Classification and Regression with Bank Marketing Campaign dataset

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Code and documentation for this project on GitHub repository as following: [https://github.com/marinagolberg/CIND820-MarGolb.git (https://github.com/marinagolberg/CIND820-MarGolb.git)](https://github.com/marinagolberg/CIND820-MarGolb.git)

In [1]:
```
#!pip install SMOTE
```

In [2]:
```
#!pip install imblearn
```

In [3]:
```
#!pip install mlxtend
```

In [4]:
```
#!pip install matplotlib
```

In [5]:
```
#!pip install seaborn
```

In [6]:
```
#pip install cufflinks
```

In [7]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from pandas import DataFrame
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import LabelEncoder
import plotly.express as px
from collections import Counter
from imblearn.over_sampling import SMOTE
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import mutual_info_classif, SelectPercentile
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
from sklearn.metrics import roc_auc_score
from mlxtend.feature_selection import SequentialFeatureSelector
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.metrics import brier_score_loss
from sklearn.feature_selection import SelectFromModel
from mlxtend.plotting import plot_sequential_feature_selection as plot_sfs
from sklearn.metrics import average_precision_score
```

In [8]:
```python
bank = pd.read_csv("bank-additional-full.csv", sep=';')
```

Attribute Information:

Input variables:

Bank client data:

1 - age (numeric)

2 - job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')

3 - marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)

4 - education (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')

5 - default: has credit in default? (categorical: 'no','yes','unknown')

6 - housing: has housing loan? (categorical: 'no','yes','unknown')

7 - loan: has personal loan? (categorical: 'no','yes','unknown')

Related with the last contact of the current campaign:

8 - contact: contact communication type (categorical: 'cellular','telephone')

9 - month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')

10 - day_of_week: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')

11 - duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y='no'). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.

Other attributes:

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

13 - pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)

14 - previous: number of contacts performed before this campaign and for this client (numeric)

15 - poutcome: outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')

Social and economic context attributes

16 - emp.var.rate: employment variation rate - quarterly indicator (numeric)

17 - cons.price.idx: consumer price index - monthly indicator (numeric)

18 - cons.conf.idx: consumer confidence index - monthly indicator (numeric)

19 - euribor3m: euribor 3 month rate - daily indicator (numeric)

20 - nr.employed: number of employees - quarterly indicator (numeric)

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

https://archive.ics.uci.edu/ml/datasets/bank+marketing (https://archive.ics.uci.edu/ml/datasets/bank+marketing)

Exploratory Data Analysis and Cleaning

In [9]:
```
bank.head(100)
```

Out[9]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	...	1
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	...	1
2	37	services	married	high.school	no	yes	no	telephone	may	mon	...	1
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	...	1
4	56	services	married	high.school	no	no	yes	telephone	may	mon	...	1
...	...	...	...	...	...	...	...	...	...	...	...	...
95	45	services	married	professional.course	no	yes	no	telephone	may	mon	...	1
96	42	management	married	university.degree	no	no	no	telephone	may	mon	...	1
97	53	admin.	divorced	university.degree	unknown	no	no	telephone	may	mon	...	1
98	37	technician	single	professional.course	no	no	no	telephone	may	mon	...	1
99	44	blue-collar	married	basic.6y	no	no	no	telephone	may	mon	...	1

100 rows × 21 columns

In [11]:

```
#basic descriptive statistics
# higth sd in  "duration", "campaign","previous", emp.var.rate,cons.conf.idx which indicates a fairl
bank.describe()
```

Out[11]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	93.575664	-40.502600	
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	0.578840	4.628198	
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	93.749000	-41.800000	
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	94.767000	-26.900000	

In [12]:

```
bank.groupby('y').mean()
```

Out[12]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.emp
y										
no	39.911185	220.844807	2.633085	984.113878	0.132374	0.248875	93.603757	-40.593097	3.811491	5176.16
yes	40.913147	553.191164	2.051724	792.035560	0.492672	-1.233448	93.354386	-39.789784	2.123135	5095.1

std bigger then mean(duration,campaign,previous,emp.var.rate,cons.conf.idx)- high variation between values, and abnormal distribution for data. A smaller standard deviation indicates that more of the data is clustered about the mean while, a larger once indicates the data are more spread out.

In [13]:
```
bank.shape
```

Out[13]:
```
(41188, 21)
```

In [14]:
```

bank['y'].value_counts()
```

Out[14]:
```
no     36548
yes     4640
Name: y, dtype: int64
```

In [15]:
```
#Some times, we want to know what percentage of the whole is
#for each value that appears in the column.
#To calculate this in pandas with the value_counts()
#method, set the argument normalize to True.
bank['y'].value_counts(normalize=True)
```

Out[15]:
```
no     0.887346
yes    0.112654
Name: y, dtype: float64
```

That makes it highly unbalanced, the positive class of target variable for 11.26%

In [16]:
```
bank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41188 non-null  int64  
 1   job             41188 non-null  object 
 2   marital         41188 non-null  object 
 3   education       41188 non-null  object 
 4   default         41188 non-null  object 
 5   housing         41188 non-null  object 
 6   loan            41188 non-null  object 
 7   contact         41188 non-null  object 
 8   month           41188 non-null  object 
 9   day_of_week     41188 non-null  object 
 10  duration        41188 non-null  int64  
 11  campaign        41188 non-null  int64  
 12  pdays           41188 non-null  int64  
 13  previous        41188 non-null  int64  
 14  poutcome        41188 non-null  object 
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object 
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

In [17]:
```
#Check the datatypes of the attributes.
bank.dtypes
```

Out[17]:
```
age                 int64
job                object
marital            object
education          object
default            object
housing            object
loan               object
contact            object
month              object
day_of_week        object
duration            int64
campaign            int64
pdays               int64
previous            int64
poutcome           object
emp.var.rate      float64
cons.price.idx    float64
cons.conf.idx     float64
euribor3m         float64
nr.employed       float64
y                  object
dtype: object
```

In [18]:
```
#Are there any missing values in the dataset?
bank.isnull().values.any()
```

Out[18]:
```
False
```

In [19]:
```
bank.isna().sum()
```

Out[19]:
```
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
dtype: int64
```

In [20]:
```
bank.isin([0]).any().any()
```

Out[20]:
```
True
```

In [21]:
```
#How many o values in every attribute
#Knn cannot have 0 or Nan

bank.isin([0]).sum()
```

Out[21]:
```
age                   0
job                   0
marital               0
education             0
default               0
housing               0
loan                  0
contact               0
month                 0
day_of_week           0
duration              4
campaign              0
pdays                15
previous          35563
poutcome              0
emp.var.rate          0
cons.price.idx        0
cons.conf.idx         0
euribor3m             0
nr.employed           0
y                     0
dtype: int64
```

In [22]:
```
#previous 35563 is "0" (35563/41188 no data in this attribute ,I will drop this attribute)
bank = bank.drop(['previous'], axis=1)
```

In [23]:
```
#Colculating the mean
duration_mean = bank['duration']
durationMean = duration_mean.mean()
durationMean
```

Out[23]:
```
258.2850101971448
```

In [24]:
```
#replacing all 0 valeuse with mean of that column
bank = bank.replace(0, durationMean)
```

In [25]:
```
bank.isin([0]).any().any()
```

Out[25]:
```
False
```

In [26]:
```
bank.isin([0]).sum()
```

Out[26]:
```
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
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

In [27]:
```python
#In the 'pdays' column, it is observed that 999 makes 96% of the values of the column.
#from attribute information 999 means client was not previously contacted.
# I suggest to drop this column as there is not enough information for further analysis.

bank['pdays'].value_counts(normalize=True)
```

Out[27]:
```
999.00000    0.963217
3.00000      0.010658
6.00000      0.010003
4.00000      0.002865
9.00000      0.001554
2.00000      0.001481
7.00000      0.001457
12.00000     0.001408
10.00000     0.001263
5.00000      0.001117
13.00000     0.000874
11.00000     0.000680
1.00000      0.000631
15.00000     0.000583
14.00000     0.000486
8.00000      0.000437
258.28501    0.000364
16.00000     0.000267
17.00000     0.000194
18.00000     0.000170
22.00000     0.000073
19.00000     0.000073
21.00000     0.000049
25.00000     0.000024
26.00000     0.000024
27.00000     0.000024
20.00000     0.000024
Name: pdays, dtype: float64
```

In [28]:
```python
bank = bank.drop(['pdays'], axis=1)
```

In [29]:
```
#In the ‘poutcome’ column, it is observed that nonexistent +
#failure makes 96.6% of the values of the column.
#from attribute information ‘poutcome’ is  outcome of
#the previous marketing campaign
# I will not drop this column as a success rate 3.3%
#might be interesting for further analysis.
bank['poutcome'].value_counts(normalize=True)
```

Out[29]:
```
nonexistent    0.863431
failure        0.103234
success        0.033335
Name: poutcome, dtype: float64
```

In [30]:
```
#campaign: number of contacts performed during this campaign and for this client
bank['campaign'].value_counts(normalize=True)
```

Out[30]:
```
1     0.428329
2     0.256628
3     0.129674
4     0.064363
5     0.038822
6     0.023769
7     0.015271
8     0.009712
9     0.006871
10    0.005463
11    0.004297
12    0.003035
13    0.002234
14    0.001675
17    0.001408
16    0.001238
15    0.001238
18    0.000801
20    0.000728
19    0.000631
21    0.000583
22    0.000413
23    0.000388
24    0.000364
27    0.000267
29    0.000243
28    0.000194
26    0.000194
25    0.000194
31    0.000170
30    0.000170
35    0.000121
32    0.000097
33    0.000097
34    0.000073
```

```
42    0.000049
40    0.000049
43    0.000049
56    0.000024
39    0.000024
41    0.000024
37    0.000024
Name: campaign, dtype: float64
```

In [31]:
```
bank['default'].value_counts(normalize=True)
```

Out[31]:
```
no         0.791201
unknown    0.208726
yes        0.000073
Name: default, dtype: float64
```

In [32]:
```
#cons.conf.idx
bank['cons.conf.idx'].value_counts()
```

Out[32]:
```
-36.4    7763
-42.7    6685
-46.2    5794
-36.1    5175
-41.8    4374
-42.0    3616
-47.1    2458
-31.4     770
-40.8     715
-26.9     447
-30.1     357
-40.3     311
-37.5     303
-50.0     282
-29.8     267
-34.8     264
-38.3     233
-39.8     229
-40.0     212
-49.5     204
-33.6     178
-34.6     174
-33.0     172
-50.8     128
-40.4      67
-45.9      10
Name: cons.conf.idx, dtype: int64
```

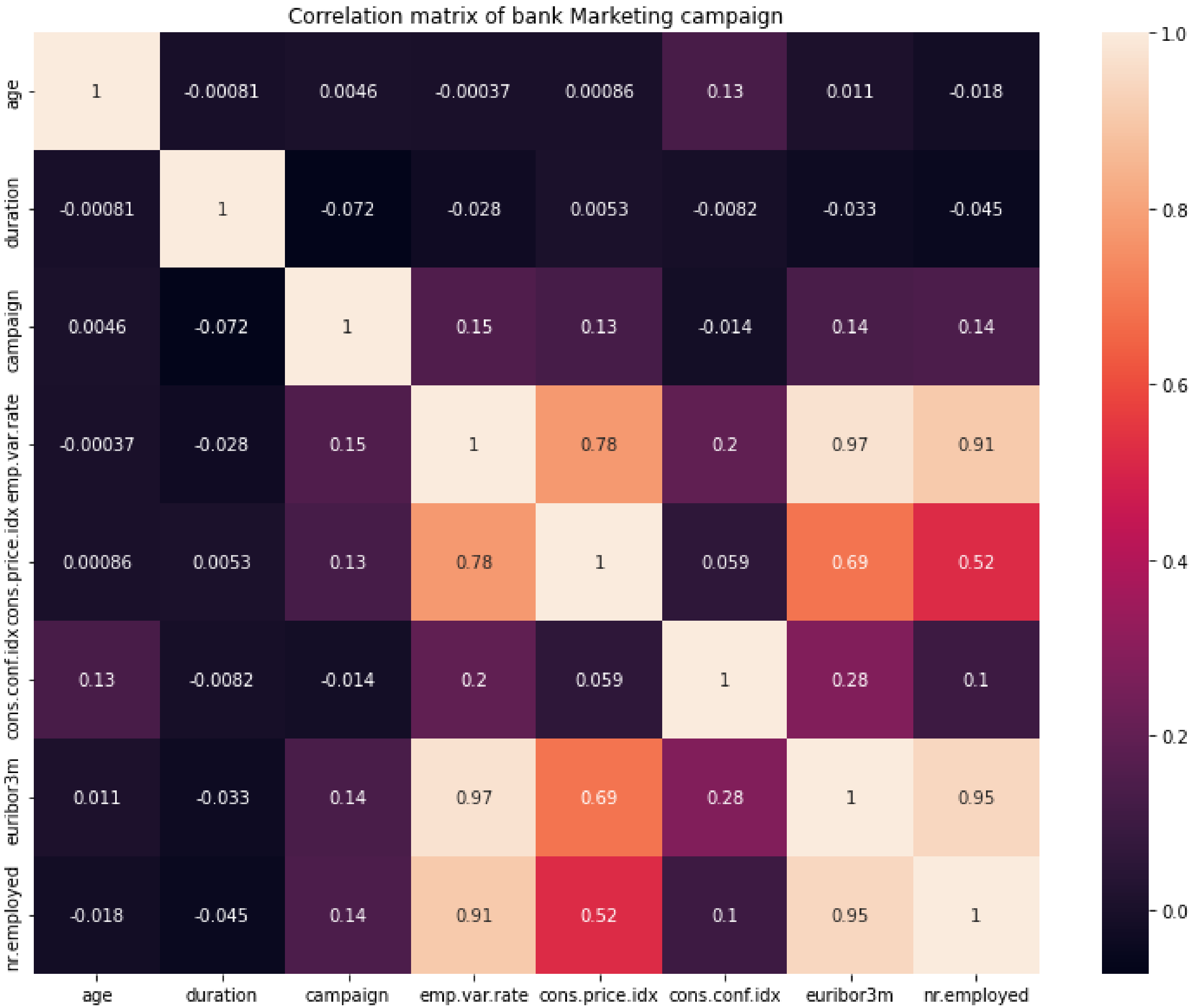
To obtain a better understanding of the dataset, the distribution of key variables and the relationships among them were plotted.

In [33]:

```
#Creatind Dataframe in Panda
df = pd.DataFrame(bank)
#print(df)
```

In [34]:

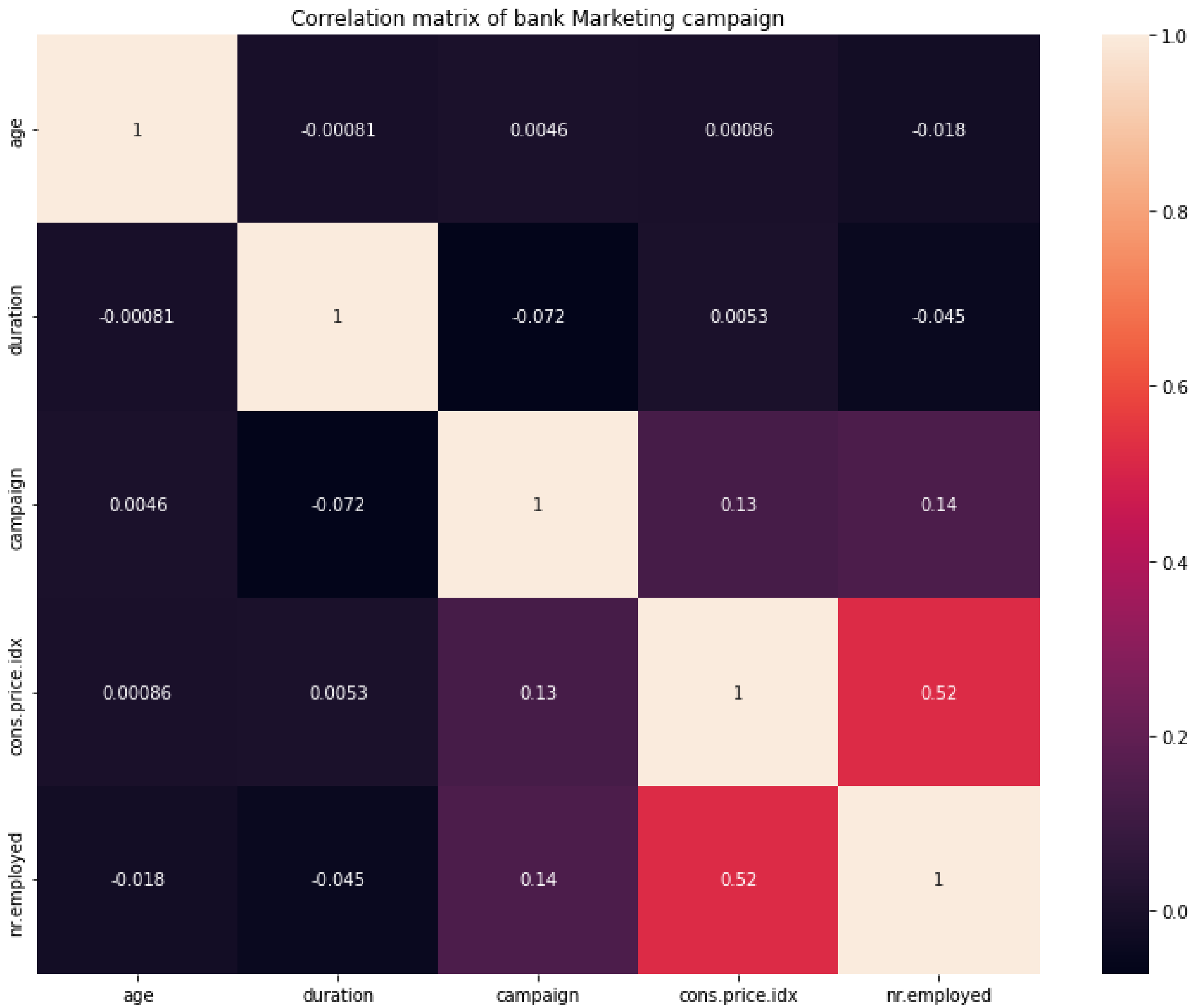
```
# taking all rows and 11 columns(without y)
plt.figure(figsize=(13, 10))
df_corr = bank.iloc[:,:18]
correlation_mat = df_corr.corr()
sns.heatmap(correlation_mat, annot = True);
plt.title("Correlation matrix of bank Marketing campaign")

#plt.xlabel("attributes")
#plt.ylabel("attributes")

plt.show()
```


Correlation matrix of bank Marketing campaign
age
duration
campaign
emp.var.rate
cons.price.idx
cons.conf.idx
euribor3m
nr.employed
1 -0.00081 0.0046 -0.00037 0.00086 0.13 0.011 -0.018
-0.00081 1 -0.072 -0.028 0.0053 -0.0082 -0.033 -0.045
0.0046 -0.072 1 0.15 0.13 -0.014 0.14 0.14
-0.00037 -0.028 0.15 1 0.78 0.2 0.97 0.91
0.00086 0.0053 0.13 0.78 1 0.059 0.69 0.52
0.13 -0.0082 -0.014 0.2 0.059 1 0.28 0.1
0.011 -0.033 0.14 0.97 0.69 0.28 1 0.95
-0.018 -0.045 0.14 0.91 0.52 0.1 0.95 1
1.0
0.8
0.6
0.4
0.2
0.0

The social and economic context attributes have correlation among themselves. Number of employees rate is highly correlated with employee variation rate Consumer price index is highly correlated with bank Euribor interest rates(euribor3m). Employee variation rate also correlates with the Euribor interest rates. All columns with a correlation of greater than 0.8 will be removed to prevent from Multicollinearity, it happens when one predictor variable in a multiple regression model can be linearly predicted from the others with a high degree of accuracy. This can lead to skewed or misleading results. The columns are 'emp.var.rate','euribor3m', and 'cons.conf.idx'.

In [35]:
```
bank = bank.drop(['emp.var.rate'], axis=1)
bank = bank.drop(['euribor3m'], axis=1)
bank = bank.drop(['cons.conf.idx'], axis=1)
```

In [36]:
```
# taking all rows and 11 columns(without y)
plt.figure(figsize=(13, 10))
df_corr = bank.iloc[:,:15]
correlation_mat = df_corr.corr()
sns.heatmap(correlation_mat, annot = True);
plt.title("Correlation matrix of bank Marketing campaign")
plt.show()
```



Correlation matrix of bank Marketing campaign
age
duration
campaign
cons.price.idx
nr.employed
1
-0.00081
0.0046
0.00086
-0.018
-0.00081
1
-0.072
0.0053
-0.045
0.0046
-0.072
1
0.13
0.14
0.00086
0.0053
0.13
1
0.52
-0.018
-0.045
0.14
0.52
1
1.0
0.8
0.6
0.4
0.2
0.0

In [38]:
```python
bank.head()
```

Out[38]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pou
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	261.0	1	none
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	149.0	1	none
2	37	services	married	high.school	no	yes	no	telephone	may	mon	226.0	1	none
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	151.0	1	none
4	56	services	married	high.school	no	no	yes	telephone	may	mon	307.0	1	none

Creating different data samples for training and testing.

In this way, we can use the training set for training our model and testing set help evaluate whether the model can generalise well to new, unseen data. In this way I will prevent overfiting.

I would divide the data set into 2 portions in the ratio of 70:30 My target variable is ‘y’ included in training and test data samples, next stepts I will divide the data set into more 2 portions

In [39]:
```python
training, testing = train_test_split(bank, test_size=0.3, random_state=25)
```

In [40]:
```python
print(f"No. of training examples: {training.shape[0]}")
print(f"No. of testing examples: {testing.shape[0]}")
```

```
No. of training examples: 28831
No. of testing examples: 12357
```

In [41]:
```python
#Let's check for duplicates
training.duplicated().any()
```

Out[41]: True

In [42]:
```
training.head()
```

Out[42]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign
8726	39	admin.	single	high.school	no	no	no	telephone	jun	wed	172.0	2
30619	50	entrepreneur	married	basic.9y	no	yes	no	telephone	may	mon	331.0	5
31121	30	blue-collar	divorced	high.school	unknown	no	no	cellular	may	wed	848.0	1
37287	33	admin.	married	high.school	no	yes	no	cellular	aug	mon	252.0	1
38307	44	admin.	divorced	high.school	no	no	no	cellular	oct	thu	634.0	1

In [43]:
```
#this doesn't seem like the case of some customers randomly having similar details.
#It looks like the data duplication happened while entering the data.
training[training.duplicated(keep = False)]
```

Out[43]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	camp
1266	39	blue-collar	married	basic.6y	no	no	no	telephone	may	thu	124.0	
20072	55	services	married	high.school	unknown	no	no	cellular	aug	mon	33.0	
18464	32	technician	single	professional.course	no	yes	no	cellular	jul	thu	128.0	
32505	35	admin.	married	university.degree	no	yes	no	cellular	may	fri	348.0	
18465	32	technician	single	professional.course	no	yes	no	cellular	jul	thu	128.0	
32516	35	admin.	married	university.degree	no	yes	no	cellular	may	fri	348.0	
20216	55	services	married	high.school	unknown	no	no	cellular	aug	mon	33.0	
1265	39	blue-collar	married	basic.6y	no	no	no	telephone	may	thu	124.0	
28476	24	services	single	high.school	no	yes	no	cellular	apr	tue	114.0	
28477	24	services	single	high.school	no	yes	no	cellular	apr	tue	114.0	

In [45]:
```
#Let's remove these duplicate rows.
training.drop_duplicates(inplace = True)
```

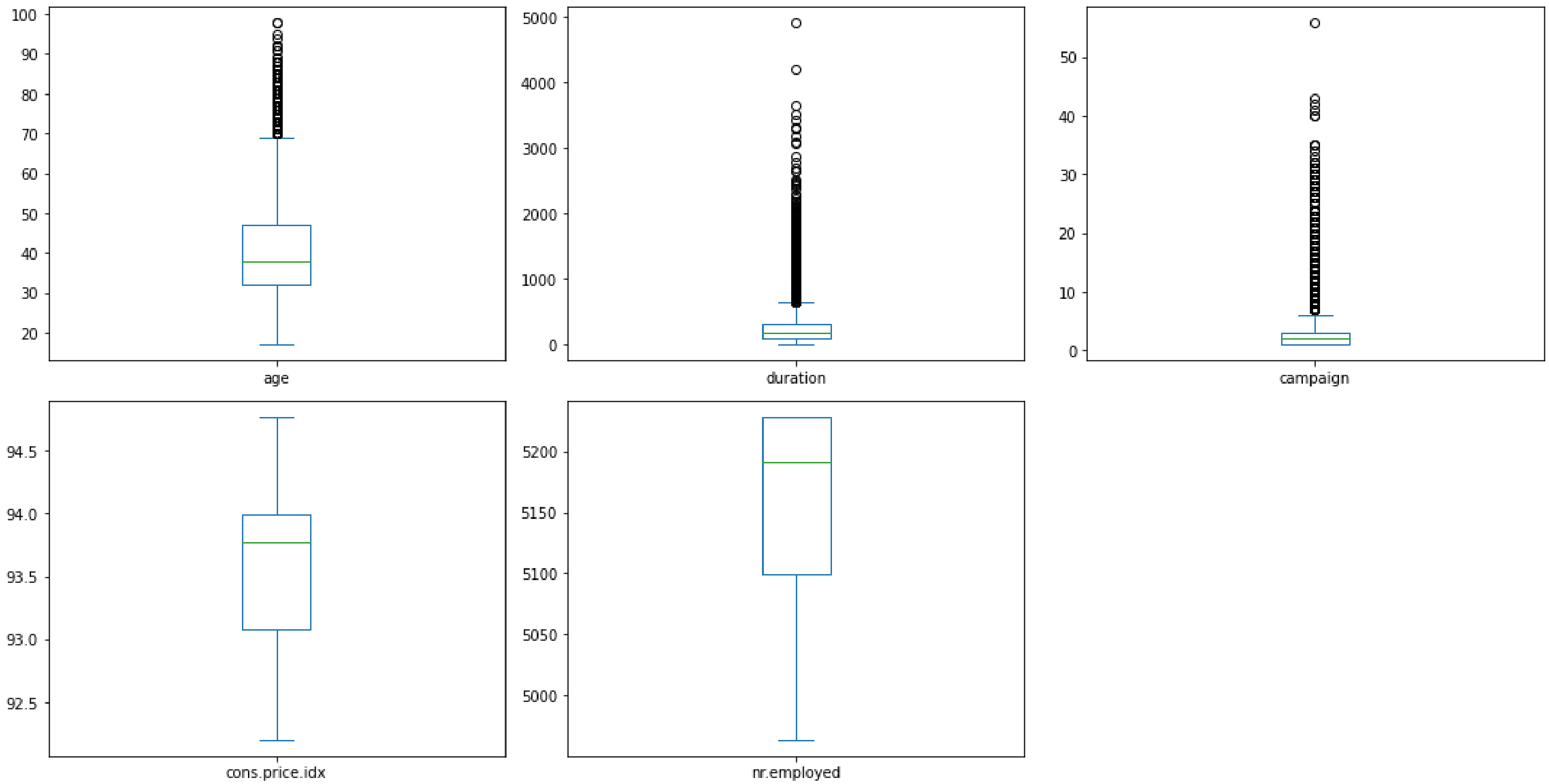
In [46]:
```
training.shape
```

Out[46]: (28826, 16)

Outliers Treatment

In [47]:
```
#We need to install cufflinks to link plotly to pandas and add the iplot method:
import cufflinks as cf
cf.go_offline()
cf.set_config_file(offline=False, world_readable=True)
```

In [48]:
```
training.plot(kind='box',subplots=True,layout=(4,3),figsize=(15,15))
plt.tight_layout()
```



On the boxplot above looks like there are outliers. Age-appropriate for the context of the attribute (min 17, max 98), Duration(is the last contact to the client in seconds max 4918 is 82 minutes for call it's too long but can be real), and maximum of Campaign looks very high 56 calls to the same customer very high but real, std bigger than mean(duration, campaign)- high variation between values, and abnormal distribution for data. Probably the minimum and maximum values are the mistakes and other values in my opinion are appropriate. I will be removing only percentile 10 and percentile 90 because different deletion percentages will cause algorithms to perform worse.

In [57]:
```
min_duration, max_duration = training.duration.quantile([0.10, 0.90])
min_duration, max_duration
```

Out[57]: (84.0, 389.0)

In [58]:
```
training[training.duration < min_duration]
```

Out[58]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campa
7639	32	services	single	high.school	no	no	no	telephone	may	fri	67.0	
21018	58	admin.	married	university.degree	no	yes	no	telephone	aug	thu	60.0	
10258	39	services	divorced	high.school	no	yes	no	telephone	jun	mon	81.0	
8717	54	technician	married	professional.course	no	yes	no	telephone	jun	wed	80.0	
30901	29	admin.	single	university.degree	no	yes	yes	cellular	may	tue	76.0	
...	...	...	...	...	...	...	...	...	...	...	...	
38510	46	blue-collar	married	basic.9y	no	yes	no	cellular	oct	tue	65.0	
29991	66	retired	married	basic.4y	no	yes	no	cellular	apr	tue	63.0	
16690	24	services	single	high.school	no	no	no	cellular	jul	wed	74.0	
7570	29	services	married	high.school	no	no	no	telephone	may	fri	76.0	
26033	31	technician	single	high.school	no	yes	no	cellular	nov	wed	77.0	

2300 rows × 16 columns

In [59]:
```
training[training.duration > max_duration]
```

Out[59]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	cam
31623	50	services	divorced	basic.9y	no	yes	no	cellular	may	thu	429.0	
36063	28	blue-collar	married	basic.9y	no	yes	no	cellular	may	tue	390.0	
24050	33	entrepreneur	married	university.degree	no	yes	no	telephone	oct	tue	454.0	
12837	52	admin.	divorced	university.degree	unknown	yes	yes	cellular	jul	tue	401.0	
24716	45	self-employed	married	university.degree	no	yes	no	cellular	nov	mon	487.0	
...	...	...	...	...	...	...	...	...	...	...	...	
4765	48	admin.	married	university.degree	no	yes	no	telephone	may	wed	396.0	
17224	26	services	married	high.school	no	yes	no	cellular	jul	fri	442.0	
9534	39	admin.	married	high.school	no	no	yes	telephone	jun	mon	422.0	
28839	30	blue-collar	married	basic.9y	no	yes	no	telephone	apr	thu	426.0	
2975	32	services	married	high.school	no	no	no	telephone	may	wed	423.0	

2300 rows × 16 columns

In [60]:
```
training = training[(training.duration<max_duration)&(training.duration>min_duration)]
training.shape
```

Out[60]: (18302, 16)

In [61]:
```
training.describe()
```

Out[61]:

	age	duration	campaign	cons.price.idx	nr.employed
count	18302.000000	18302.000000	18302.000000	18302.000000	18302.000000
mean	40.119058	196.195381	2.319528	93.570568	5165.087143
std	10.550457	80.425571	2.174224	0.581594	73.410937
min	17.000000	85.000000	1.000000	92.201000	4963.600000
25%	32.000000	128.000000	1.000000	93.075000	5099.100000
50%	38.000000	180.000000	2.000000	93.749000	5191.000000
75%	47.000000	252.000000	3.000000	93.994000	5228.100000
max	98.000000	388.000000	56.000000	94.767000	5228.100000

In [62]:
```
min_campaign, max_campaign = training.campaign.quantile([0.10, 0.90])
min_campaign, max_campaign
```

Out[62]: (1.0, 4.0)

In [63]:
```
training[training.campaign < min_campaign]
```

Out[63]:

age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	poutcome	cons.

In [64]:
```
training[training.campaign > max_campaign]
```

Out[64]:

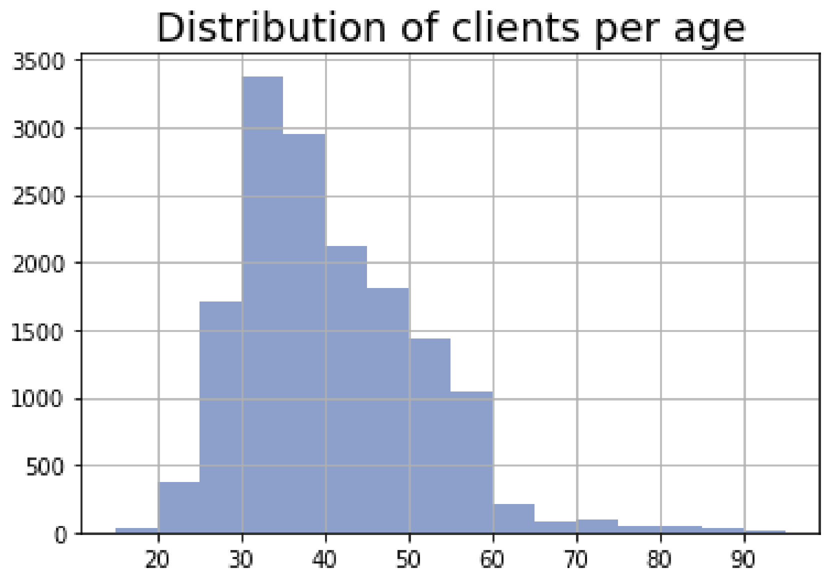
	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	ca
30619	50	entrepreneur	married	basic.9y	no	yes	no	telephone	may	mon	331.0	
11493	49	admin.	divorced	high.school	no	yes	no	telephone	jun	fri	115.0	
8492	35	blue-collar	married	basic.4y	unknown	yes	no	telephone	jun	wed	180.0	
37111	31	admin.	single	high.school	no	no	yes	telephone	jul	tue	258.0	
16807	56	services	married	high.school	unknown	yes	no	telephone	jul	thu	279.0	
...	...	...	...	...	...	...	...	...	...	...	...	
12198	40	admin.	divorced	high.school	no	no	no	telephone	jul	wed	96.0	
15326	53	management	married	high.school	no	no	no	cellular	jul	fri	91.0	
30055	61	admin.	married	university.degree	no	yes	yes	cellular	apr	thu	266.0	
4148	24	admin.	single	high.school	no	yes	no	telephone	may	mon	243.0	
17937	33	technician	married	professional.course	no	yes	yes	cellular	jul	tue	110.0	

1762 rows × 16 columns

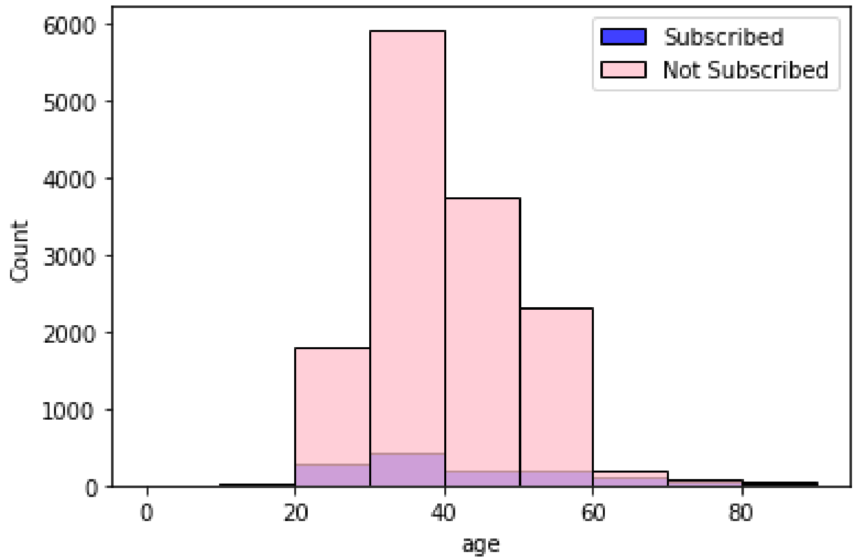
In [65]:
```
training = training[(training.campaign<max_campaign)]
training.shape
```

Out[65]:
```
(15371, 16)
```

In [66]:
```
#Let's see the distribution of clients per age.
base_color = sns.color_palette('Set2')[2]

age_bins = np.arange(15, 100, 5)
plt.hist(data = training, x = 'age', bins = age_bins, color = base_color);
plt.title("Distribution of clients per age", fontsize=18)
plt.grid();
```



In [67]:
```python
#Visualize the relationship between feature category vs dependent variable y
#type of age and deposit
bins = range(0, 100, 10)
ax = sns.histplot(training.age[training.y=='yes'],
              color='blue', kde=False, bins=bins, label='Subscribed')
sns.histplot(training.age[training.y=='no'],
         ax=ax,  # Overplots on first plot
         color='pink', kde=False, bins=bins, label="Not Subscribed")
plt.legend()
plt.show()
```



Customers who in (30-40) followed by (20-30) and (40-50) had higher percentage of subscription to deposit account

In [68]:
```
#Crosstab to display job stats with respect to y  class variable
pd.crosstab(index=training["job"], columns=training["y"])
```

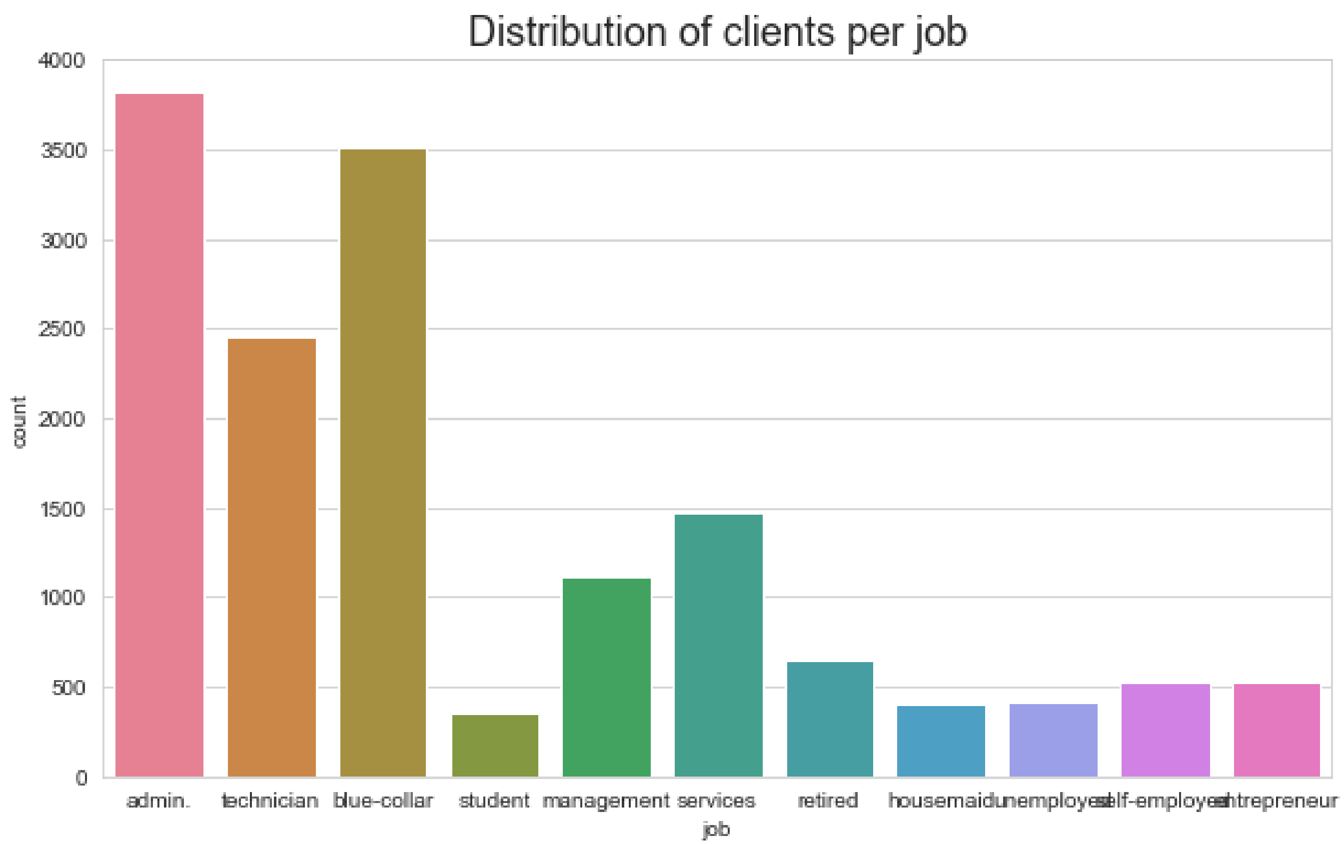
Out[68]:

y job	no	yes
admin.	3406	409
blue-collar	3419	86
entrepreneur	509	21
housemaid	380	27
management	1020	99
retired	478	176
self-employed	485	42
services	1409	60
student	249	105
technician	2259	192
unemployed	353	58
unknown	115	14

In [69]:
```
# Get names of indexes for which column job has value unknown
indexNames = training[ training['job'] == "unknown"].index
```

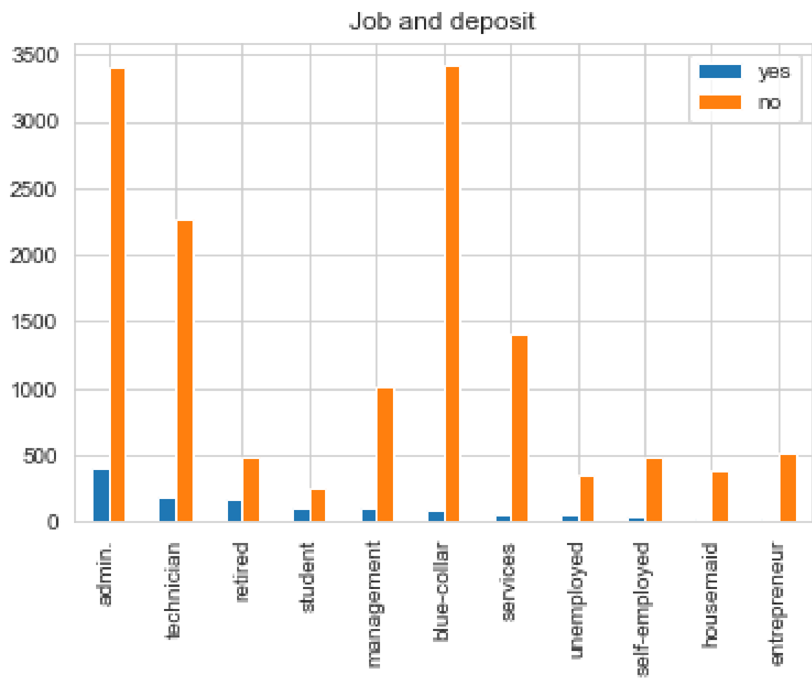
In [70]:
```
# Delete these row indexes from dataFrame
training.drop(indexNames , inplace=True)
```

In [71]:
```
#Let's see the distribution of clients per job.
sns.set_style('whitegrid')
plt.figure(figsize=(10, 6))
plt.title("Distribution of clients per job", fontsize=18)
sns.countplot(x="job", data=training, palette='husl');
```



In [72]:
```
#Visualization of relationship between feature category vs dependent variable y
#job and deposit
j_bank = pd.DataFrame()

j_bank['yes'] = training[training['y'] == 'yes']['job'].value_counts()
j_bank['no'] = training[training['y'] == 'no']['job'].value_counts()

j_bank.plot.bar(title = 'Job and deposit')
```

Out[72]: <AxesSubplot:title={'center':'Job and deposit'}>



Customers who worked in administrative position followed by technicians and blue collar made deposits

In [73]:
```
#Crosstab to display merital stats with respect to y  class variable
pd.crosstab(index=training["marital"], columns=training["y"])
```

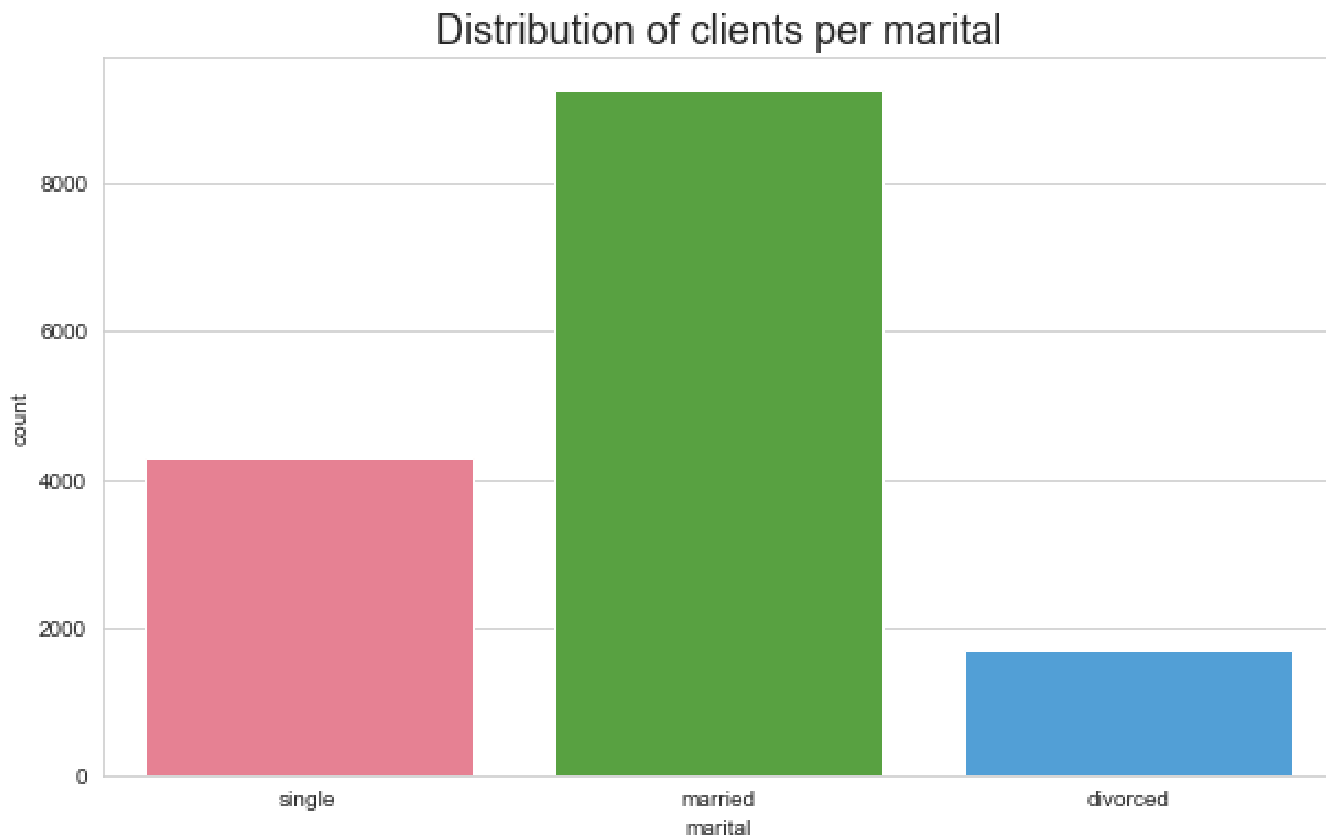
Out[73]:

y	no	yes
marital		
divorced	1553	127
married	8607	647
single	3787	499
unknown	20	2

In [74]:
```
# Get names of indexes for which column job has value unknown
indexMarital = training[ training['marital'] == "unknown"].index
```

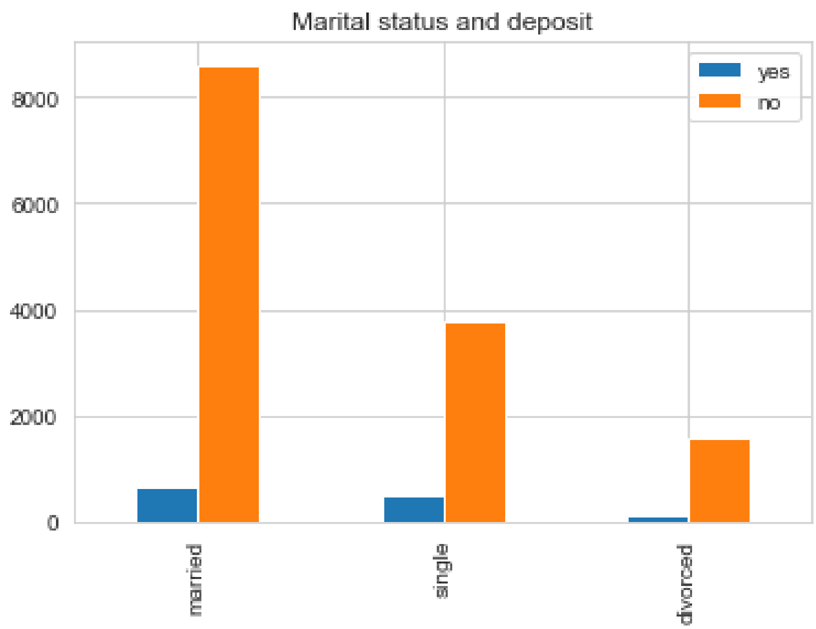
In [75]:
```
# Delete these row indexes from dataFrame
training.drop(indexMarital , inplace=True)
```

In [76]:
```
#Let's see the distribution of clients per job.
sns.set_style('whitegrid')
plt.figure(figsize=(10, 6))
plt.title("Distribution of clients per marital", fontsize=18)
sns.countplot(x="marital", data=training, palette='husl');
```



In [77]:
```
#Visualize the relationship between feature category vs dependent variable y
#marital status and deposit
j_bank = pd.DataFrame()

j_bank['yes'] = training[training['y'] == 'yes']['marital'].value_counts()
j_bank['no'] = training[training['y'] == 'no']['marital'].value_counts()

j_bank.plot.bar(title = 'Marital status and deposit')
```

Out[77]:
```
<AxesSubplot:title={'center':'Marital status and deposit'}>
```



Married customers followed by single had made deposits

In [78]:
```
#Crosstab to display education stats with respect to y  class variable
pd.crosstab(index=training["education"], columns=training["y"])
```

Out[78]:

y	no	yes
education		
basic.4y	1450	129
basic.6y	853	31
basic.9y	2133	82
high.school	3252	280
illiterate	4	1
professional.course	1743	169
university.degree	3988	512
unknown	524	69

In [79]:
```
# Get names of indexes for which column education has value unknown and illiterate
indexEducation = training[ training['education'] == "illiterate"].index
indexEducation2 = training[ training['education'] == "unknown"].index
```

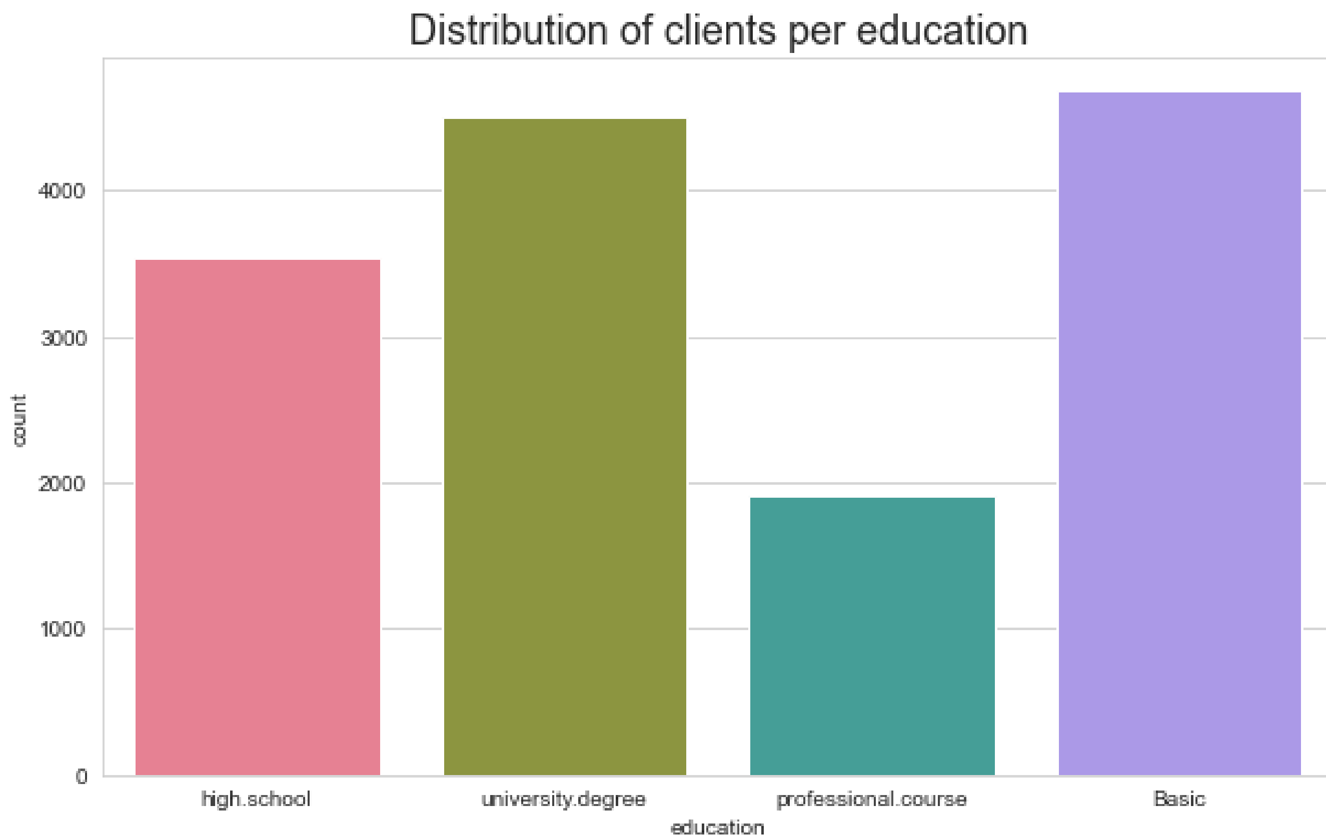
In [80]:
```
# Delete these row indexes from dataFrame
training.drop(indexEducation , inplace=True)
training.drop(indexEducation2 , inplace=True)
```

In [81]:
```
#Lets group “basic.4y”, “basic.9y” and “basic.6y” together and call them “basic”
training['education']=np.where(training['education'] =='basic.9y', 'Basic', training['education'])
training['education']=np.where(training['education'] =='basic.6y', 'Basic', training['education'])
training['education']=np.where(training['education'] =='basic.4y', 'Basic', training['education'])
```

In [82]:
```
training['education'].unique()
```

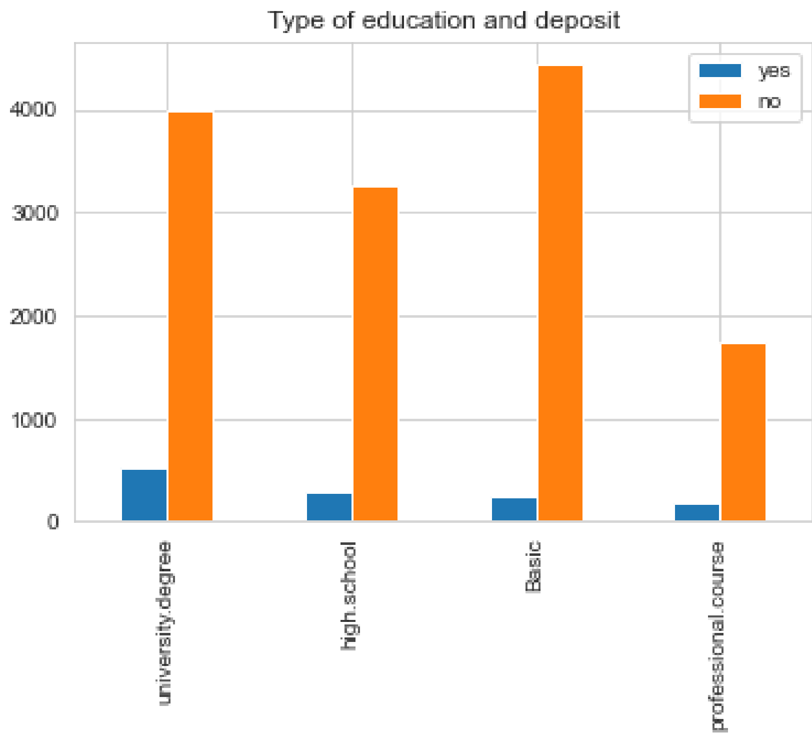
Out[82]:
```
array(['high.school', 'university.degree', 'professional.course', 'Basic'],
      dtype=object)
```

In [83]:
```
sns.set_style('whitegrid')
plt.figure(figsize=(10, 6))
plt.title("Distribution of clients per education", fontsize=18)
sns.countplot(x="education", data=training, palette='husl');
```



In [84]:
```
#Visualize the relationship between feature category vs dependent variable y
#type of education and deposit
j_bank = pd.DataFrame()

j_bank['yes'] = training[training['y'] == 'yes']['education'].value_counts()
j_bank['no'] = training[training['y'] == 'no']['education'].value_counts()

j_bank.plot.bar(title = 'Type of education and deposit')
```

Out[84]:
```
<AxesSubplot:title={'center':'Type of education and deposit'}>
```



Customers who had university degree followed by highschool had higher chence of making a deposit.

In [85]:
```python
#Crosstab to display housing stats with respect to y  class variable
pd.crosstab(index=training["housing"], columns=training["y"])
```

Out[85]:

y	no	yes
housing		
no	6038	484
unknown	332	33
yes	7049	686

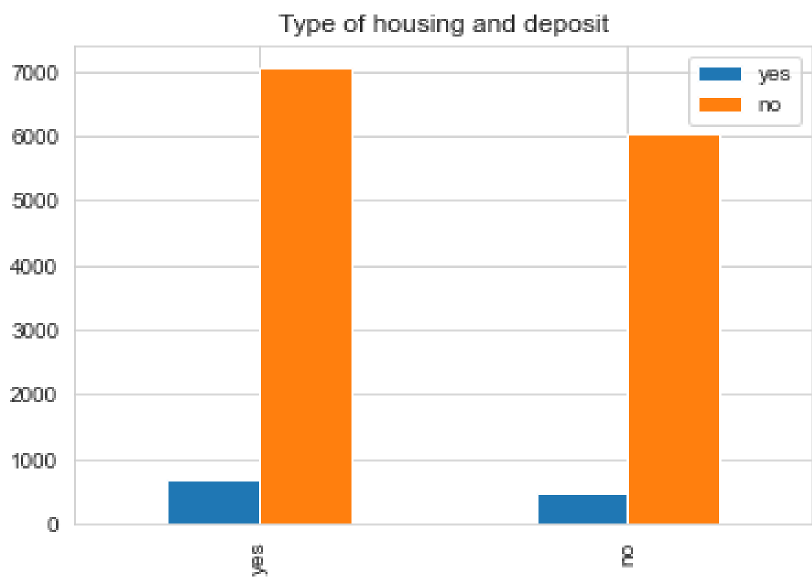
In [86]:
```python
# Get names of indexes for which column housing has value unknown
indexhousing = training[ training['housing'] == "unknown"].index
```

In [87]:
```python
# Delete these row indexes from dataFrame
training.drop(indexhousing , inplace=True)
```

In [88]:
```
sns.set_style('whitegrid')
plt.figure(figsize=(10, 6))
plt.title("Distribution of clients per housing", fontsize=18)
sns.countplot(x="housing", data=training, palette='husl');
```

In [89]:
```
#Visualize the relationship between feature category vs dependent variable y
#type of housing and deposit
j_bank = pd.DataFrame()

j_bank['yes'] = training[training['y'] == 'yes']['housing'].value_counts()
j_bank['no'] = training[training['y'] == 'no']['housing'].value_counts()

j_bank.plot.bar(title = 'Type of housing and deposit')
```

Out[89]:
```
<AxesSubplot:title={'center':'Type of housing and deposit'}>
```



Customers who had house had higher chance in making a deposit.

In [90]:

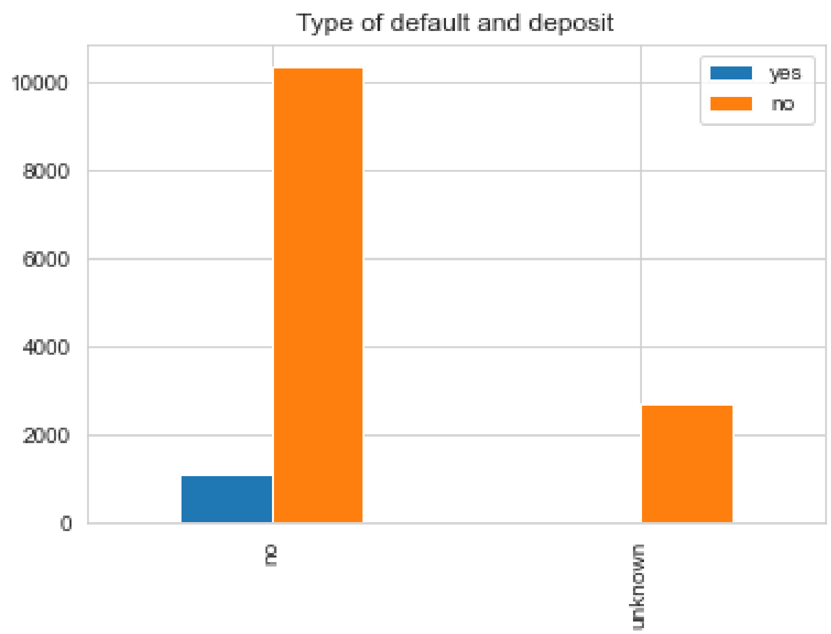
```
#Crosstab to display default stats with respect to y  class variable
pd.crosstab(index=training["default"], columns=training["y"])
```

Out[90]:

y	no	yes
default		
no	10349	1142
unknown	2736	28
yes	2	0

In [91]:
```python
#Visualize the relationship between feature category vs dependent variable y
#type of default and deposit
j_bank = pd.DataFrame()

j_bank['yes'] = training[training['y'] == 'yes']['default'].value_counts()
j_bank['no'] = training[training['y'] == 'no']['default'].value_counts()

j_bank.plot.bar(title = 'Type of default and deposit')
```

Out[91]: <AxesSubplot:title={'center':'Type of default and deposit'}>



Customers who had no default had higher chance in making a deposit.

In [92]:
```
#Crosstab to display  with y class variable
pd.crosstab(index=training["loan"], columns=training["y"])
```

Out[92]:

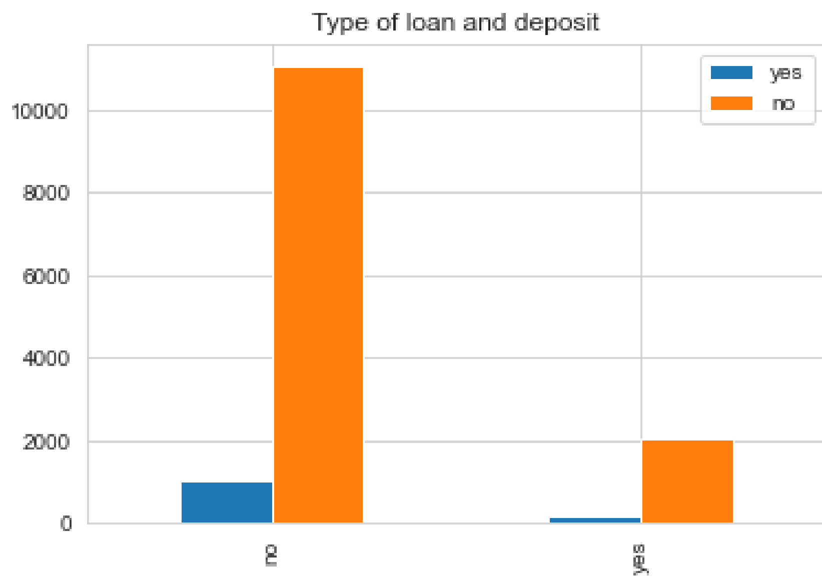
y	no	yes
loan		
no	11048	1015
yes	2039	155

In [93]:
```
# Get names of indexes for which column loan has value unknown
indexloan = training[ training['loan'] == "unknown"].index
```

In [94]:
```
# Delete these row indexes from dataFrame
training.drop(indexloan , inplace=True)
```

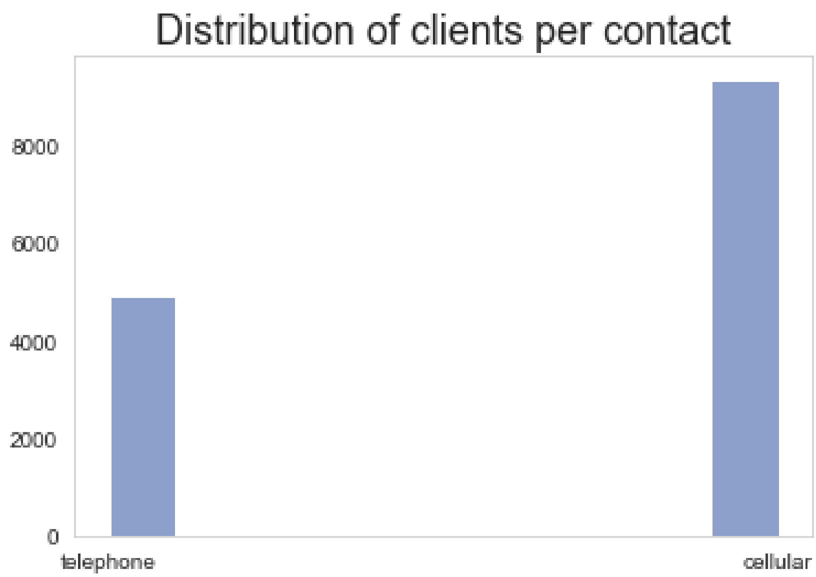
In [95]:
```python
#Visualize the relationship between feature category vs dependent variable y
#type of loan and deposit
j_bank = pd.DataFrame()


j_bank['yes'] = training[training['y'] == 'yes']['loan'].value_counts()
j_bank['no'] = training[training['y'] == 'no']['loan'].value_counts()

j_bank.plot.bar(title = 'Type of loan and deposit')
```

Out[95]:
```
<AxesSubplot:title={'center':'Type of loan and deposit'}>
```



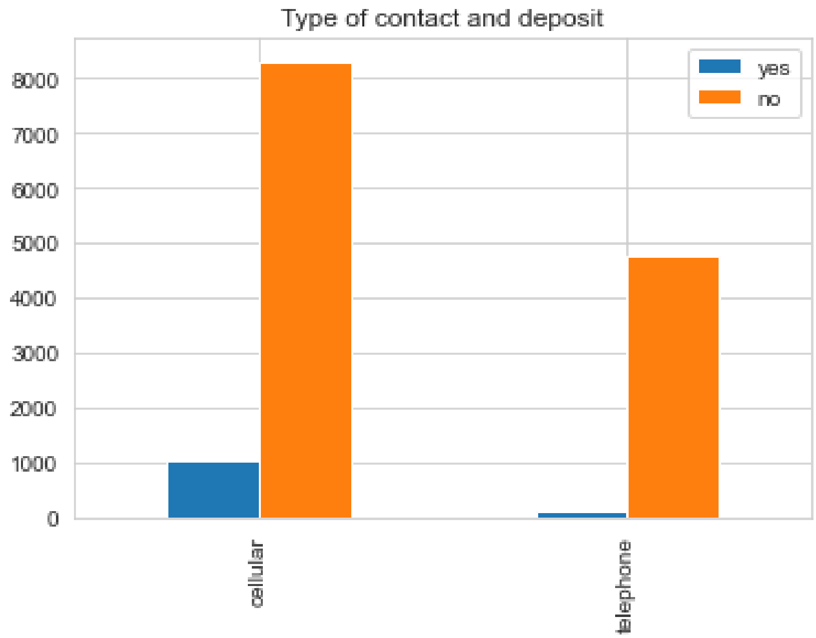
Clients that had no loan had a higher chance to subscribe to term deposits

In [96]:
```
base_color = sns.color_palette('Set2')[2]
plt.hist(data = training, x = 'contact', color = base_color);
plt.title("Distribution of clients per contact", fontsize=18)
plt.grid();
```



In [97]:
```python
#Visualize the relationship between feature category vs dependent variable y
#type of contact and deposit
j_bank = pd.DataFrame()

j_bank['yes'] = training[training['y'] == 'yes']['contact'].value_counts()
j_bank['no'] = training[training['y'] == 'no']['contact'].value_counts()

j_bank.plot.bar(title = 'Type of contact and deposit')
```

Out[97]:
```
<AxesSubplot:title={'center':'Type of contact and deposit'}>
```



Clients that was contacted by cellular had a higher chance to subscribe for term deposits

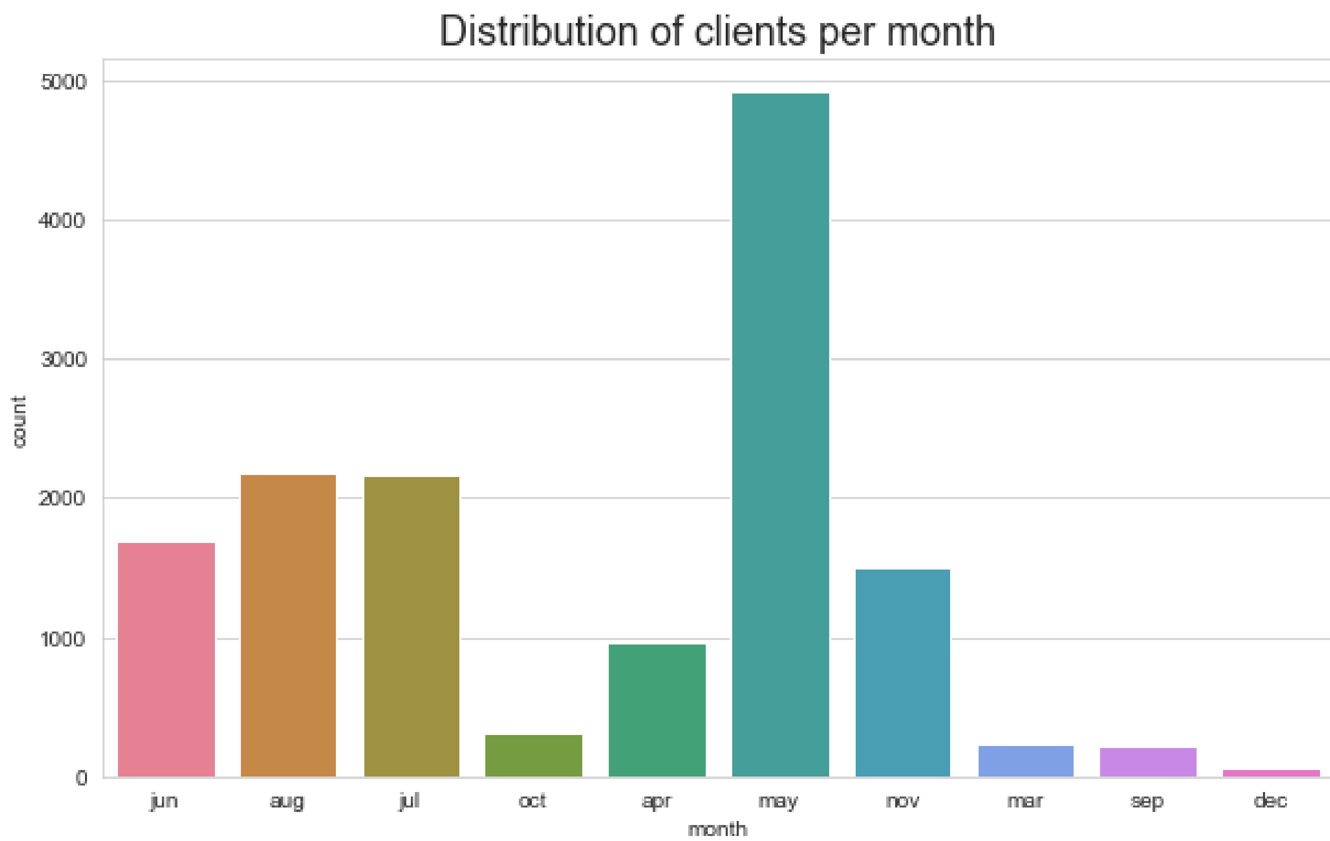
Clients that was contacted by cellular had a higher chance to subscribe for term deposits

In [98]:
```
#Crosstab to display contact stats with respect to y  class variable
pd.crosstab(index=training["contact"], columns=training["y"])
```

Out[98]:

y	no	yes
contact		
cellular	8301	1058
telephone	4786	112

In [99]:
```
sns.set_style('whitegrid')
plt.figure(figsize=(10, 6))
plt.title("Distribution of clients per month", fontsize=18)
sns.countplot(x="month", data=training, palette='husl');
```



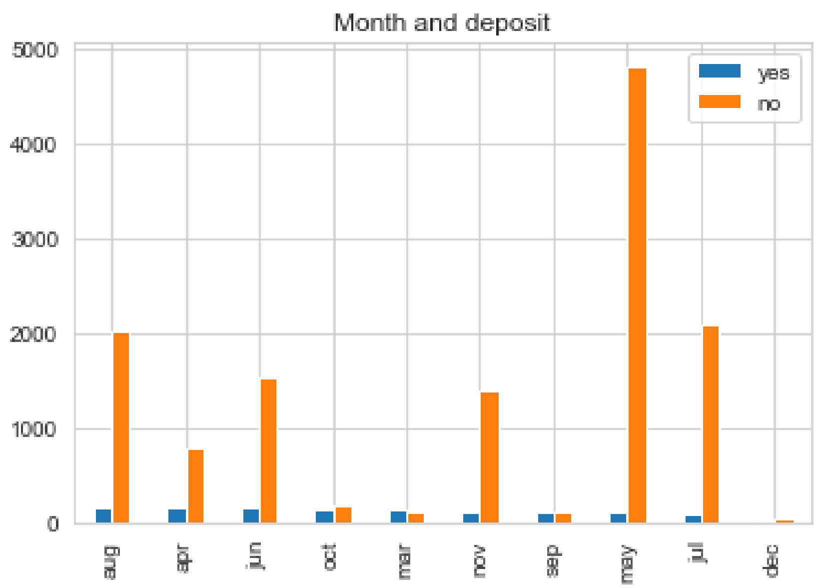
In [100]:
```
#Crosstab to display contact stats with respect to y  class variable
pd.crosstab(index=training["month"], columns=training["y"])
```

Out[100]:

y	no	yes
month		
apr	793	161
aug	2022	164
dec	31	22
jul	2087	84
jun	1538	157
mar	102	130
may	4813	100
nov	1399	107
oct	182	139
sep	120	106

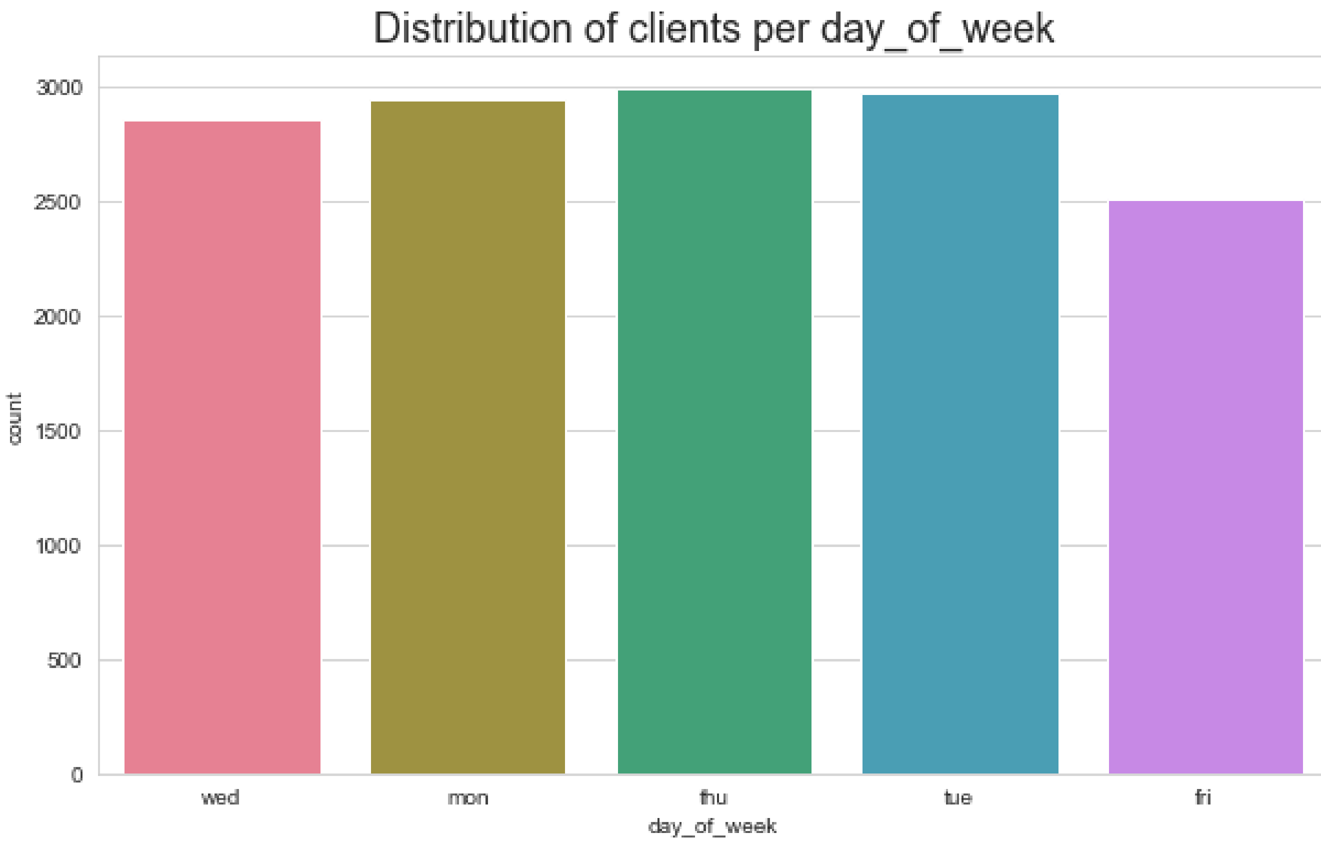
In [101]:
```python
#Visualize the relationship between feature category vs dependent variable y
#Month and deposit
j_bank = pd.DataFrame()

j_bank['yes'] = training[training['y'] == 'yes']['month'].value_counts()
j_bank['no'] = training[training['y'] == 'no']['month'].value_counts()

j_bank.plot.bar(title = 'Month and deposit')
```

Out[101]: <AxesSubplot:title={'center':'Month and deposit'}>



Most of the deposist made during May followed by August , July and June

In [102]:
```
sns.set_style('whitegrid')
plt.figure(figsize=(10, 6))
plt.title("Distribution of clients per day_of_week", fontsize=18)
sns.countplot(x="day_of_week", data=training, palette='husl');
```



In [103]:
```
#Crosstab to display day_of_week stats with respect to y  class variable
pd.crosstab(index=training["day_of_week"], columns=training["y"])
```

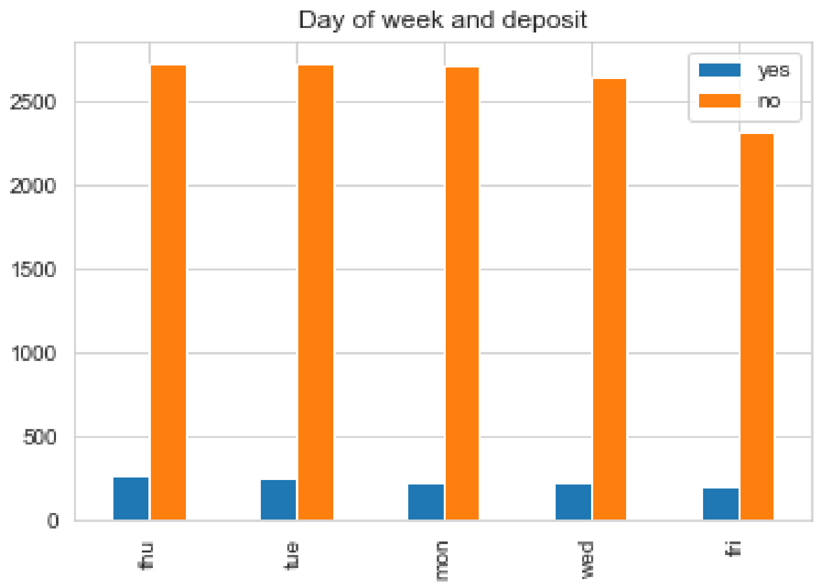
Out[103]:

y day_of_week	no	yes
fri	2307	197
mon	2710	228
thu	2719	268
tue	2716	256
wed	2635	221

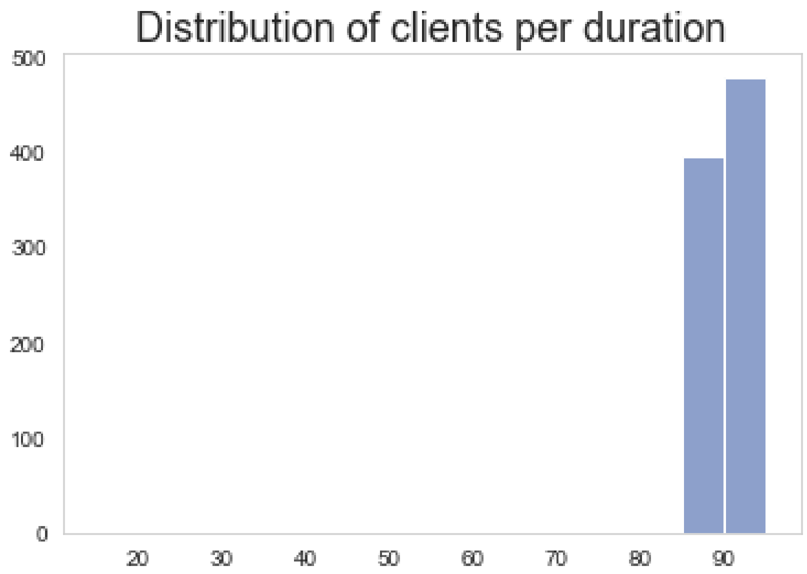
Less deposist made on Friday

In [104]:
```python
#Visualize the relationship between feature category vs dependent variable y
j_bank = pd.DataFrame()

j_bank['yes'] = training[training['y'] == 'yes']['day_of_week'].value_counts()
j_bank['no'] = training[training['y'] == 'no']['day_of_week'].value_counts()

j_bank.plot.bar(title = 'Day of week and deposit')
```

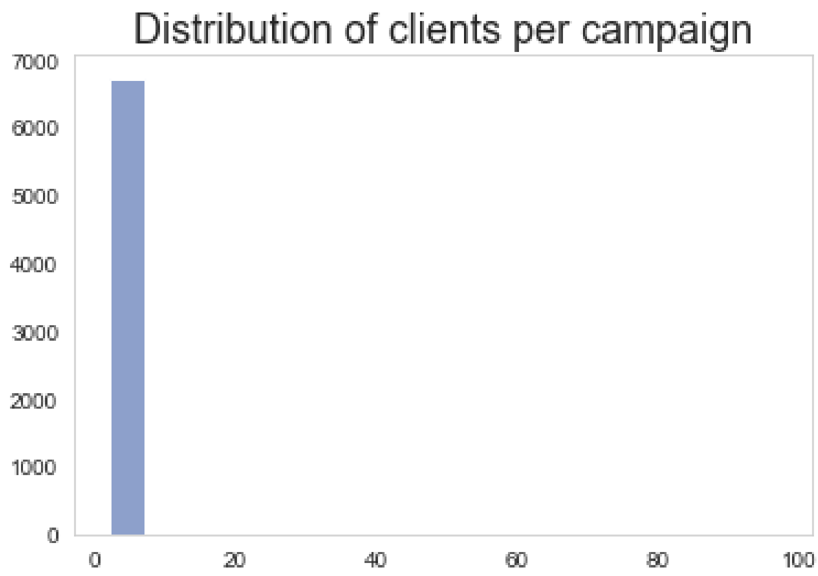
Out[104]:
```
<AxesSubplot:title={'center':'Day of week and deposit'}>
```



In [105]:
```
base_color = sns.color_palette('Set2')[2]

duration_bins = np.arange(15, 100, 5)
plt.hist(data = training, x = 'duration', bins = duration_bins, color = base_color);
plt.title("Distribution of clients per duration", fontsize=18)
plt.grid();
```



In [106]:
```
base_color = sns.color_palette('Set2')[2]

campaign_bins = np.arange(2, 100, 5)
plt.hist(data = training, x = 'campaign', bins = campaign_bins, color = base_color);
plt.title("Distribution of clients per campaign", fontsize=18)
plt.grid();
```



In [107]:

```
fig = px.scatter(training, y="campaign", x="duration", color="y")
fig.show()
```

In [108]:
```
#Crosstab to display default stats with respect to y  class variable
pd.crosstab(index=training["campaign"], columns=training["y"])
```

Out[108]:

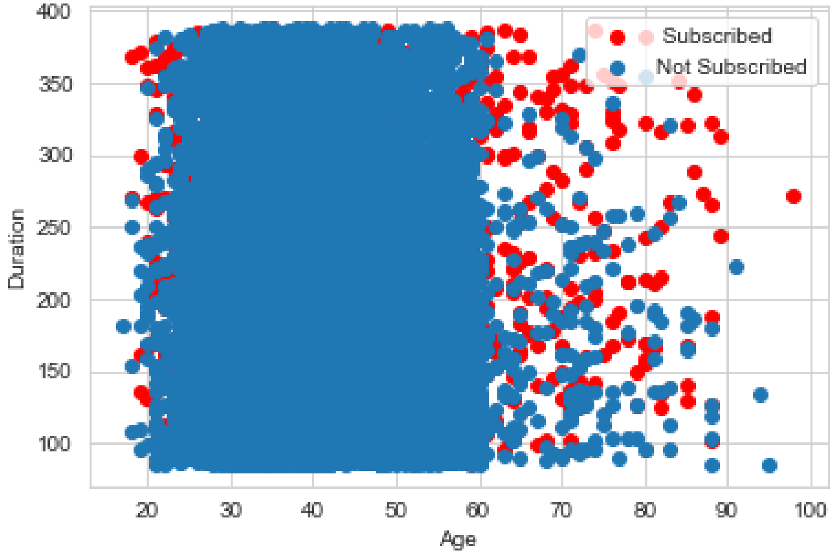
y campaign	no	yes
1	6825	705
2	4248	326
3	2014	139

campaign: is a number of contacts to client

Duration: is last contact duration, in seconds

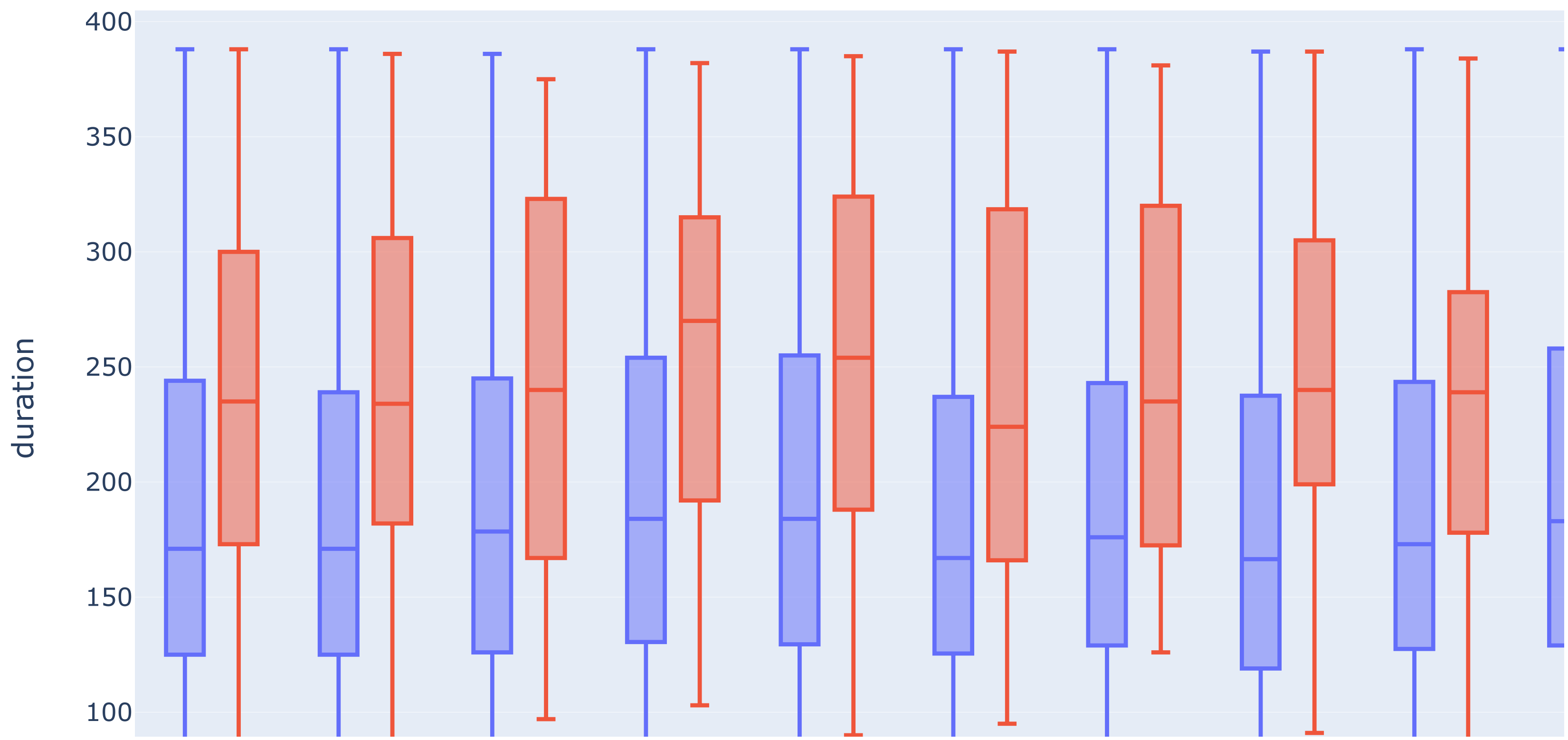
As more as employees contacted customers the less likely they made deposit

In [109]:
```
plt.scatter(x=training.age[training.y=='yes'], y=training.duration[(training.y=='yes')], c="red")
plt.scatter(x=training.age[training.y=='no'], y=training.duration[(training.y=='no')])
plt.legend([" Subscribed", "Not Subscribed"])
plt.xlabel("Age")
plt.ylabel("Duration")
plt.show()
```



In [110]:

```
fig = px.box(training, x="job", y="duration", color="y")
fig.update_traces(quartilemethod="exclusive")
fig.show()
```



The longer conversation with clients , the more likly they made deposit.

Comparing the median, the blue collar, entrepreneur and services had high duration of calls

Categorical Treatment

The dataset contains object type variables using sklearn's preprocessing tool I will encode all variables to numerical labels.

In [111]:
```
#build a new dataframe containing only the object columns.
obj_bank = training.select_dtypes(include=['object']).copy()
obj_bank.head()
```

Out[111]:

	job	marital	education	default	housing	loan	contact	month	day_of_week	poutcome	y
8726	admin.	single	high.school	no	no	no	telephone	jun	wed	nonexistent	no
37287	admin.	married	high.school	no	yes	no	cellular	aug	mon	success	yes
20981	technician	single	university.degree	no	yes	no	cellular	aug	thu	nonexistent	no
36959	admin.	single	university.degree	no	yes	no	cellular	jul	thu	nonexistent	yes
36423	student	single	high.school	no	no	no	cellular	jun	tue	nonexistent	yes

In [112]:
```
training["month"].value_counts()
```

Out[112]:
```
may    4913
aug    2186
jul    2171
jun    1695
nov    1506
apr     954
oct     321
mar     232
sep     226
dec      53
Name: month, dtype: int64
```

In [113]:
```
training.head()
```

Out[113]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaig
8726	39	admin.	single	high.school	no	no	no	telephone	jun	wed	172.0	
37287	33	admin.	married	high.school	no	yes	no	cellular	aug	mon	252.0	
20981	32	technician	single	university.degree	no	yes	no	cellular	aug	thu	118.0	
36959	46	admin.	single	university.degree	no	yes	no	cellular	jul	thu	309.0	
36423	23	student	single	high.school	no	no	no	cellular	jun	tue	310.0	

In [114]:
```
training["day_of_week"].value_counts()
```

Out[114]:
```
thu    2987
tue    2972
mon    2938
wed    2856
fri    2504
Name: day_of_week, dtype: int64
```

In [115]:
```python
#I will be converting the month and day by it's corresponding number for training set
month_dict={'may':5,'jul':7,'aug':8,'jun':6,'nov':11,'apr':4,'oct':10,'sep':9,'mar':3,'dec':12}
training['month']= training['month'].map(month_dict)

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

Out[115]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaigı
8726	39	admin.	single	high.school	no	no	no	telephone	6	4	172.0	[illegible]
37287	33	admin.	married	high.school	no	yes	no	cellular	8	2	252.0	[illegible]
20981	32	technician	single	university.degree	no	yes	no	cellular	8	5	118.0	[illegible]
36959	46	admin.	single	university.degree	no	yes	no	cellular	7	5	309.0	[illegible]
36423	23	student	single	high.school	no	no	no	cellular	6	3	310.0	[illegible]

In [116]:

```
#I will be converting the month and day by it's corresponding number for testing set
month_dict={'may':5,'jul':7,'aug':8,'jun':6,'nov':11,'apr':4,'oct':10,'sep':9,'mar':3,'dec':12}
testing['month']= testing['month'].map(month_dict)

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

Out[116]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campai
37499	32	services	married	high.school	no	no	no	cellular	8	5	100.0	
23884	43	technician	married	high.school	no	yes	no	cellular	8	6	60.0	
32970	27	services	married	basic.9y	no	yes	no	cellular	5	2	220.0	
30374	28	admin.	married	university.degree	no	no	no	cellular	4	5	115.0	
12442	42	housemaid	divorced	basic.4y	unknown	no	no	cellular	7	2	461.0	

In [117]:
```
#The dataset contains nine object type variables. I will use
#a custom function by sklearn's preprocessing tool
#to convert all nine variables to numerical labels for training set.
LabEn=LabelEncoder()

categorical_var=['job','marital', 'education','contact', 'poutcome', 'housing','default','loan','y']
for i in categorical_var:
    training[i]=LabEn.fit_transform(training[i])

training.head()
```

Out[117]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	poutcome
8726	39	0	2	1	0	0	0	1	6	4	172.0	2	1
37287	33	0	1	1	0	1	0	0	8	2	252.0	1	2
20981	32	9	2	3	0	1	0	0	8	5	118.0	2	1
36959	46	0	2	3	0	1	0	0	7	5	309.0	1	1
36423	23	8	2	1	0	0	0	0	6	3	310.0	1	1

In [118]:

```
#The dataset contains nine object type variables. I will use a custom function by sklearn's preproce
#to convert all nine variables to numerical labels for testing set.
LabEn=LabelEncoder()

categorical_var=['job','marital', 'education','contact', 'poutcome', 'housing','default','loan','y']
for i in categorical_var:
    testing[i]=LabEn.fit_transform(testing[i])

testing.head()
```

Out[118]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	poutcome
37499	32	7	1	3	0	0	0	0	8	5	100.0	1	1
23884	43	9	1	3	0	2	0	0	8	6	60.0	1	1
32970	27	7	1	2	0	2	0	0	5	2	220.0	2	1
30374	28	0	1	6	0	0	0	0	4	5	115.0	2	0
12442	42	3	0	0	1	0	0	0	7	2	461.0	2	1

In [119]:
```
#Checking if I didn't get any NaN valeuse when new lebels was created in training set
training.isna().sum()
```

Out[119]:
```
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
poutcome          0
cons.price.idx    0
nr.employed       0
y                 0
dtype: int64
```

In [120]:
```
#Checking if I didn't get any NaN valeuse when new lebels was created in testing set
testing.isna().sum()
```

Out[120]:
```
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
poutcome          0
cons.price.idx    0
nr.employed       0
y                 0
dtype: int64
```

Divide the dataset to training (X_train, y_train) and test (X_test, y_test)sets.

My data set alredy divided into 2 portions in the ratio of 70:30, my target variable is ‘y’

In [121]:
```
X_train= training.drop("y",axis=1)
y_train= training["y"]
```

In [122]:
```
X_test= testing.drop("y",axis=1)
y_test= testing["y"]
```

In [123]:
```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

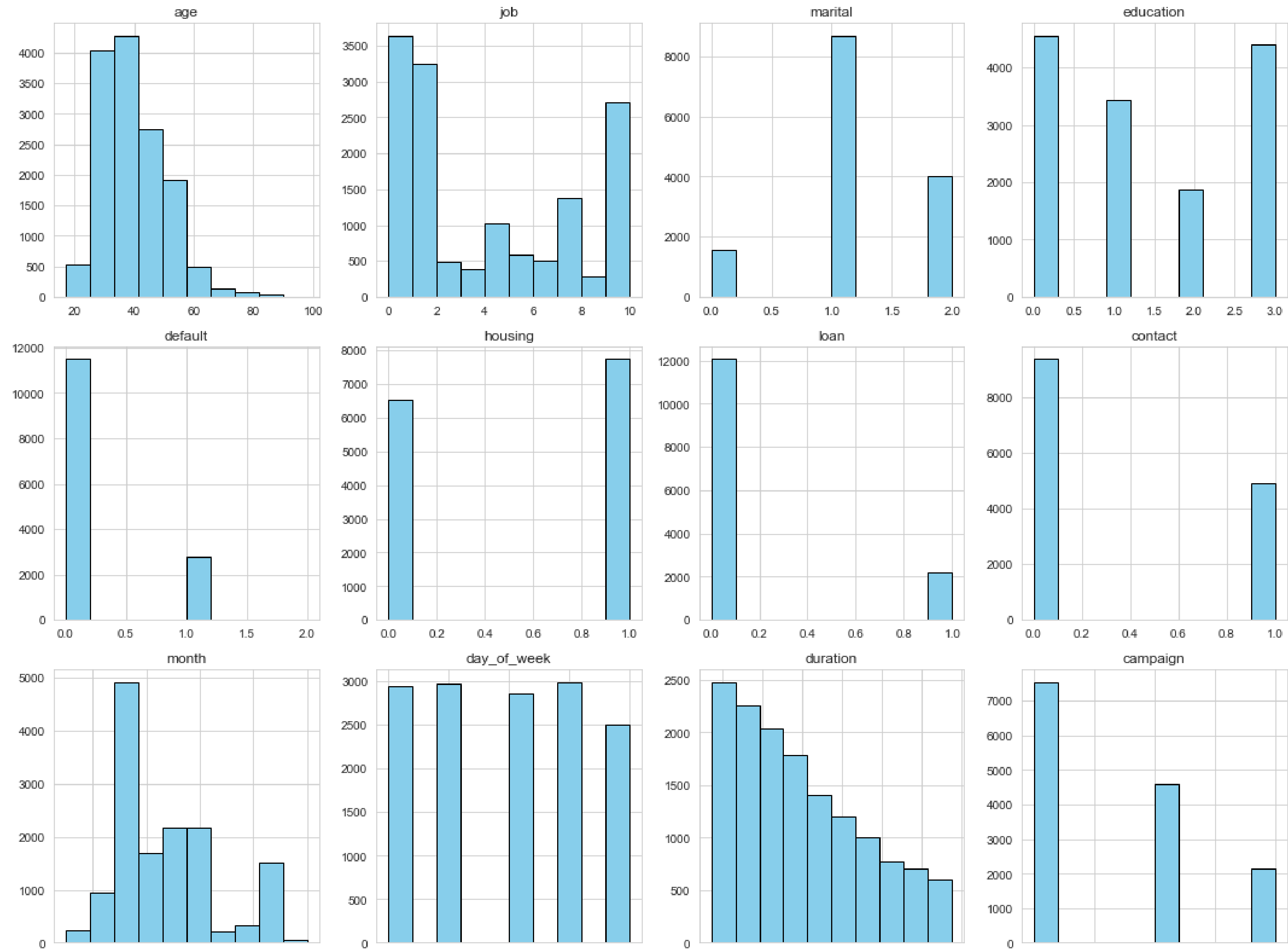
```
(14257, 15)
(14257,)
(12357, 15)
(12357,)
```

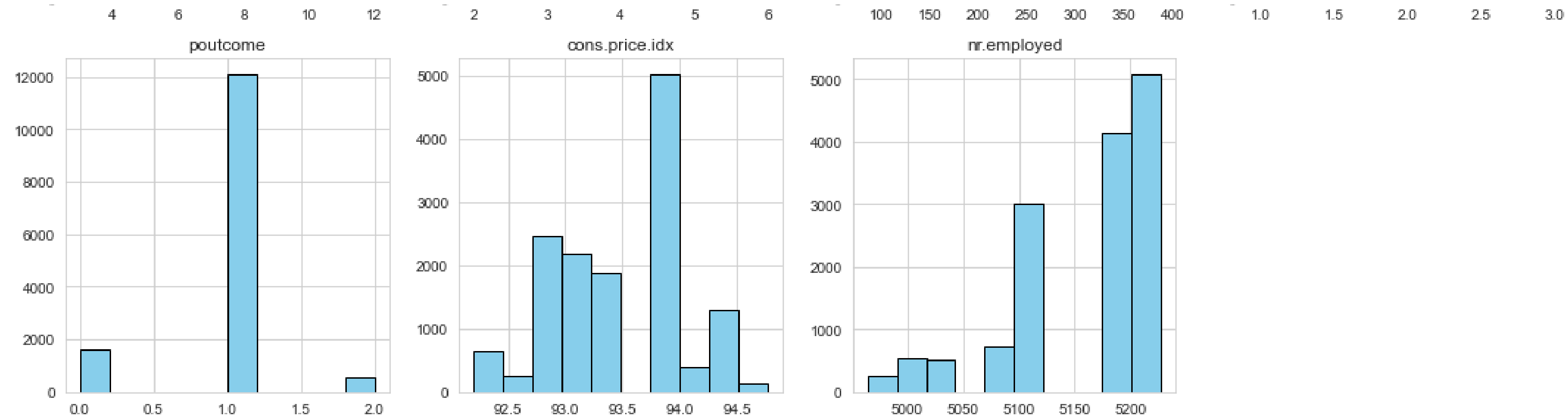
In [124]:
```
y_test.head()
```

Out[124]:
```
37499    0
23884    0
32970    0
30374    0
12442    0
Name: y, dtype: int32
```

Scaling I have tried to rescale with StandardScaler(centering the variable at zero and standardizing the variance at 1) was no effect on the algorithms and I have tried PowerTransformer(method='yeo-johnson'), had no prediction of class 1 of recall and precision. Normalization (Min-Max Scalar) technic will not work as this data doesn't need to suppress outliers, I already deleted them and more than that will cause algorithms to perform worse.

In [125]:
```python
# histograms of the variables
#Histogram for the numerical attributes
X_train.hist(figsize=(15,15),edgecolor='k',color='skyblue')
plt.tight_layout()
plt.show()
```





Oversampling using SMOTE

I will over sample only on the training data, so no information bleed from test data into the model training.

In [134]:
```
counter = Counter(y_train)
```

In [135]:
```
print("Before SMOTE", counter)
```

```
Before SMOTE Counter({0: 13087, 1: 13087})
```

In [136]:
```
smt = SMOTE()
```

In [137]:
```
X_train,y_train = smt.fit_resample(X_train,y_train)
```

In [138]:
```
print("After SMOTE", Counter(y_train))
```

```
After SMOTE Counter({0: 13087, 1: 13087})
```

In [139]:
```
y_train.isna().sum()
```

Out[139]:
```
0
```

In [140]:
```
y_test.isna().sum()
```
Out[140]:
```
0
```
In [141]:
```
y_test.isin([0]).any().any()
```
Out[141]:
```
True
```
In [142]:
```
y_train.isin([0]).any().any()
```
Out[142]:
```
True
```
In [143]:
```
print(Counter(y_test))
```
```
Counter({0: 10949, 1: 1408})
```
In [144]:
```
y_train.shape
```
Out[144]:
```
(26174,)
```
In [145]:
```
X_train.shape
```
Out[145]:
```
(26174, 15)
```
In [146]:
```
X_test.shape
```
Out[146]:
```
(12357, 15)
```
In [147]:
```
y_test.shape
```
Out[147]:
```
(12357,)
```

Classification with all Features

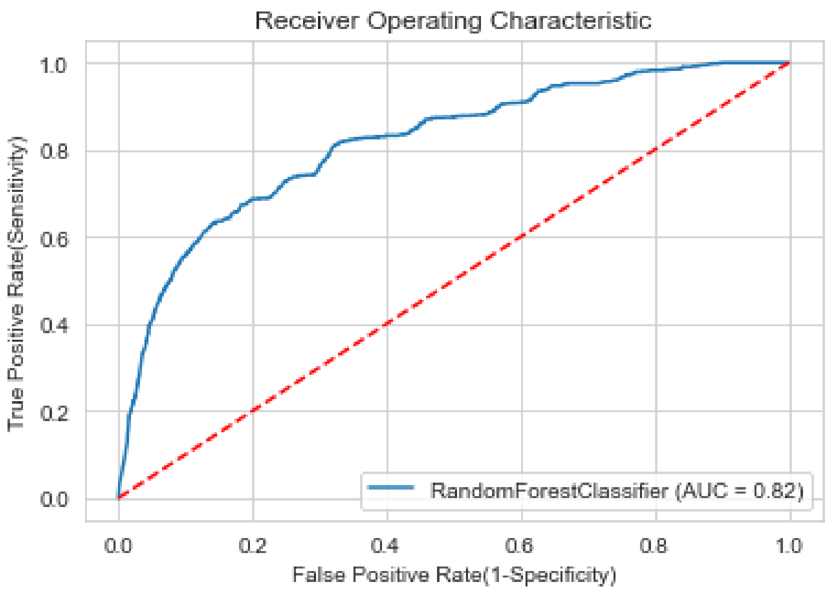
RandomForest with all 15 Features

In [148]:
```
#see the classification performance of the Random Forest using  all 15 features
# To improve the results of RF I tested n_estimators for 40,50,100,200,10000
#with max_depth of 2, 3 and 4

FullRandFor = RandomForestClassifier(n_estimators=50, random_state=43, max_depth=3)
FullRandFor.fit(X_train, y_train)

fulltrainpred = FullRandFor.predict_proba(X_train)
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, fulltrainpred[:,1])))

fulltestpred = FullRandFor.predict_proba(X_test)
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, fulltestpred[:,1])))
```

```
Accuracy on training set: 0.9523342351611803
Accuracy on test set: 0.8168103056837901
```

In [149]:
```
# draw the ROC-AUC chart
metrics.plot_roc_curve(FullRandFor, X_test, y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[149]:
```
Text(0.5, 0, 'False Positive Rate(1-Specificity)')
```



In [150]:
```
pred6 = FullRandFor.predict(X_test)
```

In [151]:
```python
print("Random Forest with all 15 Features")
cm = confusion_matrix(y_test, pred6)
print(cm)
print('\n')
print(classification_report(y_test,pred6))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
Random Forest with all 15 Features
[[9635 1314]
 [ 569  839]]


              precision    recall  f1-score   support

           0       0.94      0.88      0.91     10949
           1       0.39      0.60      0.47      1408

    accuracy                           0.85     12357
   macro avg       0.67      0.74      0.69     12357
weighted avg       0.88      0.85      0.86     12357

TP:  839 , FP:  1314 , TN:  9635 , FN: 569
```

In [152]:
```python
fulltestpred = FullRandFor.predict_proba(X_test)
prob3 = fulltestpred[:, 1]# Keeping only the values in positive label
```

In [153]:
```python
#The average precision (PR AUC) is returned by passing the
#true label & the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob3)
print(PR_AUC)
```

```
0.4176864591176433
```

In [154]:
```
#Brier skill score calculates the mean squared error between predicted
#probabilities and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0 and the worst
#has a score of 1.0. From this score, we can infer that our model
#has good performance or skill.
loss = brier_score_loss(y_test, prob3)
loss
```

Out[154]:
```
0.12267848756224509
```

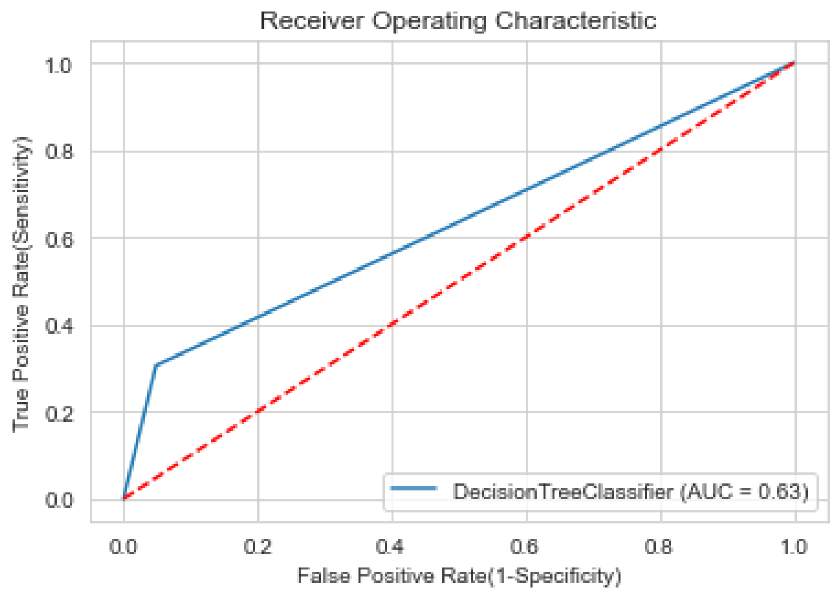
Decision Tree with all 15 Features

In [155]:
```
%%time
dtree15 = DecisionTreeClassifier()
dtree15.fit(X_train, y_train)

train_pred15 = dtree15.predict_proba(X_train)
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, train_pred15[:,1])))

test_pred15 = dtree15.predict_proba(X_test)
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, test_pred15[:,1])))
```

```
Accuracy on training set: 1.0
Accuracy on test set: 0.6284957400634347
Wall time: 144 ms
```

In [156]:
```python
# draw the ROC-AUC chart
metrics.plot_roc_curve(dtree15,X_test,y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[156]:
```
Text(0.5, 0, 'False Positive Rate(1-Specificity)')
```



In [157]:
```python
pred15 = dtree15.predict(X_test)
```

In [158]:
```python
print("DecisionTree with all 15 Features")
cm = confusion_matrix(y_test, pred15)
print(cm)
print('\n')
print(classification_report(y_test,pred15))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
DecisionTree with all 15 Features
[[10419   530]
 [  978   430]]


              precision    recall  f1-score   support

           0       0.91      0.95      0.93     10949
           1       0.45      0.31      0.36      1408

    accuracy                           0.88     12357
   macro avg       0.68      0.63      0.65     12357
weighted avg       0.86      0.88      0.87     12357

TP:  430 , FP:  530 , TN:  10419 , FN: 978
```

In [159]:
```python
test_pred15 = dtree15.predict_proba(X_test)
prob15 = test_pred15[:, 1]# Keeping only the values in positive label
```

In [160]:
```python
#The average precision (PR AUC) is returned by passing t
#he true label & the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob15)
print(PR_AUC)
```

```
0.2159381556540919
```

In [161]:
```
#Brier skill score calculates the mean squared error between
#predicted probabilities and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0 and the worst has a score of 1.0
#From this score, we can infer that our model has good performance or skill.
loss15 = brier_score_loss(y_test, prob15)
loss15
```

Out[161]:
```
0.12203609290280812
```

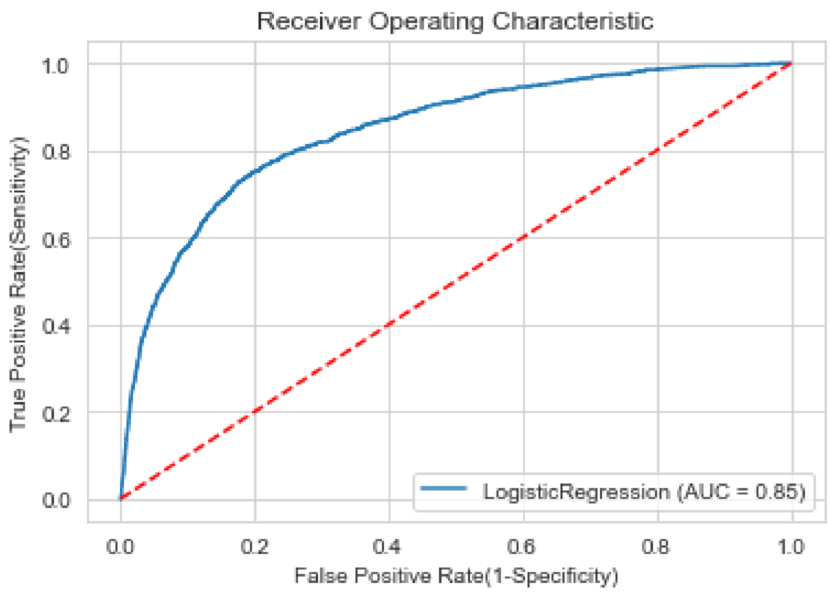
Logistic Regression with with all 15 Features

In [162]:
```
#Logistic Regression

LR15 = LogisticRegression (solver='liblinear')
LR15.fit(X_train, y_train)

LRtrain_pred15 = LR15.predict_proba(X_train)
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, LRtrain_pred15[:,1])))

LRtest_pred15 = LR15.predict_proba(X_test)
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, LRtest_pred15[:,1])))
```

```
Accuracy on training set: 0.9307314833027927
Accuracy on test set: 0.8458204853701874
```

In [163]:
```python
# draw the ROC-AUC chart
metrics.plot_roc_curve(LR15, X_test, y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[163]:
```
Text(0.5, 0, 'False Positive Rate(1-Specificity)')
```



In [164]:
```
pred16 = LR15.predict(X_test)
```

In [165]:
```
print("LogisticRegression with all 15 Features")
cm = confusion_matrix(y_test, pred16)
print(cm)
print('\n')
print(classification_report(y_test,pred16))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
LogisticRegression with all 15 Features
[[9467 1482]
 [ 481  927]]


              precision    recall  f1-score   support

           0       0.95      0.86      0.91     10949
           1       0.38      0.66      0.49      1408

    accuracy                           0.84     12357
   macro avg       0.67      0.76      0.70     12357
weighted avg       0.89      0.84      0.86     12357

TP:  927 , FP:  1482 , TN:  9467 , FN: 481
```

In [166]:
```
LRtest_pred15 = LR15.predict_proba(X_test)
prob16 = LRtest_pred15[:, 1]# Keeping only the values in positive label
```

In [167]:
```
#The average precision (PR AUC) is returned by passing the true label & the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob16)
print(PR_AUC)
```

```
0.4606694341877773
```

In [168]:
```
#Brier skill score calculates the mean squared error between predicted
#probabilities and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0 and the
#worst has a score of 1.0. From this score, we can infer that our model
#has good performance or skill.
loss16 = brier_score_loss(y_test, prob16)
loss16
```

Out[168]:
```
0.11792448625154493
```

Clasification with Filter Methods for Feature Selection-Mutual Information Gain

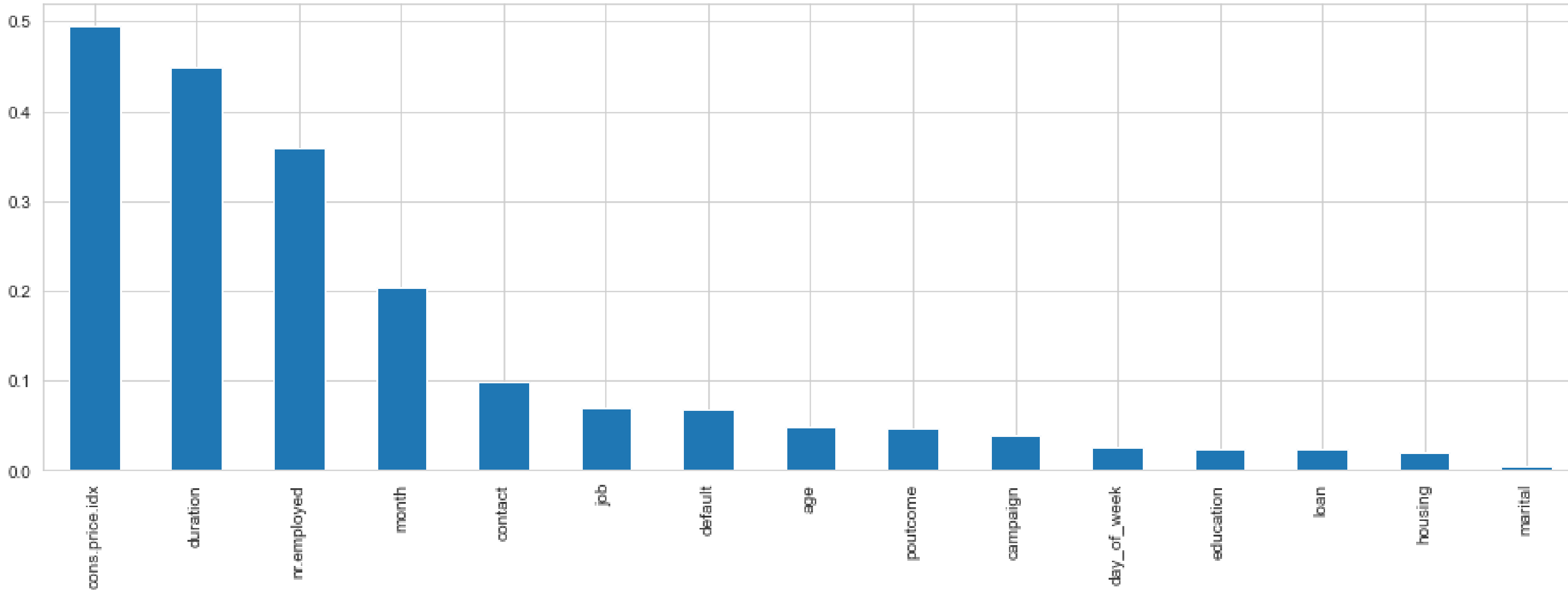
In [169]:
```
#I have tested deferent qty  of Features and found that 10  has the best accuracy for all algorithms

MI=mutual_info_classif(X_train, y_train)
```

In [170]:
```
len(MI)
```

Out[170]:
```
15
```

In [171]:
```
MI = pd.Series(MI)
MI.index = X_train.columns
```

In [172]:
```
MI.sort_values(ascending=False, inplace = True)
```

In [173]:
```
MI.plot.bar(figsize = (16,5))
```
Out[173]:
```
<AxesSubplot:>
```


In [174]:
```
#percentile=65
sel = SelectPercentile(mutual_info_classif, percentile=65).fit(X_train, y_train)
X_train.columns[sel.get_support()]
```
Out[174]:
```
Index(['age', 'job', 'default', 'contact', 'month', 'duration', 'campaign',
       'poutcome', 'cons.price.idx', 'nr.employed'],
      dtype='object')
```

In [175]:
```
len(X_train.columns[sel.get_support()])
```

Out[175]:
```
10
```

In [176]:
```
X_trainMI = sel.transform(X_train)
X_testMI = sel.transform(X_test)
```

In [177]:
```
X_trainMI.shape
```

Out[177]:
```
(26174, 10)
```

In [178]:
```
X_testMI.shape
```

Out[178]:
```
(12357, 10)
```

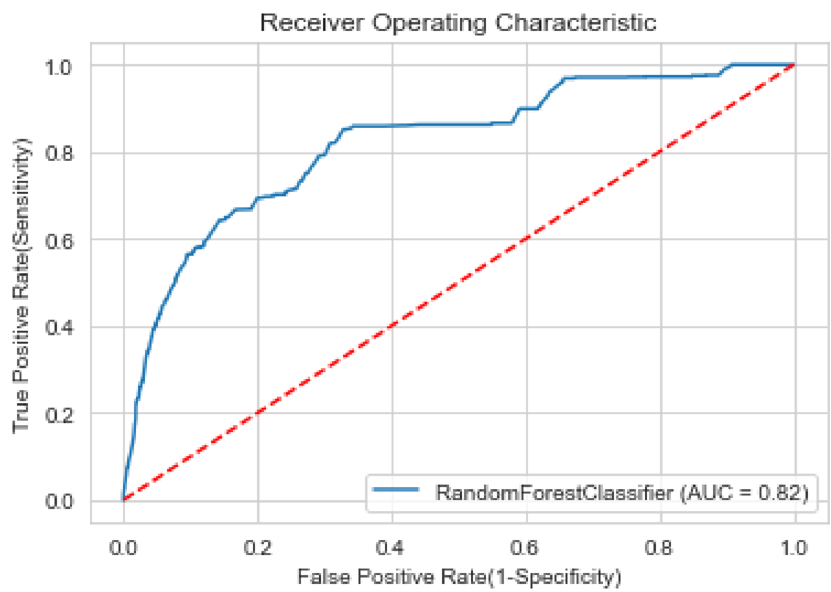
Random Forests with Mutual Information Gain-Filter

In [179]:
```
## To improve the results of RF I tested n_estimators for 40,50,100,200,10000
#with max_depth of 2, 3 and 4 and found that
#n_estimators=50 and max_depth=3 is the best combination.

RandFor = RandomForestClassifier(n_estimators=50, random_state=41, max_depth=3)
RandFor.fit(X_trainMI, y_train)

trainpred = RandFor.predict_proba(X_trainMI)
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, trainpred[:,1])))

testpred = RandFor.predict_proba(X_testMI)
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, testpred[:,1])))
```

```
Accuracy on training set: 0.953537621735943
Accuracy on test set: 0.8196679504251115
```

In [180]:
```python
# draw the ROC-AUC chart
metrics.plot_roc_curve(RandFor,X_testMI,y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[180]: Text(0.5, 0, 'False Positive Rate(1-Specificity)')



In [181]:
```python
pred3 = RandFor.predict(X_testMI)
```

In [182]:
```
print("RandomForest with Mutual Information Gain")
cm = confusion_matrix(y_test, pred3)
print(cm)
print('\n')
print(classification_report(y_test,pred3))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
RandomForest with Mutual Information Gain
[[9664 1285]
 [ 588  820]]


              precision    recall  f1-score   support

           0       0.94      0.88      0.91     10949
           1       0.39      0.58      0.47      1408

    accuracy                           0.85     12357
   macro avg       0.67      0.73      0.69     12357
weighted avg       0.88      0.85      0.86     12357

TP:  820 , FP:  1285 , TN:  9664 , FN: 588
```

In [183]:
```
#our aim is to find the brier score loss, so we will first
#calculate the probabilities for each data entry in
#X using the predict_proba() function.
```

In [184]:
```
testpred = RandFor.predict_proba(X_testMI)
prob = testpred[:, 1]# Keeping only the values in positive label
```

In [185]:
```
#The average precision (PR AUC) is returned by passing the true label & the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob)
print(PR_AUC)
```

```
0.4249346199507228
```

In [186]:
```
#Brier skill score calculates the mean squared error between predicted
#probabilities and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0 and the worst has a score of 1.0
#From this score, we can infer that our model has good performance or skill.
loss = brier_score_loss(y_test, prob)
loss
```

Out[186]:
```
0.11585612560436982
```

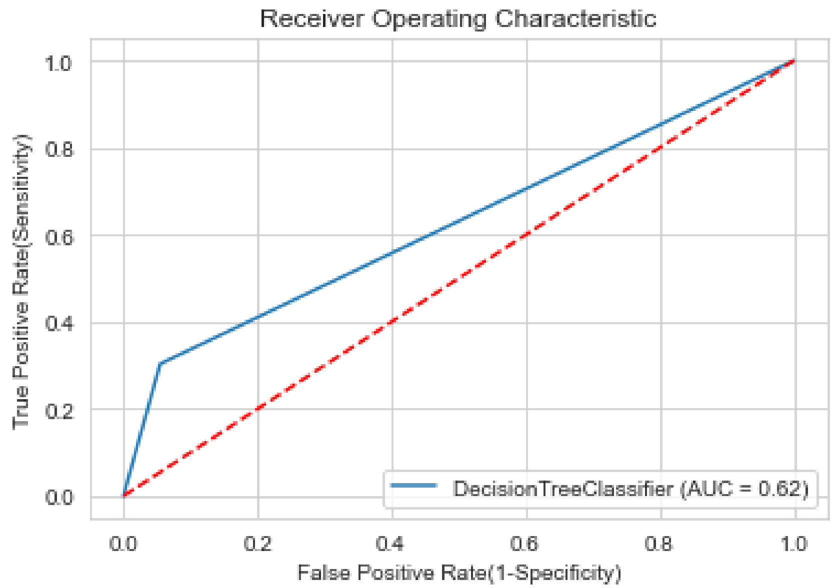
Decision Tree with Mutual Information Gain-Filter

In [187]:
```
%%time
dtreeMI = DecisionTreeClassifier()
dtreeMI.fit(X_trainMI, y_train)

train_predMI = dtreeMI.predict_proba(X_trainMI)
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, train_predMI[:,1])))

test_predMI = dtreeMI.predict_proba(X_testMI)
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, test_predMI[:,1])))
```

```
Accuracy on training set: 0.9999999883225023
Accuracy on test set: 0.624325092733666
Wall time: 120 ms
```

In [188]:
```python
# draw the ROC-AUC chart
metrics.plot_roc_curve(dtreeMI,X_testMI,y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[188]: Text(0.5, 0, 'False Positive Rate(1-Specificity)')



In [189]:
```python
pred4 = dtreeMI.predict(X_testMI)
```

In [190]:

```
print("DecisionTree with Mutual Information Gain")
cm = confusion_matrix(y_test, pred4)
print(cm)
print('\n')
print(classification_report(y_test,pred4))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
DecisionTree with Mutual Information Gain
[[10351   598]
 [  981   427]]


              precision    recall  f1-score   support

           0       0.91      0.95      0.93     10949
           1       0.42      0.30      0.35      1408

    accuracy                           0.87     12357
   macro avg       0.67      0.62      0.64     12357
weighted avg       0.86      0.87      0.86     12357

TP:  427 , FP:  598 , TN:  10351 , FN: 981
```

In [191]:

```
test_predMI = dtreeMI.predict_proba(X_testMI)
prob1 = test_predMI[:, 1]# Keeping only the values in positive label
```

In [192]:

```
#The average precision (PR AUC) is returned by passing the true
#label & the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob1)
print(PR_AUC)
```

```
0.2057248141017049
```

In [193]:
```
#Brier skill score calculates the mean squared error between predicted
#probabilities and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0 and the worst has a score of 1.0
#From this score, we can infer that our model has good performance or skill.
loss = brier_score_loss(y_test, prob1)
loss
```

Out[193]:
```
0.12778182406733027
```

Logistic Regression with Mutual Information Gain-Filter

In [194]:
```
#Logistic Regression

LR = LogisticRegression (solver='liblinear')
LR.fit(X_trainMI, y_train)

LRtrain_predMI = LR.predict_proba(X_trainMI)
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, LRtrain_predMI[:,1])))

LRtest_predMI = LR.predict_proba(X_testMI)
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, LRtest_predMI[:,1])))
```

```
Accuracy on training set: 0.9206626251275263
Accuracy on test set: 0.8747525329212299
```

In [195]:
```
# draw the ROC-AUC chart
metrics.plot_roc_curve(LR, X_testMI, y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[195]:
```
Text(0.5, 0, 'False Positive Rate(1-Specificity)')
```

In [196]:
```
pred5 = LR.predict(X_testMI)
```

In [197]:
```
print("LogisticRegression with Mutual Information Gain")
cm = confusion_matrix(y_test, pred5)
print(cm)
print('\n')
print(classification_report(y_test,pred5))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
LogisticRegression with Mutual Information Gain
[[9057 1892]
 [ 295 1113]]


              precision    recall  f1-score   support

           0       0.97      0.83      0.89     10949
           1       0.37      0.79      0.50      1408

    accuracy                           0.82     12357
   macro avg       0.67      0.81      0.70     12357
weighted avg       0.90      0.82      0.85     12357

TP:  1113 , FP:  1892 , TN:  9057 , FN: 295
```

In [198]:
```
LRtest_predMI = LR.predict_proba(X_testMI)
prob2 = LRtest_predMI[:, 1]# Keeping only the values in positive label
```

In [199]:
```
#The average precision (PR AUC) is returned by passing the true label & the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob2)
print(PR_AUC)
```

```
0.5125266956993272
```

In [200]:
```
#Brier skill score calculates the mean squared error between predicted
#probabilities and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0 and the worst has a score of 1.0
#From this score, we can infer that our model has good performance or skill.
loss = brier_score_loss(y_test, prob2)
loss
```

Out[200]:
```
0.1293542950168066
```

Classification Embedded Methods -LASSO Regularization (L1):

These methods encompass the benefits of both the wrapper and filter methods

In [201]:
```
# I have tested to find the best accuracy rate match of C = 0.002, 0.003, 0.01, 0.1, 0.5
#with max_inter = 10000 and execution time is 39.8s
#max_inter = 10000 was chosen because of the warning "ConvergenceWarning: Liblinear failed to conver
#increase the number of iterations."

Sel = SelectFromModel(LogisticRegression(penalty ='l1', C = 0.001, solver ='liblinear',max_iter=1000
```

In [202]:
```

Sel.fit(X_train, y_train)
Sel.get_support()
```

Out[202]:
```
array([ True, False, False, False, False, False, False,  True,  True,
        True,  True,  True, False,  True,  True])
```

In [203]:
```
Sel.estimator_.coef_
```

Out[203]:
```
array([[ 0.00420017,  0.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        , -0.17118194,  0.01367026, -0.01625258,
         0.00576764, -0.17479321,  0.        ,  1.03794329, -0.01915929]])
```

In [204]:
```
X_train_l1 = Sel.transform(X_train)
X_test_l1 = Sel.transform(X_test)
X_train_l1.shape
```

Out[204]:
```
(26174, 8)
```

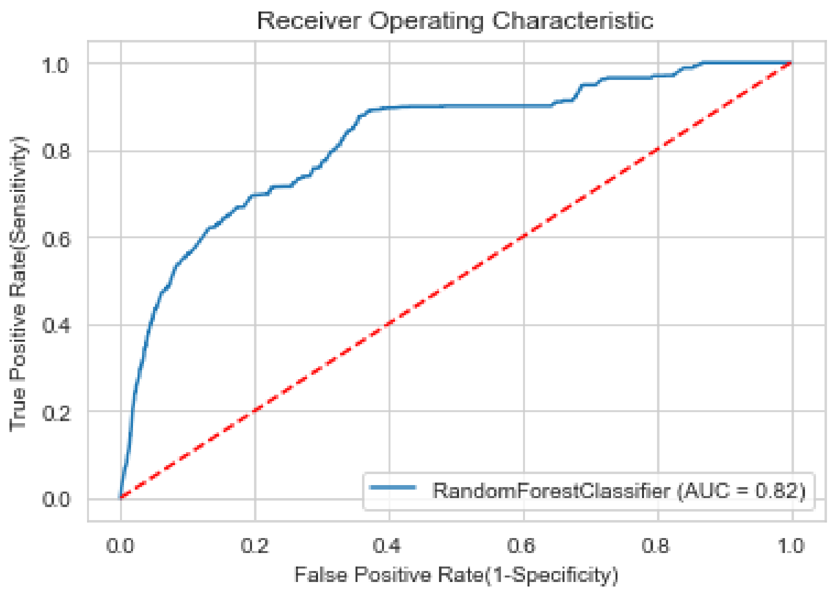
Random Forest with LASSO Regularization (L1)

In [205]:
```
# To improve the results of RF I tested n_estimators for 40,50,100,200,10000
#with max_depth of 2, 3 and 4

L1RandFor = RandomForestClassifier(n_estimators=50, random_state=43, max_depth=3)
L1RandFor.fit(X_train_l1, y_train)

L1trainpred = L1RandFor.predict_proba(X_train_l1)
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, L1trainpred[:,1])))

L1testpred = L1RandFor.predict_proba(X_test_l1)
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, L1testpred[:,1])))
```

```
Accuracy on training set: 0.9549040057431336
Accuracy on test set: 0.8238520900621892
```

In [206]:
```python
# draw the ROC-AUC chart
metrics.plot_roc_curve(L1RandFor, X_test_l1, y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[206]:
```
Text(0.5, 0, 'False Positive Rate(1-Specificity)')
```



In [207]:
```python
pred7 = L1RandFor.predict(X_test_l1)
```

In [208]:
```
print("RandomForest with LASSO Regularization (L1)")
cm = confusion_matrix(y_test, pred7)
print(cm)
print('\n')
print(classification_report(y_test,pred7))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
RandomForest with LASSO Regularization (L1)
[[9763 1186]
 [ 605  803]]


              precision    recall  f1-score   support

           0       0.94      0.89      0.92     10949
           1       0.40      0.57      0.47      1408

    accuracy                           0.86     12357
   macro avg       0.67      0.73      0.69     12357
weighted avg       0.88      0.86      0.87     12357

TP:  803 , FP:  1186 , TN:  9763 , FN: 605
```

In [209]:
```
L1testpred = L1RandFor.predict_proba(X_test_l1)
prob4 = L1testpred[:, 1]# Keeping only the values in positive label
```

In [210]:
```
#The average precision (PR AUC) is returned by passing the true label
#& the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob4)
print(PR_AUC)
```

```
0.41979331254235264
```

In [211]:
```
#Brier skill score calculates the mean squared error between predicted
#probabilities and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0 and the
#worst has a score of 1.0. From this score, we can infer that our model has good performance or skil
loss = brier_score_loss(y_test, prob4)
loss
```

Out[211]:
```
0.11472601804775759
```

Decision Tree with LASSO Regularization (L1)

In [212]:
```
%%time
dtreeL1 = DecisionTreeClassifier()
dtreeL1.fit(X_train_l1, y_train)

train_predL1 = dtreeL1.predict_proba(X_train_l1)
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, train_predL1[:,1])))

test_predL1 = dtreeL1.predict_proba(X_test_l1)
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, test_predL1[:,1])))
```

```
Accuracy on training set: 0.9999999737256301
Accuracy on test set: 0.6503772462096996
Wall time: 99.8 ms
```

In [213]:
```
# draw the ROC-AUC chart
metrics.plot_roc_curve(dtreeL1, X_test_l1, y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[213]:
```
Text(0.5, 0, 'False Positive Rate(1-Specificity)')
```

In [214]:
```
pred8= dtreeL1.predict(X_test_l1)
```

In [215]:
```
print("DecisionTree with LASSO Regularization (L1)")
cm = confusion_matrix(y_test, pred8)
print(cm)
print('\n')
print(classification_report(y_test,pred8))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
DecisionTree with LASSO Regularization (L1)
[[10394   555]
 [  913   495]]


              precision    recall  f1-score   support

           0       0.92      0.95      0.93     10949
           1       0.47      0.35      0.40      1408

    accuracy                           0.88     12357
   macro avg       0.70      0.65      0.67     12357
weighted avg       0.87      0.88      0.87     12357

TP:  495 , FP:  555 , TN:  10394 , FN: 913
```

In [216]:
```
test_predL1 = dtreeL1.predict_proba(X_test_l1)
prob5 = test_predL1[:, 1]# Keeping only the values in positive label
```

In [217]:
```
#The average precision (PR AUC) is returned by passing the true label & the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob5)
print(PR_AUC)
```

```
0.2396218543711488
```

In [219]:
```
#Brier skill score calculates the mean squared error between predicted probabilities
#and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0 and the worst has a score of 1.0
#From this score, we can infer that our model has good performance or skill.
loss = brier_score_loss(y_test, prob5)
loss
```

Out[219]:
```
0.11883952415634863
```

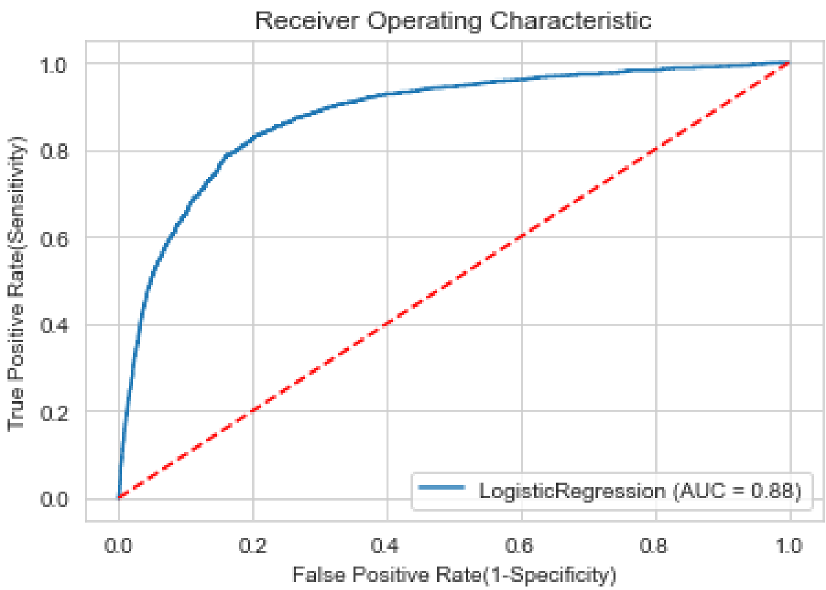
Logistic Regression with LASSO Regularization (L1)

In [220]:
```
logreg = LogisticRegression(solver='liblinear')
logreg.fit(X_train_l1, y_train)

train_predLR = logreg.predict_proba(X_train_l1)
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, train_predLR[:,1])))

test_predLR = logreg.predict_proba(X_test_l1)
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, test_predLR[:,1])))
```

```
Accuracy on training set: 0.9128377995743073
Accuracy on test set: 0.8792623042058636
```

In [221]:
```
# draw the ROC-AUC chart
metrics.plot_roc_curve(logreg, X_test_l1, y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[221]:
```
Text(0.5, 0, 'False Positive Rate(1-Specificity)')
```



In [222]:
```
pred9= logreg.predict(X_test_l1)
```

In [223]:
```
print("Logistic Regression with LASSO Regularization (L1)")
cm = confusion_matrix(y_test, pred9)
print(cm)
print('\n')
print(classification_report(y_test,pred9))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
Logistic Regression with LASSO Regularization (L1)
[[8976 1973]
 [ 277 1131]]


              precision    recall  f1-score   support

           0       0.97      0.82      0.89     10949
           1       0.36      0.80      0.50      1408

    accuracy                           0.82     12357
   macro avg       0.67      0.81      0.69     12357
weighted avg       0.90      0.82      0.84     12357

TP:  1131 , FP:  1973 , TN:  8976 , FN: 277
```

In [224]:
```
test_predLR = logreg.predict_proba(X_test_l1)
prob6 = test_predLR[:, 1]# Keeping only the values in positive label
```

In [225]:
```
#The average precision (PR AUC) is returned by passing the true label
#& the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob6)
print(PR_AUC)
```

```
0.5121310219511821
```

In [226]:
```
#Brier skill score calculates the mean squared error between predicted
#probabilities and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0 and the worst
#has a score of 1.0. From this score, we can infer that our model has good performance or skill.
loss = brier_score_loss(y_test, prob6)
loss
```

Out[226]:
```
0.13342312169106227
```

Classification with Wrapper Feature Selection - Forward feature selection

Filter methods measure the relevance of features by their correlation with dependent variable while wrapper methods measure the usefulness of a subset of feature by actually training a model on it.

In [227]:

```
# Build step forward feature selection
# estimator is  the RandomForestClassifieras   passes to the SequentialFeatureSelector function.
#The k_features specifies the number of features to select.  The forward parameter, set to True, per
#step forward feature selection. The verbose parameter is used for logging the progress of
#the feature selector, the scoring parameter defines the performance evaluation criteria
#cv refers to cross-validation folds.
sfs = SequentialFeatureSelector(RandomForestClassifier(n_jobs=-1),
           k_features=(1, 15),
           forward=True,
           verbose=2,
           scoring='roc_auc',
           cv=4)
```

In [228]:
```
# call the fit method on our feature selector
#480 seconds execution time

sfs1 = sfs.fit(np.array(X_train.fillna(0)), y_train)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    3.4s remaining:    0.0s
[Parallel(n_jobs=1)]: Done  15 out of  15 | elapsed:   20.2s finished

[2021-11-07 17:33:26] Features: 1/15 -- score: 0.972320454521692[Parallel(n_jobs=1)]: Using backe
nd SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    1.3s remaining:    0.0s
[Parallel(n_jobs=1)]: Done  14 out of  14 | elapsed:   18.5s finished

[2021-11-07 17:33:44] Features: 2/15 -- score: 0.975914616245537[Parallel(n_jobs=1)]: Using backe
nd SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    1.7s remaining:    0.0s
[Parallel(n_jobs=1)]: Done  13 out of  13 | elapsed:   22.2s finished

[2021-11-07 17:34:06] Features: 3/15 -- score: 0.9824320716420956[Parallel(n_jobs=1)]: Using back
end SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.2s remaining:    0.0s
[Parallel(n_jobs=1)]: Done  12 out of  12 | elapsed:   29.7s finished

[2021-11-07 17:34:36] Features: 4/15 -- score: 0.988020376371162[Parallel(n_jobs=1)]: Using backe
nd SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.4s remaining:    0.0s
[Parallel(n_jobs=1)]: Done  11 out of  11 | elapsed:   26.6s finished

[2021-11-07 17:35:03] Features: 5/15 -- score: 0.9902848974249361[Parallel(n_jobs=1)]: Using back
end SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.7s remaining:    0.0s
[Parallel(n_jobs=1)]: Done  10 out of  10 | elapsed:   22.4s finished

[2021-11-07 17:35:26] Features: 6/15 -- score: 0.9909083308793095[Parallel(n_jobs=1)]: Using back
end SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.1s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   9 out of   9 | elapsed:   19.7s finished
```

```
[2021-11-07 17:35:45] Features: 7/15 -- score: 0.9918592470182194[Parallel(n_jobs=1)]: Using back
end SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.1s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   8 out of   8 | elapsed:   17.7s finished

[2021-11-07 17:36:03] Features: 8/15 -- score: 0.992429870971381[Parallel(n_jobs=1)]: Using backe
nd SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.6s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   7 out of   7 | elapsed:   17.1s finished

[2021-11-07 17:36:20] Features: 9/15 -- score: 0.9930660534444601[Parallel(n_jobs=1)]: Using back
end SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.3s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   6 out of   6 | elapsed:   14.4s finished

[2021-11-07 17:36:35] Features: 10/15 -- score: 0.9935267275443798[Parallel(n_jobs=1)]: Using bac
kend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.3s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:   12.2s finished

[2021-11-07 17:36:47] Features: 11/15 -- score: 0.9939964134388621[Parallel(n_jobs=1)]: Using bac
kend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.4s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:   10.2s finished

[2021-11-07 17:36:57] Features: 12/15 -- score: 0.9942288727933337[Parallel(n_jobs=1)]: Using bac
kend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.5s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:    8.2s finished

[2021-11-07 17:37:06] Features: 13/15 -- score: 0.9943265474169658[Parallel(n_jobs=1)]: Using bac
kend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.5s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    5.0s finished

[2021-11-07 17:37:11] Features: 14/15 -- score: 0.9942224518934557[Parallel(n_jobs=1)]: Using bac
kend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.4s remaining:    0.0s
```

```
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.4s finished

[2021-11-07 17:37:13] Features: 15/15 -- score: 0.9940966099558906
```

In [229]:
```
pd.DataFrame.from_dict(sfs1 .get_metric_dict()).T
```

Out[229]:

	feature_idx	cv_scores	avg_score	feature_names	ci_bound	std_dev	std_err
1	(13,)	[0.959912278964736, 0.9770724951578482, 0.9773...	0.97232	(13,)	0.011581	0.007225	0.004171
2	(10, 13)	[0.9621772739432451, 0.9819556520913914, 0.979...	0.975915	(10, 13)	0.012806	0.007989	0.004612
3	(0, 10, 13)	[0.9774059535302874, 0.9848222265230362, 0.982...	0.982432	(0, 10, 13)	0.004789	0.002988	0.001725
4	(0, 9, 10, 13)	[0.980882046900126, 0.9900367402006205, 0.9908...	0.98802	(0, 9, 10, 13)	0.006622	0.004131	0.002385
5	(0, 9, 10, 13, 14)	[0.9827994792445047, 0.9926832974904503, 0.993...	0.990285	(0, 9, 10, 13, 14)	0.006936	0.004327	0.002498
6	(0, 1, 9, 10, 13, 14)	[0.9840913735720136, 0.9939235384622283, 0.993...	0.990908	(0, 1, 9, 10, 13, 14)	0.006424	0.004007	0.002314
7	(0, 1, 3, 9, 10, 13, 14)	[0.984537992957957, 0.9946913800730508, 0.9946...	0.991859	(0, 1, 3, 9, 10, 13, 14)	0.006813	0.00425	0.002454
8	(0, 1, 3, 8, 9, 10, 13, 14)	[0.983829510673657, 0.9954318538118496, 0.9957...	0.99243	(0, 1, 3, 8, 9, 10, 13, 14)	0.007985	0.004981	0.002876
9	(0, 1, 2, 3, 8, 9, 10, 13, 14)	[0.9848210589517039, 0.9962706370568086, 0.996...	0.993066	(0, 1, 2, 3, 8, 9, 10, 13, 14)	0.007668	0.004784	0.002762
10	(0, 1, 2, 3, 8, 9, 10, 11, 13, 14)	[0.985353144559155, 0.9971600461947263, 0.9965...	0.993527	(0, 1, 2, 3, 8, 9, 10, 11, 13, 14)	0.007666	0.004782	0.002761
11	(0, 1, 2, 3, 8, 9, 10, 11, 12, 13, 14)	[0.985485266931092, 0.9974400765030098, 0.9971...	0.993996	(0, 1, 2, 3, 8, 9, 10, 11, 12, 13, 14)	0.007932	0.004948	0.002857
12	(0, 1, 2, 3, 7, 8, 9, 10, 11, 12, 13, 14)	[0.9862860807563321, 0.9976227313621989, 0.997...	0.994229	(0, 1, 2, 3, 7, 8, 9, 10, 11, 12, 13, 14)	0.007417	0.004627	0.002672
13	(0, 1, 2, 3, 5, 7, 8, 9, 10, 11, 12, 13, 14)	[0.9861137005248654, 0.9974792601969141, 0.997...	0.994327	(0, 1, 2, 3, 5, 7, 8, 9, 10, 11, 12, 13, 14)	0.00762	0.004754	0.002745
14	(0, 1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 13, 14)	[0.9860760580251193, 0.9973389181227994, 0.997...	0.994222	(0, 1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 13, 14)	0.007566	0.00472	0.002725

	feature_idx	cv_scores	avg_score	feature_names	ci_bound	std_dev	std_err
15	(0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...	[0.9849549560320657, 0.9976654177700994, 0.997...	0.994097	(0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...	0.008483	0.005292	0.003056

In [230]:
```
sfs1.k_feature_names_
```

Out[230]:
```
('0', '1', '2', '3', '5', '7', '8', '9', '10', '11', '12', '13', '14')
```

In [231]:
```
#The best combination of features
sfs1.k_score_
```

Out[231]:
```
0.9943265474169658
```

In [232]:
```
filtered_features= X_train.columns[list(sfs1.k_feature_idx_)]
filtered_features
```

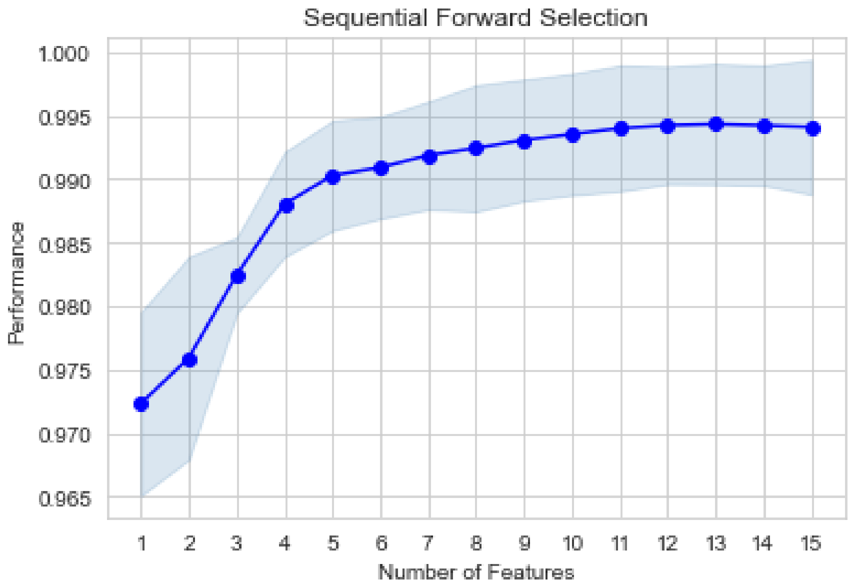
Out[232]:
```
Index(['age', 'job', 'marital', 'education', 'housing', 'contact', 'month',
       'day_of_week', 'duration', 'campaign', 'poutcome', 'cons.price.idx',
       'nr.employed'],
      dtype='object')
```

In [233]:
```
len(filtered_features)
```

Out[233]:
```
13
```

In [234]:

```
fig1 = plot_sfs(sfs1.get_metric_dict(), kind='std_dev')
plt.title('Sequential Forward Selection')
#plt.grid()
plt.show()
```

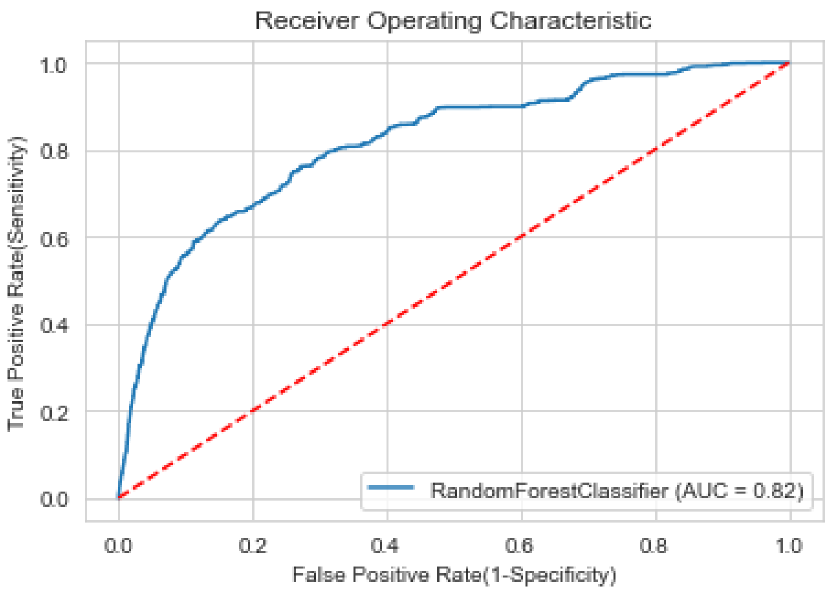


In [235]:
```
#see the classification performance of the Random Forest using  optimized
#amount of features that was chosen by forward feature selection.

# To improve the results of RF I tested n_estimators for 40,50,100,200,10000
#with max_depth of 2, 3 and 4

clf = RandomForestClassifier(n_estimators=50, random_state=41, max_depth=3)
clf.fit(X_train[filtered_features].fillna(0), y_train)

train_pred = clf.predict_proba(X_train[filtered_features].fillna(0))
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, train_pred[:,1])))

test_pred = clf.predict_proba(X_test[filtered_features].fillna(0))
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, test_pred [:,1])))
```

```
Accuracy on training set: 0.9522830205755933
Accuracy on test set: 0.8167046699989206
```

In [236]:
```
# draw the ROC-AUC chart
metrics.plot_roc_curve(clf, X_test[filtered_features], y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[236]:
```
Text(0.5, 0, 'False Positive Rate(1-Specificity)')
```



In [237]:
```
pred = clf.predict(X_test[filtered_features])
```

In [238]:
```
print("Random Forest with Forward feature selection")
cm = confusion_matrix(y_test, pred)
print(cm)
print('\n')
print(classification_report(y_test,pred))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
Random Forest with Forward feature selection
[[9745 1204]
 [ 602  806]]


              precision    recall  f1-score   support

           0       0.94      0.89      0.92     10949
           1       0.40      0.57      0.47      1408

    accuracy                           0.85     12357
   macro avg       0.67      0.73      0.69     12357
weighted avg       0.88      0.85      0.86     12357

TP:  806 , FP:  1204 , TN:  9745 , FN: 602
```

In [239]:
```
test_pred = clf.predict_proba(X_test[filtered_features].fillna(0))
prob7 = test_pred [:, 1]# Keeping only the values in positive label
```

In [240]:
```
#The average precision (PR AUC) is returned by passing the true
#label & the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob7)
print(PR_AUC)
```

```
0.4153532995903723
```

In [241]:
```
#Brier skill score calculates the mean squared error between
#predicted probabilities and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0
#and the worst has a score of 1.0
#From this score, we can infer that our model has good performance or skill.
loss = brier_score_loss(y_test, prob7)
loss
```

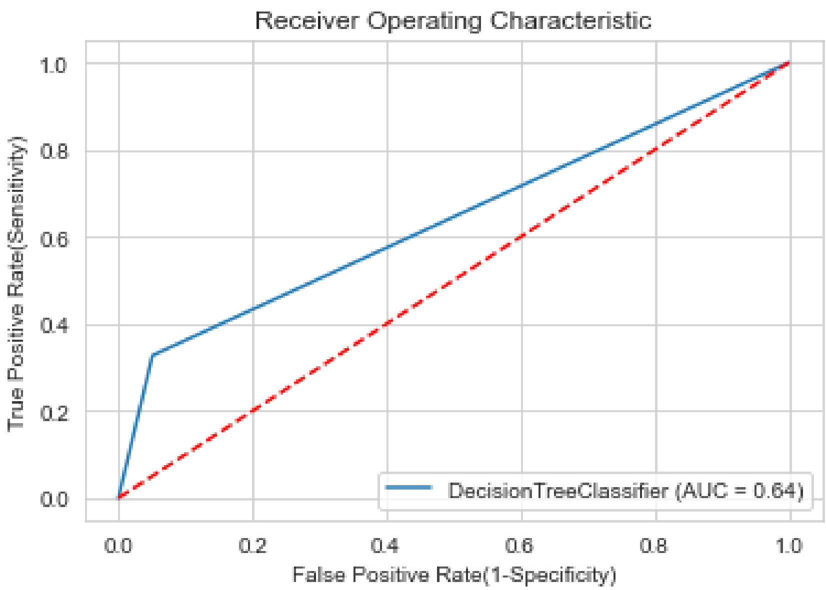
Out[241]:
```
0.11684326331451152
```

In [242]:
```
%%time
dtree = DecisionTreeClassifier()
dtree.fit(X_train[filtered_features], y_train)

train_predTree = dtree.predict_proba(X_train[filtered_features].fillna(0))
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, train_predTree[:,1])))

test_predTree = dtree.predict_proba(X_test[filtered_features].fillna(0))
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, test_predTree[:,1])))
```

```
Accuracy on training set: 1.0
Accuracy on test set: 0.6383626060183993
Wall time: 128 ms
```

In [243]:
```
# draw the ROC-AUC chart
metrics.plot_roc_curve(dtree, X_test[filtered_features], y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[243]:
```
Text(0.5, 0, 'False Positive Rate(1-Specificity)')
```



In [244]:
```
pred1 = dtree.predict(X_test[filtered_features])
```

In [245]:
```
print("DecisionTree with Forward feature selection")
cm = confusion_matrix(y_test, pred1)
print(cm)
print('\n')
print(classification_report(y_test,pred1))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
DecisionTree with Forward feature selection
[[10394   555]
 [  947   461]]


              precision    recall  f1-score   support

           0       0.92      0.95      0.93     10949
           1       0.45      0.33      0.38      1408

    accuracy                           0.88     12357
   macro avg       0.69      0.64      0.66     12357
weighted avg       0.86      0.88      0.87     12357

TP:  461 , FP:  555 , TN:  10394 , FN: 947
```

In [246]:
```
test_predTree = dtree.predict_proba(X_test[filtered_features].fillna(0))
prob8 = test_predTree[:, 1]# Keeping only the values in positive label
```

In [247]:
```
#The average precision (PR AUC) is returned by passing the true
#label & the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob8)
print(PR_AUC)
```

```
0.22519795466263254
```

In [248]:
```python
#Brier skill score calculates the mean squared error
#between predicted probabilities and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0 and the worst has a score of 1.0
#From this score, we can infer that our model has good performance or skill.
loss = brier_score_loss(y_test, prob8)
loss
```

Out[248]: 0.12155053815651048

In [249]:
```python
#Logistic Regression

LogitReg = LogisticRegression(solver='liblinear')
LogitReg.fit(X_train[filtered_features], y_train)

train_predReg = LogitReg .predict_proba(X_train[filtered_features].fillna(0))
print('Accuracy on training set: {}'.format(roc_auc_score(y_train, train_predReg[:,1])))

test_predReg = LogitReg .predict_proba(X_test[filtered_features].fillna(0))
print('Accuracy on test set: {}'.format(roc_auc_score(y_test, test_predReg [:,1])))
```

```
Accuracy on training set: 0.9207461075586638
Accuracy on test set: 0.8724195962271357
```

In [250]:
```
# draw the ROC-AUC chart
metrics.plot_roc_curve(LogitReg, X_test[filtered_features], y_test)
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(1-Specificity)')
```

Out[250]: Text(0.5, 0, 'False Positive Rate(1-Specificity)')

In [251]:
```
pred2 = LogitReg.predict(X_test[filtered_features])
```

In [252]:
```
print("Logistic Regression with Forward feature selection")
cm = confusion_matrix(y_test, pred2)
print(cm)
print('\n')
print(classification_report(y_test,pred2))
tn, fp, fn, tp=cm.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
Logistic Regression with Forward feature selection
[[9137 1812]
 [ 343 1065]]


              precision    recall  f1-score   support

           0       0.96      0.83      0.89     10949
           1       0.37      0.76      0.50      1408

    accuracy                           0.83     12357
   macro avg       0.67      0.80      0.70     12357
weighted avg       0.90      0.83      0.85     12357

TP:  1065 , FP:  1812 , TN:  9137 , FN: 343
```

In [253]:
```
test_predReg = LogitReg .predict_proba(X_test[filtered_features])
prob9 = test_predReg[:, 1]# Keeping only the values in positive label
```

In [254]:
```
#The average precision (PR AUC) is returned by passing the
#true label & the probability estimate.
# Average precision score
PR_AUC = average_precision_score(y_test, prob9)
print(PR_AUC)
```

```
0.5030885905314926
```

In [255]:
```
#Brier skill score calculates the mean squared error
#between predicted probabilities and the expected values(actuals).
#compute the Brier Score-perfect skill has a score of 0.0 and the worst has a score of 1.0
#From this score, we can infer that our model has good performance or skill.
loss = brier_score_loss(y_test, prob9)
loss
```

Out[255]:
```
0.12700417982419837
```

TP-True positives - are when you predict an observation belongs to a class and it actually does belong to that class.

FP-False positives - occur when you predict an observation belongs to a class when in reality it does not.

TN-True negatives - are when you predict an observation does not belong to a class and it actually does not belong to that class.

FN-False negatives - occur when you predict an observation does not belong to a class when in fact it does.

The confusion matrix is in the form of the array object. The dimension of the matrixes is 2*2 because the models are binary classification. It has two classes 0's that are "No" and 1's that are "Yes". Diagonal values represent accurate predictions, while non-diagonal elements are inaccurate predictions.

When to Use ROC vs. Precision-Recall Curves?

ROC curves should be used when there are roughly equal numbers of observations for each class. Precision-Recall curves should be used when there is a moderate to large class imbalance.

Results

The best combination is Filter Feature selection with method of Mutual Information Gain and the classifier Logistic Regression. Filter is the feistiest among Wrapper and Embeded Methods. Logistic Regression has the best scores with this imbalanced dataset.

AUC score for the best performed combination is 0.87. AUC score 1 represents perfect classifier, and 0.5 represents a worthless classifier.

Precision: how accurate your model is. In other words, when a model makes a prediction, how often it is correct. It is correct at 37%.

Recall: If there are patients who subscribed in the test set. The Logistic Regression model can identify it 79% of the time.

F1 is 0.5

PR_AUC can be interpreted as the probability that the scores given by a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one. LR has the best score of 50%. This score might be the most commonly used for comparing classification models for imbalanced problems.

Brier score is 0.13

In [ ]:
```

```