Visualization

May 23, 2017

In [1]:
```
import numpy as np
import pandas as pd
import warnings # current version of seaborn generates a bunch of warnings

import seaborn as sns

import matplotlib.pyplot as plt
sns.set(style="white", color_codes=True)

train = pd.read_csv("/Users/jyothi/Desktop/santender/train.csv") # the trai
test = pd.read_csv("/Users/jyothi/Desktop/santender/test.csv") # the train
```

In [2]:
```
print(train.shape)
print(test.shape)
```

```
(76020, 371)
(75818, 370)
```

In [3]:
```
print(train.drop_duplicates(subset=train.columns[1:-1]).shape)
print(train.drop_duplicates(subset=train.columns[1:]).shape)

print(train.drop_duplicates(subset=train.columns[1:-1], keep=False).shape)
print(train.drop_duplicates(subset=train.columns[1:], keep=False).shape)
```

```
(71080, 371)
(71213, 371)
(70120, 371)
(70229, 371)
```

In [ ]:

In [4]:
```
duplicate_ids = set(train['ID']).difference(set(train.drop_duplicates(subse
```

In [5]:
```
duplicate_ids_2 = set(train['ID']).difference(set(train.drop_duplicates(sub
```

In [6]:
```
print(len(duplicate_ids))
print(len(duplicate_ids_2))
```

```
5900
5791
```

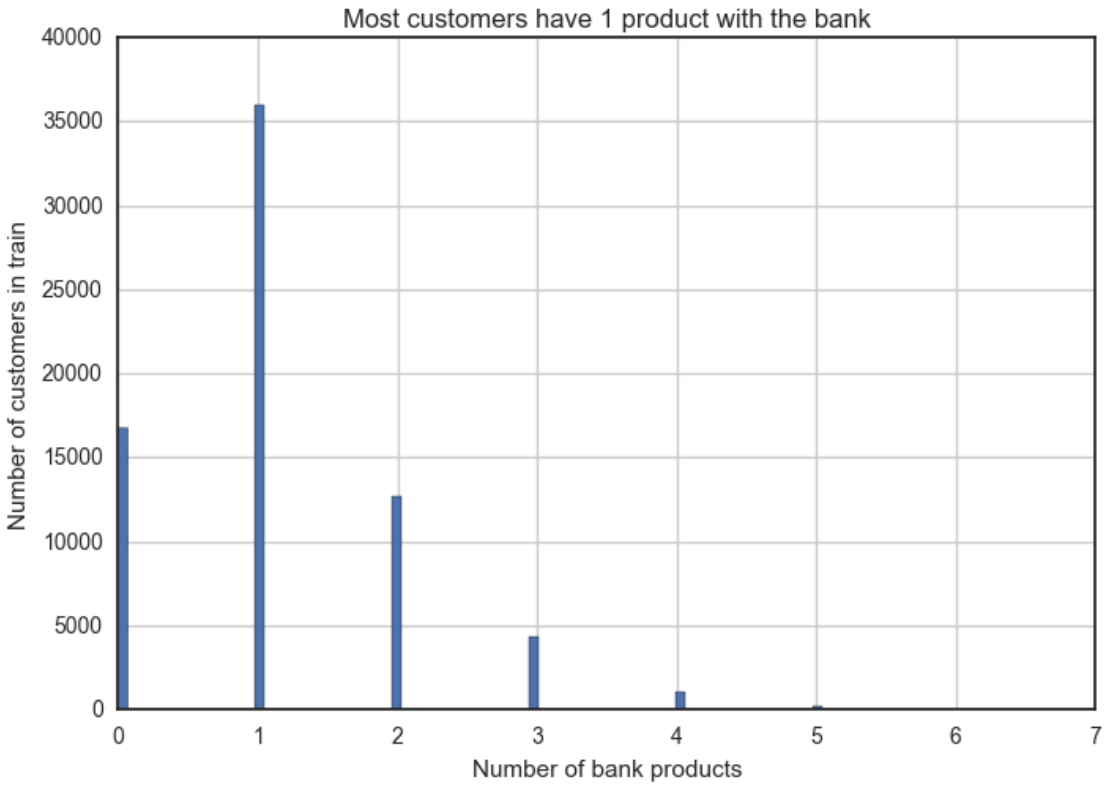
```
In [6]: to_drop = duplicate_ids.difference(duplicate_ids_2)

In [8]: len(to_drop)

Out[8]: 109

In [7]: train = train[~train['ID'].isin(to_drop)].drop_duplicates(subset=train.colu

In [8]: train.shape

Out[8]: (71104, 371)

In [9]: # happy customers have TARGET==0, unhappy custormers have TARGET==1
        # A little less then 4% are unhappy => unbalanced dataset
        df = pd.DataFrame(train.TARGET.value_counts())
        df['Percentage'] = 100*df['TARGET']/train.shape[0]
        df

Out[9]:    TARGET  Percentage
        0   68365   96.147896
        1    2739    3.852104

In [10]: # Top-10 most common values
         train.var3.value_counts()[:10]

Out[10]:  2         69260
          8           138
          9           110
          3           108
         -999999      107
          1           105
          13           98
          7            97
          4            86
          12           85
         Name: var3, dtype: int64
```

Looks like -999999 is missing value and var3 is categorical variable

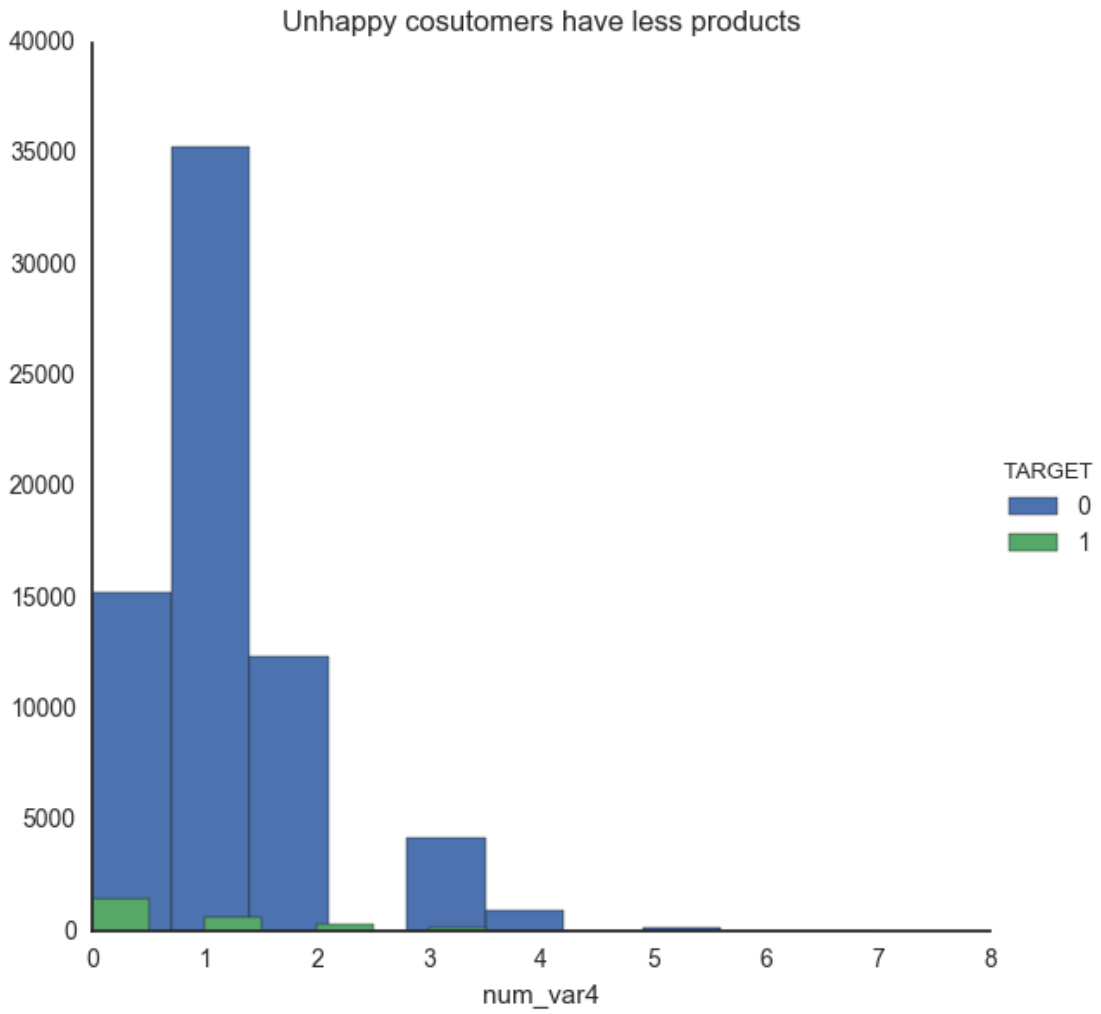
```
In [11]: features = train.columns[1:-1]
         train.insert(1, 'SumZeros', (train[features] == 0).astype(int).sum(axis=1)
         test.insert(1, 'SumZeros', (test[features] == 0).astype(int).sum(axis=1))
```

0.1 num_var4: number of bank products

```
In [12]: train.num_var4.hist(bins=100)
         plt.xlabel('Number of bank products')
         plt.ylabel('Number of customers in train')
         plt.title('Most customers have 1 product with the bank')
         plt.show()
```




```
In [13]: # Let's look at the density of the of happy/unhappy customers in function
         sns.FacetGrid(train, hue="TARGET", size=6) \
            .map(plt.hist, "num_var4") \
            .add_legend()
         plt.title('Unhappy cosutomers have less products')
         plt.show()
```



In [ ]:

In [14]:
```
train[train.TARGET==1].num_var4.hist(bins=6)
plt.title('Amount of unhappy customers in function of the number of produc
```

0.1.1 Var 38

In [ ]:

In [15]:
```
train.var38.describe()
```

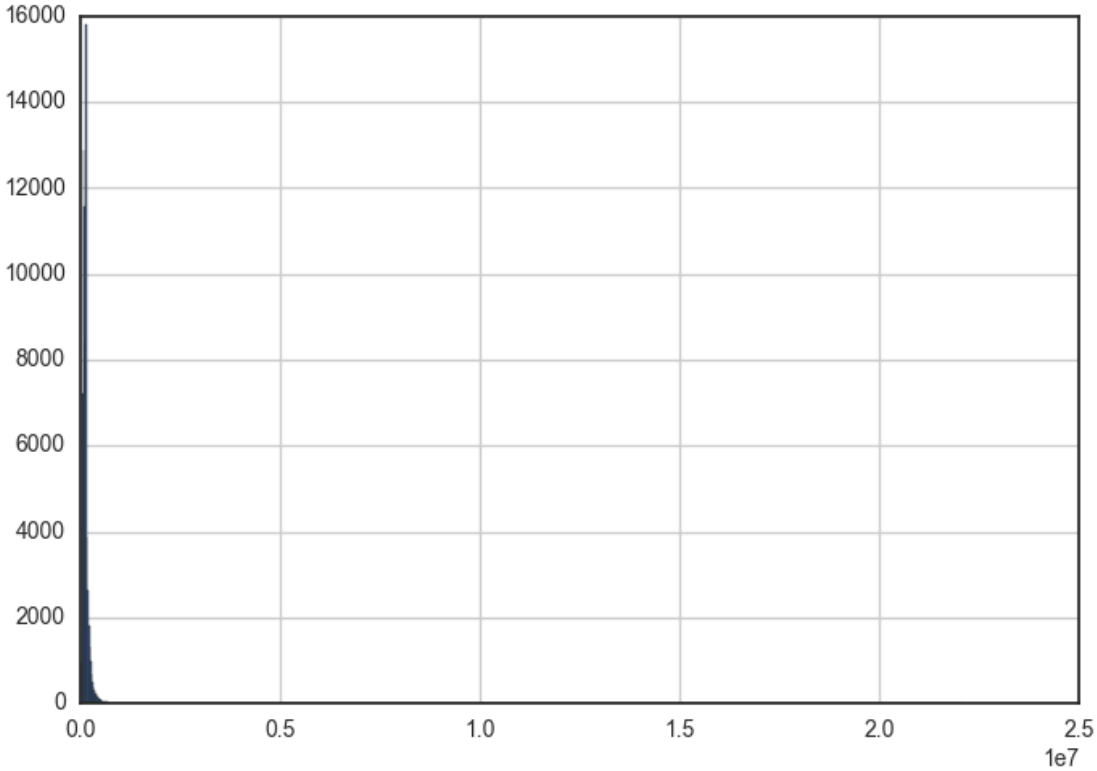
Out[15]:
```
count    7.110400e+04
mean     1.171335e+05
std      1.883718e+05
min      5.163750e+03
25%      6.582904e+04
```

```
50%       1.000394e+05
75%       1.228889e+05
max       2.203474e+07
Name: var38, dtype: float64
```

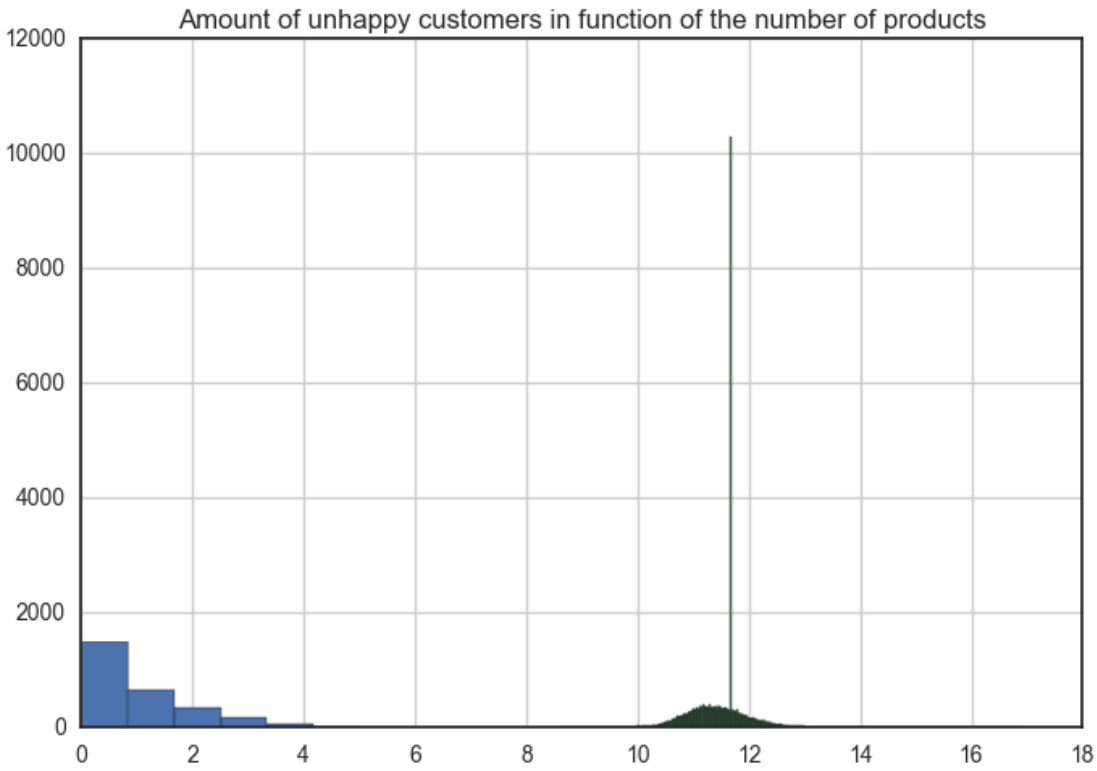
In [16]:
```
train.loc[train['TARGET']==1, 'var38'].describe()
```

Out[16]:
```
count     2.739000e+03
mean      9.794244e+04
std       1.112582e+05
min       1.113663e+04
25%       5.512641e+04
50%       8.071455e+04
75%       1.173110e+05
max       3.988595e+06
Name: var38, dtype: float64
```

In [23]:
```
# Histogram for var 38 is not normal distributed
train.var38.hist(bins=1000);

plt.show()
```



In [17]:
```
train.var38.map(np.log).hist(bins=1000);
plt.show()
```




```
In [25]: train.var38.value_counts()

Out[25]: 117310.979016    10004
         451931.220000       16
         463625.160000       12
         104563.800000       11
         288997.440000       10
         236690.340000        8
         67088.310000         7
         329603.970000        7
         128318.520000        7
         125722.440000        7
         104644.410000        7
         97639.560000         6
         100466.730000        6
         168733.620000        6
         105260.880000        6
         185385.690000        6
         235476.720000        5
         93037.680000         5
         163432.470000        5
         83174.280000         5
```

```
126065.040000        5
192920.760000        5
121603.020000        5
70813.800000         5
131353.470000        5
185784.720000        5
227397.720000        5
208961.790000        5
53324.460000         5
229351.650000        5
                   ...
215177.100000        1
215173.560000        1
84167.880000         1
477388.740000        1
215286.420000        1
84177.090000         1
84213.630000         1
84212.790000         1
215283.240000        1
84209.400000         1
83251.440000         1
84207.570000         1
111684.810000        1
84203.250000         1
84202.590000         1
215271.630000        1
84198.450000         1
84196.500000         1
84194.940000         1
83321.910000         1
117971.910000        1
84190.050000         1
84187.410000         1
84185.040000         1
84182.670000         1
84181.950000         1
215252.280000        1
84179.850000         1
84178.770000         1
131072.070000        1
Name: var38, dtype: int64
```

In [18]:
```
# the most common value is very close to the mean of the other values
train.var38[train['var38'] != 117310.979016494].mean()
```

Out[18]:
```
117104.42492602245
```

In [27]:
```
# what if we exclude the most common value
```

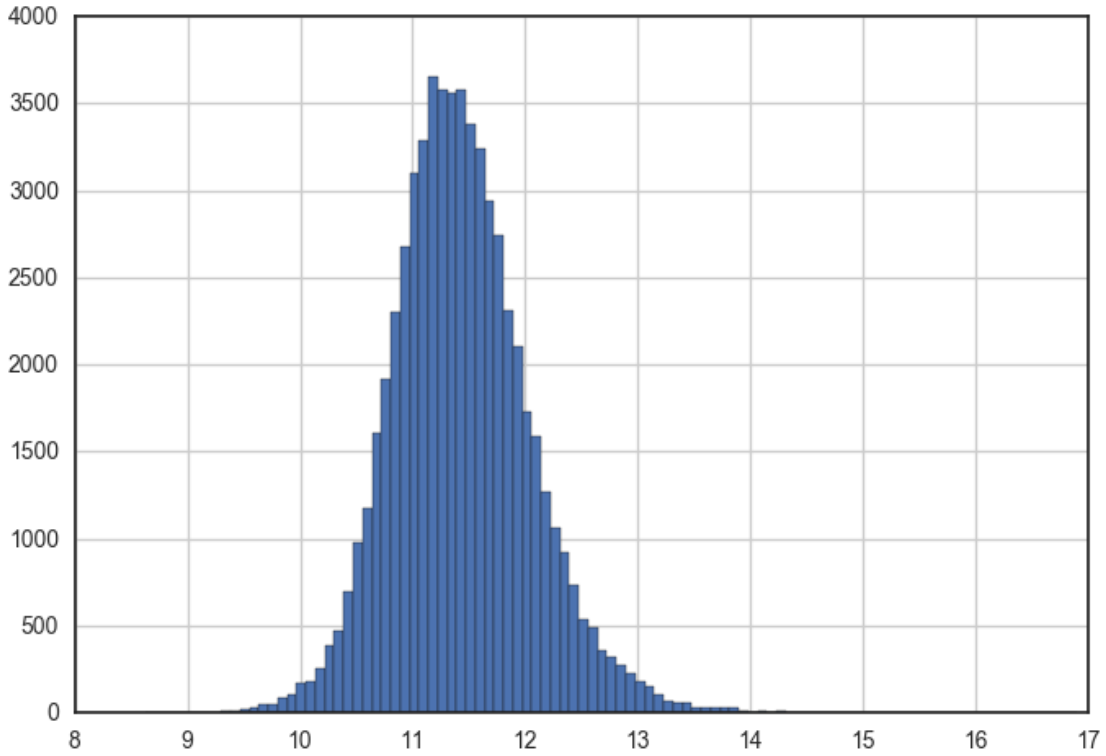
```
train.loc[~np.isclose(train.var38, 117310.979016), 'var38'].value_counts()
```

Out[27]:

451931.22	16
463625.16	12
104563.80	11
288997.44	10
236690.34	8
67088.31	7
104644.41	7
125722.44	7
128318.52	7
329603.97	7
168733.62	6
105260.88	6
185385.69	6
100466.73	6
97639.56	6
229351.65	5
208961.79	5
235476.72	5
276030.57	5
53324.46	5
33184.02	5
93037.68	5
121603.02	5
227397.72	5
131353.47	5
83174.28	5
63820.89	5
126065.04	5
71302.53	5
70813.80	5
..	
52353.12	1
84505.68	1
65688.57	1
84545.04	1
84601.05	1
84555.27	1
23749.89	1
84597.66	1
84592.86	1
84587.01	1
84585.09	1
84583.95	1
215653.56	1
84578.91	1
84577.77	1

```
84574.05      1
215645.88     1
84571.65      1
84570.66      1
84569.88      1
84567.84      1
84565.59      1
84563.91      1
84562.95      1
84560.67      1
84559.17      1
84558.96      1
84557.91      1
84556.50      1
131072.07     1
Name: var38, dtype: int64
```

In [19]:
```
# distribution
train.loc[~np.isclose(train.var38, 117310.979016), 'var38'].map(np.log).hi
plt.show()
```



In [20]:
```
# Above plot suggest we split up var38 into two variables
# var38mc == 1 when var38 has the most common value and 0 otherwise
```

```
# logvar38 is log transformed feature when var38mc is 0, zero otherwise
train['var38mc'] = np.isclose(train.var38, 117310.979016)
train['logvar38'] = train.loc[~train['var38mc'], 'var38'].map(np.log)
train.loc[train['var38mc'], 'logvar38'] = 0

test['var38mc'] = np.isclose(test.var38, 117310.979016)
test['logvar38'] = test.loc[~test['var38mc'], 'var38'].map(np.log)
test.loc[test['var38mc'], 'logvar38'] = 0
```

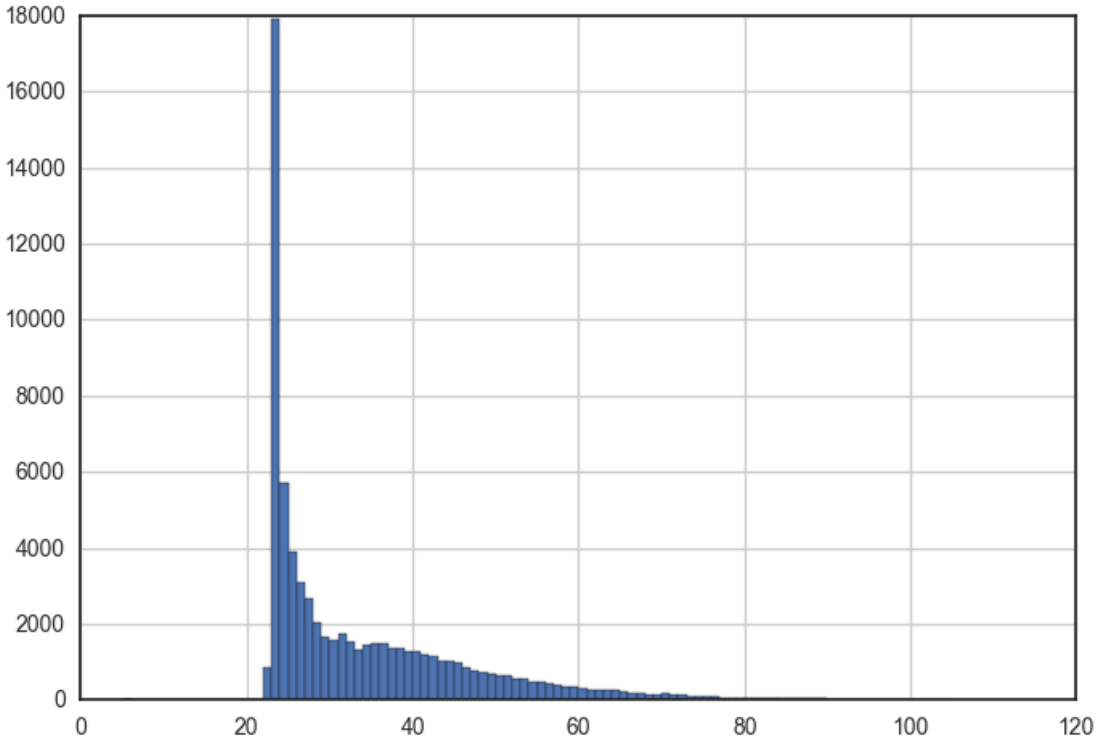
0.1.2 var 15

The most important feature for XGBoost is var15. According to a Kaggle form post var15 is the age of the customer. Let's explore var15

```
In [21]: train['var15'].describe()

Out[21]: count    71104.000000
         mean        33.553794
         std         13.102548
         min          5.000000
         25%         23.000000
         50%         28.000000
         75%         40.000000
         max        105.000000
         Name: var15, dtype: float64

In [62]: train['var15'].value_counts()

Out[62]: 23     17935
         24      5709
         25      3900
         26      3082
         27      2675
         28      2056
         31      1739
         29      1652
         30      1573
         32      1520
         35      1485
         36      1485
         34      1427
         37      1352
         38      1343
         33      1329
         39      1276
         40      1260
         41      1197
         42      1153
         43      1041
```

```
44      1011
45       978
46       867
22       850
47       754
48       745
49       680
50       644
51       640
        ...
15        26
90        25
6         21
21        21
93        20
14        19
11        19
9         18
10        17
92        16
19        16
18        14
17        13
94        12
16        12
13        11
12        10
20         9
8          9
96         7
95         6
7          6
99         6
100        6
102        4
97         3
104        2
98         1
101        1
105        1
Name: var15, dtype: int64
```

In [22]:
```
#Looks more normal, plot the histogram
train['var15'].hist(bins=100);
plt.show()
```



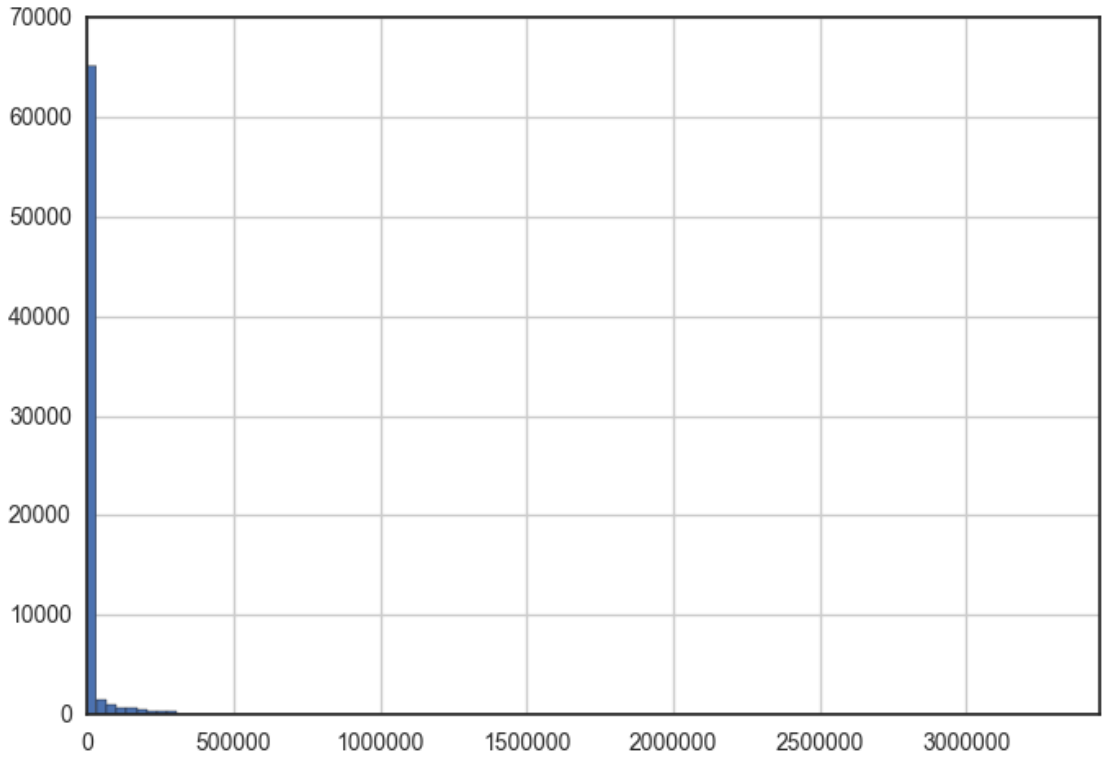
In [ ]:

In [55]: *# Let's look at the density of the age of happy/unhappy customers*

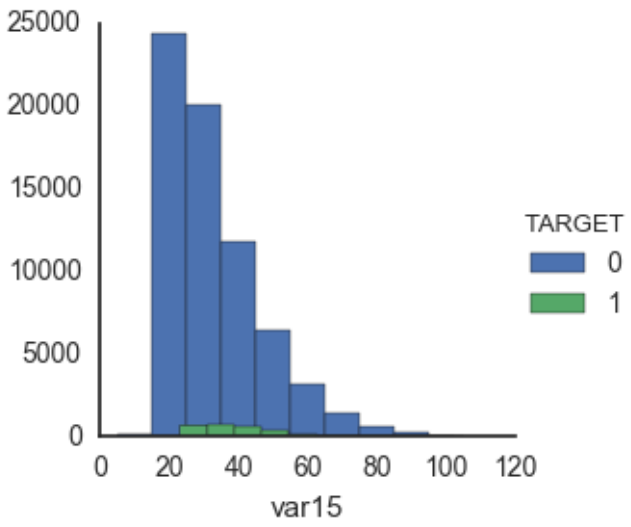
In [ ]:

In [23]:
```
# improve the plot by making the x axis logarithmic
train['log_saldo_var30'] = train.saldo_var30.map(np.log)
test['log_saldo_var30'] = test.saldo_var30.map(np.log)
```

In [24]:
```
train.saldo_var30.hist(bins=100)
plt.xlim(0, train.saldo_var30.max());
plt.show()
```

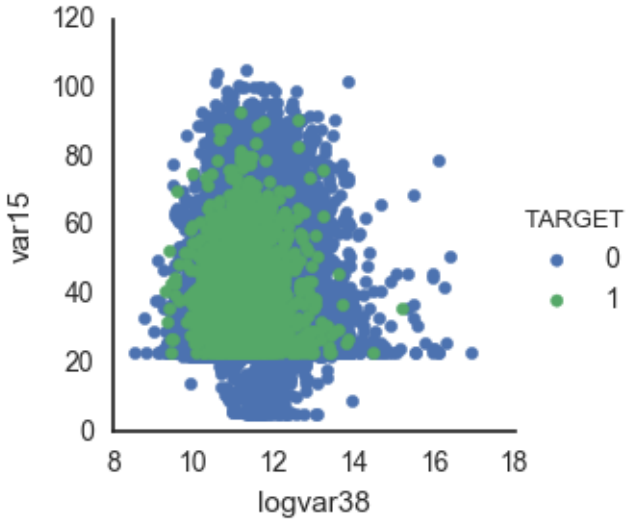



```
In [25]: # improve the plot by making the x axis logarithmic
         train['log_saldo_var30'] = train.saldo_var30.map(np.log)

         y= pd.DataFrame(train['log_saldo_var30'])
         y['TARGET'] = train["TARGET"]

In [26]:

In [ ]:

In [ ]:

In [52]: # Let's look at the density of the age of happy/unhappy customers for sal

         sns.FacetGrid(train, hue="TARGET") \
            .map(plt.hist,  "var15") \
            .add_legend()

Out[52]: <seaborn.axisgrid.FacetGrid at 0x113f65780>

In [53]: plt.show()
```



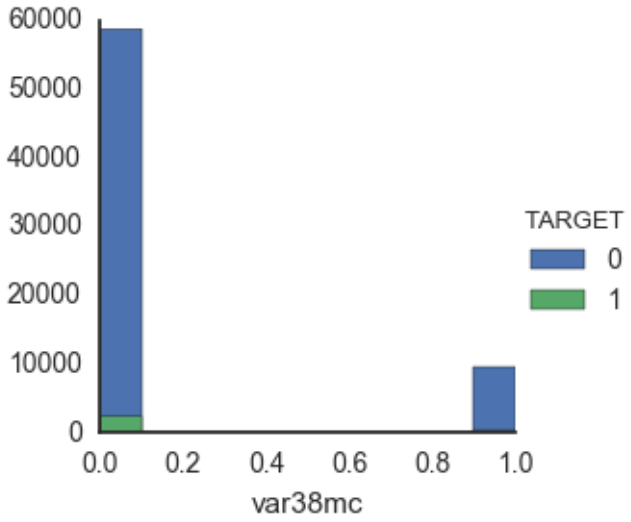

```
In [57]: sns.FacetGrid(train[~train.var38mc], hue="TARGET") \
             .map(plt.scatter, "logvar38", "var15") \
             .add_legend()
         plt.ylim([0,120]);
```

```
In [58]: plt.show()
```




```
In [59]: sns.FacetGrid(train, hue="TARGET") \
             .map(plt.hist,  "var38mc") \
             .add_legend()
```

```
Out[59]: <seaborn.axisgrid.FacetGrid at 0x1141beb38>

In [60]: plt.show()
```




```
In [61]: train.var38mc

Out[61]: 0         False
         1         False
         2         False
         3         False
         4          True
         5         False
         6         False
         7         False
         8         False
         9         False
         10        False
         11        False
         12        False
         13        False
         14        False
         15        False
         16         True
         17        False
         18        False
         19        False
         20        False
         21        False
         22         True
```

```
23       False
24        True
25       False
26       False
27       False
28       False
29       False
         ...
75988    False
75989    False
75990    False
75991     True
75992    False
75993    False
75994    False
75995    False
75997    False
75998    False
75999    False
76000     True
76001    False
76002    False
76003    False
76004    False
76005    False
76006     True
76007    False
76008    False
76009    False
76010    False
76011    False
76012     True
76013    False
76014    False
76015    False
76016    False
76017    False
76018    False
Name: var38mc, dtype: bool
```

In [ ]: