



शिक्षा मंत्रालय  
MINISTRY OF  
EDUCATION

INDIAN INSTITUTE OF TECHNOLOGY  
JODHPUR



DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING



P M R F

Prime Minister's Research Fellowship

Week 5 - Live Session

# Data Mining

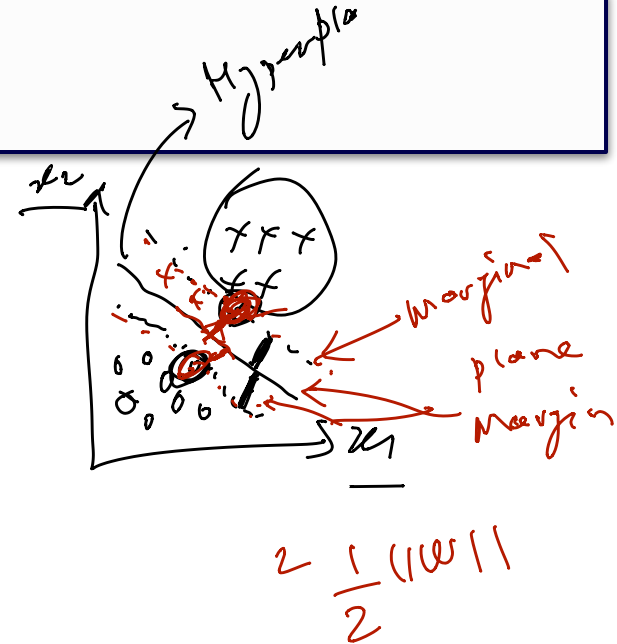
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Q1. Margin of a hyperplane is defined as:

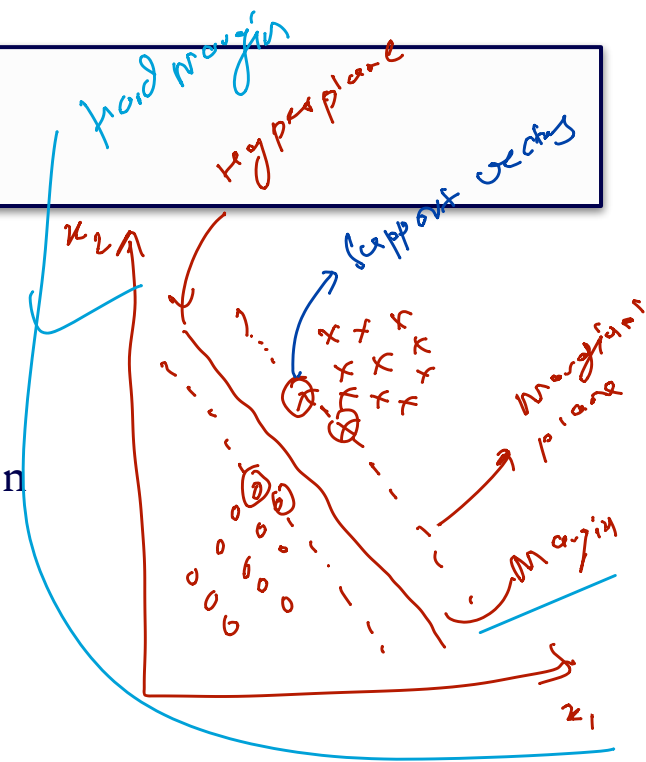
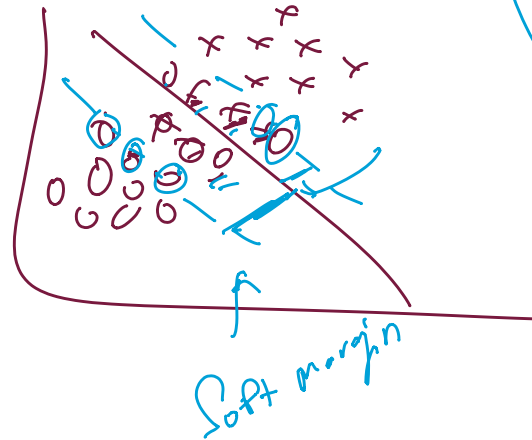
- a) The angle it makes with the axes
- b) The intercept it makes on the axes
- ☒ c) Perpendicular distance from its closest point
- d) Perpendicular distance from origin



Q2. In a hard margin support vector machine:

- a) No training instances lie inside the margin
- b) All the training instances lie inside the margin
- c) Only few training instances lie inside the margin
- d) None of the above

c = 3



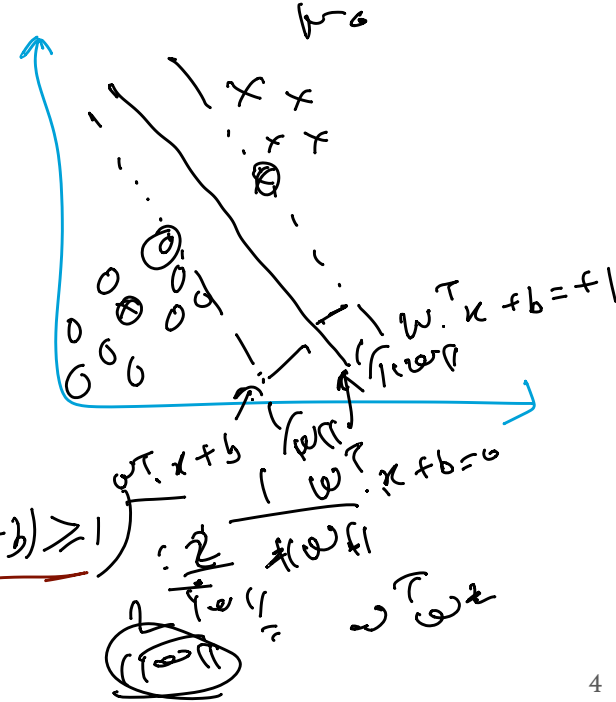
Q3. The primal optimization problem solved to obtain the hard margin optimal separating hyperplane is:

A. Minimize  $\frac{1}{2} W^T W$  such that  $y_i(W^T X_i + b) \geq 1$  for all  $i$

B. Maximize  $\frac{1}{2} W^T W$  such that  $y_i(W^T X_i + b) \geq 1$  for all  $i$

C. Minimize  $\frac{1}{2} W^T W$ , such that  $y_i(W^T X_i + b) \leq 1$  for all  $i$

D. Maximize  $\frac{1}{2} W^T W$ , such that  $y_i(W^T X_i + b) \leq 1$  for all  $i$



$$\text{max margin} = \frac{1}{\|w\|}$$

$$= \sqrt{w_1^2 + w_2^2}$$

$$(w_1, w_2) \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$= \min \frac{1}{2} \|w\|^2$$

$$= \min \frac{1}{2} w^T w$$

$$y_i(W^T X_i + b) \geq 1$$

$$\Rightarrow \frac{y_i(W^T X_i + b)}{\|w\|} \geq \frac{1}{\|w\|}$$

$$\Rightarrow \frac{y_i(W^T X_i + b)}{\|w\|} \geq \frac{1}{\|w\|}$$

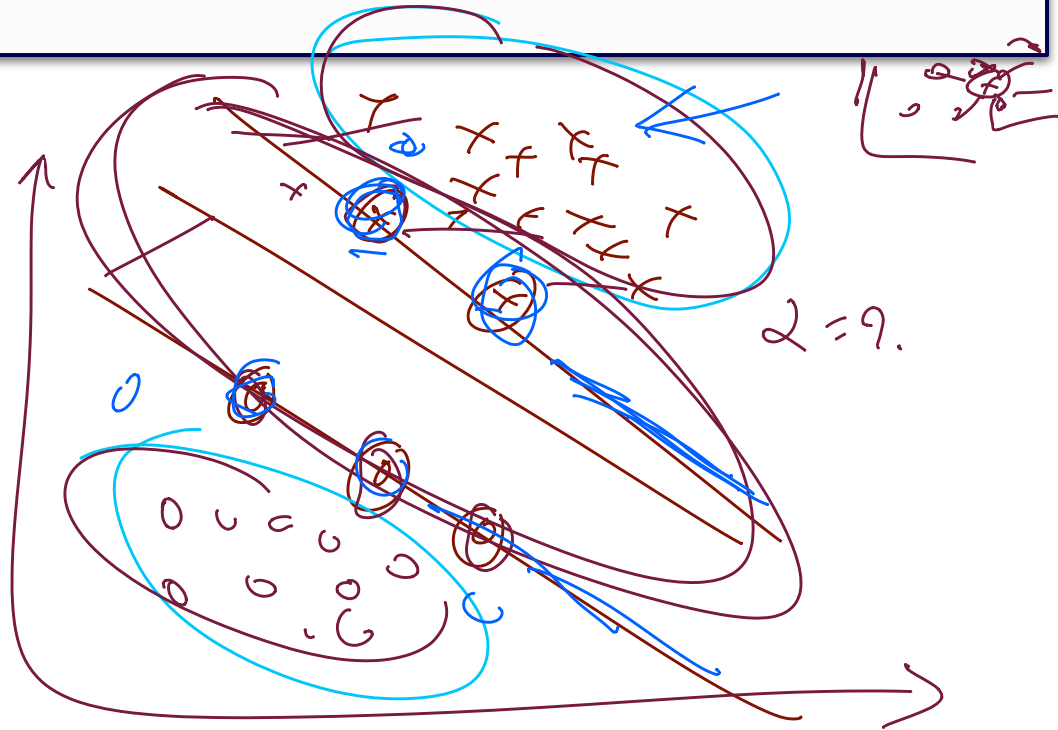
Q4. The dual optimization problem solved to obtain the hard margin optimal separating hyperplane is:

$$y_i(w^T x_i + b) \geq 1$$
$$y_i(w^T x_i + b) - 1 \geq 0$$

- A. Maximize  $\frac{1}{2} W^T W$ , such that  $y_i(W^T X_i + b) \geq 1 - \alpha_i$  for all  $i$
- B. Minimize  $\frac{1}{2} W^T W - \sum \alpha_i (y_i(W^T X_i + b) - 1)$ , such that  $\alpha_i \geq 0$ , for all  $i$
- C. Minimize  $\frac{1}{2} W^T W - \sum \alpha_i$ , such that  $y_i(W^T X_i + b) \leq 1$  for all  $i$
- D. Maximize  $\frac{1}{2} W^T W + \sum \alpha_i$ , such that  $y_i(W^T X_i + b) \leq 1$  for all  $i$

Q5. The Lagrange multipliers corresponding to the support vectors have a value:

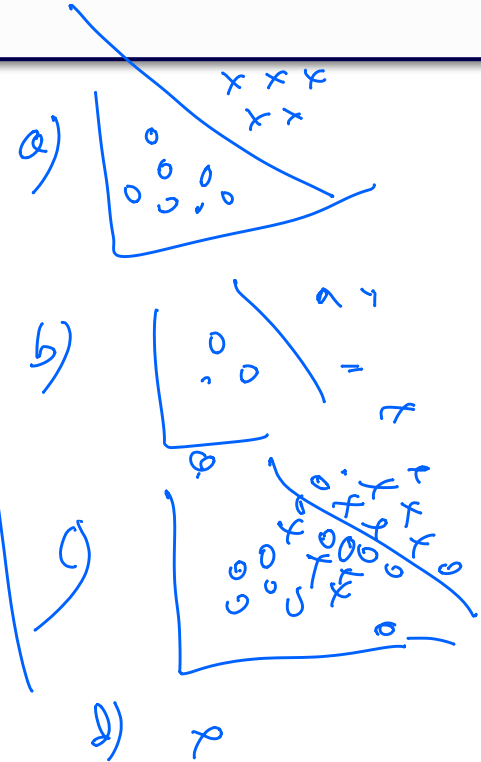
- a) Equal to zero
- b) Less than zero
- c) Greater than zero
- d) Can take on any value



Q6. The SVM's are less effective when:

- a) The data is linearly separable
- b) The data is clean and ready to use
- ☒ c) The data is noisy and contains overlapping points
- d) None of the above

(28) x  
(8) week 6  
(9) week 7



Q7. The dual optimization problem in SVM design is solved using:

- a) Linear programming
- b) Quadratic programming
- c) Dynamic programming
- d) Integer programming

