Loan Payment Prediction Analysis

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ANALYSIS OUTLINE

1. Raw data filtering & cleaning
2. Feature encoding & transformation & selection
3. Baseline Model Selection(GradientBoosting & Logistic Regression)
4. Gradient Boosting(GBM) model parameters tuning
5. Assessment data prediction
6. Future work & Improvements

Data Cleaning & Filtering

- Find all missing value representations in the raw data source. For example, '-' and 'N\A'. Use null value to replace them all.

- Check columns that have over half of the missing values. Such as `'DIF_INCOME_LAST_180DAY_R', 'DIF_RESPERIOD_LAST_180DAY_R', 'DIF_PERIOD_LAST_180DAY_R',ect`

- Check columns that have same values over the whole dataset length: none.

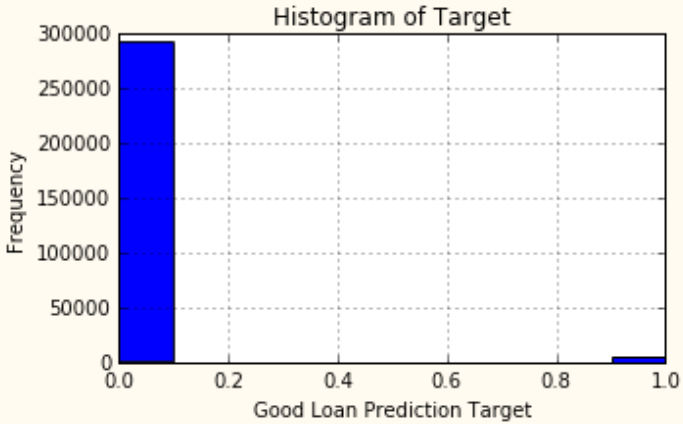
- Drop the columns with th DDATE and ID2 columns in the raw dataset, since in this dataset, I have no idea how to transform the DATE data into a useful feature. If we know the data collection date, we can transform it into how long the customer participated in the loan borrowing system. Also, we don't need ID columns for training.

- 3. Check the value distribution for all features

- 4. Output a csv file for later less IO reading time

Potential Problem: Target Data Distribution

- The TARGET column of raw data, we have very few values are 1.
- Target 1 Percent: 1.812%
- Target 0 Percent: 98.188%
- Which means, if we predict all as 1 for each customer, our prediction accuracy will be 98.188%. Therefore, we should have a model performs better than this accuracy and use AUC number to evaluate the model.

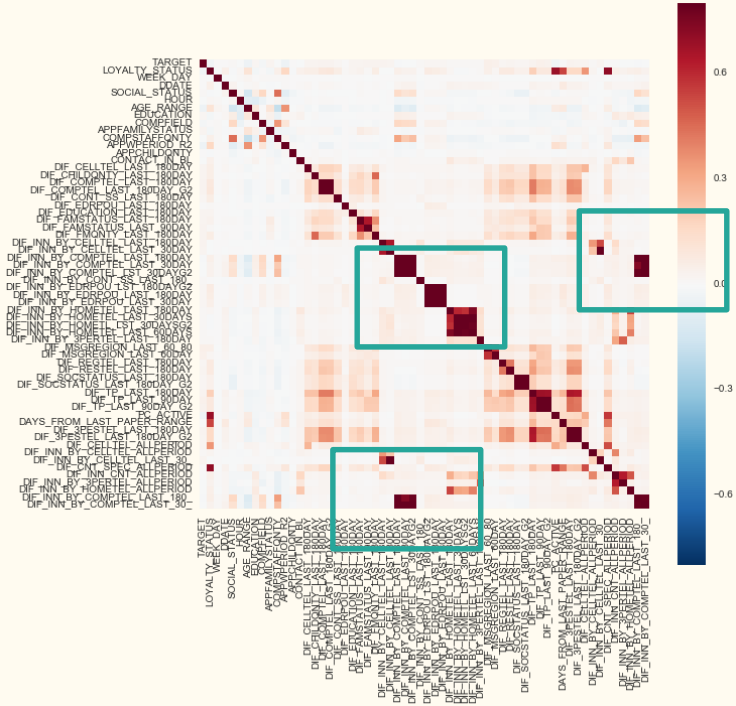


Object Data Numerical & On Hot Encoding

- Most of the features that python read in using the raw dataset are considered as Object. For example, “1-3”, “>1” columns.
- Use package LabelEncoder to encode this levels into numerical value (1,2,3,4) by its number range size.
- Categorical feature such as [‘SOCIAL_STATUS’, ‘EDUCATION’] are on hot encoded into dummy variables: SOCIAL_STATUS_1, SOCIAL_STATUS_2,...

Feature Correlation Check

- Check feature interaction & correlations. Some of them are highly correlated; thus, drop one of the highly correlated features.



Feature Selection: RFE & KBest

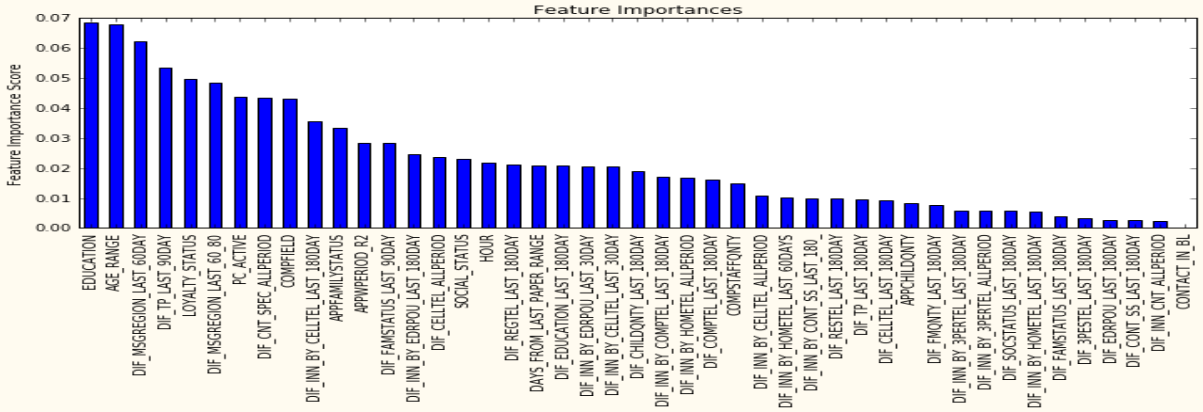
- Recursive Feature Elimination(RFE) algorithm was used to select important features among all. 60 out of 80 (including dummy variables) were selected.
- Univariate selection (Kbest), which uses a set of statistical test to find significant features were also performed to choose 60 features.

Develop Gradient Boosting Machine(GBM) Baseline Model – Use RFE Features

Baseline model performed on RFE selected features & feature importance

- Accuracy : 0.9897
- AUC Score (Train): 0.798859

- CV Score : Mean - 0.7708912 | Std - 0.01233622 | Min - 0.7505894 | Max - 0.7859253rmed on RFE selected features.

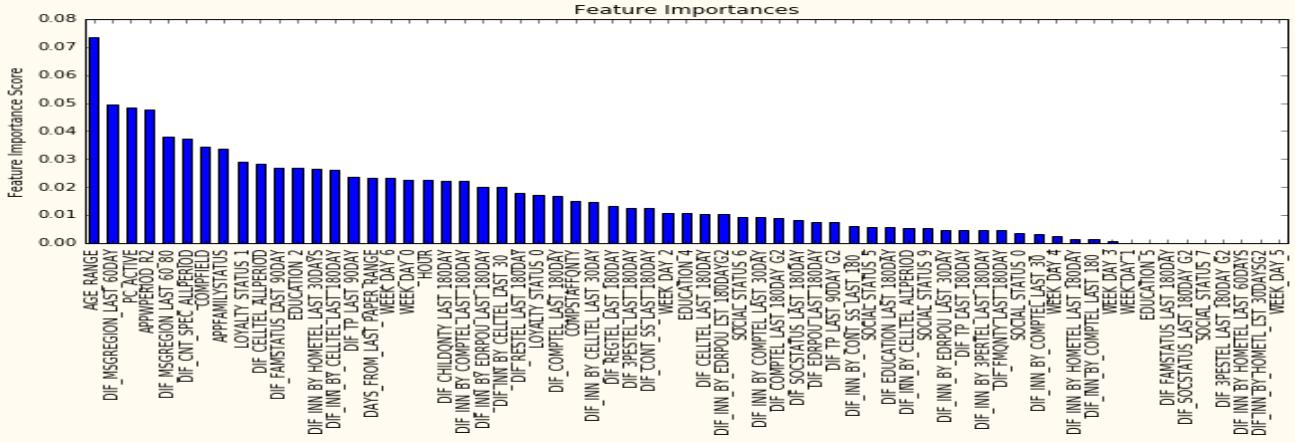


GBM Baseline Model – Use Kbest Features

Baseline model performed on KBest selected features & feature importance

- Accuracy : 0.9897
- AUC Score (Train): 0.808143

- CV Score : Mean - 0.7838879 | Std - 0.007363273 | Min - 0.7745355 | Max - 0.7954566



GBM Baseline Model -- Use All Features

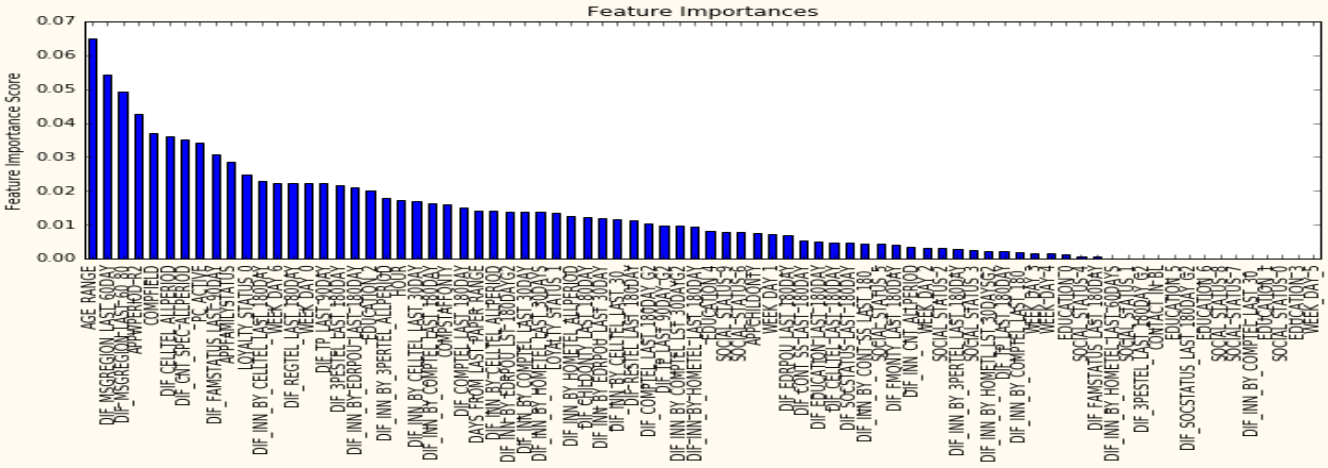
Baseline model performed on ALL features & feature importance

Accuracy : 0.9898

AUC Score (Train): 0.810849

All features: Highest AUC Score

CV Score : Mean - 0.7837371 | Std - 0.006790539 | Min - 0.7748344 | Max - 0.7951596



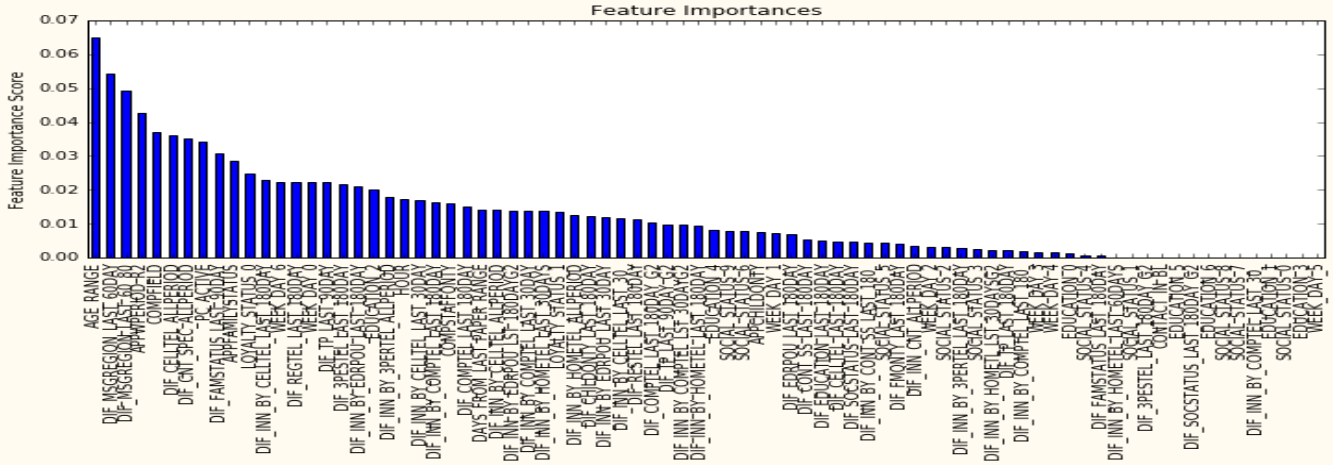
Logistic Regression Baseline Model -- All Features

Model Report

Accuracy : 0.989632605816

AUC Score (Train): 0.763690752416

CV Score : Mean – 0.75759



Since Gradient Boosting (GBM) baseline model performs better than Logistic Regression, we will use GDM to tune the parameters.

GBM Parameter Tuning

- **Step 1, tune the number of estimators**
- Initial Parameters to set with:

min_samples_split = 500 : ~usually 0.5-1% of total values (will be tuned later)

min_samples_leaf = 50 : small first, preventing over fitting (will be tuned later)

max_depth = 8 : since high number of observations and predictors, choose relatively high value (will be tuned later).

max_features = 'sqrt' : general thumb rule to start with (will be tuned later)

subsample = 0.8 : typically used value (will be tuned later)

learning_rate =0.1: fast at beginning

GBM Parameter Tuning

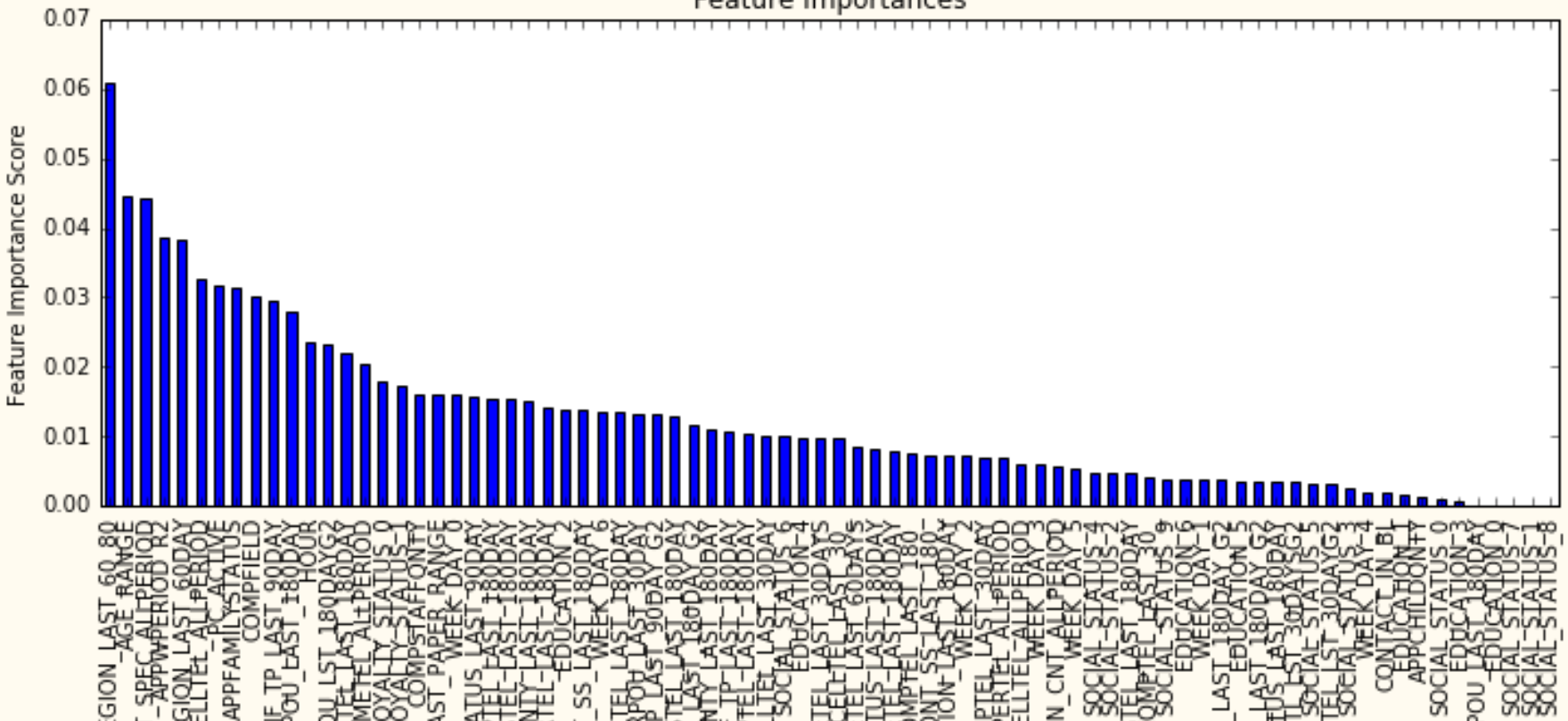
- **Step 2, tune tree specific parameters as following one by one**
- min_samples_split
- min_samples_leaf
- max_depth
- max_features
- **Step 3, tune subsample size and learning rate.**
- As learning rate decreases, the subsample size should increases as the times it decreases

GBM Final Tuned Model Performance

model_tuned = GradientBoostingClassifier(learning_rate=0.005, n_estimators=1200, max_depth=7, min_samples_split=1600, min_samples_leaf=50, subsample=0.75, random_state=10, max_features=24)

Model Report

- Accuracy : 0.9896
- AUC Score (Train): 0.838800
- CV Score : Mean - 0.7863468 | Std - 0.006260485 | Min - 0.7757783 | Max - 0.7941119


Feature Importances
Feature Importance Score
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
DIF_MSGREGION_LAST_60_80
AGE_RANGE
DIF_CNT_SPEC_ALLPERIOD
APPWPERIOD_R2
DIF_MSGREGION_LAST_60DAY
DIF_CELLTEL_ALLPERIOD
APPFAMILYSTATUS
COMPFIELD
DIF_TP_LAST_90DAY
DIF_INN_BY_EDRPOU_LAST_180DAY
HOUR
DIF_INN_BY_EDRPOU_LAST_180DAYG2
DIF_INN_BY_CELLTEL_LAST_180DAY
DIF_INN_BY_HOMETEL_ALLPERIOD
LOYALTY_STATUS_0
LOYALTY_STATUS_1
COMPSTAFFONTT
DAYS_FROM_LAST_PAPER_RANGE
WEEK_DAY_0
DIF_FAMSTATUS_LAST_30DAY
DIF_COMPTEL_LAST_180DAY
DIF_3PESTEL_LAST_180DAY
DIF_EMONTH_LAST_180DAY
DIF_INN_BY_3PERTEL_EDUCATION_2
DIF_CONT_SS_LAST_180DAY
WEEK_DAY_6
DIF_CELLTEL_LAST_180DAY
DIF_INN_BY_EDRPOU_LAST_30DAYG2
DIF_TP_LAST_90DAYG2
DIF_RESTEL_LAST_180DAY
DIF_COMPTEL_LAST_180DAYG2
DIF_CHILDONLY_LAST_180DAY
DIF_IP_LAST_180DAY
DIF_INN_BY_COMPTEL_LAST_30DAY
DIF_INN_BY_CELLTEL_LAST_30DAY
SOCIAL_STATUS_6
EDUCATION_4
DIF_INN_BY_HOMETEL_LAST_30DAYS
DIF_INN_BY_CELLTEL_LAST_60DAYS
DIF_INN_BY_HOMETEL_LAST_60DAYS
DIF_FAMSTATUS_LAST_180DAY
DIF_INN_BY_COMPTEL_LAST_180_
DIF_INN_BY_CONT_SS_LAST_180_
DIF_EDUCATION_LAST_180DAY
WEEK_DAY_2
DIF_INN_BY_COMPTEL_LAST_30DAY
DIF_INN_BY_3PERTEL_ALLPERIOD
DIF_INN_BY_CELLTEL_ALLPERIOD3
WEEK_DAY_3
DIF_INN_CNT_ALLPERIOD
WEEK_DAY_5
SOCIAL_STATUS_4
SOCIAL_STATUS_2
DIF_REGTEL_LAST_180DAY
DIF_INN_BY_COMPTEL_LAST_30_
SOCIAL_STATUS_9
EDUCATION_6
WEEK_DAY_1
DIF_3PESTEL_LAST_180DAY_G2
EDUCATION_5
DIF_SOCSTATUS_LAST_180DAY_G2
DIF_SOCSTATUS_LAST_30DAYG2
DIF_INN_BY_HOMETEL_LAST_180DAYG2
SOCIAL_STATUS_5
DIF_INN_BY_COMPTEL_LST_30DAYG2
SOCIAL_STATUS_3
WEEK_DAY_4
CONTACT_IN_BL
EDUCATION_7
APPCHILDON_7
SOCIAL_STATUS_0
EDUCATION_3
DIF_EDRPOU_LAST_180DAY
EDUCATION_0
SOCIAL_STATUS_7
SOCIAL_STATUS_1
SOCIAL_STATUS_8

GBM Final Tuned Model on Test Dataset (20% of Development Data)

Model Report

Accuracy : 0.99

AUC Score (Train): 0.884125

CV Score : Mean - 0.7777595 | Std - 0.02181214 | Min - 0.7457264 | Max - 0.8081906

Predict the Assessment Data by the Tuned Model

- Result is shown is the attached csv files
- All code written in python and in the attachment Jupyter Notebook file

Problems & Future Work & Improvements

- The highest AUC we can reach from this model is 0.83. However, All customer was predicted as Target 0 in assessment dataset. In reality, we can assess the customer by prediction probability or based on probability distribution, etc.
- Also we can improve the model by have a higher quality of dataset (more useful features instead of can't be explained ones). Then we can perform more feature transformation such as how long the customer borrow the money, how many times the customer paid back.
- Tune the GBDT parameters on larger and higher-quality dataset
- Try other models such as XGBOOST