EDA_Springleaf_screencast

December 23, 2019

This is a notebook, used in the screencast video. Note, that the data files are not present here in Jupyter hub and you will not be able to run it. But you can always download the notebook to your local machine as well as the competition data and make it interactive.

In [1]:
```
import os
import numpy as np
import pandas as pd
from tqdm import tqdm_notebook
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

import seaborn
```

In [2]:
```
def autolabel(arrayA):
    ''' label each colored square with the corresponding data value.
    If value > 20, the text is in black, else in white.
    '''
    arrayA = np.array(arrayA)
    for i in range(arrayA.shape[0]):
        for j in range(arrayA.shape[1]):
                plt.text(j,i, "%.2f"%arrayA[i,j], ha='center', va='bottom',color='w')

def hist_it(feat):
    plt.figure(figsize=(16,4))
    feat[Y==0].hist(bins=range(int(feat.min()),int(feat.max()+2)),normed=True,alpha=0.8)
    feat[Y==1].hist(bins=range(int(feat.min()),int(feat.max()+2)),normed=True,alpha=0.5)
    plt.ylim((0,1))

def gt_matrix(feats,sz=16):
    a = []
    for i,c1 in enumerate(feats):
        b = []
        for j,c2 in enumerate(feats):
            mask = (~train[c1].isnull()) & (~train[c2].isnull())
```

```
                if i>=j:
                    b.append((train.loc[mask,c1].values>=train.loc[mask,c2].values).mean())
                else:
                    b.append((train.loc[mask,c1].values>train.loc[mask,c2].values).mean())

            a.append(b)

        plt.figure(figsize = (sz,sz))
        plt.imshow(a, interpolation = 'None')
        _ = plt.xticks(range(len(feats)),feats,rotation = 90)
        _ = plt.yticks(range(len(feats)),feats,rotation = 0)
        autolabel(a)
```

```
In [3]: def hist_it1(feat):
            plt.figure(figsize=(16,4))
            feat[Y==0].hist(bins=100,range=(feat.min(),feat.max()),normed=True,alpha=0.5)
            feat[Y==1].hist(bins=100,range=(feat.min(),feat.max()),normed=True,alpha=0.5)
            plt.ylim((0,1))
```

1 Read the data

```
In [4]: train = pd.read_csv('train.csv.zip')
        Y = train.target
```

```
In [5]: test = pd.read_csv('test.csv.zip')
        test_ID = test.ID
```

2 Data overview

Probably the first thing you check is the shapes of the train and test matrices and look inside them.

```
In [6]: print 'Train shape', train.shape
        print 'Test shape',  test.shape

Train shape (145231, 1934)
Test shape (145232, 1933)
```

```
In [10]: train.head()

Out[10]:    ID VAR_0001  VAR_0002  VAR_0003  VAR_0004 VAR_0005  VAR_0006  VAR_0007  \
         0   2        H       224         0      4300        C       0.0       0.0
         1   4        H         7        53      4448        B       1.0       0.0
         2   5        H       116         3      3464        C       0.0       0.0
         3   7        H       240       300      3200        C       0.0       0.0
         4   8        R        72       261      2000        N       0.0       0.0

           VAR_0008 VAR_0009   ...   VAR_1926 VAR_1927 VAR_1928   VAR_1929  VAR_1930  \
```

```
0     False     False   ...          98        98       998  999999998        998
1     False     False   ...          98        98       998  999999998        998
2     False     False   ...          98        98       998  999999998        998
3     False     False   ...          98        98       998  999999998        998
4     False     False   ...          98        98       998  999999998        998

   VAR_1931  VAR_1932  VAR_1933  VAR_1934  target
0       998      9998      9998      IAPS       0
1       998      9998      9998      IAPS       0
2       998      9998      9998      IAPS       0
3       998      9998      9998       RCC       0
4       998      9998      9998    BRANCH       1

[5 rows x 1934 columns]
```

```
In [11]: test.head()
```

```
Out[11]:    ID VAR_0001  VAR_0002  VAR_0003  VAR_0004 VAR_0005  VAR_0006  VAR_0007  \
         0   1        R       360        25      2251        B       2.0       2.0
         1   3        R        74       192      3274        C       2.0       3.0
         2   6        R        21        36      3500        C       1.0       1.0
         3   9        R         8         2      1500        B       0.0       0.0
         4  10        H        91        39     84500        C       8.0       3.0

          VAR_0008 VAR_0009    ...     VAR_1925 VAR_1926 VAR_1927  VAR_1928   VAR_1929  \
         0    False     False    ...            0       98       98       998  999999998
         1    False     False    ...            0       98       98       998  999999998
         2    False     False    ...            0       98       98       998  999999998
         3    False     False    ...            0       98       98       998  999999998
         4    False     False    ...            0       98       98       998  999999998

            VAR_1930  VAR_1931  VAR_1932  VAR_1933  VAR_1934
         0       998       998      9998      9998      IAPS
         1       998       998      9998      9998      IAPS
         2       998       998      9998      9998      IAPS
         3       998       998      9998      9998      IAPS
         4       998       998      9998      9998      IAPS

         [5 rows x 1933 columns]
```

There are almost 2000 anonymized variables! It's clear, some of them are categorical, some look like numeric. Some numeric feateures are integer typed, so probably they are event conters or dates. And others are of float type, but from the first few rows they look like integer-typed too, since fractional part is zero, but pandas treats them as `float` since there are NaN values in that features.

From the first glance we see train has one more column `target` which we should not forget to drop before fitting a classifier. We also see `ID` column is shared between train and test, which sometimes can be succesfully used to improve the score.

It is also useful to know if there are any NaNs in the data. You should pay attention to columns with NaNs and the number of NaNs for each row can serve as a nice feature later.

```
In [13]: # Number of NaNs for each object
         train.isnull().sum(axis=1).head(15)

Out[13]: 0     25
         1     19
         2     24
         3     24
         4     24
         5     24
         6     24
         7     24
         8     16
         9     24
         10    22
         11    24
         12    17
         13    24
         14    24
         dtype: int64

In [14]: # Number of NaNs for each column
         train.isnull().sum(axis=0).head(15)

Out[14]: ID           0
         VAR_0001     0
         VAR_0002     0
         VAR_0003     0
         VAR_0004     0
         VAR_0005     0
         VAR_0006    56
         VAR_0007    56
         VAR_0008    56
         VAR_0009    56
         VAR_0010    56
         VAR_0011    56
         VAR_0012    56
         VAR_0013    56
         VAR_0014    56
         dtype: int64
```

Just by reviewing the head of the lists we immediately see the patterns, exactly 56 NaNs for a set of variables, and 24 NaNs for objects.

3 Dataset cleaning

3.0.1 Remove constant features

All 1932 columns are anonimized which makes us to deduce the meaning of the features ourselves. We will now try to clean the dataset.

It is usually convenient to concatenate train and test into one dataframe and do all feature engineering using it.

```
In [15]: traintest = pd.concat([train, test], axis = 0)
```

First we schould look for a constant features, such features do not provide any information and only make our dataset larger.

```
In [16]: # `dropna = False` makes nunique treat NaNs as a distinct value
         feats_counts = train.nunique(dropna = False)
```

```
In [17]: feats_counts.sort_values()[:10]
```

```
Out[17]: VAR_0213    1
         VAR_0207    1
         VAR_0840    1
         VAR_0847    1
         VAR_1428    1
         VAR_1165    2
         VAR_0438    2
         VAR_1164    2
         VAR_1163    2
         VAR_1162    2
         dtype: int64
```

We found 5 constant features. Let's remove them.

```
In [18]: constant_features = feats_counts.loc[feats_counts==1].index.tolist()
         print (constant_features)


         traintest.drop(constant_features,axis = 1,inplace=True)
```

```
['VAR_0207', 'VAR_0213', 'VAR_0840', 'VAR_0847', 'VAR_1428']
```

3.0.2 Remove duplicated features

Fill NaNs with something we can find later if needed.

```
In [19]: traintest.fillna('NaN', inplace=True)
```

Now let's encode each feature, as we discussed.

In [32]:
```
train_enc =  pd.DataFrame(index = train.index)

for col in tqdm_notebook(traintest.columns):
    train_enc[col] = train[col].factorize()[0]
```

We could also do something like this:

In [33]:
```
# train_enc[col] = train[col].map(train[col].value_counts())
```

The resulting data frame is very very large, so we cannot just transpose it and use .duplicated. That is why we will use a simple loop.

In [34]:
```
dup_cols = {}

for i, c1 in enumerate(tqdm_notebook(train_enc.columns)):
    for c2 in train_enc.columns[i + 1:]:
        if c2 not in dup_cols and np.all(train_enc[c1] == train_enc[c2]):
            dup_cols[c2] = c1
```

In [36]:
```
dup_cols
```

Out[36]:
```
{'VAR_0009': 'VAR_0008',
 'VAR_0010': 'VAR_0008',
 'VAR_0011': 'VAR_0008',
 'VAR_0012': 'VAR_0008',
 'VAR_0013': 'VAR_0006',
 'VAR_0018': 'VAR_0008',
 'VAR_0019': 'VAR_0008',
 'VAR_0020': 'VAR_0008',
 'VAR_0021': 'VAR_0008',
 'VAR_0022': 'VAR_0008',
 'VAR_0023': 'VAR_0008',
 'VAR_0024': 'VAR_0008',
 'VAR_0025': 'VAR_0008',
 'VAR_0026': 'VAR_0008',
 'VAR_0027': 'VAR_0008',
 'VAR_0028': 'VAR_0008',
 'VAR_0029': 'VAR_0008',
 'VAR_0030': 'VAR_0008',
 'VAR_0031': 'VAR_0008',
 'VAR_0032': 'VAR_0008',
 'VAR_0038': 'VAR_0008',
 'VAR_0039': 'VAR_0008',
```

```
 'VAR_0040': 'VAR_0008',
 'VAR_0041': 'VAR_0008',
 'VAR_0042': 'VAR_0008',
 'VAR_0043': 'VAR_0008',
 'VAR_0044': 'VAR_0008',
 'VAR_0181': 'VAR_0180',
 'VAR_0182': 'VAR_0180',
 'VAR_0189': 'VAR_0188',
 'VAR_0190': 'VAR_0188',
 'VAR_0196': 'VAR_0008',
 'VAR_0197': 'VAR_0008',
 'VAR_0199': 'VAR_0008',
 'VAR_0201': 'VAR_0051',
 'VAR_0202': 'VAR_0008',
 'VAR_0203': 'VAR_0008',
 'VAR_0210': 'VAR_0208',
 'VAR_0211': 'VAR_0208',
 'VAR_0215': 'VAR_0008',
 'VAR_0216': 'VAR_0008',
 'VAR_0221': 'VAR_0008',
 'VAR_0222': 'VAR_0008',
 'VAR_0223': 'VAR_0008',
 'VAR_0228': 'VAR_0227',
 'VAR_0229': 'VAR_0008',
 'VAR_0238': 'VAR_0089',
 'VAR_0239': 'VAR_0008',
 'VAR_0357': 'VAR_0260',
 'VAR_0394': 'VAR_0246',
 'VAR_0438': 'VAR_0246',
 'VAR_0446': 'VAR_0246',
 'VAR_0512': 'VAR_0506',
 'VAR_0527': 'VAR_0246',
 'VAR_0528': 'VAR_0246',
 'VAR_0529': 'VAR_0526',
 'VAR_0530': 'VAR_0246',
 'VAR_0672': 'VAR_0670',
 'VAR_1036': 'VAR_0916'}
```

Don't forget to save them, as it takes long time to find these.

```
In [37]: import cPickle as pickle
         pickle.dump(dup_cols, open('dup_cols.p', 'w'), protocol=pickle.HIGHEST_PROTOCOL)
```

Drop from traintest.

```
In [38]: traintest.drop(dup_cols.keys(), axis = 1,inplace=True)
```

4 Determine types

Let's examine the number of unique values.

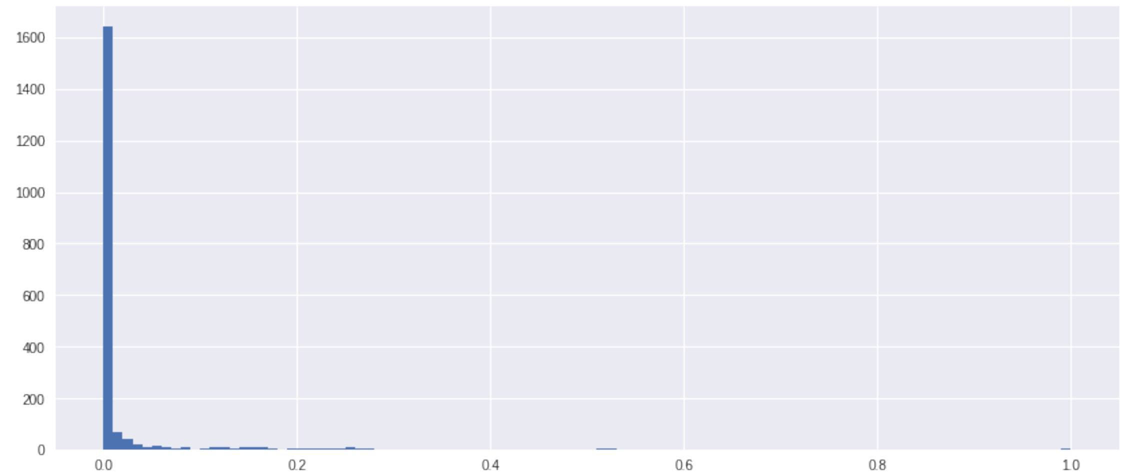
In [50]:
```
nunique = train.nunique(dropna=False)
nunique
```

Out[50]:
```
ID                145231
VAR_0001               3
VAR_0002             820
VAR_0003             588
VAR_0004            7935
VAR_0005               4
VAR_0006              38
VAR_0007              36
VAR_0008               2
VAR_0009               2
VAR_0010               2
VAR_0011               2
VAR_0012               2
VAR_0013              38
VAR_0014              38
VAR_0015              27
VAR_0016              30
VAR_0017              26
VAR_0018               2
VAR_0019               2
VAR_0020               2
VAR_0021               2
VAR_0022               2
VAR_0023               2
VAR_0024               2
VAR_0025               2
VAR_0026               2
VAR_0027               2
VAR_0028               2
VAR_0029               2
                     ...
VAR_1907              41
VAR_1908              37
VAR_1909              41
VAR_1910              37
VAR_1911             107
VAR_1912           16370
VAR_1913           25426
VAR_1914           14226
VAR_1915            1148
VAR_1916               8
```

```
VAR_1917               10
VAR_1918               86
VAR_1919              383
VAR_1920               22
VAR_1921               18
VAR_1922             6798
VAR_1923             2445
VAR_1924              573
VAR_1925               11
VAR_1926                6
VAR_1927               10
VAR_1928               30
VAR_1929              591
VAR_1930                8
VAR_1931               10
VAR_1932               74
VAR_1933              363
VAR_1934                5
target                  2
VAR_0004_mod50         50
Length: 1935, dtype: int64
```

and build a histogram of those values

```
In [44]: plt.figure(figsize=(14,6))
         _ = plt.hist(nunique.astype(float)/train.shape[0], bins=100)
```



Let's take a looks at the features with a huge number of unique values:

```
In [61]: mask = (nunique.astype(float)/train.shape[0] > 0.8)
         train.loc[:, mask]
```

Out[61]:

	ID	VAR_0212	VAR_0227
0	2	NaN	311951
1	4	9.20713e+10	2.76949e+06
2	5	2.65477e+10	654127
3	7	7.75753e+10	3.01509e+06
4	8	6.04238e+10	118678
5	14	7.73796e+10	1.76557e+06
6	16	9.70303e+10	80151
7	20	3.10981e+10	853641
8	21	7.82124e+10	1.40254e+06
9	22	1.94014e+10	2.2187e+06
10	23	3.71295e+10	2.77679e+06
11	24	3.01203e+10	434300
12	25	1.80185e+10	1.48914e+06
13	26	9.83358e+10	686666
14	28	9.33087e+10	1.4847e+06
15	30	2.01715e+10	883714
16	31	4.15638e+10	2.6707e+06
17	32	9.17617e+10	2.65485e+06
18	35	3.81344e+10	487721
19	36	NaN	2.54705e+06
20	37	3.27144e+10	1.74684e+06
21	38	1.82142e+10	2.5813e+06
22	40	7.70153e+10	2.59396e+06
23	42	4.69701e+10	1.02977e+06
24	43	9.84442e+10	1.45101e+06
25	46	NaN	2.37136e+06
26	50	9.25094e+10	665930
27	51	3.09094e+10	497686
28	52	6.06105e+10	1.95816e+06
29	54	3.78768e+10	1.62591e+06
...	...	...	...
145201	290409	8.80126e+10	1.83053e+06
145202	290412	4.6152e+10	1.02024e+06
145203	290414	9.33055e+10	1.88151e+06
145204	290415	4.63509e+10	669351
145205	290417	2.36028e+10	655797
145206	290424	3.73293e+10	1.45626e+06
145207	290426	2.38892e+10	1.9503e+06
145208	290427	6.38632e+10	596365
145209	290429	3.00602e+10	572119
145210	290431	4.33429e+10	16120
145211	290432	3.86543e+10	2.08375e+06
145212	290434	9.21391e+10	1.89779e+06
145213	290436	3.07472e+10	2.94532e+06
145214	290439	7.83326e+10	2.54726e+06
145215	290440	NaN	600318
145216	290441	2.78561e+10	602505

```
145217  290443  1.90952e+10  2.44184e+06
145218  290445  4.62035e+10  2.87349e+06
145219  290447          NaN  1.53493e+06
145220  290448  7.54282e+10  1.60102e+06
145221  290449  4.30768e+10  2.08415e+06
145222  290450  7.81325e+10  2.85367e+06
145223  290452  4.51061e+10  1.56506e+06
145224  290453  4.62223e+10  1.46815e+06
145225  290454  7.74507e+10  2.92811e+06
145226  290457  7.05088e+10  2.03657e+06
145227  290458  9.02492e+10  1.68013e+06
145228  290459  9.17224e+10  2.41922e+06
145229  290461  4.51033e+10  1.53960e+06
145230  290463  9.14114e+10   2.6609e+06

[145231 rows x 3 columns]
```

The values are not float, they are integer, so these features are likely to be even counts. Let's look at another pack of features.

```
In [64]: mask = (nunique.astype(float)/train.shape[0] < 0.8) & (nunique.astype(float)/train.shap
         train.loc[:25, mask]
```

```
Out[64]:      VAR_0541   VAR_0543  VAR_0899   VAR_1081   VAR_1082   VAR_1087  \
         0       49463     116783    112871      76857      76857     116783
         1      303472     346196    346375     341365     341365     346196
         2       94990     122601    121501     107267     107267     121501
         3       20593      59490     61890      45794      47568      59490
         4       10071      35708     34787      20475      23647      34708
         5       18877      28055     28455      21139      21139      28055
         6      321783     333565    886886     327744     327744     333565
         7        2961       5181     11084       4326       4326       5181
         8       20359      30114     33434      24969      27128      30114
         9         815       1300      7677       1197       1197       1300
         10       6088      15233     15483       7077       7077      15233
         11        432       1457      2000        621        621        757
         12        383        539       860        752       1158        539
         13      14359      47562     47562      17706      17706      47562
         14     145391     218067    214836     176627     176627     216307
         15      10040      12119     17263      10399      10399      12119
         16       4880       9607      9607       9165       9165       9607
         17      12900      35590     35781      26096      26096      35590
         18     104442     139605    150505     136419     142218     139605
         19      13898      25566     26685      20122      20122      25566
         20       3524      10033     10133       5838       5838      10033
         21     129873     204072    206946     183049     183049     204072
         22       3591      11400     17680       5565       5565      11400
         23  999999999  999999999    -99999  999999999  999999999  999999999
```

```
24       1270       4955      12201        2490        2490        4955
25       2015       2458       2458        2015        2015        2458

     VAR_1179   VAR_1180   VAR_1181
0       76857      76857      76857
1      341365     341365     176604
2      107267     107267      58714
3       45794      47568      47568
4       20475      23647      23647
5       21139      21139      20627
6      327744     327744     163944
7        4326       4326       4326
8       24969      27128      27128
9        1197       1197       1197
10       7077       7077       4033
11        621        621        621
12        752       1158       1158
13      17706      17706      17706
14     175273     175273      91019
15      10399      10399       5379
16       9165       9165       9165
17      26096      26096      19646
18     136419     142218     142218
19      20122      20122      20122
20       5838       5838       5838
21     183049     183049      96736
22       5565       5565       5565
23  999999999  999999999  999999999
24       2490       2490       2490
25       2015       2015       1008
```

These look like counts too. First thing to notice is the 23th line: 99999.., -99999 values look like NaNs so we should probably built a related feature. Second: the columns are sometimes placed next to each other, so the columns are probably grouped together and we can disentangle that.

Our conclusion: there are no floating point variables, there are some counts variables, which we will treat as numeric.

And finally, let's pick one variable (in this case 'VAR_0015') from the third group of features.

```
In [82]: train['VAR_0015'].value_counts()
```

```
Out[82]: 0.0     102382
         1.0      28045
         2.0       8981
         3.0       3199
         4.0       1274
         5.0        588
         6.0        275
         7.0        166
```

```
 8.0         97
-999.0       56
 9.0         51
 10.0        39
 11.0        18
 12.0        16
 13.0         9
 14.0         8
 15.0         8
 16.0         6
 22.0         3
 21.0         3
 19.0         1
 35.0         1
 17.0         1
 29.0         1
 18.0         1
 32.0         1
 23.0         1
Name: VAR_0015, dtype: int64
```

```
In [5]: cat_cols = list(train.select_dtypes(include=['object']).columns)
        num_cols = list(train.select_dtypes(exclude=['object']).columns)
```

5 Go through

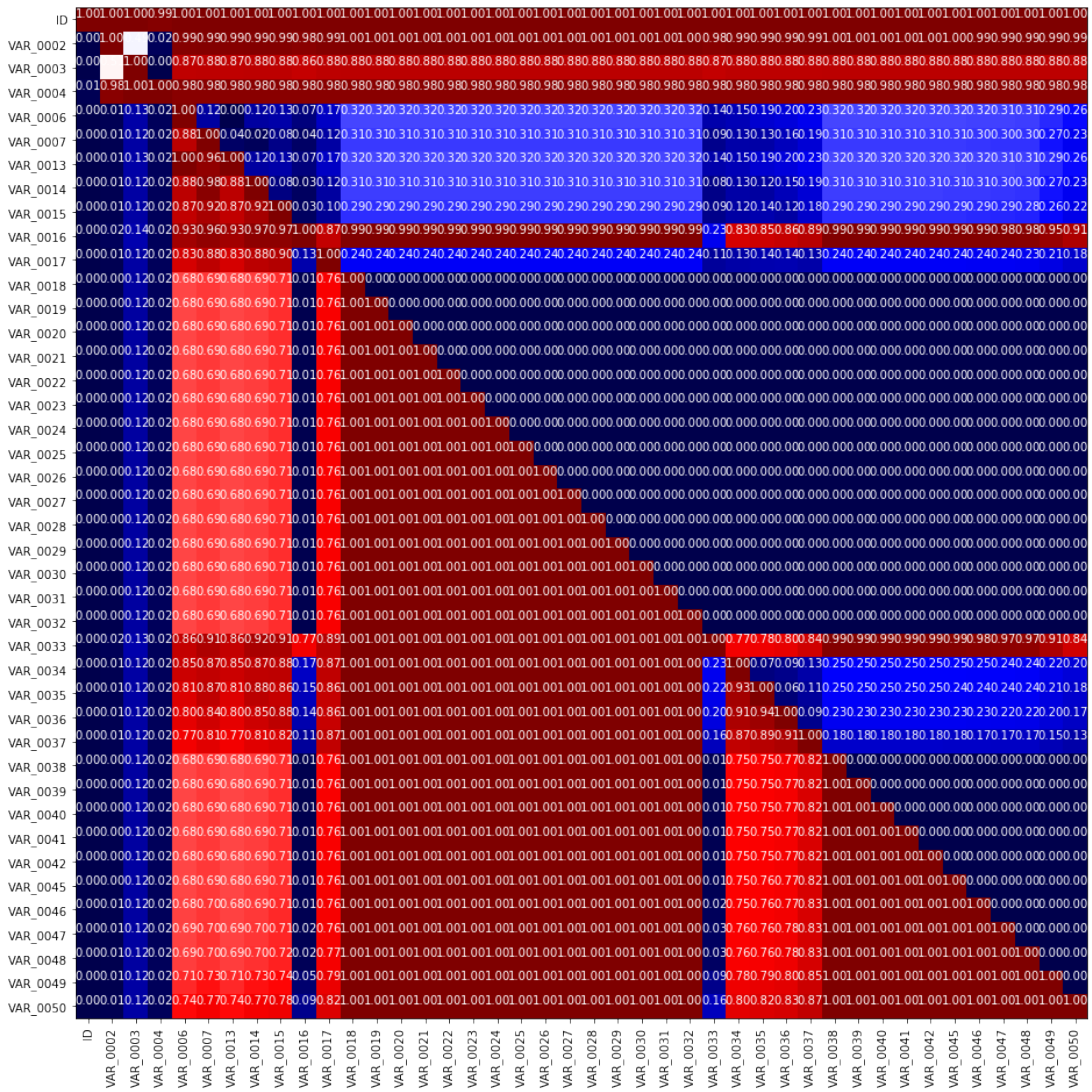
Let's replace NaNs with something first.

```
In [65]: train.replace('NaN', -999, inplace=True)
```

Let's calculate how many times one feature is greater than the other and create cross tabel out of it.

```
In [21]: # select first 42 numeric features
         feats = num_cols[:42]

         # build 'mean(feat1 > feat2)' plot
         gt_matrix(feats,16)
```



Indeed, we see interesting patterns here. There are blocks of geatures where one is strictly greater than the other. So we can hypothesize, that each column correspondes to cumulative counts, e.g. feature number one is counts in first month, second -- total count number in first two month and so on. So we immediately understand what features we should generate to make tree-based models more efficient: the differences between consecutive values.

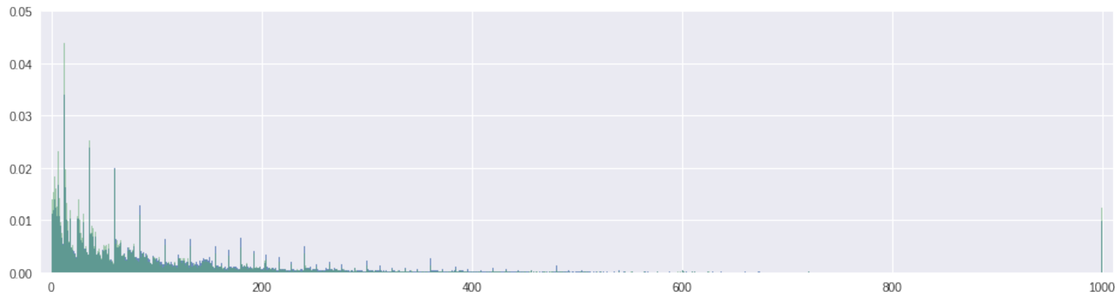
5.1 VAR_0002, VAR_0003

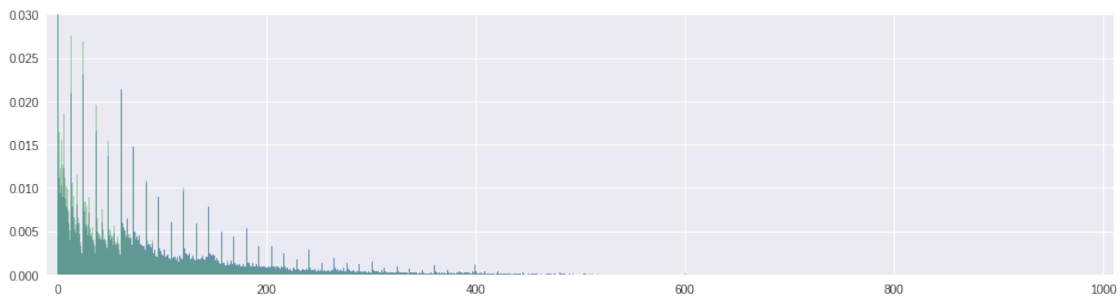
In [59]:
```
hist_it(train['VAR_0002'])
plt.ylim((0,0.05))
plt.xlim((-10,1010))

hist_it(train['VAR_0003'])
```

```
plt.ylim((0,0.03))
plt.xlim((-10,1010))
```

Out[59]: (-10, 1010)





In [39]:
```
train['VAR_0002'].value_counts()
```

Out[39]:
```
12      5264
24      4763
36      3499
60      2899
6       2657
13      2478
72      2243
48      2222
3       2171
4       1917
2       1835
84      1801
120     1786
1       1724
7       1671
26      1637
5       1624
```

```
14      1572
18      1555
8       1513
999     1510
25      1504
96      1445
30      1438
9       1306
144     1283
15      1221
27      1186
38      1146
37      1078
        ...
877        1
785        1
750        1
653        1
784        1
764        1
751        1
797        1
926        1
691        1
808        1
774        1
902        1
755        1
656        1
814        1
813        1
685        1
739        1
935        1
906        1
807        1
550        1
933        1
804        1
675        1
674        1
745        1
778        1
851        1
Name: VAR_0002, Length: 820, dtype: int64
```

In [38]:
```
train['VAR_0003'].value_counts()
```

Out[38]:
```
0       17436
```

24	3469
12	3271
60	3054
36	2498
72	2081
48	2048
6	1993
1	1797
3	1679
84	1553
2	1459
999	1428
4	1419
120	1411
7	1356
13	1297
18	1296
96	1253
14	1228
8	1216
5	1189
9	1182
30	1100
25	1100
144	1090
15	1047
61	1008
26	929
42	921
...	
560	1
552	1
550	1
804	1
543	1
668	1
794	1
537	1
531	1
664	1
632	1
709	1
597	1
965	1
852	1
648	1
596	1
466	1

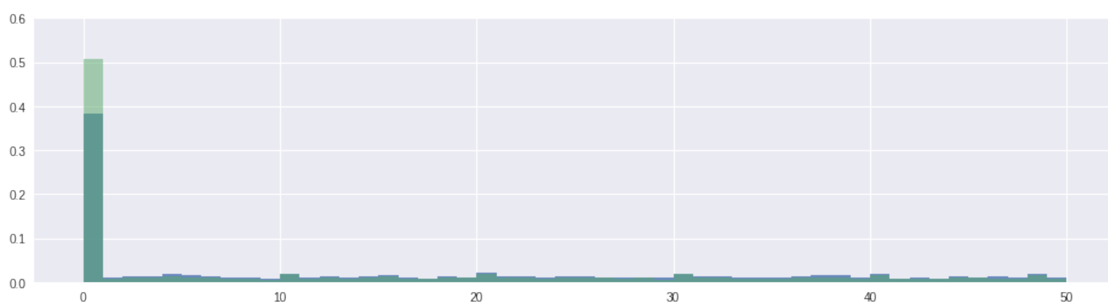
```
592         1
521         1
533         1
636         1
975         1
973         1
587         1
523         1
584         1
759         1
583         1
570         1
Name: VAR_0003, Length: 588, dtype: int64
```

We see there is something special about 12, 24 and so on, sowe can create another feature x mod 12.

5.2 VAR_0004

In [49]:
```
train['VAR_0004_mod50'] = train['VAR_0004'] % 50
hist_it(train['VAR_0004_mod50'])
plt.ylim((0,0.6))
```

Out[49]:
```
(0, 0.6)
```



6 Categorical features

Let's take a look at categorical features we have.

In [57]:
```
train.loc[:,cat_cols].head().T
```

Out[57]:
```
                                   0                    1  \
VAR_0001                           H                    H
VAR_0005                           C                    B
VAR_0008                       False                False
VAR_0009                       False                False
```

VAR_0010	False	False
VAR_0011	False	False
VAR_0012	False	False
VAR_0043	False	False
VAR_0044	[]	[]
VAR_0073	NaT	2012-09-04 00:00:00
VAR_0075	2011-11-08 00:00:00	2011-11-10 00:00:00
VAR_0156	NaT	NaT
VAR_0157	NaT	NaT
VAR_0158	NaT	NaT
VAR_0159	NaT	NaT
VAR_0166	NaT	NaT
VAR_0167	NaT	NaT
VAR_0168	NaT	NaT
VAR_0169	NaT	NaT
VAR_0176	NaT	NaT
VAR_0177	NaT	NaT
VAR_0178	NaT	NaT
VAR_0179	NaT	NaT
VAR_0196	False	False
VAR_0200	FT LAUDERDALE	SANTEE
VAR_0202	BatchInquiry	BatchInquiry
VAR_0204	2014-01-29 21:16:00	2014-02-01 00:11:00
VAR_0214	NaN	NaN
VAR_0216	DS	DS
VAR_0217	2011-11-08 02:00:00	2012-10-02 02:00:00
VAR_0222	C6	C6
VAR_0226	False	False
VAR_0229	False	False
VAR_0230	False	False
VAR_0232	True	False
VAR_0236	True	True
VAR_0237	FL	CA
VAR_0239	False	False
VAR_0274	FL	MI
VAR_0283	S	S
VAR_0305	S	S
VAR_0325	-1	H
VAR_0342	CF	EC
VAR_0352	O	O
VAR_0353	U	R
VAR_0354	O	R
VAR_0404	CHIEF EXECUTIVE OFFICER	-1
VAR_0466	-1	I
VAR_0467	-1	Discharged
VAR_0493	COMMUNITY ASSOCIATION MANAGER	-1
VAR_1934	IAPS	IAPS

	2	3	4
VAR_0001	H	H	R
VAR_0005	C	C	N
VAR_0008	False	False	False
VAR_0009	False	False	False
VAR_0010	False	False	False
VAR_0011	False	False	False
VAR_0012	False	False	False
VAR_0043	False	False	False
VAR_0044	[]	[]	[]
VAR_0073	NaT	NaT	NaT
VAR_0075	2011-12-13 00:00:00	2010-09-23 00:00:00	2011-10-15 00:00:00
VAR_0156	NaT	NaT	NaT
VAR_0157	NaT	NaT	NaT
VAR_0158	NaT	NaT	NaT
VAR_0159	NaT	NaT	NaT
VAR_0166	NaT	NaT	NaT
VAR_0167	NaT	NaT	NaT
VAR_0168	NaT	NaT	NaT
VAR_0169	NaT	NaT	NaT
VAR_0176	NaT	NaT	NaT
VAR_0177	NaT	NaT	NaT
VAR_0178	NaT	NaT	NaT
VAR_0179	NaT	NaT	NaT
VAR_0196	False	False	False
VAR_0200	REEDSVILLE	LIBERTY	FRANKFORT
VAR_0202	BatchInquiry	BatchInquiry	BatchInquiry
VAR_0204	2014-01-30 15:11:00	2014-02-01 00:07:00	2014-01-29 19:31:00
VAR_0214	NaN	NaN	NaN
VAR_0216	DS	DS	DS
VAR_0217	2011-12-13 02:00:00	2012-11-01 02:00:00	2011-10-15 02:00:00
VAR_0222	C6	C6	C6
VAR_0226	False	False	False
VAR_0229	False	False	False
VAR_0230	False	False	False
VAR_0232	True	False	True
VAR_0236	True	True	True
VAR_0237	WV	TX	IL
VAR_0239	False	False	False
VAR_0274	WV	TX	IL
VAR_0283	S	S	S
VAR_0305	P	P	P
VAR_0325	R	H	S
VAR_0342	UU	-1	-1
VAR_0352	R	R	R
VAR_0353	R	R	U
VAR_0354	-1	-1	O
VAR_0404	-1	-1	-1

VAR_0466	-1	-1	-1
VAR_0467	-1	-1	-1
VAR_0493	-1	-1	-1
VAR_1934	IAPS	RCC	BRANCH

VAR_0200, VAR_0237, VAR_0274 look like some georgraphical data thus one could generate geography related features, we will talk later in the course.

There are some features, that are hard to identify, but look, there a date columns VAR_0073 -- VAR_0179, VAR_0204, VAR_0217. It is useful to plot one date against another to find relationships.

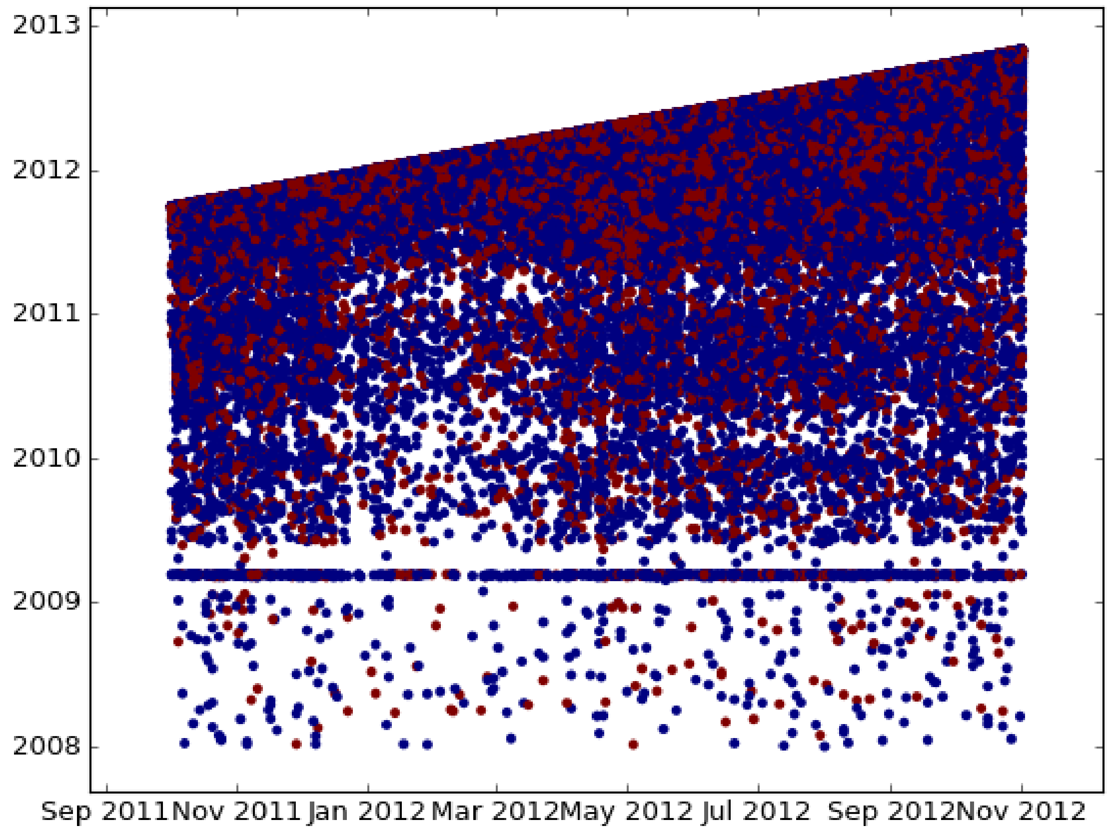
```
In [74]: date_cols = [u'VAR_0073','VAR_0075',
                      u'VAR_0156',u'VAR_0157',u'VAR_0158','VAR_0159',
                      u'VAR_0166', u'VAR_0167',u'VAR_0168',u'VAR_0169',
                      u'VAR_0176',u'VAR_0177',u'VAR_0178',u'VAR_0179',
                      u'VAR_0204',
                      u'VAR_0217']

         for c in date_cols:
             train[c] = pd.to_datetime(train[c],format = '%d%b%y:%H:%M:%S')
             test[c] = pd.to_datetime(test[c],  format = '%d%b%y:%H:%M:%S')
```

```
In [75]: c1 = 'VAR_0217'
         c2 = 'VAR_0073'

         # mask = (~test[c1].isnull()) & (~test[c2].isnull())
         # sc2(test.ix[mask,c1].values,test.ix[mask,c2].values,alpha=0.7,c = 'black')

         mask = (~train[c1].isnull()) & (~train[c2].isnull())
         sc2(train.loc[mask,c1].values,train.loc[mask,c2].values,c=train.loc[mask,'target'].valu
```



We see that one date is strictly greater than the other, so the difference between them can be a good feature. Also look at horizontal line there -- it also looks like NaN, so I would rather create a new binary feature which will serve as an idicator that our time feature is NaN.