

Residual

How to minimize misspecification Error?

Make H richer, A as well.

| ? options.

ladder notation

How to minimize estimation error?

Increase n (the sample size)

→ we can not know from where the error is coming from.

02/05

$$y = g(\bar{x}) + h^*(\bar{x}) - g(\bar{x}) +$$

ϵ (residual)

For a new observation x^* , $\hat{y} = g(x^*)$

g comes from In supervised learning $\xrightarrow{\text{historical data}}$
 $g = A(D, H) \xrightarrow{\text{model space}}$
 \downarrow
algorithm

Loan Model

$y = \{0, 1\}$ $\xrightarrow{\text{pay back loan (credit)}}$

$\xrightarrow{\text{no pay back loan}}$

→ Model is called binary classification model of $\{0, 1\}$.

Null Model: You have no features and you were to create the best model g .

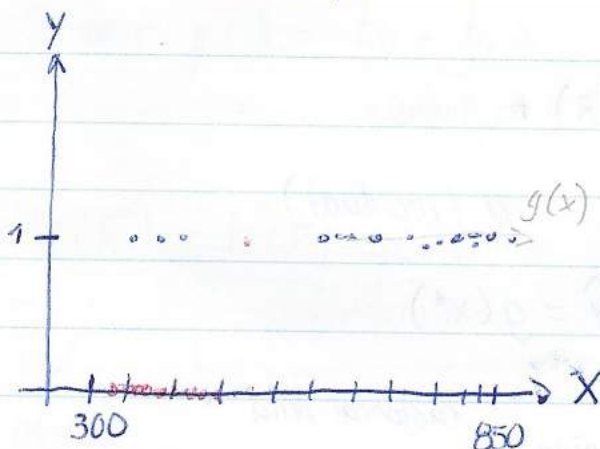
$H = y$ $g = \text{stochastic Model}(y)$

We now have one X : credit score $X = [300, 850]$

$$D = (X, y) = \left(\begin{bmatrix} 810 \\ 390 \\ 350 \\ \vdots \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix} \right)$$

same

$$D = [X | y] = \begin{bmatrix} 810 & 1 \\ 390 & 0 \\ 250 & 1 \\ \vdots & \vdots \end{bmatrix}$$



Indicator

parameter

$$\mathcal{H} = \left\{ \mathbb{1}_{x \geq \theta} : \theta \in \Theta \right\}$$

→ This is all potential models

↓ parameter space

eg. $h(x) = \mathbb{1}_{x \geq 500},$

$h(x) = \mathbb{1}_{x \geq 497.3}$

$$e \in \{-1, 0, 1\}$$

$$y = g(x) + e = e = y - \hat{y}$$

The algorithm A produces g , but g is specified by θ
 A : finds θ

How about pick θ which gives the least prediction error in D (in-sample error estimate).

$$\frac{\# \text{ errors}}{ME} = \frac{1}{n} \sum_{i=1}^n \mathbb{I} g(x_i) \neq y_i$$

all prediction model
 $\hookrightarrow D$ in sample

Misclassification Errors

$$ACC = \frac{1}{n} \sum_{i=1}^n \mathbb{I} g(x_i) = y_i$$

accuracy

$$A = \sigma_g = \underset{\theta \in \mathcal{H}}{\text{argmin}} \{ ME \}$$

$\theta \in \mathcal{H}$

↑
 objective function,
 fitness function

* is the thing that you max or minimize.

Rewrite objective function using e 's ($\overbrace{\text{in-sample residuals}}^D$)

$$ME = \frac{1}{n} \sum_{i=1}^n |e_i| \quad \overset{\text{only in binary classification}}{=} \quad \frac{1}{n} \sum_{i=1}^n e_i^2$$

SAE (Sum absolute Error)

MAE (mean Absolute Error)

SSE (Sum square residuals)

" e just
 can be (0, 1, -1)

• where $\mathcal{H} \Rightarrow$ unique values of x

X_1 : credit score

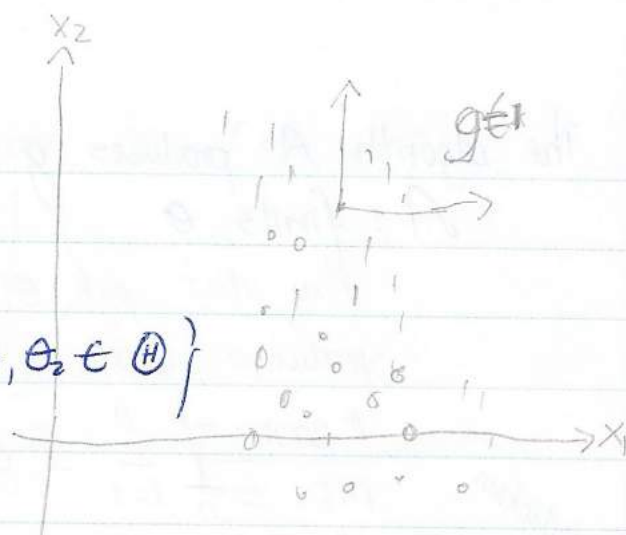
X_2 : salary

2 dimensional

$$H = \{ \mathbb{I} x_1 \geq \theta_1 \text{ \& } x_2 \geq \theta_2 : \theta_1, \theta_2 \in \mathbb{H} \}$$

$$\dim[\mathbb{H}] = 2$$

very restrictive set.



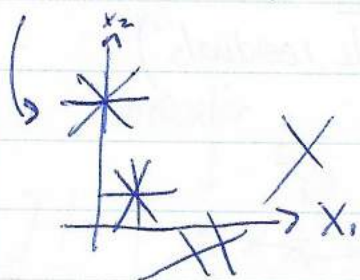
Threshold

Linear Models

parameters

$$H = \{ \mathbb{I} x_2 \geq a + bx_1 : a, b \in \mathbb{R} \} = \{ \mathbb{I} \vec{w} \cdot \vec{x} \geq 0 : \vec{w} \in \mathbb{R}^3 \}$$

H is any straight line



$$-a - bx_1 + x_2 \geq 0$$

$$w_0 + w_1 x_1 + w_2 x_2 \geq 0$$

let $\vec{x}_i = [1 \quad x_{i,1} \quad x_{i,2}]$

$$X = \begin{bmatrix} 1 & \uparrow & \uparrow \\ \vdots & \vec{x}_{0,1} & \vec{x}_{0,2} \\ 1 & \downarrow & \downarrow \end{bmatrix}$$

$$\vec{w} \cdot \vec{x} \geq 0$$

all $c\vec{w}$

are equivalent

(Solutions, $c \in \mathbb{R}$)

divide by
parameter
and go
back to
 \mathbb{R}^2

begin by \Rightarrow

Perception Learning Algorithm (1957). W, x_i p features --

Step 1: iteration $\vec{W}^{t=0} = \vec{0}$ or whatever ^{lets t denote iteration #.}

Step 2: compute $\hat{y}_i = \mathbb{1} \vec{W}^{t=0} \cdot \vec{X}_i$

Step 3: for $j = 0 \dots p$

$$W_0^{t=1} = W_0^{t=0} + \underbrace{(y_i - \hat{y}_i)}_{e_i} \quad (1)$$

$$W_1^{t=1} = W_1^{t=0} + (y_i - \hat{y}_i) (X_i, 1)$$

\vdots

$$W_p^{t=1} = W_p^{t=0} + (y_i - \hat{y}_i) (X_i, p)$$

$(W_0 + W_1)$
bias term / intercept

input, weight

Step 4: Repeat steps 2, 3 for $i = 1 \dots n$

\Rightarrow to make it smaller or bigger add #s to go out of $\vec{W} \cdot \vec{X} \geq 0$
Bigger
Smaller

Step 5: Repeat steps 2, 3, 4 until no change or some max it.

This algorithm is proven to converge if the ID is \mathbb{R}
"linearly separable" i.e. -- $\exists n$ s.t. $ME = 0$.

If not it will likely fail
produce a very poor model.

Weakness #1: requires linear separability

Weakness #2: returns any model that separates.

* Support Vector machine.

i	X ₁	X ₂	Y
1	-1	-1	0
2	1	1	1

$$-1 + X_1 + X_2 \geq 0$$

$$\Rightarrow X_2 \geq -X_1 + 1$$

$$\vec{W}^{t=0} = \vec{0}$$

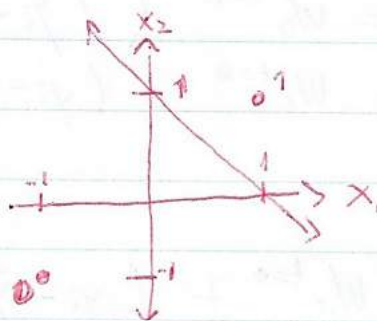
$$t=1, i=1$$

$$\hat{y}_i^{t=0} = \mathbb{1} \vec{W} - \vec{X} \geq 0 = 1$$

$$W_0^{t=1} = (0) + (-1)(1) = -1$$

$$W_1^{t=1} = (0) + (-1)(-1) = +1$$

$$W_2^{t=1} = (0) + (1)(1) = +1$$



$$t=1, i=2$$

$$\hat{y}_2 = \mathbb{1} \begin{bmatrix} -1 \\ +1 \\ +1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \geq 0 = 1$$

$$W_0^{t=1}$$

$$= (-1) + (0)(1)$$

$$W_1^{t=1} = (+1) + (0)(1)$$

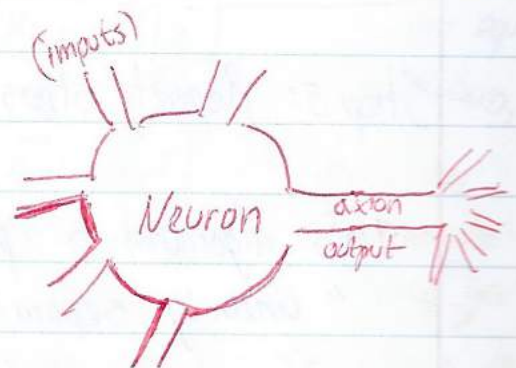
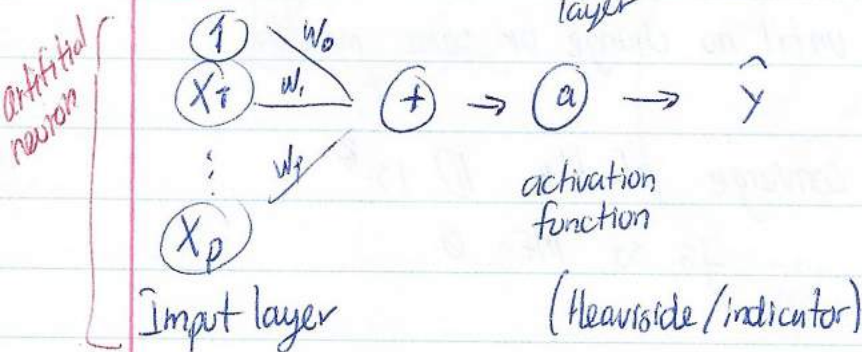
$$W_2^{t=1} = (+1) + (0)(1)$$

$$\Rightarrow \begin{bmatrix} -1 \\ +1 \\ +1 \end{bmatrix}$$

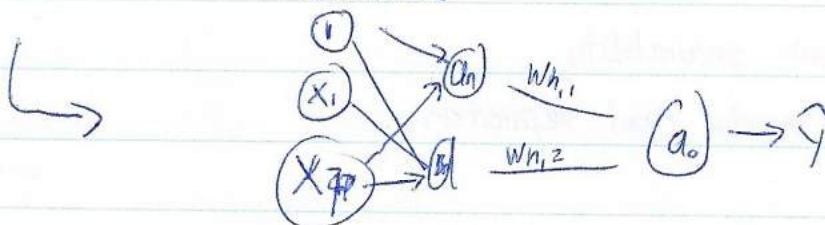
$$t=2, i=1$$

$$\hat{y}_1 = \mathbb{1} \begin{bmatrix} -1 \\ +1 \\ +1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ -1 \\ -1 \end{bmatrix} \geq 0 = 0$$

Neural Network

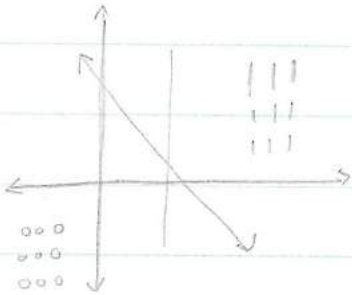


We can have different



Correct the weaknesses is the perceptron algorithm

The first weakness: assumes linear pers
but find the "best" model



MARKDOWN.

we need } else { \rightarrow same line

paste \rightarrow two print outs
 \rightarrow

0 \rightarrow true, false
1 \rightarrow true
1 \rightarrow false

Switch

Loop

for (i in 1:10) {

j = i

print(j);

}

this has to be a vector

by = 2

WE STILL HAVE i & j

still does.

sequence.