1-0
DI method 1"+" no disease)=0.2 pamethod 1 - (no disease)
P(method 1"+" no disease)=0.2 pcmethod 1"-" no disease)
be -d 1 " " has drown = 15 m as 1 " 1" how 1 many
p(method; "_" has disease) = 0.15 p(method 1"+" has disease)
Pc has disease method 1"+") = Pc method 1"+" has disease) X Pc has disease method 1"+") = Pc method 1"+" has disease) Pc has disease
pchas disease method +) = 1 pchas disease)
pc method ("t")
$= \frac{0.85 \times 0.0001}{0.85 \times 0.0001 + 0.2 \times 0.9999} = 4.25 \times 10^{-4}$
= 4.25X10 F
0.82× 0.000 + 0.2×0.1119
PI (no disease 4 method "+") = Pc method "+" no disease) X PC no disease) PC method "+") 2 X0.9999
PI (no disease method 1"+") = PC no disease)
pcmethod 1"+")
2 X0.9999
= 0.21
= 0.2 x0.9999 = 0.85 x0.0001 + 0.2x0.9999 = 0.99958
Therefore, the person should have no disease.
1-b p(method 1"+" abhas disease) = 85% p(method 1"+" no disease) = 20%
p(method 1 + 1 all has disease) = 85%
p (method 1"+" no disease) = 20%
Therefore, by ML Approach, the person should have disease.
disease.

1-C P chas disease method 1"+" method 2"+")
= Pcmethod 1"+", method 2"+" has disease) x p chas disease)
PCmethod 1"f", method 2"f")
p cmethod 1"t", method z"t" has disease)
= pc method i't' has disease) x pc method z"t" has disease)
= 0.85 × 0.96
PC method 2 "+" I no disease) = 0.07 pcmethod 2"+" has disease) = 0.98
P(method > "-" Too disease) = 0.93 P(method 2"-" modisease) = has 0.04
Dihas disease) = 0.000
Demethod 1"+", method z"+") = pemethod 1"+") x pemethod z"+")
pcmethod 1"+") = 0.2 x0.99+ 000.85x 0.0001 = 0.198085
P(method 2"+") = 0.07x0.99 + 0.96x 0.0001 = 0.069396
pc has disease method 1"+" method 2"+")
$\frac{0.85 \times 0.96 \times 0.000}{0.198085 \times 0.069396} = 6 \times 10^{-3}$ $= \frac{0.198085 \times 0.069396}{0.198085 \times 0.069396} = 6 \times 10^{-3}$ thanks of having disease.
There fore, the person only has 6×10^3 chance of having disease.

2 0	Carlol I is in
2-0	Scaled dataset
Xı	X2 label
0.68	0.79 +
1.00	1.00 +
	0.00 +
0.24	0.06 -
0-41	6 0.52 -
0.63	0.81 -
2-b	after scaling $\begin{bmatrix} 3.9 \\ 4 \end{bmatrix}$: $X = \begin{bmatrix} 1.02 \\ 0.10 \end{bmatrix}$
dist	ances: 1/x-xil/2
+	0.68 0.79 0.75
+	1.00 1.00 0.90
+	0.00 0.00 1.02
_	024 0.06 0.78
-	0.46 0.52 [0.70]
_	0.63 0.81 0.81
K=1	, therefore, the predicted label is "-"

```
3-0 QDA
 U_{+} = \begin{bmatrix} 1.833 \\ 3.200 \end{bmatrix} \Sigma_{+} = \begin{bmatrix} 2.536 & 3933 \\ 3.933 & 6.140 \end{bmatrix} \Phi_{+} = 0.5
 u = \begin{bmatrix} 1.500 \\ 2.533 \end{bmatrix} \quad \Sigma = \begin{bmatrix} 0.420 & 0.990 \\ 0.990 & 2.442 \end{bmatrix} \quad \Phi = 0.5
3-6 = (3-1)
  pc+1x) => p(x1+)·p(+)
                 =- = log | S+ | - = (X-U+) (S+) (X-U+) + log O+
  |5+|=0.103 (5+)^{-1}=|39.612-38.184-24.621
 p(-|x) \Rightarrow p(x|-) \cdot p(-)
                 = - \frac{1}{2} \log \Big \Big - \frac{1}{2} (X-U-) T(\Sigma_-) T(\Sigma_-) + \log \phi_-
                  =-98.95726
|\Sigma| = 0.046 (\Sigma -)^{-1} = \begin{bmatrix} 53.087 & -21.522 \\ 21.522 & 9.130 \end{bmatrix}
 Therefore, the class of 2 should be
3-C
pros: we can find a linear decision boundary. It simplifies
a lot of work.
cons: If the actual distributions of data are different,
it harld generate significant bias on \Sigma.
```

```
4-a add-m smoothing: m=0.2
      P(X1=Law)+)= 2+0.2
3+02x3 = 0.611
     P(X2=Yes|+)= 0+0.2 = 0.059
      P(X) = \frac{2+0.2}{3+0.2X2} = 0.647
P(X) = Low|-) = \frac{1+0.2}{4+0.2X3} = 0.261
P(X) = Yes|-) = 3+0.2
4+0.2X2 = 0.72
      P(x_3 = C_1 reen|-) = \frac{3+0.2}{4+0.2x_2} = 0.727
    4-6 P(X|+) = \frac{22}{36} \times \frac{2}{34} \times \frac{2^2}{34} = 0.023
           p(x|-) = \frac{12}{46} \times \frac{32}{44} \times \frac{32}{44} = 0.138
    4-C P(XI-) > P(XI+), the ML label for X should be
```