

Week-1

1.a. Python Program to find factorial of a Number

Source Code:

```
def factorial(n):  
    if (n==1 or n==0):  
        return 1  
    else:  
        return n * factorial(n - 1)
```

```
num = int(input('Enter the Number : '))
```

```
Enter the Number : 6
```

```
fact = factorial(num)
```

```
print("Factorial of {} is {}".format(num,fact))
```

```
Factorial of 6 is 720
```

1.b. Python Program to find Second Largest Element in an Array

Source Code:

```
def findseclargest(arr):  
    largest = arr[0]  
    sec_largest = arr[0]  
    for i in range(len(arr)):  
        if( arr[i] > largest ):  
            largest = arr[i]  
    for i in range(len(arr)):  
        if(arr[i] > sec_largest and arr[i]!=largest):  
            sec_largest = arr[i]  
    return sec_largest
```

```
x = int(input("How many elements you want to enter into the list : "))
```

How many elements you want to enter into the list : 6

```
l=list()  
for i in range(1,x+1):  
    y = int(input("Enter the Element{ } :".format(i)))  
    l.append(y)
```

```
Enter the Element1 :8  
Enter the Element2 :9  
Enter the Element3 :7  
Enter the Element4 :5  
Enter the Element5 :8  
Enter the Element6 :6
```

```
second_largest = findseclargest(l)  
print("The Second Largest Element in Array { } is {}".format(l,second_largest))
```

The Second Largest Element in Array [8, 9, 7, 5, 8, 6] is 8

1.c. Python Program for Multiplication of Two Matrices

Source Code:

```
A=[ ]
```

```
B=[ ]
```

```
m = int(input("Enter the No of Rows of Matrix A : "))
n = int(input("Enter the No of Columns of Matrix A : "))
print("Enter the Matrix A Elements : \n")
for i in range(m):
    row = [ ]
    for j in range(n):
        row.append(int(input()))
    A.append(row)
```

```
Enter the No of Rows of Matrix A : 2
Enter the No of Columns of Matrix A : 2
Enter the Matrix A Elements :
```

```
4
5
6
8
```

```
p = int(input("Enter the No of Rows of Matrix B : "))
q = int(input("Enter the No of Columns of Matrix B : "))
print("Enter the Matrix A Elements : \n")
for i in range(p):
    row=[ ]
    for j in range(q):
        row.append(int(input()))
    B.append(row)
```

```
Enter the No of Rows of Matrix B : 2
Enter the No of Columns of Matrix B : 4
Enter the Matrix A Elements :
```

```
9
8
7
5
2
4
6
3
```

```
print("Matrix - A :")
for row in A:
    print(row)
print("\nMatrix - B :")
for row in B:
    print(row)
```

```
Matrix - A :
[4, 5]
[6, 8]
```

```
Matrix - B :
[9, 8, 7, 5]
[2, 4, 6, 3]
```

```
if(n==p):
    C=[]
    for i in range(m):
        row=[]
        for j in range(q):
            row.append(0)
        C.append(row)
    for i in range(m):
        for j in range(q):
            for k in range(p):
                C[i][j] += A[i][k] * B[k][j]

    print("The Matrix Multiplication of Two Matrices is \n")
    for row in C:
        print(row)
else:
    print("Matrix Multiplication Not Possible")
```

The Matrix Multiplication of Two Matrices is

```
[46, 52, 58, 35]
[70, 80, 90, 54]
```

1.d. Python Program to print reverse of a number

Source Code:

```
x = int(input("Enter a Number : "))  
rev = 0  
num=x
```

Enter a Number : 1245

```
while num != 0:  
    rem = num % 10  
    rev = rev * 10 + rem  
    num //= 10
```

```
print("Reverse of Number { } is { } ".format(x,rev))
```

Reverse of Number 1245 is 5421

1.e.Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples. Read the training data from a .CSV file.

Dataset:

	A	B	C	D	E	F	G	H	I
1	Sky	Temp	Humidity	Wind	Water	Forecast	Enjoy		
2	Sunny	Warm	Normal	Strong	Warm	Same	Yes		
3	Sunny	Warm	High	Strong	Warm	Same	Yes		
4	Rainy	Cold	High	Strong	Warm	Change	No		
5	Sunny	Warm	High	Strong	Cool	Same	Yes		
6									
7									
8									
9									
10									
11									

Source Code:

```
import pandas as pd
import numpy as np
```

```
data = pd.read_csv('dataset.csv')
print(data)
```

```
Sky  Temp  Humidity    Wind  Water  Forecast  Enjoy
0  Sunny  Warm    Normal  Strong  Warm    Same    Yes
1  Sunny  Warm    High    Strong  Warm    Same    Yes
2  Rainy  Cold    High    Strong  Warm    Change   No
3  Sunny  Warm    High    Strong  Cool    Same    Yes
```

```
concepts = np.array (data) [: , :-1]
print(concepts)
```

```
[[ 'Sunny'  'Warm'  'Normal'  'Strong'  'Warm'  'Same' ]
 [ 'Sunny'  'Warm'  'High'    'Strong'  'Warm'  'Same' ]
 [ 'Rainy'  'Cold'  'High'    'Strong'  'Warm'  'Change' ]
 [ 'Sunny'  'Warm'  'High'    'Strong'  'Cool'  'Same' ]]
```

```
targets=np.array(data)[:,-1:]
print(targets)
```

```
[[ 'Yes' ]
 [ 'Yes' ]
 [ 'No' ]
 [ 'Yes' ]]
```

```
def train(c,t):
    for i,val in enumerate(t):
        if(val=="Yes"):
            sp = c[i].copy()
            break
        else:
            return "There are No positives"
    for i,val in enumerate(c):
        if(t[i]=="Yes"):
            for x in range(len(sp)):
                if(val[x]!=sp[x]):
                    sp[x]="?"
    return sp;
```

```
print("The Most Specific Hypothesis : ",train(concepts,targets))
```

```
The Most Specific Hypothesis :  ['Sunny' 'Warm' '?' 'Strong' '?' 'Same']
```

Week-2

2a. Implement Simple linear Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs

Dataset:

Clipboard		Font		Alignment		Number		Styles	
A1		fx		YearsExperience					
	A	B		C	D	E	F	G	
1	YearsExperience	Salary							
2	1.1	39343							
3	1.3	46205							
4	1.5	37731							
5	2	43525							
6	2.2	39891							
7	2.9	56642							
8	3	60150							
9	3.2	54445							
10	3.2	64445							
11	3.7	57189							
12	3.9	63218							
13	4	55794							
14	4	56957							
15	4.1	57081							
16	4.5	61111							
17	4.9	67938							
18	5.1	66029							
19	5.3	83088							
20	5.9	81363							
21	6	93940							
22	6.8	91738							

Source Code:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

```
dataset=pd.read_csv('Salary_Data.csv')
```

```
X=dataset.iloc[:, :-1].values
y=dataset.iloc[:, -1].values
print(X)
print(y)
```



```

[[ 1.1]
 [ 1.3]
 [ 1.5]
 [ 2. ]
 [ 2.2]
 [ 2.9]
 [ 3. ]
 [ 3.2]
 [ 3.2]
 [ 3.7]
 [ 3.9]
 [ 4. ]
 [ 4. ]
 [ 4.1]
 [ 4.5]
 [ 4.9]
 [ 5.1]
 [ 5.3]
 [ 5.9]
 [ 6. ]
 [ 6.8]
 [ 7.1]
 [ 7.9]
 [ 8.2]
 [ 8.7]
 [ 9. ]
 [ 9.5]
 [ 9.6]
 [10.3]
 [10.5]]
[ 39343.  46205.  37731.  43525.  39891.  56642.  60150.  54445.  64445.
 57189.  63218.  55794.  56957.  57081.  61111.  67938.  66029.  83088.
 81363.  93940.  91738.  98273. 101302. 113812. 109431. 105582. 116969.
112635. 122391. 121872.]

```

```

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=1/3, random_state=0)
print(X_train)
print(X_test)
print(y_train)
print(y_test)

```

```

[[ 2.9]
 [ 5.1]
 [ 3.2]
 [ 4.5]
 [ 8.2]
 [ 6.8]
 [ 1.3]
 [10.5]
 [ 3. ]
 [ 2.2]
 [ 5.9]
 [ 6. ]
 [ 3.7]
 [ 3.2]
 [ 9. ]
 [ 2. ]

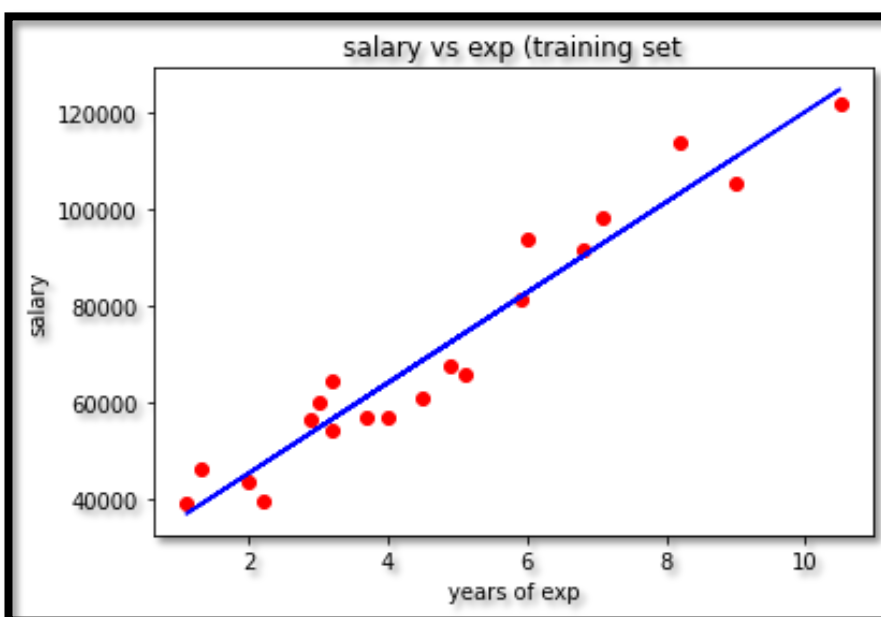
```

```
[ 1.1]
[ 7.1]
[ 4.9]
[ 4. ]]
[[ 1.5]
[10.3]
[ 4.1]
[ 3.9]
[ 9.5]
[ 8.7]
[ 9.6]
[ 4. ]
[ 5.3]
[ 7.9]]
[ 56642.  66029.  64445.  61111. 113812.  91738.  46205. 121872.  60150.
 39891.  81363.  93940.  57189.  54445. 105582.  43525.  39343.  98273.
 67938.  56957.]
[ 37731. 122391.  57081.  63218. 116969. 109431. 112635.  55794.  83088.
101302.]
```

```
from sklearn.linear_model import LinearRegression
regressor= LinearRegression()
regressor.fit(X_train, y_train)
```

```
LinearRegression()
```

```
#LinearRegression(copy_X=(True), fit_intercept=(True), n_jobs=None, normalize=(False))
y_pred=regressor.predict(X_test)
plt.scatter(X_train,y_train,color='red')
plt.plot(X_train, regressor.predict(X_train), color='blue')
plt.title('salary vs exp (training set)')
plt.xlabel('years of exp')
plt.ylabel('salary')
plt.show()
```



2b. Implement Multiple linear Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs

Dataset:

	A1		f _x	R&D Spend					
	A	B	C	D	E	F	G	H	
1	R&D Spend	Administration	Marketing Spend	State	Profit				
2	165349.2	136897.8	471784.1	New York	192261.83				
3	162597.7	151377.59	443898.53	California	191792.06				
4	153441.51	101145.55	407934.54	Florida	191050.39				
5	144372.41	118671.85	383199.62	New York	182901.99				
6	142107.34	91391.77	366168.42	Florida	166187.94				
7	131876.9	99814.71	362861.36	New York	156991.12				
8	134615.46	147198.87	127716.82	California	156122.51				
9	130298.13	145530.06	323876.68	Florida	155752.6				
10	120542.52	148718.95	311613.29	New York	152211.77				
11	123334.88	108679.17	304981.62	California	149759.96				
12	101913.08	110594.11	229160.95	Florida	146121.95				
13	100671.96	91790.61	249744.55	California	144259.4				
14	93863.75	127320.38	249839.44	Florida	141585.52				
15	91992.39	135495.07	252664.93	California	134307.35				
16	119943.24	156547.42	256512.92	Florida	132602.65				
17	114523.61	122616.84	261776.23	New York	129917.04				
18	78013.11	121597.55	264346.06	California	126992.93				
19	94657.16	145077.58	282574.31	New York	125370.37				
20	91749.16	114175.79	294919.57	Florida	124266.9				
21	86419.7	153514.11	0	New York	122776.86				
22	76253.86	113867.3	298664.47	California	118474.03				
23	78389.47	153773.43	299737.29	New York	111313.02				
24	73994.56	122782.75	303319.26	Florida	110352.25				

Source Code:

```
# Importing the libraries
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
import pandas as pd
```

```
# Importing the dataset
```

```
dataset = pd.read_csv('MLR_dataset.csv')
```

```
X = dataset.iloc[:, :-1].values
```

```
y = dataset.iloc[:, -1].values
```

```
print(X)
```

```
[[165349.2 136897.8 471784.1 'New York']  
 [162597.7 151377.59 443898.53 'California']  
 [153441.51 101145.55 407934.54 'Florida']  
 [144372.41 118671.85 383199.62 'New York']  
 [142107.34 91391.77 366168.42 'Florida']  
 [131876.9 99814.71 362861.36 'New York']  
 [134615.46 147198.87 127716.82 'California']  
 [130298.13 145530.06 323876.68 'Florida']  
 [120542.52 148718.95 311613.29 'New York']  
 [123334.88 108679.17 304981.62 'California']  
 [101913.08 110594.11 229160.95 'Florida']  
 [100671.96 91790.61 249744.55 'California']  
 [93863.75 127320.38 249839.44 'Florida']  
 [91992.39 135495.07 252664.93 'California']  
 [119943.24 156547.42 256512.92 'Florida']  
 [114523.61 122616.84 261776.23 'New York']  
 [78013.11 121597.55 264346.06 'California']  
 [94657.16 145077.58 282574.31 'New York']  
 [91749.16 114175.79 294919.57 'Florida']  
 [86419.7 153514.11 0 'New York']  
 [76253.86 113867.3 298664.47 'California']  
 [78389.47 153773.43 299737.29 'New York']  
 [73994.56 122782.75 303319.26 'Florida']]
```

```

[123334.88 108679.17 304981.62 'California']
[101913.08 110594.11 229160.95 'Florida']
[100671.96 91790.61 249744.55 'California']
[93863.75 127320.38 249839.44 'Florida']
[91992.39 135495.07 252664.93 'California']
[119943.24 156547.42 256512.92 'Florida']
[114523.61 122616.84 261776.23 'New York']
[78013.11 121597.55 264346.06 'California']
[94657.16 145077.58 282574.31 'New York']
[91749.16 114175.79 294919.57 'Florida']
[86419.7 153514.11 0.0 'New York']
[76253.86 113867.3 298664.47 'California']
[78389.47 153773.43 299737.29 'New York']
[73994.56 122782.75 303319.26 'Florida']
[67532.53 105751.03 304768.73 'Florida']
[77044.01 99281.34 140574.81 'New York']
[64664.71 139553.16 137962.62 'California']
[75328.87 144135.98 134050.07 'Florida']
[72107.6 127864.55 353183.81 'New York']
[66051.52 182645.56 118148.2 'Florida']
[65605.48 153032.06 107138.38 'New York']
[61994.48 115641.28 91131.24 'Florida']
[61136.38 152701.92 88218.23 'New York']
[63408.86 129219.61 46085.25 'California']
[55493.95 103057.49 214634.81 'Florida']
[46426.07 157693.92 210797.67 'California']
[46014.02 85047.44 205517.64 'New York']
[28663.76 127056.21 201126.82 'Florida']
[44069.95 51283.14 197029.42 'California']
[20229.59 65947.93 185265.1 'New York']
[38558.51 82982.09 174999.3 'California']
[28754.33 118546.05 172795.67 'California']
[27892.92 84710.77 164470.71 'Florida']
[23640.93 96189.63 148001.11 'California']
[15505.73 127382.3 35534.17 'New York']
[22177.74 154806.14 28334.72 'California']
[1000.23 124153.04 1903.93 'New York']
[1315.46 115816.21 297114.46 'Florida']
[0.0 135426.92 0.0 'California']
[542.05 51743.15 0.0 'New York']
[0.0 116983.8 45173.06 'California']]

```

```
# Encoding categorical data
```

```
from sklearn.compose import ColumnTransformer
```

```
from sklearn.preprocessing import OneHotEncoder
```

```
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [3])],
remainder='passthrough')
```

```
X = np.array(ct.fit_transform(X))
```

```
print(X)
```

```

[[0.0 0.0 1.0 165349.2 136897.8 471784.1]
 [1.0 0.0 0.0 162597.7 151377.59 443898.53]
 [0.0 1.0 0.0 153441.51 101145.55 407934.54]

```

```

[0.0 0.0 1.0 144372.41 118671.85 383199.62]
[0.0 1.0 0.0 142107.34 91391.77 366168.42]
[0.0 0.0 1.0 131876.9 99814.71 362861.36]
[1.0 0.0 0.0 134615.46 147198.87 127716.82]
[0.0 1.0 0.0 130298.13 145530.06 323876.68]
[0.0 0.0 1.0 120542.52 148718.95 311613.29]
[1.0 0.0 0.0 123334.88 108679.17 304981.62]
[0.0 1.0 0.0 101913.08 110594.11 229160.95]
[1.0 0.0 0.0 100671.96 91790.61 249744.55]
[0.0 1.0 0.0 93863.75 127320.38 249839.44]
[1.0 0.0 0.0 91992.39 135495.07 252664.93]
[0.0 1.0 0.0 119943.24 156547.42 256512.92]
[0.0 0.0 1.0 114523.61 122616.84 261776.23]
[1.0 0.0 0.0 78013.11 121597.55 264346.06]
[0.0 0.0 1.0 94657.16 145077.58 282574.31]
[0.0 1.0 0.0 91749.16 114175.79 294919.57]
[0.0 0.0 1.0 86419.7 153514.11 0.0]
[1.0 0.0 0.0 76253.86 113867.3 298664.47]
[0.0 0.0 1.0 78389.47 153773.43 299737.29]
[0.0 1.0 0.0 73994.56 122782.75 303319.26]
[0.0 1.0 0.0 67532.53 105751.03 304768.73]
[0.0 0.0 1.0 77044.01 99281.34 140574.81]
[1.0 0.0 0.0 64664.71 139553.16 137962.62]
[0.0 1.0 0.0 75328.87 144135.98 134050.07]
[0.0 0.0 1.0 72107.6 127864.55 353183.81]
[0.0 1.0 0.0 66051.52 182645.56 118148.2]
[0.0 0.0 1.0 65605.48 153032.06 107138.38]
[0.0 1.0 0.0 61994.48 115641.28 91131.24]
[0.0 0.0 1.0 61136.38 152701.92 88218.23]
[1.0 0.0 0.0 63408.86 129219.61 46085.25]
[0.0 1.0 0.0 55493.95 103057.49 214634.81]
[1.0 0.0 0.0 46426.07 157693.92 210797.67]
[0.0 0.0 1.0 46014.02 85047.44 205517.64]
[0.0 1.0 0.0 28663.76 127056.21 201126.82]
[1.0 0.0 0.0 44069.95 51283.14 197029.42]
[0.0 0.0 1.0 20229.59 65947.93 185265.1]
[1.0 0.0 0.0 38558.51 82982.09 174999.3]
[1.0 0.0 0.0 28754.33 118546.05 172795.67]
[0.0 1.0 0.0 27892.92 84710.77 164470.71]
[1.0 0.0 0.0 23640.93 96189.63 148001.11]
[0.0 0.0 1.0 15505.73 127382.3 35534.17]
[1.0 0.0 0.0 22177.74 154806.14 28334.72]
[0.0 0.0 1.0 1000.23 124153.04 1903.93]
[0.0 1.0 0.0 1315.46 115816.21 297114.46]
[1.0 0.0 0.0 0.0 135426.92 0.0]
[0.0 0.0 1.0 542.05 51743.15 0.0]
[1.0 0.0 0.0 0.0 116983.8 45173.06]]

```

```
# Splitting the dataset into the Training set and Test set
```

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

```
# Training the Multiple Linear Regression model on the Training set
```

```
from sklearn.linear_model import LinearRegression
```

```
regressor = LinearRegression()
```

```
regressor.fit(X_train, y_train)
```

```
LinearRegression()
```

```
# Predicting the Test set results
```

```
y_pred = regressor.predict(X_test)
```

```
np.set_printoptions(precision=2)
```

```
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
```

```
[[103015.2  103282.38]  
 [132582.28 144259.4 ]  
 [132447.74 146121.95]  
 [ 71976.1   77798.83]  
 [178537.48 191050.39]  
 [116161.24 105008.31]  
 [ 67851.69  81229.06]  
 [ 98791.73  97483.56]  
 [113969.44 110352.25]  
 [167921.07 166187.94]]
```

Week-3

3. Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample

Source Code:

```
import numpy as np
import pandas as pd
```

```
eps = np.finfo(float).eps
```

```
outlook =
'overcast,overcast,overcast,overcast,rainy,rainy,rainy,rainy,rainy,sunny,sunny,sunny,sunny,sunny'
.split(',')

temp = 'hot,cool,mild,hot,mild,cool,cool,mild,mild,hot,hot,mild,cool,mild'.split(',')

humidity =
'high,normal,high,normal,high,normal,normal,normal,high,high,high,high,normal,normal'.split(',')

windy =
'FALSE,TRUE,TRUE,FALSE,FALSE,FALSE,TRUE,FALSE,TRUE,FALSE,TRUE,FALSE,FALSE,TRUE'.split(',')

play = 'yes,yes,yes,yes,yes,yes,no,yes,no,no,no,no,yes,yes'.split(',')
```

```
#dataframe
# dataset file is comma-separated
# first row are the predictors + target, columns of dataframe

# making a dataframe
# dataframe = pd.DataFrame(dataset,columns = list(dataset))
dataset ={'outlook':outlook,'temp':temp,'humidity':humidity,'windy':windy,'play':play}

dataframe = pd.DataFrame(dataset,columns=['outlook','temp','humidity','windy','play'])
dataframe
```

outlook	temp	humidity	windy	play	
0	overcast	hot	high	FALSE	yes
1	overcast	cool	normal	TRUE	yes
2	overcast	mild	high	TRUE	yes
3	overcast	hot	normal	FALSE	yes
4	rainy	mild	high	FALSE	yes
5	rainy	cool	normal	FALSE	yes
6	rainy	cool	normal	TRUE	no
7	rainy	mild	normal	FALSE	yes
8	rainy	mild	high	TRUE	no
9	sunny	hot	high	FALSE	no
10	sunny	hot	high	TRUE	no
11	sunny	mild	high	FALSE	no
12	sunny	cool	normal	FALSE	yes
13	sunny	mild	normal	TRUE	yes

Entropy of the target attribute values

```
def find_entropy(df):
```

```
    target = df.keys()[-1] # The last dataframe column is the target attribute (playGolf)
```

```
    entropy = 0
```

```
    values = df[target].unique()
```

```
    # for each value in the target playGolf attribute values
```

```
    for value in values:
```

```
        # ratio of values occurring and entropy
```

```
        fraction = df[target].value_counts()[value] / len(df[target])
```

```
        entropy += -fraction * np.log2(fraction)
```

```
    return entropy
```

Entropy of attribute values

```
def find_entropy_attribute(df, attribute):
```

```
    target = df.keys()[-1]
```

```
    target_variables = df[target].unique() # unique values in target playGolf attribute (Yes, No)
```



```

variables = df[attribute].unique() # Identify Sunny, Overcast, Rainy

# attribute entropy      # Variables=[sunny, sunny....5, overcast1.....overcast4, Rainy1...Ra5 ]
entropy2 = 0
# for each attribute value in attribute values
for variable in variables:
    # value entropy
    entropy = 0
    # for each target value in target values (yes/no)
    for target_variable in target_variables:
        # frequency of attribute and target values (boolean indexing, pandas dataframe filtering)
        num = len(df[attribute][df[attribute] == variable][df[target] == target_variable])
        den = len(df[attribute][df[attribute] == variable])
        fraction = num / (den + eps)
        entropy += -fraction * np.log2(fraction + eps)
    fraction2 = den / len(df)
    entropy2 += -fraction2 * entropy
return abs(entropy2)

```

```

def bestClassifier(df):
    # Entropy_att = []
    # information gain array for all attributes
    IG = []
    # for all attributes excluding target
    for key in df.keys()[:-1]:
        # Entropy_att.append(find_entropy_attribute(df,key))
        # calculate and record information gain value
        IG.append(find_entropy(df) - find_entropy_attribute(df, key)) #0.940 -0.693= 0.247
    return df.keys()[:-1][np.argmax(IG)] # IG[0.247, 0.029, 0.152, 0.048 ]

```

```

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

```

```

def ID3split(df, tree=None):
    target = df.keys()[-1]
    # Here we build our decision tree

```

```

# Get attribute with maximum information gain
node = bestClassifier(df) # 0.247
# Get distinct value of that attribute e.g Salary is node and Low,Med and High are values
attributeValues = np.unique(df[node])
# Create an empty dictionary to create tree (recursive-friendly definition)
if tree is None:          # Outlook ->root node attribute
    tree = {}
    tree[node] = {}
# following loop recursively calls ID3split to create and add to the tree
# it runs till the tree is pure (leaf (result) node branches are added to the tree)
for value in attributeValues:
    # get the subtable from current node based on the value
    subtable = get_subtable(df, node, value)
    # get the most common target value in the subtable
    targetValues, counts = np.unique(subtable[target], return_counts=True)
    # if the subtable is empty, assign the leaf node to the most common target value
    if len(counts) == 1:
        tree[node][value] = targetValues[0]
    else:
        # recursively call ID3 to create subtrees
        tree[node][value] = ID3split(subtable) # Calling the function recursively
return tree

```

```

decisionTree = ID3split(dataframe)
print(decisionTree)

```

```

{'outlook': {'overcast': 'yes', 'rainy': {'windy': {'FALSE': 'yes', 'TRUE': 'no'}}, 'sunny': {'humidity': {'high': 'no', 'normal': 'yes'}}}}

```