Santander Bank Customer Transaction Prediction

Data Mining – CMPE 255

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Agenda



- Objective
- Data Overview
- Implementation
- Data Preprocessing
- Feature Engineering
- Cross Validation
- Modelling & Results
- Ensemble Modelling impact
- Challenges
- Tools Used
- Questions

Objective

Identifying who among the current customers will make certain transaction!!!

- Is the customer satisfied?
- Will a customer buy this product?
- Will customer avail this service?



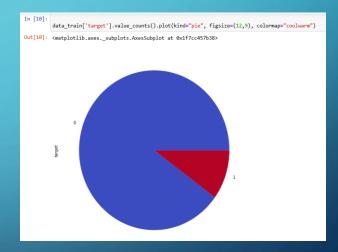
Data Overview

- Train Data: 200,000
- Test Data : 200,000
- Target Variable: Binary
 (0/1)
- Features:
 - 200 anonymous features
 - All Continuous
 Variables

data_train.head()												
	ID_code	target	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7		
0	train_0	0	8.9255	-6.7863	11.9081	5.0930	11.4607	-9.2834	5.1187	18.6266		
1	train_1	0	11.5006	-4.1473	13.8588	5.3890	12.3622	7.0433	5.6208	16.5338		
2	train_2	0	8.6093	-2.7457	12.0805	7.8928	10.5825	-9.0837	6.9427	14.6155		
3	train_3	0	11.0604	-2.1518	8.9522	7.1957	12.5846	-1.8361	5.8428	14.9250		
4	train_4	0	9.8369	-1.4834	12.8746	6.6375	12.2772	2.4486	5.9405	19.2514		
5 rows × 202 columns												
data_train.shape												
(200000, 202)												
data_train.describe()												

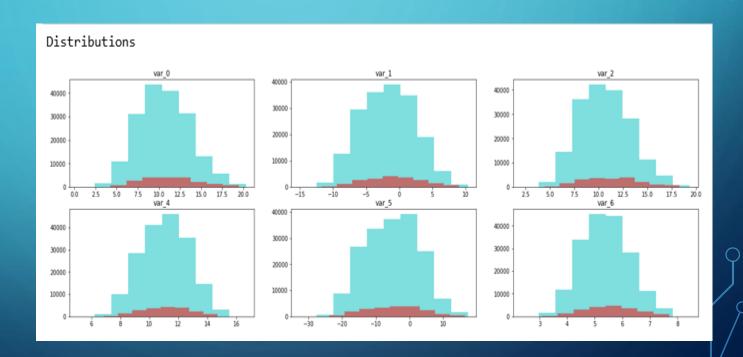
Data Visualizations

- 90% of the training data is labeled as 0, and the other 10% is labeled as 1
- Evaluation criteria:
 - ROC –AUC score
- Target 0 -179902
- Target 1 -20098



FEATURE DISTRIBUTION

The distribution of the features in in terms of class 0 and class 1



Implementation

- Missing Data, Correlation, Outlier Removal
- Model Fitting
 - Feature Engineering
 - Hyper parameter tuning and CV
 - Model Fitting
 - Model Evaluation/selection

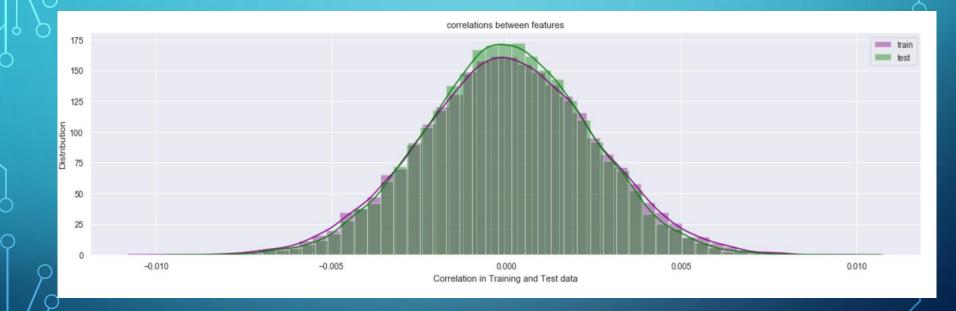
Data Preprocessing



- No missing values
- No duplicate values
- No much correlation between the features for dimension reduction

```
#Least correlated features
corr.head()
var_26 var_139
                 -0.009844
var_53 var_148
                 -0.009788
var_6 var_80
               -0.008958
var_1 var_80
               -0.008855
var_2 var_13
                 -0.008795
dtype: float64
# Most correlated Features
corr.tail()
var_146 var_169
                   0.009071
var 183 var_189
                   0.009359
var_81 var_174
                   0.009490
        var_165
                   0.009714
        var 0
var 0
                   1.000000
dtype: float64
```

Correlation



Feature Engineering

- New Features
 - Sum
 - Median
 - Mean
 - Min
 - Max
 - Standard deviation

sum	min	max	mean	std	skew	kurt	med
1456.3182	-21.4494	43.1127	7.281591	9.331540	0.101580	1.331023	6.77040
1415.3636	-47.3797	40.5632	7.076818	10.336130	-0.351734	4.110215	7.22315
1240.8966	-22.4038	33.8820	6.204483	8.753387	-0.056957	0.546438	5.89940
1288.2319	-35.1659	38.1015	6.441159	9.594064	-0.480116	2.630499	6.70260
1354.2310	-65.4863	41.1037	6.771155	11.287122	-1.463426	9.787399	6.94735



Cross Validation

- K-Fold Cross Validation with stratified sampling
- Splits data into non overlapping and mutually exclusive samples
- Use (k-1) for Training, 1 for Validation



- Logistic Regression
- Random Forest
- Cat Boost
- XGBoost
- Light Gradient Boosting

Logistic Regression

55

59

63

Model 1

Model 2

- Model 1 Logistic Regression with PCA
- Model 2 Logistic Regression with CV (7-fold) and Regularization
- Model 3 Logistic Regression with CV (10-fold) and Regularization



Random Forest

Model 1

Model 2

- Model 1 Vanilla Random Forest
- Model 2 Random Forest with CV (5-fold) and grid search
- Model 3 Random Forest with CV (5-fold) and grid search & AUC as objective function

CatBoost

69

73

90

Model 1 Model 2

- Model 1 Random parameters in CatBoost
- Model 2 CatBoost with CV (10-fold) and grid search
- Model 3 CatBoost with CV (10-fold) and grid search and wider hyper-parameter tuning

XG Boost



86

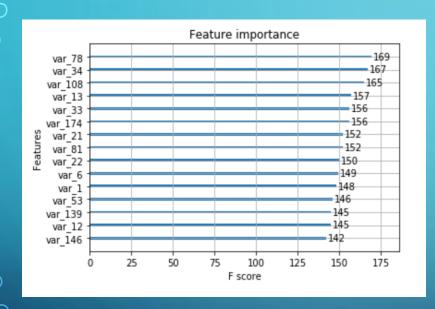
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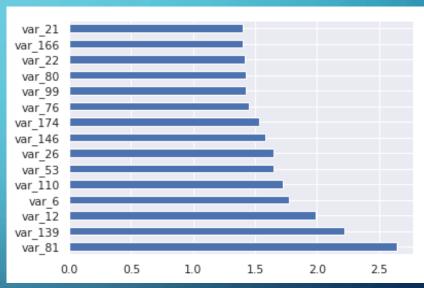
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Model 1 Model 2

- Model 1 XgBoost with grid search
- Model 2 XgBoost with CV (10-fold), L1, L2 regularization
- Model 3 XgBoost with CV (10-fold), Extra Features and wider hyper-parameter tuning

Feature Importance





XG Boost

Cat Boost

Light Gradient Boosting

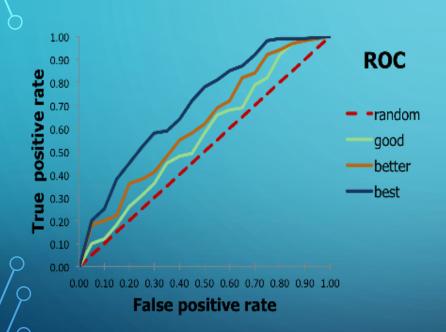
89 Model 1

- Model 1 LGB with grid search
- Model 2 LGB with more hyper parameter tuning, extra features, regularization

Ensemble Impact

- Better Performance
- AUC improvement
- GBM training take more time compared to Random Forest Bagging
- Overfitting in Boosting, hence L1 and L2 regularization parameters are also tuned
- Less likely to overfit in Random forest.
- RF is easier tune than GBM.
- Prediction time is more in RF (trees Count)

ROC-AUC Score

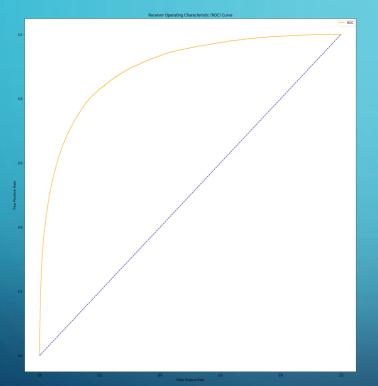


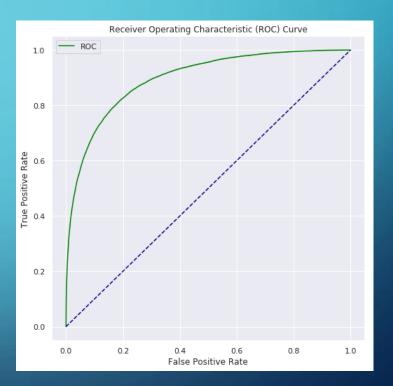
AUC: Area under ROC curve. How well model performs. How well model predicts the customer going to perform the particular transaction.

Higher the AUC, better the model

ROC Curve

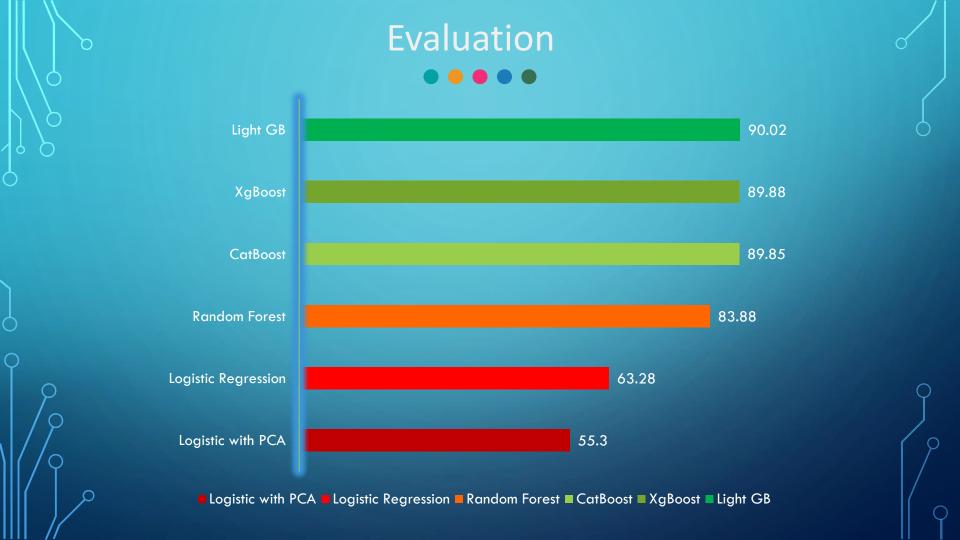






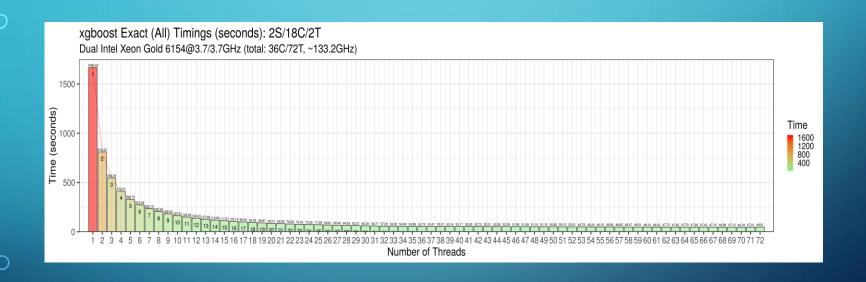
XG Boost AUC-ROC

Cat Boost



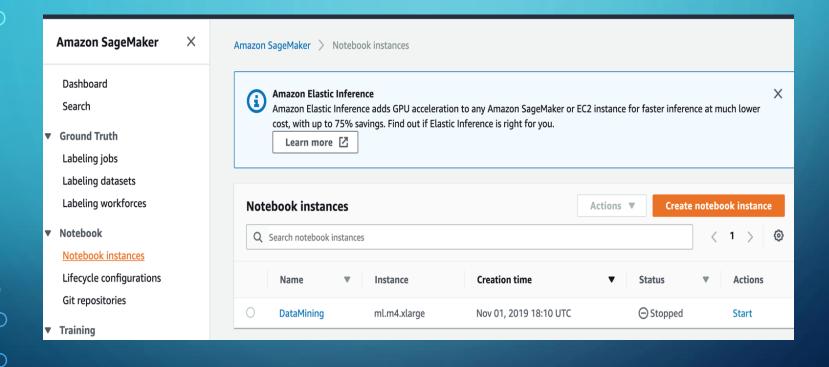


Xgboost Speed



AWS SAGE MAKER

















REFERENCES

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THANK you

QUESTIONS?