Support Vector Machines (2/2)

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Content

Kernels

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- Now, let ϕ denote a feature mapping, which maps from the attributes to the features. For instance, we can have

$$\phi(x) = \begin{bmatrix} x \\ x^2 \\ x^3 \end{bmatrix}$$

Kernels

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- We simply need to go over our previous algorithm, and replace x everywhere in it with $\phi(x)$.
- Since the algorithm can be written entirely in terms of the inner products $\langle x, z \rangle$, this means that we would replace all those inner products with $\langle \phi(x), \phi(z) \rangle$.

Kernels

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- Then, everywhere we previously had $\langle x, z \rangle$ in our algorithm, we could simply replace it with $K(x, z)$, and our algorithm would now be learning using the features ϕ.
- Something interesting is that often, $K(x, z)$ may be very inexpensive to calculate, even though $\phi(x)$ itself may be very expensive to calculate.

Kernels

- In such settings, by using in our algorithm an efficient way to calculate $K(x, z)$, we can get SVMs to learn in the high dimensional feature space given by ϕ, but without ever having to explicitly find or represent vectors $\phi(x)$.

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- Lets see an example. Suppose $x, z \in \mathbb{R}^n$, and consider

$$K(x, z) = (x^T z)^2.$$

- Note that computing $(x^T z)^2$ can be done in $O(n)$.

Kernels

We can also write this as

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Thus, we see that $K(x,z) = \phi(x)^T \phi(z)$

Kernels

Where the feature mapping $\phi(x)$ is given by

$$\phi(x) = \begin{bmatrix} x_1 x_1 \\ x_1 x_2 \\ x_1 x_3 \\ x_2 x_1 \\ x_2 x_2 \\ x_2 x_3 \\ x_3 x_1 \\ x_3 x_2 \\ x_3 x_3 \end{bmatrix}.$$

Note that while calculating the high-dimensional $\phi(x)$ requires $O(n^2)$ time, finding $K(x, z)$ takes only $O(n)$ time.

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$$= \sum_{i,j=1}^{n} (x_i x_j)(z_i z_j) + \sum_{i=1}^{n} (\sqrt{2c}x_i)(\sqrt{2c}z_i) + c^2.$$

Kernels

This corresponds to the feature mapping

$$\phi(x) = \begin{bmatrix} x_1 x_1 \\ x_1 x_2 \\ x_1 x_3 \\ x_2 x_1 \\ x_2 x_2 \\ x_2 x_3 \\ x_3 x_1 \\ x_3 x_2 \\ x_3 x_3 \\ \sqrt{2c} x_1 \\ \sqrt{2c} x_2 \\ \sqrt{2c} x_3 \\ c \end{bmatrix}.$$

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- This corresponds to all the monomials of the form $x_{i1} x_{i2} \ldots x_{ik}$ that are up to order d.
- However, despite working in dimension $O(n^d)$, computing $K(x, z)$, still takes only $O(n)$ time, and hence we never need to explicitly represent feature vectors in this very high dimensional space.

Kernels

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- Conversely, if $\phi(x)$ and $\phi(z)$ are far apart, then $K(x,z) = \phi(x)^T\phi(z)$ will be small.
- So we can think of $K(x,z)$ as some measurement of how similar are $\phi(x)$ and $\phi(z)$, or of how similar are x and z.

Kernels

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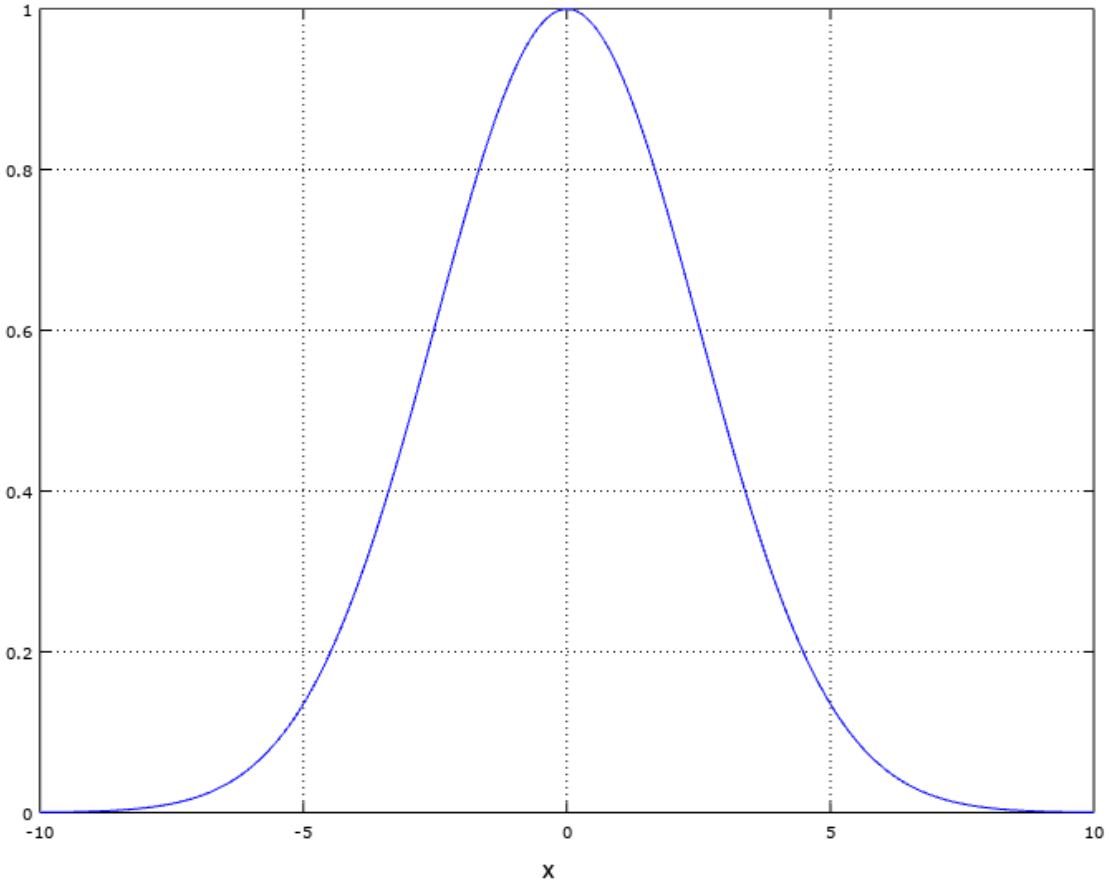
This is a reasonable measure of x and z similarity, and is close to 1 when x and z are close, and near 0 when x and z are far apart.

Kernels

Plot of the Gaussian kernel in one dimension with $x = 0$ and $\sigma = 0.2$:



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&= \exp(-(x-z)^2) \\
&= \exp(-x^2)\exp(-z^2)\exp(2xz) \\
&= \exp(-x^2)\exp(-z^2)\sum_{k=0}^{\infty}\frac{2^k(x)^k(z)^k}{k!}
\end{aligned}
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Mercer Theorem

Let $K : \mathbb{R}^n \times \mathbb{R}^n \mapsto \mathbb{R}$ be given. Then, for K to be a valid kernel, it is necessary and sufficient that for any $\{x^{(1)}, \ldots, x^{(m)}\}, (m < \infty)$, the corresponding kernel matrix is symmetric and positive semi-definite.

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where a kernel matrix $\mathcal{K}$ for a data set $\{x^{(1)}, \ldots, x^{(m)}\}, (m < \infty)$ is defined as

$$\mathcal{K} = \begin{bmatrix} K(x^{(1)}, x^{(1)}) & K(x^{(1)}, x^{(2)}) & \ldots & K(x^{(1)}, x^{(m)}) \\ K(x^{(2)}, x^{(1)}) & K(x^{(2)}, x^{(2)}) & \ldots & K(x^{(2)}, x^{(m)}) \\ \ldots & \ldots & \ldots & \ldots \\ K(x^{(m)}, x^{(1)}) & K(x^{(m)}, x^{(2)}) & \ldots & K(x^{(m)}, x^{(m)}) \end{bmatrix}.$$

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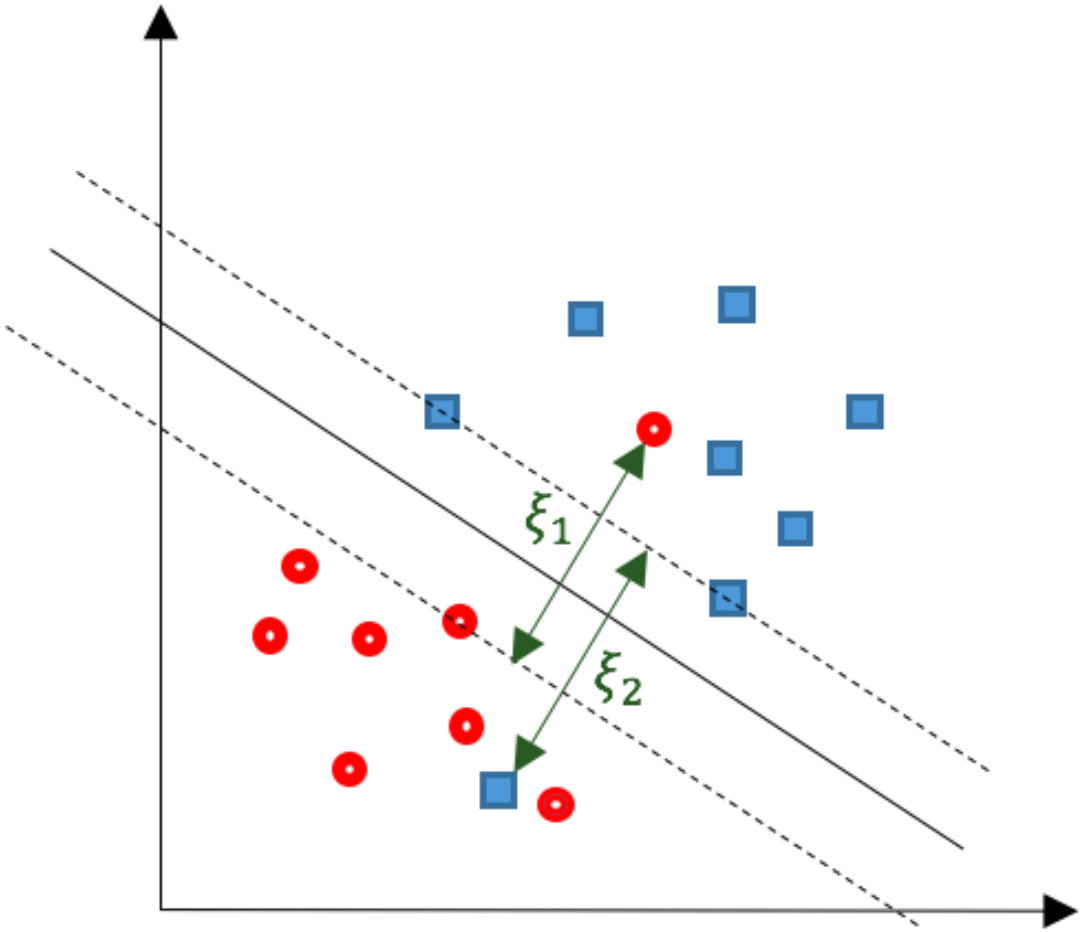
Any algorithm that can be written in terms of only the inner products $\langle x, z \rangle$ between input attribute vectors, then by replacing this with $K(x, z)$ where K is a kernel function, you can allow the algorithm to work efficiently in the high dimensional feature space corresponding to K.

The Non-Separable Case



The Non-Separable Case

To make the algorithm work for non-linearly separable datasets as well as less sensitive to outliers, we reformulate our optimization problem as follows:

$$\min_{\gamma,\mathrm{w},b} \quad \frac{1}{2}||\mathrm{w}||^2 + C\sum_{i=1}^{m}\xi_i$$

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$$\text{s.t.} \quad y^{(i)}(\mathrm{w}^T\mathrm{x}^{(i)} + b) \geq 1 - \xi_i, \quad i = 1, \ldots, m$$

$$\xi_i \geq 0, \quad i = 1, \ldots, m.$$

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Thus, examples are now allowed to have functional margin less than 1.

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- The parameter C controls the relative weighting between the twin goals of making $||\mathrm{w}||^2$ large and of ensuring that most examples have functional margin at least 1.

The Non-Separable Case

As before the Lagrangian is:

$$\mathcal{L}(\mathsf{w}, b, \xi, \alpha, r) =$$

$$\tfrac{1}{2}\mathsf{w}^T\mathsf{w} + C\sum_{i=1}^{m}\xi_i - \sum_{i=1}^{m}\alpha_i\left[y^{(i)}(\mathsf{w}^T\mathsf{x} + b) - 1 + \xi_i\right] - \sum_{i=1}^{m} r_i\xi_i.$$

where α_i and r_i are Lagrange multipliers constrained to be ≥ 0.

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where α_i and r_i are Lagrange multipliers constrained to be ≥ 0.
After setting the derivatives with respect to w and b to zero we get:

$$\begin{aligned} \max_{\alpha} \quad & W(\alpha) = \sum_{i=1}^{m}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{m} y^{(i)}y^{(j)}\alpha_i\alpha_j\langle \mathsf{x}^{(i)}, \mathsf{x}^{(j)}\rangle \\ \text{s.t.} \quad & 0 \leq \alpha_i \leq C, \quad i = 1, \ldots, m \\ & \sum_{i=1}^{m}\alpha_i y^{(i)} = 0 \end{aligned}$$

Sequential Minimal Optimization

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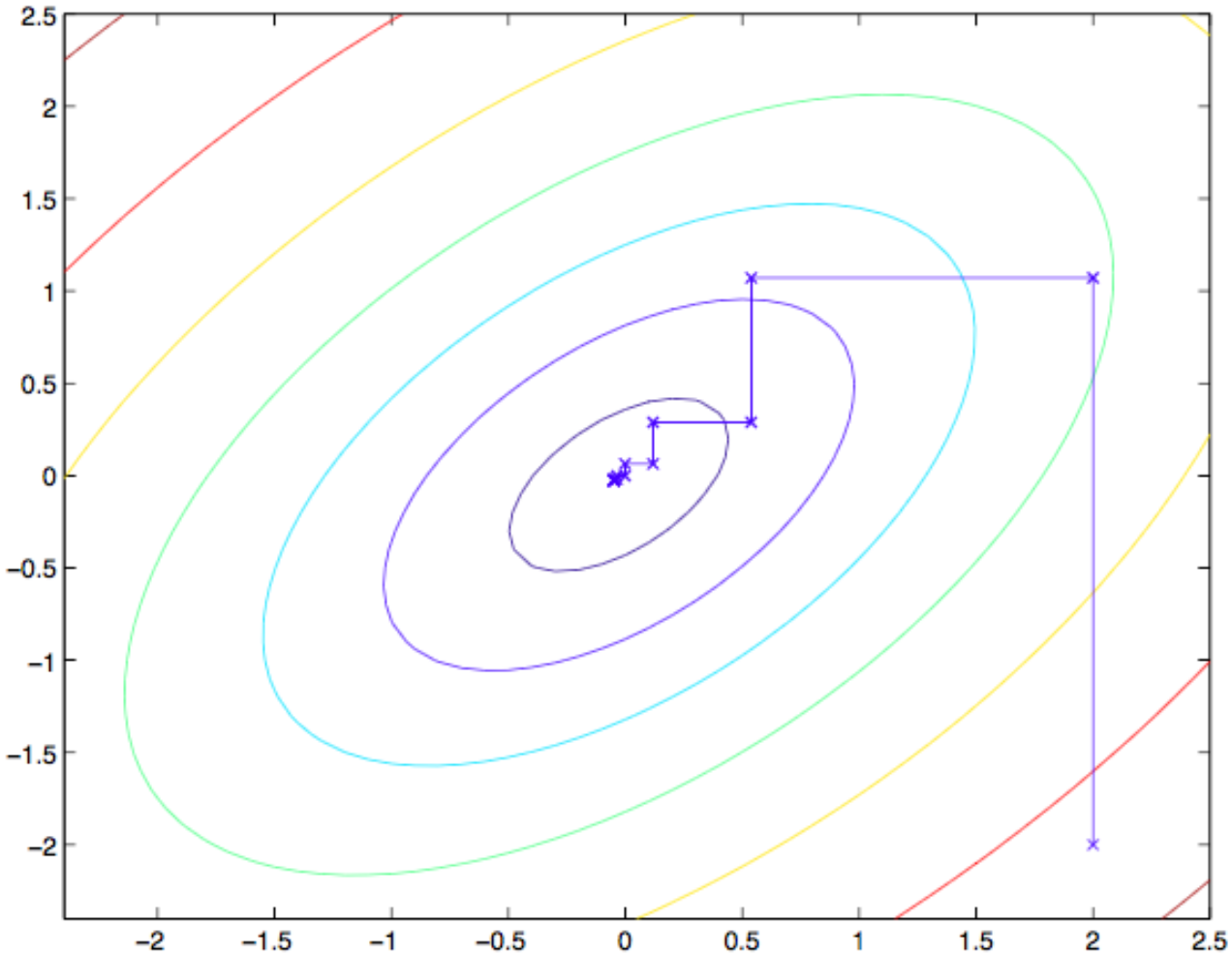
- We can use the coordinate ascent algorithm to solve it:

  Loop until convergence

  For $i = 1, \ldots, m$

  $\alpha_i := \arg\max_{\hat{\alpha}_i} W(\alpha_1, \ldots, \alpha_{i-1}, \hat{\alpha}_i, \alpha_{i+1}, \ldots, \alpha_m).$

Sequential Minimal Optimization



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From the optimization problem

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Sequential Minimal Optimization

Repeat until convergence

1. Select some pair α_i and α_j to update next.
2. Reoptimize $W(\alpha)$ with respect to α_i and α_j, while holding all the others α_k, $k \neq i, j$ fixed.

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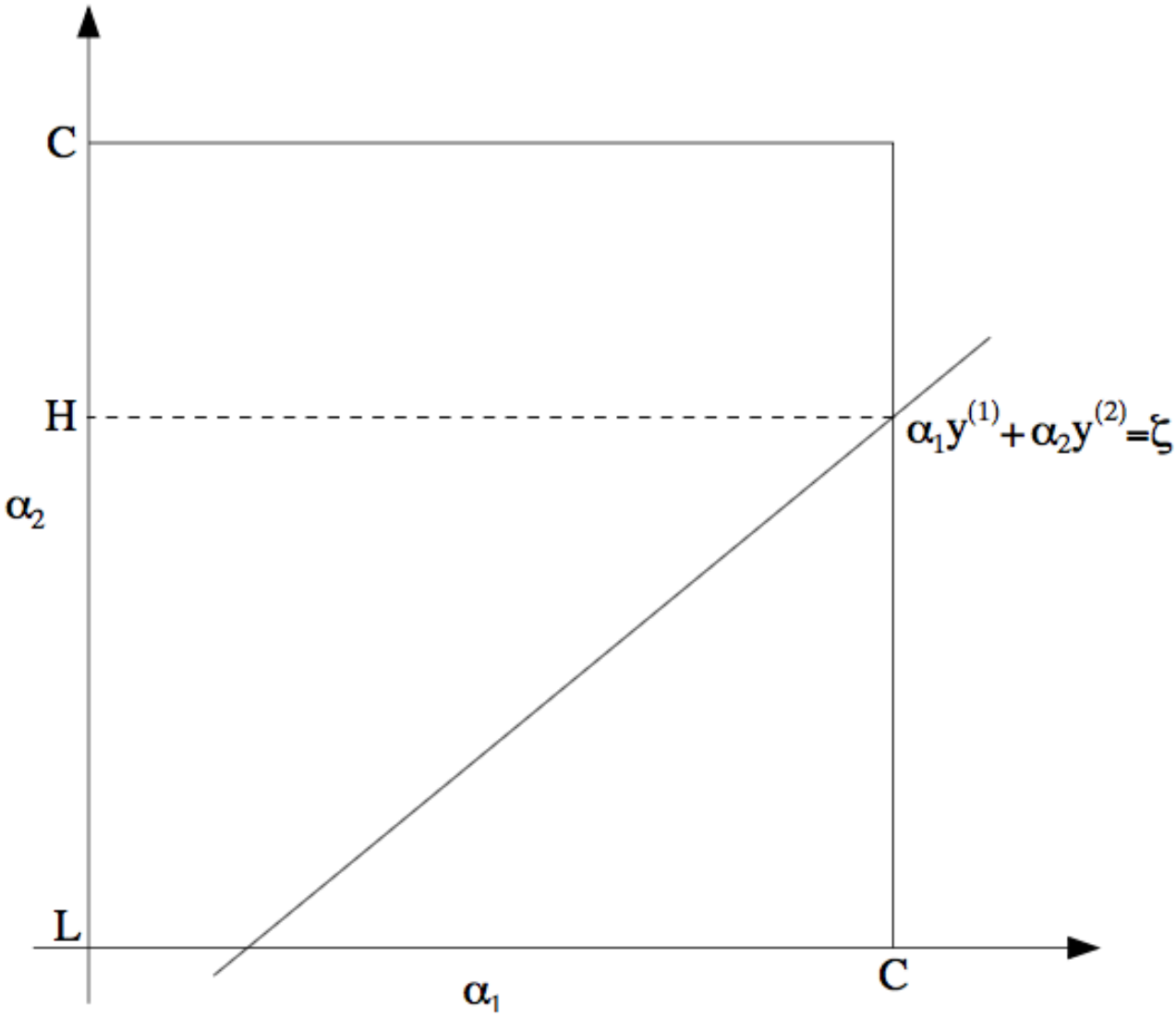
$$\alpha_1 y^{(1)} + \alpha_2 y^{(2)} = \zeta. \qquad \alpha_1 = (\zeta - \alpha_2 y^{(2)})\, y^{(1)}.$$

Sequential Minimal Optimization



Sequential Minimal Optimization

Writing our objective function $W(\alpha)$ as

$$W(\alpha_1, \alpha_2, \ldots, \alpha_m) = W((\zeta - \alpha_2 y^{(2)})\, y^{(1)}, \alpha_2, \alpha_3, \ldots, \alpha_m)$$

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Finally, having found α_2, we can calculate α_1 from $\alpha_1 = (\zeta - \alpha_2 y^{(2)})\, y^{(1)}$.

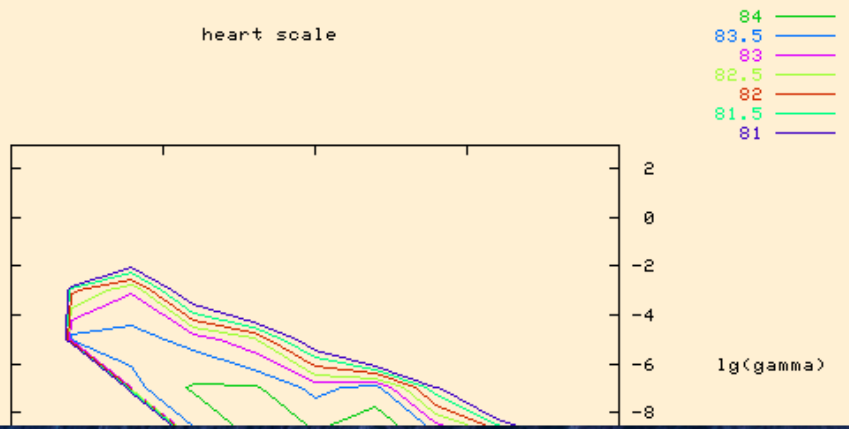
The libSVM library

csie.ntu.edu.tw

LIBSVM -- A Library for Support Vector Machines

Chih-Chung Chang and Chih-Jen Lin

NEW Version 3.21 released on December 14, 2015. It conducts some minor fixes.
NEW LIBSVM tools provides **many extensions** of LIBSVM. Please check it if you need some functions not supported in LIBSVM.
NEW We now have a nice page LIBSVM data sets providing problems in LIBSVM format.
NEW A practical guide to SVM classification is available now! (mainly written for beginners)
We now have an easy script (easy.py) for users who know NOTHING about SVM. It makes everything automatic--from data scaling to parameter selection.
The parameter selection tool grid.py generates the following contour of cross-validation accuracy. To use this tool, you also need to install python and gnuplot.



Reference

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- Christopher Bishop. **Pattern Recognition and Machine Learning**. Springer. 2006.

Thank You!

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