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#### 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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Kernel Trick

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# Guess the Percentage

- Guess what percentage of the students (who are here) started *P*1?
- 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.

Subgradient Descent

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## The Percentage

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

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# Guess the Percentage

- Guess what percentage of the students (who are here) submitted *P*1?
- 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.

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## Sharing Solutions

Use LaTeX (Word, Maple, MyScript etc).

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

- Handwritten on tablet or on paper and photo or scan (Office Lens).
- 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).

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# Shared Solution List and Feedback

- The shared solutions are listed in the Main post on Piazza.
- Thank you for the feedback! I posted the responses to those in the Feedback post on Piazza.
- Question: can you see the labels in the 3D diagrams?
- *A* : Yes.
- B : Cannot see label.
- C : Cannot see anything.

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## Maximum Margin Diagram

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## SVM Weights

• Find the weights  $w_1, w_2$  for the SVM classifier  $\mathbb{1}_{\{w_1x_{i1}+w_2x_{i2}+1\ge 0\}}$  given the training data  $x_1 = \begin{bmatrix} 0\\0 \end{bmatrix}$  and  $x_2 = \begin{bmatrix} 1\\1 \end{bmatrix}$  with  $y_1 = 1, y_2 = 0$ . •  $A: w_1 = 0, w_2 = -2$ •  $B: w_1 = -2, w_2 = 0$ •  $C: w_1 = -1, w_2 = -1$ •  $D: w_1 = -2, w_2 = -2$ 

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# SVM Weights Diagram

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## SVM Weights

- Fall 2005 Final Q15 and Fall 2006 Final Q15
- Find the weights  $w_1, w_2$  for the SVM classifier  $\mathbb{1}_{\{w_1 x_{i1}+w_2 x_{i2}+1 \ge 0\}}$  given the training data  $x_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, x_2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, x_3 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$  with  $y_1 = 1, y_2 = y_3 = 0$ . •  $A : w_1 = -1.5, w_2 = -1.5$ •  $B : w_1 = -2, w_2 = -1.5$ •  $C : w_1 = -1.5, w_2 = -2$ •  $D : w_1 = -2, w_2 = -2$ •  $E : w_1 = -4, w_2 = -4$

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# SVM Weights Diagram

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## Constrained Optimization Diagram

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## Constrained Optimization Derivation

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# Soft Margin Diagram

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## Soft Margin Derivation

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### SVM Formulations

• Hard margin:  $\min_{w} \frac{1}{2} w^{T} w \text{ such that } (2y_{i} - 1) \left( w^{T} x_{i} + b \right) \ge 1, i = 1, 2, ..., n$ 

Soft margin:

$$\min_{w} \frac{\lambda}{2} w^{T} w + \frac{1}{n} \sum_{i=1}^{n} \max\left\{0, 1 - (2y_{i} - 1) \left(w^{T} x_{i} + b\right)\right\}$$

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# Soft Margin

• 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  $\xi$  for it to satisfy the margin constraint?

$$(2y_i-1)\left(w^Tx_i+b\right) \ge 1-\xi_i, \xi_i \ge 0$$

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# Soft Margin 2

• 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  $\xi$  for it to satisfy the margin constraint?

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

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### Subgradient Descent

$$\min_{w} \frac{\lambda}{2} w^{T} w + \frac{1}{n} \sum_{i=1}^{n} \max\left\{0, 1 - (2y_{i} - 1)\left(w^{T} x_{i} + b\right)\right\}$$

- The gradient for the above expression is not defined at points with  $1 (2y_i 1) (w^T x_i + b) = 0.$
- Subgradient can be used instead of a gradient.

Subgradient Descent

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# Subgradient 1

- Which ones are subderivatives of max {x, 0} at x = 0?
- A : −1
- *B* : −0.5
- C : 0
- *D* : 0.5
- E : 1

Subgradient Descent

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# Subgradient 2

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

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#### Subgradient Descent Step Definition

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

$$\partial_{w} C \ni \lambda w - \sum_{i=1}^{n} (2y_{i} - 1) x_{i} \mathbb{1}_{\{(2y_{i} - 1)(w^{T}x_{i} + b) \ge 1\}}$$
$$\partial_{b} C \ni - \sum_{i=1}^{n} (2y_{i} - 1)) \mathbb{1}_{\{(2y_{i} - 1)(w^{T}x_{i} + b) \ge 1\}}$$

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

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## Regularization Parameter

$$w = w - \alpha \sum_{i=1}^{n} z_i \mathbb{1}_{\{z_i w \tau_{x_i \ge 1}\}} x_i - \lambda w$$
$$z_i = 2y_i - 1, i = 1, 2, ..., n$$

- 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.

Subgradient Descent

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## Kernel Trick 1D Diagram

Subgradient Descent

Kernel Trick

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# Kernelized SVM

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

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

Subgradient Descent

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# Kernel Trick for XOR

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

<i>x</i> <sub>1</sub>	<i>x</i> <sub>2</sub>	y
0	0	0
0	1	1
1	0	1
1	1	0

Kernel Trick

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## Kernel Trick for XOR

 SVM with kernel φ(x) = (x<sub>1</sub>, x<sub>1</sub>x<sub>2</sub>, x<sub>2</sub>) can correctly classify the following training set.

<i>x</i> <sub>1</sub>	<i>x</i> <sub>2</sub>	y
0	0	0
0	1	1
1	0	1
1	1	0

- *A* : True.
- B : False.

Subgradient Descent

Kernel Trick

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#### Kernel Matrix Definition

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

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

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#### 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.

$$K_{ii'} = \left(x_i^T x_{i'}\right)^2$$

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

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

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## Examples of Kernel Matrix Derivation

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### Popular Kernels

• Other popular kernels include the following.

• Linear kernel: 
$$K_{ii'} = x_i^T x_{i'}$$

- **2** Polynomial kernel:  $K_{ii'} = (x_i^T x_{i'} + 1)^d$
- **3** Radial Basis Function (Gaussian) kernel:  $K_{ii'} = \exp\left(-\frac{1}{\sigma^2} (x_i - x_{i'})^T (x_i - x_{i'})\right)$
- Gaussian kernel has infinite-dimensional feature representations. There are dual optimization techniques to find *w* and *b* for these kernels.

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## Kernel Matrix

• What is the feature vector  $\varphi(x)$  induced by the kernel  $K_{ii'} = \exp(x_i + x_{i'}) + \sqrt{x_i x_{i'}} + 3?$ 

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# Kernel Matrix Math

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## Kernel Matrix 2

- What is the feature vector  $\varphi(x)$  induced by the kernel  $K_{ii'} = 4 \exp(x_i + x_{i'}) + 2x_i x_{i'}?$
- $A: (4 \exp(x), 2\sqrt{x})$
- $B: \left(2\exp\left(x\right), \sqrt{2}\sqrt{x}\right)$
- $C: (4 \exp(x), 2x)$
- $D: (2 \exp(x), \sqrt{2}x)$
- E : None of the above

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#### Kernel Matrix Math 2 <sub>Quiz</sub>