Problem Statement 7

Mild

Normal

False

Yes

Sunny

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Question 1:

1. Implement the Naïve Bayes Classifier on the below given dataset. Test record for the given dataset is (Rainy, Cool, Normal, True).

Also test the same on a large dataset with a sample test record.

```
In [1]:
          import numpy as np
          import matplotlib.pyplot as plt
          import pandas as pd
          from sklearn.naive bayes import GaussianNB
In [2]:
          golf df=pd.read csv("golf-dataset.csv")
          golf df
Out[2]:
             Outlook Temp Humidity Windy Play Golf
          0
                Rainy
                        Hot
                                High
                                       False
                                                  No
                        Hot
                                High
                                       True
                Rainy
                                                  No
          2 Overcast
                        Hot
                                High
                                       False
                                                 Yes
                       Mild
                                High
                                       False
                                                 Yes
               Sunny
                       Cool
                                       False
               Sunny
                              Normal
                                                 Yes
               Sunny
                       Cool
                              Normal
                                       True
                                                  No
          6 Overcast
                       Cool
                              Normal
                                       True
                                                 Yes
                       Mild
                Rainy
                                High
                                       False
                                                  No
          8
                Rainy
                       Cool
                                       False
                                                 Yes
                              Normal
```

```
Outlook Temp Humidity Windy Play Golf
        10
              Rainy
                     Mild
                           Normal
                                    True
                                             Yes
        11 Overcast
                     Mild
                             High
                                    True
                                             Yes
        12 Overcast
                     Hot
                           Normal
                                   False
                                             Yes
In [3]:
         golf df.loc[len(golf df)]=['Rainy', 'Cool', 'Normal', True, 'No']
In [4]:
         train x=golf df.iloc[:,[0,1,2,3]].values
         train y=golf df.iloc[:,-1].values
In [5]:
         train x
Out[5]: array([['Rainy', 'Hot', 'High', False],
                ['Rainy', 'Hot', 'High', True],
                ['Overcast', 'Hot', 'High', False],
                ['Sunny', 'Mild', 'High', False],
                ['Sunny', 'Cool', 'Normal', False],
                ['Sunny', 'Cool', 'Normal', True],
                ['Overcast', 'Cool', 'Normal', True],
                ['Rainy', 'Mild', 'High', False],
                ['Rainy', 'Cool', 'Normal', False],
                ['Sunny', 'Mild', 'Normal', False],
                ['Rainy', 'Mild', 'Normal', True],
                ['Overcast', 'Mild', 'High', True],
                ['Overcast', 'Hot', 'Normal', False],
                ['Sunny', 'Mild', 'High', True],
                ['Rainy', 'Cool', 'Normal', True]], dtype=object)
In [6]:
         # encoding Strings before training
         from sklearn.preprocessing import LabelEncoder
         le = LabelEncoder()
         for i in range(len(train x[0])):
             train x[:,i] = le.fit transform(train x[:,i])
```

separate train and test data

```
In [7]:
          test x=train x[-1]
          test x
 Out[7]: array([1, 0, 1, 1], dtype=object)
 In [8]:
          train x=train x[:-1]
          train x
 Out[8]: array([[1, 1, 0, 0],
                [1, 1, 0, 1],
                [0, 1, 0, 0],
                [2, 2, 0, 0],
                [2, 0, 1, 0],
                 [2, 0, 1, 1],
                 [0, 0, 1, 1],
                [1, 2, 0, 0],
                [1, 0, 1, 0],
                [2, 2, 1, 0],
                 [1, 2, 1, 1],
                [0, 2, 0, 1],
                [0, 1, 1, 0],
                [2, 2, 0, 1]], dtype=object)
 In [9]:
          train y=train y[:-1]
In [10]:
          classifier = GaussianNB()
          classifier.fit(train x, train y)
Out[10]: GaussianNB()
In [11]:
          pred y=classifier.predict([test x])
         /home/paleti/.local/lib/python3.8/site-packages/sklearn/utils/validation.py:63: FutureWarning: Arrays of byt
         es/strings is being converted to decimal numbers if dtype='numeric'. This behavior is deprecated in 0.24 and
         will be removed in 1.1 (renaming of 0.26). Please convert your data to numeric values explicitly instead.
           return f(*args, **kwargs)
```

```
In [12]: pred_y
```

Out[12]: array(['Yes'], dtype='<U3')</pre>

Conclusion:

The result for the record (Rainy, Cool, Normal, True) is predicted as 'YES' by the naive bayes classifier trained on the dataset given

Test it with a large dataset

```
In [13]: heart_df=pd.read_csv("heart_2020_cleaned.csv")
   heart_df
```

Out[13]:		HeartDisease	ВМІ	Smoking	AlcoholDrinking	Stroke	PhysicalHealth	MentalHealth	DiffWalking	Sex	AgeCategory	Race
	0	No	16.60	Yes	No	No	3.0	30.0	No	Female	55-59	White
	1	No	20.34	No	No	Yes	0.0	0.0	No	Female	80 or older	White
	2	No	26.58	Yes	No	No	20.0	30.0	No	Male	65-69	White
	3	No	24.21	No	No	No	0.0	0.0	No	Female	75-79	White
	4	No	23.71	No	No	No	28.0	0.0	Yes	Female	40-44	White
	•••											
	319790	Yes	27.41	Yes	No	No	7.0	0.0	Yes	Male	60-64	Hispanic
	319791	No	29.84	Yes	No	No	0.0	0.0	No	Male	35-39	Hispanic
	319792	No	24.24	No	No	No	0.0	0.0	No	Female	45-49	Hispanic
	319793	No	32.81	No	No	No	0.0	0.0	No	Female	25-29	Hispanic
	319794	No	46.56	No	No	No	0.0	0.0	No	Female	80 or older	Hispanic

319795 rows × 18 columns

Out[14]:		HeartDisease	ВМІ	Smoking	AlcoholDrinking	Stroke	PhysicalHealth	MentalHealth	DiffWalking	Sex	AgeCategory	Race	Diabe
	0	0.0	16.60	1.0	0.0	0.0	3.0	30.0	0.0	0.0	7.0	5.0	
	1	0.0	20.34	0.0	0.0	1.0	0.0	0.0	0.0	0.0	12.0	5.0	
	2	0.0	26.58	1.0	0.0	0.0	20.0	30.0	0.0	1.0	9.0	5.0	
	3	0.0	24.21	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11.0	5.0	
	4	0.0	23.71	0.0	0.0	0.0	28.0	0.0	1.0	0.0	4.0	5.0	
	319790	1.0	27.41	1.0	0.0	0.0	7.0	0.0	1.0	1.0	8.0	3.0	
	319791	0.0	29.84	1.0	0.0	0.0	0.0	0.0	0.0	1.0	3.0	3.0	
	319792	0.0	24.24	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	3.0	
	319793	0.0	32.81	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	3.0	
	319794	0.0	46.56	0.0	0.0	0.0	0.0	0.0	0.0	0.0	12.0	3.0	

319795 rows × 18 columns

```
[ 0. , 26.58, 1. , ..., 8. , 1. , 0. ], ..., [ 0. , 24.24, 0. , ..., 6. , 0. , 0. ], [ 0. , 32.81, 0. , ..., 12. , 0. , 0. ], [ 0. , 46.56, 0. , ..., 8. , 0. , 0. ]])
```

Split the dataset into 80% training and 20% testing

```
In [17]: from sklearn.model_selection import train_test_split
In [18]: heart_train_x, heart_test_x, heart_train_y, heart_test_y = train_test_split(heart_train_x, heart_train_y, te
In [19]: classifier = GaussianNB()
    classifier.fit(heart_train_x, heart_train_y)
Out[19]: GaussianNB()
In [20]: pred_y=classifier.predict(heart_test_x)
In [21]: from sklearn.metrics import accuracy_score
    accuracy_score(heart_test_y, pred_y)
Out[21]: 0.8233399521568505
```

Conclusion:

```
Note: The Dataset contains 319795 rows
The accuracy of this model in predicting skin cancer is 82%
```

Question 2:

1. Implement the Nearest Neighbour Classifier on the given Kaggle dataset with k=7. You are free to use built-in packages for implementation.

In [22]:
 from sklearn.neighbors import KNeighborsClassifier
 from sklearn.model_selection import train_test_split
 from sklearn import preprocessing
 import matplotlib.pyplot as plt

In [23]: fruit_df=pd.read_csv("fruit_data_with_colors.txt", delim_whitespace=True)
 fruit_df

Out[23]:		fruit_label	fruit_name	fruit_subtype	mass	width	height	color_score
	0	1	apple	granny_smith	192	8.4	7.3	0.55
	1	1	apple	granny_smith	180	8.0	6.8	0.59
	2	1	apple	granny_smith	176	7.4	7.2	0.60
	3	2	mandarin	mandarin	86	6.2	4.7	0.80
	4	2	mandarin	mandarin	84	6.0	4.6	0.79
	5	2	mandarin	mandarin	80	5.8	4.3	0.77
	6	2	mandarin	mandarin	80	5.9	4.3	0.81
	7	2	mandarin	mandarin	76	5.8	4.0	0.81
	8	1	apple	braeburn	178	7.1	7.8	0.92
	9	1	apple	braeburn	172	7.4	7.0	0.89
	10	1	apple	braeburn	166	6.9	7.3	0.93
	11	1	apple	braeburn	172	7.1	7.6	0.92
	12	1	apple	braeburn	154	7.0	7.1	0.88
	13	1	apple	golden_delicious	164	7.3	7.7	0.70
	14	1	apple	golden_delicious	152	7.6	7.3	0.69
	15	1	apple	golden_delicious	156	7.7	7.1	0.69
	16	1	apple	golden_delicious	156	7.6	7.5	0.67
	17	1	apple	golden_delicious	168	7.5	7.6	0.73
	18	1	apple	cripps_pink	162	7.5	7.1	0.83

	fruit_label	fruit_name	fruit_subtype	mass	width	height	color_score
19	1	apple	cripps_pink	162	7.4	7.2	0.85
20	1	apple	cripps_pink	160	7.5	7.5	0.86
21	1	apple	cripps_pink	156	7.4	7.4	0.84
22	1	apple	cripps_pink	140	7.3	7.1	0.87
23	1	apple	cripps_pink	170	7.6	7.9	0.88
24	3	orange	spanish_jumbo	342	9.0	9.4	0.7
25	3	orange	spanish_jumbo	356	9.2	9.2	0.7
26	3	orange	spanish_jumbo	362	9.6	9.2	0.74
27	3	orange	selected_seconds	204	7.5	9.2	0.7
28	3	orange	selected_seconds	140	6.7	7.1	0.72
29	3	orange	selected_seconds	160	7.0	7.4	0.8
30	3	orange	selected_seconds	158	7.1	7.5	0.7
31	3	orange	selected_seconds	210	7.8	8.0	0.8
32	3	orange	selected_seconds	164	7.2	7.0	0.8
33	3	orange	turkey_navel	190	7.5	8.1	0.7
34	3	orange	turkey_navel	142	7.6	7.8	0.7
35	3	orange	turkey_navel	150	7.1	7.9	0.7
36	3	orange	turkey_navel	160	7.1	7.6	0.7
37	3	orange	turkey_navel	154	7.3	7.3	0.7
38	3	orange	turkey_navel	158	7.2	7.8	0.7
39	3	orange	turkey_navel	144	6.8	7.4	0.7
40	3	orange	turkey_navel	154	7.1	7.5	0.7
41	3	orange	turkey_navel	180	7.6	8.2	0.7
42	3	orange	turkey_navel	154	7.2	7.2	0.8
43	4	lemon	spanish_belsan	194	7.2	10.3	0.70
44	4	lemon	spanish_belsan	200	7.3	10.5	0.72

```
fruit subtype mass width height color_score
              fruit label fruit name
           45
                      4
                                                     186
                                                            7.2
                                                                   9.2
                                                                              0.72
                             lemon
                                     spanish belsan
           46
                      4
                                                                  10.2
                                                                              0.71
                             lemon
                                     spanish belsan
                                                     216
                                                            7.3
           47
                      4
                                     spanish belsan
                                                            7.3
                                                                   9.7
                                                                              0.72
                             lemon
                                                     196
                      4
                                                                              0.72
           48
                             lemon
                                     spanish belsan
                                                     174
                                                            7.3
                                                                  10.1
           49
                      4
                                                                   8.7
                             lemon
                                          unknown
                                                     132
                                                            5.8
                                                                              0.73
           50
                      4
                             lemon
                                                     130
                                                            6.0
                                                                  8.2
                                                                              0.71
                                          unknown
                      4
                                                                  7.5
           51
                             lemon
                                          unknown
                                                     116
                                                            6.0
                                                                              0.72
                                                                  8.0
           52
                      4
                             lemon
                                          unknown
                                                     118
                                                            5.9
                                                                              0.72
                                                                  8.4
           53
                      4
                             lemon
                                          unknown
                                                     120
                                                            6.0
                                                                              0.74
                                                                  8.5
           54
                      4
                             lemon
                                                            6.1
                                                                              0.71
                                          unknown
                                                     116
                                                            6.3
                                                                   7.7
                                                                              0.72
           55
                      4
                             lemon
                                          unknown
                                                     116
           56
                      4
                             lemon
                                                     116
                                                            5.9
                                                                   8.1
                                                                              0.73
                                          unknown
           train x=fruit df.iloc[:,[0,1,2,3,4,5]].values
           train y=fruit df.iloc[:,-1].values
           from sklearn.preprocessing import LabelEncoder
           le = LabelEncoder()
           train x[:,1] = le.fit transform(train <math>x[:,1])
           train x[:,2] = le.fit transform(train <math>x[:,2])
           train x
Out[25]: array([[1, 0, 3, 192, 8.4, 7.3],
                   [1, 0, 3, 180, 8.0, 6.8],
                  [1, 0, 3, 176, 7.4, 7.2],
                   [2, 2, 4, 86, 6.2, 4.7],
```

In [24]:

In [25]:

[2, 2, 4, 84, 6.0, 4.6], [2, 2, 4, 80, 5.8, 4.3], [2, 2, 4, 80, 5.9, 4.3], [2, 2, 4, 76, 5.8, 4.0], [1, 0, 0, 178, 7.1, 7.8], [1, 0, 0, 172, 7.4, 7.0],

```
[1, 0, 0, 166, 6.9, 7.3],
[1, 0, 0, 172, 7.1, 7.6],
[1, 0, 0, 154, 7.0, 7.1],
[1, 0, 2, 164, 7.3, 7.7],
[1, 0, 2, 152, 7.6, 7.3],
[1, 0, 2, 156, 7.7, 7.1],
[1, 0, 2, 156, 7.6, 7.5],
[1, 0, 2, 168, 7.5, 7.6],
[1, 0, 1, 162, 7.5, 7.1],
[1, 0, 1, 162, 7.4, 7.2],
[1, 0, 1, 160, 7.5, 7.5],
[1, 0, 1, 156, 7.4, 7.4],
[1, 0, 1, 140, 7.3, 7.1],
[1, 0, 1, 170, 7.6, 7.9],
[3, 3, 7, 342, 9.0, 9.4],
[3, 3, 7, 356, 9.2, 9.2],
[3, 3, 7, 362, 9.6, 9.2],
[3, 3, 5, 204, 7.5, 9.2],
[3, 3, 5, 140, 6.7, 7.1],
[3, 3, 5, 160, 7.0, 7.4],
[3, 3, 5, 158, 7.1, 7.5],
[3, 3, 5, 210, 7.8, 8.0],
[3, 3, 5, 164, 7.2, 7.0],
[3, 3, 8, 190, 7.5, 8.1],
[3, 3, 8, 142, 7.6, 7.8],
[3, 3, 8, 150, 7.1, 7.9],
[3, 3, 8, 160, 7.1, 7.6],
[3, 3, 8, 154, 7.3, 7.3],
[3, 3, 8, 158, 7.2, 7.8],
[3, 3, 8, 144, 6.8, 7.4],
[3, 3, 8, 154, 7.1, 7.5],
[3, 3, 8, 180, 7.6, 8.2],
[3, 3, 8, 154, 7.2, 7.2],
[4, 1, 6, 194, 7.2, 10.3],
[4, 1, 6, 200, 7.3, 10.5],
[4, 1, 6, 186, 7.2, 9.2],
[4, 1, 6, 216, 7.3, 10.2],
[4, 1, 6, 196, 7.3, 9.7],
[4, 1, 6, 174, 7.3, 10.1],
[4, 1, 9, 132, 5.8, 8.7],
[4, 1, 9, 130, 6.0, 8.2],
[4, 1, 9, 116, 6.0, 7.5],
[4, 1, 9, 118, 5.9, 8.0],
[4, 1, 9, 120, 6.0, 8.4],
[4, 1, 9, 116, 6.1, 8.5],
```

```
[4, 1, 9, 116, 6.3, 7.7],

[4, 1, 9, 116, 5.9, 8.1],

[4, 1, 9, 152, 6.5, 8.5],

[4, 1, 9, 118, 6.1, 8.1]], dtype=object)
```

encoding

Split the dataset into training and testing dataset: 80% training 20% testing

```
In [27]: train_x, test_x, train_y, test_y = train_test_split(train_x, train_y, test_size = 0.2, random_state=42)
```

Train using the dataset

```
In [28]:
    knn = KNeighborsClassifier(n_neighbors=7)
    knn.fit(train_x, train_y)
```

Out[28]: KNeighborsClassifier(n_neighbors=7)

Test the model using the dataset

```
In [29]: print(knn.score(test_x, test_y))
```

0.0833333333333333

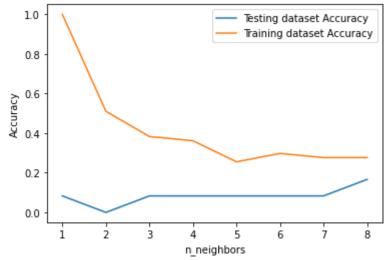
Try for more values of k - elbow graph

```
In [30]: neighbors = np.arange(1, 9)
    train_accuracy = np.empty(len(neighbors))
    test_accuracy = np.empty(len(neighbors))

for i, k in enumerate(neighbors):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(train_x, train_y)
    train_accuracy[i] = knn.score(train_x, train_y)
    test_accuracy[i] = knn.score(test_x, test_y)

plt.plot(neighbors, test_accuracy, label = 'Testing dataset Accuracy')
    plt.plot(neighbors, train_accuracy, label = 'Training dataset Accuracy')

plt.legend()
    plt.xlabel('n_neighbors')
    plt.ylabel('Accuracy')
    plt.show()
```



Question 3: [took basic code from online article]

Develop an application that simulates the working of Genetic Algorithm comprising of Basic Operators such as Selection, Crossover and

Mutation to optimize the objective function max $f(x) = x^3-2x^2+x$ within a range of (0,31). You are free to use any inbuilt / open-source

```
In [31]: import random
```

Iteration 1:

Random Intialization of Population:

```
best=100
populations =([[random.randint(0,1) for x in range(5)] for i in range(4)])
print(populations)

[[1, 0, 0, 1, 1], [1, 1, 0, 0, 1], [1, 1, 0, 0, 1], [0, 1, 1, 1, 0]]
```

Fitness Evaluation:

```
In [33]:
          def fitness evaluation(populations, best, verbose=0) :
              fit value = []
              fit score=[]
              for i in range(len(populations)) :
                  chromosome value=0
                  for j in range(len(populations[i])-1,-1,-1) :
                      chromosome value += populations[i][j]*(2**(len(populations[i])-1-j))
                  fit value.append((chromosome value**3)-2*(chromosome value**2) + (chromosome value) )
                  if(verbose==0):
                      print("Population Item = ",populations[i],"\t","Chromosome Value = ",chromosome value,"\t","Fit
              fit value, populations = zip(*sorted(zip(fit value, populations), reverse = True))
              return populations,fit value[0]
          populations, best=fitness evaluation(populations, best)
         Population Item = [1, 0, 0, 1, 1]
                                                   Chromosome Value = 19
                                                                                   Fit Value = 6156
```

```
Population Item = [1, 0, 0, 1, 1] Chromosome Value = 19 Fit Value = 6156 Population Item = [1, 1, 0, 0, 1] Chromosome Value = 25 Fit Value = 14400 Population Item = [0, 1, 1, 1, 0] Chromosome Value = 25 Fit Value = 14400 Population Item = [0, 1, 1, 1, 0] Chromosome Value = 14 Fit Value = 14400 Fit Va
```

Selection Process:

```
def selection_process(populations, verbose=0):
    parents=populations[0:2]
    if(verbose==0):
        print(parents)
    return parents
    parents=selection_process(populations)
([1, 1, 0, 0, 1], [1, 1, 0, 0, 1])
```

Crossover Process:

```
In [35]:
    def crossover_process(parents, verbose=0) :
        cross_point = random.randint(0,len(parents[0])-1)
        parents=parents + tuple([(parents[0][0:cross_point +1] +parents[1][cross_point+1:len(parents[0])])))
        parents =parents+ tuple([(parents[1][0:cross_point +1] +parents[0][cross_point+1:len(parents[0])])))

        if(verbose==0):
            print(parents)
        return parents
        parents=crossover_process(parents)

([1, 1, 0, 0, 1], [1, 1, 0, 0, 1], [1, 1, 0, 0, 1], [1, 1, 0, 0, 1])
```

Mutation Process:

```
([1, 1, 0, 0, 1], [1, 1, 0, 0, 1], [1, 1, 0, 0, 1], [1, 1, 0, 0, 1])
```

Evolution Process:

Repeat the process of Fitness Evaluation -> Selection -> Crossover -> Mutation -> Fitness Evaluation to find the best values or repeat until the solution converges to provide the optima for the function

```
In [37]:
          verbose=1
          for i in range(1000) :
             populations, best=fitness evaluation(populations, best, verbose)
             parents=selection process(populations, verbose)
             parents=crossover process(parents, verbose)
              populations=mutation process(populations, parents, verbose)
              #print(i,"\n\n")
              if(i%50==0):
                 print("Iteration = ",i,"\t","Best = ",best)
          print("Final Max Score/Value of the function:")
          print(best)
          print(" Chromosome Sequence:")
          print(populations[0])
                         Best = 14400
         Iteration = 0
         Iteration = 50
                                  Best = 14400
         Iteration = 100
                                  Best = 18252
         Iteration = 150
                                  Best = 18252
         Iteration = 200
                                  Best = 18252
         Iteration = 250
                                  Best = 18252
         Iteration = 300
                                  Best = 18252
         Iteration = 350
                                  Best = 18252
         Iteration = 400
                                  Best = 18252
         Iteration = 450
                                  Best = 18252
         Iteration = 500
                                  Best = 18252
         Iteration = 550
                                  Best = 18252
         Iteration = 600
                                  Best = 18252
         Iteration = 650
                                  Best = 18252
         Iteration = 700
                                  Best = 18252
                                  Best = 18252
         Iteration = 750
         Iteration = 800
                                  Best = 18252
                                  Best = 18252
         Iteration = 850
         Iteration = 900
                                  Best = 18252
```

Conclusion:

The Above Algorithm first finds the optima value as 8400 among the initial population, after which the algorithm slowly converges to the max of 27900 (at aroud 500 to 550 iterations) which occurs for x=31 and the solution as presented is binary digits of 5 1's.

This no of iterations is subjective as it based on many factors such as initial population , selection process, chosing crossover point and mutation bits.

In []: