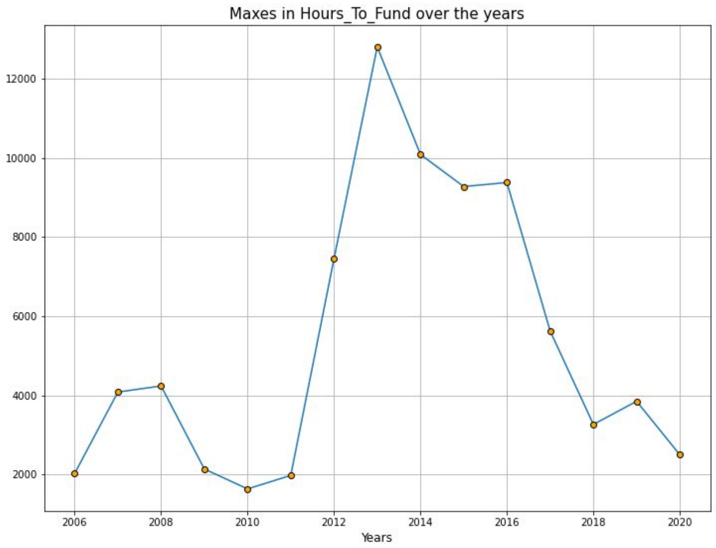
Average and Maximum Loan Amounts, by Year



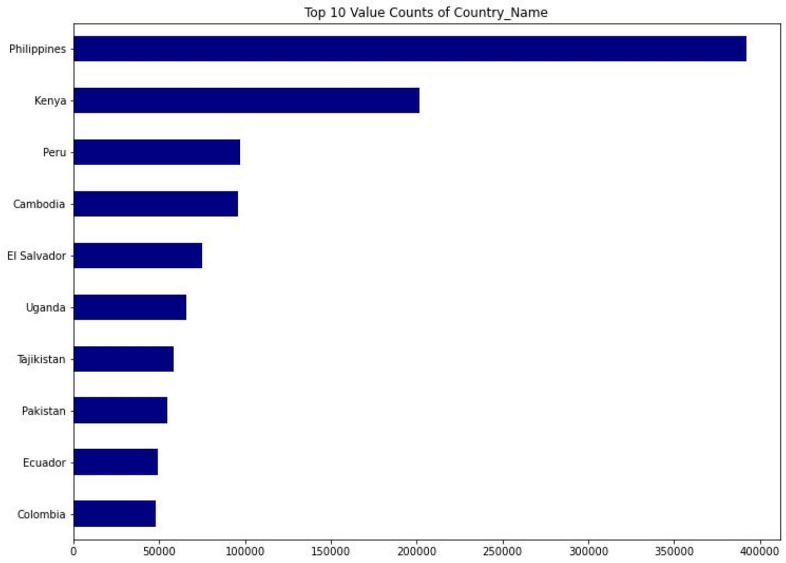


Average and Maximum Hours To Fund, by Year

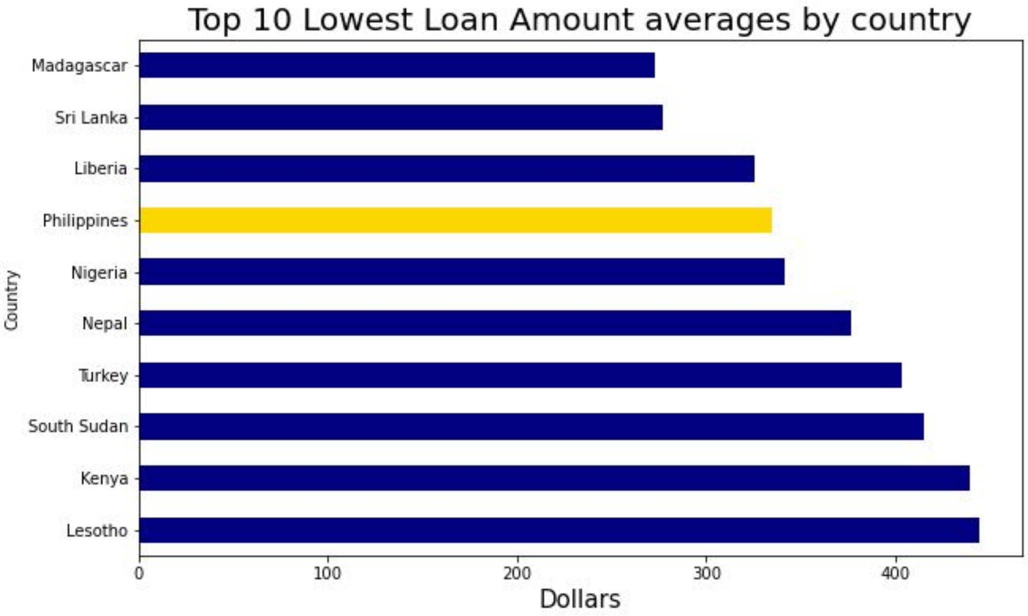




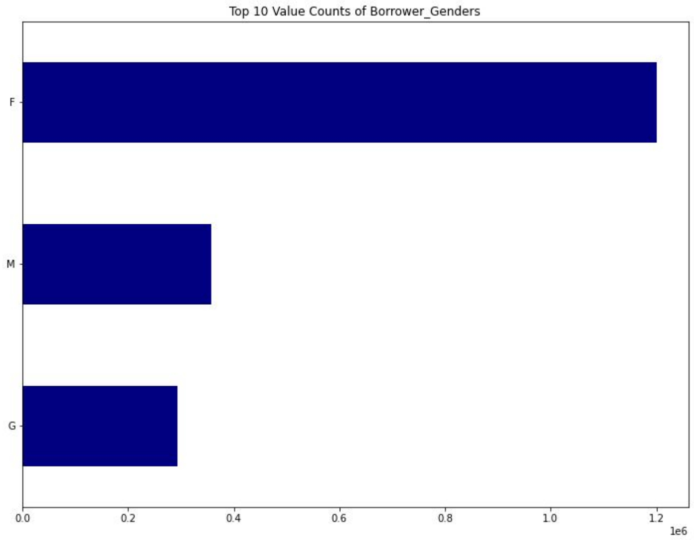
Loans by Country

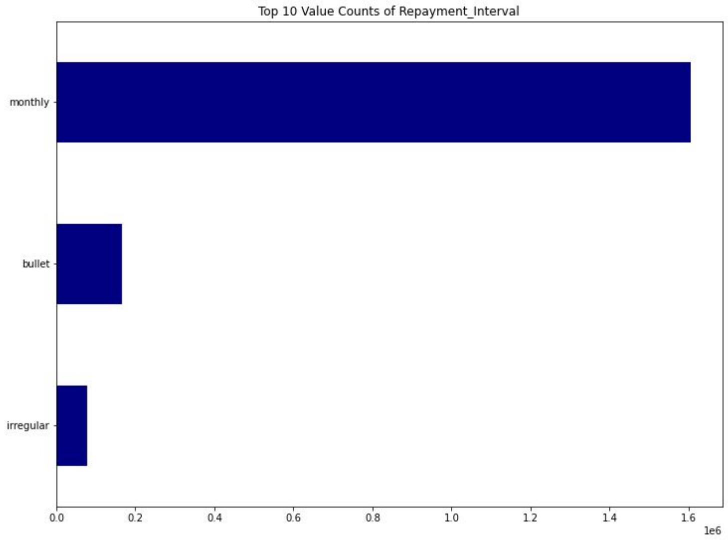


Lowest Average Loan Values by Country

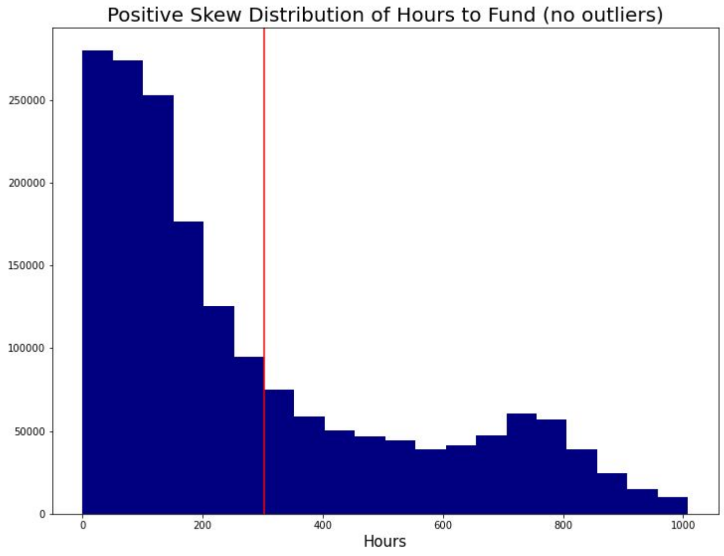


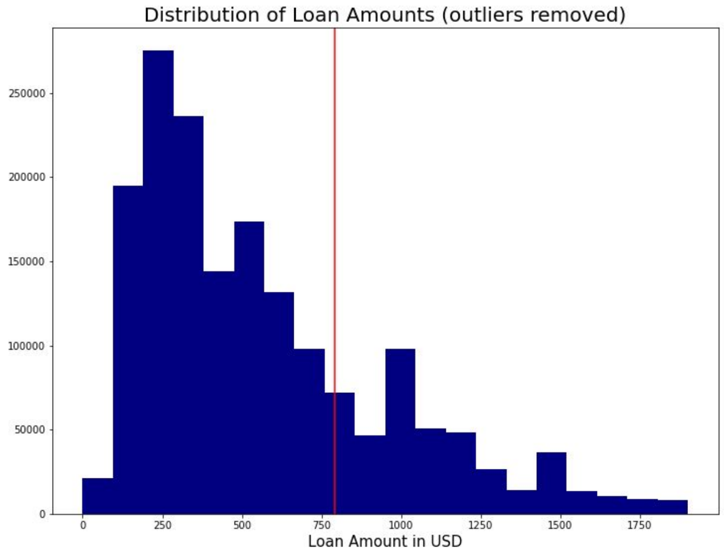
Borrower Genders and Repayment Interval Distributions





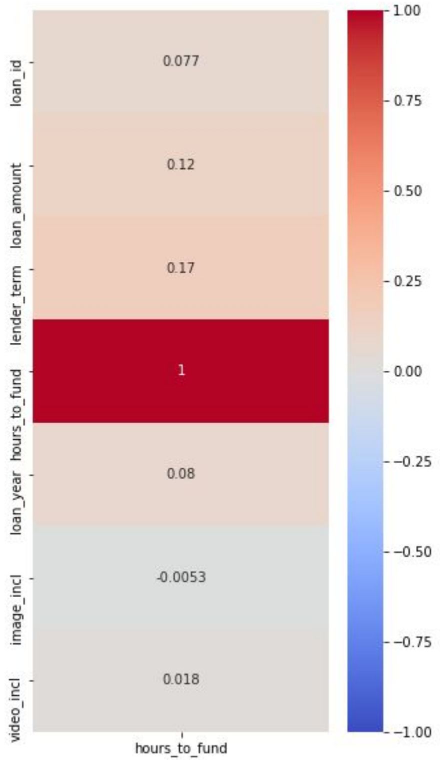
Hours to Fund and Loan Amount Distributions





- Loans <= 1008 hours to fund
- Loans < $2000

Correlations Between Numerical Features



3.
Modeling and Tuning

Parametric Models

- Models
  - OLS Linear Regression
  - GLM Poisson
- Fast to run; easy to understand and interpret
- Works better with highly correlated, numeric data

Non-parametric Models

- Models
  - Decision Tree
  - Bagging Decision Tree
  - Random Forest
- Can result in better models for prediction
- Slower to train

Model Metrics Comparison

	RMSE	R2
OLS Linear Regression	298	.163
GLM Poisson	277	N/A
Decision Tree	280	.344
Bagging Decision Tree	282	.343
Random Forest	283	.353

4. Conclusion

Conclusion

- Non-parametric models performed better
- Still significantly underperforming for a production model
- Outside factors may lead to unpredictability in time to fund for loans

Next Steps

- Development of a non-parametric neural network model.
- Learn about their lending process.

Thanks!

ANY QUESTIONS?