Prospective Customer Prediction

Problem Statement :-

A leading bank has planned to promote a newly launched product by a marketing campaign. To maximize the profit of the campaign and to ensure the campaign reach the potential customers, the customer demographic and behavioural data need be considered while planning the strategy. Build a model to predict prospective customers for a marketing campaign based on their purchase behaviour and responses to previous campaigns.

Objectives :-

1. Perform Data Analysis to derive insights on the data
2. Build models using Hyperparameter Tuning
3. Evaluate the model
4. Deploy models using Web Interface/Dashboard

Data Description

Dependent Variables are :-

Bank client data:

age: age of the consumer

job: type of job

marital: marital status

education: education qualification of consumer

default: consumer has credit in default or not

housing: consumer has housing loan or not

loan: consumer has personal loan or not

Related with the last contact of the current campaign

contact: contact communication type

month: last contact month of year

day: last contact day of the week

duration: last contact duration, in seconds

campaign: number of contacts performed during this campaign and for this client

pdays: number of days that passed by after the client was last contacted from a previous campaign

previous: number of contacts performed before this campaign and for this client

poutcome: outcome of the previous marketing campaign

Employment variation ratethe employment-to-population ratio)

Consumer Price Index: (a measure of the aggregate price level in an economy

Consumer confidence index: how optimistic or pessimistic consumers are regarding their expected financial situation

3 Months Euribor rate -the average interest rate at which a selection of banks provide one another with short-term loans in euros

20 - number of employees in the bank

Independent Variables are :-

Term Deposit: has the client subscribed a term deposit or not(Product / Target variable)

Summary of the code

- Data Cleaning

Numerical Analysis

- Exploratory Data Analysis- Checking Skewness/Correlatin/Kurtosis
- Exploratory Data Analysis- Visulization
- Preprocessing - Data cleaning (missing, outliers)
- Preprocessing - Data Transformation(normalization)

Categorical Analysis

- Exploratory Data Analysis- Visulization
- Preprocessing - Data cleaning (missing, encoding)
- Preprocessing - Data Transformation(normalization)

- Feature Selection, Creation, Removal

- Dataset is divided into train-test in ratio 4:1.
- Model Building intial model built validated the performnace across metrics across models then transformed if accuracy and variance is not good enough
- Once model is fixed grid serach and cross validation technique to find the best parameters
- Pick the model for future use
- During intial model building ,many models were not performing much only Random Forest and Logistic Regression did a decent jobs with the given data, Given the approch of model selection was of 5-3-2-1.
- Just analysed the accuracy and ROC curve accross the data and choose the Random forest/Logistic Regression for futher processs
- Grid search(Hyperparameter tuning) was carried to Random Forest Classifier for getting parameters and scores were validate (91% Accuracy and 0.73 AUC ROC Score i.e. >Logistic Regression with final parameters)

Thanks and Regards

Importing Necessary Packages

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

```
from matplotlib.pylab import rcParams
rcParams['figure.figsize']=15,8
import warnings # Ignores any warning
warnings.filterwarnings("ignore")
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, RandomizedSearchCV, GridSear
from sklearn.ensemble import RandomForestClassifier,GradientBoostingClassifier
from sklearn.feature_selection import mutual_info_classif
from sklearn import tree
from sklearn import neighbors
from sklearn import linear_model
from sklearn import svm
from sklearn.model_selection import cross_val_score
import time
from math import sqrt
from sklearn.metrics import mean_squared_error, r2_score,mean_absolute_error, conf
```

Importing Dataset

In [3]:

```
# Read data
cust_data = pd.read_csv("Predict potential customer -case_study.csv")

# Lowercase the column names
cust_data.columns = [x.lower() for x in cust_data.columns]
cust_data.columns = cust_data.columns.str.replace(' ','_')

cust_data.head()
```

Out[3]:

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

5 rows × 21 columns

In [4]:

```
cust_data.loc[cust_data['education']=="basic.9y","education"]="basic.school"
cust_data.loc[cust_data['education']=="basic.4y","education"]="basic.school"
cust_data.loc[cust_data['education']=="basic.6y","education"]="basic.school"
```

We observed that 999 was most occuringin the pdays column which talked about number of days passed after made a contact to the customer in the previous campaign. So we created a new categorical column called" "prev_c" that implies whether if the customer was contacted in the previous campaign or not. So to achieve thta we converted all the fields with 999 as "no" and others as "yes".

In [5]:

```
cust_data['prev_c']=cust_data['pdays']
cust_data.loc[cust_data['prev_c']==999,"prev_c"]="no"
cust_data.loc[cust_data['prev_c']!="no","prev_c"]="yes"
cust_data.prev_c.value_counts()
```

Out[5]:

```
no     39673
yes     1515
Name: prev_c, dtype: int64
```

In [6]:
```
cust_data=cust_data.drop(columns='pdays',axis=1)
```

Exploratory data analysis (EDA)

We have made our data loads and now we are ready to do some data exploration and come up with some inference. The goal for the EDA is to get some insight and if any irregularities are found we will correct that in the next section, Data Pre-Processing.

In [7]:
```
print("Total rows : ",cust_data.shape[0])
cust_data.info()
```

```
Total rows :  41188
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   age                             41188 non-null  int64  
 1   job                             41188 non-null  object 
 2   marital                         41188 non-null  object 
 3   education                       41188 non-null  object 
 4   default                         41188 non-null  object 
 5   housing                         41188 non-null  object 
 6   loan                            41188 non-null  object 
 7   contact                         41188 non-null  object 
 8   month                           41188 non-null  object 
 9   day_of_week                     41188 non-null  object 
 10  duration                        41188 non-null  int64  
 11  campaign                        41188 non-null  int64  
 12  previous                        41188 non-null  int64  
 13  poutcome                        41188 non-null  object 
 14  employment_variation_rate       41188 non-null  float64
 15  consumer_price_index            41188 non-null  float64
 16  consumer_confidence_index       41188 non-null  float64
 17  3_months_euribor_rate           41188 non-null  float64
 18  number_of_employees_in_the_bank 41188 non-null  float64
 19  term_deposit                    41188 non-null  object 
 20  prev_c                          41188 non-null  object 
dtypes: float64(5), int64(4), object(12)
memory usage: 6.6+ MB
```

In [8]:
```
# Checking duplicate rows
cust_data.duplicated().sum()
```

Out[8]:
```
15
```

In [9]:
```
# dropping duplicate rows
cust_data=cust_data.drop_duplicates(subset=None, keep='first', inplace=False)
print("Present rows : ",cust_data.shape[0])
```

```
Present rows :  41173
```

In [10]:
```
cust_data.columns
```

Out[10]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'previous',
       'poutcome', 'employment_variation_rate', 'consumer_price_index',
       'consumer_confidence_index', '3_months_euribor_rate',
       'number_of_employees_in_the_bank', 'term_deposit', 'prev_c'],
      dtype='object')
```

Describing the dataset and checking if something looks odd. Note describe works only for continous variables and for categorical values we have to use diiferent techniques to describe data

In [11]:
```
# Summary of data
cust_data.describe()
```

Out[11]:

	age	duration	campaign	previous	employment_variation_rate	consu
count	41173.000000	41173.000000	41173.000000	41173.000000	41173.000000	
mean	40.023462	258.320671	2.567969	0.173002	0.082059	
std	10.420951	259.312867	2.770396	0.494964	1.570858	
min	17.000000	0.000000	1.000000	0.000000	-3.400000	
25%	32.000000	102.000000	1.000000	0.000000	-1.800000	
50%	38.000000	180.000000	2.000000	0.000000	1.100000	
75%	47.000000	319.000000	3.000000	0.000000	1.400000	
max	98.000000	4918.000000	56.000000	7.000000	1.400000	

We will consider "term_deposit" as our target variable as it is the result of customer marketing analysis if a customer has bought the bank's services or not.

Numerical EDA

taking numerial variables(9) into consideration perform EDA seperately for better understanding of Data

In [12]:
```
# taking all numerical data
numerical_values = cust_data[['age','duration','campaign','previous','employment_va
                              ,'consumer_confidence_index','3_months_euribor_rate'
```

In [13]:
```
# convert term deposit to numerical data
numerical_values=numerical_values.replace(["yes","no"],[1,0])
```

In [14]:
```
numerical_values.head()
```

Out[14]:

	age	duration	campaign	previous	employment_variation_rate	consumer_price_index	consum
0	56	261	1	0	1.1	93.994	
1	57	149	1	0	1.1	93.994	
2	37	226	1	0	1.1	93.994	
3	40	151	1	0	1.1	93.994	
4	56	307	1	0	1.1	93.994	

In [15]:
```
numerical_values['number_of_employees_in_the_bank'].value_counts()
```

Out[15]:
```
5228.1    16228
5099.1     8529
5191.0     7762
5195.8     3682
5076.2     1662
5017.5     1070
4991.6      773
5008.7      650
4963.6      635
5023.5      172
5176.3       10
Name: number_of_employees_in_the_bank, dtype: int64
```

In [16]:
```
numerical_values['term_deposit'].value_counts()
```

Out[16]:
```
0    36534
1     4639
Name: term_deposit, dtype: int64
```

Taking term deposit as target variable Let's do 'Univariate' analysis

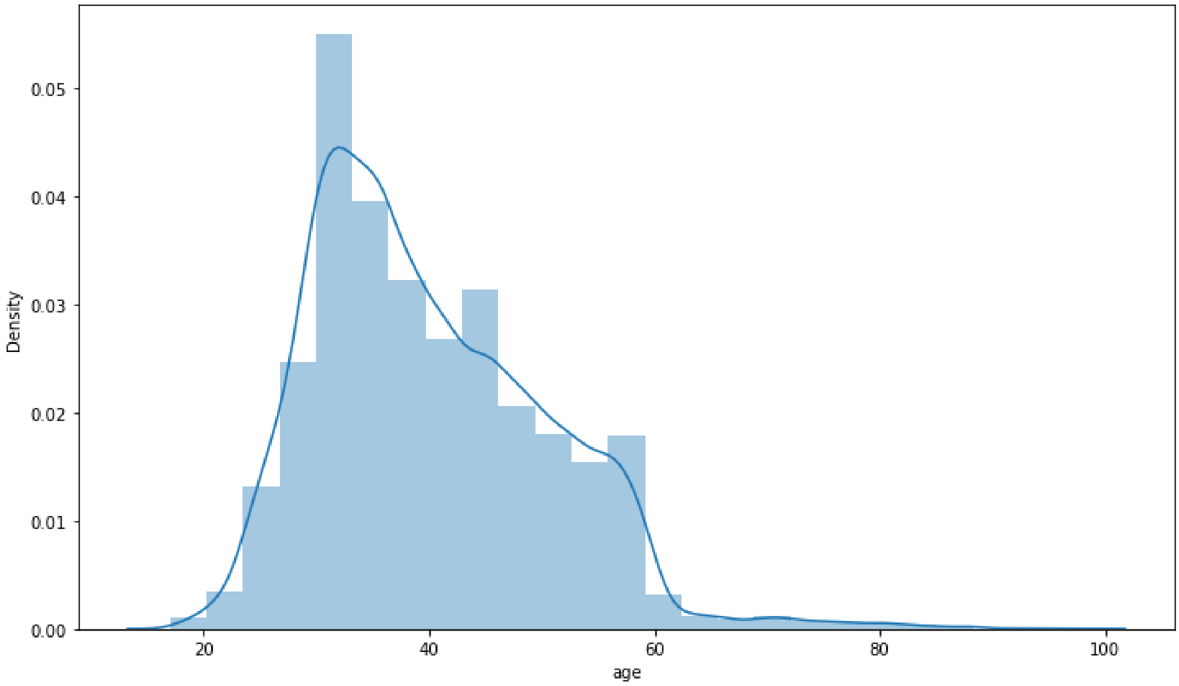
Distribution of Target variable From the below graph we could see our target is not normalized it is positive skewed and skewed towards right side so we need to normalize it we before we run model on it

In [17]:
```
numerical_values=numerical_values.astype({"term_deposit":'int64'})
numerical_values.dtypes
```

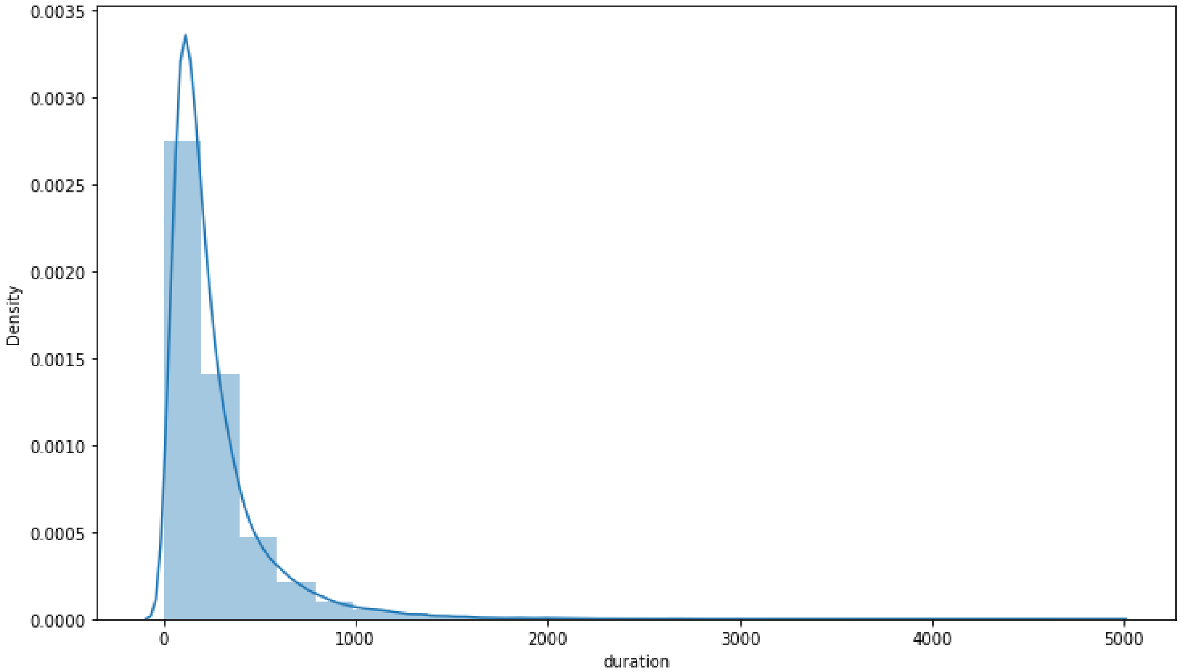
Out[17]:
```
age                                  int64
duration                             int64
campaign                             int64
previous                             int64
employment_variation_rate          float64
consumer_price_index               float64
consumer_confidence_index          float64
3_months_euribor_rate              float64
number_of_employees_in_the_bank    float64
term_deposit                         int64
dtype: object
```

In [18]:
```
for i in numerical_values:
    plt.figure(figsize=(12,7))
    sns.distplot(numerical_values[i], bins = 25)
    print ("Skew is:", numerical_values[i].skew())
    print("Kurtosis: %f" % numerical_values[i].kurt())
```

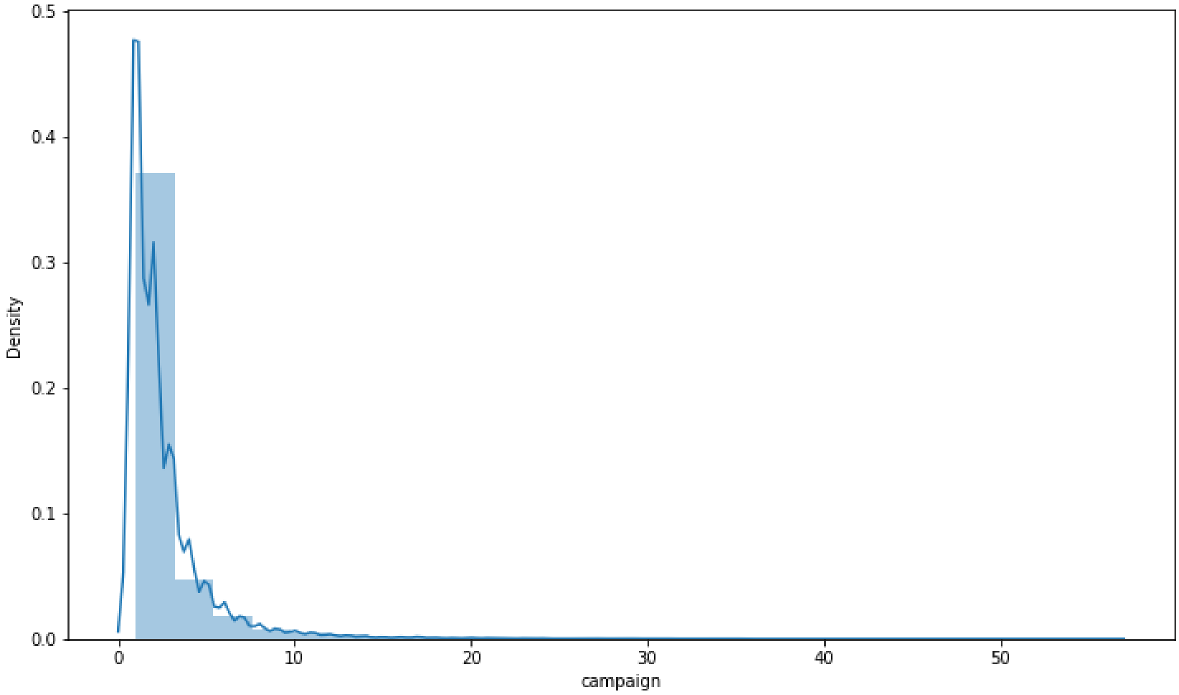
```
Skew is: 0.7846373874672642
Kurtosis: 0.791084
Skew is: 3.2627119605719987
Kurtosis: 20.242510
Skew is: 4.761900625383871
Kurtosis: 36.969647
Skew is: 3.8316393123087376
Kurtosis: 20.104059
Skew is: -0.7242843997849419
Kurtosis: -1.062331
Skew is: -0.23101786890644577
Kurtosis: -0.829631
Skew is: 0.3027819815890234
Kurtosis: -0.358982
Skew is: -0.7094251963726943
Kurtosis: -1.406448
Skew is: -1.044524898167548
Kurtosis: -0.003143
Skew is: 2.4500651365650783
Kurtosis: 4.003014
```

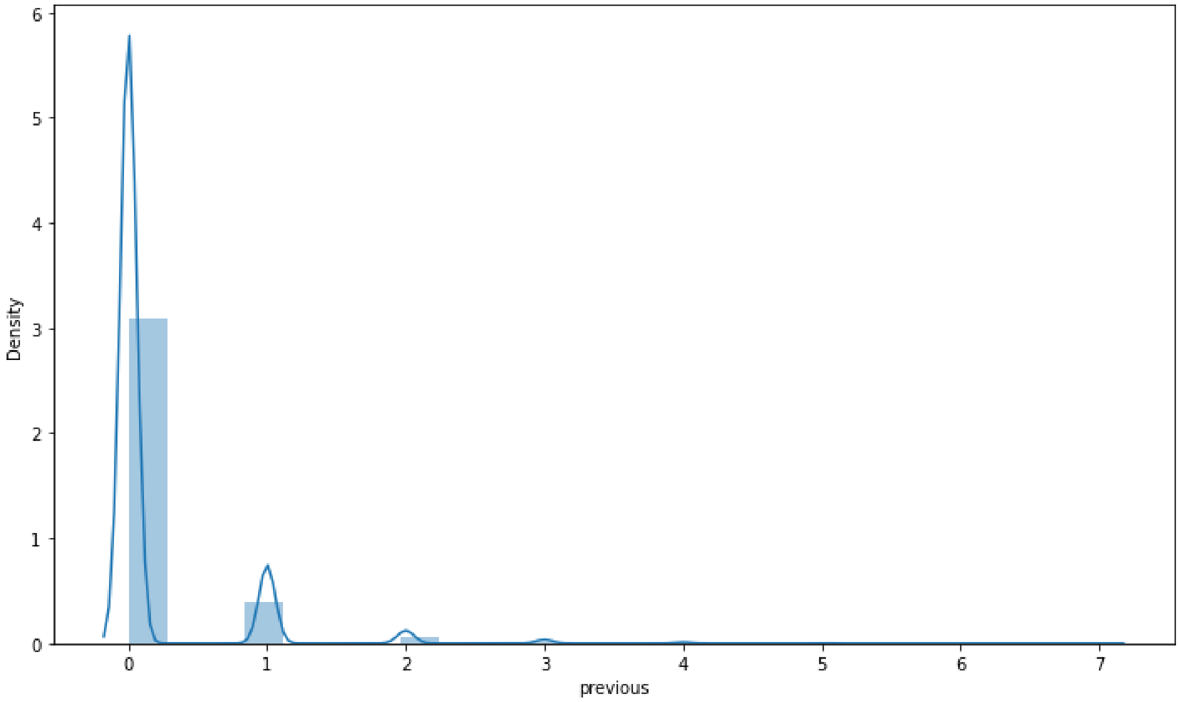


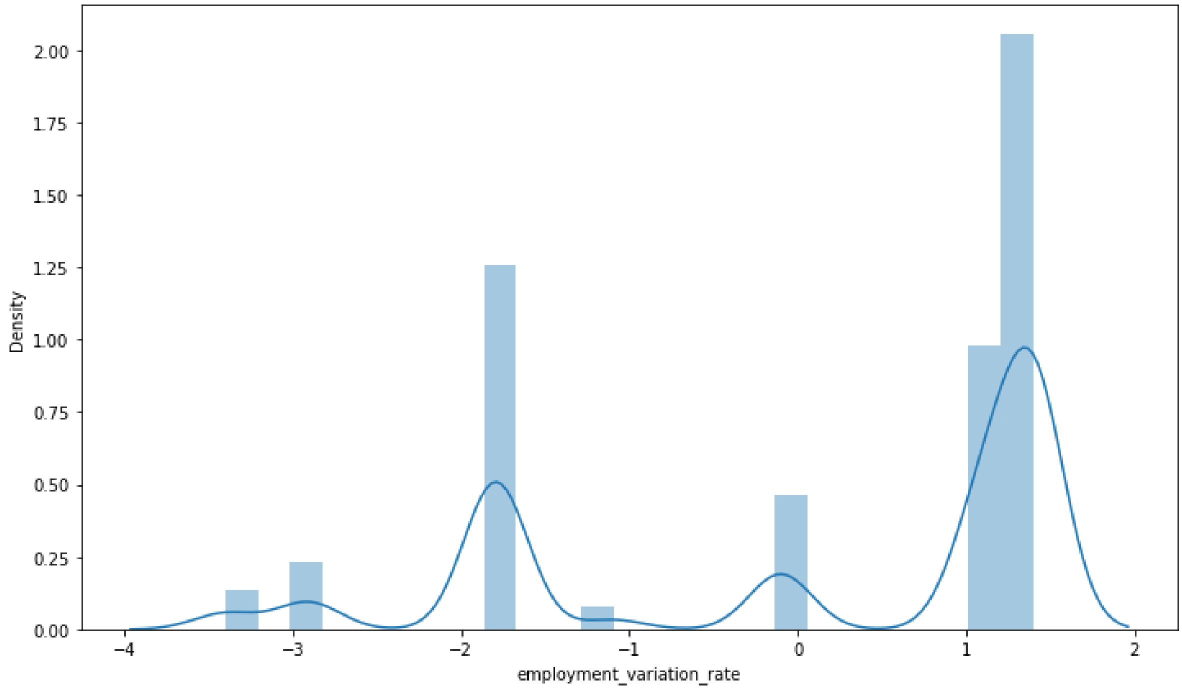
0.05
0.04
0.03
0.02
0.01
0.00
Density
20
40
60
80
100
age

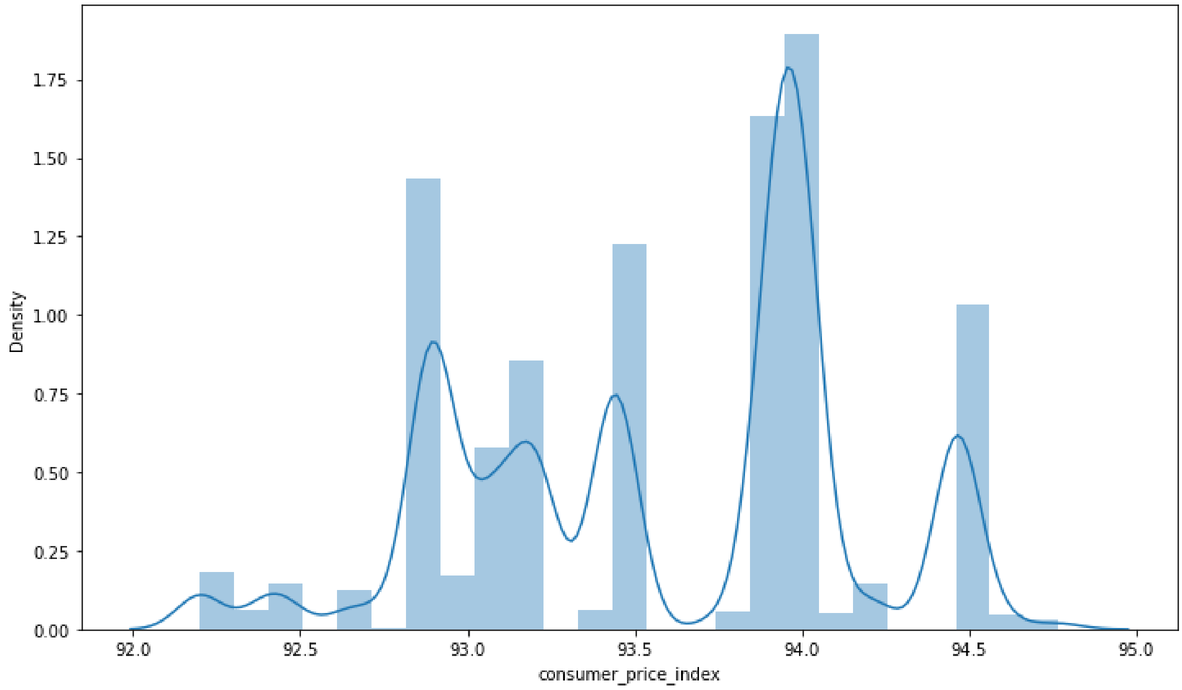


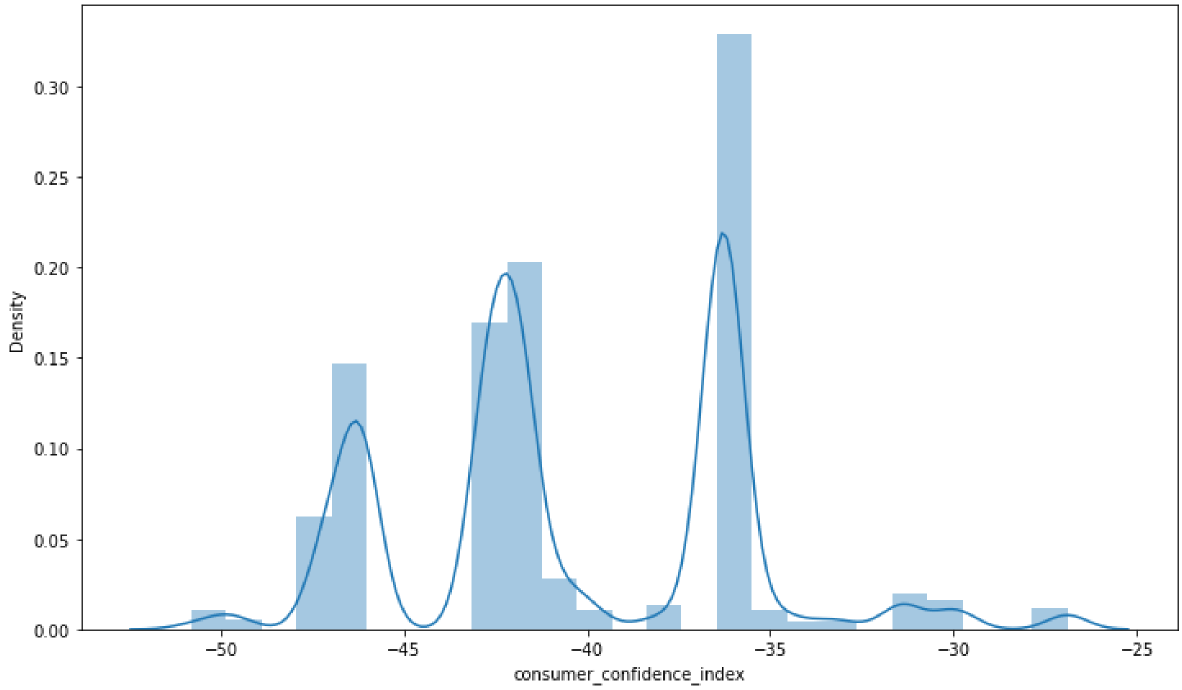
0.0035
0.0030
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
Density
0
1000
2000
3000
4000
5000
duration

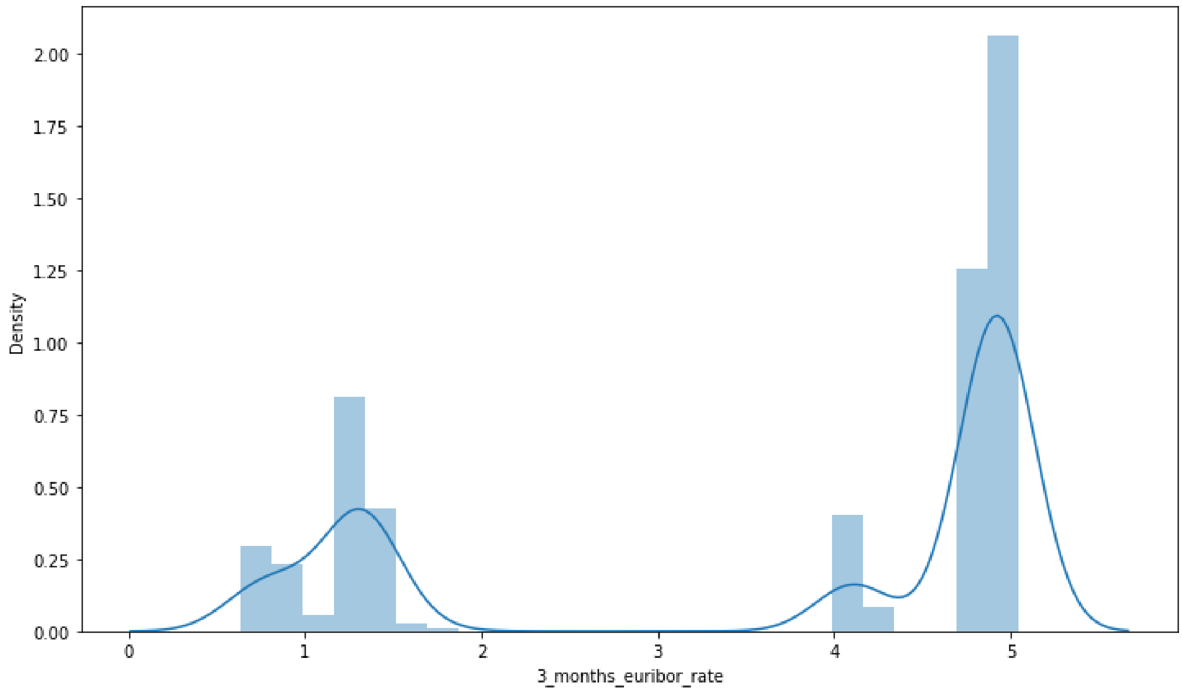

0.5
0.4
0.3
0.2
0.1
0.0
Density
0
10
20
30
40
50
campaign

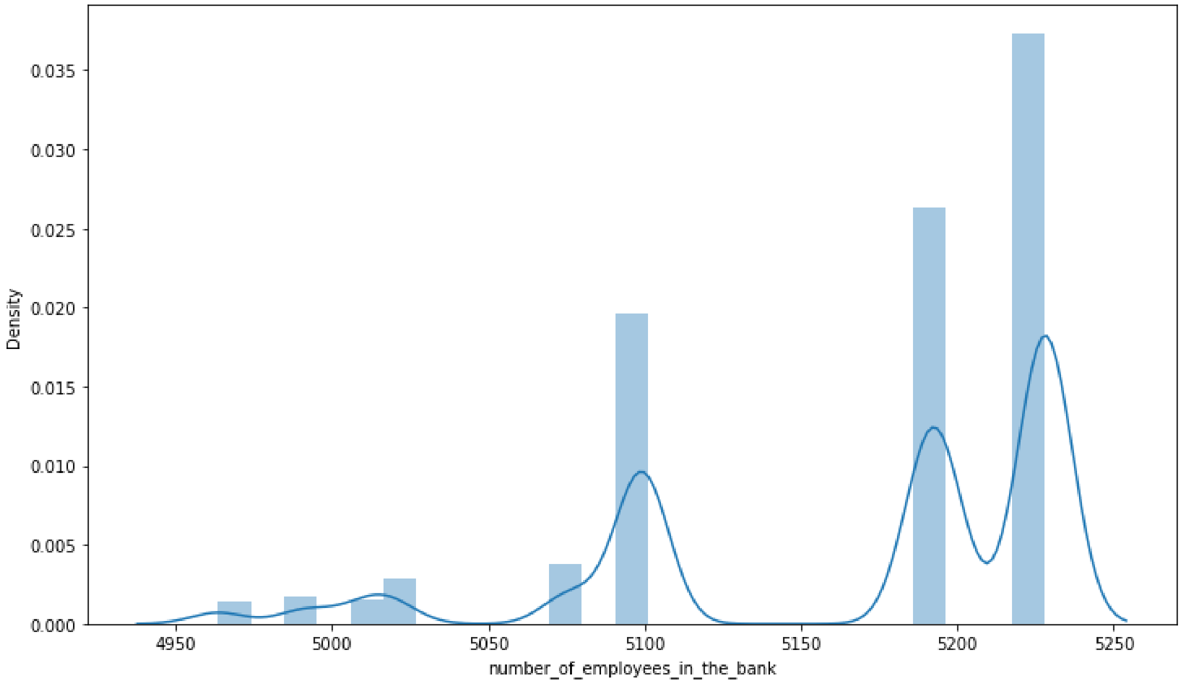

6
5
4
3
2
1
0
Density
0
1
2
3
4
5
6
7
previous

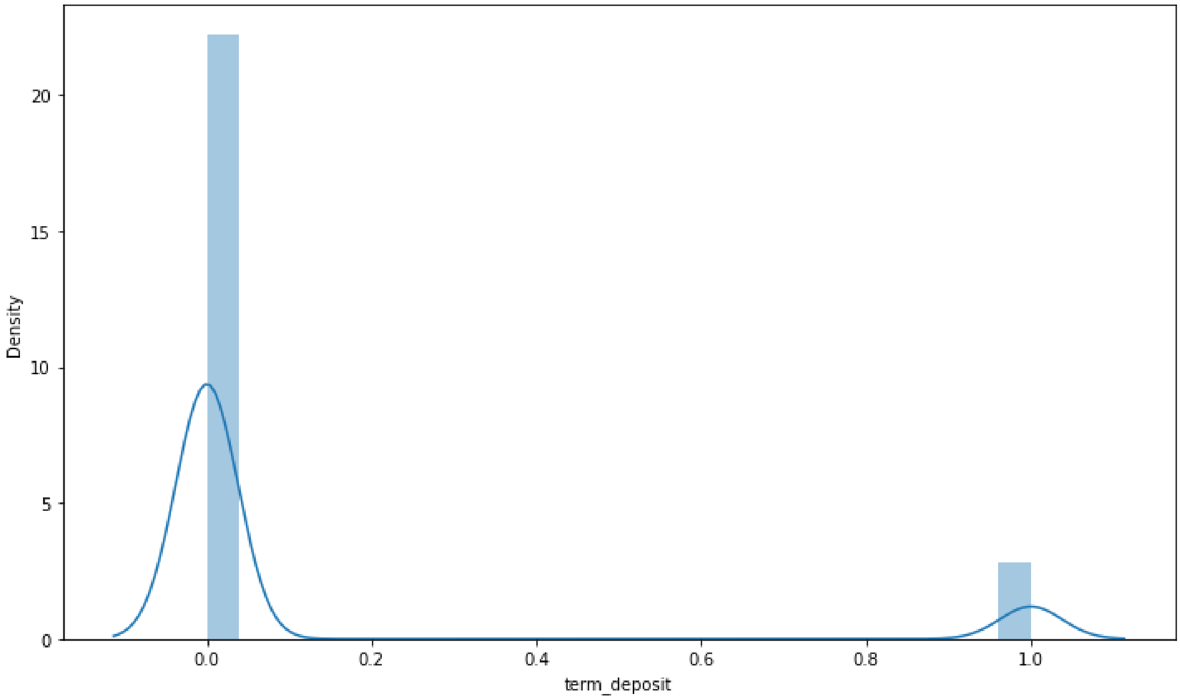

Density
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−4
−3
−2
−1
0
1
2
employment_variation_rate


Density
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
92.0
92.5
93.0
93.5
94.0
94.5
95.0
consumer_price_index


Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−50
−45
−40
−35
−30
−25
consumer_confidence_index


Density
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
1
2
3
4
5
3_months_euribor_rate

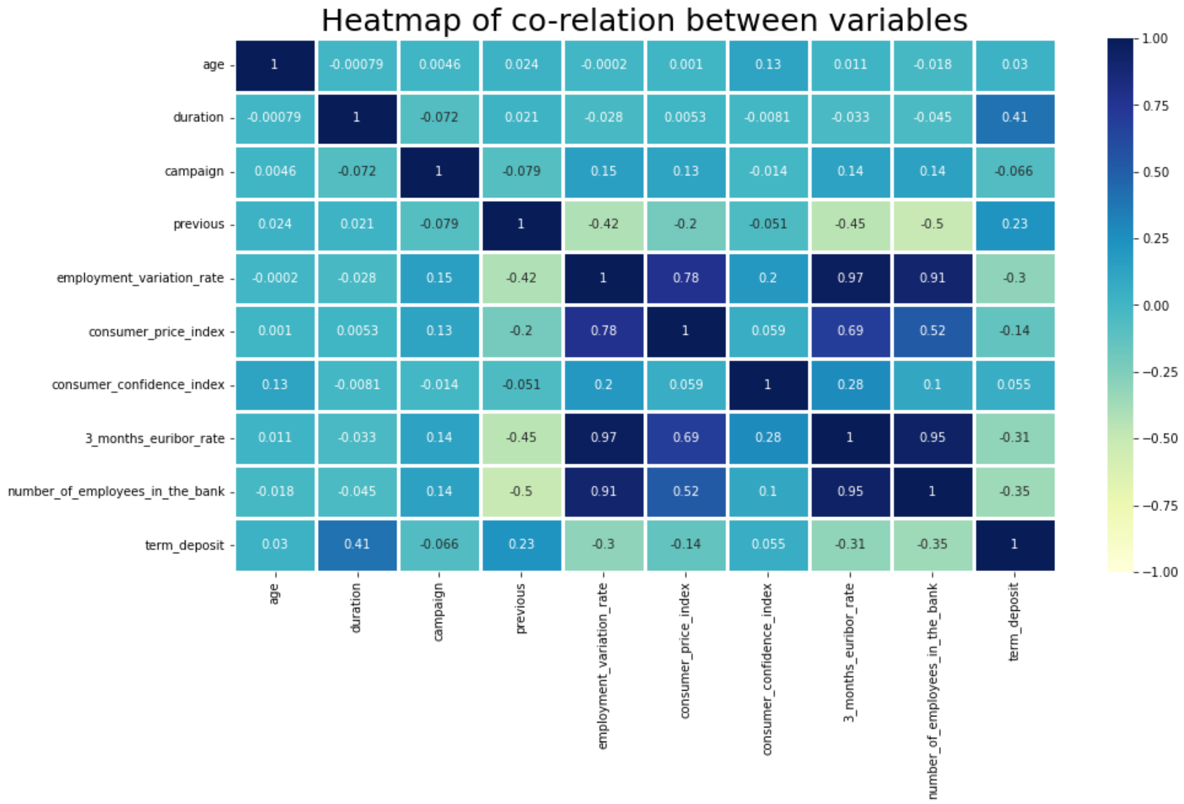




Correlation between Numerical Predictors and Target variable

Correlation between depedent variables is not a big concern as there is not much correlation between lets see how the dependent variables are correlated with Target Variable

In [19]:
```
sns.heatmap(numerical_values.corr(),annot=True,cmap='YlGnBu',vmin=-1,vmax=1,linewi
plt.title('Heatmap of co-relation between variables',fontsize=25)
plt.show()
plt.savefig('heatmap')
```

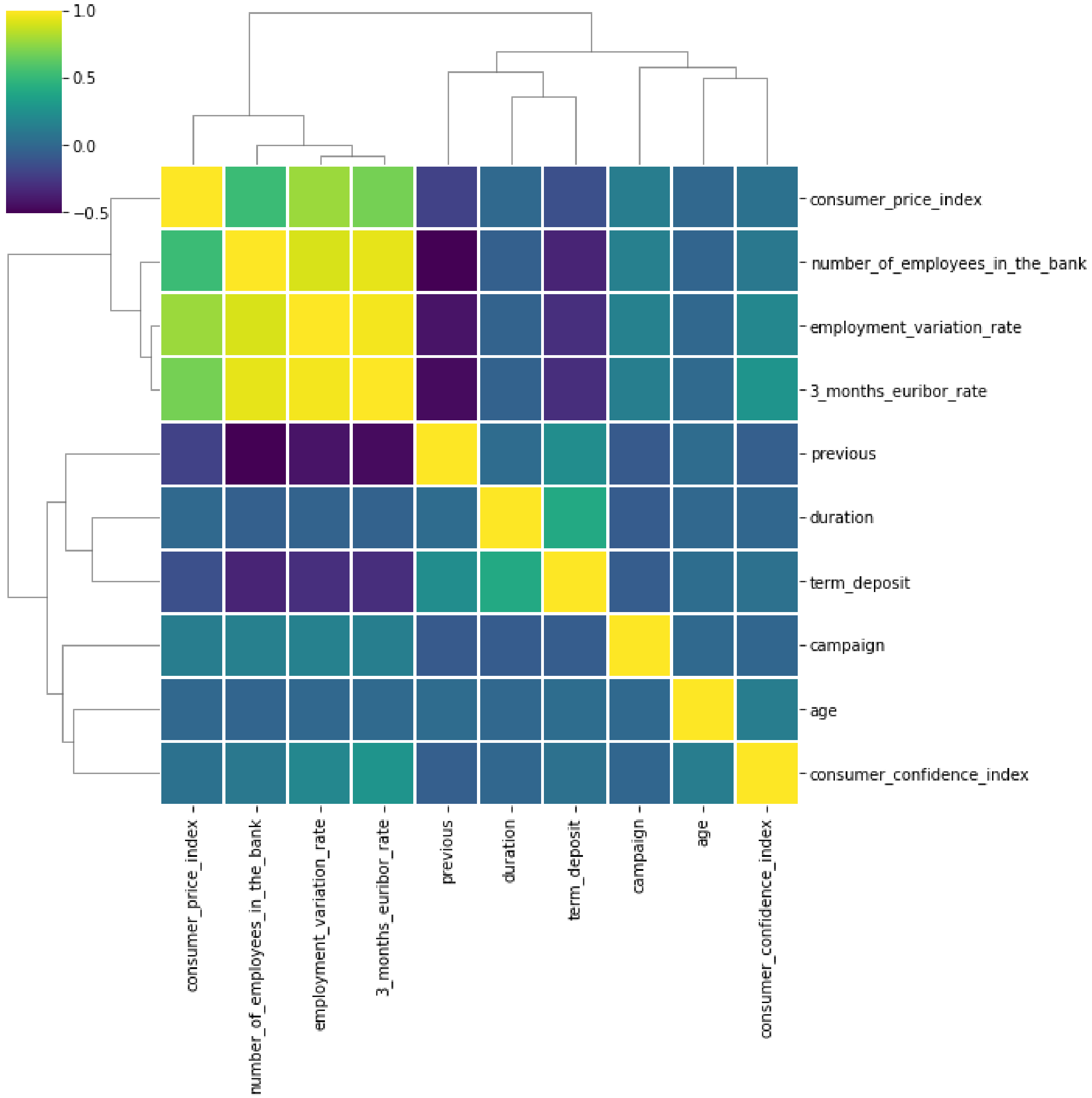


	age	duration	campaign	previous	employment_variation_rate	consumer_price_index	consumer_confidence_index	3_months_euribor_rate	number_of_employees_in_the_bank	term_deposit
age	1	-0.00079	0.0046	0.024	-0.0002	0.001	0.13	0.011	-0.018	0.03
duration	-0.00079	1	-0.072	0.021	-0.028	0.0053	-0.0081	-0.033	-0.045	0.41
campaign	0.0046	-0.072	1	-0.079	0.15	0.13	-0.014	0.14	0.14	-0.066
previous	0.024	0.021	-0.079	1	-0.42	-0.2	-0.051	-0.45	-0.5	0.23
employment_variation_rate	-0.0002	-0.028	0.15	-0.42	1	0.78	0.2	0.97	0.91	-0.3
consumer_price_index	0.001	0.0053	0.13	-0.2	0.78	1	0.059	0.69	0.52	-0.14
consumer_confidence_index	0.13	-0.0081	-0.014	-0.051	0.2	0.059	1	0.28	0.1	0.055
3_months_euribor_rate	0.011	-0.033	0.14	-0.45	0.97	0.69	0.28	1	0.95	-0.31
number_of_employees_in_the_bank	-0.018	-0.045	0.14	-0.5	0.91	0.52	0.1	0.95	1	-0.35
term_deposit	0.03	0.41	-0.066	0.23	-0.3	-0.14	0.055	-0.31	-0.35	1

<Figure size 1080x576 with 0 Axes>

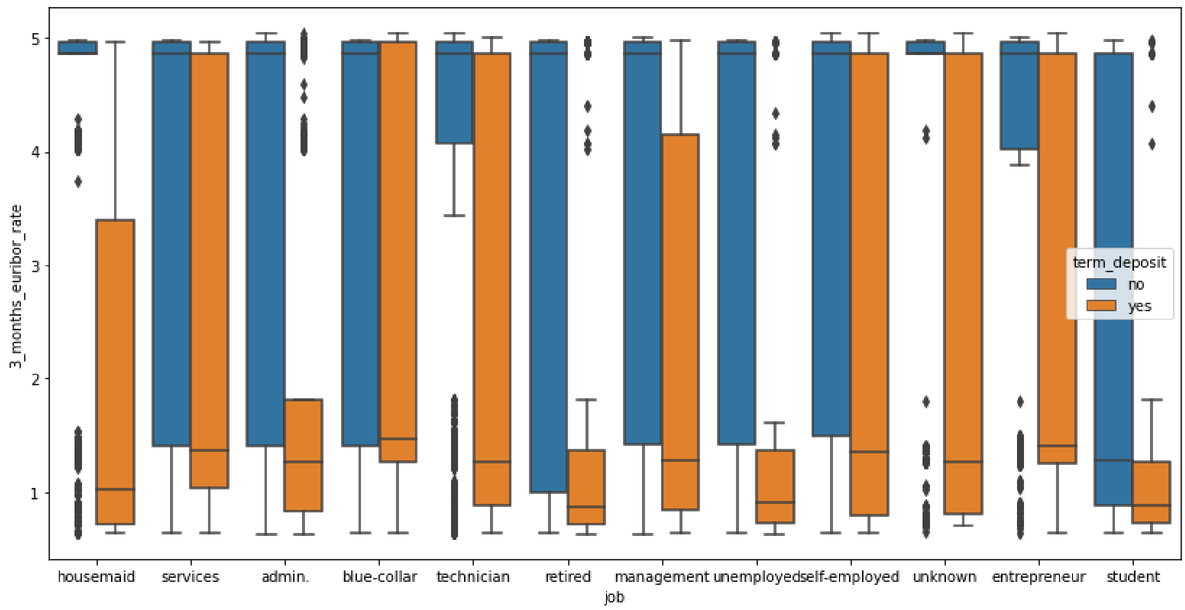
In [20]:
```
corrmat = numerical_values.corr()
cg = sns.clustermap(corrmat,cmap='viridis',linewidth=0.1);
plt.setp(cg.ax_heatmap.yaxis.get_majorticklabels(),rotation=0)
cg
```

Out[20]: <seaborn.matrix.ClusterGrid at 0x1acdcf0d940>



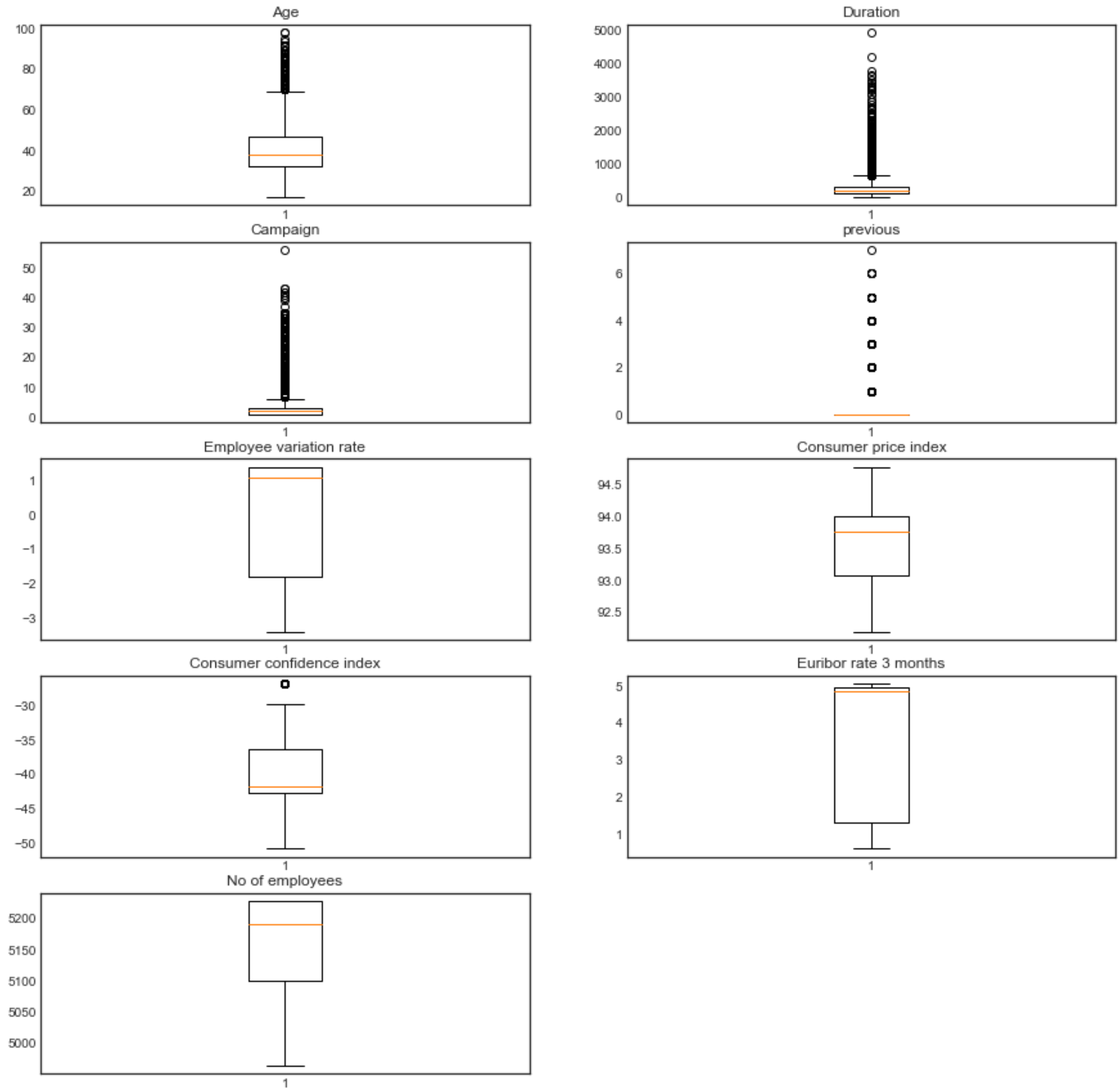
In [21]:
```python
plt.figure(figsize=[14,7])
sns.boxplot(x='job',y='3_months_euribor_rate',data=cust_data,hue='term_deposit')
```

Out[21]: <AxesSubplot:xlabel='job', ylabel='3_months_euribor_rate'>



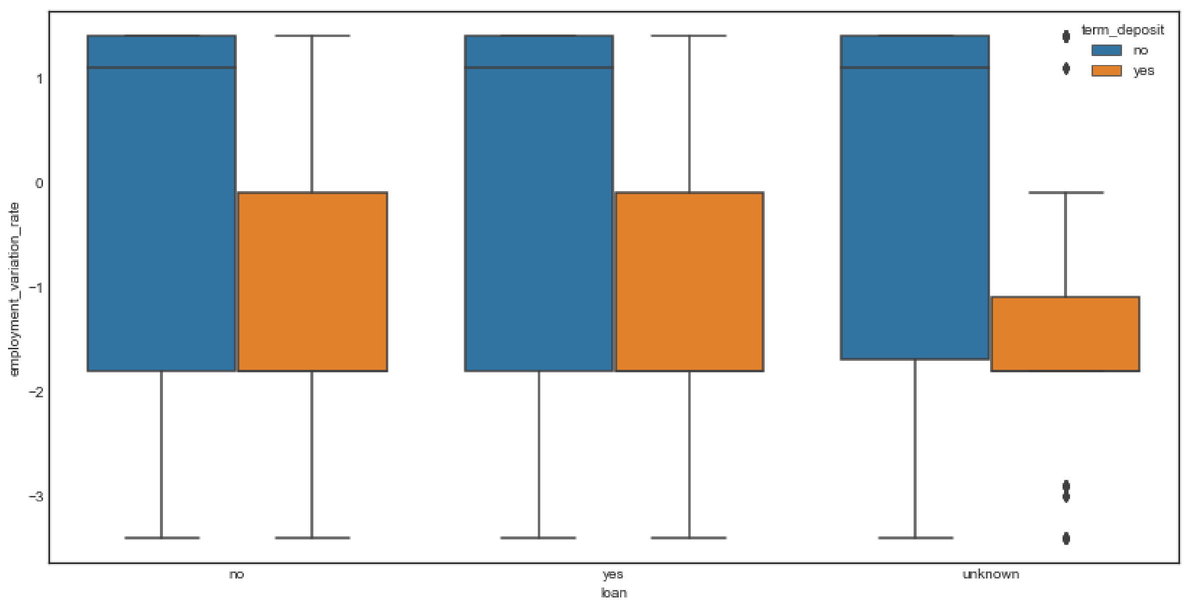
Plotting boxplot/graphs to see outliers in data.

In [22]:
```
plt.figure(figsize = (15, 15))
plt.style.use('seaborn-white')
ax=plt.subplot(5,2,1)
plt.boxplot(cust_data['age'])
ax.set_title('Age')
ax=plt.subplot(5,2,2)
plt.boxplot(cust_data['duration'])
ax.set_title('Duration')
ax=plt.subplot(5,2,3)
plt.boxplot(cust_data['campaign'])
ax.set_title('Campaign')
ax=plt.subplot(5,2,4)
plt.boxplot(cust_data['previous'])
ax.set_title('previous')
ax=plt.subplot(5,2,5)
plt.boxplot(cust_data['employment_variation_rate'])
ax.set_title('Employee variation rate')
ax=plt.subplot(5,2,6)
plt.boxplot(cust_data['consumer_price_index'])
ax.set_title('Consumer price index')
ax=plt.subplot(5,2,7)
plt.boxplot(cust_data['consumer_confidence_index'])
ax.set_title('Consumer confidence index')
ax=plt.subplot(5,2,8)
plt.boxplot(cust_data['3_months_euribor_rate'])
ax.set_title('Euribor rate 3 months')
ax=plt.subplot(5,2,9)
plt.boxplot(cust_data['number_of_employees_in_the_bank'])
ax.set_title('No of employees')
plt.savefig('outliers')
```



In [23]:
```
plt.figure(figsize=[14,7])
sns.boxplot(x='loan',y='employment_variation_rate',data=cust_data,hue='term_deposi
```

Out[23]:
```
<AxesSubplot:xlabel='loan', ylabel='employment_variation_rate'>
```



In [24]:
```
numerical_values.isna().sum()
```

Out[24]:
```
age                               0
duration                          0
campaign                          0
previous                          0
employment_variation_rate         0
consumer_price_index              0
consumer_confidence_index         0
3_months_euribor_rate             0
number_of_employees_in_the_bank   0
term_deposit                      0
dtype: int64
```

In [25]:
```
numerical_values.shape
```

Out[25]:
```
(41173, 10)
```

Categorical EDA

taking categorical variables (12) into consideration perform EDA seperately for better understanding of Data

In [26]:
```
d_cat = cust_data.select_dtypes(include = 'object').copy()
```

In [27]:
```
d_cat.head()
```

Out[27]:

	job	marital	education	default	housing	loan	contact	month	day_of_week	p
0	housemaid	married	basic.school	no	no	no	telephone	may	mon	no
1	services	married	high.school	unknown	no	no	telephone	may	mon	no
2	services	married	high.school	no	yes	no	telephone	may	mon	no
3	admin.	married	basic.school	no	no	no	telephone	may	mon	no
4	services	married	high.school	no	no	yes	telephone	may	mon	no

In [28]:
```
d_cat.columns
```

Out[28]:
```
Index(['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact',
       'month', 'day_of_week', 'poutcome', 'term_deposit', 'prev_c'],
      dtype='object')
```

In [29]:
```
print(d_cat.job.value_counts())
print(125*"-")
print(d_cat.marital.value_counts())
print(125*"-")
print(d_cat.education.value_counts())
print(125*"-")
print(d_cat.default.value_counts())
print(125*"-")
print(d_cat.housing.value_counts())
print(125*"-")
print(d_cat.loan.value_counts())
print(125*"-")
print(d_cat.contact.value_counts())
print(125*"-")
print(d_cat.month.value_counts())
print(125*"-")
print(d_cat.day_of_week.value_counts())
print(125*"-")
print(d_cat.poutcome.value_counts())
```

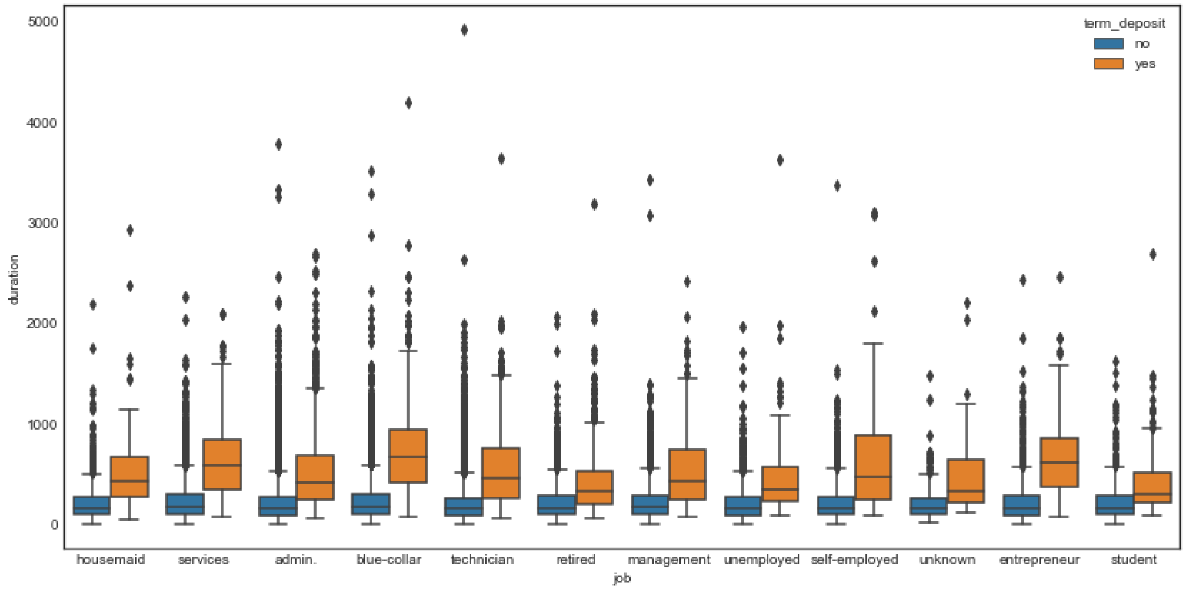
```
print(125*"-")
print(d_cat.term_deposit.value_counts())
print(125*"-")
print(d_cat.prev_c.value_counts())
```

```
admin.           10419
blue-collar       9250
technician        6739
services          3967
management        2924
retired           1718
entrepreneur      1456
self-employed     1421
housemaid         1060
unemployed        1014
student            875
unknown            330
Name: job, dtype: int64
-----------------------------------------------------------------------------------
-------------------------------------------
married     24918
single      11564
divorced     4611
unknown        80
Name: marital, dtype: int64
-----------------------------------------------------------------------------------
-------------------------------------------
basic.school           12509
university.degree      12164
high.school             9512
professional.course     5240
unknown                 1730
illiterate                18
Name: education, dtype: int64
-----------------------------------------------------------------------------------
-------------------------------------------
no         32574
unknown     8596
yes            3
Name: default, dtype: int64
-----------------------------------------------------------------------------------
-------------------------------------------
yes        21568
no         18615
unknown      990
Name: housing, dtype: int64
-----------------------------------------------------------------------------------
-------------------------------------------
no         33936
yes         6247
unknown      990
Name: loan, dtype: int64
-----------------------------------------------------------------------------------
-------------------------------------------
cellular     26132
telephone    15041
Name: contact, dtype: int64
-----------------------------------------------------------------------------------
-------------------------------------------
may    13764
jul     7169
aug     6176
jun     5318
nov     4100
apr     2631
oct      717
sep      570
mar      546
dec      182
```

```
Name: month, dtype: int64
--------------------------------------------------------------------------------------------------------------------------
thu    8618
mon    8512
wed    8133
tue    8085
fri    7825
Name: day_of_week, dtype: int64
--------------------------------------------------------------------------------------------------------------------------
nonexistent    35549
failure         4251
success         1373
Name: poutcome, dtype: int64
--------------------------------------------------------------------------------------------------------------------------
no     36534
yes     4639
Name: term_deposit, dtype: int64
--------------------------------------------------------------------------------------------------------------------------
no     39658
yes     1515
Name: prev_c, dtype: int64
```

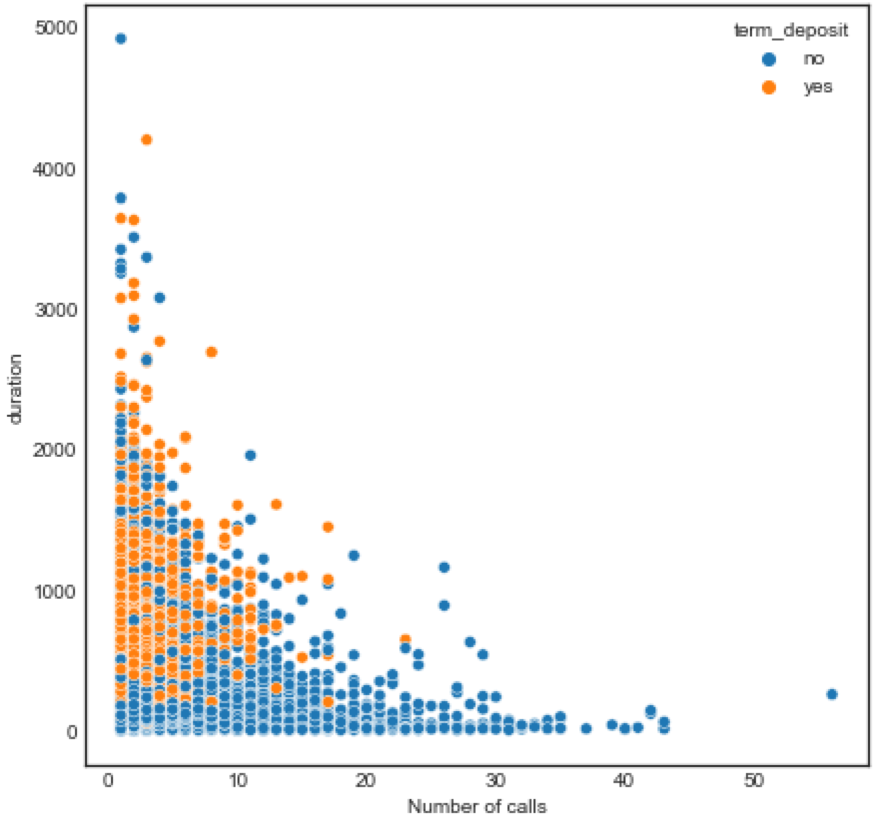
In [30]:
```python
plt.figure(figsize=[14,7])
sns.boxplot(x='job',y='duration',data=cust_data,hue='term_deposit')
```

Out[30]: <AxesSubplot:xlabel='job', ylabel='duration'>



In [31]:
```python
plt.figure(figsize=[7,7])
plt.xlabel('Number of calls')
sns.scatterplot(x='campaign',y='duration',data=cust_data,hue='term_deposit')
```

Out[31]: <AxesSubplot:xlabel='Number of calls', ylabel='duration'>



In [32]:
```
d1 = pd.crosstab(index = d_cat["job"],columns="count")
d2 = pd.crosstab(index = d_cat["marital"],columns="count")
d3= pd.crosstab(index = d_cat["education"],columns="count")
d4=pd.crosstab(index = d_cat["default"],columns="count")
d5 = pd.crosstab(index = d_cat["housing"],columns="count")
d6 = pd.crosstab(index = d_cat["loan"],columns="count")
d7= pd.crosstab(index = d_cat["contact"],columns="count")
d8=pd.crosstab(index = d_cat["month"],columns="count")
d9= pd.crosstab(index = d_cat["day_of_week"],columns="count")
d10=pd.crosstab(index = d_cat["poutcome"],columns="count")
d11=pd.crosstab(index=d_cat['prev_c'],columns='count')
```

In [33]:
```
d_yes = cust_data[cust_data['term_deposit']=='yes'].select_dtypes(include = 'objec
d_yes.head()
```

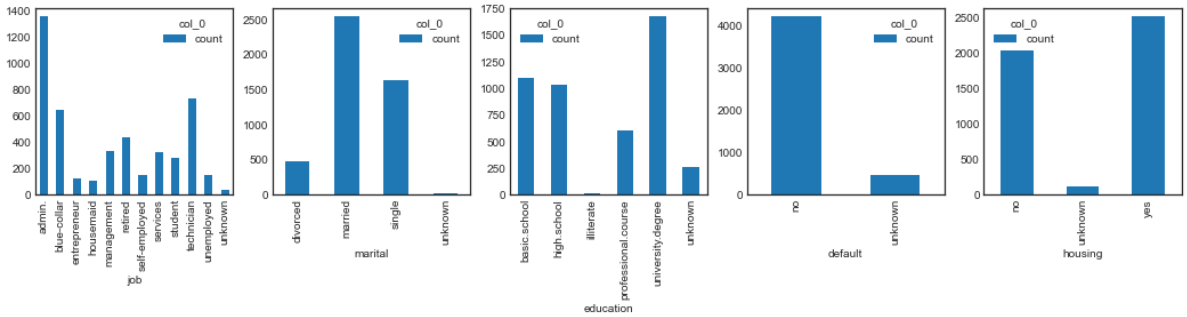
Out[33]:

	job	marital	education	default	housing	loan	contact	month	day_c
75	blue-collar	divorced	basic.school	unknown	yes	no	telephone	may	
83	entrepreneur	married	university.degree	unknown	yes	no	telephone	may	
88	technician	married	basic.school	no	no	no	telephone	may	
129	technician	married	professional.course	unknown	yes	no	telephone	may	
139	blue-collar	married	basic.school	unknown	yes	no	telephone	may	

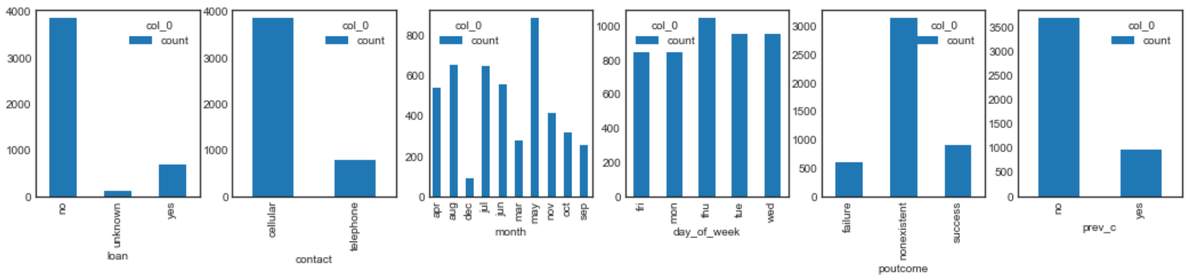
In [34]:
```
df1 = pd.crosstab(index = d_yes["job"],columns="count")
df2 = pd.crosstab(index = d_yes["marital"],columns="count")
df3= pd.crosstab(index = d_yes["education"],columns="count")
df4=pd.crosstab(index = d_yes["default"],columns="count")
df5 = pd.crosstab(index = d_yes["housing"],columns="count")
df6 = pd.crosstab(index = d_yes["loan"],columns="count")
df7= pd.crosstab(index = d_yes["contact"],columns="count")
df8=pd.crosstab(index = d_yes["month"],columns="count")
df9= pd.crosstab(index = d_yes["day_of_week"],columns="count")
```

```
df10=pd.crosstab(index = d_yes["poutcome"],columns="count")
df11=pd.crosstab(index=d_yes['prev_c'],columns='count')
```

In [35]:
```
fig,axes = plt.subplots(nrows=1, ncols=5,figsize=[18,3])
df1.plot.bar(ax=axes[0])
df2.plot.bar(ax=axes[1])
df3.plot.bar(ax=axes[2])
df4.plot.bar(ax=axes[3])
df5.plot.bar(ax=axes[4])
plt.savefig('CatvsTerm')
```



In [36]:
```
fig,axes = plt.subplots(nrows=1, ncols=6,figsize=[18,3])
df6.plot.bar(ax=axes[0])
df7.plot.bar(ax=axes[1])
df8.plot.bar(ax=axes[2])
df9.plot.bar(ax=axes[3])
df10.plot.bar(ax=axes[4])
df11.plot.bar(ax=axes[5])
plt.savefig('CatvsTerm1')
```



In [37]:
```
d_cat.isna().sum()
```

Out[37]:
```
job            0
marital        0
education      0
default        0
housing        0
loan           0
contact        0
month          0
day_of_week    0
poutcome       0
term_deposit   0
prev_c         0
dtype: int64
```

In [38]:
```
d_cat.shape
```

Out[38]:
```
(41173, 12)
```

prev_c is a derieved column to group all data in previous other than 0 as yes and 0 as no as it is treated as categorical data

Data Pre-Processing

We will utilize the insights from EDA into data pre-processing

From analysis we found that there are 41176 rows and 11 attributes with no NULL values

Checking missing data

In [39]:
```
def missing(x):
  missing_values_number=x.isnull().sum()
  missing_values_percentage=x.isnull().sum()/x.shape[0]*100
  return missing_values_number,missing_values_percentage
```

In [40]:
```
missing(cust_data)
```

Out[40]:
```
(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
 previous                         0
 poutcome                         0
 employment_variation_rate        0
 consumer_price_index             0
 consumer_confidence_index        0
 3_months_euribor_rate            0
 number_of_employees_in_the_bank  0
 term_deposit                     0
 prev_c                           0
 dtype: int64,
 age                              0.0
 job                              0.0
 marital                          0.0
 education                        0.0
 default                          0.0
 housing                          0.0
 loan                             0.0
 contact                          0.0
 month                            0.0
 day_of_week                      0.0
 duration                         0.0
 campaign                         0.0
 previous                         0.0
 poutcome                         0.0
 employment_variation_rate        0.0
 consumer_price_index             0.0
 consumer_confidence_index        0.0
 3_months_euribor_rate            0.0
 number_of_employees_in_the_bank  0.0
 term_deposit                     0.0
 prev_c                           0.0
 dtype: float64)
```

Detecting outliers

For detecting outliers Z-Score method is used.

Z-Score:

This score helps to understand if a data value is greater or smaller than mean and how far away it is from the mean. More specifically, Z score tells how many standard deviations away a data point is from the mean.

Z score = (x -mean) / std. deviation

In [41]:
```
def detect_outlier(data_1):
    threshold=3
    mean_1 = np.mean(data_1)
    std_1 =np.std(data_1)

    outliers=[]
    for y in data_1:
        z_score= (y - mean_1)/std_1
        if np.abs(z_score) > threshold:
            outliers.append(y)
    return outliers
```

In [42]:
```
def print_outliers(data_1):
    outlier_datapoints = detect_outlier(data_1)
    print("Count of outliers : ",len(outlier_datapoints))
    unique_data=set(outlier_datapoints)
    print("outlier data : ",unique_data)
    cust_data.drop
```

In [43]:
```
print_outliers(cust_data["campaign"])
print('-'*125)
print_outliers(cust_data["age"])
print('-'*125)
print_outliers(cust_data["duration"])
print('-'*125)
print_outliers(cust_data["previous"])
print('-'*125)
print_outliers(cust_data["employment_variation_rate"])
print('-'*125)
print_outliers(cust_data["consumer_confidence_index"])
print('-'*125)
print_outliers(cust_data["consumer_price_index"])
print('-'*125)
print_outliers(cust_data["3_months_euribor_rate"])
print('-'*125)
print_outliers(cust_data["number_of_employees_in_the_bank"])
```

```
Count of outliers :  869
outlier data :  {11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 2
7, 28, 29, 30, 31, 32, 33, 34, 35, 37, 39, 40, 41, 42, 43, 56}
----------------------------------------------------------------------------------
-------------------------------------------
Count of outliers :  369
outlier data :  {72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 8
8, 89, 91, 92, 94, 95, 98}
----------------------------------------------------------------------------------
-------------------------------------------
Count of outliers :  861
outlier data :  {2053, 2055, 2062, 2078, 2087, 2089, 2093, 2122, 2129, 2139, 4199,
2184, 2187, 2191, 2203, 2219, 2231, 2260, 2299, 2301, 2316, 2372, 2420, 2429, 245
3, 2456, 2462, 2486, 2516, 2621, 2635, 2653, 2680, 2692, 2769, 4918, 2870, 2926, 3
076, 3078, 1037, 1038, 1039, 1040, 1041, 1042, 1043, 1044, 1045, 3094, 1047, 1046,
1049, 1048, 1051, 1052, 1053, 1054, 1055, 1056, 1057, 1058, 1059, 1060, 1061, 106
2, 1063, 1064, 1065, 1066, 1067, 1068, 1070, 1071, 1072, 1073, 1074, 1075, 1076, 1
077, 1078, 1079, 1080, 1081, 1082, 1083, 1084, 1085, 1087, 1088, 1089, 1090, 1091,
1092, 1093, 1094, 1095, 1096, 1097, 1098, 1099, 1100, 1101, 1102, 1103, 1104, 110
5, 1106, 1108, 1109, 1110, 1111, 1112, 1114, 1117, 1118, 1119, 1120, 1121, 1122, 1
123, 1124, 1125, 1126, 1127, 1128, 1129, 1130, 1131, 1132, 1133, 1134, 1135, 1136,
1137, 1138, 3183, 1139, 1141, 1142, 1143, 1144, 1140, 1145, 1147, 1148, 1149, 115
0, 1151, 1152, 1153, 1154, 1156, 1161, 1162, 1164, 1165, 1166, 1167, 1168, 1169, 1
170, 1171, 1173, 1174, 1175, 1176, 1178, 1180, 1181, 1182, 1183, 1184, 1185, 1186,
1187, 1190, 1191, 1192, 1193, 1195, 1196, 1197, 1199, 1200, 1201, 1202, 1203, 120
4, 1205, 1206, 1207, 1208, 3253, 1210, 1211, 1212, 1214, 1217, 1218, 1220, 1221, 1
222, 1223, 1224, 1225, 1226, 1227, 1228, 1230, 1231, 1232, 1233, 1234, 1236, 1237,
1238, 3284, 1239, 1241, 1242, 1243, 1244, 1245, 1240, 1246, 1248, 1250, 1252, 125
4, 1255, 1256, 1257, 1258, 1259, 1260, 1262, 1263, 1265, 1266, 1267, 1268, 1269, 1
271, 1272, 1273, 3322, 1275, 1276, 1277, 1279, 1281, 1282, 1283, 1285, 1286, 1287,
1288, 1290, 1291, 1293, 1294, 1297, 1298, 1300, 1302, 1303, 1306, 1307, 1309, 131
0, 1311, 1313, 1317, 3366, 1318, 1319, 1321, 1323, 1326, 1327, 1328, 1329, 1330, 1
331, 1332, 1333, 1334, 1336, 1337, 1339, 1340, 1341, 1342, 1344, 1345, 1346, 1347,
1348, 1349, 1352, 1353, 1356, 1357, 1359, 1360, 1361, 1363, 1364, 1365, 1366, 136
8, 1369, 1370, 1372, 1373, 3422, 1374, 1376, 1380, 1386, 1388, 1389, 1390, 1391, 1
392, 1394, 1395, 1397, 1398, 1399, 1405, 1407, 1408, 1410, 1411, 1412, 1416, 1422,
1423, 1424, 1425, 1426, 1432, 1434, 1435, 1437, 1438, 1439, 1440, 1441, 1446, 144
7, 1448, 1449, 1452, 1456, 1460, 1461, 1462, 1463, 1464, 3509, 1467, 1468, 1469, 1
471, 1472, 1473, 1476, 1478, 1479, 1480, 1487, 1488, 1489, 1490, 1491, 1492, 1495,
1499, 1500, 1502, 1503, 1504, 1505, 1508, 1512, 1514, 1516, 1521, 1528, 1529, 153
0, 1531, 1532, 1534, 1540, 1543, 1545, 1548, 1550, 1551, 1552, 1554, 1555, 1556, 1
559, 1563, 1567, 1569, 1571, 1573, 1574, 1575, 1576, 1579, 1580, 1581, 3631, 1584,
1590, 1594, 3643, 1597, 1598, 1602, 1603, 1606, 1608, 1611, 1613, 1615, 1616, 161
7, 1618, 1622, 1623, 1624, 1628, 1640, 1642, 1649, 1662, 1663, 1665, 1666, 1669, 1
673, 1677, 1681, 1689, 1692, 1697, 1707, 1710, 1713, 1720, 1721, 1723, 1730, 1735,
3785, 1739, 1740, 1745, 1756, 1767, 1776, 1777, 1788, 1804, 1805, 1806, 1809, 181
6, 1817, 1820, 1833, 1834, 1842, 1848, 1850, 1855, 1867, 1868, 1869, 1871, 1877, 1
880, 1882, 1906, 1925, 1934, 1946, 1954, 1957, 1958, 1960, 1962, 1966, 1970, 1973,
1975, 1978, 1980, 1992, 1994, 2015, 2016, 2025, 2028, 2029, 2033, 2035}
----------------------------------------------------------------------------------
-------------------------------------------
Count of outliers :  1064
outlier data :  {2, 3, 4, 5, 6, 7}
----------------------------------------------------------------------------------
-------------------------------------------
Count of outliers :  0
outlier data :  set()
----------------------------------------------------------------------------------
-------------------------------------------
Count of outliers :  0
outlier data :  set()
----------------------------------------------------------------------------------
-------------------------------------------
Count of outliers :  0
```

```
outlier data :  set()
--------------------------------------------------------------------------------
-------------------------------------------
Count of outliers :  0
outlier data :  set()
--------------------------------------------------------------------------------
-------------------------------------------
Count of outliers :  0
outlier data :  set()
```

Removing Outliers

From above we get to know the some field like- campaign, age, duration, pdays and previous have a noticable amount of outliers. Hence we have to remove it.

For removing outliers we are using the InterQuartile Range method

InterQuartile Range(IQR) :

The interquartile range, often abbreviated IQR, is the difference between the 25th percentile (Q1) and the 75th percentile (Q3) in a dataset. It measures the spread of the middle 50% of values.

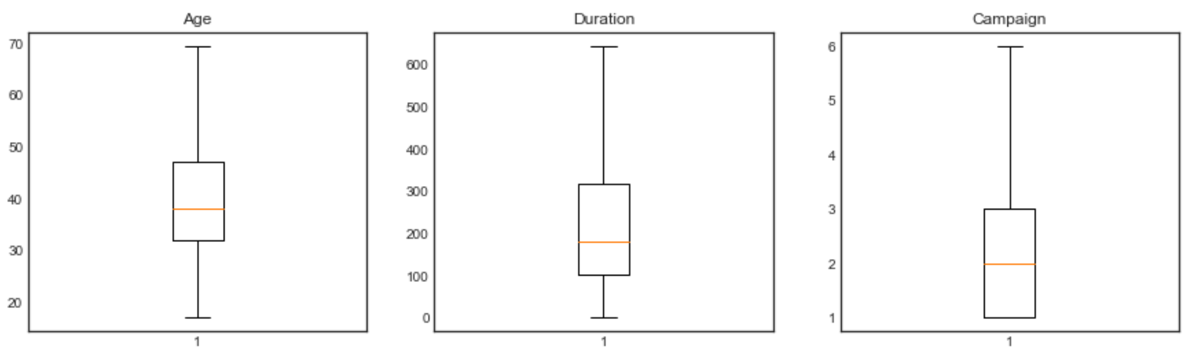
One popular method is to declare an observation to be an outlier if it has a value 1.5 times greater than the IQR or 1.5 times less than the IQR.

In [44]:
```
cols=['age','duration','campaign']
Quar=[]
for i in cols:
    Q3=np.quantile(cust_data[i],0.75)
    Q1=np.quantile(cust_data[i],0.25)
    IQR=Q3-Q1
    x=Q3+(1.5*IQR)
    Quar.append(x)
Quar
```

Out[44]:
```
[69.5, 644.5, 6.0]
```

In [45]:
```
cust_data.loc[cust_data['age']>69.5,"age"]=69.5
cust_data.loc[cust_data['duration']>644.5,"duration"]=644.5
cust_data.loc[cust_data['campaign']>6.0,"campaign"]=6.0
```

In [46]:
```
plt.figure(figsize = (15, 4))
plt.style.use('seaborn-white')
ax=plt.subplot(1,3,1)
plt.boxplot(cust_data['age'])
ax.set_title('Age')
ax=plt.subplot(1,3,2)
plt.boxplot(cust_data['duration'])
ax.set_title('Duration')
ax=plt.subplot(1,3,3)
plt.boxplot(cust_data['campaign'])
ax.set_title('Campaign')
plt.savefig('removed outliers')
```



Encoding

Encoding is a technique of converting categorical variables into numerical values so that it could be easily fitted to a machine learning model. Two types of encoding techniques are used :

1- One Hot Encoding:

One hot encoding is one method of converting data to prepare it for an algorithm and get a better prediction. With one-hot, we convert each categorical value into a new categorical column(dummies) and assign a binary value of 1 or 0 to those columns. Each integer value is represented as a binary vector. All the values are zero, and the index is marked with a 1

2- Find and Replace:

In fields like month, day_of_week we replaced the categorical values with known numerical values for modelling

In [47]:
```
cust_data.loc[cust_data['job']=='unknown','job']='unknownj'
cust_data.loc[cust_data['education']=='unknown','education']='unknowne'
cust_data.loc[cust_data['marital']=='unknown','marital']='unknownm'
```

In [48]:
```
month_d={'may':5,'jul':7,'aug':8,'jun':6,'nov':11,'apr':4,'oct':10,'sep':9,'mar':3,
cust_data['month']= cust_data['month'].map(month_d)
```

In [49]:
```
day_d={'thu':5,'mon':2,'wed':4,'tue':3,'fri':6}
cust_data['day_of_week']= cust_data['day_of_week'].map(day_d)
```

In [50]:
```
dict1={'yes':1,'no':0,'unknown':-1}
cust_data['default']=cust_data['default'].map(dict1)
cust_data['housing']=cust_data['housing'].map(dict1)
cust_data['loan']=cust_data['loan'].map(dict1)
```

In [51]:
```
dict2={'no':0,'yes':1}
cust_data['term_deposit']=cust_data['term_deposit'].map(dict2)
cust_data['prev_c']=cust_data['prev_c'].map(dict2)
```

In [52]:
```
d_contact=pd.get_dummies(cust_data['contact'], prefix='d',drop_first=True)
d_outcome=pd.get_dummies(cust_data['poutcome'], prefix='d',drop_first=True)
d_job=pd.get_dummies(cust_data['job'], prefix='d',drop_first=True)
d_education=pd.get_dummies(cust_data['education'], prefix='d',drop_first=True)
d_marital=pd.get_dummies(cust_data['marital'], prefix='d',drop_first=True)
cust_data = pd.concat([cust_data,d_contact,d_outcome,d_job,d_education,d_marital],a
cust_data.drop(['contact','poutcome','job','education','marital'],axis=1, inplace=T
```

In [53]:
```
cust_data.columns
```

Out[53]:
```
Index(['age', 'default', 'housing', 'loan', 'month', 'day_of_week', 'duration',
       'campaign', 'previous', 'employment_variation_rate',
       'consumer_price_index', 'consumer_confidence_index',
       '3_months_euribor_rate', 'number_of_employees_in_the_bank',
       'term_deposit', 'prev_c', 'd_telephone', 'd_nonexistent', 'd_success',
       'd_blue-collar', 'd_entrepreneur', 'd_housemaid', 'd_management',
       'd_retired', 'd_self-employed', 'd_services', 'd_student',
       'd_technician', 'd_unemployed', 'd_unknownj', 'd_high.school',
       'd_illiterate', 'd_professional.course', 'd_university.degree',
       'd_unknowne', 'd_married', 'd_single', 'd_unknownm'],
      dtype='object')
```

Standardization of numerical variables

Feature scaling is one of the most important data preprocessing step in machine learning. Algorithms that compute the distance between the features are biased towards numerically larger values if the data is not scaled

In [54]:
```
cust_data_scale=cust_data.copy()
Categorical_variables=['d_blue-collar','d_self-employed','d_entrepreneur','d_housem
                       'd_student','d_technician','d_unemployed','d_unknownj','d_hi
                       'd_professional.course','d_university.degree','d_unknowne',
                       'housing', 'loan', 'month', 'day_of_week','term_deposit', '(
                       'prev_c']
```

In [55]:
```
feature_scale=[feature for feature in cust_data_scale.columns if feature not in Ca
```

In [56]:
```
scaler=StandardScaler()
scaler.fit(cust_data_scale[feature_scale])
```

Out[56]:
```
StandardScaler()
```

In [57]:
```
scaled_data = pd.concat([cust_data_scale[['d_blue-collar','d_self-employed','d_entr
                                          'd_retired','d_services','d_student','d_
                                          'd_high.school','d_illiterate','d_profes
                                          'd_unknowne','d_married','d_single','d_ur
                                          'loan', 'month', 'day_of_week','term_depo
                                          'd_success', 'prev_c']].reset_index(drop=
                     pd.DataFrame(scaler.transform(cust_data_scale[feature_scale]),
                     axis=1)
scaled_data.head()
```

Out[57]:

	d_blue-collar	d_self-employed	d_entrepreneur	d_housemaid	d_management	d_retired	d_services	d_stu
0	0	0	0	1	0	0	0	
1	0	0	0	0	0	0	1	
2	0	0	0	0	0	0	1	
3	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	1	

5 rows × 38 columns

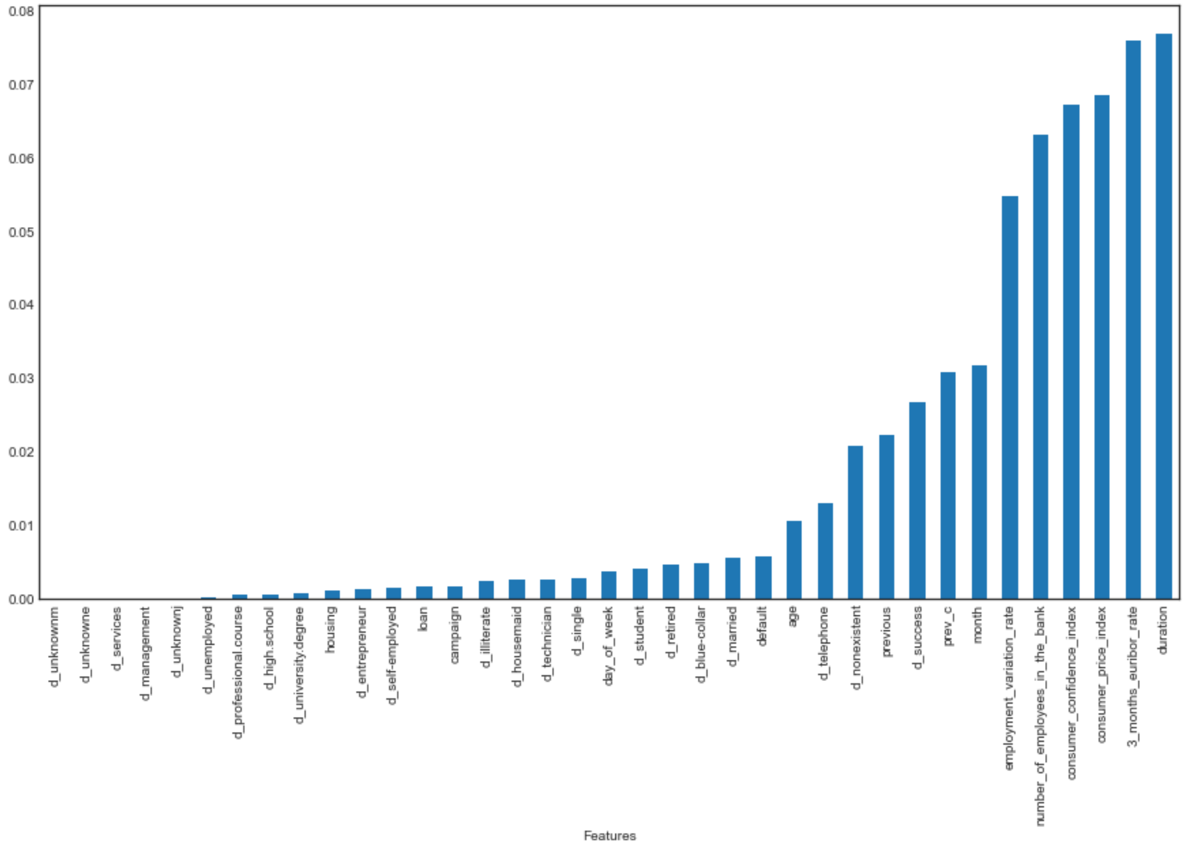
Feature Selection

Feature selection is a way of selecting the subset of the most relevant features from the original features set by removing the redundant, irrelevant, or noisy features

In [58]:
```
X=scaled_data.drop(['term_deposit'],axis=1)
y=scaled_data.term_deposit
```

In [59]:
```
imp=mutual_info_classif(X,y)
```

In [60]:
```
pd.Series(imp,index=X.columns).sort_values().plot.bar()
plt.xlabel('Features')
plt.savefig('Feature Selection')
```



From the above we found that the target variable is more dependent on 15 variables as compared to others.So we drop others

Splitting data into train and test

Dataset is divided into train-test in ratio 4:1.

In [61]:
```
X1=scaled_data.drop(['term_deposit','day_of_week','d_unknownm','d_self-employed','
                     'd_services','d_technician','d_unemployed','d_unknownj','d_un
                     'd_retired','d_blue-collar','d_single','d_student','d_profess
                     'd_telephone','d_nonexistent'],axis=1)
y1=scaled_data.term_deposit
```

In [62]:
```
X1_train, X1_test, y1_train, y1_test=train_test_split(X1,y1,test_size=0.2, random_
print('Training data size:',X1_train.shape)
print('Test data size:',X1_test.shape)
```

```
Training data size: (32938, 15)
Test data size: (8235, 15)
```

Modelling

Logistic Regression :

Logistic regression is a supervised learning algorithim. It is used to calculate or predict the probability of a binary (yes/no) event occurring. The predicted outcome is discrete and restricted to a limited number of values.

SVC :

SVC, or Support Vector Classifier, is a supervised machine learning algorithm typically used for classification tasks. SVC works by mapping data points to a high-dimensional space and then finding the optimal hyperplane that divides the data into two classes.

K-Neighbours Classifier :

Classification based on k-nearest neighbors. Classification with scalar, multivariate or functional response. The target is predicted by local interpolation of the targets associated of the nearest neighbors in the training set.

Decision Tree Classifier :

It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.This algorithm compares the values of root attribute with the record (real dataset) attribute and, based on the comparison, follows the branch and jumps to the next node.

Random Forest Classifier :

Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset. It is a bagging technique.

Here we are following the concept of 5-3-2-1 for choosing the best model of prediction

Cross validation Score for different models

It is used to a limited sample in order to estimate how the model is expected to perform in general when used to make predictions on data not used during the training of the model

In [63]:
```
print(cross_val_score(linear_model.LogisticRegression(), X1_train, y1_train, cv=10
print(cross_val_score(svm.SVC(), X1_train, y1_train, cv=10, scoring ='accuracy').m
print(cross_val_score(neighbors.KNeighborsClassifier(), X1_train, y1_train, cv=10,
print(cross_val_score( tree.DecisionTreeClassifier(), X1_train, y1_train, cv=10, s
print(cross_val_score(RandomForestClassifier(n_estimators=75,random_state=0), X1_t
```

```
0.9071892669977032
0.9062480236729638
0.897382831348571
0.8876676731990786
0.908039030004401
```

Checking different parameters for different models

Use various statistical techniques to check for best fit model

In [64]:
```
regressor = linear_model.LogisticRegression()
regressor.fit(X1_train, y1_train)

# Predicting the Test Set Results
predicted = regressor.predict(X1_test)
print('mean squared error = ',mean_squared_error(y1_test, predicted))
print('r2 score = ',r2_score(y1_test, predicted))
print('mean absolute error = ',mean_absolute_error(y1_test, predicted))
accuracy = regressor.score(X1_test, y1_test)
print(accuracy*100,'%')
linear_accuracy = round(regressor.score(X1_train,y1_train)*100,2)
print(round(linear_accuracy,2),'%')
c_matrix = confusion_matrix(y1_test, predicted)
print("Confusion Matrix:\n",c_matrix)
print("Classification Report:\n",classification_report(y1_test, predicted))
```

```
mean squared error =  0.08633879781420765
r2 score =  0.13490409616594468
mean absolute error =  0.08633879781420765
91.36612021857924 %
90.71 %
Confusion Matrix:
 [[7140  169]
 [ 542  384]]
Classification Report:
               precision    recall  f1-score   support

           0       0.93      0.98      0.95      7309
           1       0.69      0.41      0.52       926

    accuracy                           0.91      8235
   macro avg       0.81      0.70      0.74      8235
weighted avg       0.90      0.91      0.90      8235
```

In [65]:
```
# 7140+384 = 7524 , 7524+169+542=8235
# (7524/8235)*100=91.37%
```

In [66]:
```
#random forest
regressor=RandomForestClassifier(n_estimators=75,random_state=0)
regressor.fit(X1_train, y1_train)

# Predicting the Test Set Results
predicted = regressor.predict(X1_test)
print('mean squared error = ',mean_squared_error(y1_test, predicted))
print('r2 score = ',r2_score(y1_test, predicted))
print('mean absolute error = ',mean_absolute_error(y1_test, predicted))
accuracy = regressor.score(X1_test, y1_test)
print(accuracy*100,'%')
linear_accuracy = round(regressor.score(X1_train,y1_train)*100,2)
print(round(linear_accuracy,2),'%')
c_matrix = confusion_matrix(y1_test, predicted)
print("Confusion Matrix:\n",c_matrix)
print("Classification Report:\n",classification_report(y1_test, predicted))
```

```
mean squared error =  0.09058894960534304
r2 score =  0.09231850315020351
mean absolute error =  0.09058894960534304
90.9411050394657 %
99.82 %
Confusion Matrix:
 [[7011  298]
 [ 448  478]]
Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.96      0.95      7309
           1       0.62      0.52      0.56       926

    accuracy                           0.91      8235
   macro avg       0.78      0.74      0.76      8235
weighted avg       0.90      0.91      0.91      8235
```

In [67]:
```
#7011+478=7489, 7489+448+298=8235
#(7489/8235)*100=90.94%
```

In [68]:
```
regressor=svm.SVC()
regressor.fit(X1_train, y1_train)
```

```
# Predicting the Test Set Results
predicted = regressor.predict(X1_test)
print('mean squared error = ',mean_squared_error(y1_test, predicted))
print('r2 score = ',r2_score(y1_test, predicted))
print('mean absolute error = ',mean_absolute_error(y1_test, predicted))
accuracy = regressor.score(X1_test, y1_test)
print(accuracy*100,'%')
linear_accuracy = round(regressor.score(X1_train,y1_train)*100,2)
print(round(linear_accuracy,2),'%')
c_matrix = confusion_matrix(y1_test, predicted)
print("Confusion Matrix:\n",c_matrix)
print("Classification Report:\n",classification_report(y1_test, predicted))
```

```
mean squared error =  0.09095324833029751
r2 score =  0.08866830946313997
mean absolute error =  0.09095324833029751
90.90467516697025 %
90.78 %
Confusion Matrix:
 [[7198  111]
 [ 638  288]]
Classification Report:
               precision    recall  f1-score   support

           0       0.92      0.98      0.95      7309
           1       0.72      0.31      0.43       926

    accuracy                           0.91      8235
   macro avg       0.82      0.65      0.69      8235
weighted avg       0.90      0.91      0.89      8235
```

In [69]:
```
# 7198+288=7486, 7486+638+111=8235
#(7486/8235)*100=90.9%
```

In [70]:
```
regressor = neighbors.KNeighborsClassifier()
regressor.fit(X1_train, y1_train)

# Predicting the Test Set Results
predicted = regressor.predict(X1_test)
print('mean squared error = ',mean_squared_error(y1_test, predicted))
print('r2 score = ',r2_score(y1_test, predicted))
print('mean absolute error = ',mean_absolute_error(y1_test, predicted))
accuracy = regressor.score(X1_test, y1_test)
print(accuracy*100,'%')
linear_accuracy = round(regressor.score(X1_train,y1_train)*100,2)
print(round(linear_accuracy,2),'%')
c_matrix = confusion_matrix(y1_test, predicted)
print("Confusion Matrix:\n",c_matrix)
print("Classification Report:\n",classification_report(y1_test, predicted))
```

```
mean squared error =  0.09969641772920461
r2 score =  0.0010636609736154323
mean absolute error =  0.09969641772920461
90.03035822707955 %
93.01 %
Confusion Matrix:
 [[6986  323]
 [ 498  428]]
Classification Report:
               precision    recall  f1-score   support

           0       0.93      0.96      0.94      7309
           1       0.57      0.46      0.51       926

    accuracy                           0.90      8235
   macro avg       0.75      0.71      0.73      8235
weighted avg       0.89      0.90      0.90      8235
```

In [71]:

```
# 6986+428=7414, 7414+498+323=8235
# (7414/8235)*100=90.03%
```

In [72]:

```
regressor = tree.DecisionTreeClassifier()
regressor.fit(X1_train, y1_train)

print('mean squared error = ',mean_squared_error(y1_test, predicted))
print('r2 score = ',r2_score(y1_test, predicted))
print('mean absolute error = ',mean_absolute_error(y1_test, predicted))
accuracy = regressor.score(X1_test, y1_test)
print(accuracy*100,'%')
linear_accuracy = round(regressor.score(X1_train,y1_train)*100,2)
print(round(linear_accuracy,2),'%')
c_matrix = confusion_matrix(y1_test, predicted)
print("Confusion Matrix:\n",c_matrix)
print("Classification Report:\n",classification_report(y1_test, predicted))
```

```
mean squared error =  0.09969641772920461
r2 score =  0.0010636609736154323
mean absolute error =  0.09969641772920461
89.20461445051609 %
99.83 %
Confusion Matrix:
 [[6986  323]
 [ 498  428]]
Classification Report:
               precision    recall  f1-score   support

           0       0.93      0.96      0.94      7309
           1       0.57      0.46      0.51       926

    accuracy                           0.90      8235
   macro avg       0.75      0.71      0.73      8235
weighted avg       0.89      0.90      0.90      8235
```

In [73]:

```
# 6986+428=7414, 7461+498+323=8235
# (7414/8235)*100=90.03%
```

*** From above we could say all models did good with simialr accuracy in train and test data and rmse**

*** But when we took cross validation Score into consideration , we found Random Forest , Logistic Regression and Support Vector Classifier to be good**

* Then we compared F1 score and confusion matrix , we found Random forest and Logistic Regression was best fit with 90.94% accuracy in training data we can find best parameters and tun to increase the accuracy

* Now we can tune it to get the best fit model

Hyperparameter tuning

In [81]:
```
param_grid = {'C': np.logspace(-4, 4, 50), 'penalty':['l1', 'l2']}
clf = GridSearchCV(linear_model.LogisticRegression(random_state=0), param_grid,cv=!
best_model = clf.fit(X1_train,y1_train)
print(best_model.best_estimator_)
print("The mean accuracy of the model is:",best_model.score(X1_test,y1_test))
```

```
LogisticRegression(C=0.3906939937054613, random_state=0)
The mean accuracy of the model is: 0.913418336369156
```

In [82]:
```
n_estimators = [5,20,50,100] # number of trees in the random forest
max_features = ['auto', 'sqrt'] # number of features in consideration at every spl
max_depth = [int(x) for x in np.linspace(10, 120, num = 12)] # maximum number of le
min_samples_split = [2, 6, 10] # minimum sample number to split a node
min_samples_leaf = [1, 3, 4] # minimum sample number that can be stored in a leaf n
bootstrap = [True, False] # method used to sample data points

random_grid = {'n_estimators': n_estimators,

'max_features': max_features,

'max_depth': max_depth,

'min_samples_split': min_samples_split,

'min_samples_leaf': min_samples_leaf,

'bootstrap': bootstrap}
```

In [83]:
```
rf = RandomForestClassifier()
rf_random = RandomizedSearchCV(estimator = rf,param_distributions = random_grid,n_i
                               random_state=35, n_jobs = -1)
rf_random.fit(X1_train, y1_train)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

Out[83]:
```
RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(), n_iter=100,
                   n_jobs=-1,
                   param_distributions={'bootstrap': [True, False],
                                        'max_depth': [10, 20, 30, 40, 50, 60,
                                                      70, 80, 90, 100, 110,
                                                      120],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 3, 4],
                                        'min_samples_split': [2, 6, 10],
                                        'n_estimators': [5, 20, 50, 100]},
                   random_state=35, verbose=2)
```

In [84]:
```
print ('Best Parameters: ', rf_random.best_params_, ' \n')
```

```
Best Parameters:  {'n_estimators': 50, 'min_samples_split': 10, 'min_samples_lea
f': 3, 'max_features': 'sqrt', 'max_depth': 80, 'bootstrap': True}
```

ROC curve

In [85]:
```
lr = linear_model.LogisticRegression(C=0.3906939937054613, random_state=0)
```

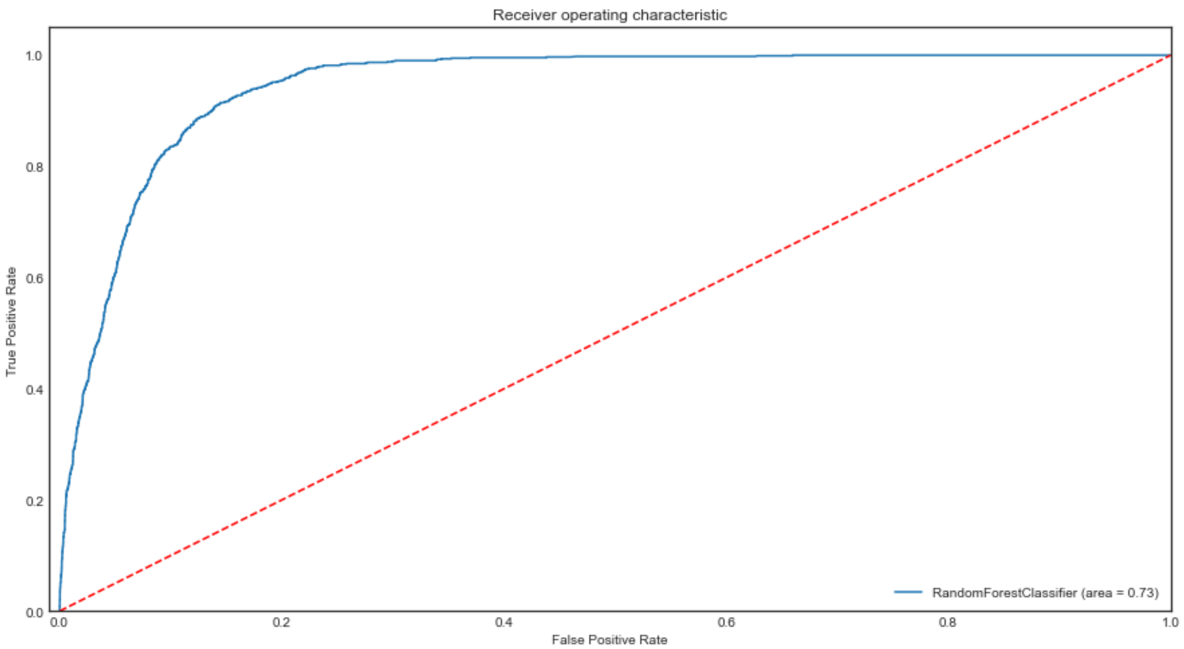
```
lr.fit(X1_train, y1_train)
y1_pred = lr.predict(X1_test)
print('Accuracy: {:.2f}'.format(lr.score(X1_test, y1_test)))
```

Accuracy: 0.91

In [86]:
```
rfc = RandomForestClassifier(n_estimators=50, min_samples_split=10, min_samples_lea
                             max_depth=80, bootstrap=True)
rfc.fit(X1_train, y1_train)
y1_pred = rfc.predict(X1_test)
print('Accuracy: {:.2f}'.format(rfc.score(X1_test, y1_test)))
```

Accuracy: 0.91

In [87]:
```
lr_roc_auc1 = roc_auc_score(y1_test, rfc.predict(X1_test))
fpr1, tpr1, thresholds1 = roc_curve(y1_test,rfc.predict_proba(X1_test)[:,1])
plt.figure()
plt.plot(fpr1, tpr1, label='RandomForestClassifier (area = %0.2f)' % lr_roc_auc1)
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('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
plt.savefig('ROC Curve')
```



<Figure size 1080x576 with 0 Axes>

From ROC curve we can say that Random Forest Classifier gives the best Result

Thank You

In [ ]: