



# 机器学习及其MATLAB实现—从基础到实践 第6课

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课程详情访问炼数成金培训网站

<http://edu.dataguru.cn>

- 第一课 MATLAB入门基础
- 第二课 MATLAB进阶与提高
- 第三课 BP神经网络
- 第四课 RBF、GRNN和PNN神经网络
- 第五课 竞争神经网络与SOM神经网络
- **第六课 支持向量机 ( Support Vector Machine, SVM )**
- 第七课 极限学习机 ( Extreme Learning Machine, ELM )
- 第八课 决策树与随机森林
- 第九课 遗传算法 ( Genetic Algorithm, GA )
- 第十课 粒子群优化 ( Particle Swarm Optimization, PSO ) 算法
- 第十一课 蚁群算法 ( Ant Colony Algorithm, ACA )
- 第十二课 模拟退火算法 ( Simulated Annealing, SA )
- 第十三课 降维与特征选择

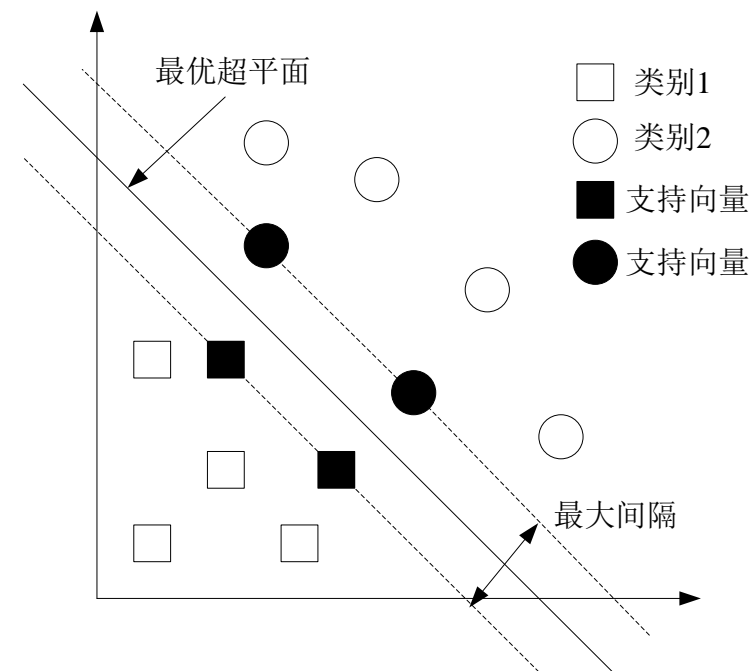
- **Support vector machines (SVMs)** are a set of related **supervised learning** methods that analyze data and recognize patterns, used for classification and regression analysis.
- The original SVM algorithm was invented by **Vladimir Vapnik** and the current standard incarnation (soft margin) was proposed by Corinna Cortes and Vladimir Vapnik.
- A support vector machine constructs a **hyperplane** or set of hyperplanes in a high or infinite dimensional space, which can be used for classification, regression, or other tasks.
- a good separation is achieved by the hyperplane that has the largest distance to the nearest training data points of any class, since in general the larger the margin the lower the generalization error of the classifier.

- We want to find the **maximum-margin hyperplane** that divides the points having  $y_i = 1$  from those having  $y_i = -1$ . Any hyperplane can be written as the set of points satisfying

$$w \cdot x + b = 0$$

- We want to choose the  $w$  and  $b$  to maximize the margin, or distance between the parallel hyperplanes that are as far apart as possible **while still separating the data**.

$$\min \frac{\|w\|^2}{2}$$
$$s.t \ y_i (w \cdot x_i + b) \geq 1, i = 1, 2, \dots, l$$



- Primal form

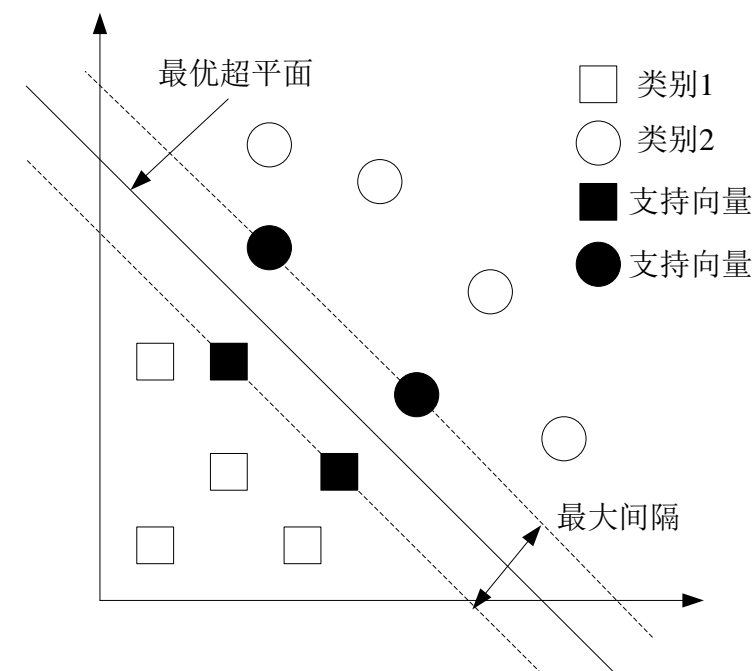
$$\min \frac{\|w\|^2}{2}$$
$$s.t \ y_i(w \cdot x_i + b) \geq 1, i=1, 2, \dots, l$$

- Dual form

$$\max Q(\alpha) = \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)$$
$$s.t \ \sum_{i=1}^l \alpha_i y_i = 0, \alpha_i \geq 0$$

- Decision function

$$f(x) = \text{sgn}(\sum_{i=1}^l \alpha_i^* y_i (x \cdot x_i) + b^*)$$
$$w^* = \sum_{i=1}^l \alpha_i^* x_i y_i \quad b^* = -\frac{1}{2} w^* \cdot (x_r + x_s)$$

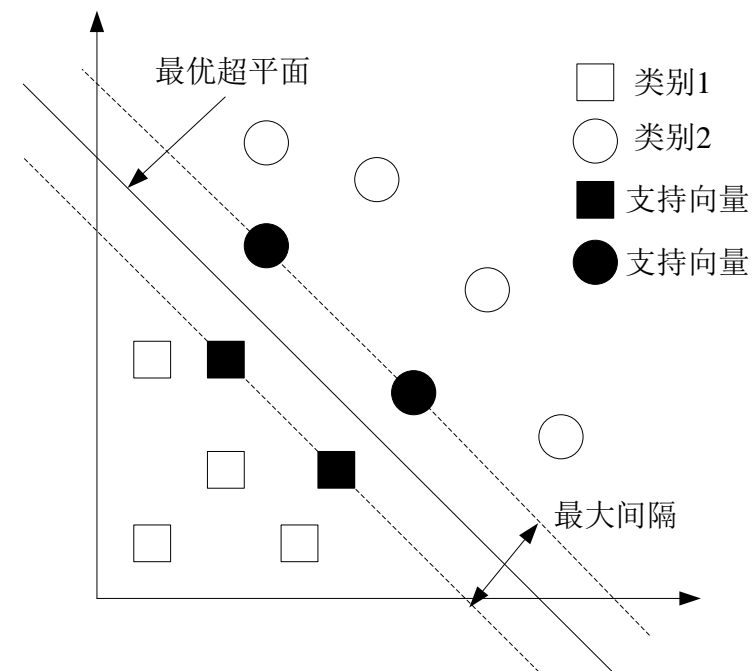


- Primal form

$$\min \frac{\|w\|^2}{2} + C \sum_{i=1}^l \xi_i$$
$$s.t \begin{cases} y_i(w \cdot x_i + b) \geq 1 - \xi_i \\ \xi_i > 0 \end{cases} \quad i = 1, 2, \dots, l$$

- Dual form

$$\max Q(\alpha) = \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)$$
$$s.t \begin{cases} \sum_{i=1}^l \alpha_i y_i = 0 \\ 0 \leq \alpha_i \leq C \end{cases} \quad i = 1, 2, \dots, l$$



# 支持向量机分类原理概述

## ● Dual form

$$K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j)$$

$$\max Q(\alpha) = \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \alpha_i \alpha_j y_i y_j K(x_i, x_j)$$

$$s.t \begin{cases} \sum_{i=1}^l \alpha_i y_i = 0, i = 1, 2, \dots, l \\ 0 \leq \alpha_i \leq C \end{cases}$$

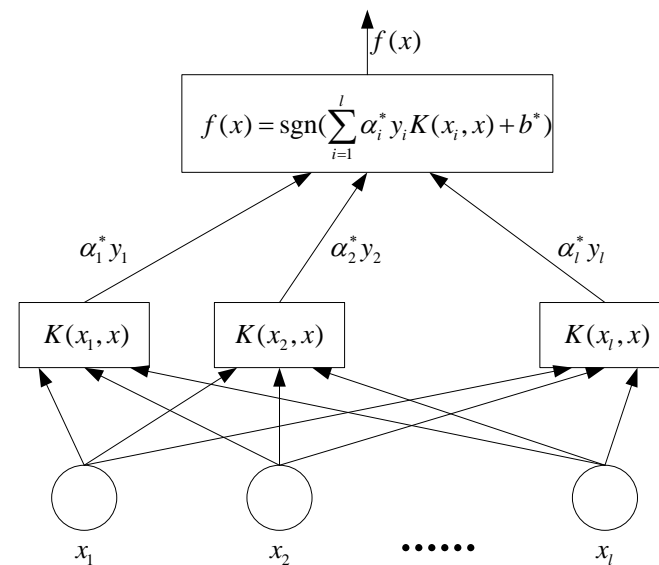
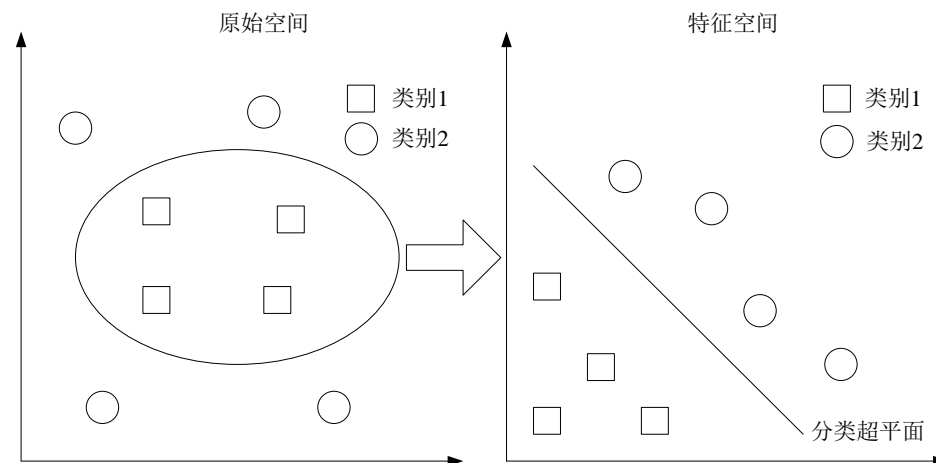
## ● Decision function

$$f(x) = \text{sgn}(w^* \cdot \Phi(x) + b^*)$$

$$= \text{sgn}(\sum_{i=1}^l \alpha_i^* y_i \Phi(x_i) \cdot \Phi(x) + b^*)$$

$$= \text{sgn}(\sum_{i=1}^l \alpha_i^* y_i K(x_i, x) + b^*)$$

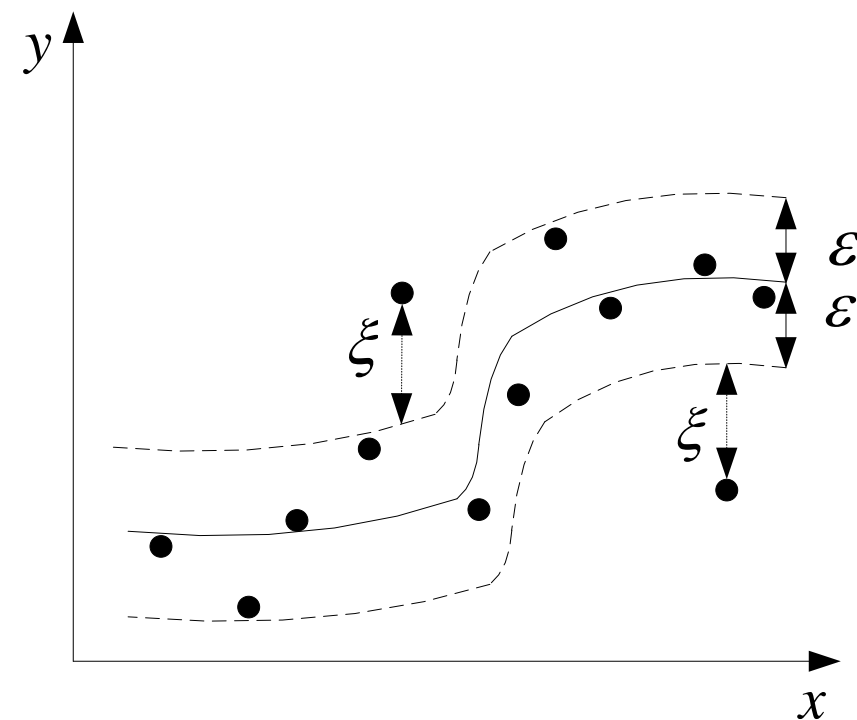
$$w^* = \sum_{i=1}^l \alpha_i^* y_i \Phi(x_i)$$





- 为了利用SVM解决回归拟合方面的问题，Vapnik等人在SVM分类的基础上引入了 **不敏感损失函数**，从而得到了回归型支持向量机（Support Vector Machine for Regression，SVR）。
- SVM应用于回归拟合分析时，其基本思想不再是寻找一个最优分类面使得两类样本分开，而是寻找一个最优分类面**使得所有训练样本离该最优分类面的误差最小**。

$$\begin{aligned} \min \quad & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) \\ \text{s.t.} \quad & \begin{cases} y_i - w \cdot \Phi(x_i) - b \leq \varepsilon + \xi_i \\ -y_i + w \cdot \Phi(x_i) + b \leq \varepsilon + \xi_i^* \\ \xi_i \geq 0, \xi_i^* \geq 0 \end{cases} \quad i = 1, 2, \dots, l \end{aligned}$$

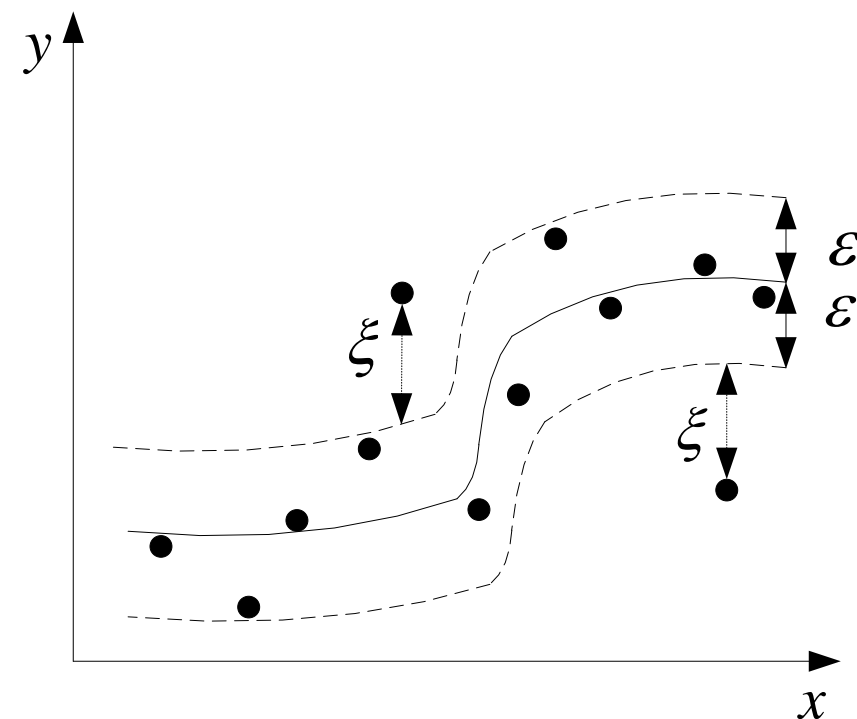


- Primal form

$$\begin{aligned} \min \quad & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) \\ \text{s.t.} \quad & \begin{cases} y_i - w \cdot \Phi(x_i) - b \leq \varepsilon + \xi_i \\ -y_i + w \cdot \Phi(x_i) + b \leq \varepsilon + \xi_i^* \end{cases} \quad i = 1, 2, \dots, l \\ & \xi_i \geq 0, \xi_i^* \geq 0 \end{aligned}$$

- Dual form

$$\begin{aligned} \max_{\alpha, \alpha^*} \quad & \left[ -\frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) K(x_i, x_j) - \sum_{i=1}^l (\alpha_i + \alpha_i^*) \varepsilon + \sum_{i=1}^l (\alpha_i - \alpha_i^*) y_i \right] \\ \text{s.t.} \quad & \begin{cases} \sum_{i=1}^l (\alpha_i - \alpha_i^*) = 0 \\ 0 \leq \alpha_i \leq C \\ 0 \leq \alpha_i^* \leq C \end{cases} \end{aligned}$$



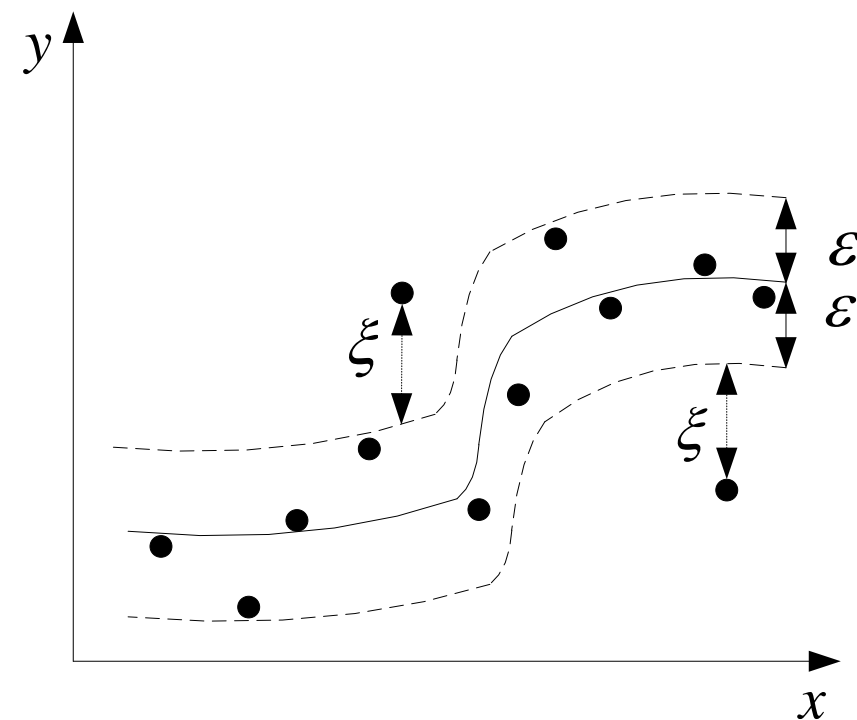
- Decision function

$$f(x) = w^* \cdot \Phi(x) + b^* = \sum_{i=1}^l (\alpha_i - \alpha_i^*) \Phi(x_i) \cdot \Phi(x) + b^*$$

$$= \sum_{i=1}^l (\alpha_i - \alpha_i^*) K(x_i, x) + b^*$$

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

$$b^* = \frac{1}{N_{nsv}} \sum_{0 < \alpha_i < C} \left[ y_i - \sum_{x_j \in SV} (\alpha_i - \alpha_i^*) K(x_i, x_j) - \varepsilon \right] \\ + \frac{1}{N_{nsv}} \sum_{0 < \alpha_i < C} \left[ y_i - \sum_{x_j \in SV} (\alpha_j - \alpha_j^*) K(x_i, x_j) + \varepsilon \right]$$



- **Multiclass SVM** aims to assign labels to instances by using support vector machines, where the labels are drawn from a finite set of several elements.
- The dominating approach for doing so is to **reduce** the single multiclass problem into multiple **binary classification** problems.
- **one-against-all**
  - Classification of new instances for one-against-all case is done by a winner-takes-all strategy, in which the classifier with the highest output function assigns the class.
- **one-against-one**
  - For the one-against-one approach, classification is done by a max-wins voting strategy, in which every classifier assigns the instance to one of the two classes, then the vote for the assigned class is increased by one vote, and finally the class with most votes determines the instance classification.

- 分块算法 ( Chunking )
- Osuna算法
- 序列最小优化算法 ( Sequential Minimal Optimization , SMO )
- 增量学习算法 ( Incremental Learning )

$$\begin{aligned} \max \quad & Q(\alpha) = \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \alpha_i \alpha_j y_i y_j K(x_i, x_j) \\ \text{s.t.} \quad & \begin{cases} \sum_{i=1}^l \alpha_i y_i = 0 \\ 0 \leq \alpha_i \leq C \end{cases}, i = 1, 2, \dots, l \end{aligned}$$

Repeat till convergence {

1. Select some pair  $\alpha_i$  and  $\alpha_j$  to update next (using a heuristic that tries to pick the two that will allow us to make the biggest progress towards the global maximum).
2. Reoptimize  $W(\alpha)$  with respect to  $\alpha_i$  and  $\alpha_j$ , while holding all the other  $\alpha_k$ 's ( $k \neq i, j$ ) fixed.

}

- **LIBSVM -- A Library for Support Vector Machines**
- **Install Tips**
  - Current Directory
  - mex -setup
  - make
  - compiler (VC 6.0)

- **meshgrid**

- Generate X and Y arrays for 3-D plots
- `[X,Y] = meshgrid(x,y)`
- 

- **svmtrain**

- Train support vector machine classifier
- `model = svmtrain(train_label,train_matrix,' libsvm_options' );`

- **svmpredict**

- Predict data using support vector machine
- `[predict_label,accuracy] = svmpredict(test_label,test_matrix,model);`

乳腺癌诊断

混凝土抗压强度预测



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# Thanks

**FAQ时间**