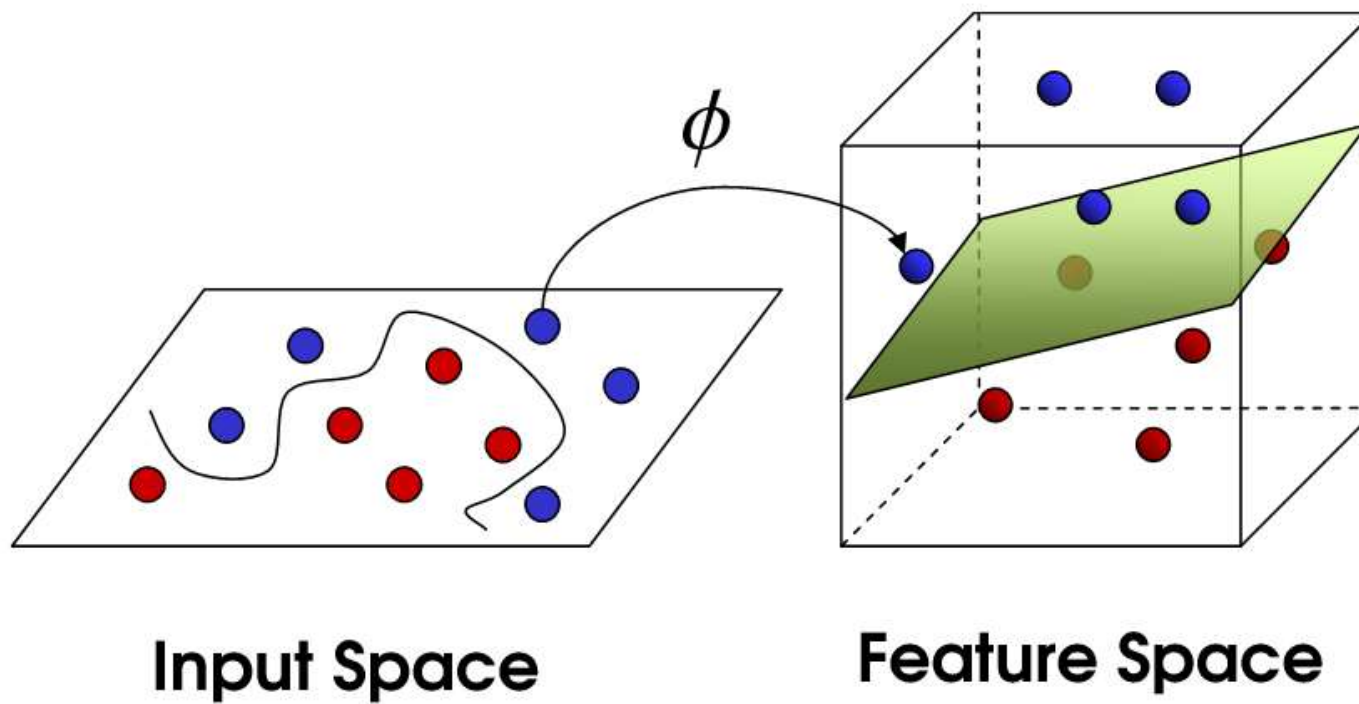


# Support Vector Machines

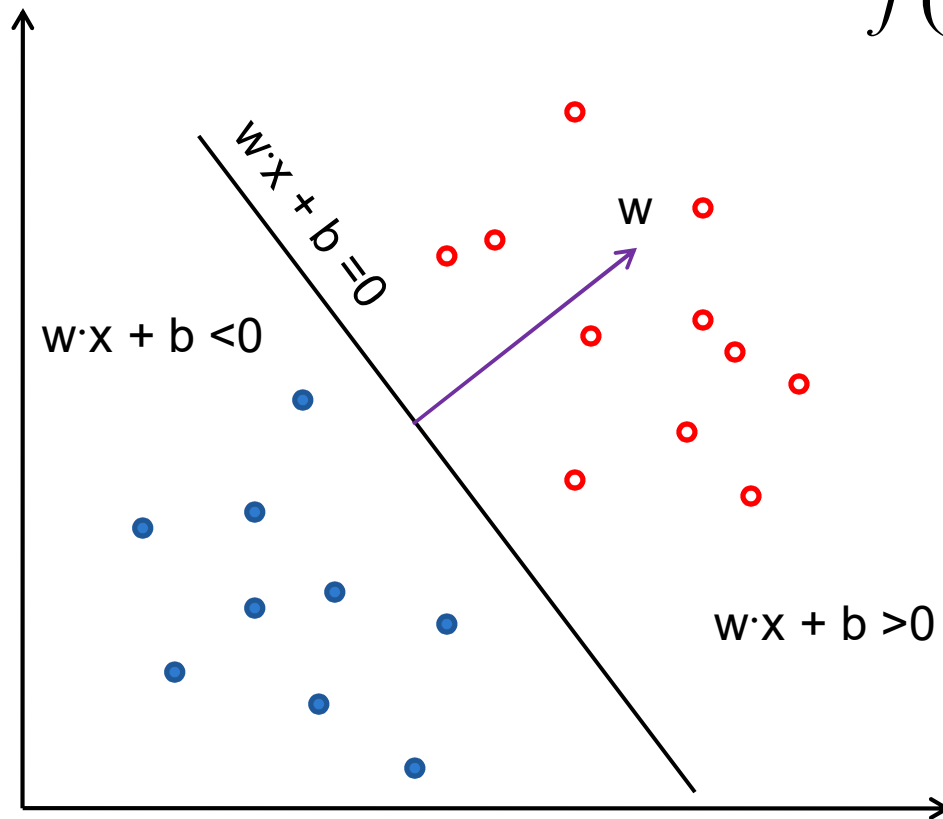
Lecturer: Dr. Bo Yuan

E-mail: [yuanb@sz.tsinghua.edu.cn](mailto:yuanb@sz.tsinghua.edu.cn)

# Overview



# Linear Classifier



$$f(x, w, b) = \text{sign}(g(x)) \\ = \text{sign}(w \cdot x + b)$$

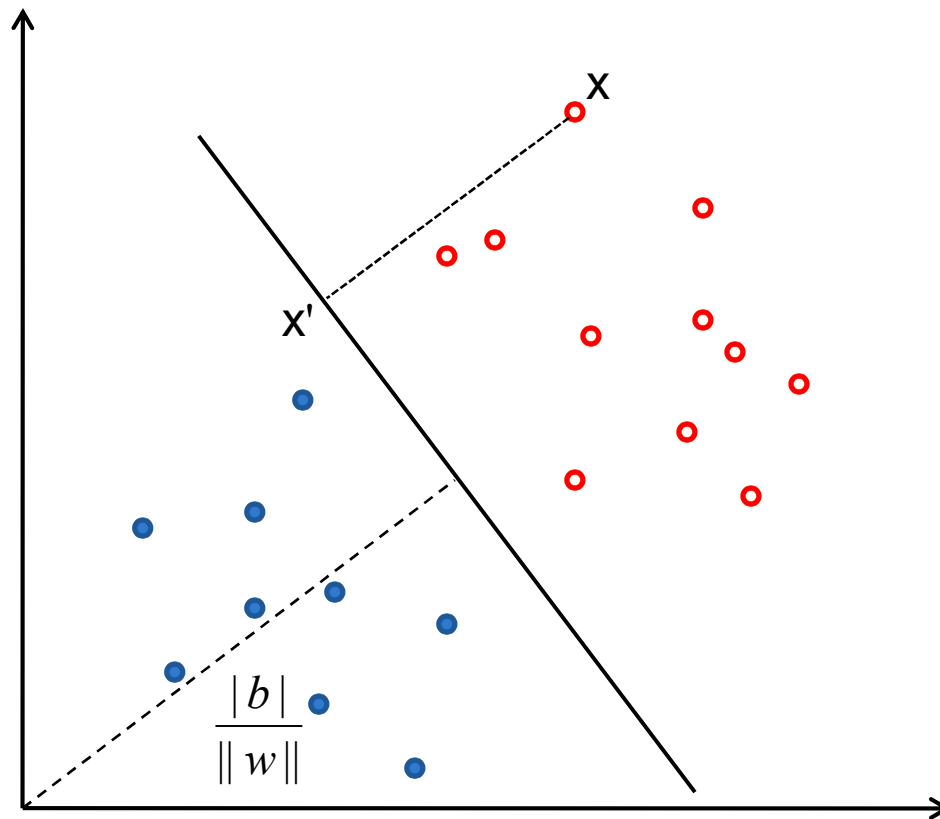
*Just in case ...*

$$w \cdot x = \sum_{i=1}^n w_i x_i$$

$$w \cdot x_1 + b = w \cdot x_2 + b$$

$$w(x_1 - x_2) = 0$$

# Distance to Hyperplane



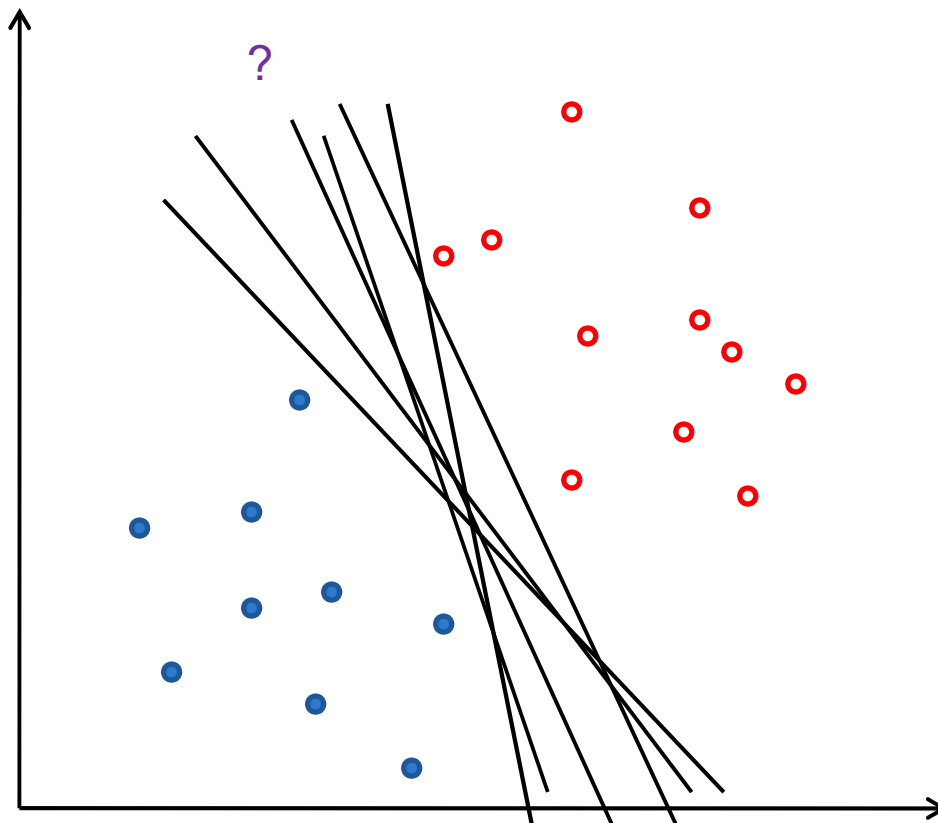
$$g(x) = w \cdot x + b$$

$$x = x' + \lambda w$$

$$\begin{aligned} g(x) &= w(x' + \lambda \cdot w) + b \\ &= w \cdot x' + b + \lambda w \cdot w \\ &= \lambda w \cdot w \end{aligned}$$

$$\begin{aligned} M &= \|x - x'\| = \|\lambda w\| \\ &= \frac{|g(x)| \times \|w\|}{w \cdot w} = \frac{|g(x)|}{\|w\|} \end{aligned}$$

# Selection of Classifiers



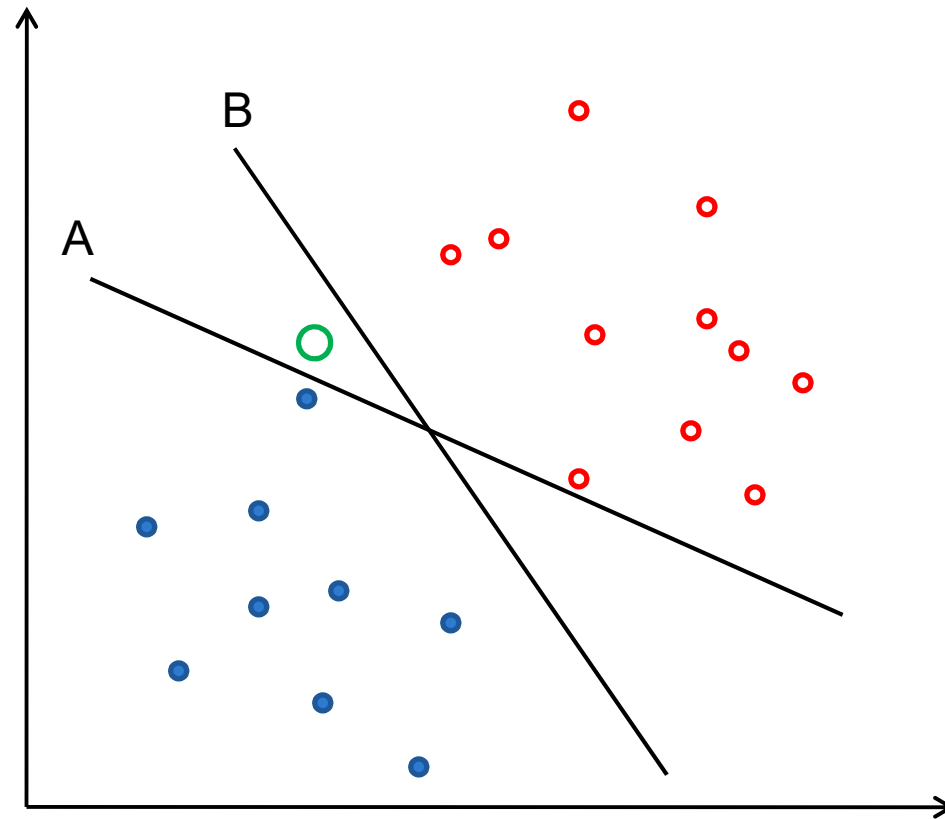
Which classifier is the best?

All have the same training error.

How about generalization?

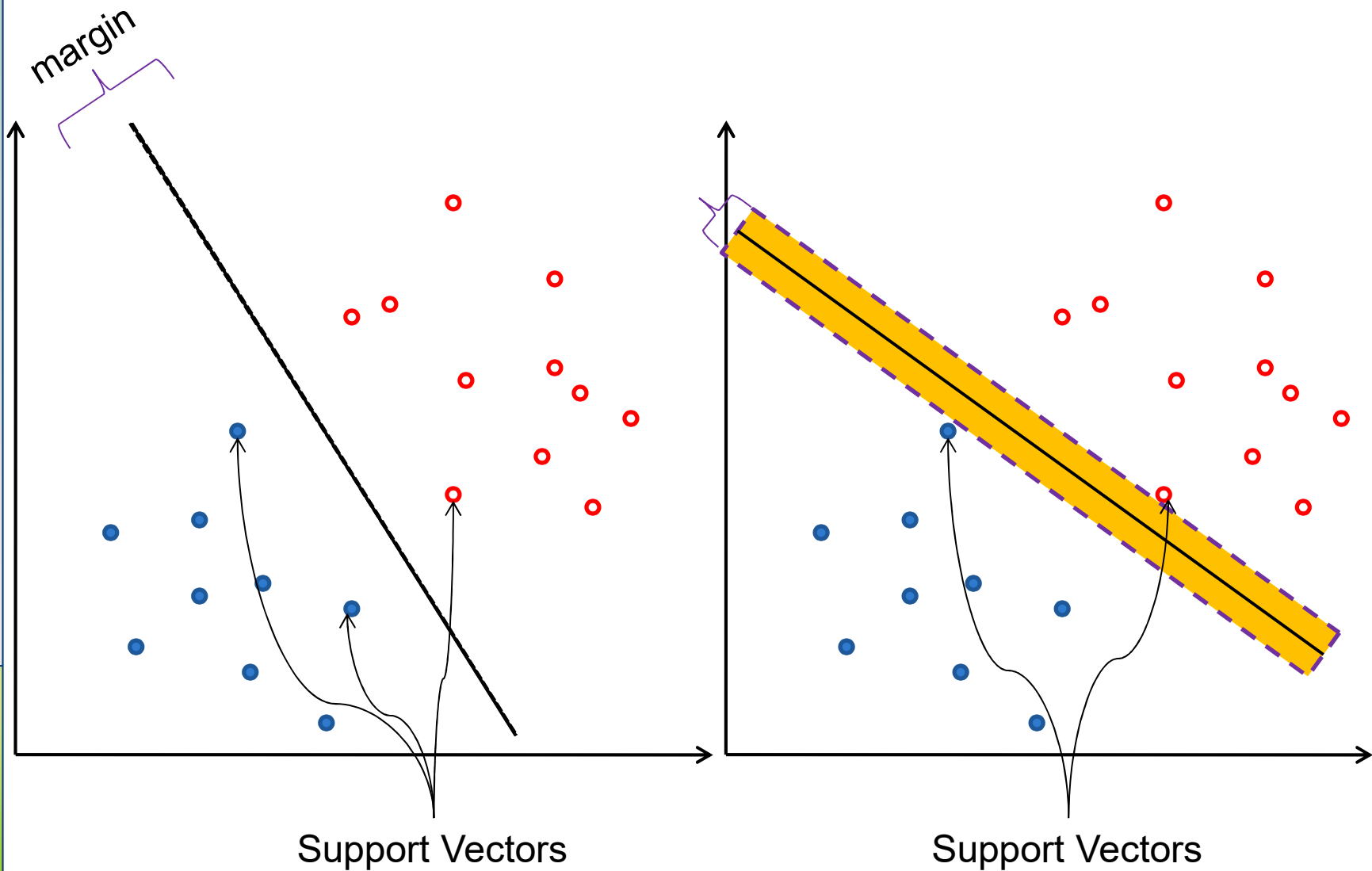


# Unknown Samples



Classifier B divides the space more consistently (unbiased).

# Margins



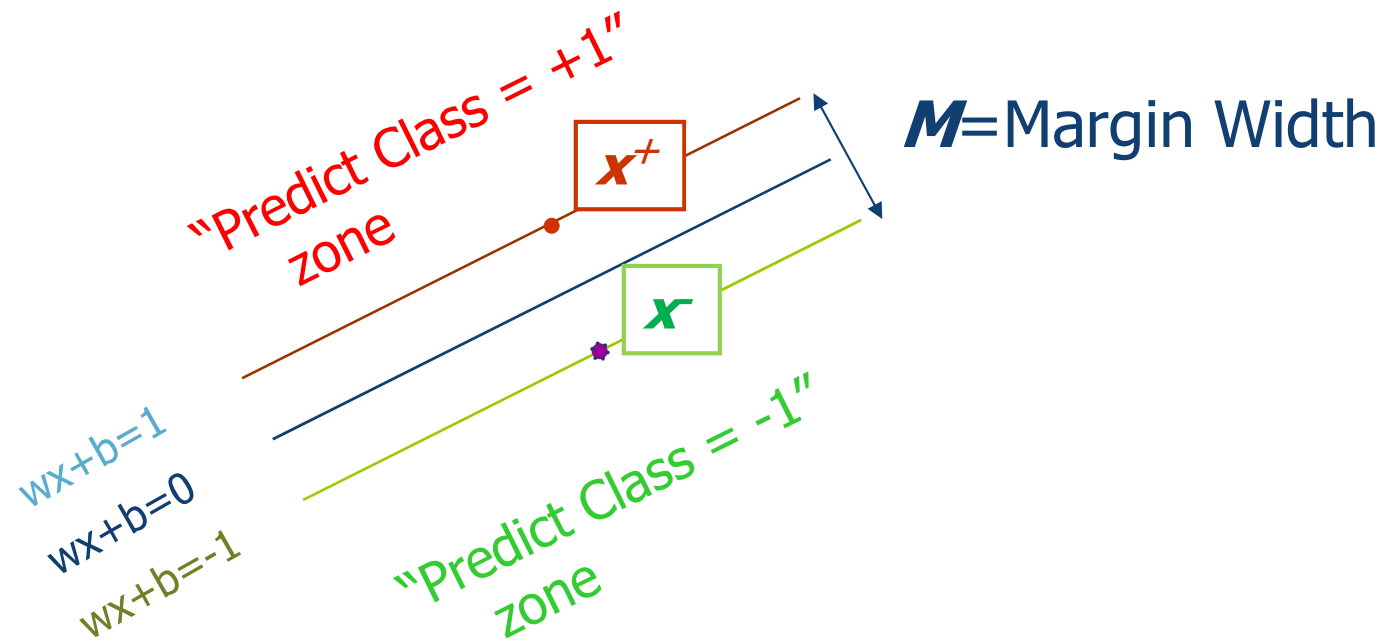
# Margins

- ❖ The margin of a linear classifier is defined as the width that the boundary could be increased by before hitting a data point.
- ❖ Intuitively, it is safer to choose a classifier with a larger margin.
- ❖ Wider buffer zone for mistakes
- ❖ The hyperplane is decided by only a few data points.
  - **Support Vectors**
  - Others can be discarded!
- ❖ Select the classifier with the maximum margin.
  - Linear Support Vector Machines (LSVM)
- ❖ How to specify the margin formally?



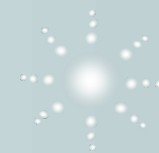


# Margins



$$M = \frac{2}{\|w\|}$$





# Objective Function

- ❖ Correctly classify all data points:

$$w \cdot x_i + b \geq 1 \quad \text{if } y_i = +1$$

$$w \cdot x_i + b \leq -1 \quad \text{if } y_i = -1$$

$$y_i(w \cdot x_i + b) - 1 \geq 0$$



- ❖ Maximize the margin:

$$\max M = \frac{2}{\|w\|} \Rightarrow \min \frac{1}{2} w^T w$$

- ❖ Quadratic Optimization Problem

- Minimize  $\Phi(w) = \frac{1}{2} w^T w$
- Subject to  $y_i(w \cdot x_i + b) \geq 1$

# Lagrange Multipliers

$$L_P \equiv \frac{1}{2} \|w\|^2 - \sum_{i=1}^l \alpha_i y_i (w \cdot x_i + b) + \sum_{i=1}^l \alpha_i$$

$$\frac{\partial L_P}{\partial w} = 0 \Rightarrow w = \sum_{i=1}^l \alpha_i y_i x_i$$

$$\frac{\partial L_P}{\partial b} = 0 \Rightarrow \sum_{i=1}^l \alpha_i y_i = 0$$

$$L_D \equiv \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i \cdot x_j$$

$$\equiv \sum_i \alpha_i - \frac{1}{2} \alpha^T H \alpha \text{ where } H_{ij} = y_i y_j x_i \cdot x_j$$

$$\text{subject to: } \sum_i \alpha_i y_i = 0 \text{ \& } \alpha_i \geq 0$$

Dual Problem

Quadratic problem again!

# Solutions of $w$ & $b$

*Support Vectors : Samples with positive  $\alpha$*

$$y_s (x_s \cdot w + b) = 1$$

$$y_s \left( \sum_{m \in S} \alpha_m y_m x_m \cdot x_s + b \right) = 1$$

$$y_s^2 \left( \sum_{m \in S} \alpha_m y_m x_m \cdot x_s + b \right) = y_s$$

$$b = y_s - \sum_{m \in S} \alpha_m y_m x_m \cdot x_s$$

$$b = \frac{1}{N_s} \sum_{s \in S} \left( y_s - \sum_{m \in S} \alpha_m y_m x_m \cdot x_s \right)$$

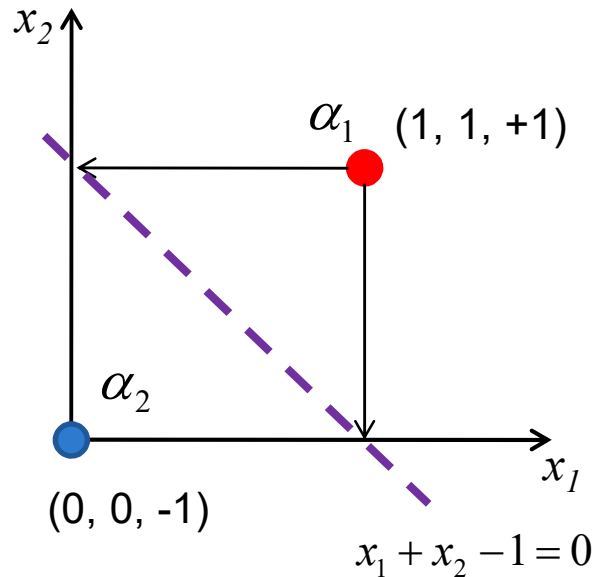
$$g(x) = \sum_{i=1}^l \alpha_i y_i x_i \cdot x + b$$



inner product



# An Example



$$\sum_{i=1}^2 \alpha_i y_i = 0 \Rightarrow \alpha_1 - \alpha_2 = 0 \Rightarrow \alpha_1 = \alpha_2$$

$$H = \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix} = \begin{bmatrix} y_1 y_1 x_1 \cdot x_1 & y_1 y_2 x_1 \cdot x_2 \\ y_2 y_1 x_2 \cdot x_1 & y_2 y_2 x_2 \cdot x_2 \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix}$$

$$L_D \equiv \sum_{i=1}^2 \alpha_i - \frac{1}{2} [\alpha_1, \alpha_2] H \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = 2\alpha_1 - \alpha_1^2$$

$$w = \sum_{i=1}^2 \alpha_i y_i x_i = 1 \times 1 \times [1, 1] + 1 \times (-1) \times [0, 0] = [1, 1]$$

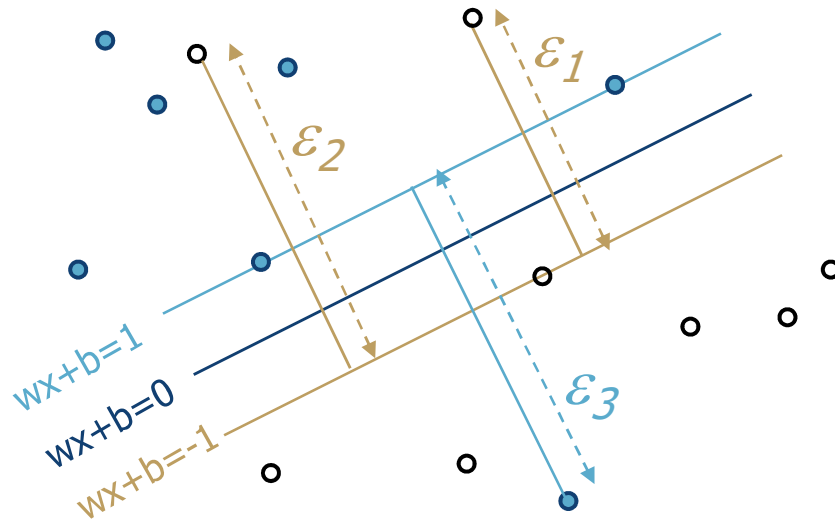
$$\alpha_1 = 1; \alpha_2 = 1$$

$$b = -wx_1 + 1 = -2 + 1 = -1$$

$$g(x) = wx + b = x_1 + x_2 - 1$$

$$M = \frac{2}{\|w\|} = \frac{2}{\sqrt{2}} = \sqrt{2}$$

# Soft Margin



$$y_i(wx_i + b) - 1 + \xi_i \geq 0$$

$$\Phi(w) = \frac{1}{2} w^t w + C \sum_i \xi_i$$

$$\xi_i \geq 0$$

$$L_P \equiv \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l \xi_i - \sum_{i=1}^l \alpha_i [y_i(w \cdot x_i + b) - 1 + \xi_i] - \sum_{i=1}^l \mu_i \xi_i$$



# Soft Margin

$$\left. \begin{aligned} \frac{\partial L_p}{\partial w} = 0 &\Rightarrow w = \sum_{i=1}^l \alpha_i y_i x_i \\ \frac{\partial L_p}{\partial b} = 0 &\Rightarrow \sum_{i=1}^l \alpha_i y_i = 0 \end{aligned} \right\} \text{ Same as before}$$

$$\frac{\partial L_p}{\partial \xi_i} = 0 \Rightarrow C = \alpha_i + \mu_i$$

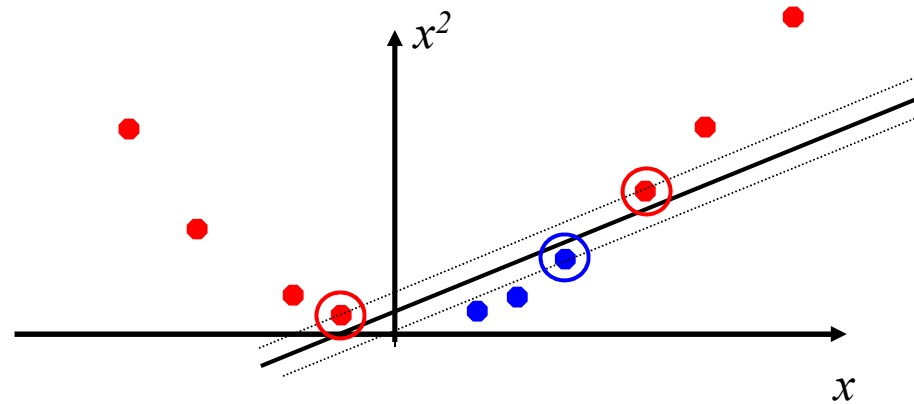
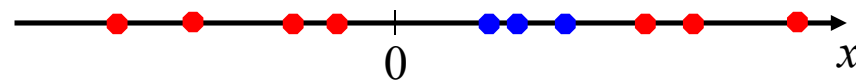
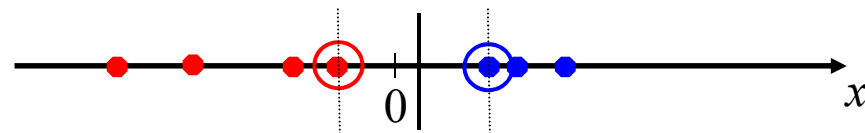
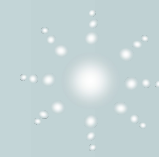
$$L_p \equiv \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l \xi_i - \sum_{i=1}^l \alpha_i [y_i (w \cdot x_i + b) - 1 + \xi_i] - \sum_{i=1}^l \mu_i \xi_i$$

$$L_D \equiv \sum_i \alpha_i - \frac{1}{2} \alpha^T H \alpha \quad \text{s.t. } 0 \leq \alpha_i \leq C \quad \text{and} \quad \sum_i \alpha_i y_i = 0$$

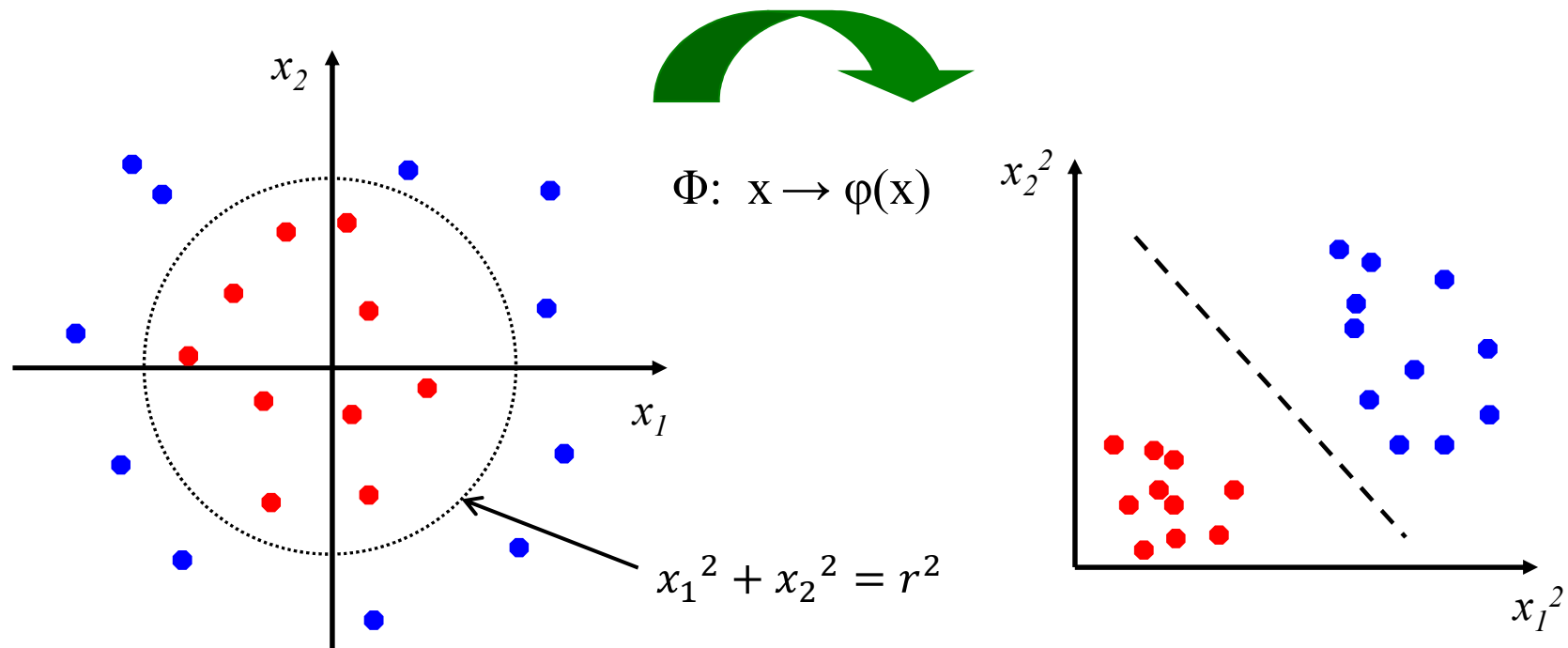




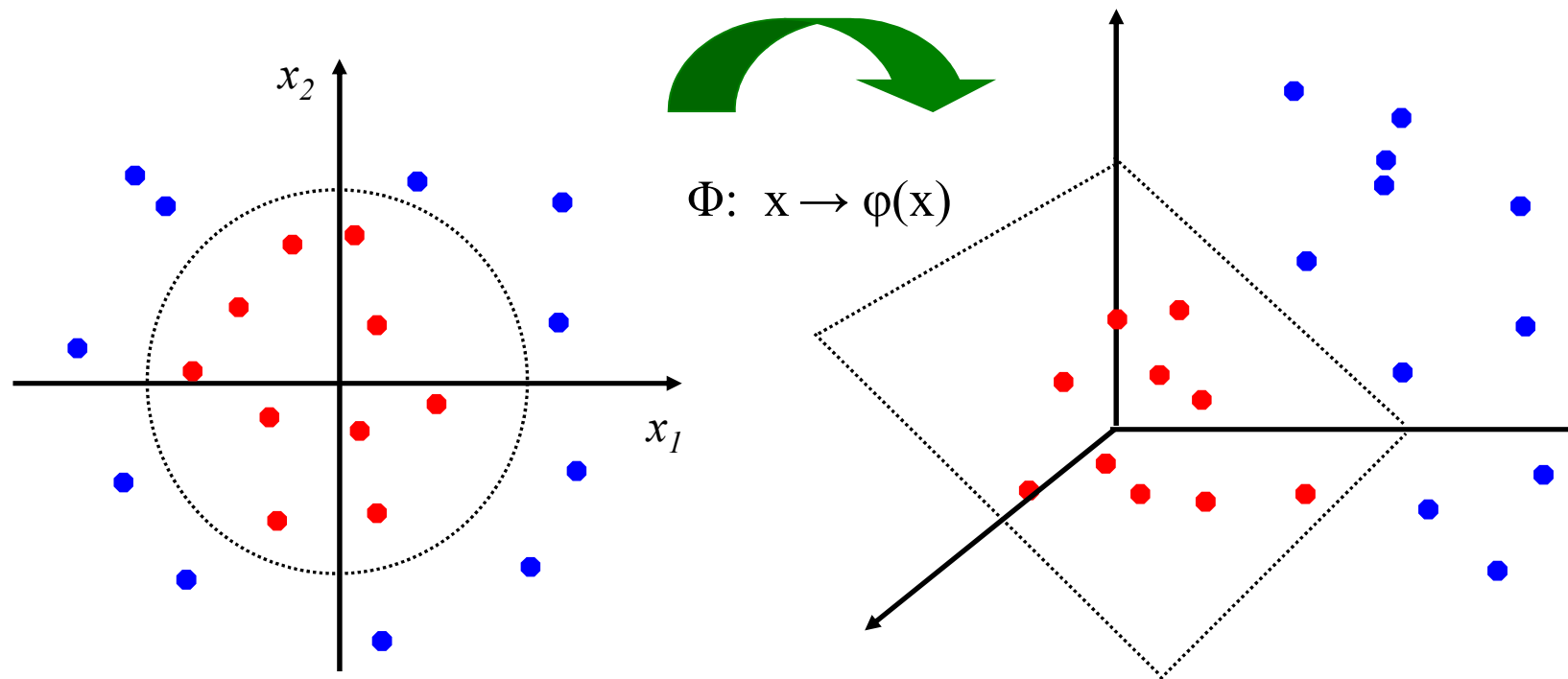
# Non-linear SVMs



# Feature Space



# Feature Space



# Quadratic Basis Functions

$$\Phi(x) = \left[ \begin{array}{c} 1 \\ \sqrt{2}x_1 \\ \sqrt{2}x_2 \\ \vdots \\ \sqrt{2}x_m \\ x_1^2 \\ x_2^2 \\ \vdots \\ x_m^2 \\ \sqrt{2}x_1x_2 \\ \sqrt{2}x_1x_3 \\ \vdots \\ \sqrt{2}x_1x_m \\ \sqrt{2}x_2x_3 \\ \vdots \\ \sqrt{2}x_2x_m \\ \vdots \\ \sqrt{2}x_{m-1}x_m \end{array} \right]$$

Constant Terms

Linear Terms

Pure Quadratic Terms

Quadratic Cross-Terms

Number of terms

$$C_{m+2}^2 = \frac{(m+2)(m+1)}{2} \approx \frac{m^2}{2}$$



22

## *It turns out ...*

$$\Phi(a) \cdot \Phi(b) = 1 + 2 \sum_{i=1}^m a_i b_i + \sum_{i=1}^m a_i^2 b_i^2 + \sum_{i=1}^{m-1} \sum_{j=i+1}^m 2a_i a_j b_i b_j$$

---

$$(a \cdot b + 1)^2 = (a \cdot b)^2 + 2a \cdot b + 1 = \left( \sum_{i=1}^m a_i b_i \right)^2 + 2 \sum_{i=1}^m a_i b_i + 1$$

$$= \sum_{i=1}^m \sum_{j=1}^m a_i b_i a_j b_j + 2 \sum_{i=1}^m a_i b_i + 1$$

$$= \sum_{i=1}^m (a_i b_i)^2 + 2 \sum_{i=1}^{m-1} \sum_{j=i+1}^m a_i b_i a_j b_j + 2 \sum_{i=1}^m a_i b_i + 1$$

---

$$K(a, b) = (a \cdot b + 1)^2 = \Phi(a) \cdot \Phi(b)$$

$O(m)$

$O(m^2)$

# Kernel Trick

- The linear classifier relies on dot products  $x_i \cdot x_j$  between vectors.
- If every data point is mapped into a high-dimensional space via some transformation  $\Phi: x \rightarrow \phi(x)$ , the dot product becomes:  $\phi(x_i) \cdot \phi(x_j)$
- A *kernel function* is some function that corresponds to an inner product in some expanded *feature* space:  $K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$
- Example:  $x=[x_1, x_2]$ ;  $K(x_i, x_j) = (1+x_i \cdot x_j)^2$

$$\begin{aligned} K(x_i, x_j) &= (1 + x_i \cdot x_j)^2 = 1 + x_{i1}^2 x_{j1}^2 + 2x_{i1} x_{j1} x_{i2} x_{j2} + x_{i2}^2 x_{j2}^2 + 2x_{i1} x_{j1} + 2x_{i2} x_{j2} \\ &= [1, x_{i1}^2, \sqrt{2}x_{i1}x_{i2}, x_{i2}^2, \sqrt{2}x_{i1}, \sqrt{2}x_{i2}] \cdot [1, x_{j1}^2, \sqrt{2}x_{j1}x_{j2}, x_{j2}^2, \sqrt{2}x_{j1}, \sqrt{2}x_{j2}] \\ &= \Phi(x_i) \cdot \Phi(x_j), \quad \text{where } \Phi(x) = [1, x_1^2, \sqrt{2}x_1x_2, x_2^2, \sqrt{2}x_1, \sqrt{2}x_2] \end{aligned}$$



# Kernels



$$\textit{Polynomial} : K(x_i, x_j) = (x_i \cdot x_j + 1)^d$$

$$\textit{Gaussian} : K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$$

$$\textit{Hyperbolic Tangent} : K(x_i, x_j) = \tanh(\kappa x_i \cdot x_j + c)$$

# String Kernel



- ❖ Calculate the similarity between text strings.
- ❖ The substring 'c-a-r' is present in both **Car** and **Custard**.
- ❖ Each substring corresponds to a dimension of the feature space.

	c-a	c-t	a-t	b-a	b-t	c-r	a-r	b-r
$\phi(\text{cat})$	$\lambda^2$	$\lambda^3$	$\lambda^2$	0	0	0	0	0
$\phi(\text{car})$	$\lambda^2$	0	0	0	0	$\lambda^3$	$\lambda^2$	0
$\phi(\text{bat})$	0	0	$\lambda^2$	$\lambda^2$	$\lambda^3$	0	0	0
$\phi(\text{bar})$	0	0	0	$\lambda^2$	0	0	$\lambda^2$	$\lambda^3$

$$K(\text{car}, \text{cat}) = \lambda^4$$

$$K(\text{car}, \text{car}) = K(\text{cat}, \text{cat}) = 2\lambda^4 + \lambda^6$$

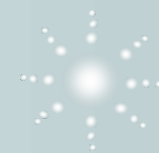
# Solutions of $w$ & $b$

$$w = \sum_{i=1}^l \alpha_i y_i \Phi(x_i)$$

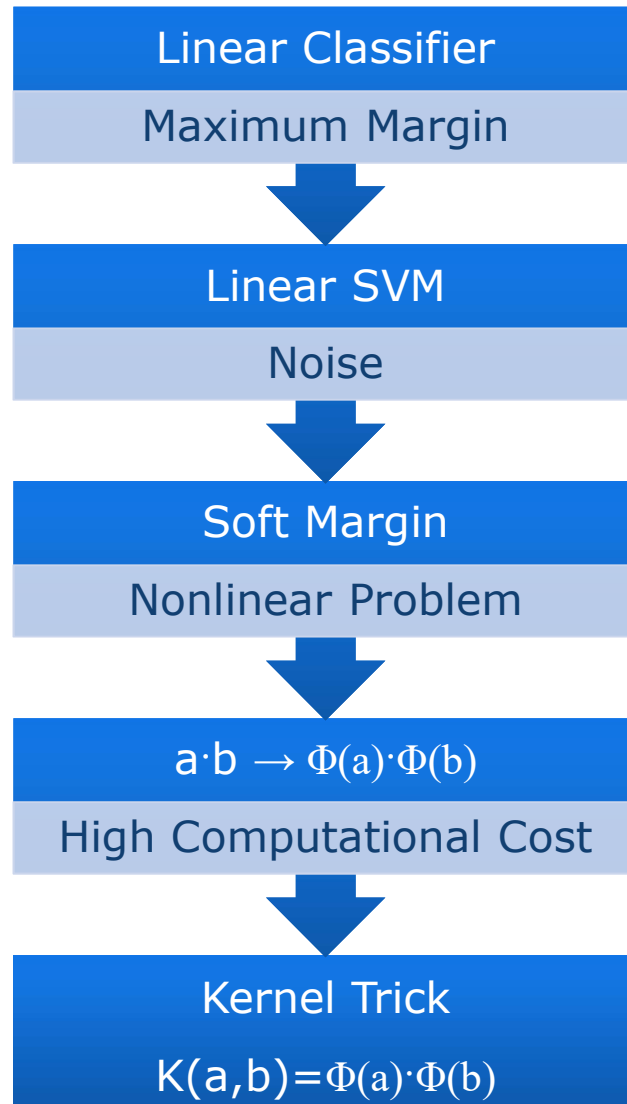
$$w \cdot \Phi(x_j) = \sum_{i=1}^l \alpha_i y_i \Phi(x_i) \cdot \Phi(x_j) = \sum_{i=1}^l \alpha_i y_i K(x_i, x_j)$$

$$b = \frac{1}{N_s} \sum_{s \in S} (y_s - \sum_{m \in S} \alpha_m y_m \Phi(x_m) \cdot \Phi(x_s)) = \frac{1}{N_s} \sum_{s \in S} (y_s - \sum_{m \in S} \alpha_m y_m K(x_m, x_s))$$

$$\boxed{g(x) = \sum_{i=1}^l \alpha_i y_i K(x_i, x) + b} \quad \longleftrightarrow \quad g(x) = w \cdot x + b = \sum_{i=1}^l \alpha_i y_i x_i \cdot x + b$$



# SVM Roadmap



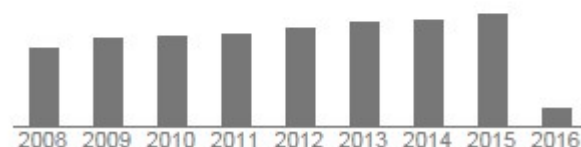
“I have a dream — one day there will be a classifier that can handle nonlinear problems ...”



# SVM Legend



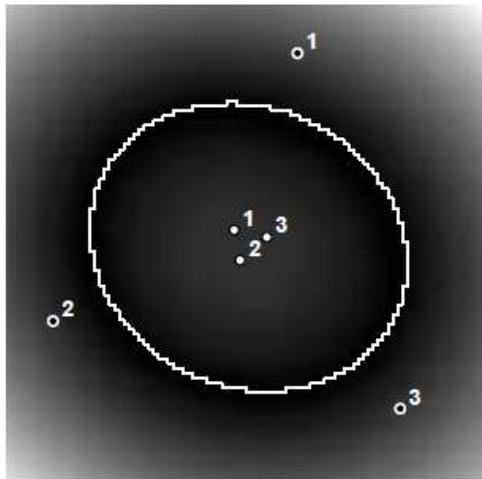
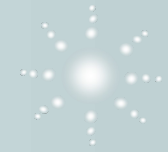
引用指数	总计	2011 年至今
引用	164864	74389
<u>h 指数</u>	109	72
i10 指数	371	270



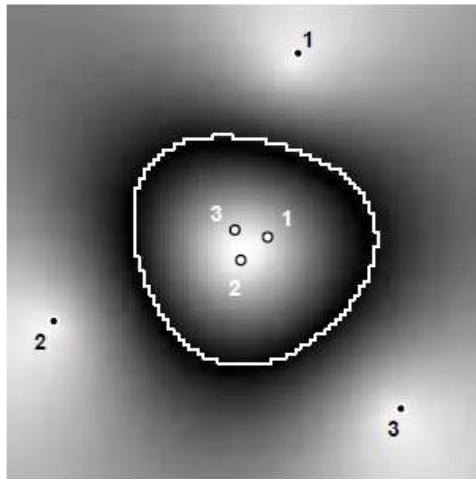
## A training algorithm for optimal margin classifiers

作者	Bernhard E Boser, Isabelle M Guyon, Vladimir N Vapnik
发表日期	1992/7/1
研讨会论文	Proceedings of the fifth annual workshop on Computational learning theory
页码范围	144-152
出版商	ACM
简介	<p>Abstract A training algorithm that maximizes the margin between the training patterns and the decision boundary is presented. The technique is applicable to a wide variety of the classification functions, including Perceptrons, polynomials, and Radial Basis Functions. The effective number of parameters is adjusted automatically to match the complexity of the problem. The solution is expressed as a linear combination of supporting patterns. These are the subset of training patterns that are closest to the decision boundary. Bounds on the ...</p>
引用总数	被引用次数: 7251

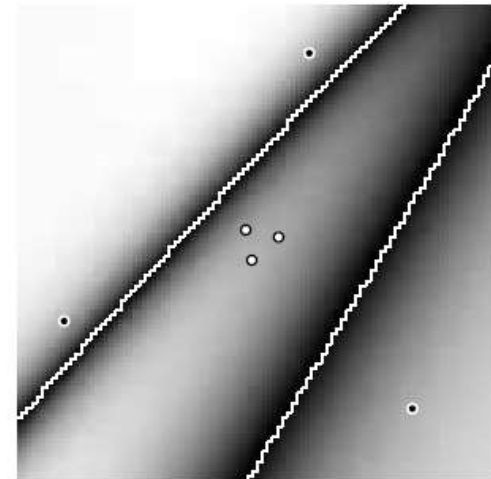
# Decision Boundaries



Polynomial



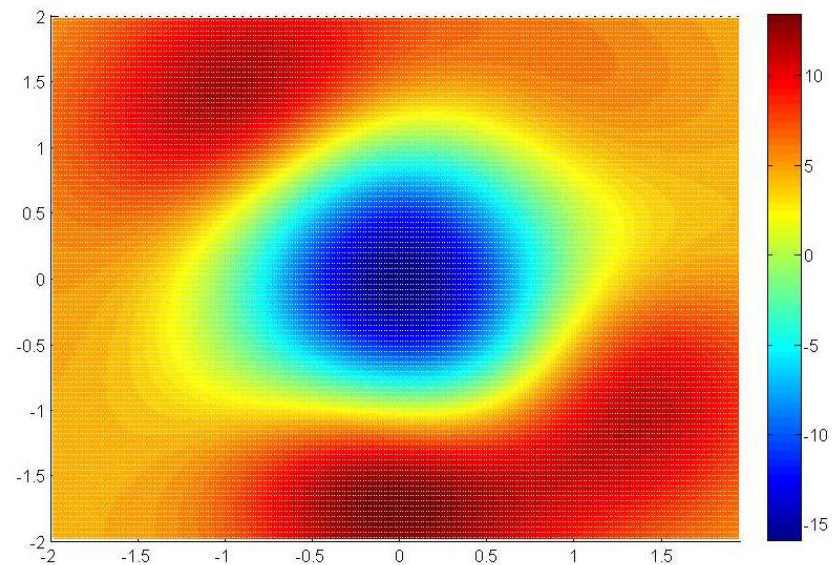
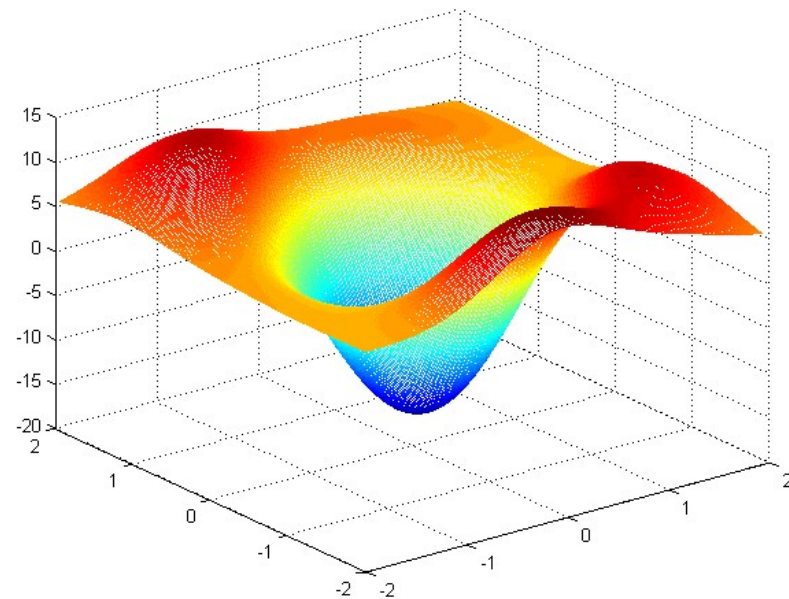
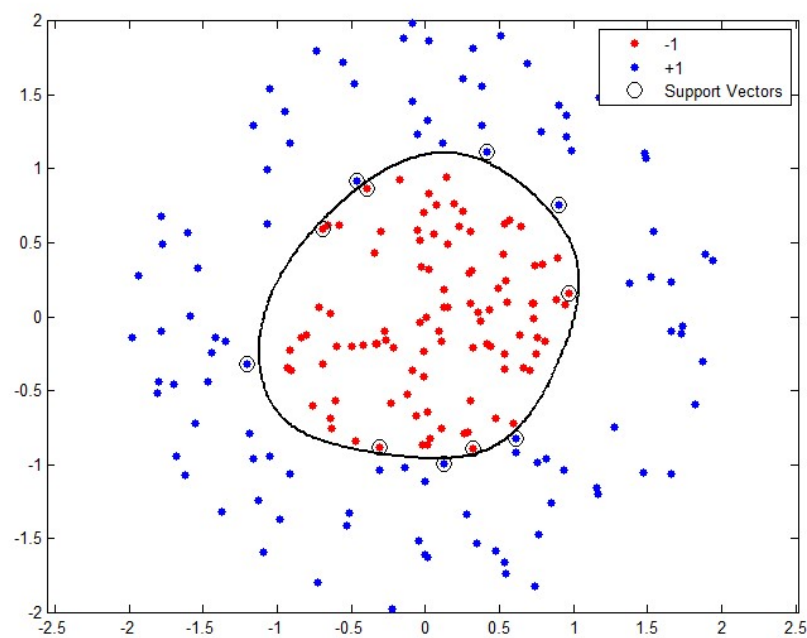
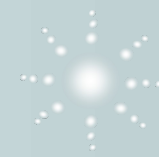
RBF



ANN

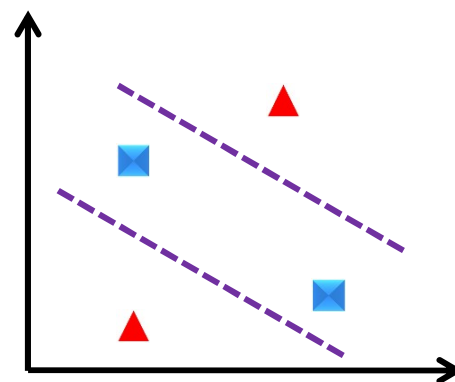
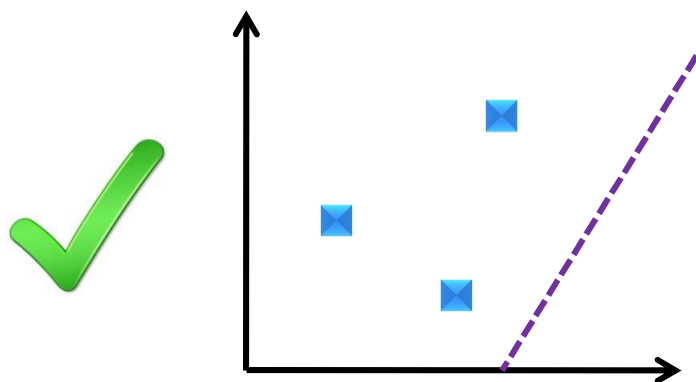
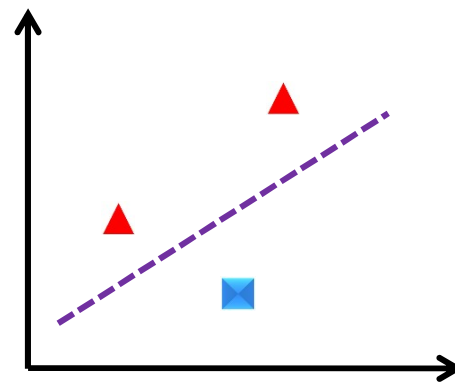
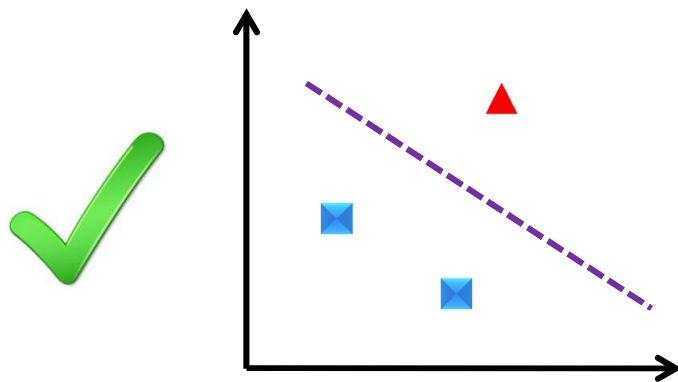


# Decision Boundaries



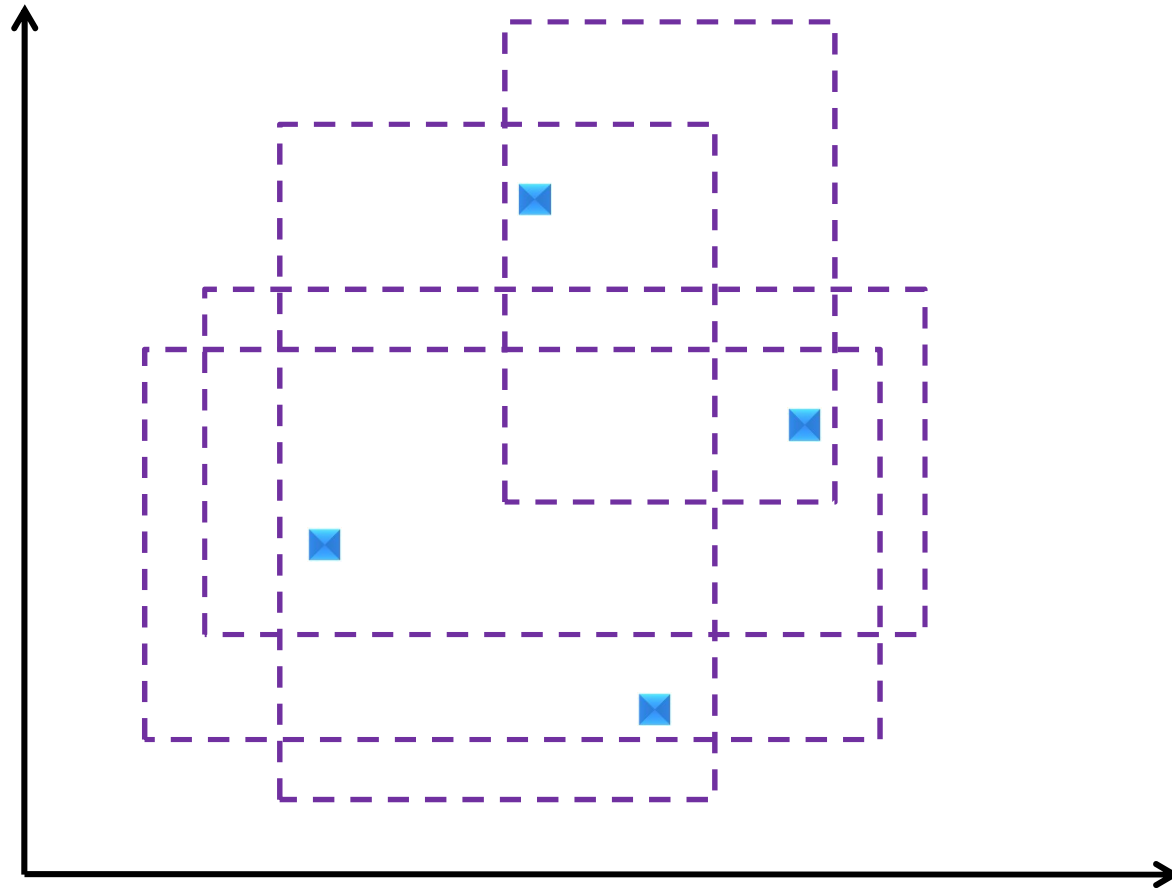
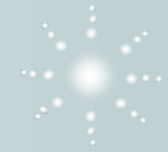


# Model Capacity



A straight line can classify (shatter) a certain set of 3 (not 4) points, regardless their labels.

# Model Capacity



A rectangle can classify (shatter) a certain set of 4 points, regardless of their labels.

# VC Dimension



- ❖ The VC dimension of a model  $M$  is  $h$  if there *exists* a set of (up to)  $h$  points that can be *shattered* by  $M$ .
- ❖ The  $h$  value of a hyperplane in  $\mathbf{R}^n$  is  $n+1$ .
- ❖ The  $h$  value of DT is roughly the number of internal nodes.
- ❖ The  $h$  value of SVM depends on the kernel function in use.
- ❖ VC dimension is pessimistic: arbitrary assignment of labels.
- ❖ Real data sets: points with same labels tend to be close to each other.

$$P\left(E_{test} < E_{train} + \sqrt{\frac{h(\log(2N / h) + 1) - \log(\eta / 4)}{N}}\right) = 1 - \eta$$

$N$ : Number of training samples

# Reading Materials

- ❖ N. Cristianini and J. Shawe-Taylor, *An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods*. Cambridge University Press, 2000.
- ❖ C. Burges, “A Tutorial on Support Vector Machines for Pattern Recognition”. *Data Mining and Knowledge Discovery*, vol. 2, pp. 121-167, 1998.
- ❖ H. Lodhi et al., “Text Classification Using String Kernels”. *The Journal of Machine Learning Research*, vol. 2, pp. 419-444, 2002.
- ❖ Online Resources
  - ❖ <http://www.kernel-machines.org/>
  - ❖ <http://www.support-vector-machines.org/>
  - ❖ <http://www.tristanfletcher.co.uk/SVM%20Explained.pdf>
  - ❖ <http://www.csie.ntu.edu.tw/~cjlin/libsvm/>