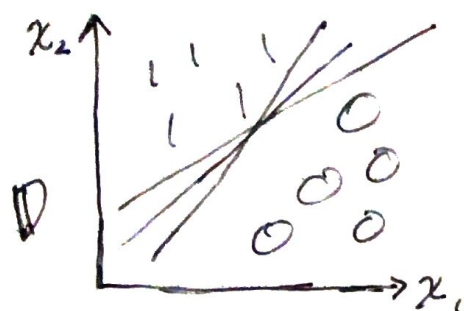
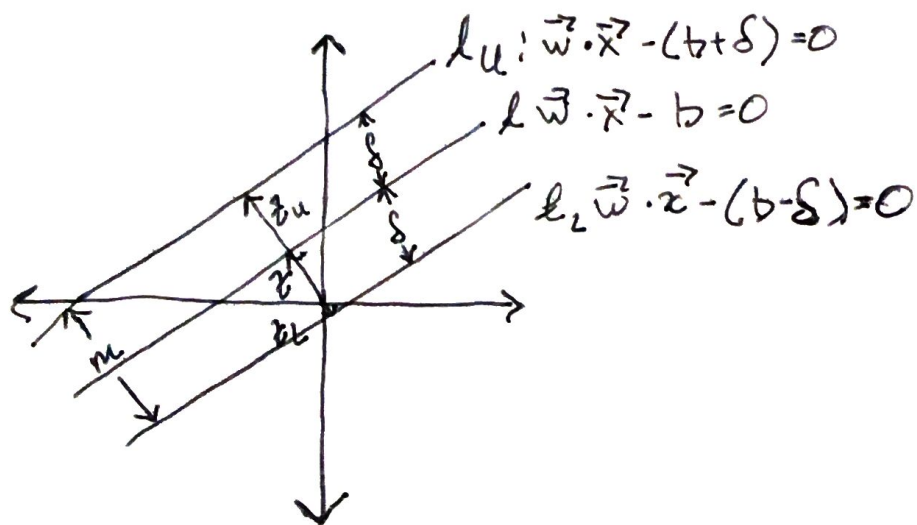


# Math 342W Lecture 5



$\Rightarrow$  Perceptron gives us some line to separate the two regions



$\Rightarrow$  Check Previous lecture for  $m$  and  $\vec{z}$

Recall that the Hesse Normal Form is overparameterized.

$\hookrightarrow \forall c \neq 0, c(\vec{w} \cdot \vec{x} - b) = 0 \Rightarrow$  represents  $l$

Let  $C = \frac{1}{\delta}, \exists \vec{w}, b$

$$l = \vec{w} \cdot \vec{x} - b = 0$$

$$l_u = \vec{w} \cdot \vec{x} - (b - 1) = 0$$

$$l_l = \vec{w} \cdot \vec{x} - (b + 1) = 0$$

Goal: Make  $m$  as large as possible  $\equiv \|\vec{w}\|$  small as possible

$\hookrightarrow$  "No points in the way", s.t.

a)  $\forall y_i = 1, \vec{x}_i \in B_u$

b)  $\forall y_i = 0, \vec{x}_i \in B_l$

a)  $\vec{x}_i$  is above  $l_u$ , which means

$\hookrightarrow x_{i2} >$  the corresponding  $x_{i2}$  on  $l_u$  at  $x_{i1}$

$$\hookrightarrow l_u: \vec{\omega} \cdot \vec{x}_i - (b+1) = 0 \Rightarrow \omega \cdot x_i = b+1$$

$$\Rightarrow \omega_1 x_{i1} + \omega_2 x_{i2} = b+1$$

$$\Rightarrow x_{i2} = \frac{1}{\omega_2} (b+1 - \omega_1 x_{i1})$$

$$\text{if } \vec{x}_i \in \beta_u \Rightarrow x_{i2} \geq \frac{1}{\omega_2} (b+1 - \omega_1 x_{i1})$$

$\vdots$

By "same" process  $\left\{ \begin{array}{l} h_u: \vec{\omega} \cdot \vec{x}_i - (b+1) \geq 0 \quad (a) \\ h_i: \vec{\omega} \cdot \vec{x}_i - (b-1) \leq 0 \quad (b) \end{array} \right.$

(a)  $\forall y_i = 1,$

$$\vec{\omega} \cdot \vec{x}_i - b - 1 \geq 0 \Rightarrow \vec{\omega} \cdot \vec{x}_i - b \geq 1$$

$$\Rightarrow \frac{1}{2}(\vec{\omega} \cdot \vec{x}_i - b) \geq \frac{1}{2} \Rightarrow (y_i - \frac{1}{2})(\vec{\omega} \cdot \vec{x}_i - b) \geq \frac{1}{2}$$

(b)  $\forall y_i = 0,$

$$\vec{\omega} \cdot \vec{x}_i - b + 1 \leq 0 \Rightarrow \vec{\omega} \cdot \vec{x}_i - b \leq -1$$

$$\Rightarrow \frac{1}{2}(\vec{\omega} \cdot \vec{x}_i - b) \leq -\frac{1}{2} \Rightarrow (y_i - \frac{1}{2})(\vec{\omega} \cdot \vec{x}_i - b) \geq \frac{1}{2}$$

$A_{\text{sum}}$ : Find  $\vec{w}, b$  s.t.

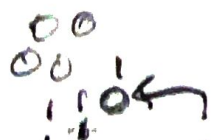
$$\forall_i (y_i - \frac{1}{2})(\vec{w} \cdot \vec{x}_i - b) \geq \frac{1}{2}, \text{ where } \|\vec{w}\| \text{ is minimal}$$

Notes

- 1) No analytical soln, need optimization heuristic
- 2) This can be shown to be a "quadratic problem"
- 3) General for all  $p \geq 2$
- 4) Wikipedia have "1" instead of a " $\frac{1}{2}$ "

$$\hookrightarrow y = \{-1, 1\}$$

$$\hookrightarrow y = \{0, \frac{1}{2}\}$$



Assume  $\vec{x}_{1,7}$  is the point where  $\{0, \frac{1}{2}\}$  "sticks out" from the group.

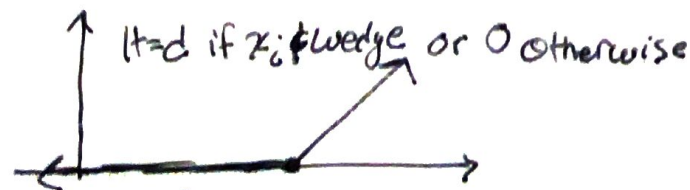
$\hookrightarrow$  SVM doesn't work now, so we need to fix this.

$$\Rightarrow (y_i - \frac{1}{2})(\vec{w} \cdot \vec{x}_i - b) \neq \frac{1}{2}$$

$\nearrow$   $d$  is a measure of the violation

$$\Rightarrow \exists d > 0, \text{ s.t. } (y_i - \frac{1}{2})(\vec{w} \cdot \vec{x}_i - b) + d = \frac{1}{2}$$

Consider "hinge loss"  $H$



$$\Rightarrow H_i = \max \left\{ 0, \frac{1}{2} - (y_i - \frac{1}{2})(\vec{w} \cdot \vec{x}_i - b) \right\}$$

$$\text{SHE} = \sum_{i=1}^n H_i$$

We want to ...

- 1) Minimize SHE
- 2) Maximize wedge width

We have two objective functions

Vapnik (1963)

$$\arg \min_{\vec{w}, b} \left\{ \frac{1}{n} \text{SHE} + \lambda \|\vec{w}\|^2 \right\}$$

↳ Let's interpret this in words

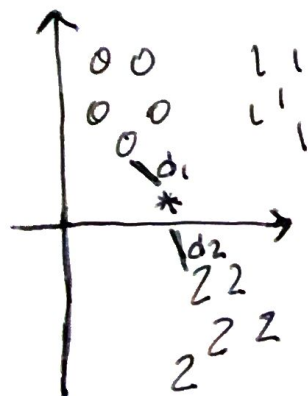
$\frac{1}{n} \text{SHE} \Rightarrow \text{Average (Sum Hinge Error)}$

$\lambda = \text{Hyperparameter or "tuning parameter"}$

$\mathcal{A}_{\text{Vapnik}}$  which you specify

$$g = \mathcal{H}(\mathcal{D}, \mathcal{Z}, \lambda) \text{ or } g = \mathcal{H}_\lambda(\mathcal{D}, \mathcal{Z})$$

$$y = \{0, 1, 2, \dots, L\}, L \geq 2$$



$$g: \mathcal{X} \rightarrow \mathcal{Y}$$

$* \Rightarrow d_1 < d_2 \Rightarrow 0$   
 Here we used  
 1 neighbor, do  
 this with  
 $2, 3, 4, \dots, \frac{L}{2}$

## Nearest Neighbors

### 1-Nearest Neighbor Algorithm

0) Find function  $d: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}_{\geq 0}$

1) Calculate  $d_i = d(\vec{x}^*, \vec{x}_i) \forall i$

2) Find  $i^* = \arg \min(d_i)$

3) Return  $y_{i^*}$

## K-Nearest Neighbor Algorithm

0) " "

1) " "

2)  $i_1^*, \dots, i_k^*$  of  $d_i$ 's

3) Return mode  $[y_{i_1^*}, y_{i_2^*}, \dots, y_{i_k^*}] \Rightarrow$  Ties Go Randomly

These are dependant on Euclidean Distance

$$\Rightarrow d = \sqrt{\sum_{j=1}^p (x_o^* - x_{i_j})^2}$$