

1)

1. F
2. F (Counter example: regression trees)
3. T
4. F (Issues: might overfit the data)
5. F
6. F (Expit instead of Gaussian)
7. F
8. F

2)

1.
Similarities: (a). $X|Y = k \sim \text{Normal}$ (b). require prior prob (generative modelling) (c). predictions are based on posterior prob.
Differences: (a). LDA assumes common within group covariance matrix, while QDA assumes different covariance. (b). LDA \sim linear decision boundary, while QDA \sim quadratic decision boundary.
2. Linear Regression yields value outside $[0,1]$, while logistic regression does not.
3.
Advantages: (a). easy to explain (b). closer to human decision making (c). can be displayed graphically (d). can easily handle qualitative variables.
Disadvantages: (a). generally weaker predictive power (b). easy to overfit.

3)

(a).

$$\begin{aligned}
 TSS &= \sum_{k=1}^K \sum_{i=1}^{n_k} (x_{ik} - \bar{x}_k + \bar{x}_k - \bar{x})^2 \\
 &= \sum_{k=1}^K \sum_{i=1}^{n_k} [(x_{ik} - \bar{x}_k)^2 + (\bar{x}_k - \bar{x})^2 + 2 * (x_{ik} - \bar{x}_k)(\bar{x}_k - \bar{x})] \\
 &= WSS + BSS + \sum_{k=1}^K \sum_{i=1}^{n_k} 2 * (x_{ik} - \bar{x}_k)(\bar{x}_k - \bar{x}) \\
 &= WSS + BSS + 2 \sum_{k=1}^K (\bar{x}_k - \bar{x}) \sum_{i=1}^{n_k} (x_{ik} - \bar{x}_k) \\
 &= WSS + BSS
 \end{aligned}$$

where $\sum_{i=1}^{n_k} (x_{ik} - \bar{x}_k) = 0$

(b).

$$\delta^2 = \frac{BSS}{TSS} = \frac{BSS}{BSS + WSS} \in [0, 1]$$

If $\delta^2 = 0$, then $BSS = 0$, which interprets no BSS.

If $\delta^2 = 1$, then $WSS = 0$, which interprets no WSS :)

(c).

$$F = \frac{n - K}{K - 1} \frac{BSS}{TSS - BSS} = \frac{n - K}{K - 1} \frac{1}{\frac{1}{n^2} - 1}$$

which shows one-to-one relationship.

4)

performance metrics < - function(cm)

a < - cm[1,1]

b < - cm[1,2]

c < - cm[2,1]

d < - cm[2,2]

tpr < - a/(a+c)

fpr < - b/(b+d)

tnr < - d/(b+d)

fnr < - c/(a+c)

specifying < - 1 - fpr

sensitivity < - tpr

return(c(.....))