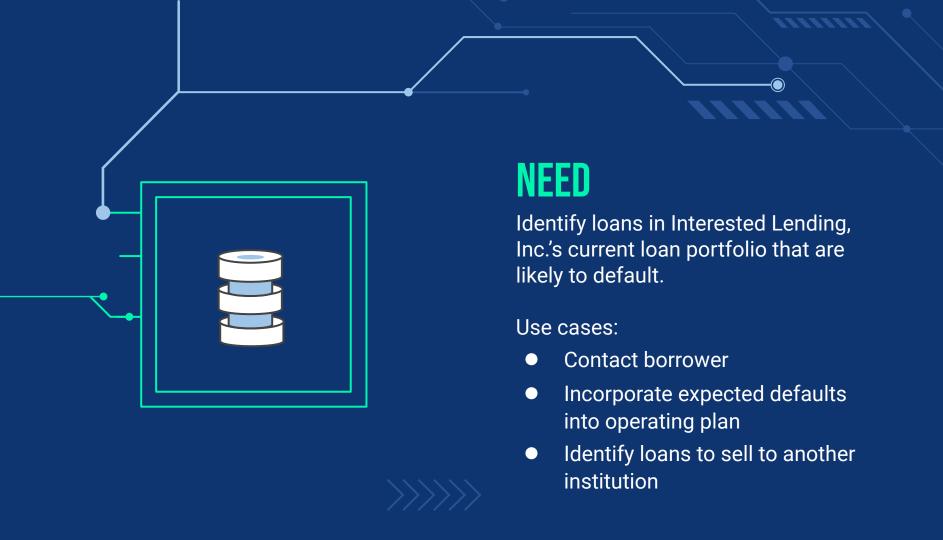
LOAN DEFAULT CLASSIFICATION

Manveer Sadhal Oct 29, 2021



DATA AND SCOPE

DATA

- Snapshot of 887,000+ individual loans.
- Filtered to approximately 250,000 loans.
- 73 columns reduced to 19 features for final model (e.g. annual income, interest rate)

SCOPE

- Current and closed loans
- Model developed with closed loans (fully paid, charged off, or defaulted).

METHODOLOGY PANDAS NUMPY MATPLOTLIB **SCIKIT-LEARN SEABORN** DATA **EVALUATE FINAL EXPLORATION & BASELINE ALTERNATE MODEL** MODEL **FEATURE MODELS SELECTION SELECTION**

XGBOOST

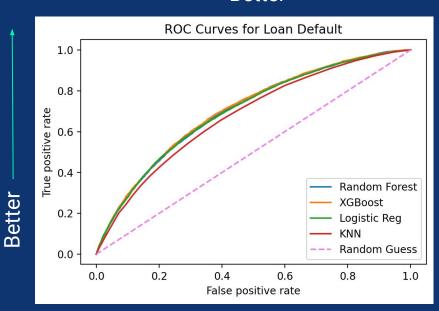
TUNE,

CROSS-VAL

& TEST

RESULTS

Better



- Logistic regression model, random forest, and XGB had nearly identical performance.
- Logistic regression selected simpler, more interpretable.

RESULTS (LOGISTIC REGRESSION)

| | Precision | Recall | F1 | |
|-----------------------|-----------|--------|------|--|
| Paid | 0.89 | 0.63 | 0.74 | |
| Default or Charge Off | 0.29 | 0.66 | 0.40 | |
| Accuracy | 0.63 | | | |
| Macro Average | 0.59 | 0.64 | 0.57 | |
| Weighted Average | 0.78 | 0.63 | 0.68 | |

Tuned to maximize F2 Final score: 0.52

RESULTS

| Feature | Coefficient |
|----------------------------|-------------|
| Interest Rate | 0.469 |
| Annual Income | -0.284 |
| Total Number of Accounts | -0.187 |
| Term of 60 months (vs. 36) | 0.176 |
| Debt to Income Ratio | 0.174 |

INTERACTIVE STREAMLIT APP

| Loan Default Classification | | |
|--|------|---|
| Enter information below. Default prediction will be displayed at the bottom of the scr | een. | |
| Annual income (USD) | | |
| 0 | | + |
| Number of accounts in collections within past 12 months (excluding medical) | | |
| 5 | - | + |
| Number of delinquencies over 30 days in the last two years | | |
| 29 | - | |
| Debt to income ratio | | |
| 29 | - | + |
| Credit inquiries in the last 6 months | | |
| 5 | - | + |
| Interest rate (%) | | |
| 29.00 | - | |
| | | |

| Number of open credit lines in borrower's file | | |
|--|---|---|
| 46 | - | + |
| Number of derogatory public records | | |
| 5 | - | + |
| Revolving debt utilization (%) | | |
| 62 | - | + |
| Total number of credit lines in borrower's file (open or closed) | | |
| 16 | - | + |
| Total number of accounts currently delinquent | | |
| 5 | - | |
| Loan Term (months) | | |
| 60 | | - |
| Loan Grade | | |
| G | | * |
| Installment (USD) | | |
| 1215 | - | + |
| Loan is expected to default! | | |

CONCLUSIONS

- Model offers predictive capability for approved loans that may go into default
- Most impactful features can inform loan screening process
- Possible actions for loans likely to default:
 - Borrower outreach
 - Identify loans to sell to other institutions
 - Account for expected loan defaults in operating plan

FUTURE WORK

- Additional feature engineering
- Model stacking
- Develop separate model to evaluate whether high risk loans should be sold
- Add functionality to app to allow user to upload CSV with data on multiple loans rather than inputting one at a time.

THANKS!









Do you have any questions?

addyouremail@freepik. com +91 620 421 838 yourcompany.com

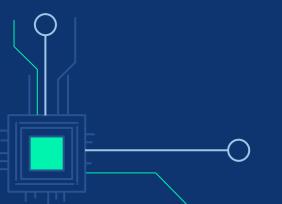
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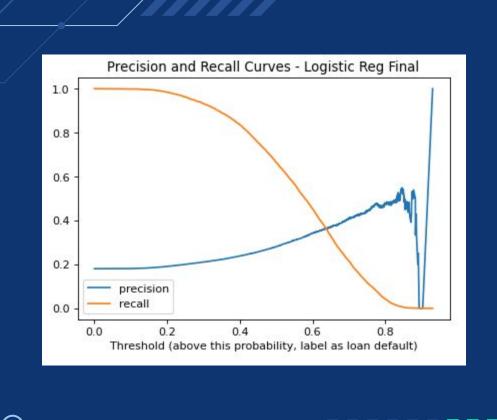




APPENDIX









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