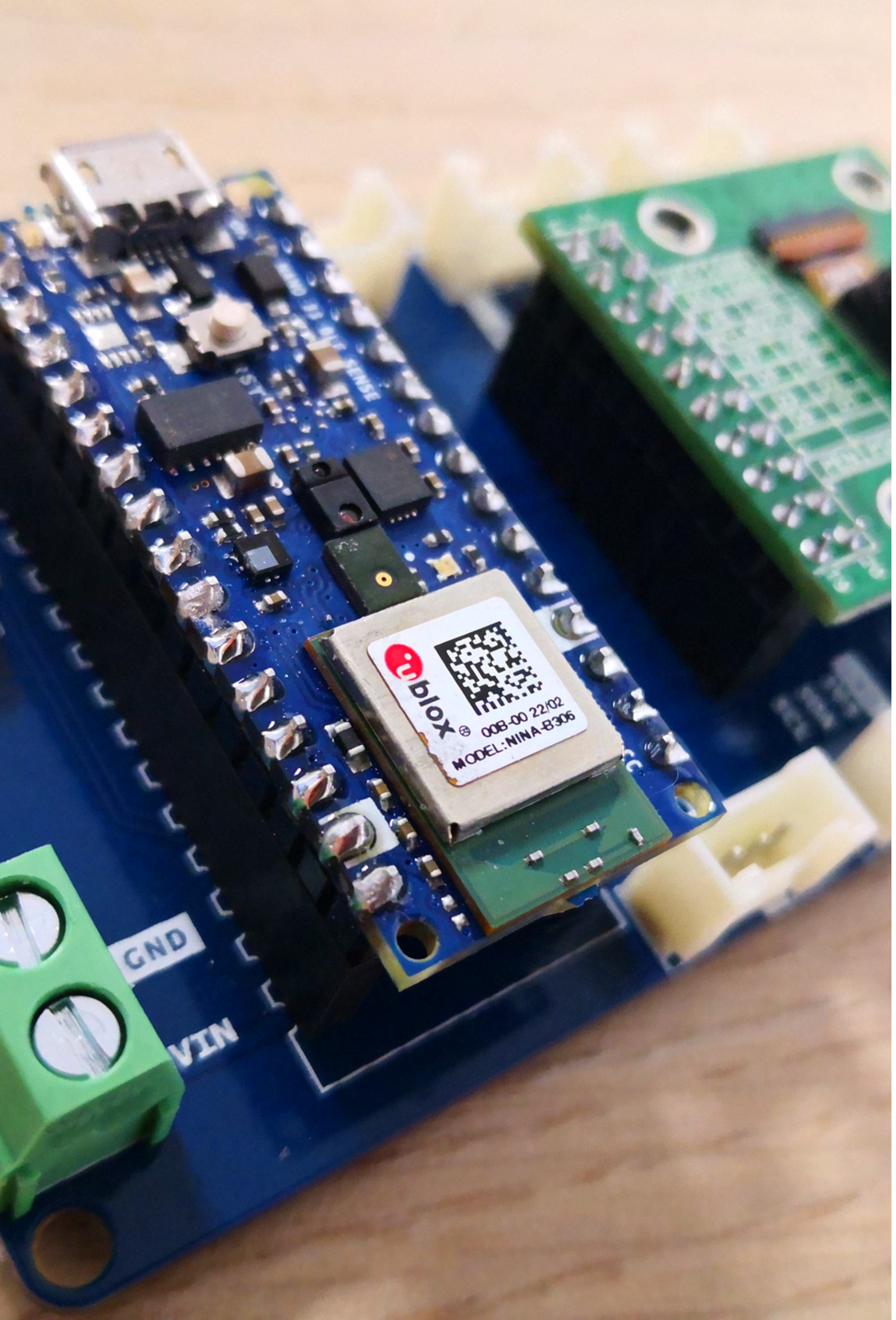
A Brief Introduction to Deep Learning

Latin American Regional Workshop on SciTinyML:
Scientific Use of Machine Learning on Low-Power Devices
July 11th, 2022

Pontificia Universidad Javeriana Bogotá — Facultad de Ingeniería

ICTP

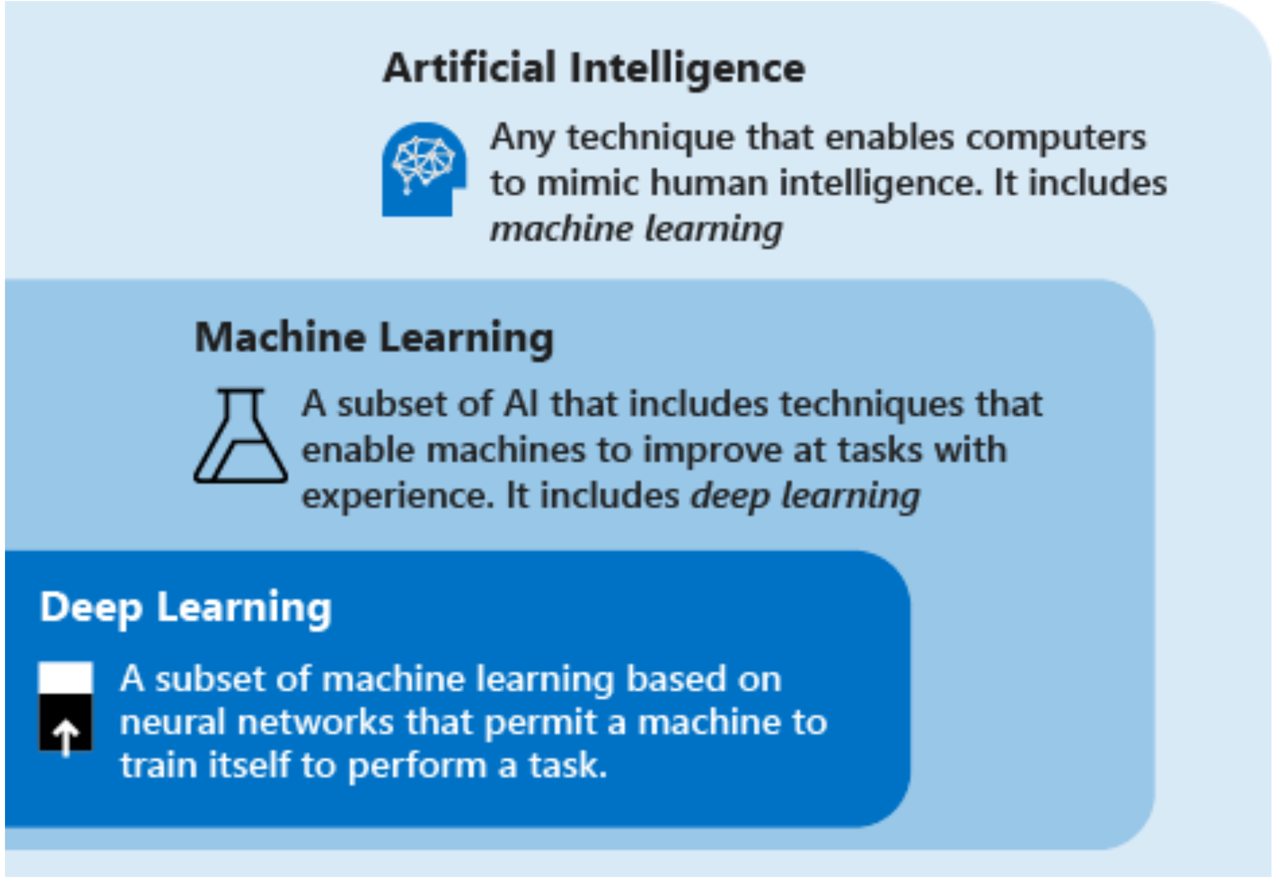
TinyML edu



Outline

- AI vs ML vs DL
- The Machine Learning Paradigm
- Finding the Best Solution and Fitting a Model
- Regression and Classification with NN
- ML Issues

AI vs. ML vs. DL



https://docs.microsoft.com/en-us/azure/machine-learning/concept-deep-learning-vs-machine-learning

General Steps for Machine Learning

On a high level, the craft of creating machine learning (ML) processes is comprised of several steps:

- Decide on the Question
- Collect and Prepare Data
- Choose a Training Method
- Train the Model
- Evaluate the Model
- Parameter Tuning
- Predict

https://microsoft.github.io/ML-For-Beginners/#/1-Introduction/4-techniques-of-ML/README?id=techniques-of-machine-learning

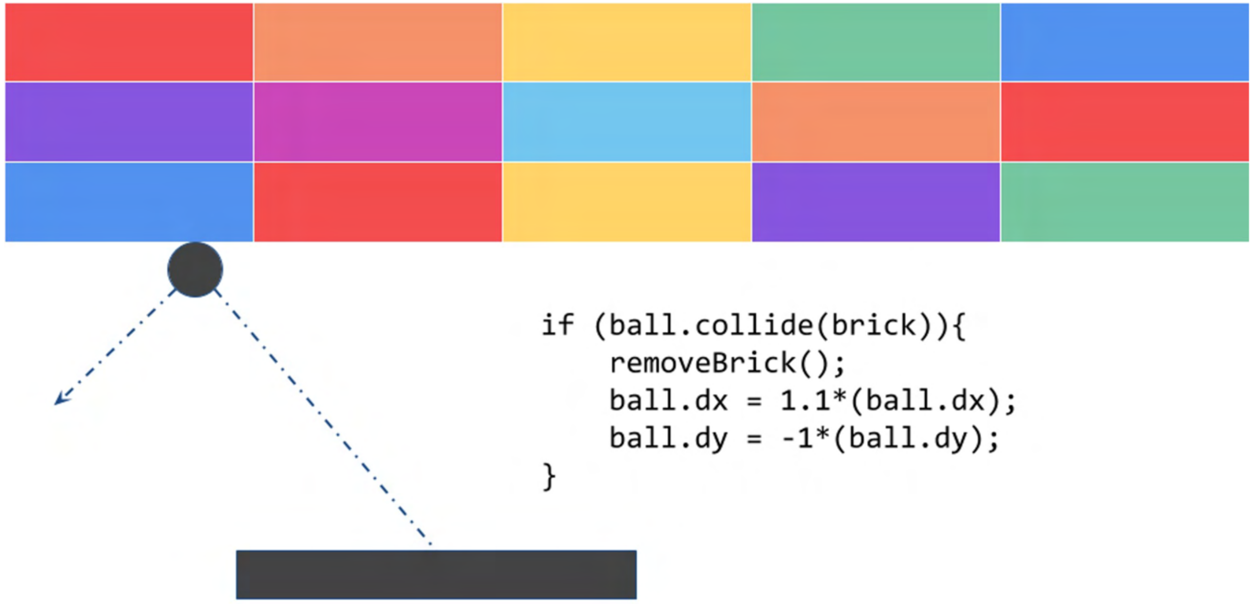
We will run through this long process

This is a first encounter with ML, but many things will be left to be experimented or developed.

The Machine Learning Paradigm

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



```
if (ball.collide(brick)){
    removeBrick();
    ball.dx = 1.1*(ball.dx);
    ball.dy = -1*(ball.dy);
}
```

The Traditional Programming Paradigm

Consider Activity Detection

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

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

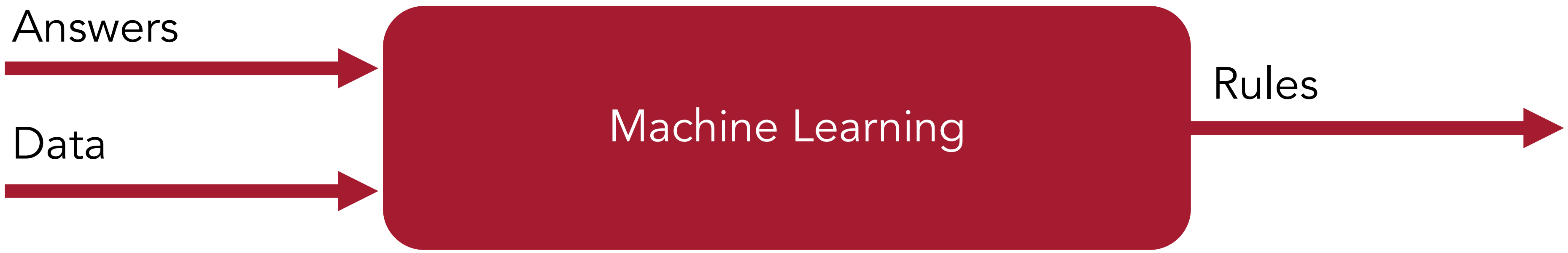
```
if(speed<4){
    status=WALKING;
} else if(speed<12){
    status=RUNNING;
} else {
    status=BIKING;
}
```

```
// ???
```

Way too complex to code!

The Traditional Programming Paradigm

The Machine Learning Paradigm



Activity Detection with Machine Learning

```
0101001010100101010
1001010101001011101
0100101010010101001
0101001010100101010
```

Label = WALKING

```
1010100101001010101
0101010010010010001
0010011111010101111
1010100100111101011
```

Label = RUNNING

```
1001010011111010101
1101010111010101110
1010101111010101011
1111110001111010101
```

Label = BIKING

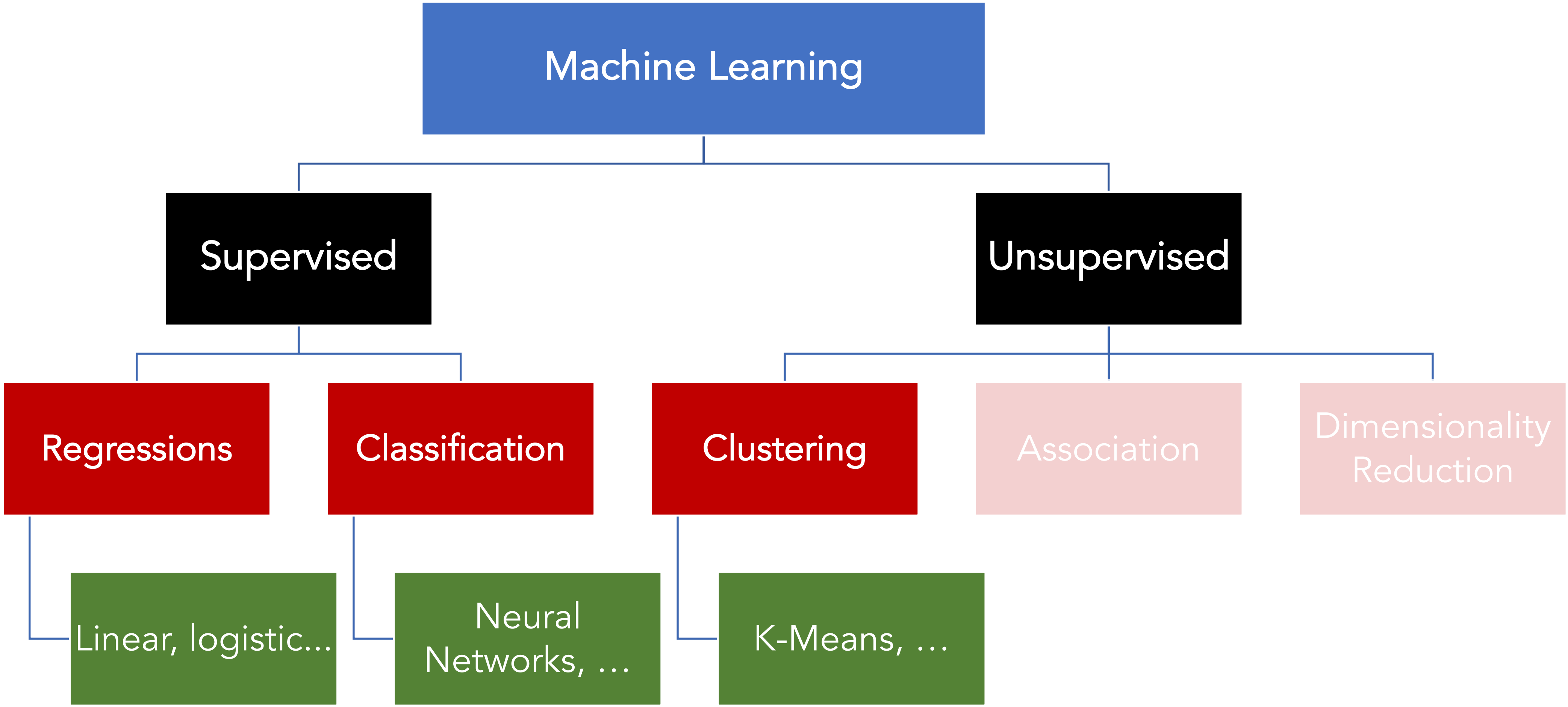
```
1111111111010011101
0011111010111110101
0101110101010101110
1010101010100111110
```

Label = GOLFING

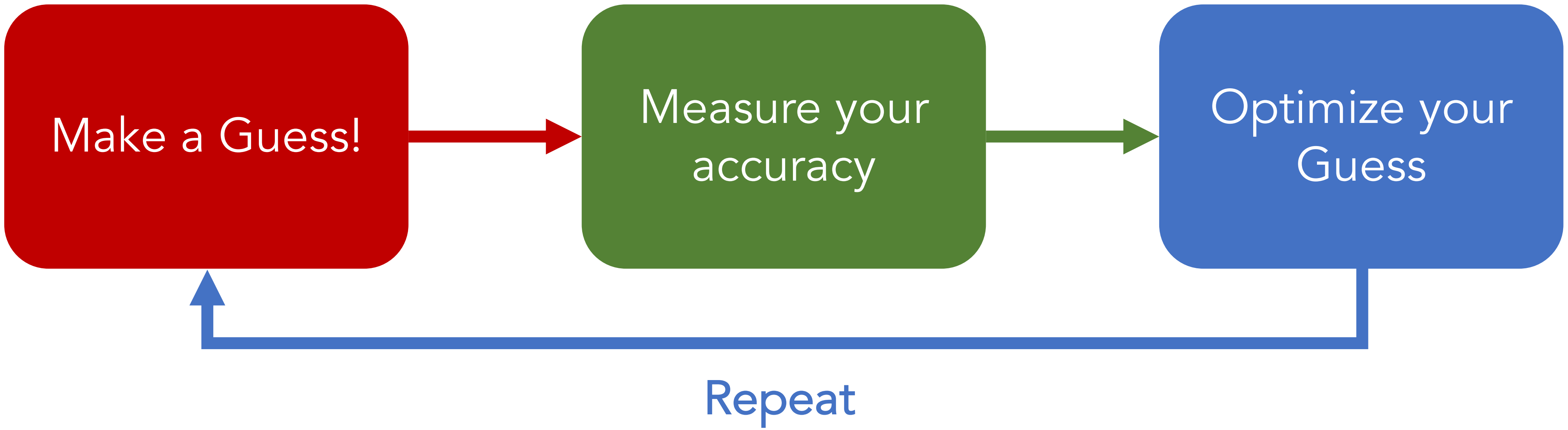
The Machine Learning Paradigm

0101001010100101010 1001010101001011101 0100101010010101001 0101001010100101010	1010100101001010101 0101010010010010001 0010011111010101111 1010100100111101011	1001010011111010101 1101010111010101110 1010101111010101011 1111110001111010101	1111111111010011101 0011111010111110101 0101110101010101110 1010101010100111110
Label = WALKING	Label = RUNNING	Label = BIKING	Label = GOLFING

Two Approaches

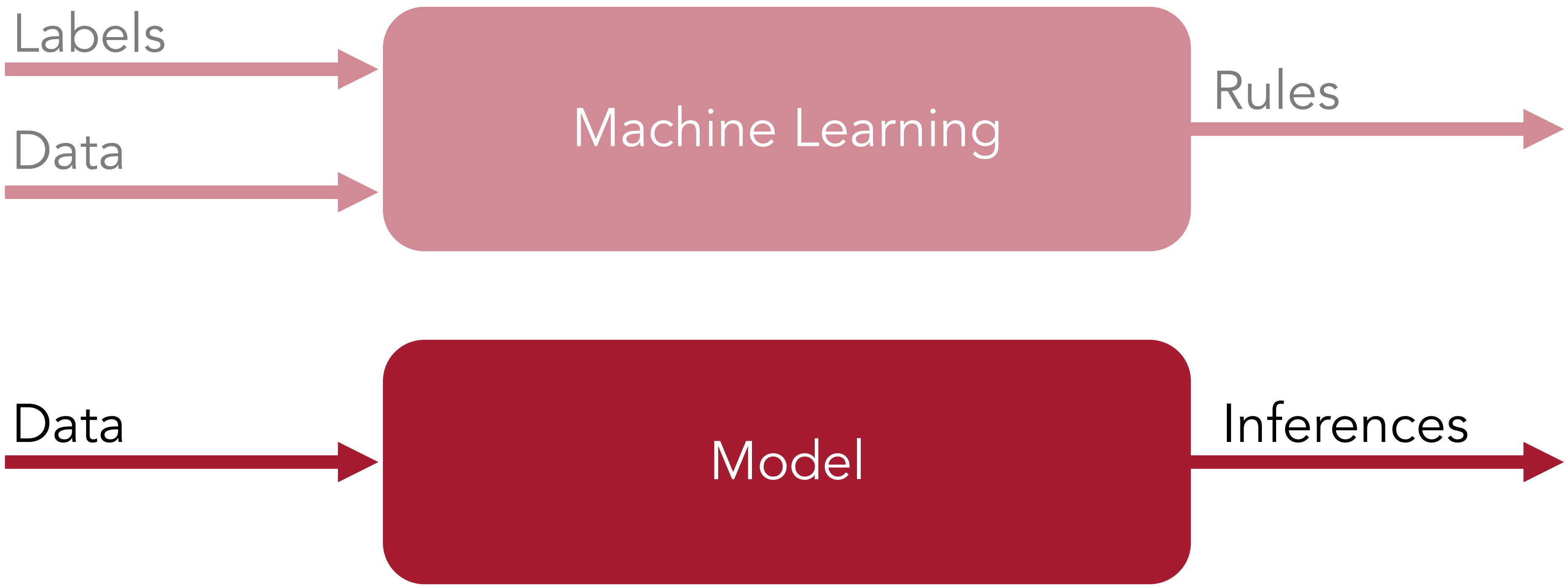


The Machine Learning Paradigm



The Machine Learning Paradigm

The Machine Learning Paradigm



How good is your model?

a way to measure your accuracy

Matching X to Y

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

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

Make a guess!

$Y = 3X - 1$

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

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

How good is the guess?

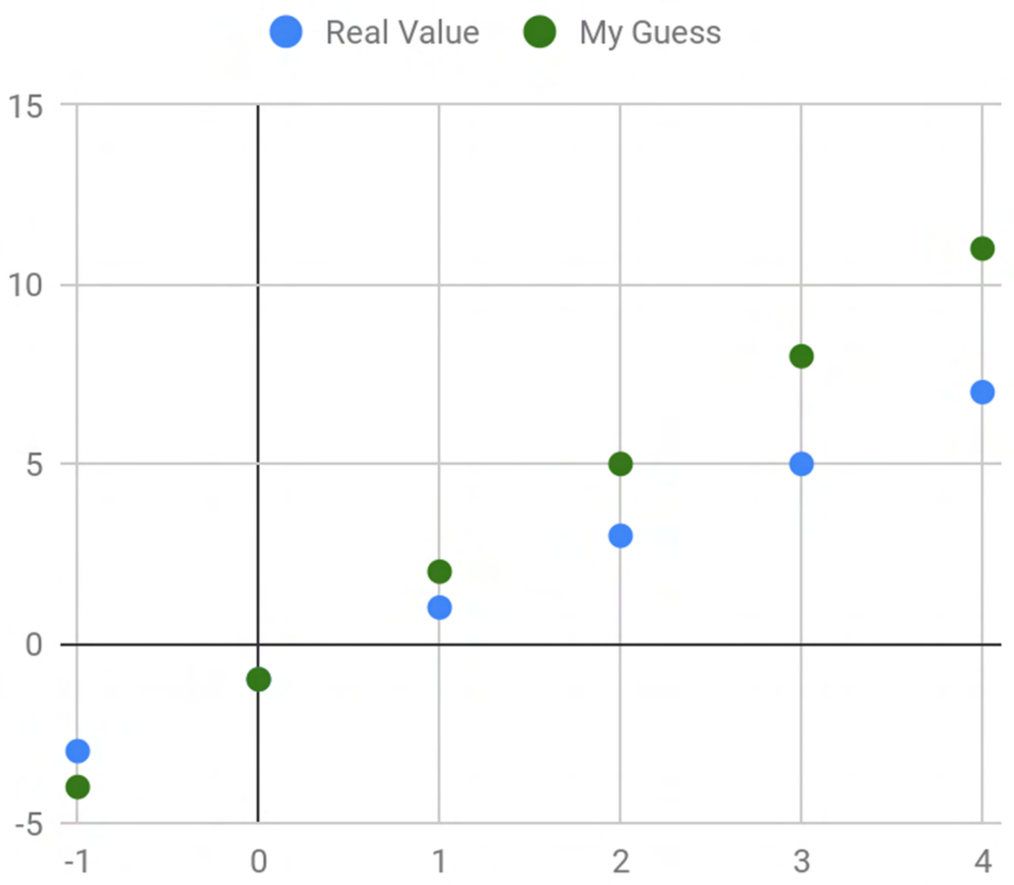
$Y = 3X - 1$

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

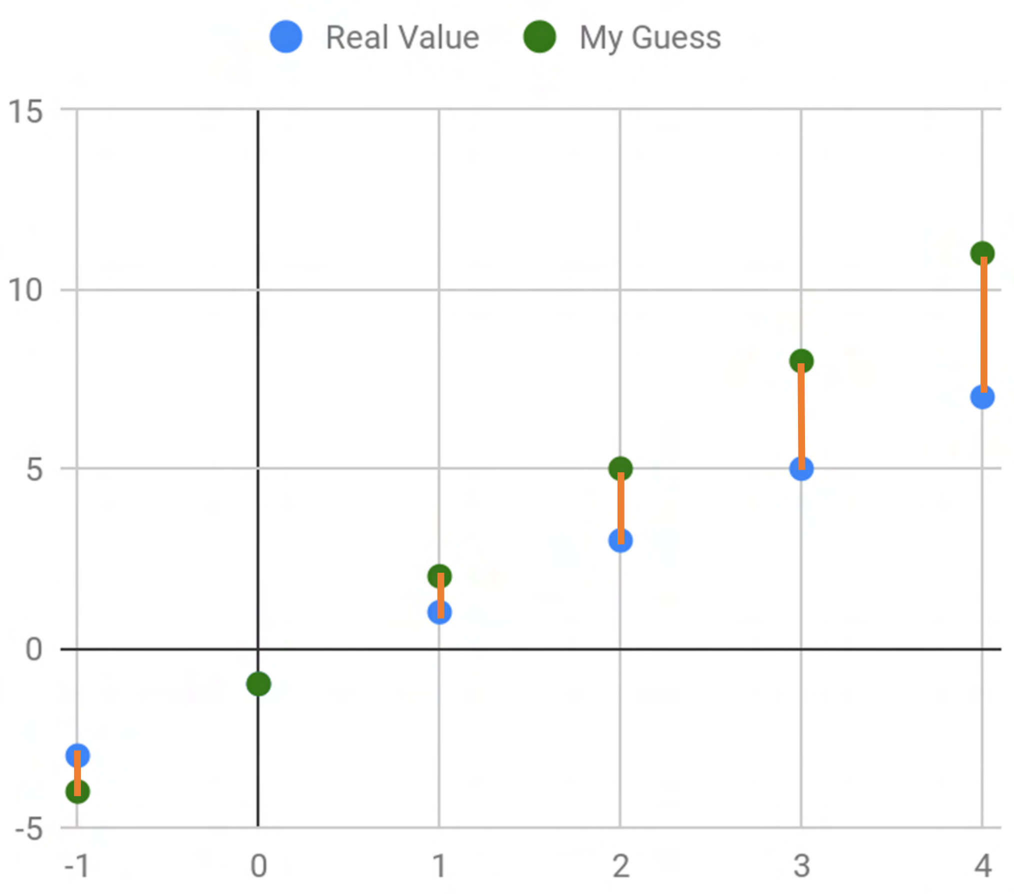
My $Y = \{ -4, -1, 2, 5, 8, 11 \}$

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

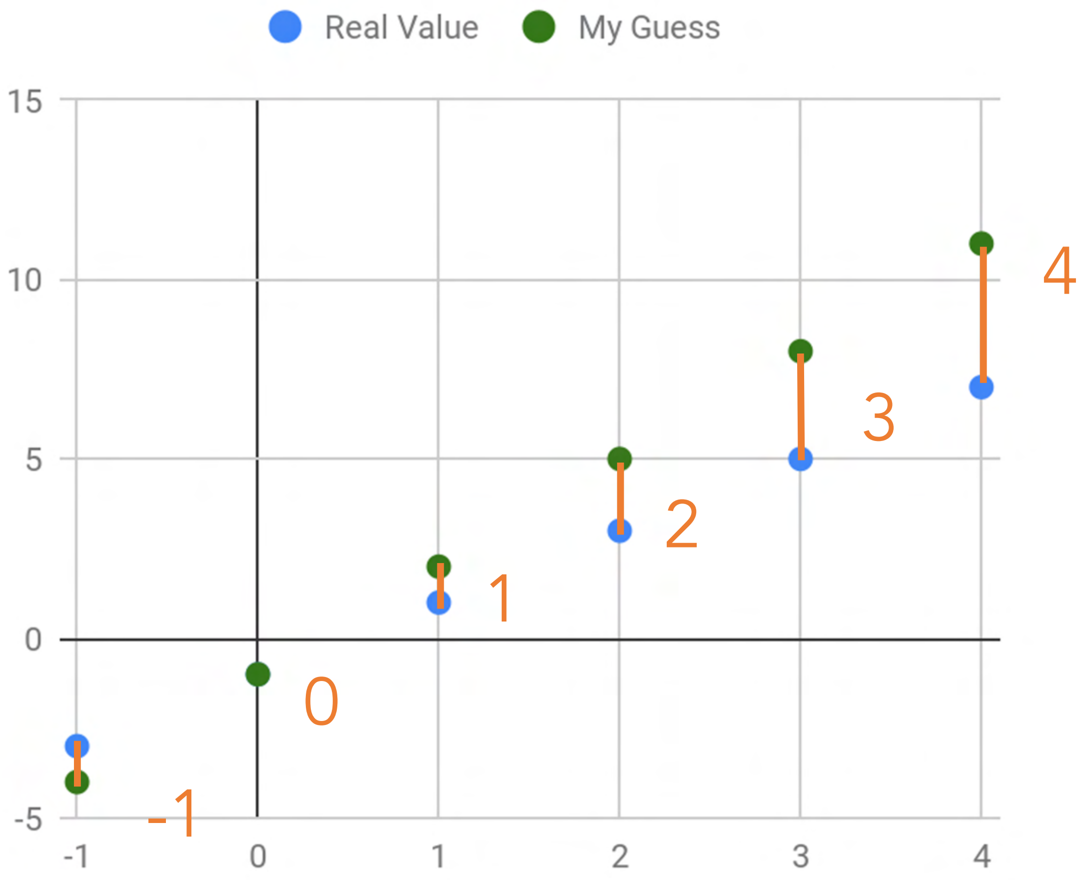
Let’s measure it!



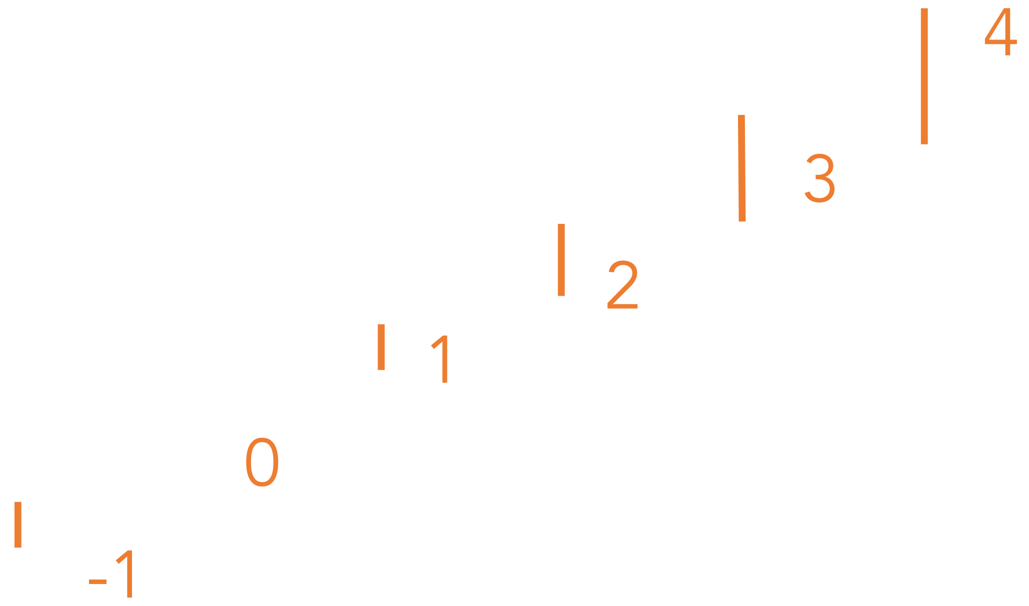
Let's measure it!



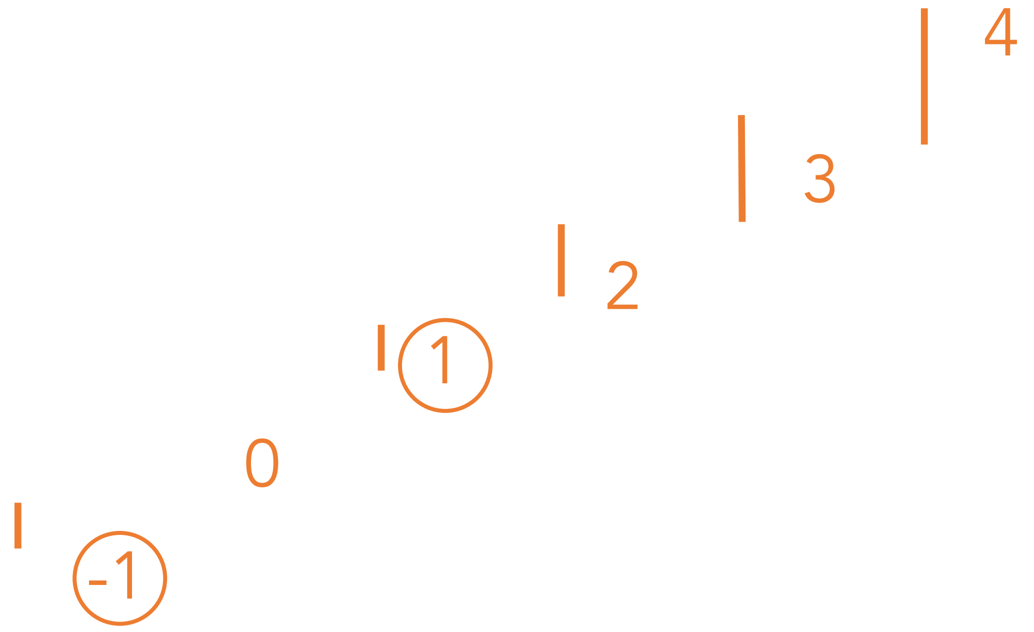
Let's measure it!



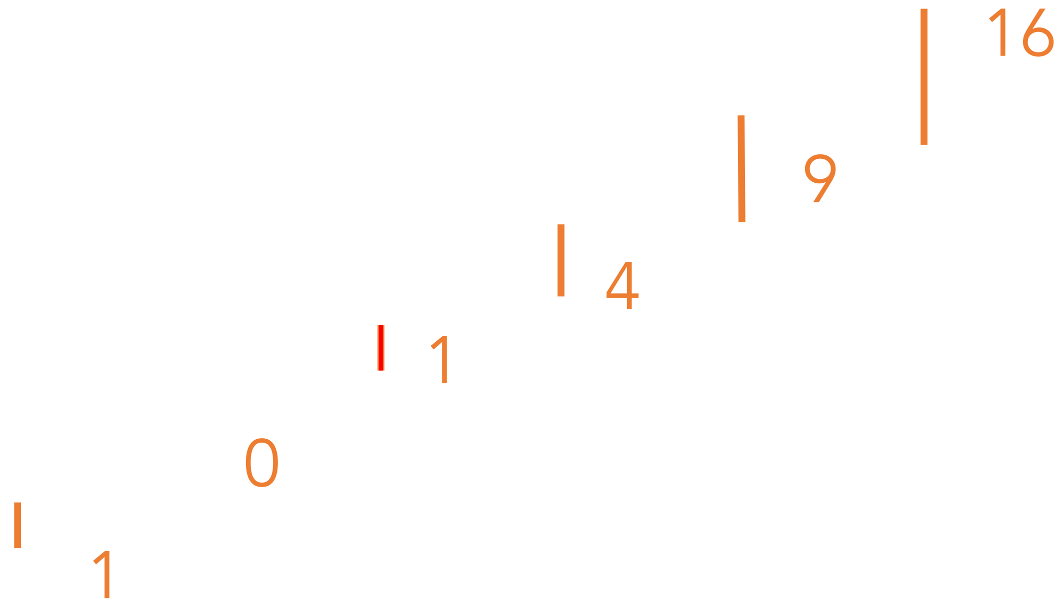
Let’s measure it!



Houston, we have a problem!



What if we square^2 them?



Total that (∑) and take the square root √

sqrt(1 + 1 + 4 + 9 + 16)

= sqrt(31)
= 5.57

Make another guess!

$Y = 2X - 2$

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

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

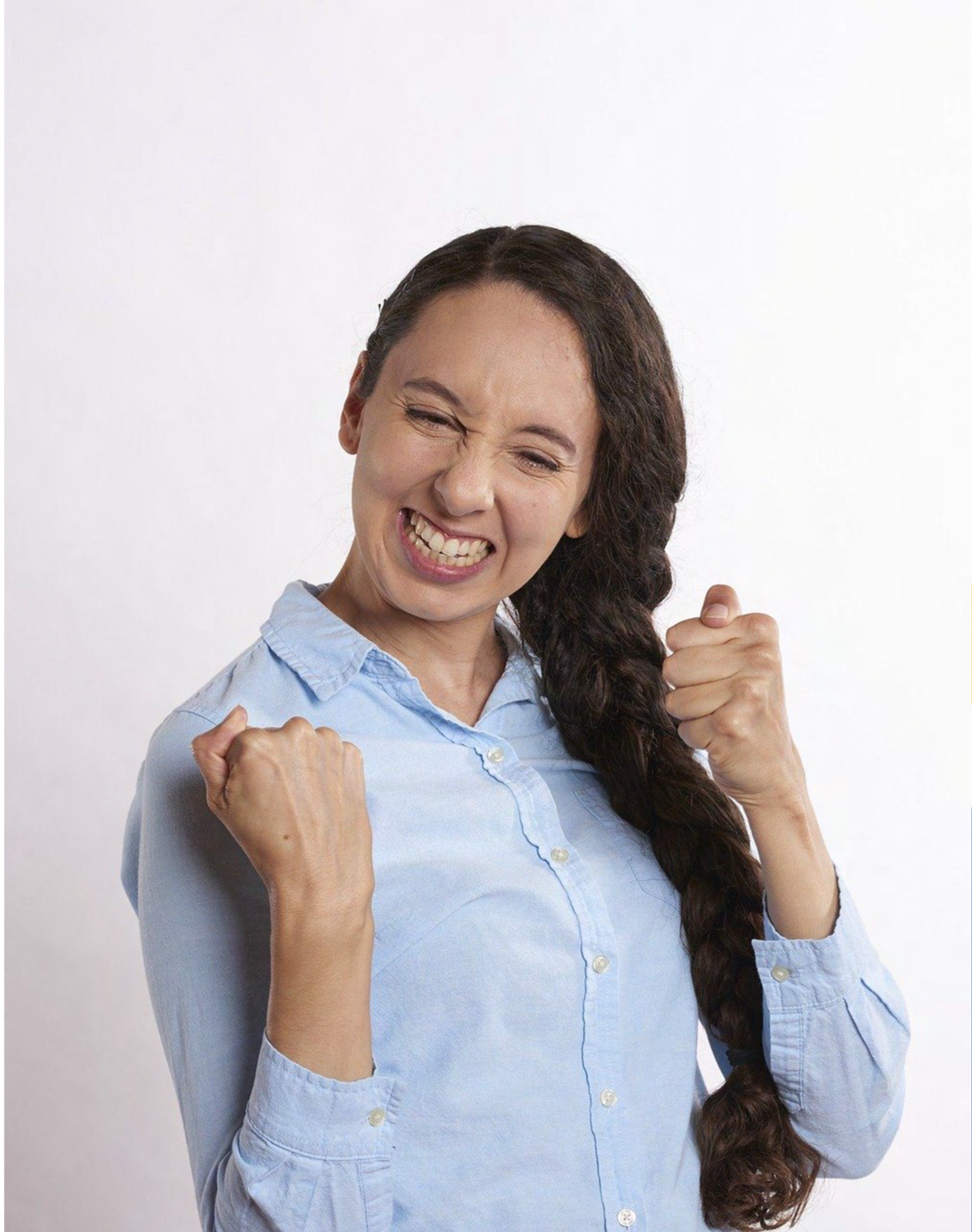
Real $Y = \{-3, -1, 1, 3, 5, 7\}$

$\text{Diff}^2 = \{1, 1, 1, 1, 1\}$

Get the same difference, repeat the same process.

sqrt(1 + 1 + 1 + 1 + 1)

= sqrt(5)
= 2.23



Make another guess!

$Y = 2X - 1$

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

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

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

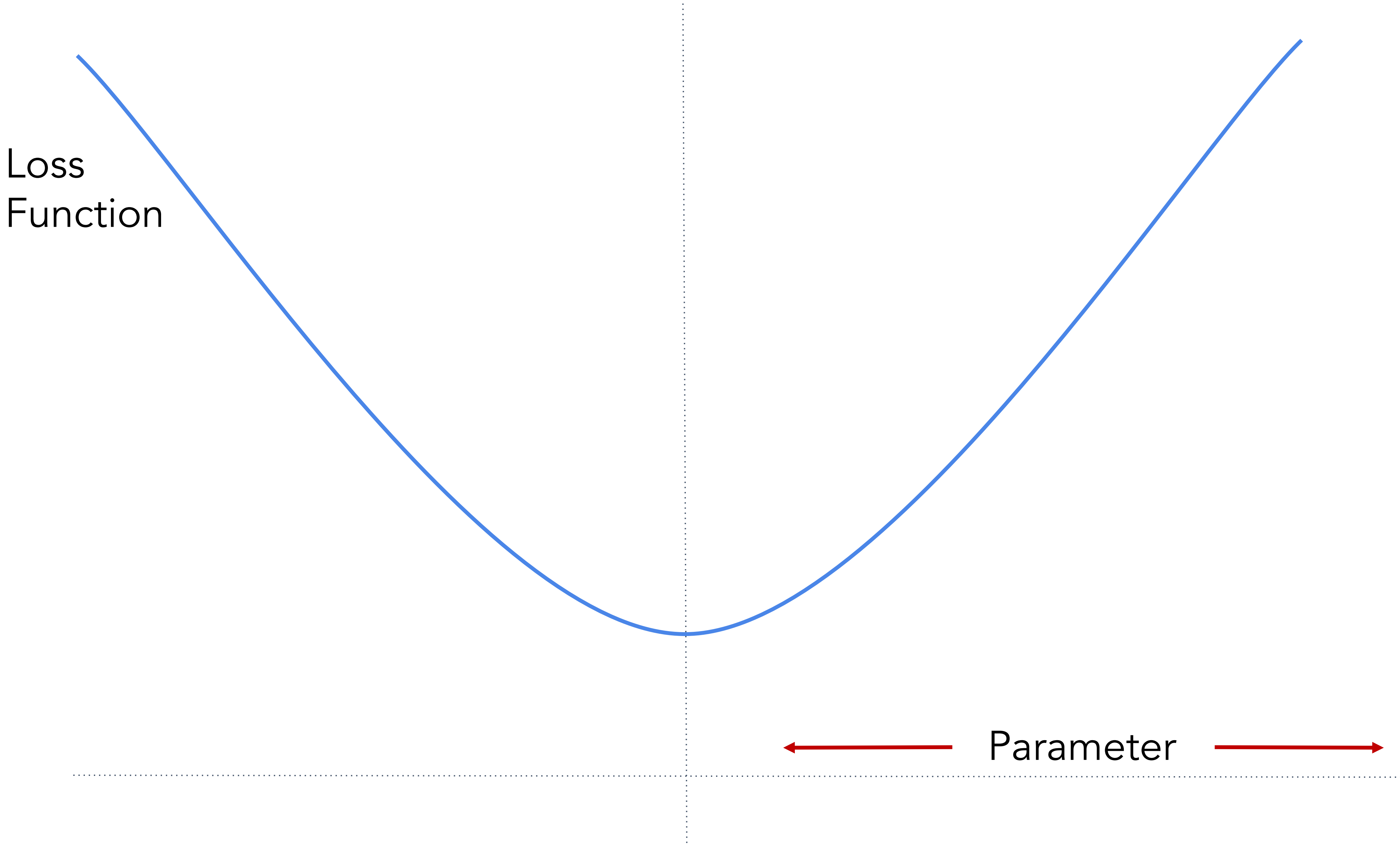
$\text{Diff}^2 = \{0, 0, 0, 0, 0\}$

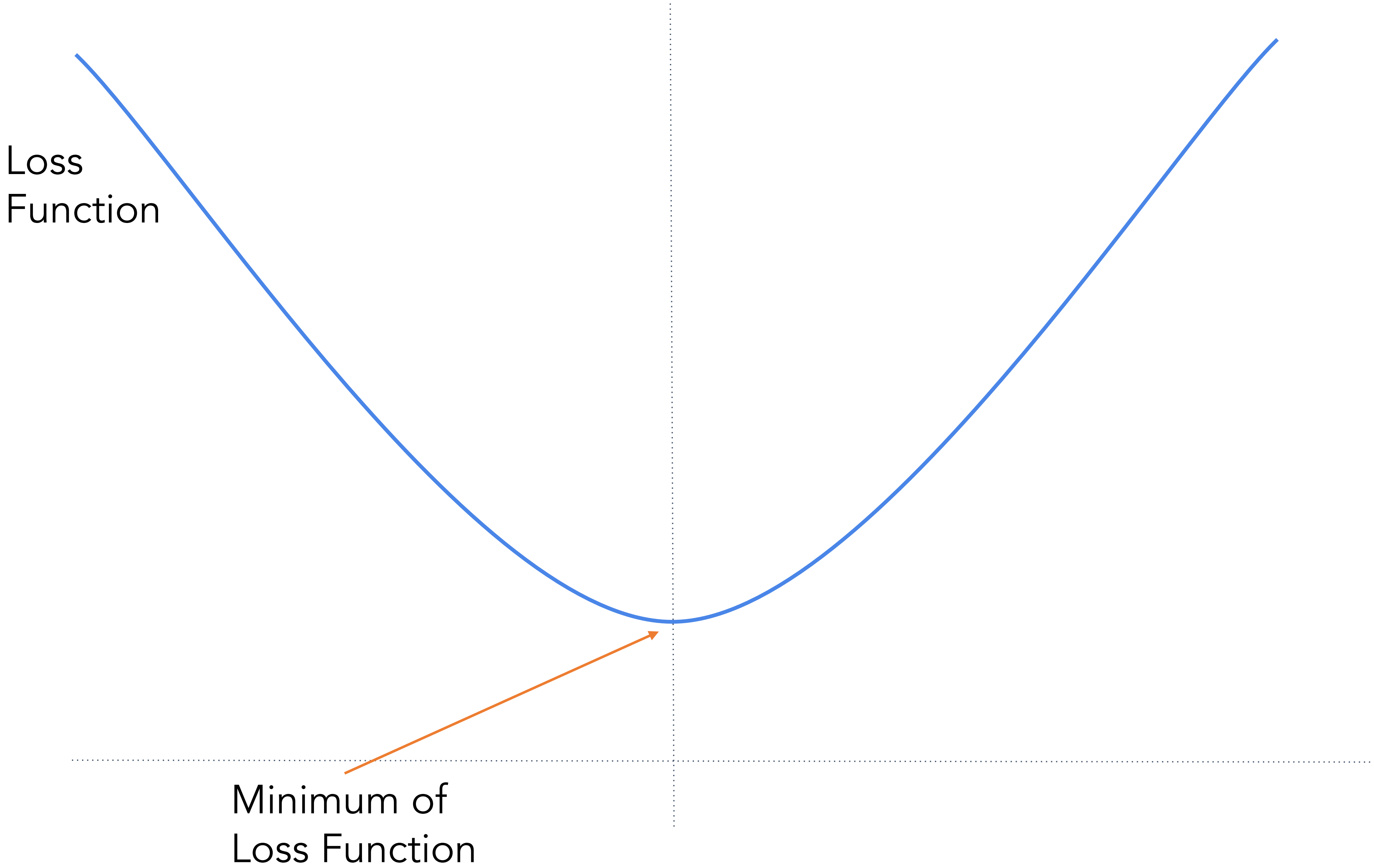
Root-mean-square deviation

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{t=1}^{T} (\hat{y}_t - y_t)^2}{T}}.$$

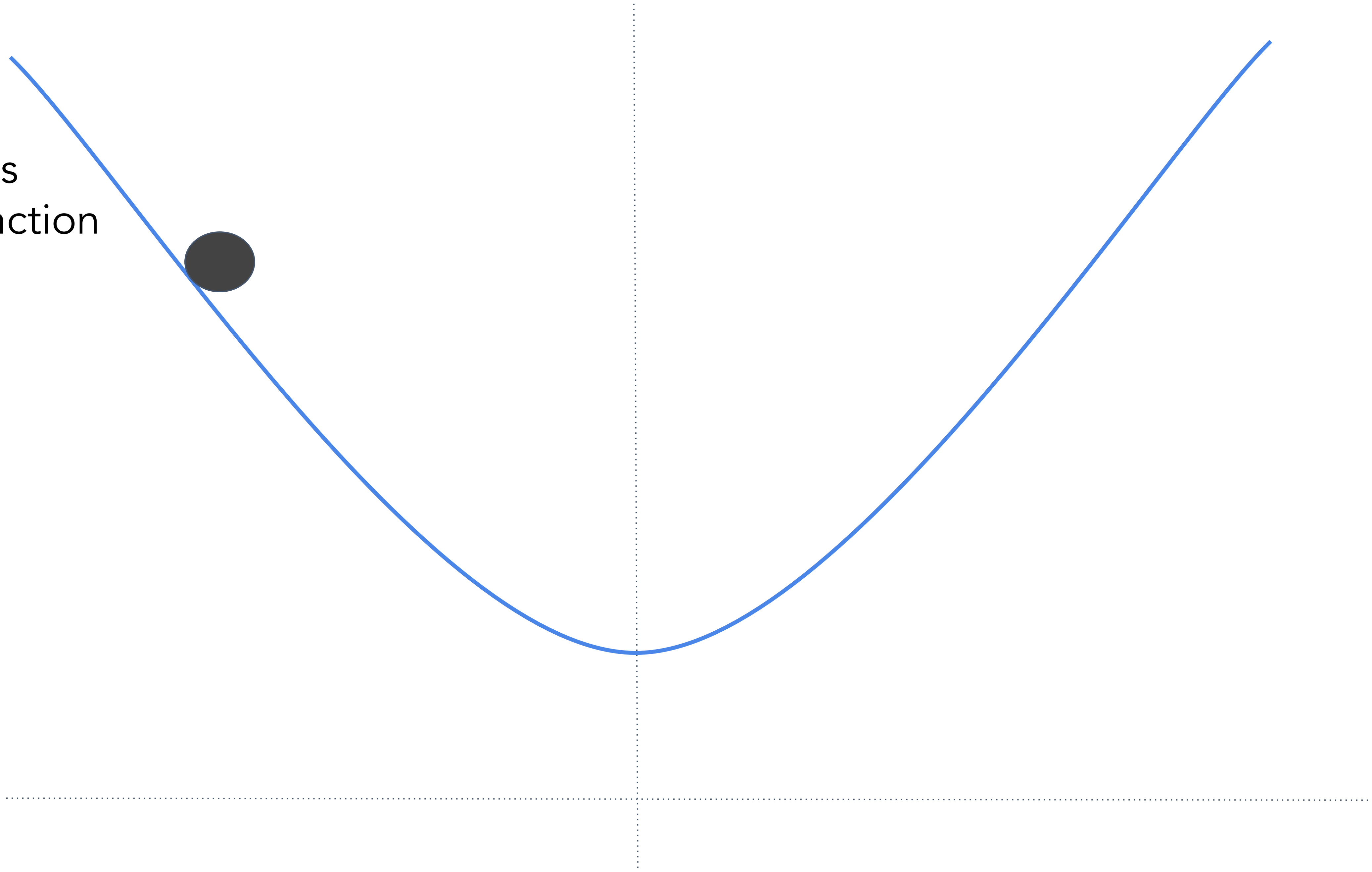
Finding out the best solution

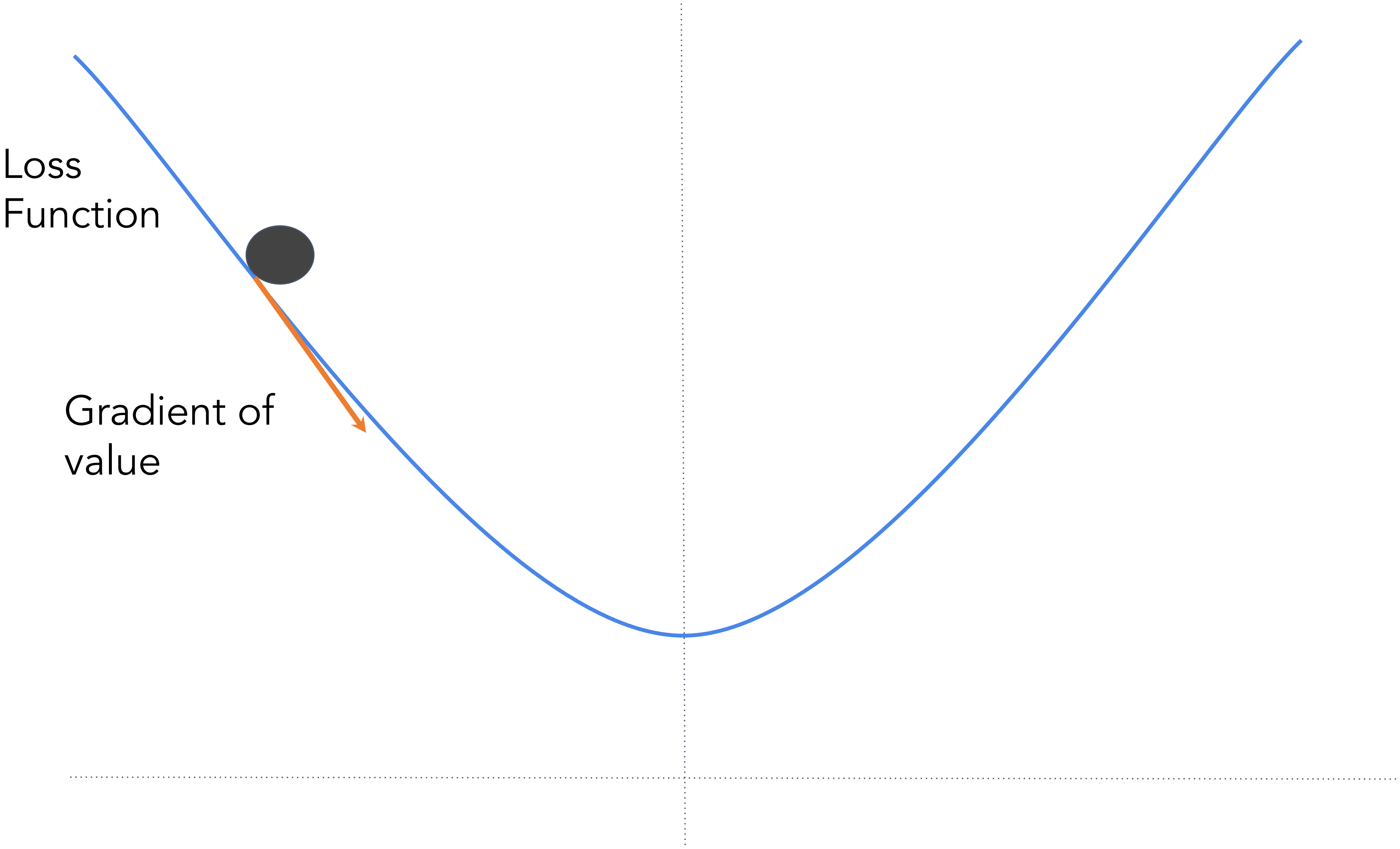
Trial and error approach

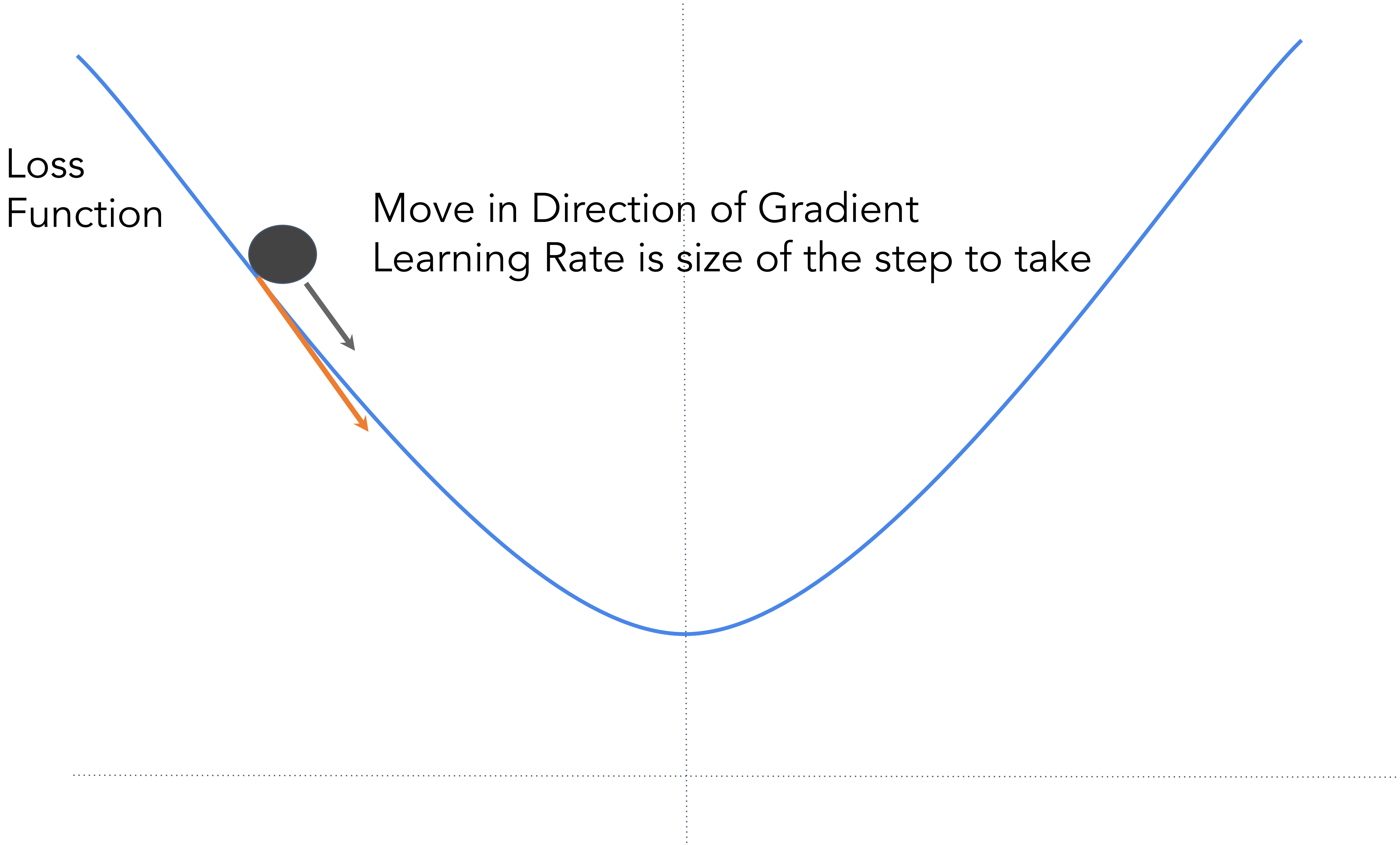

Loss
Function
Parameter


Loss
Function
Minimum of
Loss Function

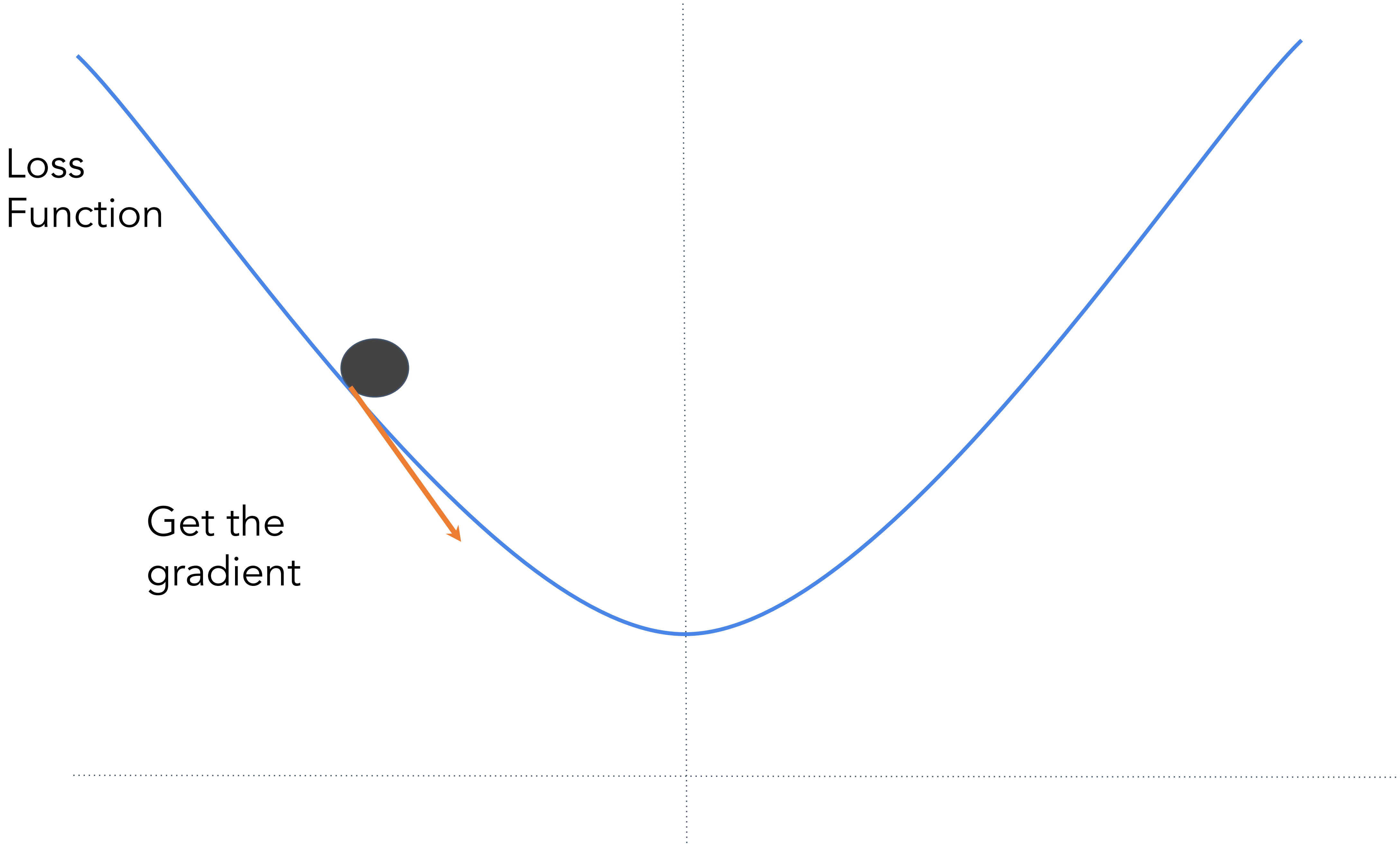
Loss Function



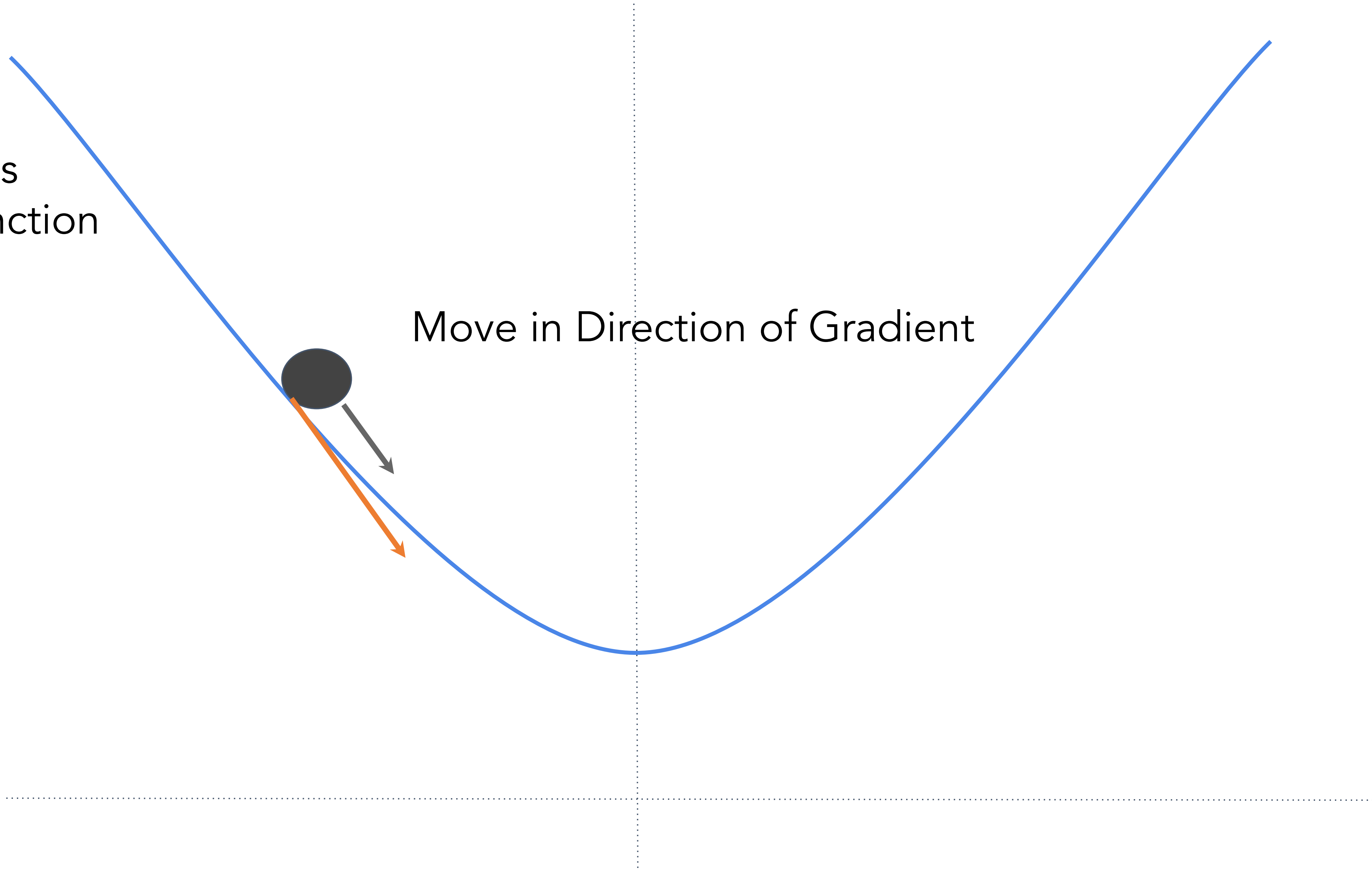

Loss
Function
Gradient of
value


Loss
Function
Move in Direction of Gradient
Learning Rate is size of the step to take


Loss
Function
End up here

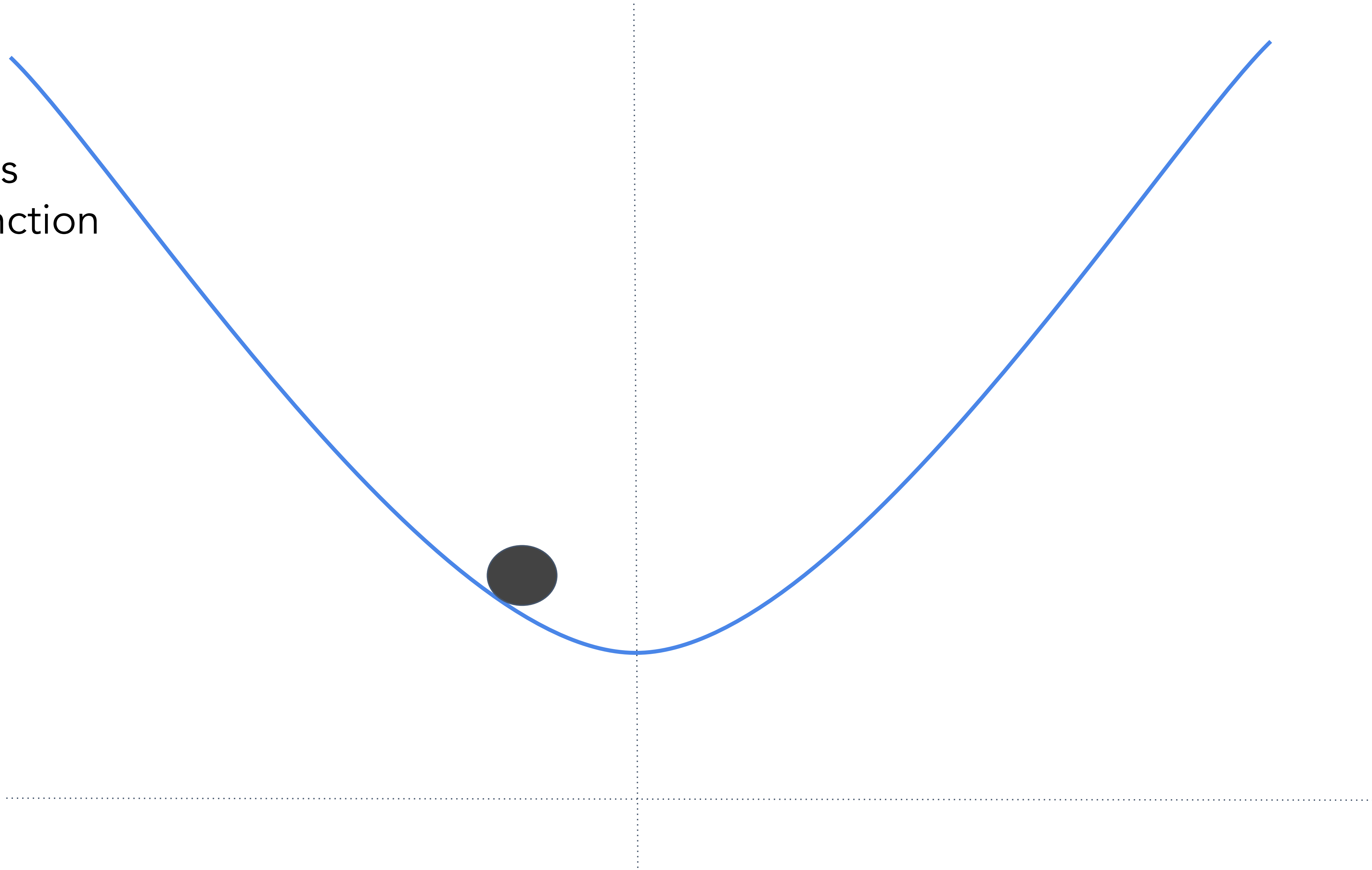

Loss
Function
Get the
gradient

Loss Function

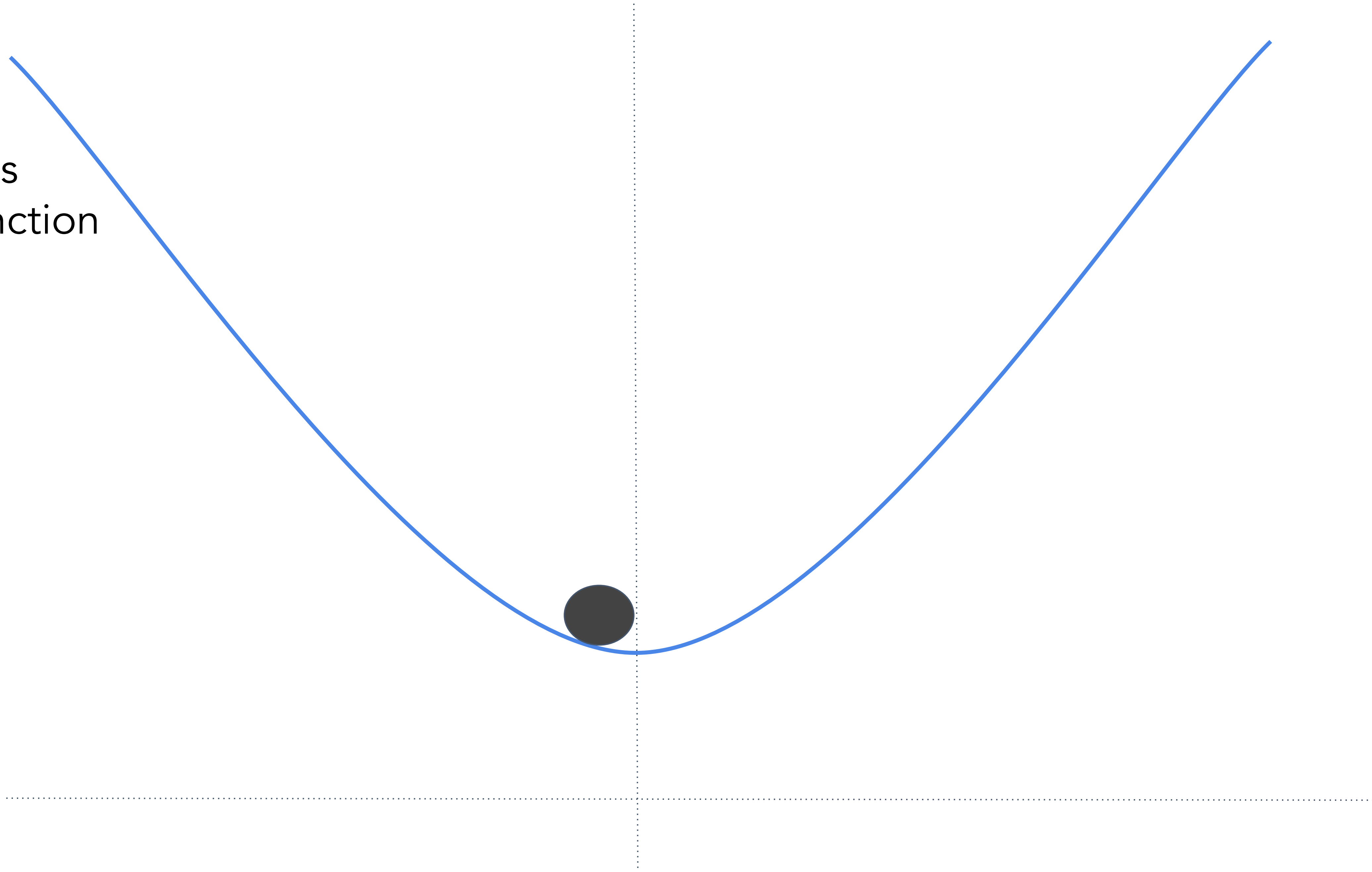


Loss Function

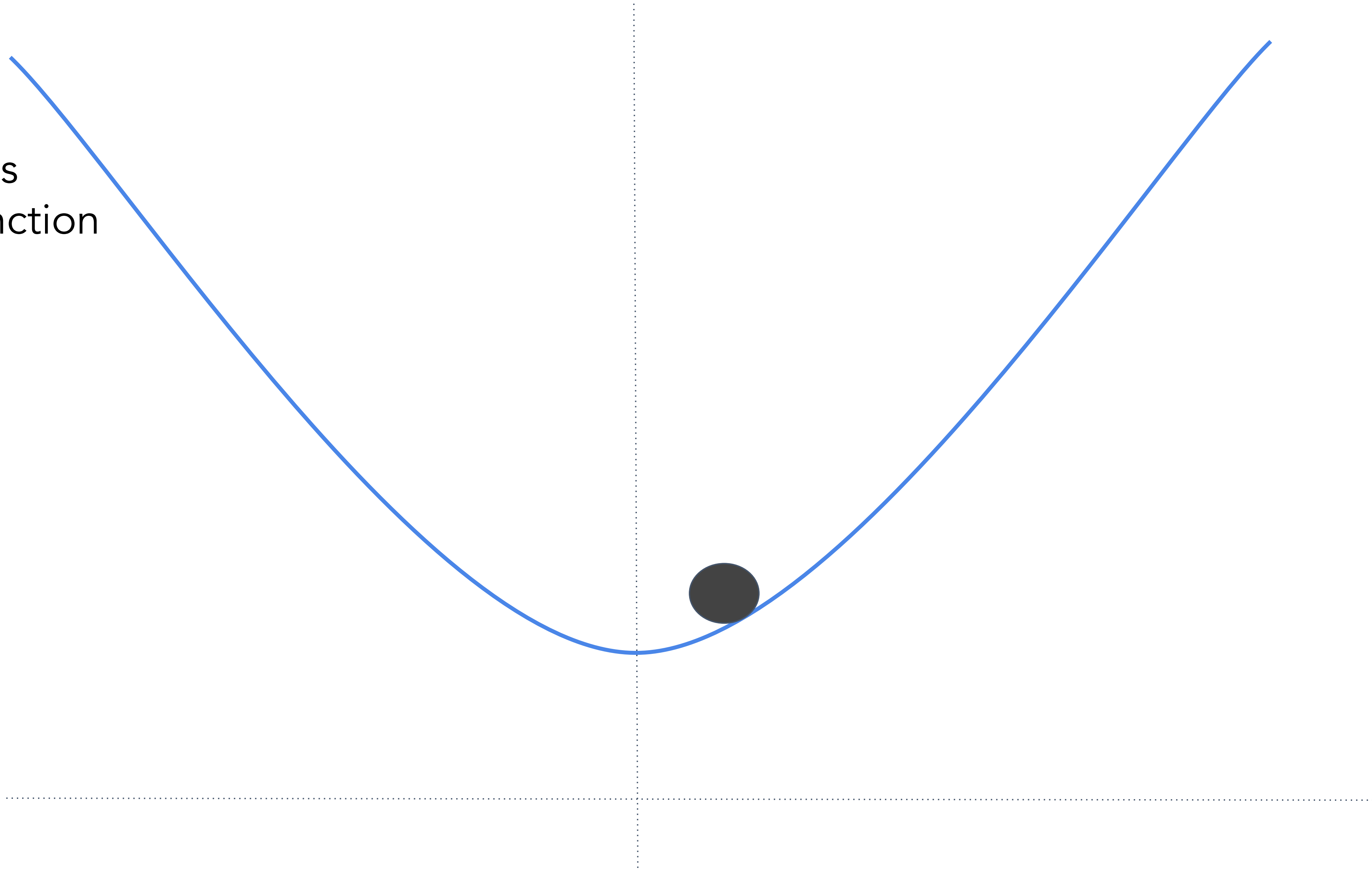
Loss Function



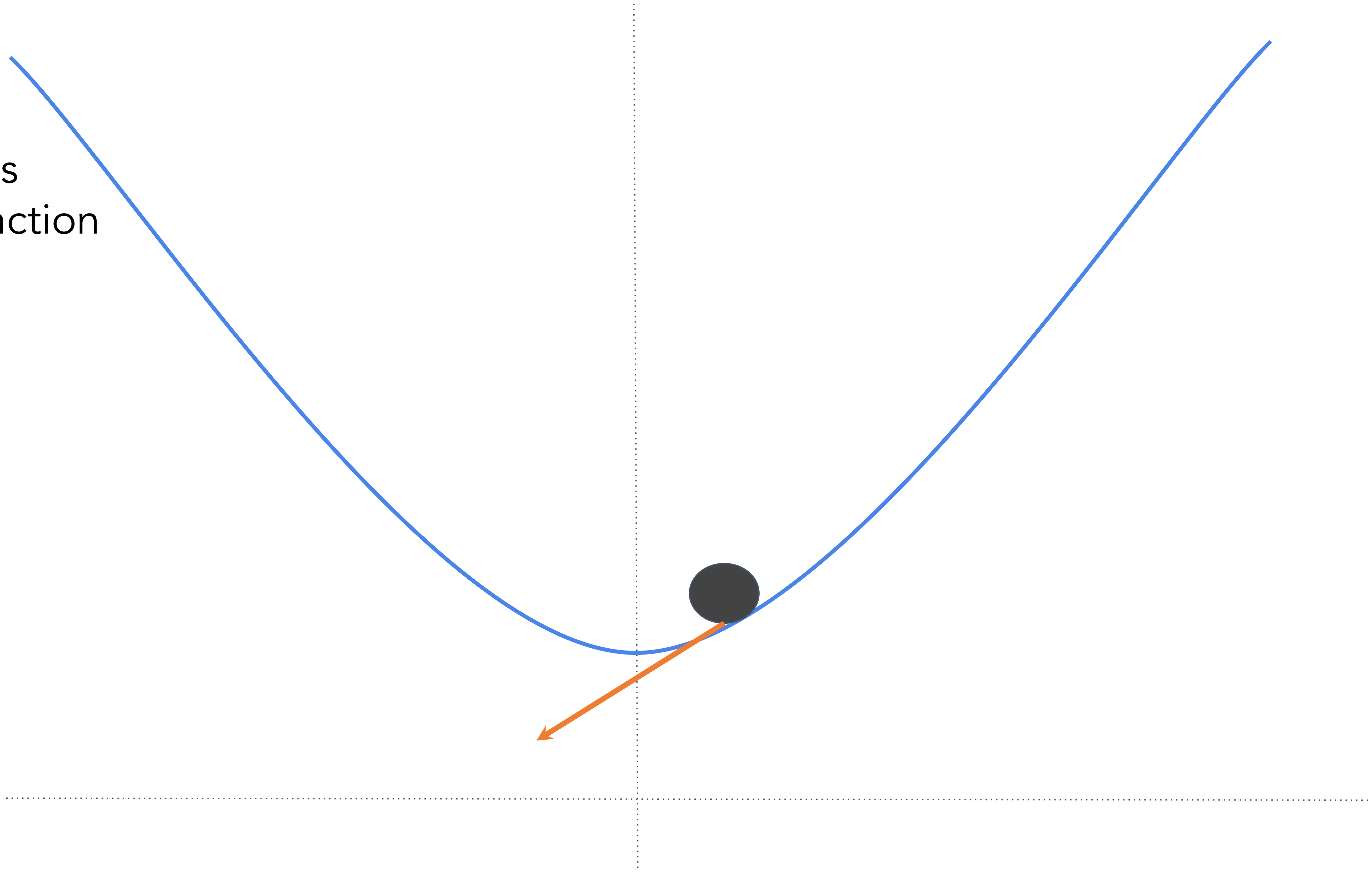
Loss Function



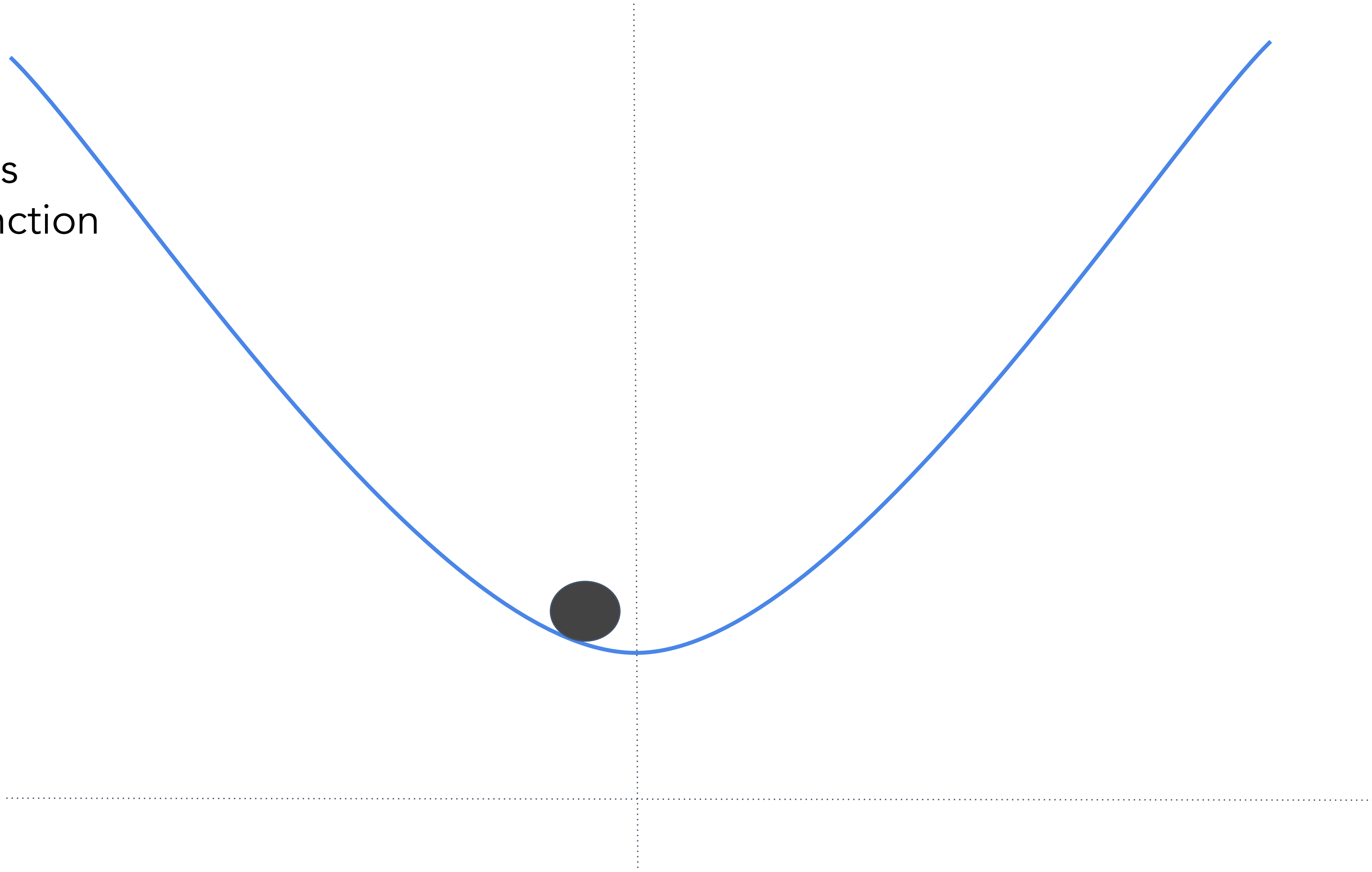
Loss Function



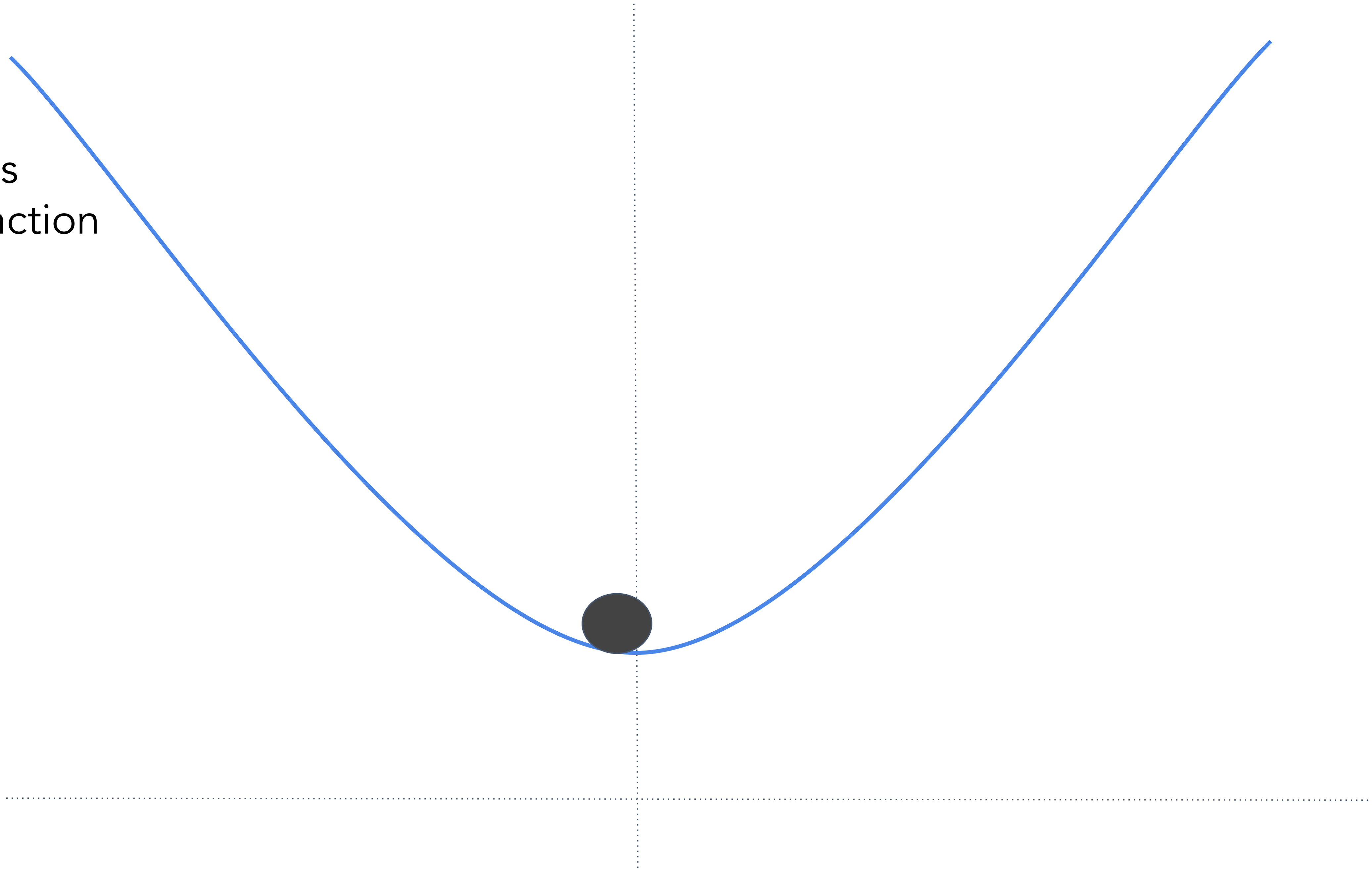
Loss Function

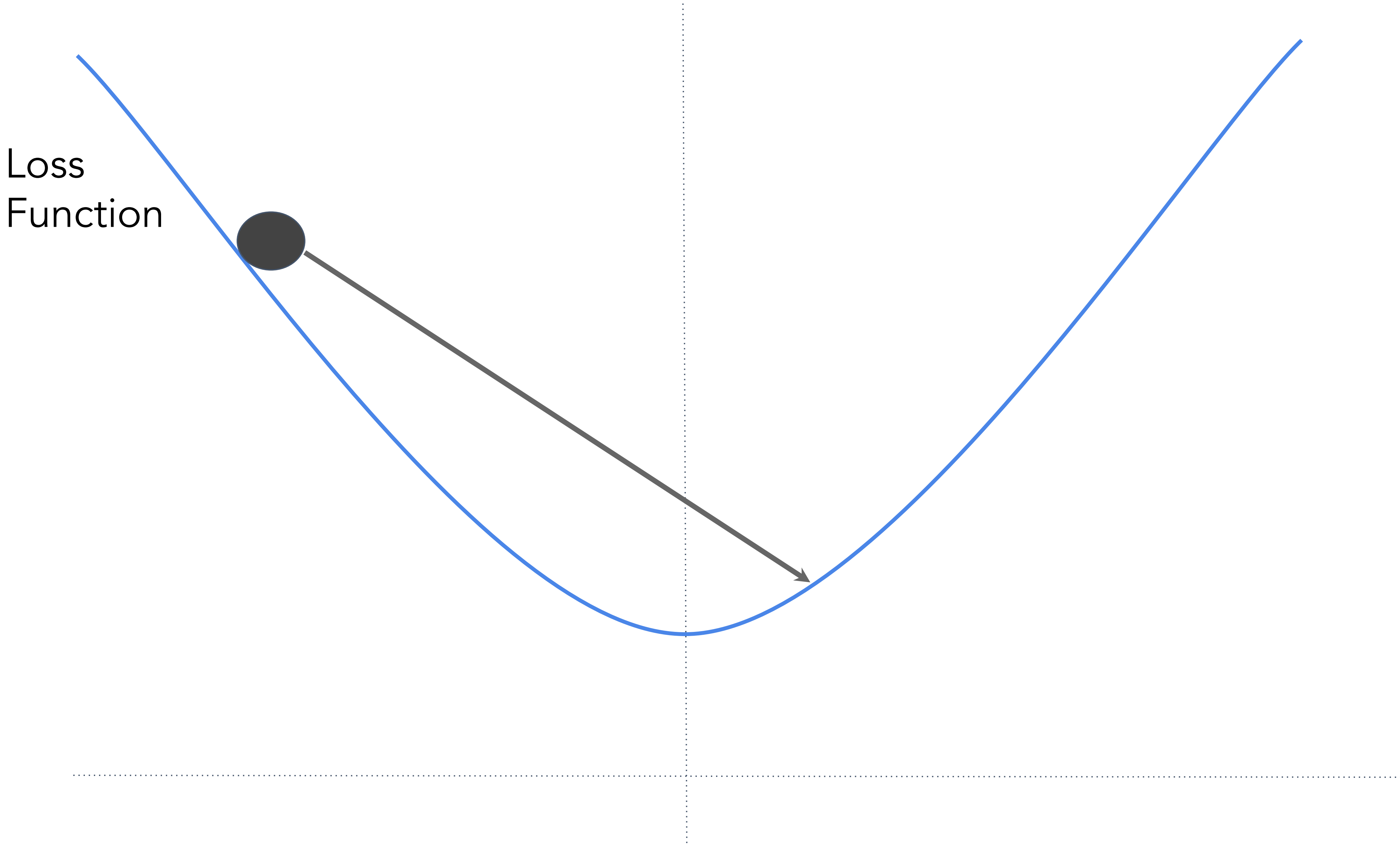


Loss Function

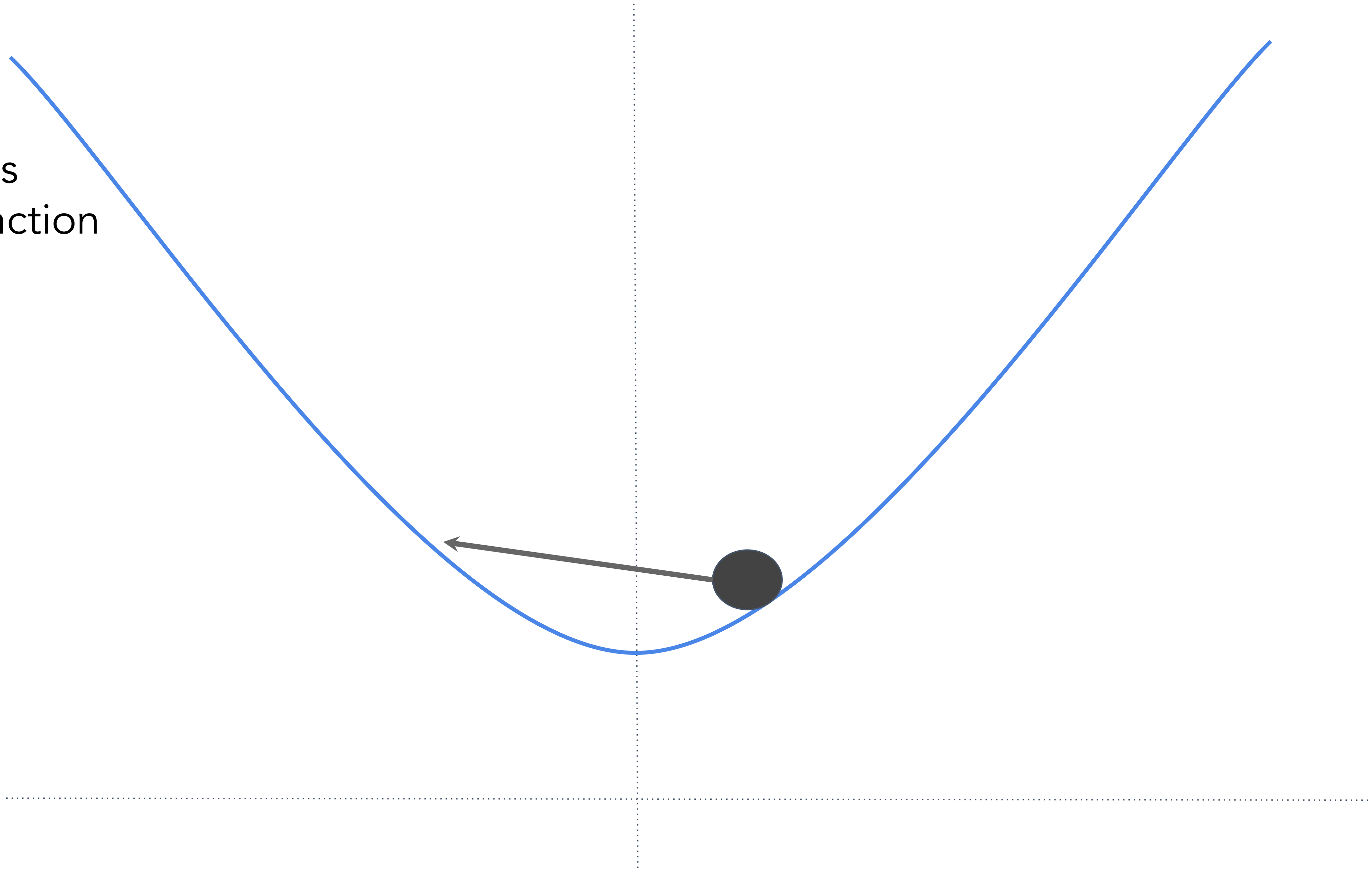


Loss Function

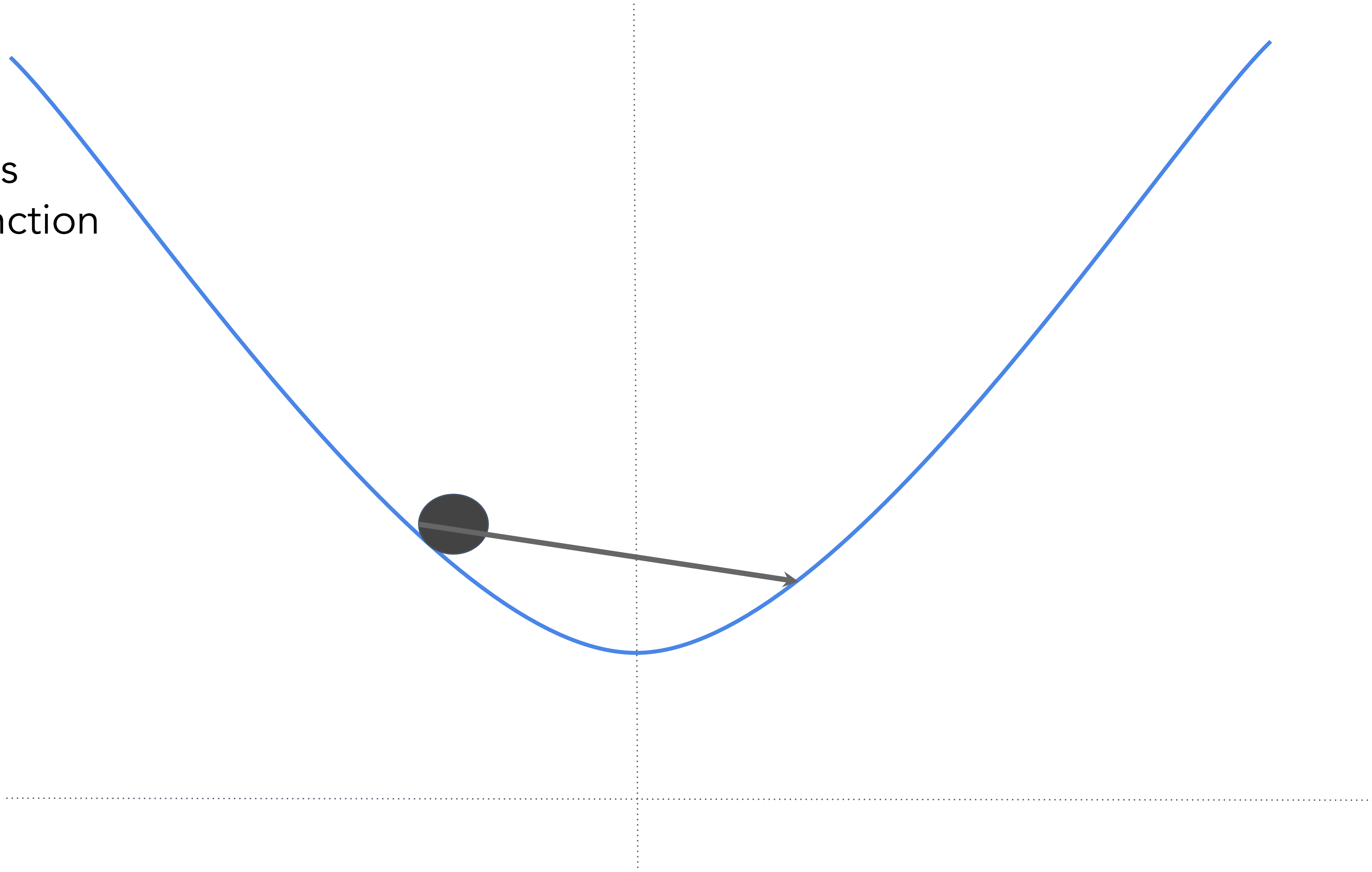


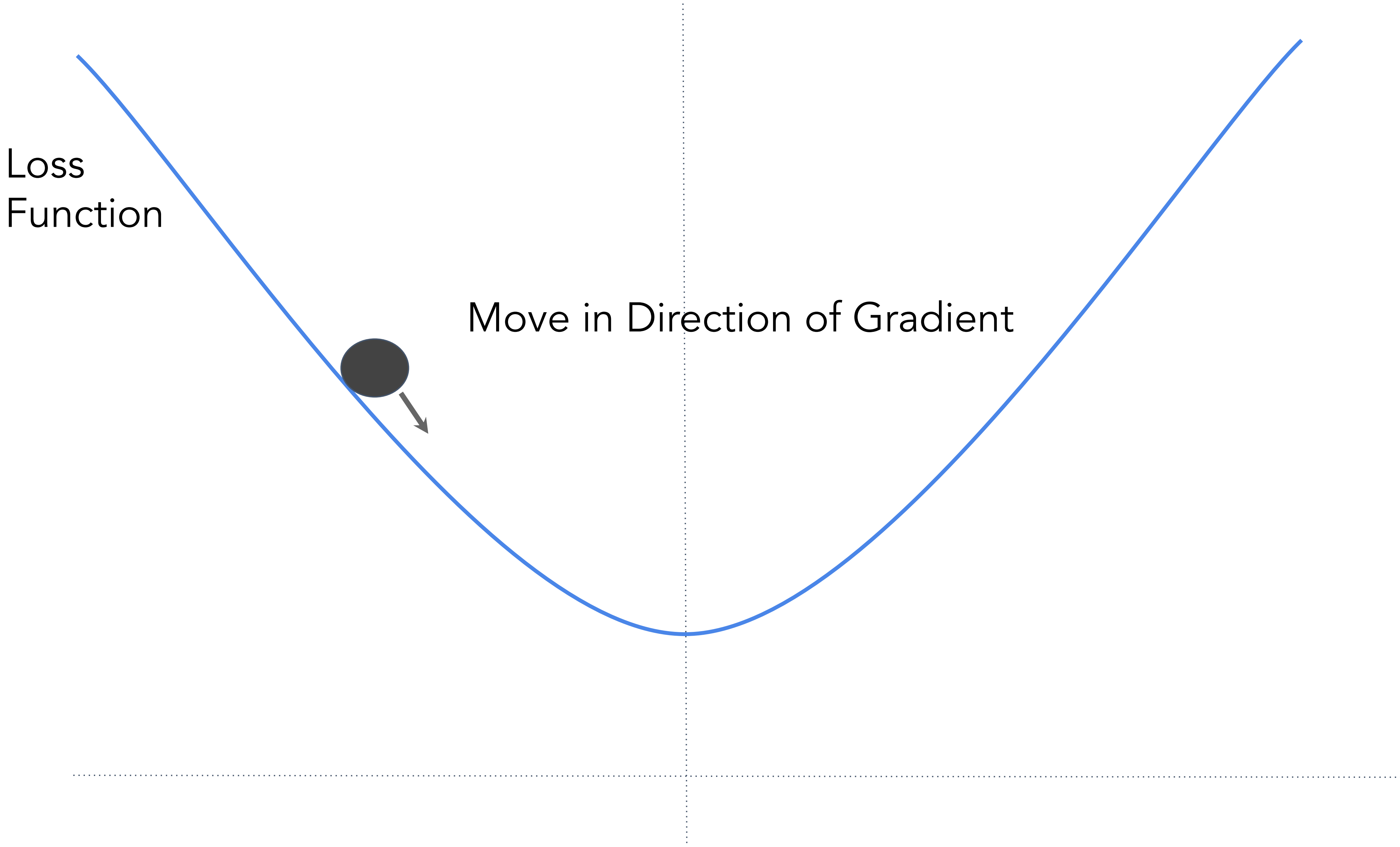

Loss
Function

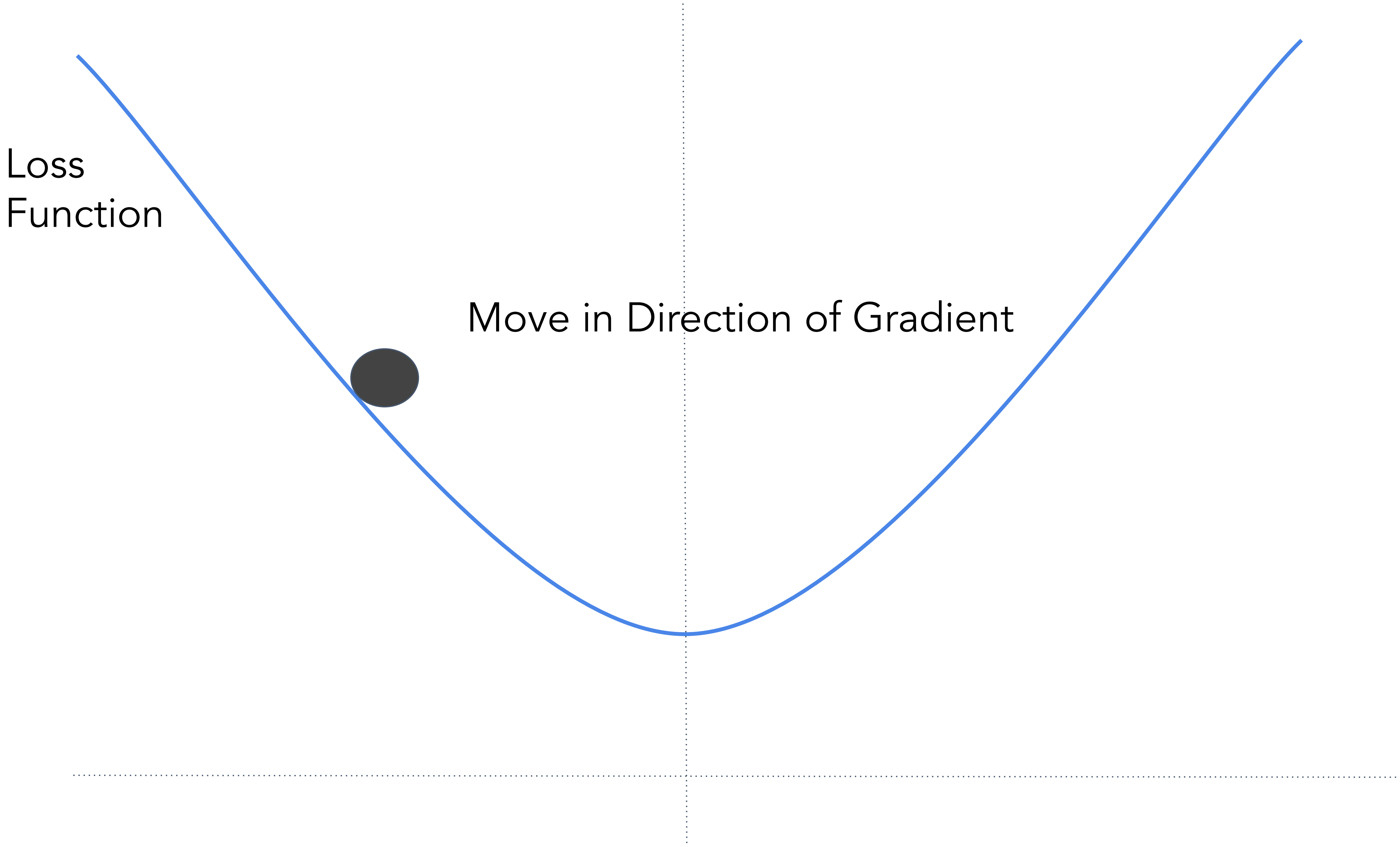
Loss Function



Loss
Function

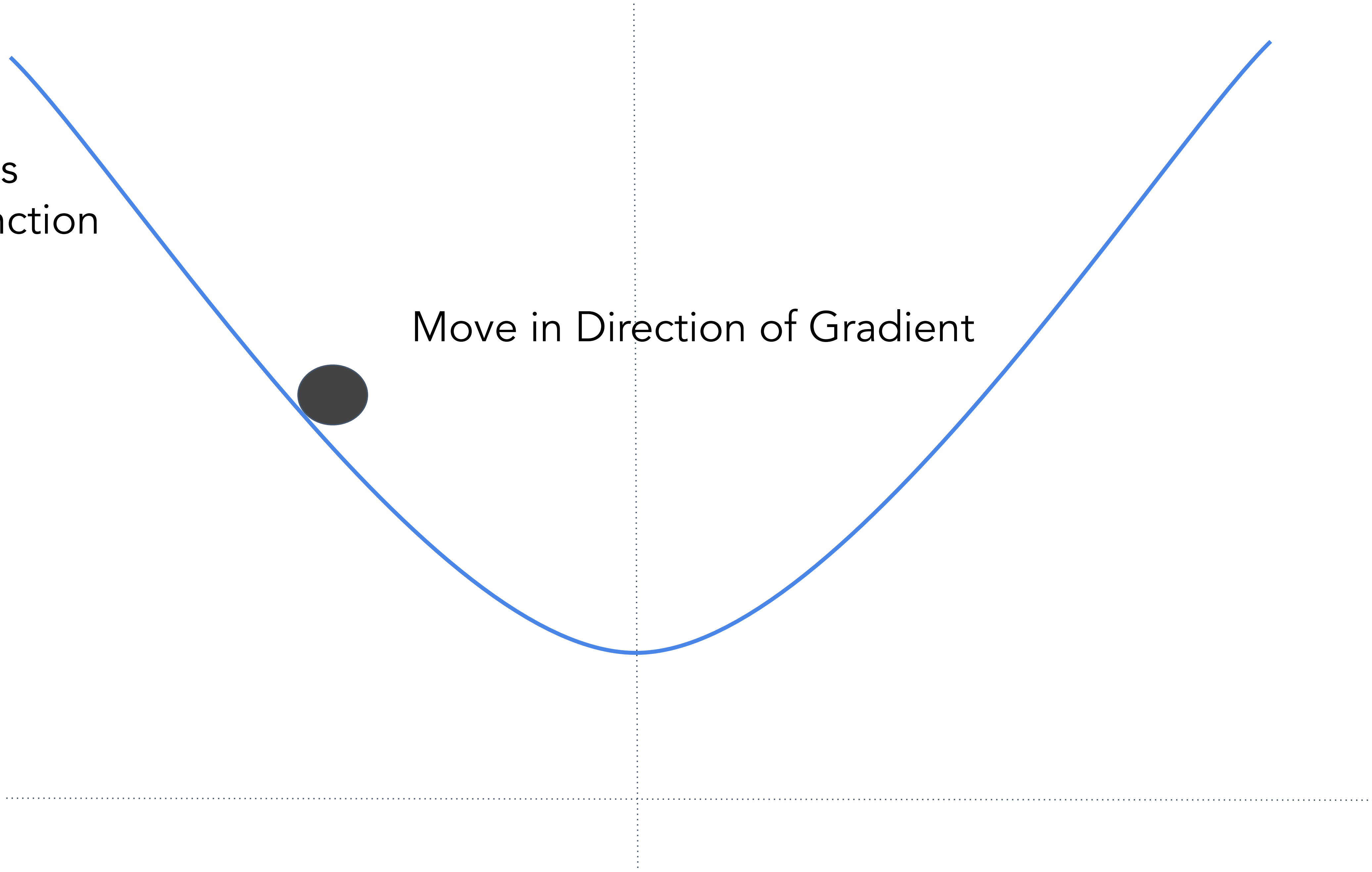



Loss
Function
Move in Direction of Gradient

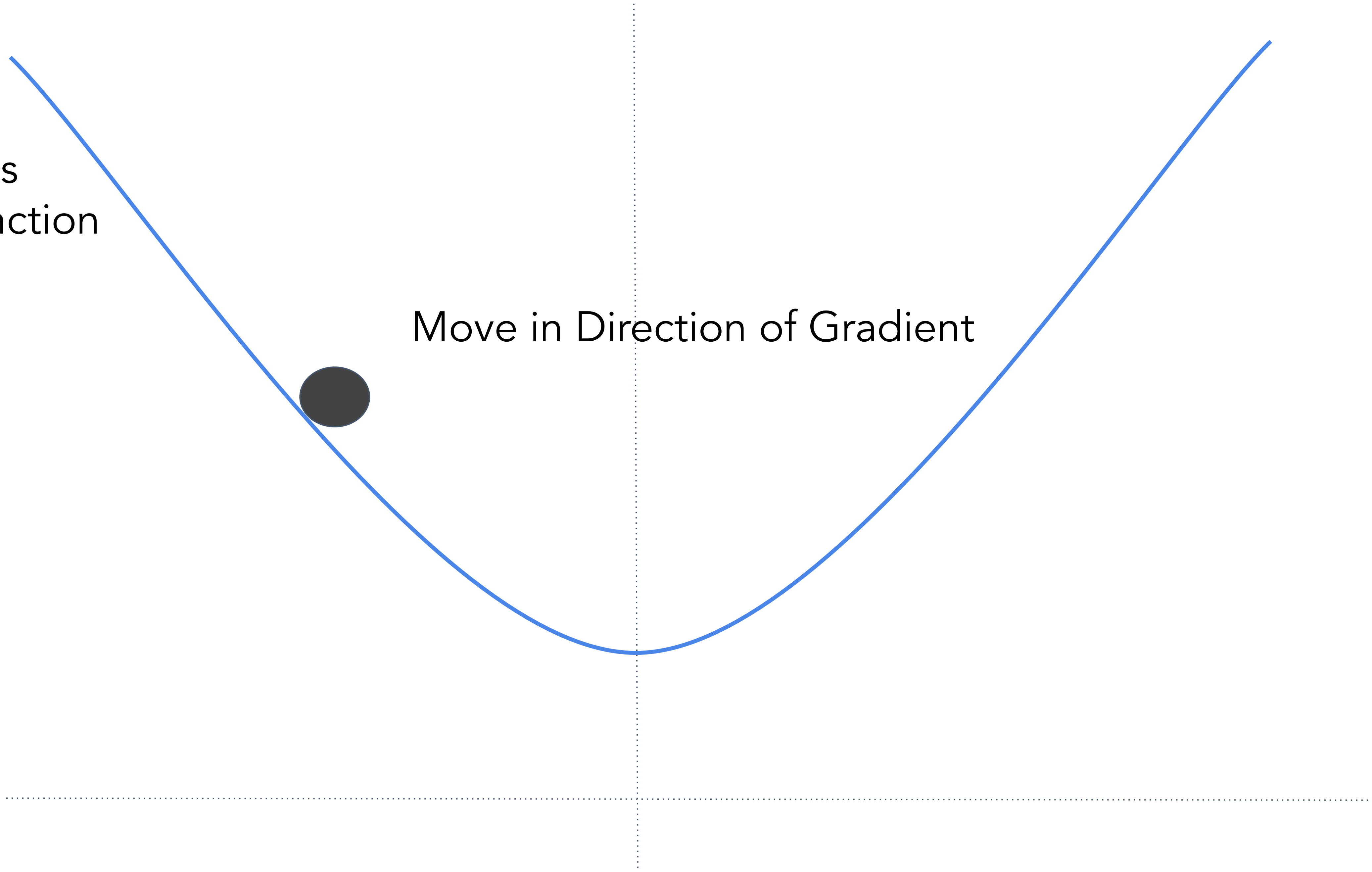


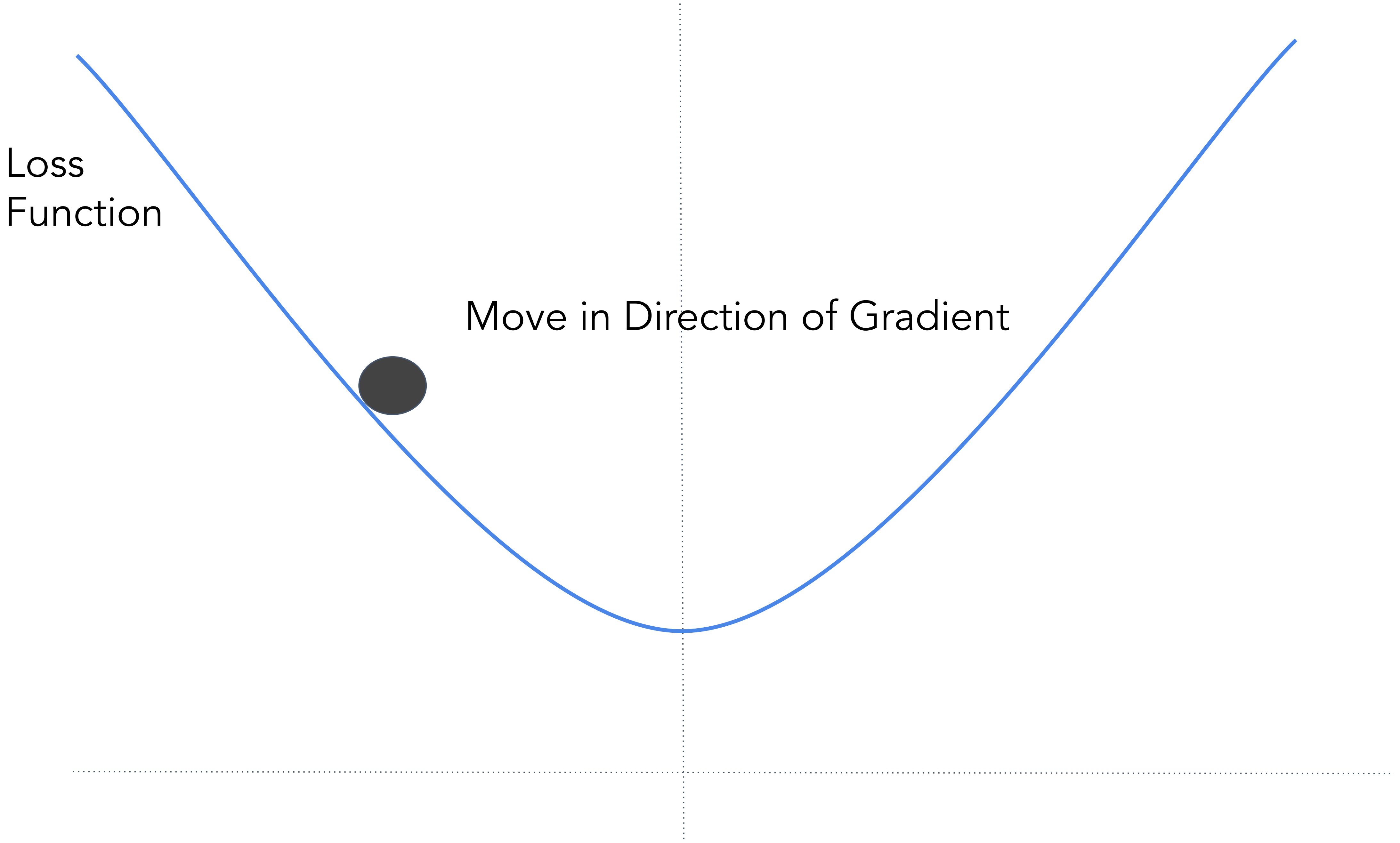
Loss
Function
Move in Direction of Gradient

Loss Function

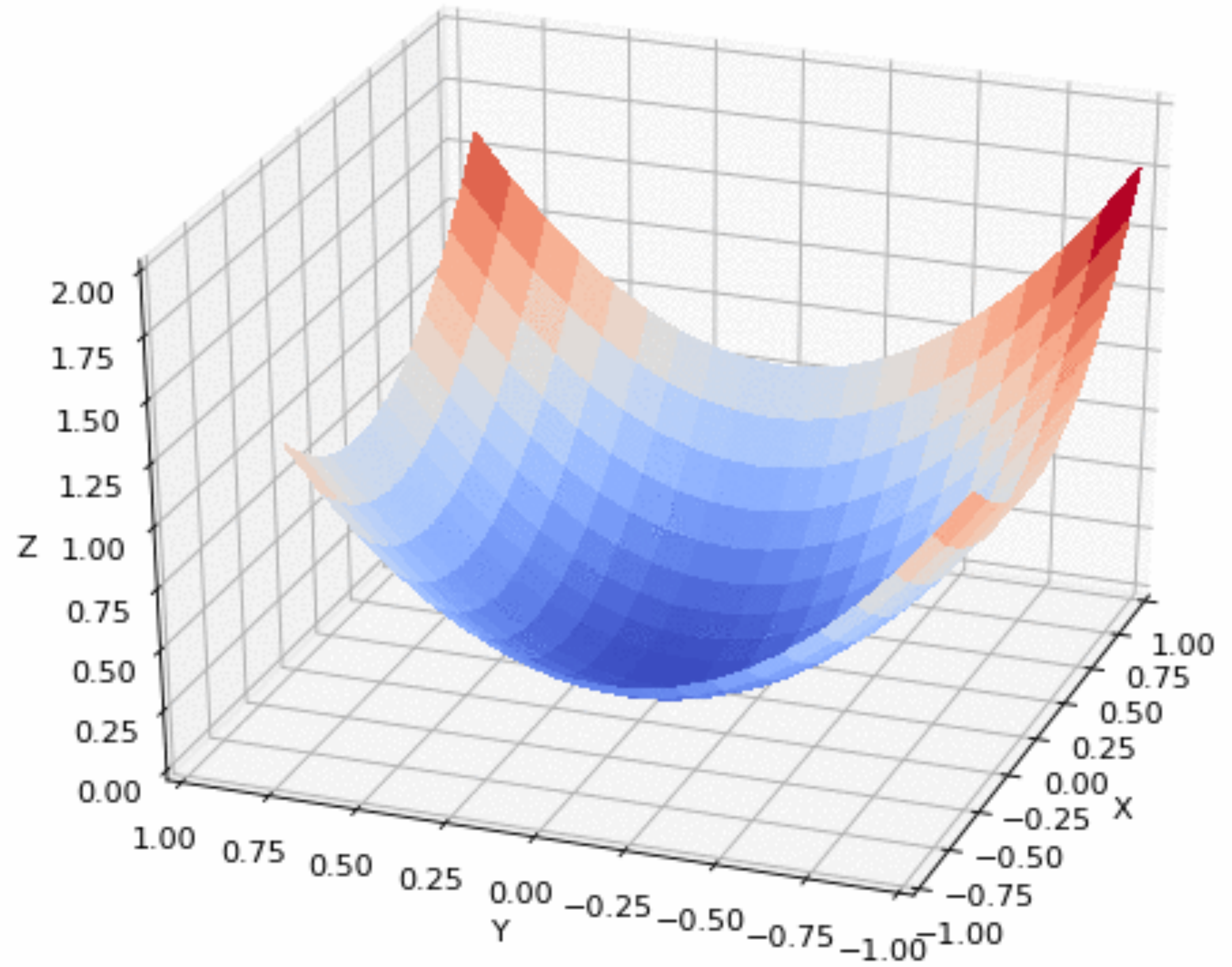


Loss Function




Loss
Function
Move in Direction of Gradient

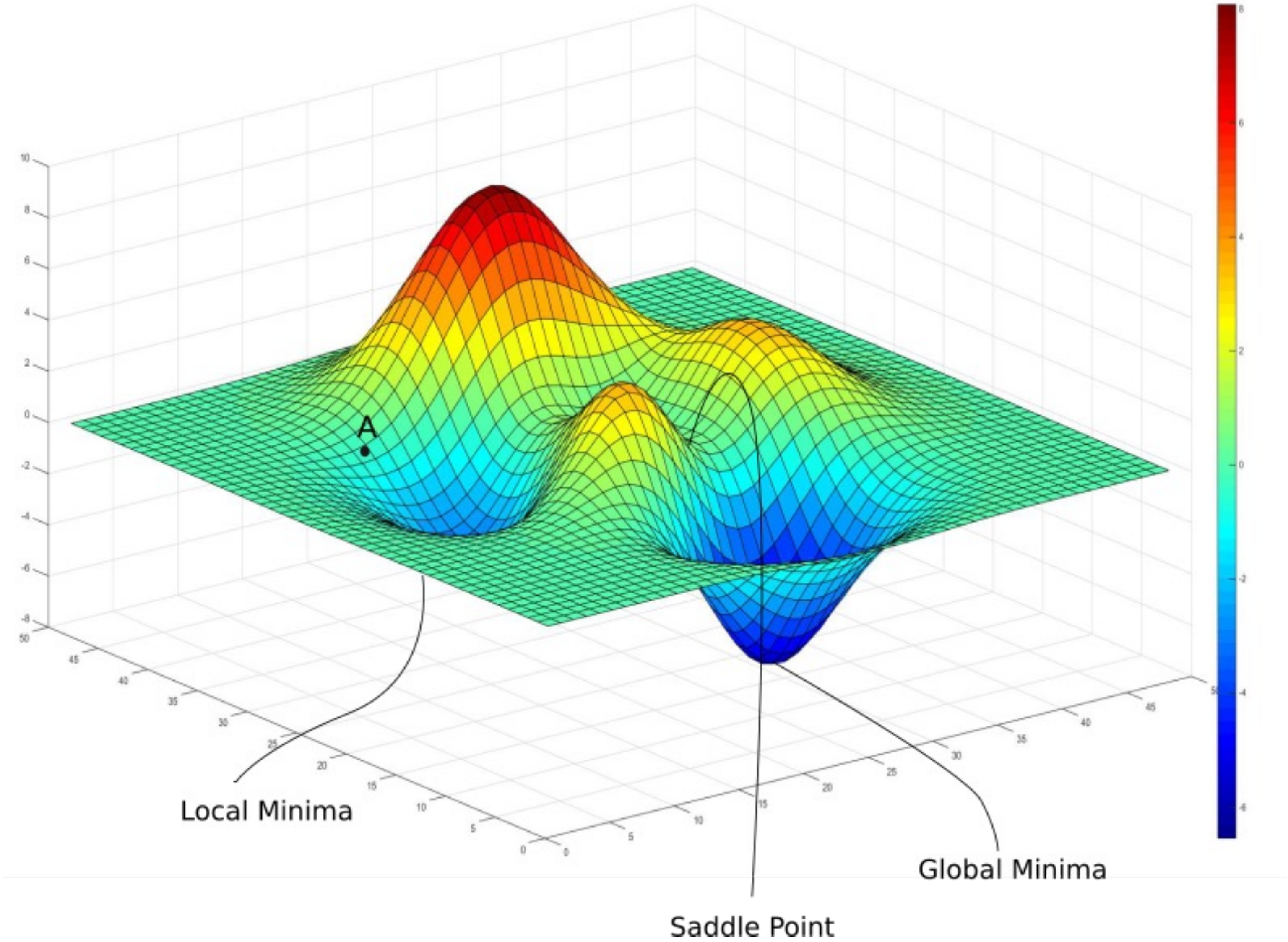
Gradient Descent for Two Parameters



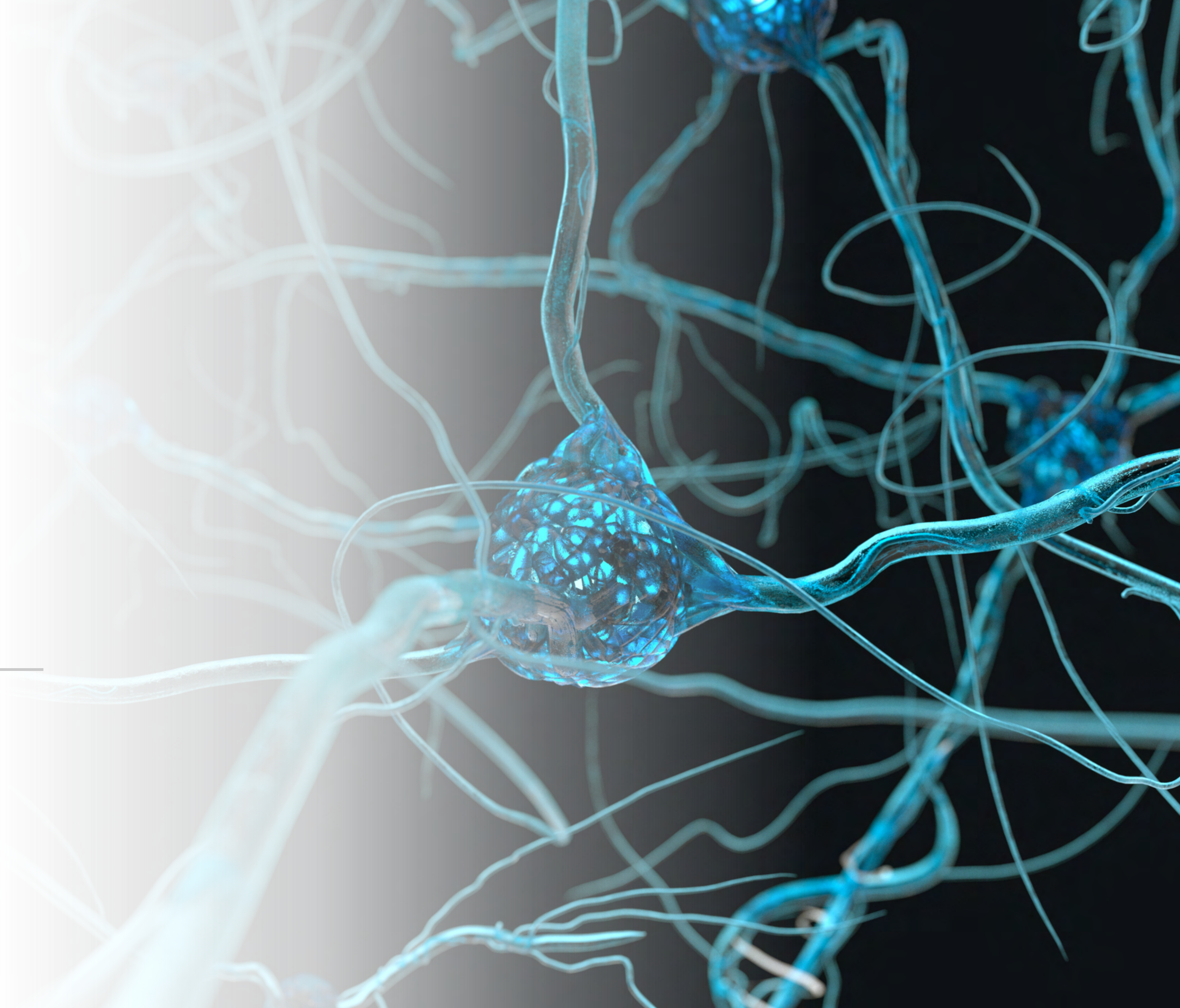
A single minima

Global minima

Gradient Descent for Two Parameters

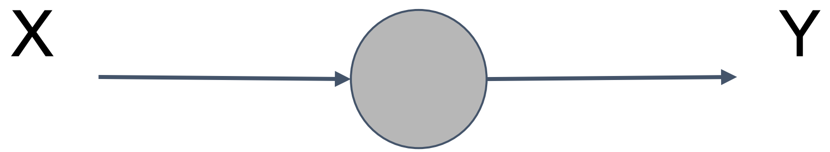


Artificial Neural Networks



A neuron

a neuron's output is a function of its inputs (in this case only one)



$$y = f(x) = wx+b$$

There are only two parameters to adjust:
The weight for each input and a bias

First scenario: a regression

Linear Regression with a Single Neuron

colab.research.google.com

Regression.ipynb

```
[2] import tensorflow as tf
    import numpy as np
    from tensorflow import keras
```

```
# define a neural network with one neuron
# for more information on TF functions see: https://www.tensorflow.org/api_docs
my_layer = keras.layers.Dense(units=1, input_shape=[1])
model = tf.keras.Sequential([my_layer])
```

1 layer, 1 neuron

```
# use stochastic gradient descent for optimization and
# the mean squared error loss function
model.compile(optimizer='sgd', loss='mean_squared_error')
```

Stochastic gradient descent

```
# define some training data (xs as inputs and ys as outputs)
xs = np.array([-1.0,  0.0, 1.0, 2.0, 3.0, 4.0], dtype=float)
ys = np.array([-3.0, -1.0, 1.0, 3.0, 5.0, 7.0], dtype=float)
```

Inputs and outputs (labels)

```
# fit the model to the data (aka train the model)
model.fit(xs, ys, epochs=500)
```

Train the model

Linear Regression with a Single Neuron

colab.research.google.com

Regression.ipynb

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ys = np.array([-3.0, -1.0, 1.0, 3.0, 5.0, 7.0], dtype=float)

# fit the model to the data (aka train the model)
model.fit(xs, ys, epochs=500)
```

```
Epoch 500/500
1/1 [==============================] - 0s 6ms/step - loss: 3.4704e-05
<keras.callbacks.History at 0x7f1d6ccd7f10>
```

```
[4] print(model.predict([10.0]))

[[18.982813]]
```

```
[5] print(model.predict(xs))

[[-2.9897861]
 [-0.992277 ]
 [ 1.005232 ]
 [ 3.0027409]
 [ 5.00025  ]
 [ 6.997759 ]]
```

```
[6] print(my_layer.get_weights())

[array([[1.997509]], dtype=float32), array([-0.992277], dtype=float32)]
```

Linear Regression with a Single Neuron

colab.research.google.com

Regression.ipynb

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# define some training data (xs as inputs and ys as outputs)
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# fit the model to the data (aka train the model)
model.fit(xs, ys, epochs=500)
```

```
Epoch 500/500
1/1 [==============================] - 0s 6ms/step - loss: 3.4704e-05
<keras.callbacks.History at 0x7f1d6ccd7f10>
```

```
[4] print(model.predict([10.0]))

[[18.982813]]
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```
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```

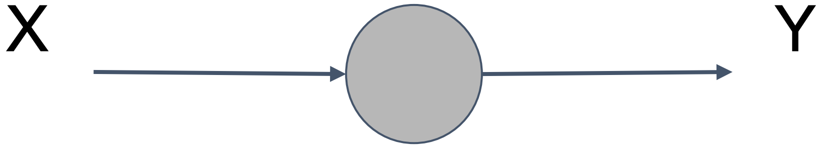
```
[6] print(my_layer.get_weights())

[array([[1.997509]], dtype=float32), array([-0.992277], dtype=float32)]
```

$Y = 2X - 1$

$Y = 1.9975X – 0.9922$

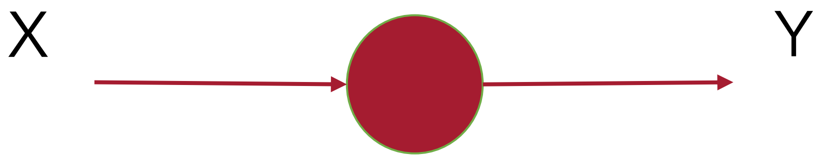
Not perfect,
but good enough for most cases!



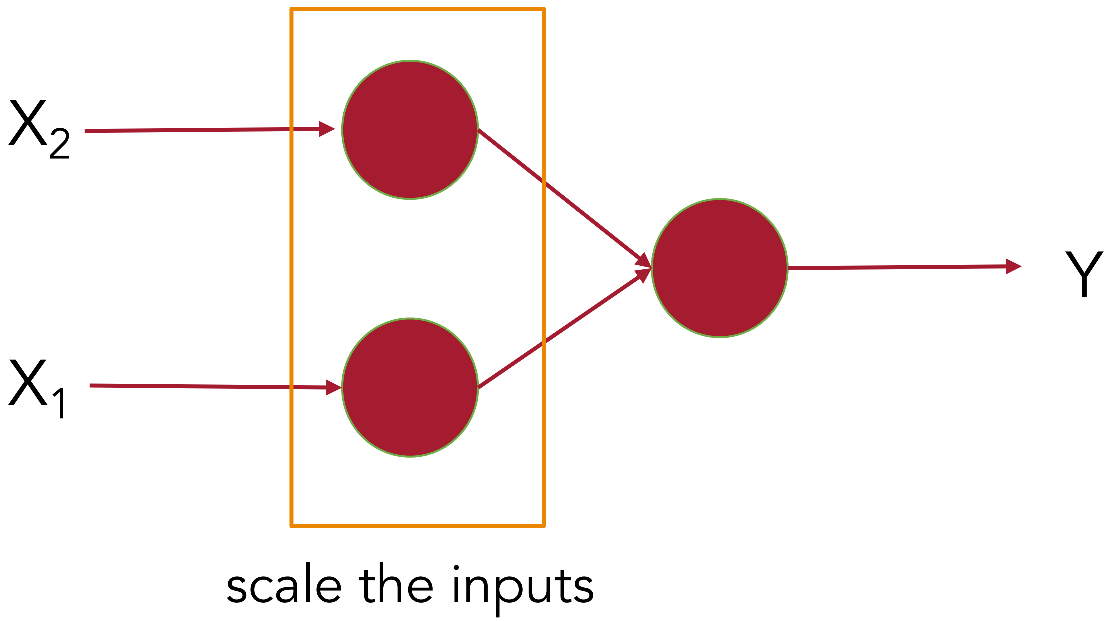
$$y = f(x) = wx+b$$

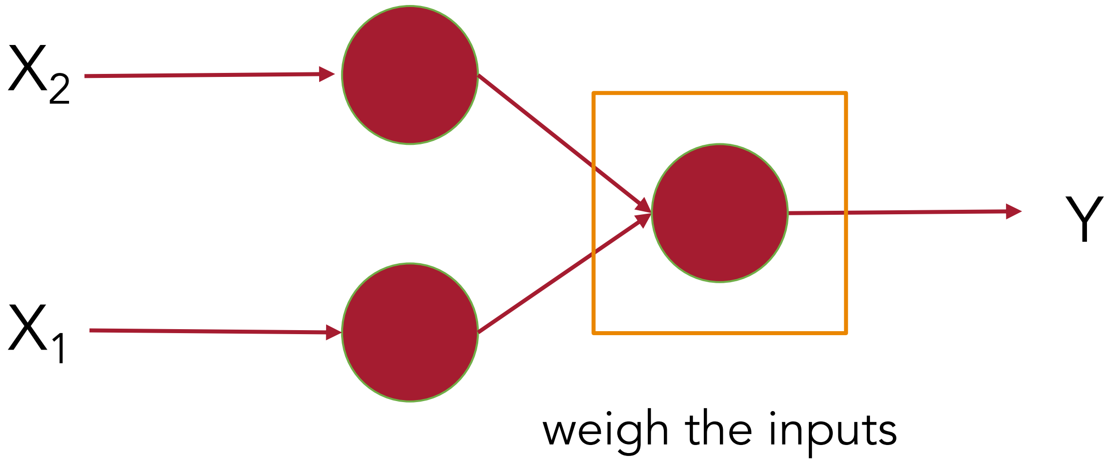
$$y = 1.9975x - 0.9922$$

Now, Classification

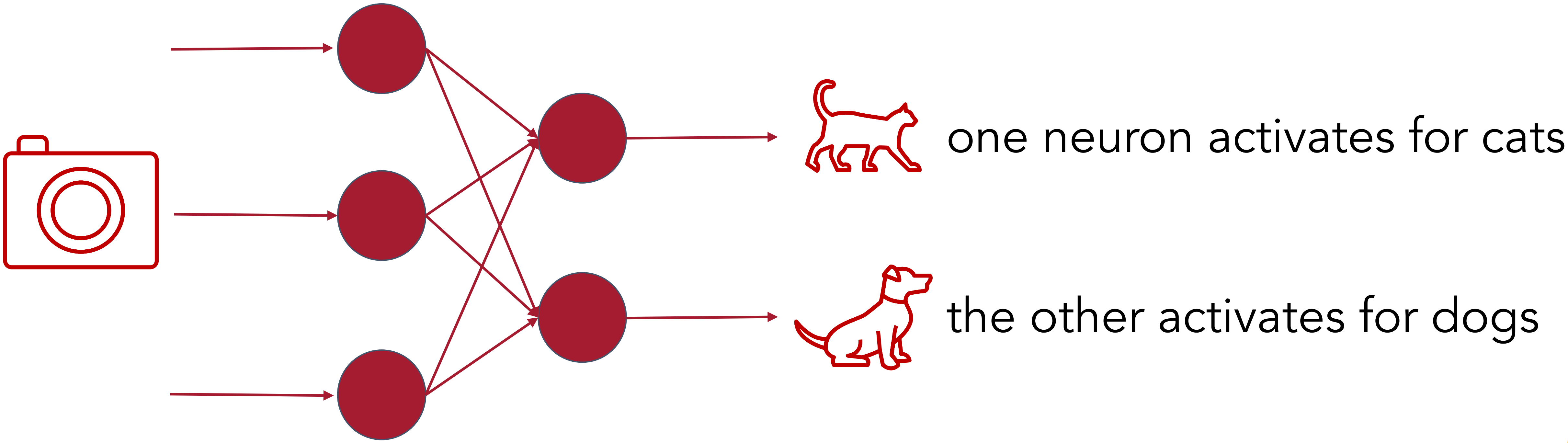


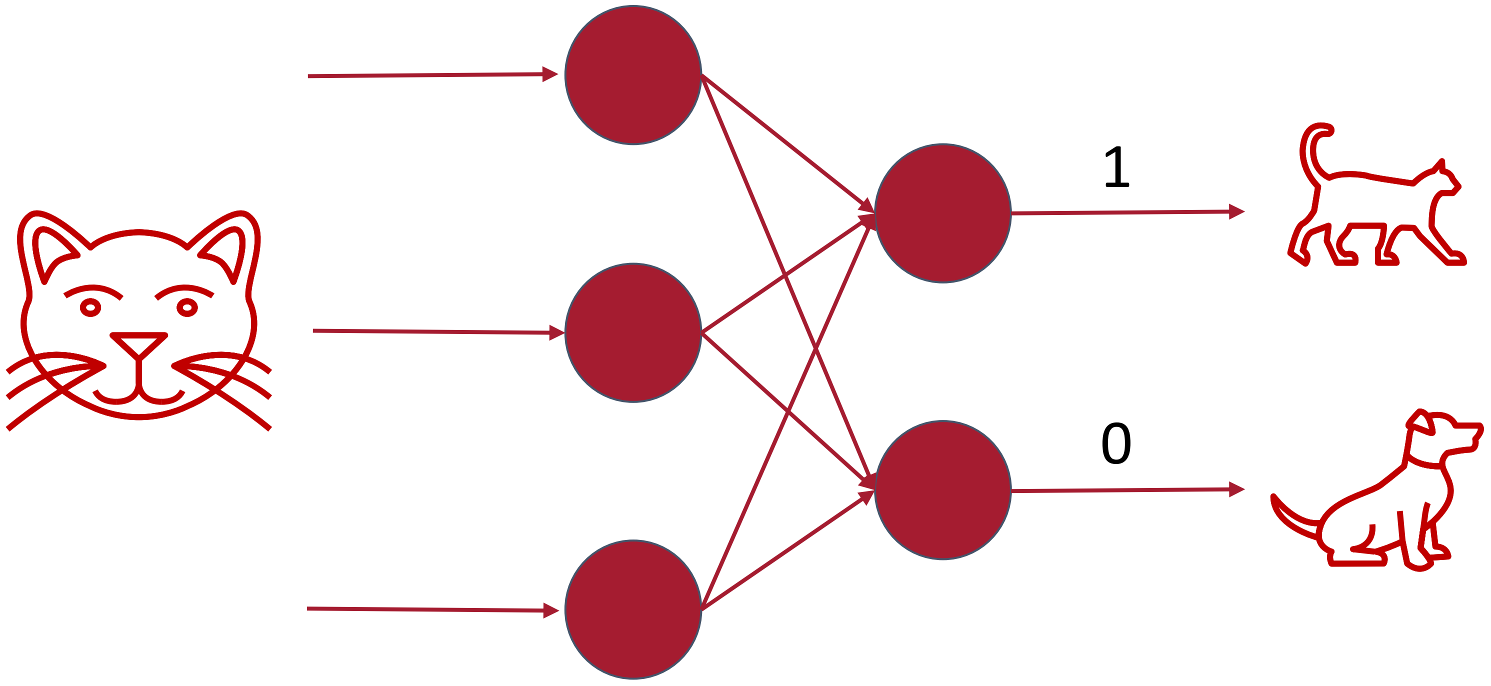
What about more than one input?

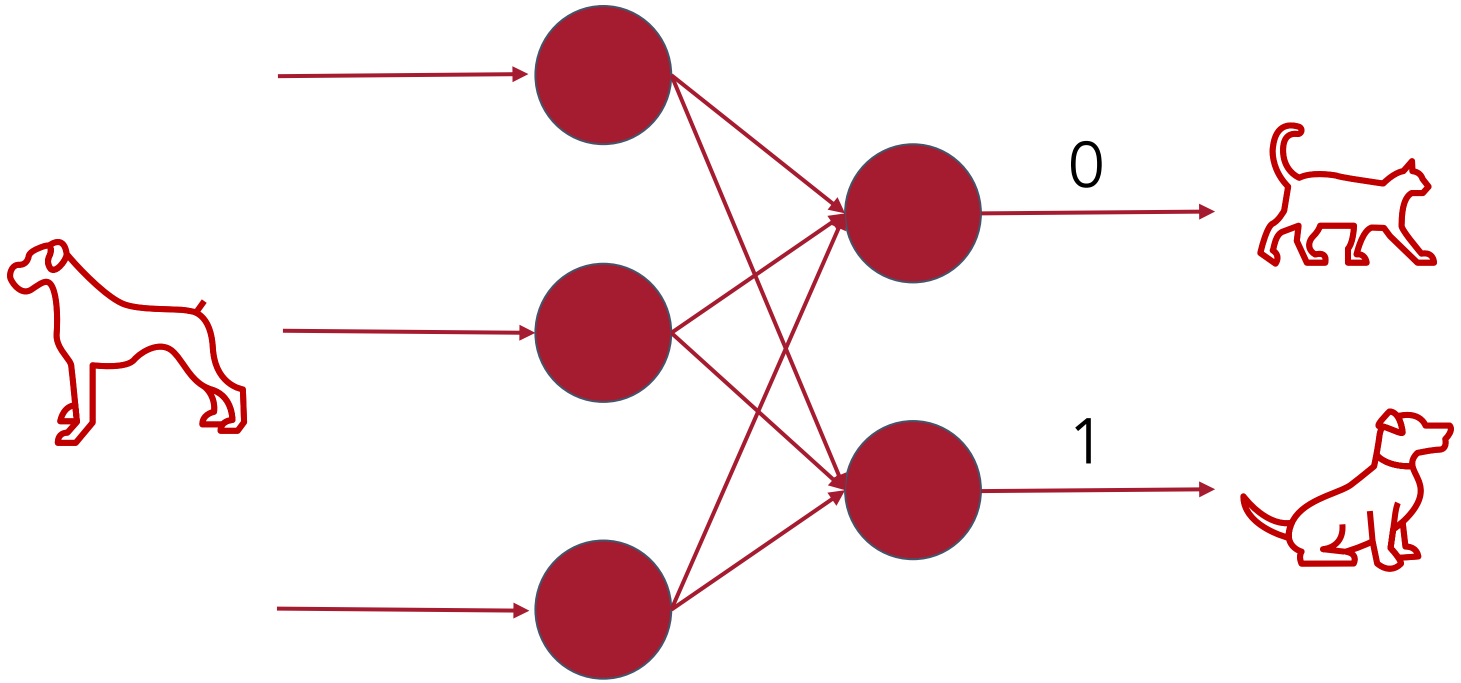

X2
X1
Y
scale the inputs

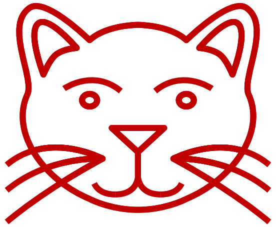
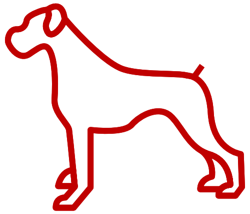


More inputs?


one neuron activates for cats
the other activates for dogs


1
0


0
1

Data	Label
	[1, 0]
	[0, 1]

We can extend this example to other domains

0	[1, 0, 0, 0, 0, 0, 0, 0, 0, 0]
1	[0, 1, 0, 0, 0, 0, 0, 0, 0, 0]
2	[0, 0, 1, 0, 0, 0, 0, 0, 0, 0]
3	[0, 0, 0, 1, 0, 0, 0, 0, 0, 0]
4	[0, 0, 0, 0, 1, 0, 0, 0, 0, 0]
5	[0, 0, 0, 0, 0, 1, 0, 0, 0, 0]
6	[0, 0, 0, 0, 0, 0, 1, 0, 0, 0]
7	[0, 0, 0, 0, 0, 0, 0, 1, 0, 0]
8	[0, 0, 0, 0, 0, 0, 0, 0, 1, 0]
9	[0, 0, 0, 0, 0, 0, 0, 0, 0, 1]

The MNIST database (Modified National Institute of Standards and Technology database) is a large database of handwritten digits that is commonly used for training various image processing systems.

0 [1, 0, 0, 0, 0, 0, 0, 0, 0, 0]

1 [0, 1, 0, 0, 0, 0, 0, 0, 0, 0]

2 [0, 0, 1, 0, 0, 0, 0, 0, 0, 0]

3 [0, 0, 0, 1, 0, 0, 0, 0, 0, 0]

4 [0, 0, 0, 0, 1, 0, 0, 0, 0, 0]

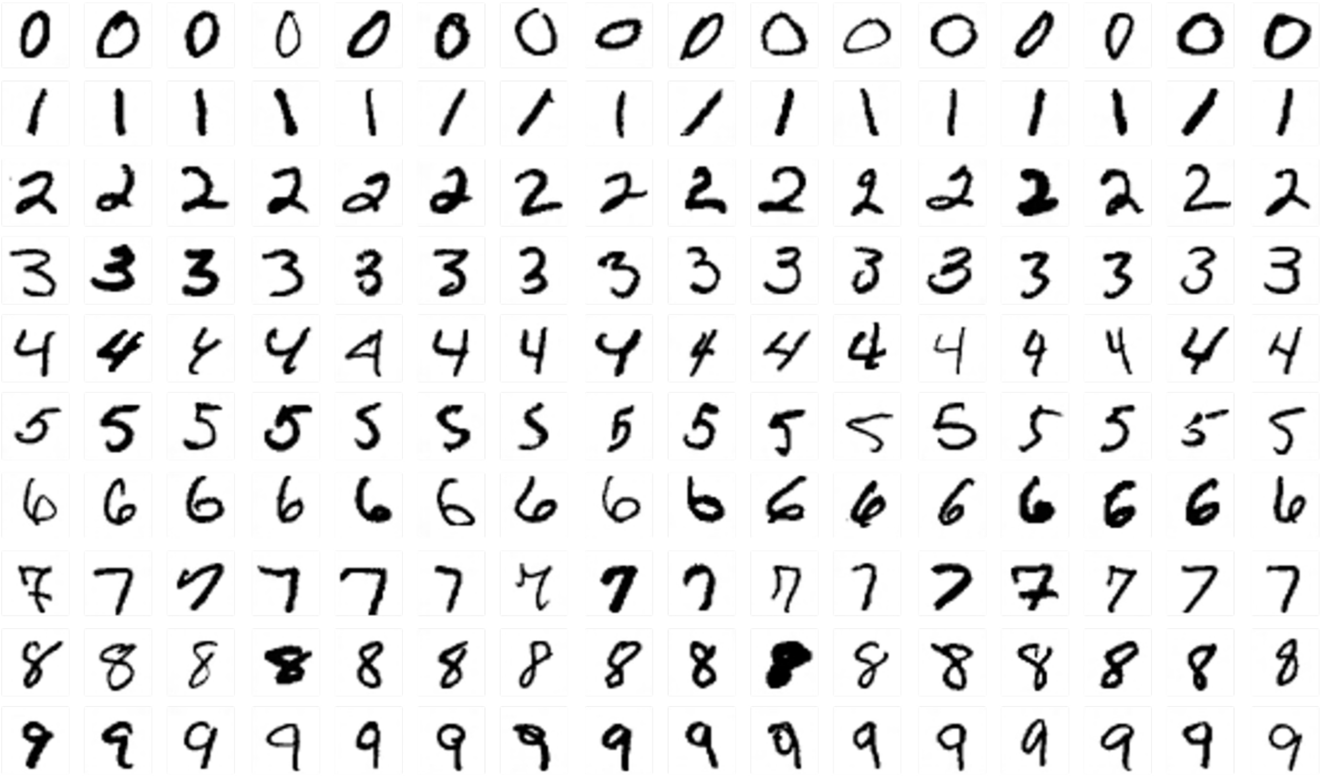
5 [0, 0, 0, 0, 0, 1, 0, 0, 0, 0]

6 [0, 0, 0, 0, 0, 0, 1, 0, 0, 0]

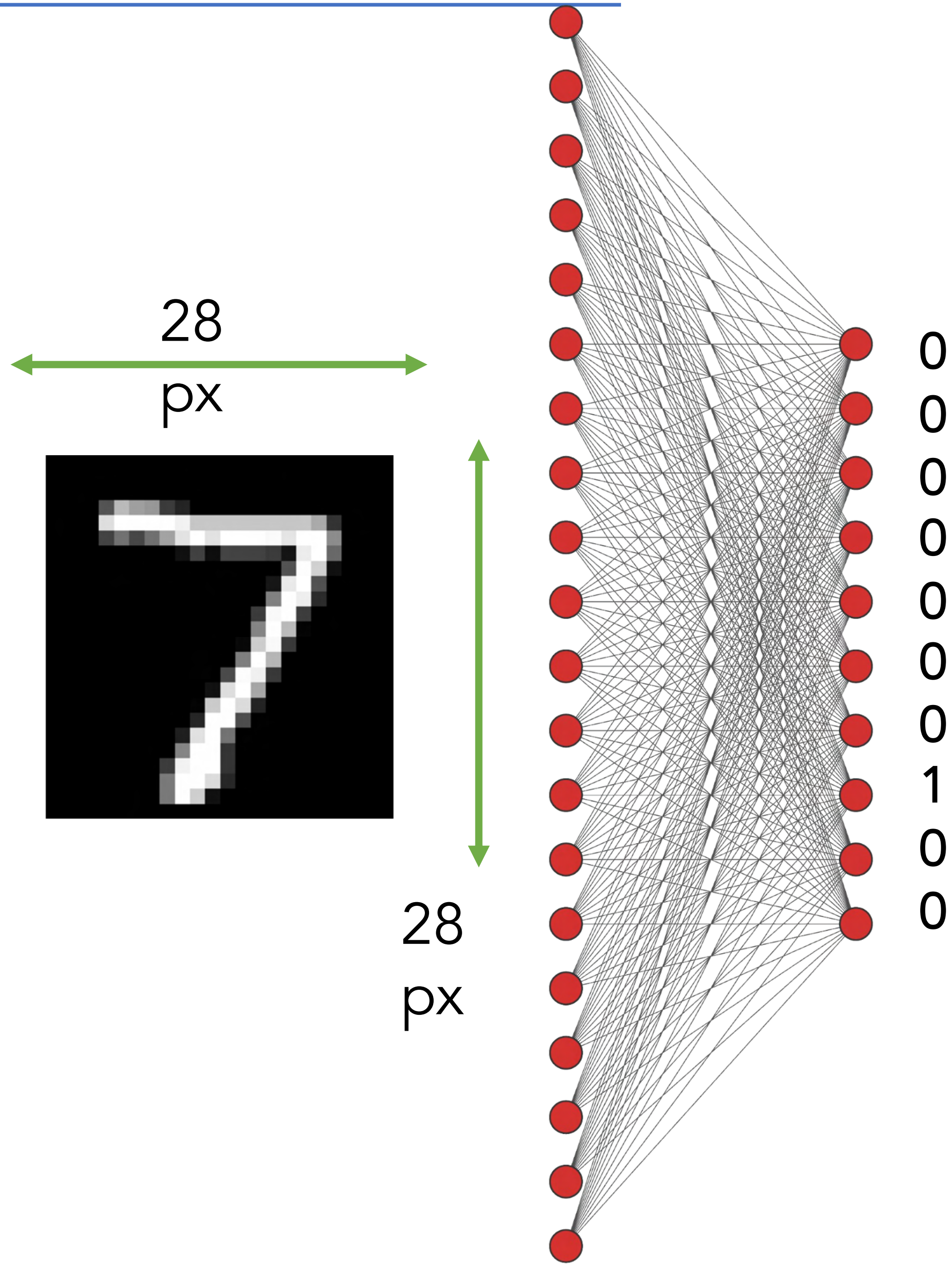
7 [0, 0, 0, 0, 0, 0, 0, 1, 0, 0]

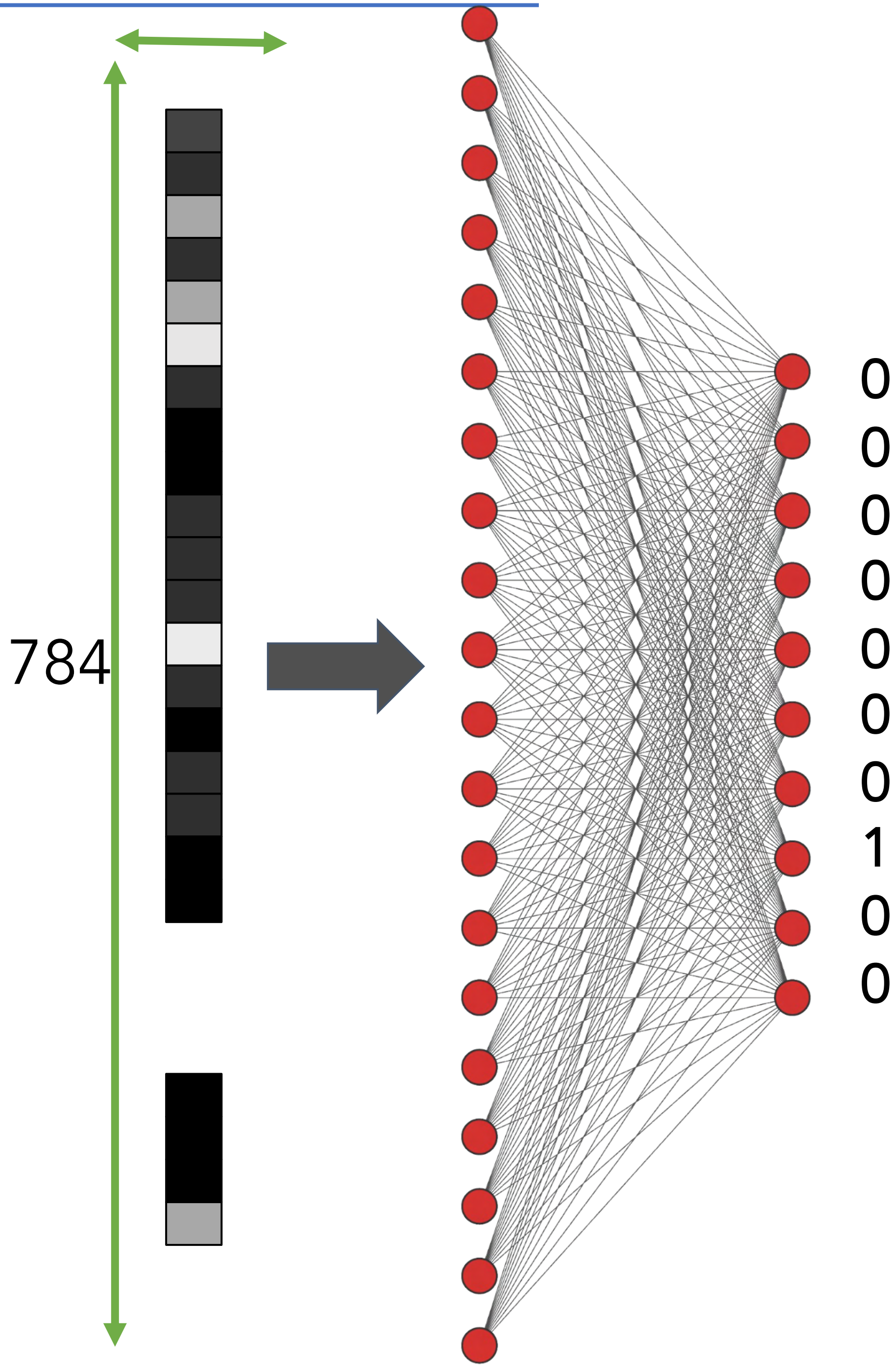
8 [0, 0, 0, 0, 0, 0, 0, 0, 1, 0]

9 [0, 0, 0, 0, 0, 0, 0, 0, 0, 1]



60,000 Labelled Training Examples
10.000 Labelled Validation Examples


28
px
28
px
0
0
0
0
0
0
0
1
0
0



784
0
0
0
0
0
0
0
1
0
0

a NN to classify the MNIST DB

colab.research.google.com

MNIST_NN.ipynb

```
import tensorflow as tf
mnist = tf.keras.datasets.fashion_mnist
(training_images, training_labels), (val_images, val_labels) = mnist.load_data()
training_images=training_images / 255.0
val_images=val_images / 255.0
model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(),
  tf.keras.layers.Dense(20, activation=tf.nn.relu),
  tf.keras.layers.Dense(10, activation=tf.nn.softmax)
])
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
model.fit(training_images, training_labels, validation_data=(val_images, val_labels), epochs=20)
```

a NN to classify the MNIST DB

colab.research.google.com
MNIST_NN.ipynb

```
Epoch 9/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3555 - accuracy: 0.8724 - val_loss: 0.4090 - val_accuracy: 0.8516
Epoch 10/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3509 - accuracy: 0.8752 - val_loss: 0.4061 - val_accuracy: 0.8537
Epoch 11/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3452 - accuracy: 0.8768 - val_loss: 0.3980 - val_accuracy: 0.8580
Epoch 12/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3398 - accuracy: 0.8783 - val_loss: 0.4052 - val_accuracy: 0.8586
Epoch 13/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3355 - accuracy: 0.8798 - val_loss: 0.4160 - val_accuracy: 0.8533
Epoch 14/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3332 - accuracy: 0.8812 - val_loss: 0.3913 - val_accuracy: 0.8609
Epoch 15/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3279 - accuracy: 0.8818 - val_loss: 0.3971 - val_accuracy: 0.8588
Epoch 16/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3250 - accuracy: 0.8839 - val_loss: 0.3945 - val_accuracy: 0.8597
Epoch 17/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3221 - accuracy: 0.8839 - val_loss: 0.3985 - val_accuracy: 0.8578
Epoch 18/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3184 - accuracy: 0.8853 - val_loss: 0.3988 - val_accuracy: 0.8595
Epoch 19/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3158 - accuracy: 0.8857 - val_loss: 0.3984 - val_accuracy: 0.8578
Epoch 20/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3140 - accuracy: 0.8856 - val_loss: 0.4069 - val_accuracy: 0.8567
<keras.callbacks.History at 0x7fe50180b750>
```

a NN to classify the MNIST DB

colab.research.google.com

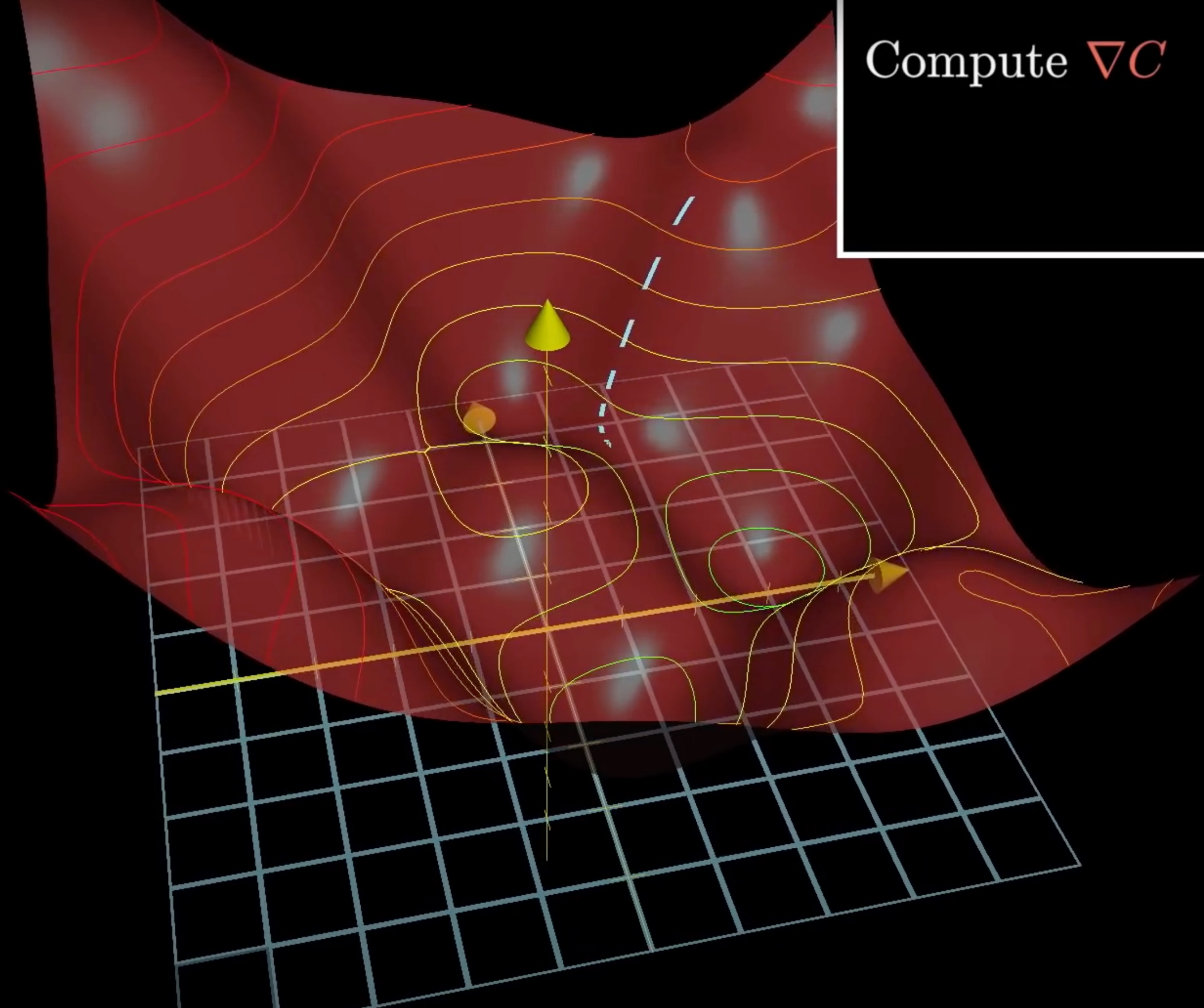
MNIST_NN.ipynb

```
Epoch 19/20
1875/1875 [==============================] - 3s 2ms/step - loss: 0.3022 - accuracy: 0.8914 - val_loss: 0.3834 - val_accuracy: 0.8659
Epoch 20/20
1875/1875 [==============================] - 4s 2ms/step - loss: 0.2996 - accuracy: 0.8910 - val_loss: 0.3911 - val_accuracy: 0.8642
<keras.callbacks.History at 0x7f033e5f5bd0>
```

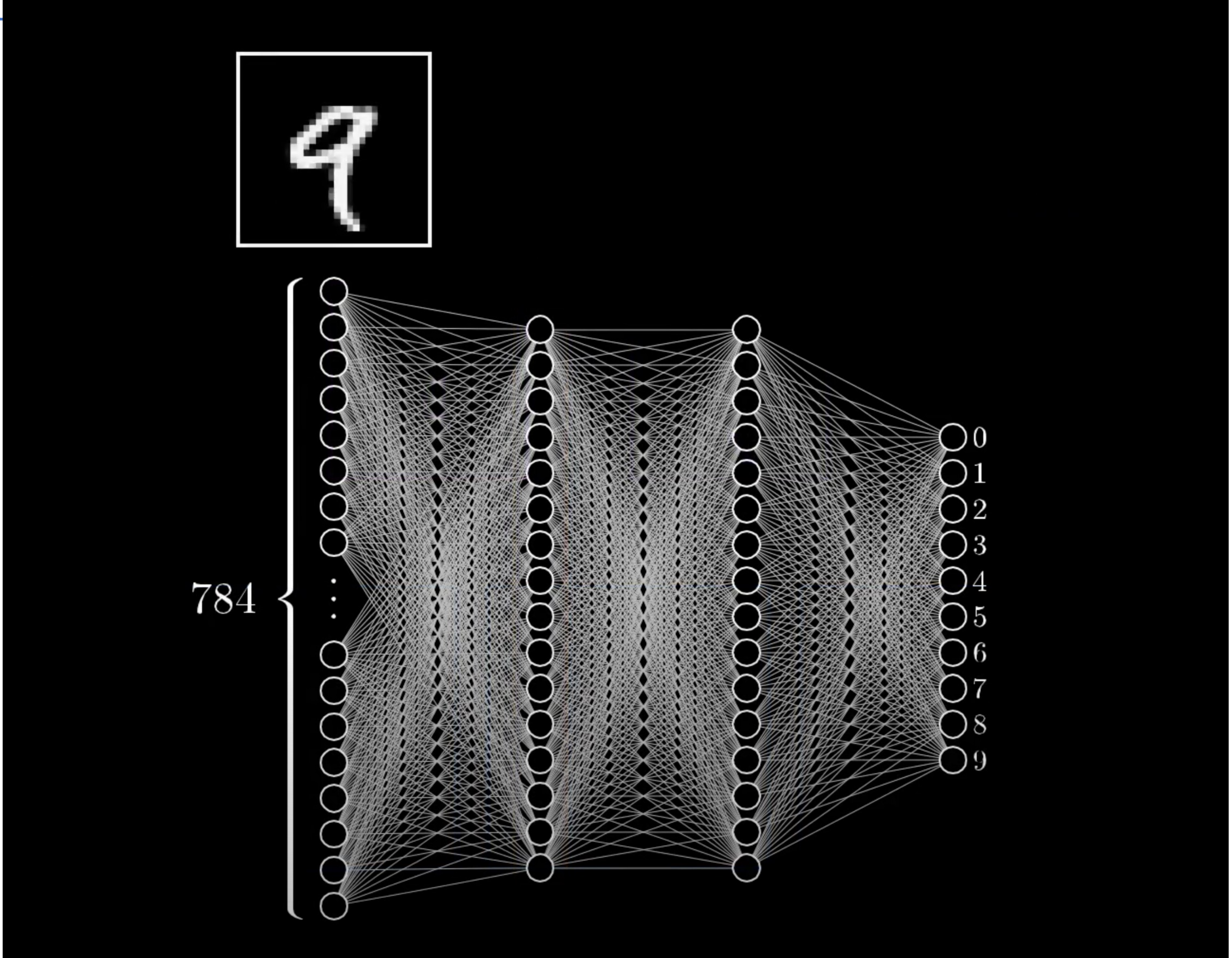
```python
model.evaluate(val_images, val_labels)

classifications = model.predict(val_images)
print(classifications[0])
print(val_labels[0])
```

```
313/313 [==============================] - 0s 1ms/step - loss: 0.3911 - accuracy: 0.8642
[5.2699960e-09 4.4460235e-10 2.9260536e-07 1.1081011e-04 1.4583268e-08
 8.1817927e-03 5.3513944e-09 5.8446459e-02 2.9248906e-05 9.3323141e-01]
9
```



Compute ∇C


784
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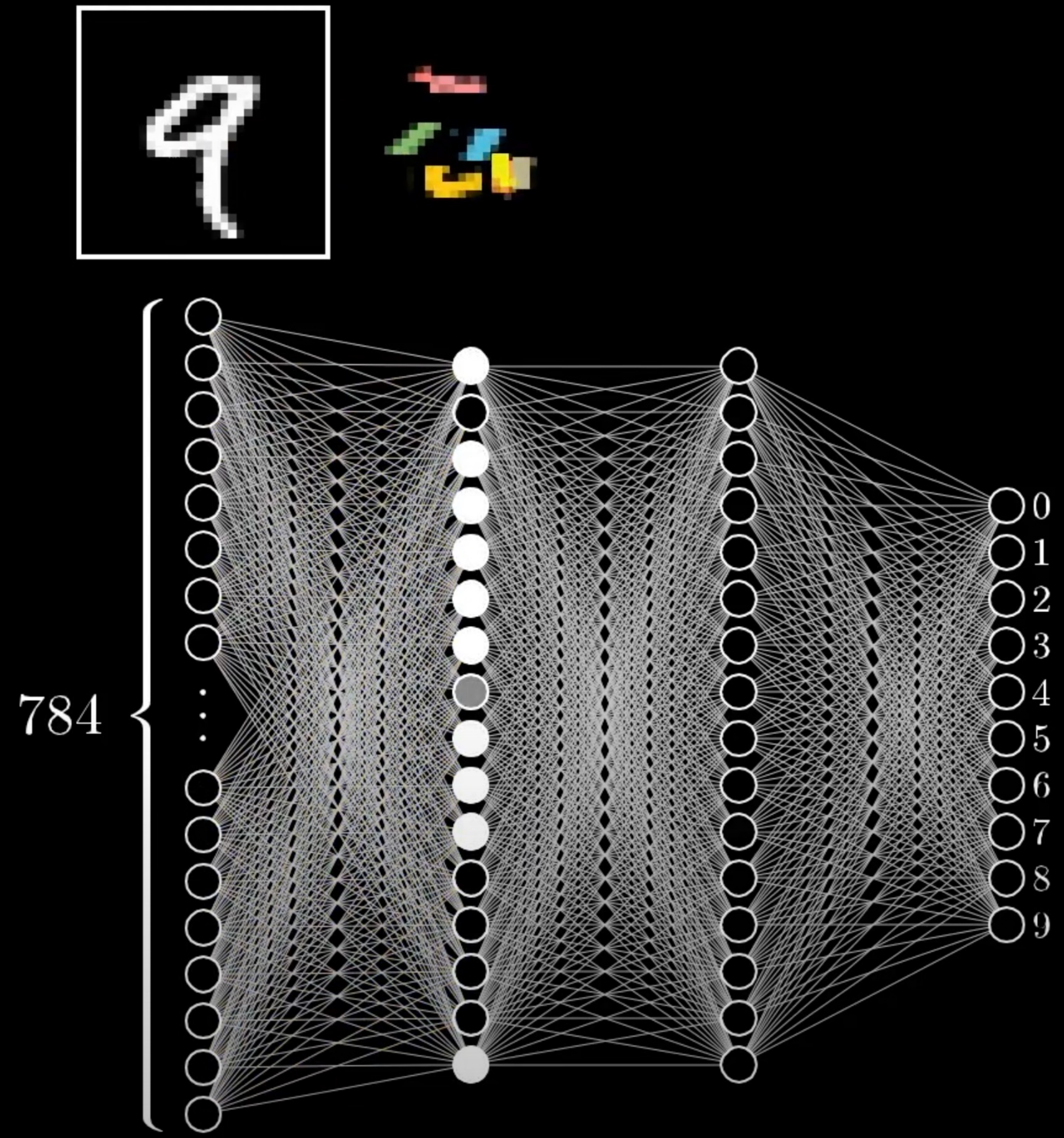

784
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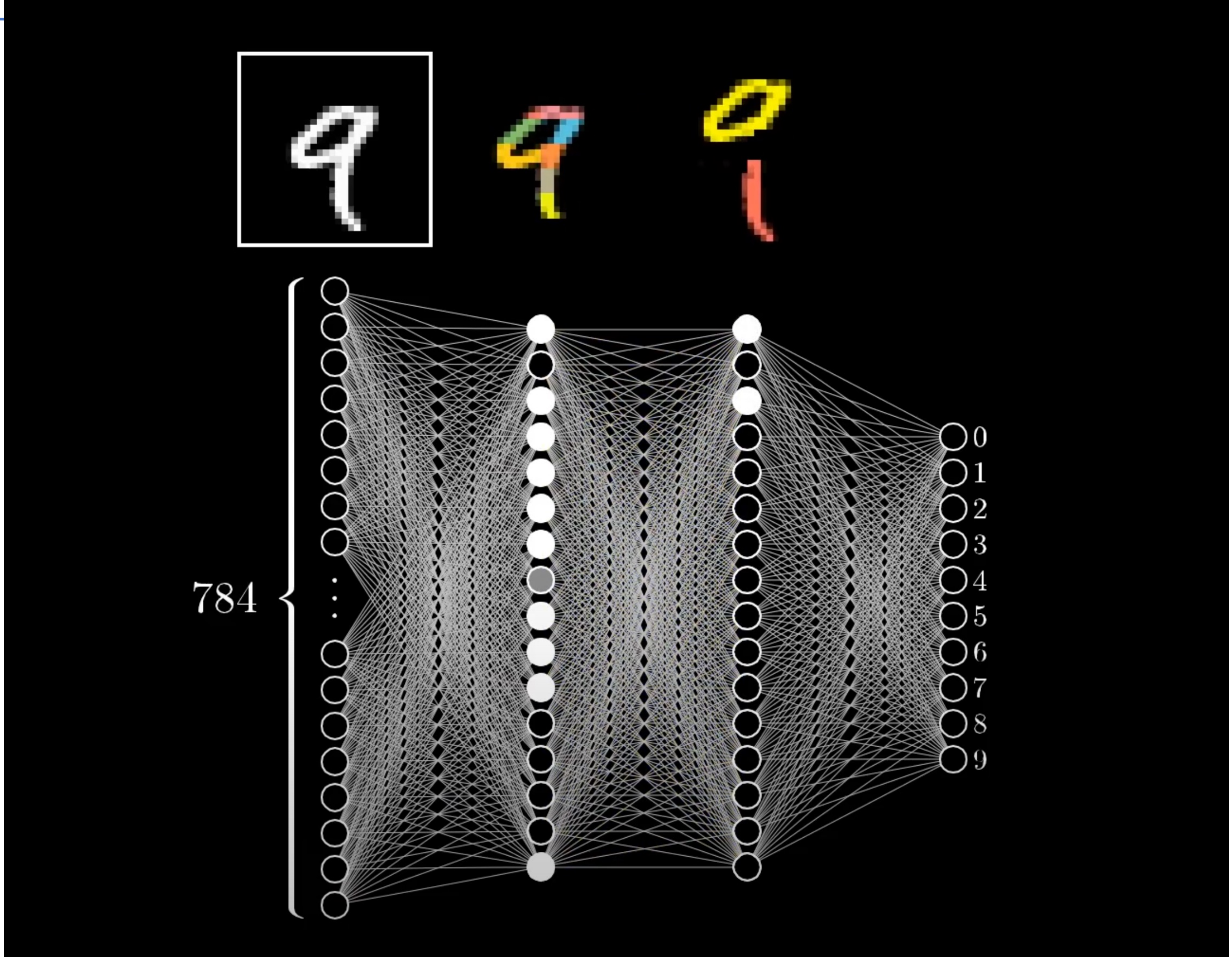
784
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1
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6
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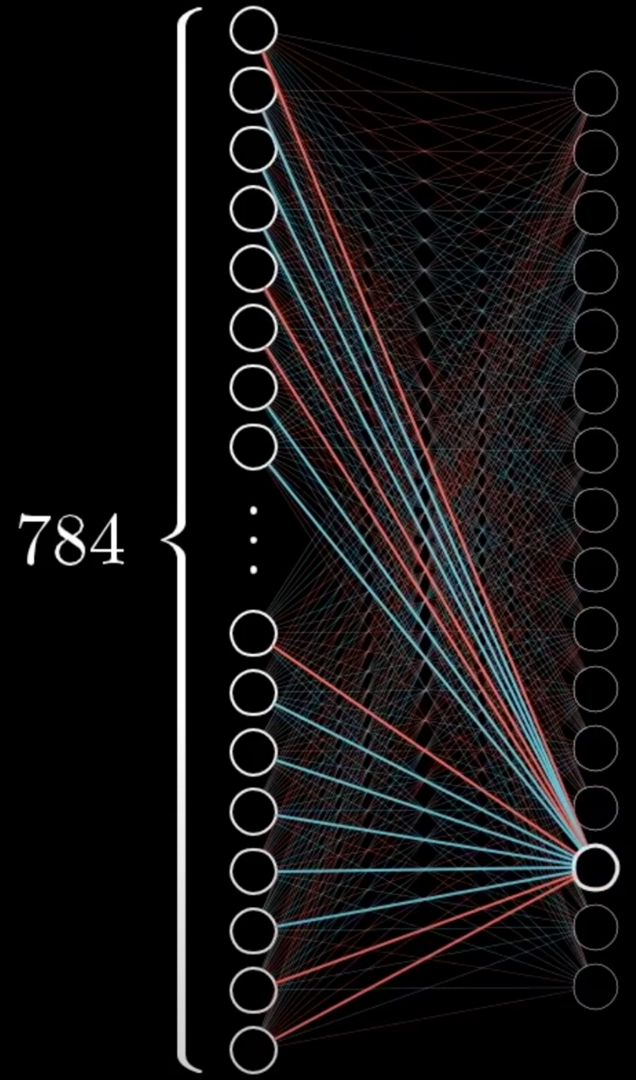
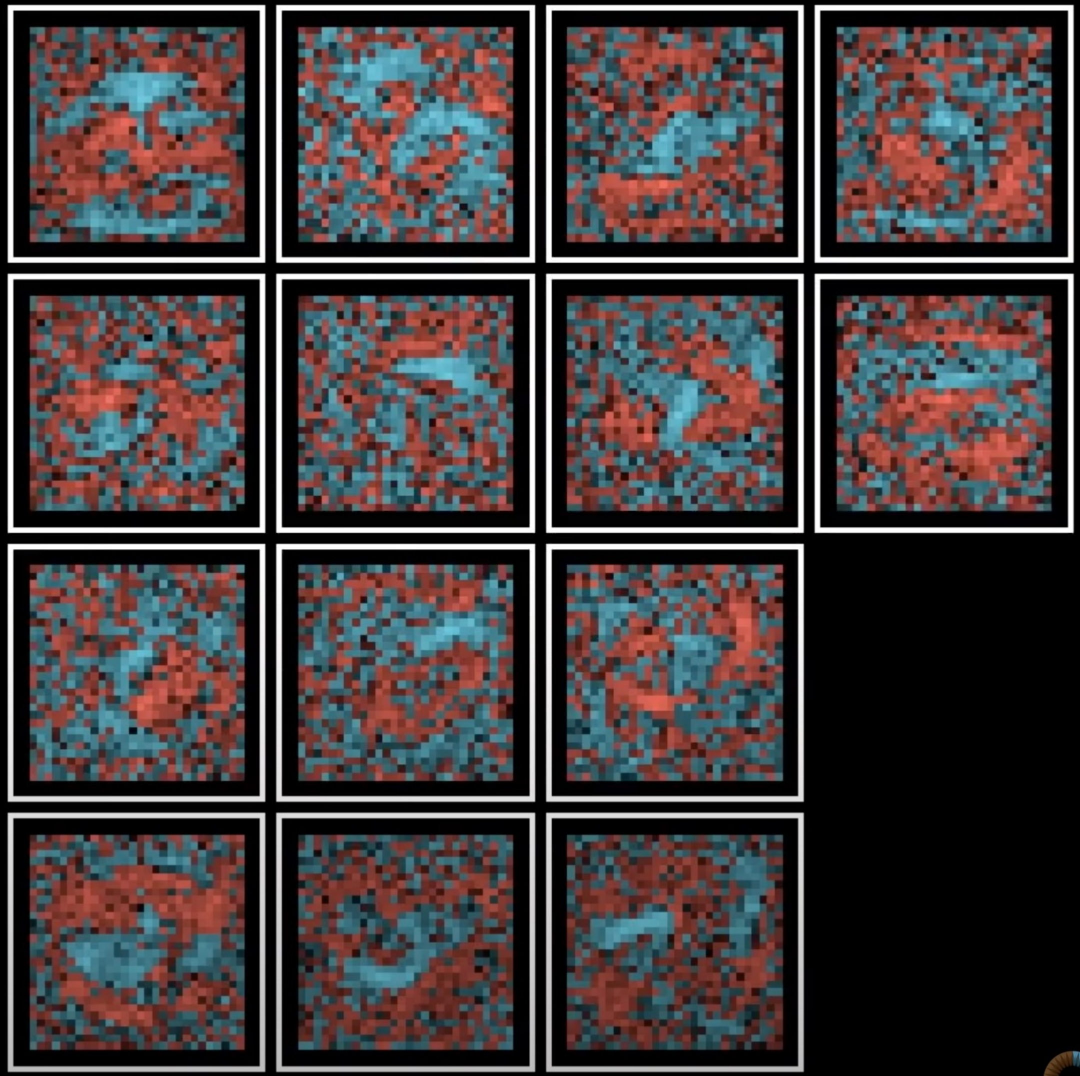
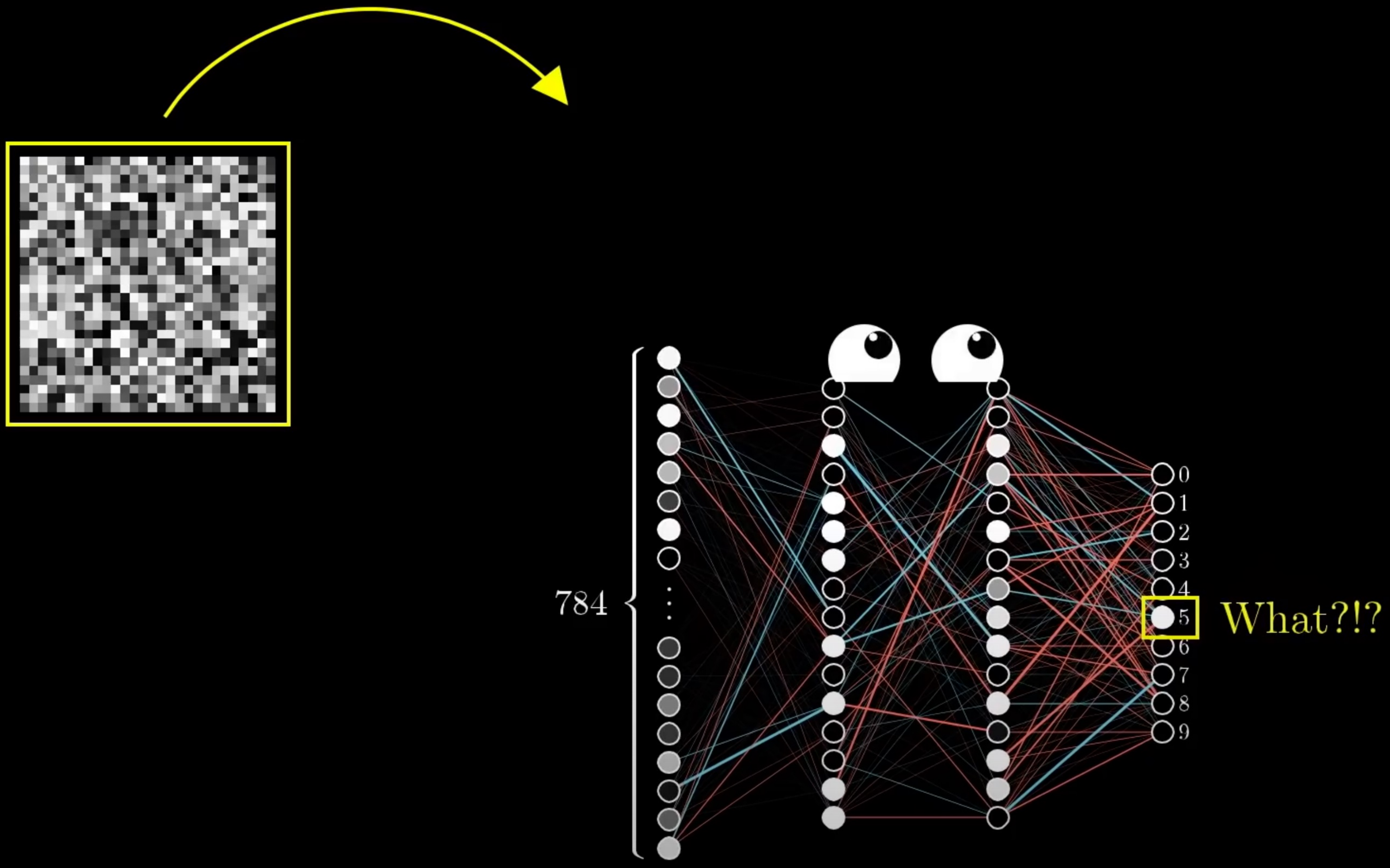
8
9

What second layer neurons look for






784
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3
4
5
6
7
8
9
What?!?

A very nice introduction to NN

- 3Blue1Brown playlist on Neural Networks
  - But what is a neural network?
    - Chapter 1 – Deep learning
    - https://youtu.be/aircAruvnKk
  - Gradient descent, how neural networks learn
    - Chapter 2 – Deep learning
    - https://youtu.be/IHZwWFHWa-w
  - What is backpropagation really doing?
    - Chapter 3 – Deep learning
    - https://youtu.be/Ilg3gGewQ5U
  - (Optional) Backpropagation calculus
    - Chapter 4 – Deep learning
    - https://youtu.be/tIeHLnjs5U8

and some issues?

Data

The network **'sees' everything**.
Has no context for measuring how well it does with data it has never previously been exposed to.

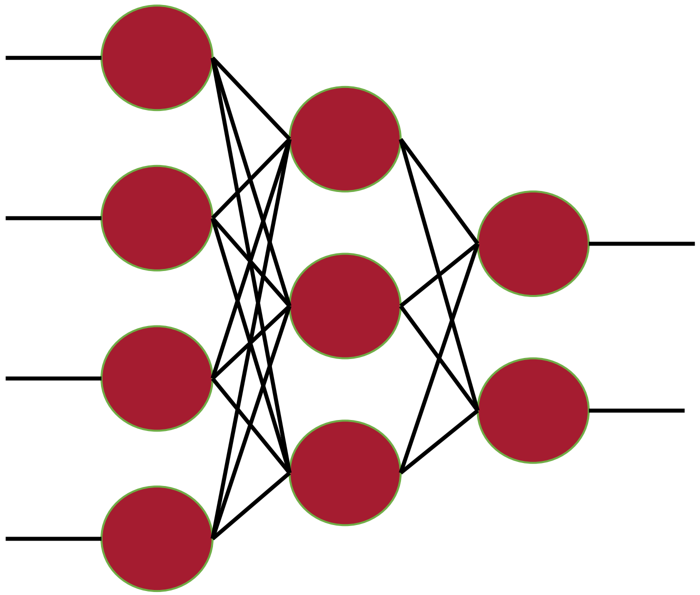
Data	Validation Data

The network 'sees' a subset of your data. You can use the rest to measure its performance against previously unseen data.

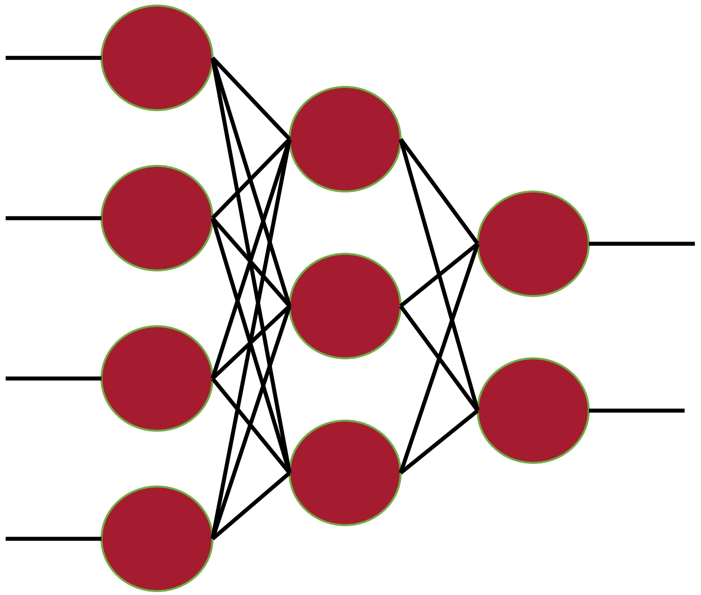
Data	Validation Data	Test Data

The network ‘sees’ a subset of your data. You can use an unseen subset to measure its accuracy while training (validation), and then another subset to measure its accuracy after it’s finished training (test).

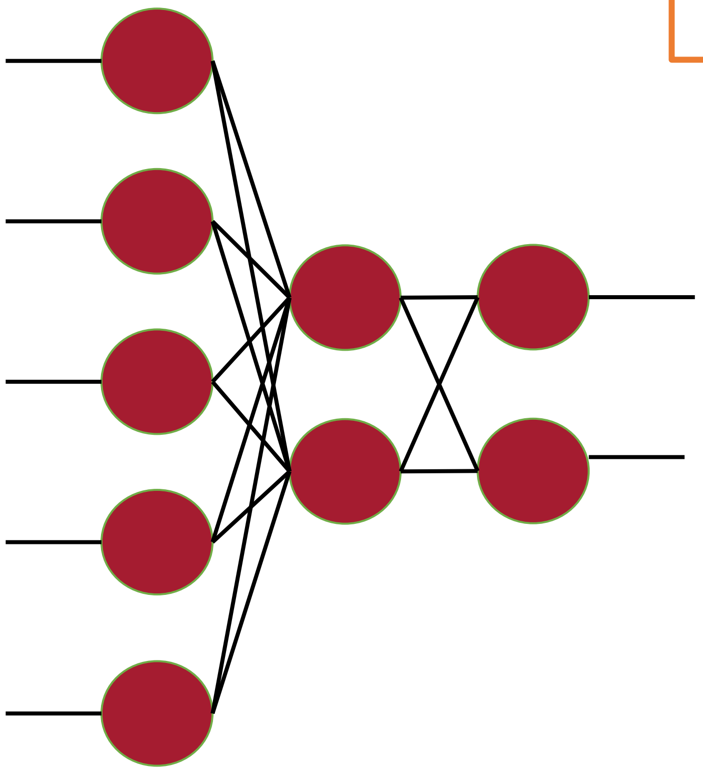
Data	Validation Data	Test Data
Accuracy: 0.999	Accuracy: 0.920	Accuracy: 0.800



Data	Validation Data	Test Data
Accuracy: 0.999	Accuracy: 0.920	Accuracy: 0.800



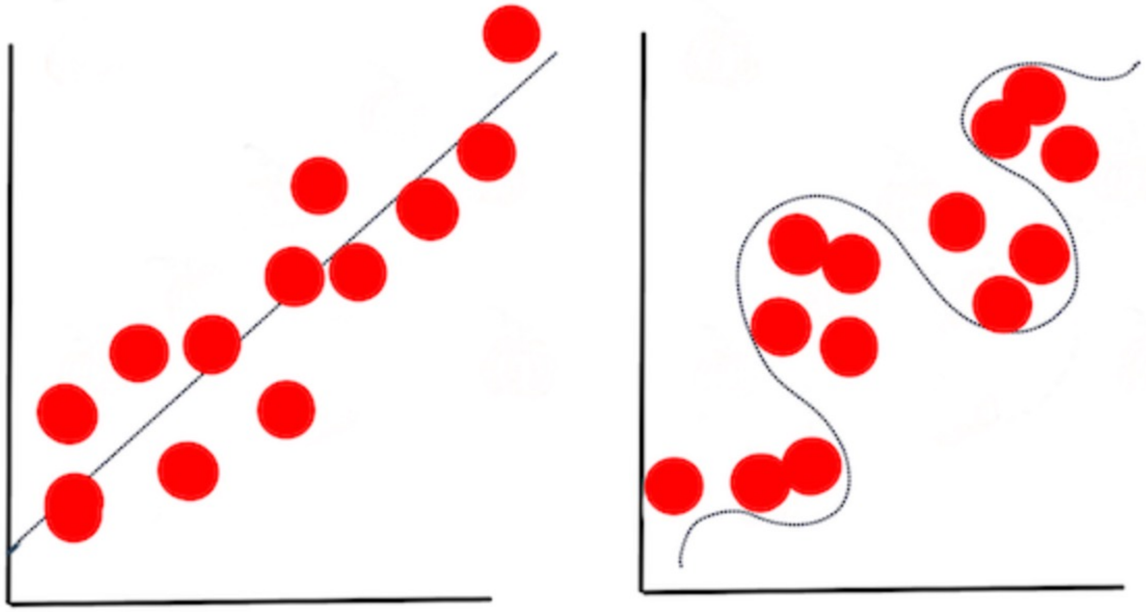
Data	Validation Data	Test Data
Accuracy: 0.942	Accuracy: 0.930	Accuracy: 0.925



Correct vs. Overfit Model

Model fitting refers to the accuracy of the model's underlying function as it attempts to analyze data with which it is not familiar.

Underfitting and overfitting are common problems that degrade the quality of the model, as the model fits either not well enough or too well.



Correct vs overfit model

https://microsoft.github.io/ML-For-Beginners/#/1-Introduction/4-techniques-of-ML/README?id=techniques-of-machine-learning

Prevent Overfitting and Imbalanced Data

Model	Train Accuracy	Test Accuracy
A	99,9%	95%
B	87%	87%
C	99,9%	45%

Test accuracy should be lower than train accuracy, but how much less accurate?

Model A is better than model B because it has a higher test accuracy, regardless its difference with the train accuracy.

Model C is a clear case of overfitting as the train accuracy is very high but the test accuracy isn't anywhere near as high.

This distinction is subjective, but comes from knowledge of your problem and data, and what magnitudes of error are acceptable.

https://docs.microsoft.com/en-us/azure/machine-learning/concept-manage-ml-pitfalls

I would like to thank:

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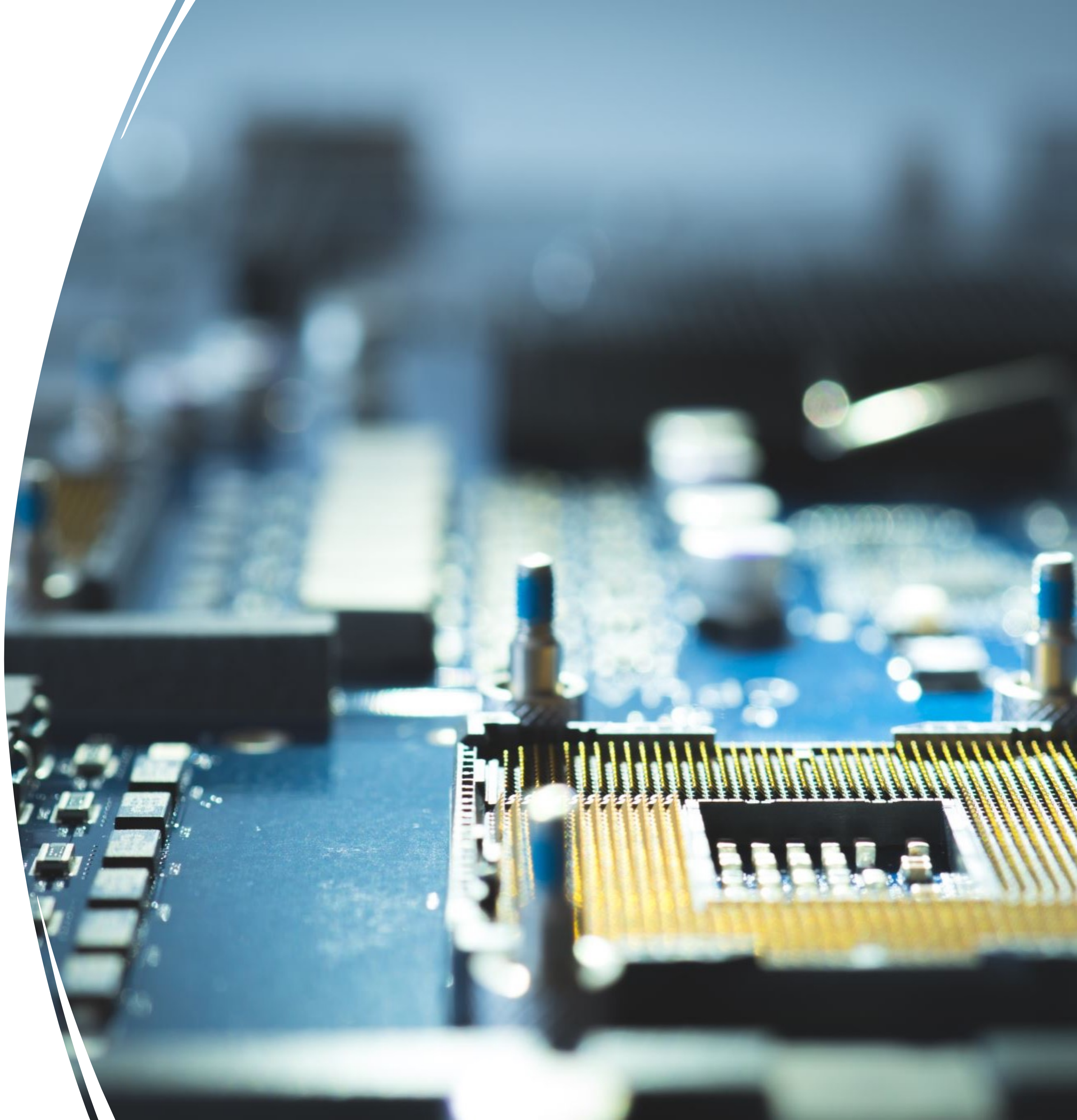

Thank you!

Prof. Diego Méndez Chaves, Ph.D

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Director of the Master Program in Electronics Engineering
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Website: www.javeriana.edu.co/blogs/diego-mendez/