In [1]:
```
#importing required libraries
import pandas as pd

import sklearn.metrics as metrics
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn import svm
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.svm import SVC

from matplotlib.pyplot import figure
```

In [2]:
```
#Loading desired file into a dataframe
df1 = pd.read_csv("Data/bank/bank-full.csv", sep=';')
df = df1[:8000]


#df = pd.read_csv("Data/bank/bank.csv", sep=';')

#Look at the shape to see rows and columns
df.shape
```

Out[2]:
```
(8000, 17)
```

In [3]:
```
#To visualize the numerical columns for potentional issues for cleaning
df.describe()
```

Out[3]:

	age	balance	day	duration	campaign	pdays	previous
count	8000.000000	8000.000000	8000.000000	8000.000000	8000.000000	8000.0	8000.0
mean	39.452125	1010.212625	17.634125	264.975250	2.542000	-1.0	0.0
std	9.254670	2466.448855	8.230977	249.763865	2.854296	0.0	0.0
min	20.000000	-3372.000000	2.000000	0.000000	1.000000	-1.0	0.0
25%	32.000000	40.000000	9.000000	118.000000	1.000000	-1.0	0.0
50%	38.000000	323.000000	16.000000	193.000000	2.000000	-1.0	0.0
75%	46.000000	1025.000000	26.000000	322.000000	3.000000	-1.0	0.0
max	61.000000	58544.000000	30.000000	3366.000000	63.000000	-1.0	0.0

In [4]:
```
#Confirming if any of the columns have nulls
df.isnull().sum()
```

Out[4]:
```
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
y            0
dtype: int64
```

In [5]:
```
#Checking the columns for categorical values that may need to be converted to int
df.dtypes
```

Out[5]:
```
age           int64
job          object
marital      object
education    object
default      object
balance       int64
housing      object
loan         object
contact      object
day           int64
month        object
duration      int64
campaign      int64
pdays         int64
previous      int64
poutcome     object
y            object
dtype: object
```

In [6]:
```
#creating a list of column names that are categorical to be changed to int
cols_encode = [
               'job',
               'marital',
               'education',
               'default',
               'housing',
               'loan',
               'contact',
               'month',
               'poutcome'
              ]

#Creating a list of int columns for later standardization
cols_int = ['age','balance','day','duration','campaign','pdays','previous']
```

In [7]:
```
df.describe()
```

Out[7]:

	age	balance	day	duration	campaign	pdays	previous
count	8000.000000	8000.000000	8000.000000	8000.000000	8000.000000	8000.0	8000.0
mean	39.452125	1010.212625	17.634125	264.975250	2.542000	-1.0	0.0
std	9.254670	2466.448855	8.230977	249.763865	2.854296	0.0	0.0
min	20.000000	-3372.000000	2.000000	0.000000	1.000000	-1.0	0.0
25%	32.000000	40.000000	9.000000	118.000000	1.000000	-1.0	0.0
50%	38.000000	323.000000	16.000000	193.000000	2.000000	-1.0	0.0
75%	46.000000	1025.000000	26.000000	322.000000	3.000000	-1.0	0.0
max	61.000000	58544.000000	30.000000	3366.000000	63.000000	-1.0	0.0

In [8]:
```
#printing unique values of categorical variables as a check
for col in cols_encode:
    print(col)
    print(df[col].unique())
    print(" ")
```

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

marital
['married' 'single' 'divorced']

education
['tertiary' 'secondary' 'unknown' 'primary']

default
['no' 'yes']

housing
['yes' 'no']

loan
['no' 'yes']

contact
['unknown']

month
['may' 'jun']

poutcome
['unknown']
```

In [9]:
```
df['y'] = df['y'].replace(['no'], 0)
df['y'] = df['y'].replace(['yes'], 1)

print(df['y'].unique())
```

```
[0 1]

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  """Entry point for launching an IPython kernel.
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
```

In [10]:
```
#Loop created to convert catagorical columns to int values via a target encoding
for c in cols_encode:

    i = 0

    unique_val = df[c].unique()

    mean_val = df.groupby(c)['y'].mean()

    for u in unique_val:
        df[c] = df[c].replace([u], mean_val[u])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  # This is added back by InteractiveShellApp.init_path()
```

In [11]:
```
#printing previoius categorical values to confirm change
for col in cols_encode:
    print(col)
    print(df[col].unique())
    print(" ")
```

```
job
[0.03083333 0.03733122 0.02953586 0.03283019 0.04545455 0.03571429
 0.03153611 0.02651934 0.03626943 0.03614458 0.01315789 0.02352941]

marital
[0.02466598 0.04086318 0.05120167]

education
[0.03450479 0.03206934 0.02393617 0.03254848]

default
[0.03243105 0.02380952]

housing
[0.03357847 0.02017654]

loan
[0.03333823 0.02602855]

contact
[0.03225]

month
[0.03242428 0.        ]

poutcome
[0.03225]
```

In [12]:
```
#Checking the columns for categorical values that may need to be converted to int
df.dtypes
```

Out[12]:
```
age            int64
job          float64
marital      float64
education    float64
default      float64
balance        int64
housing      float64
loan         float64
contact      float64
day            int64
month        float64
duration       int64
campaign       int64
pdays          int64
previous       int64
poutcome     float64
y              int64
dtype: object
```

In [13]:
```
#Creating dataframe for training without the answer column
X = df.drop(['y'], axis = 1)
print(X.shape)
X
```

(8000, 16)

Out[13]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome
0	58	0.030833	0.024666	0.034505	0.032431	2143	0.033578	0.033338	0.03225	5	0.032424	261	1	-1	0	0.03225
1	44	0.037331	0.040863	0.032069	0.032431	29	0.033578	0.033338	0.03225	5	0.032424	151	1	-1	0	0.03225
2	33	0.029536	0.024666	0.032069	0.032431	2	0.033578	0.026029	0.03225	5	0.032424	76	1	-1	0	0.03225
3	47	0.032830	0.024666	0.023936	0.032431	1506	0.033578	0.033338	0.03225	5	0.032424	92	1	-1	0	0.03225
4	33	0.045455	0.040863	0.023936	0.032431	1	0.020177	0.033338	0.03225	5	0.032424	198	1	-1	0	0.03225
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
7995	39	0.037331	0.024666	0.032069	0.032431	1965	0.033578	0.033338	0.03225	2	0.000000	65	1	-1	0	0.03225
7996	29	0.029536	0.024666	0.032069	0.032431	291	0.033578	0.033338	0.03225	2	0.000000	205	3	-1	0	0.03225
7997	46	0.032830	0.024666	0.032548	0.032431	938	0.033578	0.033338	0.03225	2	0.000000	92	2	-1	0	0.03225
7998	39	0.030833	0.024666	0.034505	0.032431	756	0.033578	0.033338	0.03225	2	0.000000	268	1	-1	0	0.03225
7999	53	0.032830	0.024666	0.032548	0.032431	1942	0.033578	0.033338	0.03225	2	0.000000	185	2	-1	0	0.03225

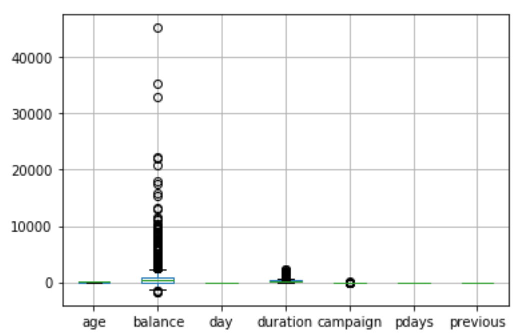
8000 rows × 16 columns

In [14]:
```
#Creating a series with the answers that will be used for training.
y = df['y']
y
```

Out[14]:
```
0       0
1       0
2       0
3       0
4       0
       ..
7995    0
7996    0
7997    0
7998    0
7999    0
Name: y, Length: 8000, dtype: int64
```

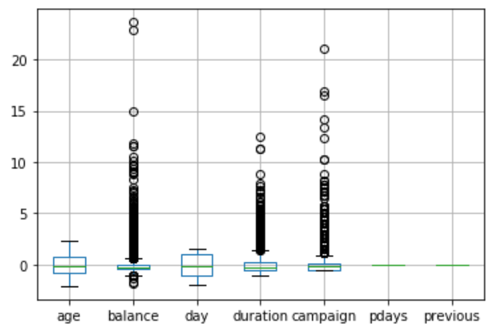
In [15]:
```
#Splitting the data elements from X and y into a test size of 20%
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
```

In [16]:
```
#Boxplots before standardization
boxplot = X_test.boxplot(column = cols_int)
```



In [17]:
```
# data standardization with  sklearn
from sklearn.preprocessing import StandardScaler

# copy of datasets
X_train_stand = X_train.copy()
X_test_stand = X_test.copy()

# apply standardization on numerical features
for i in cols_int:

    # fit on training data column
    scale = StandardScaler().fit(X_train_stand[[i]])

    # transform the training data column
    X_train_stand[i] = scale.transform(X_train_stand[[i]])

    # transform the testing data column
    X_test_stand[i] = scale.transform(X_test_stand[[i]])
```

In [18]:
```
#Boxplots after standardization
boxplot = X_train_stand.boxplot(column = cols_int)
```



In [19]:
```
#Below steps are used to train and test the model before Standardization
model = DecisionTreeClassifier()

model.fit(X_train,y_train)

y_predict = model.predict(X_test)
```

In [20]:
```
#accuracy_score will return a value between 0 and 1, 1 being 100%
score = accuracy_score(y_test, y_predict)
print(score)
#The rows are the actual and the columns are the predicted
pd.crosstab(y_test, y_predict)
```

```
0.951875
```

Out[20]:

col_0	0	1
y		
0	1503	47
1	30	20

In [21]:
```
#Printing report to look at the accuracy based on y_test
print(classification_report(y_test, y_predict))
```

```
              precision    recall  f1-score   support

           0       0.98      0.97      0.98      1550
           1       0.30      0.40      0.34        50

    accuracy                           0.95      1600
   macro avg       0.64      0.68      0.66      1600
weighted avg       0.96      0.95      0.96      1600
```

In [22]:
```
#Below steps are used to train and test the model after standardization
model = DecisionTreeClassifier()

model.fit(X_train_stand,y_train)

y_predict = model.predict(X_test_stand)
```

In [23]:
```
#accuracy_score will return a value between 0 and 1, 1 being 100%
score = accuracy_score(y_test, y_predict)
print(score)

#The rows are the actual and the columns are the predicted
pd.crosstab(y_test, y_predict)
```

```
0.95125
```

Out[23]:

col_0	0	1
y		
0	1501	49
1	29	21

For an explanation of the classificatoin report see [https://medium.com/@kohlishivam5522/understanding-a-classification-report-for-your-machine-learning-model-88815e2ce397 (https://medium.com/@kohlishivam5522/understanding-a-classification-report-for-your-machine-learning-model-88815e2ce397)](https://medium.com/@kohlishivam5522/understanding-a-classification-report-for-your-machine-learning-model-88815e2ce397)

In [24]:
```
#Printing report to look at the accuracy based on y_test
print(classification_report(y_test, y_predict))
```

```
              precision    recall  f1-score   support

           0       0.98      0.97      0.97      1550
           1       0.30      0.42      0.35        50

    accuracy                           0.95      1600
   macro avg       0.64      0.69      0.66      1600
weighted avg       0.96      0.95      0.96      1600
```

In [25]:
```
#Applying SMOTE to oversample the minority imbalance
from imblearn.over_sampling import SMOTE
sm = SMOTE()
X_train_smote, y_train_smote = sm.fit_sample(X_train_stand, y_train)
```

In [26]:
```
#Show the counts of the minority imbalance before and after SMOTE
from collections import Counter
print("Before SMOTE: ", Counter(y_train))
print("After SMOTE: ", Counter(y_train_smote))
```

```
Before SMOTE:  Counter({0: 6192, 1: 208})
After SMOTE:  Counter({0: 6192, 1: 6192})
```

In [27]:
```
#Traing the model after SMOTE
model.fit(X_train_smote,y_train_smote)
y_predict = model.predict(X_test_stand)

#accuracy_score will return a value between 0 and 1, 1 being 100%
score = accuracy_score(y_test, y_predict)

print(score)

#The rows are the actual and the columns are the predicted
pd.crosstab(y_test, y_predict)
```

```
0.95375
```

Out[27]:

col_0	0	1
y		
0	1499	51
1	23	27

In [28]:
```
#Printing report to look at the accuracy based on y_test
print(classification_report(y_test, y_predict))
```

```
              precision    recall  f1-score   support

           0       0.98      0.97      0.98      1550
           1       0.35      0.54      0.42        50

    accuracy                           0.95      1600
   macro avg       0.67      0.75      0.70      1600
weighted avg       0.96      0.95      0.96      1600
```

Recall is the ability of a classifier to find all positive instances. For each class it is defined as the ratio of true positives to the sum of true positives and false negatives.

In [29]:

```
#pip install xgboost
```

In [30]:

```
from xgboost import XGBClassifier

#Running the second model as per the requirements and to also partake in hyperparameter testing
model = XGBClassifier()
model.fit(X_train_smote,y_train_smote)
y_predict = model.predict(X_test_stand)

#accuracy_score will return a value between 0 and 1, 1 being 100%
score = accuracy_score(y_test, y_predict)
print('Test Accuracy: ', score)

#The rows are the actual and the columns are the predicted
pd.crosstab(y_test, y_predict)
```

```
Test Accuracy:  0.97125
```

Out[30]:

col_0	0	1
y		
0	1529	21
1	25	25

In [31]:

```
#Printing report to look at the accuracy based on y_test
print(classification_report(y_test, y_predict))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      1550
           1       0.54      0.50      0.52        50

    accuracy                           0.97      1600
   macro avg       0.76      0.74      0.75      1600
weighted avg       0.97      0.97      0.97      1600
```

In [32]:

```
#Create lists that can be used in the below for loops to test hyperparameters
maxD = [8, 9, 10, 11, 12]
subS = [0.25, 0.5, 0.75, 1]
nEst = [100, 200, 300, 400, 500]
learnR = [0.05, 0.1, 0.2, 0.3]
randS = [1, 2, 3 ,4]

#Create an empty dataset for holding loop results
resultSet = pd.DataFrame()

#Series of for loops for testing hyperparameters
for m in maxD:
    for s in subS:
        #for n in nEst:
            #for l in learnR:
                #for r in randS:
                    model = XGBClassifier(max_depth = m,
                                          subsample = s,
                                          n_estimators = 300,
                                          learning_rate = 0.1,
                                          random_state = 3)

                    model.fit(X_train_smote,y_train_smote)
                    y_predict = model.predict(X_test_stand)
                    y_train_predict = model.predict(X_train_stand)

                    #Can only append if ingore_index is True
                    #Loading results in empty dataframe created previous
                    resultSet = resultSet.append({'1 max_depth': m,
                                                  '2 subsample': s,
                                                  '3 n_estimators': 300, #replace with n
                                                  '4 Learning_rate': 0.1, #replace with l
                                                  '5 random_state': 3, #replace with r
                                                  'Train Accuracy': accuracy_score(y_train, y_train_predict),
                                                  'Test Accuracy': accuracy_score(y_test, y_predict)},
                                                  ignore_index = True)
```

In [33]:
```
#Loading the max value for test accuracy in a variable from resultSet dataset created in the loop
max_test = resultSet['Test Accuracy'].max()

#Extracting the records with the max test accuracy to see the parameter settings to use
rs_check = resultSet.loc[resultSet['Test Accuracy'] == max_test]
rs_check
```

Out[33]:

	1 max_depth	2 subsample	3 n_estimators	4 Learning_rate	5 random_state	Test Accuracy	Train Accuracy
13	11.0	0.5	300.0	0.1	3.0	0.974375	1.0

In [ ]:
```
#Running the second model as per the requirements after hyperparameter testing
model = XGBClassifier(max_depth = 8,
                      subsample = 0.5,
                      n_estimators = 300,
                      learning_rate = 0.1,
                      random_state = 3)
model.fit(X_train_smote,y_train_smote)
y_predict = model.predict(X_test_stand)
#accuracy_score will return a value between 0 and 1, 1 being 100%
score = accuracy_score(y_test, y_predict)
print('Test Accuracy: ', score)
#The rows are the actual and the columns are the predicted
pd.crosstab(y_test, y_predict)
```

```
Test Accuracy:  0.966875
```

Out[34]:

col_0	0	1
y		
0	1525	25
1	28	22

In [ ]:

In [ ]: