

Ans 1 (a)

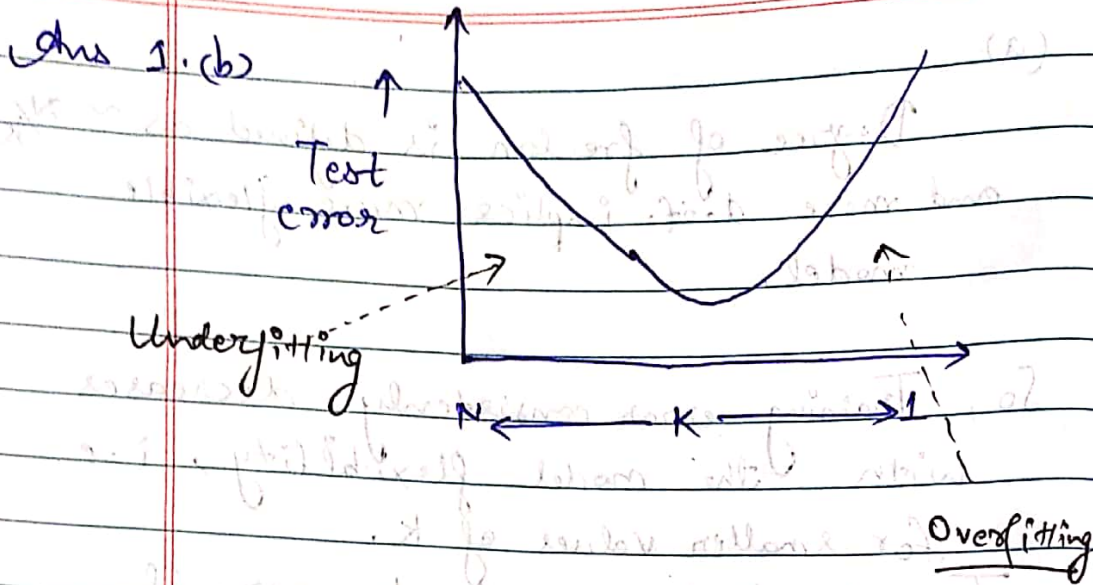
Degree of freedom is defined as  $\approx N/k$  and more d.o.f. implies more flexible model.

So, Training error consistently decreases with the model flexibility, i.e. for smaller values of  $k$ .

Typically it is dropping to zero if we increase the model flexibility enough.

So in short we can say training error decreases ~~from~~ by varying  $k$  from  $N$  to  $1$ .

The reason is  $\rightarrow$  it is due to ~~the~~ averaging of distances among the data points which tends to smoothen out predictions.



~~When we are talking about generalization error, it also implies about test error, so as we know that there's a relation error between  $K$  and test error. So we can say that  $\rightarrow$~~

- (i) When  $K$  is small, data tends to overfit, which maximizes the test error.
- (ii) Test error starts decreasing due to the generalization factor of  $K$ . It reaches minimum, which results in increase of generalization error.



Ans 1. (c). (i) Computation cost is very high because of calculating the distance between the data points for all the training samples.

(ii) Determination of value of  $K$  may be complex some time.

(ii) Also, increase in dimension tends to thin out the distribution of distances between the points, making it harder to classify.

Ans 1. (d) Yes, for  $K=1$  nearest point is the nearest neighbour.

Decision tree can be used to classify the points. ~~Decision tree can be used to classify the points. We have to make the decision for the point the nearest neighbour to given point.~~  
Yes

Ans 2. (a) Classification probability is given by Bayes theorem  $\rightarrow$

$$p(c_j|x) = \frac{p(x|c_j) p(c_j)}{p(x)}$$

$$= \frac{p(x|c_j) p(c_j)}{\sum_{k=1}^K p(x|c_k) p(c_k)}$$

so using Gaussian likelihood  $\rightarrow$  ~~Q(x)~~  
function

$$= \frac{1}{\sqrt{2\pi}\sigma_j} e^{-\frac{1}{2}\left(\frac{x-\mu_j}{\sigma_j}\right)^2} \text{ and}$$

$$\text{ML parameter estimator} \rightarrow \hat{\mu}_j = \frac{1}{N_j} \sum_{i=1}^{N_j} x_i$$

$$\hat{\sigma}_j^2 = \frac{1}{N_j} \sum_{i=1}^{N_j} (x_i - \hat{\mu}_j)^2$$

$$\hat{p}(c_j) = \frac{N_j}{\sum_{k=1}^K N_k}$$

$$\therefore \text{we have} \rightarrow \hat{\mu}_1 = 0.26$$

$$\hat{\mu}_2 = 0.8625$$



$$\text{and } \hat{\sigma}_1^2 = 0.0149$$

$$\hat{\sigma}_2^2 = 0.0092$$

$$\hat{p}(c_1) = 0.714$$

①

$$\hat{p}(c_2) = 0.2857$$

$$\text{and } p(c_1 | 0.6) = 0.6305$$

→ class probabilities →

$$P(c_1) = \frac{\text{No. of elements in class 1}}{\text{Total No. of elements}}$$

$$P(c_1) = \frac{10}{14} = 0.71428$$

$$P(c_2) = \frac{4}{14} = 0.28571$$

Similarly by putting values from eq<sup>n</sup> ①

$$\rightarrow p(x | c_1) = 0.06757$$

$$\rightarrow p(x | c_2) = 0.09831$$

$$\text{and } P(c_1|x) = \frac{P(x|c_1) \cdot P(c_1)}{P(x)}$$

$$= \frac{P(x|c_1) \cdot P(c_1)}{P(x|c_1)P(c_1) + P(x|c_2)P(c_2)}$$

$$= \frac{0.6299}{0.6299 + 0.3701}$$

$$P(c_1|x) = \boxed{0.6299} \text{ as } P(c_1|0.6)$$

$$\text{where } x = 0.6$$



Ans 2 (b) Given  $\rightarrow$

$x = (\text{goal, football, golf, defence, offence, wicket, office, strategy})$

Probab. of politics given  $x \hat{=} P(\text{politics} | x)$

Let  $t = (\text{politics})$

$$\begin{aligned} \therefore P(t | x) &= P(\text{goal} = 1 | t) * P(\text{football} = 0 | t) \\ &* P(\text{golf} = 0 | t) * P(\text{defence} = 1 | t) \\ &* P(\text{offence} = 1 | t) * P(\text{wicket} = 1 | t) \\ &* P(\text{office} = 1 | t) * P(\text{strategy} = 0 | t) \\ &* P(t) \\ &\hline P(x) \end{aligned} \quad \text{--- (1)}$$

Similarly Probability of sports can be calculated similarly.

also  $\rightarrow$

$$P(\text{politics} | x) + P(\text{sport} | x) = 1$$

$$\therefore P(\text{politics} | x) = 1$$

as

$$P(c_{\text{sports}} | x) = 0$$

$$\therefore \rightarrow P(\text{office} = 1 | c_{\text{sports}}) \text{ is } \underline{0/6}$$

$\therefore$  while multiplying all (just like eqn (i))

$$P(c_{\text{sports}} | x) = \underline{0}$$

and hence  $P(c_{\text{politics}} | x) = \underline{1}$ .

as