Machine Learning Project - 2020

By:

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Assumptions and Principles

1. The preprocessing will place on the train set as well as the test set.
2. We assume and expect that the evaluated model with the best AUC value will also have the best accuracy.

Imports and configurations:

In [1]:

```
# basic imports
import pandas as pd
import numpy as np
from numpy import interp
import seaborn as sns
import matplotlib.pyplot as plt
from pandas.plotting import scatter_matrix
import time

# Scikit-Learn imports
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import confusion_matrix

# Scikit-Learn classifiers imports
from sklearn.model_selection import KFold
from sklearn.naive_bayes import GaussianNB                            # (Gaussian) Naive Bayes
from sklearn.neighbors import KNeighborsClassifier                    # KNN
from sklearn.linear_model import LogisticRegression                   # Logistic Regression
from sklearn.neural_network import MLPClassifier                      # Artificial Neural Network
from sklearn.ensemble import RandomForestClassifier                   # Random Forest
from sklearn.ensemble import AdaBoostClassifier                       # Adaptive Boosting
from sklearn import svm                                               # Support Vector Machines


# pandas configuration
pd.set_option('display.max_columns', 999)
```

Read the data:

In [2]:

```
df = pd.read_csv("train.csv")
df_test = pd.read_csv("test_without_target.csv")
```

Initiate time counter:

In [3]:

```
starting = time.time()
```

1. Data Exploration

At first we will try to figure out the general behaviour of the given dataset, by showing each feature's behaviour.

Test set

In [4]:

```
df_test.shape
```

Out[4]:

```
(7387, 26)
```

In [5]:

```
df_test.head()
```

Out[5]:

	Unnamed: 0	0	1	2	3	4	5	6	7	8	9	10
0	0	1.534361	12.002415	2.6	67.0	97.0	F	a11	1.600000	0.650000	3	0.212177
1	1	1.632953	14.821694	3.6	72.0	78.0	M	a18	1.942857	1.328571	4	0.126069
2	2	2.330694	21.399766	5.4	64.0	53.0	A	a20	1.864286	0.992857	8	0.263743
3	3	2.560304	21.744331	5.8	20.0	71.0	N	a18	2.457143	1.257143	11	0.182740
4	4	1.391859	18.158369	4.8	44.0	42.0	F	a3	1.285714	0.892857	9	0.241681

- We can see that there's an unnecessary column: "Unnamed: 0". Let's drop it.

In [6]:

```
df_test.drop(['Unnamed: 0'],axis=1,inplace = True) # select first column, drop it and save
df_test.head()
```

Out[6]:

	0	1	2	3	4	5	6	7	8	9	10	11	
0	1.534361	12.002415	2.6	67.0	97.0	F	a11	1.600000	0.650000	3	0.212177	1022.1	102
1	1.632953	14.821694	3.6	72.0	78.0	M	a18	1.942857	1.328571	4	0.126069	1013.2	101
2	2.330694	21.399766	5.4	64.0	53.0	A	a20	1.864286	0.992857	8	0.263743	1017.2	102
3	2.560304	21.744331	5.8	20.0	71.0	N	a18	2.457143	1.257143	11	0.182740	1007.0	101
4	1.391859	18.158369	4.8	44.0	42.0	F	a3	1.285714	0.892857	9	0.241681	1020.7	102

Function for nulls checking:

In [7]:

```
def nan_table(df):
    total_nans = {}
    for feature in df.columns:
        total_nans[feature] = df[feature].isna().sum()
    df_nans = pd.DataFrame([total_nans])
    return df_nans
```

In [8]:

```
table = nan_table(df_test)
table
```

Out[8]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
0	0	0	0	25	32	423	0	3	5	0	0	41	40	0	0	627	14	14	73	356	423	31	0

In [9]:

```
df_test.shape
```

Out[9]:

```
(7387, 25)
```

Train set

In [10]:

```
df.shape
```

Out[10]:

```
(22161, 26)
```

In [11]:

```
df.head()
```

Out[11]:

	0	1	2	3	4	5	6	7	8	9	10	11	
0	1.170981	5.672133	0.6	80.0	76.0	D	a21	1.107143	0.692857	5	0.702957	1024.1	10
1	2.595788	23.203289	6.4	43.0	64.0	N	a9	1.700000	0.614286	11	0.223911	1005.3	10
2	0.972794	7.127348	0.4	63.0	100.0	C	a4	1.242857	0.428571	6	0.180848	1020.8	10
3	1.891667	17.881507	4.2	65.0	71.0	K	a15	1.050000	0.671429	10	0.181289	1021.9	10
4	1.965881	13.936969	3.2	40.0	62.0	F	a1	1.950000	1.085714	3	0.237347	1005.3	10

In [12]:

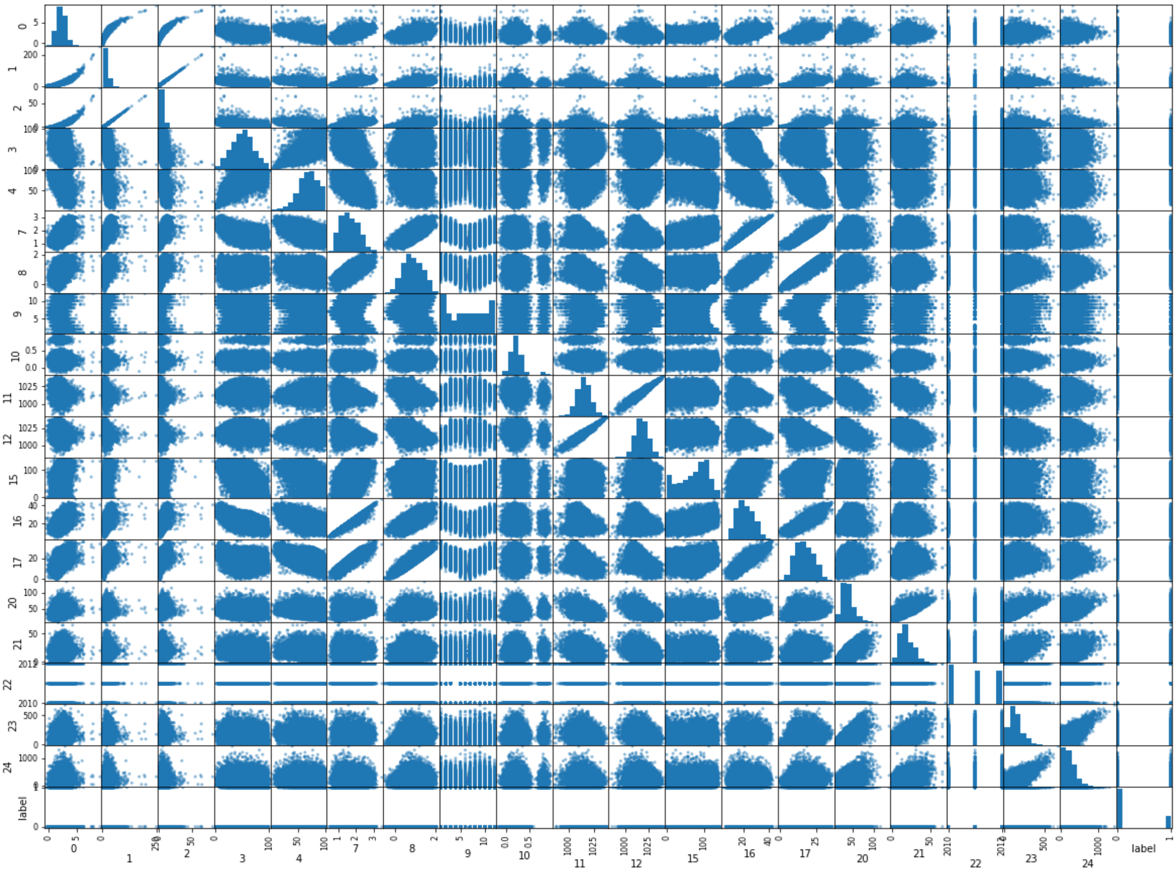
```
df.describe()
```

Out[12]:

	0	1	2	3	4	7	
count	22161.000000	22161.000000	22161.000000	22102.000000	22057.000000	22154.000000	22
mean	2.185958	19.797754	4.929620	51.547009	68.497982	1.648476	
std	0.815080	10.763614	3.572644	20.184353	18.231315	0.480275	
min	-0.490607	2.437300	0.000000	1.000000	3.000000	0.450000	
25%	1.622068	12.268371	2.400000	37.000000	57.000000	1.271429	
50%	2.167701	17.833216	4.200000	52.000000	69.000000	1.607143	
75%	2.720341	25.196446	6.600000	65.000000	82.000000	2.007143	
max	9.092011	248.877854	81.200000	100.000000	100.000000	3.435714	

In [13]:

```
scatter_matrix(df, figsize=(20, 15))
plt.show()
```



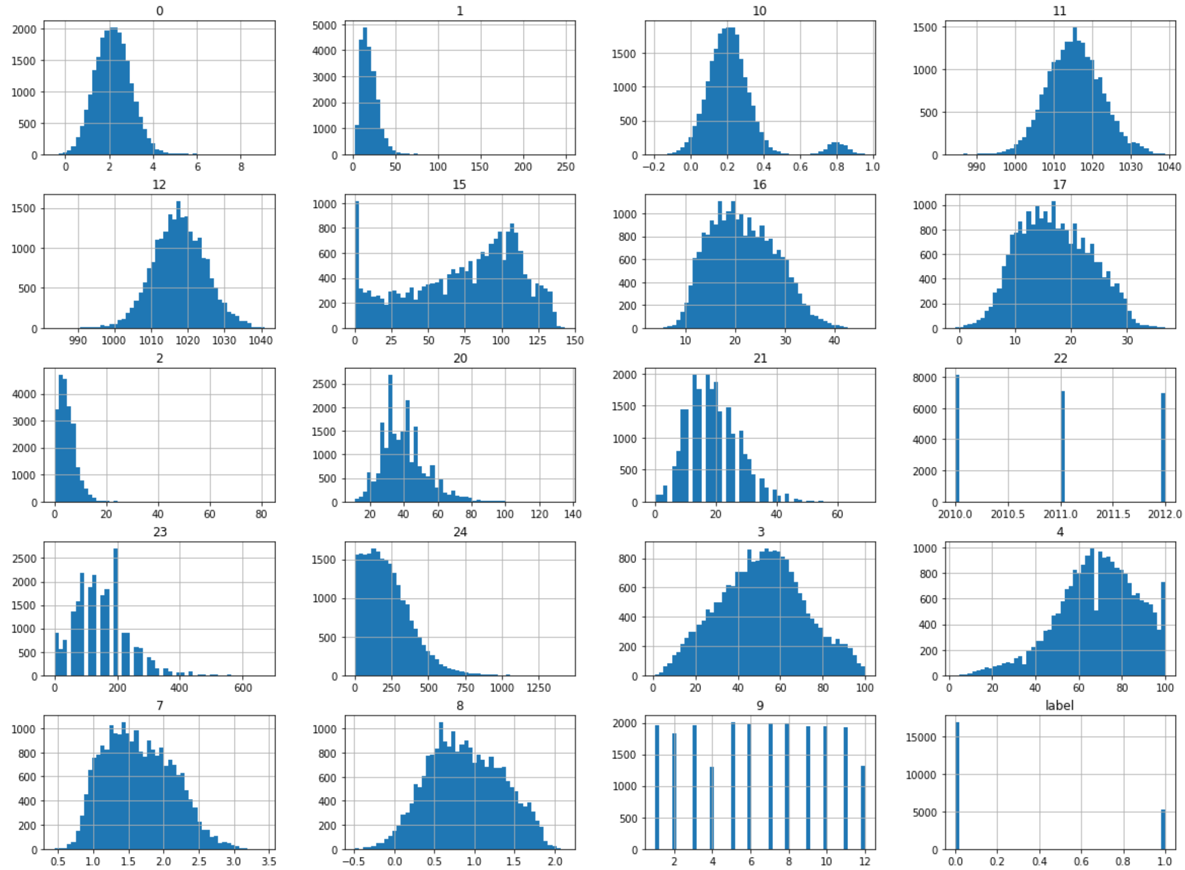
In [14]:

```
# Display info and count the types of features we have
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22161 entries, 0 to 22160
Data columns (total 26 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       22161 non-null  float64
 1   1       22161 non-null  float64
 2   2       22161 non-null  float64
 3   3       22102 non-null  float64
 4   4       22057 non-null  float64
 5   5       20812 non-null  object 
 6   6       22161 non-null  object 
 7   7       22154 non-null  float64
 8   8       22143 non-null  float64
 9   9       22161 non-null  int64  
 10  10      22161 non-null  float64
 11  11      22055 non-null  float64
 12  12      22048 non-null  float64
 13  13      22161 non-null  object 
 14  14      22161 non-null  object 
 15  15      20290 non-null  float64
 16  16      22133 non-null  float64
 17  17      22109 non-null  float64
 18  18      21951 non-null  object 
 19  19      21141 non-null  object 
 20  20      20816 non-null  float64
 21  21      22062 non-null  float64
 22  22      22161 non-null  int64  
 23  23      22061 non-null  float64
 24  24      22061 non-null  float64
 25  label   22161 non-null  int64  
dtypes: float64(17), int64(3), object(6)
memory usage: 4.4+ MB
```

In [15]:

```
df.hist(figsize=(20, 15), bins=50)
plt.show()
```



1.1. Individual Feature Exploration

Let's have a look at the features seperately, and examine each one of them.

As we can see from the above analysis:

- Feature '9' looks categorical. We will change it to be categorical instead of numeric.
- Feature '14' is numeric with "mm" at the end of each of the column's values (probably rainfall amount). Let's remove it.
- Feature '22' looks categorical. We will change it to be categorical instead of numeric.

We'll apply the changes to the train and the test set.

- **Train set update**

In [16]:

```
df['9'] = df['9'].astype('O')
df['14'] = df['14'].apply(lambda x: str(x).replace('mm','')).astype('float64') # remove 'mm
df['22'] = df['22'].astype('O')
df.head(3)
```

Out[16]:

	0	1	2	3	4	5	6	7	8	9	10	11	
0	1.170981	5.672133	0.6	80.0	76.0	D	a21	1.107143	0.692857	5	0.702957	1024.1	10:
1	2.595788	23.203289	6.4	43.0	64.0	N	a9	1.700000	0.614286	11	0.223911	1005.3	10(
2	0.972794	7.127348	0.4	63.0	100.0	C	a4	1.242857	0.428571	6	0.180848	1020.8	10:

- **Test set update**

In [17]:

```
df_test['9'] = df_test['9'].astype('O')
df_test['14'] = df_test['14'].apply(lambda x: str(x).replace('mm','')).astype('float64') #
df_test['22'] = df_test['22'].astype('O')
df_test.head(3)
```

Out[17]:

	0	1	2	3	4	5	6	7	8	9	10	11	1
0	1.534361	12.002415	2.6	67.0	97.0	F	a11	1.600000	0.650000	3	0.212177	1022.1	1026
1	1.632953	14.821694	3.6	72.0	78.0	M	a18	1.942857	1.328571	4	0.126069	1013.2	1016
2	2.330694	21.399766	5.4	64.0	53.0	A	a20	1.864286	0.992857	8	0.263743	1017.2	1020

- **Now we'll define a function for the desired feature exploration:**

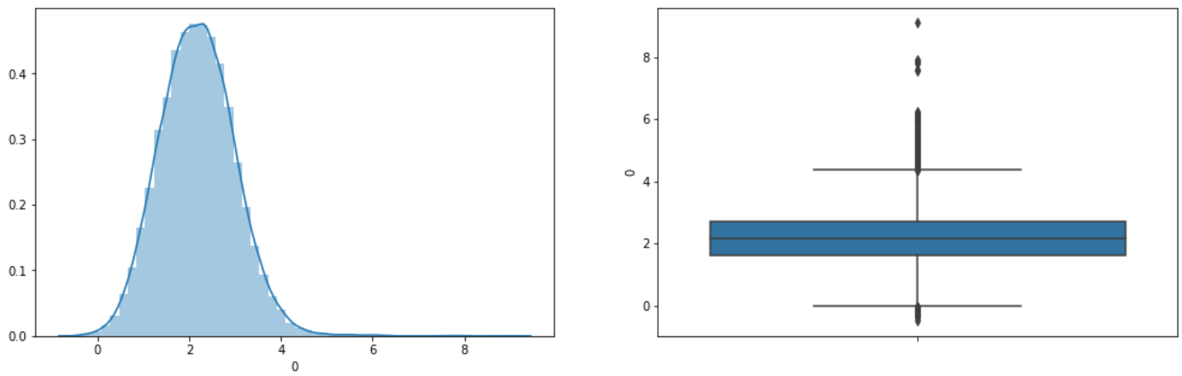
In [18]:

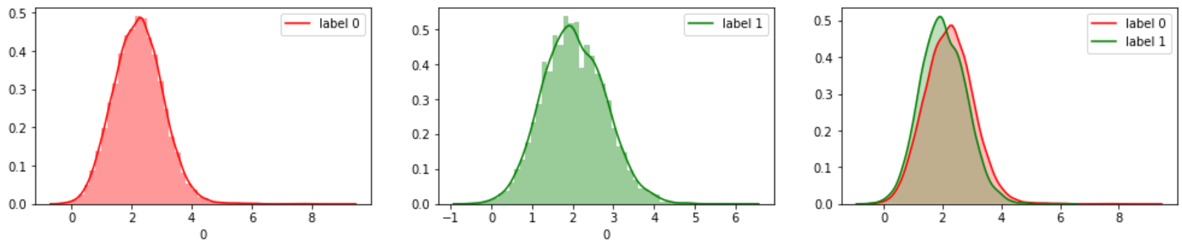
```
# define a function for feature exploration
def explore_feature(feature):
    print('Feature: %s' % (feature))
    print('------------------------')
    print(df[feature].describe())
    print('Total nulls: %s' %(df[feature].isna().sum()))

    # determine the feature's type:
    if df[feature].dtype == 'float64' or df[feature].dtype == 'int64':
        type = 0                                # 0 for numeric features
    else:
        type = 1                                # 1 for categorical/binary features

    if feature == 'label': # label column is handled differently
        fig = plt.subplots(figsize=(17,3))
        sns.countplot(df[feature],palette="Blues_d")
        plt.show()
    else:

        if type == 0:                           # numeric feature
            fig, ax = plt.subplots(1,2,figsize=(17,5))
            sns.distplot(df[feature].dropna(), ax=ax[0]) # dsitribution
            sns.boxplot(x = df[feature].dropna(), data=df, ax=ax[1], orient='v') # boxplot
            plt.show()

            fig, ax = plt.subplots(1,3,figsize=(17,3))
            # distribution for the frequencies of label '0' and '1'
            sns.distplot(df[feature][df['label'] == 0].dropna(), color='r', kde_kws={"label
            sns.distplot(df[feature][df['label'] == 1].dropna(), color='g', kde_kws={"label
            sns.kdeplot(df[feature][df['label'] == 0].dropna(),  color='r', label = 'label
            sns.kdeplot(df[feature][df['label'] == 1].dropna(), color='g', label = 'label 1
            plt.show()
        elif type == 1:                         # categorical/binary feature
            if feature=='6': # feature 6 has many categories so we handle it seperately
                fig, ax = plt.subplots(2,1,figsize=(17,8))
            else:
                fig, ax = plt.subplots(1,2,figsize=(17,3))
            order_by_categories = df[feature].value_counts().index.sort_values()
            sns.countplot(df[feature], order=order_by_categories, ax=ax[0]) # count the cat
            sns.countplot(x = feature, order=order_by_categories, hue = 'label', data = df,
            plt.show()
```

In [19]:

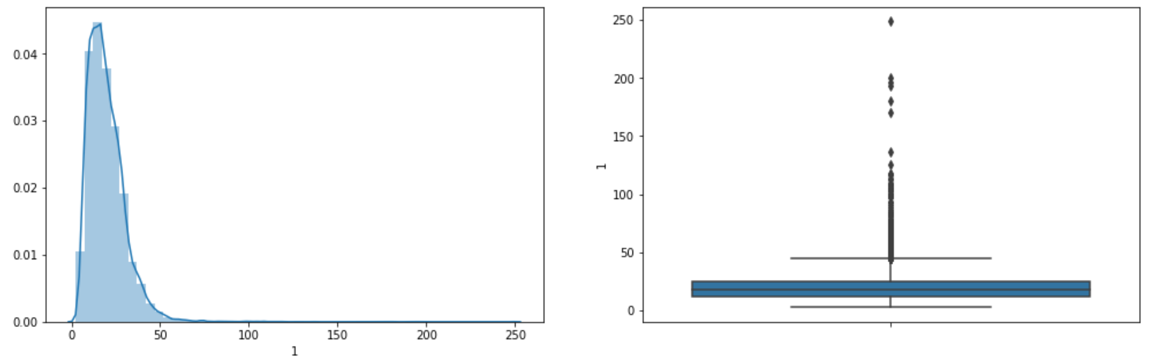
```
# Explore features in ascending order
for feature in df.columns:
    explore_feature(feature)
```

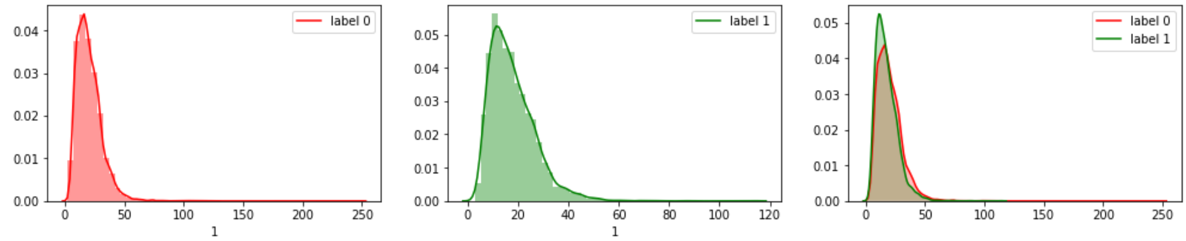
```
Feature: 0
------------------------
count    22161.000000
mean         2.185958
std          0.815080
min         -0.490607
25%          1.622068
50%          2.167701
75%          2.720341
max          9.092011
Name: 0, dtype: float64
Total nulls: 0
```



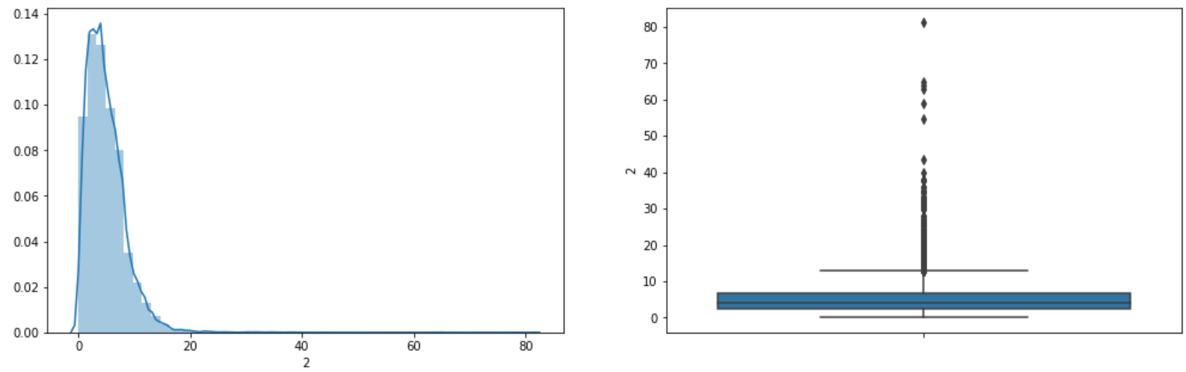


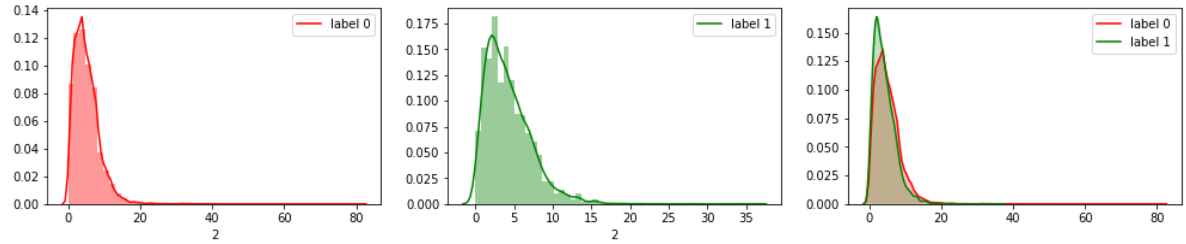

```
Feature: 1
------------------------
count    22161.000000
mean        19.797754
std         10.763614
min          2.437300
25%         12.268371
50%         17.833216
75%         25.196446
max        248.877854
Name: 1, dtype: float64
Total nulls: 0
```





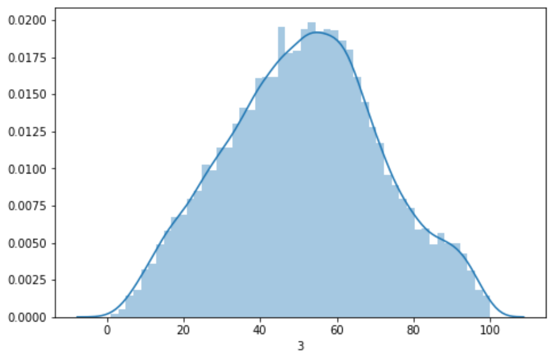

```
Feature:  2
------------------------
count    22161.000000
mean         4.929620
std          3.572644
min          0.000000
25%          2.400000
50%          4.200000
75%          6.600000
max         81.200000
Name: 2, dtype: float64
Total nulls: 0
```

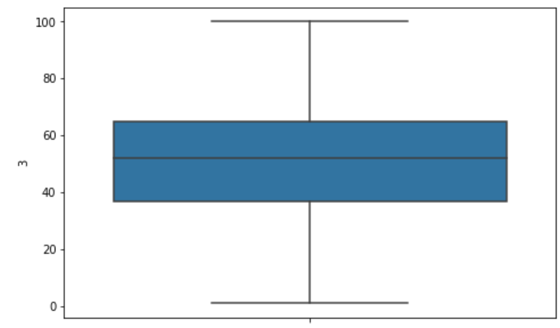


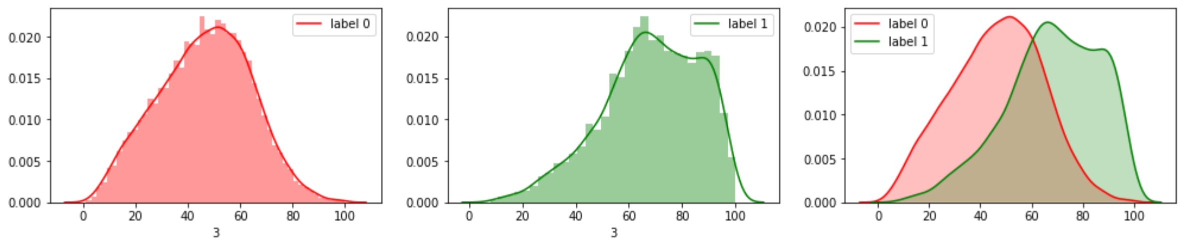



```
Feature:  3
------------------------
count    22102.000000
mean        51.547009
std         20.184353
min          1.000000
25%         37.000000
50%         52.000000
75%         65.000000
```

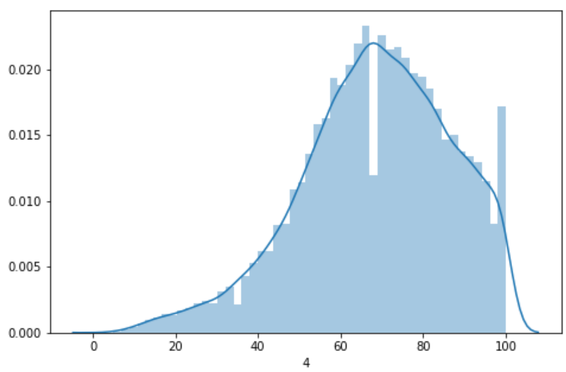
```
max          100.000000
Name: 3, dtype: float64
Total nulls: 59
```

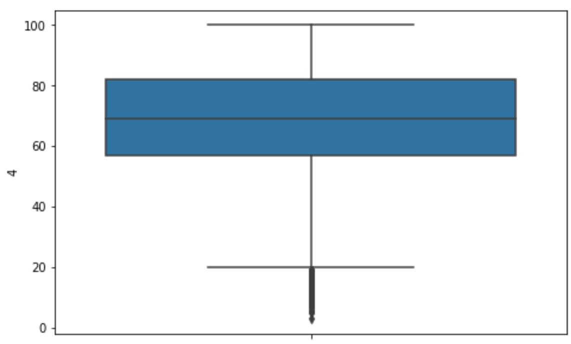


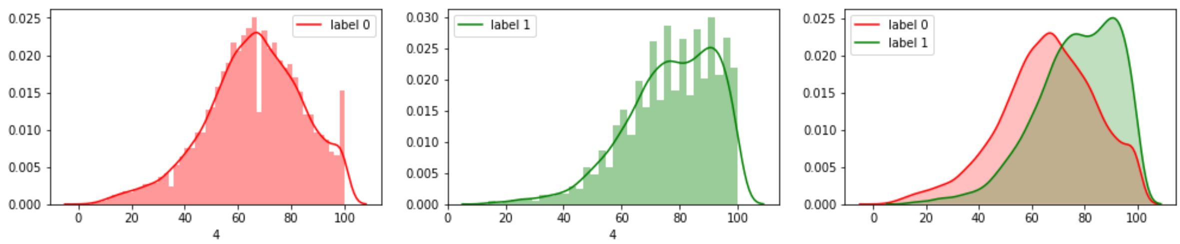




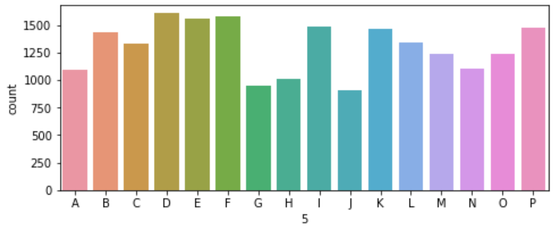

```
Feature: 4
------------------------
count    22057.000000
mean        68.497982
std         18.231315
min          3.000000
25%         57.000000
50%         69.000000
75%         82.000000
max        100.000000
Name: 4, dtype: float64
Total nulls: 104
```

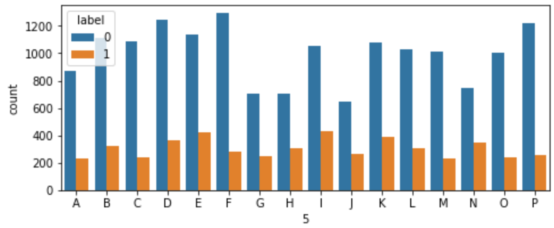




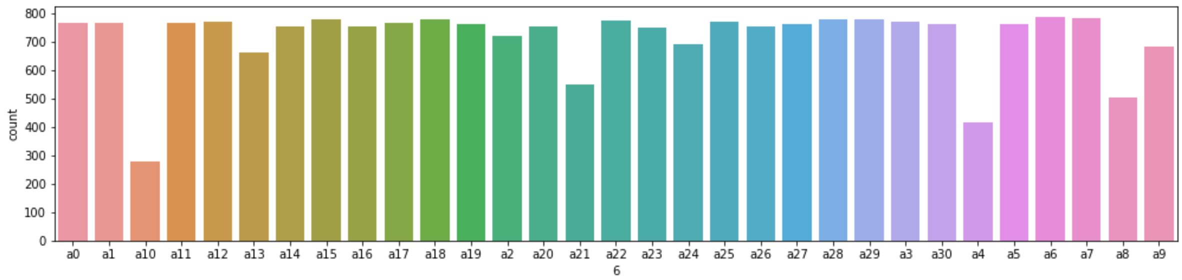


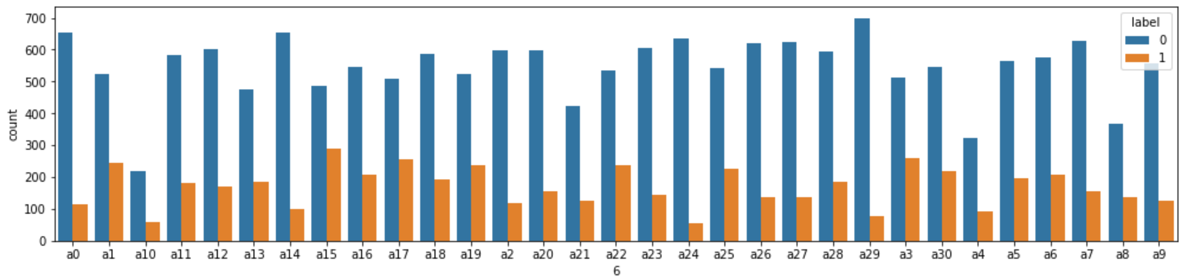
```
Feature: 5
------------------------
count      20812
unique        16
top            D
freq        1604
Name: 5, dtype: object
Total nulls: 1349
```



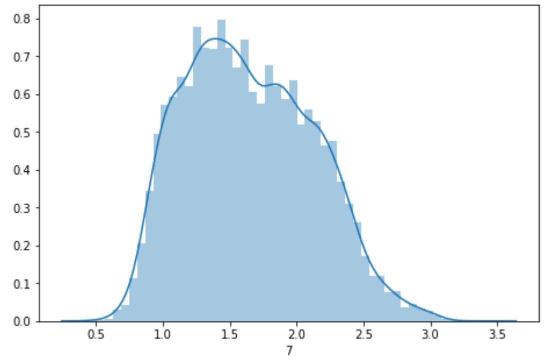


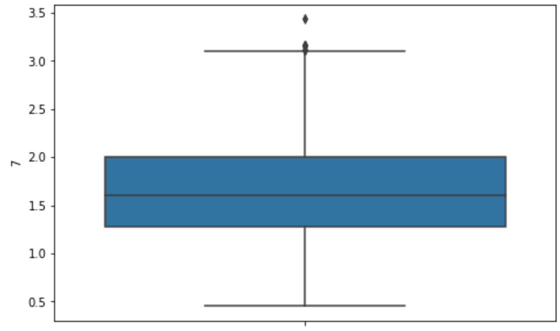

```
Feature: 6
------------------------
count      22161
unique        31
top           a6
freq         786
Name: 6, dtype: object
Total nulls: 0
```

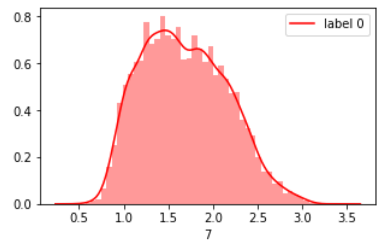


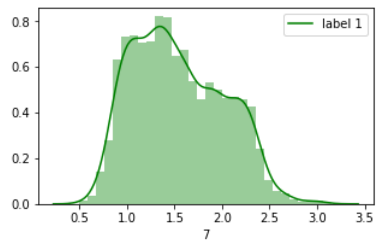


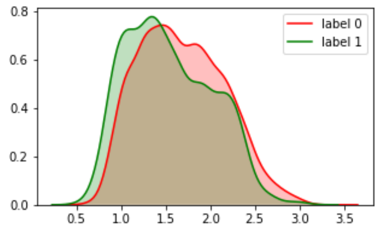
```
Feature: 7
------------------------
count    22154.000000
mean         1.648476
std          0.480275
min          0.450000
25%          1.271429
50%          1.607143
75%          2.007143
max          3.435714
Name: 7, dtype: float64
Total nulls: 7
```



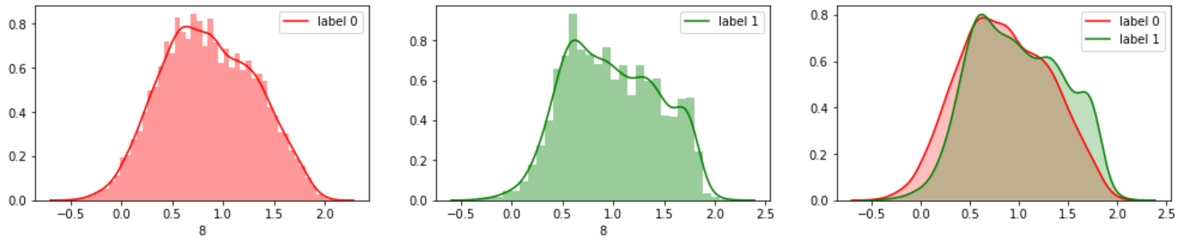




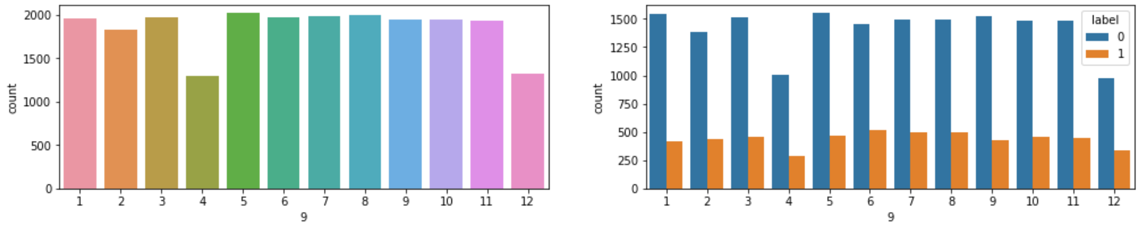




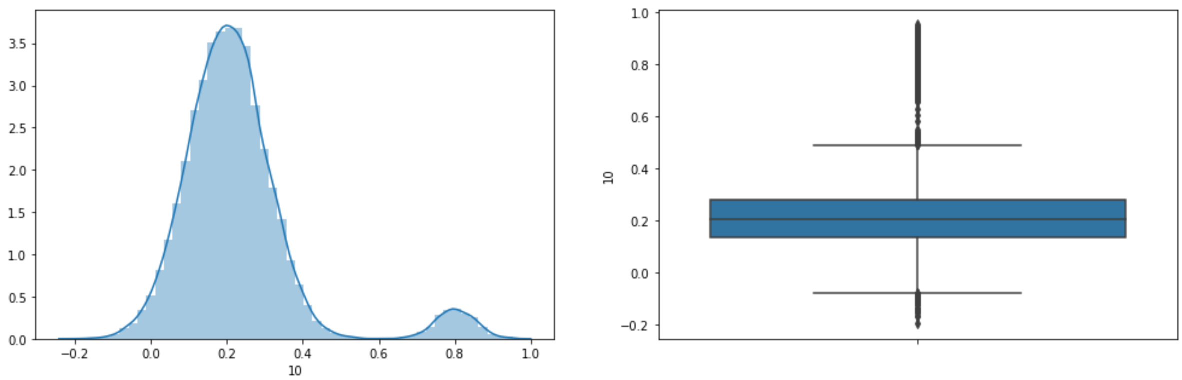

```
Feature: 8
------------------------
count    22143.000000
mean         0.888041
std          0.461375
min         -0.492857
25%          0.542857
50%          0.864286
75%          1.242857
max          2.128571
Name: 8, dtype: float64
Total nulls: 18
```

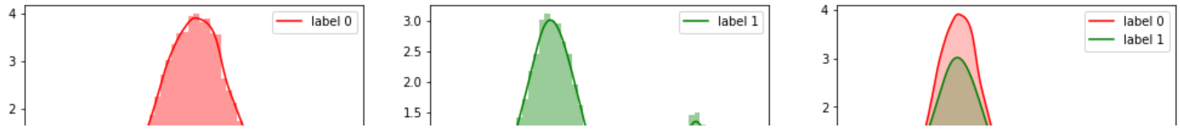



```
Feature: 9
------------------------
count     22161
unique       12
top           5
freq       2016
Name: 9, dtype: int64
Total nulls: 0
```

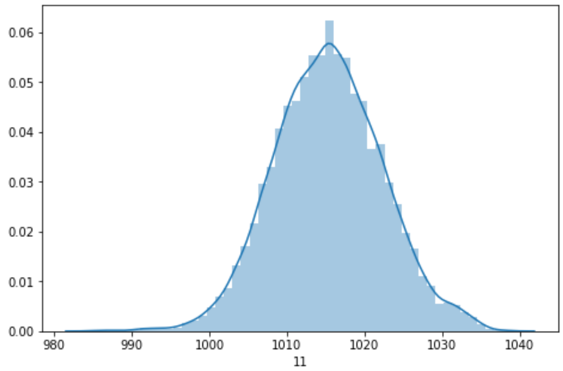


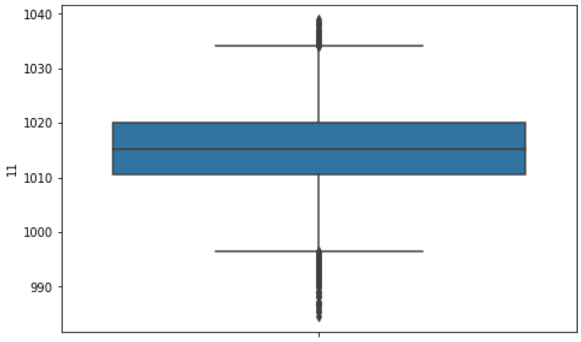

```
Feature: 10
------------------------
count    22161.000000
mean         0.228284
std          0.161565
min         -0.195661
25%          0.136002
50%          0.206457
75%          0.278929
max          0.954076
Name: 10, dtype: float64
Total nulls: 0
```

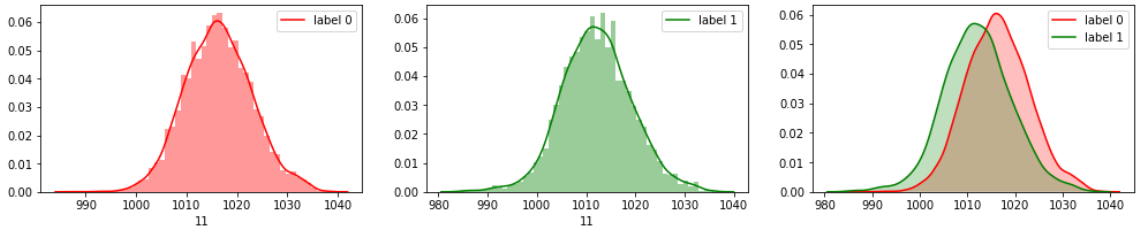




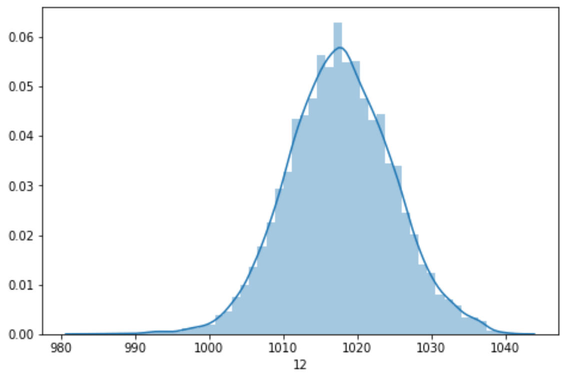

```
Feature: 11
------------------------
count    22055.000000
mean      1015.347014
std          7.011856
min        984.500000
25%       1010.600000
50%       1015.300000
75%       1020.000000
max       1038.900000
Name: 11, dtype: float64
Total nulls: 106
```

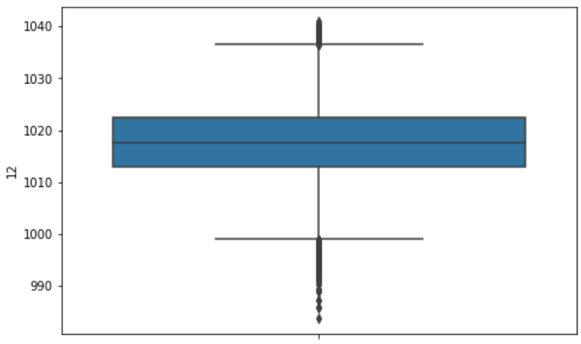


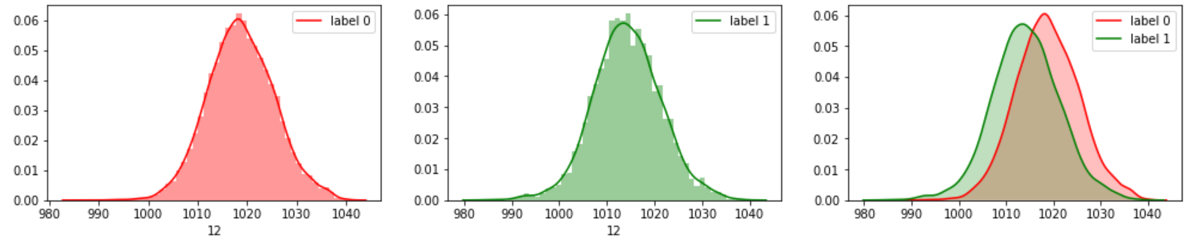




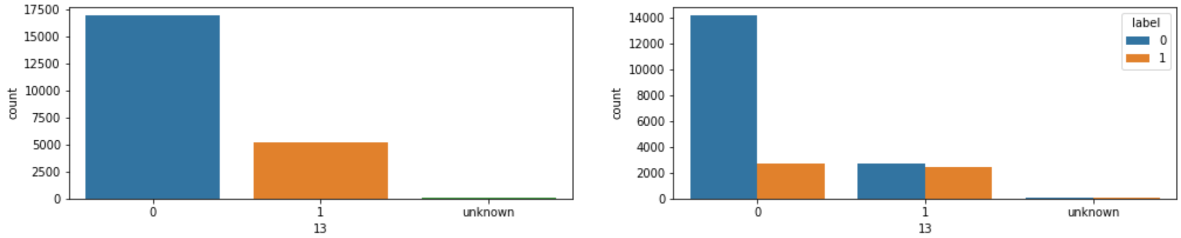

```
Feature: 12
------------------------
count    22048.000000
mean      1017.708572
std          7.085807
min        983.700000
25%       1013.000000
50%       1017.700000
75%       1022.400000
max       1040.900000
Name: 12, dtype: float64
Total nulls: 113
```



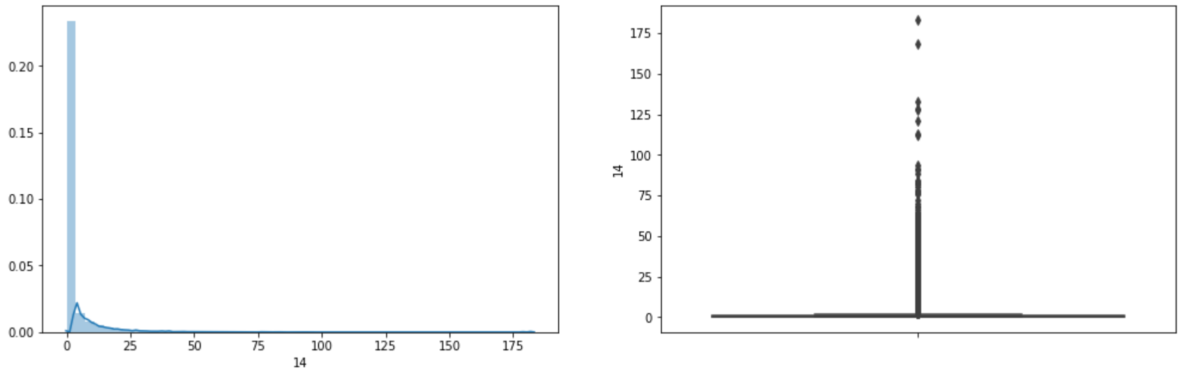


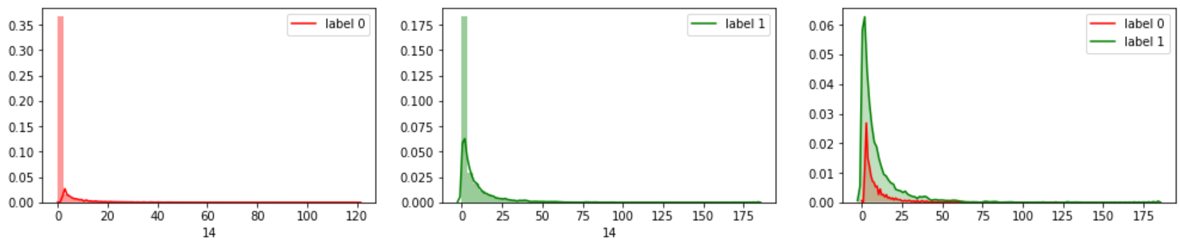



```
Feature: 13
------------------------
count      22161
unique         3
top            0
freq       16906
Name: 13, dtype: object
Total nulls: 0
```



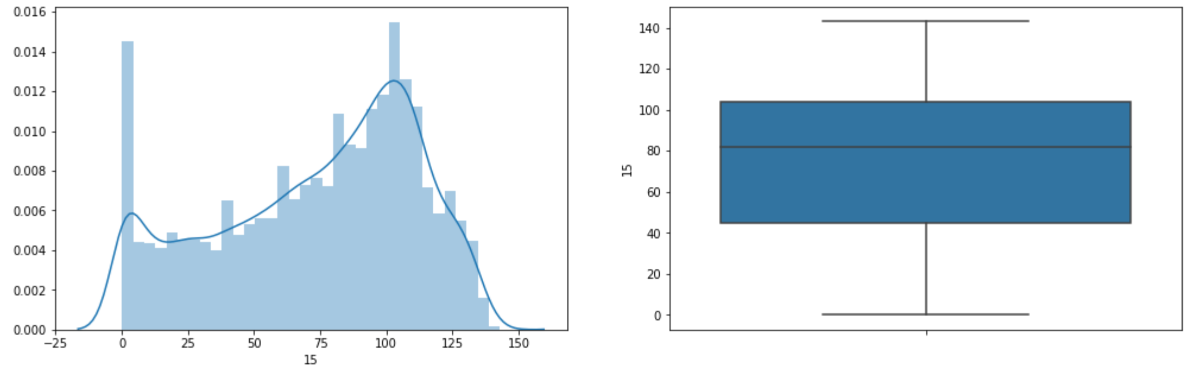

```
Feature: 14
------------------------
count    22080.000000
mean         2.289923
std          7.145425
min          0.000000
25%          0.000000
50%          0.000000
75%          0.800000
max        183.000000
Name: 14, dtype: float64
Total nulls: 81
```

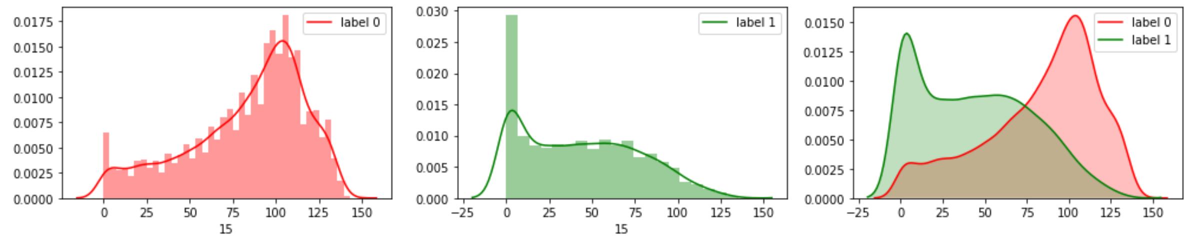




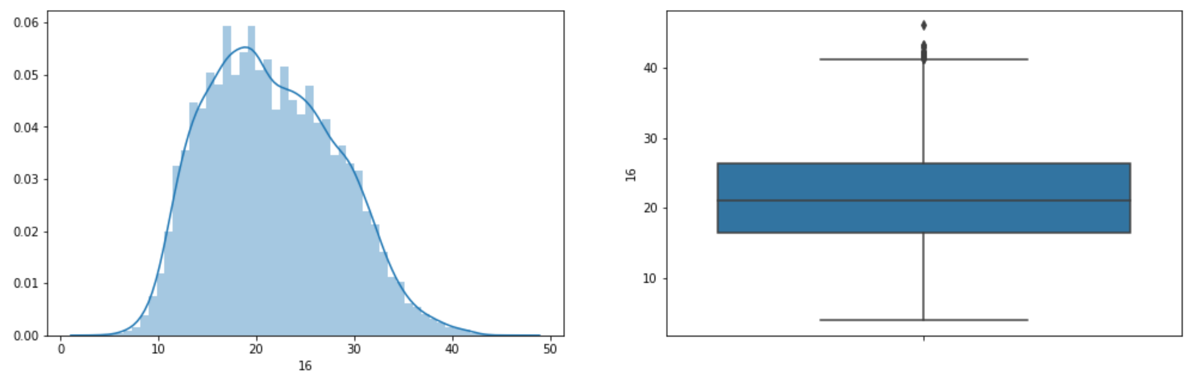

```
Feature: 15
------------------------
count    20290.000000
```

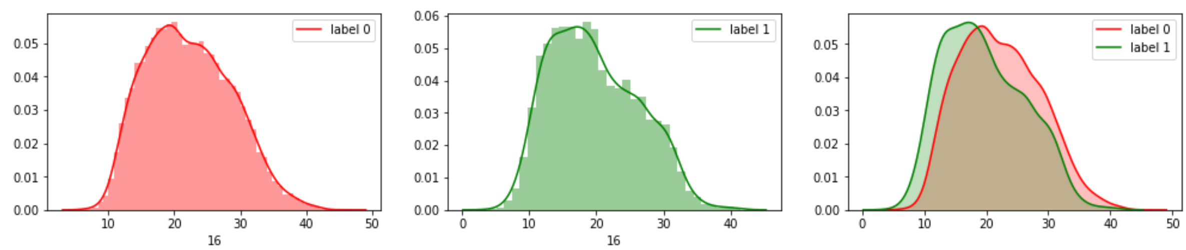
```
mean        73.685017
std         37.866780
min          0.000000
25%         45.000000
50%         82.000000
75%        104.000000
max        143.000000
Name: 15, dtype: float64
Total nulls: 1871
```



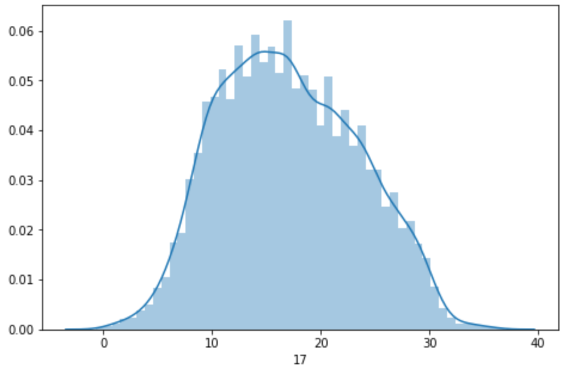


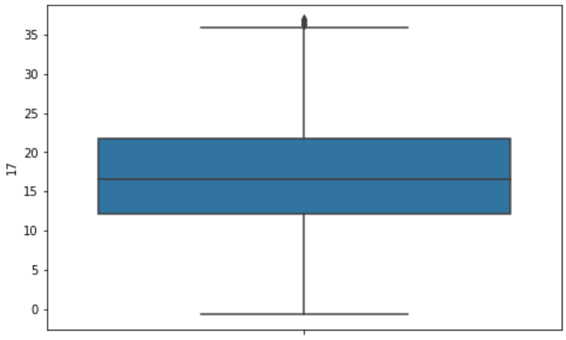

```
Feature: 16
-----------------------
count    22133.000000
mean        21.617133
std          6.602743
min          3.900000
25%         16.500000
50%         21.000000
75%         26.400000
max         46.100000
Name: 16, dtype: float64
Total nulls: 28
```

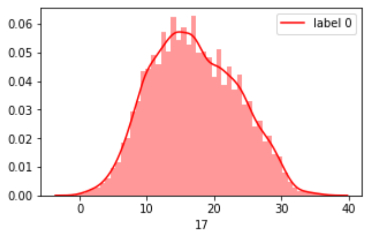


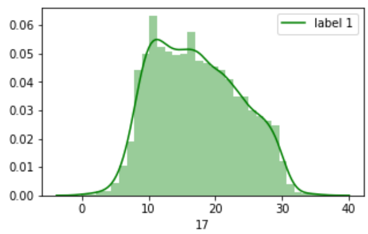


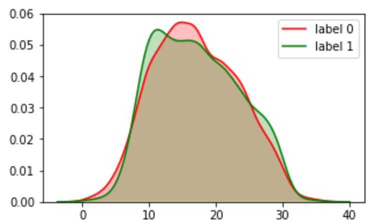
```
Feature: 17
------------------------
count    22109.000000
mean        17.065837
std          6.409174
min         -0.700000
25%         12.100000
50%         16.600000
75%         21.800000
max         36.900000
Name: 17, dtype: float64
Total nulls: 52
```



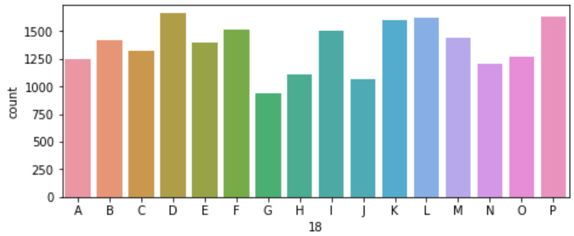


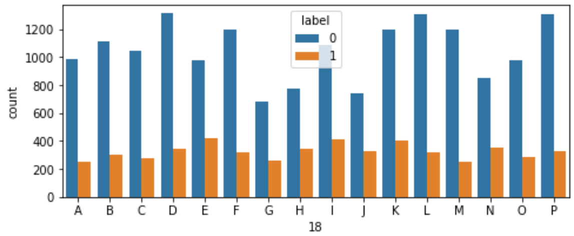






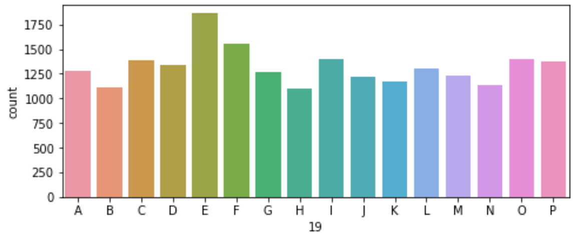

```
Feature: 18
------------------------
count     21951
unique       16
top           D
freq       1659
Name: 18, dtype: object
Total nulls: 210
```

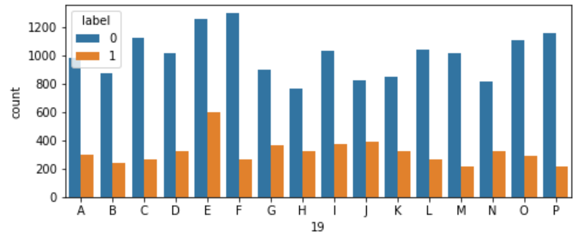




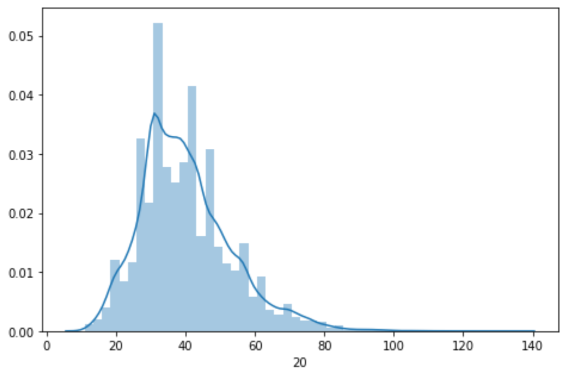

```
Feature: 19
------------------------
count     21141
unique       16
top           E
```

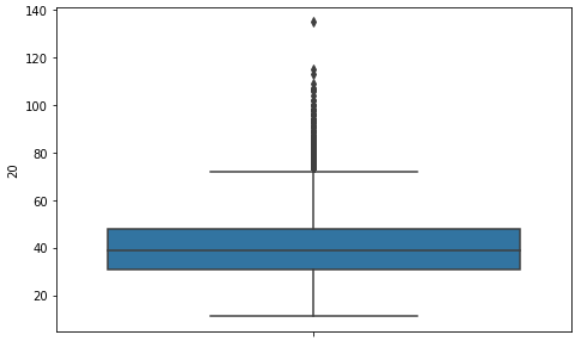
```
freq         1861
Name: 19, dtype: object
Total nulls: 1020
```

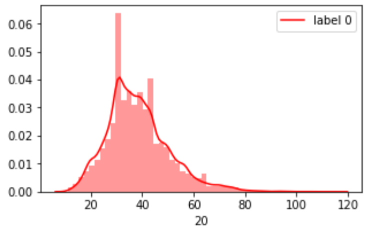


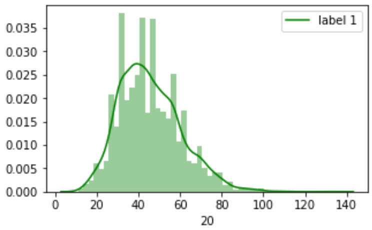


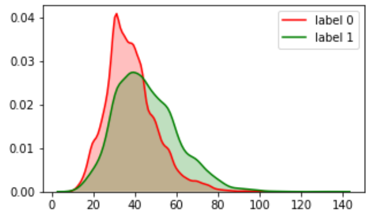

```
Feature: 20
------------------------
count    20816.000000
mean        39.995484
std         13.150807
min         11.000000
25%         31.000000
50%         39.000000
75%         48.000000
max        135.000000
Name: 20, dtype: float64
Total nulls: 1345
```



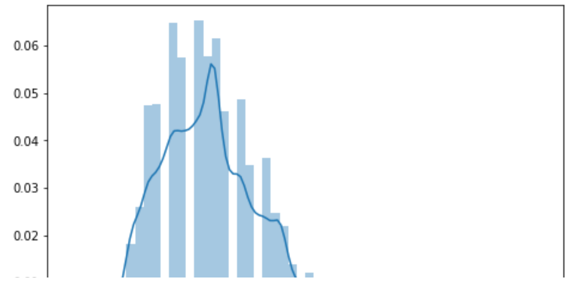


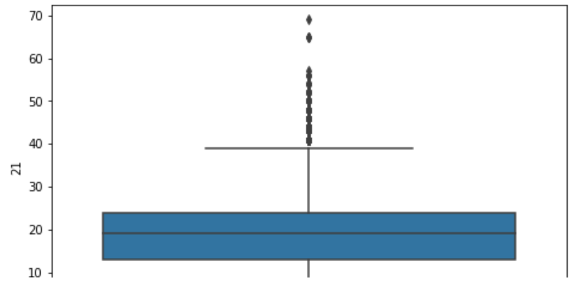


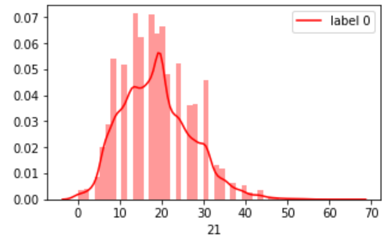


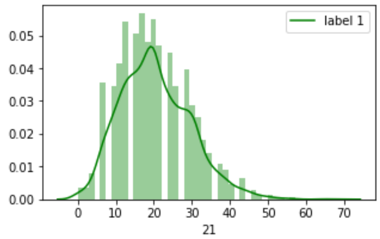


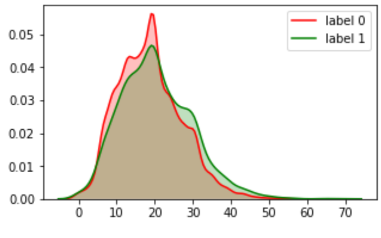

```
Feature: 21
------------------------
count    22062.000000
mean        19.101577
std          8.546933
min          0.000000
25%         13.000000
50%         19.000000
75%         24.000000
max         69.000000
Name: 21, dtype: float64
Total nulls: 99
```



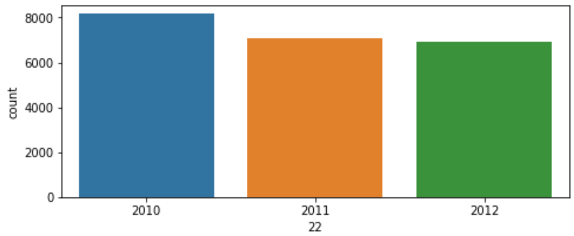


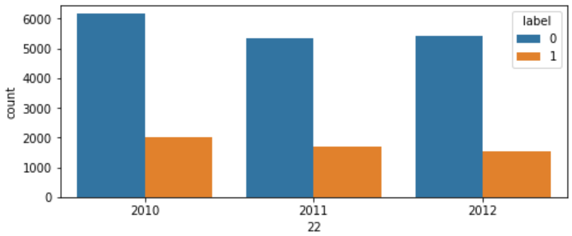




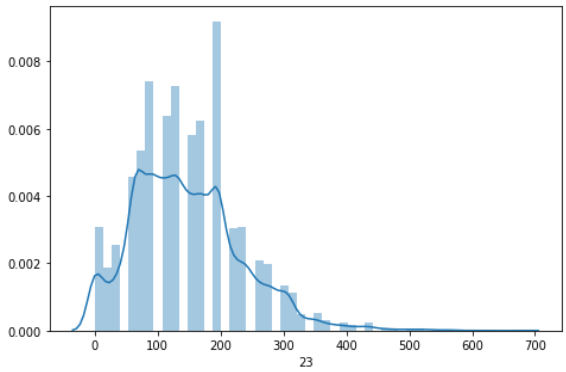


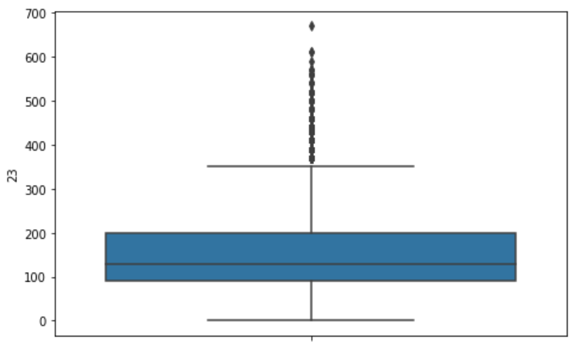

```
Feature: 22
------------------------
count     22161
unique        3
top        2010
freq       8158
Name: 22, dtype: int64
Total nulls: 0
```

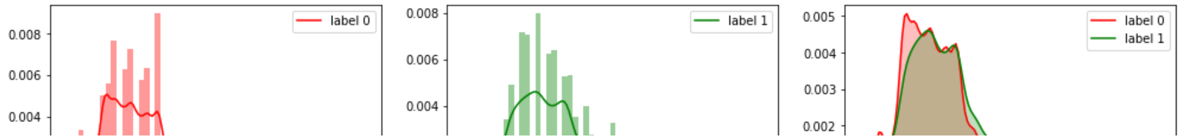




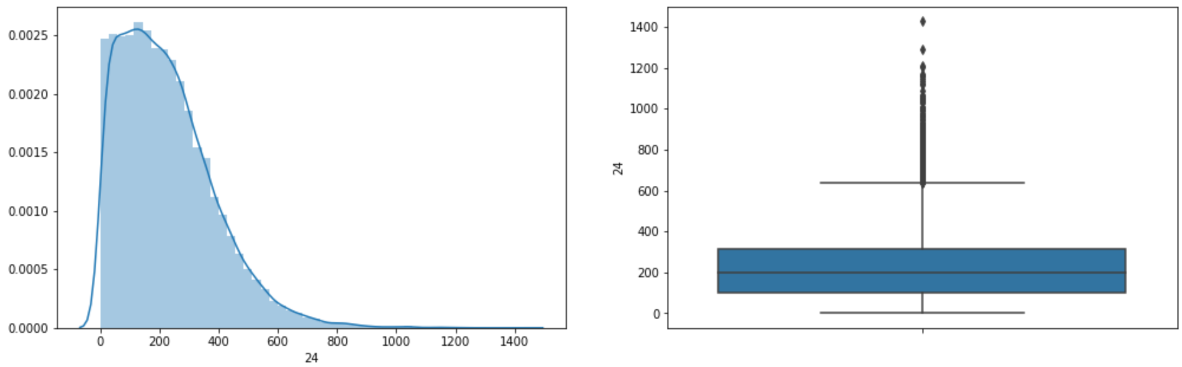

```
Feature: 23
------------------------
count    22061.000000
mean       146.971579
std         86.609704
min          0.000000
25%         90.000000
50%        130.000000
75%        200.000000
max        670.000000
Name: 23, dtype: float64
Total nulls: 100
```

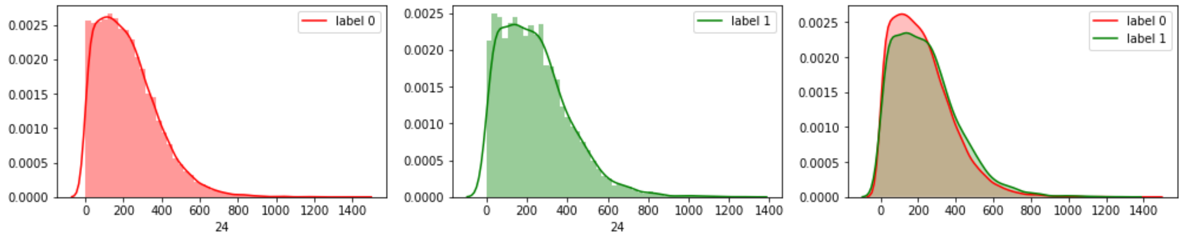




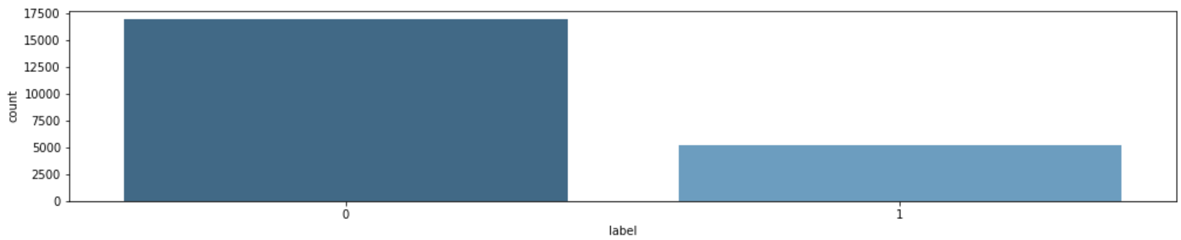



```
Feature: 24
------------------------
count    22061.000000
mean       224.835441
std        160.801099
min          0.001355
25%        100.144819
50%        199.866581
75%        316.118054
max       1426.459838
Name: 24, dtype: float64
Total nulls: 100
```





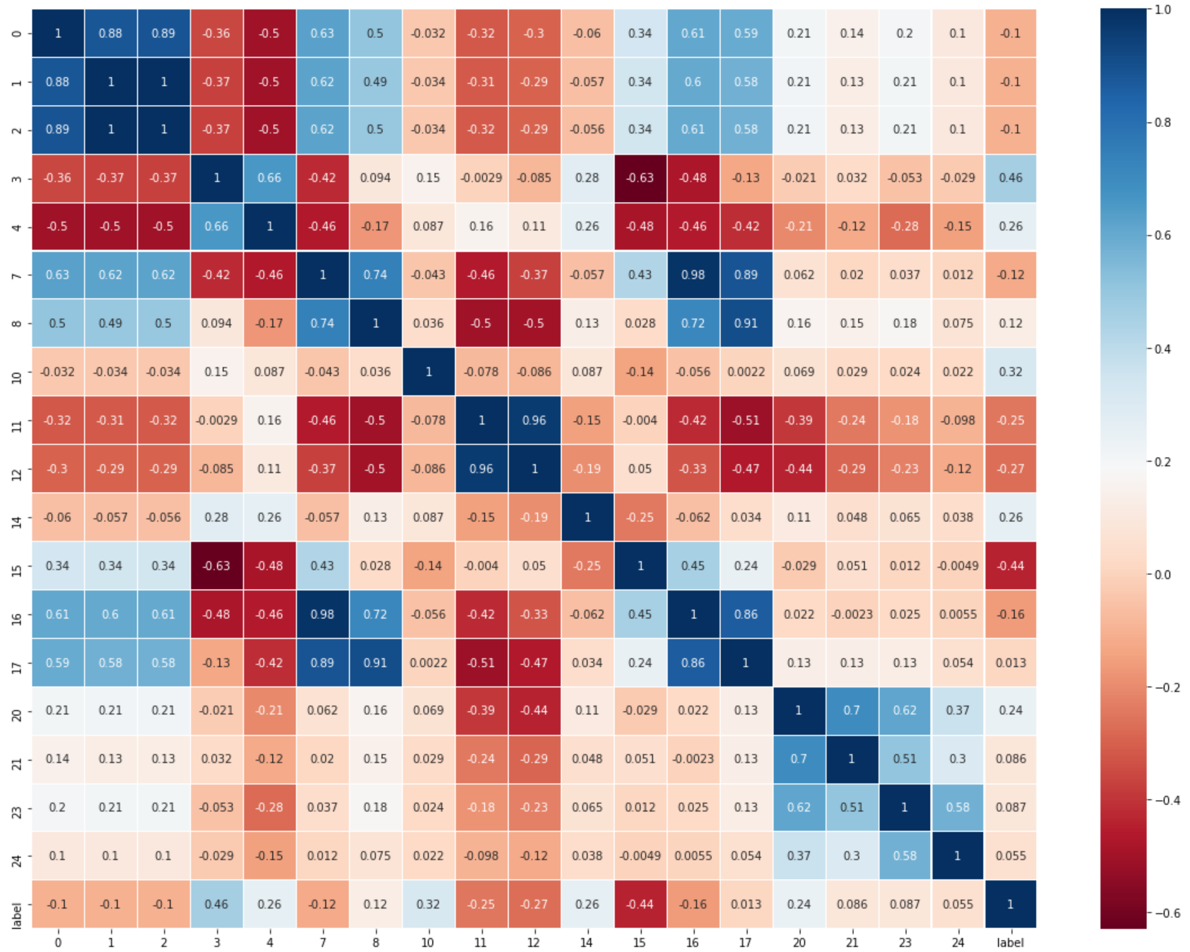

```
Feature: label
------------------------
count    22161.000000
mean         0.236451
std          0.424912
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000
Name: label, dtype: float64
Total nulls: 0
```



Heatmap of correlations

In [20]:

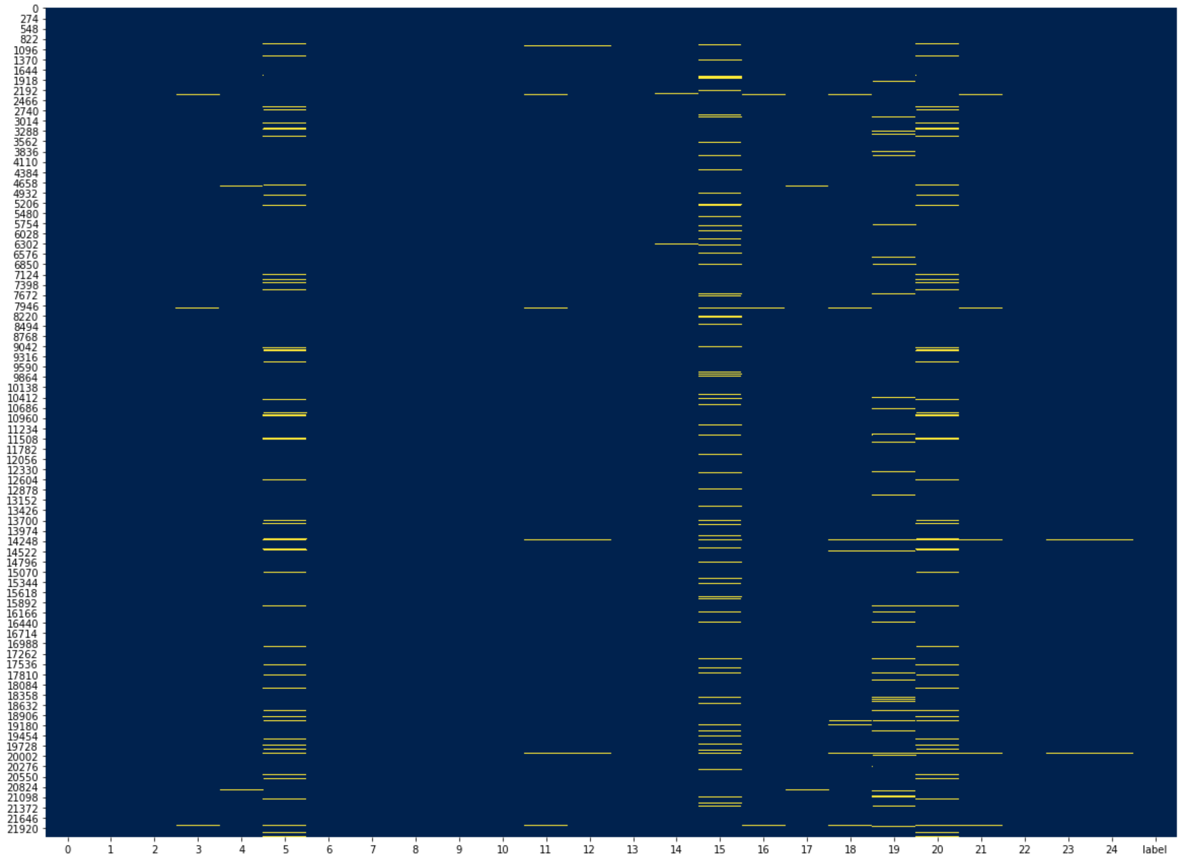
```
plt.subplots(figsize=(20,15))
sns.heatmap(df.corr(),
            annot=True, linecolor='white', linewidth='0.05', cmap="RdBu")
plt.show()
```



Heatmap of Nans (not a number values)

In [21]:

```
plt.subplots(figsize=(20,15))
sns.heatmap(df.isnull(), cbar=False, cmap="cividis")
plt.show()
```



Total Nans by features

In [22]:

```
table = nan_table(df)
table
```

Out[22]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
0	0	0	0	59	104	1349	0	7	18	0	0	106	113	0	81	1871	28	52	210	1020	1345

2. Preprocessing

2.1. Handling Missing Values

Before continuing with the preprocessing, at first we need to decide what to do with the features that have missing values.
For that matter, Features 5,6,9,13,18,19,22 are categorical, so let's handle them first.
NOTE: The changes made to the train set will also take place on the test set.

Categorical/Binaric Features

- **Feature 5**

In [23]:

```
df['5'].value_counts(dropna=False)
```

Out[23]:

```
D      1604
F      1575
E      1558
I      1485
P      1475
K      1469
B      1432
NaN    1349
L      1337
C      1330
O      1241
M      1239
N      1098
A      1097
H      1010
G       952
J       910
Name: 5, dtype: int64
```

We can see that 1349 values are NaN, so it may be important to keep them as a category:

In [24]:

```
df['5'].fillna('Other', inplace=True)
df['5'].value_counts(dropna=False)
```

Out[24]:

```
D        1604
F        1575
E        1558
I        1485
P        1475
K        1469
B        1432
Other    1349
L        1337
C        1330
O        1241
M        1239
N        1098
A        1097
H        1010
G         952
J         910
Name: 5, dtype: int64
```

In the data exploration we've noticed that features 5,18,19 have the same categories.
After examination we have seen that we're getting better results when we drop this feature.
We've kept here our try to concatinate the one-hot encoded feature.

→ Update train set:

In [25]:

```
feature_5_dummies = pd.get_dummies(df['5'])[df['5'].value_counts(dropna=False).index]
feature_5_dummies.head(3)
```

Out[25]:

	D	F	E	I	P	K	B	Other	L	C	O	M	N	A	H	G	J
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0

In [26]:

```
df.drop(['5'], axis=1, inplace=True)
#df = pd.concat([df,feature_5_dummies], axis=1)
#df.head(3)
```

In [27]:

```
df.shape
```

Out[27]:

```
(22161, 25)
```

→ Update test set:

In [28]:

```
df_test['5'].fillna('Other', inplace=True)
test_feature_5_dummies = pd.get_dummies(df_test['5'])[df_test['5'].value_counts(dropna=Fals
test_feature_5_dummies.head(3)
```

Out[28]:

	F	D	E	B	P	L	I	K	O	C	M	Other	N	A	G	J	H
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0

In [29]:

```
df_test.drop(['5'], axis=1, inplace=True)
#df_test = pd.concat([df_test,test_feature_5_dummies], axis=1)
#df_test.head()
```

In [30]:

```
df_test.shape
```

Out[30]:

```
(7387, 24)
```

- **Feature 6**

In [31]:

```
df['6'].value_counts(dropna=False)
```

Out[31]:

```
a6     786
a7     785
a18    780
a28    779
a29    779
a15    778
a22    773
a12    771
a25    770
a3     769
a0     768
a1     768
a11    767
a17    766
a5     764
a27    762
a19    762
a30    762
a26    756
a20    755
a16    753
a14    753
a23    750
a2     719
a24    691
a9     684
a13    661
a21    550
a8     503
a4     417
a10    280
Name: 6, dtype: int64
```

We can see that most of the values are the same, and there are no nulls here.
So let's not change anything and try to one-hot encoding this feature:

→ **Update train set:**

In [32]:

```
feature_6_dummies = pd.get_dummies(df['6'])
feature_6_dummies.head(3)
```

Out[32]:

	a0	a1	a10	a11	a12	a13	a14	a15	a16	a17	a18	a19	a2	a20	a21	a22	a23	a24
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

In [33]:

```
df.drop(['6'], axis=1, inplace=True)
df = pd.concat([df,feature_6_dummies], axis=1)
df.head(3)
```

Out[33]:

	0	1	2	3	4	7	8	9	10	11	12	13
0	1.170981	5.672133	0.6	80.0	76.0	1.107143	0.692857	5	0.702957	1024.1	1025.9	0
1	2.595788	23.203289	6.4	43.0	64.0	1.700000	0.614286	11	0.223911	1005.3	1008.1	0
2	0.972794	7.127348	0.4	63.0	100.0	1.242857	0.428571	6	0.180848	1020.8	1026.5	0

In [34]:

```
df.shape
```

Out[34]:

```
(22161, 55)
```

→ **Update test set:**

In [35]:

```
test_feature_6_dummies = pd.get_dummies(df_test['6'])
test_feature_6_dummies.head(3)
```

Out[35]:

	a0	a1	a10	a11	a12	a13	a14	a15	a16	a17	a18	a19	a2	a20	a21	a22	a23	a24
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0

In [36]:

```
df_test.drop(['6'], axis=1, inplace=True)
df_test = pd.concat([df_test,test_feature_6_dummies], axis=1)
df_test.head(3)
```

Out[36]:

	0	1	2	3	4	7	8	9	10	11	12	13	1
0	1.534361	12.002415	2.6	67.0	97.0	1.600000	0.650000	3	0.212177	1022.1	1026.2	0	0
1	1.632953	14.821694	3.6	72.0	78.0	1.942857	1.328571	4	0.126069	1013.2	1016.3	0	0
2	2.330694	21.399766	5.4	64.0	53.0	1.864286	0.992857	8	0.263743	1017.2	1020.7	0	0

In [37]:

```
df_test.shape
```

Out[37]:

(7387, 54)

- **Feature 9**

In [38]:

```
df['9'].value_counts(dropna=False)
```

Out[38]:

```
5     2016
8     1992
7     1987
6     1974
3     1966
1     1963
9     1949
10    1943
11    1932
2     1828
12    1316
4     1295
Name: 9, dtype: int64
```

It seems that the count of each category in this feature is almost the same.
At first, we've tried to apply one-hot encoding on the whole feature.
Then we've seen that taking only the top 5 of the most frequent categories gave us better results, so we'll use here one-hot encoding also and take only the top 5 frequent categories:

→ **Update train set:**

In [39]:

```
masking = df['9'].value_counts(dropna=False)[:5].index
feature_9_dummies = pd.get_dummies(df['9'])[masking]
feature_9_dummies = feature_9_dummies.add_prefix('feature_9_')
feature_9_dummies.head(3)
```

Out[39]:

	feature_9_5	feature_9_8	feature_9_7	feature_9_6	feature_9_3
0	1	0	0	0	0
1	0	0	0	0	0
2	0	0	0	1	0

In [40]:

```
df.drop(['9'], axis=1, inplace=True)
df = pd.concat([df,feature_9_dummies], axis=1)
df.head(3)
```

Out[40]:

	0	1	2	3	4	7	8	10	11	12	13	14
0	1.170981	5.672133	0.6	80.0	76.0	1.107143	0.692857	0.702957	1024.1	1025.9	0	0.6
1	2.595788	23.203289	6.4	43.0	64.0	1.700000	0.614286	0.223911	1005.3	1008.1	0	0.0
2	0.972794	7.127348	0.4	63.0	100.0	1.242857	0.428571	0.180848	1020.8	1026.5	0	0.0

In [41]:

```
df.shape
```

Out[41]:

(22161, 59)

→ Update test set:

In [42]:

```
test_feature_9_dummies = pd.get_dummies(df_test['9'])[masking]
test_feature_9_dummies = test_feature_9_dummies.add_prefix('feature_9_')
test_feature_9_dummies.head(3)
```

Out[42]:

	feature_9_5	feature_9_8	feature_9_7	feature_9_6	feature_9_3
0	0	0	0	0	1
1	0	0	0	0	0
2	0	1	0	0	0

In [43]:

```
df_test.drop(['9'], axis=1, inplace=True)
df_test = pd.concat([df_test,test_feature_9_dummies], axis=1)
```

In [44]:

```
df_test.shape
```

Out[44]:

(7387, 58)

- **Feature 13**

In [45]:

```
df['13'].value_counts(dropna=False)
```

Out[45]:

```
0          16906
1           5174
unknown       81
Name: 13, dtype: int64
```

We can see that we have a very small number of 'unkown' values.
We tried to use 3 methods:

1. Replace the unknown values with '0'
2. Replace the unknown values with '1'
3. Replace the unknown values using the forward-fill method (last valid observation)

Among all of the options we got our best results with replacing the unknown values with '0'.

→ **Update train set:**

In [46]:

```
df['13'].replace('unknown',np.nan, inplace=True)
df['13'].fillna(0, inplace=True)
df['13'] = df['13'].astype('int64')
df['13'].value_counts(dropna=False)
#df.drop(['13'], axis=1, inplace=True)
```

Out[46]:

```
0    16987
1     5174
Name: 13, dtype: int64
```

→ **Update test set:**

In [47]:

```
df_test['13'].replace('unknown',np.nan, inplace=True)
df_test['13'].fillna(0, inplace=True)
df_test['13'] = df_test['13'].astype('int64')
df_test['13'].value_counts(dropna=False)
#df_test.drop(['13'], axis=1, inplace=True)
```

Out[47]:

```
0    5628
1    1759
Name: 13, dtype: int64
```

- ## Feature 18

In [48]:

```
df['18'].value_counts(dropna=False)
```

Out[48]:

```
D      1659
P      1634
L      1626
K      1599
F      1517
I      1502
M      1444
B      1416
E      1399
C      1319
O      1266
A      1244
N      1206
H      1114
J      1068
G       938
NaN     210
Name: 18, dtype: int64
```

We can see that there is a small number of NaN values. so, let's combine (G+Nan) to a column 'Other':

→ Update train set:

In [49]:

```
df['18'].fillna('Other', inplace=True)
df['18'].replace('G', 'Other', inplace=True)
df['18'].value_counts(dropna=False)
```

Out[49]:

```
D        1659
P        1634
L        1626
K        1599
F        1517
I        1502
M        1444
B        1416
E        1399
C        1319
O        1266
A        1244
N        1206
Other    1148
H        1114
J        1068
Name: 18, dtype: int64
```

Now use one-hot encoding:

In [50]:

```
feature_18_dummies = pd.get_dummies(df['18'])[df['18'].value_counts(dropna=False).index]
feature_18_dummies = feature_18_dummies.add_prefix('feature_18_')
df.drop(['18'], axis=1, inplace=True)
df = pd.concat([df,feature_18_dummies], axis=1)
df.head(3)
```

Out[50]:

	0	1	2	3	4	7	8	10	11	12	13	14
0	1.170981	5.672133	0.6	80.0	76.0	1.107143	0.692857	0.702957	1024.1	1025.9	0	0.6
1	2.595788	23.203289	6.4	43.0	64.0	1.700000	0.614286	0.223911	1005.3	1008.1	0	0.0
2	0.972794	7.127348	0.4	63.0	100.0	1.242857	0.428571	0.180848	1020.8	1026.5	0	0.0

In [51]:

```
df.shape
```

Out[51]:

```
(22161, 74)
```

→ Update test set:

In [52]:

```
df_test['18'].fillna('Other', inplace=True)
df_test['18'].replace('G', 'Other', inplace=True)
df_test['18'].value_counts(dropna=False)
```

Out[52]:

```
L        564
P        553
D        551
K        546
I        520
F        512
M        499
B        484
C        476
E        452
O        444
N        401
Other    371
A        342
J        340
H        332
Name: 18, dtype: int64
```

In [53]:

```
test_feature_18_dummies = pd.get_dummies(df_test['18'])[df_test['18'].value_counts(dropna=F
test_feature_18_dummies = test_feature_18_dummies.add_prefix('feature_18_')
df_test.drop(['18'], axis=1, inplace=True)
df_test = pd.concat([df_test,test_feature_18_dummies], axis=1)
df_test.head(3)
```

Out[53]:

	0	1	2	3	4	7	8	10	11	12	13	14
0	1.534361	12.002415	2.6	67.0	97.0	1.600000	0.650000	0.212177	1022.1	1026.2	0	0.2
1	1.632953	14.821694	3.6	72.0	78.0	1.942857	1.328571	0.126069	1013.2	1016.3	0	0.2
2	2.330694	21.399766	5.4	64.0	53.0	1.864286	0.992857	0.263743	1017.2	1020.7	0	0.0

In [54]:

```
df_test.shape
```

Out[54]:

```
(7387, 73)
```

- **Feature 19**

In [55]:

```
df['19'].value_counts(dropna=False)
```

Out[55]:

```
E      1861
F      1559
I      1405
O      1396
C      1385
P      1373
D      1343
L      1303
A      1276
G      1272
M      1235
J      1216
K      1174
N      1139
B      1108
H      1096
NaN    1020
Name: 19, dtype: int64
```

Like in feature 5, we will try to add the NaN as a new category 'Other':

In [56]:

```
df['19'].fillna('Other', inplace=True)
df['19'].value_counts(dropna=False)
```

Out[56]:

```
E        1861
F        1559
I        1405
O        1396
C        1385
P        1373
D        1343
L        1303
A        1276
G        1272
M        1235
J        1216
K        1174
N        1139
B        1108
H        1096
Other    1020
Name: 19, dtype: int64
```

In the data exploration we've noticed that features 5,18,19 have the same categories.
After examination we have seen that we're getting better results when we drop this feature.
We've kept here our try to concatinate the one-hot encoded feature.

→ Update train set:

In [57]:

```
feature_19_dummies = pd.get_dummies(df['19'])[df['19'].value_counts(dropna=False).index]
feature_19_dummies = feature_19_dummies.add_prefix('feature_19_')
feature_19_dummies.head()
```

Out[57]:

	feature_19_E	feature_19_F	feature_19_I	feature_19_O	feature_19_C	feature_19_P	feature_1
0	0	0	0	0	0	0	
1	0	0	1	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

In [58]:

```
df.drop(['19'], axis=1, inplace=True)
#df = pd.concat([df,feature_19_dummies], axis=1)
#df.head(3)
```

In [59]:

```
df.shape
```

Out[59]:

```
(22161, 73)
```

→ Update test set:

In [60]:

```
df_test['19'].fillna('Other', inplace=True)
test_feature_19_dummies = pd.get_dummies(df_test['19'])[df_test['19'].value_counts(dropna=F
test_feature_19_dummies = test_feature_19_dummies.add_prefix('feature_19_')
df_test.drop(['19'], axis=1, inplace=True)
#df_test = pd.concat([df_test,test_feature_19_dummies], axis=1)
#df_test.head(3)
```

In [61]:

```
df_test.shape
```

Out[61]:

```
(7387, 72)
```

- ## Feature 22

In [62]:

```
df['22'].value_counts(dropna=False)
```

Out[62]:

```
2010    8158
2011    7058
2012    6945
Name: 22, dtype: int64
```

Let's use one-hot encoding:

→ Update train set:

In [63]:

```
feature_22_dummies = pd.get_dummies(df['22'], prefix='feature_22')
df.drop(['22'], axis=1, inplace=True)
df = pd.concat([df,feature_22_dummies], axis=1)
df.head(3)
```

Out[63]:

	0	1	2	3	4	7	8	10	11	12	13	14
0	1.170981	5.672133	0.6	80.0	76.0	1.107143	0.692857	0.702957	1024.1	1025.9	0	0.6
1	2.595788	23.203289	6.4	43.0	64.0	1.700000	0.614286	0.223911	1005.3	1008.1	0	0.0
2	0.972794	7.127348	0.4	63.0	100.0	1.242857	0.428571	0.180848	1020.8	1026.5	0	0.0

In [64]:

```
df.shape
```

Out[64]:

```
(22161, 75)
```

→ Update test set:

In [65]:

```
df_test['22'].value_counts(dropna=False)
```

Out[65]:

```
2010    2659
2011    2443
2012    2285
Name: 22, dtype: int64
```

In [66]:

```
test_feature_22_dummies = pd.get_dummies(df_test['22'], prefix='feature_22')
df_test.drop(['22'], axis=1, inplace=True)
df_test = pd.concat([df_test,test_feature_22_dummies], axis=1)
df_test.head(3)
```

Out[66]:

	0	1	2	3	4	7	8	10	11	12	13	14
0	1.534361	12.002415	2.6	67.0	97.0	1.600000	0.650000	0.212177	1022.1	1026.2	0	0.2
1	1.632953	14.821694	3.6	72.0	78.0	1.942857	1.328571	0.126069	1013.2	1016.3	0	0.2
2	2.330694	21.399766	5.4	64.0	53.0	1.864286	0.992857	0.263743	1017.2	1020.7	0	0.0

In [67]:

```
df_test.shape
```

Out[67]:

```
(7387, 74)
```

Numeric Features

- ## Feature 14

In [68]:

```
df['14'].describe()
```

Out[68]:

```
count    22080.000000
mean         2.289923
std          7.145425
min          0.000000
25%          0.000000
50%          0.000000
75%          0.800000
max        183.000000
Name: 14, dtype: float64
```

We can see from the data exploration analysis that this feature has a sagnificant amount of zeros.
After thorough examination we've also noticed a connection between this feature and feature 13.

While trying to find a correlation between the two, we've seen that when the value of the row at feature 14 is greater than 1mm, the value in feature 13 is 1, and when the value of the row at feature 14 is lower than or equal to 1mm, the value in feature 13 is 0.
Becuase of the sagnificant amount of zeros, we've decided to make feature 14 a binary one: (0) → 0, (>0) → 1. We tried to handle the missing values in the same methods as feature 13,
Here we've found that the best results are given when we are filling the missing values with '1'.

However, as a result of the findings, we've tried the following:

1. Dropping feature 14
2. Dropping feature 13
3. Keeping them both
4. Dropping them both

We've seen that the best results are given when we are keeping them both.

→ Update train set:

In [69]:

```
#df['14'].fillna(0, inplace=True)
#df['14'].fillna(method='ffill', inplace=True)
df['14'].fillna(1,inplace=True)
df['14'] = [0 if i==0.0 else 1 for i in df['14']]
df['14'].value_counts(dropna=False)
#df.drop(['14'], axis=1, inplace=True)
```

Out[69]:

```
0    13816
1     8345
Name: 14, dtype: int64
```

→ Update test set:

In [70]:

```
#df_test['14'].fillna(0, inplace=True)
#df_test['14'].fillna(method='ffill', inplace=True)
df_test['14'].fillna(1,inplace=True)
df_test['14'] = [0 if i==0.0 else 1 for i in df_test['14']]
df_test['14'].value_counts(dropna=False)
#df_test.drop(['14'], axis=1, inplace=True)
```

Out[70]:

```
0    4571
1    2816
Name: 14, dtype: int64
```

According to the features' behaviour, we decided to handle the missing values differently:

- ## Features: 3,4,7,8,11,12,15,17,24

We'll replace missing values with the <u>median</u> value of each of these numeric features:

In [71]:

```
features = ['3','4','7','8','11','12','15','17','24']

# train set and test set update
for feature in features:
    df[feature].fillna(df[feature].median(),inplace=True)           # update train set
    df_test[feature].fillna(df_test[feature].median(),inplace=True) # update test set
```

- ## Features: 16,20,21,23

We'll replace missing values with the <u>mean</u> value of each of these numeric features:

In [72]:

```
features = ['16','20','21','23']

# train set and test set update
for feature in features:
    df[feature].fillna(df[feature].mean(), inplace=True)            # update train set
    df_test[feature].fillna(df_test[feature].mean(), inplace=True) # update test set
```

Train & Test set Nans check

Check that we haven't missed something.

In [73]:

```
nan_table(df)
```

Out[73]:

	0	1	2	3	4	7	8	10	11	12	13	14	15	16	17	20	21	23	24	label	a0	a1	a10
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

In [74]:

```
nan_table(df_test)
```

Out[74]:

	0	1	2	3	4	7	8	10	11	12	13	14	15	16	17	20	21	23	24	a0	a1	a10	a11
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

2.2. Outliers Handling

Now each feature doesn't have any missing values.
So, the next step is to overview the numeric features and identify outliers. For identifying outliers, we use Interquartile Range:

$$IQR = Q_3 - Q_1$$

if $(x_i < Q_1 - 1.5 \cdot IQR)$ or $(x_i > Q_3 + 1.5 \cdot IQR)$ then x_i will be classified as an outlier.

The following function will find all the places of these outliers:

In [75]:

```
def outliers_detector(feature):
    Q1 = df[feature].quantile(0.25)
    Q3 = df[feature].quantile(0.75)
    IQR = Q3 - Q1

    outliers_places = (df[feature] < (Q1-1.5*IQR)) | (df[feature] > (Q3+1.5*IQR))
    print("Total number of %s outliers have been detected for feature %s" %(outliers_places

    return outliers_places
```

Please pay attention:

1. In this process we **remove** outliers **only from the train set**.
2. On some of the features we **apply log transform**. In this case we apply the log transform **on both train set and test set**.

Now let's overview each numeric feature:

- ## Feature 0

In [76]:

```
outliers = outliers_detector('0')
print(df['0'][outliers].value_counts())
```

```
Total number of 172 outliers have been detected for feature 0
-0.362195    1
 4.546625    1
 5.067780    1
 4.675431    1
 4.932533    1
            ..
 4.607829    1
 6.195760    1
-0.105352    1
 4.388858    1
 4.864781    1
Name: 0, Length: 172, dtype: int64
```

We can see that:

    1. The feature is normal-distributed from the graphs.
    2. The outliers are not grouped, they are scattered.

So let's remove them.

In [77]:

```
df['0'] = df['0'][~outliers]  # '~' means to keep values except the masked ones.
```

- ## Feature 1

In [78]:

```
outliers = outliers_detector('1')
print(df['1'][outliers].value_counts())
```

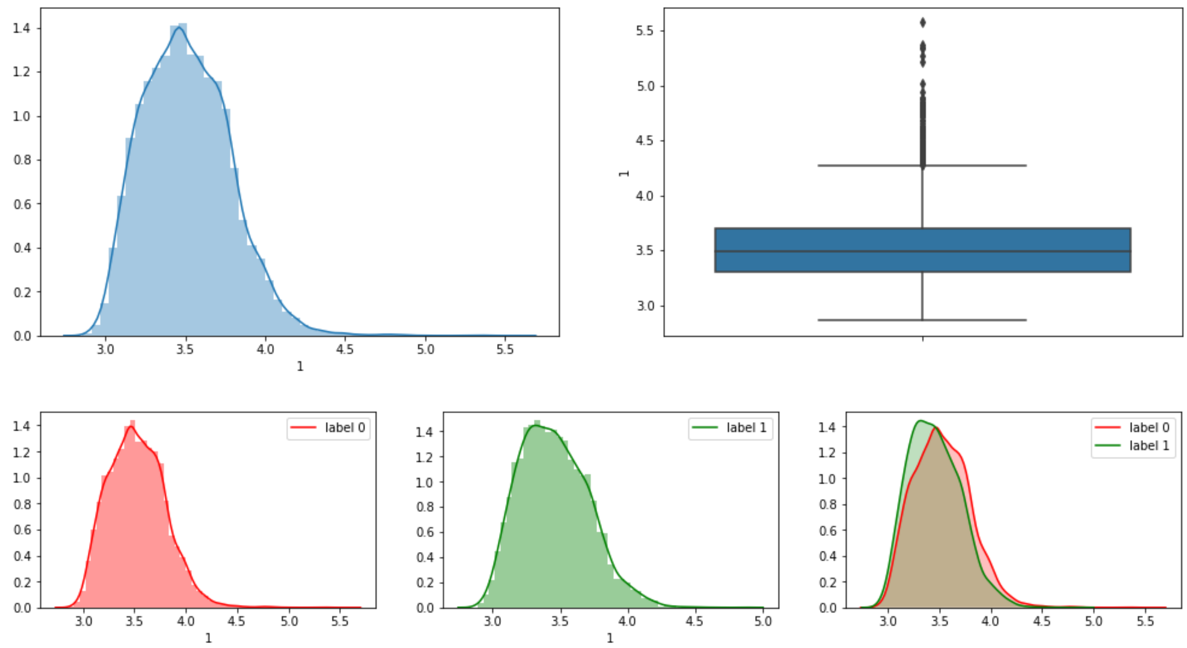
```
Total number of 499 outliers have been detected for feature 1
52.821640     1
45.593147     1
48.383619     1
44.964048     1
74.895785     1
             ..
46.370354     1
48.364510     1
100.904691    1
76.707957     1
51.472888     1
Name: 1, Length: 499, dtype: int64
```

We can see from the graphs that the feature has a log-normal distribution from the graphs.
After log transforming the feature we can see that now the feature has a normal distribution and less outliers:

In [79]:

```
df['1'] = np.log(df['1']+15)           # update train set
df_test['1'] = np.log(df_test['1']+15) # update test set

explore_feature('1')
```

```
Feature: 1
------------------------
count    22161.000000
mean         3.510274
std          0.272544
min          2.858612
25%          3.305727
50%          3.491441
75%          3.693779
max          5.575486
Name: 1, dtype: float64
Total nulls: 0
```



So we won't remove the outliers.

In [80]:

```
#df['1'] = df['1'][~outliers]  # '~' means to keep values except the masked ones.
 # updating in the test set
```

- **Feature 2**

In [81]:

```
outliers = outliers_detector('2')
print(df['2'][outliers].value_counts())
```

```
Total number of 564 outliers have been detected for feature 2
13.2    58
13.0    37
13.4    33
14.4    29
15.0    27
        ..
23.1     1
81.2     1
19.6     1
23.8     1
33.4     1
Name: 2, Length: 95, dtype: int64
```

We can see that:

```
1. The outliers are not scatterd, and a suspected number of outliers with the valu
e '13.2' were found.
2. Also, the feature looks like a tail of a distribution.
```

We tried to apply log transform to the feature, but we've seen that it lowered the models performance. So we've decided to keep the feature as it is.

In [82]:

```
#df['2'] = np.log(df['1']+15)
#df_test['2'] = np.log(df_test['1']+15)
```

- ## Feature 3

In [83]:

```
outliers = outliers_detector('3')
print(df['3'][outliers].value_counts())
```

```
Total number of 0 outliers have been detected for feature 3
Series([], Name: 3, dtype: int64)
```

No outliers here!

- ## Feature 4

In [84]:

```
outliers = outliers_detector('4')
print(df['4'][outliers].value_counts())
```

```
Total number of 235 outliers have been detected for feature 4
17.0    34
16.0    32
18.0    26
14.0    23
19.0    23
13.0    18
15.0    18
12.0    16
11.0    13
10.0    10
9.0      7
8.0      6
7.0      4
5.0      2
6.0      2
3.0      1
Name: 4, dtype: int64
```

We can see that:

1. **`The feature is has a normal-like distribution from the graphs.`**
2. **`The outliers are gruoped.`**

So for now, we'll <u>not</u> remove them.

- ## Feature 7

In [85]:

```
outliers = outliers_detector('7')
print(df['7'][outliers].value_counts())
```

```
Total number of 6 outliers have been detected for feature 7
3.157143    2
3.114286    2
3.435714    1
3.164286    1
Name: 7, dtype: int64
```

We can see that:

1. **`The feature is almost like a normal-distributed feature from the graphs.`**
2. **`The outliers are far from the center.`**

So let's remove them.

In [86]:

```
df['7'] = df['7'][~outliers]  # '~' means to keep values except the masked ones.
```

- **Feature 8**

In [87]:

```
outliers = outliers_detector('8')
print(df['8'][outliers].value_counts())
```

```
Total number of 0 outliers have been detected for feature 8
Series([], Name: 8, dtype: int64)
```

No outliers were found!

- **Feature 10**

In [88]:

```
outliers = outliers_detector('10')
print(df['10'][outliers].value_counts())
```

```
Total number of 1144 outliers have been detected for feature 10
 0.793729    1
 0.727093    1
 0.814579    1
 0.863058    1
 0.842744    1
            ..
 0.895949    1
 0.812613    1
 0.769879    1
 0.807727    1
-0.101374    1
Name: 10, Length: 1144, dtype: int64
```

As we can see in the graph, it looks like that this feature has 2 different distributions, both normal-like. The outliers given here are part of the second distribution - so we will not make any change to this feature.

- **Feature 11**

In [89]:

```
outliers = outliers_detector('11')
print(df['11'][outliers].value_counts())
```

```
Total number of 170 outliers have been detected for feature 11
1035.0    6
1034.8    6
1035.7    5
1035.2    5
1034.4    5
         ..
990.9     1
1038.9    1
1038.2    1
986.2     1
1036.7    1
Name: 11, Length: 96, dtype: int64
```

We can see that the feature is almost like a normal-distributed feature from the graphs, so we wanted to remove them at first, but we have seen that with removing these outliers our models performance are lower.
So we decided to keep it

In [90]:

```
#df['11'] = df['11'][~outliers]  # '~' means to keep values except the masked ones.
```

- ## Feature 12

In [91]:

```
outliers = outliers_detector('12')
print(df['12'][outliers].value_counts())
```

```
Total number of 218 outliers have been detected for feature 12
1036.7    12
1036.6     8
998.6      7
1037.2     6
1036.8     5
          ..
987.3      1
996.6      1
997.7      1
992.3      1
998.9      1
Name: 12, Length: 101, dtype: int64
```

This feature behaves almost like feature 11, so we wanted to remove the outliers, but we have seen that the results are better when we are keeping the feature as it is, so we won't remove them.

In [92]:

```
#df['12'] = df['12'][~outliers]  # '~' means to keep values except the masked ones.
```

- ### Feature 15

In [93]:

```
outliers = outliers_detector('15')
print(df['15'][outliers].value_counts())
```

```
Total number of 0 outliers have been detected for feature 15
Series([], Name: 15, dtype: int64)
```

No outliers here, but we tried to log transform this feature and it gave us better peformance results.

Log transform

In [94]:

```
df['15'] = np.log(df['15']+30)
df_test['15'] = np.log(df_test['15']+30)
```

- ### Feature 16

In [95]:

```
outliers = outliers_detector('16')
print(df['16'][outliers].value_counts())
```

```
Total number of 26 outliers have been detected for feature 16
41.8    4
41.3    4
42.2    3
41.4    3
41.9    2
41.5    2
43.3    1
42.3    1
42.4    1
43.2    1
46.1    1
42.9    1
41.6    1
42.0    1
Name: 16, dtype: int64
```

We can see at the graph that these outliers are grouped, so for now we won't remove them.

- ### Feature 17

In [96]:

```
outliers = outliers_detector('17')
print(df['17'][outliers].value_counts())
```

```
Total number of 4 outliers have been detected for feature 17
36.4    2
36.9    1
36.8    1
Name: 17, dtype: int64
```

Let's remove these outliers.

In [97]:

```
df['17'] = df['17'][~outliers]  # '~' means to keep values except the masked ones.
```

- ## Feature 20

In [98]:

```
outliers = outliers_detector('20')
print(df['20'][outliers].value_counts())
```

```
Total number of 795 outliers have been detected for feature 20
72.0     126
69.0     125
70.0     114
74.0      96
76.0      96
78.0      47
80.0      38
83.0      28
81.0      26
85.0      19
87.0      13
93.0      12
91.0      11
89.0      10
96.0       8
98.0       8
94.0       4
100.0      3
102.0      2
107.0      2
106.0      2
109.0      1
113.0      1
104.0      1
115.0      1
135.0      1
Name: 20, dtype: int64
```

The outliers are grouped, so we won't remove them.

- ## Feature 21

In [99]:

```
outliers = outliers_detector('21')
print(df['21'][outliers].value_counts())
```

```
Total number of 333 outliers have been detected for feature 21
41.0    92
43.0    78
44.0    46
46.0    44
48.0    23
50.0    18
52.0    15
54.0     8
56.0     4
65.0     3
57.0     1
69.0     1
Name: 21, dtype: int64
```

The outliers are grouped, so we won't remove them.

- ## Feature 23

In [100]:

```
outliers = outliers_detector('23')
print(df['23'][outliers].value_counts())
```

```
Total number of 383 outliers have been detected for feature 23
370.0    89
390.0    70
410.0    52
430.0    46
440.0    30
460.0    24
520.0    19
500.0    16
480.0    15
560.0     9
540.0     6
570.0     3
610.0     2
590.0     1
670.0     1
Name: 23, dtype: int64
```

The outliers here are grouped, as can be seen in the data exploration,
so we won't remove them.

- ## Feature 24

In [101]:

```
outliers = outliers_detector('24')
print(df['24'][outliers].value_counts())
```

```
Total number of 407 outliers have been detected for feature 24
795.628122     1
697.290696     1
678.789732     1
792.125312     1
883.651990     1
              ..
947.365790     1
801.017161     1
750.866957     1
842.595441     1
1030.228045    1
Name: 24, Length: 407, dtype: int64
```

**This feature looks like a tail of a distribution, more like a log-normal distribution.
so we log-transform it.**

→ **Log transform**

In [102]:

```
df['24'] = np.log(df['24']+10)           # train set update
df_test['24'] = np.log(df_test['24']+10) # test set update
```

- ## Rest of the features

The rest of the features are binary, so in these features we won't check for outliers.

- ## Nans check

In [103]:

```
nan_table(df)
```

Out[103]:

	0	1	2	3	4	7	8	10	11	12	13	14	15	16	17	20	21	23	24	label	a0	a1	a10
0	172	0	0	0	0	6	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0

Now, after we have removed the outliers, we drop the rows in which we have NaN values in them:

In [104]:

```
df.dropna(inplace=True)
```

Now we have to reset the index in order to preserve the sequence:

In [105]:

```
df.reset_index(inplace=True)
df.drop('index', axis=1, inplace=True)
df.head()
```

Out[105]:

	0	1	2	3	4	7	8	10	11	12	13	14
0	1.170981	3.028787	0.6	80.0	76.0	1.107143	0.692857	0.702957	1024.1	1025.9	0	1
1	2.595788	3.642922	6.4	43.0	64.0	1.700000	0.614286	0.223911	1005.3	1008.1	0	0
2	0.972794	3.096814	0.4	63.0	100.0	1.242857	0.428571	0.180848	1020.8	1026.5	0	0
3	1.891667	3.492910	4.2	65.0	71.0	1.050000	0.671429	0.181289	1021.9	1019.8	0	1
4	1.965881	3.365120	3.2	40.0	62.0	1.950000	1.085714	0.237347	1005.3	1007.8	0	0

In [106]:

```
df.shape
```

Out[106]:

(21982, 75)

- ## Nans check once again

In [107]:

```
table = nan_table(df)
table
```

Out[107]:

	0	1	2	3	4	7	8	10	11	12	13	14	15	16	17	20	21	23	24	label	a0	a1	a10	a
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

2.3. Clustering + Math Manipulations

We'll build another train set with some new features.
Later we will compare the data sets and its results

→ Train set

In [108]:

```
df1 = df.copy()
```

In [109]:

```
df1['2*0+1-2'] = 2*df1['0']+df['1']-df['2']
df1['(15*17)/100'] = (1/100)*df1['15']*df1['17']
df1['20-21+23'] = (df1['20']-df1['21'])+df1['23']
df1['7/8'] = df1['7']/df1['8']
df1.head(2)
```

Out[109]:

	0	1	2	3	4	7	8	10	11	12	13	14
0	1.170981	3.028787	0.6	80.0	76.0	1.107143	0.692857	0.702957	1024.1	1025.9	0	1	4
1	2.595788	3.642922	6.4	43.0	64.0	1.700000	0.614286	0.223911	1005.3	1008.1	0	0	4

→ Test set

In [110]:

```
df1_test = df_test.copy()
```

In [111]:

```
df1_test['2*0+1-2'] = 2*df1_test['0']+df_test['1']-df_test['2']
df1_test['(15*17)/100'] = (1/100)*df1_test['15']*df1_test['17']
df1_test['20-21+23'] = (df1_test['20']-df1_test['21'])+df1_test['23']
df1_test['7/8'] = df1_test['7']/df1_test['8']
df1_test.head(2)
```

Out[111]:

	0	1	2	3	4	7	8	10	11	12	13	14
0	1.534361	3.295926	2.6	67.0	97.0	1.600000	0.650000	0.212177	1022.1	1026.2	0	1	4
1	1.632953	3.395236	3.6	72.0	78.0	1.942857	1.328571	0.126069	1013.2	1016.3	0	1	4

In [112]:

```
df.shape,df_test.shape
```

Out[112]:

```
((21982, 75), (7387, 74))
```

In [113]:

```
df1.shape,df1_test.shape
```

Out[113]:

```
((21982, 79), (7387, 78))
```

Numeric & Categorical Data Splitting

Let's split the data to binary and numeric, so we could appropriately apply either standartization and diemnsion reduction techniques on the numeric features. After doing that we will concat the features again.

- ## Train set

In [114]:

```
df.head(2)
```

Out[114]:

	0	1	2	3	4	7	8	10	11	12	13	14
0	1.170981	3.028787	0.6	80.0	76.0	1.107143	0.692857	0.702957	1024.1	1025.9	0	1	4
1	2.595788	3.642922	6.4	43.0	64.0	1.700000	0.614286	0.223911	1005.3	1008.1	0	0	4

→ Binary Features

In [115]:

```
data_binary = df.select_dtypes(exclude=['float64'])
data_binary = data_binary.drop('label', axis=1)  # remove label from dimension reduction
data_binary.head(2)
```

Out[115]:

	13	14	a0	a1	a10	a11	a12	a13	a14	a15	a16	a17	a18	a19	a2	a20	a21	a22	a2
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

→ Numeric Features

In [116]:

```
data_numeric = df.select_dtypes(include=['float64'])
data_numeric.head(2)
```

Out[116]:

	0	1	2	3	4	7	8	10	11	12	15
0	1.170981	3.028787	0.6	80.0	76.0	1.107143	0.692857	0.702957	1024.1	1025.9	4.127134
1	2.595788	3.642922	6.4	43.0	64.0	1.700000	0.614286	0.223911	1005.3	1008.1	4.382027

In [117]:

```
data_binary.shape,data_numeric.shape
```

Out[117]:

```
((21982, 57), (21982, 17))
```

- ## Test set

In [118]:

```
df_test.head(2)
```

Out[118]:

	0	1	2	3	4	7	8	10	11	12	13	14	
0	1.534361	3.295926	2.6	67.0	97.0	1.600000	0.650000	0.212177	1022.1	1026.2	0	1	4
1	1.632953	3.395236	3.6	72.0	78.0	1.942857	1.328571	0.126069	1013.2	1016.3	0	1	4

→ Binary Features

In [119]:

```
data_binary_test = df_test.select_dtypes(exclude=['float64'])
data_binary_test.head(2)
```

Out[119]:

	13	14	a0	a1	a10	a11	a12	a13	a14	a15	a16	a17	a18	a19	a2	a20	a21	a22	a2
0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	
1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	

→ Numeric Features

In [120]:

```
data_numeric_test = df_test.select_dtypes(include=['float64'])
data_numeric_test.head(2)
```

Out[120]:

	0	1	2	3	4	7	8	10	11	12	15
0	1.534361	3.295926	2.6	67.0	97.0	1.600000	0.650000	0.212177	1022.1	1026.2	4.905275
1	1.632953	3.395236	3.6	72.0	78.0	1.942857	1.328571	0.126069	1013.2	1016.3	4.158883

In [121]:

```
data_binary_test.shape,data_numeric_test.shape
```

Out[121]:

```
((7387, 57), (7387, 17))
```

2.4. Normalization

We've tried to normalize the data by using the methods:

1. Z-Score Standard Scaling
2. Min-Max Scaler

We've found that the best results are given with the standard scaler.

→ Apply Standard Scaler on the train set

In [122]:

```
standard_scaler = StandardScaler()                                       # initiate Z-s
standard_scaler.fit(data_numeric)                                        # fit the nume
scaled_data_numeric = pd.DataFrame(standard_scaler.transform(data_numeric))  # save the sca
scaled_data_numeric.head(3)
```

Out[122]:

	0	1	2	3	4	5	6	7	
0	-1.285630	-1.826405	-1.352989	1.409001	0.407751	-1.126703	-0.418407	2.934596	1.247
1	0.547874	0.531332	0.510946	-0.433090	-0.256283	0.116807	-0.589220	-0.027995	-1.440
2	-1.540666	-1.565238	-1.417263	0.562635	1.735818	-0.842044	-0.992960	-0.294315	0.776

→ Apply Standard Scaler on the test set

In [123]:

```
standard_scaler = StandardScaler()                                                  # in
standard_scaler.fit(data_numeric_test)                                              # fi
scaled_data_numeric_test = pd.DataFrame(standard_scaler.transform(data_numeric_test))  # sa
scaled_data_numeric_test.head(3)
```

Out[123]:

	0	1	2	3	4	5	6	7	
0	-0.784622	-0.768432	-0.619773	0.752873	1.566918	-0.091028	-0.521114	-0.097998	0.9600
1	-0.664211	-0.405404	-0.349935	1.003694	0.502015	0.625860	0.957351	-0.643177	-0.3165
2	0.187941	0.323234	0.135774	0.602380	-0.899173	0.461573	0.225900	0.228487	0.2572

Min Max normalization - Not Used

In [124]:

```
"""
min_max_scaler = MinMaxScaler()
min_max_scaler.fit(data_numeric)
scaled_data_numeric = pd.DataFrame(min_max_scaler.transform(data_numeric))
scaled_data_numeric.head()
"""
```

Out[124]:

```
'\nmin_max_scaler = MinMaxScaler()\nmin_max_scaler.fit(data_numeric)\nscaled
_data_numeric = pd.DataFrame(min_max_scaler.transform(data_numeric))\nscaled
_data_numeric.head()\n'
```

In [125]:

```
"""
min_max_scaler = MinMaxScaler()
min_max_scaler.fit(data_numeric_test)
scaled_data_numeric_test = pd.DataFrame(min_max_scaler.transform(data_numeric_test))
scaled_data_numeric_test.head()
"""
```

Out[125]:

```
'\nmin_max_scaler = MinMaxScaler()\nmin_max_scaler.fit(data_numeric_test)\ns
caled_data_numeric_test = pd.DataFrame(min_max_scaler.transform(data_numeric
_test))\nscaled_data_numeric_test.head()\n'
```

2.5. Feature Selection and Dimensionality Reduction

We've chose PCA to apply dimensionality reduction.
Let's find out if we can reduced some of the dimensions of both numeric and binary features:

Let's build a relevant function to see what number of components describe 95% of the total variance in both numeric and binary datasets:

In [126]:

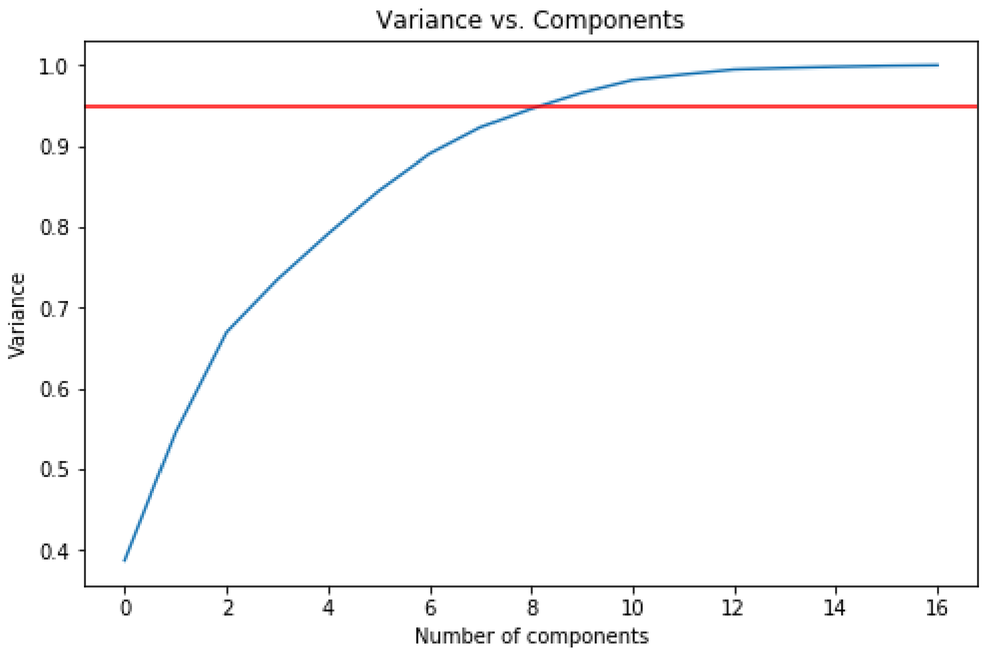
```
def pca_explain(data):
    """
    This function plots a graph of total variance vs. number of components.
    The function returns the number of components (features) that explain 95% of the total
    """
    pca = PCA().fit(data) # fitting the PCA on the data
    plt.figure(figsize=(8,5))
    explained_variance = pca.explained_variance_ratio_.cumsum()
    ideal_num_of_components = np.argwhere(explained_variance >= 0.95)[0] # at least 95% of
    plt.plot(explained_variance) # Accumulative sum of the variance
    plt.xlabel('Number of components')
    plt.ylabel('Variance')
    plt.title('Variance vs. Components')
    plt.axhline(0.95,c='r') # red line for 95% variance
    plt.show()
    print("%s components explains at least 95 percent of the variance in the data"
         % (ideal_num_of_components))
    return int(ideal_num_of_components)
```

2.5.1. Numeric Data Dimensionality Reduction

Let's see to what number of components can we reduce our numeric data:

In [127]:

```
num_of_components = pca_explain(scaled_data_numeric)
```




```
[9] components explains at least 95 percent of the variance in the data
```

We can see that 9 components describes at least 95% of the total variance.
Now we can reduce our scaled numeric data to just 9 components:

→ Train set

In [128]:

```
pca = PCA(n_components = num_of_components)
scaled_data_numeric_pca = pca.fit(scaled_data_numeric)
final_scaled_data_numeric = pd.DataFrame(scaled_data_numeric_pca.transform(scaled_data_nume
final_scaled_data_numeric.head(3)
```

Out[128]:

	0	1	2	3	4	5	6	7	
0	-4.184433	-0.800851	-2.098874	0.679930	2.605150	0.800504	-1.224099	1.155316	-0.548
1	1.354979	2.430907	1.049586	-1.264800	0.690361	-1.095793	-0.195910	-0.675204	1.851
2	-4.172393	-1.759761	-1.170518	-0.190061	-0.707972	0.821928	0.586586	-1.204634	0.068

In [129]:

```
final_scaled_data_numeric.shape
```

Out[129]:

```
(21982, 9)
```

→ Test set

In [130]:

```
scaled_data_numeric_pca = pca.fit(scaled_data_numeric_test)
final_scaled_data_numeric_test = pd.DataFrame(scaled_data_numeric_pca.transform(scaled_data
final_scaled_data_numeric_test.head(3)
```

Out[130]:

	0	1	2	3	4	5	6	7	
0	-1.770678	0.621037	0.759420	-0.232723	-0.634585	-0.601021	1.535338	2.079814	1.2772
1	-0.123224	-0.530261	-2.838999	0.080235	-1.205571	-0.138296	-0.108375	-0.290904	0.1842
2	0.992587	-0.129072	0.281755	0.087819	-0.204659	-0.703439	0.919072	0.767923	0.5549

In [131]:

```
final_scaled_data_numeric_test.shape
```

Out[131]:

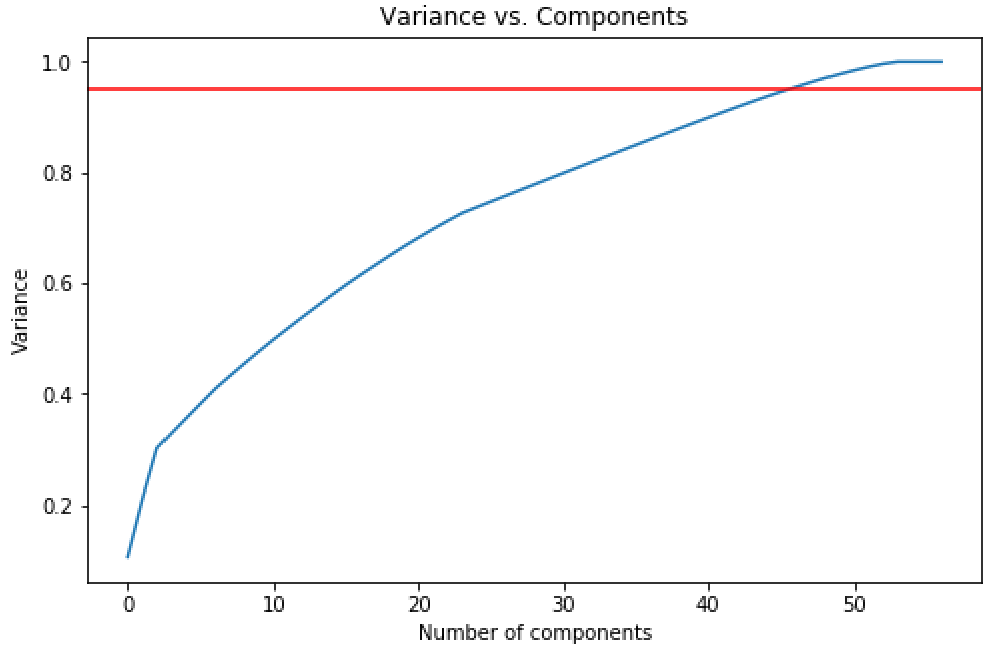
```
(7387, 9)
```

2.5.2. Binary Data Dimensionality Reduction

Let's see to what number of components can we reduce our binaric data:

In [132]:

```
num_of_components = pca_explain(data_binary)
```




```
[46] components explains at least 95 percent of the variance in the data
```

We can see that 46 components describes 95% of the total variance.
Now we can reduced our binary data to just 46 components:

→ Train set

In [133]:

```
pca = PCA(n_components = num_of_components)
data_binary_pca = pca.fit(data_binary)
final_data_binary = pd.DataFrame(data_binary_pca.transform(data_binary))
final_data_binary.columns = ['b_' + str(col) for col in final_data_binary.columns]
final_data_binary.head(3)
```

Out[133]:

	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	I
0	0.323988	-0.619957	-0.572718	-0.352887	0.823818	-0.049566	-0.197069	0.650404	-0.443
1	-0.668057	-0.216748	0.637418	0.102180	-0.013104	0.001443	-0.020575	-0.032017	0.011
2	-0.675278	-0.230681	0.630995	-0.053430	-0.116076	-0.001329	0.871009	-0.138052	-0.151

→ Test set

In [134]:

```
pca = PCA(n_components = num_of_components)

data_binary_pca = pca.fit(data_binary_test)

final_data_binary_test = pd.DataFrame(data_binary_pca.transform(data_binary_test))
final_data_binary_test.columns = ['b_' + str(col) for col in final_data_binary_test.columns
final_data_binary_test.head(3)
```

Out[134]:

	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b
0	0.068785	0.277603	0.863707	0.881948	-0.082154	-0.274077	0.011682	-0.228141	-0.0740
1	0.069643	0.270810	0.857779	0.298931	-0.074278	-0.006641	-0.027017	0.126177	0.6642
2	-0.541871	0.458901	-0.625698	-0.141440	-0.209222	0.347553	0.779813	0.145385	0.2625

2.5.3. Final train & test sets

We tried to evaluate the models:

```
1. After applying PCA on both numeric features & binaric features
2. After applying PCA only on the numeric features, while keeping the binary featu
res untouched
```

We have seen that our models have better performance when we are applying PCA only on the numeric data.

Now let's join both reduced numeric data (after PCA) and binary data:

→ Train set

In [135]:

```
final_train_set = pd.concat([final_scaled_data_numeric,data_binary],axis=1)
final_train_set.head(2)
```

Out[135]:

	0	1	2	3	4	5	6	7	
0	-4.184433	-0.800851	-2.098874	0.67993	2.605150	0.800504	-1.224099	1.155316	-0.54861
1	1.354979	2.430907	1.049586	-1.26480	0.690361	-1.095793	-0.195910	-0.675204	1.85127

→ Test set

In [136]:

```
final_test_set = pd.concat([final_scaled_data_numeric_test,data_binary_test],axis=1)
final_test_set.head(2)
```

Out[136]:

	0	1	2	3	4	5	6	7	
0	-1.770678	0.621037	0.759420	-0.232723	-0.634585	-0.601021	1.535338	2.079814	1.2772
1	-0.123224	-0.530261	-2.838999	0.080235	-1.205571	-0.138296	-0.108375	-0.290904	0.1842

In [137]:

```
final_train_set.shape,final_test_set.shape
```

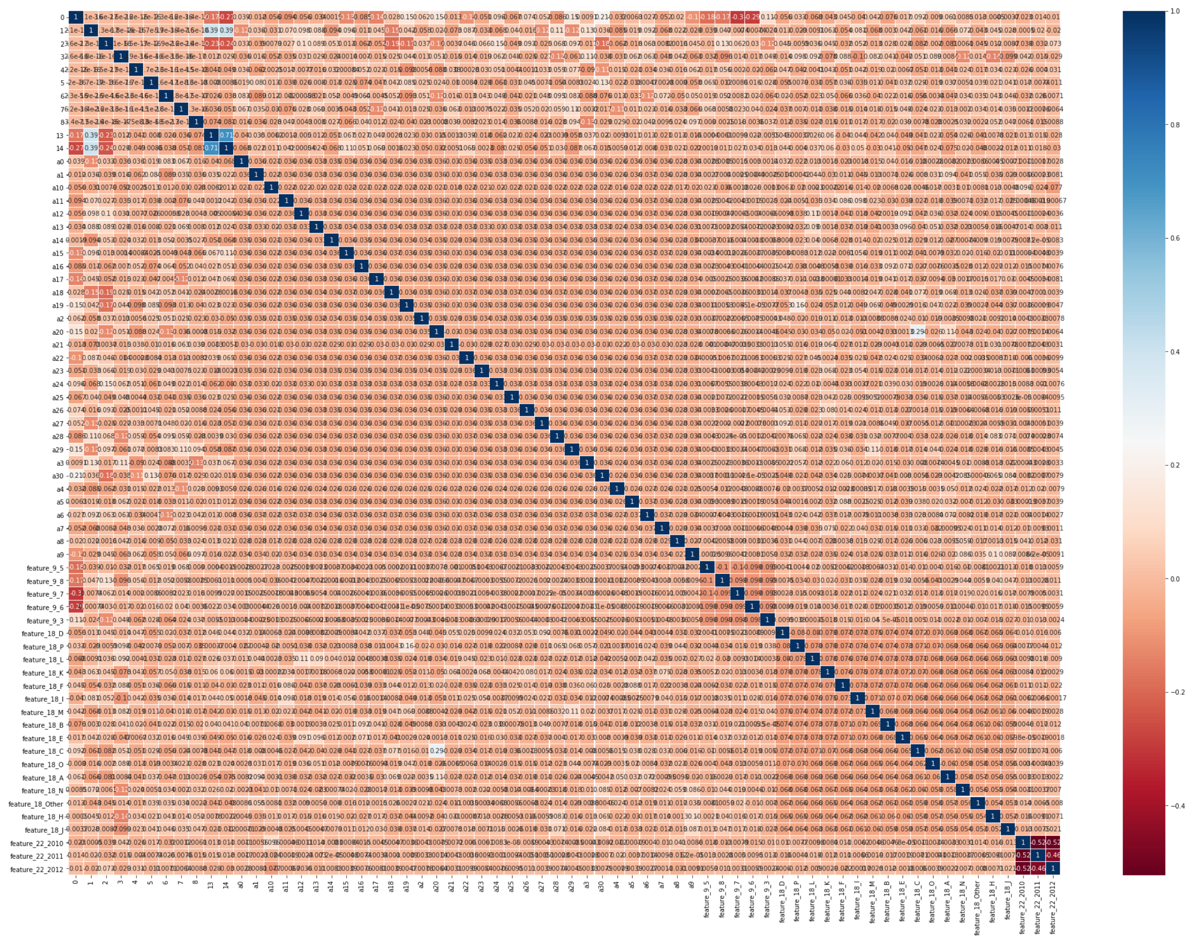
Out[137]:

((21982, 66), (7387, 66))

Now we look for correlations between features:

In [138]:

```
plt.subplots(figsize=(35,25))
sns.heatmap(final_train_set.corr(),
            annot=True, linecolor='white', linewidth='0.05', cmap="RdBu")
plt.show()
```



**Although we can see that a very small part of the features has either positive or negative correlation, we can see that the max correlation is below 0.85 and the min correlation is above -0.85.
So we decided not to drop any feature.**

Final number of features: 66

Create X_final_train and Y_final_train for the evaluation

In [139]:

```
X_final_train = final_train_set
Y_final_train = df['label']
```

And now let's return the label column to the final train set:

In [140]:

```
final_train_set = pd.concat([final_train_set,df['label']],axis=1)
final_train_set.head(3)
```

Out[140]:

	0	1	2	3	4	5	6	7	
0	-4.184433	-0.800851	-2.098874	0.679930	2.605150	0.800504	-1.224099	1.155316	-0.548
1	1.354979	2.430907	1.049586	-1.264800	0.690361	-1.095793	-0.195910	-0.675204	1.851
2	-4.172393	-1.759761	-1.170518	-0.190061	-0.707972	0.821928	0.586586	-1.204634	0.068

In [141]:

```
final_train_set.shape
```

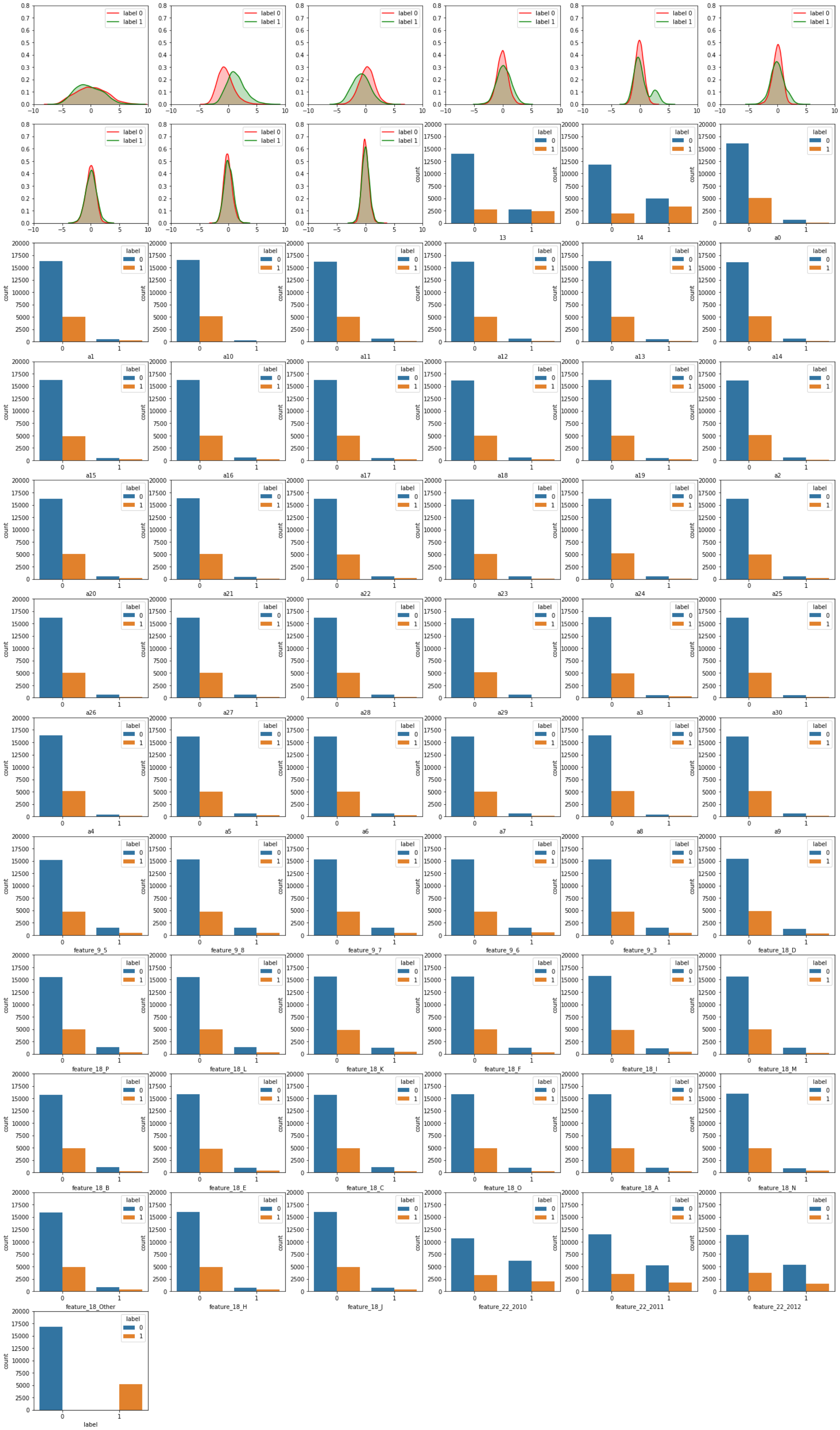
Out[141]:

```
(21982, 67)
```

Features lookout

In [142]:

```
fig = plt.figure(figsize = (25, 45))
j = 0
for feature in final_train_set.columns:
    plt.subplot(12, 6, j+1)
    j += 1
    if final_train_set[feature].dtype == 'float64':
        sns.kdeplot(final_train_set[feature][final_train_set['label'] == 0], color='r', lab
        sns.kdeplot(final_train_set[feature][final_train_set['label'] == 1], color='g', lab
        plt.legend(loc='upper right')
        plt.ylim(0,0.8)
        plt.xlim(-10,10)
    else:
        countplt = sns.countplot(x = feature, hue = 'label', data = final_train_set)
        plt.ylim(0, 20000)
        plt.legend(title='label', loc='upper right')
plt.show()
```


label 0
label 1
label
count
13
14
a0
a1
a10
a11
a12
a13
a14
a15
a16
a17
a18
a19
a2
a20
a21
a22
a23
a24
a25
a26
a27
a28
a29
a3
a30
a4
a5
a6
a7
a8
a9
feature_9_5
feature_9_8
feature_9_7
feature_9_6
feature_9_3
feature_18_D
feature_18_P
feature_18_L
feature_18_K
feature_18_F
feature_18_I
feature_18_M
feature_18_B
feature_18_E
feature_18_C
feature_18_O
feature_18_A
feature_18_N
feature_18_Other
feature_18_H
feature_18_J
feature_22_2010
feature_22_2011
feature_22_2012
label

3. Bulilding Models

Let's setup a time list for time measurements:

In [143]:

```
running_time = []
```

3.1. Initial Models Setup

We have chosen two initial models: (Gaussian) Naive Bayes and Logistic Regression.

3.1.1. (Gaussian) Naive Bayes

In [144]:

```
start = time.time()
GaussianNaiveBayes_options = {'priors' : [None],
          'var_smoothing' : [ 1e-9, 1e-7, 1e-5, 1e-3, 0.1, 1, 3]
              }

# Setup classifier, and find using GridsearchCV the best hyper-parameters
skf = KFold(n_splits=5)
GNB_best = GridSearchCV(GaussianNB(), GaussianNaiveBayes_options, cv=skf, scoring='roc_auc'
GNB_best.fit(X_final_train, Y_final_train)

print ('GNB chosen parameters (recieved best AUC): {}'.format(GNB_best.best_params_))
print ("GNB AUC score with the chosen parameters: ", GNB_best.best_score_)
total_time = (time.time()-start)/60
print("Running time: %s minutes" % (total_time))
running_time.append(total_time)
```

```
GNB chosen parameters (recieved best AUC): {'priors': None, 'var_smoothing':
0.1}
GNB AUC score with the chosen parameters:  0.8721231309700727
Running time: 0.0400595227877299 minutes
```

In [145]:

```
# final setting
GNB = GaussianNB(**GNB_best.best_params_)
```

3.1.2. Logistic Regression

In order to ensure we have the best hyperparameters chosen,
Let's setup the Logistic Regression classifier with the best hyperparameters using GridSearchCV:

In [146]:

```
start = time.time()
LogisticRegression_options = {'penalty' : ['l1', 'l2'],
                              'C' : [ 0.001, 0.01, 0.1, 0.5, 1, 10, 100],
                              'tol' : [ 0.1, 0.01, 0.001 ],
                              'max_iter' : [2000],
                              'solver' : ["liblinear"]}

# Setup classifier, and find using GridsearchCV the best hyper-parameters
kfold = KFold(n_splits = 5, shuffle = True, random_state=100)
LR_best = GridSearchCV(LogisticRegression(), LogisticRegression_options,  scoring = 'roc_au
LR_best.fit(X_final_train, Y_final_train)

print ('Logistic Regression chosen parameters (recieved best AUC): {}'.format(LR_best.best_
print ("Logistic Regression AUC score with the chosen parameters: ", LR_best.best_score_)
total_time = (time.time()-start)/60
print("Running time: %s minutes" % (total_time))
running_time.append(total_time)
```

```
Logistic Regression chosen parameters (recieved best AUC): {'C': 0.1, 'max_i
ter': 2000, 'penalty': 'l2', 'solver': 'liblinear', 'tol': 0.001}
Logistic Regression AUC score with the chosen parameters:  0.882239412962535
7
Running time: 0.10294134616851806 minutes
```

In [147]:

```
# final setting
LR = LogisticRegression(**LR_best.best_params_)
```

3.1.3. KNN - Not Used

We've found that this model doesn't fit well the data (overfitting), so we decided not to use it.

In [148]:

```
"""start = time.time()
KNN_options = {'n_neighbors' : [5,15,25],
               'weights' : [ 'uniform', 'distance'],
               'metric' : ['euclidean', 'manhattan'],
              }

# new approach: k = sqrt(num_of_samples)

# Setup classifier, and find using GridsearchCV the best hyper-parameters
kfold = KFold(n_splits = 5)
KNN_best = GridSearchCV(KNeighborsClassifier(), KNN_options, cv=kfold,  scoring='roc_auc',

KNN_best.fit(X_final_train, Y_final_train)

print ('KNN chosen parameters (recieved best AUC): {}'.format(KNN_best.best_params_))
print ("KNN AUC score with the chosen parameters: ", KNN_best.best_score_)
total_time = (time.time()-start)/60
print("Running time: %s minutes" % (total_time))
running_time.append(total_time)
"""
```

Out[148]:

```
'start = time.time()\nKNN_options = {\'n_neighbors\' : [5,15,25], \n
\'weights\' : [ \'uniform\', \'distance\'],\n               \'metric\' :
[\'euclidean\', \'manhattan\'],\n              }\n\n# new approach: k = sqrt
(num_of_samples)\n\n# Setup classifier, and find using GridsearchCV the best
hyper-parameters\nkfold = KFold(n_splits = 5)\nKNN_best = GridSearchCV(KNeig
hborsClassifier(), KNN_options, cv=kfold,  scoring=\'roc_auc\', n_jobs = -2)
\n\nKNN_best.fit(X_final_train, Y_final_train)\n\nprint (\'KNN chosen parame
ters (recieved best AUC): {}\'.format(KNN_best.best_params_))\nprint ("KNN A
UC score with the chosen parameters: ", KNN_best.best_score_)\ntotal_time =
(time.time()-start)/60\nprint("Running time: %s minutes" % (total_time))\nru
nning_time.append(total_time)\n'
```

In [149]:

```
# final setting
"""
KNN = KNeighborsClassifier(**KNN_best.best_params_)
"""
```

Out[149]:

```
'\nKNN = KNeighborsClassifier(**KNN_best.best_params_)\n'
```

3.2. Advanced Models Setup

We have chosen two advanced models: Multi-Layer Perceptron (ANN) and Adaptive Boosting (AdaBoost).

3.2.1. Multi-Layer Perceptron (ANN)

In order to ensure we have the best hyperparameters chosen,

Let's setup the MLP classifier with the best hyperparameters using GridSearchCV:

In [150]:

```
start = time.time()
ANN_options = {'activation' : ["relu"], #
               'hidden_layer_sizes' : [(10,),                # 1 small hidden layer
                                       (20,),                # another 1 small hidden layer
                                       (50, 50),             # 2 medium size layers
                                       (20, 20, 10, 10, 10), # five small layers
                                       (100,)],              # 1 big hidden layer
               'learning_rate_init' : [0.01, 0.001], #In some of the runs we saw that the n
               'random_state' :[100], # for consistent results
               'max_iter': [2000],
              }

# Setup classifier, and find using GridsearchCV the best hyper-parameters with kfold=5 as d
kfold = KFold(n_splits = 5, shuffle = True, random_state=100)
ANN_best = GridSearchCV(MLPClassifier(), ANN_options, cv=kfold, scoring = 'roc_auc', n_jobs
ANN_best.fit(X_final_train, Y_final_train)
print ('ANN chosen parameters (recieved best AUC): {}'.format(ANN_best.best_params_))
print ("ANN AUC score with the chosen parameters: ", ANN_best.best_score_)


total_time = (time.time()-start)/60
print("Running time: %s minutes" % (total_time))
running_time.append(total_time)
```

```
ANN chosen parameters (recieved best AUC): {'activation': 'relu', 'hidden_la
yer_sizes': (10,), 'learning_rate_init': 0.001, 'max_iter': 2000, 'random_st
ate': 100}
ANN AUC score with the chosen parameters:  0.9038793652782535
Running time: 7.700419616699219 minutes
```

In [151]:

```
# final setting
ANN = MLPClassifier(**ANN_best.best_params_)
```

3.2.2. Adaptive Boosting (AdaBoost)

In order to ensure we have the best hyperparameters chosen,
Let's setup the MLP classifier with the best hyperparameters using GridSearchCV:

In [152]:

```
start = time.time()
parametersOptions = {'n_estimators':[500,1000],
                     'learning_rate': [0.01,0.1,0.3],
                    'random_state' :[100]}

# Setup classifier, and find using GridsearchCV the best hyper-parameters with kfold=5 as d
kfold = KFold(n_splits = 5, shuffle = True, random_state=100)
ADB_best = GridSearchCV(AdaBoostClassifier(), parametersOptions, cv = kfold, scoring='roc_a
ADB_best.fit(X_final_train, Y_final_train)
print ('Adaptive Boosting chosen parameters (recieved best AUC): {}'.format(ADB_best.best_p
print ("Adaptive Boosting AUC score with the chosen parameters: ", ADB_best.best_score_)


total_time = (time.time()-start)/60
print("Running time: %s minutes" % (total_time))
running_time.append(total_time)
```

```
Adaptive Boosting chosen parameters (recieved best AUC): {'learning_rate':
0.1, 'n_estimators': 1000, 'random_state': 100}
Adaptive Boosting AUC score with the chosen parameters:  0.888308066475112
Running time: 5.357397683461508 minutes
```

In [153]:

```
# final setting
ADB = AdaBoostClassifier(**ADB_best.best_params_)
```

3.2.3. Random Forest - Not Used

We've found that this model doesn't fit well the data (overfitting), so we decided not to use it.

In [154]:

```
"""
start = time.time()
parametersOptions = {'min_samples_split':[4, 8, 16],
                     'max_depth':[5,8,30,50],
                     'criterion':['gini', 'entropy'],
                     'n_estimators':[30,100],
                     'random_state': [100]}

# Setup classifier, and find using GridsearchCV the best hyper-parameters with kfold=5 as d
kfold = KFold(n_splits = 5, shuffle = True, random_state=100)
RF_best = GridSearchCV(RandomForestClassifier(), parametersOptions, cv = kfold, scoring='ro
RF_best.fit(X_final_train, Y_final_train)
print ('ANN chosen parameters (recieved best AUC): {}'.format(RF_best.best_params_))
print ("ANN AUC score with the chosen parameters: ", RF_best.best_score_)

total_time = (time.time()-start)/60
print("Running time: %s minutes" % (total_time))
running_time.append(total_time)
"""
```

Out[154]:

```
'\nstart = time.time()\nparametersOptions = {\'min_samples_split\':[4, 8, 1
6], \n                     \'max_depth\':[5,8,30,50],\n
\'criterion\':[\'gini\', \'entropy\'],\n                     \'n_estimators
\':[30,100],\n                     \'random_state\': [100]}\n\n# Setup class
ifier, and find using GridsearchCV the best hyper-parameters with kfold=5 as
default\nkfold = KFold(n_splits = 5, shuffle = True, random_state=100)\nRF_b
est = GridSearchCV(RandomForestClassifier(), parametersOptions, cv = kfold,
scoring=\'roc_auc\',n_jobs = -2)\nRF_best.fit(X_final_train, Y_final_train)
\nprint (\'ANN chosen parameters (recieved best AUC): {}\'.format(RF_best.be
st_params_))\nprint ("ANN AUC score with the chosen parameters: ", RF_best.b
est_score_)\n\ntotal_time = (time.time()-start)/60\nprint("Running time: %s
minutes" % (total_time))\nrunning_time.append(total_time)\n'
```

In [155]:

```
# final setting
"""
RF = RandomForestClassifier(**RF_best.best_params_)
"""
```

Out[155]:

```
'\nRF = RandomForestClassifier(**RF_best.best_params_)\n'
```

3.2.4. Support Vector Machines - Not Used

We've found that this model doesn't fit well the data, so we decided not to use it.

In [156]:

```
"""
start = time.time()
parametersOptions = {'C': [0.001, 0.01, 0.1, 1, 10],
                      'gamma' : [0.001, 0.01, 0.1, 1],
                     'kernel': ['linear'],
                     'probability': [True]}

# Setup classifier, and find using GridsearchCV the best hyper-parameters with kfold=5 as d
kfold = KFold(n_splits = 5, shuffle = True, random_state=100)
SVM_best = GridSearchCV(svm.SVC(), parametersOptions, cv = kfold, scoring='roc_auc',n_jobs
SVM_best.fit(X_final_train, Y_final_train)
print ('SVM chosen parameters (recieved best AUC): {}'.format(SVM_best.best_params_))
print ("SVM AUC score with the chosen parameters: ", SVM_best.best_score_)

total_time = (time.time()-start)/60
print("Running time: %s minutes" % (total_time))
running_time.append(total_time)
"""
```

Out[156]:

```
'\nstart = time.time()\nparametersOptions = {\'C\': [0.001, 0.01, 0.1, 1, 1
0],\n                     \'gamma\' : [0.001, 0.01, 0.1, 1],\n
\'kernel\': [\'linear\'],\n                    \'probability\': [True]}\n\n#
Setup classifier, and find using GridsearchCV the best hyper-parameters with
kfold=5 as default\nkfold = KFold(n_splits = 5, shuffle = True, random_state
=100)\nSVM_best = GridSearchCV(svm.SVC(), parametersOptions, cv = kfold, sco
ring=\'roc_auc\',n_jobs = -2)\nSVM_best.fit(X_final_train, Y_final_train)\np
rint (\'SVM chosen parameters (recieved best AUC): {}\'.format(SVM_best.best
_params_))\nprint ("SVM AUC score with the chosen parameters: ", SVM_best.be
st_score_)\n\ntotal_time = (time.time()-start)/60\nprint("Running time: %s m
inutes" % (total_time))\nrunning_time.append(total_time)\n'
```

In [157]:

```
# final setting
#SVM = svm.SVC(**SVM_best.best_params_)
```

Total Running Time measure

In [158]:

```
print("Total models' running time: %s minutes"% (sum(running_time)))
```

```
Total models' running time: 13.200818169116975 minutes
```

4. Models Evaluation

- **We will now evaluate each model using K-Fold Cross Validation. Each K-fold will be plotted in a ROC graph, where we'll calculate the AUC for the performance comparison between the models.**
- **Then, we will calculate a score for each model**
  (where classifing wrongly a "1" target is 5 times more severe than classifing wrongly a "0" target)
- **At the end, we will measure the performance as well as overfitting for each model, in order to decide what model will be used for prediction.**

For that matter, let's define a dedicated function for plotting a ROC graph:

In [159]:

```
def KfoldProcess(X, y, clf, k):
    """
    This function trains the model using the k-folds
    X - X_train, the data to train the model
    y - Y_train, the target data
    clf - The classifier to train
    k - Number of folds to process
    """

    ##############################################################
    # Set KFolds with a random state for consistent results
    ##############################################################
    kf = KFold(n_splits = k, shuffle = True, random_state=100)

    ##############################################################
    # we catch the tpr and fpr since we need to interpolate data
    ##############################################################
    # Validation set:
    tpr_test, fpr_test, auc_test = [],[],[]
    # Train set:
    tpr_train, fpr_train, auc_train = [],[],[]

    ##############################################################
    # mean accuracy and tpr (of test)
    ##############################################################
    accuracy_test = []
    mean_tpr,mean_fpr = 0.0, np.linspace(0,1,100)

    # for confusion matrix plot
    fig, ax = plt.subplots(1,5,figsize=(25,5))
    cm = 0 # counter for ax instance

    # for confusion matrix values capture
    confusion_matrix_values = {'tp': 0, 'fp': 0, 'fn': 0, 'tn': 0}

    for train_index,test_index in kf.split(X):
        ##############################################################
        #Splitting into train and validation, based on the current fold.
        ##############################################################
        X_train, X_test = X[train_index], X[test_index]
        y_train, y_test = y[train_index], y[test_index]

        ##############################################################
        # Training the model using current fold
        ##############################################################
        clf.fit(X_train,y_train)

        ##############################################################
        # Predict current trained model using the validation set
        ##############################################################
        prob_prediction = clf.predict_proba(X_test)[:,1]
        fpr, tpr, thresholds = roc_curve(y_test, prob_prediction) #getting fpr, tpr and thr

        ##############################################################
        # Catch accuracy, tpr, fpr, auc
        ##############################################################
        prediction = clf.predict(X_test)
        accuracy_test.append(accuracy_score(prediction,y_test))
```

```
        ###############################################################
        # We interpolate the mean_tpr so all of the classifiers will be working under the s
        ###############################################################
        tpr_interp = np.interp(np.linspace(0,1,100), fpr, tpr)
        fpr_interp = np.linspace(0,1,100)
        tpr_test.append(tpr)
        fpr_test.append(fpr)
        auc_test.append(auc(fpr_interp,tpr_interp))

        mean_tpr += interp(mean_fpr,fpr,tpr)
        mean_tpr[0] = 0.0

        ###############################################################
        # Check for overfitting using the train set:
        ###############################################################
        # Predict current trained model using the train set
        prob_prediction = clf.predict_proba(X_train)[:,1]
        fpr, tpr, thresholds = roc_curve(y_train, prob_prediction) #getting fpr, tpr and th

        tpr_interp = np.interp(np.linspace(0,1,100), fpr, tpr)
        fpr_interp = np.linspace(0,1,100)
        auc_train.append(auc(fpr_interp,tpr_interp))

        tpr_train.append(tpr)
        fpr_train.append(fpr)


        ###############################################################
        # plot confusion matrix for current fold
        ###############################################################
        plot_confusion_matrix(clf, X_test, y_test, values_format="d", ax=ax[cm]) # confusio
        ax[cm].set_title("Confusion Matrix for fold #%s"%(cm+1))
        ax[cm].invert_xaxis()
        ax[cm].invert_yaxis()
        cm+=1


        ###############################################################
        # catch tn, fp, fn, tp from the confusion matrix
        ###############################################################
        tn, fp, fn, tp =  confusion_matrix(prediction,y_test).ravel()
        confusion_matrix_values['tp'] += tp
        confusion_matrix_values['fp'] += fp
        confusion_matrix_values['fn'] += fn
        confusion_matrix_values['tn'] += tn

    ###############################################################
    # Calculation of the mean TPR, mean AUC and mean accuracy
    ###############################################################
    mean_tpr = mean_tpr/k # mean of all tpr
    mean_tpr[-1] = 1.0
    mean_auc = auc(mean_fpr,mean_tpr) # Area Under the Curve of the ROC
    accuracy_mean = np.mean(accuracy_test, axis=0)
    plt.show()
    return [tpr_test, fpr_test, mean_tpr, mean_auc, auc_test,
            tpr_train, fpr_train, auc_train, accuracy_mean,
            accuracy_test, confusion_matrix_values]
```

In [160]:

```
def kFoldPlot(tpr_test, fpr_test, mean_tpr, mean_auc, auc_test,
              tpr_train, fpr_train, auc_train, accuracy_mean, accuracy_test, confusion_matr
    fig, ax = plt.subplots(2,2,figsize=(18,14))

    ##############################################################
    # Graph #1: Plot ROC and mean AUC of all folds
    ##############################################################
    ax[0,0].plot([0,1],[0,1],color = "blue", linestyle = '--')
    ax[0,0].set_title("ROC and mean AUC of all folds")
    ax[0,0].set(xlabel='False Positive Rate',ylabel='True Positive Rate')
    for i in range(len(tpr_test)):
        ax[0,0].plot(fpr_test[i], tpr_test[i], color = 'grey')
    ax[0,0].plot([0],[0],color='grey', label='K-Folds')
    ax[0,0].plot(np.linspace(0,1,100), mean_tpr, color="red", linestyle='-', label='Mean RO
    ax[0,0].legend(loc="lower right")

    ##############################################################
    # Graph #2: Plot ROC and AUC for every fold - Validation set
    ##############################################################
    ax[0,1].plot([0,1],[0,1],color = "blue", linestyle = '--')
    ax[0,1].set_title("ROC and AUC for every fold - Validation set")
    ax[0,1].set(xlabel='False Positive Rate',ylabel='True Positive Rate')
    for i in range(len(tpr_test)):
        ax[0,1].plot(fpr_test[i], tpr_test[i], label = 'Fold %s (area = %0.4f)' % (str(i+1)
    ax[0,1].legend(loc="lower right")

    ##############################################################
    # Graph #3: Plot ROC and AUC for every fold - Train set
    ##############################################################
    ax[1,0].plot([0,1],[0,1],color = "blue", linestyle = '--')
    ax[1,0].set_title("OVERFITTING CHECK: ROC and AUC for every fold - Train set")
    ax[1,0].set(xlabel='False Positive Rate',ylabel='True Positive Rate')
    for i in range(len(tpr_train)):
        ax[1,0].plot(fpr_train[i], tpr_train[i], label = 'Fold %s (area = %0.4f)' % (str(i+
    ax[1,0].legend(loc="lower right")

    ##############################################################
    # Graph #4: Accuracy vs K-Folds
    ##############################################################
    ax[1,1].bar(range(1,len(accuracy_test)+1),accuracy_test)
    for index, value in enumerate(accuracy_test): # print the value on each bar
        current_accuracy = '{:.2%}'.format(value)
        plt.text(x=index+0.78, y=value+0.01, s=current_accuracy)
    ax[1,1].set_ylim([0.65,1])
    ax[1,1].axhline(0.85,c='g')
    ax[1,1].set_title("Accuracy vs. K-Folds")
    ax[1,1].set(xlabel='K-Folds',ylabel='Accuracy')

    plt.show()
    print("Mean Accuracy: %0.8f" %(accuracy_mean))

    ##############################################################
    # the 2nd accuracy measurement calculation
    ##############################################################
    extra_accuracy = (confusion_matrix_values['tp']+confusion_matrix_values['tn'])/\
          (confusion_matrix_values['tp']+confusion_matrix_values['tn']+confusion_matrix_val

    print("Mean accuracy, where classifing wrongly a 1 target is 5 times more severe than c
          %(extra_accuracy))
```

```
    print("Mean AUC Test: %0.8f\nMean AUC Train: %0.8f\nDifference between AUC: %0.8f" % (m

    # overfitting string
    overfitting = ""
    if np.mean(auc_train) - mean_auc >= 0.1: # overfitting occurs where the difference betw
        overfitting = "Overfitting"
    else:
        overfitting = "No Overfitting"

    return [mean_tpr,mean_auc],[mean_auc, np.mean(auc_train), overfitting, accuracy_mean, e
```

Define models evaluation dictionary + an auc graph summary

In [161]:

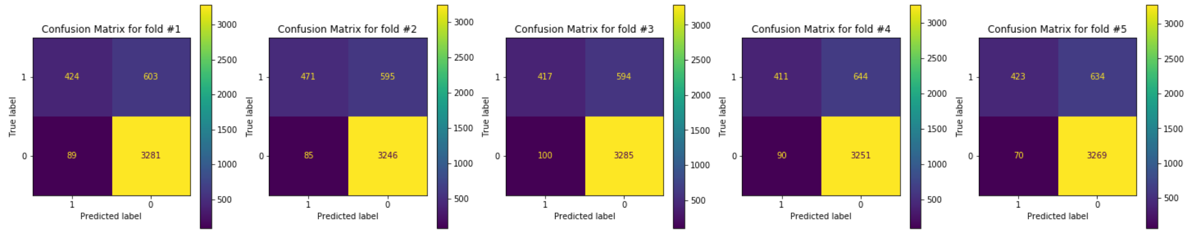
```
models_evaluation = {}
rocauc_final_graph = {}
```

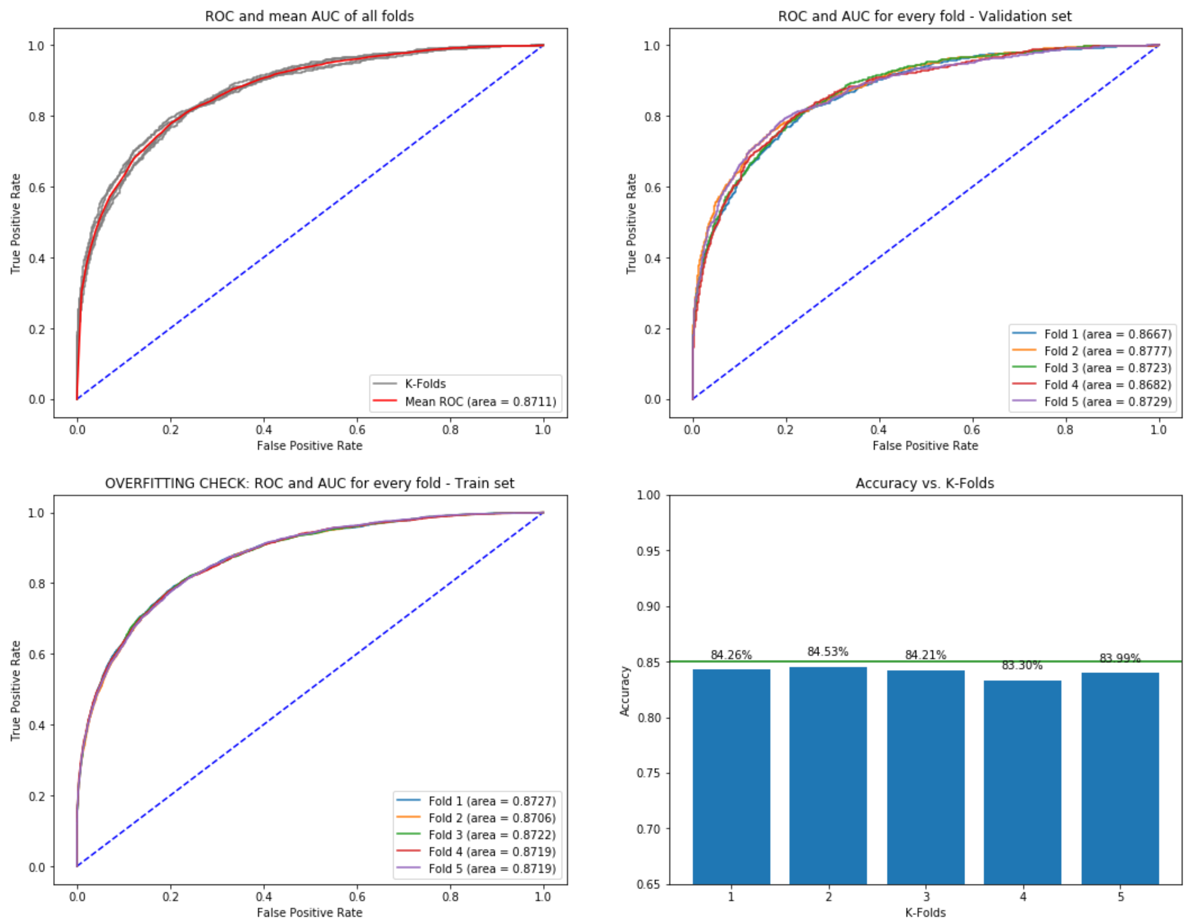
4.1. Initial Models Evaluation

4.1.1. Evaluating (Gaussian) Naive Bayes

In [162]:

```
parameters = KfoldProcess(X_final_train.values, Y_final_train.values, GNB, 5)
rocauc_final_graph["Gaussian Naive Bayes"], models_evaluation["Gaussian Naive Bayes"] = kFo
```



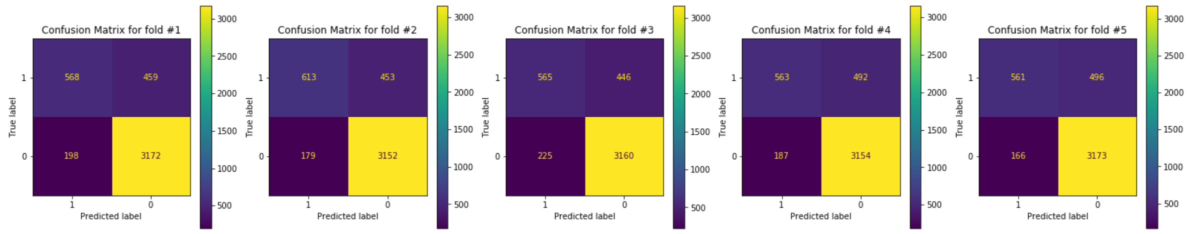


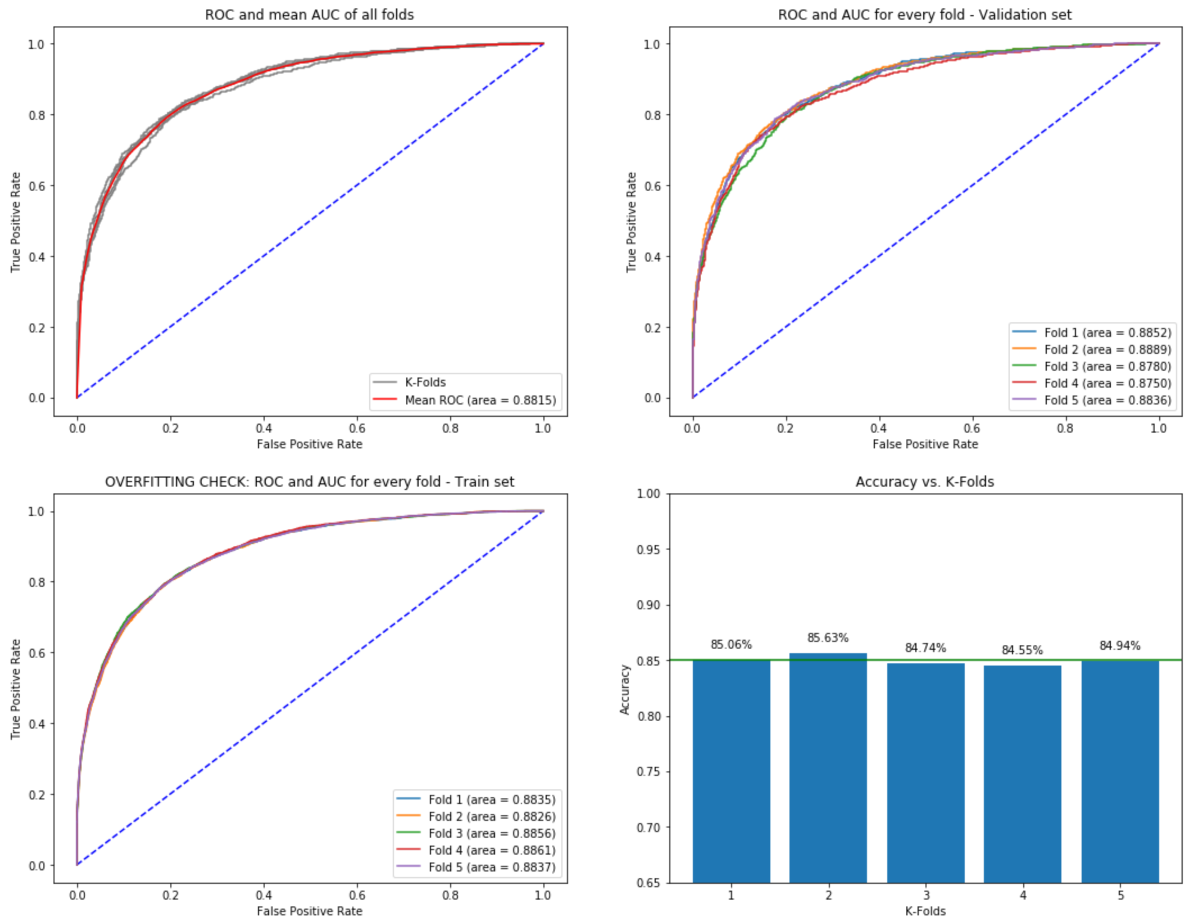

```
Mean Accuracy: 0.84059654
Mean accuracy, where classifing wrongly a 1 target is 5 times more severe th
an classifying wrongly a 0 target: 0.77907075
Mean AUC Test: 0.87111697
Mean AUC Train: 0.87184609
Difference between AUC: 0.00072912
```

4.1.2. Evaluating Logistic Regression

In [163]:

```
parameters = KfoldProcess(X_final_train.values, Y_final_train.values, LR, 5)
rocauc_final_graph["Logistic Regression"], models_evaluation["Logistic Regression"] = kFold
```






```
Mean Accuracy: 0.84983135
Mean accuracy, where classifing wrongly a 1 target is 5 times more severe th
an classifying wrongly a 0 target: 0.72401364
Mean AUC Test: 0.88154591
Mean AUC Train: 0.88432259
Difference between AUC: 0.00277668
```

4.1.3 Evaluating KNN - Not Used

In [164]:

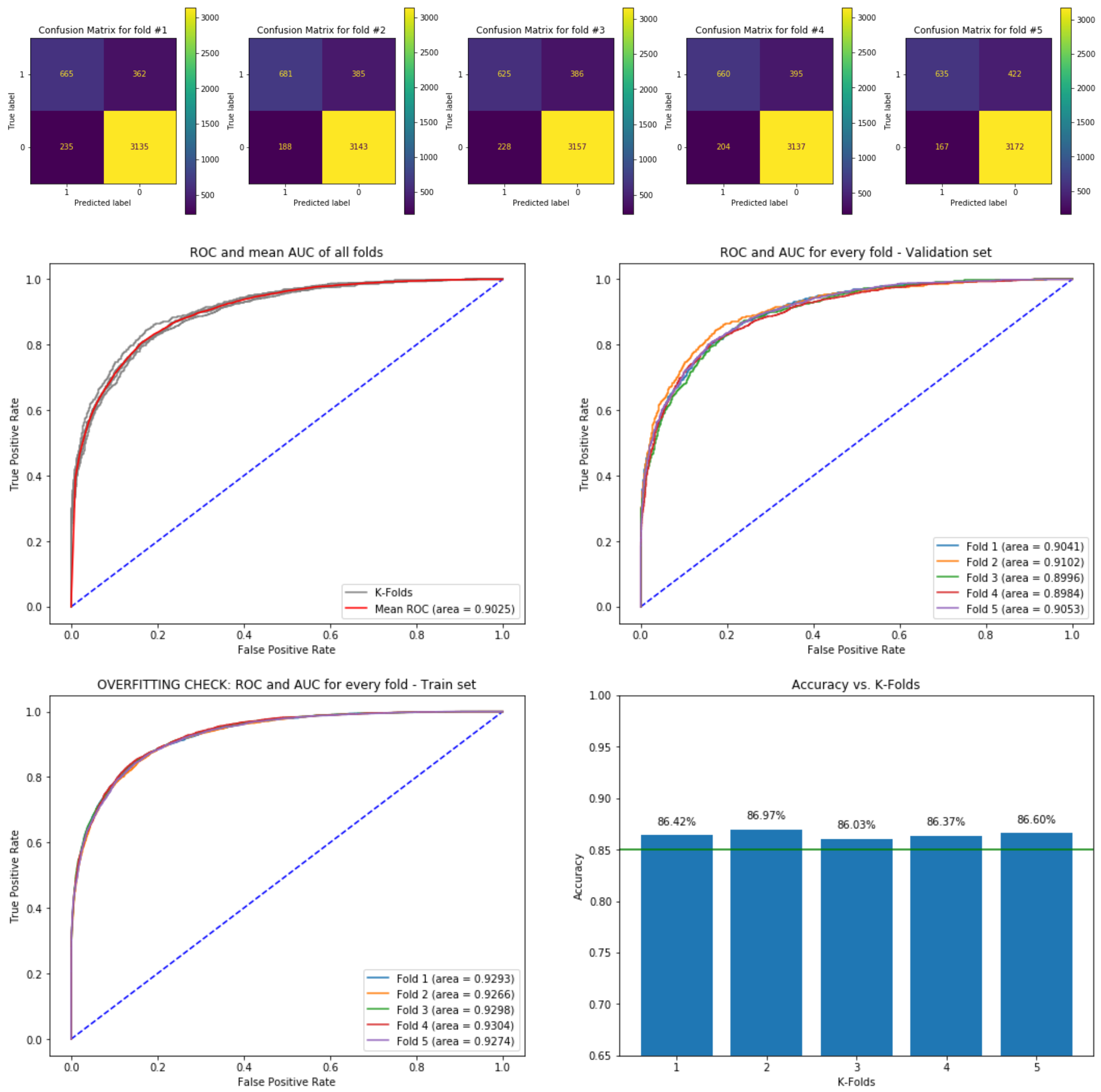
```
#parameters = KfoldProcess(X_final_train.values, Y_final_train.values, KNN, 5)
#rocauc_final_graph["K Nearest Neighbors"], models_evaluation["K Nearest Neighbors"] = kFol
```

4.2. Advanced Models Evaluation

4.2.1. Evaluating Multi-Layer Perceptron (ANN)

In [165]:

```
parameters = KfoldProcess(X_final_train.values, Y_final_train.values, ANN, 5)
rocauc_final_graph["Artificial Neural Networks"], models_evaluation["Artificial Neural Netw
```

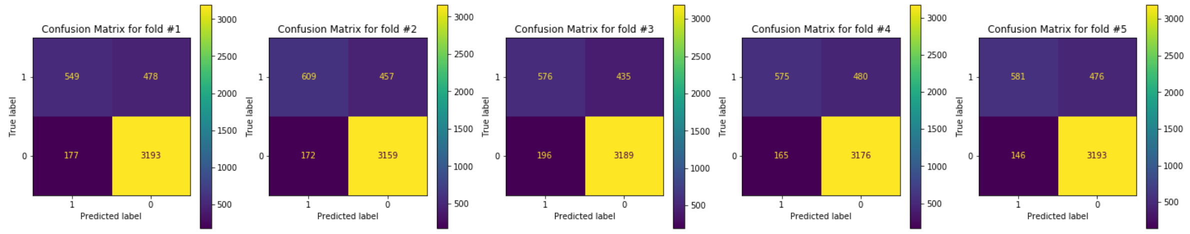


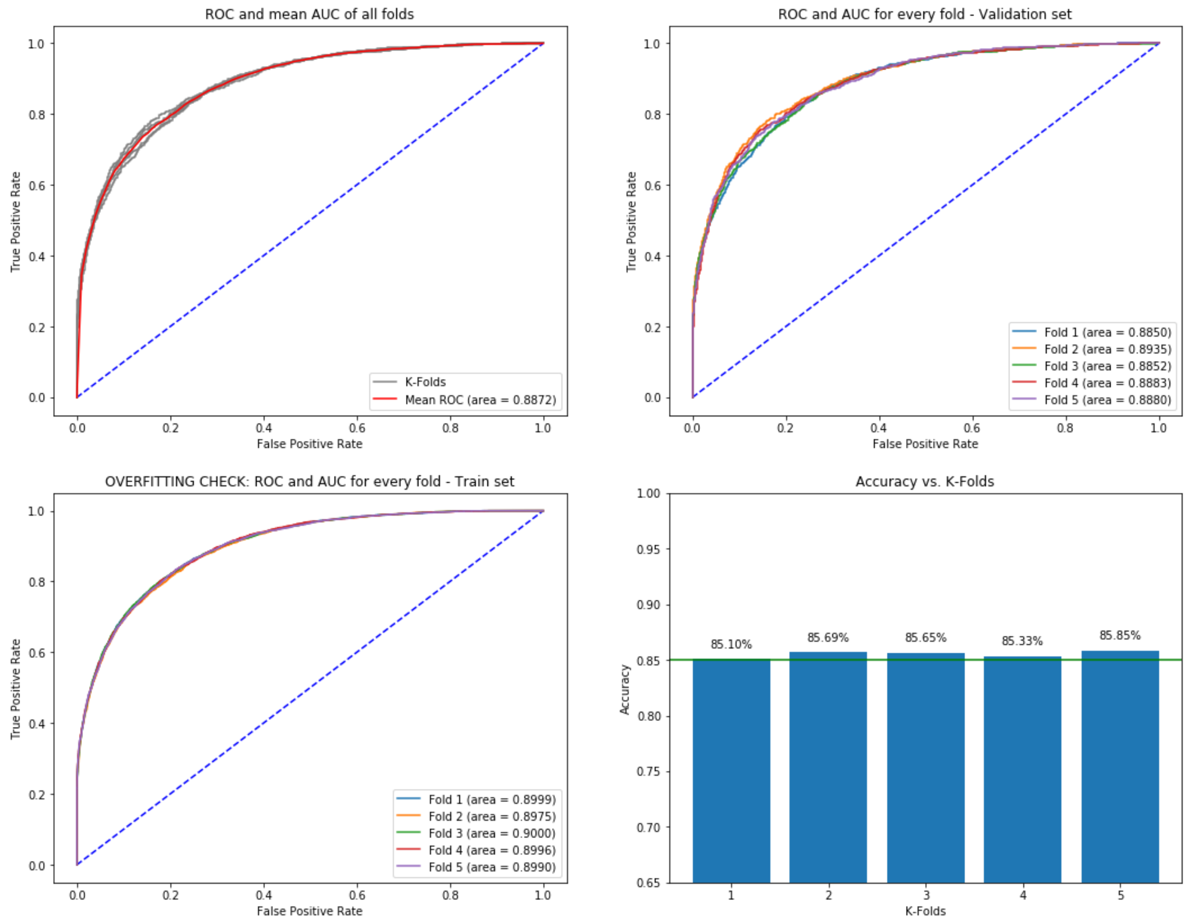

```
Mean Accuracy: 0.86479828
Mean accuracy, where classifing wrongly a 1 target is 5 times more severe th
an classifying wrongly a 0 target: 0.72919064
Mean AUC Test: 0.90248486
Mean AUC Train: 0.92869046
Difference between AUC: 0.02620560
```

4.2.2. Evaluating Adaptive Boosting (AdaBoost)

In [166]:

```
parameters = KfoldProcess(X_final_train.values, Y_final_train.values, ADB, 5)
rocauc_final_graph["Adaptive Boosting"], models_evaluation["Adaptive Boosting"] = kFoldPlot
```






```
Mean Accuracy: 0.85524531
Mean accuracy, where classifing wrongly a 1 target is 5 times more severe th
an classifying wrongly a 0 target: 0.73998268
Mean AUC Test: 0.88720830
Mean AUC Train: 0.89919722
Difference between AUC: 0.01198892
```

4.2.3. Evaluating Random Forest - Not Used

In [167]:

```
#parameters = KfoldProcess(X_final_train.values, Y_final_train.values, RF, 5)
#rocauc_final_graph["Random Forest"], models_evaluation["Random Forest"] = kFoldPlot(*param
```

4.2.4. Evaluating Support Vector Machines - Not Used

In [168]:

```
#parameters = KfoldProcess(X_final_train.values, Y_final_train.values, SVM, 5)
#rocauc_final_graph["Random Forest"], models_evaluation["Support Vector Machines"] = kFoldP
```

---

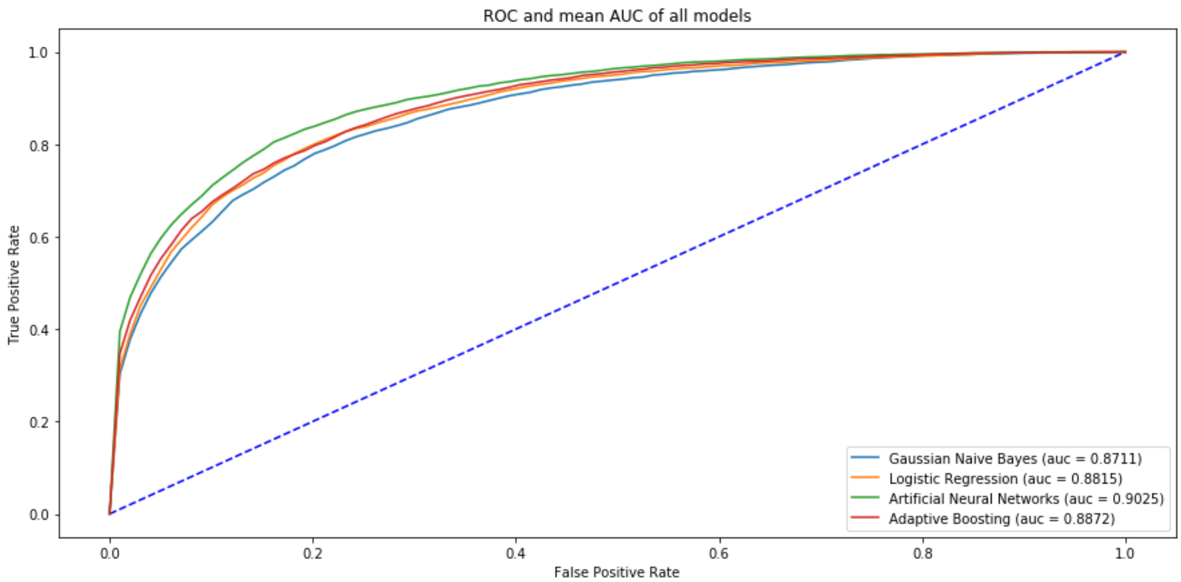
5. Chosen Model + Prediction Probabilities

Let's overview our models:

Mean ROC and AUC graph comparison

In [169]:

```
fig, ax = plt.subplots(figsize=(15,7))
plt.plot([0,1],[0,1],color = "blue", linestyle = '--')
plt.title("ROC and mean AUC of all models")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
for model in rocauc_final_graph:
    plt.plot(np.linspace(0,1,100), rocauc_final_graph[model][0], linestyle='-', label='%s (
    plt.legend(loc="lower right")

plt.show()
```



Evaluation Summary Table

In [170]:

```
evaluation_table = pd.DataFrame.from_dict(models_evaluation, orient='index',
                                          columns=['Mean AUC on test', 'Mean AUC on train', 'Overfitting Statu
```

Evaluation by AUC

In [171]:

```
evaluation_table.sort_values(by='Mean AUC on test', ascending=False, inplace=True)
evaluation_table
```

Out[171]:

	Mean AUC on test	Mean AUC on train	Overfitting Status	Accuracy	2nd Accuracy
Artificial Neural Networks	0.902485	0.928690	No Overfitting	0.864798	0.729191
Adaptive Boosting	0.887208	0.899197	No Overfitting	0.855245	0.739983
Logistic Regression	0.881546	0.884323	No Overfitting	0.849831	0.724014
Gaussian Naive Bayes	0.871117	0.871846	No Overfitting	0.840597	0.779071

In [172]:

```
print("The model with the best mean AUC: %s"%(evaluation_table.index[0]))
```

```
The model with the best mean AUC: Artificial Neural Networks
```

Evaluation by the 2nd Accuracy Measurement

In [173]:

```
evaluation_table.sort_values(by='2nd Accuracy', ascending=False, inplace=True)
evaluation_table
```

Out[173]:

	Mean AUC on test	Mean AUC on train	Overfitting Status	Accuracy	2nd Accuracy
Gaussian Naive Bayes	0.871117	0.871846	No Overfitting	0.840597	0.779071
Adaptive Boosting	0.887208	0.899197	No Overfitting	0.855245	0.739983
Artificial Neural Networks	0.902485	0.928690	No Overfitting	0.864798	0.729191
Logistic Regression	0.881546	0.884323	No Overfitting	0.849831	0.724014

In [174]:

```
print("The model with the best 2nd accuracy measure is: %s"%(evaluation_table.index[0]))
```

```
The model with the best 2nd accuracy measure is: Gaussian Naive Bayes
```

We can see that the ANN model is the best among the evaluated models by the AUC measurement,

However in the second accuracy measure the leader is (Gaussian) Naive Bayes.
We'll choose our model according to the AUC, so:

The winner is: Multi-Layer Perceptron (ANN)

We'll use this model in our predictions

In [175]:

```
chosen_model = ANN
```

5.1. Final Model Fitting

In [176]:

```
chosen_model.fit(X_final_train, Y_final_train) # fit on all train
```

Out[176]:

```
MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.
9,
              beta_2=0.999, early_stopping=False, epsilon=1e-08,
              hidden_layer_sizes=(10,), learning_rate='constant',
              learning_rate_init=0.001, max_fun=15000, max_iter=2000,
              momentum=0.9, n_iter_no_change=10, nesterovs_momentum=True,
              power_t=0.5, random_state=100, shuffle=True, solver='adam',
              tol=0.0001, validation_fraction=0.1, verbose=False,
              warm_start=False)
```

In [177]:

```
predictions = chosen_model.predict_proba(final_test_set)[:,1] # the predictions to classify
predictions_DF = pd.DataFrame(predictions)
predictions_DF.rename(columns = {0 : 'pred_proba'}, inplace = True)
predictions_DF.head(5)
```

Out[177]:

	pred_proba
0	0.050167
1	0.637781
2	0.043327
3	0.033999
4	0.046085

Write to a csv file

In [178]:

```
predictions_DF.to_csv('Submission_group_05.csv')
```

Done!

In [179]:

```
print("It took %s minutes to finish running this jupyter notebook from the first cell."%((t
```

```
It took 20.160823512077332 minutes to finish running this jupyter notebook f
rom the first cell.
```