Allstate Severity Claims Kaggle Competition

Team GrumpyKaggleKats

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kaggle

Allstate
You're in good hands.

Roadmap

Summary and Goals

Pipeline

EDA and Preprocessing

Models

Results

Further Steps

Summary and Goals

- Dataset consists of 180k+ rows for training dataset
- Id column, 116 categorical features, 12 continuous features, 1 loss column
- Features anonymized, continuous features scaled between 0 and 1

Attempt to build basic machine learning models on real world data and score high on Kaggle!

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1. Start off with applying traditional models to the training dataset
   a. **KFold validation**: train dataset split into Training and Validation data.
      i. **X_train**: Features of the training set
      ii. **Y_train**: Responses of the training set
      iii. **X_val**: Features of the validation set
      iv. **Y_val**: Responses of the validation set
   b. Train the model using the training set (X_train, Y_train)
   c. Get an average MAE of the cross-validated model
   d. Predict on the test set (test.csv)
2. Hypertune parameters and repeat!
3. Ensemble and/or stack and submit new model’s predictions to get sense of progress.

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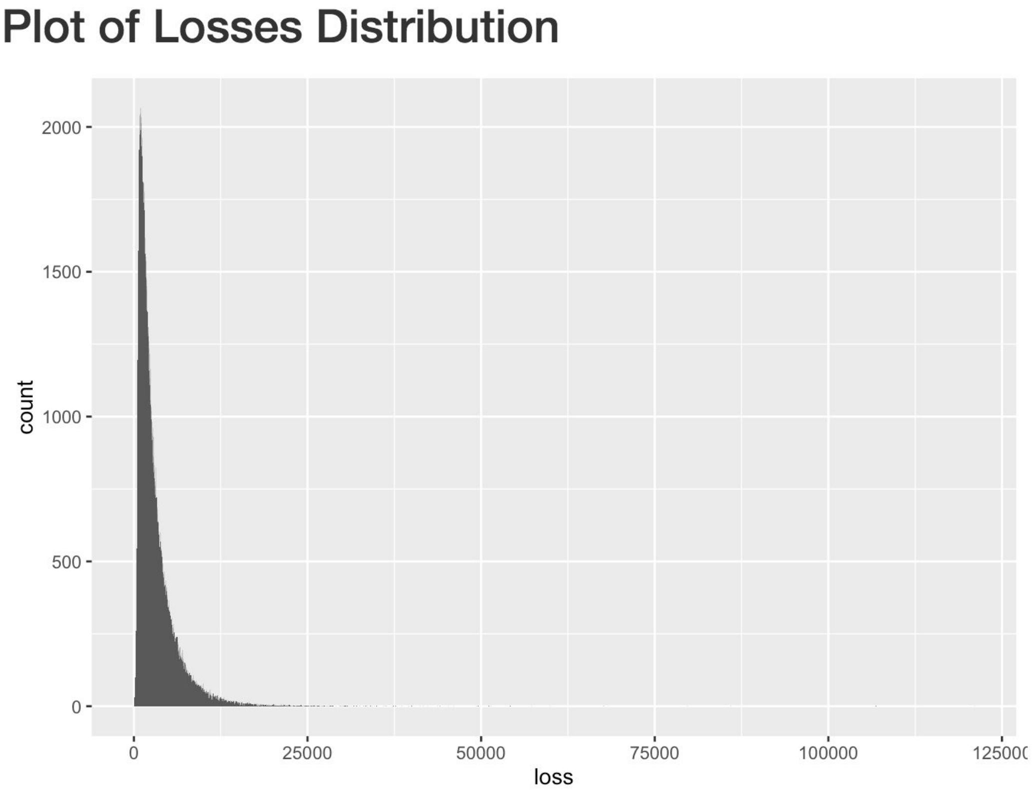
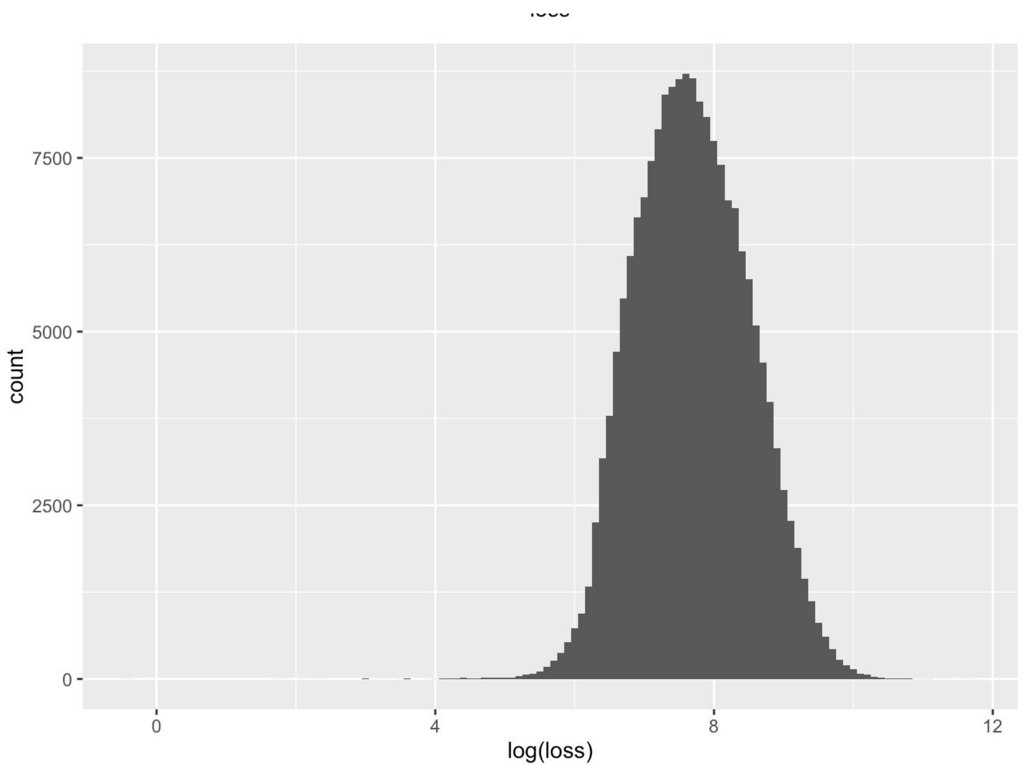
EDA - Distribution

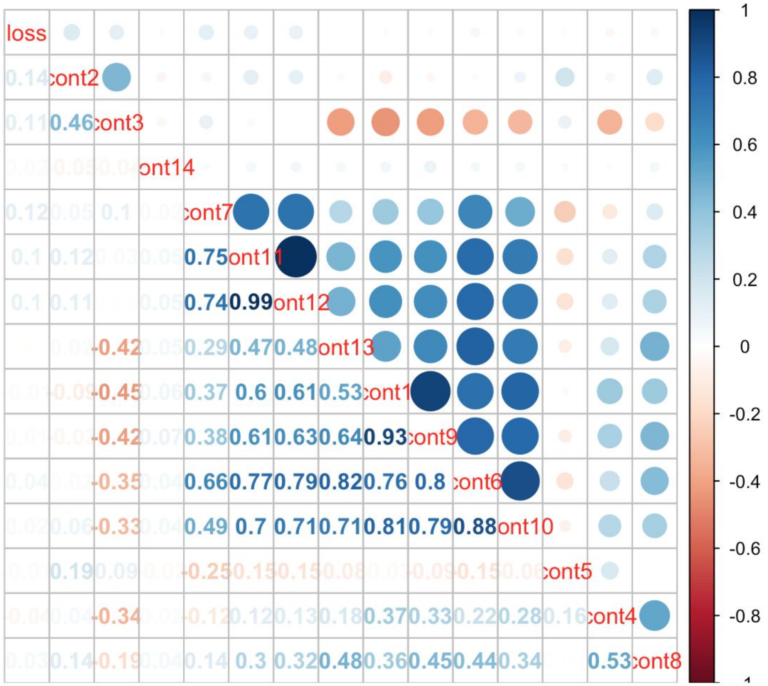


EDA - Distribution



Correlation Plot

```
M = cor(train[,118:132], method="pearson")
corrplot.mixed(M, upper = "circle", order="hclust")
```



EDA - Factor Analysis for Mixed Data

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Models - Lasso Regression

Data Preprocessing

Column Removed	Reason
id	
cat112	States column
cont1	High correlation with cont9
cont6	High correlation with cont10
cont11	High correlation with cont12

Models - Lasso Regression

Data Preprocessing

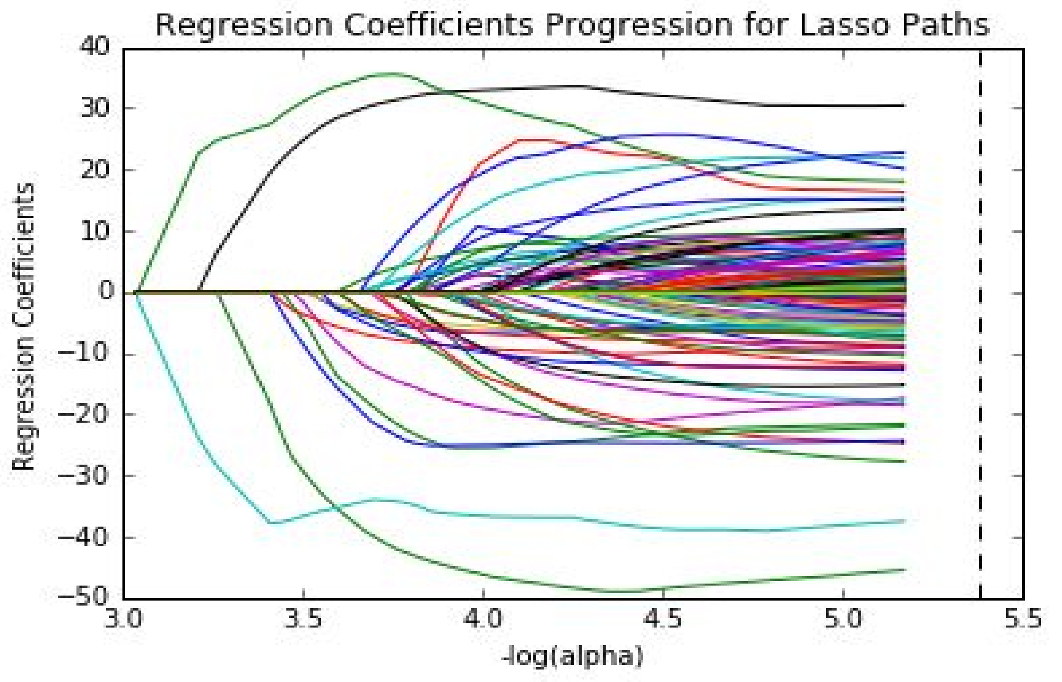
- Convert categorical data into numeric (get_dummies from pandas)

  The dummy dataset dimension: (188318, **127**) -> (150654,**1099**)

- Split the dataset (train.csv) into training and testing (8:2 ratio)
- Train the Lasso Regression model with cross validation value from 3--10
- After feature selection, only 326 columns kept

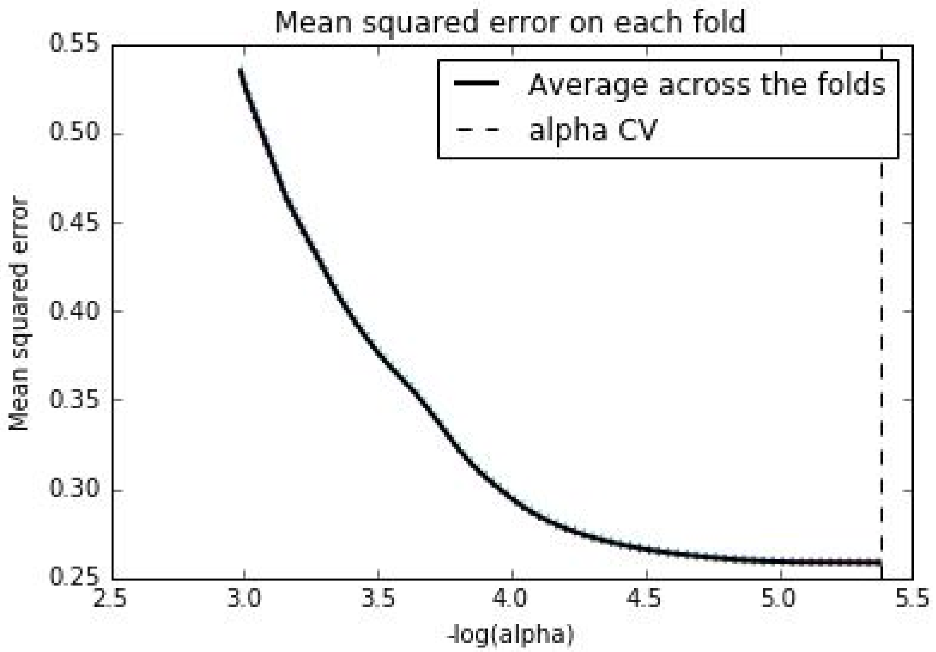
Models - Lasso Regression

- Coefficient Progression results



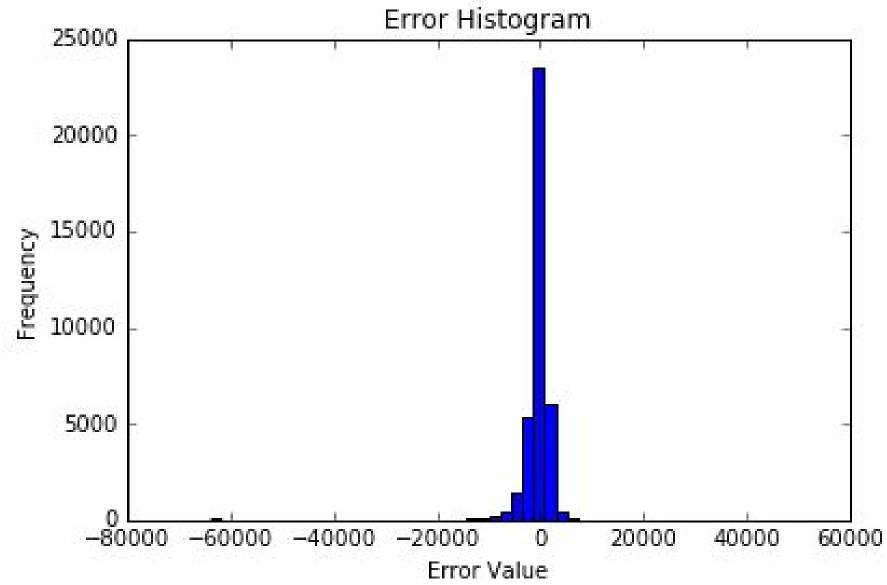
Models - Lasso Regression

- Mean squared error on each fold (5.3765326742844204)



Models - Lasso Regression

- Error distribution of Lasso Model on train.csv



- score on Kaggle: 1834.08715 on test.csv

Models - KNN

scikit-learn: KNNRegressor library

Tuning parameters:

- K - number of nearest neighbors to consider
-

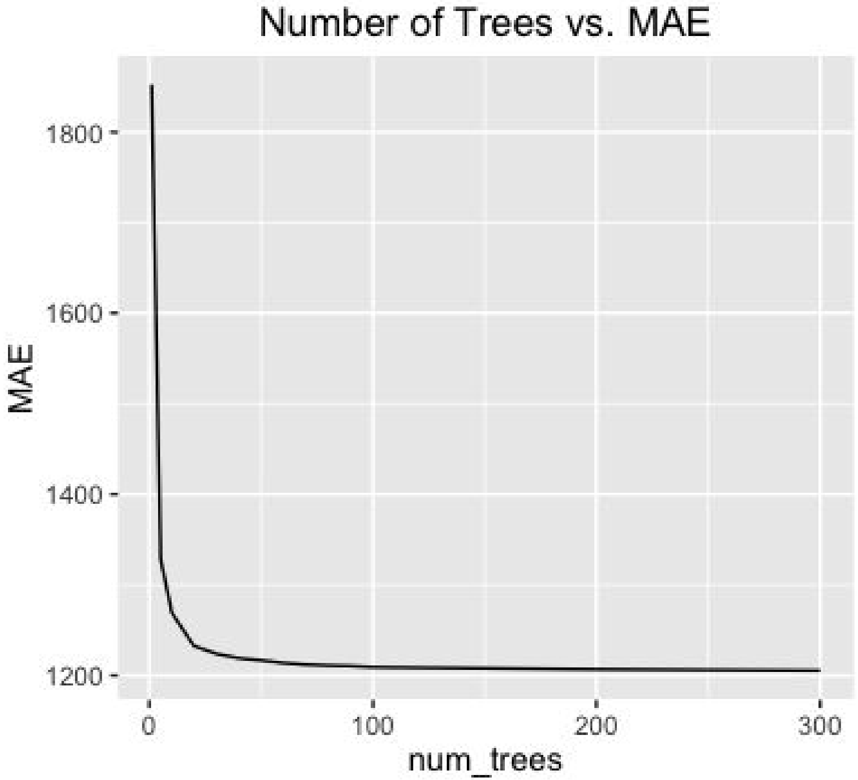
Models - Random Forest

scikit-learn: RandomForestRegressor library

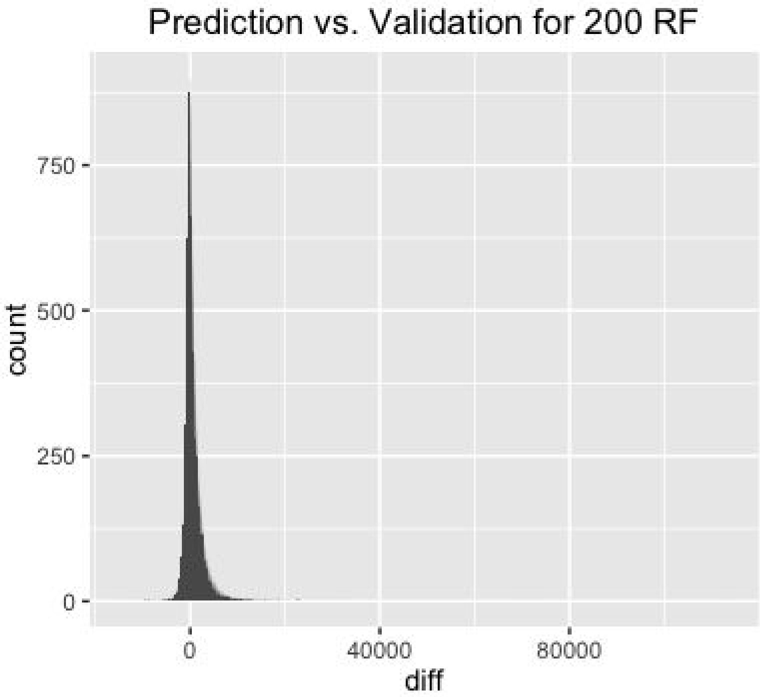
- Number of trees: [50,200]
- Max Features to Consider: sqrt(num_predictors) = sqrt(133) ≈ 11.53
- Using 10Fold Cross Validation

50 RF CV Score: 1212.226	**50 RF LB Score:** 1188.92450
200 RF CV Score: 1202.28	**200 RF LB Score:** 1187.71536

Models - Random Forest - Number of Trees



Models - Random Forest -Prediction vs. Validation Set:



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Models - Neural Network

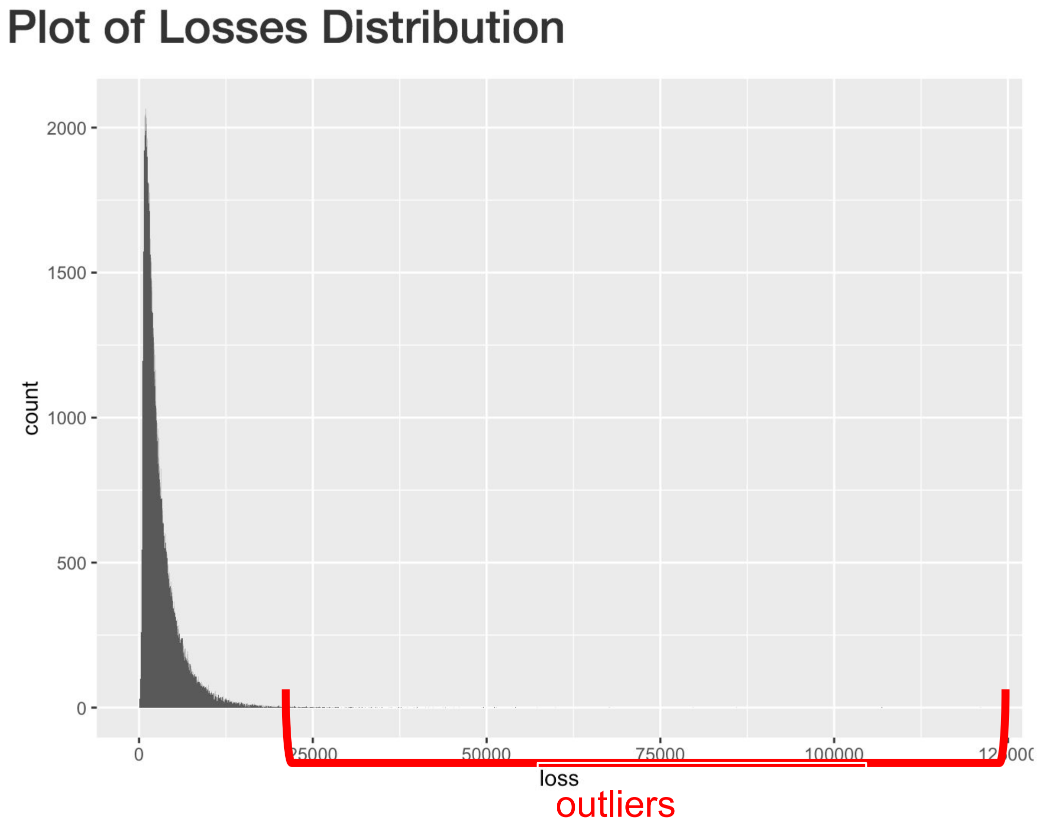
- Keras (Front-end) + Theano (Backend) python packages
- Single best model
  - Architecture : input → 400 Neurons → 200 Neurons → 50 Neurons → output
  - Regularized with dropout and batch normalization
  - 10 K-Fold with 10 bags per fold
  - Validation score: 1134
  - LB score: 1113
- Tried to add extra layers but could not reach minimal without smaller learning rate

XGBoost

- 10 K-Fold Cross Validation
- Parameters:
  - Learning rate: 0.01
  - Learning rate decay : 0.9996
  - Max trees = 10,000 with early stopping if validation score does not improve
- Validation score: 1133
- LB score: 1112
- Best single model

Outlier Analysis

- Ranges from 10340 to 121000
- Only 5315 pts out of 180k points
- 2.5% of the data but 90% of possible values
- Added feature in train set that signifies if it is an outlier
- Validation score: ~1050 with both xgboost and Neural Networks



Outlier Classification

- Goal: Train binary classifier to predict class on Test set
- Tried Logistic Regression -> 97.5% accuracy, 0.61 ROC AUC score
    - No better than just guessing all positive classes
- Tried XGBoost for classification while maximizing ROC AUC score
    - Most of the probabilities were near 0.5
    - Algorithm is very unsure of what was an outlier

Outlier Classification

- Used the Imbalanced dataset package in python to perform Synthetic Minority Oversampling Technique (SMOTE) + undersampling to generate new balanced dataset
- Ran another classifier with the results:
  - AUC of ROC: 0.8
  - Accuracy: 99.6%
- Great! Added new feature to test data and used XGBoost to run a regression: validation score: ~**1050** but LB: **1178**

Possible Reasons for Failure

- Leaderboard only displays scores on 30% of data, so 70% of data will need to deal with more outliers (unlikely but hopeful)
- Distribution for test set is different from the training set, so the classifier is not doing a good job
- Accidentally overfit to training set when we chose the cutoff based on loss variable (most likely)

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Results - Summary of Standalone Models

Kaggle Leaderboard Score:

- **Lasso Regression:** 1834.08715 (feature selection)
- **Random Forest:**

  50 Tree LB Score: 1188.92450

  200 Tree LB Score: 1187.71536

- **Neural Network:** 1113
- **XG Boost:** 1112

Results - Ensemble Models

- Average of two xgboost models and two Neural Network models
  - LB Score: 1108
- Used a optimizer to find best weights based on minimizing error of the validation sets to train loss
  - LB Score: 1105
- Simple weighted average where more weight was placed on the higher performing xgboost model and Neural Network model
  - LB Score: 1101

Final Results and Insights

- Traditional models (linear regression, random forest, kNN) did not perform as strongly
- Single best model is XGBoost
- Runner up are Neural Networks
- But an ensemble of them is *even* better

Further Steps

- Perform more hyperparameter tuning to perfect single models
- Ensemble more models to correct mistakes
- Explore stacking to further lower accuracy
- Examine outlier detection more closely, (i.e use anomaly detection algorithms instead of binary classification based on cutoff)