```
In [238]:
          import pandas as pd
          import numpy as np
          from sklearn.tree import DecisionTreeClassifier
          from sklearn.model_selection import train_test_split
          import seaborn as sns
          import matplotlib.pyplot as plt
In [239]: | bank = pd.read csv("bank.csv")
          #Returns the first 10 entries of the Dataframe -Bank
          #bank.head()
          #pd.set option('mode.chained assignment', None)
In [240]:
In [241]: #Lists the Column Names
          bank.info()
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 11162 entries, 0 to 11161
          Data columns (total 17 columns):
                       11162 non-null int64
          age
          job
                       11162 non-null object
          marital
                       11162 non-null object
                       11162 non-null object
          education
                       11162 non-null object
          default
                       11162 non-null int64
          balance
          housing
                       11162 non-null object
          loan
                       11162 non-null object
          contact
                       11162 non-null object
          day
                       11162 non-null int64
          month
                       11162 non-null object
                       11162 non-null int64
          duration
          campaign
                       11162 non-null int64
                       11162 non-null int64
          pdays
          previous
                       11162 non-null int64
                       11162 non-null object
          poutcome
                       11162 non-null object
          deposit
          dtypes: int64(7), object(10)
          memory usage: 1.4+ MB
In [242]: #Returns No of Rows and Columns (Rows, Columns)
          bank.shape
Out[242]: (11162, 17)
```

Out[243]:

	age	balance	day	duration	campaign	pdays	
count	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	111(
mean	41.231948	1528.538524	15.658036	371.993818	2.508421	51.330407	
std	11.913369	3225.413326	8.420740	347.128386	2.722077	108.758282	
min	18.000000	-6847.000000	1.000000	2.000000	1.000000	-1.000000	
25%	32.000000	122.000000	8.000000	138.000000	1.000000	-1.000000	
50%	39.000000	550.000000	15.000000	255.000000	2.000000	-1.000000	
75%	49.000000	1708.000000	22.000000	496.000000	3.000000	20.750000	
max	95.000000	81204.000000	31.000000	3881.000000	63.000000	854.000000	!

```
In [244]: y=bank['deposit']
y=y.to_frame()
y.head()
```

Out[244]:

	aeposit
0	yes
1	yes
2	yes
3	yes
4	yes

```
In [245]: X=bank
```

In [246]: | X.head()

Out[246]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	dι
(59	admin.	married	secondary	no	2343	yes	no	unknown	5	may	
•	56	admin.	married	secondary	no	45	no	no	unknown	5	may	
2	2 41	technician	married	secondary	no	1270	yes	no	unknown	5	may	
;	5 5	services	married	secondary	no	2476	yes	no	unknown	5	may	
4	5 4	admin.	married	tertiary	no	184	no	no	unknown	5	may	

```
In [247]: #Applying Train, Test Split 1st time
    X_train, X_test, y_train, y_test=train_test_split(X,y,test_size=0.4,random_state=100)
```

```
In [248]: #Print only columns of Training Data
            X train.columns
Out[248]: Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'hou
           sing',
                    'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pday
           s',
                    'previous', 'poutcome', 'deposit'],
                  dtype='object')
In [249]:
           #Display first five records from X train
            X train.head()
Out[249]:
                   age
                               iob
                                   marital education default balance housing loan
                                                                                 contact
                                                                                         day
                    45
                         housemaid
                                   married
                                                              317
                                                                                  cellular
                                                                                           8
             5541
                                            primary
                                                       no
                                                                      yes
                                                                            no
                                                              232
                                                                                telephone
                                                                                          29
             9240
                    53
                       management
                                   married
                                             tertiary
                                                       no
                                                                      yes
                                                                            no
             10826
                    24
                            student
                                    single
                                          secondary
                                                       no
                                                              493
                                                                      yes
                                                                                  cellular
                                                                                          13
                    26
             1089
                        unemployed
                                                              814
                                                                                  cellular
                                                                                          28
                                    single
                                             tertiary
                                                       no
                                                                       no
                                                                            no
             9168
                    55
                         technician married
                                           unknown
                                                             1393
                                                                               telephone
                                                       no
                                                                      yes
                                                                                          21
                                                                           yes
In [250]:
           y_train.head()
Out[250]:
                   deposit
             5541
                       no
             9240
                       no
             10826
                       no
             1089
                      yes
             9168
                       no
In [251]:
            #The following code is added to convert all the string type data into nu
            merical data
            combine =[y train,y test]
            depositmapping={'yes':1,'no': 0}
            for dt in combine :
               dt['deposit']=bank['deposit'].map(depositmapping)
            #y train.head()
In [252]:
In [253]:
            #X train.head()
```

```
In [254]: #assigning 1 to yes and 0 to no in default (X_train)
    combine=[X_train, X_test]
    depositmapping={'yes':1,'no': 0}
    for dt in combine:
        dt['deposit']=bank['deposit'].map(depositmapping)
        X_train.head()
```

Out[254]:

	age	job	marital	education	default	balance	housing	loan	contact	day	m
5541	45	housemaid	married	primary	no	317	yes	no	cellular	8	
9240	53	management	married	tertiary	no	232	yes	no	telephone	29	
10826	24	student	single	secondary	no	493	yes	no	cellular	13	
1089	26	unemployed	single	tertiary	no	814	no	no	cellular	28	
9168	55	technician	married	unknown	no	1393	yes	yes	telephone	21	

```
In [255]: #assigning 1 to yes and 0 to no in default (X_train)
    combine=[X_train, X_test]
    defaultmapping={'yes':1,'no': 0}
    for dt in combine:
        dt['default']=bank['default'].map(defaultmapping)
```

In [256]: X_train.head()

Out[256]:

	age	job	marital	education	default	balance	housing	loan	contact	day	m
55	41 45	housemaid	married	primary	0	317	yes	no	cellular	8	
92	40 53	management	married	tertiary	0	232	yes	no	telephone	29	
108	26 24	student	single	secondary	0	493	yes	no	cellular	13	
10	89 26	unemployed	single	tertiary	0	814	no	no	cellular	28	
91	68 55	technician	married	unknown	0	1393	yes	yes	telephone	21	

```
In [257]: #assigning 1 to yes and 0 to no in housing (X_train)
    combine=[X_train, X_test]
    housingmapping={'yes':1, 'no': 0}
    for dt in combine:
        dt['housing']=bank['housing'].map(housingmapping)
```

```
In [258]: X_train.head()
```

Out[258]:

```
marital education default balance housing
                                                                           loan
                                                                                    contact day m
       age
                      job
                                                     0
                                                            317
 5541
        45
               housemaid
                          married
                                      primary
                                                                        1
                                                                                    cellular
                                                                                               8
                                                                             no
 9240
        53
             management
                          married
                                       tertiary
                                                     0
                                                            232
                                                                        1
                                                                                  telephone
                                                                                              29
                                                                             no
                            single
10826
        24
                                    secondary
                                                            493
                                                                                    cellular
                                                                                              13
                  student
                                                                        1
                                                                             no
 1089
        26
             unemployed
                            single
                                       tertiary
                                                     0
                                                            814
                                                                        0
                                                                             no
                                                                                    cellular
                                                                                              28
        55
               technician married
                                     unknown
                                                     0
                                                           1393
                                                                                 telephone
                                                                                              21
 9168
                                                                        1
                                                                            yes
```

```
In [259]: #assigning 1 to yes and 0 to no in loan (X_train)
    combine=[X_train, X_test]
    loanmapping={'yes':1,'no': 0}
    for dt in combine:
        dt['loan']=bank['loan'].map(loanmapping)
```

```
In [260]: #X train.head()
```

In [261]: #Analysing Education variable to assign them numerical values
 X_train[['education','deposit']].groupby('education',as_index=False).mea
 n().sort_values('deposit',ascending=False)

Out[261]:

	education	deposit
2	tertiary	0.541836
3	unknown	0.504886
1	secondary	0.458766
0	primary	0.390055

```
In [262]: educationmapping={'primary':1,'secondary':2,'tertiary':3,'unknown':0}
    for df in combine:
        df['education']=df['education'].map(educationmapping)
```

```
In [263]: X_train.head()
```

Out[263]:

	age	job	marital	education	default	balance	housing	loan	contact	day	m
5541	45	housemaid	married	1	0	317	1	0	cellular	8	
9240	53	management	married	3	0	232	1	0	telephone	29	
10826	24	student	single	2	0	493	1	0	cellular	13	
1089	26	unemployed	single	3	0	814	0	0	cellular	28	
9168	55	technician	married	0	0	1393	1	1	telephone	21	

```
In [264]: #Analysing Marital variable to assign them numerical values
    X_train[['marital','deposit']].groupby('marital',as_index=False).mean().
    sort_values('deposit',ascending=False)
```

Out[264]:

	marital	deposit
2	single	0.553462
0	divorced	0.485640
1	married	0.436187

Out[265]:

	month	deposit
2	dec	0.945205
7	mar	0.890805
11	sep	0.862069
10	oct	0.828000
0	apr	0.617699
3	feb	0.534934
9	nov	0.441230
1	aug	0.439377
6	jun	0.438375
4	jan	0.432836
5	jul	0.423529
8	may	0.342703

```
In [267]: X_train[['poutcome', 'deposit']].groupby('poutcome', as_index=False).mean
           ().sort values('deposit', ascending=False)
Out[267]:
             poutcome
                       deposit
                     0.914157
           2
               success
                 other 0.569182
           1
                failure 0.512295
              unknown 0.410395
           3
In [268]: | poutcomemapping={'success':2,'other':1,'failure':0,'unknown':0}
          for df in combine:
              df['poutcome']=df['poutcome'].map(poutcomemapping)
In [269]: for df in combine:
              df['job']=df['job'].replace(['management','technician','unknown','ad
          min.', 'housemaid', 'self-employed', 'services',
                                            'blue-collar', 'entrepreneur'], 'rare', reg
          ex=True)
           jobmapping={'student':1,'retired':2,'unemployed':3,'rare':0}
           for df in combine:
              df['job']=df['job'].map(jobmapping)
In [270]: X final train=X train[['job','loan','month','poutcome']]
          X_final_test=X_test[['job','loan','month','poutcome']]
In [271]: X train.columns
Out[271]: Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'hou
          sing',
                  'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pday
          s',
                  'previous', 'poutcome', 'deposit'],
                dtype='object')
In [272]: from sklearn.tree import DecisionTreeClassifier
          dt=DecisionTreeClassifier(random state=101)
          dt.fit(X final train,y train)
          predict=dt.predict(X final test)
          accuracy test=round(dt.score(X final test,y test)*100,2)
           accuracy train=round(dt.score(X final train,y train)*100,2)
          print('train accuracy of decision tree classifier',accuracy_train)
          print('test accuracy of decision tree classifier',accuracy test)
          train accuracy of decision tree classifier 67.28
          test accuracy of decision tree classifier 66.81
In [273]: from sklearn.metrics import accuracy score, confusion matrix, precision
          recall fscore support
          cm = confusion matrix(y test, predict)
```

```
In [274]:
Out[274]: array([[2140,
                         244],
                 [1238,
                         843]])
In [275]:
          cm_df = pd.DataFrame(cm,
                                index = ['Deposit','Others'],
                                columns = ['Deposit','Others'])
In [276]:
          plt.figure(figsize=(5.5,4))
          sns.heatmap(cm_df, annot=True)
          plt.title(' Decision Tree \nAccuracy:{0:.3f}'.format(accuracy_test))
          plt.ylabel('True label')
          plt.xlabel('Predicted label')
          plt.show()
```

