CreditCardFraudDetection

August 28, 2019

1 Executive Summary

The goal of this project is to build supervised models to identify fraudulent events in the credit card transactions of companies in Tenness during the year of 2010. This notebook is divided into following parts:

2 Exploratory Data Analysis

```
In [71]: import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
         %matplotlib inline
```

```
In [2]: df = pd.read_excel('cardtransactions.xlsx')
```

```
In [3]: df.head()
```

```
Out[3]:    Recnum     Cardnum       Date       Merchnum       Merch description  \
        0       1  5142190439 2010-01-01  5509006296254   FEDEX SHP 12/23/09 AB#
        1       2  5142183973 2010-01-01    61003026333  SERVICE MERCHANDISE #81
        2       3  5142131721 2010-01-01  4503082993600         OFFICE DEPOT #191
        3       4  5142148452 2010-01-01  5509006296254   FEDEX SHP 12/28/09 AB#
        4       5  5142190439 2010-01-01  5509006296254   FEDEX SHP 12/23/09 AB#

          Merch state  Merch zip Transtype  Amount  Fraud
        0          TN    38118.0         P    3.62      0
        1          MA     1803.0         P   31.42      0
        2          MD    20706.0         P  178.49      0
        3          TN    38118.0         P    3.62      0
        4          TN    38118.0         P    3.62      0
```

```
In [4]: print("The dataset has", df.shape[0], "rows and", df.shape[1],"columns." )
```

```
The dataset has 96753 rows and 10 columns.
```

```
In [5]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 96753 entries, 0 to 96752
Data columns (total 10 columns):
Recnum               96753 non-null int64
Cardnum              96753 non-null int64
Date                 96753 non-null datetime64[ns]
Merchnum             93378 non-null object
Merch description    96753 non-null object
Merch state          95558 non-null object
Merch zip            92097 non-null float64
Transtype            96753 non-null object
Amount               96753 non-null float64
Fraud                96753 non-null int64
dtypes: datetime64[ns](1), float64(2), int64(3), object(4)
memory usage: 7.4+ MB
```

2.1 Cardnum

In [6]:
```
# The number of transactions under each card number
df['Cardnum'].value_counts().head()
```

Out[6]:
```
5142148452    1192
5142184598     921
5142189108     663
5142297710     583
5142223373     579
Name: Cardnum, dtype: int64
```

In [7]:
```
# The number of unique card number in the dataset
print("There are", len(df['Cardnum'].unique()), "unique card number in the dataset")
```

```
There are 1645 unique card number in the dataset
```

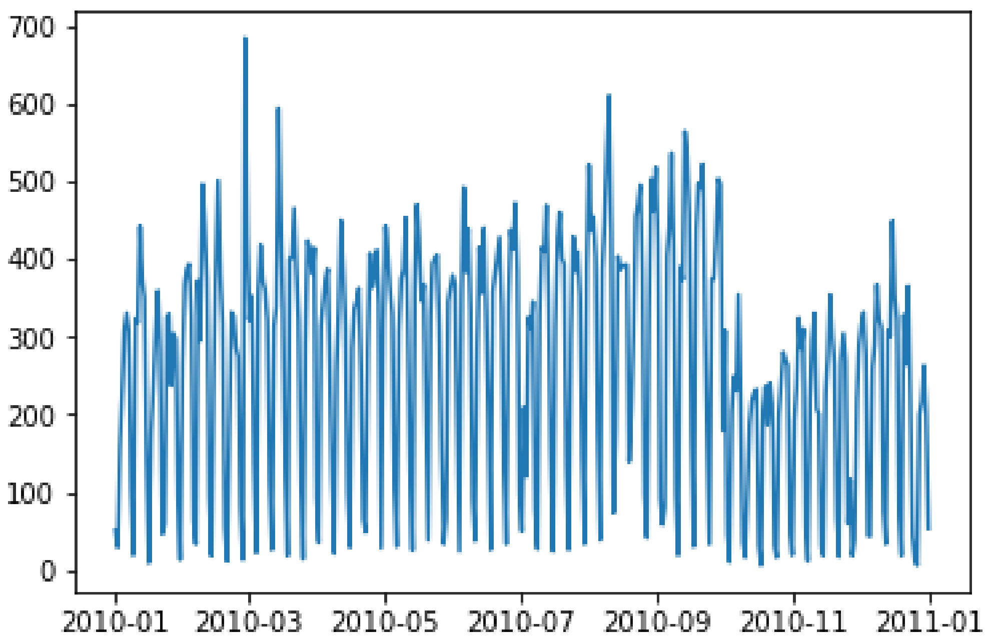
2.2 Date

In [8]:
```
df['Date'].value_counts().head()
```

Out[8]:
```
2010-02-28    684
2010-08-10    610
2010-03-15    594
2010-09-13    564
2010-08-09    536
Name: Date, dtype: int64
```

In [9]:
```
# The number of transactions by date
plt.plot(df['Date'].value_counts().sort_index());
```

```
/anaconda3/lib/python3.6/site-packages/pandas/plotting/_converter.py:129: FutureWarning: Using

To register the converters:
        >>> from pandas.plotting import register_matplotlib_converters
        >>> register_matplotlib_converters()
  warnings.warn(msg, FutureWarning)
```




```
In [10]: print("There are", len(df['Date'].unique()), "days in the dataset")
```

```
There are 365 days in the dataset
```

2.3 Merchant Number

```
In [11]: df['Merchnum'].value_counts().head()
```

```
Out[11]: 930090121224     9310
         5509006296254    2131
         9900020006406    1714
         602608969534     1092
         4353000719908    1020
         Name: Merchnum, dtype: int64
```

```
In [12]: df[df['Merchnum'].isnull()].head()
```

```
Out[12]:      Recnum     Cardnum       Date Merchnum         Merch description  \
         97       98  5142167414 2010-01-03      NaN  CONVENIENCE CHECK FEE(%)
         115     116  5142182128 2010-01-03      NaN              GRAINGER #973
         135     136  5142126842 2010-01-03      NaN    AUTOMATED OFFICE PRODU
         163     164  5142127276 2010-01-03      NaN  CONVENIENCE CHECK FEE(%)
         168     169  5142132574 2010-01-03      NaN        ROLL CALL NEWSPAPER

             Merch state  Merch zip Transtype   Amount  Fraud
         97          NaN        NaN         D    89.00      0
         115          IL    60089.0         P   327.34      0
         135          MD    20706.0         P  2110.00      0
         163         NaN        NaN         D  4444.00      0
         168          DC    20001.0         P   104.69      0
```

```
In [13]: print("There are", len(df['Merchnum'].unique()), "merchants in the dataset.")
```

```
There are 13092 merchants in the dataset.
```

```
In [14]: print("There are",sum(df['Merchnum'].isnull()),"NAs in merchant number.")
```

```
There are 3375 NAs in merchant number.
```

2.4 Merch State

```
In [15]: df['Merch state'].value_counts().head()
```

```
Out[15]: TN    12035
         VA     7872
         CA     6817
         IL     6508
         MD     5398
         Name: Merch state, dtype: int64
```

```
In [16]: df[df['Merch state'].isnull()].head()
```

```
Out[16]:      Recnum     Cardnum       Date Merchnum         Merch description  \
         97       98  5142167414 2010-01-03      NaN  CONVENIENCE CHECK FEE(%)
         163     164  5142127276 2010-01-03      NaN  CONVENIENCE CHECK FEE(%)
         262     263  5142257575 2010-01-04      NaN   RETAIL DEBIT ADJUSTMENT
         272     273  5142124791 2010-01-04      NaN   RETAIL DEBIT ADJUSTMENT
         400     401  5142276099 2010-01-04      NaN   RETAIL DEBIT ADJUSTMENT

             Merch state  Merch zip Transtype   Amount  Fraud
         97          NaN        NaN         D    89.00      0
         163         NaN        NaN         D  4444.00      0
         262         NaN        NaN         P   320.00      0
         272         NaN        NaN         P   970.00      0
         400         NaN        NaN         P    82.59      0
```

In [17]:
```
print("There are",len(df['Merch state'].unique()),"states in the dataset.")
#Something is wrong with the merchant state column, which needs to be paid attention
```

```
There are 228 states in the dataset.
```

2.5 Merch Zip

In [18]:
```
df['Merch zip'].value_counts().head()
```

Out[18]:
```
38118.0    11868
63103.0     1650
8701.0      1267
22202.0     1250
60061.0     1221
Name: Merch zip, dtype: int64
```

In [19]:
```
print("There are", len(df['Merch zip'].unique()), "zip codes in the dataset.")
```

```
There are 4568 zip codes in the dataset.
```

In [20]:
```
df[df['Merch zip'].isnull()].head()
```

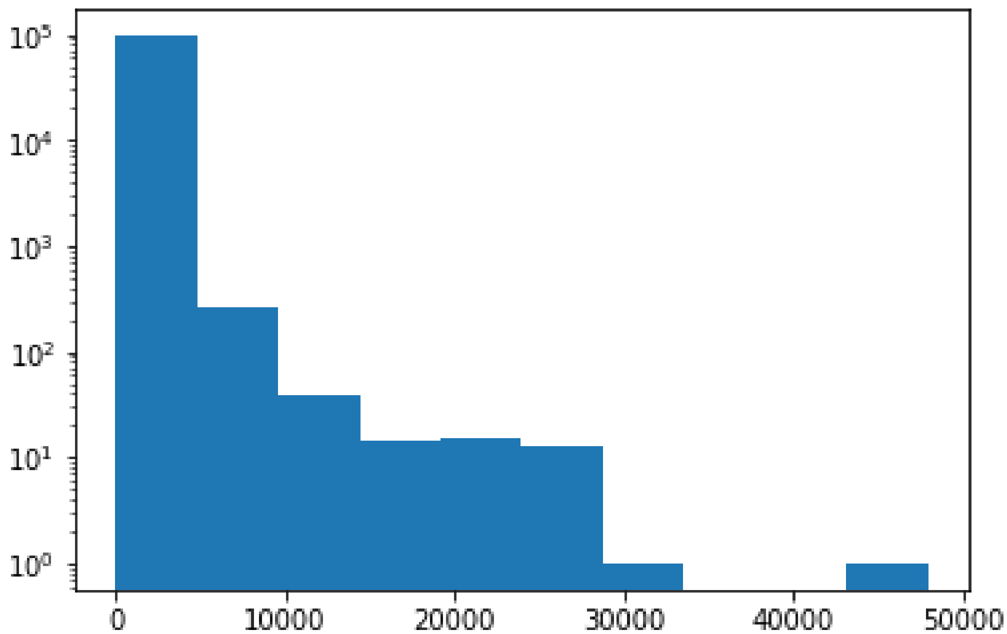
Out[20]:
```
    Recnum     Cardnum       Date       Merchnum      Merch description  \
51      52  5142204384 2010-01-02  5000006000095  IBM INTERNET  01000025
54      55  5142146340 2010-01-02  5000006000095  IBM INTERNET  01000025
55      56  5142260984 2010-01-02  5000006000095  IBM INTERNET  01000025
58      59  5142204384 2010-01-02  5000006000095  IBM INTERNET  01000025
59      60  5142204384 2010-01-02  5000006000095  IBM INTERNET  01000025

   Merch state  Merch zip Transtype  Amount  Fraud
51          NY        NaN         P   20.15      0
54          NY        NaN         P   23.90      0
55          NY        NaN         P   19.95      0
58          NY        NaN         P   20.15      0
59          NY        NaN         P   20.15      0
```

2.6 Amount

In [21]:
```
df['Amount'].describe()
```

Out[21]:
```
count    9.675300e+04
mean     4.278857e+02
std      1.000614e+04
min      1.000000e-02
25%      3.348000e+01
50%      1.379800e+02
75%      4.282000e+02
max      3.102046e+06
Name: Amount, dtype: float64
```

In [22]:
```python
# print the distribution of amount excluding outlier on a log scale
plt.hist(df.loc[df['Amount'] != max(df['Amount']),'Amount'])
plt.yscale('log')
```



2.7 Fraud

In [23]:
```python
# imbalanced dataset with few frauds
df['Fraud'].value_counts()
```

Out[23]:
```
0    95694
1     1059
Name: Fraud, dtype: int64
```

3 Data Cleaning

Some data cleaning to do:

In [24]:
```python
df = df[(df['Transtype'] == 'P') & (df['Amount'] != max(df['Amount']))]
```

In [25]:
```python
states = ["AL", "AK", "AZ", "AR", "CA", "CO", "CT", "DC", "DE", "FL", "GA",
          "HI", "ID", "IL", "IN", "IA", "KS", "KY", "LA", "ME", "MD",
          "MA", "MI", "MN", "MS", "MO", "MT", "NE", "NV", "NH", "NJ",
          "NM", "NY", "NC", "ND", "OH", "OK", "OR", "PA", "RI", "SC",
          "SD", "TN", "TX", "UT", "VT", "VA", "WA", "WV", "WI", "WY"]
```

In [26]:
```python
df.loc[(~df['Merch state'].isin(states) & (~df['Merch state'].isnull())),'Merch state
```

```
In [27]: len(df['Merch state'].unique()) # 51 states plus nan and other
```

```
Out[27]: 53
```

```
In [28]: # fill merch state
         state_ref = df.groupby('Merch zip')['Merch state'].apply(lambda x: x.mode()).reset_inc
         state_ref = state_ref[state_ref['level_1']==0].iloc[:,[0,2]]
         state_ref.columns = ['Merch zip','state ref']
```

```
In [29]: df = df.merge(state_ref, on='Merch zip',how='left')
         df['Merch state'] = df['Merch state'].fillna(df['state ref']).fillna('TN')
```

```
In [30]: sum(df['Merch state'].isnull())
```

```
Out[30]: 0
```

```
In [31]: # fill merch zip
         zip_ref = df.groupby(["Merch state","Cardnum"])['Merch zip'].apply(lambda x: x.mode()
         zip_ref = zip_ref[zip_ref.level_2==0].iloc[:,[0,1,3]]
         zip_ref.columns = ["Merch state","Cardnum","zip ref"]
```

```
In [32]: df = df.merge(zip_ref, on=["Merch state","Cardnum"],how='left')
```

```
In [33]: zip_ref2 = df.groupby(["Merch state"])['Merch zip'].apply(lambda x: x.mode()).reset_in
         zip_ref2 = zip_ref2[zip_ref2.level_1==0].iloc[:,[0,2]]
         zip_ref2.columns = ["Merch state","zip ref2"]
```

```
In [34]: df = df = df.merge(zip_ref2, on=["Merch state"],how='left')
```

```
In [35]: df['Merch zip'] = df['Merch zip'].fillna(df['zip ref']).fillna(df['zip ref2']).fillna
```

```
In [36]: sum(df['Merch zip'].isnull())
```

```
Out[36]: 0
```

```
In [37]: merch_ref = df.groupby(['Merch state','Cardnum'])['Merchnum'].apply(lambda x: x.mode(
         merch_ref = merch_ref[merch_ref.level_2 == 0].iloc[:,[0,1,3]]
         merch_ref.columns = ["Merch state","Cardnum","merch ref"]

         df = df.merge(merch_ref, on=['Merch state','Cardnum'],how='left')

         merch_ref2 = df.groupby(['Merch state'])['Merchnum'].apply(lambda x: x.mode()).reset_i
         merch_ref2 = merch_ref2[merch_ref2.level_1 == 0].iloc[:,[0,2]]
         merch_ref2.columns = ["Merch state","merch ref2"]

         df = df.merge(merch_ref2, on=['Merch state'],how='left')
```

```
In [38]: df['Merchnum'] = df['Merchnum'].fillna(df['merch ref']).fillna(df['merch ref2']).filln
```

```
In [39]: sum(df['Merchnum'].isnull())
```

```
Out[39]: 0

In [40]: df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 96397 entries, 0 to 96396
Data columns (total 15 columns):
Recnum                 96397 non-null int64
Cardnum                96397 non-null int64
Date                   96397 non-null datetime64[ns]
Merchnum               96397 non-null object
Merch description      96397 non-null object
Merch state            96397 non-null object
Merch zip              96397 non-null float64
Transtype              96397 non-null object
Amount                 96397 non-null float64
Fraud                  96397 non-null int64
state ref              92030 non-null object
zip ref                95195 non-null float64
zip ref2               96205 non-null float64
merch ref              95336 non-null object
merch ref2             96397 non-null object
dtypes: datetime64[ns](1), float64(4), int64(3), object(7)
memory usage: 11.8+ MB


In [41]: df = df.drop(columns=['state ref','zip ref','zip ref2','merch ref','merch ref2','Mercl

In [63]: df.head()

Out[63]:    Recnum     Cardnum       Date       Merchnum Merch state  Merch zip  \
         0       1  5142190439 2010-01-01  5509006296254          TN    38118.0
         1       2  5142183973 2010-01-01    61003026333          MA     1803.0
         2       3  5142131721 2010-01-01  4503082993600          MD    20706.0
         3       4  5142148452 2010-01-01  5509006296254          TN    38118.0
         4       5  5142190439 2010-01-01  5509006296254          TN    38118.0

            Amount  Fraud
         0    3.62      0
         1   31.42      0
         2  178.49      0
         3    3.62      0
         4    3.62      0
```

4 Feature Engineering

There are four types of variables to create: amount variable, frequency variable, recency variable and velocity change variable. Groups include card number, merchant number, card number and merchant zip code.

Amount Variable: for each group, the average, maximum, total amount over the past 1, 7 and 14 days Frequency Variable: for each group, the number of transactions over the past 1, 7 and 14 days Recency Variable: for each group, the difference between current date and most recent transaction date

```
In [66]: df.set_index('Date',inplace=True)
```

```
In [67]: df.head()
```

```
Out[67]:             Recnum     Cardnum        Merchnum Merch state  Merch zip  Amount  \
         Date
         2010-01-01       1  5142190439   5509006296254          TN    38118.0    3.62
         2010-01-01       2  5142183973     61003026333          MA     1803.0   31.42
         2010-01-01       3  5142131721   4503082993600          MD    20706.0  178.49
         2010-01-01       4  5142148452   5509006296254          TN    38118.0    3.62
         2010-01-01       5  5142190439   5509006296254          TN    38118.0    3.62

                     Fraud
         Date
         2010-01-01      0
         2010-01-01      0
         2010-01-01      0
         2010-01-01      0
         2010-01-01      0
```

4.1 Amount Variable

4.1.1 By Cardnum

```
In [68]: avg_card_1 = df.groupby(['Cardnum'])['Amount'].rolling('1d').mean().reset_index()
         avg_card_1['order'] = avg_card_1.groupby(['Cardnum', 'Date']).cumcount() + 1
         avg_card_7 = df.groupby(['Cardnum'])['Amount'].rolling('7d').mean().reset_index()
         avg_card_7['order'] = avg_card_7.groupby(['Cardnum', 'Date']).cumcount() + 1
         avg_card_14 = df.groupby(['Cardnum'])['Amount'].rolling('14d').mean().reset_index()
         avg_card_14['order'] = avg_card_14.groupby(['Cardnum', 'Date']).cumcount() + 1

         max_card_1 = df.groupby(['Cardnum'])['Amount'].rolling('1d').max().reset_index()
         max_card_1['order'] = max_card_1.groupby(['Cardnum', 'Date']).cumcount() + 1
         max_card_7 = df.groupby(['Cardnum'])['Amount'].rolling('7d').max().reset_index()
         max_card_7['order'] = max_card_7.groupby(['Cardnum', 'Date']).cumcount() + 1
         max_card_14 = df.groupby(['Cardnum'])['Amount'].rolling('14d').max().reset_index()
         max_card_14['order'] = max_card_14.groupby(['Cardnum', 'Date']).cumcount() + 1

         sum_card_1 = df.groupby(['Cardnum'])['Amount'].rolling('1d').sum().reset_index()
         sum_card_1['order'] = sum_card_1.groupby(['Cardnum', 'Date']).cumcount() + 1
         sum_card_7 = df.groupby(['Cardnum'])['Amount'].rolling('7d').sum().reset_index()
         sum_card_7['order'] = sum_card_7.groupby(['Cardnum', 'Date']).cumcount() + 1
         sum_card_14 = df.groupby(['Cardnum'])['Amount'].rolling('14d').sum().reset_index()
         sum_card_14['order'] = sum_card_14.groupby(['Cardnum', 'Date']).cumcount() + 1
```

```
In [69]: card_amount = df.copy()
         card_amount  = card_amount.reset_index()
         card_amount['order'] = card_amount.groupby(['Cardnum', 'Date']).cumcount() + 1
         card_amount = card_amount[['Date','Cardnum','Amount','order']]
```

```
In [70]: merged_card_amount = card_amount \
         .merge(avg_card_1, on = ['Date', 'Cardnum', 'order'], how = 'left', suffixes=['', '_av
         .merge(avg_card_7, on = ['Date', 'Cardnum', 'order'], how = 'left', suffixes=['', '_av
         .merge(avg_card_14, on = ['Date', 'Cardnum', 'order'], how = 'left', suffixes=['', '_a
         .merge(max_card_1, on = ['Date', 'Cardnum', 'order'], how = 'left', suffixes=['', '_ma
         .merge(max_card_7, on = ['Date', 'Cardnum', 'order'], how = 'left', suffixes=['', '_ma
         .merge(max_card_14, on = ['Date', 'Cardnum', 'order'], how = 'left', suffixes=['', '_m
         .merge(sum_card_1, on = ['Date', 'Cardnum', 'order'], how = 'left', suffixes=['', '_su
         .merge(sum_card_7, on = ['Date', 'Cardnum', 'order'], how = 'left', suffixes=['', '_su
         .merge(sum_card_14, on = ['Date', 'Cardnum', 'order'], how = 'left', suffixes=['', '_s
```

```
In [71]: merged_card_amount.head()
```

Out[71]:

	Date	Cardnum	Amount	order	Amount_avg_card_1	Amount_avg_card_7
0	2010-01-01	5142190439	3.62	1	3.62	3.62
1	2010-01-01	5142183973	31.42	1	31.42	31.42
2	2010-01-01	5142131721	178.49	1	178.49	178.49
3	2010-01-01	5142148452	3.62	1	3.62	3.62
4	2010-01-01	5142190439	3.62	2	3.62	3.62

	Amount_avg_card_14	Amount_max_card_1	Amount_max_card_7
0	3.62	3.62	3.62
1	31.42	31.42	31.42
2	178.49	178.49	178.49
3	3.62	3.62	3.62
4	3.62	3.62	3.62

	Amount_max_card_14	Amount_sum_card_1	Amount_sum_card_7
0	3.62	3.62	3.62
1	31.42	31.42	31.42
2	178.49	178.49	178.49
3	3.62	3.62	3.62
4	3.62	7.24	7.24

	Amount_sum_card_14
0	3.62
1	31.42
2	178.49
3	3.62
4	7.24

4.1.2 Merchant Number

In [72]:
```
avg_merchant_1 = df.groupby(['Merchnum'])['Amount'].rolling('1d').mean().reset_index(
avg_merchant_1['order'] = avg_merchant_1.groupby(['Merchnum', 'Date']).cumcount() + 1
avg_merchant_7 = df.groupby(['Merchnum'])['Amount'].rolling('7d').mean().reset_index(
avg_merchant_7['order'] = avg_merchant_7.groupby(['Merchnum', 'Date']).cumcount() + 1
avg_merchant_14 = df.groupby(['Merchnum'])['Amount'].rolling('14d').mean().reset_inde
avg_merchant_14['order'] = avg_merchant_14.groupby(['Merchnum', 'Date']).cumcount() +

max_merchant_1 = df.groupby(['Merchnum'])['Amount'].rolling('1d').max().reset_index()
max_merchant_1['order'] = max_merchant_1.groupby(['Merchnum', 'Date']).cumcount() + 1
max_merchant_7 = df.groupby(['Merchnum'])['Amount'].rolling('7d').max().reset_index()
max_merchant_7['order'] = max_merchant_7.groupby(['Merchnum', 'Date']).cumcount() + 1
max_merchant_14 = df.groupby(['Merchnum'])['Amount'].rolling('14d').max().reset_index
max_merchant_14['order'] = max_merchant_14.groupby(['Merchnum', 'Date']).cumcount() +

sum_merchant_1 = df.groupby(['Merchnum'])['Amount'].rolling('1d').sum().reset_index()
sum_merchant_1['order'] = sum_merchant_1.groupby(['Merchnum', 'Date']).cumcount() + 1
sum_merchant_7 = df.groupby(['Merchnum'])['Amount'].rolling('7d').sum().reset_index()
sum_merchant_7['order'] = sum_merchant_7.groupby(['Merchnum', 'Date']).cumcount() + 1
sum_merchant_14 = df.groupby(['Merchnum'])['Amount'].rolling('14d').sum().reset_index
sum_merchant_14['order'] = sum_merchant_14.groupby(['Merchnum', 'Date']).cumcount() +
```

In [73]:
```
merchant_amount = df.copy()
merchant_amount  = merchant_amount.reset_index()
merchant_amount['order'] = merchant_amount.groupby(['Merchnum', 'Date']).cumcount() +
merchant_amount = merchant_amount[['Date','Merchnum','Amount','order']]
```

In [74]:
```
merged_amount_merchant = merchant_amount \
.merge(avg_merchant_1, on = ['Date', 'Merchnum', 'order'], how = 'left', suffixes=[''
.merge(avg_merchant_7, on = ['Date', 'Merchnum', 'order'], how = 'left', suffixes=[''
.merge(avg_merchant_14, on = ['Date', 'Merchnum', 'order'], how = 'left', suffixes=['
.merge(max_merchant_1, on = ['Date', 'Merchnum', 'order'], how = 'left', suffixes=[''
.merge(max_merchant_7, on = ['Date', 'Merchnum', 'order'], how = 'left', suffixes=[''
.merge(max_merchant_14, on = ['Date', 'Merchnum', 'order'], how = 'left', suffixes=['
.merge(sum_merchant_1, on = ['Date', 'Merchnum', 'order'], how = 'left', suffixes=[''
.merge(sum_merchant_7, on = ['Date', 'Merchnum', 'order'], how = 'left', suffixes=[''
.merge(sum_merchant_14, on = ['Date', 'Merchnum', 'order'], how = 'left', suffixes=['
```

In [75]:
```
merged_amount_merchant.head()
```

Out[75]:
```
         Date       Merchnum  Amount  order  Amount_avg_merchant_1  \
0 2010-01-01  5509006296254    3.62      1                   3.62
1 2010-01-01    61003026333   31.42      1                  31.42
2 2010-01-01  4503082993600  178.49      1                 178.49
3 2010-01-01  5509006296254    3.62      2                   3.62
4 2010-01-01  5509006296254    3.62      3                   3.62

   Amount_avg_merchant_7  Amount_avg_merchant_14  Amount_max_merchant_1  \
```

```
0                  3.62                 3.62                3.62
1                 31.42                31.42               31.42
2                178.49               178.49              178.49
3                  3.62                 3.62                3.62
4                  3.62                 3.62                3.62

   Amount_max_merchant_7  Amount_max_merchant_14  Amount_sum_merchant_1  \
0                  3.62                 3.62                3.62
1                 31.42                31.42               31.42
2                178.49               178.49              178.49
3                  3.62                 3.62                7.24
4                  3.62                 3.62               10.86

   Amount_sum_merchant_7  Amount_sum_merchant_14
0                  3.62                 3.62
1                 31.42                31.42
2                178.49               178.49
3                  7.24                 7.24
4                 10.86                10.86
```

4.1.3 Cardnum and Zip code

```
In [76]: avg_card_zip_1 = df.groupby(['Cardnum', 'Merch zip'])['Amount'].rolling('1d').mean().r
         avg_card_zip_1['order'] = avg_card_zip_1.groupby(['Cardnum', 'Merch zip', 'Date']).cum
         avg_card_zip_7 = df.groupby(['Cardnum', 'Merch zip'])['Amount'].rolling('7d').mean().r
         avg_card_zip_7['order'] = avg_card_zip_7.groupby(['Cardnum', 'Merch zip', 'Date']).cum
         avg_card_zip_14 = df.groupby(['Cardnum', 'Merch zip'])['Amount'].rolling('14d').mean()
         avg_card_zip_14['order'] = avg_card_zip_14.groupby(['Cardnum', 'Merch zip', 'Date']).c

         max_card_zip_1 = df.groupby(['Cardnum', 'Merch zip'])['Amount'].rolling('1d').max().re
         max_card_zip_1['order'] = max_card_zip_1.groupby(['Cardnum', 'Merch zip', 'Date']).cum
         max_card_zip_7 = df.groupby(['Cardnum', 'Merch zip'])['Amount'].rolling('7d').max().re
         max_card_zip_7['order'] = max_card_zip_7.groupby(['Cardnum', 'Merch zip', 'Date']).cum
         max_card_zip_14 = df.groupby(['Cardnum', 'Merch zip'])['Amount'].rolling('14d').max()
         max_card_zip_14['order'] = max_card_zip_14.groupby(['Cardnum', 'Merch zip', 'Date']).c

         sum_card_zip_1 = df.groupby(['Cardnum', 'Merch zip'])['Amount'].rolling('1d').sum().re
         sum_card_zip_1['order'] = sum_card_zip_1.groupby(['Cardnum', 'Merch zip', 'Date']).cum
         sum_card_zip_7 = df.groupby(['Cardnum', 'Merch zip'])['Amount'].rolling('7d').sum().re
         sum_card_zip_7['order'] = sum_card_zip_7.groupby(['Cardnum', 'Merch zip', 'Date']).cum
         sum_card_zip_14 = df.groupby(['Cardnum', 'Merch zip'])['Amount'].rolling('14d').sum()
         sum_card_zip_14['order'] = sum_card_zip_14.groupby(['Cardnum', 'Merch zip', 'Date']).c

In [77]: card_zip_amount = df.copy()
         card_zip_amount = card_zip_amount.reset_index()
         card_zip_amount['order'] = card_zip_amount.groupby(['Cardnum', 'Merch zip', 'Date']).c
         card_zip_amount = card_zip_amount[['Date','Merch zip','Cardnum','Amount','order']]

In [78]: merged_card_zip_amount = card_zip_amount \
```

```
.merge(avg_card_zip_1, on = ['Date', 'Merch zip', 'Cardnum', 'order'], how = 'left', s
.merge(avg_card_zip_7, on = ['Date', 'Merch zip', 'Cardnum', 'order'], how = 'left', s
.merge(avg_card_zip_14, on = ['Date', 'Merch zip', 'Cardnum', 'order'], how = 'left',
.merge(max_card_zip_1, on = ['Date', 'Merch zip', 'Cardnum', 'order'], how = 'left', s
.merge(max_card_zip_7, on = ['Date', 'Merch zip', 'Cardnum', 'order'], how = 'left', s
.merge(max_card_zip_14, on = ['Date', 'Merch zip', 'Cardnum', 'order'], how = 'left',
.merge(sum_card_zip_1, on = ['Date', 'Merch zip', 'Cardnum', 'order'], how = 'left', s
.merge(sum_card_zip_7, on = ['Date', 'Merch zip', 'Cardnum', 'order'], how = 'left', s
.merge(sum_card_zip_14, on = ['Date', 'Merch zip', 'Cardnum', 'order'], how = 'left',
```

In [80]:
```
merged_card_zip_amount.head()
```

Out[80]:
```
         Date  Merch zip     Cardnum  Amount  order  Amount_avg_card_zip_1  \
0  2010-01-01    38118.0  5142190439    3.62      1                   3.62
1  2010-01-01     1803.0  5142183973   31.42      1                  31.42
2  2010-01-01    20706.0  5142131721  178.49      1                 178.49
3  2010-01-01    38118.0  5142148452    3.62      1                   3.62
4  2010-01-01    38118.0  5142190439    3.62      2                   3.62

   Amount_avg_card_zip_7  Amount_avg_card_zip_14  Amount_max_card_zip_1  \
0                   3.62                    3.62                   3.62
1                  31.42                   31.42                  31.42
2                 178.49                  178.49                 178.49
3                   3.62                    3.62                   3.62
4                   3.62                    3.62                   3.62

   Amount_max_card_zip_7  Amount_max_card_zip_14  Amount_sum_card_zip_1  \
0                   3.62                    3.62                   3.62
1                  31.42                   31.42                  31.42
2                 178.49                  178.49                 178.49
3                   3.62                    3.62                   3.62
4                   3.62                    3.62                   7.24

   Amount_sum_card_zip_7  Amount_sum_card_zip_14
0                   3.62                    3.62
1                  31.42                   31.42
2                 178.49                  178.49
3                   3.62                    3.62
4                   7.24                    7.24
```

In [105]:
```
Amount = pd.concat([df,merged_card_amount.iloc[:,4:],
         merged_amount_merchant.iloc[:,4:],
         merged_card_zip_amount.iloc[:,5:]],axis=1)
```

4.2 Frequency Variable

In [108]:
```
df.set_index('Date',inplace=True)
```

Out[108]:
```
              Recnum     Cardnum      Merchnum Merch state  Merch zip  Amount  \
Date
```

```
2010-01-01       1  5142190439  5509006296254          TN    38118.0    3.62
2010-01-01       2  5142183973    61003026333          MA     1803.0   31.42
2010-01-01       3  5142131721  4503082993600          MD    20706.0  178.49
2010-01-01       4  5142148452  5509006296254          TN    38118.0    3.62
2010-01-01       5  5142190439  5509006296254          TN    38118.0    3.62

            Fraud  order_cardnum  order_merchnum  order_card_zip
Date
2010-01-01      0              1               1               1
2010-01-01      0              1               1               1
2010-01-01      0              1               1               1
2010-01-01      0              1               2               1
2010-01-01      0              2               3               2
```

In [ ]:
```
def frequency(df, groupby, timewindow, unique_id=None):
    '''
    :param df: DataFrame with Date as index, sorted by index
    :param groupby: list
    :param timewindow: int (day)
    :param unique_id: stirng
    :return: DataFrame
    '''
    df_temp = df.copy()
    df_temp.sort_index(inplace=True)
    df_temp['Count'] = 1
    time_name = df_temp.index.name
    df_temp['order'] = df_temp.groupby(groupby + [time_name]).cumcount() + 1
    time_df = df_temp.groupby(groupby)['Count'].rolling(str(timewindow) + 'd').sum()
    time_df = time_df.reset_index()
    time_df.rename(columns={'Count': '_'.join(groupby) + '_' + str(timewindow) + '_Cou
    time_df['order'] = time_df.groupby(groupby + [time_name]).cumcount() + 1
    res_df = df_temp.merge(time_df, on=[time_name] + groupby + ['order'])
    print('_'.join(groupby) + '_' + str(timewindow) + '_Count' + ' Completed')
    if not unique_id:
        return res_df

    return res_df[[unique_id, '_'.join(groupby) + '_' + str(timewindow) + '_Count']]
```

In [126]:
```
freq_card_1 = frequency(df,['Cardnum'],1,'Recnum')
freq_card_7 =  frequency(df,['Cardnum'],7,'Recnum')
freq_card_14 =  frequency(df,['Cardnum'],14,'Recnum')
```

```
Cardnum_1_Count Completed
Cardnum_7_Count Completed
Cardnum_14_Count Completed
```

In [125]:
```
freq_merchant_1 = frequency(df,['Merchnum'],1,'Recnum')
freq_merchant_7 = frequency(df,['Merchnum'],7,'Recnum')
freq_merchant_14 = frequency(df,['Merchnum'],14,'Recnum')
```

```
Merchnum_1_Count Completed
Merchnum_7_Count Completed
Merchnum_14_Count Completed
```

```
In [127]: freq_card_zip_1 = frequency(df,['Cardnum','Merch zip'],1,'Recnum')
          freq_card_zip_7 = frequency(df,['Cardnum','Merch zip'],7,'Recnum')
          freq_card_zip_14 = frequency(df,['Cardnum','Merch zip'],14,'Recnum')
```

```
Cardnum_Merch zip_1_Count Completed
Cardnum_Merch zip_7_Count Completed
Cardnum_Merch zip_14_Count Completed
```

```
In [140]: Frequency = freq_card_1.merge(freq_card_7,on='Recnum').merge(freq_card_14,on='Recnum
                      merge(freq_merchant_1,on='Recnum'). merge(freq_merchant_7,on='Recnum'). r
                      merge(freq_card_zip_1,on='Recnum').merge(freq_card_zip_7,on='Recnum').me
```

```
In [141]: Frequency.head()
```

```
Out[141]:    Recnum  Cardnum_1_Count  Cardnum_7_Count  Cardnum_14_Count  \
          0       1              1.0              1.0               1.0
          1       2              1.0              1.0               1.0
          2       3              1.0              1.0               1.0
          3       4              1.0              1.0               1.0
          4       5              2.0              2.0               2.0

             Merchnum_1_Count  Merchnum_7_Count  Merchnum_14_Count  \
          0               1.0               1.0                1.0
          1               1.0               1.0                1.0
          2               1.0               1.0                1.0
          3               2.0               2.0                2.0
          4               3.0               3.0                3.0

             Cardnum_Merch zip_1_Count  Cardnum_Merch zip_7_Count  \
          0                        1.0                        1.0
          1                        1.0                        1.0
          2                        1.0                        1.0
          3                        1.0                        1.0
          4                        2.0                        2.0

             Cardnum_Merch zip_14_Count
          0                         1.0
          1                         1.0
          2                         1.0
          3                         1.0
          4                         2.0
```

4.3 Recency Variable

In [151]:
```
df.head()
```

Out[151]:
```
            Recnum     Cardnum        Merchnum Merch state  Merch zip  Amount  \
Date
2010-01-01       1  5142190439  5509006296254           TN    38118.0    3.62
2010-01-01       2  5142183973    61003026333           MA     1803.0   31.42
2010-01-01       3  5142131721  4503082993600           MD    20706.0  178.49
2010-01-01       4  5142148452  5509006296254           TN    38118.0    3.62
2010-01-01       5  5142190439  5509006296254           TN    38118.0    3.62

            Fraud
Date
2010-01-01      0
2010-01-01      0
2010-01-01      0
2010-01-01      0
2010-01-01      0
```

In [147]:
```
def recency(df, groupby, unique=None):
    '''
    :param df: DataFrame with Date as index, sorted by index
    :param groupby: list
    :param unique_id: stirng
    :return: DataFrame
    '''
    df_temp = df.copy()
    df_temp.sort_index(inplace = True)
    time_name = df_temp.index.name
    df_temp.reset_index(inplace = True)

    df_temp = df_temp[[unique_id] + groupby + [time_name]]
    df_temp['order'] = df_temp.groupby(groupby).cumcount() + 1
    df_temp_right = df_temp.copy()
    df_temp_right['order'] = df_temp_right['order'] + 1
    df_comb = df_temp.merge(df_temp_right, on = groupby + ['order'])
    df_comb['_'.join(groupby) + '_last_time'] = df_comb[time_name + '_x'] - df_comb[
    df_comb.rename(columns = {unique_id + '_x': unique_id}, inplace = True)
    print('_'.join(groupby) + '_last_time' + ' Completed')
    return df_comb[[unique_id, '_'.join(groupby) + '_last_time']]
```

In [161]:
```
rec_cardnum = recency(df, ['Cardnum'], 'Recnum')
rec_merchant = recency(df, ['Merchnum'], 'Recnum')
rec_card_zip = recency(df, ['Cardnum','Merch zip'], 'Recnum')
```

```
Cardnum_last_time Completed
Merchnum_last_time Completed
Cardnum_Merch zip_last_time Completed
```

```
In [171]: rec_card_zip
```

Out[171]:

	Recnum	Cardnum_Merch zip_last_time
0	5	0
1	10	0
2	12	0
3	16	0
4	17	0
5	21	0
6	22	0
7	23	0
8	28	0
9	30	0
10	34	0
11	37	0
12	40	0
13	42	0
14	44	0
15	48	0
16	59	0
17	60	0
18	61	0
19	62	0
20	65	0
21	66	0
22	67	0
23	69	0
24	70	0
25	72	0
26	73	0
27	76	0
28	78	0
29	100	0
...	...	...
63985	96718	286
63986	96719	29
63987	96721	16
63988	96723	2
63989	96724	8
63990	96725	15
63991	96726	0
63992	96727	24
63993	96728	4
63994	96729	0
63995	96730	331
63996	96731	43
63997	96733	0
63998	96735	139

```
63999   96736                          0
64000   96737                          1
64001   96738                        327
64002   96739                          8
64003   96740                         55
64004   96742                         46
64005   96743                          9
64006   96744                        149
64007   96745                          0
64008   96746                          2
64009   96747                        324
64010   96748                          0
64011   96749                         37
64012   96750                         11
64013   96752                         26
64014   96753                          2

[64015 rows x 2 columns]
```

```
In [170]: rec_cardnum.shape, rec_merchant.shape, rec_card_zip.shape

Out[170]: ((94754, 2), (83307, 2), (64015, 2))

In [164]: rec_cardnum['Cardnum_last_time'] = rec_cardnum['Cardnum_last_time'].apply(lambda a :
          rec_merchant['Merchnum_last_time'] = rec_merchant['Merchnum_last_time'].apply(lambda
          rec_card_zip['Cardnum_Merch zip_last_time'] = rec_card_zip['Cardnum_Merch zip_last_t

In [172]: Recency = rec_cardnum.merge(rec_merchant,on='Recnum',how='left').merge(rec_card_zip,o

In [174]: Recency.sort_values('Recnum',inplace=True)

In [175]: Recency.head()

Out[175]:    Recnum  Cardnum_last_time  Merchnum_last_time  Cardnum_Merch zip_last_time
          0       5                  0                 0.0                          0.0
          1      10                  0                 0.0                          0.0
          2      12                  0                 0.0                          0.0
          3      16                  0                 0.0                          0.0
          4      17                  0                 0.0                          0.0

In [192]: Variables = Amount.merge(Frequency, on='Recnum',how='left').merge(Recency, on='Recnum

In [193]: Variables.head()

Out[193]:         Date  Recnum     Cardnum       Merchnum Merch state  Merch zip  \
          0 2010-01-01       1  5142190439  5509006296254          TN    38118.0
          1 2010-01-01       2  5142183973    61003026333          MA     1803.0
          2 2010-01-01       3  5142131721  4503082993600          MD    20706.0
          3 2010-01-01       4  5142148452  5509006296254          TN    38118.0
```

```
4 2010-01-01       5  5142190439  5509006296254          TN    38118.0

   Amount  Fraud  order_cardnum  order_merchnum  ...  Cardnum_14_Count  \
0    3.62      0              1               1  ...               1.0
1   31.42      0              1               1  ...               1.0
2  178.49      0              1               1  ...               1.0
3    3.62      0              1               2  ...               1.0
4    3.62      0              2               3  ...               2.0

   Merchnum_1_Count  Merchnum_7_Count  Merchnum_14_Count  \
0               1.0               1.0                1.0
1               1.0               1.0                1.0
2               1.0               1.0                1.0
3               2.0               2.0                2.0
4               3.0               3.0                3.0

   Cardnum_Merch zip_1_Count  Cardnum_Merch zip_7_Count  \
0                        1.0                        1.0
1                        1.0                        1.0
2                        1.0                        1.0
3                        1.0                        1.0
4                        2.0                        2.0

   Cardnum_Merch zip_14_Count  Cardnum_last_time  Merchnum_last_time  \
0                         1.0                NaN                 NaN
1                         1.0                NaN                 NaN
2                         1.0                NaN                 NaN
3                         1.0                NaN                 NaN
4                         2.0                0.0                 0.0

   Cardnum_Merch zip_last_time
0                          NaN
1                          NaN
2                          NaN
3                          NaN
4                          0.0

[5 rows x 50 columns]
```

In [195]:
```
Variables.drop(columns=['Date','Cardnum','Merchnum','Merch state','Merch zip','Amoun
Variables.fillna(-1,inplace=True)
```

In [208]:
```
Variables.shape
```

Out[208]:
```
(96397, 41)
```

5 Feature Selection

```
In [209]: # First ten months is training and testing set, last two months is out-of-time set
          train_test = Variables.iloc[:83970,]
          oot = Variables.iloc[83970:,]
```

```
In [210]: train_test.shape, oot.shape
```

```
Out[210]: ((83970, 41), (12427, 41))
```

```
In [211]: train_test.head()
```

```
Out[211]:    Recnum  Fraud  Amount_avg_card_1  Amount_avg_card_7  Amount_avg_card_14  \
          0       1      0               3.62               3.62                3.62
          1       2      0              31.42              31.42               31.42
          2       3      0             178.49             178.49              178.49
          3       4      0               3.62               3.62                3.62
          4       5      0               3.62               3.62                3.62

             Amount_max_card_1  Amount_max_card_7  Amount_max_card_14  \
          0               3.62               3.62                3.62
          1              31.42              31.42               31.42
          2             178.49             178.49              178.49
          3               3.62               3.62                3.62
          4               3.62               3.62                3.62

             Amount_sum_card_1  Amount_sum_card_7  ...  Cardnum_14_Count  \
          0               3.62               3.62  ...               1.0
          1              31.42              31.42  ...               1.0
          2             178.49             178.49  ...               1.0
          3               3.62               3.62  ...               1.0
          4               7.24               7.24  ...               2.0

             Merchnum_1_Count  Merchnum_7_Count  Merchnum_14_Count  \
          0               1.0               1.0                1.0
          1               1.0               1.0                1.0
          2               1.0               1.0                1.0
          3               2.0               2.0                2.0
          4               3.0               3.0                3.0

             Cardnum_Merch zip_1_Count  Cardnum_Merch zip_7_Count  \
          0                        1.0                        1.0
          1                        1.0                        1.0
          2                        1.0                        1.0
          3                        1.0                        1.0
          4                        2.0                        2.0

             Cardnum_Merch zip_14_Count  Cardnum_last_time  Merchnum_last_time  \
          0                         1.0               -1.0                -1.0
```

```
1                          1.0                -1.0                -1.0
2                          1.0                -1.0                -1.0
3                          1.0                -1.0                -1.0
4                          2.0                 0.0                 0.0

   Cardnum_Merch zip_last_time
0                         -1.0
1                         -1.0
2                         -1.0
3                         -1.0
4                          0.0

[5 rows x 41 columns]
```

5.1 KS score and Fraud Detection Rate Selection

```
In [216]: def KS_FDR_Selection(df):
              df['Random'] = np.random.ranf(len(df))
              nvars = df.shape[1]
              goods = df[df['Fraud']==0]
              bads = df[df['Fraud']==1]

              n_goods = goods.shape[0]
              n_bads = bads.shape[0]

              KS = pd.DataFrame(np.zeros((nvars,3)))
              i=0
              for column in df:
                  KS.loc[i,0] = column
                  i+=1

              KS.columns = ['field','ks','FDR']

              import scipy.stats as sps
              i = 0
              for column in df:
                  KS['ks'][i] = sps.ks_2samp(goods[column],bads[column])[0]
                  i+=1

              KS.sort_values('ks',ascending=False,inplace=True)


              topRows = int(round(len(df)*0.03))
              j=0
              for column in df:
                  desc = df.sort_values(column,ascending=False).head(topRows)
                  asce = df.sort_values(column,ascending=True).head(topRows)
                  FDR_desc = sum(desc.loc[:,'Fraud'])/n_bads
```

```
            FDR_asce = sum(asce.loc[:,'Fraud'])/n_bads
            FDRate = np.maximum(FDR_desc,FDR_asce)
            KS.loc[j,'FDR'] = FDRate
            j+=1

        KS.sort_values('ks',ascending=False,inplace=True)


        KS['ks_rank'] = KS['ks'].rank(ascending=True)
        KS['FDR_rank'] = KS['FDR'].rank(ascending=True)
        KS['average_rank'] = (KS['ks_rank'] + KS['FDR_rank'])/2
        KS.sort_values('average_rank',ascending=False,inplace=True)

        return KS
```

In [218]:
```
KS = KS_FDR_Selection(train_test)
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: 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: http://pandas.pydata.org/pandas-docs/stable/indexing.html

/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:21: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

In [219]:
```
KS.head()
```

Out[219]:
```
                     field        ks       FDR  ks_rank  FDR_rank  \
1                    Fraud  1.000000  1.000000     42.0      42.0
27    Amount_sum_card_zip_7  0.678647  0.635227     41.0      41.0
28   Amount_sum_card_zip_14  0.668920  0.628409     40.0      40.0
26    Amount_sum_card_zip_1  0.603443  0.550000     37.0      39.0
9         Amount_sum_card_7  0.598221  0.519318     35.0      37.0

    average_rank
1           42.0
27          41.0
28          40.0
26          38.0
9           36.0
```

In [225]:
```
num_to_keep = round(train_test.shape[1]/2)
cols_keep = list(KS['field'][1:num_to_keep])
cols_keep.insert(0,'Fraud')
cols_keep.insert(0,'Recnum')
train_test_new = train_test.filter(cols_keep, axis=1)
```

```
In [226]: train_test_new.shape
```

```
Out[226]: (83970, 22)
```

5.2 Stepwise Regression Selection

```
In [233]: from sklearn.linear_model import LogisticRegression
          from sklearn.feature_selection import RFECV
          from sklearn.feature_selection import RFE
```

```
In [236]: Y = train_test_new['Fraud']
          data = train_test_new.drop(columns=['Recnum','Fraud'])
```

```
In [237]: data.shape, Y.shape
```

```
Out[237]: ((83970, 20), (83970,))
```

```
In [238]: model = LogisticRegression()
          rfecv = RFECV(estimator=model, step=1, cv=3, verbose=3, n_jobs=-1, scoring='roc_auc')
          rfecv.fit(data, Y)
```

```
Fitting estimator with 20 features.


/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear 
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)


Fitting estimator with 19 features.


/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear 
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)


Fitting estimator with 18 features.


/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear 
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
```

```
Fitting estimator with 17 features.

/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear :
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De:
  FutureWarning)

Fitting estimator with 16 features.

/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear :
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De:
  FutureWarning)

Fitting estimator with 15 features.

/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear :
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De:
  FutureWarning)

Fitting estimator with 14 features.

/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear :
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De:
  FutureWarning)

Fitting estimator with 13 features.

/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear :
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De:
  FutureWarning)

Fitting estimator with 12 features.
```

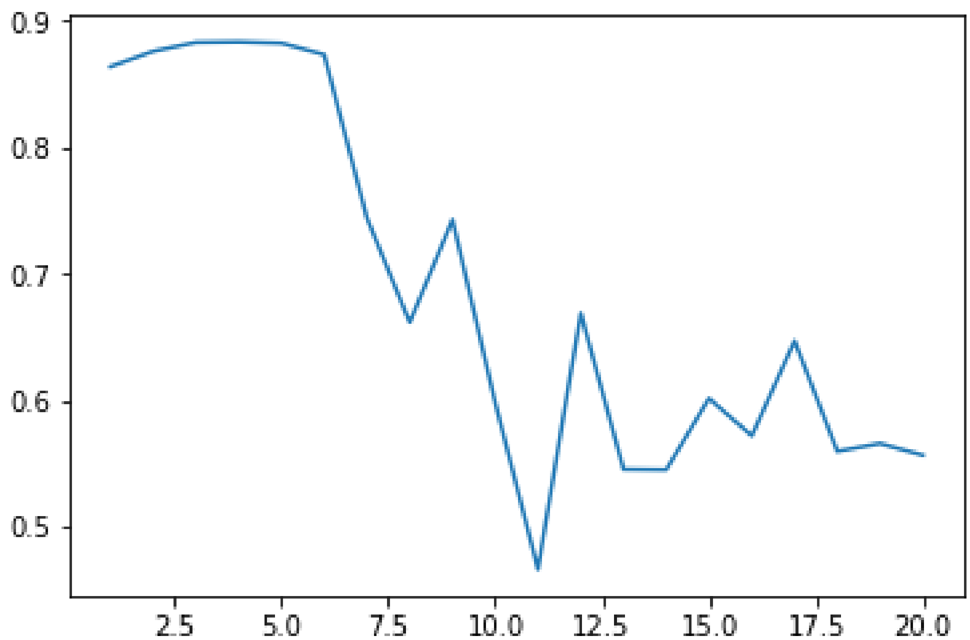
```
/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear f
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Def
  FutureWarning)

Fitting estimator with 11 features.

/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear f
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Def
  FutureWarning)

Fitting estimator with 10 features.
Fitting estimator with 9 features.

/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Def
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear f
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Def
  FutureWarning)

Fitting estimator with 8 features.
Fitting estimator with 7 features.

/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Def
  FutureWarning)

Fitting estimator with 6 features.

/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Def
  FutureWarning)

Fitting estimator with 5 features.

/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Def
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Def
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Def
  FutureWarning)
```

Out[238]: RFECV(cv=3,

```
   estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=T
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
   min_features_to_select=1, n_jobs=-1, scoring='roc_auc', step=1,
   verbose=3)
```

In [239]:

```
import matplotlib.pyplot as plt
%matplotlib inline
plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_);
```



In [240]:

```
var_selected = pd.DataFrame(sorted(zip(map(lambda x: round(x), rfecv.ranking_), data
pd.options.display.max_rows = 150
var_selected
```

Out[240]:

	ranking	variables
0	1	Amount_avg_card_1
1	1	Amount_avg_card_7
2	1	Amount_avg_card_zip_7
3	1	Amount_max_card_zip_7
4	2	Amount_max_card_1
5	3	Amount_max_card_zip_1
6	4	Amount_max_card_7
7	5	Amount_max_merchant_1
8	6	Amount_max_card_14

```
9          7  Amount_max_card_zip_14
10         8       Amount_sum_card_1
11         9   Amount_avg_card_zip_1
12        10   Amount_sum_card_zip_1
13        11  Amount_sum_card_zip_14
14        12   Amount_sum_merchant_1
15        13   Amount_avg_merchant_1
16        14  Amount_avg_card_zip_14
17        15       Amount_sum_card_7
18        16      Amount_sum_card_14
19        17   Amount_sum_card_zip_7
```

In [245]:
```python
var_use = list(var_selected.iloc[:15,1])
```

In [247]:
```python
df_res = Variables.filter(var_use,axis=1)
```

In [254]:
```python
#df_res.to_csv('expert_variables.csv')
```

6 Models

In [42]:
```python
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB
```

In [43]:
```python
data = pd.read_csv('expert_variables.csv',index_col=0)
```

In [44]:
```python
data['Fraud'] = df['Fraud']
```

In [45]:
```python
data.head()
```

Out[45]:
```
   Amount_avg_card_1  Amount_avg_card_7  Amount_avg_card_zip_7  \
0               3.62               3.62                   3.62
1              31.42              31.42                  31.42
2             178.49             178.49                 178.49
3               3.62               3.62                   3.62
4               3.62               3.62                   3.62

   Amount_max_card_zip_7  Amount_max_card_1  Amount_max_card_zip_1  \
0                   3.62               3.62                   3.62
1                  31.42              31.42                  31.42
2                 178.49             178.49                 178.49
3                   3.62               3.62                   3.62
4                   3.62               3.62                   3.62

   Amount_max_card_7  Amount_max_merchant_1  Amount_max_card_14  \
0               3.62                   3.62                3.62
```

```
1            31.42                  31.42               31.42
2           178.49                 178.49              178.49
3             3.62                   3.62                3.62
4             3.62                   3.62                3.62

   Amount_max_card_zip_14  Amount_sum_card_1  Amount_avg_card_zip_1  \
0                    3.62               3.62                   3.62
1                   31.42              31.42                  31.42
2                  178.49             178.49                 178.49
3                    3.62               3.62                   3.62
4                    3.62               7.24                   3.62

   Amount_sum_card_zip_1  Amount_sum_card_zip_14  Amount_sum_merchant_1  Fraud
0                   3.62                    3.62                   3.62      0
1                  31.42                   31.42                  31.42      0
2                 178.49                  178.49                 178.49      0
3                   3.62                    3.62                   7.24      0
4                   7.24                    7.24                  10.86      0
```

In [46]:
```
train_test = data.iloc[:83970,]
oot = data.iloc[83970:,]
```

In [76]:
```
train_test.shape, oot.shape
```

Out[76]:
```
((83970, 16), (12427, 16))
```

In [47]:
```
Y = train_test['Fraud']
X = train_test.drop(columns='Fraud')
```

In [48]:
```
X_train, X_test, y_train, y_test = train_test_split(X,Y,test_size=0.2,random_state=0)
```

In [49]:
```
X_oot = oot.drop(columns='Fraud')
y_oot = oot['Fraud']
```

In [50]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape, X_oot.shape, y_oot.shape
```

Out[50]:
```
((67176, 15), (16794, 15), (67176,), (16794,), (12427, 15), (12427,))
```

In [51]:
```
# Define performance measure metrics
def Fraud_test(model, X, Y):
    df = pd.DataFrame()
    y_pred = model.predict(X)
    y_proba = model.predict_proba(X)
    y_proba = y_proba[:,1]

    df['y_proba'] = y_proba
    df['y_pred'] = y_pred
    df['y_real'] = Y.values
```

```
        df.sort_values(by = 'y_proba',ascending=False,inplace=True)
        three_percent = df.iloc[:int(df.shape[0]*0.03),:]

        fdr = three_percent[three_percent['y_real']==1].shape[0]/sum(Y)

        return fdr
```

6.1 Logistic Regression

```
In [89]: d_log = {}
         for c in [0.1,0.5,1,2,10]:
             log = LogisticRegression(C=c)
             log.fit(X_train,y_train)

             train_fdr = Fraud_test(log,X_train,y_train)
             test_fdr = Fraud_test(log,X_test,y_test)
             oot_fdr = Fraud_test(log,X_oot,y_oot)

             d_log[c] = [train_fdr,test_fdr,oot_fdr]
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear
  "the number of iterations.", ConvergenceWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear
  "the number of iterations.", ConvergenceWarning)
```

```
In [90]: d_log
```

```
Out[90]: {0.1: [0.3988919667590028, 0.3670886075949367, 0.2737430167597765],
          0.5: [0.4002770083102493, 0.3670886075949367, 0.27932960893854747],
          1: [0.389196675900277, 0.36075949367088606, 0.2569832402234637],
          2: [0.3988919667590028, 0.37341772151898733, 0.30726256983240224],
          10: [0.40443213296398894, 0.37341772151898733, 0.27932960893854747]}
```

6.2 Random Forest

In [92]:
```
d_rfc = {}
for estimator in [20,50,100,200,500]:
    for depth in [2,5,10,15,20]:
        rfc = RandomForestClassifier(n_estimators=estimator, max_depth=depth,random_s
        rfc.fit(X_train,y_train)
        d_rfc[str(estimator)+'/'+str(depth)] = [Fraud_test(rfc,X_train,y_train),Fraud_
```

In [93]:
```
d_rfc
```

Out[93]:
```
{'20/2': [0.6565096952908587, 0.5949367088607594, 0.37988826815642457],
 '20/5': [0.7506925207756233, 0.6835443037974683, 0.4245810055865922],
 '20/10': [0.9002770083102493, 0.8481012658227848, 0.5977653631284916],
 '20/15': [0.9833795013850416, 0.8481012658227848, 0.5698324022346368],
 '20/20': [1.0, 0.8227848101265823, 0.4972067039106145],
 '50/2': [0.6745152354570637, 0.6075949367088608, 0.4692737430167598],
 '50/5': [0.7686980609418282, 0.7025316455696202, 0.48044692737430167],
 '50/10': [0.9141274238227147, 0.8544303797468354, 0.6089385474860335],
 '50/15': [0.997229916897507, 0.8734177215189873, 0.5754189944134078],
 '50/20': [1.0, 0.8607594936708861, 0.5810055865921788],
 '100/2': [0.6759002770083102, 0.6139240506329114, 0.4692737430167598],
 '100/5': [0.7686980609418282, 0.689873417721519, 0.5586592178770949],
 '100/10': [0.9044321329639889, 0.8607594936708861, 0.6089385474860335],
 '100/15': [1.0, 0.879746835443038, 0.5977653631284916],
 '100/20': [1.0, 0.8734177215189873, 0.5810055865921788],
 '200/2': [0.6759002770083102, 0.6329113924050633, 0.4692737430167598],
 '200/5': [0.778393351800554, 0.7025316455696202, 0.5083798882681564],
 '200/10': [0.9127423822714681, 0.8607594936708861, 0.6033519553072626],
 '200/15': [1.0, 0.8734177215189873, 0.5810055865921788],
 '200/20': [1.0, 0.8607594936708861, 0.5698324022346368],
 '500/2': [0.6772853185595568, 0.6329113924050633, 0.4692737430167598],
 '500/5': [0.7797783933518005, 0.7088607594936709, 0.5418994413407822],
 '500/10': [0.9224376731301939, 0.8607594936708861, 0.6089385474860335],
 '500/15': [1.0, 0.8924050632911392, 0.5865921787709497],
 '500/20': [1.0, 0.8670886075949367, 0.5810055865921788]}
```

6.3 Gradient Boosted Tree

In [95]:
```
d_gbc = {}

for estimator in [500,1000,1500]:
    gbc = GradientBoostingClassifier(learning_rate=0.1,n_estimators=estimator)
    gbc.fit(X_train,y_train)
    d_gbc[str(estimator)] = [Fraud_test(gbc,X_train,y_train),Fraud_test(gbc,X_test,y_
```

In [96]:
```
d_gbc
```

```
Out[96]: {'500': [0.9764542936288089, 0.8860759493670886, 0.3128491620111732],
          '1000': [0.9986149584487535, 0.9050632911392406, 0.4022346368715084],
          '1500': [1.0, 0.8987341772151899, 0.4245810055865922]}
```

6.4 Naive Bayes

```
In [97]: gnb = GaussianNB()
         gnb.fit(X_train,y_train)
```

```
Out[97]: GaussianNB(priors=None, var_smoothing=1e-09)
```

```
In [98]: (Fraud_test(gnb,X_train,y_train),Fraud_test(gnb,X_test,y_test),Fraud_test(gnb,X_oot,y_
```

```
Out[98]: (0.628808864265928, 0.5822784810126582, 0.41899441340782123)
```

7 Result

```
In [54]: rfc = RandomForestClassifier(n_estimators=500, max_depth=10,random_state=0)
         rfc.fit(X_train,y_train)
```

```
Out[54]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=10, max_features='auto', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=500, n_jobs=None,
                     oob_score=False, random_state=0, verbose=0, warm_start=False)
```

```
In [55]: def Table(fea,lab):

             prob=pd.DataFrame(rfc.predict_proba(fea))
             result=pd.concat([pd.DataFrame(lab).reset_index(),prob],axis=1)
             sort=result[['Fraud',1]].sort_values(by=1,ascending=False)
             sort=sort.reset_index().reset_index()

             groups=sort.groupby(pd.cut(sort.level_0,100))

             #initialize
             CumRecord=0
             CumGood=0
             CumBad=0
             TotalGoods=len(sort[sort["Fraud"]==0])
             TotalBads=len(sort[sort["Fraud"]==1])

             GoodsPer=[]
             BadsPer=[]
             CumRecords=[]
             CumGoods=[]
             CumBads=[]
```

```
        CumGoodsPer=[]
        CumBadsPer=[]
        KS=[]
        FPR=[]

        bins=np.linspace(1,20,20)
        Records=groups.count().Fraud
        Goods=Records-(groups.sum().Fraud)
        Bads=groups.sum().Fraud

        #Convert series into a list
        RecordsList=Records.tolist()[:20]
        GoodsList=Goods.tolist()[:20]
        BadsList=Bads.tolist()[:20]

        for i in range(20):
            Record=RecordsList[i]
            Good=GoodsList[i]
            Bad=BadsList[i]

            GoodPer=Good/Record
            BadPer=Bad/Record
            CumRecord+=Record
            CumGood+=Good
            CumBad+=Bad
            CumGoodPer=CumGood/TotalGoods
            CumBadPer=CumBad/TotalBads

            GoodsPer.append(GoodPer)
            BadsPer.append(BadPer)
            CumRecords.append(CumRecord)
            CumGoods.append(CumGood)
            CumBads.append(CumBad)
            CumGoodsPer.append(CumGoodPer)
            CumBadsPer.append(CumBadPer)
            KS.append(CumBadPer-CumGoodPer)
            FPR.append(CumGood/CumBad)

        table=pd.DataFrame([bins.tolist(),RecordsList,GoodsList,BadsList,GoodsPer,BadsPer
                            CumRecords,CumGoods,CumBads,
                            CumGoodsPer,CumBadsPer,KS,FPR]).transpose()
        table.columns=["Population Bin %","# Records","# Goods","# Bads",
                            "% Goods", "% Bads", "Total # Records",
                            "Cumulative Good","Cumulative Bad","% Good",
                            "% Bad (FDR)","KS","FPR"]
        return table
```

```
In [58]: train = Table(X_train,y_train)
```

```
test = Table(X_test,y_test)
oot = Table(X_oot,y_oot)
```

In [57]:
```
train.head()
```

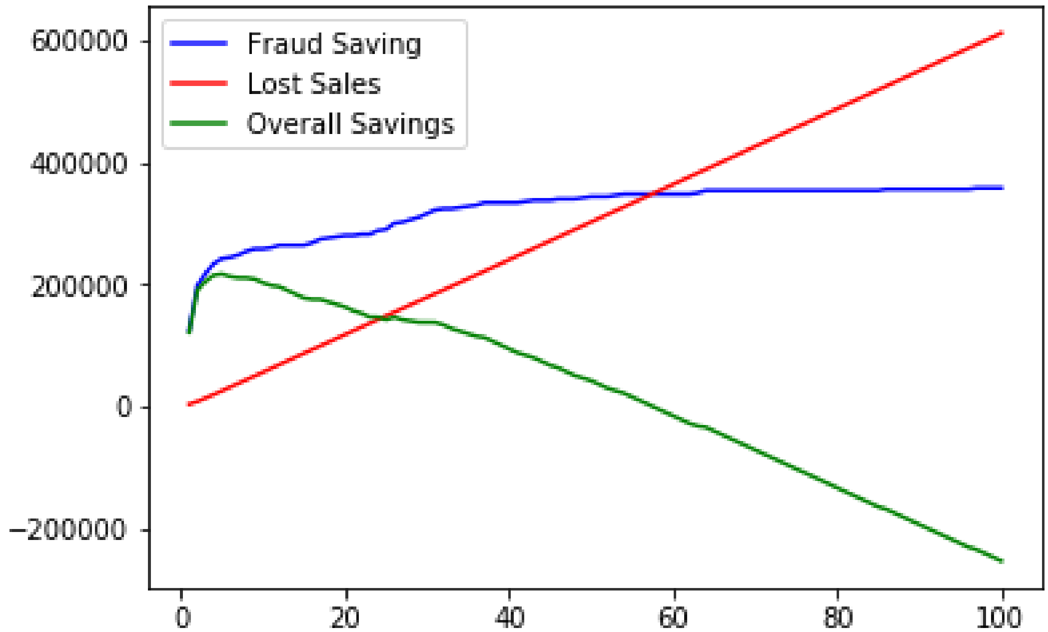
Out[57]:
```
   Population Bin %  # Records  # Goods  # Bads   % Goods    % Bads  \
0               1.0      672.0     83.0   589.0  0.123512  0.876488
1               2.0      672.0    623.0    49.0  0.927083  0.072917
2               3.0      672.0    644.0    28.0  0.958333  0.041667
3               4.0      672.0    658.0    14.0  0.979167  0.020833
4               5.0      671.0    658.0    13.0  0.980626  0.019374

   Total # Records  Cumulative Good  Cumulative Bad    % Good  % Bad (FDR)  \
0            672.0             83.0           589.0  0.001249     0.815789
1           1344.0            706.0           638.0  0.010624     0.883657
2           2016.0           1350.0           666.0  0.020315     0.922438
3           2688.0           2008.0           680.0  0.030216     0.941828
4           3359.0           2666.0           693.0  0.040118     0.959834

         KS       FPR
0  0.814540  0.140917
1  0.873033  1.106583
2  0.902123  2.027027
3  0.911612  2.952941
4  0.919716  3.847042
```

In [61]:
```
def FraudSaving(t=20,g=100):

    prob=pd.DataFrame(rfc.predict_proba(X_oot))
    result=pd.concat([pd.DataFrame(y_oot).reset_index(),prob],axis=1)
    sort=result[['Fraud',1]].sort_values(by=1,ascending=False)
    sort=sort.reset_index().reset_index()

    groups=sort.groupby(pd.cut(sort.level_0,g))

    bins=(np.linspace(1,g,100)/g)*100
    Records=groups.count().Fraud
    Goods=Records-(groups.sum().Fraud)
    Bads=groups.sum().Fraud

    #Convert series into a list
    binsList=bins.tolist()[:t]
    RecordsList=Records.tolist()[:t]
    GoodsList=Goods.tolist()[:t]
    BadsList=Bads.tolist()[:t]

    #declare list
    FraudSavingL=[]
```

```
    LostSalesL=[]
    OverallSavingL=[]

    #initialize
    FraudSaving=0
    LostSales=0
    OverallSaving=0

    for i in range(t):
        Record=RecordsList[i]
        Good=GoodsList[i]
        Bad=BadsList[i]

        FraudSaving+=2000*Bad
        LostSales+=50*Good
        OverallSaving+=2000*Bad-50*Good

        FraudSavingL.append(FraudSaving)
        LostSalesL.append(LostSales)
        OverallSavingL.append(OverallSaving)


    table=pd.DataFrame([binsList,RecordsList,GoodsList,BadsList,
                        FraudSavingL,LostSalesL,OverallSavingL]).transpose()
    table.columns=["Population Bin %","# Records","# Goods","# Bads",
                   "Fraud Saving","Lost Sales","Overall Savings"]
    return table
```

```
In [62]: FraudSavingT=FraudSaving(t=100)
```

```
In [64]: plt.plot('Population Bin %',"Fraud Saving",data=FraudSavingT,color='blue')
         plt.plot('Population Bin %',"Lost Sales",data=FraudSavingT,color='red')
         plt.plot('Population Bin %',"Overall Savings",data=FraudSavingT,color='green')
         plt.legend(['Fraud Saving','Lost Sales','Overall Savings'])
         plt.show()
```




```
In [67]: FraudSavingT[FraudSavingT['Overall Savings'] == max(FraudSavingT['Overall Savings'])]

Out[67]:    Population Bin %  # Records  # Goods  # Bads  Fraud Saving  Lost Sales  \
         4               5.0      124.0    120.0     4.0      242000.0     25050.0

            Overall Savings
         4         216950.0
```

Therefore, looking at 5% of total population would optimize the company's overall savings in this scenario.