Kaggle Competition:

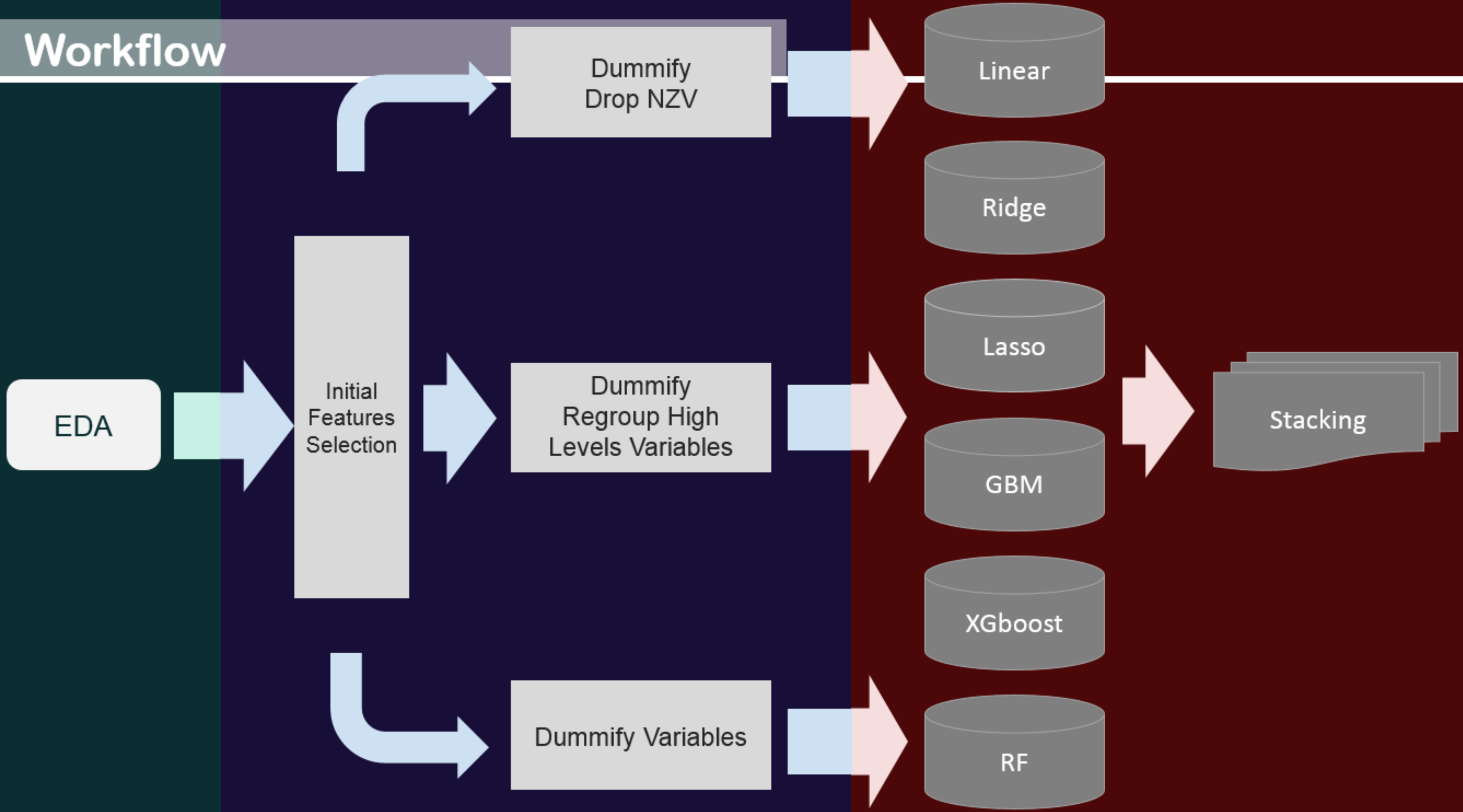
Allstate Claims Severity

Team KGW : Wen Li . Lei Zhang . Chuan Hong . Lydia Kan

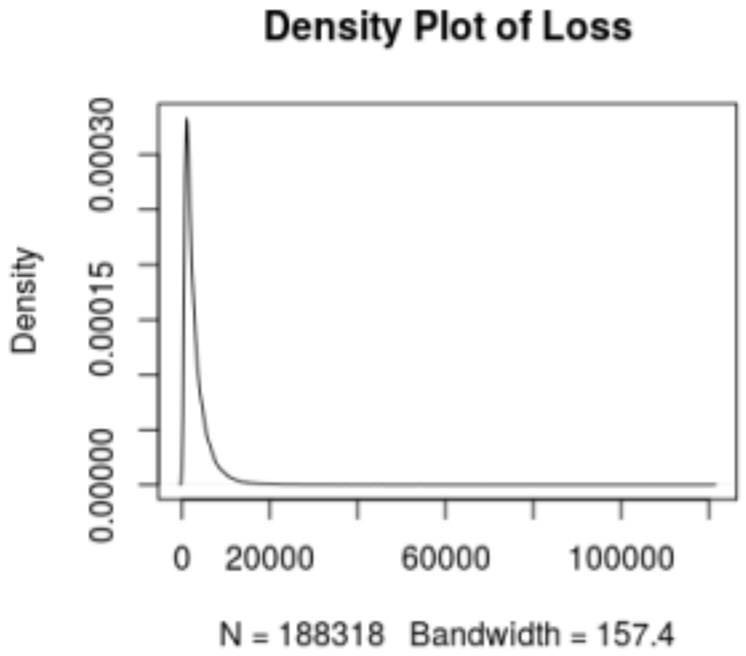
Content

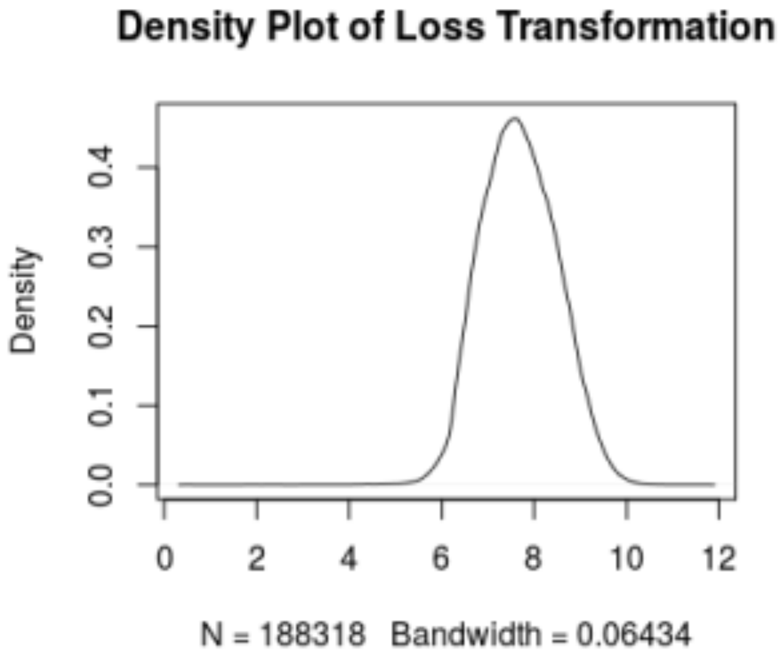
- Workflow
- EDA
- Initial Features Selection
- Feature Engineering
- Supervised Learning
- Results and Finding
- Future Works

Workflow


EDA
Initial Features Selection
Dummify
Drop NZV
Dummify
Regroup High Levels Variables
Dummify Variables
Linear
Ridge
Lasso
GBM
XGboost
RF
Stacking

Graphic EDA: Output Variable





Numeric Graphic: Dataset

Categorical Variables

- 116 Variables
- cat1 – cat116
- Levels 2 - 326

Continuous Variables

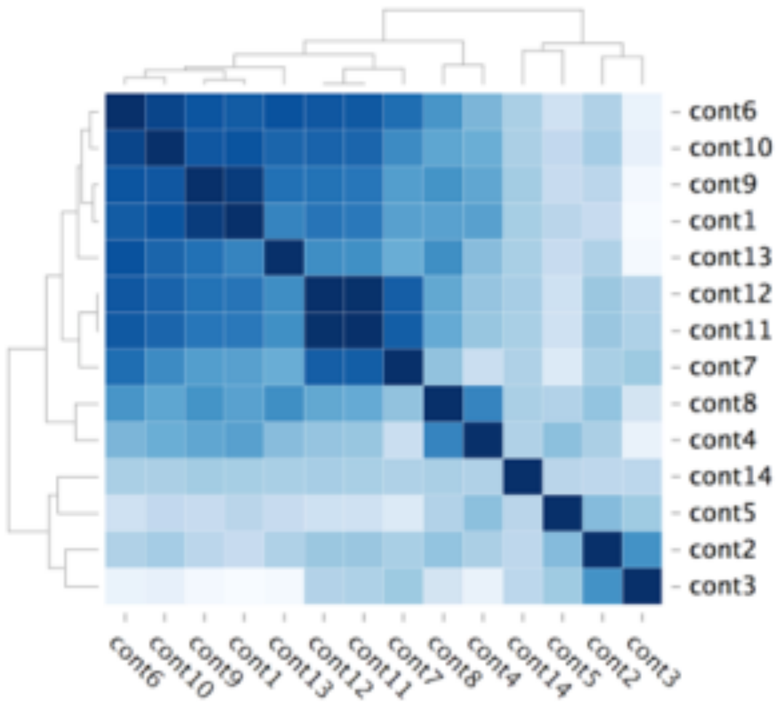
- 14 Variables
- cont1 – cont14

Numeric Graphic: The Categorical Variables

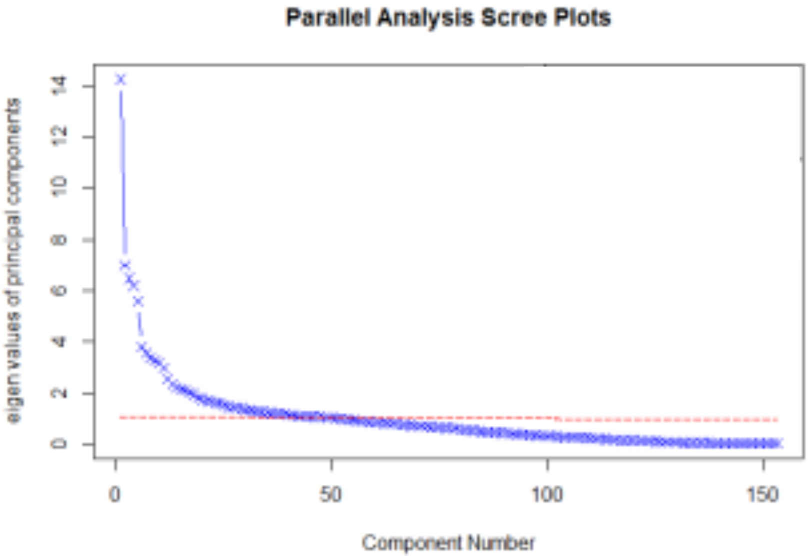
Variable	Train	Test	Variable	Train	Test
cat89	I	F	cat105	R S	
cat90	G		cat106		Q
cat92	F	G E	cat109	BM CJ BV BY BT B BF BP J AG AK	AD
cat96		H	cat110	BK H BN DV EI BD BI AN AF CB EH	BH CA EN
cat99		U	cat111	D	L
cat101	N U		cat113	BE T AC	AA R
cat102	H J		cat114	X	
cat103		M	cat116	BI V BL X FS P GQ AY MF JD AH EV CC AB W AM IK AT JO AS JN BF DY IB EQ JT AP MB C IO DQ HO MT FO JI FN HU IX	AQ EM FY AI N ET KO BJ IW DB LP MX BR BH JS ER A BN BE IS LS HS EX

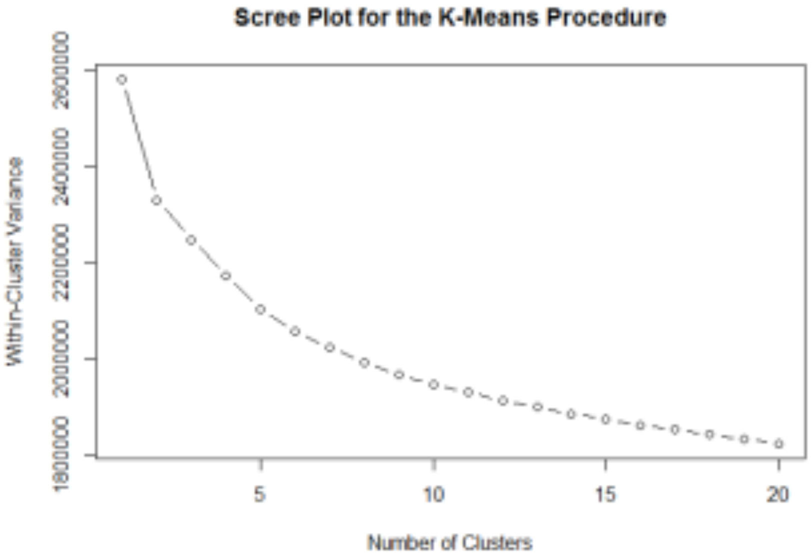
Graphic EDA: Input Variable

Correlations of all continuous variables



Initial Features Selection: Unsupervised





- ➢ **Goal: Check if the models are able to simplify the dimensions**
- ➢ **Result: There is no significant classification**

Features Engineering

Dummify Categorical Variables (Keep All Features)

Pro:
Keep all information

Con:
Take too much time / Overfitting

-Dummify Categorical Variables ->> Drop Near Zero Variance

Pro:
Time saving

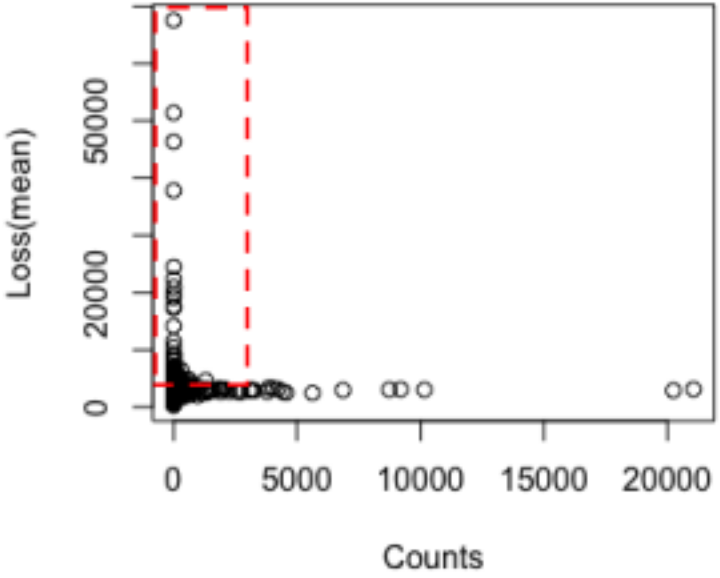
Con:
High error and may lose some information

Select the Variables Have > = 15L >> Group the Levels (variables) by Count and Avg of Loss >> Dummify Categorical Variables

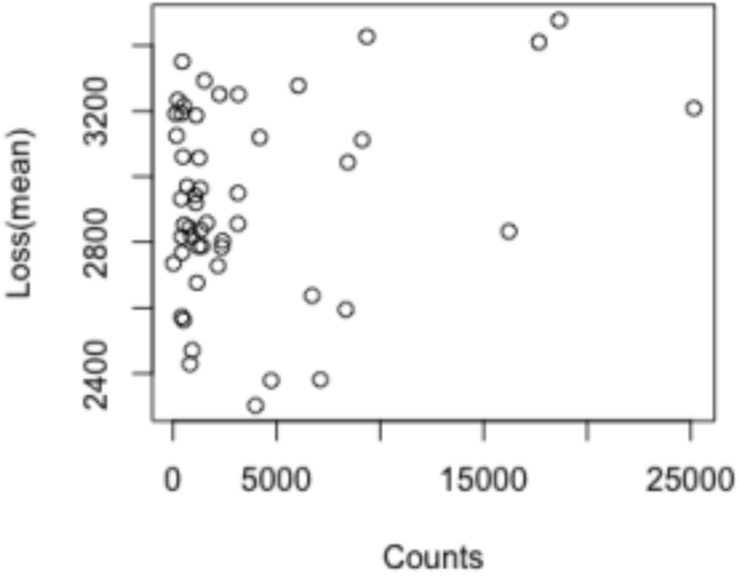
Pro:
Do Not throw away useful features

Con:
Multiple ways to group variables

Features Engineering



cat116
326 levels → 10 new groups



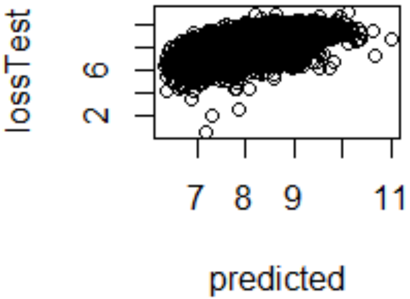
cat112
51 levels → 11 new groups

Supervised Models

Multiple Linear Regression

Features Engineering: Drop NZV

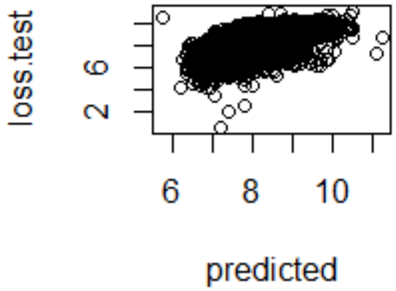
RMSE: 0.57659



Multiple Linear Regression

Features Engineering: Drop Correlated V. + New Group

RMSE: 0.56557



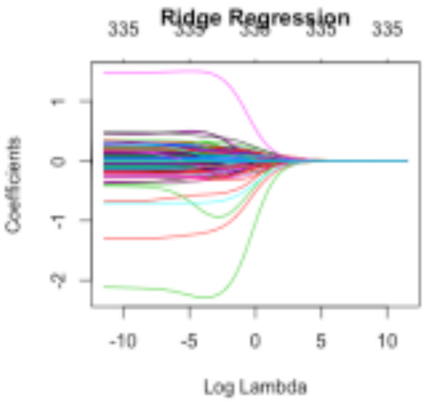
Supervised Models

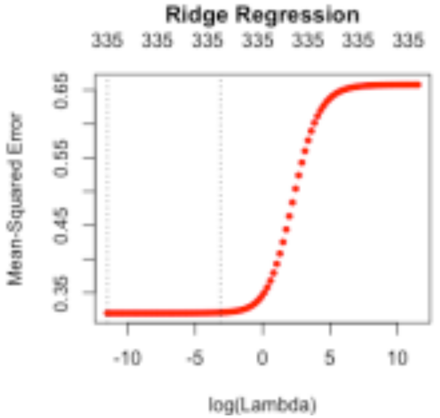
Ridge Regression

Features Engineering: New Group

Parameter: Lambda 1e-05

RMSE: 0.56414



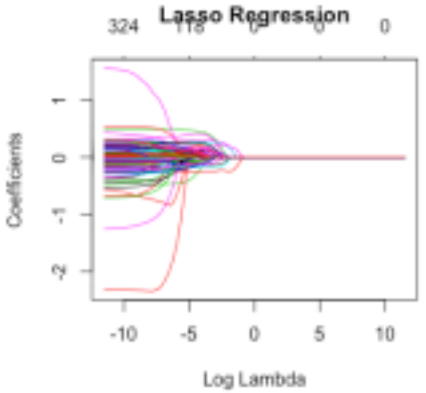


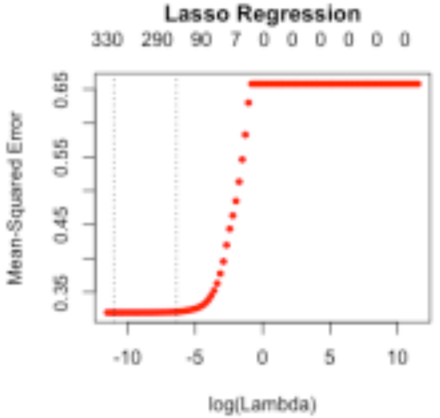
Lasso Regression

Features Engineering: New Group

Parameter: Lambda 1.592283e-05

RMSE: 0.56415





Supervised Models

Random Forest

Features Engineering: NZV

Parameter: Number of trees = 500 , No. of Variables tried at each split = 51

RMSE: 2014.217

Supervised Models

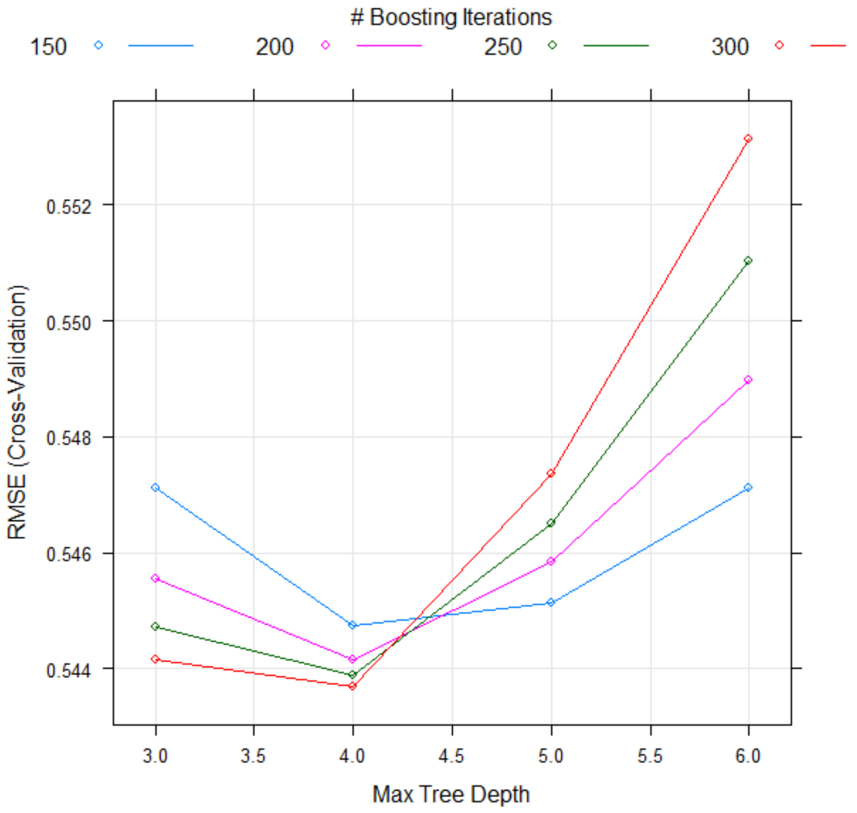
XGBoost - xgbTree

Features Engineering: New Group

RMSE: 0.5436

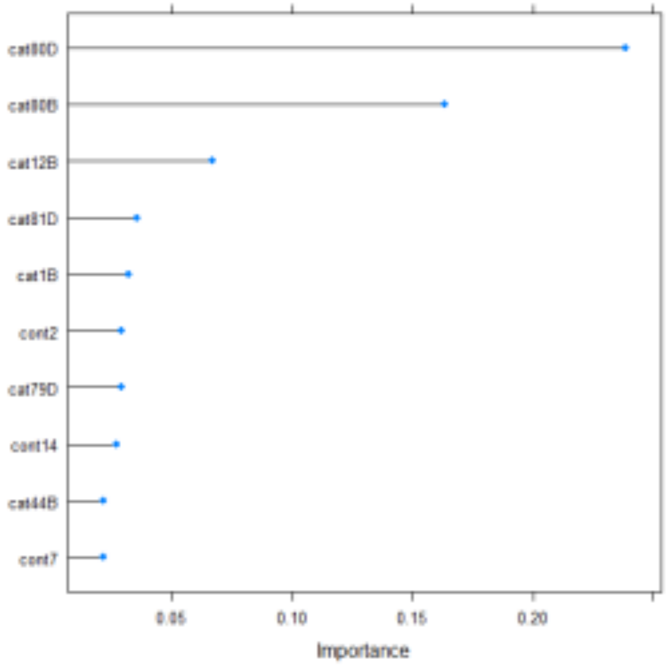
Parameter:

nrounds = 300
max_depth = 4
eta = 0.3
gamma = 0
colsample_bytree = 0.8
min_child_weight = 1
subsample = 0.75

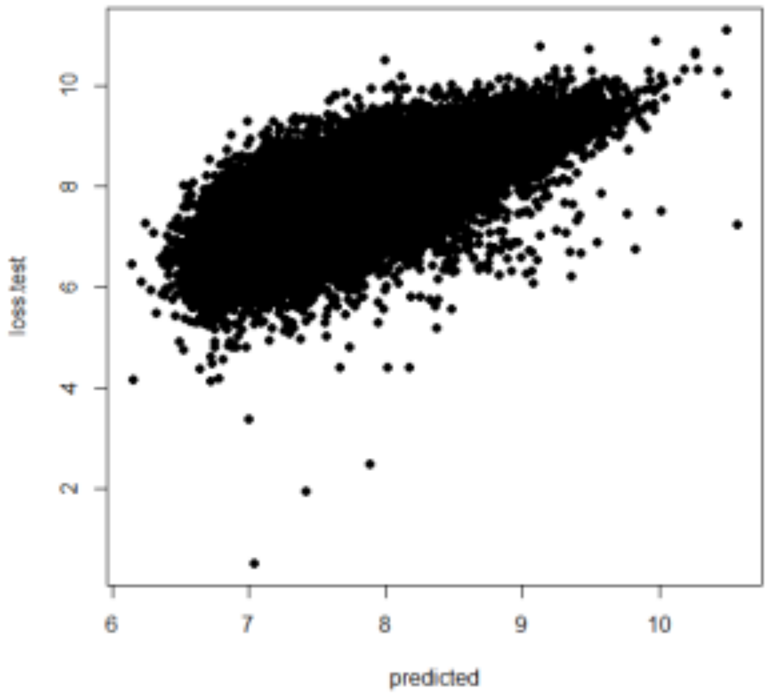


Supervised Models

Relative importance of variables (top10)



Scatter plot of loss.test vs. predicted loss



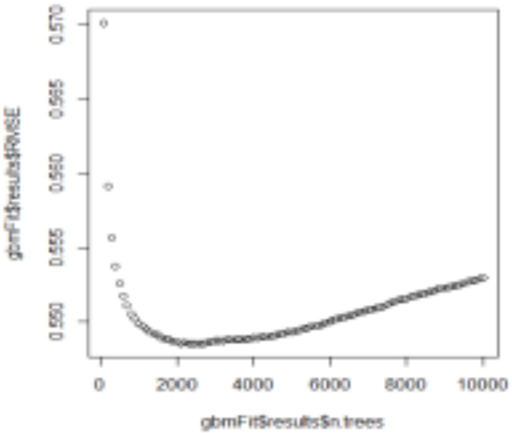
Supervised Models

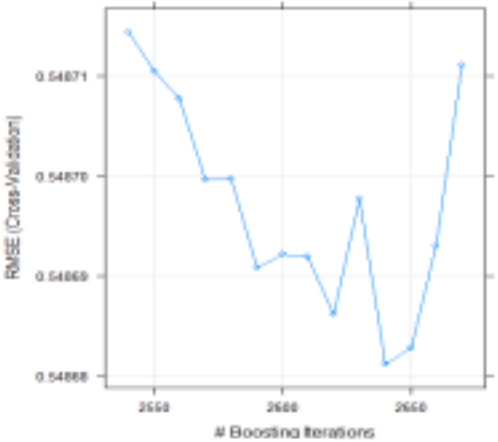
<u>Gradient Boost</u>

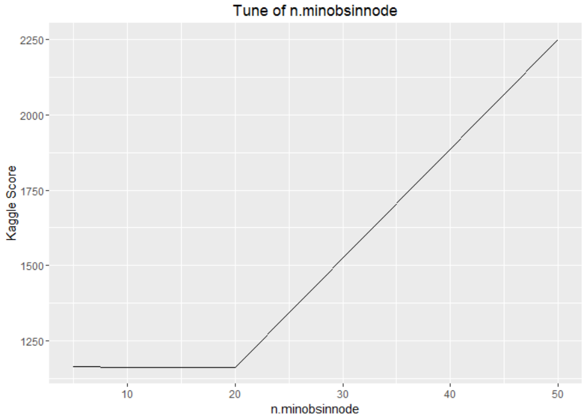
Features Engineering: NZV

Parameter: ntree=2640
n.minobsev = 20
interation.depth = 5
shinkage = 0.1

RMSE: 0.51







Increase Kaggle score by tuning parameters

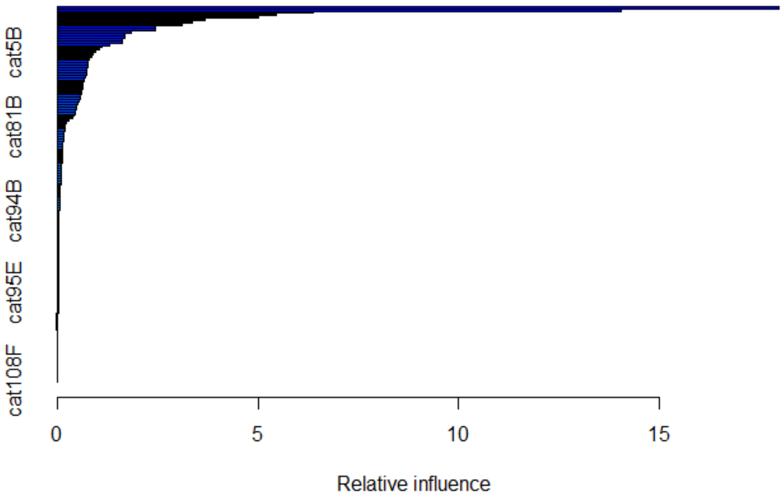
ntree
2600: 1163.89861
2640: 1162.56392

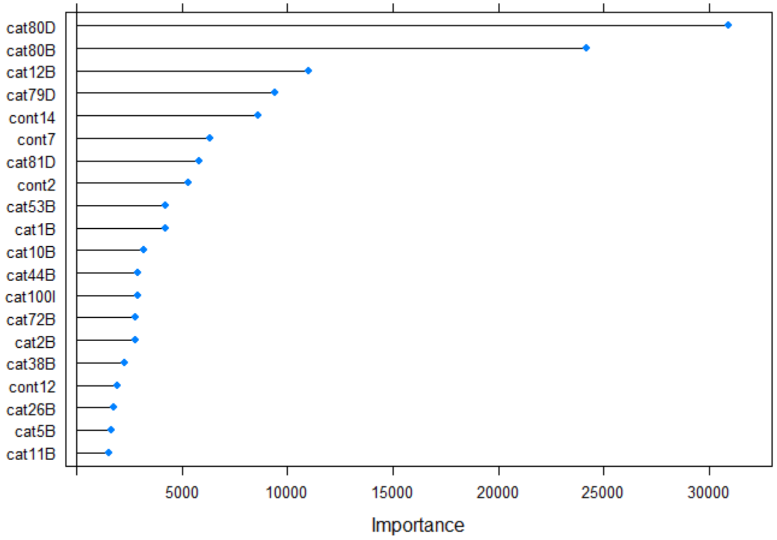
n.minobsev
50: 2251.57822
5: 1165.24778
10: 1162.56392
20: 1162.22589

Supervised Models

Importance of Variables

- cat99R, cat99T, cat108F : 0.000000000000
- 83 out of 153 variables influence more than 0.05





Results and Finding

Model	Features Engineering	Parameters	RMSE	Kaggle Score
MLR	Drop NZV		0.57659	
MLR	Drop High Cor + New Group		0.56557	
Ridge	New Group	Lambda: 1e-05	0.56414	
Lasso	New Group	Lmabda: 1.592283e-05	0.56415	
RandomForest	Drop NZV	Ntree: 500 mtry = 51	2014.217	
GBM	Drop NZV	Ntree: 2640 n.Minobsev: 20	0.51	**1162.22589**
XGB (xgbTree)	New Group	nrounds = 300 max_depth = 4 eta = 0.3 gamma = 0.2 colsample_bytree =0.6 min_child_weight = 1 subsample = 0.85	0.5436	

Future Works

1. **Gradient Boosting with “zv”**

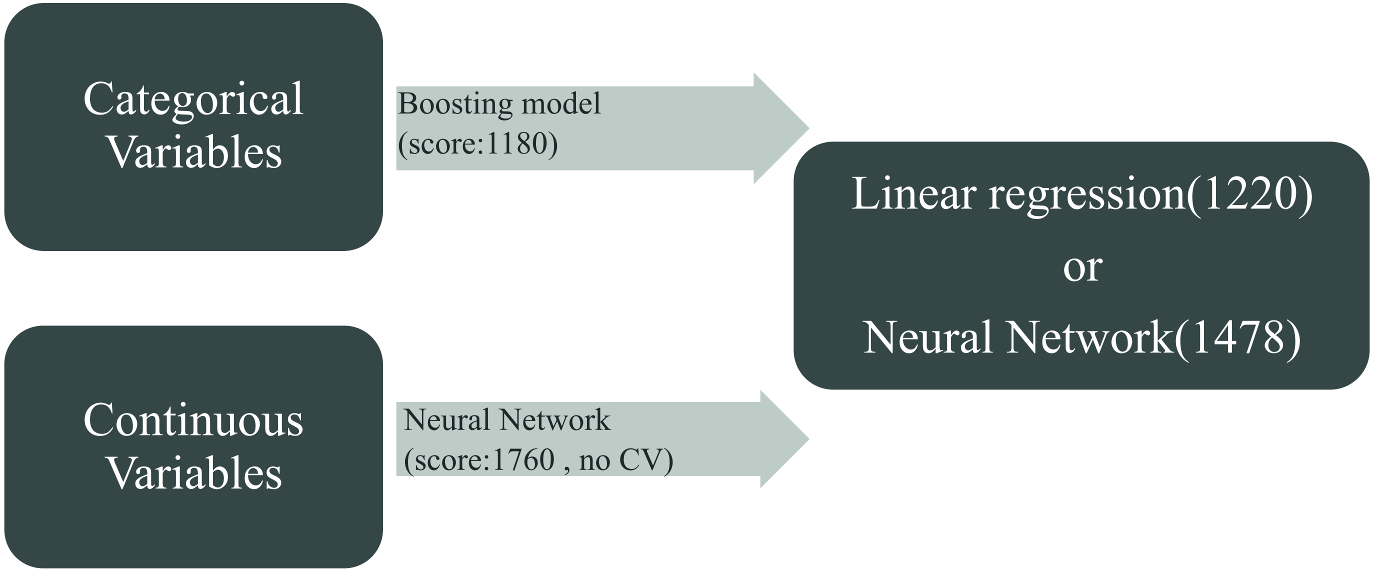
    - “nzv” cut off the variables with 5% less variance
    - The kaggle score of our best boosting model is 5.6% higher than rank 1
    - With all variables, tune the parameter again

2. **Improve the neural network and Stack different models to get higher accuracy**

3. **Another approach of feature engineering**

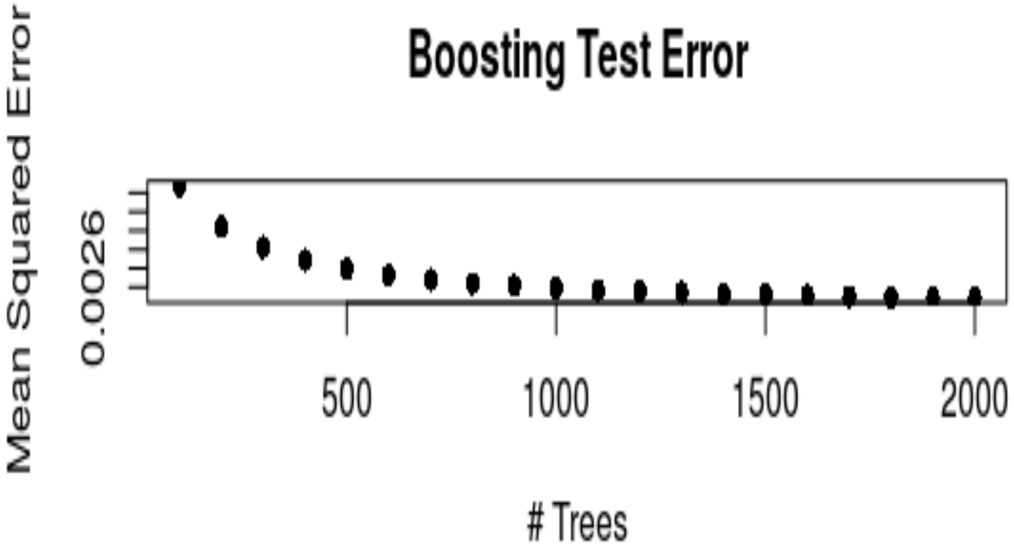
Parallel Calculation

❖ Split the data to 2 sub-data



Boosting with only category

Good model only with category



Linear Stack

Coefficients:	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-3180.060884493	87.679805716	-36.26902	< 0.0000000000000000222	***
con	1.501115426	0.040627824	36.94797	< 0.0000000000000000222	***
cat	1.137519885	0.002996952	379.55892	< 0.0000000000000000222	***

```
Residual standard error: 1975.458 on 131819 degrees of freedom
Multiple R-squared: 0.5332921, Adjusted R-squared: 0.533285
F-statistic: 75312.67 on 2 and 131819 DF, p-value: <
0.00000000000000022204
```

Linear Stack—not perfect: need non-linear term