

CS540 Introduction to Artificial Intelligence

Lecture 5

Young Wu

Based on lecture slides by Jerry Zhu, Yingyu Liang, and Charles Dyer

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Guess the Percentage

Admin

Q1

- Guess what percentage of the students (who are here) started $P1$?
- A : 0 to 20 percent.
- B : 20 to 40 percent.
- C : 40 to 60 percent.
- **D** : 60 to 80 percent.
- E : 80 to 100 percent.

Room : CS540 E

The Percentage Admin

Q2

- Did you start $P1$?
- A :
- B : Yes.
- C :
- D : No.
- E :

62%

Sharing Solutions

Admin

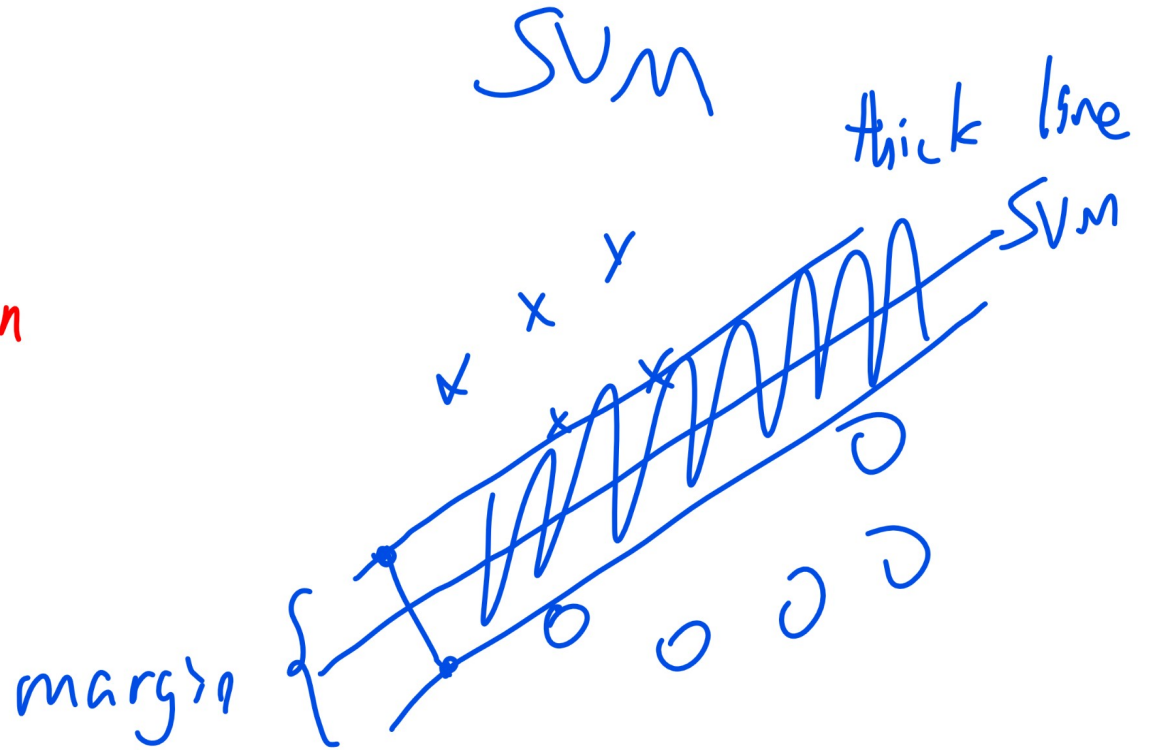
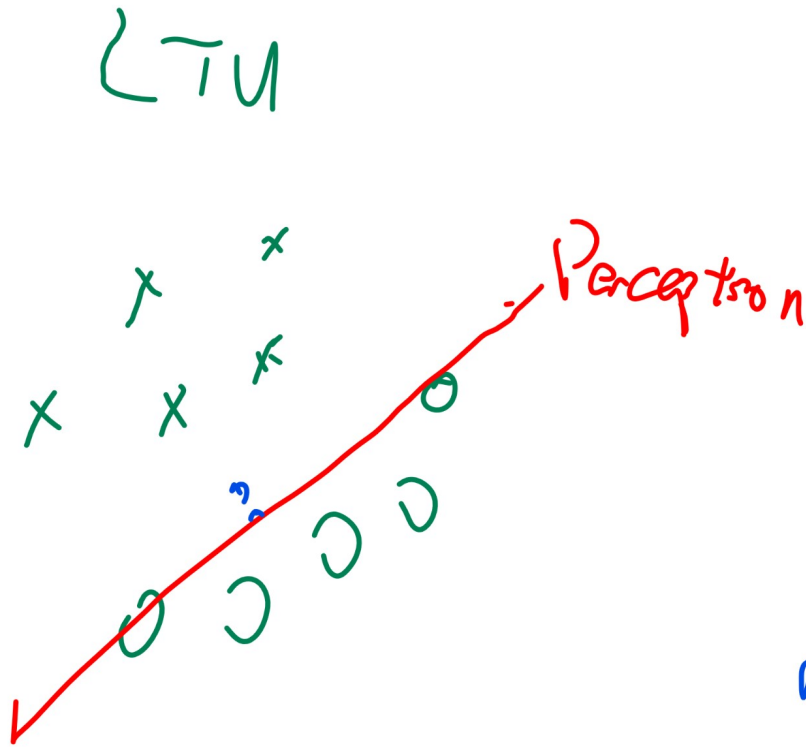
- 1 Use LaTeX (Word, Maple, MyScript etc).

$\text{sqrt}((a_1^2) / (2 \text{ pi}))$ is difficult to read compared to $\sqrt{\frac{a_1^2}{2\pi}}$.

- 2 Handwritten on tablet or on paper and photo or scan (Office Lens).
- 3 Other suggestions?
 - Remember to make it a public Piazza Note (not a Question).
 - I will either "good note" the post or leave a comment: if I leave a comment (please update your answers, reply to my comment, and remember to make the reply "unresolved" so I can see).

Maximum Margin Diagram

Motivation



SVM Weights

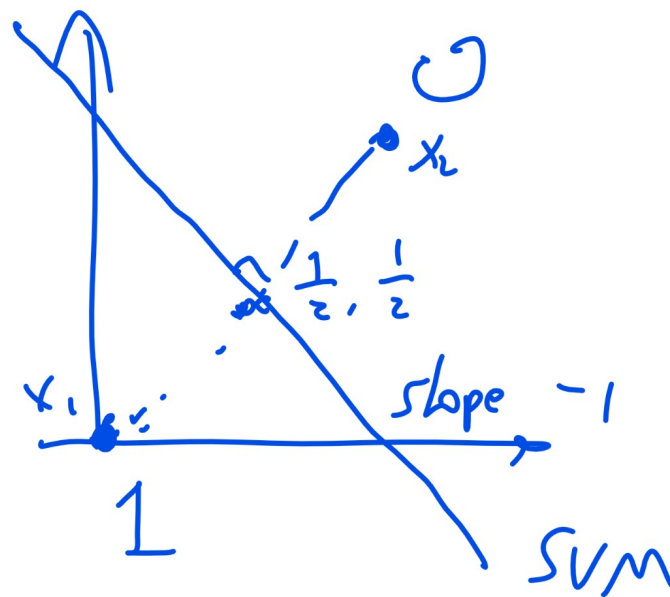
Quiz

- Find the weights w_1, w_2 for the SVM classifier

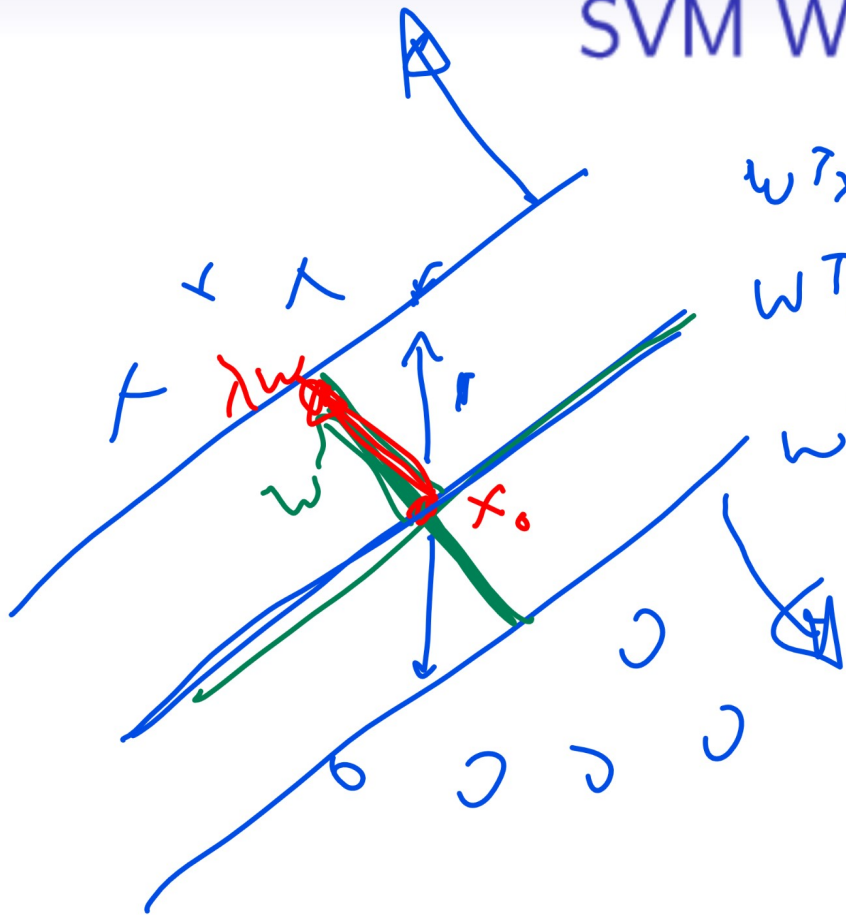
$\mathbb{1}_{\{w_1 x_{i1} + w_2 x_{i2} + 1 \geq 0\}}$ given the training data $x_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$ and

$x_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ with $y_1 = 1, y_2 = 0$.

- A: $w_1 = 0, w_2 = -2$
- B: $w_1 = -2, w_2 = 0$
- C: $w_1 = -1, w_2 = -1$**
- D: $w_1 = -2, w_2 = -2$



SVM Weights Diagram



Quiz

$$w^T x + b + 1 = 0$$

$$w^T x + b = 0$$

$$w^T x + b - 1 > 0$$

$x_0 + \lambda w$

$$w^T (x_0 - \lambda w) + b + 1 = 0$$

$$w^T (x_0 + \lambda w) + b - 1 = 0$$

$$2 \lambda w^T w = 2$$

$$\lambda = \frac{1}{w^T w}$$

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

thickness

$$= \|\lambda w\| = \lambda \|w\|$$

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

Constrained Optimization Diagram

half-margin

Definition

$$s.t. \begin{cases} w^T x_i + b + 1 \geq 0 & \text{if } y_i = 0 \\ w^T x_i + b - 1 \leq 0 & \text{if } y_i = 1 \end{cases}$$

arg max

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

arg min

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

~~$w^T w$~~

s.t.

$$(2y_i - 1)(w^T x_i + b) \leq 1$$

$$\begin{cases} y_i = 1 \Rightarrow 1 \\ y_i = 0 \Rightarrow -1 \end{cases}$$

Hard Margin SVM.

allow mistake
 ↳ there is a cost (loss)

Constrained Optimization Derivation

Definition

Soft Margin Derivation

Definition

penalty parameter

$$\min \quad \frac{1}{2} w^T w + \lambda \sum_{i=1}^n \xi_i$$

s.t.

$$(2y_i - 1)(w^T x_i + b) \leq 1 - \xi_i$$

$$\xi_i \geq 0$$

Soft Margin

Quiz

- Let $w = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ and $b = 3$. For the point $x = \begin{bmatrix} 4 \\ 5 \end{bmatrix}$, $y = 0$, what is the smallest slack variable ξ for it to satisfy the margin constraint?

$$(2y_i - 1)(w^T x_i + b) \geq 1 - \xi, \quad \xi_i \geq 0$$

$$-1(14 + 3) \geq 1 - \xi_i$$

$$\xi_i \geq 0$$

$$\xi_i \geq 18$$

$$\xi_i = 18$$



Soft Margin 2

Quiz

Q6 • Let $w = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ and $b = 3$. For the point $x = \begin{bmatrix} -4 \\ -5 \end{bmatrix}$, $y = 0$, what is the smallest slack variable ξ for it to satisfy the margin constraint?

- A : -12
- B : -10
- C : 0
- D : 10
- E : 12

$$(2y_i - 1) (x_i^T w + b) \leq 1 - \xi_i$$

$$\xi_i \geq 0$$

$$-1 (-14 + 3) \leq 1 - \xi_i$$

$$\xi_i \geq -10$$



Subgradient 1

Quiz

• Which ones are subderivatives of $\max\{x, 0\}$ at $x = 0$?

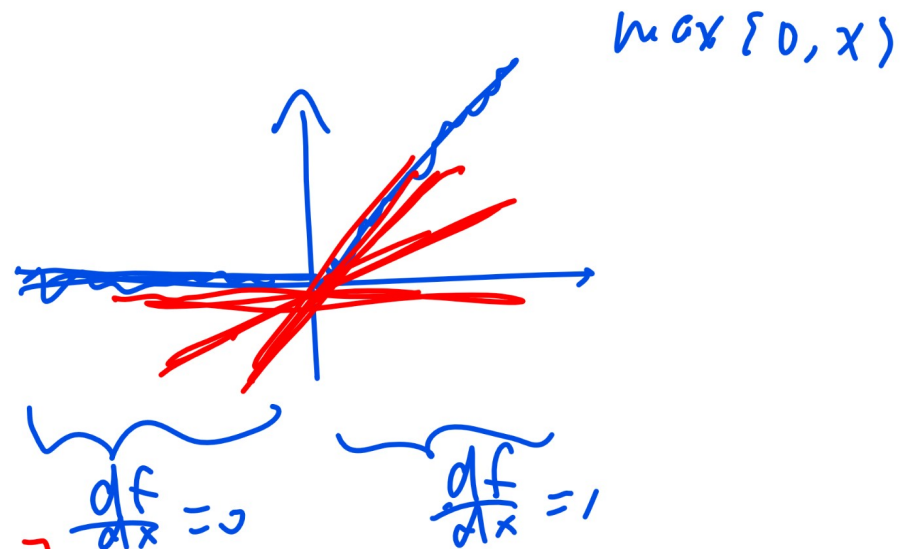
• A: -1

• B: -0.5

• C: 0

• D: 0.5

• E: 1



$$\partial \max\{x, 0\} /_0 = [0, 1]$$

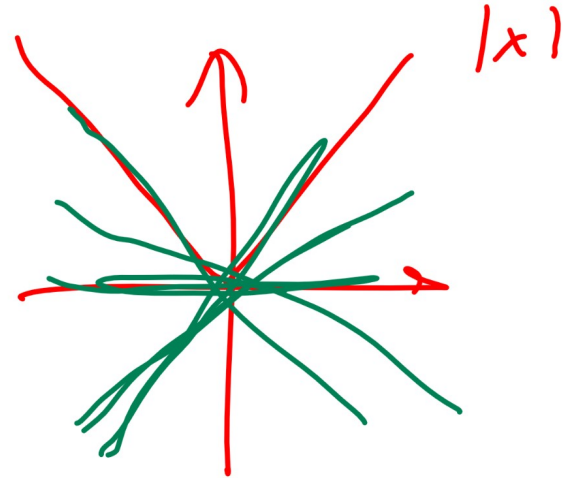
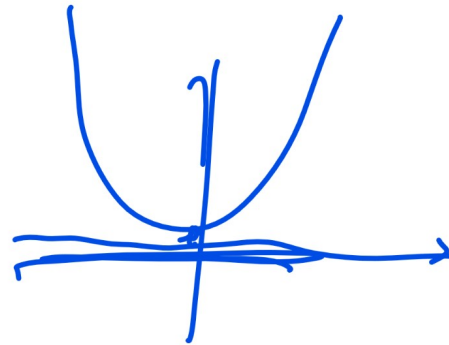
Subgradient 2

Quiz

$|x|^2$

Q7

- Which ones are subderivatives of $|x|$ at $x = 0$?
- A : -1
- B : -0.5
- C : 0
- D : 0.5
- E : 1



Subgradient Descent Step

Definition

- One possible set of subgradients with respect to w and b are the following.

$$\partial_w C \ni \lambda w - \sum_{i=1}^n (2y_i - 1) x_i \mathbb{1}_{\{(2y_i - 1)(w^T x_i + b) \geq 1\}}$$

$$\partial_b C \ni - \sum_{i=1}^n (2y_i - 1) \mathbb{1}_{\{(2y_i - 1)(w^T x_i + b) \geq 1\}}$$

- The gradient descent step is the same as usual, using one of the subgradients in place of the gradient.

Regularization Parameter

Definition

$$w \leftarrow \frac{\partial C}{\partial w} - \lambda w$$

subgrad.

$$w = w - \alpha \sum_{i=1}^n z_i \mathbb{1}_{\{z_i w^T x_i \geq 1\}} x_i - \lambda w$$

$$z_i = 2y_i - 1, i = 1, 2, \dots, n$$

$$+ \frac{1}{2} \lambda \|w\|^2$$

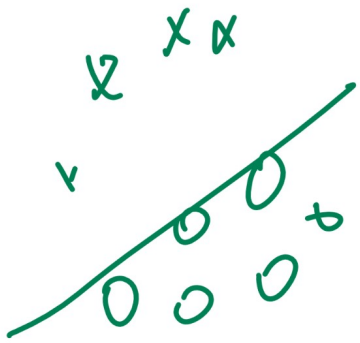
SVM

- λ is usually called the regularization parameter because it reduces the magnitude of w the same way as the parameter λ in L2 regularization.
- The stochastic subgradient descent algorithm for SVM is called PEGASOS: Primal Estimated sub-GrAdient SOLver for Svm.

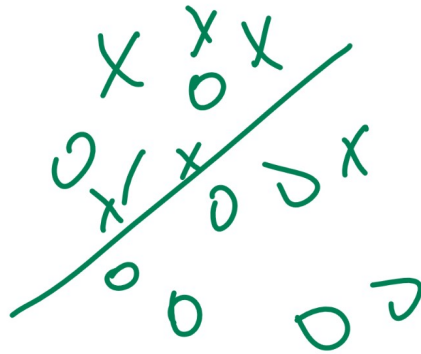
Kernel Trick 1D Diagram

Motivation

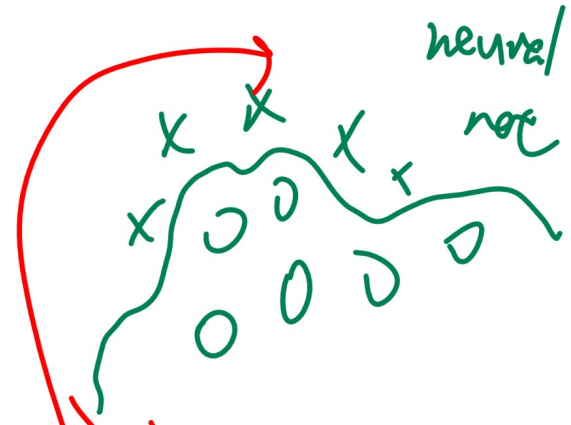
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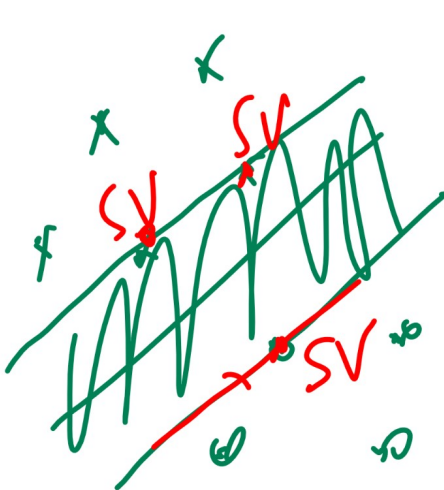
LT4



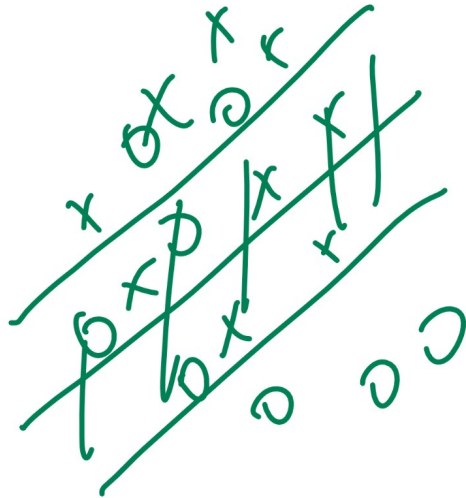
logistic



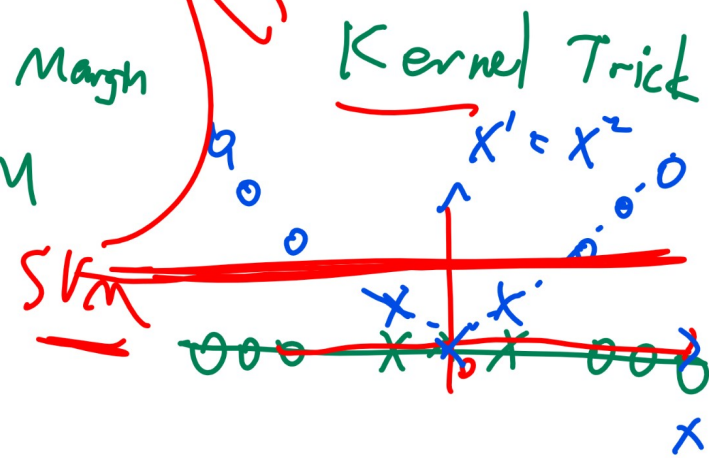
neural net



Hard Margin SVM



Soft Margin SVM



Kernelized SVM

Definition

- With a feature map φ , the SVM can be trained on new data points $\{(\varphi(x_1), y_1), (\varphi(x_2), y_2), \dots, (\varphi(x_n), y_n)\}$.
- The weights w correspond to the new features $\varphi(x_i)$.
- Therefore, test instances are transformed to have the same new features.

$$\hat{y}_i = \mathbb{1}_{\{w^T \varphi(x_i) \geq 0\}}$$

Kernel Trick for XOR

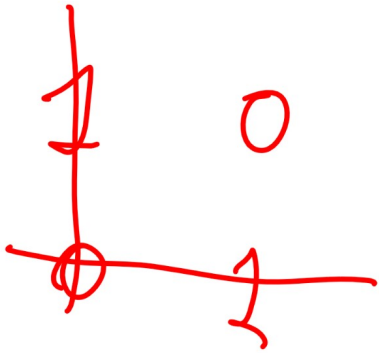
Quiz

x_1, x_2 add $x_1^2 + x_2^2$

- SVM with quadratic kernel $\varphi(x) = (x_1^2, \sqrt{2}x_1x_2, x_2^2)$ can correctly classify the following training set?

x_1	x_2	y
0	0	0
0	1	1
1	0	1
1	1	0

x_1'	x_2'	x_3'	y'
0	0	0	0
0	0	1	1
1	0	0	1
1	$\sqrt{2}$	1	0



Kernel Trick for XOR

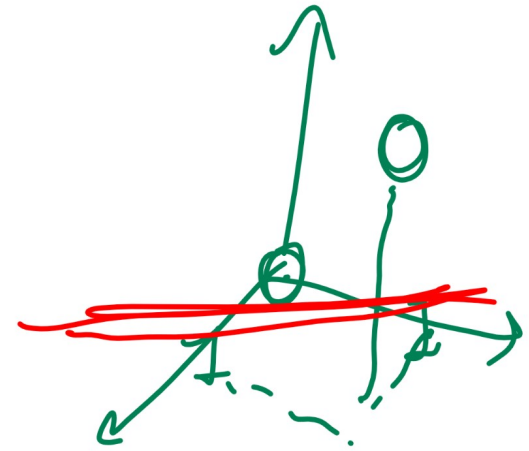
Quiz

- SVM with kernel $\varphi(x) = (x_1, x_1x_2, x_2)$ can correctly classify the following training set.

Q8

x_1	x_2	y
0	0	0
0	1	1
1	0	1
1	1	0

x_3
0
0
0
1



- A : True.
- B : False.

Kernel Matrix

Definition

- The feature map is usually represented by a $n \times n$ matrix K called the Gram matrix (or kernel matrix).

$$K_{ii'} = \varphi(x_i)^T \varphi(x_{i'})$$

$$K = \begin{bmatrix} \phi(x_1)^T \phi(x_1) \\ \phi(x_2)^T \phi(x_1) \\ \phi(x_3)^T \phi(x_1) \end{bmatrix}$$

~~# n x # n~~
n x # n

Examples of Kernel Matrix

Definition

- For example, if $\varphi(x) = (x_1^2, \sqrt{2}x_1x_2, x_2^2)$, then the kernel matrix can be simplified.

$$K_{ij'} = (x_i^T x_{j'})^2$$

*Symmetric
positive semi-definite,*

- Another example is the quadratic kernel $K_{ij'} = (x_i^T x_{j'} + 1)^2$. It can be factored to have the following feature representations.

$$\varphi(x) = (x_1^2, x_2^2, \sqrt{2}x_1x_2, \sqrt{2}x_1, \sqrt{2}x_2, 1)$$

Popular Kernels

Discussion

- Other popular kernels include the following.

① Linear kernel: $K_{ii'} = x_i^T x_{i'}$ → sum

② Polynomial kernel: $K_{ii'} = (x_i^T x_{i'} + 1)^d$

- ③ Radial Basis Function (Gaussian) kernel:

$$K_{ii'} = \exp\left(-\frac{1}{\sigma^2} (x_i - x_{i'})^T (x_i - x_{i'})\right)$$

→ $\phi^T \phi$

- Gaussian kernel has infinite-dimensional feature representations. There are dual optimization techniques to find w and b for these kernels.

Kernel Matrix

Quiz

- What is the feature vector $\phi(x)$ induced by the kernel

$(K_{ii'} = \exp(x_i + x_{i'}) + \sqrt{x_i x_{i'}} + 3?)$

$= \phi(x_i)^T \phi(x_{i'})$

$= \underbrace{e^{x_i}}_{x_i} \underbrace{e^{x_{i'}}}_{x_{i'}} + \underbrace{\sqrt{x_i}}_{x_i} \underbrace{\sqrt{x_{i'}}}_{x_{i'}} + \underbrace{\sqrt{3}}_{x_i} \underbrace{\sqrt{3}}_{x_{i'}}$

$= [e^{x_i}, \sqrt{x_i}, \sqrt{3}] \begin{bmatrix} e^{x_{i'}} \\ \sqrt{x_{i'}} \\ \sqrt{3} \end{bmatrix}$

$\phi(x) = \begin{pmatrix} e^x \\ \sqrt{x} \\ \sqrt{3} \end{pmatrix}$

Kernel Matrix 2

Quiz

Q9

- What is the feature vector $\phi(x)$ induced by the kernel

$$K_{ii'} = 4 \exp(x_i + x_{i'}) + 2x_i x_{i'}$$

$$\Rightarrow \phi(x_i)^T \phi(x_{i'})$$

- A : $(4 \exp(x), 2\sqrt{x})$
- B : $(2 \exp(x), \sqrt{2}\sqrt{x})$
- C : $(4 \exp(x), 2x)$
- D : $(2 \exp(x), \sqrt{2}x)$
- E : None of the above

$$\frac{2e^{x_i}}{x_i} \frac{2e^{x_{i'}}}{x_{i'}} + \underbrace{\sqrt{2}x_i}_{\sqrt{2}x_i} \underbrace{\sqrt{2}x_{i'}}_{\sqrt{2}x_{i'}}$$

$$\left[2e^{x_i}, \sqrt{2}x_i \right] \begin{bmatrix} 2e^{x_{i'}} \\ \sqrt{2}x_{i'} \end{bmatrix}$$

Kernel Matrix Math 2

Quiz