



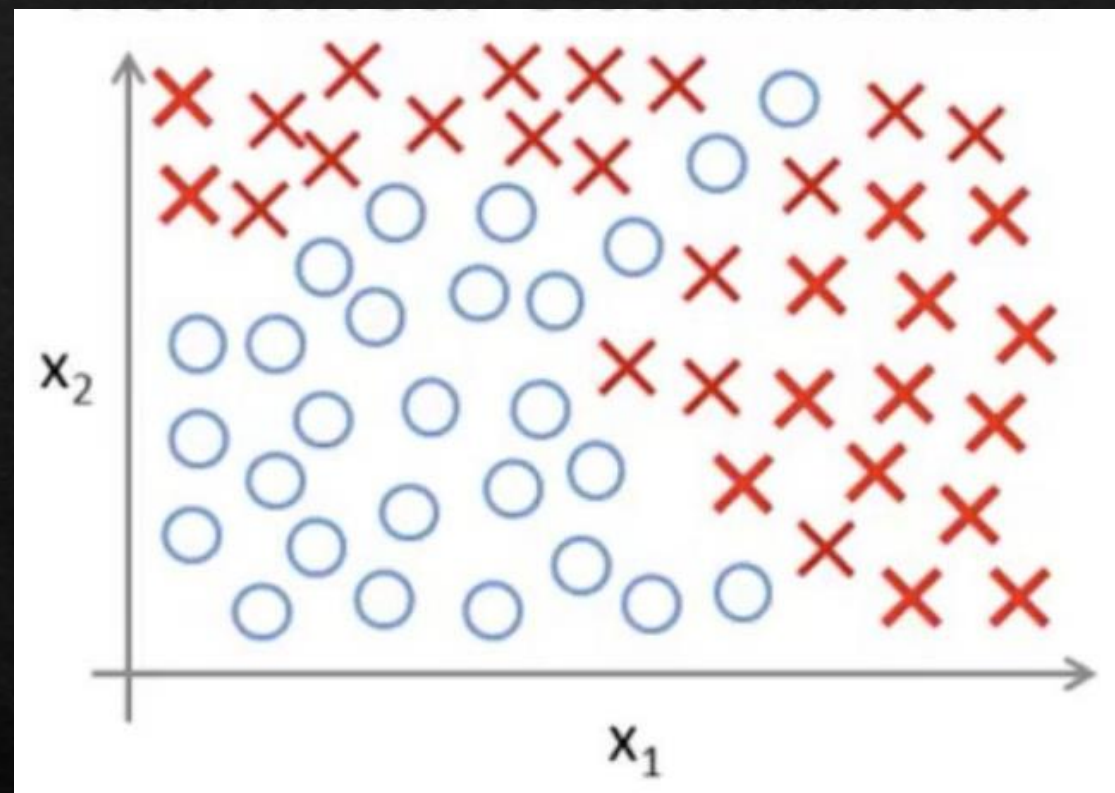
# Sztuczne sieci neuronowe

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Wprowadzenie

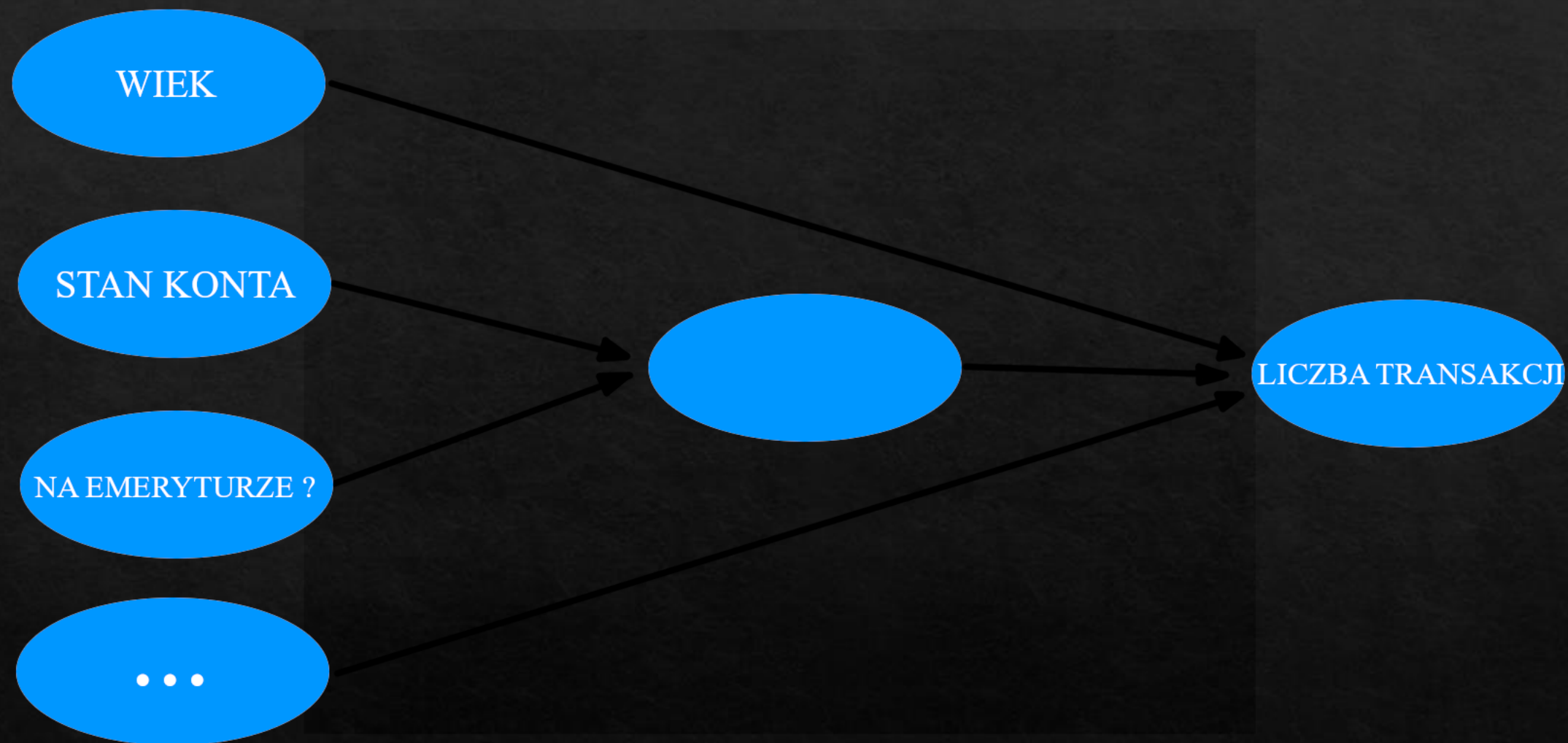
# Plan na dzisiaj

- ◊ Funkcja kosztu (loss function)
- ◊ Regularyzacja
- ◊ Backpropagation czyli w jaki sposób sieci się uczą
- ◊ Optymalizacje
- ◊ Hiperparametry sieci
- ◊ Przeuczenie
- ◊ Strojenie modelu





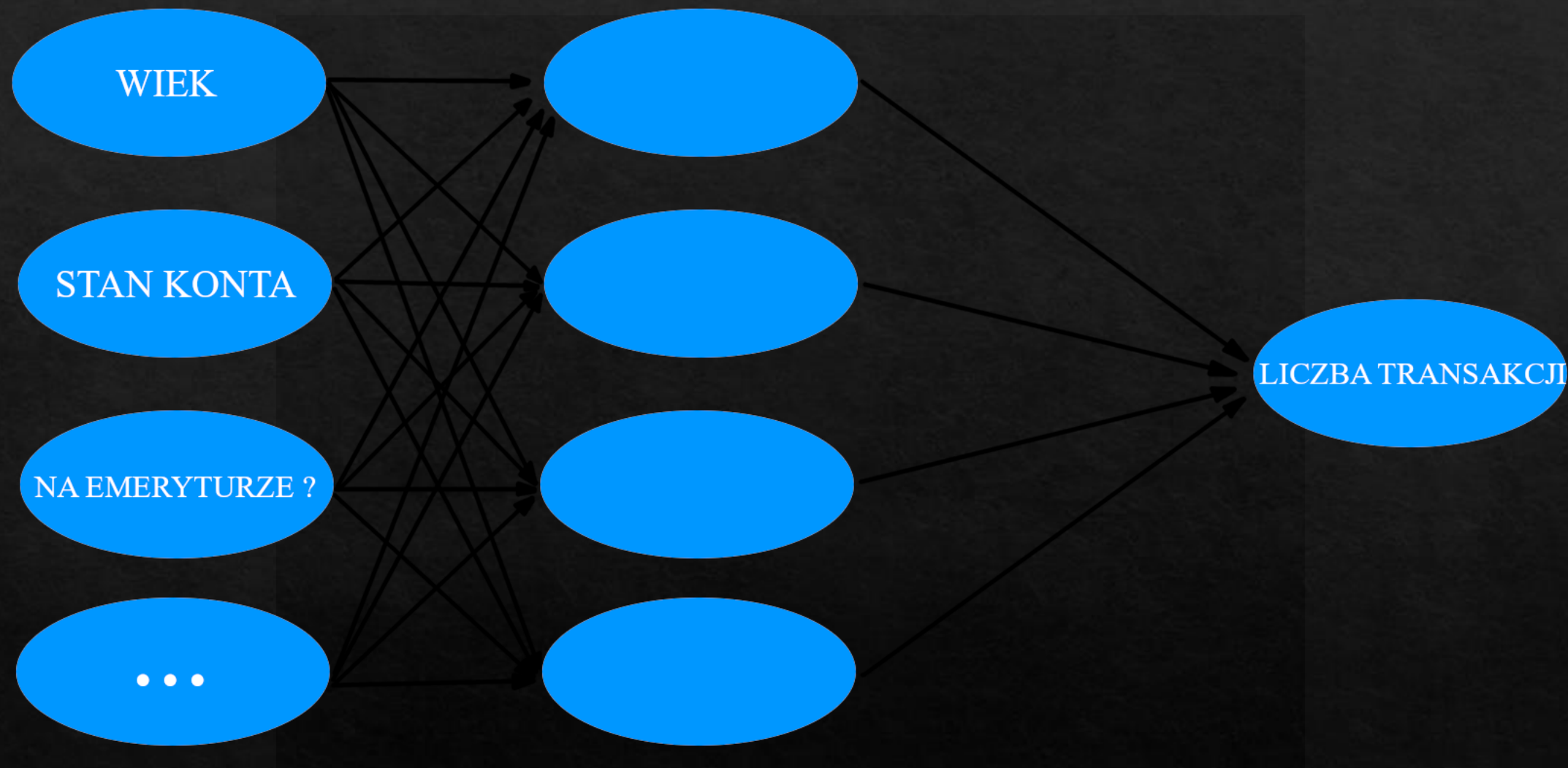




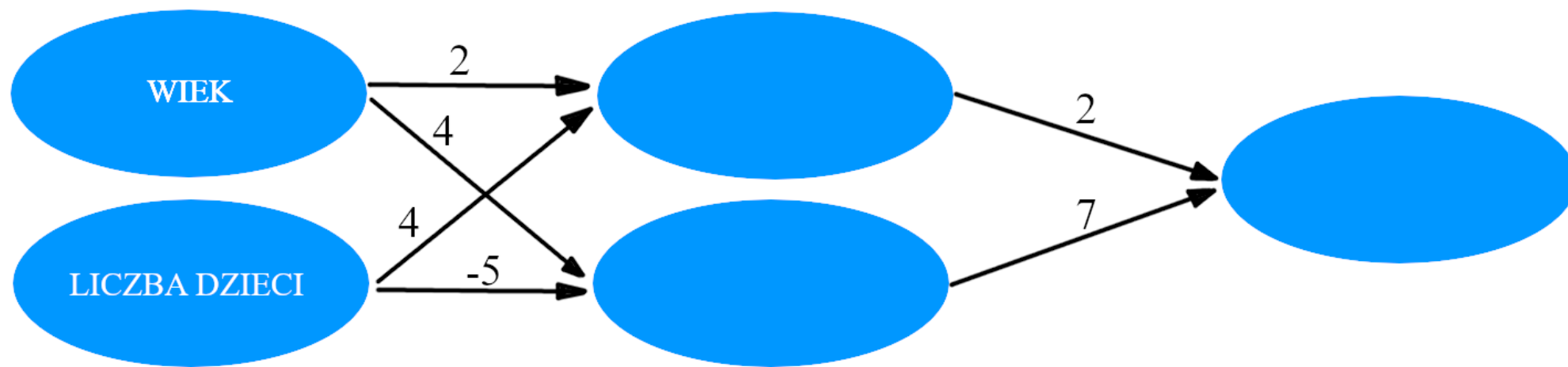
WARSTWA  
WEJŚCIOWA

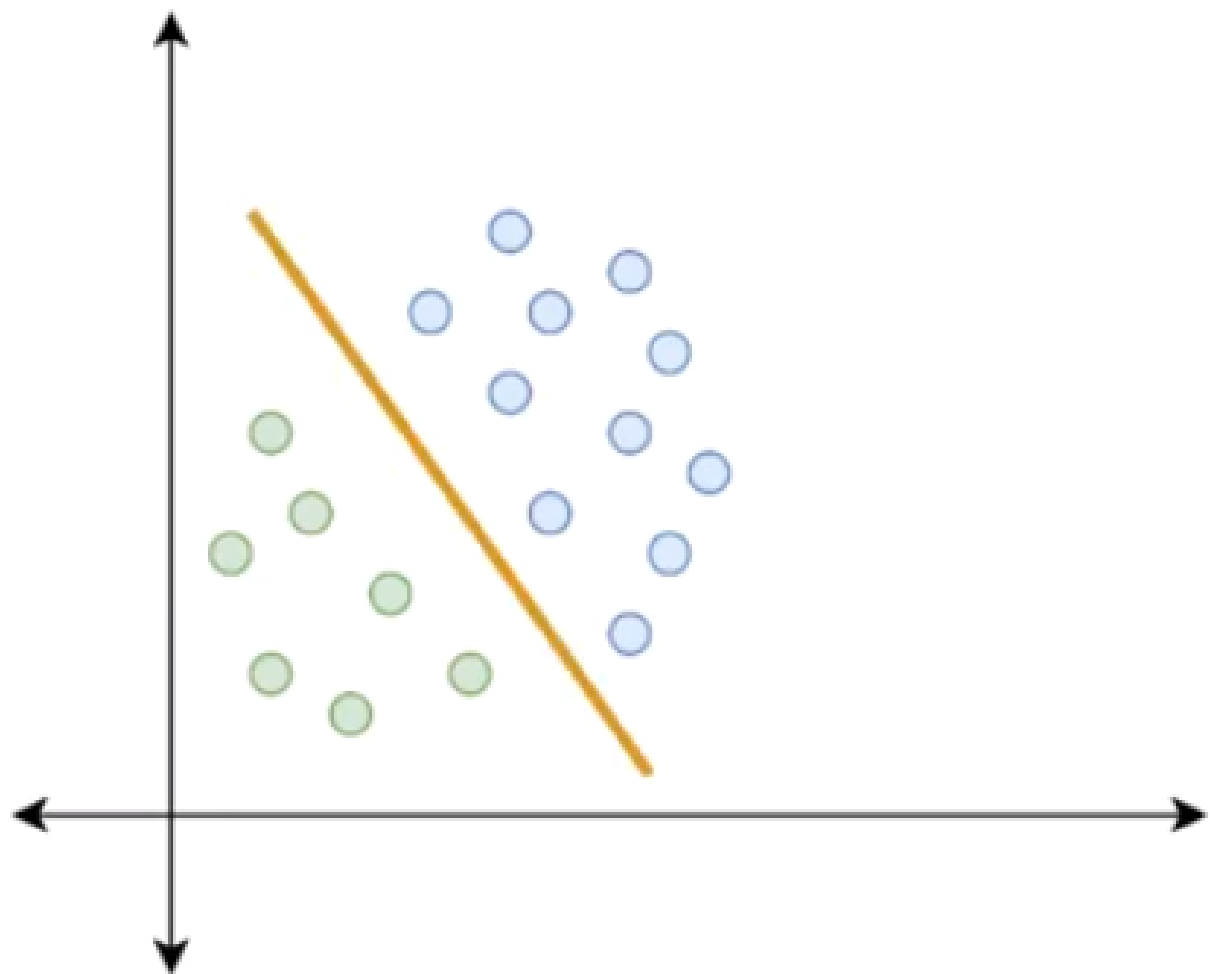
WARSTWA  
UKRYTA

WARSTWA  
WYJŚCIOWA

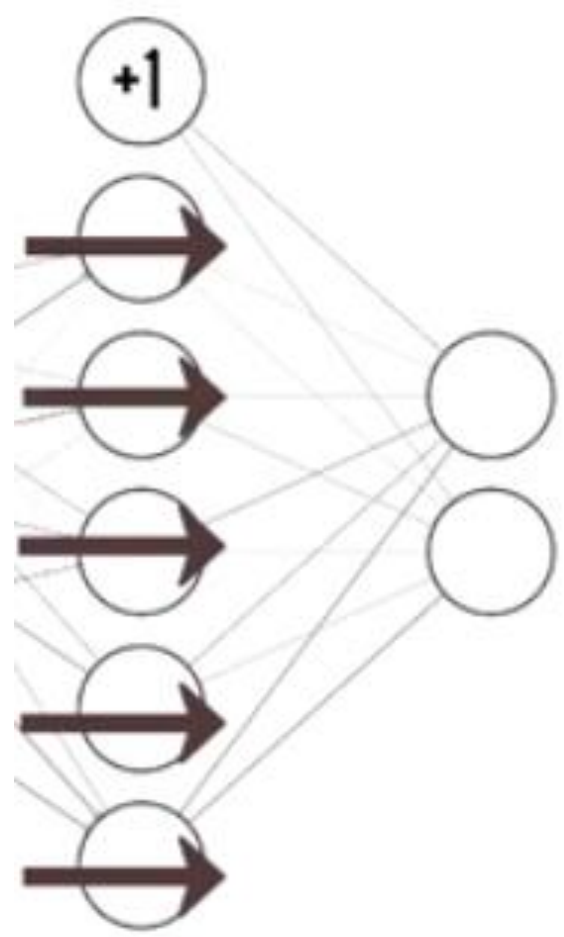
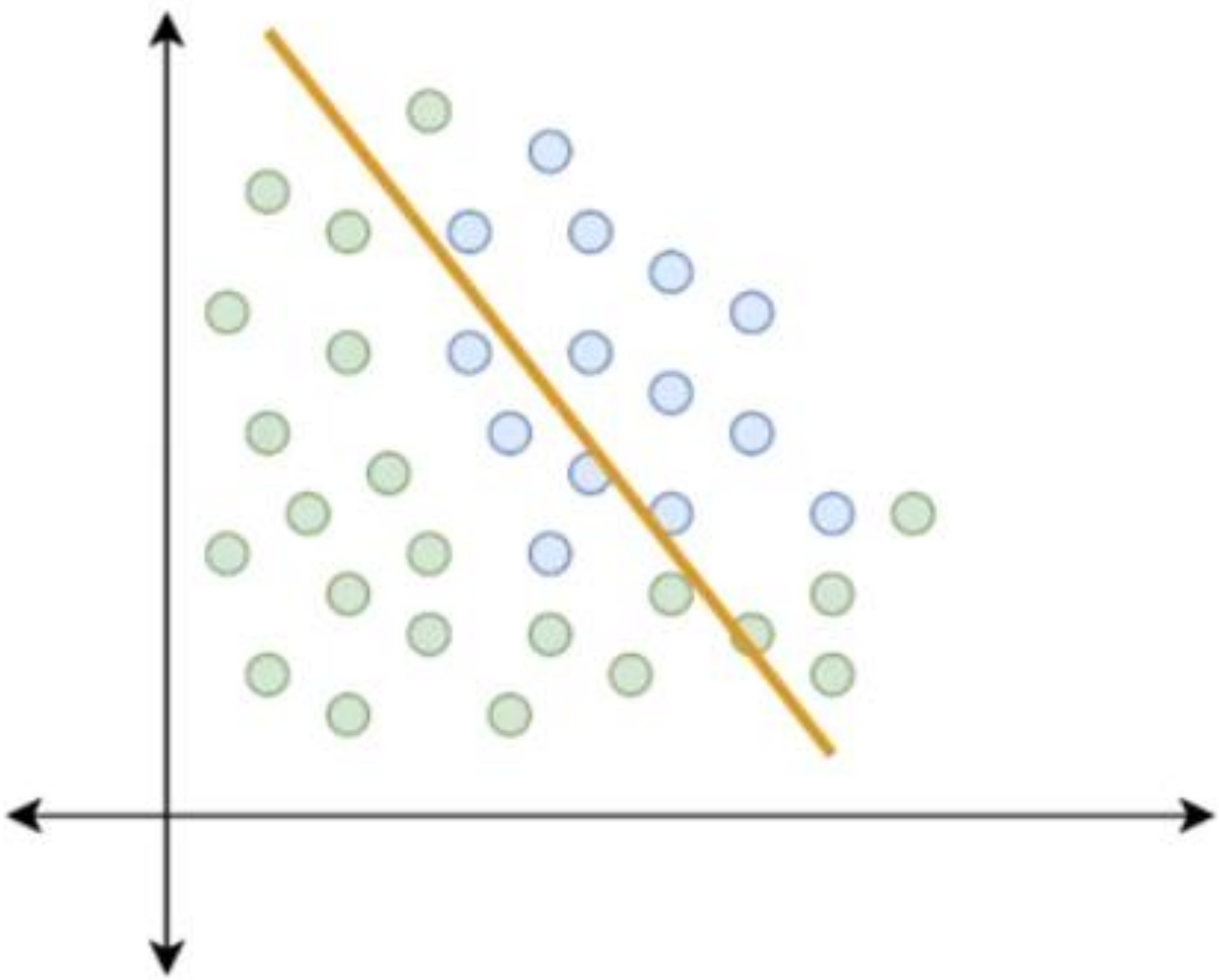


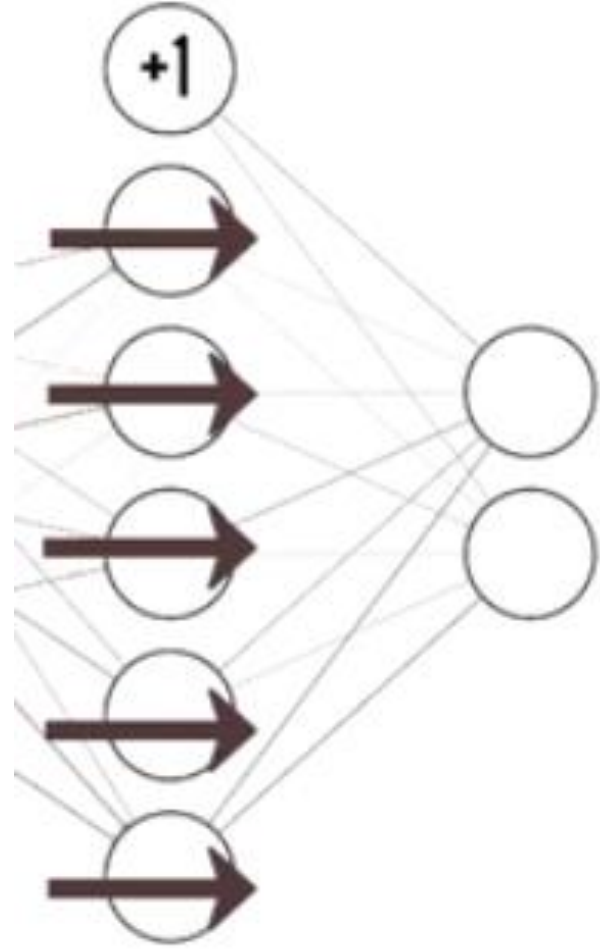
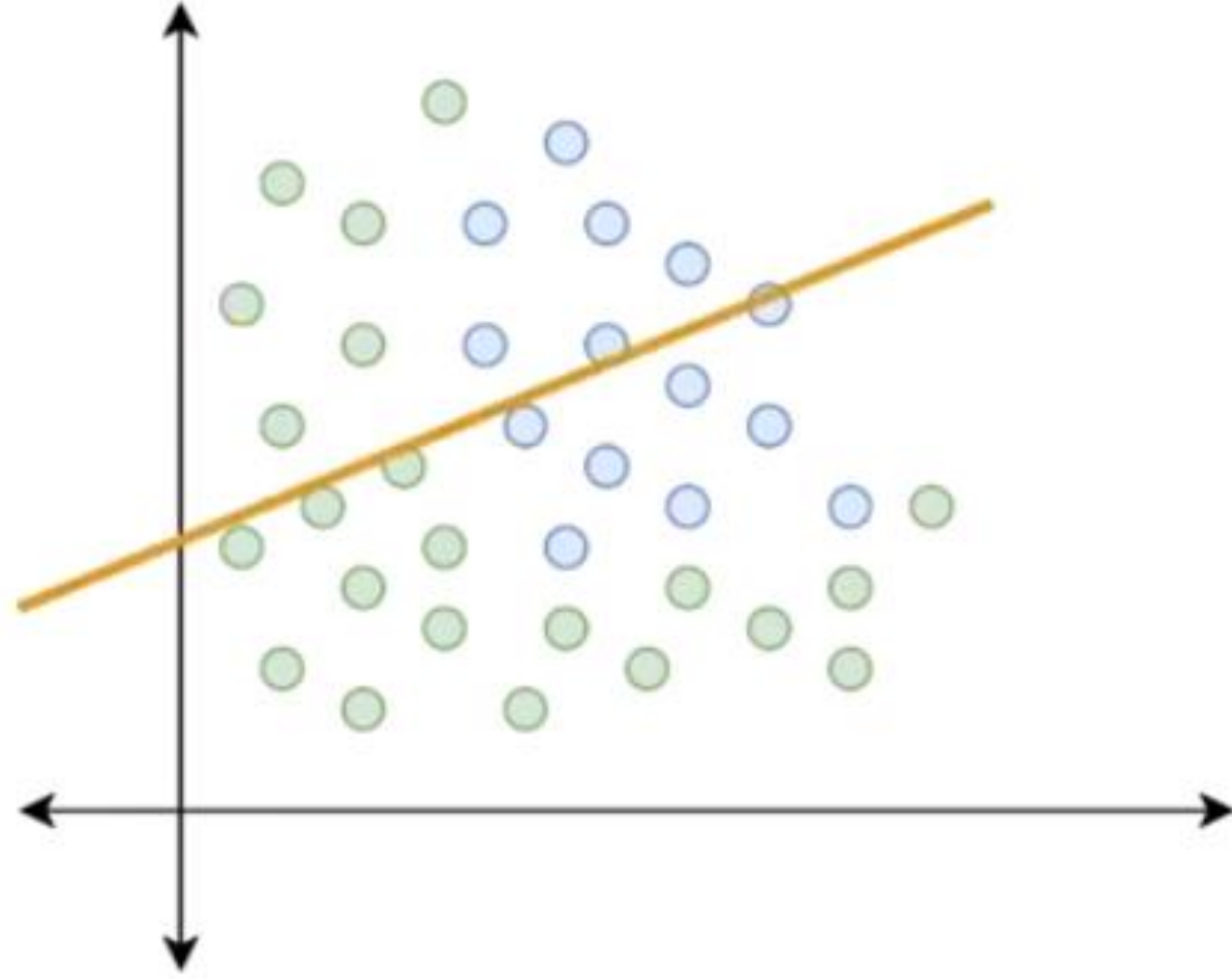
## Forward propagation

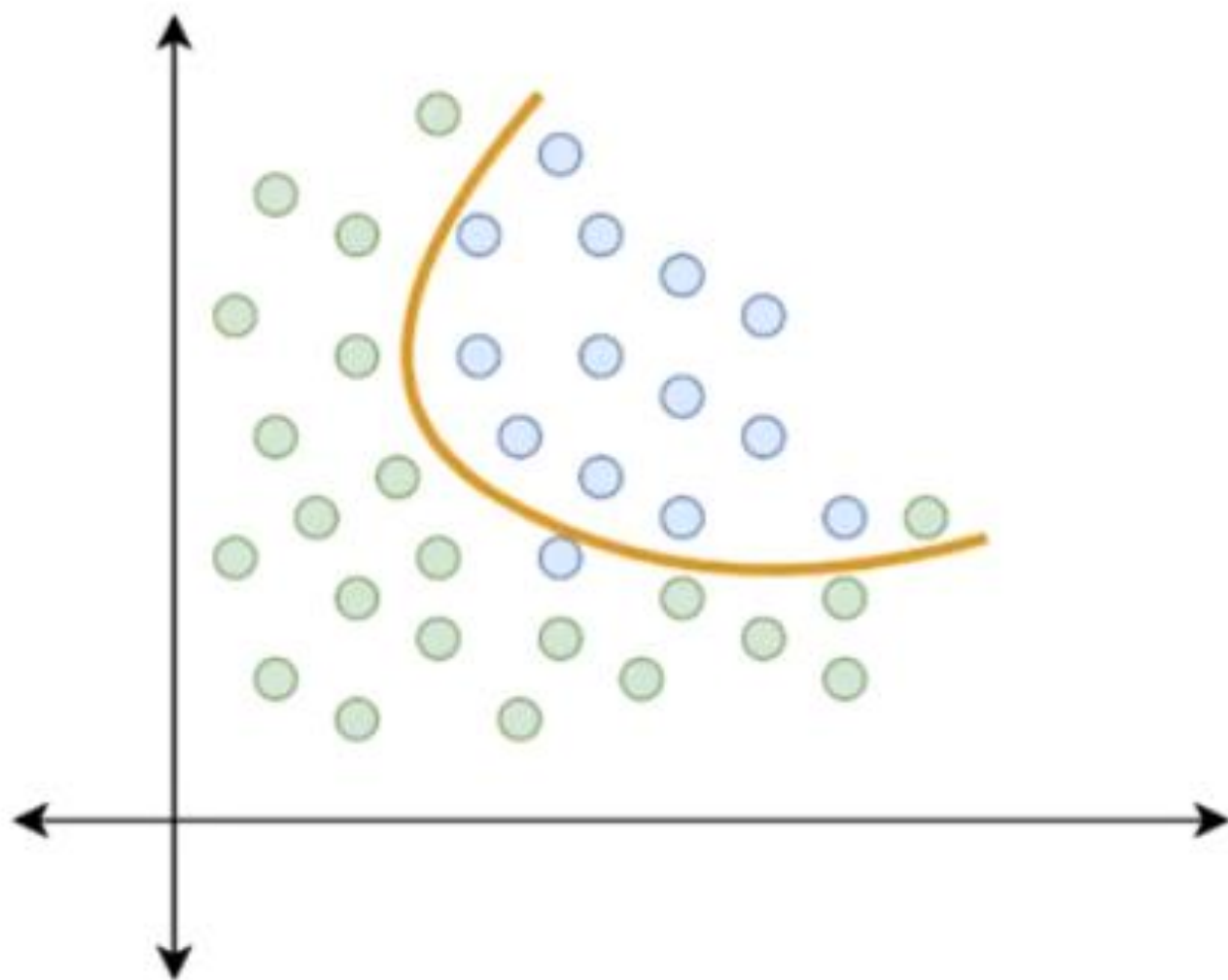
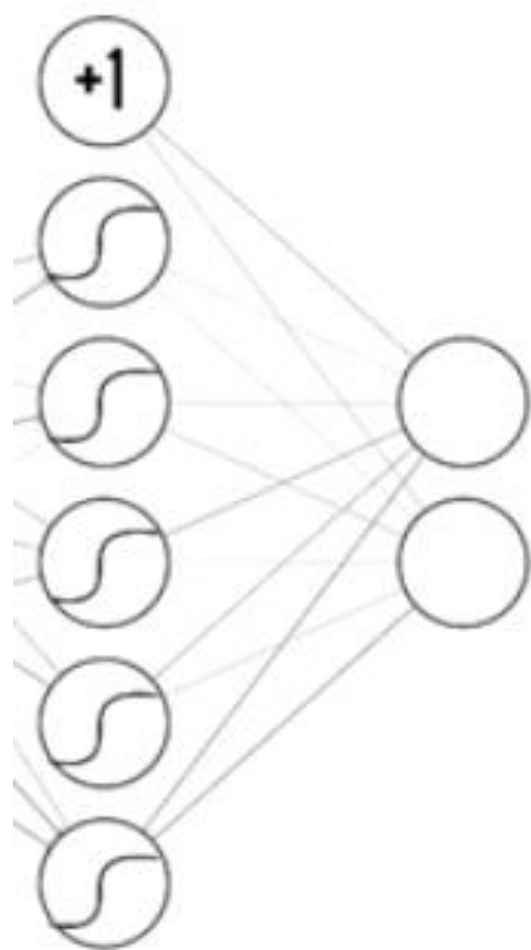


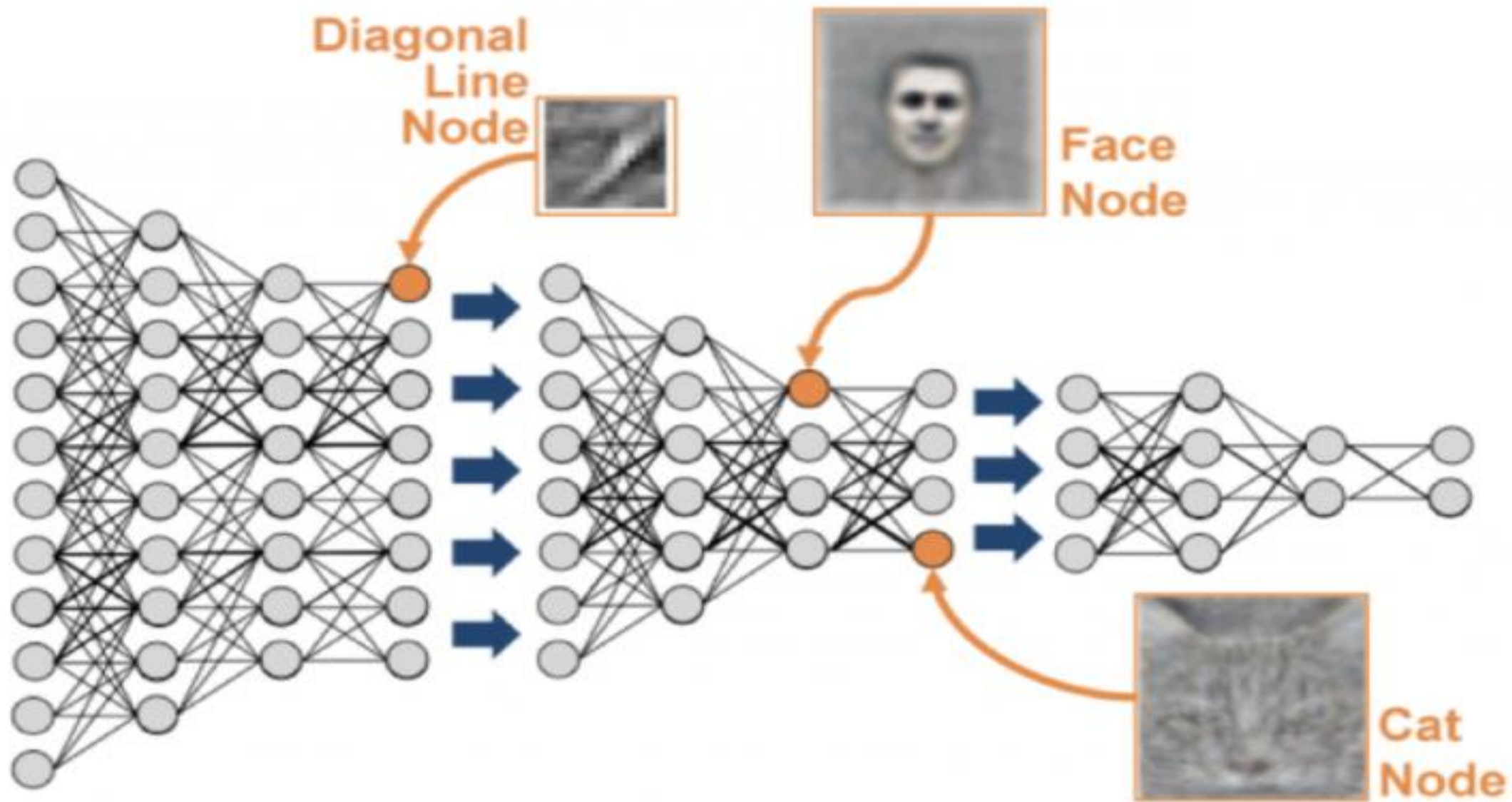




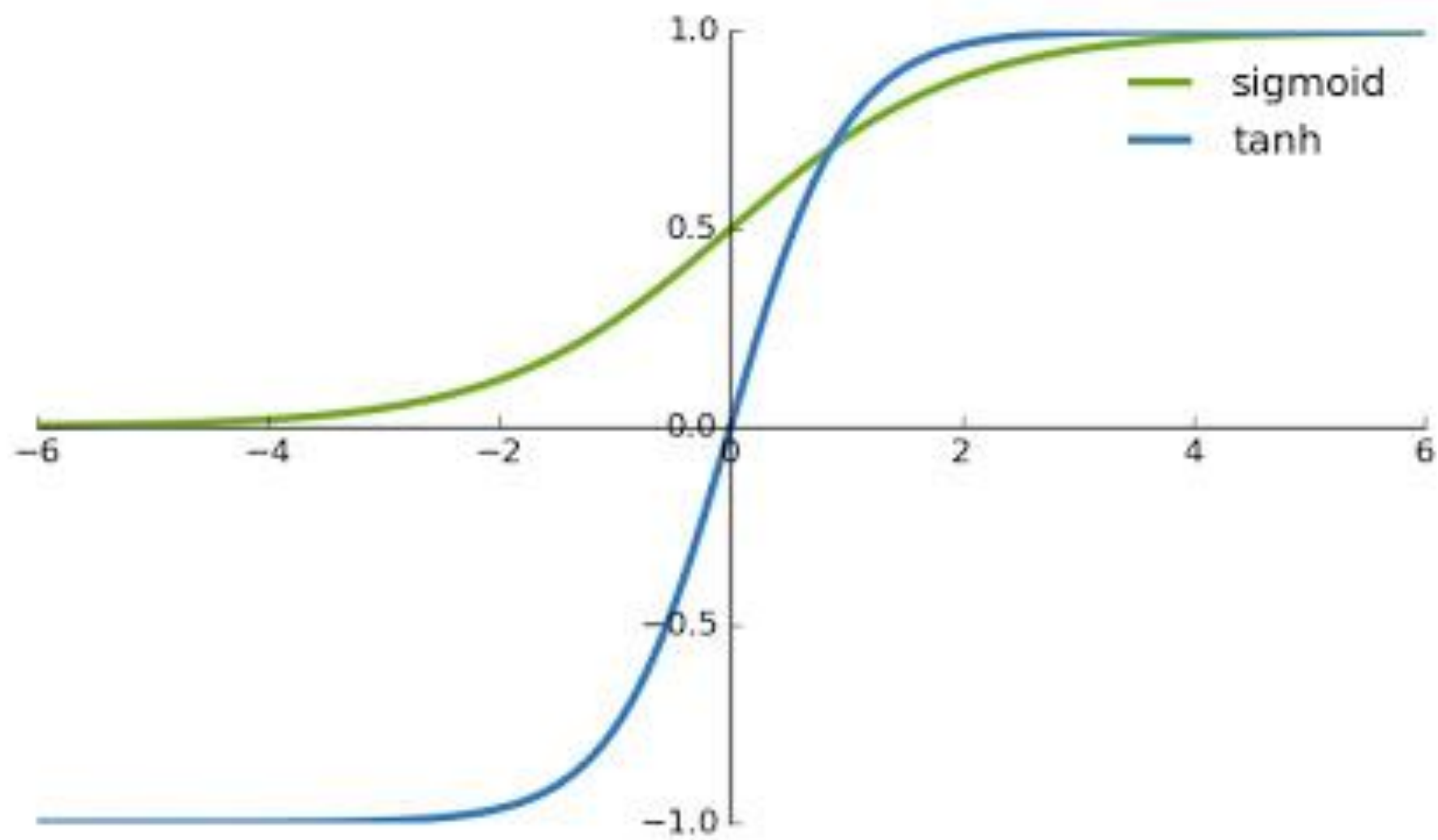


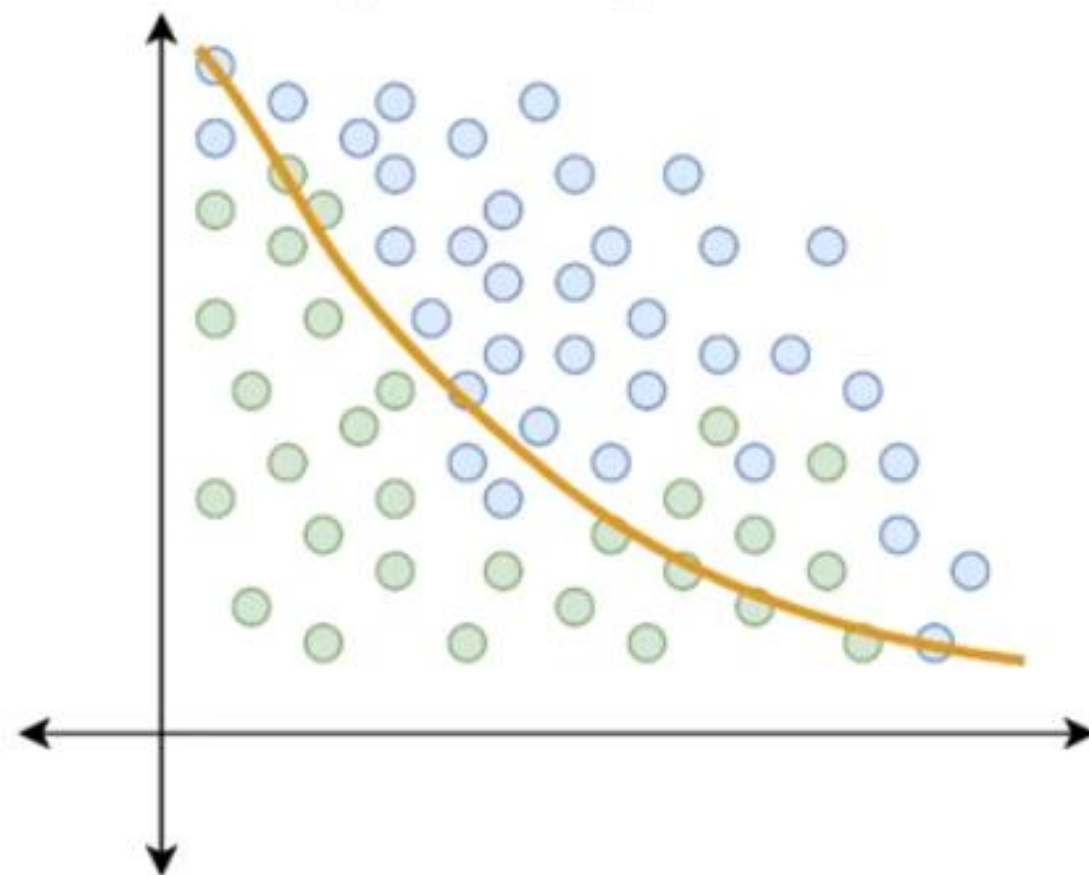
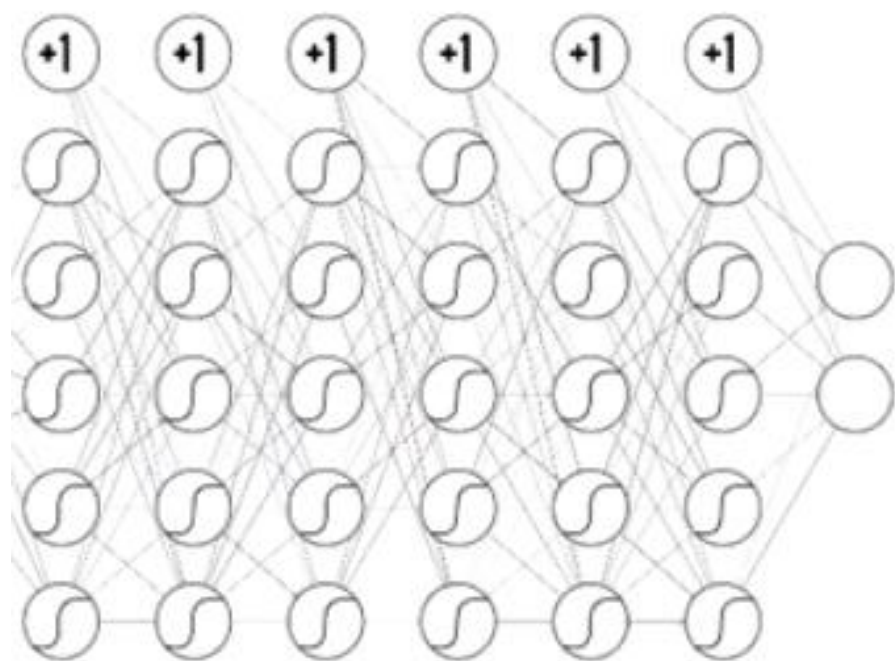


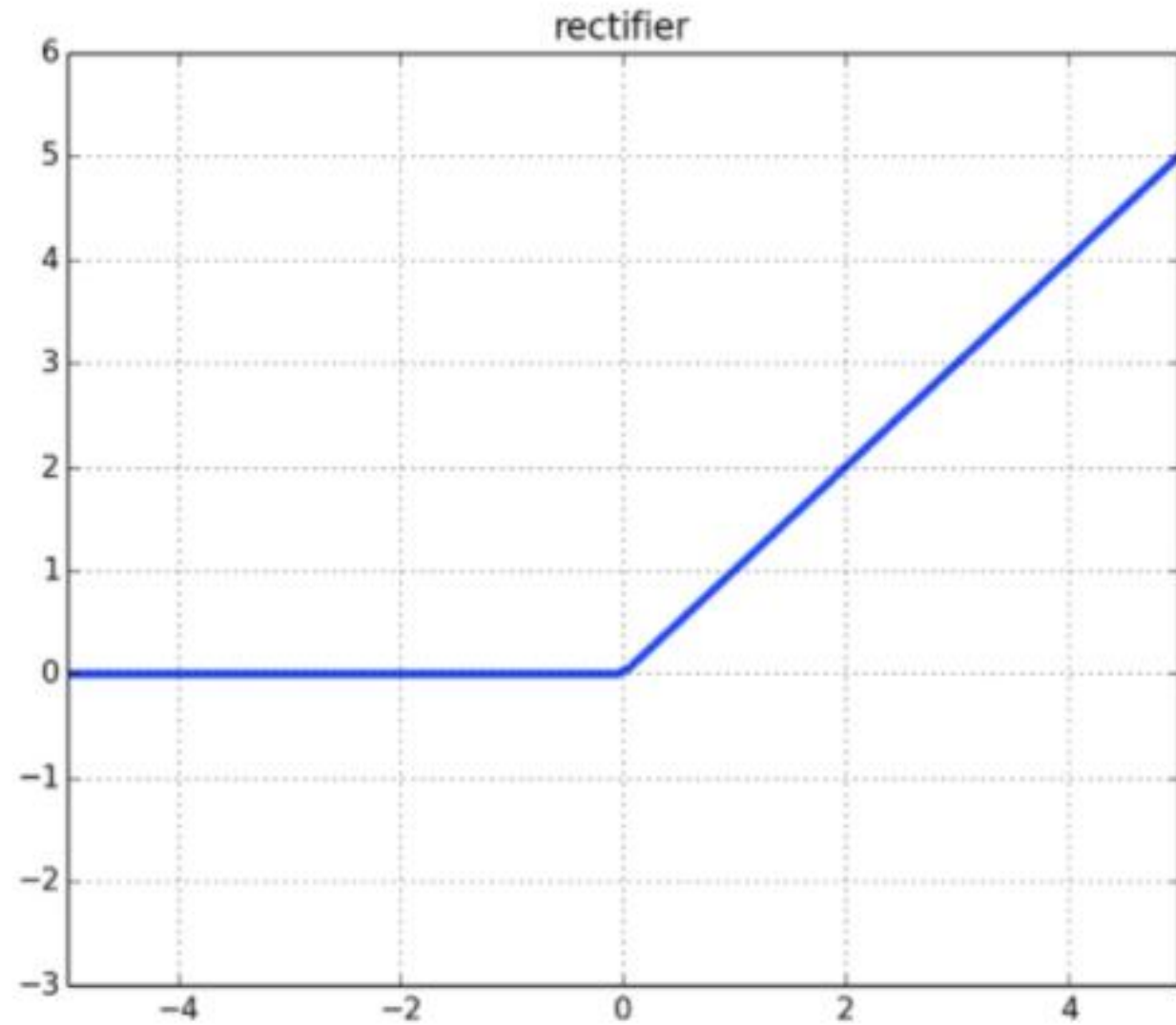




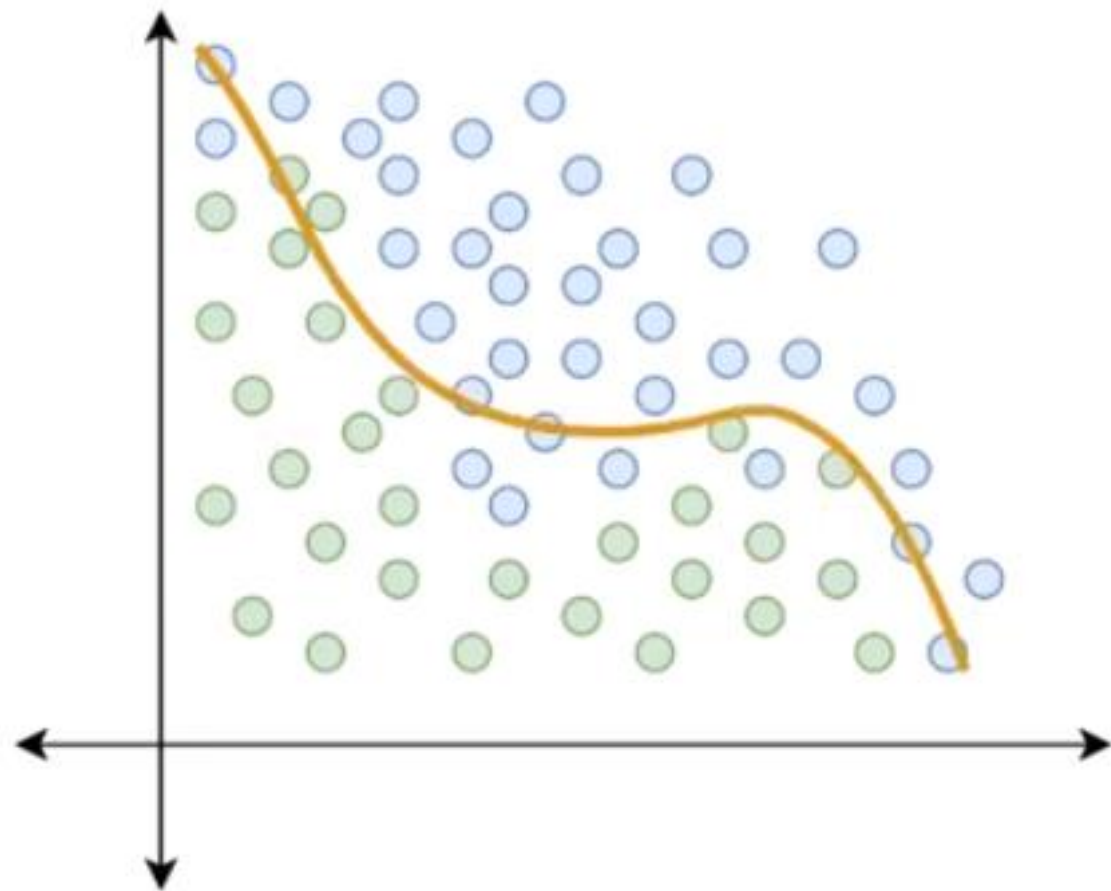
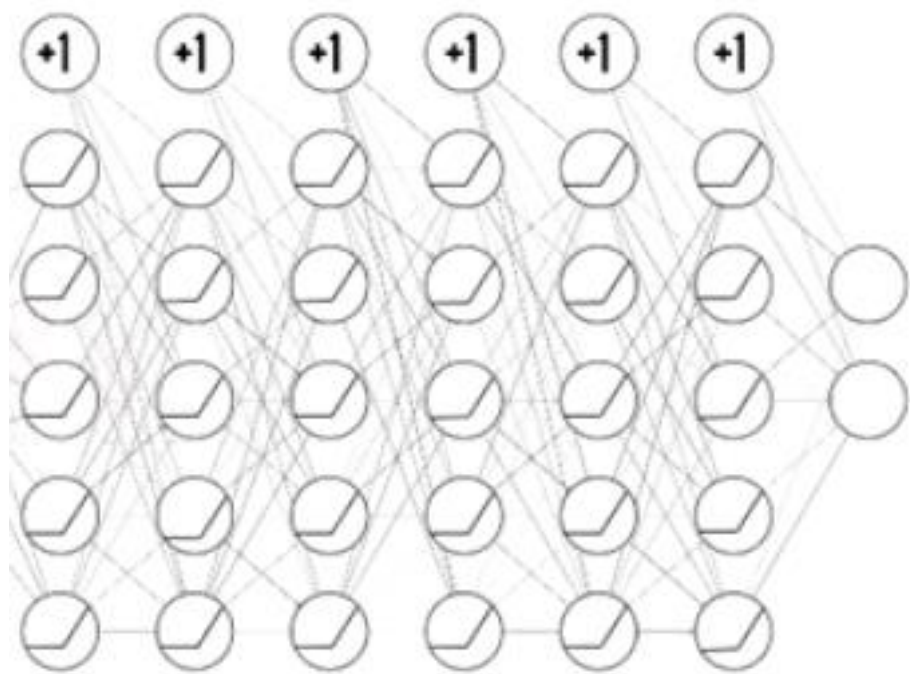






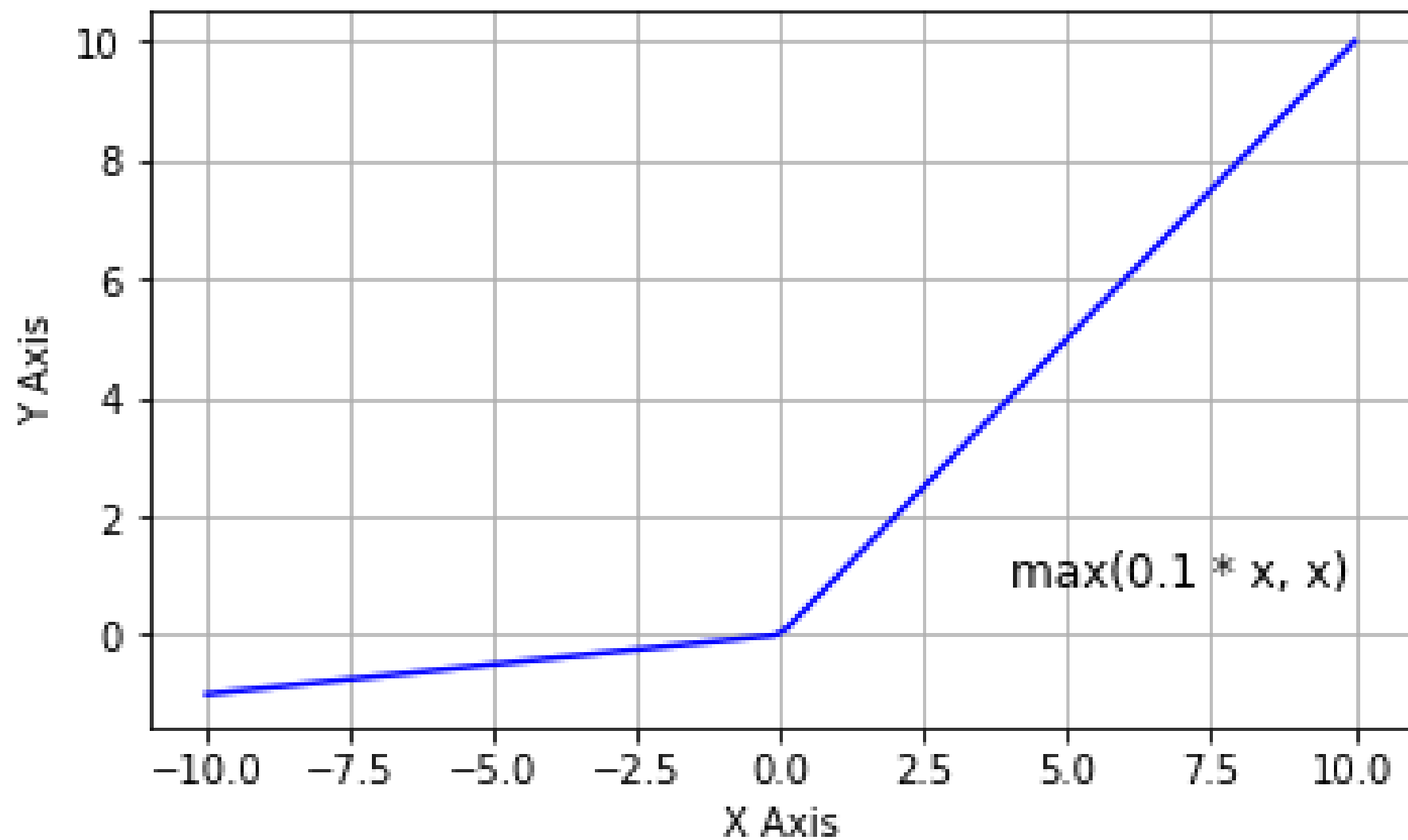











$$RELU(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases}$$



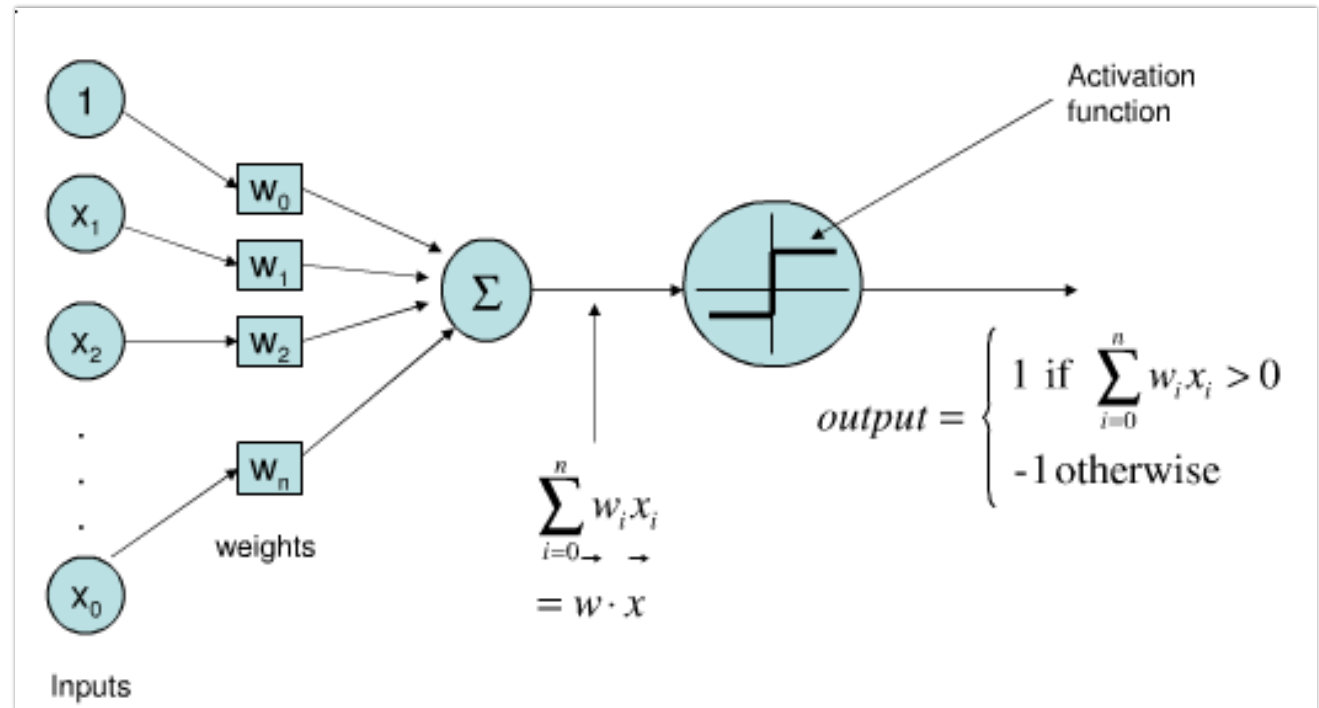


## Leaky ReLU Activation Function

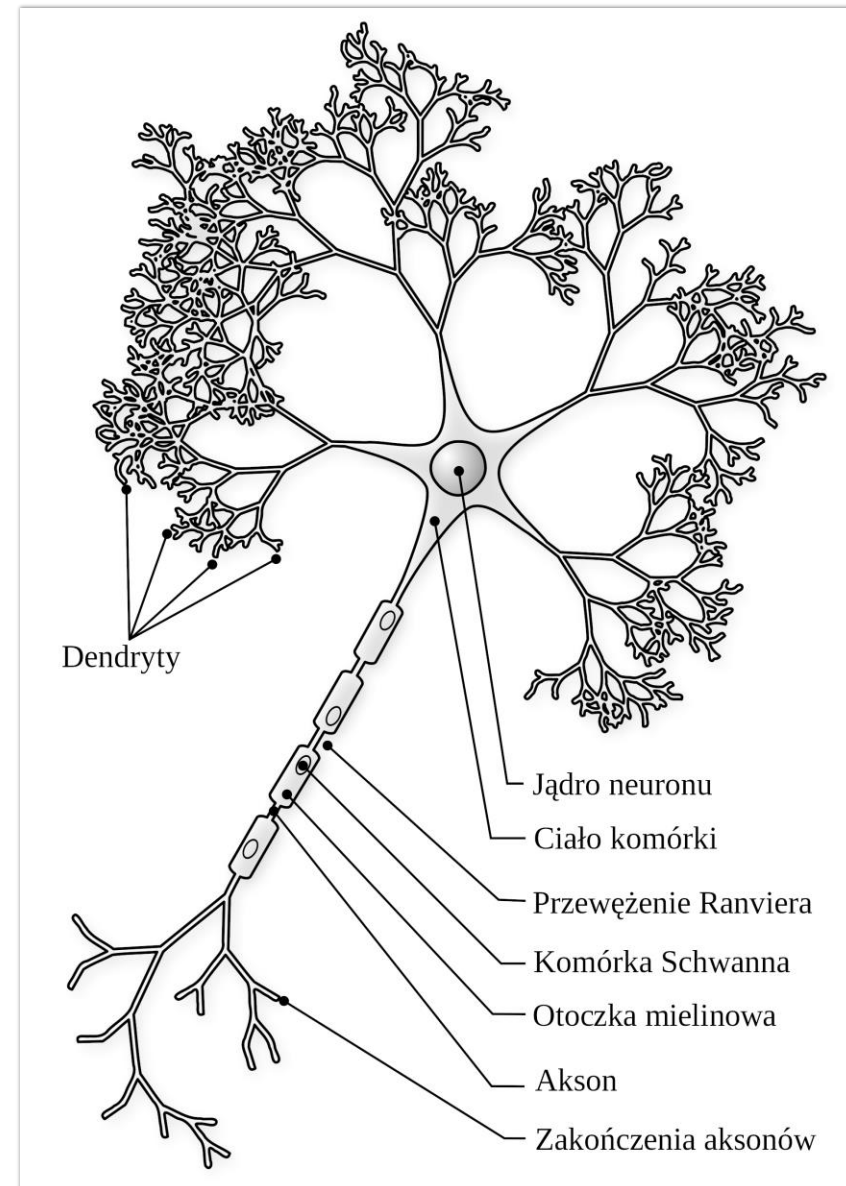


Identity		$f(x) = x$	$f'(x) = 1$
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$
Logistic (a.k.a Soft step)		$f(x) = \frac{1}{1 + e^{-x}}$	$f'(x) = f(x)(1 - f(x))$
TanH		$f(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$
ArcTan		$f(x) = \tan^{-1}(x)$	$f'(x) = \frac{1}{x^2 + 1}$
Rectified Linear Unit (ReLU)		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Parameteric Rectified Linear Unit (PReLU) [2]		$f(x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Exponential Linear Unit (ELU) [3]		$f(x) = \begin{cases} \alpha(e^x - 1) & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} f(x) + \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
SoftPlus		$f(x) = \log_e(1 + e^x)$	$f'(x) = \frac{1}{1 + e^{-x}}$

# Perceptron

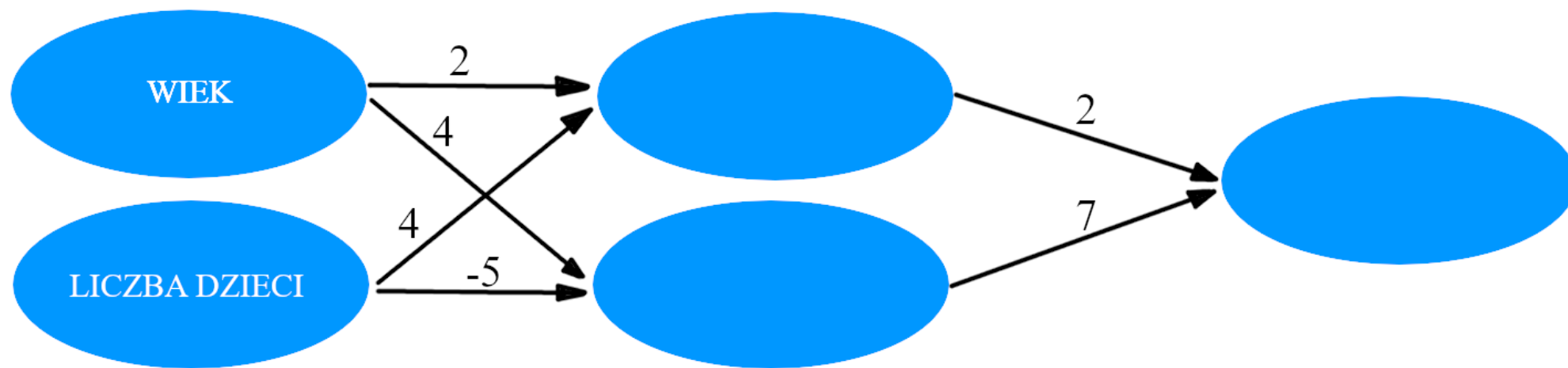


# Neuron





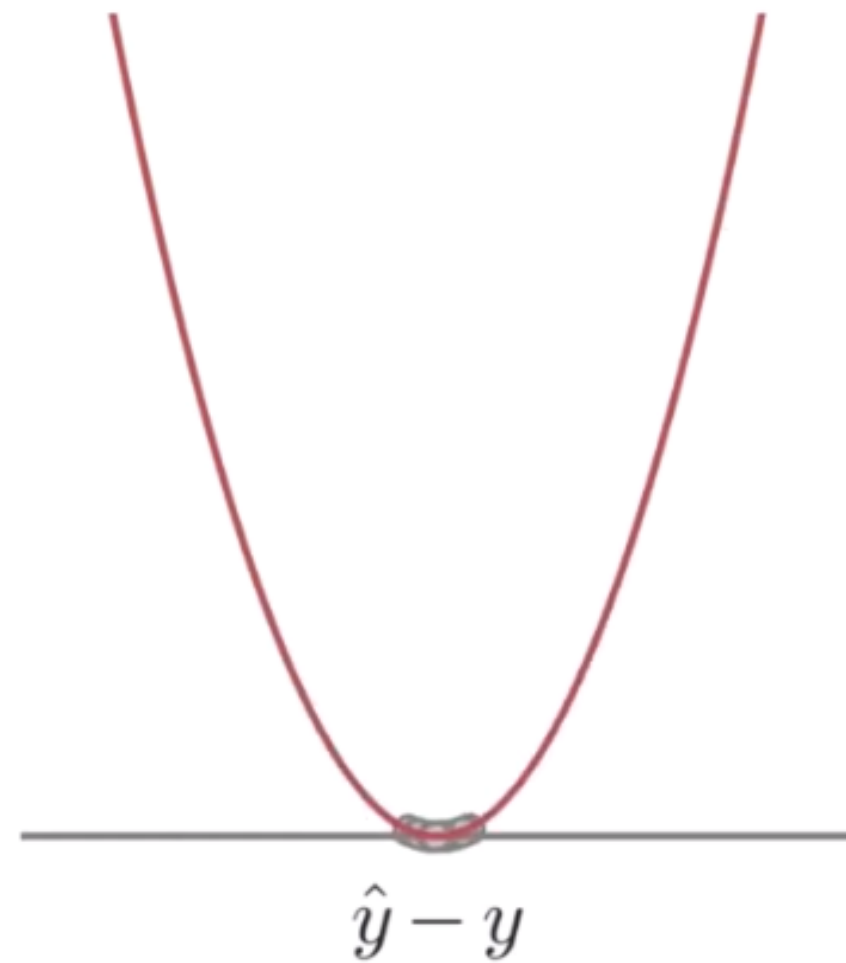
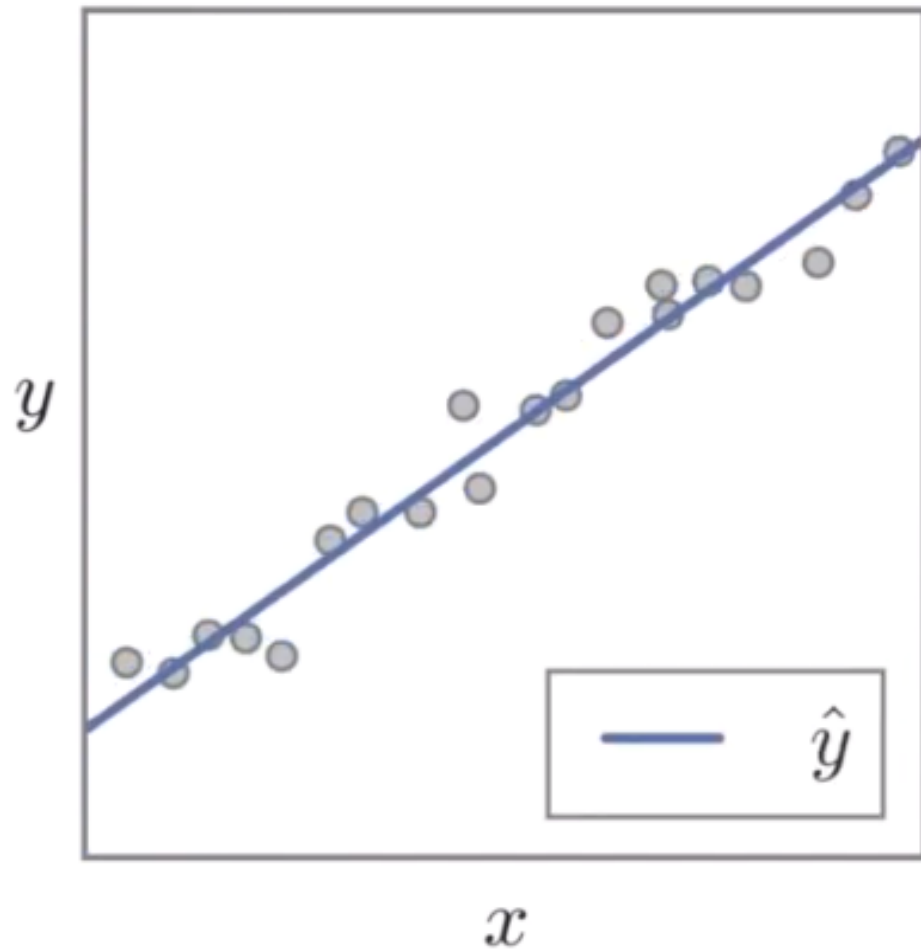
Target = 33



Prediction	Actual	Error
10	20	-10
8	3	5
6	1	5

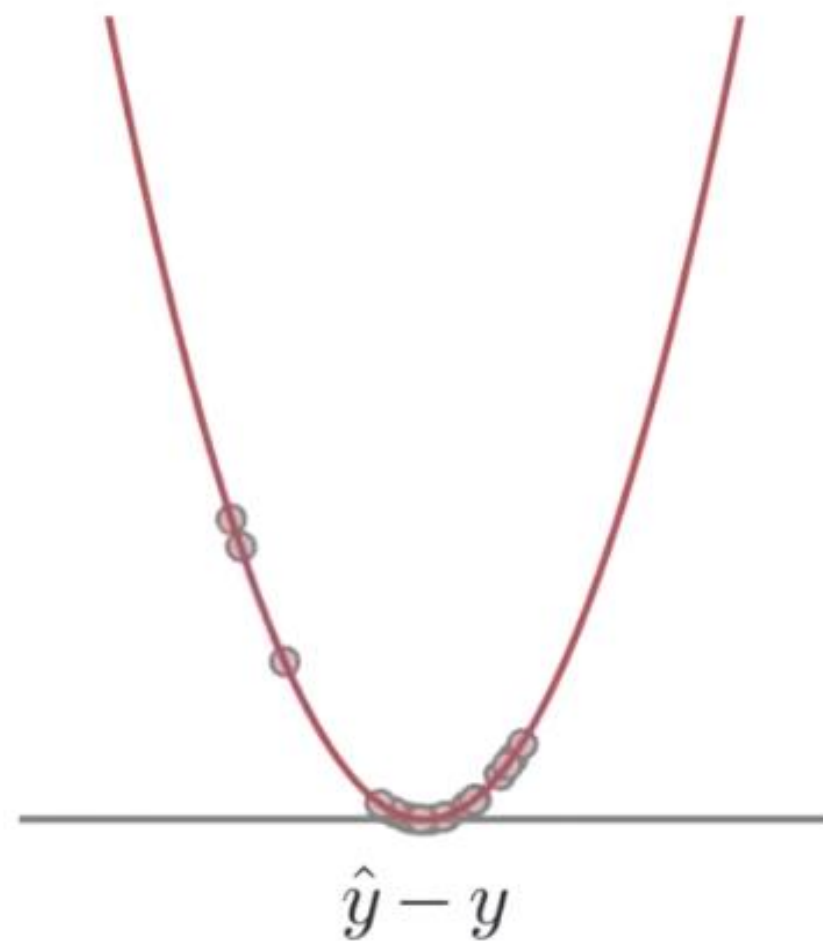
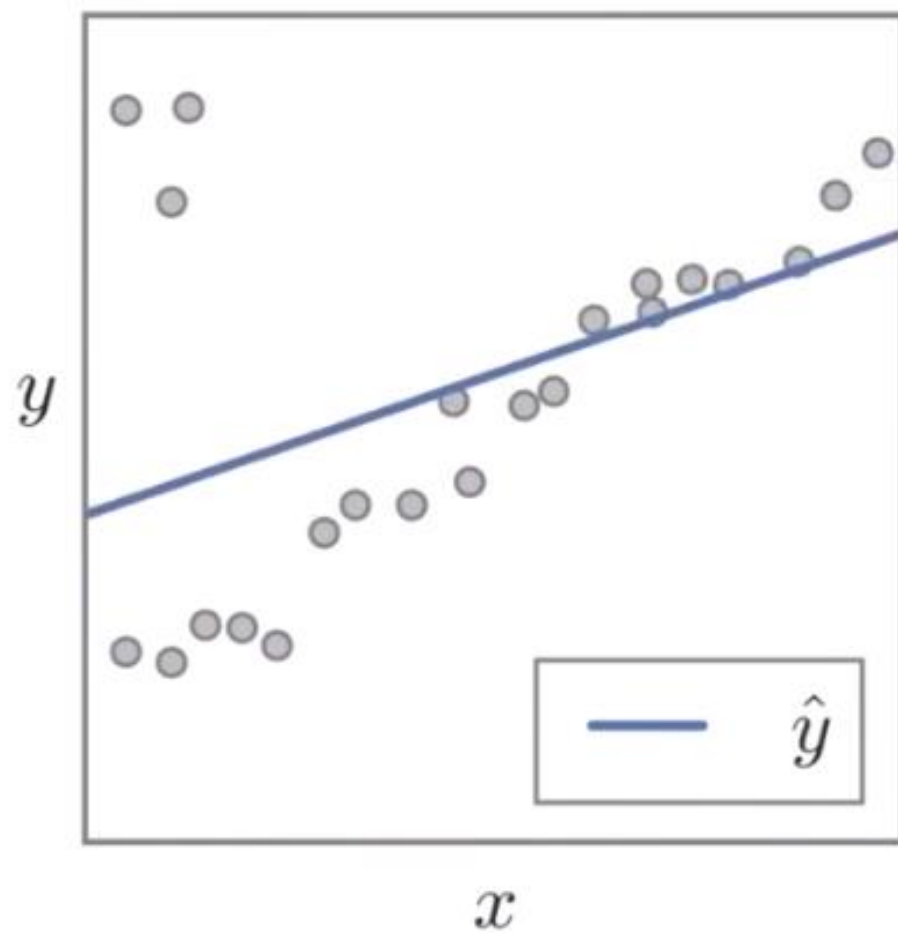
Prediction	Actual	Error	Squared Error
10	20	-10	100
8	3	5	25
6	1	5	25

# 1. Squared Loss = $(\hat{y} - y)^2$

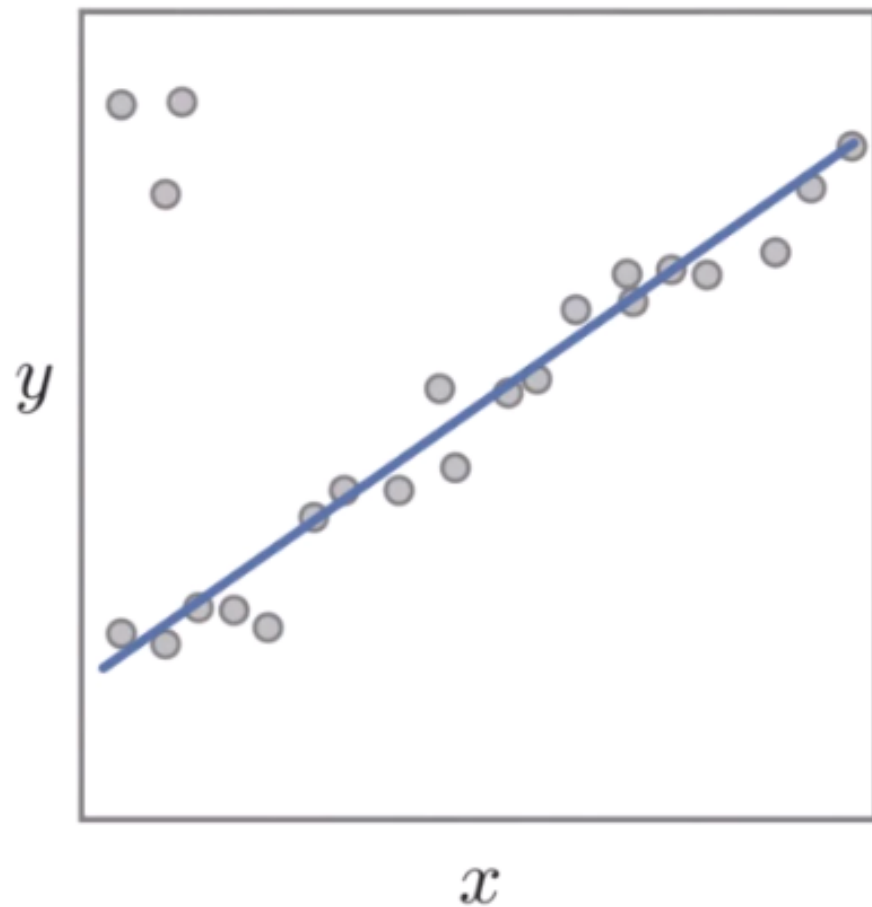


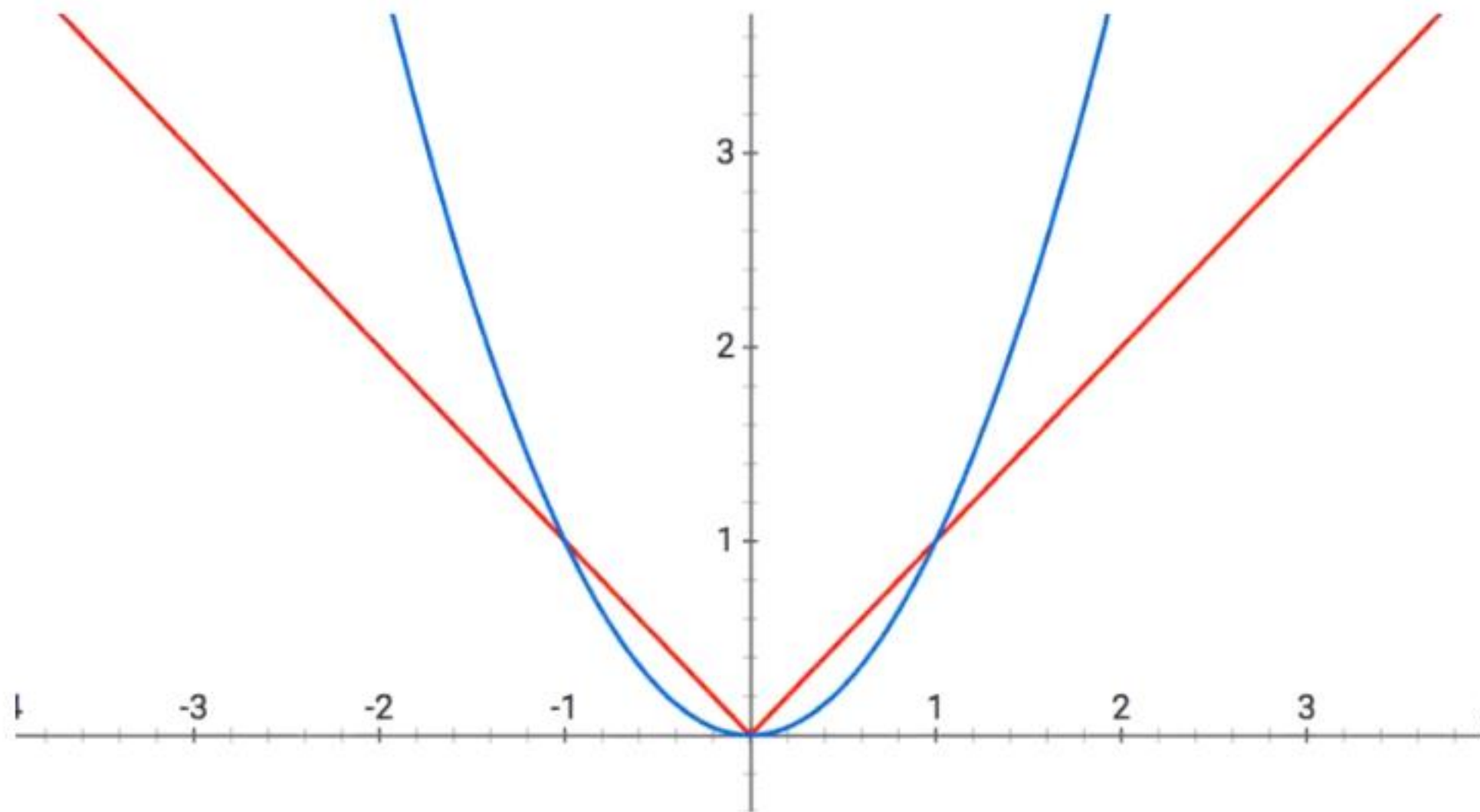


# 1. Squared Loss $= (\hat{y} - y)^2$

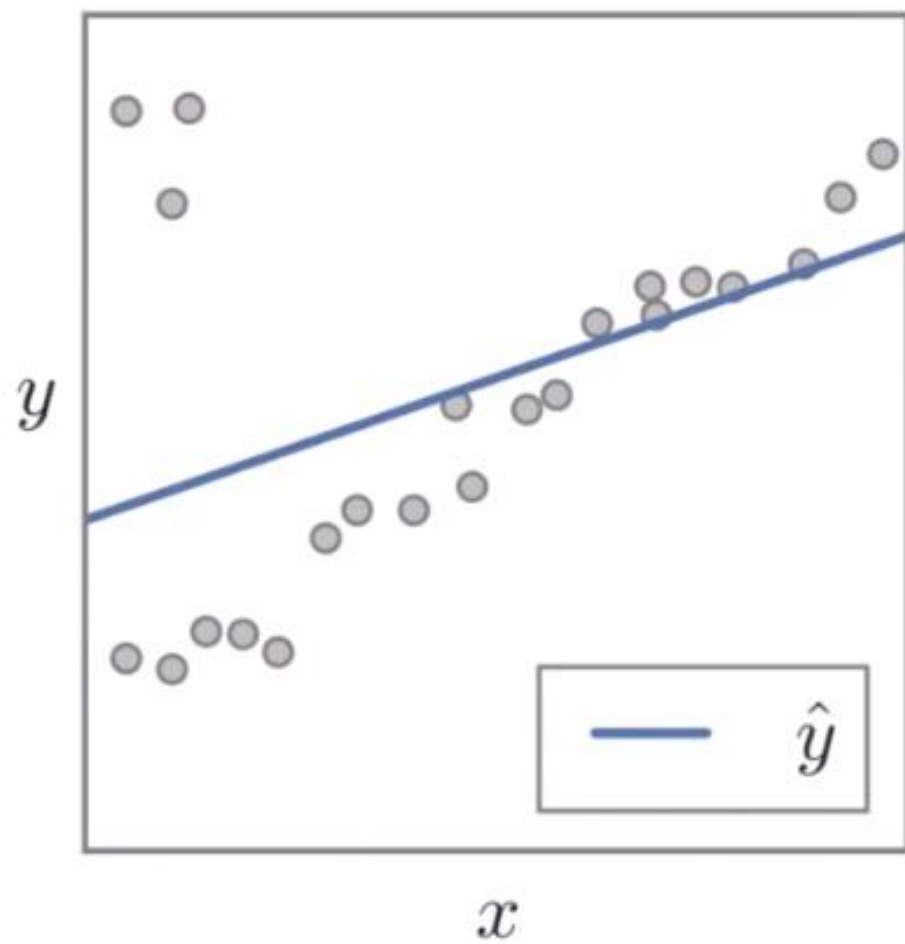


## 2. Absolute Loss = $|\hat{y} - y|$

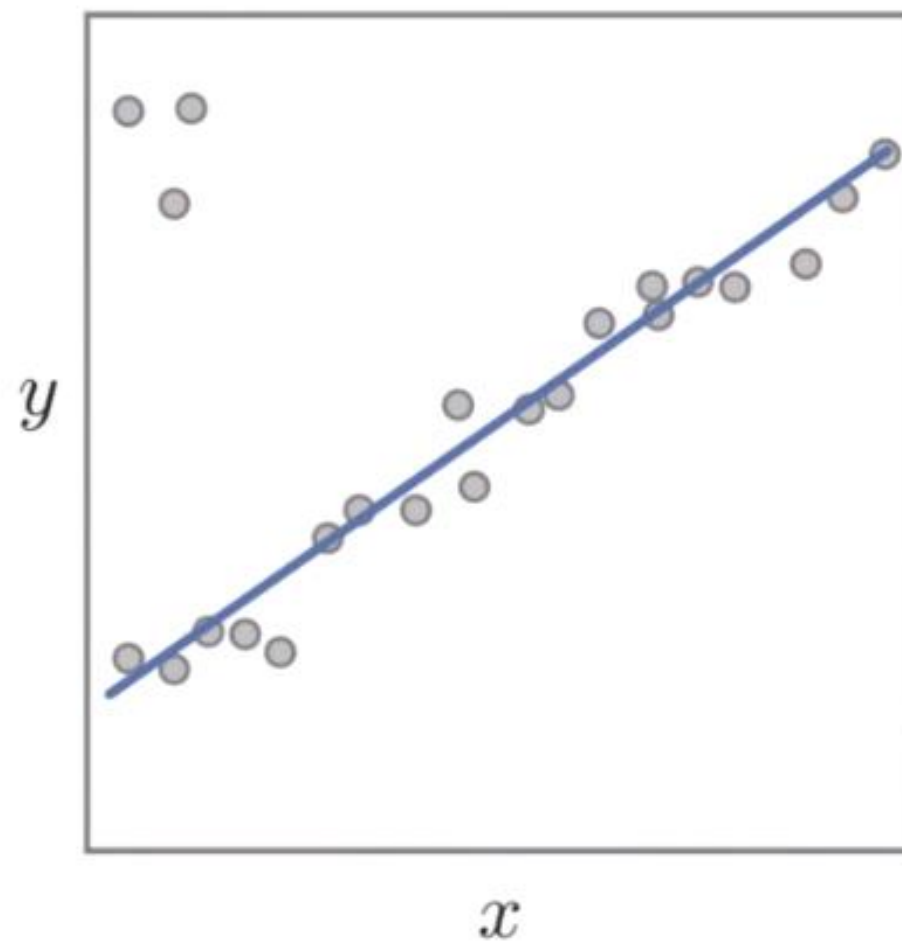




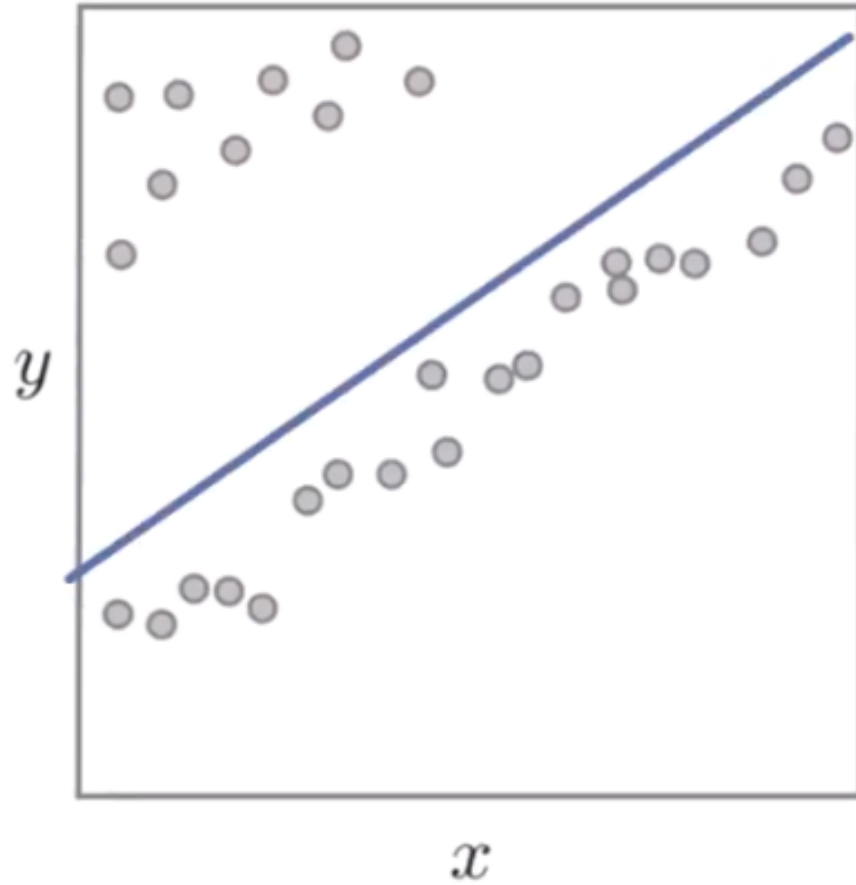
## Squared Loss



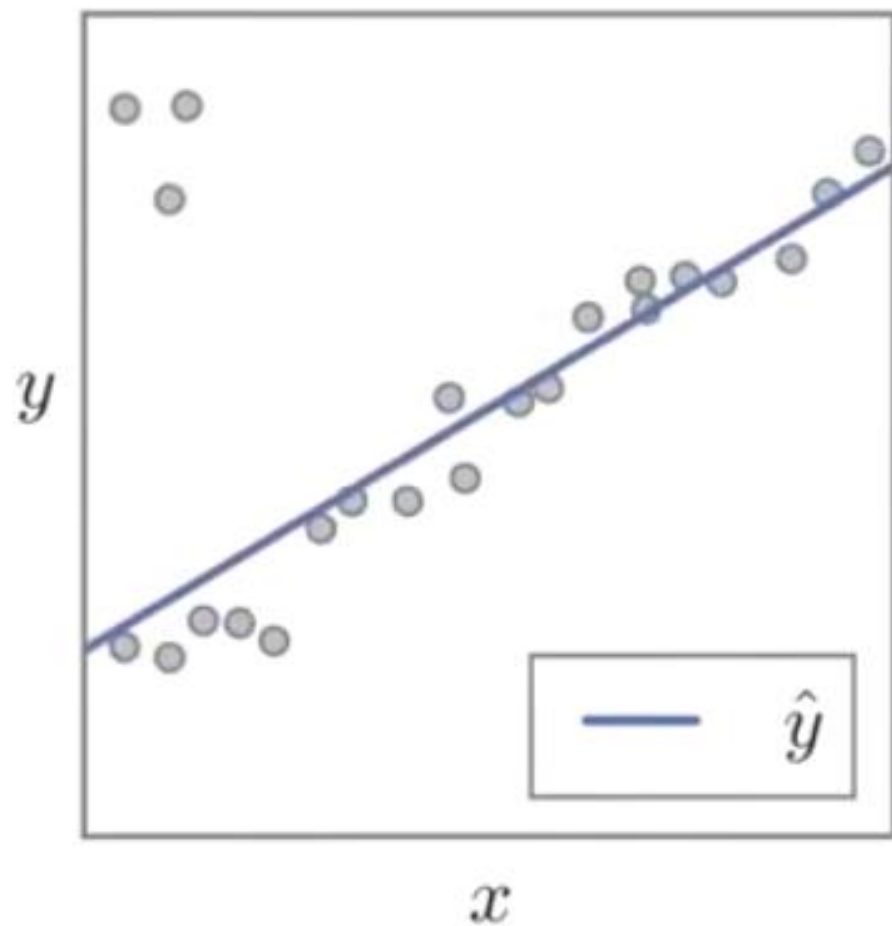
## Absolute Loss



**3. Pseudo-Huber Loss**  $= \begin{cases} (y - \hat{y})^2 & ; |y - \hat{y}| \leq \alpha \\ |y - \hat{y}| & ; \text{otherwise} \end{cases}$

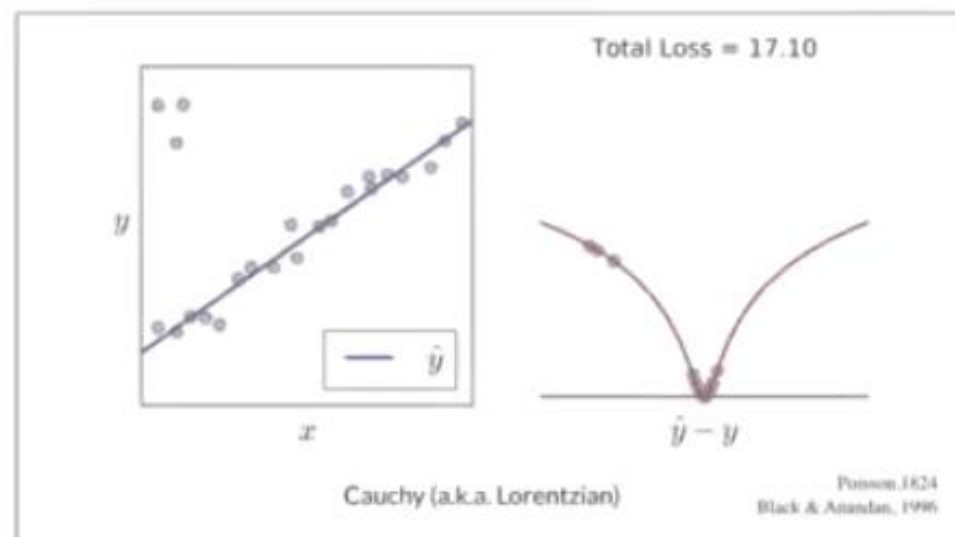
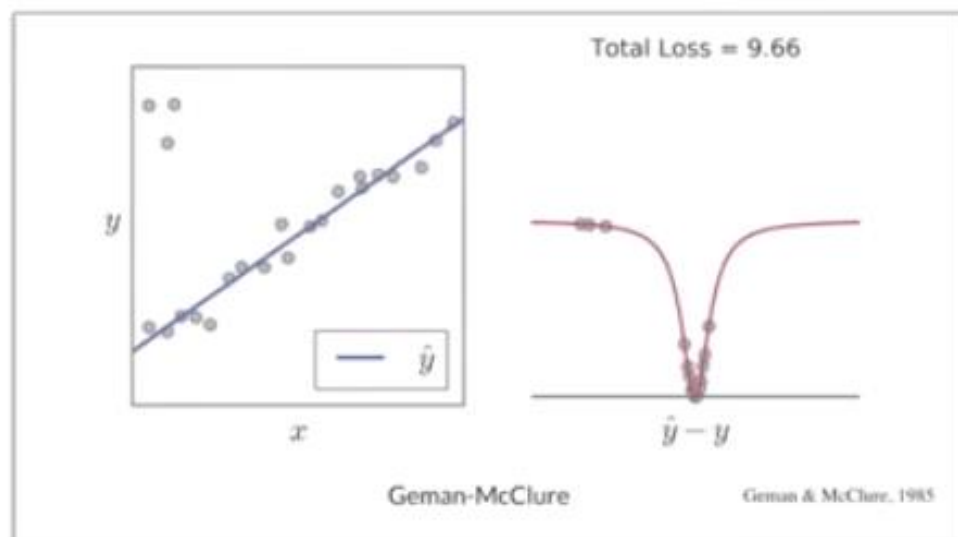
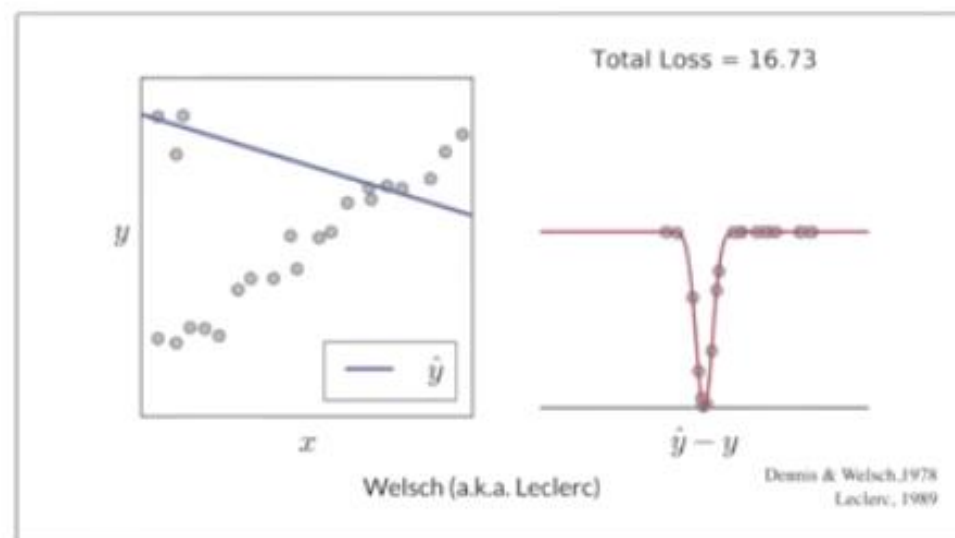
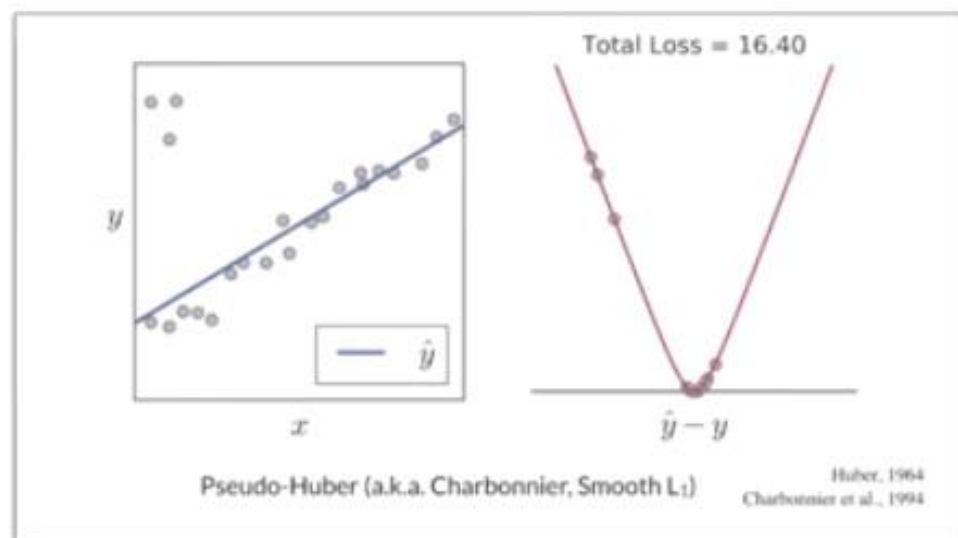


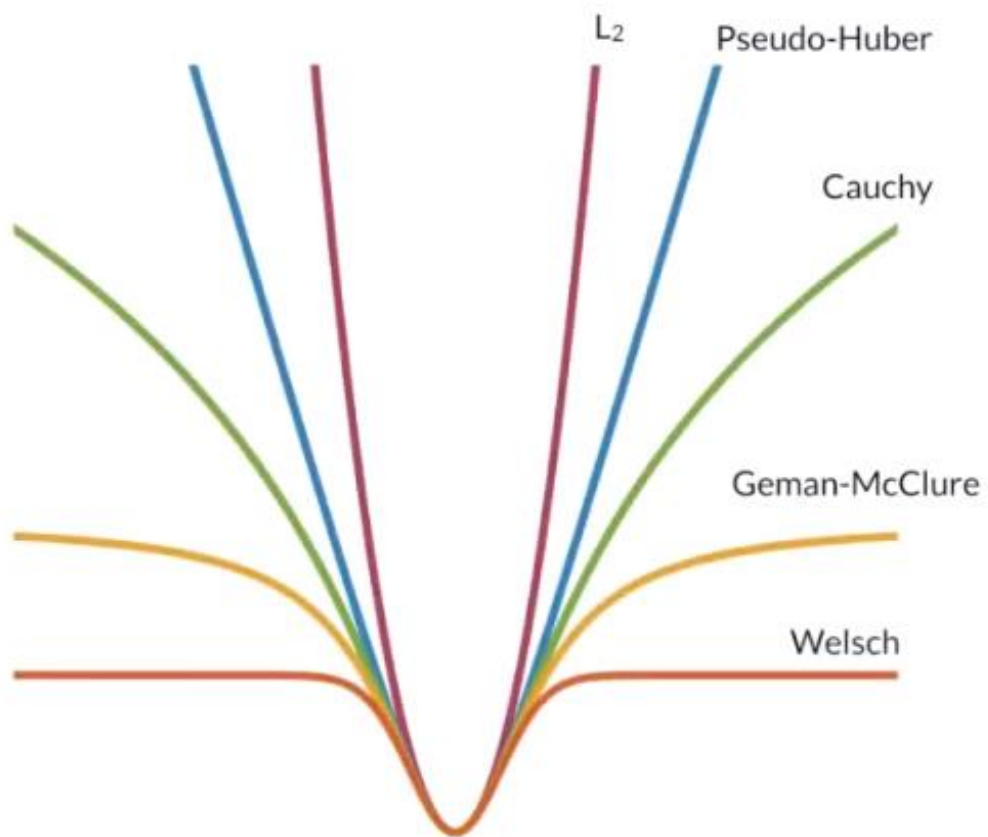




Pseudo-Huber (a.k.a. Charbonnier, Smooth  $L_1$ )

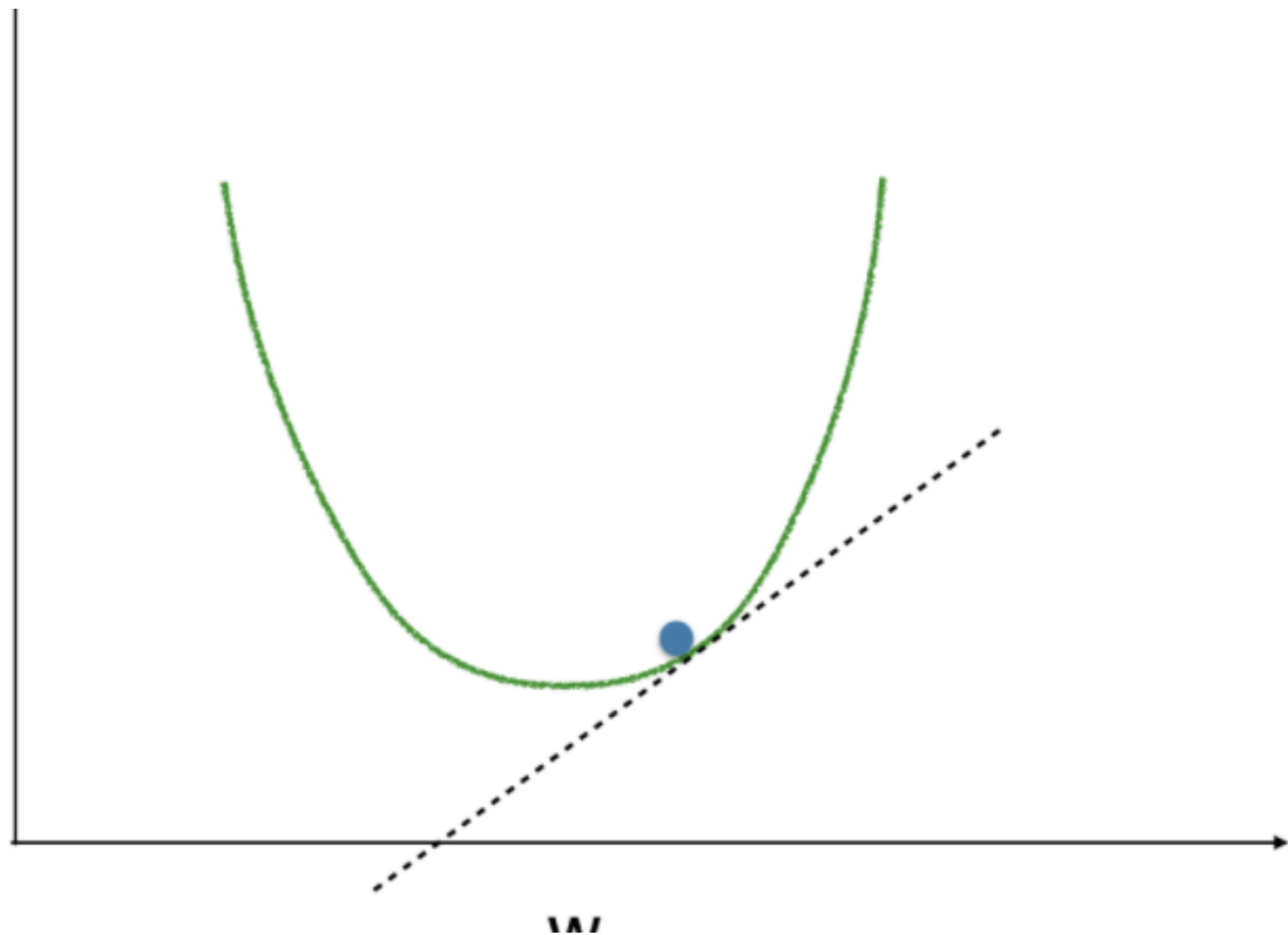
Huber, 1964  
Charbonnier et al., 1994



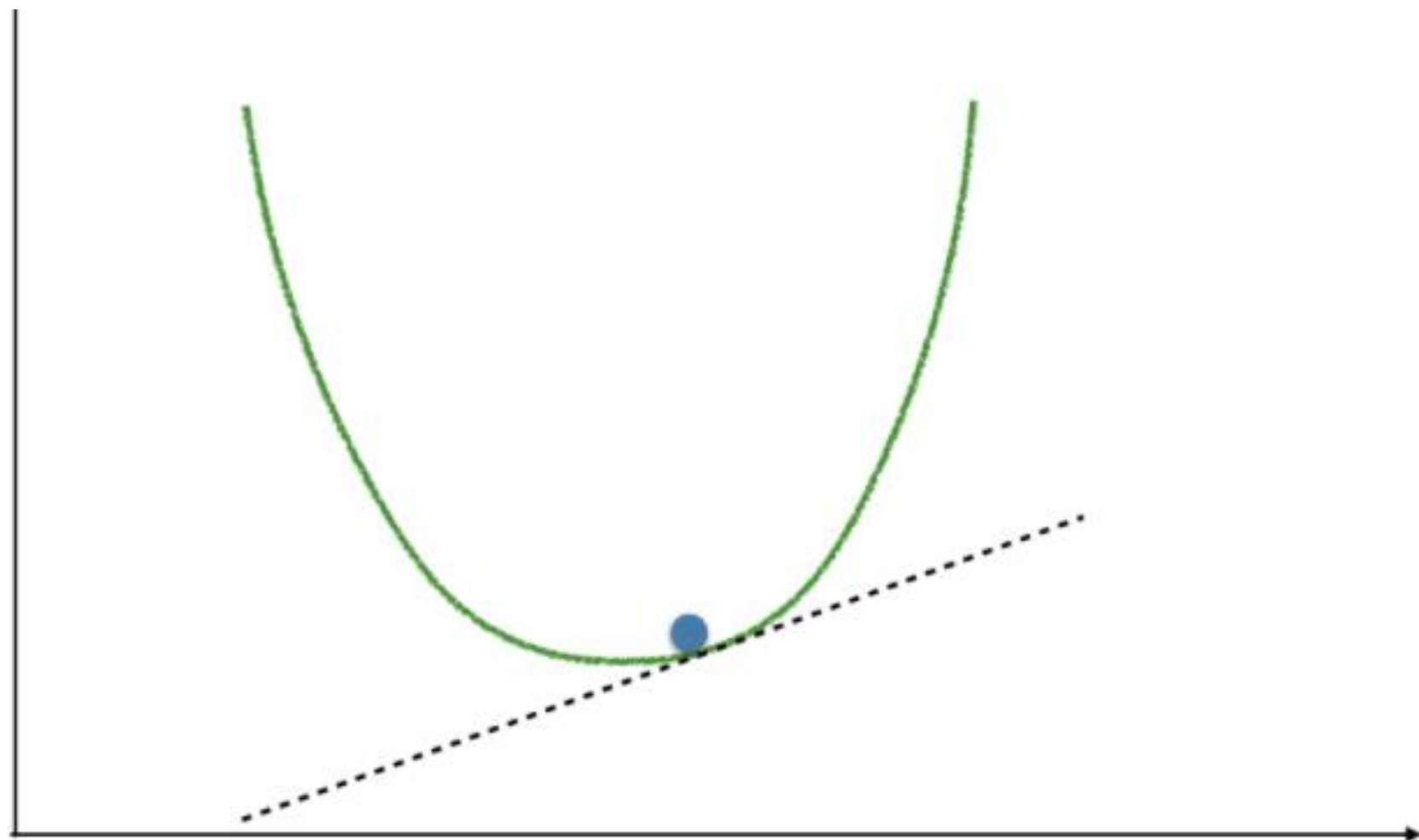


$$\rho(x, \alpha) = \frac{|2 - \alpha|}{\alpha} \left( \left( \frac{x^2}{|2 - \alpha|} + 1 \right)^{\frac{\alpha}{2}} - 1 \right)$$

Loss(w)



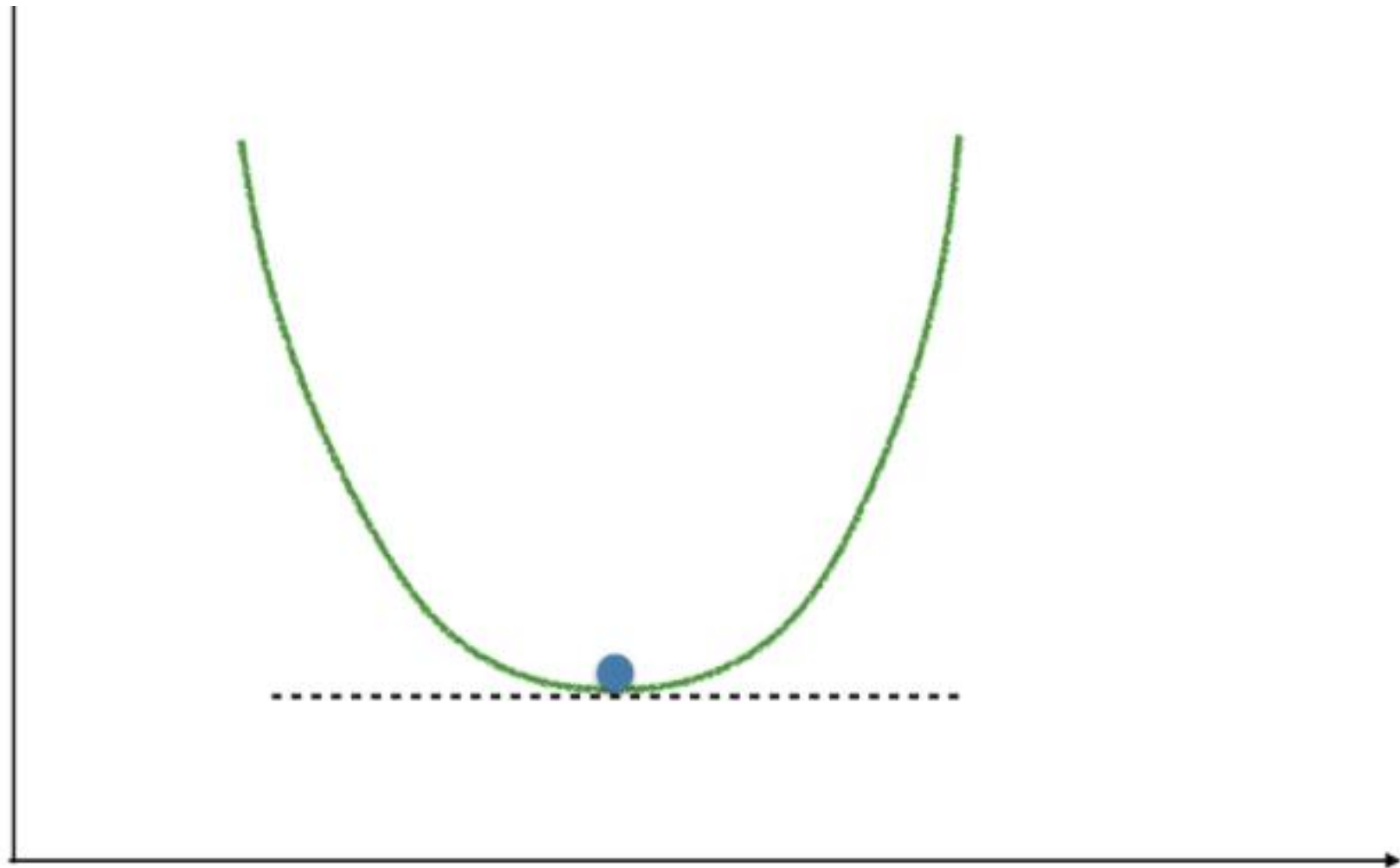
Loss(w)



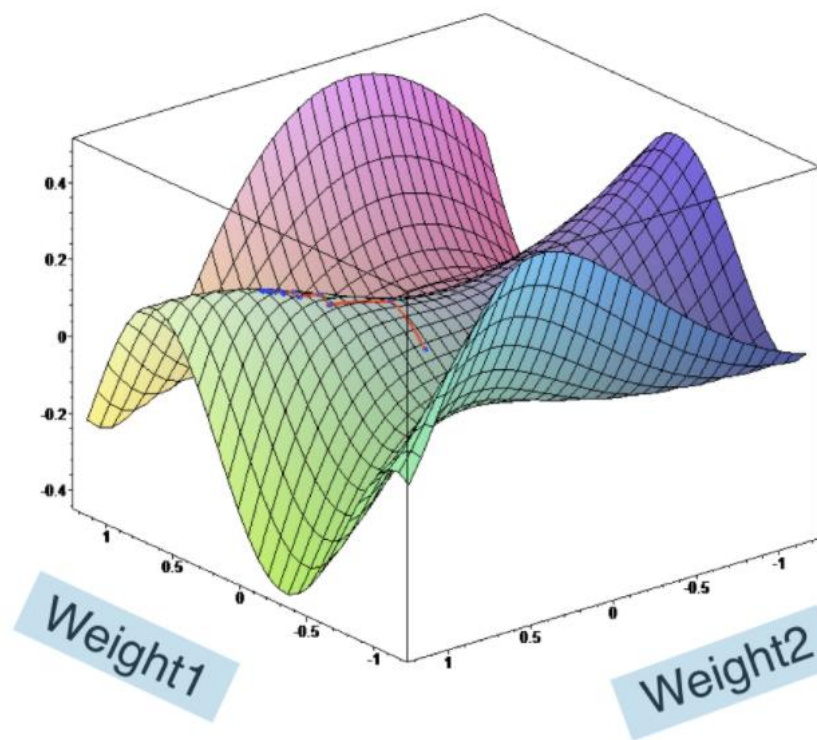
$w$



Loss( $w$ )



$w$



Loss function

shot_clock	dribbles	touch_time	shot_dis	close_def_ dis	shot_result
10.8	2	1.9	7.7	1.3	1
3.4	0	0.8	28.2	6.1	0
0	3	2.7	10.1	0.9	0
10.3	2	1.9	17.2	3.4	0

shot\_result

1

0

0

0



Outcome 0

Outcome 1

0

1

1

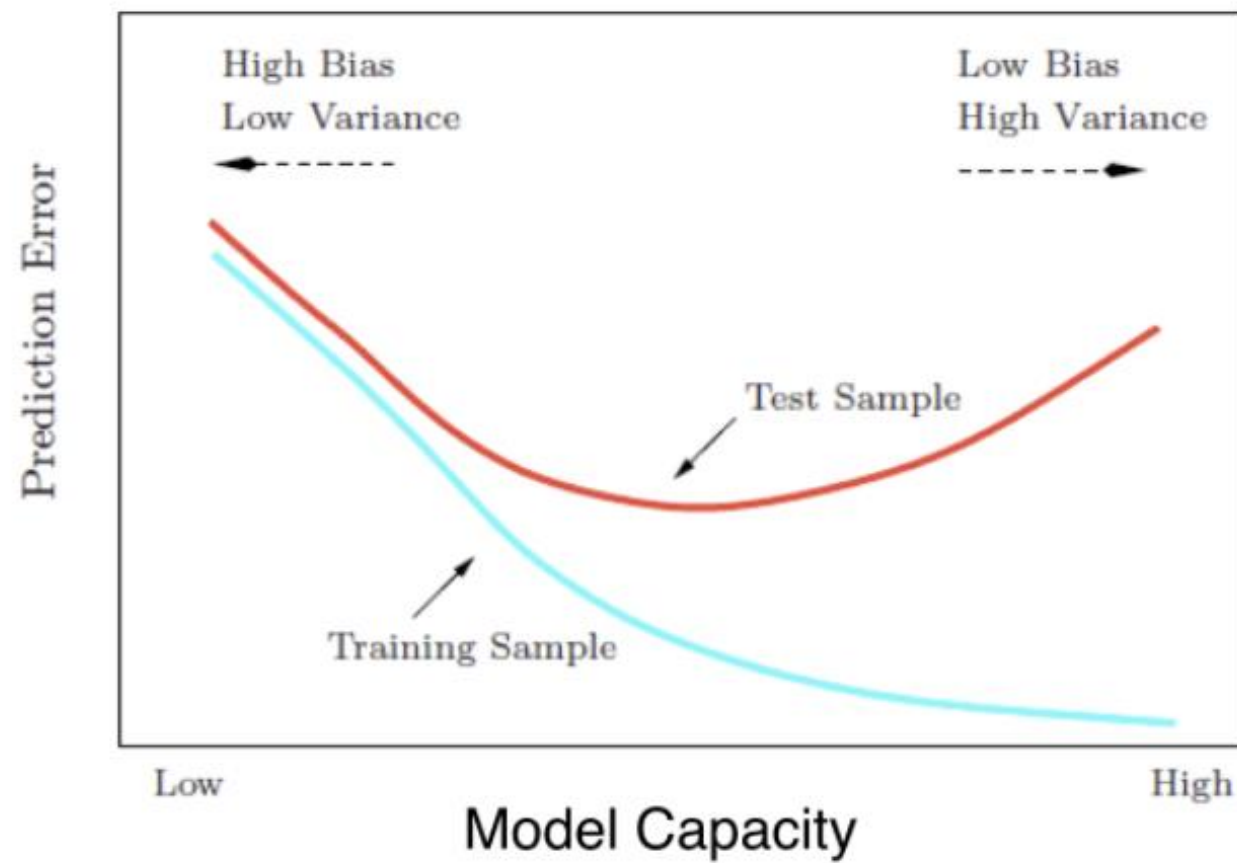
0

1

0

1

0



Hidden Layers	Nodes Per Layer	Mean Squared Error	Next Step
1	100	5.4	Increase Capacity
1	250	4.8	Increase Capacity
2	250	4.4	Increase Capacity
3	250	4.5	Decrease Capacity
3	200	4.3	Done