MGT-415: Data Science in Practice

Project Notebook
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ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

I Python Dependencies

In [1]:
```
! pip install missingno #missing data
! pip install inblearn #over/undersampling
```

```
Requirement already satisfied: missingno in
/home/zaratras/anaconda3/lib/python3.7/site-packages (0.4.1)
Requirement already satisfied: scipy in /home/zaratras/anaconda3/lib/python3.7/site-
packages (from missingno) (1.2.1)
Requirement already satisfied: matplotlib in
/home/zaratras/anaconda3/lib/python3.7/site-packages (from missingno) (3.0.3)
Requirement already satisfied: seaborn in /home/zaratras/anaconda3/lib/python3.7/site-
packages (from missingno) (0.9.0)
Requirement already satisfied: numpy in /home/zaratras/anaconda3/lib/python3.7/site-
packages (from missingno) (1.16.3)
Requirement already satisfied: cycler>=0.10 in
/home/zaratras/anaconda3/lib/python3.7/site-packages (from matplotlib->missingno)
(0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/home/zaratras/anaconda3/lib/python3.7/site-packages (from matplotlib->missingno)
(1.0.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/home/zaratras/anaconda3/lib/python3.7/site-packages (from matplotlib->missingno)
(2.3.1)
Requirement already satisfied: python-dateutil>=2.1 in
/home/zaratras/anaconda3/lib/python3.7/site-packages (from matplotlib->missingno)
(2.8.0)
Requirement already satisfied: pandas>=0.15.2 in
/home/zaratras/anaconda3/lib/python3.7/site-packages (from seaborn->missingno)
(0.24.2)
Requirement already satisfied: six in /home/zaratras/anaconda3/lib/python3.7/site-
packages (from cycler>=0.10->matplotlib->missingno) (1.12.0)
Requirement already satisfied: setuptools in
/home/zaratras/anaconda3/lib/python3.7/site-packages (from
kiwisolver>=1.0.1->matplotlib->missingno) (40.8.0)
Requirement already satisfied: pytz>=2011k in
/home/zaratras/anaconda3/lib/python3.7/site-packages (from
pandas>=0.15.2->seaborn->missingno) (2018.9)
Collecting inblearn
  Could not find a version that satisfies the requirement inblearn (fromversions: )
No matching distribution found for inblearn
```

II Dataset Analysis

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno

######################################

import numpy as np
```

```
import scipy.stats as sc
import pandas as pd

import seaborn as sns
import matplotlib as mpl

import matplotlib.pyplot as plt
from IPython.display import display

import statsmodels.api as sm

from sklearn.model_selection import train_test_split
from statsmodels.stats import outliers_influence as oi

from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression

from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import log_loss
from sklearn.metrics import mean_squared_error
from sklearn.feature_selection import RFE
from sklearn import metrics


from sklearn.ensemble import IsolationForest
from sklearn.model_selection import cross_val_predict
#######################################################

from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn import metrics

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn import metrics

from matplotlib.colors import ListedColormap
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import make_moons, make_circles, make_classification
#from sklearn.neural_network import MLPClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.gaussian_process.kernels import RBF
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.calibration import CalibratedClassifierCV

######################################
```

```
#from sklearn.datasets import load_iris
from sklearn import preprocessing

from scipy import interp
from sklearn import datasets, neighbors
from sklearn.metrics import auc, roc_curve
from sklearn.model_selection import StratifiedKFold

from imblearn.over_sampling import ADASYN, SMOTE, RandomOverSampler, SMOTENC
from imblearn.combine import SMOTEENN
from imblearn.under_sampling import ClusterCentroids,
RandomUnderSampler,EditedNearestNeighbours


from imblearn.pipeline import make_pipeline
from imblearn import FunctionSampler
######################################
import warnings
warnings.filterwarnings("ignore")
pd.set_option('display.max_colwidth', 250)
sns.set()
```

II Basic Info

```
In [3]: dsdata = pd.read_excel('Data/full_dataset.xlsx')
        dsdata = dsdata.replace('unknown', np.nan)
        dsdata = dsdata.replace('nonexistent', np.nan)

        dsdata.head()
```

```
Out[3]:    age        job  marital    education default housing loan    contact month  \
        0   56  housemaid  married     basic.4y      no      no   no  telephone   may
        1   57   services  married  high.school     NaN      no   no  telephone   may
        2   37   services  married  high.school      no     yes   no  telephone   may
        3   40     admin.  married     basic.6y      no      no   no  telephone   may
        4   56   services  married  high.school      no      no  yes  telephone   may

          day_of_week  ...  campaign  pdays  previous  poutcome emp.var.rate  \
        0         mon  ...         1    999         0       NaN          1.1
        1         mon  ...         1    999         0       NaN          1.1
        2         mon  ...         1    999         0       NaN          1.1
        3         mon  ...         1    999         0       NaN          1.1
        4         mon  ...         1    999         0       NaN          1.1

           cons.price.idx  cons.conf.idx  euribor3m  nr.employed   y
        0          93.994          -36.4      4.857       5191.0  no
        1          93.994          -36.4      4.857       5191.0  no
        2          93.994          -36.4      4.857       5191.0  no
        3          93.994          -36.4      4.857       5191.0  no
        4          93.994          -36.4      4.857       5191.0  no

        [5 rows x 21 columns]
```

```
In [4]: dsdata.dtypes
```

```
Out[4]: age                     int64
        job                    object
```

```
marital             object
education           object
default             object
housing             object
loan                object
contact             object
month               object
day_of_week         object
duration             int64
campaign             int64
pdays                int64
previous             int64
poutcome            object
emp.var.rate       float64
cons.price.idx     float64
cons.conf.idx      float64
euribor3m          float64
nr.employed        float64
y                   object
dtype: object
```

II Input variables:

a. bank client data: 1 - age (numeric)
2 - job : type of job (categorical: ‘admin.’,‘blue-collar’,‘entrepreneur’,‘housemaid’,‘management’,‘retired’,‘self-employed’,‘services’,‘student’,‘technician’,‘unemployed’,‘unknown’)
3 - marital : marital status (categorical: ‘divorced’,‘married’,‘single’,‘unknown’; note: ‘divorced’ means divorced or widowed)
4 - education (categorical: ‘basic.4y’,‘basic.6y’,‘basic.9y’,‘high.school’,‘illiterate’,‘professional.course’,‘university.degree’,‘unkn
5 - default: has credit in default? (categorical: ‘no’,‘yes’,‘unknown’)
6 - housing: has housing loan? (categorical: ‘no’,‘yes’,‘unknown’)
7 - loan: has personal loan? (categorical: ‘no’,‘yes’,‘unknown’)

1. related with the last contact of the current campaign:

8 - contact: contact communication type (categorical: ‘cellular’,‘telephone’)
9 - month: last contact month of year (categorical: ‘jan’, ‘feb’, ‘mar’, . . . , ‘nov’, ‘dec’)
10 - day_of_week: last contact day of the week (categorical: ‘mon’,‘tue’,‘wed’,‘thu’,‘fri’)
11 - duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y=‘no’). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.

2. other attributes:

12 - campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
13 - pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
14 - previous: number of contacts performed before this campaign and for this client (numeric)
15 - poutcome: outcome of the previous marketing campaign (categorical: ‘failure’,‘nonexistent’,‘success’)

3. social and economic context attributes

16 - emp.var.rate: employment variation rate - quarterly indicator (numeric)
17 - cons.price.idx: consumer price index - monthly indicator (numeric)
18 - cons.conf.idx: consumer confidence index - monthly indicator (numeric)
19 - euribor3m: euribor 3 month rate - daily indicator (numeric)
20 - nr.employed: number of employees - quarterly indicator (numeric)

4. Output variable (desired target):

21 - y - has the client subscribed a term deposit? (binary: 'yes','no')

II Variable Description

In [5]:
```
#describe the "Object" type elements

dsdata.describe(include=['O'])
```

Out[5]:
```
           job  marital          education default housing   loan   contact  \
count    40858    41108              39457   32591   40198  40198     41188
unique      11        3                  7       2       2      2         2
top     admin.  married  university.degree      no     yes     no  cellular
freq     10422    24928              12168   32588   21576  33950     26144

        month day_of_week poutcome      y
count   41188       41188     5625  41188
unique     10           5        2      2
top       may         thu  failure     no
freq    13769        8623     4252  36548
```

In [6]:
```
#describe the "numerical" type elements

dsdata.describe()
```

Out[6]:
```
               age      duration      campaign         pdays      previous  \
count  41188.00000  41188.000000  41188.000000  41188.000000  41188.000000
mean      40.02406    258.285010      2.567593    962.475454      0.172963
std       10.42125    259.279249      2.770014    186.910907      0.494901
min       17.00000      0.000000      1.000000      0.000000      0.000000
25%       32.00000    102.000000      1.000000    999.000000      0.000000
50%       38.00000    180.000000      2.000000    999.000000      0.000000
75%       47.00000    319.000000      3.000000    999.000000      0.000000
max       98.00000   4918.000000     56.000000    999.000000      7.000000

       emp.var.rate  cons.price.idx  cons.conf.idx     euribor3m   nr.employed
count  41188.000000    41188.000000   41188.000000  41188.000000  41188.000000
mean       0.081886       93.575664     -40.502600      3.621291   5167.035911
std        1.570960        0.578840       4.628198      1.734447     72.251528
min       -3.400000       92.201000     -50.800000      0.634000   4963.600000
25%       -1.800000       93.075000     -42.700000      1.344000   5099.100000
50%        1.100000       93.749000     -41.800000      4.857000   5191.000000
75%        1.400000       93.994000     -36.400000      4.961000   5228.100000
max        1.400000       94.767000     -26.900000      5.045000   5228.100000
```

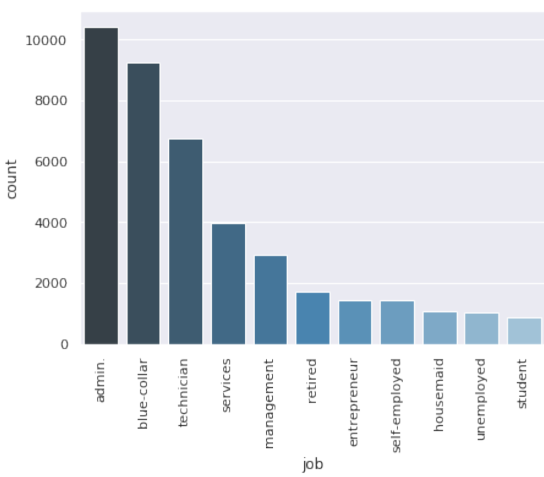
In [7]:
```
dsdata['y'].value_counts()
```

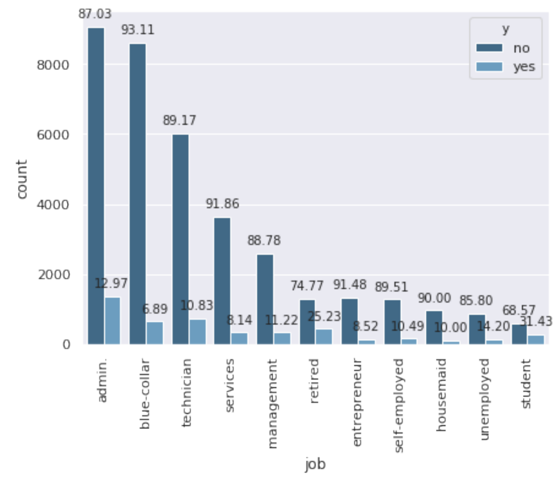
```
Out[7]: no     36548
        yes     4640
        Name: y, dtype: int64
```

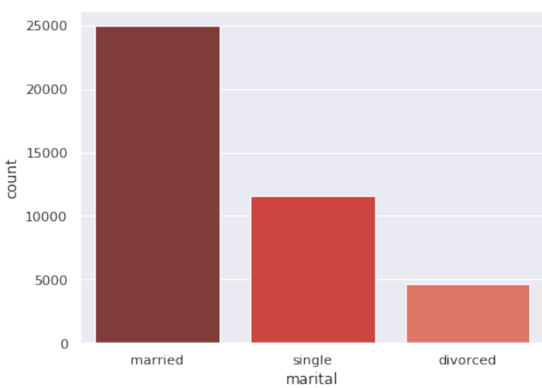
```
In [ ]:
```

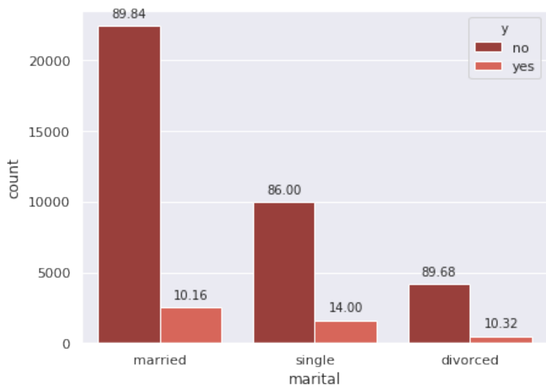
II Variable Distribution

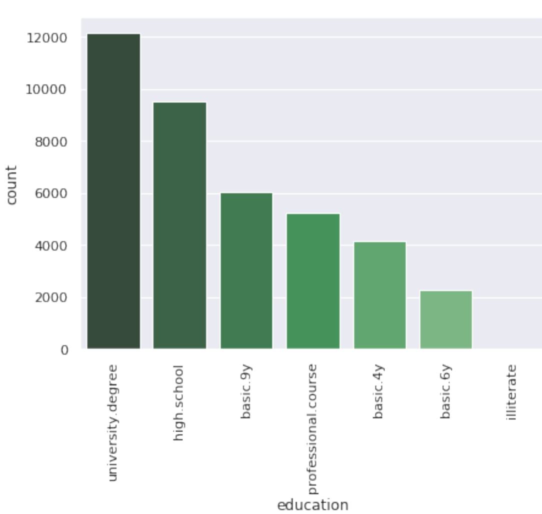
```
In [8]: # Barplots for categorical (object) variables and comparison between yes/no in
        deposit(y)
        colors = ['Blues_d', 'Reds_d', 'Greens_d', 'Oranges_d', 'Blues_r', 'Reds_r', 'Greens_r',
        'Oranges_r', 'mako', 'Reds_d','BuPu_r']
        color_coef=0
        total = float(len(dsdata))
        for column in dsdata.columns:
            if dsdata[column].dtype == "O":
                if column=='job' or column=='education':
                    x = dsdata[column].value_counts()
                    fig,ax=plt.subplots(1,2,figsize=(15,5))
                    t = sns.countplot(x=column, data=dsdata,
        palette=colors[color_coef],order=dsdata[column].value_counts().index, ax=ax[0])
                    t.set_xticklabels(t.get_xticklabels(), rotation=90)
                    g = sns.countplot(x=dsdata[column], hue=dsdata['y'],
        palette=colors[color_coef], order=dsdata[column].value_counts().index, ax=ax[1])
                    i=0
                    for p in g.patches:
                            length = len(g.patches)/2
                            total = x[i]
                            g.annotate(format(p.get_height()/total*100,'.2f'), (p.get_x() +
        p.get_width() / 2., p.get_height()), ha = 'center', va = 'center', xytext = (0, 10),
        textcoords = 'offset points')
                            i +=1
                            if i==length:
                                i=0
                    g.set_xticklabels(g.get_xticklabels(), rotation=90)
                else:
                    x = dsdata[column].value_counts()
                    fig,ax=plt.subplots(1,2,figsize=(15,5))
                    t = sns.countplot(x=column, data=dsdata, palette=colors[color_coef],
        order=dsdata[column].value_counts().index, ax=ax[0])
                    g = sns.countplot(x=dsdata[column], hue=dsdata['y'],
        palette=colors[color_coef],order=dsdata[column].value_counts().index, ax=ax[1])
                    if column=='default' or column=='y':
                        pass
                    else:
                        i=0
                        for p in g.patches:
                                length = len(g.patches)/2
                                total = x[i]
                                g.annotate(format(p.get_height()/total*100,'.2f'), (p.get_x() +
        p.get_width() / 2., p.get_height()), ha = 'center', va = 'center', xytext = (0, 10),
        textcoords = 'offset points')
                                i +=1
                                if i==length:
                                    i=0
                color_coef +=1
```

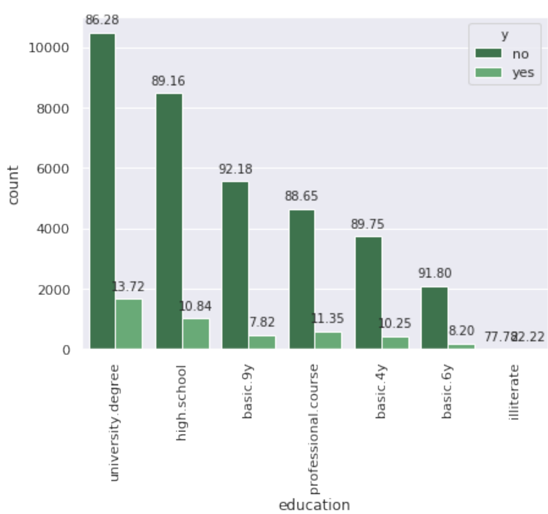

count
job
admin.
blue-collar
technician
services
management
retired
entrepreneur
self-employed
housemaid
unemployed
student

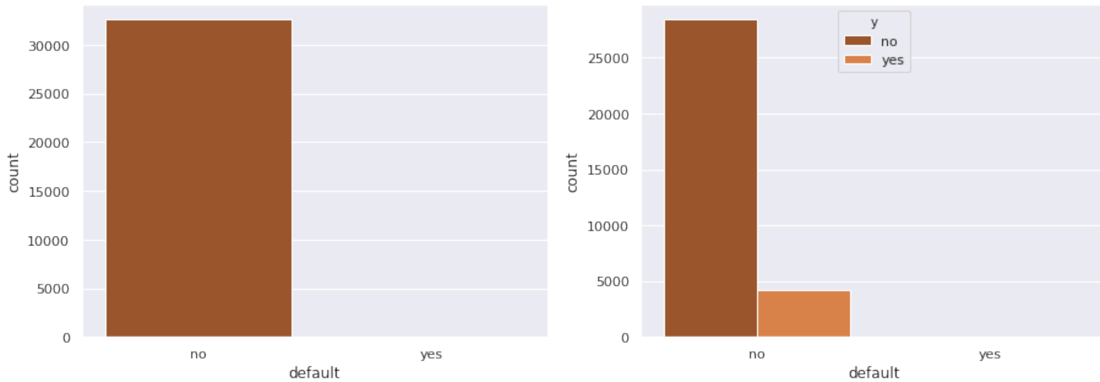

y
no
yes
count
job
87.03
12.97
93.11
6.89
89.17
10.83
91.86
8.14
88.78
11.22
74.77
25.23
91.48
8.52
89.51
10.49
90.00
10.00
85.80
14.20
68.57
31.43
admin.
blue-collar
technician
services
management
retired
entrepreneur
self-employed
housemaid
unemployed
student

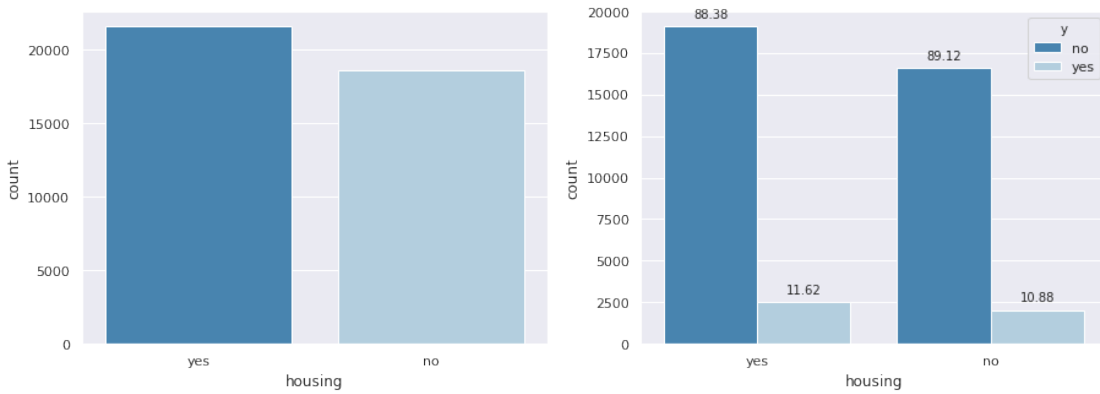

count
marital
married
single
divorced

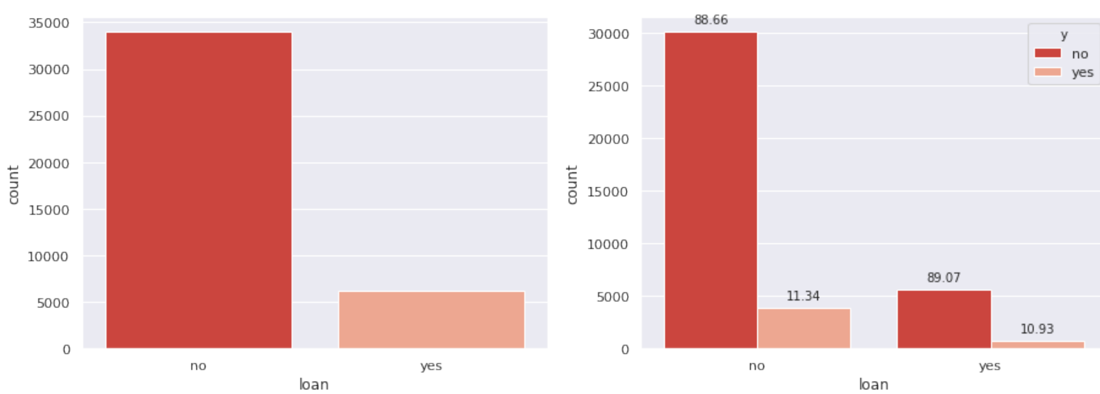

y
no
yes
count
marital
89.84
10.16
86.00
14.00
89.68
10.32
married
single
divorced

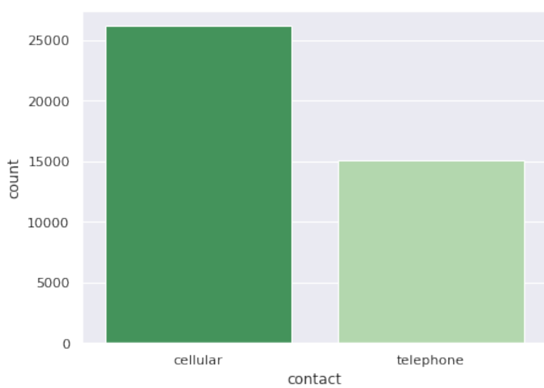

count
education
university.degree
high.school
basic.9y
professional.course
basic.4y
basic.6y
illiterate

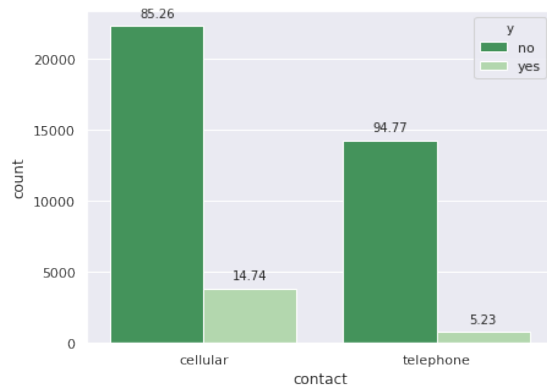

y
no
yes
count
education
86.28
13.72
89.16
10.84
92.18
7.82
88.65
11.35
89.75
10.25
91.80
8.20
77.78
22.22
university.degree
high.school
basic.9y
professional.course
basic.4y
basic.6y
illiterate

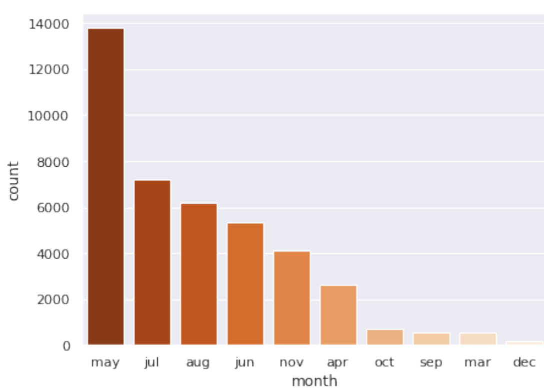

count
default
no
yes
y
no
yes

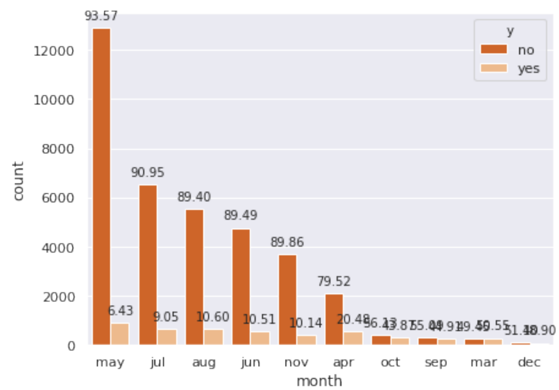

count
housing
yes
no
y
no
yes
88.38
11.62
89.12
10.88

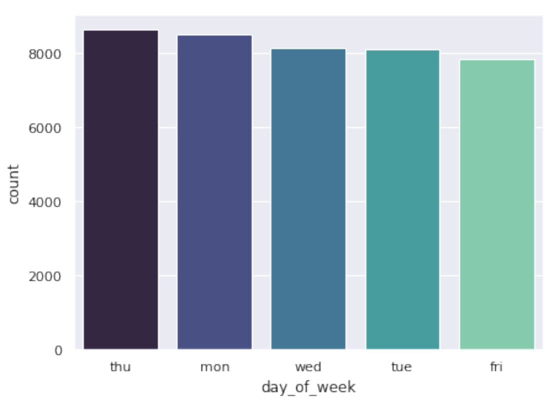

count
loan
no
yes
y
no
yes
88.66
11.34
89.07
10.93

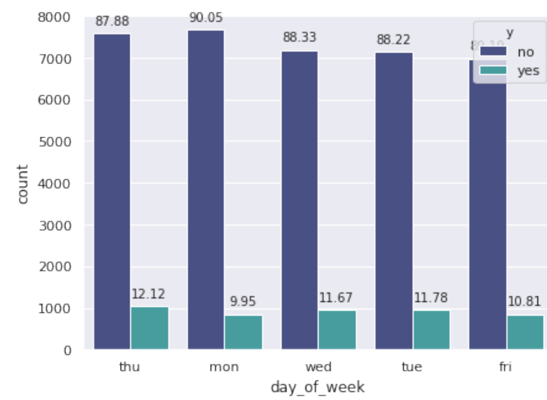

count
0
5000
10000
15000
20000
25000
cellular
telephone
contact

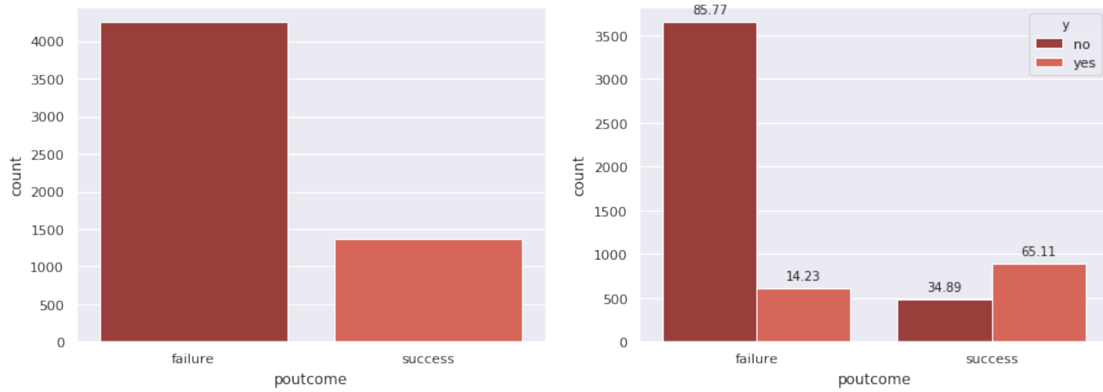

count
0
5000
10000
15000
20000
85.26
14.74
94.77
5.23
y
no
yes
cellular
telephone
contact

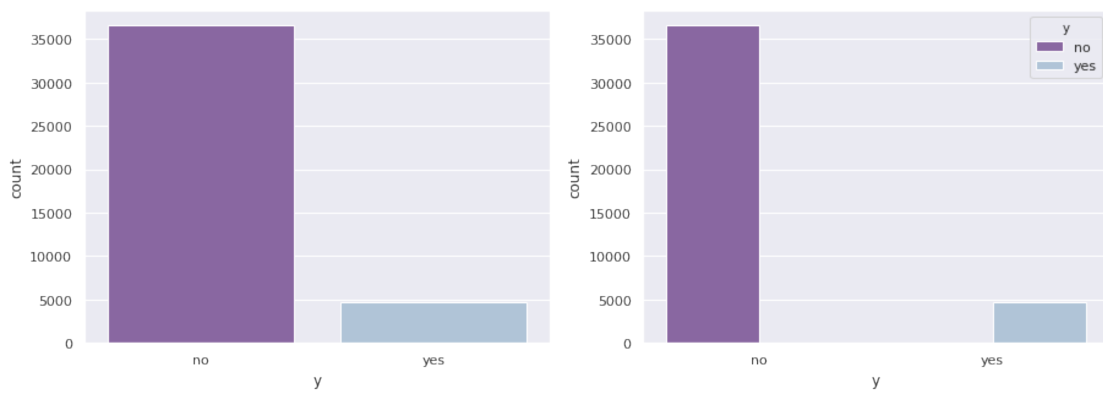

count
0
2000
4000
6000
8000
10000
12000
14000
may
jul
aug
jun
nov
apr
oct
sep
mar
dec
month


count
0
2000
4000
6000
8000
10000
12000
93.57
6.43
90.95
9.05
89.40
10.60
89.49
10.51
89.86
10.14
79.52
20.48
y
no
yes
may
jul
aug
jun
nov
apr
oct
sep
mar
dec
month

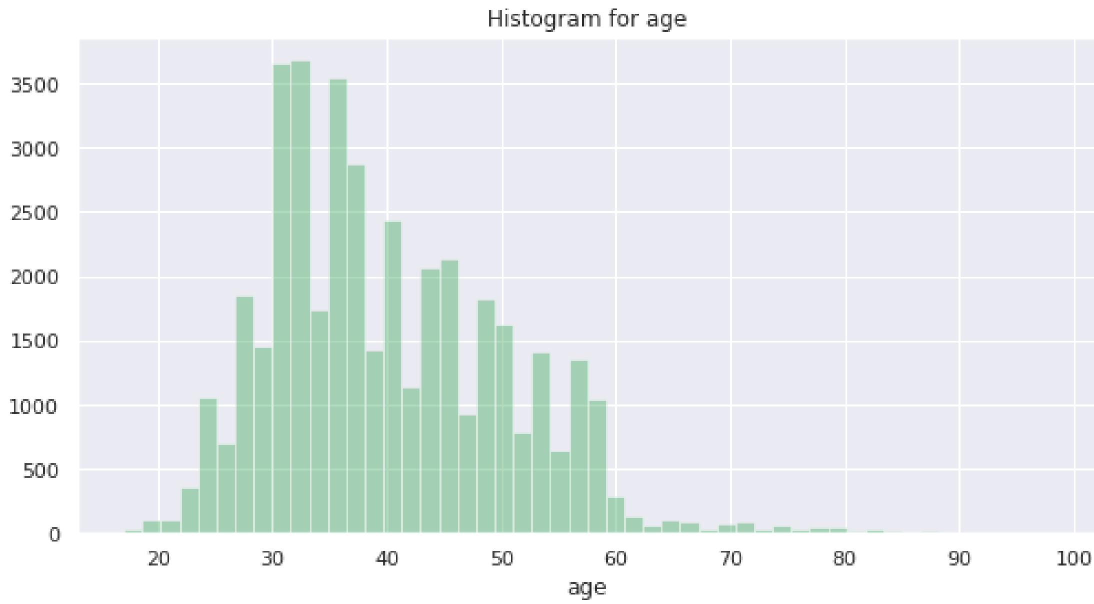

count
0
2000
4000
6000
8000
thu
mon
wed
tue
fri
day_of_week

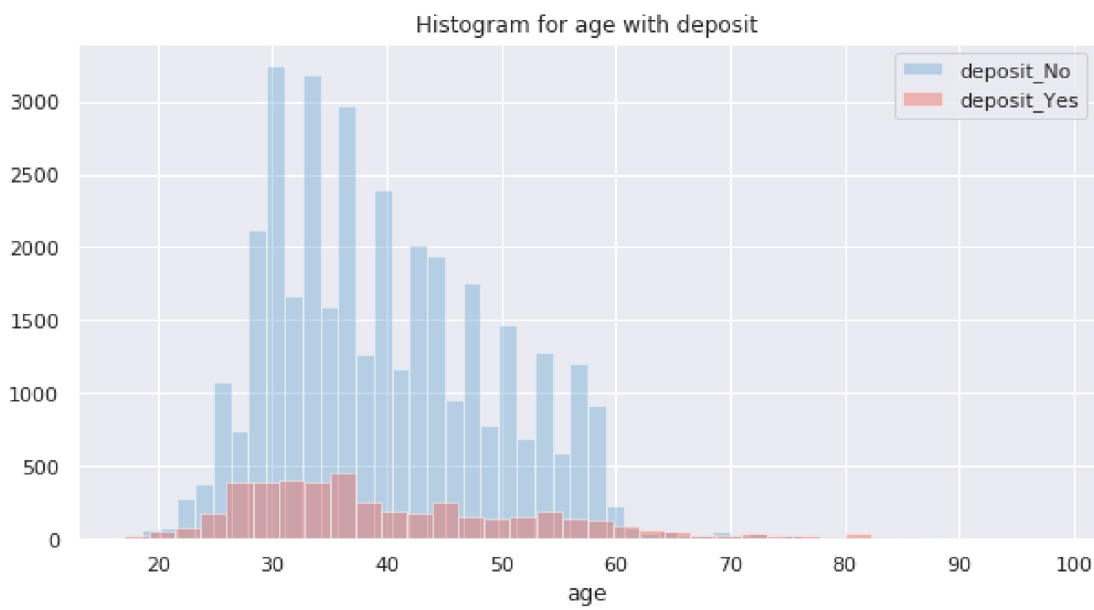

count
0
1000
2000
3000
4000
5000
6000
7000
8000
87.88
12.12
90.05
9.95
88.33
11.67
88.22
11.78
10.81
y
no
yes
thu
mon
wed
tue
fri
day_of_week

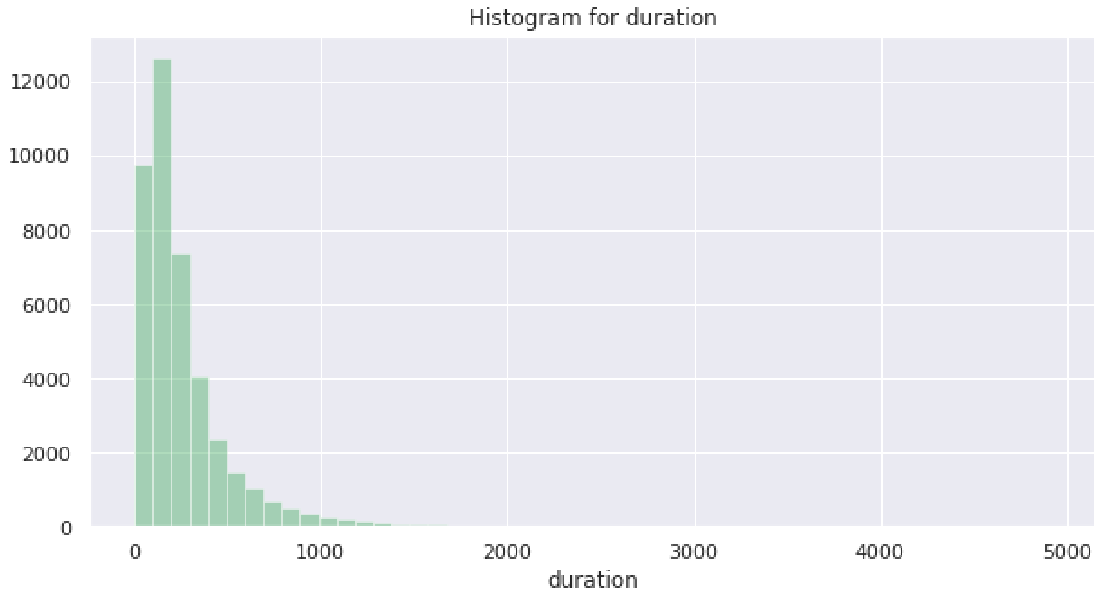


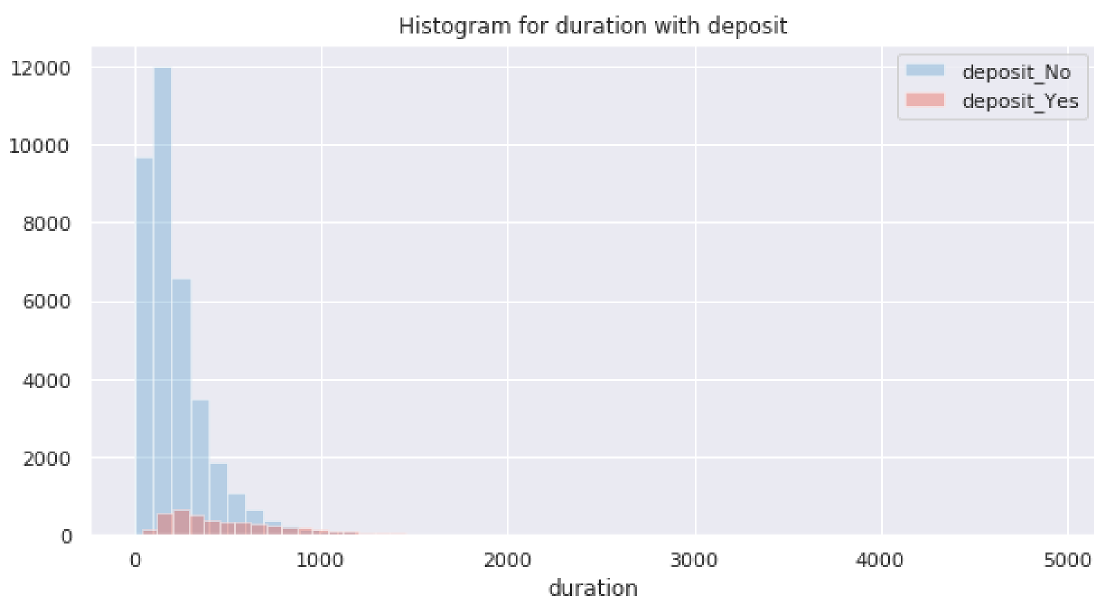


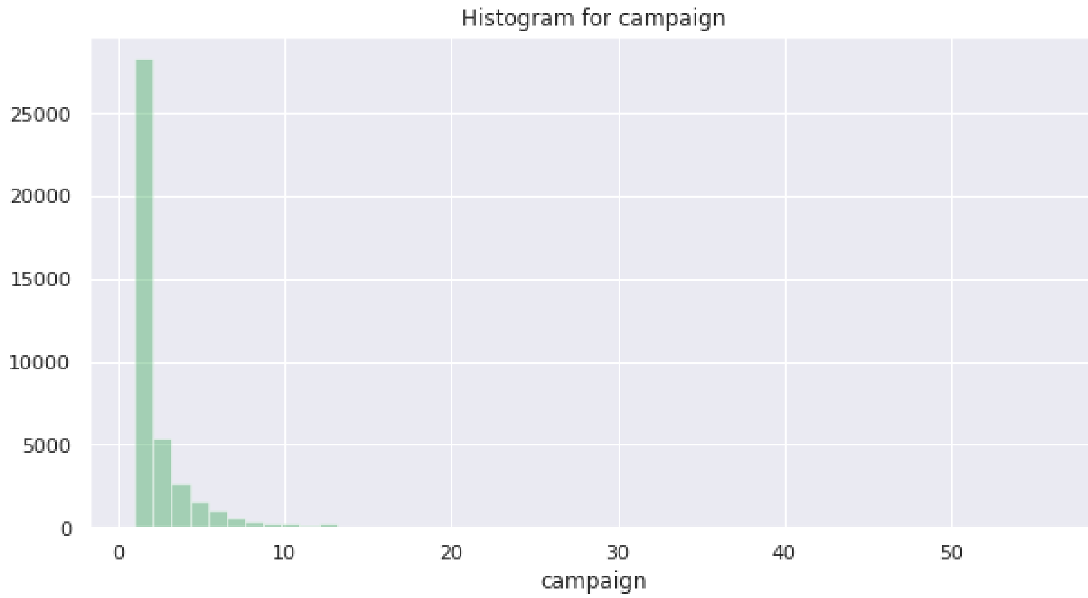

```
In [9]: def histogram(variable):
            plt.figure(figsize=(10, 5))
            plt.title("Histogram for {}".format(variable))
            ax = sns.distplot(dsdata[variable],color=sns.color_palette("RdYlGn_r")[0],kde=False)

        def histogram_by_deposit(feature):
            plt.figure(figsize=(10, 5))
            plt.title("Histogram for {} with deposit".format(feature))
            ax0 = sns.distplot(dsdata[dsdata["y"]=="no"][feature],color=sns.color_palette("Blues
        _d")[4],kde=False, label="deposit_No")
            ax1 = sns.distplot(dsdata[dsdata["y"]=="yes"][feature],color=sns.color_palette("Reds
        _d")[4],kde=False, label="deposit_Yes")
            plt.legend()

In [10]: # histogram for numerical variables
         column = "job"
         for column in dsdata.columns:
             if dsdata[column].dtype == "int64" or dsdata[column].dtype == "float64":
                 histogram(column)
                 histogram_by_deposit(column)
```

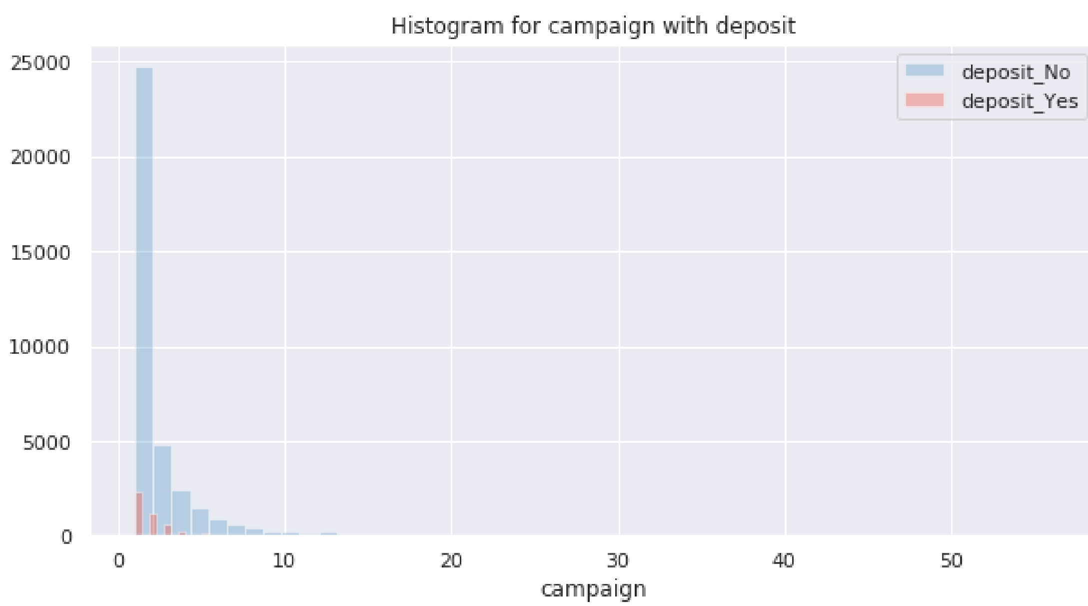

Histogram for age
3500
3000
2500
2000
1500
1000
500
0
20
30
40
50
60
70
80
90
100
age

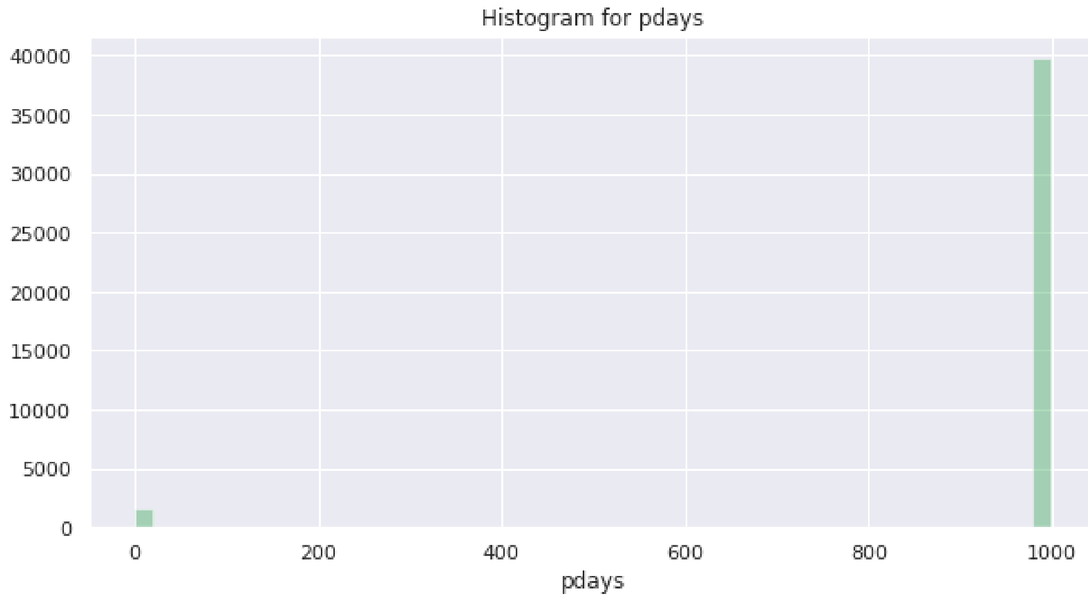

Histogram for age with deposit
deposit_No
deposit_Yes
3000
2500
2000
1500
1000
500
0
20
30
40
50
60
70
80
90
100
age

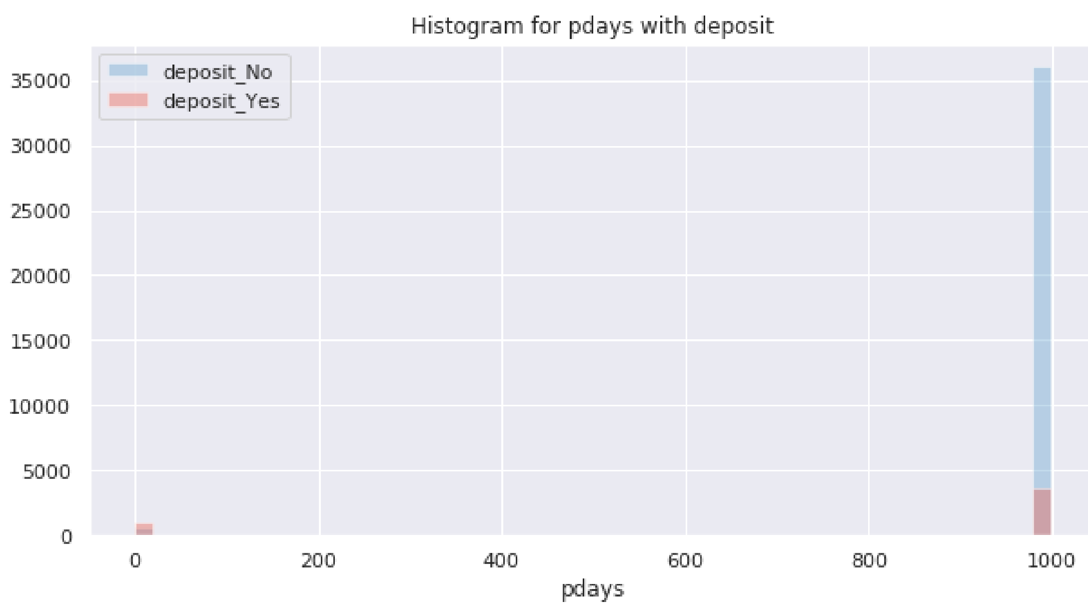

Histogram for duration
12000
10000
8000
6000
4000
2000
0
0
1000
2000
3000
4000
5000
duration

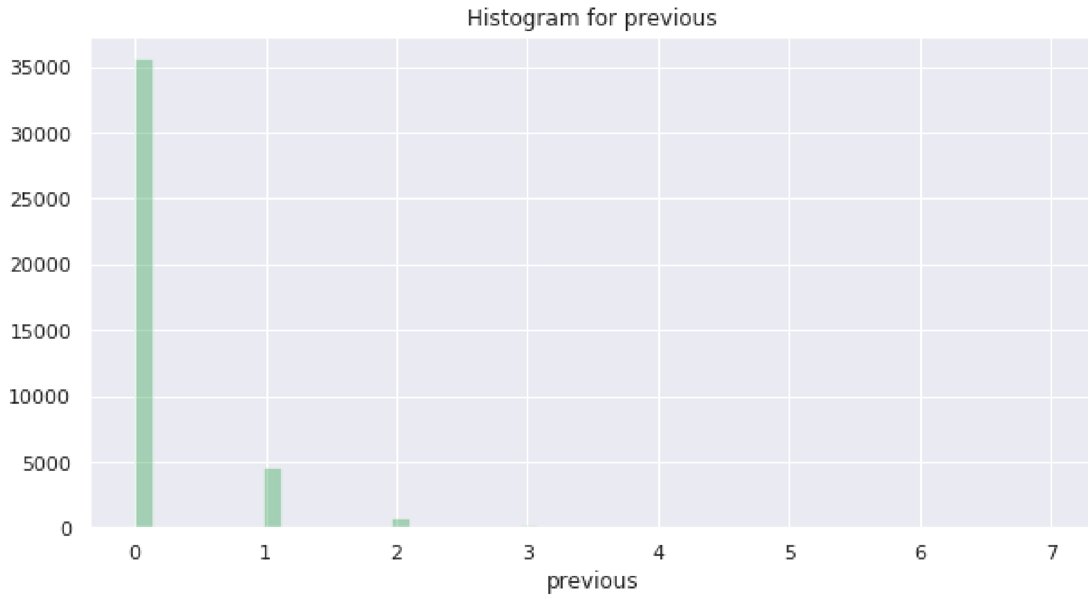

Histogram for duration with deposit
deposit_No
deposit_Yes
12000
10000
8000
6000
4000
2000
0
0
1000
2000
3000
4000
5000
duration

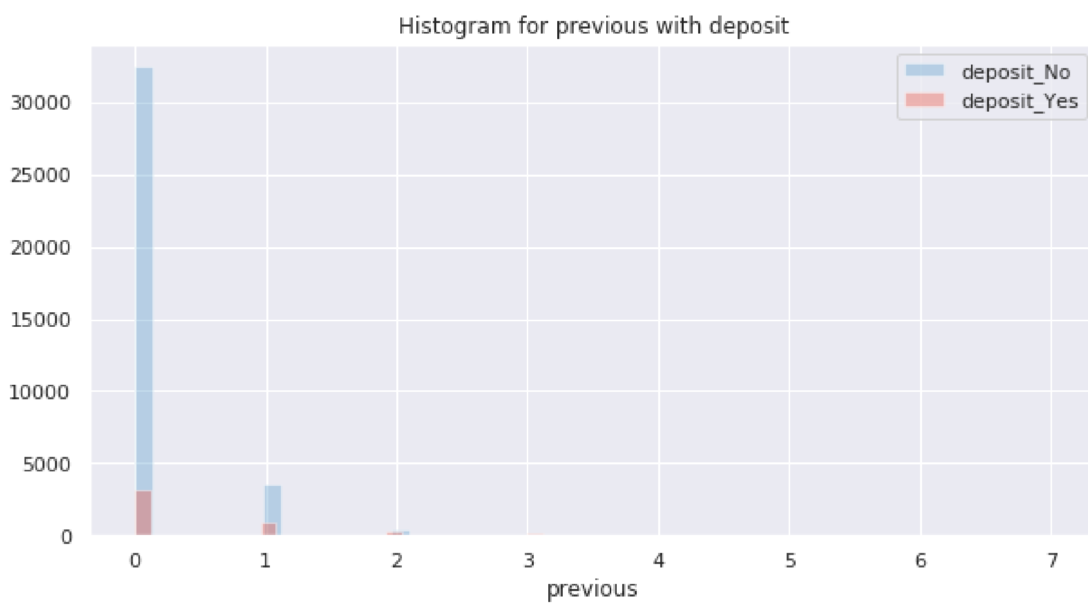

Histogram for campaign
25000
20000
15000
10000
5000
0
0
10
20
30
40
50
campaign

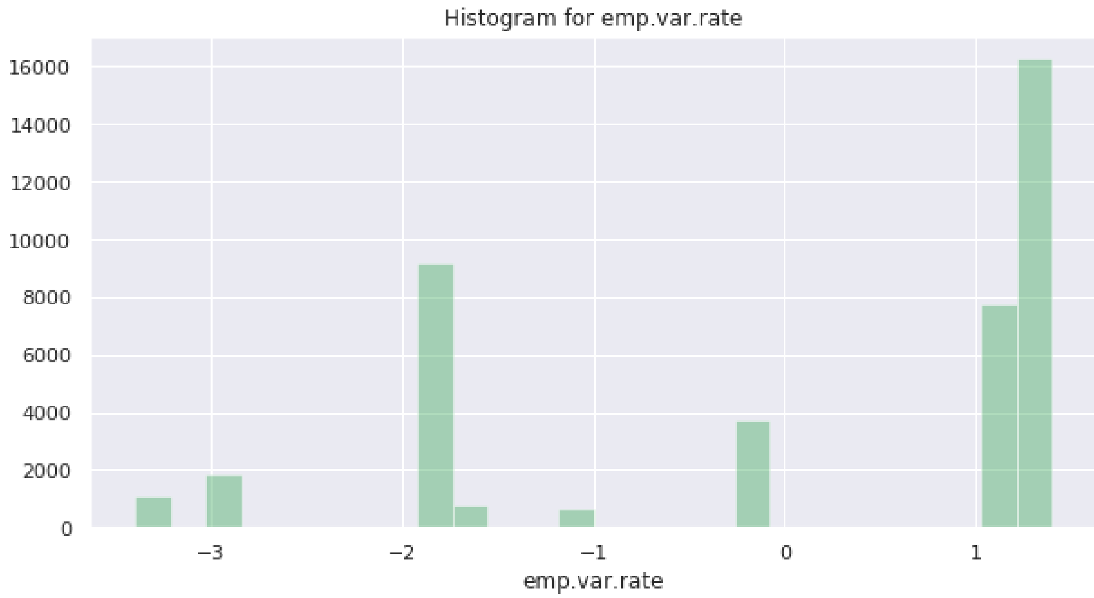

Histogram for campaign with deposit
deposit_No
deposit_Yes
25000
20000
15000
10000
5000
0
0
10
20
30
40
50
campaign

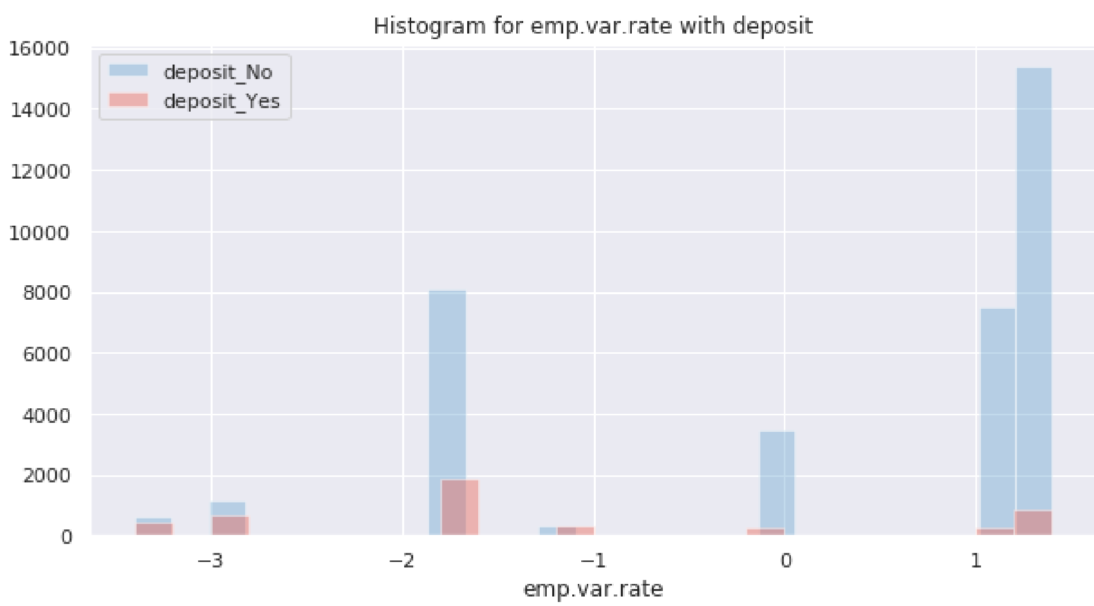

Histogram for pdays
40000
35000
30000
25000
20000
15000
10000
5000
0
0
200
400
600
800
1000
pdays

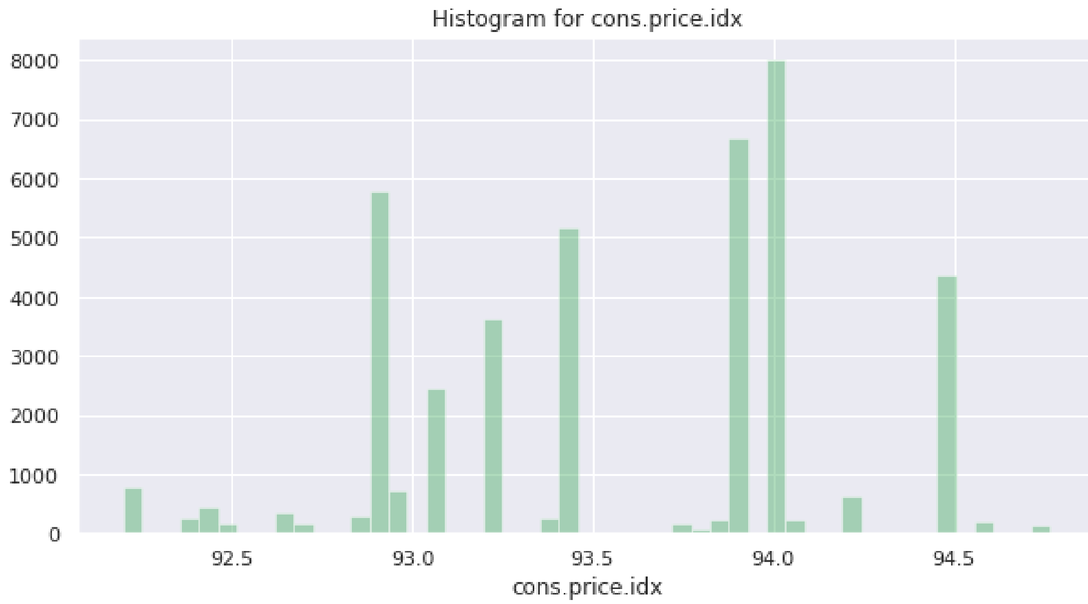

Histogram for pdays with deposit
deposit_No
deposit_Yes
35000
30000
25000
20000
15000
10000
5000
0
0
200
400
600
800
1000
pdays

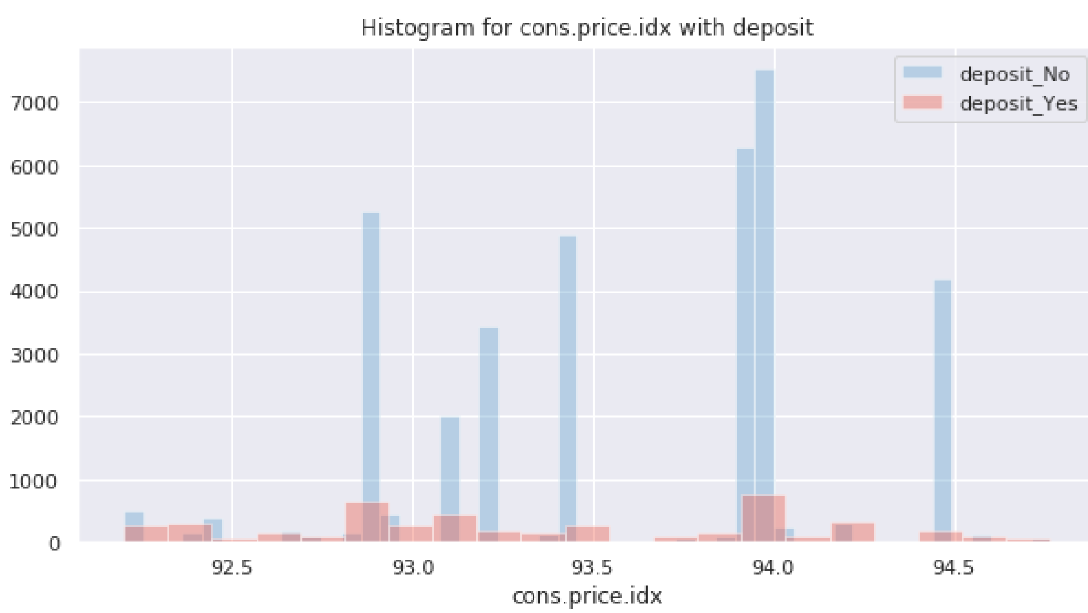

Histogram for previous
35000
30000
25000
20000
15000
10000
5000
0
0 1 2 3 4 5 6 7
previous

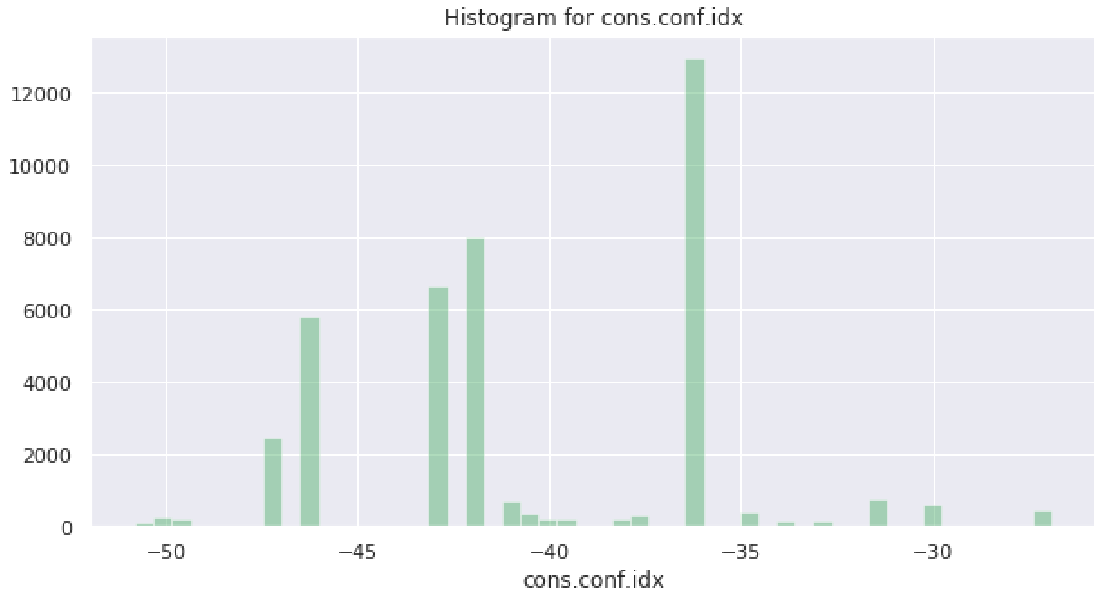

Histogram for previous with deposit
deposit_No
deposit_Yes
30000
25000
20000
15000
10000
5000
0
0 1 2 3 4 5 6 7
previous

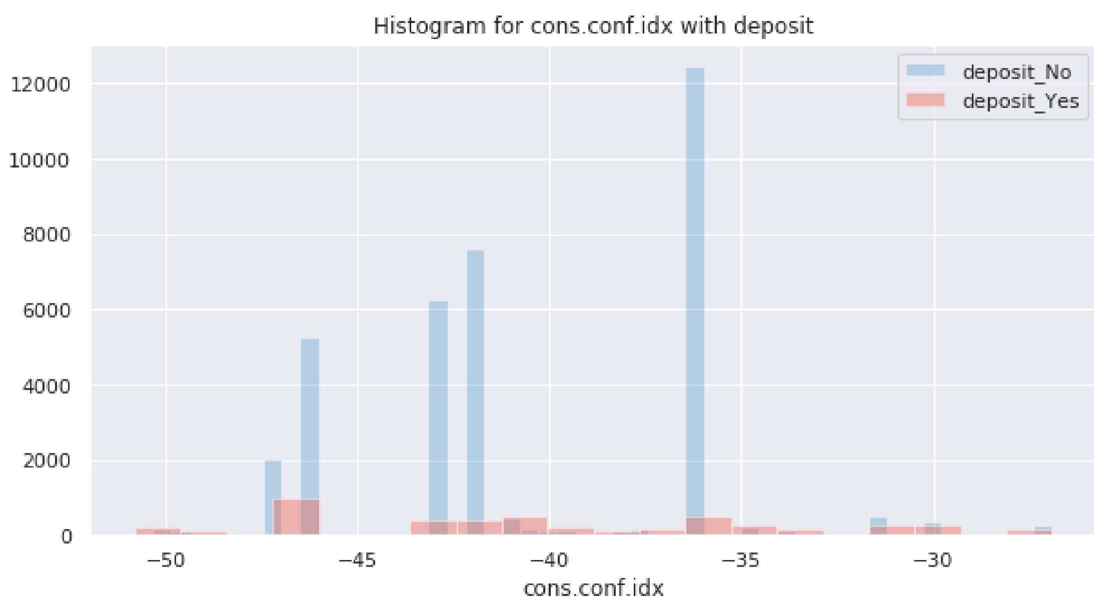

Histogram for emp.var.rate
16000
14000
12000
10000
8000
6000
4000
2000
0
−3
−2
−1
0
1
emp.var.rate

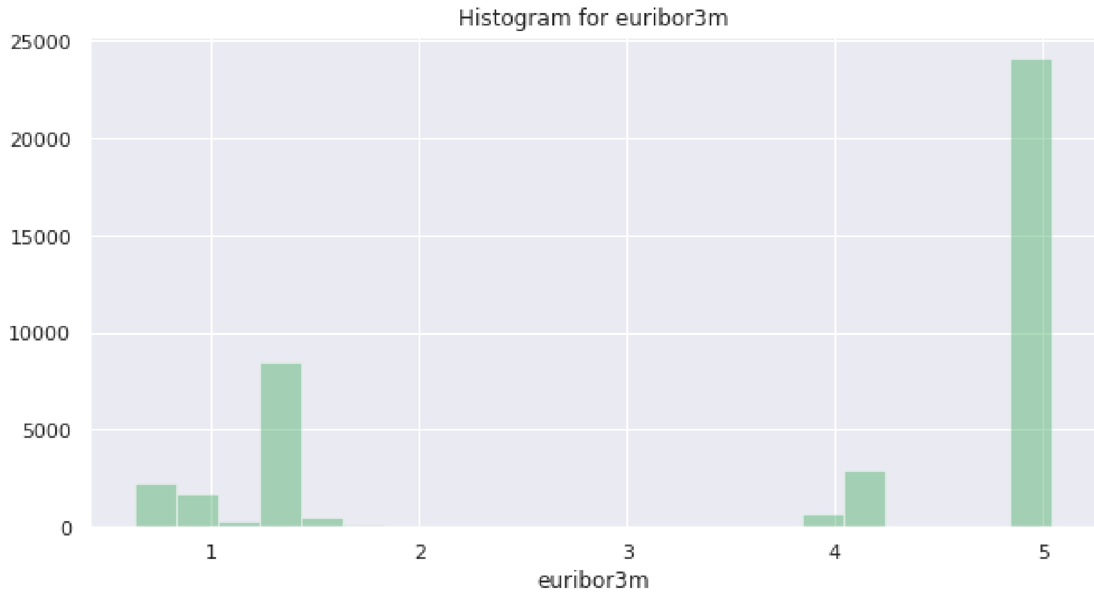

Histogram for emp.var.rate with deposit
deposit_No
deposit_Yes
16000
14000
12000
10000
8000
6000
4000
2000
0
−3
−2
−1
0
1
emp.var.rate

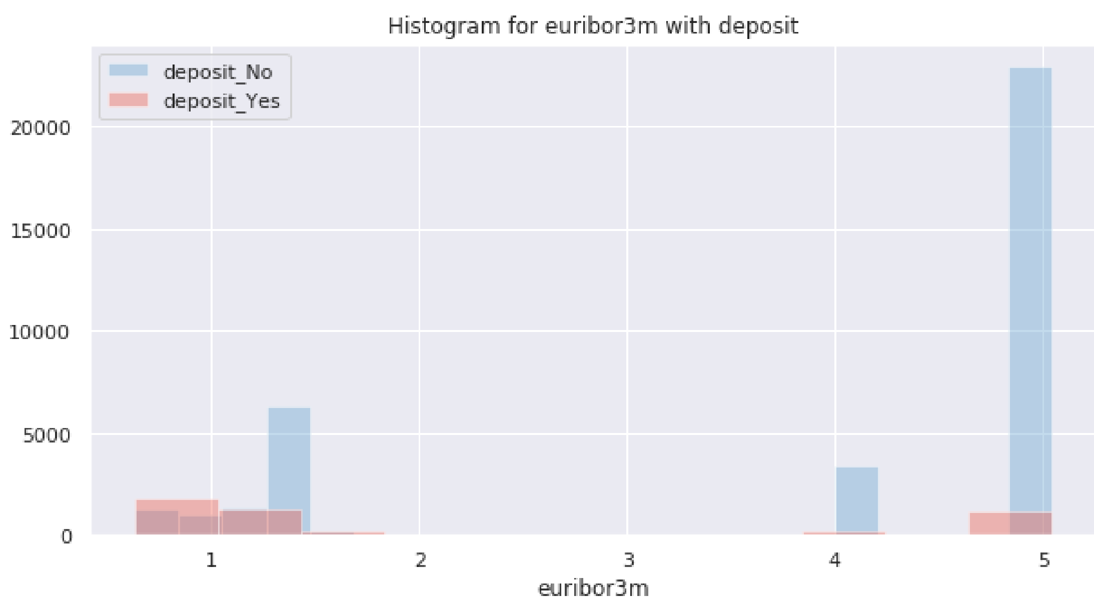

Histogram for cons.price.idx
8000
7000
6000
5000
4000
3000
2000
1000
0
92.5
93.0
93.5
94.0
94.5
cons.price.idx

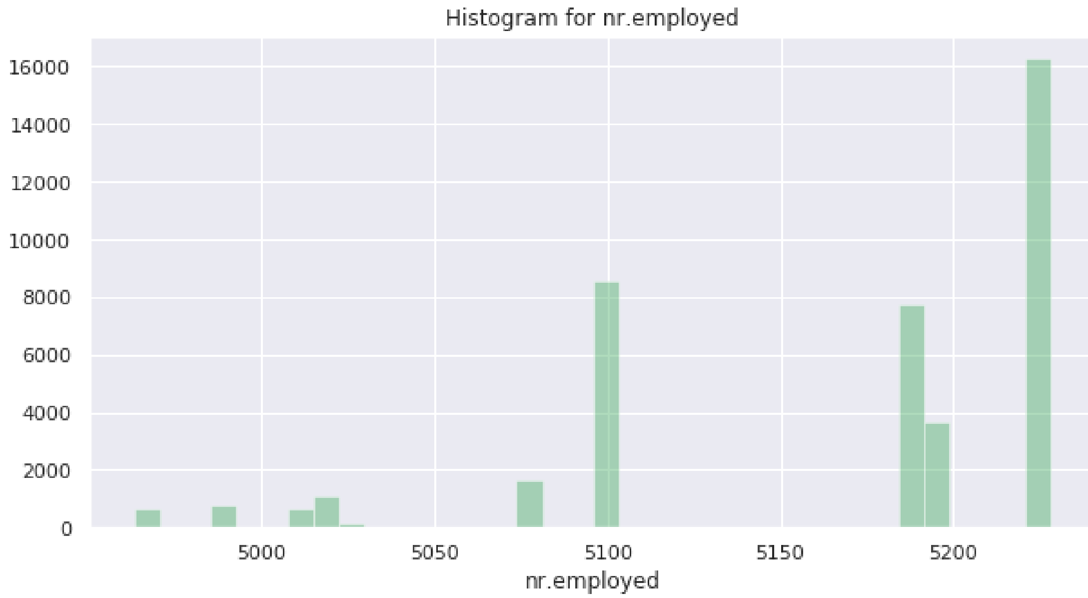

Histogram for cons.price.idx with deposit
deposit_No
deposit_Yes
7000
6000
5000
4000
3000
2000
1000
0
92.5
93.0
93.5
94.0
94.5
cons.price.idx

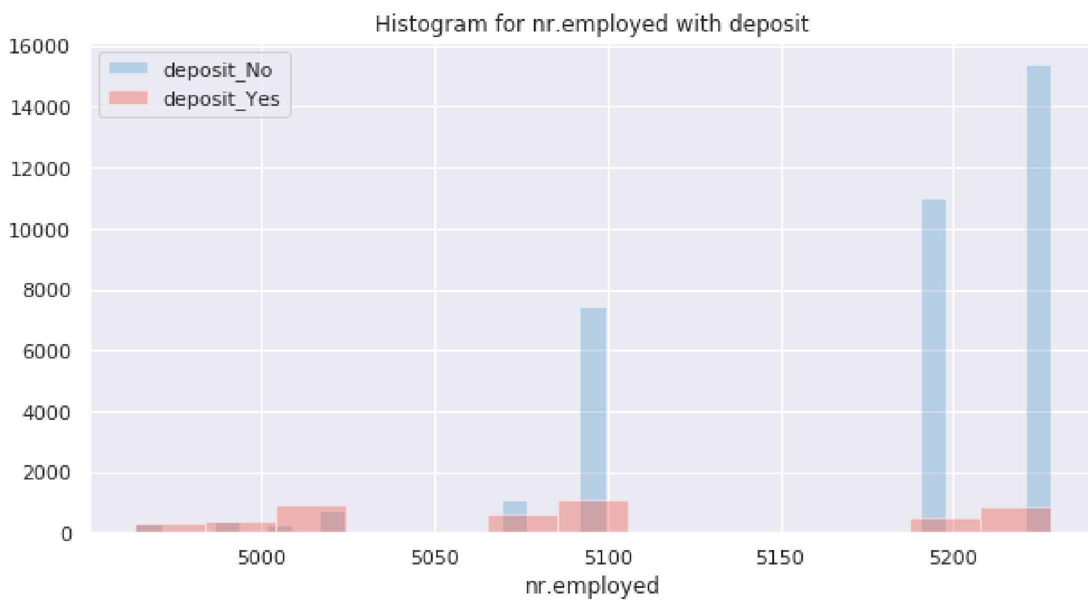

Histogram for cons.conf.idx
12000
10000
8000
6000
4000
2000
0
−50
−45
−40
−35
−30
cons.conf.idx


Histogram for cons.conf.idx with deposit
deposit_No
deposit_Yes
12000
10000
8000
6000
4000
2000
0
−50
−45
−40
−35
−30
cons.conf.idx


Histogram for euribor3m
25000
20000
15000
10000
5000
0
1
2
3
4
5
euribor3m

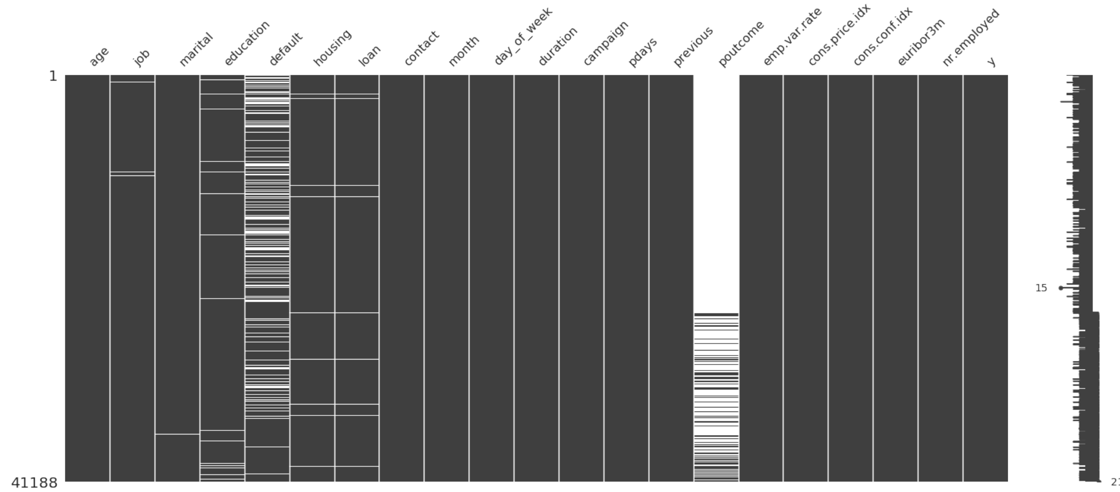

Histogram for euribor3m with deposit
deposit_No
deposit_Yes
20000
15000
10000
5000
0
1
2
3
4
5
euribor3m



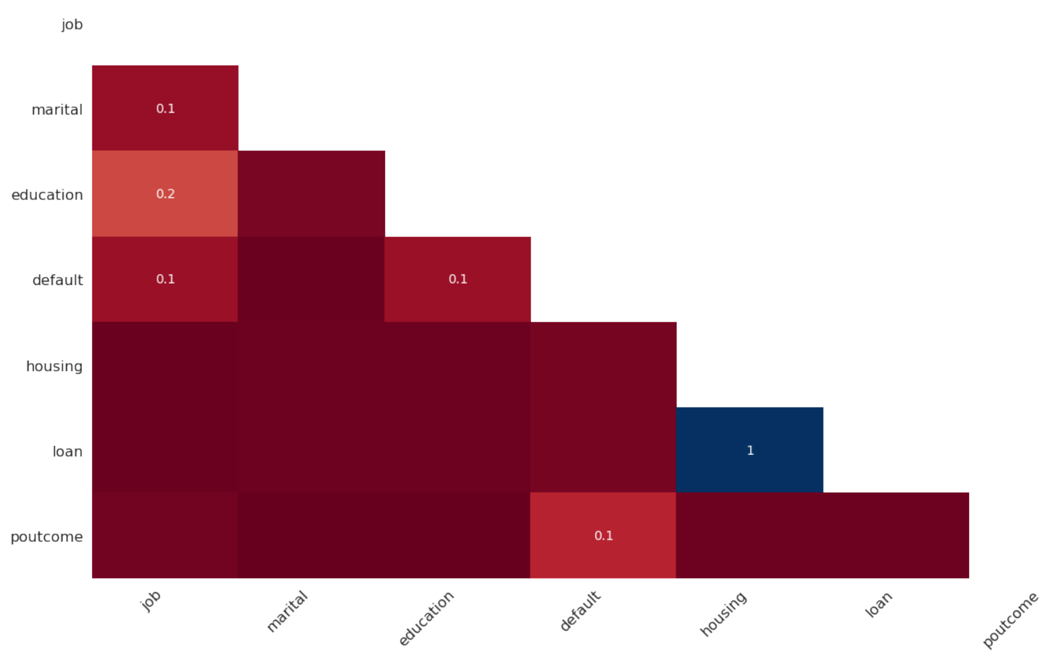


III Missing Data Handling

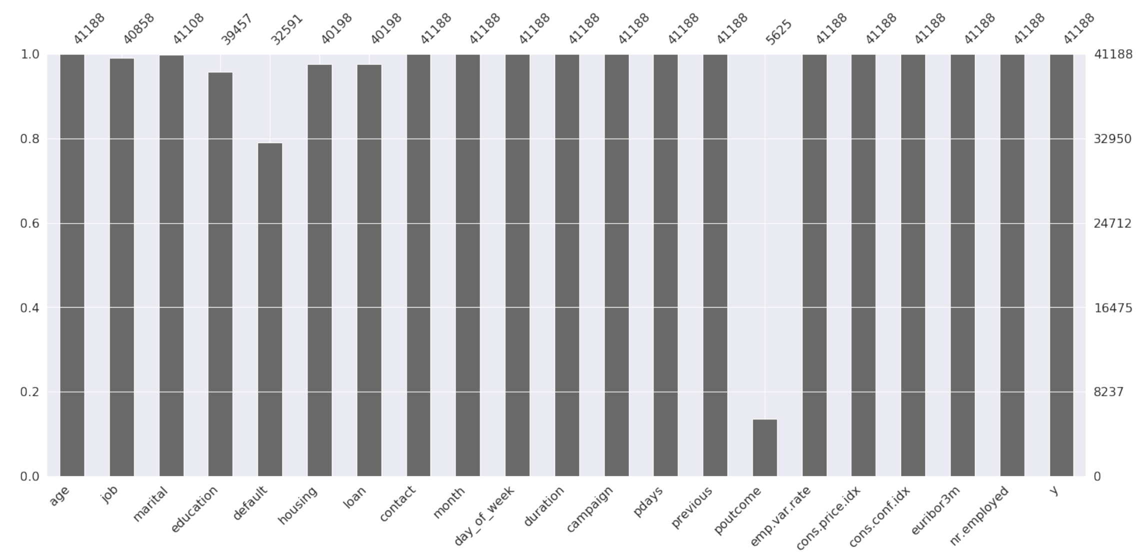
In [11]:
```
#visualizing missing data

msno.matrix(dsdata)
plt.show()
```



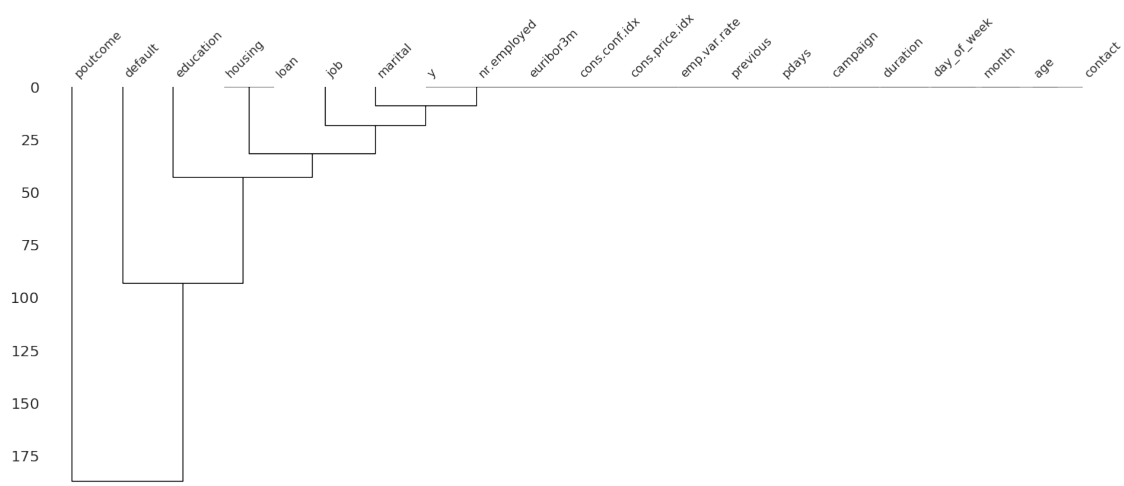

```
In [12]: #nullity correlation: how strongly the presence or absence of one variable affects the
         presence of another
         msno.heatmap(dsdata)
         plt.show()
         missing = ['job','marital','education','default','housing','loan','poutcome']
         ds_missing = dsdata[missing]
```




```
In [13]: msno.bar(dsdata)
         plt.show()
```



In [14]:
```
msno.dendrogram(dsdata)
plt.show()
```



In [15]:
```
#ds_missing.head(25)
```

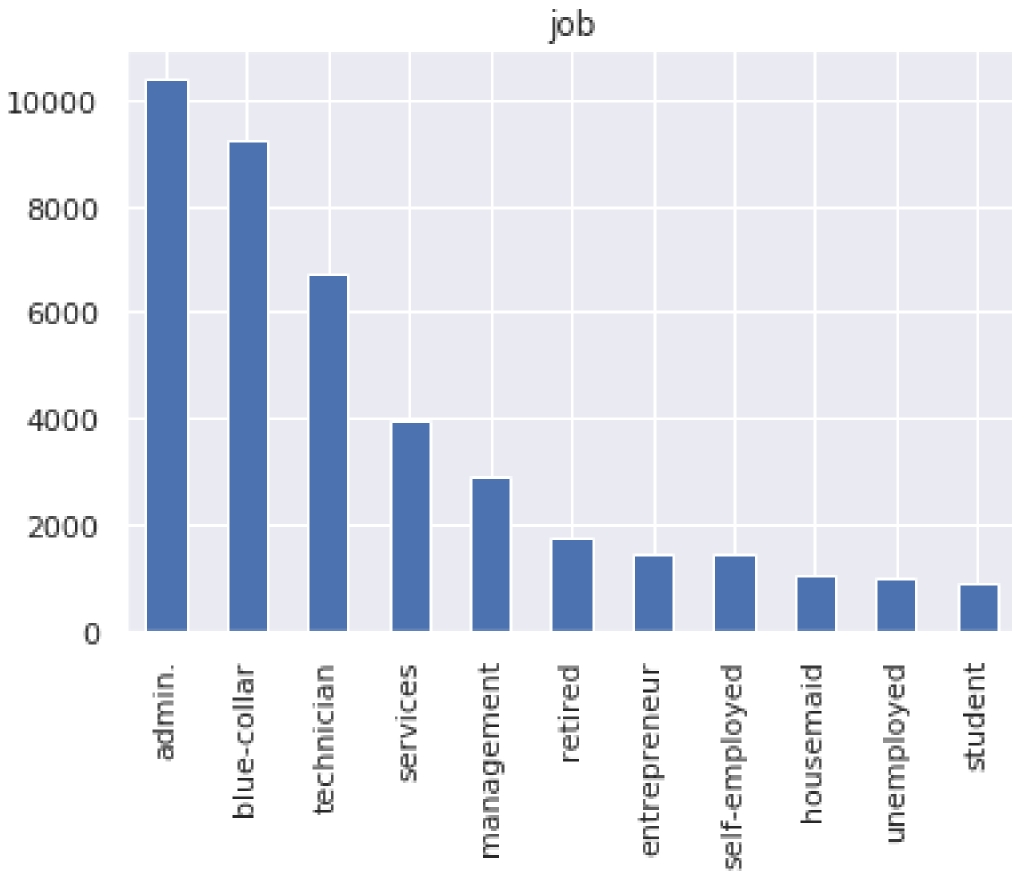
In [ ]:

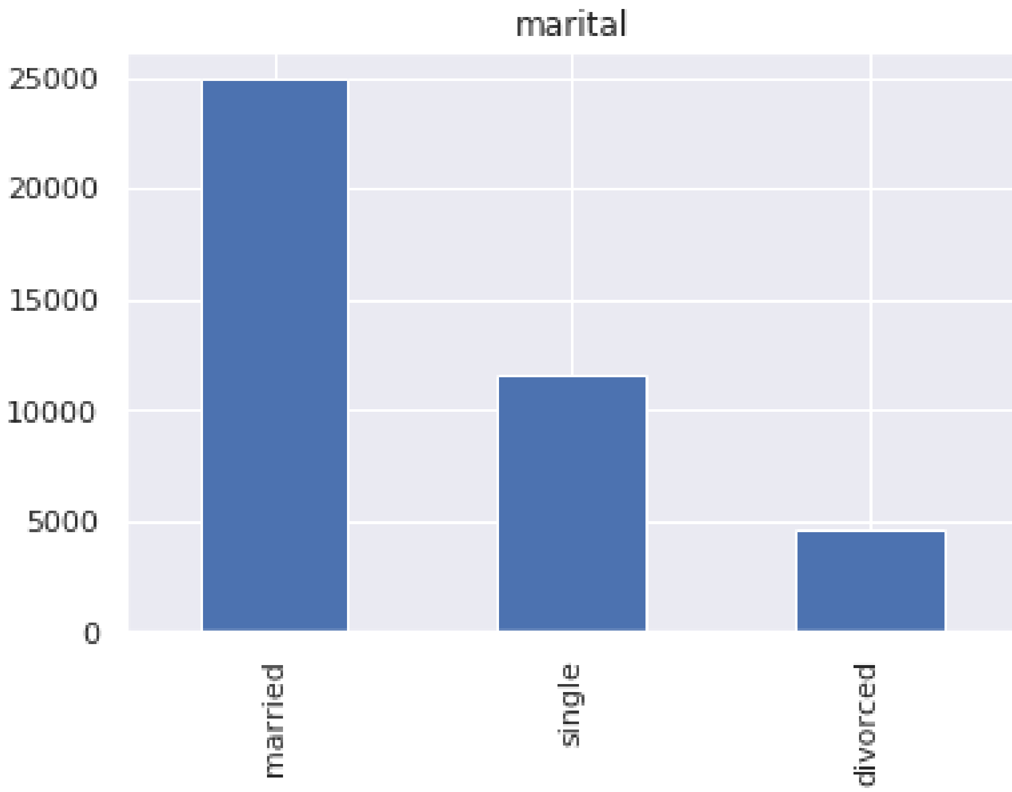
In [16]:
```
for col in list(ds_missing.columns):
    print(ds_missing[col].value_counts(),'\n')
```

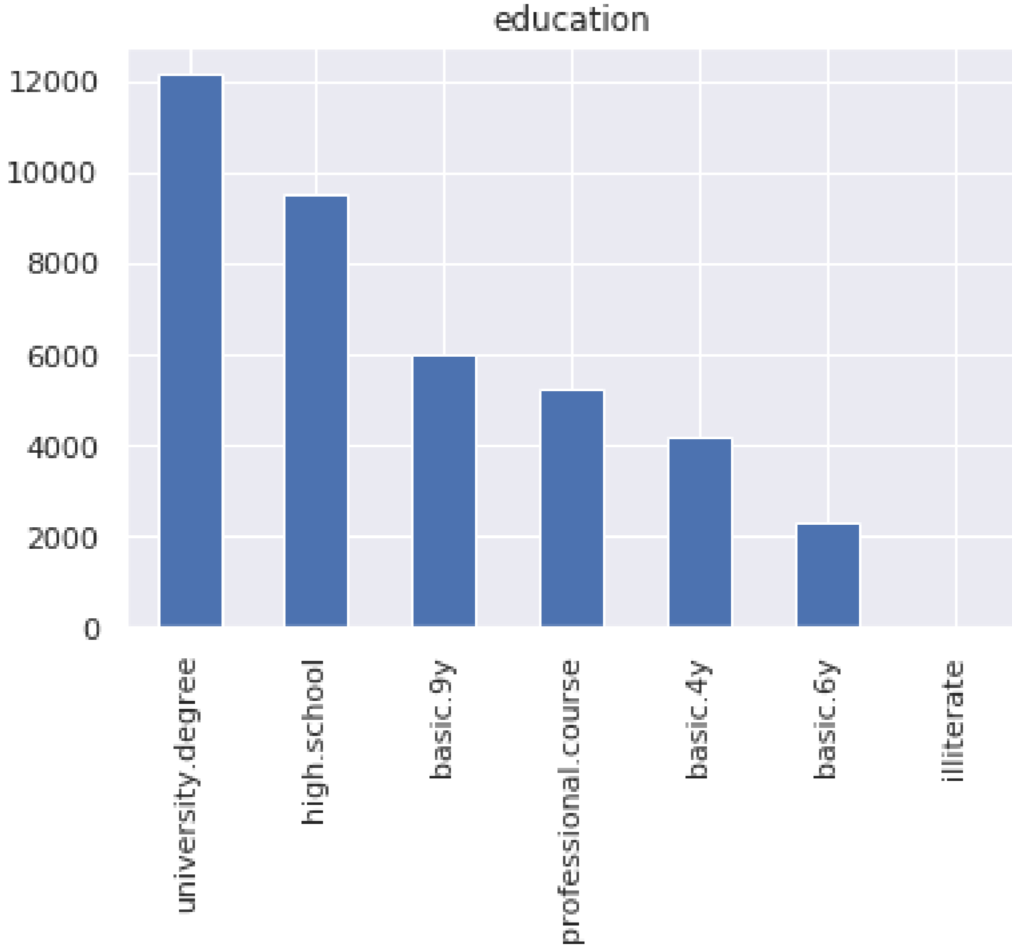
```
admin.           10422
blue-collar       9254
technician        6743
services          3969
management        2924
retired           1720
entrepreneur      1456
```

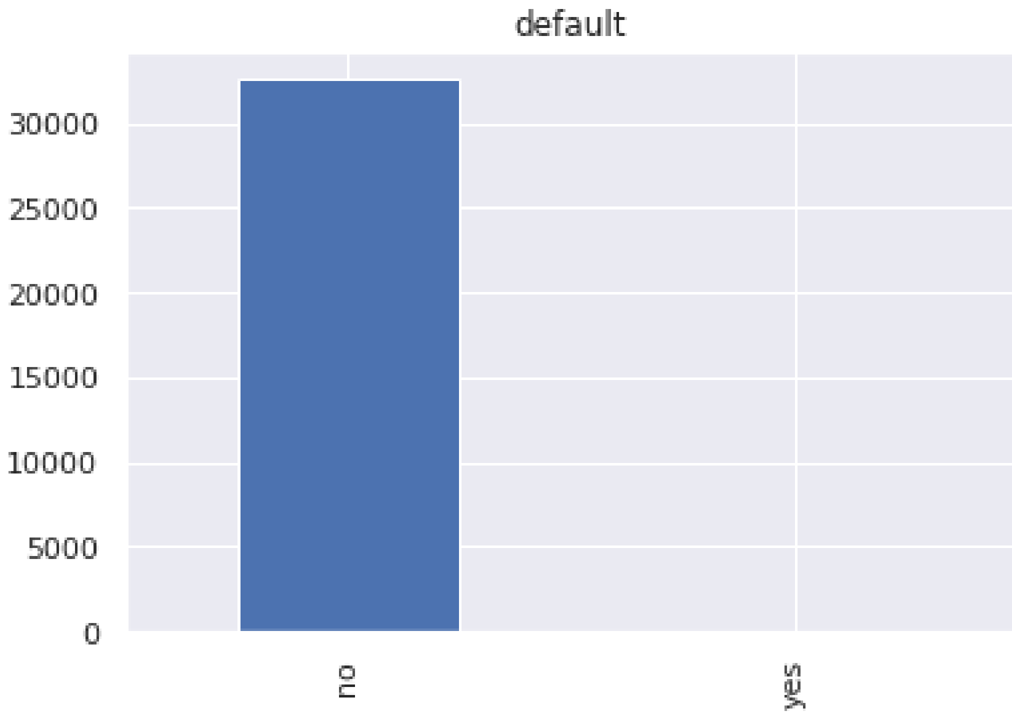
```
self-employed     1421
housemaid         1060
unemployed        1014
student            875
Name: job, dtype: int64

married     24928
single      11568
divorced     4612
Name: marital, dtype: int64

university.degree      12168
high.school             9515
basic.9y                6045
professional.course     5243
basic.4y                4176
basic.6y                2292
illiterate                18
Name: education, dtype: int64

no     32588
yes        3
Name: default, dtype: int64

yes    21576
no     18622
Name: housing, dtype: int64

no     33950
yes     6248
Name: loan, dtype: int64

failure    4252
success    1373
Name: poutcome, dtype: int64
```

```
In [17]: for col in list(ds_missing.columns):
             if ds_missing[col].dtype == "O":
                 ds_missing[col].value_counts().plot(kind='bar')
                 plt.title(col)
                 plt.show()
```

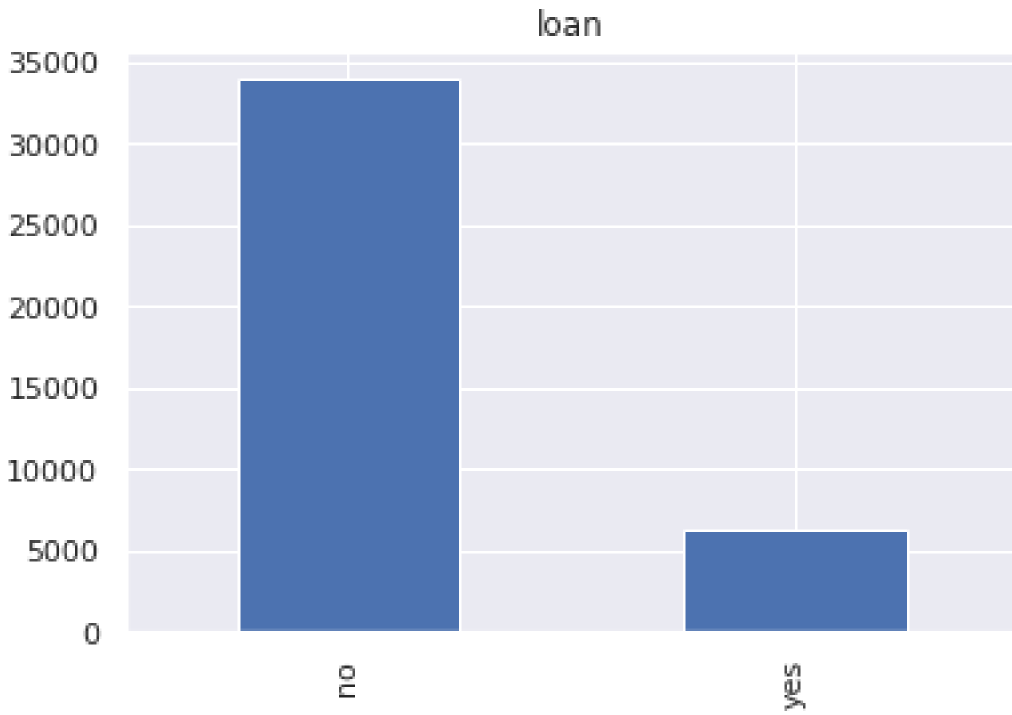

job
10000
8000
6000
4000
2000
0
admin.
blue-collar
technician
services
management
retired
entrepreneur
self-employed
housemaid
unemployed
student

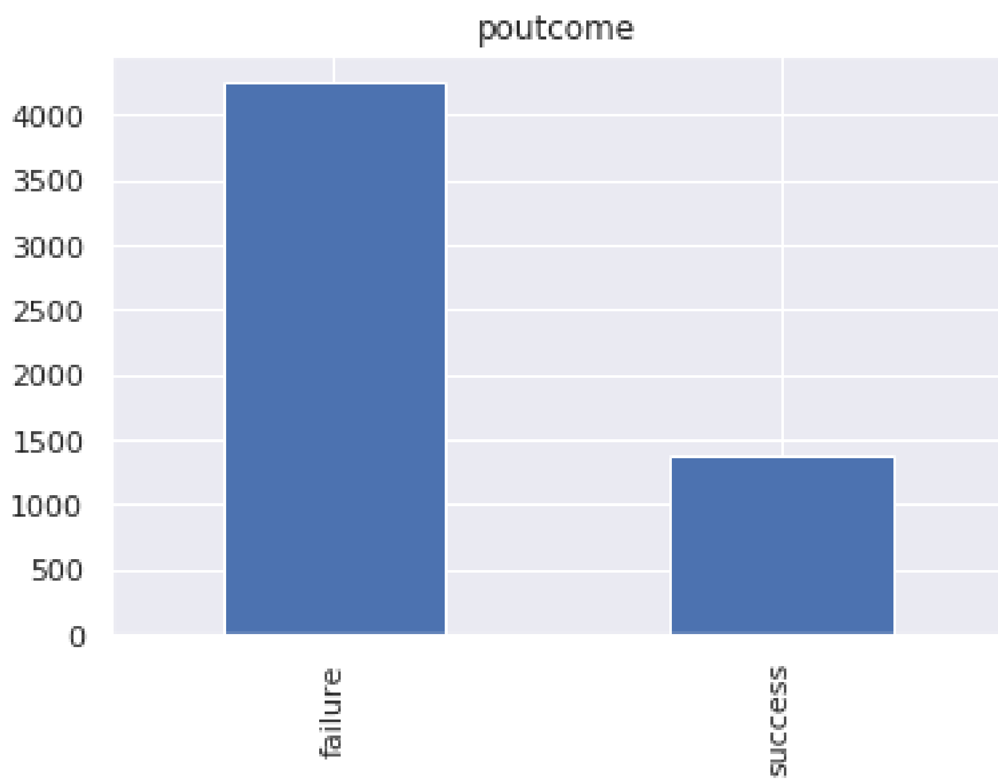

marital
25000
20000
15000
10000
5000
0
married
single
divorced


education
12000
10000
8000
6000
4000
2000
0
university.degree
high.school
basic.9y
professional.course
basic.4y
basic.6y
illiterate


default
30000
25000
20000
15000
10000
5000
0
no
yes


housing
20000
15000
10000
5000
0
yes
no






```
In [18]: ds_missing.head(5)
```

```
Out[18]:          job  marital    education default housing loan poutcome
         0  housemaid  married     basic.4y      no      no   no      NaN
         1   services  married  high.school     NaN      no   no      NaN
         2   services  married  high.school      no     yes   no      NaN
         3     admin.  married     basic.6y      no      no   no      NaN
         4   services  married  high.school      no      no  yes      NaN
```

```
In [19]: missing2 = ['job', 'marital', 'education', 'housing', 'loan']
```

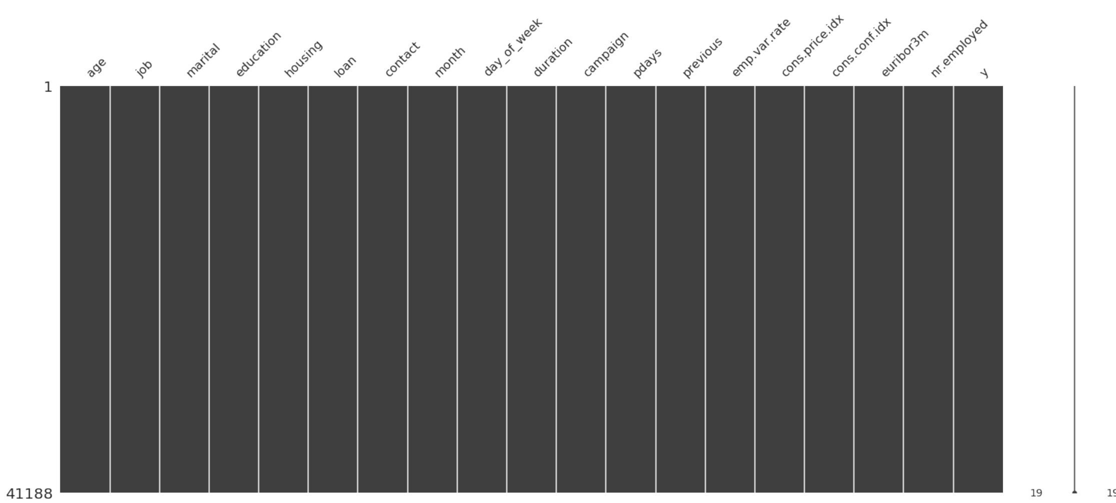
III Interpolation of categorical variables through empirical distributions

```
In [20]: dsdata2 = dsdata.copy()
         dsdata2 = dsdata2.drop(columns=['poutcome','default']) #too many missing values, and
         zero variance variable
         #dsdata2.shape
```

```
In [21]: #fill missing data at random from discrete distribution corresponding to histogram
         def dist_random_selection(col, num):
             arr = list(col.value_counts().index)
             prob = np.array(list(col.value_counts().values))
             p_norm = prob.sum()
             prob = prob/p_norm
             return np.random.choice(arr, num, replace=True, p=prob)

         def fill_missing(data,missing):
             for col in list(data[missing].columns):
                 count = len(data[col][data[col].isnull()])
                 data[col][data[col].isnull()] = dist_random_selection(data[col],count)
             return data
```

```
In [22]: dsdata3 = fill_missing(dsdata2, missing2)
```

```
In [23]: msno.matrix(dsdata3)
         plt.show()
```



IV Feature Selection

```
In [24]: dsdata3.shape

Out[24]: (41188, 19)

In [25]: # Data preparation
         dsn = dsdata3.copy()
         dsn.describe(include=['O'])
         # Drop missing value
         #dsn2 = dsn.copy().dropna() HELL NO!!!!!!! XD,
         # That drops about 10,000 columns...

Out[25]:            job  marital          education housing   loan   contact  month  \
         count    41188    41188              41188   41188  41188     41188  41188
         unique      11        3                  7       2      2         2     10
         top     admin.  married  university.degree     yes     no  cellular    may
         freq     10509    24977              12702   22121  34784     26144  13769

               day_of_week      y
         count       41188  41188
         unique          5      2
         top           thu     no
         freq         8623  36548

In [26]: # Create dummy
         def make_dummies(dsn):
             numvar = ['age','campaign','pdays','previous','emp.var.rate','cons.price.idx','cons.
         conf.idx','euribor3m','nr.employed']
             nonnumvar = ['job','marital','education','month','day_of_week'] #WE ONLY NEED THE
         CATEGORICALS, DONT INCLUDE BINARIES!!

             for c,var in enumerate(nonnumvar):
                 dummy = pd.get_dummies(dsn[var],drop_first=True)
                 dsn = dsn.drop(columns=[var])
                 dsn = pd.concat([dsn, dummy], axis=1)
                 #print(var)
                 #display(dummy.head(5))
             return dsn

         def make_numeric(dsn):
             for c,var in enumerate(['housing','loan','contact']):
                 dsn[var] = dsn[var].astype("category").cat.codes

             return dsn

         dsn2 = make_dummies(dsn) #make dummies out of categoricals
         dsn2 = make_numeric(dsn2) #make binaries out of yes/no
         dsn2.info()
         #dsn2.describe()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 45 columns):
age                      41188 non-null int64
housing                  41188 non-null int8
loan                     41188 non-null int8
```

```
contact                 41188 non-null int8
duration                41188 non-null int64
campaign                41188 non-null int64
pdays                   41188 non-null int64
previous                41188 non-null int64
emp.var.rate            41188 non-null float64
cons.price.idx          41188 non-null float64
cons.conf.idx           41188 non-null float64
euribor3m               41188 non-null float64
nr.employed             41188 non-null float64
y                       41188 non-null object
blue-collar             41188 non-null uint8
entrepreneur            41188 non-null uint8
housemaid               41188 non-null uint8
management              41188 non-null uint8
retired                 41188 non-null uint8
self-employed           41188 non-null uint8
services                41188 non-null uint8
student                 41188 non-null uint8
technician              41188 non-null uint8
unemployed              41188 non-null uint8
married                 41188 non-null uint8
single                  41188 non-null uint8
basic.6y                41188 non-null uint8
basic.9y                41188 non-null uint8
high.school             41188 non-null uint8
illiterate              41188 non-null uint8
professional.course     41188 non-null uint8
university.degree       41188 non-null uint8
aug                     41188 non-null uint8
dec                     41188 non-null uint8
jul                     41188 non-null uint8
jun                     41188 non-null uint8
mar                     41188 non-null uint8
may                     41188 non-null uint8
nov                     41188 non-null uint8
oct                     41188 non-null uint8
sep                     41188 non-null uint8
mon                     41188 non-null uint8
thu                     41188 non-null uint8
tue                     41188 non-null uint8
wed                     41188 non-null uint8
dtypes: float64(5), int64(5), int8(3), object(1), uint8(31)
memory usage: 4.8+ MB
```

```
In [27]: # Drop priori
         dsn3 = dsn2.drop(columns=['duration']) #remove output and duration, which should not be
         known a priori
```

```
In [28]: # Data Normalization

         # separate the data from the target attributes
         X = dsn3.drop(columns=['y'])
         #Y = pd.get_dummies(dsn3['y'],drop_first=True,dummy_na=True)

         # normalize the data attributes
```

```
normalized_X = preprocessing.normalize(X)
```

```
In [29]: # MAKE NORMALIZED DF
         X_n = pd.DataFrame(normalized_X)
         X_n.columns = X.columns
```

```
In [30]: # Check the correlation

         # NORMALIZE THE DATA !
         corr = X_n.corr()
         # Generate a mask for the upper triangle
         sns.set(style="white")
         mask = np.zeros_like(corr, dtype=np.bool)
         mask[np.triu_indices_from(mask)] = True

         # Set up the matplotlib figure
         f, ax = plt.subplots(figsize=(11, 9))

         # Generate a custom diverging colormap
         cmap = sns.diverging_palette(220, 10, as_cmap=True)

         # Draw the heatmap with the mask and correct aspect ratio
         sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
                     square=True, linewidths=.5, cbar_kws={"shrink": .76})
         f.show()
```

IV Feature Selection

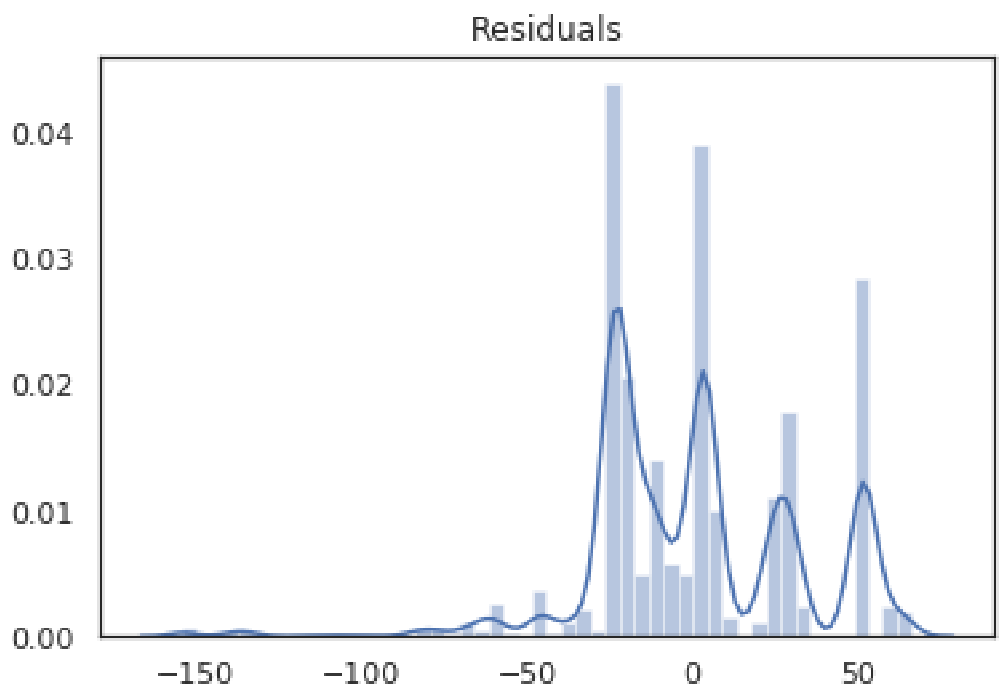
```
In [31]: def print_VIF(X):
             colnames = list(X.columns)
             for i in range(X.shape[1]):
                 print(oi.variance_inflation_factor(X.values, i), colnames[i])

         print("Variance Inflation Factors:")
         print_VIF(X)
```

```
Variance Inflation Factors:
25.699421717728164 age
2.187347297019118 housing
1.1884217905667915 loan
5.168655621475389 contact
1.9403265754912258 campaign
45.31697288715908 pdays
2.0804063875271255 previous
93.67968903223512 emp.var.rate
62381.33728205274 cons.price.idx
```

```
389.93355428533994 cons.conf.idx
785.1827162631885 euribor3m
80095.1601608278 nr.employed
2.998359623841996 blue-collar
1.1801111052746007 entrepreneur
1.208239433519948 housemaid
1.3392985940698983 management
1.5422587461133799 retired
1.1596803634308726 self-employed
1.5653551621374622 services
1.1949262756217893 student
2.077822521405796 technician
1.124826196191629 unemployed
6.547908953431982 married
4.031673284036735 single
1.598731702634765 basic.6y
2.6330516709015193 basic.9y
4.342608264937074 high.school
1.0051487332377531 illiterate
3.007594830576488 professional.course
5.7058176510336525 university.degree
8.131916021936958 aug
1.1411179834728389 dec
5.437300515663982 jul
3.78227309374364 jun
1.2543889589126438 mar
7.5898279431870295 may
3.9328083828264737 nov
1.5991916740322096 oct
1.518849245189762 sep
2.0996206920666816 mon
2.118840553704938 thu
2.056199982646952 tue
2.0552587590547184 wed
```

1. intermediate regression on economic variables for VIF

```
In [32]: economic = ['emp.var.rate','cons.price.idx','cons.conf.idx','euribor3m']
         numeric = sm.OLS(X['nr.employed'].values,X[economic].values).fit()
         sns.distplot(numeric.resid)
         plt.title("Residuals")
         plt.show()
         display(numeric.summary())
```



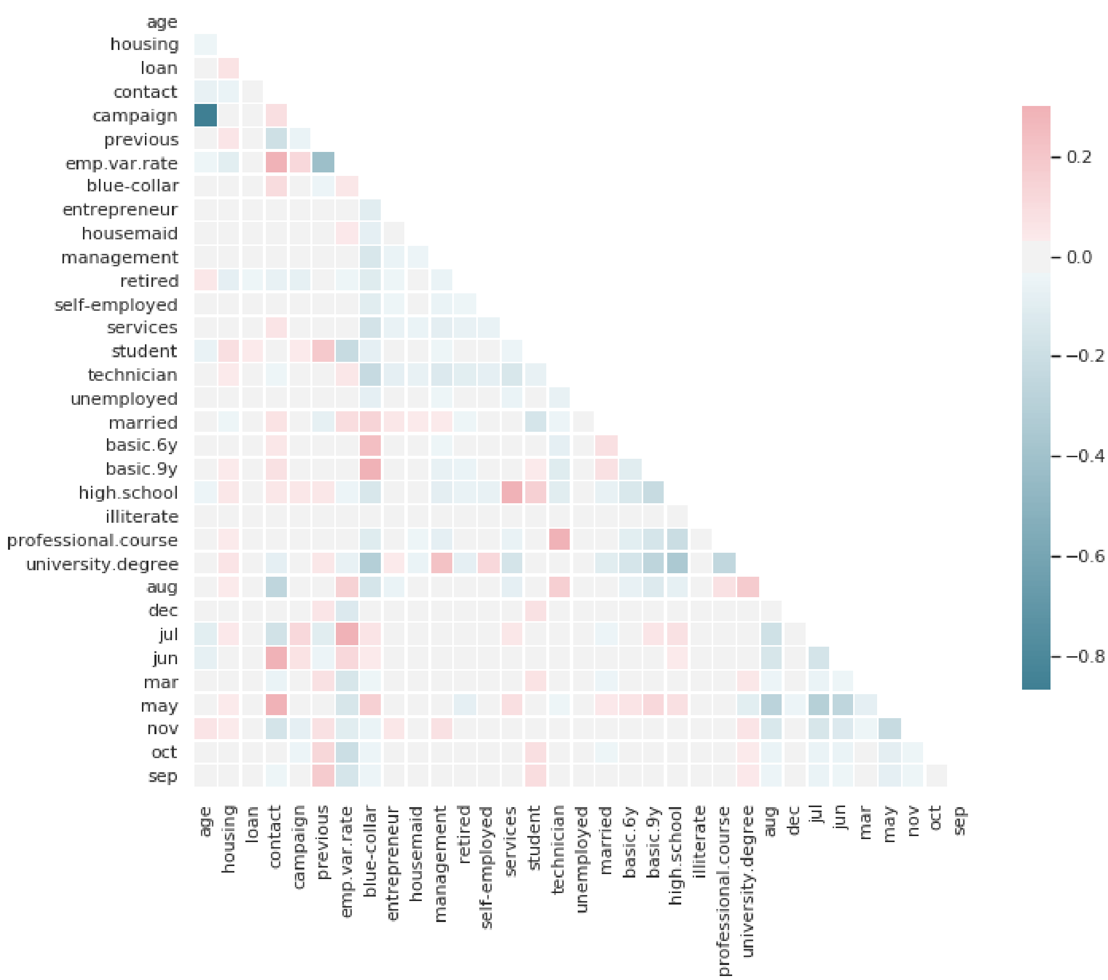

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                  1.000
Method:                 Least Squares   F-statistic:                 2.623e+08
Date:                Fri, 10 May 2019   Prob (F-statistic):               0.00
Time:                        14:05:52   Log-Likelihood:            -2.0167e+05
No. Observations:               41188   AIC:                         4.034e+05
Df Residuals:                   41184   BIC:                         4.034e+05
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
x1           -63.3977      0.445   -142.626      0.000     -64.269     -62.526
x2            50.2830      0.027   1890.625      0.000      50.231      50.335
x3            -3.7858      0.038    -99.832      0.000      -3.860      -3.711
x4            86.5789      0.416    208.289      0.000      85.764      87.394
==============================================================================
Omnibus:                     3472.453   Durbin-Watson:                   0.002
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             9896.607
Skew:                          -0.464   Prob(JB):                         0.00
Kurtosis:                       5.215   Cond. No.                         387.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
"""
```

```
In [33]: dsn4 = X.copy()
         dsn4 = X.drop(columns=['nr.employed','euribor3m','cons.price.idx','cons.conf.idx'])

         print("Variance Inflation Factors:")
         print_VIF(dsn4)
```

```
Variance Inflation Factors:
18.795212167761804 age
2.1680344085946066 housing
1.186587839574958 loan
3.764577280072294 contact
1.9215346653769463 campaign
27.27979619302259 pdays
1.7329058424985795 previous
2.5131426179783563 emp.var.rate
2.826150727152902 blue-collar
1.1735843768089205 entrepreneur
1.192256422293572 housemaid
1.3361058353560156 management
1.5358166880014659 retired
1.1549681725521808 self-employed
1.541617342271284 services
1.1675162611834708 student
2.046333858599015 technician
1.1167136673732803 unemployed
6.030824907822872 married
3.538584478475322 single
1.5287117971689477 basic.6y
2.4156871535745448 basic.9y
3.7703535660523375 high.school
1.0046374774886204 illiterate
2.7470776917530637 professional.course
4.867456484498119 university.degree
3.91727535314813 aug
1.0774840887974682 dec
4.41102740372729 jul
3.358396917545775 jun
1.1875430357287888 mar
6.319548041788819 may
2.5120859115787244 nov
1.273633542385804 oct
1.2196007096354973 sep
2.051357368207603 mon
2.058402558227157 thu
2.0140216689556043 tue
2.0109137649930435 wed
```

```
In [34]: dsn4 = dsn4.drop(columns=['pdays'])
         dsn4 = dsn4.drop(columns=['mon','thu','tue','wed'])
         dsn4 = dsn4.drop(columns=['single'])
         #dsn4 = dsn4.drop(columns=['campaign'])

         # NORMALIZE THE DATA !
         normalized_X = preprocessing.normalize(dsn4)

         X_n = pd.DataFrame(normalized_X)
```

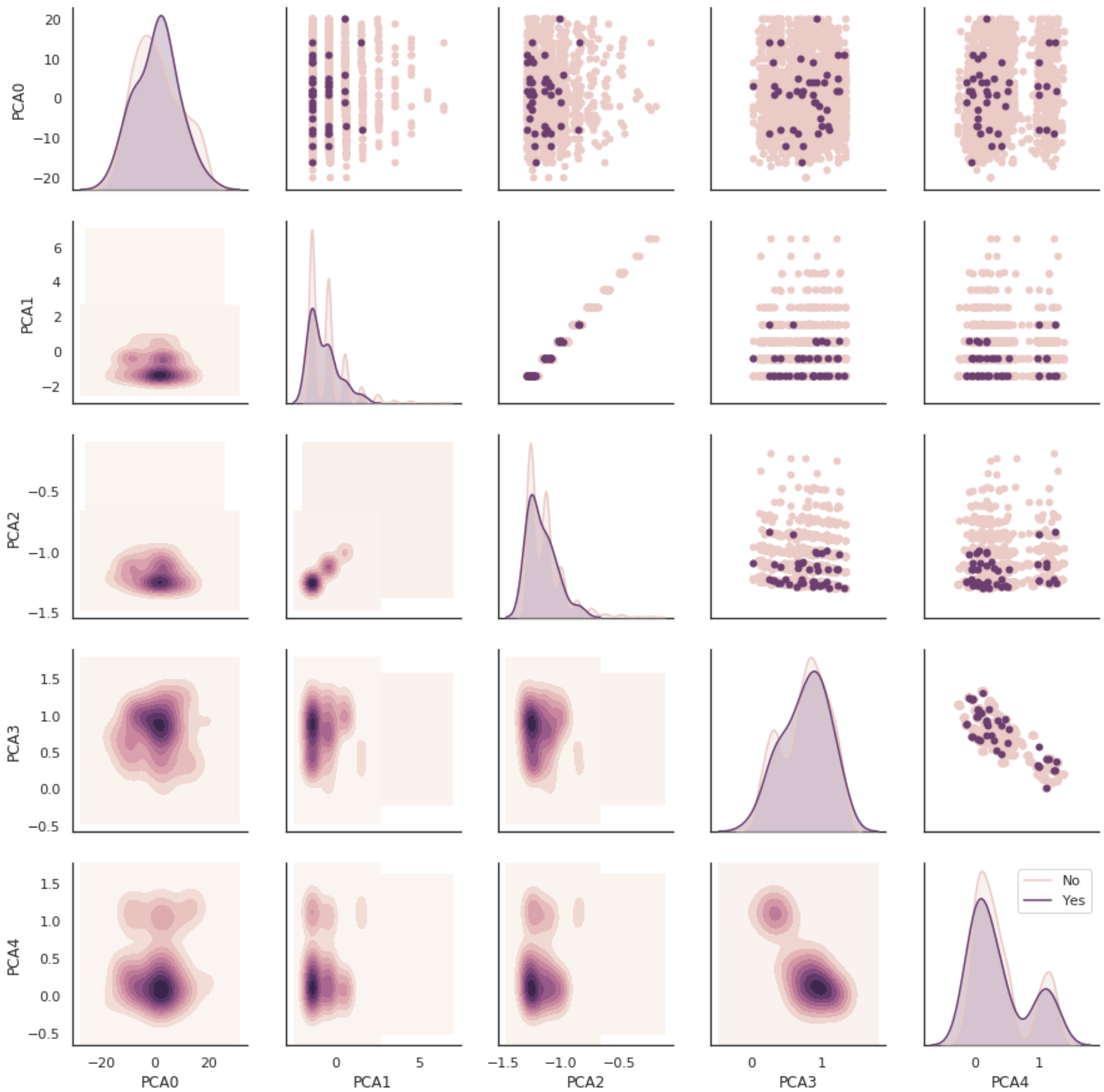
```python
X_n.columns = dsn4.columns


#plt.figure(figsize=(12,8))
corr = X_n.corr()

# Generate a mask for the upper triangle
sns.set(style="white")
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .75})
plt.show()
```



IV Outlier Detection

1. PCA

```
In [35]: from sklearn.decomposition import PCA
         from sklearn.preprocessing import StandardScaler

In [ ]:

In [36]: X = dsn4#dsn4.drop(columns=['y'])

         #sns.pairplot(X)
         # Plot the data
         #fig = plt.figure(figsize=(12,8))
         #with plt.style.context(('ggplot')):
         #    plt.plot( X.T)
         #    plt.show()

In [ ]:

In [37]: pcaA = PCA()
         pcaX = pcaA.fit_transform(X)#.fit_transform(StandardScaler().fit_transform(X))
         # PCA & score
         print(pcaA.explained_variance_ratio_[:5])

[0.89099929 0.06367829 0.02046383 0.00326929 0.00232139]


In [38]: # Compute the euclidean distance ( 3 PC )
         euclidean = np.zeros(X.shape[0])
         for i in range(3):
             euclidean += (pcaX[:,i] - np.mean(pcaX[:,:3]))**2/np.var(pcaX[:,:3])

         #colors = [plt.cm.jet(float(i)/max(euclidean)) for i in euclidean]

In [39]: X_pca = pd.DataFrame(pcaX, columns=['PCA%i' % i for i in range(X.shape[1])],
         index=X.index)

In [40]: colors = ["blue", "blue"]
         pal = sns.xkcd_palette(colors)

         pal = [sns.cubehelix_palette(light=1)[1], sns.cubehelix_palette(light=1)[4]]

In [41]: sns.set_style('white')
         cmap = sns.cubehelix_palette(light=1, as_cmap=True)


         df = X_pca.copy()
         df['y']  = dsdata['y']
         df = df[['PCA0','PCA1','PCA2','PCA3','PCA4','y']]
         df = df.iloc[:2000]
         g = sns.PairGrid(df, diag_sharey=False, hue='y', palette=pal)
         g.map_lower(sns.kdeplot, cmap=cmap, shade=True)
         g.map_upper(sns.scatterplot, linewidth=0)
         g.map_diag(sns.kdeplot, shade=True)
         plt.legend(['No','Yes'])
         plt.show()
```



In [42]:
```
'''
colors = [plt.cm.jet(float(i)/max(euclidean)) for i in euclidean]
fig = plt.figure(figsize=(8,6))
with plt.style.context(('ggplot')):
    plt.scatter(pcaX[:, 0], pcaX[:, 1], c=colors, edgecolors='k')
    plt.xlabel('PC1')
    plt.ylabel('PC2')
    plt.title('Score Plot')
plt.show()
'''
a = 0
```

2. Z-score

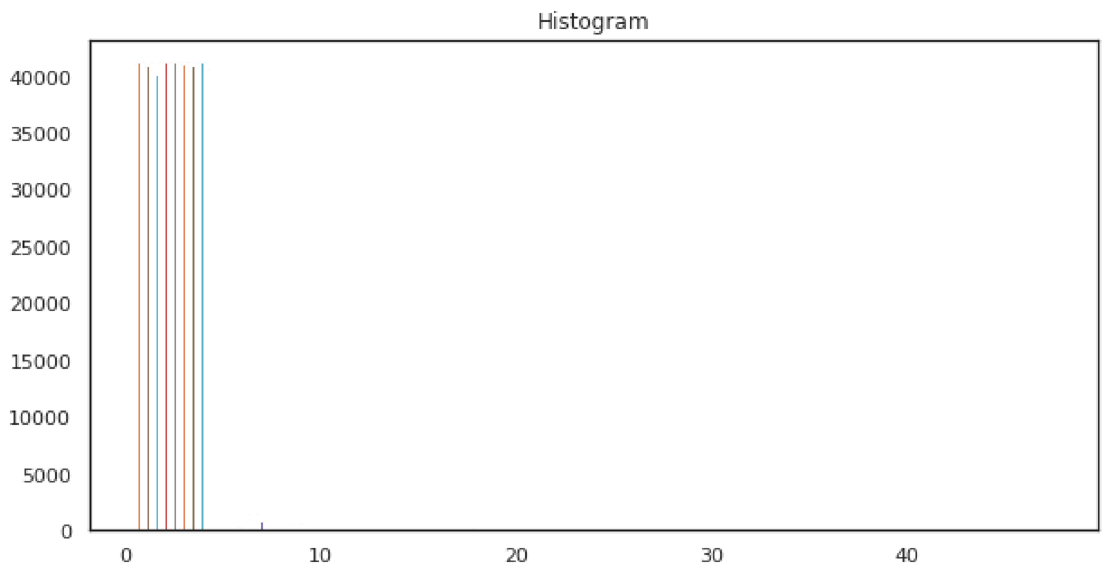
In [43]:
```
#NORMALIZATION????
```

In [44]:
```
from scipy import stats

dsn5 = dsn4.copy()

zX = np.abs(stats.zscore(X))
```

In [45]:
```
X.shape
```

Out[45]: (41188, 33)

In [46]:
```
def histogram(variable):
    plt.figure(figsize=(10, 5))
    plt.title("Histogram")
    ax = plt.hist(zX)

histogram(zX)
```



In [47]:
```
dsn5 = dsn5[(zX < 10).all(axis=1)]
dsn5 = dsn5.drop(columns = ['dec','illiterate'])
dsn5.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 40949 entries, 0 to 41187
Data columns (total 31 columns):
age                      40949 non-null int64
housing                  40949 non-null int8
loan                     40949 non-null int8
contact                  40949 non-null int8
campaign                 40949 non-null int64
previous                 40949 non-null int64
emp.var.rate             40949 non-null float64
blue-collar              40949 non-null uint8
entrepreneur             40949 non-null uint8
housemaid                40949 non-null uint8
management               40949 non-null uint8
retired                  40949 non-null uint8
```

```
self-employed          40949 non-null uint8
services               40949 non-null uint8
student                40949 non-null uint8
technician             40949 non-null uint8
unemployed             40949 non-null uint8
married                40949 non-null uint8
basic.6y               40949 non-null uint8
basic.9y               40949 non-null uint8
high.school            40949 non-null uint8
professional.course    40949 non-null uint8
university.degree      40949 non-null uint8
aug                    40949 non-null uint8
jul                    40949 non-null uint8
jun                    40949 non-null uint8
mar                    40949 non-null uint8
may                    40949 non-null uint8
nov                    40949 non-null uint8
oct                    40949 non-null uint8
sep                    40949 non-null uint8
dtypes: float64(1), int64(3), int8(3), uint8(24)
memory usage: 2.6 MB
```

In [48]:
```
X = dsn5#.drop(columns=['y'])
Y = dsdata['y'][X.index].astype("category").cat.codes
Y.value_counts()
```

Out[48]:
```
0    36405
1     4544
dtype: int64
```

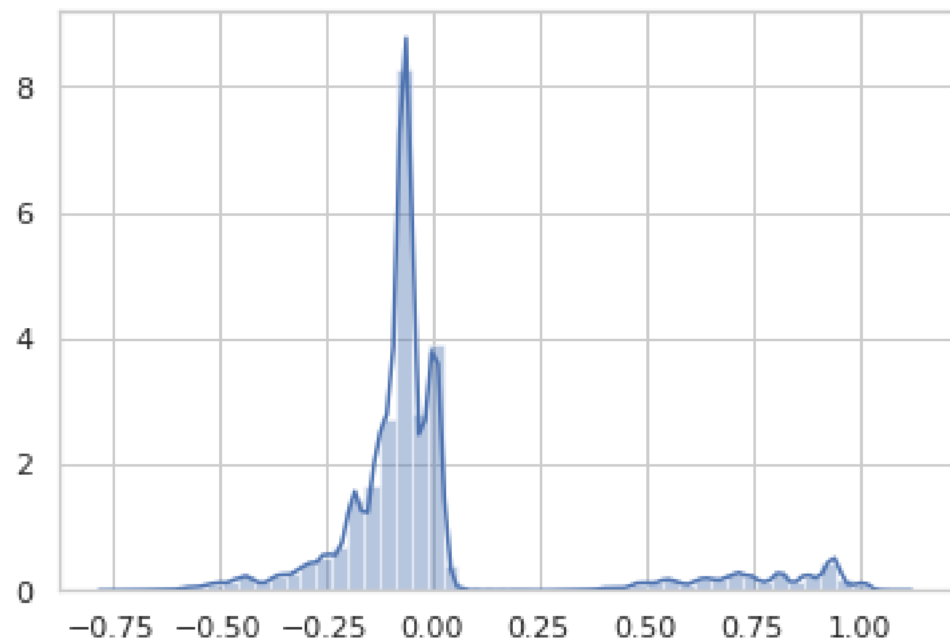
V Prediction

In [49]:
```
sns.set_style('whitegrid')
```

In [ ]:

In [50]:
```
X_ = sm.add_constant(X)
model = sm.OLS(Y,X_).fit()

print("Distribution of OLS residuals")
sns.distplot(model.resid)
plt.show()
display(model.summary())
```

```
Distribution of OLS residuals
```



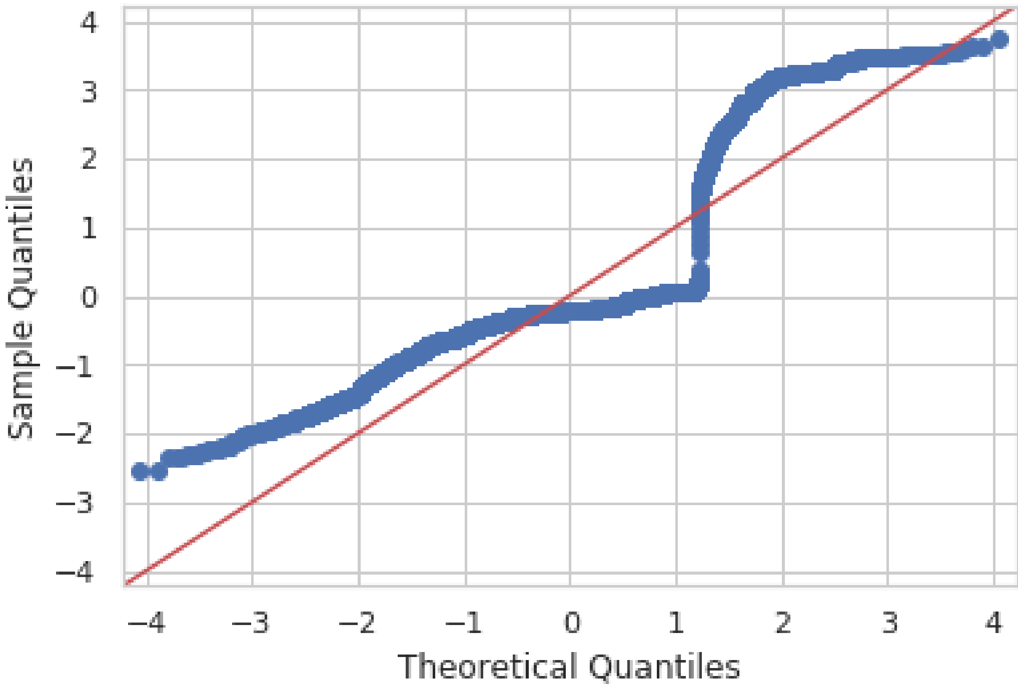

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.144
Model:                            OLS   Adj. R-squared:                  0.144
Method:                 Least Squares   F-statistic:                     222.7
Date:                Fri, 10 May 2019   Prob (F-statistic):               0.00
Time:                        14:06:10   Log-Likelihood:                -7489.8
No. Observations:               40949   AIC:                         1.504e+04
Df Residuals:                   40917   BIC:                         1.532e+04
Df Model:                          31
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
const                   0.0891      0.012      7.683      0.000       0.066       0.112
age                     0.0003      0.000      1.696      0.090   -4.42e-05       0.001
housing                -0.0049      0.003     -1.701      0.089      -0.011       0.001
loan                   -0.0021      0.004     -0.520      0.603      -0.010       0.006
contact                 0.0288      0.005      6.192      0.000       0.020       0.038
campaign               -0.0035      0.001     -6.257      0.000      -0.005      -0.002
previous                0.0686      0.003     20.832      0.000       0.062       0.075
emp.var.rate           -0.0529      0.001    -36.062      0.000      -0.056      -0.050
blue-collar            -0.0218      0.005     -4.178      0.000      -0.032      -0.012
entrepreneur           -0.0210      0.008     -2.546      0.011      -0.037      -0.005
housemaid              -0.0076      0.010     -0.776      0.438      -0.027       0.012
management             -0.0127      0.006     -2.046      0.041      -0.025      -0.001
retired                 0.0438      0.009      5.026      0.000       0.027       0.061
self-employed          -0.0155      0.008     -1.865      0.062      -0.032       0.001
services               -0.0178      0.006     -3.094      0.002      -0.029      -0.007
```

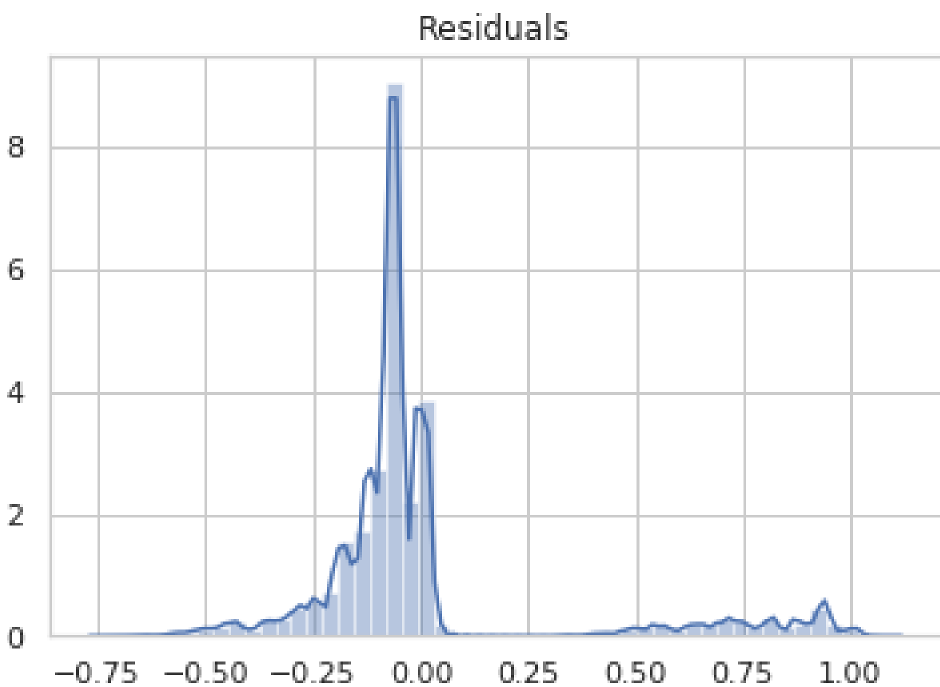
```
student                  0.0771      0.011      7.178      0.000       0.056       0.098
technician              -0.0070      0.005     -1.366      0.172      -0.017       0.003
unemployed               0.0019      0.010      0.199      0.842      -0.017       0.021
married                 -0.0033      0.003     -1.062      0.288      -0.010       0.003
basic.6y                 0.0013      0.008      0.167      0.868      -0.014       0.016
basic.9y                -0.0083      0.006     -1.397      0.162      -0.020       0.003
high.school             -0.0042      0.006     -0.686      0.493      -0.016       0.008
professional.course      0.0013      0.007      0.183      0.855      -0.012       0.015
university.degree        0.0090      0.006      1.456      0.145      -0.003       0.021
aug                      0.0495      0.008      6.375      0.000       0.034       0.065
jul                      0.0677      0.008      8.752      0.000       0.053       0.083
jun                      0.0342      0.008      4.465      0.000       0.019       0.049
mar                      0.2778      0.014     20.256      0.000       0.251       0.305
may                     -0.0495      0.007     -7.536      0.000      -0.062      -0.037
nov                     -0.0273      0.008     -3.622      0.000      -0.042      -0.013
oct                      0.1579      0.012     12.753      0.000       0.134       0.182
sep                      0.1714      0.014     12.625      0.000       0.145       0.198
==============================================================================
Omnibus:                    16009.730   Durbin-Watson:                   1.812
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            54082.712
Skew:                           2.043   Prob(JB):                         0.00
Kurtosis:                       6.873   Cond. No.                         570.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
"""
```

In [51]:
```python
alpha = 0.05
a = model.pvalues < alpha

X2 = X_[X_.columns[a]]
X2 = sm.add_constant(X2)
print("Not Statistically significant regressors are:")
print(list(X_.columns[~a]))
```

```
Not Statistically significant regressors are:
['age', 'housing', 'loan', 'housemaid', 'self-employed', 'technician', 'unemployed',
'married', 'basic.6y', 'basic.9y', 'high.school', 'professional.course',
'university.degree']
```

In [52]:
```python
model2 = sm.OLS(Y,X2).fit(cov_type='HC0')
sm.qqplot(model2.resid, sc.norm, fit=True, line='45')
plt.show()
sns.distplot(model2.resid)
plt.title('Residuals')
plt.show()
display(model2.summary())
print("Variance Inflation Factors:")
print_VIF(X2)
```






```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
```

```
Dep. Variable:                      y   R-squared:                       0.144
Model:                            OLS   Adj. R-squared:                  0.143
Method:                 Least Squares   F-statistic:                     188.4
Date:                Fri, 10 May 2019   Prob (F-statistic):               0.00
Time:                        14:06:11   Log-Likelihood:                -7503.5
No. Observations:               40949   AIC:                         1.505e+04
Df Residuals:                   40930   BIC:                         1.521e+04
Df Model:                          18
Covariance Type:                  HC0
================================================================================
                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.0936      0.009     10.393      0.000       0.076       0.111
contact          0.0294      0.006      5.296      0.000       0.019       0.040
campaign        -0.0035      0.000     -8.867      0.000      -0.004      -0.003
previous         0.0688      0.005     13.464      0.000       0.059       0.079
emp.var.rate    -0.0531      0.002    -25.669      0.000      -0.057      -0.049
blue-collar     -0.0238      0.003     -7.031      0.000      -0.030      -0.017
entrepreneur    -0.0173      0.007     -2.348      0.019      -0.032      -0.003
management      -0.0055      0.006     -0.945      0.345      -0.017       0.006
retired          0.0509      0.010      5.147      0.000       0.032       0.070
services        -0.0197      0.005     -4.166      0.000      -0.029      -0.010
student          0.0751      0.015      4.980      0.000       0.046       0.105
aug              0.0515      0.011      4.799      0.000       0.030       0.072
jul              0.0677      0.010      6.508      0.000       0.047       0.088
jun              0.0342      0.010      3.406      0.001       0.015       0.054
mar              0.2794      0.023     12.308      0.000       0.235       0.324
may             -0.0504      0.009     -5.821      0.000      -0.067      -0.033
nov             -0.0268      0.010     -2.808      0.005      -0.046      -0.008
oct              0.1589      0.021      7.690      0.000       0.118       0.199
sep              0.1730      0.023      7.647      0.000       0.129       0.217
==============================================================================
Omnibus:                    16022.479   Durbin-Watson:                   1.810
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            54146.902
Skew:                           2.045   Prob(JB):                         0.00
Kurtosis:                       6.874   Cond. No.                         50.7
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
"""


Variance Inflation Factors:
21.134835195011743 const
2.4230593529335542 contact
1.035602184712304 campaign
1.2461663846573323 previous
2.525902975234939 emp.var.rate
1.176311232198173 blue-collar
1.0429912415669762 entrepreneur
1.0693348771898068 management
1.0610369988444968 retired
1.0977835821445638 services
1.0476733948390058 student
3.718192758459077 aug
4.160433242738336 jul
```

```
3.2062143149574265 jun
1.1978096592691139 mar
4.6599163715584835 may
2.4696254452997293 nov
1.2793457906752723 oct
1.2250455192107061 sep
```

In [53]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X2.values, Y.values, test_size=0.25)

reg = LinearRegression()
reg = reg.fit(X_train,Y_train)

y_hat = reg.predict(X_test)

print('Test accuracy:',np.round(reg.score(np.round(X_test), Y_test),3), ', MSE Loss
is:', mean_squared_error(Y_test,y_hat))
```

```
Test accuracy: 0.145 , MSE Loss is: 0.08108139598792455
```

In [ ]:

VI Classification

In [54]:
```
def plot_hist2(df,df2,df_col):
    df = df.dropna()
    df2 = df2.dropna()
    for d in df_col:
        print("Empirical Distribution of Variable "+d)
        fig, axes = plt.subplots(1,2,figsize=(15,9))
        sns.distplot(df[d],ax=axes[0])
        sns.distplot(df2[d],ax=axes[1])
        axes[0].set_ylabel("Probability")
        axes[1].set_ylabel("Probability")
        plt.suptitle("Empirical Probability Distribution of Numerical Variable "+d)
        plt.show()

def get_num_cols(df):
    idx = df.select_dtypes(exclude='object').columns.values
    dF = df[idx].dropna() #remove NaNs or else it cant plot
    return dF.columns

def calculate_metrics(y_test,y_hat):
    c = confusion_matrix(y_test, y_hat)
    print("Confusion matrix is:")
    print(c)
    print("We have",c[0][0]+c[1][1],"correct observations and",c[0][1]+c[1][0],
"misclassifications.")
    print(classification_report(y_test, y_hat))
    plt.figure(figsize=(6,6))
    sns.heatmap(c,cmap="YlGnBu",annot=True,fmt='g')
    plt.show()

def plot_ROC(y_test,X_test,classifier):
```

```
    roc = roc_auc_score(y_test, classifier.predict(X_test))
    fpr, tpr, _ = roc_curve(y_test, classifier.predict_proba(X_test)[:,1])
    plt.figure(figsize=(12,12))
    plt.plot(fpr, tpr, label='Classifier area ='+str(np.round(roc,2)))
    plt.plot([0, 1], [0, 1],'--')

    plt.xlabel('FPR')
    plt.ylabel('TPR')
    plt.title('ROC curve')
    plt.legend()

    plt.xlim([-0.01, 1.0])
    plt.ylim([0.0, 1.01])
    plt.show()


def plot_ROC2(L_Y,L_X,L_YHAT,L_PROB,L_NAME):

    plt.figure(figsize=(12,12))
    for i in range(len(L_Y)):
        roc = roc_auc_score(L_Y[i], L_YHAT[i])
        fpr, tpr, _ = roc_curve(L_Y[i], L_PROB[i][:,1])
        plt.plot(fpr, tpr, label=L_NAME[i]+', area ='+str(np.round(roc,2)))
    plt.plot([0, 1], [0, 1],'--')

    plt.xlabel('FPR')
    plt.ylabel('TPR')
    plt.title('ROC curve')
    plt.legend()

    plt.xlim([-0.01, 1.0])
    plt.ylim([0.0, 1.01])
    plt.show()



def MAE(y_test,y_hat):
    return np.abs(y_test-y_hat).sum()#/y_test.shape[0]
```

VI Logistic Regression with PCA

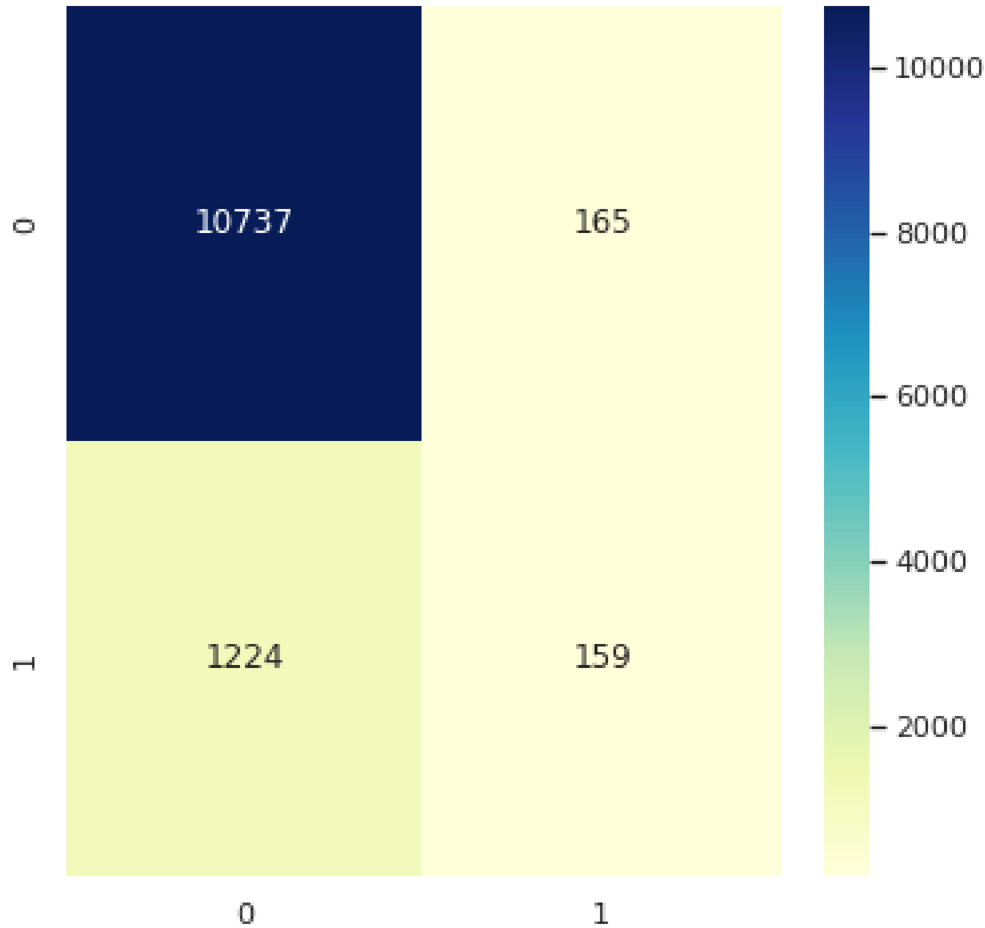
```
In [55]: pcaXmodel = PCA(n_components=5, whiten=True)
         pc = pcaXmodel.fit_transform(X)#.fit_transform(StandardScaler().fit_transform(X))
         print(pcaXmodel.explained_variance_ratio_[:5])

         proj = pcaXmodel.inverse_transform(pc)
         a = pd.DataFrame(proj)[list((np.ones((31,1))-1).cumsum().ravel())]

         X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3,
         random_state=0)
         lr = LogisticRegression().fit(X_train,y_train)

         y_hat = lr.predict(X_test)
         print('Test accuracy:',np.round(lr.score(X_test, y_test),3), ', Cross Entropy Loss is:',
         log_loss(y_test,y_hat))
```

```
        print(MAE(y_test,y_hat))

        #pcaXmodel =
        PCA(n_components=5).fit_transform(X)#.fit_transform(StandardScaler().fit_transform(X))
```

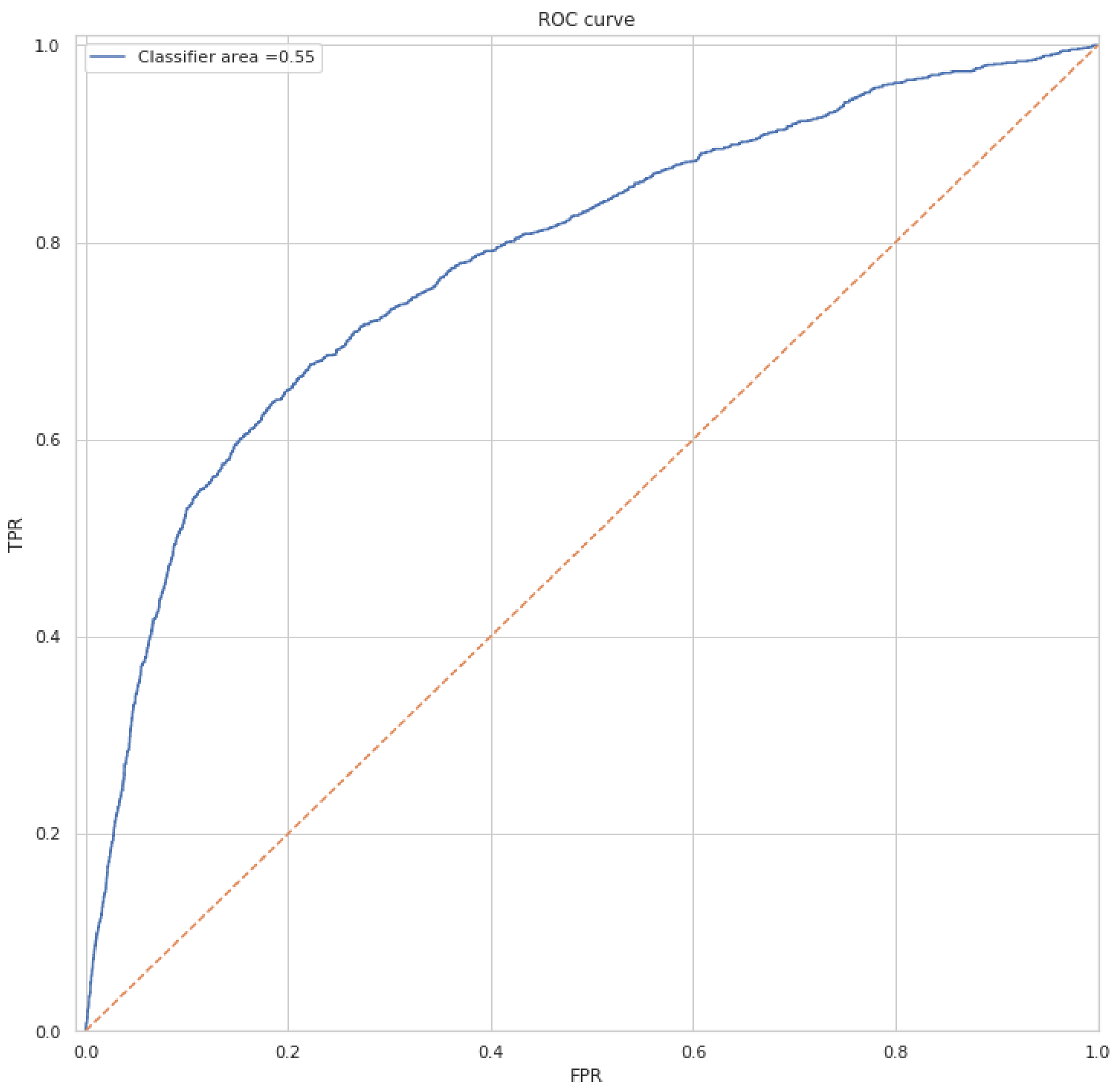
```
[0.89682587 0.05748246 0.0204958  0.00333079 0.00236176]
Test accuracy: 0.887 , Cross Entropy Loss is: 3.905127582100686
1389
```

```
In [56]: calculate_metrics(y_test,y_hat)
         plot_ROC(y_test,X_test,lr)
```

```
Confusion matrix is:
[[10737   165]
 [ 1224   159]]
We have 10896 correct observations and 1389 misclassifications.
              precision    recall  f1-score   support

           0       0.90      0.98      0.94     10902
           1       0.49      0.11      0.19      1383

   micro avg       0.89      0.89      0.89     12285
   macro avg       0.69      0.55      0.56     12285
weighted avg       0.85      0.89      0.85     12285
```



10737
165
1224
159
0
1
0
1
10000
8000
6000
4000
2000




```
In [57]: a.shape
```

```
Out[57]: (40949, 31)
```

```
In [58]: logit = sm.Logit(Y, X).fit()
         display(logit.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.293562
         Iterations 7


<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:                      y   No. Observations:                40949
Model:                          Logit   Df Residuals:                    40918
Method:                           MLE   Df Model:                           30
```

```
Date:                 Fri, 10 May 2019   Pseudo R-squ.:              0.1577
Time:                         14:06:12   Log-Likelihood:            -12021.
converged:                        True   LL-Null:                   -14272.
                                         LLR p-value:                 0.000
=======================================================================================
                          coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------------
age                    -0.0208      0.001    -13.966      0.000      -0.024      -0.018
housing                -0.1384      0.034     -4.108      0.000      -0.204      -0.072
loan                   -0.0677      0.048     -1.424      0.154      -0.161       0.025
contact                -0.2694      0.051     -5.239      0.000      -0.370      -0.169
campaign               -0.0805      0.010     -8.272      0.000      -0.100      -0.061
previous                0.3956      0.026     15.024      0.000       0.344       0.447
emp.var.rate           -0.4211      0.014    -31.187      0.000      -0.448      -0.395
blue-collar            -0.6715      0.060    -11.141      0.000      -0.790      -0.553
entrepreneur           -0.3916      0.105     -3.731      0.000      -0.597      -0.186
housemaid              -0.3927      0.121     -3.249      0.001      -0.630      -0.156
management             -0.2096      0.072     -2.903      0.004      -0.351      -0.068
retired                 0.4508      0.089      5.043      0.000       0.276       0.626
self-employed          -0.3553      0.099     -3.579      0.000      -0.550      -0.161
services               -0.4390      0.071     -6.214      0.000      -0.577      -0.301
student                -0.0562      0.089     -0.630      0.529      -0.231       0.119
technician             -0.2691      0.058     -4.633      0.000      -0.383      -0.155
unemployed             -0.2013      0.106     -1.902      0.057      -0.409       0.006
married                -0.0648      0.037     -1.746      0.081      -0.138       0.008
basic.6y               -0.4636      0.091     -5.101      0.000      -0.642      -0.285
basic.9y               -0.6431      0.067     -9.652      0.000      -0.774      -0.512
high.school            -0.7244      0.059    -12.370      0.000      -0.839      -0.610
professional.course    -0.5780      0.071     -8.130      0.000      -0.717      -0.439
university.degree      -0.6507      0.056    -11.619      0.000      -0.760      -0.541
aug                    -0.2108      0.065     -3.234      0.001      -0.338      -0.083
jul                     0.0587      0.066      0.890      0.373      -0.071       0.188
jun                    -0.0449      0.069     -0.655      0.512      -0.179       0.089
mar                     0.9619      0.098      9.778      0.000       0.769       1.155
may                    -0.9716      0.056    -17.424      0.000      -1.081      -0.862
nov                    -0.6523      0.070     -9.367      0.000      -0.789      -0.516
oct                     0.2948      0.093      3.183      0.001       0.113       0.476
sep                     0.4243      0.100      4.253      0.000       0.229       0.620
=======================================================================================
"""
```

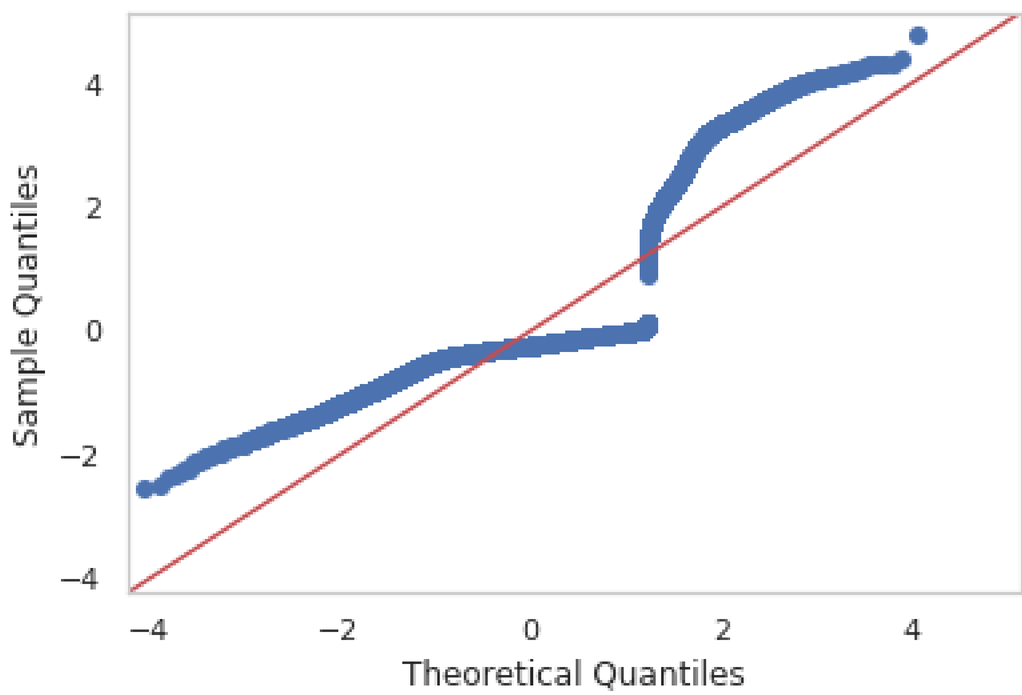
```
In [59]: sns.set_style('whitegrid')
         alpha = 0.05
         a = logit.pvalues < alpha

         X3 = X[X.columns[a]]
         print("Not Statistically significant regressors are:")
         print(list(X.columns[~a]))
```

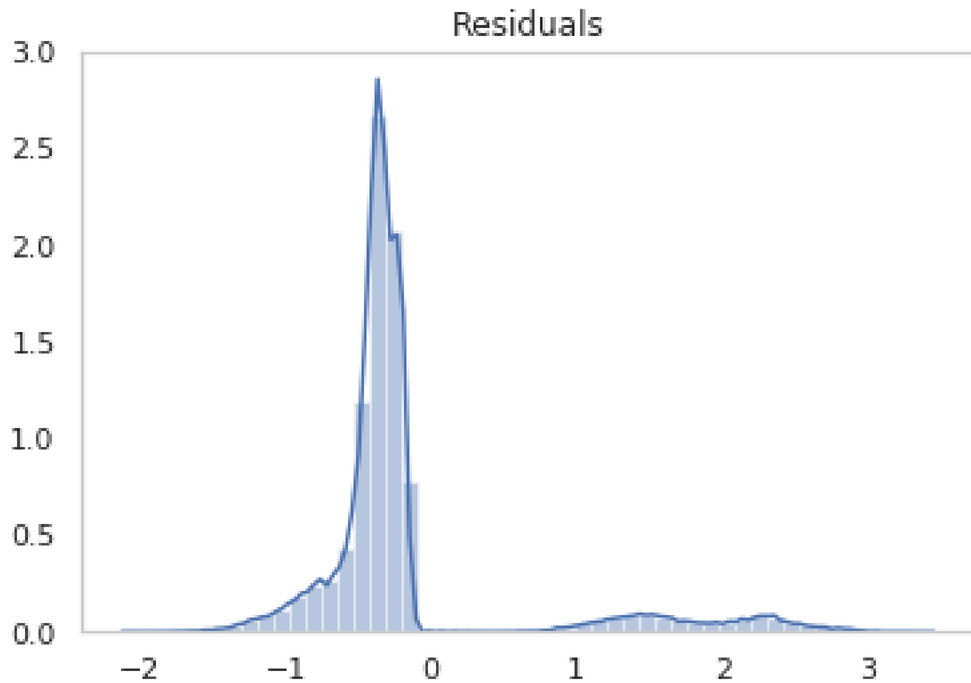
```
Not Statistically significant regressors are:
['loan', 'student', 'unemployed', 'married', 'jul', 'jun']
```

```
In [60]: model2 = sm.Logit(Y.values,X3.values).fit()
         sm.qqplot(model2.resid_dev, sc.norm, fit=True, line='45')
         plt.grid()
```

```
plt.show()
sns.distplot(model2.resid_dev)
plt.title('Residuals')
plt.grid()
plt.show()
display(model2.summary())
print("Variance Inflation Factors:")
print_VIF(X3)
```

```
Optimization terminated successfully.
         Current function value: 0.293698
         Iterations 7
```






```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:                      y   No. Observations:               40949
Model:                          Logit   Df Residuals:                   40924
Method:                           MLE   Df Model:                          24
Date:                Fri, 10 May 2019   Pseudo R-squ.:                 0.1573
Time:                        14:06:12   Log-Likelihood:               -12027.
converged:                       True   LL-Null:                      -14272.
                                        LLR p-value:                    0.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
x1            -0.0219      0.001    -16.668      0.000      -0.024      -0.019
x2            -0.1418      0.034     -4.226      0.000      -0.208      -0.076
x3            -0.3036      0.047     -6.481      0.000      -0.395      -0.212
x4            -0.0805      0.010     -8.349      0.000      -0.099      -0.062
x5             0.3958      0.026     15.082      0.000       0.344       0.447
x6            -0.4135      0.012    -34.306      0.000      -0.437      -0.390
x7            -0.6559      0.058    -11.275      0.000      -0.770      -0.542
x8            -0.3819      0.104     -3.668      0.000      -0.586      -0.178
x9            -0.3692      0.120     -3.084      0.002      -0.604      -0.135
x10           -0.2024      0.071     -2.842      0.004      -0.342      -0.063
x11            0.4948      0.088      5.640      0.000       0.323       0.667
x12           -0.3397      0.099     -3.446      0.001      -0.533      -0.146
x13           -0.4211      0.069     -6.071      0.000      -0.557      -0.285
x14           -0.2481      0.057     -4.384      0.000      -0.359      -0.137
x15           -0.4730      0.090     -5.268      0.000      -0.649      -0.297
x16           -0.6526      0.065    -10.086      0.000      -0.779      -0.526
x17           -0.7189      0.055    -13.006      0.000      -0.827      -0.611
```

```
x18          -0.5823      0.069     -8.402      0.000      -0.718      -0.446
x19          -0.6397      0.053    -12.089      0.000      -0.743      -0.536
x20          -0.2317      0.054     -4.328      0.000      -0.337      -0.127
x21           0.9615      0.093     10.315      0.000       0.779       1.144
x22          -0.9750      0.045    -21.635      0.000      -1.063      -0.887
x23          -0.6670      0.061    -10.973      0.000      -0.786      -0.548
x24           0.2965      0.088      3.378      0.001       0.124       0.469
x25           0.4162      0.095      4.400      0.000       0.231       0.602
==============================================================================
"""


Variance Inflation Factors:
10.59285135212034 age
2.1189581199142262 housing
2.5784705320747205 contact
1.9652236412758264 campaign
1.3877212802827528 previous
1.8225304898784933 emp.var.rate
2.348372356176547 blue-collar
1.14163524129405 entrepreneur
1.1512800634732347 housemaid
1.2940384604988566 management
1.4834937610887158 retired
1.1261108332839098 self-employed
1.4471899518339966 services
1.902603411017963 technician
1.3953800724789436 basic.6y
2.0079977473739965 basic.9y
2.6741950884656536 high.school
2.297931584308367 professional.course
3.3016071127980133 university.degree
1.6385893838857952 aug
1.0728676709603513 mar
2.2099886621689033 may
1.3450595960370224 nov
1.1412686812851054 oct
1.1068452368839075 sep
```

In [ ]:

```
In [61]: logit = sm.Logit(Y.values, pc).fit()
         display(logit.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.673024
         Iterations 4


<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:                      y   No. Observations:                40949
Model:                          Logit   Df Residuals:                    40944
Method:                           MLE   Df Model:                            4
```

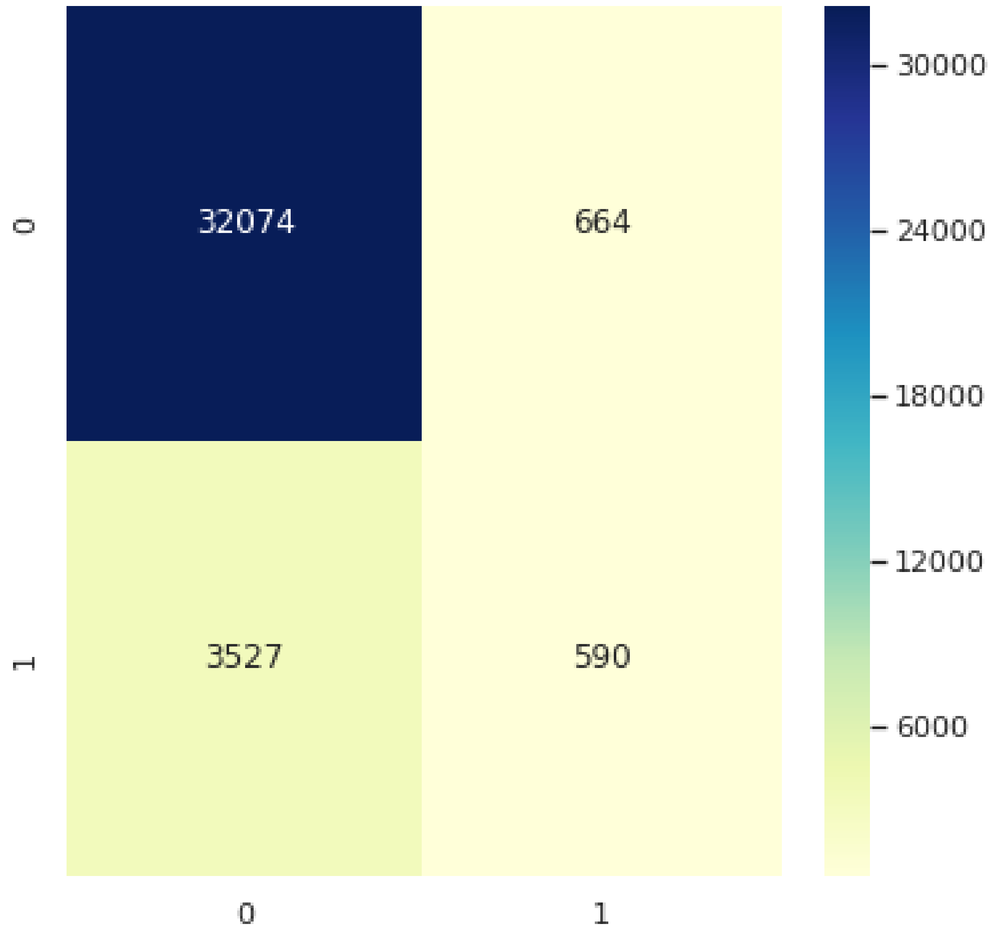
```
Date:                Fri, 10 May 2019   Pseudo R-squ.:                 -0.9310
Time:                        14:06:14   Log-Likelihood:                -27560.
converged:                       True   LL-Null:                       -14272.
                                        LLR p-value:                     1.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
x1             0.0352      0.010      3.449      0.001       0.015       0.055
x2            -0.1188      0.010    -11.713      0.000      -0.139      -0.099
x3             0.3641      0.010     35.551      0.000       0.344       0.384
x4            -0.1408      0.010    -13.967      0.000      -0.161      -0.121
x5            -0.0248      0.010     -2.464      0.014      -0.044      -0.005
==============================================================================
"""
```

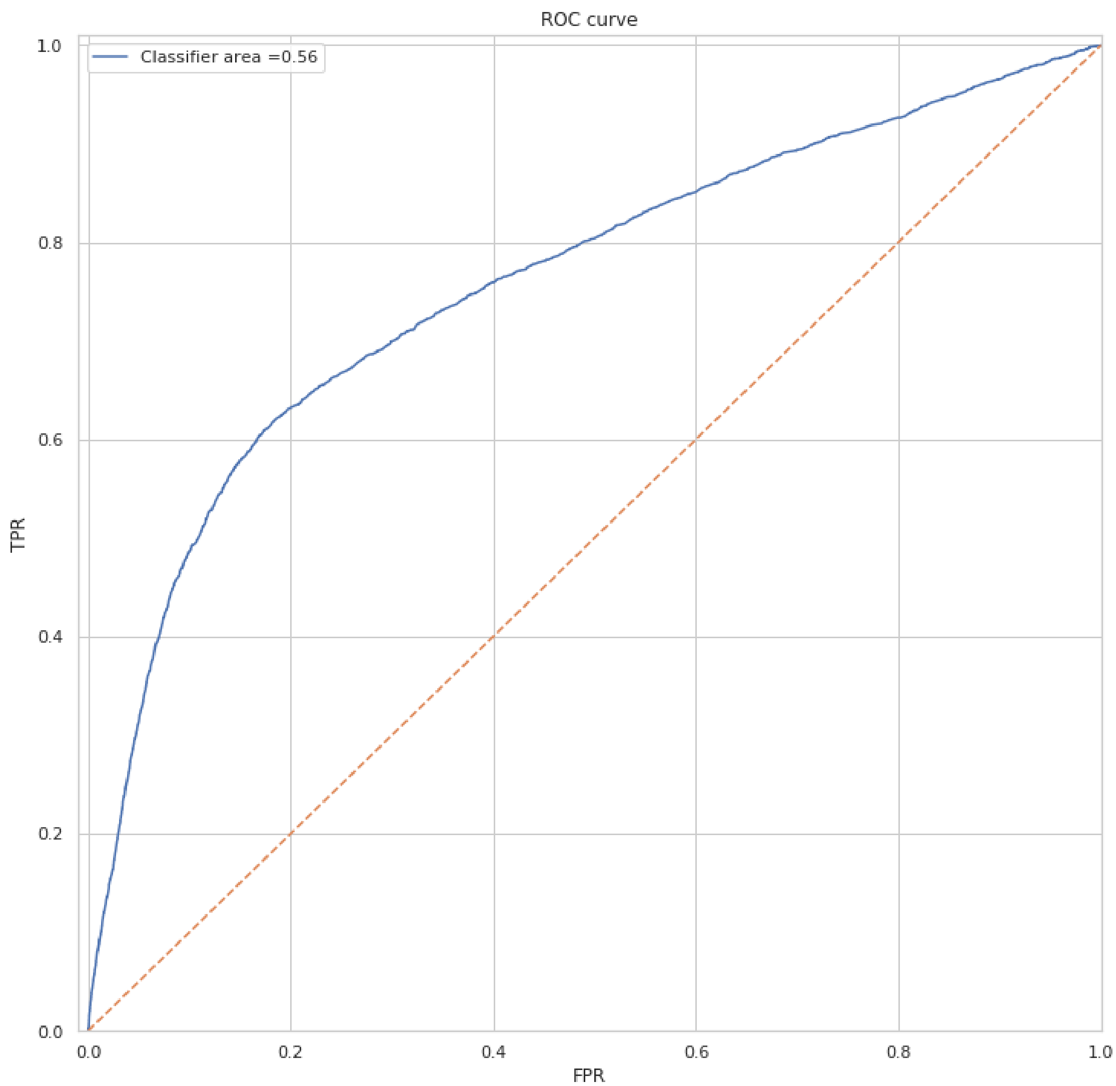
```
In [ ]:
```

1. *AdaBoost Classifier*

```
In [62]: X_train, X_test, Y_train, Y_test = train_test_split(X.values, Y.values, test_size=0.9)

         clf_rdfore = AdaBoostClassifier()
         clf_rdfore = clf_rdfore.fit(X_train,Y_train)

         y_hat = clf_rdfore.predict(X_test)


         print('Test accuracy:',np.round(clf_rdfore.score(X_test, Y_test),3), ', Cross Entropy
         Loss is:', log_loss(Y_test,y_hat))
         calculate_metrics(Y_test,y_hat)
         plot_ROC(Y_test,X_test,clf_rdfore)
         MAE(Y_test,y_hat)
```

```
Test accuracy: 0.886 , Cross Entropy Loss is: 3.9276229223650616
Confusion matrix is:
[[32074   664]
 [ 3527   590]]
We have 32664 correct observations and 4191 misclassifications.
              precision    recall  f1-score   support

           0       0.90      0.98      0.94     32738
           1       0.47      0.14      0.22      4117

   micro avg       0.89      0.89      0.89     36855
   macro avg       0.69      0.56      0.58     36855
weighted avg       0.85      0.89      0.86     36855
```


32074
664
3527
590
0
1
0
1
30000
24000
18000
12000
6000



Out[62]: 4191

2. SVC

VII Unbalanced Data Problem

```
In [63]: sns.set_style('whitegrid')
```

```
In [64]: def make_balanced(X,Y):
             DF = X.copy()
             DF['Y'] = Y
             DF_Yes = DF[DF.Y==1]#.info()
             DF_No = DF[DF.Y==0]#.info()
             DF_B = DF_No.sample(len(DF_Yes))
             D = pd.concat([DF_B,DF_Yes])
             D = D.reindex(np.random.permutation(D.index))
```

```
        D = D[:int(len(D)/2)]#, D[int(len(D)/2):]
        return D
```

```
In [65]: D = make_balanced(X,Y)
```

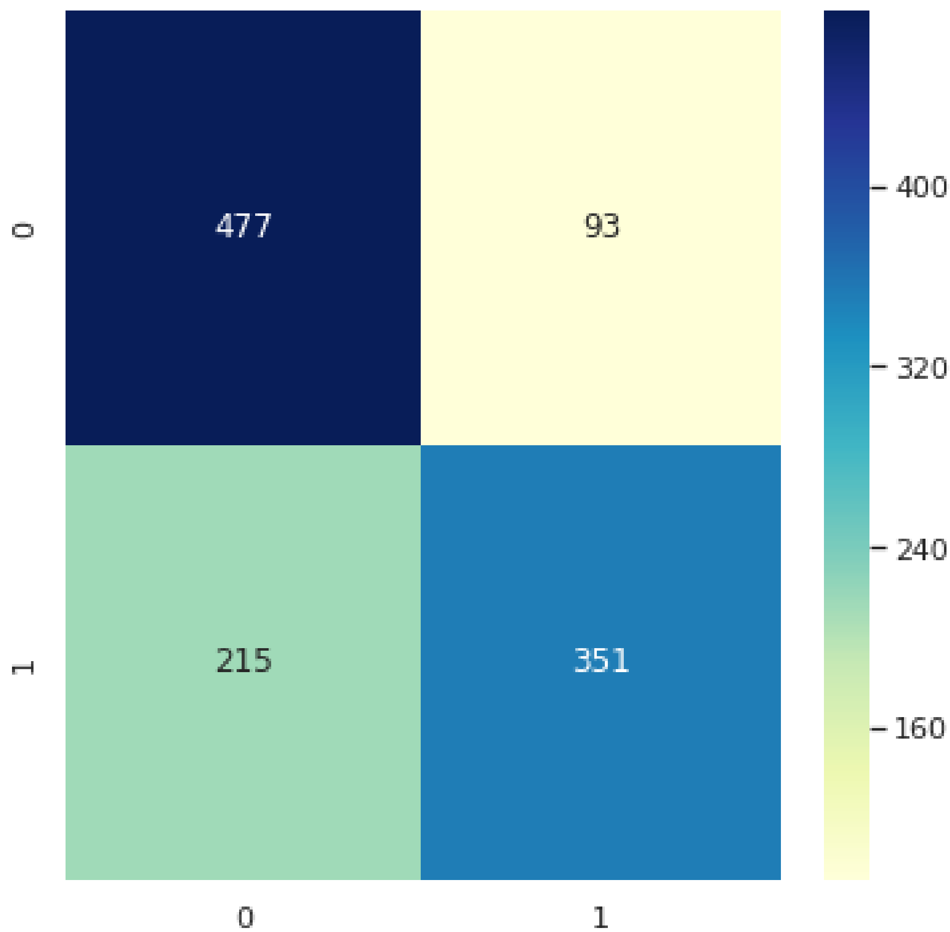
```
In [66]: D.shape
```

```
Out[66]: (4544, 32)
```

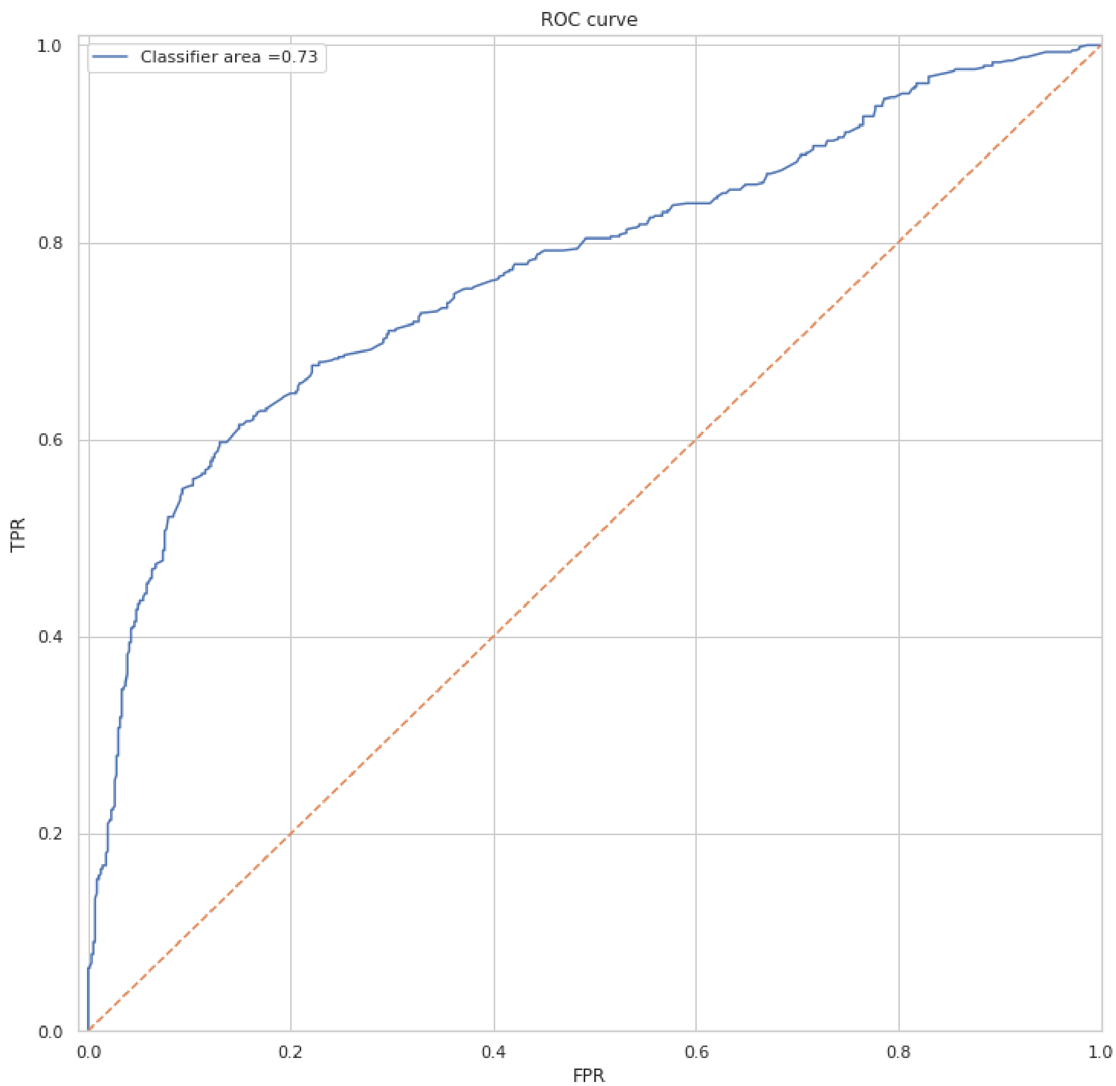
```
In [67]: X_B = D.drop(columns='Y')
         Y_B = D['Y']
```

```
In [68]: X_train, X_test, Y_train, Y_test = train_test_split(X_B.values, Y_B.values,
         test_size=0.25)
         clf_rdfore = AdaBoostClassifier()
         clf_rdfore = clf_rdfore.fit(X_train,Y_train)

         y_hat = clf_rdfore.predict(X_test)


         print('Test accuracy:',np.round(clf_rdfore.score(X_test, Y_test),3), ', Cross Entropy
         Loss is:', log_loss(Y_test,y_hat))
         calculate_metrics(Y_test,y_hat)
         plot_ROC(Y_test,X_test,clf_rdfore)
         MAE(Y_test,y_hat)
```

```
Test accuracy: 0.729 , Cross Entropy Loss is: 9.364452017775967
Confusion matrix is:
[[477  93]
 [215 351]]
We have 828 correct observations and 308 misclassifications.
              precision    recall  f1-score   support

           0       0.69      0.84      0.76       570
           1       0.79      0.62      0.70       566

   micro avg       0.73      0.73      0.73      1136
   macro avg       0.74      0.73      0.73      1136
weighted avg       0.74      0.73      0.73      1136
```



0
1
477
93
215
351
0
1
400
320
240
160



Out[68]: 308

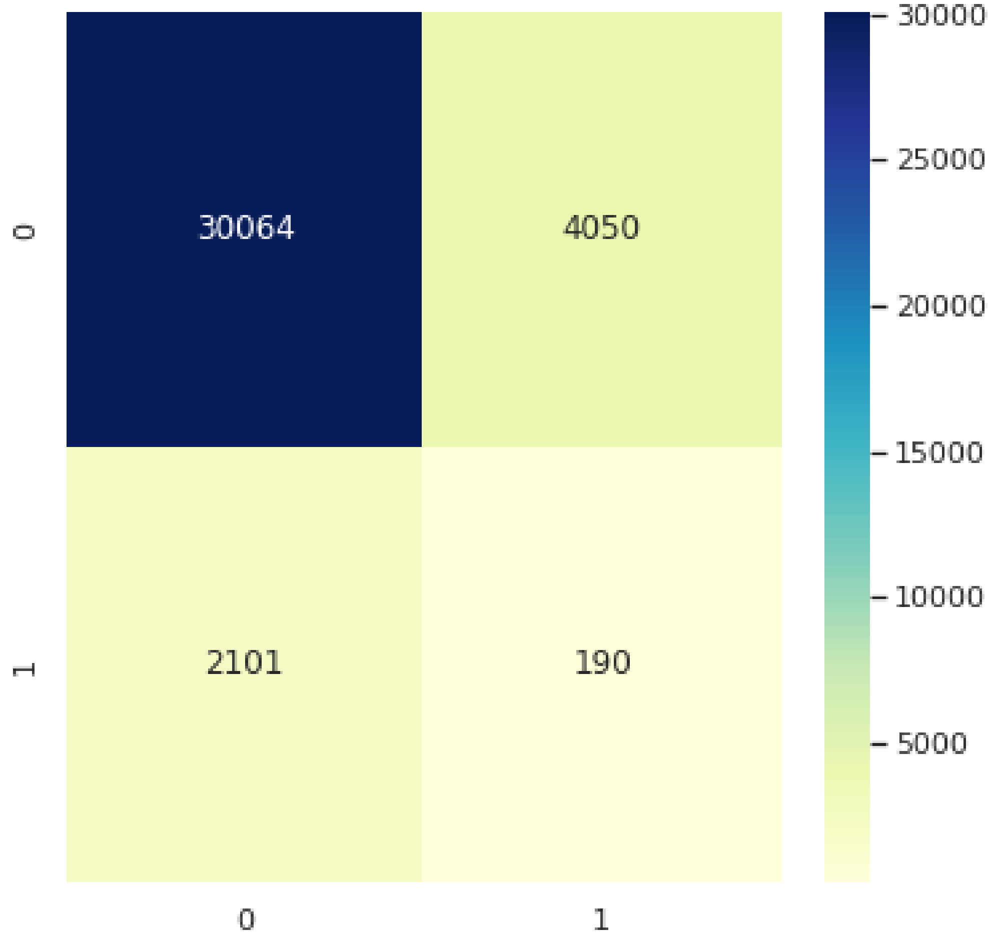
In [69]:
```
X_R = X.drop(D.index)
Y_R = Y.drop(D.index)
```

In [70]:
```
C = [LogisticRegression(), AdaBoostClassifier(), KNeighborsClassifier(),
RandomForestClassifier()]

def calc_sampling_imb(X,Y):
    L_NAME = ['lr','ada','knn','rforest']
    L_X, L_Y, L_YHAT, L_PROB = [],[],[],[]

    for cl in C:
        y_hat = cross_val_predict(cl, X, Y, cv=10, n_jobs=-1)
        probs = cross_val_predict(cl, X, Y, cv=10, method='predict_proba',n_jobs=-1)

        #print('Test accuracy:',np.round(c.score(X_R, Y_R),3), ', Cross Entropy Loss
is:', log_loss(Y_R,y_hat))
```

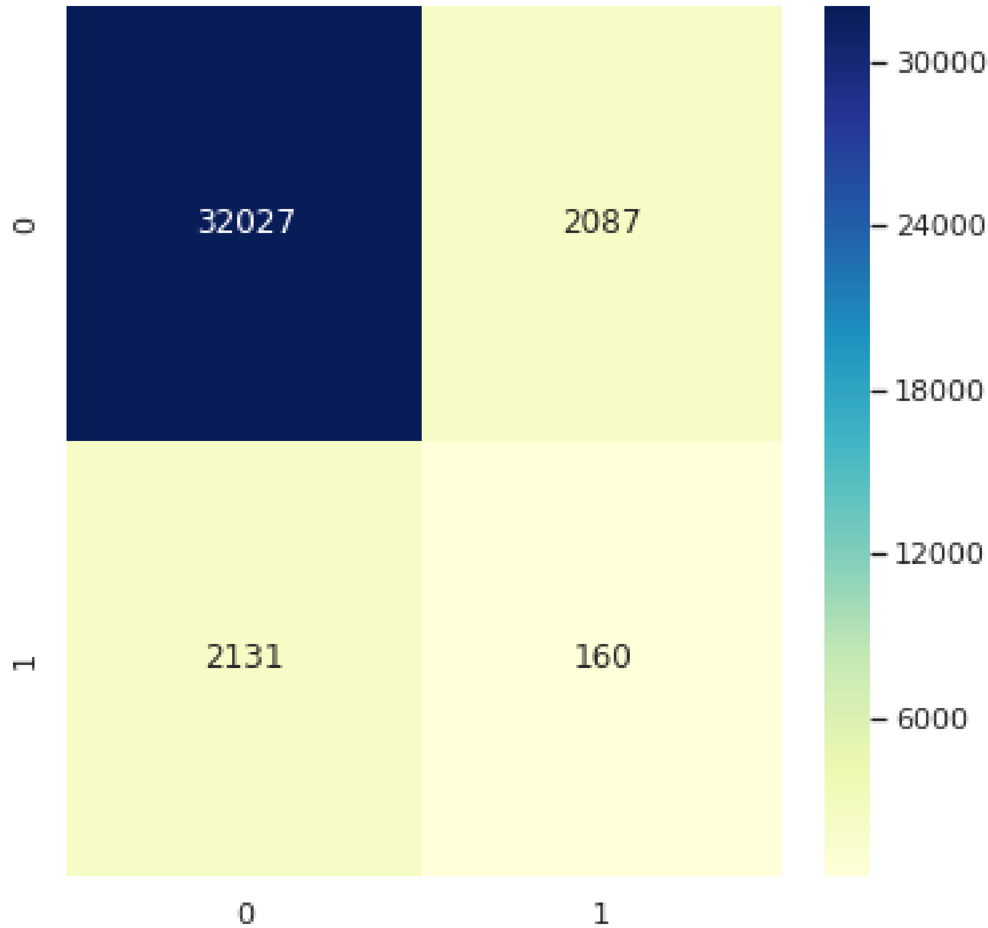
```
            calculate_metrics(Y,y_hat)
            #plot_ROC(Y_R,X,c)
            print('MAE:',MAE(Y,y_hat))

                            #L_NAME.append(name)
            L_X.append(X.values)
            L_Y.append(Y.values)
            L_YHAT.append(y_hat)
            L_PROB.append(probs)

        plot_ROC2(L_Y,L_X,L_YHAT,L_PROB,L_NAME)

        #plot_ROC3(L_Y,L_X,L_CLASS,L_NAME)
```

```
In [71]: calc_sampling_imb(X_R,Y_R)
```

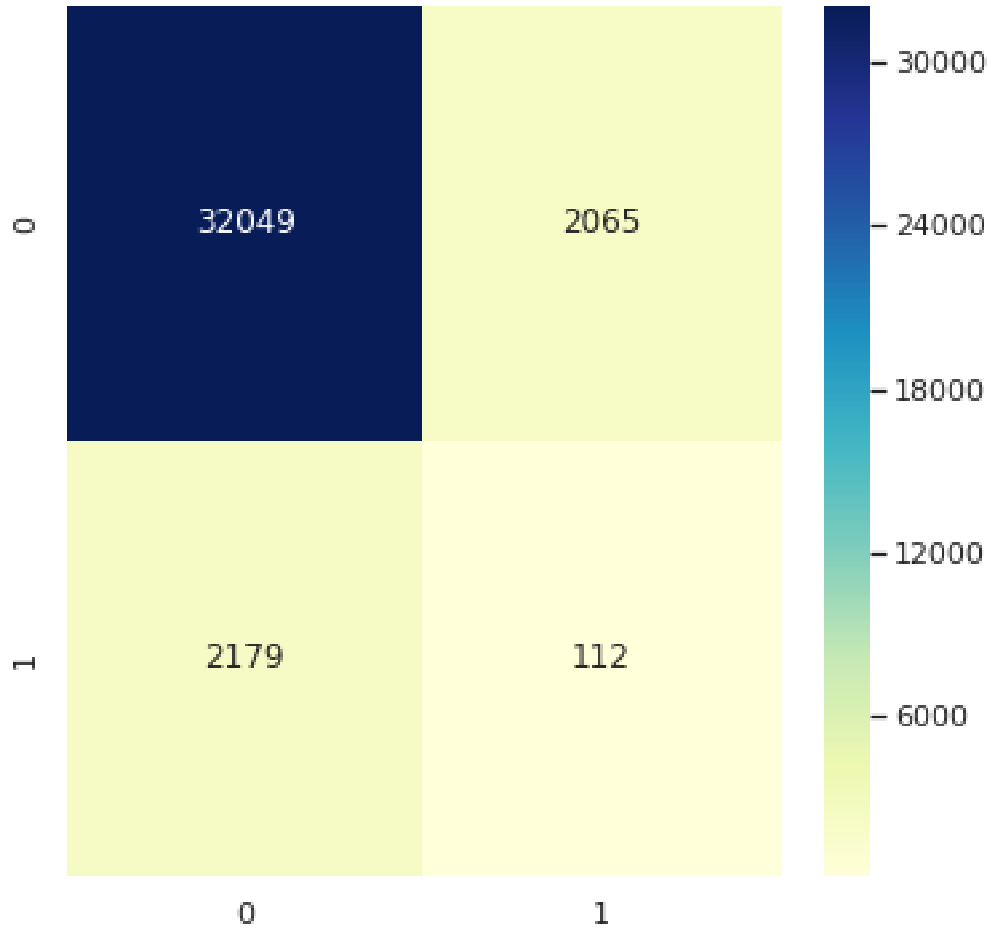
```
Confusion matrix is:
[[30064  4050]
 [ 2101   190]]
We have 30254 correct observations and 6151 misclassifications.
              precision    recall  f1-score   support

           0       0.93      0.88      0.91     34114
           1       0.04      0.08      0.06      2291

   micro avg       0.83      0.83      0.83     36405
   macro avg       0.49      0.48      0.48     36405
weighted avg       0.88      0.83      0.85     36405
```



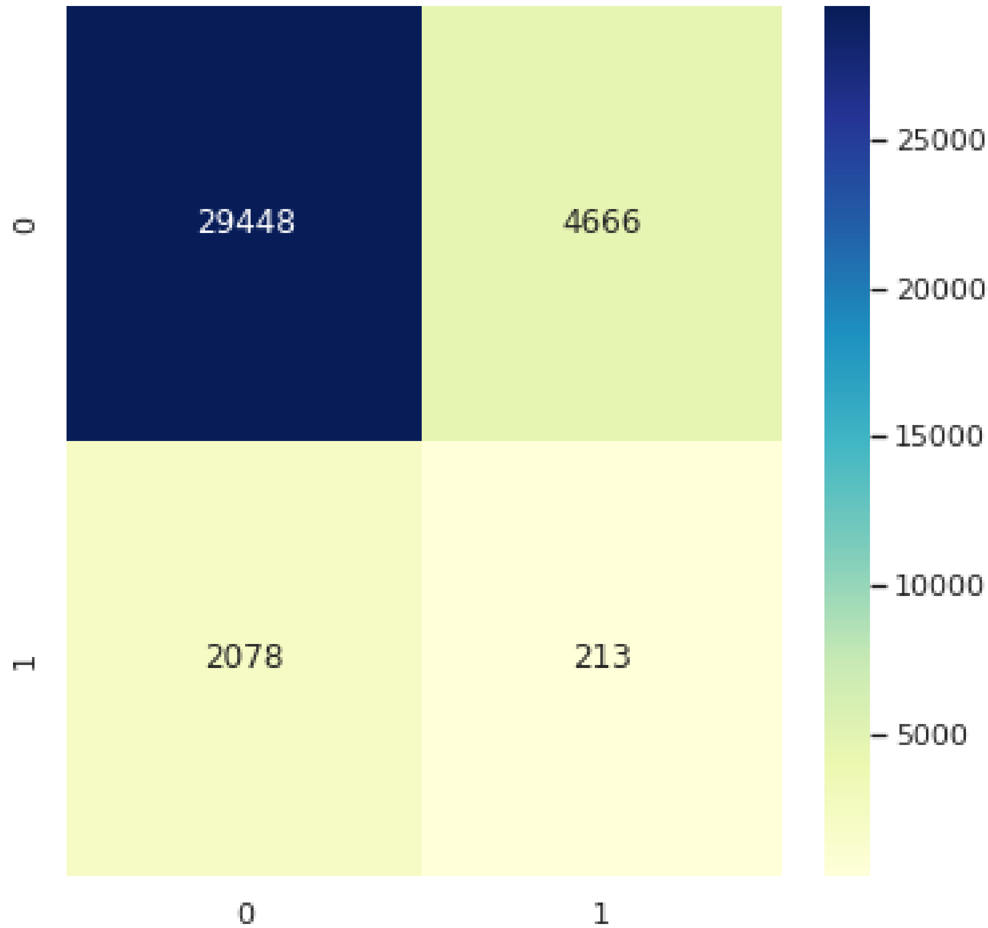

```
MAE: 6151
Confusion matrix is:
[[32027  2087]
 [ 2131   160]]
We have 32187 correct observations and 4218 misclassifications.
              precision    recall  f1-score   support

           0       0.94      0.94      0.94     34114
           1       0.07      0.07      0.07      2291

   micro avg       0.88      0.88      0.88     36405
   macro avg       0.50      0.50      0.50     36405
weighted avg       0.88      0.88      0.88     36405
```



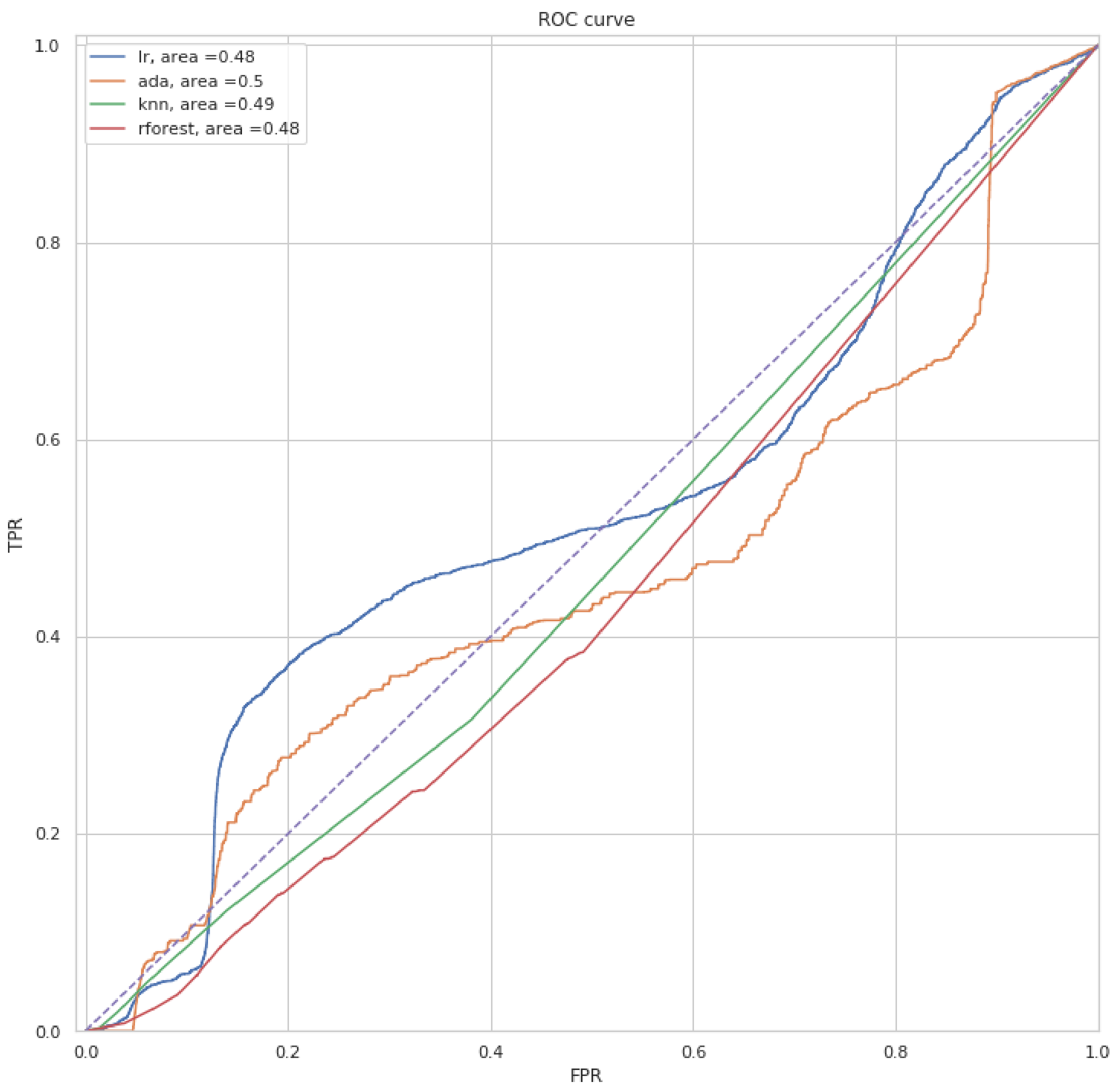

```
MAE: 4218
Confusion matrix is:
[[32049  2065]
 [ 2179   112]]
We have 32161 correct observations and 4244 misclassifications.
              precision    recall  f1-score   support

           0       0.94      0.94      0.94     34114
           1       0.05      0.05      0.05      2291

   micro avg       0.88      0.88      0.88     36405
   macro avg       0.49      0.49      0.49     36405
weighted avg       0.88      0.88      0.88     36405
```




```
MAE: 4244
Confusion matrix is:
[[29448  4666]
 [ 2078   213]]
We have 29661 correct observations and 6744 misclassifications.
              precision    recall  f1-score   support

           0       0.93      0.86      0.90     34114
           1       0.04      0.09      0.06      2291

   micro avg       0.81      0.81      0.81     36405
   macro avg       0.49      0.48      0.48     36405
weighted avg       0.88      0.81      0.84     36405
```



MAE: 6744

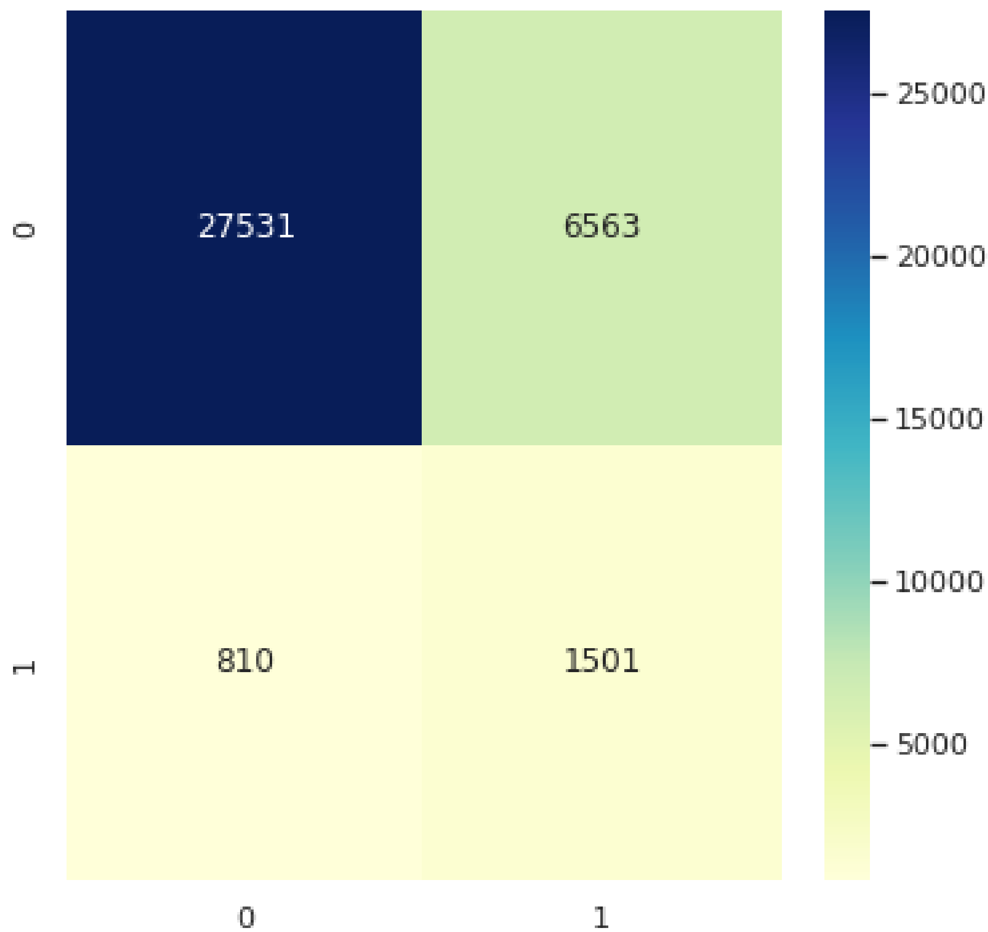



```
In [72]: def train_B_test(X,Y):
             L_NAME = ['lr','ada','knn','rforest']
             L_X, L_Y, L_YHAT, L_PROB = [],[],[],[]

             D = make_balanced(X,Y)
             X_B = D.drop(columns='Y')
             Y_B = D['Y']

             X_R = X.drop(D.index)
             Y_R = Y.drop(D.index)

             for i,cl in enumerate(C):

                 c = cl.fit(X_B,Y_B)
                 y_hat = c.predict(X_R)
                 probs = c.predict_proba(X_R)
                 print(L_NAME[i])
                 print('Test accuracy:',np.round(c.score(X_R, Y_R),3), ', Cross Entropy Loss
```

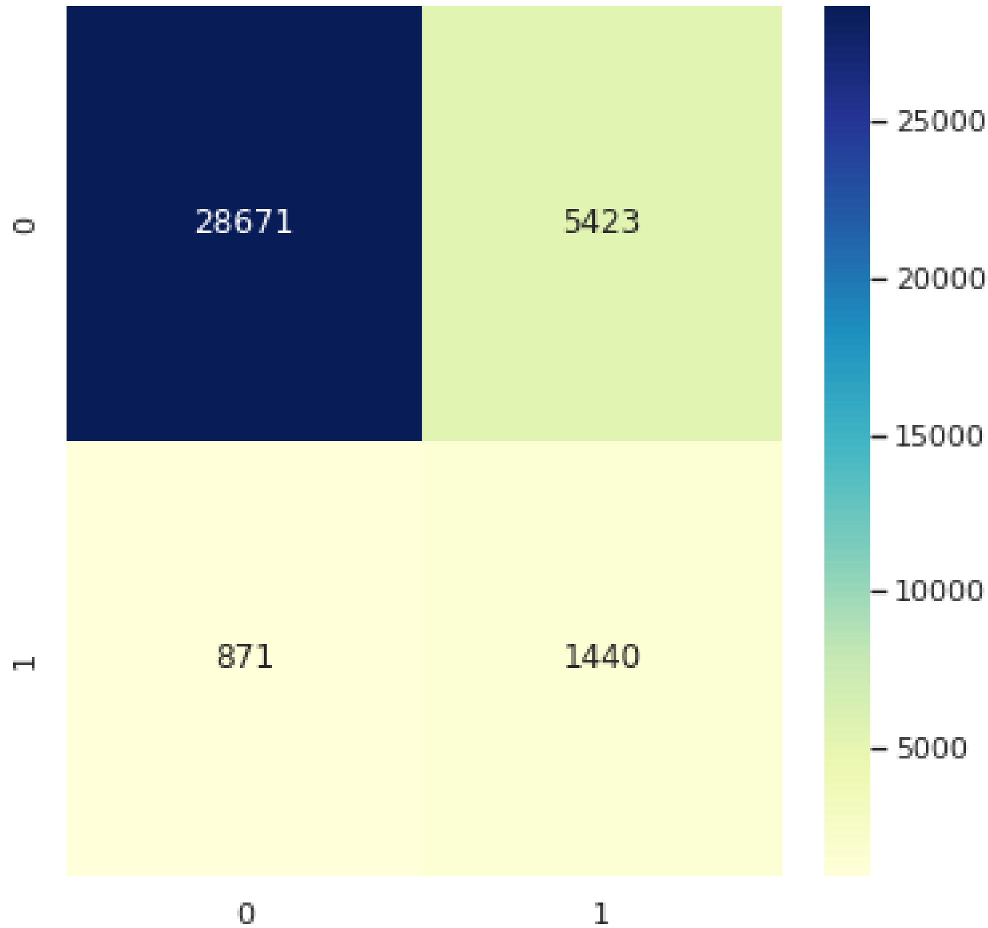
```
        is:', log_loss(Y_R,y_hat))
                calculate_metrics(Y_R,y_hat)
                MAE(Y_R,y_hat)

                L_X.append(X_R.values)
                L_Y.append(Y_R.values)
                L_YHAT.append(y_hat)
                L_PROB.append(probs)

            plot_ROC2(L_Y,L_X,L_YHAT,L_PROB,L_NAME)
```

```
In [73]: train_B_test(X,Y)
```

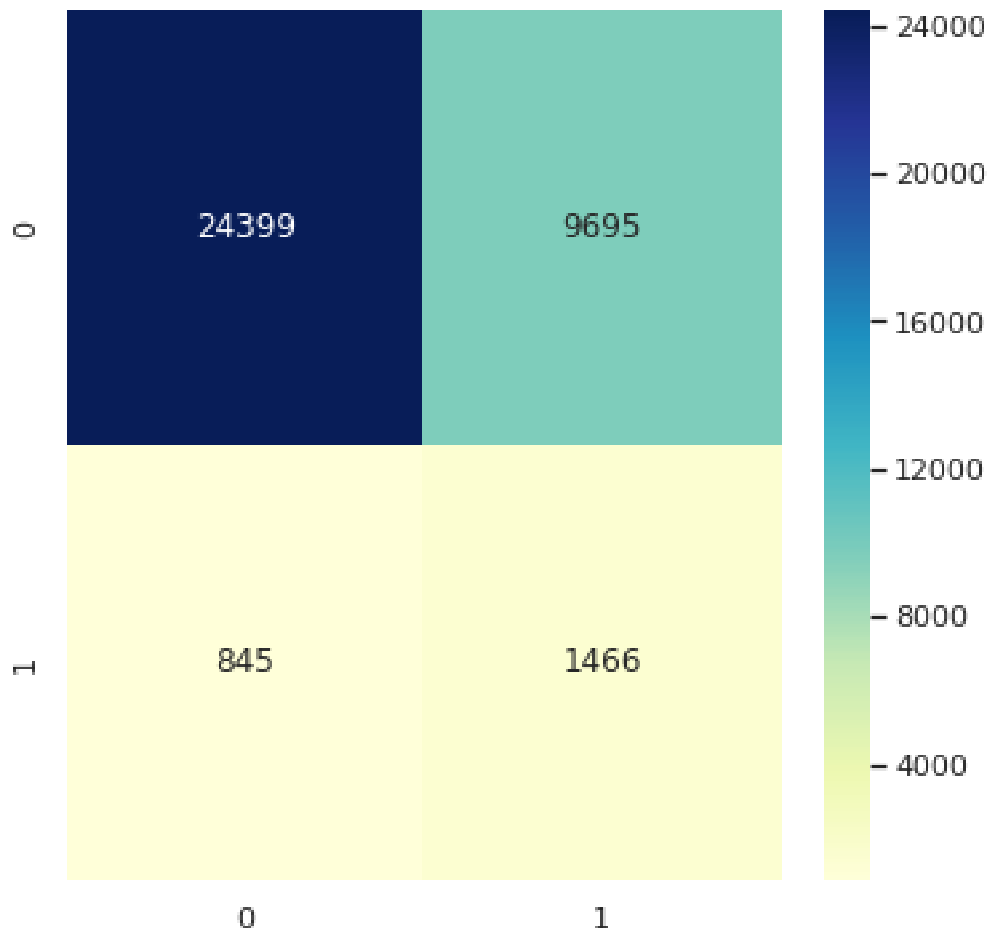
```
lr
Test accuracy: 0.797 , Cross Entropy Loss is: 6.995183247290505
Confusion matrix is:
[[27531  6563]
 [  810  1501]]
We have 29032 correct observations and 7373 misclassifications.
              precision    recall  f1-score   support

           0       0.97      0.81      0.88     34094
           1       0.19      0.65      0.29      2311

   micro avg       0.80      0.80      0.80     36405
   macro avg       0.58      0.73      0.59     36405
weighted avg       0.92      0.80      0.84     36405
```



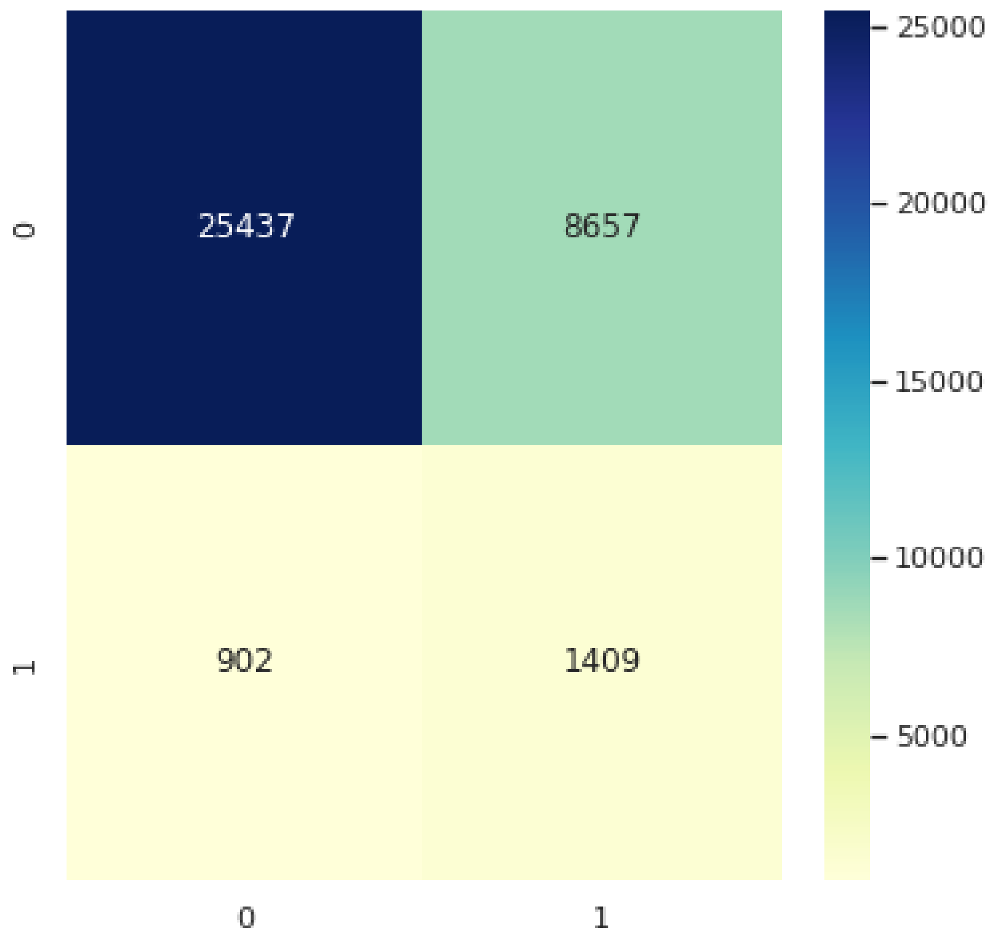

```
ada
Test accuracy: 0.827 , Cross Entropy Loss is: 5.971470810230238
Confusion matrix is:
[[28671  5423]
 [  871  1440]]
We have 30111 correct observations and 6294 misclassifications.
              precision    recall  f1-score   support

           0       0.97      0.84      0.90     34094
           1       0.21      0.62      0.31      2311

   micro avg       0.83      0.83      0.83     36405
   macro avg       0.59      0.73      0.61     36405
weighted avg       0.92      0.83      0.86     36405
```

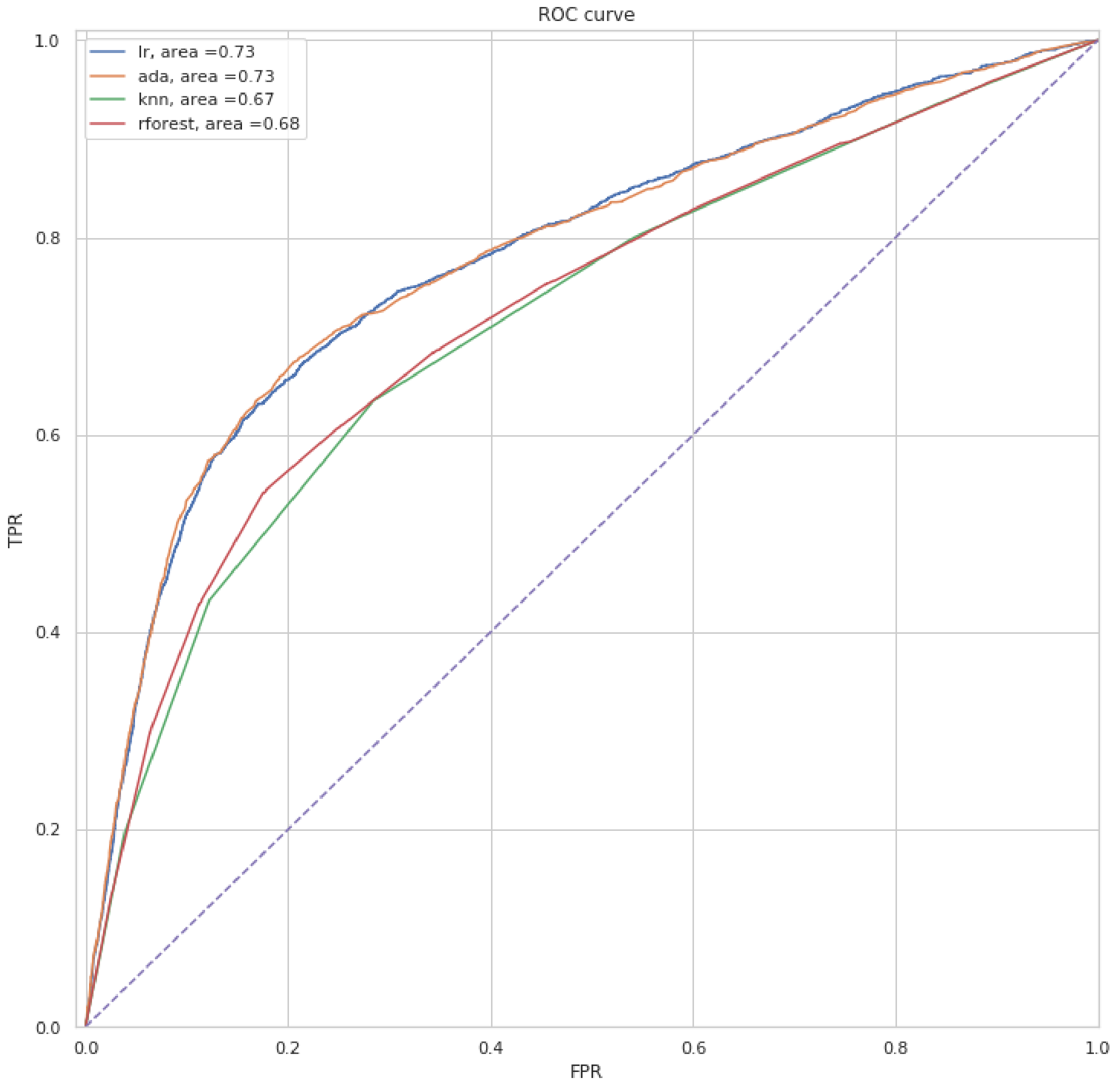



```
knn
Test accuracy: 0.71 , Cross Entropy Loss is: 9.999902631491398
Confusion matrix is:
[[24399  9695]
 [  845  1466]]
We have 25865 correct observations and 10540 misclassifications.
              precision    recall  f1-score   support

           0       0.97      0.72      0.82     34094
           1       0.13      0.63      0.22      2311

   micro avg       0.71      0.71      0.71     36405
   macro avg       0.55      0.67      0.52     36405
weighted avg       0.91      0.71      0.78     36405
```




```
rforest
Test accuracy: 0.737 , Cross Entropy Loss is: 9.069168676662667
Confusion matrix is:
[[25437  8657]
 [  902  1409]]
We have 26846 correct observations and 9559 misclassifications.
              precision    recall  f1-score   support

           0       0.97      0.75      0.84     34094
           1       0.14      0.61      0.23      2311

   micro avg       0.74      0.74      0.74     36405
   macro avg       0.55      0.68      0.53     36405
weighted avg       0.91      0.74      0.80     36405
```


25437
8657
902
1409
0
1
0
1
25000
20000
15000
10000
5000



VII Test Over/Under Sampling Methods

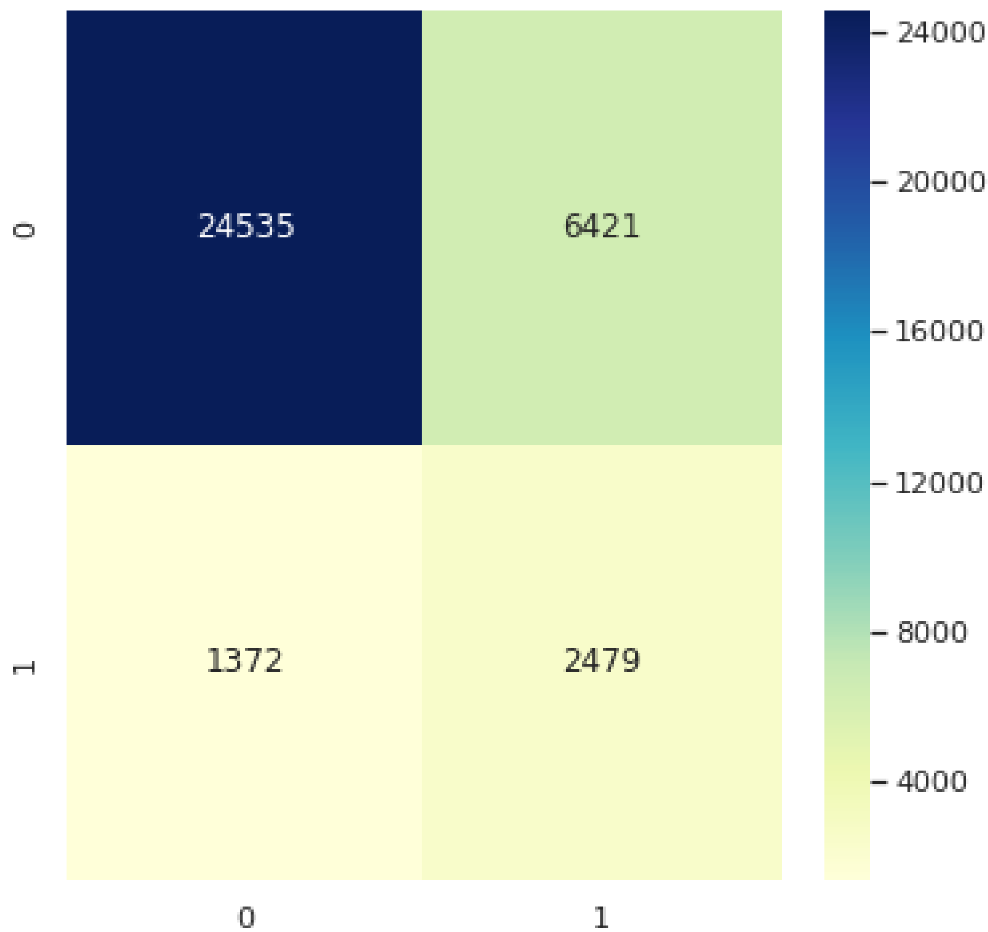
In [74]:
```
sns.set_style('whitegrid')
```

In [96]:
```
def calc_performance(c,name):

    classifier = [name, c]

    over_samplers = [
        #['ADA-SYN', ADASYN()],
        ['ROS', RandomOverSampler()],
        ['RUS', RandomUnderSampler()],
        #['SMOTENC', SMOTENC()],
        ['SMOTEENN', SMOTEENN()],
        ['ENN', EditedNearestNeighbours()],
    ]
```

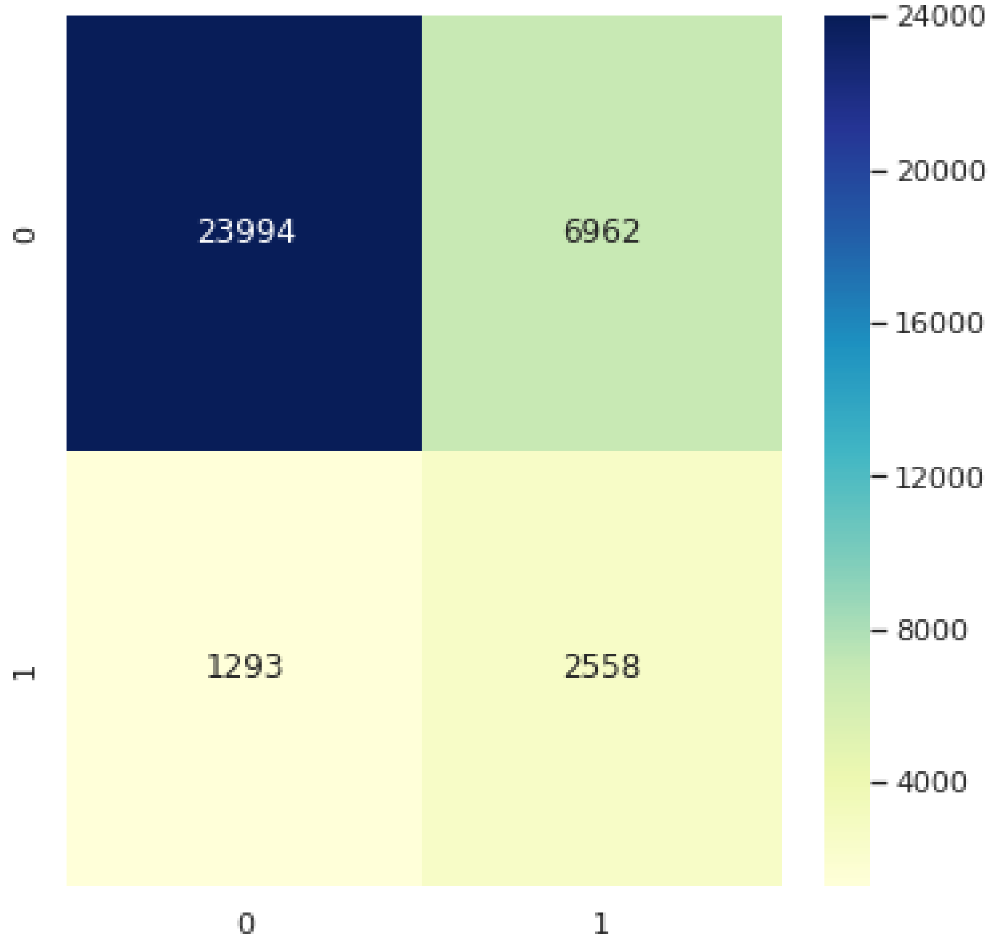
```
    pipelines = [
        ['{}-{}'.format(s[0], classifier[0]),
         make_pipeline(s[1], classifier[1])]
        for s in over_samplers
    ]


    calc_sampling(pipelines,X,Y)


def calc_sampling(pipelines,X,Y):
    L_NAME, L_X, L_Y, L_YHAT, L_PROB = [],[],[],[],[]

    X_train, X_test, Y_train, Y_test = train_test_split(X.values, Y.values,
test_size=0.85)
    for name, pipeline in pipelines:

        p = pipeline.fit(X_train,Y_train)
        y_hat = p.predict(X_test)
        probs = p.predict_proba(X_test)
        calculate_metrics(Y_test,y_hat)

        L_NAME.append(name)
        L_X.append(X_test)
        L_Y.append(Y_test)
        L_YHAT.append(y_hat)
        L_PROB.append(probs)

    plot_ROC2(L_Y,L_X,L_YHAT,L_PROB,L_NAME)
```

```
In [97]: NAME = ['LogisticRegression','AdaBoost','KNN','RForest']
         C_dict = dict(zip(NAME,C))

         for name,c in C_dict.items():
             calc_performance(c,name)
```

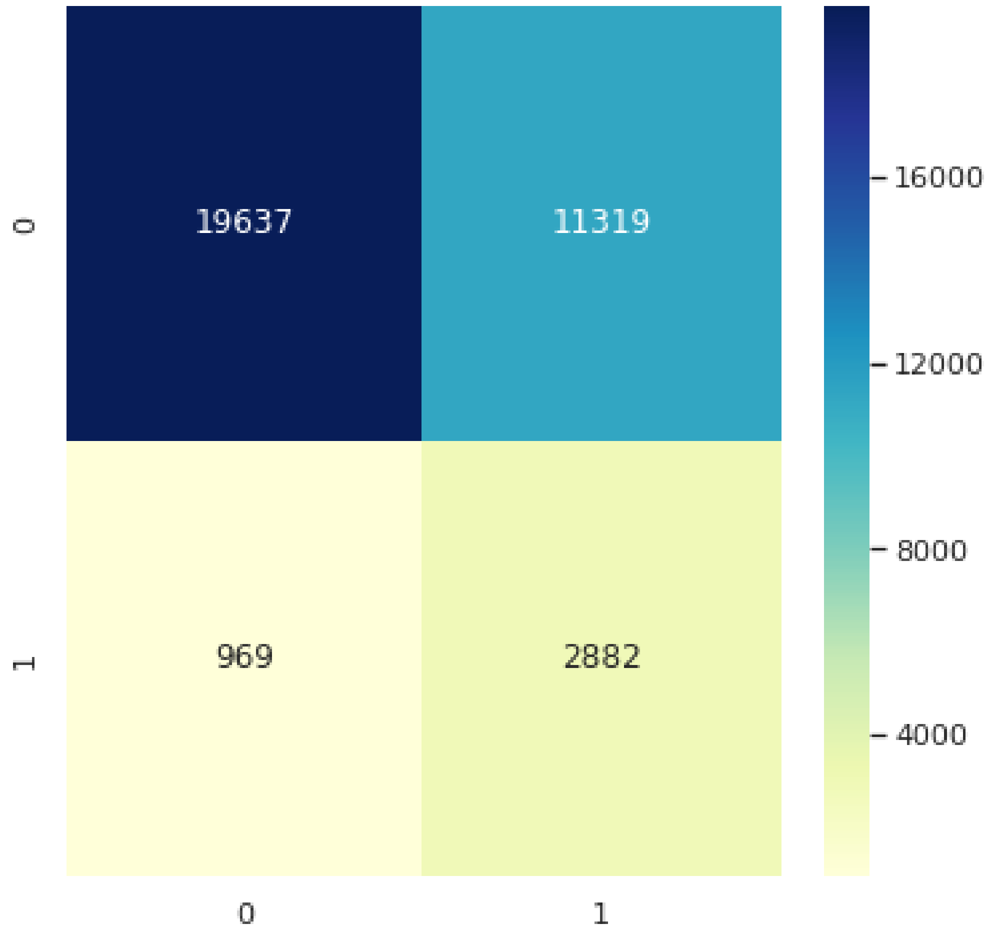
```
Confusion matrix is:
[[24535  6421]
 [ 1372  2479]]
We have 27014 correct observations and 7793 misclassifications.
              precision    recall  f1-score   support

           0       0.95      0.79      0.86     30956
           1       0.28      0.64      0.39      3851

   micro avg       0.78      0.78      0.78     34807
   macro avg       0.61      0.72      0.63     34807
weighted avg       0.87      0.78      0.81     34807
```



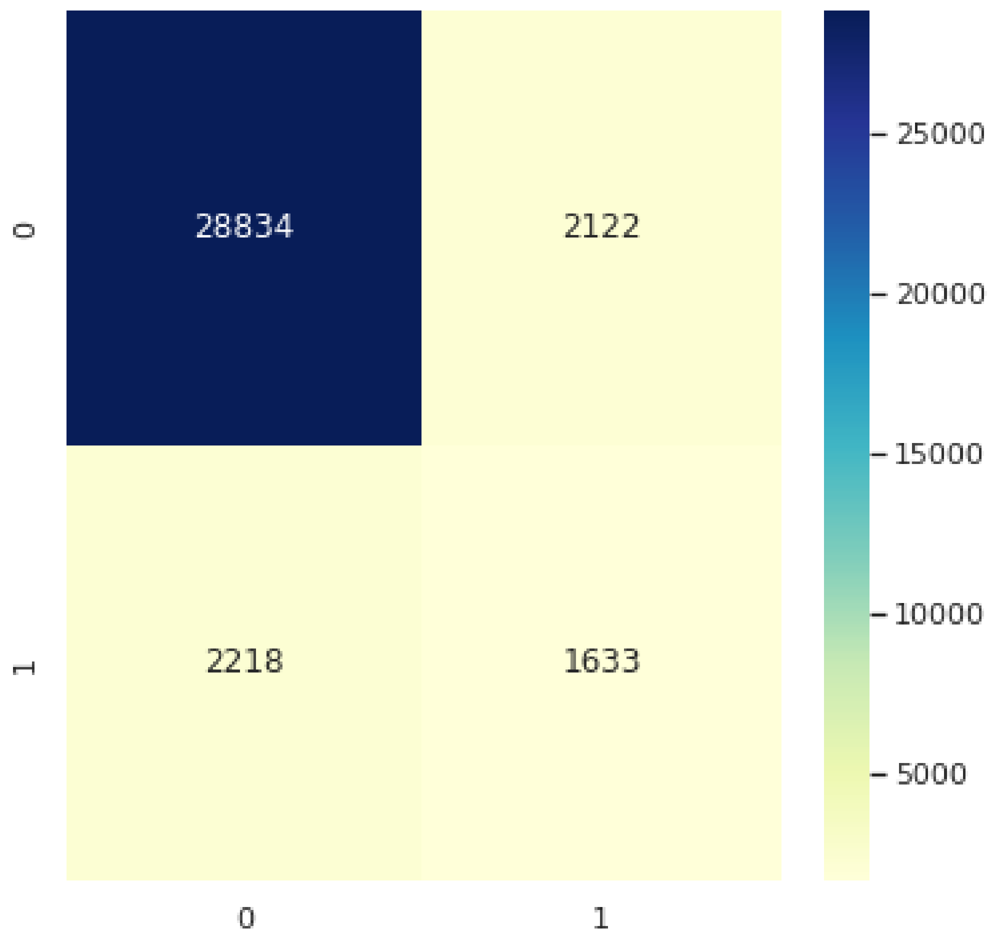

```
Confusion matrix is:
[[23994  6962]
 [ 1293  2558]]
We have 26552 correct observations and 8255 misclassifications.
              precision    recall  f1-score   support

           0       0.95      0.78      0.85     30956
           1       0.27      0.66      0.38      3851

   micro avg       0.76      0.76      0.76     34807
   macro avg       0.61      0.72      0.62     34807
weighted avg       0.87      0.76      0.80     34807
```



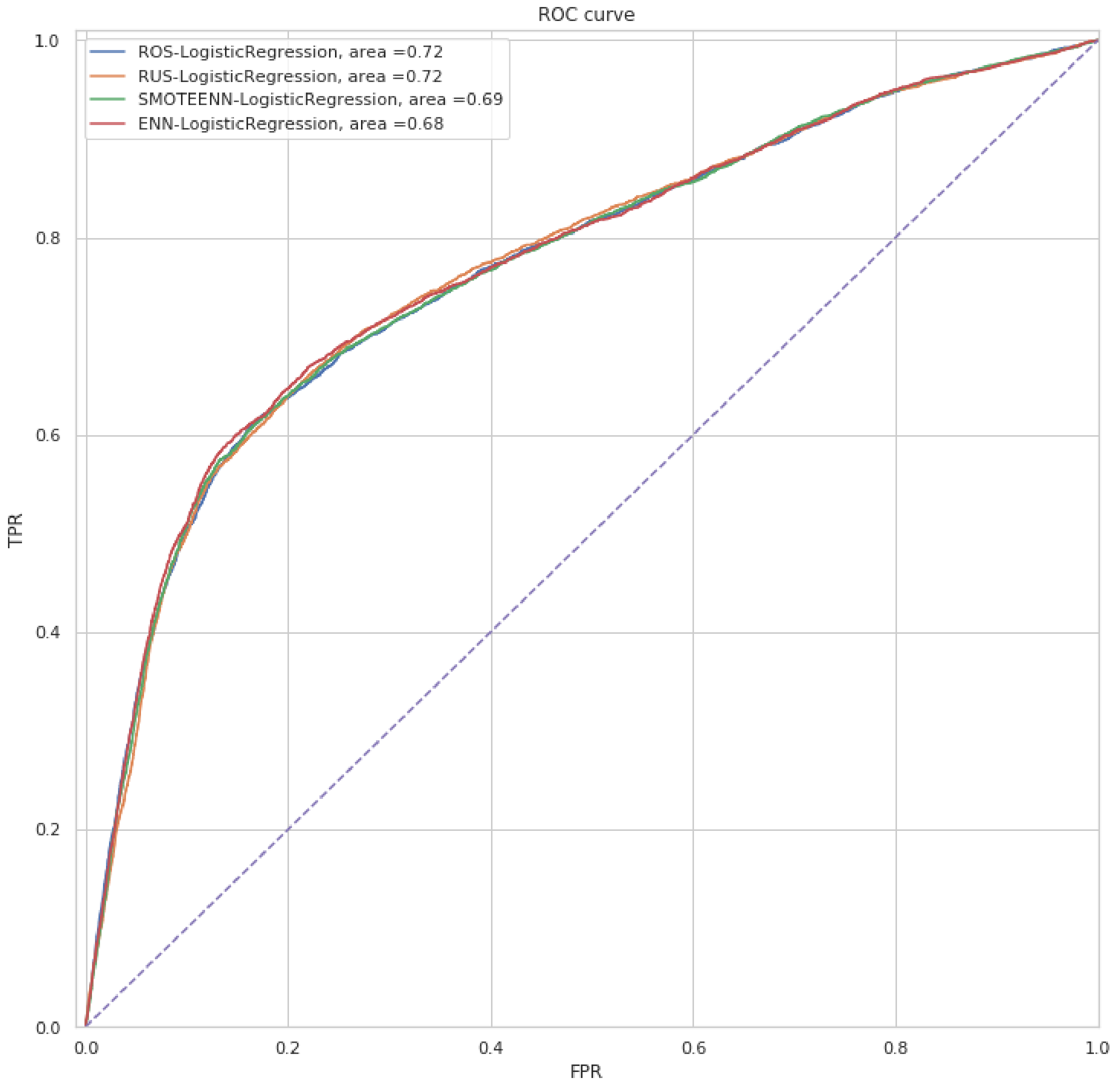

```
Confusion matrix is:
[[19637 11319]
 [  969  2882]]
We have 22519 correct observations and 12288 misclassifications.
              precision    recall  f1-score   support

           0       0.95      0.63      0.76     30956
           1       0.20      0.75      0.32      3851

   micro avg       0.65      0.65      0.65     34807
   macro avg       0.58      0.69      0.54     34807
weighted avg       0.87      0.65      0.71     34807
```



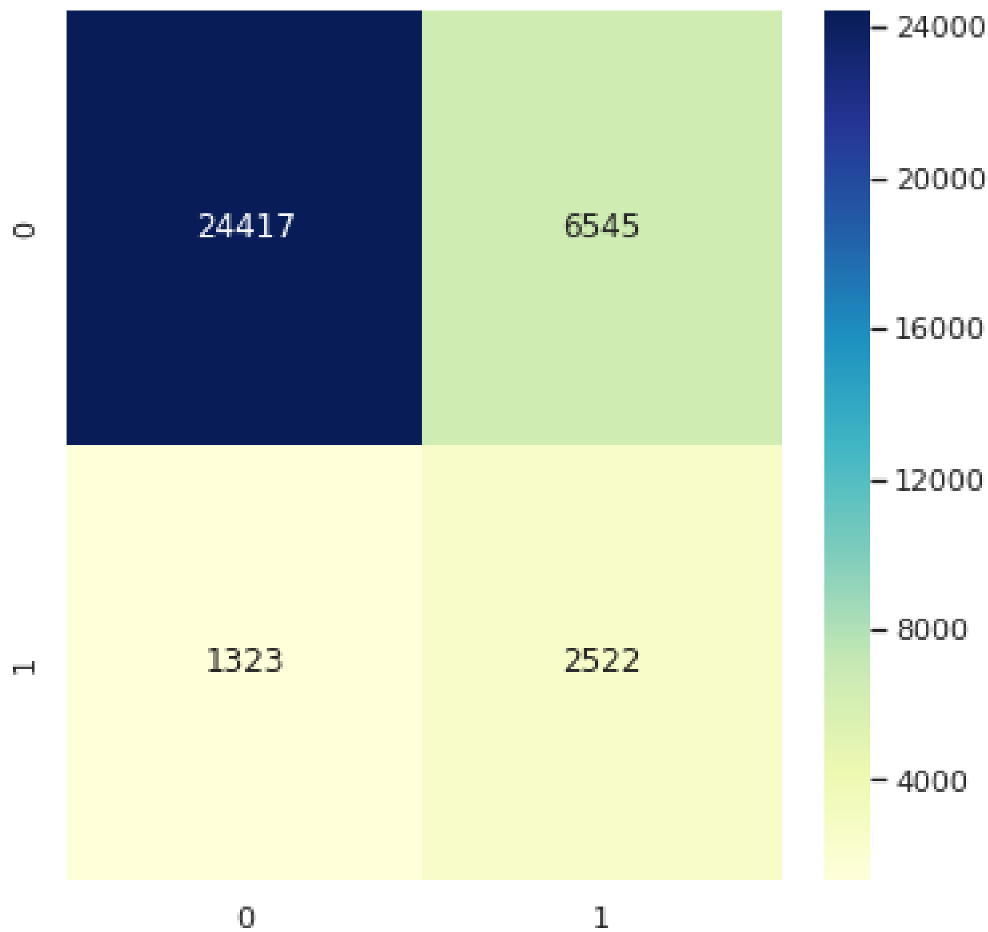

```
Confusion matrix is:
[[28834  2122]
 [ 2218  1633]]
We have 30467 correct observations and 4340 misclassifications.
              precision    recall  f1-score   support

           0       0.93      0.93      0.93     30956
           1       0.43      0.42      0.43      3851

   micro avg       0.88      0.88      0.88     34807
   macro avg       0.68      0.68      0.68     34807
weighted avg       0.87      0.88      0.87     34807
```



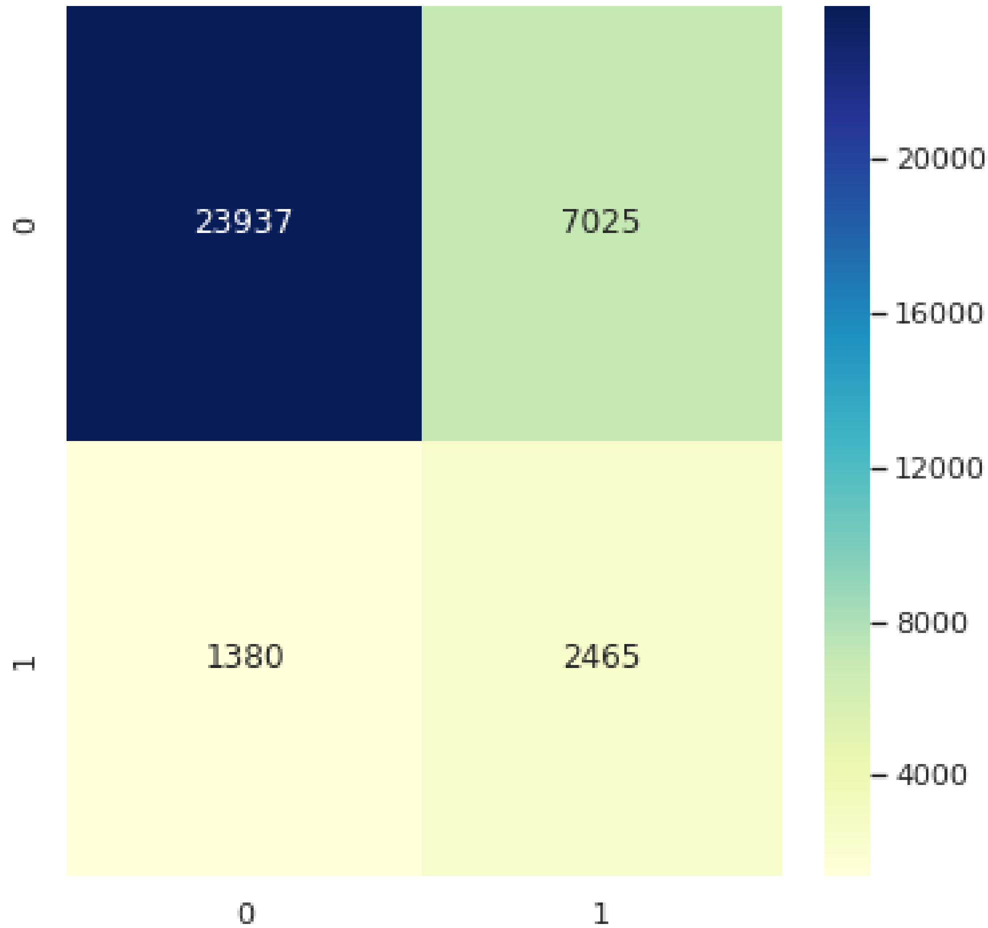
0
1
28834
2122
2218
1633
0
1
25000
20000
15000
10000
5000



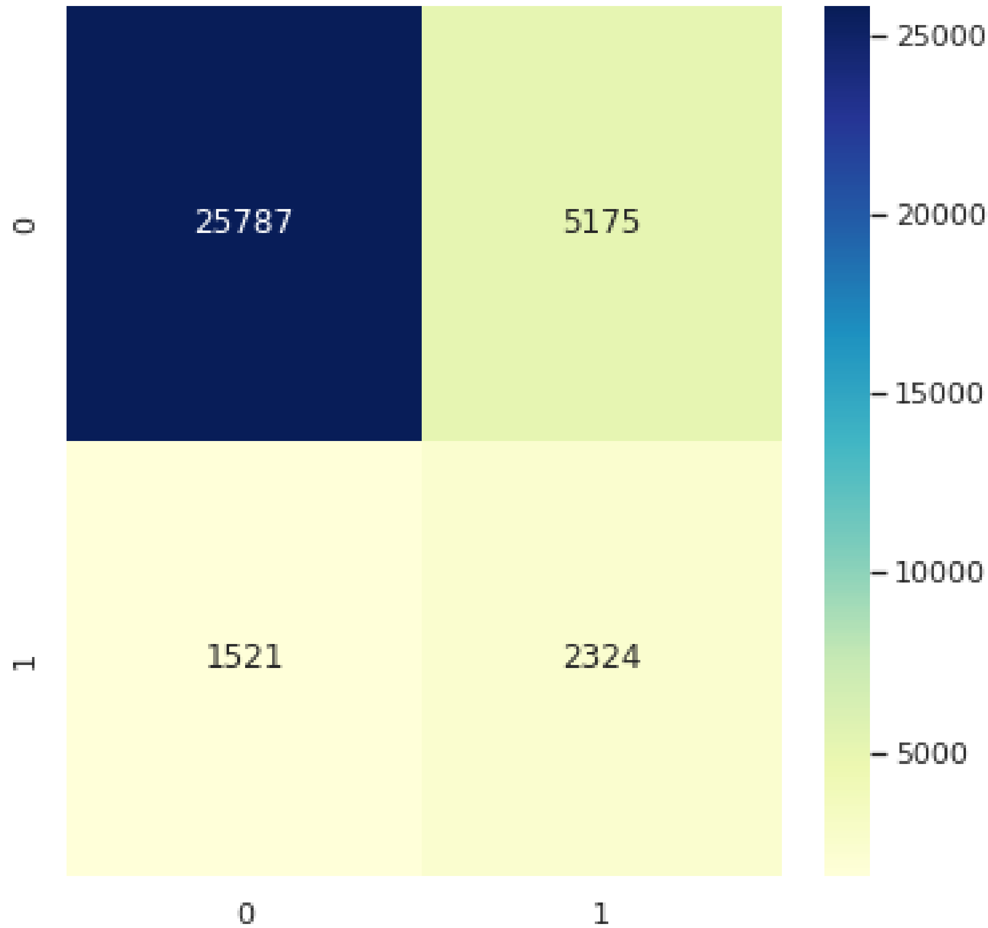

```
Confusion matrix is:
[[24417  6545]
 [ 1323  2522]]
We have 26939 correct observations and 7868 misclassifications.
              precision    recall  f1-score   support

           0       0.95      0.79      0.86     30962
           1       0.28      0.66      0.39      3845

   micro avg       0.77      0.77      0.77     34807
   macro avg       0.61      0.72      0.63     34807
weighted avg       0.87      0.77      0.81     34807
```



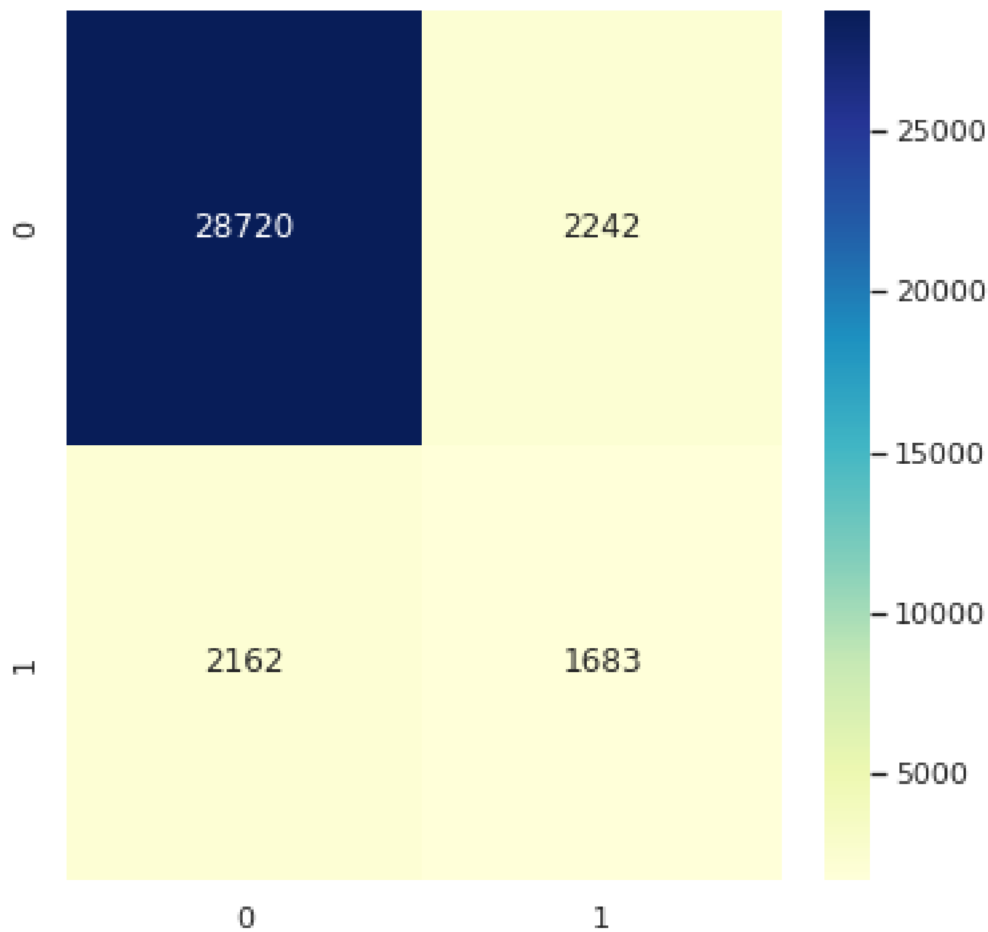

```
Confusion matrix is:
[[23937  7025]
 [ 1380  2465]]
We have 26402 correct observations and 8405 misclassifications.
              precision    recall  f1-score   support

           0       0.95      0.77      0.85     30962
           1       0.26      0.64      0.37      3845

   micro avg       0.76      0.76      0.76     34807
   macro avg       0.60      0.71      0.61     34807
weighted avg       0.87      0.76      0.80     34807
```

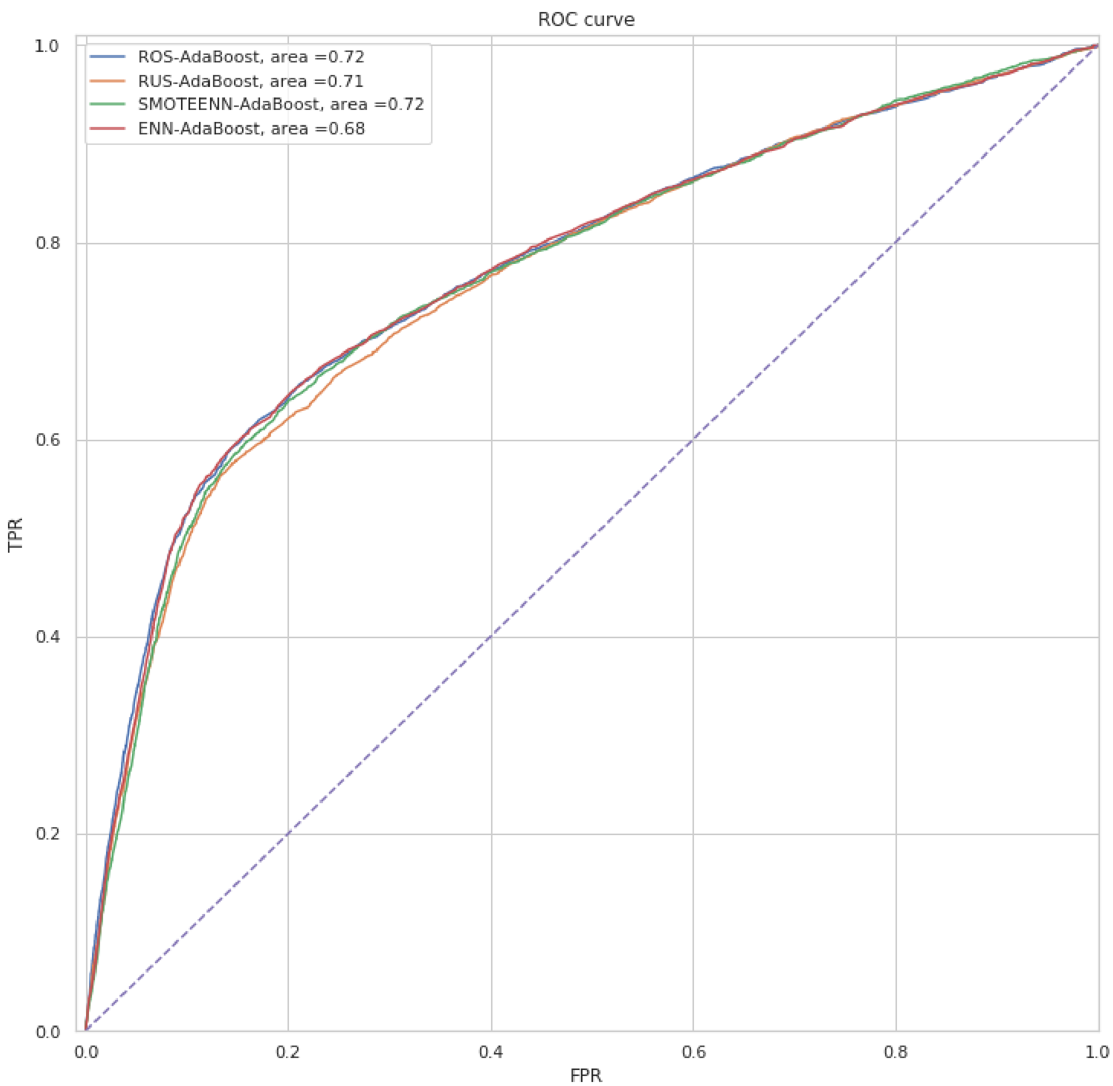



```
Confusion matrix is:
[[25787  5175]
 [ 1521  2324]]
We have 28111 correct observations and 6696 misclassifications.
              precision    recall  f1-score   support

           0       0.94      0.83      0.89     30962
           1       0.31      0.60      0.41      3845

   micro avg       0.81      0.81      0.81     34807
   macro avg       0.63      0.72      0.65     34807
weighted avg       0.87      0.81      0.83     34807
```

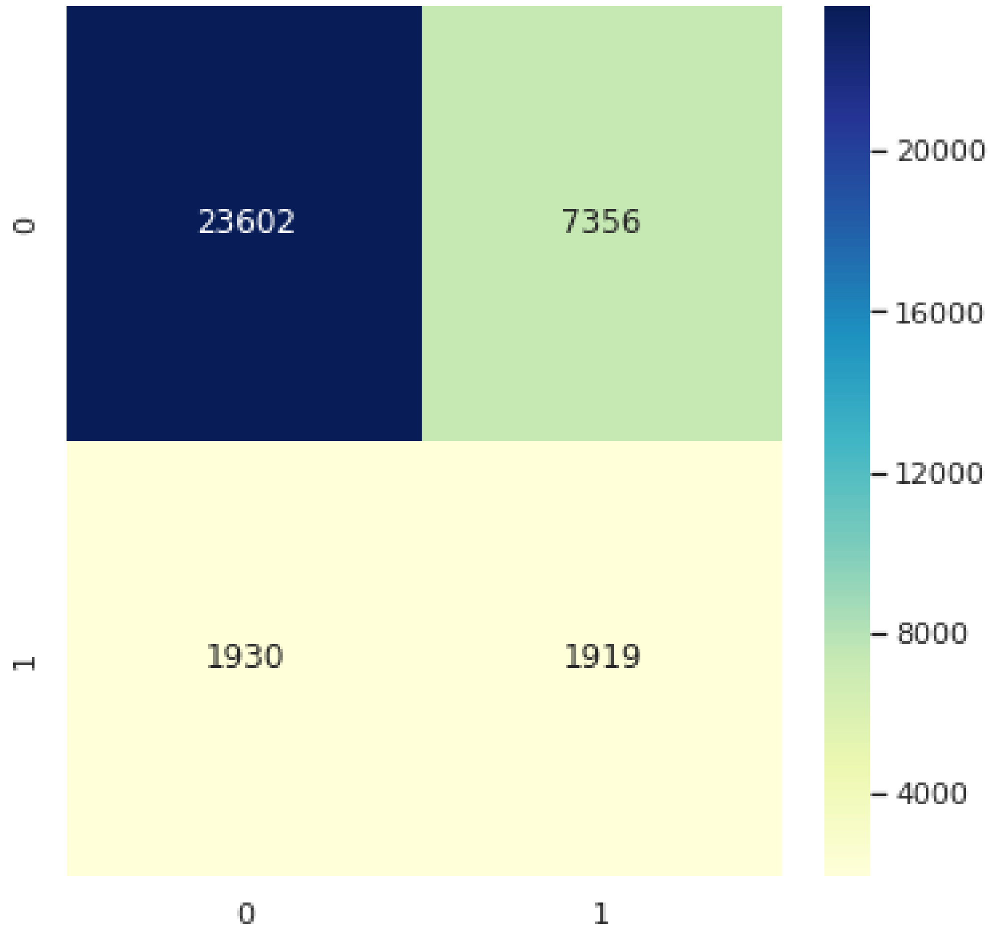



```
Confusion matrix is:
[[28720  2242]
 [ 2162  1683]]
We have 30403 correct observations and 4404 misclassifications.
              precision    recall  f1-score   support

           0       0.93      0.93      0.93     30962
           1       0.43      0.44      0.43      3845

   micro avg       0.87      0.87      0.87     34807
   macro avg       0.68      0.68      0.68     34807
weighted avg       0.87      0.87      0.87     34807
```

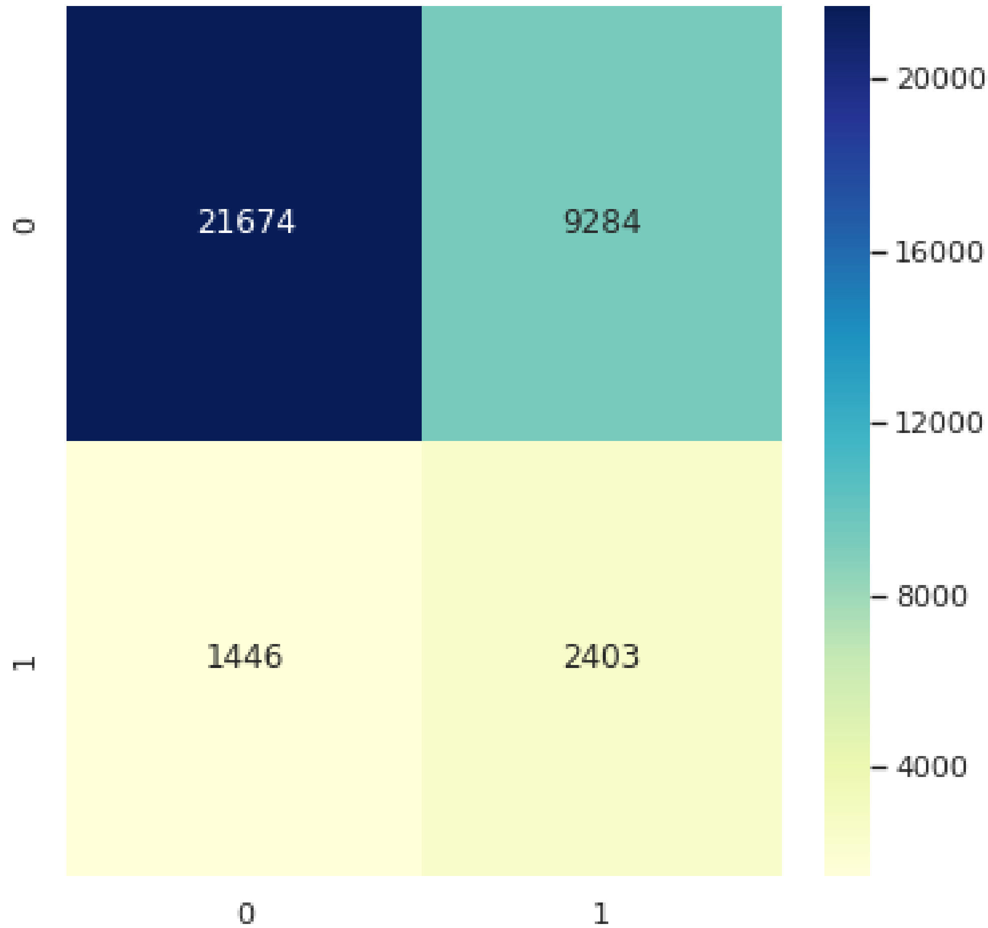

28720
2242
2162
1683
0
1
0
1
25000
20000
15000
10000
5000



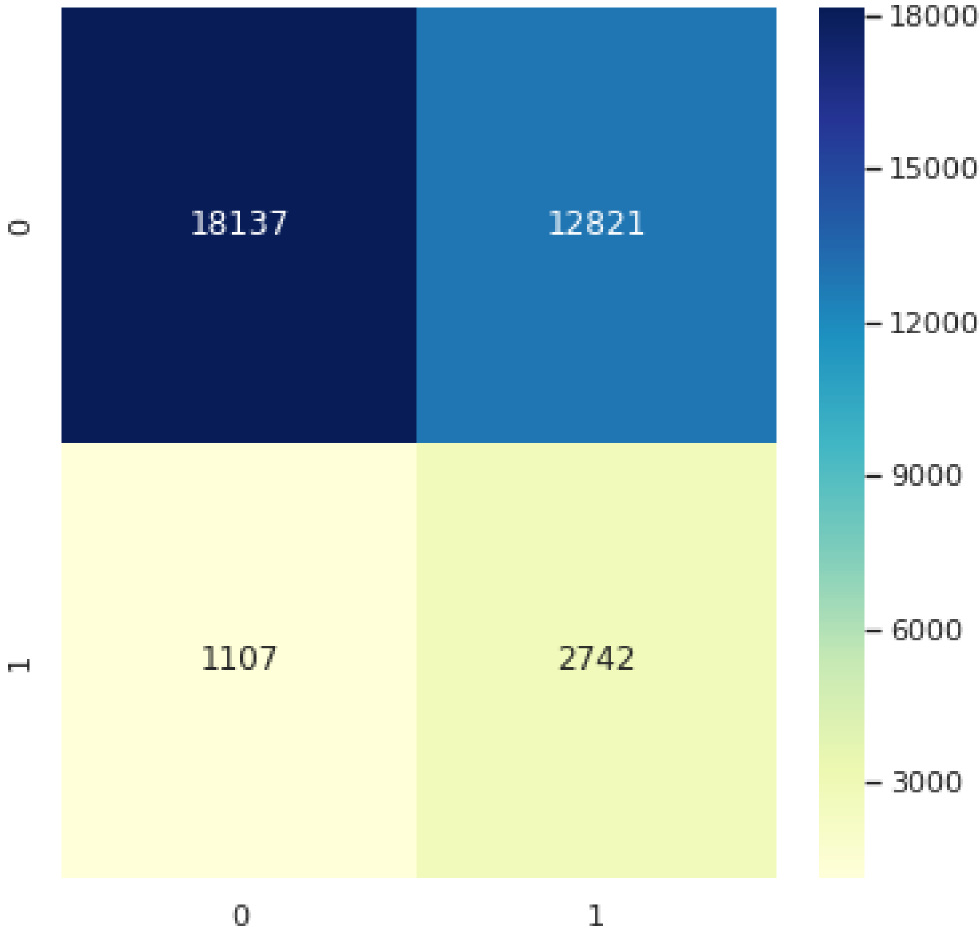

```
Confusion matrix is:
[[23602  7356]
 [ 1930  1919]]
We have 25521 correct observations and 9286 misclassifications.
              precision    recall  f1-score   support

           0       0.92      0.76      0.84     30958
           1       0.21      0.50      0.29      3849

   micro avg       0.73      0.73      0.73     34807
   macro avg       0.57      0.63      0.56     34807
weighted avg       0.85      0.73      0.78     34807
```



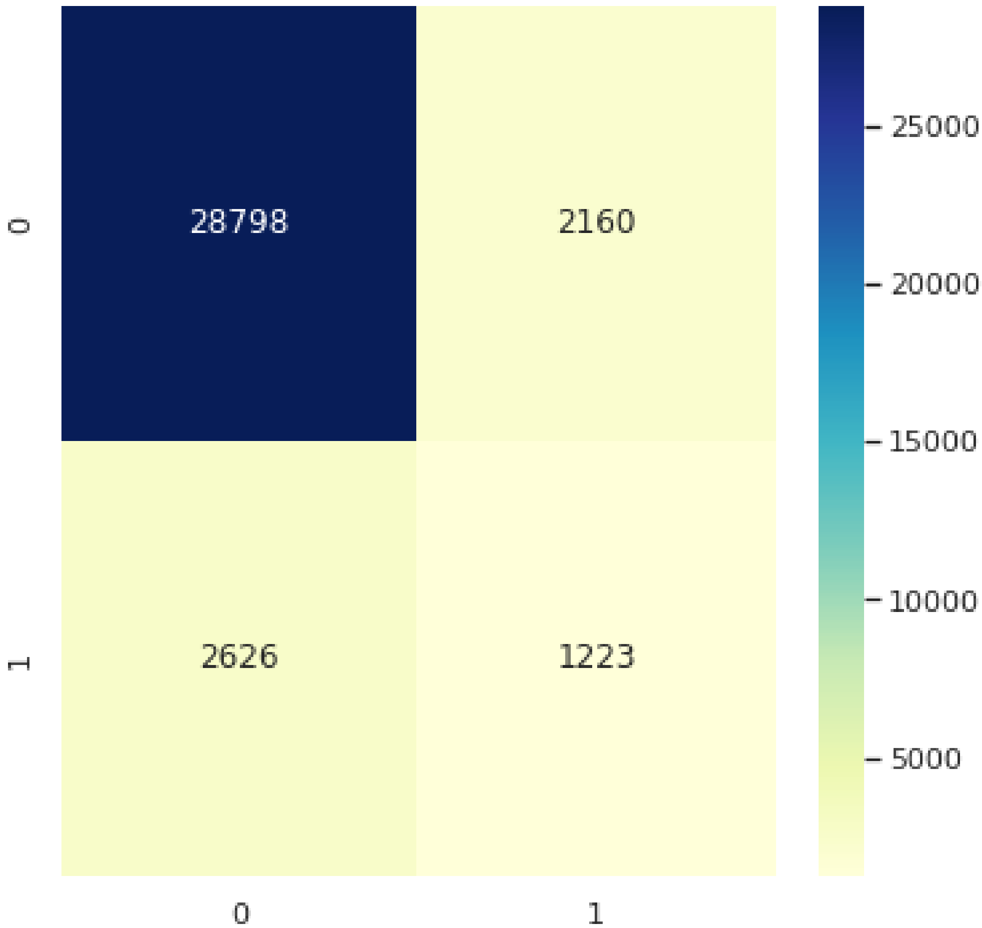

```
Confusion matrix is:
[[21674  9284]
 [ 1446  2403]]
We have 24077 correct observations and 10730 misclassifications.
              precision    recall  f1-score   support

           0       0.94      0.70      0.80     30958
           1       0.21      0.62      0.31      3849

   micro avg       0.69      0.69      0.69     34807
   macro avg       0.57      0.66      0.56     34807
weighted avg       0.86      0.69      0.75     34807
```



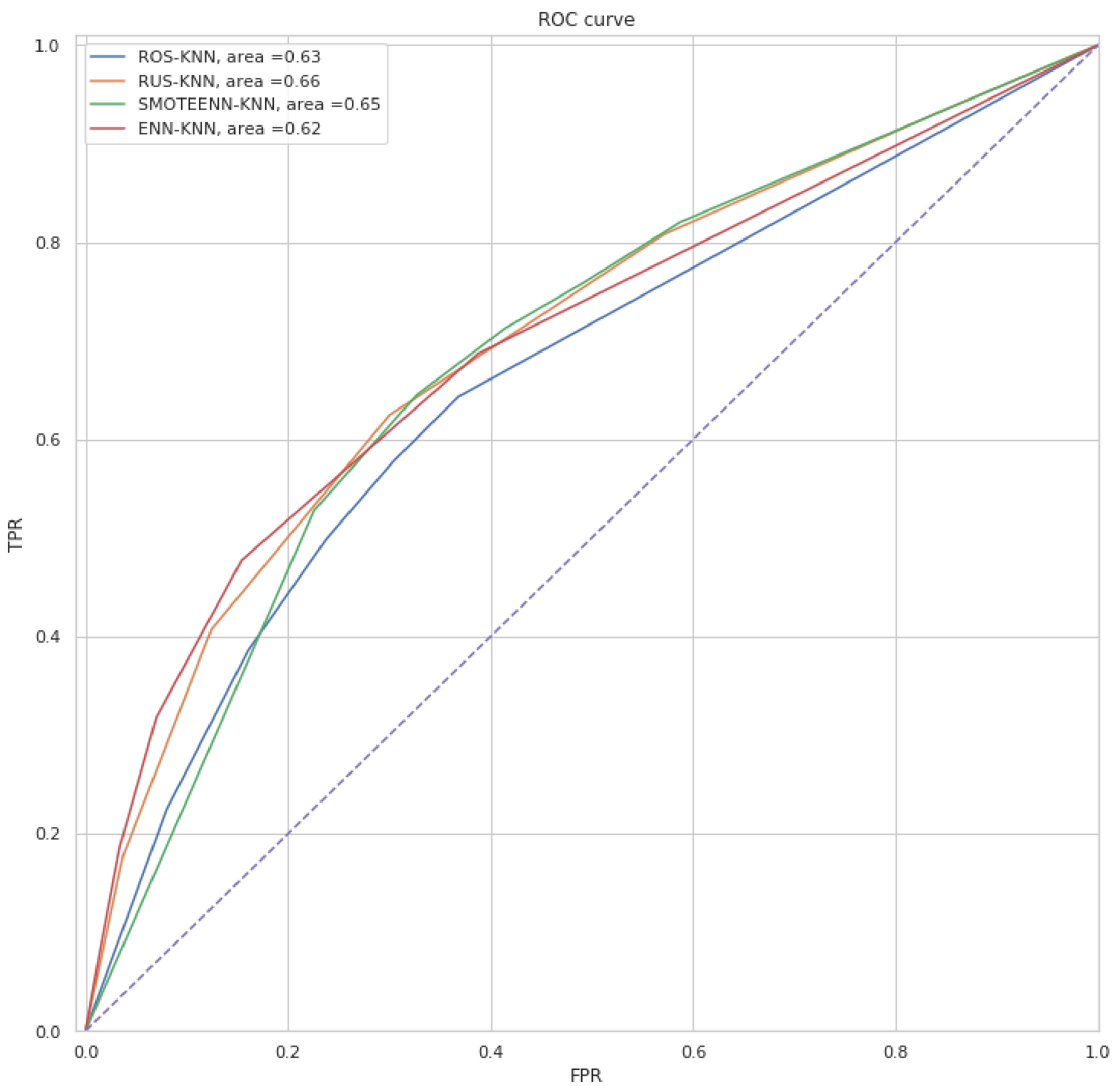

```
Confusion matrix is:
[[18137 12821]
 [ 1107  2742]]
We have 20879 correct observations and 13928 misclassifications.
              precision    recall  f1-score   support

           0       0.94      0.59      0.72     30958
           1       0.18      0.71      0.28      3849

   micro avg       0.60      0.60      0.60     34807
   macro avg       0.56      0.65      0.50     34807
weighted avg       0.86      0.60      0.67     34807
```



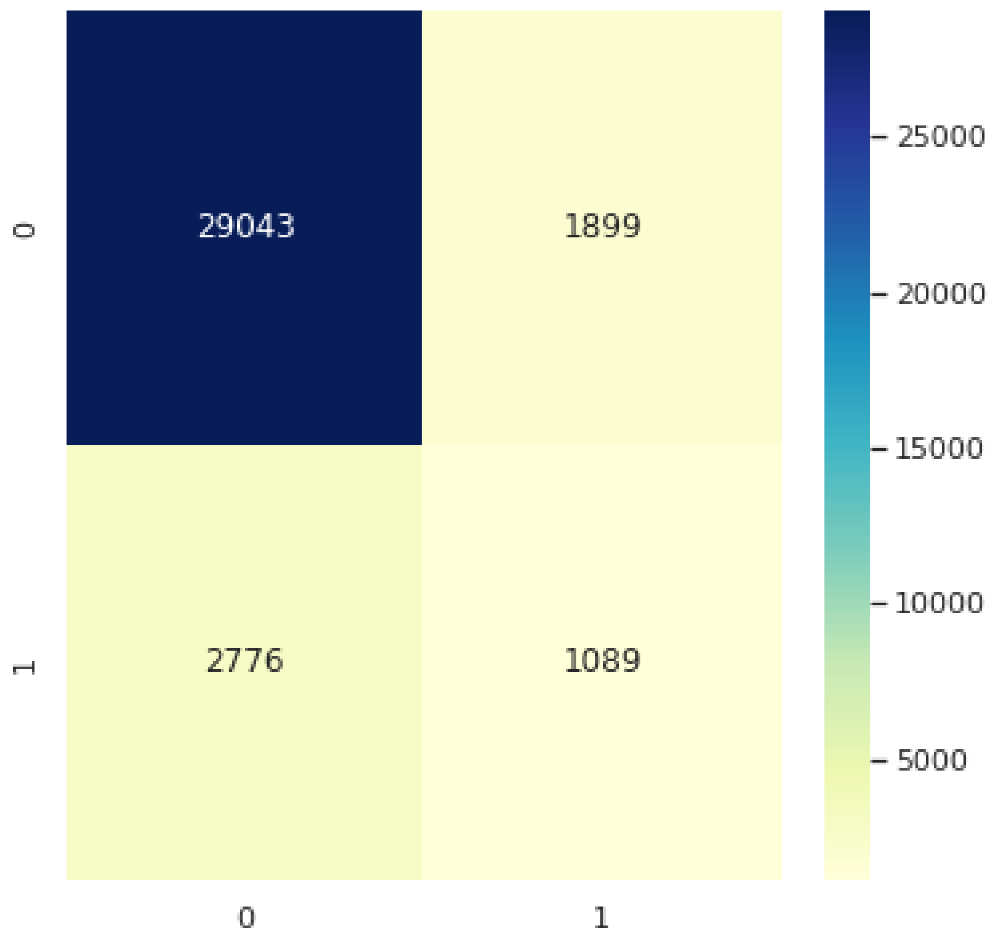

```
Confusion matrix is:
[[28798  2160]
 [ 2626  1223]]
We have 30021 correct observations and 4786 misclassifications.
              precision    recall  f1-score   support

           0       0.92      0.93      0.92     30958
           1       0.36      0.32      0.34      3849

   micro avg       0.86      0.86      0.86     34807
   macro avg       0.64      0.62      0.63     34807
weighted avg       0.86      0.86      0.86     34807
```



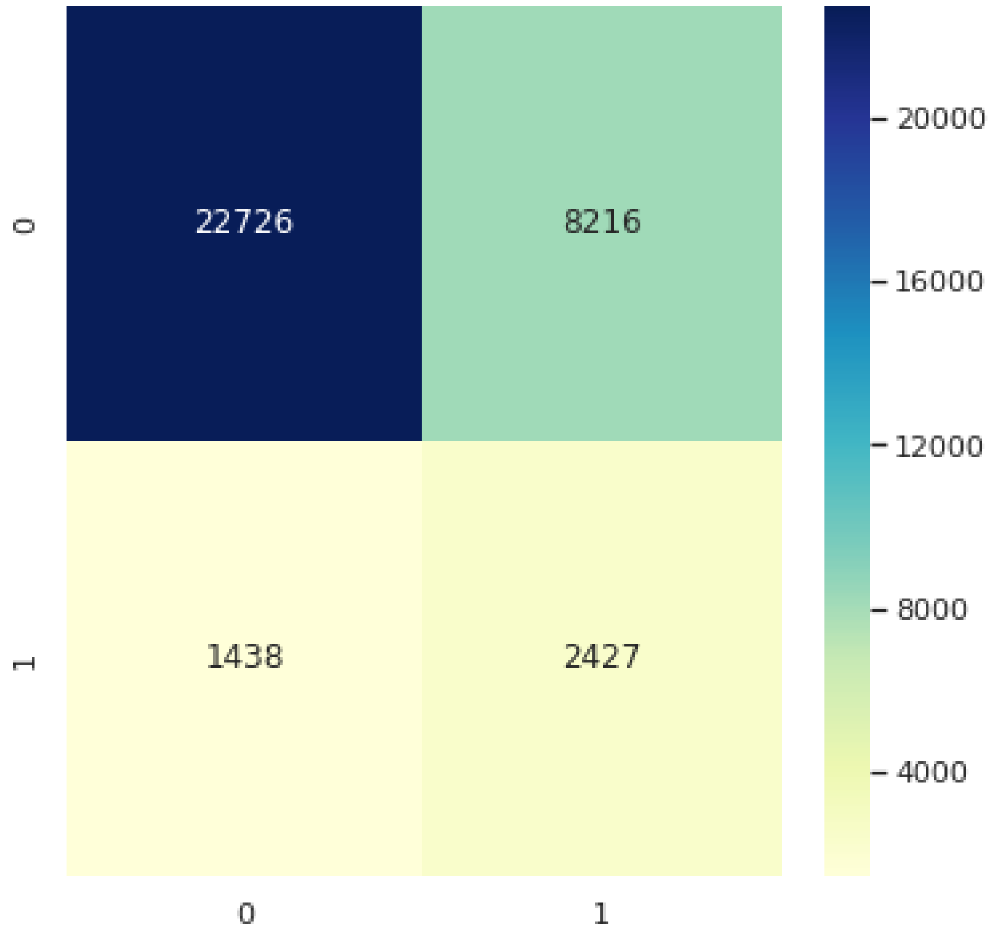
28798
2160
2626
1223
0
1
0
1
25000
20000
15000
10000
5000



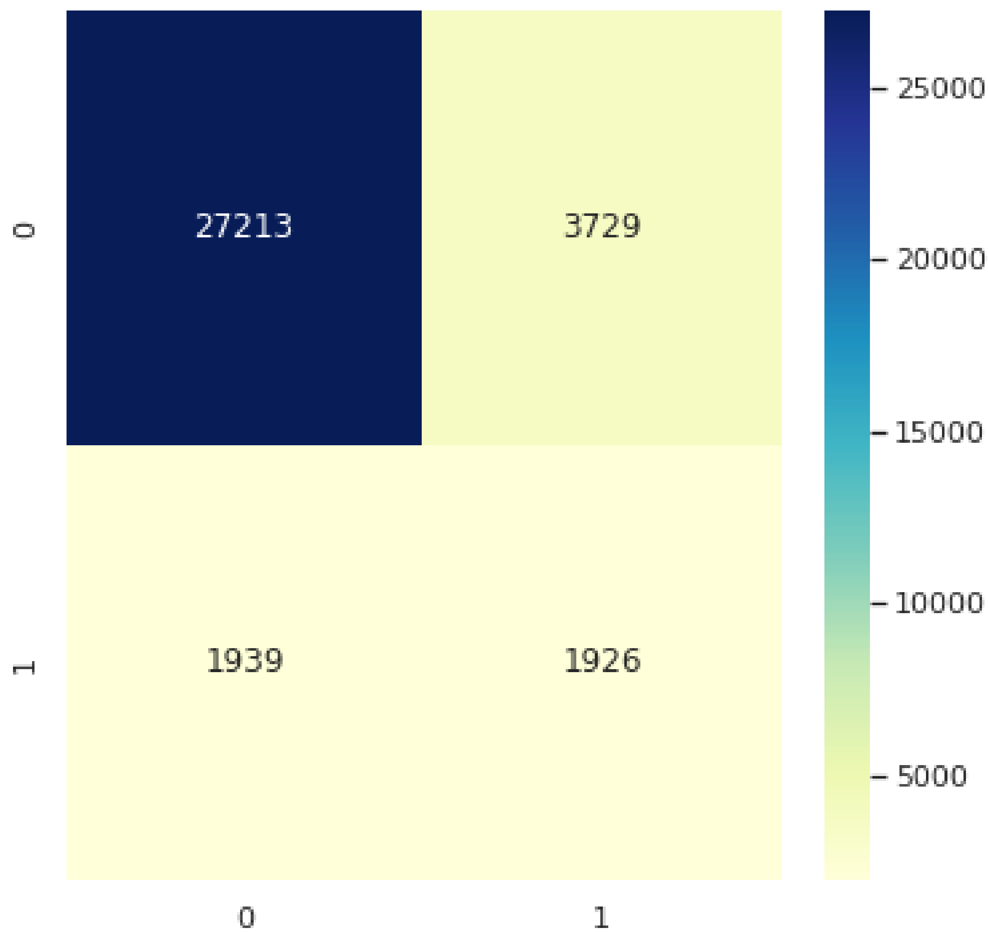

```
Confusion matrix is:
[[29043  1899]
 [ 2776  1089]]
We have 30132 correct observations and 4675 misclassifications.
              precision    recall  f1-score   support

           0       0.91      0.94      0.93     30942
           1       0.36      0.28      0.32      3865

   micro avg       0.87      0.87      0.87     34807
   macro avg       0.64      0.61      0.62     34807
weighted avg       0.85      0.87      0.86     34807
```



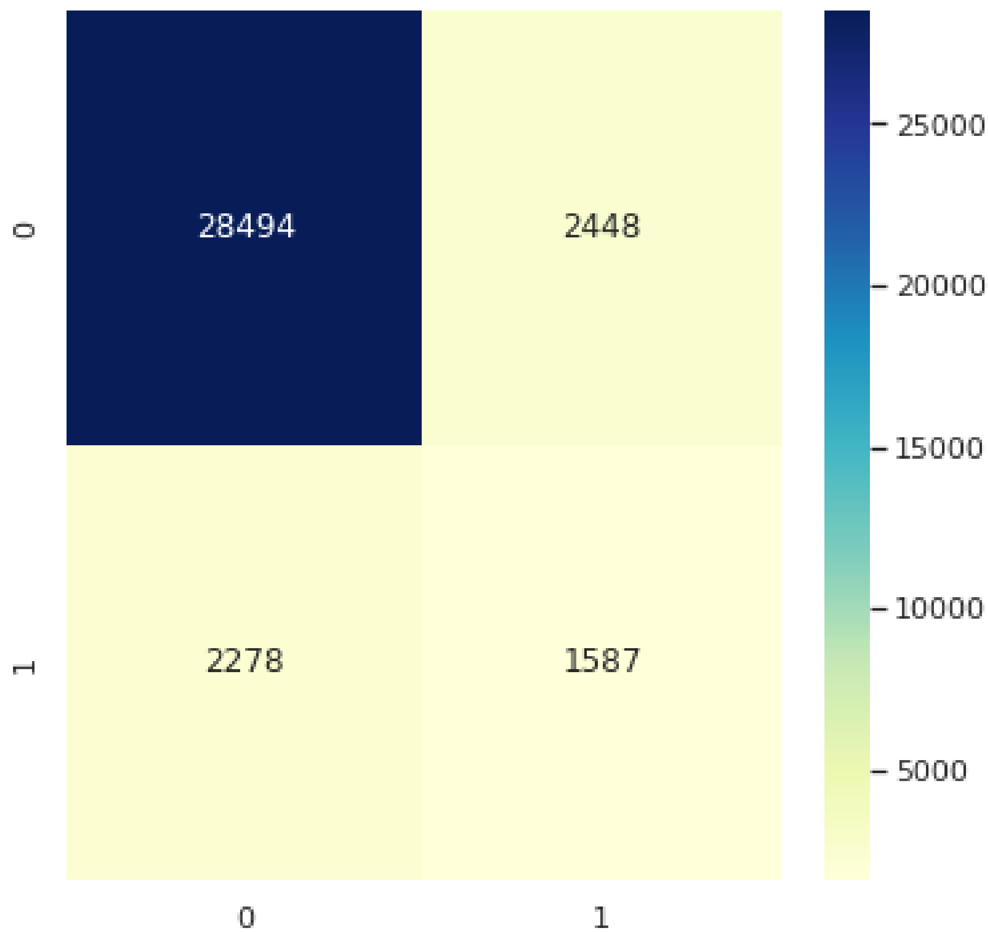

```
Confusion matrix is:
[[22726  8216]
 [ 1438  2427]]
We have 25153 correct observations and 9654 misclassifications.
              precision    recall  f1-score   support

           0       0.94      0.73      0.82     30942
           1       0.23      0.63      0.33      3865

   micro avg       0.72      0.72      0.72     34807
   macro avg       0.58      0.68      0.58     34807
weighted avg       0.86      0.72      0.77     34807
```

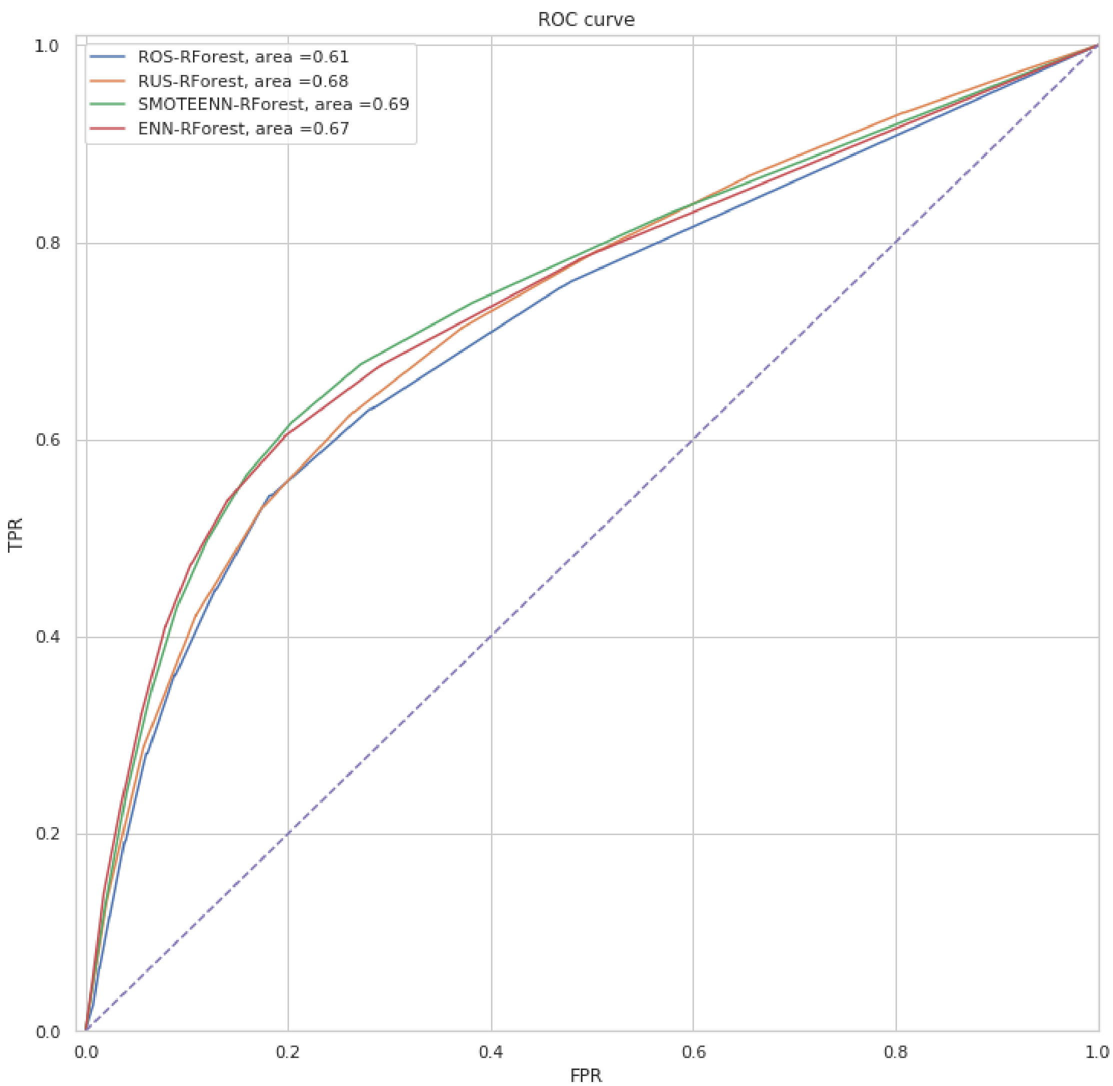



```
Confusion matrix is:
[[27213  3729]
 [ 1939  1926]]
We have 29139 correct observations and 5668 misclassifications.
              precision    recall  f1-score   support

           0       0.93      0.88      0.91     30942
           1       0.34      0.50      0.40      3865

   micro avg       0.84      0.84      0.84     34807
   macro avg       0.64      0.69      0.66     34807
weighted avg       0.87      0.84      0.85     34807
```




```
Confusion matrix is:
[[28494  2448]
 [ 2278  1587]]
We have 30081 correct observations and 4726 misclassifications.
              precision    recall  f1-score   support

           0       0.93      0.92      0.92     30942
           1       0.39      0.41      0.40      3865

   micro avg       0.86      0.86      0.86     34807
   macro avg       0.66      0.67      0.66     34807
weighted avg       0.87      0.86      0.87     34807
```


28494
2448
2278
1587
0
1
0
1
25000
20000
15000
10000
5000



VII selection of relevant variables from balanced dataset

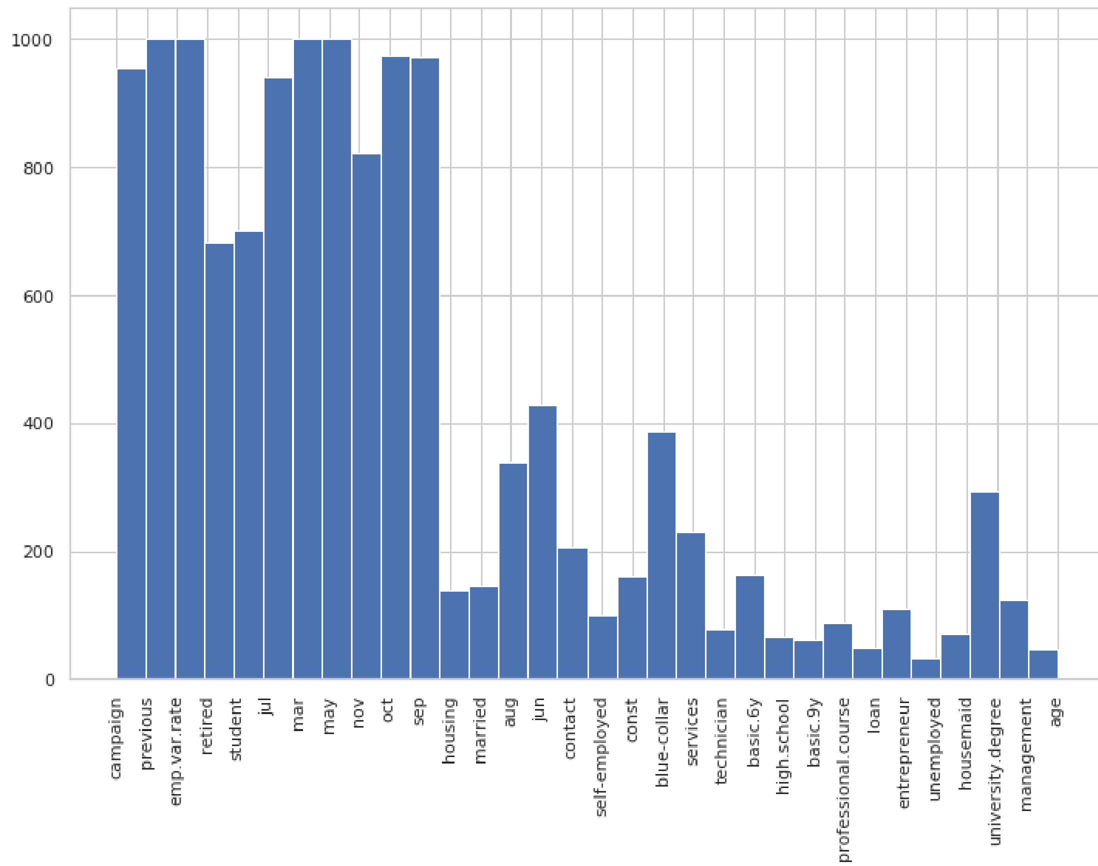
```
In [86]: L, Counts,Coeffs = [],[],[]
         for i in range(1000):
             D = make_balanced(X,Y)
             X_B = D.drop(columns='Y')
             Y_B = D['Y']

             X_B = sm.add_constant(X_B)

             logit = sm.Logit(Y_B, X_B).fit(disp=0)
             #display(logit.summary())

             alpha = 0.10
             a = logit.pvalues < alpha
```

```
            X4 = X_B[X_B.columns[a]]
            #print("Not Statistically significant regressors are:")
            temp = list(X_B.columns[a])
            L.append(temp)
            Counts.append(len(temp))
            Coeffs.append(logit.params.loc[temp])
```

In [ ]:

In [87]:
```
L = [y for x in L for y in x]
```

In [88]:
```
plt.figure(figsize=(12,8))
plt.hist(L,bins=len(set(L)))
plt.xticks(rotation=90)
plt.show()
```



In [89]:
```
from collections import Counter
d = Counter(L)

import operator
sorted_d = dict(sorted(d.items(), key=operator.itemgetter(1), reverse=True))
```

In [90]:
```
TopVars = []
print('Most frequently significant variables:')
for i, (k,v) in enumerate(sorted_d.items()):
    if v > 500:
```

```
                print(k, ':',v)
                TopVars.append(k)
```

```
Most frequently significant variables:
previous : 1000
emp.var.rate : 1000
mar : 1000
may : 1000
oct : 974
sep : 972
campaign : 954
jul : 940
nov : 822
student : 702
retired : 683
```

```
In [91]: V = []
         for v in TopVars:
             summ = 0
             count = 0
             for c in Coeffs:
                 try:
                     summ += c.loc[v]
                     count +=1
                 except KeyError:
                     pass
             V.append(summ/count)
```

```
In [92]: list(np.round(np.array(V),3))
```

```
Out[92]: [0.348, -0.481, 1.32, -0.601, 0.881, 0.88, -0.049, 0.495, -0.425, 0.578, 0.493]
```

```
In [93]: list(np.round(np.exp(np.array(V)),3))
```

```
Out[93]: [1.417, 0.618, 3.742, 0.548, 2.413, 2.412, 0.952, 1.641, 0.654, 1.782, 1.637]
```

```
In [ ]:
```