Using an SVM

SVM in Practice

Support Vector Machines

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Gaussian kernel:

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and/or m large

Kernel (similarity) functions:

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$x \rightarrow \begin{matrix} f_1 \\ f_2 \\ \vdots \\ f_m \end{matrix}$

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$x \in \mathbb{R}^n$

$\boxed{\|x - l\|^2}$

$v = x - l$

$\|v\|^2 = v_1^2 + v_2^2 + \cdots + v_n^2$

$= \underbrace{(x_1 - l_1)^2}_{1000 \text{ feet}^2} + \underbrace{(x_2 - l_2)^2}_{1\text{-}5 \text{ bedrooms}} + \cdots + (x_n - l_n)^2 .$

Other choices of kernel

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Many off-the-shelf kernels available:

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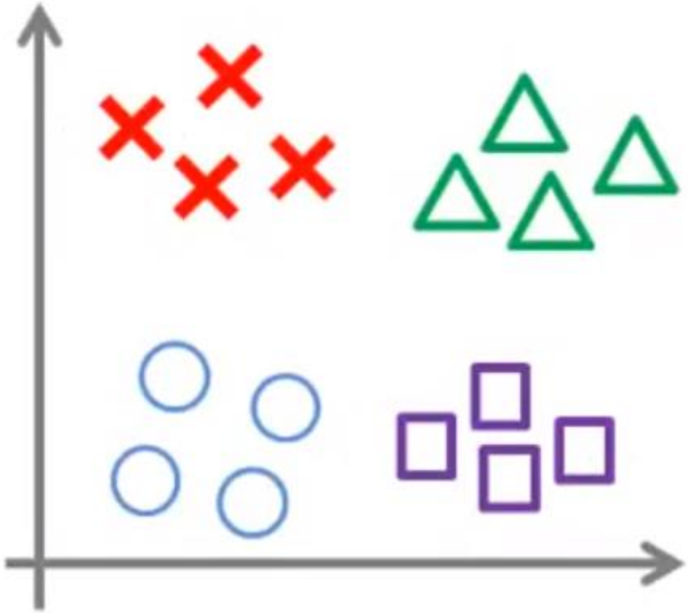
- More esoteric: String kernel, chi-square kernel, histogram intersection kernel, ...

Multi-class classification



$$y \in \{1, 2, 3, \ldots, K\}$$

Many SVM packages already have built-in multi-class classification functionality.

Otherwise, use one-vs.-all method. (Train K SVMs, one to distinguish $y = i$ from the rest, for $i = 1, 2, \ldots, K$), get $\theta^{(1)}, \theta^{(2)}, \ldots, \theta^{(K)}$

Pick class i with largest $(\theta^{(i)})^T x$

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Use logistic regression, or SVM without a kernel ("linear kernel")

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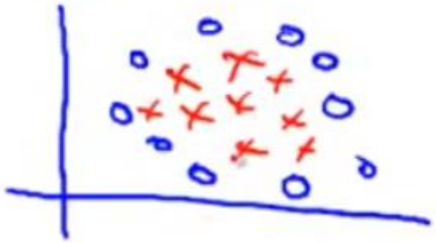
Use SVM with Gaussian kernel



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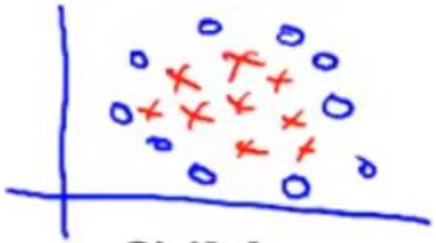

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Packages are good but they struggle if there are too many data.

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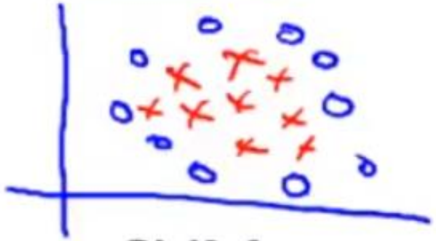

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Neural network likely to work well for most of these settings, but may be slower to train.

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