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Faculty of Media

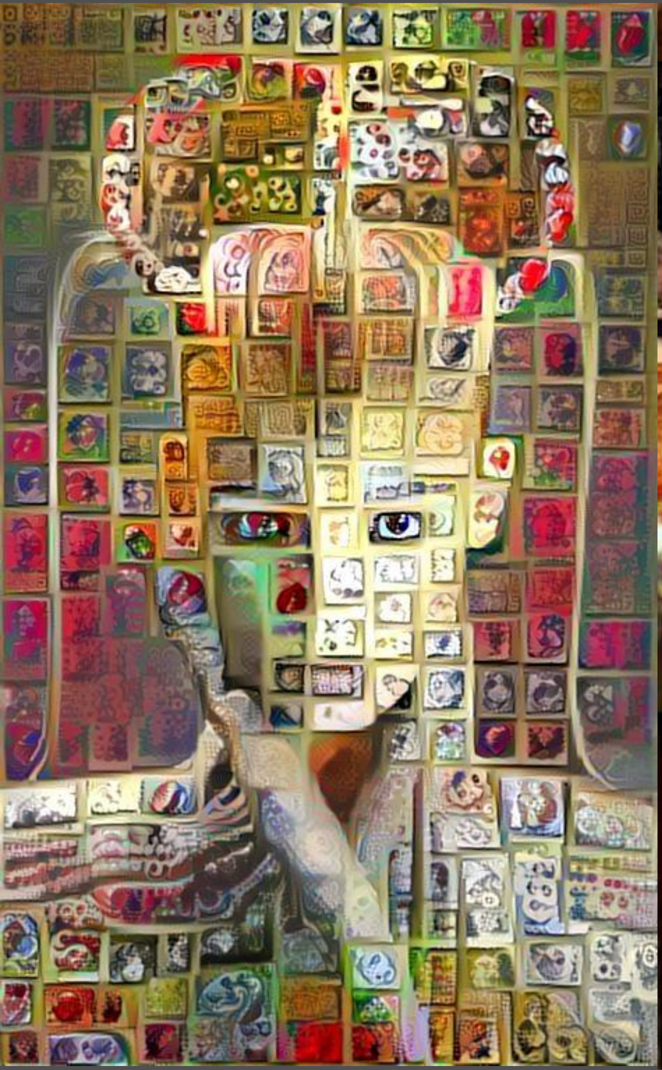
MIREVI

NeuralNets 1

with Neural Nets

MODALG SoSe18

News & Motivation



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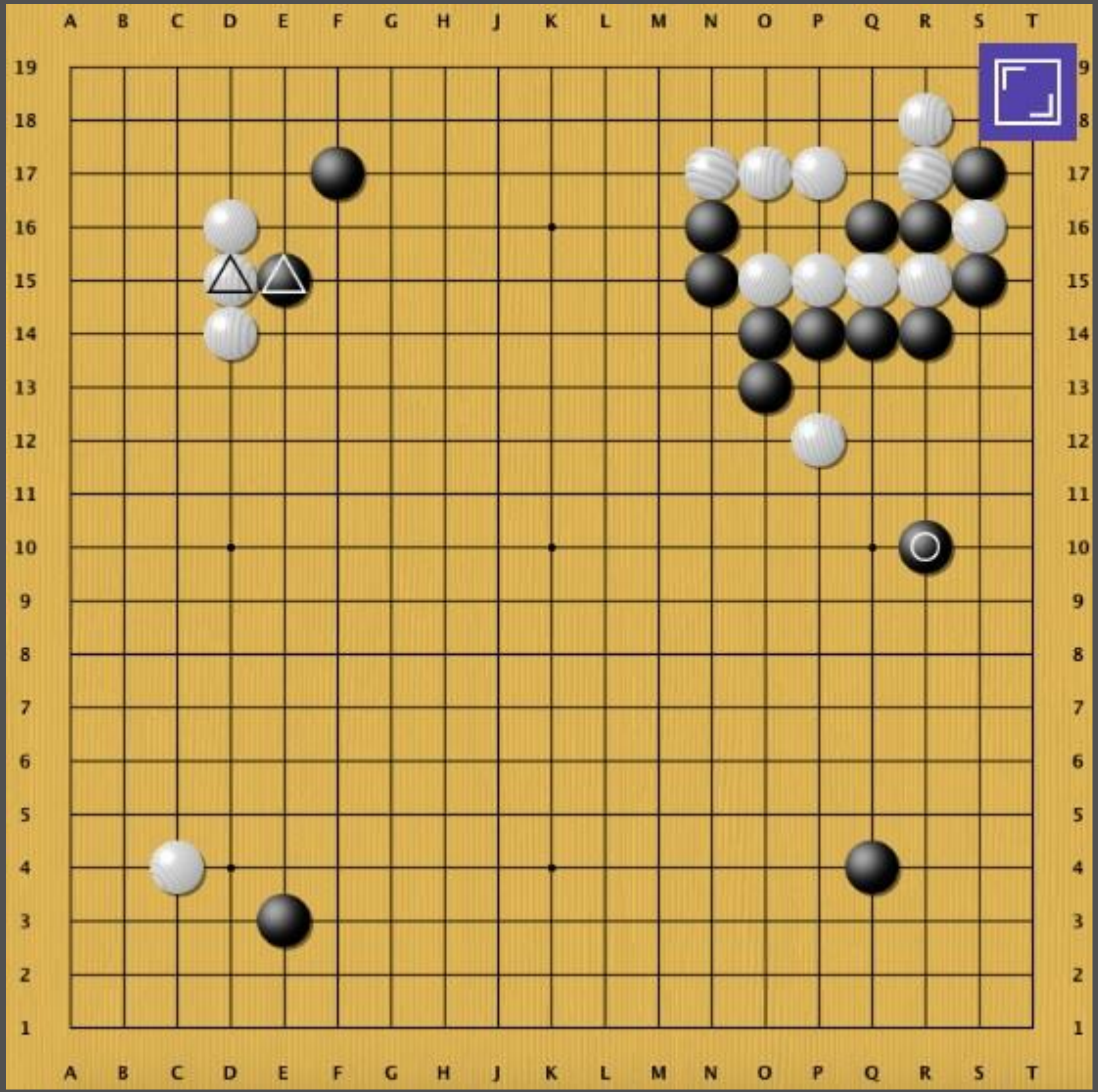


Click-o-Tron
The Future Of Women's Hair: What's The Secret?
Posted 10/10/15 06:50:00
Nobme Borroston
Staff writer


CSU

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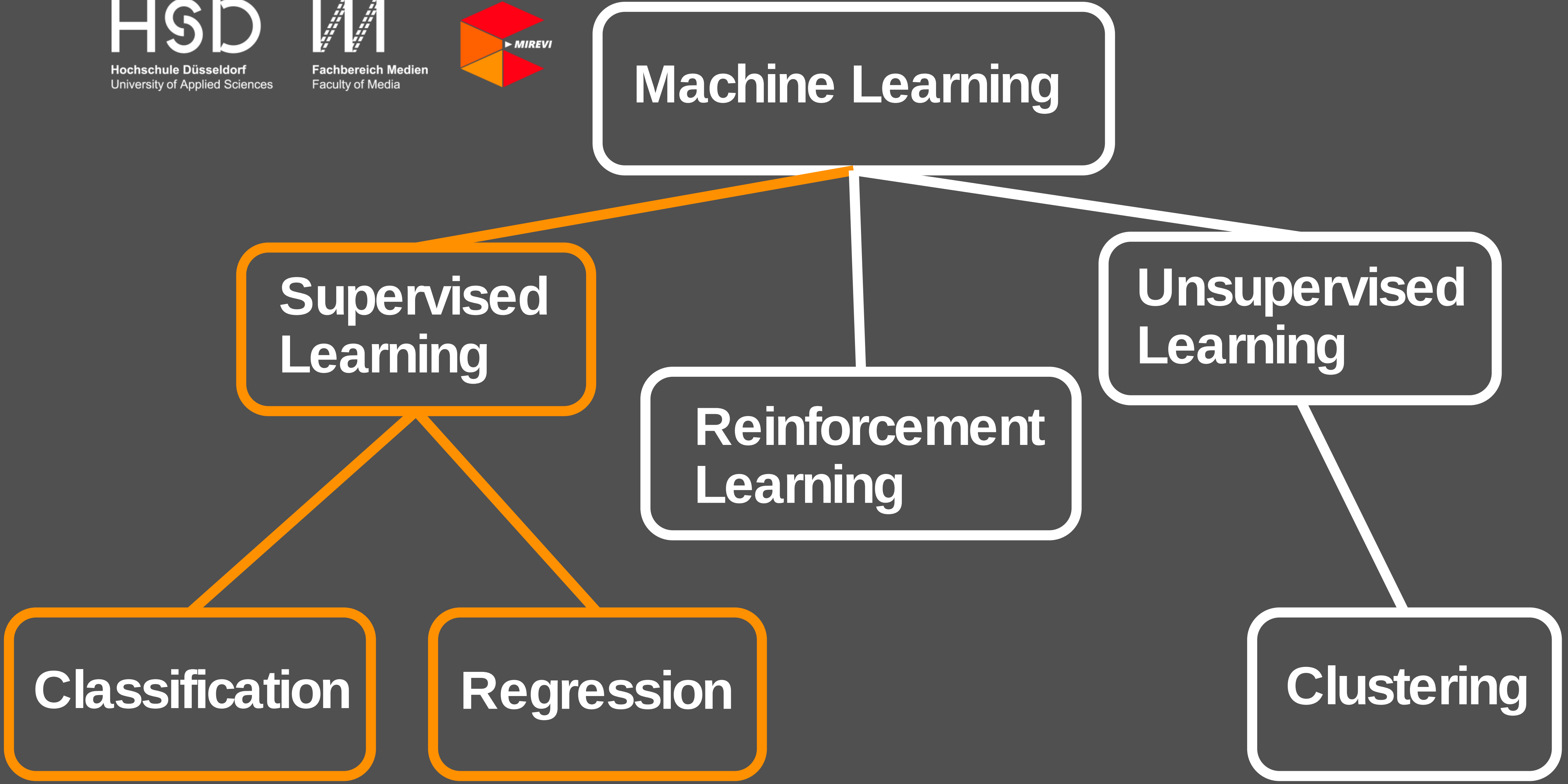
Robot teaches itself how to dress people

Topics:

- Repetition Classification & Regression
- Learning Rate
- Perceptron & Training
- Multilayer Perceptron


Machine Learning
Supervised Learning
Reinforcement Learning
Unsupervised Learning
Classification
Regression
Clustering

Supervised Learning

Classification

Discrete: $y \in N$

Regression

Continous: $y \in R$

Data

#Rooms/1	Area/m²	Price/$
4	70	1.000
3	65	800
2	40	400
…	…	…

Data

Feature 1

#Rooms/1	Area/m²	Price/$
4	70	1.000
3	65	800
2	40	400
…	…	…

Data

Feature 2

#Rooms/1	Area/m²	Price/$
4	70	1.000
3	65	800
2	40	400
…	…	…

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Data

Feature 3

#Rooms/1	Area/m²	Price/$
4	70	1.000
3	65	800
2	40	400
…	…	…

Data

Example 1

#Rooms/1	Area/m²	Price/$
4	70	1.000
3	65	800
2	40	400
…	…	…

Data

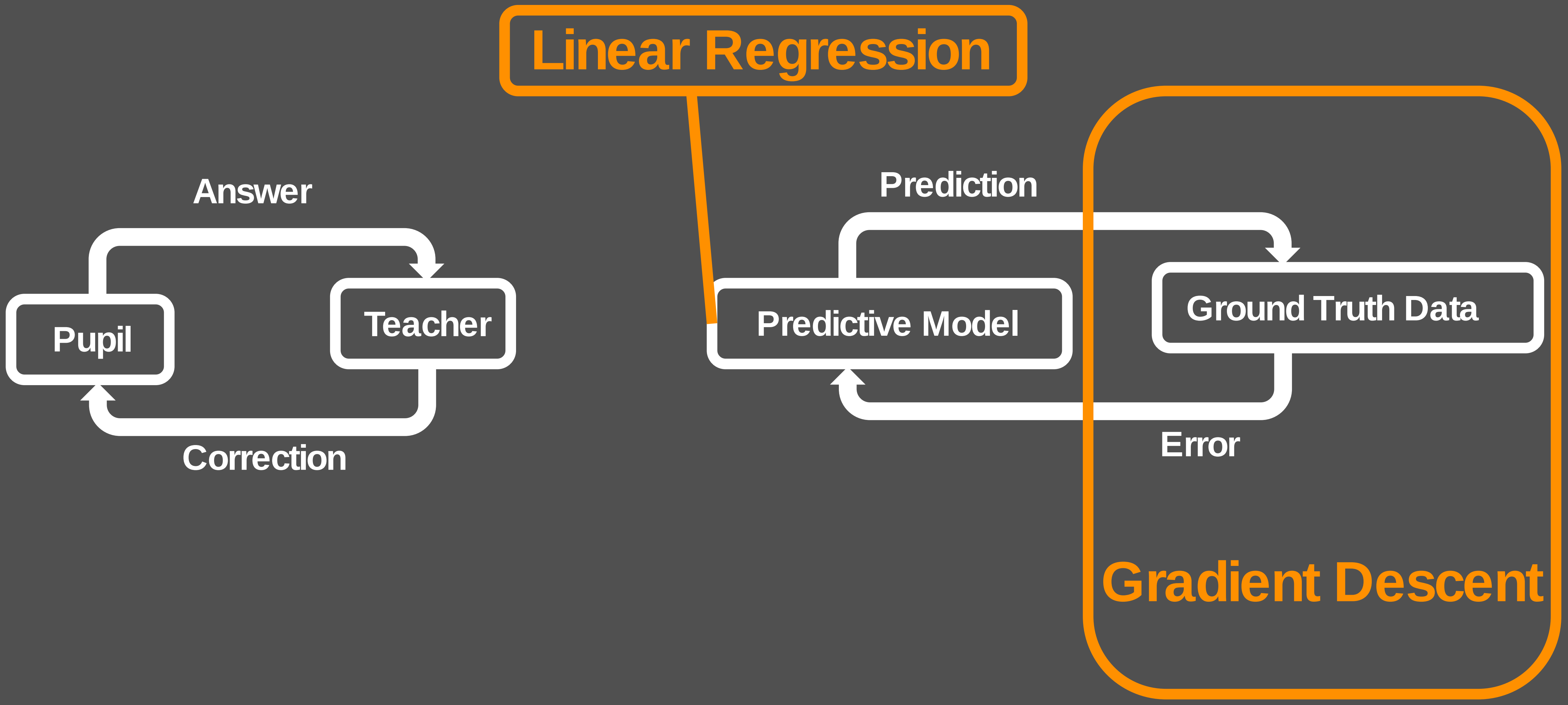
Example 2

#Rooms/1	Area/m²	Price/$
4	70	1.000
3	65	800
2	40	400
…	…	…

Data

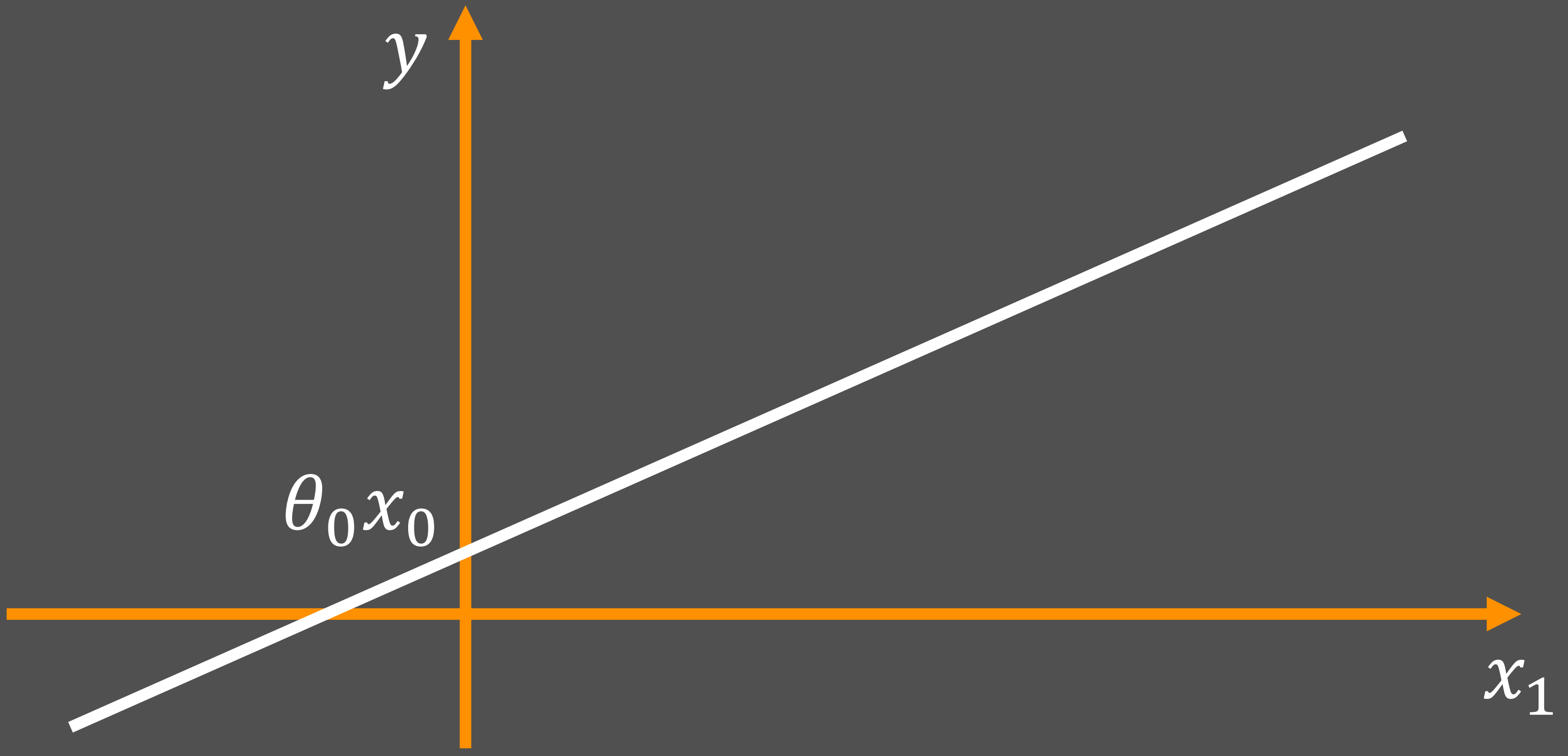
Example 3

#Rooms/1	Area/m²	Price/$
4	70	1.000
3	65	800
2	40	400
…	…	…

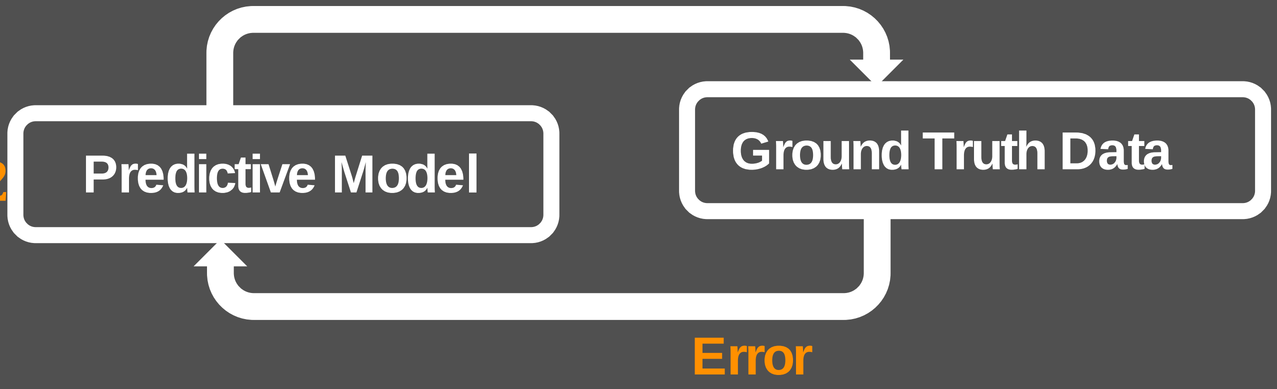

Linear Regression
Answer
Pupil
Teacher
Correction
Prediction
Predictive Model
Ground Truth Data
Error
Gradient Descent

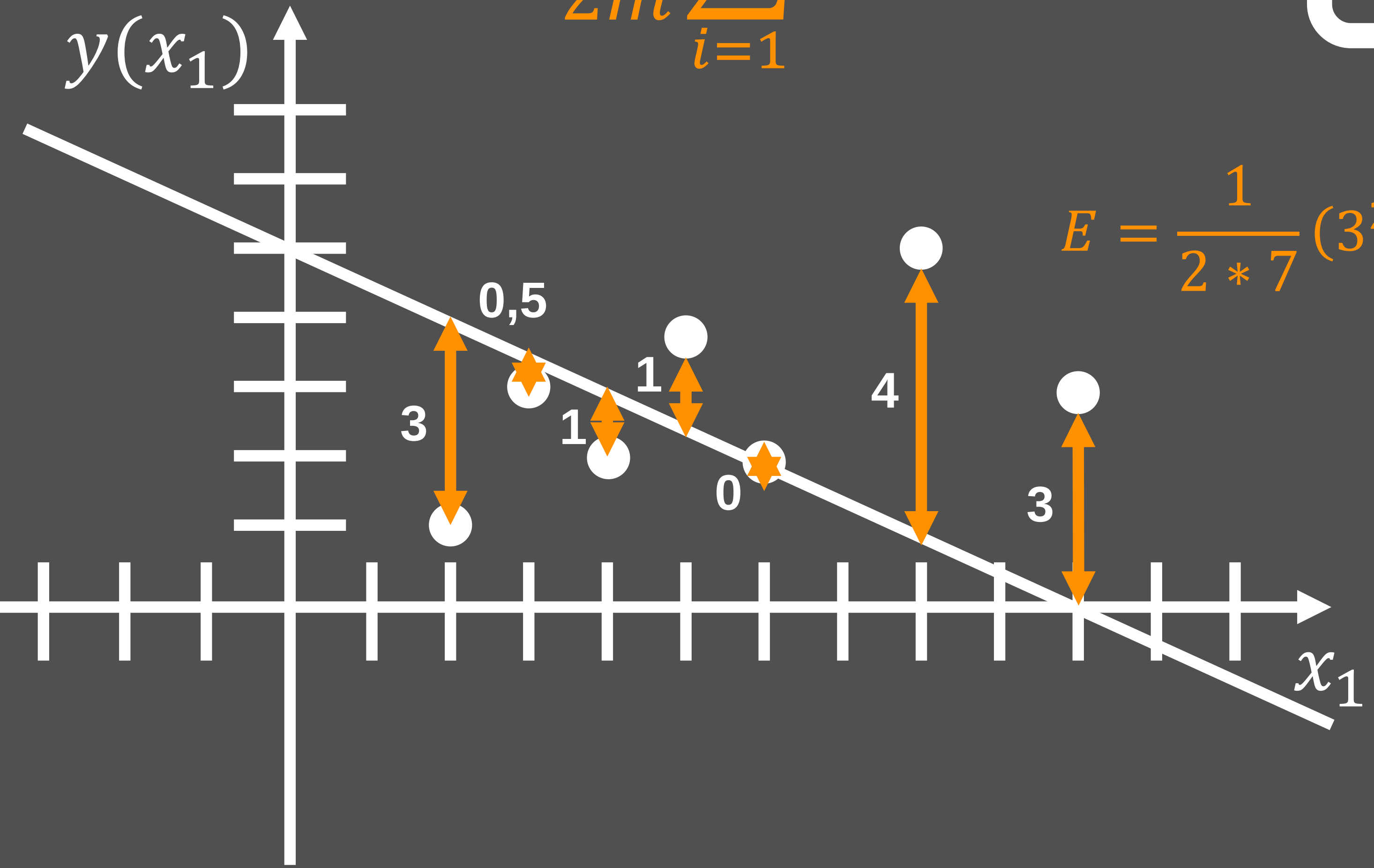
Slope of the line depends on weights θ_0, θ_1

$$\hat{y} = \theta_1 x_1 + \theta_0 x_0$$



$$E = \frac{1}{2m}\sum_{i=1}^{m}(\hat{y}_i - y_i)^2$$



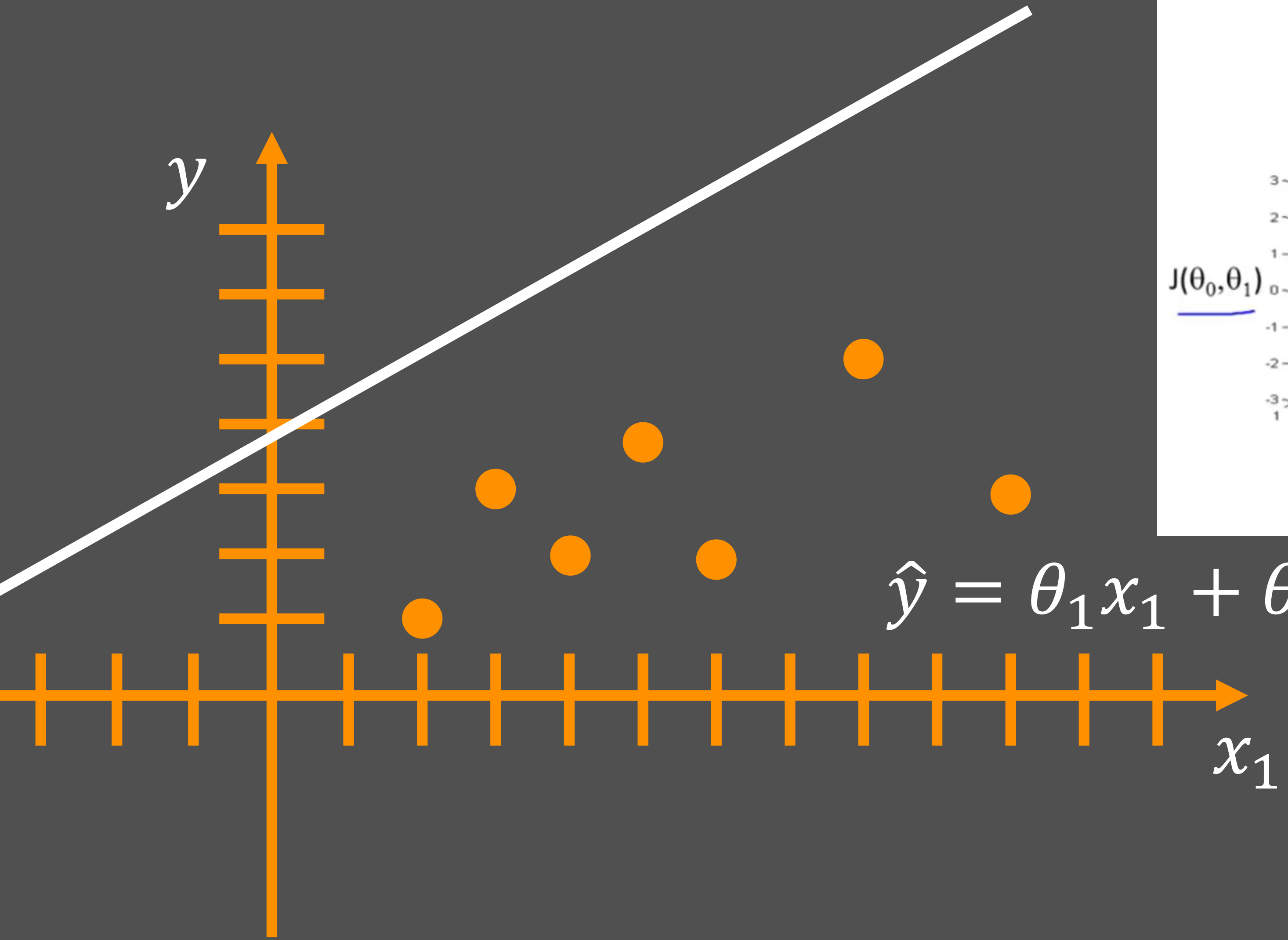


$$E = \frac{1}{2*7}(3^2 + 0{,}5^2 + 1^2 + 1^2 + 0^2 + 4^2 + 3^2)$$

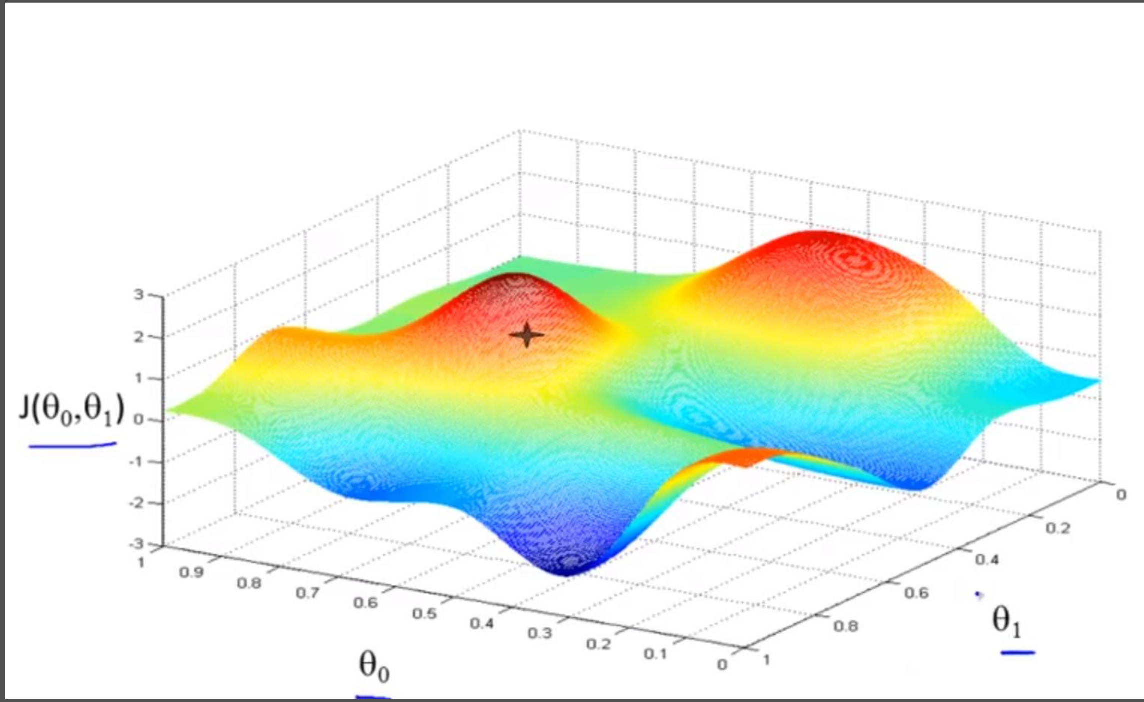
$$E = 2.859$$

$$m = 7$$

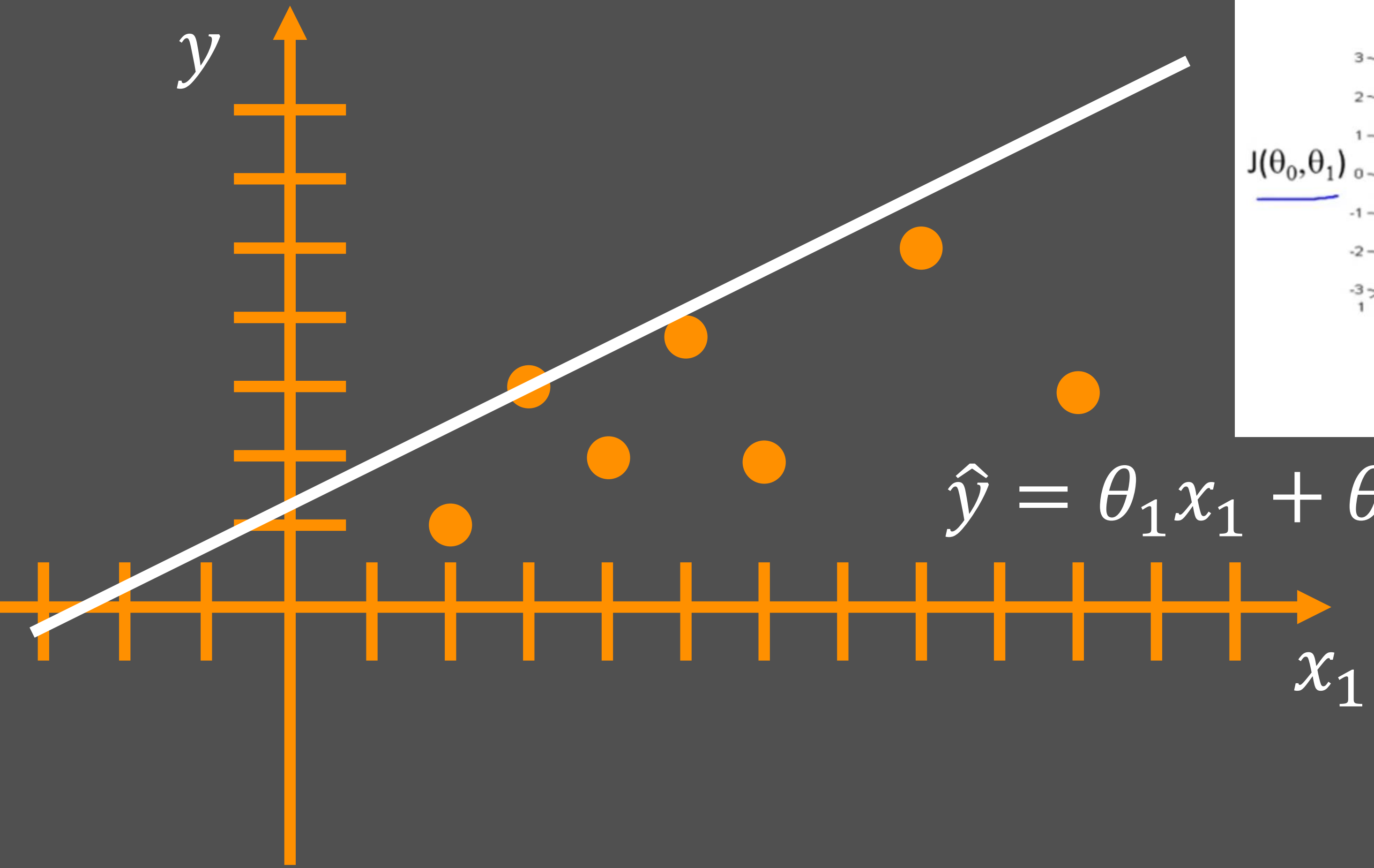
Gradient Descent



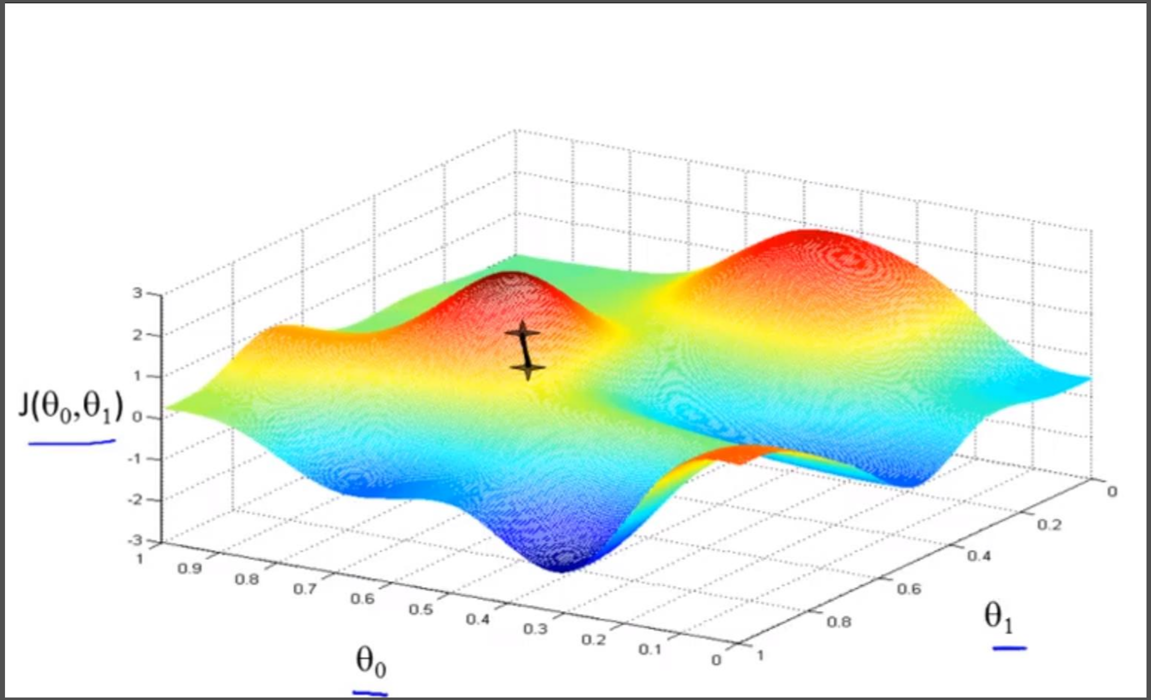
$$\hat{y} = \theta_1 x_1 + \theta_0 x_0$$



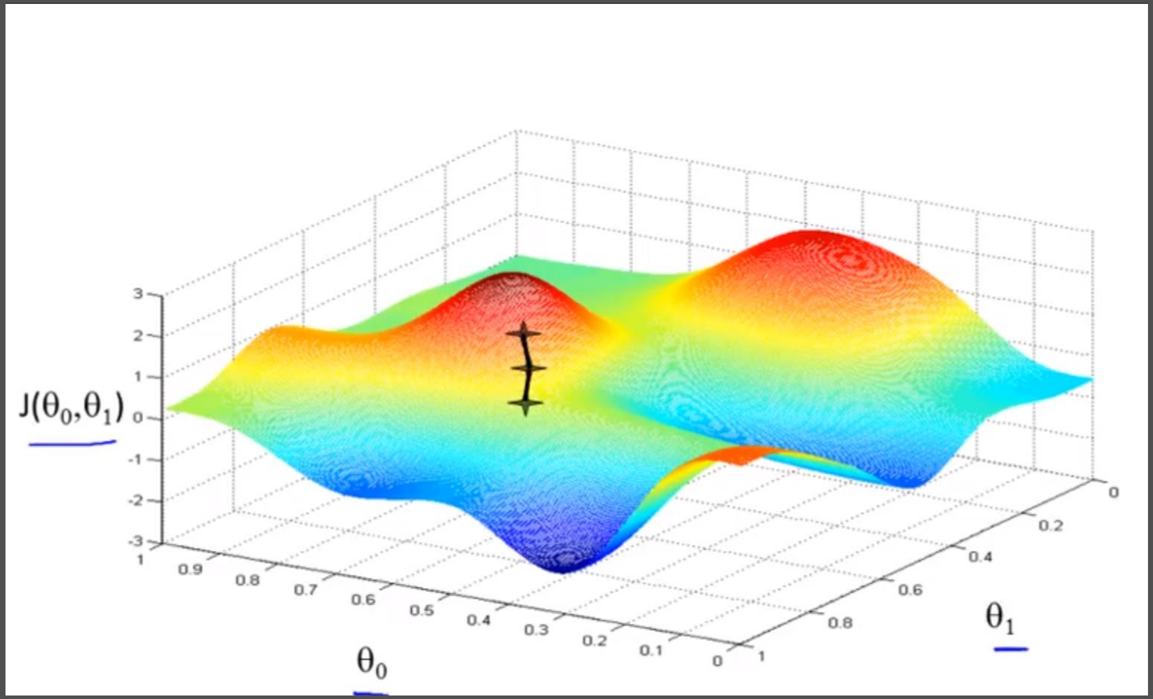
Gradient Descent

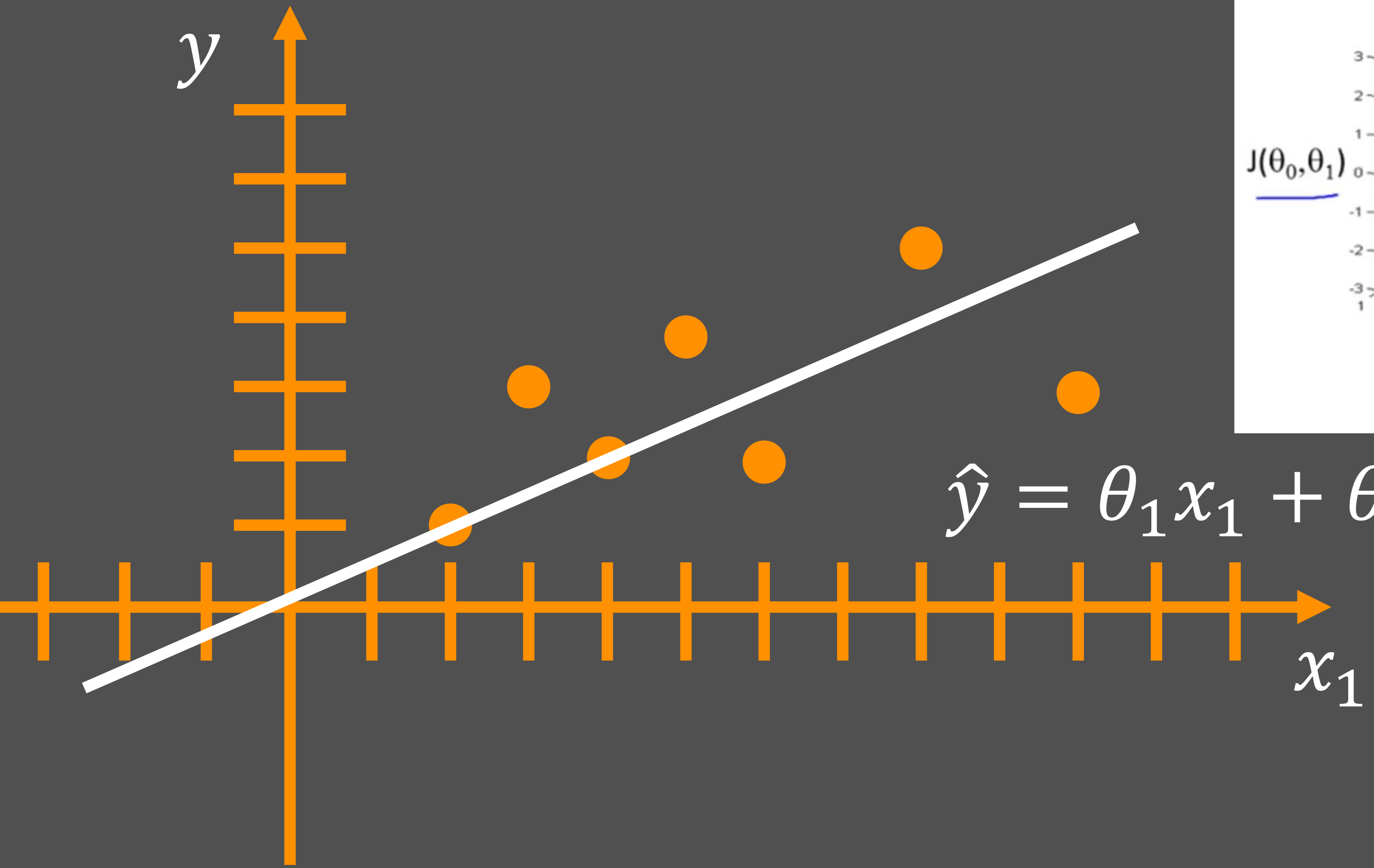


$$\hat{y} = \theta_1 x_1 + \theta_0 x_0$$



Gradient Descent





$$\hat{y} = \theta_1 x_1 + \theta_0 x_0$$

Learning Rate

Start with random θ_0, θ_1

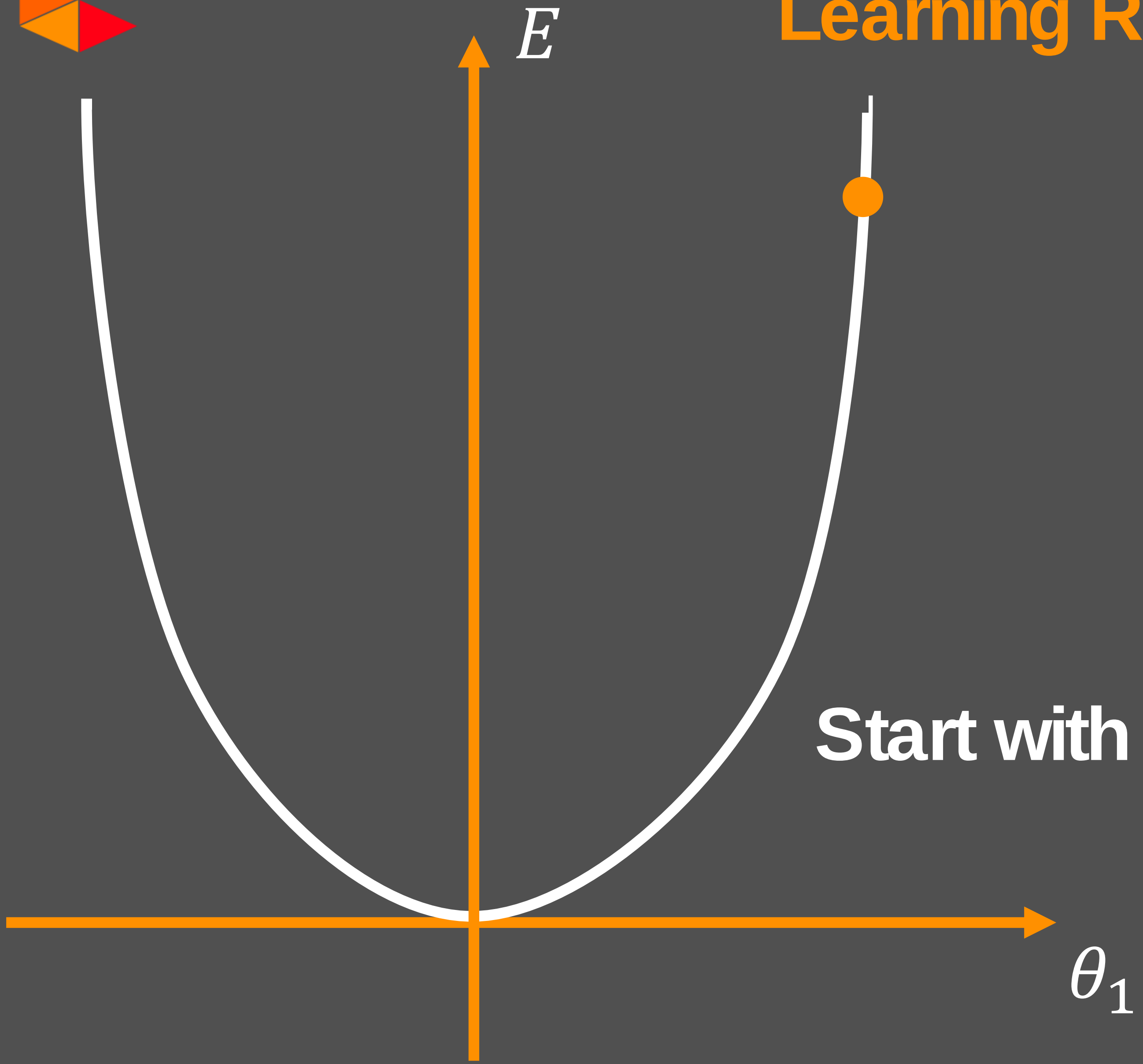
repeat until convergence{

$$\theta_0 := \theta_0 - \alpha * \frac{\partial E(\theta_0, \theta_1)}{\partial \theta_0}$$

$$\theta_1 := \theta_1 - \alpha * \frac{\partial E(\theta_0, \theta_1)}{\partial \theta_1}$$

}

Learning Rate $\alpha = 1$



Start with random θ_1

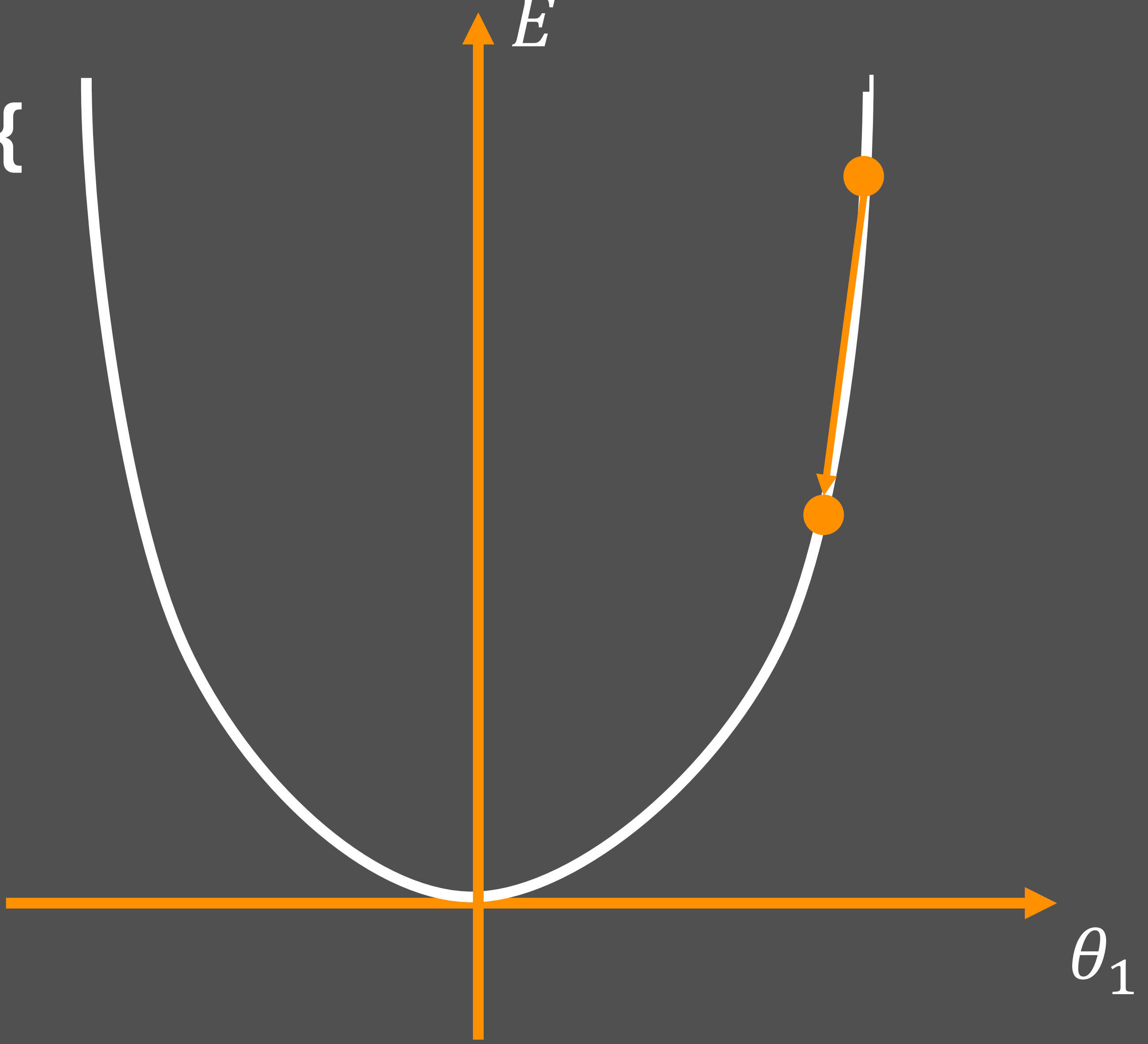
repeat until convergence{

$$\theta_1 := \theta_1 - \alpha * \frac{\partial E(\theta_1)}{\partial \theta_1}$$

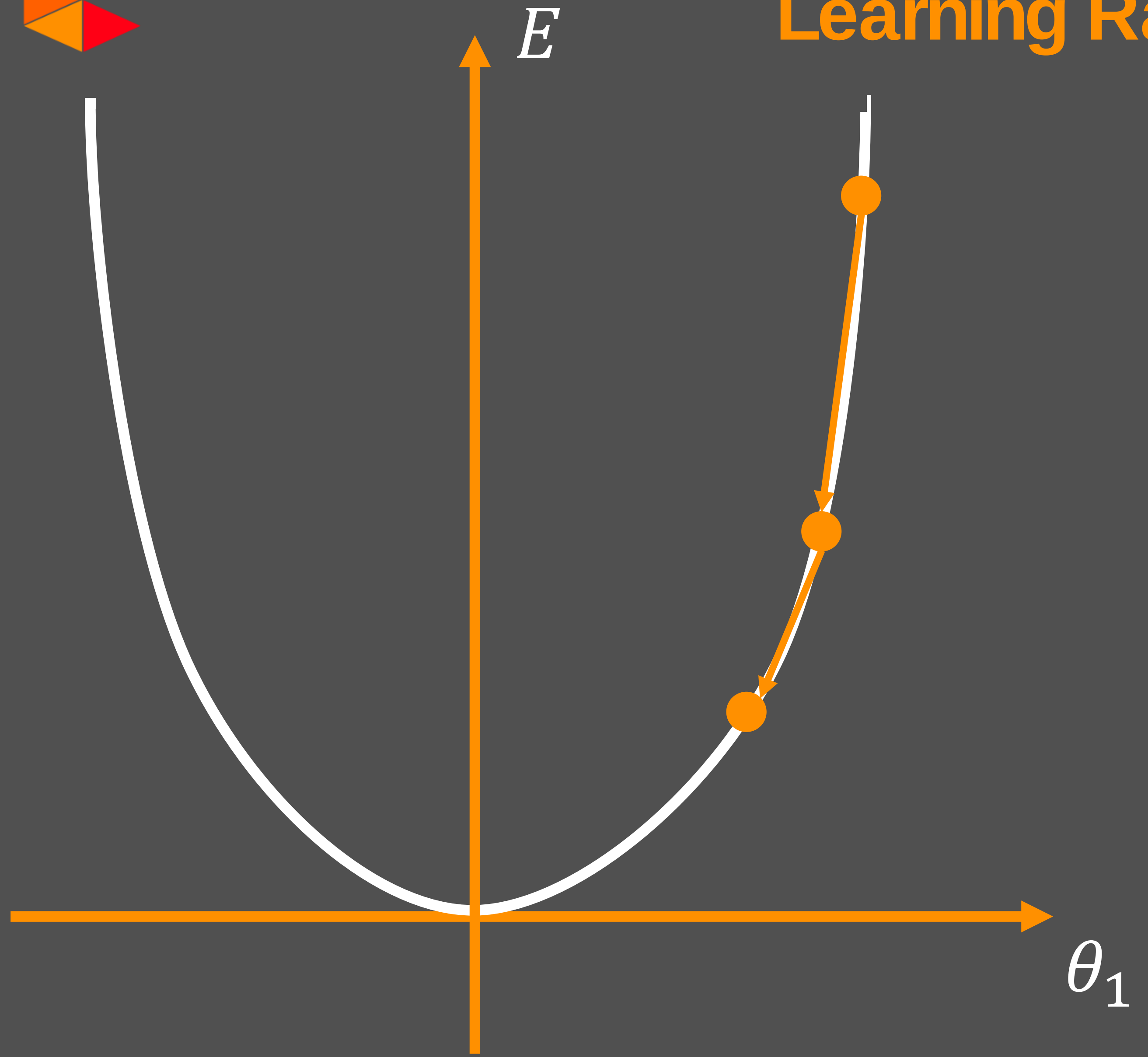
}

α: **Learning Rate**

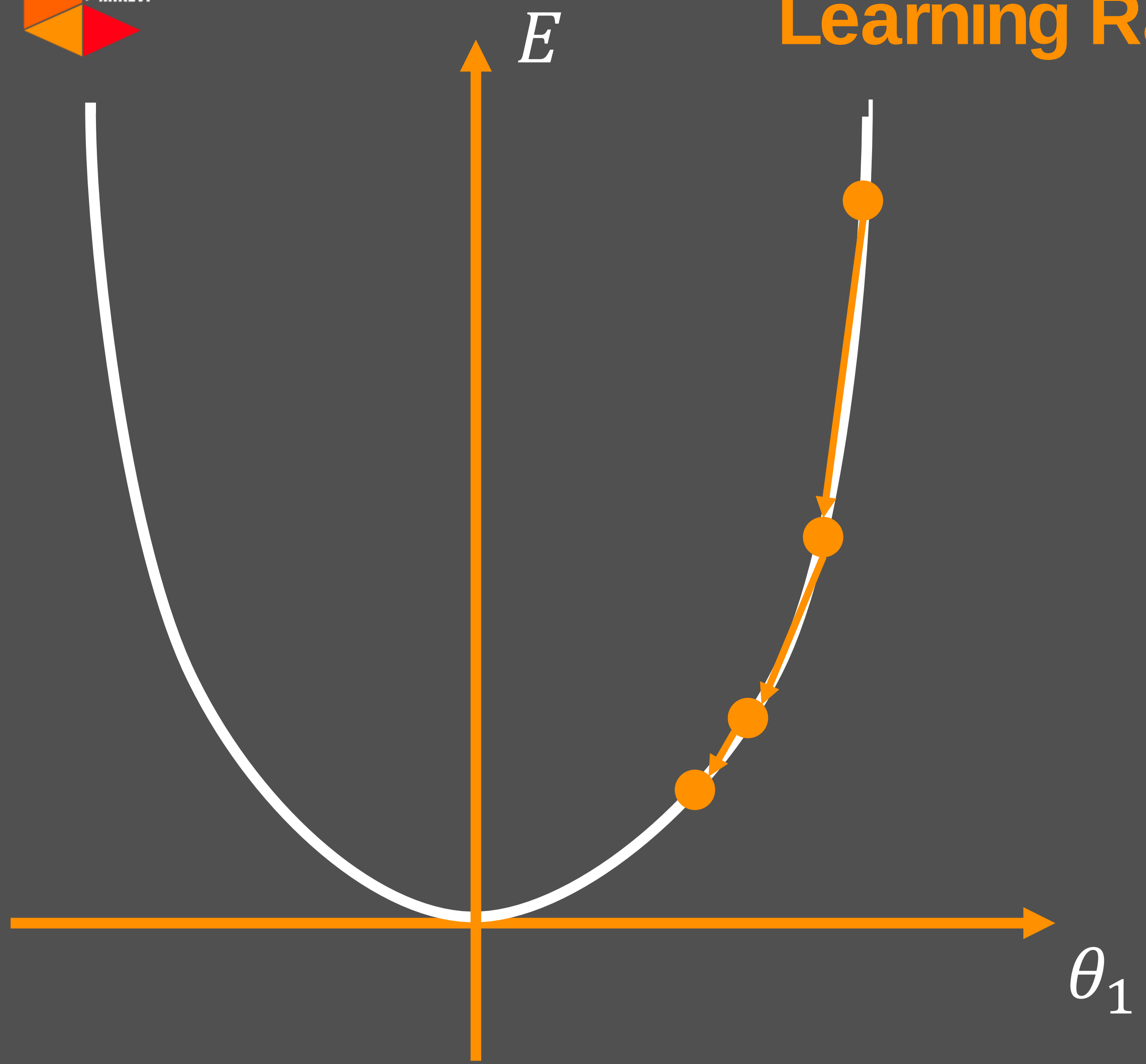
$$\alpha = 1$$



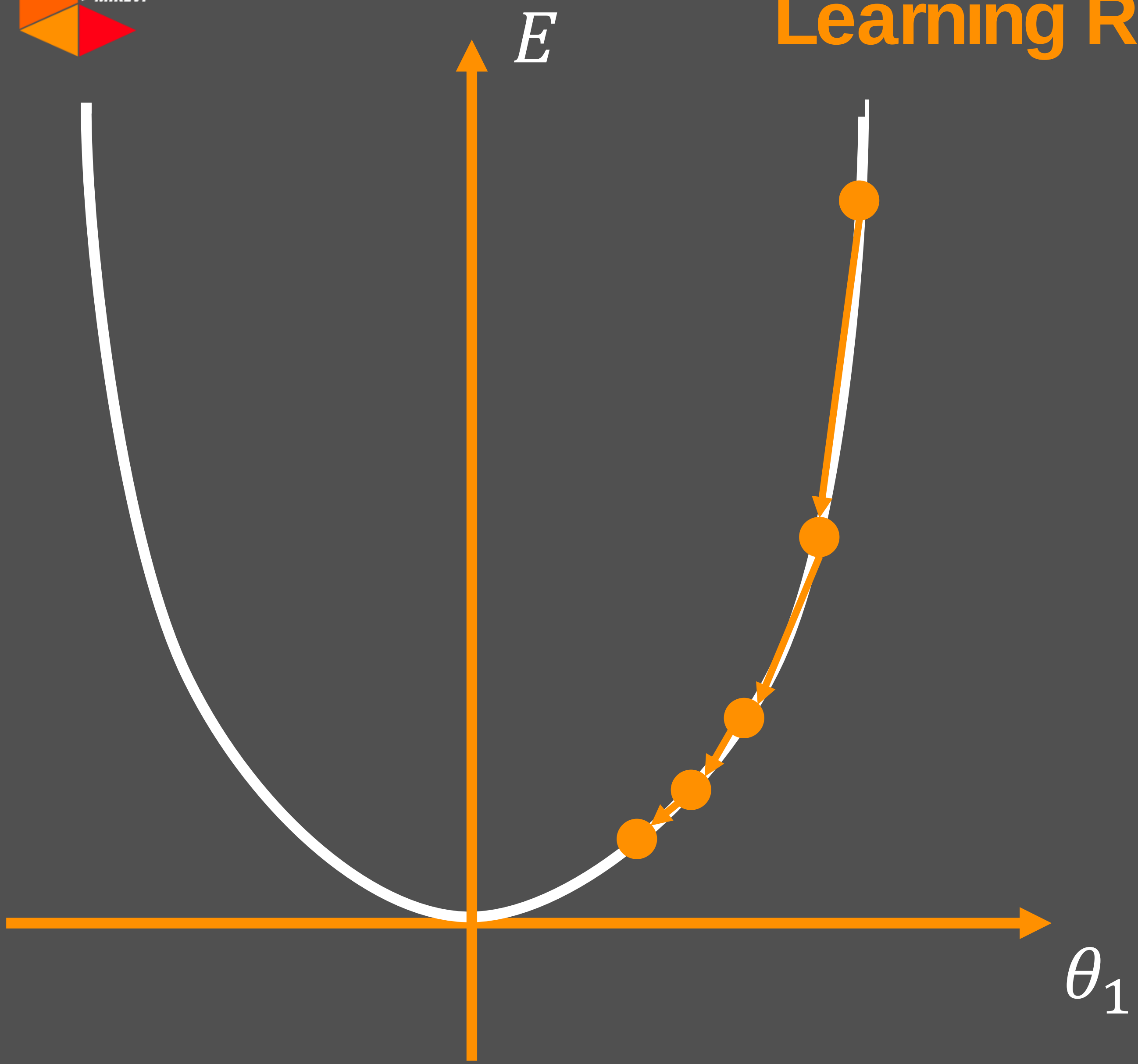
Learning Rate $\alpha = 1$



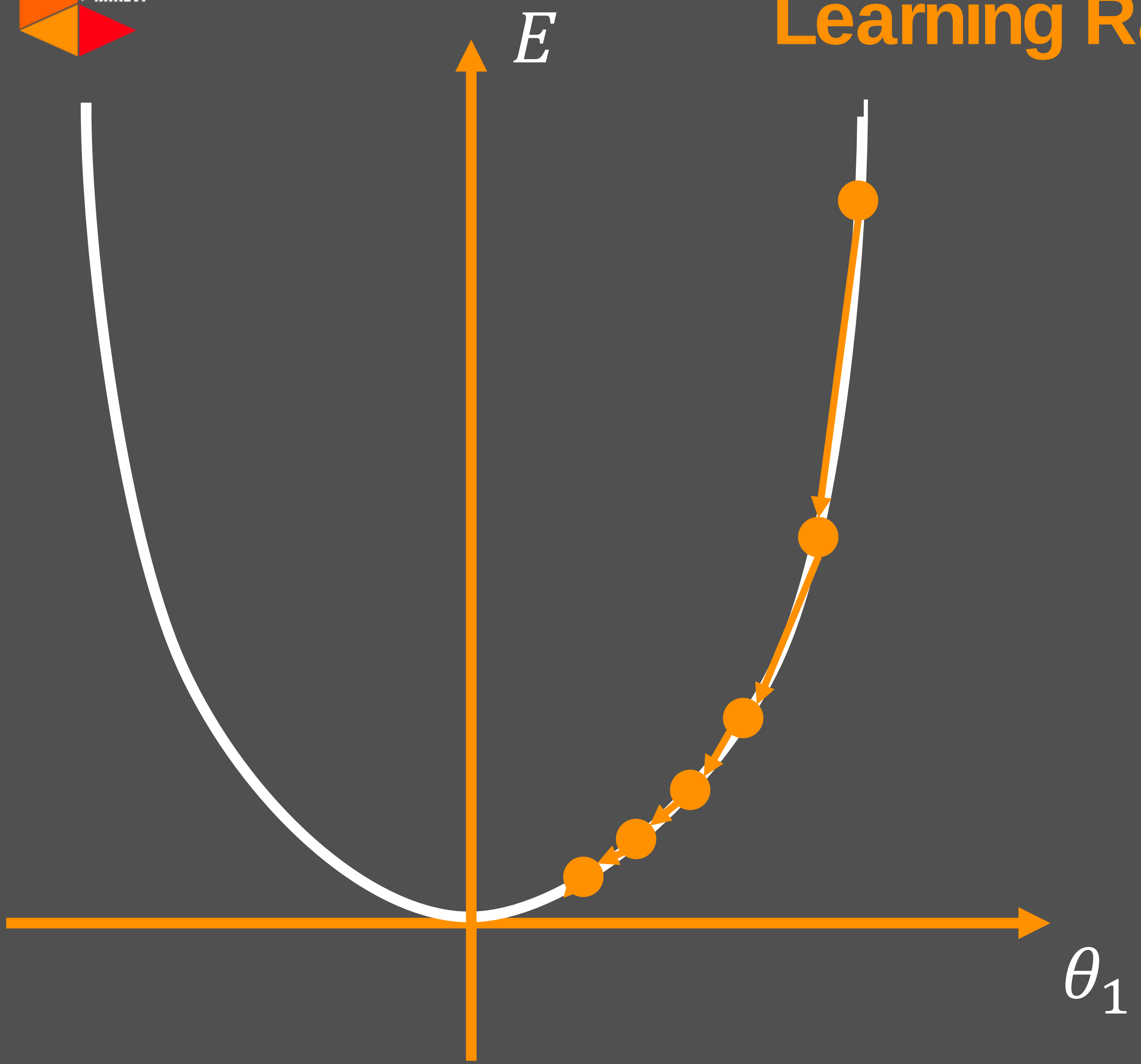
Learning Rate $\alpha = 1$



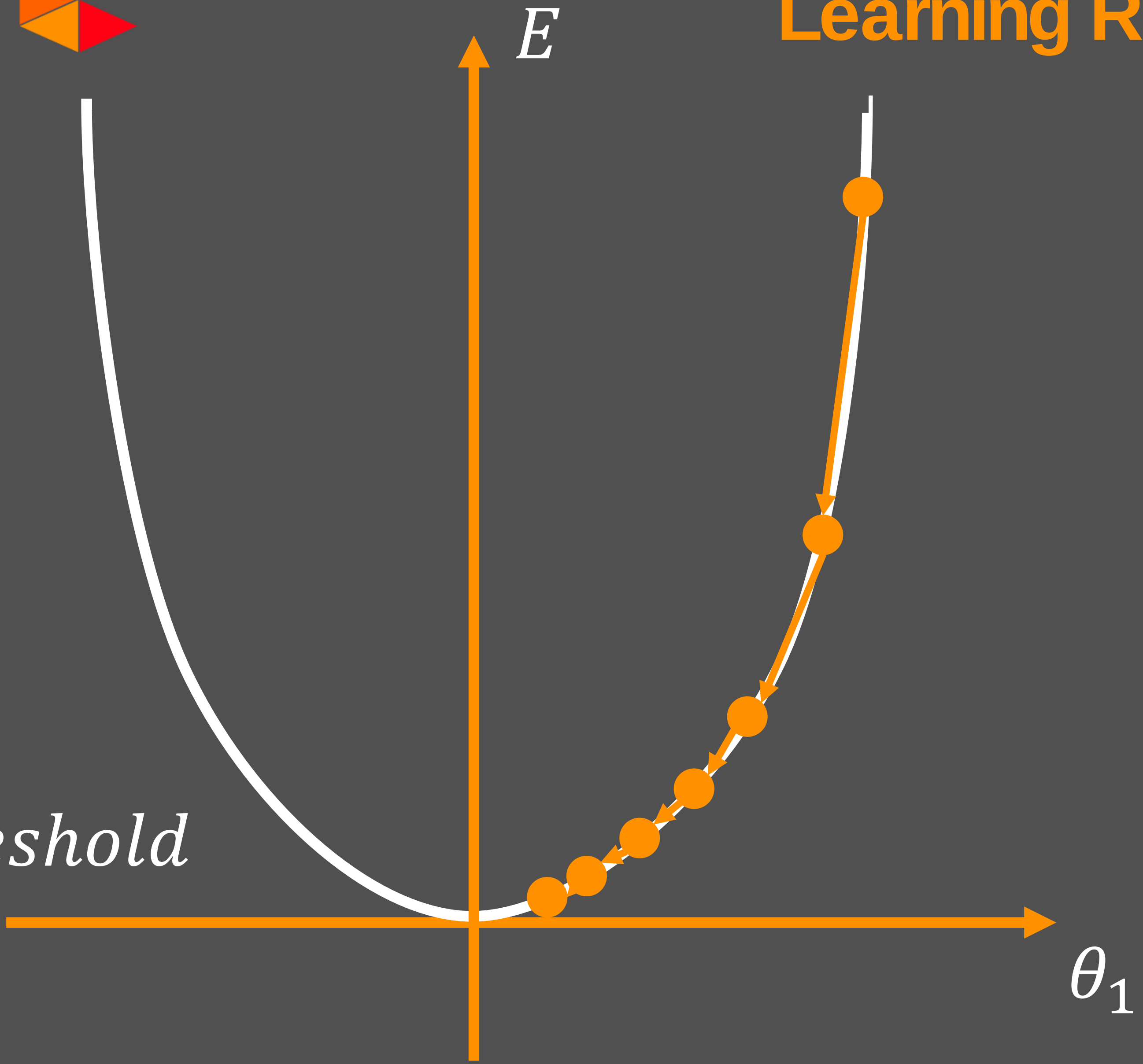
Learning Rate $\alpha = 1$



Learning Rate $\alpha = 1$



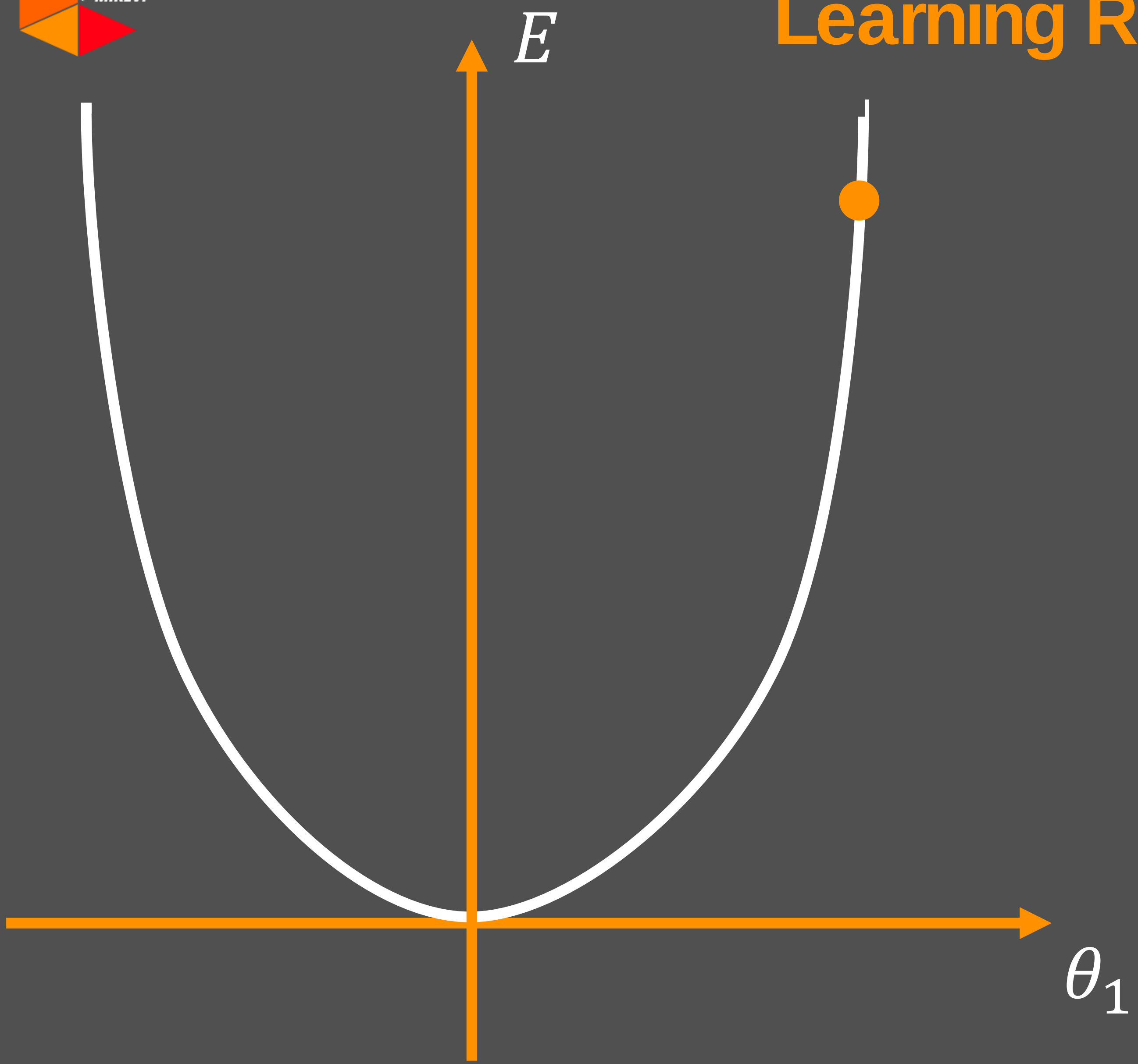
Learning Rate $\alpha = 1$



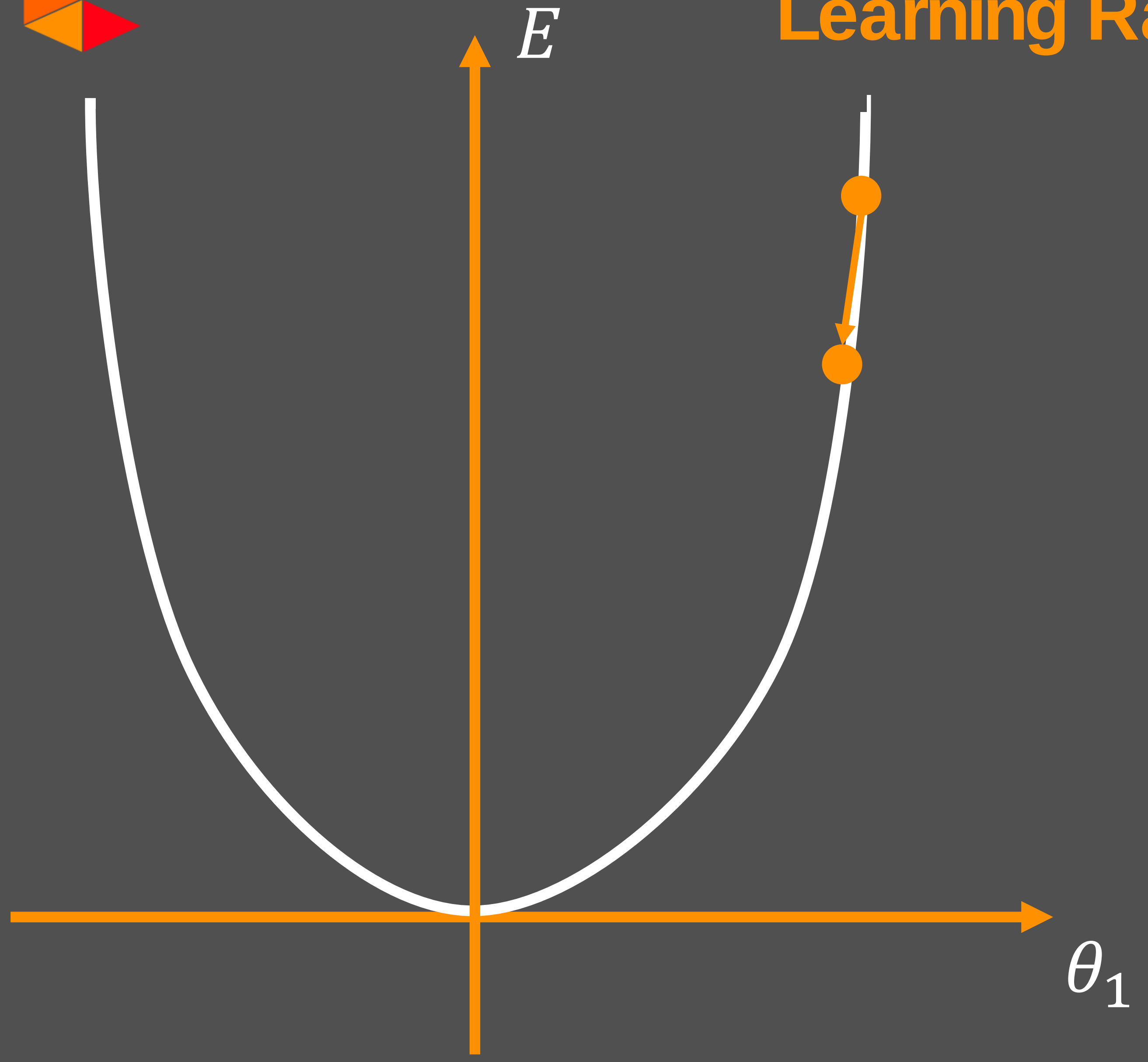
$e.g.: E < threshold$

$$\alpha = 0.5$$

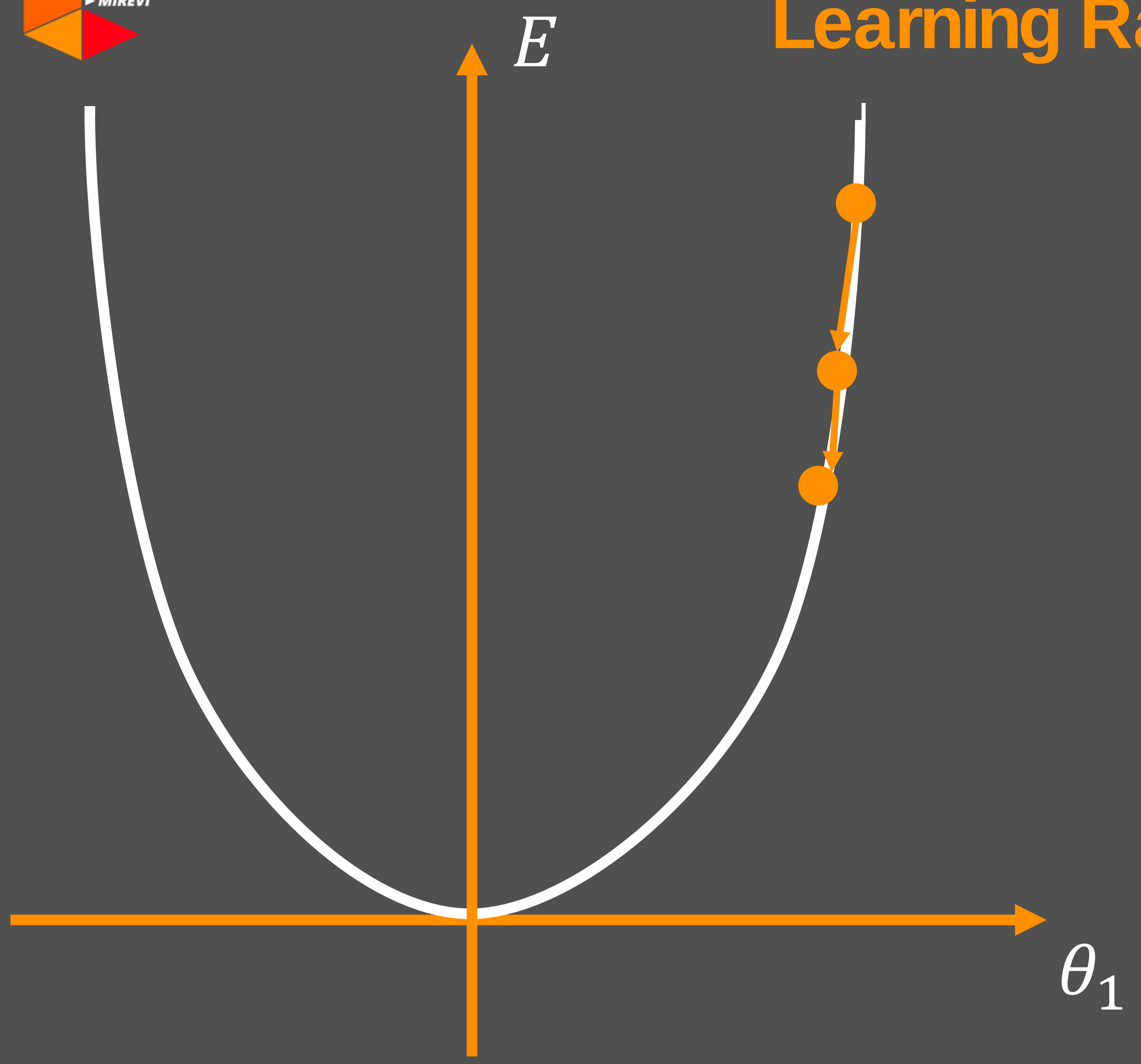
Learning Rate $\alpha = 0.5$



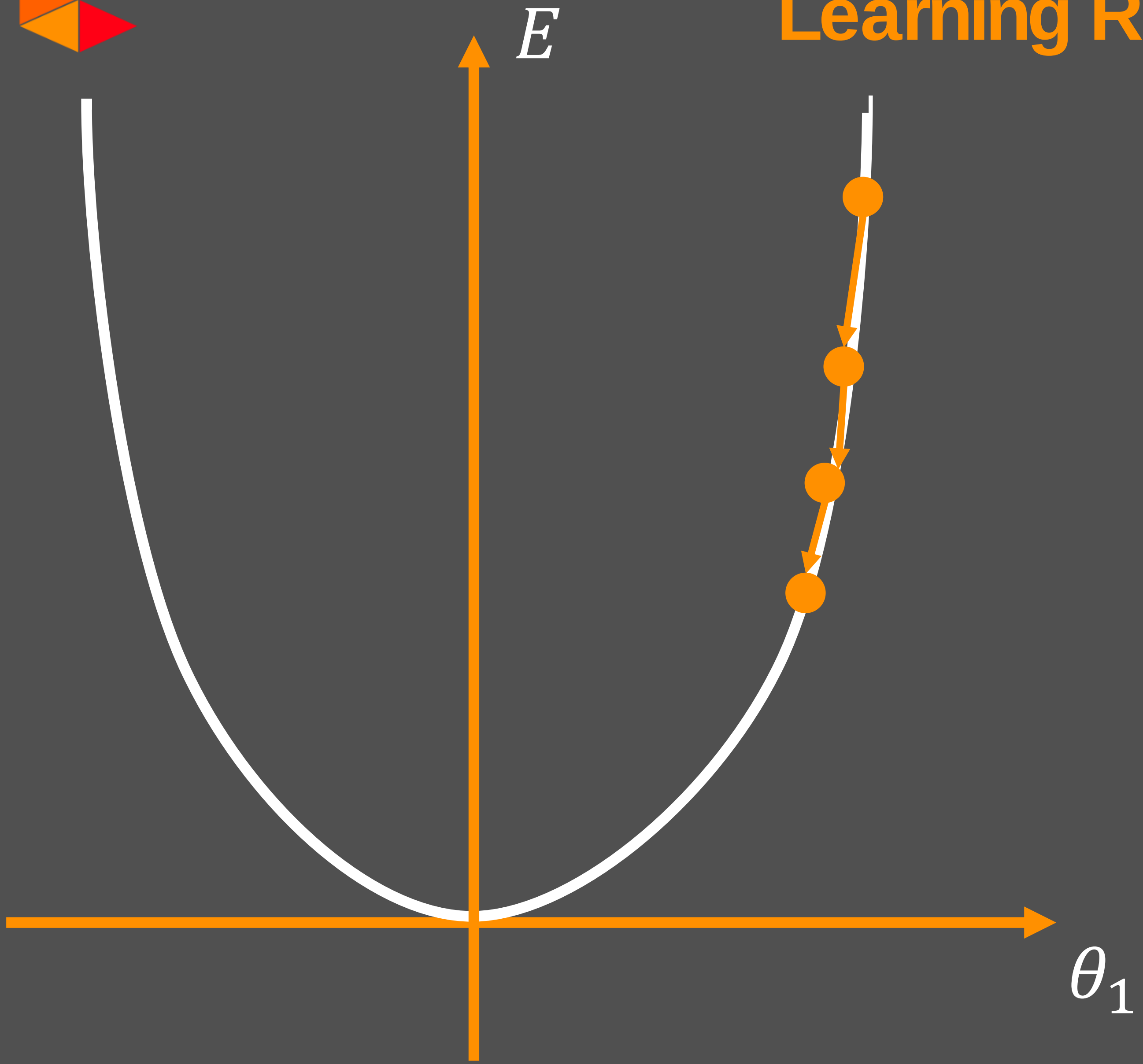
Learning Rate $\alpha = 0.5$



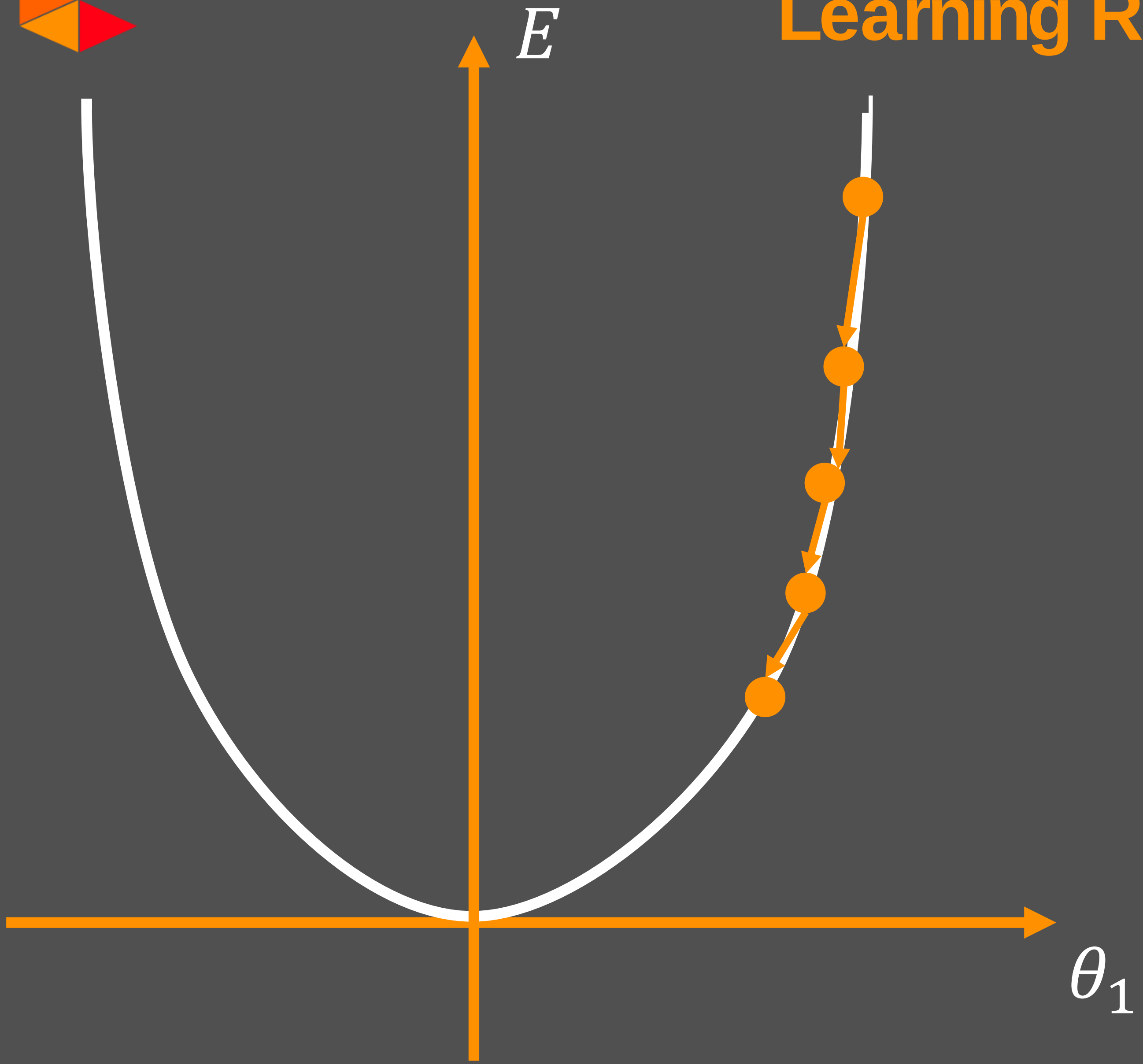
Learning Rate $\alpha = 0.5$



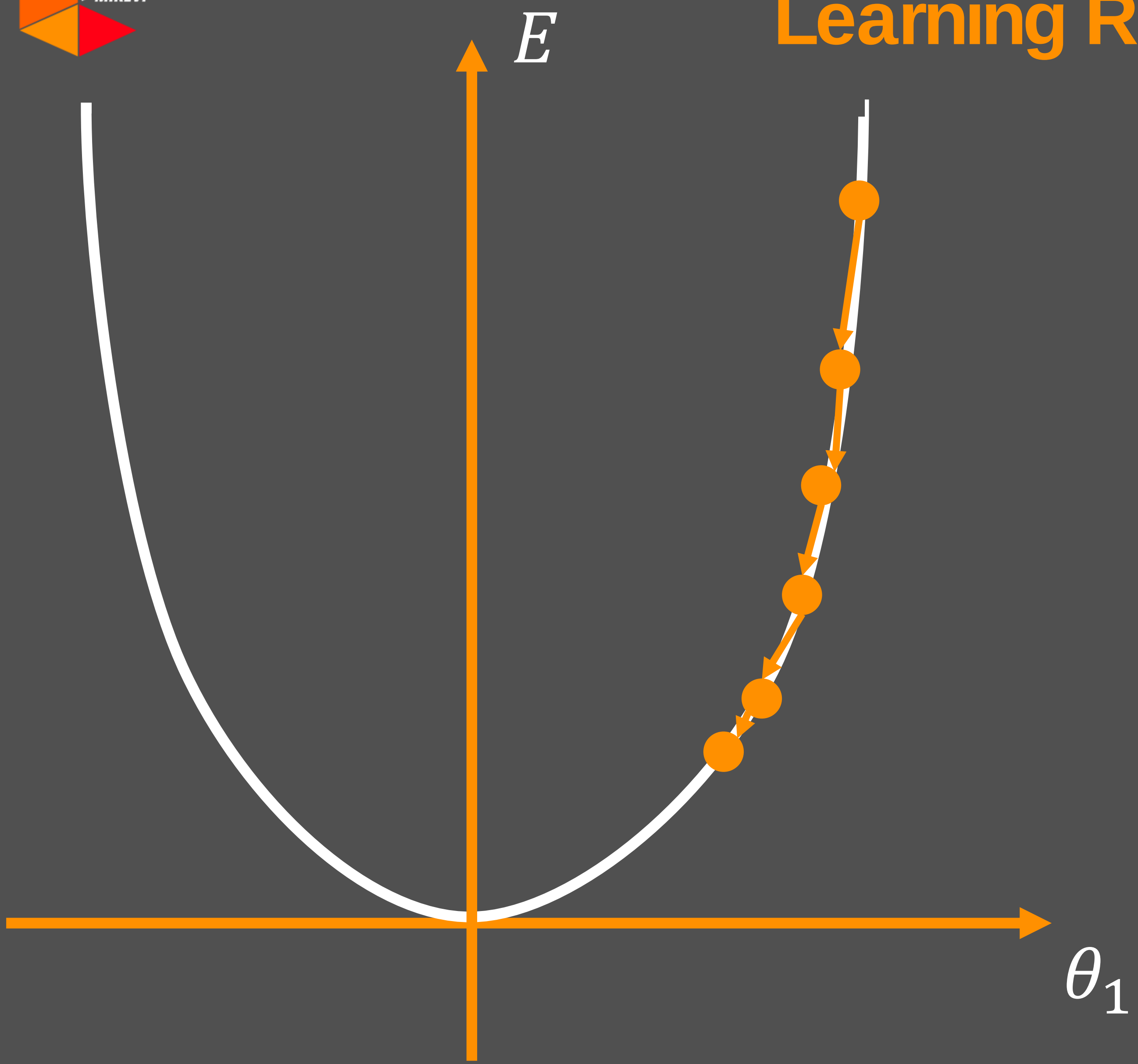
Learning Rate $\alpha = 0.5$



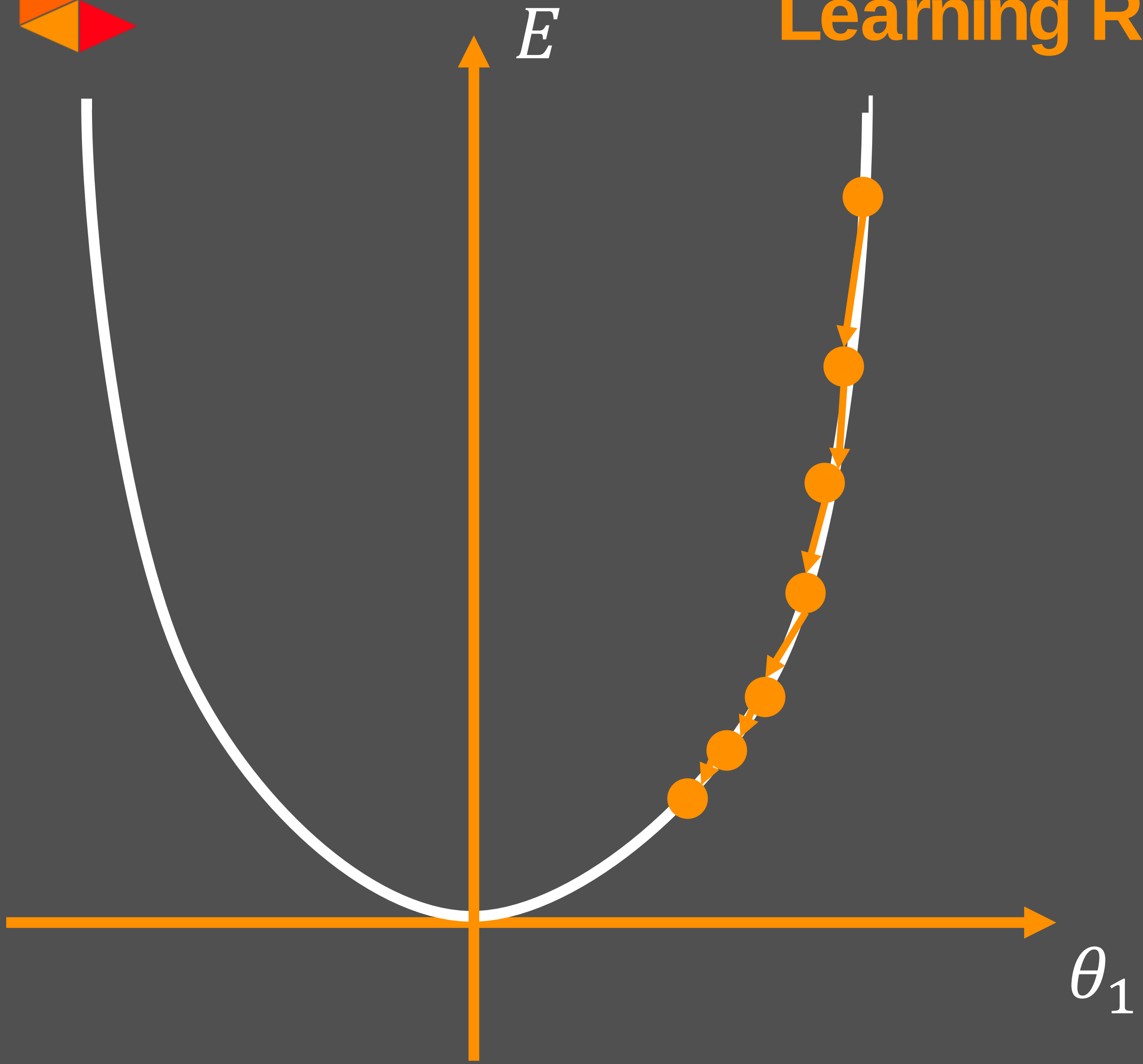
Learning Rate $\alpha = 0.5$



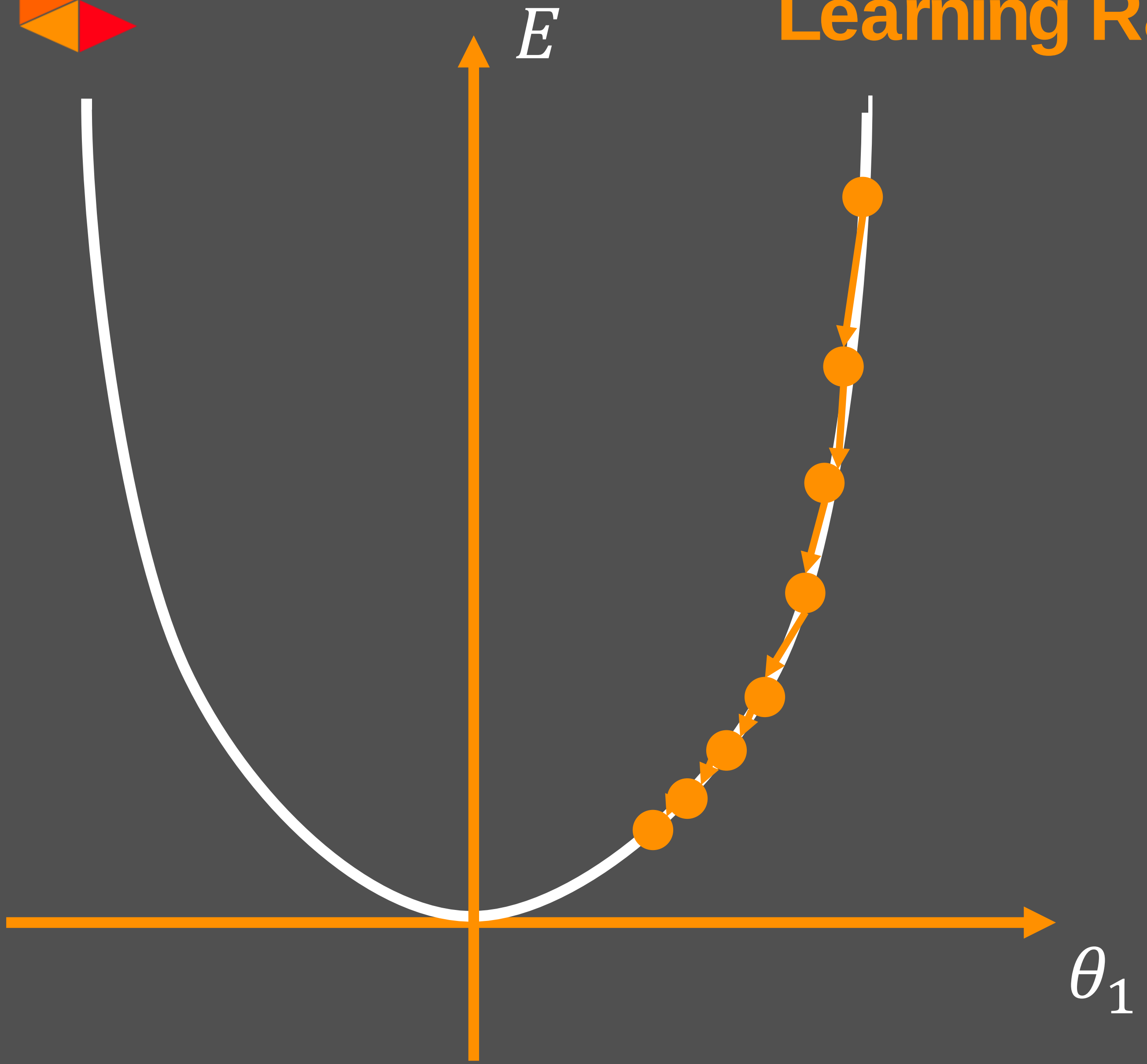
Learning Rate $\alpha = 0.5$



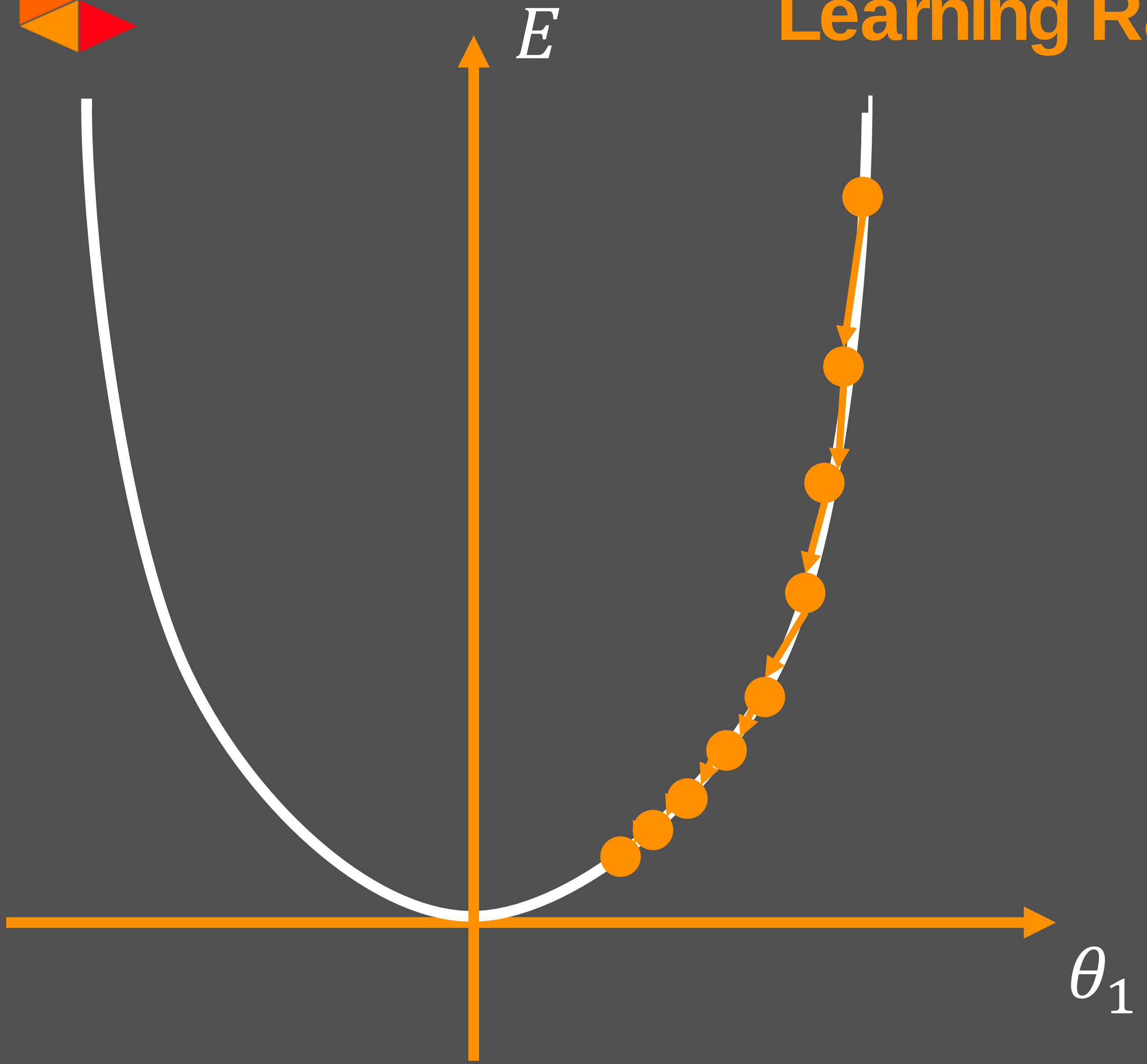
Learning Rate $\alpha = 0.5$



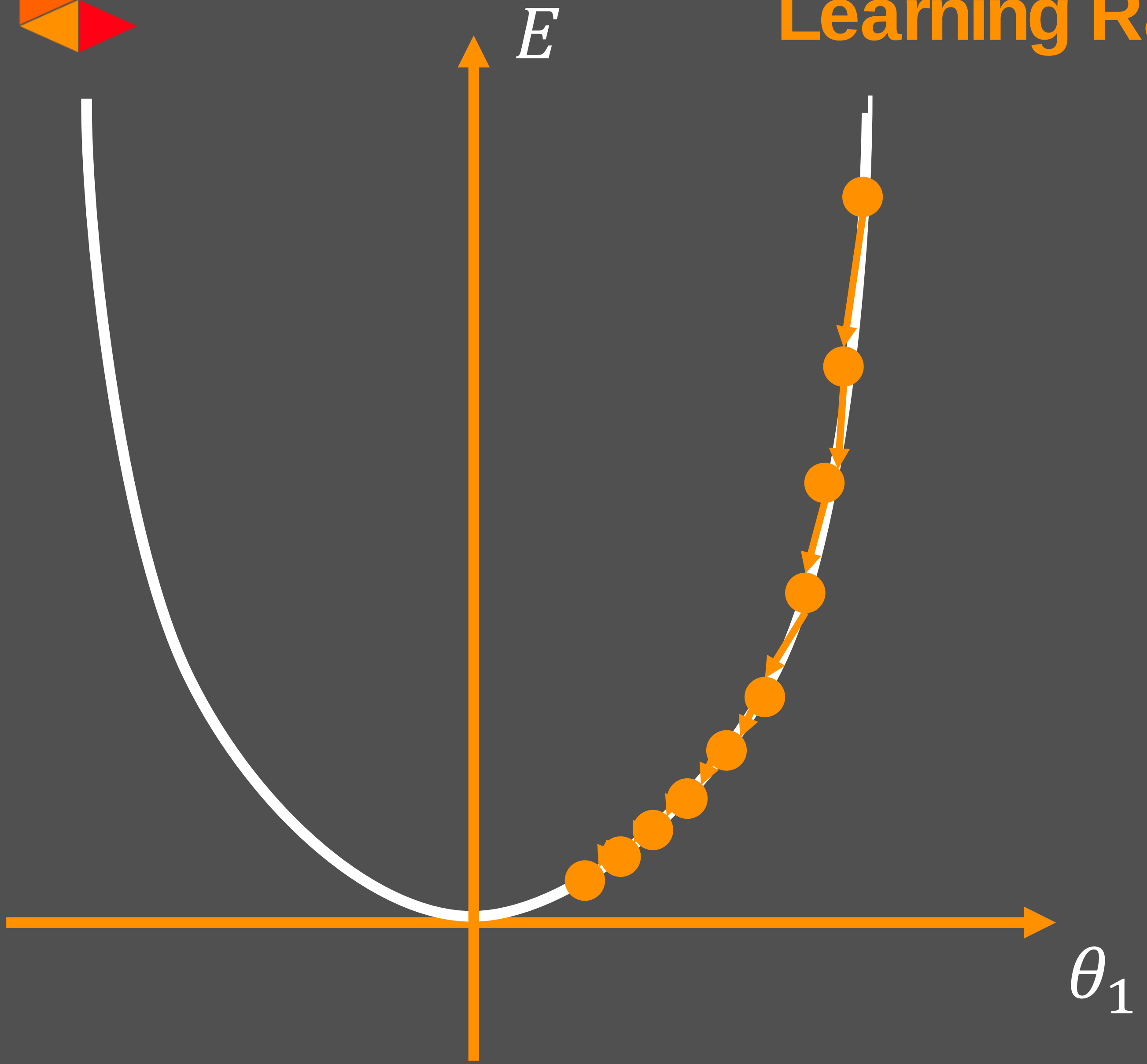
Learning Rate $\alpha = 0.5$



Learning Rate $\alpha = 0.5$

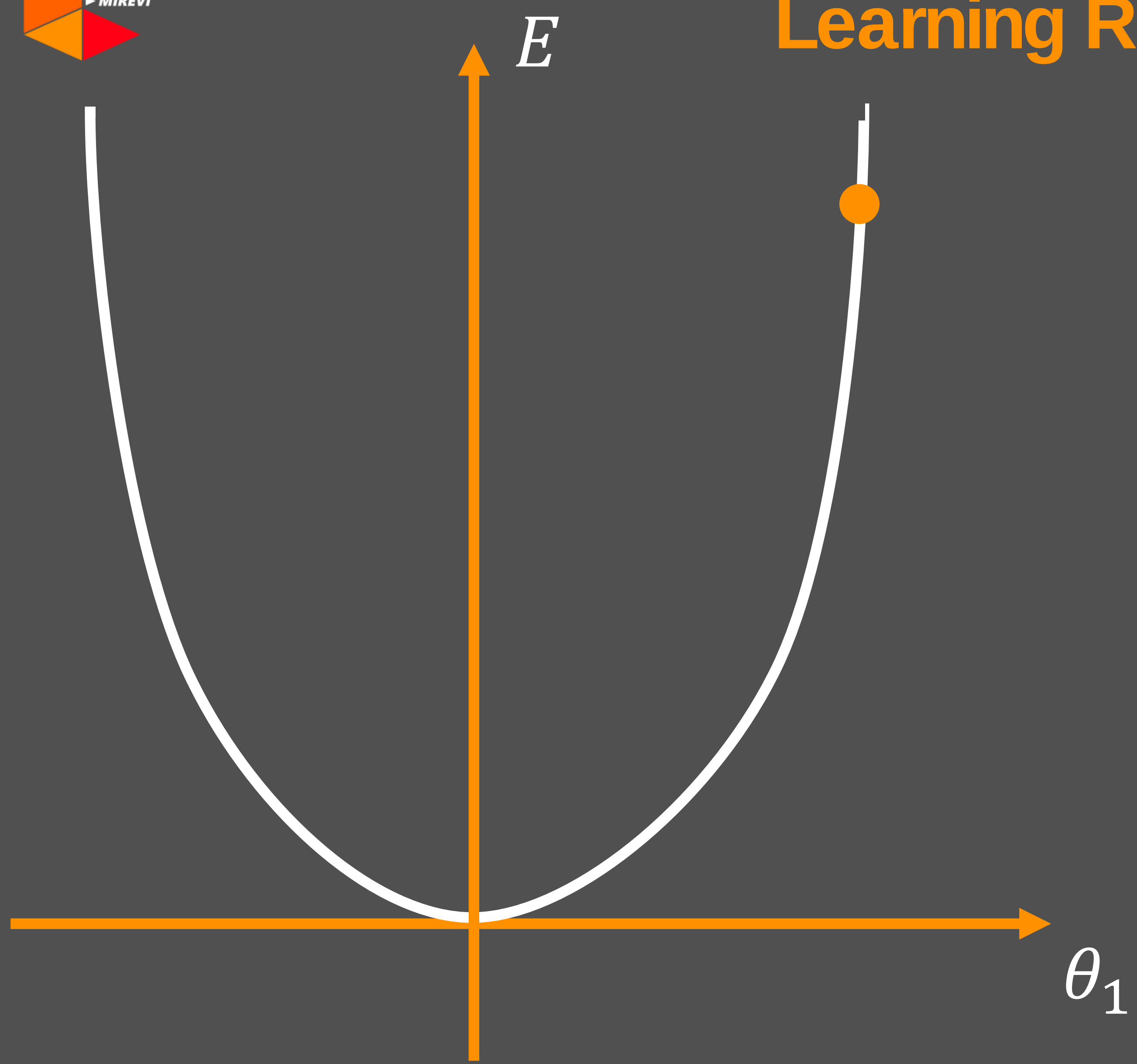


Learning Rate $\alpha = 0.5$

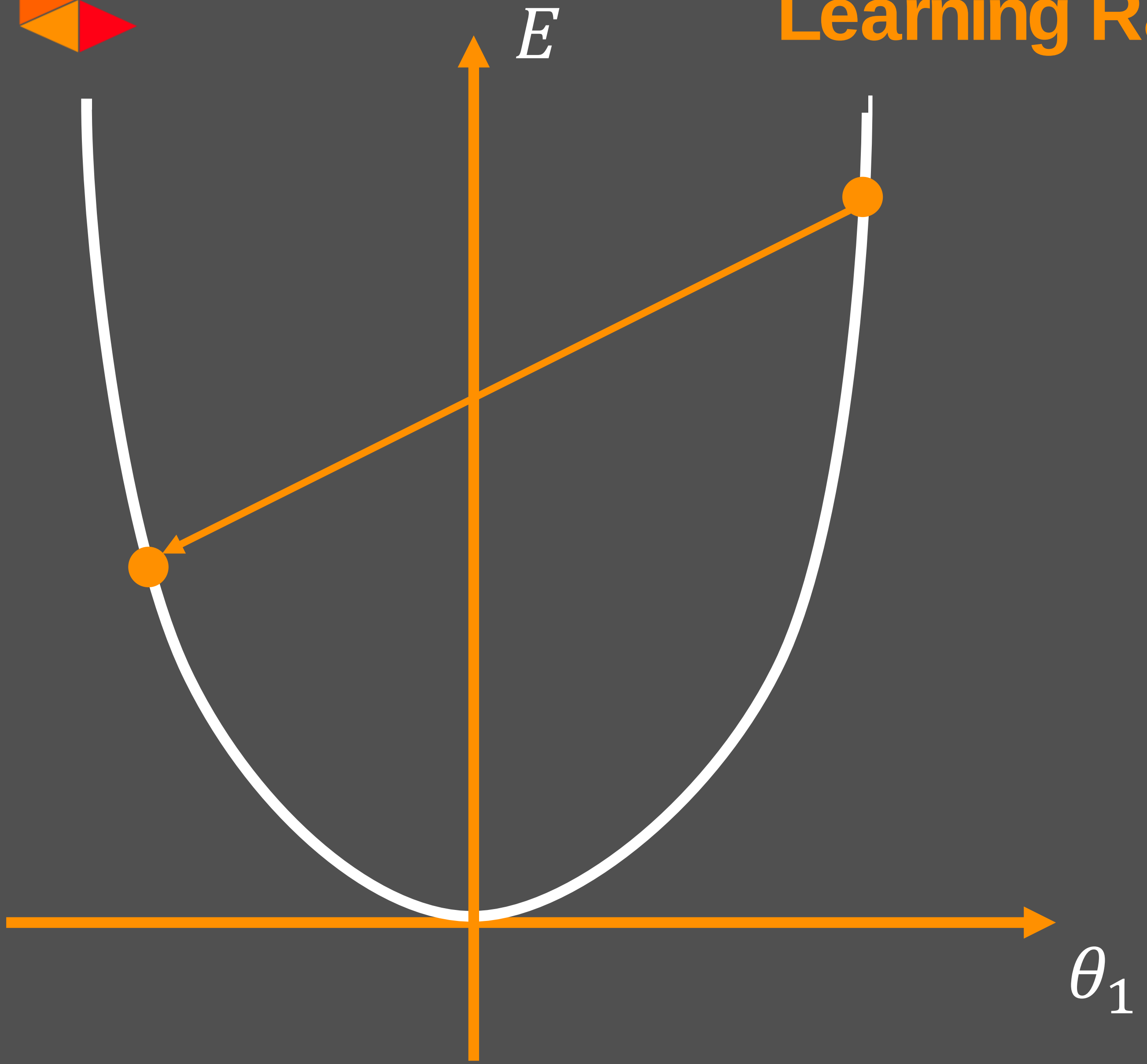


$$\alpha = 4$$

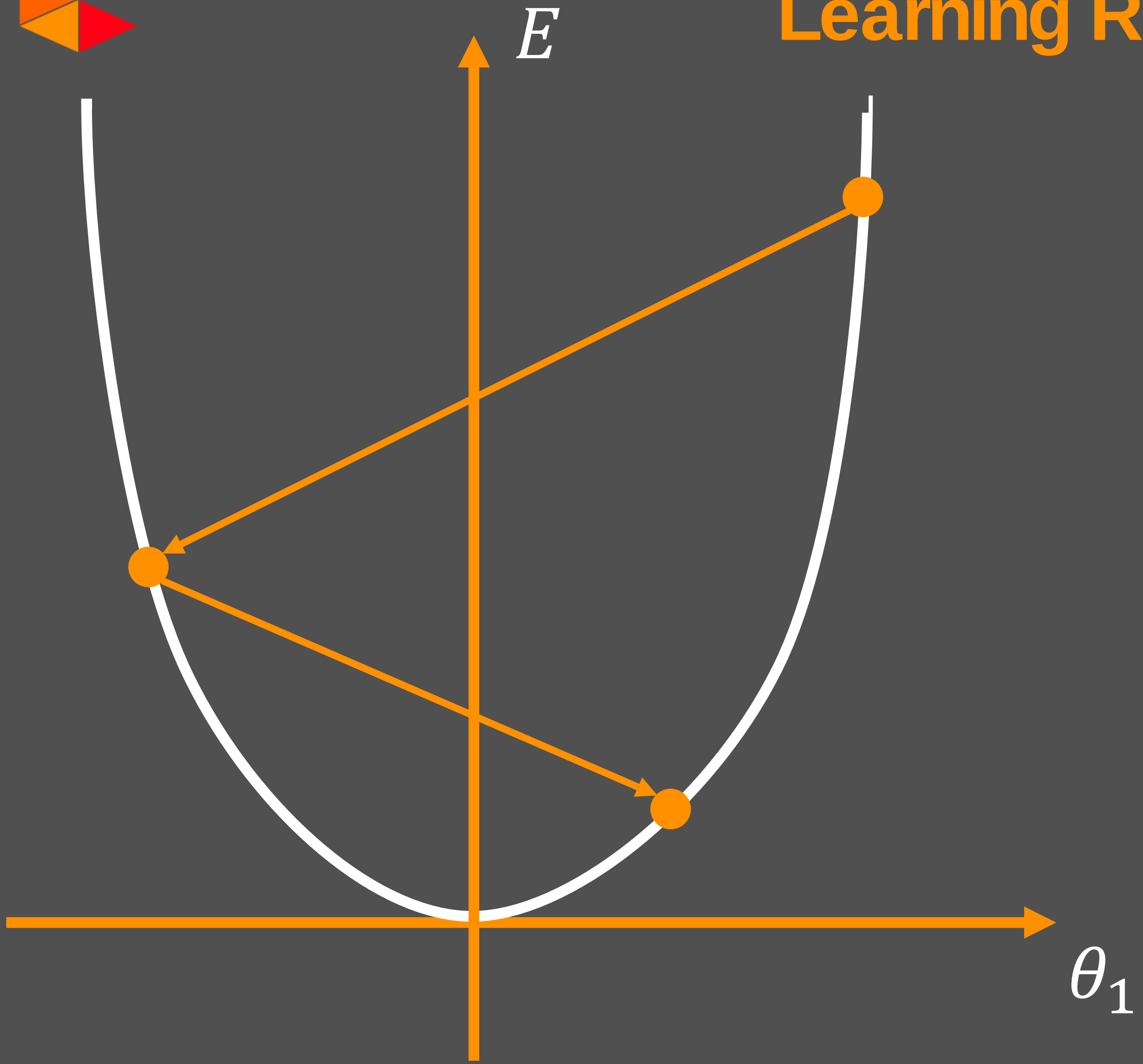
Learning Rate $\alpha = 4$



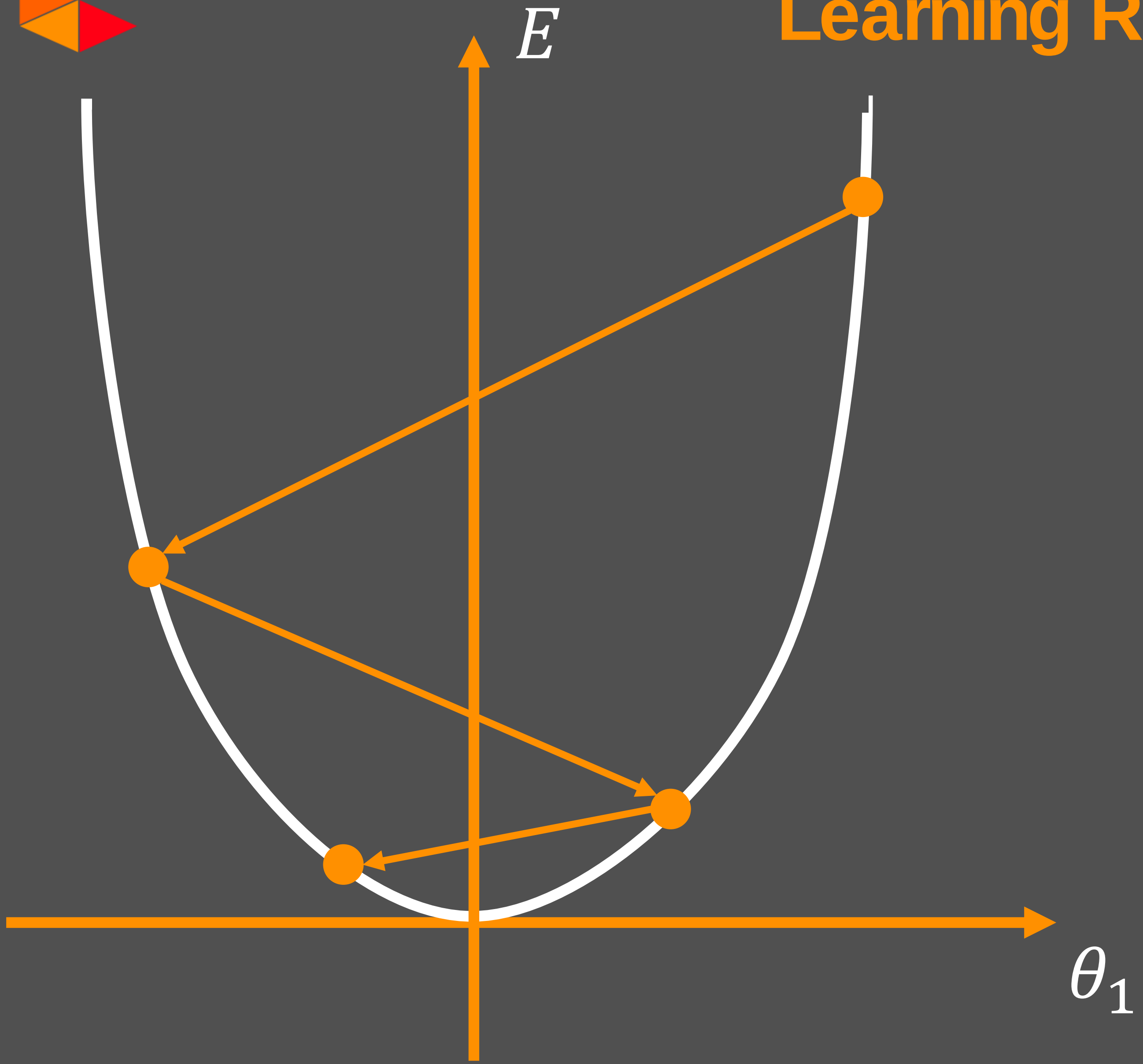
Learning Rate $\alpha = 4$



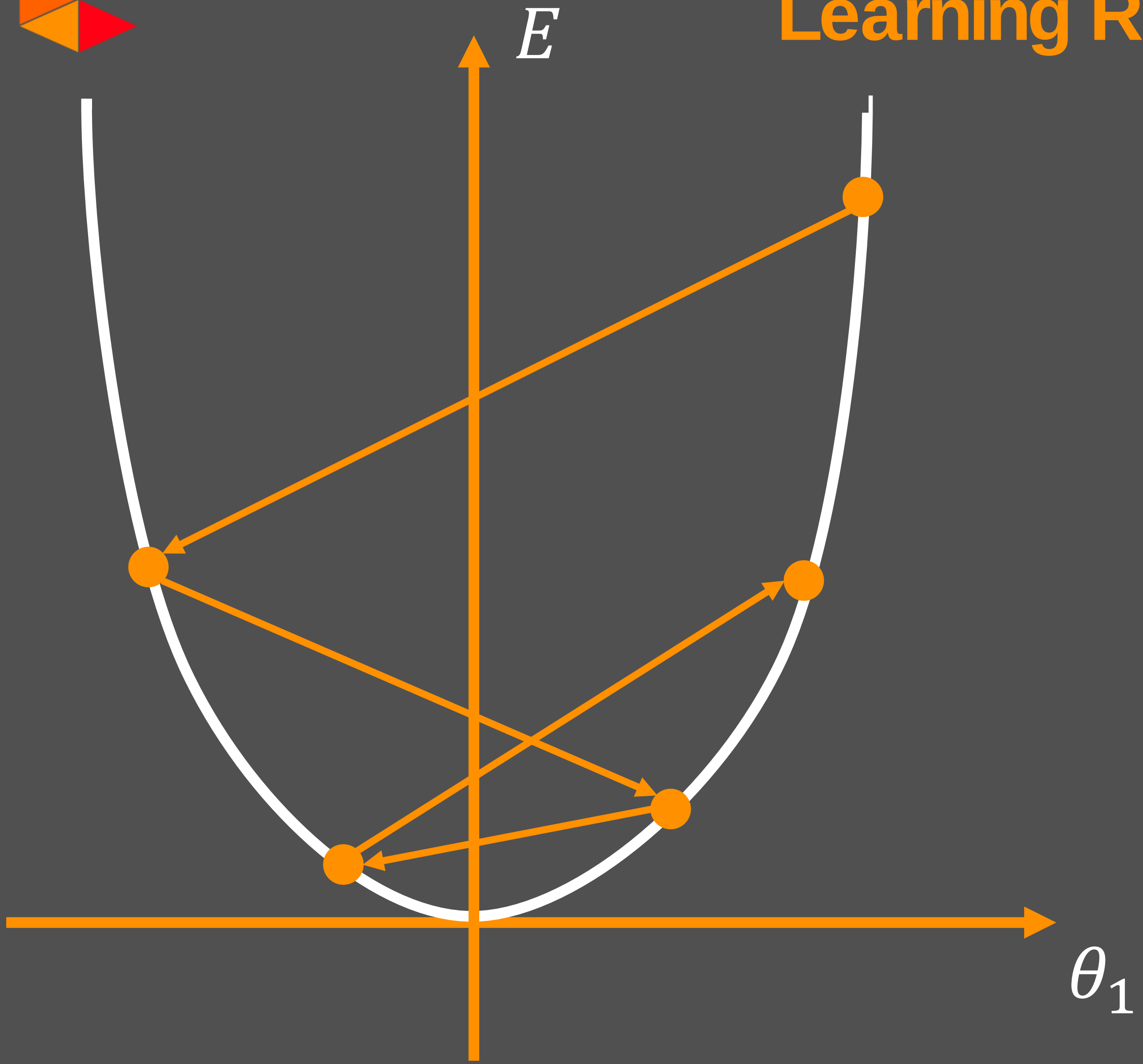
Learning Rate $\alpha = 4$



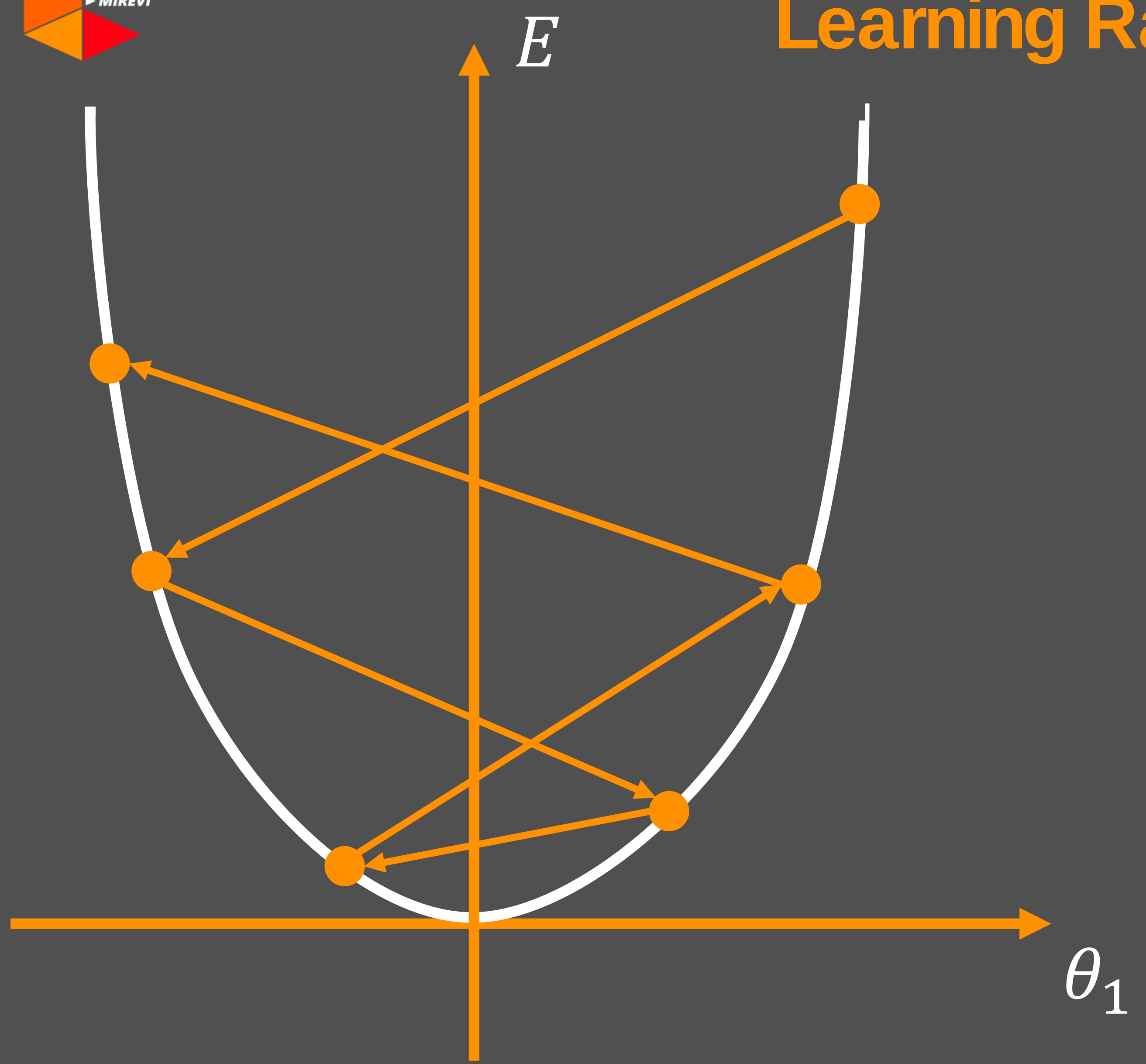
Learning Rate $\alpha = 4$



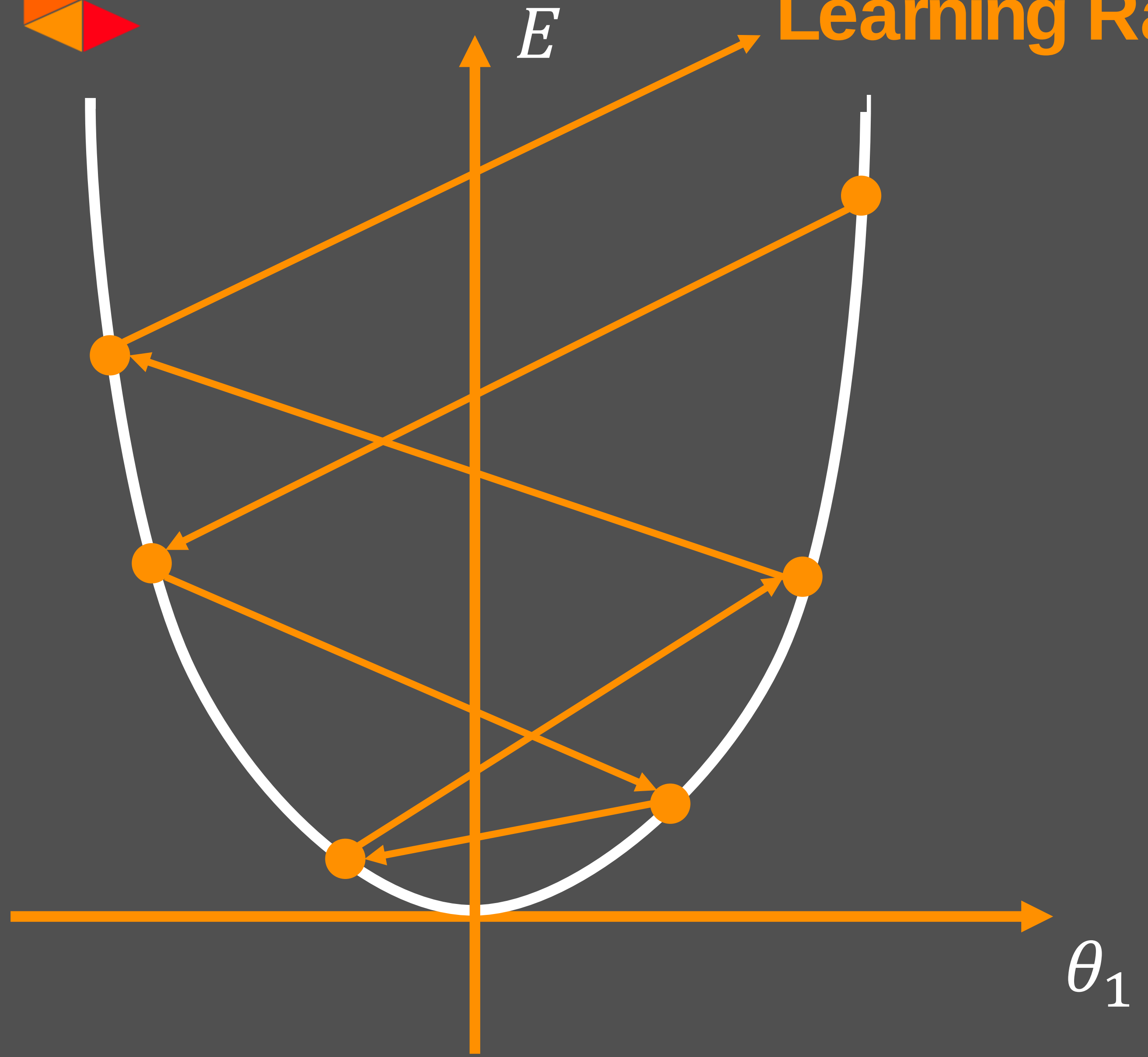
Learning Rate $\alpha = 4$



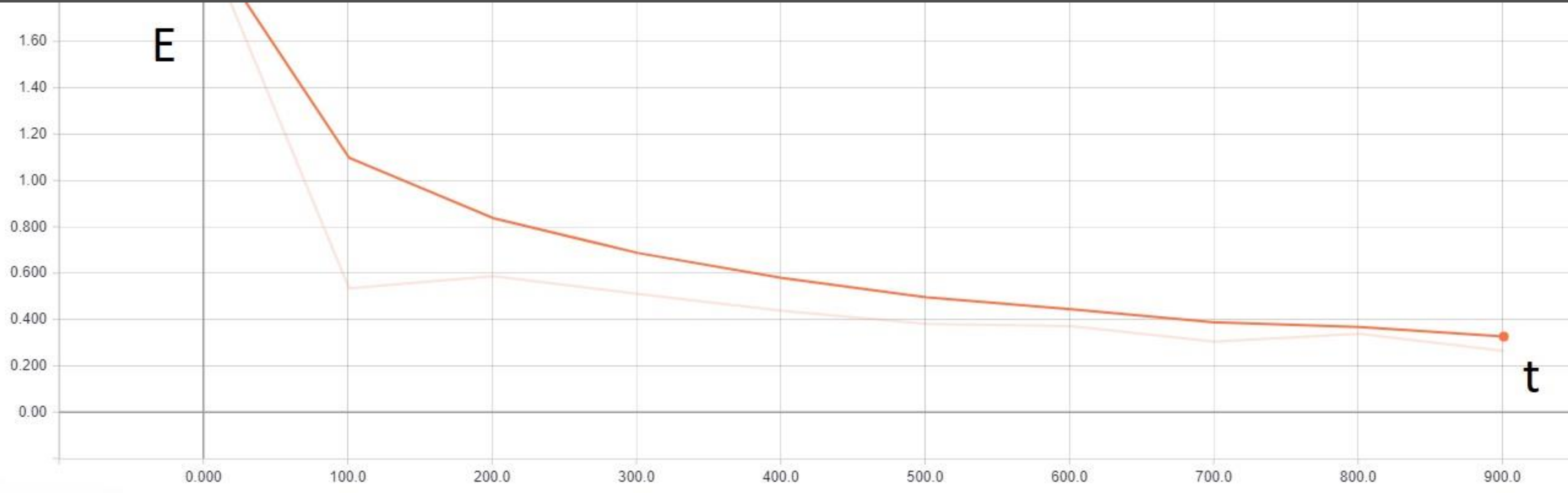
Learning Rate $\alpha = 4$



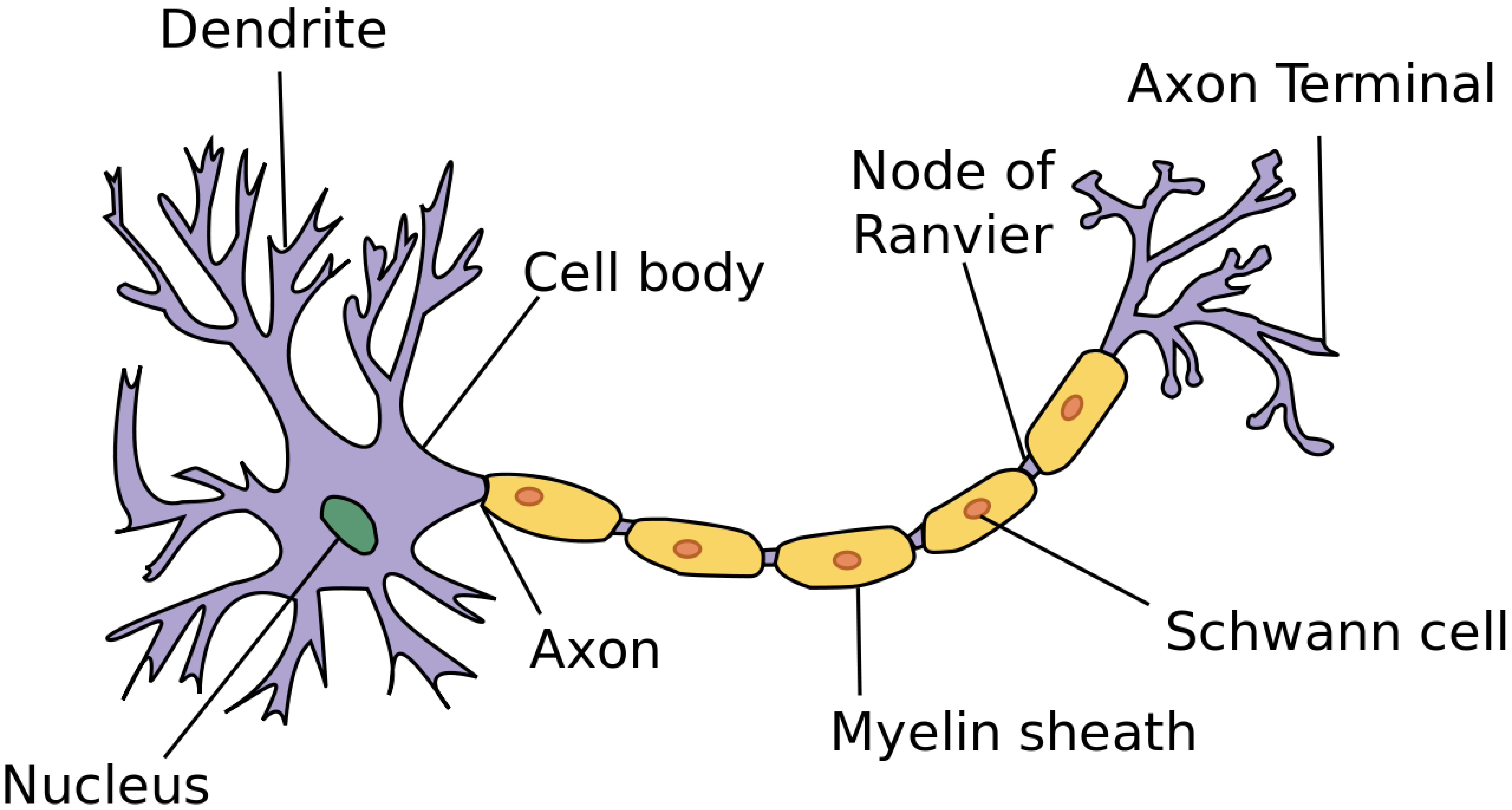
Learning Rate $\alpha = 4$

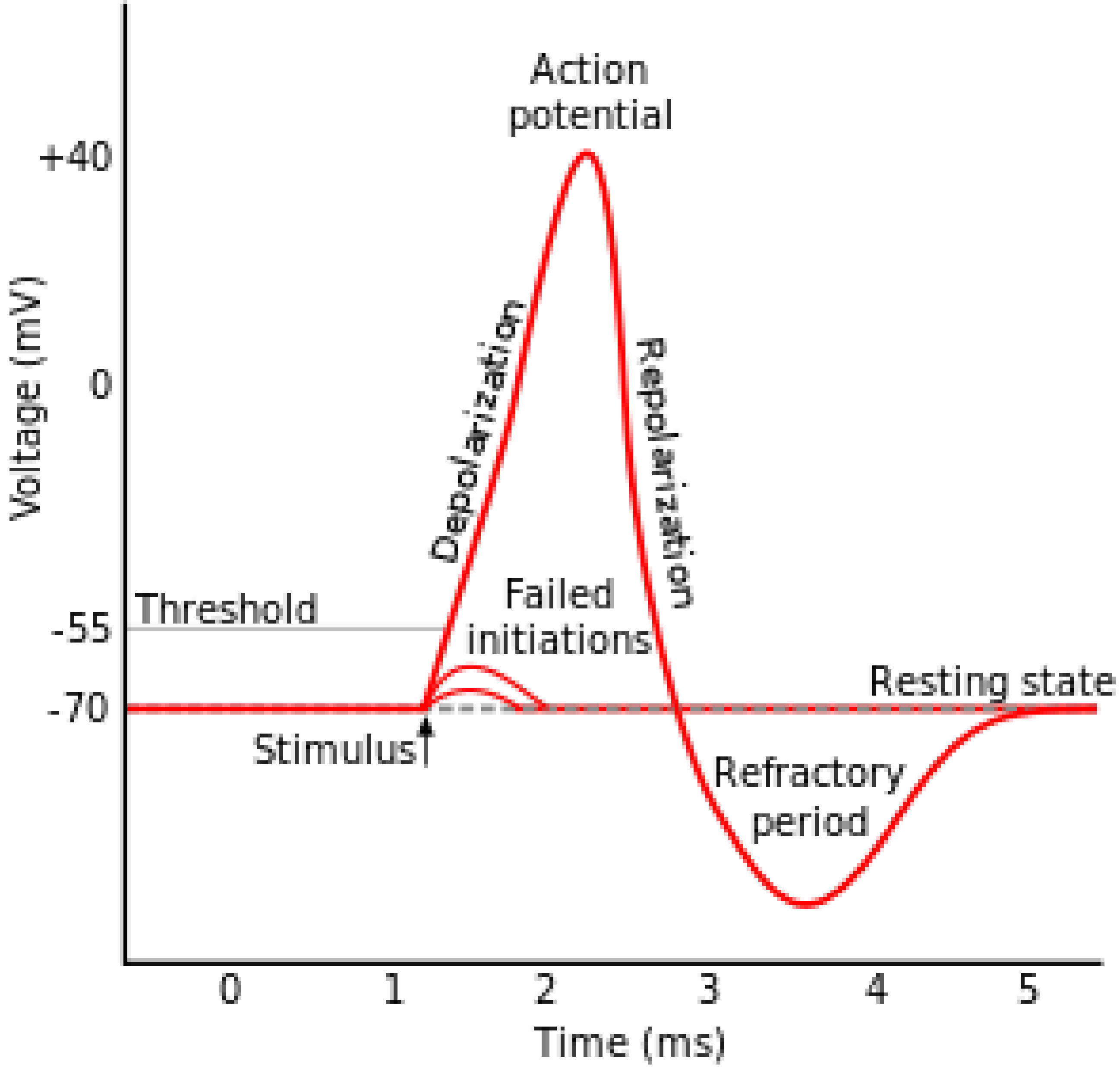


- **Choose good learning rate α by testing**
- **e.g.** $\alpha = i, i \in \{0.01, 0.03, 0.09, 0.1, 0.3, 0.9, 1, 3, 9\}$



Towards Neural Nets


Dendrite
Axon Terminal
Node of
Ranvier
Cell body
Axon
Schwann cell
Myelin sheath
Nucleus


Action
potential
+40
0
-55
-70
Voltage (mV)
Depolarization
Repolarization
Threshold
Failed
initiations
Resting state
Stimulus
Refractory
period
0
1
2
3
4
5
Time (ms)

Perceptron

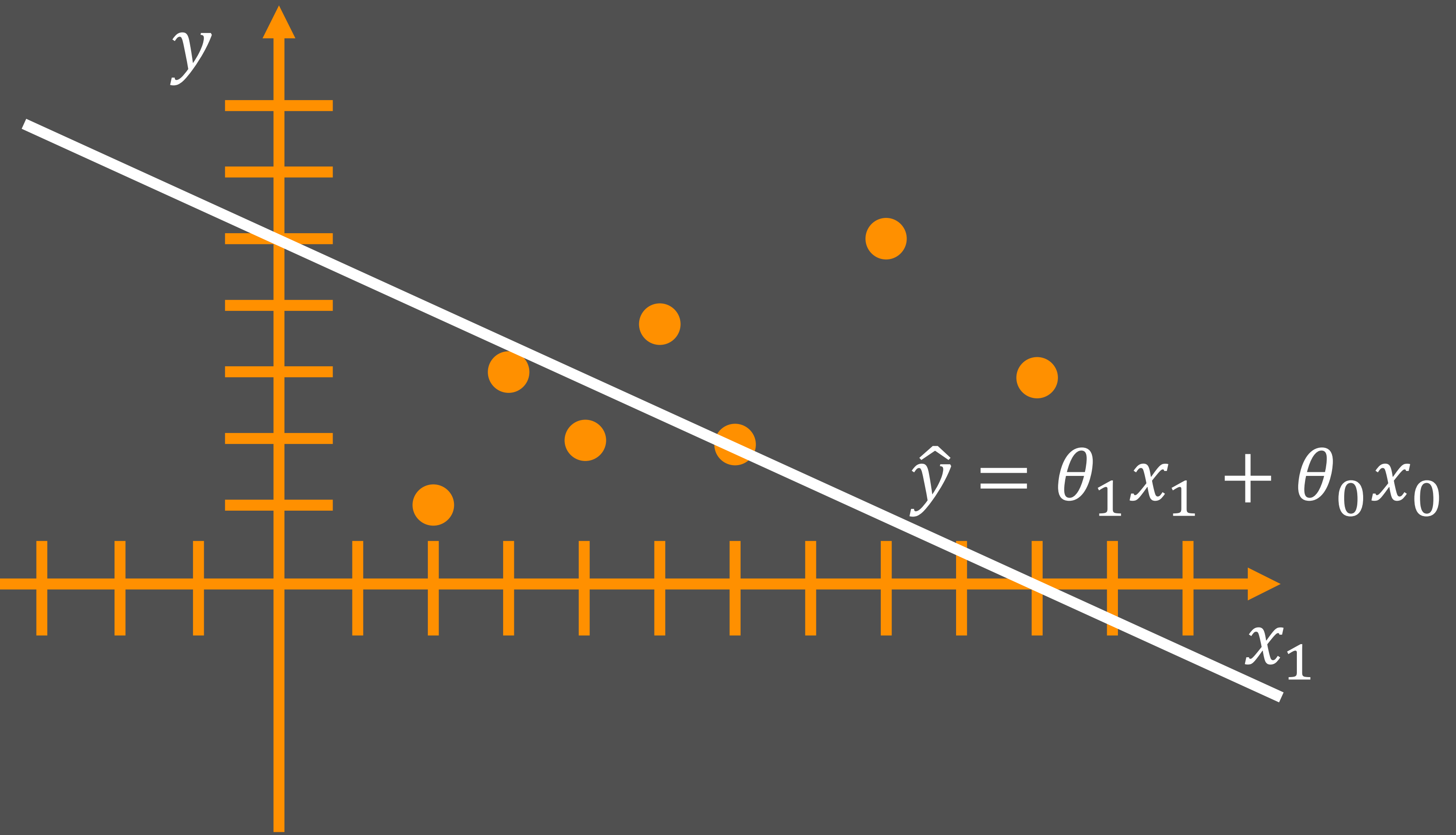
- Binary Classification
- Element of Neural Net
- Weighted Sum
- Activation Function
- Decision Boundary

$$y=f(x)$$

Elements of Perceptron

- **Activation Function** $\mathrm{y} = a(z)$
- **Weighted Sum** $z = \theta x$

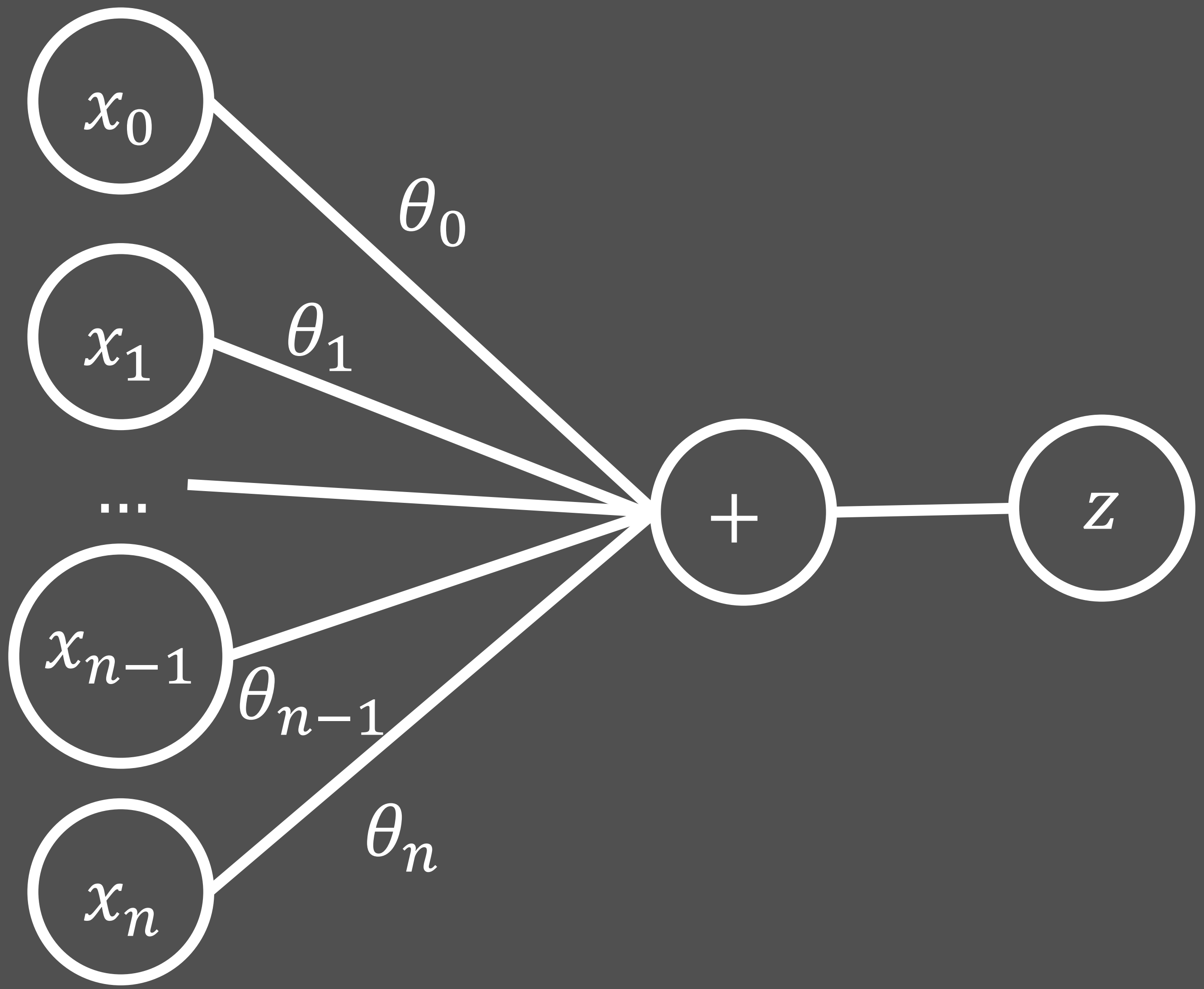
Weighted Sum:



Perceptron

Weighted Sum $z = \theta x$

- $z = \theta x = \theta_n * x_n + \theta_{n-1} * x_{n-1} + \cdots + \theta_1 * x_1 + \theta_0 * x_0$
- θ: Weigths
- x: Data
- $x_0 = 1$

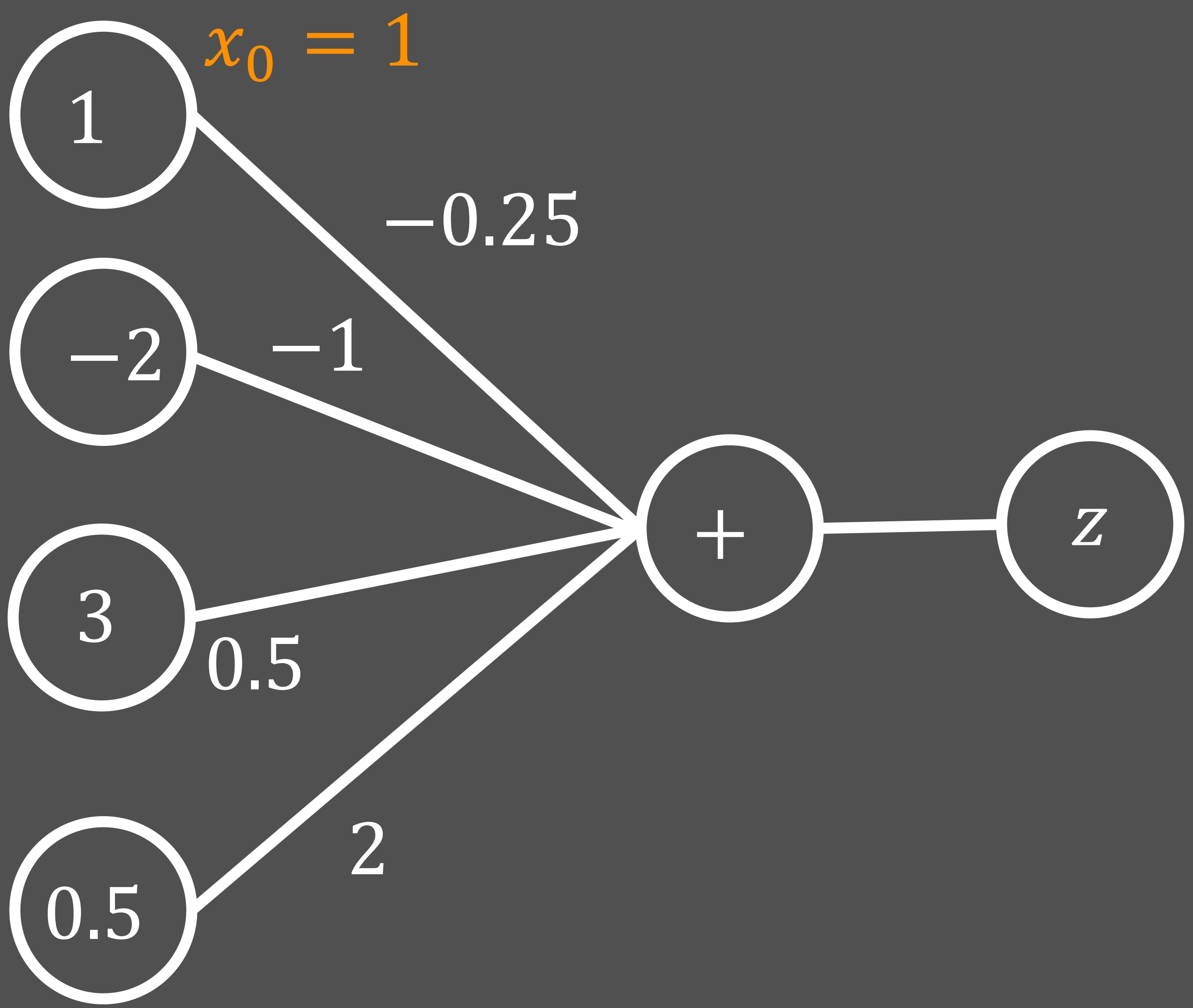


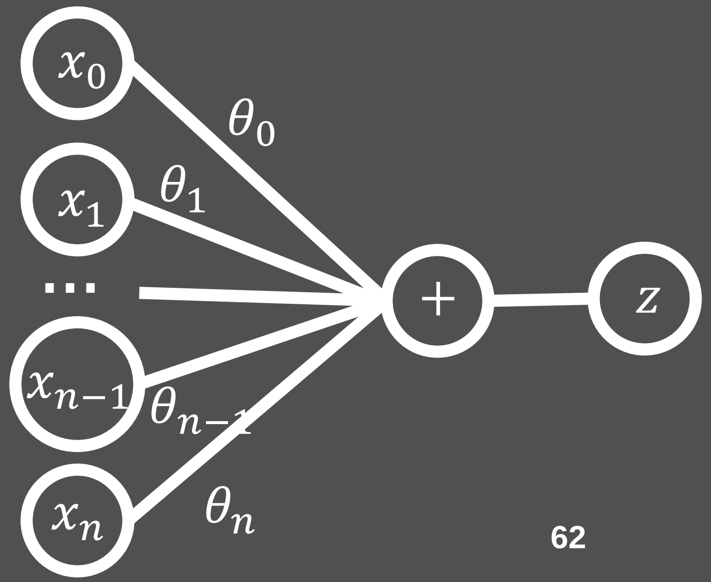
Weighted Sum

- $z = \theta x$
- θ: **Weigths**
- x: **Data**
- $x_0 = 1$

Weighted Sum

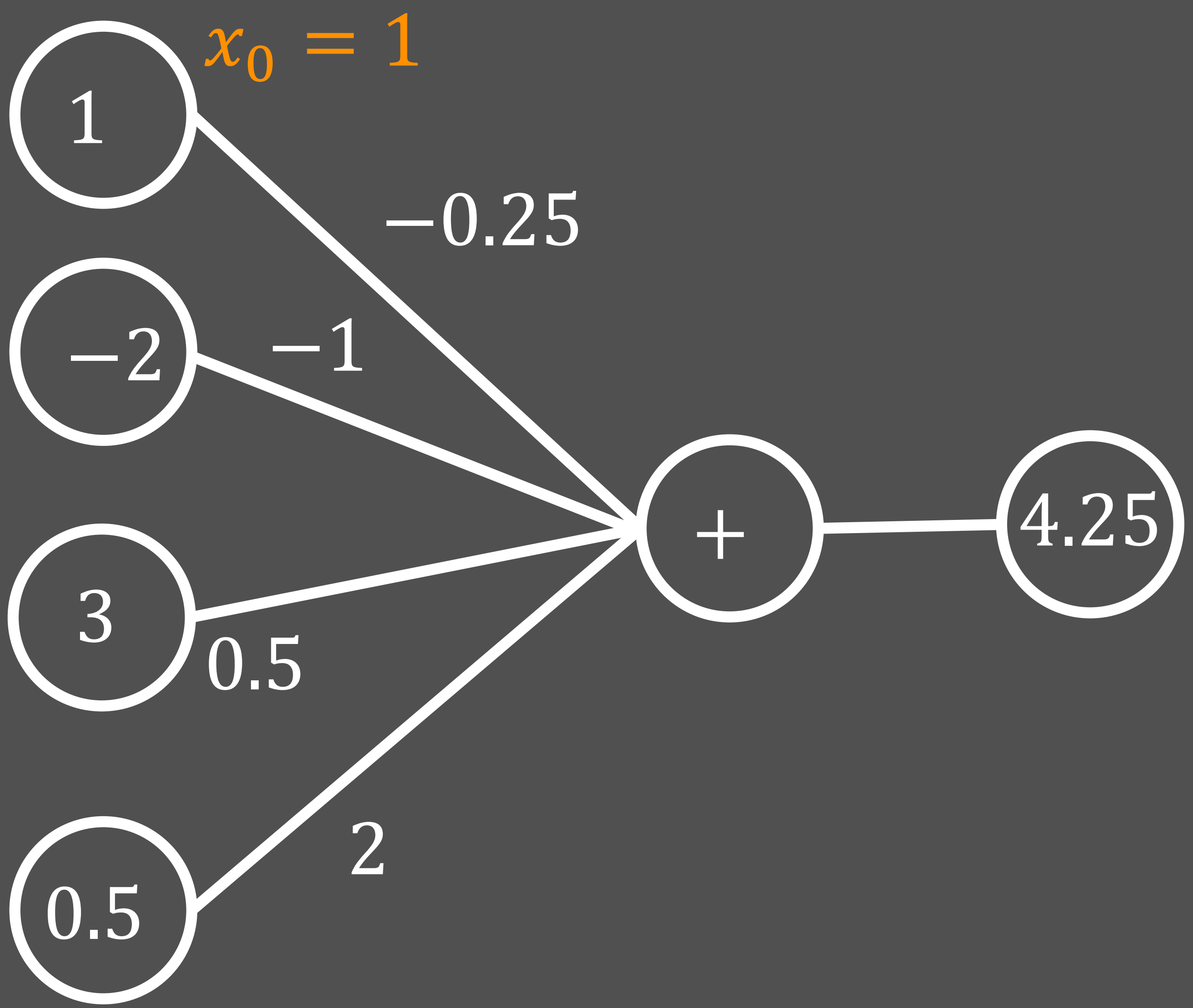
- $z = \theta x$
- θ: Weigths
- x: Data
- $x_0 = 1$

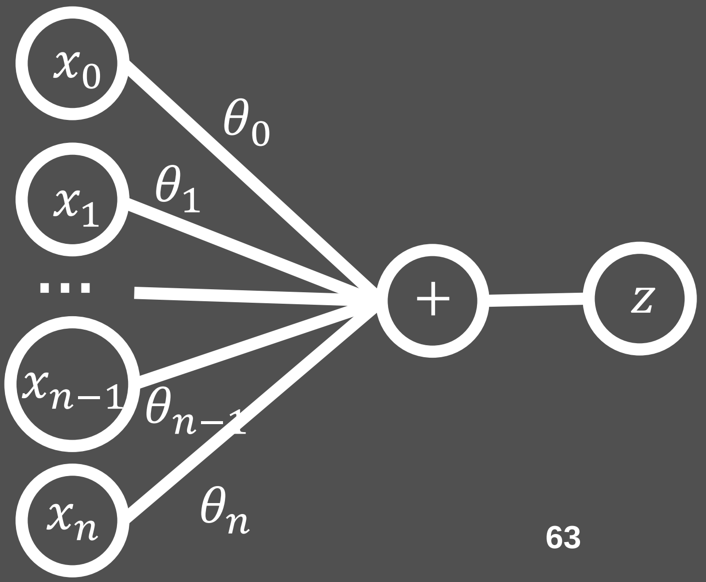




Weighted Sum

- $z = \theta x$
- θ: Weigths
- x: Data
- $x_0 = 1$



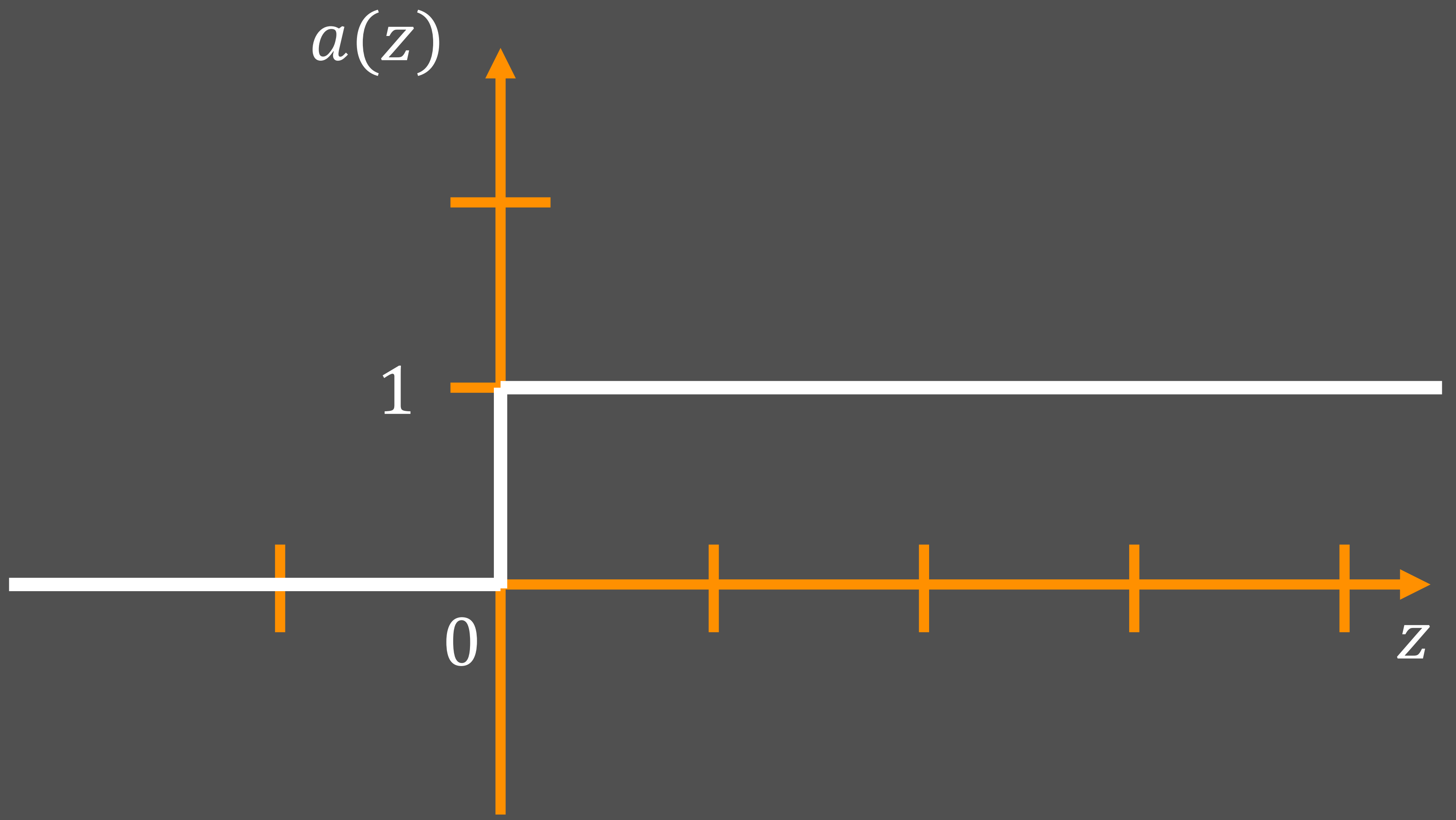


Perceptron

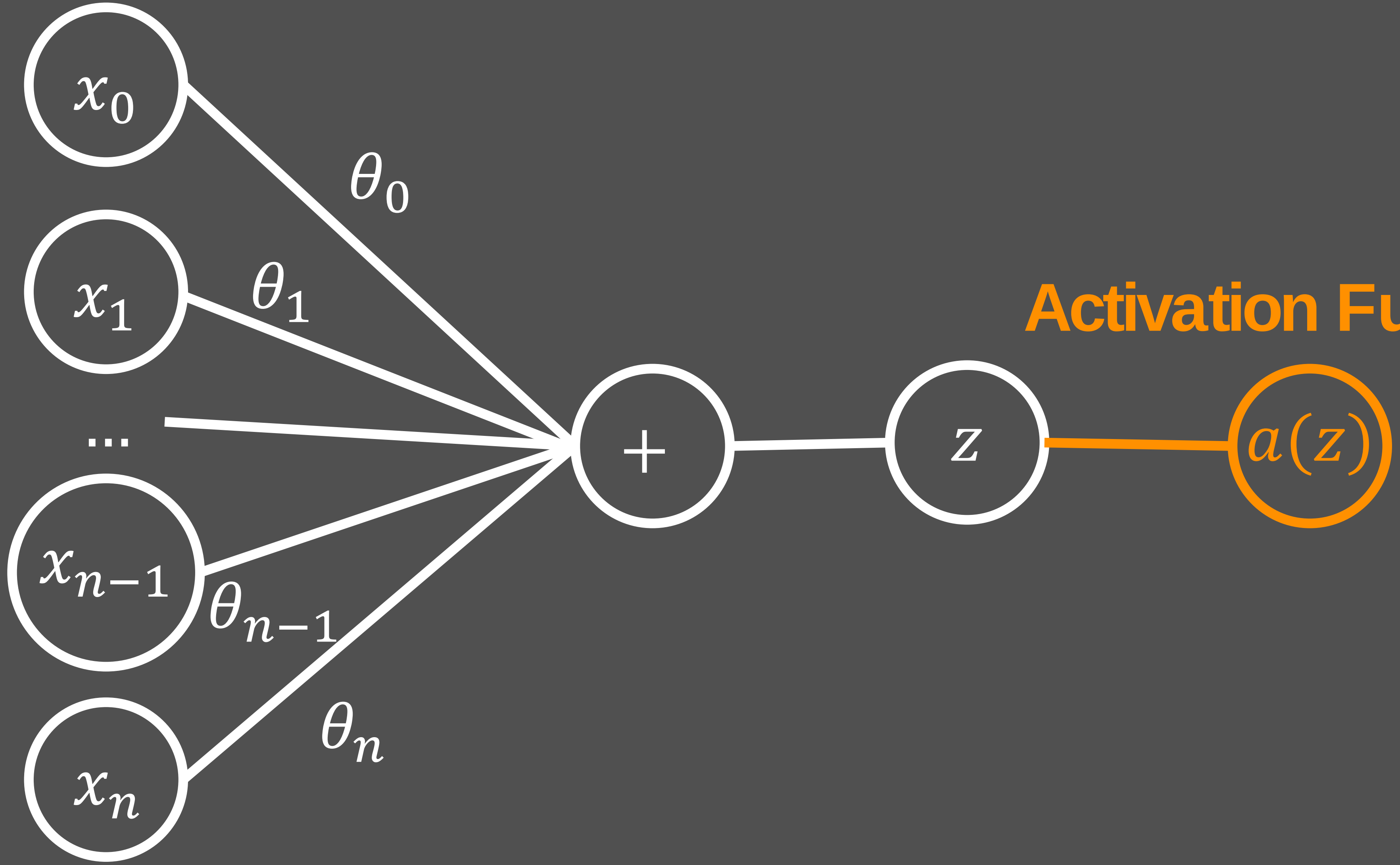
Activation Function $y = a(z)$

Binary Threshold Unit: $a(z) = \begin{cases} 0, z < 0 \\ 1, z \geq 0 \end{cases}$

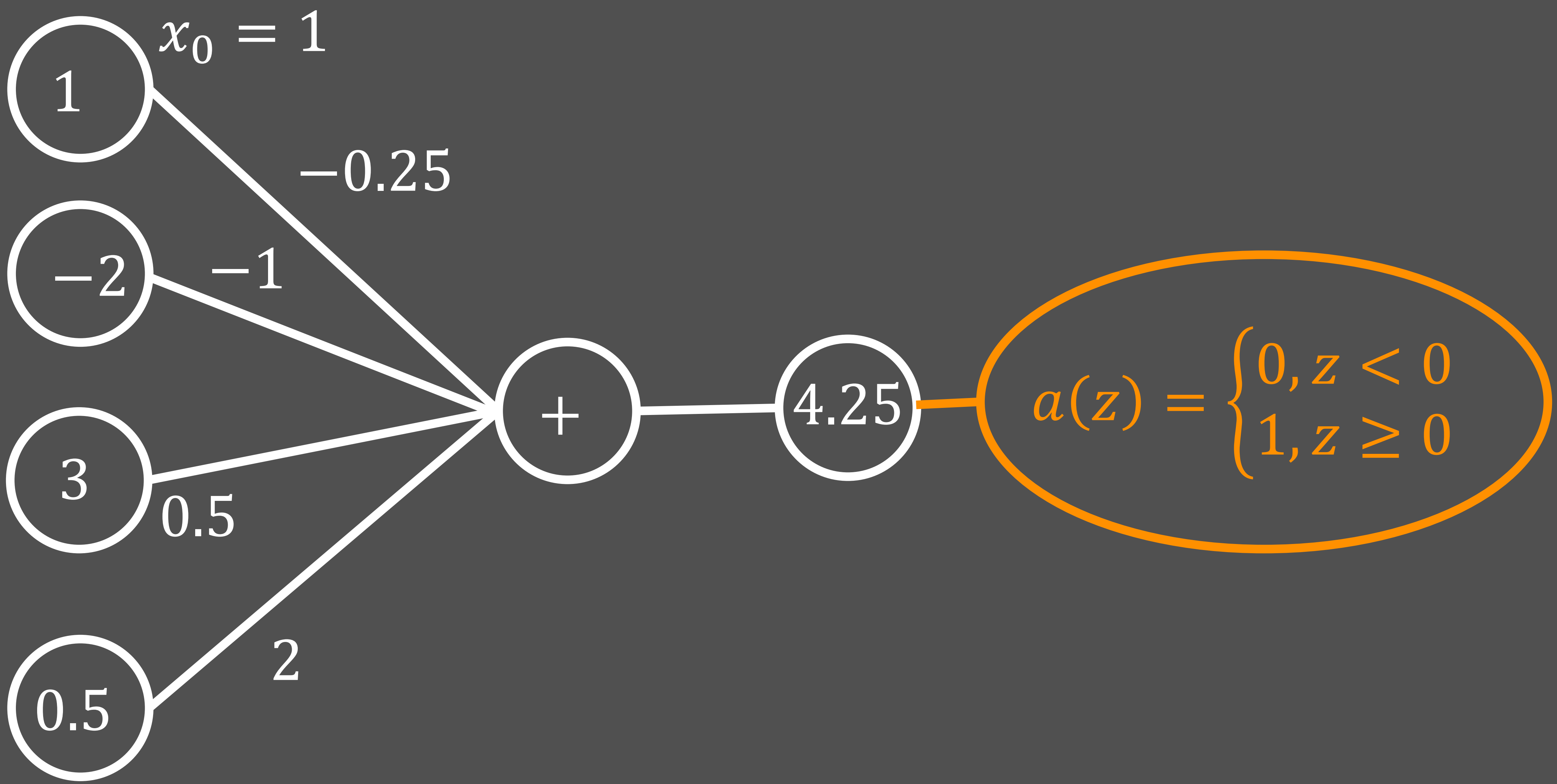
Perceptron



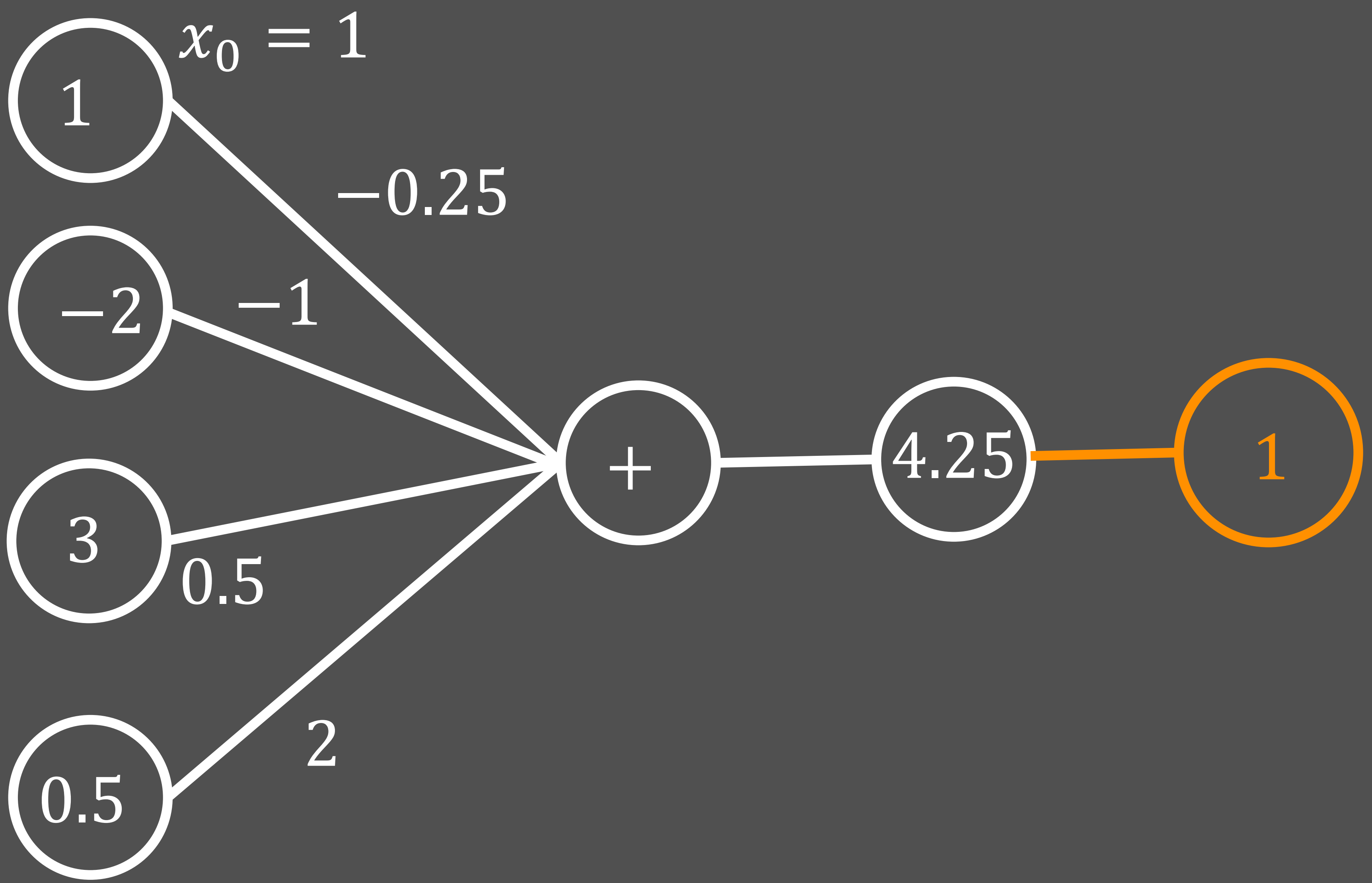
Perceptron


x_0
x_1
...
x_{n-1}
x_n
θ_0
θ_1
θ_{n-1}
θ_n
$+$
z
Activation Function
$a(z)$

Perceptron

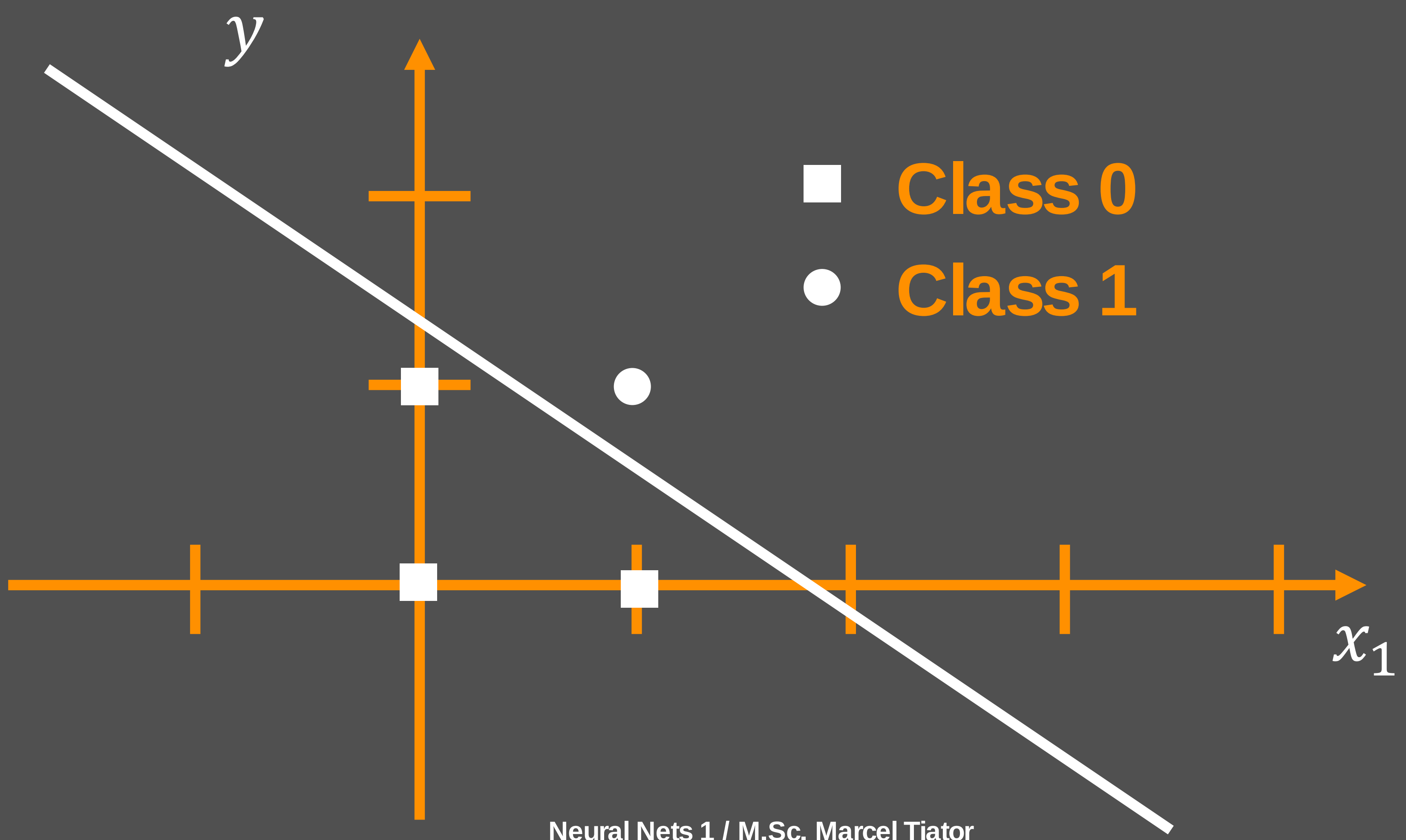


Perceptron

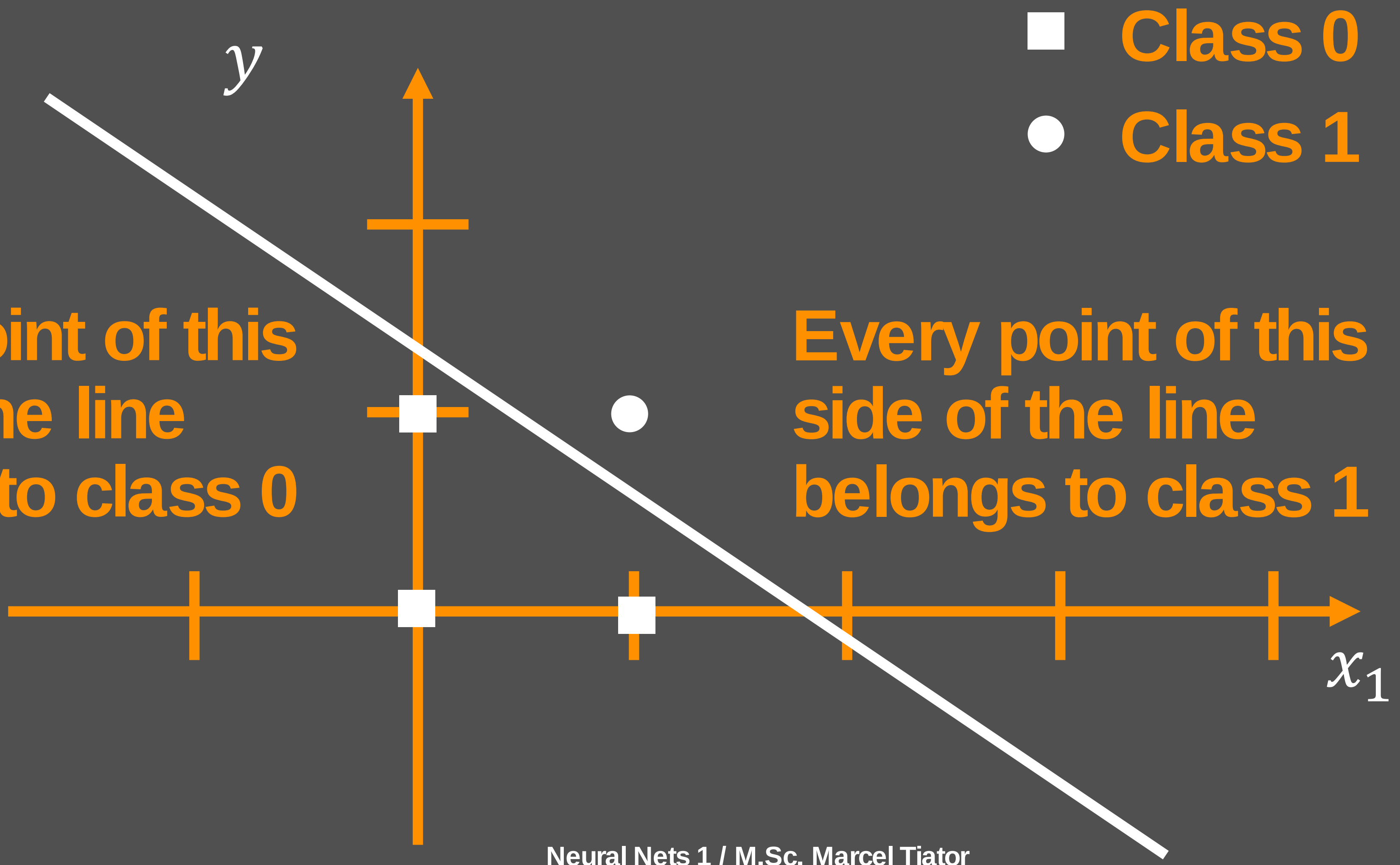


Linear Classifier

Binary Classification



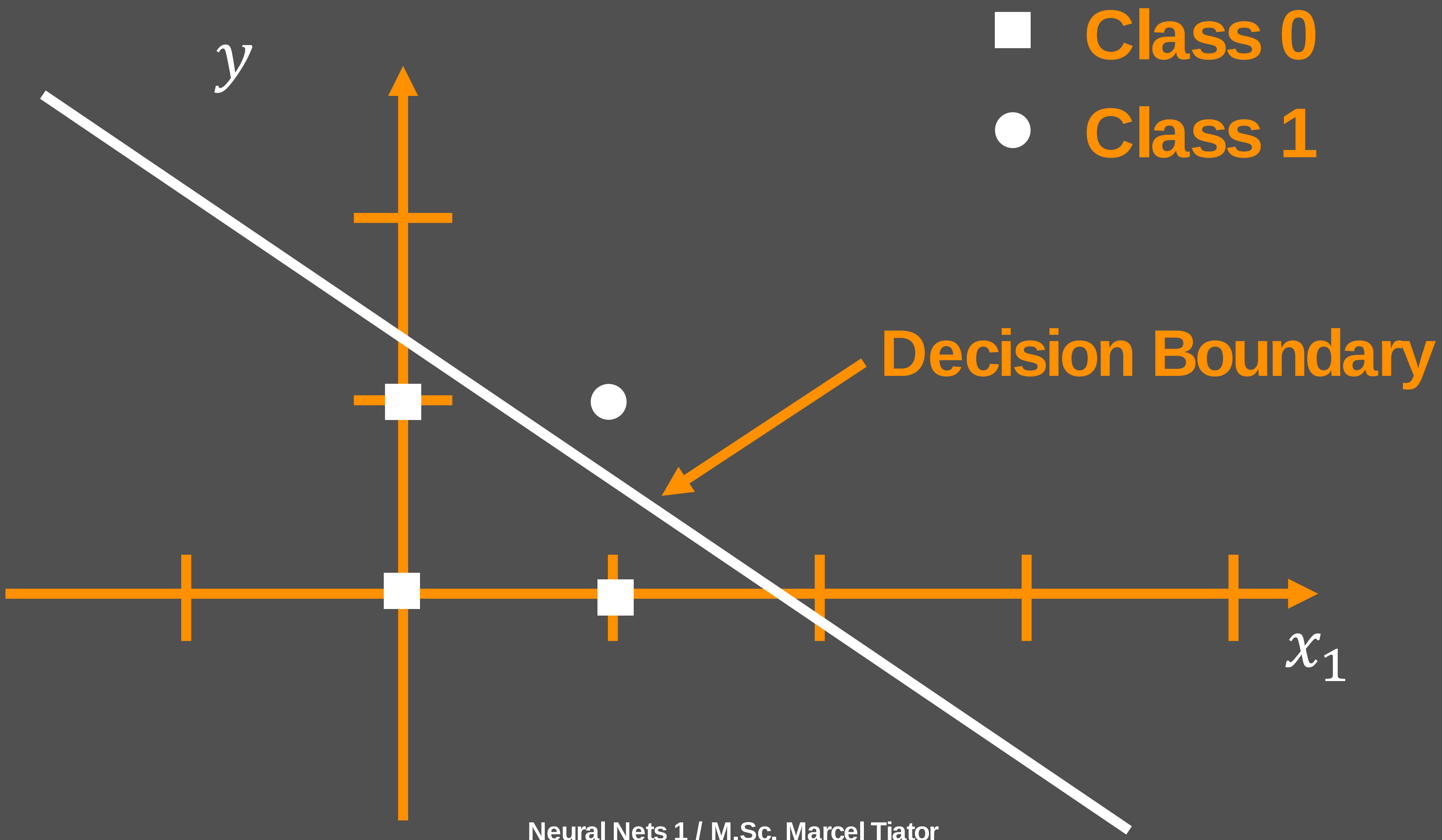
Binary Classification



Every point of this side of the line belongs to class 0

Every point of this side of the line belongs to class 1

Binary Classification



Perceptron

Training:

Initialize weights randomly

do{

error=false

d=0

foreach x in trainingsset{

$\hat{y}$=Prediction(x), $\hat{y}\epsilon\{0,1\}$

$\mathrm{d} = \mathrm{y} - \hat{y}, y\epsilon\{0,1\}$

if($d == 1$) $\theta = \theta + x$

elif ($d == -1$) $\theta = \theta - x$

error =error | $d \neq 0$

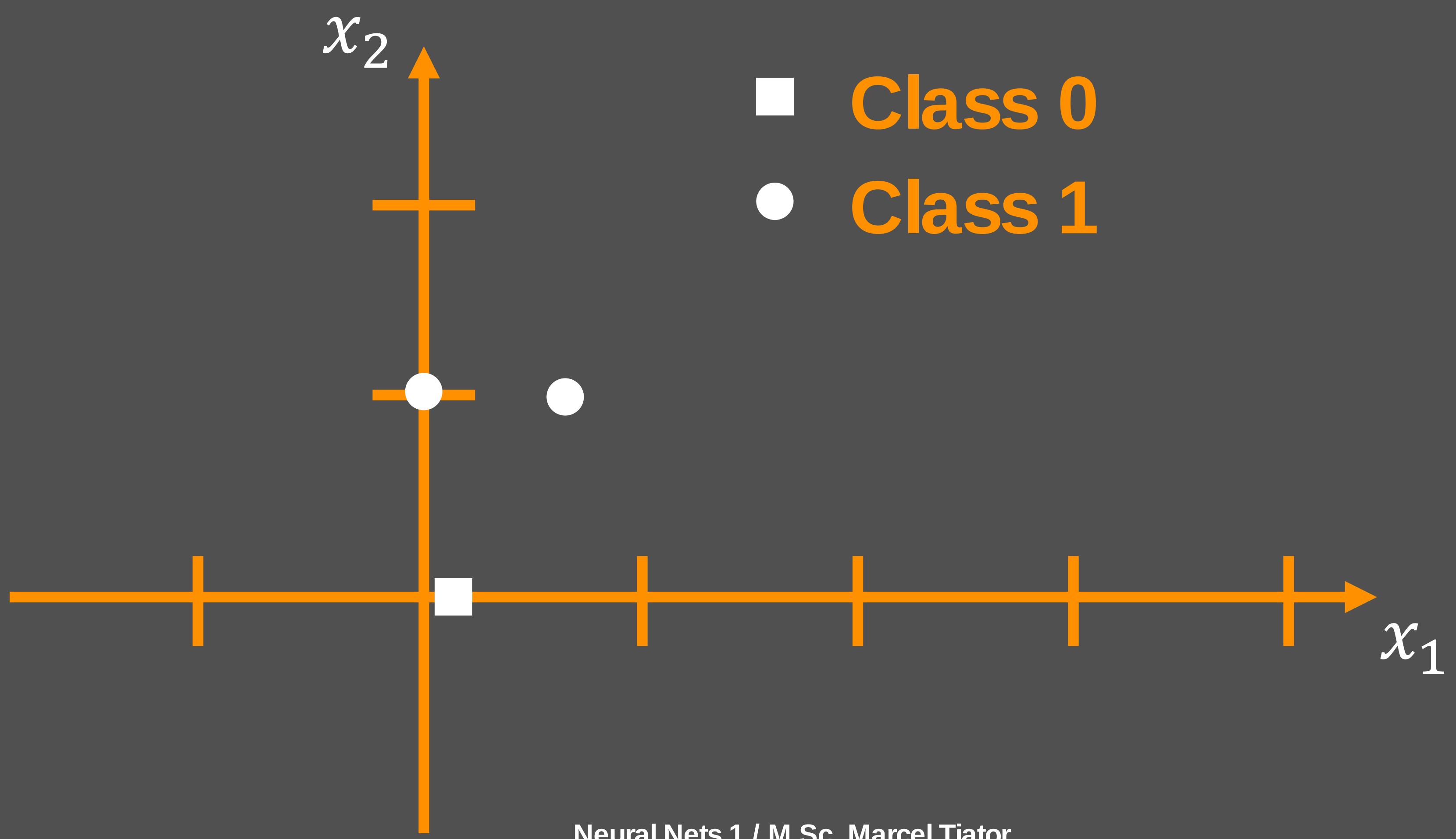
}

} while(error)

Perceptron

x_1	x_2	y
0.1	0	0
0.6	1	1
0	1	1

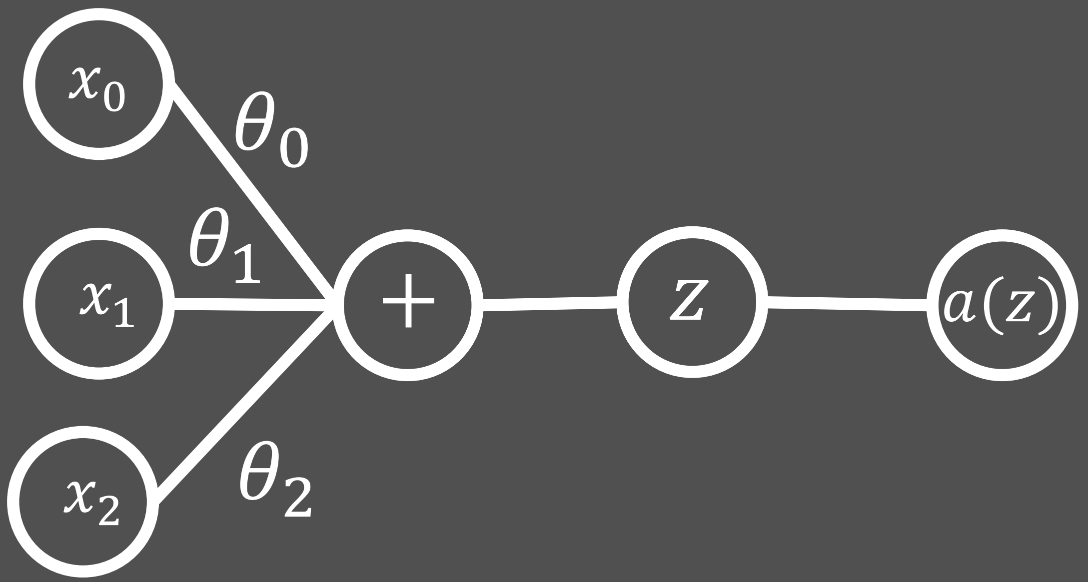
Visualization of data

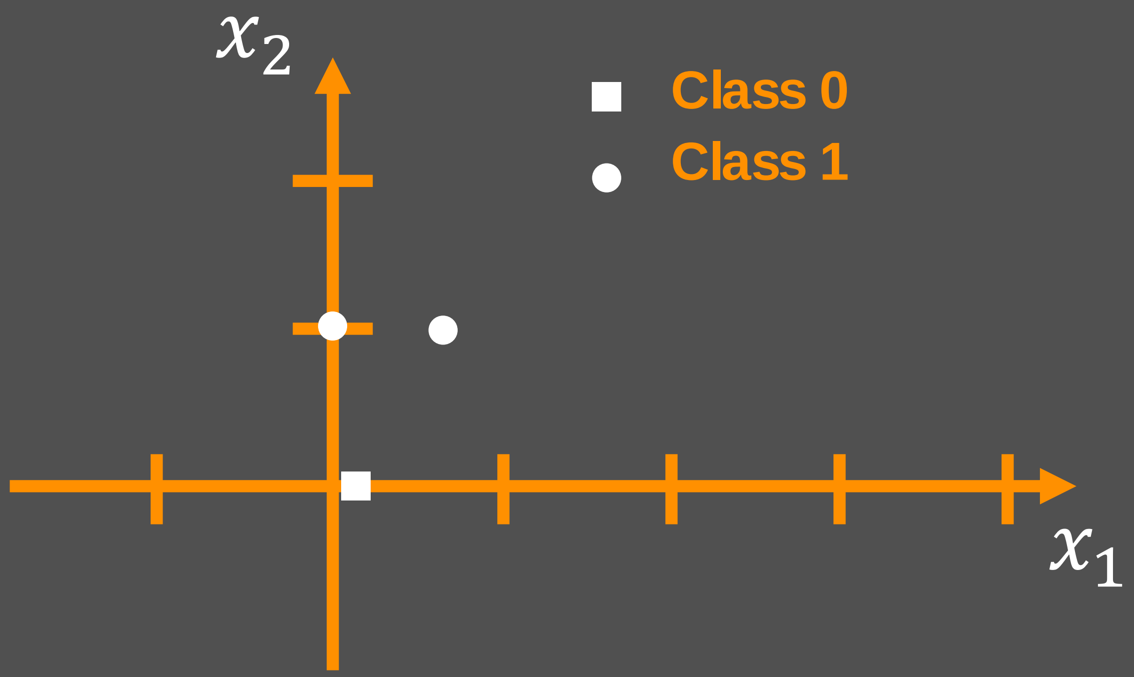


Append x_0

x_0	x_1	x_2	y
1	0.1	0	0
1	0.6	1	1
1	0	1	1

Perceptron-Model





Perceptron

Initialize weights randomly

$\theta_0 = -0.5, \theta_1 = 1, \theta_2 = -1$

foreach x **in trainingsset{**

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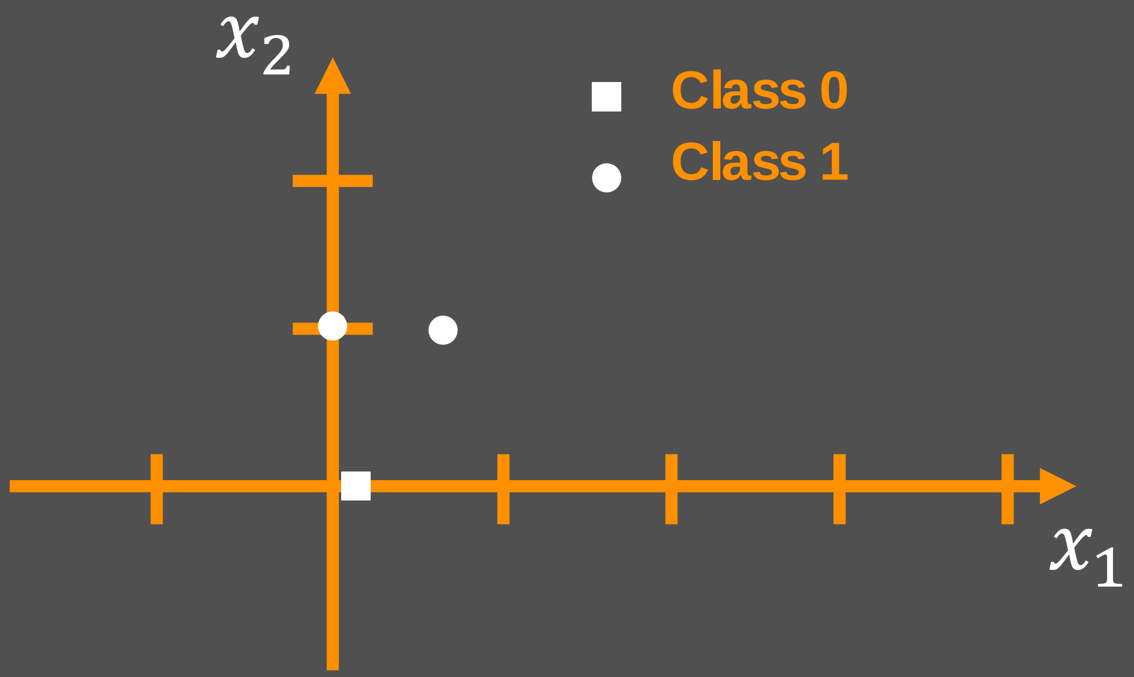

Perceptron

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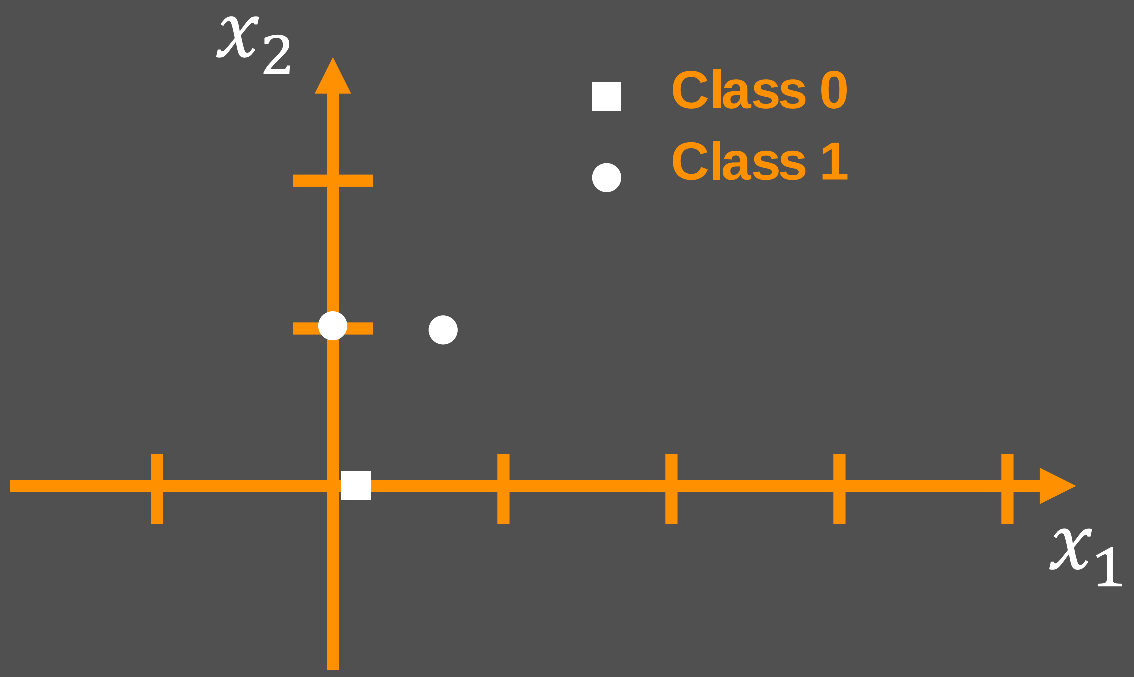

Perceptron

Perceptron-Model

$$z = \theta_2 * x_2 + \theta_1 * x_1 + \theta_0 * x_0$$

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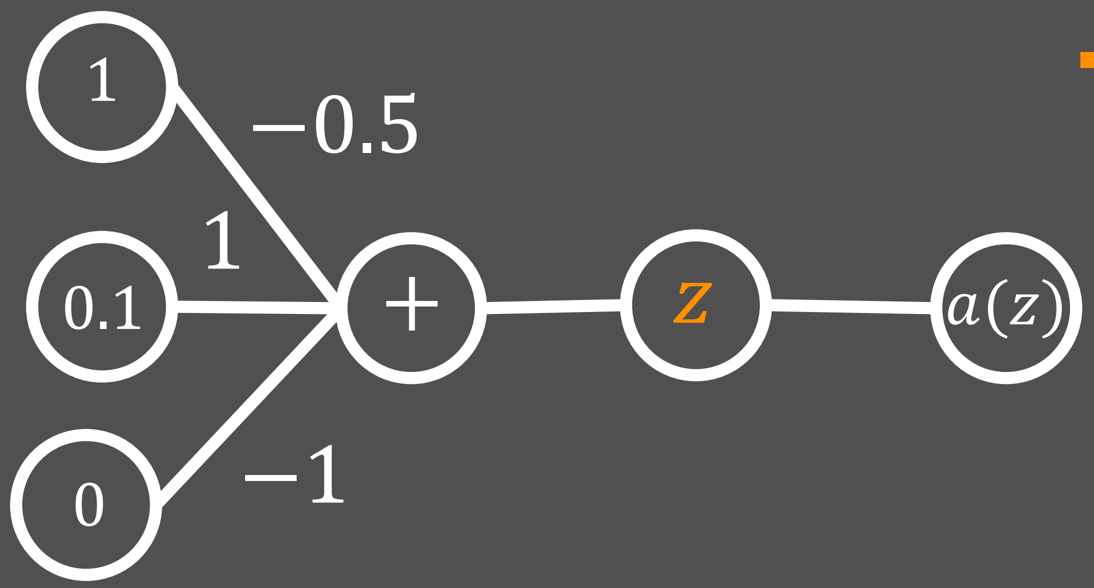

x_0	x_1	x_2	y
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1	0	1	1

Perceptron

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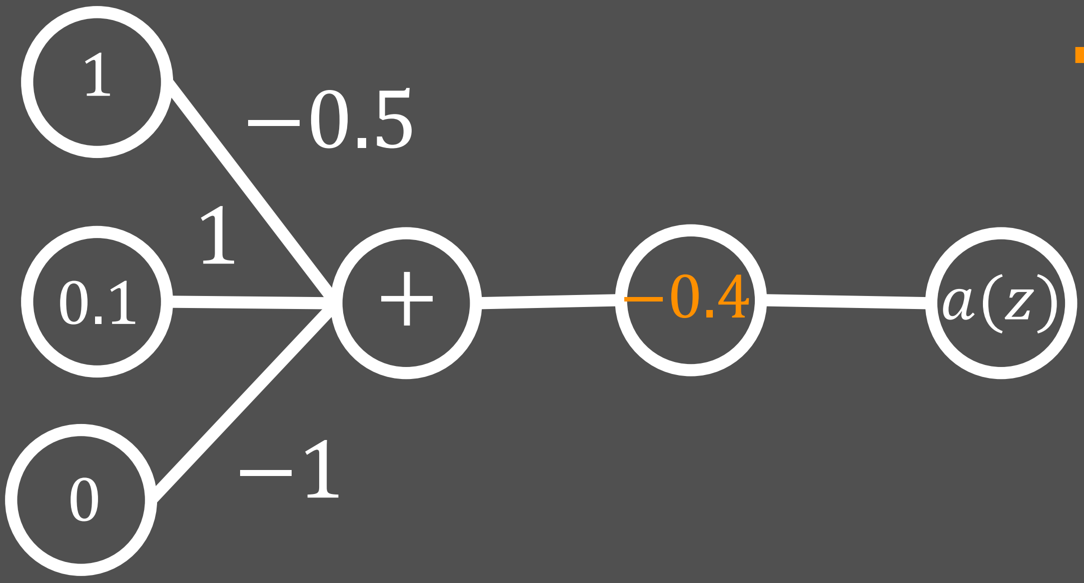

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Perceptron

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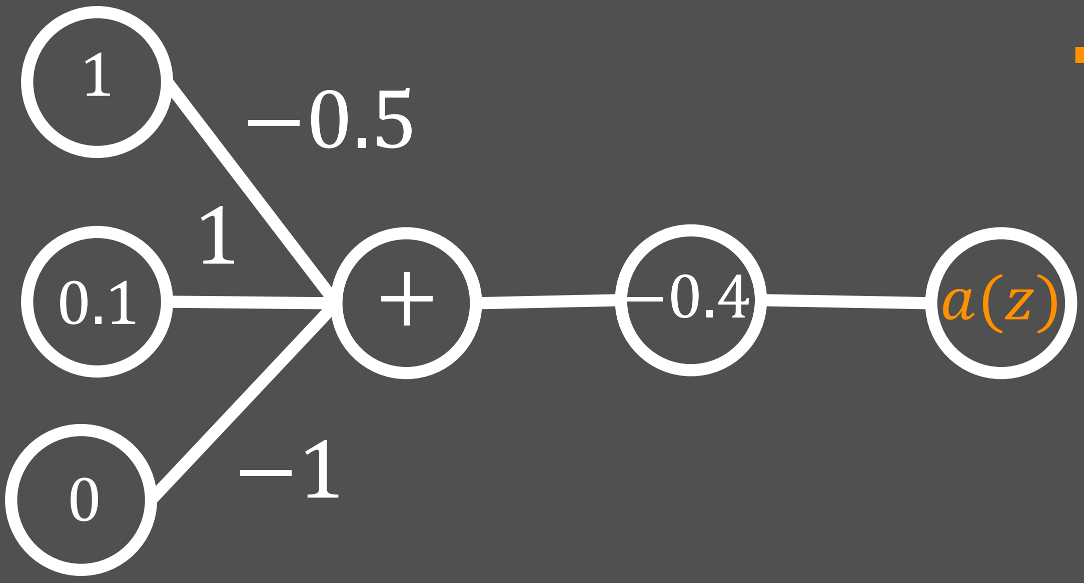
$$\theta_0 = -0.5, \theta_1 = 1, \theta_2 = -1$$

$$a(z) = \begin{cases} 0, z < 0 \\ 1, z \geq 0 \end{cases}$$



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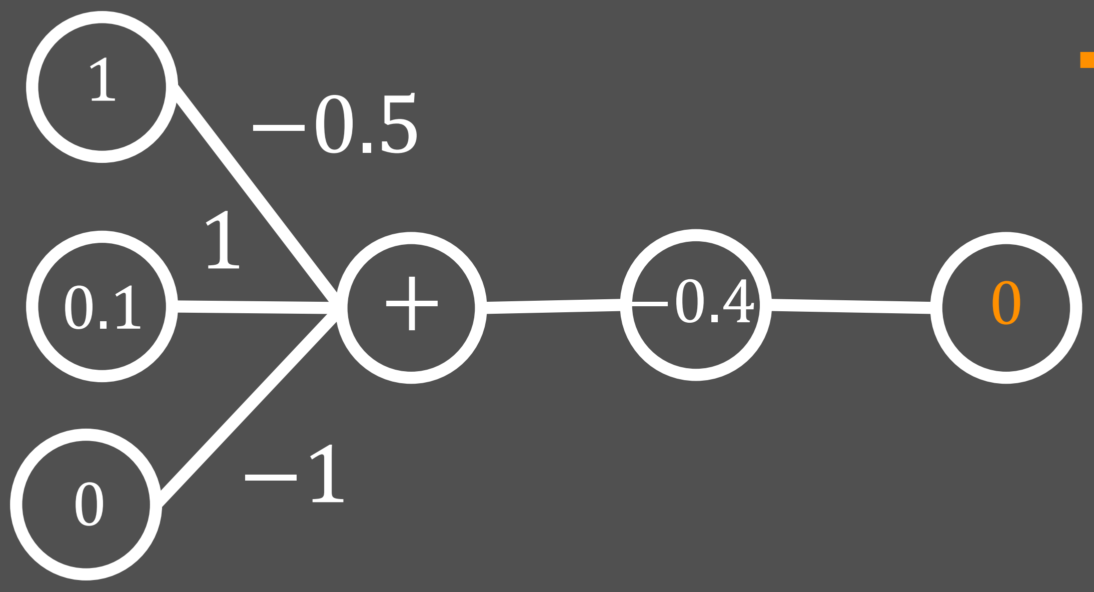

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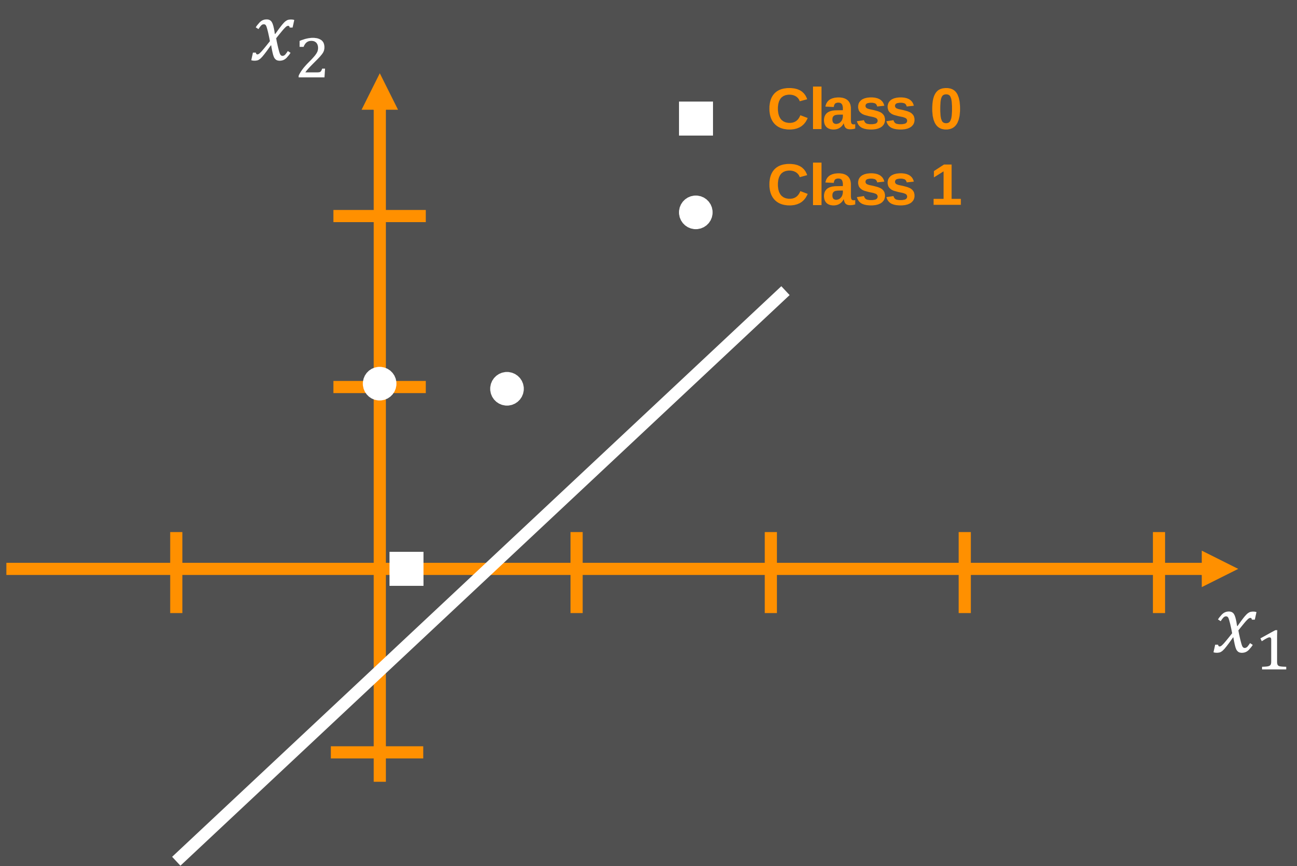

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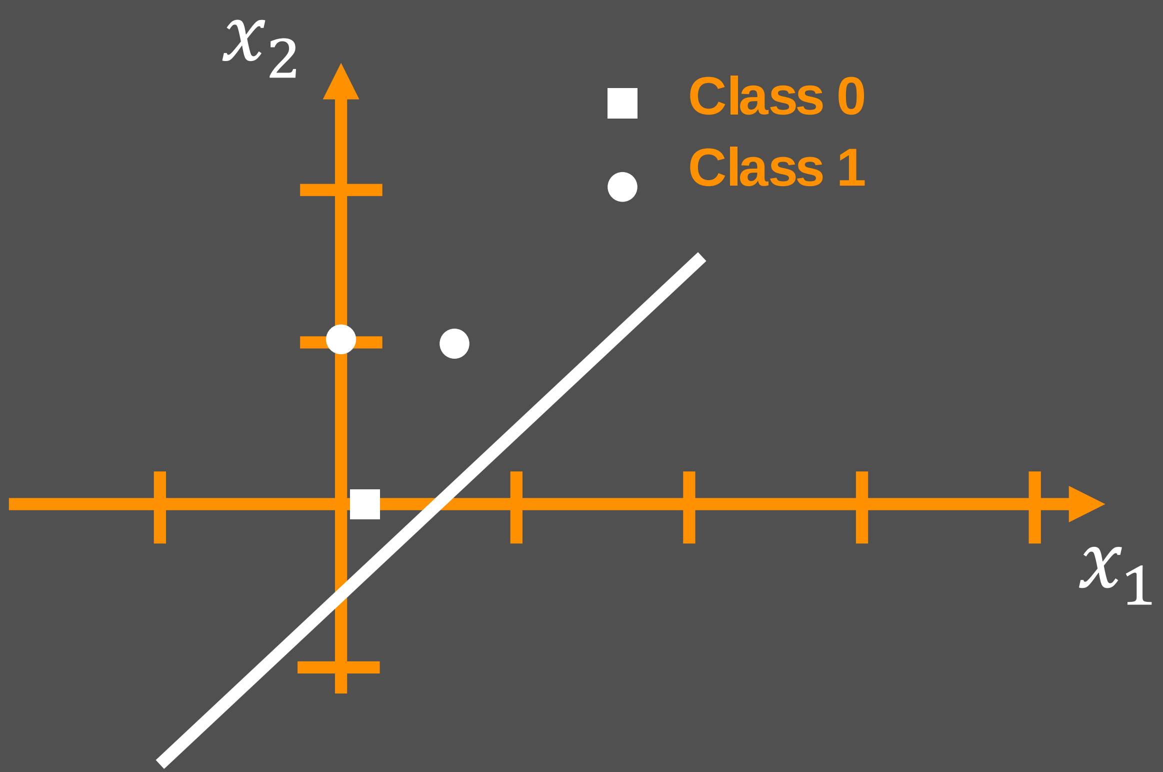

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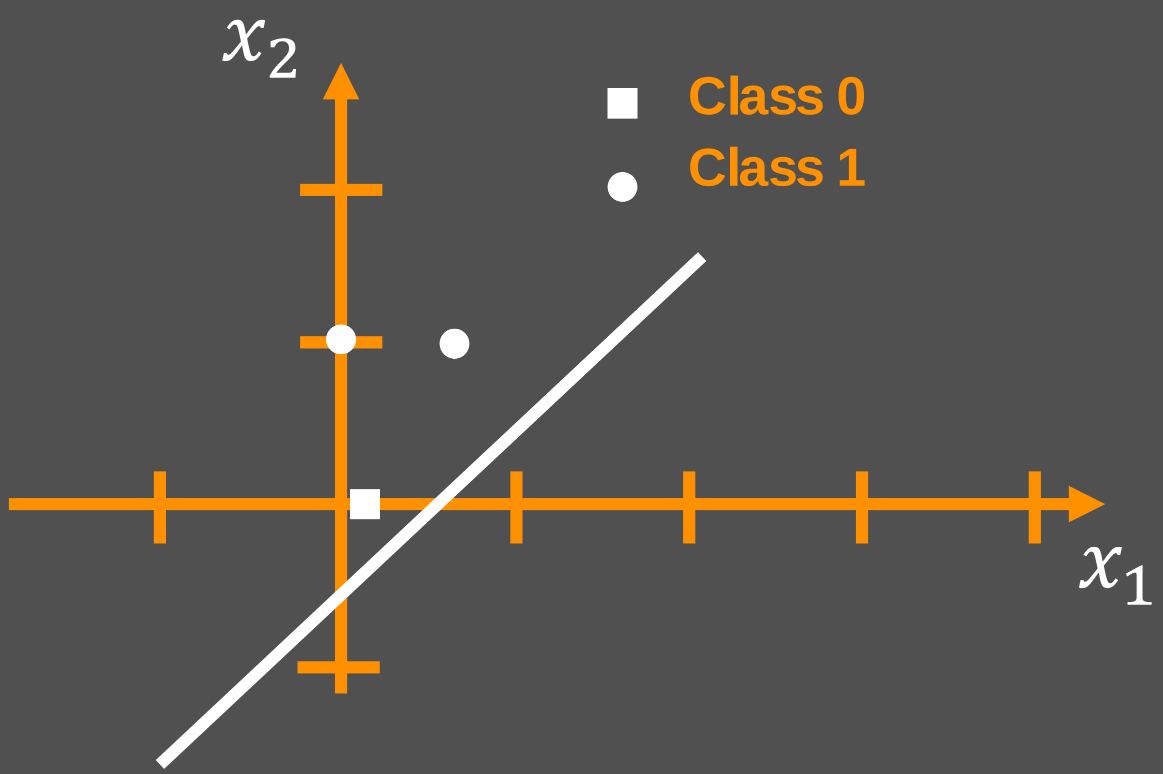

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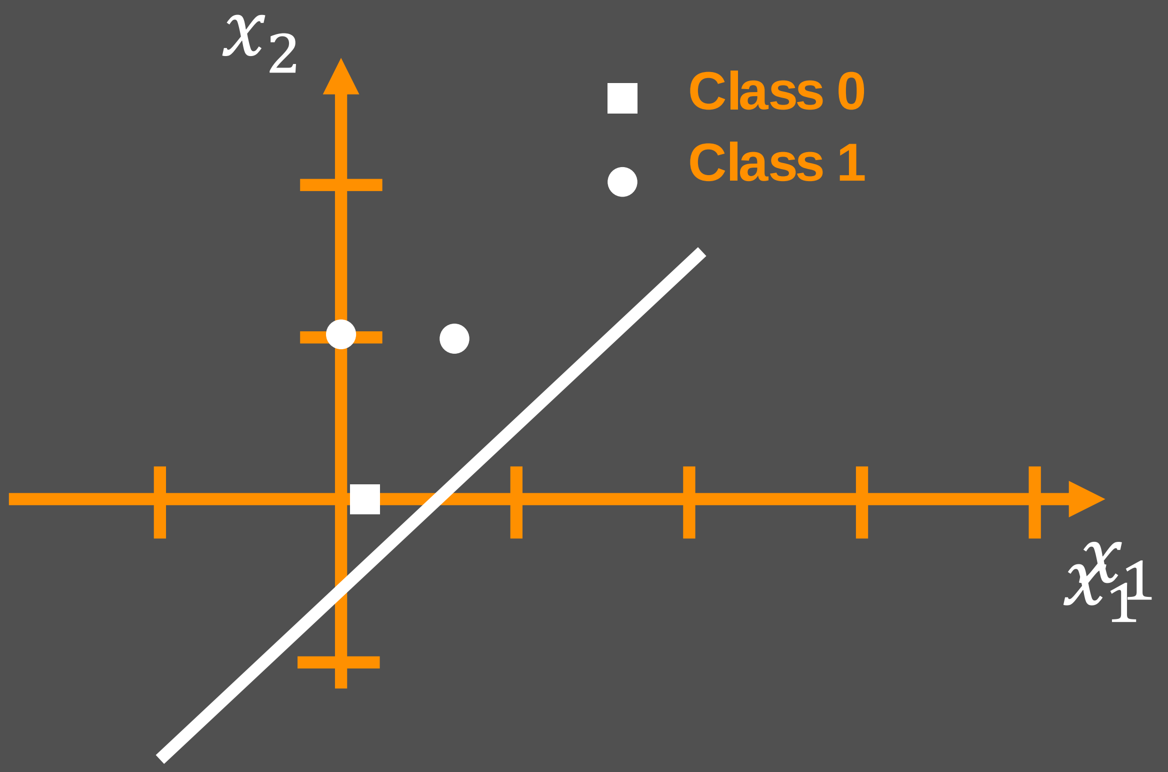

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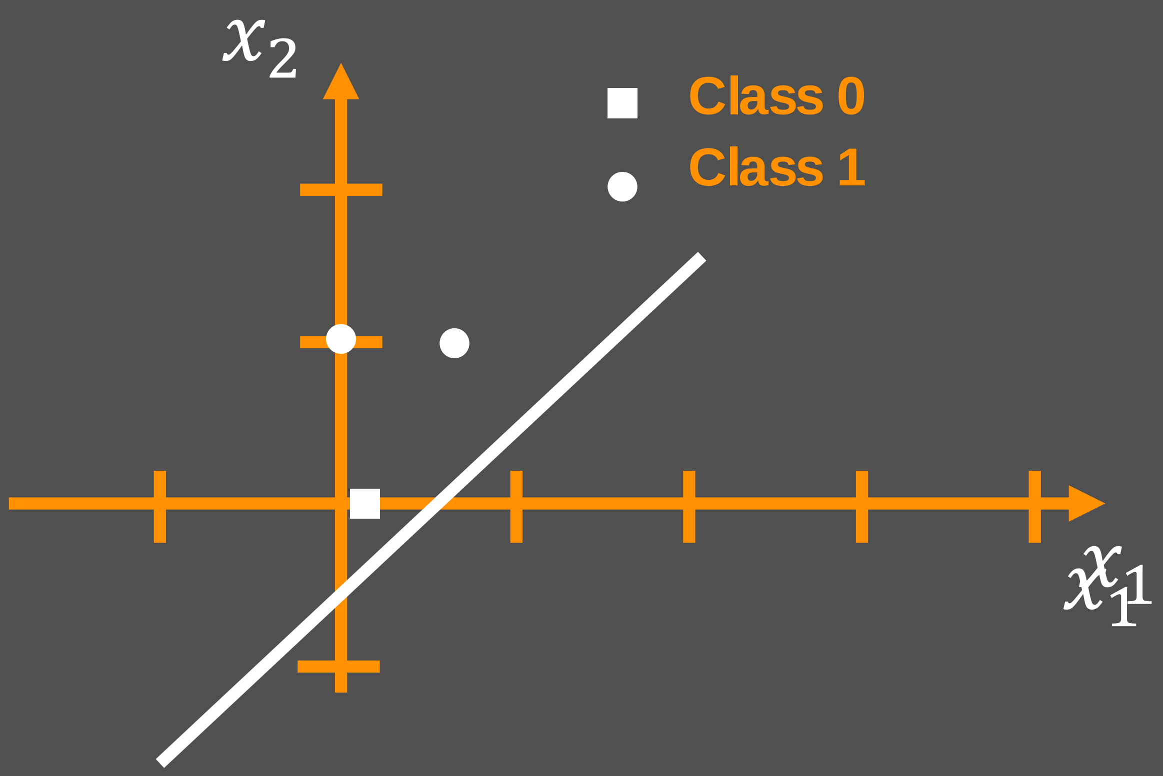

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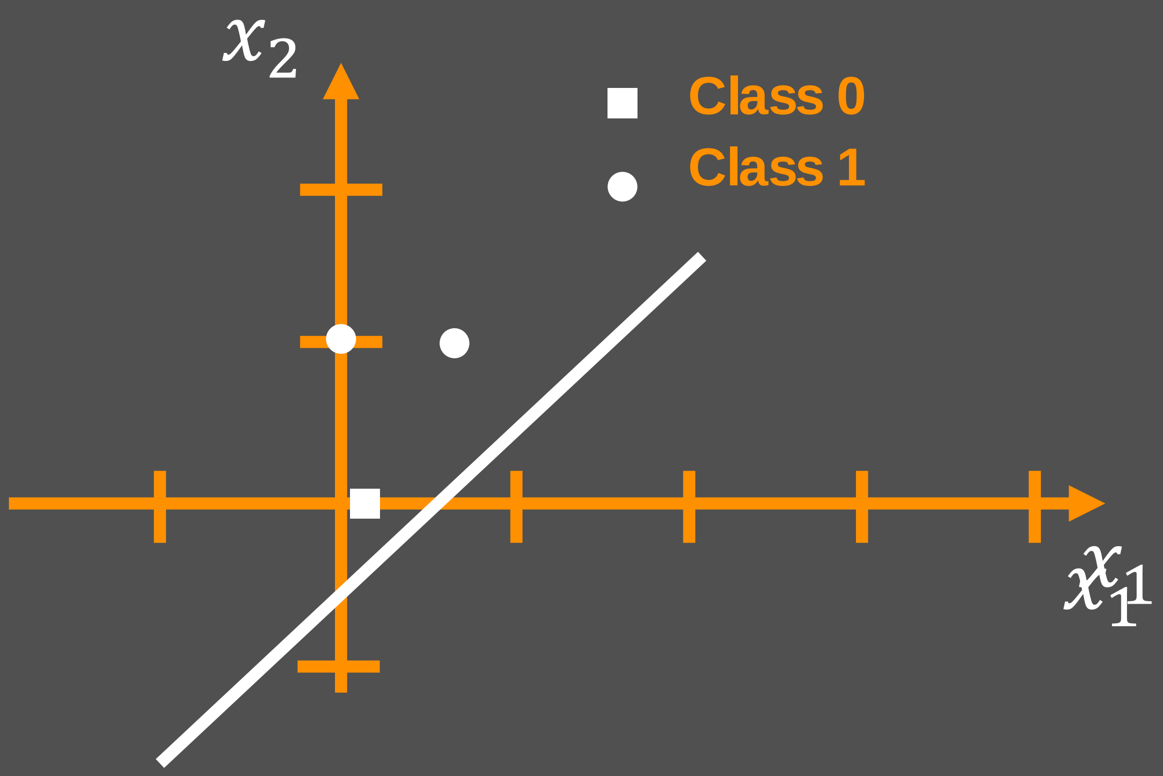

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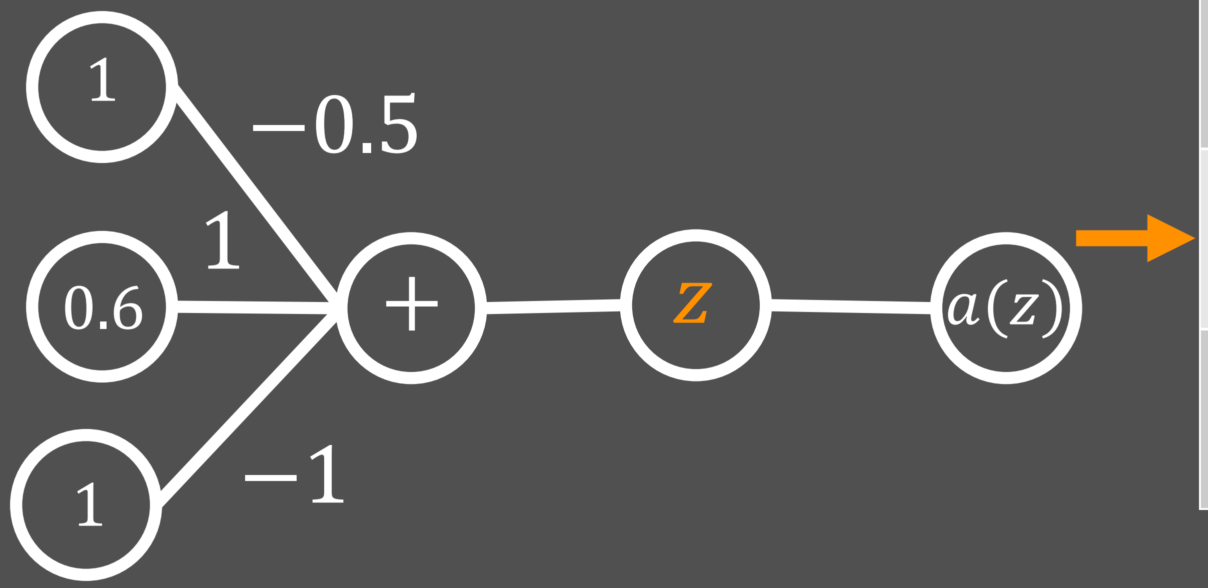

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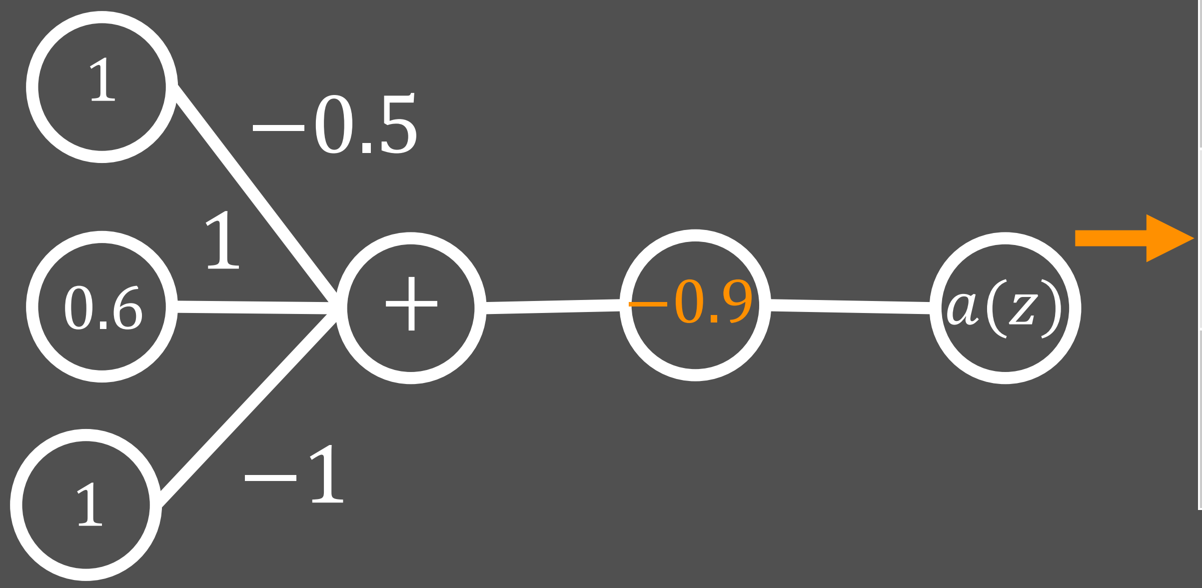

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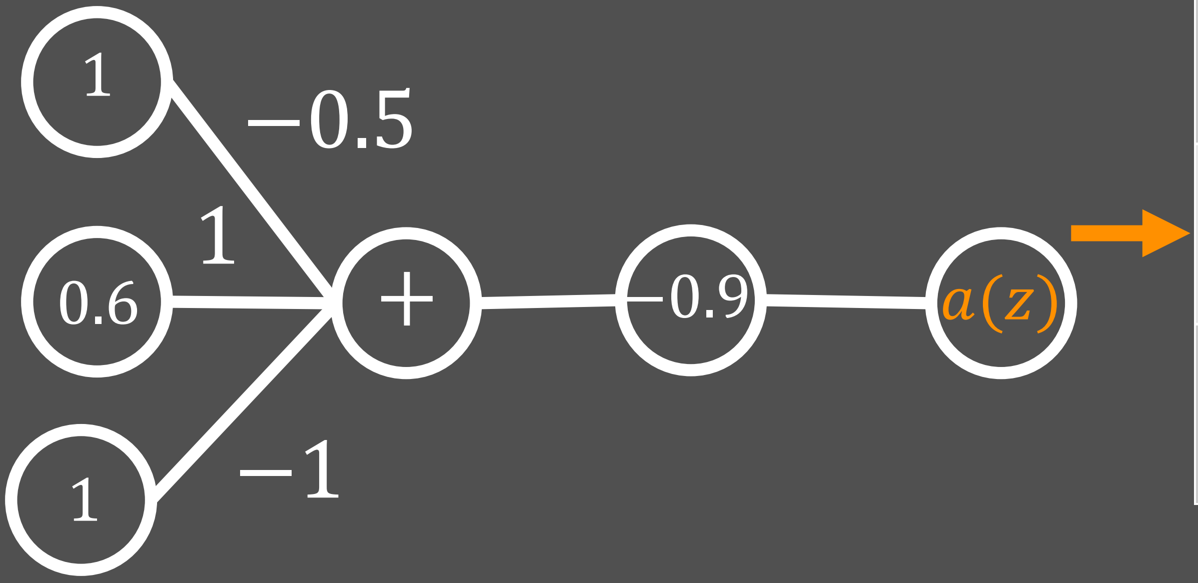

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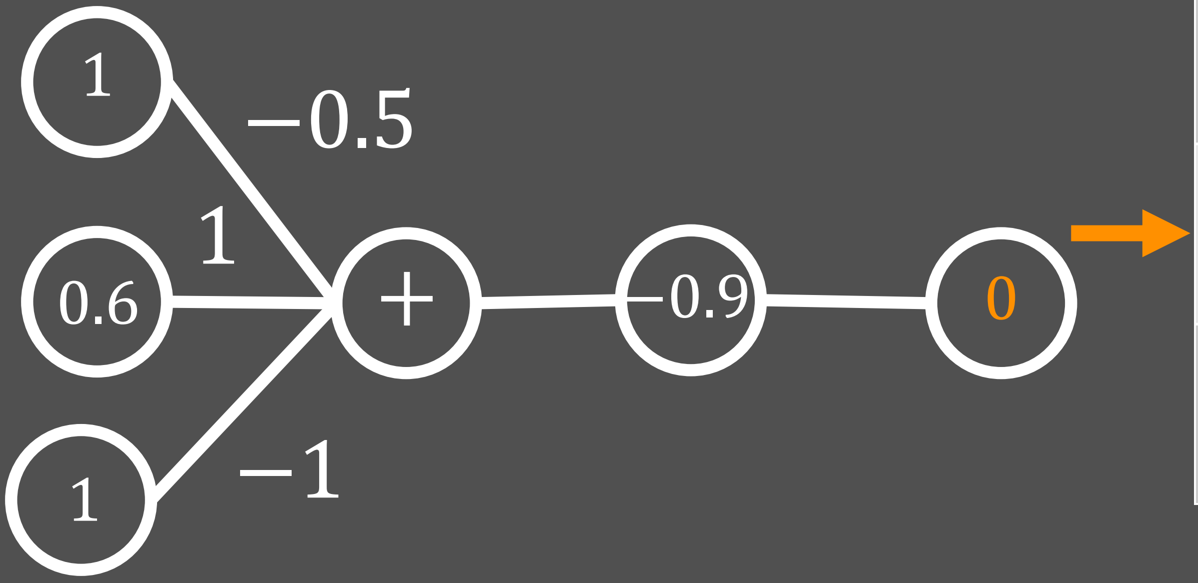

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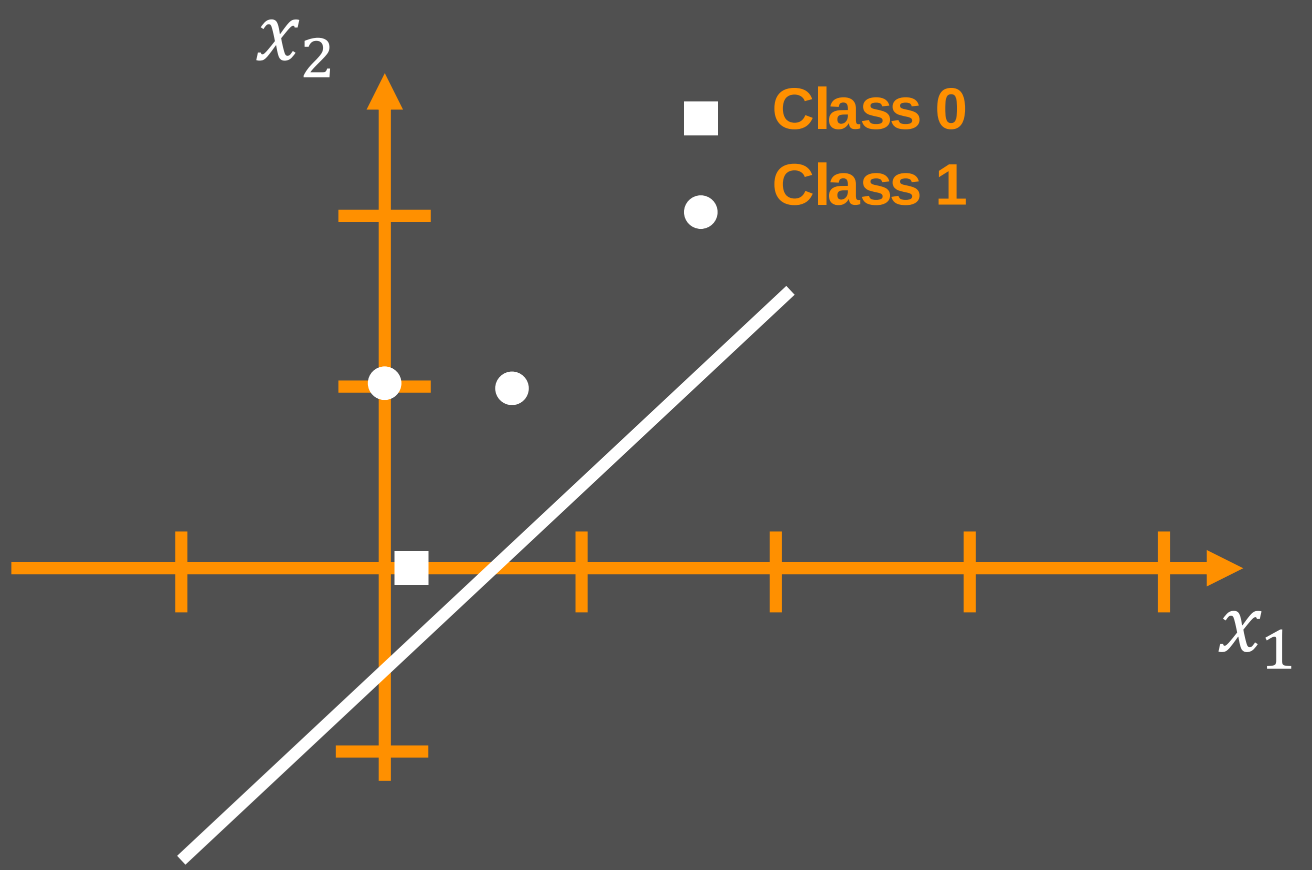

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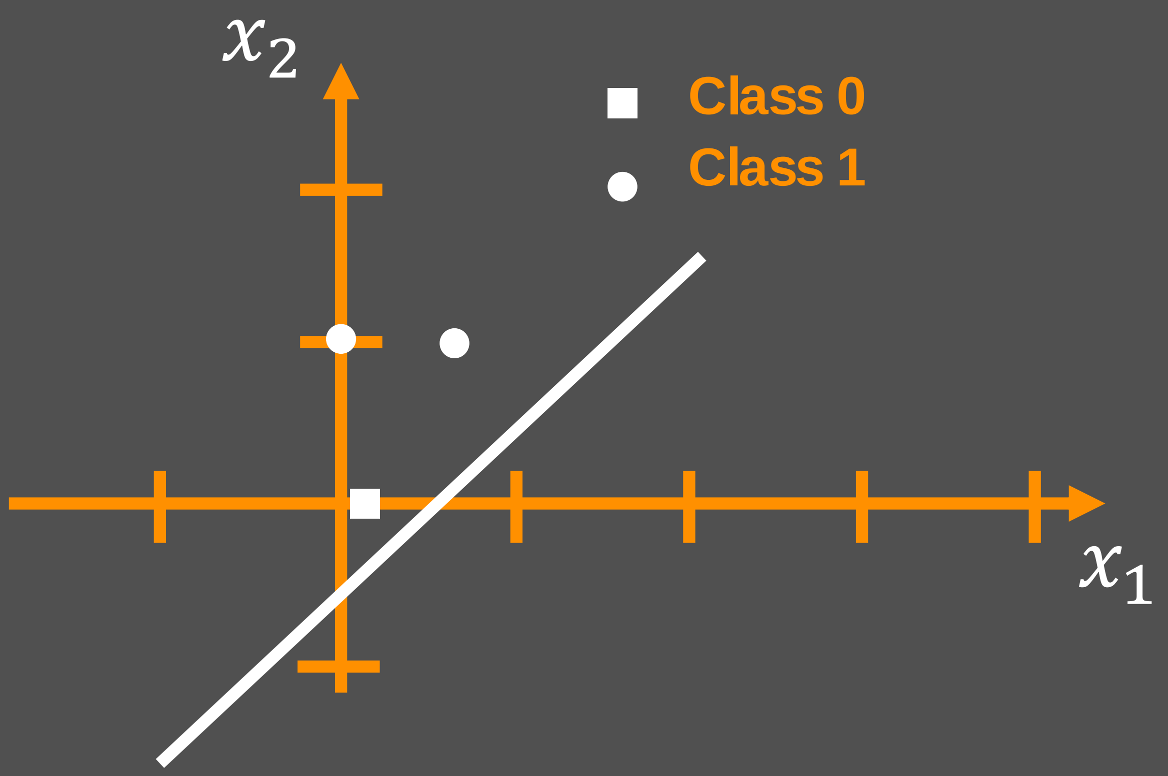

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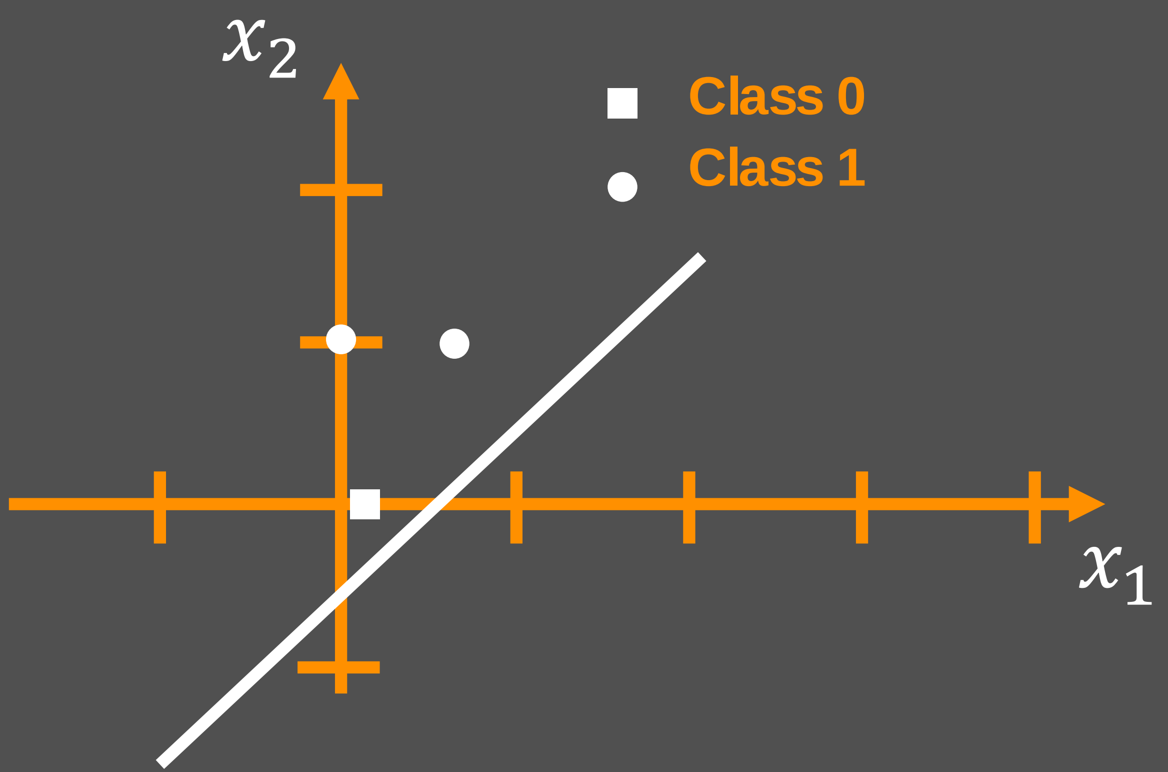

Perceptron

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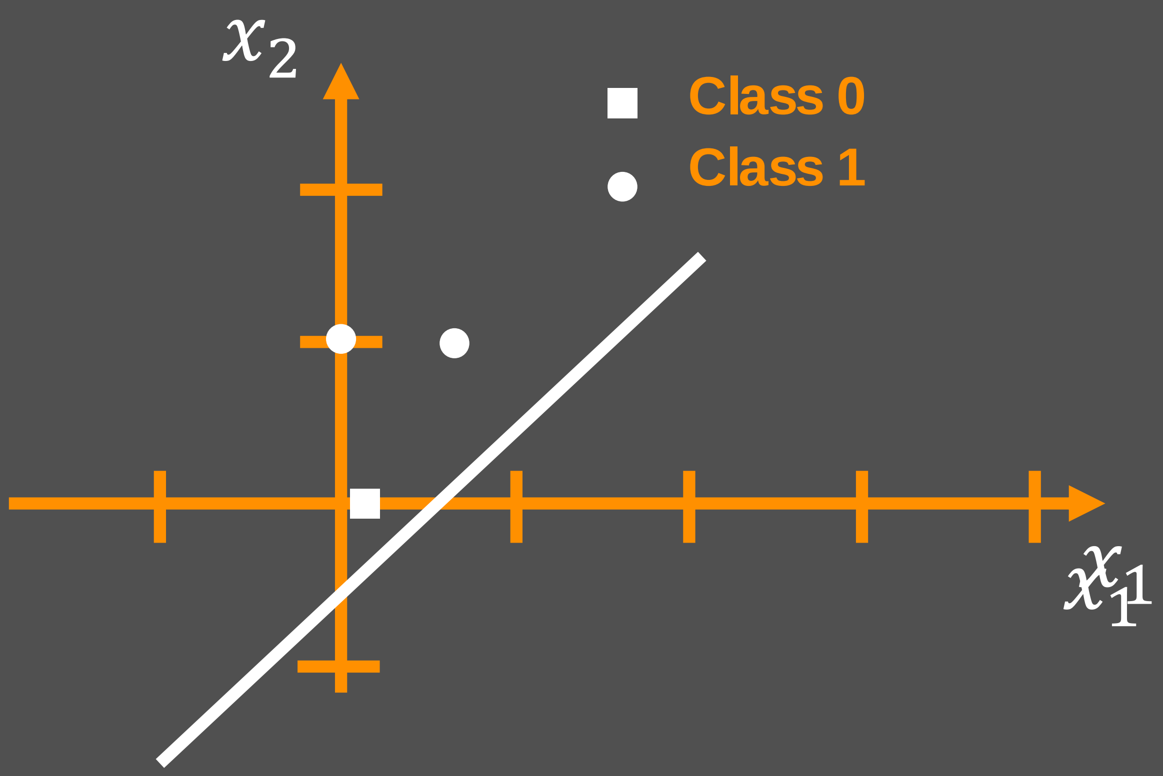

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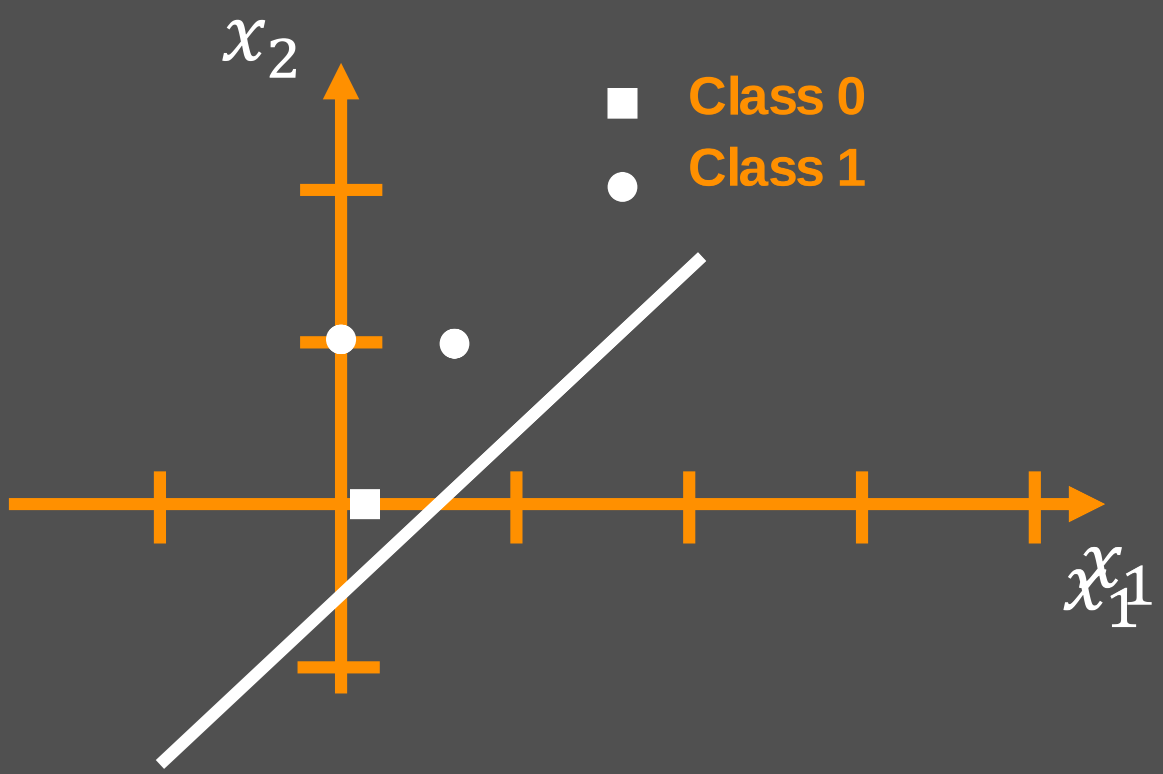

if(d==1) θ=θ+x

$$\theta = \begin{pmatrix} -0.5 \\ 1 \\ -1 \end{pmatrix} + \begin{pmatrix} 1 \\ 0.6 \\ 1 \end{pmatrix}$$

$$\theta = \begin{pmatrix} 0.5 \\ 1.6 \\ 0 \end{pmatrix}$$

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$$x_2\theta_2 + x_1\theta_1 + x_0\theta_0 = 0$$
$$1.6x_1 + 0.5 = 0$$
$$x_1 = -\frac{0.5}{1.6} = -0.3125$$

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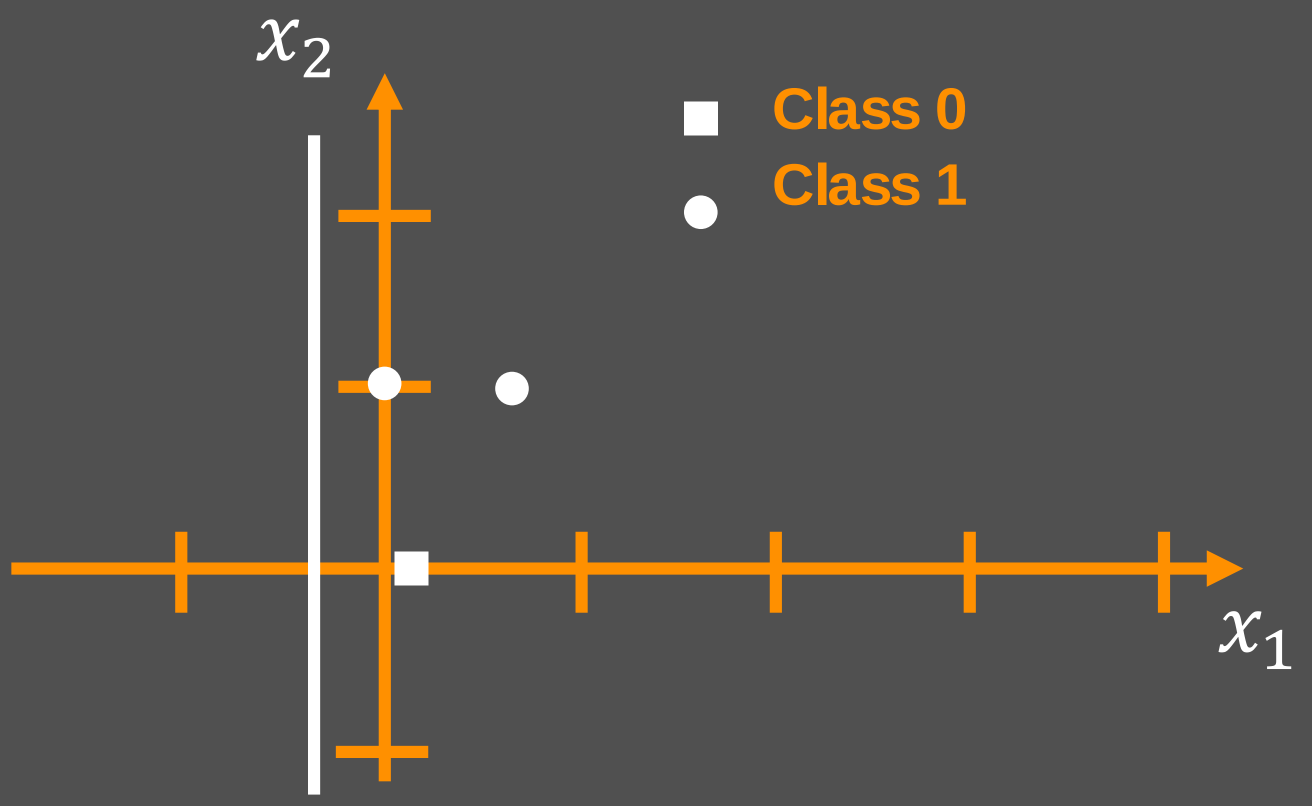

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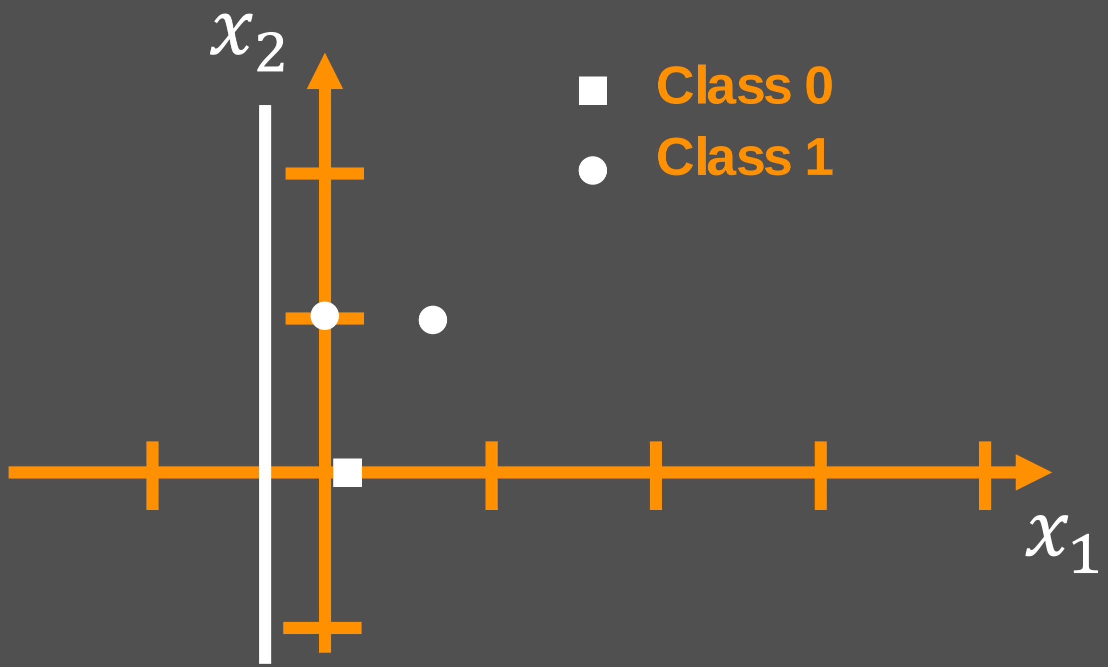

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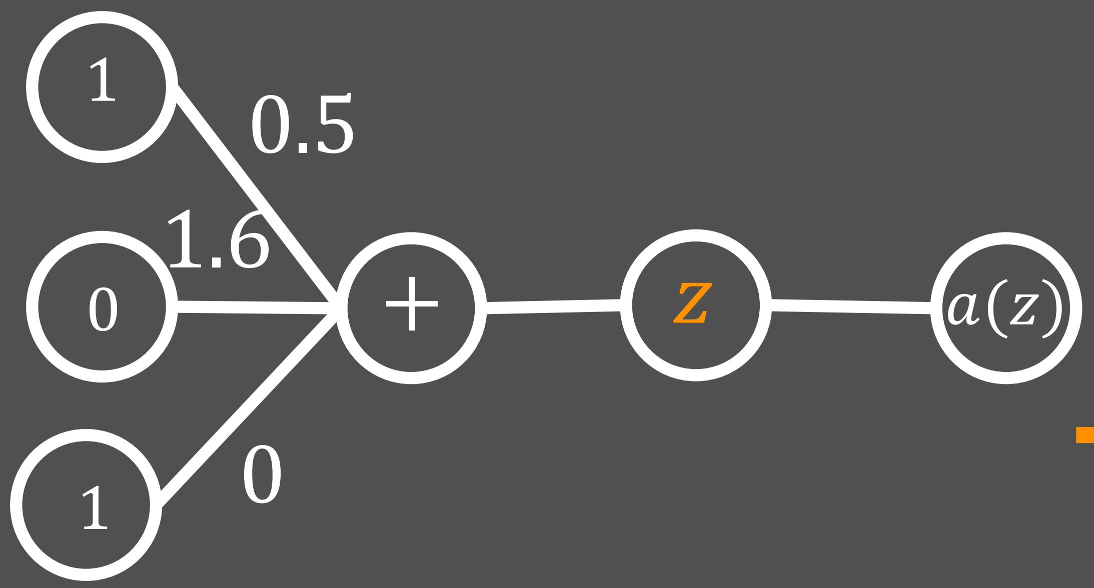

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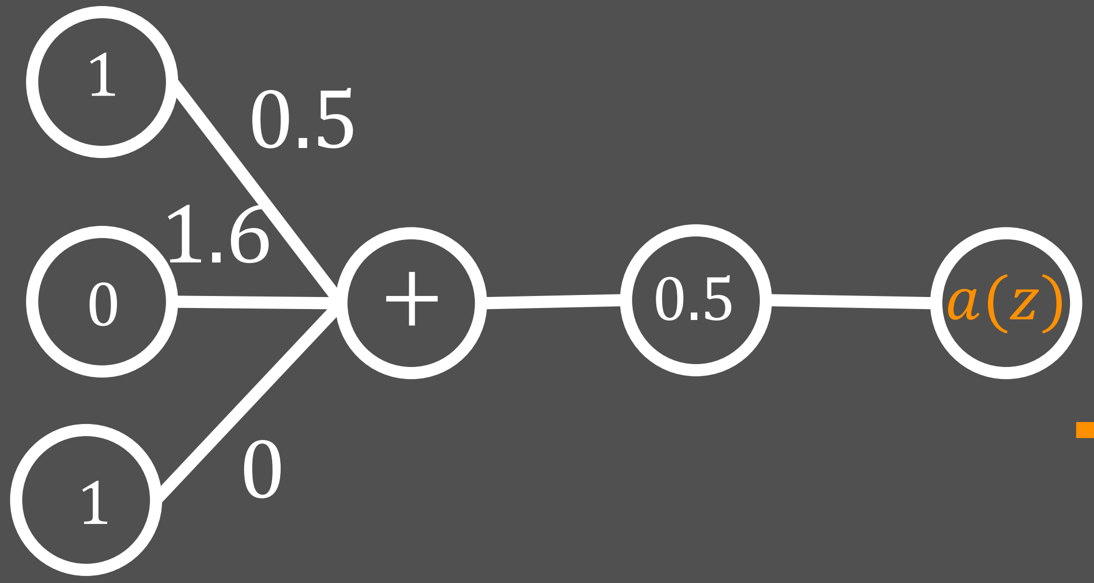

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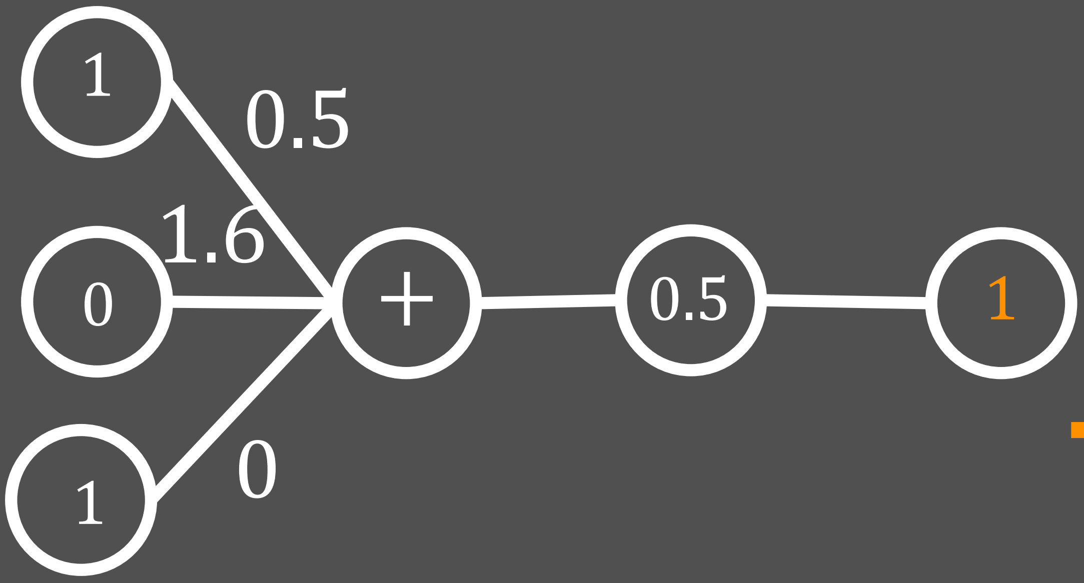

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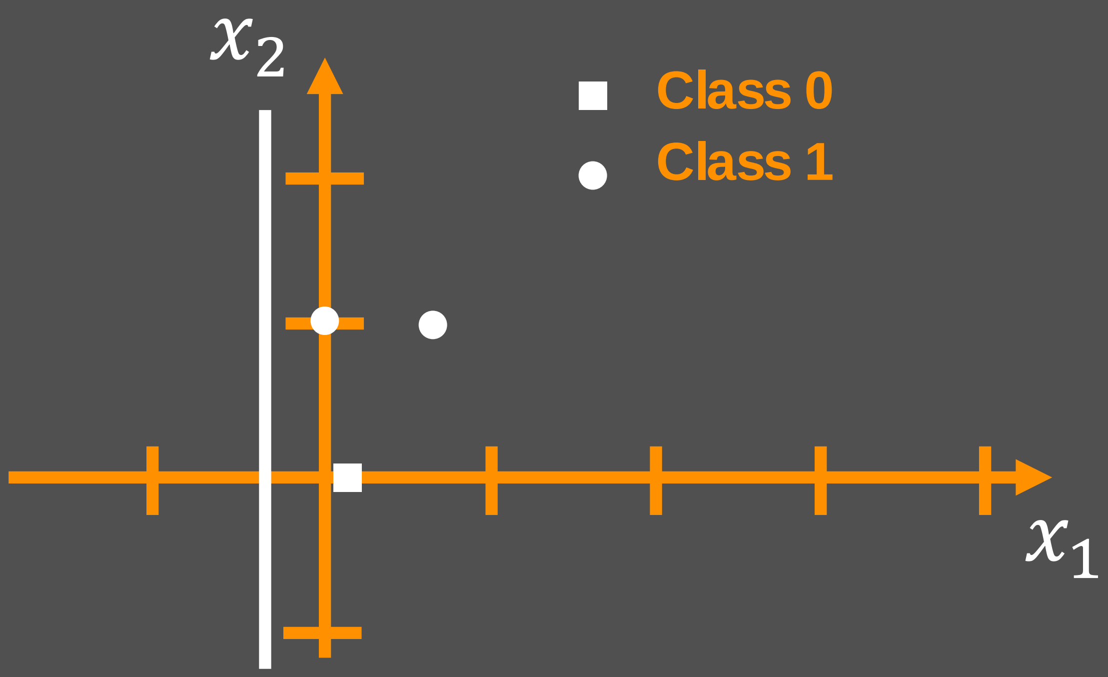

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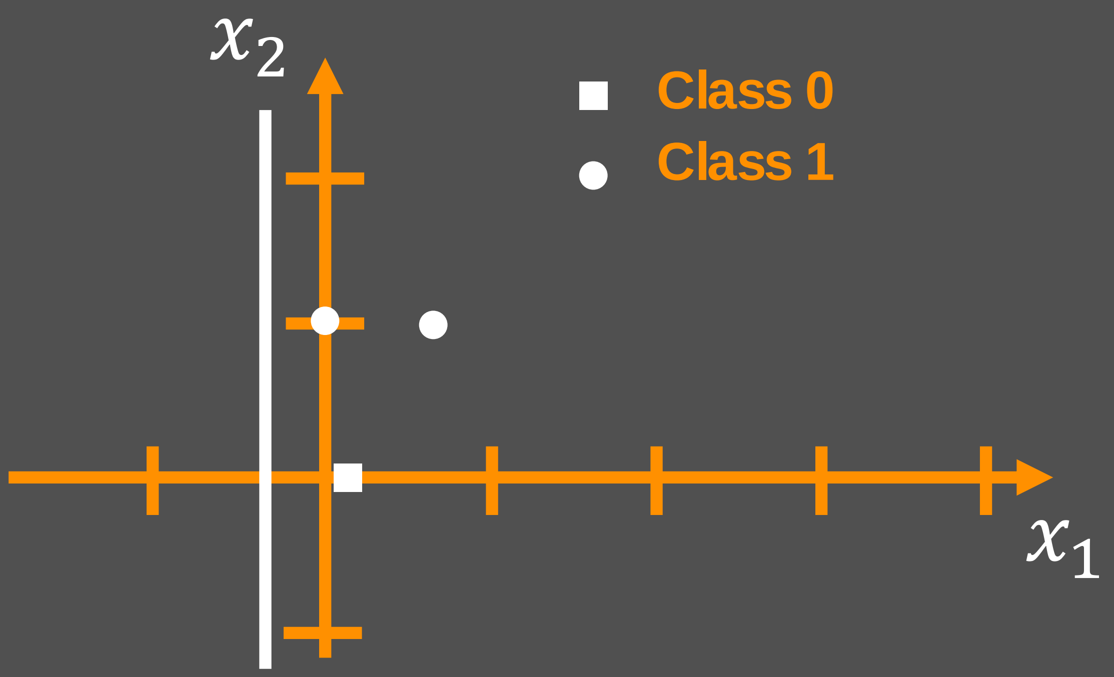

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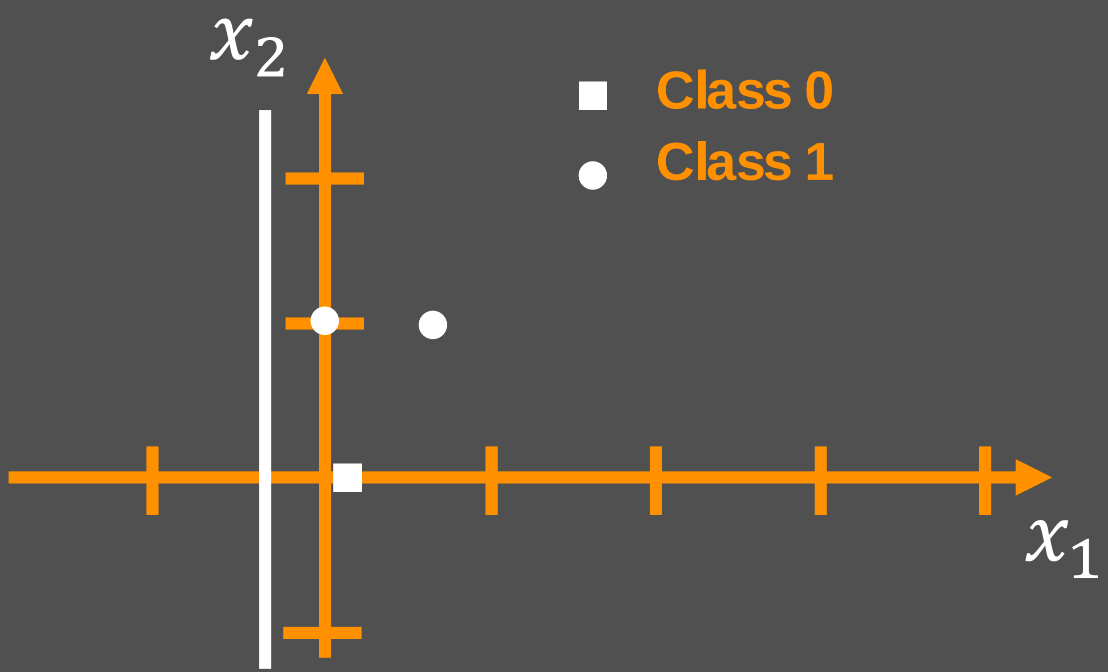

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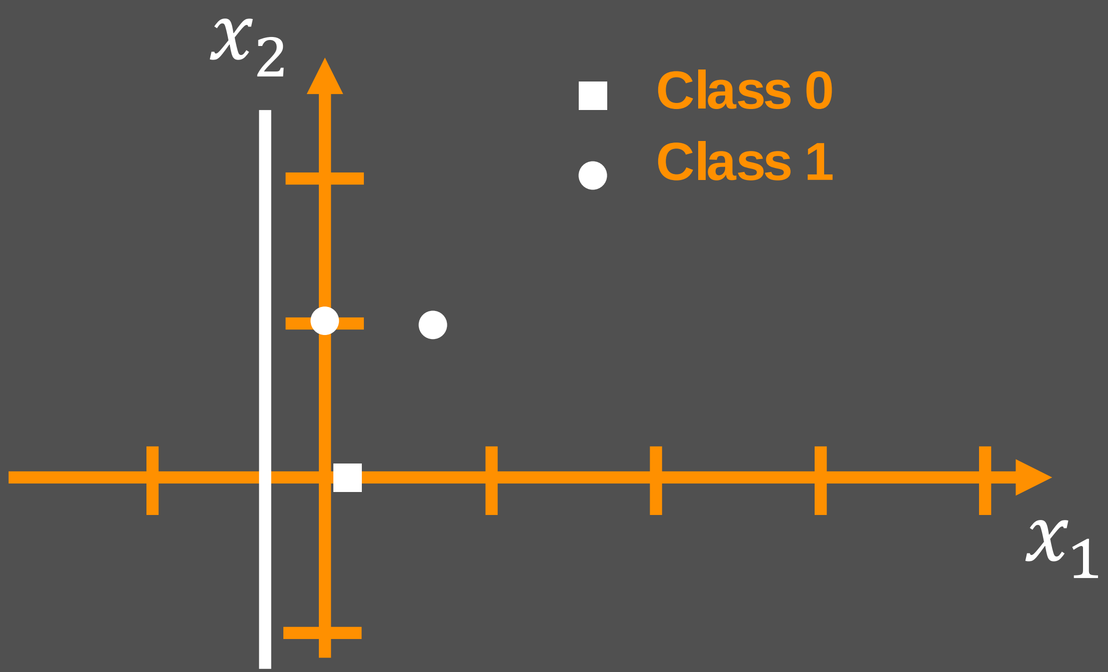

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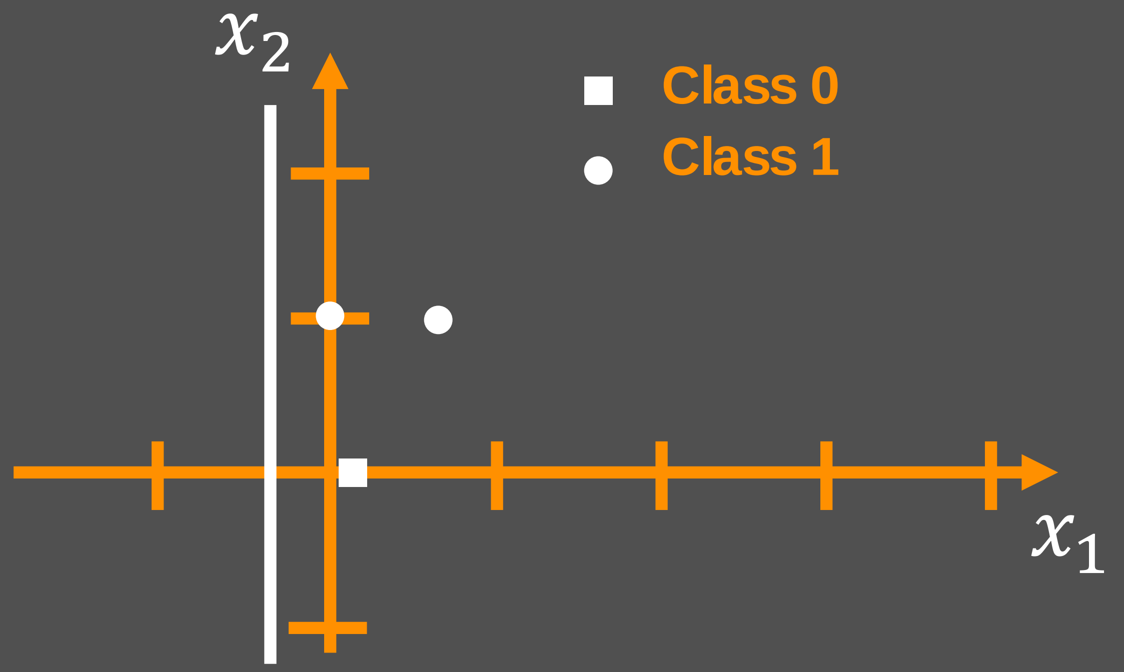
}

$$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0$$

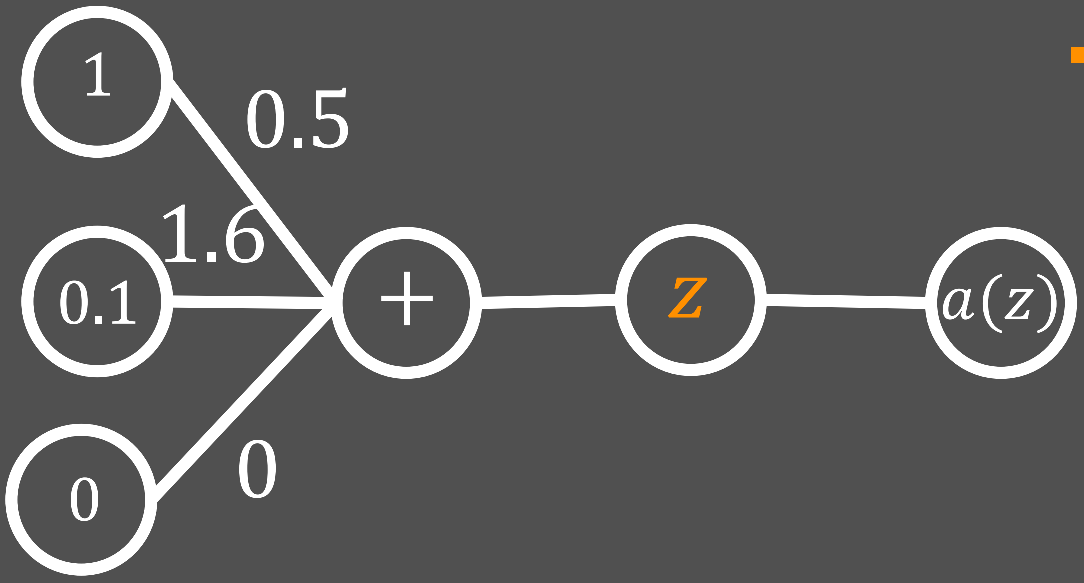


Perceptron

Perceptron-Model

$z = \theta_1 * x_1 + \theta_0 * x_0$

$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0$



x_0	x_1	x_2	y
1	0.1	0	0
1	0.6	1	1
1	0	1	1

Perceptron

Perceptron-Model

$z = \theta_1 * x_1 + \theta_0 * x_0$

$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0$

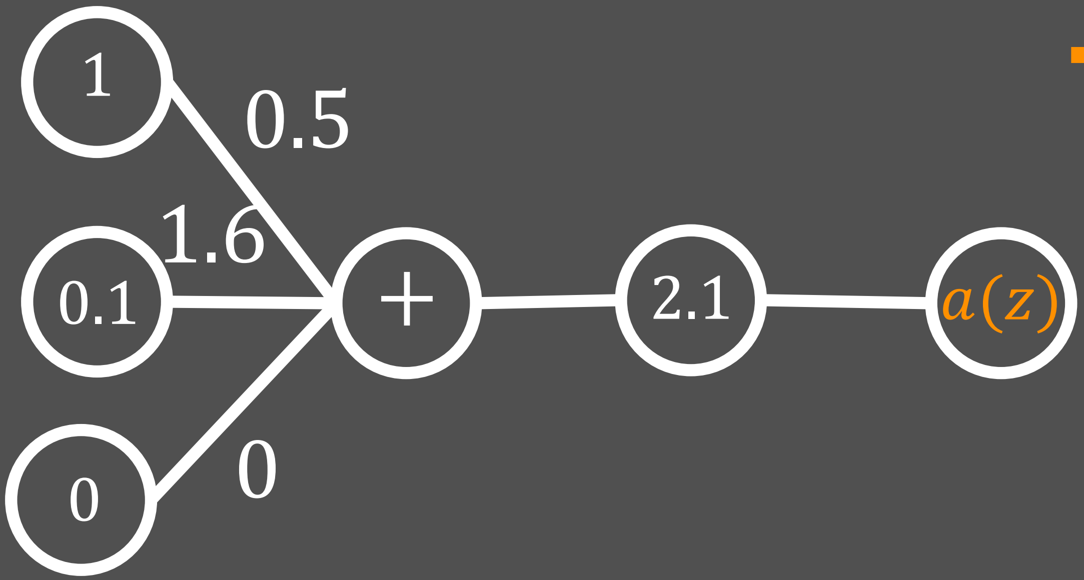
x_0	x_1	x_2	y
1	0.1	0	0
1	0.6	1	1
1	0	1	1

Perceptron

Perceptron-Model

$$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0$$

$$a(z) = \begin{cases} 0, z < 0 \\ 1, z \geq 0 \end{cases}$$

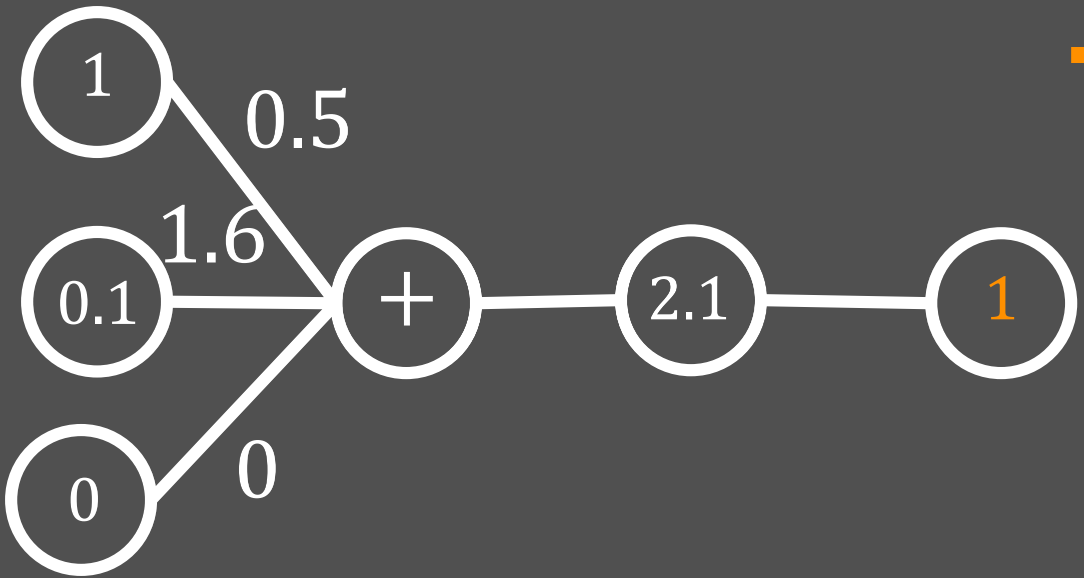


x_0	x_1	x_2	y
1	0.1	0	0
1	0.6	1	1
1	0	1	1

Perceptron-Model

$$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0$$

$$\hat{y} = a(z) = \begin{cases} 0, z < 0 \\ 1, z \geq 0 \end{cases}$$



x_0	x_1	x_2	y
1	0.1	0	0
1	0.6	1	1
1	0	1	1

Perceptron

Initialize weights randomly

foreach x in trainingsset{

  $\hat{y}$**=Prediction(**x**),** $\hat{y}\epsilon\{0,1\}$

  $\mathrm{d} = \mathrm{y} - \hat{y}, y\epsilon\{0,1\}$

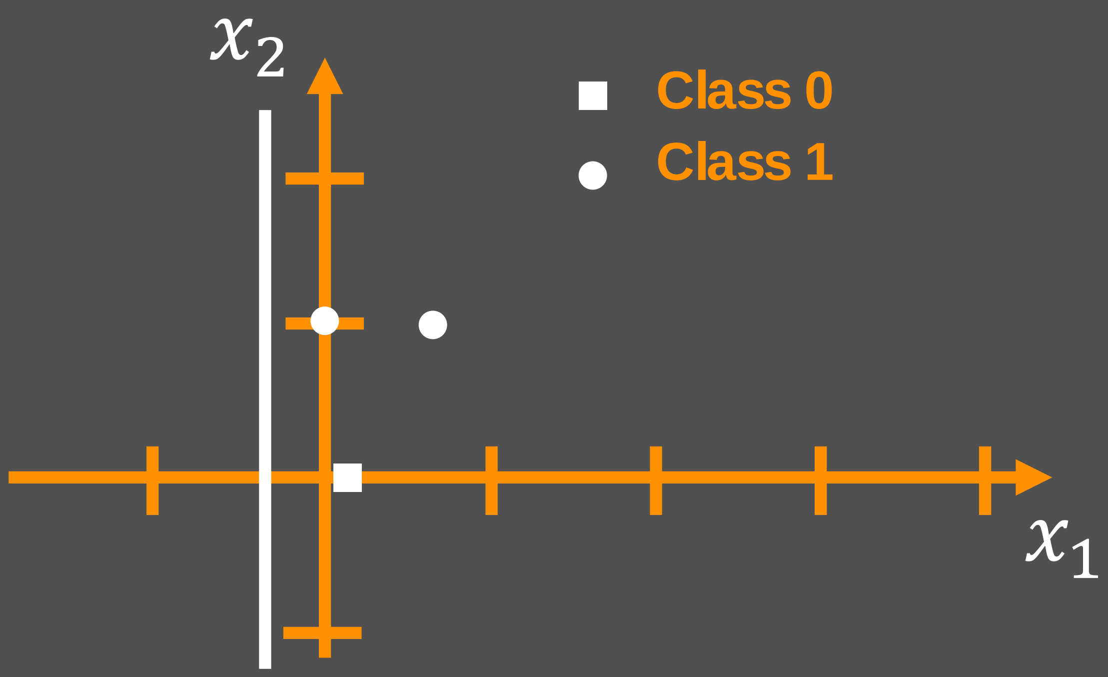
  if($d == 1$**)** $\theta = \theta + x$

  elif ($d == -1$**)** $\theta = \theta - x$

}

$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0,$

$\hat{y} = 1$



Perceptron

Initialize weights randomly

foreach x in trainingsset{

  $\hat{y}$=Prediction(x), $\hat{y}\epsilon\{0,1\}$

  $\mathrm{d} = \mathrm{y} - \hat{y}, y\epsilon\{0,1\}$

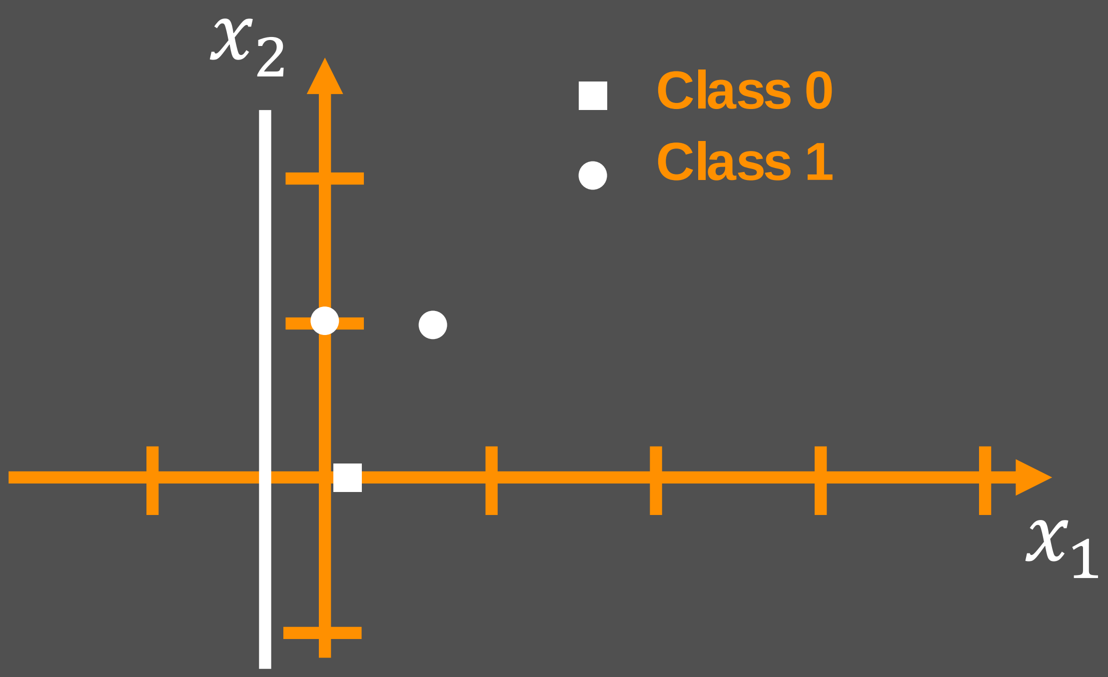
  if($d == 1$) $\theta = \theta + x$

  elif ($d == -1$) $\theta = \theta - x$

}

$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0,$

$\hat{y} = 1$



Hochschule Düsseldorf
University of Applied Sciences
Fachbereich Medien
Faculty of Media

Perceptron

Initialize weights randomly

foreach x in trainingsset{

 $\hat{y}$=**Prediction**(x), $\hat{y}\epsilon\{0,1\}$

 $\mathrm{d} = \mathrm{y} - \hat{y}, y\epsilon\{0,1\}$

 if($d == 1$) $\theta = \theta + x$

 elif ($d == -1$) $\theta = \theta - x$

}

$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0,$
$\hat{y} = 1, d = -1$

x_0	x_1	x_2	y
1	0.1	0	0
1	0.6	1	1
1	0	1	1

Perceptron

Initialize weights randomly

foreach x **in trainingsset{**

$\hat{y}$=**Prediction(**x**),** $\hat{y}\epsilon\{0,1\}$

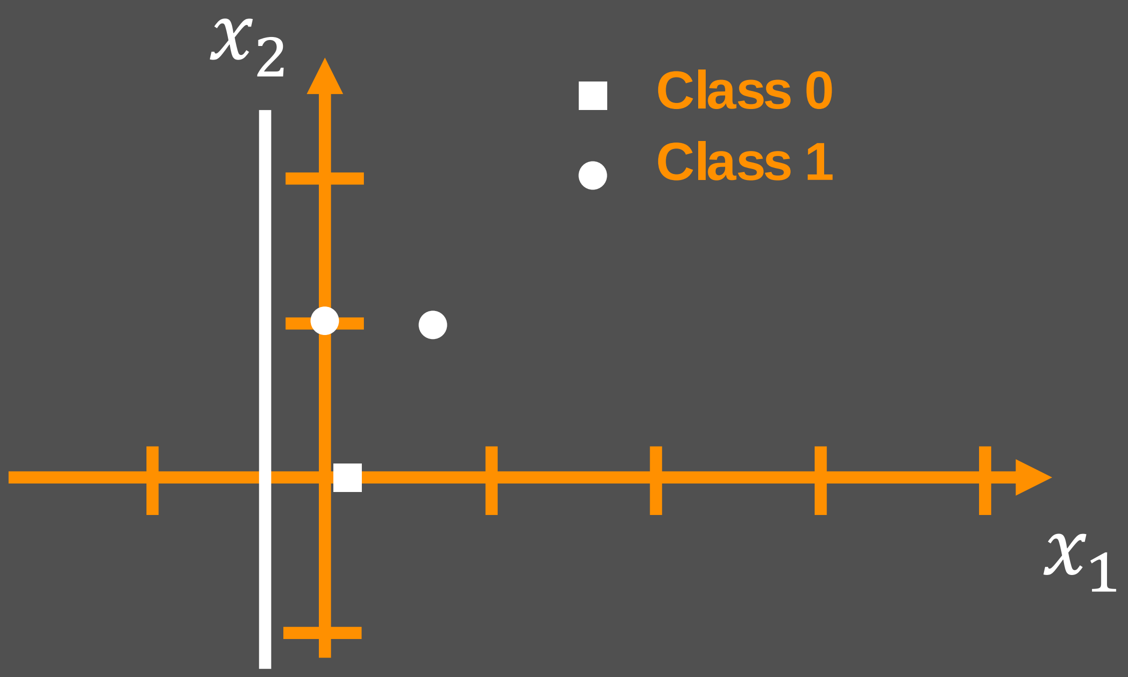
$\mathrm{d} = \mathrm{y} - \hat{y}, y\epsilon\{0,1\}$

if($d == 1$**)** $\theta = \theta + x$

elif ($d == -1$**)** $\theta = \theta - x$

}

$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0,$
$\hat{y} = 1, d = -1$



Perceptron

Initialize weights randomly

foreach x **in trainingsset{**

$\hat{y}$=**Prediction(**x**)**, $\hat{y}\epsilon\{0,1\}$

$\mathrm{d} = \mathrm{y} - \hat{y}, y\epsilon\{0,1\}$

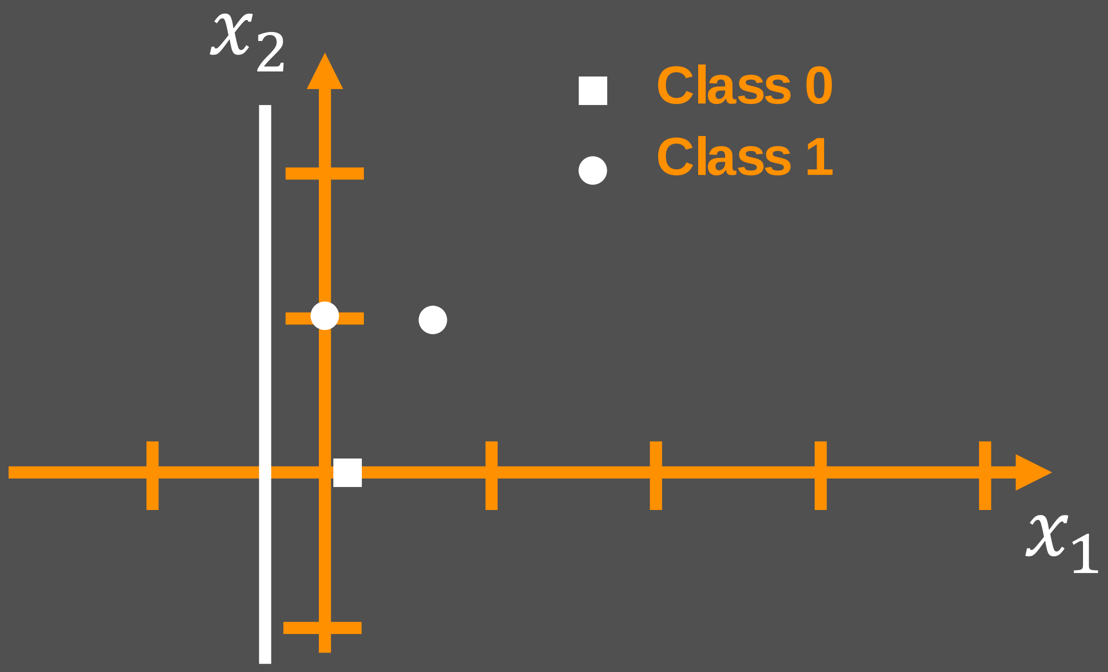
if($d == 1$**)** $\theta = \theta + x$

elif ($d == -1$**)** $\theta = \theta - x$

}

$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0,$

$\hat{y} = 1, d = -1$



Perceptron

Initialize weights randomly

foreach x **in trainingsset{**

$\hat{y}$=**Prediction(**x**),** $\hat{y}\epsilon\{0,1\}$

$\mathrm{d} = \mathrm{y} - \hat{y}, y\epsilon\{0,1\}$

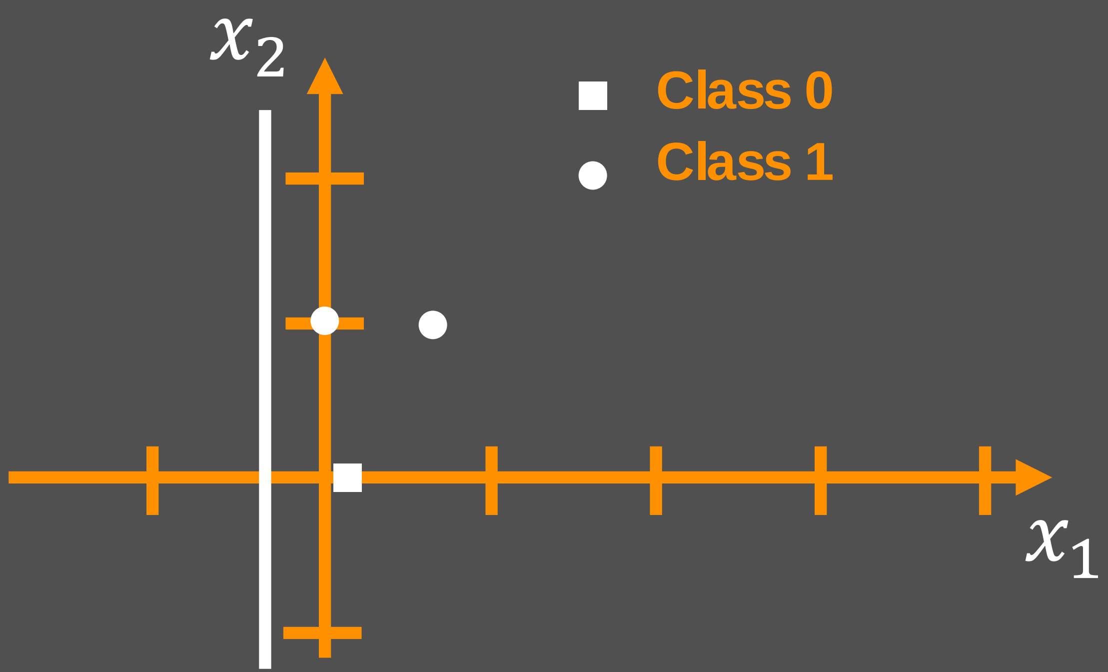
if($d == 1$**)** $\theta = \theta + x$

elif ($d == -1$**)** $\theta = \theta - x$

}

$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0,$

$\hat{y} = 1, d = -1$



if(d==-1) θ=θ-x

$$\theta = \begin{pmatrix} 0.5 \\ 1.6 \\ 0 \end{pmatrix} - \begin{pmatrix} 1 \\ 0.1 \\ 0 \end{pmatrix}$$

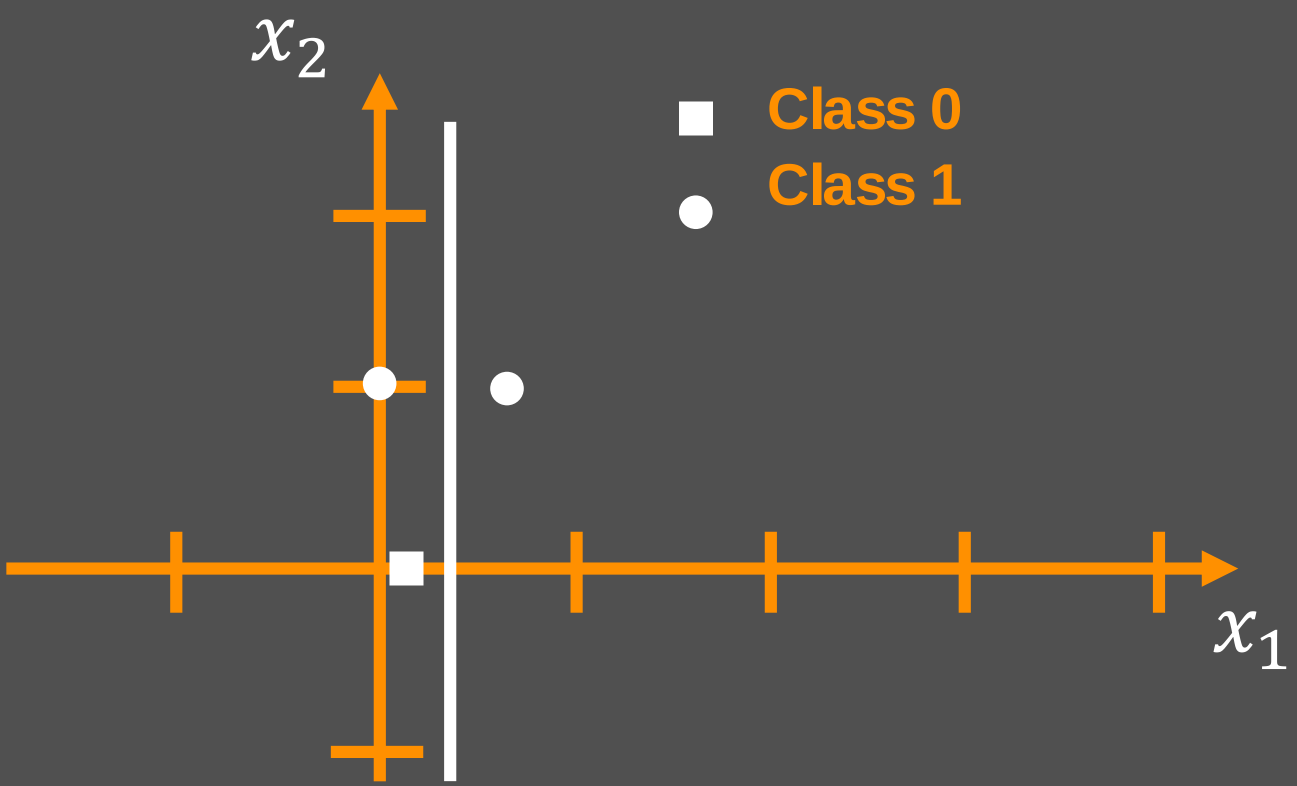
$$\theta = \begin{pmatrix} -0.5 \\ 1.5 \\ 0 \end{pmatrix}$$

$\theta_0 = 0.5, \theta_1 = 1.6, \theta_2 = 0,$
$\hat{y} = 0, d = -1$

x_0	x_1	x_2	y
1	0.1	0	0
1	0.6	1	1
1	0	1	1

$$x_2\theta_2 + x_1\theta_1 + x_0\theta_0 = 0$$
$$1.5x_1 - 0.5 = 0$$
$$x_1 = \frac{0.5}{1.5} = \frac{1}{3}$$

$$\theta_0 = -0.5, \theta_1 = 1.5, \theta_2 = 0$$



Two iterations later…

Perceptron

Initialize weights randomly

foreach x **in trainingsset{**

$\hat{y}$=**Prediction(**x**)**, $\hat{y}\epsilon\{0,1\}$

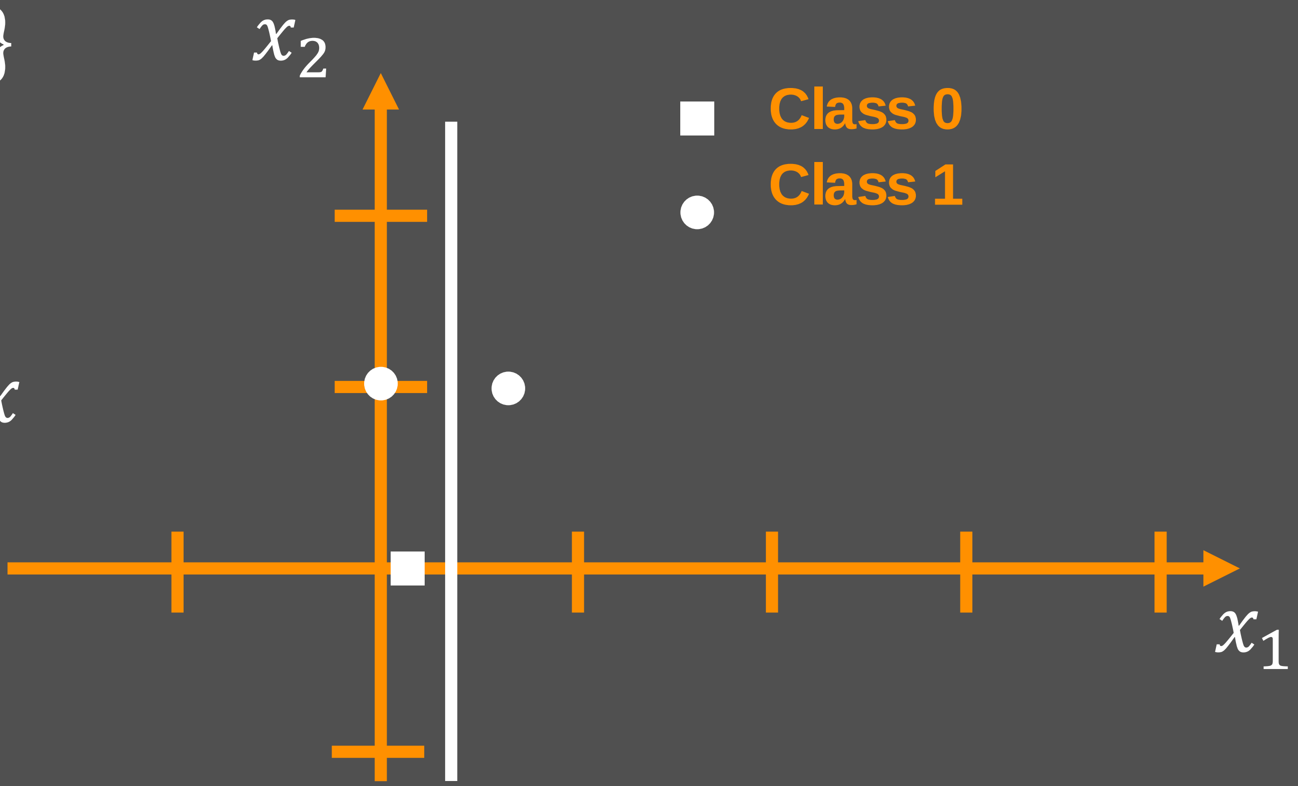
$\mathrm{d} = \mathrm{y} - \hat{y}, y\epsilon\{0,1\}$

if($d == 1$**)** $\theta = \theta + x$

elif ($d == -1$**)** $\theta = \theta - x$

}

$\theta_0 = -0.5, \theta_1 = 1.5, \theta_2 = 0,$
$\hat{y} = 0, d = 1$



if(d**==1)** θ**=**θ**+**x

$$\theta = \begin{pmatrix} 0.5 \\ 1.5 \\ 0 \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$

$$\theta = \begin{pmatrix} 1.5 \\ 1.5 \\ 1 \end{pmatrix}$$

$\theta_0 = -0.5, \theta_1 = 1.5, \theta_2 = 0,$
$\hat{y} = 0, d = 1$

x_0	x_1	x_2	y
1	0.1	0	0
1	0.6	1	1
1	0	1	1

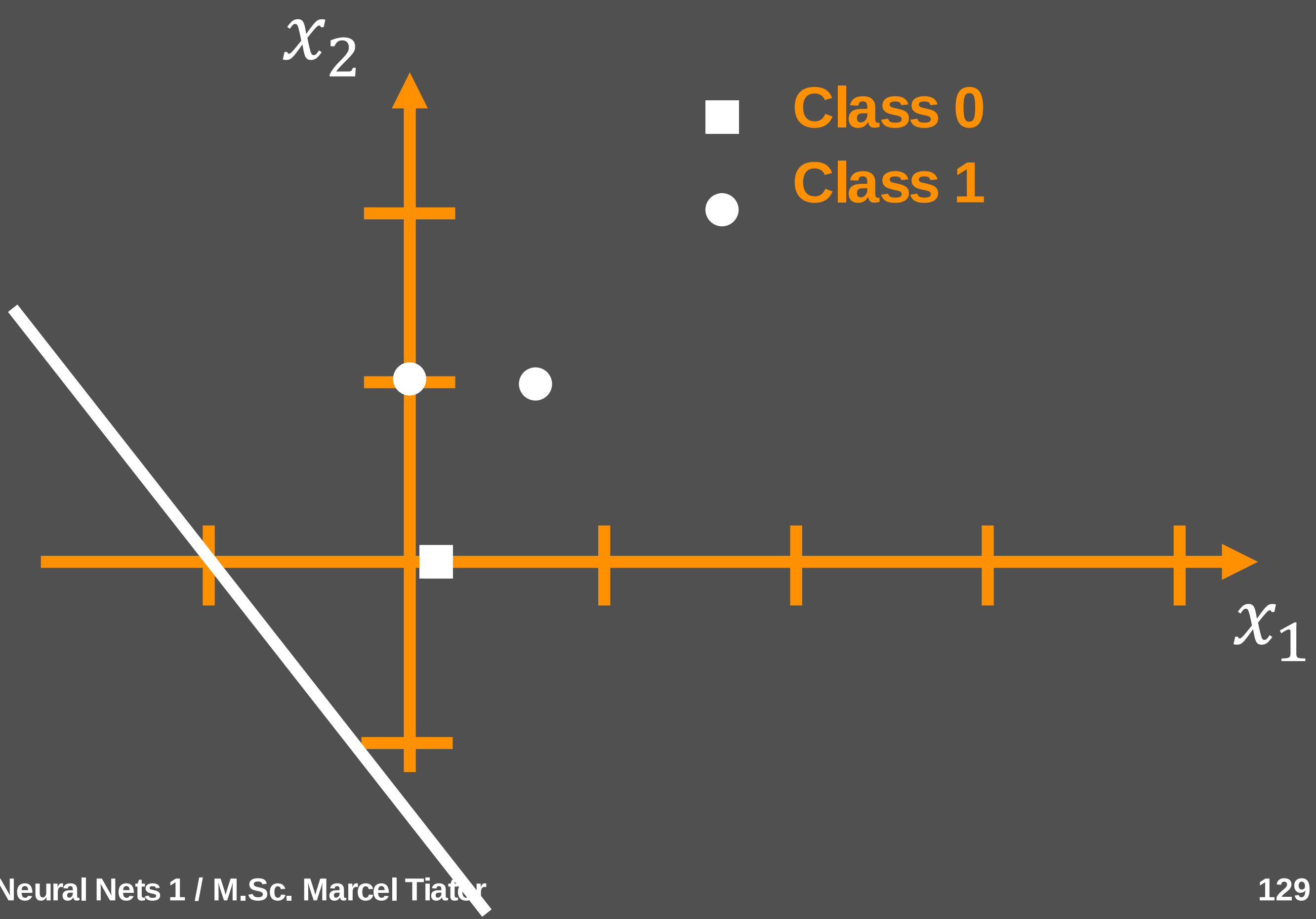
$$x_2\theta_2 + x_1\theta_1 + x_0\theta_0 = 0$$

$$x_2 = \frac{-(x_1\theta_1+x_0\theta_0)}{\theta_2}$$

$$x_2 = \frac{-(1.5x_1+1.5)}{1}$$

$$x_2 = -1.5(x_1 + 1)$$

$$\theta_0 = 1.5, \theta_1 = 1.5, \theta_2 = 1$$



One iteration later…

Perceptron

Initialize weights randomly

foreach x **in trainingsset{**

$\hat{y}$=**Prediction(**x**),** $\hat{y} \epsilon \{0,1\}$

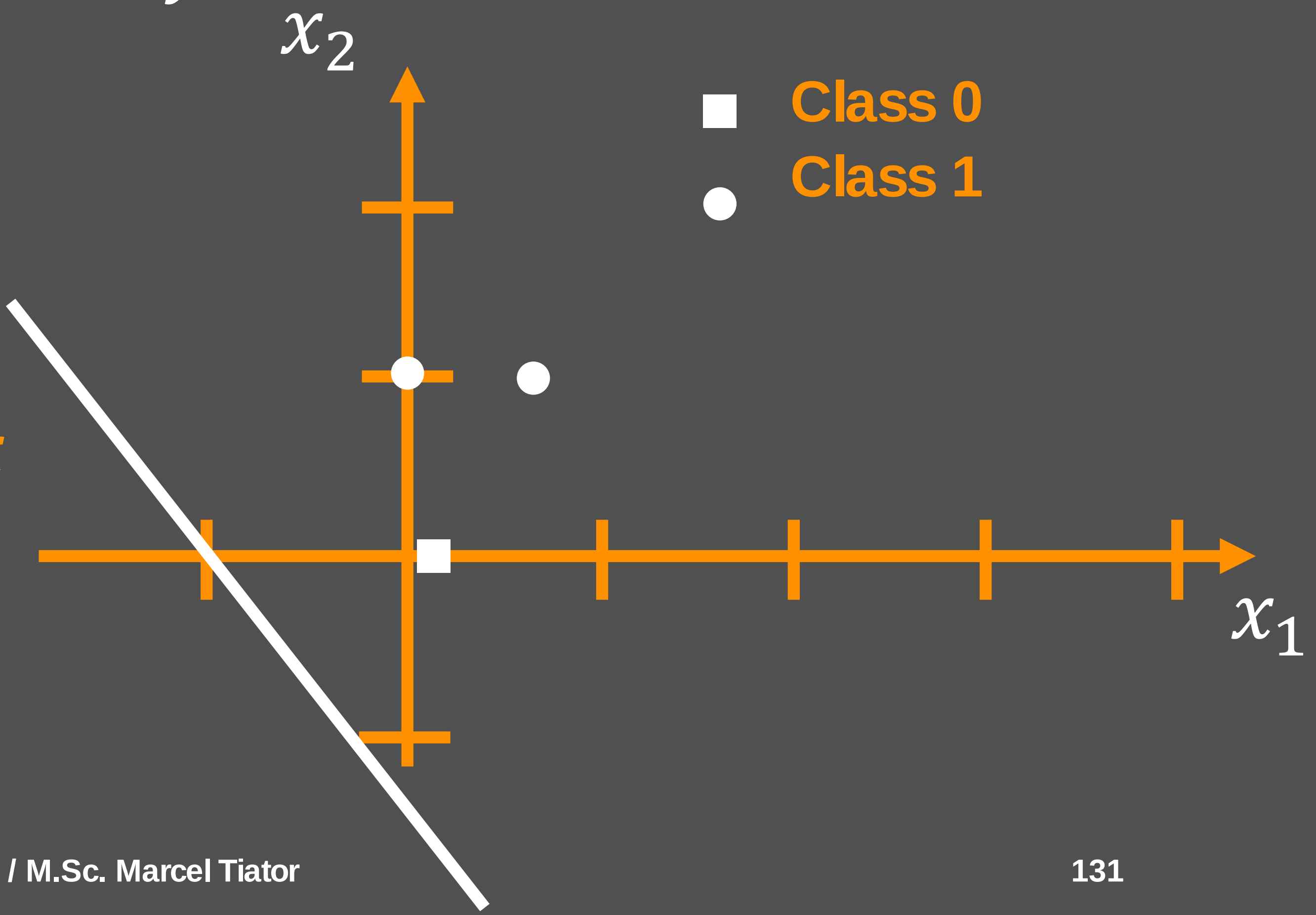
$\mathrm{d} = \mathrm{y} - \hat{y}, y \epsilon \{0,1\}$

if($d == 1$**)** $\theta = \theta + x$

elif ($d == -1$**)** $\theta = \theta - x$

}

$\theta_0 = 1.5, \theta_1 = 1.5, \theta_2 = 1,$
$\hat{y} = 1, d = -1$



if(d==-1) θ=θ-x

$$\theta = \begin{pmatrix} 1.5 \\ 1.5 \\ 1 \end{pmatrix} - \begin{pmatrix} 1 \\ 0.1 \\ 0 \end{pmatrix}$$

$$\theta = \begin{pmatrix} 0.5 \\ 1.4 \\ 1 \end{pmatrix}$$

$\theta_0 = 1.5, \theta_1 = 1.5, \theta_2 = 1,$
$\hat{y} = 1, d = -1$

x_0	x_1	x_2	y
1	0.1	0	0
1	0.6	1	1
1	0	1	1

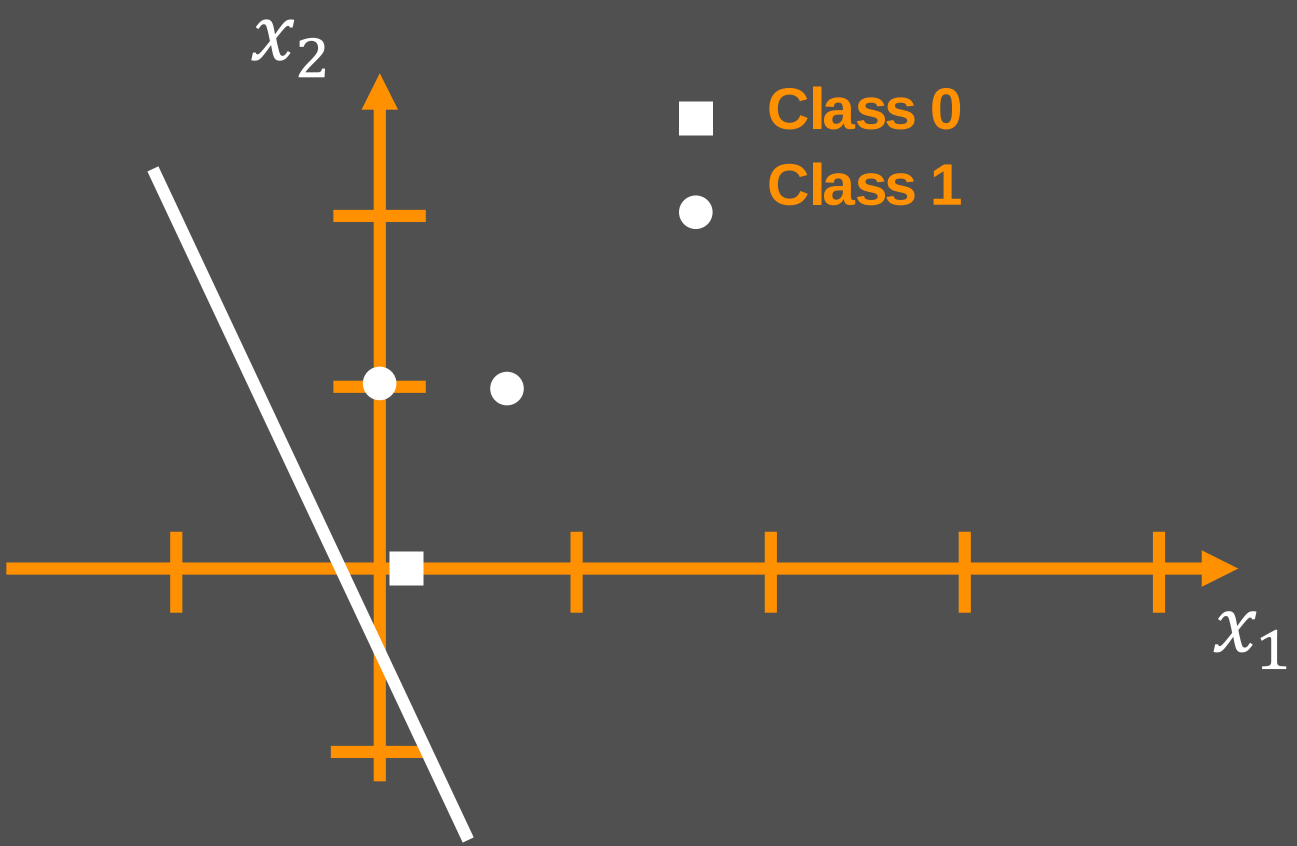
$$x_2\theta_2 + x_1\theta_1 + x_0\theta_0 = 0$$

$$x_2 = \frac{-(x_1\theta_1 + x_0\theta_0)}{\theta_2}$$

$$x_2 = \frac{-(1.4x_1 + 0.5)}{1}$$

$$x_2 = -1.4(x_1 + 0.357)$$

$$\theta_0 = 0.5, \theta_1 = 1.4, \theta_2 = 1$$



Two iterations later…

Perceptron

Initialize weights randomly

foreach x in trainingsset{

$\hat{y}$=**Prediction(x),** $\hat{y}\epsilon\{0,1\}$

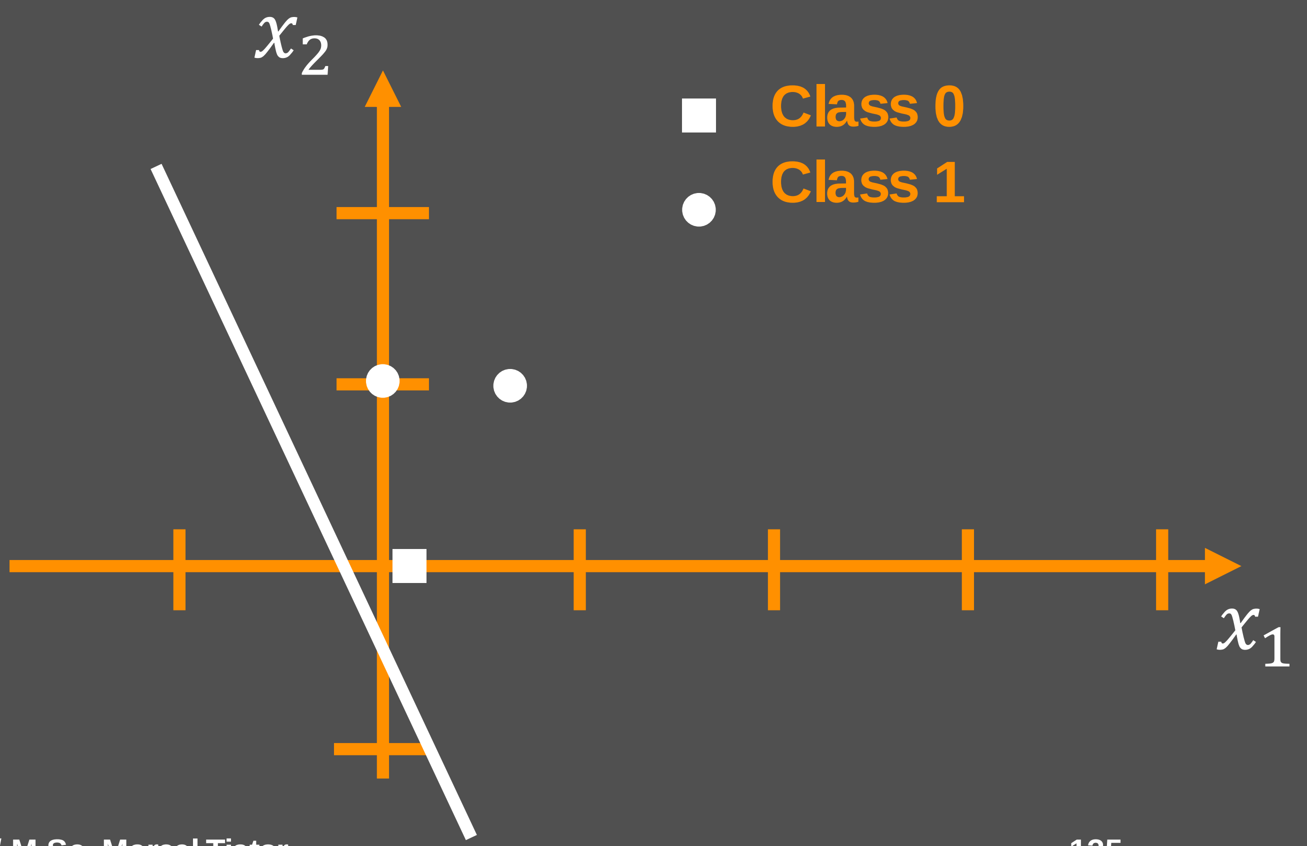
$\mathrm{d} = \mathrm{y} - \hat{y}, y\epsilon\{0,1\}$

if($d == 1$**)** $\theta = \theta + x$

elif ($d == -1$**)** $\theta = \theta - x$

}

$\theta_0 = 0.5, \theta_1 = 1.4, \theta_2 = 1,$
$\hat{y} = 1, d = -1$



if(d==-1) θ=θ-x

$$\theta = \begin{pmatrix} 0.5 \\ 1.4 \\ 1 \end{pmatrix} - \begin{pmatrix} 1 \\ 0.1 \\ 0 \end{pmatrix}$$

$$\theta = \begin{pmatrix} -0.5 \\ 1.3 \\ 1 \end{pmatrix}$$

$$\theta_0 = 0.5, \theta_1 = 1.4, \theta_2 = 1,$$
$$\hat{y} = 1, d = -1$$

x_0	x_1	x_2	y
1	0.1	0	0
1	0.6	1	1
1	0	1	1

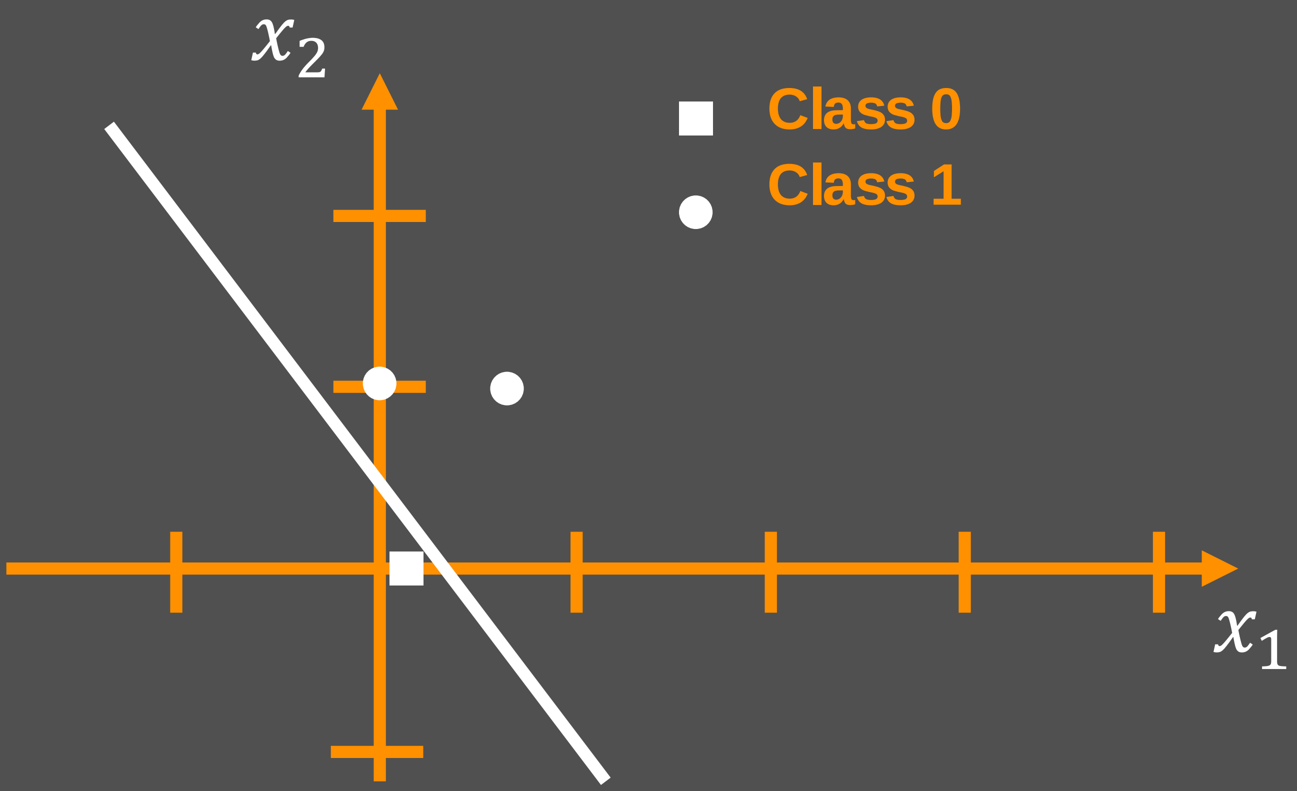
$$x_2\theta_2 + x_1\theta_1 + x_0\theta_0 = 0$$

$$x_2 = \frac{-(x_1\theta_1 + x_0\theta_0)}{\theta_2}$$

$$x_2 = \frac{-(1.3x_1 - 0.5)}{1}$$

$$x_2 = -1.3(x_1 - 0.385)$$

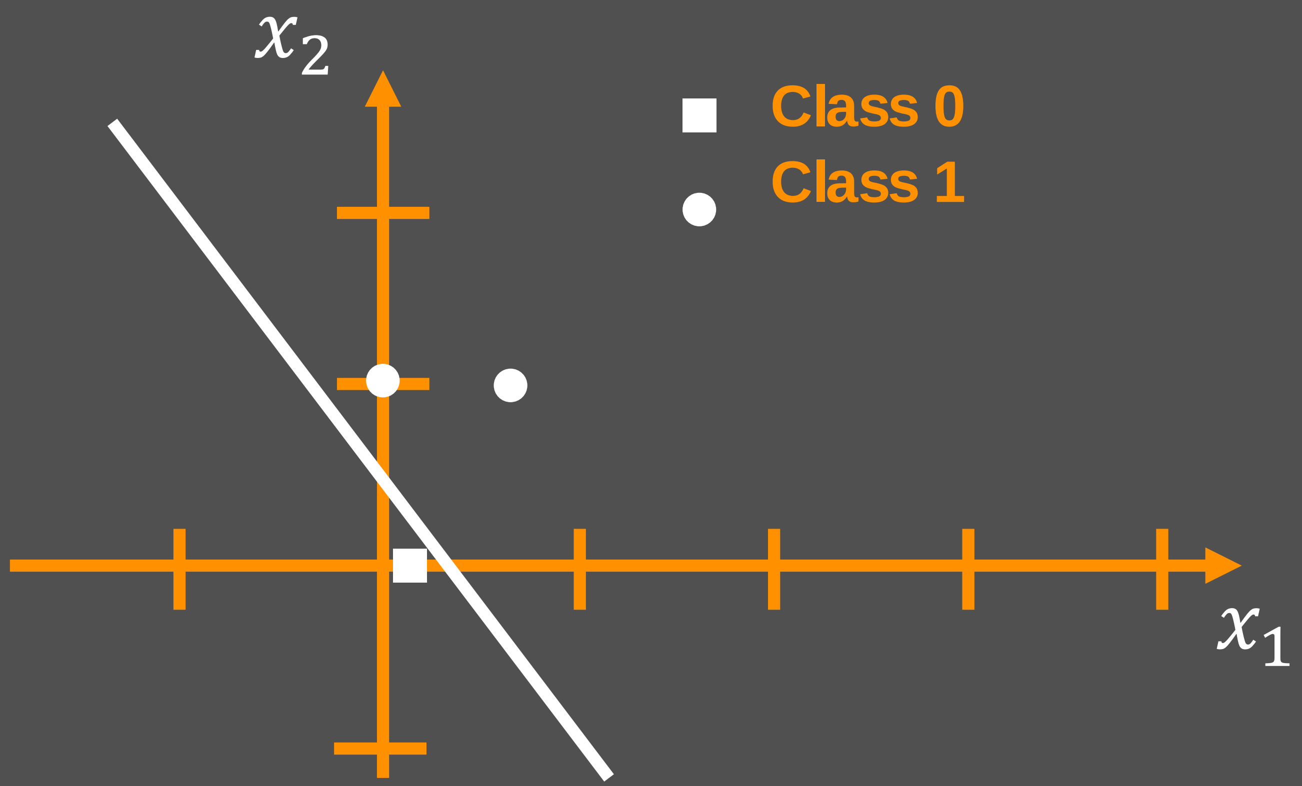
$$\theta_0 = -0.5, \theta_1 = 1.3, \theta_2 = 1$$



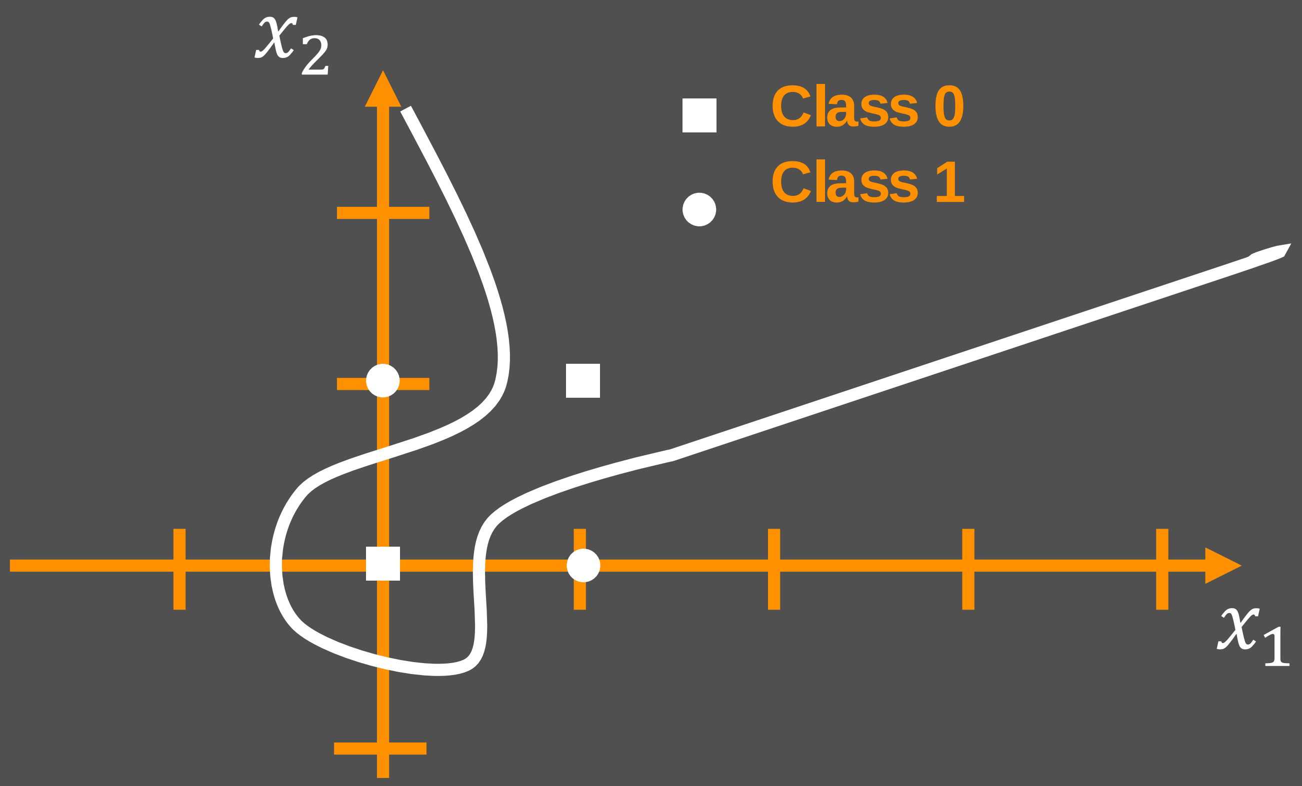
Training Finished!

Binary Classification with Perceptron

- Need linearly seperable dataset



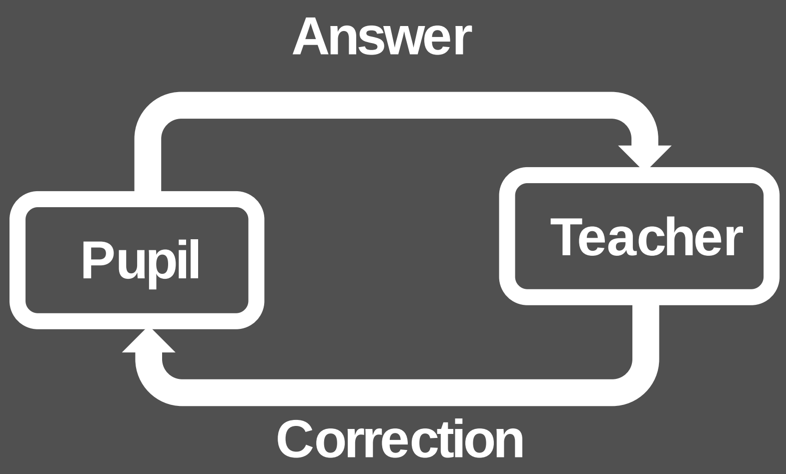
Assume a more complex problem

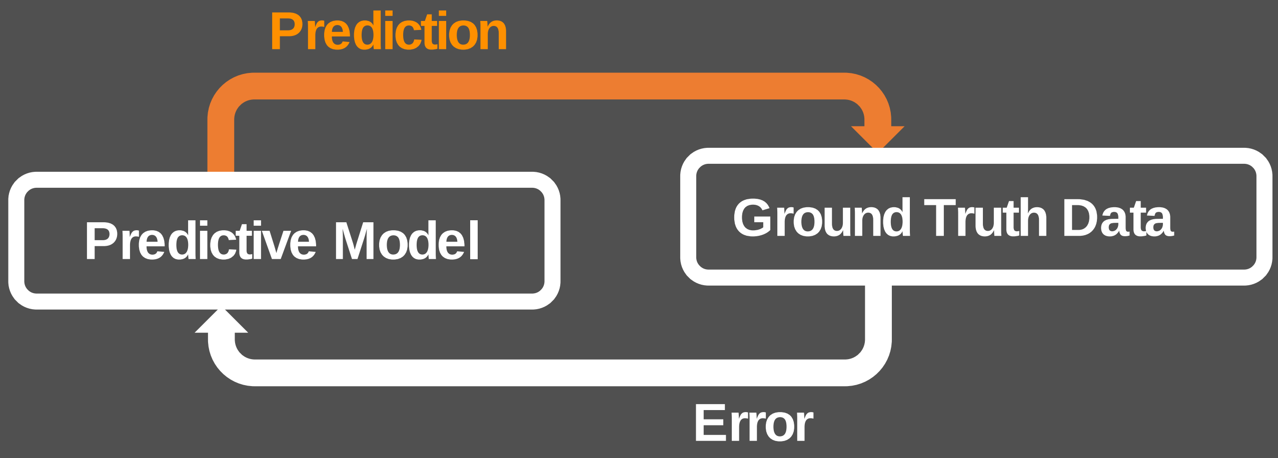


Multilayer Perceptron (MLP)

Two Processes:

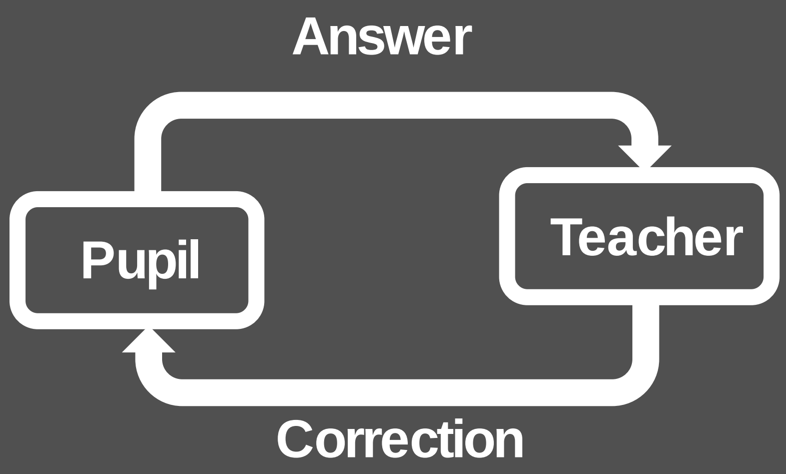
- Forward Propagation (Prediction)
- Backward Propagation (Weight Tuning)

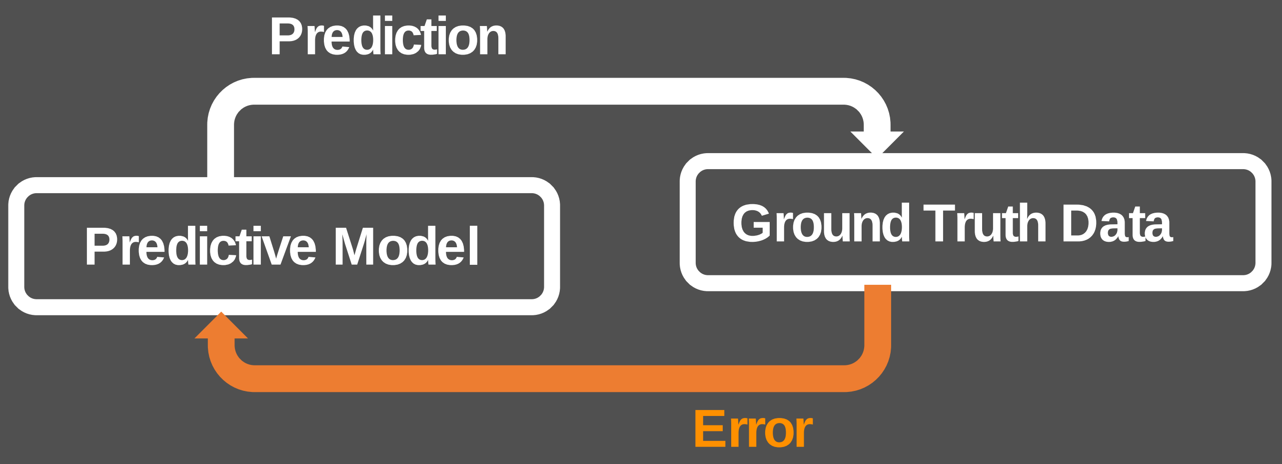




Two Processes:

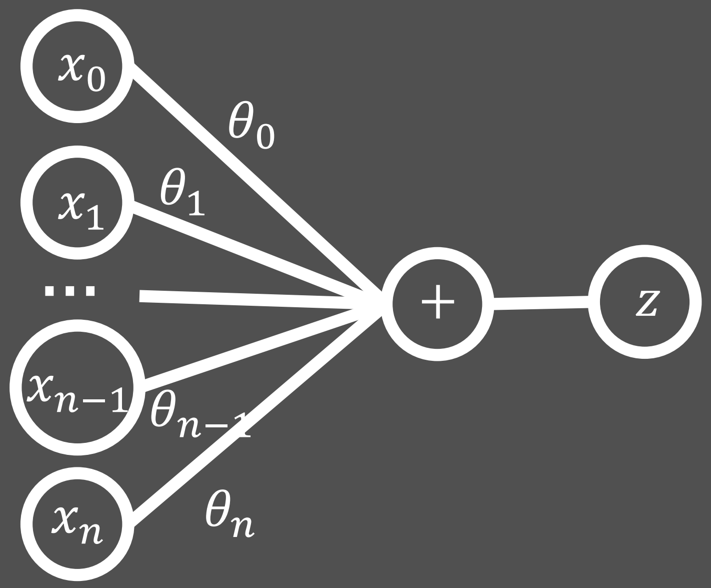
- Forward Propagation (Prediction)
- Backward Propagation (Weight Tuning)



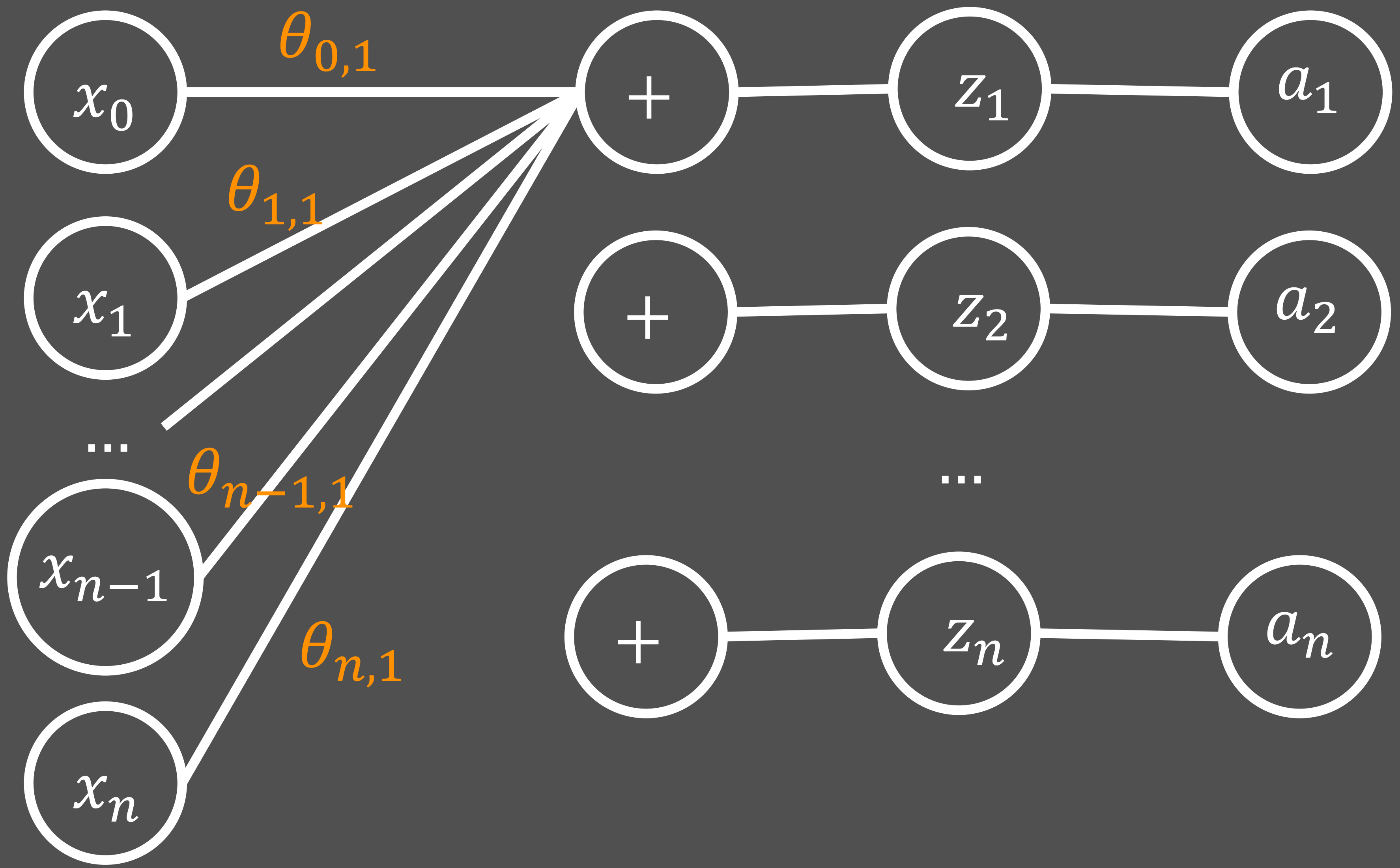


Forward Propagation

- Compute multiple weighted sums z_i
- Activate them to get $a_i(z_i)$
- Remember from Perceptron: $z = \theta x$

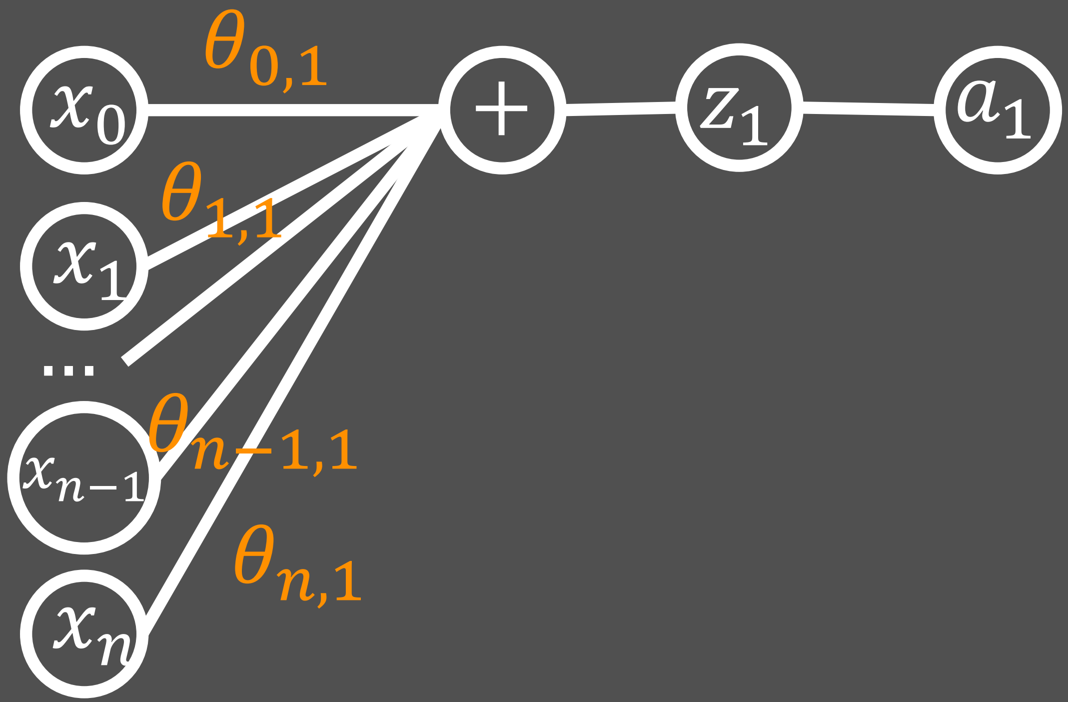


Forward Propagation

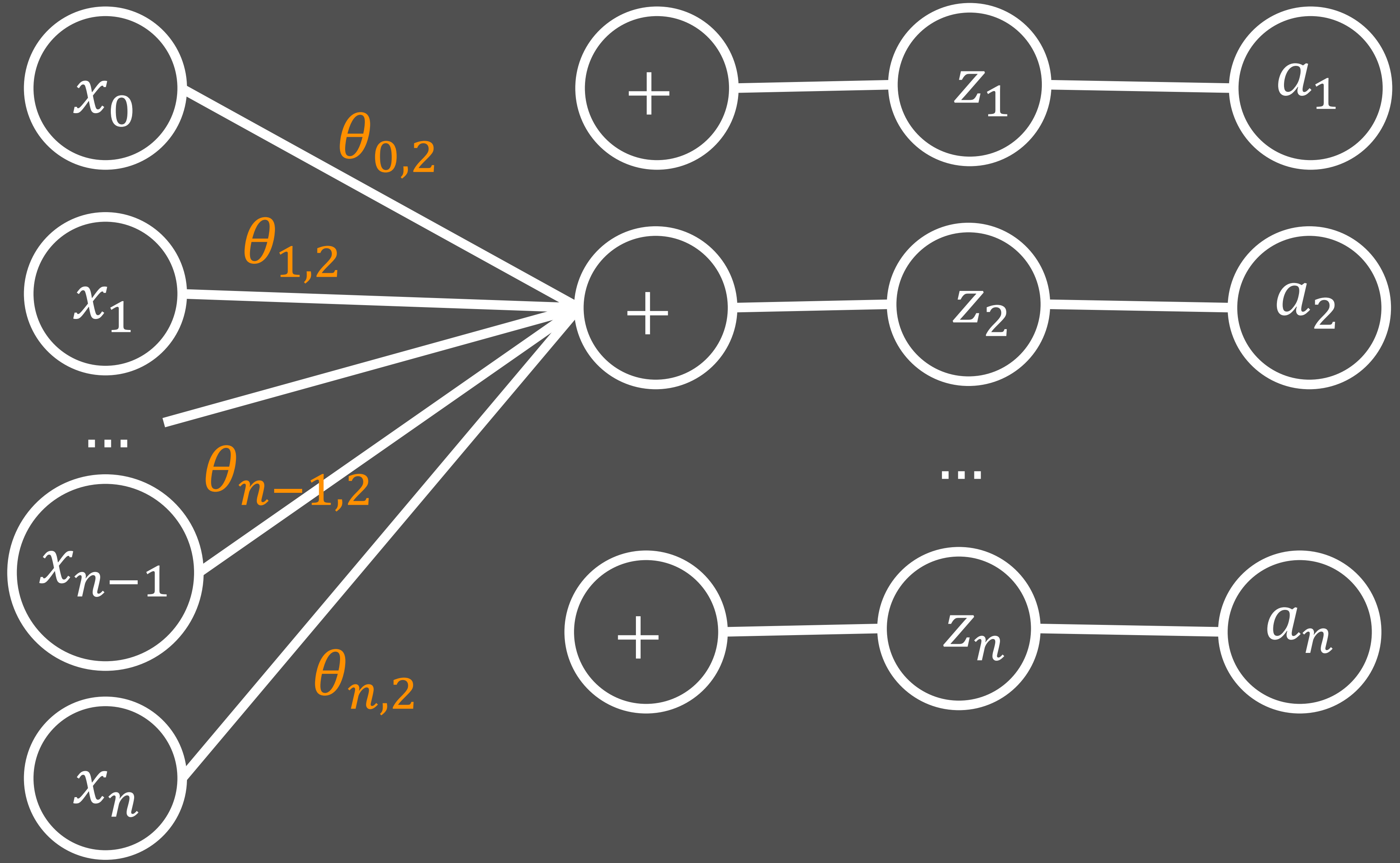


$$z_{to} = \theta_{from,to} x_{from}$$

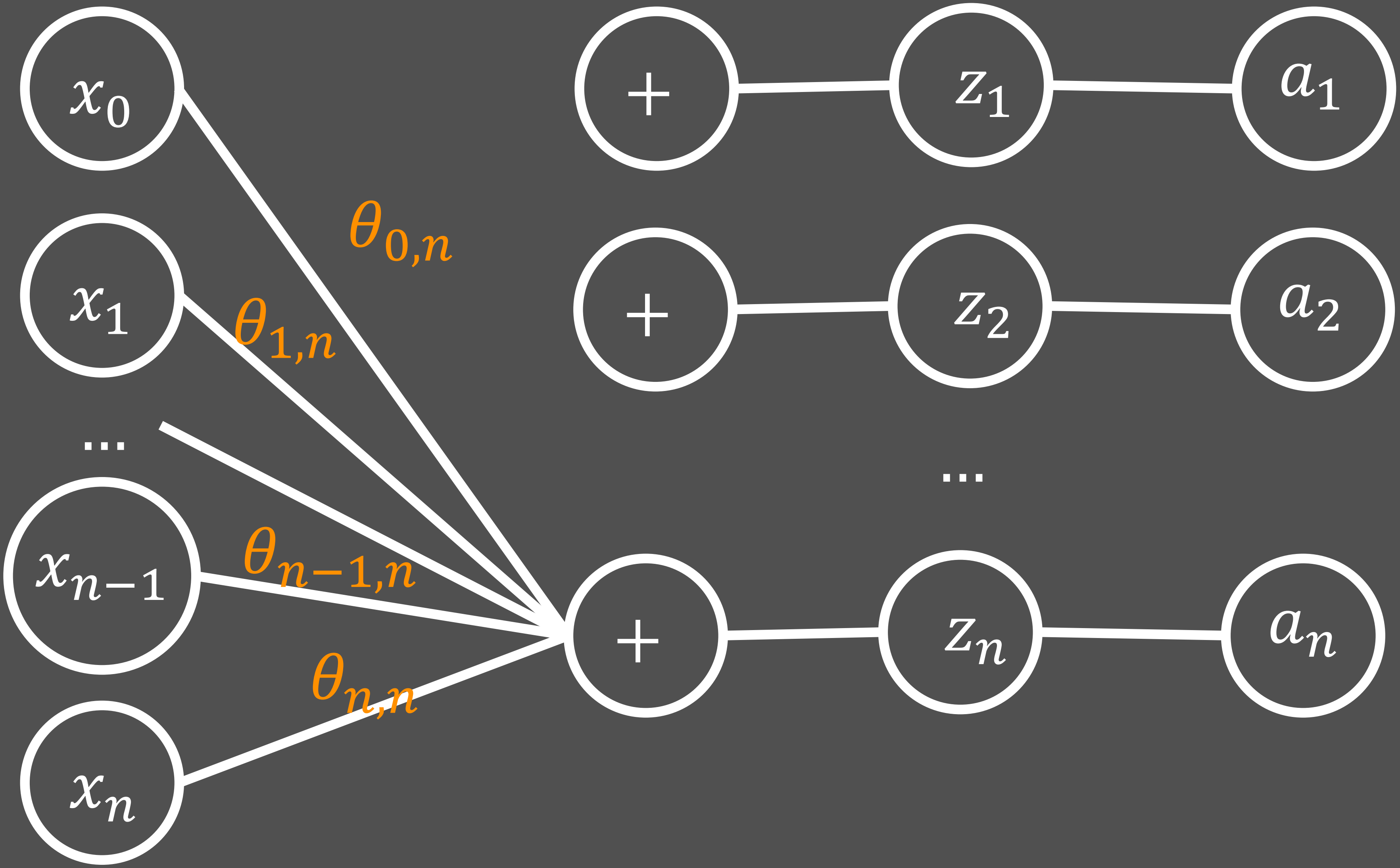
e.g. $z_1 = \theta_{0,1} x_0$



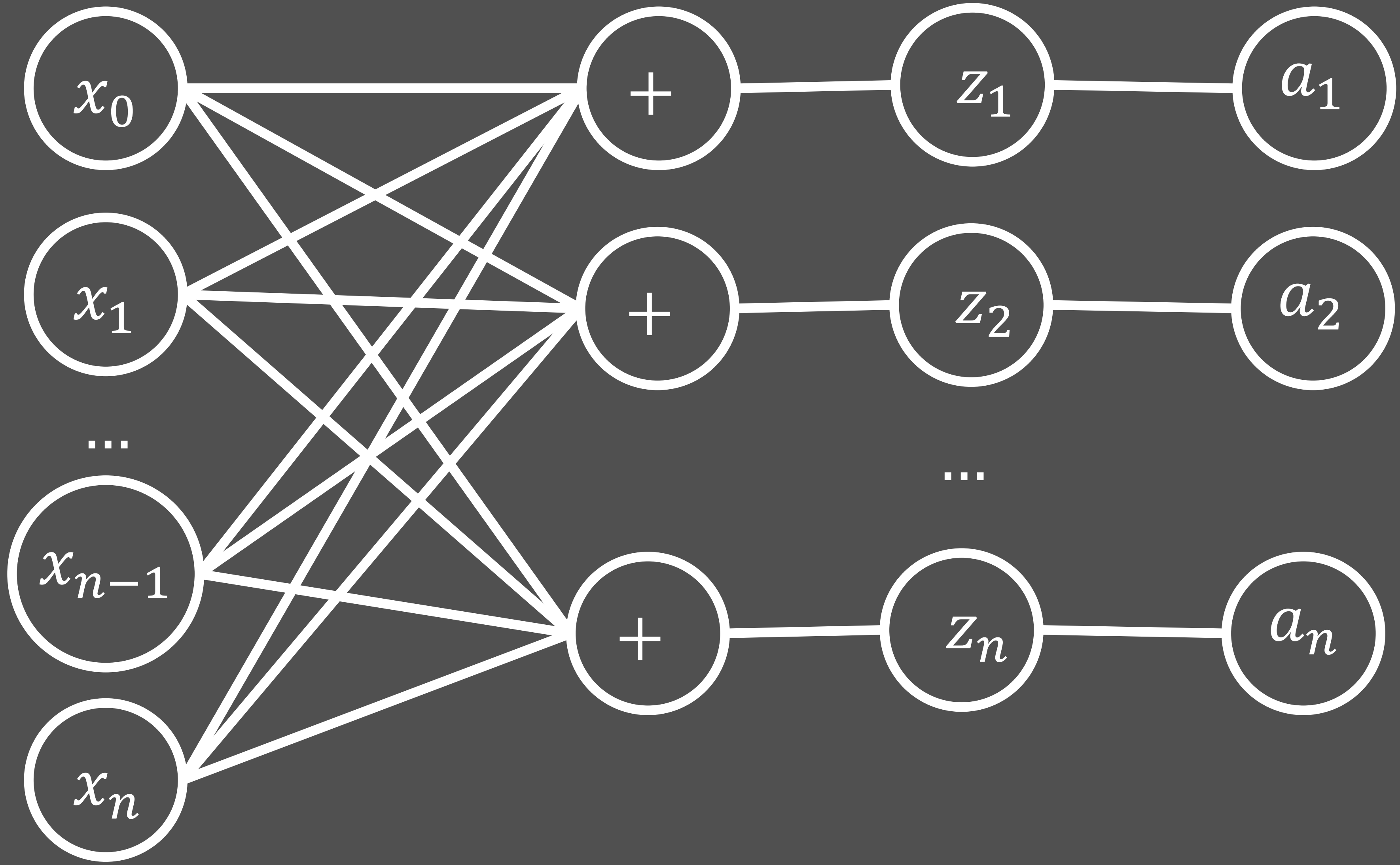
Forward Propagation



Forward Propagation

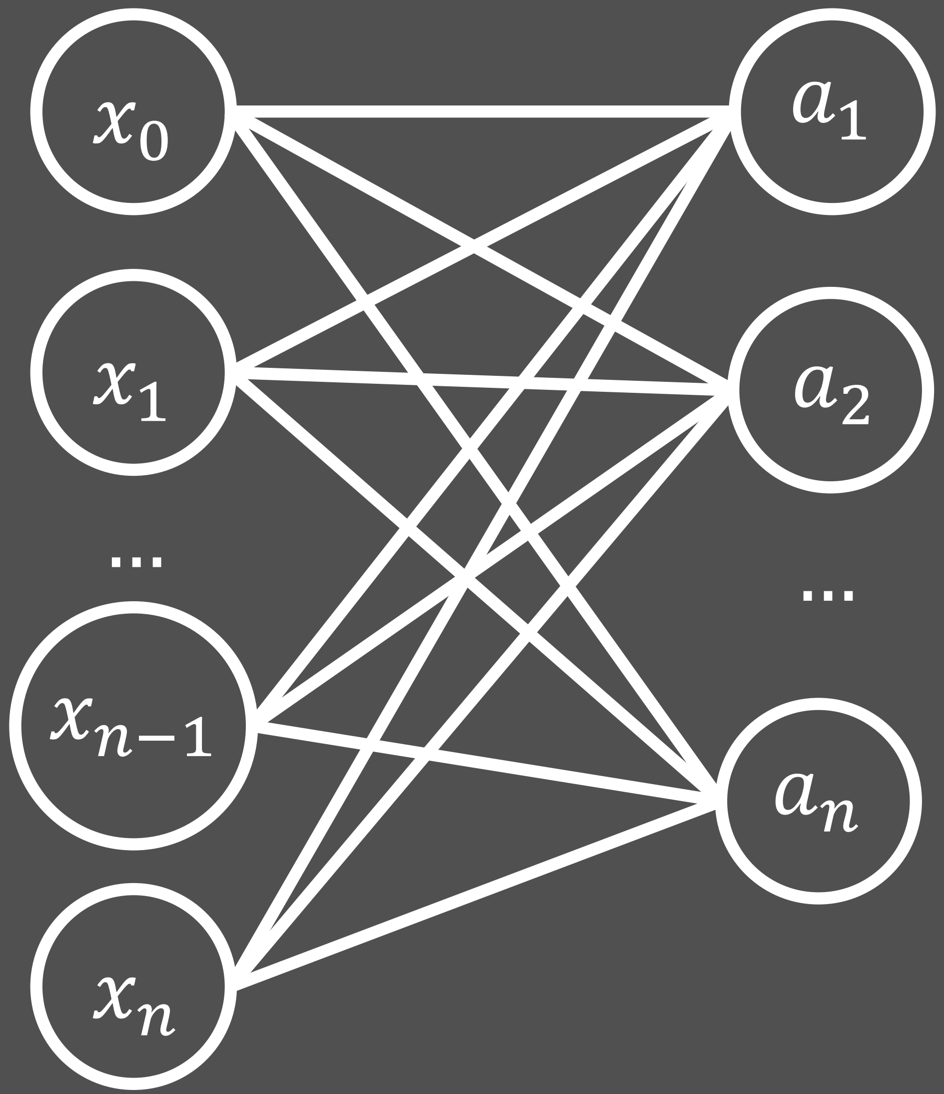


Forward Propagation

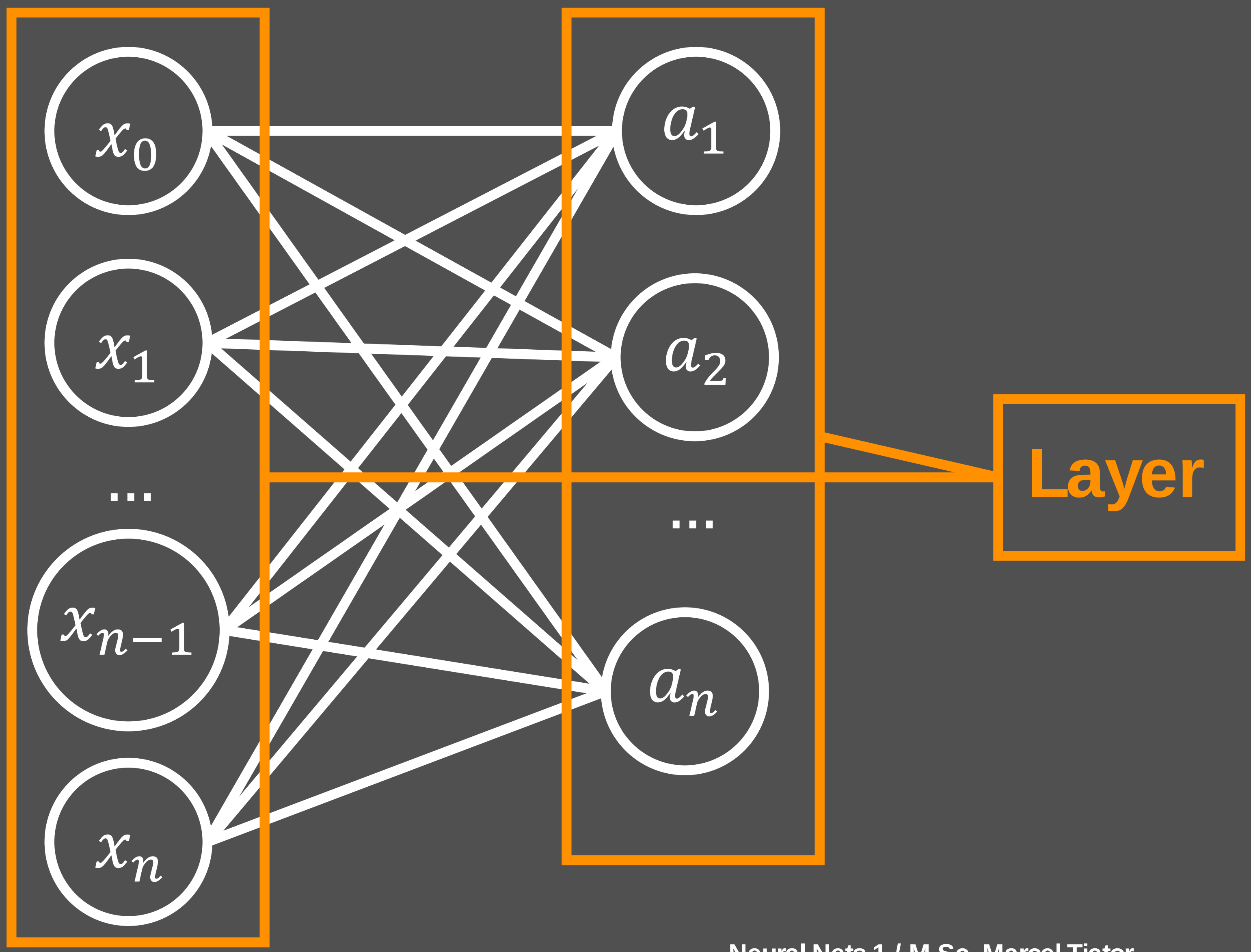


In Short (without z)

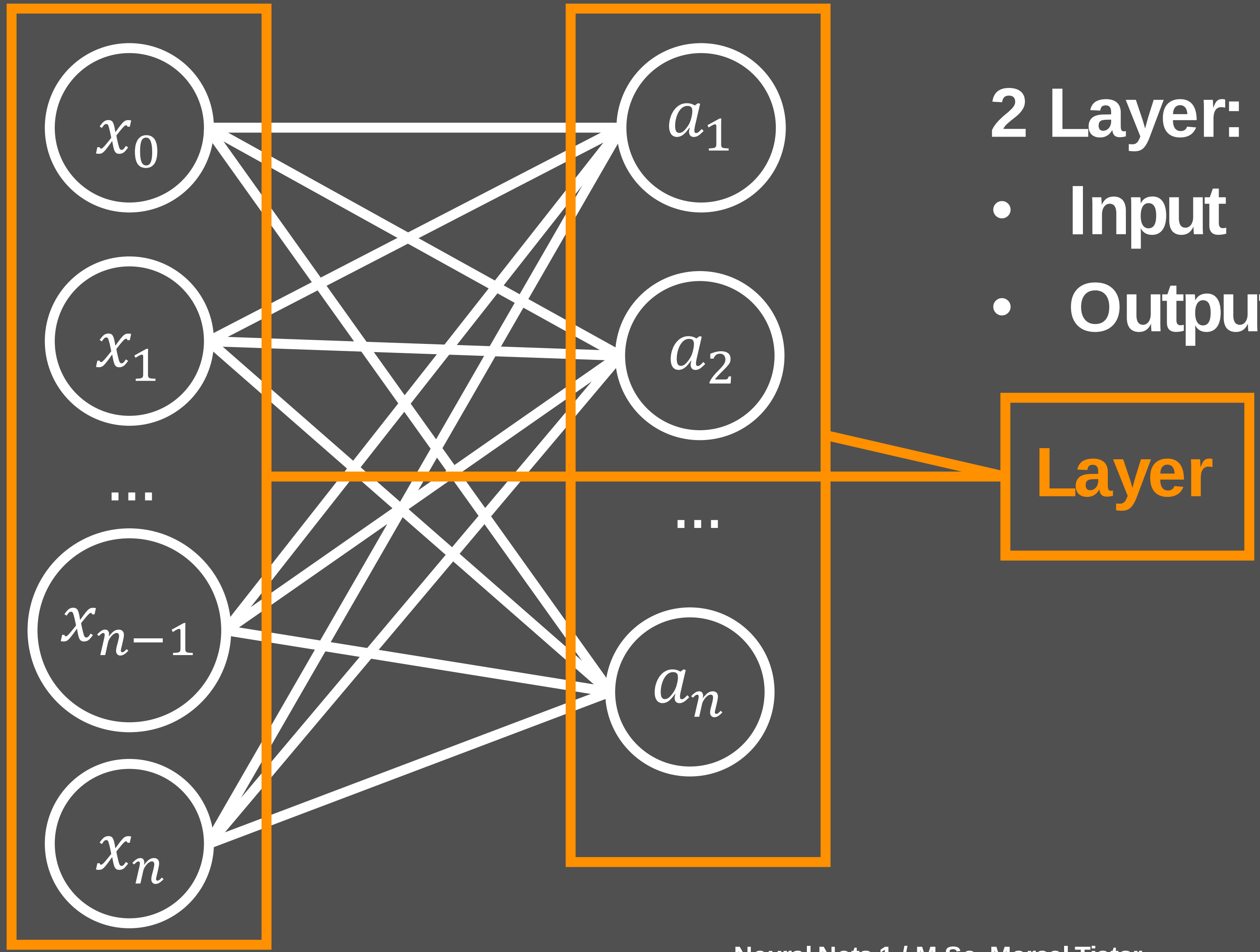
Forward Propagation



Forward Propagation



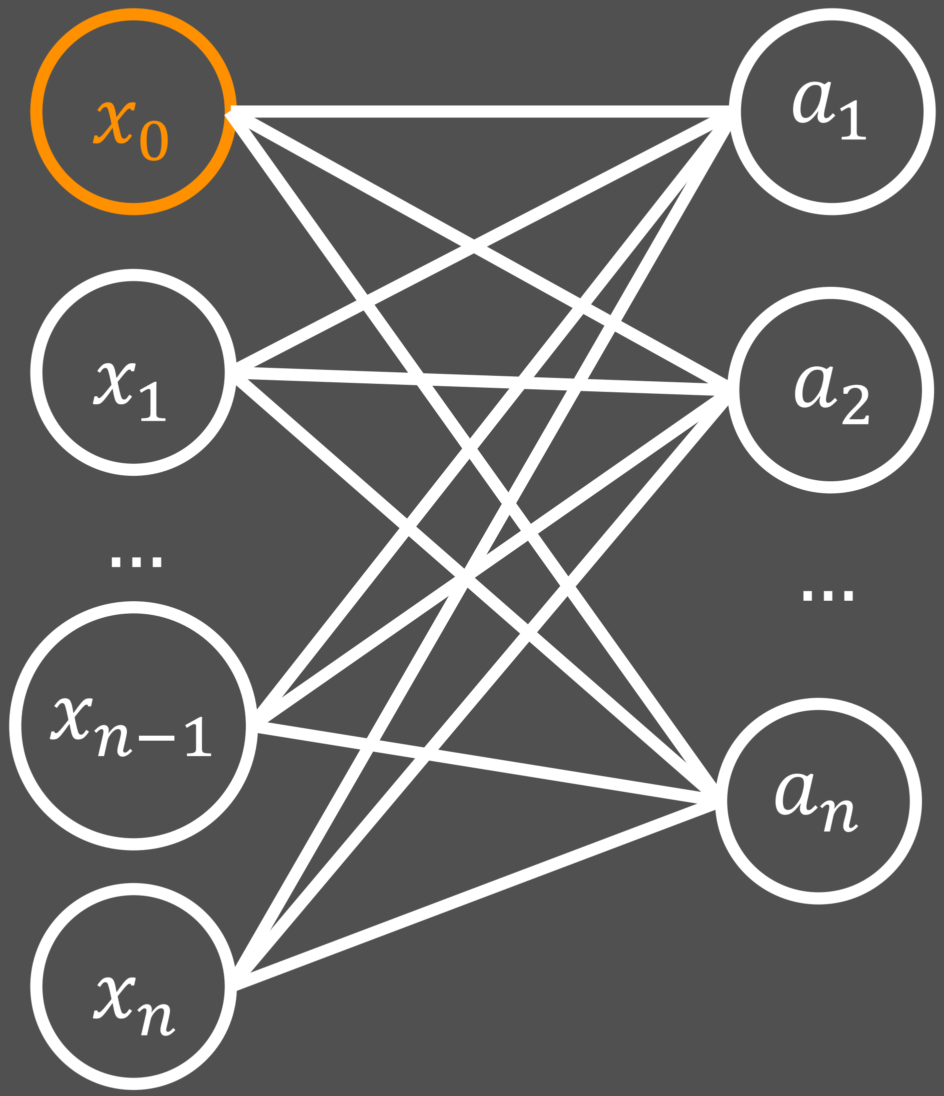
Forward Propagation



2 Layer:

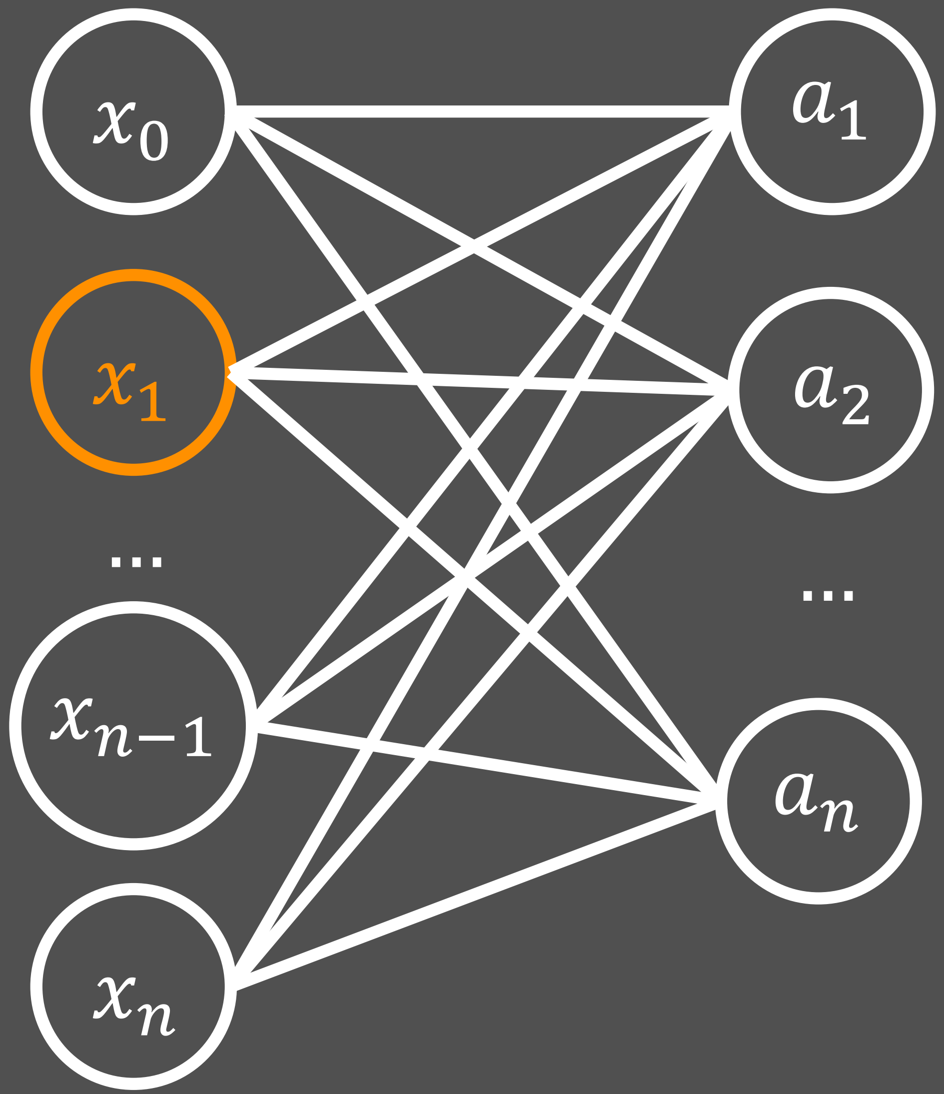
- **Input**
- **Output**

Forward Propagation



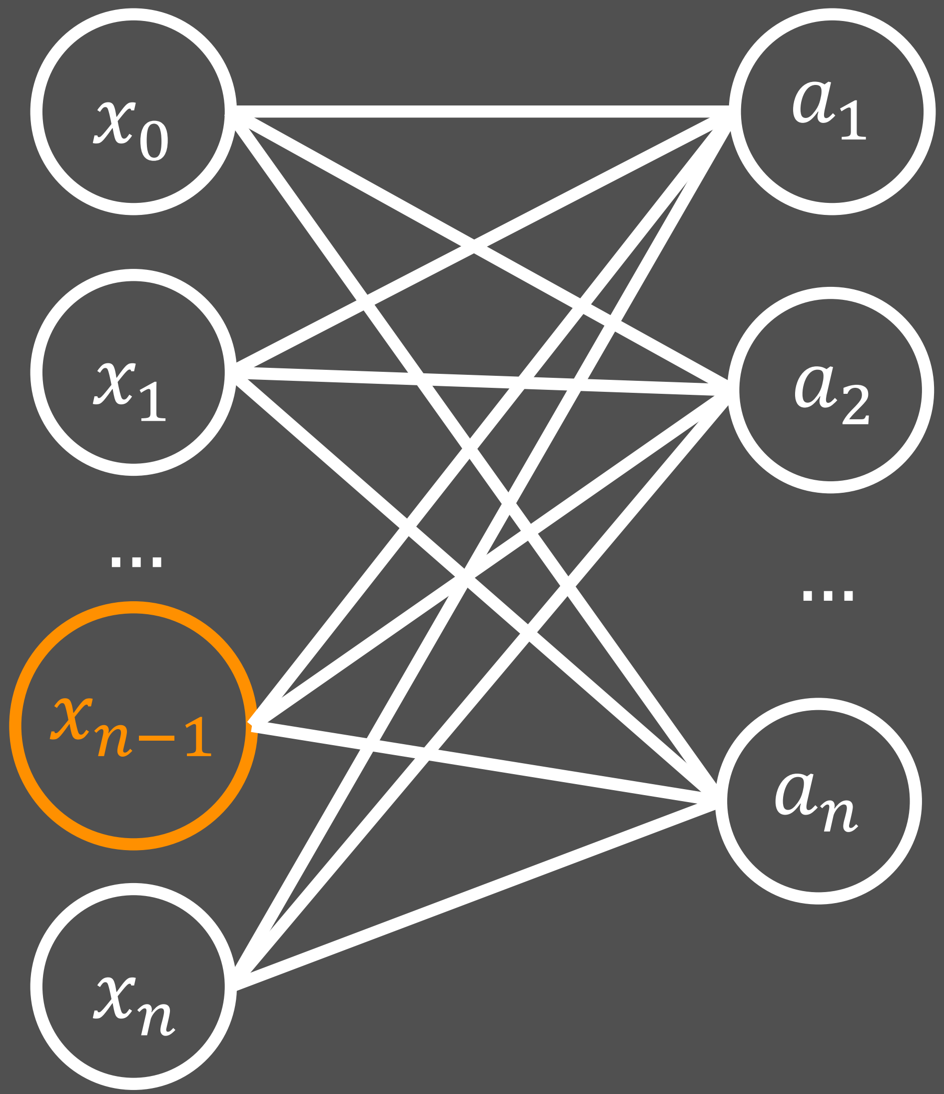
Input Neuron

Forward Propagation



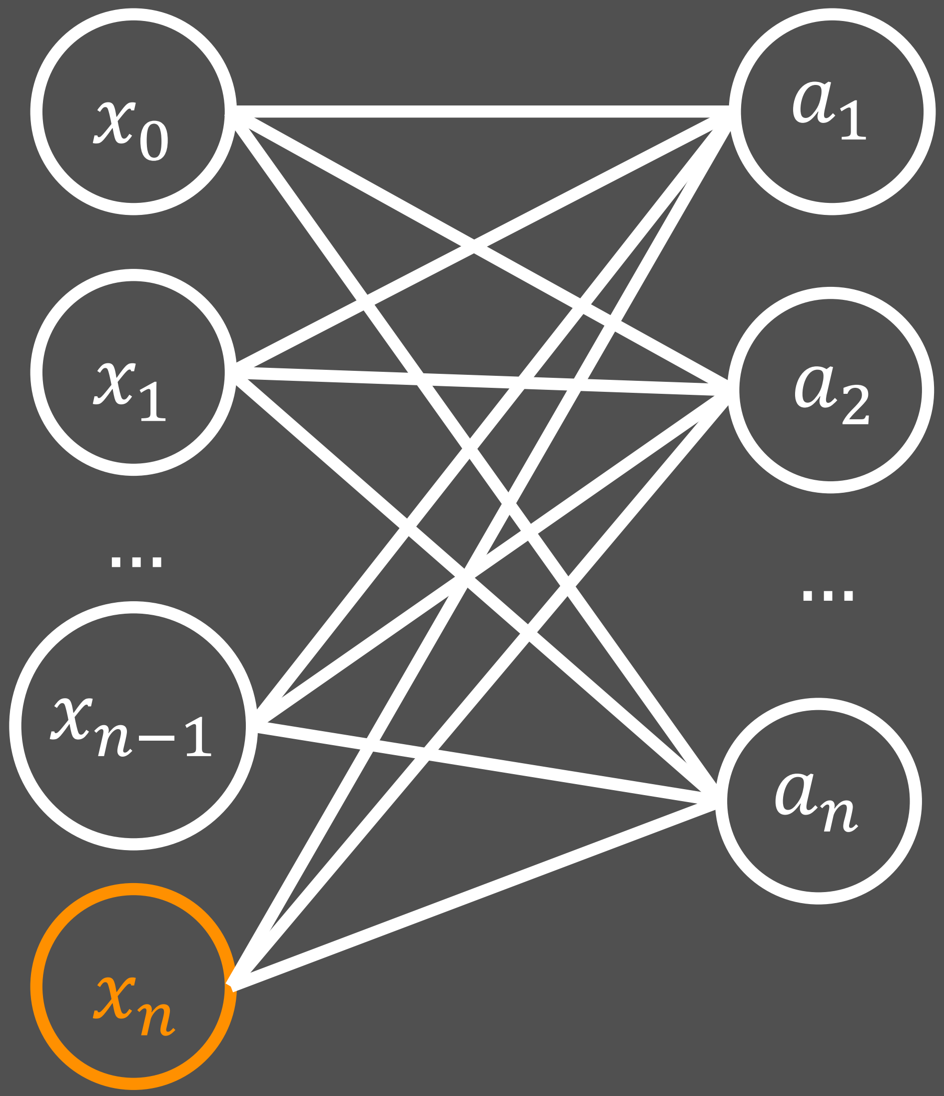
Input Neuron

Forward Propagation



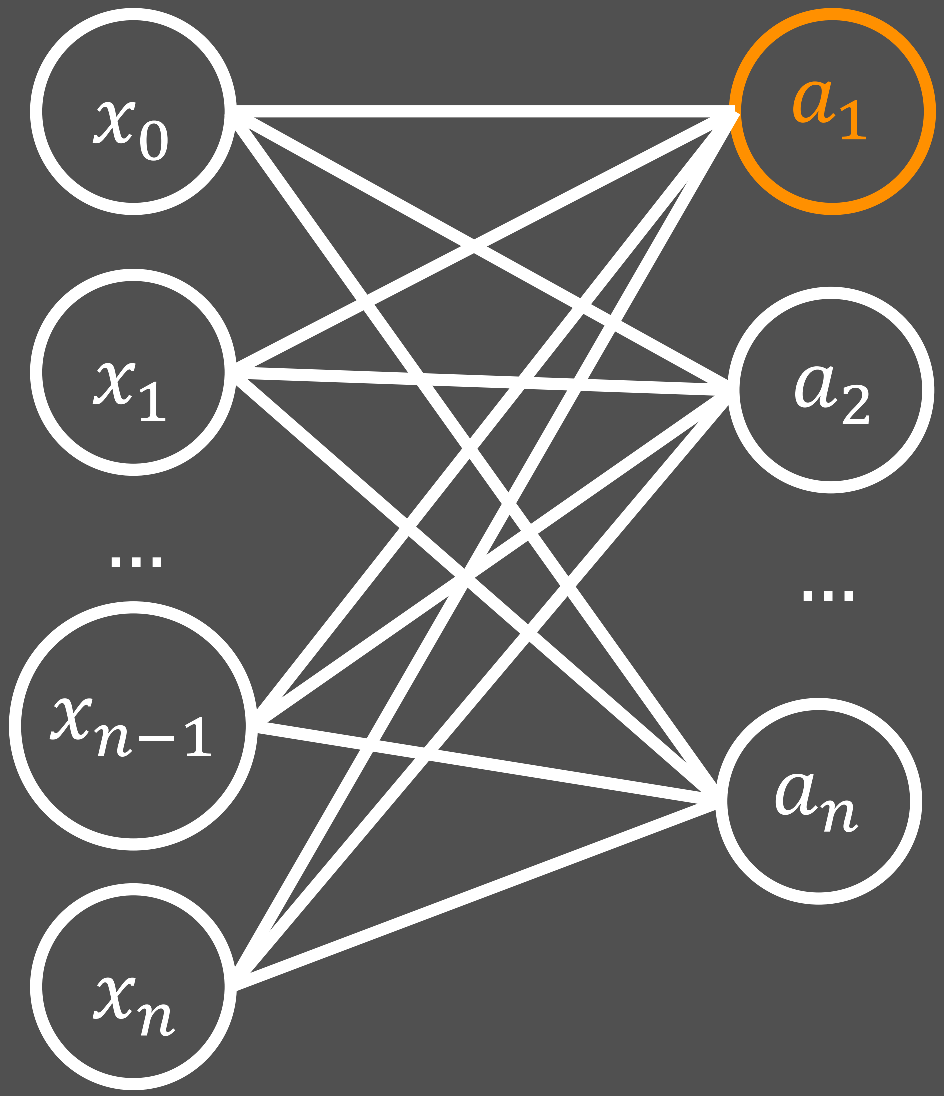
Input Neuron

Forward Propagation



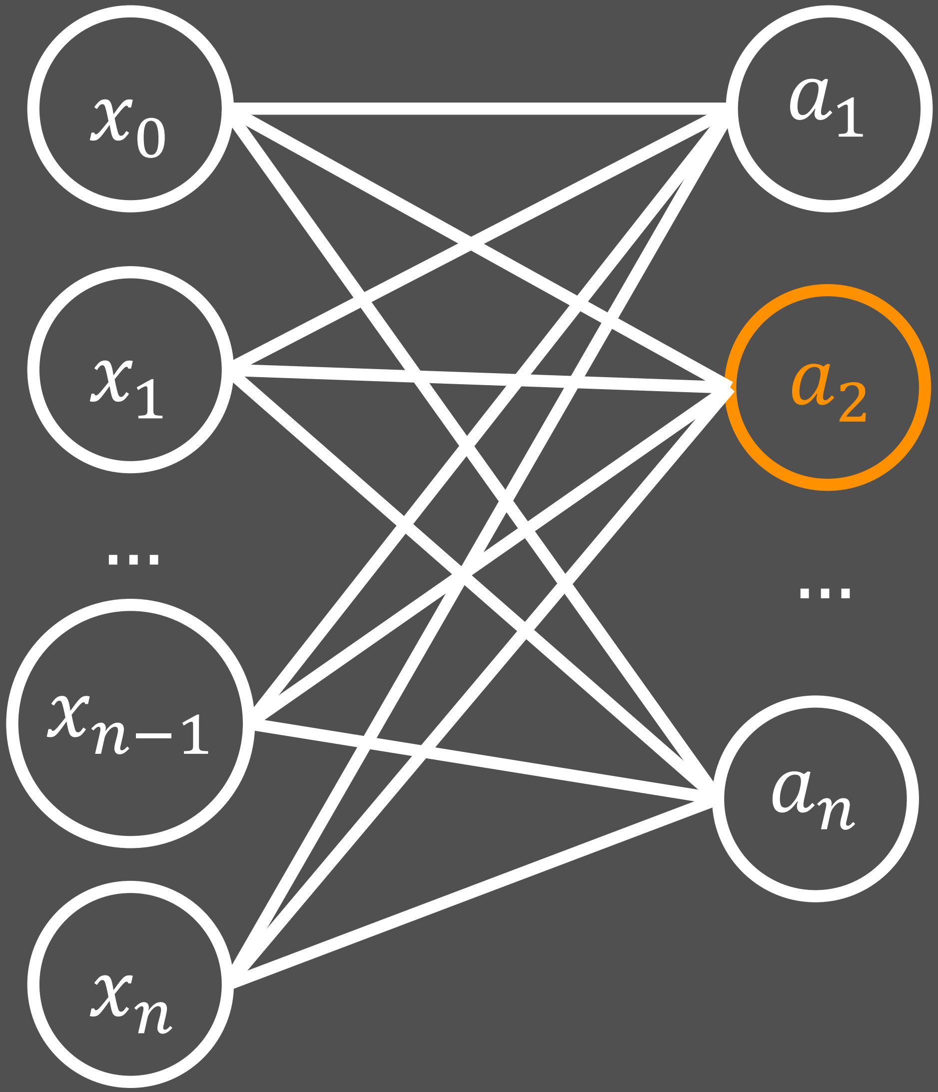
Input Neuron

Forward Propagation



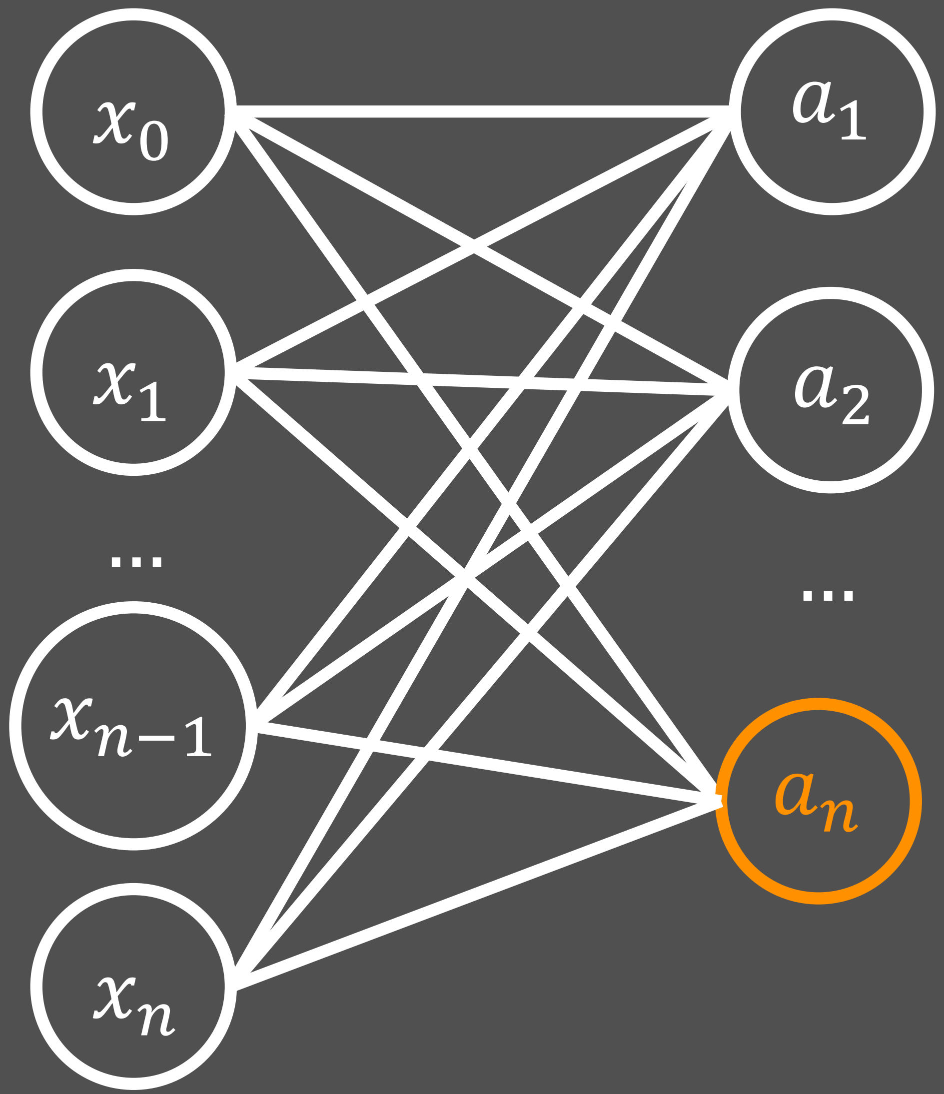
Output Neuron

Forward Propagation



Output Neuron

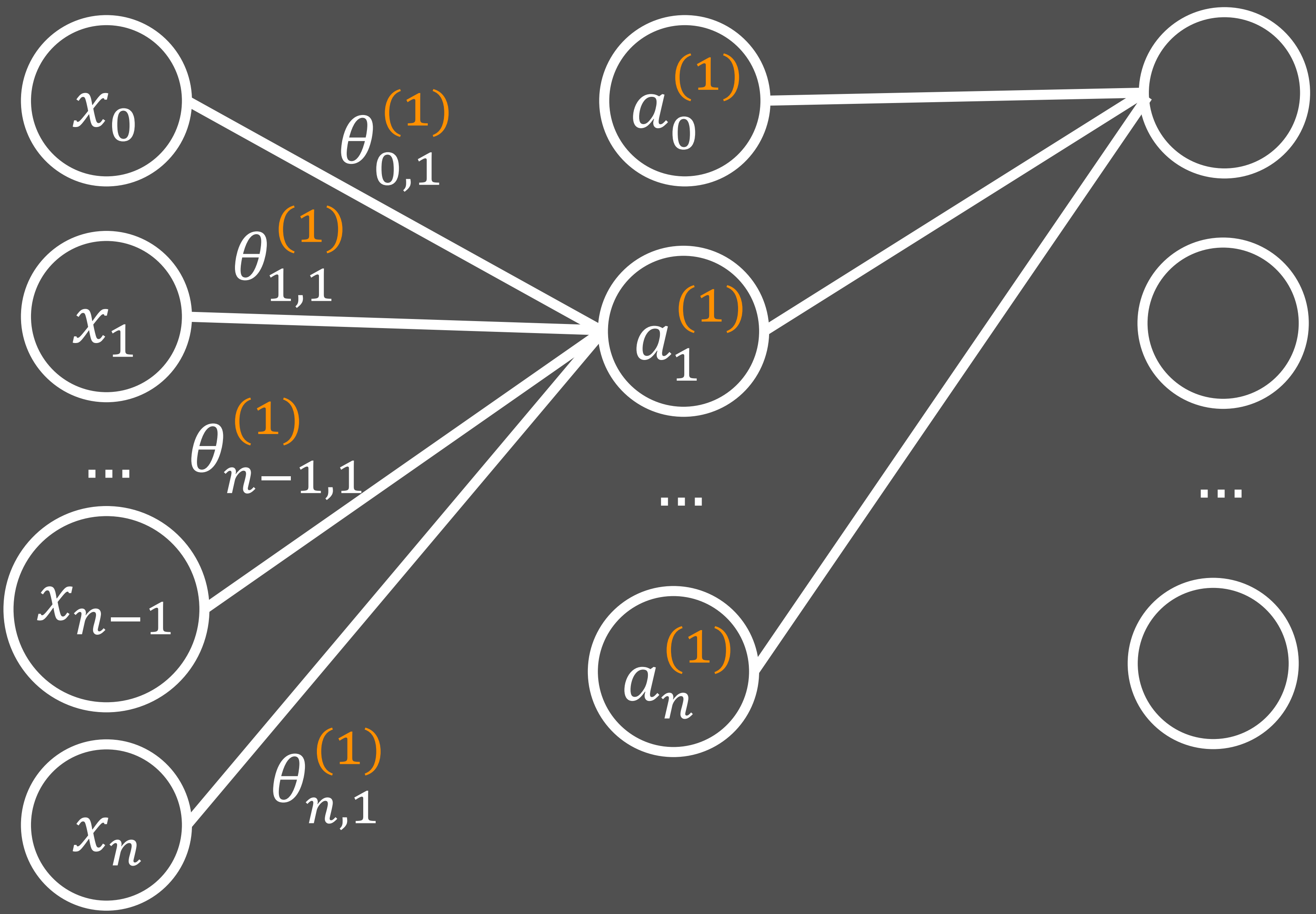
Forward Propagation



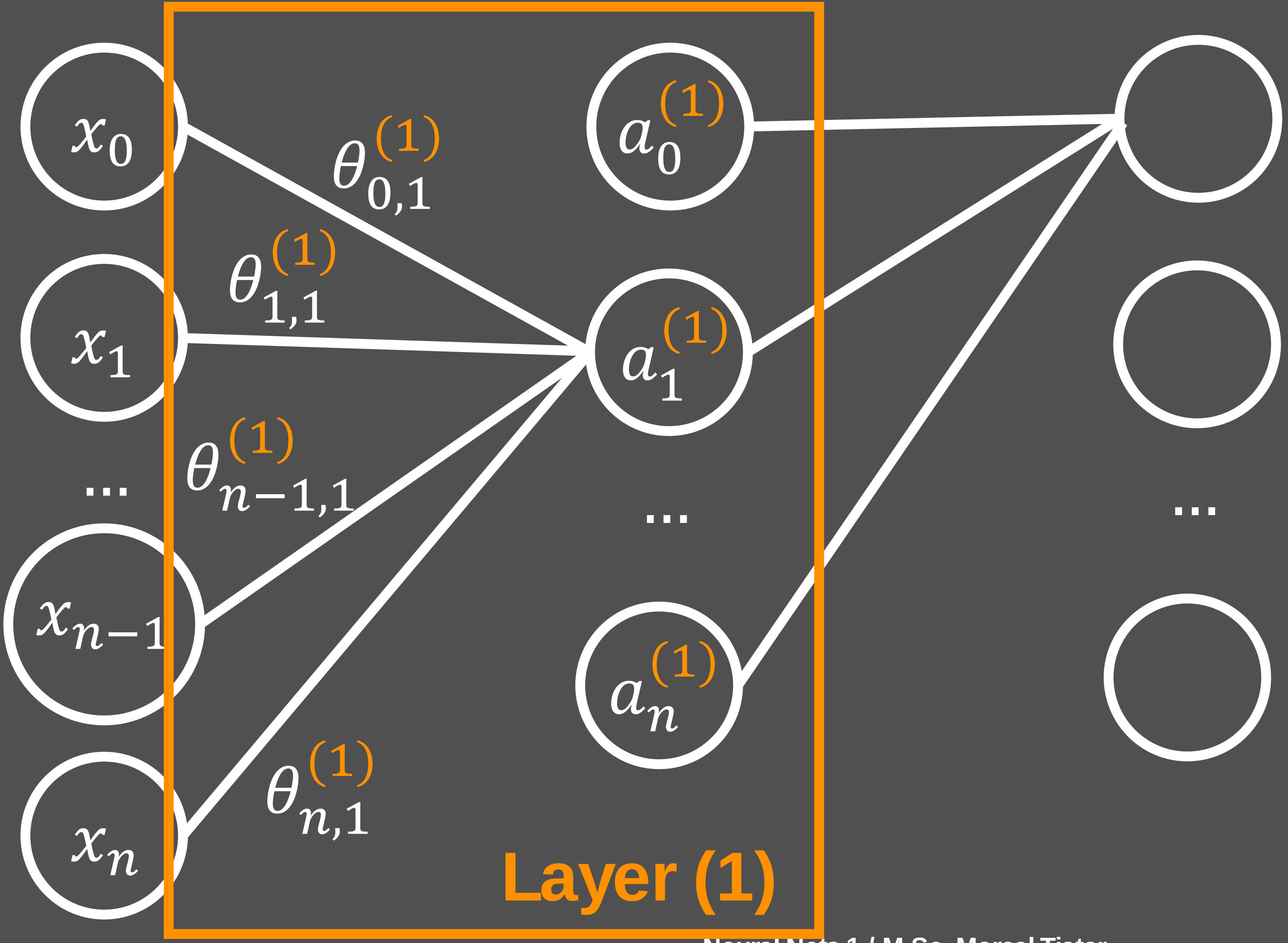
Output Neuron

Add More Layer!

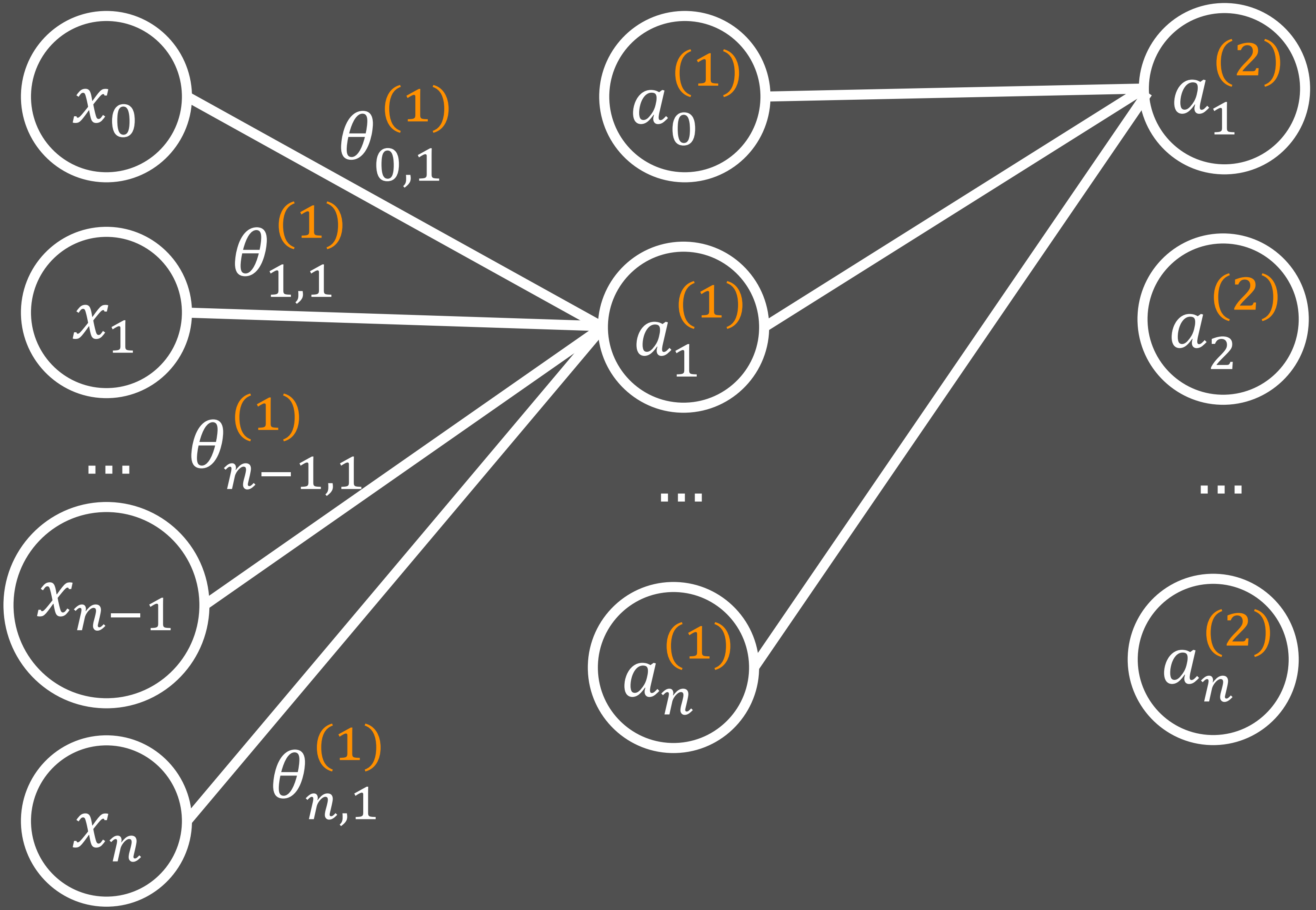
Forward Propagation



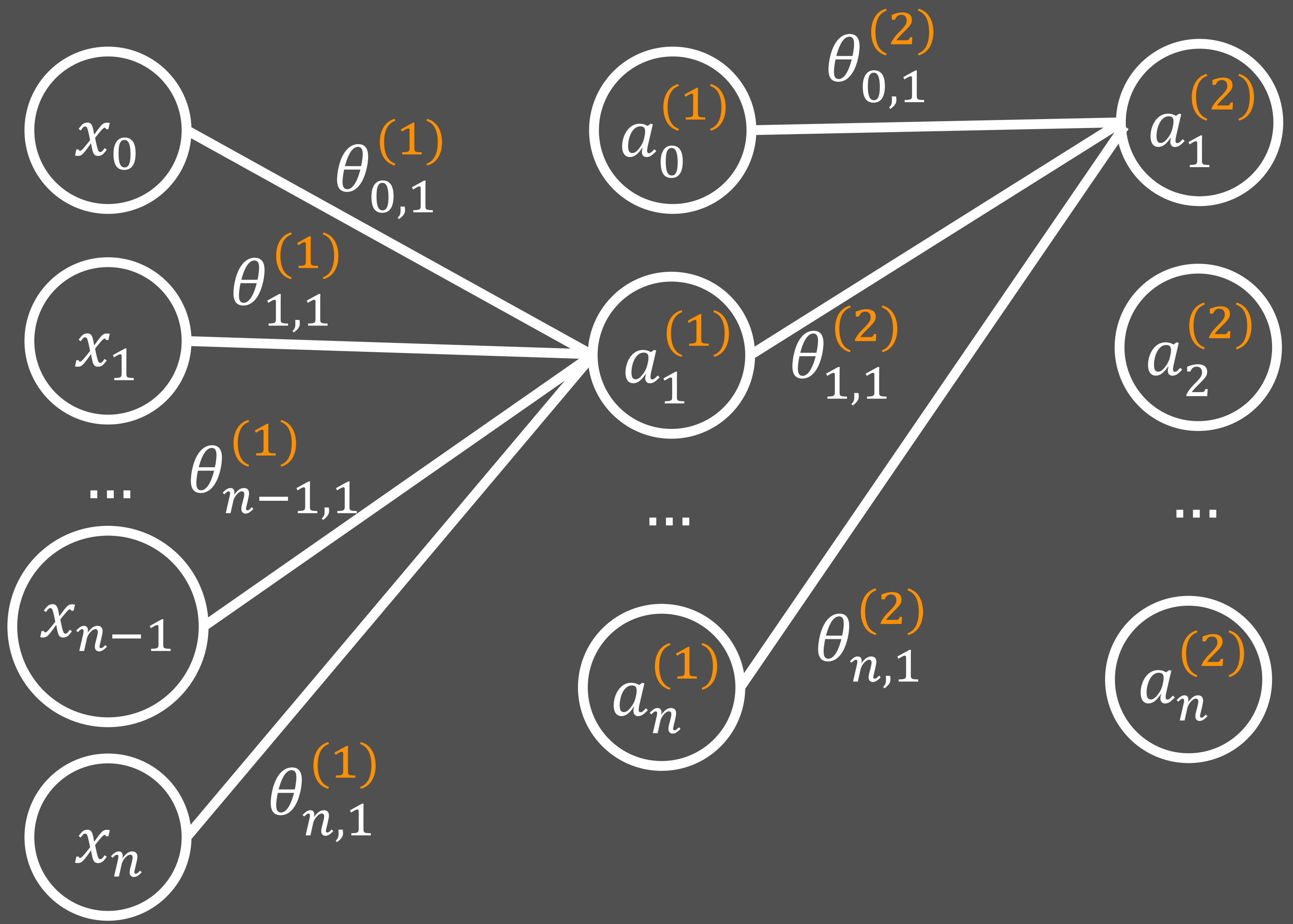
Forward Propagation



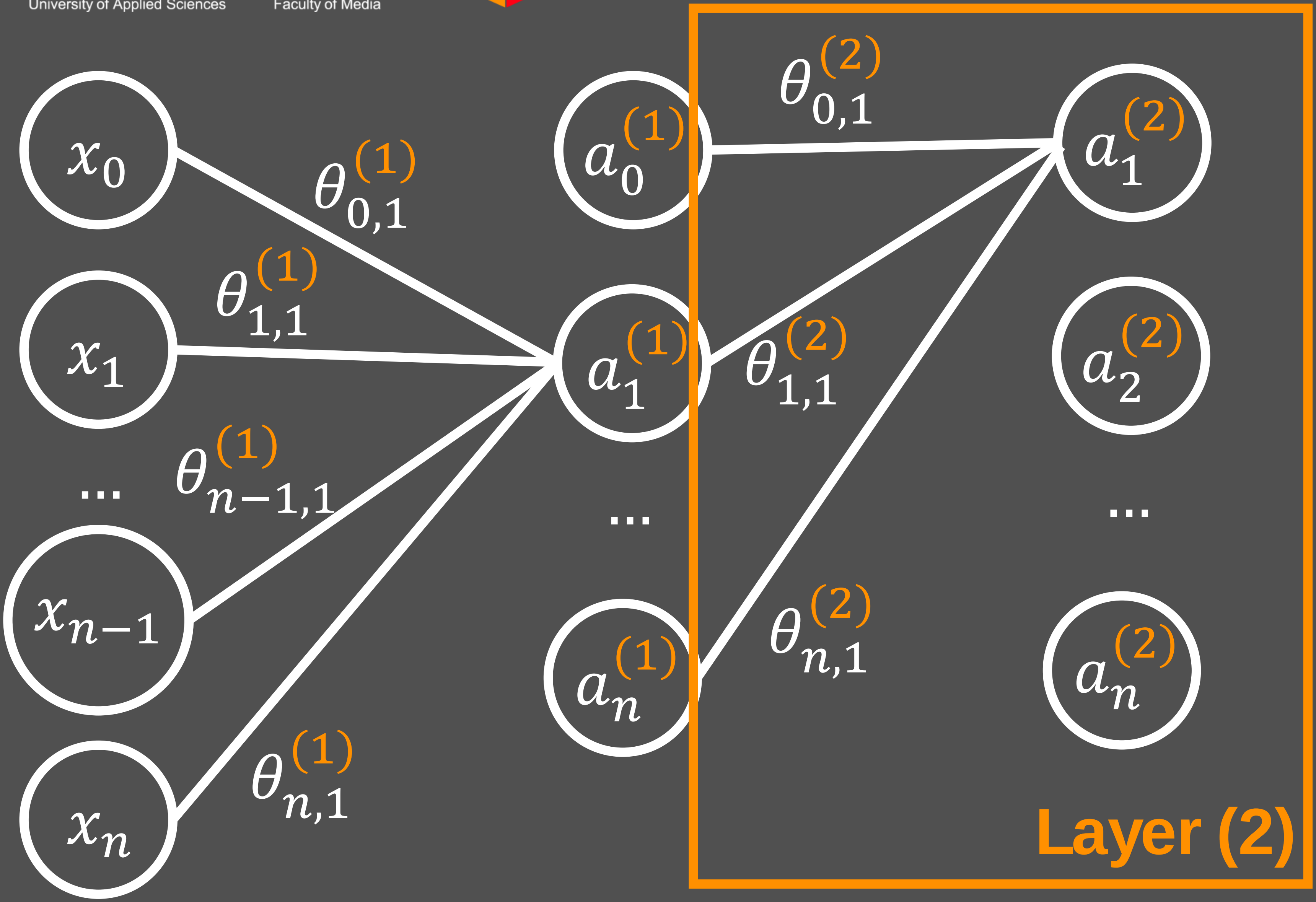
Forward Propagation



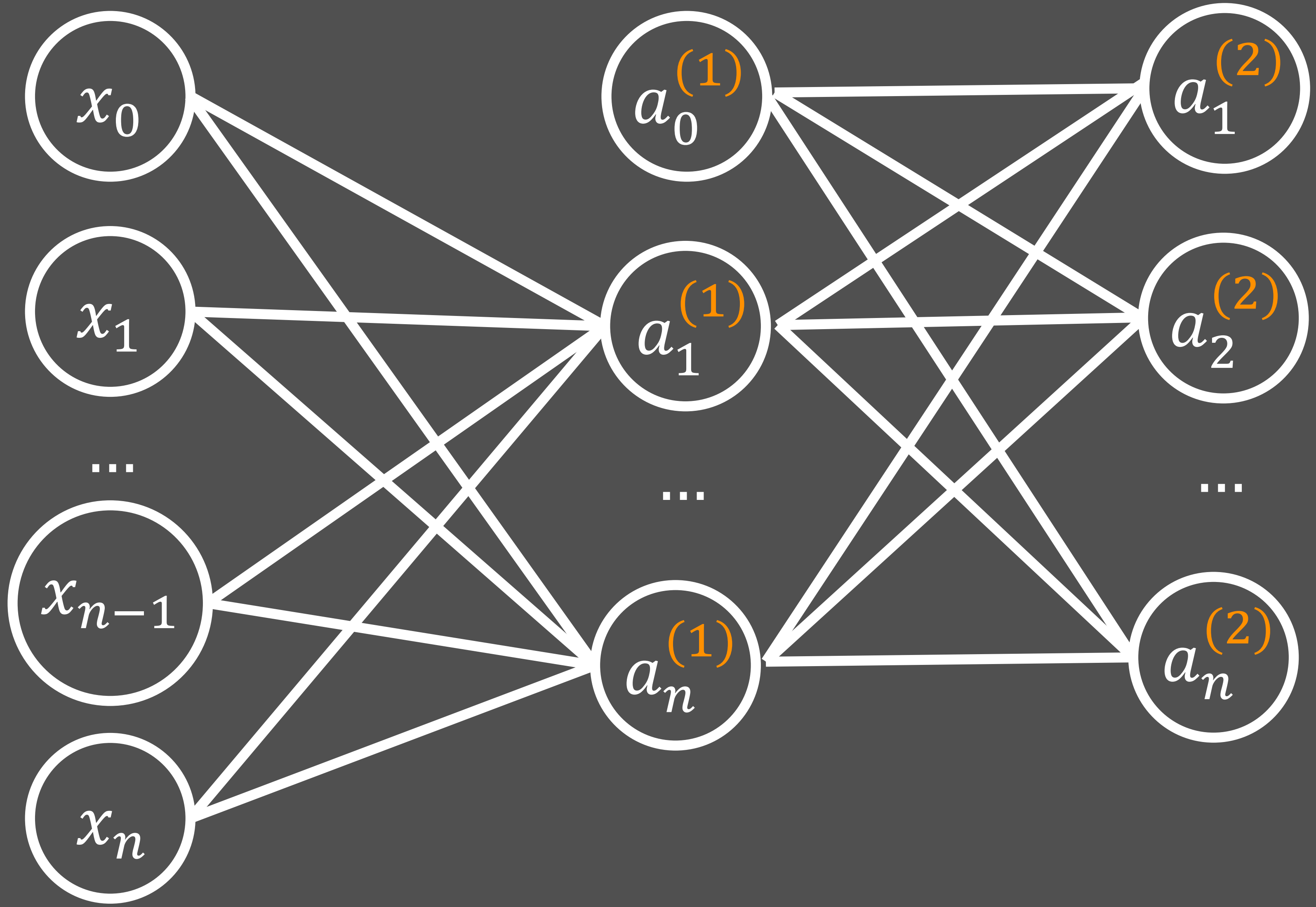
Forward Propagation



Forward Propagation

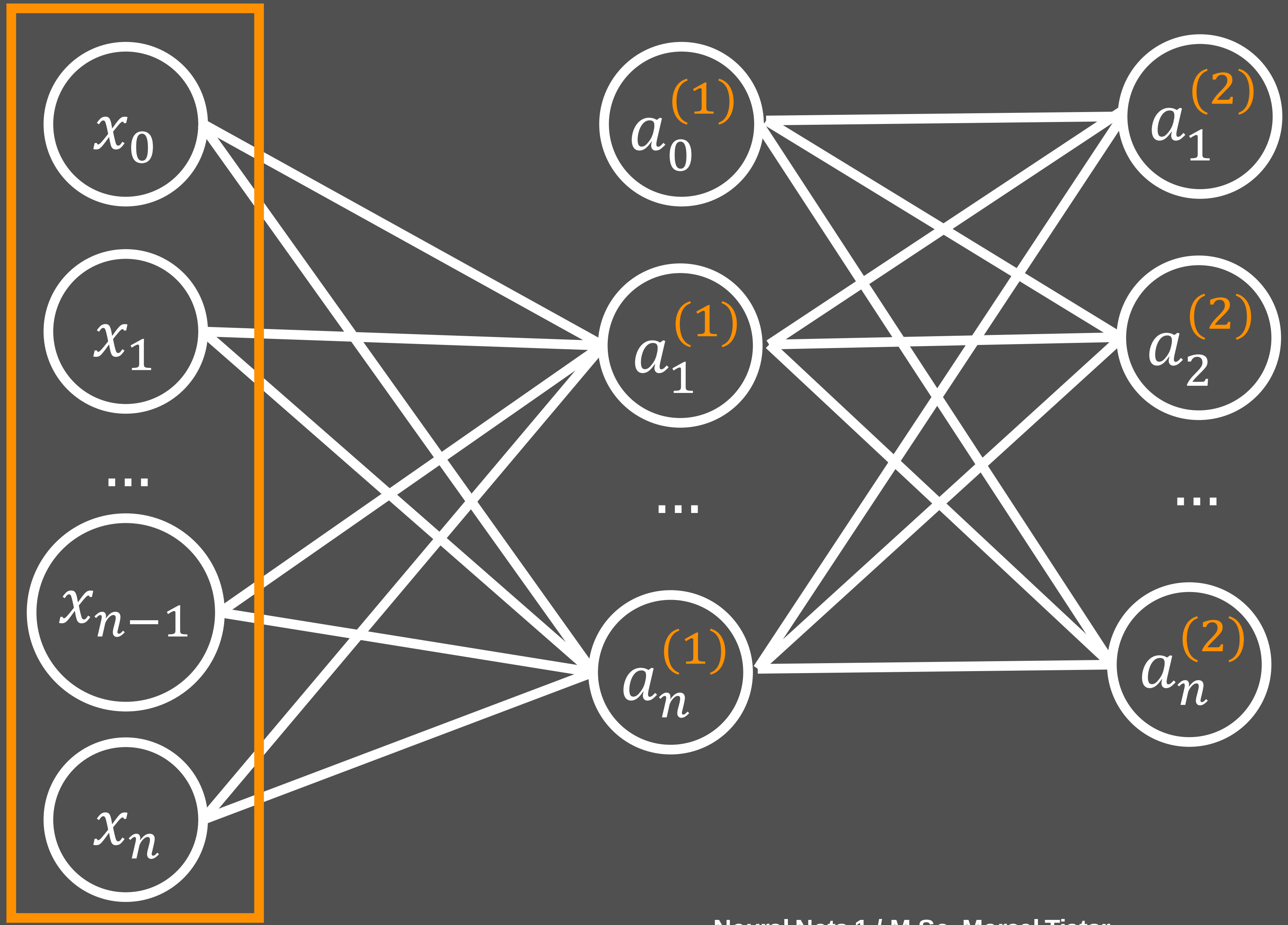


Forward Propagation



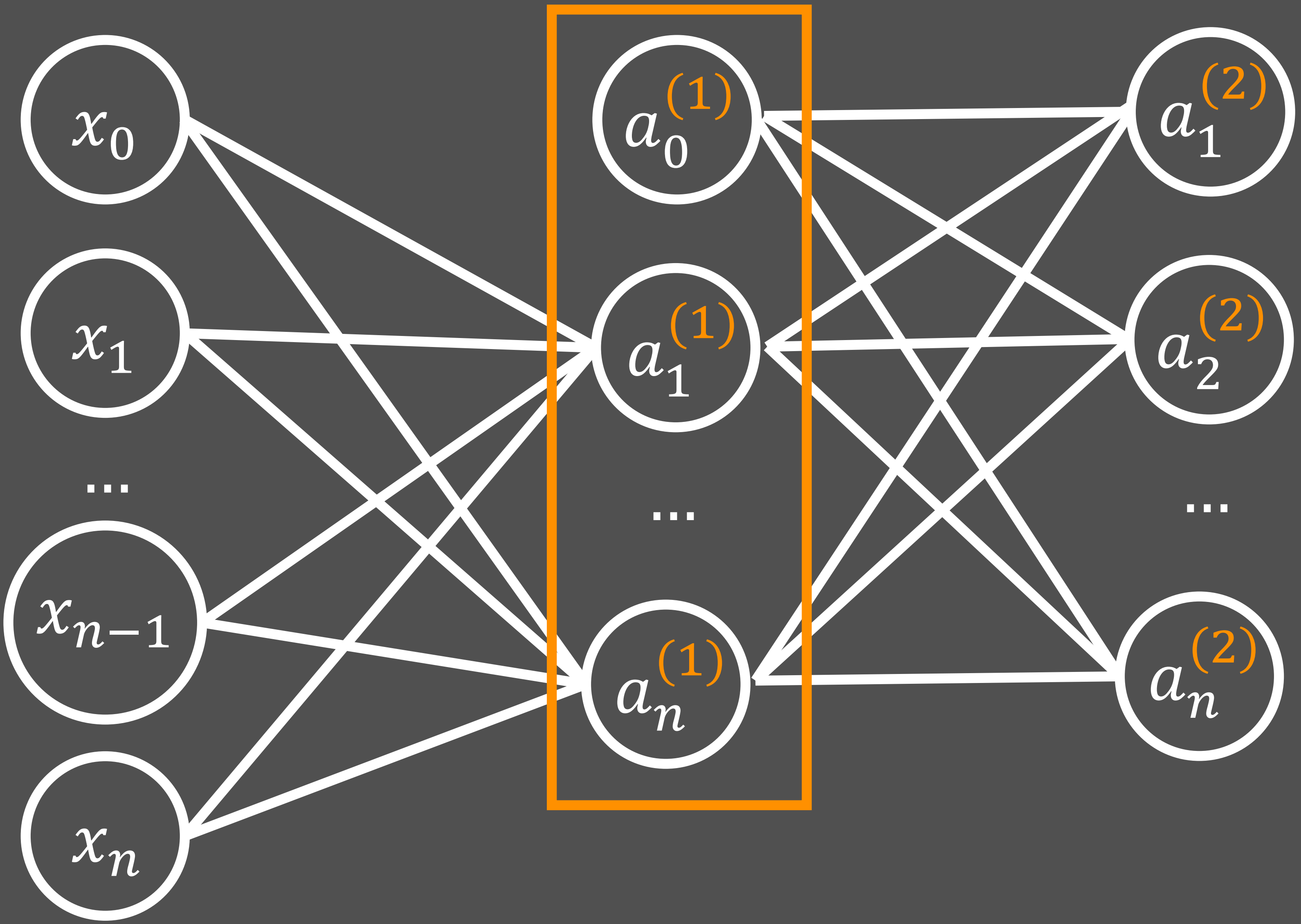
Forward Propagation

Input Layer



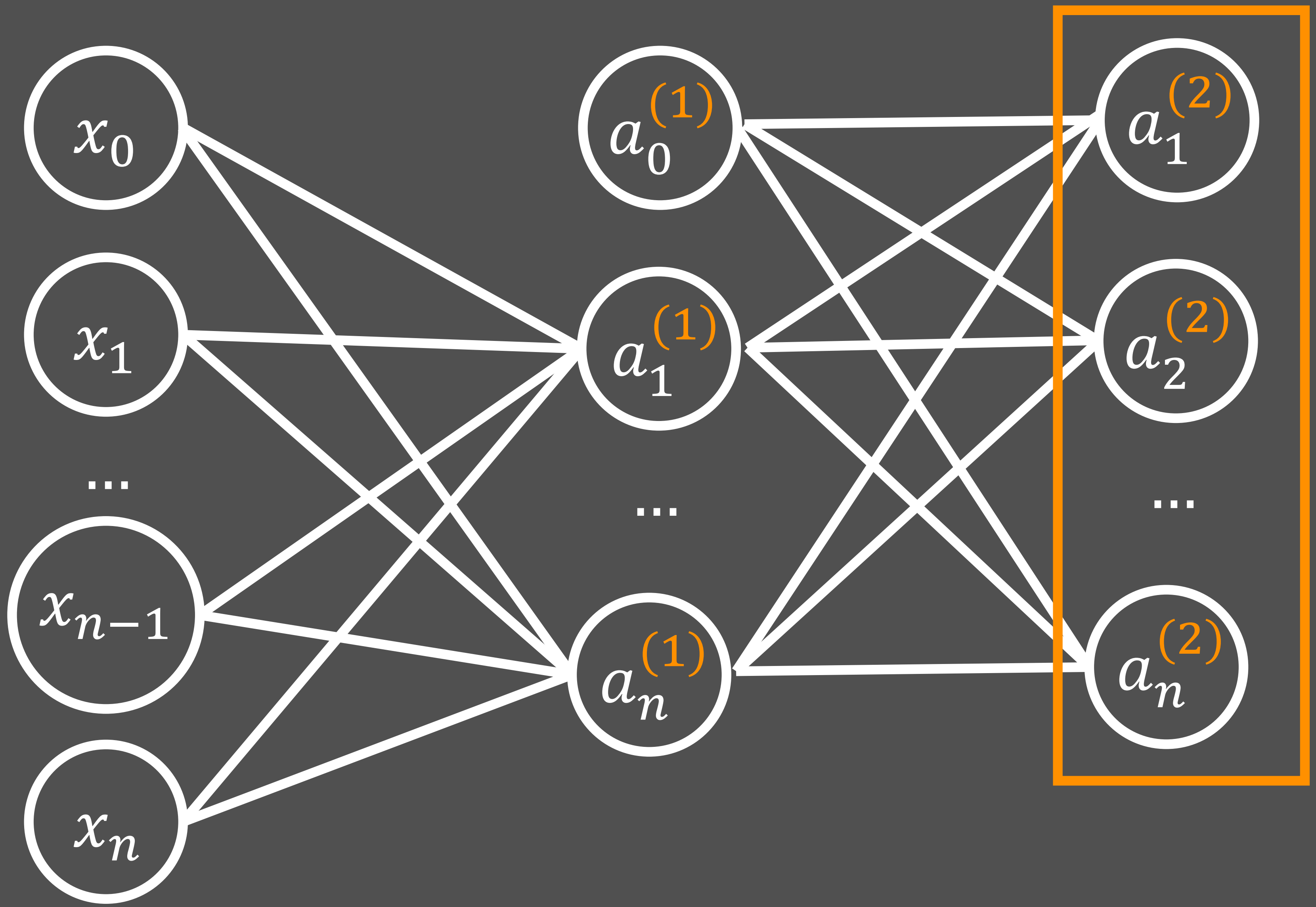
Forward Propagation

Hidden Layer



Forward Propagation

Output Layer



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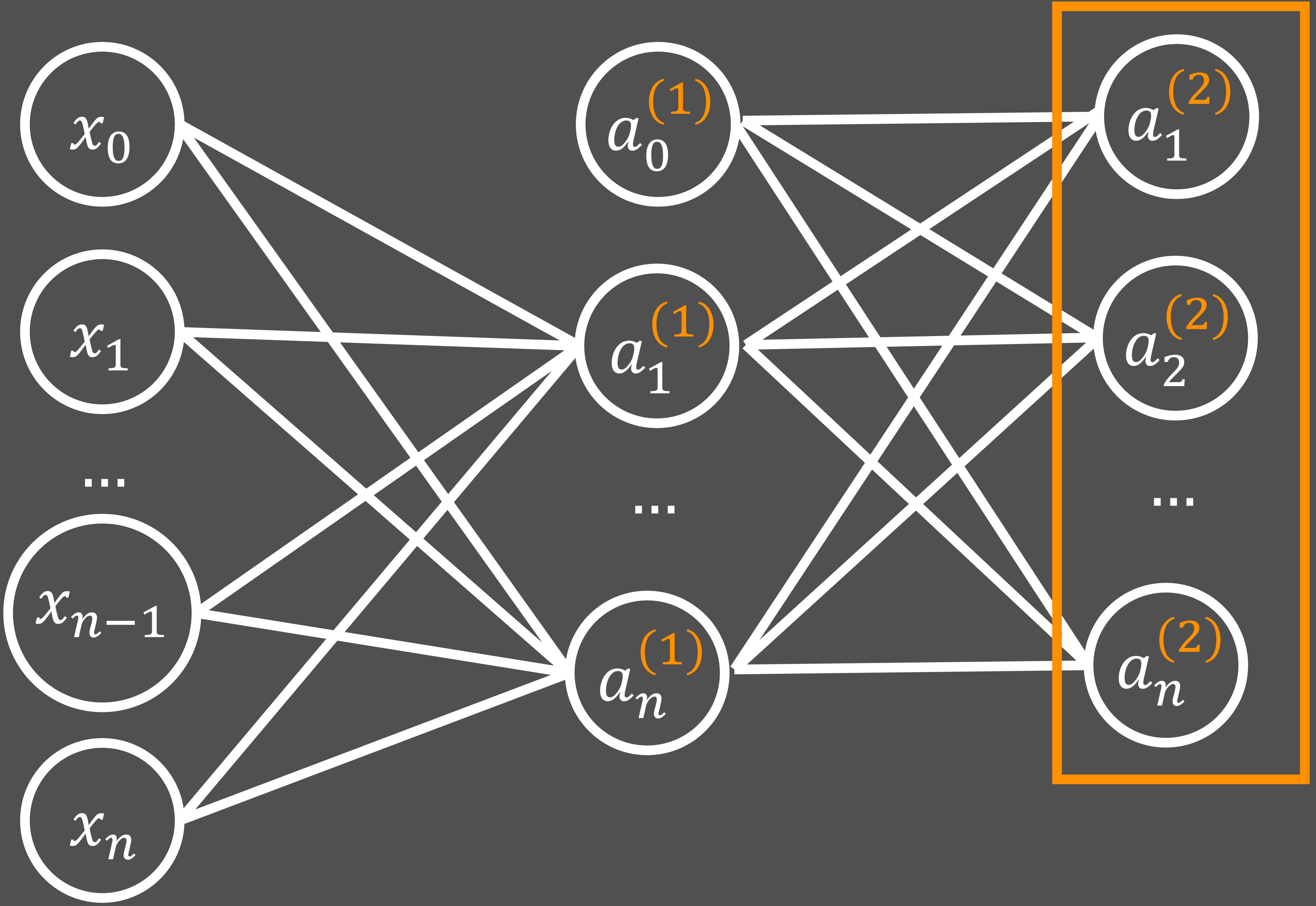
Fachbereich Medien
Faculty of Media

Forward Propagation



Output Layer:

- Multiclass Classification
- Each neuron could be interpreted as class probability

Forward Propagation

- Object Recognition
- Assume 4 classes
- L-Layer (L is the last layer)

$a_1^{(L)}$ Car

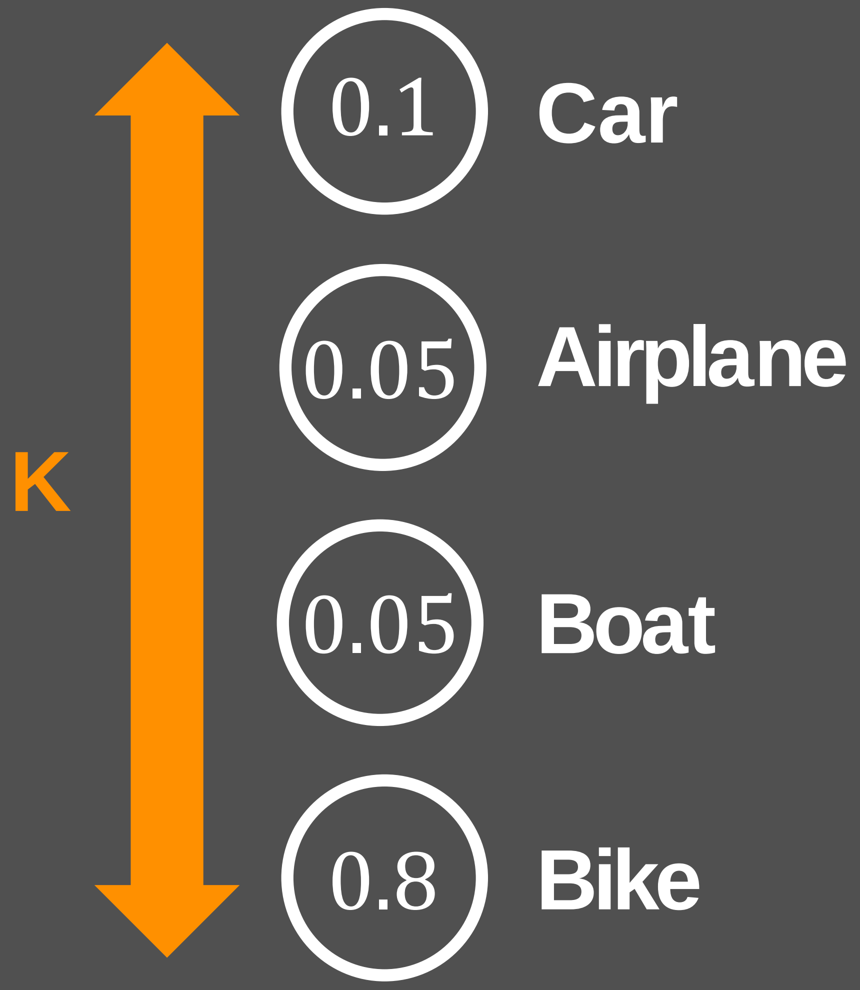
$a_2^{(L)}$ Airplane

$a_3^{(L)}$ Boat

$a_4^{(L)}$ Bike

Forward Propagation

- Object Recognition
- Assume 4 classes
- L-Layer (L is the last layer)
- Softmax: $a = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}$
- Use Softmax for the last Layer



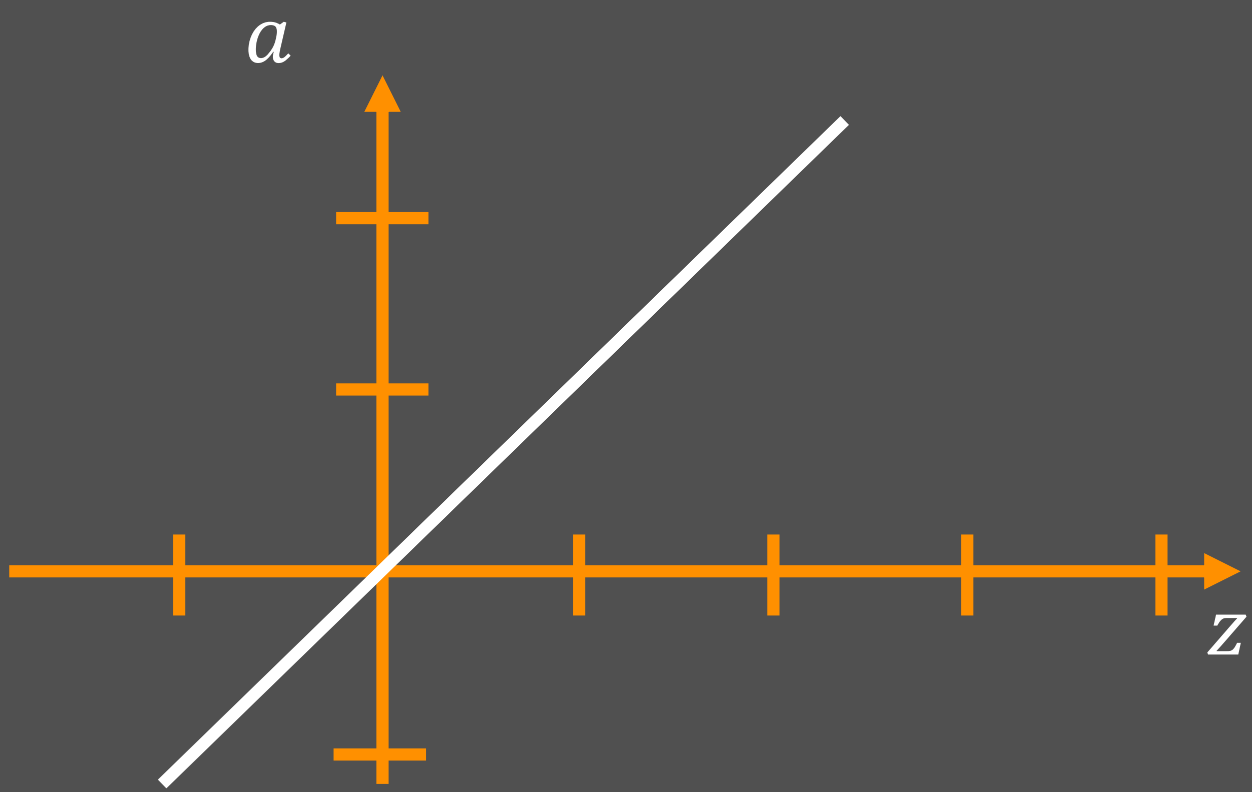
Forward Propagation

Hidden Layer Activation Functions $a(z)$:

- **Linear Neuron:** $a(z) = z$
- **Binary Threshold Unit:** $a(z) = \begin{cases} 0, z < 0 \\ 1, z \geq 0 \end{cases}$
- **Rectified Linear (ReLu):** $a(z) = \begin{cases} 0, z < 0 \\ z, z \geq 0 \end{cases}$
- **Sigmoid:** $a(z) = \frac{1}{1+e^{-z}}$
- **Tanh:** $a(z) = \tanh(z)$

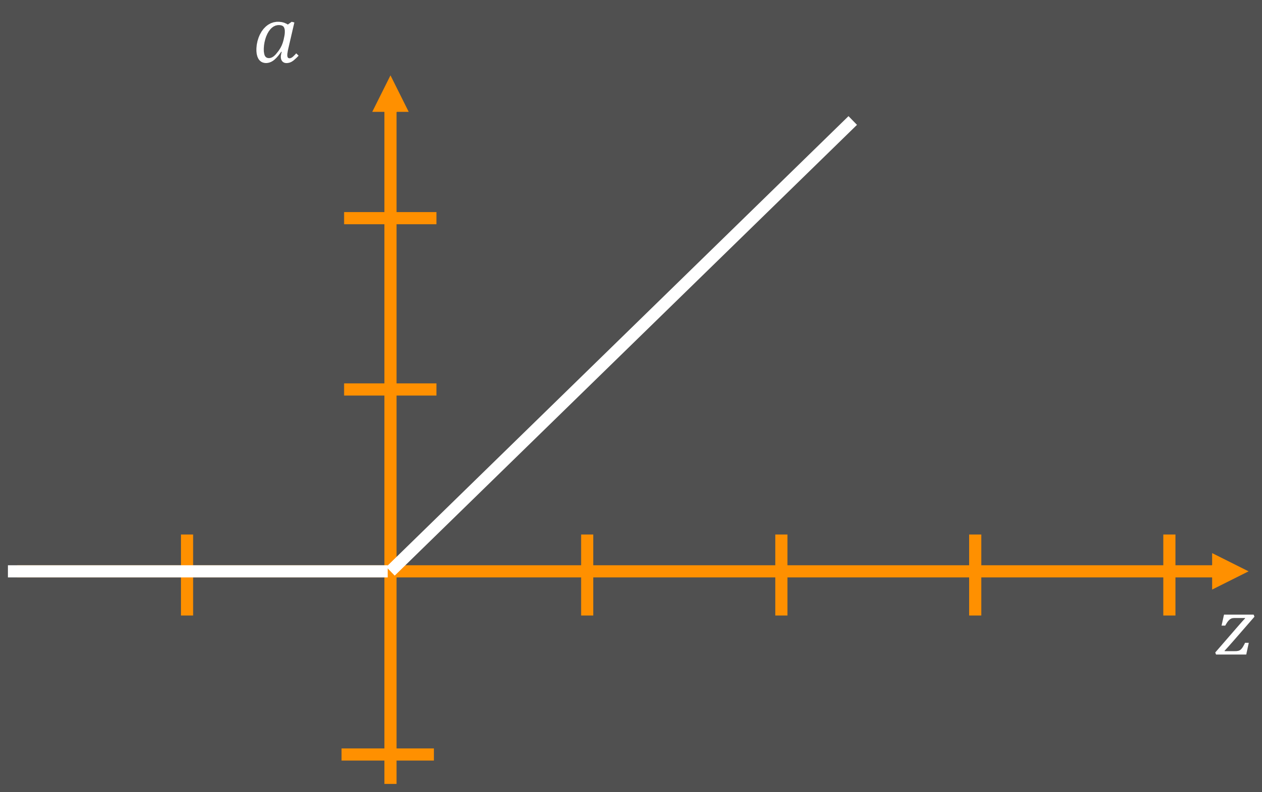
Forward Propagation

Linear Neuron: $a(z) = z$



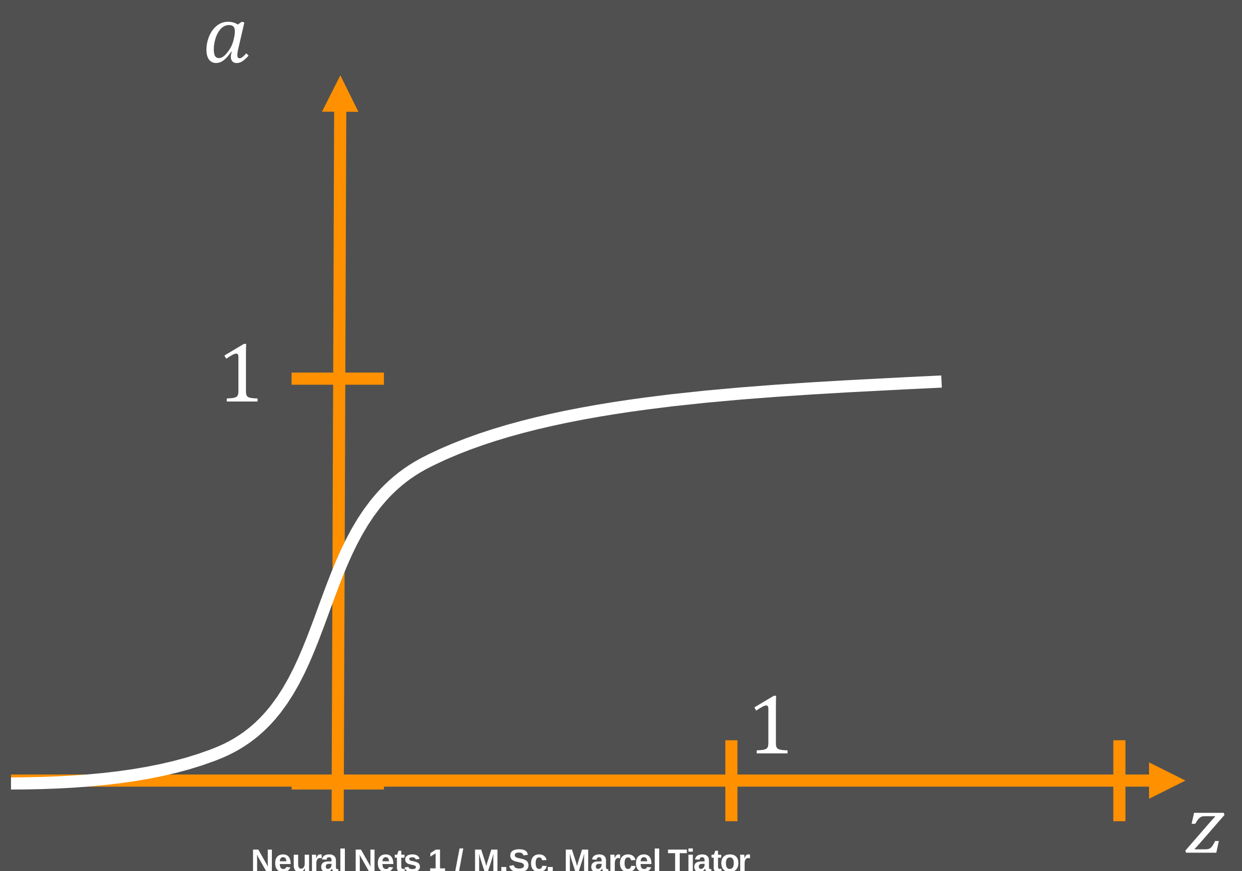
Forward Propagation

Rectified Linear (ReLu): $a(z) = \begin{cases} 0, z < 0 \\ z, z \geq 0 \end{cases}$



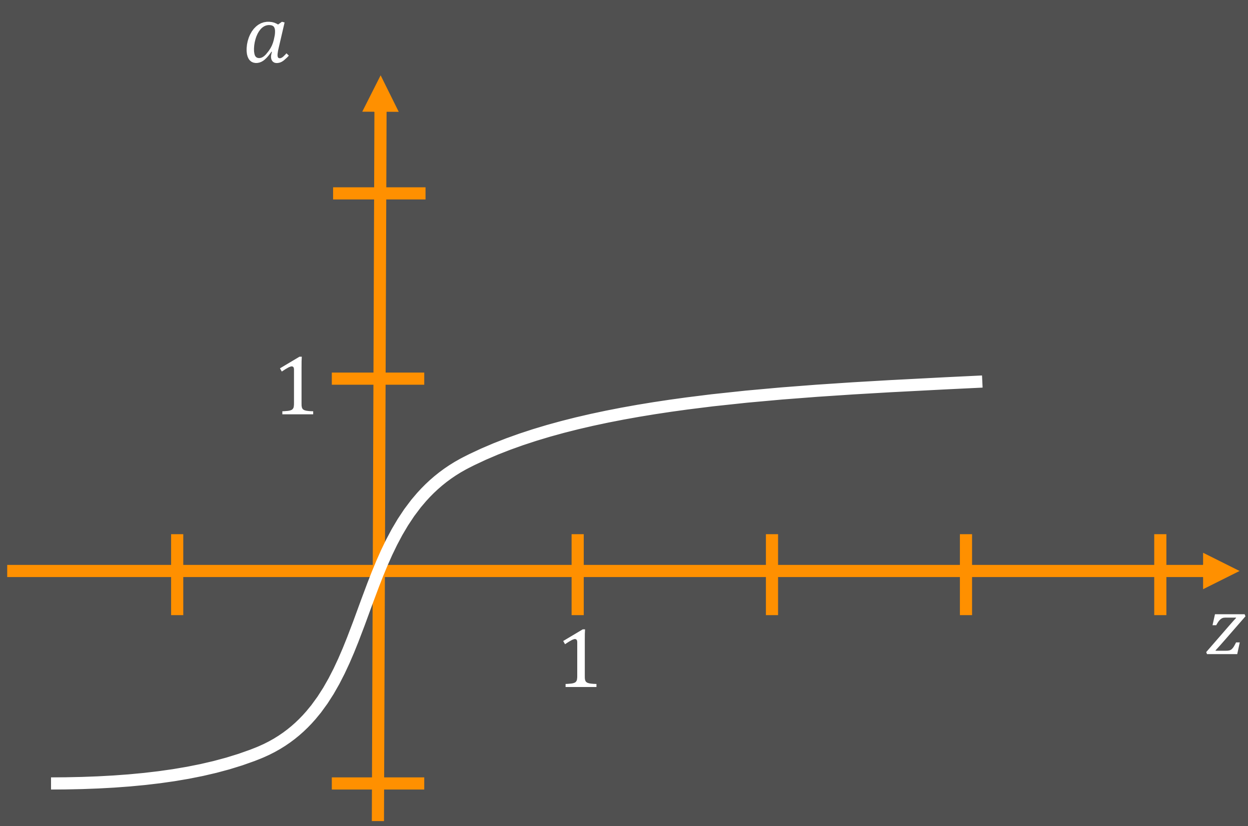
Forward Propagation

- **Sigmoid:** $a(z) = \frac{1}{1+e^{-z}}$



Forward Propagation

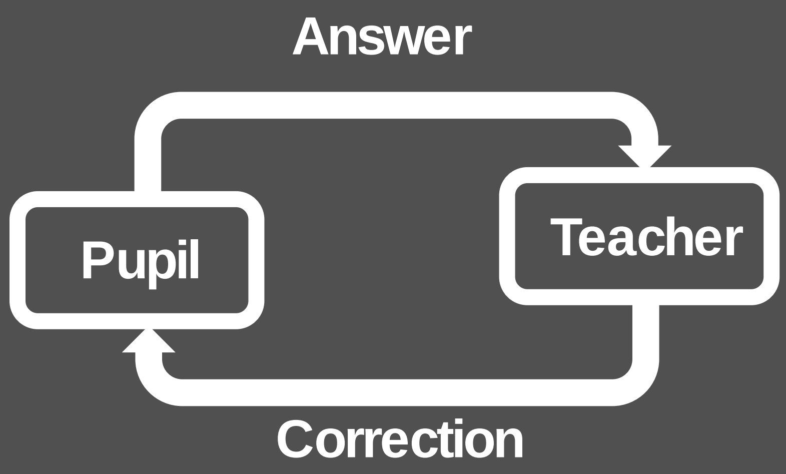
- **Tanh:** $a(z) = \tanh(z)$

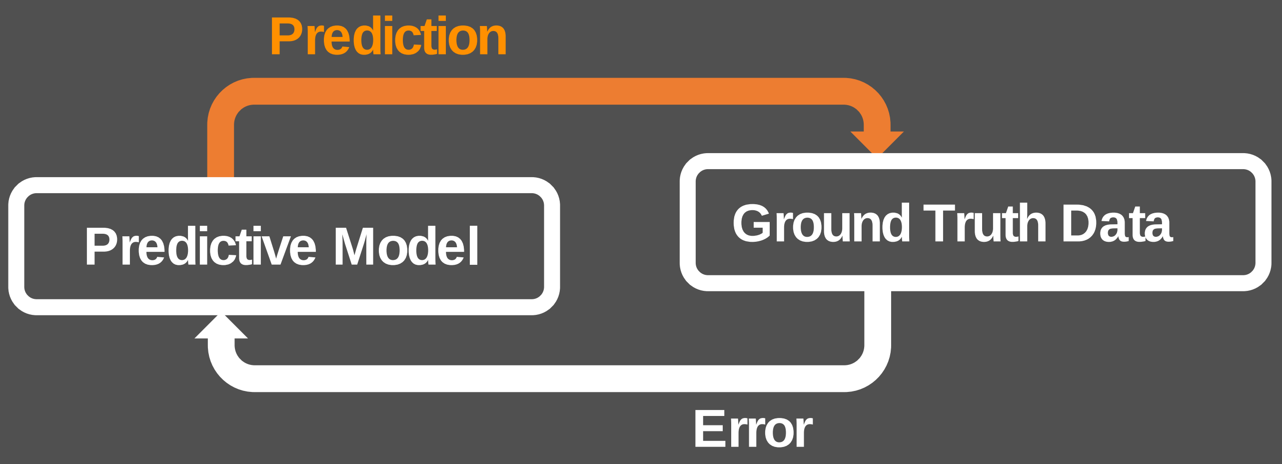


Backward Propagation

Two Processes:

- Forward Propagation (Prediction)
- Backward Propagation (Weight Tuning)

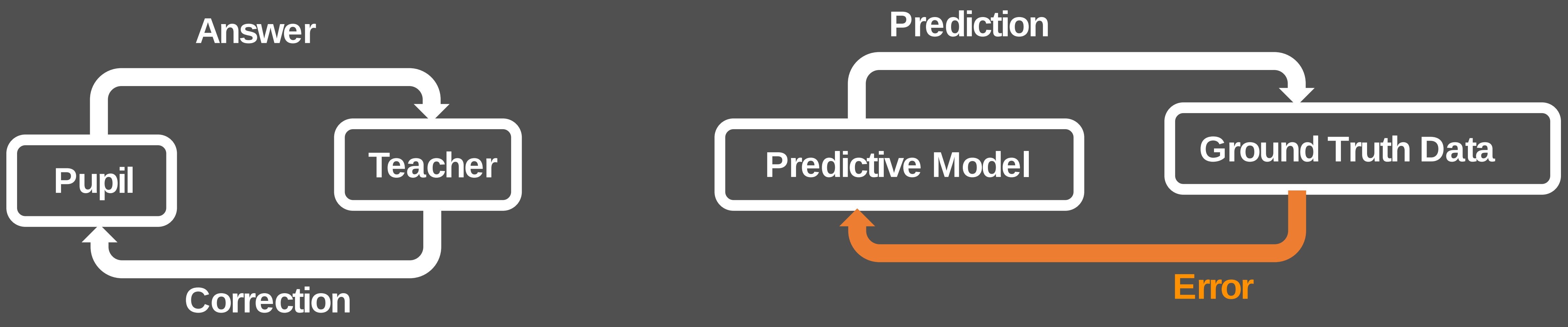




Backward Propagation

Two Processes:

- Forward Propagation (Prediction)
- Backward Propagation (Weight Tuning)



Backward Propagation

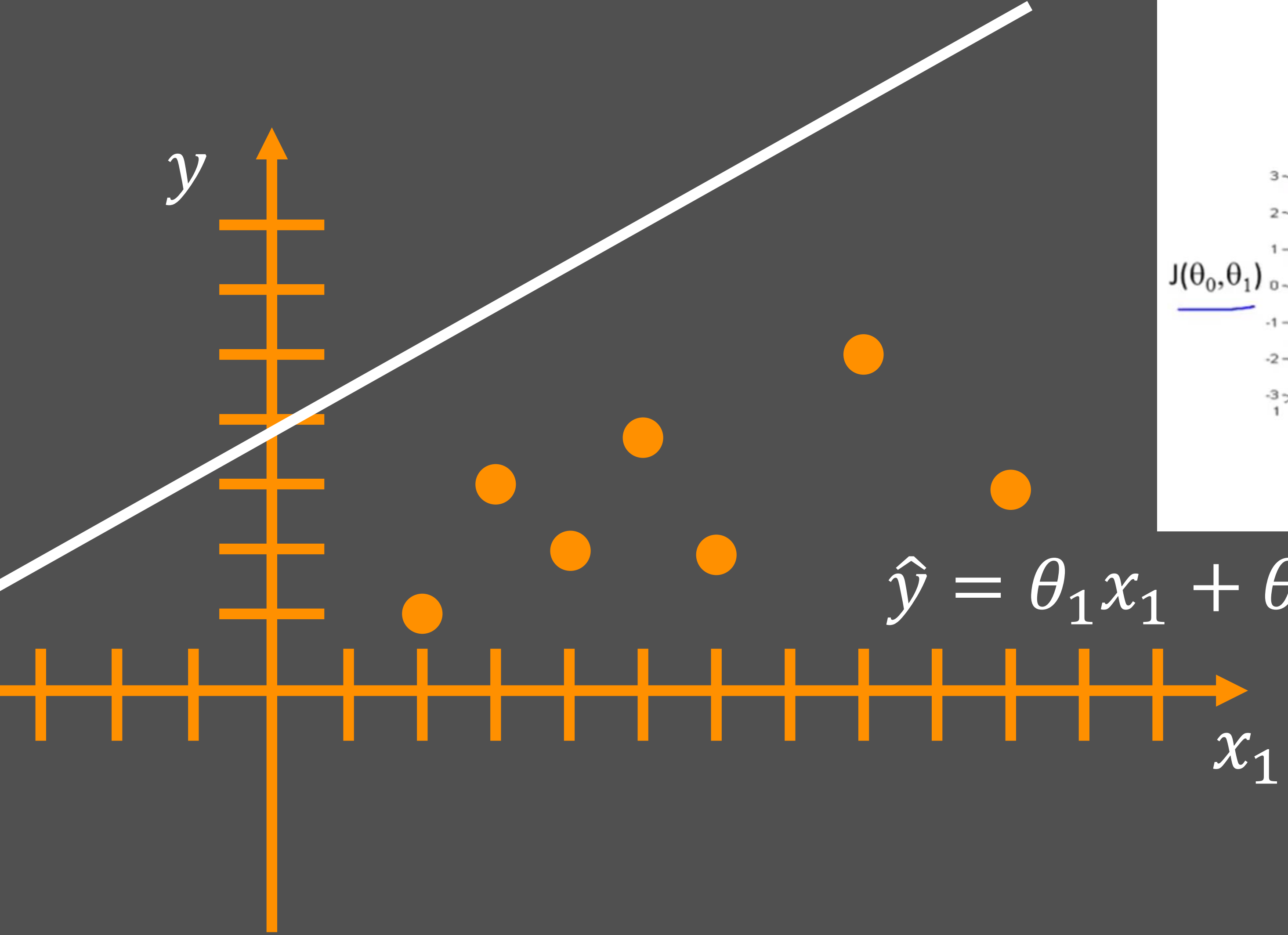
Training of MLP:

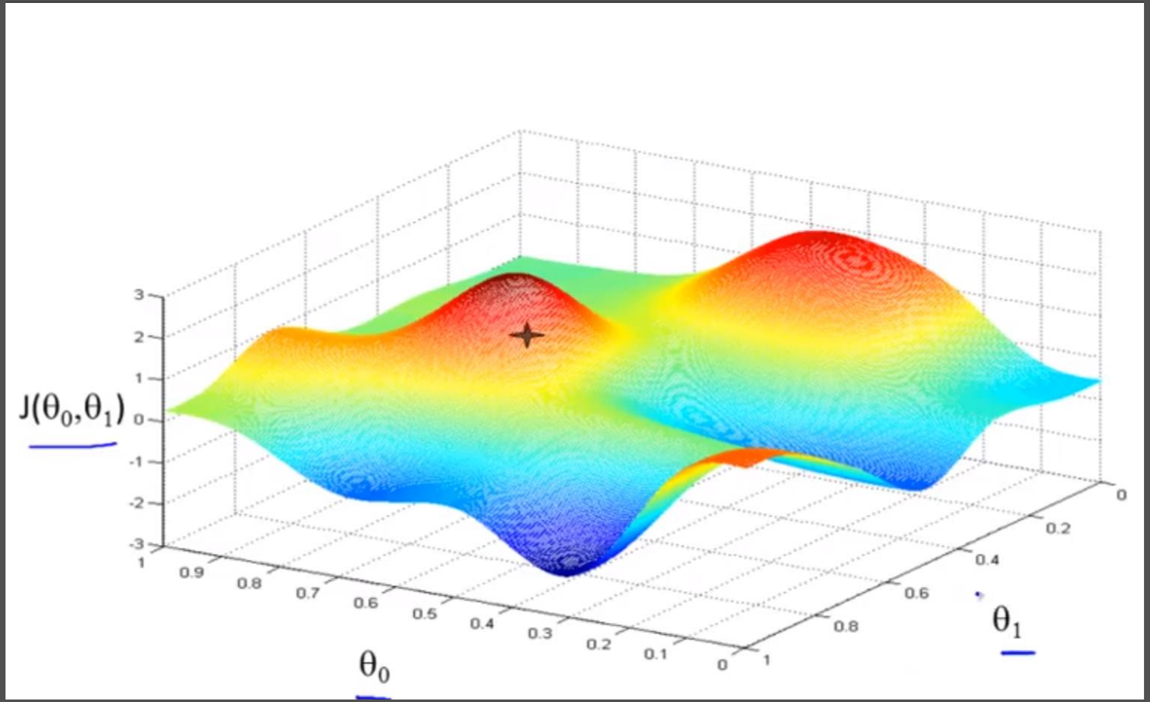
- Use Gradient-Based Algorithm: Backpropagation
- Similar to Gradient Descent
- Weight-Update is more complex

Backward Propagation

- Assume, we get some Output $\hat{y}$ from MLP
- Compute function $E = \frac{1}{2m}\sum_{t=1}^{m}(\hat{y}_t - y_t)^2$
- Want to $\min\limits_{\Theta_{i,j}^{(l)}} E(\Theta_{i,j}^{(l)})$ so calculate $\frac{\partial E(\Theta_{i,j}^{(l)})}{\partial \Theta_{i,j}^{(l)}}$
- Use $\frac{\partial E(\Theta_{i,j}^{(l)})}{\partial \Theta_{i,j}^{(l)}}$ to update weights with learning rate
- $\Theta_{i,j}^{(l)} := \Theta_{i,j}^{(l)} - \alpha \frac{\partial E(\Theta_{i,j}^{(l)})}{\partial \Theta_{i,j}^{(l)}}$

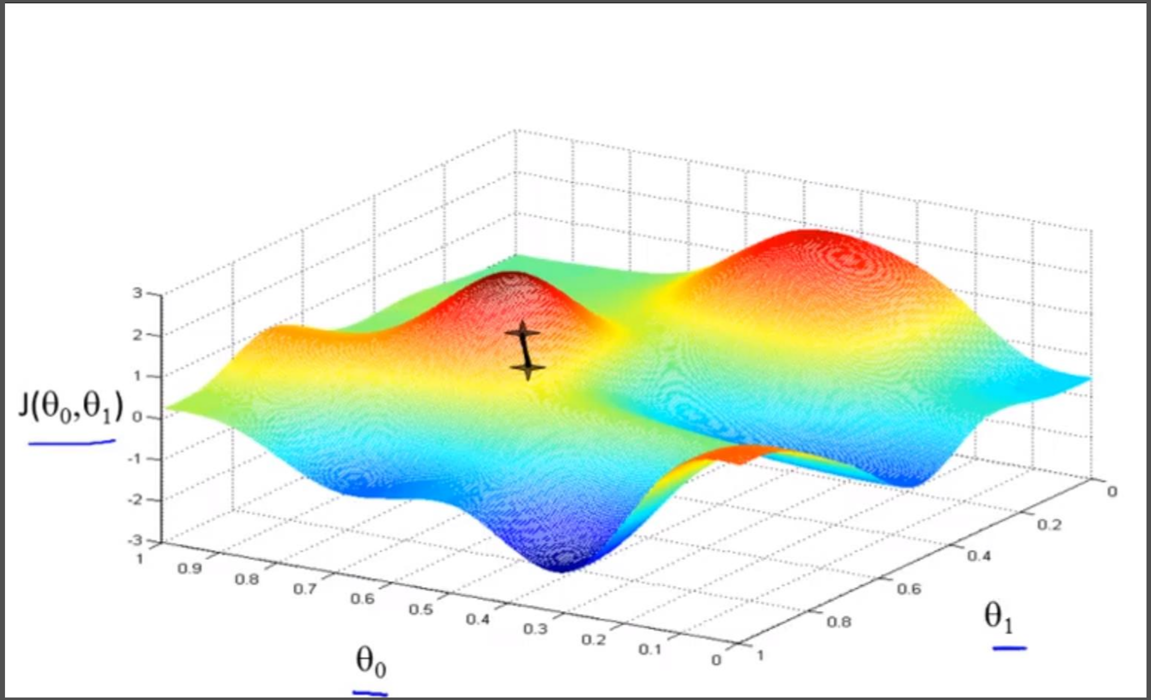
Backward Propagation

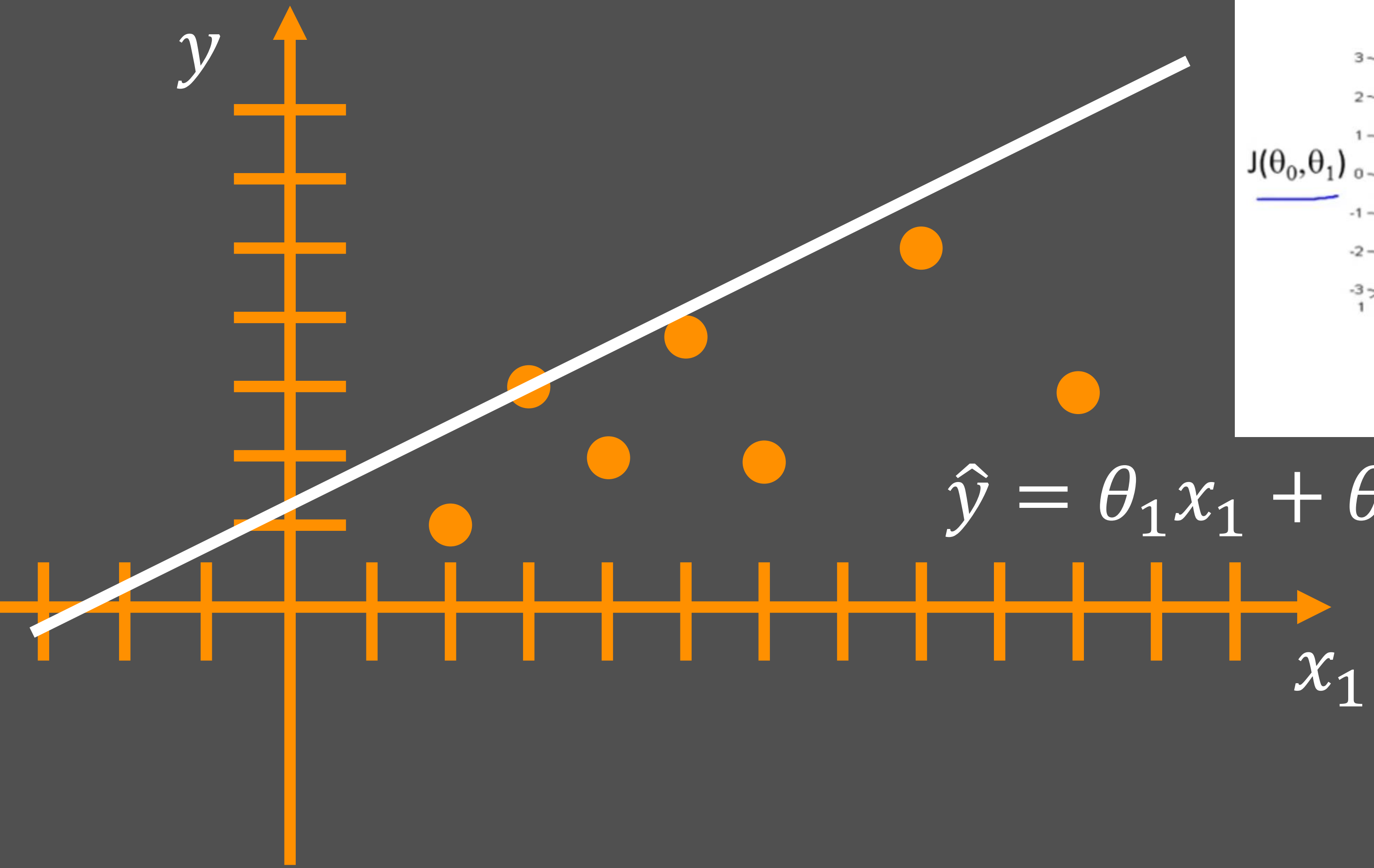




$$\hat{y} = \theta_1 x_1 + \theta_0 x_0$$

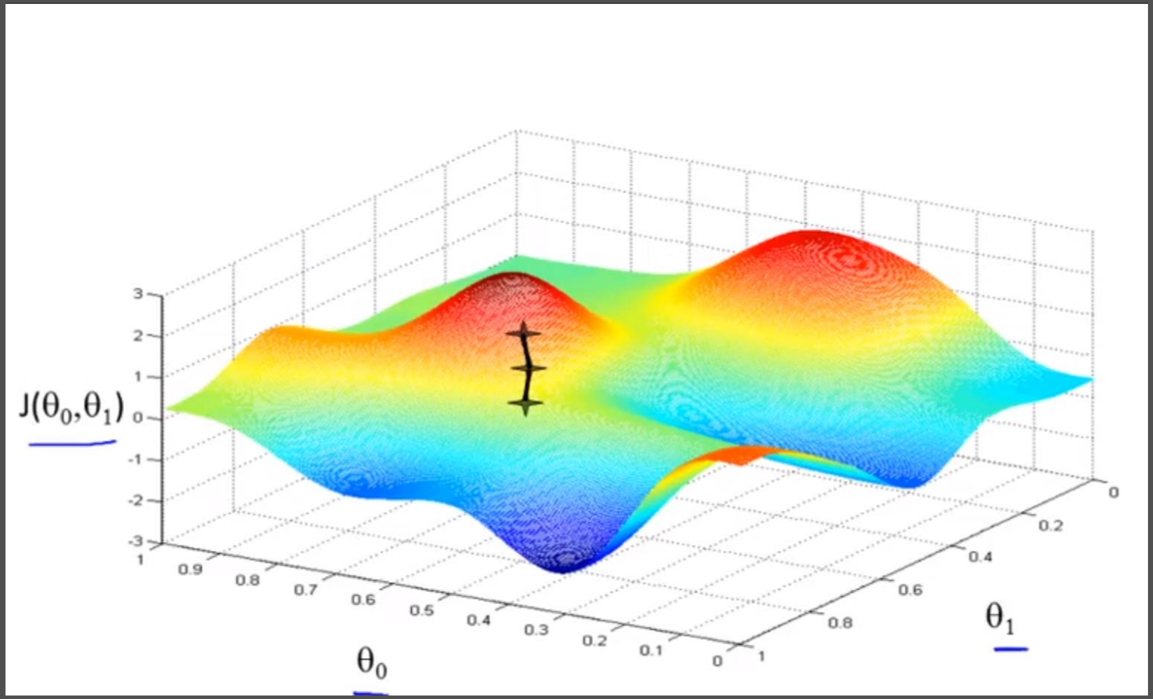
Backward Propagation

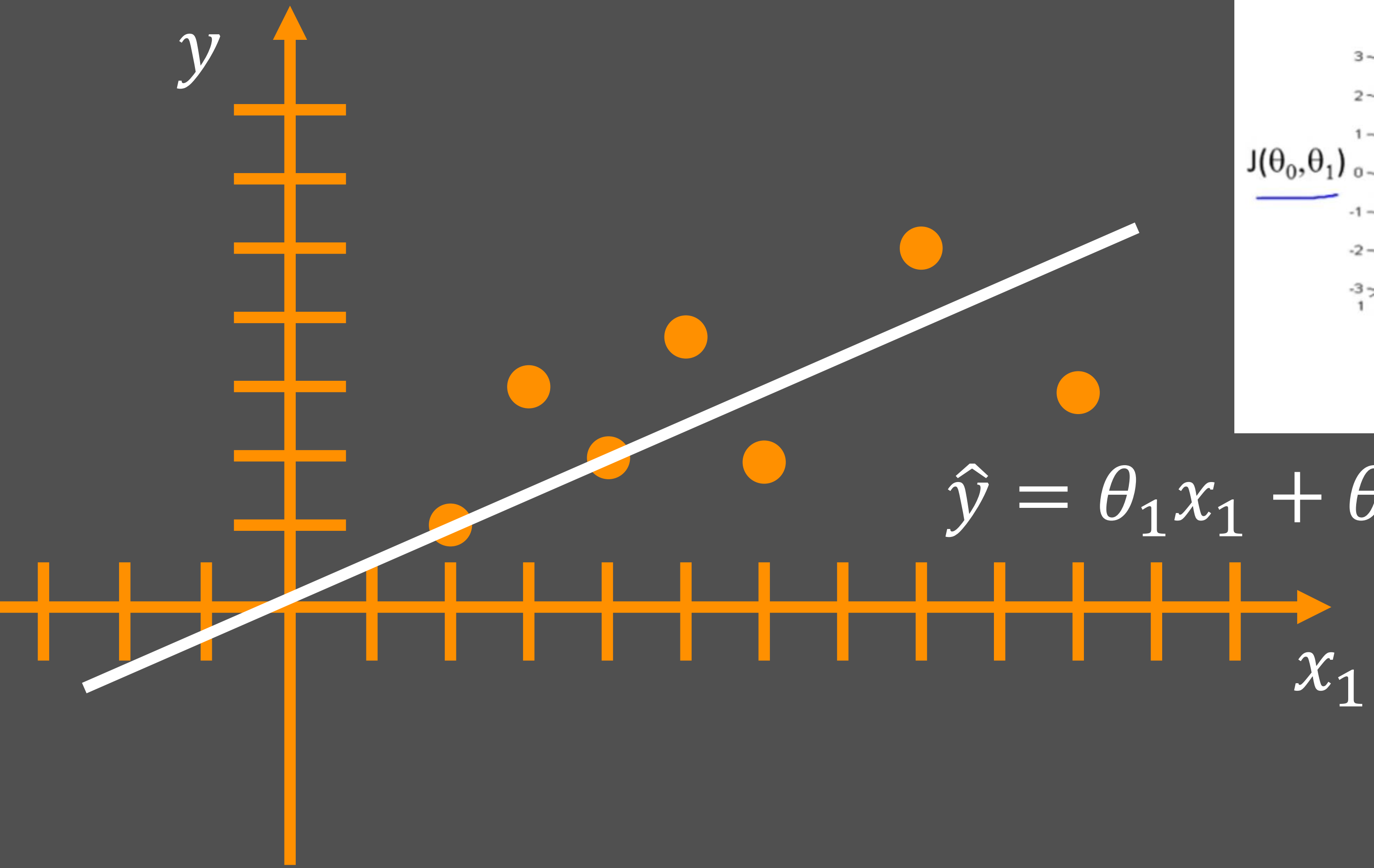




$$\hat{y} = \theta_1 x_1 + \theta_0 x_0$$

Backward Propagation





$$\hat{y} = \theta_1 x_1 + \theta_0 x_0$$

Hands-On Session

3 Scripts:

- estimator.py: Script that trains a DNNClassifier
- load_data.py: Utility functions to load data
- predict.py: Real world prediction with unlabeled data

Your task:

- Fill in the gaps which are highlighted with TODO
- Use internet and documentation

- Pull code & slides from repository
  - https://github.com/mati3230/modalg181
- Download dataset from Nextcloud
  - iris_flower and Magic_Gamma_Telescope
  - https://nextcloud.mirevi.medien.hs-duesseldorf.de/index.php/s/kPXwJiac7vTQVeu