Kaggle Competition:

Allstate Claims Severity

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- EDA
- Initial Features Selection
- Feature Engineering
- Supervised Learning
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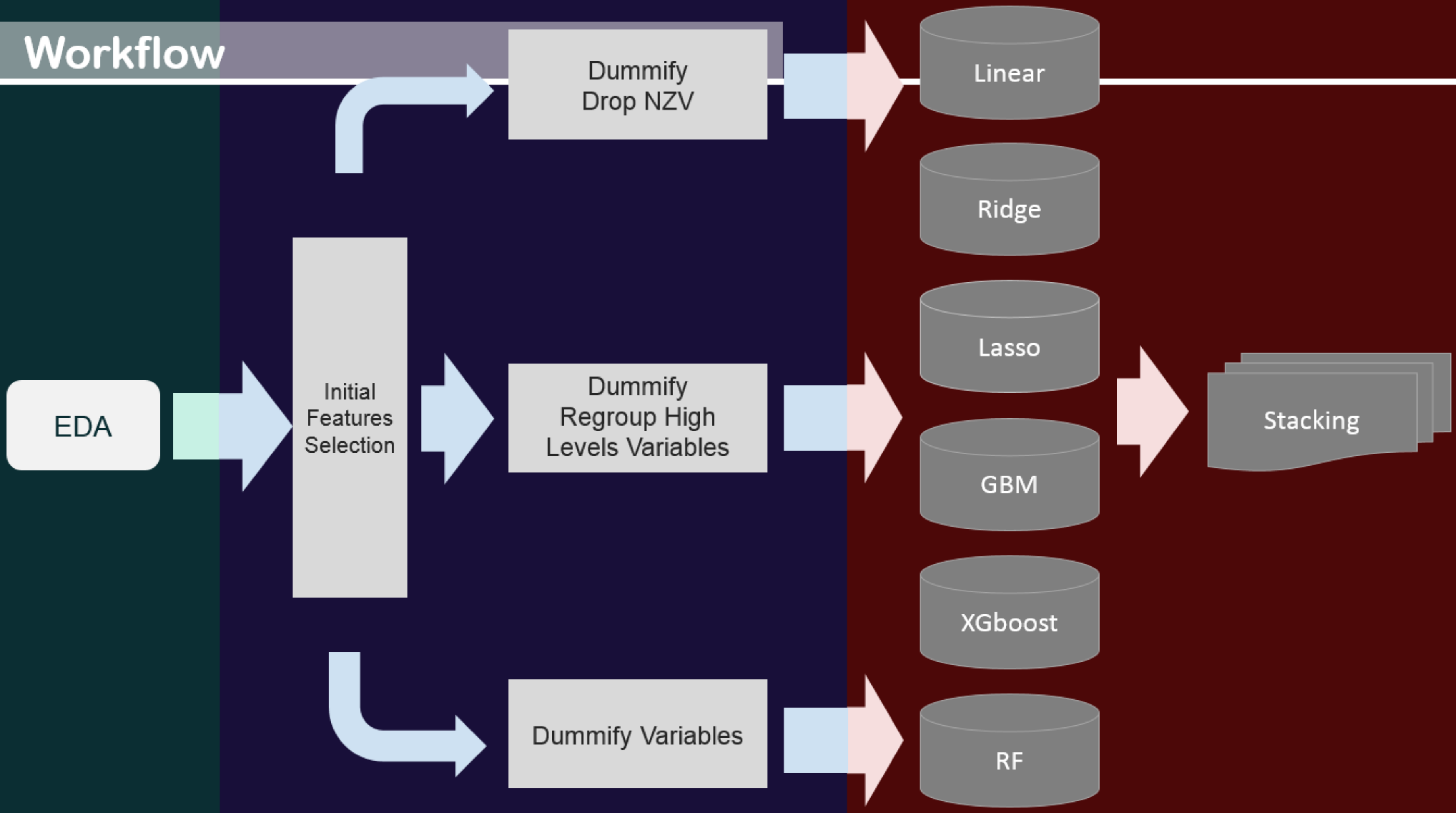
Workflow



EDA

Initial Features Selection

Dummify Drop NZV

Dummify Regroup High Levels Variables

Dummify Variables

Linear

Ridge

Lasso

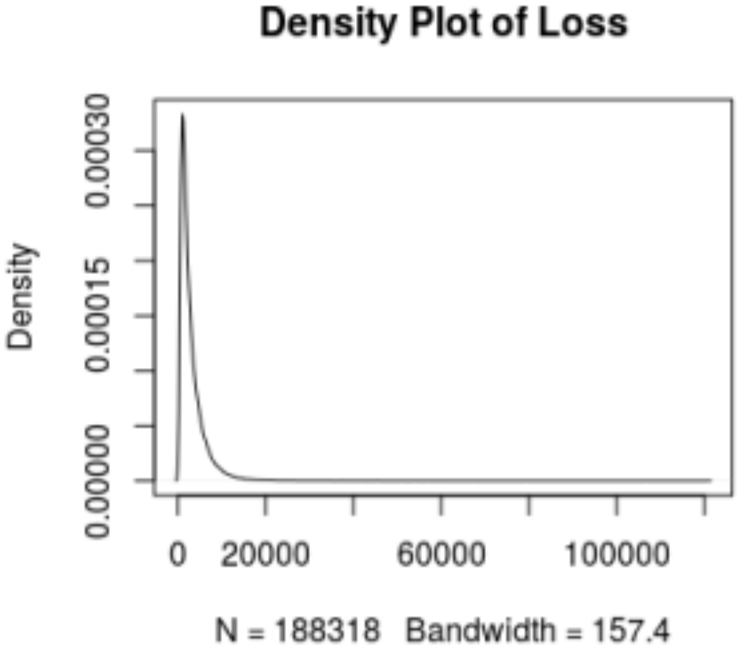
GBM

XGboost

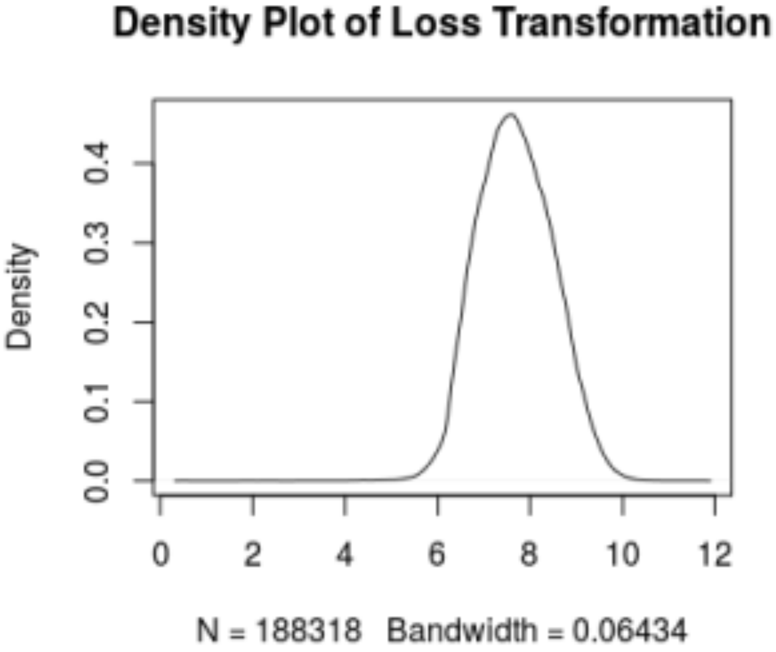
RF

Stacking

Graphic EDA: Output Variable

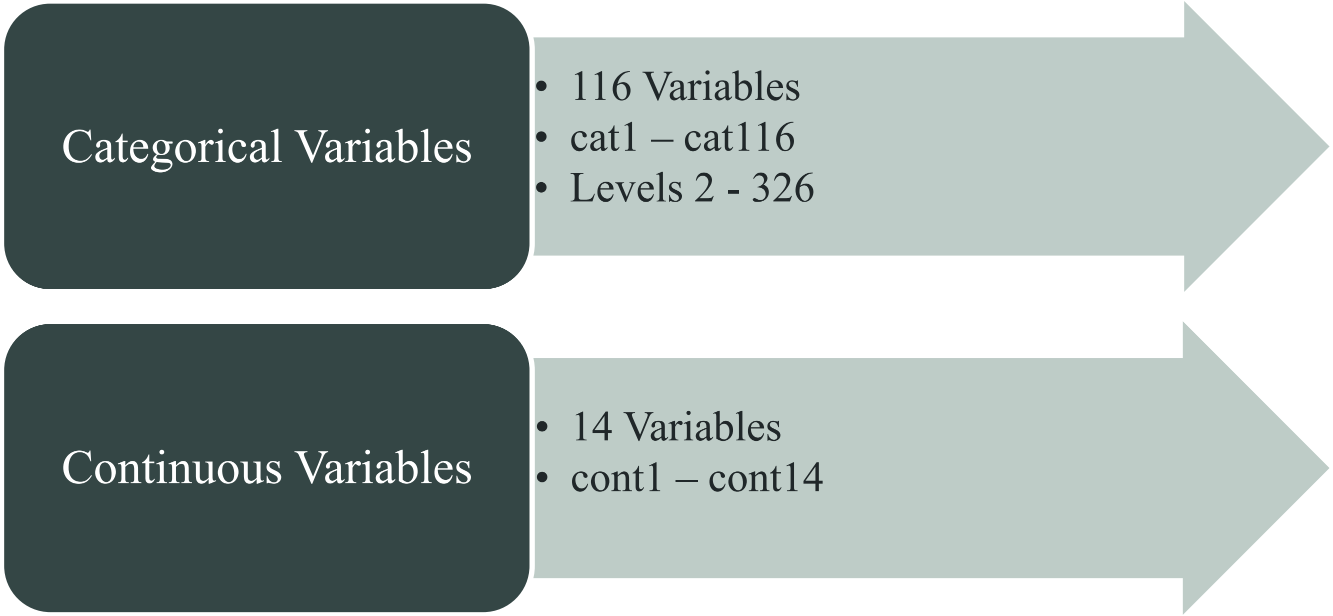


Density Plot of Loss



Density Plot of Loss Transformation

Numeric Graphic: Dataset



Categorical Variables

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

Continuous Variables

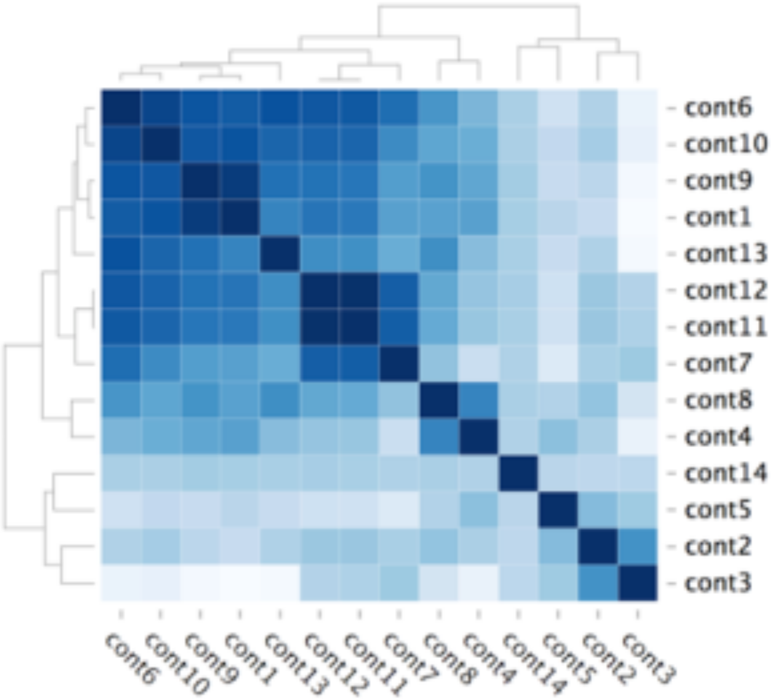
- 14 Variables
- cont1 – cont14

Numeric Graphic: The Categorical Variables

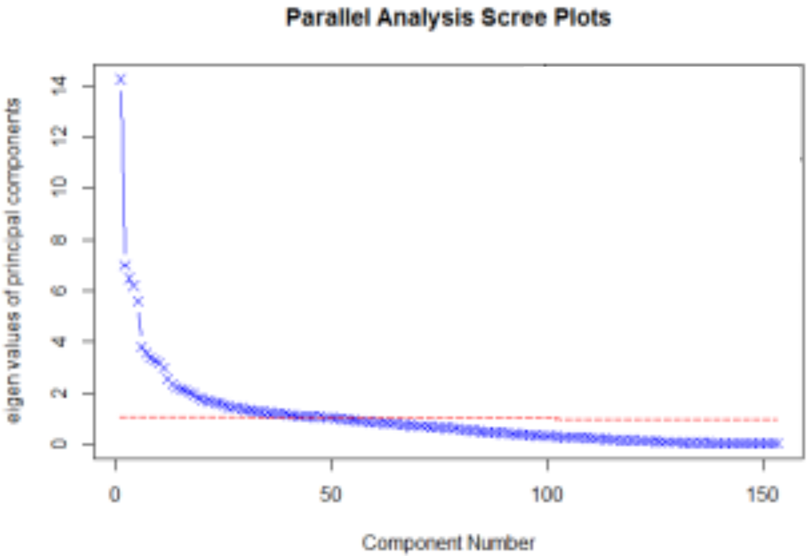
Variable	Train	Test	Variable	Train	Test
cat89	I	F	cat105	R S	
cat90	G		cat106		Q
cat92	F	G E	cat109	BM CJ BV BY BT B BF BP J AG AK	AD
cat96		H	cat110	BK H BN DV EI BD BI AN AF CB EH	BH CA EN
cat99		U	cat111	D	L
cat101	N U		cat113	BE T AC	AA R
cat102	H J		cat114	X	
cat103		M	cat116	BI V BL X FS P GQ AY 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

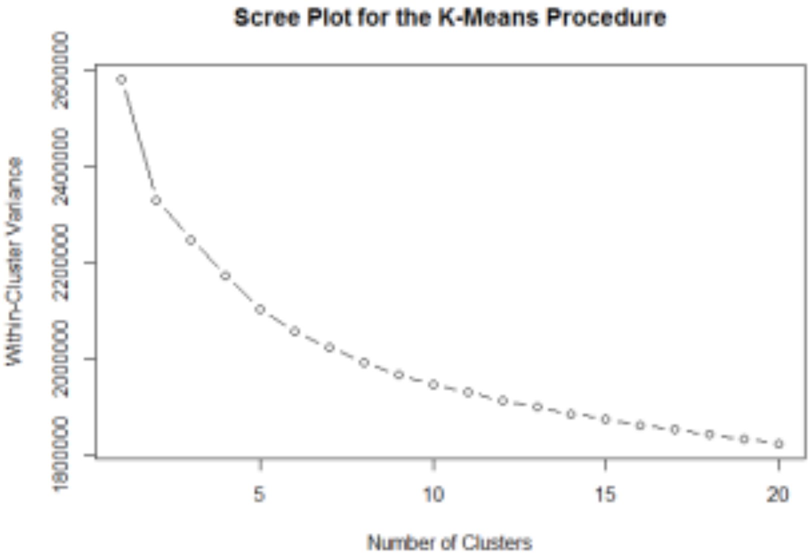
Graphic EDA: Input Variable

Correlations of all continuous variables



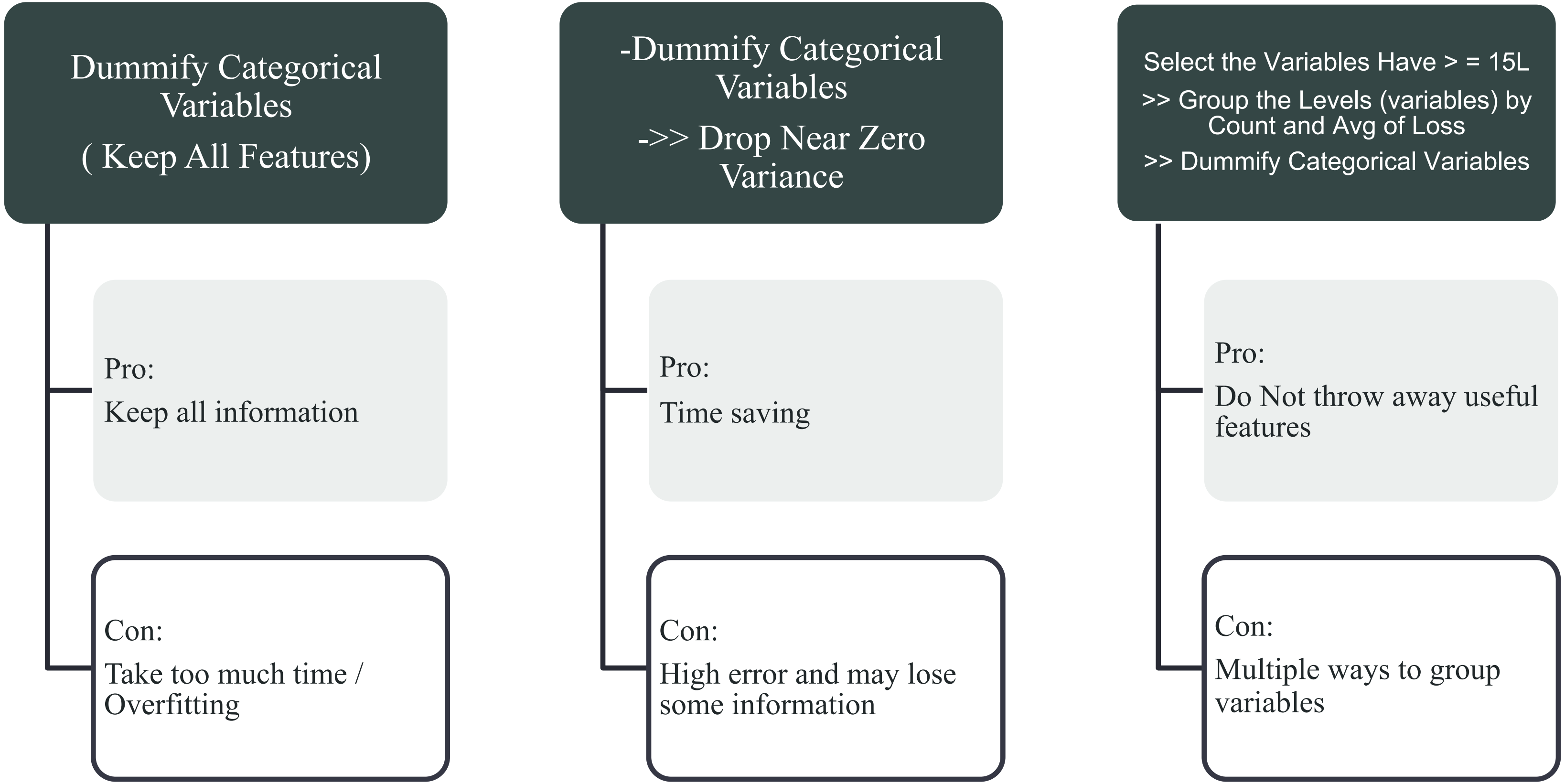
Initial Features Selection: Unsupervised





- ➢ **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

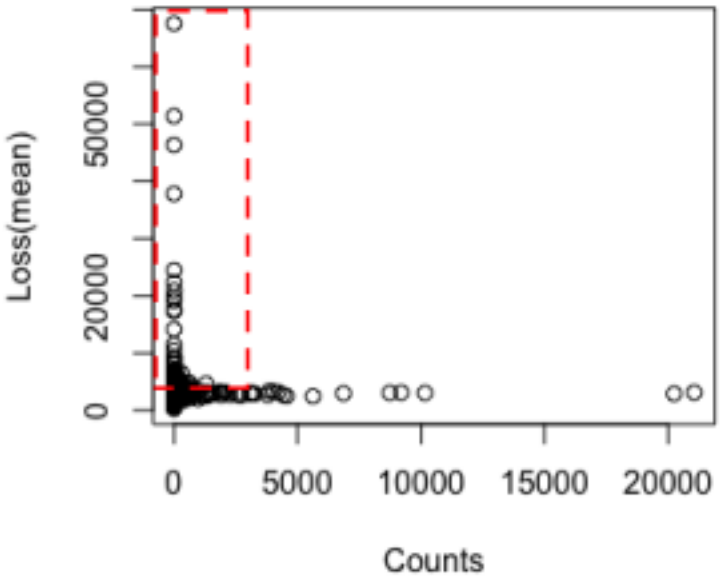
Pro:

Do Not throw away useful features

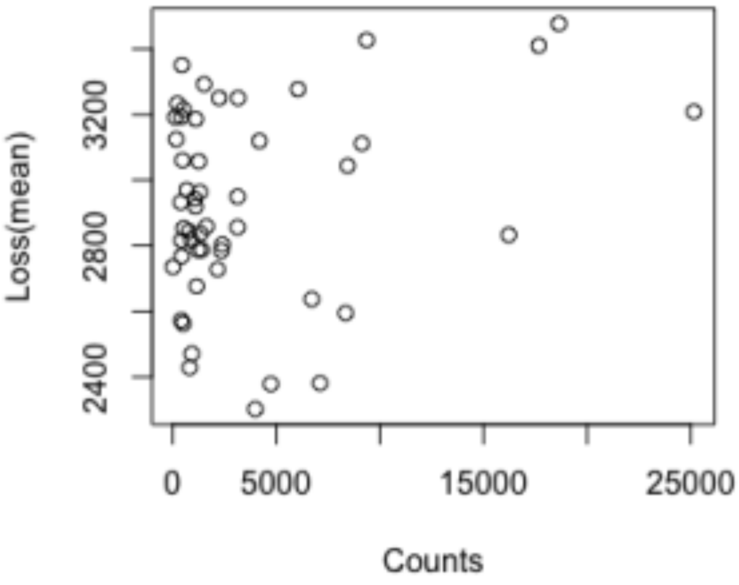
Con:

Multiple ways to group variables

Features Engineering



cat116
326 levels → 10 new groups



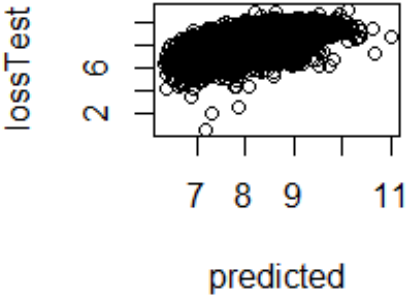
cat112
51 levels → 11 new groups

Supervised Models

Multiple Linear Regression

Features Engineering: Drop NZV

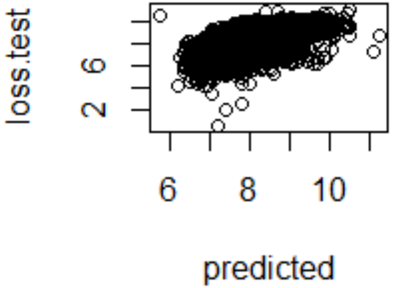
RMSE: 0.57659



Multiple Linear Regression

Features Engineering: Drop Correlated V. + New Group

RMSE: 0.56557



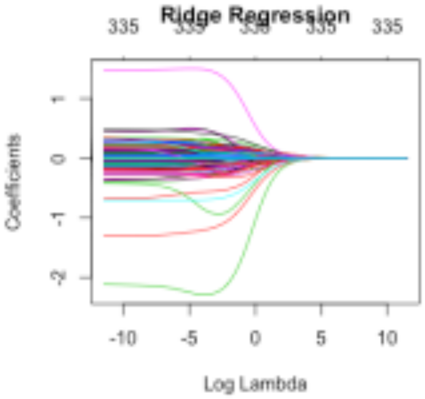
Supervised Models

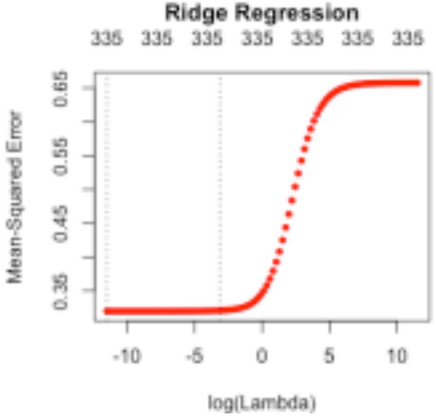
Ridge Regression

Features Engineering: New Group

Parameter: Lambda 1e-05

RMSE: 0.56414



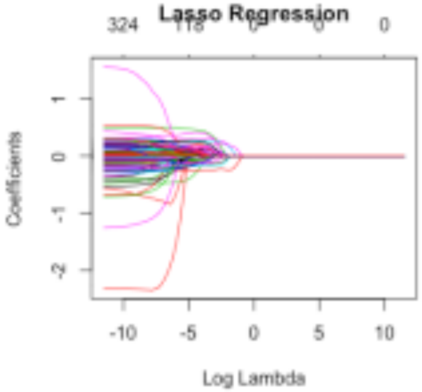


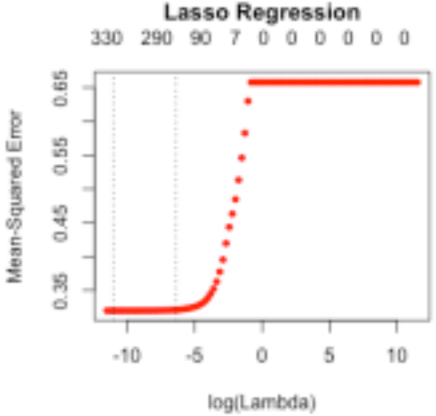
Lasso Regression

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

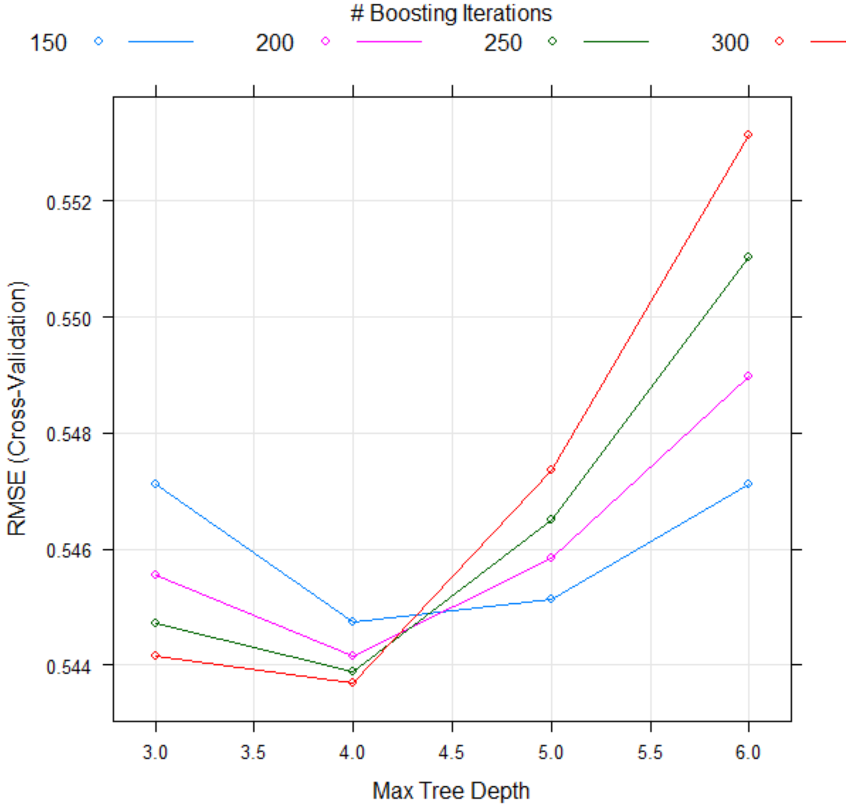
XGBoost - xgbTree

Features Engineering: New Group

RMSE: 0.5436

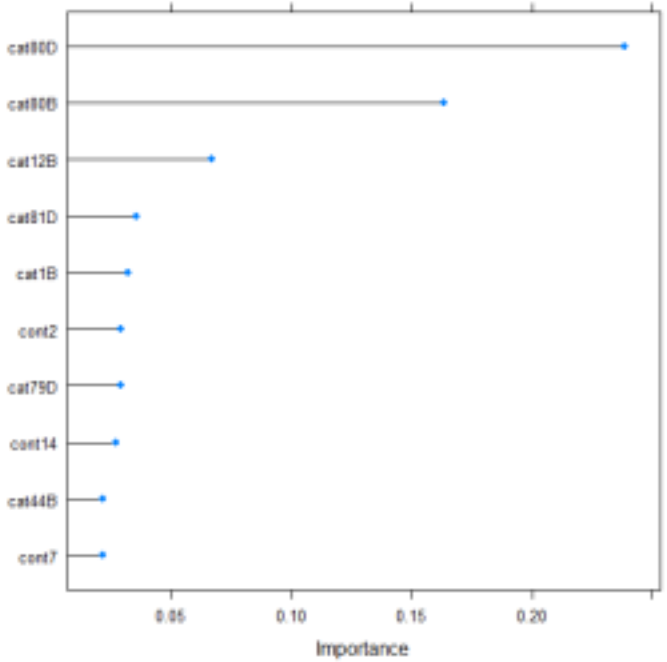
Parameter:

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

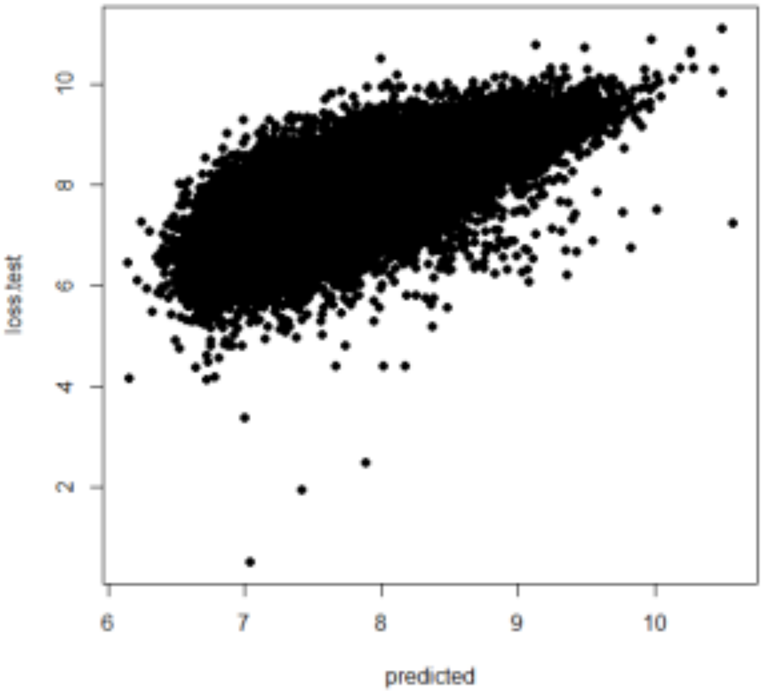


Supervised Models

Relative importance of variables (top10)



Scatter plot of loss.test vs. predicted loss



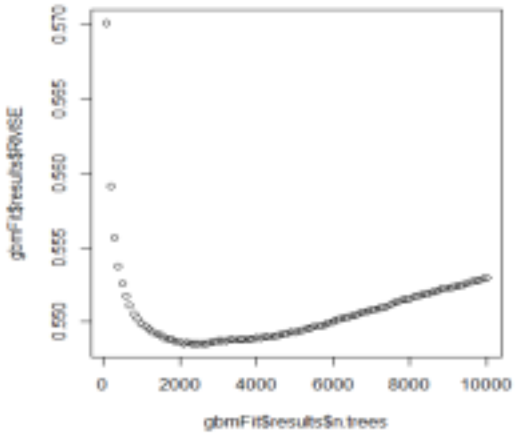
Supervised Models

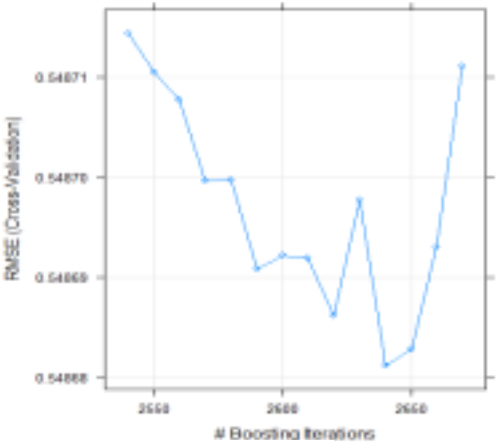
Gradient Boost

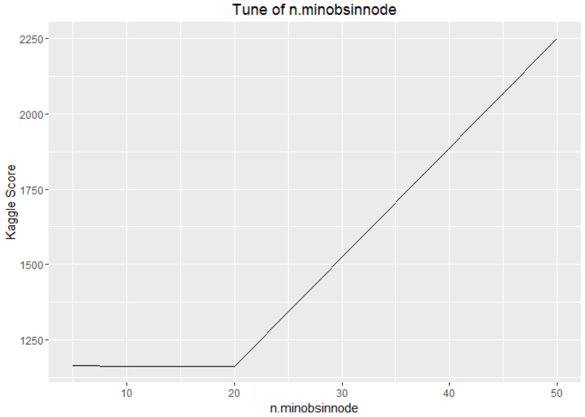
Features Engineering: NZV

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

RMSE: 0.51







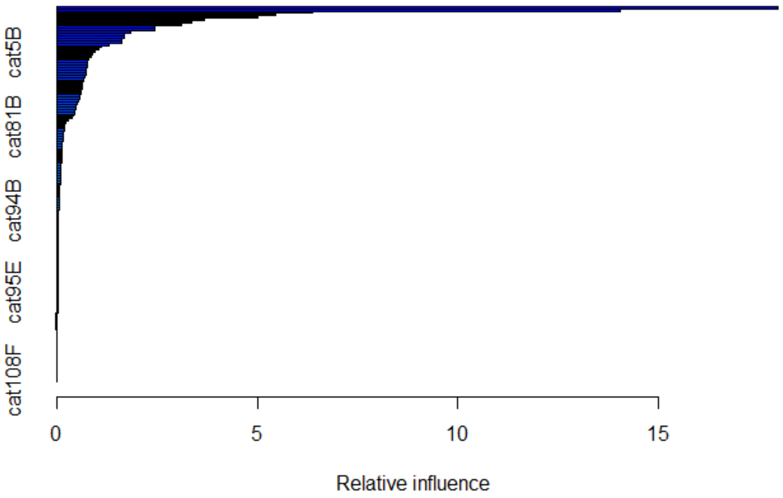
Increase Kaggle score by tuning parameters

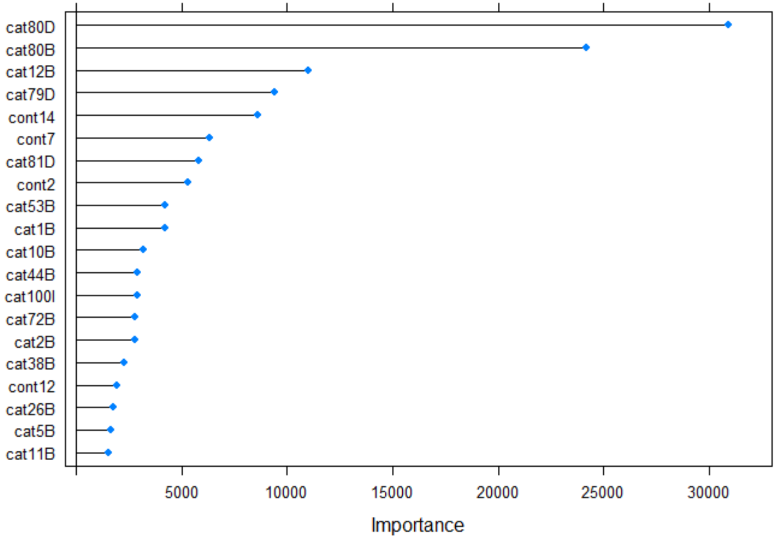
ntree	*n.minobsev*
2600: 1163.89861	50: 2251.57822
2640: 1162.56392	5: 1165.24778
	10: 1162.56392
	20: 1162.22589

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**

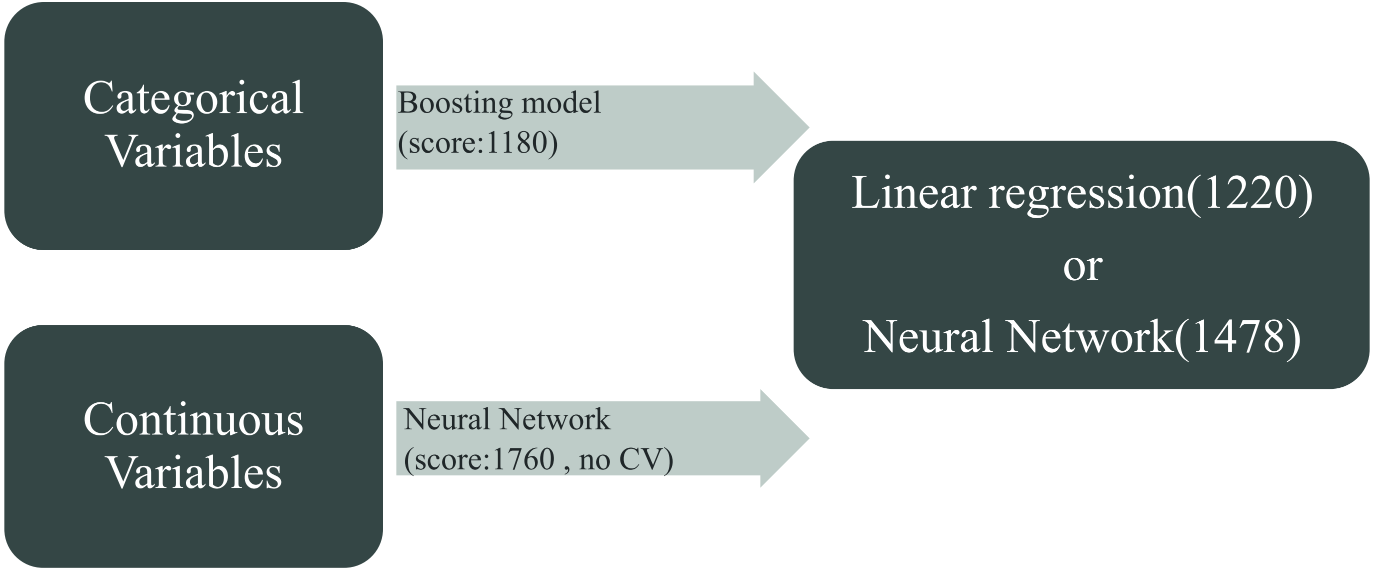
XGB (xgbTree)	New Group	nrounds = 300
		max_depth = 4
		eta = 0.3
		gamma = 0.2
		colsample_bytree =0.6
		min_child_weight = 1
		subsample = 0.85
			0.5436	

Extra Works

- **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

Extra Works: Parallel Calculation

- Split the data to 2 sub-data



Categorical Variables

Boosting model
(score:1180)

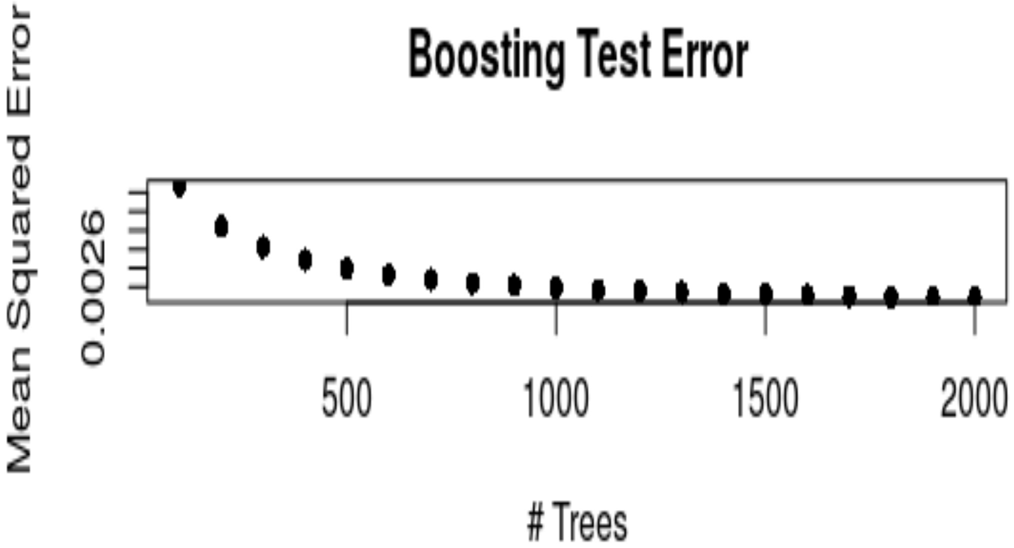
Continuous Variables

Neural Network
(score:1760 , no CV)

Linear regression(1220)
or
Neural Network(1478)

Boosting with only category

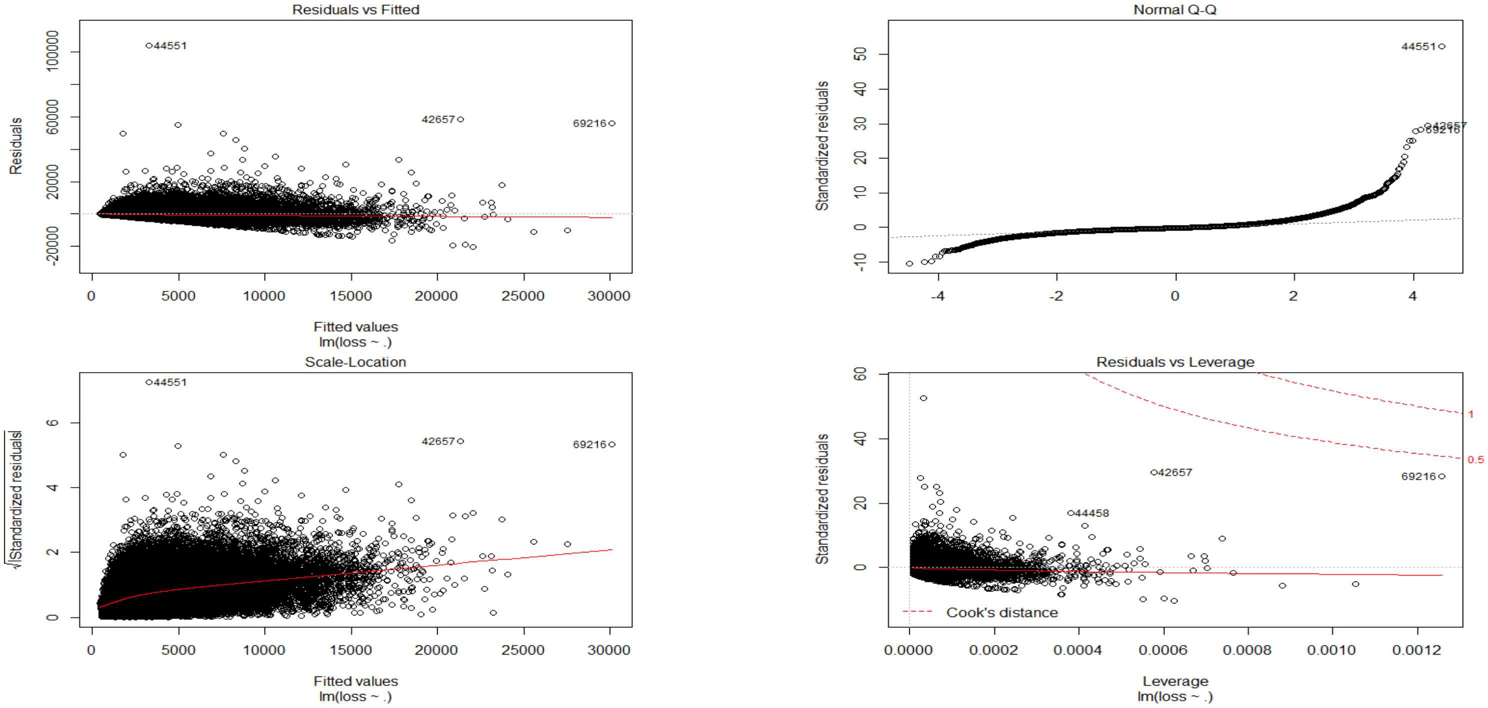
Good model only with category



Linear Stack

```
                  Coefficients:   Estimate Std. Error    t value    Pr(>|t|)

(Intercept) -3180.060884493 87.679805716       -36.26902 < 0.000000000000000222 ***

con            1.501115426        0.040627824        36.94797   < 0.000000000000000222 ***

cat            1.137519885        0.002996952       379.55892   < 0.000000000000000222 ***

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


Residuals vs Fitted
Residuals
-20000
20000
60000
100000
0
5000
10000
15000
20000
25000
30000
44551
42657
69216
Fitted values
lm(loss ~ .)
Normal Q-Q
Standardized residuals
-10
0
10
20
30
40
50
-4
-2
0
2
4
44551
42657
69216
Scale-Location
√|Standardized residuals|
0
2
4
6
0
5000
10000
15000
20000
25000
30000
44551
42657
69216
Fitted values
lm(loss ~ .)
Residuals vs Leverage
Standardized residuals
0
20
40
60
0.0000
0.0002
0.0004
0.0006
0.0008
0.0010
0.0012
1
0.5
42657
69216
44458
Cook's distance
Leverage
lm(loss ~ .)