# HengLiEnShaun_task2

August 5, 2021

[1]:
```
import pandas as pd
import numpy as np
import re
import matplotlib.pyplot as plt
import seaborn as sns
eps = np.finfo(float).eps
from numpy import log2 as log
import sys

adultdata = pd.read_csv('adult.data',␣
 ↪names=["Age","Workclass","FNLWGT","Education","Education-num",\
                                                          ␣
 ↪"Marital_status","Occupation","Relationship","Race","Sex",\
                                                          ␣
 ↪"Capital-gain","Capital-loss","Hours-per-week","Native-country",\
                                                           "Class"])
attName = ["Age","Workclass","FNLWGT","Education-num",\
           "Marital_status","Occupation","Race","Sex",\
           "Capital-gain","Capital-loss","Hours-per-week","Native-country"]
adultdata
```

[1]:
```
       Age         Workclass  FNLWGT   Education  Education-num  \
0       39         State-gov   77516   Bachelors             13
1       50  Self-emp-not-inc   83311   Bachelors             13
2       38           Private  215646     HS-grad              9
3       53           Private  234721        11th              7
4       28           Private  338409   Bachelors             13
…     …               …     …         …           …
32556   27           Private  257302  Assoc-acdm             12
32557   40           Private  154374     HS-grad              9
32558   58           Private  151910     HS-grad              9
32559   22           Private  201490     HS-grad              9
32560   52      Self-emp-inc  287927     HS-grad              9

            Marital_status         Occupation   Relationship   Race  \
0            Never-married       Adm-clerical  Not-in-family  White
1       Married-civ-spouse    Exec-managerial        Husband  White
```

```
2                 Divorced   Handlers-cleaners   Not-in-family   White
3       Married-civ-spouse   Handlers-cleaners         Husband   Black
4       Married-civ-spouse      Prof-specialty            Wife   Black
…                        …                   …             …       …
32556   Married-civ-spouse        Tech-support            Wife   White
32557   Married-civ-spouse   Machine-op-inspct         Husband   White
32558              Widowed        Adm-clerical       Unmarried   White
32559        Never-married        Adm-clerical       Own-child   White
32560   Married-civ-spouse     Exec-managerial            Wife   White

           Sex  Capital-gain  Capital-loss  Hours-per-week  Native-country  \
0         Male          2174             0              40   United-States
1         Male             0             0              13   United-States
2         Male             0             0              40   United-States
3         Male             0             0              40   United-States
4       Female             0             0              40            Cuba
…          …             …             …               …               …
32556   Female             0             0              38   United-States
32557     Male             0             0              40   United-States
32558   Female             0             0              40   United-States
32559     Male             0             0              20   United-States
32560   Female         15024             0              40   United-States

        Class
0       <=50K
1       <=50K
2       <=50K
3       <=50K
4       <=50K
…       …
32556   <=50K
32557    >50K
32558   <=50K
32559   <=50K
32560    >50K

[32561 rows x 15 columns]
```

[2]:

```python
adulttest = pd.read_csv('adult.test',␣
↪names=["Age","Workclass","FNLWGT","Education","Education-num",\
                                                      ␣
↪"Marital_status","Occupation","Relationship","Race","Sex",\
                                                      ␣
↪"Capital-gain","Capital-loss","Hours-per-week","Native-country",\
                                                      "Class"])
adulttest = adulttest.drop([0])
adulttest
```

[2]:
```
         Age       Workclass    FNLWGT      Education  Education-num  \
1       25         Private  226802.0           11th            7.0
2       38         Private   89814.0        HS-grad            9.0
3       28       Local-gov  336951.0     Assoc-acdm           12.0
4       44         Private  160323.0   Some-college           10.0
5       18               ?  103497.0   Some-college           10.0
…      ..              …         …              …            …
16277   39         Private  215419.0      Bachelors           13.0
16278   64               ?  321403.0        HS-grad            9.0
16279   38         Private  374983.0      Bachelors           13.0
16280   44         Private   83891.0      Bachelors           13.0
16281   35    Self-emp-inc  182148.0      Bachelors           13.0

            Marital_status          Occupation     Relationship  \
1            Never-married   Machine-op-inspct        Own-child
2       Married-civ-spouse     Farming-fishing          Husband
3       Married-civ-spouse     Protective-serv          Husband
4       Married-civ-spouse   Machine-op-inspct          Husband
5            Never-married                   ?        Own-child
…                        …                   …              …
16277             Divorced      Prof-specialty    Not-in-family
16278              Widowed                   ?   Other-relative
16279   Married-civ-spouse      Prof-specialty          Husband
16280             Divorced        Adm-clerical        Own-child
16281   Married-civ-spouse     Exec-managerial          Husband

                      Race      Sex  Capital-gain  Capital-loss  \
1                    Black     Male           0.0           0.0
2                    White     Male           0.0           0.0
3                    White     Male           0.0           0.0
4                    Black     Male        7688.0           0.0
5                    White   Female           0.0           0.0
…                        …       …             …            …
16277                White   Female           0.0           0.0
16278                Black     Male           0.0           0.0
16279                White     Male           0.0           0.0
16280   Asian-Pac-Islander     Male        5455.0           0.0
16281                White     Male           0.0           0.0

        Hours-per-week  Native-country    Class
1                 40.0   United-States   <=50K.
2                 50.0   United-States   <=50K.
3                 40.0   United-States    >50K.
4                 40.0   United-States    >50K.
5                 30.0   United-States   <=50K.
…                    …              …      …
16277             36.0   United-States   <=50K.
```

```
16278             40.0   United-States   <=50K.
16279             50.0   United-States   <=50K.
16280             40.0   United-States   <=50K.
16281             60.0   United-States    >50K.

[16281 rows x 15 columns]
```

[3]:
```python
import random
def train_test_split(df, test_size):

    if isinstance(test_size, float):
        test_size = round(test_size * len(df))

    indices = df.index.tolist()
    test_indices = random.sample(population=indices, k=test_size)

    test_df = df.loc[test_indices]
    train_df = df.drop(test_indices)

    return train_df, test_df
```

[4]:
```python
adultdatatrain, adultdatapostpruning = train_test_split(adultdata, 0.33)
```

[5]:
```python
adultdatatrain
```

[5]:
```
        Age          Workclass  FNLWGT   Education  Education-num  \
0        39          State-gov   77516   Bachelors             13
1        50   Self-emp-not-inc   83311   Bachelors             13
2        38            Private  215646     HS-grad              9
3        53            Private  234721        11th              7
4        28            Private  338409   Bachelors             13
…      …                   …      …          …            …
32554    53            Private  321865     Masters             14
32557    40            Private  154374     HS-grad              9
32558    58            Private  151910     HS-grad              9
32559    22            Private  201490     HS-grad              9
32560    52       Self-emp-inc  287927     HS-grad              9

             Marital_status          Occupation    Relationship    Race  \
0             Never-married        Adm-clerical   Not-in-family   White
1        Married-civ-spouse     Exec-managerial         Husband   White
2                  Divorced   Handlers-cleaners   Not-in-family   White
3        Married-civ-spouse   Handlers-cleaners         Husband   Black
4        Married-civ-spouse      Prof-specialty            Wife   Black
…                         …                   …             …       …
32554    Married-civ-spouse     Exec-managerial         Husband   White
32557    Married-civ-spouse   Machine-op-inspct         Husband   White
```

```
32558            Widowed       Adm-clerical     Unmarried   White
32559      Never-married       Adm-clerical     Own-child   White
32560  Married-civ-spouse   Exec-managerial          Wife   White

          Sex  Capital-gain  Capital-loss  Hours-per-week  Native-country  \
0        Male          2174             0              40   United-States
1        Male             0             0              13   United-States
2        Male             0             0              40   United-States
3        Male             0             0              40   United-States
4      Female             0             0              40            Cuba
…         …          …            …              …             …
32554    Male             0             0              40   United-States
32557    Male             0             0              40   United-States
32558  Female             0             0              40   United-States
32559    Male             0             0              20   United-States
32560  Female         15024             0              40   United-States

        Class
0       <=50K
1       <=50K
2       <=50K
3       <=50K
4       <=50K
…       …
32554    >50K
32557    >50K
32558   <=50K
32559   <=50K
32560    >50K

[21816 rows x 15 columns]
```

[6]:
```
adultdatapostpruning
```

[6]:
```
       Age         Workclass  FNLWGT     Education  Education-num  \
29959  43            Private   69333       HS-grad              9
2857   28                  ?  157813          11th              7
19690  38   Self-emp-not-inc  334366  Some-college             10
7238   29            Private  183009     Bachelors             13
2710   50            Private   92079  Some-college             10
…    …                 …      …          …              …
32045  20            Private  184045  Some-college             10
15924  72            Private   33404          10th              6
19417  44            Private  151985       Masters             14
27911  21            Private  245572           9th              5
11363  32            Private  209808  Some-college             10
```

```
            Marital_status          Occupation    Relationship  \
29959   Married-civ-spouse   Machine-op-inspct         Husband
2857              Divorced                   ?       Unmarried
19690   Married-civ-spouse     Farming-fishing            Wife
7238         Never-married      Prof-specialty   Not-in-family
2710    Married-civ-spouse        Tech-support         Husband
…                      …                   …             …
32045        Never-married               Sales       Unmarried
15924              Widowed        Adm-clerical   Not-in-family
19417   Married-civ-spouse     Exec-managerial            Wife
27911        Never-married       Other-service       Own-child
11363   Married-civ-spouse               Sales         Husband

                      Race      Sex  Capital-gain  Capital-loss  \
29959                White     Male             0             0
2857                 White   Female             0             0
19690                White   Female             0             0
7238                 Other   Female             0          1590
2710                 White     Male             0             0
…                      …      …            …            …
32045                Black   Female             0             0
15924                White   Female             0             0
19417                White   Female             0             0
27911   Amer-Indian-Eskimo     Male             0             0
11363                White     Male             0          1740

       Hours-per-week  Native-country   Class
29959              48   United-States   <=50K
2857               58          Canada   <=50K
19690              15   United-States   <=50K
7238               40   United-States   <=50K
2710               45   United-States    >50K
…                …              …     …
32045              30   United-States   <=50K
15924              20   United-States   <=50K
19417              24   United-States    >50K
27911              40   United-States   <=50K
11363              47   United-States   <=50K

[10745 rows x 15 columns]
```

[7]:

```python
# Calculate Entropy of dataset
def findEntropy(df):
    #print('Calculating entropy..........')
    #print(f'df (findEntropy): \n{df}')
    Class = df.keys()[-1]    #To make the code generic, changing target variable
 ↪class name
```

```
    entropy = 0
    values = df[Class].unique()

    for value in values:
        fraction = df[Class].value_counts()[value] / len(df[Class])
        entropy += -fraction * np.log2(fraction)
    return entropy
```

[8]:
```
# Calculate Entropy by attribute
def findEntropyAttribute(df,attribute):
    #print('Calculating entropy by attribute..........')
    #print(f'df (findEntropy): \n{df}')
    #print('attribute (findEntropyAttribute): ', attribute)
    Class = df.keys()[-1]   #To make the code generic, changing target variable␣
 ↪class name

    target_variables = df[Class].unique() #This gives all 'Yes' and 'No'
    variables = df[attribute].unique()    #This gives different features in␣
 ↪that attribute (like 'Hot','Cold' in Temperature)

    entropy2 = 0
    for variable in variables:
        entropy = 0
        for target_variable in target_variables:
            num = len(df[attribute][df[attribute] == variable][df[Class] ==␣
 ↪target_variable])
            den = len(df[attribute][df[attribute] == variable])
            fraction = num / (den+eps)
            entropy += -fraction * log(fraction+eps)
        fraction2 = den / len(df)
        entropy2 += -fraction2 * entropy

    return abs(entropy2)
```

[9]:
```
# Calculate information gain and return the best splitting node (feature)
def infoGain(df):
    #print('Calculate information gain ..........')
    #print(f'df (findEntropy): \n{df}')
    IG = []
    for key in df.keys()[:-1]:
        IG.append(findEntropy(df) - findEntropyAttribute(df,key))

    return df.keys()[:-1][np.argmax(IG)]
```

[10]:
```
def giniImpurity2(valueCounts):
    #print('Calculating gini impurity ..........')
    #print(f'df (findEntropy): \\n{df}')
```

```
    #print('valueCounts.keys(): ', valueCounts.keys())
    n = valueCounts.sum()
    p_sum = 0
    for key in valueCounts.keys():
        p_sum = p_sum  +  (valueCounts[key] / n ) * (valueCounts[key] / n )
        gini = 1 - p_sum

    return gini
```

[11]:
```
# Calculating  gini impurity for the attiributes
def giniSplitAtt2(df, attName):
    #print('Calculating gini impurity by attribute..........')
    #print(f'df (giniSplitAtt2): \\n{df}')
    #print('attName (giniSplitAtt2): ', attName)
    attValues = df[attName].value_counts()
    gini_A = 0
    for key in attValues.keys():
        dfKey = df[className][df[attName] == key].value_counts()
        numOfKey = attValues[key]
        n = df.shape[0]
        gini_A = gini_A + (( numOfKey / n) * giniImpurity2(dfKey))

    return gini_A
```

[12]:
```
def giniIndex2(df, attributeNames):
    #print('Calculate gini index2 ..........')
    #print(f'df (findEntropy): \\n{df}')
    #print('attributeNames (giniIndex2): ', attributeNames)
    giniAttribute = {}
    minValue = sys.maxsize
    for key in attributeNames:
        #print('=====================================> key (giniIndex2): ', key)
        giniAttribute[key] = giniSplitAtt2(df, key)
        if giniAttribute[key] < minValue:
            minValue = giniAttribute[key]
            selectedAttribute = key
        #print(f'Gini for {key} is {giniAttribute[key]:.3f}')
    minValue = min(giniAttribute.values())
    #selectedAttribute = min(giniAttribute.keys())
    #print('^^^^^^^^^^^^^^^^ minValue (giniIndex2): ', minValue)
    #print('^^^^^^^^^^^^^^^^ giniIndex2 methods is returning (giniIndex2):',␣
 ↪selectedAttribute)
    return selectedAttribute
```

[13]:
```
def getSubtable(df, node, value):
    return df[df[node] == value].reset_index(drop=True)
```

[14]:

```
print(findEntropy(adultdatatrain))
```

0.7916055274436617

[15]:

```
print(findEntropy(adultdatapostpruning))
```

0.8058870769537714

[16]:

```
print(findEntropy(adulttest))
```

0.788708184990964

[17]:

```
print(findEntropyAttribute(adultdatatrain, 'Age'))
```

0.6964351954649428

[18]:

```
print(findEntropyAttribute(adultdatapostpruning, 'Age'))
```

0.695114351673674

[19]:

```
print(findEntropyAttribute(adulttest, 'Age'))
```

0.6904502539000037

[20]:

```
print(infoGain(adultdatatrain))
```

FNLWGT

[21]:

```
def buildTree(df,model,tree=None):
    # print('@@@@@@@@@@@@@@@@@@ Building a classification tree...................
↪.............')
    # print(f'DataFrame: \n{df}')
    # print('tree (buildTree): ', tree)
    Class = df.keys()[-1]    #To make the code generic, changing target variable␣
↪class name
    # print('Class (buildTree): ', Class)
    #Here we build our decision tree

    #Get attribute with maximum information gain
    #print('model (buildTree): infoGain')

    if model == 'infoGain':
        #print('Calling infoGain(df)')
        node = infoGain(df)
    else:
        #print('Calling giniIndex2')
        node = giniIndex2(df, attName)

    # print('node (buildTree): ', node)
```

```
    #Get distinct value of that attribute e.g Salary is node and Low,Med and␣
↪High are values
    attValueBT = np.unique(df[node])
    # print('attValue (buildTree): ', attValueBT)
    #Create an empty dictionary to create tree
    if tree is None:
        tree = {}
        tree[node] = {}

    #We make loop to construct a tree by calling this function recursively.
    #In this we check if the subset is pure and stops if it is pure.

    for value in attValueBT:
        # print('value (buildTree): ', value)
        subtable = getSubtable(df,node,value)

        clValue,counts = np.unique(subtable[className],return_counts=True)

        if len(counts) == 1: # Checking purity of subset
            # print('###########################################**********␣
↪Recursive call 1 **********')
            # print('node (buildTree): ', node)
            # print('value (buildTree): ', tree)
            tree[node][value] = clValue[0]
        else:
            # print('###########################################**********␣
↪Recursive call 2 **********')
            # print('node (buildTree): ', node)
            # print('value (buildTree): ', tree)
            # print(f'subtable (buildTree): \n{subtable}')
            tree[node][value] = buildTree(subtable, model) # Calling the␣
↪function recursively
    # print('############################################ tree to return␣
↪(buildTree) ----->: ', tree)
    return tree
```

[22]:
```
import pprint
className = 'Education'
#className = 'creditRating'
print('Target Class: ', className)
model = 'gini'
#model = 'infoGain'
t=buildTree(adultdatatrain, model)
pprint.pprint(t)
```

```
Target Class:  Education
{'Education-num': {1: ' Preschool',
```

```
                    2: ' 1st-4th',
                    3: ' 5th-6th',
                    4: ' 7th-8th',
                    5: ' 9th',
                    6: ' 10th',
                    7: ' 11th',
                    8: ' 12th',
                    9: ' HS-grad',
                    10: ' Some-college',
                    11: ' Assoc-voc',
                    12: ' Assoc-acdm',
                    13: ' Bachelors',
                    14: ' Masters',
                    15: ' Prof-school',
                    16: ' Doctorate'}}
```

[23]:

```
# Calculating  gini impurity for the attiributes
def gini_split_a(attribute_name):
    attribute_values = adultdatatrain[attribute_name].value_counts()
    gini_A = 0
    # print('class_name: ', className)
    # print('attribute_values: ', attribute_values)
    for key in attribute_values.keys():
        df_k = adultdatatrain[className][adultdata[attribute_name] == key].
 ↪value_counts()
        n_k = attribute_values[key]
        n = adultdatatrain.shape[0]
        gini_A = gini_A + (( n_k / n) * giniImpurity2(df_k))
    return gini_A

#attribute_names =  ['age', 'income', 'student', 'creditRating']
gini_attiribute ={}
for key in attName:
    gini_attiribute[key] = gini_split_a(key)
    print(f'Gini for {key} is {gini_attiribute[key]:.3f}')
```

```
Gini for Age is 0.787
Gini for Workclass is 0.804
Gini for FNLWGT is 0.200
Gini for Education-num is 0.000
Gini for Marital_status is 0.805
Gini for Occupation is 0.760
Gini for Race is 0.807
Gini for Sex is 0.808
Gini for Capital-gain is 0.800
Gini for Capital-loss is 0.803
Gini for Hours-per-week is 0.798
Gini for Native-country is 0.802
```

```
[24]: # Compute Gini gain values to find the best split
# An attribute has maximum Gini gain is selected for splitting.

min_value = min(gini_attiribute.values())
print('The minimum value of Gini Impurity : {0:.3} '.format(min_value))
print('The maximum value of Gini Gain     : {0:.3} '.format(1-min_value))

selected_attribute = min(gini_attiribute.keys())
print('The selected attiribute is: ', selected_attribute)
```

```
The minimum value of Gini Impurity : 0.0
The maximum value of Gini Gain     : 1.0
The selected attiribute is:  Age
```

# 1 Classification

```
[25]: def check_purity(data):

    label_column = data[:, -1]
    unique_classes = np.unique(label_column)

    if len(unique_classes) == 1:
        return True
    else:
        return False
```

```
[26]: def get_potential_splits(data):

    potential_splits = {}
    _, n_columns = data.shape
    for column_index in range(n_columns - 1): # excluding the last column which␣
↪is the label
        values = data[:, column_index]
        unique_values = np.unique(values)

        potential_splits[column_index] = unique_values

    return potential_splits
```

```
[27]: def calculate_entropy(data):

    label_column = data[:, -1]
    _, counts = np.unique(label_column, return_counts=True)

    probabilities = counts / counts.sum()
    entropy = sum(probabilities * -np.log2(probabilities))
```

```
    return entropy

def calculate_overall_entropy(data_below, data_above):

    n = len(data_below) + len(data_above)
    p_data_below = len(data_below) / n
    p_data_above = len(data_above) / n

    overall_entropy =  (p_data_below * calculate_entropy(data_below)
                      + p_data_above * calculate_entropy(data_above))

    return overall_entropy

def calculate_mse(data):
    actual_values = data[:, -1]
    if len(actual_values) == 0:   # empty data
        mse = 0

    else:
        prediction = np.mean(actual_values)
        mse = np.mean((actual_values - prediction) **2)

    return mse


def calculate_overall_metric(data_below, data_above, metric_function):

    n = len(data_below) + len(data_above)
    p_data_below = len(data_below) / n
    p_data_above = len(data_above) / n

    overall_metric =  (p_data_below * metric_function(data_below)
                     + p_data_above * metric_function(data_above))

    return overall_metric


def determine_best_split(data, potential_splits):

    overall_entropy = 9999
    for column_index in potential_splits:
        for value in potential_splits[column_index]:
            data_below, data_above = split_data(data,␣
↪split_column=column_index, split_value=value)
            current_overall_entropy = calculate_overall_entropy(data_below,␣
↪data_above)
```

```
            if current_overall_entropy <= overall_entropy:
                overall_entropy = current_overall_entropy
                best_split_column = column_index
                best_split_value = value

    return best_split_column, best_split_value
```

[28]:
```
def split_data(data, split_column, split_value):

    split_column_values = data[:, split_column]

    data_below = data[split_column_values <= split_value]
    data_above = data[split_column_values >  split_value]

    return data_below, data_above
```

[29]:
```
def classify_data(data):

    label_column = data[:, -1]
    unique_classes, counts_unique_classes = np.unique(label_column,␣
 ↪return_counts=True)

    index = counts_unique_classes.argmax()
    classification = unique_classes[index]

    return classification
```

[30]:
```
def decision_tree_algorithm(df, counter=0, min_samples=2, max_depth=5):

    # data preparations
    if counter == 0:
        global COLUMN_HEADERS
        COLUMN_HEADERS = df.columns
        data = df.values
    else:
        data = df


    # base cases
    if (check_purity(data)) or (len(data) < min_samples) or (counter ==␣
 ↪max_depth):
        classification = classify_data(data)

        return classification


    # recursive part
```

```
    else:
        counter += 1

        # helper functions
        potential_splits = get_potential_splits(data)
        split_column, split_value = determine_best_split(data, potential_splits)
        data_below, data_above = split_data(data, split_column, split_value)

        # instantiate sub-tree
        feature_name = COLUMN_HEADERS[split_column]
        question = "{} <= {}".format(feature_name, split_value)
        sub_tree = {question: []}

        # find answers (recursion)
        yes_answer = decision_tree_algorithm(data_below, counter, min_samples,␣
↪max_depth)
        no_answer = decision_tree_algorithm(data_above, counter, min_samples,␣
↪max_depth)

        # If the answers are the same, then there is no point in asking the␣
↪qestion.
        # This could happen when the data is classified even though it is not␣
↪pure
        # yet (min_samples or max_depth base cases).
        if yes_answer == no_answer:
            sub_tree = yes_answer
        else:
            sub_tree[question].append(yes_answer)
            sub_tree[question].append(no_answer)

        return sub_tree
```

[31]:
```
def predict_example(example, tree):

    # tree is just a root node
    if not isinstance(tree, dict):
        return tree

    question = list(tree.keys())[0]
    feature_name, comparison_operator, value = question.split()

    if str(example[feature_name]) == value:
        answer = tree[question][0]
    else:
        answer = tree[question][1]

    # base case
```

```python
    if not isinstance(answer, dict):
        return answer

    # recursive part
    else:
        residual_tree = answer
        return predict_example(example, residual_tree)
```

[32]:
```python
def make_predictions(df, tree):

    if len(df) != 0:
        predictions = df.apply(predict_example, args=(tree,), axis=1)
    else:
        # "df.apply()"" with empty dataframe returns an empty dataframe,
        # but "predictions" should be a series instead
        predictions = pd.Series()

    return predictions
```

[33]:
```python
def classify_example(example, tree):
    if isinstance(tree, str):
        return tree
    else:
        question = list(tree.keys())[0]

    feature_name, comparison_operator, value = question.split()

    # ask question
    if example[feature_name] == value:
        answer = tree[question][0]
    else:
        answer = tree[question][1]

    # base case
    if not isinstance(answer, dict):
        return answer

    # recursive part
    else:
        residual_tree = answer
        return classify_example(example, residual_tree)
```

[34]:
```python
def calculate_accuracy(df, tree):

    df["classification"] = df.apply(classify_example, axis=1, args=(tree,))
    df["classification_correct"] = df["classification"] == df["Class"]
```

```
    accuracy = df["classification_correct"].mean()

    return accuracy
```

[35]:
```
tree = decision_tree_algorithm(adultdatatrain, max_depth=3)
```

[36]:
```
pprint.pprint(tree)
```

```
{'Relationship <=  Husband': [{'Education-num <= 12': [{'Capital-gain <= 5013':
['  '
 '<=50K',
 '  '
 '>50K']},
                                                       ' >50K']},
                              {'Capital-gain <= 6849': [' <=50K', ' >50K']}]}
```

[37]:
```
print(calculate_accuracy(adultdatapostpruning, tree))
```

```
0.24662633783154955
```

## 2 Post pruning

[38]:
```
def filter_df(df, question):
    feature, comparison_operator, value = question.split()

    df_yes = df[df[feature].astype(str) == value]
    df_no  = df[df[feature].astype(str) != value]

    return df_yes, df_no
```

[39]:
```
def determine_leaf(df_train):
    return df_train.Class.value_counts().index[0]
```

[40]:
```
def determine_errors(df_val, tree):
    predictions = make_predictions(df_val, tree)
    actual_values = df_val.Class

    # number of errors
    return sum(predictions != actual_values)
```

[41]:
```
def pruning_result(tree, df_train, df_val):

    leaf = determine_leaf(df_train)
    errors_leaf = determine_errors(df_val, leaf)
    errors_decision_node = determine_errors(df_val, tree)

    if errors_leaf <= errors_decision_node:
```

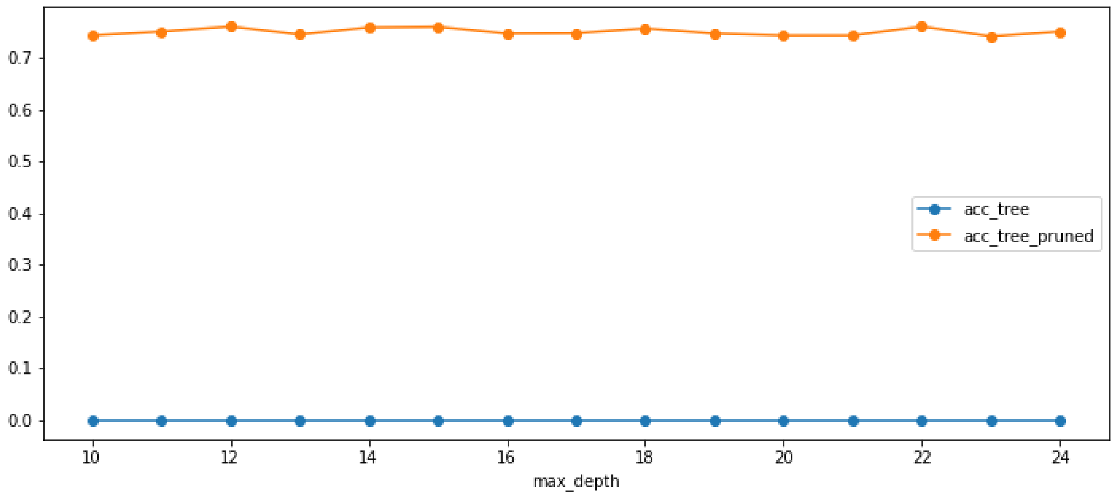
```python
        return leaf
    else:
        return tree
```

[42]:
```python
def post_pruning(tree, df_train, df_val):

    question = list(tree.keys())[0]
    yes_answer, no_answer = tree[question]

    # base case
    if not isinstance(yes_answer, dict) and not isinstance(no_answer, dict):
        return pruning_result(tree, df_train, df_val)

    # recursive part
    else:
        df_train_yes, df_train_no = filter_df(df_train, question)
        df_val_yes, df_val_no = filter_df(df_val, question)

        if isinstance(yes_answer, dict):
            yes_answer = post_pruning(yes_answer, df_train_yes, df_val_yes)

        if isinstance(no_answer, dict):
            no_answer = post_pruning(no_answer, df_train_no, df_val_no)

        tree = {question: [yes_answer, no_answer]}

        return pruning_result(tree, df_train, df_val)
```

[43]:
```python
metrics = {"max_depth": [], "acc_tree": [], "acc_tree_pruned": []}
for n in range(10, 25):
    df_train, df_test = train_test_split(adultdatapostpruning, test_size=0.15)
    df_train, df_val = train_test_split(df_train, test_size=0.15)

    tree = decision_tree_algorithm(df_train, max_depth=n)
    tree_pruned = post_pruning(tree, df_train, df_val)

    metrics["max_depth"].append(n)
    metrics["acc_tree"].append(calculate_accuracy(df_test, tree))
    metrics["acc_tree_pruned"].append(calculate_accuracy(df_test, tree_pruned))

df_metrics = pd.DataFrame(metrics)
df_metrics = df_metrics.set_index("max_depth")
```

[44]:
```python
df_metrics.plot(figsize=(12, 5), marker="o")
```

[44]:
```
<AxesSubplot:xlabel='max_depth'>
```


0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
10
12
14
16
18
20
22
24
max_depth
acc_tree
acc_tree_pruned

[ ]: