

IDS 575

(I)

$P_{X,Y}((X=x, Y=y))$

$P_{X_1, X_2, Y}((X_1=x_1, X_2=x_2, Y=y))$

X_1	X_2	Y	$P()$
0	0	0	$\frac{1}{8}$
0	0	1	$\frac{1}{8}$
\vdots			
\vdots			
1	1	1	$\frac{1}{8}$

$X : p \text{ dim}$

$Y : 1 \text{ dim}$

$X = \begin{bmatrix} \end{bmatrix}_{N \times p}$

$Y = \begin{bmatrix} \end{bmatrix}_{N \times 1}$

Expected (squared) prediction error (EPE)

$$= E_{X,Y} [(Y - f(x))^2]$$

loss function

$$\rightarrow (Y - f(x))^2$$

Obj

$$= \sum_x \sum_y P(X=x, Y=y) \cdot (y - f(x))^2$$

$$\sum_{i=1}^N (y_i - f(x_i))^2$$

Goal: find the best function 'f'

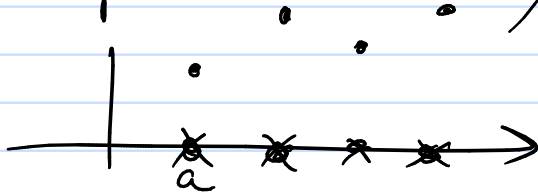
$$= \sum_x \sum_y P(Y=y | X=x) \cdot \underline{P(X=x)} (y - f(x))^2$$

$$= \sum_x \underbrace{P(X=x)}_{E_x} \left[\sum_y \underbrace{P(Y=y|X=x)}_{E_{Y|X}} (y - f(x))^2 \right]$$

$$\min_f \rightarrow E_x \left[\underbrace{E_{Y|X} \left[(y - \underline{f(x)})^2 \right]}_{\text{depends on } x} \right]$$

x	y	P()
a	.	.
b	.	.
c	.	.
d	.	.

X is 1dim



$$E_x \left[E_{y|x} \left[\underbrace{(y - \underline{f(x)})^2} \right] \right]$$

$$\frac{d}{dz} z^2 = 2z$$

$$\min_z \sum_y \underbrace{P(Y=y|X=x)} \cdot (y - \underbrace{z})^2$$

$$\frac{d}{dz} (y-z)^2 = -2(y-z)$$

Set derivative equal to 0

$$\sum_y P(Y=y|X=x) (y-z) = 0$$

$$\Rightarrow \underbrace{\sum_y P(Y=y|X=x) \cdot y}_{=z} = z \underbrace{\left(\sum_y P(Y=y|X=x) \right)}_1$$

$$\underline{\underline{E[Y|X=x'] = f(x')}}$$

$$f(x) = \underline{\underline{E[Y|X=x]}} \leftarrow \text{"regression function"}$$

① k-n-n

k=3

$$\begin{bmatrix} 0 & 1 \\ 1 & 2 \\ 5 & 4 \\ 3 & 3 \end{bmatrix}$$

X

$$\begin{bmatrix} 1 \\ 2 \\ 3 \\ 0 \end{bmatrix}$$

Y

$$x^{\text{test}} = [2, 2]$$

3 nearest neighbors

k-n-n
① 'k' ② distance

$$E[Y|X=x] \stackrel{\textcircled{1}}{\approx} \frac{1}{k} \sum_{\substack{i \text{ such} \\ \text{that } x_i = x}} y_i \stackrel{\textcircled{2}}{\approx} \frac{1}{k} \sum_{\substack{i \text{ such that} \\ x_i \approx x}} y_i \quad (\textcircled{k})$$

$$Y = \begin{cases} 0 & 1/2 \\ 1 & 1/2 \end{cases} \quad E[Y] = 1/2$$

$$y_1 \dots y_{100} \quad E[Y] \approx \frac{1}{n} \sum y_i$$

~~G~~ majority vote (g_i if $x_i \approx x$)

Linear model $f(x) = \underline{\underline{\beta^T x}} = [\beta^1 \beta^2] \begin{bmatrix} x^1 \\ x^2 \end{bmatrix} = \beta^1 x^1 + \beta^2 x^2$

$$f(x) = \underline{\underline{E[Y|X=x] = \beta^T x}}$$

$$\min_{\beta} EPE = \min_{\beta} E_{XY} [(Y - \beta^T X)^2]$$

$$\beta = (E_x [X X^T])^{-1} E_{XY} (X \cdot Y)$$

$$\begin{bmatrix} x^1 \\ x^2 \end{bmatrix}_{2 \times 1} \underbrace{\begin{bmatrix} x^1 & x^2 \end{bmatrix}}_{1 \times 2} = \begin{bmatrix} \quad \\ \quad \end{bmatrix}_{2 \times 2}$$

Data: (X, Y)

Dist (X, Y)

$$\hat{\beta} = (X^T X)^{-1} X^T Y \quad X = \begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix}_{N \times d} \quad Y = \begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix}_{N \times 1}$$
$$\beta^{\text{dist}} = (E[X X^T])^{-1} E[X Y]$$

Q: is M not invertible? $p \times p$

$$\begin{bmatrix} | & | & | \end{bmatrix} = \begin{bmatrix} 5 & 1 \\ 2 & 2 \\ 3 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 6 \\ 4 \\ 4 \\ 2 \end{bmatrix}_{N \times p}$$

$$\begin{bmatrix} 1 & 5 & 2 \\ 2 & 6 & 4 \\ 3 & 7 & 6 \end{bmatrix}$$

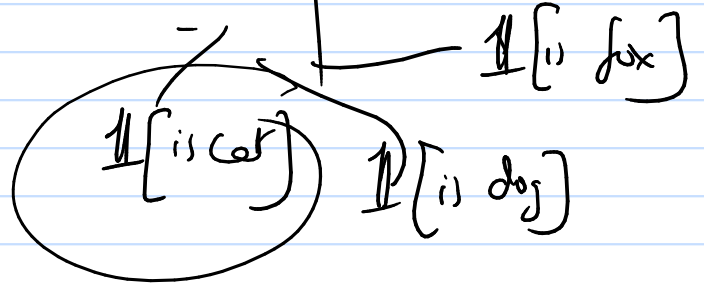
$X_1 = \{\text{Cat, dog, fox}\}$

$$X = \begin{bmatrix} 1 & \text{Cat} \\ 2 & \text{dog} \\ 3 & \text{fox} \\ 4 & \text{dog} \end{bmatrix}$$

$$\sum_{[] \cdot y} P(X = \begin{bmatrix} x^1 \\ \vdots \\ x^p \end{bmatrix}, Y = y) \cdot \begin{bmatrix} x^1 \\ \vdots \\ x^p \end{bmatrix} \cdot y$$

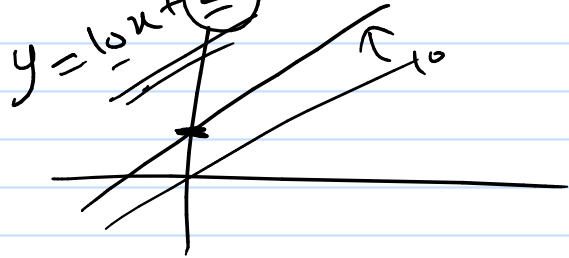
$$X = \begin{bmatrix} 1 & 1 & 0 & 0 & 1 \\ 2 & 0 & 1 & 0 & 1 \\ 3 & 0 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 1 \end{bmatrix}$$

$x_i \rightarrow$



$$f(x) = \beta^T x + c$$

$$\begin{bmatrix} \beta^1 \\ \beta^2 \\ c \end{bmatrix} = \begin{bmatrix} \beta^1 & \beta^2 & c \end{bmatrix} \begin{bmatrix} x^1 \\ x^2 \\ 1 \end{bmatrix}$$



② EPE for Classification → Bayes' Classifier ←

③ Issues with k-nn

④ Relatives of EPE, k-nn & linear models

Scoring for classification.

$$\begin{matrix} \downarrow \\ \rightarrow \end{matrix} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \cong \begin{bmatrix} 0 & 5 \\ 10 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 5 & 5 \\ 5 & 0 & 10 \\ 5 & 5 & 0 \end{bmatrix}_{3 \times 3} = L \Leftrightarrow L \left(G = \overset{1,2,3}{\downarrow} k, \hat{G}(x) = k' \right)$$

$$EPE = E_x \left[\sum_{k=1}^K P(G=k|X) \cdot L(G=k, \underline{G(X)}) \right]$$

$$\begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}$$

$$\min_z \sum_{k=1}^K P(G=k|X=\underline{x}) \cdot L(G=k, z)$$

$$P_{GX}(G=k, X=x)$$

$z = \text{cat}$ $z = \text{fox}$
 $z = \text{dog}$

$$P(G=\text{cat}) = .3$$

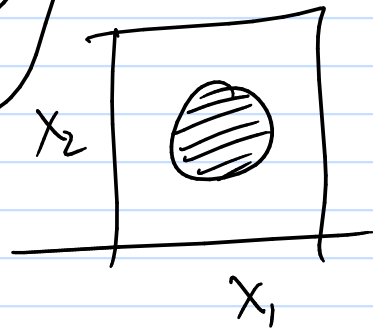
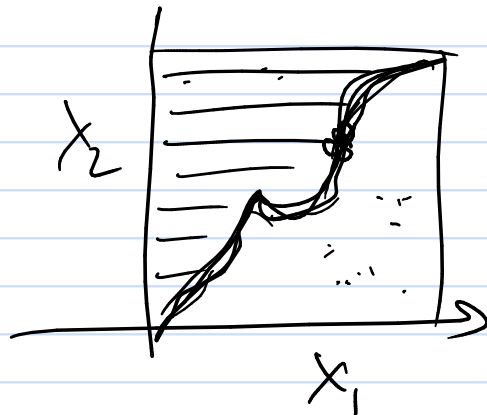
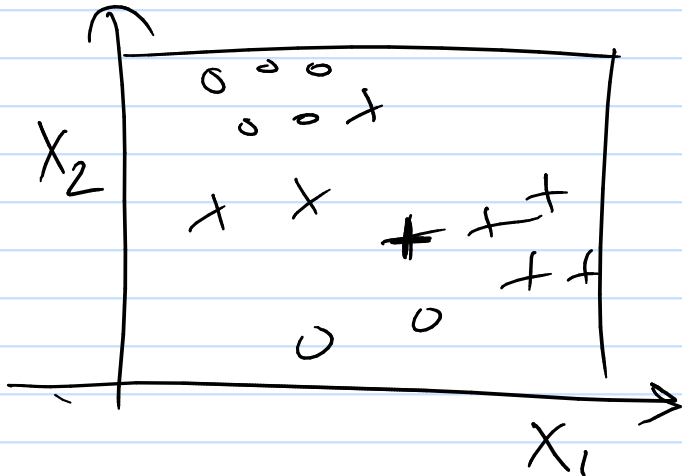
$$P(G=\text{dog}) = .4$$

$$P(G=\text{fox}) = .3$$

best classifier for $X = x$ is

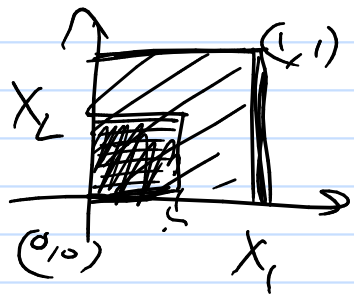
$$\arg \max_{k=1,2,3} P(G=k | X=x)$$

Bayes classifier



② Why is k-nn not enough.

P are finite defining "neighbors"

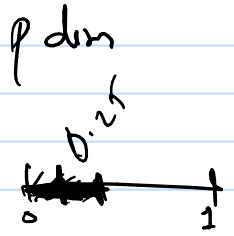
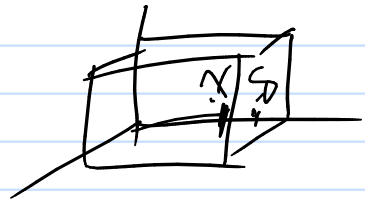
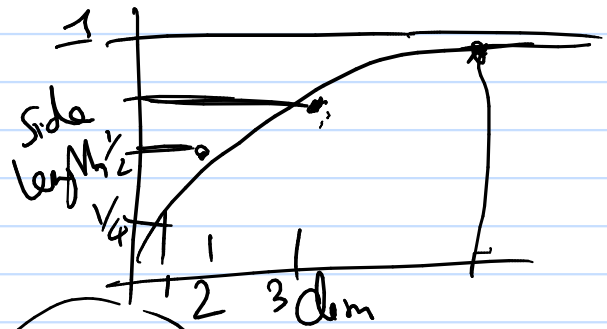


1d: $\frac{1}{4}$
 2d: region = $\frac{1}{4}$
 3d: $\frac{1}{4}$

Side length = $\frac{1}{2} = r^{1/2}$

$(\frac{1}{4})^{1/3}$

$(\frac{1}{4})^{1/p}$



Relatives

knn

→

kernel method

$$\text{pred} = \frac{\sum_{i=1, \dots, N} K(x_i, x^{\text{test}}) \cdot y_i}{\sum_{i=1, \dots, N} K(x_i, x^{\text{test}})}$$

linear model →

?