

Live Interaction #7:

25th February 2024

E-masters Next Generation Wireless Technologies

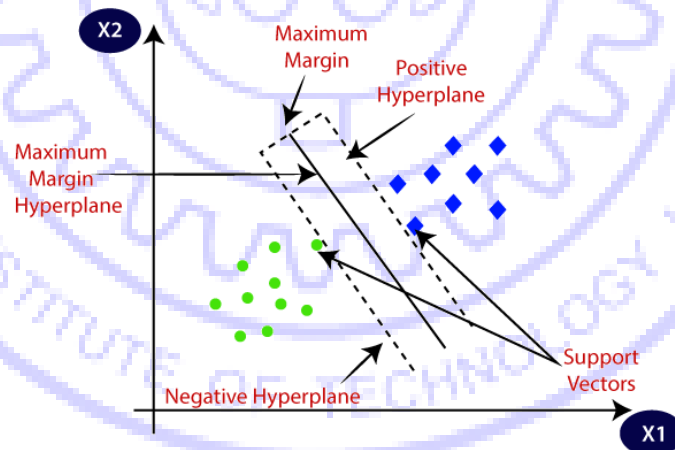
EE902 Advanced ML Techniques for Wireless Technology

► SVM:

$$\max \frac{2}{\|\bar{\mathbf{a}}\|_2} \equiv \min \|\bar{\mathbf{a}}\|$$

$$\mathcal{C}_0: \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \geq 1, 1 \leq i \leq M$$

$$\mathcal{C}_1: \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \leq -1, M+1 \leq i \leq 2M$$



- We introduce a new variable y_i

$$\mathcal{C}_0: y_i = 1, 1 \leq i \leq M$$

$$\mathcal{C}_1: y_i = -1, M+1 \leq i \leq 2M$$

- SVM

$$\max \frac{2}{\|\bar{\mathbf{a}}\|_2} \equiv \min \|\bar{\mathbf{a}}\|$$

$$\mathcal{C}_0: y_i(\bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b) \geq 1, 1 \leq i \leq M$$

$$\mathcal{C}_1: y_i(\bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b) \geq 1, M+1 \leq i \leq 2M$$

- Therefore, the equivalent problem is

$$\begin{aligned} & \min \|\bar{\mathbf{a}}\| \\ & y_i(\bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b) \geq 1 \\ & \min \frac{1}{2} \|\bar{\mathbf{a}}\|^2 \\ & -(y_i(\bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b) - 1) \leq 0 \end{aligned}$$

- What is the next step?

$$\frac{1}{2} \|\bar{\mathbf{a}}\|^2 - \sum_{i=1}^{2M} \lambda_i (y_i(\bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b) - 1)$$

- Setting gradient with respect to $\bar{\mathbf{a}}$ and set it equal to 0.

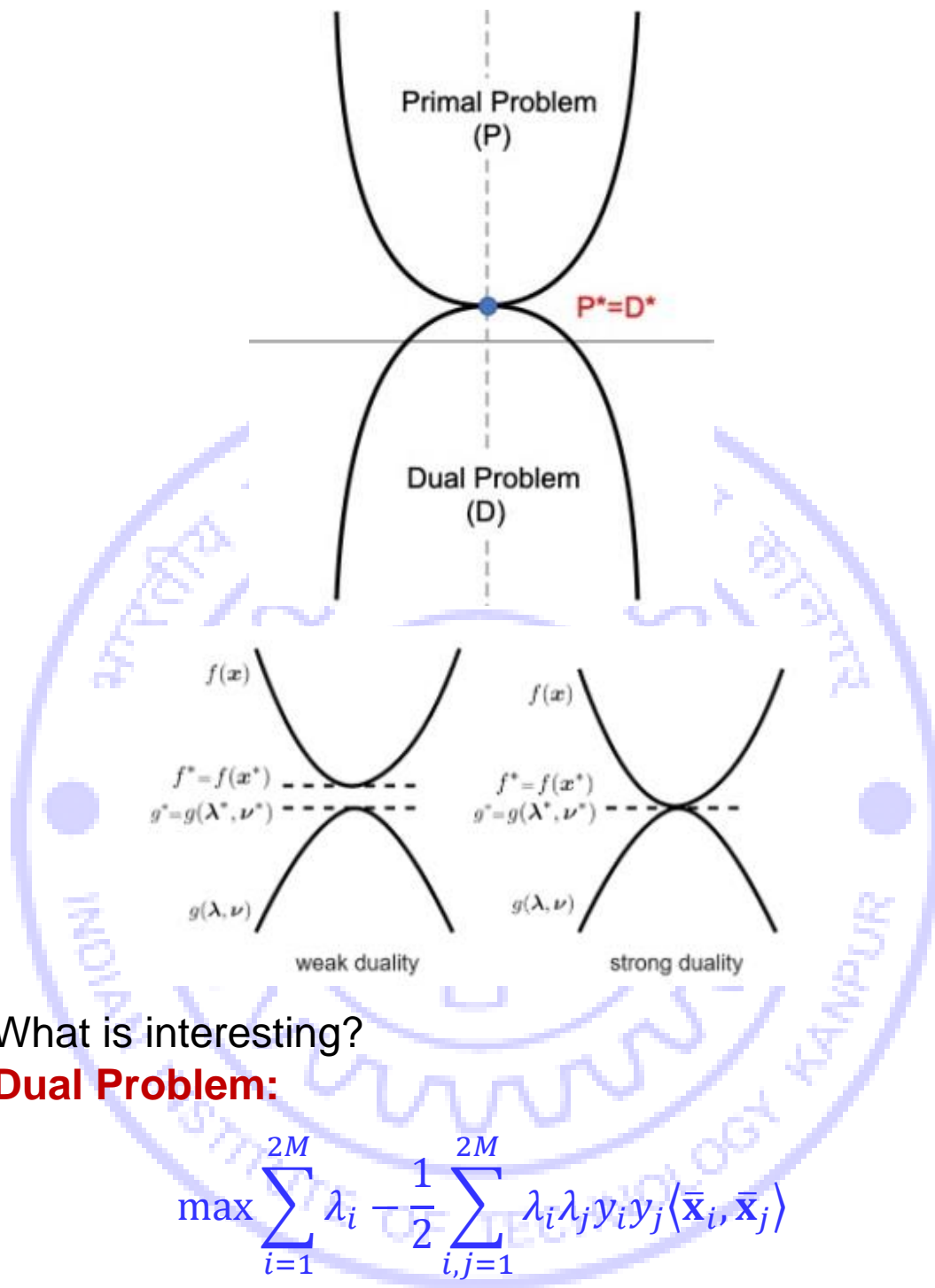
$$\bar{\mathbf{a}} = \sum_{i=1}^{2M} \lambda_i y_i \bar{\mathbf{x}}_i$$

- **Complementary slackness.**
 ► The support vectors are those points for which $\lambda_i \neq 0$.
 ► **Dual Problem:**

$$\max \sum_{i=1}^{2M} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{2M} \lambda_i \lambda_j y_i y_j \bar{\mathbf{x}}_i^T \bar{\mathbf{x}}_j$$

$$\text{subject to } \lambda_i \geq 0$$

$$\sum_{i=1}^{2M} \lambda_i y_i = 0$$



- What is interesting?
- **Dual Problem:**

$$\max \sum_{i=1}^{2M} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{2M} \lambda_i \lambda_j y_i y_j \langle \bar{\mathbf{x}}_i, \bar{\mathbf{x}}_j \rangle$$

subject to $\lambda_i \geq 0$

$$\sum_{i=1}^{2M} \lambda_i y_i = 0$$

- The inner product can be replaced by a suitable **Kernel** which can be **non-linear** in nature.

$$\max \sum_{i=1}^{2M} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{2M} \lambda_i \lambda_j y_i y_j K(\bar{\mathbf{x}}_i, \bar{\mathbf{x}}_j)$$

subject to $\lambda_i \geq 0$

$$\sum_{i=1}^{2M} \lambda_i y_i = 0$$

- This helps us consider **non-linear features**!!

$$K(\bar{\mathbf{x}}_i, \bar{\mathbf{x}}_j) = \phi^T(\bar{\mathbf{x}}_i) \phi(\bar{\mathbf{x}}_j) = (\bar{\mathbf{x}}_i^T \bar{\mathbf{x}}_j)^2$$

$$\phi(\bar{\mathbf{x}}_i) = \begin{bmatrix} x_i(1)x_i(1) \\ x_i(1)x_i(2) \\ x_i(1)x_i(3) \\ x_i(2)x_i(1) \\ x_i(2)x_i(2) \\ x_i(2)x_i(3) \\ x_i(3)x_i(1) \\ x_i(3)x_i(2) \\ x_i(3)x_i(3) \end{bmatrix} = \bar{\mathbf{x}}_i \otimes \bar{\mathbf{x}}_i$$

- Popular kernel: **Gaussian Kernel**

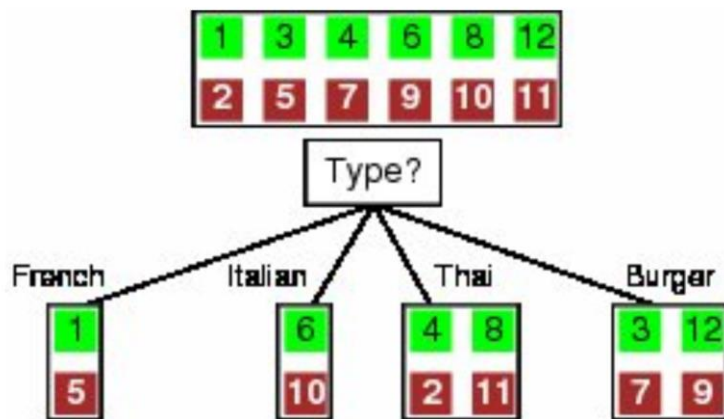
$$K(\bar{\mathbf{x}}_i, \bar{\mathbf{x}}_j) = \exp\left(-\frac{\|\bar{\mathbf{x}}_i - \bar{\mathbf{x}}_j\|^2}{2\sigma^2}\right)$$

- This can be written as the inner product between two **infinite dimensional** feature vectors!!

Example	Input Attributes										Goal WillWait
	Alt	Bar	Fri	Hun	Pat	Price	Rain	Res	Type	Est	
x ₁	Yes	No	No	Yes	Some	\$\$\$	No	Yes	French	0-10	y ₁ = Yes
x ₂	Yes	No	No	Yes	Full	\$	No	No	Thai	30-60	y ₂ = No
x ₃	No	Yes	No	No	Some	\$	No	No	Burger	0-10	y ₃ = Yes
x ₄	Yes	No	Yes	Yes	Full	\$	Yes	No	Thai	10-30	y ₄ = Yes
x ₅	Yes	No	Yes	No	Full	\$\$\$	No	Yes	French	>60	y ₅ = No
x ₆	No	Yes	No	Yes	Some	\$\$	Yes	Yes	Italian	0-10	y ₆ = Yes
x ₇	No	Yes	No	No	None	\$	Yes	No	Burger	0-10	y ₇ = No
x ₈	No	No	No	Yes	Some	\$\$	Yes	Yes	Thai	0-10	y ₈ = Yes
x ₉	No	Yes	Yes	No	Full	\$	Yes	No	Burger	>60	y ₉ = No
x ₁₀	Yes	Yes	Yes	Yes	Full	\$\$\$	No	Yes	Italian	10-30	y ₁₀ = No
x ₁₁	No	No	No	No	None	\$	No	No	Thai	0-10	y ₁₁ = No
x ₁₂	Yes	Yes	Yes	Yes	Full	\$	No	No	Burger	30-60	y ₁₂ = Yes

- Choose the feature that maximizes the **information gain**.

$$H(X) - H(X|Y)$$



- What is $H(X)$?

$$H(X) = H\left(\frac{1}{2}, \frac{1}{2}\right) = 1$$

$$H(X|\text{French}) = 1$$

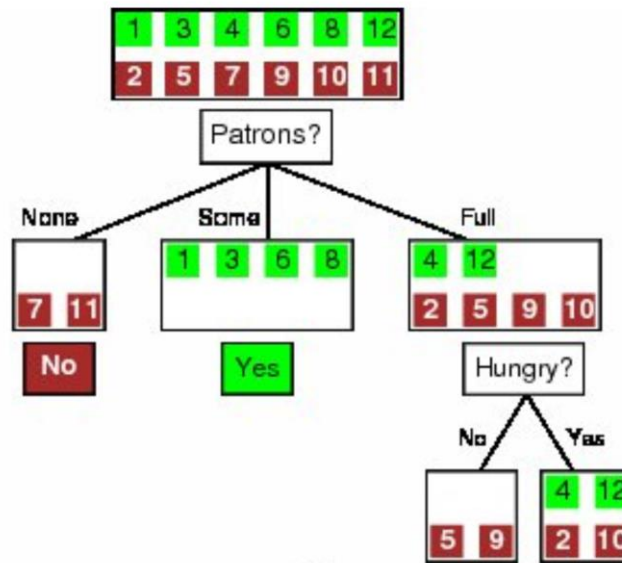
$$H(X|\text{Italian}) = 1$$

$$H(X|\text{Thai}) = 1$$

$$H(X|\text{Burger}) = 1$$

$$H(X|\text{Type}) = \frac{1}{6} \times 1 + \frac{1}{6} \times 1 + \frac{1}{3} \times 1 + \frac{1}{3} \times 1 = 1$$

$$H(X) - H(X|\text{TYPE}) = 0$$



- ▶ **Assignment #7 Deadline: 1st March Friday 11:59 PM.**
- ▶ **Live interaction #8: 3rd March Sunday 2:00 – 3:00 PM.**
- ▶ **Assignment #8 Deadline: 7th March Thursday 11:59 PM.**
- ▶ **Assignment #7, 8 Discussion: 8th March Friday 8:00 PM – 8:30 PM.**
- ▶ **Quiz #4: 8th March Friday 9:00 - 9:45 PM.**
- ▶ **Final Exam: 10th March Sunday 9:00 AM – 12:00 PM. (Please check!!)**