CS540 Introduction to Artificial Intelligence
Lecture 5

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

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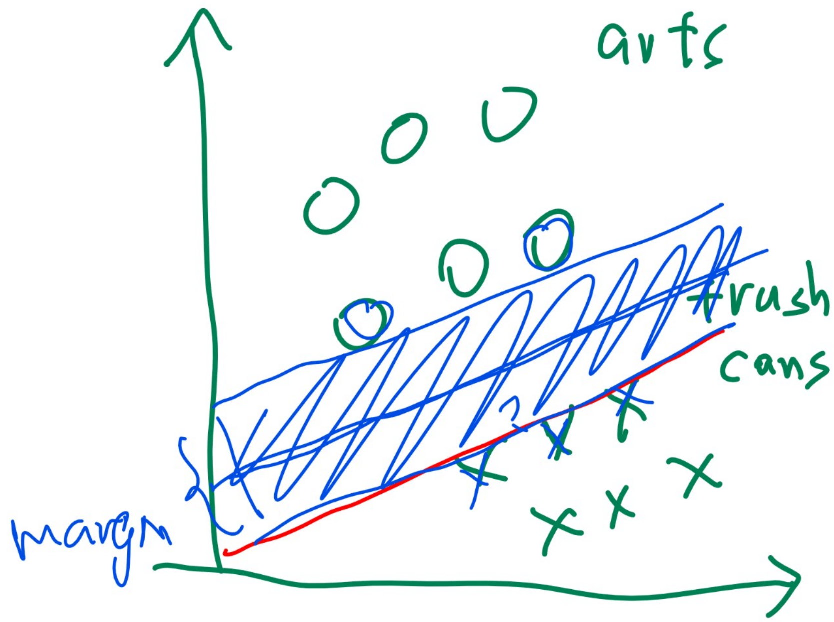
Maximum Margin Diagram

Motivation



min mistake

WW84 max margin

Margin and Support Vectors

Motivation

- The perceptron algorithm finds any line (w, b) that separates the two classes.

$$\hat{y}_i = \mathbb{1}_{\{w^T x_i + b \geqslant 0\}}$$

- The margin is the maximum width (thickness) of the line before hitting any data point.
- The instances that the thick line hits are called support vectors.
- The model that finds the line that separates the two classes with the widest margin is call support vector machine (SVM).

Support Vector Machine

Description

- The problem is equivalent to minimizing the squared norm of the weights $\|w\|^2 = w^T w$ subject to the constraint that every instance is classified correctly (with the margin).
- Use subgradient descent to find the weights and the bias.

Finding the Margin

Definition

- Define two planes: plus plane $w^T x + b = 1$ and minus plane $w^T x + b = -1$.
- The distance between the two planes is $\frac{2}{\sqrt{w^T w}}$.
- If all of the instances with $y_i = 1$ are above the plus plane and all of the instances with $y_i = 0$ are below the minus plane, then the margin is $\frac{2}{\sqrt{w^T w}}$.

Constrained Optimization Derivation

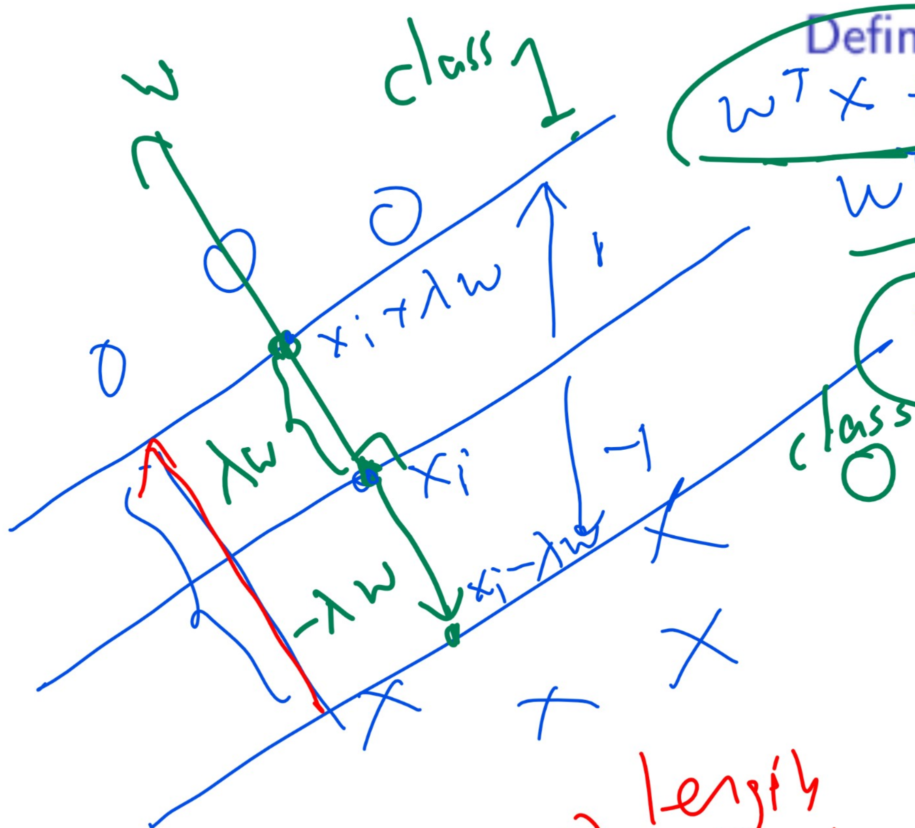
Definition

$w^Tx + b = +1$ ← plus line

$w_2 = 1$

$w^Tx + b = 0$

$w^Tx + b = -1$ ← minus line



$\cancel{w^T}(x_i + \lambda w) + \cancel{b} = 1$

$\cancel{w^T}(x_i - \lambda w) + \cancel{b} = -1$

$2\lambda w^T w = 2$

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

margin $2\lambda \|w\|$ → length of w → $\sqrt{w^Tw}$

$$\frac{2}{w^Tw}\sqrt{w^Tw} = \boxed{\frac{2}{\sqrt{w^Tw}}}$$

Constrained Optimization

Definition

- The goal is to maximize the margin subject to the constraint that the plus plane and the minus plane separates the instances with $y_i = 0$ and $y_i = 1$.

$$\max_w \frac{2}{\sqrt{w^T w}} \text{ such that } \begin{cases} (w^T x_i + b) \leqslant -1 & \text{if } y_i = 0 \\ (w^T x_i + b) \geqslant 1 & \text{if } y_i = 1 \end{cases}, i = 1, 2, ..., n$$

- The two constrains can be combined.

$$\max_w \frac{2}{\sqrt{w^T w}} \text{ such that } (2y_i - 1)\left(w^T x_i + b\right) \geqslant 1, i = 1, 2, ..., n$$

$y_i = 0 \longrightarrow -1$

$y_i = 1 \longrightarrow 1$

Hard Margin SVM

Definition

max $\frac{1}{x}$ $\sqrt{x}$ x

$$\max_{w} \frac{2}{\sqrt{w^T w}} \text{ such that } (2y_i - 1)\left(w^T x_i + b\right) \geqslant 1, i = 1, 2, ..., n$$

Same w

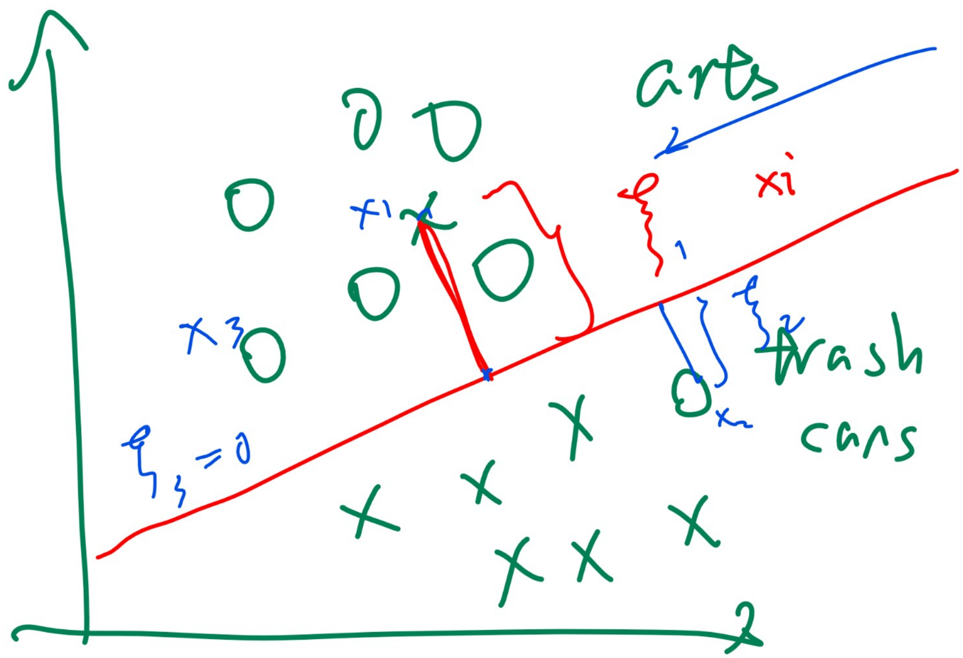
- This is equivalent to the following minimization problem, called hard margin SVM.

min x

$$\min_{w} \frac{1}{2} w^T w \text{ such that } (2y_i - 1)\left(w^T x_i + b\right) \geqslant 1, i = 1, 2, ..., n$$

Soft Margin Diagram

Definition



Soft Margin

Definition

- To allow for mistakes classifying a few instances, slack variables are introduced.
- The cost of violating the margin is given by some constant $\frac{1}{\lambda}$.
- Using slack variables ξ_i, the problem can be written as the following.

ksai

margin

Cost from mistakes

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

average mistake

such that $(2y_i - 1)\left(w^T x_i + b\right) \geqslant 1 - \xi_i, \boxed{\xi_i \geqslant 0,} i = 1, 2, ..., n$

Soft Margin SVM

Definition

as small as possible

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

such that $(2y_i - 1)\left(w^T x_i + b\right) \geqslant 1 - \xi_i, \xi_i \geqslant 0, i = 1, 2, ..., n$

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

- This is equivalent to the following minimization problem, called soft margin SVM.

$$\min_{w} \frac{\lambda}{2} w^T w + \frac{1}{n} \sum_{i=1}^{n} \underbrace{\max\left\{0, 1 - (2y_i - 1)\left(w^T x_i + b\right)\right\}}_{\xi_i}$$

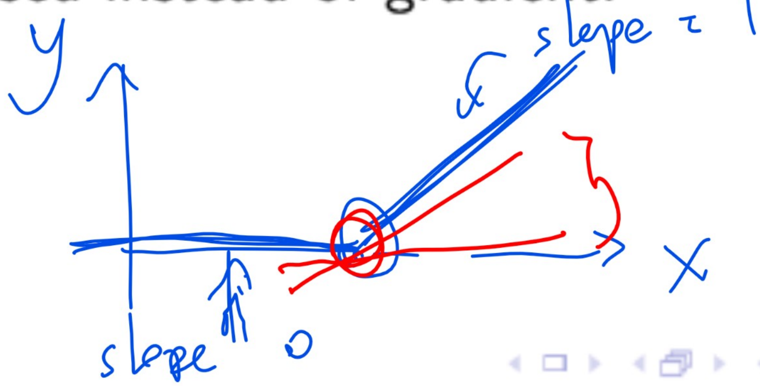
Subgradient Descent

Definition

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

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

$y = \max(0, x)$



Subgradient

- The subderivative at a point of a convex function in one dimension is the set of slopes of the lines that are tangent to the function at that point.
- The subgradient is the version for higher dimensions.
- The subgradient $\partial f(x)$ is formally defined as the following set.

$$\partial f(x) = \left\{ v : f(x') \geqslant f(x) + v^T (x' - x) \ \forall\, x' \right\}$$

Subgradient Descent Step

Definition

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

∈

set   is an element of

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

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

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

Class Notation and Bias Term

Definition

- Usually, for SVM, the bias term is not included and updated. Also, the classes are -1 and +1 instead of 0 and 1. Let the labels be $z_i \in \{-1, +1\}$ instead of $y_i \in \{0, 1\}$. The gradient steps are usually written the following way.

$$\boxed{w = (1 - \lambda)\, w - \alpha \sum_{i=1}^{n} z_i \mathbb{1}_{\{z_i w^T x_i \geqslant 1\}} x_i}$$

$$z_i = 2y_i - 1, i = 1, 2, ..., n$$

+1, -1

$\sum (y_i - a_i)\, x_i$

Regularization Parameter

Definition

$\|w\|^2 \to w^T w$

L2

λw

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

$$z_i = 2y_i - 1, i = 1, 2, ..., n$$

- 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.

PEGASOS Algorithm

Algorithm

- Inputs: instances: $\{x_i\}_{i=1}^{n}$ and $\{z_i = 2y_i - 1\}_{i=1}^{n}$
- Outputs: weights: $\{w_j\}_{j=1}^{m}$
- Initialize the weights.

$$w_j \sim \text{ Unif } [0, 1]$$

- Randomly permute (shuffle) the training set and performance subgradient descent for each instance i.

$$w = (1 - \lambda)\, w - \alpha z_i \mathbb{1}_{\{z_i w^T x_i \geqslant 1\}} x_i$$

- Repeat for a fixed number of iterations.

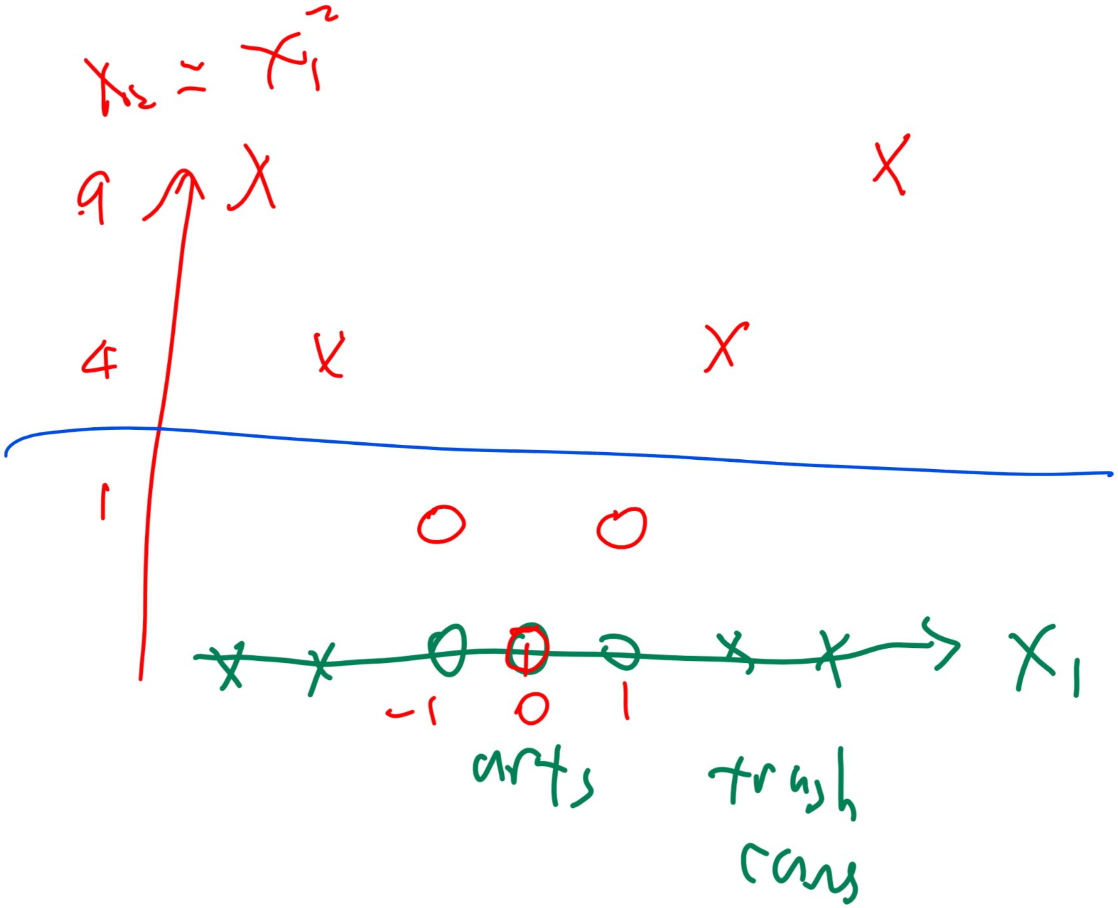
Kernel Trick

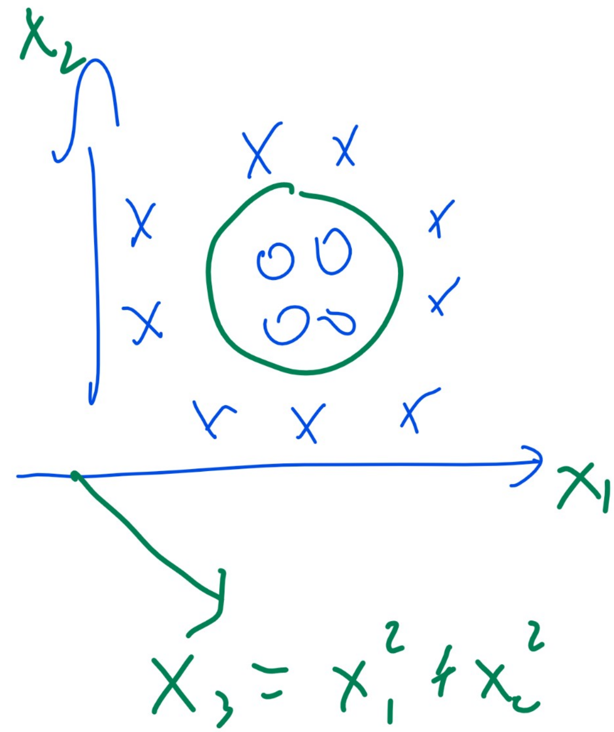
Discussion

- If the classes are not linearly separable, more features can be created.
- For example, a 1 dimensional x can be mapped to $\varphi(x) = (x, x^2)$.
- Another example is to map a 2 dimensional (x_1, x_2) to $\varphi(x = (x_1, x_2)) = (x_1^2, \sqrt{2}x_1x_2, x_2^2)$.

Kernel Trick 1D Diagram

Discussion





Kernelized SVM

Discussion

fee

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

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

Kernel Matrix

Discussion

NOT # features

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

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

\# of instances

2 instances

$$K = \begin{bmatrix} \varphi(x_1)^T\varphi(x_1) & \varphi(x_1)^T\varphi(x_2) \\ & \varphi(x_2)^T\varphi(x_2) \end{bmatrix}$$

2

Examples of Kernel Matrix

Discussion

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

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

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

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

Kernel Matrix Characterization

Discussion

- A matrix K is kernel (Gram) matrix if and only if it is symmetric positive semidefinite.
- Positive semidefiniteness is equivalent to having non-negative eigenvalues.

Popular Kernels

Discussion

- Other popular kernels include the following.

1. Linear kernel: $K_{ii'} = x_i^T x_{i'}$ SVm
2. Polynomial kernel: $K_{ii'} = \left(x_i^T x_{i'} + 1\right)^d$
3. Radial Basis Function (Gaussian) kernel:
$$K_{ii'} = \exp\left(-\frac{1}{\sigma^2}\left(x_i - x_{i'}\right)^T\left(x_i - x_{i'}\right)\right)$$

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