DMAssignmnt

September 6, 2019

1 Problem Statement:

The Bank Marketing data is related with direct marketing campaigns of a Portuguese banking institution.

- The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be (or not) subscribed.
- The classification goal is to predict if the client will subscribe a Term Deposit Taken (variable y).

1.0.1 Predictor / Independent Variables :

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 Status** : marital status (categorical: "divorced", "married", "single", "unknown")
4. **Education** : (categorical: "basic.4y", "basic.6y", "basic.9y", "high.school", "illiterate", "professional.course", "university.degree", "unknown")
5. **Credit Default:** has credit in default? (categorical: "no", "yes", "unknown").
6. **Housing Loan** : has housing loan? (categorical: "no", "yes", "unknown")
7. **Personal Loan** : has personal loan? (categorical: "no", "yes", "unknown")

1.0.2 Target / Dependent Variable :

1. **Term Deposit Taken**: has the client subscribed a term deposit ? (binary: "1" means "Yes", "0" means "No")

[0]:
```
import pandas as pd
import matplotlib.pyplot as plt
import copy
import numpy as np
```

```python
import seaborn as sns
import pydotplus
import warnings
import operator
from sklearn.model_selection import train_test_split
from sklearn import datasets
from sklearn import svm
from sklearn import preprocessing as preprocess
from sklearn import model_selection
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_validate
from sklearn import metrics
from matplotlib.pyplot import gcf
from sklearn.metrics import confusion_matrix
from sklearn.tree import export_graphviz
from sklearn.externals.six import StringIO
from IPython.display import Image
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from matplotlib import pyplot
warnings.filterwarnings('ignore')
```

[0]:
```python
df = pd.read_excel('Bank Data for case study assignment.xlsx')
```

[0]:
```python
# View the First 5 rows of DataFrame :

df.head()
```

[0]:
```
   age          job marital status  ... housing loan? Personal loan   y
0   30   unemployed        married  ...            no            no  no
1   33     services        married  ...           yes           yes  no
2   35   management         single  ...           yes            no  no
3   30   management        married  ...           yes           yes  no
4   59  blue-collar        married  ...           yes            no  no

[5 rows x 8 columns]
```

[0]:
```python
# View the Last 5 rows of DataFrame :

df.tail()
```

[0]:
```
      age            job marital status  ... housing loan? Personal loan   y
1016   33       services        married  ...           NaN            no  no
1017   57  self-employed        married  ...           yes           yes  no
1018   57     technician        married  ...            no            no  no
1019   28    blue-collar        married  ...            no            no  no
1020   44   entrepreneur         single  ...           yes           yes  no
```

```
[5 rows x 8 columns]
```

#Perform exploratory data analysis

[0]:
```
df.columns
```

[0]:
```
Index(['age', 'job', 'marital status ', 'education', 'credit default?',
       'housing loan?', 'Personal loan', 'y'],
      dtype='object')
```

[0]:
```
df.shape
```

[0]:
```
(1021, 8)
```

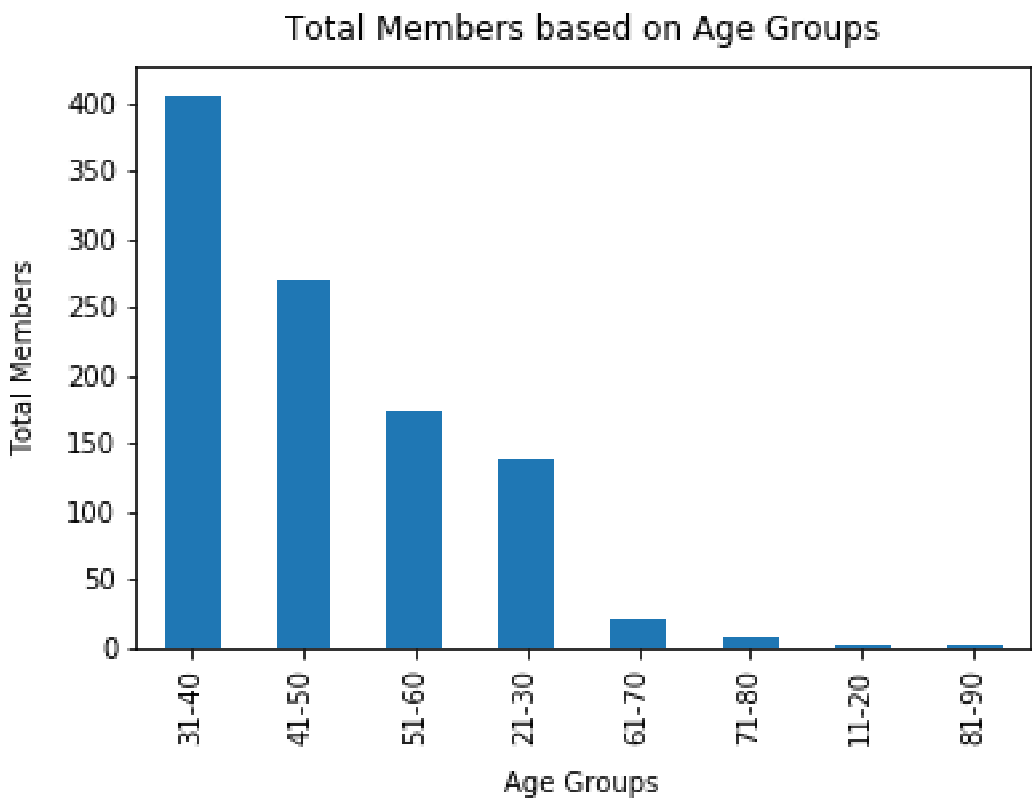
1.1 Individual Data Field analysis

1.1.1 Age Field - data analysis

[0]:
```
# Binning the Data of Age to make it Categorical :

df['Age'] = pd.cut(df['age'], [10, 20, 30,40, 50, 60, 70, 80, 90],␣
 ↪labels=['11-20', '21-30', '31-40', '41-50', '51-60', '61-70', '71-80',␣
 ↪'81-90'])
```

[0]:
```
# Unique Age Values :

print("Age - Unique Values :\n\n",          df['Age'].unique(),'\n')
print("Age - No of Unique Values :\n\n",    df['Age'].nunique(),'\n')
# print("Age - Frequency Count Values :\n\n", data['Age'].value_counts())
print("Age - Frequency Count Values :\n\n", df['Age'].value_counts().
 ↪plot(kind="bar"))
plt.xlabel("Age Groups", labelpad=10)
plt.ylabel("Total Members", labelpad=10)
plt.title("Total Members based on Age Groups", y=1.02);
```

```
Age - Unique Values :

 [21-30, 31-40, 51-60, 41-50, 11-20, 61-70, 71-80, 81-90]
Categories (8, object): [11-20 < 21-30 < 31-40 < 41-50 < 51-60 < 61-70 < 71-80 <
81-90]

Age - No of Unique Values :

 8

Age - Frequency Count Values :

 AxesSubplot(0.125,0.125;0.775x0.755)
```



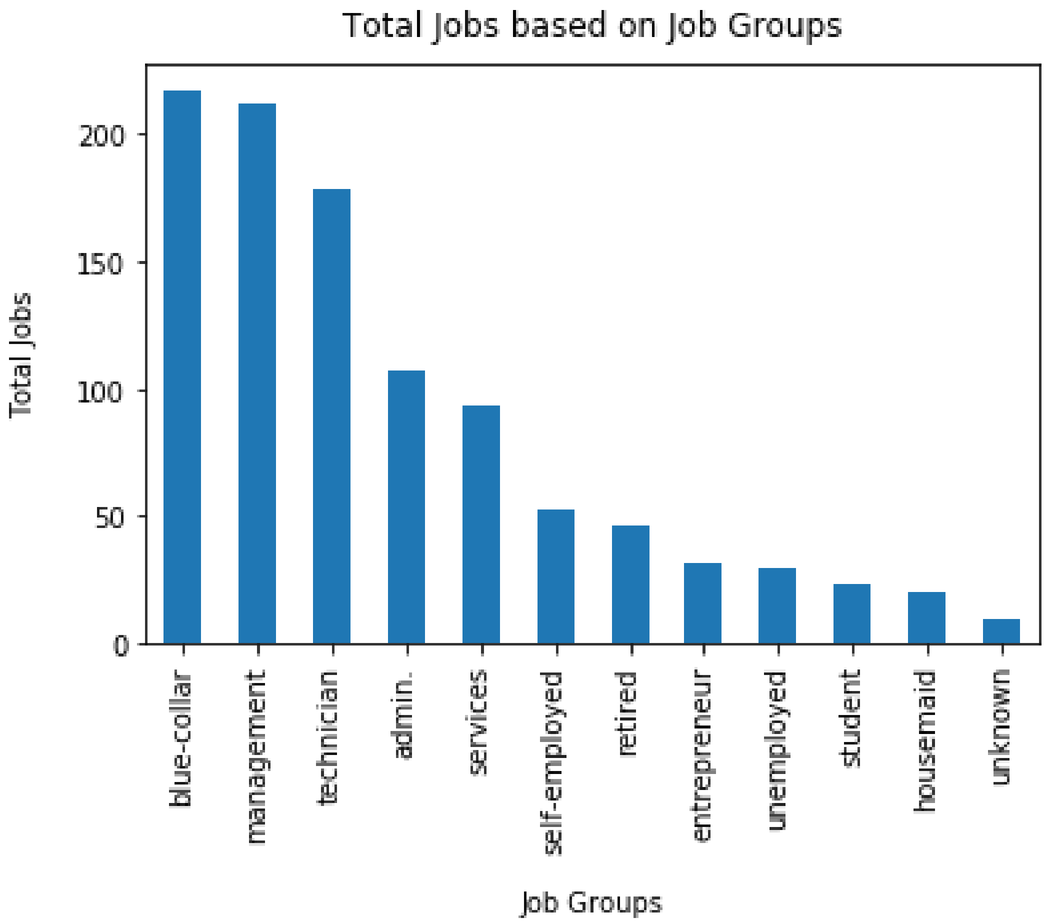
1.1.2 Job Field - data analysis

[0]:
```
# Unique Job Values :

print("Job - Unique Values :\n\n",          df['job'].unique(),'\n\n')
print("Job - No of Unique Values :\n\n",    df['job'].nunique(),'\n\n')
print("Job - Frequency Count Values :\n\n", df['job'].value_counts().
 ↪plot(kind="bar"))
plt.xlabel("Job Groups", labelpad=14)
plt.ylabel("Total Jobs", labelpad=14)
plt.title("Total Jobs based on Job Groups", y=1.02);
```

```
Job - Unique Values :

 ['unemployed' 'services' 'management' 'blue-collar' 'self-employed'
 'technician' 'entrepreneur' 'admin.' 'student' 'housemaid' 'retired' nan
 'unknown']


Job - No of Unique Values :
```

```
12
```

```
Job - Frequency Count Values :

 AxesSubplot(0.125,0.125;0.775x0.755)
```

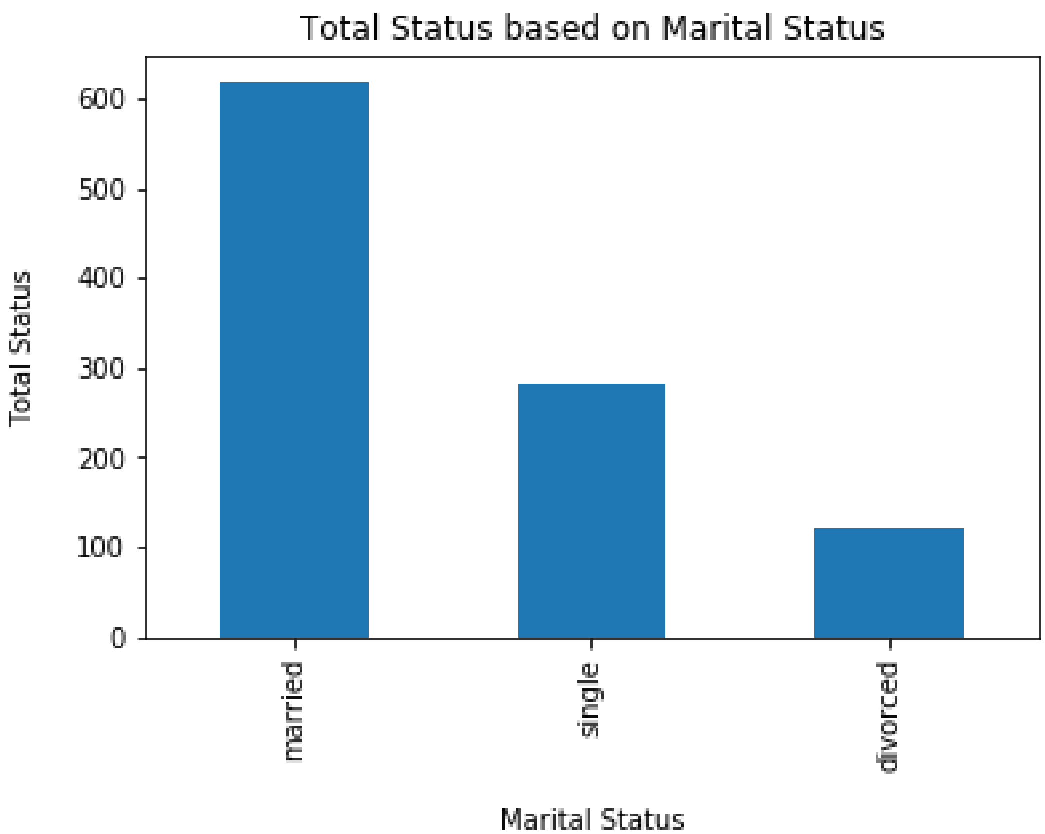


1.1.3 Marital Status Field - data analysis

[0]:
```python
# Unique Marital Status Values :

print("Marital Status - Unique Values :\n\n",          df['marital status '].
 ↪unique(),'\n\n')
print("Marital Status - No of Unique Values :\n\n",    df['marital status '].
 ↪nunique(),'\n\n')
print("Marital Status - Frequency Count Values :\n\n", df['marital status '].
 ↪value_counts().plot(kind="bar"))
plt.xlabel("Marital Status", labelpad=14)
```

```
plt.ylabel("Total Status", labelpad=14)
plt.title("Total Status based on Marital Status", y=1);
```

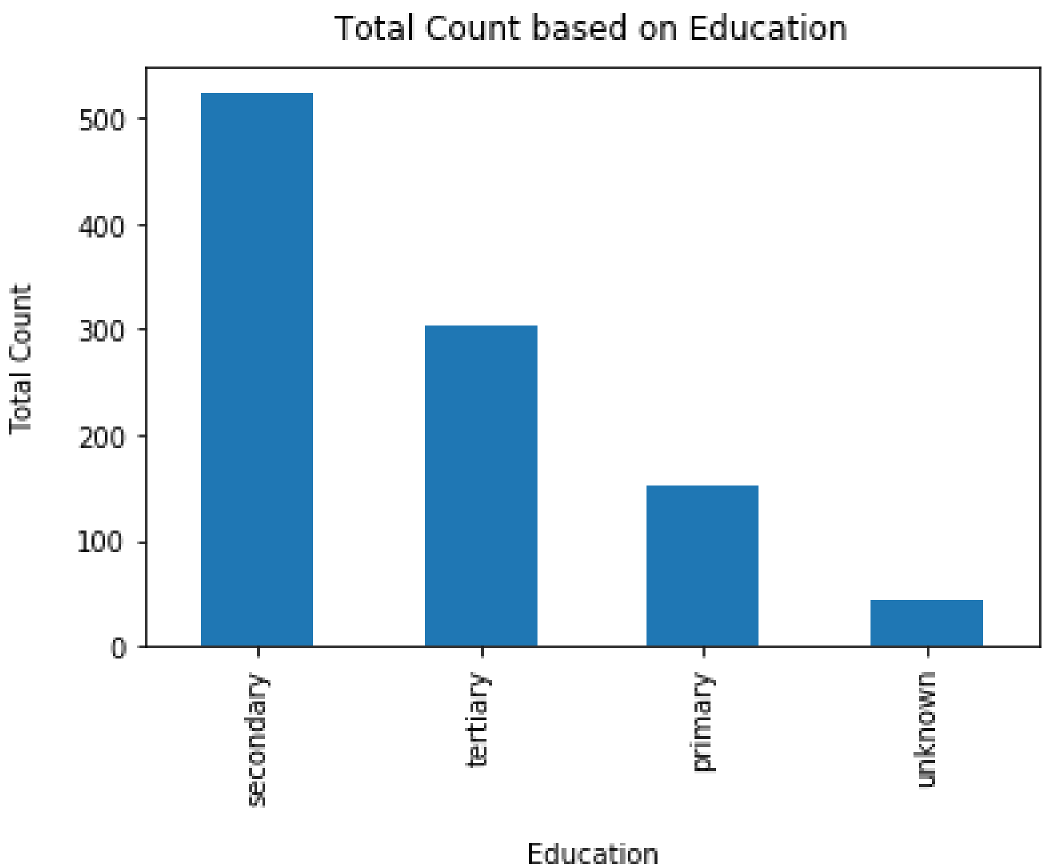
```
Marital Status - Unique Values :

 ['married' 'single' 'divorced' nan]


Marital Status - No of Unique Values :

 3


Marital Status - Frequency Count Values :

 AxesSubplot(0.125,0.125;0.775x0.755)
```



1.1.4 Education Field - data analysis

[0]:
```
# Unique Education Values :

print("Education - Unique Values :\n\n",                df['education'].
 ↪unique(),'\n\n')
print("Education - No of Unique Values :\n\n",          df['education'].
 ↪nunique(),'\n\n')
print("Education - Frequency Count Values :\n\n", df['education'].
 ↪value_counts().plot(kind="bar"))
plt.xlabel("Education", labelpad=14)
plt.ylabel("Total Count", labelpad=14)
plt.title("Total Count based on Education", y=1.02);

# NOTE : We have Inconsistent 4th Category - 'unknown'.
```

```
Education - Unique Values :

 ['primary' 'secondary' 'tertiary' 'unknown' nan]


Education - No of Unique Values :

 4


Education - Frequency Count Values :

 AxesSubplot(0.125,0.125;0.775x0.755)
```

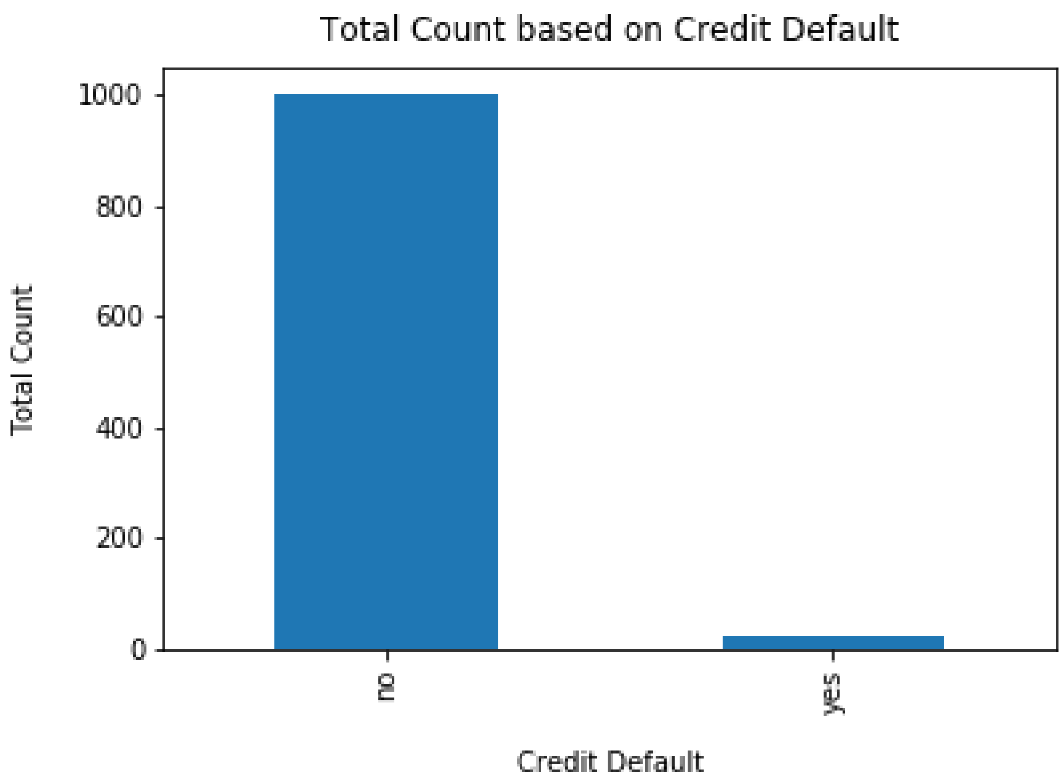


1.1.5 Credit Defaul Field - data analysis

[0]:
```
# Unique Credit Default Values :

print("Credit Default - Unique Values :\n\n",          df['credit default?'].
 ↪unique(),'\n\n')
print("Credit Default - No of Unique Values :\n\n",    df['credit default?'].
 ↪nunique(),'\n\n')
print("Credit Default - Frequency Count Values :\n\n", df['credit default?'].
 ↪value_counts().plot(kind="bar"))
plt.xlabel("Credit Default", labelpad=14)
plt.ylabel("Total Count", labelpad=14)
plt.title("Total Count based on Credit Default", y=1.02);
```

```
Credit Default - Unique Values :

 ['no' 'yes' nan]
```

```
Credit Default - No of Unique Values :

 2


Credit Default - Frequency Count Values :

 AxesSubplot(0.125,0.125;0.775x0.755)
```

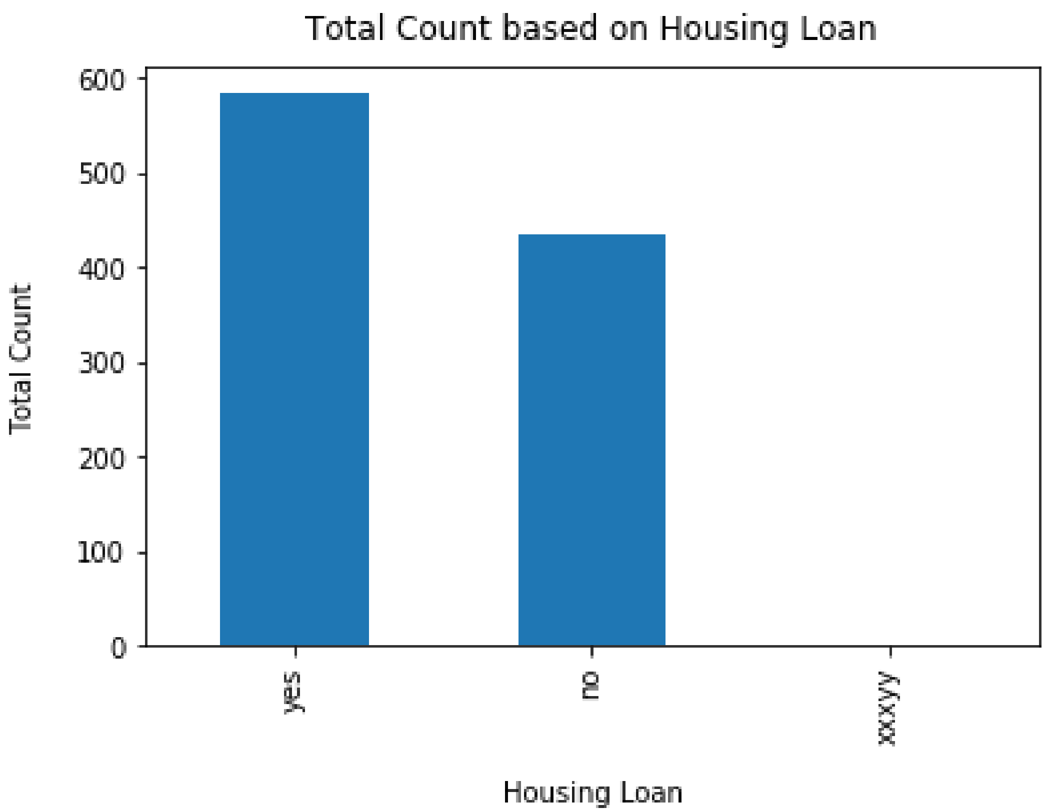


1.1.6 Housing Loan Field - data analysis

[0]:
```
# Unique Housing Loan Values :

print("Housing Loan - Unique Values :\n\n",           df['housing loan?'].
 ↪unique(),'\n\n')
print("Housing Loan - No of Unique Values :\n\n",     df['housing loan?'].
 ↪nunique(),'\n\n')
print("Housing Loan - Frequency Count Values :\n\n", df['housing loan?'].
 ↪value_counts().plot(kind="bar"))
plt.xlabel("Housing Loan", labelpad=14)
plt.ylabel("Total Count", labelpad=14)
plt.title("Total Count based on Housing Loan", y=1.02);
```

```
# NOTE : We have Inconsistent 3rd Category - 'xxxyy'.
```

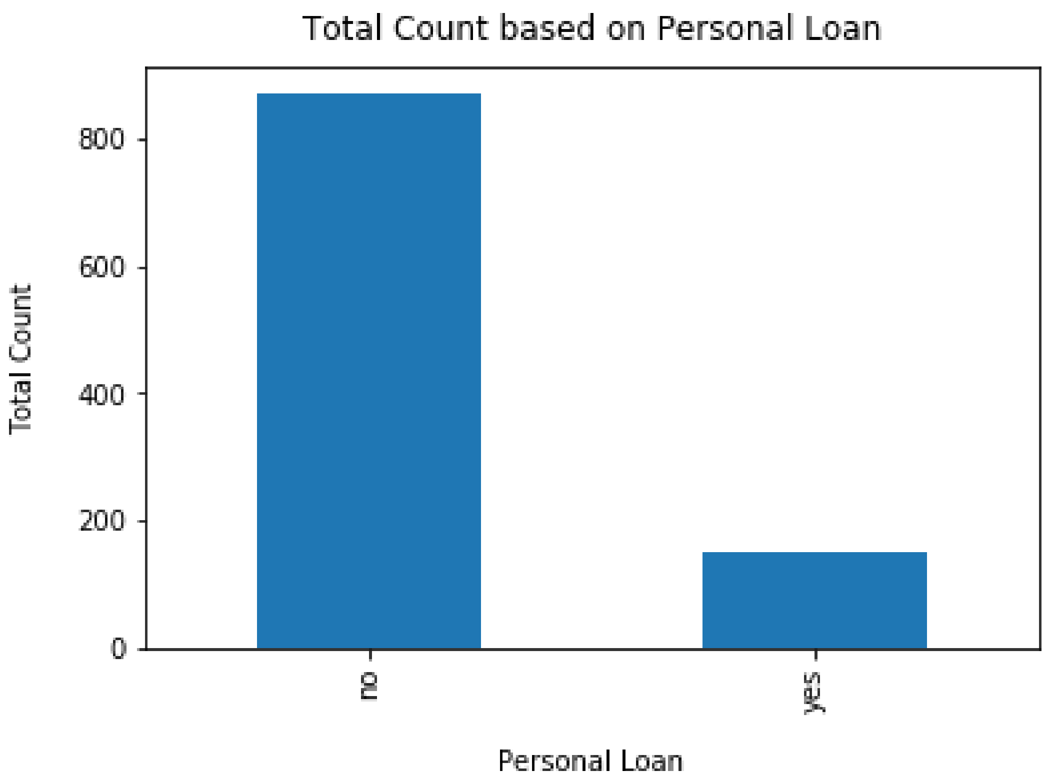
```
Housing Loan - Unique Values :

 ['no' 'yes' nan 'xxxyy']


Housing Loan - No of Unique Values :

 3


Housing Loan - Frequency Count Values :

 AxesSubplot(0.125,0.125;0.775x0.755)
```



1.1.7 Personal Loan Field - data analysis

[0]:
```
# Unique Personal Loan Values :

print("Personal Loan - Unique Values :\n\n",       df['Personal loan'].
 ↪unique(),'\n\n')
print("Personal Loan - No of Unique Values :\n\n", df['Personal loan'].
 ↪nunique(),'\n\n')
print("Personal Loan - Frequency Count Values :\n\n", df['Personal loan'].
 ↪value_counts().plot(kind="bar"))
plt.xlabel("Personal Loan", labelpad=14)
plt.ylabel("Total Count", labelpad=14)
plt.title("Total Count based on Personal Loan", y=1.02);
```

```
Personal Loan - Unique Values :

 ['no' 'yes' nan]


Personal Loan - No of Unique Values :

 2


Personal Loan - Frequency Count Values :

 AxesSubplot(0.125,0.125;0.775x0.755)
```

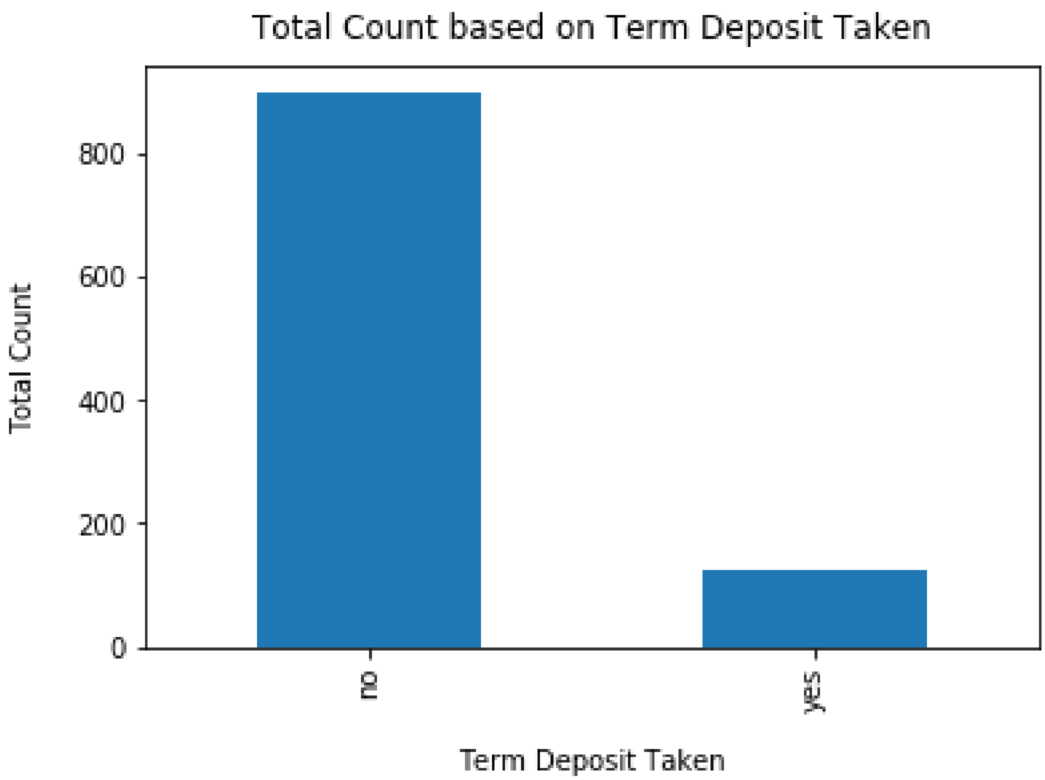


1.1.8 Term Deposit Taken Field - data analysis

[0]:
```
# Unique Term Deposit Taken Values :

print("Term Deposit Taken - Unique Values :\n\n",       df['y'].unique(),'\n\n')
print("Term Deposit Taken - No of Unique Values :\n\n", df['y'].
 ↪nunique(),'\n\n')
print("Term Deposit Taken - Frequency Count Values :\n\n", df['y'].
 ↪value_counts().plot(kind="bar"))
plt.xlabel("Term Deposit Taken", labelpad=14)
plt.ylabel("Total Count", labelpad=14)
plt.title("Total Count based on Term Deposit Taken", y=1.02);
```

```
Term Deposit Taken - Unique Values :

 ['no' 'yes']


Term Deposit Taken - No of Unique Values :

 2
```

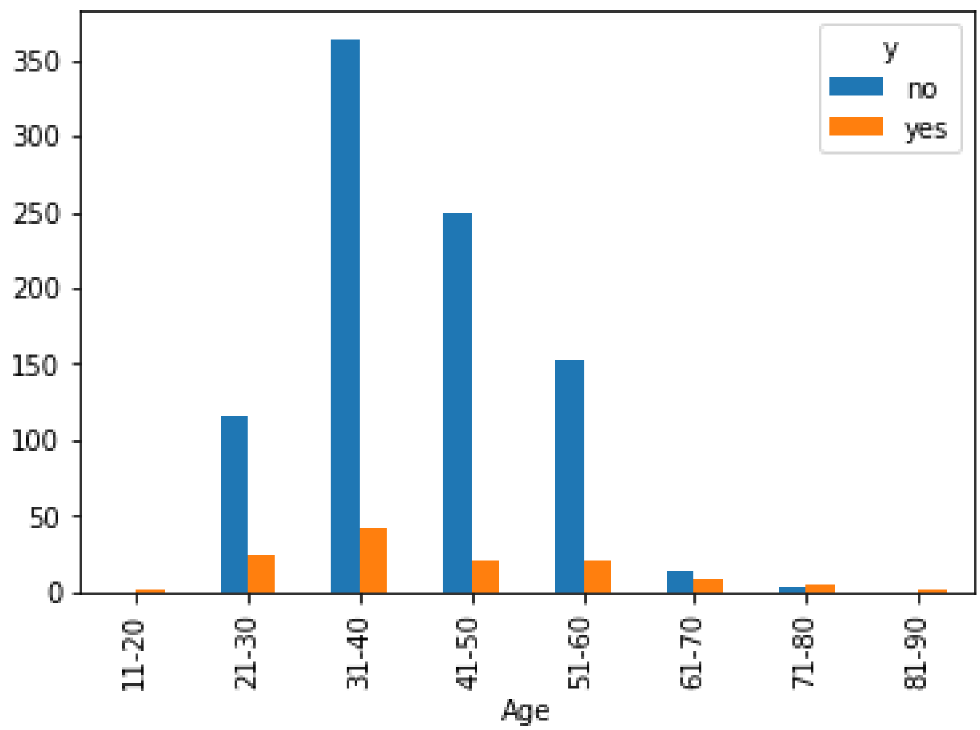
```
Term Deposit Taken - Frequency Count Values :

 AxesSubplot(0.125,0.125;0.775x0.755)
```

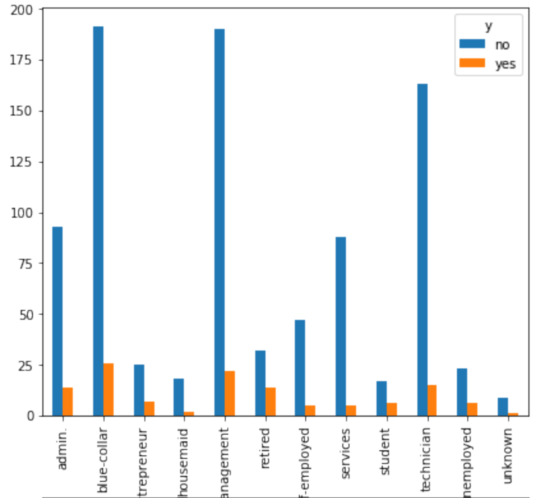


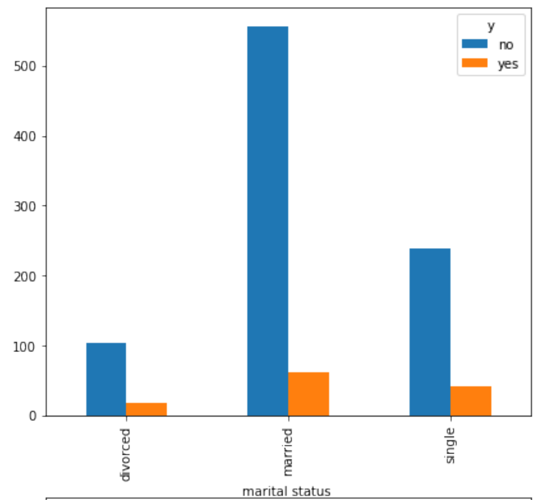
1.2 Combined data Analysis

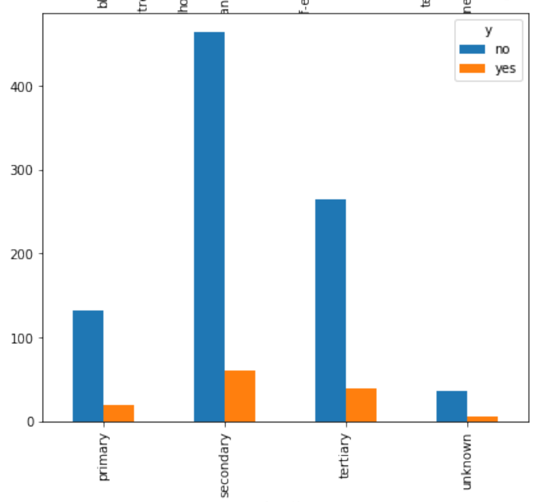
[0]:
```
df.groupby(['Age'])['y'].value_counts().unstack().plot(kind='bar')
fig,ax= plt.subplots(3,2,figsize=(15,20))
df.groupby(['job'])['y'].value_counts().unstack().plot(kind='bar',ax=ax[0,0])
df.groupby(['marital status '])['y'].value_counts().unstack().
 ↪plot(kind='bar',ax=ax[0,1])
df.groupby(['education'])['y'].value_counts().unstack().
 ↪plot(kind='bar',ax=ax[1,0])
df.groupby(['credit default?'])['y'].value_counts().unstack().
 ↪plot(kind='bar',ax=ax[1,1])
df.groupby(['housing loan?'])['y'].value_counts().unstack().
 ↪plot(kind='bar',ax=ax[2,0])
df.groupby(['Personal loan'])['y'].value_counts().unstack().
 ↪plot(kind='bar',ax=ax[2,1])
```

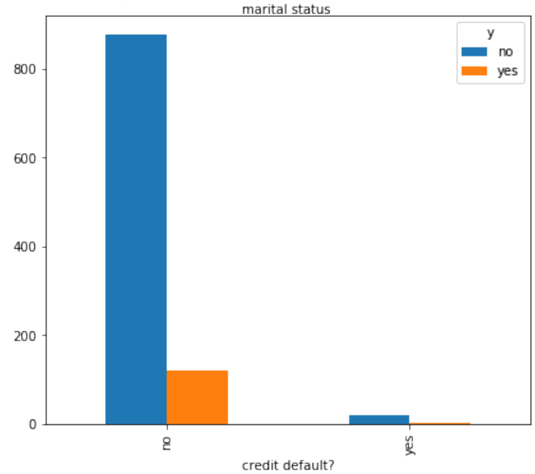
[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1b21f7db38>

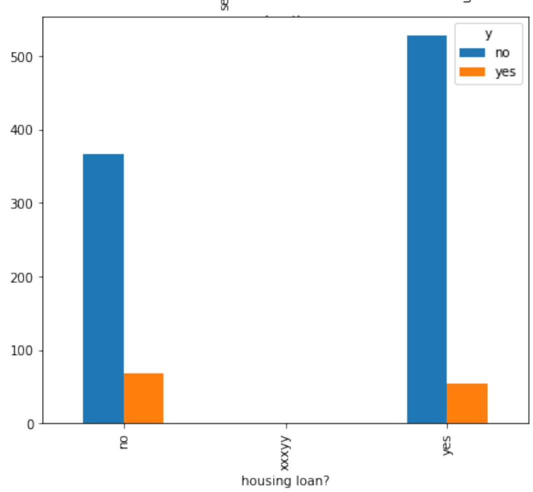


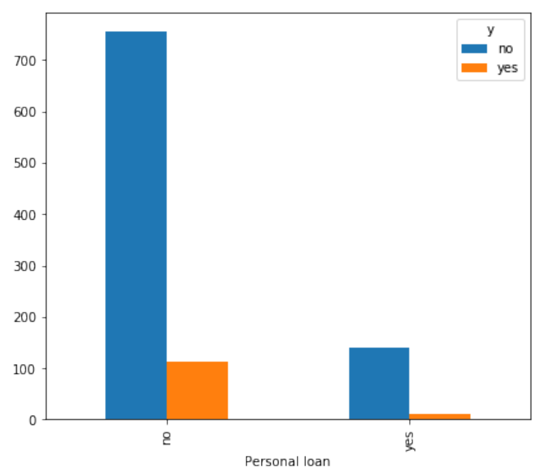

y
no
yes
0
25
50
75
100
125
150
175
200
admin.
blue-collar
trepreneur
housemaid
anagement
retired
f-employed
services
student
technician
nemployed
unknown


y
no
yes
0
100
200
300
400
500
divorced
married
single
marital status


y
no
yes
0
100
200
300
400
primary
secondary
tertiary
unknown


y
no
yes
0
200
400
600
800
no
yes
credit default?


y
no
yes
0
100
200
300
400
500
no
xxxyy
yes
housing loan?


y
no
yes
0
100
200
300
400
500
600
700
no
yes
Personal loan

1.3 Analysis Based on Data exploratory

From the combined data exporatory it is seen that below people have more chances to subscribe term deposit 1. Age: 31 to 50 2. Job: blue-collar, technician and management 3. Marital status: married 4. Education: secondary 5. Credit default: no 6. Housing loan: yes 7. Personal loan: no

2 Preprocess the data :

2.0.1 1. Dropping NA Values:

[0]:
```
#Data information before preprocessing
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1021 entries, 0 to 1020
Data columns (total 9 columns):
age                 1021 non-null int64
job                 1019 non-null object
marital status      1020 non-null object
education           1020 non-null object
credit default?     1020 non-null object
housing loan?       1019 non-null object
Personal loan       1019 non-null object
y                   1021 non-null object
Age                 1021 non-null category
dtypes: category(1), int64(1), object(7)
memory usage: 65.3+ KB
```

[0]:
```
# Data frame length before preprocessing
len(df)
```

[0]: 1021

[0]:
```
# Printing Sum of Missing Values in Each Column :
total_null = df.isnull().sum().sort_values(ascending=False)
print(total_null)
```

```
Personal loan      2
housing loan?      2
job                2
credit default?    1
education          1
marital status     1
Age                0
y                  0
age                0
dtype: int64
```

[0]:
```
df1 = df[df.isna().any(axis=1)]
```

[0]:
```
df1.index
```

[0]:
```
Int64Index([79, 97, 108, 109, 168, 1000, 1004, 1016], dtype='int64')
```

[0]:
```
df3 = df.drop(df1.index.tolist())
```

[0]:
```
# Data information after preprocessing
df3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1013 entries, 0 to 1020
Data columns (total 9 columns):
age                1013 non-null int64
job                1013 non-null object
marital status     1013 non-null object
education          1013 non-null object
credit default?    1013 non-null object
housing loan?      1013 non-null object
Personal loan      1013 non-null object
y                  1013 non-null object
Age                1013 non-null category
dtypes: category(1), int64(1), object(7)
memory usage: 72.6+ KB
```

[0]:
```
# Data frame length after preprocessing
len(df3)
```

[0]:
```
1013
```

2.0.2 Replacing anamoly with max occurence

In Housing Loan Field - data analysis it is seen that there is an inappropriate value (xxxyy). Replacing with max occurence of the field

[0]:
```
df['housing loan?'] = df['housing loan?'].str.replace('xxxyy','yes')
```

3 Select Training data, test data

[0]:
```
label_encode_job = preprocess.LabelEncoder()
label_encode_marital = preprocess.LabelEncoder()
label_encode_eduction = preprocess.LabelEncoder()
label_encode_credit = preprocess.LabelEncoder()
label_encode_housing = preprocess.LabelEncoder()
label_encode_person = preprocess.LabelEncoder()
label_encode_y = preprocess.LabelEncoder()
```

[0]:
```
label_encode_job.fit(df3['job'].tolist())
label_encode_marital.fit(df3['marital status '].tolist())
label_encode_eduction.fit(df3['education'].tolist())
label_encode_credit.fit(df3['credit default?'].tolist())
label_encode_housing.fit(df3['housing loan?'].tolist())
label_encode_person.fit(df3['Personal loan'].tolist())
label_encode_y.fit(df3['y'].tolist())
```

[0]:
```
LabelEncoder()
```

[0]:
```
job_ = label_encode_job.transform(df3['job'].tolist())
marital_ = label_encode_marital.transform(df3['marital status '].tolist())
education_ = label_encode_eduction.transform(df3['education'].tolist())
credit_ = label_encode_credit.transform(df3['credit default?'].tolist())
housing_ = label_encode_housing.transform(df3['housing loan?'].tolist())
person_ = label_encode_person.transform(df3['Personal loan'].tolist())
y_ = label_encode_y.transform(df3['y'].tolist())
```

[0]:
```
df_2 = copy.copy(df3)
```

[0]:
```
#df_2.drop(['Age'], axis=1)
del df_2['Age']
```

[0]:
```
df_2.head()
```

[0]:
```
   age          job marital status   ... housing loan? Personal loan   y
0   30   unemployed         married  ...            no            no  no
1   33     services         married  ...           yes           yes  no
2   35   management          single  ...           yes            no  no
3   30   management         married  ...           yes           yes  no
4   59  blue-collar         married  ...           yes            no  no

[5 rows x 8 columns]
```

[0]:
```
feature_cols =['age','job','matrial_status ', 'education',␣
↪'credit','housing_loan', 'personal_loan']
```

[0]:
```
df_to_use = pd.DataFrame(data=list(zip(df_2.age.
↪tolist(),job_,marital_,education_,credit_,housing_,person_,y_)),
             columns=['age','job','matrial_status ', 'education',␣
↪'credit','housing_loan', 'personal_loan','y'])
```

[0]:
```
y = df_to_use.y
X = df_to_use.drop('y', axis=1)
```

[0]:
```
train_data, test_data, train_y, test_y = model_selection.train_test_split(X, y,␣
↪test_size=0.2, random_state=13)
```

[0]:
```
train_data[:10]
```

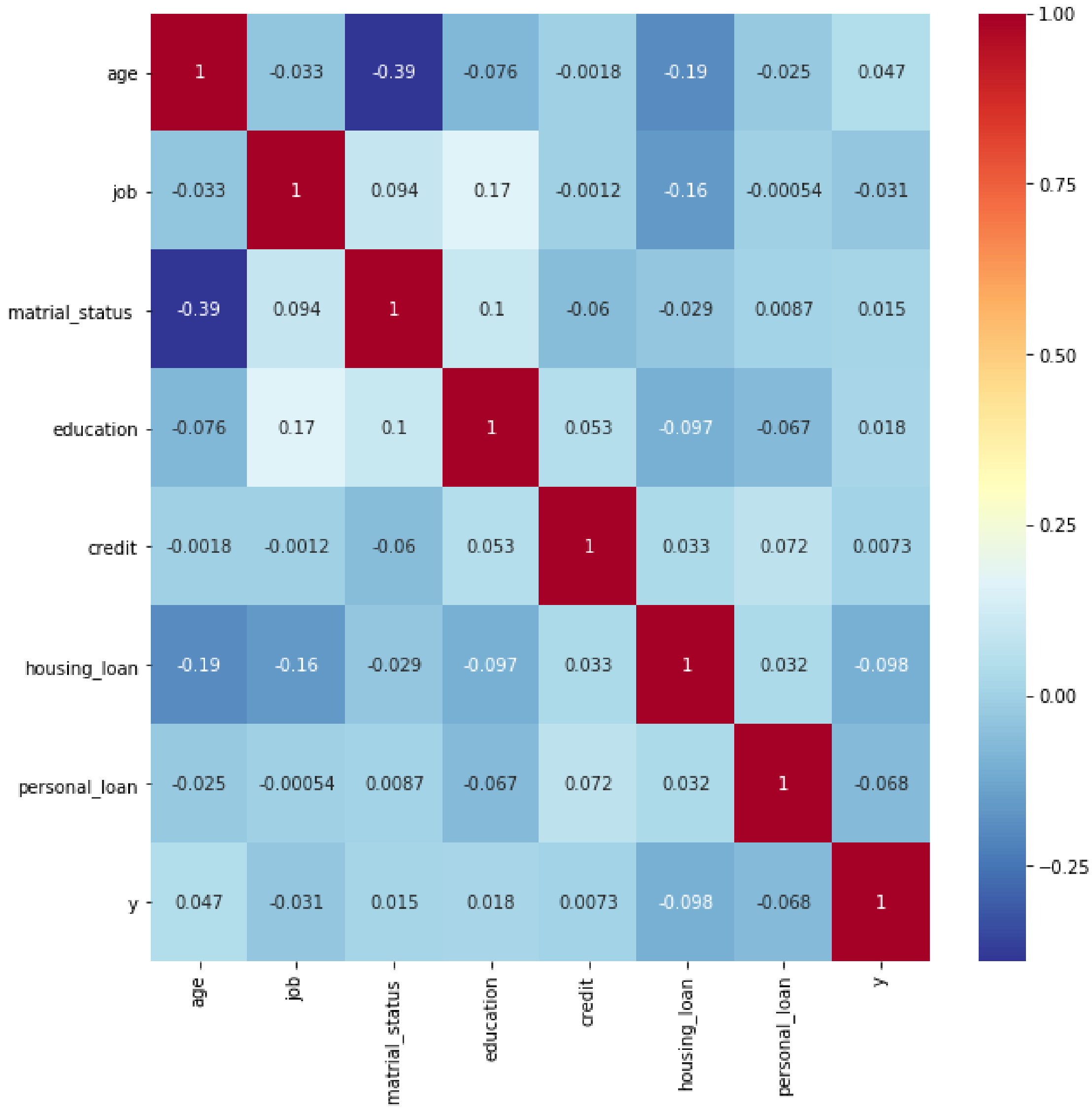
[0]:
```
     age  job  matrial_status   education  credit  housing_loan  personal_loan
66    31    7                1          1       0             2              0
293   38    2                1          1       0             2              1
```

329	30	4	2	2	0	0	0
754	50	6	0	2	0	2	0
727	46	9	1	1	0	0	1
514	61	5	1	1	0	0	0
888	29	4	2	2	0	2	0
133	34	4	2	2	0	0	0
219	54	4	1	0	0	2	0
573	59	1	1	0	0	2	0

4 Correlation analysis

[0]:
```
plt.figure(figsize=(10,10))
sns.heatmap(df_to_use[['age','job','matrial_status ', 'education',␣
 ↪'credit','housing_loan', 'personal_loan','y']].corr(),
            annot=True,cmap ='RdYlBu_r')
```

[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1b1e5fd860>
```



5 Train and test the model

Building the classifier with criterion Entropy

[0]:
```
# Building the classifier with criterion Entropy
decision_tree_classifier = DecisionTreeClassifier(criterion="entropy",␣
↪max_depth=3, random_state=13)
# Training the classifier
decision_tree_classifier.fit(train_data,train_y)
```

[0]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
```

```
                                 min_samples_leaf=1, min_samples_split=2,
                                 min_weight_fraction_leaf=0.0, presort=False,
                                 random_state=13, splitter='best')
```

[0]:
```
prediction = decision_tree_classifier.predict(test_data)
```

[0]:
```
prediction
```

[0]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0])
```

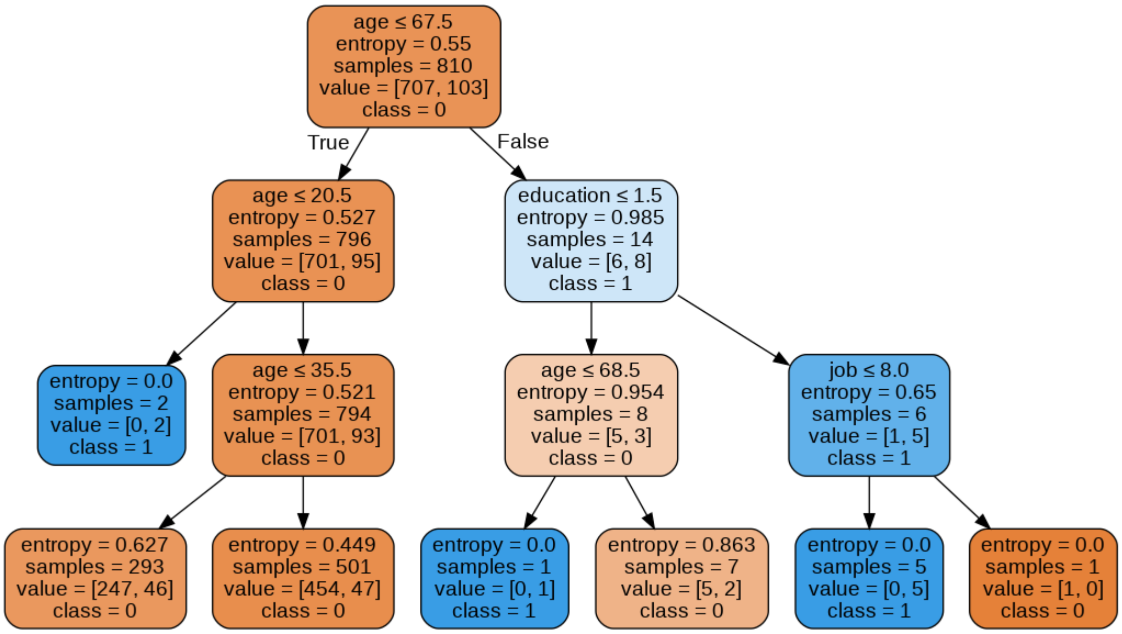
[0]:
```
# We are calculating accuracy on testing data
accuracy = metrics.accuracy_score(test_y,prediction)
```

[0]:
```
print('Accuracy of the Decision tree with Entropy index : ', accuracy*100)
```

```
Accuracy of the Decision tree with Entropy index :  90.64039408866995
```

[0]:
```
dot_data = StringIO()
export_graphviz(decision_tree_classifier, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True,feature_names =␣
 ↪feature_cols,class_names=['0','1'])
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('DecisionTree_Entropy.png')
Image(graph.create_png())
```

[0]:



[0]:

[0]:

[0]:

Building the classifier with criterion Gini

[0]:
```
decision_tree_classifier = DecisionTreeClassifier(criterion="gini",␣
↪max_depth=3, random_state=13)
# Training the classifier
decision_tree_classifier.fit(train_data,train_y)
```

[0]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=13, splitter='best')
```

[0]:
```
prediction = decision_tree_classifier.predict(test_data)
```

[0]:
```
prediction
```

[0]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
```

```
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0])
```

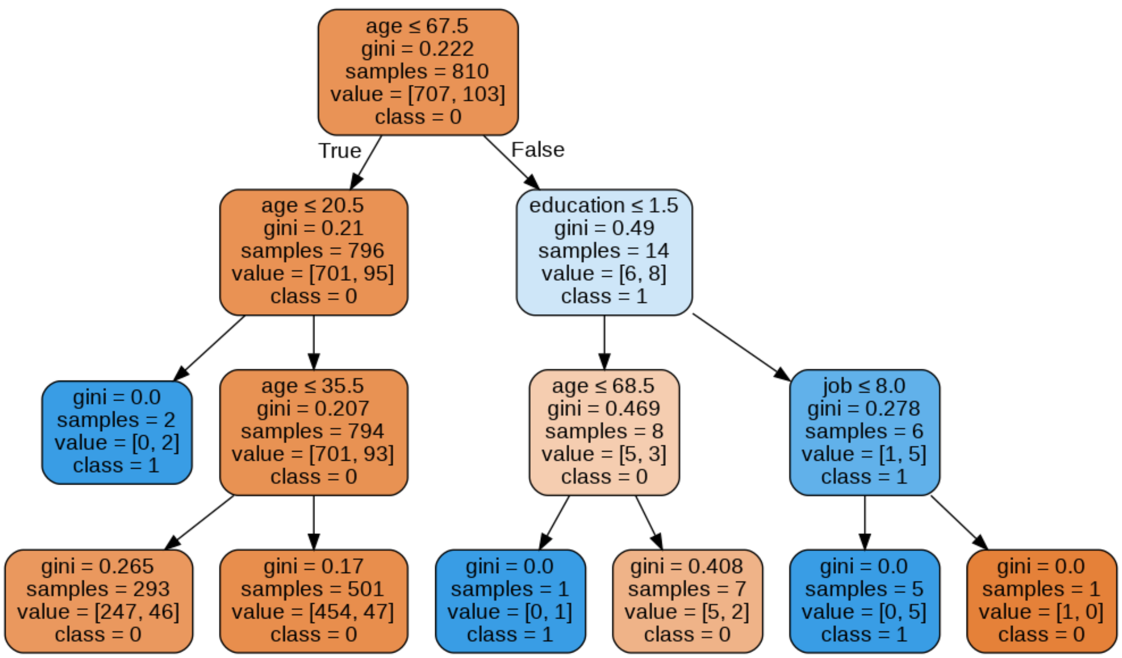
[0]:
```
#calculating accuracy on testing data
accuracy = metrics.accuracy_score(test_y,prediction)
```

[0]:
```
print('Accuracy of the Decision tree with Gini index : ', accuracy*100)
```

```
Accuracy of the Decision tree with Gini index :  90.64039408866995
```

[0]:
```
dot_data = StringIO()
export_graphviz(decision_tree_classifier, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True,feature_names =␣
 ↪feature_cols,class_names=['0','1'])
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('DecisionTree_Gini.png')
Image(graph.create_png())
```

[0]:

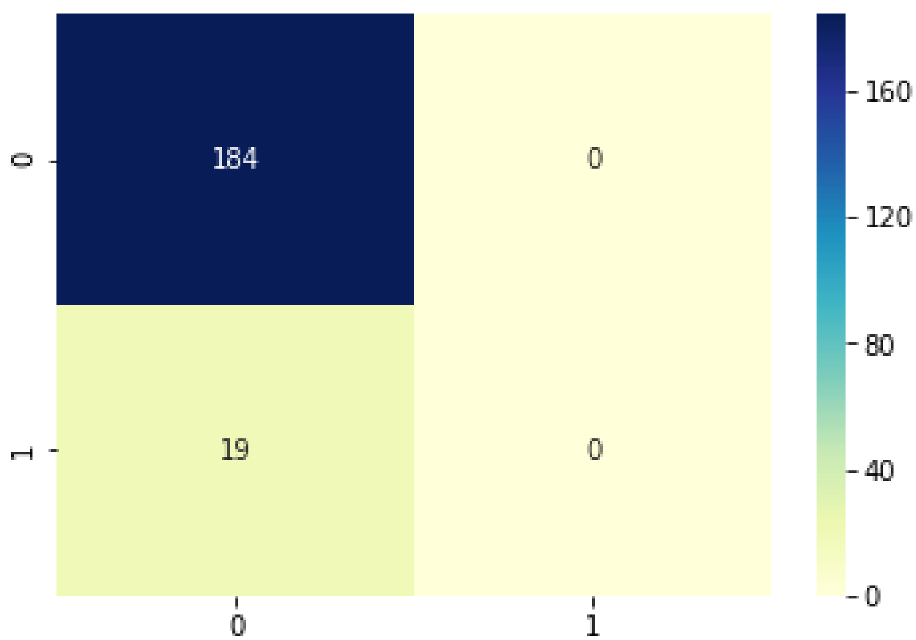


Analysis
Buiding the classifier with criterian entropy and Gini provides the same accuracy.

6 Evaluate the model performance

[0]:
```
plt = sns.heatmap(pd.DataFrame(metrics.confusion_matrix(test_y,prediction)),␣
↪annot=True, cmap="YlGnBu" ,fmt='g')

#Confusion Matrix
confusion_matrix=metrics.confusion_matrix(test_y,prediction)
print(confusion_matrix)

#Classification Report
classification_report=metrics.classification_report(test_y,prediction)
print(classification_report)
```

```
[[184   0]
 [ 19   0]]
              precision    recall  f1-score   support

           0       0.91      1.00      0.95       184
           1       0.00      0.00      0.00        19

    accuracy                           0.91       203
   macro avg       0.45      0.50      0.48       203
weighted avg       0.82      0.91      0.86       203
```



[0]:
```
# Cross validation using gini index and entropy 15 cv
# ROC and AUC curve plotting]
```

7 Cross validation

[0]:
```
score = model_selection.cross_validate(decision_tree_classifier, train_data,␣
↪train_y, cv=15, return_estimator=True, n_jobs=-1)
```

[0]:
```
test_score = []
estimator = []
for key, value in score.items():
    if key == 'test_score':
        test_score.append(value)
    if key == 'estimator':
        estimator.append(value)
    else:

      continue
```

[0]:
```
#estimator
estimator[0][3]
```

[0]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=13, splitter='best')
```

[0]:
```
max_index, max_value = max(enumerate(test_score), key=operator.itemgetter(1))
```

[0]:
```
max_estimator = estimator[max_index]
```

[0]:
```
max_estimator
```

[0]:
```
(DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                        max_features=None, max_leaf_nodes=None,
                        min_impurity_decrease=0.0, min_impurity_split=None,
                        min_samples_leaf=1, min_samples_split=2,
                        min_weight_fraction_leaf=0.0, presort=False,
                        random_state=13, splitter='best'),
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                        max_features=None, max_leaf_nodes=None,
                        min_impurity_decrease=0.0, min_impurity_split=None,
                        min_samples_leaf=1, min_samples_split=2,
                        min_weight_fraction_leaf=0.0, presort=False,
                        random_state=13, splitter='best'),
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                        max_features=None, max_leaf_nodes=None,
```

```
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=13, splitter='best'),
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=13, splitter='best'),
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=13, splitter='best'),
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=13, splitter='best'),
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=13, splitter='best'),
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=13, splitter='best'),
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=13, splitter='best'),
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=13, splitter='best'),
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
```

```
                        max_features=None, max_leaf_nodes=None,
                        min_impurity_decrease=0.0, min_impurity_split=None,
                        min_samples_leaf=1, min_samples_split=2,
                        min_weight_fraction_leaf=0.0, presort=False,
                        random_state=13, splitter='best'),
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                        max_features=None, max_leaf_nodes=None,
                        min_impurity_decrease=0.0, min_impurity_split=None,
                        min_samples_leaf=1, min_samples_split=2,
                        min_weight_fraction_leaf=0.0, presort=False,
                        random_state=13, splitter='best'),
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                        max_features=None, max_leaf_nodes=None,
                        min_impurity_decrease=0.0, min_impurity_split=None,
                        min_samples_leaf=1, min_samples_split=2,
                        min_weight_fraction_leaf=0.0, presort=False,
                        random_state=13, splitter='best'),
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                        max_features=None, max_leaf_nodes=None,
                        min_impurity_decrease=0.0, min_impurity_split=None,
                        min_samples_leaf=1, min_samples_split=2,
                        min_weight_fraction_leaf=0.0, presort=False,
                        random_state=13, splitter='best'),
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                        max_features=None, max_leaf_nodes=None,
                        min_impurity_decrease=0.0, min_impurity_split=None,
                        min_samples_leaf=1, min_samples_split=2,
                        min_weight_fraction_leaf=0.0, presort=False,
                        random_state=13, splitter='best'))
```

[0]:
```
predicts = estimator[0][3].predict_proba(test_data)
```

[0]:
```
predicts
```

[0]:
```
array([[0.85064935, 0.14935065],
       [0.85064935, 0.14935065],
       [0.85064935, 0.14935065],
       [0.85064935, 0.14935065],
       [0.90531178, 0.09468822],
       [0.90531178, 0.09468822],
       [0.90531178, 0.09468822],
       [0.90531178, 0.09468822],
       [0.85064935, 0.14935065],
       [0.85064935, 0.14935065],
       [0.85064935, 0.14935065],
       [0.85064935, 0.14935065],
       [0.90531178, 0.09468822],
       [0.85064935, 0.14935065],
```

```
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.71428571, 0.28571429],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
```

```
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
```

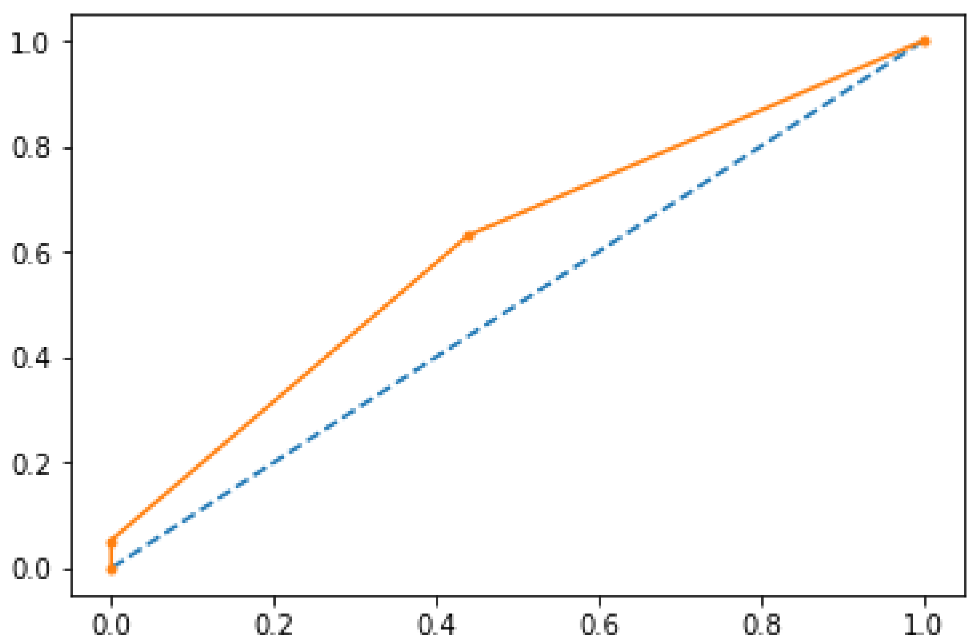
```
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
```

```
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.90531178, 0.09468822],
[0.85064935, 0.14935065],
[0.85064935, 0.14935065],
```

```
[0.90531178, 0.09468822]])
```

[0]:
```
# keep probabilities for the positive outcome only
probs = predicts[:, 1]
# calculate AUC
auc = roc_auc_score(test_y, probs)
print('AUC: %.3f' % auc)
# calculate roc curve
fpr, tpr, thresholds = roc_curve(test_y, probs)
# plot no skill
pyplot.plot([0, 1], [0, 1], linestyle='--')
# plot the roc curve for the model
pyplot.plot(fpr, tpr, marker='.')
# show the plot
pyplot.show()
```

```
AUC: 0.607
```



8 Inference

Data exploratory * Provided the detailed analysis of each and every attribute of the data set using plots. * Found the anamoly in housing loan column with value xxxyy which is handled in data preprocessing.

Data preprocessing * Dropping NA Values: From the given dataset, it is seen that 8 records have empty values. Since it is negligible (< 1%) these entries can be deleted. *Replacing with max occurence of the field: The anamoly in housing column with value “xxxyy” replaced with maximum occurence value(“yes”) of the field.

Data selection, Model creation and testing * From the given data set, 80% data is used for training purpose and remaining 20% is used for testing purpose. * Verified the accuracy with both entropy and gini index classifier criterion.

Evaluate the model performance * Evaluated the model performance with confusion matrix and classification report.

Cross Validation * Used Cross validate function (sklearn.model_selection.cross_validate) since 1) It allows specifying multiple metrics for evaluation. 2) It returns a dict containing fit-times, score-times (and optionally training scores as well as fitted estimators) in addition to the test score. * AUC score obtained by using cross validate function for the given data set is 0.607.