bold text

Bank Term Deposit Classifier

bold text

Data Collection

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
!pip install --upgrade openpyxl
!pip install imblearn
```

```
Requirement already satisfied: openpyxl in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: et-xmlfile in /usr/local/lib/python3.7/dist-packa
Requirement already satisfied: imblearn in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: imbalanced-learn in /usr/local/lib/python3.7/dist-
Requirement already satisfied: scikit-learn>=0.24 in /usr/local/lib/python3.7/di
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/
```

```
from google.colab import files
file = files.upload()  #uploading the file
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in

```
Saving bank-additional-full.xlsx to bank-additional-full.xlsx
```

```
df = pd.read_excel("bank-additional-full.xlsx")
#df = pd.read_csv("bank-additional-full.csv")
df.head()
```

	age	job	marital	education	default	housing	loan	contact	month	day_
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	

Data Processing

```
print ("The shape of the  data is (row, column):"+ str(df.shape))
print (df.info())
```

```
The shape of the  data is (row, column):(41188, 22)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 22 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  y               41188 non-null  object
 21  age_group       41188 non-null  float64
dtypes: float64(6), int64(5), object(11)
memory usage: 6.9+ MB
None
```

```
df.dtypes #Datatype
```

```
age                 int64
job                object
marital            object
education          object
default            object
housing            object
loan               object
contact            object
```

```
month              object
day_of_week        object
duration            int64
campaign            int64
pdays               int64
previous            int64
poutcome           object
emp.var.rate      float64
cons.price.idx    float64
cons.conf.idx     float64
euribor3m         float64
nr.employed       float64
y                  object
age_group         float64
dtype: object
```

```
df.describe() #Statistics
```

	age	duration	campaign	pdays	previous	emp.var.rate
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960
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

```
df.head()
```

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

5 rows × 22 columns

```
print("Job:",df.job.value_counts(),sep = '\n') #Calculatig the count of each categori
```

```
print("-"*50)
print("Marital:",df.marital.value_counts(),sep = '\n')
print("-"*50)
print("Education:",df.education.value_counts(),sep = '\n')
print("-"*50)
print("Default:",df.default.value_counts(),sep = '\n')
print("-"*50)
print("Housing loan:",df.housing.value_counts(),sep = '\n')
print("-"*50)
print("Personal loan:",df.loan.value_counts(),sep = '\n')
print("-"*50)
print("Contact:",df.contact.value_counts(),sep = '\n')
print("-"*50)
print("Month:",df.month.value_counts(),sep = '\n')
print("-"*50)
print("Day:",df.day_of_week.value_counts(),sep = '\n')
print("-"*50)
print("Previous outcome:",df.poutcome.value_counts(),sep = '\n')
print("-"*50)
print("Outcome of this campaign:",df.y.value_counts(),sep = '\n')
```

```
Job:
admin.           10422
blue-collar       9254
technician        6743
services          3969
management        2924
retired           1720
entrepreneur      1456
self-employed     1421
housemaid         1060
unemployed        1014
student            875
unknown            330
Name: job, dtype: int64
--------------------------------------------------
Marital:
married     24928
single      11568
divorced     4612
unknown        80
Name: marital, dtype: int64
--------------------------------------------------
Education:
schooling              12513
university.degree      12168
high.school             9515
professional.course     5243
unknown                 1731
illiterate                18
Name: education, dtype: int64
--------------------------------------------------
Default:
```

```
no          32588
unknown      8597
yes             3
Name: default, dtype: int64
--------------------------------------------------
Housing loan:
yes         21576
no          18622
unknown       990
Name: housing, dtype: int64
--------------------------------------------------
Personal loan:
no          33950
yes          6248
unknown       990
Name: loan, dtype: int64
--------------------------------------------------
Contact:
cellular     26144
telephone    15044
Name: contact, dtype: int64
--------------------------------------------------
Month:
may    13769
jul     7174
aug     6178
```

```
print('Columns with null values:',df.isnull().sum(), sep = '\n')
```

```
Columns with null values:
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
y                 0
age_group         0
dtype: int64
```

```
#Grouping few education categories
```

```
lst=['basic.9y','basic.6y','basic.4y']
for i in lst:
    df.loc[df['education'] == i, 'education'] = "schooling"
```

```
df['education'].value_counts()
```

```
schooling              12513
university.degree      12168
high.school             9515
professional.course     5243
unknown                 1731
illiterate                18
Name: education, dtype: int64
```

```
#Creating age groups

df.loc[df['age']<=30, 'age_group'] = 20
df.loc[df['age'].between(31,39), 'age_group'] = 30
df.loc[df['age'].between(40,49), 'age_group'] = 40
df.loc[df['age'].between(50,59), 'age_group'] = 50
df.loc[df['age']>=60, 'age_group'] = 60
```

```
df.head(n=15)
```

```
filtered_df=df.copy()
```

```
filtered_df= filtered_df.replace('unknown',np.nan)
filtered_df
```

	age	job	marital	education	default	housing	loan	contact	mo

```
filtered_df= filtered_df.replace('unknown',np.nan)
filtered_df= filtered_df.replace(999,np.nan)
filtered_df
```

	age	job	marital	education	default	housing	loan	contact	mo
0	56	housemaid	married	schooling	no	no	no	telephone	
1	57	services	married	high.school	NaN	no	no	telephone	
2	37	services	married	high.school	no	yes	no	telephone	
3	40	admin.	married	schooling	no	no	no	telephone	
4	56	services	married	high.school	no	no	yes	telephone	
...	...	...	...	...	...	...	...	...	
41183	73	retired	married	professional.course	no	yes	no	cellular	
41184	46	blue-collar	married	professional.course	no	no	no	cellular	
41185	56	retired	married	university.degree	no	yes	no	cellular	
41186	44	technician	married	professional.course	no	no	no	cellular	
41187	74	retired	married	professional.course	no	yes	no	cellular	

41188 rows × 22 columns

```
print('Columns with null values:',filtered_df.isnull().sum(), sep = '\n')
print(filtered_df.isnull().sum()/df.shape[0]*100) #Calculating Percentage of Null Valu
```

```
Columns with null values:
age                    0
job                  330
marital               80
education           1731
default             8597
housing              990
loan                 990
contact                0
month                  0
day_of_week            0
duration               2
campaign               0
pdays              39673
previous               0
poutcome               0
emp.var.rate           0
cons.price.idx         0
cons.conf.idx          0
```

```
euribor3m           0
nr.employed         0
y                   0
age_group           0
dtype: int64
age                 0.000000
job                 0.801204
marital             0.194231
education           4.202680
default            20.872584
housing             2.403613
loan                2.403613
contact             0.000000
month               0.000000
day_of_week         0.000000
duration            0.004856
campaign            0.000000
pdays              96.321744
previous            0.000000
poutcome            0.000000
emp.var.rate        0.000000
cons.price.idx      0.000000
cons.conf.idx       0.000000
euribor3m           0.000000
nr.employed         0.000000
y                   0.000000
age_group           0.000000
dtype: float64
```

```
filtered_df=filtered_df.drop(columns=['default','pdays']) #Dropping the  column as 20%
```

```
#Imputing
df_missing = filtered_df.isna().sum()
```

```
df_missing_cols = df_missing[df_missing > 0]
df_missing_cols

index_cols = df_missing_cols.index
cols_list = list(index_cols)

filtered_df[cols_list] = filtered_df[cols_list].fillna(filtered_df.groupby('age_group'
```

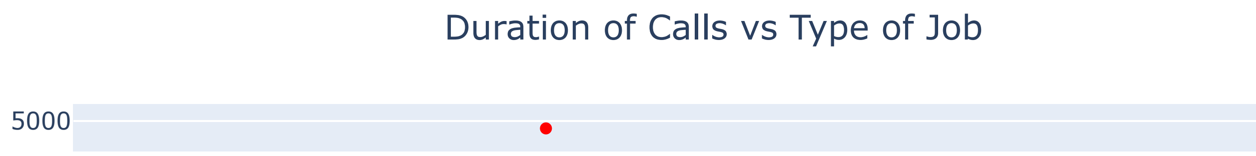
```
filtered_df
```

	age	job	marital	education	housing	loan	contact	month	day_
0	56	housemaid	married	schooling	no	no	telephone	may	
1	57	services	married	high.school	no	no	telephone	may	
2	37	services	married	high.school	yes	no	telephone	may	
3	40	admin.	married	schooling	no	no	telephone	may	
4	56	services	married	high.school	no	yes	telephone	may	
...	...	...	...	...	...	...	...	...	
41183	73	retired	married	professional.course	yes	no	cellular	nov	
41184	46	blue-collar	married	professional.course	no	no	cellular	nov	
41185	56	retired	married	university.degree	yes	no	cellular	nov	
41186	44	technician	married	professional.course	no	no	cellular	nov	

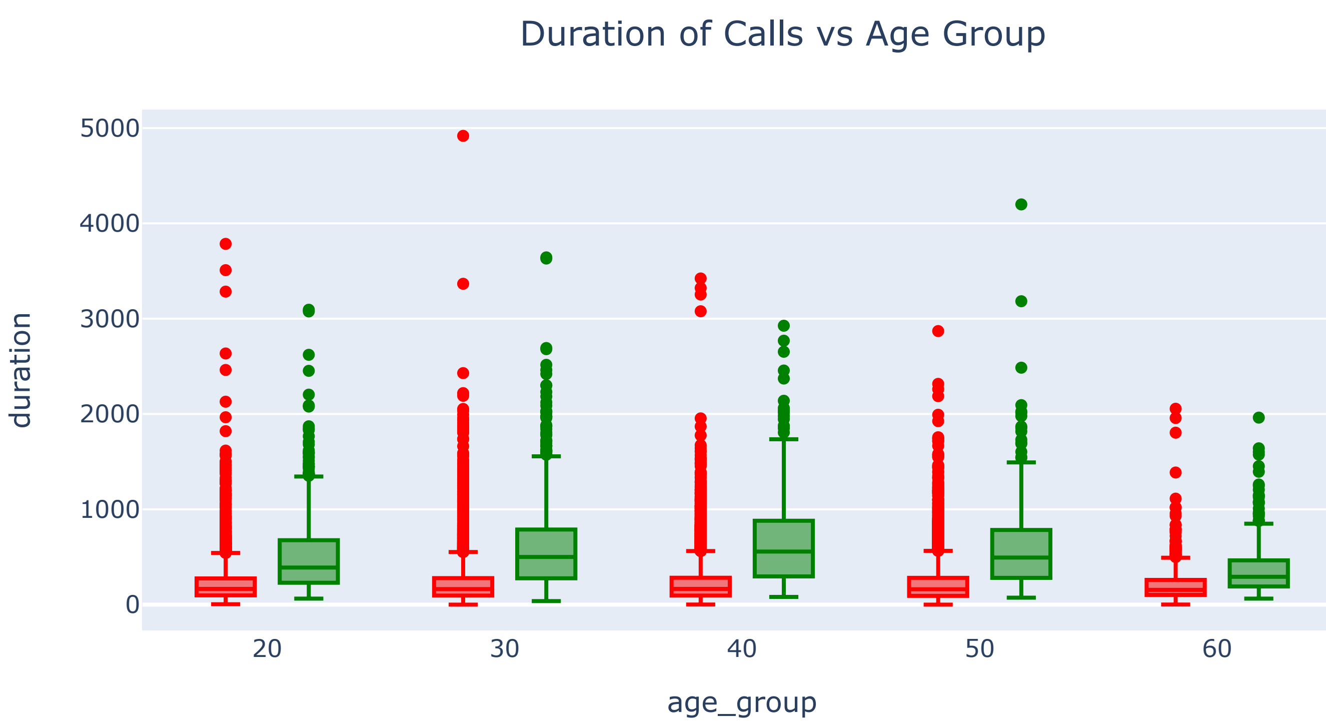
Visualization

```
import plotly.express as px
```

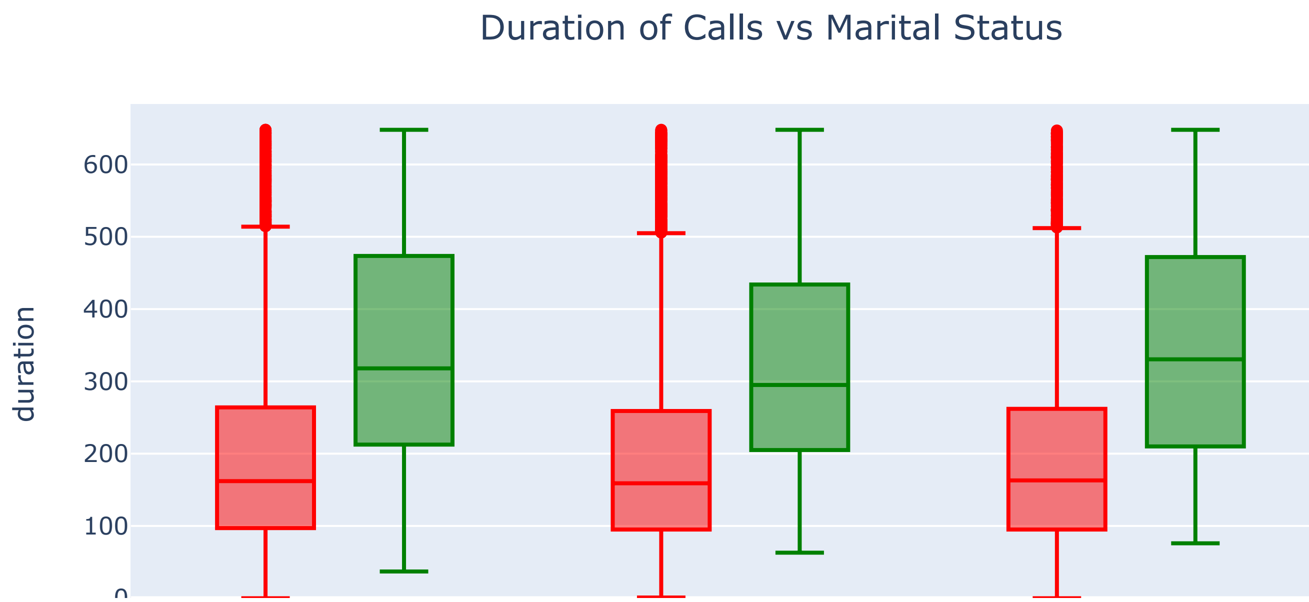
```
fig = px.box(filtered_df, x="job", y="duration",width=800, height=400, color="y" ,colo
fig.update_layout(
    title={
        'text': "Duration of Calls vs Type of Job",
        'y':0.96,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},legend_title_text='Term Deposit')
```



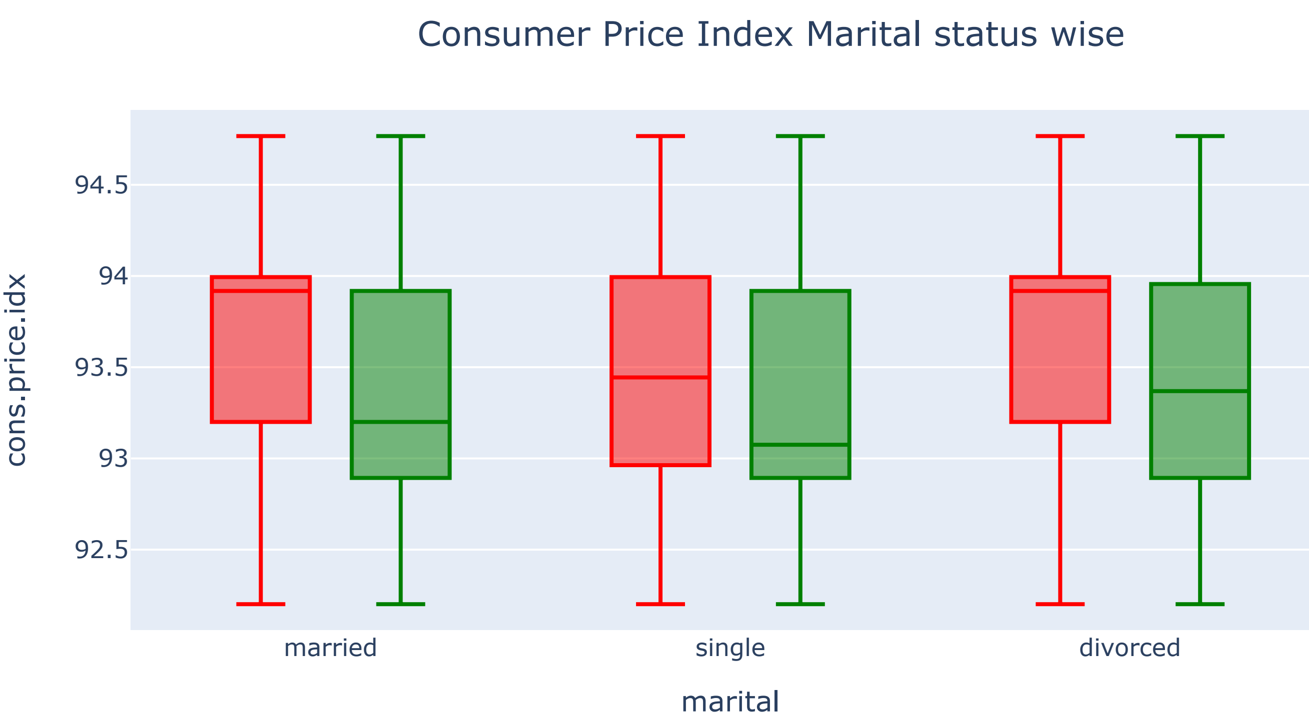

```
fig = px.box(filtered_df, x="age_group", y="duration" ,width=800, height=400,color="y'
fig.update_layout(
    title={
        'text': "Duration of Calls vs Age Group",
        'y':0.96,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},legend_title_text='Term Deposit')
```




```
fig = px.box(filtered_df, x="marital", y="duration", color="y",width=800, height=400 ,
fig.update_layout(
    title={
        'text': "Duration of Calls vs Marital Status",
        'y':0.96,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},legend_title_text='Term Deposit')
```




```
fig = px.box(filtered_df, x="marital", y="cons.price.idx", width=800, height=400,colo
fig.update_layout(
    title={
        'text': "Consumer Price Index Marital status wise",
        'y':0.96,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},legend_title_text='Term Deposit')
```

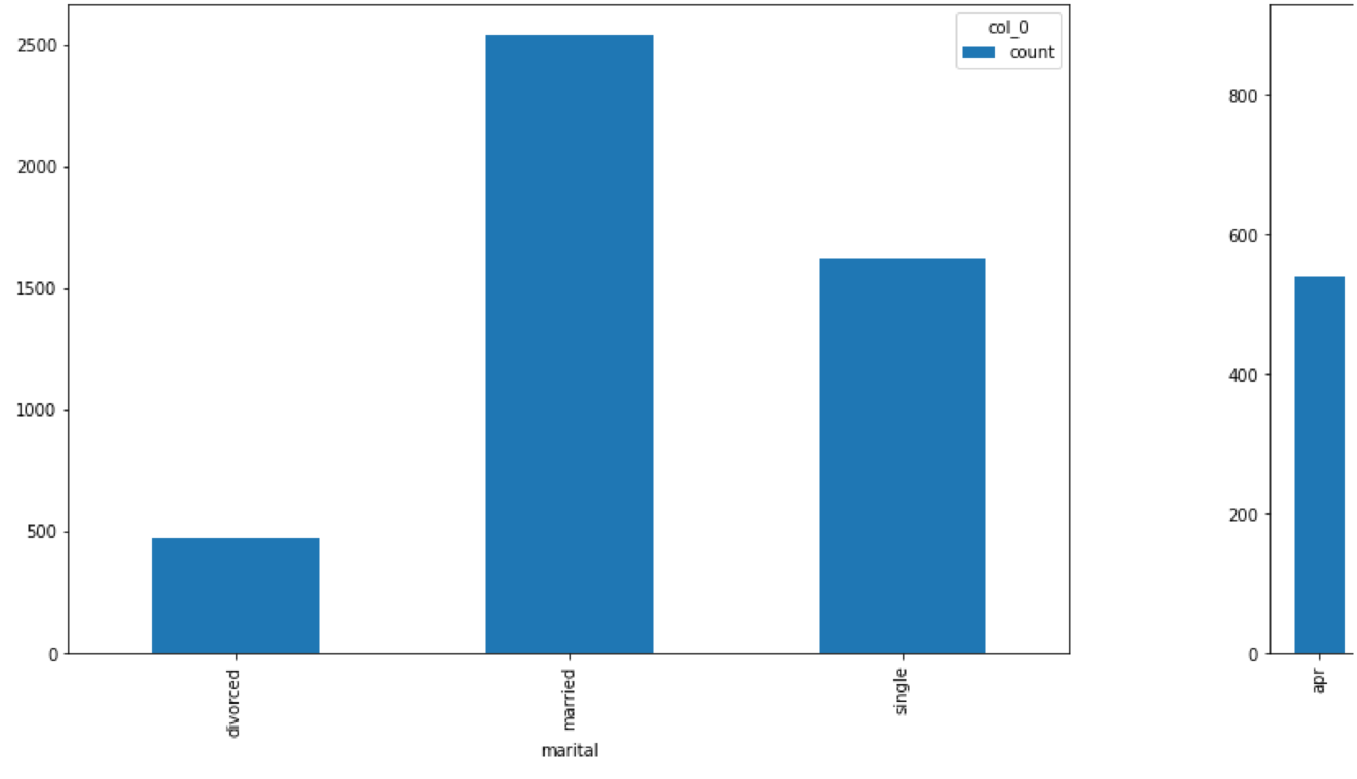


Conclusion: There are very minute differences among the price index.

Married leads have considerably have an upper hand as they have index contributing as couple

```
import matplotlib.pyplot as plt
df_bank = filtered_df[filtered_df['y']=='yes']


df1 = pd.crosstab(index = df_bank ["marital"],columns="count")
df2 = pd.crosstab(index = df_bank ["month"],columns="count")
df3= pd.crosstab(index = df_bank ["job"],columns="count")
df4=pd.crosstab(index = df_bank ["education"],columns="count")



fig, axes = plt.subplots(nrows=2, ncols=2,figsize=(24,16))
df1.plot.bar(ax=axes[0,0])
df2.plot.bar(ax=axes[0,1])
df3.plot.bar(ax=axes[1,0])
df4.plot.bar(ax=axes[1,1])
```

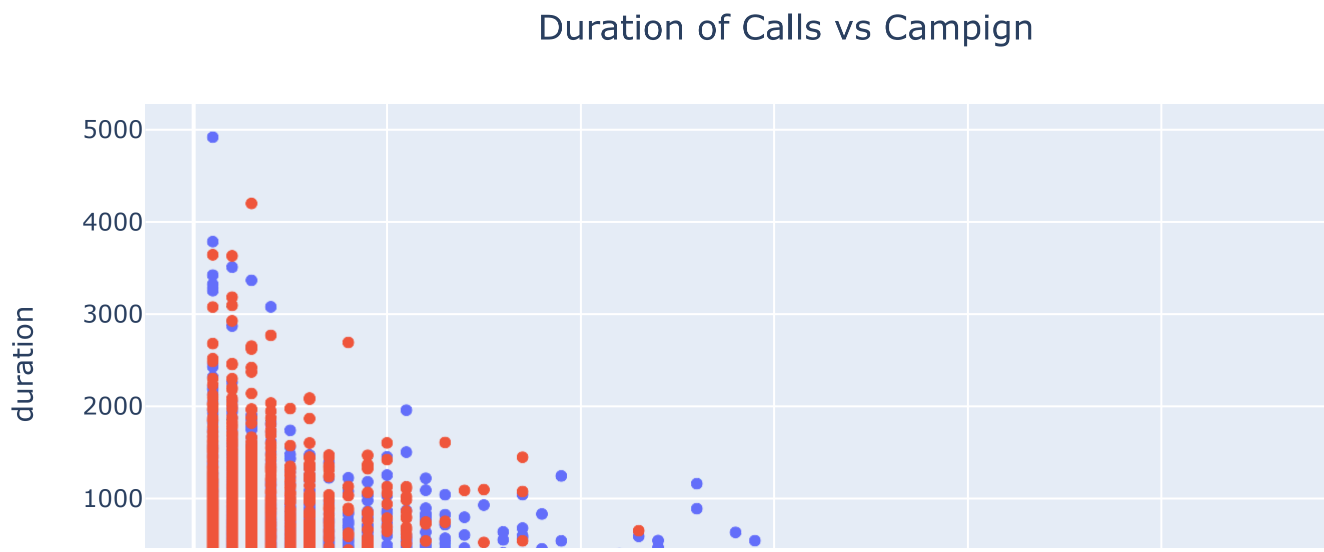
<matplotlib.axes._subplots.AxesSubplot at 0x7ff8cce1f910>




```
df1
```

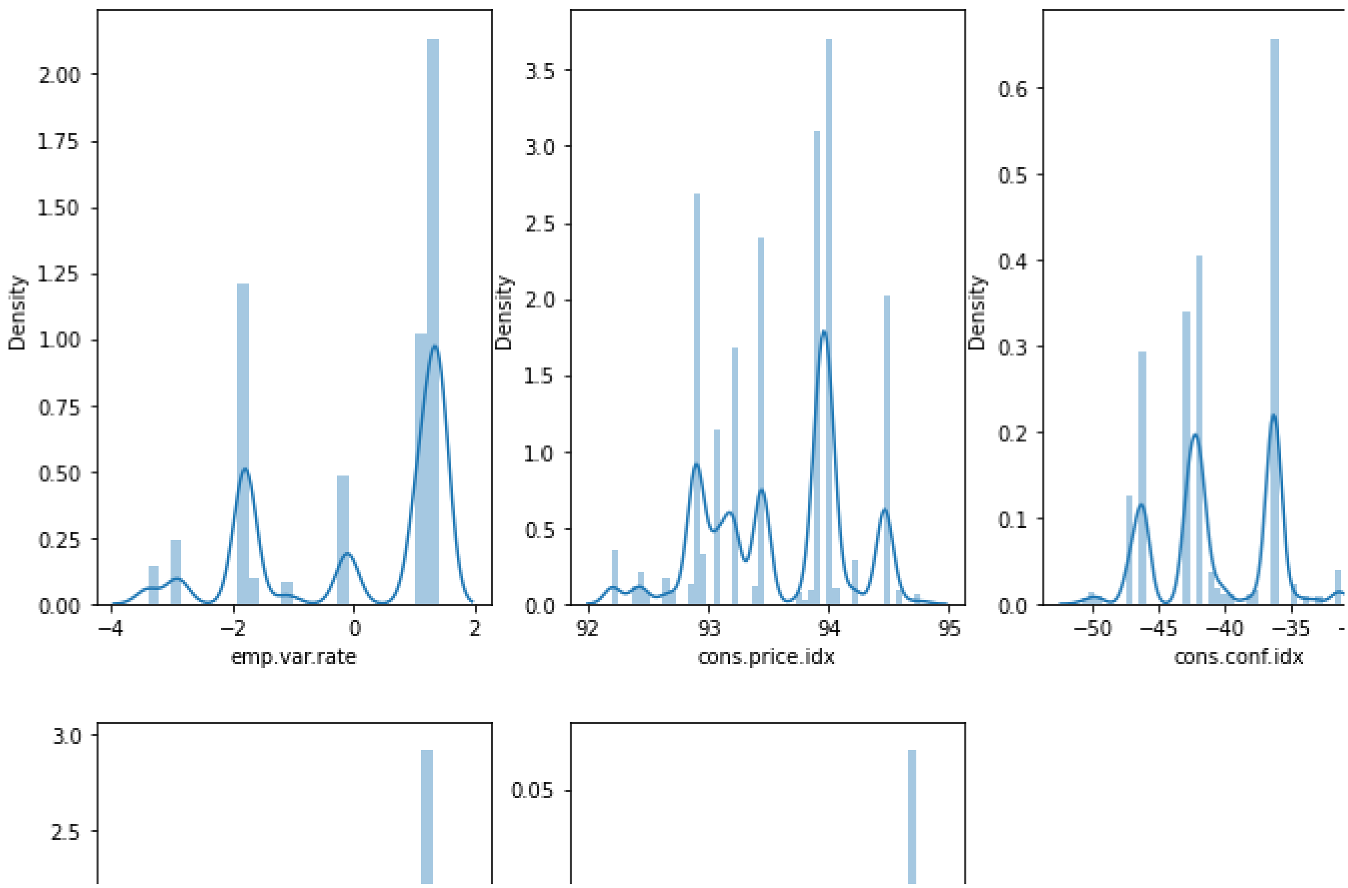
col_0	count
marital	
divorced	476
married	2541
single	1623

```
fig = px.scatter(filtered_df, x="campaign", y="duration", width=800, height=400,color=
fig.update_layout(
    title={
        'text': "Duration of Calls vs Campign",
        'y':0.96,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},legend_title_text='Term Deposit')
```

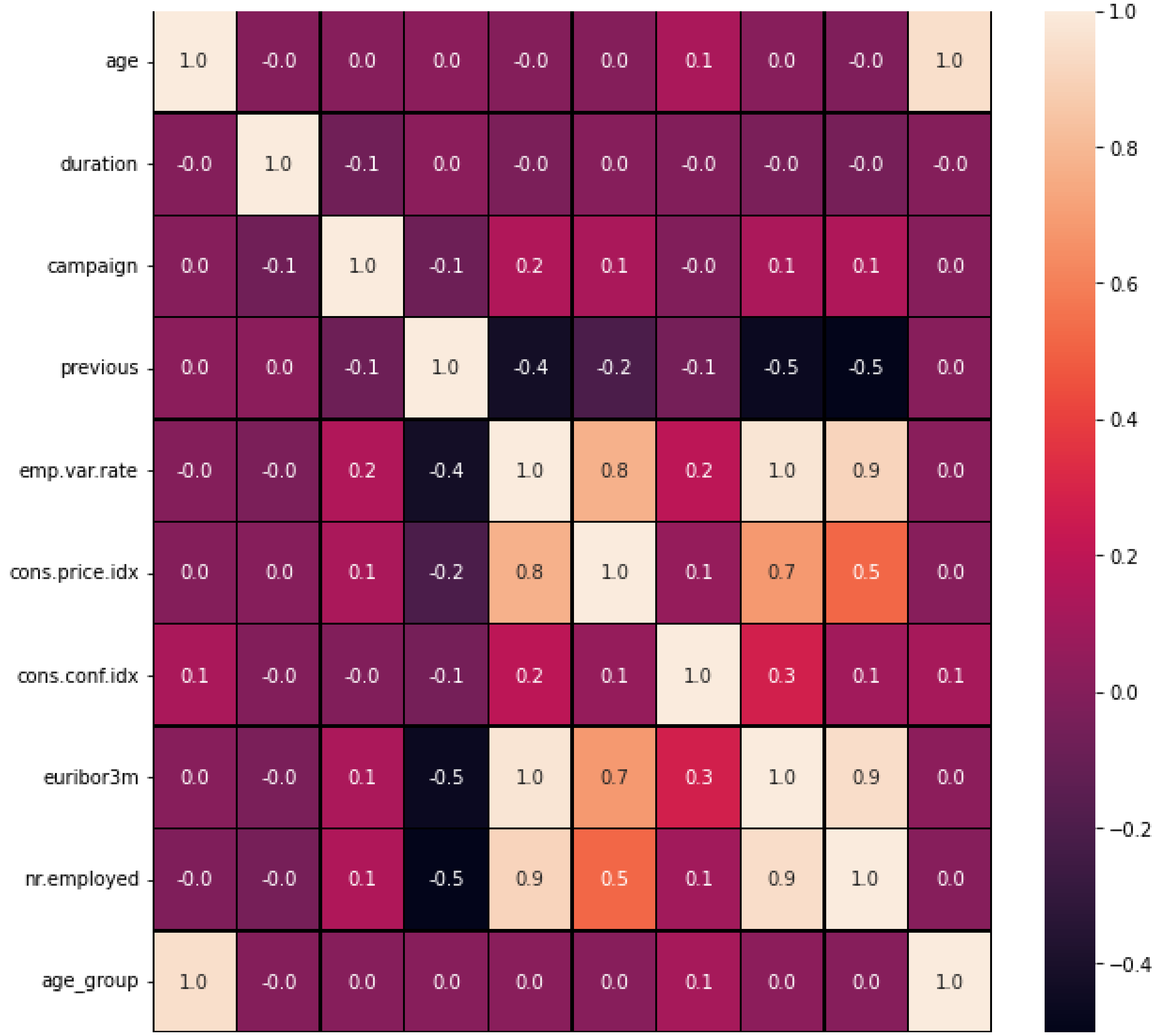



```
plt.subplot(231)
sns.distplot(filtered_df['emp.var.rate'])
fig = plt.gcf()
fig.set_size_inches(12,12)

plt.subplot(232)
sns.distplot(filtered_df['cons.price.idx'])
fig = plt.gcf()
fig.set_size_inches(12,12)

plt.subplot(233)
sns.distplot(filtered_df['cons.conf.idx'])
fig = plt.gcf()
fig.set_size_inches(12,12)

plt.subplot(234)
sns.distplot(filtered_df['euribor3m'])
fig = plt.gcf()
fig.set_size_inches(12,12)

plt.subplot(235)
sns.distplot(filtered_df['nr.employed'])
fig = plt.gcf()
fig.set_size_inches(12,12)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarn
`distplot` is a deprecated function and will be removed in a future version. Ple
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarn
`distplot` is a deprecated function and will be removed in a future version. Ple
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarn
`distplot` is a deprecated function and will be removed in a future version. Ple
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarn
`distplot` is a deprecated function and will be removed in a future version. Ple
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarn
`distplot` is a deprecated function and will be removed in a future version. Ple
```




```
f,ax=plt.subplots(figsize=(10,10))
sns.heatmap(filtered_df.corr(),annot=True,linewidths=0.5,linecolor="black",fmt=".1f",a
plt.show()
```




```
filtered_df=filtered_df.drop(columns=['nr.employed'])
```

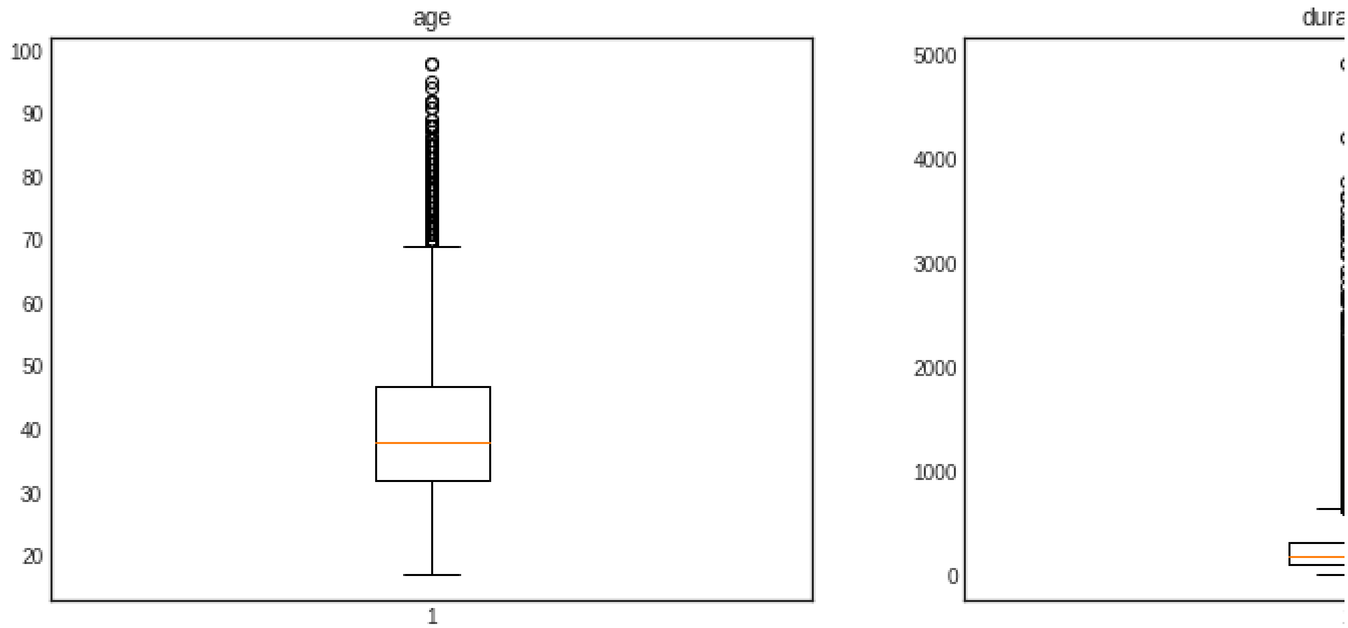
du am pre .va pri .cc irit mp e_

The nr.employed column was dropped as it is highly coorelated to two other columnsemp.var.rate and euibor3m

```
#Boxplot to check the outliers
import matplotlib.pyplot as plt

plt.figure(figsize = (15, 30))
plt.style.use('seaborn-white')
ax=plt.subplot(521)
plt.boxplot(filtered_df['age'])
ax.set_title('age')
ax=plt.subplot(522)
plt.boxplot(filtered_df['duration'])
ax.set_title('duration')
ax=plt.subplot(523)
plt.boxplot(filtered_df['campaign'])
ax.set_title('campaign')
```

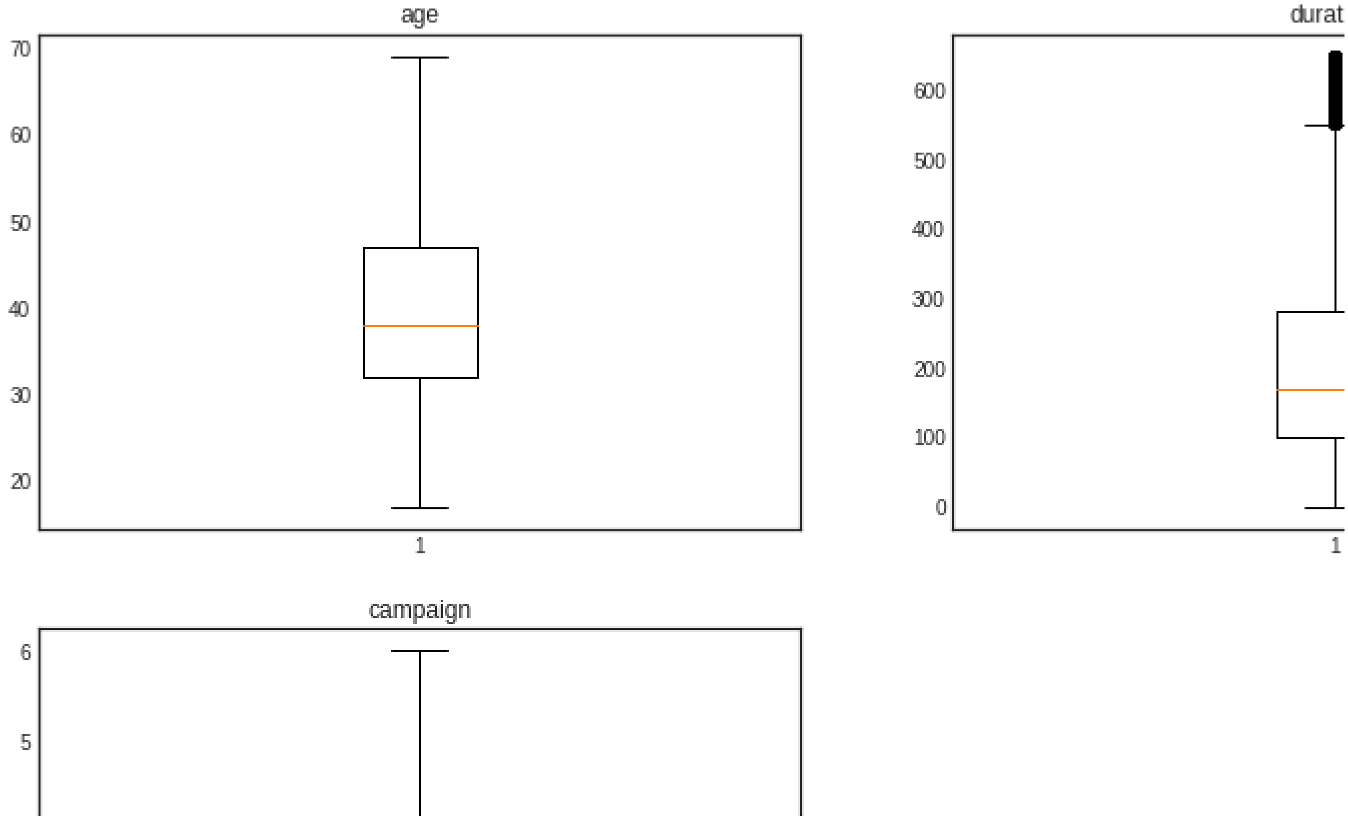
```
ax=plt.subplot(524)
plt.boxplot(filtered_df['previous'])
ax.set_title('previous')
ax=plt.subplot(525)
plt.boxplot(filtered_df['emp.var.rate'])
ax.set_title('Employee variation rate')
ax=plt.subplot(526)
plt.boxplot(filtered_df['cons.price.idx'])
ax.set_title('Consumer price index')
ax=plt.subplot(527)
plt.boxplot(filtered_df['cons.conf.idx'])
ax.set_title('Consumer confidence index')
ax=plt.subplot(528)
plt.boxplot(filtered_df['euribor3m'])
ax.set_title('euribor3m')
```

```
Text(0.5, 1.0, 'euribor3m')
```



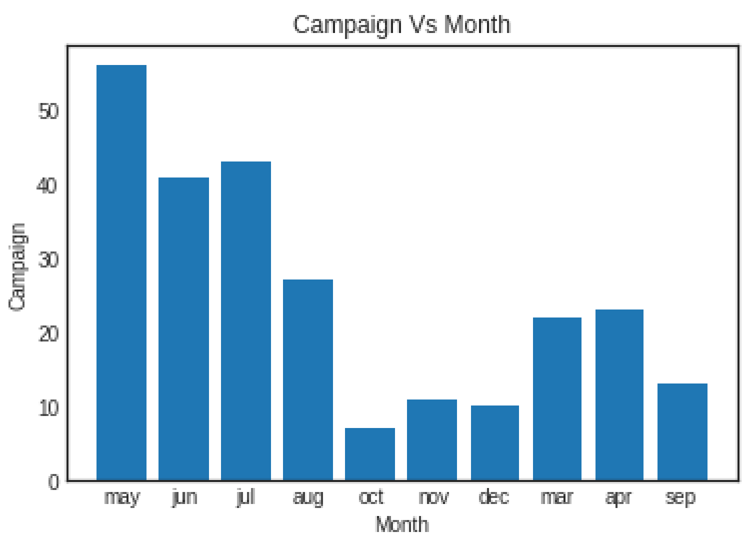

```
#Handling the outliers
numerical_features=['age','campaign','duration']
for cols in numerical_features:
    Q1 = filtered_df[cols].quantile(0.25)
    Q3 = filtered_df[cols].quantile(0.75)
    IQR =Q3 - Q1

    filter = (filtered_df[cols] >= Q1 - 1.5 * IQR) & (filtered_df[cols] <= Q3 + 1.5 *I
    filtered_df=filtered_df.loc[filter]

plt.figure(figsize = (15, 10))
plt.style.use('seaborn-white')
ax=plt.subplot(221)
plt.boxplot(filtered_df['age'])
ax.set_title('age')
ax=plt.subplot(222)
plt.boxplot(filtered_df['duration'])
ax.set_title('duration')
ax=plt.subplot(223)
plt.boxplot(filtered_df['campaign'])
ax.set_title('campaign')
```

```
Text(0.5, 1.0, 'campaign')
```




```
plt.bar(df['month'], df['campaign'])
plt.title('Campaign Vs Month')
plt.xlabel('Month')
plt.ylabel('Campaign')
```

```
Text(0, 0.5, 'Campaign')
```



Model Exploration

```
bank_features=filtered_df.copy()
```

```
bank_features
```

	age	job	marital	education	housing	loan	contact	month	da
0	56	housemaid	married	schooling	no	no	telephone	may	
1	57	services	married	high.school	no	no	telephone	may	
2	37	services	married	high.school	yes	no	telephone	may	
3	40	admin.	married	schooling	no	no	telephone	may	
4	56	services	married	high.school	no	yes	telephone	may	
...	...	...	...	...	...	...	...	...	
41181	37	admin.	married	university.degree	yes	no	cellular	nov	
41182	29	unemployed	single	schooling	yes	no	cellular	nov	
41184	46	blue-collar	married	professional.course	no	no	cellular	nov	
41185	56	retired	married	university.degree	yes	no	cellular	nov	
41186	44	technician	married	professional.course	no	no	cellular	nov	

35563 rows × 19 columns

```
month_dict={'may':5,'jul':7,'aug':8,'jun':6,'nov':11,'apr':4,'oct':10,'sep':9,'mar':3,
bank_features['month']= bank_features['month'].map(month_dict)

day_dict={'thu':5,'mon':2,'wed':4,'tue':3,'fri':6}
bank_features['day_of_week']= bank_features['day_of_week'].map(day_dict)
```

```
bank_features.loc[:, ['month', 'day_of_week']].head()
```

	month	day_of_week
0	5	2
1	5	2
2	5	2
3	5	2
4	5	2

```
dictionary={'yes':1,'no':0}
bank_features['housing']=bank_features['housing'].map(dictionary)
```

```
bank_features['loan']=bank_features['loan'].map(dictionary)
bank_features
```

	age	job	marital	education	housing	loan	contact	month	da
0	56	housemaid	married	schooling	0	0	telephone	5	
1	57	services	married	high.school	0	0	telephone	5	
2	37	services	married	high.school	1	0	telephone	5	
3	40	admin.	married	schooling	0	0	telephone	5	
4	56	services	married	high.school	0	1	telephone	5	
...	...	...	...	...	...	...	...	...	
41181	37	admin.	married	university.degree	1	0	cellular	11	
41182	29	unemployed	single	schooling	1	0	cellular	11	
41184	46	blue-collar	married	professional.course	0	0	cellular	11	
41185	56	retired	married	university.degree	1	0	cellular	11	
41186	44	technician	married	professional.course	0	0	cellular	11	

35563 rows × 19 columns

```
bank_job=bank_features['job'].value_counts().to_dict()
bank_ed=bank_features['education'].value_counts().to_dict()
```

```
bank_features['job']=bank_features['job'].map(bank_job)
bank_features['education']=bank_features['education'].map(bank_ed)
```

```
bank_features.loc[:,['job','education']].head()
```

	job	education
0	899	11572
1	3456	8288
2	3456	8288
3	9194	11572
4	3456	8288

```
marital_dict={'single':1,'married':2 ,'divorced':3}
bank_features['marital']= bank_features['marital'].map(marital_dict)
```

```
bank_features
```

	age	job	marital	education	housing	loan	contact	month	day_of_week
0	56	899	2	11572	0	0	telephone	5	2
1	57	3456	2	8288	0	0	telephone	5	2
2	37	3456	2	8288	1	0	telephone	5	2
3	40	9194	2	11572	0	0	telephone	5	2
4	56	3456	2	8288	0	1	telephone	5	2
...	...	...	...	...	...	...	...	...	...
41181	37	9194	2	11135	1	0	cellular	11	6
41182	29	887	1	11572	1	0	cellular	11	6
41184	46	8254	2	4554	0	0	cellular	11	6
41185	56	1158	2	11135	1	0	cellular	11	6
41186	44	5892	2	4554	0	0	cellular	11	6

35563 rows × 19 columns

```
bank_features=bank_features.drop(columns=['age_group'])
```

```
dummy_contact=pd.get_dummies(bank_features['contact'], prefix='dummy',drop_first=True)
dummy_outcome=pd.get_dummies(bank_features['poutcome'], prefix='dummy',drop_first=True
bank_features = pd.concat([bank_features,dummy_contact,dummy_outcome],axis=1)
bank_features.drop(['contact','poutcome'],axis=1, inplace=True)
```

```
dummy_contact
```

	dummy_telephone
0	1
1	1
2	1
3	1
4	1
...	...
41181	0

```
bank_features.loc[:,['dummy_telephone','dummy_nonexistent','dummy_success']].head()
```

	dummy_telephone	dummy_nonexistent	dummy_success
0	1	1	0
1	1	1	0
2	1	1	0
3	1	1	0
4	1	1	0

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

from sklearn.ensemble import ExtraTreesClassifier
```

```
bank_features
```

	age	job	marital	education	housing	loan	month	day_of_week	duration
0	56	899	2	11572	0	0	5	2	261
1	57	3456	2	8288	0	0	5	2	149
2	37	3456	2	8288	1	0	5	2	226
3	40	9194	2	11572	0	0	5	2	151
4	56	3456	2	8288	0	1	5	2	307

Standardization

```
bank_scale=bank_features.copy()
Categorical_variables=['job', 'education',  'housing', 'loan', 'month',
       'day_of_week','y', 'dummy_telephone', 'dummy_nonexistent',
       'dummy_success', 'marital']
```

```
feature_scale=[feature for feature in bank_scale.columns if feature not in Categorical
```

```
scaler=StandardScaler()
scaler.fit(bank_scale[feature_scale])
```

```
StandardScaler()
```

```
scaled_data = pd.concat([bank_scale[['job', 'education','housing', 'loan', 'month',
       'day_of_week','y', 'dummy_telephone', 'dummy_nonexistent',
       'dummy_success' ,'marital']].reset_index(drop=True),
                    pd.DataFrame(scaler.transform(bank_scale[feature_scale]), columns=
                    axis=1)
scaled_data.head()
```

	job	education	housing	loan	month	day_of_week	y	dummy_telephone	dummy_
0	899	11572	0	0	5	2	no	1	
1	3456	8288	0	0	5	2	no	1	
2	3456	8288	1	0	5	2	no	1	
3	9194	11572	0	0	5	2	no	1	
4	3456	8288	0	1	5	2	no	1	

```
X=scaled_data.drop(['y'],axis=1)
y=scaled_data.y

model = ExtraTreesClassifier()
model.fit(X,y)
```

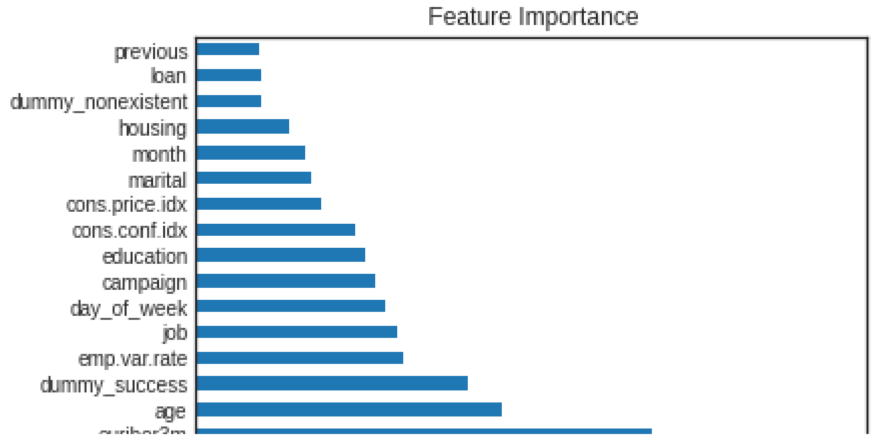
```
ExtraTreesClassifier()
```

```
X
```

	job	education	housing	loan	month	day_of_week	dummy_telephone	dummy_
0	899	11572	0	0	5	2	1	
1	3456	8288	0	0	5	2	1	
2	3456	8288	1	0	5	2	1	
3	9194	11572	0	0	5	2	1	
4	3456	8288	0	1	5	2	1	
...	...	...	...	...	...	...	...	
35558	9194	11135	1	0	11	6	0	
35559	887	11572	1	0	11	6	0	
35560	8254	4554	0	0	11	6	0	
35561	1158	11135	1	0	11	6	0	
35562	5892	4554	0	0	11	6	0	

35563 rows × 18 columns

```
#Feature selection
feat_importances = pd.Series(model.feature_importances_, index=X.columns)
feat_importances.nlargest(17).plot(kind='barh')
plt.title (" Feature Importance")
plt.figure(figsize = (45, 10))
plt.show()
```




```
X=scaled_data.drop(['dummy_telephone','previous','loan','month','housing','y'],axis=1)
y=scaled_data.y
```

```
X
```

	job	education	day_of_week	dummy_nonexistent	dummy_success	marital	
0	899	11572	2	1	0	2	1.
1	3456	8288	2	1	0	2	1.
2	3456	8288	2	1	0	2	-0.
3	9194	11572	2	1	0	2	0.
4	3456	8288	2	1	0	2	1.
...	...	...	...	...	...	...	
35558	9194	11135	6	1	0	2	-0.
35559	887	11572	6	0	1	1	-1.
35560	8254	4554	6	1	0	2	0.
35561	1158	11135	6	1	0	2	1.
35562	5892	4554	6	1	0	2	0.

35563 rows × 13 columns

Model Exploration

```
a1=X
b1=y
```

```
from imblearn.over_sampling import RandomOverSampler
```

```
ros = RandomOverSampler(sampling_strategy="not majority") # oversampling
X_res, y_res = ros.fit_resample(a1, b1)

X_res.shape[0] - a1.shape[0]
```

```
29791
```

```
#Splitting the Data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res,train_size=0.8,randon
print("Input Training:",X_train.shape)
print("Input Test:",X_test.shape)
print("Output Training:",y_train.shape)
print("Output Test:",y_test.shape)
```

```
Input Training: (52283, 13)
Input Test: (13071, 13)
Output Training: (52283,)
Output Test: (13071,)
```

```
#Training the model
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import BernoulliNB
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
logreg_cv = LogisticRegression(random_state=0)
dt_cv=DecisionTreeClassifier()
knn_cv=KNeighborsClassifier()
nb_cv=BernoulliNB()
gb_cv=GradientBoostingClassifier()
rf_cv=RandomForestClassifier()
dc_cv=DecisionTreeClassifier()
cv_dict = {0: 'Logistic Regression', 1: 'Decision Tree',2:'KNN',3:'Naive Bayes',4:'Gra
cv_models=[logreg_cv,dt_cv,knn_cv,nb_cv,gb_cv,rf_cv]
```

```
for i,model in enumerate(cv_models):
    print("{} Train Accuracy: {}".format(cv_dict[i],cross_val_score(model, X_train, y_
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:818: Co

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
```

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressio

```
Logistic Regression Train Accuracy: 0.8449783512455534
Decision Tree Train Accuracy: 0.9723619403511989
KNN Train Accuracy: 0.9302258972310475
Naive Bayes Train Accuracy: 0.785551763007453
GradientBoosting Train Accuracy: 0.8988390537150025
RandomForestClassifier Train Accuracy: 0.975804734717518
```

Logistic Regression

```
#Hyper Tuning
from sklearn.model_selection import GridSearchCV
param_grid = {'C': np.logspace(-4, 4, 50),
             'penalty':['l1', 'l2']}
clf = GridSearchCV(LogisticRegression(random_state=0), param_grid,cv=5, verbose=0,n_jo
best_model = clf.fit(X_train,y_train)
print(best_model.best_estimator_)
print("The mean accuracy of the model is:",best_model.score(X_test,y_test))
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_validation.py:37
250 fits failed out of a total of 500.
The score on these train-test partitions for these parameters will be set to nan
If these failures are not expected, you can try to debug them by setting error_s

Below are more details about the failures:
--------------------------------------------------------------------------------
250 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_validati
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py
    solver = _check_solver(self.solver, self.penalty, self.dual)
  File "/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py
    % (solver, penalty)
ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got l1 penalty.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_search.py:972: U
        nan 0.83966113        nan 0.84071308        nan 0.84226236
        nan 0.84295085        nan 0.84283613        nan 0.84551381
        nan 0.84474875        nan 0.84417495        nan 0.84444273
        nan 0.84507389        nan 0.84499741        nan 0.84488267
        nan 0.8455521         nan 0.84428974        nan 0.84591548
        nan 0.84599197        nan 0.84448099        nan 0.84541815
        nan 0.84530339        nan 0.84522693        nan 0.8449974
        nan 0.84492088        nan 0.84442357        nan 0.84486351
        nan 0.84450008        nan 0.84526518        nan 0.8446531
        nan 0.84488264        nan 0.84522693        nan 0.84543733
        nan 0.84465311        nan 0.84438532        nan 0.84480613
        nan 0.84494002        nan 0.84484438        nan 0.84495915
        nan 0.8445766         nan 0.84492089        nan 0.84494003
```

```
           nan 0.84469136        nan 0.84515043        nan 0.84509304
           nan 0.84494002        nan 0.84488264        nan 0.84497828
           nan 0.84497828        nan 0.84474874]
  category=UserWarning,
LogisticRegression(C=0.08685113737513521, random_state=0)
The mean accuracy of the model is: 0.8483666131129982
```

```
#Best Model
logreg = LogisticRegression(C=0.3906939937054613, random_state=0)
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logreg.s
```

```
Accuracy of logistic regression classifier on test set: 84.58
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:818: Co

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressio
```

```
print('Accuracy of logistic regression classifier on train set: {:.2f}'.format(logreg.
```

```
Accuracy of logistic regression classifier on train set: 84.28
```

```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n",confusion_matrix)
```

```
Confusion Matrix:
 [[5488 1140]
 [ 862 5581]]
```

```
from sklearn.metrics import classification_report

report_logisitc = classification_report(y_test, y_pred)
```

```
print(report_logisitc)
```

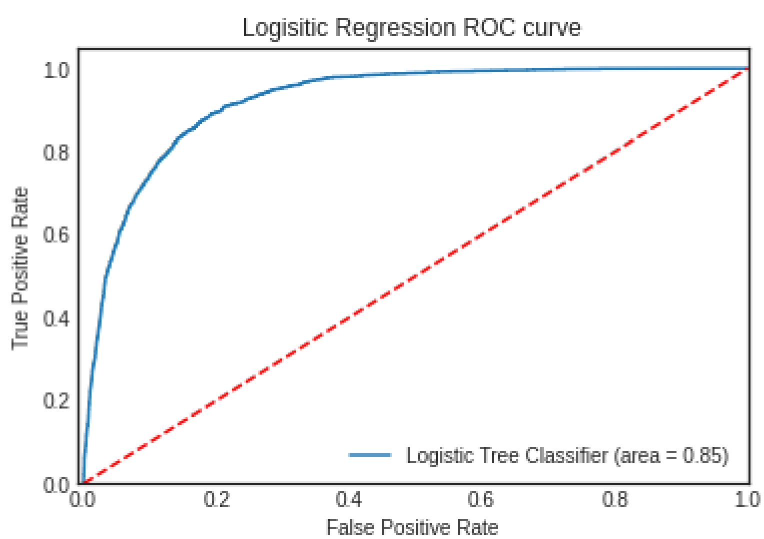
```
              precision    recall  f1-score   support

          no       0.86      0.83      0.85      6628
         yes       0.83      0.87      0.85      6443

    accuracy                           0.85     13071
```

```
    macro avg       0.85      0.85      0.85     13071
 weighted avg       0.85      0.85      0.85     13071
```

```
ss=pd.DataFrame(y_pred)
ss.replace(('yes', 'no'), (1, 0), inplace=True)

pp=pd.DataFrame(y_test)
pp.replace(('yes', 'no'), (1, 0), inplace=True)
```

```
from sklearn import metrics
```

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
Logistic_roc_auc = roc_auc_score(y_test,ss)
fpr, tpr, thresholds = roc_curve(pp, logreg.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Tree Classifier (area = %0.2f)' % Logistic_roc_auc
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title("Logisitic Regression ROC curve")
plt.legend(loc="lower right")
plt.show()
```




```
recall_specificity = metrics.recall_score(ss, pp, pos_label=1)
recall_sensitivity = metrics.recall_score(ss, pp, pos_label=0)
print(recall_sensitivity) #Class of interest - Yes
print(recall_specificity)
```

```
0.864251968503937
0.830382383573873
```

Gradient Boosting

```
#Hyper Tuning
param_grid = {
    #"loss":["deviance"],
    "learning_rate": [0.01, 0.025, 0.05, 0.075, 0.1, 0.15, 0.2],
    "min_samples_split": np.linspace(1, 8, 8),
    "min_samples_leaf": np.linspace(0.1, 0.5, 5),
    "max_depth":[3,5,8],
    #"max_features":["log2","sqrt"],
    #"criterion": ["friedman_mse",  "mae"],
    #"subsample":[0.5, 0.618, 0.8, 0.85, 0.9, 0.95, 1.0],
    "n_estimators":[50, 100, 120, 150]
    }
clf1 = GridSearchCV(GradientBoostingClassifier(random_state=0), param_grid,cv=5, verbo
best_model_z = clf1.fit(X_train,y_train)
print(best_model_z.best_estimator_)
print("The mean accuracy of the model is:",best_model_z.score(X_test,y_test))
```

```
gb_cv.get_params()
```

```
{'ccp_alpha': 0.0,
 'criterion': 'friedman_mse',
 'init': None,
 'learning_rate': 0.1,
 'loss': 'deviance',
 'max_depth': 3,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_iter_no_change': None,
 'random_state': None,
 'subsample': 1.0,
 'tol': 0.0001,
 'validation_fraction': 0.1,
 'verbose': 0,
 'warm_start': False}
```

```
# Best Parameters
gradientBoostingModel=GradientBoostingClassifier(learning_rate= 0.1,
 max_depth= 3,
 min_samples_leaf=1,
 min_samples_split= 2,
```

```
 n_estimators =100)
```

```
gradientBoostingModel.fit(X_train,y_train)
```

```
    GradientBoostingClassifier()
```

```
print("The mean accuracy of the model is:",gradientBoostingModel.score(X_test,y_test))
y_pred = gradientBoostingModel.predict(X_test)

print('Accuracy of Gradient on test set: {:.2f}'.format(gradientBoostingModel.score(X_
```

```
    The mean accuracy of the model is: 0.9006196924489328
    Accuracy of Gradient on test set: 90.06
```

```
print('Accuracy of Gradient Booster classifier on train set: {:.2f}'.format(gradientBo
```

```
    Accuracy of Gradient Booster classifier on train set: 89.99
```

```
from sklearn.metrics import confusion_matrix
```

```
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n",cm)
```

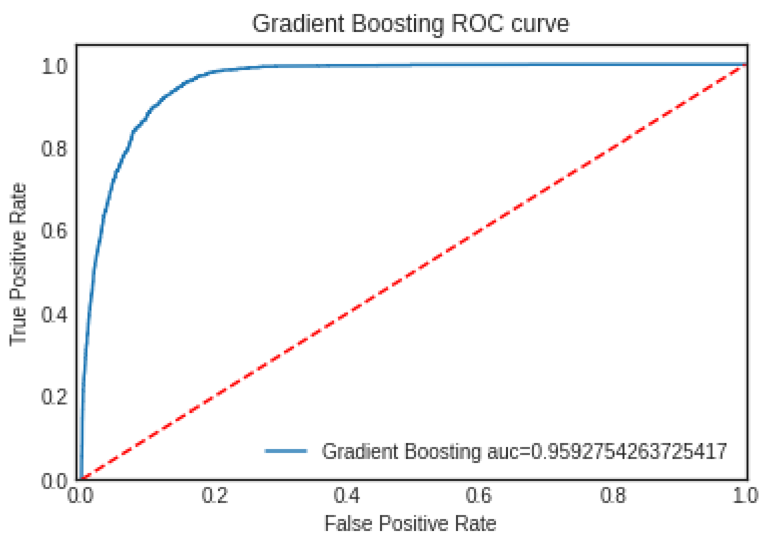
```
    Confusion Matrix:
     [[5672  956]
     [ 383 6060]]
```

```
from sklearn.metrics import classification_report

report_GB = classification_report(y_test,y_pred)
```

```
print(report_GB)
```

```
                  precision    recall  f1-score   support

              no       0.94      0.86      0.89      6628
             yes       0.86      0.94      0.90      6443

        accuracy                           0.90     13071
       macro avg       0.90      0.90      0.90     13071
    weighted avg       0.90      0.90      0.90     13071
```

```
from sklearn import metrics
pp=pd.DataFrame(y_test)
pp.replace(('yes', 'no'), (1, 0), inplace=True)

y_pred_proba = gradientBoostingModel.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(pp,  y_pred_proba)
auc = metrics.roc_auc_score(pp, y_pred_proba)
plt.plot(fpr,tpr,label="Gradient Boosting auc="+str(auc))
plt.legend(loc=4)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])
plt.title("Gradient Boosting ROC curve")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.show()
```

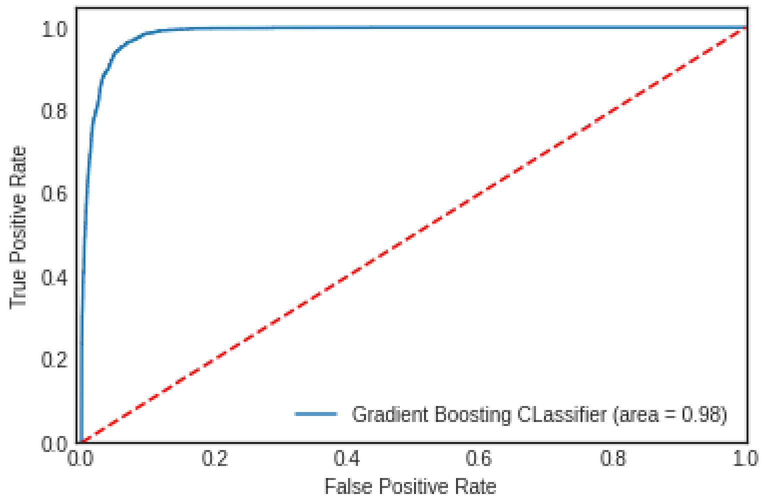



```
ss=pd.DataFrame(y_pred)
ss.replace(('yes', 'no'), (1, 0), inplace=True)


recall_specificity = metrics.recall_score(ss, pp, pos_label=1)
recall_sensitivity = metrics.recall_score(ss, pp, pos_label=0)
print(recall_sensitivity) #Class of interest - Yes
print(recall_specificity)
```

```
0.936746490503716
0.863740022805017
```

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
Gradient_roc_auc = roc_auc_score(y_test,ss)
fpr, tpr, thresholds = roc_curve(ss, gradientBoostingModel.predict_proba(X_test)[:,1])
plt.figure()
```

```
plt.plot(fpr, tpr, label='Gradient Boosting CLassifier (area = %0.2f)' % Gradient_roc_
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.show()
```



KNN

```
#Hyper Tuning
knn_cv=KNeighborsClassifier()
from sklearn.model_selection import GridSearchCV
k_range = list(range(1, 31))
param_grid = dict(n_neighbors=k_range)

# defining parameter range
clf_knn= GridSearchCV(knn_cv, param_grid, cv=10, scoring='accuracy', return_train_scor
```

```
grid_search=clf_knn.fit(X_train, y_train)
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

```
print(grid_search.best_params_)
```

```
{'n_neighbors': 1}
```

Note: Not training the model with 'n_neighbors': 1 as on trainining and testing we get to know that

```
pp=pd.DataFrame(y_pred)
pp.replace(('yes', 'no'),(1, 0),inplace=True)
```

```
#Best Model
knn_cv_model=KNeighborsClassifier(n_neighbors=4)
knn_cv_model.fit(X_train,y_train)

print("The mean accuracy of the model is:",knn_cv_model.score(X_test,y_test))
y_pred = knn_cv_model.predict(X_test)

print('Accuracy of KNN on test set: {:.2f}'.format(knn_cv_model.score(X_test, y_test)
```

```
    The mean accuracy of the model is: 0.9534848137097391
    Accuracy of KNN on test set: 0.95
```

```
knn_cv_model.get_params
```

```
    <bound method BaseEstimator.get_params of KNeighborsClassifier(n_neighbors=4)>
```

```
print('Accuracy of KNN on train set: {:.2f}'.format(knn_cv_model.score(X_train, y_trai
```

```
    Accuracy of KNN on train set: 97.33
```

```
from sklearn.metrics import confusion_matrix
```

```
confusion_matrix = confusion_matrix(y_test,y_pred)
print("Confusion Matrix:\n",confusion_matrix)
```

```
    Confusion Matrix:
     [[6033  595]
     [  15 6428]]
```

```
from sklearn.metrics import classification_report

report_KNN = classification_report(y_test,y_pred)
```

```
print(report_KNN)
```

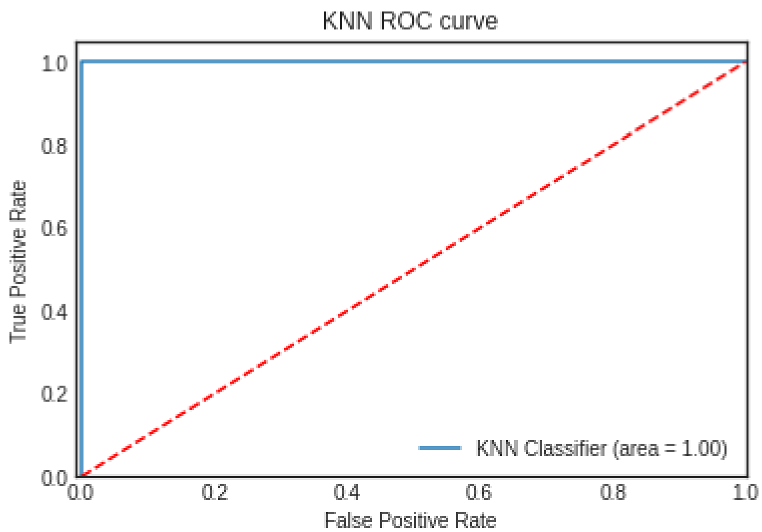
```
                  precision    recall  f1-score   support

              no       1.00      0.91      0.95      6628
             yes       0.92      1.00      0.95      6443
```

```
    accuracy                          0.95     13071
   macro avg       0.96      0.95      0.95     13071
weighted avg       0.96      0.95      0.95     13071
```

```
from sklearn import metrics
```

```
y_pred_proba = knn_cv_model.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(pp,  y_pred_proba)
KNN_auc = metrics.roc_auc_score(pp, y_pred_proba)

plt.legend(loc=4)
plt.plot(fpr, tpr, label='KNN Classifier (area = %0.2f)' % KNN_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title("KNN ROC curve")
plt.legend(loc="lower right")
plt.show()
```

```
No handles with labels found to put in legend.
```




```
ss=pd.DataFrame(y_pred)
ss.replace(('yes', 'no'), (1, 0), inplace=True)

pp=pd.DataFrame(y_test)
pp.replace(('yes', 'no'), (1, 0), inplace=True)
```

```
recall_specificity = metrics.recall_score(ss, pp, pos_label=1)
recall_sensitivity = metrics.recall_score(ss, pp, pos_label=0)
print(recall_sensitivity) #Class of interest - Yes
print(recall_specificity)
```

```
0.9975198412698413
0.9152783710664958
```

Random Forest

```
#Hyper Tuning
#Grid Search for RF
param_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [100, 200, 300, 1000]
}

#param_grid = {
#    'n_estimators': [200,500],
#    'max_features': [.5,.7],
#    'bootstrap': [False, True],
#    'max_depth':[3,6]
#}

clf_rf = GridSearchCV(RandomForestClassifier(random_state=0), param_grid,cv=3, verbose
best_model_rf = clf_rf.fit(X_train,y_train)
print(best_model_rf.best_estimator_)
print("The mean accuracy of the model is:",best_model_rf.score(X_test,y_test))


#Best Model
rf_model = RandomForestClassifier(max_depth=80, max_features=3, min_samples_leaf=3,
                       min_samples_split=8, n_estimators=1000, random_state=0)
rf_model.fit(X_train,y_train)
```

```
RandomForestClassifier(max_depth=80, max_features=3, min_samples_leaf=3,
                       min_samples_split=8, n_estimators=1000, random_state=0)
```

```
print("The mean accuracy of the model is:",rf_model.score(X_test,y_test))
y_pred = rf_model.predict(X_test)

print('Accuracy of Gradient on test set: {:.2f}'.format(rf_model.score(X_test, y_test)
```

```
The mean accuracy of the model is: 0.9648075893198684
Accuracy of Gradient on test set: 96.48
```

```
print('Accuracy of Random Forest classifier on train set: {:.2f}'.format(rf_model.scor
```

```
Accuracy of Random Forest classifier on train set: 98.06
```

```
from sklearn.metrics import confusion_matrix


confusion_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n",confusion_matrix)
```

```
Confusion Matrix:
 [[6174  454]
 [   0 6443]]
```

```
report_rf = classification_report(y_test, y_pred)


print(report_rf)
```

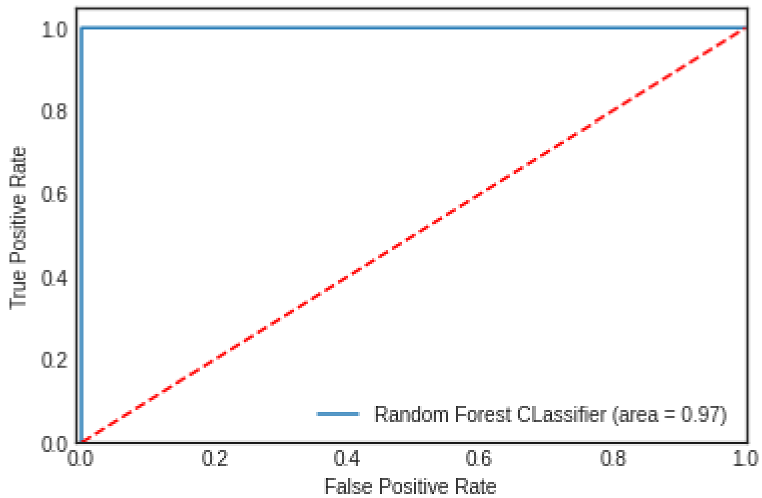
```
              precision    recall  f1-score   support

          no       1.00      0.93      0.96      6628
         yes       0.94      1.00      0.97      6443

    accuracy                           0.97     13071
   macro avg       0.97      0.97      0.97     13071
weighted avg       0.97      0.97      0.97     13071
```

```
ss=pd.DataFrame(y_pred)
ss.replace(('yes', 'no'), (1, 0), inplace=True)

pp=pd.DataFrame(y_test)
pp.replace(('yes', 'no'), (1, 0), inplace=True)


recall_sensitivity = metrics.recall_score(ss, pp, pos_label=0)
recall_specificity = metrics.recall_score(ss, pp, pos_label=1)
print(recall_sensitivity) #Class of interest - Yes
print(recall_specificity)
```

```
0.9988691437802908
0.9353291672721988
```

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
RF_roc_auc = roc_auc_score(y_test,ss)
fpr, tpr, thresholds = roc_curve(ss, rf_model.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Random Forest CLassifier (area = %0.2f)' % RF_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
```

```
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.show()
```



Decision Tree

```
#Hyper Tuning
param_grid = {

    'max_depth': range(25, 45),

    'max_features': range(2, 11)}



clf_dt = GridSearchCV(DecisionTreeClassifier(random_state=0), param_grid,cv=3, verbose

best_model_dt = clf_dt.fit(X_train,y_train)

print(best_model_dt.best_estimator_)

print("The mean accuracy of the model is:",best_model_dt.score(X_test,y_test))
```

```
DecisionTreeClassifier(max_depth=27, max_features=7, random_state=0)
The mean accuracy of the model is: 0.9759008492081708
```

```
#Best Model
dt_cv=DecisionTreeClassifier(max_depth=28, max_features=6, random_state=0)
dt_cv.fit(X_train,y_train)
```

```
print("The mean accuracy of the model is:",dt_cv.score(X_test,y_test))
y_pred = dt_cv.predict(X_test)

print('Accuracy of Decision Tree Classifier on test set: {:.2f}'.format(dt_cv.score(X_
```

```
    The mean accuracy of the model is: 0.9764363858924336
    Accuracy of Decision Tree Classifier on test set: 0.98
```

```
print('Accuracy of Decision Tree classifier on train set: {:.2f}'.format(dt_cv.score(X
```

```
    Accuracy of Decision Tree classifier on train set: 99.98
```

```
from sklearn.metrics import confusion_matrix
```

```
confusion_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n",confusion_matrix)
```

```
    Confusion Matrix:
     [[6326  302]
     [   0 6443]]
```

```
from sklearn.metrics import classification_report

report_decision_tree = classification_report(y_test, y_pred)
```

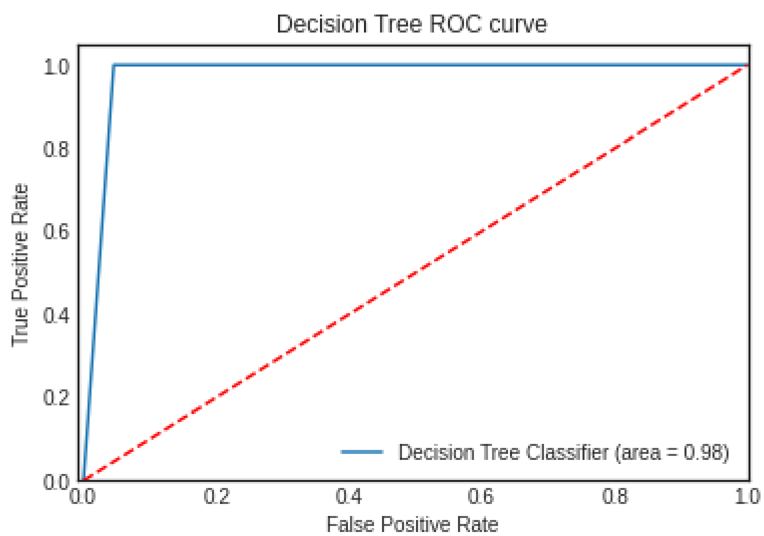
```
print(report_decision_tree)
```

```
                  precision    recall  f1-score   support

              no       1.00      0.95      0.98      6628
             yes       0.96      1.00      0.98      6443

        accuracy                           0.98     13071
       macro avg       0.98      0.98      0.98     13071
    weighted avg       0.98      0.98      0.98     13071
```

```
ss=pd.DataFrame(y_pred)
ss.replace(('yes', 'no'), (1, 0), inplace=True)
```

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
fpr, tpr, thresholds = roc_curve(pp, dt_cv.predict_proba(X_test)[:,1])
Decision_roc_auc = roc_auc_score(y_test,dt_cv.predict_proba(X_test)[:,1])
```

```
plt.figure()
plt.plot(fpr, tpr, label='Decision Tree Classifier (area = %0.2f)' % Decision_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title("Decision Tree ROC curve")
plt.legend(loc="lower right")
plt.show()
```



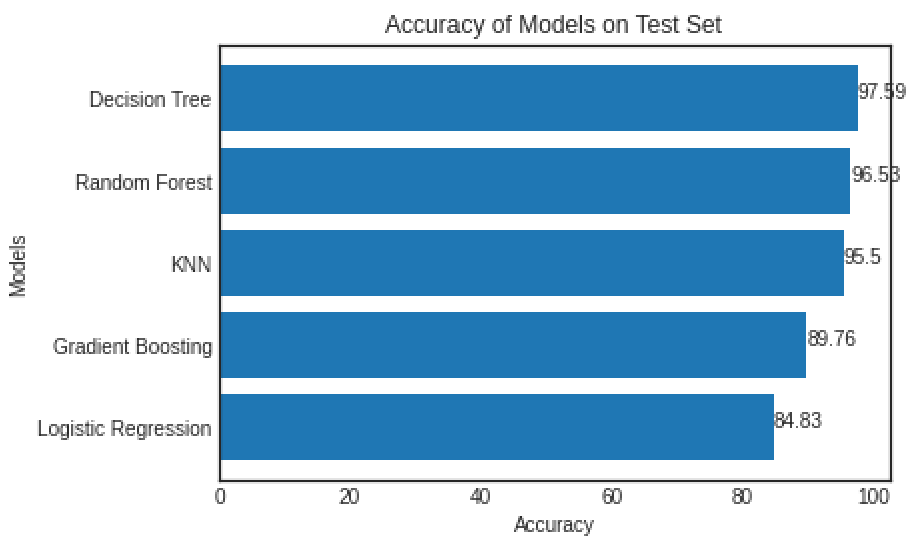

```
recall_specificity = metrics.recall_score(ss, pp, pos_label=1)
recall_sensitivity = metrics.recall_score(ss, pp, pos_label=0)
print(recall_sensitivity) #Class of interest - Yes
print(recall_specificity)
```

```
1.0
0.9552260934025204
```

```
#best_model_data = [['Logistic Regression',84.83],['Gradient Boosting',89.76],['KNN',9
#final_model = pd.DataFrame(best_model_data, columns = ['Model','Accuracy (in%)'])

#final_model = pd.DataFrame(
#    {"Accuracy (in%)": [84.83, 89.76, 95.5, 96.53, 97.59]},
#    index = ['Logistic Regression','Gradient Boosting','KNN','Random Forest','Decisic
#final_model.plot.bar()

#final_model['Accuracy (in%)'].plot(kind="barh")
#plt.title("Accuracy of Models")
#plt.ylabel("Accuracy")
#plt.xlabel("Models")
```

```
import matplotlib.pyplot as plt
x = ['Logistic Regression','Gradient Boosting','KNN','Random Forest','Decision Tree']
```

```
y = [84.83, 89.76, 95.5, 96.53, 97.59]
plt.barh(x, y)

for index, value in enumerate(y):
    plt.text(value, index,
             str(value))
plt.title("Accuracy of Models on Test Set")
plt.xlabel("Accuracy")
plt.ylabel("Models")
plt.figure(figsize = (1000, 200))
plt.show()
```




```
<Figure size 72000x14400 with 0 Axes>
```