STAT 5232 – Generalized Linear Model Final Project

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Abstract—**In this project, we built machine learning algorithms for the prediction of loan defaulters based on Lending Club data. Our main goal is to correctly identify defaulter's accuracy metric so that lending club can decide whether a person is fit for sanctioning a loan or not in the future. We dealt with several issues, such as imbalanced data, dirty data, combined with multiple categorical variable columns. Using cross validation, we fit four models on the test datasets, including logistic regression, random forest, XGBoost, and Averaging Ensemble. The calculation metrics include accuracy score, recall score, area under curve (AUC) and model fitting time. XGBoost algorithm gave the best results in terms of training/test accuracy and training/test recall scores.**

I. Purpose of Analysis

Since all three of us are into predictive analytics, we want to utilize what we have learned from class, such as modeling logistic regressions and dealing with categorical variables. Loan financing and lending payments have become such a big component in our daily life. In the industry, more and more companies are utilizing machine learning algorithms to predict loan defaults. Therefore, we decided to analyze the data from Lending Club and build predictive modeling using classification methods.

II. Introduction

We will go step by step for building machine learning algorithms for the prediction of loan defaulters based on certain variables from Lending Club. Our main goal is to correctly identify defaulter's accuracy metric (True positives + True negative) so that lending club can decide whether a person is fit for sanctioning a loan or not in the future.

III. Company Overview

Lending Club (https://www.lendingclub.com/) is a peer to peer lending company based in the United States, in which investors provide funds for potential borrowers and investors earn a profit depending on the risk they take (the borrowers credit score). Lending Club provides the "bridge" between investors and borrowers.

IV. Data Overview

The dataset contains complete loan data for all loans issued through the 2017-2018, including the current loan status (Current, Late, Fully Paid, etc.) and latest payment information. The file containing loan data through the "present" contains complete loan data for all loans issued through the previous completed calendar quarter. Additional features include credit scores, number of finance inquiries, address including zip codes, and state, and collections among others. The processed raw data is about 620MB, which contains about 500 thousand observations and 140+ variables.

The processed data is stored on Google Drive (https://drive.google.com/drive/u/1/folders/1MSkrU1IaPpamwulqDBbJ1RR_dYuUYuNc). And access is available to all users with Columbia Lionmail.

	Unnamed: 0	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	...
0	1	NaN	NaN	30000.0	30000.0	30000.0	36 months	7.34%	930.99	A	...
1	2	NaN	NaN	34825.0	34825.0	34825.0	60 months	12.61%	785.45	C	...
2	3	NaN	NaN	2600.0	2600.0	2600.0	36 months	7.96%	81.43	A	...
3	4	NaN	NaN	20000.0	20000.0	20000.0	60 months	9.92%	424.16	B	...
4	5	NaN	NaN	17000.0	17000.0	17000.0	60 months	20.39%	454.10	D	...

Figure 1: Data Overview

V. Software Description

Both R and Python were utilized in our project. Detailed codes are provided in the Appendix. We used R to combine the datasets downloaded from Lending Club, and used Python for the rest of the analysis. Also, we utilized Google Cloud Platform Virtual Machine to perform our analysis.

VI. Exploratory Data Analysis

A. *Preprocessing*

After taking an initial look at the dataset, the percentage of missing data in many columns are far more than we can work with. So, we decide to remove columns having more than 49% of missing values.

	Missing Values	% of Total Values
desc	495250	100.0
url	495250	100.0
member_id	495250	100.0
id	495242	100.0
orig_projected_additional_accrued_interest	495017	100.0
payment_plan_start_date	494980	99.9
hardship_reason	494980	99.9
hardship_status	494980	99.9
deferral_term	494980	99.9
hardship_amount	494980	99.9
hardship_start_date	494980	99.9
hardship_end_date	494980	99.9
hardship_dpd	494980	99.9
hardship_length	494980	99.9
hardship_loan_status	494980	99.9

Figure 2: Missing Values %

B. *Define Loan Status*

Based on Janio Bachmann's report named "Lending Club Loan Analysis", we decide to define the bad loans including "Charged Off", "Default", "Does not meet the credit policy. Status: Charged Off", "In Grace Period", "Late (16-30 days)", "Late (31-120 days)". And the rest of the loan categories belong to good loans. Figure 3 shows a detail breakdown of the loan status before going through loan condition conversion, and Figure 4 shows the percentage after conversion.

Clearly over 96% of the data belong to good loans, while 3.6% belong to bad loan. This is going to be a big issue later on in our analysis, and we will talk about how to deal with this (imbalanced data) later in section IX.C.

```
Current               437318
Fully Paid             40240
Charged Off             6942
Late (31-120 days)      6509
In Grace Period         2901
Late (16-30 days)       1323
Default                    9
Name: loan_status, dtype: int64
```

Figure 3: Loan Type Counts

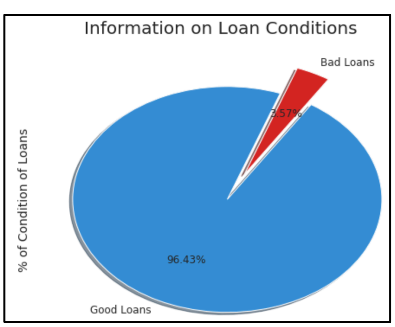

Figure 4: Loan Condition Percentage

C. *EDA*

We first examined the relationship between loan condition and loan amount, payment plan (Figure 5). Clearly, none of the good loans tends to have payment plan while some of the bad loans do.

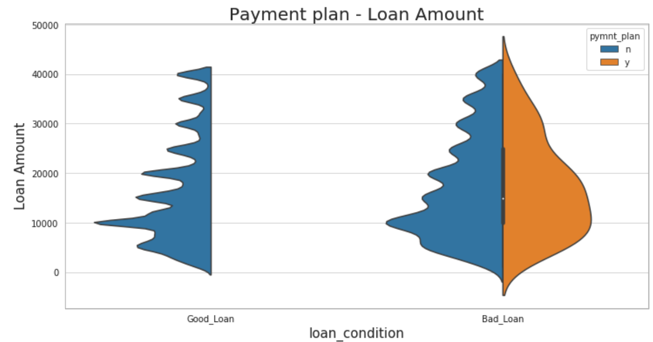

Figure 5: Payment plan vs. Loan Condition

Then we looked at the relationship between loan condition and interest rate, loan grade (Figure 6). It appears that for the same grade level, the interest rate level for bad loans is higher than its corresponding rate for good loans. This makes intuitive sense because people who tend to default will be charged for a higher spread (higher interest rate).

Figure 7 also confirmed this hypothesis. Compared with the distribution of good loans, bad loans tend to be more positively skewed.

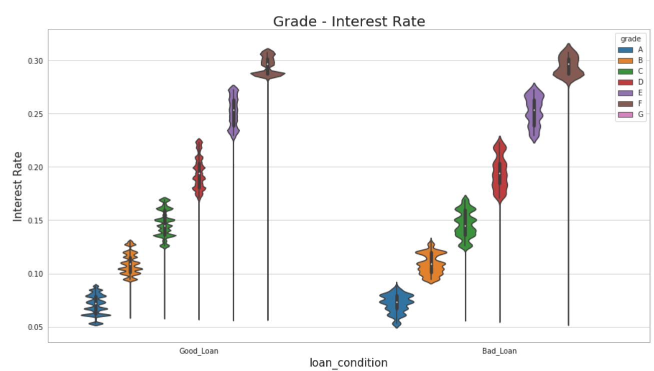

Figure 6: Loan Condition vs Grade

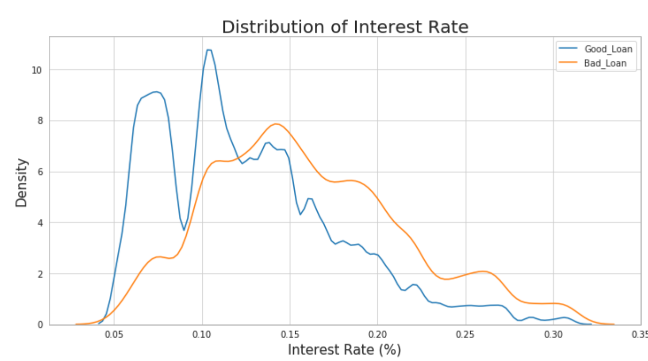

Figure 7: Loan Condition vs. Interest Rate

Then we try to examine if there's any geographical effect by looking at the state column. According to Figure 8 and 9, clearly bigger states like California, New York and Texas tend to have more loan amounts, for both good and bad loans. We do want to include state parameter in our final model because we found states like Illinois seems to have higher good-bad loans, compared to some other states like New York.

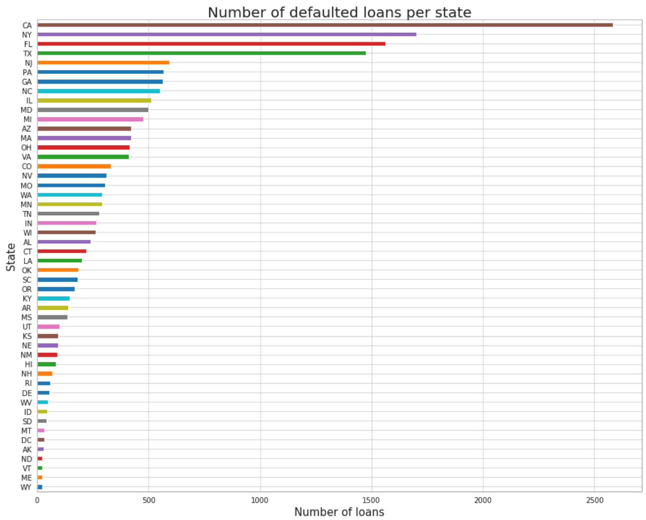

Figure 8: Number of Bad Loans by States

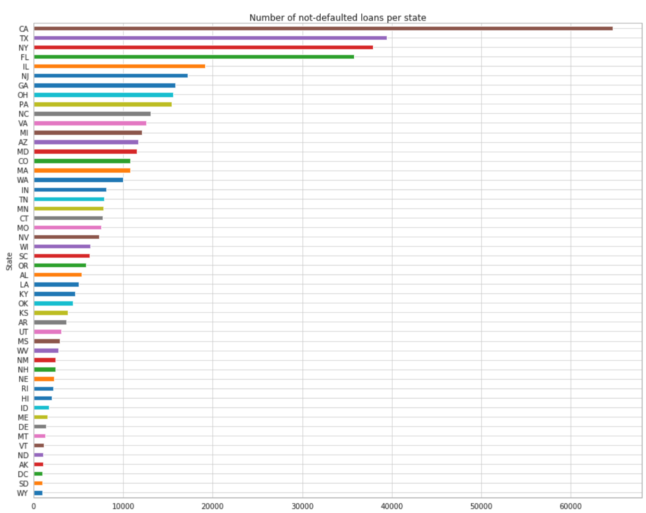

Figure 9: Number of Good Loans by State

VII. Feature Engineering

After adopting the research theory from Janio and combining the results from boxplot analysis, we finally determined the following 23 predictors to be included in our prediction model: loan amount, funded amount, funded amount committed by investors, term, interest rate, installment, grade, sub-grade, homeownership, annual income, verification status, issue date, payment plan, purpose, address state, debt payment to obligation ratio, delinquency for the past two years, inquiry in the past 6 month, times of opening account, Number of derogatory public records, revolving balance, utilization rate, number of total accounts.

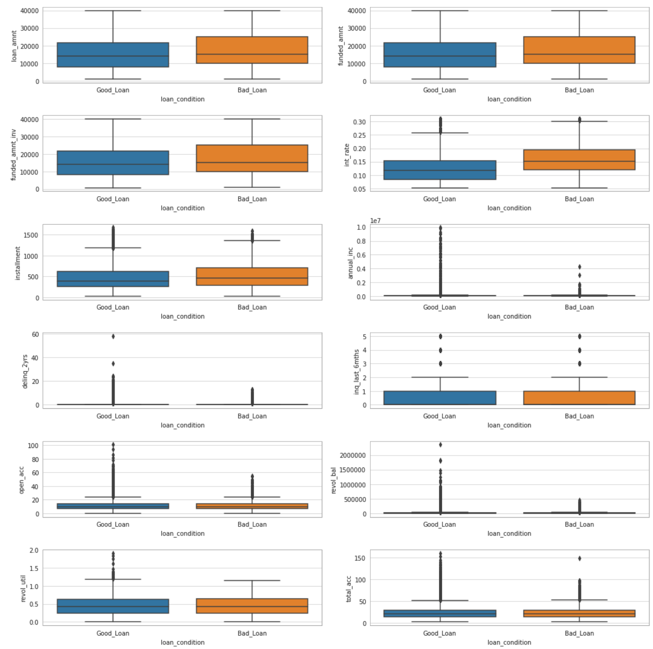

Figure 10: Boxplots on the selected predictors

VIII. Dealing with Categorical Variables

Among the selected variables, five of them are categorical variables. In Python, we can use techniques such as label encoding and one hot encoding to convert them into dummy variables for further analysis. Then the datasets look like the following (Figure 11).

term	int_rate	installment	annual_inc	issue_d	pymnt_plan	dti	...	addr_state_SD	addr_state_TN	addr_state_TX
0	0.0734	930.99	95000.0	2018	0	16.18	...	0	0	1
1	0.1261	785.45	125000.0	2018	0	21.31	...	0	0	0
0	0.0796	81.43	62000.0	2018	0	19.61	...	0	0	0
1	0.0992	424.16	110000.0	2018	0	10.56	...	0	0	0
1	0.2039	454.10	52000.0	2018	0	15.65	...	0	0	0

Figure 11: Data Overview after Converting to Dummy Variables

IX. Other Issues to Consider Before Modeling

A. *Normalization*

Normalization is a technique often applied as part of data preparation for machine learning. Urvashi Jaitley in her blog "Why Data Normalization is necessary for Machine Learning models" made a good summary point on data normalization. She believed the goal of normalization is to change the values of numeric columns in the dataset to a common scale, without distorting differences in the ranges of values.

It makes sense for us to normalize our datasets, because some of the features have different ranges.

B. *Train-Validation-Test Split*

Tarang Shah had a great discussion on this topic in his blog "About Train, Validation and Test Sets in Machine Learning". Training set is the sample of data used to fit the model, validation set is the sample of data used to provide an unbiased evaluation of a model fit on the training dataset while tuning model hyperparameters, while the test set is the sample of data used to provide an unbiased evaluation of a final model fit on the training dataset.

Here, we decided to hold about 50% data for training set, 20% for validation set, and the rest 30% for test set.

Later in the sections, we will also talk about the use of cross validation to tune our prediction models.

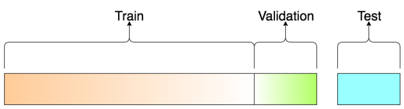

Figure 12: Visualization on Dataset Split (Tarang Shah)

C. *Imbalanced Data*

Following up with the loan condition percentage we showed earlier in the report, the other issue we are facing when we deal with this project is that we are having a really imbalanced dataset. It's known that some of the machine learning algorithms are very sensitive to imbalanced data. When we are dealing with imbalanced datasets, the most common methods are oversampling and downsampling. Some of the supervised learning problems will suffer from imbalanced data, therefore, it's very crucial to apply some of these methods before we build up the models. The most famous ones are SMOTE and NearMiss.

According to "SMOTE AND NEAR MISS IN PYTHON: MACHINE LEARNING IN IMBALANCED DATASETS", written by Saeed Abdul Rahim, SMOTE is an oversampling method. What it does is, it creates synthetic of the minority class. Hence making the minority class equal to the majority class. SMOTE does this by selecting similar records and altering that record one column at a time by a random amount within the difference to the neighboring records. On the other hand, NearMiss is an under-sampling technique. Instead of resampling the Minority class, using a distance, this will make the majority class equal to minority class.

After utilizing SMOTE method, the total number of datasets is oversampled to 233224 counts and the processing time is about 25.71 seconds. Meanwhile, NearMiss methods down-sample the number of data counts to only 8600 and the processing takes 407.18 seconds. Based on the results (Figure 13 and 14), we decided to use SMOTE method for the rest of analysis because the results are more appealing. Here we apply logistic regression with the same parameters, and the only difference is the input dataset. Figure 13 shows the result for SMOTE method, and Figure 14 is for NearMiss. Both the accuracy and recall scores for SMOTE methods are much higher. This is not surprising because we lost many useful data during downsampling process.

```
print_score(log_reg_r, 0, 0, X_val, y_val, train=False)
Test Result:

accuracy score: 0.647260

recall score: 0.644764

Classification Report:
             precision    recall  f1-score   support

          0       0.07      0.71      0.13      3757
          1       0.98      0.64      0.78     99883

avg / total       0.95      0.65      0.76    103640


Confusion Matrix:
 [[ 2681  1076]
 [35482 64401]]
```

Figure 13: SMOTE Result

```
print_score(log_reg_d, 0, 0, X_val, y_val, train=False)
Test Result:

accuracy score: 0.347192

recall score: 0.330627

Classification Report:
             precision    recall  f1-score   support

          0       0.04      0.79      0.08      3757
          1       0.98      0.33      0.49     99883

avg / total       0.94      0.35      0.48    103640


Confusion Matrix:
 [[ 2959   798]
 [66859 33024]]
```

Figure 14: NearMiss Result

D. *Parallel Processing*

Lastly, in order to maximize computational power, we want to explore parallel processing. Fortunately, this can be easily done in Python, because majority of the machine learning packages has built in parallel processing features.

The GCP Virtual Machine we built has 8 cores, 52GB RAM, and 40 GB storage space. Most of the time, we performed the analysis using 7 cores. Further details are shown in Python codes in the Appendix.

X. MODELING

A. *Logistic Regression*

Logistic regression models the probabilities for classification problems with two possible outcomes. For classification, we prefer probabilities between 0 and 1, so we wrap the right side of the equation into the logistic function. This forces the output to assume only values between 0 and 1.

$$P(y^{(i)} = 1) = \frac{1}{1 + exp(-(\beta_0 + \beta_1 x_1^{(i)} + \ldots + \beta_p x_p^{(i)}))}$$

Figure 15: Logistic Regression Formula

Performing cross validation, the algorithm suggests using L1 penalty and 0.5 as the penalty tuning parameter.

Figure 16 below shows the cross-validation result using logistic regression. The accuracy score is about 0.711 and the recall score is about 0.687. And the model fitting time is about 1298.6 seconds.

```
print_score(log_reg_best, x_train0_r, y_train0_r, 0, 0, train=True)

Train Result:

accuracy score: 0.711348

recall score: 0.687161

Classification Report:
              precision    recall  f1-score   support

          0       0.70      0.74      0.72    333107
          1       0.72      0.69      0.70    333107

avg / total       0.71      0.71      0.71    666214


Confusion Matrix:
 [[245012  88095]
 [104209 228898]]

Average Accuracy:        0.711216
Accuracy SD:             0.001293

print("--- %s seconds ---" % (log_reg_time6 - log_reg_time5))

--- 1298.6267139911652 seconds ---
```

Figure 16: Logistic Regression CV Results

B. ***Random Forest***

Random Forest is a supervised learning algorithm. Like you can already see from its name, it creates a forest and makes it somehow random. The forest it builds, is an ensemble of Decision Trees, most of the time trained with the "bagging" method. The general idea of the bagging method is that a combination of learning models increases the overall result.

Performing cross validation, the algorithm suggests using 250 as the number of estimators, 11 as the maximum depth, and 2 as the minimum number of splits.

Figure 17 below shows the cross-validation result using logistic regression. The accuracy score is about 0.917 and the recall score is about 0.938. And the model fitting time is about 157.9 seconds.

```
print_score(clf_rf_best, x_train0_r, y_train0_r, 0, 0, train=True)

Train Result:

accuracy score: 0.917265

recall score: 0.938188

Classification Report:
              precision    recall  f1-score   support

          0       0.94      0.90      0.92    333107
          1       0.90      0.94      0.92    333107

avg / total       0.92      0.92      0.92    666214


Confusion Matrix:
 [[298578  34529]
 [ 20590 312517]]

Average Accuracy:        0.913166
Accuracy SD:             0.025433

print("--- %s seconds ---" % (clf_rf_time4 - clf_rf_time3))

--- 157.8775873184204 seconds ---
```

Figure 17: Random Forest CV Results

In Python, we can also look into the feature importance of this random forest model. Figure 18 tells us the most important predictor is number of inquiries in the last 6 months, verification status and home ownership.

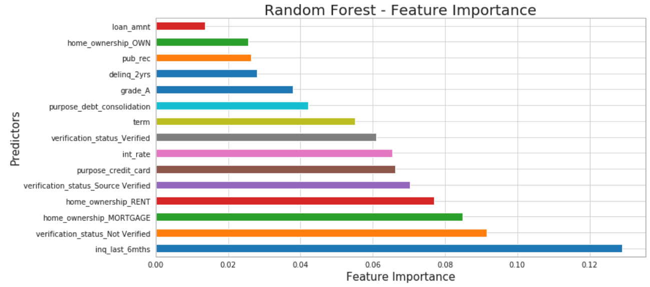

Figure 18: Random Forest Feature Importance

C. ***XGBoost***

Before getting into XGBoost, it makes more sense to start with boosting algorithms. In boosting, the trees are built sequentially such that each subsequent tree aims to reduce the errors of the previous tree. Each tree learns from its predecessors and updates the residual errors. Hence, the tree that grows next in the sequence will learn from an updated version of the residuals.

XGBoost (Extreme Gradient Boosting) belongs to a family of boosting algorithms and uses the gradient boosting (GBM) framework at its core. It is an optimized distributed gradient boosting library, which proves to be faster and better than traditional boosting methods.

Performing cross validation, the algorithm suggests using 200 as the number of estimators, 7 as the maximum depth, and 0.3 as the learning rate.

Figure 19 below shows the cross-validation result using logistic regression. The accuracy score is about 0.982 and the recall score is about 0.999. And the model fitting time is about 218.4 seconds.

```
print_score(clf_xg_best, x_train0_r, y_train0_r, 0, 0, train=True)

Train Result:

accuracy score: 0.982441

recall score: 0.999955

Classification Report:
              precision    recall  f1-score   support

          0       1.00      0.96      0.98    333107
          1       0.97      1.00      0.98    333107

avg / total       0.98      0.98      0.98    666214


Confusion Matrix:
 [[321424  11683]
 [    15 333092]]

Average Accuracy:        0.980807
Accuracy SD:             0.036781

print("--- %s seconds ---" % (clf_xg_time4 - clf_xg_time3))

--- 218.42041444778442 seconds ---
```

Figure 19: XGBoost CV Results

Similarly, we can try to understand the feature importance of this XGBoost model (Figure 20). The top three predictors are interest rate, debt payment to obligation ratio, and utilization rate. Comparing this feature chart with the previous chart on random forest, we notice many of the top predictors are dramatically different.

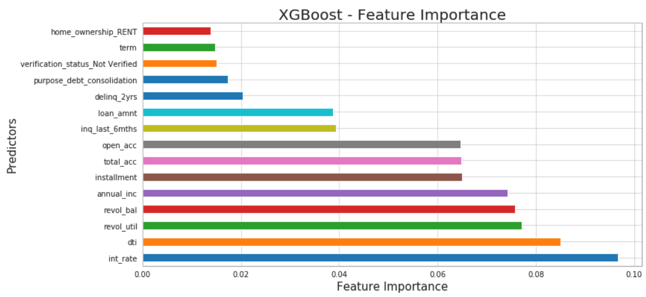

Figure 20: XGBoost Feature Importance

D. *Averaging Ensemble*

Ensemble averaging is the process of creating multiple models and combining them to produce a desired output. Here we combined all logistic regression, random forest, and XGBoost into the ensemble model.

Figure 21 below shows the cross-validation result using logistic regression. The accuracy score is about 0.944 and the recall score is about 0.950. And the model fitting time is about 1407.9 seconds.

```
print_score(ensemble_best, x_train0_r, y_train0_r, 0, 0, train=True)
 Train Result:

 accuracy score: 0.943511

 recall score: 0.950235

 Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.94      0.94    333107
           1       0.94      0.95      0.94    333107

 avg / total       0.94      0.94      0.94    666214


 Confusion Matrix:
  [[312050  21057]
  [ 16577 316530]]

 Average Accuracy:         0.939275
 Accuracy SD:              0.027609

print("--- %s seconds ---" % (ensemble_time2 - ensemble_time1))
 --- 1407.9327342510223 seconds ---
```

Figure 21: Ensemble CV Results

XI. Model Evaluation

Finally, we fit the four models on the test datasets and we obtained the results shown in Figure 22. The evaluation metrics include accuracy score, recall score, area under curve (AUC) and model fitting time.

Not surprising, XGBoost algorithm gave the best results in terms of training/test accuracy and training/test recall scores, while its AUC is just slightly worse than logistic regression and its model fitting time takes just slightly longer than Random Forest.

	ML Name	Train Accuracy	Test Accuracy	Train Recall	Test Recall	Test AUC	Model Fit Time (sec)
2	XGBoost	0.982441	0.964385	0.999955	0.999559	0.738	218.420
3	Averaging Ensemble	0.943511	0.951019	0.950235	0.982066	0.754	1407.933
1	Random Forest	0.917265	0.909683	0.938188	0.936639	0.687	157.878
0	Logistic Regression	0.711348	0.688881	0.687161	0.688368	0.758	1298.627

Figure 22: Comparison between Models

Overall, we do believe XGBoost provides the best performance, as our main goal, as described in introduction, is to correctly identify defaulter's accuracy metric (True positives + True negative). The result is not surprising, because XGBoost is probably one of the best supervised learning models out there right now, in terms of speed and performance.

XII. Future Improvements

In terms of future improvements, we might want to look on other techniques or variables to further improve the prediction power of the algorithm, for example, deep learning and neural network.

Regarding datasets, one of the drawbacks from the dataset is the limited number of people who defaulted on their loan. Even though we may have successfully dealt with this issue with techniques such as oversampling and downsampling, there may be other techniques out there which can further improve the results.

The other drawback is that we may want to utilize all available datasets starting from year 2007 to end of 2018. However, for our project, due to time constraints, we could only select a subset of the data available, which only runs from beginning of 2017 to end of 2018.

XIII. Conclusion

Determining the loan outcome, like many financial predictions, is clearly not an easy task. Throughout the project, we have confronted and dealt with several issues, such as imbalanced data and imperfect data. We also selected logistic regression as the baseline model, and extended to Random Forest, XGBoost, and Averaging Ensemble.

In summary, we have successfully built machine learning algorithms to predict the people who might default on their loans. This can be further used by Lending Club for their analysis.

XIV. CONTRIBUTION

This project is completed by the collaborative effort by Yiding Xie, Zhibo Zhou, and Gye Hyun Baek. Specifically, here is a detailed breakdown:

Yiding Xie: EDA, Data Cleaning, Model Building, Tuning and Prediction, Citation, Report, Poster
Zhibo Zhou: EDA, Data Cleaning, Report, Citation, Additional Analysis, Poster
Gye Hyun Baek: Topic Pick, Model Selection and Comparison, Report, Poster

XV. GITHUB LINK

A copy of this report, as well as all the codes used, is also available on Github: https://github.com/dreamiter/Loan-Default-Prediction-on-Lending-Club-Data

XVI. REFERENCE

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GLM_Appendix

Yiding Xie

4/21/2019

Set controls

```
set.seed(2019)
df.dir <- "/Users/timxie/Downloads/Issued Loan Data/"
#df1.dir <- "/Users/timxie/Downloads/Test Loan Data/"
wip.dir <- "/Users/timxie/Desktop/Columbia University/Spring 2019/STAT 5232/Project/WIP/"

run.loadfile <- F
```

Load files (Accepted)

```
if (run.loadfile){
  raw.data <- NULL
  files <- list.files(df.dir)

  system.time(for (f in files) {
    temp <- read.csv(paste0(df.dir,f, collapse = ""), header = T, stringsAsFactors = F, skip = 1)
    raw.data <- rbind(raw.data,temp)
  })
  rm(temp)

  save(raw.data, file = paste0(wip.dir,"raw_data.RData"))
  write.csv(raw.data, file = paste0(wip.dir,"train_data.csv"))
}
```

Load files (test data)

```
if (run.loadfile){
  raw.data <- NULL
  files <- list.files(df1.dir)

  system.time(for (f in files) {
    temp <- read.csv(paste0(df1.dir,f, collapse = ""), header = T, stringsAsFactors = F, skip = 1)
    raw.data <- rbind(raw.data,temp)
  })
  rm(temp)

  #save(raw.data, file = paste0(wip.dir,"raw_data.RData"))
  write.csv(raw.data, file = paste0(wip.dir,"test_data.csv"))
}
```

GLM_Final_Project_v9

May 2, 2019

GLM Final Project
STAT GR5232
May 6th, 2019
Yiding Xie (yx2443)
Zhibo Zhou (zz2520)
Gye Hyun Baek (gb2508)

1 Import Library

```
In [3]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        sns.set_style('whitegrid')
        import warnings
        import gc
        import time
        import xgboost as xgb
        import multiprocessing
        import sys
        import pickle

        warnings.simplefilter(action='ignore', category=FutureWarning)
        warnings.simplefilter(action='ignore', category=DeprecationWarning)
        %matplotlib inline

        from sklearn import preprocessing
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.model_selection import train_test_split
        from sklearn.model_selection import cross_val_score, cross_val_predict
        from sklearn.linear_model import LogisticRegression
        from sklearn.metrics import accuracy_score, recall_score, classification_report, confusi
        from sklearn.metrics import roc_curve, auc, roc_auc_score, r2_score
        from sklearn.preprocessing import StandardScaler
        from imblearn.over_sampling import SMOTE
        from imblearn.under_sampling import NearMiss
```

```
from sklearn.model_selection import KFold, StratifiedKFold, GridSearchCV
from sklearn.ensemble import VotingClassifier
```

2 Set up

```
In [4]: seed = 2019

        num_core = multiprocessing.cpu_count()
        print("There are " + str(num_core) + " cores on this machine.")
```

```
There are 8 cores on this machine.
```

3 Import Data

```
In [5]: df0 = pd.read_csv('/home/glm2class2019/2018_data.csv', low_memory=False)
        df0.head()
```

```
Out[5]:    Unnamed: 0   id  member_id  loan_amnt  funded_amnt  funded_amnt_inv  \
        0           1  NaN        NaN    30000.0      30000.0          30000.0
        1           2  NaN        NaN    34825.0      34825.0          34825.0
        2           3  NaN        NaN     2600.0       2600.0           2600.0
        3           4  NaN        NaN    20000.0      20000.0          20000.0
        4           5  NaN        NaN    17000.0      17000.0          17000.0

                 term int_rate  installment grade        ...          \
        0   36 months    7.34%       930.99     A        ...
        1   60 months   12.61%       785.45     C        ...
        2   36 months    7.96%        81.43     A        ...
        3   60 months    9.92%       424.16     B        ...
        4   60 months   20.39%       454.10     D        ...

          hardship_payoff_balance_amount hardship_last_payment_amount  \
        0                            NaN                          NaN
        1                            NaN                          NaN
        2                            NaN                          NaN
        3                            NaN                          NaN
        4                            NaN                          NaN

          disbursement_method debt_settlement_flag  debt_settlement_flag_date  \
        0                Cash                    N                        NaN
        1                Cash                    N                        NaN
        2                Cash                    N                        NaN
        3                Cash                    N                        NaN
        4                Cash                    N                        NaN

          settlement_status settlement_date settlement_amount settlement_percentage  \
```

```
0                NaN              NaN                NaN                    NaN
1                NaN              NaN                NaN                    NaN
2                NaN              NaN                NaN                    NaN
3                NaN              NaN                NaN                    NaN
4                NaN              NaN                NaN                    NaN

   settlement_term
0              NaN
1              NaN
2              NaN
3              NaN
4              NaN

[5 rows x 146 columns]
```

In [6]:
```
df0.shape
```

Out[6]:
```
(495250, 146)
```

4 Define function

In [7]:
```
def null_values(df):
        mis_val = df.isnull().sum()
        mis_val_percent = 100 * df.isnull().sum() / len(df)
        mis_val_table = pd.concat([mis_val, mis_val_percent], axis=1)
        mis_val_table_ren_columns = mis_val_table.rename(
        columns = {0 : 'Missing Values', 1 : '% of Total Values'})
        mis_val_table_ren_columns = mis_val_table_ren_columns[
            mis_val_table_ren_columns.iloc[:,1] != 0].sort_values(
        '% of Total Values', ascending=False).round(1)
        print ("Dataframe has " + str(df.shape[1]) + " columns.\n"
            "There are " + str(mis_val_table_ren_columns.shape[0]) +
              " columns that have missing values.")
        return mis_val_table_ren_columns

def loan_condition(status):
    if status in bad_loan:
        return 'Bad_Loan'
    else:
        return 'Good_Loan'
```

5 Initial Data Check

In [8]:
```
## Drop 1st column
df0.drop('Unnamed: 0', axis=1, inplace=True)
```

```
## Check missing values by percentage
miss_values = null_values(df0)
miss_values.head(15)
```

```
Dataframe has 145 columns.
There are 145 columns that have missing values.
```

Out[8]:

	Missing Values	% of Total Values
desc	495250	100.0
url	495250	100.0
member_id	495250	100.0
id	495242	100.0
orig_projected_additional_accrued_interest	495017	100.0
payment_plan_start_date	494980	99.9
hardship_reason	494980	99.9
hardship_status	494980	99.9
deferral_term	494980	99.9
hardship_amount	494980	99.9
hardship_start_date	494980	99.9
hardship_end_date	494980	99.9
hardship_dpd	494980	99.9
hardship_length	494980	99.9
hardship_loan_status	494980	99.9

In [9]:
```
ignore_column = miss_values.index.values[miss_values.iloc[:,1] >= 49]

## Drop NA Columns
df0.drop(ignore_column,axis=1,inplace=True)

## Drop NA rows
df0.dropna(subset=['loan_amnt'],axis = 'index',inplace=True)

df0.shape
```

Out[9]: (495242, 102)

6 Define Good and Bad Loans

In [10]:
```
df0["loan_status"].value_counts()
```

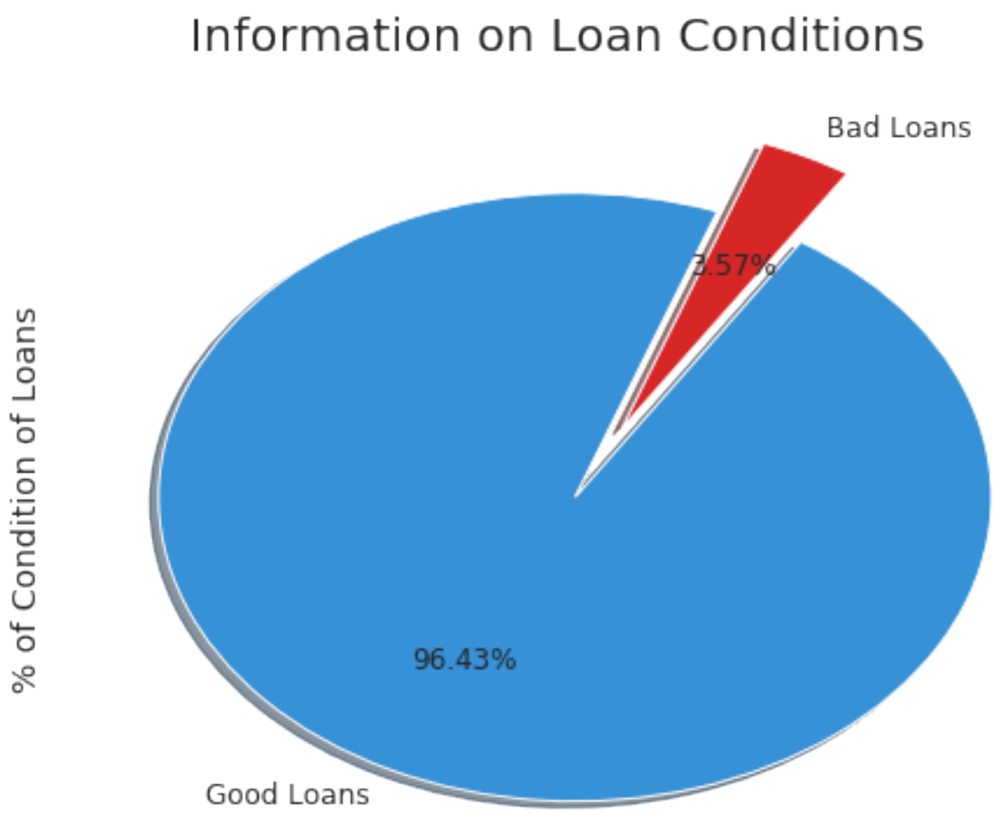
Out[10]:
```
Current               437318
Fully Paid             40240
Charged Off             6942
Late (31-120 days)      6509
In Grace Period         2901
Late (16-30 days)       1323
Default                    9
Name: loan_status, dtype: int64
```

In [11]:
```
bad_loan = ["Charged Off", "Default", "Does not meet the credit policy. Status:Charged
            "Late (16-30 days)", "Late (31-120 days)"]

df0['loan_condition'] = np.nan
df0['loan_condition'] = df0['loan_status'].apply(loan_condition)
```

In [12]:
```
print(sum(df0['loan_condition']=='Bad_Loan'))  ## Number of Bad Loan
print(sum(df0['loan_condition']!='Bad_Loan'))  ## Number of Good Loan
```

```
17684
477558
```

In [13]:
```
fig = plt.figure(figsize=(8,6))
colors = ["#3791D7", "#D72626"]
labels ="Good Loans", "Bad Loans"

plt.suptitle('Information on Loan Conditions', fontsize=20)

df0["loan_condition"].value_counts().plot.pie(explode=[0,0.25], autopct='%1.2f%%', shad
                                             labels=labels, fontsize=12, startangle=70)

# ax[0].set_title('State of Loan', fontsize=16)
plt.ylabel('% of Condition of Loans', fontsize=14)
plt.show()
```



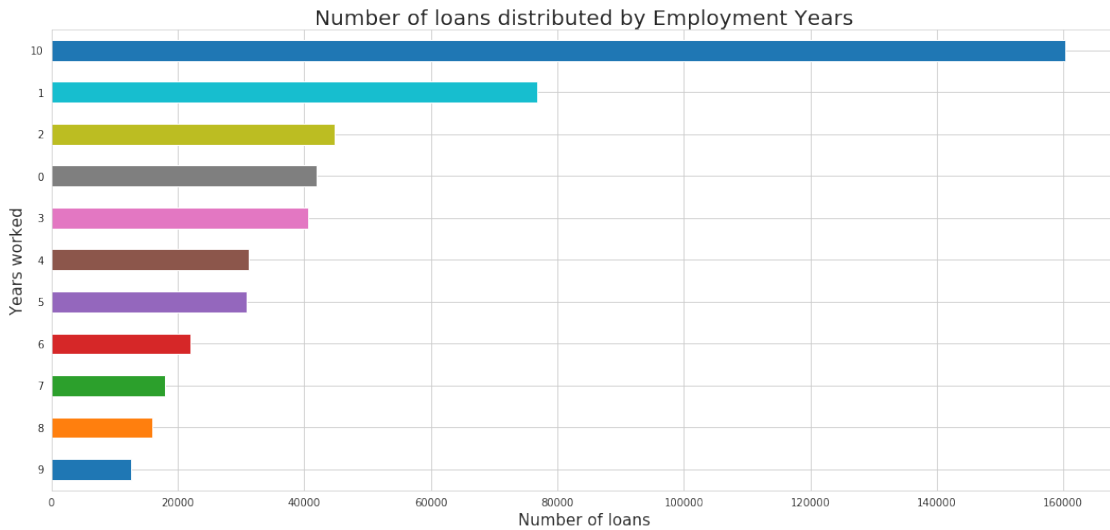
7 Data Cleaning (1st Clean)

```
In [14]: ## Convert time variables
         df0['issue_d']= pd.to_datetime(df0['issue_d']).apply(lambda x: int(x.strftime('%Y')))
         #df['last_pymnt_d']= pd.to_datetime(df['last_pymnt_d'].fillna('2019-01-01')).apply(lamb
         #df['last_credit_pull_d']= pd.to_datetime(df['last_credit_pull_d'].fillna("2019-01-01")
         #df['earliest_cr_line']= pd.to_datetime(df['earliest_cr_line'].fillna('2001-08-01')).ap

         ## Convert percentage to float
         df0['int_rate'] = df0['int_rate'].str.rstrip('%').astype('float') / 100.0
         df0['revol_util'] = df0['revol_util'].str.rstrip('%').astype('float') / 100.0
```

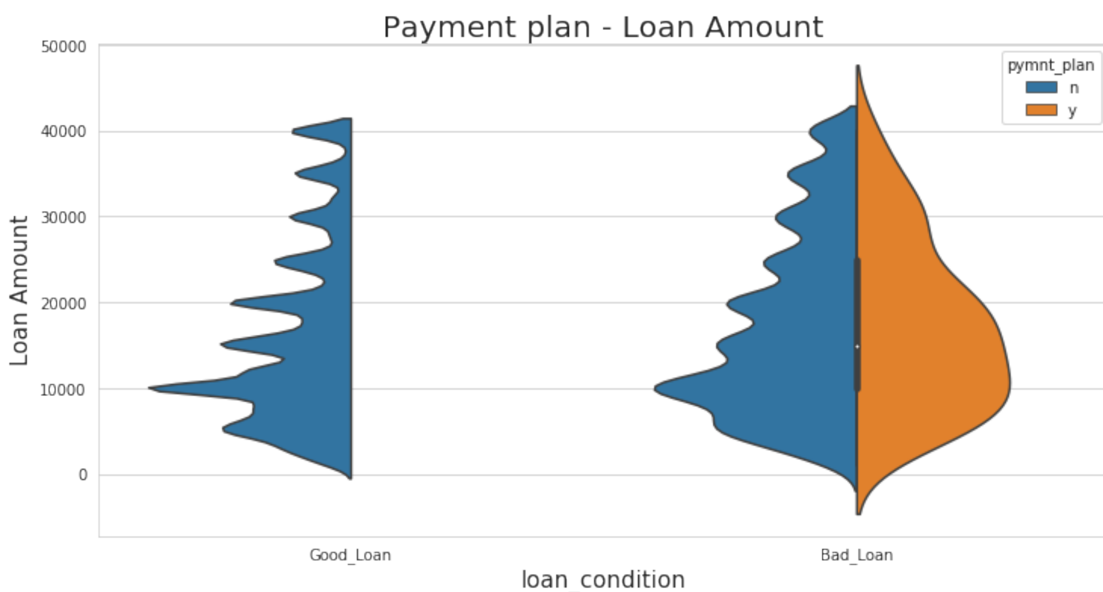
8 EDA

```
In [9]: df0['emp_length'].head(5)
        df0['emp_length'].fillna(value=0,inplace=True)
        df0['emp_length'].replace(to_replace='[^0-9]+', value='', inplace=True, regex=True)
        df0['emp_length'].value_counts().sort_values().plot(kind='barh',figsize=(18,8))
```

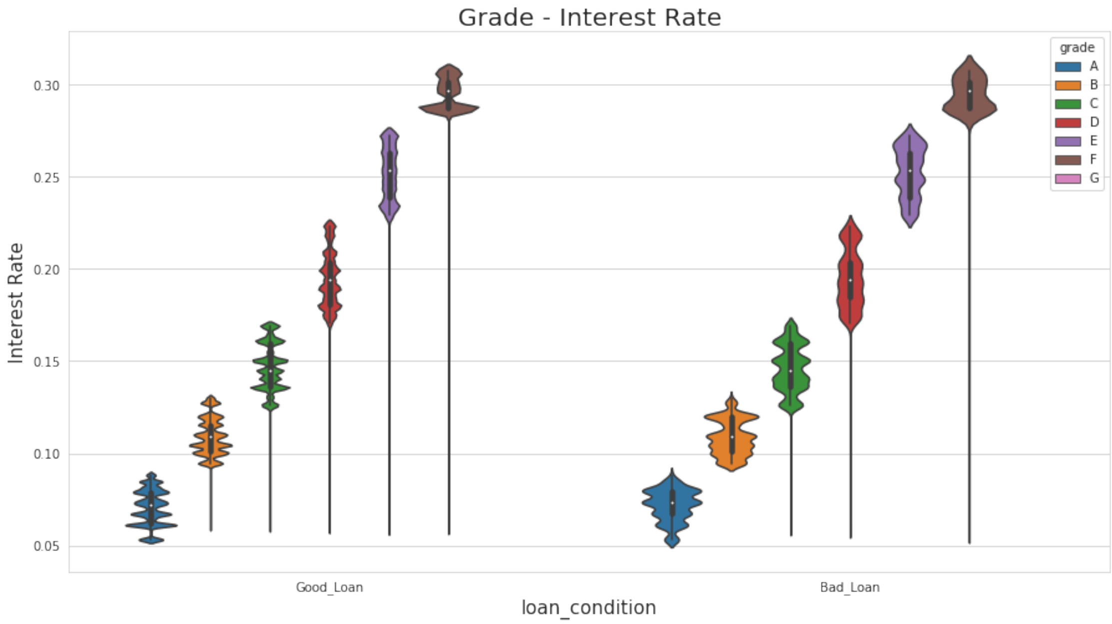
```
plt.title('Number of loans distributed by Employment Years',fontsize=20)
plt.xlabel('Number of loans',fontsize=15)
plt.ylabel('Years worked',fontsize=15)
plt.show()
```



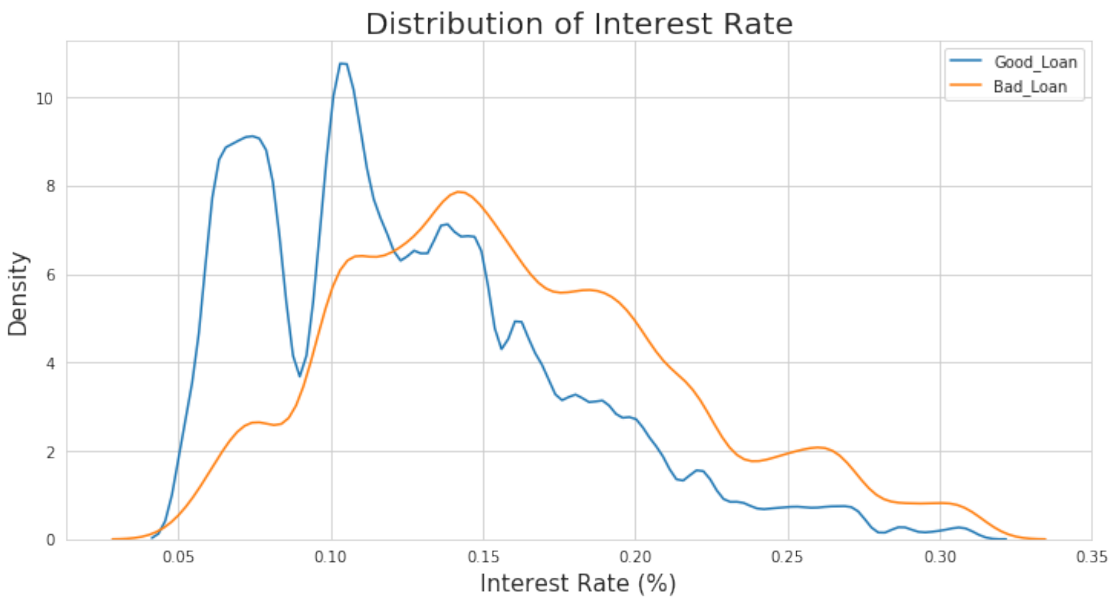

```
In [10]: fig = plt.figure(figsize=(12,6))
         sns.violinplot(x="loan_condition",y="loan_amnt",data=df0, hue="pymnt_plan", split=True)
         plt.title("Payment plan - Loan Amount", fontsize=20)
         plt.xlabel("loan_condition", fontsize=15)
         plt.ylabel("Loan Amount", fontsize=15)
         plt.show()
```



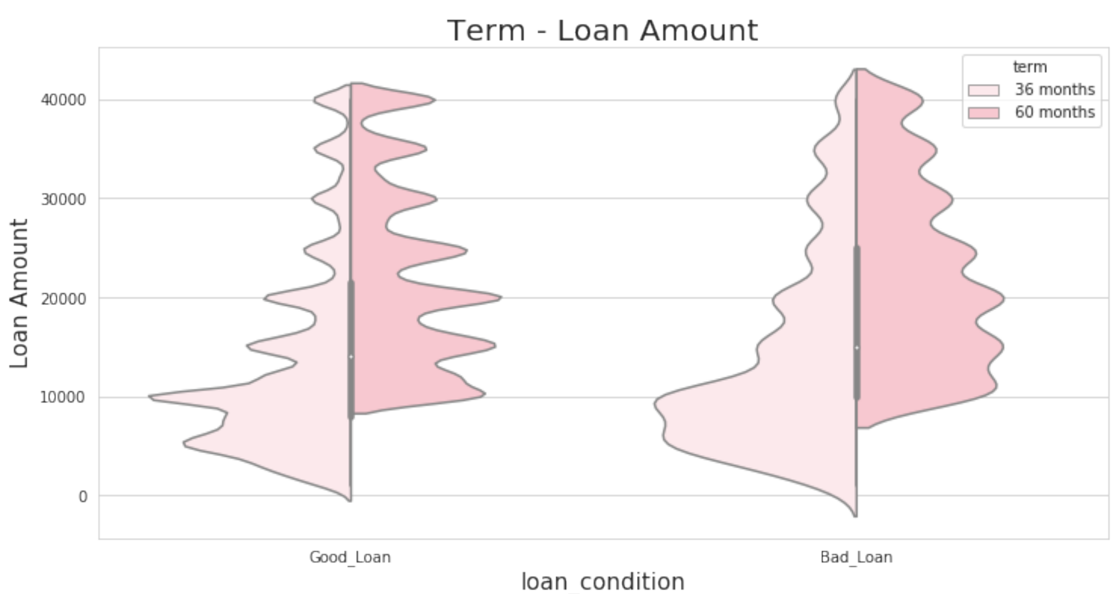
In [17]:
```
fig = plt.figure(figsize=(15,8))
sns.violinplot(x="loan_condition",y="int_rate",data=df0[df0['grade'] != 'G'],
               hue="grade",hue_order=['A','B','C','D','E','F','G'])
plt.title("Grade - Interest Rate", fontsize=20)
plt.xlabel("loan_condition", fontsize=15)
plt.ylabel("Interest Rate", fontsize=15)
plt.show()
```



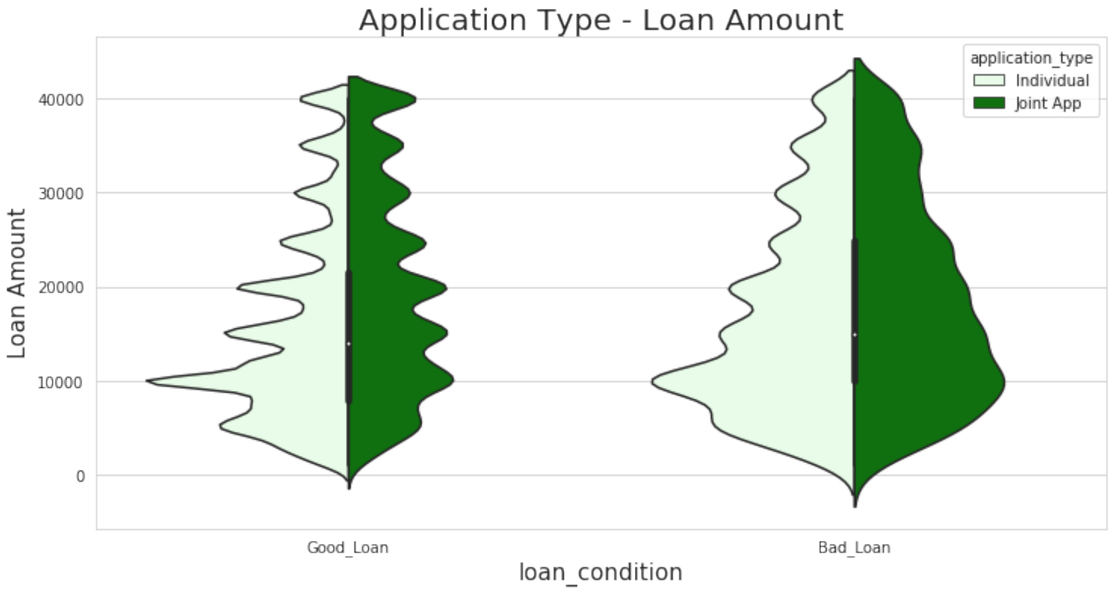
In [16]:
```
fig = plt.figure(figsize=(12,6))
sns.kdeplot(df0.loc[df0['loan_condition'] == 'Good_Loan', 'int_rate'], label = 'Good_Lo
sns.kdeplot(df0.loc[df0['loan_condition'] == 'Bad_Loan', 'int_rate'], label = 'Bad_Loan
plt.xlabel('Interest Rate (%)',fontsize=15)
plt.ylabel('Density',fontsize=15)
plt.title('Distribution of Interest Rate',fontsize=20)
plt.show()
```



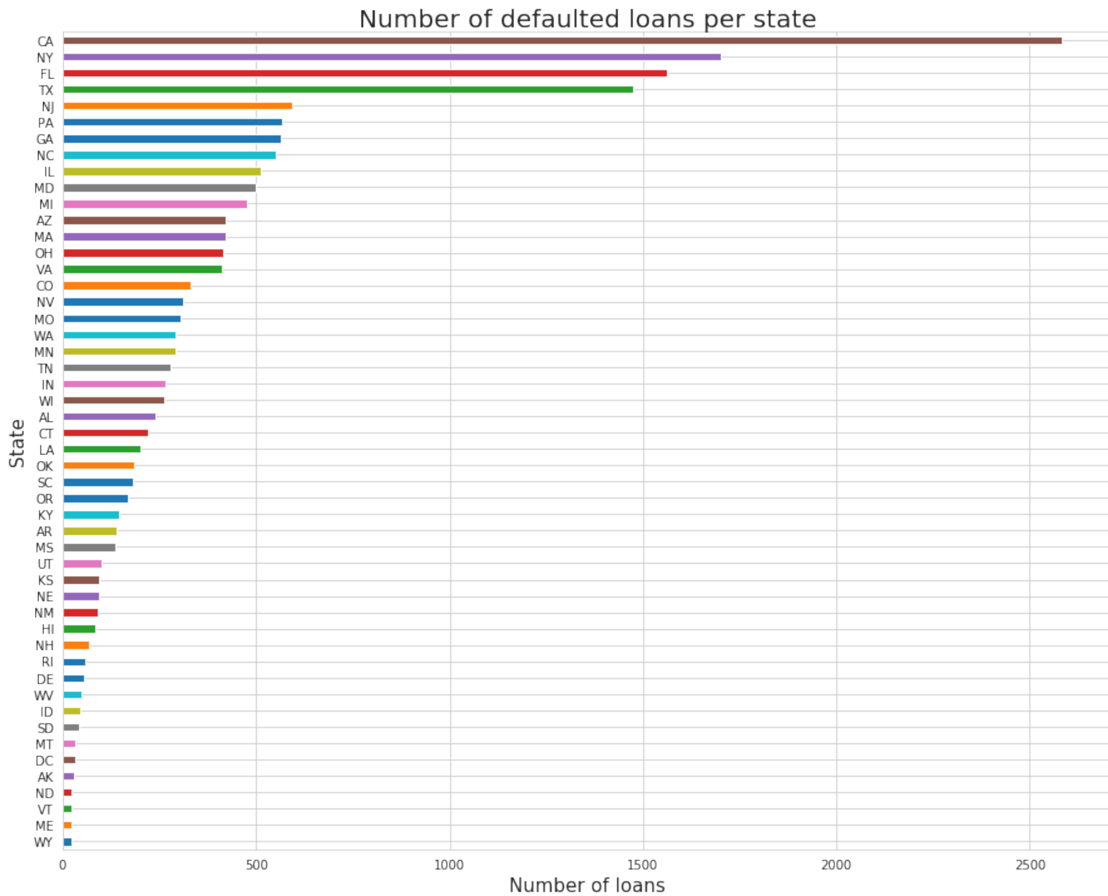
In [13]:
```
fig = plt.figure(figsize=(12,6))
sns.violinplot(x="loan_condition",y="loan_amnt",data=df0, hue="term", split=True,color=
plt.title("Term - Loan Amount", fontsize=20)
plt.xlabel("loan_condition", fontsize=15)
plt.ylabel("Loan Amount", fontsize=15)
plt.show()
```



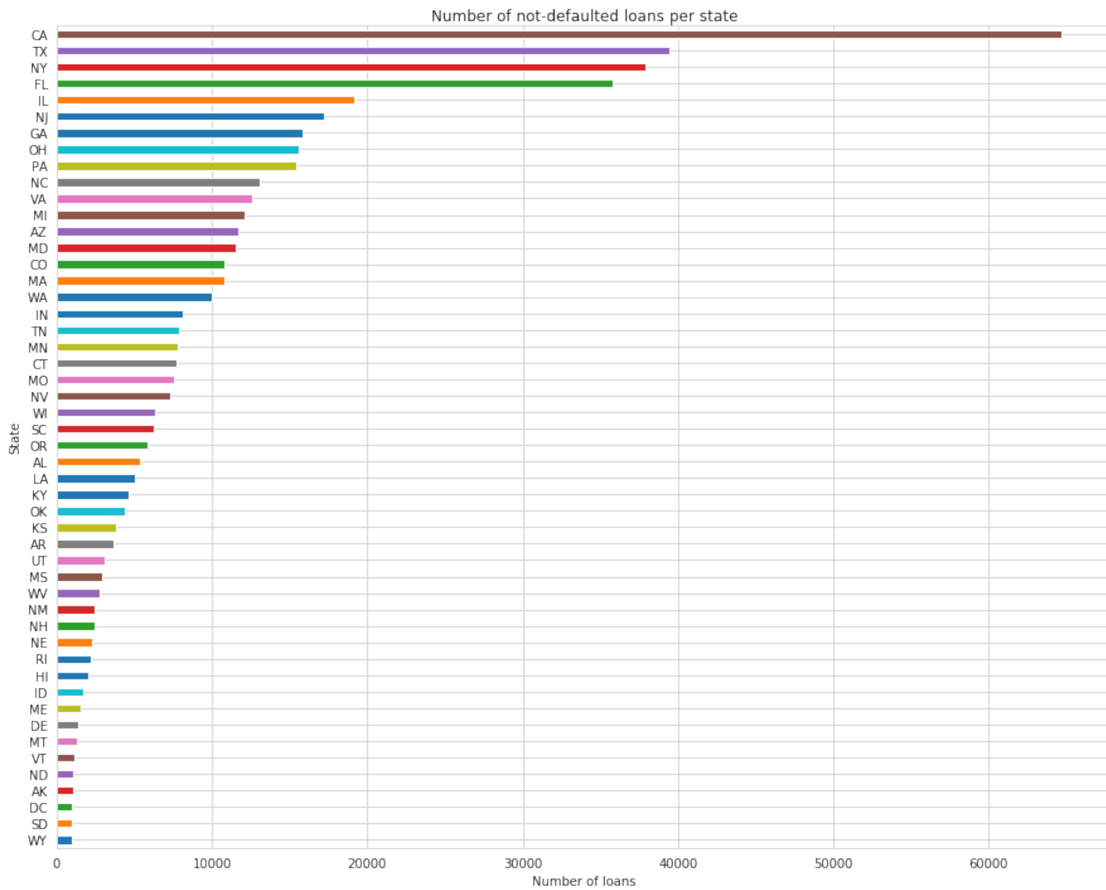
```
In [14]: fig = plt.figure(figsize=(12,6))
         sns.violinplot(x="loan_condition",y="loan_amnt",data=df0, hue="application_type", split
         plt.title("Application Type - Loan Amount", fontsize=20)
         plt.xlabel("loan_condition", fontsize=15)
         plt.ylabel("Loan Amount", fontsize=15)
         plt.show()
```




```
In [19]: fig = plt.figure(figsize=(15,12))
         df0[df0['loan_condition']=='Bad_Loan'].groupby('addr_state')['loan_condition'].count().
         plt.ylabel('State',fontsize=15)
         plt.xlabel('Number of loans',fontsize=15)
         plt.title('Number of defaulted loans per state',fontsize=20)
         plt.show()
```

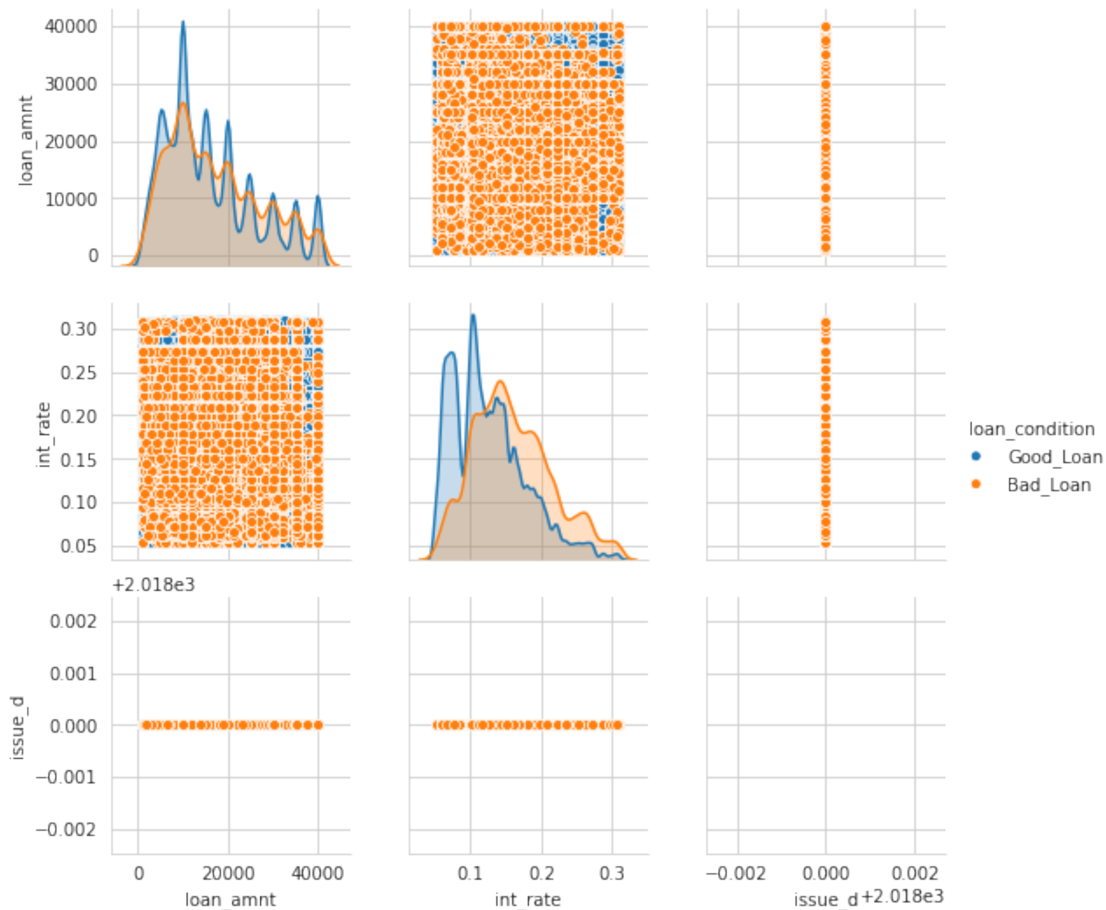



```
In [18]: fig = plt.figure(figsize=(15,12))
         df0[df0['loan_condition']=='Good_Loan'].groupby('addr_state')['loan_condition'].count()
         plt.ylabel('State')
         plt.xlabel('Number of loans')
         plt.title('Number of not-defaulted loans per state')
         plt.show()
```




```
In [17]: eda_cols = ['loan_amnt', 'term', 'int_rate', 'grade', 'issue_d', 'loan_condition']

         sns.pairplot(df0[eda_cols], kind="scatter", hue='loan_condition')
         plt.show()
```

```
/home/glm2class2019/anaconda3/lib/python3.5/site-packages/statsmodels/nonparametric/kde.py:488:
  binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)
/home/glm2class2019/anaconda3/lib/python3.5/site-packages/statsmodels/nonparametric/kdetools.py:
  FAC1 = 2*(np.pi*bw/RANGE)**2
```



9 Feature Engineering

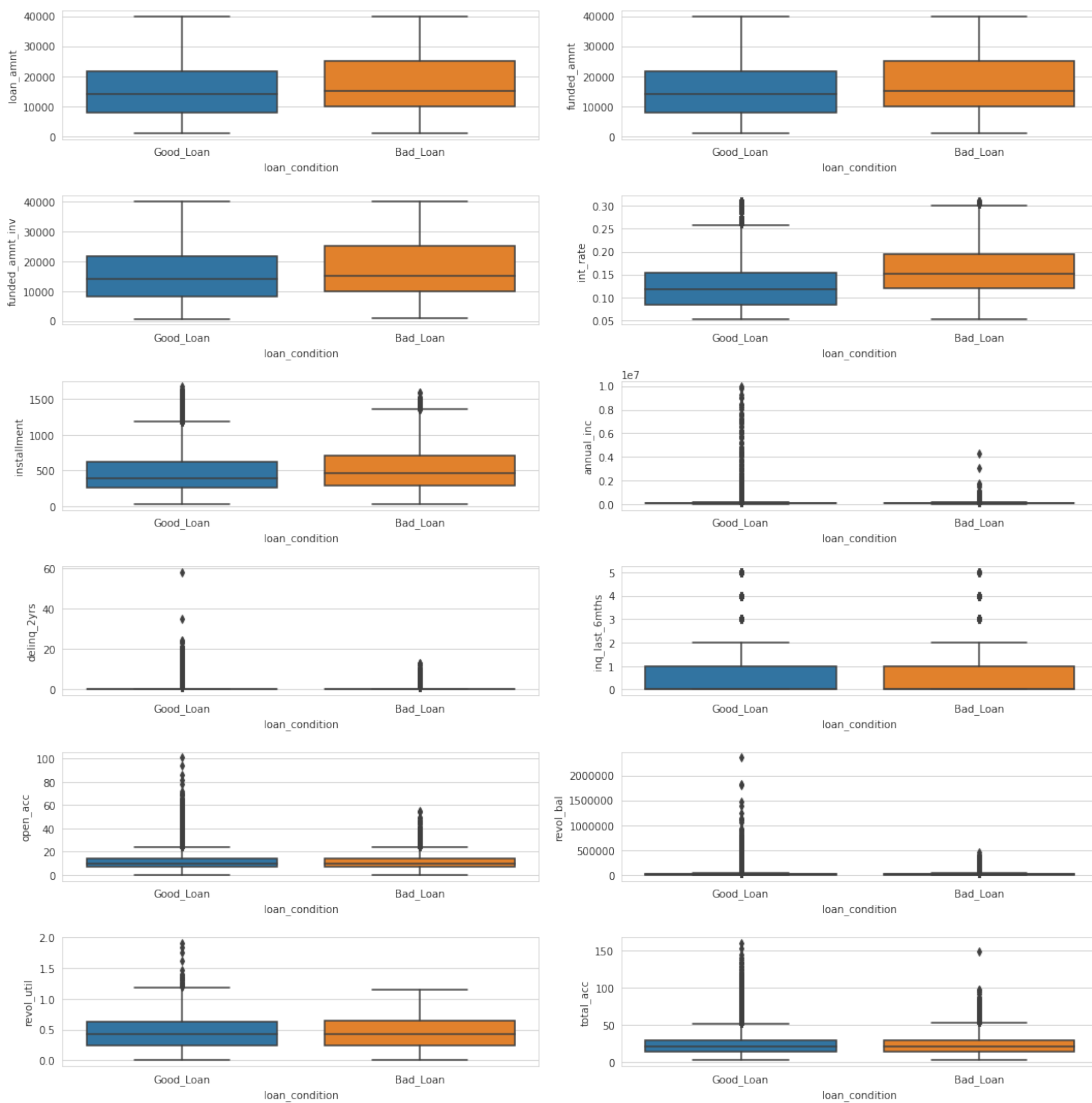
9.1 Variable Selection

```
In [132]: feature_col = ['loan_amnt', 'funded_amnt', 'funded_amnt_inv', 'term',
                         'int_rate', 'installment', 'grade', 'sub_grade', 'home_ownership',
                         'annual_inc', 'verification_status', 'issue_d','pymnt_plan',
                         'purpose', 'addr_state', 'dti', 'delinq_2yrs', 'inq_last_6mths',
                         #'mths_since_last_delinq', 'open_acc', 'pub_rec', 'revol_bal',
                         'open_acc', 'pub_rec', 'revol_bal',
                         'revol_util', 'total_acc', 'loan_condition']

          df0 = df0[feature_col]
```

9.2 More EDA (Boxplots on selected variables)

```
In [133]: ## Generating 3*4 matrix of box plots
          fig, axes = plt.subplots(6, 2, figsize = (15,15))
```

```
axes = axes.flatten()

j = 0
for i in [0,1,2,4,5,9,16,17,18,20,21,22]:
    sns.boxplot(x="loan_condition", y=df0.iloc[:,i], data=df0, orient='v', ax=axes[j])
    j = j+1

plt.tight_layout()
plt.show()
```



10 Data Clean (2nd Clean - Categorical Variables)

In [19]:
```
## Label Encoding (Yes/No)
count = 0
for col in df0:
    if df0[col].dtype == 'object':
        if len(list(df0[col].unique())) <= 2:
            le = preprocessing.LabelEncoder()
            df0[col] = le.fit_transform(df0[col])
            count += 1
            print (col + " : label encoding done!")
        elif len(list(df0[col].unique())) >= 10:
            print (col + " : has more than 10 unique values!")
            print (len(list(df0[col].unique())))

print('%d columns were label encoded.' % count)

## One Hot Encoding
#df.drop(['emp_title','title','zip_code','desc'],axis=1,inplace=True)
```

```
term : label encoding done!
sub_grade : has more than 10 unique values!
35
pymnt_plan : label encoding done!
purpose : has more than 10 unique values!
13
addr_state : has more than 10 unique values!
50
loan_condition : label encoding done!
3 columns were label encoded.
```

In [20]:
```
# Convert the rest of the object parameters to dummy variables
df0 = pd.get_dummies(df0)

# dropping all remaining null values
df0.dropna(inplace=True)
```

In [22]:
```
df0.head()
```

Out[22]:
```
   loan_amnt  funded_amnt  funded_amnt_inv  term  int_rate  installment  \
0    30000.0      30000.0          30000.0     0    0.0734       930.99
1    34825.0      34825.0          34825.0     1    0.1261       785.45
2     2600.0       2600.0           2600.0     0    0.0796        81.43
3    20000.0      20000.0          20000.0     1    0.0992       424.16
4    17000.0      17000.0          17000.0     1    0.2039       454.10

   annual_inc  issue_d  pymnt_plan    dti      ...        addr_state_SD  \
0     95000.0     2018           0  16.18      ...                    0
```

```
1    125000.0     2018           0  21.31      ...                 0
2     62000.0     2018           0  19.61      ...                 0
3    110000.0     2018           0  10.56      ...                 0
4     52000.0     2018           0  15.65      ...                 0

   addr_state_TN  addr_state_TX  addr_state_UT  addr_state_VA  addr_state_VT  \
0              0              1              0              0              0
1              0              0              0              0              0
2              0              0              0              0              0
3              0              0              0              1              0
4              0              0              0              0              0

   addr_state_WA  addr_state_WI  addr_state_WV  addr_state_WY
0              0              0              0              0
1              0              0              0              0
2              0              0              0              0
3              0              0              0              0
4              0              0              0              0

[5 rows x 130 columns]
```

11 Train-Validation-Test Split

In [23]:
```
# Test set: 30%
# Train set: 49%
# Validation set: 21%

## Split out Test set
X_train0, X_test, y_train0, y_test = train_test_split(df0.drop('loan_condition',axis=1)
                                        df0['loan_condition'], test_size=0.3, random_st

## Merge df back for easy processing
df = pd.concat([X_train0, y_train0], axis=1, join_axes=[X_train0.index])

## Split Train & Validation
X_train, X_val, y_train, y_val = train_test_split(X_train0, y_train0, test_size=0.3, ra
```

12 Pre-Modeling

12.1 Custom Function

In [24]:
```
# Create Classification Report function

def print_score(clf, X_train, y_train, X_test, y_test, train=True):
    if train:
        print("Train Result:\n")
        print("accuracy score: {0:.6f}\n".format(accuracy_score(y_train, clf.predict(X_
```

```
        print("recall score: {0:.6f}\n".format(recall_score(y_train, clf.predict(X_trai
        print("Classification Report: \n {}\n".format(classification_report(y_train, cl
        print("Confusion Matrix: \n {}\n".format(confusion_matrix(y_train, clf.predict(

        res = cross_val_score(clf, X_train, y_train, cv=5, scoring='accuracy')
        print("Average Accuracy: \t {0:.6f}".format(np.mean(res)))
        print("Accuracy SD: \t\t {0:.6f}".format(np.std(res)))

    elif train==False:
        print("Test Result:\n")
        print("accuracy score: {0:.6f}\n".format(accuracy_score(y_test, clf.predict(X_t
        print("recall score: {0:.6f}\n".format(recall_score(y_test, clf.predict(X_test)
        print("Classification Report: \n {}\n".format(classification_report(y_test, clf
        print("Confusion Matrix: \n {}\n".format(confusion_matrix(y_test, clf.predict(X


# Create ROC Curve plotter

def print_roc(model, X, Y):
    probs = model.predict_proba(X)
    preds = probs[:,1]
    fpr, tpr, threshold = roc_curve(Y, preds)
    roc_auc = auc(fpr, tpr)

    plt.title('ROC Curve')
    plt.plot(fpr, tpr, 'b', label = 'AUC = %0.3f' % roc_auc)
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1],'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()
```

12.2 Normalization, SMOTE Oversampling, NearMiss Downsampling

12.2.1 Normalization

```
In [25]: # Standardizing features by removing the mean and scaling to unit variance

         sc = StandardScaler()
         X_train0 = sc.fit_transform(X_train0)
         X_train = sc.transform(X_train)
         X_val = sc.transform(X_val)
```

Normalization is a technique often applied as part of data preparation for machine learning.

Urvashi Jaitley in her blog “Why Data Normalization is necessary for Machine Learning models” made a good summary point on data normalization. She believed the goal of normalization is to change the values of numeric columns in the dataset to a common scale, without distorting differences in the ranges of values.

It makes sense for us to normalize our datasets, because some of the features have different ranges.

12.2.2 Oversampling

```
In [26]: # Oversampling only the training set using SMOTE

         sampling_time1 = time.time()

         sm = SMOTE(random_state=seed+2, n_jobs=7)
         x_train0_r, y_train0_r = sm.fit_sample(X_train0, y_train0)
         x_train_r, y_train_r = sm.fit_sample(X_train, y_train)

         sampling_time2 = time.time()

         np.bincount(y_train_r)

Out[26]: array([233224, 233224])

In [27]: print("--- %s seconds ---" % (sampling_time2 - sampling_time1))

--- 25.7192165851593 seconds ---
```

12.2.3 Downsampling

```
In [28]: # Downsampling using NearMiss Method

         sampling_time3 = time.time()

         nr = NearMiss(random_state=seed-2, n_jobs=7)
         x_train0_d, y_train0_d = nr.fit_sample(X_train0, y_train0)
         x_train_d, y_train_d = nr.fit_sample(X_train, y_train)

         sampling_time4 = time.time()

         np.bincount(y_train_d)

Out[28]: array([8600, 8600])

In [29]: print("--- %s seconds ---" % (sampling_time4 - sampling_time3))

--- 407.1889154911041 seconds ---
```

When we are dealing with imbalanced datasets, the most common methods are oversampling and downsampling. Some of the supervised learning problems will suffer from imbalanced data, therefore, it's very crucial to apply some of these methods before we build up the models. The most famous ones are SMOTE and NearMiss.

According to "SMOTE AND NEAR MISS IN PYTHON: MACHINE LEARNING IN IMBALANCED DATASETS", written by Saeed Abdul Rahim, SMOTE is an over-sampling method. What it does is, it creates synthetic (not duplicate) samples of the minority class. Hence making the minority class equal to the majority class. SMOTE does this by selecting similar records and altering that record one column at a time by a random amount within the difference to the neighbouring records.

On the other hand, NearMiss is an under-sampling technique. Instead of resampling the Minority class, using a distance, this will make the majority class equal to minority class.

We will analyze these two methods in later sections.

13 Modeling

13.1 Logistic Regression

13.1.1 Comparing SMOTE vs. NearMiss

```
In [30]: # Creating a baseline for accuracy and recall using Logistic regression
         # Also calculate execution time

         log_reg_time1 = time.time()

         log_reg_r = LogisticRegression(C = 0.001,random_state=seed+3)
         log_reg_r.fit(x_train_r, y_train_r)

         log_reg_time2 = time.time()

In [31]: print_score(log_reg_r, 0, 0, X_val, y_val, train=False)
```

```
Test Result:

accuracy score: 0.647260

recall score: 0.644764

Classification Report:
              precision    recall  f1-score   support

          0       0.07      0.71      0.13      3757
          1       0.98      0.64      0.78     99883

avg / total       0.95      0.65      0.76    103640


Confusion Matrix:
 [[ 2681  1076]
 [35482 64401]]
```

```
In [32]: print("--- %s seconds ---" % (log_reg_time2 - log_reg_time1))
```

```
--- 30.817432403564453 seconds ---
```

```
In [33]: # Creating a baseline for accuracy and recall using Logistic regression
         # Also calculate execution time

         log_reg_time3 = time.time()

         log_reg_d = LogisticRegression(C = 0.001,random_state=seed+3)
         log_reg_d.fit(x_train_d, y_train_d)

         log_reg_time4 = time.time()
```

```
In [34]: print_score(log_reg_d, 0, 0, X_val, y_val, train=False)
```

```
Test Result:

accuracy score: 0.347192

recall score: 0.330627

Classification Report:
              precision    recall  f1-score   support

          0       0.04      0.79      0.08      3757
          1       0.98      0.33      0.49     99883

avg / total       0.94      0.35      0.48    103640


Confusion Matrix:
 [[ 2959   798]
 [66859 33024]]
```

```
In [35]: print("--- %s seconds ---" % (log_reg_time4 - log_reg_time3))
```

```
--- 0.3795938491821289 seconds ---
```

Looking at the comparison between the results from SMOTE and NearMiss, despite the fact that the overall processing time using NearMiss method is much shorter than that for using SMOTE method, both the accuracy and recall score using SMOTE method are much higher. This is not surprising because we lost many useful data during downsampling process.

Therefore, I would like to proceed with SMOTE method in later sections.

13.1.2 Logistic Regression (With Cross Validation)

```
In [36]: # Set up parameters

         penalty = ['l1','l2']
         C = [0.005,0.001,0.05,0.01,0.5,0.1]
         random_state=[seed+10]
         lr_para = dict(penalty=penalty,C=C,random_state=random_state)

In [37]: # Grid Search CV

         log_reg_cv = GridSearchCV(LogisticRegression(), lr_para, n_jobs=num_core-1)
         log_reg_cv.fit(x_train0_r, y_train0_r)

         print("tuned hyperparameters: (best parameters) \n", log_reg_cv.best_params_)
```

```
tuned hyperparameters: (best parameters)
 {'random_state': 2029, 'penalty': 'l1', 'C': 0.5}
```

```
In [38]: # Building Model

         log_reg_time5 = time.time()

         log_reg_best = LogisticRegression(penalty='l1', C=0.5, random_state=seed-10)
         log_reg_best.fit(x_train0_r, y_train0_r)

         log_reg_time6 = time.time()

In [39]: print_score(log_reg_best, x_train0_r, y_train0_r, 0, 0, train=True)
```

```
Train Result:

accuracy score: 0.711348

recall score: 0.687161

Classification Report:
              precision    recall  f1-score   support

          0       0.70      0.74      0.72    333107
          1       0.72      0.69      0.70    333107

avg / total       0.71      0.71      0.71    666214


Confusion Matrix:
 [[245012  88095]
 [104209 228898]]
```

```
Average Accuracy:          0.711216
Accuracy SD:                  0.001293
```

```
In [40]: print("--- %s seconds ---" % (log_reg_time6 - log_reg_time5))
```

```
--- 1298.6267139911652 seconds ---
```

```
In [ ]:
```

13.2 Random Forest

13.2.1 Random Forest (No Tuning)

```
In [41]: # Creating RF Model
         # Also calculate execution time

         clf_rf_time1 = time.time()

         clf_rf = RandomForestClassifier(n_estimators=100,
                                         n_jobs=7, random_state=seed+4)
         clf_rf.fit(x_train_r, y_train_r)

         clf_rf_time2 = time.time()
```

```
In [42]: print_score(clf_rf, 0, 0, X_val, y_val, train=False)
```

```
Test Result:

accuracy score: 0.963557

recall score: 0.999660

Classification Report:
              precision    recall  f1-score   support

          0       0.29      0.00      0.01      3757
          1       0.96      1.00      0.98     99883

avg / total       0.94      0.96      0.95    103640


Confusion Matrix:
 [[   14  3743]
 [   34 99849]]
```

```
In [43]: print("--- %s seconds ---" % (clf_rf_time2 - clf_rf_time1))
```

```
--- 56.934871435165405 seconds ---
```

13.2.2 Random Forest (With Cross Validation)

```
In [44]: # Set up parameters

         n_estimators = [150,200,250]
         max_depth = [7,9,11]
         min_samples_split = [2,3]
         n_jobs = [num_core-1]
         random_state = [seed+20]
         rf_para = dict(n_estimators=n_estimators, max_depth=max_depth, n_jobs=n_jobs,
                        min_samples_split=min_samples_split, random_state=random_state)
```

```
In [45]: # Grid Search CV

         clf_rf_cv = GridSearchCV(RandomForestClassifier(), rf_para,
                                  n_jobs=num_core-1)
         clf_rf_cv.fit(x_train0_r, y_train0_r)

         print("tuned hyperparameters: (best parameters) \n", clf_rf_cv.best_params_)
```

```
tuned hyperparameters: (best parameters)
 {'random_state': 2039, 'n_estimators': 250, 'max_depth': 11, 'n_jobs': 7, 'min_samples_split':
```

```
In [46]: # Building Model

         clf_rf_time3 = time.time()

         clf_rf_best = RandomForestClassifier(n_estimators=250, max_depth=11,
                                   min_samples_split=2, n_jobs=7, random_state=seed-10)
         clf_rf_best.fit(x_train0_r, y_train0_r)

         clf_rf_time4 = time.time()
```

```
In [47]: print_score(clf_rf_best, x_train0_r, y_train0_r, 0, 0, train=True)
```

```
Train Result:

accuracy score: 0.917265

recall score: 0.938188

Classification Report:
              precision    recall  f1-score   support
```

```
           0       0.94      0.90      0.92    333107
           1       0.90      0.94      0.92    333107

avg / total        0.92      0.92      0.92    666214


Confusion Matrix:
 [[298578  34529]
 [ 20590 312517]]

Average Accuracy:           0.913166
Accuracy SD:                   0.025433
```

```
In [48]: print("--- %s seconds ---" % (clf_rf_time4 - clf_rf_time3))
```

```
--- 157.8775873184204 seconds ---
```

13.3 XGBoost

13.3.1 XGBoost (No Tuning)

```
In [49]: # Creating XGBoost Model
         # Also calculate execution time

         clf_xg_time1 = time.time()

         clf_xg = xgb.XGBClassifier(objective ='binary:logistic', max_depth=5,
                                    learning_rate=0.1, n_estimators=150,
                                    n_jobs=7, random_state=seed+5)
         clf_xg.fit(x_train_r, y_train_r)

         clf_xg_time2 = time.time()
```

```
In [50]: print_score(clf_xg, 0, 0, X_val, y_val, train=False)
```

```
Test Result:

accuracy score: 0.963971

recall score: 0.999990

Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.01      0.01      3757
           1       0.96      1.00      0.98     99883
```

```
avg / total       0.96      0.96      0.95    103640


Confusion Matrix:
 [[   24  3733]
 [    1 99882]]
```

```
In [51]: print("--- %s seconds ---" % (clf_xg_time2 - clf_xg_time1))
```

```
--- 82.51269268989563 seconds ---
```

13.3.2 XGBoost (With Cross Validation)

```
In [52]: # Set up parameters

         max_depth=[5,7,9]
         learning_rate=[0.3,0.5]
         n_estimators=[150,200]
         n_jobs = [num_core-1]
         random_state = [seed+30]
         xg_para = dict(n_estimators=n_estimators, max_depth=max_depth, n_jobs=n_jobs,
                        learning_rate=learning_rate, random_state=random_state)
```

```
In [53]: # Grid Search CV

         clf_xg_cv = GridSearchCV(xgb.XGBClassifier(), xg_para,
                                  n_jobs=num_core-1)
         clf_xg_cv.fit(x_train0_r, y_train0_r)

         print("tuned hyperparameters: (best parameters) \n", clf_xg_cv.best_params_)
```

```
tuned hyperparameters: (best parameters)
 {'random_state': 2049, 'learning_rate': 0.3, 'max_depth': 7, 'n_jobs': 7, 'n_estimators': 200}
```

```
In [54]: # Building Model

         clf_xg_time3 = time.time()

         clf_xg_best = xgb.XGBClassifier(objective ='binary:logistic', max_depth=7,
                                 learning_rate=0.3, n_estimators=200,
                                 n_jobs=7, random_state=seed+5)
         clf_xg_best.fit(x_train0_r, y_train0_r)

         clf_xg_time4 = time.time()
```

```
In [55]: print_score(clf_xg_best, x_train0_r, y_train0_r, 0, 0, train=True)
```

```
Train Result:

accuracy score: 0.982441

recall score: 0.999955

Classification Report:
              precision    recall  f1-score   support

          0       1.00      0.96      0.98    333107
          1       0.97      1.00      0.98    333107

avg / total       0.98      0.98      0.98    666214


Confusion Matrix:
 [[321424  11683]
 [    15 333092]]

Average Accuracy:           0.980807
Accuracy SD:                   0.036781
```

```
In [89]: print("--- %s seconds ---" % (clf_xg_time4 - clf_xg_time3))
```

```
--- 218.42041444778442 seconds ---
```

13.4 Averaging Ensemble

```
In [85]: # Building Model

         ensemble_time1 = time.time()

         ensemble_best = VotingClassifier(estimators=
                         [('lr', log_reg_best),('rf', clf_rf_best),('xg', clf_xg_best)],
                         voting='soft', n_jobs=7)
         ensemble_best.fit(x_train0_r, y_train0_r)

         ensemble_time2 = time.time()
```

```
In [58]: print_score(ensemble_best, x_train0_r, y_train0_r, 0, 0, train=True)
```

```
Train Result:

accuracy score: 0.943511
```

```
recall score: 0.950235

Classification Report:
              precision    recall  f1-score   support

          0       0.95      0.94      0.94    333107
          1       0.94      0.95      0.94    333107

avg / total       0.94      0.94      0.94    666214


Confusion Matrix:
 [[312050  21057]
 [ 16577 316530]]

Average Accuracy:          0.939275
Accuracy SD:                  0.027609
```

```
In [90]: print("--- %s seconds ---" % (ensemble_time2 - ensemble_time1))
```

```
--- 1407.9327342510223 seconds ---
```

13.5 Save & Load Models (if necessary)

```
In [80]: # Save Model for future use
         save_option = False

         if save_option == True:
             pickle.dump(log_reg_best, open('/home/glm2class2019/GLM/log_reg.sav', 'wb'))
             pickle.dump(clf_rf_best, open('/home/glm2class2019/GLM/clf_rf.sav', 'wb'))
             pickle.dump(clf_xg_best, open('/home/glm2class2019/GLM/clf_xg.sav', 'wb'))
             pickle.dump(ensemble_best, open('/home/glm2class2019/GLM/ensemble.sav', 'wb'))
```

```
In [87]: # Load Model for future use
         load_option = False

         if load_option == True:
             log_reg_best = pickle.load(open('/home/glm2class2019/GLM/log_reg.sav', 'rb'))
             clf_rf_best = pickle.load(open('/home/glm2class2019/GLM/clf_rf.sav', 'rb'))
             clf_xg_best = pickle.load(open('/home/glm2class2019/GLM/clf_xg.sav', 'rb'))
             ensemble_best = pickle.load(open('/home/glm2class2019/GLM/ensemble.sav', 'rb'))
```

14 Model Evaluation (Test Set)

14.1 Initial Check

```
In [59]: y_test.shape
```

Out[59]: (148056,)

14.2 Normalization

In [60]:
```
# Standardizing features by removing the mean and scaling to unit variance
X_test = sc.transform(X_test)
```

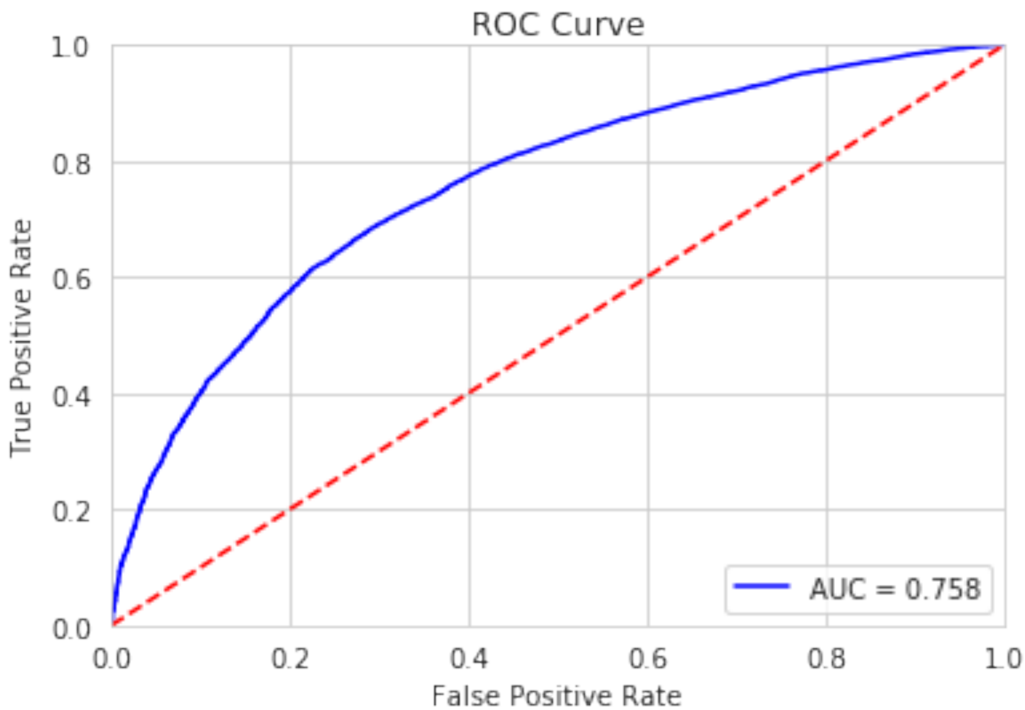
14.3 Prediction

14.3.1 Logistic Regression

In [61]:
```
print_score(log_reg_best, 0, 0, X_test, y_test, train=False)
```

```
Test Result:

accuracy score: 0.688881

recall score: 0.688368

Classification Report:
              precision    recall  f1-score   support

          0       0.08      0.70      0.14      5256
          1       0.98      0.69      0.81    142800

avg / total       0.95      0.69      0.79    148056


Confusion Matrix:
 [[ 3694  1562]
 [44501 98299]]
```

In [62]:
```
print_roc(log_reg_best, X_test, y_test)
```

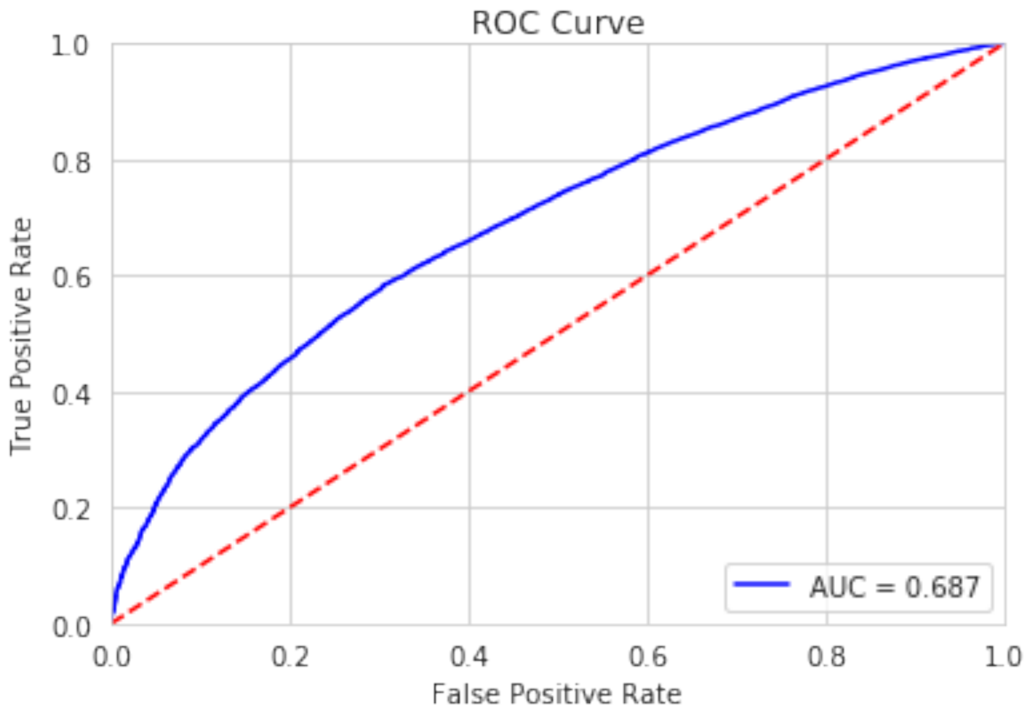


14.3.2 Random Forest

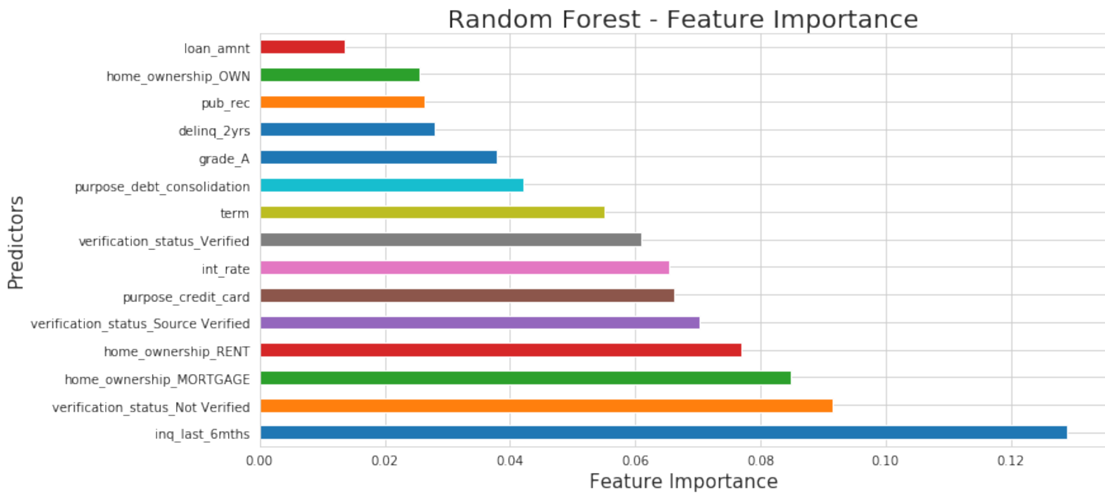
```
In [63]: print_score(clf_rf_best, 0, 0, X_test, y_test, train=False)
```

```
Test Result:

accuracy score: 0.909683

recall score: 0.936639

Classification Report:
              precision    recall  f1-score   support

          0       0.09      0.18      0.12      5256
          1       0.97      0.94      0.95    142800

avg / total       0.94      0.91      0.92    148056


Confusion Matrix:
 [[   932   4324]
 [  9048 133752]]
```

In [64]: print_roc(clf_rf_best, X_test, y_test)



In [65]:
```
rf_feat = pd.Series(clf_rf_best.feature_importances_,
                    index=df.drop('loan_condition',axis=1).columns)

fig = plt.figure(figsize=(12,6))
rf_feat.nlargest(15).plot(kind='barh')
plt.title("Random Forest - Feature Importance", fontsize=20)
plt.xlabel("Feature Importance", fontsize=15)
plt.ylabel("Predictors", fontsize=15)
plt.show()
```

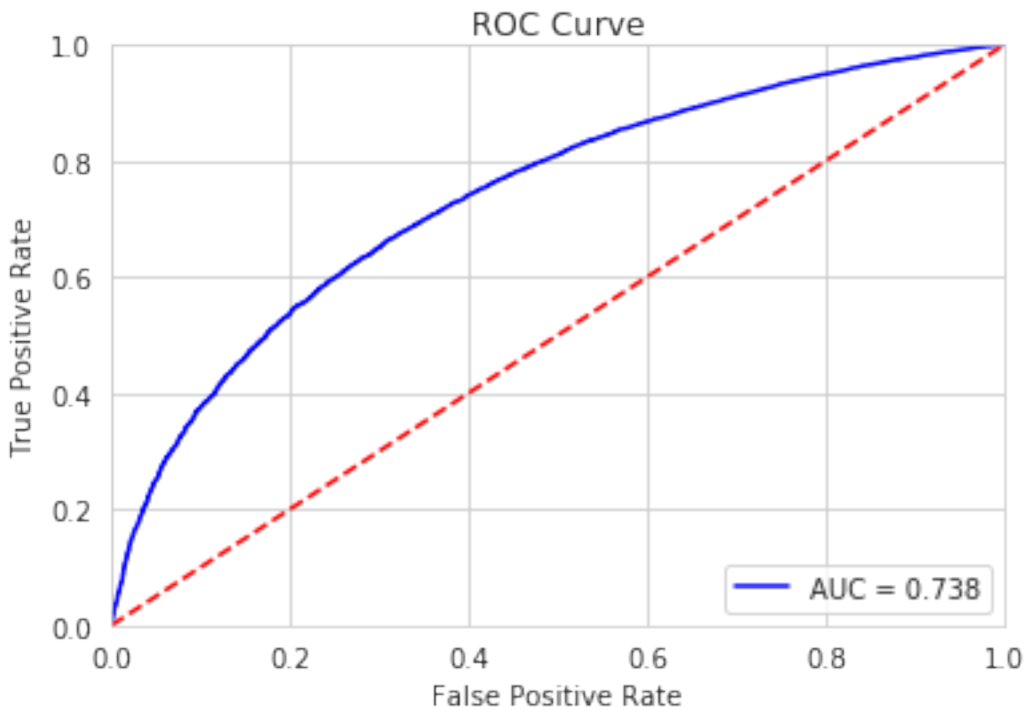


14.3.3 XGBoost

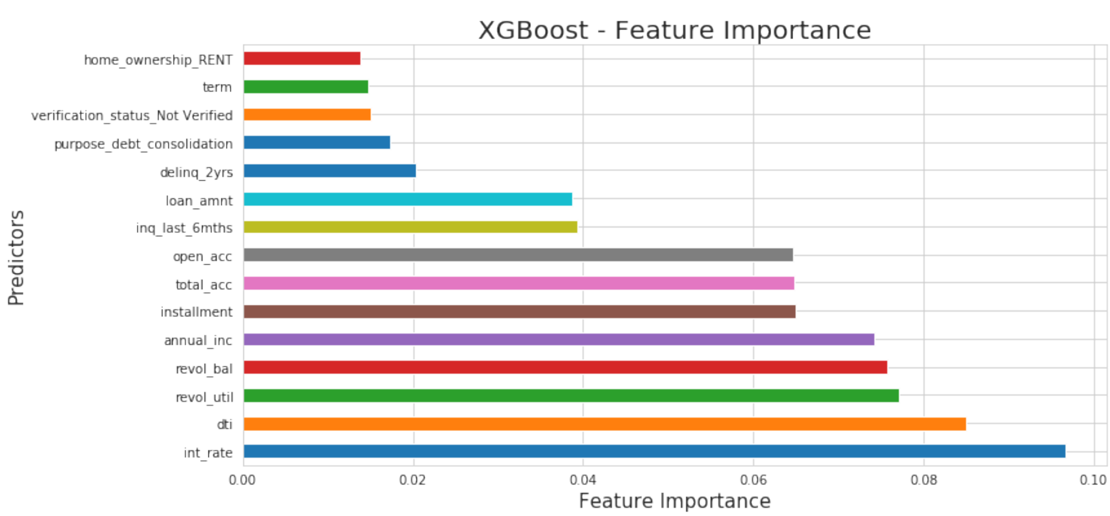
```
In [66]: print_score(clf_xg_best, 0, 0, X_test, y_test, train=False)
```

```
Test Result:

accuracy score: 0.964385

recall score: 0.999559

Classification Report:
              precision    recall  f1-score   support

          0       0.42      0.01      0.02      5256
          1       0.96      1.00      0.98    142800

avg / total       0.95      0.96      0.95    148056


Confusion Matrix:
 [[    46   5210]
 [    63 142737]]
```

```
In [67]: print_roc(clf_xg_best, X_test, y_test)
```




```
In [68]: xg_feat = pd.Series(clf_xg_best.feature_importances_,
                             index=df.drop('loan_condition',axis=1).columns)

         fig = plt.figure(figsize=(12,6))
         xg_feat.nlargest(15).plot(kind='barh')
         plt.title("XGBoost - Feature Importance", fontsize=20)
         plt.xlabel("Feature Importance", fontsize=15)
         plt.ylabel("Predictors", fontsize=15)
         plt.show()
```

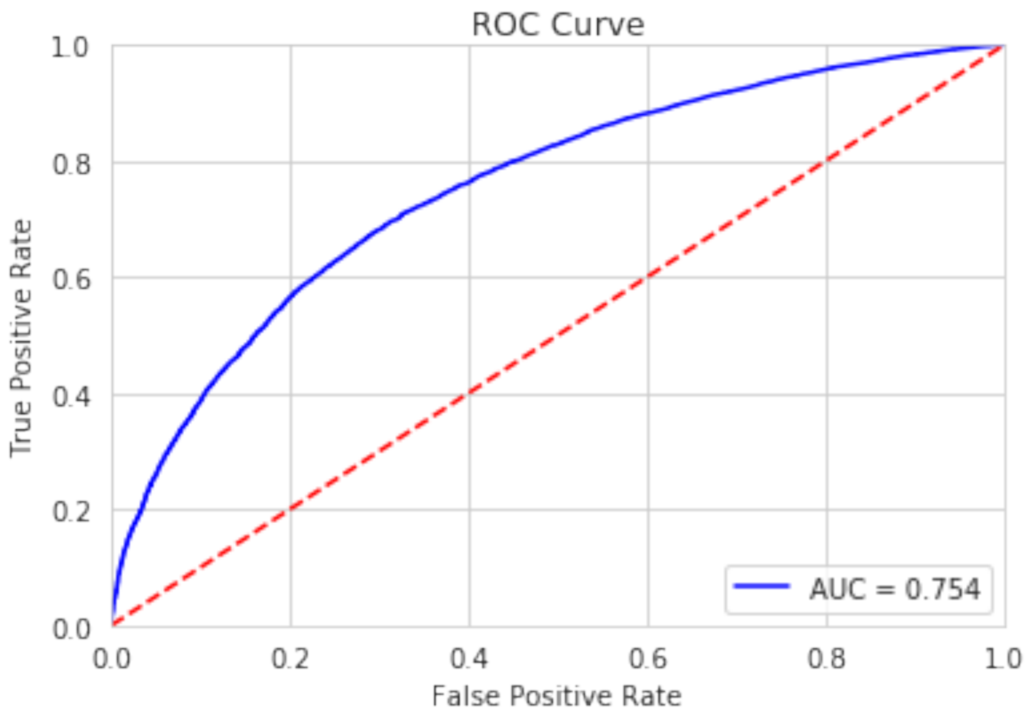


14.3.4 Averaging Ensemble

```
In [72]: print_score(ensemble_best, 0, 0, X_test, y_test, train=False)
```

```
Test Result:

accuracy score: 0.951019

recall score: 0.982066

Classification Report:
              precision    recall  f1-score   support

          0       0.18      0.11      0.13      5256
          1       0.97      0.98      0.97    142800

avg / total       0.94      0.95      0.94    148056


Confusion Matrix:
 [[   565   4691]
 [  2561 140239]]
```

```
In [73]: print_roc(ensemble_best, X_test, y_test)
```



14.4 Comparison

In [91]:
```
ML_columns = []
ML_compare = pd.DataFrame(columns = ML_columns)

# Logisitic Regression
ML_compare.loc[0,'ML Name'] = 'Logistic Regression'
ML_compare.loc[0, 'Train Accuracy'] = 0.711348
ML_compare.loc[0, 'Test Accuracy'] = 0.688881
ML_compare.loc[0, 'Train Recall'] = 0.687161
ML_compare.loc[0, 'Test Recall'] = 0.688368
ML_compare.loc[0, 'Test AUC'] = 0.758
ML_compare.loc[0, 'Model Fit Time (sec)'] = 1298.627

# Random Forest
ML_compare.loc[1,'ML Name'] = 'Random Forest'
ML_compare.loc[1, 'Train Accuracy'] = 0.917265
ML_compare.loc[1, 'Test Accuracy'] = 0.909683
ML_compare.loc[1, 'Train Recall'] = 0.938188
ML_compare.loc[1, 'Test Recall'] = 0.936639
ML_compare.loc[1, 'Test AUC'] = 0.687
ML_compare.loc[1, 'Model Fit Time (sec)'] = 157.878

# XGBoost
```

```
ML_compare.loc[2,'ML Name'] = 'XGBoost'
ML_compare.loc[2, 'Train Accuracy'] = 0.982441
ML_compare.loc[2, 'Test Accuracy'] = 0.964385
ML_compare.loc[2, 'Train Recall'] = 0.999955
ML_compare.loc[2, 'Test Recall'] = 0.999559
ML_compare.loc[2, 'Test AUC'] = 0.738
ML_compare.loc[2, 'Model Fit Time (sec)'] = 218.420

# Averaging Ensemble
ML_compare.loc[3,'ML Name'] = 'Averaging Ensemble'
ML_compare.loc[3, 'Train Accuracy'] = 0.943511
ML_compare.loc[3, 'Test Accuracy'] = 0.951019
ML_compare.loc[3, 'Train Recall'] = 0.950235
ML_compare.loc[3, 'Test Recall'] = 0.982066
ML_compare.loc[3, 'Test AUC'] = 0.754
ML_compare.loc[3, 'Model Fit Time (sec)'] = 1407.933
```

```
In [92]: ML_compare.sort_values(by = ['Test Accuracy'], ascending = False, inplace = True)
         ML_compare
```

```
Out[92]:               ML Name  Train Accuracy  Test Accuracy  Train Recall  \
         2             XGBoost        0.982441       0.964385      0.999955
         3  Averaging Ensemble        0.943511       0.951019      0.950235
         1       Random Forest        0.917265       0.909683      0.938188
         0 Logistic Regression        0.711348       0.688881      0.687161

            Test Recall  Test AUC  Model Fit Time (sec)
         2     0.999559     0.738               218.420
         3     0.982066     0.754              1407.933
         1     0.936639     0.687               157.878
         0     0.688368     0.758              1298.627
```

```
In [ ]:
```

15 Reference

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```
In [ ]:
```