Customer Classification for Bank Direct Marketing

1. Overview

As It is a marketing problem a lot of resources are included and it is very important to optimise results to save resources. The target variable is ‘deposit’ which reads yes or no based on success or failure of phone calls. Finding out only those clients which have higher chances of saying yes to subscription of term deposit , will save a lot of manhours and efforts. Predicting as many positives as possible out of actual positives from dataset is the goal here, thus recall has been chosen as one of the performance matrices along with an accuracy score. As our data are imbalanced, we used oversampling method during the model building process. After preprocessing the data, we build nine model including baseline model. The optimal model we get is Random Forest Classifier.

2. Business Understanding

A term deposit is a cash investment held at a financial institution. Your money is invested for an agreed rate of interest over a fixed amount of time, or term. The bank has various outreach plans to sell term deposits to their customers such as email marketing, advertisements, telephonic marketing, and digital marketing.

The older marketing options have contributed minimal in increasing the business of banks. Due to internal competition and financial crisis European Banks were under pressure to increase their financial assets. They offered long term deposits with good interest rates to the people using direct marketing strategy but contacting many people takes lot of time and success rate is also less. So they want to take help of the technology to come up with a solution that increases the efficiency by making fewer calls but improves the success rate.Portuguese Banking Institution has provided the data related to marketing campaigns that took over phone calls. Finding out the characteristics that are helping Bank to make customers successfully subscribe for deposits, which helps in increasing campaign efficiently and selecting high value customers.

The goal of this project is to building Machine Learning model that learns the unknown patterns and classifying whether client will subscribe(yes/no) a term deposit (variable y).

3. Data Understanding

Data set is taken from [UCI Machine Learning repository (https://archive.ics.uci.edu/ml/datasets/Bank+Marketing)](https://archive.ics.uci.edu/ml/datasets/Bank+Marketing). This data based on direct marketing campaigns of a Portuguese banking institution. The marketing campaigns are based on phone calls and related to 17 campaigns, which occurred from May 2008 to November 2010. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be (or not) subscribed.

3.1 Loading Data Modelling Libraries

In [1]:
```
# Importing necessary libraries
import pandas as pd
import numpy as np
import csv
# setting pandas display to avoid scientific notation in my dataframes
pd.options.display.float_format = '{:.3f}'.format
# Data visualization
import seaborn as sns
sns.set_style('whitegrid')
import matplotlib.pyplot as plt
%matplotlib inline
# Seaborn's beautiful styling
import seaborn as sns
sns.set_style('darkgrid', {'axes.facecolor': '0.9'})

# Model building sklearn
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (accuracy_score, recall_score,f1_score, auc,
confusion_matrix, classification_report, precision_recall_curve)
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import average_precision_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import RandomForestClassifier
from imblearn.ensemble import RUSBoostClassifier
from scipy import stats
from sklearn.dummy import DummyClassifier
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from sklearn.preprocessing import OneHotEncoder
from collections import Counter
from imblearn.over_sampling import SMOTENC
# to get rid of the warnings
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
# Downloading dataset
df = pd.read_csv('dataset/bank-full.csv', delimiter=';', quotechar='"',
                 encoding='utf8', quoting=csv.QUOTE_ALL, skipinitialspace=True)
```

In [3]:
```
# Displaying first 5 rows
df.head()
```

Out[3]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	p
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	

In [4]:
```
#  Information about the DataFrame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        45211 non-null  int64 
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64 
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64 
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64 
 12  campaign   45211 non-null  int64 
 13  pdays      45211 non-null  int64 
 14  previous   45211 non-null  int64 
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

In [5]:
```
# 5 summary statistics
df.describe()
```

Out[5]:

	age	balance	day	duration	campaign	pdays	previous
count	45211.000	45211.000	45211.000	45211.000	45211.000	45211.000	45211.000
mean	40.936	1362.272	15.806	258.163	2.764	40.198	0.580
std	10.619	3044.766	8.322	257.528	3.098	100.129	2.303
min	18.000	-8019.000	1.000	0.000	1.000	-1.000	0.000
25%	33.000	72.000	8.000	103.000	1.000	-1.000	0.000
50%	39.000	448.000	16.000	180.000	2.000	-1.000	0.000
75%	48.000	1428.000	21.000	319.000	3.000	-1.000	0.000
max	95.000	102127.000	31.000	4918.000	63.000	871.000	275.000

3.2. Data Preprocessing

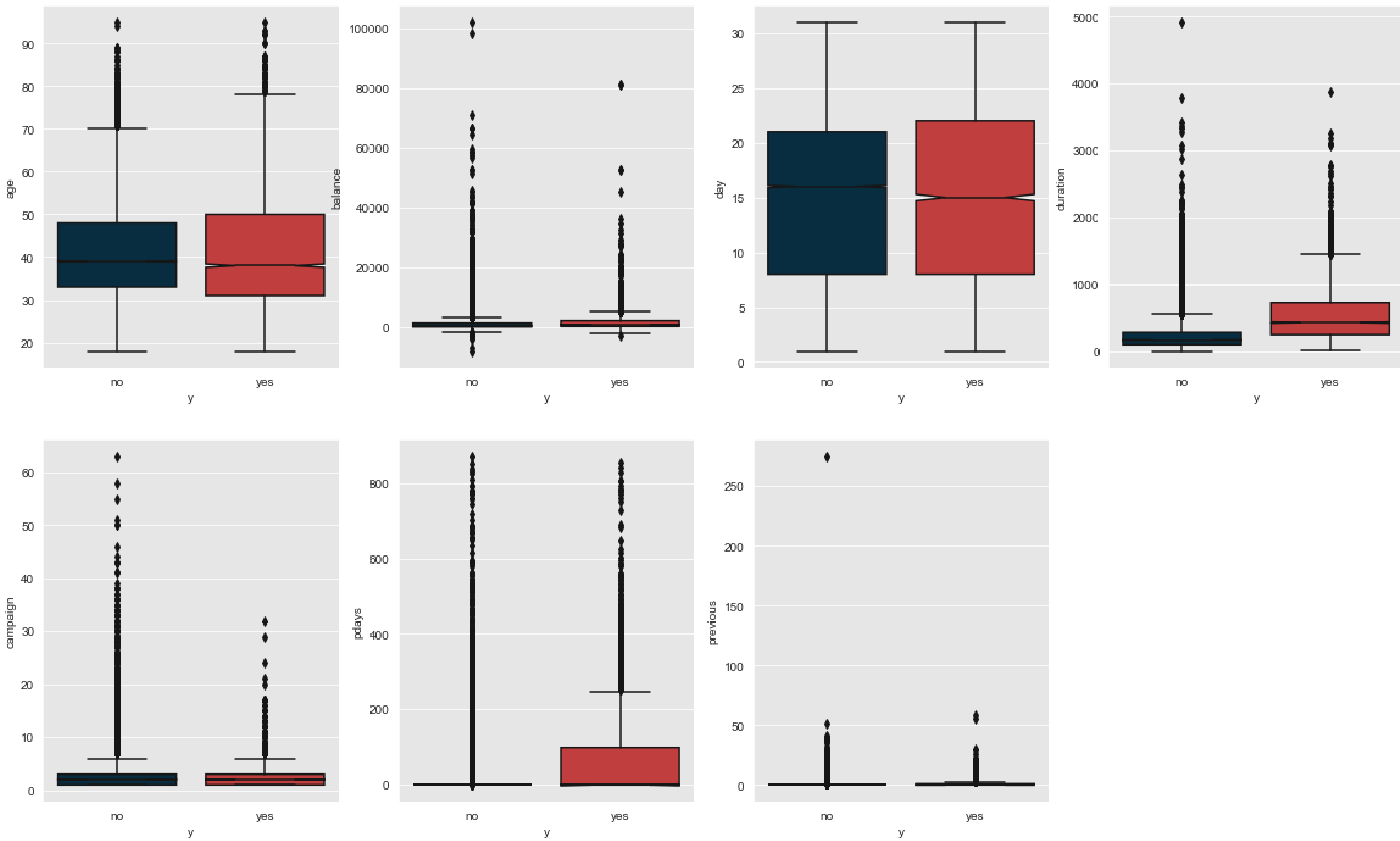
Handling Missing Values

In [6]:
```
# Checking for Null values
df.isna().sum()
```

Out[6]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

Checking for Outliers

In [7]:
```
# Plotting outliers
fig, axes = plt.subplots(nrows = 2, ncols = 4)    # axes is 2d array (2x4)
axes = axes.flatten()
fig.set_size_inches(20, 12)
colors =['#003049','#D62828']
num_col = df.select_dtypes('int64')
for ax, col in zip(axes, num_col.columns):
    sns.boxplot(x='y', y=df[col],ax = ax,  notch= True, data=df, palette=colors)
    axes.flat[-1].set_visible(False) # to remove last plot
```



From the above boxplot we can say that for both the customers that subscibed or didn't subscribe a term deposit, has a median age of around 36/40.

Outlier removal means deleting extreme values from dataset before perform analyses. We aim to delete any dirty data while retaining true extreme values.

It's a tricky procedure because it's often impossible to tell the two types apart for sure. Deleting true outliers may lead to a biased dataset and an inaccurate conclusion.

We will just drop some outliers exceeding the upper fence in `duration` `previous` columns

In [8]:
```
# Dropping extreme values
df.drop(df[df['duration'] > 4500].index, inplace = True)
df.drop(df[df['previous'] > 250].index, inplace = True)
```

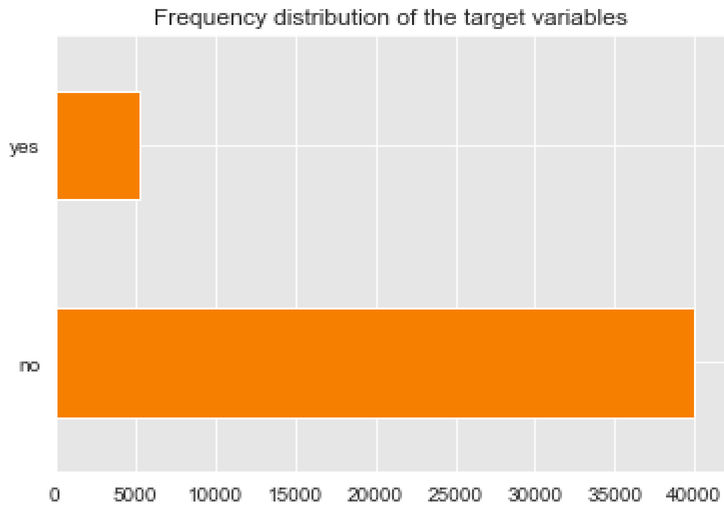
In [9]:
```
# Checking lenth of DataFrame
df.shape
```

Out[9]:
```
(45209, 17)
```

Data Distribution

In [10]:
```
# Checking for class balance
df['y'].value_counts().plot(kind='barh', title="Frequency distribution of the target variables", color='#F77F00'
```

Out[10]:
```
<AxesSubplot:title={'center':'Frequency distribution of the target variables'}>
```



This is an imbalanced classification means that there are too few examples of the minority class for a model to effectively learn the decision boundary.

In [11]:
```
# Renaming target column
df.rename(columns={"y": "target"}, inplace=True)
```

In [12]:
```
# Checking for unique values
df.target.unique()
```

Out[12]:
```
array(['no', 'yes'], dtype=object)
```

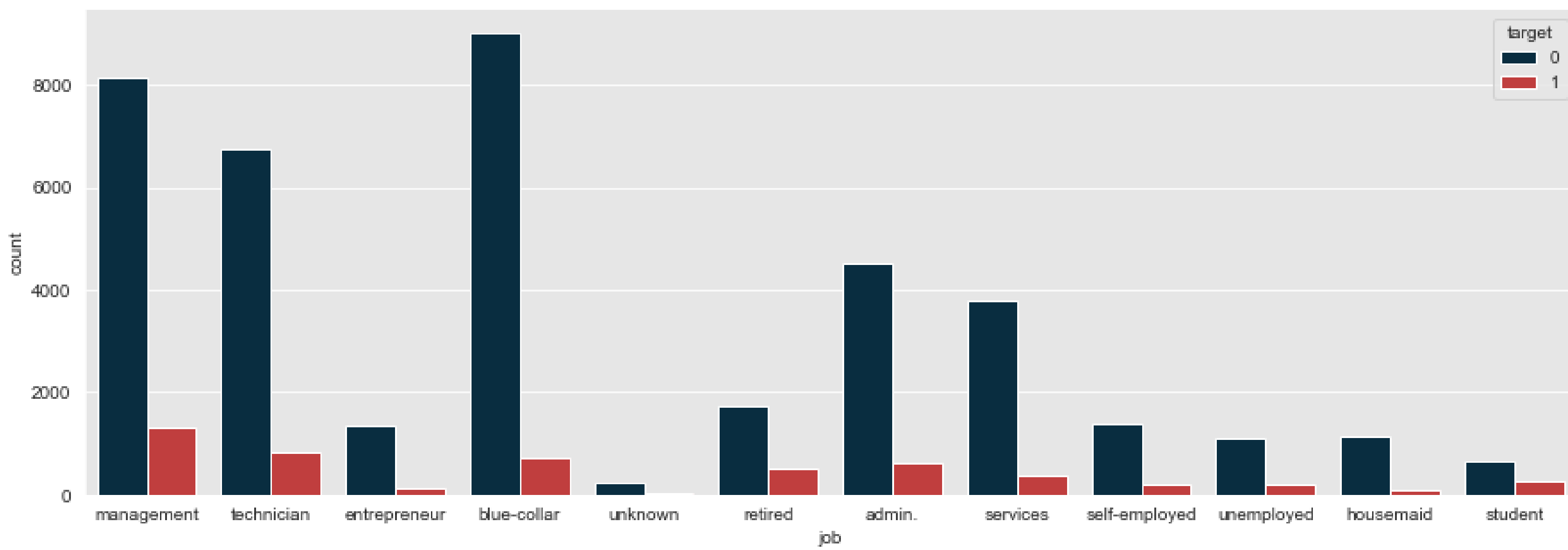
In [13]:
```
# Changing values from str to numeric val
df['target'] = df['target'].map({'yes': 1, 'no': 0})
```

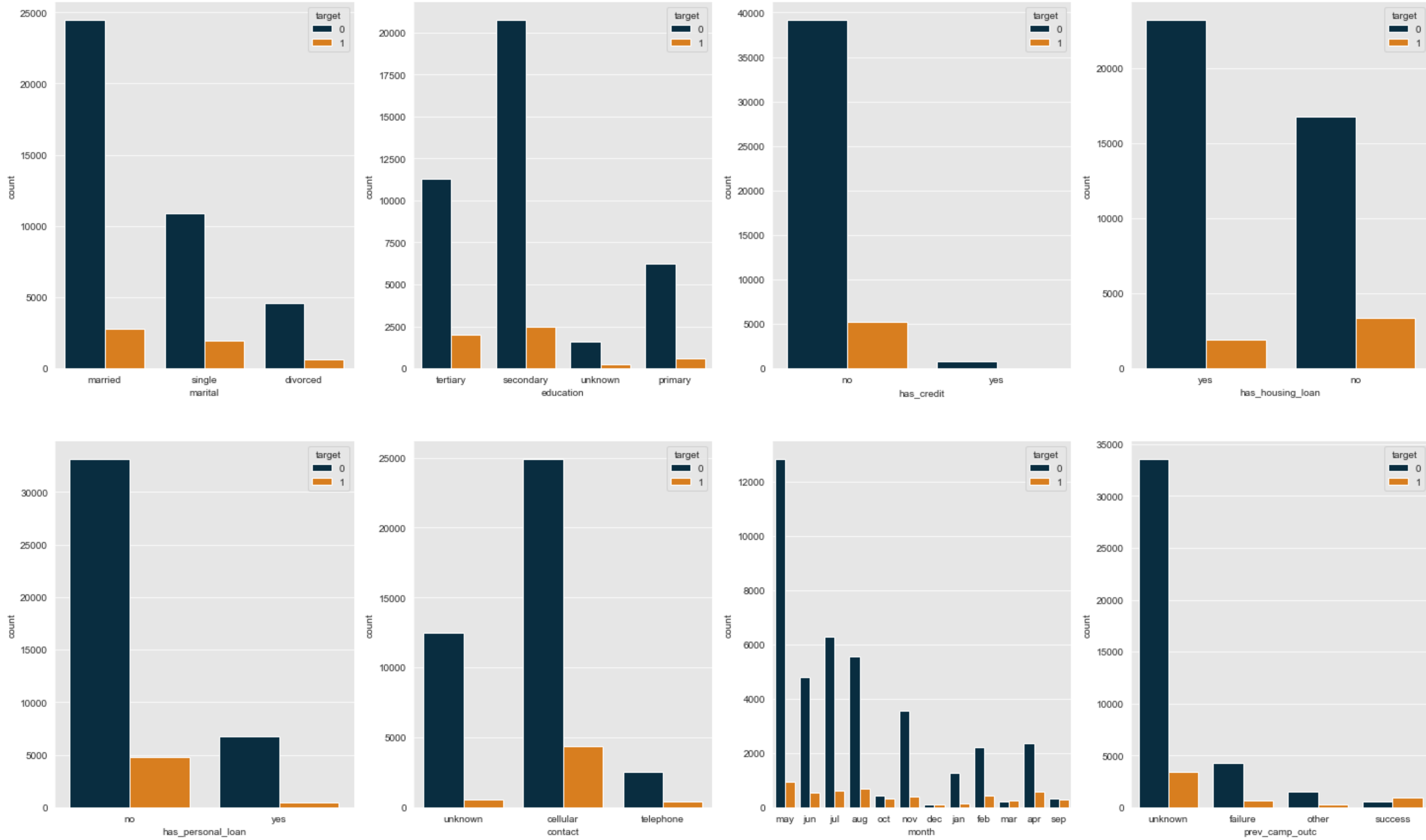
In [14]:
```
# Displaying non-object data type columns
df.dtypes[df.dtypes == 'object']
```

Out[14]:
```
job          object
marital      object
education    object
default      object
housing      object
loan         object
contact      object
month        object
poutcome     object
dtype: object
```

In [15]:
```
# Renaming some columns
df.rename(columns = {'default':'has_credit', 'housing':'has_housing_loan',
                     'loan':'has_personal_loan', 'poutcome':'prev_camp_outc'}, inplace = True)
```

In [16]:
```
# Plotting distribution of categorical values
'''
Since 'job' column contains more value types  I will plot it seperately
'''
plt.figure(figsize=[15,5])
sns.countplot( x='job', data=df, hue='target', palette=colors)
sns.despine()

fig, axes = plt.subplots(nrows = 2, ncols = 4)
axes = axes.flatten()
fig.set_size_inches(25, 15)
colors =['#003049','#F77F00']
# Selecting categorical values
cat_col = df[['marital','education','has_credit',
              'has_housing_loan','has_personal_loan',
              'contact','month','prev_camp_outc',]]
for ax, col in zip(axes, cat_col.columns):
    sns.countplot( x=df[col],ax = ax,  data=df, hue='target', palette=colors)
    sns.despine()
```




target
0
1
count
married
single
divorced
marital
tertiary
secondary
unknown
primary
education
no
yes
has_credit
yes
no
has_housing_loan
no
yes
has_personal_loan
unknown
cellular
telephone
contact
may
jun
jul
aug
oct
nov
dec
jan
feb
mar
apr
sep
month
unknown
failure
other
success
prev_camp_outc

- According to the above plot, we can see that the customers who work in management positions have the highest rate of subscribing to a term deposit, but they are also the higher after the blue-collar professions when it comes to not subscribing
- Customers who have a personal loans are more inclined to subscribe to a term deposit.
- Mostly married and single marital people made subscriptions compare to the people who are divorced.
- Most people after receiving their secondary or tertiary educations can afford term deposits.
- Majority subscribed customers were contacted via cellular phones.

The *unknown* variables will be removed due to do not represent an impact over the dataset

In [17]:
```
# Dropping 'unknown' row values
df = df[df.job != 'unknown']
df = df[df.education != 'unknown']
df=  df[df.contact !='unknown']
```

In [18]:
```
# Counting unique values within the 'pdays' clumn
'''
number of days that passed by after the client was last contacted from
a previous campaign (numeric, -1 means client was not previously contacted)
'''
df.pdays.value_counts()
```

Out[18]:
```
-1      23059
 182      151
 92       138
 183      120
 91       115
          ...
 774        1
 550        1
 486        1
 470        1
 32         1
Name: pdays, Length: 530, dtype: int64
```

In [19]:
```
# Replacing negative value to 0
df['pdays'] = df['pdays'].replace({-1: 0})
```

In [20]:
```
# Getting copy of the original DataFrame fo future Synthetic Resampling
df_copy = df.copy()
```

In [21]:
```
df_copy.head()
```

Out[21]:

	age	job	marital	education	has_credit	balance	has_housing_loan	has_personal_loan	contact	day	month	duration
12657	27	management	single	secondary	no	35	no	no	cellular	4	jul	255
12658	54	blue-collar	married	primary	no	466	no	no	cellular	4	jul	297
12659	43	blue-collar	married	secondary	no	105	no	yes	cellular	4	jul	668
12660	31	technician	single	secondary	no	19	no	no	telephone	4	jul	65
12661	27	technician	single	secondary	no	126	yes	yes	cellular	4	jul	436

In [22]:
```
# Changing categorical values from str into int
df['has_credit']= df['has_credit'].map({'yes': 1, 'no' : 0})
df['has_housing_loan']= df['has_housing_loan'].map({'yes': 1, 'no' : 0})
df['has_personal_loan']= df['has_personal_loan'].map({'yes': 1, 'no' : 0})
```

In [23]:
```
# Building correlation matrix
corr = df.corr()
corr.style.background_gradient(cmap='PuBu')
```

Out[23]:

	age	has_credit	balance	has_housing_loan	has_personal_loan	day	duration	campaign	pdays	pr
age	1.000000	-0.009217	0.099586	-0.170506	-0.010080	0.013408	0.007284	0.007998	-0.034087	-0.0
has_credit	-0.009217	1.000000	-0.060991	-0.010241	0.083693	0.021191	-0.010487	0.026288	-0.031144	-0.0
balance	0.099586	-0.060991	1.000000	-0.055906	-0.089250	-0.002580	0.020112	-0.021608	-0.004943	0.0
has_housing_loan	-0.170506	-0.010241	-0.055906	1.000000	0.044992	-0.065008	-0.005408	-0.056585	0.220058	0.0
has_personal_loan	-0.010080	0.083693	-0.089250	0.044992	1.000000	0.008700	-0.016453	0.021411	-0.032607	-0.0
day	0.013408	0.021191	-0.002580	-0.065008	0.008700	1.000000	-0.038947	0.215524	-0.126226	-0.
duration	0.007284	-0.010487	0.020112	-0.005408	-0.016453	-0.038947	1.000000	-0.092979	-0.000398	-0.0
campaign	0.007998	0.026288	-0.021608	-0.056585	0.021411	0.215524	-0.092979	1.000000	-0.108776	-0.0
pdays	-0.034087	-0.031144	-0.004943	0.220058	-0.032607	-0.126226	-0.000398	-0.108776	1.000000	0.5
previous	-0.002396	-0.021915	0.016416	0.097612	-0.017559	-0.077114	-0.000913	-0.045538	0.520895	1.0
target	0.031161	-0.029111	0.054905	-0.133455	-0.084206	-0.046304	0.397735	-0.090407	0.071381	0.0

The most correlated feature to the target is last contact duration of the customers. Next comes the number of days that passed by after the client was last contacted from a previous campaign and number of contacts performed before this campaign showing a correlatio to the target value. Thus this two are highly multicollinear among each other. Having a housing loan also correlated to the number of days that passed by after the client was last contacted from a previous campaign.

3.4 Data Encoding

Machine learning models require all input and output variables to be numeric. This means that our DataFrame contains categorical data, so we must encode it to numbers before we can fit and evaluate a model. Thus we will apply get_dummies function to convert categorical variables into dummy/indicator variables.

In [24]:
```
# Checking for the columns with 'object' data types
df.dtypes[df.dtypes == 'object']
```

Out[24]:
```
job                object
marital            object
education          object
contact            object
month              object
prev_camp_outc     object
dtype: object
```

In [25]:
```
# Checking for the unique values
df.prev_camp_outc.value_counts()
```

Out[25]:
```
unknown    23064
failure     4679
other       1749
success     1413
Name: prev_camp_outc, dtype: int64
```

In [26]:
```
# Changing values
df = df.replace({'prev_camp_outc': {'other':'unknown'}})
```

In [27]:
```
# Selecting categorical columns
cat_col = df[['job','marital','education','contact','month','prev_camp_outc']]
```

In [28]:
```
# Getting the first 5 rows
cat_col.head()
```

Out[28]:

	job	marital	education	contact	month	prev_camp_outc
12657	management	single	secondary	cellular	jul	unknown
12658	blue-collar	married	primary	cellular	jul	unknown
12659	blue-collar	married	secondary	cellular	jul	unknown
12660	technician	single	secondary	telephone	jul	unknown
12661	technician	single	secondary	cellular	jul	unknown

In [29]:
```
# Converting categorical data into dummy variables
df_dummies = pd.get_dummies( cat_col, drop_first=True)
```

In [30]:
```
# Getting the first 5 rows of Dummy variables
df_dummies.head()
```

Out[30]:

	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employed	job_services	job_student	job_technician	jo
12657	0	0	0	1	0	0	0	0	0	
12658	1	0	0	0	0	0	0	0	0	
12659	1	0	0	0	0	0	0	0	0	
12660	0	0	0	0	0	0	0	0	1	
12661	0	0	0	0	0	0	0	0	1	

5 rows × 28 columns

In [31]:
```
# Dropping columns from original DataFrame
df.drop(cat_col, axis=1, inplace=True)
```

In [32]:
```
# Checking back the DataFrame
df.head()
```

Out[32]:

	age	has_credit	balance	has_housing_loan	has_personal_loan	day	duration	campaign	pdays	previous	target
12657	27	0	35	0	0	4	255	1	0	0	0
12658	54	0	466	0	0	4	297	1	0	0	0
12659	43	0	105	0	1	4	668	2	0	0	0
12660	31	0	19	0	0	4	65	2	0	0	0
12661	27	0	126	1	1	4	436	4	0	0	0

In [33]:
```
# Merging encoded df to original DataFrame back
df = pd.merge(
    left=df,
    right=df_dummies,
    left_index=True,
    right_index=True,
)
```

In [34]:
```
# Getting a concise summary of the DataFrame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30905 entries, 12657 to 45210
Data columns (total 39 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   age                  30905 non-null  int64
 1   has_credit           30905 non-null  int64
 2   balance              30905 non-null  int64
 3   has_housing_loan     30905 non-null  int64
 4   has_personal_loan    30905 non-null  int64
 5   day                  30905 non-null  int64
 6   duration             30905 non-null  int64
 7   campaign             30905 non-null  int64
 8   pdays                30905 non-null  int64
 9   previous             30905 non-null  int64
 10  target               30905 non-null  int64
 11  job_blue-collar      30905 non-null  uint8
 12  job_entrepreneur     30905 non-null  uint8
 13  job_housemaid        30905 non-null  uint8
 14  job_management       30905 non-null  uint8
 15  job_retired          30905 non-null  uint8
 16  job_self-employed    30905 non-null  uint8
 17  job_services         30905 non-null  uint8
 18  job_student          30905 non-null  uint8
 19  job_technician       30905 non-null  uint8
 20  job_unemployed       30905 non-null  uint8
 21  marital_married      30905 non-null  uint8
 22  marital_single       30905 non-null  uint8
 23  education_secondary  30905 non-null  uint8
 24  education_tertiary   30905 non-null  uint8
 25  contact_telephone    30905 non-null  uint8
 26  month_aug            30905 non-null  uint8
 27  month_dec            30905 non-null  uint8
 28  month_feb            30905 non-null  uint8
 29  month_jan            30905 non-null  uint8
 30  month_jul            30905 non-null  uint8
 31  month_jun            30905 non-null  uint8
 32  month_mar            30905 non-null  uint8
 33  month_may            30905 non-null  uint8
 34  month_nov            30905 non-null  uint8
```

```
 35  month_oct              30905 non-null  uint8
 36  month_sep              30905 non-null  uint8
 37  prev_camp_outc_success  30905 non-null  uint8
 38  prev_camp_outc_unknown  30905 non-null  uint8
dtypes: int64(11), uint8(28)
memory usage: 4.9 MB
```

In [35]:
```
# Getting the first 5 rows
df.head()
```

Out[35]:

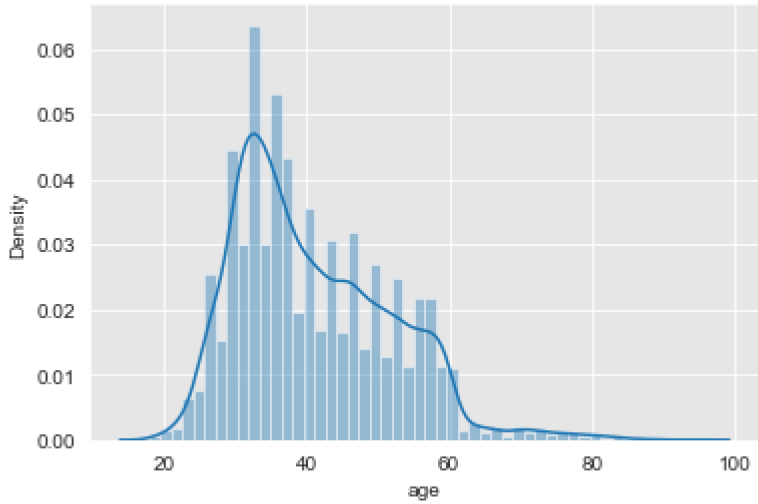
	age	has_credit	balance	has_housing_loan	has_personal_loan	day	duration	campaign	pdays	previous	...	month_jan	month_
12657	27	0	35	0	0	4	255	1	0	0	...	0	
12658	54	0	466	0	0	4	297	1	0	0	...	0	
12659	43	0	105	0	1	4	668	2	0	0	...	0	
12660	31	0	19	0	0	4	65	2	0	0	...	0	
12661	27	0	126	1	1	4	436	4	0	0	...	0	

5 rows × 39 columns

3.5 Feature Engineering

In [36]:
```
# Plotting distribution of age column
sns.distplot(df.age)
```

Out[36]:
```
<AxesSubplot:xlabel='age', ylabel='Density'>
```



In [37]:
```
# Getting the age groups
#'''
# Young people:       18<age≤30
#Middle-aged people: 30<age≤60
#Old people:         60<age≤100
#'''
#df['age'] = pd.cut(x=df['age'], bins=[18,30,60,100], labels=[1,2,3])
```

In [38]:
```
# Counting unique categorical values
#df.age.value_counts()
```

4. Model Building

Performing Train-Test Split

We will further split the data into train test sets whcih allows us to simulate how a model would perform on new/unseen data. The training and validation data set is split into an *80:20* ratio.

In [39]:
```
# Target&Feature setting
y = df['target']
X = df.drop(columns='target')
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=27, stratify=y)
print (X_train.shape,y_train.shape)
print (X_test.shape,y_test.shape)
```

```
(24724, 38) (24724,)
(6181, 38) (6181,)
```

Model-1. Baseline Model (Dummy Classifier) / Pipeline

We normalize after splitting our data into training and test sets. This is to avoid information "leaking" from our test set into our training set . Normalization (also sometimes called Standardization or Scaling) means making sure that all of the data are represented at the same scale. The most common way to do this is to convert all numerical values to z-scores.

To be able to truly understand and then improve our model's performance, first we need to establish a baseline called a *Dummy Classifier* for the data that we have. A dummy classifier is exactly what it sounds like! It is a classifier model that makes predictions without trying to find patterns in the data.

Insights of a Confusion Matrix:

The main purpose of a confusion matrix is to see how our model is performing when it comes to classifying potential clients that are likely to suscribe to a term deposit.

- Positive/Negative: Type of Class (label) ["No", "Yes"] True/False: Correctly or Incorrectly classified by the model.

True Positives (Bottom-Right Square): This is the percentage of **correctly** classifications of the "Yes" class or potenial clients that are willing to subscribe term deposit.

False Positive (Bottom-Left Square), means the client do NOT SUBSCRIBED to term deposit, but the model thinks he did. It is not good because we think that we already have that client but we dont and maybe we lost him in other future campaings.

True Negatives (Top-Left Square): This is the percentage of **correctly** classifications of the "No" class or potenial clients that are not willing to suscribe a term deposit

False Negative (Top-Right Square), means the client SUBSCRIBED to term deposit, but the model said he dont. In this case its ok, we have that client and in the future we'll discovery that in truth he's already our client.

So, our objective here, is to find the best model by confusion matrix with the lowest False Positive(FP) and highest True Positive(TP) as possible. In addition we primarily care about correctly identifying subscribed clients to a term deposit, so the recall score becomes more important.

In [40]:
```
# Instantiating the Dummy Classifier and creating pipeline
scaler = StandardScaler()
dummy_clf = DummyClassifier(random_state=2, strategy='stratified')

dummy_pipe = Pipeline(steps=[('ss',scaler),
                            ('model',dummy_clf)])
# fitting the  Baseline model
dummy_pipe.fit(X_train, y_train)

print(f'Training Score:', dummy_pipe.score(X_train, y_train))
print(f'Testing Score', dummy_pipe.score(X_test, y_test))
```

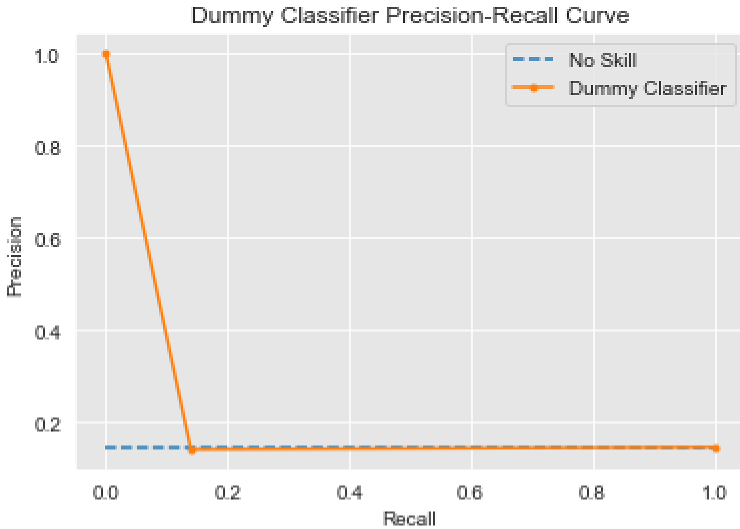
```
Training Score: 0.7525076848406407
Testing Score 0.7503640187671897
```

In [41]:
```
# Defining function for Model Evaluation
def model_evaluation(model_pipe, X_test, y_test, name):

    y_pred = model_pipe.predict(X_test)
# define evaluation procedure
    rec_score = recall_score(y_test, y_pred)*100

# Classification report
    print(f'Testing Recall Score of {name} : {round(rec_score,2)}%')
    print('-------------------------------------')
    print(classification_report(y_test, y_pred))
# Confusion matrix
    print (f'Confusion Matrix for {name}')
    plot_confusion_matrix(model_pipe,
    X_test,
    y_test,
    normalize='true',
    cmap='Blues_r',
    display_labels= ['Not Subscribed', 'Subscribed'],
    values_format='.0%')
    title= 'Confusion Matrix'
    plt.grid(False) #removes grid lines from plot


# Plotting precision and recall curve
    y_score = model_pipe.predict_proba(X_test)[:, 1]
    precision, recall, thresholds = precision_recall_curve(y_test, y_score)
    fig, ax = plt.subplots()
    no_skill = len(y_test[y_test==1]) / len(y_test)
    ax.plot([0, 1], [no_skill, no_skill], linestyle='--', label='No Skill')
    ax.plot(recall, precision, marker='.', label=name)
    #add axis labels to plot
    ax.set_title(f'{name} Precision-Recall Curve')
    ax.set_ylabel('Precision')
    ax.set_xlabel('Recall')
    ax.legend()
    #display plot
    plt.show()
    print ("Area Under PR Curve(AP): %0.2f" % average_precision_score(y_test, y_score))
    print('-------------------------------------')
```

In [42]:
```
model_evaluation(dummy_pipe, X_test,y_test, 'Dummy Classifier')
```

```
Testing Recall Score of Dummy Classifier : 13.95%
------------------------------------
              precision    recall  f1-score   support

           0       0.85      0.85      0.85      5278
           1       0.14      0.14      0.14       903

    accuracy                           0.75      6181
   macro avg       0.50      0.50      0.50      6181
weighted avg       0.75      0.75      0.75      6181
```

Confusion Matrix for Dummy Classifier

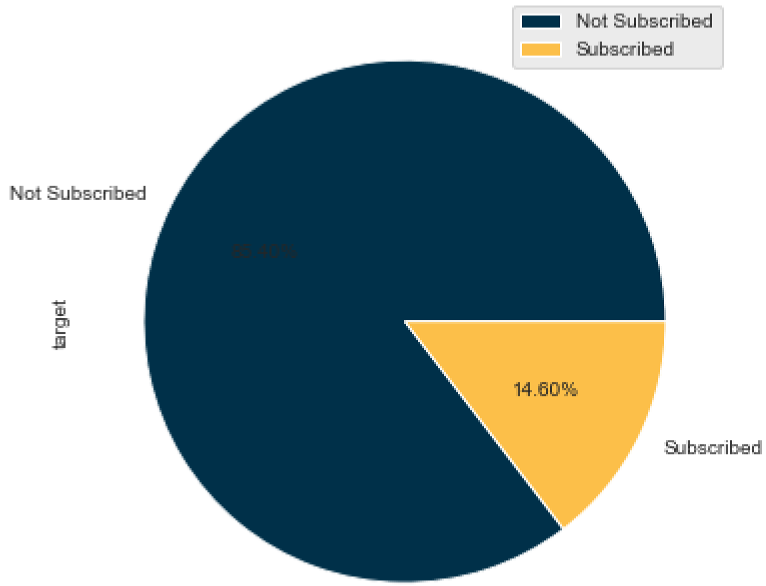



```
Area Under PR Curve(AP): 0.15
------------------------------------
```

Lets display the proportion of our target classes

The baseline model evaluated 86% of False Negative (FN) values and 85% of True Negative (TN). Model could be effected by class imbalance. With this in mind, we confirm the imbalance problem related above. So, we will set class_weight parameter into *'balanced'* to solve this issue. This adjusts so total weights are equal accross classes; in other words, members of the majority (not-subscribed) class will be given less weight than members of the minority (subscribed) class.

In [43]:
```
# Plotting class distribution in terms of the %
labels = ["Not Subscribed", "Subscribed"]
plt.figure(figsize = (10,6))
colors =['#003049','#FCBF49']
y.value_counts().plot.pie(labels=labels,autopct='%1.2f%%', colors=colors );
plt.legend()
plt.show()
```



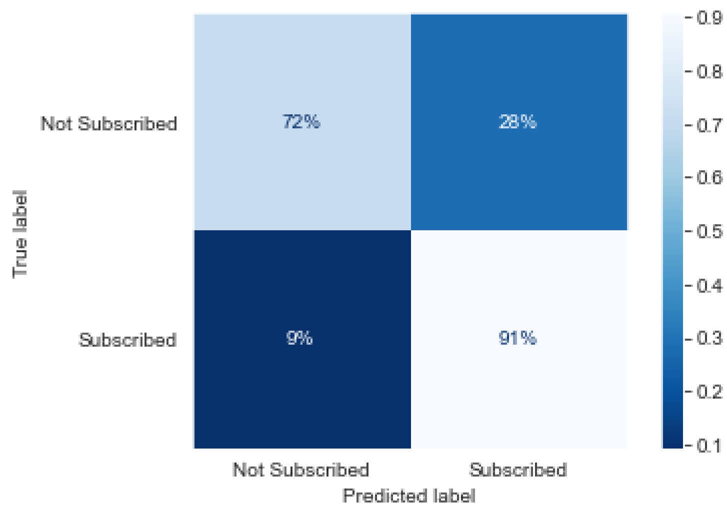
Model-2. Logistic Regression / balanced class_weight / Pipeline

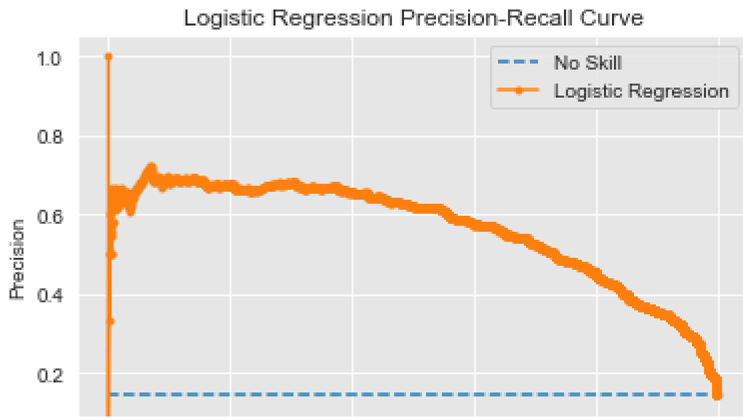
In [44]:
```
# Instantiating the Logistic Regression Model and creating pipeline
scaler = StandardScaler()
logreg_clf= LogisticRegression(fit_intercept=False,
                           random_state=27,
                           C=1e3,
                           solver='liblinear',
                           class_weight='balanced',
                           max_iter=1e3)

logreg_pipe = Pipeline(steps=[('ss',scaler),
                            ('logreg',logreg_clf),
                              ])
# fitting the logistic regression model
logreg_pipe.fit(X_train, y_train)
print(f'Training Score:',logreg_pipe.score(X_train, y_train))
print(f'Testing Score',logreg_pipe.score(X_test, y_test))
```

```
Training Score: 0.7526694709593916
Testing Score 0.7430836434233943
```

In [45]:
```
# Logistic Regression Model evaluations
model_evaluation(logreg_pipe, X_test, y_test, 'Logistic Regression')
```

```
Testing Recall Score of Logistic Regression : 90.7%
------------------------------------
              precision    recall  f1-score   support

           0       0.98      0.72      0.83      5278
           1       0.35      0.91      0.51       903

    accuracy                           0.74      6181
   macro avg       0.67      0.81      0.67      6181
weighted avg       0.89      0.74      0.78      6181

Confusion Matrix for Logistic Regression
```






```
Area Under PR Curve(AP): 0.57
------------------------------------
```

Logistic Regression with balanced class_weight parameter increased Recall up to 91%. We will try to rebuild LogReg Model by addressing imbalanced datasets through oversampling the minority target class. These examples don’t add any new information to the model. Instead, new examples can be synthesized from the existing examples. This is a type of data augmentation for the minority class and is referred to as the *Synthetic Minority Over-sampling Technique for Nominal and Continuous.*, or **SMOTENC** for short.

In [46]:
```
df.campaign.unique()
```

Out[46]:
```
array([ 1,  2,  4,  3,  6,  5, 19,  9,  8,  7, 14, 15, 11, 12, 30, 33, 13,
       20, 10, 24, 26, 35, 17, 27, 16, 31, 28, 21, 18, 23, 22, 29, 25, 34,
       36, 39, 43, 32, 38, 50, 44], dtype=int64)
```

In [47]:
```
df.head(15).T
```

Out[47]:

	12657	12658	12659	12660	12661	12662	12663	12664	12665	12666	12667	12668	12669	12670	12671
age	27	54	43	31	27	28	50	29	25	38	36	32	44	37	48
has_credit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
balance	35	466	105	19	126	-127	1329	343	192	43	-272	4805	1146	380	1355
has_housing_loan	0	0	0	0	1	1	1	0	0	0	0	0	0	1	0
has_personal_loan	0	0	1	0	1	0	1	0	0	1	1	1	0	1	0
day	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
duration	255	297	668	65	436	1044	141	39	112	135	53	138	178	548	134
campaign	1	1	2	2	4	3	2	2	2	3	6	3	2	2	2
pdays	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
previous	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
target	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
job_blue-collar	0	1	1	0	0	1	1	1	1	1	0	1	0	1	0
job_entrepreneur	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
job_housemaid	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
job_management	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
job_retired	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
job_self-employed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
job_services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
job_student	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
job_technician	0	0	0	1	1	0	0	0	0	0	1	0	1	0	0
job_unemployed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
marital_married	0	1	1	0	0	0	1	0	0	1	0	0	1	1	1
marital_single	1	0	0	1	1	1	0	1	1	0	1	0	0	0	0
education_secondary	1	0	1	1	1	1	1	0	1	1	1	0	0	0	1
education_tertiary	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

	12657	12658	12659	12660	12661	12662	12663	12664	12665	12666	12667	12668	12669	12670	12671
contact_telephone	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0
month_aug	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
month_dec	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
month_feb	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
month_jan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
month_jul	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
month_jun	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
month_mar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
month_may	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
month_nov	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
month_oct	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
month_sep	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
prev_camp_outc_success	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
prev_camp_outc_unknown	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

In [48]:
```
df.shape
```

Out[48]:
```
(30905, 39)
```

In [49]:
```
#cat_feat_mask = [col for col in X_train if np.isin(X_train[col].unique(), [0, 1]).all()]
#cat_indices = list(X_train.iloc[:,np.r_[1, 3,4,7:39]].columns.values)
```

In [50]:
```python
#Instantiate SMOTENC algorithm along with an index of the categorical feature columns
smote_nc = SMOTENC(categorical_features=[1,3,4,8,9,10,
                                         11,12,13,14,15,16,17,18,19,20,
                                         21,22,23,24,25,26,27,28,29,30,
                                         31,32,33,34,35,36,37],
                    random_state=27,  # for reproducibility
                    sampling_strategy='auto') # samples only the minority class
# Fitting SMOTENC
X_train_res, y_train_res = smote_nc.fit_resample(X_train, y_train)
# Preview class distributions before and after over-sampling
print('Original class distribution: \n')
print(y_train.value_counts())
print('----------------------------------------')
print('Synthetic sample class distribution: \n')
print(pd.Series(y_train_res).value_counts())
```

```
Original class distribution: 

0    21114
1     3610
Name: target, dtype: int64
-----------------------------------------
Synthetic sample class distribution: 

1    21114
0    21114
Name: target, dtype: int64
```

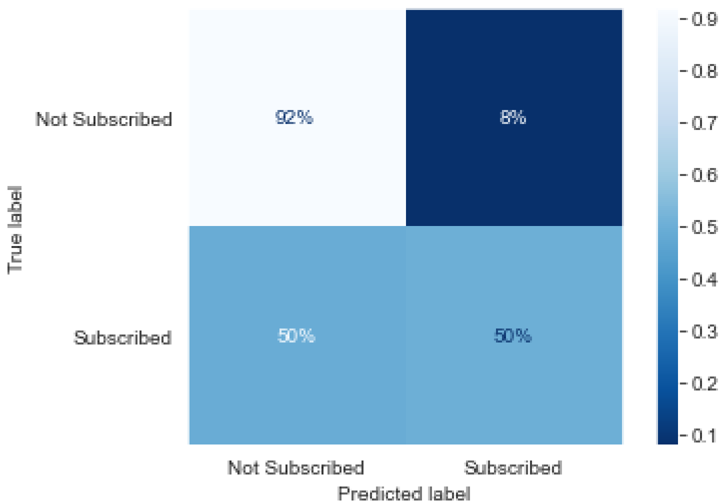
Model-3. Logistic Regression / SMOTENC / Pipeline

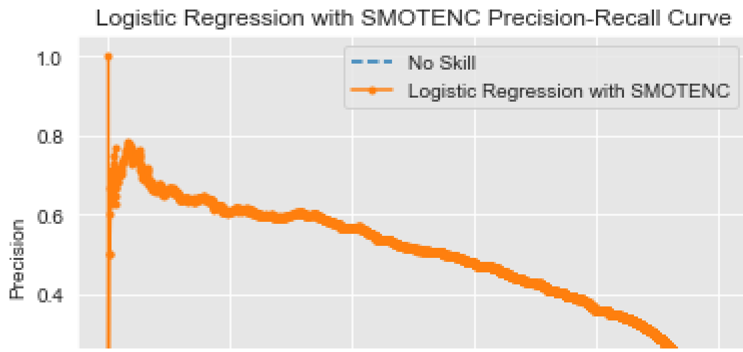
In [51]:
```
# Fitting the Logistic Regression Model
scaler = StandardScaler()
logreg_sm_clf= LogisticRegression(fit_intercept=False,
                           random_state=27,
                           C=1e9,
                           solver='lbfgs',
                           max_iter=1e3,
                           penalty='l2',
                            )

logreg_sm_pipe = Pipeline(steps=[('ss',scaler),
                            ('logreg_sm',logreg_sm_clf),
                              ])
logreg_sm_pipe.fit(X_train_res, y_train_res)
print(f'Training Accuracy Score:',logreg_sm_pipe.score(X_train_res, y_train_res))
print(f'Testing Accuracy Score',logreg_sm_pipe.score(X_test, y_test))
```

```
Training Accuracy Score: 0.9044236051908686
Testing Accuracy Score 0.8576282154991102
```

In [52]:
```
model_evaluation(logreg_sm_pipe, X_test, y_test, 'Logistic Regression with SMOTENC')
```

```
Testing Recall Score of Logistic Regression with SMOTENC : 50.5%
------------------------------------
              precision    recall  f1-score   support

           0       0.92      0.92      0.92      5278
           1       0.51      0.50      0.51       903

    accuracy                           0.86      6181
   macro avg       0.71      0.71      0.71      6181
weighted avg       0.86      0.86      0.86      6181

Confusion Matrix for Logistic Regression with SMOTENC
```






```
Area Under PR Curve(AP): 0.50
------------------------------------
```

Logistic Regression Model with SMOTE did increase an accuracy but slightly overfitted. Thus we will build tree based models and try to find hyper parameters against overfitting through GridSearch by balancing the class weights.

Model-4. Decision Tree Classifier/ balanced class_weight/ Pipeline / Grid Search

In [53]:
```python
dt_clf = DecisionTreeClassifier(random_state=27)


# Creating pipeline for Decision Tree Classifier
dt_pipe = Pipeline(steps=[('ss',scaler),
                            ('dt',dt_clf)])
# Defining Hyperparameters
dt_params ={
    'dt__class_weight':['balanced'],
    'dt__criterion':['entropy','gini'],
    'dt__splitter':["best", "random"],
    'dt__max_depth': [i for i in range(2,11,2)],
    'dt__min_samples_leaf': [0.1, 0.5, 5],
}
# Fitting the model

# Function to create a grid search containing pipeline
def perform_gridsearch(model_pipe, params):
    return GridSearchCV(estimator=model_pipe,
                        param_grid=params,
                        scoring='recall',
                        cv=10,
                        n_jobs=-1)
dt_gs = perform_gridsearch(dt_pipe, dt_params)

dt_gs.fit(X_train,y_train)
```

Out[53]:
```
GridSearchCV(cv=10,
             estimator=Pipeline(steps=[('ss', StandardScaler()),
                                       ('dt',
                                        DecisionTreeClassifier(random_state=27))]),
             n_jobs=-1,
             param_grid={'dt__class_weight': ['balanced'],
                         'dt__criterion': ['entropy', 'gini'],
                         'dt__max_depth': [2, 4, 6, 8, 10],
                         'dt__min_samples_leaf': [0.1, 0.5, 5],
                         'dt__splitter': ['best', 'random']},
             scoring='recall')
```

In [54]:
```
print(f'Training Score:',dt_gs.score(X_train, y_train))
print(f'Testing Score',dt_gs.score(X_test, y_test))
```

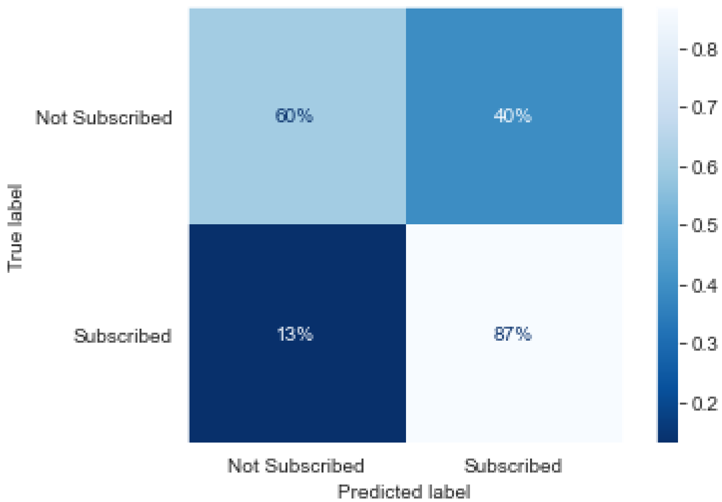
```
Training Score: 0.8603878116343491
Testing Score 0.8682170542635659
```

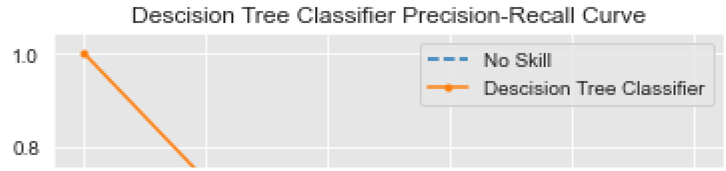
In [55]:
```
# Picking the best parameters for the model
dt_gs.best_params_
```

Out[55]:
```
{'dt__class_weight': 'balanced',
 'dt__criterion': 'entropy',
 'dt__max_depth': 2,
 'dt__min_samples_leaf': 5,
 'dt__splitter': 'best'}
```

In [56]:
```
# Model Evaluation on cross-validation
model_evaluation(dt_gs.best_estimator_, X_test, y_test, 'Descision Tree Classifier')
```

```
Testing Recall Score of Descision Tree Classifier : 86.82%
------------------------------------
              precision    recall  f1-score   support

           0       0.96      0.60      0.74      5278
           1       0.27      0.87      0.41       903

    accuracy                           0.64      6181
   macro avg       0.62      0.74      0.58      6181
weighted avg       0.86      0.64      0.69      6181

Confusion Matrix for Descision Tree Classifier
```






```
Area Under PR Curve(AP): 0.35
------------------------------------
```

Fortunately we have resolved the overfitting and achieved pretty well validation score of 86.82%. The recall presents 87% of positive cases that were correctly identified which has proved the best method to overcome imbalance data.

Model-5. Random Forest Classifier / balanced class_weight/ Pipeline/ Grid Search

In [57]:
```
scaler = StandardScaler()
# Instantiating Random Forest Clf model
rf_clf = RandomForestClassifier(random_state=27)

rf_pipe = Pipeline(steps=[('ss',scaler),
                          ('rf',rf_clf),
                            ])

# Setting hyperparameters for Grid Search
rf_params = {
    'rf__criterion':['gini','entropy'],
     'rf__class_weight':['balanced'],
     'rf__max_depth': [2,4,6],
     'rf__max_features': ['auto', 'sqrt'],
     'rf__min_samples_leaf': [1, 2, 4],
     'rf__min_samples_split': [2,4, 8],
     }

rf_gs = perform_gridsearch(rf_pipe, rf_params)

# Fitting the Random Forest Clf model
rf_gs.fit(X_train, y_train)
```

Out[57]:
```
GridSearchCV(cv=10,
             estimator=Pipeline(steps=[('ss', StandardScaler()),
                                       ('rf',
                                        RandomForestClassifier(random_state=27))]),
             n_jobs=-1,
             param_grid={'rf__class_weight': ['balanced'],
                         'rf__criterion': ['gini', 'entropy'],
                         'rf__max_depth': [2, 4, 6],
                         'rf__max_features': ['auto', 'sqrt'],
                         'rf__min_samples_leaf': [1, 2, 4],
                         'rf__min_samples_split': [2, 4, 8]},
             scoring='recall')
```

In [58]:
```
print(f'Training Score:',rf_gs.score(X_train, y_train))
print(f'Testing Score',rf_gs.score(X_test, y_test))
```

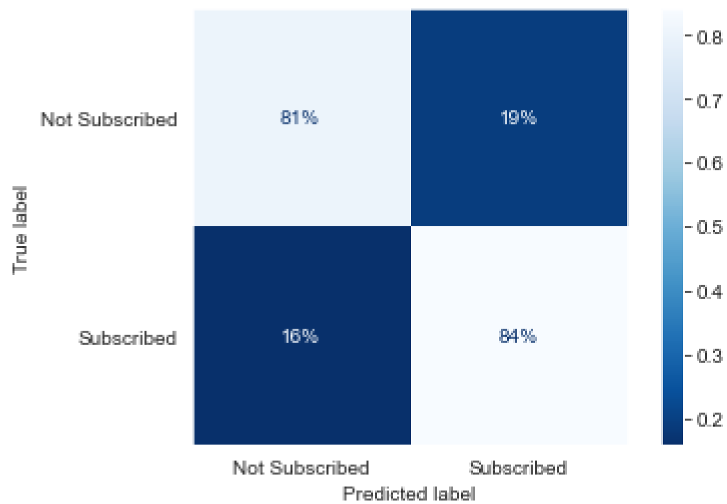
```
Training Score: 0.8498614958448754
Testing Score 0.840531561461794
```

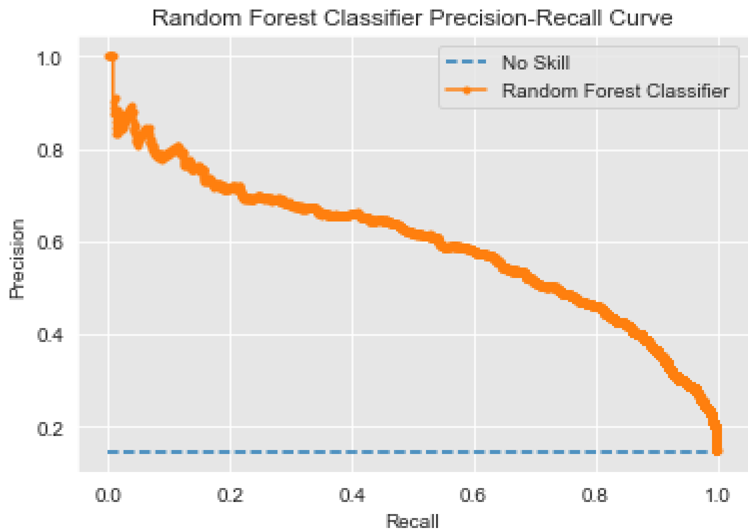
In [59]:
```
rf_gs.best_params_
```

Out[59]:
```
{'rf__class_weight': 'balanced',
 'rf__criterion': 'entropy',
 'rf__max_depth': 6,
 'rf__max_features': 'auto',
 'rf__min_samples_leaf': 1,
 'rf__min_samples_split': 2}
```

In [60]:
```
# Evaluating the Model performance on cross-validation
model_evaluation(rf_gs.best_estimator_, X_test, y_test, 'Random Forest Classifier')
```

```
Testing Recall Score of Random Forest Classifier : 84.05%
------------------------------------
              precision    recall  f1-score   support

           0       0.97      0.81      0.88      5278
           1       0.43      0.84      0.56       903

    accuracy                           0.81      6181
   macro avg       0.70      0.82      0.72      6181
weighted avg       0.89      0.81      0.83      6181

Confusion Matrix for Random Forest Classifier
```






```
Area Under PR Curve(AP): 0.59
------------------------------------
```

The Random Fores Classifier did good job both in training and testing accuracy without overfitting the model. Despite reducing recall by 4%, we dropped by almost half the false positive score.

Model-6. K-Nearest Neighbors Classifier / SMOTENC/ Pipeline

In [68]:
```
# Instantiating   and fitting kNN Model
# I have setup n_jobs=-1 to use all cpus in my env
scaler = StandardScaler()
knn_clf = KNeighborsClassifier(leaf_size=20, n_neighbors= 10,
                               p=1,weights='distance', n_jobs=-1)

knn_pipe = Pipeline(steps=[('ss',scaler),
                            ('knn',knn_clf),
                              ])
knn_pipe.fit(X_train_res, y_train_res)
```

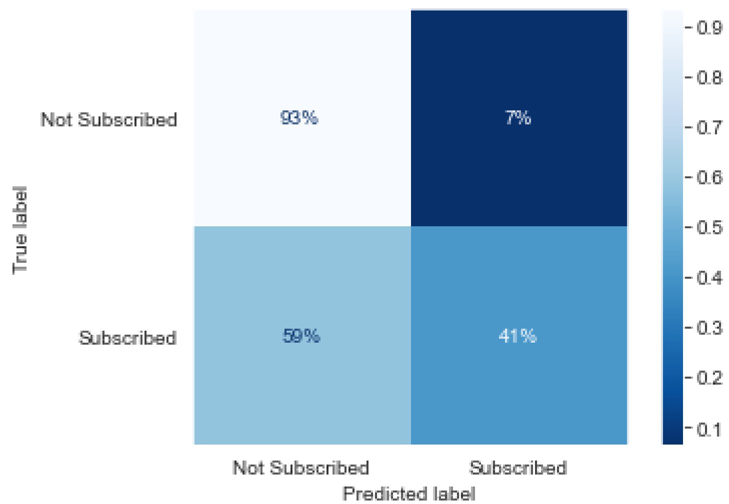
Out[68]:
```
Pipeline(steps=[('ss', StandardScaler()),
                ('knn',
                 KNeighborsClassifier(leaf_size=20, n_jobs=-1, n_neighbors=10,
                                      p=1, weights='distance'))])
```

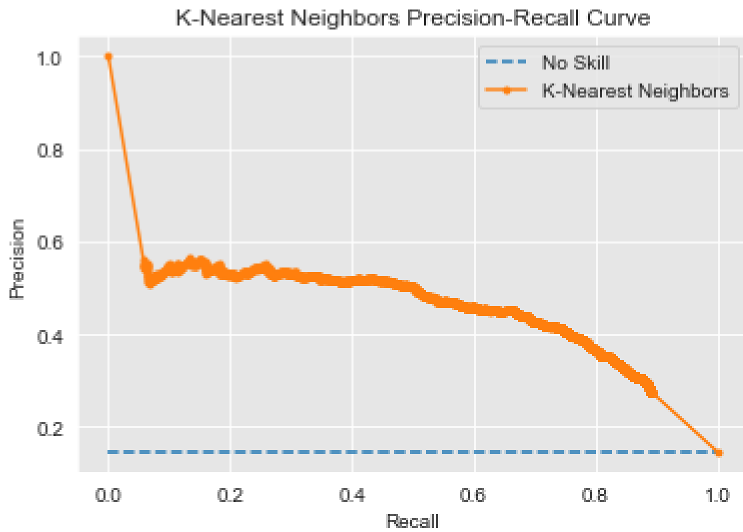
In [69]:
```
print(f'Training Score:',knn_pipe.score(X_train_res, y_train_res))
print(f'Testing Score',knn_pipe.score(X_test, y_test))
```

```
Training Score: 1.0
Testing Score 0.8582753599741142
```

In [70]:
```
# Model evaluation
model_evaluation(knn_pipe, X_test, y_test,'K-Nearest Neighbors')
```

```
Testing Recall Score of K-Nearest Neighbors : 41.31%
-----------------------------------
              precision    recall  f1-score   support

           0       0.90      0.93      0.92      5278
           1       0.52      0.41      0.46       903

    accuracy                           0.86      6181
   macro avg       0.71      0.67      0.69      6181
weighted avg       0.85      0.86      0.85      6181

Confusion Matrix for K-Nearest Neighbors
```






```
Area Under PR Curve(AP): 0.44
------------------------------------
```

The K-Nearest Neighbours model along with an oversamplinf method payed too much attention to every little detail and made a very complex decision boundary which lead to overfitting. This model did well in predicting not subscribed customers.

Another technique that can be used to improve our classification performance is boosting. While data sampling was designed with the class imbalance problem in mind, boosting is a technique that can improve the performance of any weak classifier (whether or not the data is imbalanced). Further I will try to apply the most common boosting algorithms such:

- Gradient Boosting Classifier
- Extreme Gradient Boosting (XGBoost) Classifier
- RUSBoost Classifier
- Light Gradient Boosted Machine (LGBM) Classifier

Model-7. Gradient Boosting Classifier / SMOTENC / Pipeline

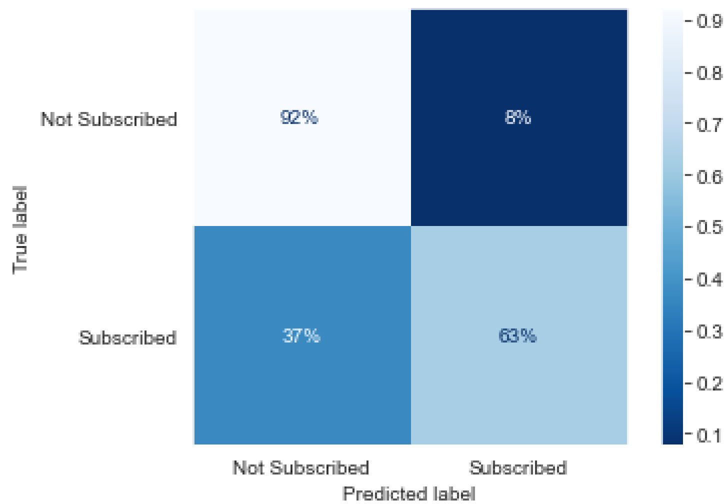
In [71]:
```
scaler = StandardScaler()

# Instantiating the GBosting model
gbt_clf = GradientBoostingClassifier(learning_rate = 0.1, max_depth = 5,
                                     min_samples_leaf = 3, n_estimators = 200,
                                     subsample = 0.6, random_state=27)
```

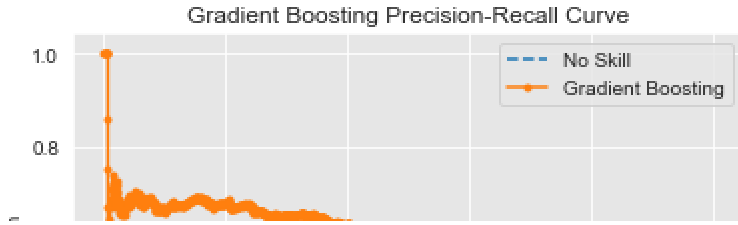
In [72]:
```
gbt_pipe = Pipeline(steps=[('ss', scaler),
                          ('gbt', gbt_clf)])
# Fitting and Evaluating GBoosting Model
gbt_pipe.fit(X_train_res,y_train_res)
print(f'Training Score:',gbt_pipe.score(X_train_res, y_train_res))
print(f'Testing Score',gbt_pipe.score(X_test, y_test))
```

```
Training Score: 0.9437103343752961
Testing Score 0.8786604109367416
```

In [73]:
```
model_evaluation(gbt_pipe, X_test, y_test,'Gradient Boosting')
```

```
Testing Recall Score of Gradient Boosting : 63.12%
------------------------------------
              precision    recall  f1-score   support

           0       0.94      0.92      0.93      5278
           1       0.58      0.63      0.60       903

    accuracy                           0.88      6181
   macro avg       0.76      0.78      0.77      6181
weighted avg       0.88      0.88      0.88      6181

Confusion Matrix for Gradient Boosting
```






```
Area Under PR Curve(AP): 0.58
------------------------------------
```

Gradient Boosting Classifier is somewhat overfitted but not much as k-NN. This model considerably decreased false positive, meaning the client does NOT SUBSCRIBE to a term deposit, but the model thinks he did.

Next, I will use a specific implementation of the Gradient Boosting method which uses more accurate approximations to find the best tree model called Extreme Gradient Boosting.

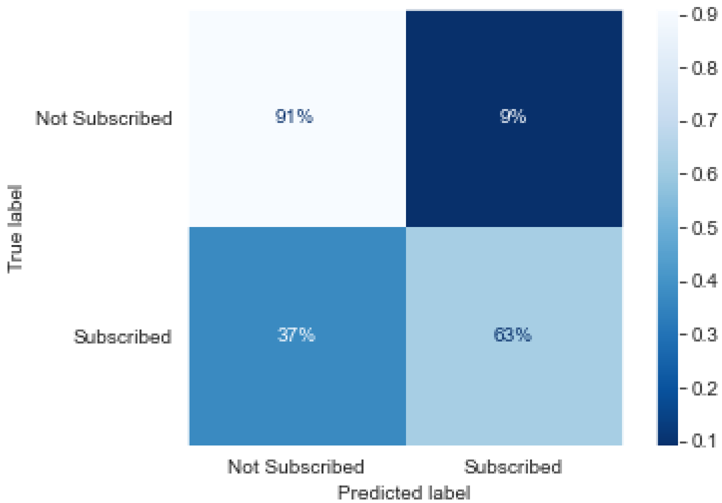
Model-8. XGBoost Classifier / SMOTENC / Pipeline

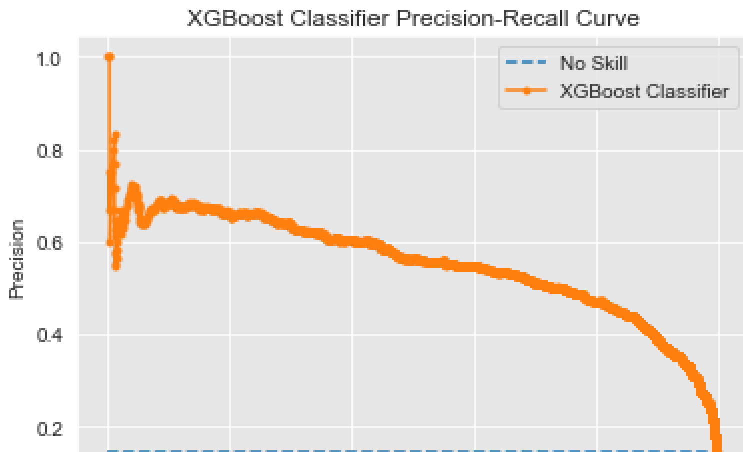
In [74]:
```
scaler = StandardScaler()
# Instantiating the XGBoost Model
xgb_clf = XGBClassifier(learning_rate=0.4, max_depth = 10, min_child_weight = 1,
                        n_estimators = 200, scale_pos_weight = 2, subsample = .5,
                        random_state=23)


xgb_pipe = Pipeline(steps=[('ss',scaler),
                            ('xgb',xgb_clf),
                              ])
xgb_pipe.fit(X_train_res, y_train_res)

print(f'Training Score:',xgb_pipe.score(X_train_res, y_train_res))
print(f'Testing Score',xgb_pipe.score(X_test, y_test))
```

```
[15:21:39] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric used with
the objective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd lik
e to restore the old behavior.
Training Score: 0.9999763190300275
Testing Score 0.8673353826241709
```

In [75]:
```
# Fitting and Evaluating the XGBoost model
#print(f'Training Score:',gbt_pipe.score(X_train_res, y_train_res))
#print(f'Testing Score',gbt_pipe.score(X_test, y_test))

model_evaluation(xgb_pipe, X_test, y_test, 'XGBoost Classifier')
```

```
Testing Recall Score of XGBoost Classifier : 62.68%
------------------------------------
              precision    recall  f1-score   support

           0       0.93      0.91      0.92      5278
           1       0.54      0.63      0.58       903

    accuracy                           0.87      6181
   macro avg       0.74      0.77      0.75      6181
weighted avg       0.88      0.87      0.87      6181

Confusion Matrix for XGBoost Classifier
```






```
Area Under PR Curve(AP): 0.55
------------------------------------
```

XGBoost model along with oversampling techniquealso did overfit. Recall stayed stable around 63% both in Gradient Boosting and XGBoost classifiers.

Next, I will build a so-called novel hybrid data sampling/boosting algorithm called RUSBoost, which is designed to improve the performance of models trained on skewed data. RUSBoost applies random undersampling (RUS), a technique which randomly removes examples from the majority class

Model-9. RUSBoost Classifier / Pipeline /Grid Search

In [61]:
```
rusboost_clf = RUSBoostClassifier(
        n_estimators=20,
        learning_rate=1.0,
        sampling_strategy='auto',
        random_state=27,
    )
rusboost_pipe = Pipeline(steps=[('ss',scaler),
                            ('rusbst',rusboost_clf),
                              ])
# set up the hyperparameter space
# the default implementation as 2 hyperparameters to optimize
rusboost_params = {
    'rusbst__n_estimators':[10,50,100,150],
    'rusbst__learning_rate':[0.0001, 0.1,0.5,1],
}

rusbst_gs = perform_gridsearch(rusboost_pipe, rusboost_params)
```

In [62]:
```
rusbst_gs.fit(X_train,y_train)
```

Out[62]:
```
GridSearchCV(cv=10,
             estimator=Pipeline(steps=[('ss', StandardScaler()),
                                       ('rusbst',
                                        RUSBoostClassifier(n_estimators=20,
                                                           random_state=27))]),
             n_jobs=-1,
             param_grid={'rusbst__learning_rate': [0.0001, 0.1, 0.5, 1],
                         'rusbst__n_estimators': [10, 50, 100, 150]},
             scoring='recall')
```

In [63]:
```
print(f'Training Score:',rusbst_gs.score(X_train, y_train))
print(f'Testing Score',rusbst_gs.score(X_test, y_test))
```

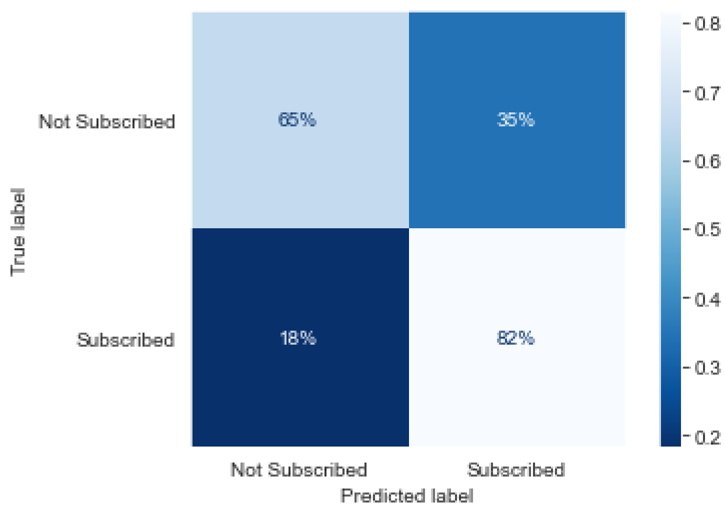
```
Training Score: 0.8160664819944599
Testing Score 0.8161683277962348
```

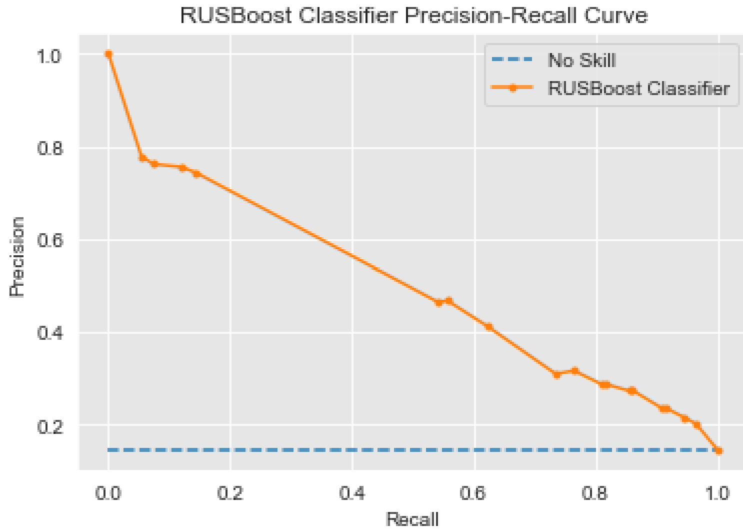
In [64]:
```
rusbst_gs.best_params_
```

Out[64]:
```
{'rusbst__learning_rate': 0.1, 'rusbst__n_estimators': 10}
```

In [65]:
```
model_evaluation(rusbst_gs.best_estimator_, X_test, y_test, 'RUSBoost Classifier')
```

```
Testing Recall Score of RUSBoost Classifier : 81.62%
------------------------------------
              precision    recall  f1-score   support

           0       0.95      0.65      0.78      5278
           1       0.29      0.82      0.43       903

    accuracy                           0.68      6181
   macro avg       0.62      0.74      0.60      6181
weighted avg       0.86      0.68      0.73      6181

Confusion Matrix for RUSBoost Classifier
```






```
Area Under PR Curve(AP): 0.43
------------------------------------
```

We overcame overfitting within this model and got a recall score of 82% which is better compared to previously built boosting algorithms.

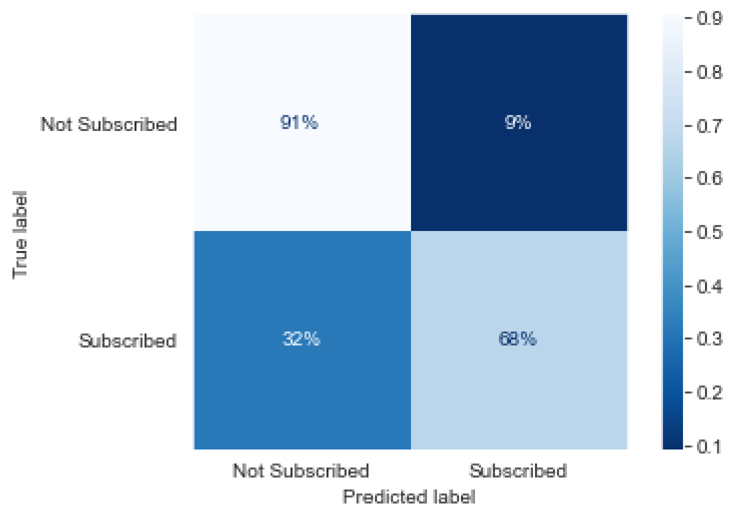
Model-9. LGBM Classifier / SMOTENC/ Grid Search

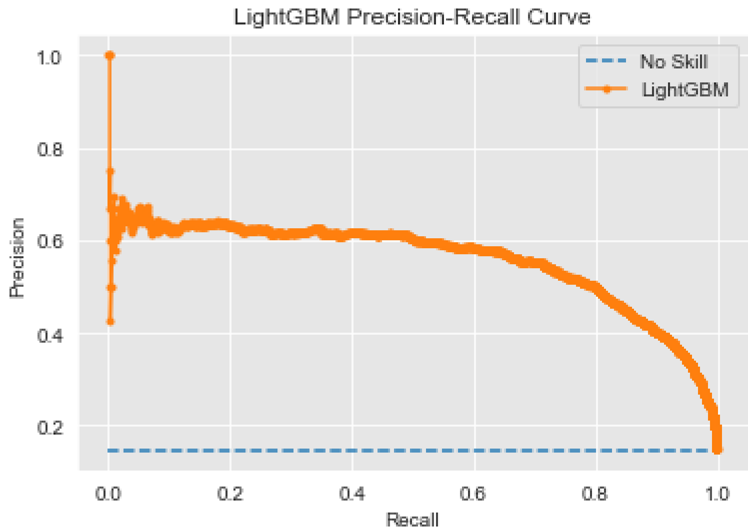
LightGBM extends the gradient boosting algorithm by adding a type of automatic feature selection as well as focusing on boosting examples with larger gradients. This can result in a dramatic speedup of training and improved predictive performance.

In [76]:
```
scaler = StandardScaler()
# Instantiating the LGBMClassifier
lgbm_clf = LGBMClassifier(max_depth=4,
                          boosting_type='goss',
                          n_estimators=145)

lgbm_pipe = Pipeline(steps=[('ss', scaler),
                          ('lgbm', lgbm_clf)])
```

In [77]:
```
# Fitting the model
lgbm_pipe.fit(X_train_res, y_train_res)

print(f'Training Score:',lgbm_pipe.score(X_train_res, y_train_res))
print(f'Testing Score',lgbm_pipe.score(X_test, y_test))
# Model Evaluation on cross validation
model_evaluation(lgbm_pipe, X_test, y_test, 'LightGBM')
```

```
Training Score: 0.9253339016766127
Testing Score 0.8736450412554603
Testing Recall Score of LightGBM : 67.66%
------------------------------------
              precision    recall  f1-score   support

           0       0.94      0.91      0.92      5278
           1       0.56      0.68      0.61       903

    accuracy                           0.87      6181
   macro avg       0.75      0.79      0.77      6181
weighted avg       0.89      0.87      0.88      6181

Confusion Matrix for LightGBM
```






```
Area Under PR Curve(AP): 0.56
------------------------------------
```

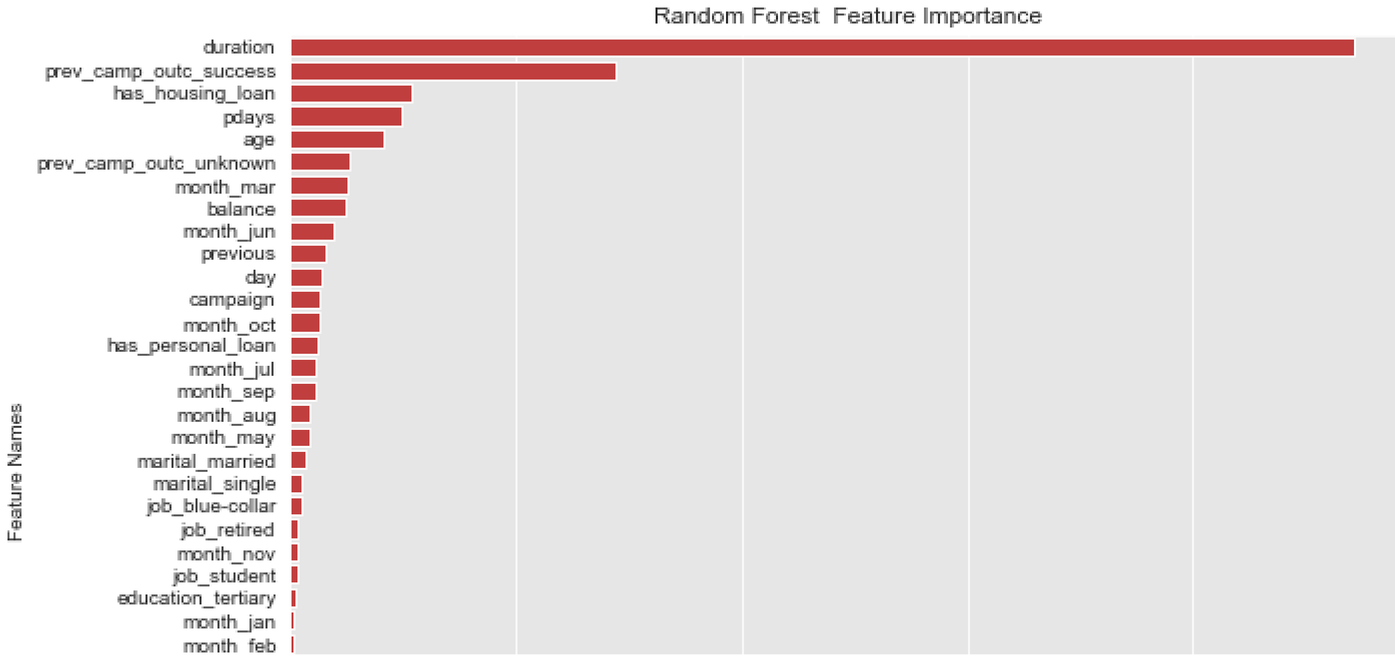
Light Gradient Boosted Machine Classifier could not increase recall score and slightly overfitted.

5. Conclusion

Among all models that I build, Logistic Regression and Random Forest algorithms performed well. An oversampling technique such as SMOTENC did not much help on models' performance. As a final and best model I chose Random Forest with the recall score 84% and an accuracy score 84%. Mainly model does a good job of decreasing false-positive which leads to avoiding losing future customers but identifying them as SUBSCRIBED.

In [205]:
```
def plot_feature_importance(importance,model,title):

# creating arrays from feature importance and feature names
    feature_importance = np.array(importance)
    feature_names = np.array(model)

# creating a DataFrame using a Dictionary
    data={'feature_names':feature_names,'feature_importance':feature_importance}
    df_ = pd.DataFrame(data)

# sortimg the DataFrame in order decreasing feature importance
    df_.sort_values(by=['feature_importance'], ascending=False,inplace=True)

# plotting the importances
    plt.figure(figsize=(10,8))
    sns.barplot(x=df_['feature_importance'], y=df_['feature_names'], color='#D62828' )
# adding the labels
    plt.title(title + 'Feature Importance')
    plt.xlabel('Feature Importance')
    plt.ylabel('Feature Names')
```

In [208]:
```
plot_feature_importance(rf_gs.best_estimator_.named_steps['rf'].feature_importances_, X.columns, 'Random Forest
```



Recommendation Based On Model Performance

- Develop a marketing strategies during the Calls: Since duration of the call is the feature that most positively correlates with whether a potential client will subscribe to a term deposit or not, by providing an interesting questionnaire for potential clients during the calls the conversation length might increase. Of course, this does not assure us that the potential client will suscribe to a term deposit! Nevertheless, we don't loose anything by implementing a strategy that will increase the level of engagement of the potential client leading to an increase probability of suscribing to a term deposit.
- The successful outcome of the previous marketing campaign did positively affect customers to subscribe to upcoming campaigns.I would highly recommend developing a loyalty program for the previously subscribed clients by giving them some bonuses and unique offers.
- House Loans and Balances: Potential clients in the average and high balances are less likely to have a house loan and therefore, more likely to open a term deposit. Lastly, the next marketing campaign should focus on individuals of average and high balances in order to increase the likelihood of subscribing to a term deposit

Future Considertion

This modelling is based on behaviour of clients and not on their motivations. The features reveal the actions of client but not his/her thought process. So more descriptive features can be useful here for example interview summary. In that case natural language processing will give better results. In these times of crisis preserving the relationship with best customers is more crucial than ever. Using these results bank can specifically target clients and gain higher success in their endeavours. Saving a lot of time by not focusing on clients with less probability is yet another advantages of this project.