Break Through Tech Machine Learning Week 3

April 14, 2023

1 Assignment 3: Building a Decision Tree After Feature Transformations

[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 implement the following steps to build a Decision Tree classification model:

1. Load the "cell2celltrain" 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 of its predictions
5. Plot the training set accuracy

1.1 Part 1. Load the Data Set

We will work with the "cell2celltrain" data set.

[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)
```

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)
```

For the purpose of this assignment, we will remove the `Married` column due to missing values

[5]:
```
df.drop(columns = ['Married'], inplace=True)
```

1.2 Part 2. One-Hot Encode Categorical Values

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

1.2.1 a. Find the Columns Containing String Values

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

[6]:
```
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: Add all of the column names whos values are of type 'object' to a list named to_encode.

[7]:

```
# YOUR CODE HERE

#solution:
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]:

```
ServiceArea     747
CreditRating      7
PrizmCode         4
Occupation        8
dtype: int64
```

For all of the columns except for ServiceArea, it should be straightforward to replace a given column with a set of several new binary columns for each unique value. However, let's first deal with the special case of ServiceArea.

1.2.2 b. One Hot-Encoding 'ServiceArea': The Top 10 Values

Take a look at the number of unique values of the `ServiceArea` column. There are two many unique values in the `ServiceArea` column to attempt to create a new binary indicator column per value! 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.

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

[9]:
```
# YOUR CODE HERE

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

[9]:
```
['NYCBRO917',
 'HOUHOU281',
 'DALDAL214',
 'NYCMAN917',
 'APCFCH703',
 'DALFTW817',
 'SANSAN210',
 'APCSIL301',
 'SANAUS512',
 'SFROAK510']
```

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_NYCBRO917'. Use the NumPy `np.where()`function to accomplish this.

[10]:
```
# 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.

[11]:
```
# YOUR CODE HERE

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

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

[12]:
```
df.head()
```

[12]:

```
   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]
```

1.2.3 c. One Hot-Encoding all Remaining Columns: All Unique Values per Column

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 column names and create new columns for all unique values. 1. Use a loop to loop over the column names in `to_encode` 2. In the loop: 1. Use the Pandas `pd.get_dummies()` function and save the result to variable `temp_df` 2. Use `df.join` to join `temp_df` with DataFrame `df`

[13]:

```
# YOUR CODE HERE

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

[14]:

```
df.head()
```

[14]:

```
   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

[15]:
```
# YOUR CODE HERE

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

[16]:
```
df.columns
```

[16]:
```
Index(['CustomerID', 'Churn', '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'],
      dtype='object')
```

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

[17]:
```
# YOUR CODE HERE

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

[17]:
```
False
```

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.

[18]:
```
# 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 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'.

[19]:
```
# 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 datasets are what you expected:

[20]:
```
print(X_train.shape)
print(X_test.shape)
```

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

1.5 Part 5. Fit a Decision Tree Classifer and Evaluate the Model

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.

Task: Complete the function to make it work.

[21]:
```
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.
    '''

     # 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)


    # 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
```

1.5.1 Train on Different Hyperparameter Values

Task: Train two Decision Tree classifiers using your function.

- one with a low value of depth
- one high value of depth

Specify the minimum number of samples at the leaf node to be equal to 1 for both trees. Save the resulting accuracy scores to list `acc`. Print the list.

[22]:
```
depth1= 2 # YOUR CODE HERE (solutions will vary)
depth2 = 5 # YOUR CODE HERE (solutions will vary)
leaf = 1

max_depth_range = [depth1, depth2]
acc = []

# YOUR CODE HERE

### Solution:

for md in max_depth_range:
    score = train_test_DT(X_train, X_test, y_train, y_test, 1, md)
    print('Max Depth=' + str(md) + ', accuracy score: ' + str(score))
    acc.append(float(score))
```

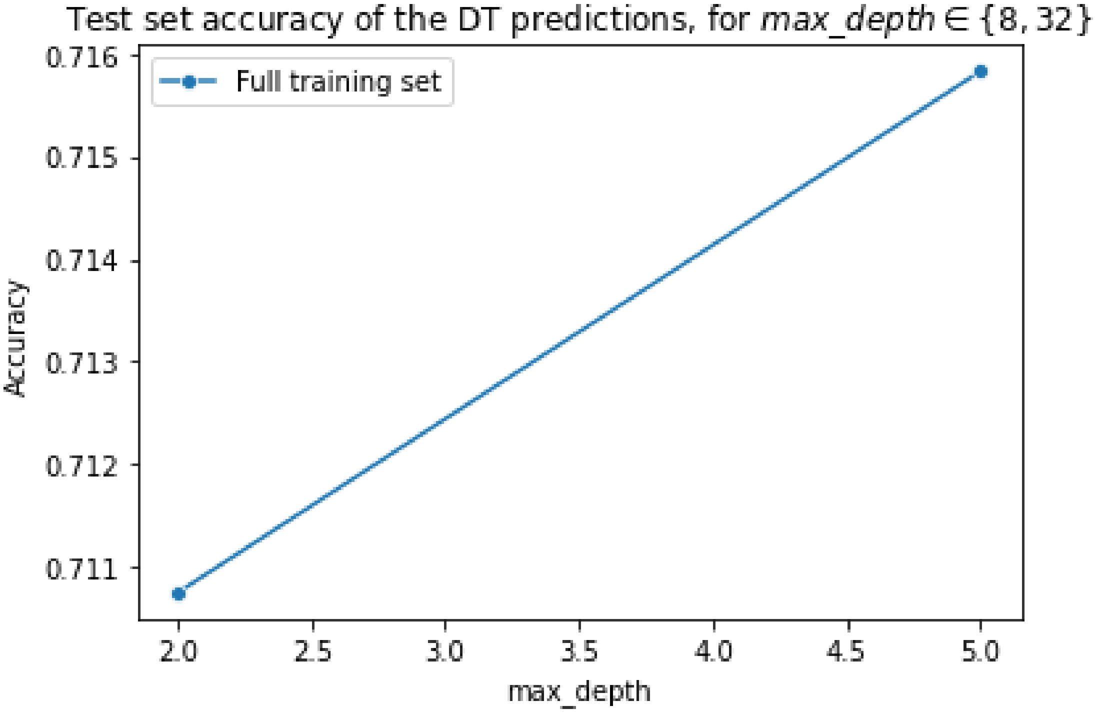
```
Max Depth=2, accuracy score: 0.7107411034933072
Max Depth=5, accuracy score: 0.715834149526608
```

Task: Visualize the results (Hint: use a `seaborn` lineplot).

[23]:
```
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()
```



Analysis: Experiment with different values for `max_depth`. Add these values to the list `max_depth_range` (i.e. change the values, create a list containing more values), retrain your model 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.