Finalized_Notebook

April 14, 2021

1 Credit Default Prediction: Code Notebook with Annotations

Code is in Python using Jupyter Notebook
Exported using LaTex
(n) indicates code reference was used, go to code references at the bottom to find references with links

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2 Exploratory Data Analysis

Importing packages used in our analysis:
Numpy for scientific computing
Pandas for dealing with data tables
Matplotlib and seaborn for visualization
Statsmodels for calculating multicollinearity
Sklearn for building models and model interpretation, hyperparameter tuning
Autoimpute for imputation

[230]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sn
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import RepeatedStratifiedKFold, GridSearchCV,␣
↪learning_curve, ShuffleSplit
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_curve, roc_auc_score
from autoimpute.imputations import SingleImputer
```

Importing all of our data sets:

[235]:
```
df_test = pd.read_csv('Simulated_Data_Test.csv')
df_train = pd.read_csv('Simulated_Data_Train.csv')
df_validation = pd.read_csv('Simulated_Data_Validation.csv')
```

The first thing is to just get a basic summary of the train data we were given by looking at the raw data.

As we can see below, all variables except for state are of type float, and upon first glance it seems that the train data has imported correctly.

[240]:
```
print(df_train.sample)
print(df_train.dtypes)
```

```
<bound method NDFrame.sample of        tot_credit_debt  avg_card_debt
credit_age  credit_good_age  card_age  \
0              80826.71      15872.99       300.0           114.0      292.0
1              96052.60      12178.02       281.0           102.0      232.0
```

2	75212.76	12052.24	261.0	149.0	260.0
3	70727.84	8416.80	227.0	93.0	223.0
4	41604.47	10611.97	249.0	136.0	241.0
…	…	…	…	…	…
19995	104765.01	13905.40	182.0	84.0	165.0
19996	83990.07	10325.02	320.0	129.0	280.0
19997	107606.69	17838.79	290.0	168.0	271.0
19998	78787.72	11447.61	208.0	104.0	194.0
19999	78296.90	10053.16	348.0	175.0	299.0

	non_mtg_acc_past_due_12_months_num	non_mtg_acc_past_due_6_months_num	\
0	0.0	0.0	
1	0.0	0.0	
2	0.0	0.0	
3	2.0	1.0	
4	0.0	0.0	
…	…	…	
19995	0.0	0.0	
19996	0.0	0.0	
19997	1.0	0.0	
19998	0.0	0.0	
19999	0.0	0.0	

	mortgages_past_due_6_months_num	credit_past_due_amount	\
0	0.0	0.00	
1	0.0	0.00	
2	0.0	0.00	
3	1.0	11013.96	
4	0.0	0.00	
…	…	…	
19995	0.0	0.00	
19996	0.0	0.00	
19997	0.0	0.00	
19998	0.0	0.00	
19999	0.0	0.00	

	inq_12_month_num	…	card_open_36_month_num	auto_open_ 36_month_num	\
0	3.0	…	0.0	0.0	
1	2.0	…	1.0	0.0	
2	1.0	…	0.0	1.0	
3	0.0	…	1.0	0.0	
4	0.0	…	0.0	0.0	
…	…	…	…	…	
19995	4.0	…	0.0	0.0	
19996	0.0	…	0.0	0.0	
19997	3.0	…	0.0	1.0	
19998	1.0	…	0.0	0.0	
19999	2.0	…	0.0	0.0	

```
       uti_card  uti_50plus_pct  uti_max_credit_line  uti_card_50plus_pct  \
0      0.365902        0.475594             0.410504                  NaN
1      0.542786        0.543158             0.535147             0.587351
2      0.323678        0.321776             0.348713             0.413293
3      0.448721        0.422809             0.491365             0.466810
4      0.644030        0.619987             0.546655             0.588442
…         …              …                    …                   …
19995  0.437699        0.557576             0.472592             0.481113
19996  0.637746        0.484714             0.734825                  NaN
19997  0.486259        0.563475             0.406215             0.463120
19998  0.299035        0.283815             0.255758             0.281647
19999  0.574453        0.540931             0.540706             0.512513

       ind_acc_XYZ  rep_income  States Default_ind
0              0.0     69000.0      AL         0.0
1              0.0     61000.0      FL         0.0
2              0.0         NaN      AL         0.0
3              0.0     79000.0      SC         1.0
4              1.0         NaN      LA         0.0
…             …          …     …          …
19995          1.0         NaN      GA         0.0
19996          0.0     87000.0      NC         0.0
19997          0.0     63000.0      SC         0.0
19998          0.0     71000.0      AL         0.0
19999          0.0     85000.0      AL         0.0

[20000 rows x 21 columns]>
tot_credit_debt                       float64
avg_card_debt                         float64
credit_age                            float64
credit_good_age                       float64
card_age                              float64
non_mtg_acc_past_due_12_months_num    float64
non_mtg_acc_past_due_6_months_num     float64
mortgages_past_due_6_months_num       float64
credit_past_due_amount                float64
inq_12_month_num                      float64
card_inq_24_month_num                 float64
card_open_36_month_num                float64
auto_open_ 36_month_num               float64
uti_card                              float64
uti_50plus_pct                        float64
uti_max_credit_line                   float64
uti_card_50plus_pct                   float64
ind_acc_XYZ                           float64
rep_income                            float64
States                                 object
```

```
Default_ind                            float64
dtype: object
```

Before we get ahead of ourselves, we want to check that there is nothing wrong with the test and validation datasets when compared to the train dataset.

Everything seems to be in order: correct data types, same number of variables, nothing seems out of the ordinary.

[236]:
```python
print(df_validation.sample)
print(df_validation.dtypes)
```

```
<bound method NDFrame.sample of       tot_credit_debt  avg_card_debt  credit_age
credit_good_age  card_age  \
0            63651.27        9019.99       484.0             242.0     395.0
1           105559.29       16692.19       212.0             118.0     211.0
2            96062.99       10509.13       255.0             123.0     180.0
3            84417.40       13873.96       330.0             175.0     328.0
4           100623.91       15592.09       207.0             101.0     128.0
…                …              …     …                …        …
2995         90748.88       11481.81       274.0             161.0     268.0
2996        101930.98       15242.30       243.0             161.0     213.0
2997         74738.73       12175.49       351.0             179.0     271.0
2998        120357.58       14477.70       308.0             178.0     298.0
2999         74240.17       11873.45       341.0             181.0     333.0

      non_mtg_acc_past_due_12_months_num  non_mtg_acc_past_due_6_months_num  \
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
…                                  …                                …
2995                                 0.0                                0.0
2996                                 0.0                                0.0
2997                                 0.0                                0.0
2998                                 0.0                                0.0
2999                                 0.0                                0.0

      mortgages_past_due_6_months_num  credit_past_due_amount  \
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
…                               …                     …
2995                              0.0                     0.0
2996                              0.0                     0.0
2997                              0.0                     0.0
```

```
2998                             0.0                     0.0
2999                             0.0                     0.0

      inq_12_month_num  …  card_open_36_month_num  auto_open_ 36_month_num  \
0                  0.0  …                     0.0                      0.0
1                  4.0  …                     0.0                      1.0
2                  2.0  …                     0.0                      0.0
3                  1.0  …                     0.0                      0.0
4                  6.0  …                     0.0                      0.0
…                    …  …                       …                        …
2995               0.0  …                     0.0                      1.0
2996               2.0  …                     0.0                      1.0
2997               2.0  …                     0.0                      0.0
2998               2.0  …                     0.0                      1.0
2999               4.0  …                     1.0                      1.0

      uti_card  uti_50plus_pct  uti_max_credit_line  uti_card_50plus_pct  \
0     0.619761        0.624652             0.506910             0.530109
1     0.428082        0.533489             0.340476             0.388792
2     0.437217        0.422643             0.418459             0.450523
3     0.651360        0.566563             0.399319             0.562153
4     0.586265        0.504849             0.652576             0.576409
…          …             …                   …                    …
2995  0.573039        0.665278             0.638087             0.559056
2996  0.582873        0.662823             0.408222             0.564803
2997  0.735002        0.586252             0.527243             0.651801
2998  0.478272        0.545468             0.531942             0.557991
2999  0.702814        0.658051             0.680245             0.736850

      ind_acc_XYZ  rep_income  States Default_ind
0             0.0     66000.0      FL         1.0
1             0.0     55000.0      MS         0.0
2             0.0     86000.0      MS         0.0
3             0.0    110000.0      MS         0.0
4             1.0         NaN      NC         0.0
…            …          …     …          …
2995          0.0     76000.0      FL         0.0
2996          0.0     65000.0      AL         0.0
2997          0.0     85000.0      LA         0.0
2998          1.0         NaN      NC         0.0
2999          0.0     47000.0      MS         0.0

[3000 rows x 21 columns]>
tot_credit_debt                      float64
avg_card_debt                        float64
credit_age                           float64
credit_good_age                      float64
card_age                             float64
```

```
non_mtg_acc_past_due_12_months_num    float64
non_mtg_acc_past_due_6_months_num     float64
mortgages_past_due_6_months_num       float64
credit_past_due_amount                float64
inq_12_month_num                      float64
card_inq_24_month_num                 float64
card_open_36_month_num                float64
auto_open_ 36_month_num               float64
uti_card                              float64
uti_50plus_pct                        float64
uti_max_credit_line                   float64
uti_card_50plus_pct                   float64
ind_acc_XYZ                           float64
rep_income                            float64
States                                 object
Default_ind                           float64
dtype: object
```

[238]:

```python
print(df_test.sample)
print(df_test.dtypes)
```

```
<bound method NDFrame.sample of       tot_credit_debt  avg_card_debt  credit_age
credit_good_age  card_age  \
0            40477.81        7766.64       322.0            181.0     235.0
1           106760.98       16606.98       323.0            144.0     273.0
2           121428.34       13910.13       361.0            189.0     350.0
3            96515.05       15436.78       344.0            203.0     343.0
4           123760.22       14213.25       370.0            177.0     347.0
…                 …             …        …               …        …
4995         90788.44       11646.36       203.0             80.0     180.0
4996         91052.81       16505.20       291.0            122.0     285.0
4997         71061.71       11512.18       348.0            191.0     303.0
4998         82162.45       10014.90       357.0            163.0     339.0
4999        116943.32       18042.56       192.0             99.0     189.0

      non_mtg_acc_past_due_12_months_num  non_mtg_acc_past_due_6_months_num  \
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
…                                  …                                 …
4995                                 0.0                                0.0
4996                                 0.0                                0.0
4997                                 0.0                                0.0
4998                                 0.0                                0.0
4999                                 0.0                                0.0
```

```
      mortgages_past_due_6_months_num  credit_past_due_amount  \
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
…                                   …                       …
4995                              0.0                     0.0
4996                              0.0                     0.0
4997                              0.0                     0.0
4998                              0.0                     0.0
4999                              0.0                     0.0

      inq_12_month_num  …  card_open_36_month_num  auto_open_ 36_month_num  \
0                  2.0  …                     0.0                      1.0
1                  2.0  …                     0.0                      0.0
2                  0.0  …                     0.0                      0.0
3                  0.0  …                     0.0                      0.0
4                  0.0  …                     0.0                      0.0
…                    …  …                       …                        …
4995               0.0  …                     0.0                      0.0
4996               3.0  …                     0.0                      0.0
4997               3.0  …                     1.0                      1.0
4998               1.0  …                     0.0                      0.0
4999               4.0  …                     1.0                      0.0

      uti_card  uti_50plus_pct  uti_max_credit_line  uti_card_50plus_pct  \
0     0.588301        0.711887             0.538456             0.633699
1     0.707799        0.739732             0.562194             0.746901
2     0.479711        0.434104             0.374705             0.458438
3     0.443710        0.474768             0.372028             0.582352
4     0.571004        0.472634             0.605137             0.577697
…          …             …                    …                    …
4995  0.444254        0.629877             0.496559             0.398411
4996  0.330706        0.353832             0.485601             0.286623
4997  0.469755        0.478526             0.460937             0.443688
4998  0.089534        0.259846             0.127144             0.178131
4999  0.575263        0.593724             0.626940             0.503552

      ind_acc_XYZ  rep_income  States Default_ind
0             0.0     26000.0      FL         0.0
1             1.0     47000.0      AL         0.0
2             0.0     71000.0      MS         0.0
3             1.0     68000.0      AL         0.0
4             0.0     76000.0      GA         0.0
…               …           …       …           …
4995          0.0     94000.0      LA         0.0
4996          1.0     73000.0      SC         0.0
```

```
4997          1.0     94000.0      LA         0.0
4998          0.0     70000.0      MS         0.0
4999          0.0    111000.0      MS         0.0

[5000 rows x 21 columns]>
tot_credit_debt                      float64
avg_card_debt                        float64
credit_age                           float64
credit_good_age                      float64
card_age                             float64
non_mtg_acc_past_due_12_months_num    float64
non_mtg_acc_past_due_6_months_num     float64
mortgages_past_due_6_months_num       float64
credit_past_due_amount               float64
inq_12_month_num                     float64
card_inq_24_month_num                float64
card_open_36_month_num               float64
auto_open_ 36_month_num              float64
uti_card                             float64
uti_50plus_pct                       float64
uti_max_credit_line                  float64
uti_card_50plus_pct                  float64
ind_acc_XYZ                          float64
rep_income                           float64
States                                object
Default_ind                          float64
dtype: object
```

Now we will garner summary stats about the all the variables. Important notes: - reported income mean is much higher than national mean. - 7.93% of population in train data set has defaulted - 25.855% of population already had an account with XYZ - All utilization variables have a mean around 50% - Standard deviation is relatively large for average card debt (0.66 as a proportion of the mean).

[49]:
```
df_train.describe()
```

[49]:
```
       tot_credit_debt  avg_card_debt    credit_age  credit_good_age  \
count     20000.000000   20000.000000  20000.000000     20000.000000
mean      94563.702530   14088.235475    296.697000       149.771750
std       23546.443862    9314.495936     61.711702        34.016476
min        2367.430000    2363.120000     54.000000        21.000000
25%       78743.750000   11321.502500    255.000000       127.000000
50%       94670.630000   13243.750000    297.000000       150.000000
75%      110329.335000   15196.060000    339.000000       172.000000
max      188890.960000   99999.000000    545.000000       296.000000

           card_age  non_mtg_acc_past_due_12_months_num  \
count  20000.000000                         20000.00000
```

mean	268.015200	0.11135
std	59.364769	0.43389
min	41.000000	0.00000
25%	227.000000	0.00000
50%	268.000000	0.00000
75%	308.000000	0.00000
max	520.000000	4.00000

	non_mtg_acc_past_due_6_months_num	mortgages_past_due_6_months_num	\
count	20000.000000	20000.000000	
mean	0.027400	0.030200	
std	0.171903	0.171142	
min	0.000000	0.000000	
25%	0.000000	0.000000	
50%	0.000000	0.000000	
75%	0.000000	0.000000	
max	2.000000	1.000000	

	credit_past_due_amount	inq_12_month_num	card_inq_24_month_num	\
count	20000.000000	20000.000000	20000.000000	
mean	329.287867	1.762700	3.409600	
std	2073.899357	1.740816	2.926697	
min	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	1.000000	
50%	0.000000	1.000000	3.000000	
75%	0.000000	3.000000	5.000000	
max	32662.980000	10.000000	18.000000	

	card_open_36_month_num	auto_open_ 36_month_num	uti_card	\
count	20000.000000	20000.000000	20000.000000	
mean	0.163050	0.141000	0.503157	
std	0.386099	0.349607	0.109354	
min	0.000000	0.000000	0.065120	
25%	0.000000	0.000000	0.429611	
50%	0.000000	0.000000	0.502800	
75%	0.000000	0.000000	0.577412	
max	2.000000	2.000000	0.969289	

	uti_50plus_pct	uti_max_credit_line	uti_card_50plus_pct	ind_acc_XYZ	\
count	20000.000000	20000.000000	17945.000000	20000.000000	
mean	0.511007	0.507629	0.489594	0.258550	
std	0.113456	0.108624	0.119701	0.437849	
min	0.033749	0.005174	0.000000	0.000000	
25%	0.435171	0.433550	0.409794	0.000000	
50%	0.509922	0.507193	0.490074	0.000000	
75%	0.588418	0.581376	0.569036	1.000000	
max	0.988964	1.000000	0.970776	1.000000	

```
          rep_income   Default_ind
count   18430.000000  20000.000000
mean    75499.511666      0.079300
std     16361.955146      0.270213
min     12000.000000      0.000000
25%     64000.000000      0.000000
50%     75000.000000      0.000000
75%     86000.000000      0.000000
max    150000.000000      1.000000
```

We want to check which values are missing.

At this point, we are considering dropping the reported income variable due to its self reported nature.

We will need to find a way to deal with uti_card_50plus_pct as that may be an important variable.

[23]:
```
print(df_train.isnull().sum())
print(df_train[['uti_card_50plus_pct','rep_income']].isnull().sum())
```

```
tot_credit_debt                         0
avg_card_debt                           0
credit_age                              0
credit_good_age                         0
card_age                                0
non_mtg_acc_past_due_12_months_num      0
non_mtg_acc_past_due_6_months_num       0
mortgages_past_due_6_months_num         0
credit_past_due_amount                  0
inq_12_month_num                        0
card_inq_24_month_num                   0
card_open_36_month_num                  0
auto_open_ 36_month_num                 0
uti_card                                0
uti_50plus_pct                          0
uti_max_credit_line                     0
uti_card_50plus_pct                  2055
ind_acc_XYZ                             0
rep_income                           1570
AL                                      0
FL                                      0
GA                                      0
LA                                      0
MS                                      0
NC                                      0
SC                                      0
```

```
Default_ind                                 0
dtype: int64
uti_card_50plus_pct     2055
rep_income              1570
dtype: int64
```

It is important to compare the statistics of the defaulting population to the non defaulting population.

We note the following: - The mean average card debt, credit past due amount, and utilization variables are much higher in the defaulting population than the non-defaulting population - For average card debt and credit past due amount, the defaulting population had a much greater std, suggesting high variance in the defaulting population - Reported income stats for both populations is very similar

[8]:
```
defaulting_population = df_train[df_train["Default_ind"] == 1]
non_defaulting_population = df_train[df_train["Default_ind"] == 0]
```

[9]:
```
defaulting_population.describe()
```

[9]:
```
       tot_credit_debt  avg_card_debt   credit_age  credit_good_age  \
count      1586.000000    1586.000000  1586.000000      1586.000000
mean      91915.567554   17880.428821   275.160151       140.535309
std       29920.362673   21195.058690    61.986033        33.557997
min        6898.500000    2363.120000    54.000000        21.000000
25%       70589.517500    9864.232500   233.000000       118.000000
50%       91235.590000   13125.530000   274.000000       140.000000
75%      112973.610000   16356.372500   316.000000       163.000000
max      188890.960000   99999.000000   521.000000       274.000000

          card_age  non_mtg_acc_past_due_12_months_num  \
count  1586.000000                         1586.000000
mean    247.708701                            0.706810
std      58.602115                            1.035236
min      41.000000                            0.000000
25%     206.000000                            0.000000
50%     247.000000                            0.000000
75%     288.000000                            2.000000
max     463.000000                            4.000000

       non_mtg_acc_past_due_6_months_num  mortgages_past_due_6_months_num  \
count                        1586.000000                      1586.000000
mean                            0.249685                         0.268600
std                             0.473343                         0.443371
min                             0.000000                         0.000000
25%                             0.000000                         0.000000
50%                             0.000000                         0.000000
75%                             0.000000                         1.000000
```

max	2.000000	1.000000

	credit_past_due_amount	inq_12_month_num	card_inq_24_month_num	\
count	1586.000000	1586.000000	1586.000000	
mean	3060.922629	2.288777	4.163934	
std	5777.479779	1.867494	3.137177	
min	0.000000	0.000000	0.000000	
25%	0.000000	1.000000	2.000000	
50%	0.000000	2.000000	4.000000	
75%	4905.157500	4.000000	6.000000	
max	32662.980000	9.000000	15.000000	

	card_open_36_month_num	auto_open_ 36_month_num	uti_card	\
count	1586.000000	1586.000000	1586.000000	
mean	0.192938	0.149433	0.560360	
std	0.419524	0.356627	0.110701	
min	0.000000	0.000000	0.208749	
25%	0.000000	0.000000	0.487653	
50%	0.000000	0.000000	0.564220	
75%	0.000000	0.000000	0.636084	
max	2.000000	1.000000	0.969289	

	uti_50plus_pct	uti_max_credit_line	uti_card_50plus_pct	ind_acc_XYZ	\
count	1586.000000	1586.000000	1412.000000	1586.000000	
mean	0.557966	0.551171	0.544364	0.206810	
std	0.114920	0.109630	0.123059	0.405145	
min	0.163960	0.186306	0.118153	0.000000	
25%	0.476796	0.476078	0.462664	0.000000	
50%	0.558708	0.550171	0.547647	0.000000	
75%	0.638486	0.623271	0.629132	0.000000	
max	0.894996	1.000000	0.970776	1.000000	

	rep_income	Default_ind
count	1457.000000	1586.0
mean	74522.992450	1.0
std	16775.126303	0.0
min	26000.000000	1.0
25%	63000.000000	1.0
50%	74000.000000	1.0
75%	85000.000000	1.0
max	123000.000000	1.0

[242]:
```
non_defaulting_population.describe()
```

[242]:

	tot_credit_debt	avg_card_debt	credit_age	credit_good_age	\
count	18414.000000	18414.000000	18414.000000	18414.000000	
mean	94791.786710	13761.613413	298.551971	150.567286	

std	22901.385098	7363.255055	61.336991	33.939197
min	2367.430000	4595.020000	78.000000	27.000000
25%	79292.612500	11401.827500	257.000000	128.000000
50%	94912.085000	13251.240000	299.000000	151.000000
75%	110188.782500	15138.300000	340.000000	173.000000
max	182858.990000	99999.000000	545.000000	296.000000

	card_age	non_mtg_acc_past_due_12_months_num	\
count	18414.000000	18414.000000	
mean	269.764201	0.060063	
std	59.106129	0.281161	
min	56.000000	0.000000	
25%	229.000000	0.000000	
50%	270.000000	0.000000	
75%	310.000000	0.000000	
max	520.000000	3.000000	

	non_mtg_acc_past_due_6_months_num	mortgages_past_due_6_months_num	\
count	18414.000000	18414.000000	
mean	0.008255	0.009667	
std	0.090481	0.097845	
min	0.000000	0.000000	
25%	0.000000	0.000000	
50%	0.000000	0.000000	
75%	0.000000	0.000000	
max	1.000000	1.000000	

	credit_past_due_amount	inq_12_month_num	card_inq_24_month_num	\
count	18414.000000	18414.000000	18414.000000	
mean	94.011842	1.717389	3.344629	
std	1048.877699	1.722024	2.898779	
min	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	1.000000	
50%	0.000000	1.000000	3.000000	
75%	0.000000	3.000000	5.000000	
max	24211.550000	10.000000	18.000000	

	card_open_36_month_num	auto_open_ 36_month_num	uti_card	\
count	18414.000000	18414.000000	18414.000000	
mean	0.160476	0.140274	0.498230	
std	0.382987	0.348996	0.107830	
min	0.000000	0.000000	0.065120	
25%	0.000000	0.000000	0.425885	
50%	0.000000	0.000000	0.498045	
75%	0.000000	0.000000	0.571530	
max	2.000000	2.000000	0.922326	

```
       uti_50plus_pct  uti_max_credit_line  uti_card_50plus_pct   ind_acc_XYZ  \
count    18414.000000         18414.000000         16533.000000  18414.000000
mean         0.506963             0.503879             0.484916      0.263006
std          0.112418             0.107720             0.118243      0.440278
min          0.033749             0.005174             0.000000      0.000000
25%          0.431793             0.430766             0.405870      0.000000
50%          0.506286             0.503482             0.485286      0.000000
75%          0.583785             0.577646             0.563275      1.000000
max          0.988964             0.971640             0.949959      1.000000

          rep_income  Default_ind
count   16973.000000      18414.0
mean    75583.338243          0.0
std     16323.783467          0.0
min     12000.000000          0.0
25%     65000.000000          0.0
50%     76000.000000          0.0
75%     87000.000000          0.0
max    150000.000000          0.0
```

Do we have enough observations for the amount of explanatory variables? One way to check this for regression analysis is the rule of ten test. If $10k/p > n$, there are too many explanatory variables and not enough observations. - k = explantory variables = 20 - p = probability that account defaulted = 0.0793 (found in summary stats) - n = number of observations = 20,000

Data has passed rule of ten test since 20,000 is much larger than 2522.

For random forest, the number of observations is less of a concern for us as random forests are good with both large and small data sets.

[201]:
```python
print((10 * 20) / 0.0793)
```

```
2522.068095838588
```

We can check for multicollinearity by finding each variable's variance inflation factor. This is extremely important to consider for the logistic regression model, as one of the main assumptions is that there is little to no collinearity explantory variables.

As can be seen, there are many VIF values which are greater than 10, an unacceptable result. Additionally, there some VIF values that are less than 10 but greater than 5, a cause for concern (1).

[17]:
```python
def calc_vif(X):

    vif = pd.DataFrame()
    vif["variables"] = X.columns
    vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.
↪shape[1])]
```

```
    return(vif)

columns = []
for num in range(0,18):
    if num == 16:
        pass
    else:
        columns.append(num)

calc_vif(df_train.iloc[:,columns])
```

[17]:

	variables	VIF
0	tot_credit_debt	16.224066
1	avg_card_debt	3.835799
2	credit_age	232.525965
3	credit_good_age	52.883615
4	card_age	174.509147
5	non_mtg_acc_past_due_12_months_num	4.612476
6	non_mtg_acc_past_due_6_months_num	3.462795
7	mortgages_past_due_6_months_num	6.670029
8	credit_past_due_amount	6.570714
9	inq_12_month_num	7.769188
10	card_inq_24_month_num	9.002325
11	card_open_36_month_num	1.188654
12	auto_open_ 36_month_num	1.172338
13	uti_card	78.503559
14	uti_50plus_pct	46.474318
15	uti_max_credit_line	49.135164
16	ind_acc_XYZ	1.348725

Let's check for collinearity between specific variables, including the response variable. This will help shed light on which explanotory variables are colinear, which will be extremely important for logistic regression. We will also discover which explanatory variables we may consider to have too low of a correlation to the default indicator, which we want to minimize for our random tree model.

To create a correlation matrix of all variables, we will firstly create dummy variables for the states.

[204]:
```
dummies = pd.get_dummies(df_train['States'])
default_ind = df_train['Default_ind']
df_train = df_train.drop(columns=['States', 'Default_ind'])
df_train = df_train.join(dummies)
df_train = df_train.join(default_ind)
```

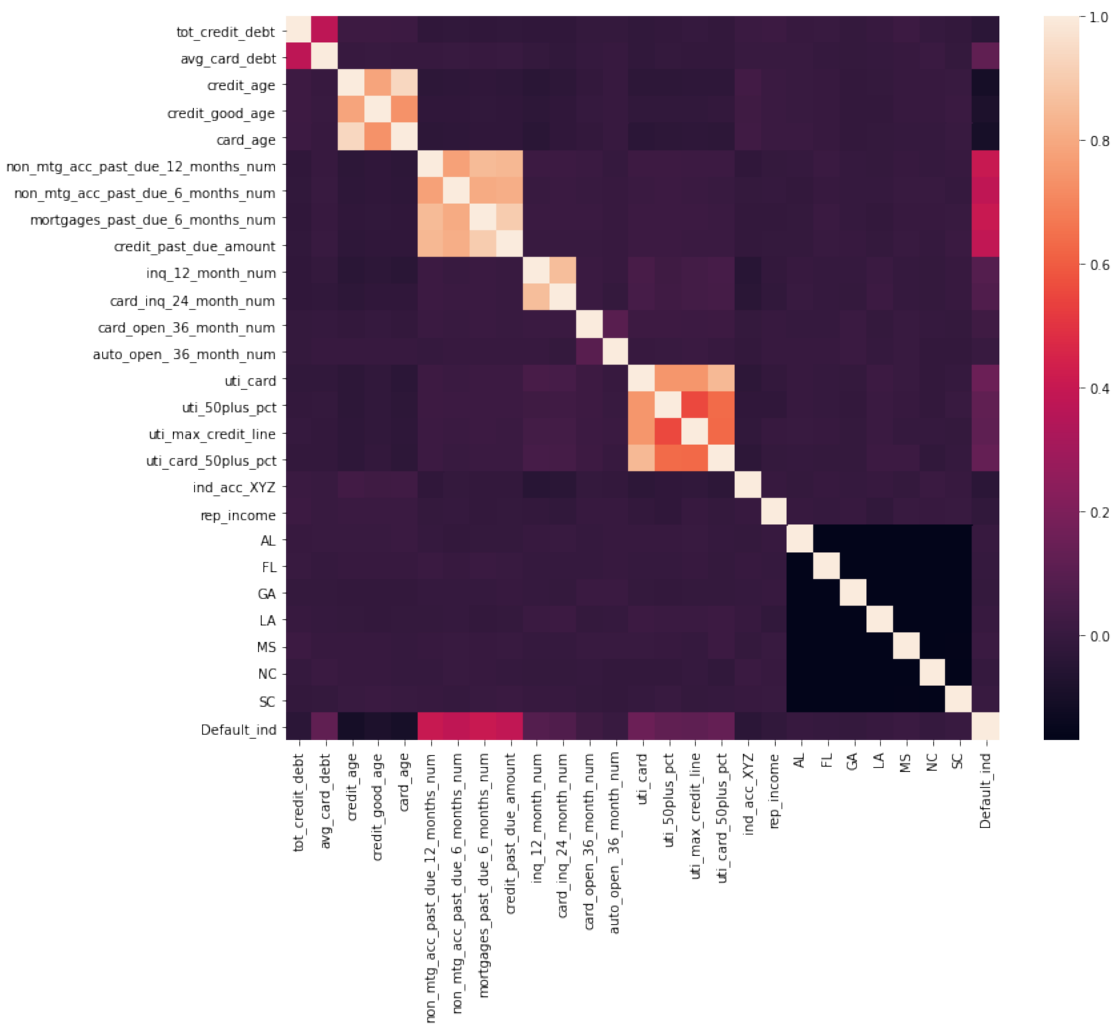
Now the data is ready for a correlation matrix.

Logistic regression notes:

It seems that reported income does not have a high correlation with the response variable. This confirms to us that it is no longer worth keeping. The first five columns present unacceptable levels of colinearity. With no easy way to combine them, the four with least amount of correlation to the response variable will be dropped. Since the 12 month and 24 month card inquiry variables are highly colinear and since the 24 month card inquiry variable is cumulative, we will drop the 12 month card inquiry variable.

Random forest notes:
For now, we will consider credit age, credit good age, and card age to have too low of a correlation to the default indicator and disregard them for our random tree model.

[22]:
```python
columns = []
fig, ax = plt.subplots(figsize=(12,10))
for num in range(0,27):
    columns.append(num)
corrMatrix = df_train.iloc[:,columns].corr()
sn.heatmap(corrMatrix, annot=False, ax=ax)
plt.show()
```

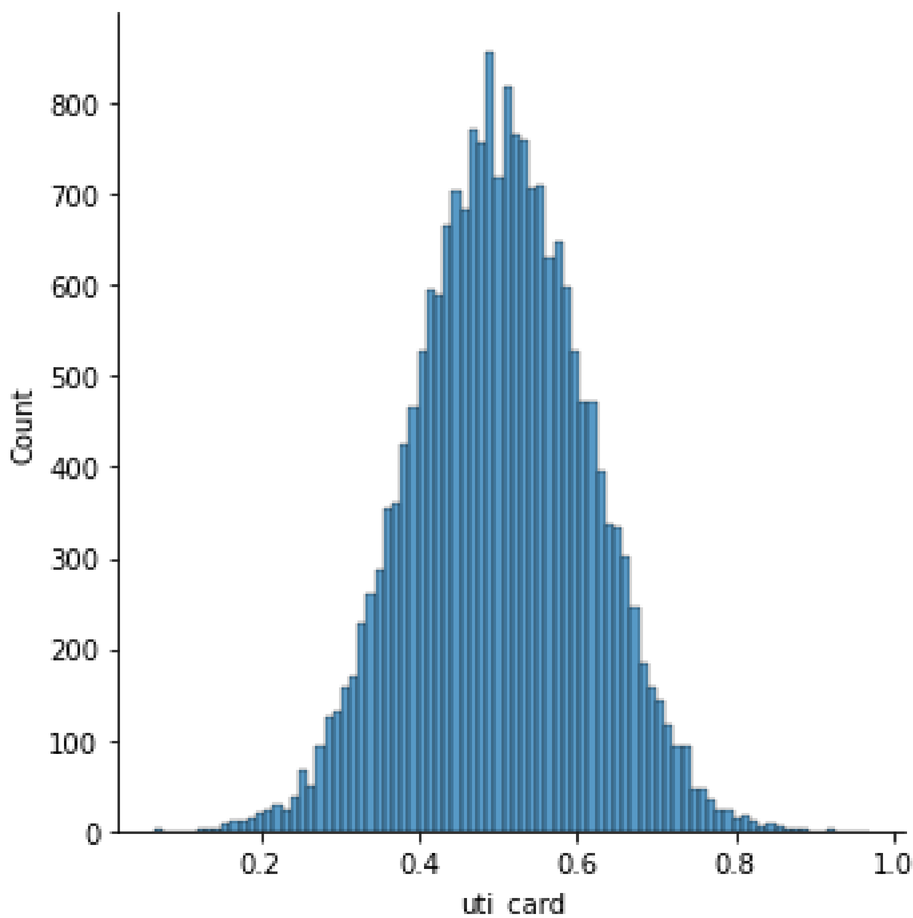


For logistic regression, we will need to deal with missing values, as the model will not do this for us. Since the only variable with missing values we decided to keep is uti_card_50plus_pct, we will need to find a way to deal with missing values for this column. Our first idea is, since utilization variables have high collinearity and are on the same scale, to combine all utilization variables into a mean utilization variable which will consider uti_card_50plus_pct only if available for the observation. To make sure this is feasable, we must first check the normality of the utilization variables.

As can be seen below, the distribution of all utilization variables is approximately normal, meaning that mean utilization could be a useful variable.

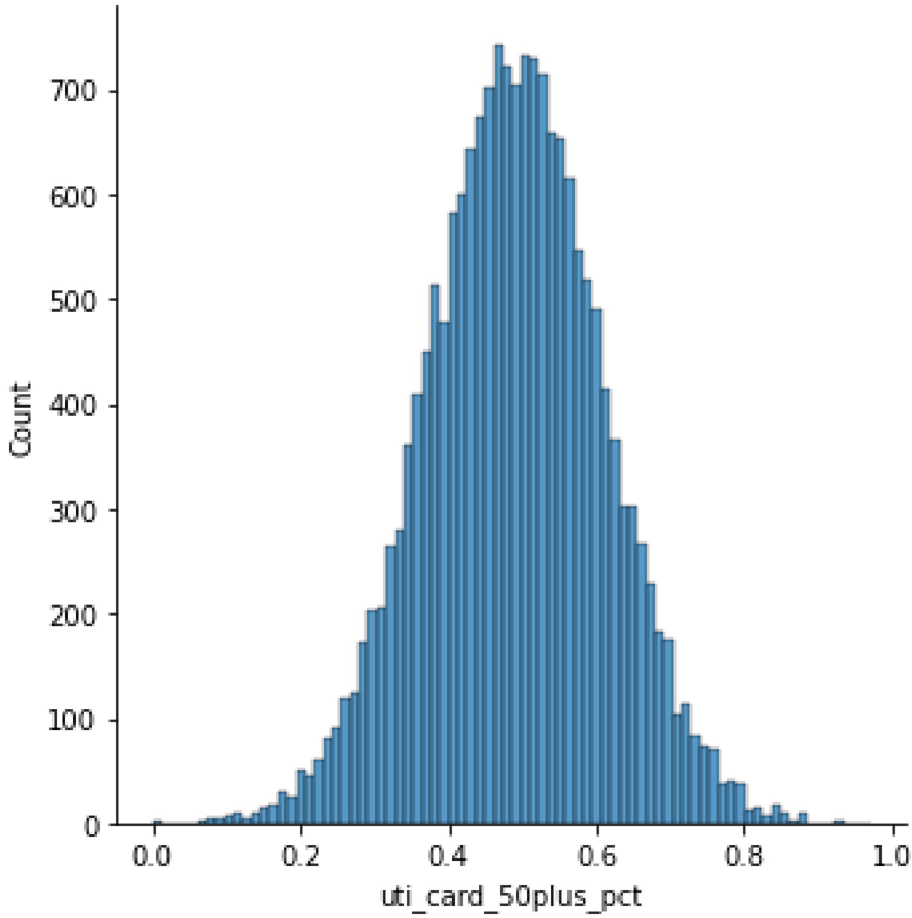
[13]:
```
sn.displot(df_train,x="uti_card")
```

[13]: <seaborn.axisgrid.FacetGrid at 0x2126627ed30>



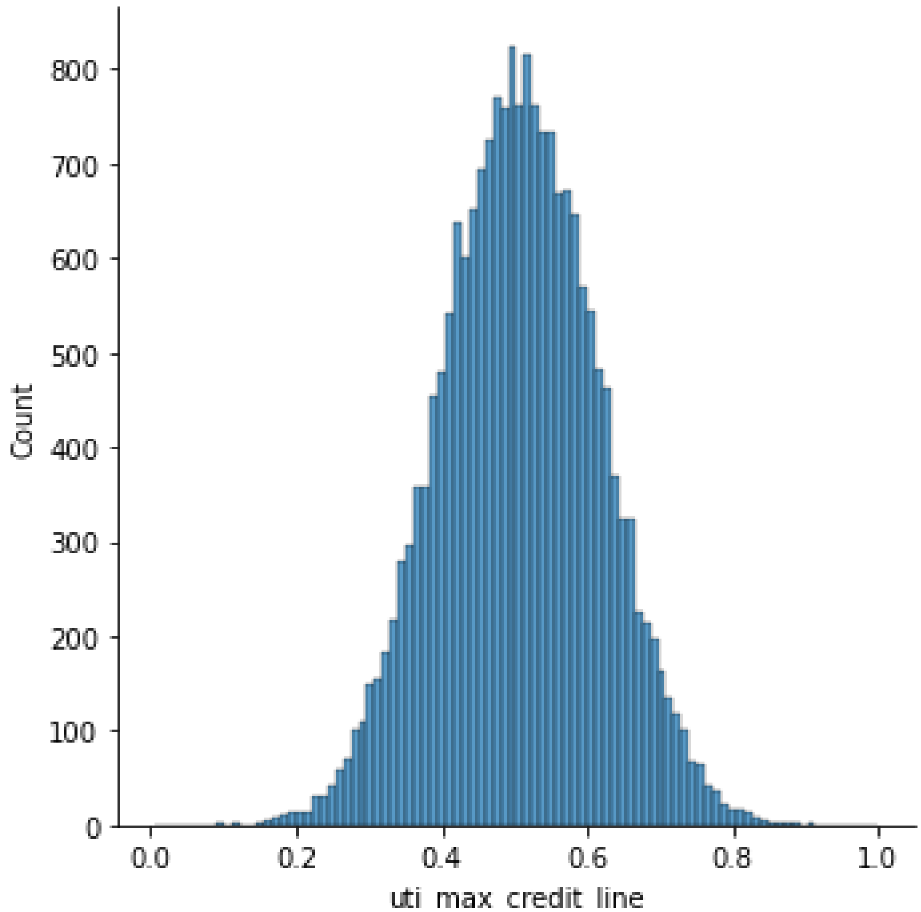
[18]:
```
sn.displot(df_train,x="uti_card_50plus_pct")
```

[18]: <seaborn.axisgrid.FacetGrid at 0x212669e4a00>



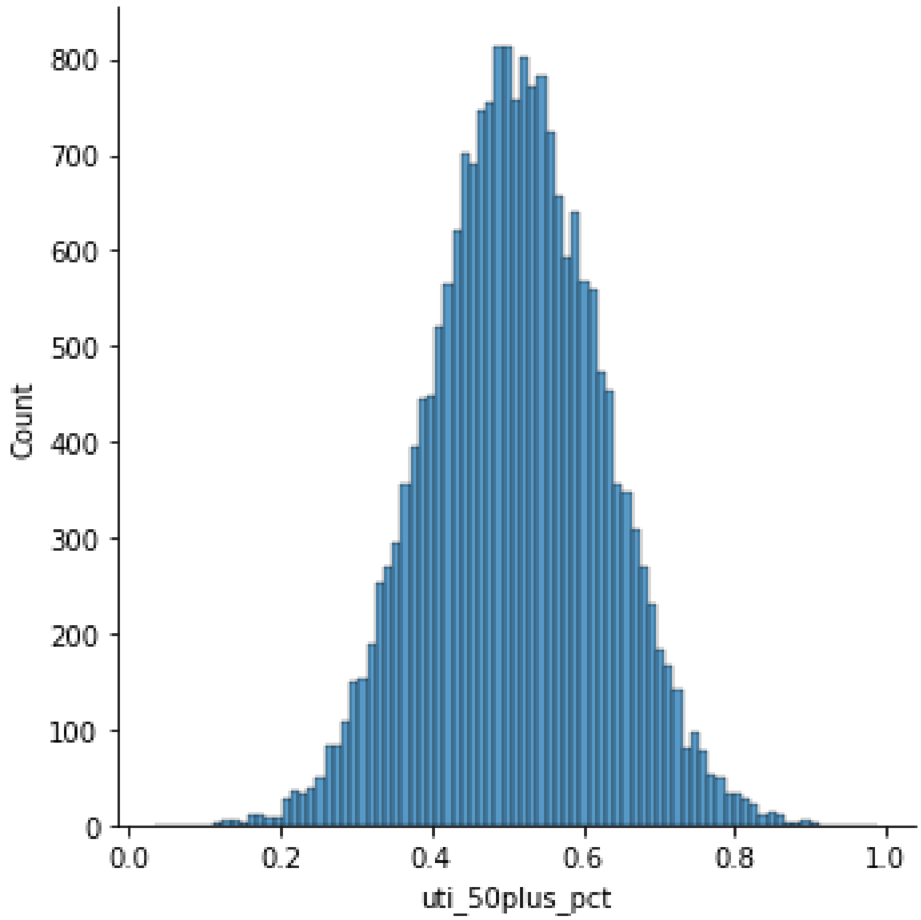
[15]:
```
sn.displot(df_train,x="uti_max_credit_line")
```

[15]: <seaborn.axisgrid.FacetGrid at 0x212669ee790>



[19]:
```
sn.displot(df_train,x="uti_50plus_pct")
```

[19]: <seaborn.axisgrid.FacetGrid at 0x212672312e0>



3 Data Preprocessing - Logistic Regression

We have already determined based on EDA which explanatory variables need to be dropped:tot__credit__debt, credit__age, credit__good__age, card__age, rep__income,inq__12__month__num.

[205]:
```
df_train = df_train.drop(columns=["tot_credit_debt", "credit_age",␣
↪"credit_good_age", "card_age","rep_income","inq_12_month_num"])
```

Next comes the process of combining all utilization variables into one variable, and replacing all the instances with the new overlapping variable. By taking the average utilization, we are able to preserve the available data in uti__card__50plus__pct.

[206]:
```
util_vars = ["uti_card", "uti_50plus_pct", "uti_max_credit_line",␣
↪"uti_card_50plus_pct"]
util_credit = df_train[util_vars]
util_credit["mean"] = util_credit.mean(axis=1)
```

```
df_train = df_train.drop(columns=["uti_50plus_pct", "uti_max_credit_line",␣
↪"uti_card_50plus_pct"])
df_train["uti_card"] = util_credit["mean"]
df_train = df_train.rename(columns={"uti_card":"mean_uti"})
```

```
<ipython-input-206-543dfd05b1c6>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  util_credit["mean"] = util_credit.mean(axis=1)
```

Past due variables have unacceptable levels of colinearity. It makes sense to combine the non mortgage and mortgages past due 6 month variables as they span the same time period and are highly colinear. For now, the other past due variables are not dropped due to their high correlation with the response variable.

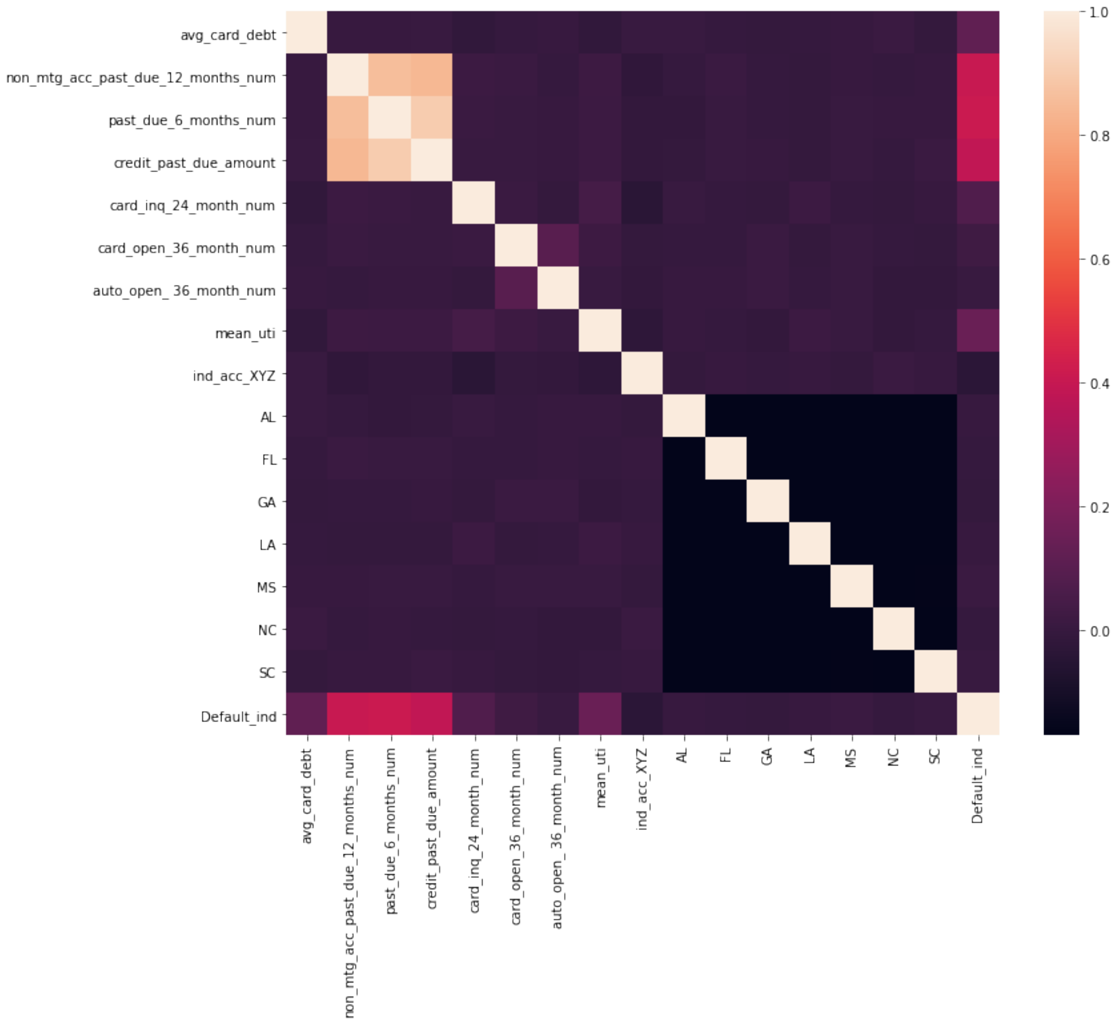
[207]:
```
past_due_vars = ["non_mtg_acc_past_due_6_months_num",␣
↪"mortgages_past_due_6_months_num"]
past_due_credit = df_train[past_due_vars]
past_due_credit["past_due_6_months_num"] =␣
↪past_due_credit["non_mtg_acc_past_due_6_months_num"] +␣
↪past_due_credit["mortgages_past_due_6_months_num"]

df_train = df_train.drop(columns=["mortgages_past_due_6_months_num"])
df_train["non_mtg_acc_past_due_6_months_num"] =␣
↪past_due_credit["past_due_6_months_num"]
df_train = df_train.rename(columns={"non_mtg_acc_past_due_6_months_num":
↪"past_due_6_months_num"})
```

```
<ipython-input-207-db6338c54e88>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  past_due_credit["past_due_6_months_num"] =
past_due_credit["non_mtg_acc_past_due_6_months_num"] +
past_due_credit["mortgages_past_due_6_months_num"]
```

We will check collinearity and multicollinearity again to see if we have reduced it to an acceptable level.

While colinearity between the past due variables' colinearity is worrying, they are simply too valuable to drop for now due to their high linearity with the response variable. The VIF values give an encouraging picture, however, as values, while slightly high, are in an acceptable range (1).

[31]:
```
columns = []
fig, ax = plt.subplots(figsize=(12,10))
for num in range(0,17):
    columns.append(num)
corrMatrix = df_train.iloc[:,columns].corr()
sn.heatmap(corrMatrix, annot=False, ax=ax)
plt.show()
```



[33]:
```
columns = []
for num in range(0,16):
     columns.append(num)

calc_vif(df_train.iloc[:,columns])
```

[33]:

```
                         variables       VIF
0                     avg_card_debt  1.000904
1  non_mtg_acc_past_due_12_months_num  4.245805
2               past_due_6_months_num  6.522983
3              credit_past_due_amount  5.945257
4               card_inq_24_month_num  1.004331
5              card_open_36_month_num  1.010175
6             auto_open_ 36_month_num  1.009894
7                          mean_uti  1.004178
8                       ind_acc_XYZ  1.002969
9                                AL  5.388244
10                               FL  5.303679
11                               GA  5.263706
12                               LA  5.365403
13                               MS  5.287676
14                               NC  5.340952
15                               SC  5.242121
```

Last thing left to do is normalize data:

[208]:

```
df_train_norm=((df_train-df_train.min())/(df_train.max()-df_train.min()))*20
```

Check preprocessed data:

Everything seems to be in order. Time to move on to model building.

[36]:

```
print(df_train_norm.sample)
print(df_train_norm.shape)
print(df_train_norm.dtypes)
```

```
<bound method NDFrame.sample of        avg_card_debt
non_mtg_acc_past_due_12_months_num  \
0           2.767399                             0.0
1           2.010511                             0.0
2           1.984746                             0.0
3           1.240052                            10.0
4           1.689717                             0.0
…              …                              …
19995       2.364352                             0.0
19996       1.630937                             0.0
19997       3.170078                             5.0
19998       1.860892                             0.0
19999       1.575249                             0.0

       past_due_6_months_num  credit_past_due_amount  card_inq_24_month_num  \
0                   0.000000                0.000000               4.444444
1                   0.000000                0.000000               4.444444
2                   0.000000                0.000000               3.333333
3                  13.333333                6.744002               1.111111
```

```
4                  0.000000                0.000000                2.222222
…                     …                      …                     …
19995              0.000000                0.000000                4.444444
19996              0.000000                0.000000                1.111111
19997              0.000000                0.000000                3.333333
19998              0.000000                0.000000                2.222222
19999              0.000000                0.000000                4.444444

       card_open_36_month_num  auto_open_ 36_month_num   mean_uti  \
0                         0.0                      0.0   7.470849
1                        10.0                      0.0  10.830203
2                         0.0                     10.0   5.839036
3                        10.0                      0.0   8.470172
4                         0.0                      0.0  12.018333
…                          …                      …         …
19995                     0.0                      0.0   9.213416
19996                     0.0                      0.0  12.499806
19997                     0.0                     10.0   9.027027
19998                     0.0                      0.0   4.049374
19999                     0.0                      0.0  10.581955

       ind_acc_XYZ    AL    FL    GA    LA   MS    NC    SC  Default_ind
0              0.0  20.0   0.0   0.0   0.0  0.0   0.0   0.0          0.0
1              0.0   0.0  20.0   0.0   0.0  0.0   0.0   0.0          0.0
2              0.0  20.0   0.0   0.0   0.0  0.0   0.0   0.0          0.0
3              0.0   0.0   0.0   0.0   0.0  0.0   0.0  20.0         20.0
4             20.0   0.0   0.0   0.0  20.0  0.0   0.0   0.0          0.0
…             …   …    …    …    …    …    …    …          …
19995         20.0   0.0   0.0  20.0   0.0  0.0   0.0   0.0          0.0
19996          0.0   0.0   0.0   0.0   0.0  0.0  20.0   0.0          0.0
19997          0.0   0.0   0.0   0.0   0.0  0.0   0.0  20.0          0.0
19998          0.0  20.0   0.0   0.0   0.0  0.0   0.0   0.0          0.0
19999          0.0  20.0   0.0   0.0   0.0  0.0   0.0   0.0          0.0

[20000 rows x 17 columns]>
(20000, 17)
avg_card_debt                         float64
non_mtg_acc_past_due_12_months_num    float64
past_due_6_months_num                 float64
credit_past_due_amount                float64
card_inq_24_month_num                 float64
card_open_36_month_num                float64
auto_open_ 36_month_num               float64
mean_uti                              float64
ind_acc_XYZ                           float64
AL                                    float64
FL                                    float64
GA                                    float64
```

```
LA                                      float64
MS                                      float64
NC                                      float64
SC                                      float64
Default_ind                             float64
dtype: object
```

4 Model Building and Testing - Logistic Regression

We will begin by performing hyper parameter optimization on the validation data set for logistic regression. In order to do this, we must manipulate the validation data set in the same way we have manipulated the training data set.

[209]:

```
dummies = pd.get_dummies(df_validation['States'])
default_ind = df_validation['Default_ind']
df_validation = df_validation.
 ↪drop(columns=["Default_ind","States","tot_credit_debt", "credit_age",␣
 ↪"credit_good_age", "card_age","rep_income","inq_12_month_num"])
df_validation = df_validation.join(dummies)
df_validation = df_validation.join(default_ind)
util_vars = ["uti_card", "uti_50plus_pct", "uti_max_credit_line",␣
 ↪"uti_card_50plus_pct"]
util_credit = df_validation[util_vars]
util_credit["mean"] = util_credit.mean(axis=1)
df_validation = df_validation.drop(columns=["uti_50plus_pct",␣
 ↪"uti_max_credit_line", "uti_card_50plus_pct"])
df_validation["uti_card"] = util_credit["mean"]
df_validation = df_validation.rename(columns={"uti_card":"mean_uti"})
past_due_vars = ["non_mtg_acc_past_due_6_months_num",␣
 ↪"mortgages_past_due_6_months_num"]
past_due_credit = df_validation[past_due_vars]
past_due_credit["past_due_6_months_num"] =␣
 ↪past_due_credit["non_mtg_acc_past_due_6_months_num"] +␣
 ↪past_due_credit["mortgages_past_due_6_months_num"]
df_validation = df_validation.drop(columns=["mortgages_past_due_6_months_num"])
df_validation["non_mtg_acc_past_due_6_months_num"] =␣
 ↪past_due_credit["past_due_6_months_num"]
df_validation = df_validation.
 ↪rename(columns={"non_mtg_acc_past_due_6_months_num":"past_due_6_months_num"})
df_validation_norm=((df_validation-df_validation.min())/(df_validation.
 ↪max()-df_validation.min()))*20
```

```
<ipython-input-209-959fbd1f3629>:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  util_credit["mean"] = util_credit.mean(axis=1)
<ipython-input-209-959fbd1f3629>:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  past_due_credit["past_due_6_months_num"] =
past_due_credit["non_mtg_acc_past_due_6_months_num"] +
past_due_credit["mortgages_past_due_6_months_num"]
```

Everything looks in order:

```
[39]: print(df_validation_norm.sample)
      print(df_validation_norm.shape)
      print(df_validation_norm.dtypes)
```

```
<bound method NDFrame.sample of       avg_card_debt
non_mtg_acc_past_due_12_months_num  \
0          1.258527                                 0.0
1          2.838983                                 0.0
2          1.565286                                 0.0
3          2.258434                                 0.0
4          2.612365                                 0.0
…              …                                …
2995       1.765656                                 0.0
2996       2.540309                                 0.0
2997       1.908553                                 0.0
2998       2.382803                                 0.0
2999       1.846333                                 0.0

      past_due_6_months_num  credit_past_due_amount  card_inq_24_month_num  \
0                       0.0                     0.0               0.000000
1                       0.0                     0.0              10.769231
2                       0.0                     0.0               4.615385
3                       0.0                     0.0               1.538462
4                       0.0                     0.0              13.846154
…                     …                     …                     …
2995                    0.0                     0.0               0.000000
2996                    0.0                     0.0               0.000000
2997                    0.0                     0.0               6.153846
2998                    0.0                     0.0               3.076923
2999                    0.0                     0.0              10.769231

      card_open_36_month_num  auto_open_ 36_month_num   mean_uti  ind_acc_XYZ  \
0                        0.0                      0.0  14.171756          0.0
1                        0.0                     10.0   9.861754          0.0
2                        0.0                      0.0  10.139092          0.0
```

```
3                           0.0                          0.0  13.427118          0.0
4                           0.0                          0.0  14.453941         20.0
…                         …                        …         …          …
2995                        0.0                         10.0  15.295818          0.0
2996                        0.0                         10.0  13.714113          0.0
2997                        0.0                          0.0  15.768993          0.0
2998                        0.0                         10.0  12.947497         20.0
2999                       10.0                         10.0  17.795304          0.0

        AL    FL   GA    LA    MS    NC   SC  Default_ind
0      0.0  20.0  0.0   0.0   0.0   0.0  0.0         20.0
1      0.0   0.0  0.0   0.0  20.0   0.0  0.0          0.0
2      0.0   0.0  0.0   0.0  20.0   0.0  0.0          0.0
3      0.0   0.0  0.0   0.0  20.0   0.0  0.0          0.0
4      0.0   0.0  0.0   0.0   0.0  20.0  0.0          0.0
…    …   …   …   …   …    …  …          …
2995   0.0  20.0  0.0   0.0   0.0   0.0  0.0          0.0
2996  20.0   0.0  0.0   0.0   0.0   0.0  0.0          0.0
2997   0.0   0.0  0.0  20.0   0.0   0.0  0.0          0.0
2998   0.0   0.0  0.0   0.0   0.0  20.0  0.0          0.0
2999   0.0   0.0  0.0   0.0  20.0   0.0  0.0          0.0

[3000 rows x 17 columns]>
(3000, 17)
avg_card_debt                          float64
non_mtg_acc_past_due_12_months_num    float64
past_due_6_months_num                  float64
credit_past_due_amount                 float64
card_inq_24_month_num                  float64
card_open_36_month_num                 float64
auto_open_ 36_month_num                float64
mean_uti                               float64
ind_acc_XYZ                            float64
AL                                     float64
FL                                     float64
GA                                     float64
LA                                     float64
MS                                     float64
NC                                     float64
SC                                     float64
Default_ind                            float64
dtype: object
```

We will now perform hyperparamter tuning using our validation data set (2a).

The parameters we have chosen are: - solvers: newtown conjugate gradient, limited memory bfgs, and liblinear - penalty: l2 only (since it works for all three solvers) - C values: 100, 10, 1.0, 0.1, 0.01

[210]:
```
model = LogisticRegression()
solvers = ['newton-cg', 'lbfgs', 'liblinear']
penalty = ['l2']
c_values = [100, 10, 1.0, 0.1, 0.01]
grid = dict(solver=solvers,penalty=penalty,C=c_values)
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
grid_search = GridSearchCV(estimator=model, param_grid=grid, n_jobs=-1, cv=cv,␣
↪scoring='accuracy',error_score=0)
grid_result = grid_search.fit(df_validation_norm.iloc[:,range(0,16)],␣
↪df_validation_norm.iloc[:,16])
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.937778 using {'C': 0.1, 'penalty': 'l2', 'solver': 'liblinear'}
0.937667 (0.009195) with: {'C': 100, 'penalty': 'l2', 'solver': 'newton-cg'}
0.937667 (0.009195) with: {'C': 100, 'penalty': 'l2', 'solver': 'lbfgs'}
0.937667 (0.009195) with: {'C': 100, 'penalty': 'l2', 'solver': 'liblinear'}
0.937667 (0.009195) with: {'C': 10, 'penalty': 'l2', 'solver': 'newton-cg'}
0.937667 (0.009195) with: {'C': 10, 'penalty': 'l2', 'solver': 'lbfgs'}
0.937667 (0.009195) with: {'C': 10, 'penalty': 'l2', 'solver': 'liblinear'}
0.937667 (0.009195) with: {'C': 1.0, 'penalty': 'l2', 'solver': 'newton-cg'}
0.937667 (0.009195) with: {'C': 1.0, 'penalty': 'l2', 'solver': 'lbfgs'}
0.937667 (0.009195) with: {'C': 1.0, 'penalty': 'l2', 'solver': 'liblinear'}
0.937667 (0.009195) with: {'C': 0.1, 'penalty': 'l2', 'solver': 'newton-cg'}
0.937667 (0.009195) with: {'C': 0.1, 'penalty': 'l2', 'solver': 'lbfgs'}
0.937778 (0.009081) with: {'C': 0.1, 'penalty': 'l2', 'solver': 'liblinear'}
0.937778 (0.008664) with: {'C': 0.01, 'penalty': 'l2', 'solver': 'newton-cg'}
0.937778 (0.008664) with: {'C': 0.01, 'penalty': 'l2', 'solver': 'lbfgs'}
0.936667 (0.008300) with: {'C': 0.01, 'penalty': 'l2', 'solver': 'liblinear'}
```

Based on this, the most accurate model has the following hyperparameters: - solver: liblinear - penalty: l2 - C value: 0.1

Train model based on chosen hyperparameters using the train data set:

[211]:
```
lrModel = LogisticRegression(C = 0.1, penalty = "l2",solver="liblinear")
lrModel = lrModel.fit(df_train_norm.iloc[:,range(0,16)], df_train_norm.iloc[:
↪,16])
```

Transforming test data to match training data:

[212]:
```
dummies = pd.get_dummies(df_test['States'])
default_ind = df_test['Default_ind']
df_test = df_test.drop(columns=["Default_ind","States","tot_credit_debt",␣
↪"credit_age", "credit_good_age", "card_age","rep_income","inq_12_month_num"])
```

```
df_test = df_test.join(dummies)
df_test = df_test.join(default_ind)
util_vars = ["uti_card", "uti_50plus_pct", "uti_max_credit_line",␣
↪"uti_card_50plus_pct"]
util_credit = df_test[util_vars]
util_credit["mean"] = util_credit.mean(axis=1)
df_test = df_test.drop(columns=["uti_50plus_pct", "uti_max_credit_line",␣
↪"uti_card_50plus_pct"])
df_test["uti_card"] = util_credit["mean"]
df_test = df_test.rename(columns={"uti_card":"mean_uti"})
past_due_vars = ["non_mtg_acc_past_due_6_months_num",␣
↪"mortgages_past_due_6_months_num"]
past_due_credit = df_test[past_due_vars]
past_due_credit["past_due_6_months_num"] =␣
↪past_due_credit["non_mtg_acc_past_due_6_months_num"] +␣
↪past_due_credit["mortgages_past_due_6_months_num"]
df_test = df_test.drop(columns=["mortgages_past_due_6_months_num"])
df_test["non_mtg_acc_past_due_6_months_num"] =␣
↪past_due_credit["past_due_6_months_num"]
df_test = df_test.rename(columns={"non_mtg_acc_past_due_6_months_num":
↪"past_due_6_months_num"})
df_test_norm=((df_test-df_test.min())/(df_test.max()-df_test.min()))*20
```

```
<ipython-input-212-fd2b47dd7047>:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  util_credit["mean"] = util_credit.mean(axis=1)
<ipython-input-212-fd2b47dd7047>:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  past_due_credit["past_due_6_months_num"] =
past_due_credit["non_mtg_acc_past_due_6_months_num"] +
past_due_credit["mortgages_past_due_6_months_num"]
```

Check data:

[43]:
```
print(df_test_norm.sample)
print(df_test_norm.shape)
print(df_test_norm.dtypes)
```

```
<bound method NDFrame.sample of        avg_card_debt
non_mtg_acc_past_due_12_months_num  \
```

```
0         0.723813                                  0.0
1         2.571408                                  0.0
2         2.007778                                  0.0
3         2.326841                                  0.0
4         2.071129                                  0.0
…           …                                     …
4995      1.534659                                  0.0
4996      2.550137                                  0.0
4997      1.506616                                  0.0
4998      1.193691                                  0.0
4999      2.871439                                  0.0

      past_due_6_months_num  credit_past_due_amount  card_inq_24_month_num  \
0                       0.0                     0.0               5.333333
1                       0.0                     0.0               5.333333
2                       0.0                     0.0               1.333333
3                       0.0                     0.0               0.000000
4                       0.0                     0.0               0.000000
…                     …                     …                     …
4995                    0.0                     0.0               5.333333
4996                    0.0                     0.0               6.666667
4997                    0.0                     0.0               6.666667
4998                    0.0                     0.0               2.666667
4999                    0.0                     0.0              10.666667

      card_open_36_month_num  auto_open_ 36_month_num   mean_uti  ind_acc_XYZ  \
0                        0.0                     10.0  13.749481          0.0
1                        0.0                      0.0  15.757954         20.0
2                        0.0                      0.0   8.624625          0.0
3                        0.0                      0.0   9.514111         20.0
4                        0.0                      0.0  12.012403          0.0
…                      …                      …         …           …
4995                     0.0                      0.0  10.194068          0.0
4996                     0.0                      0.0   6.574378         20.0
4997                    10.0                     10.0   9.373143         20.0
4998                     0.0                      0.0   0.907474          0.0
4999                    10.0                      0.0  12.528196          0.0

        AL    FL    GA    LA    MS   NC    SC  Default_ind
0      0.0  20.0   0.0   0.0   0.0  0.0   0.0          0.0
1     20.0   0.0   0.0   0.0   0.0  0.0   0.0          0.0
2      0.0   0.0   0.0   0.0  20.0  0.0   0.0          0.0
3     20.0   0.0   0.0   0.0   0.0  0.0   0.0          0.0
4      0.0   0.0  20.0   0.0   0.0  0.0   0.0          0.0
…    …   …   …   …   …   …   …               …
4995   0.0   0.0   0.0  20.0   0.0  0.0   0.0          0.0
4996   0.0   0.0   0.0   0.0   0.0  0.0  20.0          0.0
4997   0.0   0.0   0.0  20.0   0.0  0.0   0.0          0.0
```

```
4998    0.0    0.0    0.0    0.0   20.0   0.0    0.0            0.0
4999    0.0    0.0    0.0    0.0   20.0   0.0    0.0            0.0

[5000 rows x 17 columns]>
(5000, 17)
avg_card_debt                          float64
non_mtg_acc_past_due_12_months_num     float64
past_due_6_months_num                  float64
credit_past_due_amount                 float64
card_inq_24_month_num                  float64
card_open_36_month_num                 float64
auto_open_ 36_month_num                float64
mean_uti                               float64
ind_acc_XYZ                            float64
AL                                     float64
FL                                     float64
GA                                     float64
LA                                     float64
MS                                     float64
NC                                     float64
SC                                     float64
Default_ind                            float64
dtype: object
```

Scoring test data:

[139]:
```
lrModel.score(df_test_norm.iloc[:,range(0,16)], df_test_norm.iloc[:,16])
```

[139]:
```
0.9358
```

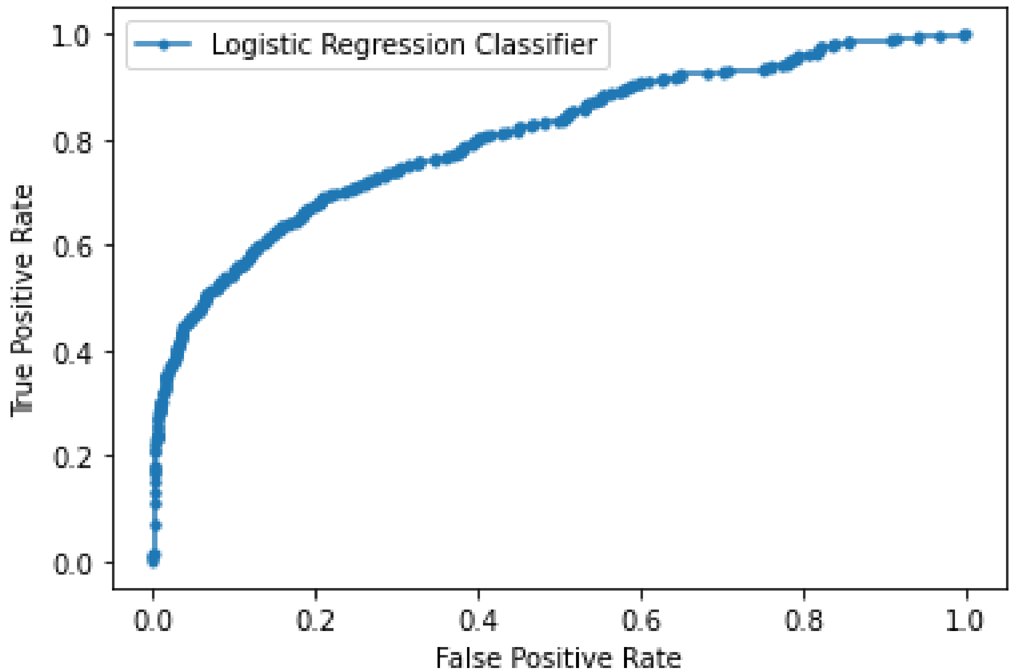
Testing with a confusion matrix:

[140]:
```
confusion_matrix(df_test_norm.iloc[:,16],lrModel.predict(df_test_norm.iloc[:
 ↪,range(0,16)]))
```

[140]:
```
array([[4552,   47],
       [ 274,  127]], dtype=int64)
```

Interpreting logistic regression model using ROC curve (2b):

[131]:
```
lr_probs = lr.predict_proba(df_test_norm.iloc[:,range(0,16)])
lr_probs = lr_probs[:, 1]
lr_fpr, lr_tpr, _ = roc_curve(df_test_norm.iloc[:,16], lr_probs, pos_label = 20.
 ↪0)
plt.plot(lr_fpr, lr_tpr, marker='.', label='Logistic Regression Classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```



Find feature importance (2c):

A positive score indicates the greater the value of the feature, the more likely the person is to default, while a negative score indicates the greater the value of the feature, the less likely the person is to default.

A high absolute score indicates strong importance in model, while a low absolute score indicates weak importance in model.

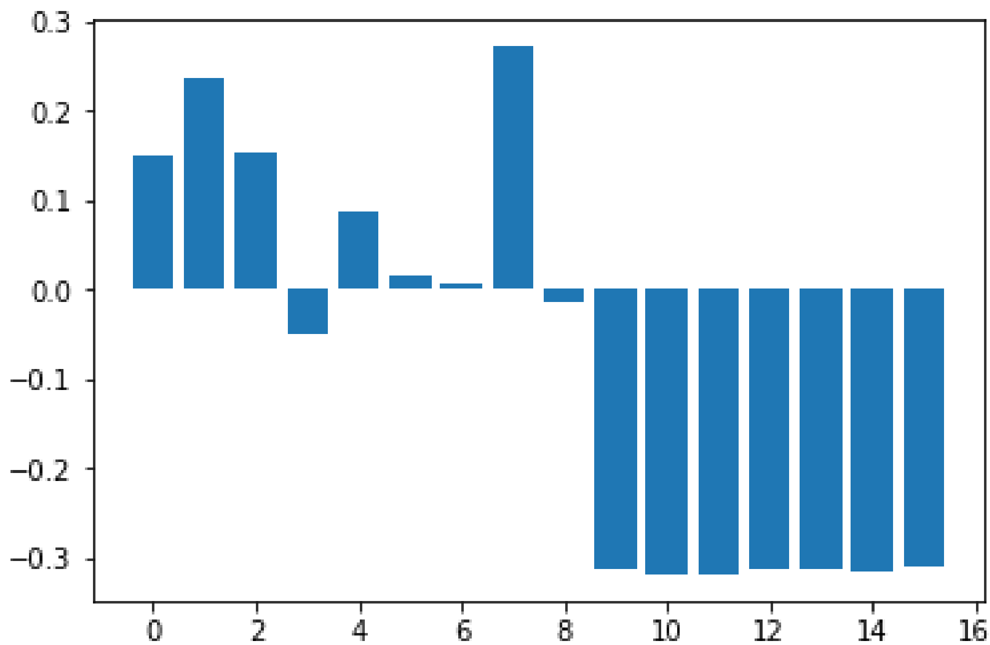
Important Notes: - Having had an account in XYZ does not seem to impact the model by much - Average card debt, past due variables for 12 and 6 months, and utilization variables seem to have the greatest impact - Although the state variables seem to cause a great impact, in reality each observation must be one of them, and thus, the difference between them is the only thing that matters for interpretation. In this case, since the importance of all state variables is very close overall, it seems that states do not have a great deal of impact on model prediction

[179]:
```
variables = []
for var in df_train_norm.columns:
    variables.append(var)
importance = lrModel.coef_[0]
index = 0
for i,v in enumerate(importance):
    print('Feature: {variable}\n Score: {v}\n\n'.format(variable =␣
 ↪variables[index],v = v))
    index += 1
```

```
plt.bar([x for x in range(len(importance))], importance)
plt.show()
```

```
Feature: avg_card_debt
 Score: 0.1499596391270964


Feature: non_mtg_acc_past_due_12_months_num
 Score: 0.23556759045910966


Feature: past_due_6_months_num
 Score: 0.1542133033538216


Feature: credit_past_due_amount
 Score: -0.04906488819908006


Feature: card_inq_24_month_num
 Score: 0.08606432328090474


Feature: card_open_36_month_num
 Score: 0.016807004273557042


Feature: auto_open_ 36_month_num
 Score: 0.006285595831829881


Feature: mean_uti
 Score: 0.27185106310181156


Feature: ind_acc_XYZ
 Score: -0.013710761590003758


Feature: AL
 Score: -0.3130380831427379


Feature: FL
 Score: -0.317889156327858


Feature: GA
```

```
 Score: -0.318481497908399


Feature: LA
 Score: -0.31415871337745066


Feature: MS
 Score: -0.3113582401283215


Feature: NC
 Score: -0.31565900138163133


Feature: SC
 Score: -0.3103977152431603
```



5 Data Preprocessing - Random Forests

We will reimport the data since we will be using a different approach to data preprocessing in preperation of random forest model.

[144]:
```
df_test = pd.read_csv('Simulated_Data_Test.csv')
df_train = pd.read_csv('Simulated_Data_Train.csv')
df_validation = pd.read_csv('Simulated_Data_Validation.csv')
```

Based on EDA, we have determined which explanatory variables need to be dropped: rep_income, credit_age, credit_good_age, and card_age.

[145]:
```
df_train = df_train.drop(columns=["credit_age", "credit_good_age",␣
↪"card_age","rep_income"])
```

Next, let's create dummy variables for states

[146]:
```
dummies = pd.get_dummies(df_train['States'])
default_ind = df_train['Default_ind']
df_train = df_train.drop(columns=['States', 'Default_ind'])
df_train = df_train.join(dummies)
df_train = df_train.join(default_ind)
```

We need to get rid of NA values next. let's check how many there are:

[147]:
```
print(df_train.isnull().sum())
```

```
tot_credit_debt                        0
avg_card_debt                          0
non_mtg_acc_past_due_12_months_num     0
non_mtg_acc_past_due_6_months_num      0
mortgages_past_due_6_months_num        0
credit_past_due_amount                 0
inq_12_month_num                       0
card_inq_24_month_num                  0
card_open_36_month_num                 0
auto_open_ 36_month_num                0
uti_card                               0
uti_50plus_pct                         0
uti_max_credit_line                    0
uti_card_50plus_pct                 2055
ind_acc_XYZ                            0
AL                                     0
FL                                     0
GA                                     0
LA                                     0
MS                                     0
NC                                     0
SC                                     0
Default_ind                            0
dtype: int64
```

We want to preserve the utilization features as we are not concenred with collinearity for this model. Thus, we have two options: - Remove observations or column with missing values. - Impute missing values for uti_card_50plus_pct

Removing observations will rid us of 10% of our data, which is not ideal. Removing uti_card_50plus_pct is detrimental since we will be getting rid of a feature which is highly correlated with the response variable. Thus we decide to impute the missing values of uti_card_50plus_pct.

We know uti_card_50plus_pct is highly collinear with the other utilization features. Therefore, we will be using simple mean impuation with the utilization variables.

[148]:
```
imputer = SingleImputer(
strategy='mean',
predictors=['uti_max_credit_line','uti_50plus_pct','uti_card'],
seed = 100)
imputed_df_train = imputer.fit_transform(df_train)
```

Check if imputation was succesful:

[149]:
```
print(imputed_df_train.isnull().sum())
```

```
tot_credit_debt                        0
avg_card_debt                          0
non_mtg_acc_past_due_12_months_num     0
non_mtg_acc_past_due_6_months_num      0
mortgages_past_due_6_months_num        0
credit_past_due_amount                 0
inq_12_month_num                       0
card_inq_24_month_num                  0
card_open_36_month_num                 0
auto_open_ 36_month_num                0
uti_card                               0
uti_50plus_pct                         0
uti_max_credit_line                    0
uti_card_50plus_pct                    0
ind_acc_XYZ                            0
AL                                     0
FL                                     0
GA                                     0
LA                                     0
MS                                     0
NC                                     0
SC                                     0
Default_ind                            0
dtype: int64
```

Check data:

Everything looks ready for the model.

[150]:
```
print(imputed_df_train.sample)
print(imputed_df_train.shape)
```

```python
print(imputed_df_train.dtypes)
```

```
<bound method NDFrame.sample of        tot_credit_debt  avg_card_debt  
non_mtg_acc_past_due_12_months_num  \
0            80826.71       15872.99                                  0.0
1            96052.60       12178.02                                  0.0
2            75212.76       12052.24                                  0.0
3            70727.84        8416.80                                  2.0
4            41604.47       10611.97                                  0.0
…                 …             …                             …
19995       104765.01       13905.40                                  0.0
19996        83990.07       10325.02                                  0.0
19997       107606.69       17838.79                                  1.0
19998        78787.72       11447.61                                  0.0
19999        78296.90       10053.16                                  0.0

       non_mtg_acc_past_due_6_months_num  mortgages_past_due_6_months_num  \
0                                    0.0                              0.0
1                                    0.0                              0.0
2                                    0.0                              0.0
3                                    1.0                              1.0
4                                    0.0                              0.0
…                                  …                              …
19995                                0.0                              0.0
19996                                0.0                              0.0
19997                                0.0                              0.0
19998                                0.0                              0.0
19999                                0.0                              0.0

       credit_past_due_amount  inq_12_month_num  card_inq_24_month_num  \
0                        0.00               3.0                    4.0
1                        0.00               2.0                    4.0
2                        0.00               1.0                    3.0
3                    11013.96               0.0                    1.0
4                        0.00               0.0                    2.0
…                       …                …                    …
19995                    0.00               4.0                    4.0
19996                    0.00               0.0                    1.0
19997                    0.00               3.0                    3.0
19998                    0.00               1.0                    2.0
19999                    0.00               2.0                    4.0

       card_open_36_month_num  auto_open_ 36_month_num  …  \
0                         0.0                      0.0  …
1                         1.0                      0.0  …
2                         0.0                      1.0  …
3                         1.0                      0.0  …
4                         0.0                      0.0  …
```

```
…                      …                     …  …
19995                   0.0                      0.0  …
19996                   0.0                      0.0  …
19997                   0.0                      1.0  …
19998                   0.0                      0.0  …
19999                   0.0                      0.0  …

       uti_card_50plus_pct  ind_acc_XYZ  AL  FL  GA  LA  MS  NC  SC  \
0                 0.489594          0.0   1   0   0   0   0   0   0
1                 0.587351          0.0   0   1   0   0   0   0   0
2                 0.413293          0.0   1   0   0   0   0   0   0
3                 0.466810          0.0   0   0   0   0   0   0   1
4                 0.588442          1.0   0   0   0   1   0   0   0
…                    …          …   ..  ..  ..  ..  ..  ..  ..
19995             0.481113          1.0   0   0   1   0   0   0   0
19996             0.489594          0.0   0   0   0   0   0   1   0
19997             0.463120          0.0   0   0   0   0   0   0   1
19998             0.281647          0.0   1   0   0   0   0   0   0
19999             0.512513          0.0   1   0   0   0   0   0   0

       Default_ind
0              0.0
1              0.0
2              0.0
3              1.0
4              0.0
…            …
19995          0.0
19996          0.0
19997          0.0
19998          0.0
19999          0.0

[20000 rows x 23 columns]>
(20000, 23)
tot_credit_debt                        float64
avg_card_debt                          float64
non_mtg_acc_past_due_12_months_num     float64
non_mtg_acc_past_due_6_months_num      float64
mortgages_past_due_6_months_num        float64
credit_past_due_amount                 float64
inq_12_month_num                       float64
card_inq_24_month_num                  float64
card_open_36_month_num                 float64
auto_open_ 36_month_num                float64
uti_card                               float64
uti_50plus_pct                         float64
uti_max_credit_line                    float64
```

```
uti_card_50plus_pct                    float64
ind_acc_XYZ                            float64
AL                                       uint8
FL                                       uint8
GA                                       uint8
LA                                       uint8
MS                                       uint8
NC                                       uint8
SC                                       uint8
Default_ind                            float64
dtype: object
```

6 Model Building and Testing - Random Forests

We will firstly preprocess the validation data set in same way as train set to prepare for hyperparameter tuning.

[151]:
```
df_validation = df_validation.drop(columns=["credit_age", "credit_good_age",␣
 ↪"card_age","rep_income"])
dummies = pd.get_dummies(df_validation['States'])
default_ind = df_validation['Default_ind']
df_validation = df_validation.drop(columns=['States', 'Default_ind'])
df_validation = df_validation.join(dummies)
df_validation = df_validation.join(default_ind)
imputed_df_validation = imputer.fit_transform(df_validation)
```

Check validation data:

Everything looks in order.

[152]:
```
print(imputed_df_validation.sample)
print(imputed_df_validation.shape)
print(imputed_df_validation.dtypes)
```

```
<bound method NDFrame.sample of       tot_credit_debt  avg_card_debt
non_mtg_acc_past_due_12_months_num  \
0            63651.27        9019.99                                   0.0
1           105559.29       16692.19                                   0.0
2            96062.99       10509.13                                   0.0
3            84417.40       13873.96                                   0.0
4           100623.91       15592.09                                   0.0
…                 …             …                                  …
2995         90748.88       11481.81                                   0.0
2996        101930.98       15242.30                                   0.0
2997         74738.73       12175.49                                   0.0
2998        120357.58       14477.70                                   0.0
2999         74240.17       11873.45                                   0.0
```

```
      non_mtg_acc_past_due_6_months_num  mortgages_past_due_6_months_num  \
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
…                                     …                                …
2995                                0.0                              0.0
2996                                0.0                              0.0
2997                                0.0                              0.0
2998                                0.0                              0.0
2999                                0.0                              0.0

      credit_past_due_amount  inq_12_month_num  card_inq_24_month_num  \
0                        0.0               0.0                    0.0
1                        0.0               4.0                    7.0
2                        0.0               2.0                    3.0
3                        0.0               1.0                    1.0
4                        0.0               6.0                    9.0
…                          …                 …                      …
2995                     0.0               0.0                    0.0
2996                     0.0               2.0                    0.0
2997                     0.0               2.0                    4.0
2998                     0.0               2.0                    2.0
2999                     0.0               4.0                    7.0

      card_open_36_month_num  auto_open_ 36_month_num  …  \
0                        0.0                      0.0  …
1                        0.0                      1.0  …
2                        0.0                      0.0  …
3                        0.0                      0.0  …
4                        0.0                      0.0  …
…                          …                        …  …
2995                     0.0                      1.0  …
2996                     0.0                      1.0  …
2997                     0.0                      0.0  …
2998                     0.0                      1.0  …
2999                     1.0                      1.0  …

      uti_card_50plus_pct  ind_acc_XYZ  AL  FL  GA  LA  MS  NC  SC  \
0                0.530109          0.0   0   1   0   0   0   0   0
1                0.388792          0.0   0   0   0   0   1   0   0
2                0.450523          0.0   0   0   0   0   1   0   0
3                0.562153          0.0   0   0   0   0   1   0   0
4                0.576409          1.0   0   0   0   0   0   1   0
…                       …            …  ..  ..  ..  ..  ..  ..  ..
2995             0.559056          0.0   0   1   0   0   0   0   0
2996             0.564803          0.0   1   0   0   0   0   0   0
```

```
2997            0.651801          0.0   0   0   0   1   0   0   0
2998            0.557991          1.0   0   0   0   0   0   1   0
2999            0.736850          0.0   0   0   0   0   1   0   0

      Default_ind
0             1.0
1             0.0
2             0.0
3             0.0
4             0.0
…           …
2995          0.0
2996          0.0
2997          0.0
2998          0.0
2999          0.0

[3000 rows x 23 columns]>
(3000, 23)
tot_credit_debt                        float64
avg_card_debt                          float64
non_mtg_acc_past_due_12_months_num     float64
non_mtg_acc_past_due_6_months_num      float64
mortgages_past_due_6_months_num        float64
credit_past_due_amount                 float64
inq_12_month_num                       float64
card_inq_24_month_num                  float64
card_open_36_month_num                 float64
auto_open_ 36_month_num                float64
uti_card                               float64
uti_50plus_pct                         float64
uti_max_credit_line                    float64
uti_card_50plus_pct                    float64
ind_acc_XYZ                            float64
AL                                       uint8
FL                                       uint8
GA                                       uint8
LA                                       uint8
MS                                       uint8
NC                                       uint8
SC                                       uint8
Default_ind                            float64
dtype: object
```

We will now perform hyperparamter tuning using our validation data set (2a).

The parameters we have chosen are: - Number of estimators: 10, 100, 1000 - Max features: square root, log base 2

[90]:
```
model = RandomForestClassifier()
n_estimators = [10, 100, 1000]
max_features = ['sqrt', 'log2']
grid = dict(n_estimators=n_estimators,max_features=max_features)
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
grid_search = GridSearchCV(estimator=model, param_grid=grid, n_jobs=-1, cv=cv,␣
↪scoring='accuracy',error_score=0)
grid_result = grid_search.fit(imputed_df_validation.iloc[:,range(0,22)],␣
↪imputed_df_validation.iloc[:,22])
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.941111 using {'max_features': 'log2', 'n_estimators': 100}
0.936222 (0.009574) with: {'max_features': 'sqrt', 'n_estimators': 10}
0.940667 (0.010306) with: {'max_features': 'sqrt', 'n_estimators': 100}
0.940556 (0.009929) with: {'max_features': 'sqrt', 'n_estimators': 1000}
0.937778 (0.009480) with: {'max_features': 'log2', 'n_estimators': 10}
0.941111 (0.010830) with: {'max_features': 'log2', 'n_estimators': 100}
0.940444 (0.010532) with: {'max_features': 'log2', 'n_estimators': 1000}
```

Based on this, the most accurate model has the following hyperparameters: - Number of estimators: 100 - Max features: log base 2

Train model based on chosen hyperparameters using the train data set:

[153]:
```
rfModel = RandomForestClassifier(max_features="log2",n_estimators=100)
rfModel = rfModel.fit(imputed_df_train.iloc[:,range(0,22)], imputed_df_train.
↪iloc[:,22])
```

Transforming test data to match training data:

[154]:
```
df_test = df_test.drop(columns=["credit_age", "credit_good_age",␣
↪"card_age","rep_income"])
dummies = pd.get_dummies(df_test['States'])
default_ind = df_test['Default_ind']
df_test = df_test.drop(columns=['States', 'Default_ind'])
df_test = df_test.join(dummies)
df_test = df_test.join(default_ind)
imputed_df_test = imputer.fit_transform(df_test)
```

Check data:

[155]:
```
print(imputed_df_test.sample)
print(imputed_df_test.shape)
print(imputed_df_test.dtypes)
```

```
<bound method NDFrame.sample of       tot_credit_debt  avg_card_debt
non_mtg_acc_past_due_12_months_num  \
0            40477.81        7766.64                                 0.0
1           106760.98       16606.98                                 0.0
2           121428.34       13910.13                                 0.0
3            96515.05       15436.78                                 0.0
4           123760.22       14213.25                                 0.0
…                 …              …                             …
4995         90788.44       11646.36                                 0.0
4996         91052.81       16505.20                                 0.0
4997         71061.71       11512.18                                 0.0
4998         82162.45       10014.90                                 0.0
4999        116943.32       18042.56                                 0.0

      non_mtg_acc_past_due_6_months_num  mortgages_past_due_6_months_num  \
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
…                                 …                              …
4995                                0.0                              0.0
4996                                0.0                              0.0
4997                                0.0                              0.0
4998                                0.0                              0.0
4999                                0.0                              0.0

      credit_past_due_amount  inq_12_month_num  card_inq_24_month_num  \
0                        0.0               2.0                    4.0
1                        0.0               2.0                    4.0
2                        0.0               0.0                    1.0
3                        0.0               0.0                    0.0
4                        0.0               0.0                    0.0
…                      …                …                    …
4995                     0.0               0.0                    4.0
4996                     0.0               3.0                    5.0
4997                     0.0               3.0                    5.0
4998                     0.0               1.0                    2.0
4999                     0.0               4.0                    8.0

      card_open_36_month_num  auto_open_ 36_month_num  …  \
0                        0.0                      1.0  …
1                        0.0                      0.0  …
2                        0.0                      0.0  …
3                        0.0                      0.0  …
4                        0.0                      0.0  …
…                      …                       …  …
4995                     0.0                      0.0  …
```

```
4996                    0.0                      0.0  …
4997                    1.0                      1.0  …
4998                    0.0                      0.0  …
4999                    1.0                      0.0  …

      uti_card_50plus_pct  ind_acc_XYZ  AL  FL  GA  LA  MS  NC  SC  \
0                0.633699          0.0   0   1   0   0   0   0   0
1                0.746901          1.0   1   0   0   0   0   0   0
2                0.458438          0.0   0   0   0   0   1   0   0
3                0.582352          1.0   1   0   0   0   0   0   0
4                0.577697          0.0   0   0   1   0   0   0   0
…                     …            …   ..  ..  ..  ..  ..  ..  ..
4995             0.398411          0.0   0   0   0   1   0   0   0
4996             0.286623          1.0   0   0   0   0   0   0   1
4997             0.443688          1.0   0   0   0   1   0   0   0
4998             0.178131          0.0   0   0   0   0   1   0   0
4999             0.503552          0.0   0   0   0   0   1   0   0

      Default_ind
0             0.0
1             0.0
2             0.0
3             0.0
4             0.0
…           …
4995          0.0
4996          0.0
4997          0.0
4998          0.0
4999          0.0

[5000 rows x 23 columns]>
(5000, 23)
tot_credit_debt                        float64
avg_card_debt                          float64
non_mtg_acc_past_due_12_months_num     float64
non_mtg_acc_past_due_6_months_num      float64
mortgages_past_due_6_months_num        float64
credit_past_due_amount                 float64
inq_12_month_num                       float64
card_inq_24_month_num                  float64
card_open_36_month_num                 float64
auto_open_ 36_month_num                float64
uti_card                               float64
uti_50plus_pct                         float64
uti_max_credit_line                    float64
uti_card_50plus_pct                    float64
ind_acc_XYZ                            float64
```

```
AL                                    uint8
FL                                    uint8
GA                                    uint8
LA                                    uint8
MS                                    uint8
NC                                    uint8
SC                                    uint8
Default_ind                         float64
dtype: object
```

Scoring test data:

```
[156]: rfModel.score(imputed_df_test.iloc[:,range(0,22)], imputed_df_test.iloc[:,22])
```

```
[156]: 0.9366
```

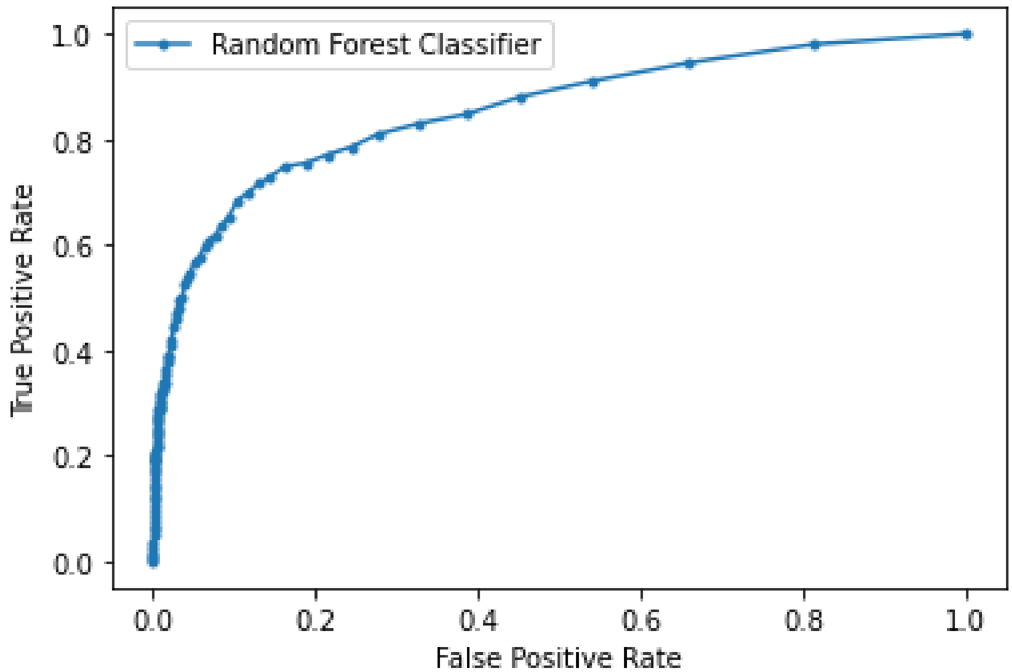
Testing with a confusion matrix:

```
[157]: confusion_matrix(imputed_df_test.iloc[:,22],rfModel.predict(imputed_df_test.
        ↪iloc[:,range(0,22)]))
```

```
[157]: array([[4568,   31],
              [ 286,  115]], dtype=int64)
```

ROC curve for random forest classifier (2b):

```
[158]: rf_probs = rfModel.predict_proba(imputed_df_test.iloc[:,range(0,22)])
       rf_probs = rf_probs[:, 1]
       rf_fpr, rf_tpr, _ = roc_curve(imputed_df_test.iloc[:,22], rf_probs)
       plt.plot(rf_fpr, rf_tpr, marker='.', label='Random Forest Classifier')
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.legend()
       plt.show()
```



Find feature importance (2c):

The higher the score, the more important the feature.

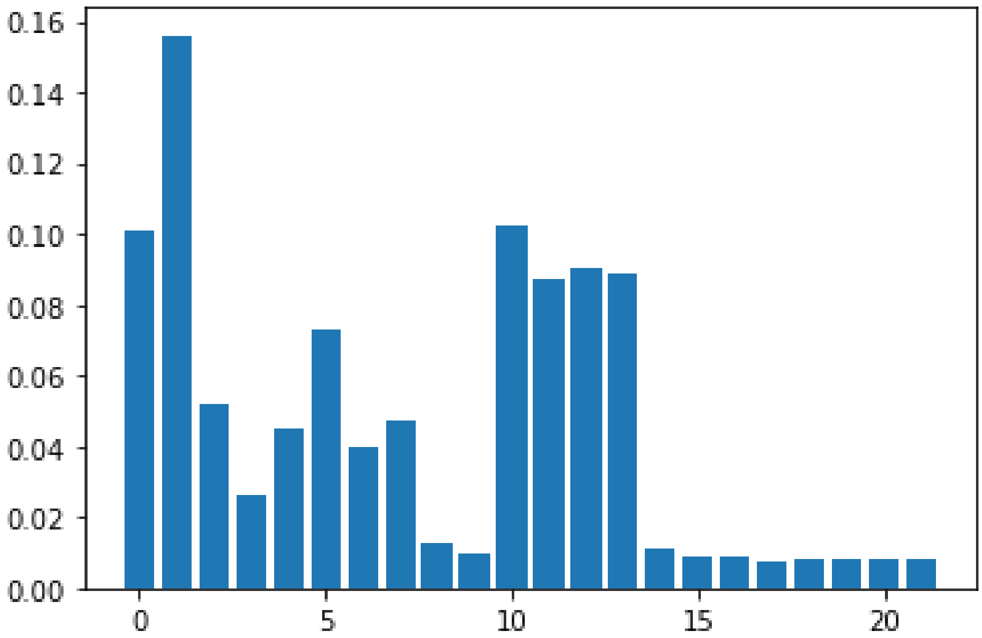
Important Notes: - Despite not presenting much correlation with response variable, total credit debt and average card debt play the most important roles in determining defaults - Utilization variables are all very important - State, XYZ previous account indicator, and credit products opened in 36 months variables play a marginal role

[182]:
```
variables = []
for var in imputed_df_train.columns:
    variables.append(var)
importance = rfModel.feature_importances_
index = 0
for i,v in enumerate(importance):
    print('Feature: {variable}\n Score: {v}\n\n'.format(variable =␣
 ↪variables[index],v = v))
    index += 1
plt.bar([x for x in range(len(importance))], importance)
plt.show()
```

```
Feature: tot_credit_debt
 Score: 0.10116110103522905
```

```
Feature: avg_card_debt
 Score: 0.15612549704029433


Feature: non_mtg_acc_past_due_12_months_num
 Score: 0.051588433741830204


Feature: non_mtg_acc_past_due_6_months_num
 Score: 0.026114066030776564


Feature: mortgages_past_due_6_months_num
 Score: 0.04471094287968974


Feature: credit_past_due_amount
 Score: 0.07272974478355873


Feature: inq_12_month_num
 Score: 0.040155479644069965


Feature: card_inq_24_month_num
 Score: 0.0476335411984235


Feature: card_open_36_month_num
 Score: 0.012521132722843388


Feature: auto_open_ 36_month_num
 Score: 0.009328620784239058


Feature: uti_card
 Score: 0.10270683546384929


Feature: uti_50plus_pct
 Score: 0.08696333953190324


Feature: uti_max_credit_line
 Score: 0.09047046122791504
```

```
Feature: uti_card_50plus_pct
 Score: 0.08913573380667056


Feature: ind_acc_XYZ
 Score: 0.011392454240505133


Feature: AL
 Score: 0.008526349581013072


Feature: FL
 Score: 0.00890519489911215


Feature: GA
 Score: 0.007348783410222652


Feature: LA
 Score: 0.008199211337674586


Feature: MS
 Score: 0.008037655223021628


Feature: NC
 Score: 0.008202140317150004


Feature: SC
 Score: 0.008043281100008147
```

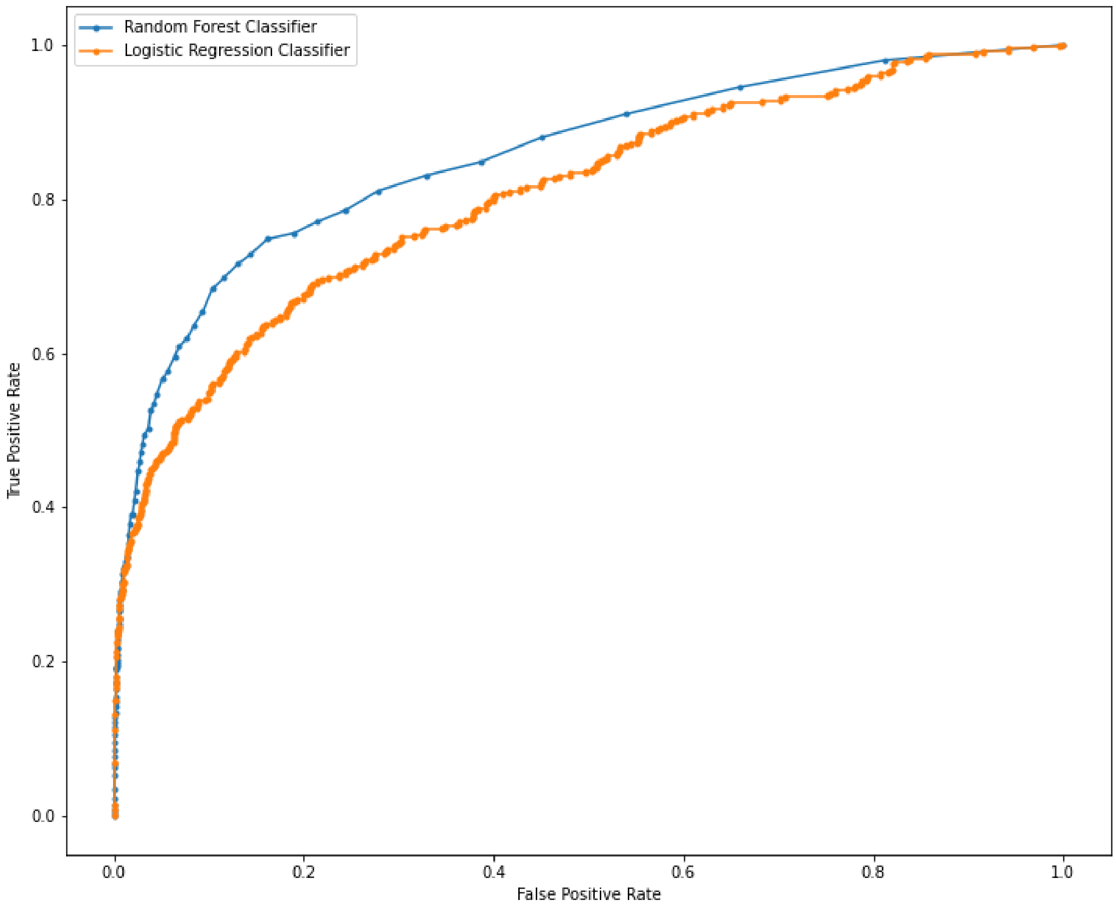


7 Comparing Models

Comparing ROC curves and AUC (2b):

Random forest performs better, as expected, because the true positive rate was better. This is confirmed by the AUC calculation as well.

[229]:
```
fig, ax = plt.subplots(figsize=(12,10))
plt.plot(rf_fpr, rf_tpr, marker='.', label='Random Forest Classifier')
plt.plot(lr_fpr, lr_tpr, marker='.', label='Logistic Regression Classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```



[136]:
```
lr_auc = roc_auc_score(df_test_norm.iloc[:,16], lr_probs)
rf_auc = roc_auc_score(imputed_df_test.iloc[:,22], rf_probs)
print('Logistic Regression: ROC AUC=%.3f' % (lr_auc))
print('Random Forest: ROC AUC=%.3f' % (rf_auc))
```

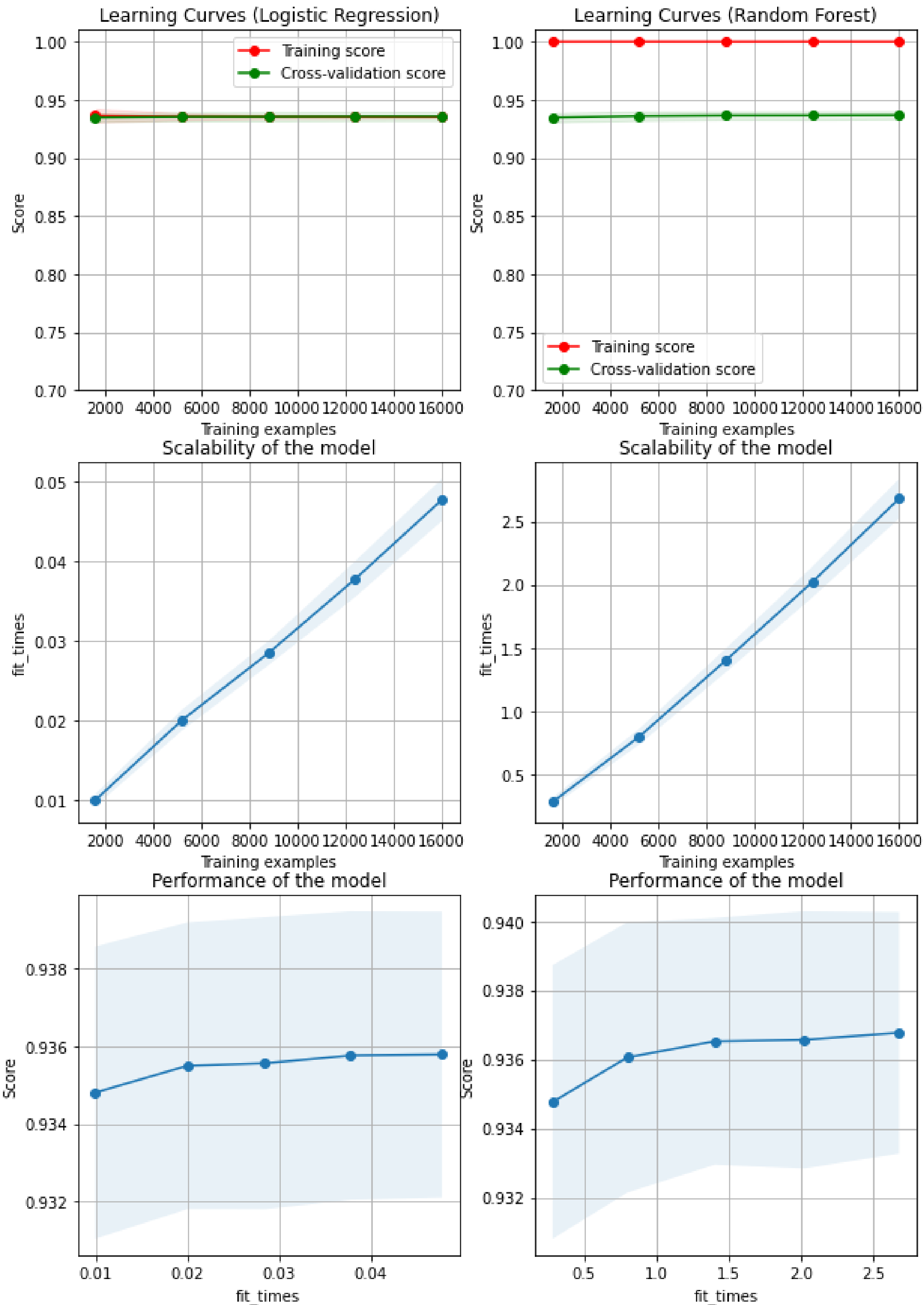
```
Logistic Regression: ROC AUC=0.806
Random Forest: ROC AUC=0.852
```

Comparing Learning curves (3): - While the training score for the random forest model is very high (a natural consequence of an algorithm that is extremely robust), the cross validation scores are very comperable throughout - Unsurpisingly, logistic regression is found to be much more scalable - Model performence is slightly higher for random forest model

[161]:
```
def plot_learning_curve(estimator, title, X, y, axes=None, ylim=None, cv=None,
                        n_jobs=None, train_sizes=np.linspace(.1, 1.0, 5)):
    if axes is None:
        _, axes = plt.subplots(1, 3, figsize=(20, 5))

    axes[0].set_title(title)
```

```
    if ylim is not None:
        axes[0].set_ylim(*ylim)
    axes[0].set_xlabel("Training examples")
    axes[0].set_ylabel("Score")

    train_sizes, train_scores, test_scores, fit_times, _ = \
        learning_curve(estimator, X, y, cv=cv, n_jobs=n_jobs,
                       train_sizes=train_sizes,
                       return_times=True)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    fit_times_mean = np.mean(fit_times, axis=1)
    fit_times_std = np.std(fit_times, axis=1)

    axes[0].grid()
    axes[0].fill_between(train_sizes, train_scores_mean - train_scores_std,
                         train_scores_mean + train_scores_std, alpha=0.1,
                         color="r")
    axes[0].fill_between(train_sizes, test_scores_mean - test_scores_std,
                         test_scores_mean + test_scores_std, alpha=0.1,
                         color="g")
    axes[0].plot(train_sizes, train_scores_mean, 'o-', color="r",
                 label="Training score")
    axes[0].plot(train_sizes, test_scores_mean, 'o-', color="g",
                 label="Cross-validation score")
    axes[0].legend(loc="best")

    axes[1].grid()
    axes[1].plot(train_sizes, fit_times_mean, 'o-')
    axes[1].fill_between(train_sizes, fit_times_mean - fit_times_std,
                         fit_times_mean + fit_times_std, alpha=0.1)
    axes[1].set_xlabel("Training examples")
    axes[1].set_ylabel("fit_times")
    axes[1].set_title("Scalability of the model")

    axes[2].grid()
    axes[2].plot(fit_times_mean, test_scores_mean, 'o-')
    axes[2].fill_between(fit_times_mean, test_scores_mean - test_scores_std,
                         test_scores_mean + test_scores_std, alpha=0.1)
    axes[2].set_xlabel("fit_times")
    axes[2].set_ylabel("Score")
    axes[2].set_title("Performance of the model")

    return plt
```

```
fig, axes = plt.subplots(3, 2, figsize=(10, 15))

X, y = df_train_norm.iloc[:,range(0,16)], df_train_norm.iloc[:,16]
title = "Learning Curves (Logistic Regression)"
cv = ShuffleSplit(n_splits=100, test_size=0.2, random_state=0)

plot_learning_curve(lrModel, title, X, y, axes=axes[:, 0], ylim=(0.7, 1.01),
                    cv=cv, n_jobs=4)

X, y = imputed_df_train.iloc[:,range(0,22)], imputed_df_train.iloc[:,22]
title = "Learning Curves (Random Forest)"
cv = ShuffleSplit(n_splits=50, test_size=0.2, random_state=0)
plot_learning_curve(rfModel, title, X, y, axes=axes[:, 1], ylim=(0.7, 1.01),
                    cv=cv, n_jobs=4)

plt.show()
```


Learning Curves (Logistic Regression)
Training score
Cross-validation score
Score
Training examples
Learning Curves (Random Forest)
Training score
Cross-validation score
Score
Training examples
Scalability of the model
fit_times
Training examples
Scalability of the model
fit_times
Training examples
Performance of the model
Score
fit_times
Performance of the model
Score
fit_times

8 Code References

Thank you to the following:
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(2) Jason Brownlee, PhD of Machine Learning Mastery:
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b. How to Use ROC Curves and Precision-Recall Curves for Classification in Python
c. How to Calculate Feature Importance With Python
(3) SKLearn:
Plotting Learning Curves