btt004_week3_assignment-solution

May 1, 2024

1 Assignment 3: Train Decision Trees After Data Preparation

[1]:
```
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns

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

In this assignment, you will practice the fourth step of the machine learning life cycle and train machine learning models that will be used to solve a classification problem. Namely, you will train decision tree classifiers. You will complete the following tasks:

1. Build your DataFrame and define your ML problem:
    - Load the "cell2cell" data set into a DataFrame
    - Define the label - what are you predicting?
2. Prepare your data:
    - Handle missing data
    - Perform feature engineering by converting categorical features to one-hot encoded values
    - Identify features
3. Create labeled examples from the data set
4. Split the data into training and test data sets
5. Train two models and evaluate their performances:
    - Fit two Decision Tree classifiers to the training data using different hyperparameter values per classifier
    - Evaluate the accuracy of both model's predictions
    - Plot the resulting accuracy scores
6. Analysis:

- Experiment with different hyperparameter values: train multiple decision tree classifiers using different hyperparameter values and compare the accuracy scores to find which configuration yields the best performing model.

1.1 Part 1. Build Your DataFrame and Define Your ML Problem

Load a Data Set and Save it as a Pandas DataFrame We will work with the "cell2celltrain" data set. This version of the data set will need data preparation before it can be used for modeling.

[2]:
```
# Do not remove or edit the line below:
filename = os.path.join(os.getcwd(), "data", "cell2celltrain.csv")
```

Task: Load the data and save it to DataFrame `df`.

[3]:
```
# YOUR CODE HERE

# Solution
df = pd.read_csv(filename, header=0)
```

Inspect the Data **Task**: Display the shape of `df` -- that is, the number of records (rows) and variables (columns)

[4]:
```
# YOUR CODE HERE

# Solution
df.shape
```

[4]:
```
(51047, 58)
```

Define the Label Once again, this is a binary classification problem in which we will predict customer churn. The label is the `Churn` column.

Identify Features We will determine the features after we prepare our data in the section below.

1.2 Part 2. Prepare Your Data

You will perform step three of the machine learning life cycle and prepare your data for modeling. You will first clean your data by handling missing values and will then perform feature engineering by transforming categorical features using one-hot encoding.

1.2.1 a. Identify and Handle Missing Data

Task: Check if Dataframe `df` contains missing values, and sum up the resulting values by columns. Save this sum to variable `nan_count`. Print the results.

[5]:
```
#nan_count = # YOUR CODE HERE
#nan_count

### Solution:
nan_count = np.sum(df.isnull(), axis = 0)
nan_count
```

[5]:
```
CustomerID                    0
Churn                         0
ServiceArea                  24
ChildrenInHH                  0
HandsetRefurbished            0
HandsetWebCapable             0
TruckOwner                    0
RVOwner                       0
HomeownershipKnown            0
BuysViaMailOrder              0
RespondsToMailOffers          0
OptOutMailings                0
NonUSTravel                   0
OwnsComputer                  0
HasCreditCard                 0
NewCellphoneUser              0
NotNewCellphoneUser           0
OwnsMotorcycle                0
MadeCallToRetentionTeam       0
CreditRating                  0
PrizmCode                     0
Occupation                    0
Married                   19700
MonthlyRevenue                0
MonthlyMinutes                0
TotalRecurringCharge          0
DirectorAssistedCalls         0
OverageMinutes                0
RoamingCalls                  0
PercChangeMinutes             0
PercChangeRevenues            0
DroppedCalls                  0
BlockedCalls                  0
UnansweredCalls               0
CustomerCareCalls             0
ThreewayCalls                 0
ReceivedCalls                 0
OutboundCalls                 0
InboundCalls                  0
PeakCallsInOut                0
OffPeakCallsInOut             0
DroppedBlockedCalls           0
CallForwardingCalls           0
CallWaitingCalls              0
MonthsInService               0
UniqueSubs                    0
ActiveSubs                    0
```

```
Handsets                       0
HandsetModels                  0
CurrentEquipmentDays           0
AgeHH1                         0
AgeHH2                         0
RetentionCalls                 0
RetentionOffersAccepted        0
ReferralsMadeBySubscriber      0
IncomeGroup                    0
AdjustmentsToCreditRating      0
HandsetPrice                   0
dtype: int64
```

Notice that the `married` column contains many missing values. There are different ways to handle missing values in your data. You have practiced imputing missing values by replacing them with means. Another way to handle missing values is to remove the column that contains these values. In this case, replacing missing values in the `married` column with means doesn't quite make sense since the column contains boolean values, so let's remove the `married` column.

Task: Remove the `married` column from DataFrame `df`.

[6]:
```
# YOUR CODE HERE
# solution:
df.drop(columns = ['Married'], inplace=True)
```

The only other column that contains missing values is the `ServiceArea` column. Let's inspect the `ServiceArea` column to get an idea of what kind of values are in this column.

[7]:
```
df['ServiceArea']
```

[7]:
```
0        SEAPOR503
1        PITHOM412
2        MILMIL414
3        PITHOM412
4        OKCTUL918
           ...
51042    LAXSFN818
51043    LAXCDG310
51044    LAXCDG310
51045    NEVPOW619
51046    NEVPOW619
Name: ServiceArea, Length: 51047, dtype: object
```

[8]:
```
df['ServiceArea'].dtype
```

[8]:
```
dtype('O')
```

Task: Note that the `ServiceArea` columns contains string data types. Replace every entry in the column `ServiceArea` that contains a `NaN` value with the string `unavailable`.

[9]:
```
# YOUR CODE HERE
```

```
# Solution:
df['ServiceArea'].fillna('unavailable', inplace=True)
```

Task: Inspect DataFrame `df` to see the if it still has missing values by once again summing up the missing values by columns.

[10]:
```
# YOUR CODE HERE


# Solution:

np.sum(df.isnull(), axis = 0)
```

[10]:
```
CustomerID                 0
Churn                      0
ServiceArea                0
ChildrenInHH               0
HandsetRefurbished         0
HandsetWebCapable          0
TruckOwner                 0
RVOwner                    0
HomeownershipKnown         0
BuysViaMailOrder           0
RespondsToMailOffers       0
OptOutMailings             0
NonUSTravel                0
OwnsComputer               0
HasCreditCard              0
NewCellphoneUser           0
NotNewCellphoneUser        0
OwnsMotorcycle             0
MadeCallToRetentionTeam    0
CreditRating               0
PrizmCode                  0
Occupation                 0
MonthlyRevenue             0
MonthlyMinutes             0
TotalRecurringCharge       0
DirectorAssistedCalls      0
OverageMinutes             0
RoamingCalls               0
PercChangeMinutes          0
PercChangeRevenues         0
DroppedCalls               0
BlockedCalls               0
UnansweredCalls            0
CustomerCareCalls          0
ThreewayCalls              0
ReceivedCalls              0
```

```
OutboundCalls                0
InboundCalls                 0
PeakCallsInOut               0
OffPeakCallsInOut            0
DroppedBlockedCalls          0
CallForwardingCalls          0
CallWaitingCalls             0
MonthsInService              0
UniqueSubs                   0
ActiveSubs                   0
Handsets                     0
HandsetModels                0
CurrentEquipmentDays         0
AgeHH1                       0
AgeHH2                       0
RetentionCalls               0
RetentionOffersAccepted      0
ReferralsMadeBySubscriber    0
IncomeGroup                  0
AdjustmentsToCreditRating    0
HandsetPrice                 0
dtype: int64
```

1.2.2 b. Perform One-Hot Encoding

To train a decision tree model, we must first transform the string-valued categorical features into numerical boolean values using one-hot encoding.

Find the Columns Containing String Values

[11]:
```
df.dtypes
```

[11]:
```
CustomerID                     int64
Churn                           bool
ServiceArea                   object
ChildrenInHH                    bool
HandsetRefurbished              bool
HandsetWebCapable               bool
TruckOwner                      bool
RVOwner                         bool
HomeownershipKnown              bool
BuysViaMailOrder                bool
RespondsToMailOffers            bool
OptOutMailings                  bool
NonUSTravel                     bool
OwnsComputer                    bool
HasCreditCard                   bool
NewCellphoneUser                bool
```

```
NotNewCellphoneUser              bool
OwnsMotorcycle                   bool
MadeCallToRetentionTeam          bool
CreditRating                   object
PrizmCode                      object
Occupation                     object
MonthlyRevenue                float64
MonthlyMinutes                float64
TotalRecurringCharge          float64
DirectorAssistedCalls         float64
OverageMinutes                float64
RoamingCalls                  float64
PercChangeMinutes             float64
PercChangeRevenues            float64
DroppedCalls                  float64
BlockedCalls                  float64
UnansweredCalls               float64
CustomerCareCalls             float64
ThreewayCalls                 float64
ReceivedCalls                 float64
OutboundCalls                 float64
InboundCalls                  float64
PeakCallsInOut                float64
OffPeakCallsInOut             float64
DroppedBlockedCalls           float64
CallForwardingCalls           float64
CallWaitingCalls              float64
MonthsInService               float64
UniqueSubs                    float64
ActiveSubs                    float64
Handsets                      float64
HandsetModels                 float64
CurrentEquipmentDays          float64
AgeHH1                        float64
AgeHH2                        float64
RetentionCalls                float64
RetentionOffersAccepted       float64
ReferralsMadeBySubscriber     float64
IncomeGroup                   float64
AdjustmentsToCreditRating     float64
HandsetPrice                  float64
dtype: object
```

Task: Find all of the columns whose values are of type 'object' and add the column names to a list named `to_encode`.

[12]:
```
#to_encode = # YOUR CODE HERE
```

```
#solution:
to_encode = list(df.select_dtypes(include=['object']).columns)
```

Let's look at the number of unique values each column has:

[13]:
```
df[to_encode].nunique()
```

[13]:
```
ServiceArea      748
CreditRating       7
PrizmCode          4
Occupation         8
dtype: int64
```

Notice that all of the columns except for ServiceArea contain a small number of unique values. For these columns, it should be straightforward to use one-hot encoding to replace the column with a set of new binary columns for each unique value.

However, ServiceArea contains a large number of unique values. Let's first deal with the special case of ServiceArea.

One Hot-Encoding 'ServiceArea': The Top 10 Values Notice that column ServiceArea has 747 potential values. This means we would have to create 747 new binary indicator columns - one column per unique value. That is too many!

Transforming this many categorical values would slow down the computation down the line. One thing we could do is to see if some of the values in ServiceArea are occurring frequently. We will then one-hot encode just those frequent values. Let's one-hot encode only the top ten most frequent values in column ServiceArea.

Task: Get the top 10 most frequent values in the ServiceArea column and store them in list top_10_SA.

Hint: Use Pandas value_counts() method to obtain the most frequently occurring values in descending order. Then use the head() method to obtain the top ten most frequently occuring values. Finally, extract only the column values and save them to list top_10_SA.

[14]:
```
# YOUR CODE HERE

### Solution:
top_10_SA = list(df['ServiceArea'].value_counts().head(10).index)
top_10_SA
```

[14]:
```
['NYCBRO917',
 'HOUHOU281',
 'DALDAL214',
 'NYCMAN917',
 'APCFCH703',
 'DALFTW817',
 'SANSAN210',
 'APCSIL301',
 'SANAUS512',
 'SFROAK510']
```

Now that we have obtained the ten most frequent values for ServiceArea, let's use one-hot encoding to transform DataFrame df to represent these values numerically.

Task: Write a `for` loop that loops through every value in `top_10_SA` and creates one-hot encoded columns, titled 'ServiceArea'+ '_' + <service area value>'. For example, there will be a column named `ServiceArea_DALDAL214`.

Each of these new ten columns will have a value of either 0 or 1. 1 means that the row in question had that corresponding value present in the original `ServiceArea` column. For example, row 47 in DataFrame `df` originally had the value `DALDAL214` in column `ServiceArea`. After one-hot encoding, row 47 will have the value of 1 in new column `ServiceArea_DALDAL214`.

Use the NumPy `np.where()`function to accomplish this.

[15]:
```
# YOUR CODE HERE

# Solution
for value in top_10_SA:

    ## Create columns and their values
    df['ServiceArea_'+ value] = np.where(df['ServiceArea']==value,1,0)
```

Task: 1. Drop the original, multi-valued `ServiceArea` column from the DataFrame `df`. 2. Remove 'ServiceArea' from the `to_encode` list.

[16]:
```
# YOUR CODE HERE

# Solution
# Remove the original column from your DataFrame df
df.drop(columns = 'ServiceArea', inplace=True)

# Remove from list to_encode
to_encode.remove('ServiceArea')
```

Inspect DataFrame `df` and see the new columns and their values.

[17]:
```
df.columns
```

[17]:
```
Index(['CustomerID', 'Churn', 'ChildrenInHH', 'HandsetRefurbished',
       'HandsetWebCapable', 'TruckOwner', 'RVOwner', 'HomeownershipKnown',
       'BuysViaMailOrder', 'RespondsToMailOffers', 'OptOutMailings',
       'NonUSTravel', 'OwnsComputer', 'HasCreditCard', 'NewCellphoneUser',
       'NotNewCellphoneUser', 'OwnsMotorcycle', 'MadeCallToRetentionTeam',
       'CreditRating', 'PrizmCode', 'Occupation', 'MonthlyRevenue',
       'MonthlyMinutes', 'TotalRecurringCharge', 'DirectorAssistedCalls',
       'OverageMinutes', 'RoamingCalls', 'PercChangeMinutes',
       'PercChangeRevenues', 'DroppedCalls', 'BlockedCalls', 'UnansweredCalls',
       'CustomerCareCalls', 'ThreewayCalls', 'ReceivedCalls', 'OutboundCalls',
       'InboundCalls', 'PeakCallsInOut', 'OffPeakCallsInOut',
       'DroppedBlockedCalls', 'CallForwardingCalls', 'CallWaitingCalls',
       'MonthsInService', 'UniqueSubs', 'ActiveSubs', 'Handsets',
       'HandsetModels', 'CurrentEquipmentDays', 'AgeHH1', 'AgeHH2',
       'RetentionCalls', 'RetentionOffersAccepted',
       'ReferralsMadeBySubscriber', 'IncomeGroup', 'AdjustmentsToCreditRating',
       'HandsetPrice', 'ServiceArea_NYCBRO917', 'ServiceArea_HOUHOU281',
```

```
       'ServiceArea_DALDAL214', 'ServiceArea_NYCMAN917',
       'ServiceArea_APCFCH703', 'ServiceArea_DALFTW817',
       'ServiceArea_SANSAN210', 'ServiceArea_APCSIL301',
       'ServiceArea_SANAUS512', 'ServiceArea_SFROAK510'],
      dtype='object')
```

[18]:
```
df.head()
```

[18]:
```
   CustomerID  Churn  ChildrenInHH  HandsetRefurbished  HandsetWebCapable  \
0     3000002   True         False               False               True
1     3000010   True          True               False              False
2     3000014  False          True               False              False
3     3000022  False         False               False               True
4     3000026   True         False               False              False

   TruckOwner  RVOwner  HomeownershipKnown  BuysViaMailOrder  \
0       False    False                True              True
1       False    False                True              True
2       False    False               False             False
3       False    False                True              True
4       False    False                True              True

   RespondsToMailOffers  ...  ServiceArea_NYCBRO917  ServiceArea_HOUHOU281  \
0                  True  ...                      0                      0
1                  True  ...                      0                      0
2                 False  ...                      0                      0
3                  True  ...                      0                      0
4                  True  ...                      0                      0

   ServiceArea_DALDAL214  ServiceArea_NYCMAN917  ServiceArea_APCFCH703  \
0                      0                      0                      0
1                      0                      0                      0
2                      0                      0                      0
3                      0                      0                      0
4                      0                      0                      0

   ServiceArea_DALFTW817  ServiceArea_SANSAN210  ServiceArea_APCSIL301  \
0                      0                      0                      0
1                      0                      0                      0
2                      0                      0                      0
3                      0                      0                      0
4                      0                      0                      0

  ServiceArea_SANAUS512 ServiceArea_SFROAK510
0                     0                     0
1                     0                     0
2                     0                     0
3                     0                     0
```

```
4                     0                      0

[5 rows x 66 columns]
```

Let's inspect column `ServiceArea_DALDAL214` in row 47. Remember, it should have a value of 1.

[19]:
```
df.loc[47]['ServiceArea_DALDAL214']
```

[19]:
```
1
```

One Hot-Encode all Remaining Columns All 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: In the code cell below, iterate over the column names contained in `to_encode` and one-hot encode these columns. In the loop: 1. Use the Pandas `pd.get_dummies()` function to one-hot encode the column and save the resulting DataFrame to variable `df_encoded` 2. Use `df.join` to join DataFrame `df_encoded` with DataFrame `df`

[20]:
```
# YOUR CODE HERE

# SOLUTION
for colname in to_encode:
    df_encoded = pd.get_dummies(df[colname], prefix=colname +'_')
    df = df.join(df_encoded)
```

[21]:
```
df.head()
```

[21]:
```
   CustomerID  Churn  ChildrenInHH  HandsetRefurbished  HandsetWebCapable  \
0     3000002   True         False               False               True
1     3000010   True          True               False              False
2     3000014  False          True               False              False
3     3000022  False         False               False               True
4     3000026   True         False               False              False

   TruckOwner  RVOwner  HomeownershipKnown  BuysViaMailOrder  \
0       False    False                True              True
1       False    False                True              True
2       False    False               False             False
3       False    False                True              True
4       False    False                True              True

   RespondsToMailOffers  ...  PrizmCode__Suburban  PrizmCode__Town  \
0                  True  ...                    1                0
1                  True  ...                    1                0
2                 False  ...                    0                1
3                  True  ...                    0                0
4                  True  ...                    0                0

   Occupation__Clerical  Occupation__Crafts  Occupation__Homemaker  \
```

```
0                      0                    0                       0
1                      0                    0                       0
2                      0                    1                       0
3                      0                    0                       0
4                      0                    0                       0

   Occupation__Other  Occupation__Professional  Occupation__Retired  \
0                  0                         1                    0
1                  0                         1                    0
2                  0                         0                    0
3                  1                         0                    0
4                  0                         1                    0

  Occupation__Self  Occupation__Student
0                0                    0
1                0                    0
2                0                    0
3                0                    0
4                0                    0

[5 rows x 85 columns]
```

Task: Remove all the original columns from DataFrame df

[22]:
```
# YOUR CODE HERE

# Solution
df.drop(columns = to_encode ,axis=1, inplace=True)
```

Task: Check that the data does not contain any missing values. The absence of missing values is necessary for training a Decision Tree model.

[23]:
```
# YOUR CODE HERE

# solution
df.isnull().values.any()
```

[23]:
```
False
```

Identify Features Let's inspect the transformed DataFrame df. These will be our features.

[31]:
```
list(df.loc[:, df.columns != 'Churn'])
```

[31]:
```
['CustomerID',
 'ChildrenInHH',
 'HandsetRefurbished',
 'HandsetWebCapable',
 'TruckOwner',
 'RVOwner',
 'HomeownershipKnown',
 'BuysViaMailOrder',
```

```
'RespondsToMailOffers',
'OptOutMailings',
'NonUSTravel',
'OwnsComputer',
'HasCreditCard',
'NewCellphoneUser',
'NotNewCellphoneUser',
'OwnsMotorcycle',
'MadeCallToRetentionTeam',
'MonthlyRevenue',
'MonthlyMinutes',
'TotalRecurringCharge',
'DirectorAssistedCalls',
'OverageMinutes',
'RoamingCalls',
'PercChangeMinutes',
'PercChangeRevenues',
'DroppedCalls',
'BlockedCalls',
'UnansweredCalls',
'CustomerCareCalls',
'ThreewayCalls',
'ReceivedCalls',
'OutboundCalls',
'InboundCalls',
'PeakCallsInOut',
'OffPeakCallsInOut',
'DroppedBlockedCalls',
'CallForwardingCalls',
'CallWaitingCalls',
'MonthsInService',
'UniqueSubs',
'ActiveSubs',
'Handsets',
'HandsetModels',
'CurrentEquipmentDays',
'AgeHH1',
'AgeHH2',
'RetentionCalls',
'RetentionOffersAccepted',
'ReferralsMadeBySubscriber',
'IncomeGroup',
'AdjustmentsToCreditRating',
'HandsetPrice',
'ServiceArea_NYCBRO917',
'ServiceArea_HOUHOU281',
'ServiceArea_DALDAL214',
```

```
'ServiceArea_NYCMAN917',
'ServiceArea_APCFCH703',
'ServiceArea_DALFTW817',
'ServiceArea_SANSAN210',
'ServiceArea_APCSIL301',
'ServiceArea_SANAUS512',
'ServiceArea_SFROAK510',
'CreditRating__1-Highest',
'CreditRating__2-High',
'CreditRating__3-Good',
'CreditRating__4-Medium',
'CreditRating__5-Low',
'CreditRating__6-VeryLow',
'CreditRating__7-Lowest',
'PrizmCode__Other',
'PrizmCode__Rural',
'PrizmCode__Suburban',
'PrizmCode__Town',
'Occupation__Clerical',
'Occupation__Crafts',
'Occupation__Homemaker',
'Occupation__Other',
'Occupation__Professional',
'Occupation__Retired',
'Occupation__Self',
'Occupation__Student']
```

1.3 Part 3: Create Labeled Examples from the Data Set

Task: Create labeled examples from DataFrame `df`. In the code cell below carry out the following steps:

- Get the `Churn` column from DataFrame `df` and assign it to the variable `y`. This will be our label.
- Get all other columns from DataFrame `df` and assign them to the variable `X`. These will be our features.

[25]:
```python
# YOUR CODE HERE

### Solution:
y = df['Churn']
X = df.drop(columns = 'Churn', axis=1)
```

1.4 Part 4: Create Training and Test Data Sets

Task: In the code cell below create training and test data sets out of the labeled examples.

1. Use Scikit-learn's `train_test_split()` function to create the data sets.

2. Specify:

   - A test set that is 30 percent (.30) of the size of the data set.
   - A seed value of '123'.

[26]:
```
# X_train, X_test, y_train, y_test = # YOUR CODE HERE

### Solution:
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=123)
```

Check that the dimensions of the training and test data sets are what you expected:

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

```
(35732, 81)
(15315, 81)
```

1.5 Part 5. Train Decision Tree Classifiers and Evaluate Their Performances

The code cell below contains a shell of a function named `train_test_DT()`. This function should 1. train a Decision Tree classifier on the training data 2. test the resulting model on the test data 3. compute and return the accuracy score of the resulting predicted class labels on the test data

Task: Complete the function to make it work.

[28]:
```
def train_test_DT(X_train, X_test, y_train, y_test, depth, leaf=1,␣
↪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:
        depth := The maximum depth of the tree
        leaf := The minimum number of samples required to be at a leaf node.
            We have assigned a default value of 1 to the leaf parameter
        crit := The function to be used to measure the quality of a split.
            We have assigned a default value of 'entropy' to the crit parameter.
↪ Note that
            scikit-learn's default value is gini.
    '''

     # 1. Create the  Scikit-learn DecisionTreeClassifier model object below␣
↪and assign to variable 'model'
      # YOUR CODE HERE

     ### SOLUTION
    model = DecisionTreeClassifier(criterion = crit, max_depth = depth,␣
↪min_samples_leaf = leaf)
```

```python
    # 2. Fit the model to the training data below
     # YOUR CODE HERE

    # SOLUTION
    model.fit(X_train, y_train)

    # 3. Make predictions on the test data and assign the result to the
 ↪variable 'class_label_predictions' below
     # YOUR CODE HERE

    #SOLUTION
    class_label_predictions = model.predict(X_test)

    # 4. Compute the accuracy and save the result to the variable 'acc_score'
 ↪below
     # YOUR CODE HERE

     #SOLUTION
    acc_score = accuracy_score(y_test, class_label_predictions)



    return acc_score
```

Train Decision Tree Classifiers Using Different Hyperparameter Values Task: Complete the code cell below to train two Decision Tree classifiers using your function. Save the resulting accuracy scores to the list acc.

Choose the two values for max depth to pass as arguments to your function: - one with a low value of max depth - one high value of max depth

Print the max depth and resulting accuracy score.

[29]:
```python
depth1= 2 # YOUR CODE HERE (solutions will vary)
depth2 = 5 # YOUR CODE HERE (solutions will vary)

max_depth_range = [depth1, depth2]
acc = []

for md in max_depth_range:
    # YOUR CODE HERE
    # solution:
    score = train_test_DT(X_train, X_test, y_train, y_test,  md)
    print('Max Depth=' + str(md) + ', accuracy score: ' + str(score))
    acc.append(float(score))
```

```
Max Depth=2, accuracy score: 0.7107411034933072
Max Depth=5, accuracy score: 0.715834149526608
```

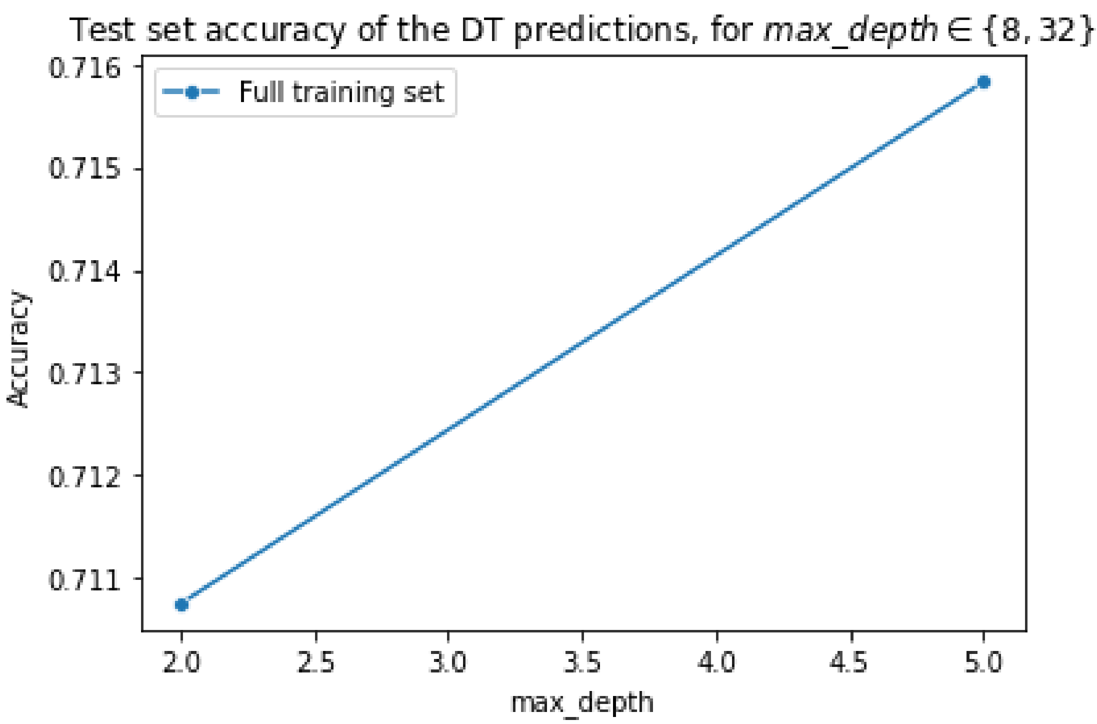
Task: Visualize the results using a `seaborn` lineplot. The x axis should correspond to the depths contained in list `max_depth_range` and the y axis should corrsponds to the accuracy scores contained in the list `acc`.

Consult the online documentation for more information about `seaborn` lineplots.

[30]:
```
fig = plt.figure()
ax = fig.add_subplot(111)

# YOUR CODE HERE
# solution
p = sns.lineplot(x=max_depth_range, y=acc, marker='o', label = 'Full training␣
 ↪set')


plt.title('Test set accuracy of the DT predictions, for $max\_depth\in\{8,␣
 ↪32\}$')
ax.set_xlabel('max_depth')
ax.set_ylabel('Accuracy')
plt.show()
```



1.6 Part 6: Analysis

Experiment with different values for `max_depth`. Add these new values to the list `max_depth_range`, retrain your models and rerun with the visualization cell above. Compare the different accuracy scores.

Once you find the best value for `max_depth`, experiment with different values for `leaf` and compare the different accuracy scores.

Is there one model configuration that yields the best score? Record your findings in the cell below.