SKILLCRAFT TECHNOLOGY INTERNSHIP TASK-3

Build a decision tree classifier to predict whether a customer will purchase a product or service based on their demographic and behavioral data. Use a dataset such as the Bank Marketing dataset from the UCI machine Learning Repository

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn import datasets
from io import StringIO
from sklearn.tree import export_graphviz
from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn import metrics
%matplotlib inline
```

```
# Load data file
bank=pd.read_csv('../input/bank.csv')
bank.head()
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5	may	1042	1	-1
1	56	admin.	married	secondary	no	45	no	no	unknown	5	may	1467	1	-1
2	41	technician	married	secondary	no	1270	yes	no	unknown	5	may	1389	1	-1
3	55	services	married	secondary	no	2476	yes	no	unknown	5	may	579	1	-1
4	54	admin.	married	tertiary	no	184	no	no	unknown	5	may	673	2	-1

```
# Load data file
bank=pd.read_csv('../input/bank.csv')
bank.head()
```

```
# Check if the data set contains any null values - Nothing found!
bank[bank.isnull().any(axis=1)].count()
```

```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
deposit      0
dtype: int64
```

```
# Check if the data set contains any null values - Nothing found!
bank[bank.isnull().any(axis=1)].count()
```

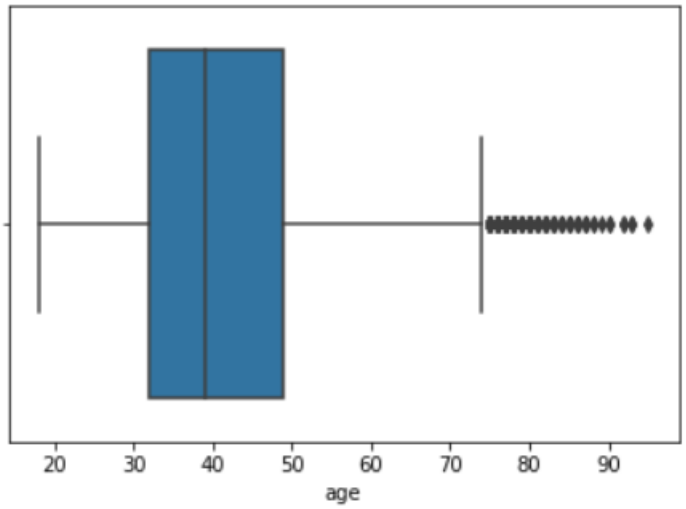
```
bank.describe()
```

	age	balance	day	duration	campaign	pdays	previous
count	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000
mean	41.231948	1528.538524	15.658036	371.993818	2.508421	51.330407	0.832557
std	11.913369	3225.413326	8.420740	347.128386	2.722077	108.758282	2.292007
min	18.000000	-6847.000000	1.000000	2.000000	1.000000	-1.000000	0.000000
25%	32.000000	122.000000	8.000000	138.000000	1.000000	-1.000000	0.000000
50%	39.000000	550.000000	15.000000	255.000000	2.000000	-1.000000	0.000000
75%	49.000000	1708.000000	22.000000	496.000000	3.000000	20.750000	1.000000
max	95.000000	81204.000000	31.000000	3881.000000	63.000000	854.000000	58.000000

```
# Check if the data set contains any null values - Nothing found!
bank[bank.isnull().any(axis=1)].count()
```

```
bank.describe()
```

```
# Boxplot for 'age'
g = sns.boxplot(x=bank["age"])
```

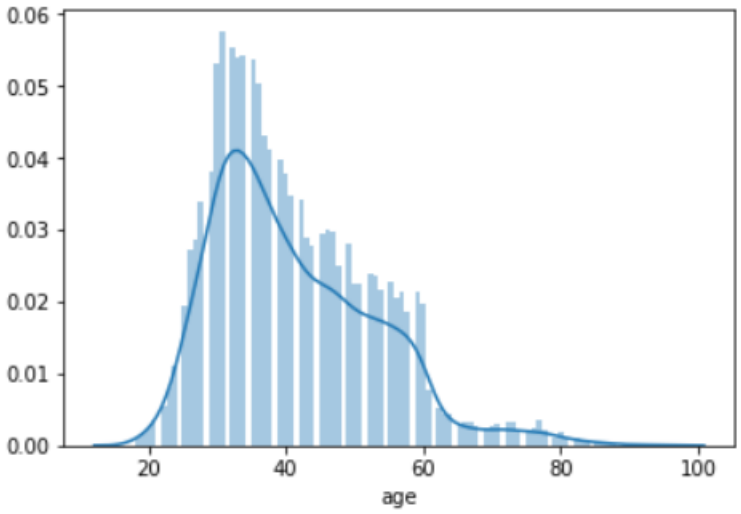



```
bank.describe()
```

```
# Boxplot for 'age'
g = sns.boxplot(x=bank["age"])
```

```
# Distribution of Age
sns.distplot(bank.age, bins=100)
```

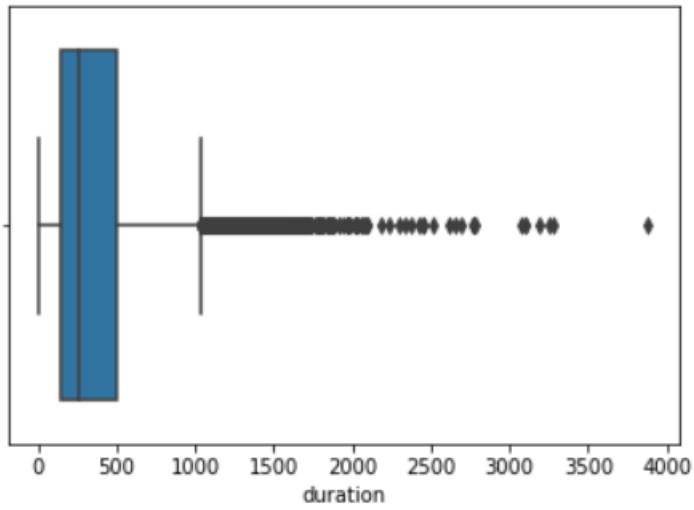
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f116798e2b0>
```




```
# Boxplot for 'age'
g = sns.boxplot(x=bank["age"])
```

```
# Distribution of Age
sns.distplot(bank.age, bins=100)
```

```
# Boxplot for 'duration'
g = sns.boxplot(x=bank["duration"])
```



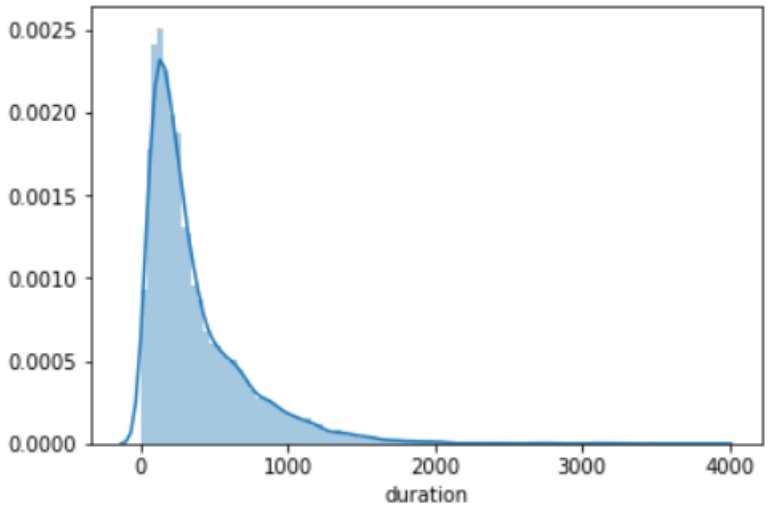

```
# Distribution of Age
sns.distplot(bank.age, bins=100)
```

```
# Boxplot for 'duration'
g = sns.boxplot(x=bank["duration"])
```

+ Code + Markdown

```
sns.distplot(bank.duration, bins=100)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f11677eaba8>
```




```
# Make a copy for parsing
bank_data = bank.copy()
```

```
# Boxplot for 'duration'
g = sns.boxplot(x=bank["duration"])
```

```
sns.distplot(bank.duration, bins=100)
```

---------- job ----------

```
# Explore People who made a deposit Vs Job category
jobs = ['management','blue-collar','technician','admin.','services','retired','self-employed','student',\
        'unemployed','entrepreneur','housemaid','unknown']

for j in jobs:
    print("{:15} : {:5}". format(j, len(bank_data[(bank_data.deposit == "yes") & (bank_data.job ==j)])))
```

```
management      :  1301
blue-collar     :   708
technician      :   840
admin.          :   631
services        :   369
retired         :   516
self-employed   :   187
student         :   269
unemployed      :   202
entrepreneur    :   123
housemaid       :   109
unknown         :    34
```

```
# Explore People who made a deposit Vs Job category
jobs = ['management','blue-collar','technician','admin.','services','retired','self-employed','student',\
        'unemployed','entrepreneur','housemaid','unknown']

for j in jobs:
    print("{:15} : {:5}". format(j, len(bank_data[(bank_data.deposit == "yes") & (bank_data.job ==j)])))
```

```
# Different types of job categories and their counts
bank_data.job.value_counts()
```

```
management       2566
blue-collar      1944
technician       1823
admin.           1334
services          923
retired           778
self-employed     405
student           360
unemployed        357
entrepreneur      328
housemaid         274
unknown            70
Name: job, dtype: int64
```

```
# Combine similar jobs into categiroes
bank_data['job'] = bank_data['job'].replace(['management', 'admin.'], 'white-collar')
bank_data['job'] = bank_data['job'].replace(['services','housemaid'], 'pink-collar')
bank_data['job'] = bank_data['job'].replace(['retired', 'student', 'unemployed', 'unknown'], 'other')
```

```
# New value counts
bank_data.job.value_counts()
```

```
white-collar     3900
blue-collar      1944
technician       1823
other            1565
pink-collar      1197
self-employed     405
entrepreneur      328
Name: job, dtype: int64
```

---------- poutcome ----------

```
# New value counts
bank_data.job.value_counts()
```

```
bank_data.poutcome.value_counts()
```

```
unknown    8326
failure    1228
success    1071
other       537
Name: poutcome, dtype: int64
```

```
# New value counts
bank_data.job.value_counts()
```

```
bank_data.poutcome.value_counts()
```

```
# Combine 'unknown' and 'other' as 'other' isn't really match with either 'success' or 'failure'
bank_data['poutcome'] = bank_data['poutcome'].replace(['other'] , 'unknown')
bank_data.poutcome.value_counts()
```

```
unknown    8863
failure    1228
success    1071
Name: poutcome, dtype: int64
```

---------- contact ----------

```
# Combine 'unknown' and 'other' as 'other' isn't really match with either 'success' or 'failure'
bank_data['poutcome'] = bank_data['poutcome'].replace(['other'] , 'unknown')
bank_data.poutcome.value_counts()
```

```
# Drop 'contact', as every participant has been contacted.
bank_data.drop('contact', axis=1, inplace=True)
```

---------- default ----------

```
# Combine 'unknown' and 'other' as 'other' isn't really match with either 'success' or 'failure'
bank_data['poutcome'] = bank_data['poutcome'].replace(['other'] , 'unknown')
bank_data.poutcome.value_counts()
```

```
# Drop 'contact', as every participant has been contacted.
bank_data.drop('contact', axis=1, inplace=True)
```

```
# values for "default" : yes/no
bank_data["default"]
bank_data['default_cat'] = bank_data['default'].map( {'yes':1, 'no':0} )
bank_data.drop('default', axis=1,inplace = True)
```

---------- housing ----------

```
# values for "default" : yes/no
bank_data["default"]
bank_data['default_cat'] = bank_data['default'].map( {'yes':1, 'no':0} )
bank_data.drop('default', axis=1,inplace = True)
```

```
# values for "housing" : yes/no
bank_data["housing_cat"]=bank_data['housing'].map({'yes':1, 'no':0})
bank_data.drop('housing', axis=1,inplace = True)
```

---------- loan ----------

```
# values for "loan" : yes/no
bank_data["loan_cat"] = bank_data['loan'].map({'yes':1, 'no':0})
bank_data.drop('loan', axis=1, inplace=True)
```

---------- month, day ----------

```
# values for "loan" : yes/no
bank_data["loan_cat"] = bank_data['loan'].map({'yes':1, 'no':0})
bank_data.drop('loan', axis=1, inplace=True)
```

```
# day  : last contact day of the month
# month: last contact month of year
# Drop 'month' and 'day' as they don't have any intrinsic meaning
bank_data.drop('month', axis=1, inplace=True)
bank_data.drop('day', axis=1, inplace=True)
```

---------- deposit ----------

```
# values for "deposit" : yes/no
bank_data["deposit_cat"] = bank_data['deposit'].map({'yes':1, 'no':0})
bank_data.drop('deposit', axis=1, inplace=True)
```

---------- pdays ----------

```
# pdays: number of days that passed by after the client was last contacted from a previous campaign
#       -1 means client was not previously contacted

print("Customers that have not been contacted before:", len(bank_data[bank_data.pdays==-1]))
print("Maximum values on padys    :", bank_data['pdays'].max())
```

```
Customers that have not been contacted before: 8324
Maximum values on padys    : 854
```

```
# Map padys=-1 into a large value (10000 is used) to indicate that it is so far in the past that it has no
bank_data.loc[bank_data['pdays'] == -1, 'pdays'] = 10000
```

```
# Create a new column: recent_pdays
bank_data['recent_pdays'] = np.where(bank_data['pdays'], 1/bank_data.pdays, 1/bank_data.pdays)

# Drop 'pdays'
bank_data.drop('pdays', axis=1, inplace = True)
```

```
bank_data.tail()
```

	age	job	marital	education	balance	duration	campaign	previous	poutcome	default_cat	housing_cat	loan_c
11157	33	blue-collar	single	primary	1	257	1	0	unknown	0	1	0
11158	39	pink-collar	married	secondary	733	83	4	0	unknown	0	0	0
11159	32	technician	single	secondary	29	156	2	0	unknown	0	0	0
11160	43	technician	married	secondary	0	9	2	5	failure	0	0	1
11161	34	technician	married	secondary	0	628	1	0	unknown	0	0	0

---------- Convert to dummy values ----------

```
bank_data.tail()
```

```
# Convert categorical variables to dummies
bank_with_dummies = pd.get_dummies(data=bank_data, columns = ['job', 'marital', 'education', 'poutcome']
                                   prefix = ['job', 'marital', 'education', 'poutcome'])
bank_with_dummies.head()
```

	age	balance	duration	campaign	previous	default_cat	housing_cat	loan_cat	deposit_cat	recent_pdays	...	marital_divorc
0	59	2343	1042	1	0	0	1	0	1	0.0001	...	0
1	56	45	1467	1	0	0	0	0	1	0.0001	...	0
2	41	1270	1389	1	0	0	1	0	1	0.0001	...	0
3	55	2476	579	1	0	0	1	0	1	0.0001	...	0
4	54	184	673	2	0	0	0	0	1	0.0001	...	0

```
# Convert categorical variables to dummies
bank_with_dummies = pd.get_dummies(data=bank_data, columns = ['job', 'marital', 'education', 'poutcome']
                                   prefix = ['job', 'marital', 'education', 'poutcome'])
bank_with_dummies.head()
```

```
bank_with_dummies.shape
```

(11162, 27)

```
# Convert categorical variables to dummies
bank_with_dummies = pd.get_dummies(data=bank_data, columns = ['job', 'marital', 'education', 'poutcome']
                                   prefix = ['job', 'marital', 'education', 'poutcome'])
bank_with_dummies.head()
```

```
bank_with_dummies.shape
```

```
bank_with_dummies.describe()
```

	age	balance	duration	campaign	previous	default_cat	housing_cat	loan_cat	
count	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11
mean	41.231948	1528.538524	371.993818	2.508421	0.832557	0.015051	0.473123	0.130801	0.4
std	11.913369	3225.413326	347.128386	2.722077	2.292007	0.121761	0.499299	0.337198	0.4
min	18.000000	-6847.000000	2.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.0
25%	32.000000	122.000000	138.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.0
50%	39.000000	550.000000	255.000000	2.000000	0.000000	0.000000	0.000000	0.000000	0.0
75%	49.000000	1708.000000	496.000000	3.000000	1.000000	0.000000	1.000000	0.000000	1.0
max	95.000000	81204.000000	3881.000000	63.000000	58.000000	1.000000	1.000000	1.000000	1.0

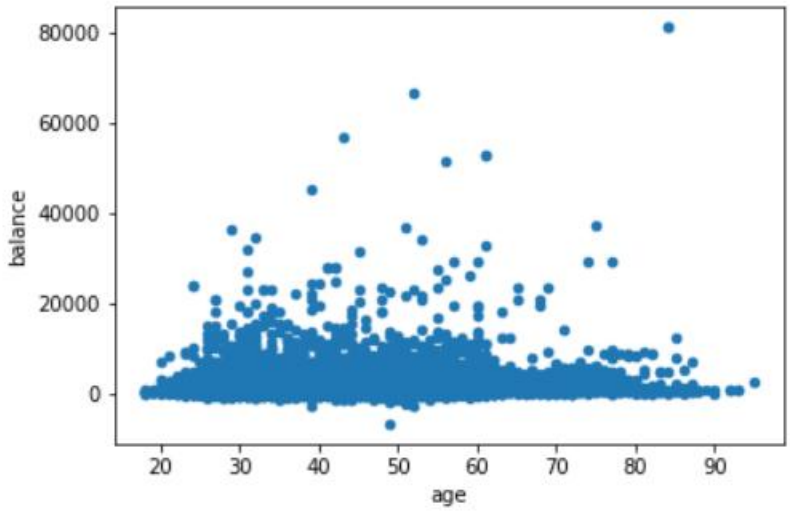
8 rows × 27 columns

```
bank_with_dummies.shape
```

```
bank_with_dummies.describe()
```

```
# Scatterplot showing age and balance
bank_with_dummies.plot(kind='scatter', x='age', y='balance');

# Across all ages, majority of people have savings of less than 20000.
```



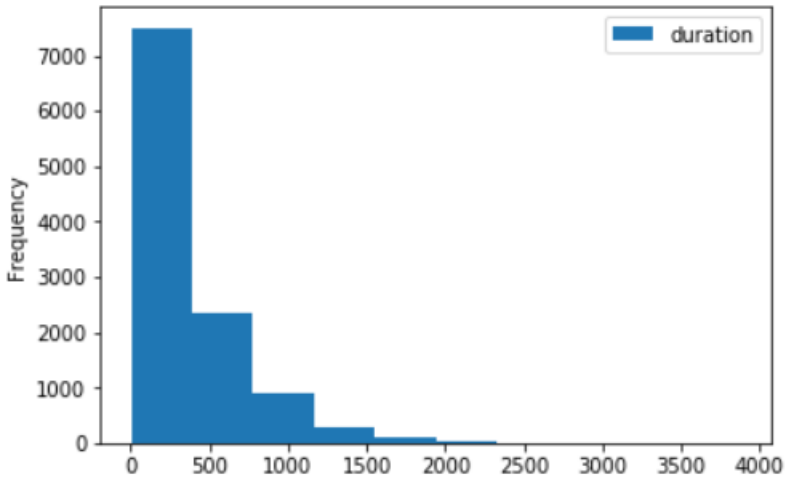
```
bank_with_dummies.shape
```

```
bank_with_dummies.describe()
```

```
# Scatterplot showing age and balance
bank_with_dummies.plot(kind='scatter', x='age', y='balance');

# Across all ages, majority of people have savings of less than 20000.
```

```
bank_with_dummies.plot(kind='hist', x='poutcome_success', y='duration');
```



```
# Scatterplot showing age and balance
bank_with_dummies.plot(kind='scatter', x='age', y='balance');

# Across all ages, majority of people have savings of less than 20000.
```

```
bank_with_dummies.plot(kind='hist', x='poutcome_success', y='duration');
```

```
# People who sign up to a term deposite
bank_with_dummies[bank_data.deposit_cat == 1].describe()
```

	age	balance	duration	campaign	previous	default_cat	housing_cat	loan_cat	deposit_
count	5289.000000	5289.000000	5289.000000	5289.000000	5289.000000	5289.000000	5289.000000	5289.000000	5289.0
mean	41.670070	1804.267915	537.294574	2.141047	1.170354	0.009832	0.365854	0.091511	1.0
std	13.497781	3501.104777	392.525262	1.921826	2.553272	0.098676	0.481714	0.288361	0.0
min	18.000000	-3058.000000	8.000000	1.000000	0.000000	0.000000	0.000000	0.000000	1.0
25%	31.000000	210.000000	244.000000	1.000000	0.000000	0.000000	0.000000	0.000000	1.0
50%	38.000000	733.000000	426.000000	2.000000	0.000000	0.000000	0.000000	0.000000	1.0
75%	50.000000	2159.000000	725.000000	3.000000	1.000000	0.000000	1.000000	0.000000	1.0
max	95.000000	81204.000000	3881.000000	32.000000	58.000000	1.000000	1.000000	1.000000	1.0

```
bank_with_dummies.plot(kind='hist', x='poutcome_success', y='duration');
```

```
# People who sign up to a term deposite
bank_with_dummies[bank_data.deposit_cat == 1].describe()
```

```
a term deposite having a personal loan (loan_cat) and housing loan (housing_cat)
s[(bank_with_dummies.deposit_cat == 1) & (bank_with_dummies.loan_cat) & (bank_with_dummies.housing_cat)])
```

```
# People signed up to a term deposite having a personal loan (loan_cat) and housing loan (housing_cat)
len(bank_with_dummies[(bank_with_dummies.deposit_cat == 1) & (bank_with_dummies.loan_cat) & (bank_with_du
```

+ Code + Markdown

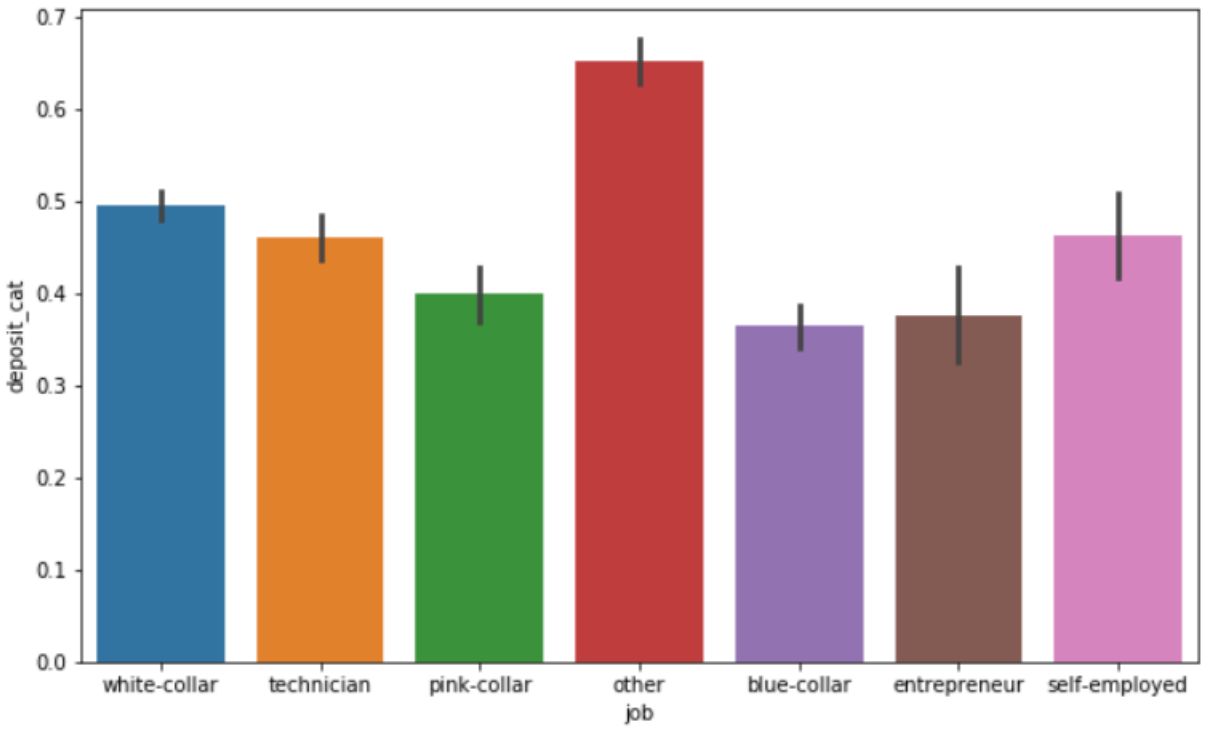
```
# People signed up to a term deposite with a credit default
len(bank_with_dummies[(bank_with_dummies.deposit_cat == 1) & (bank_with_dummies.default_cat ==1)])
```

52

```
# People signed up to a term deposite with a credit default
len(bank_with_dummies[(bank_with_dummies.deposit_cat == 1) & (bank_with_dummies.default_cat ==1)])
```

```
# Bar chart of job Vs deposite
plt.figure(figsize = (10,6))
sns.barplot(x='job', y = 'deposit_cat', data = bank_data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f11f97b9710>
```



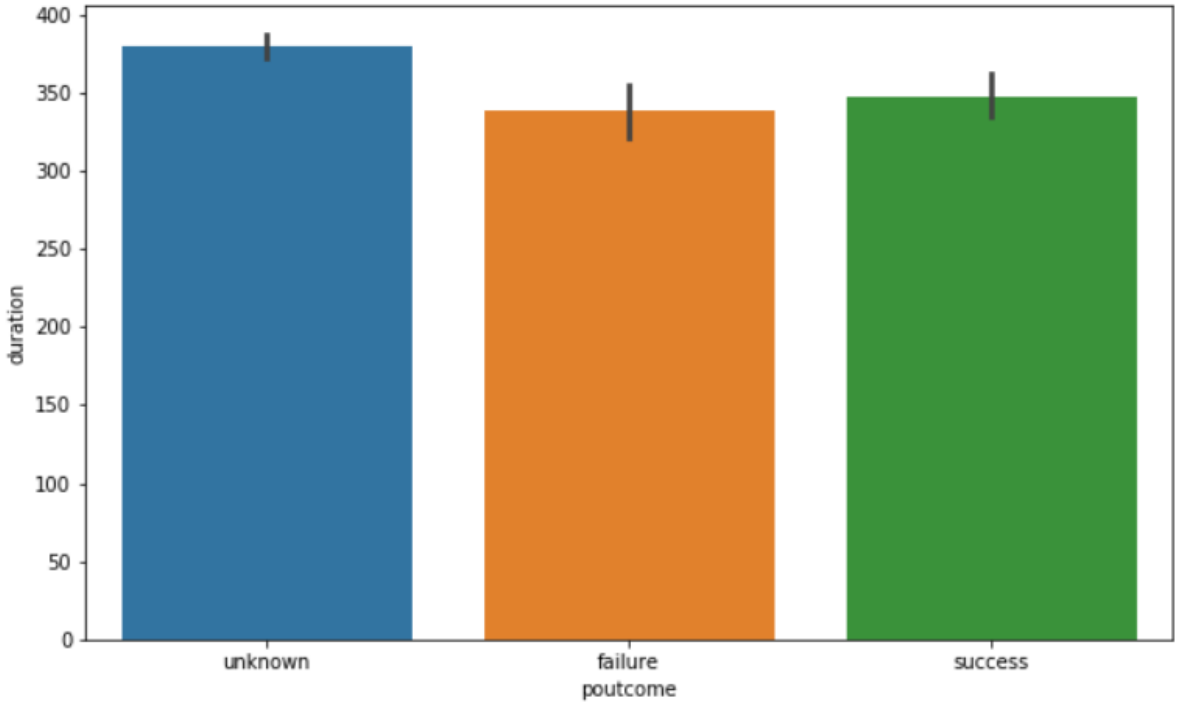
```
# People signed up to a term deposite with a credit default
len(bank_with_dummies[(bank_with_dummies.deposit_cat == 1) & (bank_with_dummies.default_cat ==1)])
```

```
# Bar chart of job Vs deposite
plt.figure(figsize = (10,6))
sns.barplot(x='job', y = 'deposit_cat', data = bank_data)
```

```
# Bar chart of "previous outcome" Vs "call duration"

plt.figure(figsize = (10,6))
sns.barplot(x='poutcome', y = 'duration', data = bank_data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1167643080>
```



```
# make a copy
bankcl = bank_with_dummies
```

```
# The Correltion matrix
corr = bankcl.corr()
corr
```

	age	balance	duration	campaign	previous	default_cat	housing_cat	loan_cat	deposit_cat	r
age	1.000000	0.112300	0.000189	-0.005278	0.020169	-0.011425	-0.168700	-0.031418	0.034901	0
balance	0.112300	1.000000	0.022436	-0.013894	0.030805	-0.060954	-0.077092	-0.084589	0.081129	-
duration	0.000189	0.022436	1.000000	-0.041557	-0.026716	-0.009760	0.035051	-0.001914	0.451919	-
campaign	-0.005278	-0.013894	-0.041557	1.000000	-0.049699	0.030975	0.006660	0.034722	-0.128081	-
previous	0.020169	0.030805	-0.026716	-0.049699	1.000000	-0.035273	-0.000840	-0.022668	0.139867	0
default_cat	-0.011425	-0.060954	-0.009760	0.030975	-0.035273	1.000000	0.011076	0.076434	-0.040680	-
housing_cat	-0.168700	-0.077092	0.035051	0.006660	-0.000840	0.011076	1.000000	0.076761	-0.203888	-
loan_cat	-0.031418	-0.084589	-0.001914	0.034722	-0.022668	0.076434	0.076761	1.000000	-0.110580	-
deposit_cat	0.034901	0.081129	0.451919	-0.128081	0.139867	-0.040680	-0.203888	-0.110580	1.000000	0
recent_pdays	0.019102	-0.004379	-0.014868	-0.026296	0.122076	-0.011290	-0.029350	-0.012697	0.034457	1
job_blue-collar	-0.066567	-0.046220	0.029986	0.005522	-0.039939	0.022779	0.189848	0.057956	-0.100840	-
job_entrepreneur	0.024176	0.005039	-0.000908	0.013883	-0.022470	0.022060	0.011492	0.042631	-0.034443	0
job_other	0.296418	0.050744	0.010680	-0.050212	0.031191	-0.018130	-0.233309	-0.096196	0.144408	0
job_pink-collar	-0.027942	-0.041063	0.005345	0.011958	-0.028623	-0.007173	0.043884	0.014969	-0.051717	-
job_self-employed	-0.023163	0.020264	0.013506	0.001776	-0.002338	0.007493	-0.016903	0.004299	-0.004707	-
job_technician	-0.082716	0.003802	-0.010440	0.021738	0.002035	0.003109	0.006551	0.006864	-0.011557	-
job_white-collar	-0.080122	0.013780	-0.031980	0.001944	0.034929	-0.013425	-0.012111	-0.007871	0.031621	0

job_white-collar	-0.080122	0.013780	-0.031980	0.001944	0.034929	-0.013425	-0.012111	-0.007871	0.031621	0
marital_divorced	0.186349	-0.017586	0.021364	-0.006828	-0.026566	0.019633	0.007430	0.026463	0.005228	-
marital_married	0.318436	0.025431	-0.036179	0.047722	-0.005176	-0.006819	0.036305	0.044148	-0.092157	0
marital_single	-0.467799	-0.014994	0.023847	-0.046165	0.023817	-0.006255	-0.043817	-0.065288	0.094632	0
education_primary	0.231150	-0.000673	0.013405	0.019915	-0.024852	0.013858	0.017002	0.006854	-0.063002	-
education_secondary	-0.094400	-0.070609	0.003820	-0.013834	-0.004620	-0.000618	0.118514	0.079583	-0.051952	-
education_tertiary	-0.101372	0.069128	-0.006813	-0.005427	0.028146	-0.011768	-0.114955	-0.067513	0.094598	0
education_unknown	0.077761	0.014596	-0.015887	0.012976	-0.011898	0.005421	-0.053191	-0.050249	0.014355	0
poutcome_failure	-0.008071	0.001695	-0.033966	-0.080188	0.335870	-0.024650	0.087741	0.006264	0.020714	0
poutcome_success	0.062114	0.045603	-0.022578	-0.091807	0.325477	-0.040272	-0.136299	-0.080370	0.286642	0
poutcome_unknown	-0.038992	-0.034524	0.042725	0.128907	-0.496921	0.048403	0.031375	0.053686	-0.224785	-

```
# The Correltion matrix
corr = bankcl.corr()
corr
```

```
# Heatmap
plt.figure(figsize = (10,10))
cmap = sns.diverging_palette(220, 10, as_cmap=True)
sns.heatmap(corr, xticklabels=corr.columns.values, yticklabels=corr.columns.values, cmap=cmap, vmax=.3,
plt.title('Heatmap of Correlation Matrix')
```


```
# Heatmap
plt.figure(figsize = (10,10))
cmap = sns.diverging_palette(220, 10, as_cmap=True)
sns.heatmap(corr, xticklabels=corr.columns.values, yticklabels=corr.columns.values, cmap=cmap, vmax=.3,
plt.title('Heatmap of Correlation Matrix')
```

```
# Extract the deposte_cat column (the dependent variable)
corr_deposite = pd.DataFrame(corr['deposit_cat'].drop('deposit_cat'))
corr_deposite.sort_values(by = 'deposit_cat', ascending = False)
```

	deposit_cat
duration	0.451919
poutcome_success	0.286642
job_other	0.144408
previous	0.139867
marital_single	0.094632
education_tertiary	0.094598
balance	0.081129
age	0.034901
recent_pdays	0.034457
job_white-collar	0.031621
poutcome_failure	0.020714
education_unknown	0.014355
marital_divorced	0.005228
job_self-employed	-0.004707
job_technician	-0.011557
job_entrepreneur	-0.034443
default_cat	-0.040680

poutcome_failure	0.020714
education_unknown	0.014355
marital_divorced	0.005228
job_self-employed	-0.004707
job_technician	-0.011557
job_entrepreneur	-0.034443
default_cat	-0.040680
job_pink-collar	-0.051717
education_secondary	-0.051952
education_primary	-0.063002
marital_married	-0.092157
job_blue-collar	-0.100840
loan_cat	-0.110580
campaign	-0.128081
housing_cat	-0.203888
poutcome_unknown	-0.224785

```
# Extract the deposte_cat column (the dependent variable)
corr_deposite = pd.DataFrame(corr['deposit_cat'].drop('deposit_cat'))
corr_deposite.sort_values(by = 'deposit_cat', ascending = False)
```

```
# Train-Test split: 20% test data
data_drop_deposite = bankcl.drop('deposit_cat', 1)
label = bankcl.deposit_cat
data_train, data_test, label_train, label_test = train_test_split(data_drop_deposite, label, test_size =
```

+ Code + Markdown

```
# Decision tree with depth = 2
dt2 = tree.DecisionTreeClassifier(random_state=1, max_depth=2)
dt2.fit(data_train, label_train)
dt2_score_train = dt2.score(data_train, label_train)
print("Training score: ",dt2_score_train)
dt2_score_test = dt2.score(data_test, label_test)
print("Testing score: ",dt2_score_test)
```

```
Training score:  0.728525030799
Testing score:  0.726824899239
```

```
# Decision tree with depth = 2
dt2 = tree.DecisionTreeClassifier(random_state=1, max_depth=2)
dt2.fit(data_train, label_train)
dt2_score_train = dt2.score(data_train, label_train)
print("Training score: ",dt2_score_train)
dt2_score_test = dt2.score(data_test, label_test)
print("Testing score: ",dt2_score_test)
```

```
# Decision tree with depth = 3
dt3 = tree.DecisionTreeClassifier(random_state=1, max_depth=3)
dt3.fit(data_train, label_train)
dt3_score_train = dt3.score(data_train, label_train)
print("Training score: ",dt3_score_train)
dt3_score_test = dt3.score(data_test, label_test)
print("Testing score: ",dt3_score_test)
```

```
Training score:  0.770411020271
Testing score:  0.757277205553
```

```
# Decision tree with depth = 3
dt3 = tree.DecisionTreeClassifier(random_state=1, max_depth=3)
dt3.fit(data_train, label_train)
dt3_score_train = dt3.score(data_train, label_train)
print("Training score: ",dt3_score_train)
dt3_score_test = dt3.score(data_test, label_test)
print("Testing score: ",dt3_score_test)
```

```
# Decision tree with depth = 4
dt4 = tree.DecisionTreeClassifier(random_state=1, max_depth=4)
dt4.fit(data_train, label_train)
dt4_score_train = dt4.score(data_train, label_train)
print("Training score: ",dt4_score_train)
dt4_score_test = dt4.score(data_test, label_test)
print("Testing score: ",dt4_score_test)
```

```
Training score:  0.788554149401
Testing score:  0.774294670846
```

```
# Decision tree with depth = 4
dt4 = tree.DecisionTreeClassifier(random_state=1, max_depth=4)
dt4.fit(data_train, label_train)
dt4_score_train = dt4.score(data_train, label_train)
print("Training score: ",dt4_score_train)
dt4_score_test = dt4.score(data_test, label_test)
print("Testing score: ",dt4_score_test)
```

```
# Decision tree with depth = 6
dt6 = tree.DecisionTreeClassifier(random_state=1, max_depth=6)
dt6.fit(data_train, label_train)
dt6_score_train = dt6.score(data_train, label_train)
print("Training score: ",dt6_score_train)
dt6_score_test = dt6.score(data_test, label_test)
print("Testing score: ",dt6_score_test)
```

```
Training score:  0.808041214022
Testing score:  0.779668607255
```

```python
# Decision tree with depth = 6
dt6 = tree.DecisionTreeClassifier(random_state=1, max_depth=6)
dt6.fit(data_train, label_train)
dt6_score_train = dt6.score(data_train, label_train)
print("Training score: ",dt6_score_train)
dt6_score_test = dt6.score(data_test, label_test)
print("Testing score: ",dt6_score_test)
```

```python
# Decision tree: To the full depth
dt1 = tree.DecisionTreeClassifier()
dt1.fit(data_train, label_train)
dt1_score_train = dt1.score(data_train, label_train)
print("Training score: ", dt1_score_train)
dt1_score_test = dt1.score(data_test, label_test)
print("Testing score: ", dt1_score_test)
```

```
Training score:  1.0
Testing score:  0.741155396328
```

```
# Decision tree: To the full depth
dt1 = tree.DecisionTreeClassifier()
dt1.fit(data_train, label_train)
dt1_score_train = dt1.score(data_train, label_train)
print("Training score: ", dt1_score_train)
dt1_score_test = dt1.score(data_test, label_test)
print("Testing score: ", dt1_score_test)
```

```
print('{:10} {:20} {:20}'.format('depth', 'Training score','Testing score'))
print('{:10} {:20} {:20}'.format('-----', '--------------','-------------'))
print('{:1} {:>25} {:>20}'.format(2, dt2_score_train, dt2_score_test))
print('{:1} {:>25} {:>20}'.format(3, dt3_score_train, dt3_score_test))
print('{:1} {:>25} {:>20}'.format(4, dt4_score_train, dt4_score_test))
print('{:1} {:>25} {:>20}'.format(6, dt6_score_train, dt6_score_test))
print('{:1} {:>23} {:>20}'.format("max", dt1_score_train, dt1_score_test))
```

```
depth      Training score       Testing score
-----      --------------       -------------
2        0.7285250307985217   0.7268248992386923
3         0.770411020271027   0.7572772055530677
4        0.7885541494008288    0.774294670846395
6        0.8080412140217269   0.7796686072548141
max                     1.0   0.7411553963278101
```

```
print('{:10} {:20} {:20}'.format('depth', 'Training score','Testing score'))
print('{:10} {:20} {:20}'.format('-----', '--------------','-------------'))
print('{:1} {:>25} {:>20}'.format(2, dt2_score_train, dt2_score_test))
print('{:1} {:>25} {:>20}'.format(3, dt3_score_train, dt3_score_test))
print('{:1} {:>25} {:>20}'.format(4, dt4_score_train, dt4_score_test))
print('{:1} {:>25} {:>20}'.format(6, dt6_score_train, dt6_score_test))
print('{:1} {:>23} {:>20}'.format("max", dt1_score_train, dt1_score_test))
```

```
# Let's generate the decision tree for depth = 2
# Create a feature vector
features = bankcl.columns.tolist()

# Uncomment below to generate the digraph Tree.
#tree.export_graphviz(dt2, out_file='tree_depth_2.dot', feature_names=features)
```

Contents of "tree_depth_2.dot":

```
digraph Tree {
node [shape=box] ;
0 [label="duration <= 206.5\ngini = 0.4986\nsamples = 8929\nvalue = [4700, 4229]"] ;
1 [label="poutcome_failure <= 0.5\ngini = 0.3274\nsamples = 3612\nvalue = [2867, 745]"] ;
0 -> 1 [labeldistance=2.5, labelangle=45, headlabel="True"] ;
2 [label="gini = 0.2733\nsamples = 3380\nvalue = [2828, 552]"] ;
1 -> 2 ;
3 [label="gini = 0.2797\nsamples = 232\nvalue = [39, 193]"] ;
1 -> 3 ;
4 [label="duration <= 441.5\ngini = 0.4518\nsamples = 5317\nvalue = [1833, 3484]"] ;
0 -> 4 [labeldistance=2.5, labelangle=-45, headlabel="False"] ;
5 [label="gini = 0.4996\nsamples = 2762\nvalue = [1340, 1422]"] ;
4 -> 5 ;
6 [label="gini = 0.3114\nsamples = 2555\nvalue = [493, 2062]"] ;
4 -> 6 ;
}
```

```
# Let's generate the decision tree for depth = 2
# Create a feature vector
features = bankcl.columns.tolist()

# Uncomment below to generate the digraph Tree.
#tree.export_graphviz(dt2, out_file='tree_depth_2.dot', feature_names=features)
```

```
# Two classes: 0 = not signed up,  1 = signed up
dt2.classes_
```

```
array([0, 1])
```

```
# Two classes: 0 = not signed up,  1 = signed up
dt2.classes_
```

```
# Create a feature vector
features = data_drop_deposite.columns.tolist()

features
```

```
['age',
 'balance',
 'duration',
 'campaign',
 'previous',
 'default_cat',
 'housing_cat',
 'loan_cat',
 'recent_pdays',
 'job_blue-collar',
 'job_entrepreneur',
 'job_other',
 'job_pink-collar',
 'job_self-employed',
 'job_technician',
 'job_white-collar',
 'marital_divorced',
 'marital_married',
 'marital_single',
 'education_primary',
 'education_secondary',
 'education_tertiary',
```

```
'loan_cat',
'recent_pdays',
'job_blue-collar',
'job_entrepreneur',
'job_other',
'job_pink-collar',
'job_self-employed',
'job_technician',
'job_white-collar',
'marital_divorced',
'marital_married',
'marital_single',
'education_primary',
'education_secondary',
'education_tertiary',
'education_unknown',
'poutcome_failure',
'poutcome_success',
'poutcome_unknown']
```

```
# Create a feature vector
features = data_drop_deposite.columns.tolist()

features
```

```
# Investigate most important features with depth =2

dt2 = tree.DecisionTreeClassifier(random_state=1, max_depth=2)

# Fit the decision tree classifier
dt2.fit(data_train, label_train)

fi = dt2.feature_importances_

l = len(features)
for i in range(0,len(features)):
    print('{:.<20} {:3}'.format(features[i],fi[i]))
```

```
age.................. 0.0
balance.............. 0.0
duration............. 0.849306123902405
campaign............. 0.0
previous............. 0.0
default_cat......... 0.0
housing_cat......... 0.0
loan_cat............. 0.0
recent_pdays........ 0.0
job_blue-collar..... 0.0
job_entrepreneur.... 0.0
job_other............ 0.0
job_pink-collar..... 0.0
job_self-employed... 0.0
job_technician...... 0.0
job_white-collar.... 0.0
marital_divorced.... 0.0
marital_married..... 0.0
marital_single...... 0.0
education_primary... 0.0
education_secondary. 0.0
education_tertiary.. 0.0
```

```
job_other........... 0.0
job_pink-collar..... 0.0
job_self-employed... 0.0
job_technician...... 0.0
job_white-collar.... 0.0
marital_divorced.... 0.0
marital_married..... 0.0
marital_single...... 0.0
education_primary... 0.0
education_secondary. 0.0
education_tertiary.. 0.0
education_unknown... 0.0
poutcome_failure.... 0.0
poutcome_success.... 0.15069387609759496
poutcome_unknown.... 0.0
```

```python
# Investigate most important features with depth =2

dt2 = tree.DecisionTreeClassifier(random_state=1, max_depth=2)

# Fit the decision tree classifier
dt2.fit(data_train, label_train)

fi = dt2.feature_importances_

l = len(features)
for i in range(0,len(features)):
    print('{:.<20} {:3}'.format(features[i],fi[i]))
```

```python
# According to feature importance results, most importtant feature is the "Duration"
# Let's calculte statistics on Duration
print("Mean duration   : ", data_drop_deposite.duration.mean())
print("Maximun duration: ", data_drop_deposite.duration.max())
print("Minimum duration: ", data_drop_deposite.duration.min())
```

```
Mean duration   :  371.99381831213043
Maximun duration:  3881
Minimum duration:  2
```

```
# According to feature importance results, most importtant feature is the "Duration"
# Let's calculte statistics on Duration
print("Mean duration   : ", data_drop_deposite.duration.mean())
print("Maximun duration: ", data_drop_deposite.duration.max())
print("Minimum duration: ", data_drop_deposite.duration.min())
```

```
# Predict: Successful deposite with a call duration = 371 sec

print(dt2.predict_proba(np.array([0, 0, 371, 0, 0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0]).reshape(1
print(dt2.predict(np.array([0, 0, 371, 0, 0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0]).reshape(1, -1))
# column 0: probability for class 0 (not signed for term deposite) & column 1: probability for class 1
# Probability of Successful deposite = 0.51484432
```

```
[[ 0.48515568  0.51484432]]
[1]
```


```
# Predict: Successful deposite with a call duration = 371 sec

print(dt2.predict_proba(np.array([0, 0, 371, 0, 0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0]).reshape(1
print(dt2.predict(np.array([0, 0, 371, 0, 0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0]).reshape(1, -1))
# column 0: probability for class 0 (not signed for term deposite) & column 1: probability for class 1
# Probability of Successful deposite = 0.51484432
```


+ Code + Markdown

```
# Predict: Successful deposite with a maximun call duration = 3881 sec

print(dt2.predict_proba(np.array([0, 0, 3881, 0, 0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0]).reshape(
print(dt2.predict(np.array([0, 0, 3881, 0, 0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0]).reshape(1, -1))
```

```
[[ 0.19295499  0.80704501]]
[1]
```


```
# Predict: Successful deposite with a maximun call duration = 3881 sec

print(dt2.predict_proba(np.array([0, 0, 3881, 0, 0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0]).reshape(
print(dt2.predict(np.array([0, 0, 3881, 0, 0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0]).reshape(1, -1))
```


```
# Get a row with poutcome_success = 1
#bank_with_dummies[(bank_with_dummies.poutcome_success == 1)]
data_drop_deposite.iloc[985]
```

age	46.000000
balance	3354.000000
duration	522.000000
campaign	1.000000
previous	1.000000
default_cat	0.000000
housing_cat	1.000000
loan_cat	0.000000
recent_pdays	0.005747
job_blue-collar	0.000000
job_entrepreneur	0.000000
job_other	1.000000
job_pink-collar	0.000000
job_self-employed	0.000000
job_technician	0.000000
job_white-collar	0.000000
marital_divorced	1.000000
marital_married	0.000000
marital_single	0.000000
education_primary	0.000000
education_secondary	1.000000

```
job_pink-collar          0.000000
job_self-employed        0.000000
job_technician           0.000000
job_white-collar         0.000000
marital_divorced         1.000000
marital_married          0.000000
marital_single           0.000000
education_primary        0.000000
education_secondary      1.000000
education_tertiary       0.000000
education_unknown        0.000000
poutcome_failure         0.000000
poutcome_success         1.000000
poutcome_unknown         0.000000
Name: 985, dtype: float64
```

```
# Get a row with poutcome_success = 1
#bank_with_dummies[(bank_with_dummies.poutcome_success == 1)]
data_drop_deposite.iloc[985]
```

```
ct: Probability for above

lt2.predict_proba(np.array([46,3354,522,1,1,0,1,0,0.005747,0,0,1,0,0,0,0,1,0,0,0,1,0,0,0,1,0]).reshape(1,
ctree.predict(np.array([46,3354,522,1,1,0,1,0,0.005747,0,0,1,0,0,0,0,1,0,0,0,1,0,0,0,1,0]).reshape(1, -1)))
```

```
[[ 0.19295499  0.80704501]]
```

```
ct: Probability for above

lt2.predict_proba(np.array([46,3354,522,1,1,0,1,0,0.005747,0,0,1,0,0,0,0,1,0,0,0,1,0,0,0,1,0]).reshape(1,
ctree.predict(np.array([46,3354,522,1,1,0,1,0,0.005747,0,0,1,0,0,0,0,1,0,0,0,1,0,0,0,1,0]).reshape(1, -1)))
```

```
# Make predictions on the test set
preds = dt2.predict(data_test)

# Calculate accuracy
print("\nAccuracy score: \n{}".format(metrics.accuracy_score(label_test, preds)))

# Make predictions on the test set using predict_proba
probs = dt2.predict_proba(data_test)[:,1]

# Calculate the AUC metric
print("\nArea Under Curve: \n{}".format(metrics.roc_auc_score(label_test, probs)))
```

```
Accuracy score:
0.7268248992386923

Area Under Curve:
0.7880265888143609
```