Subgradient Descent

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### CS540 Introduction to Artificial Intelligence Lecture 5

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

June 6, 2022

Subgradient Descent

Kernel Trick

## Guess the Percentage

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## The Percentage



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## Guess the Percentage

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## Sharing Solutions

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## Shared Solution List and Feedback

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## Maximum Margin Diagram

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# SVM Weights

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# SVM Weights Diagram

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# SVM Weights

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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

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# Soft Margin

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### Soft Margin 2 <sub>Quiz</sub>

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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.

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# Subgradient 1

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# Subgradient 2

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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.

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# Kernel Trick 1D Diagram

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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.

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

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# Kernel Trick for XOR

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# Kernel Trick for XOR

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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 Quiz

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# Kernel Matrix Math

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

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