①✓ supervised learning 的算法中，各算法比较相似，但 Data Amount 等因素往往起了决定作用。
Feture 选择
Regularization 的参数

② 先从LR开始，再讲怎么修改，引出SVM。

Support Vector Machines

Optimization objective

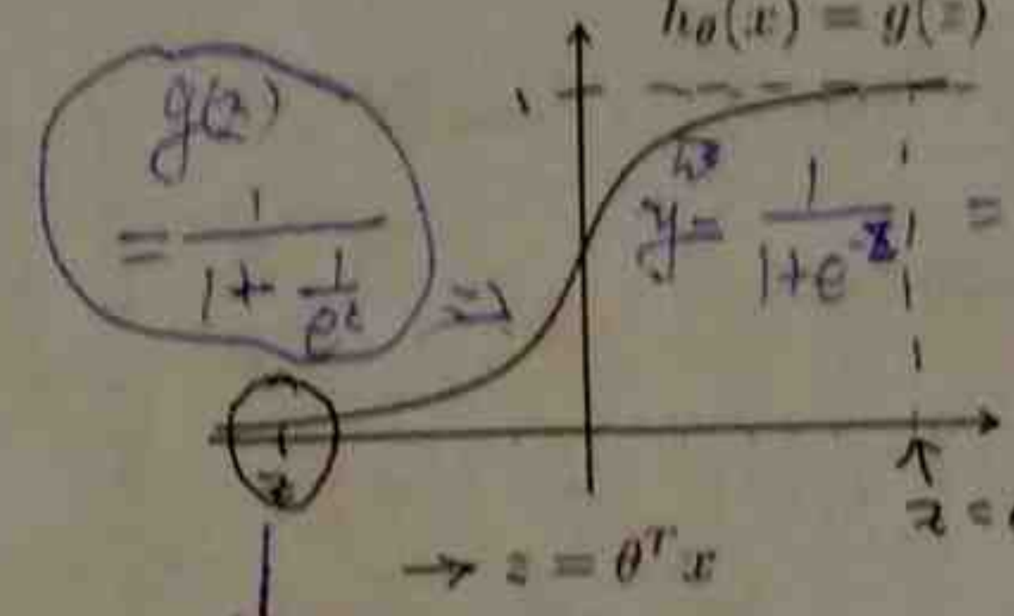
Machine Learning

① 但SVM非常powerful 在both 工业界和学术界
③ SVM 与神经网络相比 clearner，与Logistic Regression相比 powerful

Alternative view of logistic regression

先从讲LR开始。
hypothes function

$$\rightarrow h_\theta(x) = \frac{1}{1+e^{-\theta^T x}}$$



$z \rightarrow +\infty$ $y \rightarrow 1$
$z = 0$ $y = \frac{1}{2}$
$z \rightarrow -\infty$ $y \rightarrow 0$

If $y = 1$, we want $h_\theta(x) \approx 1$, $\theta^T x \gg 0$ $\rightarrow +\infty$
If $y = 0$, we want $h_\theta(x) \approx 0$, $\theta^T x \ll 0$ $\rightarrow -\infty$
$z = \theta^T x$

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②

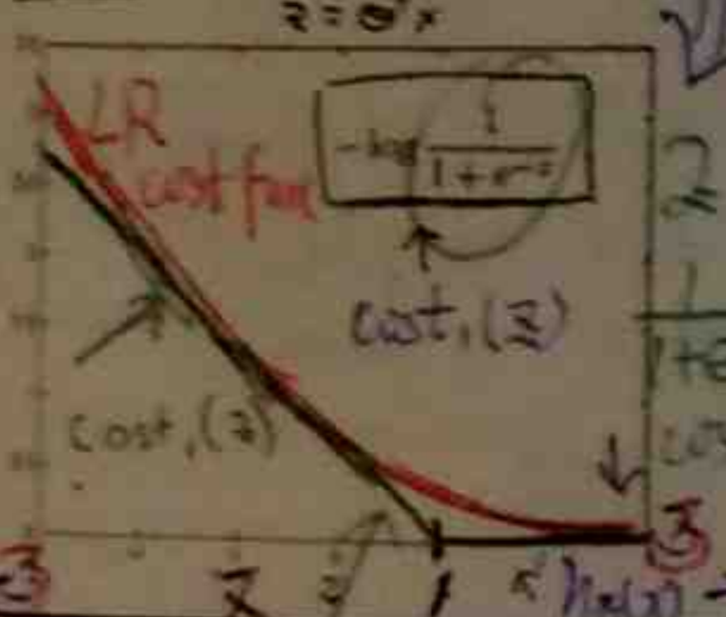
Alternative view of logistic regression

(x,y) 每个example contribute a term of cost function

Cost of example: $-(y \log h_\theta(x) + (1-y)\log(1-h_\theta(x)))$ ← cost function

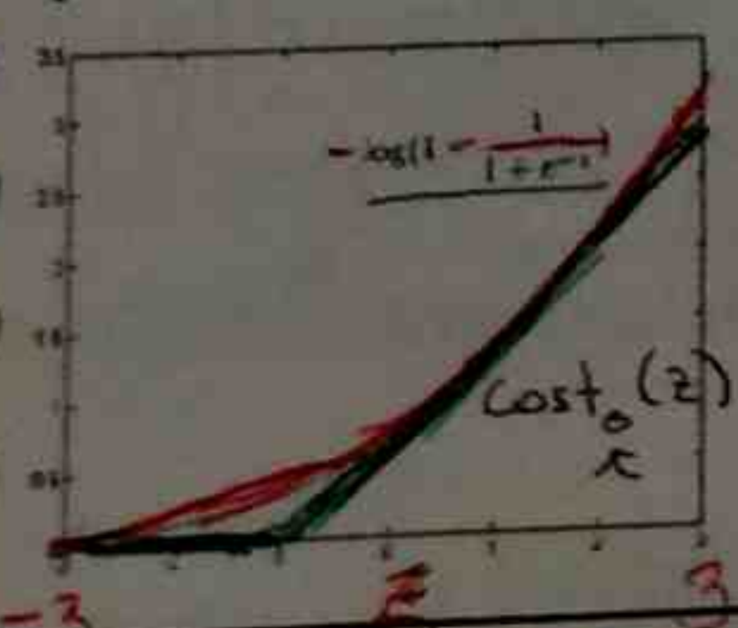
$$= \boxed{-y \log \frac{1}{1+e^{-\theta^T x}}} - \boxed{(1-y)\log(1 - \frac{1}{1+e^{-\theta^T x}})} \leftarrow \text{代入 } h_\theta(x)$$

If $y = 1$ (want $\theta^T x \gg 0$): $z = \theta^T x$



y=1 y=0
$z \in (0, +\infty)$
$\frac{1}{1+e^{-z}} \in (0,1)$
cost $\in (+, 0)$

If $y = 0$ (want $\theta^T x \ll 0$):



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$h_\theta(x) \rightarrow +\infty$
$z = h_\theta(x) \rightarrow -\infty$
修改cost function
$cost(z) \rightarrow 0$
$z = \theta^T x \rightarrow +\infty$ $cost(z) \rightarrow 0$
$\frac{1}{1+e^{-z}} \rightarrow 1$
$y = -\log h$
$1 - z_0 = \frac{1}{1+e^{-z}} \rightarrow 0$
$z_0 = 1 - \frac{1}{1+e^{-z}} \rightarrow 1$
$\log(1 - \frac{1}{1+e^{z}}) \rightarrow 0$
$cost(z_0) \rightarrow 0$

Support vector machine

Logistic regression: 最小化cost func

把括号外的"-"移到括号内。

$$\min_\theta \frac{1}{m}\left[\sum_{i=1}^m y^{(i)}\left(\underbrace{-\log h_\theta(x^{(i)})}_{cost_1(\theta^T x^{(i)})}\right) + (1-y^{(i)})\left(\underbrace{(-\log(1-h_\theta(x^{(i)})))}_{cost_0(\theta^T x^{(i)})}\right)\right] + \frac{\lambda}{2m}\sum_{j=1}^n \theta_j^2$$

有 $\frac{\lambda}{m}$

Support vector machine:

不修改训练出的 θ。
$\min_u ((u-5)^2+1) \rightarrow u = 5$
$\min_u 10((u-5)^2+10) \rightarrow u = 5$

没有 $\frac{1}{m}$ 不改变最优 θ 值

用 $A + \lambda B$ 来控制 θ。
$C = \frac{1}{\lambda}$ C 的作用类似 $\frac{1}{\lambda}$，让
用 $CA + B$ 来控制 θ。
没有 $\frac{\lambda}{m}$ 也以
$C = \frac{1}{\lambda}$
则
$CA + B = A + \lambda B$
?

$$\min_\theta C \sum_{i=1}^m \left[y^{(i)} \underline{cost_1(\theta^T x^{(i)})} + (1-y^{(i)}) \underline{cost_0(\theta^T x^{(i)})}\right] + \frac{1}{2}\sum_{i=1}^n \theta_j^2$$

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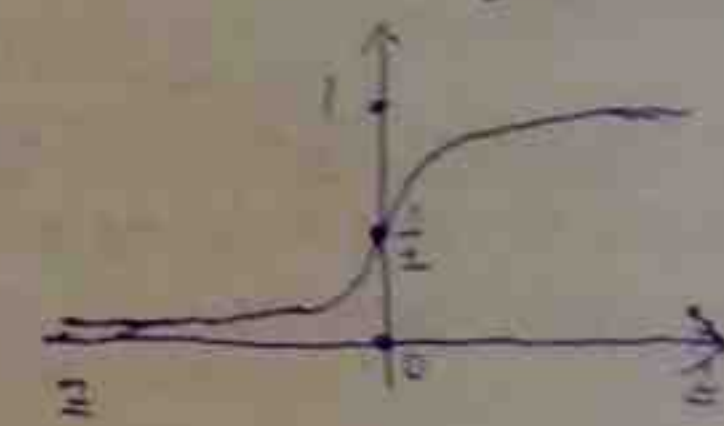
只是换了一个 Regularization Term ?
从 λ 换为 C。

hypothesis function of LR.

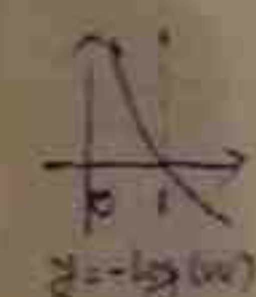
$\boxed{↗}$ $h_\theta(x) = \frac{1}{1+e^{-\theta^T x}} \Leftrightarrow g(z) = \frac{1}{1+\frac{1}{e^z}}$



$\boxed{↙}$ $y=1$时，$z \to +\infty$，$g(z) \to 1$，$-\log(g(z)) \to 0$

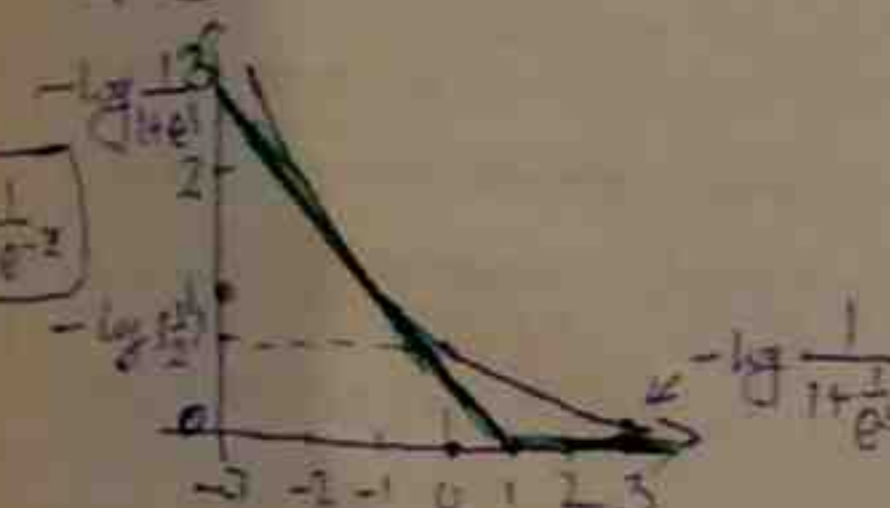
虽然 $g(z) > \frac{1}{2}$，$z>0$，但假定 $z \to -\infty$ 时，

$z \to -\infty$，$g(z) \to 0$，$-\log(g(z)) \to +\infty$



因此

$\boxed{\Gamma(z) = -\log \frac{1}{1+e^{-z}}}$



$\boxed{z = -\theta^T x}$

同理可推 $y=0$ 时.

对正例，预测得越准，cost越小 (→0)
对正例，预测得越不准，cost越大 (→+∞)

SVM: cost function 作些修改　同理可推 $y=0$ 时

分为两段直线

$z>1$ 时，—

$z<1$ 时 ＼

SVM hypothesis

$$\min_\theta C \sum_{i=1}^{m} \left[y^{(i)} cost_1(\theta^T x^{(i)}) + (1 - y^{(i)}) cost_0(\theta^T x^{(i)}) \right] + \frac{1}{2} \sum_{i=1}^{n} \theta_j^2$$

Hypothesis:

$z = \theta^T x$

$h_\theta(x) = \begin{cases} 1 & \text{if } \theta^T x \geq 0 \\ 0 & \text{otherwise.} \end{cases}$

不输出概率，直接判断

LR 不同 $z \geq 0$

$h_\theta(x) \begin{cases} \geq 0.5 & \text{if } \theta^T x \geq 0 \quad 期望 \theta^T x \to +\infty \\ < 0.5 & \text{otherwise} \quad 期望 \theta^T x \to -\infty \end{cases}$

$z < 0$

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Support Vector Machines

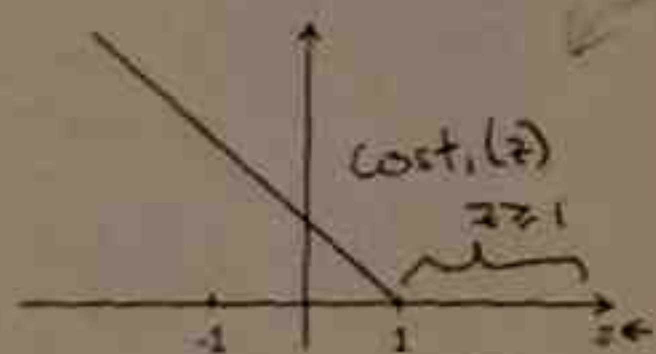
Large Margin Intuition

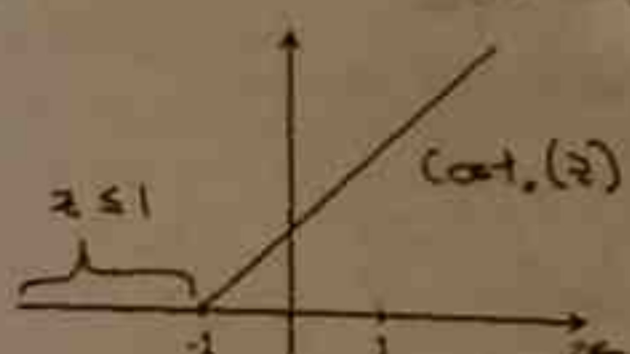
Machine Learning

SVM · Large Margin Classifier

Support Vector Machine

$$\to \min_\theta C \sum_{i=1}^{m} \left[y^{(i)} \underline{cost_1(\theta^T x^{(i)})} + (1 - y^{(i)}) \underline{cost_0(\theta^T x^{(i)})} \right] + \frac{1}{2} \sum_{i=1}^{n} \theta_j^2$$





→ If $y = 1$, we want $\theta^T x \geq 1$ (not just ≥ 0) $\theta^T x \geq 0 \; 1$

→ If $y = 0$, we want $\theta^T x \leq -1$ (not just < 0) $\theta^T x \leq 0 \; -1$

$C = 100{,}000$

当C非常大时

不像LR中，是希望用≥0，<来作为判断依据

但SVM不同，是以≥1，≤-1来作为判断依据

(Large Margin)

safety margin factor

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SVM Decision Boundary 当C非常大时，这部分被希望趋于0

$$\min_\theta C \underbrace{\boxed{\sum_{i=1}^{m} \left[y^{(i)} cost_1(\theta^T x^{(i)}) + (1 - y^{(i)}) cost_0(\theta^T x^{(i)}) \right]}}_{=0} + \frac{1}{2} \sum_{i=1}^{n} \theta_j^2$$

Whenever $y^{(i)} = 1$:

$\theta^T x^{(i)} \geq 1$

Whenever $y^{(i)} = 0$:

$\theta^T x^{(i)} \leq -1$

$\min_\theta \; \cancel{C \times 0} + \frac{1}{2} \sum_{i=1}^{n} \theta_j^2$

s.t. $\theta^T x^{(i)} \geq 1$ if $y^{(i)} = 1$

$\theta^T x^{(i)} \leq -1$ if $y^{(i)} = 0$

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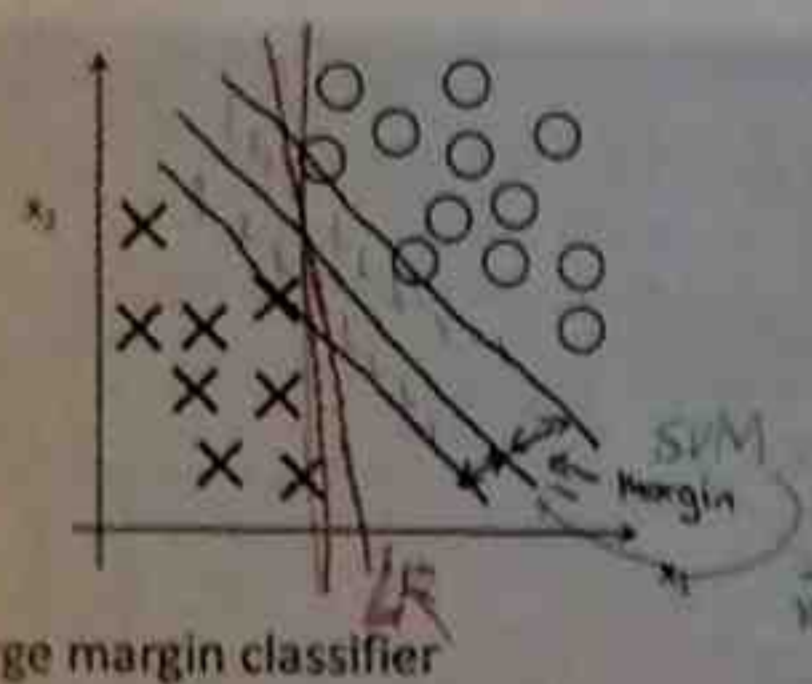
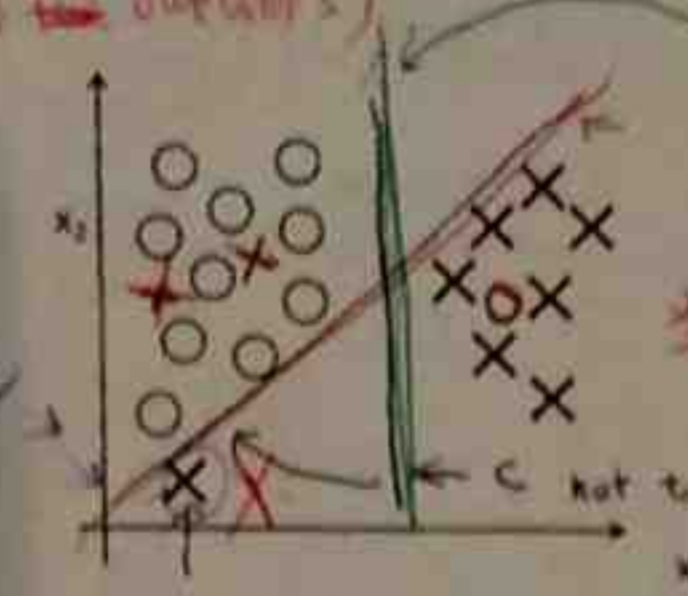
SVM Decision Boundary: Linearly separable case



Large margin classifier

Large margin classifier in presence of outliers

(sensitive to ~~the~~ outliers)

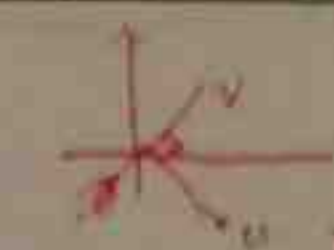


$\rightarrow$ C very large

$\frac{1}{\lambda}$

$(C = \frac{1}{\lambda})$

C大，等价于 λ小，无 regulization



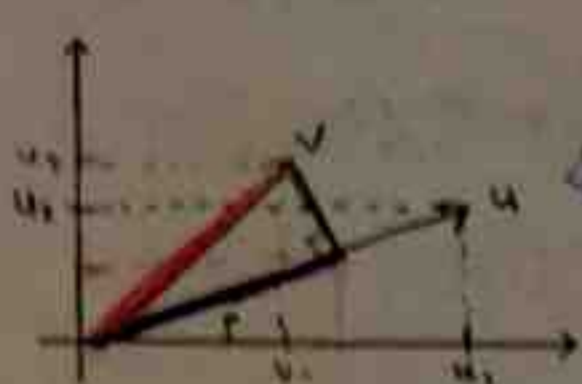
$v_1 u_1 + v_2 u_2 = 0$

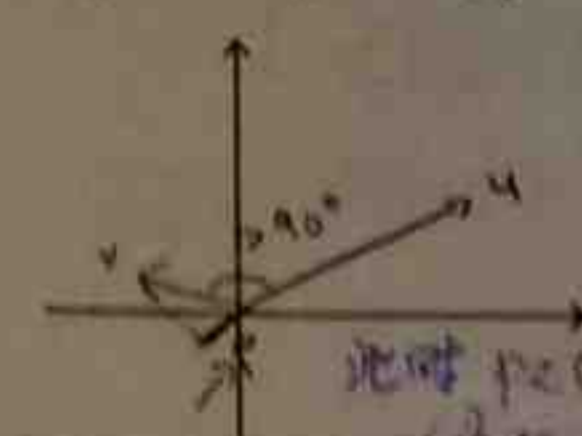
Support Vector Machines

The mathematics behind large margin classification (optional)

Machine Learning

Vector Inner Product





$u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$ $v = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$

内积 $u^T v = ?$ $[u_1 \ u_2] \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$

norm of u $\|u\|$ = length of vector u

$= \sqrt{u_1^2 + u_2^2} \in \mathbb{R}$

p = length of projection of v onto u.

signed

$u^T v = \underline{p} \cdot \underline{\|u\|}$ $= v^T u$

$= u_1 v_1 + u_2 v_2$ $p \in \mathbb{R}$

内积定义

$u^T v = p \cdot \|u\|$

$p < 0$

此时 $p<0$

(夹角大于90°)

3种算内积的方法

$u^T v$ $u_1 v_1 + u_2 v_2$

$v^T u$

$p \cdot \|u\|$

$\theta_0 = 0$，$n=2$ 简化到只有2个 feature

SVM Decision Boundary

$w = (\sqrt{w})^2$

$$\min_\theta \frac{1}{2}\sum_{j=1}^{n}\theta_j^2 = \frac{1}{2}(\theta_1^2+\theta_2^2) = \frac{1}{2}\left(\sqrt{\theta_1^2+\theta_2^2}\right)^2 = \frac{1}{2}\|\theta\|^2$$

$= \|\theta\|$

cost func

s.t. $\boxed{\theta^T x^{(i)} \geq 1}$ if $y^{(i)} = 1$

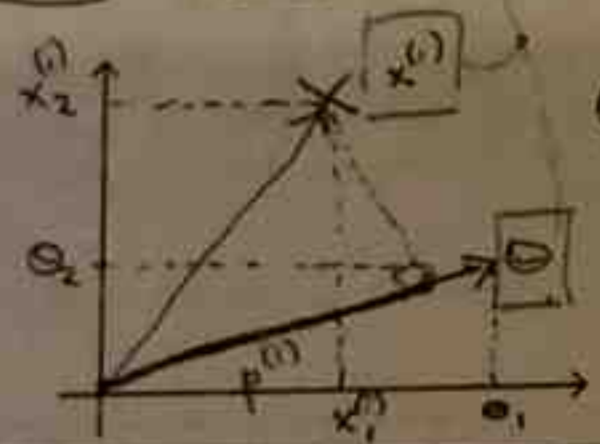
$\theta^T x^{(i)} \leq -1$ if $y^{(i)} = 0$

Simplification: $\theta_0 = 0$ $n=2$

$\begin{bmatrix}\theta_0\\ \theta_1\\ \theta_2\end{bmatrix}$ $\theta_0 = 0$

$\theta^T x^{(i)} = ?$

$u^T v$



$\theta^T x^{(i)} = \boxed{p^{(i)} \cdot \|\theta\|}$

$= \theta_1 x_1^{(i)} + \theta_2 x_2^{(i)}$

因此 $\theta^T x^{(i)} \geq 1$

$\theta^T x^{(i)} \leq -1$

可以替换为

$p^{(i)} \cdot \|\theta\| \geq 1$

$p^{(i)} \cdot \|\theta\| \leq -1$

SVM Decision Boundary

让 $\theta_0 = 0$ 来简化 {选择 boundary，使得 θ 最小}

$$\min_\theta \frac{1}{2}\sum_{j=1}^{n}\theta_j^2 = \frac{1}{2}\|\theta\|^2$$

s.t. $\boxed{p^{(i)} \cdot \|\theta\| \geq 1}$ if $y^{(i)} = 1$

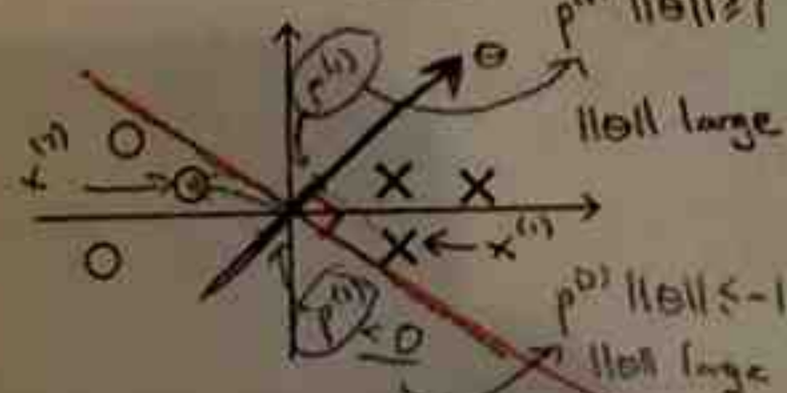
$p^{(i)} \cdot \|\theta\| \leq -1$ if $y^{(i)} = 1$

C very large

where $p^{(i)}$ is the projection of $x^{(i)}$ onto the vector θ.

Simplification: $\theta_0 = 0$

$\theta_0 \neq 0$

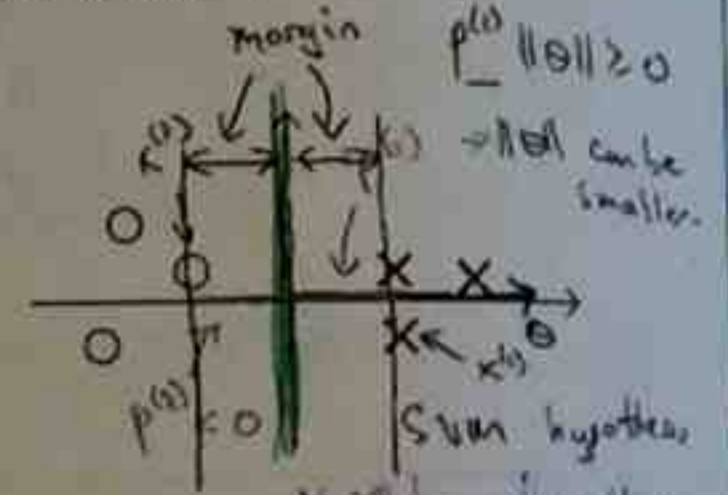


$p^{(i)}\|\theta\| \geq 1$

$\|\theta\|$ large

$p^{(i)}\|\theta\| \leq -1$

$\|\theta\|$ large



margin

$p^{(i)}\|\theta\| \geq 0$

$\to \|\theta\|$ can be smaller.

SVM hypothesis

如果 boundary 比较大，$p^{(1)}$，$p^{(2)}$ 也较大，所以容易让 $\|\theta\|$ 变小

对于 x，C 在 θ 上投影 $p^{(1)} > 0$，$p^{(2)} < 0$

都非常小，使得 $\|\theta\|$ 非常大，

但我们的 objective 是让 $\|\theta\|$ 小

不好，margin 太小

why SVM 不会选这条 boundary

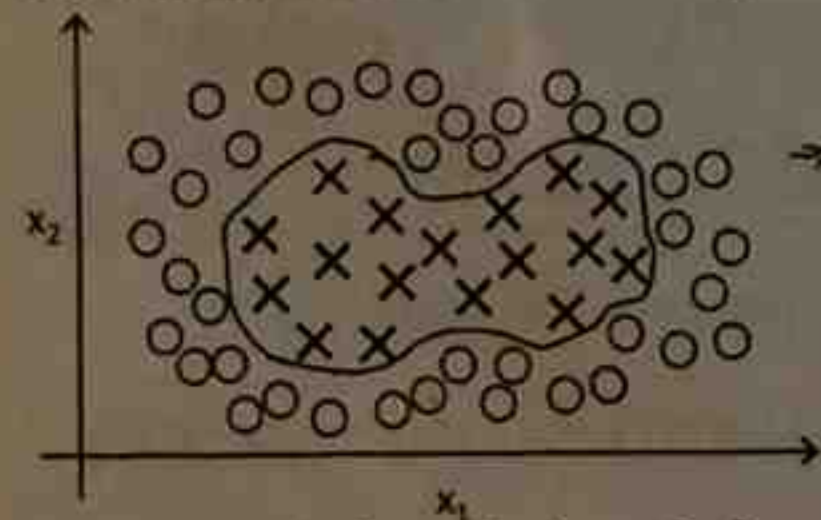
Support Vector Machines

Kernels I

Machine Learning

处理复杂的非线性分类

Non-linear Decision Boundary



Predict $y = 1$ if

$$\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1 x_2 + \theta_4 x_1^2 + \theta_5 x_2^2 + \cdots > 0$$

$h_\theta(x) = \begin{cases} 1 & \text{if } \theta_0 + \theta_1 x_1 + \cdots \geq 0 \\ 0 & \text{otherwise} \end{cases}$

$\to \theta_0 + \theta_1 f_1 + \theta_2 f_2 + \theta_3 f_3 + \cdots$

$f_1 = x_1$, $f_2 = x_2$, $f_3 = x_1 x_2$, $f_4 = x_1^2$, $f_5 = x_2^2 \ldots$

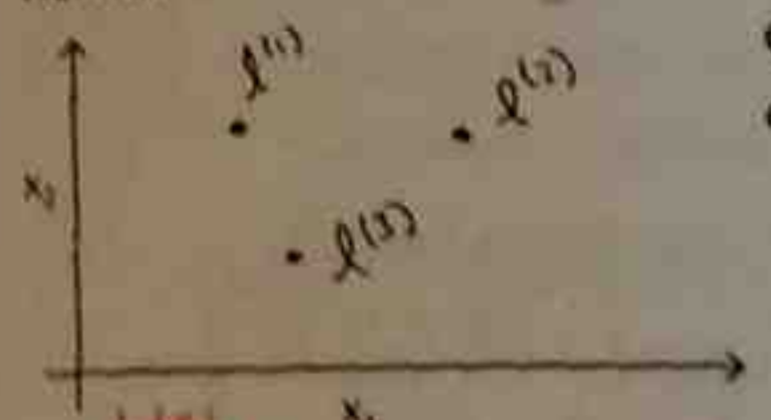
Is there a different / better choice of the features $f_1, f_2, f_3, \ldots$?

我们不知道这些 f_i 是否有用

并且 expensive

Kernel

如何定义新features



Given x, compute new feature depending on proximity to landmarks $l^{(1)}, l^{(2)}, l^{(3)}$ （人工选择）

$\|w\|$ $w = x - l^{(1)}$ 向量长度

Given 一个样本 x:

新 new features

$f_1 = \text{similarity}(x, l^{(1)}) = \exp\left(-\frac{\|x - l^{(1)}\|^2}{2\sigma^2}\right)$

$f_2 = \text{similarity}(x, l^{(2)}) = \exp\left(-\frac{\|x - l^{(2)}\|^2}{2\sigma^2}\right)$

$f_3 = \text{similarity}(x, l^{(3)}) = \exp(\dots)$

相似度函数 Kernel (Gaussian Kernels) $k(x, l^{(1)})$

这个叫 高斯 kernels）

还有其它 kernel

Kernels and Similarity

$$f_1 = \text{similarity}(x, l^{(1)}) = \exp\left(-\frac{\|x - l^{(1)}\|^2}{2\sigma^2}\right) = \boxed{\exp\left(-\frac{\sum_{j=1}^{n}(x_j - l_j^{(1)})^2}{2\sigma^2}\right)}$$

忽略 x_0 （总为1）

If $x \approx l^{(1)}$:

$$f_1 \approx \exp\left(-\frac{0^2}{2\sigma^2}\right) \approx 1 \quad e^0$$

If x if far from $l^{(1)}$:

$$f_1 = \exp\left(-\frac{(\text{large number})^2}{2\sigma^2}\right) \approx 0. \quad e^{-\infty}$$

$l^{(1)} \to f_1$

$l^{(2)} \to f_2$

$l^{(3)} \to f_3$

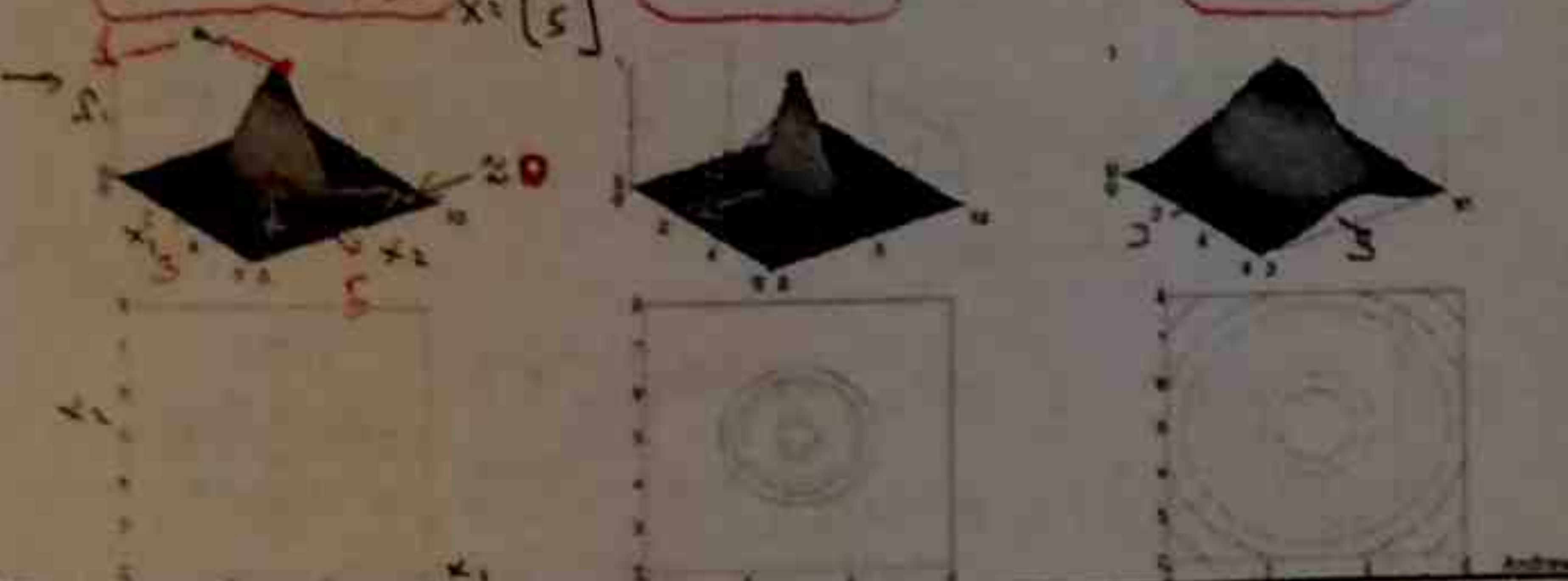
x

Example:

plot 一个新增的 feature 看起来像什么

$l^{(1)} = \begin{bmatrix} 3 \\ 5 \end{bmatrix}$, $f_1 = \exp\left(-\frac{\|x - l^{(1)}\|^2}{2\sigma^2}\right)$ 2 feature x_1, x_2

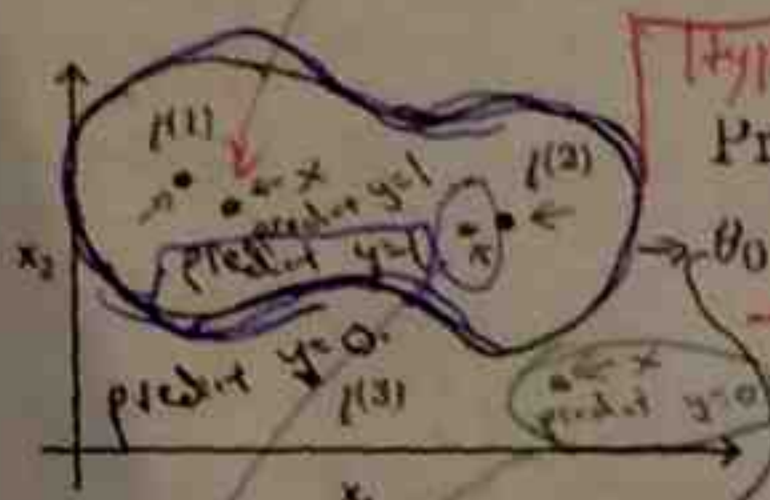
$\sigma^2 = 1$ $x = \begin{bmatrix} 3 \\ 5 \end{bmatrix}$ $\sigma^2 = 0.5$ $\sigma^2 = 3$



$\sigma^2 = 0.5$ kernel 下降到0更快

$\sigma^2 = 3$ kernel 下降到0更慢

如果有一个 example 位于这里，会怎样



Hypothesis function

Predict "1" when

$$\theta_0 + \theta_1 f_1 + \theta_2 f_2 + \theta_3 f_3 \ge 0$$

例如 训练出了

$\theta_0 = -0.5, \quad \theta_1 = 1, \quad \theta_2 = 1, \quad \theta_3 = 0$

$f_1 \approx 1, \quad f_2 \approx 0, \quad f_3 \approx 0.$

$\to \theta_0 + \theta_1 \times 1 + \theta_2 \times 0 + \theta_3 \times 0$ （代入 x）

$= -0.5 + 1 = 0.5 \ge 0$ （代入 θ） 得 $0.5 \ge 0$ predict 1.

另一 example predict $y=0$

$f_1, f_2, f_3 \approx 0$

$\to \theta_0 + \theta_1 \cdot 0 + \dots = -0.5 < 0$

第3个 example，可以预测 $y=1$，因为发现 接近 $l^{(1)}, l^{(2)}$ 的都是 $y=1$；远离的都是 $y=0$

推导到更复杂的非线性分类 $\Leftarrow$ 通过 landmark 找到 $y=1$ 的 boundary.

① 找 landmark.
② 用 GK 找 …
来 build $h_\theta(x)$

⇒ How to find landmarks
放在 m个 training examples 上
$l^{(1)}$ $l^{(2)}$ … $l^{(m)}$
m个 examples ⇒ m个 landmark

对于任意一个 … 计算 … (下面的)

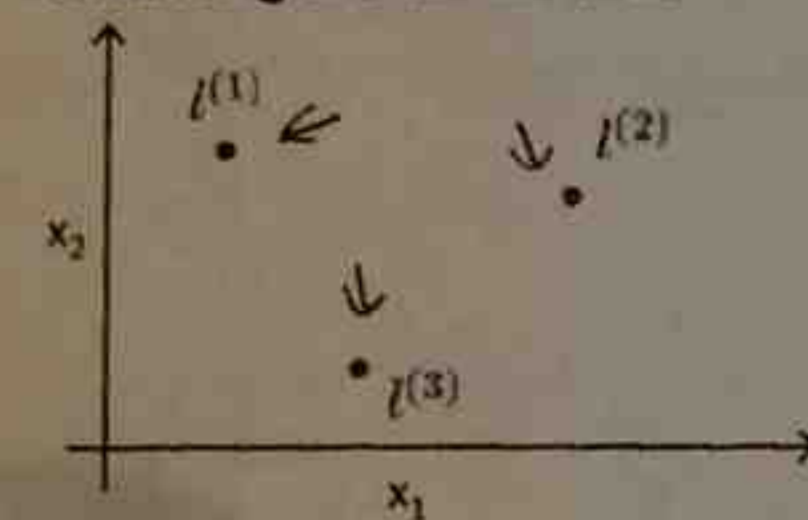
Support Vector Machines

Kernels II

Machine Learning

① detail
② how to use
③ bias-variance problems

Choosing the landmarks



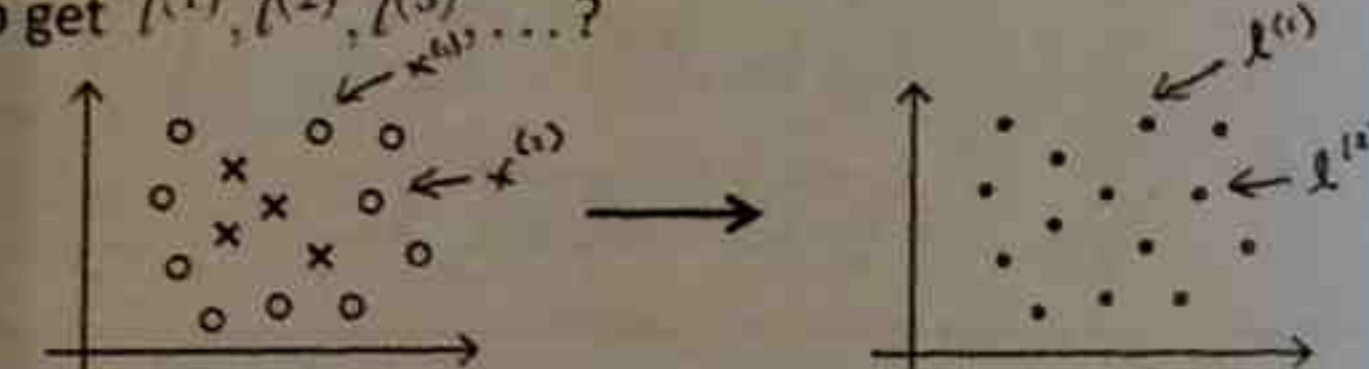
Given x:

$\rightarrow f_i = \text{similarity}(x, l^{(i)})$

GK $= \exp\left(-\frac{\|x - l^{(i)}\|^2}{2\sigma^2}\right) \leftarrow$

Predict $y = 1$ if $\theta_0 + \theta_1 f_1 + \theta_2 f_2 + \theta_3 f_3 \geq 0 \leftarrow$

Where to get $l^{(1)}, l^{(2)}, l^{(3)}, \ldots$?



$l^{(1)}$
$l^{(2)}$
$\vdots$
$l^{(m)}$

SVM with Kernels

(所有 examples) 变 m个 landmark

→ Given $(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(m)}, y^{(m)})$,

→ choose $l^{(1)} = x^{(1)}, l^{(2)} = x^{(2)}, \ldots, l^{(m)} = x^{(m)}$.

Given example x:

$\rightarrow f_1 = \text{similarity}(x, l^{(1)})$

$\rightarrow f_2 = \text{similarity}(x, l^{(2)})$

…

$$\Rightarrow f = \begin{bmatrix} f_0 \\ f_1 \\ f_2 \\ \vdots \\ f_m \end{bmatrix} \quad f_0 = 1$$

Train / Cross Val / Test set

For training example $(x^{(i)}, y^{(i)})$:

$$x^{(i)} \rightarrow \begin{array}{l} f_1^{(i)} = \text{sim}(x^{(i)}, l^{(1)}) \\ f_2^{(i)} = \text{sim}(x^{(i)}, l^{(2)}) \\ \vdots \\ f_i^{(i)} = \text{sim}(x^{(i)}, l^{(i)}) = \exp(-\frac{0}{2\sigma^2}) = 1 \\ \vdots \\ f_m^{(i)} = \text{sim}(x^{(i)}, l^{(m)}) \end{array}$$

$x^{(i)} \in \mathbb{R}^{n+1}$ (or $\mathbb{R}^n$) →

$$f^{(i)} = \begin{bmatrix} f_0^{(i)} \\ f_1^{(i)} \\ \vdots \\ f_m^{(i)} \end{bmatrix} \quad f_0^{(i)} = 1$$

其中有一个 landmark 就是 example 自己

用 feature vector 来表示 training example

SVM with Kernels

用x与landmark相似度算一个 feature

Hypothesis: Given x, compute features $f \in \mathbb{R}^{m+1}$ $\quad \theta \in \mathbb{R}^{m+1}$

→ Predict "y=1" if $\theta^T f \geq 0$

$\theta_0 f_0 + \theta_1 f_1 + \cdots + \theta_m f_m$

n=m

Training:

$$\rightarrow \min_\theta C \sum_{i=1}^{m} y^{(i)} cost_1(\theta^T f^{(i)}) + (1 - y^{(i)}) cost_0(\theta^T f^{(i)}) + \frac{1}{2} \sum_{j=1}^{n=m} \theta_j^2$$

$\cancel{\theta^T x^{(i)}}$ $\quad \theta^T f^{(i)}$

原来的 cost function → θ_0

不用 $\theta^T x^{(i)}$ 改用 $\theta^T f^{(i)}$

$- \sum_j \theta_j^2 = \theta^T \theta \leftarrow \theta = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_m \end{bmatrix}$ (ignore θ_0)

$\|\theta\|^2$

$m = 10{,}000$

$- \rightarrow \underbrace{\theta^T M \theta}_{\text{Matrix}}$

很多SVM会换一下 $\theta^T M \theta$
虽然目标都是 minimize $\|\theta\|$ 实际上 $m = n$.
会让 svm 更有效

Kernel 用在 LR上会很慢.

如何选参数来平衡 bias/variance

SVM parameters:

$C\ (= \frac{1}{\lambda})$. → Large C: Lower bias, high variance. (small λ)

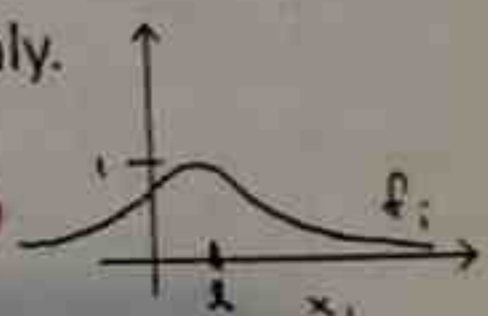
→ Small C: Higher bias, low variance. (large λ)

Large σ^2: Features f_i vary more smoothly.

→ Higher bias, lower variance.

$\exp\left(-\frac{\|x-l^{(i)}\|^2}{2\sigma^2}\right)$ σ大时，⇒

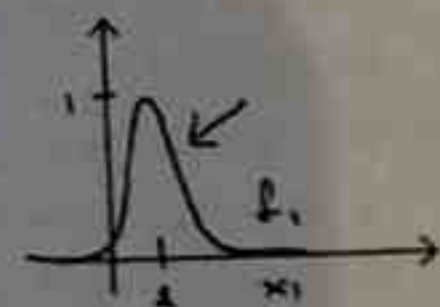
容易欠拟合 不容易过拟合



Small σ^2: Features f_i vary less smoothly.

Lower bias, higher variance.

容易过拟合 不容易欠拟合



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Machine Learning

Support Vector Machines

Using an SVM

Use SVM software package (e.g. liblinear, libsvm, ...) to solve for parameters θ. 那怎么用呢，也都要

Need to specify:

→ Choice of parameter C.

Choice of kernel (similarity function):

E.g. No kernel ("linear kernel")

Predict "y = 1" if $\theta^T x \geq 0$

$\theta_0 + \theta_1 x_1 + \cdots + \theta_n x_n \geq 0$ $x \in \mathbb{R}^{n+1}$

→ n large, m small

→选择1：不用kernel，拟合线性的边界 当feature很多(n大) example很少(m小)时候用

→ Gaussian kernel:

$x \in \mathbb{R}^n$, n small and/or m large

$f_i = \exp\left(-\frac{\|x-l^{(i)}\|^2}{2\sigma^2}\right)$, where $l^{(i)} = x^{(i)}$.

Need to choose σ^2.

feature少，样本多时，

用kernel来拟合一个复杂的非线性模型

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有些要自己实现一个kernel

Kernel (similarity) functions: $x^{(i)}$ $l^{(j)} = x^{(j)}$

```
function f = kernel(x1,x2)
```

$$f = \exp\left(-\frac{\|x1 - x2\|^2}{2\sigma^2}\right)$$

```
return
```

例如高斯 kernel

$x \to f_1, f_2, \ldots, f_m$

→ Note: Do perform feature scaling before using the Gaussian kernel. $x \in \mathbb{R}^n$

$\|x - l\|^2$ $v = x - l$

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

$= (x_1 - l_1)^2 + (x_2 - l_2)^2 + \cdots + (x_n - l_n)^2$

1000 feet² 1-5 bedrooms

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feature scaling 是有必要的

要归一到同一个区间段

Other choices of kernel

: Linear kernel, meaning no kernel, 多为此 kernel

Note: Not all similarity functions $\text{similarity}(x, l)$ make valid kernels.
→ (Need to satisfy technical condition called "Mercer's Theorem" to make sure SVM packages' optimizations run correctly, and do not diverge).

访数学方法用的太多未学, 不会还未讲述

Many off-the-shelf kernels available:

- Polynomial kernel: $k(x, l) = (x^T l)^2$, $(x^T l)^3$, $(x^T l + 1)^3$, $(x^T l + 5)^4$, $(x^T l + \text{constant})^{\text{degree}}$

  通常比高斯 kernel 差, X 与 L 都 negative

- More esoteric: String kernel, chi-square kernel, histogram intersection kernel, ... $\text{sim}(x, l)$

  其他 kernel; 估有会用这一个

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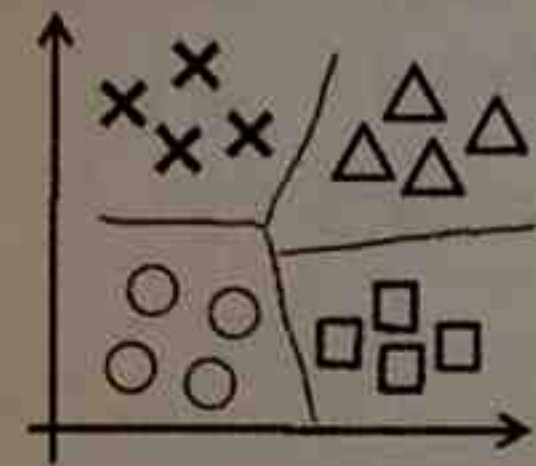
Multi-class classification



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

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 $(\theta^{(i)})^T x$

$y=1$ $y=2$ ... $\theta=K$

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用 K 个 model 全都预测一下
分到得分最高的那个类别中

Logistic regression vs. SVMs

n = number of features ($x \in \mathbb{R}^{n+1}$), m = number of training examples

→ If n is large (relative to m): (e.g. $n \geq m$, $n = 10{,}000$, $m = 10$ 至 1000)
→ Use logistic regression, or SVM without a kernel ("linear kernel")

} 特征够多了, 用 LR 就可以

→ If n is small, m is intermediate: ($n = 1$-1000, $m = 10$-$10{,}000$)
→ Use SVM with Gaussian kernel

} 特征少, 样本也量也不是太多

If n is small, m is large: ($n = 1$-1000, $m = 50{,}000+$)
→ Create/add more features, then use logistic regression or SVM without a kernel

} 样本量太大了, 还是加特征采用 LR 释放的问题

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

神经网络都不错
只是训练比较慢

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LR 与 SVM-NO-KERNEL 很相似

SVM : Convex optimization ✗ worry for local optimization problem
Natural Network : 一般也不用担心 local optimization problem
但还是比较慢