Support Vector Machine (SVM)

- e", e", e"; landmarks
- → given x, compute new features based on proximity to these landmark:

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

$$= \exp\left(-\frac{\|x - \ell^{(1)}\|^2}{2\delta^2}\right)$$

$$f_z = similarity \left(x, \ell^{(2)}\right)$$
Kernels

Preclicted unit

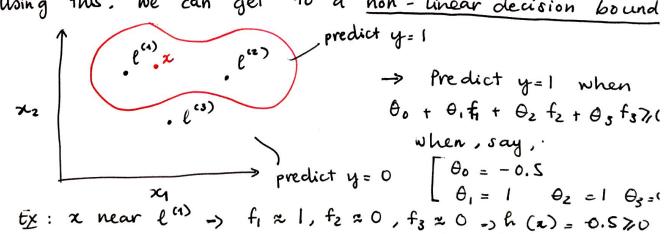
- This similarity function is called Kernel Function.
- Note: ||x l'11)||² → Fuclid distance $= \sum_{j=1}^{n} (x_j - \ell_j^{(i)})^2 \quad \text{in } f_1$
- If x ≈ l⁽¹⁾ ⇒ distance ≈ 0, hence:

$$f_1 \approx \exp\left(-\frac{o^2}{2S^2}\right) = \exp(o) \approx 1$$

If x is far from l"),

$$f_1 \approx \exp\left(-\frac{large number^2}{2f^2}\right) \approx 0$$

Using this, we can get to a non-linear decision bound



SVM with Kernels

Given
$$(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), ..., (x^{(m)}, y^{(m)})$$

Choose $\ell^{(1)} = x^{(1)}, \ell^{(2)} = x^{(2)}, ..., \ell^{(m)} = x^{(m)}$

Then, given an example x:

$$f_{1} = sim \left(x, \ell^{(1)}\right)$$

$$f_{2} = sim \left(x, \ell^{(2)}\right)$$

$$\vdots$$

$$f = \begin{bmatrix} f_{0} \\ f_{1} \\ f_{2} \\ \vdots \\ f_{m} \end{bmatrix}$$

For training example (x", y"):

$$\chi^{(i)} \rightarrow \chi^{(i)} + \int_{1}^{(i)} = \sin \left(\chi^{(i)}, \ell^{(i)}\right)$$

$$f_{i}^{(i)} = \sin \left(\chi^{(i)}, \ell^{(i)}\right) \rightarrow \vdots$$

$$= \exp\left(-\frac{0}{2\delta^{2}}\right) \quad f_{m}^{(i)} = \sin \left(\chi^{(i)}, \ell^{(m)}\right)$$

$$f_{i}^{(i)} = 1$$

$$\int_{0}^{(i)} \chi^{(i)} + \int_{0}^{(i)} \chi^$$

- · m training examples -> m landmarks
- <u>Hypothesis</u>: Given x, compute features $f \in \mathbb{R}^{m+1}$ Predict "y=1" if $\frac{\theta^T f}{\theta} \neq 0$ $\frac{\theta}{\theta} + \theta_1 f_1 + \theta_2 f_2 + ... + \theta_m f_m$

we have: $\theta \in \mathbb{R}^{m+1}$

• How to get the set of θ ? => wring SVM training algo.

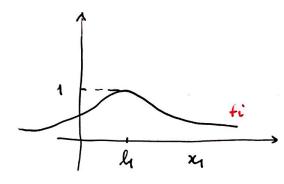
min $C \stackrel{m}{\underset{i=1}{\sum}} y^{(i)} \cdot cost, (\theta^T f^{(i)}) + (1-y^{(i)}) \cdot cost_0 (\theta^T f^{(i)}) + \frac{1}{2} \stackrel{n}{\underset{j=1}{\sum}} \theta_j, \underbrace{n=m}$

SVM parameters

 $C\left(-\frac{1}{\lambda}\right)$ $C\left(-\frac{1}{\lambda$

5² · Large σ² » features fi vary more smoothly

=) higher bias, lower voliance



• Small 62 -> features f; vary less smoothly -> Lower bias, higher variance

