

# I. Pen-and-paper

1)

	Class = 0	Class = 1			
	$P(Class = 0) = \frac{4}{10} = 0.4$	$P(Class = 1) = \frac{6}{10} = 0.6$			
у1	$\mu = \frac{1}{4} \times \sum_{i=1}^{4} x_i = 0.25$ $\sigma = \sqrt{\frac{1}{4} \times \sum_{i=1}^{4} (x_i - \mu)^2} = 0.2380$ $P(y1 Class = 0) = N(\mu, \sigma^2)$	$\mu = \frac{1}{6} \times \sum_{i=5}^{10} x_i = 0.05$ $\sigma = \sqrt{\frac{1}{6} \times \sum_{i=5}^{10} (x_i - \mu)^2} = 0.2881$ $P(y1 Class = 1) = N(\mu, \sigma^2)$			
y2	$P(A   Class = 0) = \frac{2}{4} = 0.5$ $P(B   Class = 0) = \frac{1}{4} = 0.25$ $P(C   Class = 0) = \frac{1}{4} = 0.25$	$P(A   Class = 1) = \frac{1}{6} = 0.1667$ $P(B   Class = 1) = \frac{2}{6} = 0.3333$ $P(C   Class = 1) = \frac{3}{6} = 0.5$			
y3/y4	$\mu = \frac{1}{4} \times \sum_{i=1}^{4} \left[ x_{iy3} \ x_{iy4} \right] = [0.2 \ 0.25]$ $\Sigma = \begin{bmatrix} cov(y_3, y_3) & cov(y_3, y_4) \\ cov(y_4, y_3) & cov(y_4, y_4) \end{bmatrix}$ $= \begin{bmatrix} 0.1800 & 0.1800 \\ 0.1800 & 0.2500 \end{bmatrix}$ $ \Sigma  = cov(y_3, y_3) \times cov(y_3, y_4)$ $- cov(y_4, y_3) \times cov(y_4, y_4)$ $= 0.0126$ $\Sigma^{-1} = \begin{bmatrix} \frac{cov(y_4, y_4)}{ \Sigma } & -\frac{cov(y_3, y_4)}{ \Sigma } \\ -\frac{cov(y_4, y_3)}{ \Sigma } & \frac{cov(y_3, y_3)}{ \Sigma } \end{bmatrix}$ $= \begin{bmatrix} 19.8413 & -14.2857 \\ -14.2857 & 14.2857 \end{bmatrix}$ $P(y_3, y_4 Class = 0) = N(\mu, \Sigma)$	$\mu = \frac{1}{6} \times \sum_{i=5}^{10} [x_{iy3} x_{iy4}] = [0.1167 \ 0.0833]$ $\Sigma = \begin{bmatrix} cov(y_3, y_3) & cov(y_3, y_4) \\ cov(y_4, y_3) & cov(y_4, y_4) \end{bmatrix}$ $= \begin{bmatrix} 0.1097 & 0.1223 \\ 0.1223 & 0.2137 \end{bmatrix}$ $ \Sigma  = cov(y_3, y_3) \times cov(y_3, y_4)$ $- cov(y_4, y_3) \times cov(y_4, y_4)$ $= 0.0085$ $\Sigma^{-1} = \begin{bmatrix} \frac{cov(y_4, y_4)}{ \Sigma } & -\frac{cov(y_3, y_4)}{ \Sigma } \\ -\frac{cov(y_4, y_3)}{ \Sigma } & \frac{cov(y_3, y_3)}{ \Sigma } \end{bmatrix}$ $= \begin{bmatrix} 25.2362 & -14.4488 \\ -14.4488 & 12.9528 \end{bmatrix}$ $P(y_3, y_4 Class = 1) = N(\mu, \Sigma)$			

 $\textbf{2)} \quad P(Class = c \mid x_i) = P(Class = c) \times P\big(y1_{x_i} \mid Class = c\big) \times P\big(y2_{x_i} \mid Class = c\big) \times P\big(y3_{x_i}, y4_{x_i} \mid Class = c\big), c = 0 \cup 1$ 

		Class(0)	Class(1)	
		P(y1 = 0.6 Class = 0) = 0.5686	P(Y1 = 0.6 Class = 1) = 0.2239	0
-	X I	P(y2 = A Class = 0) = 0.5	P(Y2 = A Class = 1) = 0.1667	U
		$P(y3 = 0.2, y4 = 0.4 \mid Class = 0) = 1.2074$	P(Y3 = 0.2, Y4 = 0.4   Class = 1) = 1.2109	
		P(Class = 0 x1) = 0.13731	P(Class = 1 x1) = 0.02711	
	x2	P(y1 = 0.1 Class = 0) = 1.3741	P(Y1 = 0.1 Class = 1) = 1.3641	1
•	12	P(y2 = B Class = 0) = 0.25	P(Y2 = B Class = 1) = 0.3333	1
		$P(y3 = -0.1, y4 = -0.4 \mid Class = 0) = 0.4603$	P(Y3 = -0.1, Y4 = -0.4   Class = 1) = 0.9561	
		P(Class = 0 x2) = 0.06325	P(Class = 1 x2) = 0.26082	



	P(y1 = 0.2 Class = 0) = 1.6393	P(Y1 = 0.2 Class = 1) = 1.2092	0
ΛJ	P(y2 = A Class = 0) = 0.5	P(Y2 = A Class = 1) = 0.1667	
	$P(y3 = -0.1, y4 = 0.2 \mid Class = 0) = 0.7066$	P(Y3 = -0.1, Y4 = 0.2 Class = 1) = 0.6084	
	P(Class = 0 x3) = 0.23167	P(Class = 1 x3) = 0.07356	
x4	P(y1 = 0.1 Class = 0) = 1.3741	P(Y1 = 0.1 Class = 1) = 1.3641	1
λŦ	P(y2 = C Class = 0) = 0.25	P(Y2 = C Class = 1) = 0.5	1
	$P(y3 = 0.8, y4 = 0.8 \mid Class = 0) = 0.5124$	P(Y3 = 0.8, Y4 = 0.8   Class = 1) = 0.2030	
	P(Class = 0 x4) = 0.07041	P(Class = 1 x4) = 0.08308	
x5	P(y1 = 0.3 Class = 0) = 1.6393	P(Y1 = 0.3 Class = 1) = 0.9503	1
ХЭ	P(y2 = B Class = 0) = 0.25	P(Y2 = B Class = 1) = 0.3333	
	$P(y3 = 0.1, y4 = 0.3 \mid Class = 0) = 1.1743$	P(Y3 = 0.1, Y4 = 0.3   Class = 1) = 1.2064	
	P(Class = 0 x5) = 0.19250	P(Class = 1 x5) = 0.22926	
	P(y1 = -0.1 Class = 0) = 0.5686	P(Y1 = -0.1 Class = 1) = 1.2092	1
х6	P(y2 = C Class = 0) = 0.25	P(Y2 = C Class = 1) = 0.5	1
	$P(y3 = 0.2, y4 = -0.2 \mid Class = 0) = 0.3338$	P(Y3 = 0.2, Y4 = -0.2 Class = 1) = 0.6707	
	P(Class = 0 x6) = 0.01898	P(Class = 1 x6) = 0.24330	
	P(y1 = -0.3 Class = 0) = 0.1162	P(Y1 = -0.3 Class = 1) = 0.6620	1
X/	P(y2 = C Class = 0) = 0.25	P(Y2 = C Class = 1) = 0.5	
	$P(y3 = -0.1, y4 = 0.2 \mid Class = 0) = 0.7066$	P(Y3 = -0.1, Y4 = 0.2   Class = 1) = 0.6084	
	P(Class = 0 x7) = 0.00821	P(Class = 1 x7) = 0.12083	
	P(y1 = 0.2 Class = 0) = 1.6393	P(Y1 = 0.2 Class = 1) = 1.2092	1
XO	P(y2 = B Class = 0) = 0.25	P(Y2 = B Class = 1) = 0.3333	1
	$P(y3 = 0.5, y4 = 0.6 \mid Class = 0) = 1.0847$	P(Y3 = 0.5, Y4 = 0.6   Class = 1) = 0.8399	
	P(Class = 0 x8) = 0.17782	P(Class = 1 x8) = 0.20311	
	P(y1 = 0.4 Class = 0) = 1.3741	P(Y1 = 0.4 Class = 1) = 0.6620	0
X9	P(y2 = A Class = 0) = 0.5	P(Y2 = A Class = 1) = 0.1667	
	$P(y3 = -0.4, y4 = -0.7 \mid Class = 0) = 0.2174$	P(Y3 = -0.4, Y4 = -0.7   Class = 1) = 0.3876	
	P(Class = 0 x9) = 0.05976	P(Class = 1 x9) = 0.02566	
x10	P(y1 = -0.2 Class = 0) = 0.2807	P(Y1 = -0.2 Class = 1) = 0.9503	1
XIU	P(y2 = C Class = 0) = 0.25	P(Y2 = C Class = 1) = 0.5	1
	P(y3 = 0.4, y4 = 0.3 Class = 0) = 1.0804	P(Y3 = 0.4, Y4 = 0.3   Class = 1) = 1.1247	
	P(Class = 0 x10) = 0.03033	P(Class = 1 x10) = 0.32062	
		•	_

	Predicted				
		0	1		
Real	0	2	2		
Keai	1	1	5		

Predicted
 
$$Precision(P) = \frac{TP}{TP + FP} = \frac{5}{5 + 2} = 0.7143$$

 2
 2

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 5

$$Recall(R) = \frac{TP}{TP + FN} = \frac{5}{5 + 1} = 0.8333$$

3) 
$$F1 = \frac{(\beta^2 + 1) \times P \times R}{\beta^2 \times P + R} = \frac{2 \times 0.7143 \times 0.8333}{0.7143 + 0.8333} = 0.7692$$

4) 
$$P(Class = c \mid x_i) = \frac{P(Class = c \mid x_i)}{P(Class = 0 \mid x_i) + P(Class = 1 \mid x_i)}, c = 0 \cup 1$$

Probabilities	Real Class	0.3	0.4	0.5	0.6	0.7	0.8	0.9
P(Class = 0 x1) = 0.8351	0	0	0	0	0	0	0	1
P(Class = 0 x2) = 0.1952	0	1	1	1	1	1	1	1
P(Class = 0 x3) = 0.7590	0	0	0	0	0	0	1	1

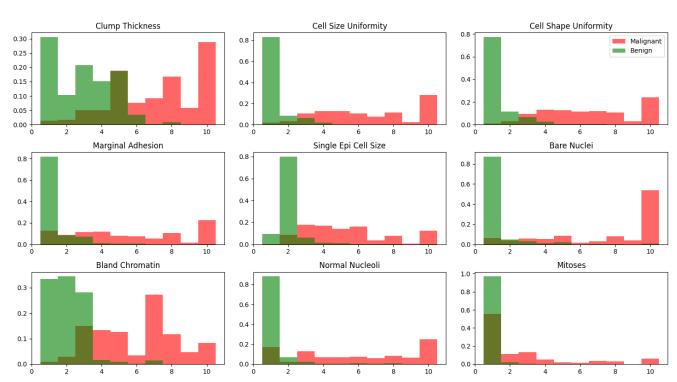


P(Class = 0 x4) = 0.4587	0	0	0	1	1	1	1	1
P(Class = 0 x5) = 0.4564	1	0	0	1	1	1	1	1
P(Class = 0 x6) = 0.0724	1	1	1	1	1	1	1	1
P(Class = 0 x7) = 0.0636	1	1	1	1	1	1	1	1
P(Class = 0 x8) = 0.4668	1	0	0	1	1	1	1	1
P(Class = 0 x9) = 0.6996	1	0	0	0	0	1	1	1
P(Class = 0 x10) = 0.0864	1	1	1	1	1	1	1	1
Threshold	-	0.6	0.6	0.7	0.7	0.8	0.7	0.6

From the table we can identify that the decision probability threshold that optimizes training accuracy is 0,7. This means that we can classify xi as being of Class 0 if  $P(Class = 0|xi) \ge 0,7$ , or Class 1 otherwise.

### II. Programming and critical analysis

5)



**6)** From this data we can see that K=5 has better accuracy, and therefore is less susceptible to overfitting.

<i>K</i>	3	5	7	
Accuracy	0.9692668371696506	0.9721867007672635	0.9707161125319693	

- 7) The hypotheses H0, "kNN is statistically inferior or equal to Naïve Bayes (multinomial assumption)", returned a P-Value of 0.0003537432054576055. From this we can safely reject H0 for a significance level of 0.0004 and accept H1," kNN is statistically superior to Naïve Bayes (multinomial assumption)".
- 8) Two reasons that explain the difference in performance between kNN and Naïve Bayes are:
  - 1. Naïve Bayes assumes that every variable is independent, but looking at **7**), that doesn't seem to be the case:
  - 2. Not enough data to train Naïve Bayes enough to correctly predict the class.



#### III. APPENDIX

```
import matplotlib.pyplot as plt
import numpy as num
from scipy.io import arff
from scipy.stats import ttest_rel
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import KFold, cross_val_score
from sklearn.naive_bayes import MultinomialNB
file = open("breast.w.arff", "r")
data, meta = arff.loadarff(file)
#5)
bins = [1,2,3,4,5,6,7,8,9,10,11]
for features, i in zip(meta.names()[:-1], range(1,10)):
    plt.subplot(3,3,i)
   dh = [data[(data["Class"]==b'benign')][features], data[(data["Class"]==b'malignant')][features]]
    plt.hist(dh, bins=bins, align='left', color=['g','r'], label=['Benign','Malignant'], alpha=0.6,
histtype='stepfilled', density=True)
    if i==3: plt.legend()
    plt.title(features.replace("_"," "))
plt.show()
#6)
input = data[meta.names()[:-1]].tolist()
output = data["Class"].tolist()
kFol = KFold(n_splits=10, shuffle=True, random_state=47)
crossKNN=[[],[],[]]
for i,k in zip(range(3,8,2),range(3)):
    classifier = KNeighborsClassifier(n neighbors=i weights='uniform', metric='euclidean')
   crossKNN[k] = cross_val_score(classifier, input, output, scoring='accuracy', cv = kFol)
   kErr = num.average(crossKNN[k])
    print("Accuracy K={}: {}".format(i,kErr))
#7)
classifier = MultinomialNB()
crossNB = cross_val_score(classifier, input, output, scoring='accuracy', cv = kFol)
pval = ttest_rel(crossKNN[0], crossNB, alternative='greater').pvalue
print("p-value:",pval)
```