Machine Learning Capstone Project

Definition

Project Overview

In recent years there has been a trend in financial institutions towards greater use of models in decision making, driven in part by government regulations but manifest in all areas of management. Nowadays a high proportion of bank decisions are automated through decision models. These decision models can be a combination of statistical or machine learning based models and a set of rules. With increased use algorithmic trading, an automated electronic platform that execute trade commands which have been pre-programmed by time, price or volume, and can start without manual intervention, the need to include model based decision into the automated trading is also increasing. Government regulations like Basel III also encourage banks to use decision models, which involves modeling risk in a trade and setting a threshold to decide whether the trade should be made or not.

Many investment banks trade loan backed securities. If a loan defaults, it leads to devaluation of the securitized product. That is why banks use risk models to identify loans at risk and predict loans that might default in near future. Risk models are also used to decide on approving a loan request by a borrower.

Problem Statement

The goal is to find a model to predict loans that are likely to default and identify attributes that contribute to bad loans, so that it can be used to deny future loan applications. Loan data needs to be analyzed to see which attributes have high correlation with loan being default. The attributes that have significant correlation with loan being default, can be used to build a machine learning model to predict likelihood of future loans being defaulted. This can then be used to assign a risk score to future loans and a threshold can be set, so loans exceeding a certain risk score can be automatically denied.

Since we are trying to predict if a loan will default or not as opposed to predicting the amount of profit or loss that will be incurred, this is a classification problem. Our classification model will use financial data like interest rate, FICO score, debt to income ratio and credit utilization etc., instead of personal information like race, gender, age and residency, so we can be assured that our model does not violate any discrimination laws.

The loan data used here are for consumer loans. So most loans are expected to be short term loans and missing monthly installment has heavy penalty.

Metrics

Looking at the dataset, we can see that out of 5000 loans there are 1533 loans that have defaulted and 3467 loans that were paid. With such an imbalanced dataset, accuracy score might not be a good choice. Accuracy score measures fraction of correctly identified labels. So accuracy score will be high if we detect loans that will default and loans that will not default. For credit risk it is more important to detect loans that will default than the ones that will not. F1 score is created out of a combination of precision and recall and it is a better measure of fraction of true positives or loans that will default. So we need to look at F1 Score as the metrics to measure model performance.

Analysis

Data Exploration

I will be using data from Lending Club (https://www.lendingclub.com/info/download-data.action). Lending Club is the world's largest online marketplace connecting borrowers and investors.

The file LoansImputed.csv in project folder contains complete loan data for all loans issued through the time period stated.

Variables in Data Set

Dependent Variable

- **not.fully.paid**: A binary variable. 1 means borrower defaulted and 0 means monthly payments are made on time

Independent Variables

- **credit.policy**: 1 if borrower meets credit underwriting criteria and 0 otherwise
- **purpose**: The reason for the loan
- **int.rate**: Annual interest rate for the loan (14% is stored as 0.14)
- **installment**: Monthly payment to be made for the loan
- **log.annual.inc**: Natural log of self-reported annual income of the borrower
- **dti**: Debt to Income ratio of the borrower
- **fico**: FICO credit score of the borrower
- **days.with.cr.line**: Number of days' borrower has had credit line

- **revol.bal**: The borrower's revolving balance (Principal loan amount still remaining)
- **revol.util**: Amount of credit line utilized by borrower as percentage of total available credit
- **inq.last.6mths**: Borrowers credit inquiry in last 6 months
- **delinq.2yrs**: Number of times borrower was delinquent in last 2 years
- **pub.rec**: Number of derogatory public record borrower has (Bankruptcy, tax liens and judgements etc.)

Below is summary of the dataset (Panda df.describe())

```
credit.policy     int.rate  installment  log.annual.inc         dti
count    5000.000000  5000.000000  5000.000000     5000.000000  5000.000000
mean        0.896200     0.120816   308.325968       10.911819    12.308698
std         0.305031     0.025336   197.307080        0.598897     6.754521
min         0.000000     0.060000    15.690000        7.600902     0.000000
25%         1.000000     0.100800   163.550000       10.545341     7.067500
50%         1.000000     0.121800   260.640000       10.915088    12.300000
75%         1.000000     0.137900   407.510000       11.277203    17.652500
max         1.000000     0.216400   926.830000       14.528354    29.960000

              fico  days.with.cr.line       revol.bal   revol.util
count  5000.000000        5000.000000     5000.000000  5000.000000
mean    710.926000        4510.713433    15872.533200    46.395622
std      37.026757        2418.553606    31116.319033    29.138604
min     617.000000         180.041667        0.000000     0.000000
25%     682.000000        2790.041667     3328.500000    22.300000
50%     707.000000        4080.000000     8605.000000    45.700000
75%     737.000000        5640.281250    18155.250000    70.500000
max     827.000000       16259.041670  1207359.000000   106.500000

       inq.last.6mths  delinq.2yrs      pub.rec  not.fully.paid   annualincome
count       5000.0000   5000.00000  5000.000000     5000.000000     5000.00000
mean           1.4068      0.16140     0.066800        0.306600    66260.20820
std            1.9897      0.49699     0.257587        0.461128    56864.18592
min            0.0000      0.00000     0.000000        0.000000     2000.00000
25%            0.0000      0.00000     0.000000        0.000000    38000.00000
50%            1.0000      0.00000     0.000000        0.000000    55000.00000
75%            2.0000      0.00000     0.000000        1.000000    79000.00000
max           33.0000      6.00000     3.000000        1.000000  2039784.00000
```

Below are first five rows of the dataset (Panda df.head())

```
credit.policy             purpose  int.rate  installment  log.annual.inc
0              1  debt_consolidation     0.1496       194.02       10.714418
1              1           all_other     0.1114       131.22       11.002100
2              1         credit_card     0.1343       678.08       11.884489
3              1           all_other     0.1059        32.55       10.433822
4              1      small_business     0.1501       225.37       12.269047

     dti  fico  days.with.cr.line  revol.bal  revol.util  inq.last.6mths
0   4.00   667        3180.041667       3839        76.8               0
1  11.08   722        5116.000000      24220        68.6               0
2  10.15   682        4209.958333      41674        74.1               0
```

```
3  14.47   687        1110.000000       4485        36.9               1
4   6.45   677        6240.000000      56411        75.3               0

   delinq.2yrs  pub.rec  not.fully.paid  annualincome
0            0        1               1         45000
1            0        0               1         60000
2            0        0               1        145000
3            0        0               1         33990
4            0        0               1        213000
```

Below is summary of the dataset that contains data for loans that defaulted

```
       credit.policy     int.rate  installment  log.annual.inc          dti
count    1533.000000  1533.000000  1533.000000     1533.000000  1533.000000
mean        0.661448     0.132452   342.785114       10.885023    13.195838
std         0.473372     0.025495   223.948527        0.666718     7.006769
min         0.000000     0.070500    15.910000        7.600902     0.000000
25%         0.000000     0.115400   168.640000       10.491274     7.830000
50%         1.000000     0.131600   287.310000       10.878047    13.340000
75%         1.000000     0.148200   491.300000       11.276633    18.830000
max         1.000000     0.216400   926.830000       13.458836    29.960000

              fico  days.with.cr.line       revol.bal   revol.util
count  1533.000000        1533.000000     1533.000000  1533.000000
mean    697.828441        4393.541259    21066.293542    52.255075
std      33.756808        2431.785491    49905.689359    29.057906
min     617.000000         180.041667        0.000000     0.000000
25%     672.000000        2759.958333     3323.000000    29.900000
50%     692.000000        4050.000000     8850.000000    53.900000
75%     717.000000        5580.041667    20616.000000    77.000000
max     822.000000       15692.000000  1207359.000000   106.500000

       inq.last.6mths  delinq.2yrs      pub.rec  not.fully.paid   annualincome
count     1533.000000  1533.000000  1533.000000            1533    1533.000000
mean         2.330724     0.174821     0.091324               1   67360.671885
std          2.933480     0.520562     0.292659               0   59224.859089
min          0.000000     0.000000     0.000000               1    2000.000000
25%          0.000000     0.000000     0.000000               1   36000.000000
50%          1.000000     0.000000     0.000000               1   53000.000000
75%          3.000000     0.000000     0.000000               1   78955.000000
max         33.000000     4.000000     2.000000               1  700000.000000
```

Below is summary of dataset that contains data for loans that did not default

```
       credit.policy     int.rate  installment  log.annual.inc          dti
count           3467  3467.000000  3467.000000     3467.000000  3467.000000
mean               1     0.115671   293.089201       10.923667    11.916432
std                0     0.023498   182.272593        0.566024     6.603058
min                1     0.060000    15.690000        8.342840     0.000000
25%                1     0.096300   159.920000       10.585573     6.775000
50%                1     0.116600   249.680000       10.915088    11.860000
75%                1     0.131600   394.360000       11.277203    17.120000
max                1     0.208600   914.420000       14.528354    29.420000

              fico  days.with.cr.line      revol.bal   revol.util
```

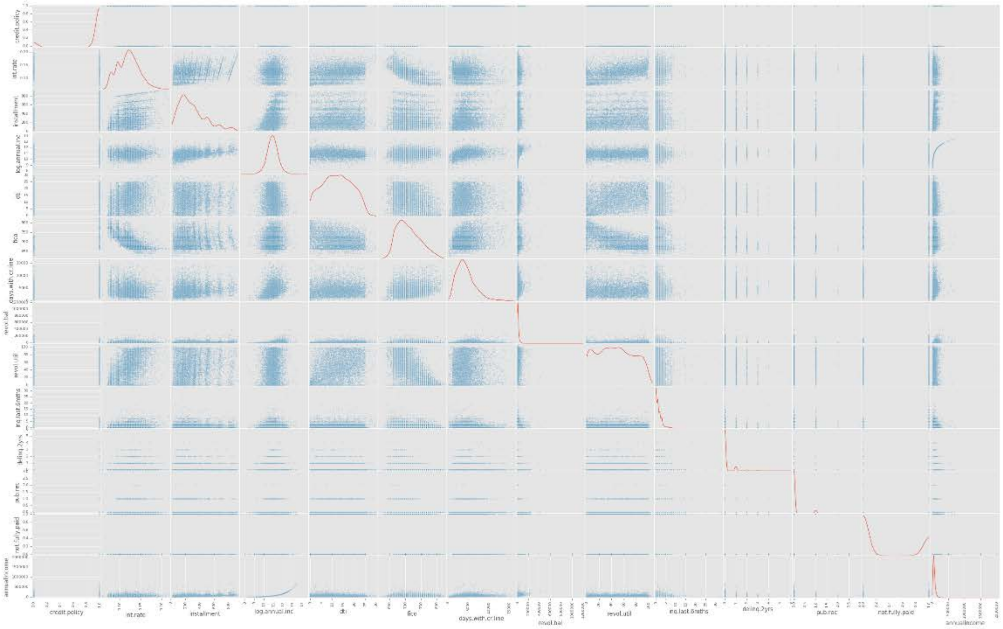
```
count  3467.000000        3467.000000    3467.000000  3467.000000
mean    716.717335        4562.523339   13576.013268    43.804753
std      36.935882        2411.216297   16685.502884    28.800678
min     627.000000        1110.000000       0.000000     0.000000
25%     687.000000        2820.000000    3343.000000    18.950000
50%     712.000000        4109.041667    8507.000000    42.100000
75%     742.000000        5669.958333   17448.500000    66.950000
max     827.000000       16259.041670  149527.000000    99.700000

       inq.last.6mths  delinq.2yrs      pub.rec  not.fully.paid
count     3467.000000  3467.000000  3467.000000            3467
mean         0.998269     0.155466     0.055956               0
std          1.166961     0.486163     0.239701               0
min          0.000000     0.000000     0.000000               0
25%          0.000000     0.000000     0.000000               0
50%          1.000000     0.000000     0.000000               0
75%          2.000000     0.000000     0.000000               0
max          8.000000     6.000000     3.000000               0

         annualincome
count     3467.000000
mean     65773.617248
std      55790.362442
min       4200.000000
25%      39560.000000
50%      55000.000000
75%      79000.000000
max    2039784.000000
```

The following observations can be made from looking at statistical summary of the data

- 100% of the accounts that are not default, had met credit underwriting criteria and out of the accounts that are defaulted 66% had met credit underwriting criteria. This means not meeting credit underwriting criteria should be used as primary reason to deny loan application.
- Mean interest rate of loans that defaulted is 13% and for loans that are current is 11%. That means loans that default tend to have higher interest rates.
- Mean installment of loans that defaulted is 342 and for current loans it is 293. This means loans that default tend to have higher installment payments.
- Mean debt to income ratio of defaulted loans is 13.2 and for current loans it is 11.9. This means loans that default tend to have higher debt to income ratio
- Mean revolving balance of default loans is 21066.3 and for current loans it is 13576. This means loans that default tend to have higher revolving balance.
- Mean credit utilization of default loans is 52.25 and for current loans it is 43.8. This means loans that default tend to have higher credit utilization
- Mean credit inquiry of default loans is 2.33 and for current loans it is 0.998. This means loans that default tend to have higher credit inquiry
- Income level, fico score, purpose, days with credit, public record and delinquent in past 2 years don’t seem to have a significant correlation with loans being default.

Exploratory Visualization

The plot below shows correlation matrix of all the features in the dataset (available as correlation.png and correlation.pdf in the same folder)



From the plot it can be seen that there is strong correlation between interest rate, amount of credit line utilized and debt to income ratio and there is inverse correlation between fico score and interest rate. Strong correlation or positive correlation means both variables rise or fall together. For the loan data this means people who have utilized more credit line tend to have higher interest rate, higher debt to income ratio and lower fico score. Having correlation between variables can make them redundant in machine learning models as they do not offer any additional information.

Algorithms and Techniques

This is a classification problem as we are trying to predict whether a loan will default or not. The dependent variable not.fully.paid is binary variable that can only be 0 or 1.

The algorithm needs to be fast as loans applied online need approval decision immediately. There is not a lot of data or time needed to train the model. So neural network would not be a good fit.

I will be using Logistic Regression, Support Vector Machine and Extra Trees Classifier to build the model and make prediction and pick the best model based on F1 score.

Logistic regression converts the dependent variable from a classification type to a probability and then uses linear regression to predict the probability of the dependent variable. Eventually a threshold is used to convert the probability of dependent variable to a classification variable by using the logic if the probability is above threshold then true otherwise false. Logistic regression can be used to solve binary classification problem. Its strength is that it can give probability of the dependent variable, so we can have a measure of likelihood of the dependent variable. Its weakness is that given a threshold, it will not be able to determine class of some dependent variable that are equal to the threshold. Another major limitation of logistic regression is that as the number of features increase, larger sample sizes are to make prediction. Since we only have 14 features, logistic regression can work for our use case. Logistic regression is also easy to interpret.

Support Vector Machine models the features as points in space and tries to form boundary lines between different classes of variables, thus separating each class of features into different planes. Its strength is in dividing features that have a clear separation. It can quickly separate different classes of features when they are distinctively apart. Its weakness is that it fails in situation when points are uniformly distributed. Since the current data can be divided into two classes, support vector machine can separate them into two planes. One issue with SVMs is having to choose a kernel function. Finding the right kernel function is not trivial in many cases. SVMs are known to have good generalization performance, but can be slow in test phase. SVMs are effective in high dimensional spaces. Even when number of features exceed the number of samples SVM can still give good results, but can have poor performance when number of features is much greater than number of samples. Unlike logistic regression, SVM does not give probability and finding probability after classifying labels using SVM requires complex k-fold algorithms, which can have poor performance. SVM is suitable for current scenario, because we only need to determine if loan will default or not and we are not required to give probability estimates. The number of features are also not that large.

Extra Trees Classifier is an ensemble algorithm. It uses an ensemble of trees and then averages the output from all the trees. It is comparably fast, works with large number of features and can give better accuracy than Logistic Regression or Support Vector Machine.

We need to apply feature scaling to the dataset before using any of these machine learning models on them. The main advantage of scaling is to avoid attributes in greater numeric ranges dominating those in smaller numeric ranges. Another advantage especially for SVM is to avoid numerical difficulties during the calculation. Because kernel values usually depend on the inner products of feature vectors. In case of linear kernel and the polynomial kernel, large attribute values might cause numerical problems.

Feature scaling is achieved by subtracting mean value of each feature from itself and then scaling it by dividing features by their standard deviation. This transforms all features to have mean close to 0 and standard deviation close to 1, making it an approximate Gaussian distribution. BoxCox was also attempted for feature scaling, but it raised value exception as some feature values were negative.

Benchmark

Credit utilization seems to be one of the primary feature that determines if a loan is likely to default. We could assume that everyone who has 50% credit utilization is going to default. Looking at the dataset 54.59% of the loans that defaulted had credit utilization of 50% or more. We can use this as benchmark to evaluate model performance.

Baseline F1 Calculation

Total number of loans that defaulted = 1533

Loans with more than 50% credit utilization that defaulted = TP = 837

Loans with 50% or less credit utilization that defaulted = FN = 696

Total number of loans that did not default = 3467

Loans with more than 50% credit utilization that did not default = FP = 1433

Loans with 50% or less credit utilization that did not default = TN = 2034

Precision = P = TP / (TP + FP) = 837 / (837 + 1433) = 0.3687

Recall = R = TP / (TP + FN) = 837 / (837 + 696) = 0.5459

Baseline F1 score = 2*P*R / (P+R) = 2 * 0.3687 * 0.5459 / (0.3687 + 0.5459) = 0.4401

Our objective is to find a model that can perform better than the baseline F1 score of 0.44.

Methodology

Data Preprocessing

There were no missing values in the dataset. Looking at the data it seems purpose is a set of categorical string values consisting of 'debt_consolidation', ‘all_other’, 'credit_card’, ‘small_business’, ‘home_improvement’, 'educational’, ‘major_purchase'. This is converted to numerical factor values from 0 to 6. OneHotEncoding is then applied on purpose. Feature scaling is then performed to normalize the data. Feature scaling was done by dividing each feature with its mean. As described in algorithms and techniques section, feature scaling was necessary to avoid large features from dominating and SVM needs features to be scaled to avoid large numerical issue. Dataset is split into training and testing set with 30% or 1500 data points in testing set and rest 3500 in training set.

Implementation

First the dependent variable is separated from independent variable to create labels and features as separate data frames. The data set is split into training and testing set. Logistic Regression, Support Vector Machine and Extra Trees Classifier algorithms are tried to see which one gives the best result. The table below shows the results

Method	Training accuracy	Test accuracy	F1 Score	Training time (sec)	Prediction time (sec)
LogisticRegression	0.805	0.787	0.5267	0.02	0.0
SVM	0.808	0.788	0.5078	2.414	0.116
ExtraTreesClassifier	1	0.78	0.5487	0.049	0.0

Refinement

Since ExtraTreesClassifier has the best F1 score it is used as the final model for prediction. Even though The models run very fast and return results within seconds. Using GridSearchCV on ExtraTreesClassifier with n_estimators values from 1 to 32 model F1 score was measured programmatically and the model with best F1 score was selected.

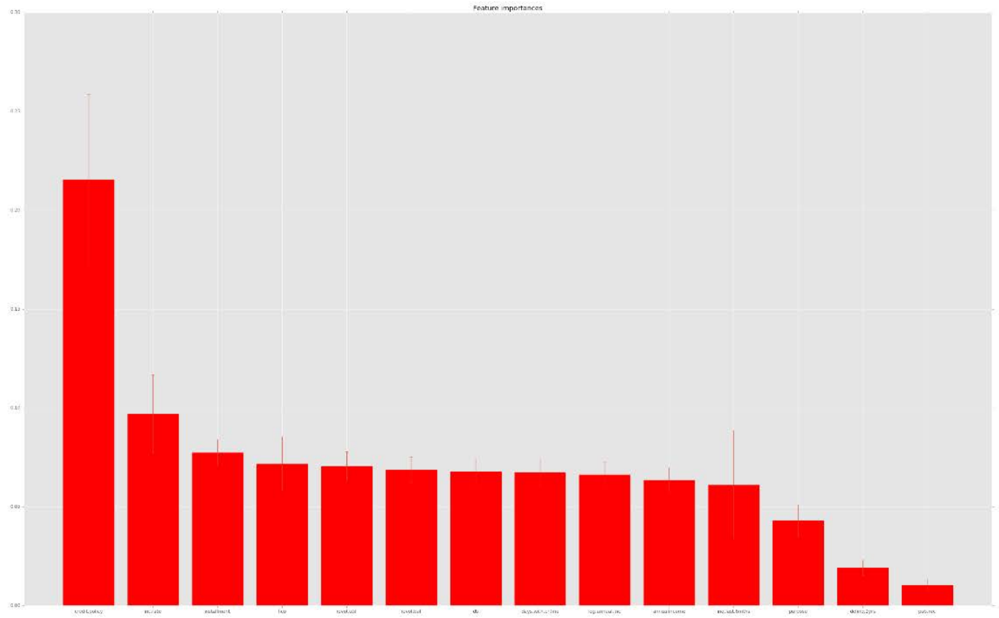
The final model has F1 score 0.54, which is not an improvement over the default parameter. So ExtraTreesClassifier with default parameter is the best model for our use case. The final parameters used for ExtraTreesClassifier, which are the default parameters are as follows

```
{'warm_start': False, 'oob_score': False, 'n_jobs': 1, 'verbose': 0, 'max_leaf_nodes':
None, 'bootstrap': False, 'min_samples_leaf': 1, 'n_estimators': 10,
'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'criterion': 'gini',
'random_state': None, 'max_features': 'auto', 'max_depth': None, 'class_weight': None}
```

Results

Model Evaluation and Validation

Using ExtraTreesClassifier in sklearn, the features are ranked by importance as shown in figure below (available as featureranking.png and featureranking.pdf in the same folder)



It seems the most important features in the order of importance are:

1. credit.policy
2. int.rate
3. installment
4. fico
5. revol.util
6. revol.bal
7. dti
8. days.with.cr.line
9. log.annual.inc
10. annualincome
11. inq.last.6mths
12. purpose
13. delinq.2yrs
14. pub.rec

This is in line with what we found from data exploration.

Justification

The final model has accuracy score of 78% and F1 score 0.54, which is more than the rough estimate of accuracy score 54.59% and F1 score 0.44

Conclusion

This model can be used to predict loans that will be at risk. This can be used to decide whether to approve a loan or not and proactive action can be taken on existing loans that are likely to default.

In order to find a model to predict whether a loan will default or not, I used historical data of past loans where some defaulted and some didn't. By analyzing the data, it was discovered that there is strong correlation between interest rate, amount of credit line utilized and debt to income ratio and there is inverse correlation between fico score and interest rate. This was in line with our general understanding of credit utilization. Accounts that have higher credit utilization and higher debt to income ratio are more likely to default and they tend to have higher interest rate.

After data transformation and feature scaling, the data was split into training and testing set. LogisticRegression, Support Vector Machine and ExtraTreesClassifier algorithms were used to train a model and predict if loan will default or not. Using F1 score, it was found that ExtraTreesClassifier had the best performance. Using GridSearchCV it was found that the ExtraTreesClassifier works best with default parameters in this case. The final model could be used in an online system to take decision on loan applications.

Although there were no difficulties in implementing the model and it performs better than educated guess, there are still more options that could be tried to improve the decision model even further. For example, using feature ranking, we know which features influence loans to default the most. We could use a threshold for feature importance and eliminate features below a certain importance level. We can experiment with different number of best features selected and use it to make prediction and finally select the most optimal feature set based on our chosen metrics. This is not done in this project to save time. Another issue was the availability of similar datasets from different sources, which could be used to test how well the model generalizes to different datasets.

Another option is to use deep learning. A neural network with closed planar shape could be used in this use case. Although deep learning would take more time to train. A model could be trained with historical data and then be used to take decision in an online system and then be updated periodically by training with new data as they become available. A problem with neural network is that training the model can be non-deterministic depending on initial parameters chosen, adding an additional layer of complexity. Another problem with neural network is they are not probabilistic, so we cannot differentiate between a loan that is 90% likely to default as opposed to a loan that is only 10% likely to default, thus losing valuable insight on the prediction.

Use of neural networks to predict loan being default is beyond the scope for this project.