$H4_{-5}$

October 26, 2020

1 Decision Tree for the Use Case "Playing Tennis" using ID3 method

cepts & Algorithms". DHBW Stuttgart (WS2020) By Brian Brandner and Daniel Rück 26. October 2020

The ID3 (Iterative Dichotomiser 3) method is used to generate a decision tree from a dataset. To achieve this the algorithm needs the **Entropy** formula to determine impurity of data and the Information Gain, which indicates the most relevant dataset attribut

1.1 Import of libraries

- ${\bf pandas}$ loads the dataset and provids necessary frame details
- math calculates in the alogarithm to the base 2
- ${\bf pprint}$ prints the dictionary storage
- $\bf IPython$ uses display, Math and Latex to for printing the formula
- · sys version information to python

```
[1]: # libraries to import
     import pandas as pd
import math
     import pprint
     from IPython.display import display, Math, Latex
      # python version check library
     import sys
     \# print python version, for some imports this version number is viewed as
     print("python {}".format(sys.version))
    # version of pandas
print("pandas {}".format(pd.__version__))
```

```
Overcast
                     Mild
       Rainy
                              High
       Rainy
                     Cool
                            Normal
                                           Yes
       Rainy
                     Cool
                            Normal
   Overcast
                     Cool
                                           Yes
                            Normal
       Sunny
                     Mila
                            High
Normal
                                            No
       Sunny
                                           Yes
       Rainv
                     Mild
                            Normal
                                           Yes
                     Mild
   Overcast
11
                     Mild
                              High
                                           Yes
12 Overcast
                     Hot
                            Normal
       Rainy
                              High
```

1.5 Root-Node

1.5.1 Total Entropy of the whole dataframe

- $\mathbf{tempStorage}$ $\mathbf{variable}$ to store selected informations
- \mathbf{df} loaded data frame object, function groupby(['Column']) selects the passed column, function size() of it counts column variables
- [5]: # fracture dataframe to export data to compute tempStorage = df.groupby(['Play']).size() tempStorage
- [5]: Play Yes dtype: int64
 - yesCount variable holds column value "Yes" count
 noCount variable holds column value "No" count

 - aggreg Elements in Column
 aggregTotal Elements in Column for Information Gain calculation
 - ${f entropyTotal}$ calculated entropy

```
[6]: # write values to variables
        yesCount = tempStorage['Yes']
noCount = tempStorage['No']
aggreg = yesCount + noCount
aggregTotal = aggreg
         entropyTotal = -(((yesCount/aggreg)*math.log2(yesCount/aggreg)) + ((noCount/
--aggreg)*math.log2(noCount/aggreg)))
```

```
python 3.6.9 (default, Oct 8 2020, 12:12:24)
pandas 1.1.3
```

1.2 Entropy formula

II - greek Eta, Entropy

S - Dataset

p(x_i) - Proportion of classification to results (Quantity of Yes or No / sum of Yes and No)

$$H(S) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i)$$

1.3 Information Gain formula

IG - Information Gain

S - Dataset

C - Column

H(S_Total) - Total entropy of the dataframe

 $p(Z_Column)$ - Value count of active column divided by max column length

H(S Column) - Entropy of active column value

$$IG(S,C) = H(S_{Total}) - \sum p(Z_{Column}) * H(S_{Column})$$

1.4 Load dataset and view dataframe

• df - object storage variable

- \mathbf{pd} - pandas call of function "read_csv" with parameters FILE.csv and separator semicolon

[4]: Outlook Temperature Humidity Windy Play Hot Sunny High F No Sunny Hot High

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```
print("H(S) = {0:.5f}\n".format(entropyTotal))
```

H(S) = 0.94029

1.5.2 Entropy of column Outlook

This time a selection of two columns is necessary, first column combined with result column (in this example: 'Play') size() provides again the amount of value frequency

```
[7]: # Overview of two selected columns
    df.groupby(['Outlook', 'Play']).size()
```

```
[7]: Outlook Play
    Overcast
              Yes
    Rainy
              No
              Yes
    Sunny
              No
    dtype: int64
```

To access the data, a call for the column value is needed.

For 'Overcast' only "Yes" is an option, hence noCount is set to 0 and the formular misses the addition of its calculation

```
[8]: # fracture dataframe to export compute data
tempStorage = df.groupby(['Outlook', 'Play']).size()['Overcast']
      yesCount = tempStorage['Yes']
      noCount = 0
aggreg = yesCount + noCount
       aggregOvercast = aggreg
      entropyOvercast = -((yesCount/aggreg)*math.log2(yesCount/aggreg))
```

For "Sunny" and "Rainy" both result classifications are available

```
[9]: # fracture dataframe to export compute data
     tempStorage = df.groupby(['Outlook', 'Play']).size()['Sunny']
     # write values to variables
     yesCount = tempStorage['Yes']
     noCount = tempStorage['No']
```

```
aggreg = yesCount + noCount
aggregSunny = aggreg
entropySunny = -(((yesCount/aggreg)*math.log2(yesCount/aggreg))) + ((noCount/
--aggreg)*math.log2(noCount/aggreg)))
# fracture dataframe to emport compute data
tempStorage = df.groupby(['Outlook', 'Play']).size()['Rainy']
# write values to variables
yesCount = tempStorage['Yes']
noCount = tempStorage['No']
aggregPainy = aggreg
entropyRainy = -(((yesCount/aggreg)*math.log2(yesCount/aggreg)) + ((noCount/
--aggreg)*math.log2(noCount/aggreg)))
```

Print out the calculated Entropy values

```
[10]: print("H(Outlook == Overcast) = {0:.5f}".format(entropyOvercast))
print("H(Outlook == Sunny) = {0:.5f}".format(entropySunny))
print("H(Outlook == Rainy) = {0:.5f}".format(entropyRainy))

H(Outlook == Overcast) = -0.00000
H(Outlook == Sunny) = 0.97095
H(Outlook == Rainy) = 0.97095
```

 $\begin{tabular}{ll} \textbf{Information Gain for column Outlook} & Finally the Information Gain analyse for the selected column 'Outlook' \\ \end{tabular}$

Print out the calculated Information Gain value

```
[12]: print("IG(S, outlook) = {0:.5f}\n".format(infoGain))
```

IG(S, outlook) = 0.24675

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```
H(Temperature == Hot) = 1.00000
H(Temperature == Mild) = 0.91830
H(Temperature == Cool) = 0.81128
```

Information Gain for column Temperature

IG(S, Temperature) = 0.02922

1.5.4 Entropy of column Humidity

1.5.3 Entropy of column Temperature

Repeat procedure for each column

```
[13]: # fracture dataframe to export data to compute
        tempStorage = df.groupby(['Temperature', 'Play']).size()['Hot']
       # write values to variables
       yesCount = tempStorage['Yes']
noCount = tempStorage['No']
       aggreg = yesCount + noCount
aggregHot = aggreg
       entropyHot = -(((yesCount/aggreg)*math.log2(yesCount/aggreg)) + ((noCount/
         ⇒aggreg)*math.log2(noCount/aggreg)))
        # fracture dataframe to emport data to compute
tempStorage = df groupby(['Temperature', 'Play']).size()['Mild']
       yesCount = tempStorage['Yes']
noCount = tempStorage['No']
        aggreg = yesCount + noCount
        aggregMild = aggreg
       entropyMild = -(((yesCount/aggreg)*math.log2(yesCount/aggreg)) + ((noCount/
--aggreg)*math.log2(noCount/aggreg)))
        # fracture dataframe to export data to compute
        tempStorage = df.groupby(['Temperature', 'Play']).size()['Cool']
        # write values to variables
       yesCount = tempStorage['Yes']
noCount = tempStorage['No']
aggreg = yesCount + noCount
aggregCool = aggreg
       entropyCool = -(((yesCount/aggreg)*math.log2(yesCount/aggreg)) + ((noCount/
         aggreg) *math.log2(noCount/aggreg)))
       print("H(Temperature == Hot) = {0:.5f}".format(entropyHot))
       print("H(Temperature == Mild) = {0:.5f}".format(entropyMild))
print("H(Temperature == Cool) = {0:.5f}".format(entropyCool))
```

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```
print("H(Humidity == Normal) = {0:.5f}".format(entropyNormal))

H(Humidity == High) = 0.98523
H(Humidity == Normal) = 0.59167
```

Information Gain for column Humidity

IG(S, Humidity) = 0.15184

1.5.5 Entropy of column Windy

2 Overview Information Gain for the Root-Node

2.1 Select Root-Node based on highest Information Gain value

Pretty print out the collected Information Gain vaules with column name.

Reset of the dictionary with selected node as root.

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${\bf 2.2.2} \quad {\bf Entropy \ of \ column \ Temperature \ for \ branch \ Sunny}$

```
[22]: # fracture dataframe to export compute data
tempStorage = dfS.groupby(['Temperature', 'Play']).size()['Hot']
        # write values to variables
       yesCount = 0
       noCount = tempStorage['No']
aggreg = yesCount + noCount
aggregHot = aggreg
       entropyHot = -((noCount/aggreg)*math.log2(noCount/aggreg))
        tempStorage = dfS.groupby(['Temperature', 'Play']).size()['Mild']
       # write values to variables
yesCount = tempStorage['Yes']
       noCount = tempStorage['No']
aggreg = yesCount + noCount
        aggregMild = aggreg
       entropyMild = -(((yesCount/aggreg)*math.log2(yesCount/aggreg)) + ((noCount/
          aggreg) *math.log2(noCount/aggreg)))
        tempStorage = dfS.groupby(['Temperature', 'Play']).size()['Cool']
        # write values to variables
       yesCount = tempStorage['Yes']
noCount = 0
       aggreg = yesCount + noCount
aggregCool = aggreg
        entropyCool = -((yesCount/aggreg)*math.log2(yesCount/aggreg))
       print("H(Temperature == Hot) = {0:.5f}".format(entropyHot))
print("H(Temperature == Mild) = {0:.5f}".format(entropyMild))
print("H(Temperature == Cool) = {0:.5f}".format(entropyCool))
       H(Temperature == Hot) = -0.00000
      H(Temperature == Mild) = 1.00000
H(Temperature == Cool) = -0.00000
```



2.2 Branch Sunny

```
    dfS - modified dataframe object to filter for specific string
```

```
[20]: dfS = df.loc[df['Outlook'] == 'Sunny']
     dfS
Γ201:
        Outlook Temperature Humidity Windy Play
           Sunny
                                 High
                                          F No
T No
     1
          Sunny
                        Hot
                                 High
           Sunny
                        Mild
                                 High
                                              No
                               Normal
           Sunny
                        Cool
                                             Yes
          Sunny
     10
                       Mild
                               Normal
                                             Yes
```

2.2.1 Total entropy of branch Sunny dataframe

```
[21]: # fracture dataframe to export compute data
tempStorage = dfS.groupby(['Play']).size()

# write values to variables
yesCount = tempStorage['Yes']
noCount = tempStorage['Yos']
aggreg = yesCount + noCount
aggregTotal = aggreg
entropyTotal = -(((yesCount/aggreg)*math.log2(yesCount/aggreg)) + ((noCount/-aggreg)*math.log2(noCount/aggreg)))
print("H(S) = {0:.5f}\n".format(entropyTotal))
H(S) = 0.97095
```

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2.2.3 Entropy of column Humidity for branch Sunny

Information Gain for column Humidity

```
[25]: offsetEntropy = (aggregHigh/aggregTotal)*entropyHigh + (aggregNormal/
--aggregTotal)*entropyNormal
infoGain = entropyTotal - offsetEntropy
infoGainDict['Outlook']['BranchSunny']['Humidity'] = infoGain
print("IG(S, Humidity) = {0:.5f}\n".format(infoGain))
```

IG(S, Humidity) = 0.97095

2.2.4 Entropy of column Windy for branch Sunny

13

2.4.1 High value

```
[29]: dfSH = dfS.loc[dfS['Humidity'] == 'High']
dfSH
```

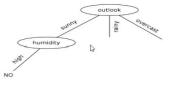
[29]: Outlook Temperature Humidity Windy Play
0 Sunny Hot High F No
1 Sunny Hot High T No

All results of the dataframe are "No", hence no calculation of entropy necessary

[30]: infoGainDict["Outlook"]['BranchSunny']['Humidity']['High'] = "No"

 ${\rm Leaf\ end\ -\ No}$

Decision tree



2.4.2 Normal value

```
[31]: dfSH = dfS.loc[dfS['Humidity'] == 'Normal']
dfSH
```

[31]: Outlook Temperature Humidity Windy Play
8 Sunny Cool Normal F Yes
10 Sunny Mild Normal T Yes

All results of the dataframe are "Yes", hence no calculation of entropy necessary

[32]: infoGainDict["Outlook"]['BranchSunny']['Humidity']['Normal'] = "Yes"

Leaf end - Yes

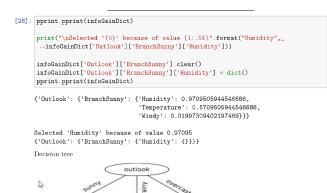
Decision tree

Information Gain for column Windy

IG(S, Windy) = 0.01997

2.3 Overview Information Gain Branch Sunny

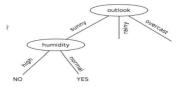
2.3.1 Select Node based on highest Information Gain value



2.4 Subnode Humidity of Branch Sunny

humidity

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2.5 Branch Overcast

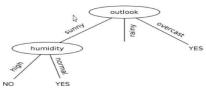


All results of the dataframe are "Yes", hence no calculation of entropy necessary

[34]: infoGainDict["Outlook"]['BranchOvercast'] = "Yes"

Leaf end - Yes

Decision tree



2.6 Branch Rainy

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```
[35]: dfR = df.loc[df['Outlook'] == 'Rainy']
[35]:
          Outlook Temperature Humidity Windy Play
                             Mild
Cool
                                      High
Normal
             Rainy
                                                     F Yes
             Rainy
             Rainv
                              Cool
                                       Normal
                                                          No
             Rainy
                              Mild
                                       Normal
       13
             Rainy
                              Mild
                                         High
      2.6.1 Total entropy of branch Rainy dataframe
[36]: # fracture dataframe to export compute data
       tempStorage = dfR.groupby(['Play']).size()
        # write values to variables
       # write values to variables
yesCount = tempStorage['Yes']
noCount = tempStorage['No']
aggreg = yesCount + noCount
aggregTotal = aggreg
       \label{eq:count_aggreg} $$ entropy Total = -(((yesCount/aggreg)*math.log2(yesCount/aggreg)) + ((noCount/aggreg)*math.log2(noCount/aggreg))) $$ $$
       print("H(S) = {0:.5f}\n".format(entropyTotal))
      H(S) = 0.97095
      2.6.2 Entropy of column Temperature for branch Rainy
       tempStorage = dfR.groupby(['Temperature', 'Play']).size()['Mild']
```

[37]: # fracture dataframe to emport compute data
tempStorage = dfR.groupby(['Temperature', 'Play']).size()['Mild']

write values to variables
yesCount = tempStorage['Yes']
noCount = tempStorage['No']
aggreg = yesCount + noCount
aggregMild = aggreg
entropyMild = -(((yesCount/aggreg)*math.log2(yesCount/aggreg)) + ((noCount/
---aggreg)*math.log2(noCount/aggreg)))

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2.6.4 Entropy of column Windy for branch Rainy

IG(S, Humidity) = 0.01997

```
[41]: # fracture dataframe to export compute data

tempStorage = dfR.groupby(['Windy', 'Play']).size()['T']

# write values to variables

yesCount = 0

noCount = tempStorage['No']

aggreg = yesCount + noCount

aggregTrue = aggreg
```

2.6.3 Entropy of column Humidity for branch Rainy

IG(S, Temperature) = 0.01997

```
[39]: # fracture dataframe to export compute data
tempStorage = dfR.groupby(['Humidity', 'Play']).size()['High']

# urite values to variables
yesCount = tempStorage['Yes']
ncCount = tempStorage['Yes']
aggreg = yesCount + ncCount
aggregHigh = aggreg
```

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Information Gain for column Windy

[42]: offsetEntropy = (aggregTrue/aggregTotal)*entropyTrue + (aggregFalse/
--aggregTotal)*entropyFalse
infoGain = entropyTotal - offsetEntropy

infoGainDict['Outlook']['BranchRainy']['Windy'] = infoGain

print("IG(S, Windy) = {0:.5f}\n".format(infoGain))

2.7 Overview Information Gain Branch Rainy

IG(S, Windy) = 0.97095

2.7.1 Select Node based on highest Information Gain value

```
{'Outlook': {'BranchOvercast': 'Yes',
           'BranchRainy': {'Humidity': 0.01997309402197489,
                         'Temperature': 0.01997309402197489, 
'Windy': 0.9709505944546686},
           'BranchSunny': {'Humidity': {'High': 'No', 'Normal': 'Yes'}}}
Selected 'Windy' because of value 0.97095
```

2.8 Subnode Windy of Branch Rainy

2.8.1 High value

```
[44]: dfRW = dfR.loc[dfR['Windy'] == 'T']
```

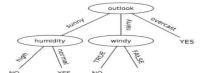
Outlook Temperature Humidity Windy Play Rainy Cool Normal T No 13 Rainy Mild High T No

All results of the dataframe are "No", hence no calculation of entropy necessary

[45]: infoGainDict["Outlook"]['BranchRainy']['Windy']['T'] = "No"

Leaf end - No Decision tree

[49]:



Outlook Temperature Humidity Windy Play

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```
0
                 Sunny
                                    Hot
                                                High
                                                                 No
                  Sunny
                                     Hot
                                                High
             Overcast
                                    Hot
                                                High
                                                                Yes
                                                                 Yes
                  Rainy
                                                High
                  Rainv
                                    Cool
                                             Normal
                                                                Yes
                                                                No
Yes
                  Rainy
                                    Cool
                                             Normal
             Overcast
                                    Cool
                                             Normal
                  Sunny
                                    Mild
                                               High
                                                                 No
                                            Normal
                  Sunny
                  Rainy
                                    Mild
                                             Normal
                                                                Yes
        10
                  Sunny
                                    Mild
                                             Normal
                                                                Yes
             Overcast
        11
                                    Mild
                                               High
                                                                Yes
            Overcast
Rainy
        12
                                    Hot
                                    Mild
                                                High
[50]: def getEntropy(yesCount, noCount, sumYesNo):
    if (yesCount == 0):
                   return -((noCount/sumYesNo)*math.log2(noCount/sumYesNo))
             elif (noCount
                   return -((yesCount/sumYesNo)*math.log2(yesCount/sumYesNo))
                   return -(((yesCount/sumYesNo)*math.log2(yesCount/sumYesNo)) + ((noCount/
           sumYesNo) *math.log2(noCount/sumYesNo)))
        def getInformationGain(totalDict, selectedDict):
    totalEntropy = totalDict['Entropy']
    totalAggCount = totalDict['AggCount']
             sumSelected = 0
             for f in selectedDict:
                   I in selectedIncompared in the selectedAggCount = selectedDict[f]['AggCount'] selectedEntropy = selectedDict[f]['Entropy'] sumSelected += ((selectedAggCount/totalAggCount)*selectedEntropy)
             return totalEntropy - sumSelected
          #return totalEntropy - ((mO/totalAggCount)*outcastEntropy + (mS/-totalAggCount)*sunnyEntropy + (mR/mD)*rainyEntropy)
        def runThrough(dataFrame, node, blackList):
    collist = dataFrame.columns
    resCol = 'Play'
             resItems = pd.Series(dataFrame[resCol]).unique()
             autdic = {}
             autdic[node] = {}
             #################### Total Entropy
```

2.8.2 Normal value

```
[46]: dfRW = dfR.loc[dfR['Windy'] == 'F']
       Outlook Temperature Humidity Windy Play
         Rainv
                      Mild
                              High
                                           Yes
                      Cool
                             Normal
                      Mild
                             Normal
```

All results of the dataframe are "Yes", hence no calculation of entropy necessary

[47]: infoGainDict["Outlook"]['BranchRainy']['Windy']['F'] = "Yes"

Rainy

Decision tree



[48]: #Final pprint of the dicitionary pprint.pprint(infoGainDict)

```
[]:
\mathbb{E}[1]:
```

2.9 Automation try

reads dataframe and selects root node

```
[49]: df = pd.read_csv("playTennis.csv", sep=';')
```

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```
aggCount = dataFrame.groupby([resCol]).size()[1] + dataFrame.groupby([resCol]).size()[0]
  totalEntropy = getEntropy(dataFrame.groupby([resCol]).size()[1], dataFrame.groupby([resCol]).size()[0], aggCount)
    for i in colList:
         1 in collst:
if (i = resCol and i not in blackList):
    autdic[node][i] = {}
    uniqueItems = pd.Series(dataFrame[i]).unique()
    for n in uniqueItems:
                    autdic[node][i][n] = {}
                    try:
                      yesCount = dataFrame.groupby([i, resCol]).size()[n]['Yes']
                     yesCount = 0
                    try:
noCount = dataFrame.groupby([i, resCol]).size()[n]['No']
                      noCount = 0
                    autdic[node][i][n]['AggCount'] = yesCount+noCount
autdic[node][i][n]['Entropy'] =_
  getEntropy(yesCount,noCount,yesCount+noCount)
     return autdic
### "Main"
blackList = {}
rootDictEntropy = runThrough(df, "root", "")
rootDictInformationGain = {}
for i in rootDictEntropy['root']:
    if i != "total":
         rootDictInformationGain[i] =
  getInformationGain(rootDictEntropy['root']['total'],_
  rootDictEntropy['root'][i])
print("Entropies for total and subsets of Root-Node:")
pprint.pprint(rootDictEntropy)
```