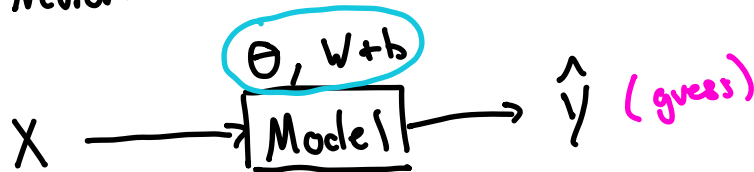


A Single Neuron

- ✓ Data
- ✓ Regression vs Classification
- Neuron



Data

$$D = \{X, Y\}$$

input ↗
Label (Known) ↗

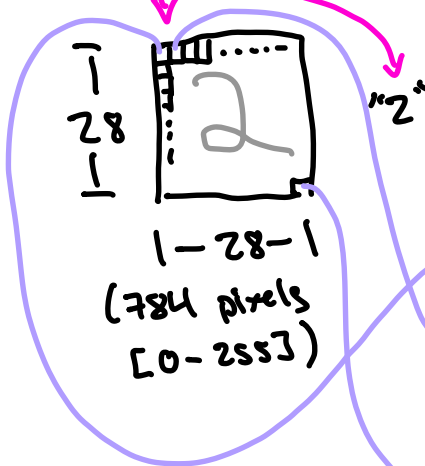
Supervised Learning

Example Problem: Image of Digit Classification

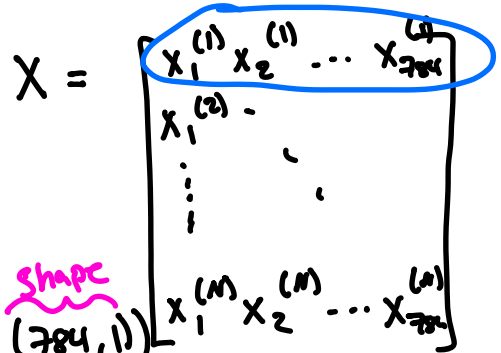
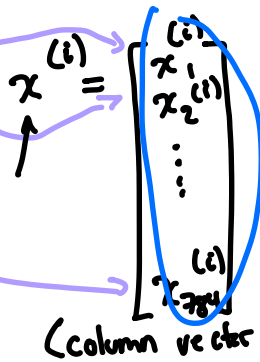
Matrix

X : all of our training images

Y : the label for each image



- Capital \rightarrow matrix
- Lower case \rightarrow column vector



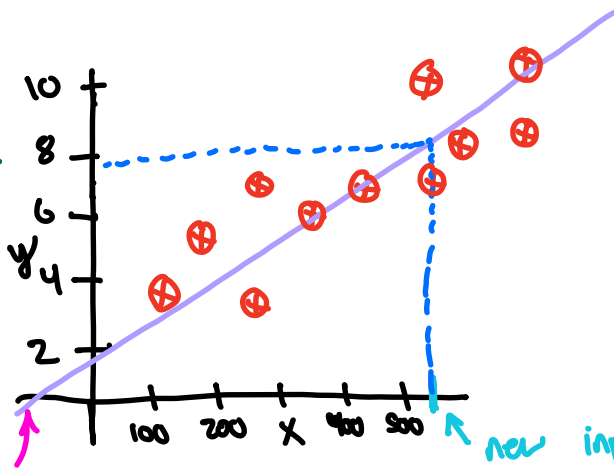
$y^{(i)}$
 no subscript = 2

$y^{(i)} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}$

← "0"
 ← "1"
 ← "2"
 ← "q"

One-hot encoding

Linear Regression



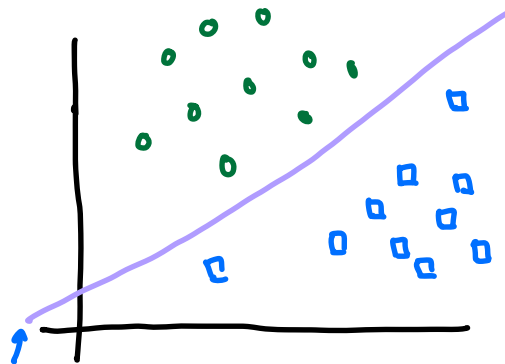
What is the relationship between the input "x" and output "y"?

What is this line?

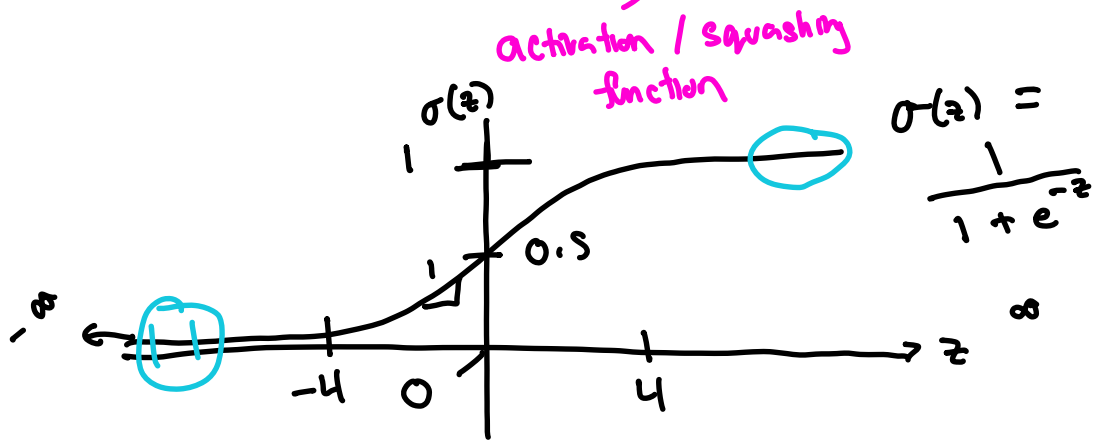
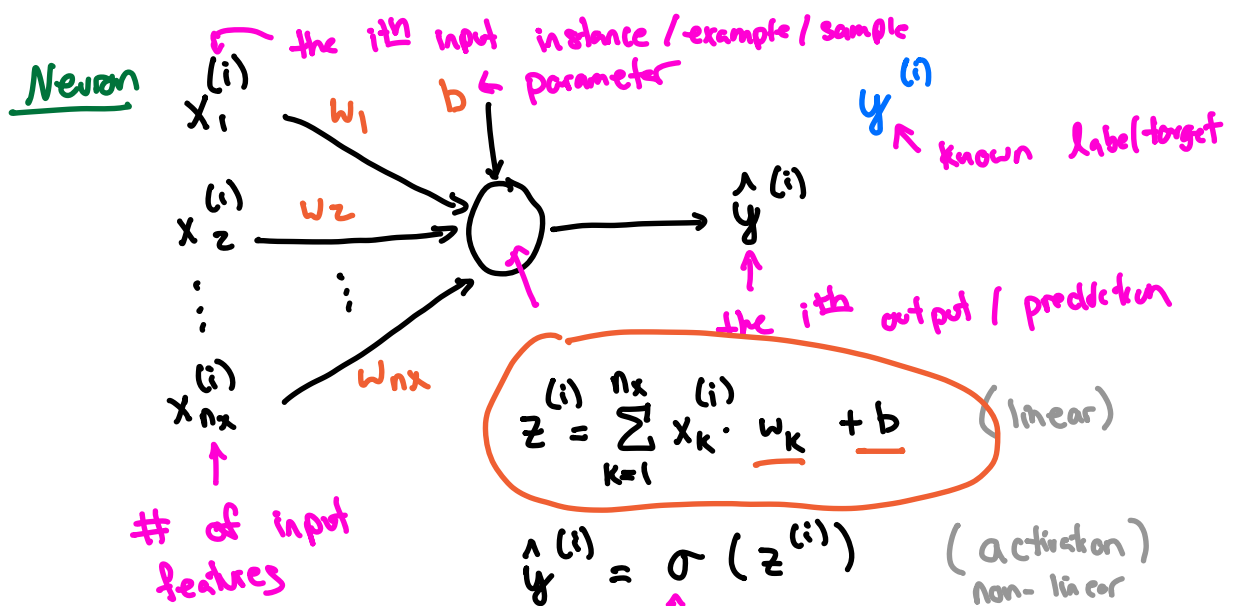
Model: $\hat{y} = mx + b$
 \uparrow \uparrow
 slope \uparrow \uparrow
 bias

new input value, we don't know the true value for y

Binary Classifier



$\hat{y} = mx + b > 0$
 We want the output to be T/F, 1/0, 1/-1



Goal: We want to find values for w_k and b such that $\hat{y}^{(i)} \approx y^{(i)}$ for all values of i .

What is a good objective function?
loss

Mean Difference

$$L(\hat{y}^{(i)}, y^{(i)}) = \hat{y}^{(i)} - y^{(i)}$$

Does not work very well.

\hat{y}	y	\mathcal{L}
0	0	0
0	1	-1
1	0	-1
1	1	0

This is a problem

$$\mathcal{L}(\hat{y}^{(i)}, y^{(i)}) = \frac{1}{N} |\hat{y}^{(i)} - y^{(i)}| \quad \text{MAE}$$

$$\mathcal{L}(\hat{y}^{(i)}, y^{(i)}) = \frac{1}{N} (\hat{y}^{(i)} - y^{(i)})^2 \quad \text{MSE}$$

$$= (\hat{y}^{(i)} - y^{(i)})^2 \quad \text{SSE}$$

$$= \frac{1}{2N} (\hat{y}^{(i)} - y^{(i)})^2 \quad \text{Half-MSE}$$

$$\mathcal{L}(\hat{Y}, Y) = \frac{1}{2N} \sum_{i=1}^N (\hat{y}^{(i)} - y^{(i)})^2 \quad \text{Equiv.}$$

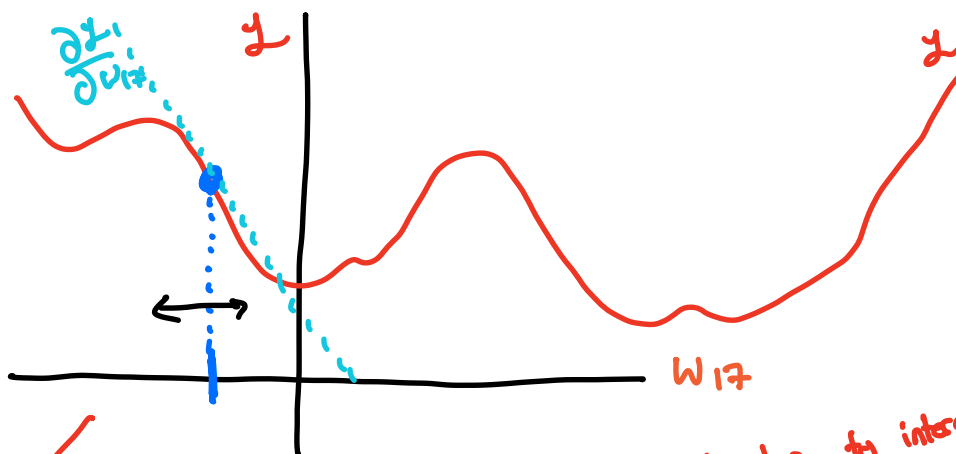
$$\mathcal{L}(\hat{y}^{(i)}, y^{(i)}) = y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)})$$

Binary Cross Entropy Loss

$$\hat{y}^{(i)} \in [0, 1] \quad \text{Range}$$

$$y^{(i)} \in \{0, 1\} \quad \text{Set}$$

How do I use \mathcal{L} to find better values for w_i, b ?



$$\frac{\partial \mathcal{L}}{\partial w_{17}} = 0$$

Closed-Form solution

Bad due to interactions among parameters

$$\frac{\partial \mathcal{L}}{\partial w_{17}}$$

∂ partial derivative
 d derivative

$$w_{17} = w_{17} - \alpha \frac{\partial \mathcal{L}}{\partial w_{17}}$$

learning Rate

$$\frac{\partial \mathcal{L}}{\partial \omega_k} = \frac{\partial \left(y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}) \right)}{\partial \omega_k}$$

$$= \frac{\partial \mathcal{L}^{(i)}}{\partial \hat{y}^{(i)}} \cdot \frac{\partial \hat{y}^{(i)}}{\partial z^{(i)}} \cdot \frac{\partial z^{(i)}}{\partial \omega_k}$$

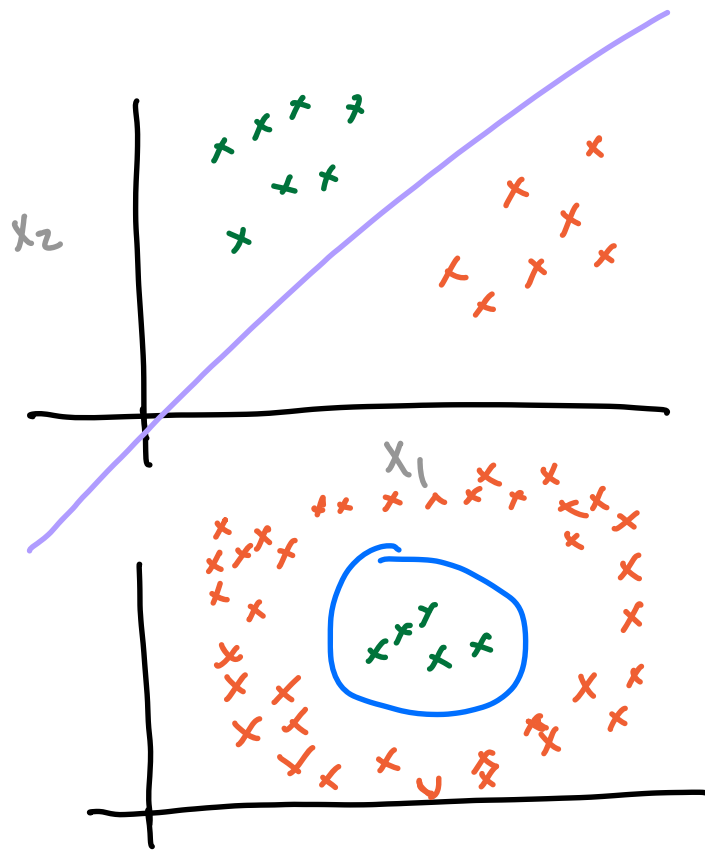
$$= \frac{1}{N} \sum_{i=1}^N (\hat{y}^{(i)} - y^{(i)}) X$$

$$\frac{\partial \mathcal{L}}{\partial b} = \frac{1}{N} \sum_{i=1}^N (\hat{y}^{(i)} - y^{(i)})$$

loop

$$\omega_k = \omega_k - \alpha \frac{\partial \mathcal{L}}{\partial \omega_k}$$

$$b = b - \alpha \frac{\partial \mathcal{L}}{\partial b}$$



★ Single Neurons cannot handle data that is not linearly separable.
hyperplanerly

→ Neural Network