

PROBLEM 1B

To prove: $P(Y|X) = \frac{1}{1+e^{-Y(\beta_0+\beta_1 X)}}$ if $Y \in \{-1, 1\}$

Given: $P(Y=+1|X) = S(\beta_0+\beta_1 X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X)}}$

$$\Rightarrow P(Y=-1|X) = 1 - S(\beta_0+\beta_1 X) = \frac{1+e^{-(\beta_0+\beta_1 X)} - 1}{1+e^{-(\beta_0+\beta_1 X)}}$$

$$= \frac{e^{-(\beta_0+\beta_1 X)}}{e^{-(\beta_0+\beta_1 X)} [e^{(\beta_0+\beta_1 X)} + 1]} = \frac{1}{1+e^{(\beta_0+\beta_1 X)}}$$

Thus, to generalize, we use Y as a coefficient in the exponential term

Hence Proved.

To prove: Log likelihood for n data points can be:

$$\ln L(\beta_0, \beta_1) = - \sum_{i=1}^n \ln(1+e^{-Y_i(\beta_0+\beta_1 X_i)})$$

We know from above that $L(\beta_0, \beta_1) = \prod_{i=1}^n \frac{1}{1+e^{-Y_i(\beta_0+\beta_1 X_i)}}$

$$\Rightarrow \ln(L(\beta_0, \beta_1)) = \sum_{i=1}^n \frac{1}{1+e^{-Y_i(\beta_0+\beta_1 X_i)}} = \sum_{i=1}^n (\ln(1) - \ln(1+e^{-Y_i(\beta_0+\beta_1 X_i)}))$$

$$= - \sum_{i=1}^n \ln(1+e^{-Y_i(\beta_0+\beta_1 X_i)})$$

Hence Proved.

3 A] Given: $P(X=x, Y=y) = P(Y=y) P(X=x|Y=y)$

Distribution support $x \in \mathbb{R}, y \in \{-1, +1\}$

$$P(Y=+1) = P(Y=-1) = \frac{1}{2}$$

$$P(X=x|Y=+1) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-5)^2}{2}}$$

$$P(X=x|Y=-1) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x+5)^2}{2}}$$

Prove $P(X=x, Y=y) = \frac{1}{2\sqrt{2\pi}} e^{-\frac{(x+5y)^2}{2}} \Rightarrow$ This is easy
just multiply
 $P(Y=y)$ for both
 $+1$ & -1 cases

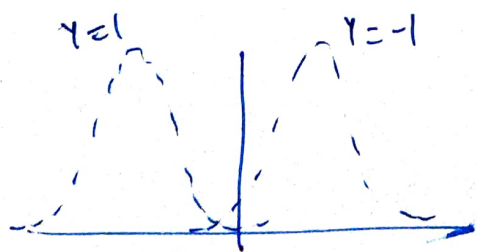
3 B] $P(X=x|Y=+1)$

$P(X=x|Y=-1)$ in a single figure

3 C] Write Bayes optimal classifier $h^*(x)$ given P

\Rightarrow classify x based on a threshold

\Rightarrow this threshold can be 0 because each $Y=1$ & -1 is unimodal & symmetric peaks w/ $X=0$ as axis of symmetry



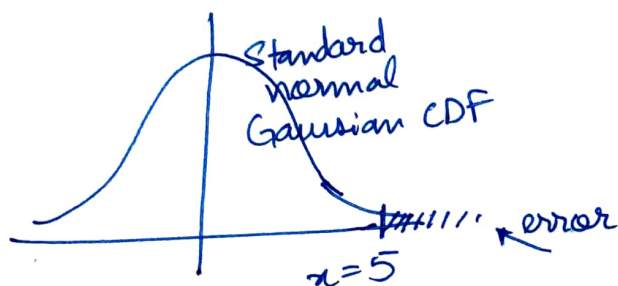
Optimal classifier

$$x = \begin{cases} < 0 & y = 1 \\ > 0 & y = -1 \end{cases}$$

3d) compute error of Bayes optimal classifier

$$\Pr(h^*(x) \neq y) = E_{(x,y) \sim P} [\mathbb{1}_{h^*(x) \neq y}]$$

result should be of the form $1 - \Phi(c)$ where Φ is Gaussian CDF



$$1 - \Phi(5)$$

$$3e] \Pr(Y=+1 | X=x) = \frac{1}{1 + e^{-\beta_0 - \beta_1 x}}$$

show that the given distribution satisfies this assumption

$$\Pr(Y=+1 | X=x) = \frac{\Pr(Y=+1 \& X=x)}{\Pr(X=x)} = \frac{\Pr(X=x | Y=+1) \Pr(Y=+1)}{\Pr(X=x)}$$

$$\begin{aligned} \Pr(X=x) &= \Pr(X=x | Y=+1) \cdot \Pr(Y=+1) + \Pr(X=x | Y=-1) \cdot \Pr(Y=-1) \\ &= \frac{1}{2} (\Pr(X=x | Y=+1) + \Pr(X=x | Y=-1)) \end{aligned}$$

$$P(Y=+1|X=x) = \frac{\frac{1}{2} \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-5)^2}{2}}}{\frac{1}{2} \left(\frac{1}{\sqrt{2\pi}} e^{-\frac{(x-5)^2}{2}} + \frac{1}{\sqrt{2\pi}} e^{-\frac{(x+5)^2}{2}} \right)}$$

$a = x - 5$
 $1 - a = x + 5$
 $10 + a = x + 5$

$$= \frac{1}{1 + \frac{e^{-\frac{(x+5)^2}{2}}}{e^{-\frac{(x-5)^2}{2}}}}$$

$$= \frac{1}{1 + e^{-\frac{1}{2}(x^2 + 25 + 10x - x^2 - 25 + 10x)}}$$

$$\frac{1}{1 + e^{-\beta_0 - \beta_1 x}} = \frac{1}{1 + e^{-10x}}$$

$$\Rightarrow \boxed{\beta_0 = 0, \beta_1 = 10}$$

$$4) \min_{c_1, \dots, c_k} \sum_{i=1}^n \|x_i - c(x_i)\|_2^2$$

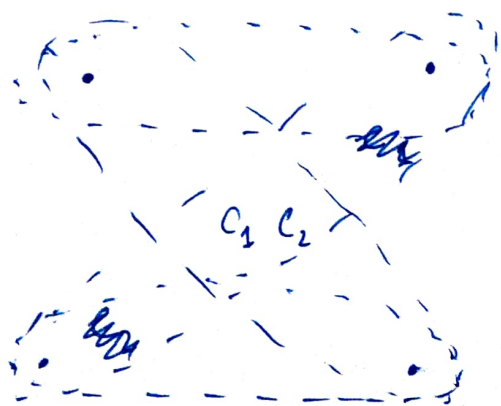
show k-means does not always find optimal objective

Given: OPT is optimal objective

For every $t > 1$, show \exists an instance of the above optimization problem for which k-means might find a solution whose objective value $\geq t \cdot \text{OPT}$

i.e. Find x_1, \dots, x_n for which k-means with some bad initialization of centers will output a set of centers that achieves an objective of $t \cdot \text{OPT}$

Start w/ example of 4 points in a 2D plane
2 clusters; generalize this example to
p-dimensions, n data points, k clusters



clusters
Always stuck crossing diagonal
& keep switching main/off diagonal