CircleUp Data Science Take-Home Assignment

March 31, 2018

1 Summary

We analysed the CircleUp dataset with python3 libraries *Pandas*, *Numpy*, *Scipy*, *Matplotlib*, *Seeborn* and *Scikit-learn*. Data have been locally downloaded in .csv files format and imported in Pandas data frames to be manipulated.

1.1 Question 1

To find the solutions we used the `user_message dataset`.

- #### 1.1.1 Point 1:

  The list of users that added more than 500 pieces of content is the following:

User ID	Number of Content
9484	1163
9676	722
12116	688
3924	686
2052	640
10878	601
5999	566
8962	551
11578	544
2434	526
17616	526
3532	523
10530	521
11271	503

Details of the analysis are Section 1.3.

-

1.1.2 Point 2:

In order to find which users grew more rapidly in the last year, we need a measure of how fast they incremented the customer engagment in a given period. Such measurement can be obtained from a linear regression of the variable `total_engagement` versus the `content_created_date`. Then our metric (`growing_rate`), is rapresented by the slope of the fitted line. The bigger the slope, the faster the customer engagment growing. Finally, ranking the users based on this metric we found the top 10 fastest growing users:

user_id	growing_rate
3924	115.35
2052	91.11
4527	17.67
9484	9.31
12116	6.52
9770	4.33
3063	4.22
7215	3.61
5833	3.00
4711	2.73

Section 1.4 the details of the analysis, and more considerations about the manipulation of the variable `content_created_date`.

As last check, we added also some Section 1.5 of our `Growing rate` metric.

1.2 Question 2

To answer the second question of the assignment, we build a supervised learning models using the `user`, `user_features` and `model_test_file` dataset. In order to predict the two classes of `response` outcome, we built and compared the performances of two different learning algorithms: **Support Vector Machine** and **Random Forest**.

As first, we performed an exploratory data analysis (Section 1.7) to better understand features properties and behaviour. We applyied some features transformation as: eliminating isolated extreme values, taking logaritmic values and rescaling in order to understand possible correlations among features, and to put them in a better shape for feeding the model training.

We decided to train the classification models excluding few of the features inside the `user_features` dataset. We observed that the performance of the **SVM** learning algorithm is better than the **Random Forest**, especially in predicting the less represented *class* (`response` equal to 1). Details and results of the analysis are Section 1.6.

Looking for better results, we also used the complete list of features, conveniently transformed (see Section 1.12), to train the **SVM** model, but the Section 1.13 are completely comparable.]

Finally we predicted the `response` for the users in the `model_test_file`, using the **SVM** model trained with the subset of features. Section 1.14 the results.

1.3 Ranking of best users based on numbers of content created

In [3]:
```
# Import libraries
import numpy as np
impo# Import dataset in Pandas data frame
message_data = pd.read_csv('data/user_message.csv')
message_data.head()rt pandas as pd
```

In [4]:
```
# Import dataset in Pandas data frame
message_data = pd.read_csv('data/user_message.csv')
message_data.head()
```

Out[4]:

	user_id	content_created_date	content_count	total_engagement
0	20	1/1/2015	1	52
1	20	1/2/2015	1	72
2	20	1/10/2015	1	83
3	20	1/12/2015	1	45
4	20	1/16/2015	1	102

In [5]:
```
# Sum over content_count by user
df_by_user = message_data.groupby('user_id').sum()
```

In [6]:
```
# Select and Sort
df = df_by_user[(df_by_user['content_count']>500)]
df.sort_values(by='content_count', ascending=False)
```

Out[6]:

user_id	content_count	total_engagement
9484	1163	954382
9676	722	204249
12116	688	1243620
3924	686	16661950
2052	640	22826604
10878	601	194024
5999	566	373659
8962	551	53325
11578	544	90666
2434	526	30128
17616	526	180460
3532	523	91546
10530	521	16539
11271	503	71157

1.4 Fastest Growing users

In order to find the faster growing user, first of all, we need to reshape and trasform our dataset. First step is to convert the variable `content_created_date` from *string* to *date*. Then, we transform each *date* in the corresponding *number of days since '2015-01-01'*.

```
In [7]: # Convert strings of date in a date object
        message_data['content_created_date'] = pd.to_datetime(message_data['content_created_date
        message_data.head()
```

```
Out[7]:    user_id content_created_date  content_count  total_engagement
        0       20           2015-01-01              1                52
        1       20           2015-01-02              1                72
        2       20           2015-01-10              1                83
        3       20           2015-01-12              1                45
        4       20           2015-01-16              1               102
```

```
In [ ]: # Select only needed variables
        df = message_data[['user_id', 'content_created_date', 'total_engagement']]
```

```
In [8]: # convert date in day_since to be able to apply regression
        df['days_since'] = (df.content_created_date - pd.to_datetime('2015-01-01') ).astype('tim
        df.head()
```

```
Out[8]:    user_id content_created_date  total_engagement  days_since
        0       20           2015-01-01                52         0.0
        1       20           2015-01-02                72         1.0
        2       20           2015-01-10                83         9.0
        3       20           2015-01-12                45        11.0
        4       20           2015-01-16               102        15.0
```

To perform the linear regression with `stats.linregress`, we need to have for each user a list of `days_since`, and a list of `total_engagement` that correspond to our x and y variables.

```
In [11]: # reshape df to have a list of 'days_since' for each user
         dfreshaped_x = df.groupby('user_id')['days_since'].apply(list)
         dfreshaped_x.head()
```

```
Out[11]: user_id
         20      [0.0, 1.0, 9.0, 11.0, 15.0, 21.0, 23.0, 25.0, ...
         134     [28.0, 29.0, 32.0, 37.0, 62.0, 63.0, 64.0, 65...
         635     [120.0, 121.0, 122.0, 123.0, 124.0, 125.0, 126...
         950     [4.0, 49.0, 55.0, 56.0, 60.0, 61.0, 67.0, 75.0...
         1034    [4.0, 11.0, 12.0, 13.0, 18.0, 20.0, 25.0, 41.0...
         Name: days_since, dtype: object
```

```
In [12]: # reshape df to have a list of 'total_engagement' for each user
         dfreshaped_y = df.groupby('user_id')['total_engagement'].apply(list)
         dfreshaped_y.head()
```

```
Out[12]: user_id
         20      [52, 72, 83, 45, 102, 35, 92, 33, 39, 109, 54,...
         134     [68, 44, 12, 13, 18, 69, 121, 23, 61, 34, 22, ...
         635     [67, 37, 20, 36, 20, 7, 16, 25, 15, 4, 7, 14, ...
         950     [18, 20, 8, 13, 6, 16, 8, 14, 12, 15, 15, 8, 1...
         1034    [22, 28, 18, 12, 29, 26, 45, 50, 29, 29, 33, 2...
         Name: total_engagement, dtype: object
```

```
In [16]: # Reshape data to have it in a useful format
         data = {'days_since':dfreshaped_x, 'total_engagement':dfreshaped_y}
         day_eng_list_df = pd.DataFrame(data)
         day_eng_list_df.head()
```

```
Out[16]:                                                days_since  \
         user_id
         20       [0.0, 1.0, 9.0, 11.0, 15.0, 21.0, 23.0, 25.0, ...
         134      [28.0, 29.0, 32.0, 37.0, 62.0, 63.0, 64.0, 65...
         635      [120.0, 121.0, 122.0, 123.0, 124.0, 125.0, 126...
         950      [4.0, 49.0, 55.0, 56.0, 60.0, 61.0, 67.0, 75.0...
         1034     [4.0, 11.0, 12.0, 13.0, 18.0, 20.0, 25.0, 41.0...

                                                  total_engagement
         user_id
         20       [52, 72, 83, 45, 102, 35, 92, 33, 39, 109, 54,...
         134      [68, 44, 12, 13, 18, 69, 121, 23, 61, 34, 22, ...
         635      [67, 37, 20, 36, 20, 7, 16, 25, 15, 4, 7, 14, ...
         950      [18, 20, 8, 13, 6, 16, 8, 14, 12, 15, 15, 8, 1...
         1034     [22, 28, 18, 12, 29, 26, 45, 50, 29, 29, 33, 2...
```

Another important analysis step is to check how many points (`days_since`, `total_engagement`) there are for each users. Because too few points could affect the quality of the linear regression fit resulting in an innacurate *slope* calculation. We choosed to exclude users with less than 10 entries in the data frame.

```
In [22]: # sanity check on the lenght of the lists in order to have a meaning regression points
         day_eng_list_df['counts'] = day_eng_list_df['days_since'].apply(len)
         day_eng_list_df.head()
```

```
Out[22]:                                                days_since  \
         user_id
         20       [0.0, 1.0, 9.0, 11.0, 15.0, 21.0, 23.0, 25.0, ...
         134      [28.0, 29.0, 32.0, 37.0, 62.0, 63.0, 64.0, 65...
         635      [120.0, 121.0, 122.0, 123.0, 124.0, 125.0, 126...
         950      [4.0, 49.0, 55.0, 56.0, 60.0, 61.0, 67.0, 75.0...
         1034     [4.0, 11.0, 12.0, 13.0, 18.0, 20.0, 25.0, 41.0...

                                                  total_engagement  counts
         user_id
         20       [52, 72, 83, 45, 102, 35, 92, 33, 39, 109, 54,...      84
         134      [68, 44, 12, 13, 18, 69, 121, 23, 61, 34, 22, ...      55
         635      [67, 37, 20, 36, 20, 7, 16, 25, 15, 4, 7, 14, ...     126
         950      [18, 20, 8, 13, 6, 16, 8, 14, 12, 15, 15, 8, 1...     113
         1034     [22, 28, 18, 12, 29, 26, 45, 50, 29, 29, 33, 2...      73
```

```
In [23]: # Remove users with less than 10 entrie per list of days_since and total_engagement
         cut_df = day_eng_list_df[day_eng_list_df['counts']>10]
```

Now, we define a function that performs the regression using `stats.linregress`, and returns the slope of the regression line.

```
In [25]: # Function definition
         from scipy import stats

         def linreg(row):
             slope, intercept, r_value, p_value, std_err = stats.linregress(row['days_since'], r
             return slope
```

Finally, we apply our `linreg` function to the reshaped data frame, and add a new column with the *slope* of the regression line. This new parameter is the the `growing_rate` metric that we could use to find the faster growing users.

```
In [29]: # Apply linreg function to cut_df data frame
         cut_df['growing_rate'] = cut_df.apply(linreg, axis=1)
```

```
C:\Users\Michela\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

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

The final answer to point 2 of Question 1 is the following table of the 10 users with the higher `growing rate`.

```
In [63]: # Sort and select first 10 users
         sorted_df = cut_df.sort_values('growing_rate', ascending=False)
         sorted_df[:10]
```

```
Out[63]:                                                    days_since  \
         user_id
         3924     [0.0, 1.0, 2.0, 4.0, 6.0, 7.0, 8.0, 10.0, 13.0...
         2052     [0.0, 1.0, 2.0, 4.0, 5.0, 6.0, 7.0, 9.0, 11.0,...
         4527     [0.0, 1.0, 6.0, 11.0, 16.0, 20.0, 23.0, 26.0, ...
         9484     [109.0, 110.0, 111.0, 112.0, 113.0, 114.0, 115...
         12116    [5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 11.0, 12.0, 13...
         9770     [17.0, 23.0, 53.0, 79.0, 80.0, 81.0, 82.0, 83...
         3063     [4.0, 7.0, 11.0, 14.0, 18.0, 22.0, 23.0, 26.0,...
         7215     [109.0, 110.0, 111.0, 112.0, 113.0, 114.0, 115...
         5833     [4.0, 8.0, 13.0, 19.0, 22.0, 35.0, 36.0, 47.0,...
         4711     [6.0, 9.0, 10.0, 12.0, 14.0, 16.0, 18.0, 20.0,...

                                                  total_engagement  counts  \
         user_id
         3924     [21991, 56394, 26564, 17767, 36185, 21713, 236...     318
         2052     [17273, 16608, 25792, 31585, 211897, 296452, 1...     298
```

```
4527     [274, 471, 308, 327, 362, 560, 374, 352, 295, ...      119
9484     [2039, 2994, 3229, 5582, 5287, 4302, 2554, 350...      198
12116    [1490, 4267, 5118, 907, 2507, 1038, 5417, 4488...      302
9770     [528, 10431, 4948, 4966, 4985, 529, 528, 488, ...      243
3063     [509, 370, 385, 574, 566, 538, 603, 422, 352, ...       81
7215     [136, 228, 164, 86, 340, 290, 180, 199, 196, 1...      219
5833     [2082, 1544, 1504, 688, 963, 1611, 928, 2973, ...       34
4711     [653, 143, 153, 124, 205, 163, 148, 229, 172, ...      185

         growing_rate
user_id
3924       115.351638
2052        91.111386
4527        17.673102
9484         9.315306
12116        6.518727
9770         4.326168
3063         4.223012
7215         3.613537
5833         3.007240
4711         2.731612
```

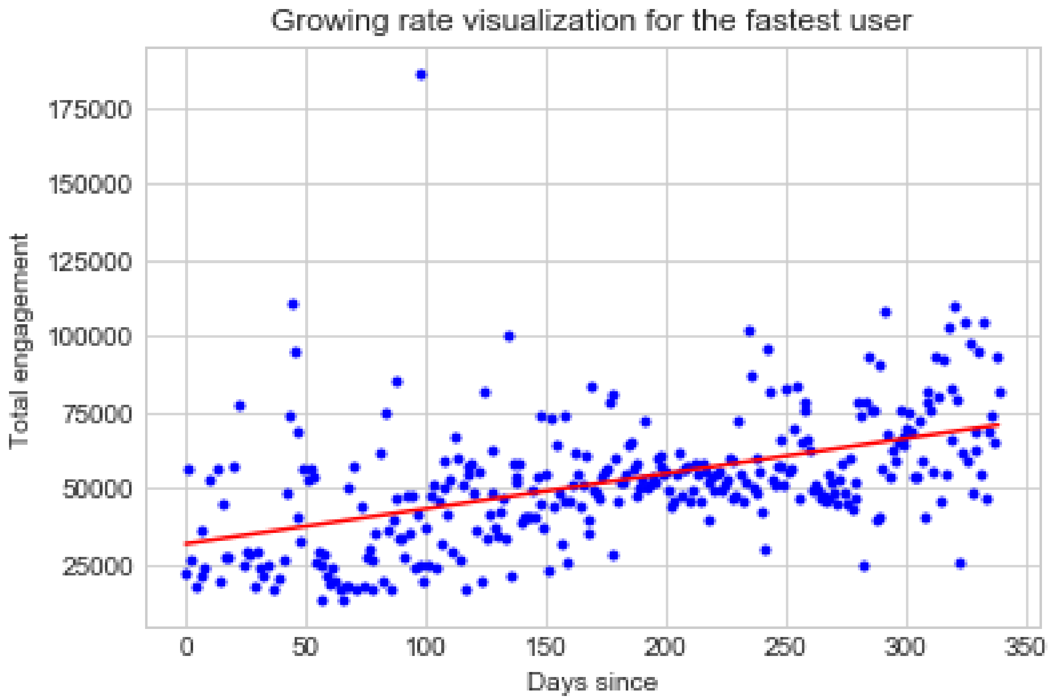
1.5 Visualization of Growing rate

In order to check our results we visualized the regression line for the first and last ranked users.

In [282]:
```
# Select arrays of points for the first user and last users
x_coord=sorted_df.loc[:, 'days_since']
y_coord=sorted_df.loc[:, 'total_engagement']

x1 = x_coord.iloc[0]
y1 = y_coord.iloc[0]
x9 = x_coord.iloc[9]
y9 = y_coord.iloc[9]
```

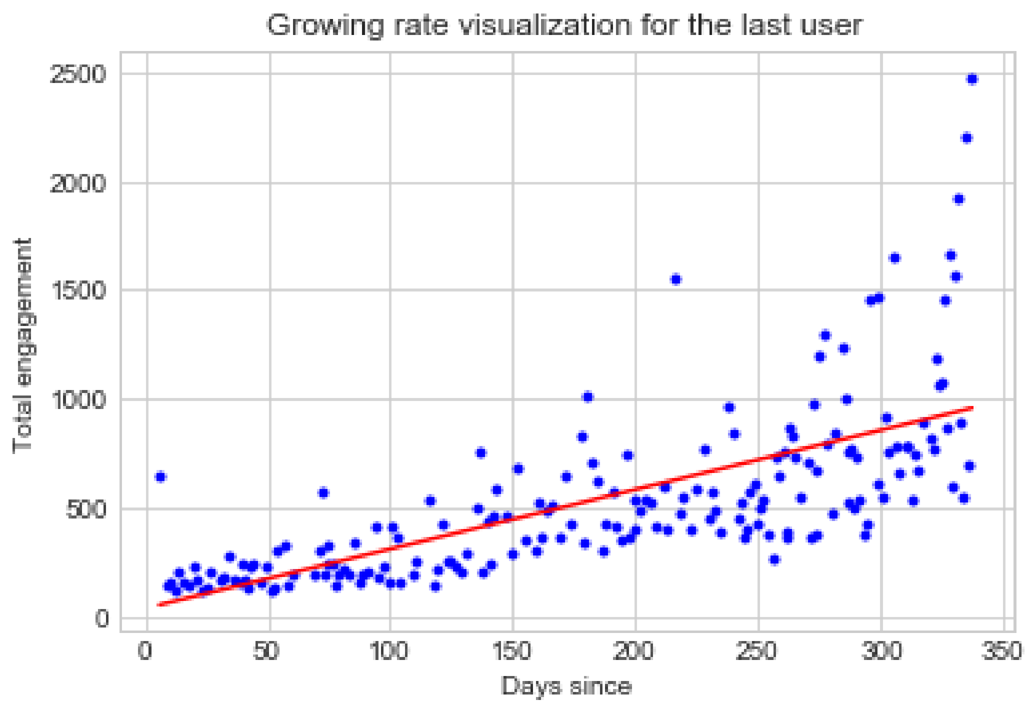
In [288]:
```
# Plot point and regression line
import matplotlib.pyplot as plt

plt.title('Growing rate visualization for the fastest user')
plt.xlabel('Days since')
plt.ylabel('Total engagement')
plt.plot(x1, y1, 'b.')
slope, intercept, r_value, p_value, std_err = stats.linregress(x1, y1)
plt.plot(x1, slope * np.array(x1) + intercept, 'r-')
print("slope =", slope)
```

```
slope = 115.3516377750555
```




```
In [287]: # Plot point and regression line
          plt.title('Growing rate visualization for the last user')
          plt.xlabel('Days since')
          plt.ylabel('Total engagement')
          plt.plot(x9, y9, 'b.')
          slope, intercept, r_value, p_value, std_err = stats.linregress(x9, y9)
          plt.plot(x9, slope * np.array(x9) + intercept, 'r-')
          print("slope =", slope)
```

```
slope = 2.731612298914138
```



1.6 Learning Models

```
In [68]: # Import libraries
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         %matplotlib inline

In [69]: # import data
         features = pd.read_csv('data/user_features.csv')
         users = pd.read_csv('data/user.csv')

In [70]: features.head()

Out[70]:    var_1  var_2  var_3     var_4      var_5  var_6  var_7    var_8  var_9  \
         0      1      1      0   1740115  38.637588     26      0   0.0000      0
         1      1      1    362   9803192  30.901522     11    237   1.7553      0
         2      1      1   3279   3694516  45.933998    329    638  13.1270      0
         3      1      1    213  18185084  34.120554    162     65   2.4769      0
         4      0      0    226         0  23.700552      3     99   5.0404      0

            var_10  var_11   var_12  user_id
         0    2542       0  0.87499   154531
         1     117      17  0.79306   156315
```

```
2    1313      380  0.94425   149607
3     168       12  0.57251    26755
4     119      156  0.45718   149734
```

In [71]:
```python
users.head()
```

Out[71]:
```
   response  user_id
0         0   154531
1         0   156315
2         0   149607
3         0    26755
4         0   149734
```

In [72]:
```python
# put togheter to have the final dataset
train = users.set_index('user_id').join(features.set_index('user_id'))
```

In [73]:
```python
train.head()
```

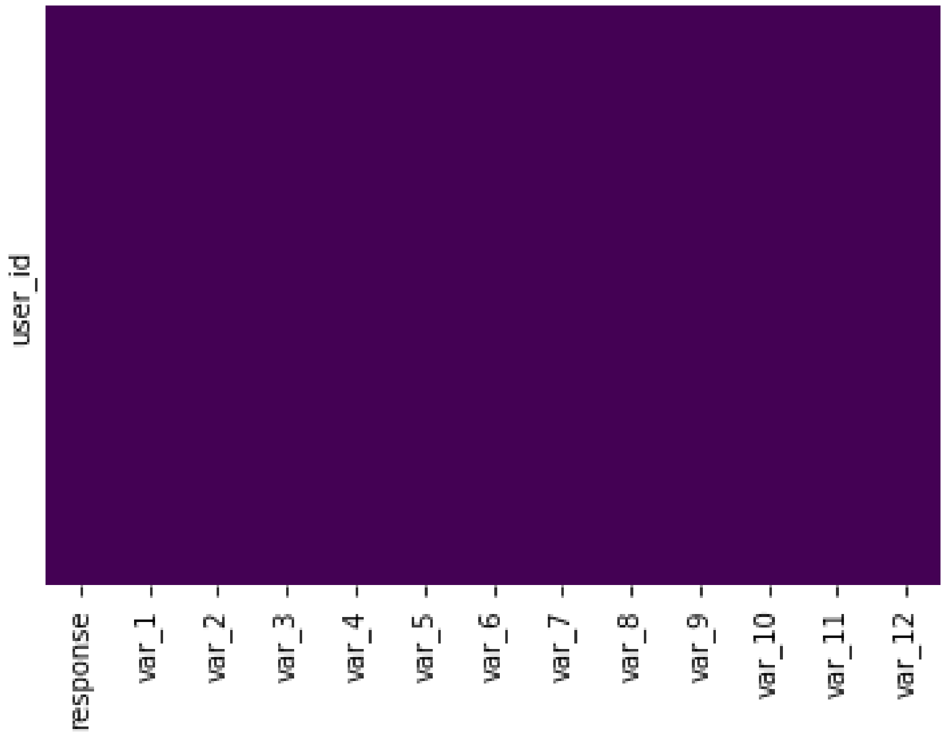
Out[73]:
```
         response  var_1  var_2  var_3     var_4      var_5  var_6  var_7  \
user_id
154531          0      1      1      0   1740115  38.637588     26      0
156315          0      1      1    362   9803192  30.901522     11    237
149607          0      1      1   3279   3694516  45.933998    329    638
26755           0      1      1    213  18185084  34.120554    162     65
149734          0      0      0    226         0  23.700552      3     99

           var_8  var_9  var_10  var_11   var_12
user_id
154531    0.0000      0    2542       0  0.87499
156315    1.7553      0     117      17  0.79306
149607   13.1270      0    1313     380  0.94425
26755     2.4769      0     168      12  0.57251
149734    5.0404      0     119     156  0.45718
```

1.7 Exploratory Data Analysis

The first and most important step for the analysis is to try to have a clear understanding of our data. In order to do this, we checked for missing values, controlled the *balance* of the two sample of `response`, and took a closer look at the feautures.

In [22]:
```python
# Check for Missing Data
sns.heatmap(train.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

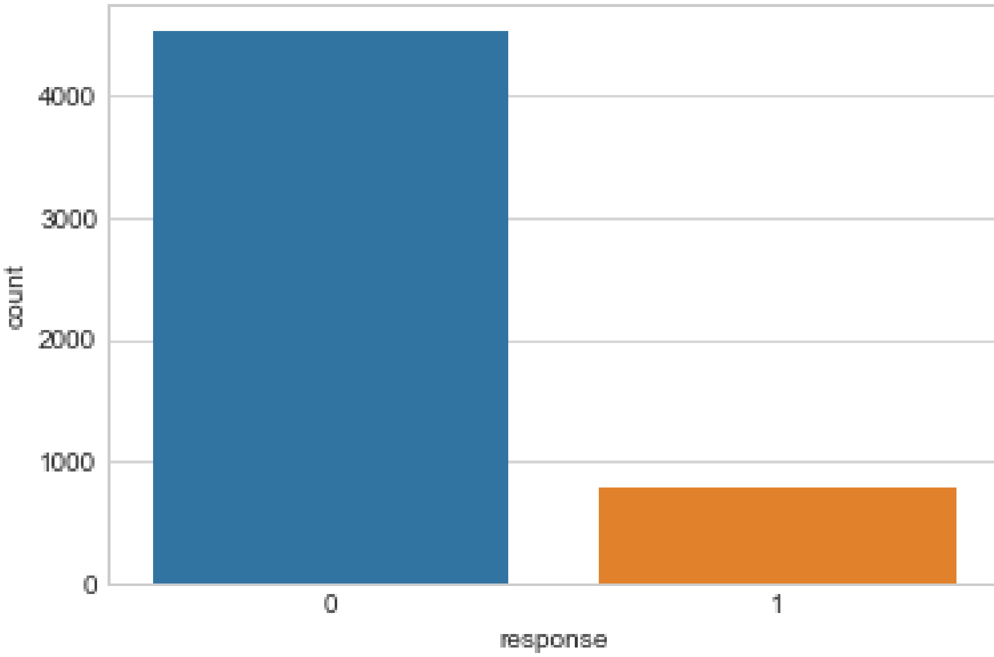
Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x21bf44bde80>
```



From the above heatmap is clear that the dataset does not contain any null value. All the values in the dataset are numeric, so no operation on the features are needed up to this point.

It is important to check which is the ratio between the two classes of `response` in the dataset, to control if it is balanced or not.

```
In [75]: # Chek the percentage of outcome
         sns.set_style('whitegrid')
         sns.countplot(x='response',data=train)

Out[75]: <matplotlib.axes._subplots.AxesSubplot at 0x23719355710>
```



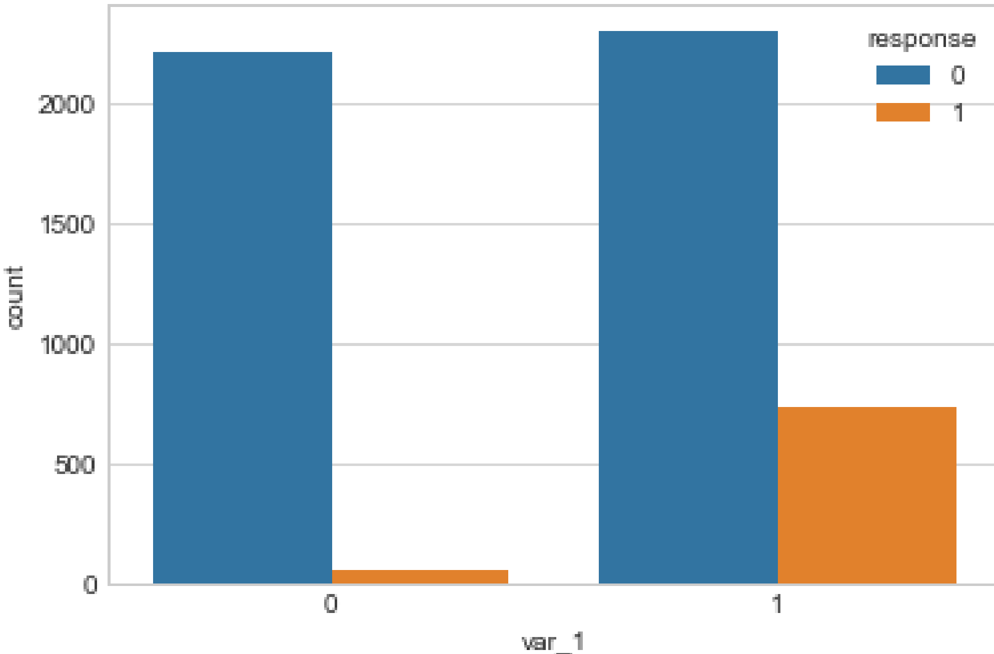

```
In [76]: # Calsculate the % of sample
         train['response'].value_counts()

Out[76]: 0    4516
         1     801
         Name: response, dtype: int64
```

The two classes of `response` are not equally rapresented. 82.3% of sample is 0 and only 17.7% is 1. This could affect the learning model. The predictive model could be biased and inaccurate because the second class is poor represented.

1.8 A closer look at the features

`Vars_1` and `var_2` are categorical variables (0,1), no continuos values. So we could take a look at their relation with the outcome `response` in order to check if they are strong predictor or not. In the *histograms* below we plotted the `response` variable using color to distinguish the values 0 or 1 in `var_1` and `var_2` variables respectively.

```
In [289]: # Check if var_1 is a strong predictior or not
          sns.set_style('whitegrid')
          sns.countplot(x='var_1',hue='response', data=train)

Out[289]: <matplotlib.axes._subplots.AxesSubplot at 0x2371ad653c8>
```

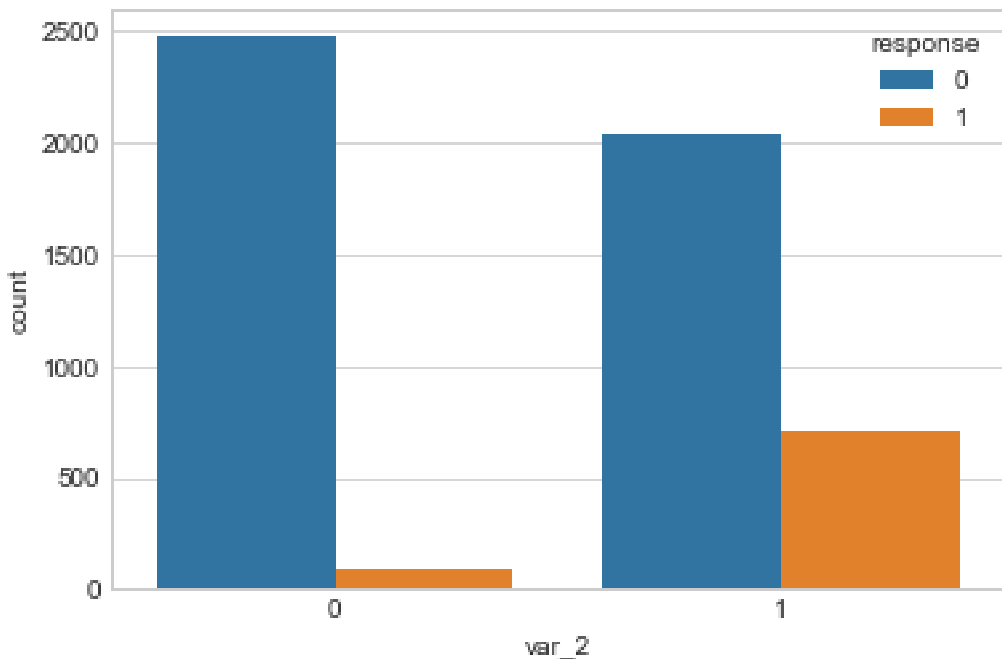


As you can see, almost all the values of `response = 1` are contained in `var_1 = 1`. In other words, we can be pretty confident that when `var_1` is 0, the probability to get a `response = 1` is very poor. This is certainly a property that our classifier will take advantage of.

A similar behaviour is observed in `var_2` (see plot below).

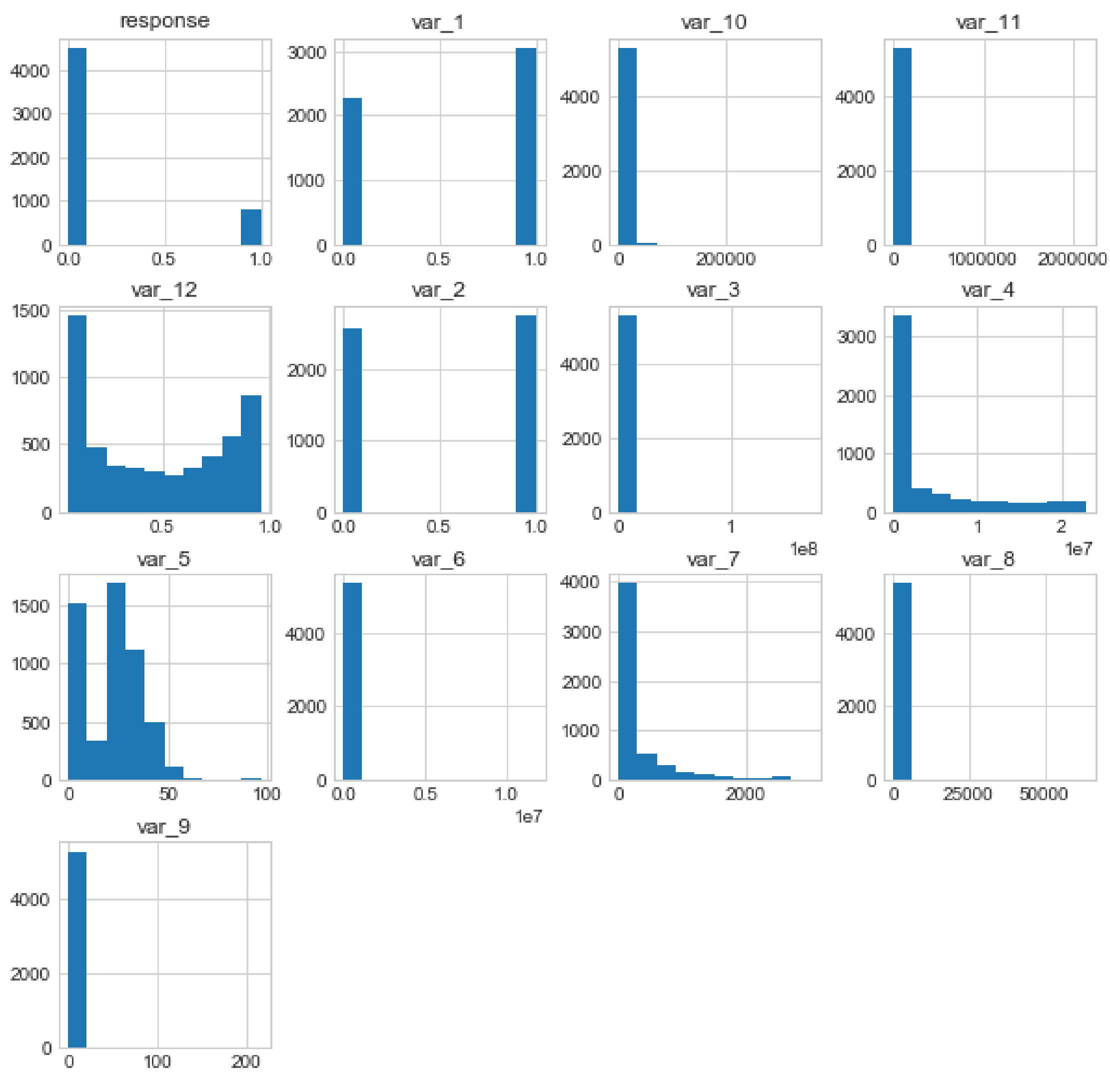
In [290]:
```
# Check if var_2 is a strong prediction or not
sns.set_style('whitegrid')
sns.countplot(x='var_2',hue='response', data=train)
```

Out[290]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x23720517898>
```



Let's take a look to the other variables distribution and their possible correlations. In fact, not having self-explaining names, we do not know what they are and how they could be related to the outcome and between them.

```
In [80]: # Features plots
         train.hist(figsize=(10,10));
```



From the above distributions it is clear that variables `var_3`, `var_4`, `var_6`, `var_8`, `var_9`, `var_10` and `var_11` present lot of outliers and span multiple order of magnitude. So we could take the logaritimc value and than chek for possible correlations.

1.9 Taking logaritmic value of some features

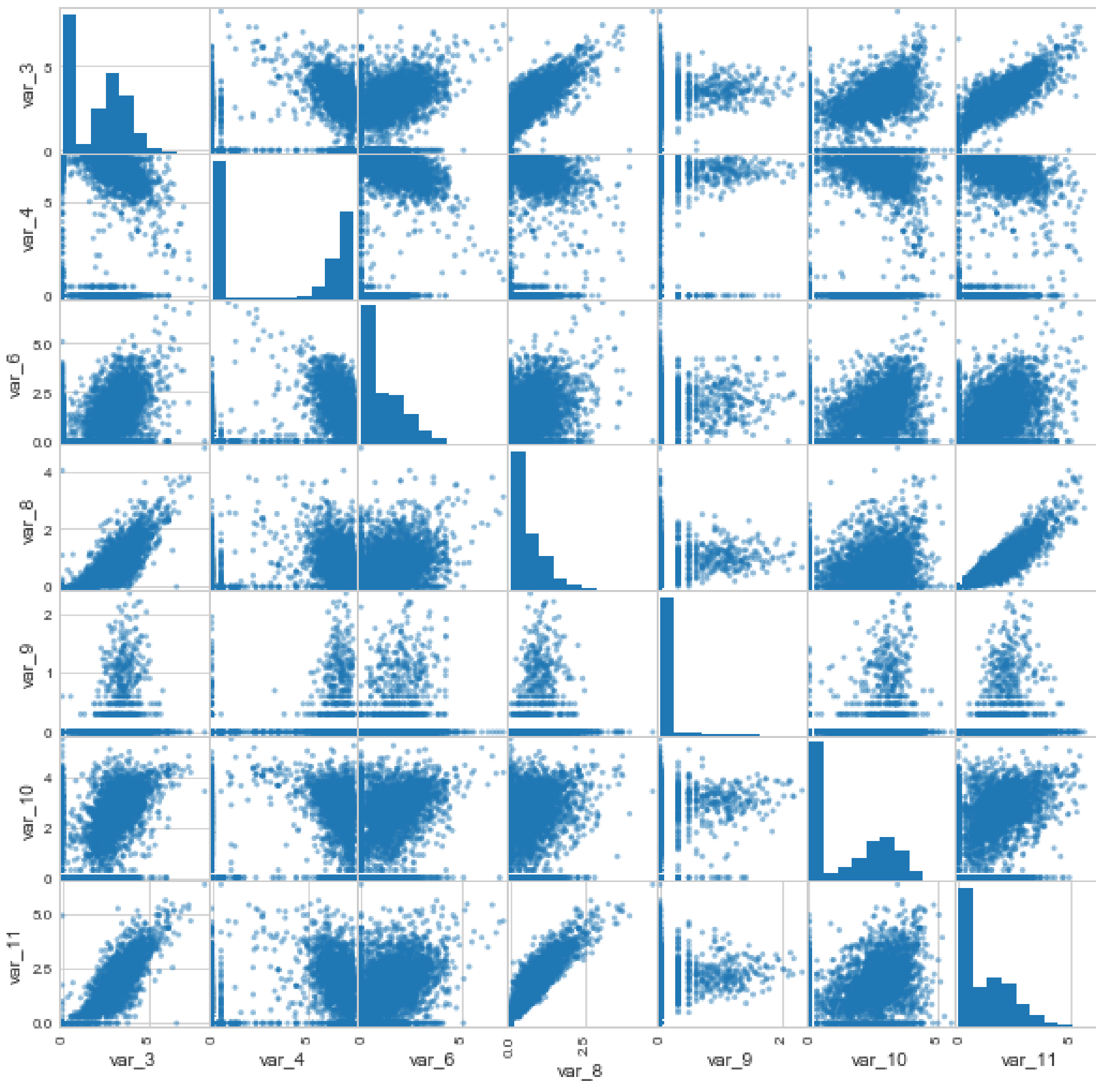
In order to apply the logaritmic transformation to misbehaving features we created a proper function: `log_transform`, that takes as input the dataset, and the list of variable to transform, and returns the modified data frame.

```
In [82]: # Define a function to apply log to a list of variables
         def log_transform(df, var_list):
             for var in var_list:
                 df[var] = df[var].apply(lambda x: np.log10(x+1))
```

```
In [83]: # apply the func
         log_transform(train, ['var_3','var_4','var_6','var_8','var_9','var_10','var_11'])
```

Now we could chek for possible correlations visually and than, after that, take a look at the Person coefficient to have a numerical estimation of the correlation.

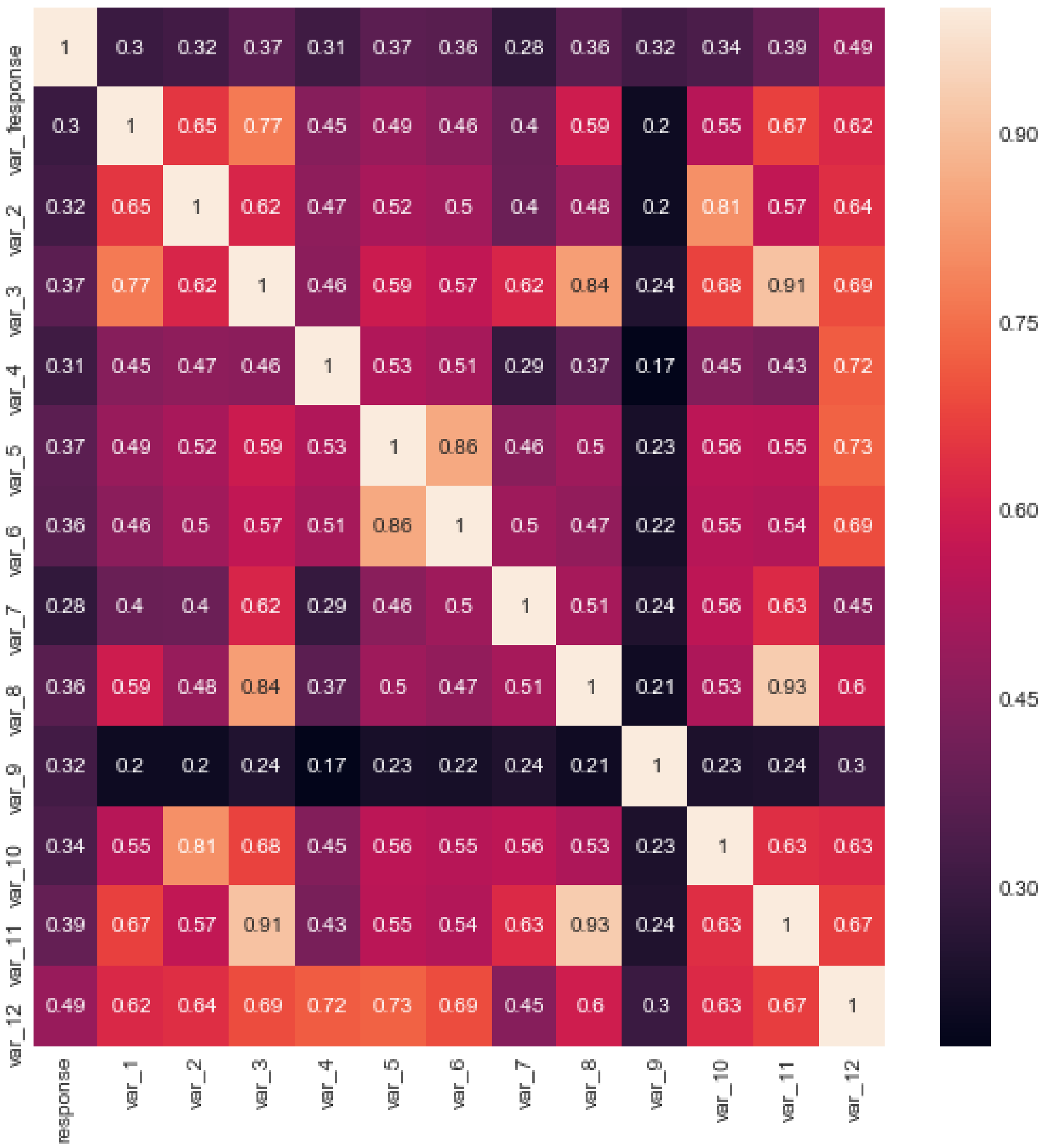
```
In [84]: # check the correlation
         pd.plotting.scatter_matrix(train[['var_3','var_4','var_6', 'var_8','var_9', 'var_10', '
         plt.show()
```



From the above scatter plots it appear that with the exception of `var_9`, the other features seems to be all correlated with different intensity. For `var_8` and `var_11` the correlation is really strong. They are also correlated with `var_3`. We have checked also the Person coefficient to have a numeric estimation of the correlation.

In [85]:
```python
# check the perasons coefficients
corr_matrix = train.corr()
#corr_matrix
# plot the heatmap
plt.subplots(figsize=(9,9))
sns.heatmap(corr_matrix, annot=True, xticklabels=corr_matrix.columns, yticklabels=corr_
```

Out[85]: <matplotlib.axes._subplots.AxesSubplot at 0x2371b9e95c0>



So, from the above heatmap appears also some correlation between *normal* features and *misbehaving*. For example, var_5 and var_6, var_10 and var_2. Furthemore, var_4 seems to be *an-*

ticorrelated with var_3, and slightly also with var_6 and var_8. So we decide to try to use only a subsample of features to train the learnig model.

1.10 Support Vector Machine Classifier (SVM)

As first attempt to model our dataset, we build a SVM classifier using only a subset of features. So first of all, we selected the features.

```
In [176]: # Subsetting the train dataset
          trainmod = train[['response','var_1','var_2','var_5','var_7','var_12']]
          trainmod.head()
```

```
Out[176]:          response  var_1  var_2      var_5  var_7   var_12
          user_id
          154531          0      1      1  38.637588      0  0.87499
          156315          0      1      1  30.901522    237  0.79306
          149607          0      1      1  45.933998    638  0.94425
          26755           0      1      1  34.120554     65  0.57251
          149734          0      0      0  23.700552     99  0.45718
```

Un important step in the building and training our model is to divide our datset in a train and a test sample. So we could use the test sample to evaluate the model performances.

```
In [190]: # Split the dataset in train and test
          from sklearn.model_selection import train_test_split
          X_train, X_test, y_train, y_test = train_test_split(trainmod.drop('response',axis=1),
                                                              trainmod['response'], test_size=0.
                                                              random_state=101)
```

1.10.1 Features Scaling

In order to have better results from the **SVM** classifier we need to rescale our features.

```
In [191]: # Features rescaling
          from sklearn.preprocessing import StandardScaler
          scaler = StandardScaler()

          scaler.fit(X_train)
          X_train=scaler.transform(X_train)
          X_test=scaler.transform(X_test)
```

1.10.2 Build the classifier

Now we are ready to build the classifier. We used the class_weight='balanced' parameter to try to taking into account the bad balance of our dataset, where the *class* 0 is the most represented.

```
In [179]: # Buiding the classifier
          from sklearn.svm import SVC
          svc_model = SVC(class_weight='balanced')
```

```
In [180]: # Model fit
          svc_model.fit(X_train,y_train)

Out[180]: SVC(C=1.0, cache_size=200, class_weight='balanced', coef0=0.0,
            decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
            max_iter=-1, probability=False, random_state=None, shrinking=True,
            tol=0.001, verbose=False)

In [181]: # Model predictions
          svc_pred = svc_model.predict(X_test)
```

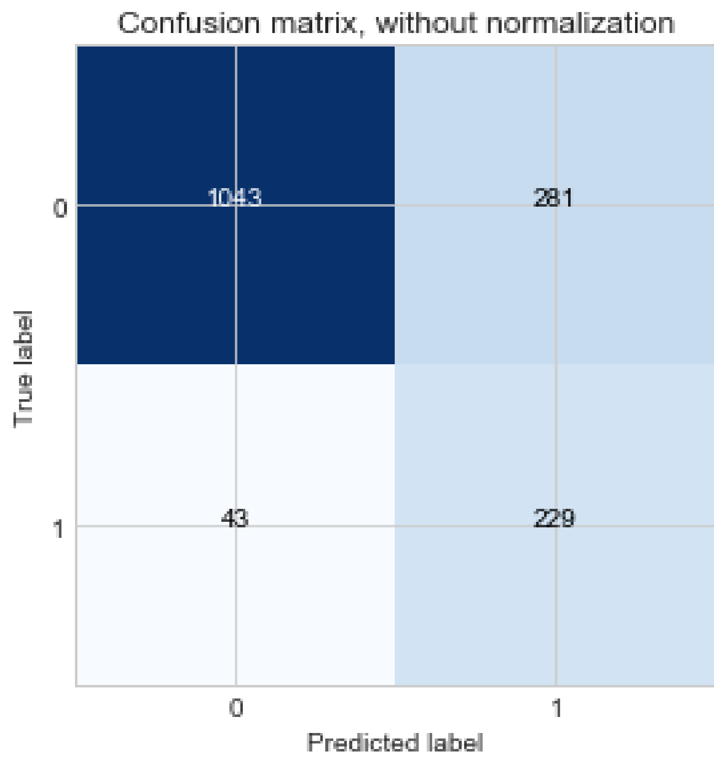
1.10.3 Model evaluation

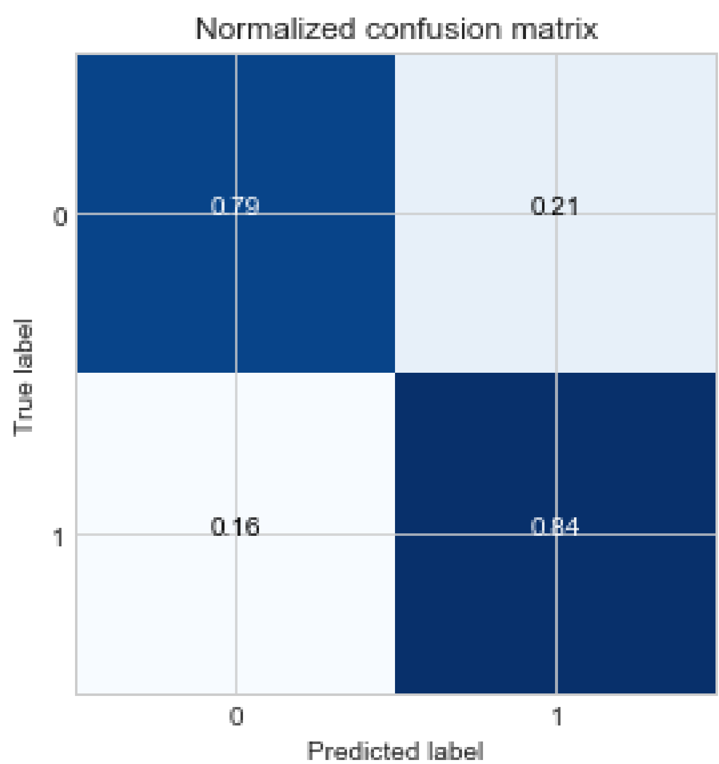
Finally we need to evaluate our model in order to estimate his performances. We could take a look at the ***Confusion Matrix*** and at some estimators like ***accurancy***, ***precision***, ***recal*** and ***F1-score***.

```
In [182]: # Model eveluation
          import itertools
          from sklearn.metrics import classification_report,confusion_matrix
          from sklearn import metrics

          def plot_confusion_matrix(cm, classes,
                                    normalize=False,
                                    title='Confusion matrix',
                                    cmap=plt.cm.Blues):
              """
              This function prints and plots the confusion matrix.
              Normalization can be applied by setting `normalize=True`.
              """
              if normalize:
                  cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                  print("Normalized confusion matrix")
              else:
                  print('Confusion matrix, without normalization')

              print(cm)

              plt.imshow(cm, interpolation='nearest', cmap=cmap)
              plt.title(title)
              #plt.colorbar()
              tick_marks = np.arange(len(classes))
              #plt.xticks(tick_marks, classes, rotation=45)
              plt.xticks(tick_marks, classes)
              plt.yticks(tick_marks, classes)

              fmt = '.2f' if normalize else 'd'
              thresh = cm.max() / 2.
              for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
                  plt.text(j, i, format(cm[i, j], fmt),
```

```
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")

        plt.tight_layout()
        plt.ylabel('True label')
        plt.xlabel('Predicted label')

    # Compute confusion matrix
    cnf_matrix = confusion_matrix(y_test,svc_pred)
    np.set_printoptions(precision=2)

    class_names = ['0', '1']

    # Plot non-normalized confusion matrix
    plt.figure()
    plot_confusion_matrix(cnf_matrix, classes=class_names,
                          title='Confusion matrix, without normalization')

    # Plot normalized confusion matrix
    plt.figure()
    plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                          title='Normalized confusion matrix')

    plt.show()
    #accurancy = float(cnf_matrix[0][0] + cnf_matrix[1][1])/cnf_matrix.sum()
    #print(accurancy)
    print(classification_report(y_test,svc_pred))
```

```
Confusion matrix, without normalization
[[1043  281]
 [  43  229]]
Normalized confusion matrix
[[0.79 0.21]
 [0.16 0.84]]
```


Confusion matrix, without normalization
1043
281
43
229
True label
Predicted label
0
1


Normalized confusion matrix
0.79
0.21
0.16
0.84
True label
Predicted label
0
1

```
             precision    recall  f1-score   support

          0       0.96      0.79      0.87      1324
          1       0.45      0.84      0.59       272

avg / total       0.87      0.80      0.82      1596
```

With the **SVM** classifier we obtained a **True Positive Rate** (***Recall*** or ***Sensitivity***) of 79% for `response` class 0 and 84% for `response` class 1. Those values are not so high, but correclty balanced, taking into account the different weight of the two samples.

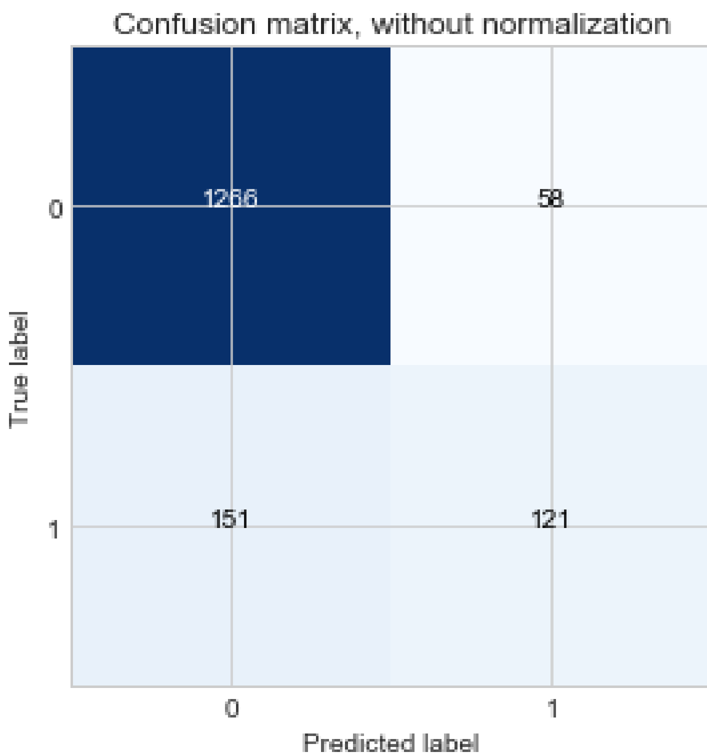
1.11 Random Forest Classifier

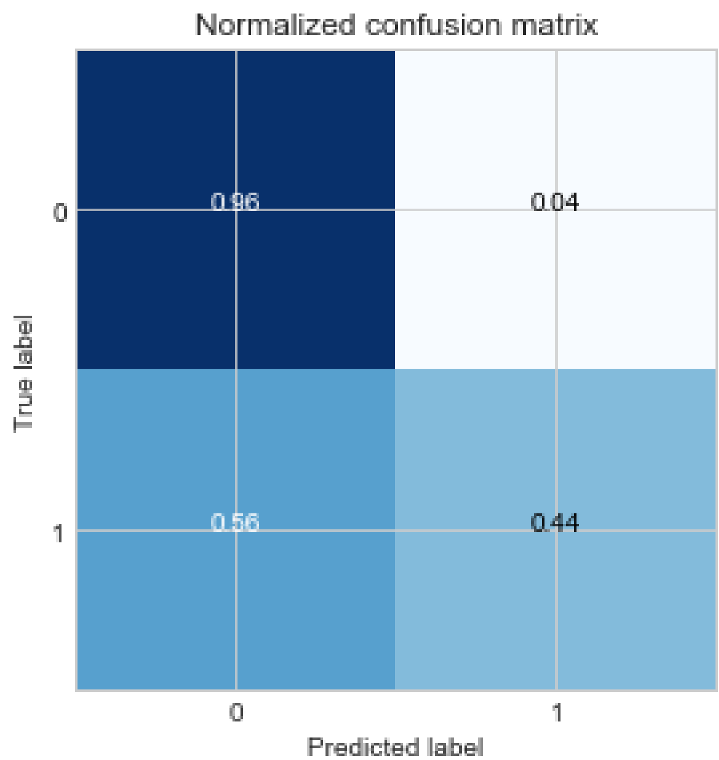
In order to try to obtain a better classification for our dataset, we builded also a **Random Forest classifier**, with the same subset of features.

```
In [95]: from sklearn.ensemble import RandomForestClassifier
         rfc = RandomForestClassifier(class_weight='balanced', n_estimators=101)

In [96]: rfc.fit(X_train, y_train)

Out[96]: RandomForestClassifier(bootstrap=True, class_weight='balanced',
                     criterion='gini', max_depth=None, max_features='auto',
                     max_leaf_nodes=None, min_impurity_decrease=0.0,
                     min_impurity_split=None, min_samples_leaf=1,
                     min_samples_split=2, min_weight_fraction_leaf=0.0,
                     n_estimators=101, n_jobs=1, oob_score=False, random_state=None,
                     verbose=0, warm_start=False)

In [97]: rfc_pred = rfc.predict(X_test)

In [117]: # Compute confusion matrix
          cnf_matrix = confusion_matrix(y_test, rfc_pred)
          np.set_printoptions(precision=2)

          class_names = ['0', '1']

          # Plot non-normalized confusion matrix
          plt.figure()
          plot_confusion_matrix(cnf_matrix, classes=class_names,
                                title='Confusion matrix, without normalization')

          # Plot normalized confusion matrix
          plt.figure()
```

```
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')

plt.show()
#accurancy = float(cnf_matrix[0][0] + cnf_matrix[1][1])/cnf_matrix.sum()
#print(accurancy)
print(classification_report(y_test,rfc_pred))
```

```
Confusion matrix, without normalization
[[1266   58]
 [ 151  121]]
Normalized confusion matrix
[[0.96 0.04]
 [0.56 0.44]]
```






```
             precision    recall  f1-score   support

          0       0.89      0.96      0.92      1324
          1       0.68      0.44      0.54       272

avg / total       0.86      0.87      0.86      1596
```

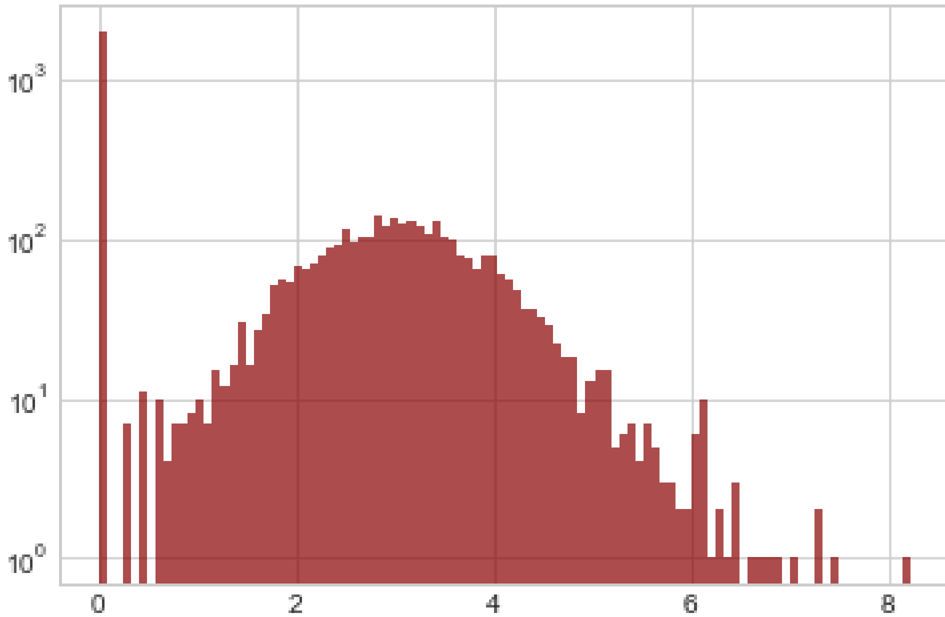
Using the **Random Forest** classifier the ***sensitivity*** for `response` 0 is quite better than the results of the **SVM**, respectively 96% and 79%. But for `response` 1 the ***True Positive Rate*** is very bad, 44% versus 84% with **SVM** classifier. So, we could say that the **Support Vector Machine** represents a good model to fit our dataset, and we will use it for *predictions* of new data.

1.12 Data Cleaning and Features Transformation

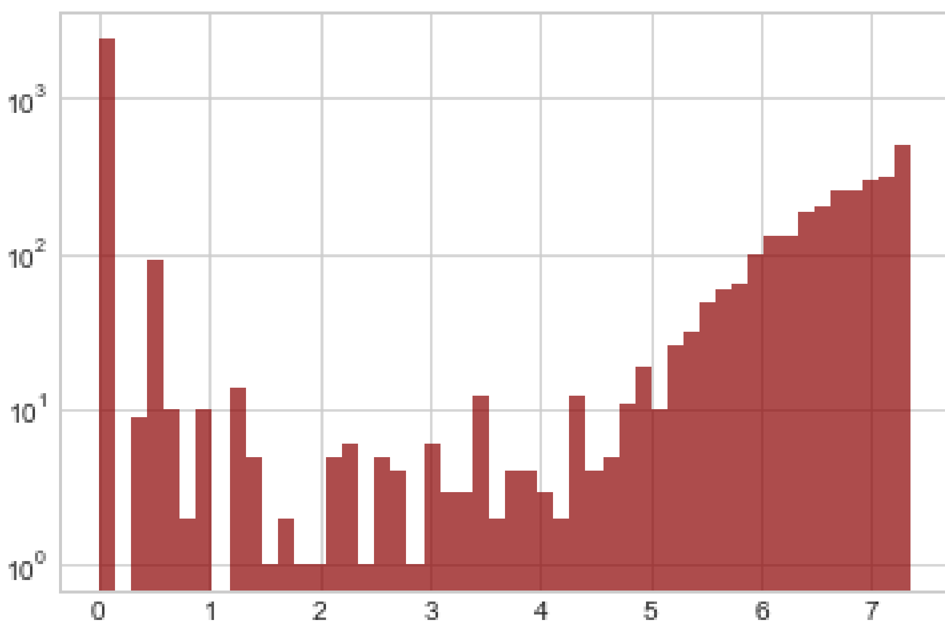
As last step of our analysis we tryied to re-apply the learning model using all the features in order to check if the algorithm performances became better. But, to be useful, `var_3`, `var_4`, `var_6`, `var_9` and `var_10` need to be cleaned. Following plots show a closer look at those *critical* variables. We cutted the outliers values and took the logaritmic values in order to reduce the number of order of magnitude spanned from the variables.

```
In [118]: # Plot var_3
          train['var_3'].hist(bins=100,color='darkred',alpha=0.7, log=True)
```

```
Out[118]: <matplotlib.axes._subplots.AxesSubplot at 0x2371e3b8400>
```



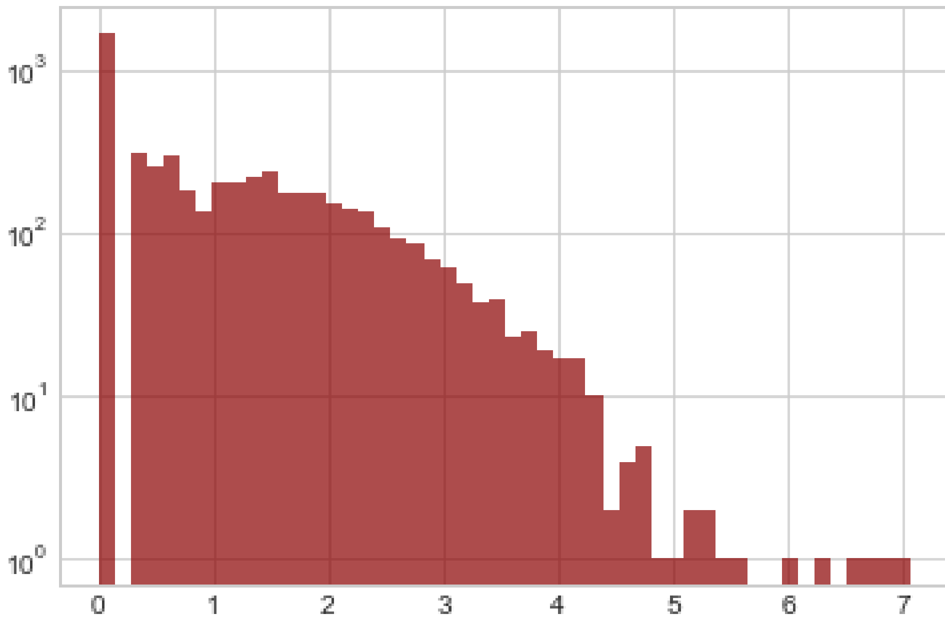

```
In [119]: train['var_4'].hist(bins=50,alpha=0.7,color='darkred',log=True)

Out[119]: <matplotlib.axes._subplots.AxesSubplot at 0x23719a1c8d0>
```



It seams all the values of `var_4` are concentraded at 0 and than there is a very long tail.

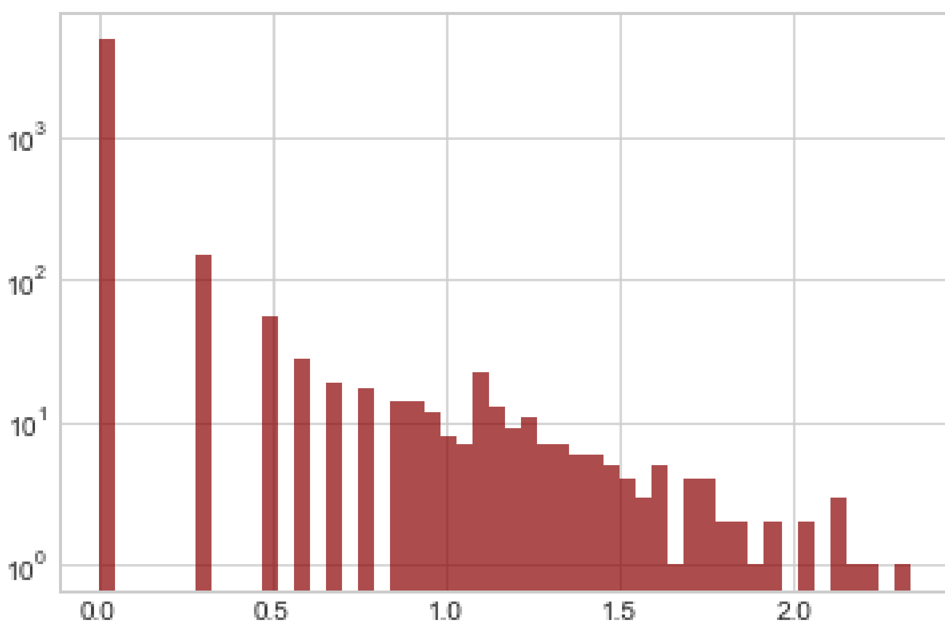
```
In [120]: train['var_6'].hist(bins=50,color='darkred',alpha=0.7, log=True)
```

```
Out[120]: <matplotlib.axes._subplots.AxesSubplot at 0x2371b22eeb8>
```



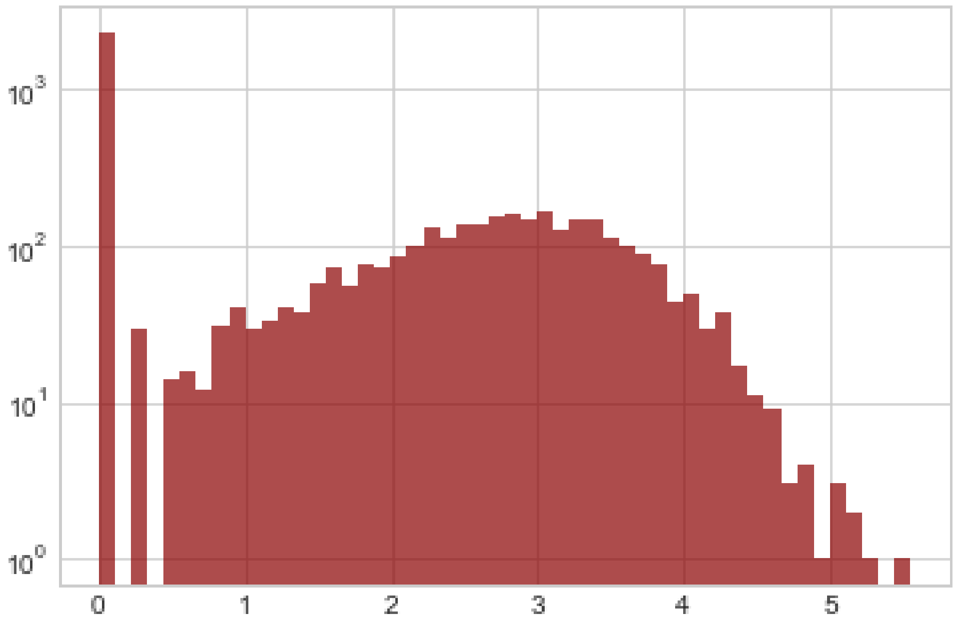

```
In [121]: train['var_9'].hist(bins=50,color='darkred',alpha=0.7, log=True)
```

```
Out[121]: <matplotlib.axes._subplots.AxesSubplot at 0x2371e1376d8>
```



In [122]:
```
train['var_10'].hist(bins=50,color='darkred',alpha=0.7, log=True)
```

Out[122]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2371b3ebba8>
```



1.13 Training SVM model after data cleaning

After features transformation, we applyied the **SVM** classifier with the complete list of features, removing only features higly correlated: `var_4`, `var_8` and `var_11`.

In [233]:
```
# Subsetting the train dataset
new_trainmod = train[['response','var_1','var_2', 'var_3','var_5', 'var_6','var_7', 'v
```

In [234]:
```
# Split samples
X_train, X_test, y_train, y_test = train_test_split(new_trainmod.drop('response',axis=
                                                    new_trainmod['response'], test_siz
                                                    random_state=101)
```

In [235]:
```
# Rescaling features
newscaler = StandardScaler()
newscaler.fit(X_train)
X_train = newscaler.transform(X_train)
X_test = newscaler.transform(X_test)
```

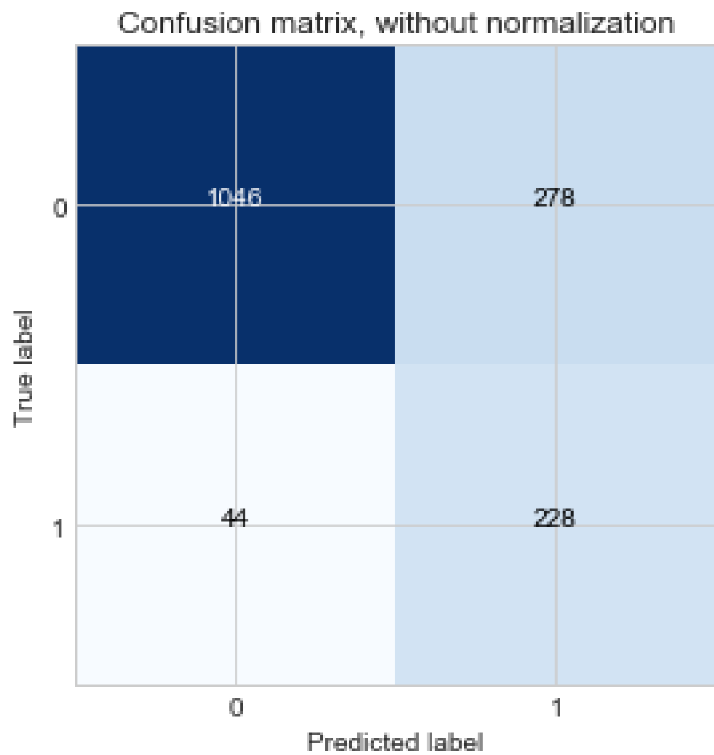
In [236]:
```
# Model fit
svc_new_model = SVC(class_weight='balanced')
svc_new_model.fit(X_train,y_train)
```

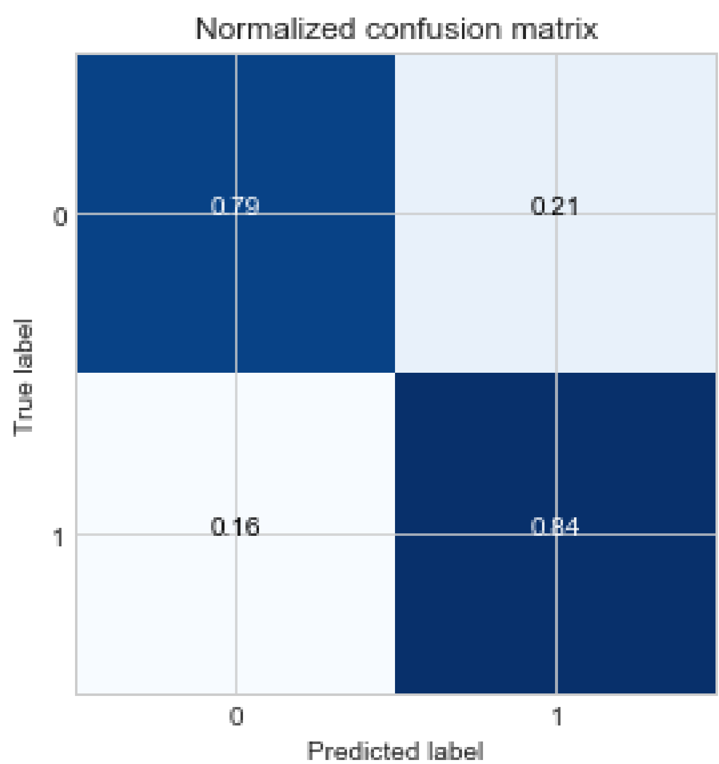
Out[236]: SVC(C=1.0, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)

In [237]:
```
# Model predictions
svc_new_pred = svc_new_model.predict(X_test)
```

In [238]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, svc_new_pred)
np.set_printoptions(precision=2)

class_names = ['0', '1']

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')

plt.show()
#accurancy = float(cnf_matrix[0][0] + cnf_matrix[1][1])/cnf_matrix.sum()
#print(accurancy)
print(classification_report(y_test,svc_new_pred))
```

```
Confusion matrix, without normalization
[[1046  278]
 [  44  228]]
Normalized confusion matrix
[[0.79 0.21]
 [0.16 0.84]]
```


Confusion matrix, without normalization
1046
278
44
228
0
1
True label
0
1
Predicted label


Normalized confusion matrix
0.79
0.21
0.16
0.84
0
1
True label
0
1
Predicted label

```
             precision    recall  f1-score   support

          0       0.96      0.79      0.87      1324
          1       0.45      0.84      0.59       272

avg / total       0.87      0.80      0.82      1596
```

New results are completely comparable with the model builded and trained with only the subset of the features. The inclusion of the other features did not improved the performances of the learning algorithm, as aspected. Indeed, even after the *logarithimc* transformation most part of the features values are concentrated at zero, suppressing the weight of the other values. Unfortunatly we cannot remove those *sparks* at zero from the dataset without loosing the most part of it. We tried and we obtained only few hundreds of data, quite unuseful to build and train whatever learning model.

In search of better performances, we also used **GridSearch** to try to optimize the paramenters *C* and *gamma* of the **SVM** models, but with the option *class_weight='balanced'* GridSearchCV diverged resulting in a totally wrong classification.

1.14 New data classification with SVM algorithm

At this point we will use the trained **SVM** model to predict the `response` on a new dataset. First of all, we need to import the new data in a Pandas dataframe and apply all the transformation we did on training sample.

```
In [199]: # Import data
          test = pd.read_csv('data/model_test_file.csv')
          test.head()
```

```
Out[199]:    var_1  var_2  var_3     var_4      var_5  var_6  var_7    var_8  var_9  \
          0      1      1    193  11248797  33.254023     17     40  77.7500      0
          1      1      1  14631   2396429  42.681445   1005   1582  56.3211      0
          2      1      1    385   3521953  33.501102    294    105   8.4952     26
          3      0      0      0         0   0.000000      0      0   0.0000      0
          4      1      1   6672   2913930  34.344784  10582     30   0.7667      0

             var_10  var_11   var_12  user_id
          0     583    3055  0.60563   154472
          1    4082   53187  0.88451   151147
          2     162      37  0.86154    10543
          3       0       0  0.10018   136986
          4     133       7  0.68598   137008
```

We need to remove same features as in the training analysis that results in a better performances. So we exclude `var_3`, `var_4`, `var_6`, `var_8`, `var_9`, `var_10` and `var_11`.

```
In [200]: # Drop misbehaving features
          #test.drop(['var_3', 'var_4','var_6','var_8','var_9','var_10','var_11','user_id'],axis
          testmod = test.drop(['var_3', 'var_4','var_6','var_8','var_9','var_10','var_11'],axis=
          # Set user_id as index
          testmod = testmod.set_index('user_id')
          testmod.head()
```

```
Out[200]:          var_1  var_2      var_5  var_7    var_12
          user_id
          154472       1      1  33.254023     40  0.60563
          151147       1      1  42.681445   1582  0.88451
          10543        1      1  33.501102    105  0.86154
          136986       0      0   0.000000      0  0.10018
          137008       1      1  34.344784     30  0.68598
```

Now, we need to *reshape* a bit the data frame to have the right format for the learning model.

```
In [202]: # Reshaping
          X_test_newsample = testmod.as_matrix()
```

Now we are ready to apply the **SVM** model we builded and trained with only the *good* features. But firt we have to *rescale* also the new test data.

```
In [203]: # rescaling
          X_test_newsample = scaler.transform(X_test_newsample)
```

The predictions of our **SVM** learning model are:

```
In [204]: # apply SVM
          svc_new_pred = svc_model.predict(X_test_newsample)
```

```
In [208]: # see the results taking a look at the predictions created
          testmod['new_pred'] = svc_new_pred
          testmod
```

```
Out[208]:          var_1  var_2      var_5  var_7    var_12  new_pred
          user_id
          154472       1      1  33.254023     40  0.60563         0
          151147       1      1  42.681445   1582  0.88451         1
          10543        1      1  33.501102    105  0.86154         1
          136986       0      0   0.000000      0  0.10018         0
          137008       1      1  34.344784     30  0.68598         0
          137059       0      0   0.000000      0  0.08061         0
          137253       0      0   0.000000      0  0.08061         0
          137323       1      1  29.925298     20  0.77864         1
          171652       1      1   0.000000   1810  0.67349         0
          137341       1      1  34.572958    399  0.83240         1
          137768       1      1  22.663224    236  0.25554         0
          137822       1      1  32.954738    450  0.59736         0
```

137879	0	0	26.804861	217	0.71104	0
137984	1	1	35.802761	190	0.92892	1
138103	1	1	0.000000	1	0.17138	0
138200	1	1	26.361832	380	0.55178	0
138405	1	1	38.972069	563	0.92875	1
138439	0	0	15.813438	0	0.38118	0
138473	0	0	22.014121	0	0.07780	0
138483	0	0	26.903693	0	0.65279	0
138582	0	0	0.000000	0	0.08061	0
138606	1	0	0.000000	85	0.15566	0
138738	0	0	21.820799	240	0.10255	0
138948	0	0	0.000000	0	0.08061	0
139606	0	0	0.000000	0	0.14191	0
149425	1	1	43.409466	1563	0.93951	1
149419	1	0	27.236982	36	0.81458	1
150894	1	1	51.120647	1342	0.89298	1
141733	0	0	18.876661	0	0.20673	0
144653	1	1	24.671342	222	0.90147	1
147263	1	1	39.009098	27	0.81860	1
147793	0	0	0.000000	0	0.10714	0
148663	1	1	43.537221	957	0.93709	1
149065	1	0	29.102700	3	0.33104	0
149643	0	0	0.000000	0	0.41157	0
149792	1	1	0.000000	835	0.16774	0
10420	1	0	48.228613	0	0.35088	0
152535	1	1	22.981221	69	0.38972	0
153169	1	1	0.000000	457	0.73181	1
153389	0	1	0.000000	0	0.11321	0
153395	1	0	0.000000	55	0.35629	0
154070	0	0	0.000000	0	0.08061	0
154777	0	0	0.000000	0	0.08061	0
168361	0	0	0.000000	1123	0.10630	0
168689	1	1	26.400655	695	0.31953	0
168840	1	0	26.877454	5	0.50921	0
168845	1	1	0.000000	17	0.28022	0
168862	1	1	28.673564	1403	0.65822	0
168864	1	1	21.923702	13	0.69437	0
168989	1	1	0.000000	183	0.29884	0
168991	1	1	30.403461	702	0.75216	1
169591	0	0	0.000000	0	0.06707	0
169636	1	0	0.000000	4	0.10986	0
169853	0	0	23.274683	0	0.30361	0
259509	1	1	26.417065	787	0.80725	1
260608	1	1	40.801757	885	0.94547	1
602671	1	1	24.499112	101	0.52842	0
602672	0	0	15.846660	0	0.09382	0
8107	1	1	45.499149	89	0.77027	1