UCLA ANDERSON MFE APPLIED FINANCE PROJECT

WITH MOTOLEASE LLC

CREDIT ANALYSIS:

CONSUMER CREDIT DEFAULT PREDICTION USING MACHINE LEARNING

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AGENDA

1. Motivation
2. Data and Features
3. Methodology
4. Conclusion

MOTIVATION

CONSUMER CREDIT MODELING

- **Definition:**
  - Likelihood the person will default on their debt
- **Data/factors:**
  - Credit activity
    - Credit mix, credit balances, payment patterns
    - Bankruptcy filings, collection items
    - Credit inquiries
  - Financial personal information (e.g. income)
  - Non-financial personal information (e.g. education level)
- **Usage:**
  - Mortgages
  - Credit cards, installment loans, etc.
  - Automobile and other vehicle financing

TYPICAL MEASUREMENT – CREDIT SCORE

- **Definition:**
  - A numerical value based on a person's credit files' analysis in order to represent the creditworthiness of an individual

- **Types:**
  - **FICO:** 300 – 850
  - **Experian:** 330 – 830
  - **Equifax:** 300 – 850
  - **TransUnion:** 300 – 850

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EXAMPLE – FICO SCORE

- Calculated based on consumer credit files of Experian, Equifax, and TransUnion
- Used by the major banks and credit grantors
- General components:
  - 35%: payment history
  - 30%: debt burden
  - 15%: length of credit history
  - 10%: types of credit used
  - 10%: hard credit

EXAMPLE – FICO SCORE

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THE CLIENT

- **MotoLease LLC** originates and services motorcycle leases
- Significant investments into software-based credit decision systems
- Ability to make most credit decisions in 60 seconds
- 90% approval rate
- Leases offered through a network of dealers

MOTIVATION

- Typical consumer credit score models are not specialized for motorcycle financing industry
- Certain factors not considered for credit scores may be useful for predicting defaults on motorcycle leases

MAIN OBJECTIVE

- Derive and identify **2 to 5 new features** from MotoLease's data to add to their current existing model
- Ensure our model is robust to missing data
- Develop and enhance machine learning model to improve accuracy of default prediction

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DATA AND FEATURES

DATA DOMAIN

- Data on 16,000 lease applicants
- Leases were funded between March 2015 and September 2017
- Default status is determined one year after the lease was funded
  - 42% default rate
- Default status is binary and defined by MotoLease
  - Recovery rates are out of scope
- Each lease has a unique identifier for mapping to input datasets

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DATA STRUCTURE

- Output dataset
  - Default vs. non-default leases (16,000 x 9)

- Input datasets
  - Credit scores (included in Default vs. non-default leases)
  - Tradelines (210,000 x 33)
  - Inquiries (140,000 x 12)
  - Collections (65,000 x 28)
  - Credit summary (18,000 x 42)

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AN ILLUSTRATION OF OUR DATA STRUCTURE

» **Input data:**

Tradelines (shown below), Inquiries, Public Records, Collections, Credit Summary

Id	Account type	Utilization ratio
5123	Credit card	34%
5123	Credit card	12%
5123	Mortgage	N/A
5123	Auto loan	N/A
651	Mortgage	N/A
651	Mortgage	N/A
52	Credit card	60%

» **Output data:**

Default vs. Non-Default Leases

Id	Defaulted
5123	0
651	0
52	1
99	1

CHALLENGES RELATED TO DATA STRUCTURE

- Data is not provided in a flat format
  - I.e. one table with $Y, X_1, X_2, X_3, \ldots X_N$
  - Varying amounts of data are available for different applicants
- Categorical variables have hundreds of different values
  - E.g. lender name, account type, creditor industry
- There are interactions between variables
  - E.g. credit card balance has other coefficient than mortgage balance

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OUR APPROACH TO FEATURE ENGINEERING

- Create as many features as possible, take care of overfitting in a separate step
- Brainstorm within our team and research credit agency methodologies
- For categorical variables, create subtotals and counts for the most common values only
  - Include count(credit cards)
  - Exclude count('401k Loan Repayment')

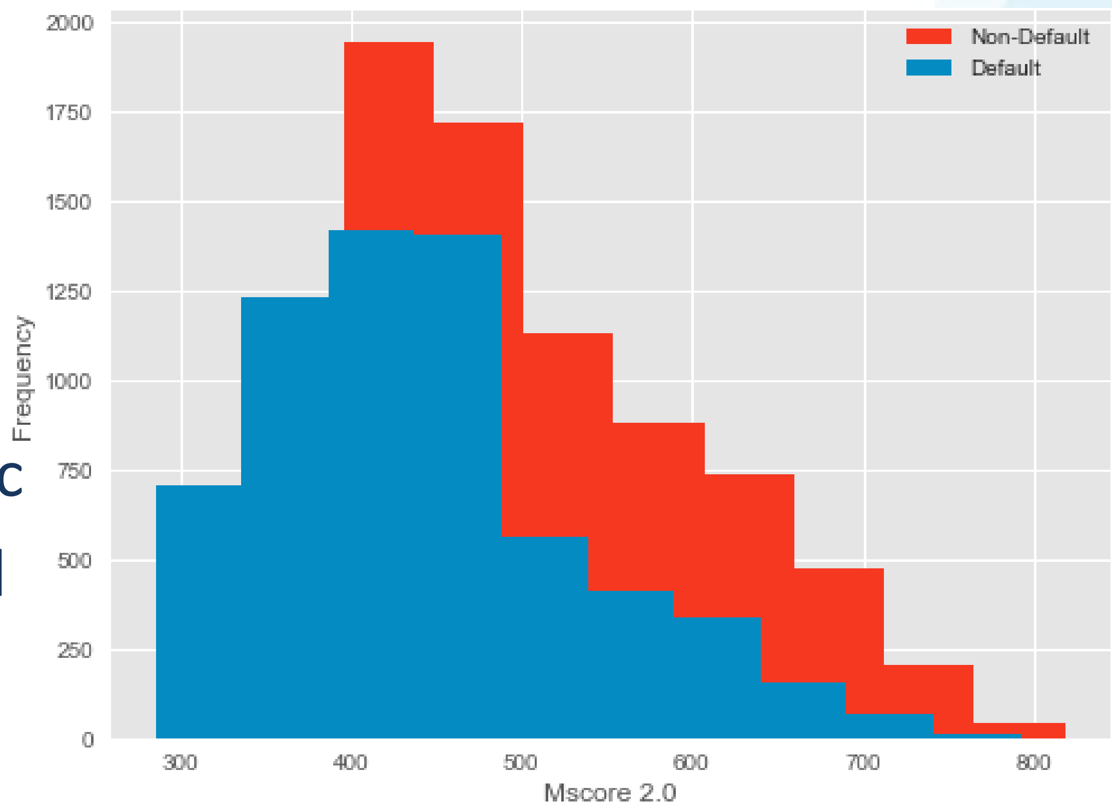
UNIVERSE OF FEATURES

# of features	% N/A	Type of features
9	0	External credit scores, payment-to-income, debt-to-income
2	0	Counts of collection items, separated by collection item status
6	0	Counts of credit inquiries, separated by type of credit
8	0	Sums/means/maxima of past due amounts, balances, limits, monthly rates, high credit
5	0	Ratios of balance sums/means/maxima to limits, high credit
18	0	Counts of tradelines, separated by tradeline status, lender types, account types, loan types, ownership types
2	0	Features on frequency and range of tradeline open dates
10	0	Payment pattern
23	4	Various utilization ratios, from alternative data source
12	4	Various counts of tradelines, public records, inquiries, from alternative data source
95	**4**	**Total**

METHODOLOGY

KOLMOGOROV-SMIRNOV (K-S) STATISTIC

- K-S test
  - determine if two data-sets differ significantly
  - Non-parametric
  - KS statistic and P value



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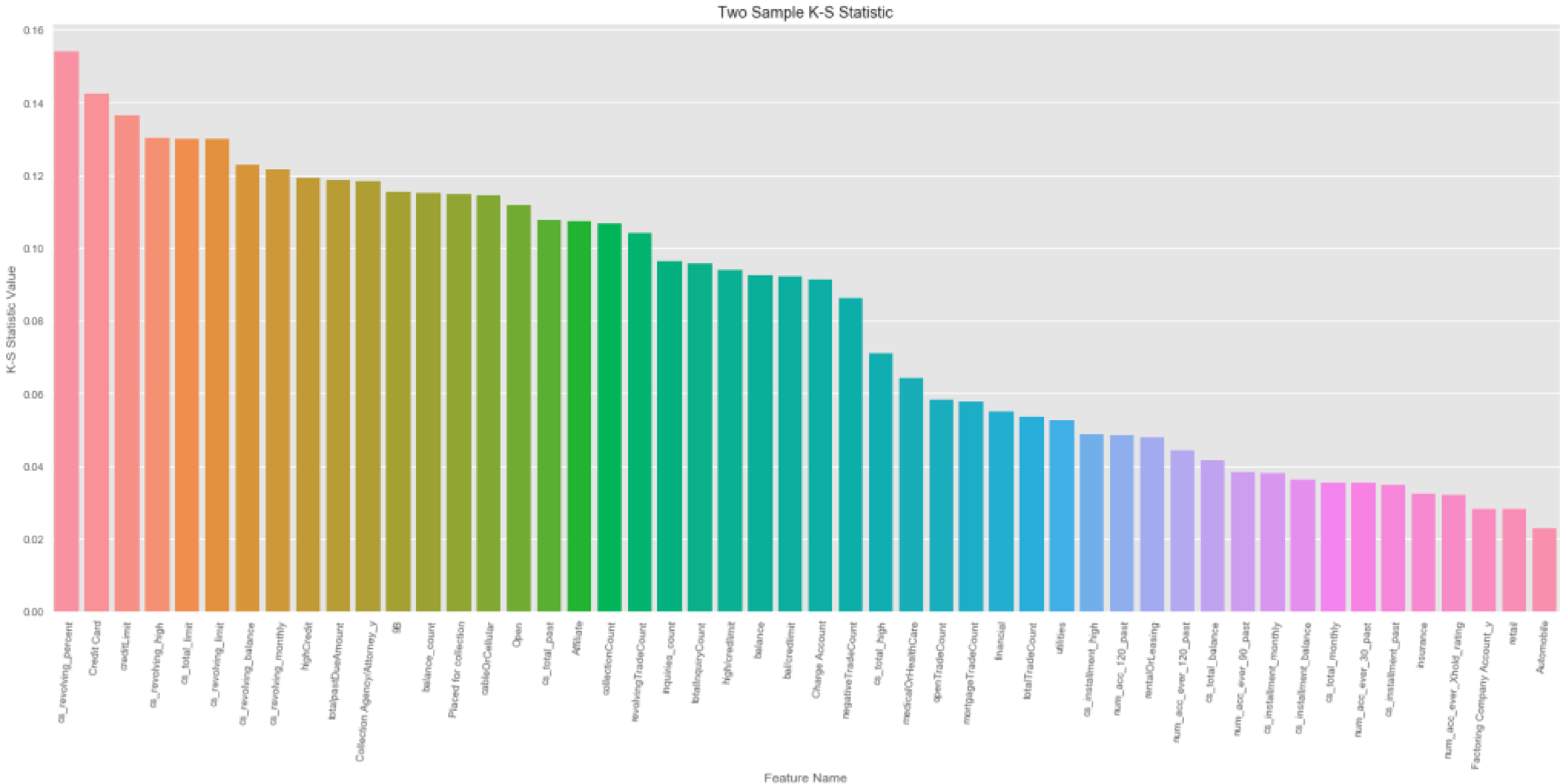
FEATURE SELECTION

- Sort on KS statistic
- Number of tree splits

TOP FEATURES BY K-S



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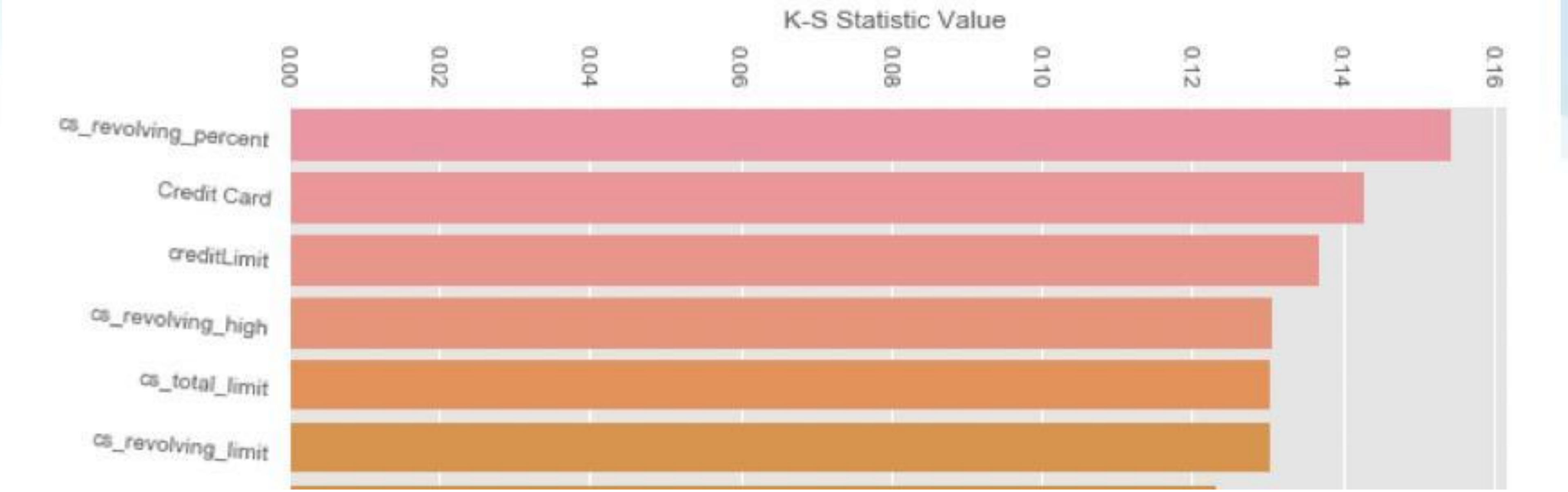
TOP FEATURES BY K-S



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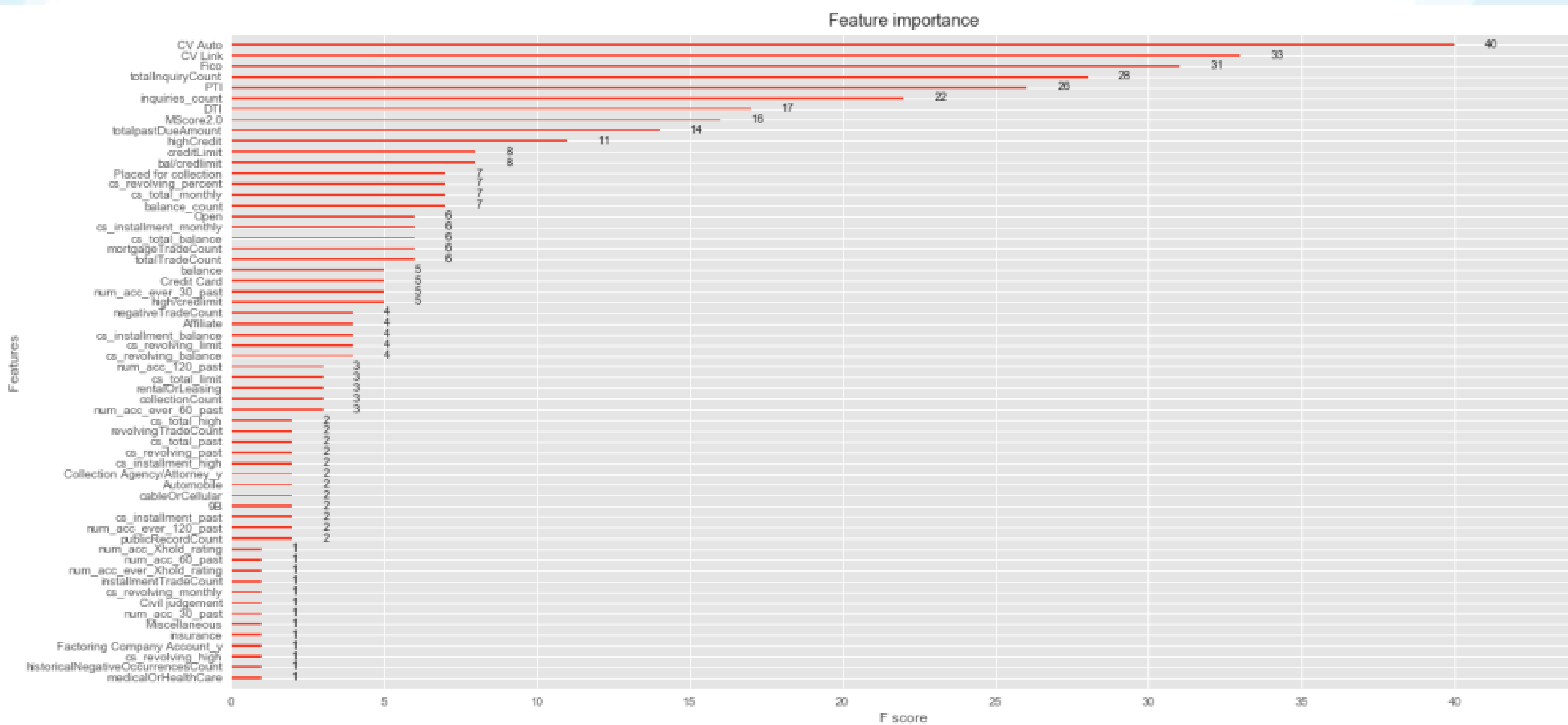
TOP FEATURES BY TREE SPLITS



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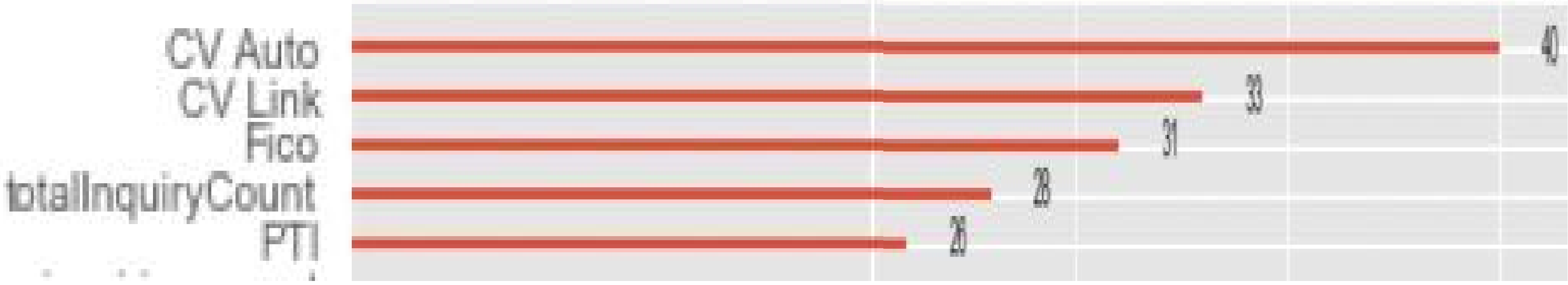
TOP FEATURES BY TREE SPLITS



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FEATURE SELECTION FOR MSCORE

- **Goal**
  - Identify 2-5 features to improve the MSCORE
  - Metric AUC - TPR vs FPR
- **Approach**
  - Top ~25 features ranked by K-S/tree splits
  - $\binom{25}{5}$ Logistic regressions, ~53k
  - Compared AUC of top feature combinations

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MACHINE LEARNING TECHNIQUES

- **Models**
  - Logistic Regression
  - XGBoost
- **Cross-validation**
  - Tune the number of gradient boosting rounds
- **Bayesian Optimization**
  - Tune the hyperparameters
- **Bootstrap Aggregating** (Bagging)

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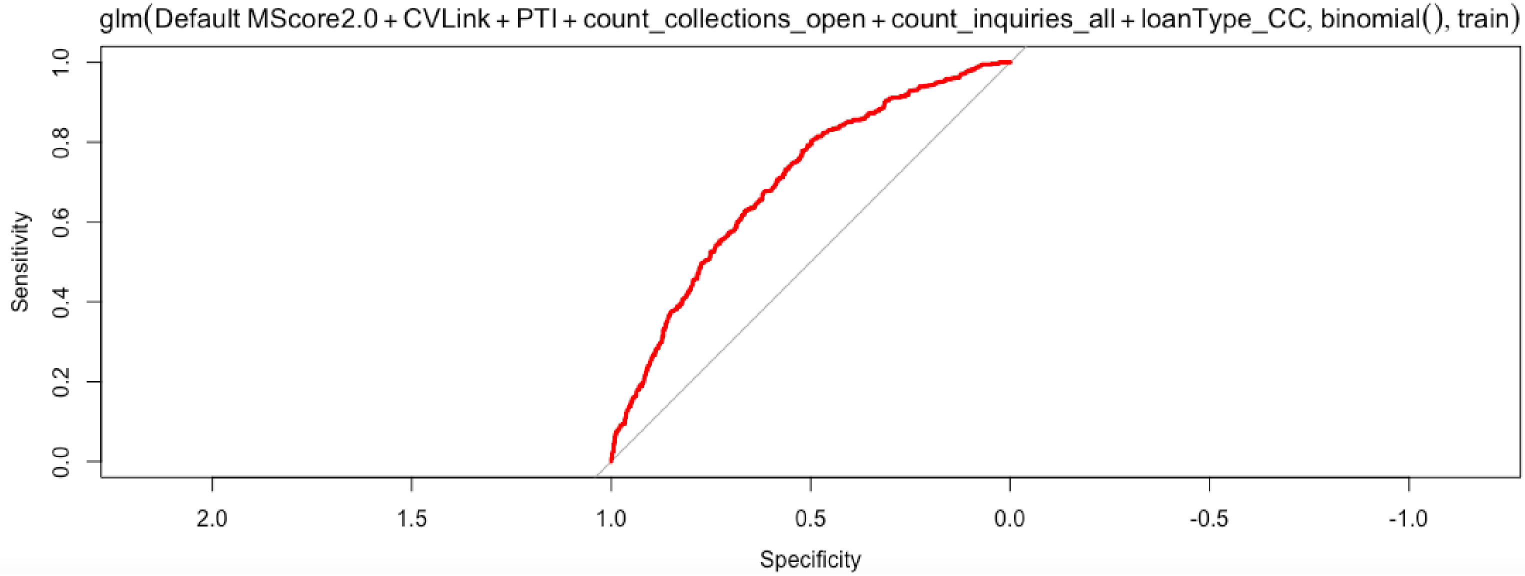
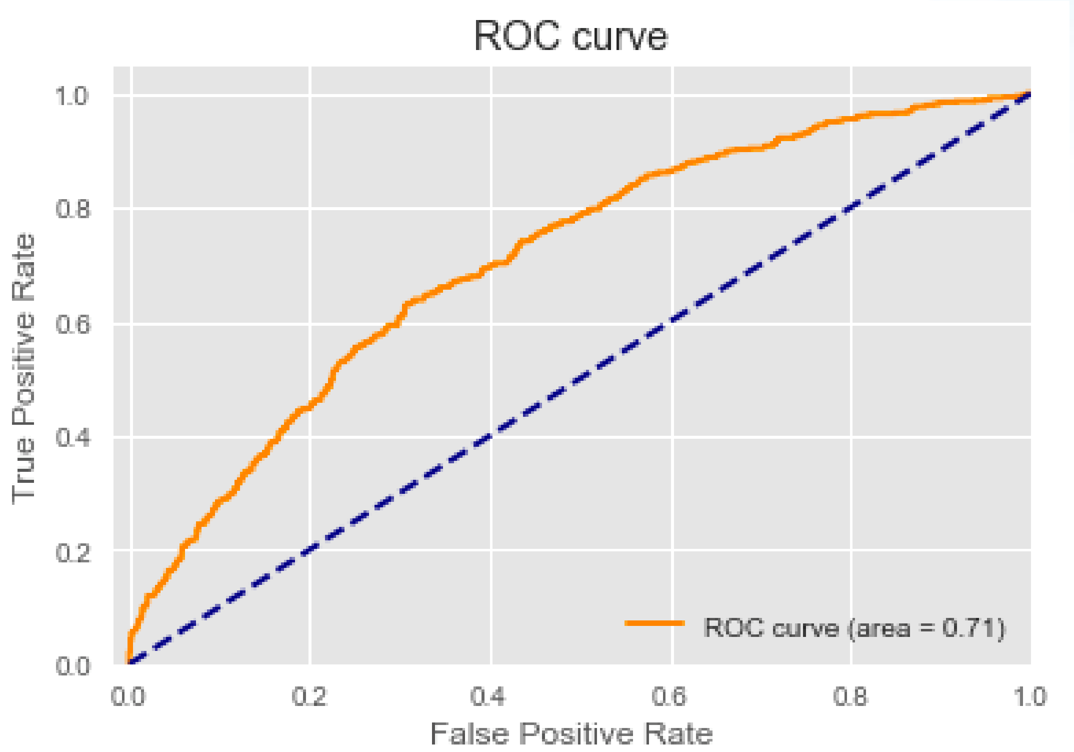
MODELS

- **Logistic regression**
  - AUC = .70



MODELS

- **XGBoost**
  - AUC = .71



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ADDED FEATURES

- CVLINK : Credit Vision custom score based on alternative and trended data
- PTI: Payment to income ratio
- Count of inquiries
- Count of open collections
- Loan Type : No. of credit cards

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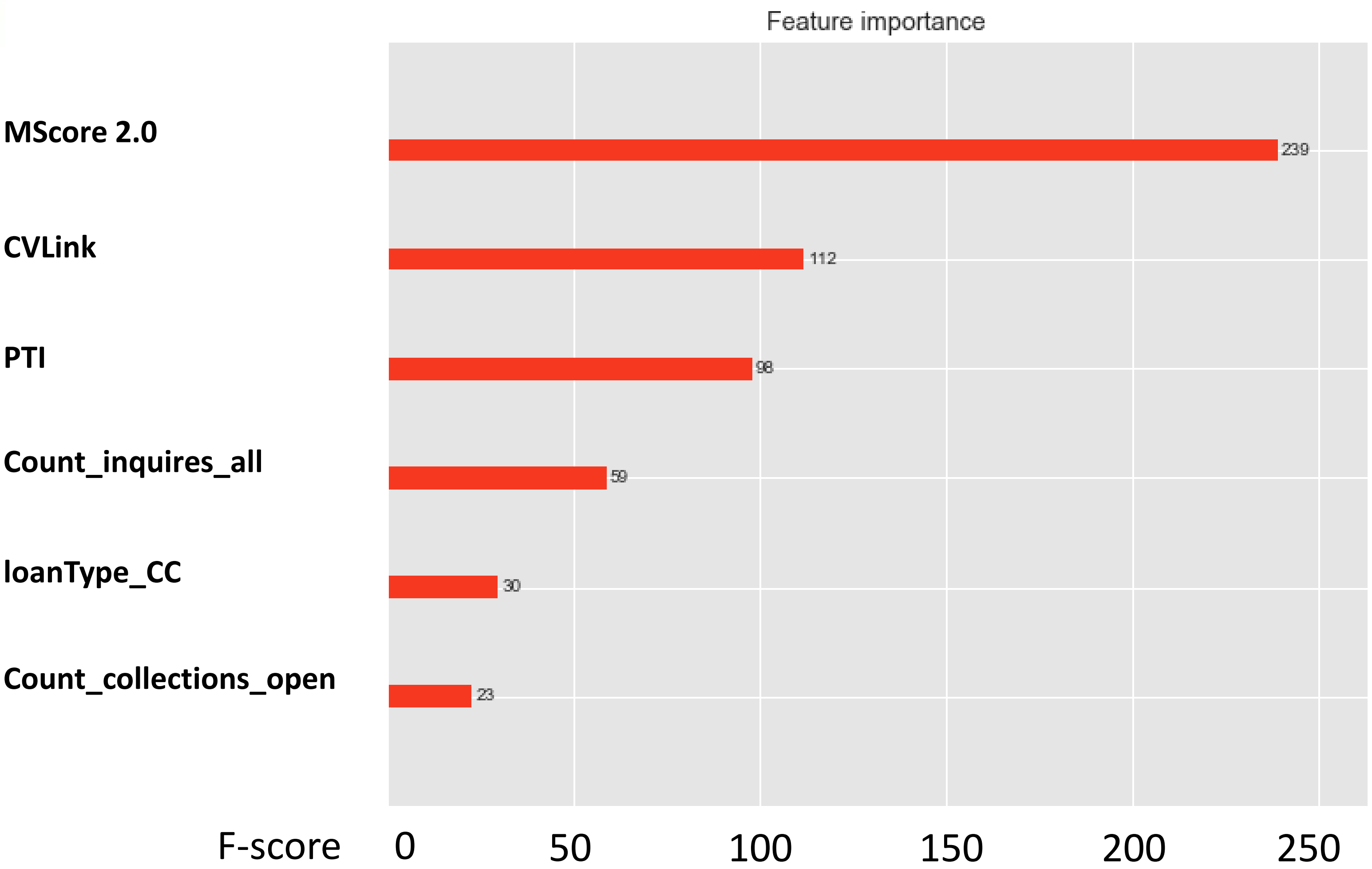
FINAL FEATURES



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RESULTS

- AUC of existing M-Score: 0.63
- AUC with added features (Logistic): 0.70
- AUC with added features (XGBoost): 0.71

CONCLUSION

INSIGNIFICANT FEATURES

- Most categorical variables (e.g. lender type)
- Payment Pattern
- Utilization Ratios: Amount of credit used

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```
Call:
glm(formula = Default ~ MScore2.0 + CVLink + PTI + count_collections_open +
    count_inquiries_all + loanType_CC, family = binomial(), data = train)

Deviance Residuals:
   Min       1Q   Median       3Q      Max
-4.800   -1.017   -0.667    1.136    2.432

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)            1.7391279  0.1818032   9.566  < 2e-16 ***
MScore2.0             -0.0034093  0.0002281 -14.947  < 2e-16 ***
CVLink                -0.0024298  0.0003443  -7.058 1.69e-12 ***
PTI                    0.0713066  0.0041095  17.352  < 2e-16 ***
count_collections_open 0.0146020  0.0037856   3.857 0.000115 ***
count_inquiries_all    0.0314918  0.0026097  12.067  < 2e-16 ***
loanType_CC           -0.0667365  0.0085244  -7.829 4.92e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 20214  on 14823  degrees of freedom
Residual deviance: 18562  on 14817  degrees of freedom
AIC: 18576

Number of Fisher Scoring iterations: 5
```

FEATURE IMPACT ON DEFAULTS

- CVLINK (Negative Impact)
- PTI (Positive Impact)
- Count of inquiries (Positive Impact)
- Count of open collections (Positive Impact)
- No. of credit cards (Negative Impact)

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