Machine Learning Engineer Nanodegree

Capstone Project

Santander Customer Transaction Prediction

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I. Definition

Project Overview

This project is based on Kaggle competition described at
https://www.kaggle.com/c/santander-customer-transaction-prediction

The problem is in finance domain. Santander is a commercial bank and financial services company. They are looking for ways to help their customers understand their financial health and identify which products and services might help them achieve their monetary goals.
The challenge is to identify which customers will make a specific transaction in the future, irrespective of the amount of money transacted. The data provided for this competition has the same structure as the real data Santander has available to solve this problem.

Problem Statement

As described in challenge, we have to use various machine learning techniques on given dataset to predict which customer will make specific transaction in future. We are provided with an anonymized dataset containing numeric feature variables, the binary target column, and a string ID_code column. The task is to predict the value of target column in the test set.

Datasets and Inputs

	ID_code	target	var_0	var_1	var_2
1	train_0	0	8.9255	-6.7863	11.9081
2	train_1	0	11.5006	-4.1473	13.8588
3	train_2	0	8.6093	-2.7457	12.0805
4	train_3	0	11.0604	-2.1518	8.9522
5	train_4	0	9.8369	-1.4834	12.8746

Santander has provided a single data file – train.csv for this problem. See above a sample of the data provided. The file is in CSV format. It contains 202 columns and 200K rows. Each row has an ID and target, followed by 200 attributes. “target” column is a binary value. Value of 1 represents that the customer will make a transaction. This is the column that needs to be predicted.
The distribution of the “target” column (column to be predicted) in the training dataset is as follows:

VALUE	% OF RECORDS
0	99.02
1	00.98

The value of 1 is found in less than 1% of cases. This is an **unbalanced dataset**.

1. **Imbalanced dataset** is relevant primarily in the context of supervised machine learning involving two or more classes.
2. **Imbalance** means that the number of data points available for different the classes is different.

Solution Outline

We have been provided a labelled data set for training. This allows the use of supervised machine learning algorithms to solve this problem.

I will explore various machine learning models suitable for binary classification. Using training dataset, I will train these models to learn the target function that best maps the input variables to the output variable. I will explore different values of hyper parameters for each model, in order to get the best target function.

I will compare these models using the metric defined in the next section.

Metrics

The solution is expected to predict which customer will make a transaction. The prediction will be based on the 200 attributes provided in Santander data. The prediction will be specified by a binary variable against the ID specified in the input. Value of 1 indicates a prediction that the customer will make a transaction in future.

As the target variable is skewed (only 1% of records have target as 0), we must not use simple accuracy calculation as a metric. Even a naive model, which always predicts 0 as target, will have an accuracy score of 99%. This would be clearly misleading metric. Hence I decided to use AUC - ROC as the evaluation metric for this problem.

AUC - ROC is a performance measurement technique for classification problems at various threshold settings. ROC is a probability curve and AUC represents degree or measure of separability. It tells how much the model is capable of distinguishing between classes. Higher the AUC, better the model is at predicting 0s as 0s and 1s as 1s. By analogy, Higher the AUC, better the model .

Solution will be evaluated on area under the AUC-ROC curve between the predicted probability and the observed target. Below graph shows an example of this curve.

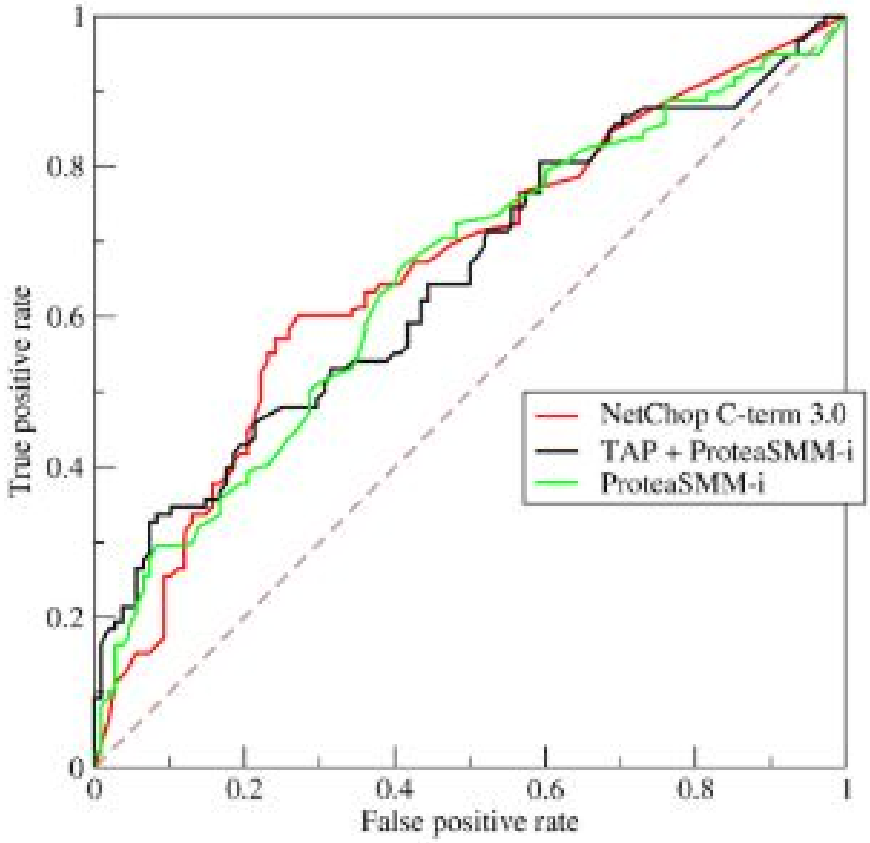
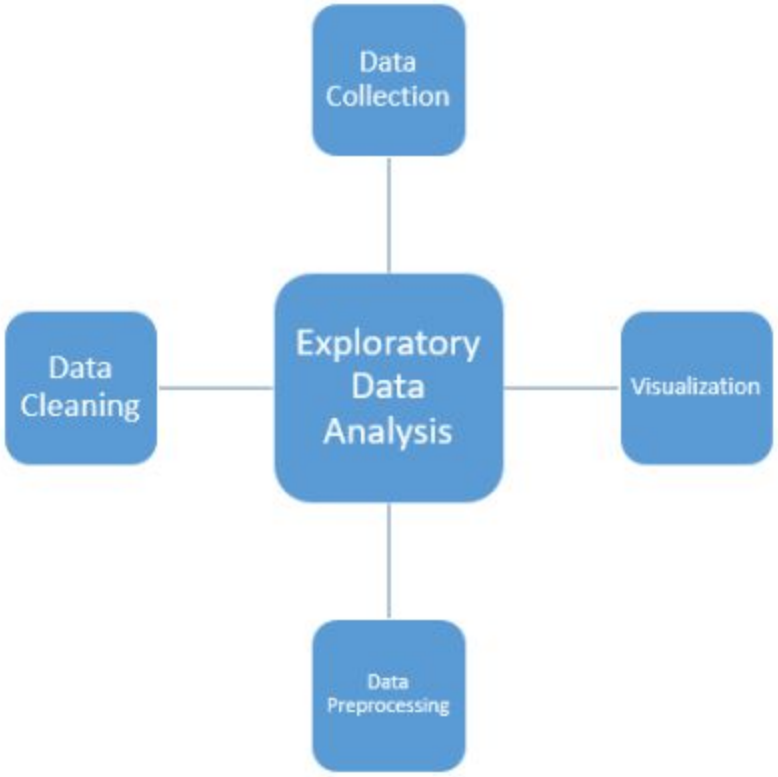


Image courtesy: https://en.wikipedia.org/wiki/Receiver_operating_characteristic

II. Analysis

Data Exploration



As stated earlier we are provided with anonymized dataset containing numeric feature variables, the binary target column, and a string ID_code column.The task is to predict the value of target column in the test set.

	ID_code	target	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	var_8	var_9	var_10	var_
0	train_0	0	8.9255	-6.7863	11.9081	5.0930	11.4607	-9.2834	5.1187	18.6266	-4.9200	5.7470	2.9252	3.1
1	train_1	0	11.5006	-4.1473	13.8588	5.3890	12.3622	7.0433	5.6208	16.5338	3.1468	8.0851	-0.4032	8.0
2	train_2	0	8.6093	-2.7457	12.0805	7.8928	10.5825	-9.0837	6.9427	14.6155	-4.9193	5.9525	-0.3249	-11.
3	train_3	0	11.0604	-2.1518	8.9522	7.1957	12.5846	-1.8361	5.8428	14.9250	-5.8609	8.2450	2.3061	2.8
4	train_4	0	9.8369	-1.4834	12.8746	6.6375	12.2772	2.4486	5.9405	19.2514	6.2654	7.6784	-9.4458	-12.

```
test_df = pd.read_csv('../input/test.csv')
test_df[:5]
```

	ID_code	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	var_8	var_9	var_10	var_11
0	test_0	11.0656	7.7798	12.9536	9.4292	11.4327	-2.3805	5.8493	18.2675	2.1337	8.8100	-2.0248	-4.3554
1	test_1	8.5304	1.2543	11.3047	5.1858	9.1974	-4.0117	6.0196	18.6316	-4.4131	5.9739	-1.3809	-0.3310
2	test_2	5.4827	-10.3581	10.1407	7.0479	10.2628	9.8052	4.8950	20.2537	1.5233	8.3442	-4.7057	-3.0422
3	test_3	8.5374	-1.3222	12.0220	6.5749	8.8458	3.1744	4.9397	20.5660	3.3755	7.4578	0.0095	-5.0659
4	test_4	11.7058	-0.1327	14.1295	7.7506	9.1035	-8.5848	6.8595	10.6048	2.9890	7.1437	5.1025	-3.2827

Train contains:

- **ID_code** (string);
- **target**;
- **200** numerical variables, named from **var_0** to **var_199**;

Test contains:

- **ID_code** (string);
- **200** numerical variables, named from **var_0** to **var_199**;

Each row has an ID and target, followed by 200 attributes. “target” column is a binary value. Value of 1 represents that the customer will make a transaction. This is the column that needs to be predicted.

As shown in distribution of target column in training dataset, the dataset is unbalanced.

There are no missing data in train and test datasets.

```
train_df.describe()
```

	target	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	var_
count	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.0000(
mean	0.100490	10.679914	-1.627622	10.715192	6.796529	11.078333	-5.065317	5.408949	16.545850	0.28416
std	0.300653	3.040051	4.050044	2.640894	2.043319	1.623150	7.863267	0.866607	3.418076	3.33263
min	0.000000	0.408400	-15.043400	2.117100	-0.040200	5.074800	-32.562600	2.347300	5.349700	-10.5055(
25%	0.000000	8.453850	-4.740025	8.722475	5.254075	9.883175	-11.200350	4.767700	13.943800	-2.3178(
50%	0.000000	10.524750	-1.608050	10.580000	6.825000	11.108250	-4.833150	5.385100	16.456800	0.3937(
75%	0.000000	12.758200	1.358625	12.516700	8.324100	12.261125	0.924800	6.003000	19.102900	2.9379(
max	1.000000	20.315000	10.376800	19.353000	13.188300	16.671400	17.251600	8.447700	27.691800	10.1513(

8 rows × 201 columns

We can make few observations here:

- standard deviation is relatively large for both train and test variable data;
- min, max, mean, sdt values for train and test data looks quite close;
- mean values are distributed over a large range.

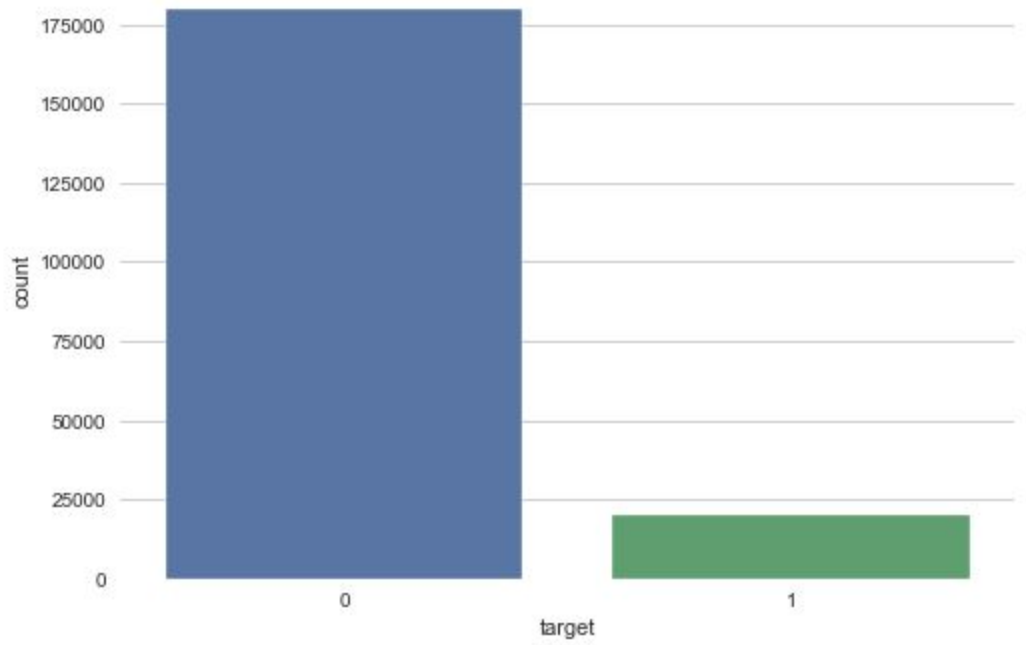
The number of values in train and test set is the same.

Exploratory Visualization

Let's check the distribution of **target** value in train dataset.

```
target = train_df['target']
train = train_df.drop(["ID_code", "target"], axis=1)
sns.set_style('whitegrid')
sns.countplot(target)
```

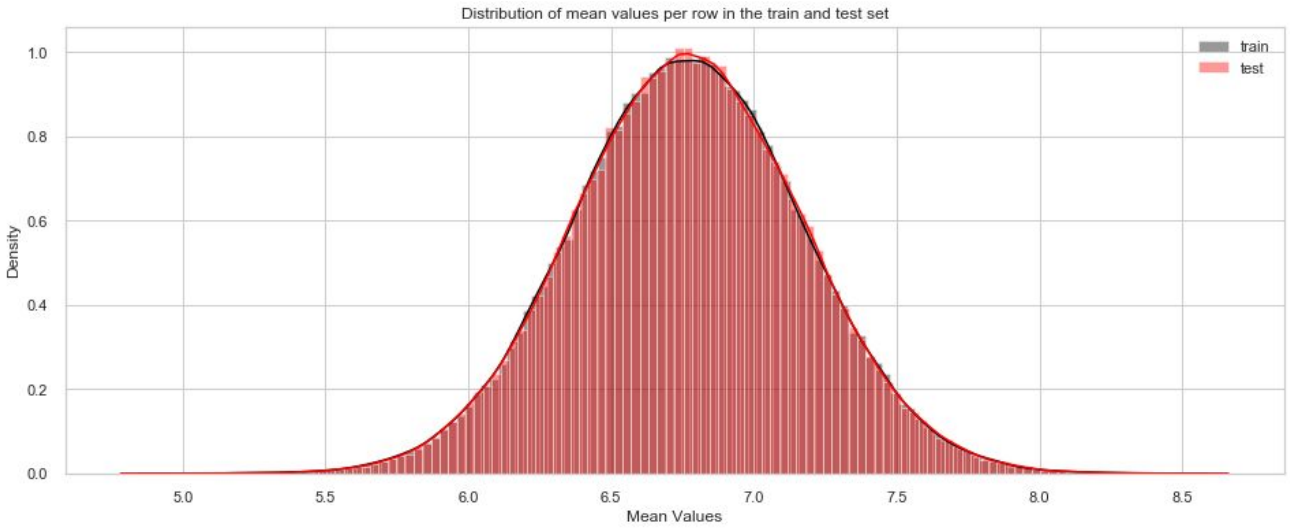
```
<matplotlib.axes._subplots.AxesSubplot at 0x19382c74cc0>
```



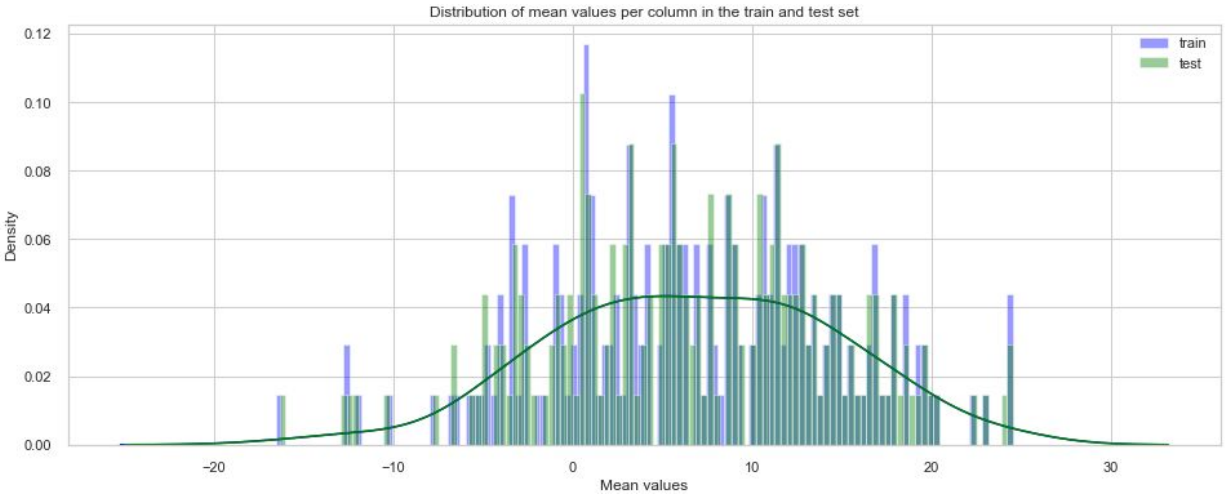
There are 10.049% target values with 1 The data is unbalanced with respect with target value.

Distribution of mean and Standard Deviation

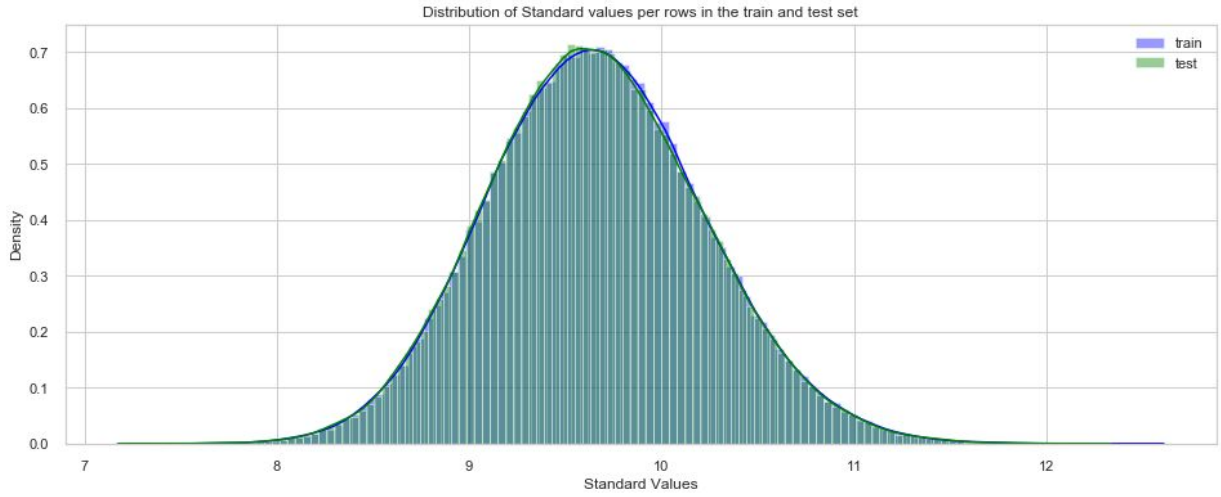
Let's check the **distribution of the mean values per row** in the train and test set.



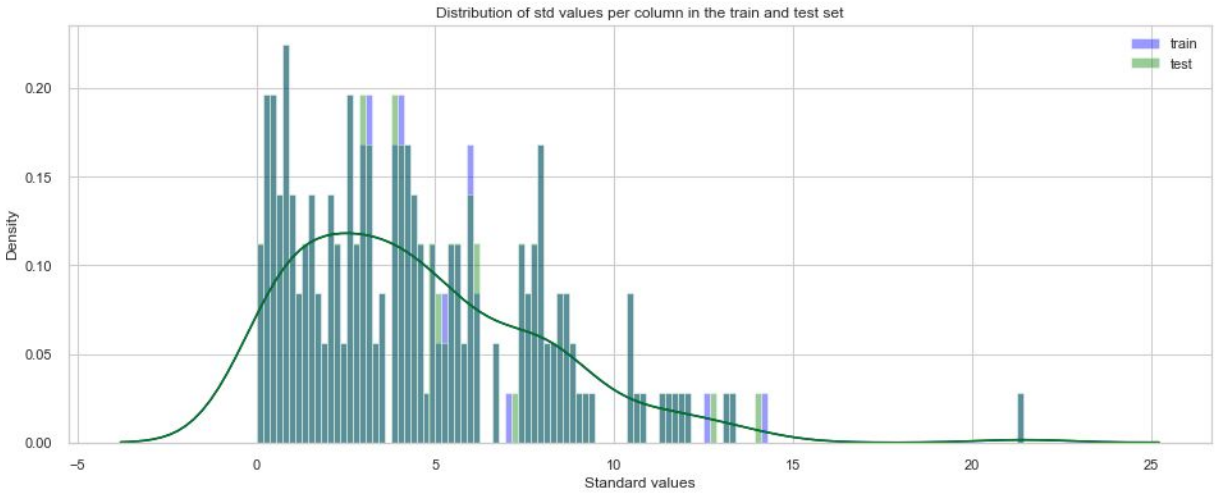
Let's check the **distribution of the mean values per column** in the train and test set.



Let's show the distribution of standard deviation of values per row for train and test datasets.

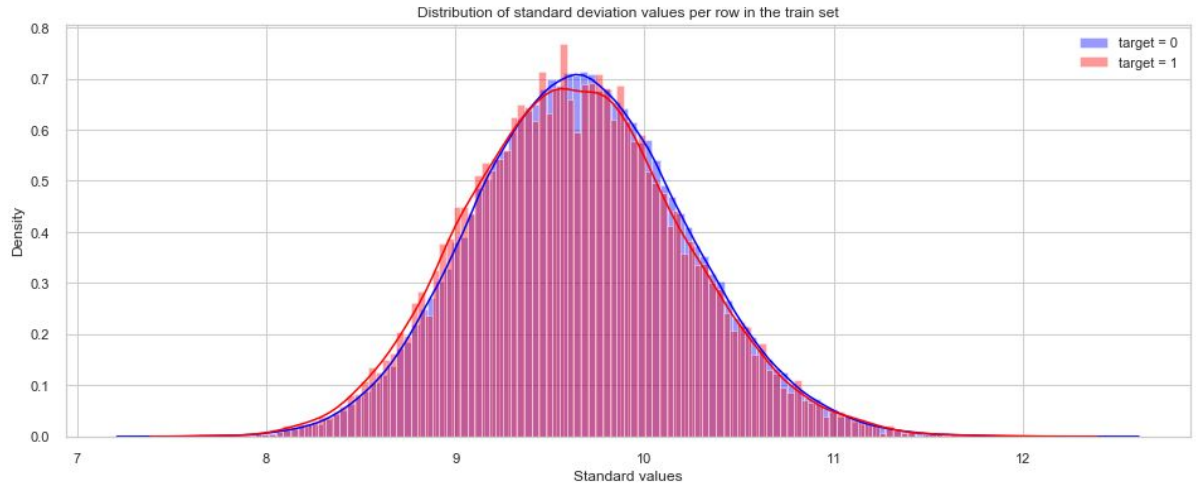


Let's check the **distribution of the standard deviation of values per column** in the train and test datasets.

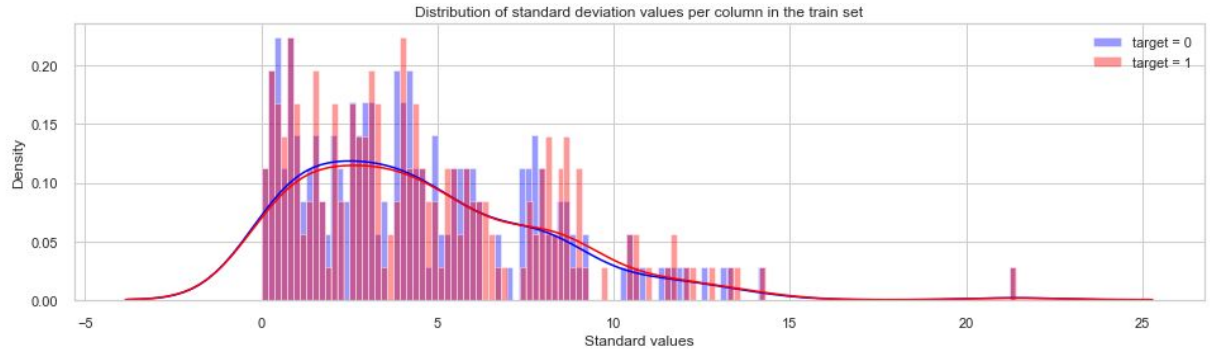


Code

The **distribution of the standard deviation per row** in the train dataset, grouped by value of target:



Let's check the distribution of standard deviation per columns in the train and test datasets.



Benchmark

I implemented a naïve solution as benchmark model. The training data distribution shows that “target” has value 1 in less than 1% of records. In other words, the transaction is expected to happen in very rare cases. We will implement a naïve model which always predicts “target” value of 0. This will be our model to use as benchmark. We will use the evaluation metric - “**Area under the ROC curve between the predicted probability and the observed target**” - to measure the performance of benchmark model. The solution we develop must do better than the benchmark model in predicting transactions.

```
oof = np.zeros(len(train_df))
predictions = np.zeros(len(test_df))
print("CV score: {:<8.5f}".format(roc_auc_score(target, oof)))
```

```
CV score: 0.50000
```

Here benchmark model have a score of **0.5** on the chosen metric. Our implementation must beat this benchmark.

III. Methodology

Data Preprocessing

For this project, the data has been provided by Santander bank. I verified that the data is in a format that is appropriate for machine learning. I verified the following attributes of the data.

All the feature columns are specified as numerical values. There are no string labels or categorical values. Hence, data transformation - like on-hot encoding is not required.

The values are populated completely. Hence we do not have to handle null/blank cases.

The distribution of values in the train and test data is similar. I have plotted mean, standard deviation, distribution of the columns to check the distribution of data.

Implementation

I have used the following main main technologies in the project:

1. Jupyter Notebook as IDE
2. Python3 as programming language
3. Numpy and Pandas modules for numeric functions, algorithms and data manipulation
4. Scikit-learn for Machine Learning models.Lightgbm module for Light Gradient Boosting model.
5. Matplotlib for plotting graphs.

I solved this problem by implementing the following machine learning models:

1. Logistic Regression
2. Decision Trees
3. Random Forest
4. Light Gradient Boosting Model

For each model implementation I followed the following steps:

1. Split the training dataset provided by Santander into train and test data set.
2. Create the model.
3. Train the model using train part data set.
4. Validate the model using test part of data set.
5. I used Stratified K-folds technique. This is a good for cross-validation.
6. Measure performance using “Area under ROC curve” method.
7. Run the model on the testing data set provided by Santander.

8. Submit the predictions on test data to Kaggle and get the AU-ROC score on testing data.

Algorithms and Techniques

For this problem we will try to implement following models:

1. **Logistic Regression**

   Logistic regression is the appropriate regression analysis to conduct when the dependent variable is binary. Like all regression analysis, the logistic regression is a predictive analysis. Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables.

- Pros
  - low variance
  - provides probabilities for outcomes
  - works well with diagonal (feature) decision boundaries
  - NOTE: logistic regression can also be used with kernel methods
- Cons
  - high bias

Here initial model with defining only the regularization parameter (C) yielded 0.6 AUC. Since this is an unbalanced dataset, we need to define another parameter 'class_weight = balanced' which will give equal weights to both the targets irrespective of their representation in the training dataset.

2. **Random Forest**

   Random Forest is a supervised learning algorithm. It builds multiple decision trees and merges them together to get a more accurate and stable prediction.Random Forest is a flexible, easy to use machine learning algorithm that produces, even without hyper-parameter tuning, a great result most of the

time. It is also one of the most used algorithms, because it's simplicity and the fact that it can be used for both classification and regression tasks.
Here we built random forest model with parameters like class_weight, random_state, and hyperparameters like max_features and min_sample_leaf as earlier. We have also defined the n_estimators which is a compulsory parameter. This defines the number of decision trees that will be present in the forest.

Pros and cons are :

- Pros
    - Decorrelates trees (relative to bagged trees)
        - important when dealing with mulitple features which may be correlated
    - reduced variance (relative to regular trees)
- Cons
    - Not as easy to visually interpret

3. **Decision Trees:**

Decision tree is the most powerful and popular tool for classification and prediction. A Decision tree is a flowchart like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label.

The parameters here are class_weight to deal with unbalanced target variable, random_state for reproducibility of same trees. The feature max_features and min_sample_leaf are used to prune the tree and avoid overfitting to the training data.

Max_features defines what proportion of available input features will be used to create tree.

Min_sample_leaf restricts the minimum number of samples in a leaf node, making sure none of the leaf nodes has less than 80 samples in it. If leaf nodes have less samples it implies we have grown the tree too much and trying to predict each sample very precisely, thus leading to overfitting.

Pros and cons are :

- Pros
    - easy to interpret visually when the trees only contain several levels
    - Can easily handle qualitative (categorical) features
    - Works well with decision boundaries parallel to the feature axis
- Cons
    - prone to overfitting
    - possible issues with diagonal decision boundaries

4. **Light Gradient Boosting Method**

   Light GBM is a gradient boosting framework that uses tree based learning algorithm. It grows tree vertically while other algorithm grows trees horizontally meaning that Light GBM grows tree leaf-wise while other algorithm grows level-wise. Leaf-wise algorithm can reduce more loss than a level-wise algorithm.

   It is ‘Light’ because of its high speed. It can handle large data, requires low memory to run and focuses on accuracy of results. Also supports GPU learning and thus data scientists/ Kagglers are widely using LGBM for data science application development.

Refinement

After trying out 4 different models, I decided to go with Light Gradient Boosting Decision Tree model, based on the performance with default parameters. I further experimented

with various model parameters to find the optimal parameters where score was maximum and pace of training was acceptable.

Initially I tried the model with default parameters. With these settings we got an AUC-ROC score of **0.8799**. Also, the training was very slow. It took about **40 minutes** to complete the training on my computer.

I then tried with following gridparams in Grid search:

- `num_leaves': [6,8,13,16]`

Large `num_leaves` helps to improve accuracy but might to overfitting.
Best param for num_leaves was found to be 13.

- `'boost' : ['gbdt', 'dart']`

For better accuracy best param was found to be **gbdt**.

- `'learning_rate': [0.0085, 0.001]`

The best result was found for parameter value of **0.0085**.

After trying various combinations and values of the hyper parameters, I was able to achieve the best AUC-ROC score of **0.9006**. Also, the pace of training was quite fast. The entire training process lasted close to **10 minutes** with optimal set of parameters. The following table summarizes the difference between the default model parameters and optimal set of parameters found after GridSearch and experimentation.

Parameter	**Default Value**	**Optimal Value**
num_leaves	13	31
boost	gbdt	gbdt
learning_rate	0.1	0.0085

reg_alpha	0.0	0.13
bagging_freq	0	5
bagging_fraction	1.0	0.38
boost_from_average	false	false
feature_fraction	1.0	0.04
max_depth	-1	-1
metric	auc	auc
min_data_in_leaf	80	20
min_sum_hessian_in_leaf	10.0	0.001
num_threads	8	0
objective	regression	binary

Challenges

The challenges I faced were related to the understanding and usage of the models. I read various articles to understand what the models are and their strengths and weaknesses. During implementation I had to understand the APIs for each model and the different hyper-parameters for them. The hyper-parameters have a major impact on how the models perform. I tried a number of variations and referred to existing implementations, to get an idea of the values for these parameters.

IV. Results

Model Evaluation and Validation

I found the best performance with Lightgbm model. So I further refined the model using following parameters. I have listed below the final values of the parameters:

1. `bagging_fraction` = 0.38. This causes the model to randomly select part of data without resampling.
2. `bagging_freq` = 5: frequency for bagging. Model performs bagging after every 5 iterations.
3. `boosting` = 'gbdt' (Gradient Boosting Decision Tree)
4. `feature_fraction` = 0.04. LightGBM will randomly select part of features on each iteration. This fraction helps speed up training and helps avoid over-fitting
5. `min_data_in_leaf` = 80. This helps in avoiding overfitting by making sure that decision tree does not branch too much to fit all data points.
6. `reg_alpha, reg_lambda` : L1 and L2 regularization parameters respectively.

Here is output of final model :

```
Fold 0
Training until validation scores don't improve for 2000 rounds.
[5000]    training's auc: 0.925151 valid_1's auc: 0.898164
[10000]   training's auc: 0.940839 valid_1's auc: 0.901261
Early stopping, best iteration is:
[10313]   training's auc: 0.941697 valid_1's auc: 0.901416
Fold 1
Training until validation scores don't improve for 2000 rounds.
[5000]    training's auc: 0.925388 valid_1's auc: 0.897582
[10000]   training's auc: 0.941018 valid_1's auc: 0.899296
[15000]   training's auc: 0.953868 valid_1's auc: 0.899497
Early stopping, best iteration is:
[13782]   training's auc: 0.950925 valid_1's auc: 0.899681
Fold 2
Training until validation scores don't improve for 2000 rounds.
```

```
[5000]    training's auc: 0.925878 valid_1's auc: 0.889935
[10000]   training's auc: 0.941418 valid_1's auc: 0.892076
Early stopping, best iteration is:
[11513]   training's auc: 0.945485 valid_1's auc: 0.892175
Fold 3
Training until validation scores don't improve for 2000 rounds.
[5000]    training's auc: 0.924659 valid_1's auc: 0.904102
[10000]   training's auc: 0.940607 valid_1's auc: 0.905769
Early stopping, best iteration is:
[10923]   training's auc: 0.943171 valid_1's auc: 0.905987
Fold 4
Training until validation scores don't improve for 2000 rounds.
[5000]    training's auc: 0.925614 valid_1's auc: 0.891877
[10000]   training's auc: 0.941327 valid_1's auc: 0.893826
Early stopping, best iteration is:
[10605]   training's auc: 0.943012 valid_1's auc: 0.893983
Fold 5
Training until validation scores don't improve for 2000 rounds.
[5000]    training's auc: 0.925178 valid_1's auc: 0.898885
[10000]   training's auc: 0.940922 valid_1's auc: 0.900185
Early stopping, best iteration is:
[9350]    training's auc: 0.939083 valid_1's auc: 0.900302
Fold 6
Training until validation scores don't improve for 2000 rounds.
[5000]    training's auc: 0.925004 valid_1's auc: 0.899852
[10000]   training's auc: 0.940738 valid_1's auc: 0.901646
Early stopping, best iteration is:
[12882]   training's auc: 0.948373 valid_1's auc: 0.90194
Fold 7
Training until validation scores don't improve for 2000 rounds.
[5000]    training's auc: 0.924914 valid_1's auc: 0.902972
[10000]   training's auc: 0.940771 valid_1's auc: 0.903942
Early stopping, best iteration is:
```

```
[9521]    training's auc: 0.939434 valid_1's auc: 0.904041
Fold 8
Training until validation scores don't improve for 2000 rounds.
[5000]    training's auc: 0.925311 valid_1's auc: 0.895958
[10000]   training's auc: 0.940975 valid_1's auc: 0.898577
Early stopping, best iteration is:
[9921]    training's auc: 0.940758 valid_1's auc: 0.898601
Fold 9
Training until validation scores don't improve for 2000 rounds.
[5000]    training's auc: 0.924939 valid_1's auc: 0.902262
[10000]   training's auc: 0.940664 valid_1's auc: 0.904108
Early stopping, best iteration is:
[9434]    training's auc: 0.939099 valid_1's auc: 0.904243
Fold 10
Training until validation scores don't improve for 2000 rounds.
[5000]    training's auc: 0.924827 valid_1's auc: 0.9049
[10000]   training's auc: 0.940561 valid_1's auc: 0.907107
Early stopping, best iteration is:
[10575]   training's auc: 0.942145 valid_1's auc: 0.907266
Fold 11
Training until validation scores don't improve for 2000 rounds.
[5000]    training's auc: 0.925507 valid_1's auc: 0.897642
[10000]   training's auc: 0.941211 valid_1's auc: 0.899253
Early stopping, best iteration is:
[11925]   training's auc: 0.946349 valid_1's auc: 0.899353
CV score: 0.90062
```

The final model is very successful in predicting the customer transactions. The score on “Area under the ROC curve” metric is around 0.9. This indicates the model can fairly accurately predict the target value.

As observed from above output, validation score for every fold is ~0.9 which indicates **stability of this model**.

Justification

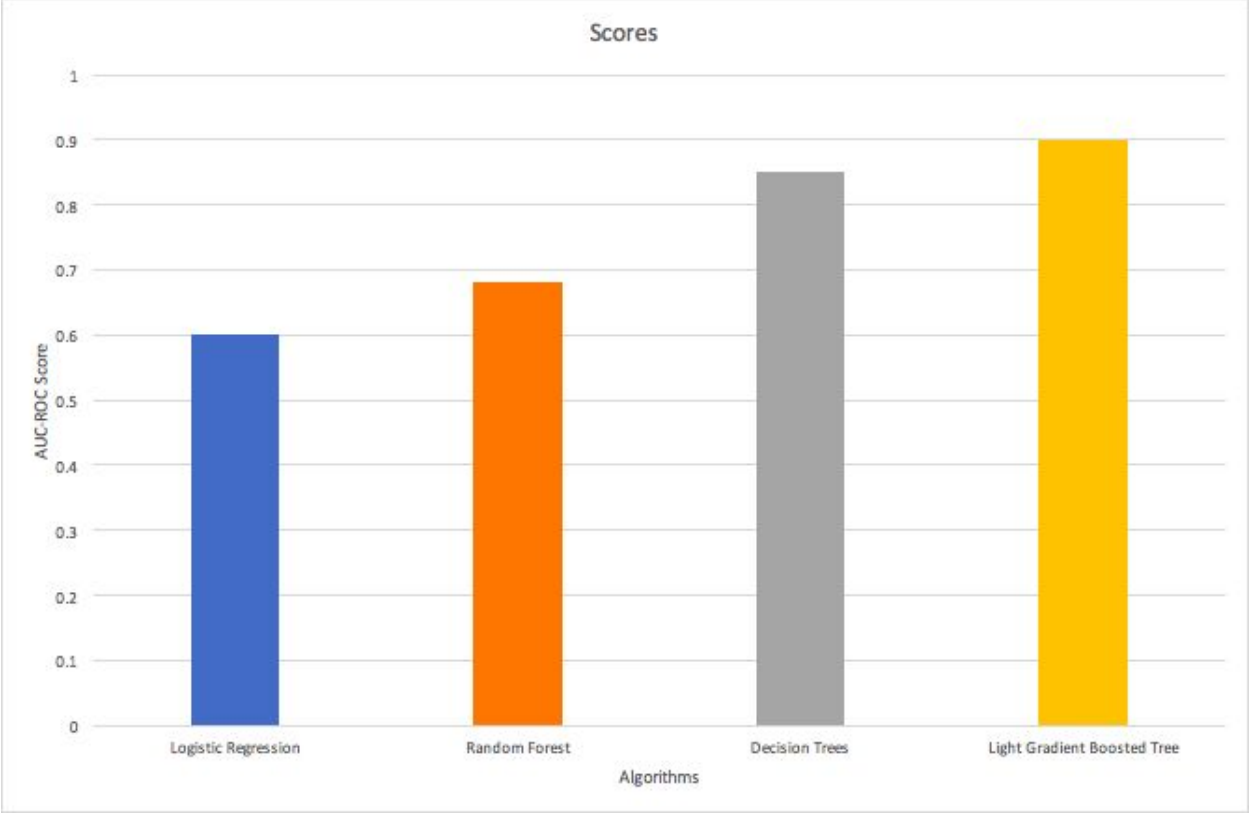
The benchmark model scored around 0.5 for the selected metric (Area under ROC curve).

The final model (Gradient Boosting Decision Tree) scored around **0.9** on this metric. This indicates that I was successful in achieving the goal of creating and training a model using the given training data, that can accurately predict customer transactions.

V. Conclusion

Free-Form Visualization

The graph below shows a comparison of how the various algorithms performed on the problem.



The graph indicates how the performance was improved using different methods. As we can see, performance of Light GBM model was the best among the algorithms chosen.

Reflection

The process used in the project can be summarized using the following steps:

1. Identify the problem (I chose the Santander problem).
2. Analyze the requirements.
3. Download the dataset.
4. Explore the dataset by visualize it in various ways.
5. Create a benchmark.
6. Explore various classification algorithms and implement them for the problem.
7. Compare the performance of the algorithms and choose the most promising one.

8. Further tune the hyper-parameters of the chosen algorithm.

I found steps 6 and 8 to be the most challenging. It required understanding each algorithm, finding the relevant APIs and trying out various values of the parameters.

I found that the most interesting was the ability to predict the transactions to a high degree of accuracy. I have been able to successfully predict customer transactions based on given data attributes. This is a good outcome for the project. This establishes that the machine learning techniques used here have practical application in the field of finance. This can be useful in predicting if a customer will buy a certain product or to predict loan default, fraud or other such anomalous transaction.

The Gradient Boosting Decision Trees model gave excellent performance for this problem. LightGBM library I used gives good performance and is easy to use. This was a good discovery for me.

Improvement

I can further Improve this project in the following ways:

1. The score of 0.90 can be further improved. A very promising approach is to create new features based on the domain knowledge or based on the EDA we usually do as the first step. Tuning the model or creating a more sophisticated stacked architecture helps to improve the score too.
2. I have not made a difference between past and future transactions. This code should be further tested to check if past inputs can help in predicting future transactions.
3. Deal with overfitting using these parameters:
    1. Small Maximum Depth
    2. Large Minimum Data in a Leaf
    3. Small Feature and Bagging Fraction
4. Improve the training speed
    1. Small Bagging Fraction
    2. Early Stopping Round

5. Use small learning_rate with large num_iterations for better accuracy
6. Ideally, the value of `num_leaves` should be less than or equal to `2^(max_depth)`. Value more than this will result in overfitting