

CS840a
Learning and Computer Vision
Prof. Olga Veksler

Lecture 7

SVM

Some pictures from C. Burges

SVM

- Said to start in 1979 with Vladimir Vapnik's paper
- Major developments throughout 1990's
- Elegant theory
 - Has good generalization properties
- Have been applied to diverse problems very successfully in the last 10-15 years
- One of the most important developments in pattern recognition in the last 15 years

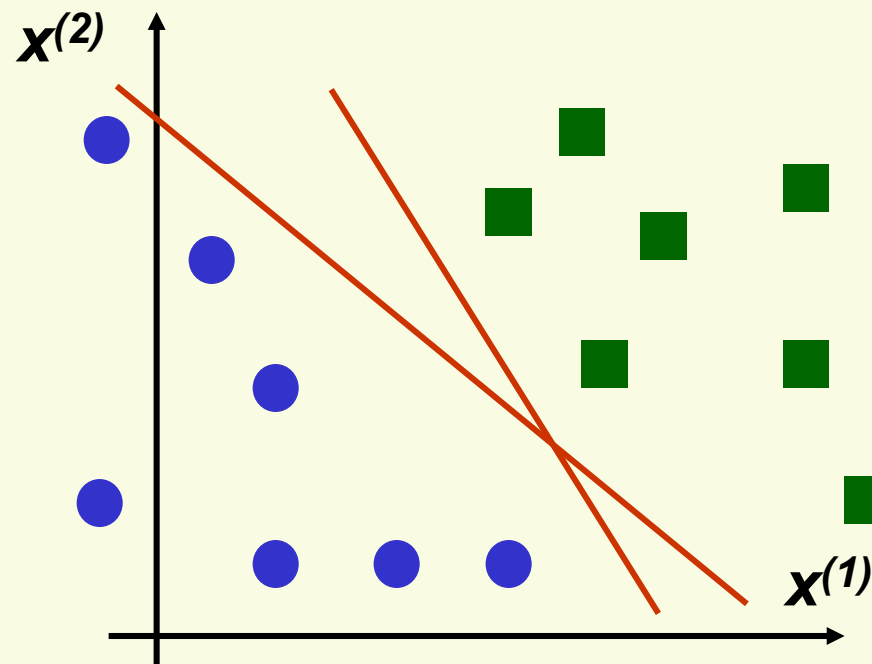


Linear Discriminant Functions

- A discriminant function is linear if it can be written as

$$g(\mathbf{x}) = \mathbf{w}^t \mathbf{x} + w_0$$

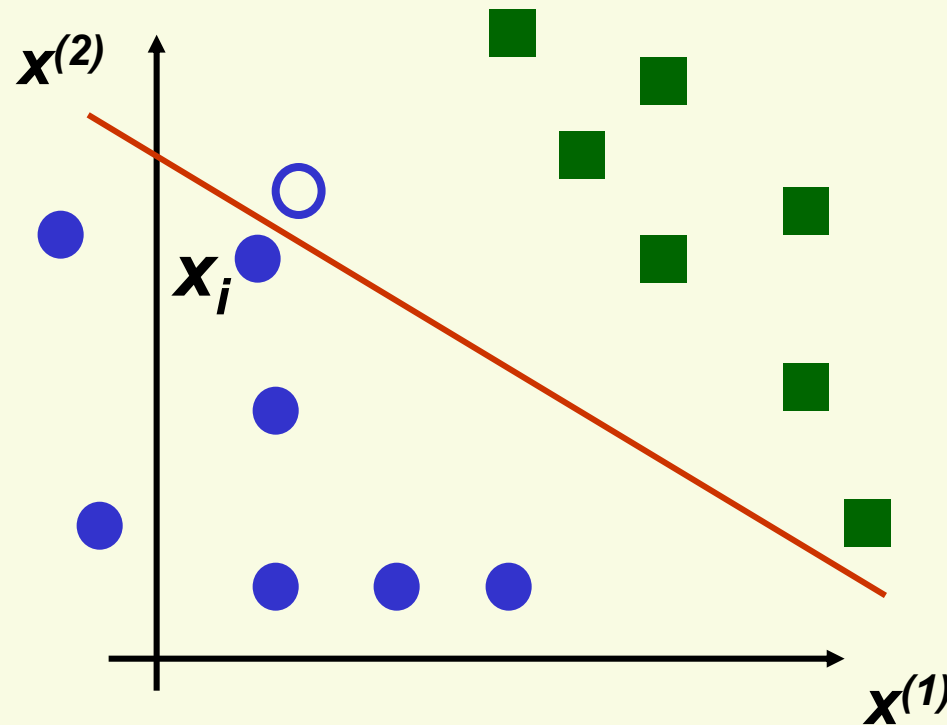
$g(\mathbf{x}) > 0 \Rightarrow \mathbf{x} \in \text{class 1}$
$g(\mathbf{x}) < 0 \Rightarrow \mathbf{x} \in \text{class 2}$



- which separating hyperplane should we choose?

Linear Discriminant Functions

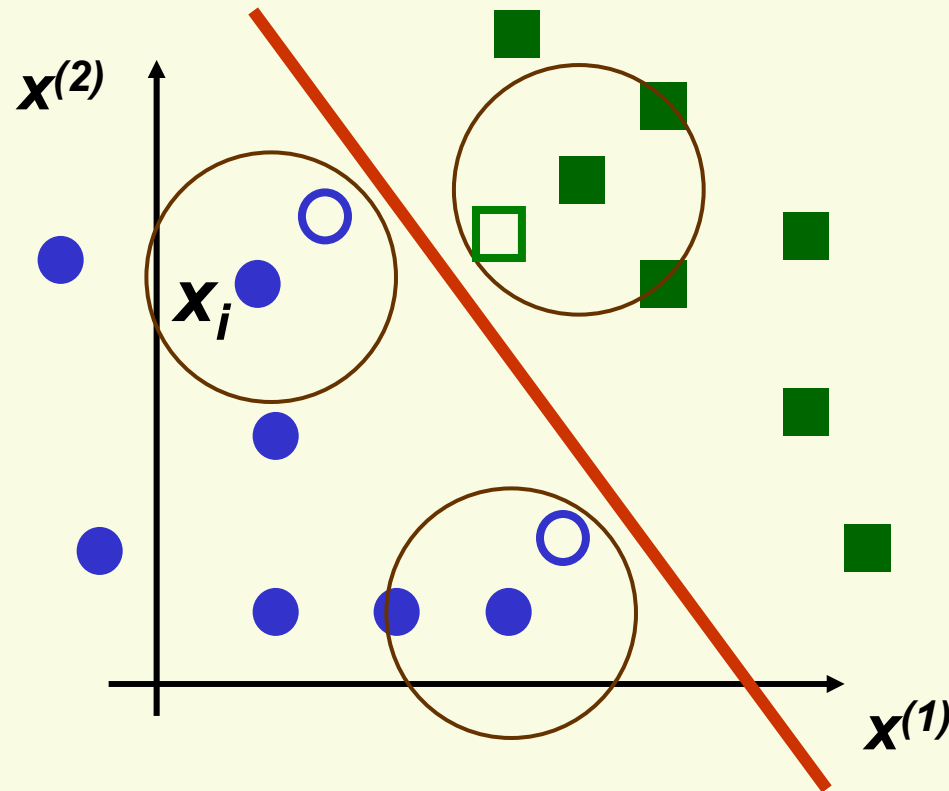
- Training data is just a subset of all possible data
- Suppose hyperplane is close to sample \mathbf{x}_i
- If we see new sample close to sample i , it is likely to be on the wrong side of the hyperplane



- Poor generalization (performance on unseen data)

Linear Discriminant Functions

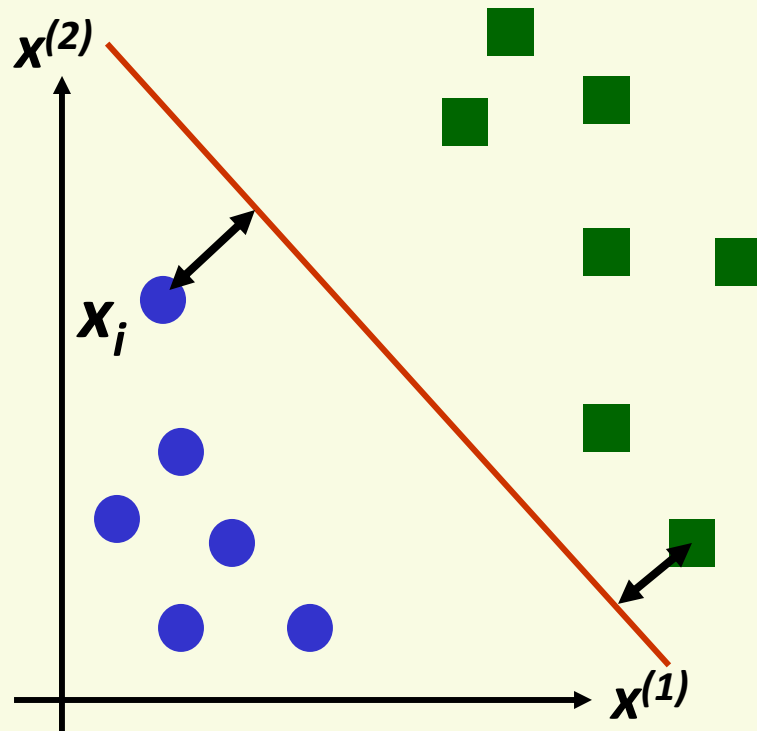
- Hyperplane as far as possible from any sample



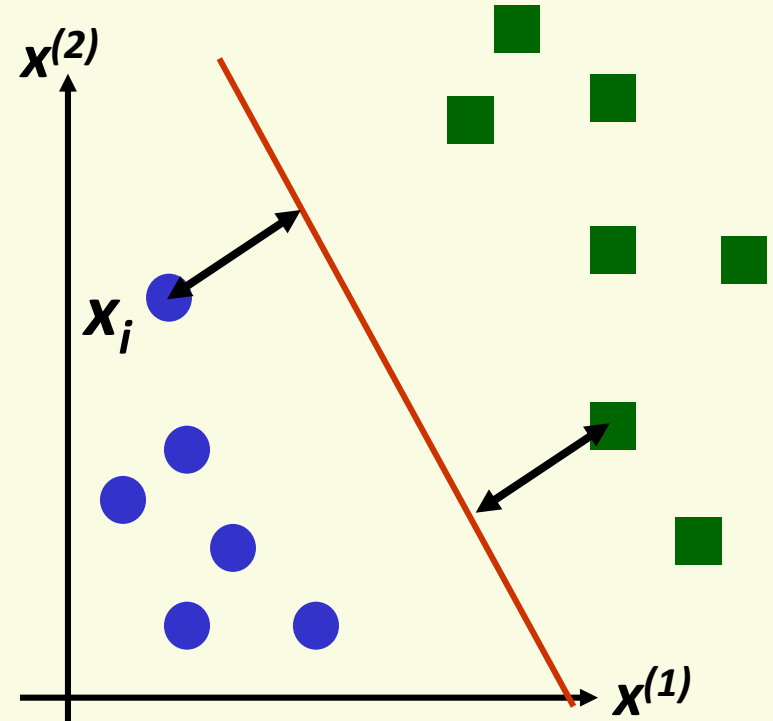
- New samples close to old samples will be classified correctly
- Good generalization

SVM

- Idea: maximize distance to the closest example



smaller distance

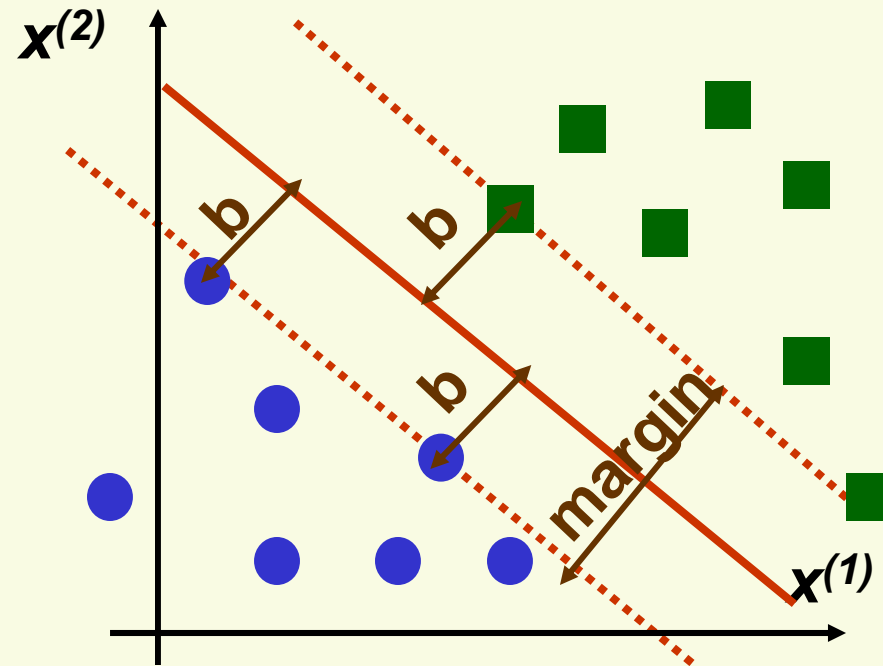


larger distance

- For the optimal hyperplane
 - distance to the closest negative example = distance to the closest positive example

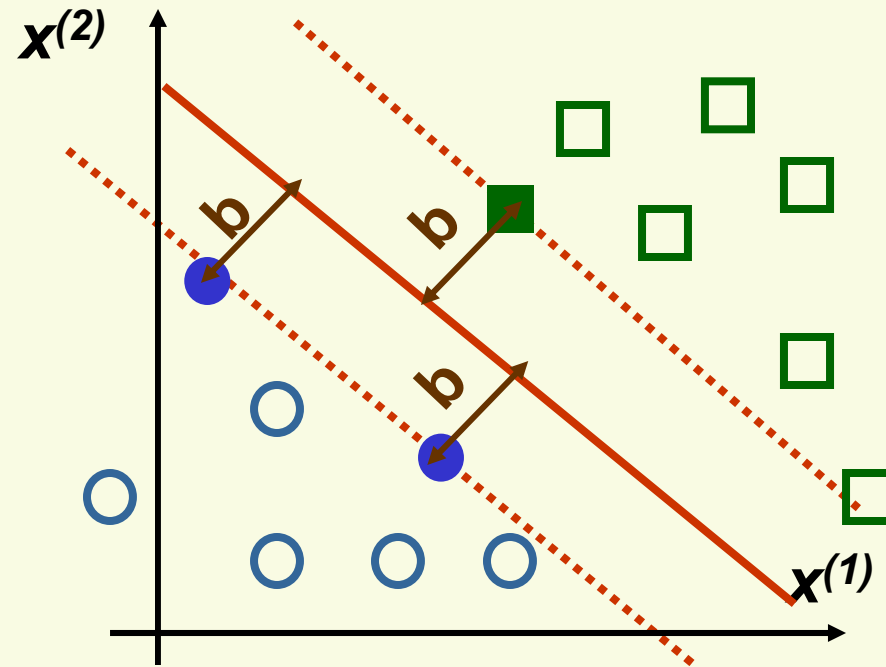
SVM: Linearly Separable Case

- SVM: maximize the *margin*



- *margin* is twice the absolute value of distance b of the closest example to the separating hyperplane
- Better generalization (performance on test data)
 - in practice
 - and in theory

SVM: Linearly Separable Case



- **Support vectors** are samples closest to separating hyperplane
 - they are the most difficult patterns to classify
 - Optimal hyperplane is completely defined by support vectors
 - of course, we do not know which samples are support vectors without finding the optimal hyperplane

SVM: Formula for the Margin

- $g(\mathbf{x}) = \mathbf{w}^t \mathbf{x} + w_0$
- absolute distance between \mathbf{x} and the boundary $g(\mathbf{x}) = 0$

$$\frac{|\mathbf{w}^t \mathbf{x} + w_0|}{\|\mathbf{w}\|}$$

- distance is unchanged for hyperplane

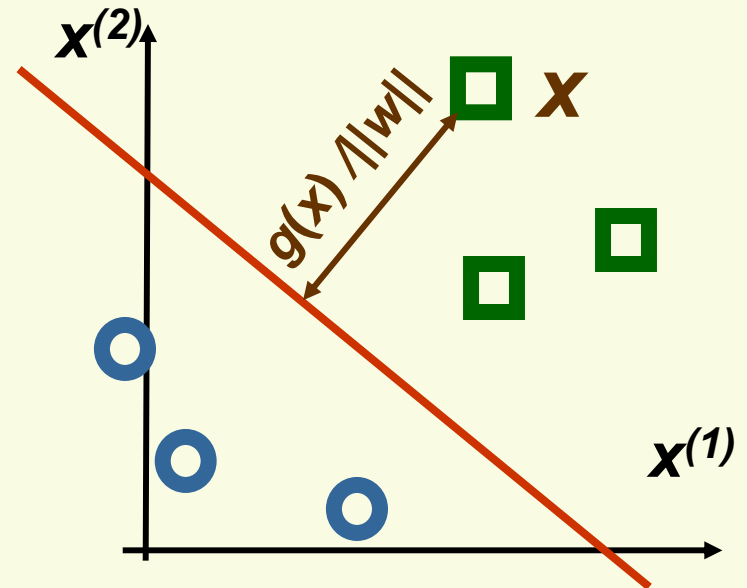
$$g_1(\mathbf{x}) = \alpha g(\mathbf{x})$$

$$\frac{|\alpha \mathbf{w}^t \mathbf{x} + \alpha w_0|}{\|\alpha \mathbf{w}\|} = \frac{|\mathbf{w}^t \mathbf{x} + w_0|}{\|\mathbf{w}\|}$$

- Let \mathbf{x}_i be an example closest to the boundary. Set

$$|\mathbf{w}^t \mathbf{x}_i + w_0| = 1$$

- Now the largest margin hyperplane is unique



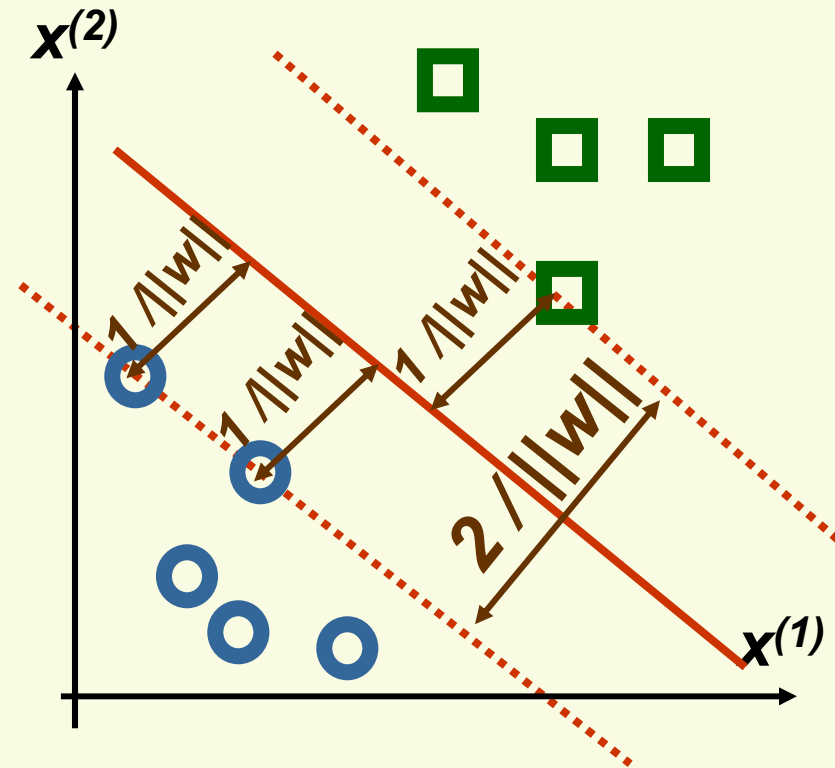
SVM: Formula for the Margin

- For uniqueness, set $|\mathbf{w}^t \mathbf{x}_i + \mathbf{w}_0| = 1$ for any example \mathbf{x}_i closest to the boundary
- now distance from closest sample \mathbf{x}_i to $g(\mathbf{x}) = 0$ is

$$\frac{|\mathbf{w}^t \mathbf{x}_i + \mathbf{w}_0|}{\|\mathbf{w}\|} = \frac{1}{\|\mathbf{w}\|}$$

- Thus the margin is

$$m = \frac{2}{\|\mathbf{w}\|}$$



SVM: Optimal Hyperplane

- Maximize margin $m = \frac{2}{\|\mathbf{w}\|}$
- subject to constraints
$$\begin{cases} \mathbf{w}^t \mathbf{x}_i + \mathbf{w}_0 \geq 1 & \text{if } \mathbf{x}_i \text{ is positive example} \\ \mathbf{w}^t \mathbf{x}_i + \mathbf{w}_0 \leq -1 & \text{if } \mathbf{x}_i \text{ is negative example} \end{cases}$$
- Let $\begin{cases} \mathbf{z}_i = 1 & \text{if } \mathbf{x}_i \text{ is positive example} \\ \mathbf{z}_i = -1 & \text{if } \mathbf{x}_i \text{ is negative example} \end{cases}$
- Can convert our problem to

$$\begin{aligned} & \text{minimize } J(\mathbf{w}) = \frac{1}{2} \|\mathbf{w}\|^2 \\ & \text{constrained to } \mathbf{z}_i (\mathbf{w}^t \mathbf{x}_i + \mathbf{w}_0) \geq 1 \quad \forall i \end{aligned}$$

- $J(\mathbf{w})$ is a quadratic function, thus there is a single global minimum

SVM: Optimal Hyperplane

- Use Kuhn-Tucker theorem to convert our problem to:

$$\begin{aligned} \text{maximize} \quad & L_D(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j \mathbf{z}_i \mathbf{z}_j \mathbf{x}_i^t \mathbf{x}_j \\ \text{constrained to} \quad & \alpha_i \geq 0 \quad \forall i \quad \text{and} \quad \sum_{i=1}^n \alpha_i \mathbf{z}_i = \mathbf{0} \end{aligned}$$

- $\alpha = \{\alpha_1, \dots, \alpha_n\}$ are new variables, one for each sample
- Can rewrite $L_D(\alpha)$ using n by n matrix \mathbf{H} :

$$L_D(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix}^t \mathbf{H} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix}$$

- where the value in the i th row and j th column of \mathbf{H} is

$$\mathbf{H}_{ij} = \mathbf{z}_i \mathbf{z}_j \mathbf{x}_i^t \mathbf{x}_j$$

SVM: Optimal Hyperplane

- Use Kuhn-Tucker theorem to convert our problem to:

$$\begin{aligned} \text{maximize} \quad & L_D(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j z_i z_j \mathbf{x}_i^t \mathbf{x}_j \\ \text{constrained to} \quad & \alpha_i \geq 0 \quad \forall i \quad \text{and} \quad \sum_{i=1}^n \alpha_i z_i = 0 \end{aligned}$$

- $\alpha = \{\alpha_1, \dots, \alpha_n\}$ are new variables, one for each sample
- $L_D(\alpha)$ can be optimized by quadratic programming
- $L_D(\alpha)$ formulated in terms of α
 - depends on \mathbf{w} and \mathbf{w}_0

SVM: Optimal Hyperplane

- After finding the optimal $\alpha = \{\alpha_1, \dots, \alpha_n\}$
 - For every sample i , one of the following must hold
 - $\alpha_i = 0$ (sample i is not a support vector)
 - $\alpha_i \neq 0$ and $\mathbf{z}_i(\mathbf{w}^t \mathbf{x}_i + \mathbf{w}_0 - \mathbf{1}) = \mathbf{0}$ (sample i is support vector)
 - can find \mathbf{w} using
$$\mathbf{w} = \sum_{i=1}^n \alpha_i \mathbf{z}_i \mathbf{x}_i$$
 - can solve for \mathbf{w}_0 using any $\alpha_i > 0$ and
$$\mathbf{w}_0 = \frac{\mathbf{1}}{\mathbf{z}_i} - \mathbf{w}^t \mathbf{x}_i$$
 and $\alpha_i [\mathbf{z}_i (\mathbf{w}^t \mathbf{x}_i + \mathbf{w}_0) - \mathbf{1}] = \mathbf{0}$
- Final discriminant function:

$$g(\mathbf{x}) = \left(\sum_{\mathbf{x}_i \in \mathcal{S}} \alpha_i \mathbf{z}_i \mathbf{x}_i \right)^t \mathbf{x} + \mathbf{w}_0$$

- where \mathcal{S} is the set of support vectors

$$\mathcal{S} = \{\mathbf{x}_i \mid \alpha_i \neq \mathbf{0}\}$$

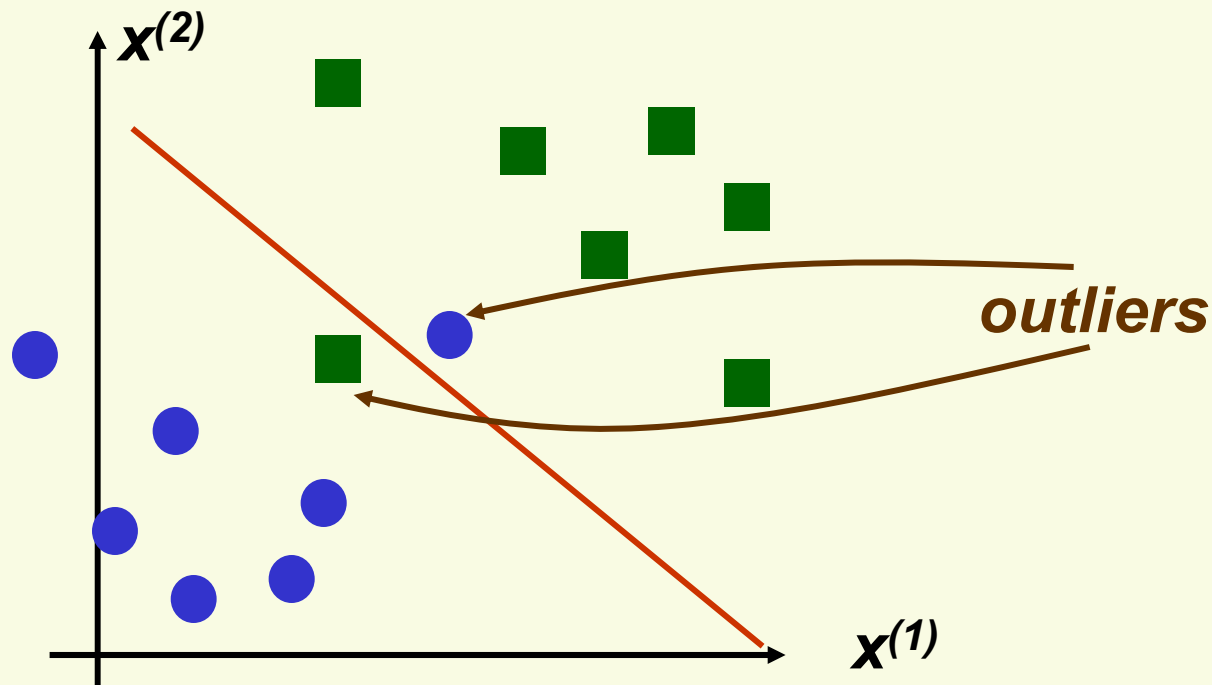
SVM: Optimal Hyperplane

$$\begin{aligned} \text{maximize} \quad & L_D(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j z_i z_j \mathbf{x}_i^t \mathbf{x}_j \\ \text{constrained to} \quad & \alpha_i \geq 0 \quad \forall i \quad \text{and} \quad \sum_{i=1}^n \alpha_i z_i = 0 \end{aligned}$$

- $L_D(\alpha)$ depends on the number of samples, not on dimension of samples
- samples appear only through the dot products $\mathbf{x}_i^t \mathbf{x}_j$
- This will become important when looking for a **nonlinear** discriminant function, as we will see soon
- Code available on the web to optimize

SVM: Non Separable Case

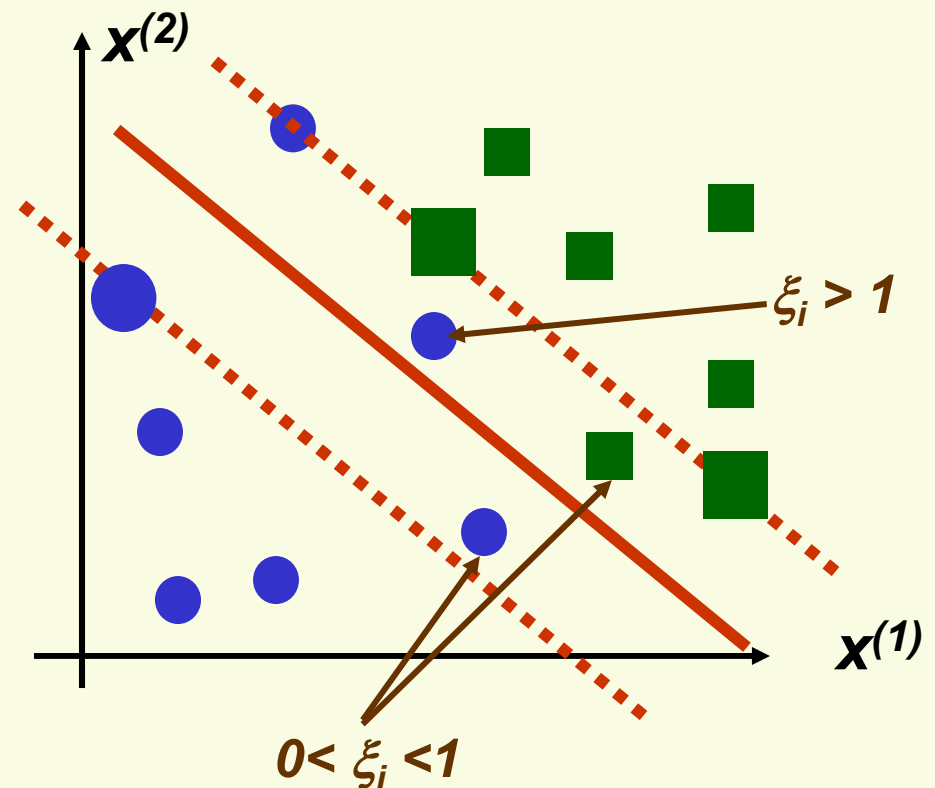
- Data is most likely to be not linearly separable, but linear classifier may still be appropriate



- Can apply SVM in non linearly separable case
 - data should be “almost” linearly separable for good performance

SVM: Non Separable Case

- Use non-negative slack variables ξ_1, \dots, ξ_n
 - one for each sample
- Change constraints from $\mathbf{z}_i(\mathbf{w}^t \mathbf{x}_i + \mathbf{w}_0) \geq 1 \quad \forall i$ to
$$\mathbf{z}_i(\mathbf{w}^t \mathbf{x}_i + \mathbf{w}_0) \geq 1 - \xi_i \quad \forall i$$
- ξ_i is a measure of deviation from the ideal for sample i
 - $\xi_i > 1$ sample i is on the wrong side of the separating hyperplane
 - $0 < \xi_i < 1$ sample i is on the right side of separating hyperplane but within the region of maximum margin



SVM: Non Separable Case

- Would like to minimize

$$J(\mathbf{w}, \xi_1, \dots, \xi_n) = \frac{1}{2} \|\mathbf{w}\|^2 + \beta \sum_{i=1}^n I(\xi_i > 0)$$

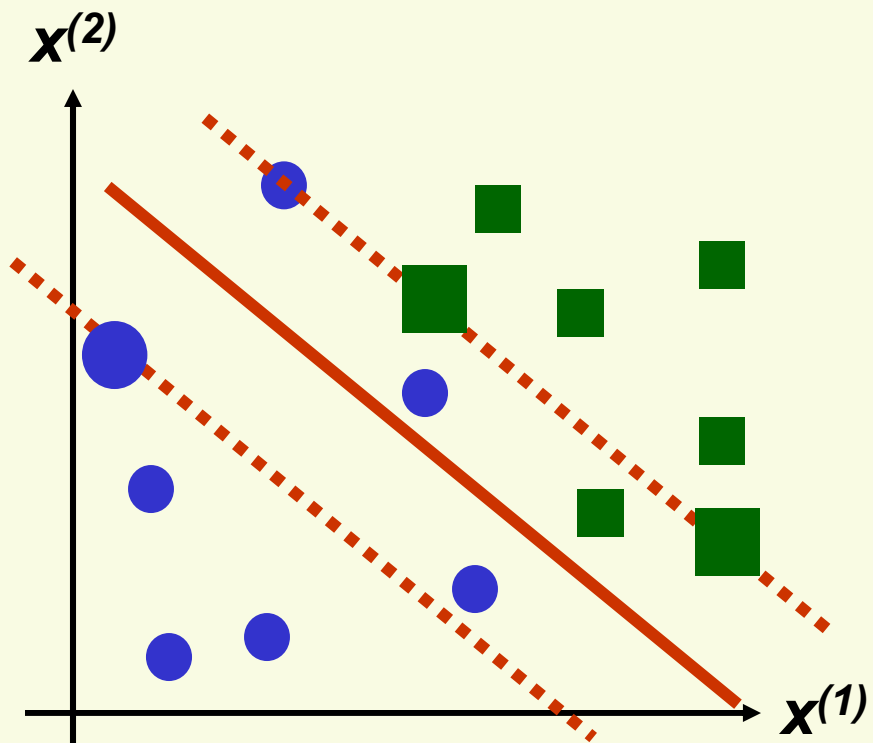
of samples not in ideal location

- where $I(\xi_i > 0) = \begin{cases} 1 & \text{if } \xi_i > 0 \\ 0 & \text{if } \xi_i \leq 0 \end{cases}$
- constrained to $\mathbf{z}_i (\mathbf{w}^t \mathbf{x}_i + w_0) \geq 1 - \xi_i$ and $\xi_i \geq 0 \quad \forall i$
- β measures relative weight of first and second terms
 - if β is small, we allow a lot of samples not in ideal position
 - if β is large, we want to have very few samples not in ideal position
 - choosing β appropriately is important

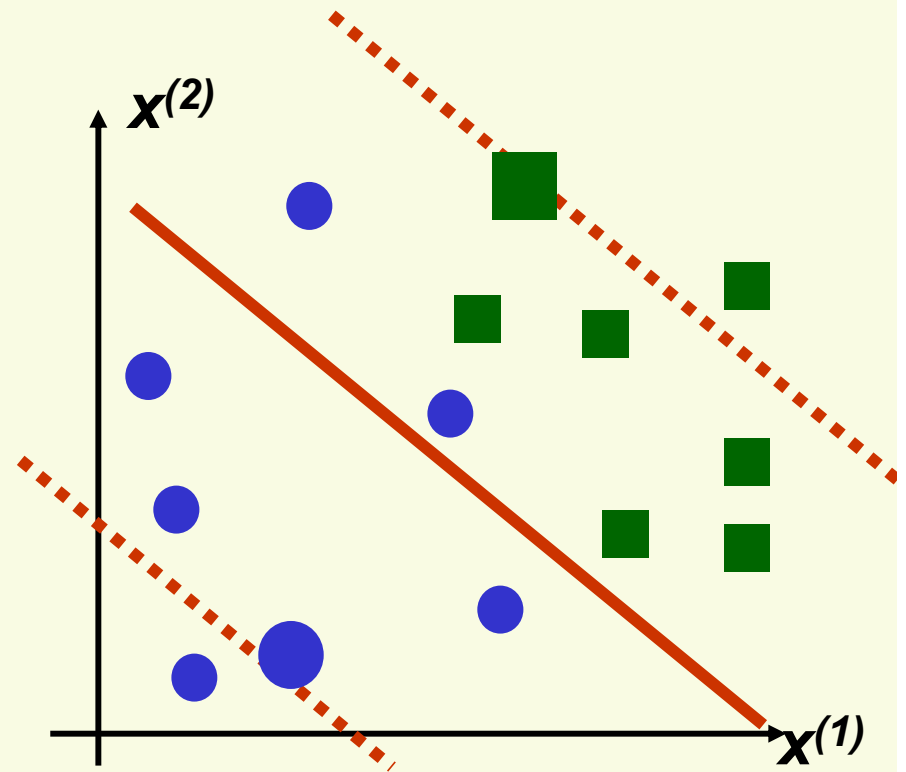
SVM: Non Separable Case

$$J(w, \xi_1, \dots, \xi_n) = \frac{1}{2} \|w\|^2 + \beta \sum_{i=1}^n I(\xi_i > 0)$$

of examples not in ideal location



large β , few samples not in ideal position



small β , a lot of samples not in ideal position

SVM: Non Separable Case

- Unfortunately this minimization problem is NP-hard due to discontinuity of functions $I(\xi_i)$

$$J(\mathbf{w}, \xi_1, \dots, \xi_n) = \frac{1}{2} \|\mathbf{w}\|^2 + \beta \sum_{i=1}^n I(\xi_i > 0)$$

*# of examples
not in ideal location*

- where $I(\xi_i > 0) = \begin{cases} 1 & \text{if } \xi_i > 0 \\ 0 & \text{if } \xi_i \leq 0 \end{cases}$
- constrained to $\mathbf{z}_i (\mathbf{w}^t \mathbf{x}_i + \mathbf{w}_0) \geq 1 - \xi_i$ and $\xi_i \geq 0 \quad \forall i$

SVM: Non Separable Case

- Instead we minimize

$$J(\mathbf{w}, \xi_1, \dots, \xi_n) = \frac{1}{2} \|\mathbf{w}\|^2 + \beta \sum_{i=1}^n \xi_i$$

a measure of # of misclassified examples

- constrained to
$$\begin{cases} \mathbf{z}_i (\mathbf{w}^t \mathbf{x}_i + w_0) \geq 1 - \xi_i & \forall i \\ \xi_i \geq 0 & \forall i \end{cases}$$

- Use Kuhn-Tucker theorem to converted to

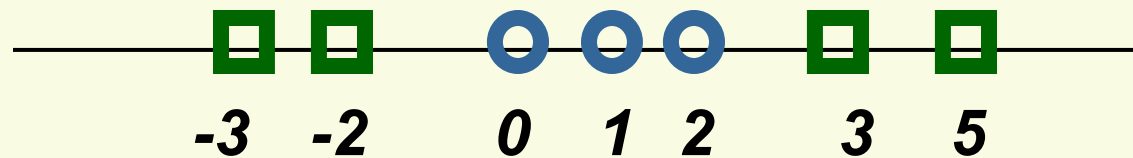
$$\begin{aligned} &\text{maximize} && L_D(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j \mathbf{z}_i \mathbf{z}_j \mathbf{x}_i^t \mathbf{x}_j \\ &\text{constrained to} && \mathbf{0} \leq \alpha_i \leq \beta \quad \forall i \quad \text{and} \quad \sum_{i=1}^n \alpha_i \mathbf{z}_i = \mathbf{0} \end{aligned}$$

- find \mathbf{w} using
$$\mathbf{w} = \sum_{i=1}^n \alpha_i \mathbf{z}_i \mathbf{x}_i$$
- solve for w_0 using any $0 < \alpha_i < \beta$ and
$$\alpha_i [\mathbf{z}_i (\mathbf{w}^t \mathbf{x}_i + w_0) - 1] = 0$$

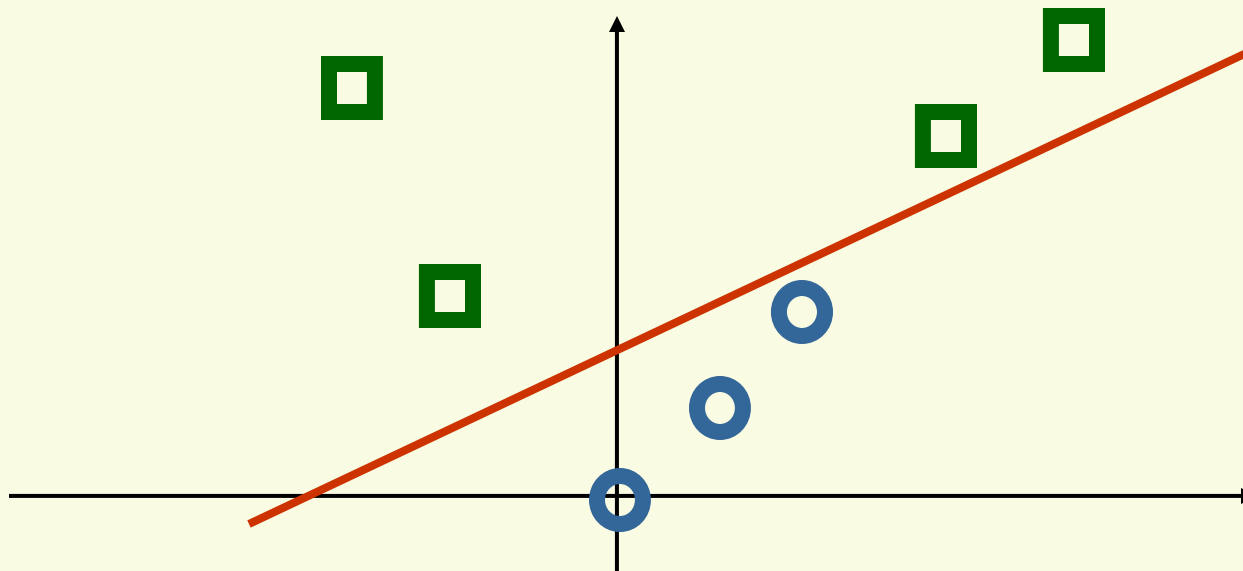
Non Linear Mapping

- Cover's theorem:
 - *"pattern-classification problem cast in a high dimensional space non-linearly is more likely to be linearly separable than in a low-dimensional space"*

- One dimensional space, not linearly separable

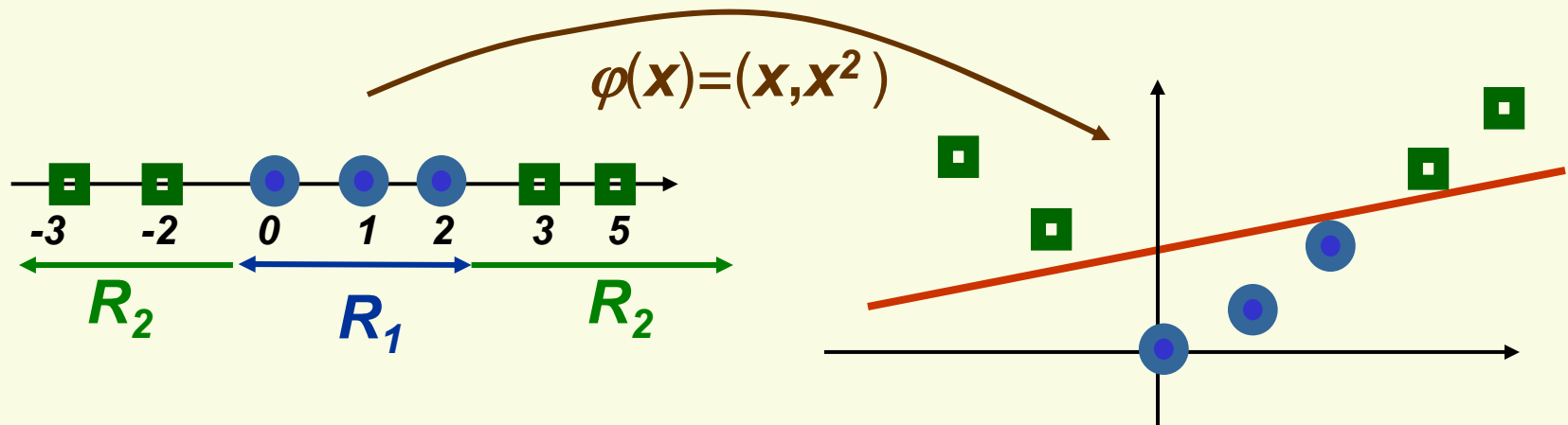


- Lift to two dimensional space with $\phi(\mathbf{x})=(\mathbf{x},\mathbf{x}^2)$



Non Linear Mapping

- To solve a non linear problem with a linear classifier
 1. Project data \mathbf{x} to high dimension using function $\phi(\mathbf{x})$
 2. Find a linear discriminant function for transformed data $\phi(\mathbf{x})$
 3. Final nonlinear discriminant function is $\mathbf{g}(\mathbf{x}) = \mathbf{w}^t \phi(\mathbf{x}) + w_0$

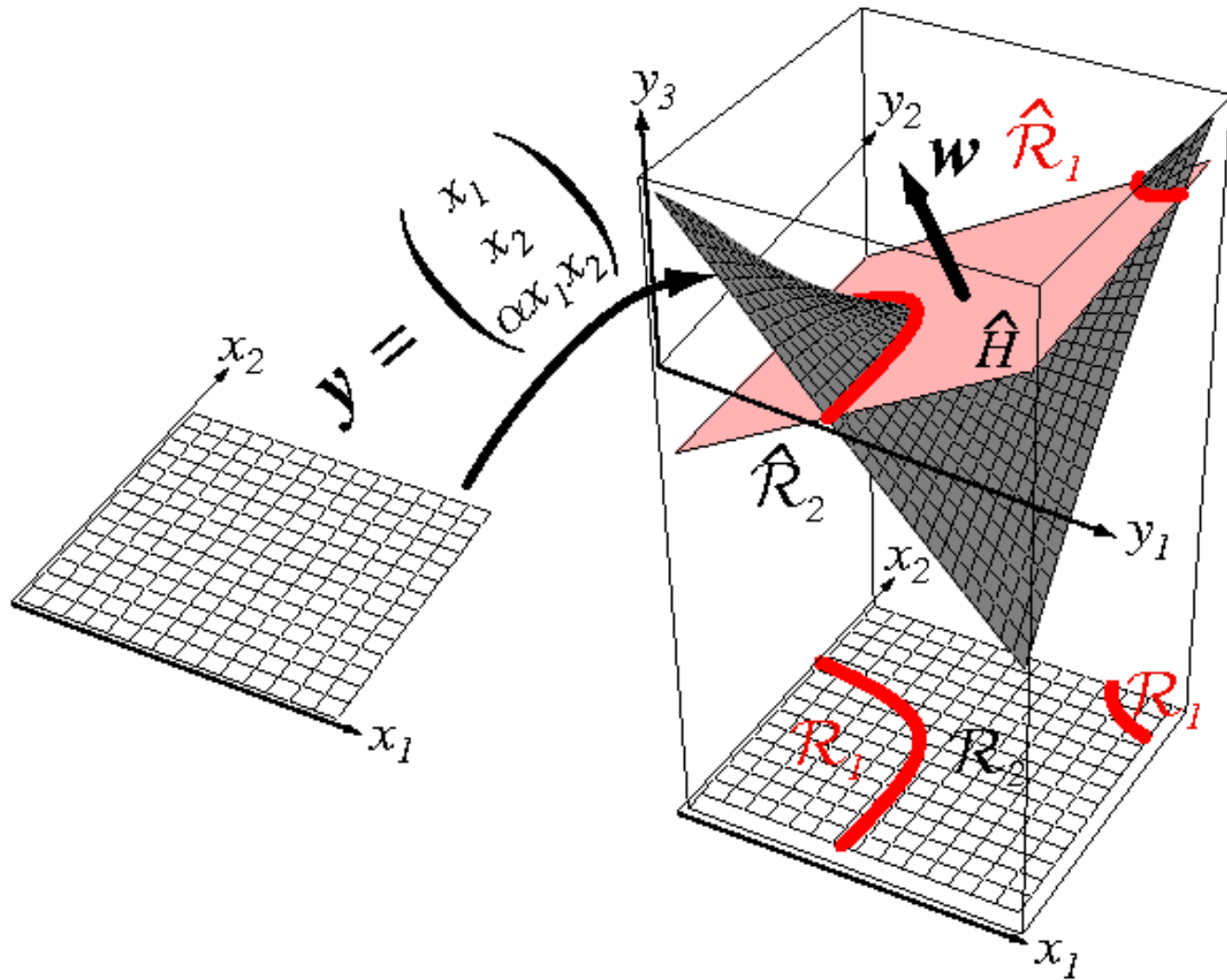


- In 2D, discriminant function is linear

$$\mathbf{g}\left(\begin{bmatrix} \mathbf{x}^{(1)} \\ \mathbf{x}^{(2)} \end{bmatrix}\right) = [\mathbf{w}_1 \quad \mathbf{w}_2] \begin{bmatrix} \mathbf{x}^{(1)} \\ \mathbf{x}^{(2)} \end{bmatrix} + w_0$$

- In 1D, discriminant function is not linear $\mathbf{g}(\mathbf{x}) = \mathbf{w}_1 \mathbf{x} + \mathbf{w}_2 \mathbf{x}^2 + w_0$

Non Linear Mapping: Another Example



Non Linear SVM

- Can use any linear classifier after lifting data into a higher dimensional space. However we will have to deal with the “curse of dimensionality”
 1. poor generalization to test data
 2. computationally expensive
- SVM avoids the “curse of dimensionality” problems by
 - enforcing largest margin permits good generalization
 - It can be shown that generalization in SVM is a function of the margin, independent of the dimensionality
 - computation in the higher dimensional case is performed only implicitly through the use of *kernel* functions

Non Linear SVM: Kernels

- Recall SVM optimization

$$\text{maximize } L_D(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j \mathbf{z}_i \mathbf{z}_j \mathbf{x}_i^t \mathbf{x}_j$$

- Note this optimization depends on samples \mathbf{x}_i only through the dot product $\mathbf{x}_i^t \mathbf{x}_j$
- If we lift \mathbf{x}_i to high dimension using $\boldsymbol{\varphi}(\mathbf{x})$, need to compute high dimensional product $\boldsymbol{\varphi}(\mathbf{x}_i)^t \boldsymbol{\varphi}(\mathbf{x}_j)$

$$\text{maximize } L_D(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j \mathbf{z}_i \mathbf{z}_j \boldsymbol{\varphi}(\mathbf{x}_i)^t \boldsymbol{\varphi}(\mathbf{x}_j)$$

$$K(\mathbf{x}_i, \mathbf{x}_j)$$

- Idea: find *kernel* function $K(\mathbf{x}_i, \mathbf{x}_j)$ s.t.
$$K(\mathbf{x}_i, \mathbf{x}_j) = \boldsymbol{\varphi}(\mathbf{x}_i)^t \boldsymbol{\varphi}(\mathbf{x}_j)$$

Non Linear SVM: Kernels

$$\text{maximize } L_D(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j z_i z_j \varphi(\mathbf{x}_i)^t \varphi(\mathbf{x}_j)$$

$K(\mathbf{x}_i, \mathbf{x}_j)$

- Then we only need to compute $K(\mathbf{x}_i, \mathbf{x}_j)$ instead of $\varphi(\mathbf{x}_i)^t \varphi(\mathbf{x}_j)$
- “kernel trick”: do not need to perform operations in high dimensional space explicitly

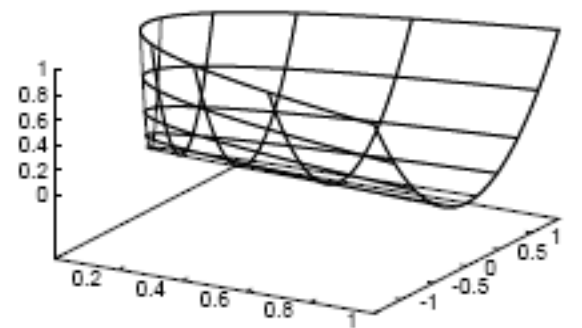
Non Linear SVM: Kernels

- Suppose we have 2 features and $K(\mathbf{x}, \mathbf{y}) = (\mathbf{x}^t \mathbf{y})^2$
- Which mapping $\boldsymbol{\varphi}(\mathbf{x})$ does it correspond to?

$$\begin{aligned} K(\mathbf{x}, \mathbf{y}) &= (\mathbf{x}^t \mathbf{y})^2 = \left(\begin{bmatrix} \mathbf{x}^{(1)} & \mathbf{x}^{(2)} \end{bmatrix} \begin{bmatrix} \mathbf{y}^{(1)} \\ \mathbf{y}^{(2)} \end{bmatrix} \right)^2 = (\mathbf{x}^{(1)} \mathbf{y}^{(1)} + \mathbf{x}^{(2)} \mathbf{y}^{(2)})^2 \\ &= (\mathbf{x}^{(1)} \mathbf{y}^{(1)})^2 + 2(\mathbf{x}^{(1)} \mathbf{y}^{(1)})(\mathbf{x}^{(2)} \mathbf{y}^{(2)}) + (\mathbf{x}^{(2)} \mathbf{y}^{(2)})^2 \\ &= \begin{bmatrix} (\mathbf{x}^{(1)})^2 & \sqrt{2} \mathbf{x}^{(1)} \mathbf{x}^{(2)} & (\mathbf{x}^{(2)})^2 \end{bmatrix} \begin{bmatrix} (\mathbf{y}^{(1)})^2 & \sqrt{2} \mathbf{y}^{(1)} \mathbf{y}^{(2)} & (\mathbf{y}^{(2)})^2 \end{bmatrix}^t \end{aligned}$$

- Thus

$$\boldsymbol{\varphi}(\mathbf{x}) = \begin{bmatrix} (\mathbf{x}^{(1)})^2 & \sqrt{2} \mathbf{x}^{(1)} \mathbf{x}^{(2)} & (\mathbf{x}^{(2)})^2 \end{bmatrix}$$



Non Linear SVM: Kernels

- How to choose kernel function $K(\mathbf{x}_i, \mathbf{x}_j)$?
 - $K(\mathbf{x}_i, \mathbf{x}_j)$ should correspond to product $\boldsymbol{\varphi}(\mathbf{x}_i)^t \boldsymbol{\varphi}(\mathbf{x}_j)$ in a higher dimensional space
 - Mercer's condition tells us which kernel function can be expressed as dot product of two vectors
 - Kernel's not satisfying Mercer's condition can be sometimes used, but no geometrical interpretation
- Some common choices (satisfying Mercer's condition):
 - Polynomial kernel
- Gaussian radial Basis kernel (data is lifted in infinite dimensions)

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{1}{2\sigma^2} \|\mathbf{x}_i - \mathbf{x}_j\|^2\right)$$

Non Linear SVM

- search for separating hyperplane in high dimension

$$\mathbf{w}\varphi(\mathbf{x}) + \mathbf{w}_0 = 0$$

- Choose $\varphi(\mathbf{x})$ so that the first ("0"th) dimension is the augmented dimension with feature value fixed to 1

$$\varphi(\mathbf{x}) = [1 \quad \mathbf{x}^{(1)} \quad \mathbf{x}^{(2)} \quad \mathbf{x}^{(1)}\mathbf{x}^{(2)}]^t$$

- Threshold parameter \mathbf{w}_0 gets folded into the weight vector \mathbf{w}

$$[\mathbf{w}_0 \quad \mathbf{w}] \begin{bmatrix} 1 \\ * \\ \varphi(\mathbf{x}) \end{bmatrix} = 0$$

Non Linear SVM

- Will not use notation $\mathbf{a} = [\mathbf{w}_0 \ \mathbf{w}]$, we'll use old notation \mathbf{w} and seek hyperplane through the origin

$$\mathbf{w}\varphi(\mathbf{x}) = 0$$

- If the first component of $\varphi(\mathbf{x})$ is not $\mathbf{1}$, the above is equivalent to saying that the hyperplane has to go through the origin in high dimension
 - removes only one degree of freedom
 - But we have introduced many new degrees when we lifted the data in high dimension

Non Linear SVM Receptie

- Start with data $\mathbf{x}_1, \dots, \mathbf{x}_n$ which lives in feature space of dimension d
- Choose kernel $K(\mathbf{x}_i, \mathbf{x}_j)$ or function $\boldsymbol{\varphi}(\mathbf{x}_i)$ which takes sample \mathbf{x}_i to a higher dimensional space
- Find the largest margin linear discriminant function in the higher dimensional space by using quadratic programming package to solve:

$$\begin{aligned} &\text{maximize } L_D(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j \mathbf{z}_i \mathbf{z}_j K(\mathbf{x}_i, \mathbf{x}_j) \\ &\text{constrained to } \mathbf{0} \leq \alpha_i \leq \beta \quad \forall i \quad \text{and} \quad \sum_{i=1}^n \alpha_i \mathbf{z}_i = \mathbf{0} \end{aligned}$$

Non Linear SVM Recipe

- Weight vector \mathbf{w} in the high dimensional space:

$$\mathbf{w} = \sum_{\mathbf{x}_i \in \mathcal{S}} \alpha_i \mathbf{z}_i \varphi(\mathbf{x}_i)$$

- where \mathcal{S} is the set of support vectors $\mathcal{S} = \{\mathbf{x}_i \mid \alpha_i \neq 0\}$
- Linear discriminant function of largest margin in the high dimensional space:

$$\mathbf{g}(\varphi(\mathbf{x})) = \mathbf{w}^t \varphi(\mathbf{x}) = \left(\sum_{\mathbf{x}_i \in \mathcal{S}} \alpha_i \mathbf{z}_i \varphi(\mathbf{x}_i) \right)^t \varphi(\mathbf{x})$$

- Non linear discriminant function in the original space:

$$\mathbf{g}(\mathbf{x}) = \left(\sum_{\mathbf{x}_i \in \mathcal{S}} \alpha_i \mathbf{z}_i \varphi(\mathbf{x}_i) \right)^t \varphi(\mathbf{x}) = \sum_{\mathbf{x}_i \in \mathcal{S}} \alpha_i \mathbf{z}_i \varphi^t(\mathbf{x}_i) \varphi(\mathbf{x}) = \sum_{\mathbf{x}_i \in \mathcal{S}} \alpha_i \mathbf{z}_i \mathbf{K}(\mathbf{x}_i, \mathbf{x})$$

- decide class 1 if $\mathbf{g}(\mathbf{x}) > 0$, otherwise decide class 2

Non Linear SVM

- Nonlinear discriminant function

$$g(\mathbf{x}) = \sum_{\mathbf{x}_i \in S} \alpha_i \mathbf{z}_i K(\mathbf{x}_i, \mathbf{x})$$

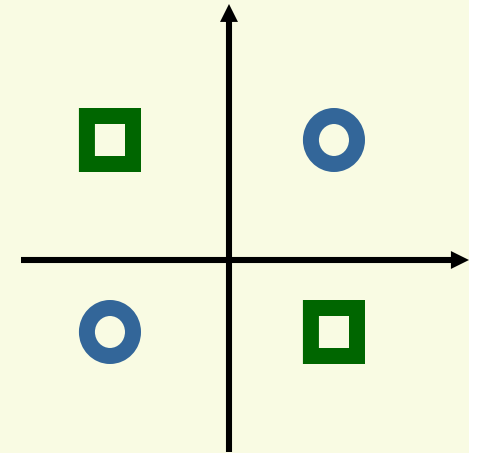
$$g(\mathbf{x}) = \sum \begin{array}{|l} \text{weight of support} \\ \text{vector } \mathbf{x}_i \end{array} \begin{array}{|l} \mp 1 \end{array} \begin{array}{|l} \text{"inverse distance"} \\ \text{from } \mathbf{x} \text{ to} \\ \text{support vector } \mathbf{x}_i \end{array}$$

most important
training samples,
i.e. support vectors

$$K(\mathbf{x}_i, \mathbf{x}) = \exp\left(-\frac{1}{2\sigma^2} \|\mathbf{x}_i - \mathbf{x}\|^2\right)$$

SVM Example: XOR Problem

- Class 1: $\mathbf{x}_1 = [1, -1]$, $\mathbf{x}_2 = [-1, 1]$
- Class 2: $\mathbf{x}_3 = [1, 1]$, $\mathbf{x}_4 = [-1, -1]$
- Use polynomial kernel of degree 2:



- $K(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i^t \mathbf{x}_j + 1)^2$

- This kernel corresponds to mapping

$$(\mathbf{x}) = \left[1 \quad \sqrt{2} \mathbf{x}^{(1)} \quad \sqrt{2} \mathbf{x}^{(2)} \quad \sqrt{2} \mathbf{x}^{(1)} \mathbf{x}^{(2)} \quad (\mathbf{x}^{(1)})^2 \quad (\mathbf{x}^{(2)})^2 \right]^t$$

- Need to maximize

$$L_D(\alpha) = \sum_{i=1}^4 \alpha_i \frac{1}{2} \sum_{i=1}^4 \sum_{j=1}^4 \alpha_i \alpha_j z_i z_j (\mathbf{x}_i^t \mathbf{x}_j + 1)^2$$

constrained to $\mathbf{0} \leq \alpha_i \quad \forall i$ and $\alpha_1 + \alpha_2 - \alpha_3 - \alpha_4 = 0$

SVM Example: XOR Problem

- Can rewrite $L_D(\alpha) = \sum_{i=1}^4 \alpha_i - \frac{1}{2} \alpha^t H \alpha$
 - where $\alpha = [\alpha_1 \ \alpha_2 \ \alpha_3 \ \alpha_4]^t$ and $H = \begin{bmatrix} 9 & 1 & -1 & -1 \\ 1 & 9 & -1 & -1 \\ -1 & -1 & 9 & 1 \\ -1 & -1 & 1 & 9 \end{bmatrix}$
- Take derivative with respect to α and set it to $\mathbf{0}$
$$\frac{d}{d\alpha} L_D(\alpha) = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} - \begin{bmatrix} 9 & 1 & -1 & -1 \\ 1 & 9 & -1 & -1 \\ -1 & -1 & 9 & 1 \\ -1 & -1 & 1 & 9 \end{bmatrix} \alpha = \mathbf{0}$$
- Solution to the above is $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \mathbf{0.25}$
 - satisfies the constraints $\forall i, \mathbf{0} \leq \alpha_i$ and $\alpha_1 + \alpha_2 - \alpha_3 - \alpha_4 = \mathbf{0}$
 - all samples are support vectors

SVM Example: XOR Problem

$$\mathbf{\phi}(\mathbf{x}) = \left[1 \quad \sqrt{2}\mathbf{x}^{(1)} \quad \sqrt{2}\mathbf{x}^{(2)} \quad \sqrt{2}\mathbf{x}^{(1)}\mathbf{x}^{(2)} \quad (\mathbf{x}^{(1)})^2 \quad (\mathbf{x}^{(2)})^2 \right]^t$$

- Weight vector \mathbf{w} is:

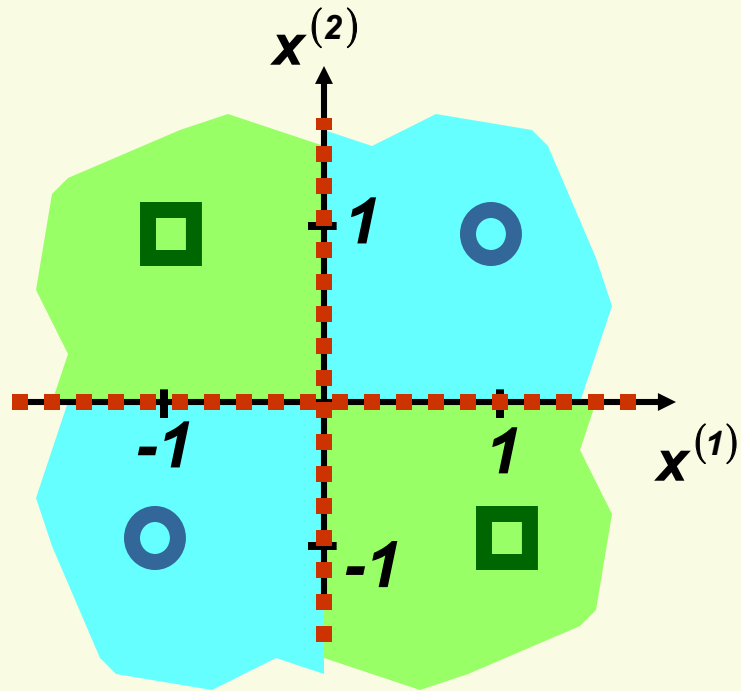
$$\begin{aligned} \mathbf{w} &= \sum_{i=1}^4 \alpha_i \mathbf{z}_i \phi(\mathbf{x}_i) = 0.25(\phi(\mathbf{x}_1) + \phi(\mathbf{x}_2) - \phi(\mathbf{x}_3) - \phi(\mathbf{x}_4)) \\ &= \begin{bmatrix} 0 & 0 & 0 & \sqrt{2} & 0 & 0 \end{bmatrix} \end{aligned}$$

- Thus the nonlinear discriminant function is:

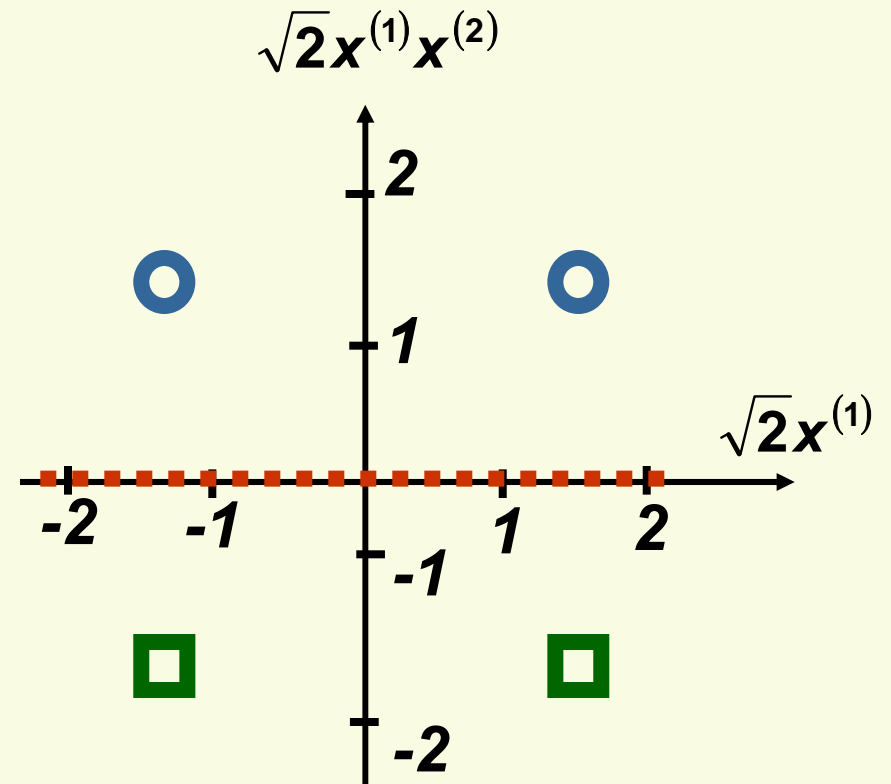
$$\mathbf{g}(\mathbf{x}) = \mathbf{w}\phi(\mathbf{x}) = \sum_{i=1}^6 \mathbf{w}_i \phi_i(\mathbf{x}) = \sqrt{2}(\sqrt{2}\mathbf{x}^{(1)}\mathbf{x}^{(2)}) = 2\mathbf{x}^{(1)}\mathbf{x}^{(2)}$$

SVM Example: XOR Problem

$$g(\mathbf{x}) = -2x^{(1)}x^{(2)}$$

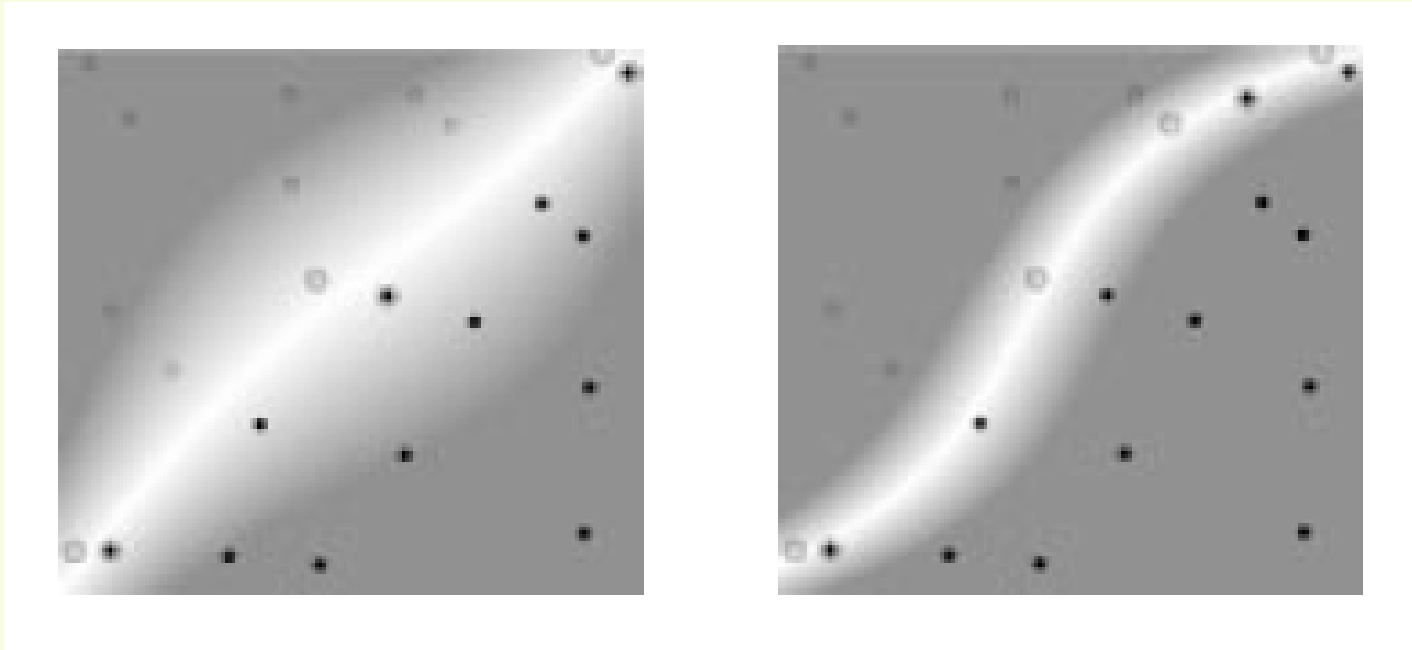


decision boundaries nonlinear



decision boundary is linear

Degree 3 Polynomial Kernel



- In linearly separable case (on the left), decision boundary is roughly linear, indicating that dimensionality is controlled
- Nonseparable case (on the right) is handled by a polynomial of degree 3

SVM Summary

- Advantages:
 - Based on nice theory
 - excellent generalization properties
 - objective function has no local minima
 - can be used to find non linear discriminant functions
 - Complexity of the classifier is characterized by the number of support vectors rather than the dimensionality of the transformed space
- Disadvantages:
 - tends to be slower than other methods
 - quadratic programming is computationally expensive
 - Not clear how to choose the Kernel