Classification Problem of Bank's Telemarketing Campaign: Project #3

- **Student name:** Natalia Edelson
- **Student pace:** Flex
- **Scheduled project review date/time:** 12/12/22
- **Instructor name:** Morgan Jones
- **Blog post URL:** https://medium.com/@nataliagoncharov/classification-problem-of-banks-telemarketing-campaign-project-3-79633e899e3

Importing Libraries

In [27]:

```
# Pandas and Matplotlib

import pandas as pd
import numpy as np
np.random.seed(0)
import seaborn as sns
import matplotlib.gridspec as gridspec
import matplotlib.pyplot as plt

#Sk-learn

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, f1_score, classifi
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import precision_score, recall_score, accuracy_score
from sklearn.metrics import f1_score, confusion_matrix
from sklearn.metrics import plot_confusion_matrix
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import auc, roc_curve, roc_auc_score, precision_recall_curv
from sklearn.model_selection import cross_val_score,KFold
from sklearn.metrics import f1_score,precision_score,recall_score, plot_confusio
from sklearn.metrics import plot_roc_curve,classification_report
import warnings
import random
from matplotlib import cm
from sklearn.model_selection import GridSearchCV
warnings.filterwarnings('ignore')
import time
import seaborn as sns
import seaborn
```

```
%matplotlib inline
from xgboost import XGBClassifier
from sklearn.model_selection import cross_validate
from sklearn.preprocessing import StandardScaler
import re
from sklearn.pipeline import Pipeline

from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.svm import SVC
from tqdm.notebook import tqdm
import warnings
warnings.filterwarnings('ignore')
```

Data Set - Variables Explanation

- `age` - age of the costumer (numeric)
- `job` type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')
- `marital` marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)
- `education` - (categorical:'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university
- `default` - has credit in default? (categorical: 'no','yes','unknown')
- `housing` has housing loan? (categorical: 'no','yes','unknown')
- `loan` - has personal loan? (categorical: 'no','yes','unknown')
- `contact` - contact communication type (categorical: 'cellular','telephone')
- `month` -last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')
- `day_of_week` -last contact day of the week (categorical: 'mon','tue','wed','thu','fri')
- `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.

- `campaign` -number of contacts performed during this campaign and for this client (numeric, includes last contact)

- `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)
- `previous` -number of contacts performed before this campaign and for this client (numeric)
- `poutcome` - outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')
- `emp.var.rate` - employment variation rate - quarterly indicator (numeric)
- `cons.price.idx` - consumer price index - monthly indicator (numeric)
- `cons.conf.idx` - consumer confidence index - monthly indicator (numeric)
- `uribor3m` - euribor 3 month rate - daily indicator (numeric)
- `nr.employed` - number of employees - quarterly indicator (numeric)
- `subscribed` - has the client subscribed a term deposit? (binary: 'yes','no')

In [28]:
```
# Upload the data and view it

df_bank = pd.read_excel('bank.xlsx')
df_bank.head()
```

Out[28]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon
1	57	services	married	high.school	unknown	no	no	telephone	may	mon
2	37	services	married	high.school	no	yes	no	telephone	may	mon
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon
4	56	services	married	high.school	no	no	yes	telephone	may	mon

5 rows × 21 columns

In [29]:
```
# Replace the name of the target variable from 'y' to 'subscribed' for clarity p

df_bank = df_bank.rename({'y': 'subscribed'}, axis=1)  # new method
```

In [30]:
```
# Check the overall data, data type, and number of entries. Spot null values.

df_bank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
```

```
 1   job             41188 non-null  object
 2   marital         41188 non-null  object
 3   education       41188 non-null  object
 4   default         41188 non-null  object
 5   housing         41188 non-null  object
 6   loan            41188 non-null  object
 7   contact         41188 non-null  object
 8   month           41188 non-null  object
 9   day_of_week     41188 non-null  object
 10  duration        41188 non-null  int64
 11  campaign        41188 non-null  int64
 12  pdays           41188 non-null  int64
 13  previous        41188 non-null  int64
 14  poutcome        41188 non-null  object
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  subscribed      41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

In [31]:
```
# Check the shape of the data 21 columns and 41,188 raws

df_bank.shape
```

Out[31]:
```
(41188, 21)
```

In [32]:
```
# List all the columns
df_bank.columns
```

Out[32]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'subscribed'],
      dtype='object')
```

Cleaning the Data

Checking for Null Values

In [33]:
```
# Using isnull method and sum it up
df_bank.isnull().sum()
```

Out[33]:
```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
```

```
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
subscribed        0
dtype: int64
```

In [34]:
```
# Checking for object values

cat_df = df_bank.select_dtypes('object')
cat_df.head()
```

Out[34]:

	job	marital	education	default	housing	loan	contact	month	day_of_week	pou
0	housemaid	married	basic.4y	no	no	no	telephone	may	mon	none
1	services	married	high.school	unknown	no	no	telephone	may	mon	none
2	services	married	high.school	no	yes	no	telephone	may	mon	none
3	admin.	married	basic.6y	no	no	no	telephone	may	mon	none
4	services	married	high.school	no	no	yes	telephone	may	mon	none

Unknown Values

There are many unknown values and here I break down the percentage of the unknown values to see which ones would be okay to remove from the data.

In [35]:
```
# Checking for the frequency of values of each column
for colname in cat_df.columns:
    try:
        print(colname, cat_df[colname].value_counts(normalize=True)[:10])
    except:
        print(colname, cat_df[colname].value_counts(normalize=True))

    print('\n')
```

```
job admin.           0.253035
blue-collar      0.224677
technician       0.163713
services         0.096363
management       0.070992
retired          0.041760
entrepreneur     0.035350
self-employed    0.034500
housemaid        0.025736
unemployed       0.024619
Name: job, dtype: float64


marital married     0.605225
single      0.280859
divorced    0.111974
unknown     0.001942
Name: marital, dtype: float64


education university.degree      0.295426
```

```
high.school            0.231014
basic.9y               0.146766
professional.course    0.127294
basic.4y               0.101389
basic.6y               0.055647
unknown                0.042027
illiterate             0.000437
Name: education, dtype: float64


default no         0.791201
unknown    0.208726
yes        0.000073
Name: default, dtype: float64


housing yes        0.523842
no         0.452122
unknown    0.024036
Name: housing, dtype: float64


loan no         0.824269
yes        0.151695
unknown    0.024036
Name: loan, dtype: float64


contact cellular     0.634748
telephone    0.365252
Name: contact, dtype: float64


month may    0.334296
jul    0.174177
aug    0.149995
jun    0.129115
nov    0.099568
apr    0.063902
oct    0.017432
sep    0.013839
mar    0.013256
dec    0.004419
Name: month, dtype: float64


day_of_week thu    0.209357
mon    0.206711
wed    0.197485
tue    0.196416
fri    0.190031
Name: day_of_week, dtype: float64


poutcome nonexistent    0.863431
failure        0.103234
success        0.033335
Name: poutcome, dtype: float64


subscribed no     0.887346
yes    0.112654
Name: subscribed, dtype: float64
```

marital

**unknown 0.001942

education

**unknown 0.042027

default

**unknown 0.208726

housing yes

**unknown 0.024036

loan

**unknown 0.024036

In [36]:
```
# The unkown values replaced with None and then dropped
unknown_col = ['job','marital', 'education', 'loan', 'housing']

for col in unknown_col:
    df_bank[col] = df_bank[col].replace('unknown', None)
    #df_bank[col] = df_bank[col].fillna(df[col].mode())
    df_bank.dropna(axis=0, subset=[col], inplace = True)
```

Handling Duplicates

In [37]:
```
# Check for duplicates
df_bank.duplicated().sum()
```

Out[37]: 12

In [38]:
```
# Remove dupicates
df_bank = df_bank.drop_duplicates()
```

In [39]:
```
# Doble check for duplicates

df_bank.duplicated().sum()
```

Out[39]: 0

Exploratory Data Analysis

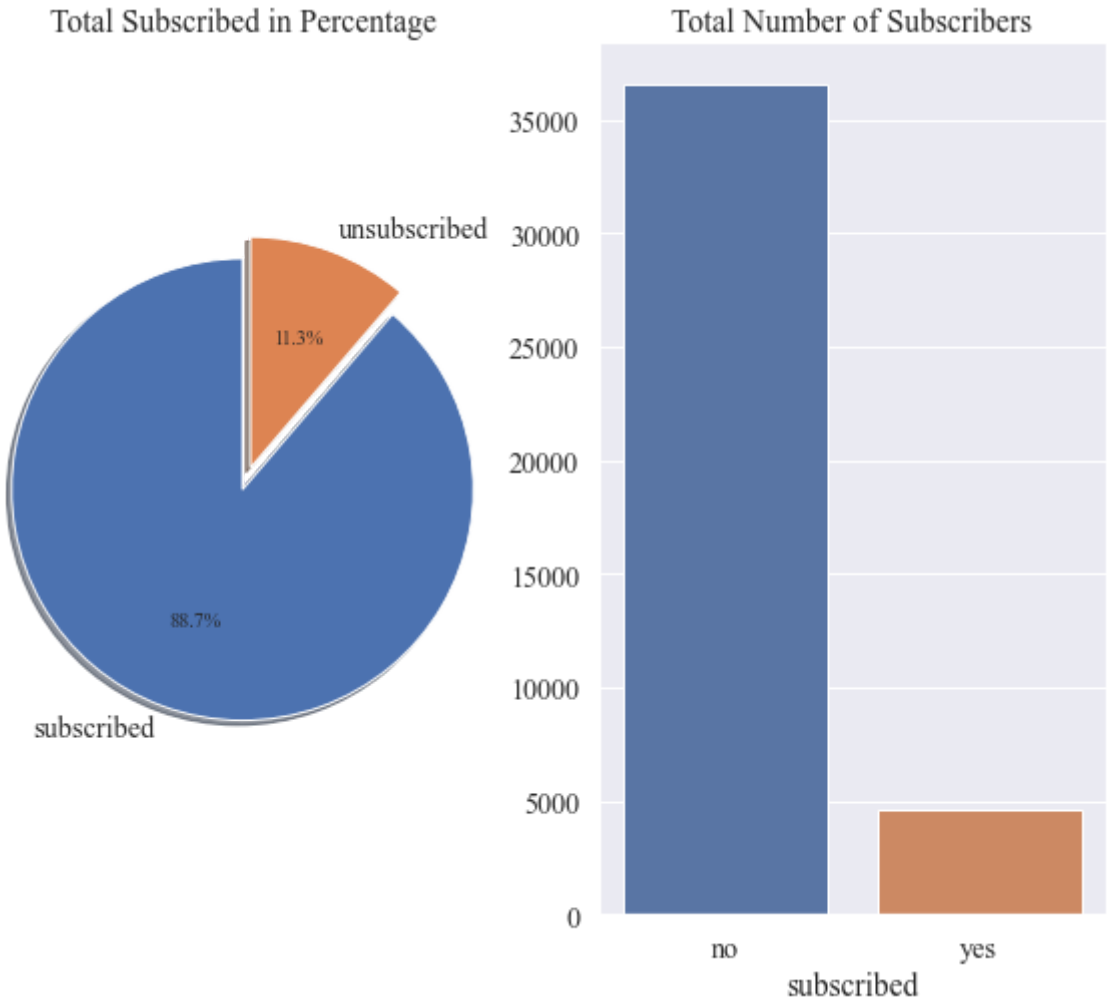
Checking if the data is balanced

In [40]:

```
# Plot the target variables in order to examine whether the data is imbalanced.

subscribe_vc = df_bank['subscribed'].value_counts()
subscribe_vc
```

Out[40]:
```
no     36537
yes     4639
Name: subscribed, dtype: int64
```

In [41]:
```
# Pie chart, where the slices will be ordered and plotted counter-clockwise:
# Reference: https://matplotlib.org/stable/gallery/pie_and_polar_charts/pie_feat

labels = 'subscribed', 'unsubscribed'
sizes = df_bank['subscribed'].value_counts()
explode = (0, 0.1)  # only "explode" the 2nd slice

fig, ax = plt.subplots(1,2,figsize=(10,8))


ax[0].pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%',
        shadow=True, startangle=90)
ax[0].axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
ax[0].set_title('Total Subscribed in Percentage', fontname='Times New Roman')


sns.countplot('subscribed', data=df_bank, ax=ax[1])

ax[1].set_title('Total Number of Subscribers', fontname='Times New Roman')
ax[1].set_ylabel('')

plt.show()
```



The data is imbalanced - only 11.3% costumes subscribed to the bank campaign. Later on, when we build the model, it will need to be dealt with. Most models can't produce proper results when the data is imbalanced.

In [42]:
```
# Check the distribution of data type


print("Data types and their frequency\n{}".format(df_bank.dtypes.value_counts()))
```

```
Data types and their frequency
object     11
int64       5
float64     5
dtype: int64
```

In [43]:
```
# Check balance of target data

df_bank['subscribed'].value_counts()
```

Out[43]:
```
no     36537
yes     4639
Name: subscribed, dtype: int64
```

In [44]:
```
# Check for unique values for all the columns

df_bank.nunique()
```

Out[44]:
```
age                78
job                11
marital             3
education           7
default             3
housing             2
loan                2
contact             2
month              10
day_of_week         5
duration         1544
campaign           42
pdays              27
previous            8
poutcome            3
emp.var.rate       10
cons.price.idx     26
cons.conf.idx      26
euribor3m         316
nr.employed        11
subscribed          2
dtype: int64
```

Exploring Continiuous Variables

In [45]:
```
# Checking the distribution for the categorical variables c

df_bank.describe()
```

Out[45]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons
count	41176.00000	41176.000000	41176.000000	41176.000000	41176.000000	41176.000000	411
mean	40.02380	258.315815	2.567879	962.464810	0.173013	0.081922	
std	10.42068	259.305321	2.770318	186.937102	0.494964	1.570883	
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	

Correlation

In [46]:
```
# Create a function that captures the numerical variables.

numerical_var = [feature for feature in df_bank.columns if ((df_bank[feature].dt
print('Number of continuous variables: ', len(numerical_var))

# visualise the numerical variables
df_bank_num = df_bank[numerical_var].head()


df_bank_num
```

```
Number of continuous variables:  10
```

Out[46]:

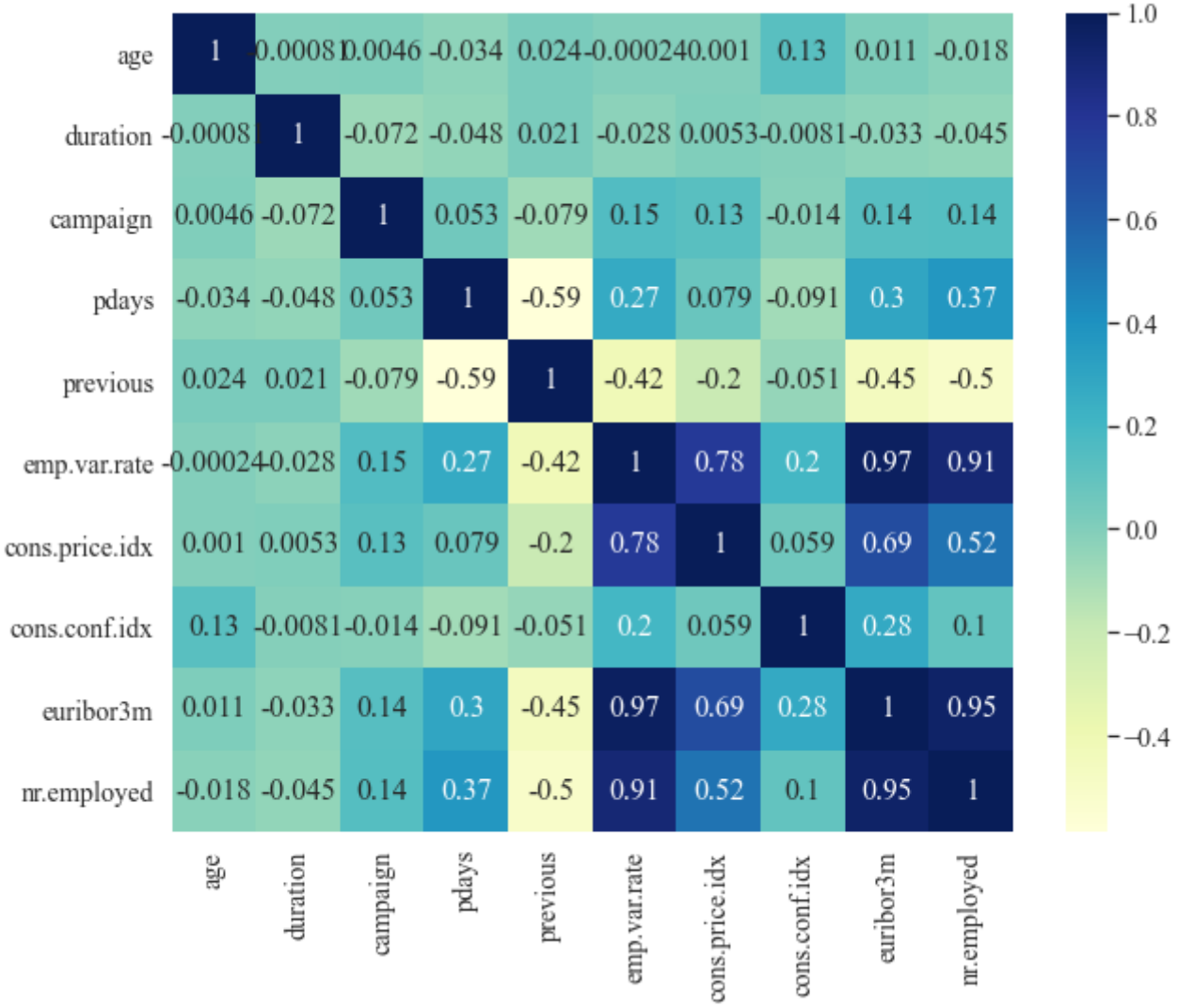
	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor
0	56	261	1	999	0	1.1	93.994	-36.4	4.8
1	57	149	1	999	0	1.1	93.994	-36.4	4.8
2	37	226	1	999	0	1.1	93.994	-36.4	4.8
3	40	151	1	999	0	1.1	93.994	-36.4	4.8
4	56	307	1	999	0	1.1	93.994	-36.4	4.8

In [47]:

```
# Checking the correlation metrics.

sns.set_theme(context='notebook', style='darkgrid', palette='deep', font='Times
              font_scale= 1.3, color_codes=True, rc=None)

plt.figure(figsize=(10,8))

sns.heatmap(df_bank.corr(),cmap='YlGnBu',annot=True)



plt.show
```

Out[47]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [48]:
```
# Select upper triangle of correlation matrix, removing corr. higher than 0.95

corr_matrix = df_bank.corr()
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.boo

# Using a loop that would scan for high correlation 0.95 and
# would remove the respective variable.

to_drop = [column for column in upper.columns if any(upper[column] > 0.90)]

to_drop
```

Out[48]:
```
['euribor3m', 'nr.employed']
```

These are the variables suggested 'euribor3m', 'nr.employed' - there are multiple strong relationships. 'emp.var.rate' and euribor3m as well as emp.car.rate with 'nr.employed'.

I will remove 'nr.employed' and 'emp.var.rate' since 'euribor3m' is likely to be an important part of decision making for individuals when they decide to Subscribe or not to Subscribe.

In [49]:
```
# Drop the respective features
```

```
to_drop = ['nr.employed', 'emp.var.rate']

df_bank.drop(to_drop, axis=1, inplace=True)
```

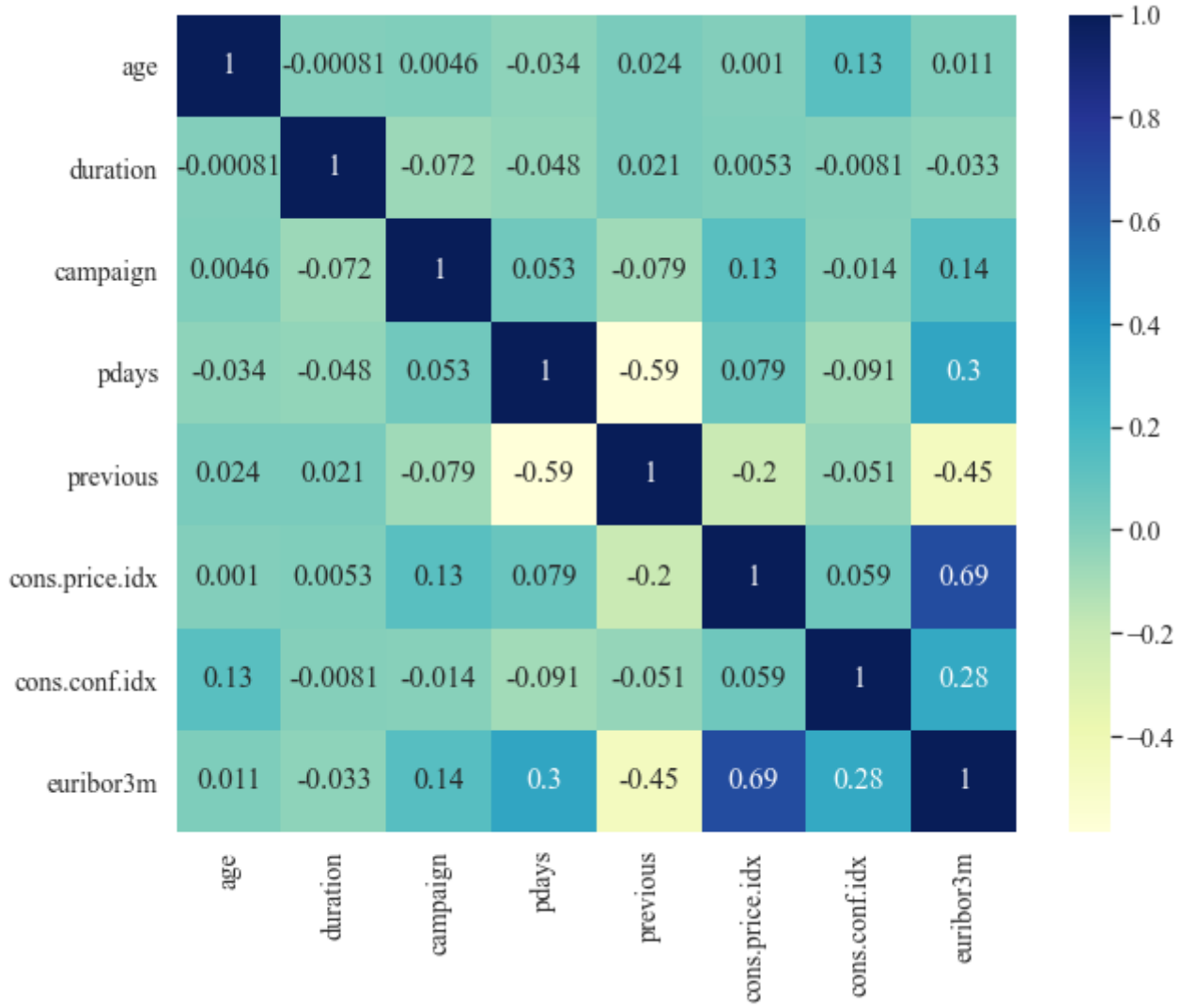
In [50]:
```
# Scan the data again to verify that the variables were removed.
df_bank.head()
```

Out[50]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon
1	57	services	married	high.school	unknown	no	no	telephone	may	mon
2	37	services	married	high.school	no	yes	no	telephone	may	mon
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon
4	56	services	married	high.school	no	no	yes	telephone	may	mon

In [51]:
```
# Checking again the correlation metrics.


sns.set_theme(context='notebook', style='darkgrid', palette='deep', font='Times
              font_scale= 1.3, color_codes=True, rc=None)

plt.figure(figsize=(10,8))

sns.heatmap(df_bank.corr(),cmap='YlGnBu',annot=True)


plt.show
```

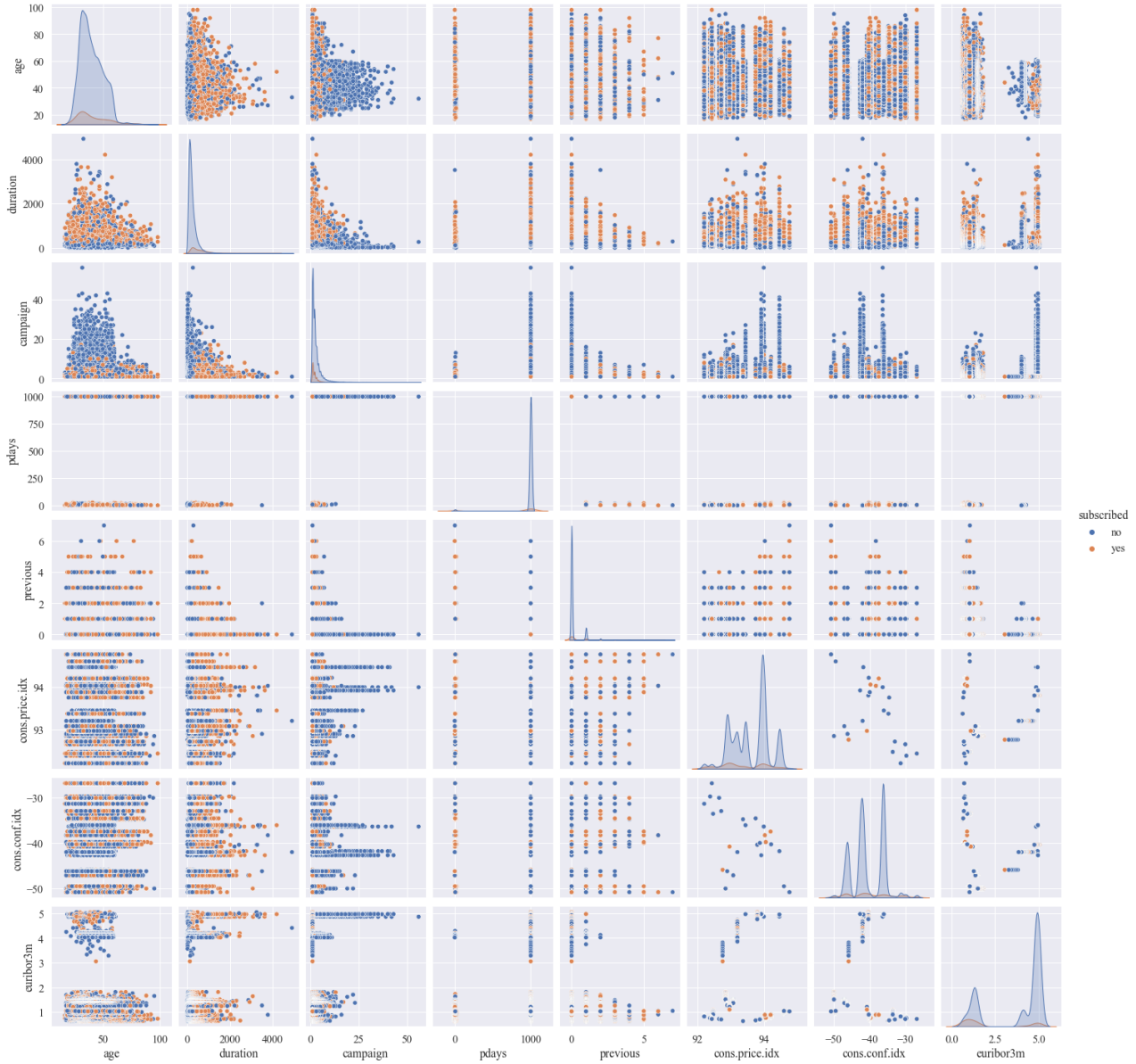
Out[51]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



Pairplot

In [53]:
```
# I will plot pairplot - using the hue 'subscribed' in order to spot any pattern

plt.figure(figsize=(50,40))
sns.pairplot(df_bank, hue='subscribed')
#ax.legend()
```

Out[53]:
```
<seaborn.axisgrid.PairGrid at 0x7fac8acc1df0>
<Figure size 3600x2880 with 0 Axes>
```

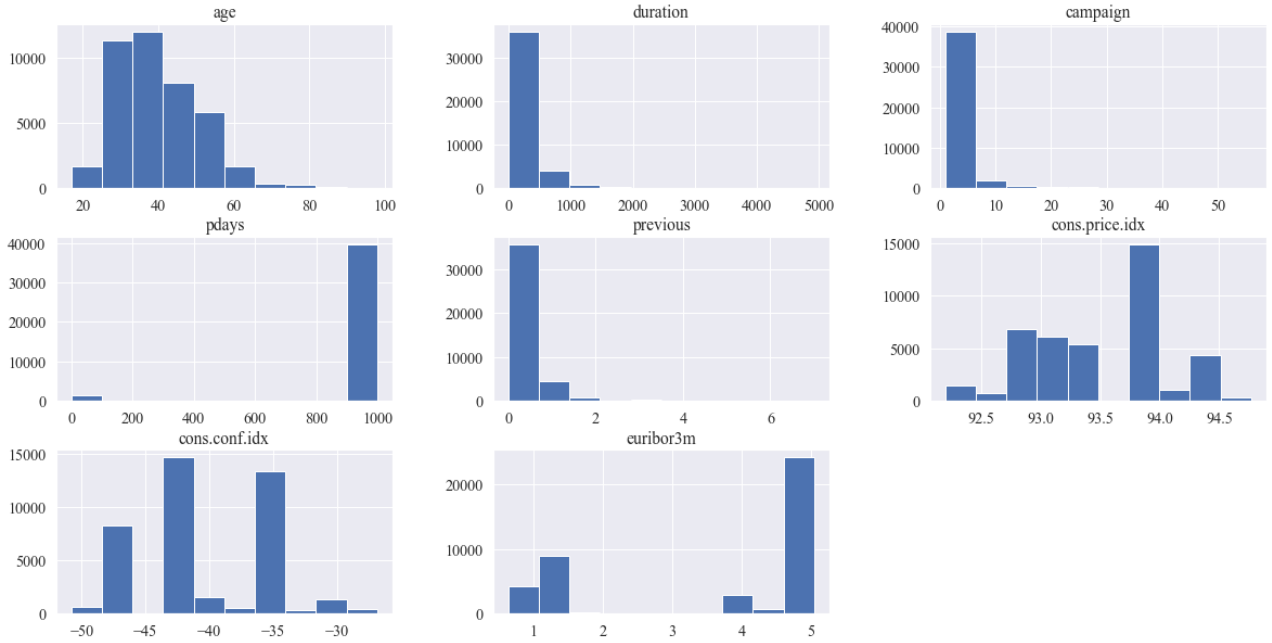


Notes from pairplot - most variables are categorical. The continuous variables show various types of distribution.

Histogram

In [54]:

```
# Plot a histogram to take a closer look at the distribution.

df_bank.hist(figsize= [20,10])
plt.show()
```



Visualize Numerical Variables

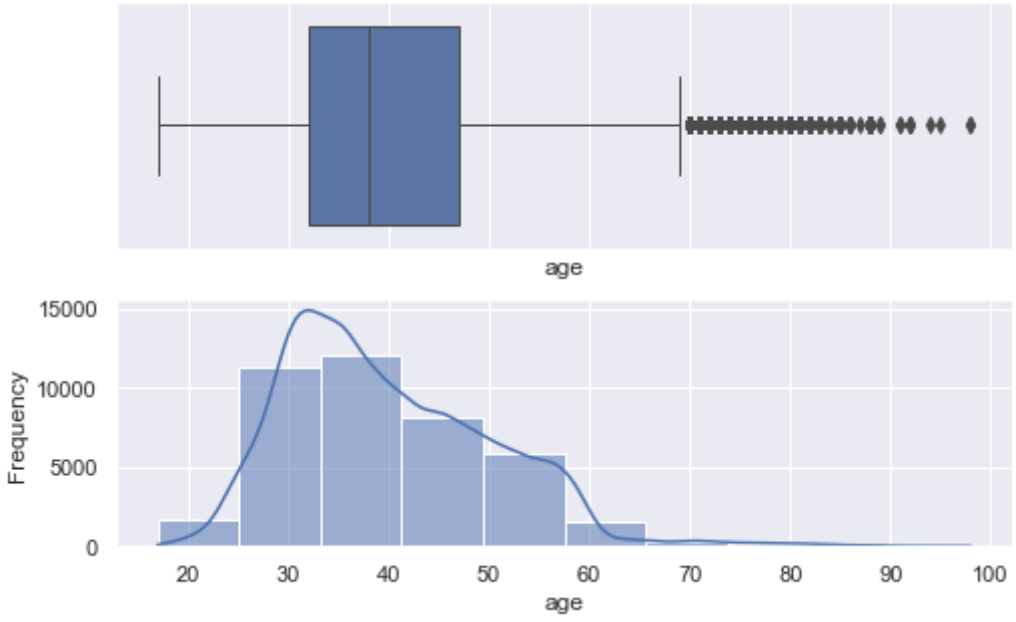
In [55]:
```
# Here is another way to get the numerical data using _get_numeric _data functio

numeric_data = df_bank._get_numeric_data()
numeric_data.head()
```

Out[55]:

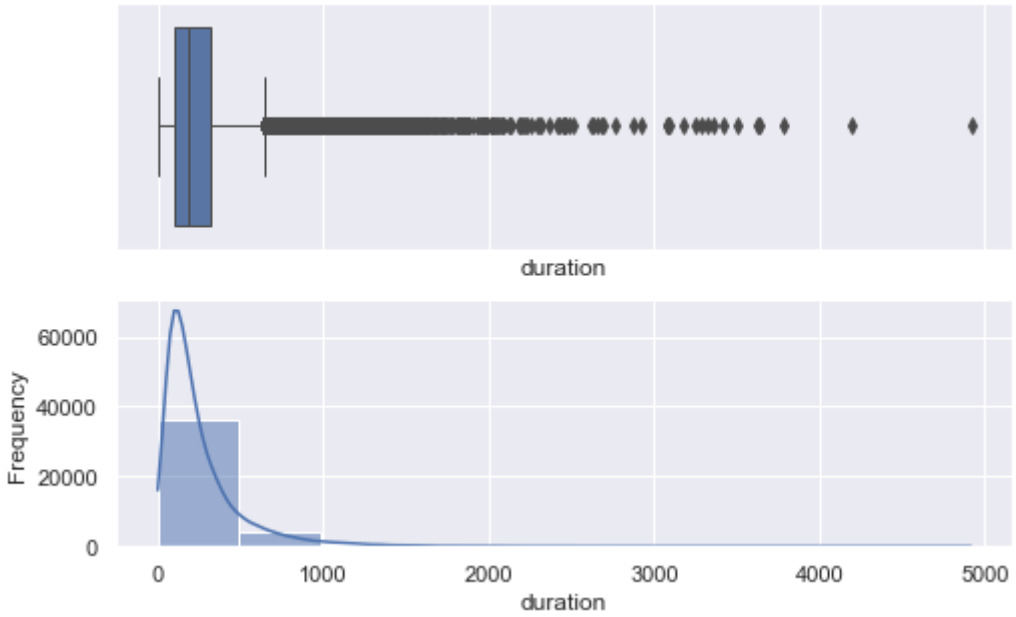
	age	duration	campaign	pdays	previous	cons.price.idx	cons.conf.idx	euribor3m
0	56	261	1	999	0	93.994	-36.4	4.857
1	57	149	1	999	0	93.994	-36.4	4.857
2	37	226	1	999	0	93.994	-36.4	4.857
3	40	151	1	999	0	93.994	-36.4	4.857
4	56	307	1	999	0	93.994	-36.4	4.857

In [56]:
```
# In this plot, we dive a little closer into the distribution of the numerical c

for i in numeric_data.columns:
    plt.figure()
    plt.tight_layout()
    sns.set(rc={"figure.figsize":(8, 5)})
    f, (ax_box, ax_hist) = plt.subplots(2, sharex=True)
    plt.gca().set(xlabel= i,ylabel='Frequency')
    sns.boxplot(numeric_data[i], ax=ax_box , linewidth= 1.0)
    sns.histplot(numeric_data[i], ax=ax_hist , bins = 10,kde=True)
```

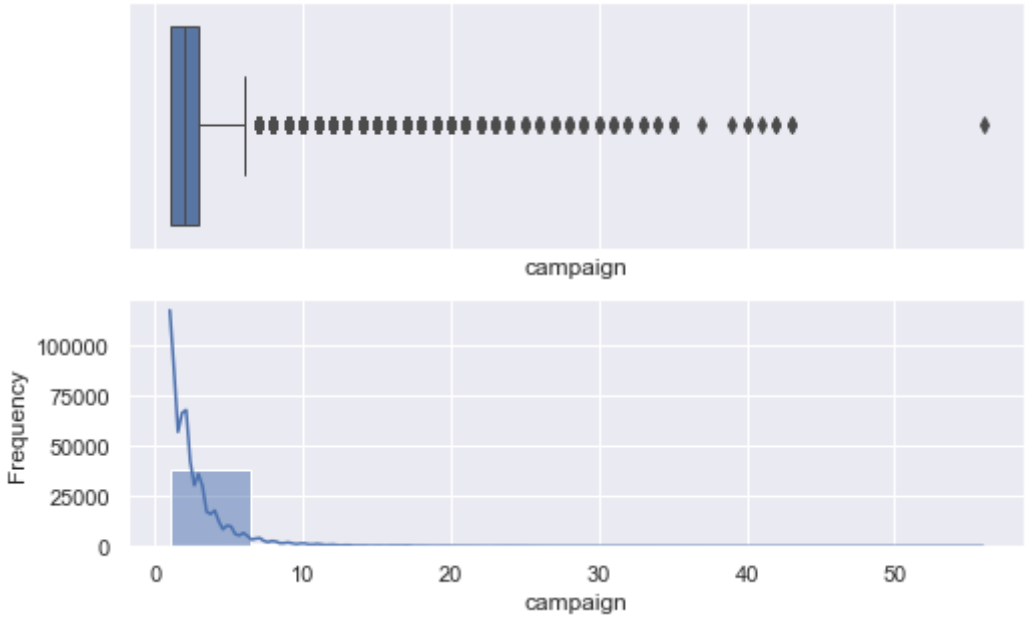
```
<Figure size 432x288 with 0 Axes>
```



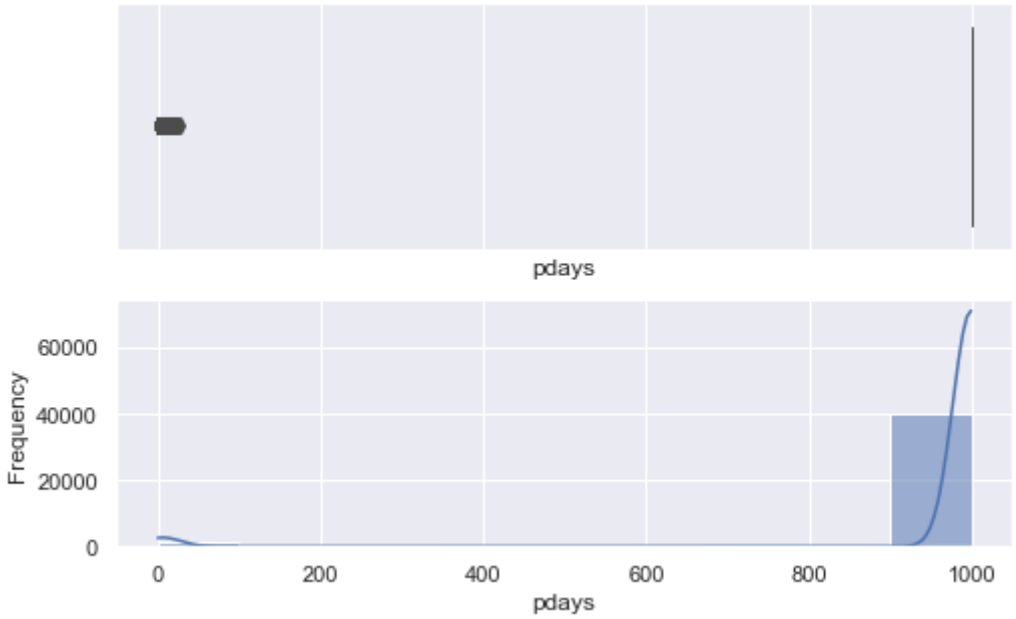

```
<Figure size 576x360 with 0 Axes>
```



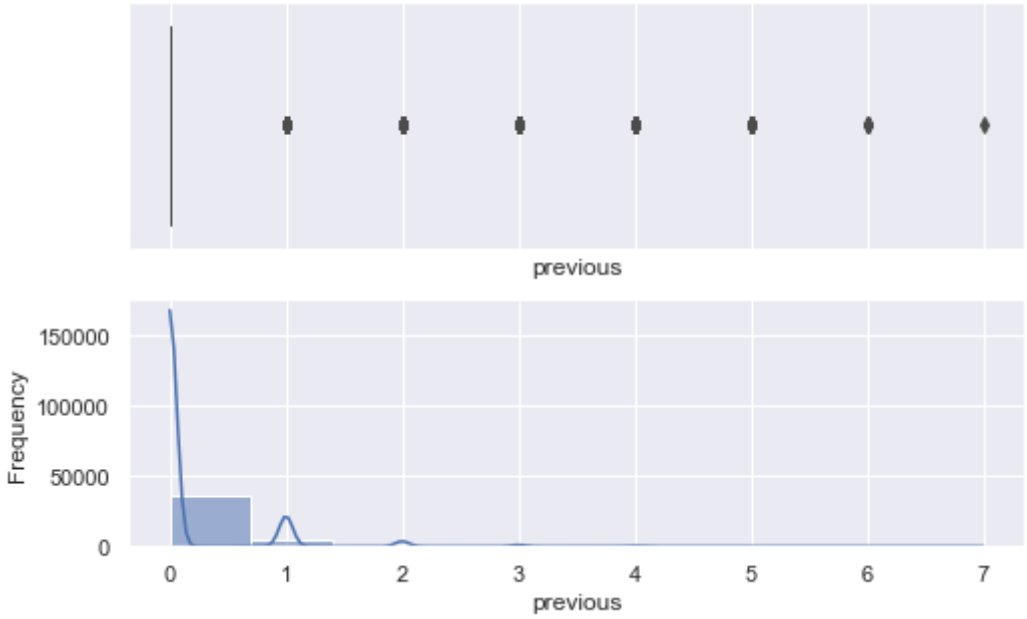

```
<Figure size 576x360 with 0 Axes>
```



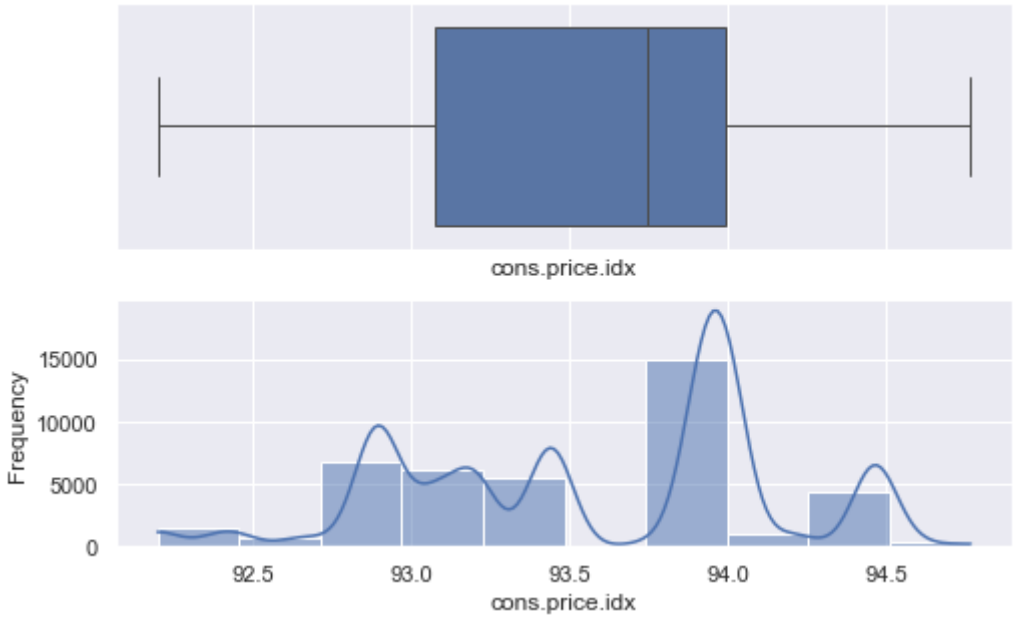

```
<Figure size 576x360 with 0 Axes>
```



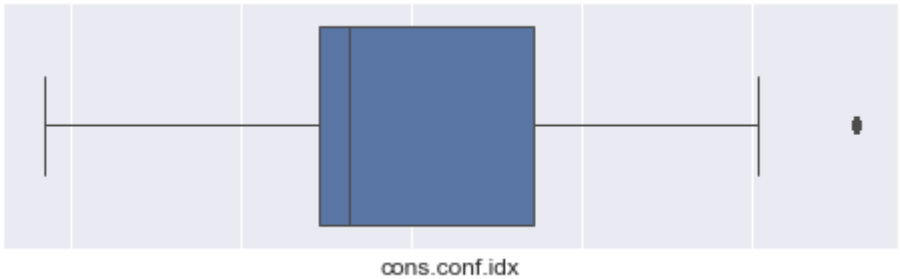

```
<Figure size 576x360 with 0 Axes>
```

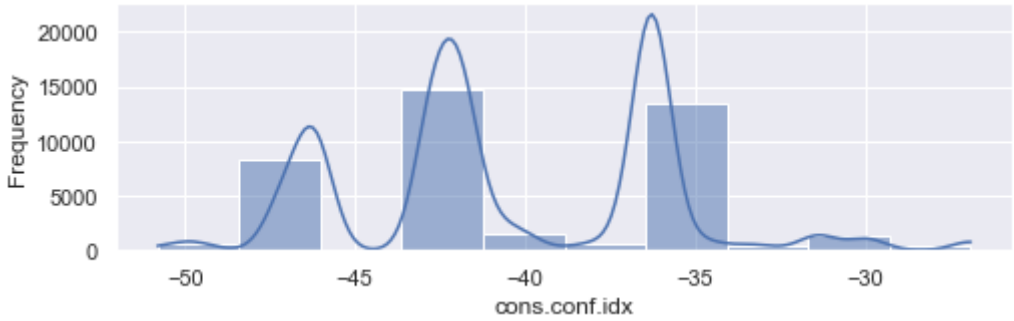



```
<Figure size 576x360 with 0 Axes>
```

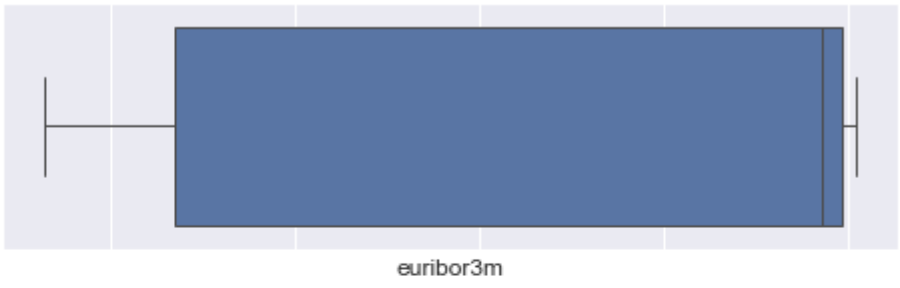


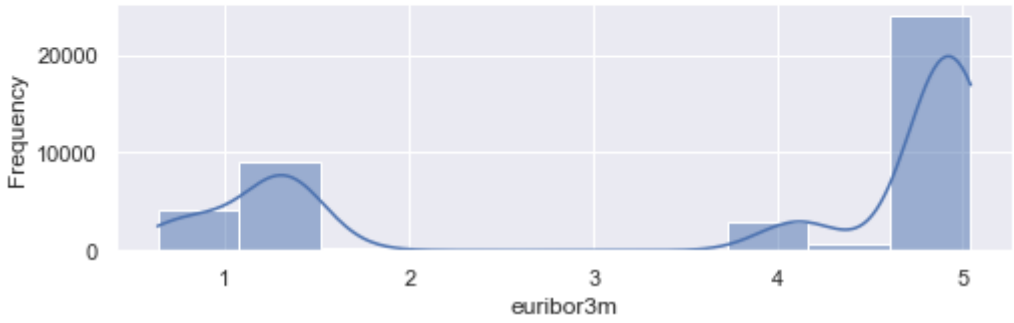

```
<Figure size 576x360 with 0 Axes>
```






```
<Figure size 576x360 with 0 Axes>
```





Age: most of the population was from 30 to 50 years old.

Duration: most calls ranged from a minute to 8.5 minutes.

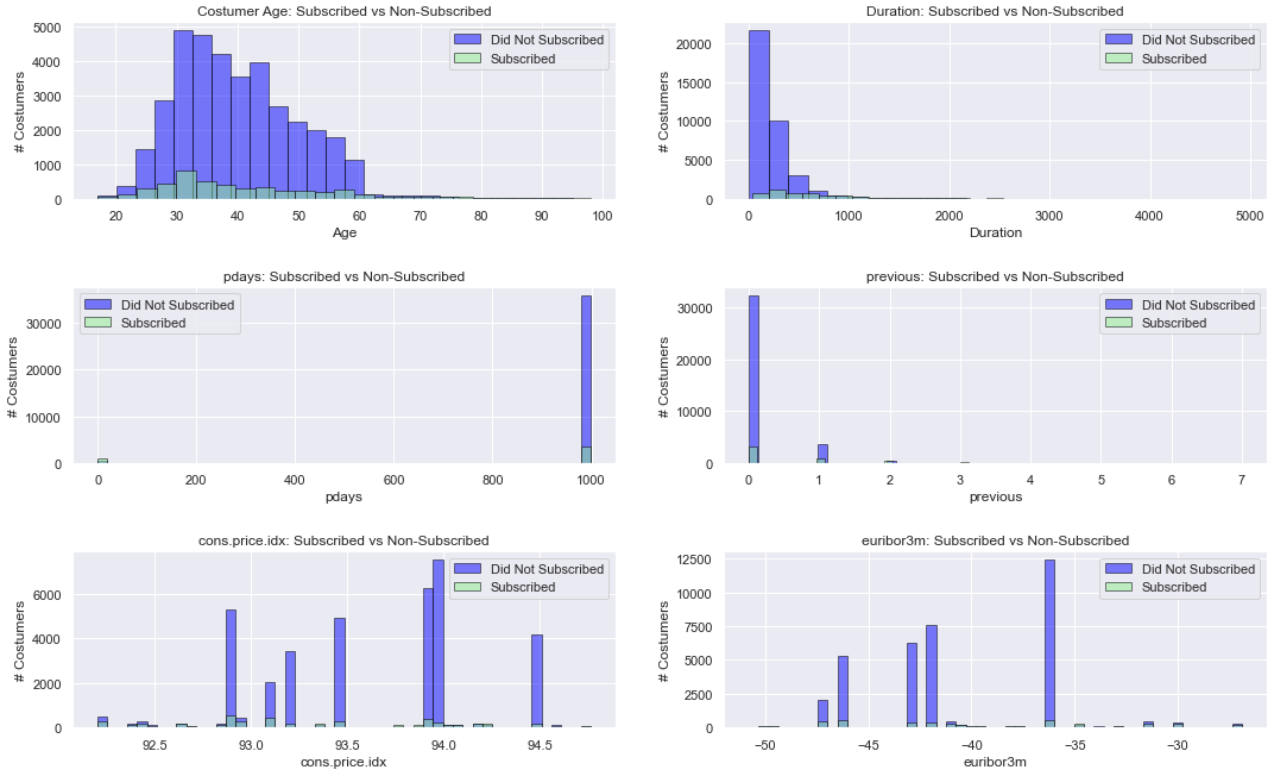
In [57]:
```
# Using a lambda function  - I replace all the dots with the underlying symbol.


df_bank.columns = list(map(lambda x: x.replace('.', '_'),
                           df_bank.columns))
```

In [58]:
```
# Plotting the numerical variables in relationship to subscribers versus
# people who did not subscribe.
print('Statistical Summary ')
print('\n')
print('Subscribed')
print(df_bank[df_bank['subscribed']=='yes'][['age','duration','pdays','previous'
```

```
                                                'cons_price_idx',
                                                'cons_conf_idx']].describe().transp
# print('--'*40)
# print('')

# Subplots of Numeric Features
sns.set_style('darkgrid')
fig = plt.figure(figsize = (18,15))
fig.subplots_adjust(hspace = .50)


ax1 = fig.add_subplot(421)
ax1.hist(df_bank[df_bank['subscribed']=='no'].age, bins = 25,
         label ='Did Not Subscribed', alpha = .50,edgecolor= 'black',color ='blu
ax1.hist(df_bank[df_bank['subscribed']=='yes'].age, bins = 25,
         label = 'Subscribed', alpha = .50, edgecolor = 'black',color = 'lightgr
ax1.set_title('Costumer Age: Subscribed vs Non-Subscribed')
ax1.set_xlabel('Age')
ax1.set_ylabel('# Costumers')
ax1.legend(loc = 'upper right')

ax2 = fig.add_subplot(422)
ax2.hist(df_bank[df_bank['subscribed']=='no'].duration,
         bins = 25, label = 'Did Not Subscribed', alpha = .50,
         edgecolor ='black', color = 'blue')
ax2.hist(df_bank[df_bank['subscribed']=='yes'].duration,
         bins = 25, label = 'Subscribed', alpha = .50,
         edgecolor = 'black',color ='lightgreen')
ax2.set_title('Duration: Subscribed vs Non-Subscribed')
ax2.set_xlabel('Duration')
ax2.set_ylabel('# Costumers')
ax2.legend(loc = 'upper right')

ax3 = fig.add_subplot(423)


ax3.hist(df_bank[df_bank['subscribed']=='no'].pdays, bins = 50,
         label = 'Did Not Subscribed', alpha = .50, edgecolor ='black', color =
ax3.hist(df_bank[df_bank['subscribed']=='yes'].pdays, bins = 50,
         label = 'Subscribed', alpha = .50, edgecolor = 'black',color ='lightgre
ax3.set_title('pdays: Subscribed vs Non-Subscribed')
ax3.set_xlabel('pdays')
ax3.set_ylabel('# Costumers')
ax3.legend(loc = 'upper right')


ax4 = fig.add_subplot(424)


ax4.hist(df_bank[df_bank['subscribed']=='no'].previous,
         bins = 50, label = 'Did Not Subscribed', alpha = .50, edgecolor ='black
         color = 'blue')
ax4.hist(df_bank[df_bank['subscribed']=='yes'].previous,
         bins = 50, label = 'Subscribed', alpha = .50, edgecolor = 'black',
         color ='lightgreen')
ax4.set_title('previous: Subscribed vs Non-Subscribed')
ax4.set_xlabel('previous')
ax4.set_ylabel('# Costumers')
ax4.legend(loc = 'upper right')
```

```
ax5 = fig.add_subplot(425)

ax5.hist(df_bank[df_bank['subscribed']=='no'].cons_price_idx,
         bins = 50, label = 'Did Not Subscribed', alpha = .50,
         edgecolor ='black', color = 'blue')
ax5.hist(df_bank[df_bank['subscribed']=='yes'].cons_price_idx,
         bins = 50, label = 'Subscribed', alpha = .50, edgecolor = 'black',
         color ='lightgreen')
ax5.set_title('cons.price.idx: Subscribed vs Non-Subscribed')
ax5.set_xlabel('cons.price.idx')
ax5.set_ylabel('# Costumers')
ax5.legend(loc = 'upper right')



ax6 = fig.add_subplot(426)


ax6.hist(df_bank[df_bank['subscribed']=='no'].cons_conf_idx, bins = 50,
         label = 'Did Not Subscribed', alpha = .50, edgecolor ='black', color =
ax6.hist(df_bank[df_bank['subscribed']=='yes'].cons_conf_idx, bins = 50,
         label = 'Subscribed', alpha = .50, edgecolor = 'black',color ='lightgre
ax6.set_title('euribor3m: Subscribed vs Non-Subscribed')
ax6.set_xlabel('euribor3m')
ax6.set_ylabel('# Costumers')
ax6.legend(loc = 'upper right')

ax3.legend()

plt.show()
```

```
Statistical Summary


Subscribed
                 count        mean         std     min      25%    50%  \
age             4639.0   40.912266   13.838838  17.000   31.000   37.0
duration        4639.0  553.256090  401.190736  37.000  253.500  449.0
pdays           4639.0  791.990946  403.439220   0.000  999.000  999.0
previous        4639.0    0.492779    0.860406   0.000    0.000    0.0
cons_price_idx  4639.0   93.354577    0.676592  92.201   92.893   93.2
cons_conf_idx   4639.0  -39.791119    6.139657 -50.800  -46.200  -40.4

                    75%       max
age              50.000    98.000
duration        741.500  4199.000
pdays           999.000   999.000
previous          1.000     6.000
cons_price_idx   93.918    94.767
cons_conf_idx   -36.100   -26.900
```



Certain elements are evident -

* A prospective client is more likely to subscribe without having any previous contacts.

* People in their 30s are more likely to subscribe.

* Certain indices are showing a small increase in likelihood.

Age

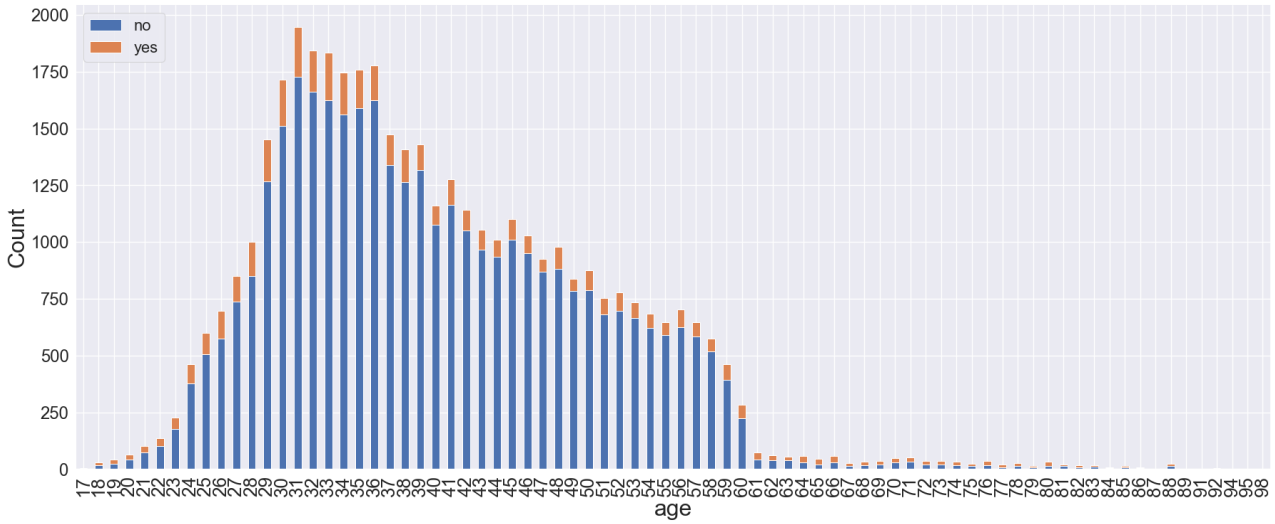
In [59]:

```
# Plotting specific ages to see which ones subscribed the most.

def myplot(colname):

    df_plot = df_bank.groupby(['subscribed',
                               colname]).size().reset_index().pivot(columns='sub
                                                                    index=colnam
    df_plot['total'] = df_plot.sum(axis=1)
#     df_plot['no'] = df_plot['no']*100/df_plot['total']
#     df_plot['yes'] = df_plot['yes']*100/df_plot['total']
    df_plot.drop('total',axis=1,inplace=True)
#     df_plot.sort_values('yes',ascending=False,inplace=True)

#     fig.set_size_inches(20, 8)


    df_plot.plot(kind='bar', stacked=True, figsize=(30,12))


    plt.xlabel(colname, fontsize=32)
```

```
    plt.ylabel('Count', fontsize=32)
    plt.xticks(rotation = 90,fontsize=26)
    plt.yticks(rotation = 0,fontsize=24)
    plt.grid(True, color = "white", linewidth = "1.4", linestyle = "-")
    plt.legend(loc=2, prop={'size': 22})

    #ax.set_title('Age Count Distribution', fontsize=28)

    sns.despine()
```

In [60]:

```
myplot('age')
```



I decided to create ranges of ages since it will give a better sense of what group to target.

In [61]:

```
# Here are the  bins  based on the values observed above.
# 5 values will result in 4 bins

bins = [17, 35, 36, 55, 56, 65, 66, 98]


#We'll pd.cut method to separate data into bins.
df_bank['bins_age'] = pd.cut(df_bank['age'], bins)

# I will use .cat.as_unordered() method transforming the data to
# ordered categories.
# bins_age_built = bins_yr_built.cat.as_unordered()
# bins_yr_built.head()
```

In [62]:

```
# Rechaeck data set for bins column.

df_bank.head()
```

Out[62]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon
1	57	services	married	high.school	unknown	no	no	telephone	may	mon

	age	job	marital	education	default	housing	loan	contact	month	day_of_week
2	37	services	married	high.school	no	yes	no	telephone	may	mon
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon
4	56	services	married	high.school	no	no	yes	telephone	may	mon

In [63]:
```
# Assigning a name for a demographic age group for each bin.

df_bank = df_bank.assign(age_group=pd.cut(df_bank['age'], bins=[17, 35,  55,  65
                                 right=False, labels = ['Young_Adults','Middle_Aged
                                                        'Older_Adults','Seniors']))
```

In [64]:
```
# Make an independent copy so I won't need to run the notebook from the top.
df_bank_copy = df_bank.copy()
```

Information about the contacted prospects

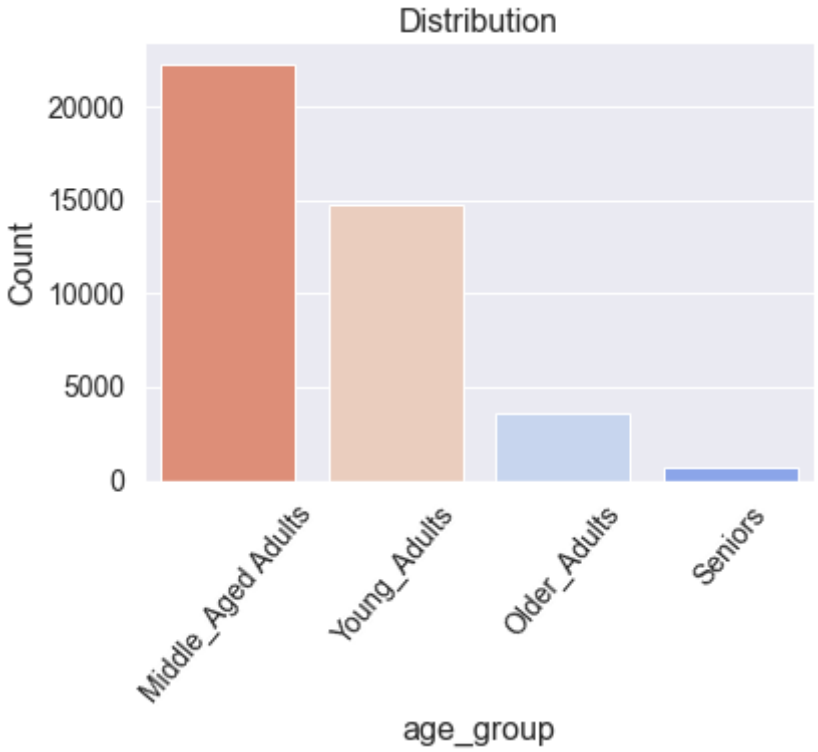
I will create a function that will calculate each variable's distribution and plot the information. It is important to see the sample of people who have been contacted. In instances where the sample is low (e.g. less than 100), I will omit to calculate the percentage change since it will be insignificantnt.

In [65]:
```
# Building a "countplot" function that will plot the distribution for each categ

def countplot(colname):
    fig, ax = plt.subplots()
    fig.set_size_inches(6, 4)
    sns.countplot(x = colname, data = df_bank, order = df_bank[colname].value_co
                  palette = "coolwarm_r")
    ax.set_xlabel(colname, fontsize=16)
    ax.set_ylabel('Count', fontsize=16)
    plt.xticks(rotation = 50,fontsize=16)
    plt.yticks(rotation = 0,fontsize=16)
    ax.set_title('Distribution', fontsize=16)
    ax.tick_params(labelsize=14)
    sns.despine()
```

In [66]:
```
# Count the age groups
df_bank["age_group"].value_counts()
```

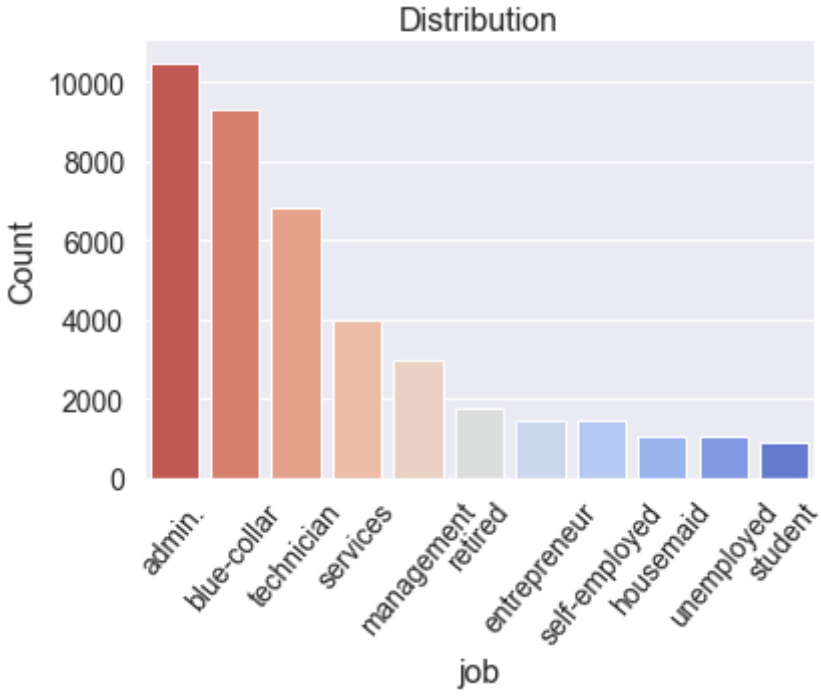
Out[66]:
```
Middle_Aged Adults    22197
Young_Adults          14751
Older_Adults           3566
Seniors                 660
Name: age_group, dtype: int64
```

In [67]:
```
bcountplot('age_group')
```



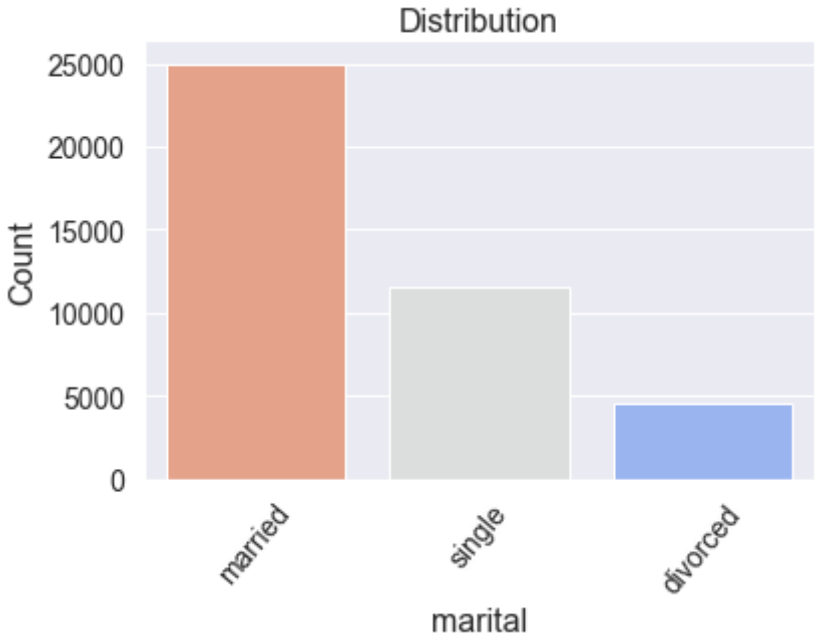
The majority of the people contacted were middle-aged and young adults. Even though only 660 senor people were contacted, there are still enough sample of people to draw information about their behavior.

In [68]:
```
countplot('job')
```



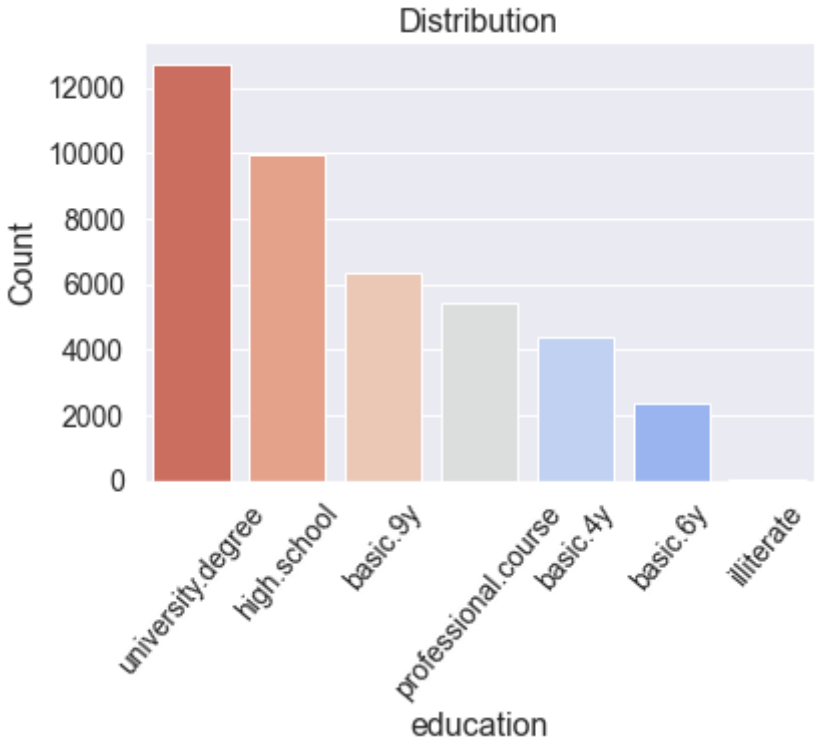
The sample of the population that was mainly included in the job category was: Admin, Blue-color Technician.

In [69]:
```
countplot('marital')
```



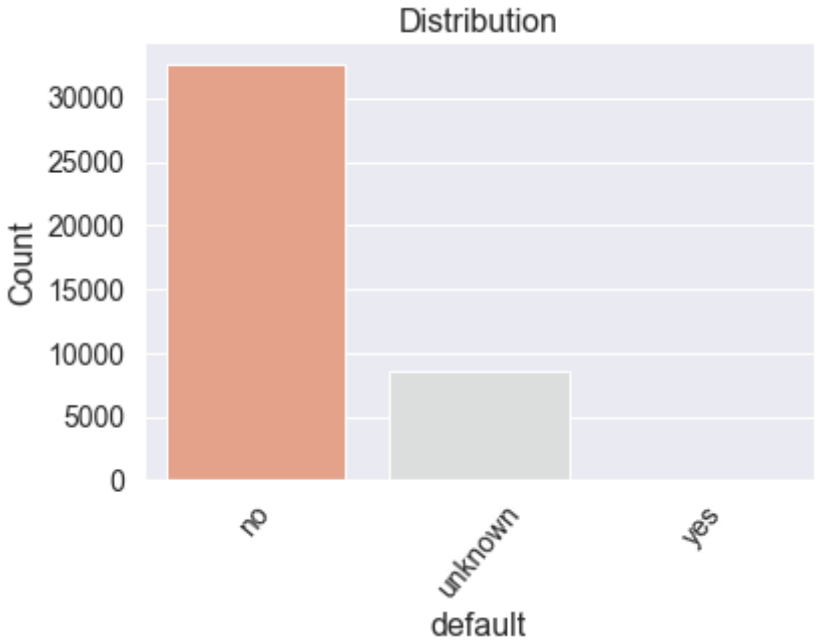
In terms of marital status, there were twice as many married people as single and one-fourth divorced.

In [70]:
```
countplot('education')
```



There were twice as many individuals with a university degree who were contacted than individuals who had 9 years of schooling.

In [71]:
```
countplot('default')
```



Most individuals who were contacted did not default on their credit.

In [72]:
```
countplot('housing')
```

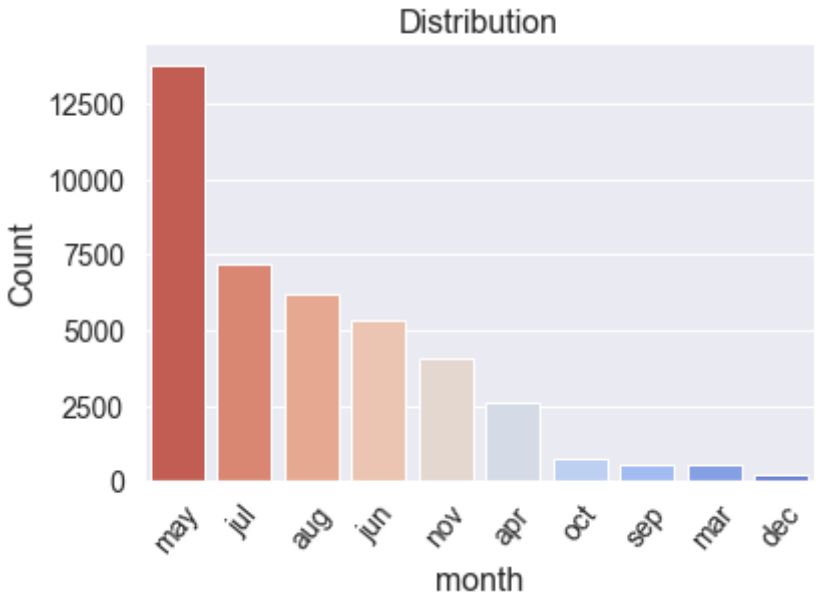
Individuals with or without housing loans were contacted in a similar population size.

In [73]:
```
df_bank['month'].value_counts()
```

Out[73]:
```
may    13767
jul     7169
aug     6176
jun     5318
nov     4100
apr     2631
oct      717
sep      570
```

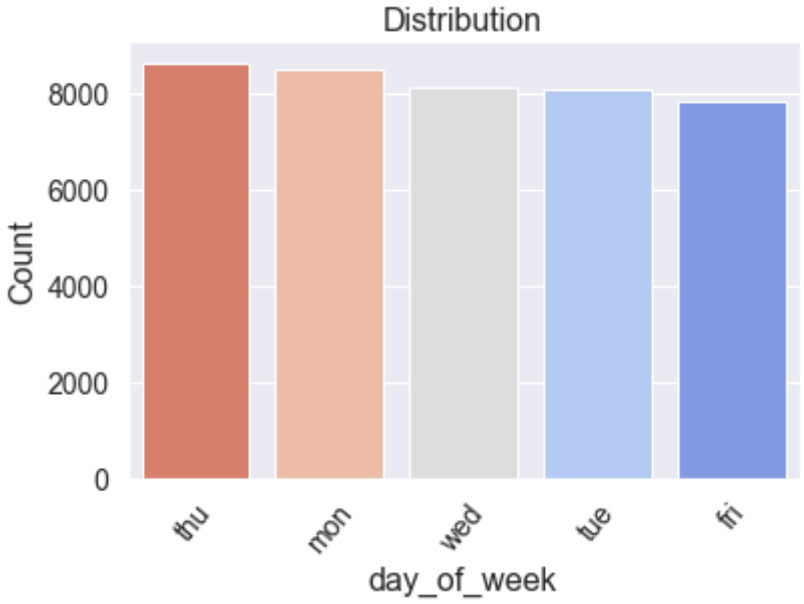
```
mar      546
dec      182
Name: month, dtype: int64
```

In [74]:
```
countplot('month')
```



While May has been the month where most of the calls were made (twice as much as Jan, Aug, and June) the days of the week were evenly distributed.

In [75]:
```
countplot('day_of_week')
```



Individuals were contacted during the week, (roughly equaliy distributed Mon. to Fri.)

Individuals subscribe from each segment (in terms of percentage)

In [76]:
```
# Building a function that first extracts a data set with a given column and
```

```
# a subscribed column.

def statPlot(colname):

    ############# crarte df ################
    df = df_bank[[colname,'subscribed']]

    df  = df.groupby([colname,
                              'subscribed']).size().reset_index().pivot(columns=
                                                                        index=co
                                                                    values=0)


    df['percentage_of_subscribers']= df['yes']*100/(df['no']+ df['yes'])
    # df_job['percentage_of_unsubscribers']= df_job['no']/(df_job['no']+ df_job[
    df.dropna(inplace=True)
    df= df.sort_values('percentage_of_subscribers').reset_index()
    df[colname] = df[colname].astype('str')

    ##### PLOT ####################
    plt.figure(figsize=(15,5))
    ax = sns.barplot(df[colname],df['percentage_of_subscribers'],
                     palette="vlag")
    for bars in ax.containers:
        ax.bar_label(bars, fmt="%.2f%%")
    plt.xticks(rotation = 50)
    plt.show()
```

In [77]:
```
# list all the columns
list(df_bank)
```

Out[77]:
```
['age',
 'job',
 'marital',
 'education',
 'default',
 'housing',
 'loan',
 'contact',
 'month',
 'day_of_week',
 'duration',
 'campaign',
 'pdays',
 'previous',
 'poutcome',
 'cons_price_idx',
 'cons_conf_idx',
 'euribor3m',
 'subscribed',
 'bins_age',
 'age_group']
```

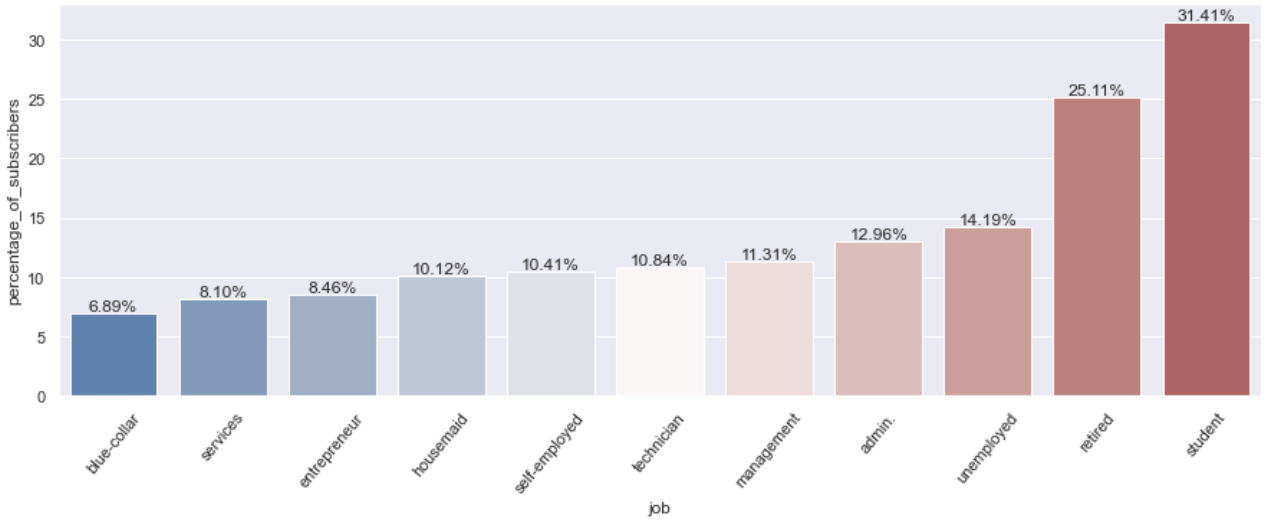
In [78]:
```
# Creating a list so it would be easy to grab to run it in the function's loop.


imp_col= ['job',
 'marital',
 'education',
```

```
 'default',
 'housing',
 'loan',
 'contact',
 'month',
 'day_of_week',
 'campaign',
'age_group']
```

In [79]:
```
df_bank[['job', 'subscribed']].value_counts()
```

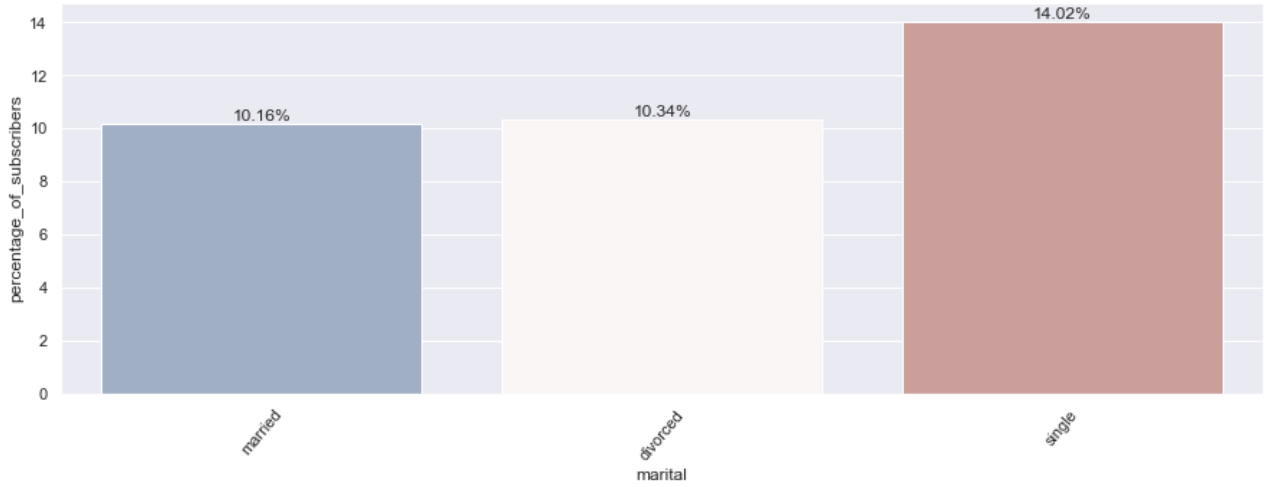
Out[79]:
```
job            subscribed
admin.         no            9138
blue-collar    no            8670
technician     no            6065
services       no            3674
management     no            2618
admin.         yes           1361
entrepreneur   no            1342
retired        no            1306
self-employed  no            1283
housemaid      no             959
unemployed     no             877
technician     yes            737
blue-collar    yes            642
student        no             605
retired        yes            438
management     yes            334
services       yes            324
student        yes            277
self-employed  yes            149
unemployed     yes            145
entrepreneur   yes            124
housemaid      yes            108
dtype: int64
```

In [80]:
```
# Running functionfor the 'job' column

statPlot('job')
```

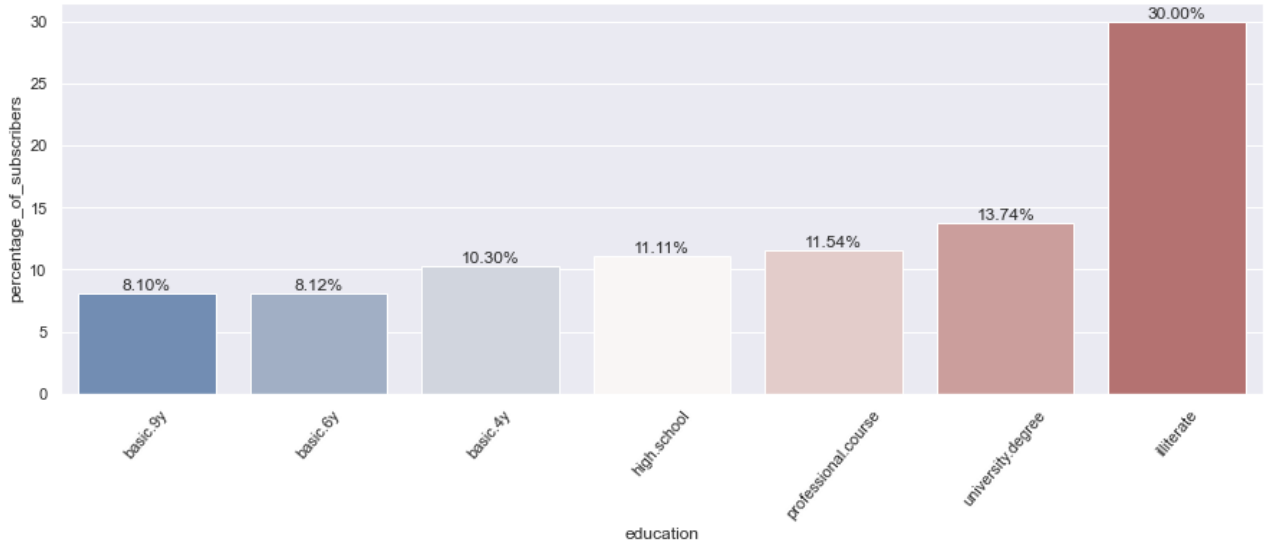


In [81]:
```
# Running functionfor the 'marital' column
```

```
statPlot('marital')
```



In [82]:
```
# Running functionfor the 'education' column

statPlot('education')
```



In [83]:
```
# String to be searched in start of string
# https://www.geeksforgeeks.org/python-pandas-series-str-count/

search ="illiterate"

# count of occurrence of a and creating new column
df_bank["count"]= df_bank["education"].str.count(search, re.I)

# display
df_bank["count"].value_counts()
```

Out[83]:
```
0    41156
1       20
Name: count, dtype: int64
```

In [84]:
```
print("of Illiterate:")
```

```
#20/41156 = 0.00048
20 *.3
```

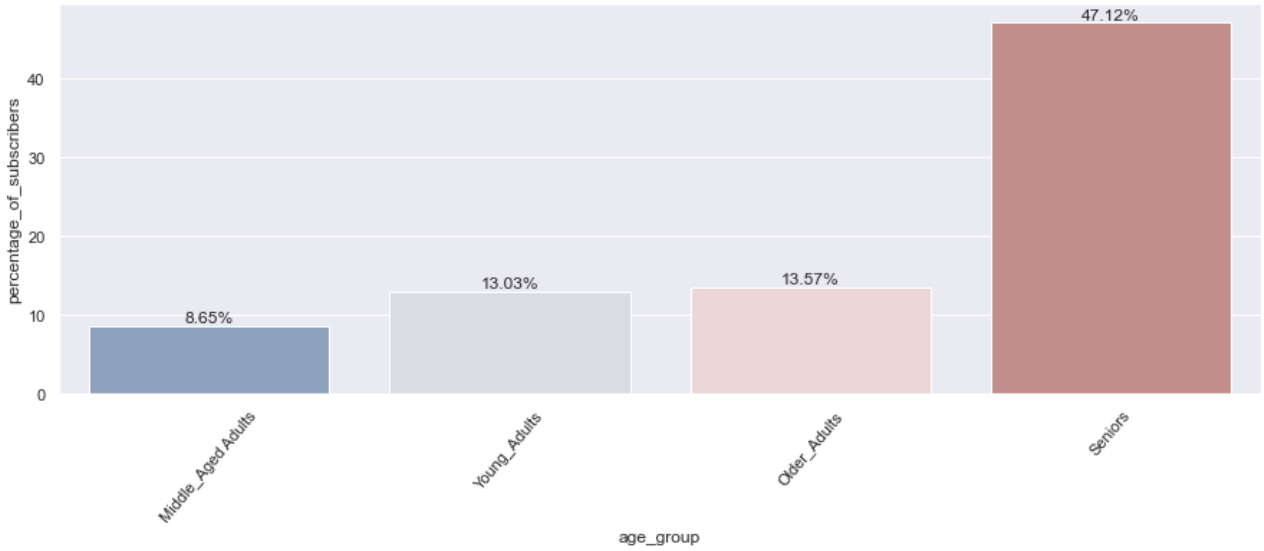
```
of Illiterate:
```

Out[84]:
```
6.0
```

In [85]:
```
df_bank['education']
```

Out[85]:
```
0                   basic.4y
1                high.school
2                high.school
3                   basic.6y
4                high.school
                   ...
41183    professional.course
41184    professional.course
41185      university.degree
41186    professional.course
41187    professional.course
Name: education, Length: 41176, dtype: object
```

In [86]:
```
b# Running function for the 'age_group' column

statPlot('age_group')
```

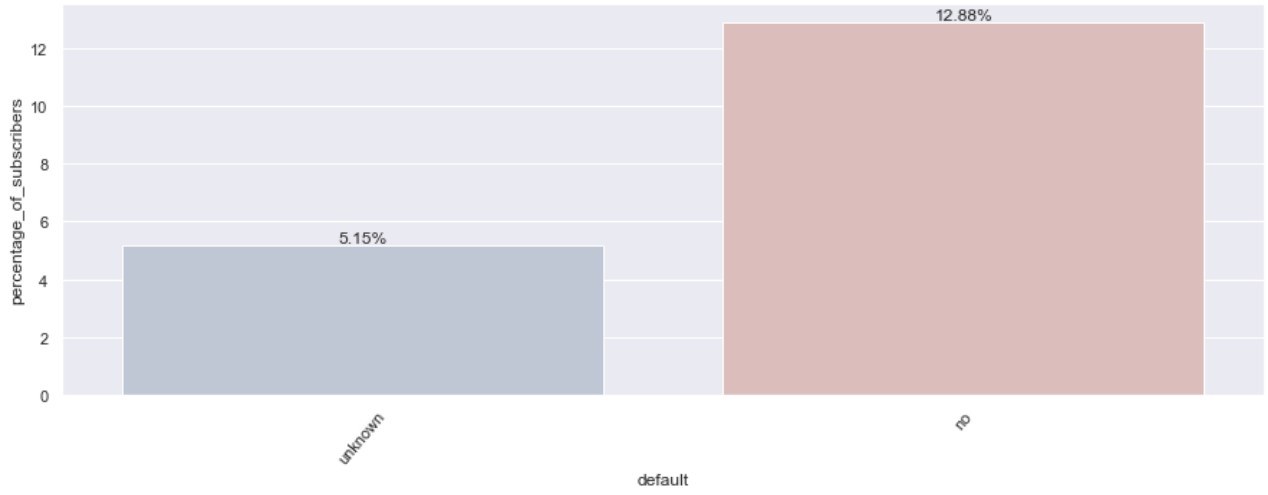


In [87]:
```
df_bank[['age_group', 'subscribed']].value_counts()
```

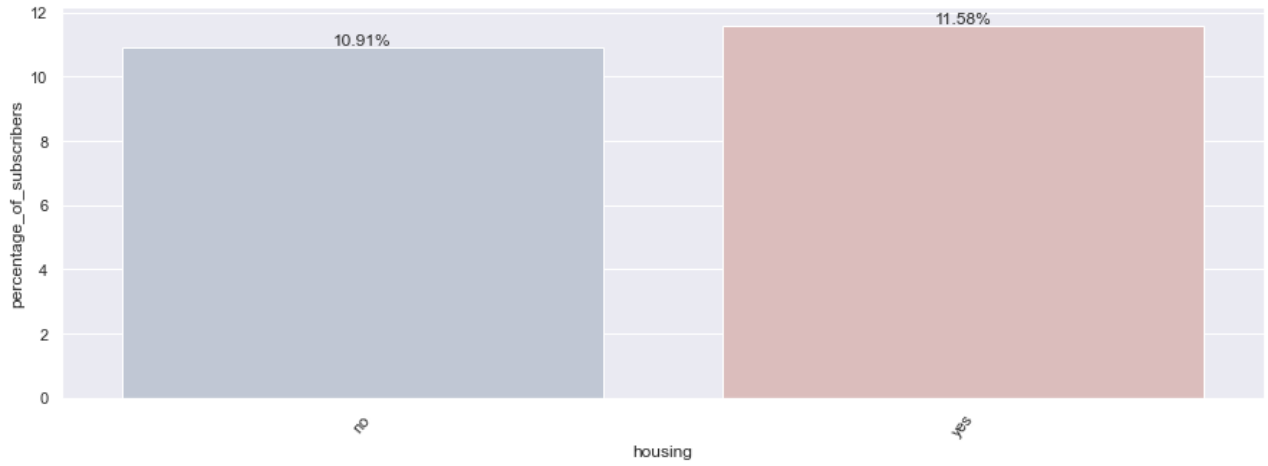
Out[87]:
```
age_group           subscribed
Middle_Aged Adults  no            20277
Young_Adults        no            12829
Older_Adults        no             3082
Young_Adults        yes            1922
Middle_Aged Adults  yes            1920
Older_Adults        yes             484
Seniors             no              349
                    yes             311
dtype: int64
```

In [88]:
```
# Running function for the 'default' column
```

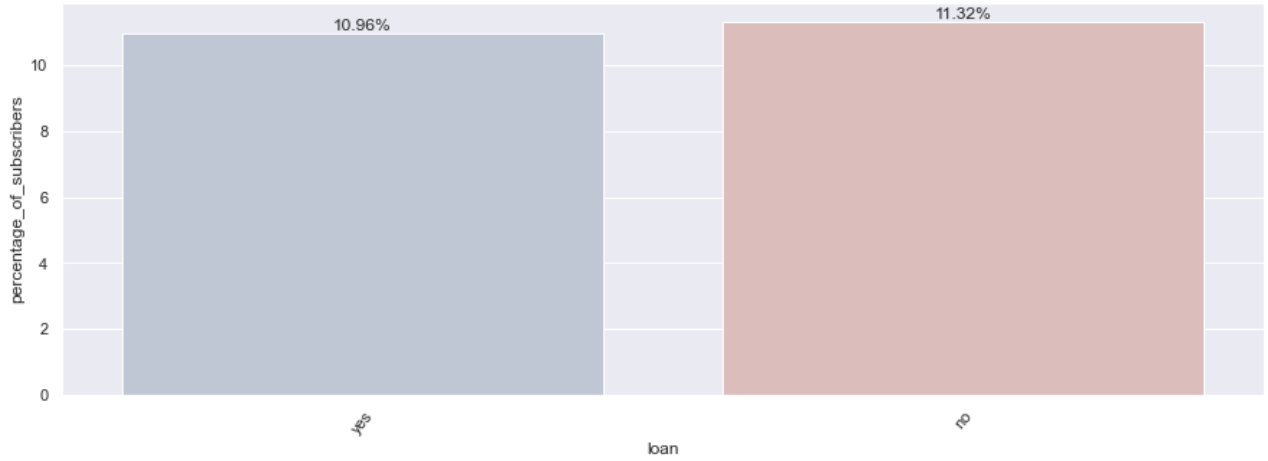
```
statPlot('default')
```



In [89]:
```
statPlot('housing')
```



In [90]:
```
# Running function for the 'loan' column
statPlot('loan')
```



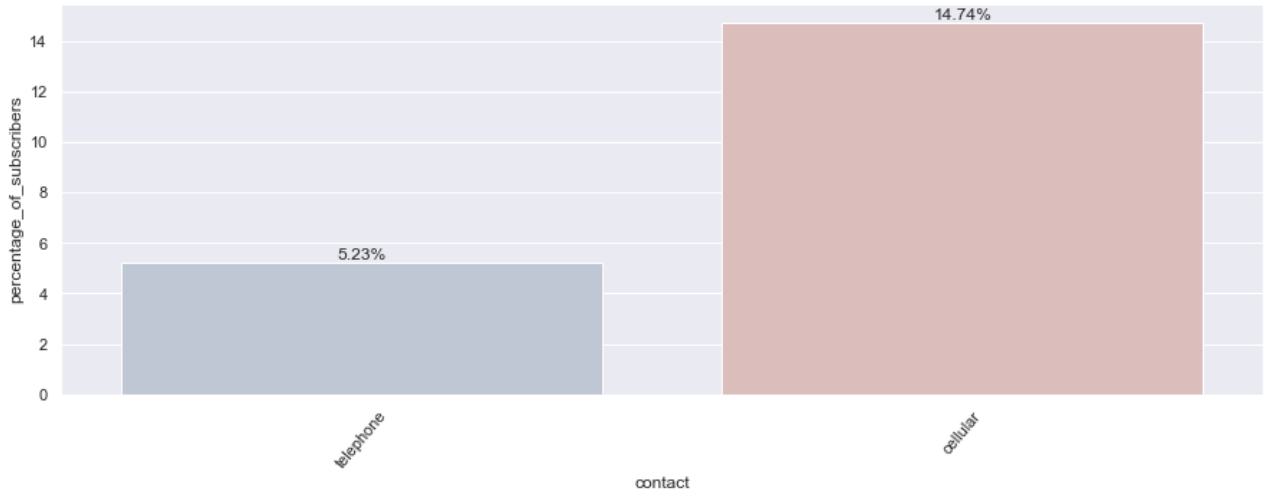
In [91]:
```
df_bank[['contact','subscribed']].value_counts()
```

Out[91]:
```
contact    subscribed
cellular   no            22283
telephone  no            14254
cellular   yes            3852
telephone  yes             787
dtype: int64
```

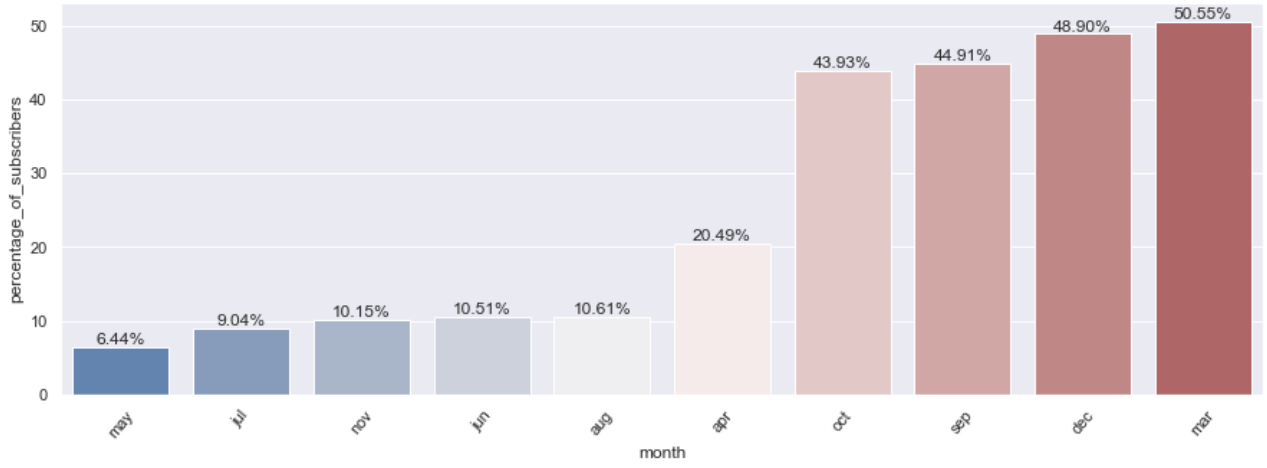
In [92]:
```
df_bank['contact'].value_counts()
```

Out[92]:
```
cellular     26135
telephone    15041
Name: contact, dtype: int64
```

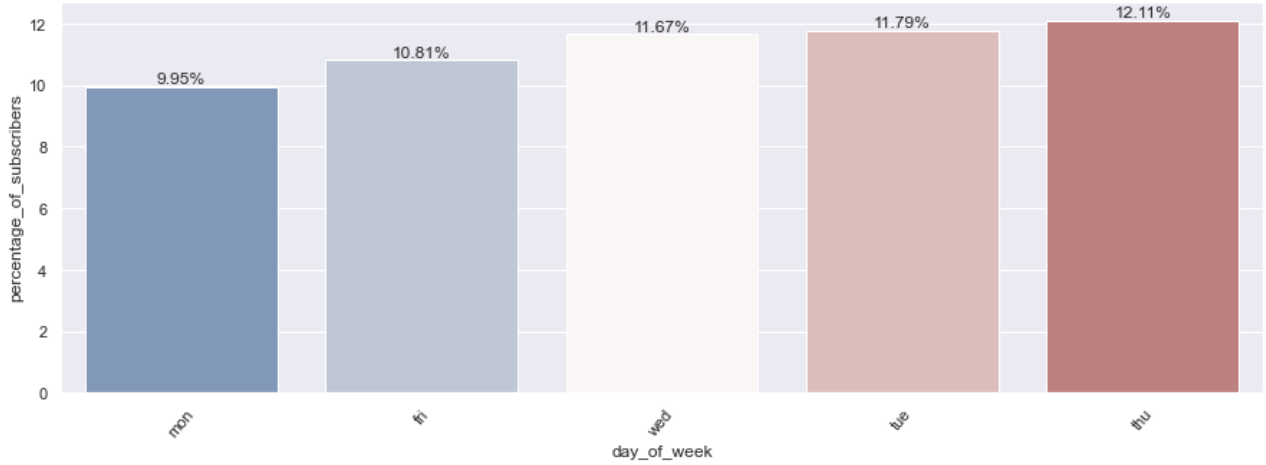
In [93]:
```
# Running function for the 'contact' column
statPlot('contact')
```



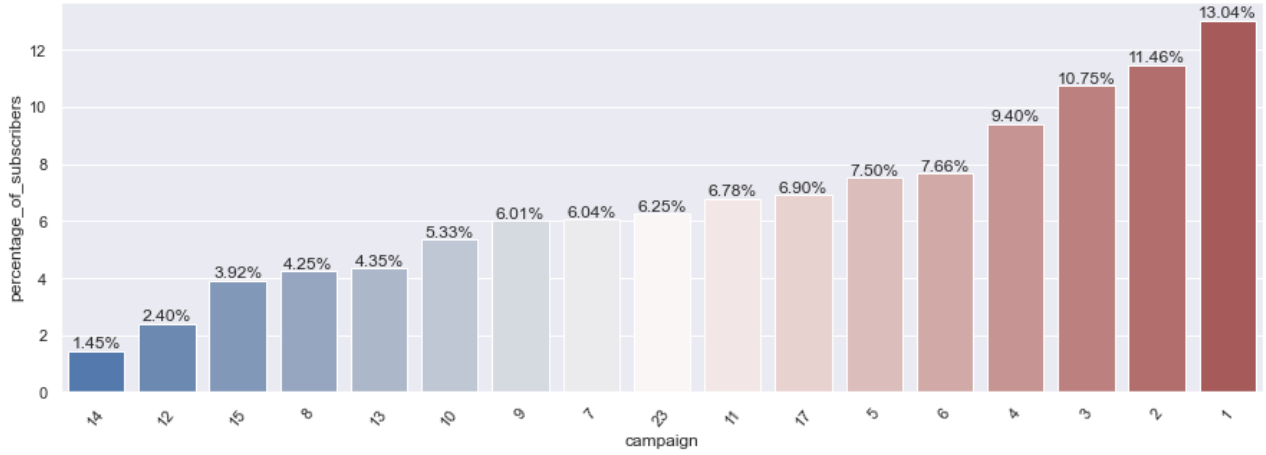
In [94]:
```
# Running function for the 'month' column

statPlot('month')
```



In [95]:
```
# Running function for the 'day_of_week' column

statPlot('day_of_week')
```



In [96]:
```
# Running function for the 'campaign' column

statPlot('campaign')
```



Notes on the graphs:

- Job: Top three subscribers were: Students 31.43%, Retired Individuals: 25.23% and unemployed 14.2%. Students were twice as likely to subscribe than unemployed individuals.
- Marital Status: Didn't play a major role. There was not a significant difference among the individuals who were single, married, or divorced.
- Education: There are six illiterate people included in this analysis. Therefore, there is not enough data to make any conclusion for that category.
- The highest percentage was by individuals those holding a university degree of 13.72%, and people who have taken professional courses 11.35%.
- Default: People who did not default on their loans were 12% more likely to subscribe than the individuals who did default on their loan.
- Loan: Having a loan did not make a major difference.

- Contact: Contacting individuals through a cellular phone was twice as likely to lead to a subscription.
- Month: October, September, December, and March were the most successful months of the year. Prospects are three times more likely to subscribe to the bank campaign of term deposits.
- Day of the week: There was no major difference among the days of the week in terms of the likelihood of subscribing.
- Campaign: the highest percentage of subscribers came from individuals who were contacted 1-4 times.

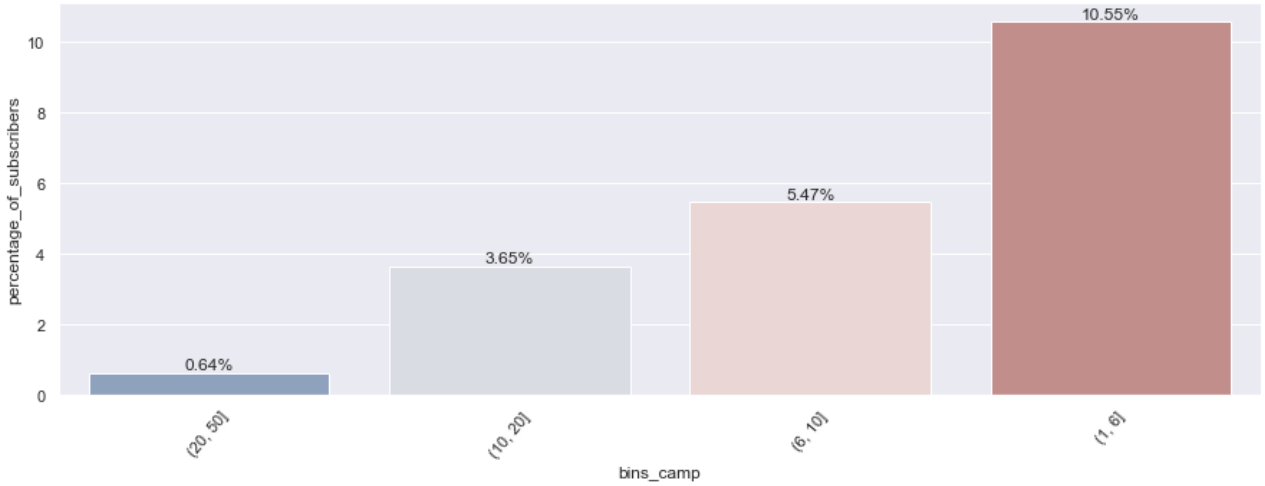
Adding bins for the 'campaign' column - for the presentation

In [97]:
```
df_bank["campaign"].describe()
```

Out[97]:
```
count    41176.000000
mean         2.567879
std          2.770318
min          1.000000
25%          1.000000
50%          2.000000
75%          3.000000
max         56.000000
Name: campaign, dtype: float64
```

In [98]:
```
#Here are the  bins  based on the values observed above.
# 5 values will result in 4 bins

bins = [1, 6, 10, 20, 50]

#We'll pd.cut method to separate data into bins.
df_bank['bins_camp'] = pd.cut(df_bank['campaign'], bins)

# I will use .cat.as_unordered() method transforming the data to
# ordered categories.
# bins_age_built = bins_yr_built.cat.as_unordered()
# bins_yr_built.head()
```

In [99]:
```
statPlot('bins_camp')
```



Building Classification Models

I will drop off the 'duration' column since the time of the call will not be known before contacting the prospect, and therefore including it in the model would create an unrealistic prediction. The variables included need to be known prior to the campaign call to assist businesses in targeting certain segments of the population.

In [100…
```
df_bank.drop(['duration','bins_age','bins_camp'],axis=1,inplace=True)
```

In [101…
```
# Changing 'Yes' to '1' and 'No' to '0' in order to have numerical values for
# our target variable.
dic_sub = {'yes':1,'no':0}

df_bank['subscribed'] = df_bank['subscribed'].map(dic_sub)

df_bank['subscribed']
```

Out[101…
```
0         0
1         0
2         0
3         0
4         0
         ..
41183     1
41184     0
41185     0
41186     1
41187     0
Name: subscribed, Length: 41176, dtype: int64
```

In [102…
```
# Splitting my data frame into X( independent variables) and y (dependent/target

X = df_bank.drop("subscribed", axis=1)
y = df_bank["subscribed"]
```

In [103…
```
# Look into object data
```

```
X.select_dtypes('object')
```

Out[103…

	job	marital	education	default	housing	loan	contact	month	day_of_
0	housemaid	married	basic.4y	no	no	no	telephone	may	
1	services	married	high.school	unknown	no	no	telephone	may	
2	services	married	high.school	no	yes	no	telephone	may	
3	admin.	married	basic.6y	no	no	no	telephone	may	
4	services	married	high.school	no	no	yes	telephone	may	
...	...	...	...	...	...	...	...	...	
41183	retired	married	professional.course	no	yes	no	cellular	nov	
41184	blue-collar	married	professional.course	no	no	no	cellular	nov	
41185	retired	married	university.degree	no	yes	no	cellular	nov	
41186	technician	married	professional.course	no	no	no	cellular	nov	
41187	retired	married	professional.course	no	yes	no	cellular	nov	

41176 rows × 10 columns

In [104…

```
#  converting the data type into sting

df_bank['age_group'] = df_bank['age_group'].astype('str')
```

In [105…

```
# Double checking for Null values.
X.isna().sum()
```

Out[105…

```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
campaign          0
pdays             0
previous          0
poutcome          0
cons_price_idx    0
cons_conf_idx     0
euribor3m         0
age_group         2
count             0
dtype: int64
```

In [106…

```
# Drop Null values from the 'age_group' column

df_bank = df_bank.dropna(axis=0, subset=['age_group'])
```

In [107…
```
# Double check that there are no Null values

df_bank.isna().sum()
```

Out[107…
```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
campaign          0
pdays             0
previous          0
poutcome          0
cons_price_idx    0
cons_conf_idx     0
euribor3m         0
subscribed        0
age_group         0
count             0
dtype: int64
```

Score Function

We built a function that captures the classified models, trains them, and produces the scoring results (Accuracy, Precious Recall, and F1_Score). We added an "if statement" with a display element to have the option to not display when unnecessary.

In [108…
```
# Building a function that will fit the model and then fit it to produce predict

def Train_Test_Scores(model,display=False):

    model.fit(X_train,y_train)
    y_preds = model.predict(X_test)

    # Store the score for later evaluation of the model.

    train_acc = model.score(X_train,y_train)
    test_acc = model.score(X_test,y_test)
    precision = precision_score(y_test,y_preds)
    recall = recall_score(y_test,y_preds)
    f1 = f1_score(y_test,y_preds)

    # Allowing the display to switch off for later on when I just need to functi
    # for other purposes like creating a data frame of the scoring.

    if display:
        print('Training_Accuracy:',  train_acc)
        print('Test_Accuracy:', test_acc)

        print('Precision:', precision)
        print('Recall:', recall)
        print('F1_Score:', f1)
```

```
        plot_confusion_matrix(model, X_test, y_test, cmap="Blues")


    return train_acc,test_acc,precision,recall,f1
```

Note on Scaling:

We are scaling the data using the Standard Scaler method. Standardize the data by making the mean of the distribution zero and the majority of the data will be between -1 and 1.

In [109…
```
# Splitting the data into X and y - y is the target variable.


X = df_bank.drop("subscribed", axis=1)
y = df_bank["subscribed"]

# Extracting the index in order to know which ones are the categorical variables
# Testing if it equals to '0' - object.
cat_indx = [indx for indx,tp in enumerate(X.dtypes) if tp=='O']

# Creating a separate list for numerical and categorical variables.

cat_col = list(X.select_dtypes('object'))
num_col = list(set(X) - set(cat_col))
```

SMOTE

Given that our data is unbalanced, where only 11% of the individuals subscribed and not even equality represented with the group that unsubscribed, it can lead to inaccurate results when we employ a predictive model. In such scenarios of class imbalance, it is recommended to use Synthetic Minority Over - Sampling Technique. We implemented SMOTE- Nominal and Continuous ('SMOTE-NC') since our data contains categorical and numerical data.

In [110…
```
# Applying Smote

from imblearn.over_sampling import SMOTENC #importing SMOTENC

smt = SMOTENC(categorical_features=cat_indx, random_state=2)
X_smote, y_smote = smt.fit_resample(X, y)
```

In [111…
```
y_smote.value_counts()
```

Out[111…
```
0    36537
1    36537
Name: subscribed, dtype: int64
```

In [187…
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote, test_size
```

Focus on Accuracy

In this project, false positives and false negatives are both equally important.

Reaching out to a prospect incorrectly labeled as a potential subscriber will lead to the bank losing money on marketing efforts. At the same time, if a potential subscriber is labeled incorrectly as a non-subscribers and the bank will not contact them – the bank would lose business with an individual that would otherwise subscribe to a term deposit.

Given that the data is now balanced, I can rely on the accuracy score for model valuation.

Pipeline

We inserted the pipeline as part of a function so that it can loop around when we employed the various classified models.

In [113…

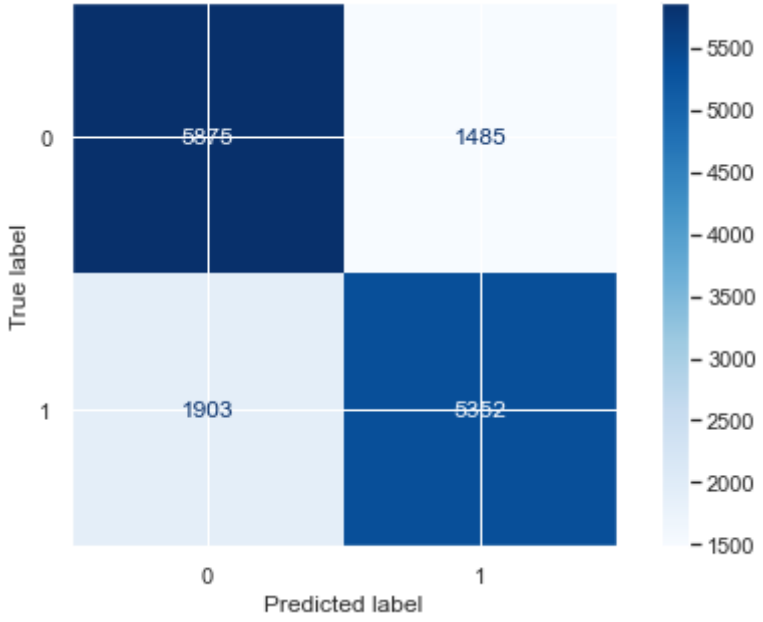
```
# Pipeline function

def custom_pipeline(clf,display=False):

    num_attribs = num_col # Continuous columns
    cat_attribs = cat_col # Categorical columns

    # When the data passed through the pipeline,
    # it went through the first step of StandardSclare() and OneHotEncoder().
    preprocessor = ColumnTransformer([
            ("num", StandardScaler(), num_attribs),
            ("cat", OneHotEncoder(), cat_attribs),
        ])

    model = Pipeline(steps=[("preprocessor", preprocessor), ('model', clf)])
    model.fit(X_train,y_train)

    # The adjusted data fit the model/classifier and ultimately produced
    # predictive values for the testing and training data and reverted back to
    # the model scoring.

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

    y_pred = model.predict(X_test)
    X_probs = model.predict_proba(X_test)
    train_acc,test_acc,precision,recall,f1 = Train_Test_Scores(model,display)

    print("")
    return train_acc,test_acc,precision,recall,f1,y_pred,X_probs[:,1],model
```

Logistic Regression Model

In [114…

```
# Running logistic regression
lr = custom_pipeline(LogisticRegression(),display=True)
```

```
Training_Accuracy: 0.7674780615474093
Test_Accuracy: 0.7681833732466644
Precision: 0.782799473453269
Recall: 0.7376981392143349
F1_Score: 0.7595799034913425
```



In [115…

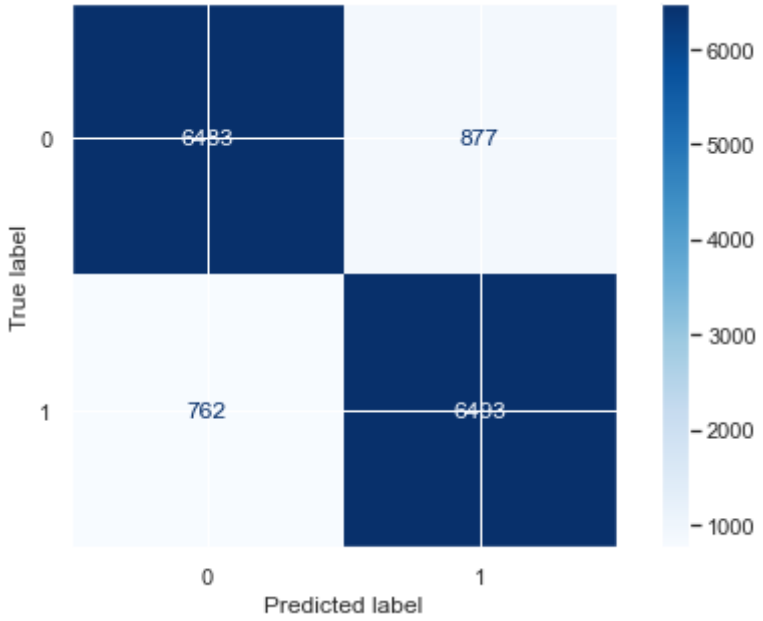
```
# print(classification_report(y_test,val[-1]))
```

Decision Tree Model

In [116…

```
# Running Decision Tree
dt = custom_pipeline(DecisionTreeClassifier(), display= True)
```

```
Training_Accuracy: 0.9958090285499239
Test_Accuracy: 0.8878549435511461
Precision: 0.8810040705563094
Recall: 0.8949689869055824
F1_Score: 0.887931623931624
```

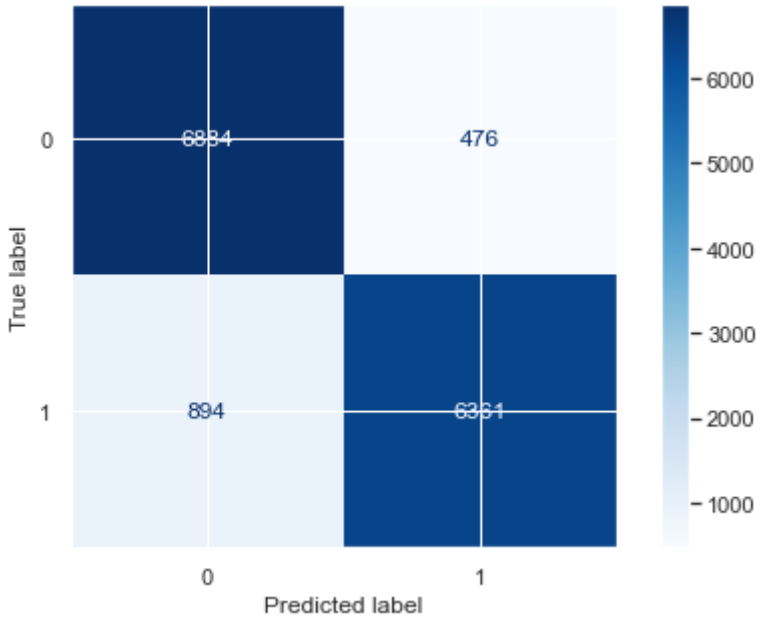


XG Boost Model

In [117…

```
# Running XG Boost
xgboost = custom_pipeline(XGBClassifier(n_jobs=-1),display= True)
```

```
[12:23:52] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-4
3e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Startin
g in XGBoost 1.3.0, the default evaluation metric used with the objective 'binar
y:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if
you'd like to restore the old behavior.
[12:23:56] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-4
3e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Startin
g in XGBoost 1.3.0, the default evaluation metric used with the objective 'binar
y:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if
you'd like to restore the old behavior.
Training_Accuracy: 0.9206623445491712
Test_Accuracy: 0.9062606910708176
Precision: 0.9303788211203744
Recall: 0.8767746381805651
F1_Score: 0.9027817201248935
```

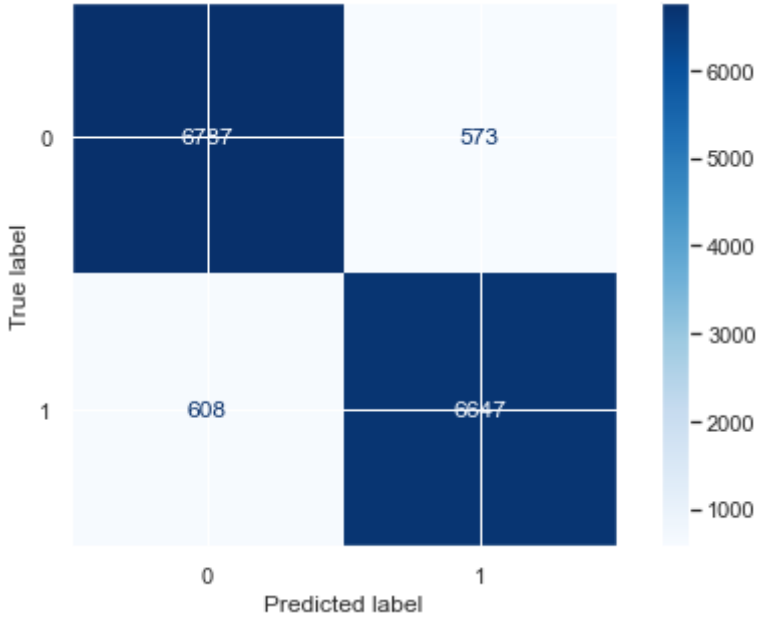


Random Forest Model

In [118…

```
# Running Random Forest
rf = custom_pipeline(RandomForestClassifier(),display= True)
```

```
Training_Accuracy: 0.9958090285499239
Test_Accuracy: 0.9191926103318508
Precision: 0.9206371191135734
Recall: 0.9161957270847692
F1_Score: 0.9184110535405872
```



In [119…
```
rf
```

Out[119…
```
(0.9958090285499239,
 0.9191926103318508,
 0.9206371191135734,
 0.9161957270847692,
 0.9184110535405872,
 array([0, 0, 1, ..., 0, 1, 0]),
 array([0.04 , 0.39 , 0.91 , ..., 0.125, 0.73 , 0.04 ]),
 Pipeline(steps=[('preprocessor',
                  ColumnTransformer(transformers=[('num', StandardScaler(),
                                                   ['count', 'euribor3m',
                                                    'campaign', 'pdays',
                                                    'previous', 'cons_price_id
x',
                                                    'cons_conf_idx', 'age']),
                                                  ('cat', OneHotEncoder(),
                                                   ['job', 'marital',
                                                    'education', 'default',
                                                    'housing', 'loan', 'contac
t',
                                                    'month', 'day_of_week',
                                                    'poutcome',
                                                    'age_group'])])),
                 ('model', RandomForestClassifier())]))
```

In [120…
```
# pipe_models[-2]
```

function-pipeline

Evaluating Models

In [121…
```
# Creating a data frame to collect all the results and evaluate them

models_DataFrame = pd.DataFrame(columns=['Model','Train_Accuracy','Test_Accuracy
                                         'Precision','Recall','F1_score'])
```

```
list_models = [LogisticRegression(),DecisionTreeClassifier(),
               RandomForestClassifier(n_jobs=-1),XGBClassifier(n_jobs=-1)]

model_names = 'Lositic_Regression  Decision_Tree Random_Forest XGboost'.split()

from tqdm import tqdm
x_probs  = []
pipe_models = []

for model,model_name in tqdm(zip(list_models,model_names)):
    train_acc,test_acc,precision,recall,f1,_,x_prob,pipe_model = custom_pipeline
    x_probs.append(x_prob)
    pipe_models.append(pipe_model)
    models_DataFrame.loc[len(models_DataFrame)] = [model_name,train_acc,test_acc
```

```
1it [00:01,  1.80s/it]

2it [00:02,  1.44s/it]

3it [00:05,  2.14s/it]
[12:24:17] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-4
3e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Startin
g in XGBoost 1.3.0, the default evaluation metric used with the objective 'binar
y:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if
you'd like to restore the old behavior.
[12:24:21] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-4
3e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Startin
g in XGBoost 1.3.0, the default evaluation metric used with the objective 'binar
y:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if
you'd like to restore the old behavior.
4it [00:13,  3.45s/it]
```

In [122…

```
# Diplay data frame
models_DataFrame
```

Out[122…

	Model	Train_Accuracy	Test_Accuracy	Precision	Recall	F1_score
0	Lositic_Regression	0.767478	0.768183	0.782799	0.737698	0.759580
1	Decision_Tree	0.995809	0.887444	0.881840	0.892901	0.887336
2	Random_Forest	0.995792	0.918235	0.919319	0.915644	0.917478
3	XGboost	0.920662	0.906261	0.930379	0.876775	0.902782

In [123…

```
# Checking which one was the top performer
models_DataFrame.sort_values('Test_Accuracy',ascending=False).values[0][0]
```

Out[123…

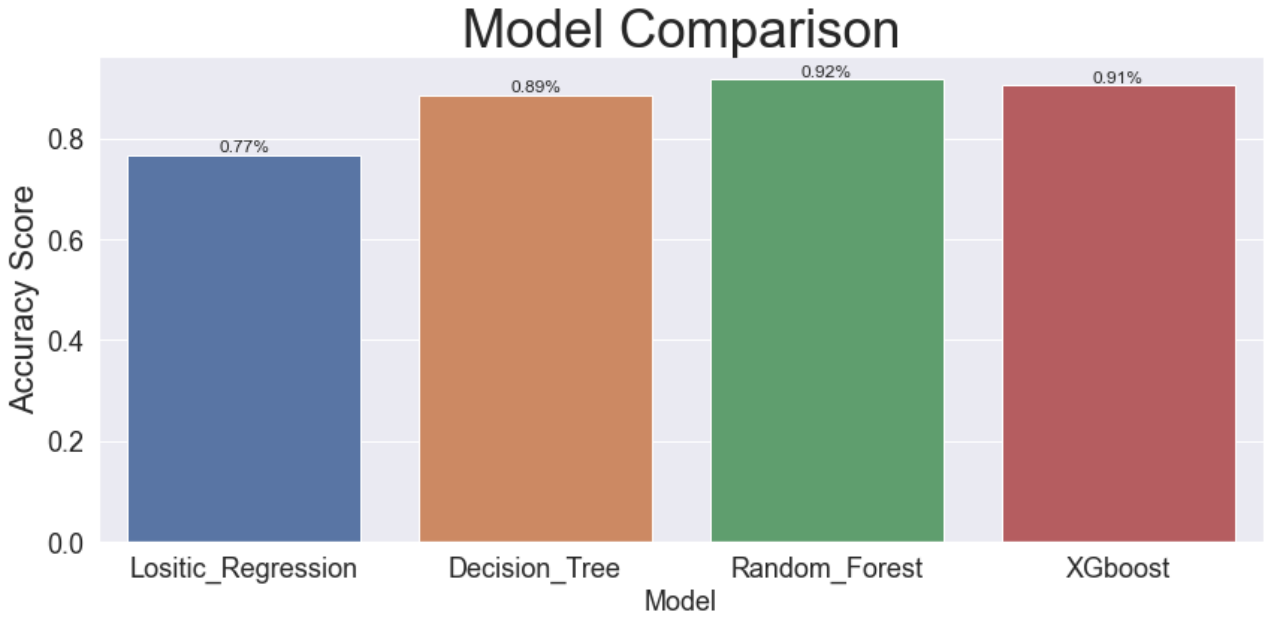
```
'Random_Forest'
```

In [124…

```
# Preparing for plotting x and y axis
x_plot = models_DataFrame["Model"]
y_plot = models_DataFrame["Test_Accuracy"]
```

In [125…

```
# Plotting model results

fig, ax = plt.subplots(figsize=(12,6))

sns.barplot(x=x_plot, y=y_plot)

# Lable and define fontsize for main and axis titles.

plt.xlabel('Model', fontsize=18)
plt.ylabel('Accuracy Score', fontsize=22)
plt.title('Model Comparison', fontsize=35)
plt.tick_params(axis='both', which='major', labelsize=18)

for bars in ax.containers:
        ax.bar_label(bars, fmt="%.2f%%")
#Set x-axis tick labels.


plt.tight_layout()
plt.show()
```



Hyperparameter Tuning using GridSearch

Xgboost - Hyperparameter Tuning

In [126…

```
# Checking the location of the model and its keys

pipeline_xgboost = pipe_models[-1]
pipeline_xgboost .get_params().keys()
```

Out[126… dict_keys(['memory', 'steps', 'verbose', 'preprocessor', 'model', 'preprocessor_
_n_jobs', 'preprocessor__remainder', 'preprocessor__sparse_threshold', 'preproce
ssor__transformer_weights', 'preprocessor__transformers', 'preprocessor__verbos
e', 'preprocessor__num', 'preprocessor__cat', 'preprocessor__num__copy', 'prepro
cessor__num__with_mean', 'preprocessor__num__with_std', 'preprocessor__cat__cate

```
gories', 'preprocessor__cat__drop', 'preprocessor__cat__dtype', 'preprocessor__c
at__handle_unknown', 'preprocessor__cat__sparse', 'model__objective', 'model__us
e_label_encoder', 'model__base_score', 'model__booster', 'model__colsample_bylev
el', 'model__colsample_bynode', 'model__colsample_bytree', 'model__gamma', 'mode
l__gpu_id', 'model__importance_type', 'model__interaction_constraints', 'model__
learning_rate', 'model__max_delta_step', 'model__max_depth', 'model__min_child_w
eight', 'model__missing', 'model__monotone_constraints', 'model__n_estimators',
'model__n_jobs', 'model__num_parallel_tree', 'model__random_state', 'model__reg_
alpha', 'model__reg_lambda', 'model__scale_pos_weight', 'model__subsample', 'mod
el__tree_method', 'model__validate_parameters', 'model__verbosity'])
```

In [127…

```
# The below cells are commented since  it takes a couple of hours to runthough a

# params_xgBoost = {
#         'model__min_child_weight': [1, 5, 10,15,20],
# #         'model__gamma': [0.5, 1, 1.5, 2, 5,6,7,8],
#         'model__subsample': [0.6, 0.8, 1.0],
# #         'model__colsample_bytree': [0.6, 0.8, 1.0],
#         'model__max_depth': [3, 4, 5,6,7,8]
#         }
```

In [128…

```
# Using GridSearch to find the best parameters

# GrifSearch

# grid_clf_xgboost = GridSearchCV(pipeline_xgboost, params_xgBoost, scoring='acc
#                         cv=3, n_jobs=-1,verbose=3)
```

In [129…

```
# Fitting the model

# xgboost_tuned = grid_clf_xgboost.fit(X_train, y_train)
```

In [130…

```
# Obtaining best parameters

# best_param = xgboost_tuned.best_params_
# best_param
```

In [131…

```
best_param = {'model__max_depth': 8, 'model__min_child_weight': 1, 'model__subsa
```

In [132…

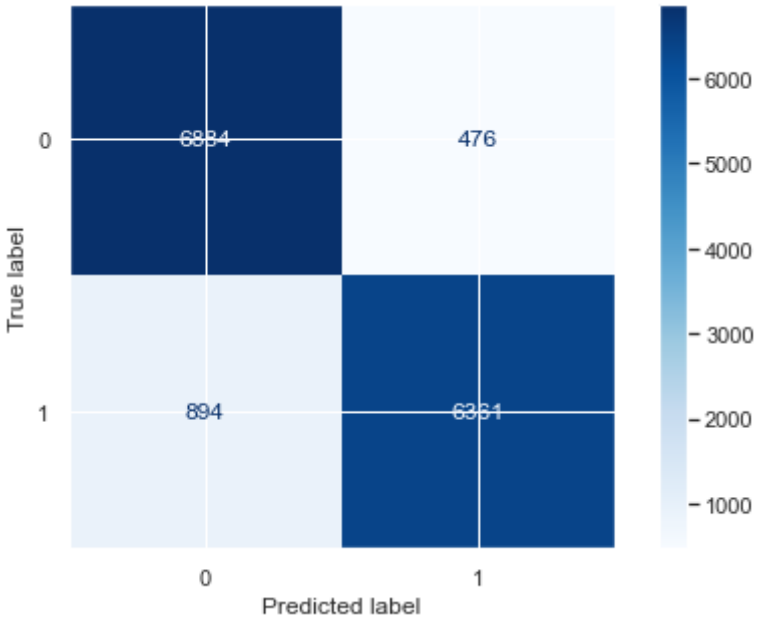
```
# Storing the best parameters
# {'model__max_depth': 8, 'model__min_child_weight': 1, 'model__subsample': 0.8}
```

In [133…

```
# Checking the tuned result for XG boost

model_tuned_pipeline_xgboost = custom_pipeline(XGBClassifier(**best_param),displ
```

```
[12:24:25] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-4
3e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:541:
Parameters: { model__max_depth, model__min_child_weight, model__subsample } migh
t not be used.

  This may not be accurate due to some parameters are only used in language bind
ings but
```

```
  passed down to XGBoost core.  Or some parameters are not used but slip through
this
  verification. Please open an issue if you find above cases.


[12:24:25] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-4
3e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Startin
g in XGBoost 1.3.0, the default evaluation metric used with the objective 'binar
y:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if
you'd like to restore the old behavior.
[12:24:29] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-4
3e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:541:
Parameters: { model__max_depth, model__min_child_weight, model__subsample } migh
t not be used.

  This may not be accurate due to some parameters are only used in language bind
ings but
  passed down to XGBoost core.  Or some parameters are not used but slip through
this
  verification. Please open an issue if you find above cases.


[12:24:29] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-4
3e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Startin
g in XGBoost 1.3.0, the default evaluation metric used with the objective 'binar
y:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if
you'd like to restore the old behavior.
Training_Accuracy: 0.9206623445491712
Test_Accuracy: 0.9062606910708176
Precision: 0.9303788211203744
Recall: 0.8767746381805651
F1_Score: 0.9027817201248935
```



In [134…

```
# Named_steps['model']  allows us to see the details of al the parameters,

model_tuned_pipeline_xgboost[-1].named_steps['model']
```

Out[134…

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
```

```
                    min_child_weight=1, missing=nan, model__max_depth=8,
                    model__min_child_weight=1, model__subsample=0.8,
                    monotone_constraints='()', n_estimators=100, n_jobs=8,
                    num_parallel_tree=1, random_state=0, reg_alpha=0, reg_lambda=1,
                    scale_pos_weight=1, subsample=1, tree_method='exact',
                    validate_parameters=1, verbosity=None)
```

In [135…

```
# Looking at the steps
model_tuned_pipeline_xgboost
```

Out[135…

```
(0.9206623445491712,
 0.9062606910708176,
 0.9303788211203744,
 0.8767746381805651,
 0.9027817201248935,
 array([0, 1, 1, ..., 0, 1, 0]),
 array([0.07020947, 0.5874478 , 0.8636114 , ..., 0.030653  , 0.8801508 ,
        0.09180609], dtype=float32),
 Pipeline(steps=[('preprocessor',
                  ColumnTransformer(transformers=[('num', StandardScaler(),
                                                   ['count', 'euribor3m',
                                                    'campaign', 'pdays',
                                                    'previous', 'cons_price_id
x',
                                                    'cons_conf_idx', 'age']),
                                                  ('cat', OneHotEncoder(),
                                                   ['job', 'marital',
                                                    'education', 'default',
                                                    'housing', 'loan', 'contac
t',
                                                    'month', 'day_of_week',
                                                    'poutcome',
                                                    'age_group'])])),
                 ('model',
                  XGBClassifier(base_sco...
                                learning_rate=0.300000012, max_delta_step=0,
                                max_depth=6, min_child_weight=1, missing=nan,
                                model__max_depth=8, model__min_child_weight=1,
                                model__subsample=0.8, monotone_constraints='()',
                                n_estimators=100, n_jobs=8, num_parallel_tree=1,
                                random_state=0, reg_alpha=0, reg_lambda=1,
                                scale_pos_weight=1, subsample=1,
                                tree_method='exact', validate_parameters=1,
                                verbosity=None))]))
```

In [136…

```
# Obtaining the propbilies for XG Boost

y_probs_xgboost_t = model_tuned_pipeline_xgboost[-2]
y_probs_xgboost_t
```

Out[136…

```
array([0.07020947, 0.5874478 , 0.8636114 , ..., 0.030653  , 0.8801508 ,
       0.09180609], dtype=float32)
```

Random Forest - Hyperparameter Tuning

In [137…

```
# Verifying that this is where Random Forest is stored.
pipe_models[-2]
```

Out[137…

```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num', StandardScaler(),
```

```
                                                  ['count', 'euribor3m',
                                                   'campaign', 'pdays',
                                                   'previous', 'cons_price_idx',
                                                   'cons_conf_idx', 'age']),
                                                 ('cat', OneHotEncoder(),
                                                  ['job', 'marital',
                                                   'education', 'default',
                                                   'housing', 'loan', 'contact',
                                                   'month', 'day_of_week',
                                                   'poutcome',
                                                   'age_group'])])),
                        ('model', RandomForestClassifier(n_jobs=-1))])
```

In [138…

```
# Checking the location of the model and its keys


pipeline_rf = pipe_models[-2]
pipeline_rf.get_params().keys() # Checking the keys for the parameters
```

Out[138…

```
dict_keys(['memory', 'steps', 'verbose', 'preprocessor', 'model', 'preprocessor_
_n_jobs', 'preprocessor__remainder', 'preprocessor__sparse_threshold', 'preproce
ssor__transformer_weights', 'preprocessor__transformers', 'preprocessor__verbos
e', 'preprocessor__num', 'preprocessor__cat', 'preprocessor__num__copy', 'prepro
cessor__num__with_mean', 'preprocessor__num__with_std', 'preprocessor__cat__cate
gories', 'preprocessor__cat__drop', 'preprocessor__cat__dtype', 'preprocessor__c
at__handle_unknown', 'preprocessor__cat__sparse', 'model__bootstrap', 'model__cc
p_alpha', 'model__class_weight', 'model__criterion', 'model__max_depth', 'model_
_max_features', 'model__max_leaf_nodes', 'model__max_samples', 'model__min_impur
ity_decrease', 'model__min_impurity_split', 'model__min_samples_leaf', 'model__m
in_samples_split', 'model__min_weight_fraction_leaf', 'model__n_estimators', 'mo
del__n_jobs', 'model__oob_score', 'model__random_state', 'model__verbose', 'mode
l__warm_start'])
```

In [139…

```
# The below cells are commented since  it takes a couple of hours to runthough a

# param_grid_rf = {
#     'model__n_estimators': [100, 300, 600, 900, 1200],
#      'model__max_features': [2, 4,6,8,10,12,14],
#      'model__max_depth' : [50, 100, 200],
#      'model__criterion' :['gini', 'entropy']
# }
```

In [140…

```
# # GrifSearch
# grid_clf_rf = GridSearchCV(pipeline_rf, param_grid_rf, scoring='accuracy',
#                            cv=3, n_jobs=-1,verbose=2)
```

In [141…

```
# grid_clf_rf.fit(X_train, y_train)
```

In [142…

```
# best_params_rf = grid_clf_rf.best_params_
```

In [143…

```
# Using the best parameters
best_params_rf = {'model__criterion': 'gini',
 'model__max_depth': 200,
 'model__max_features': 14,
 'model__n_estimators': 900}
```

In [144…
```
# Checking Parameters
best_params_rf
```

Out[144…
```
{'model__criterion': 'gini',
 'model__max_depth': 200,
 'model__max_features': 14,
 'model__n_estimators': 900}
```

In [145…
```
# Removing '_' - to match the code out side of the pipeline
best_params_rf = {k.split('__')[1]:best_params_rf[k] for k in best_params_rf}
```

In [146…
```
# RandomForestClassifier(criterion='gini',max_depth=200, )

# {'model__criterion': 'gini',
#  'model__max_depth': 200,
#  'model__max_features': 14,
#  'model__n_estimators': 900}
```

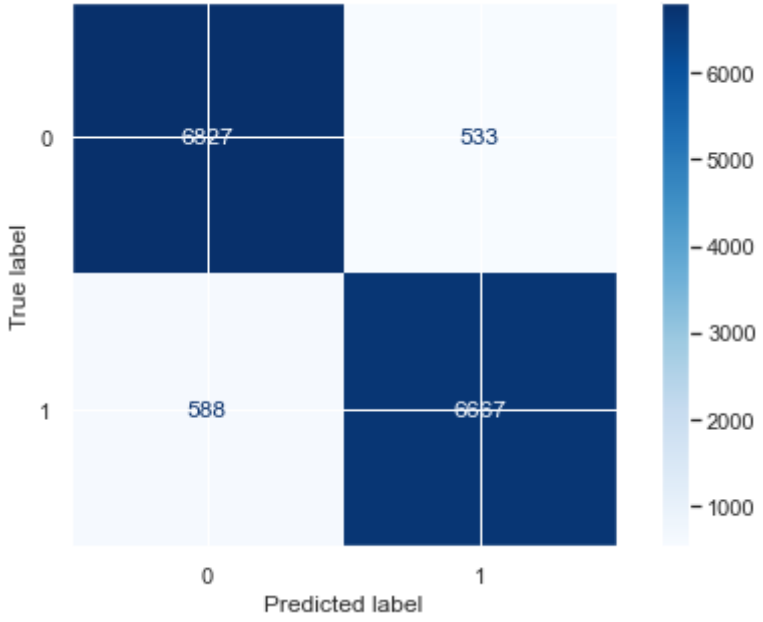
In [147…
```
# Applying best parameters
clf_rf = RandomForestClassifier(**best_params_rf)
```

In [148…
```
# Checking if worked
clf_rf
```

Out[148…
```
RandomForestClassifier(max_depth=200, max_features=14, n_estimators=900)
```

In [149…
```
# Model tuned results
model_tuned_pipeline_rf = custom_pipeline(clf_rf,display=True)
```

```
Training_Accuracy: 0.9958090285499239
Test_Accuracy: 0.9232979815258296
Precision: 0.9259722222222222
Recall: 0.9189524465885596
F1_Score: 0.9224489795918368
```



Before and After Hyper Tunning - Receiver Operating Characteristic ("ROC")

In [150…
```
# Displaying the results step by step

model_tuned_pipeline_rf
```

Out[150…
```
(0.9958090285499239,
 0.9232979815258296,
 0.9259722222222222,
 0.9189524465885596,
 0.9224489795918368,
 array([0, 0, 1, ..., 0, 1, 0]),
 array([0.05888889, 0.25      , 0.89444444, ..., 0.07525397, 0.72768519,
        0.04      ]),
 Pipeline(steps=[('preprocessor',
                  ColumnTransformer(transformers=[('num', StandardScaler(),
                                                   ['count', 'euribor3m',
                                                    'campaign', 'pdays',
                                                    'previous', 'cons_price_id
x',
                                                    'cons_conf_idx', 'age']),
                                                  ('cat', OneHotEncoder(),
                                                   ['job', 'marital',
                                                    'education', 'default',
                                                    'housing', 'loan', 'contac
t',
                                                    'month', 'day_of_week',
                                                    'poutcome',
                                                    'age_group'])])),
                 ('model',
                  RandomForestClassifier(max_depth=200, max_features=14,
                                         n_estimators=900))]))
```

In [151…
```
list_models
```

Out[151…
```
[LogisticRegression(),
```

```
DecisionTreeClassifier(),
RandomForestClassifier(n_jobs=-1),
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=-1, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)]
```

In [152…
```
# Random Forest - Tuned with best parameters
x_probs[2]
```

Out[152…
```
array([0.1       , 0.26      , 0.93      , ..., 0.06333333, 0.73333333,
       0.02      ])
```

In [153…
```
#NEED TO CHANE THE MODLES  ONLY rf_recall_t is correct
```

In [154…
```
# Checking x_probs for Randon Forest
x_probs
```

Out[154…
```
[array([0.11788034, 0.80084101, 0.43681956, ..., 0.09284231, 0.88515423,
        0.166515  ]),
 array([0., 1., 1., ..., 0., 0., 0.]),
 array([0.1       , 0.26      , 0.93      , ..., 0.06333333, 0.73333333,
        0.02      ]),
 array([0.07020947, 0.5874478 , 0.8636114 , ..., 0.030653  , 0.8801508 ,
        0.09180609], dtype=float32)]
```

ROC PLOT

In [155…
```
# Locating Random Forest without tuning
x_probs[3]
```

Out[155…
```
array([0.07020947, 0.5874478 , 0.8636114 , ..., 0.030653  , 0.8801508 ,
       0.09180609], dtype=float32)
```

In [156…
```
# Locating Random Forest with tuning
model_tuned_pipeline_rf[6]
```

Out[156…
```
array([0.05888889, 0.25      , 0.89444444, ..., 0.07525397, 0.72768519,
       0.04      ])
```

In [157…
```
x_probs[-3]
```

Out[157…
```
array([0., 1., 1., ..., 0., 0., 0.])
```

In [158…
```
model_tuned_pipeline_xgboost[6]
```

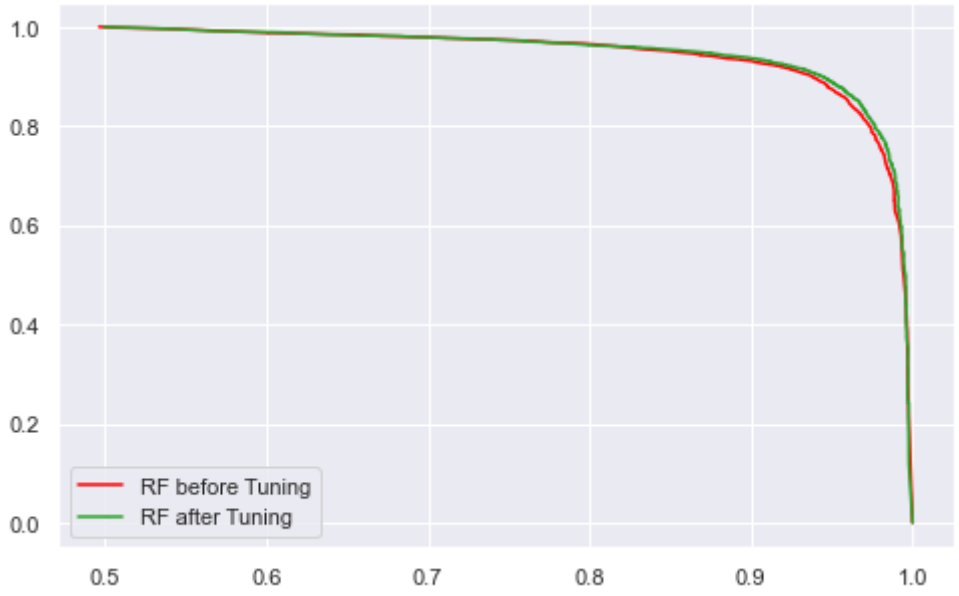
Out[158…
```
array([0.07020947, 0.5874478 , 0.8636114 , ..., 0.030653  , 0.8801508 ,
       0.09180609], dtype=float32)
```

In [159…
```
# Generate probablities to plot for Random Forest

rf_precision, rf_recall, rf_thresholds = precision_recall_curve(y_test, x_probs[

rf_precision_t, rf_recall_t, rf_threshold_t = precision_recall_curve(y_test, mod
```

In [160…
```
# Generate probablities to plot for XgBoost

xg_precision, xg_recall, xg_thresholds = precision_recall_curve(y_test, x_probs[

xg_precision_t, xg_recall_t, xg_threshold_t = precision_recall_curve(y_test, mod
```

In [161…
```
print(' ROC for Random Forest Before and After Hyper Tunning  ')

# Subplot for ROC

#fig, axs = (figsize=(15, 5))

#fig, axs = plt.subplots(1, 2,figsize=(15, 5))

# Random Forest Before Tuning Plot
plt.plot(rf_precision, rf_recall, color='red', label="RF before Tuning")


#Random Forest After Tuning Plot

plt.plot(rf_precision_t, rf_recall_t, 'tab:green', label="RF after Tuning")

plt.legend()
plt.show()
```

```
ROC for Random Forest Before and After Hyper Tunning
```



In [162…
```
x_probs[2]
```

Out[162…
```
array([0.1       , 0.26      , 0.93      , ..., 0.06333333, 0.73333333,
       0.02      ])
```

In [163…
```
model_tuned_pipeline_rf[6]
```

Out[163…
```
array([0.05888889, 0.25      , 0.89444444, ..., 0.07525397, 0.72768519,
       0.04      ])
```

Feature of Importance

Feature of Importance for Random Forst

In [164…
```
# Step 5 - predict values
pipe_models[-2]
```

Out[164…
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num', StandardScaler(),
                                                  ['count', 'euribor3m',
                                                   'campaign', 'pdays',
                                                   'previous', 'cons_price_idx',
                                                   'cons_conf_idx', 'age']),
                                                 ('cat', OneHotEncoder(),
                                                  ['job', 'marital',
                                                   'education', 'default',
                                                   'housing', 'loan', 'contact',
                                                   'month', 'day_of_week',
                                                   'poutcome',
                                                   'age_group'])])),
                ('model', RandomForestClassifier(n_jobs=-1))])
```

In [165…
```
# In order to obtain the column names, including the columns that have been dumm
# I would need to go back to X-train and use the get_dummies feature.
pipeline_col = num_col + list(pd.get_dummies(X_train[cat_col]))
pipeline_col
```

Out[165…
```
['count',
 'euribor3m',
 'campaign',
 'pdays',
 'previous',
 'cons_price_idx',
 'cons_conf_idx',
 'age',
 'job_admin.',
 'job_blue-collar',
 'job_entrepreneur',
 'job_housemaid',
 'job_management',
 'job_retired',
 'job_self-employed',
 'job_services',
 'job_student',
 'job_technician',
 'job_unemployed',
 'marital_divorced',
 'marital_married',
 'marital_single',
 'education_basic.4y',
 'education_basic.6y',
 'education_basic.9y',
 'education_high.school',
 'education_illiterate',
 'education_professional.course',
```

```
'education_university.degree',
'default_no',
'default_unknown',
'default_yes',
'housing_no',
'housing_yes',
'loan_no',
'loan_yes',
'contact_cellular',
'contact_telephone',
'month_apr',
'month_aug',
'month_dec',
'month_jul',
'month_jun',
'month_mar',
'month_may',
'month_nov',
'month_oct',
'month_sep',
'day_of_week_fri',
'day_of_week_mon',
'day_of_week_thu',
'day_of_week_tue',
'day_of_week_wed',
'poutcome_failure',
'poutcome_nonexistent',
'poutcome_success',
'age_group_Middle_Aged Adults',
'age_group_Older_Adults',
'age_group_Seniors',
'age_group_Young_Adults']
```

In [166…

```
#Double check x_train variables

X_train
```

Out[166…

	age	job	marital	education	default	housing	loan	contact	month
26596	50	technician	married	high.school	no	yes	no	telephone	nov
20458	41	technician	married	professional.course	no	no	no	cellular	aug
11003	41	services	married	basic.9y	no	yes	no	telephone	jun
18253	44	admin.	divorced	high.school	no	yes	no	cellular	jul
14277	36	admin.	single	high.school	unknown	yes	yes	cellular	jul
...	...	...	...	...	...	...	...	...	...
37194	44	admin.	married	university.degree	no	yes	no	cellular	aug
6265	34	blue-collar	married	basic.9y	no	no	yes	telephone	may
54886	35	technician	married	professional.course	no	no	no	telephone	may

	age	job	marital	education	default	housing	loan	contact	month
860	40	management	married	university.degree	no	yes	no	telephone	may
15795	19	student	single	basic.9y	unknown	yes	no	cellular	jul

58459 rows × 19 columns

In [167…
```
# Locate where model is stored in -2

rf_model = pipe_models[-2].named_steps['model']
rf_model
```

Out[167…
```
RandomForestClassifier(n_jobs=-1)
```

In [168…
```
# Another way to locate where model is stored in -2

pipe_models[-2].steps[1][1]
```

Out[168…
```
RandomForestClassifier(n_jobs=-1)
```

In [169…
```
#pipe_models[-2][-2].named_steps['model']
```

In [170…
```
# Full pipeline overview

pipe_models
```

Out[170…
```
[Pipeline(steps=[('preprocessor',
                  ColumnTransformer(transformers=[('num', StandardScaler(),
                                                   ['count', 'euribor3m',
                                                    'campaign', 'pdays',
                                                    'previous', 'cons_price_id
x',
                                                    'cons_conf_idx', 'age']),
                                                  ('cat', OneHotEncoder(),
                                                   ['job', 'marital',
                                                    'education', 'default',
                                                    'housing', 'loan', 'contac
t',
                                                    'month', 'day_of_week',
                                                    'poutcome',
                                                    'age_group'])])),
                 ('model', LogisticRegression())]),
 Pipeline(steps=[('preprocessor',
                  ColumnTransformer(transformers=[('num', StandardScaler(),
                                                   ['count', 'euribor3m',
                                                    'campaign', 'pdays',
                                                    'previous', 'cons_price_id
x',
                                                    'cons_conf_idx', 'age']),
                                                  ('cat', OneHotEncoder(),
                                                   ['job', 'marital',
                                                    'education', 'default',
                                                    'housing', 'loan', 'contac
t',
```

```
                                                  'month', 'day_of_week',
                                                  'poutcome',
                                                  'age_group'])])),
                 ('model', DecisionTreeClassifier())]),
 Pipeline(steps=[('preprocessor',
                  ColumnTransformer(transformers=[('num', StandardScaler(),
                                                   ['count', 'euribor3m',
                                                    'campaign', 'pdays',
                                                    'previous', 'cons_price_id
x',
                                                    'cons_conf_idx', 'age']),
                                                  ('cat', OneHotEncoder(),
                                                   ['job', 'marital',
                                                    'education', 'default',
                                                    'housing', 'loan', 'contac
t',
                                                    'month', 'day_of_week',
                                                    'poutcome',
                                                    'age_group'])])),
                 ('model', RandomForestClassifier(n_jobs=-1))]),
 Pipeline(steps=[('preprocessor',
                  ColumnTransformer(transformers=[('num', StandardScaler(),
                                                   ['count', 'euribor3m',
                                                    'campaign', 'pdays',
                                                    'previous', 'cons_price_id
x',
                                                    'cons_conf_idx', 'age']),
                                                  ('cat', OneHotEncoder(),
                                                   ['job', 'marital',
                                                    'education', 'default',
                                                    'housing', 'loan', 'contac
t',
                                                    'month', 'day_of_week',
                                                    'poutcome',
                                                    'age_group'])])),
                 ('model',
                  XGBClassifier(base_sco...
                                colsample_bytree=1, gamma=0, gpu_id=-1,
                                importance_type='gain',
                                interaction_constraints='',
                                learning_rate=0.300000012, max_delta_step=0,
                                max_depth=6, min_child_weight=1, missing=nan,
                                monotone_constraints='()', n_estimators=100,
                                n_jobs=-1, num_parallel_tree=1, random_state=0,
                                reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
                                subsample=1, tree_method='exact',
                                validate_parameters=1, verbosity=None))])]
```

In [171…

```
# Random Forest check for prediction
model_tuned_pipeline_rf[5]
```

Out[171…

```
array([0, 0, 1, ..., 0, 1, 0])
```

In [172…

```
# Store predictions
y_pred_rf = model_tuned_pipeline_rf[5]
```

In [173…

```
# Store features

f_imp = clf_rf.feature_importances_
```

In [174…
```
#f_imp = val[-1].steps[1][1].feature_importances_
```

In [175…
```
# Create a data frame for the important features from the tuned Random Forest mo

f_imp_df = pd.DataFrame({'imp':f_imp,'col':pipeline_col})
```

In [176…
```
# Sort values

f_imp_df = f_imp_df.sort_values('imp',ascending=False).head(10)
```

In [177…
```
# Display results for the important features

f_imp_df
```

Out[177…

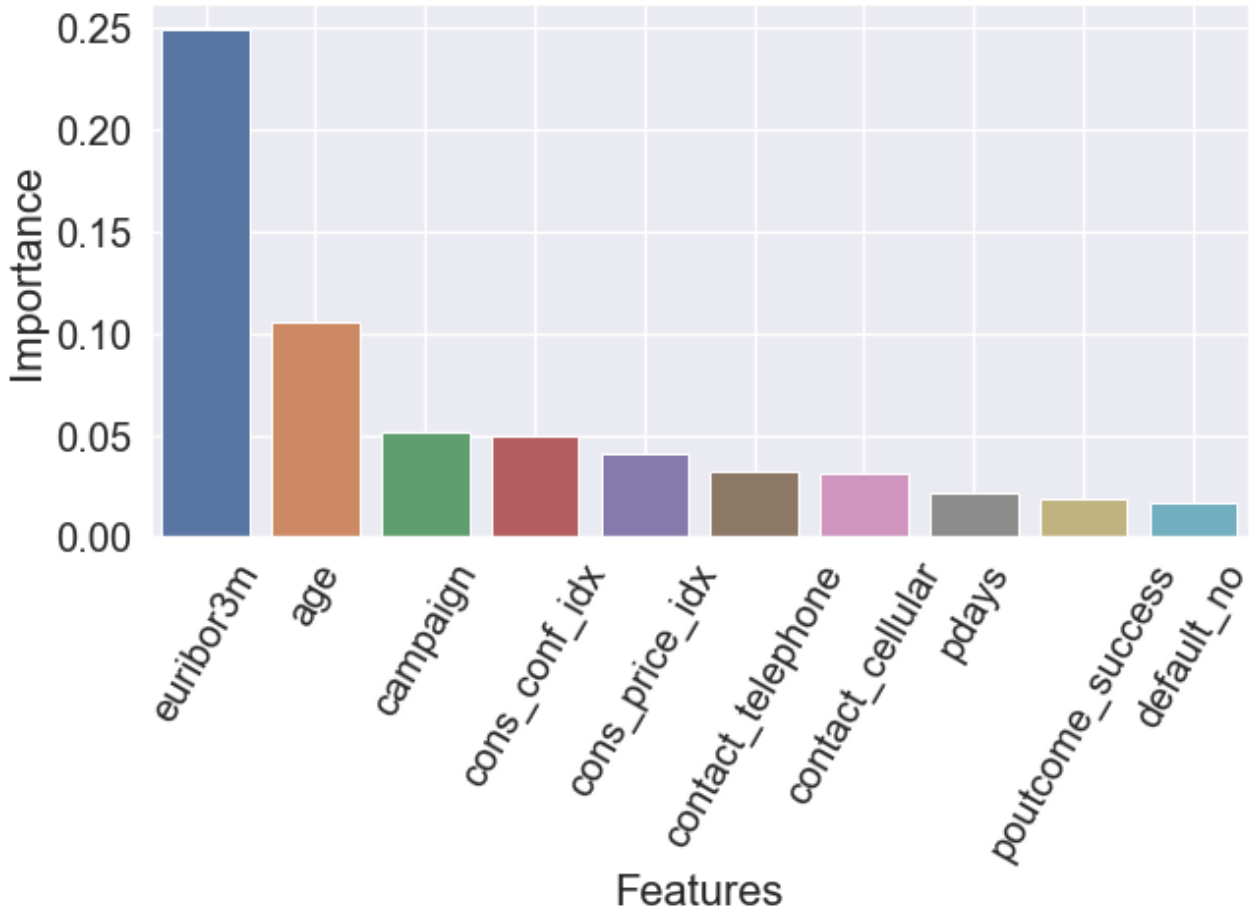
	imp	col
1	0.249701	euribor3m
7	0.105155	age
2	0.051120	campaign
6	0.049933	cons_conf_idx
5	0.041324	cons_price_idx
37	0.032082	contact_telephone
36	0.031510	contact_cellular
3	0.021474	pdays
55	0.019058	poutcome_success
29	0.017027	default_no

In [178…
```
# Display results for the important features

f_imp_df['col'].to_list()
```

Out[178…
```
['euribor3m',
 'age',
 'campaign',
 'cons_conf_idx',
 'cons_price_idx',
 'contact_telephone',
 'contact_cellular',
 'pdays',
 'poutcome_success',
 'default_no']
```

In [179…
```
# Plot important features

plt.figure(figsize=(10,5))

sns.barplot(data=f_imp_df, x="col", y="imp")
```

```
plt.xlabel("Features", fontsize=22)

plt.ylabel('Importance', fontsize=22)

plt.xticks(rotation = 60,fontsize=20)

plt.yticks(rotation = 0,fontsize=20)

plt.grid(True, color = "white", linewidth = "1.4", linestyle = "-")

plt.show()
```



In [180…

```
# Look into the classification report

report = classification_report(y_test, y_pred_rf)

print(report)
```

```
              precision    recall  f1-score   support

           0       0.92      0.93      0.92      7360
           1       0.93      0.92      0.92      7255

    accuracy                           0.92     14615
   macro avg       0.92      0.92      0.92     14615
weighted avg       0.92      0.92      0.92     14615
```

Confusion Matrix

In [181…
```
# Build  a confutation matrix with percentage and storing
# "True Neg","False Pos","False Neg","True Pos"

tn, fp, fn, tp = confusion_matrix(y_test,y_pred_rf).ravel()
```

In [182…
```
# Display

tn, fp, fn, tp
```

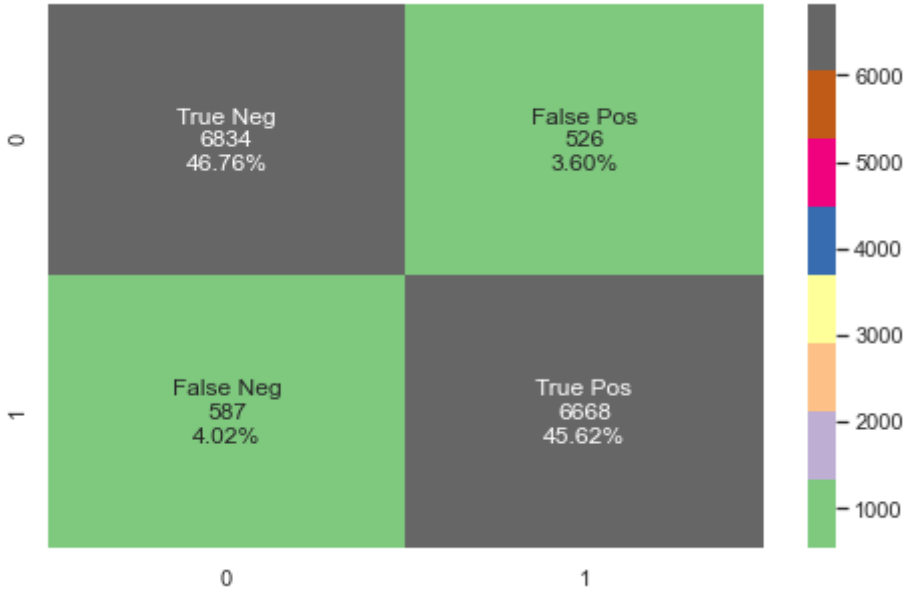
Out[182… (6834, 526, 587, 6668)

In [183…
```
# Confusion matrix

cf_matrix = confusion_matrix(y_test,y_pred_rf)
cf_matrix
```

Out[183…
```
array([[6834,  526],
       [ 587, 6668]])
```

In [184…
```
# Storing results

tn, fp, fn, tp = cf_matrix.ravel()
```

In [186…
```
# Customizing the matrix

# Adding names
group_names = ["True Neg","False Pos","False Neg","True Pos"]
group_counts = ["{0:0.0f}".format(value) for value in cf_matrix.flatten()]

# Formatting and adding percentages
group_percentages = ["{0:.2%}".format(value) for value in cf_matrix.flatten()/np

# Connecting the names with the numbers

labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in zip(group_names,group_counts,gro

# Apply heat map
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(cf_matrix, annot=labels, fmt='', cmap='Accent')
plt.show()
```



Let's look closer into how well the model predicted subscribers versus non-subscribers.

- We predicted correctly 93% of the time that an individual would not subscribe.
- We predicted correctly 92% of the time that an individual would subscribe.
- We predicted incorrectly 7% of the time that an individual would not subscribe.
- We predicted incorrectly 8% of the time that an individual would subscribe.

Conclusions:

In this project,we implemented data analysis and predictive classified models to predict term deposit subscriptions at a Portuguese bank institution. With the accuracy of 93% using Random Forest, the following business recommendations are:

- Pay close attention to socioeconomic data: 3 Month Euribor rate - The Euribor rate is based on the average interest rates at which Eurozone banks lend funds to other banks. Ramp up the campaign when rates are high. A prospect is more likely to invest in a term deposit knowing that they will receive a high interest rate. Consumer Confidence Index - Individuals are more likely to invest if their financial situation is good and if the country's outlook is optimistic.

- Target telemarketing calls toward select the individuals who belong to a specific age group and occupation. Seniors, and Students, and Retired Individuals are more likely to subscribe to a term deposit.

- Conduct the campaign during specific months. March, September, and October have been shown to have a higher rate of subscriptions.