Problem 1

	$X_1 = 1$	$X_1=2$	#
#Y=1	31	22	53
#Y = 2	40	19	59
#Y = 3	34	54	88
#	105	95	

Calculating probabilities

$$P(Y = 1|X_1 = 1) = \frac{31}{105}, P(Y = 1|X_1 = 2) = \frac{22}{95}, P(Y = 2|X_1 = 2) = \frac{40}{105},$$

$$P(Y = 2|X_1 = 2) = \frac{19}{95}, P(Y = 3|X_1 = 1) = \frac{34}{105}, P(Y = 3|X_1 = 2) = \frac{54}{95}$$

$$P(Y = 1|X_2 = 1) = \frac{25}{96}, P(Y = 1|X_2 = 2) = \frac{28}{104}, P(Y = 2|X_2 = 2) = \frac{36}{96},$$

$$P(Y = 2|X_2 = 2) = \frac{33}{104}, P(Y = 3|X_2 = 1) = \frac{45}{96}, P(Y = 3|X_2 = 2) = \frac{43}{104}$$

$$P(Y = 1|X_3 = A) = \frac{35}{50}, P(Y = 1|X_3 = B) = \frac{15}{50}, P(Y = 2|X_3 = C) = \frac{1}{50},$$

$$P(Y = 2|X_3 = D) = \frac{2}{50}, P(Y = 3|X_3 = A) = \frac{14}{50}, P(Y = 3|X_3 = B) = \frac{25}{50}$$

$$P(Y = 1|X_3 = C) = \frac{15}{50}, \ P(Y = 1|X_3 = D) = \frac{5}{50}, \ P(Y = 2|X_3 = A) = \frac{1}{50},$$
$$P(Y = 2|X_3 = B) = \frac{10}{50}, \ P(Y = 3|X_3 = C) = \frac{34}{50}, \ P(Y = 3|X_3 = D) = \frac{43}{104}$$

Entropy:

$$H = \sum_{i=1}^{n} P(X_i) \log_2(P(X_i))$$

$$\begin{split} H_{initial} &= \frac{53}{200} \log_2 \frac{53}{200} + \frac{59}{200} \log_2 \frac{59}{200} + \frac{88}{200} \log_2 \frac{88}{200} = 1.5484 \\ H_{X_1=1} &= \frac{31}{105} \log_2 \frac{31}{105} + \frac{40}{105} \log_2 \frac{40}{105} + \frac{34}{105} \log_2 \frac{34}{105} = 1.5768 \\ H_{X_1=2} &= \frac{22}{95} \log_2 \frac{22}{95} + \frac{19}{95} \log_2 \frac{19}{95} + \frac{54}{95} \log_2 \frac{54}{95} = 1.4163 \\ H_{X_2=1} &= \frac{25}{96} \log_2 \frac{25}{96} + \frac{26}{96} \log_2 \frac{26}{96} + \frac{45}{96} \log_2 \frac{45}{96} = 1.5282 \\ H_{X_2=2} &= \frac{28}{104} \log_2 \frac{28}{104} + \frac{33}{104} \log_2 \frac{33}{104} + \frac{43}{104} \log_2 \frac{43}{104} = 1.56197 \\ H_{X_3=A} &= \frac{35}{50} \log_2 \frac{35}{50} + \frac{14}{50} \log_2 \frac{15}{50} + \frac{15}{50} \log_2 \frac{15}{50} = 0.98729 \\ H_{X_3=B} &= \frac{15}{50} \log_2 \frac{15}{50} + \frac{25}{50} \log_2 \frac{25}{50} + \frac{10}{50} \log_2 \frac{10}{50} = 1.4854 \\ H_{X_3=C} &= \frac{1}{50} \log_2 \frac{1}{50} + \frac{15}{50} \log_2 \frac{15}{50} + \frac{34}{50} \log_2 \frac{34}{50} = 1.0123 \\ H_{X_3=D} &= \frac{2}{50} \log_2 \frac{5}{50} + \frac{5}{50} \log_2 \frac{5}{50} + \frac{40}{50} \log_2 \frac{43}{50} = 0.7050 \\ H_{X_3=\sim A} &= \frac{18}{150} \log_2 \frac{18}{150} + \frac{45}{150} \log_2 \frac{45}{150} + \frac{87}{150} \log_2 \frac{87}{150} = 1.3439 \\ H_{X_3=\sim B} &= \frac{38}{50} \log_2 \frac{38}{150} + \frac{34}{150} \log_2 \frac{34}{150} + \frac{78}{150} \log_2 \frac{54}{150} = 1.5794 \\ H_{X_3=\sim D} &= \frac{51}{150} \log_2 \frac{51}{150} + \frac{54}{150} \log_2 \frac{39}{150} + \frac{45}{150} \log_2 \frac{45}{150} = 1.58087 \\ H_{X_3=(A,B)} &= \frac{50}{150} \log_2 \frac{50}{150} + \frac{39}{150} \log_2 \frac{39}{150} + \frac{11}{150} \log_2 \frac{15}{150} = 1.3800 \\ H_{X_3=(A,C)} &= \frac{36}{100} \log_2 \frac{36}{100} + \frac{29}{100} \log_2 \frac{29}{100} + \frac{35}{100} \log_2 \frac{35}{100} = 1.5786 \\ \end{pmatrix}$$

$$H_{X_3=(A,D)} = \frac{37}{100} \log_2 \frac{37}{100} + \frac{19}{100} \log_2 \frac{19}{100} + \frac{44}{100} \log_2 \frac{44}{100} = 1.5071$$

$$H_{X_3=(B,C)} = \frac{16}{100} \log_2 \frac{16}{100} + \frac{40}{100} \log_2 \frac{40}{100} + \frac{44}{100} \log_2 \frac{44}{100} = 1.4729$$

$$H_{X_3=(B,D)} = \frac{17}{100} \log_2 \frac{17}{100} + \frac{30}{100} \log_2 \frac{30}{100} + \frac{53}{100} \log_2 \frac{53}{100} = 1.4411$$

$$H_{X_3=(C,D)} = \frac{3}{100} \log_2 \frac{3}{100} + \frac{20}{100} \log_2 \frac{20}{100} + \frac{77}{100} \log_2 \frac{77}{100} = 0.9064$$

Information Gain

$$IG = H_{initial} - \left(P_{split_1} * H_{split_1} + P_{split_2} * H_{split_2}\right)$$

$$IG_{X_1} = 1.5484 - \left(\frac{105}{200} * 1.5768 + \frac{95}{200} * 1.4163\right) = 0.29365$$

$$IG_{X_2} = 1.5484 - \left(\frac{96}{200} * 1.5282 + \frac{104}{200} * 1.56197\right) = 0$$

$$IG_{X_3=(A,\sim A)} = 1.5484 - \left(\frac{50}{200} * 0.98729 + \frac{150}{200} * 1.3439\right) = 0.2936$$

$$IG_{X_3=(B,\sim B)} = 1.5484 - \left(\frac{50}{200} * 1.4854 + \frac{150}{200} * 1.4777\right) = 0.0687$$

$$IG_{X_3=(C,\sim C)} = 1.5484 - \left(\frac{50}{200} * 1.0123 + \frac{150}{200} * 1.5794\right) = 0.1107$$

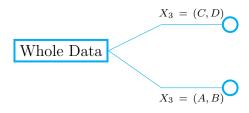
$$IG_{X_3=(D,\sim D)} = 1.5484 - \left(\frac{50}{200} * 0.7050 + \frac{150}{200} * 1.58087\right) = 0.1864$$

$$IG_{X_3=((A,B),(C,D))} = 1.5484 - \left(\frac{100}{200} * 1.3800 + \frac{100}{200} * 0.9064\right) = 0.4052$$

$$IG_{X_3=((A,C),(B,D))} = 1.5484 - \left(\frac{100}{200} * 1.5786 + \frac{100}{200} * 1.4411\right) = 0.3854$$

$$IG_{X_3=((A,D),(B,C))} = 1.5484 - \left(\frac{100}{200} * 1.5071 + \frac{100}{200} * 1.4729\right) = 0.06159$$

Maximum information gain happens when we split $X_3 = ((A, B), (C, D))$

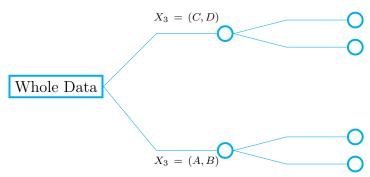


$$P(Y=1|X_1=1) = \frac{31}{105}, P(Y=1|X_1=2) = \frac{22}{95}, P(Y=2|X_1=2) = \frac{40}{105},$$

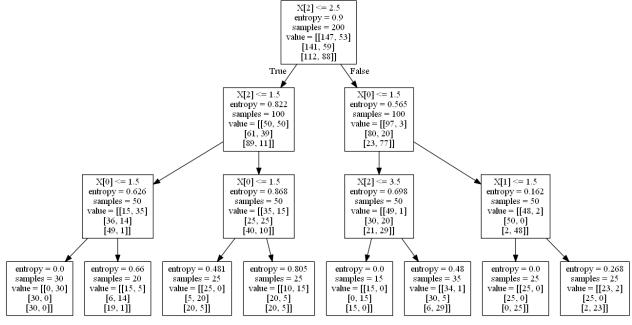
	$X_1 = 1$	$X_1=2$	#
#Y=1	30	20	50
#Y = 2	20	19	39
#Y = 3	5	6	11
#	55	45	

$$P(Y = 2|X_1 = 2) = \frac{19}{95}, P(Y = 3|X_1 = 1) = \frac{34}{105}, P(Y = 3|X_1 = 2) = \frac{54}{95}$$

Similarly doing these calculations till depth = 3 i.e. 2 more iterations



One more layer



Accuracy = 0.855

Problem 2

Case 1: X = (2, 1, A)

Case 1:
$$X = (2, 1, A)$$

$$P(X_1 = 2 \mid Y = 1) = \frac{P(X_1 = 2 \cap Y = 1)}{P(Y = 1)} = \frac{\frac{12}{170}}{\frac{43}{170}} = 0.28$$

$$P(X_2 = 1 \mid Y = 1) = \frac{P(X_2 = 1 \cap Y = 1)}{P(Y = 1)} = \frac{\frac{15}{170}}{\frac{43}{170}} = 0.35$$

$$P(X_3 = A \mid Y = 1) = \frac{P(X_3 = A \cap Y = 1)}{P(Y = 1)} = \frac{\frac{32}{170}}{\frac{43}{170}} = 0.74$$

$$\implies P(X \mid Y = 1) = 0.072$$

$$P(Y = 1 \mid X) = \frac{P(Y = 1 \cap X)}{P(Y = 1)} = 0.45$$

$$P(Y = 2 \cap X)$$

$$P(Y = 1)$$

$$P(Y = 2 \mid X) = \frac{P(Y = 2 \cap X)}{P(Y = 1)} = 0.086$$

$$P(Y = 3 \mid X) = \frac{P(Y = 3 \cap X)}{P(Y = 1)} = 0.04$$

Confidence = 0.45 Final Prediction (Max P(Y = i - X)) $\implies Y = 1$

Case 2:
$$X = (2, 1, B)P(X - Y = 1) = \frac{P(X \cap Y = 1)}{P(Y = 1)} = \frac{12 * 8 * 15}{43 * 43 * 43} = 0.018$$

$$P(Y = 1|X) = \frac{P(Y = 1 \cap X)}{P(X)} = 0.12$$

$$P(X|Y=2) = \frac{P(X \cap Y=2)}{P(Y=2)} = \frac{11 * 22 * 12}{45 * 45 * 45} = 0.031$$

$$P(Y = 2|X) = \frac{P(Y = 2 \cap X)}{P(X)} = 0.023$$

$$P(X|Y=3) = \frac{P(X \cap Y=3)}{P(Y=3)} = \frac{48 * 39 * 9}{82 * 82 * 82} = 0.031$$

$$P(Y = 3|X) = \frac{P(Y = 3 \cap X)}{P(X)} = 0.39$$

Confidence = 0.39 Final Prediction (Max P(Y = i - X)) $\implies Y = 3$

$$\textbf{Case 3:} X = (2,1,D) \\ \\ P(X - Y = 1) = \ \frac{P(X \cap Y = 1)}{P(Y = 1)} = \frac{12*2*15}{43*43*43} = 0.0045$$

$$P(Y = 1|X) = \frac{P(Y = 1 \cap X)}{P(X)} = 0.026$$

$$P(X|Y=2) = \frac{P(X \cap Y=2)}{P(Y=2)} = \frac{11*5*12}{45*45*45} = 0.0072$$

$$P(Y = 2|X) = \frac{P(Y = 2 \cap X)}{P(X)} = 0.044$$

$$P(X|Y=3) = \frac{P(X \cap Y=3)}{P(Y=3)} = \frac{48 * 39 * 38}{82 * 82 * 82} = 0.0129$$

$$P(Y = 3|X) = \frac{P(Y = 3 \cap X)}{P(X)} = 0.89$$

Confidence = 0.89 Final Prediction (Max P(Y = i - X)) $\implies Y = 3$

$$\textbf{Case 4}: X = (1,1,C) \\ \\ P(X - Y = 1) = \ \frac{P(X \cap Y = 1)}{P(Y = 1)} = \frac{31*1*15}{43*43*43} = 0.0058$$

$$P(Y = 1|X) = \frac{P(Y = 1 \cap X)}{P(X)} = 0.02$$

$$P(X|Y=2) = \frac{P(X \cap Y=2)}{P(Y=2)} = \frac{34 * 12 * 12}{45 * 45 * 45} = 0.04$$

$$P(Y = 2|X) = \frac{P(Y = 2 \cap X)}{P(X)} = 0.18$$

$$P(X|Y=3) = \frac{P(X \cap Y=3)}{P(Y=3)} = \frac{34 * 39 * 34}{82 * 82 * 82} = 0.082$$

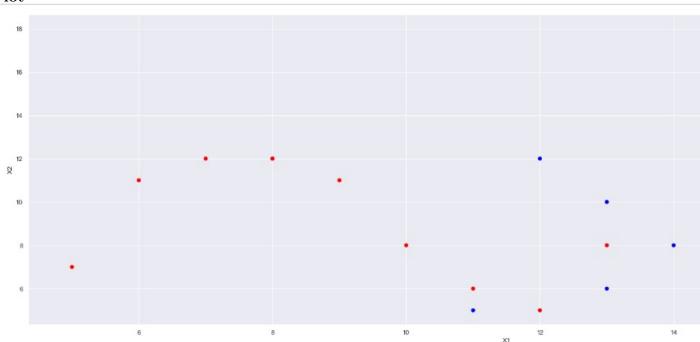
$$P(Y = 3|X) = \frac{P(Y = 3 \cap X)}{P(X)} = 0.68$$

Confidence = 0.68 Final Prediction (Max P(Y = i — X)) \implies Y = 3

Accuracy = 0.74

Problem 3

Plot



Looking at plot it is clear that a good split can be $X_1 = 10$ Split will be done only if information gain is positive

$$\begin{split} H_{initial} &= -\frac{10}{20} \log_2 \frac{10}{20} - \frac{10}{20} * \log_2 \frac{10}{20} = 1 \\ H(X_1 \leq 11) &= -\frac{8}{9} \log_2 \frac{8}{9} - \frac{1}{9} * \log_2 \frac{1}{9} = 0.5032 \\ H(X_1 > 11) &= -\frac{2}{11} \log_2 \frac{2}{11} - \frac{9}{11} * \log_2 \frac{9}{11} = 0.6840 \\ \mathrm{IG} &= 1 - \left(\frac{9}{20} * 0.5032 - \frac{11}{20} * 0.6840\right) = 39736 \\ \mathrm{Best \ Split:} \ X_1 &= 11 \end{split}$$

Problem 4

$$\begin{array}{l} \mu_{X_1} = 11.65 \\ \mu_{X_1} = 9.55 \\ stdDev_{X_1} = 3.674593 \\ stdDev_{X_2} = 3.379115 \end{array}$$

Algorithm 1: Normal Distribution

```
import numpy as np
import pandas as pd
from sklearn import tree
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import accuracy_score
from sklearn import tree
import pydot
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
%matplotlib inline
from IPython.display import Image
X = np.array([
              [5, 7],
               [7, 12],
               [12, 5],
               [10, 8],
                [6, 11],
                [13, 8],
               [8, 12],
               [9, 11],
                [11, 6],
                8, 12],
               [13, 6],
               [14, 8],
               [17, 15],
               [15, 9],
               [13, 10],
               [11, 5],
                [16, 18],
               [15, 7],
              [12, 12],
              [18, 9]
])
\underline{Y} = \text{np.array} \left( \begin{bmatrix} 1 \ , \ 1 \ , \ 1 \ , \ 1 \ , \ 1 \ , \ 1 \ , \ 1 \ , \ 1 \ , \ 1 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ , \ 2 \ 
X = pd.DataFrame(X, columns = ['X1', 'X2'])
Y = pd.DataFrame(Y, columns=['Y1'])
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
y_{pred} = gnb. fit(X, Y). predict(X)
# y_pred is [1, 1, 2, 1, 1, 2, 1, 1, 1, 1, 2, 2, 2, 2, 2, 1, 2, 2, 2]
 proba_y_pred = gnb.predict_proba(X)
 array([[9.99859060e-01, 1.40939825e-04],
                        [9.96573067e-01, 3.42693259e-03],
```

```
[3.94899482e-01, 6.05100518e-01],
[9.12468590e-01, 8.75314104e-02],
[9.99325593e-01, 6.74406701e-04],
[2.89854322e-01, 7.10145678e-01],
[9.87238614e-01, 1.27613857e-02],
[9.65393545e-01, 3.46064553e-02],
[7.15417535e-01, 2.84582465e-01],
[9.87238614e-01, 1.27613857e-02],
[2.35537973e-01, 7.64462027e-01],
[1.35388601e-01, 8.64611399e-01],
[2.31921435e-03, 9.97680786e-01],
[6.07414639e-02, 9.39258536e-01],
[2.77679262e-01, 7.22320738e-01],
[6.57758049e-01, 3.42241951e-01],
[6.76505314e-04, 9.99323495e-01],
[5.47271837e-02, 9.45272816e-01],
[4.16302198e-01, 5.83697802e-01],
[6.28435643e-03, 9.93715644e-01]])
```

For $X_2 = 7$ when $X_1 = 5$ predicted probability falls lowest, hence X_2