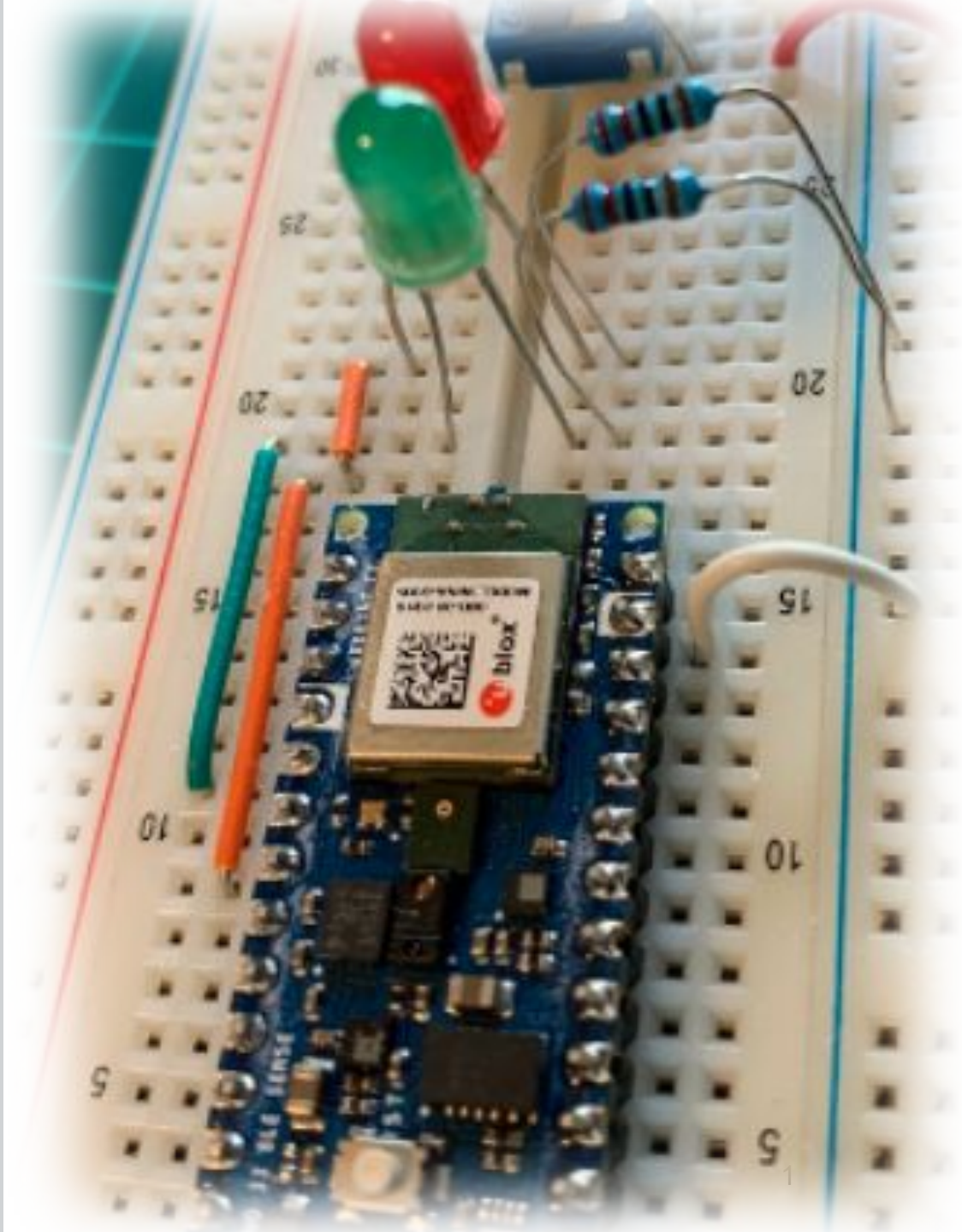
IESTI01 – TinyML

Embedded Machine Learning

5. The Machine Learning Paradigm



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UNIFEI

The Machine Learning Paradigm

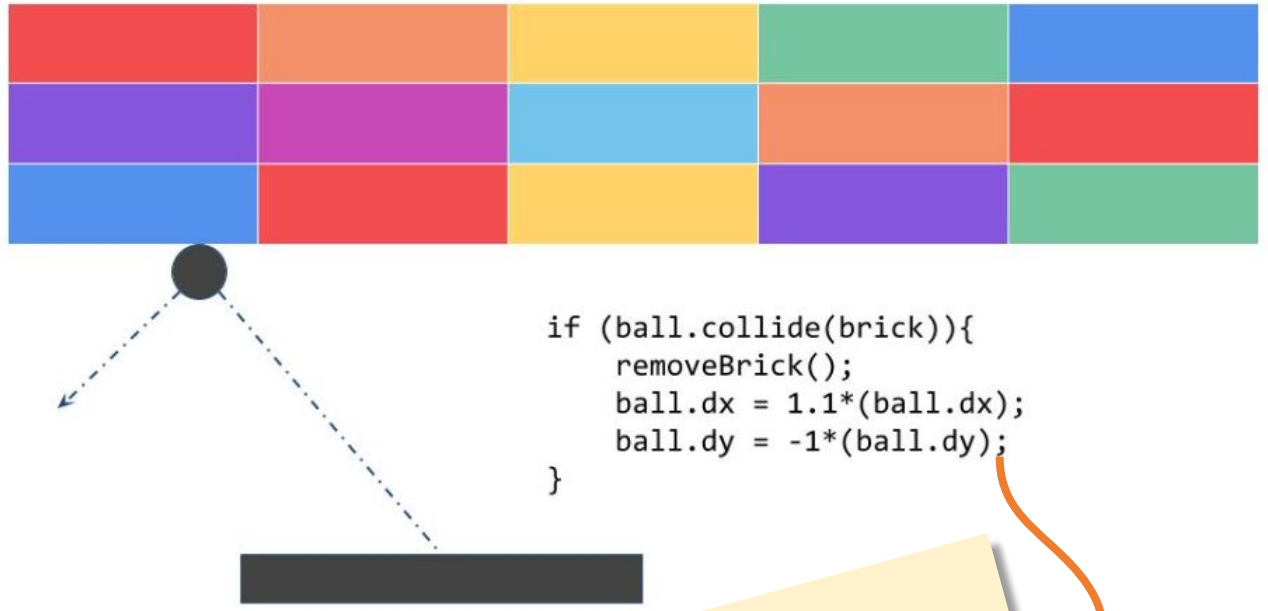
From coding to learning…

Explicit Coding

Defining rules that determine behavior of a program

Everything is pre-calculated and pre-determined by the programmer

Scenarios are limited by program complexity



Rules

- If the ball collides with the brick:
  - Remove brick
  - Change ball direction
  - Increase ball speed
- …

https://en.wikipedia.org/wiki/Breakout_(video_game)

The Traditional Programming Paradigm

Consider Activity Detection

```
if(speed<4){
    status=WALKING;
}
```

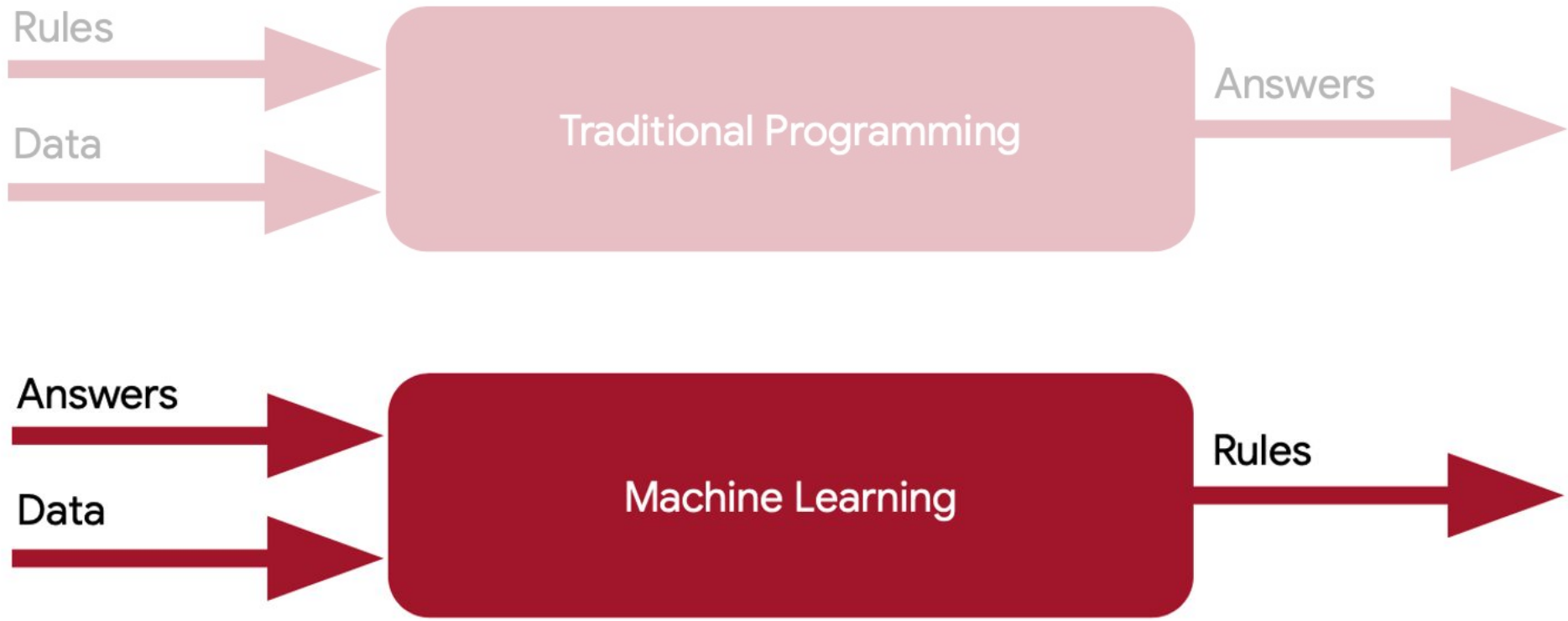
```
if(speed<4){
    status=WALKING;
} else {
    status=RUNNING;
}
```

```
if(speed<4){
    status=WALKING;
} else if(speed<12){
    status=RUNNING;
} else {
    status=BIKING;
}
```

```
// ???
```

The Traditional Programming Paradigm

The Traditional Programming Paradigm



Activity Detection with Machine Learning

```
0101001010100101010
1001010101001011101
0100101010010101001
0101001010100101010
```

Label = WALKING

```
1010100101001010101
0101010010010010001
0010011111010101111
1010100100111101011
```

Label = RUNNING

```
1001010011111010101
1101010111010101110
1010101111010101011
1111110001111010101
```

Label = BIKING

```
1111111111010011101
0011111010111110101
0101110101010101110
1010101010100111110
```

Label = GOLFING

The Machine Learning Paradigm

```
0101001010100101010
1001010101001011101
0100101010010101001
0101001010100101010
```

Label = WALKING

```
1010100101001010101
0101010010010010001
0010011111010101111
1010100100111101011
```

Label = RUNNING

```
1001010011111010101
1101010111010101110
1010101111010101011
1111110001111010101
```

Label = BIKING

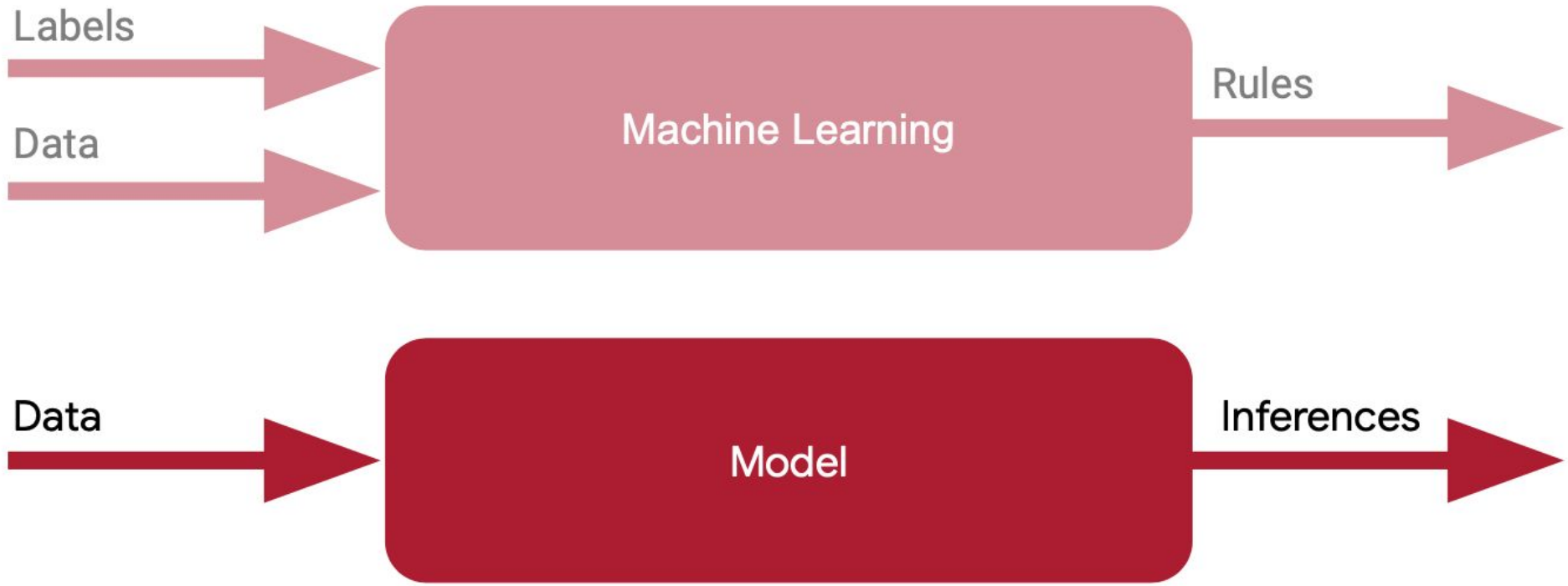
```
1111111111010011101
0011111010111110101
0101110101010101110
1010101010100111110
```

Label = GOLFING

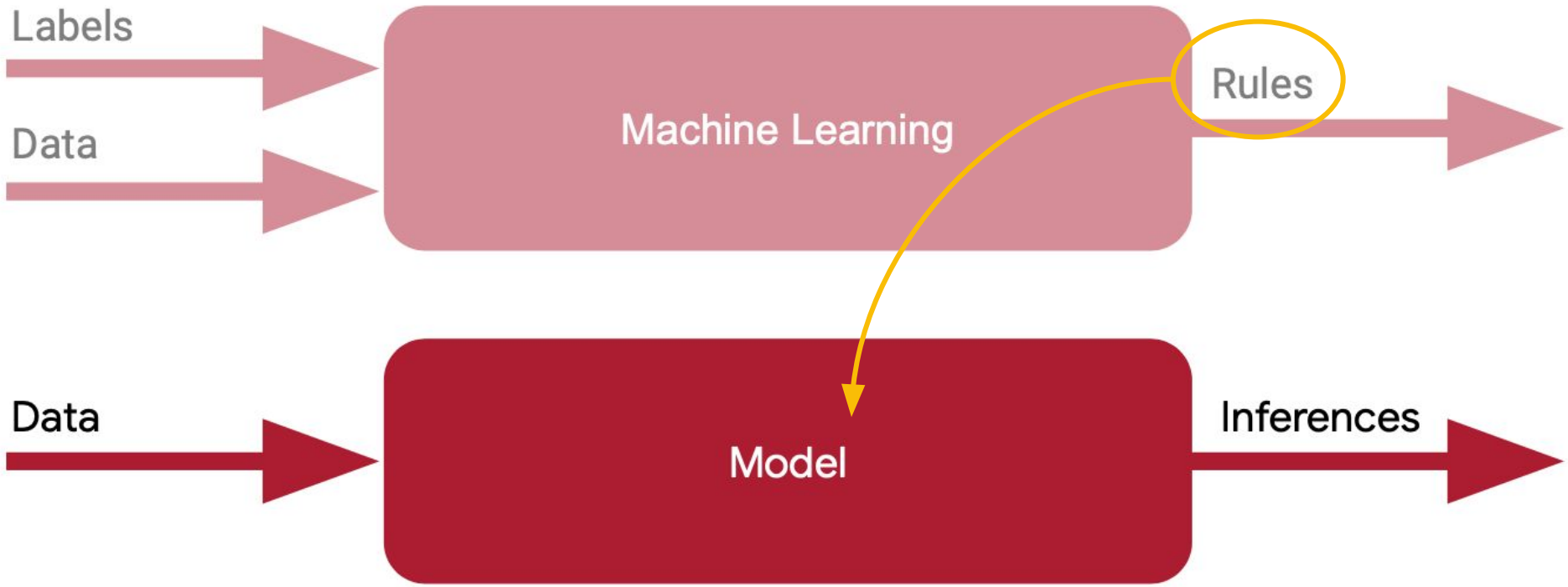
The Machine Learning Paradigm

The Machine Learning Paradigm

The Machine Learning Paradigm

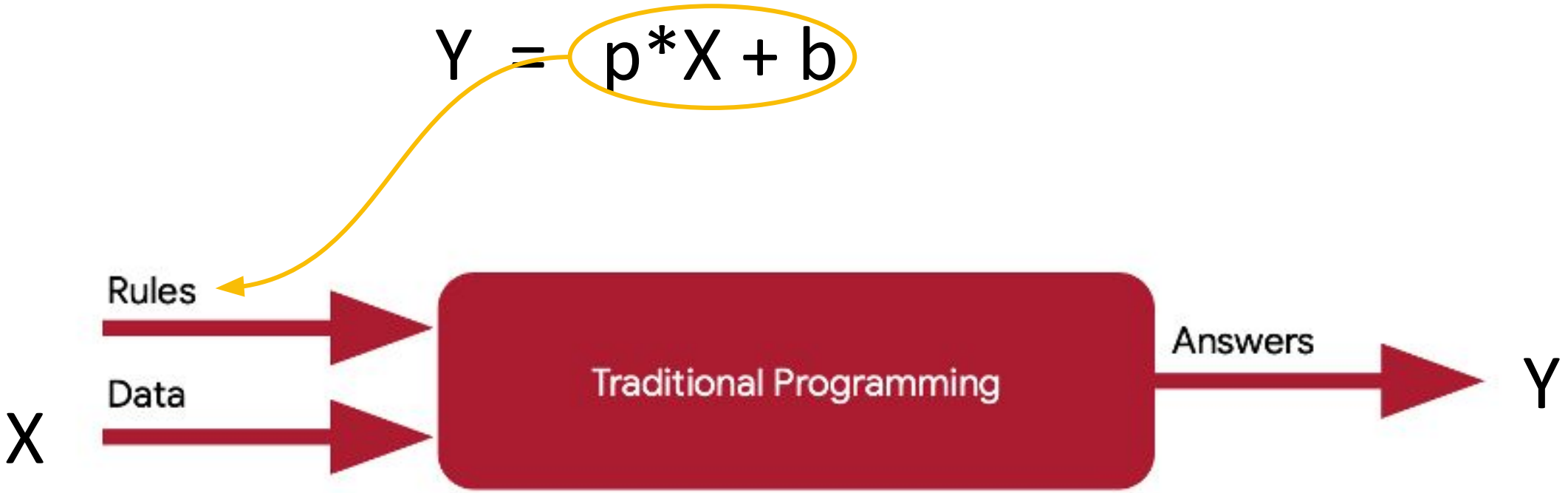


The Machine Learning Paradigm



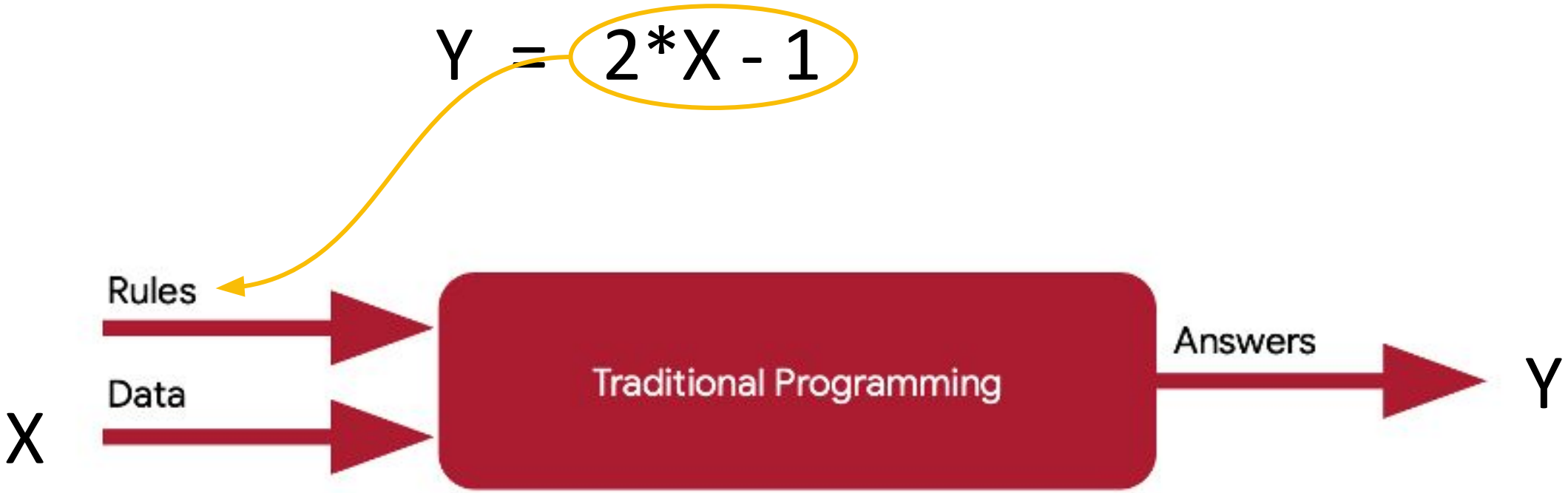
Thinking about loss…

A way to measure your accuracy



X = { -1, 0, 1, 2, 3, 4 }

Y = {?, ?, ? ,?, ?, ?}



X = { -1, 0, 1, 2, 3, 4 }

Y = { -3, -1, 1, 3, 5, 7 }

Matching X to Y

$X = \{ -1, 0, 1, 2, 3, 4 \}$

$Y = \{ -3, -1, 1, 3, 5, 7 \}$

Matching X to Y

X = { -1, 0, 1, 2, 3, 4 }

Y = { -3, -1, 1, 3, 5, 7 }

$$Y = p*X + b$$

Matching X to Y

X = { -1, 0, 1, 2, 3, 4 }

Y = { -3, -1, 1, 3, 5, 7 }

$$Y = p*X + b$$

Matching X to Y

Input

X = { -1, 0, 1, 2, 3, 4 }

Y = { -3, -1, 1, 3, 5, 7 }

Target

Y = p*X + b

Parameters

Make a guess!

Y = 3X - 1

p = +3
b = -1

X = { -1, 0, 1, 2, 3, 4 }

Y = { -4, -1, 2, 5, 8, 11 }

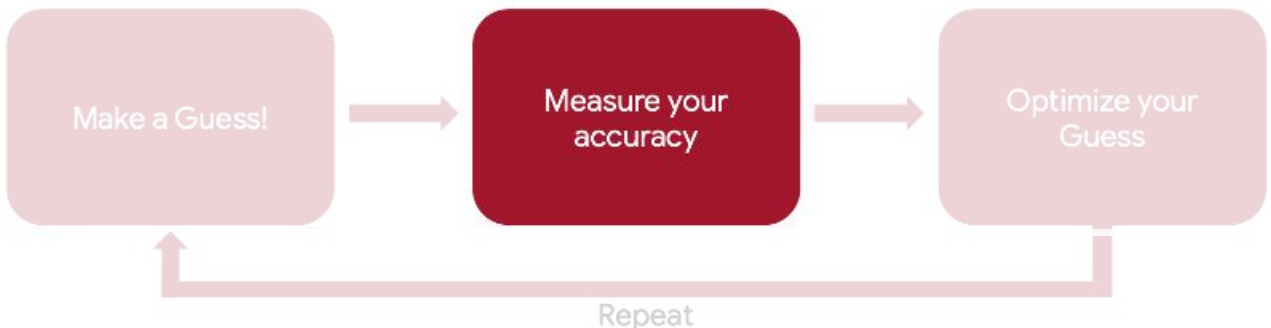
How good is the guess?

Y = 3X - 1

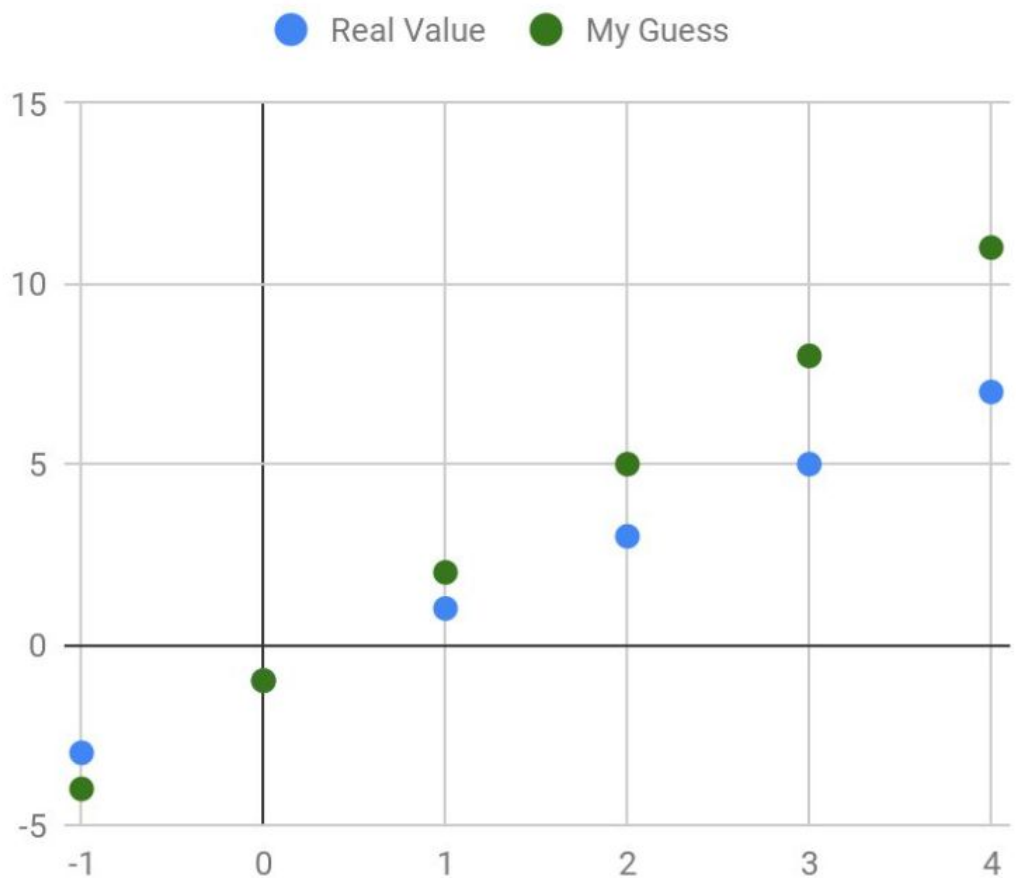
X = { -1, 0, 1, 2, 3, 4 }

My Y = { -4, -1, 2, 5, 8, 11 }

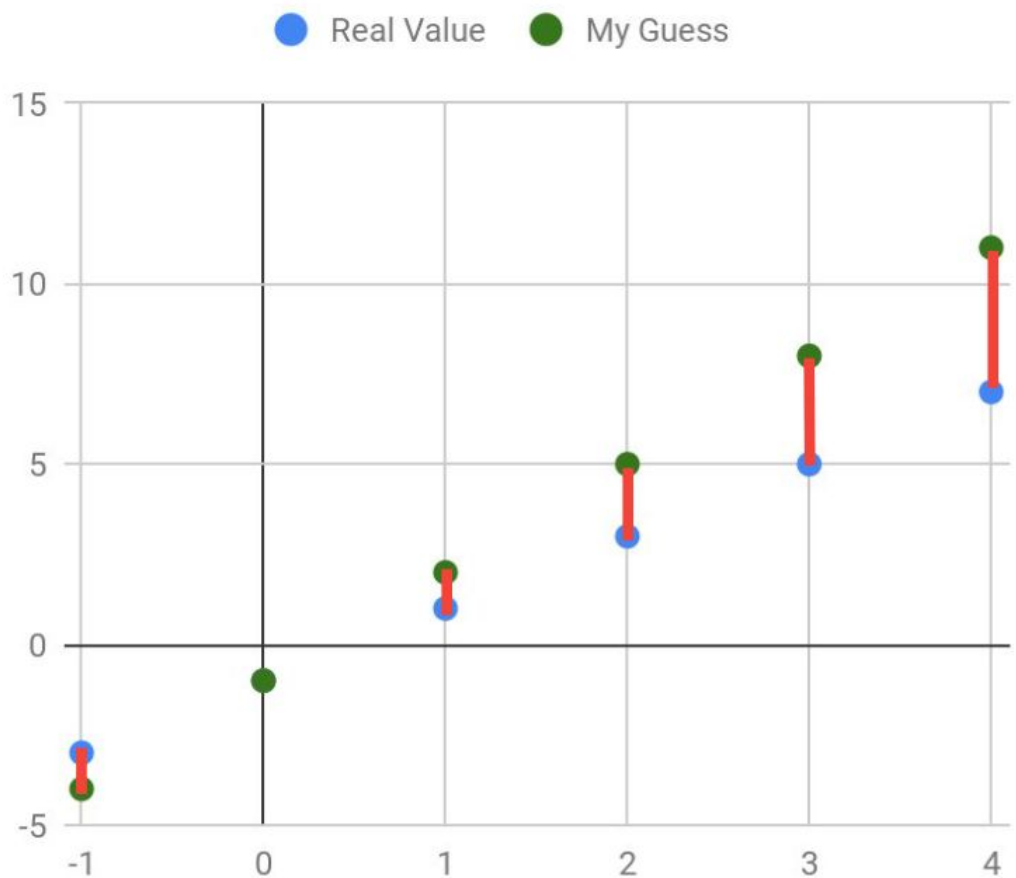
Real Y = { -3, -1, 1, 3, 5, 7 }



Let’s measure it!

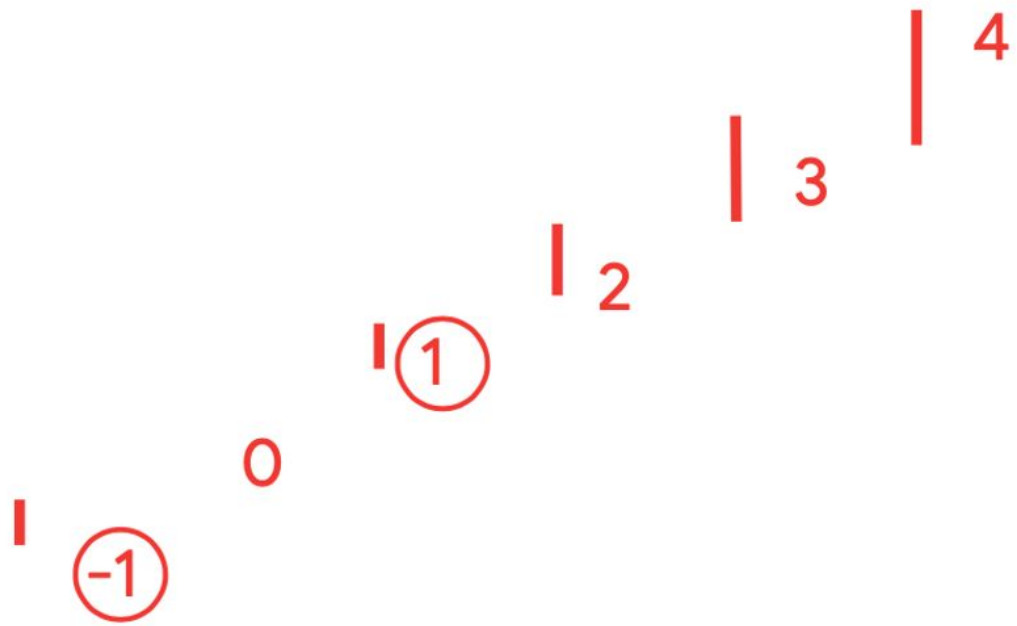


Let’s measure it!



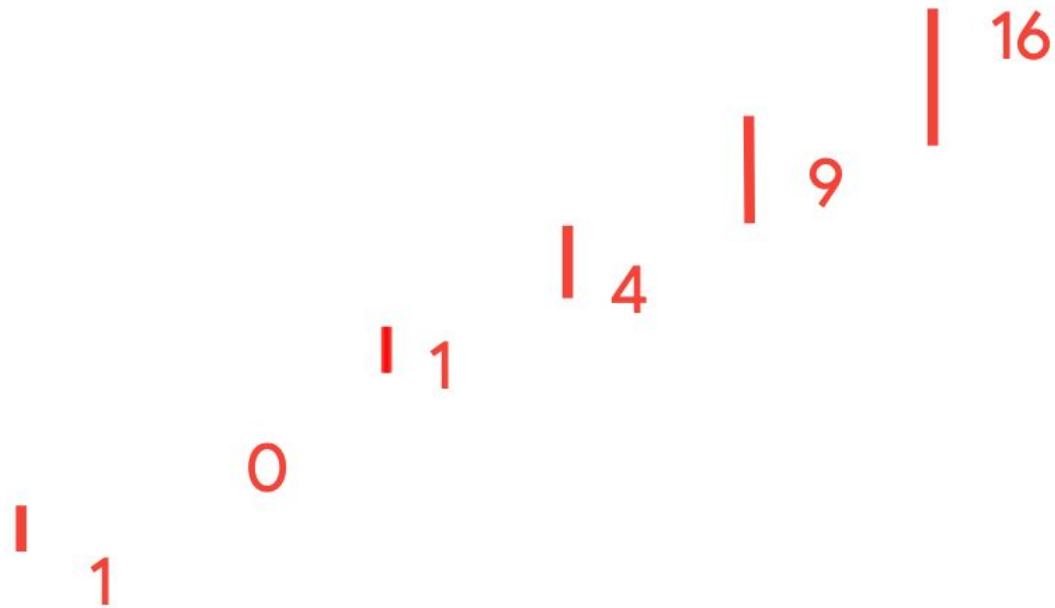
Let’s measure it!

Houston, we have a problem!



Houston, we have a problem!

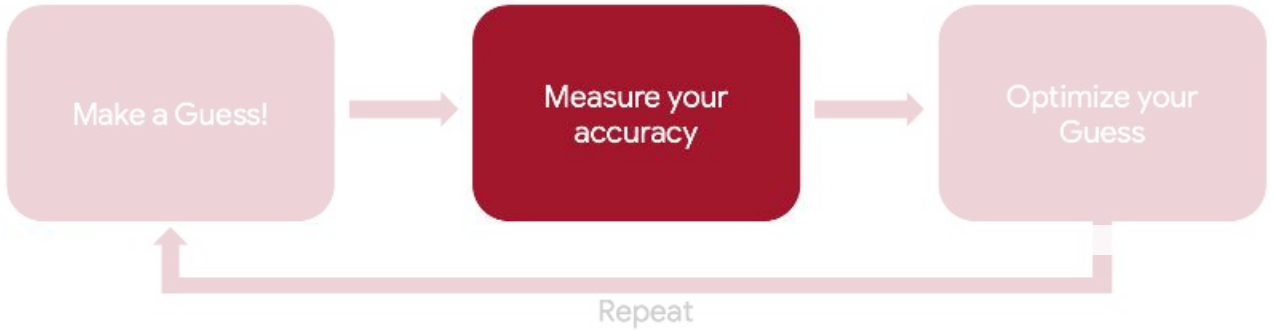
What if we **square**^{2} them?



Calculate de mean error:

= (1 + 1 + 4 + 9 + 16) / 6

= 5.17



Make another guess!

Y = 2X - 2

p = +2
b = -2

X = { -1, 0, 1, 2, 3, 4 }

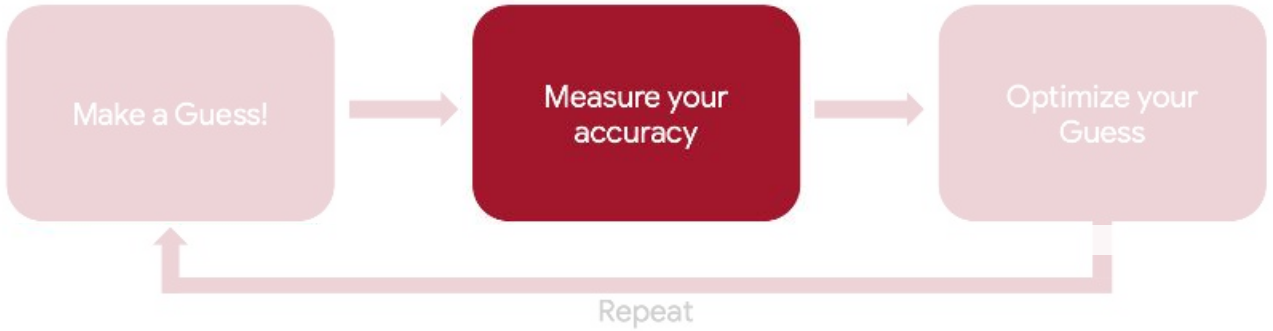
My Y = { -4, -2, 0, 2, 4, 6 }

Real Y = {-3, -1, 1, 3, 5, 7}

Diff^2 = {1, 1, 1, 1, 1, 1}

Get the same difference, repeat the same process.

= (1 + 1 + 1 + 1 + 1 + 1) / 6
= 1.00



Make another guess!

Y = 2X - 1

X = { -1, 0, 1, 2, 3, 4 }

My Y = { -3, -1, 1, 3, 5, 7 }

Real Y = {-3, -1, 1, 3, 5, 7}

Diff^2 = {0, 0, 0, 0, 0, 0}

Make another guess!

$Y = 2X - 1$

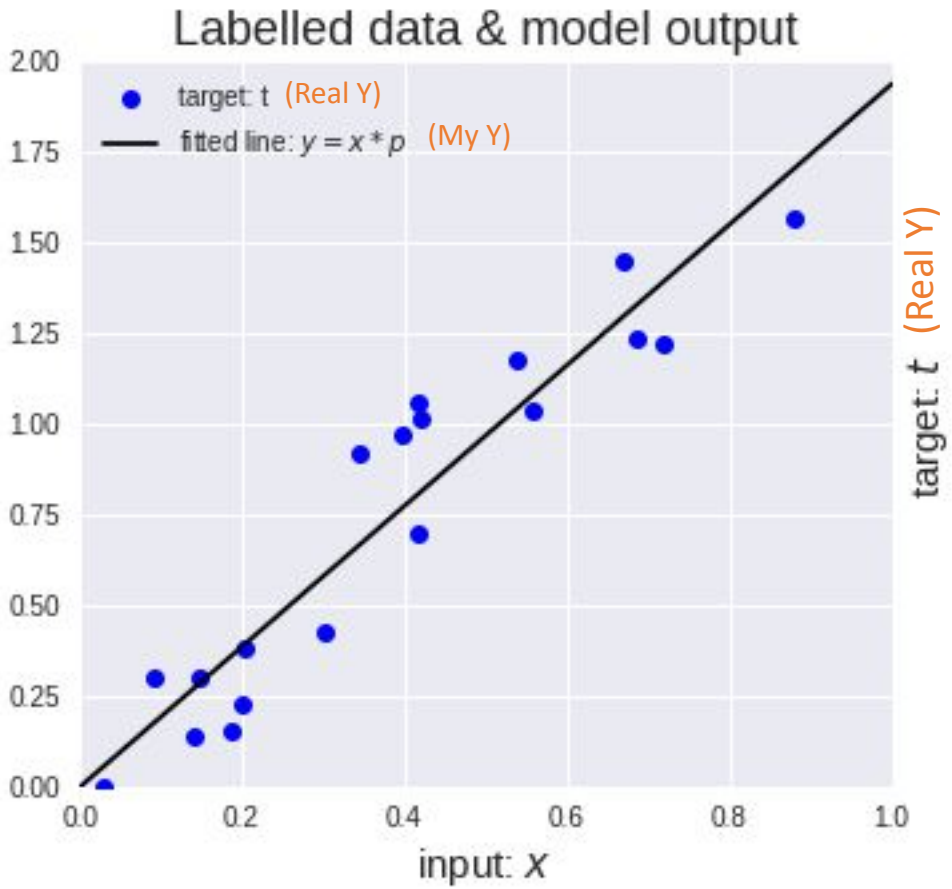
Parameters

$X = \{ -1, 0, 1, 2, 3, 4 \}$

My $Y = \{ -3, -1, 1, 3, 5, 7 \}$

Real $Y = \{-3, -1, 1, 3, 5, 7\}$

$Diff^2 = \{0, 0, 0, 0, 0, 0\}$



Make another guess!

Y = 2X - 1

Parameters

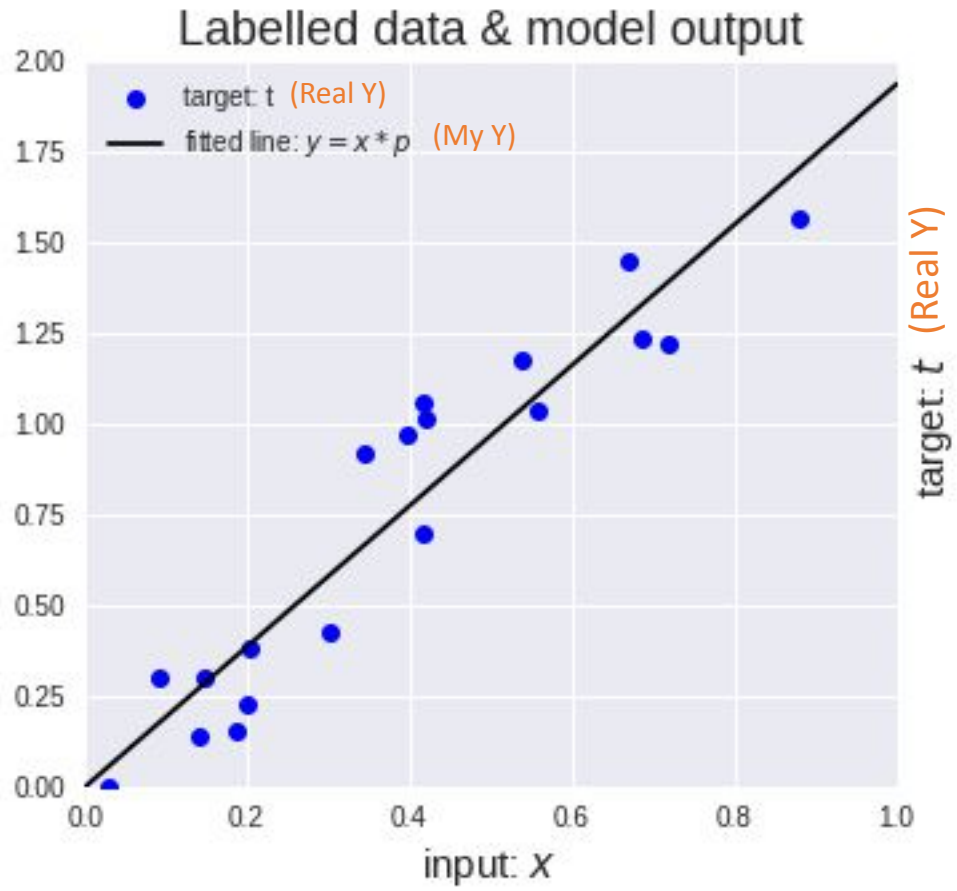
X = { -1, 0, 1, 2, 3, 4 }

My Y = { -3, -1, 1, 3, 5, 7 }

Real Y = {-3, -1, 1, 3, 5, 7}

MSE = {0, 0, 0, 0, 0, 0} / 6

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$



Mean **S**quared **E**rror: Goal: Minimum as possible!

Make another guess!

Y = 2X - 1

Parameters

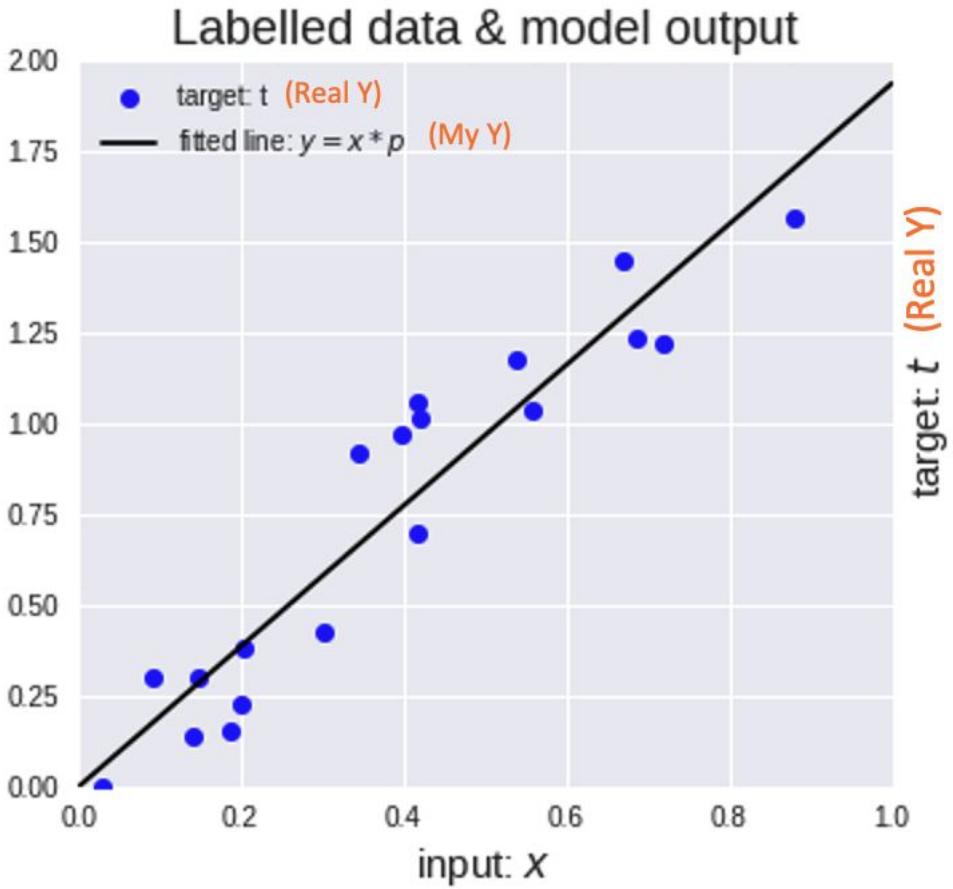
X = { -1, 0, 1, 2, 3, 4 }

My Y = { -3, -1, 1, 3, 5, 7 }

Real Y = {-3, -1, 1, 3, 5, 7}

MSE = {0, 0, 0, 0, 0, 0} / 6

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$



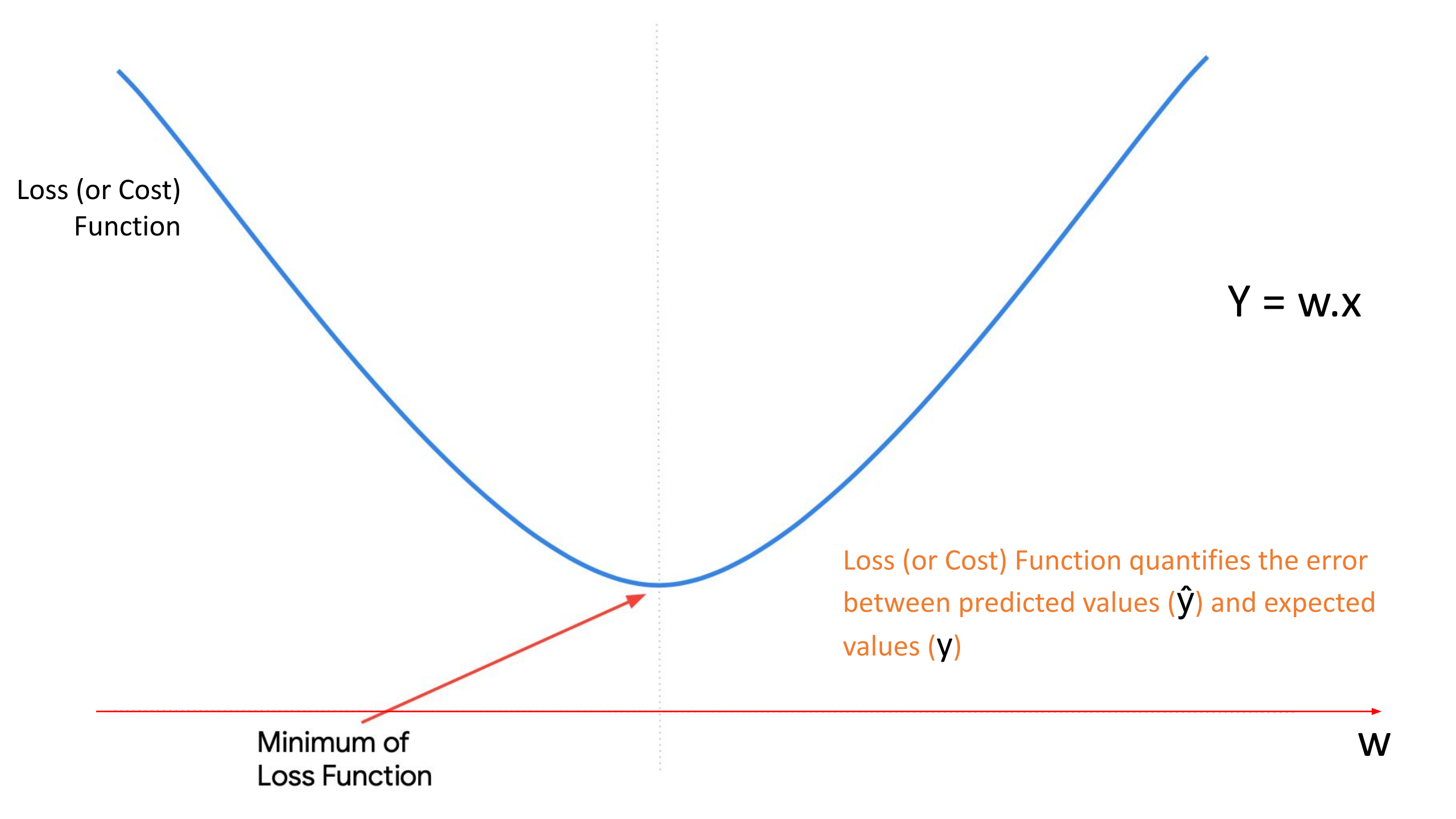
Mean Squared Error: Goal: Minimum as possible!

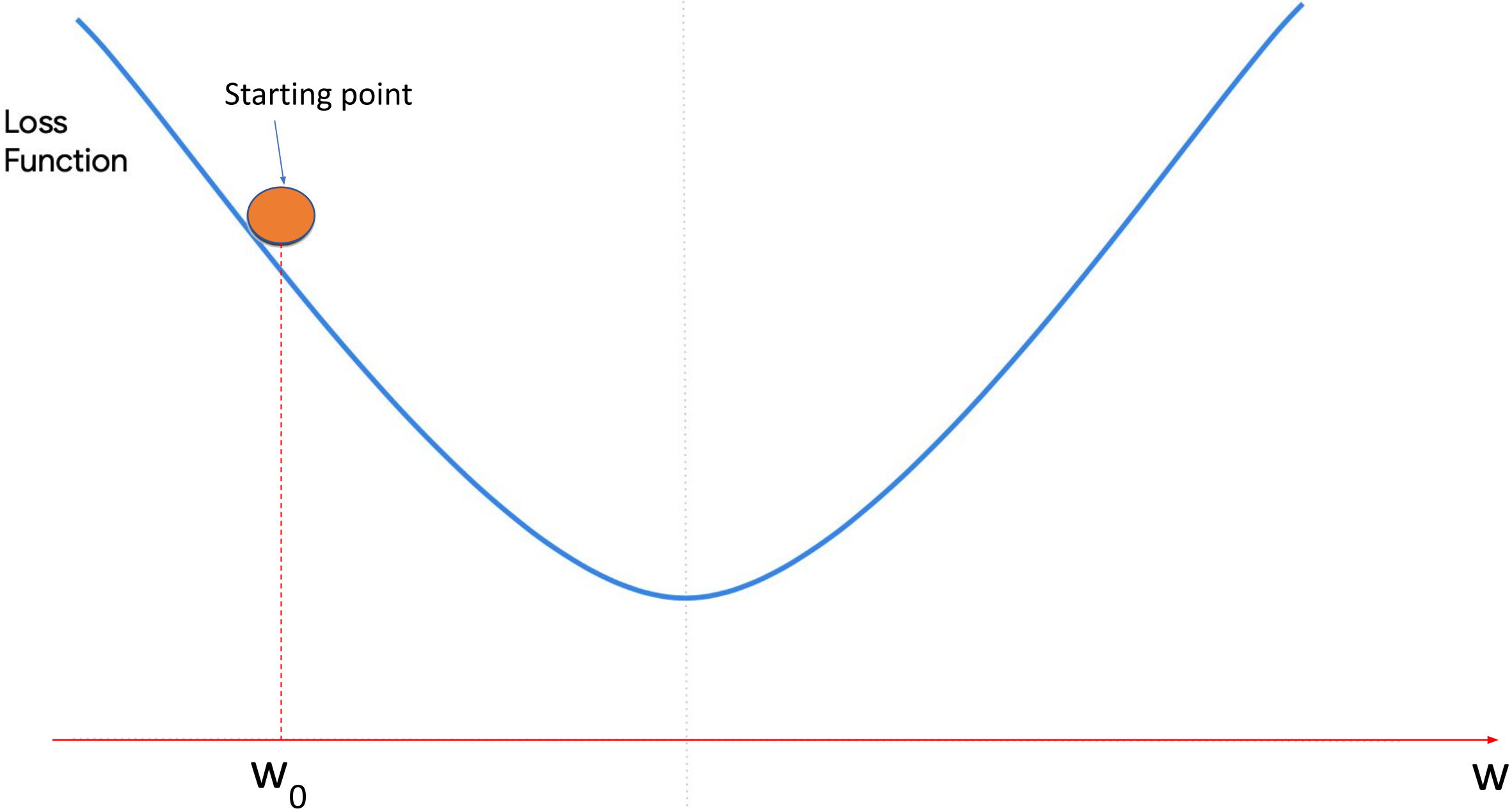
Exploring Loss and Cost Function

Code Time!

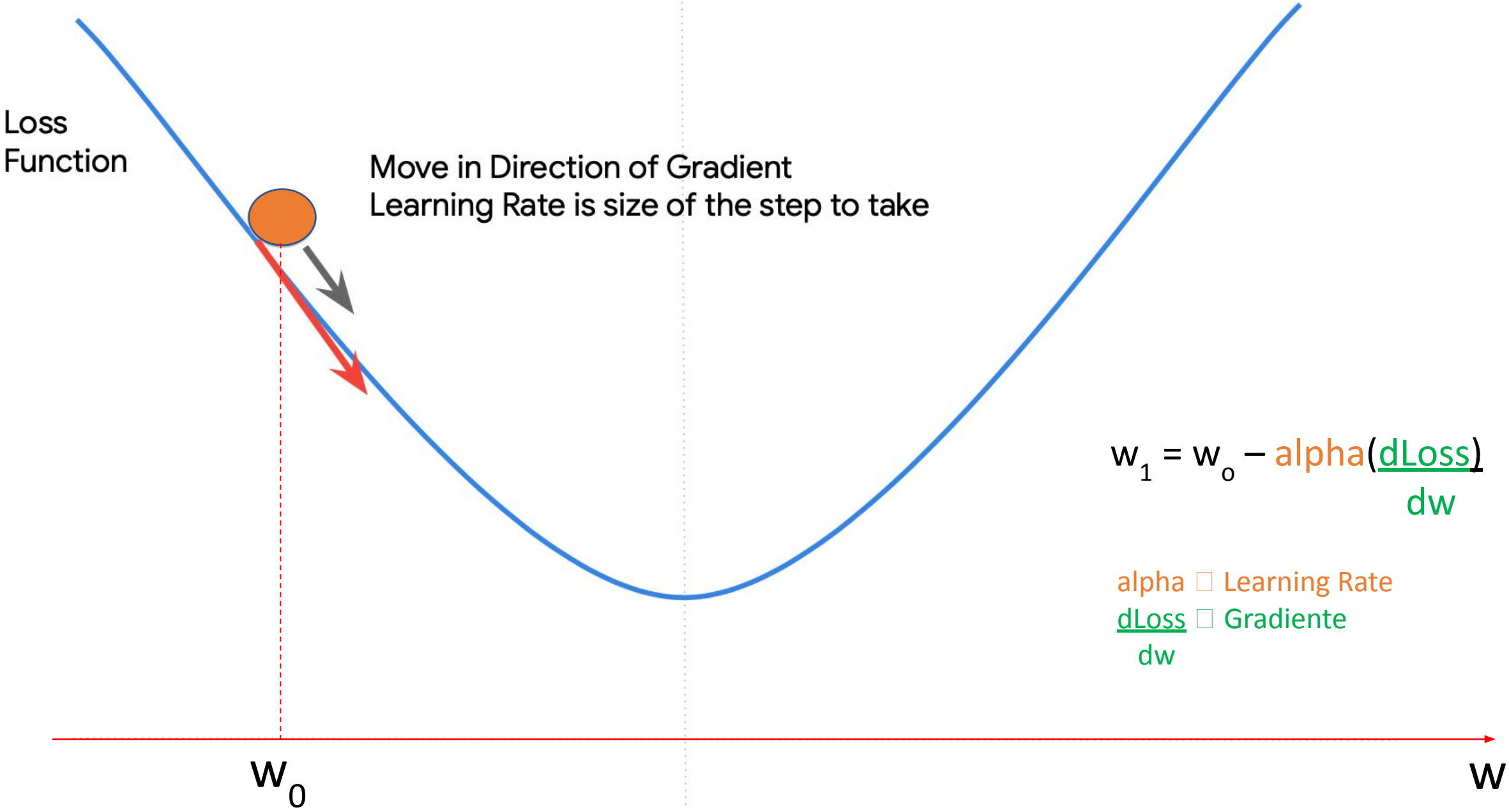
Minimizing loss…

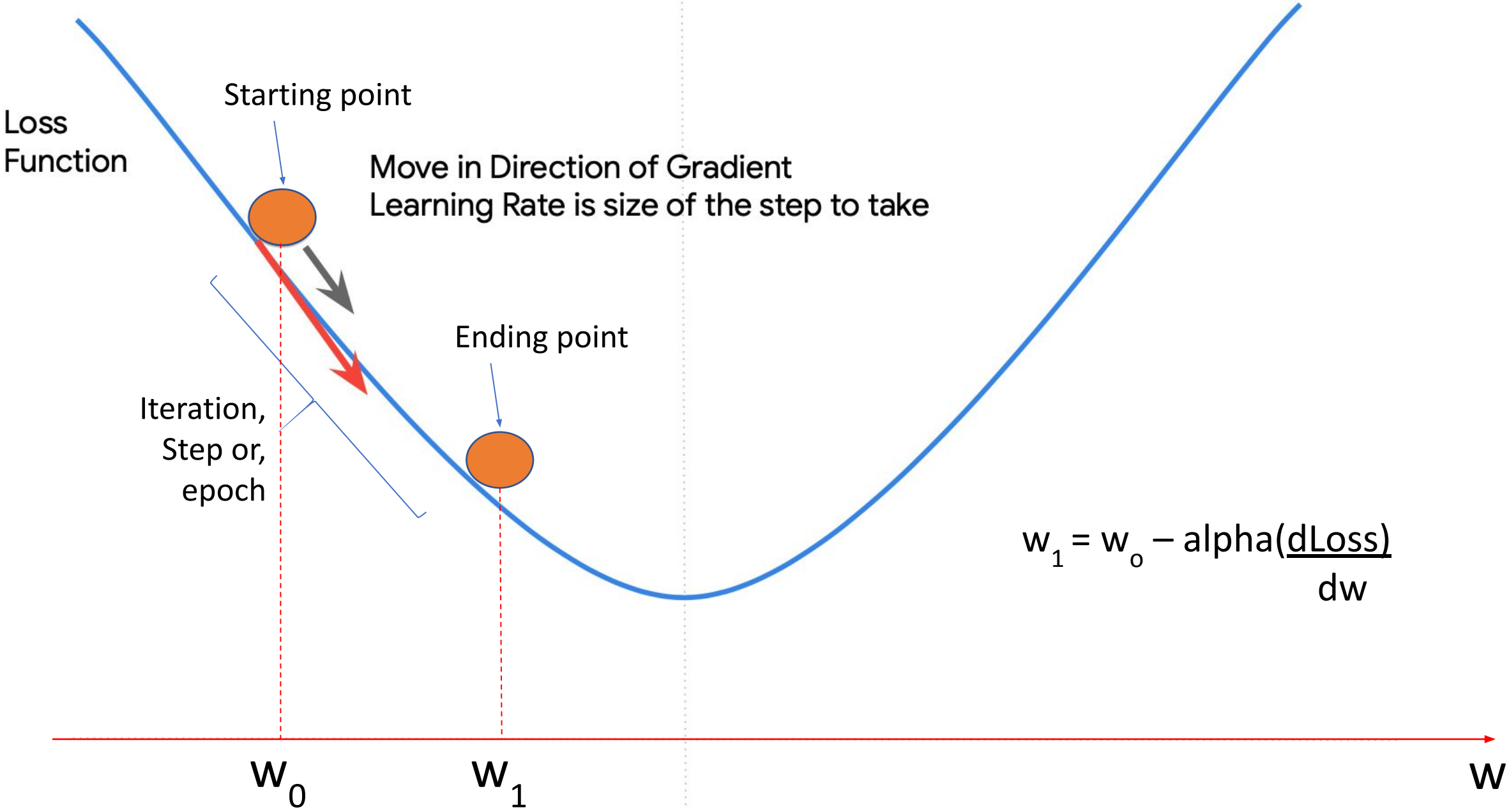
Moving down the curve…

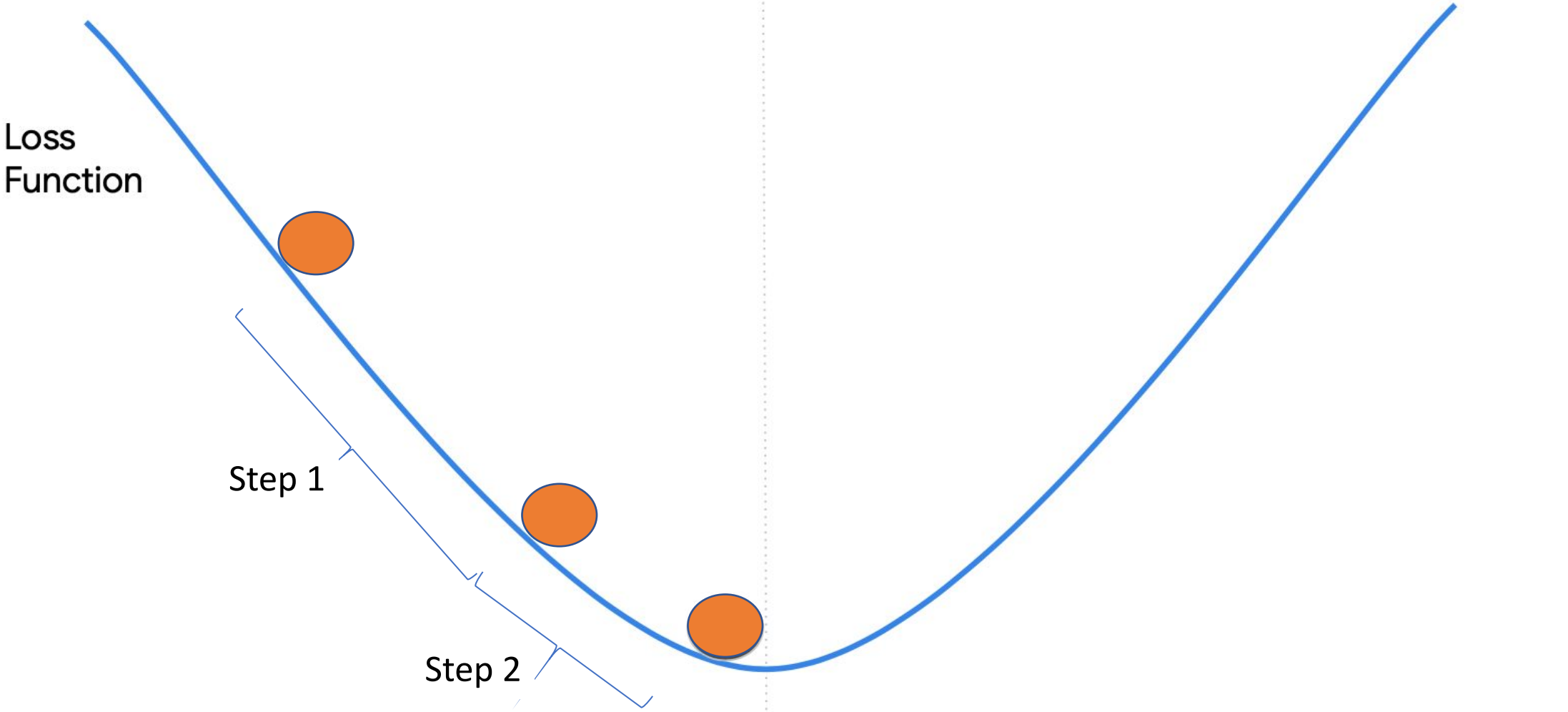

Loss (or Cost)
Function
Y = w.x
Loss (or Cost) Function quantifies the error between predicted values (ŷ) and expected values (y)
Minimum of
Loss Function
w


Loss
Function
Starting point
w_0
w


Loss
Function
Gradient of
value
Goal: To minime our loss function by moving in
a direction indicated of the gradient
w_0
w

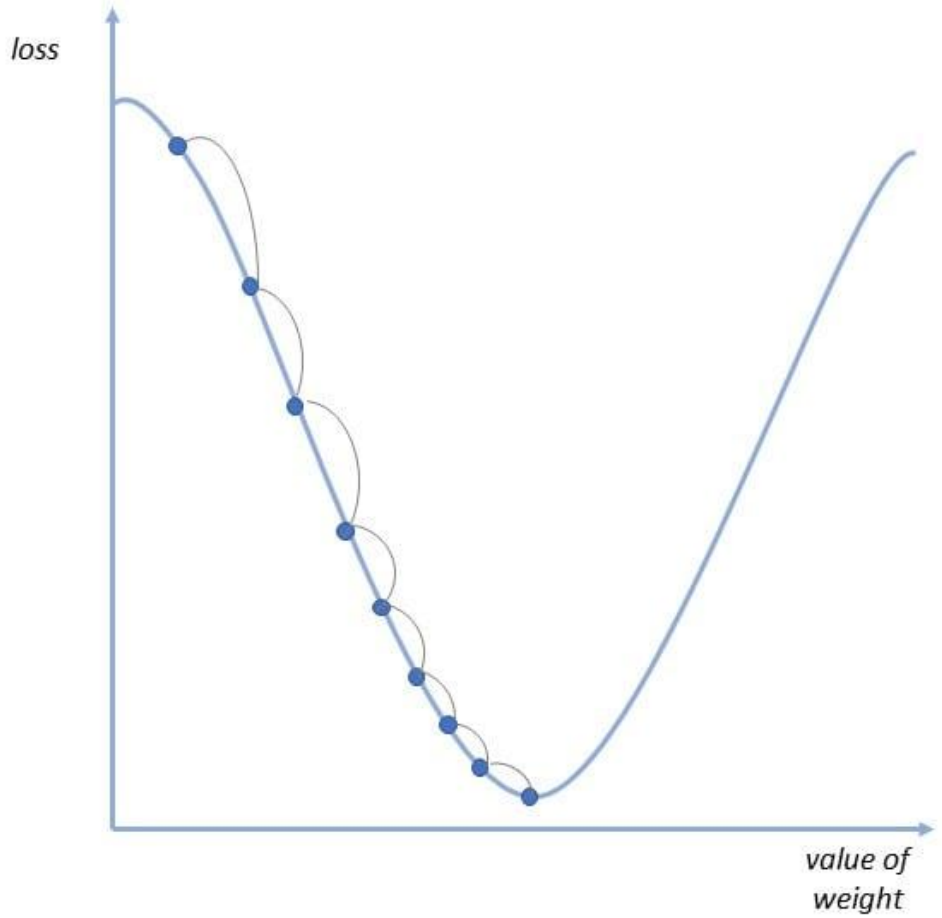

Loss
Function
Move in Direction of Gradient
Learning Rate is size of the step to take
$w_1 = w_o - \text{alpha}\left(\frac{dLoss}{dw}\right)$
alpha □ Learning Rate
$\frac{dLoss}{dw}$ □ Gradiente
w_0
w


Loss Function
Starting point
Move in Direction of Gradient
Learning Rate is size of the step to take
Ending point
Iteration, Step or, epoch
$w_1 = w_o - \text{alpha}(\frac{dLoss}{dw})$
w_0
w_1
w

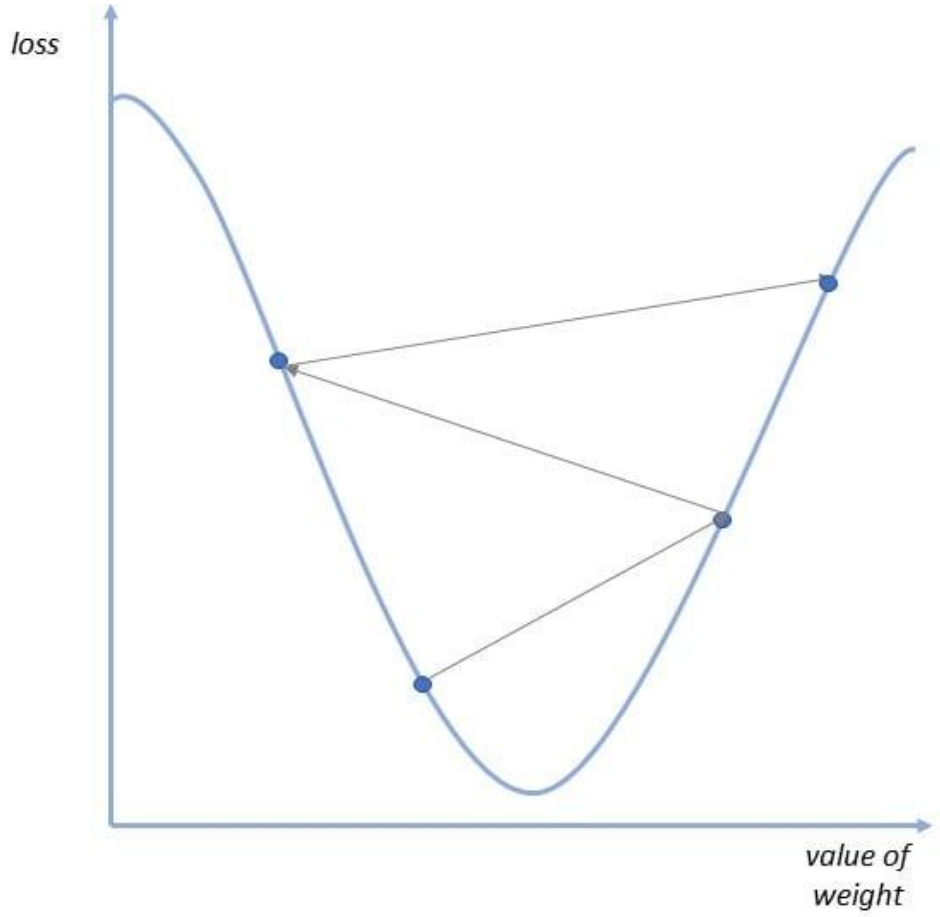

Loss
Function
Step 1
Step 2

It is important to choose the correct Learning Rate (size of the step)

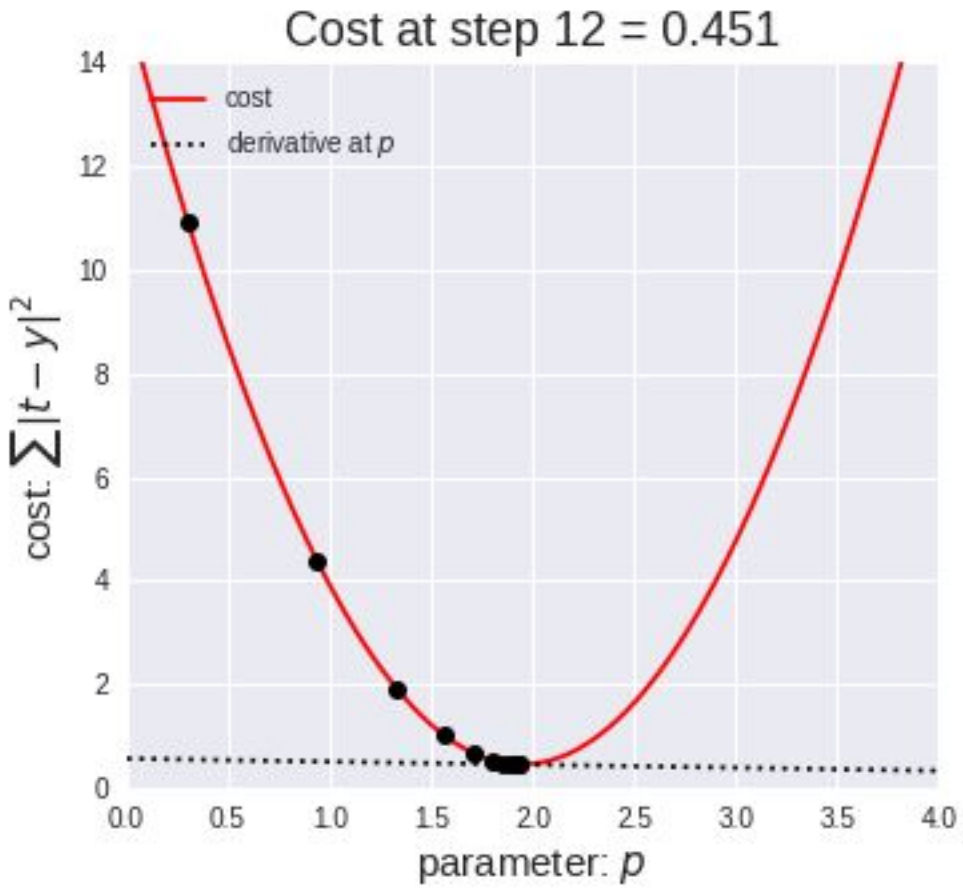
If the **Learning Rate** is too small it may take a long time to reach the minimum

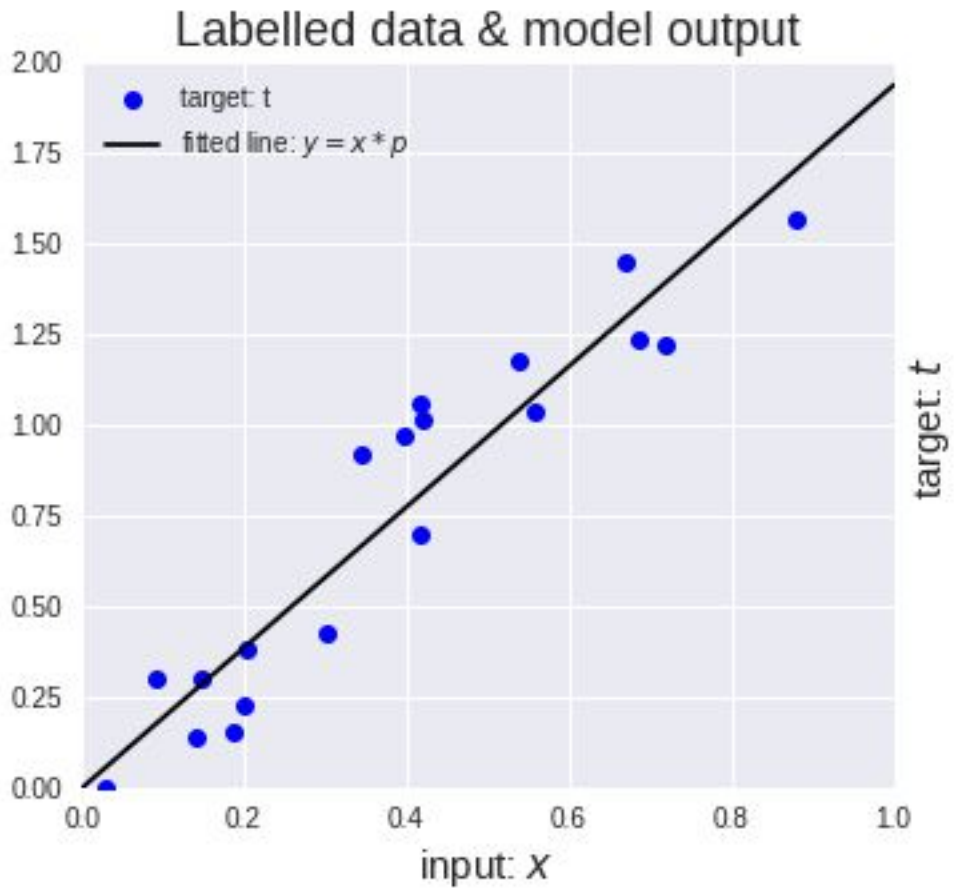


If the **Learning Rate** is too large we may never reach the minimum

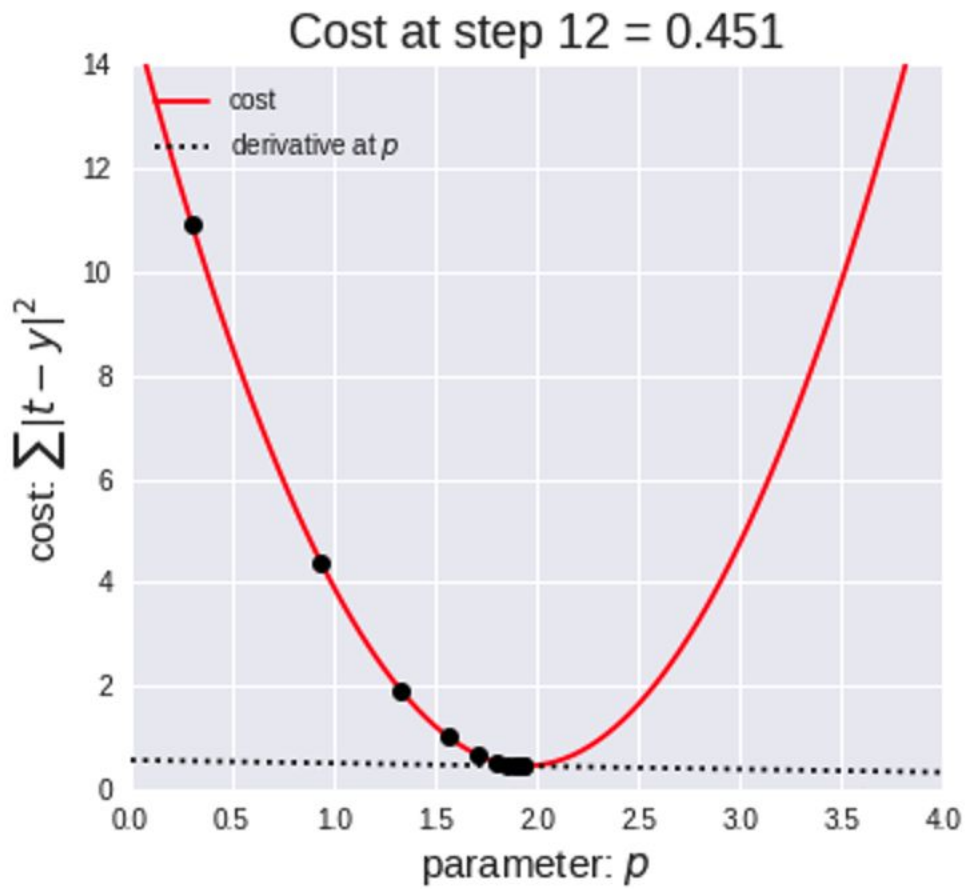


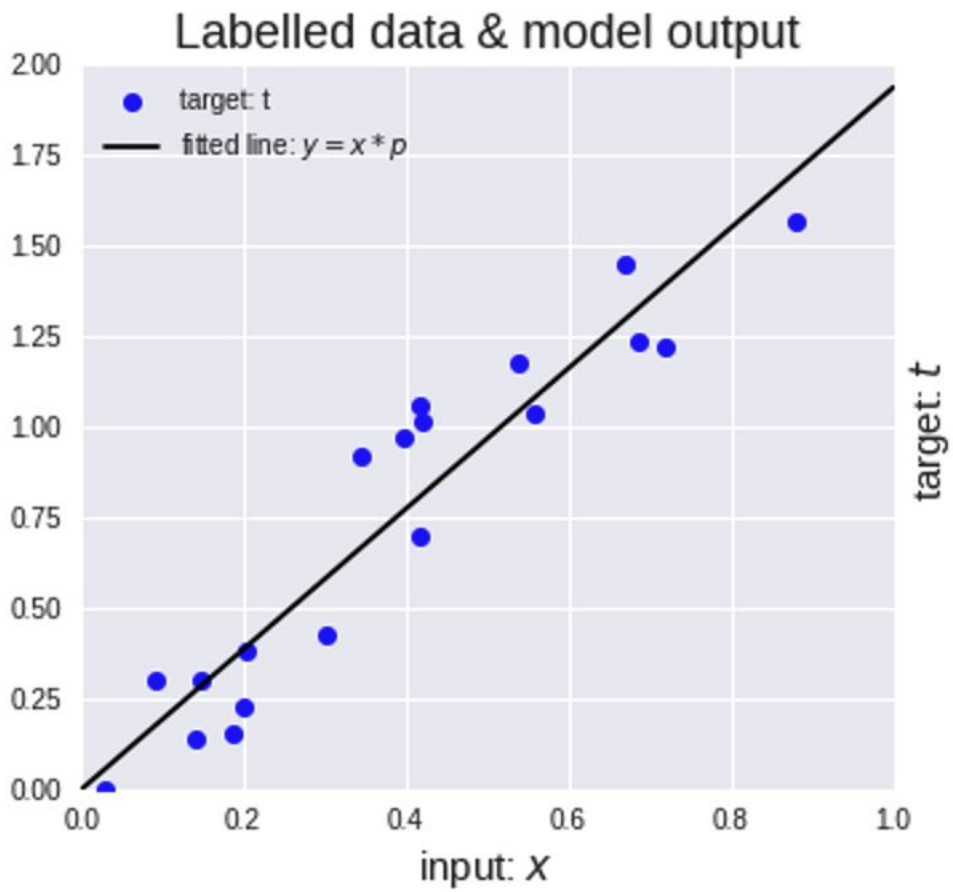
Gradient Descent algorithm





Gradient Descent algorithm



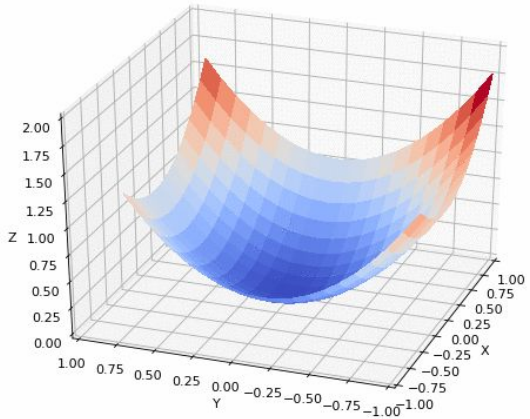


The Machine Learning Paradigm

The Machine Learning Paradigm

Epochs

(Back-Propagation)



Reading Material

Main references

- Harvard School of Engineering and Applied Sciences - CS249r: Tiny Machine Learning
- Professional Certificate in Tiny Machine Learning (TinyML) – edX/Harvard
- Introduction to Embedded Machine Learning - Coursera/Edge Impulse
- Computer Vision with Embedded Machine Learning - Coursera/Edge Impulse
- Fundamentals textbook: “Deep Learning with Python” by François Chollet
- Applications & Deploy textbook: “TinyML” by Pete Warden, Daniel Situnayake
- Deploy textbook “TinyML Cookbook” by Gian Marco Iodice

I want to thank Shawn Hymel and Edge Impulse, Pete Warden and Laurence Moroney from Google, Professor Vijay Janapa Reddi and Brian Plancher from Harvard, and the rest of the TinyMLedu team for preparing the excellent material on TinyML that is the basis of this course at UNIFEI.

The IESTI01 course is part of the **TinyML4D**, an initiative to make TinyML education available to everyone globally.

Thanks

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