Lab3

August 8, 2023

1 Lab 3: Training Decision Tree & KNN Classifiers

[1]:
```
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns
pd.options.mode.chained_assignment = None


from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
```

In this Lab session, you will implement the following steps:

1. Load the Airbnb "listings" data set
2. Convert categorical features to one-hot encoded values
3. Split the data into training and test sets
4. Fit a Decision Tree classifier and evaluate the accuracy

- Plot the accuracy of the DT model as a function of hyperparameter max depth

5. Fit a KNN classifier and evaluate the accuracy

- Plot the accuracy of the KNN model as a function of hyperparameter k

1.1 Part 1. Load the Dataset

We will work with a preprocessed version of the Airbnb NYC "listings" data set.

Task: load the data set into a Pandas DataFrame variable named `df`:

[2]:
```
# Do not remove or edit the line below:
filename = os.path.join(os.getcwd(), "data", "airbnb.csv.gz")

# YOUR CODE HERE
df=pd.read_csv(filename)
```

[3]:
```
df.shape
```

[3]:
```
(28022, 44)
```

[4]:
```
df.head(10)
```

[4]:
```
   host_response_rate  host_acceptance_rate  host_is_superhost  \
0            0.800000              0.170000              False
1            0.090000              0.690000              False
2            1.000000              0.250000              False
3            1.000000              1.000000              False
4            0.890731              0.768297              False
5            1.000000              1.000000               True
6            1.000000              1.000000              False
7            1.000000              1.000000              False
8            1.000000              0.000000              False
9            1.000000              0.990000               True

   host_listings_count  host_total_listings_count  host_has_profile_pic  \
0                  8.0                        8.0                  True
1                  1.0                        1.0                  True
2                  1.0                        1.0                  True
3                  1.0                        1.0                  True
4                  1.0                        1.0                  True
5                  3.0                        3.0                  True
6                  1.0                        1.0                  True
7                  3.0                        3.0                  True
8                  2.0                        2.0                  True
9                  1.0                        1.0                  True

   host_identity_verified neighbourhood_group_cleansed        room_type  \
0                    True                    Manhattan  Entire home/apt
1                    True                     Brooklyn  Entire home/apt
2                    True                     Brooklyn  Entire home/apt
3                   False                    Manhattan     Private room
4                    True                    Manhattan     Private room
5                    True                     Brooklyn     Private room
6                    True                     Brooklyn  Entire home/apt
7                    True                    Manhattan     Private room
8                    True                     Brooklyn     Private room
9                    True                     Brooklyn  Entire home/apt

   accommodates  ...  review_scores_communication  review_scores_location  \
0             1  ...                         4.79                    4.86
1             3  ...                         4.80                    4.71
2             4  ...                         5.00                    4.50
3             2  ...                         4.42                    4.87
4             1  ...                         4.95                    4.94
```

```
5           2  ...                         4.82                    4.87
6           3  ...                         4.80                    4.67
7           1  ...                         4.95                    4.84
8           1  ...                         5.00                    5.00
9           4  ...                         4.91                    4.93

   review_scores_value instant_bookable  calculated_host_listings_count  \
0                 4.41            False                               3
1                 4.64            False                               1
2                 5.00            False                               1
3                 4.36            False                               1
4                 4.92            False                               1
5                 4.73            False                               3
6                 4.57             True                               1
7                 4.84             True                               1
8                 5.00            False                               2
9                 4.78             True                               2

   calculated_host_listings_count_entire_homes  \
0                                            3
1                                            1
2                                            1
3                                            0
4                                            0
5                                            1
6                                            1
7                                            0
8                                            0
9                                            1

   calculated_host_listings_count_private_rooms  \
0                                             0
1                                             0
2                                             0
3                                             1
4                                             1
5                                             2
6                                             0
7                                             1
8                                             2
9                                             1

   calculated_host_listings_count_shared_rooms  reviews_per_month  \
0                                            0               0.33
1                                            0               4.86
2                                            0               0.02
3                                            0               3.68
```

```
4                                                   0            0.87
5                                                   0            1.48
6                                                   0            1.24
7                                                   0            1.82
8                                                   0            0.07
9                                                   0            3.05

   n_host_verifications
0                     9
1                     6
2                     3
3                     4
4                     7
5                     7
6                     7
7                     5
8                     5
9                     8

[10 rows x 44 columns]
```

[5]:
```
df.columns
```

[5]:
```
Index(['host_response_rate', 'host_acceptance_rate', 'host_is_superhost',
       'host_listings_count', 'host_total_listings_count',
       'host_has_profile_pic', 'host_identity_verified',
       'neighbourhood_group_cleansed', 'room_type', 'accommodates',
       'bathrooms', 'bedrooms', 'beds', 'amenities', 'price', 'minimum_nights',
       'maximum_nights', 'minimum_minimum_nights', 'maximum_minimum_nights',
       'minimum_maximum_nights', 'maximum_maximum_nights',
       'minimum_nights_avg_ntm', 'maximum_nights_avg_ntm', 'has_availability',
       'availability_30', 'availability_60', 'availability_90',
       'availability_365', 'number_of_reviews', 'number_of_reviews_ltm',
       'number_of_reviews_l30d', 'review_scores_rating',
       'review_scores_cleanliness', 'review_scores_checkin',
       'review_scores_communication', 'review_scores_location',
       'review_scores_value', 'instant_bookable',
       'calculated_host_listings_count',
       'calculated_host_listings_count_entire_homes',
       'calculated_host_listings_count_private_rooms',
       'calculated_host_listings_count_shared_rooms', 'reviews_per_month',
       'n_host_verifications'],
      dtype='object')
```

1.2 Part 2. One-Hot Encode Categorical Values

Transform the string-valued categorical features into numerical boolean values using one-hot encoding.

1.2.1 a. Find the Columns Containing String Values

First, let us identify all features that need to be one-hot encoded:

[6]:
```
df.dtypes
```

[6]:
```
host_response_rate                              float64
host_acceptance_rate                            float64
host_is_superhost                                  bool
host_listings_count                             float64
host_total_listings_count                       float64
host_has_profile_pic                               bool
host_identity_verified                             bool
neighbourhood_group_cleansed                     object
room_type                                        object
accommodates                                      int64
bathrooms                                       float64
bedrooms                                        float64
beds                                            float64
amenities                                        object
price                                           float64
minimum_nights                                    int64
maximum_nights                                    int64
minimum_minimum_nights                          float64
maximum_minimum_nights                          float64
minimum_maximum_nights                          float64
maximum_maximum_nights                          float64
minimum_nights_avg_ntm                          float64
maximum_nights_avg_ntm                          float64
has_availability                                   bool
availability_30                                   int64
availability_60                                   int64
availability_90                                   int64
availability_365                                  int64
number_of_reviews                                 int64
number_of_reviews_ltm                             int64
number_of_reviews_l30d                            int64
review_scores_rating                            float64
review_scores_cleanliness                       float64
review_scores_checkin                           float64
review_scores_communication                     float64
review_scores_location                          float64
review_scores_value                             float64
instant_bookable                                   bool
calculated_host_listings_count                    int64
calculated_host_listings_count_entire_homes       int64
calculated_host_listings_count_private_rooms      int64
calculated_host_listings_count_shared_rooms       int64
reviews_per_month                               float64
```

```
n_host_verifications                                         int64
dtype: object
```

Task: add all of the column names of variables of type 'object' to a list named `to_encode`

[7]:
```
# YOUR CODE HERE
to_encode=list(df.select_dtypes(include=['object']).columns)
```

Let's take a closer look at the candidates for one-hot encoding

[8]:
```
df[to_encode].nunique()
```

[8]:
```
neighbourhood_group_cleansed        5
room_type                           4
amenities                       25020
dtype: int64
```

Notice that one column stands out as containing two many values for us to attempt to transform. For this exercise, the best choice is to simply remove this column. Of course, this means losing potentially useful information. In a real-life situation, you would want to retain all of the information in a column, or you could selectively keep information in.

In the code cell below, drop this column from Dataframe `df` and from the `to_encode` list.

[9]:
```
# YOUR SOLUTION HERE
column_to_drop='amenities'
df=df.drop(column_to_drop,axis=1)
to_encode.remove(column_to_drop)
```

1.2.2 b. One-Hot Encode all Unique Values

All of the other columns in `to_encode` have reasonably small numbers of unique values, so we are going to simply one-hot encode every unique value of those columns.

Task: complete the code below to create one-hot encoded columns Tip: Use the sklearn `OneHotEncoder` class

[10]:
```
from sklearn.preprocessing import OneHotEncoder

# Create the encoder:
encoder = OneHotEncoder(sparse=False)

# Apply the encoder:
df_enc = pd.DataFrame(encoder.fit_transform(df[to_encode]))

# Reinstate the original column names:
df_enc.columns = encoder.get_feature_names(to_encode)
```

[11]:
```
df_enc.head()
```

[11]:
```
   neighbourhood_group_cleansed_Bronx  neighbourhood_group_cleansed_Brooklyn  \
0                                 0.0                                    0.0
1                                 0.0                                    1.0
2                                 0.0                                    1.0
3                                 0.0                                    0.0
```

```
4                                  0.0                                      0.0

   neighbourhood_group_cleansed_Manhattan  \
0                                     1.0
1                                     0.0
2                                     0.0
3                                     1.0
4                                     1.0

   neighbourhood_group_cleansed_Queens  \
0                                  0.0
1                                  0.0
2                                  0.0
3                                  0.0
4                                  0.0

   neighbourhood_group_cleansed_Staten Island  room_type_Entire home/apt  \
0                                         0.0                        1.0
1                                         0.0                        1.0
2                                         0.0                        1.0
3                                         0.0                        0.0
4                                         0.0                        0.0

   room_type_Hotel room  room_type_Private room  room_type_Shared room
0                   0.0                     0.0                    0.0
1                   0.0                     0.0                    0.0
2                   0.0                     0.0                    0.0
3                   0.0                     1.0                    0.0
4                   0.0                     1.0                    0.0
```

Task: You can now remove the original columns that we have just transformed from DataFrame df.

[12]:
```
# YOUR CODE HERE
df.drop(columns=to_encode,inplace=True)
```

[13]:
```
df.head()
```

[13]:
```
   host_response_rate  host_acceptance_rate  host_is_superhost  \
0            0.800000              0.170000              False
1            0.090000              0.690000              False
2            1.000000              0.250000              False
3            1.000000              1.000000              False
4            0.890731              0.768297              False

   host_listings_count  host_total_listings_count  host_has_profile_pic  \
0                  8.0                        8.0                  True
1                  1.0                        1.0                  True
2                  1.0                        1.0                  True
```

```
3                 1.0                        1.0                 True
4                 1.0                        1.0                 True

   host_identity_verified  accommodates  bathrooms  bedrooms  ...  \
0                    True             1        1.0  1.323567  ...
1                    True             3        1.0  1.000000  ...
2                    True             4        1.5  2.000000  ...
3                   False             2        1.0  1.000000  ...
4                    True             1        1.0  1.000000  ...

   review_scores_communication  review_scores_location  review_scores_value  \
0                         4.79                    4.86                 4.41
1                         4.80                    4.71                 4.64
2                         5.00                    4.50                 5.00
3                         4.42                    4.87                 4.36
4                         4.95                    4.94                 4.92

   instant_bookable  calculated_host_listings_count  \
0             False                               3
1             False                               1
2             False                               1
3             False                               1
4             False                               1

   calculated_host_listings_count_entire_homes  \
0                                            3
1                                            1
2                                            1
3                                            0
4                                            0

   calculated_host_listings_count_private_rooms  \
0                                             0
1                                             0
2                                             0
3                                             1
4                                             1

   calculated_host_listings_count_shared_rooms  reviews_per_month  \
0                                            0               0.33
1                                            0               4.86
2                                            0               0.02
3                                            0               3.68
4                                            0               0.87

   n_host_verifications
0                     9
```

```
1                        6
2                        3
3                        4
4                        7

[5 rows x 41 columns]
```

Task: You can now join the transformed categorical features contained in `df_enc` with DataFrame `df`

[14]:
```
# YOUR CODE HERE
df=pd.concat([df,df_enc],axis=1)
```

Glance at the resulting column names:

[15]:
```
df.columns
```

[15]:
```
Index(['host_response_rate', 'host_acceptance_rate', 'host_is_superhost',
       'host_listings_count', 'host_total_listings_count',
       'host_has_profile_pic', 'host_identity_verified', 'accommodates',
       'bathrooms', 'bedrooms', 'beds', 'price', 'minimum_nights',
       'maximum_nights', 'minimum_minimum_nights', 'maximum_minimum_nights',
       'minimum_maximum_nights', 'maximum_maximum_nights',
       'minimum_nights_avg_ntm', 'maximum_nights_avg_ntm', 'has_availability',
       'availability_30', 'availability_60', 'availability_90',
       'availability_365', 'number_of_reviews', 'number_of_reviews_ltm',
       'number_of_reviews_l30d', 'review_scores_rating',
       'review_scores_cleanliness', 'review_scores_checkin',
       'review_scores_communication', 'review_scores_location',
       'review_scores_value', 'instant_bookable',
       'calculated_host_listings_count',
       'calculated_host_listings_count_entire_homes',
       'calculated_host_listings_count_private_rooms',
       'calculated_host_listings_count_shared_rooms', 'reviews_per_month',
       'n_host_verifications', 'neighbourhood_group_cleansed_Bronx',
       'neighbourhood_group_cleansed_Brooklyn',
       'neighbourhood_group_cleansed_Manhattan',
       'neighbourhood_group_cleansed_Queens',
       'neighbourhood_group_cleansed_Staten Island',
       'room_type_Entire home/apt', 'room_type_Hotel room',
       'room_type_Private room', 'room_type_Shared room'],
      dtype='object')
```

Check for missing values.

[16]:
```
# YOUR CODE HERE
missing_values=df.isnull().sum()
```

1.3 Part 3. Create Training and Test Data Sets

1.3.1 a. Create Labeled Examples

Task: Choose columns from our data set to create labeled examples.

In the `airbnb` dataset, we will choose column `host_is_superhost` to be the label. The remaining columns will be the features.

Obtain the features from DataFrame `df` and assign to `X`. Obtain the label from DataFrame `df` and assign to `Y`

[17]:
```
# YOUR CODE HERE
X=df.drop('host_is_superhost',axis=1)
y=df['host_is_superhost']
```

[18]:
```
print("Number of examples: " + str(X.shape[0]))
print("\nNumber of Features:" + str(X.shape[1]))
print(str(list(X.columns)))
```

```
Number of examples: 28022

Number of Features:49
['host_response_rate', 'host_acceptance_rate', 'host_listings_count',
'host_total_listings_count', 'host_has_profile_pic', 'host_identity_verified',
'accommodates', 'bathrooms', 'bedrooms', 'beds', 'price', 'minimum_nights',
'maximum_nights', 'minimum_minimum_nights', 'maximum_minimum_nights',
'minimum_maximum_nights', 'maximum_maximum_nights', 'minimum_nights_avg_ntm',
'maximum_nights_avg_ntm', 'has_availability', 'availability_30',
'availability_60', 'availability_90', 'availability_365', 'number_of_reviews',
'number_of_reviews_ltm', 'number_of_reviews_l30d', 'review_scores_rating',
'review_scores_cleanliness', 'review_scores_checkin',
'review_scores_communication', 'review_scores_location', 'review_scores_value',
'instant_bookable', 'calculated_host_listings_count',
'calculated_host_listings_count_entire_homes',
'calculated_host_listings_count_private_rooms',
'calculated_host_listings_count_shared_rooms', 'reviews_per_month',
'n_host_verifications', 'neighbourhood_group_cleansed_Bronx',
'neighbourhood_group_cleansed_Brooklyn',
'neighbourhood_group_cleansed_Manhattan', 'neighbourhood_group_cleansed_Queens',
'neighbourhood_group_cleansed_Staten Island', 'room_type_Entire home/apt',
'room_type_Hotel room', 'room_type_Private room', 'room_type_Shared room']
```

1.3.2 b. Split Examples into Training and Test Sets

Task: In the code cell below create training and test sets out of the labeled examples using Scikit-learn's `train_test_split()` function.

Specify: * A test set that is one third (.33) of the size of the data set. * A seed value of '123'.

[26]:
```
# YOUR CODE HERE
test_size=0.33
random_seed=123
```

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=test_size,random_state=random_see
```

Check that the dimensions of the training and test datasets are what you expected

[27]:
```
print(X_train.shape)
print(X_test.shape)
```

```
(18774, 49)
(9248, 49)
```

1.4 Part 4. Implement a Decision Tree Classifier

The code cell below contains a shell of a function named `train_test_DT()`. This function should train a Decision Tree classifier on the training data, test the resulting model on the test data, and compute and return the accuracy score of the resulting predicted class labels on the test data. Remember to use `DecisionTreeClassifier()` to create a model object.

Task: Complete the function to make it work.

[32]:
```
def train_test_DT(X_train, X_test, y_train, y_test, leaf, depth,␣
↪crit='entropy'):
    '''
    Fit a Decision Tree classifier to the training data X_train, y_train.
    Return the accuracy of resulting predictions on the test set.
    Parameters:
        leaf := The minimum number of samples required to be at a leaf node
        depth := The maximum depth of the tree
        crit := The function to be used to measure the quality of a split.␣
↪Default: gini.
    '''


      # YOUR CODE HERE
   ␣
↪model=DecisionTreeClassifier(min_samples_leaf=leaf,max_depth=depth,criterion=crit)
    model.fit(X_train,y_train)
    y_pred=model.predict(X_test)
    acc_score=model.score(X_test,y_test)

    return acc_score
```

Visualization The cell below contains a function that you will use to compare the accuracy results of training multiple models with different hyperparameter values.

Function `visualize_accuracy()` accepts two arguments: 1. a list of hyperparamter values 2. a list of accuracy scores

Both lists must be of the same size.

[33]:
```
# Do not remove or edit the code below

def visualize_accuracy(hyperparam_range, acc):
    fig = plt.figure()
    ax = fig.add_subplot(111)
    p = sns.lineplot(x=hyperparam_range, y=acc, marker='o', label = 'Full␣
↪training set')

    plt.title('Test set accuracy of the model predictions, for ' + ','.
↪join([str(h) for h in hyperparam_range]))
    ax.set_xlabel('Hyperparameter value')
    ax.set_ylabel('Accuracy')
    plt.show()
```

Train on Different Values of Hyperparameter Max Depth Task:

Complete function `train_multiple_trees()` in the code cell below. The function should train multiple decision trees and return a list of accuracy scores.

The function will:

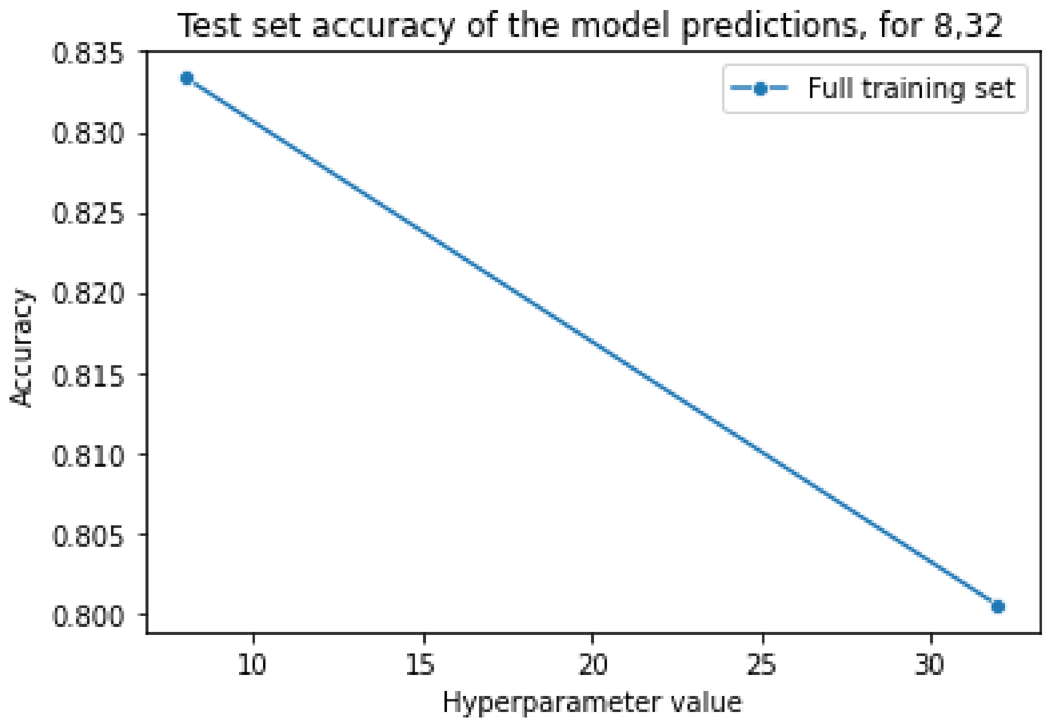
1. accept list `max_depth_range` and `leaf` as parameters; list `max_depth_range` will contain multiple values for hyperparameter max depth.
2. loop over list `max_depth_range` and at each iteration:
    a. index into list `max_depth_range` to obtain a value for max depth
    b. call `train_test_DT` with the training and test set, the value of max depth, and the value of `leaf`
    c. print the resulting accuracy score
    d. append the accuracy score to list `accuracy_list`

[34]:
```
def train_multiple_trees(max_depth_range, leaf):

    accuracy_list = []

    # YOUR CODE HERE
    for max_depth in max_depth_range:
        acc_score=train_test_DT(X_train,X_test,y_train,y_test,leaf,max_depth)
        print(f"Max Depth: {max_depth},Accuracy:{acc_score}")
        accuracy_list.append(acc_score)
    return accuracy_list
```

The code cell below tests function `train_multiple_trees()` and calls function `visualize_accuracy()` to visualize the results.

[35]:
```
max_depth_range = [8, 32]
leaf = 1

acc = train_multiple_trees(max_depth_range, leaf)

visualize_accuracy(max_depth_range, acc)
```

```
Max Depth: 8,Accuracy:0.8333693771626297
Max Depth: 32,Accuracy:0.8004974048442907
```



Analysis: Is this graph conclusive for determining a good value of max depth?

No, this graph does not have enough data points to accurately determine the best value. There are only two values of max depth found-- 8 and 32. Between them, however, it is seen that a max depth of 8 yielded a higher accuracy than the max depth of 32.

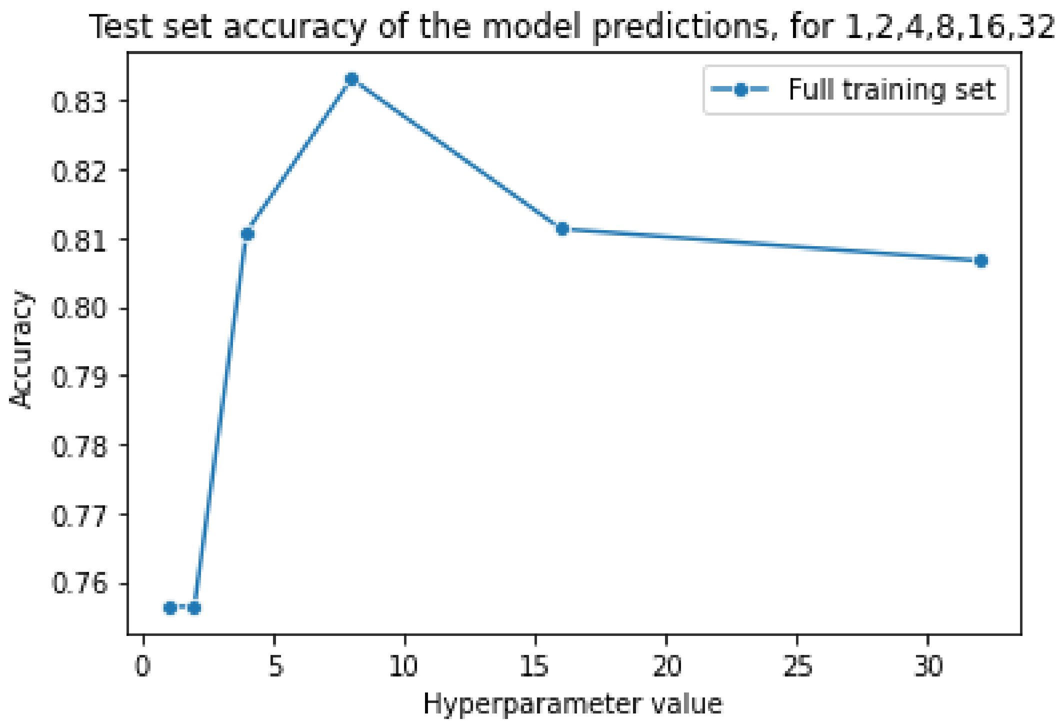
Task: Let's train on more values for max depth.

In the code cell below:

1. call `train_multiple_trees()` with arguments `max_depth_range` and `leaf`
2. call `visualize_accuracy()` with arguments `max_depth_range` and `acc`

[48]:
```python
max_depth_range = [2**i for i in range(6)]
leaf = 1
acc = train_multiple_trees(max_depth_range,leaf)

visualize_accuracy(max_depth_range,acc)
```

```
Max Depth: 1,Accuracy:0.7563797577854672
Max Depth: 2,Accuracy:0.7563797577854672
Max Depth: 4,Accuracy:0.810878027681661
Max Depth: 8,Accuracy:0.8331531141868512
Max Depth: 16,Accuracy:0.811310553633218
Max Depth: 32,Accuracy:0.8066608996539792
```



Analysis: Analyze this graph. Keep in mind that this is the performance on the test set, and pay attention to the scale of the y-axis. Answer the following questions in the cell below. How would you go about choosing the best model based on this plot? Is it conclusive? What other hyperparameters of interest would you want to vary to make sure you are finding the best model fit?

This graph shows that the best model performance is at a max depth of 8 with the highest accuracy score of 0.807, but it is not conclusive. To figure out the best model more conclusively, other hyperparameters such as min_samples_leaf, max_leaf_nodes, or crit. would be useful to vary. Varying these hyperparameters and then seeing their effects on model performance would let you see the combination that maximuzes accuracy on unseen data.

1.5 Part 5. Implement a KNN Classifier

Note: In this section you will train KNN classifiers using the same training and test data.

The code cell below contains a shell of a function named `train_test_knn()`. This function should train a KNN classifier on the training data, test the resulting model on the test data, and compute and return the accuracy score of the resulting predicted class labels on the test data.

Remember to use `KNeighborsClassifier()` to create a model object and call the method with one parameter: `n_neighbors = k`.

Task: Complete the function to make it work.

[49]:
```
def train_test_knn(X_train, X_test, y_train, y_test, k):
    '''
    Fit a k Nearest Neighbors classifier to the training data X_train, y_train.
    Return the accuracy of resulting predictions on the test data.
    '''

    # YOUR CODE HERE
    model=KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train,y_train)
    acc_score=model.score(X_test,y_test)

    return acc_score
```

Train on Different Values of Hyperparameter K Task:

Just as you did above, complete function `train_multiple_knns()` in the code cell below. The function should train multiple KNN models and return a list of accuracy scores.

The function will:

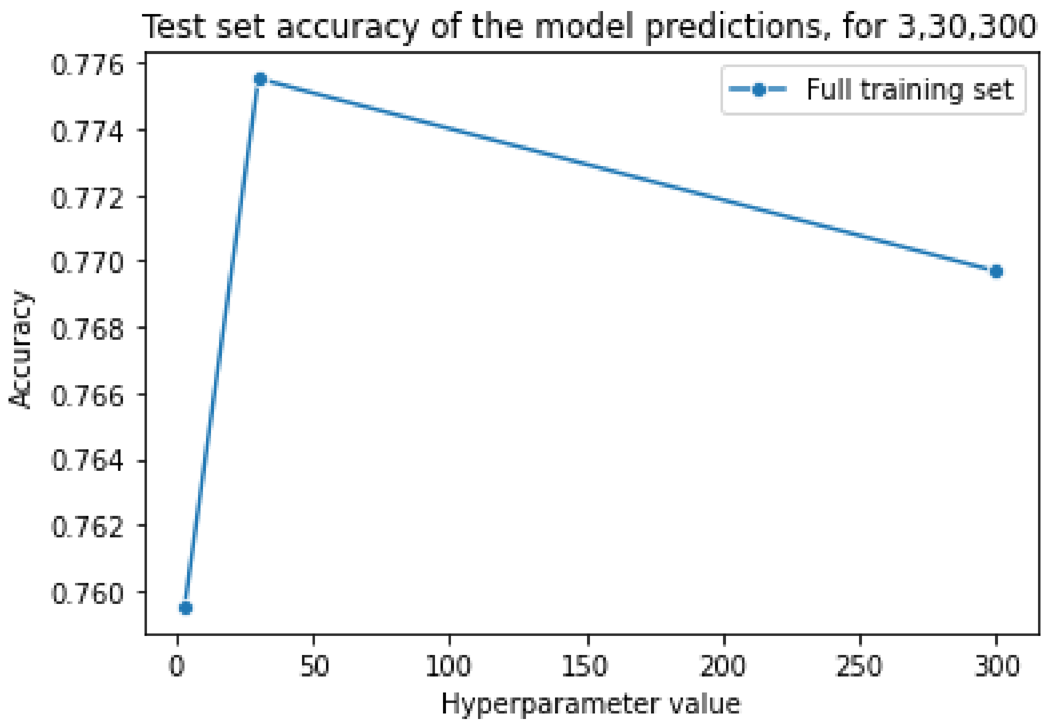
1. accept list `k_range` as a parameter; this list will contain multiple values for hyperparameter *k*
2. loop over list `k_range` and at each iteration:
   a. index into list `k_range` to obtain a value for *k*
   b. call `train_test_knn` with the training and test set, and the value of *k*
   c. print the resulting accuracy score
   d. append the accuracy score to list `accuracy_list`

[50]:
```
def train_multiple_knns(k_range):

    accuracy_list = []

    # YOUR CODE HERE
    for k in k_range:
        acc_score=train_test_knn(X_train,X_test,y_train,y_test,k)
        print(f"K:{k},Accuracy:{acc_score}")
        accuracy_list.append(acc_score)

    return accuracy_list
```

The code cell below uses your `train_multiple_knn()` function to train 3 KNN models, specifying three values for *k*: 3, 30, and 300. It calls function `visualize_accuracy()` to visualize the results. Note: this make take a second.

[51]:
```
k_range = [3, 30, 300]
acc = train_multiple_knns(k_range)

visualize_accuracy(k_range, acc)
```

```
K:3,Accuracy:0.759515570934256
K:30,Accuracy:0.7755190311418685
K:300,Accuracy:0.7696799307958477
```



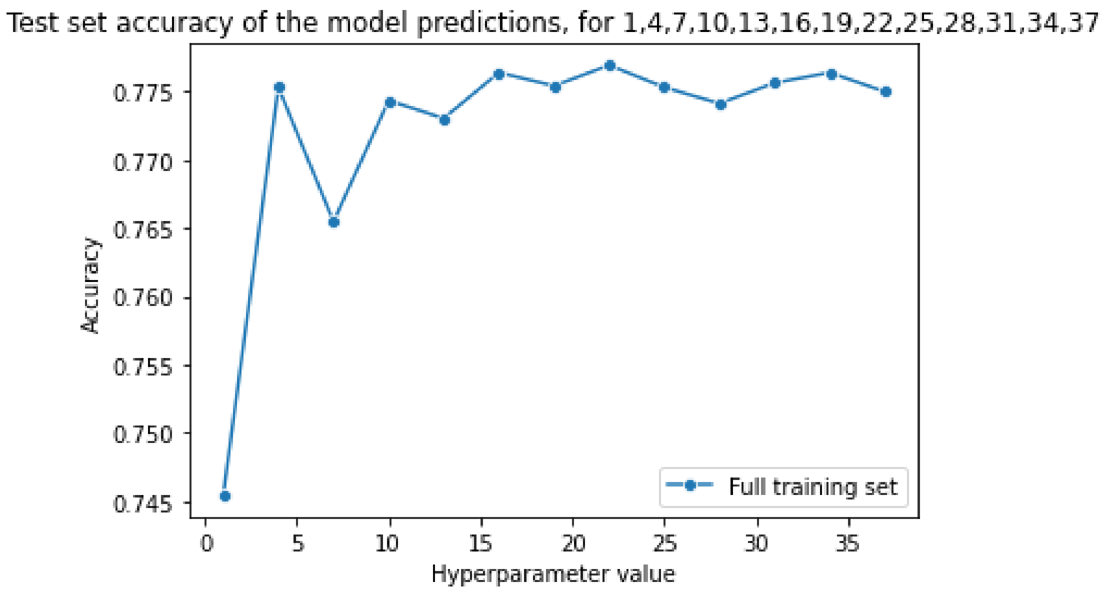
Task: Let's train on more values for *k*
In the code cell below:

1. call `train_multiple_knns()` with argument `k_range`
2. call `visualize_accuracy()` with arguments `k_range` and the resulting accuracy list obtained from `train_multiple_knns()`

[54]:
```
k_range = np.arange(1, 40, step = 3)

# YOUR CODE HERE
acc_knn=train_multiple_knns(k_range)
visualize_accuracy(k_range,acc_knn)
```

```
K:1,Accuracy:0.7454584775086506
K:4,Accuracy:0.77530276816609
K:7,Accuracy:0.7654628027681661
K:10,Accuracy:0.7743295847750865
K:13,Accuracy:0.7730320069204152
K:16,Accuracy:0.7763840830449827
K:19,Accuracy:0.7754108996539792
K:22,Accuracy:0.776924740484429
K:25,Accuracy:0.77530276816609
K:28,Accuracy:0.7741133217993079
K:31,Accuracy:0.7756271626297578
```

```
K:34,Accuracy:0.7763840830449827
K:37,Accuracy:0.7749783737024222
```



Analysis: Compare the performance of the KNN model relative to the Decision Tree model, with various hyperparameter values and record your findings in the cell below.

The KNN model shows generally stable performance accuracy accross K values, with only a small variation in accuracy scores. The decision Tree model shows accuracy scores ranging from 0.756 to 0.833 in comparison to KNNs 0.745 to 0.777. Because of this, the Decision Tree model outperformed the KNN model when considering the accuracy on this dataset.

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