

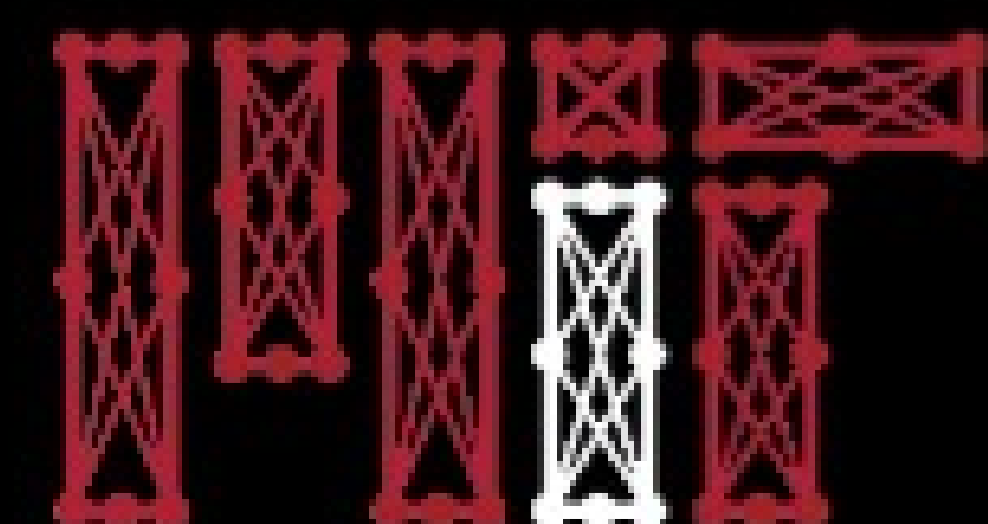


Introduction to Deep Learning

Alexander Amini

MIT 6.S191

January 18, 2021



6.S191 Introduction to Deep Learning

introtodeeplearning.com [@MITDeepLearning](https://twitter.com/MITDeepLearning)





Hi everybody, and welcome to MIT 6.S191

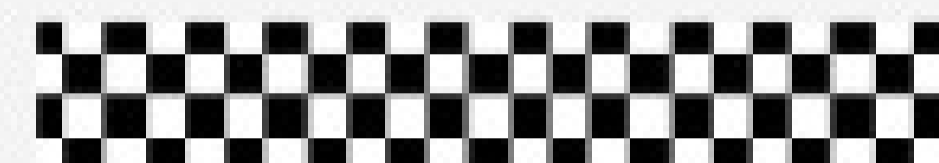


  • 4 months ago
Omg i wish my classes were this cool...




 • 3 months ago
I'm aware of the capabilities of DeepFakes but to create it for a class intro is just amazing! This is how you practice what you teach. Love it

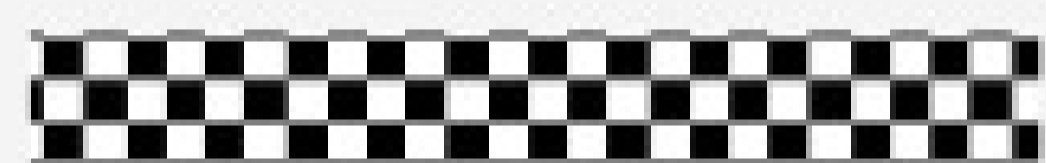


 • 5 months ago
THAT INTRO TO THE LECTURE IS SAVAGE!!!



  • 3 months ago
This is the best example of a Course that sells itself. 😄

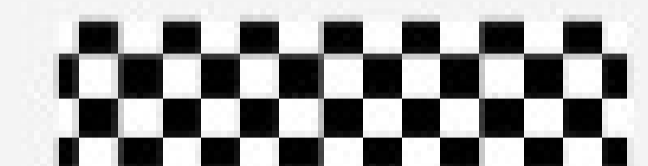


 • 3 months ago
That is easily the cleanest visual deepfake I've ever seen. It must have taken ages to render, because it just looks flawless.

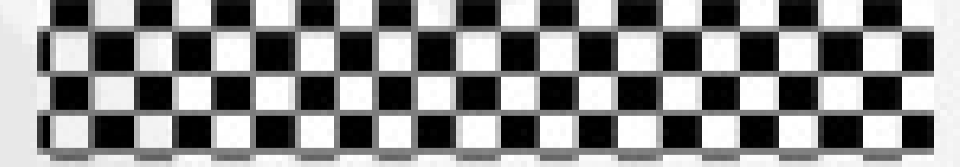


 • 3 months ago
Plot twist: that actually was the real Obama.

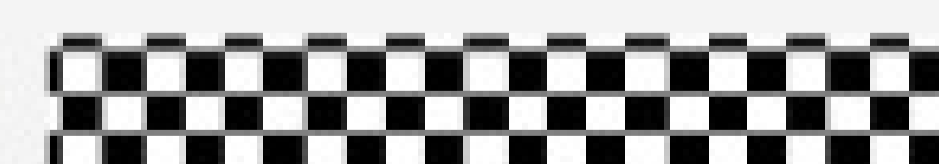


 • 2 months ago
WOW WOW WOW i am amazed.



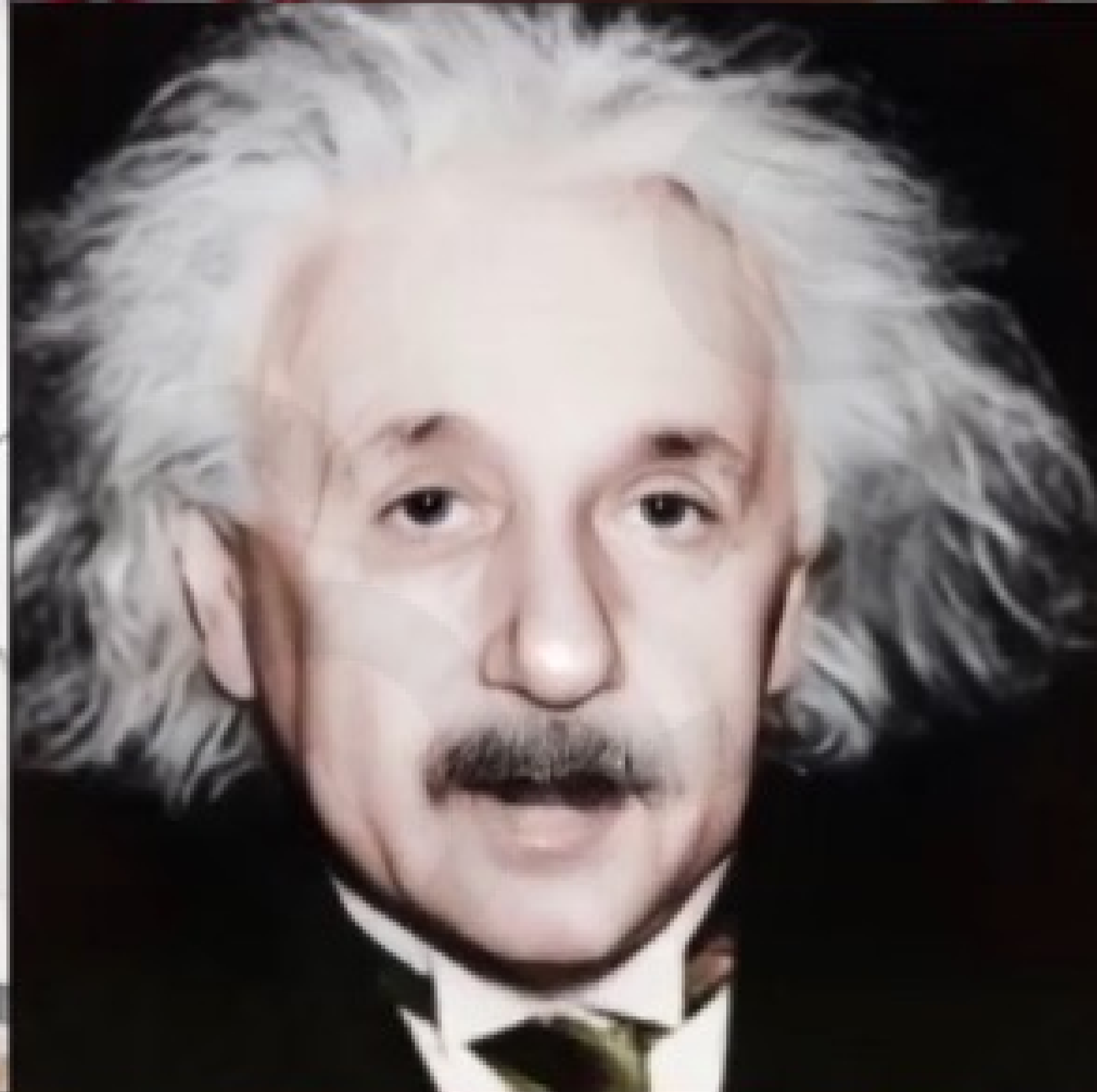
 • 10 months ago
Did not see that coming! Simply Amazing! 🔥



 • 4 months ago
damn.... i was about to ask "how can we be sure that the welcoming video is not synthesized?" , then i kept watching till the end xD







What is Deep Learning?

ARTIFICIAL INTELLIGENCE

Any technique that enables computers to mimic human behavior



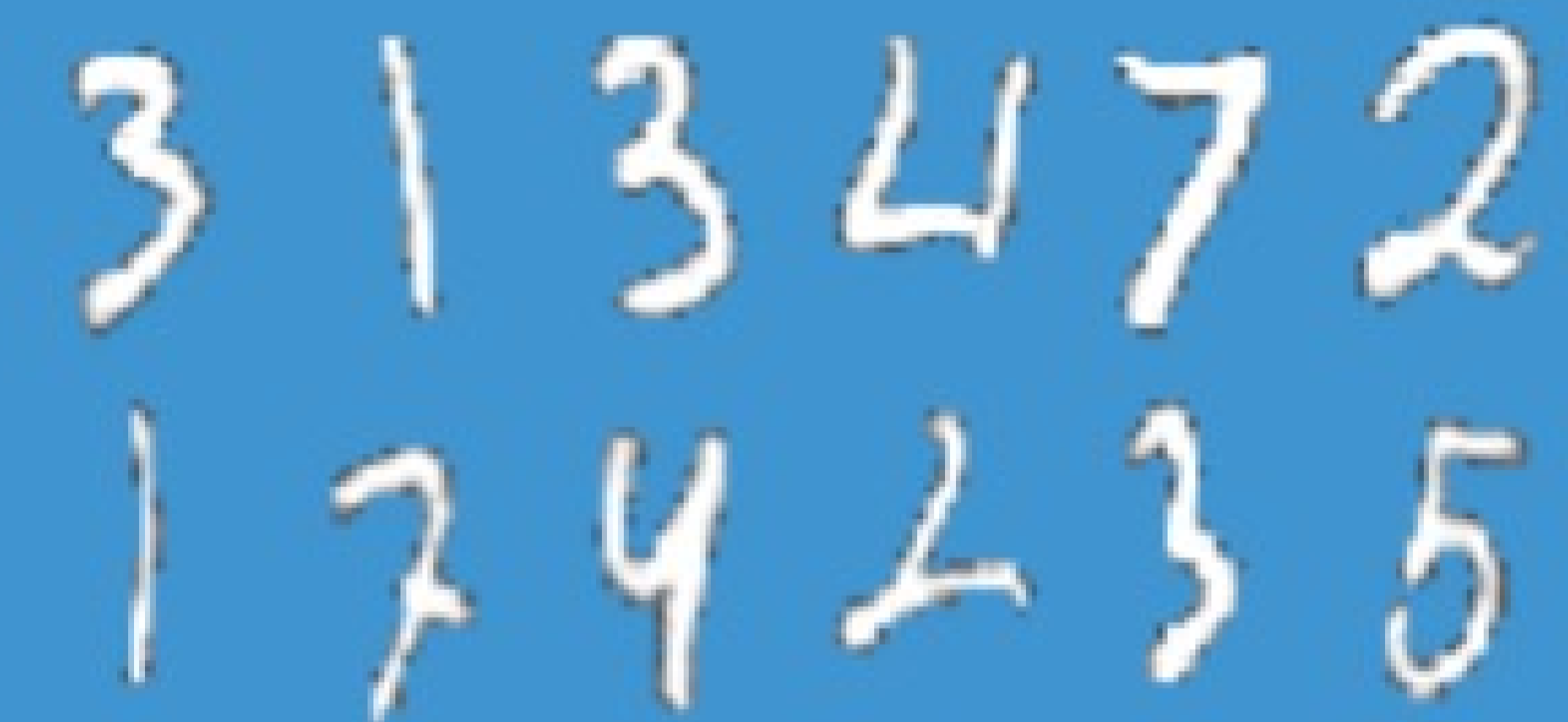
MACHINE LEARNING

Ability to learn without explicitly being programmed



DEEP LEARNING

Extract patterns from data using neural networks



Lecture Schedule



- 1/18/21 – 1/29/21
- Graded P/D/F; 6 Units
- Lecture + Lab Breakdown
- 1 Final Assignment



Intro to Deep Learning

Lecture 1

Jan. 18, 2021

[Slides] [Video] coming soon!



Deep Computer Vision

Lecture 3

Jan. 20, 2021

[Slides] [Video] coming soon!



Deep Reinforcement Learning

Lecture 5

Jan. 22, 2021

[Slides] [Video] coming soon!



Evidential Deep Learning

Lecture 7

Jan. 26, 2021

[Slides] [Video] coming soon!



Guest Lecture

Lecture 9

Jan. 27, 2021

[Info] [Slides] [Video] coming soon!



Guest Lecture

Lecture 11

Jan. 28, 2021

[Info] [Slides] [Video] coming soon!



Project Presentations

Project Pitches

Jan. 29, 2021



Deep Sequence Modeling

Lecture 2

Jan. 19, 2021

[Slides] [Video] coming soon!



Deep Generative Modeling

Lecture 4

Jan. 21, 2021

[Slides] [Video] coming soon!



Limitations and New Frontiers

Lecture 6

Jan. 25, 2021

[Slides] [Video] coming soon!



Bias and Fairness

Lecture 8

Jan. 26, 2021

[Slides] [Video] coming soon!



Guest Lecture

Lecture 10

Jan. 27, 2021

[Info] [Slides] [Video] coming soon!



Guest Lecture

Lecture 12

Jan. 28, 2021

[Info] [Slides] [Video] coming soon!



Project Presentations

Project Pitches

Jan. 29, 2021



Intro to TensorFlow; Music Generation

Software Lab 1

Due Jan. 20, 2021

[Code] coming soon!

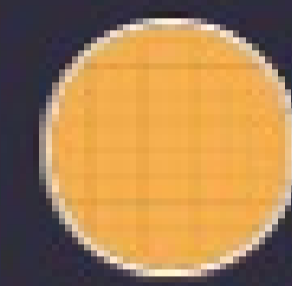


De-biasing Facial Recognition Systems

Software Lab 2

Due Jan. 22, 2021

[Paper] [Code] coming soon!



Pixels-to-Control Learning

Software Lab 3

Due Jan. 26, 2021

[Code] coming soon!



Project Proposals

Work on Final Proposals

Due Jan. 27, 2021



Final Project

Paper review

Due Jan. 28, 2021



Final Project

Work on Final Projects



Awards Ceremony

Winners announced!

Jan. 29, 2021

Final Class Project

Option 1: Proposal Presentation

- At least 1 registered student to be prize eligible
- Present a novel deep learning research idea or application
- 3 minutes (strict)
- Presentations on **Friday, Jan 29**
- Submit groups by **Wed 1/27 11:59pm ET** to be eligible
- Submit slide by **Thu 1/28 11:59pm ET** to be eligible
- Instructions:

- Judged by a panel of judges
- Top winners are awarded:



NVIDIA 3080 GPU



4x Google Home Max



3x Display Monitors

Final Class Project

Option 1: Proposal Presentation

- At least 1 registered student to be prize eligible
- Present a novel deep learning research idea or application
- 3 minutes (strict)
- Presentations on Friday, Jan 29
- Submit groups by Wednesday 11:59pm ET to be eligible
- Submit slide by Thursday 11:59pm ET to be eligible
- Instructions:

Option 2: Write a 1-page review of a deep learning paper

- Grade is based on clarity of writing and technical communication of main ideas
- Due Thu Jan 28 11:59pm ET

Labs and Prizes

Lab 1: Music Generation



Beats Headphones

Lab 2: Computer Vision



24" HD Display Monitor

Lab 3: Reinforcement Learning



Quadcopter Drone

Class Support

- Software labs + office hours in Gather.Town
- Piazza: <http://piazza.com/mit/spring2021/6s191>
 - Useful for discussing labs
- Course Website: <http://introtodeeplearning.com>
 - Lecture schedule
 - Slides and lecture recordings
 - Software labs
 - Grading policy
- Email us: introtodeeplearning-staff@mit.edu

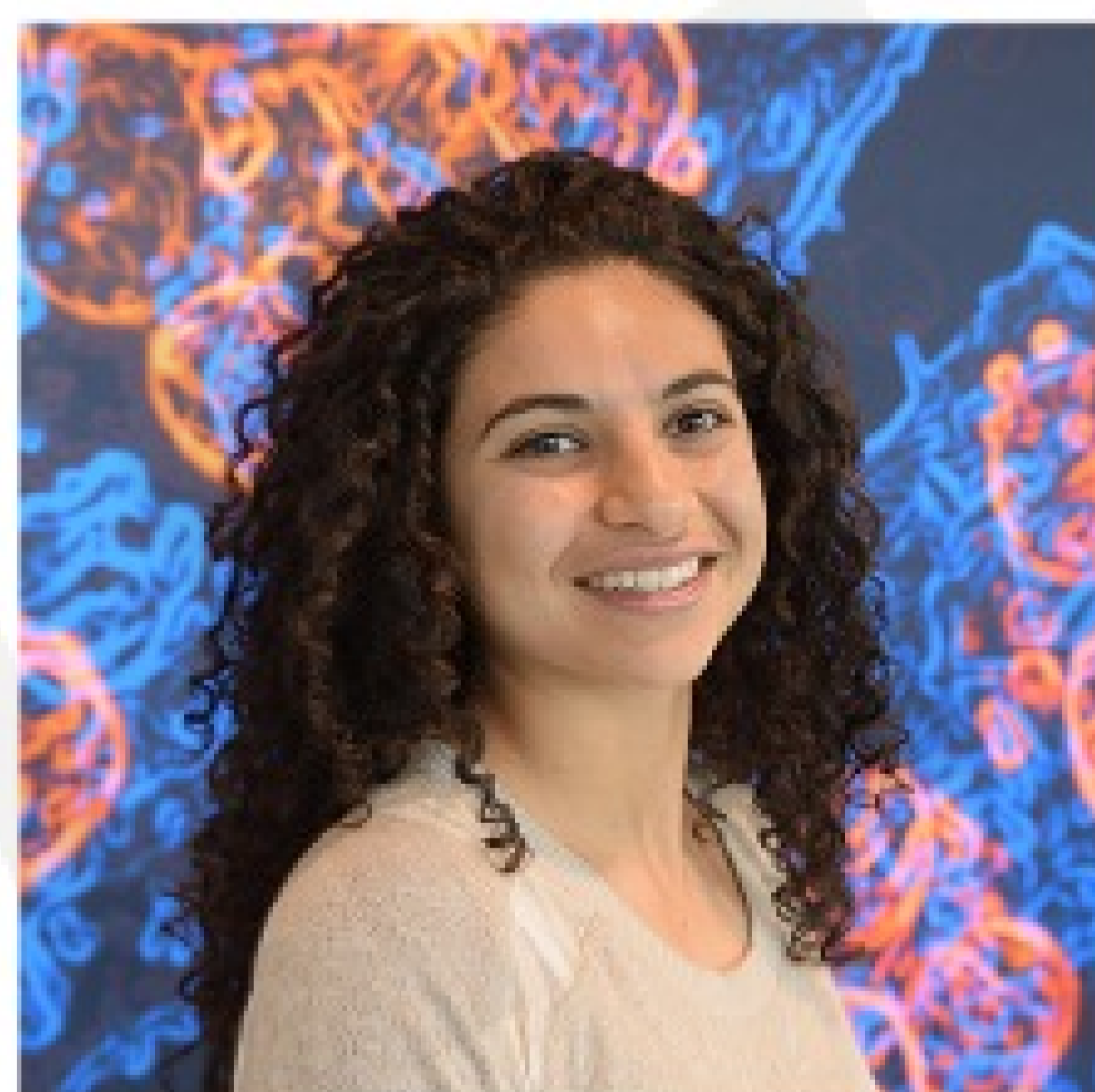


Course Staff

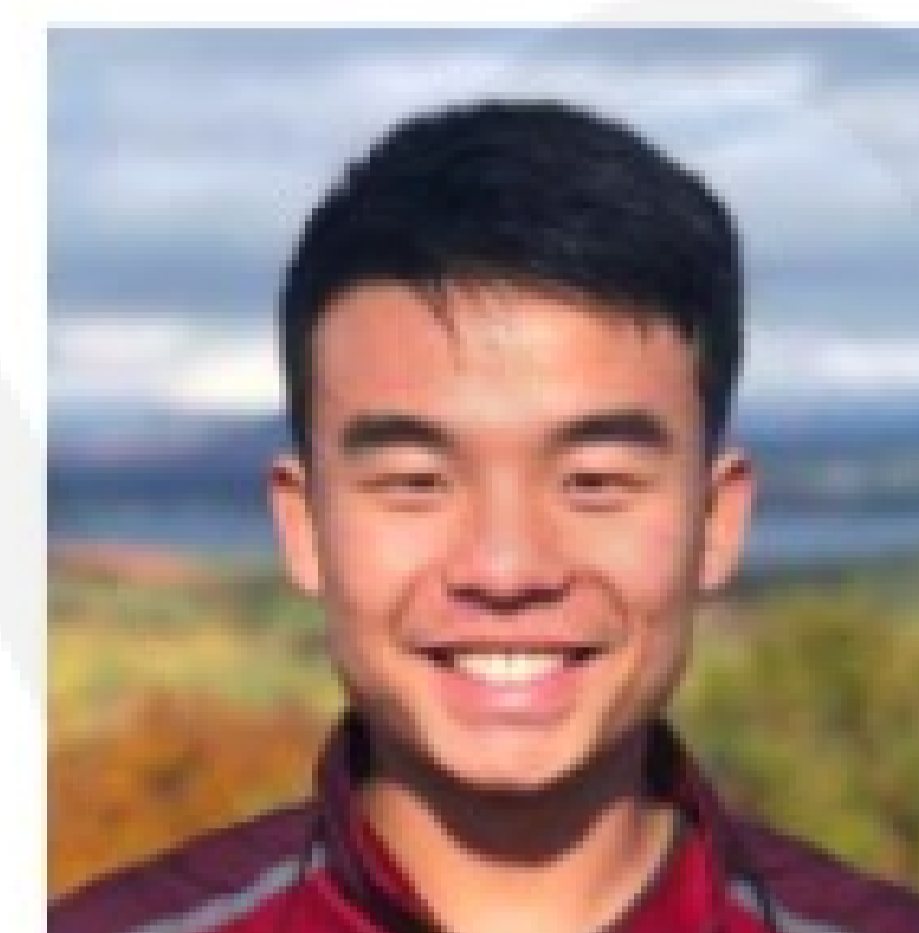
Alexander Amini
Lead Organizer



Ava Soleimany
Lead Organizer



Carmen



Gilbert



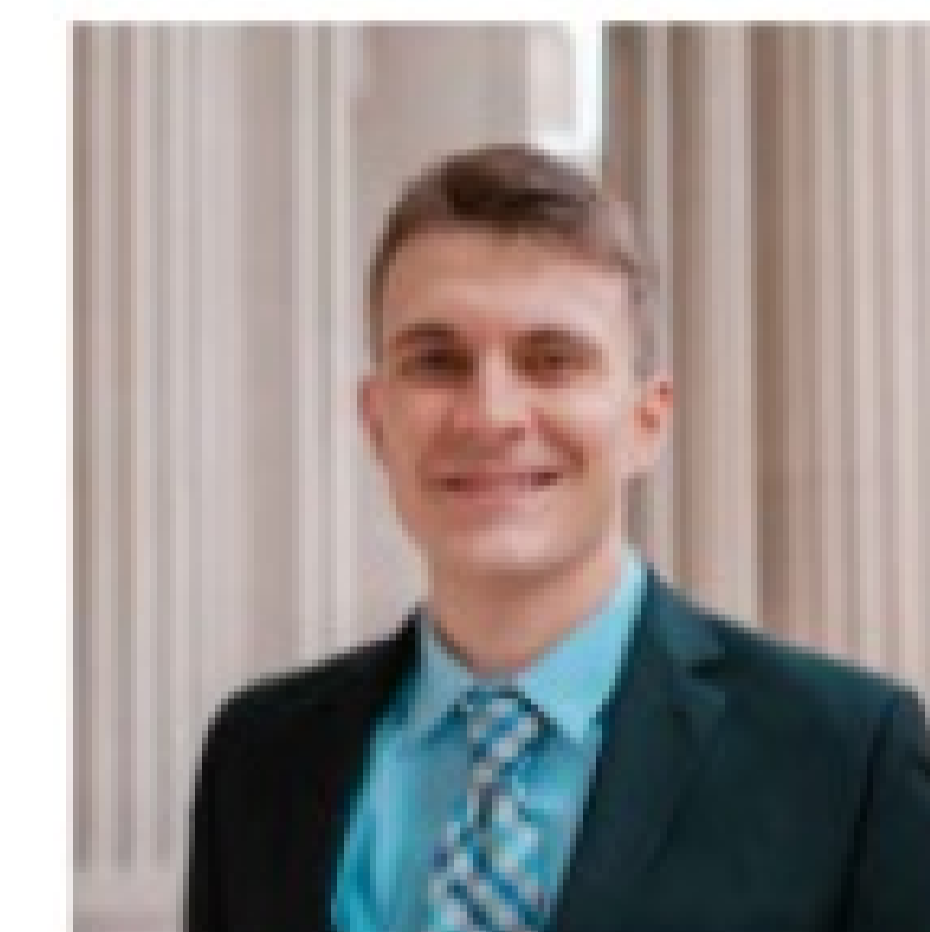
Jacob



Julia



Kristian



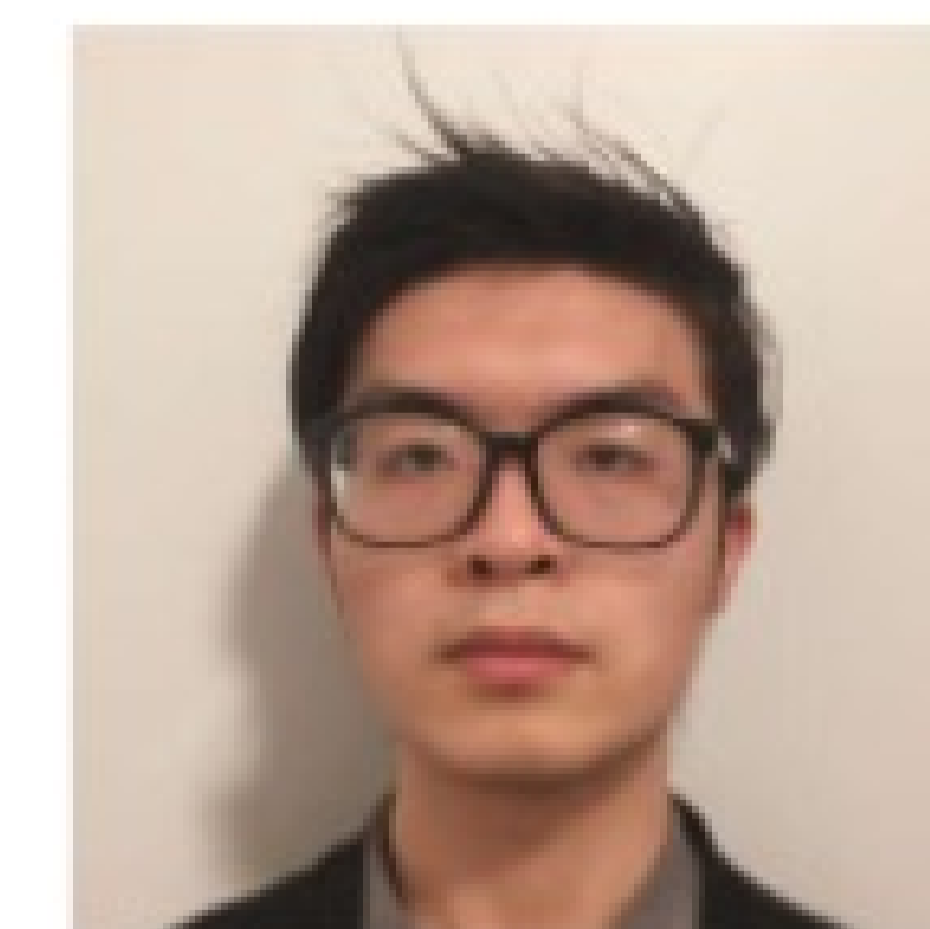
Ryan



Sam



Shinjini



William

introtodeeplearning-staff@mit.edu

Thanks to Sponsors!



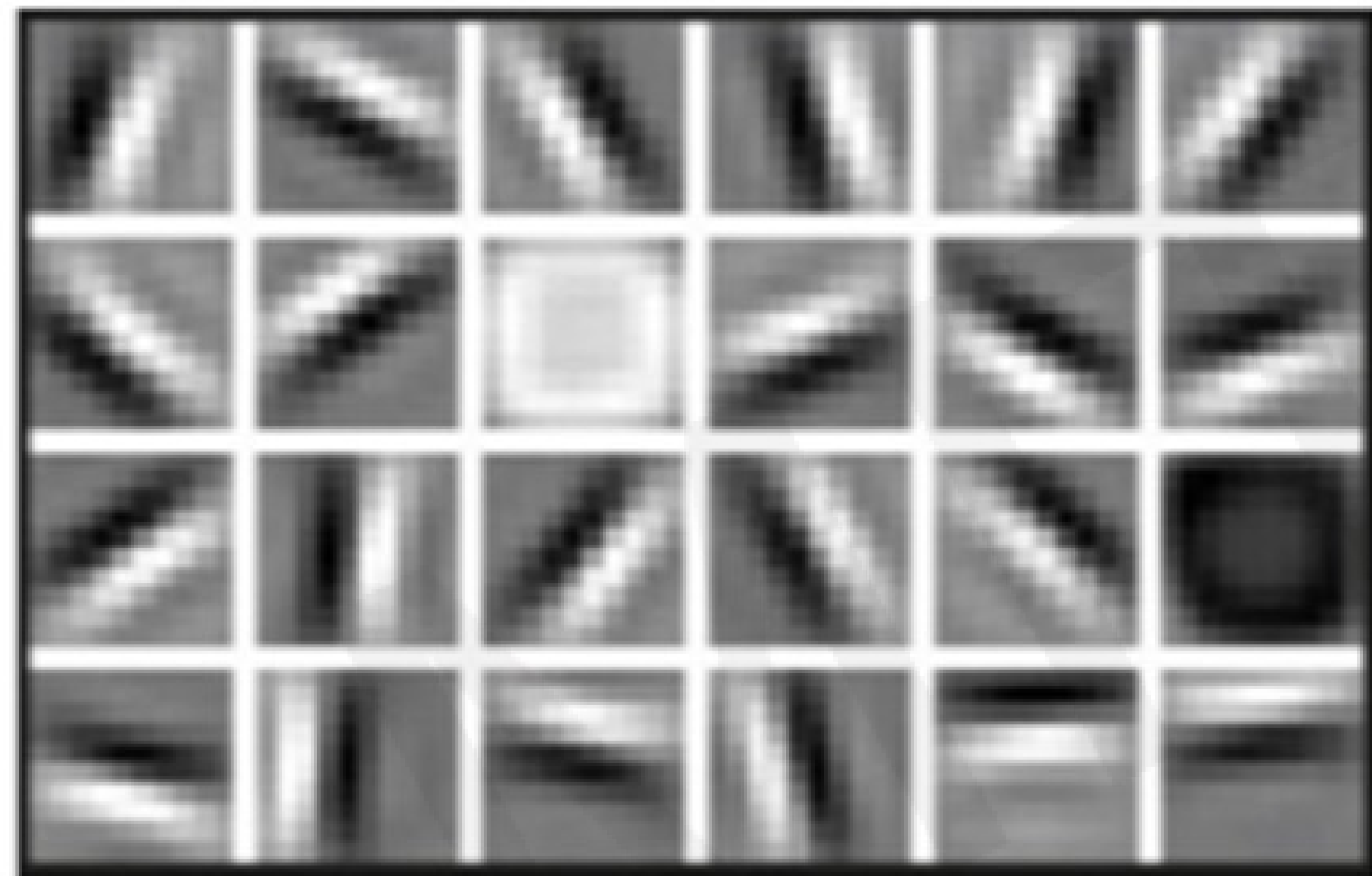
Why Deep Learning and Why Now?

Why Deep Learning?

Hand engineered features are time consuming, brittle, and not scalable in practice

Can we learn the **underlying features** directly from data?

Low Level Features



Lines & Edges

Mid Level Features



Eyes & Nose & Ears

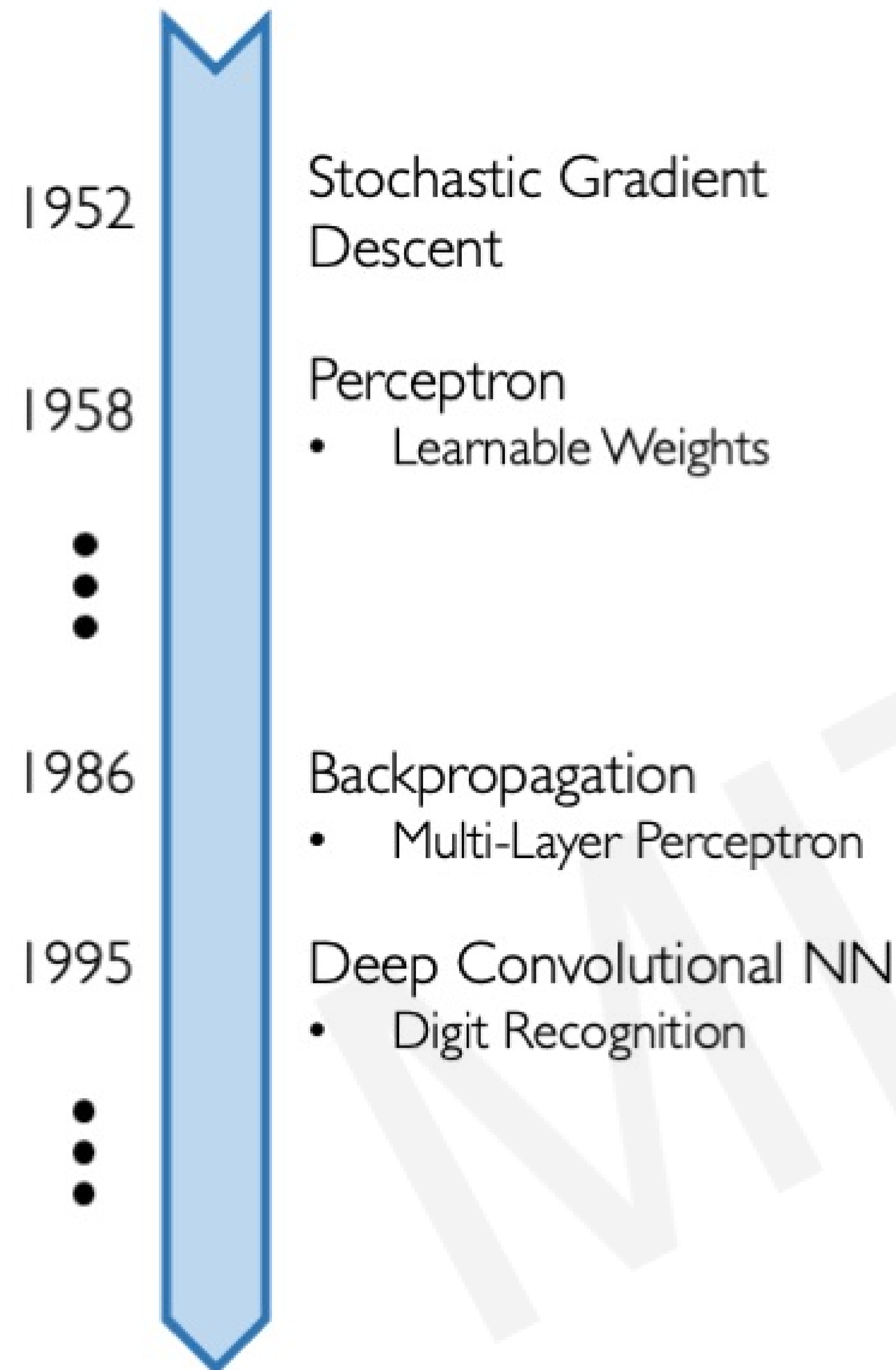
High Level Features



Facial Structure

Why Now?

Neural Networks date back decades, so why the resurgence?



1. Big Data

- Larger Datasets
- Easier Collection & Storage

IMAGENET



WIKIPEDIA
The Free Encyclopedia



2. Hardware

- Graphics Processing Units (GPUs)
- Massively Parallelizable



3. Software

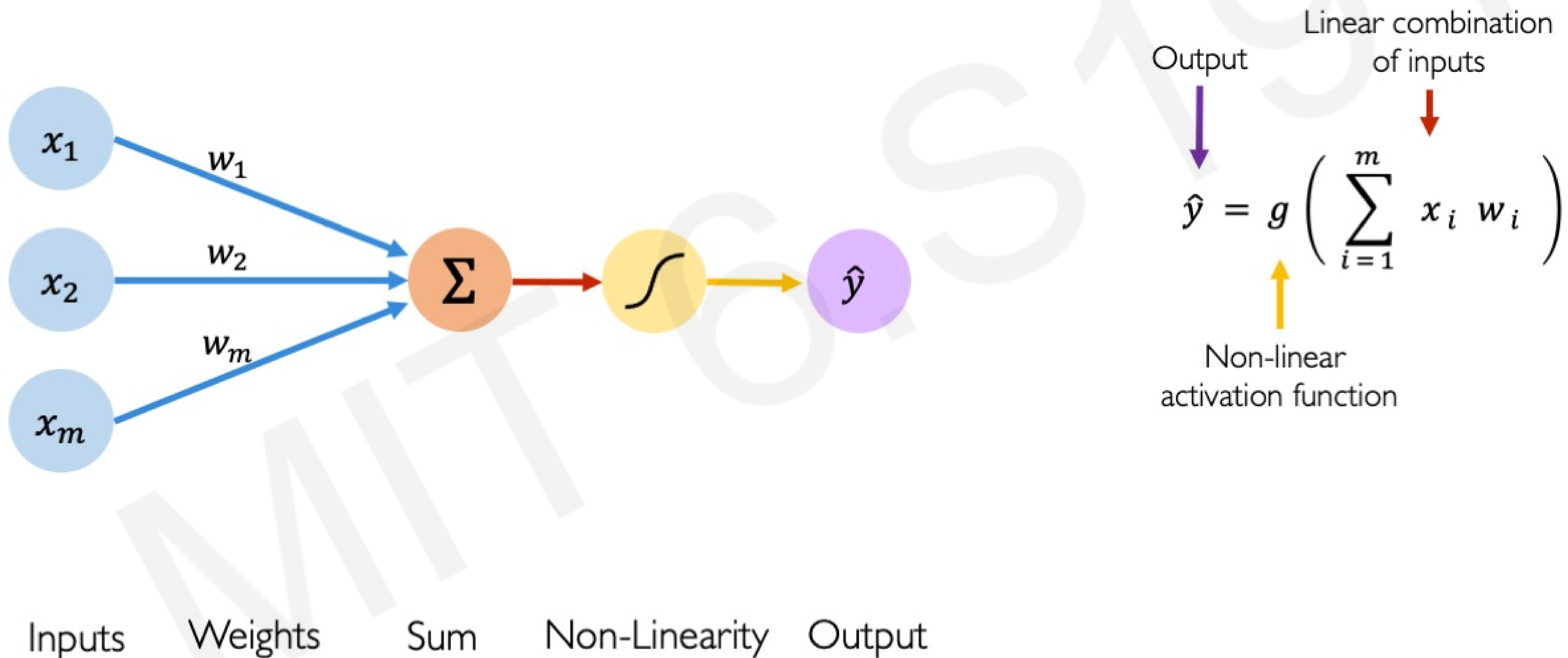
- Improved Techniques
- New Models
- Toolboxes



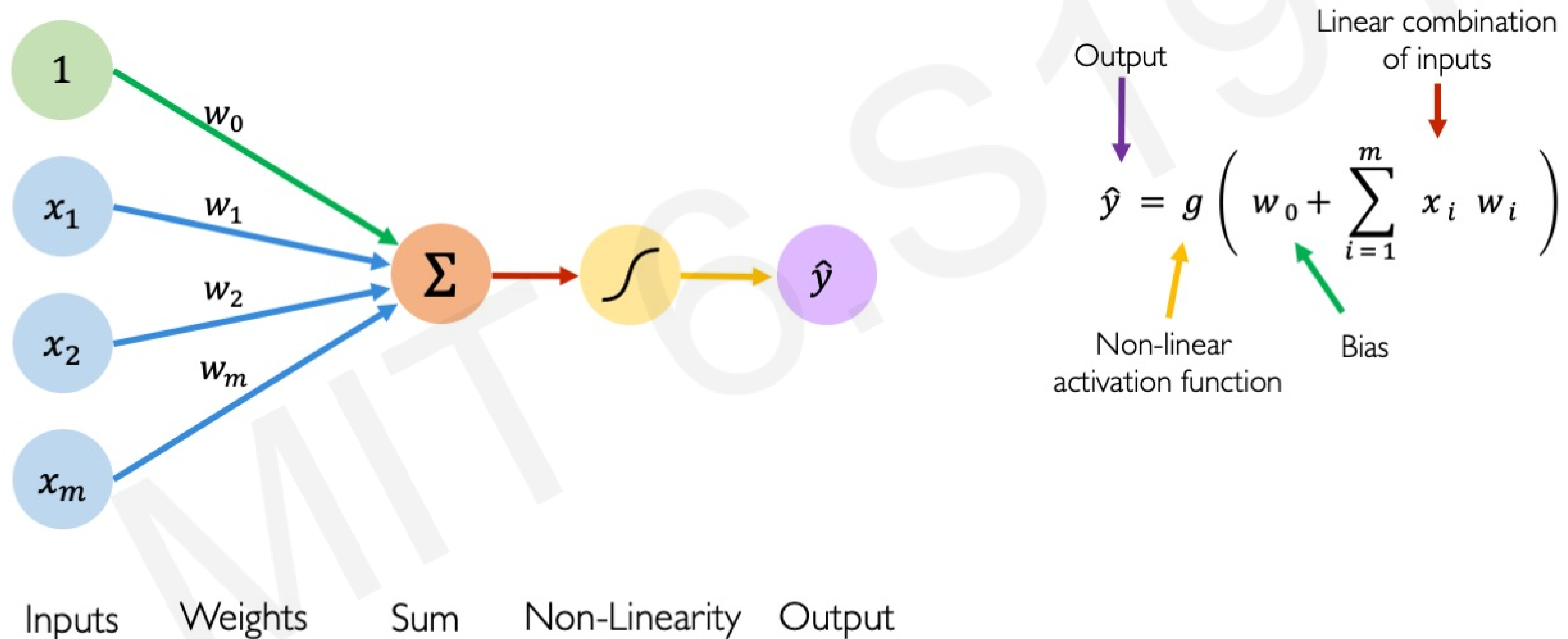
The Perceptron

The structural building block of deep learning

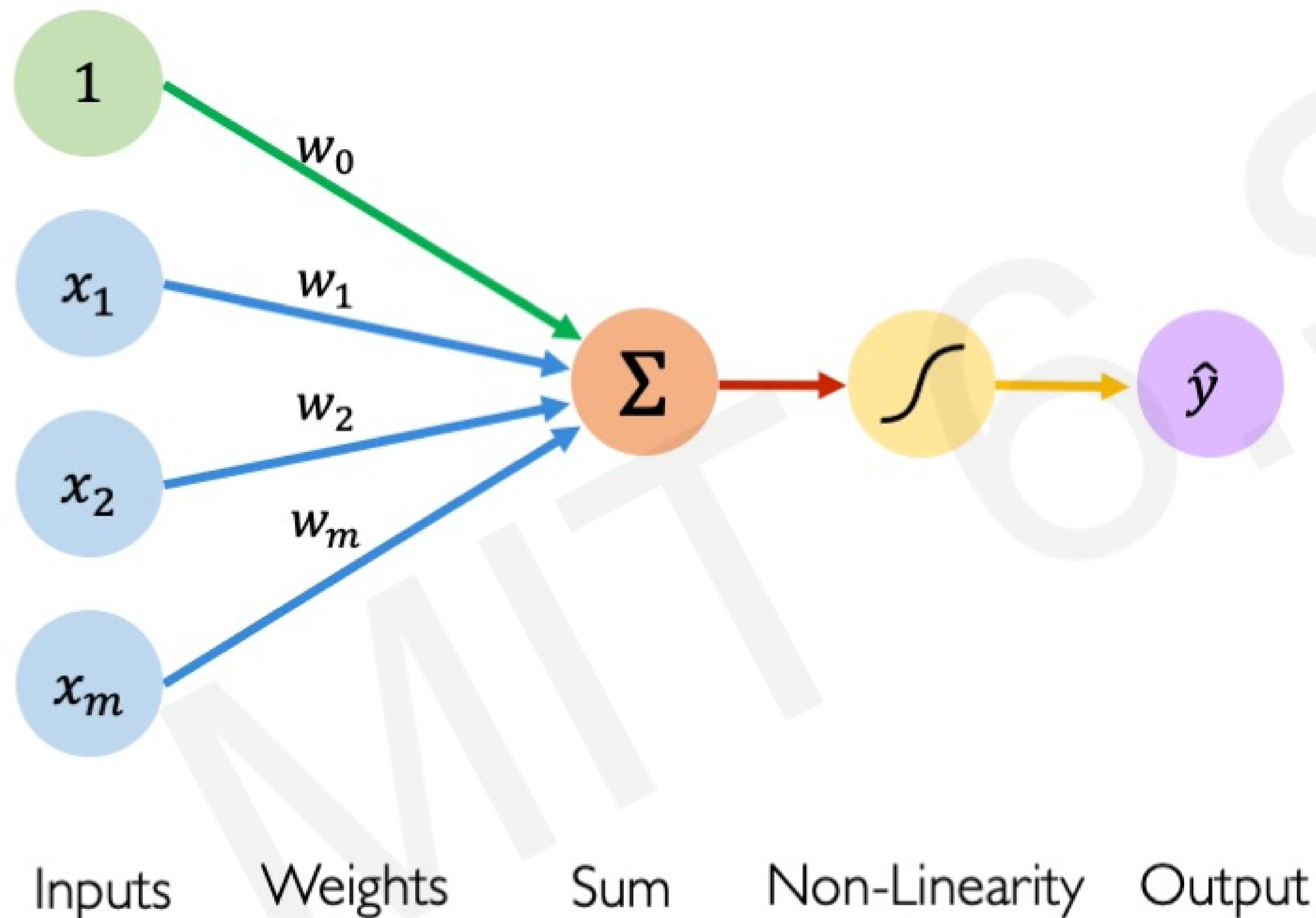
The Perceptron: Forward Propagation



The Perceptron: Forward Propagation



The Perceptron: Forward Propagation

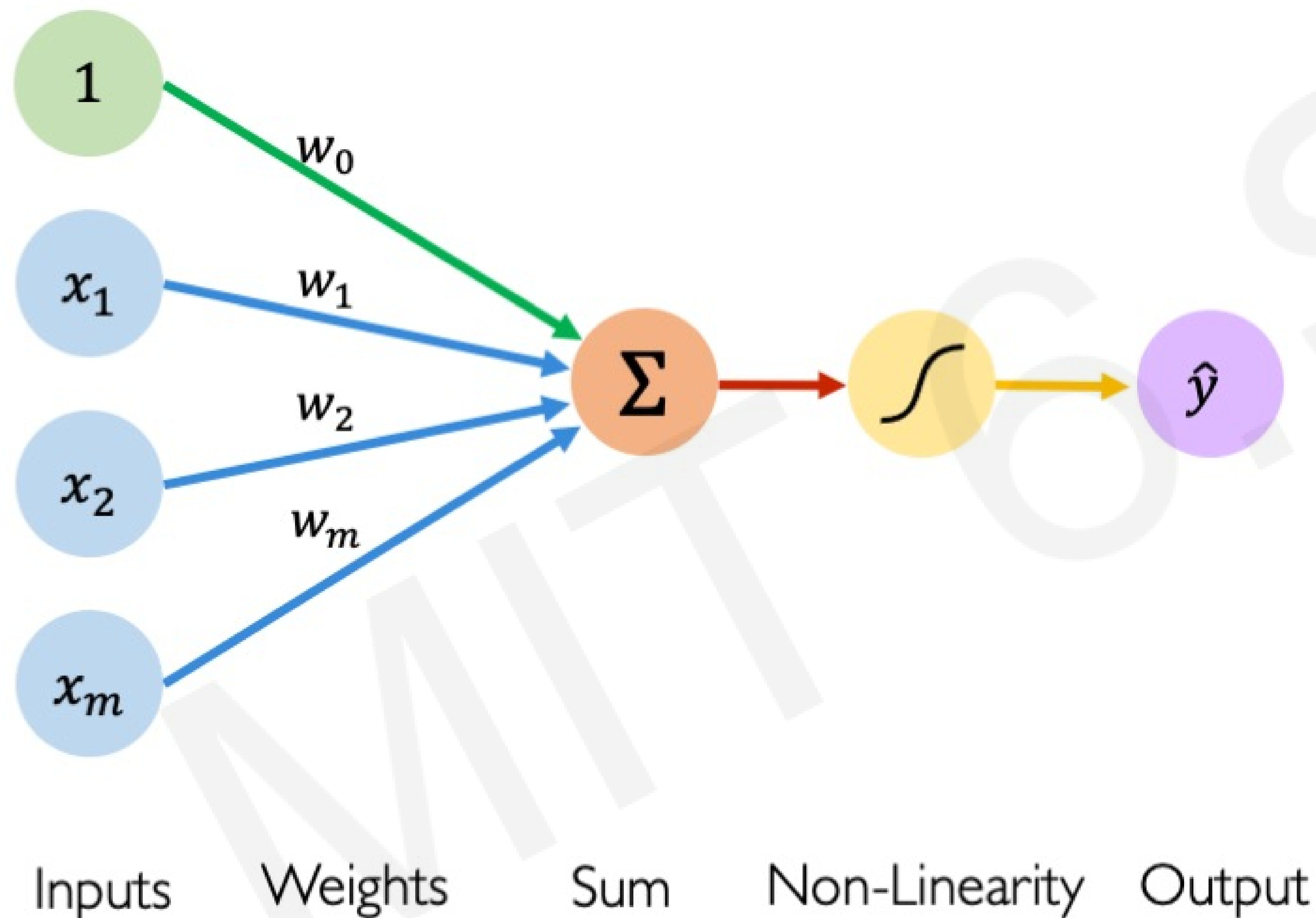


$$\hat{y} = g \left(w_0 + \sum_{i=1}^m x_i w_i \right)$$

$$\hat{y} = g (w_0 + \mathbf{X}^T \mathbf{W})$$

where: $\mathbf{X} = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix}$ and $\mathbf{W} = \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix}$

The Perceptron: Forward Propagation

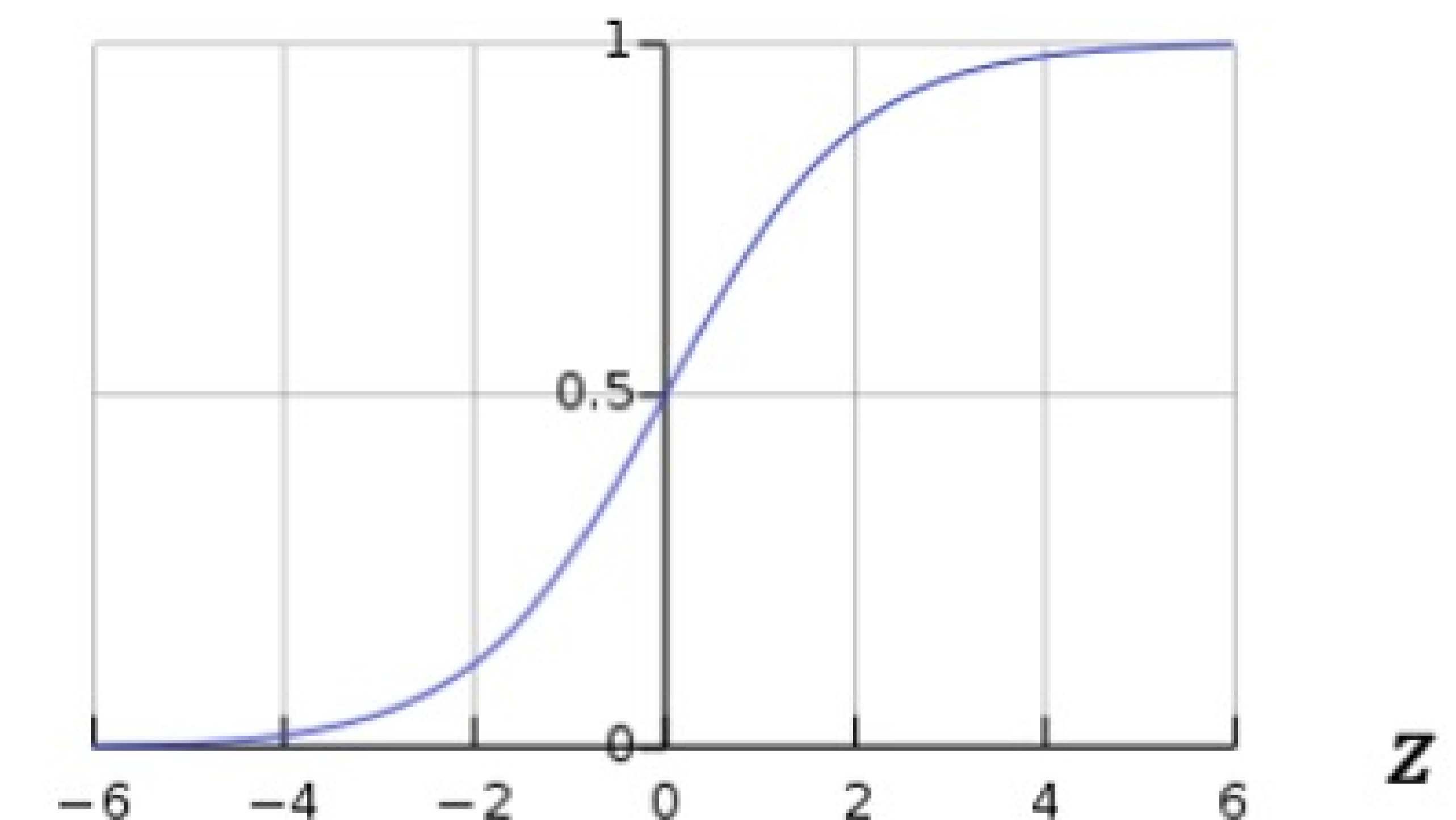


Activation Functions

$$\hat{y} = g(w_0 + \mathbf{X}^T \mathbf{W})$$

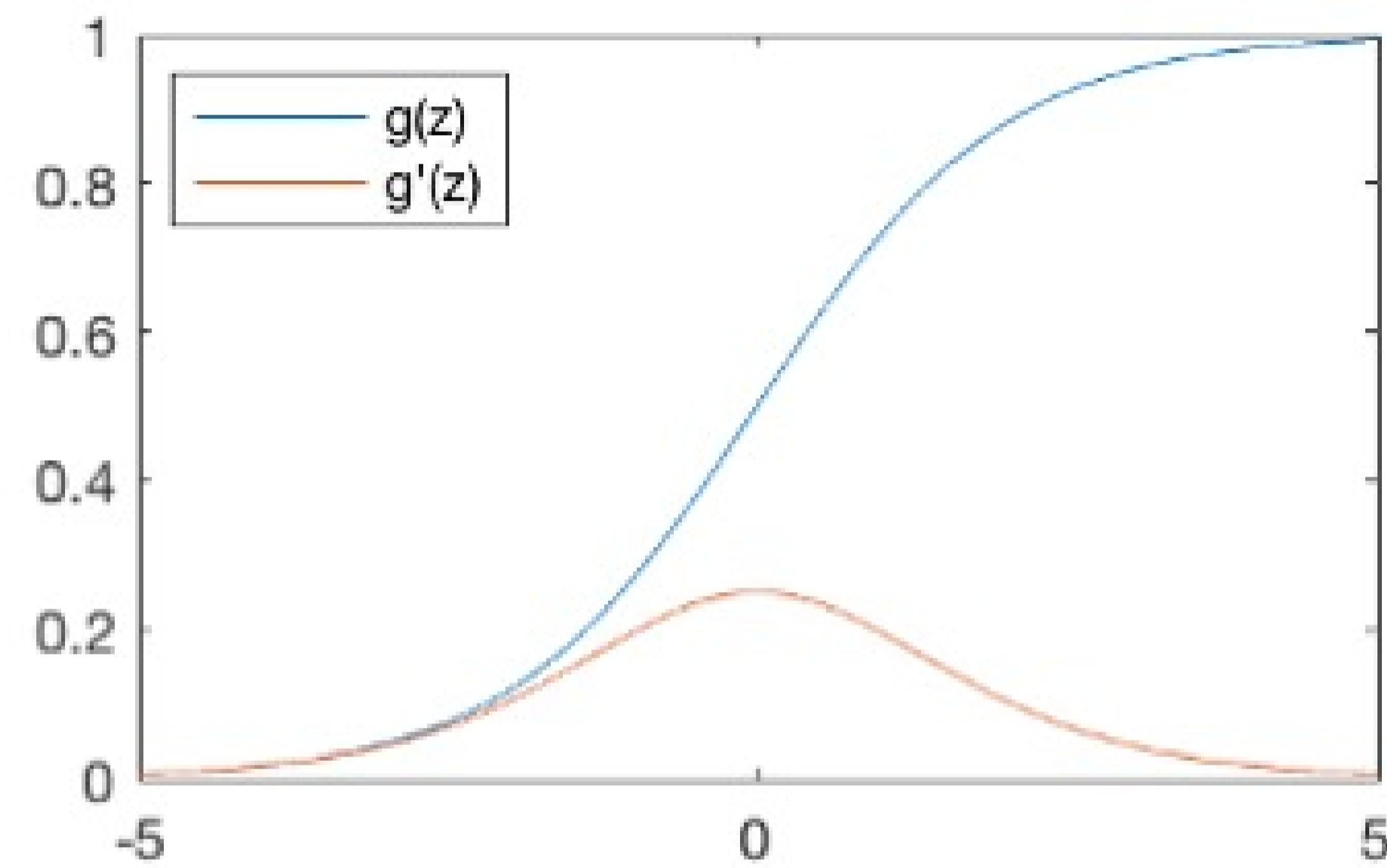
- Example: sigmoid function

$$g(z) = \sigma(z) = \frac{1}{1 + e^{-z}}$$



Common Activation Functions

Sigmoid Function

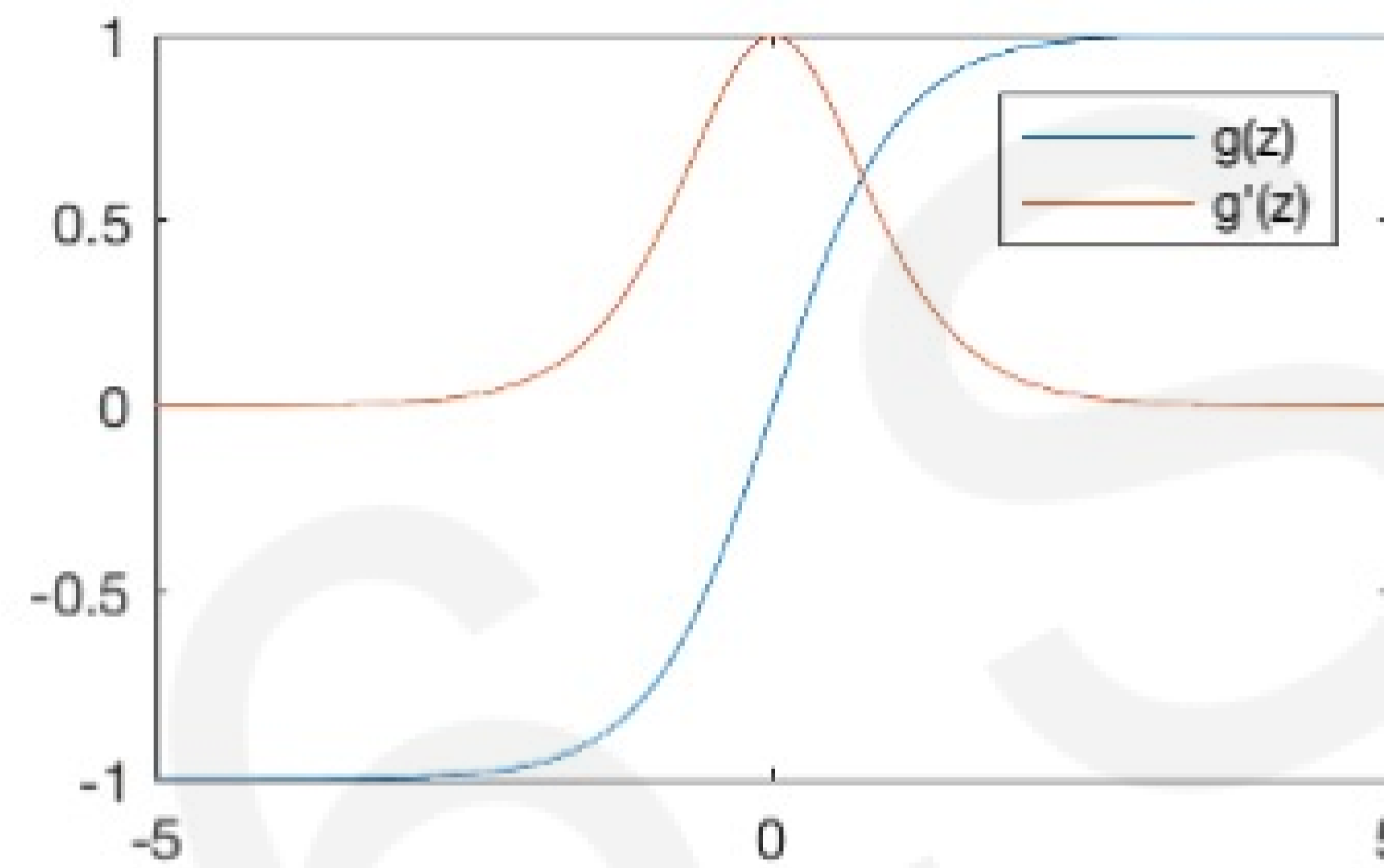


$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g'(z) = g(z)(1 - g(z))$$

 `tf.math.sigmoid(z)`

Hyperbolic Tangent

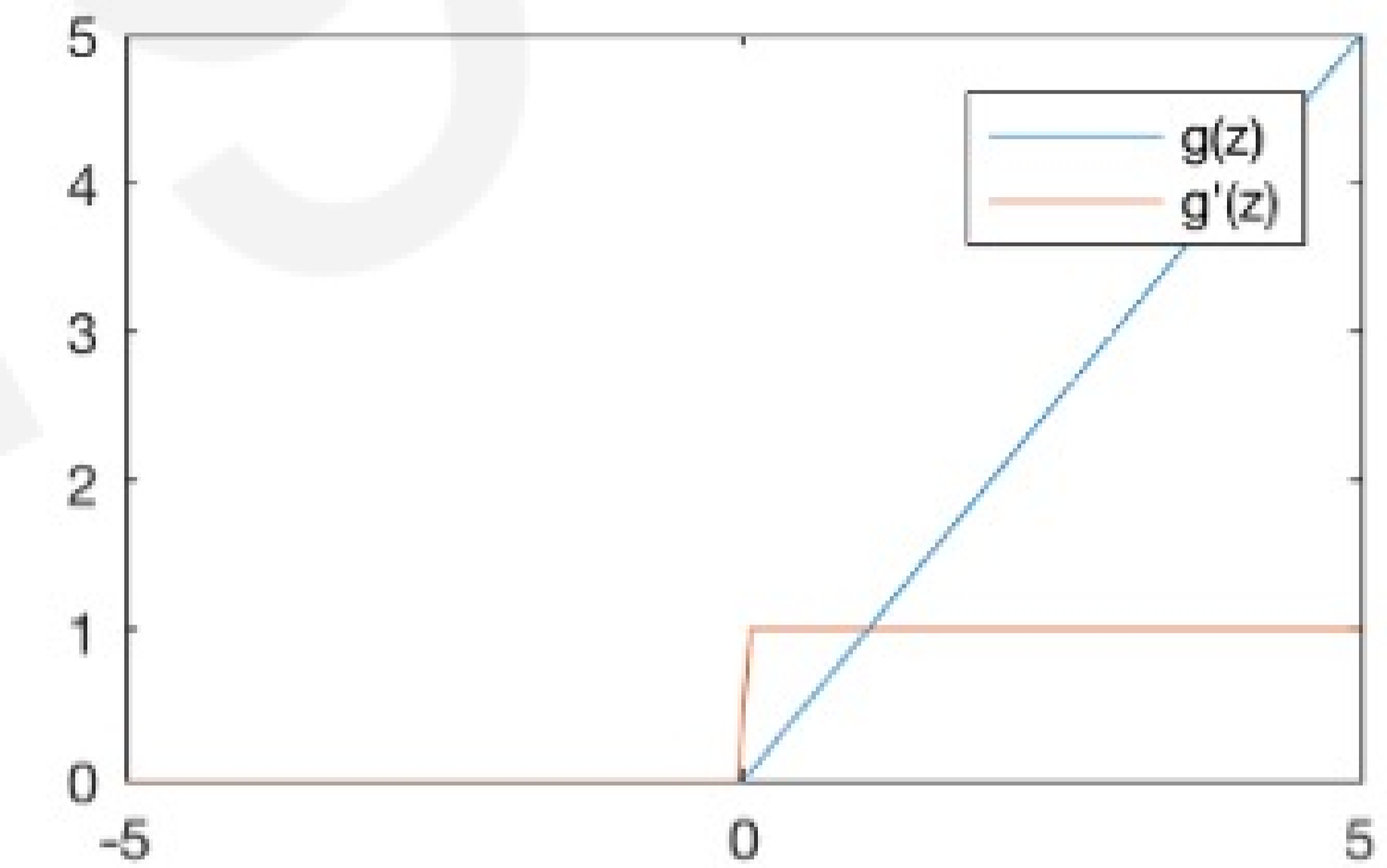


$$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

$$g'(z) = 1 - g(z)^2$$

 `tf.math.tanh(z)`

Rectified Linear Unit (ReLU)



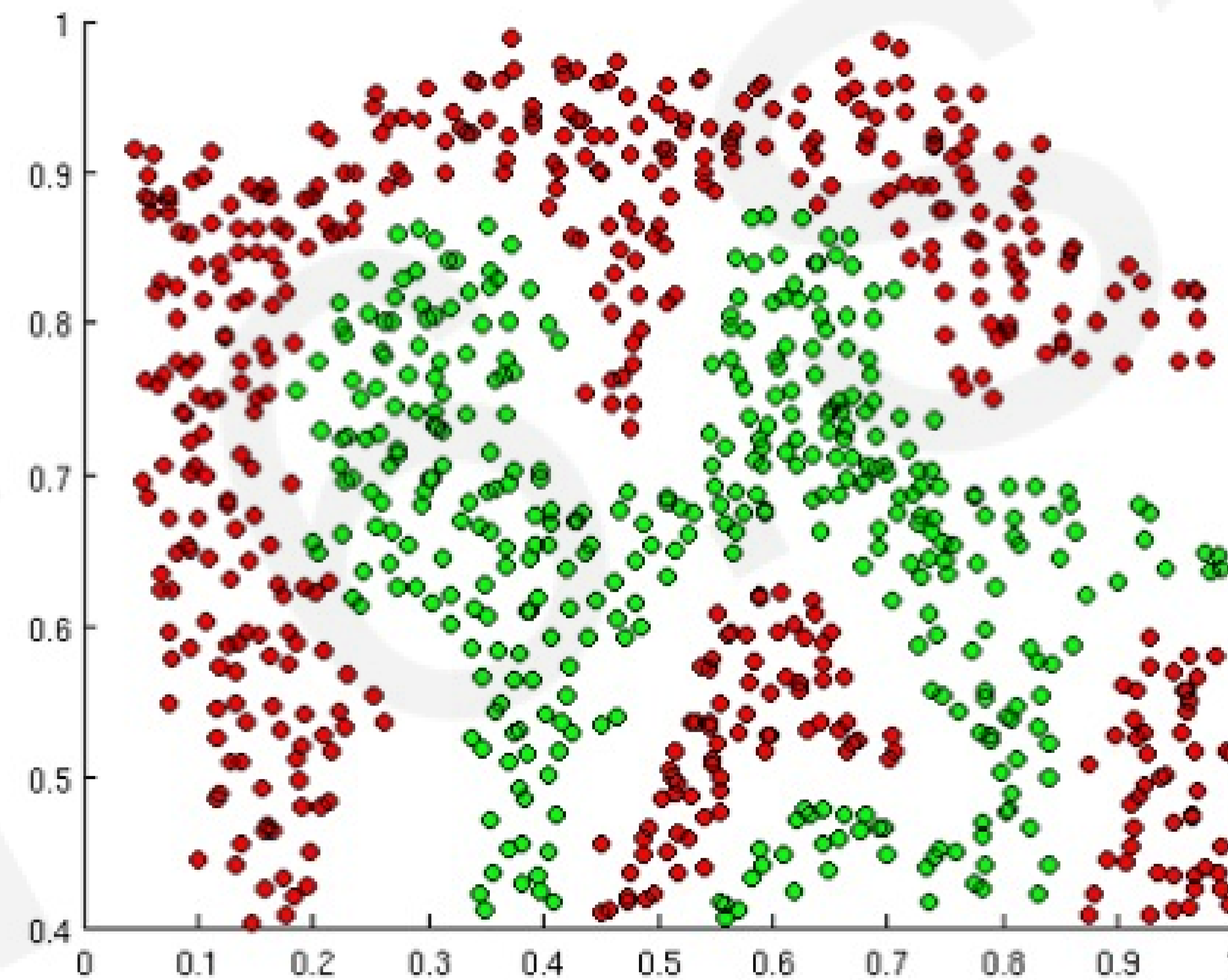
$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

 `tf.nn.relu(z)`

Importance of Activation Functions

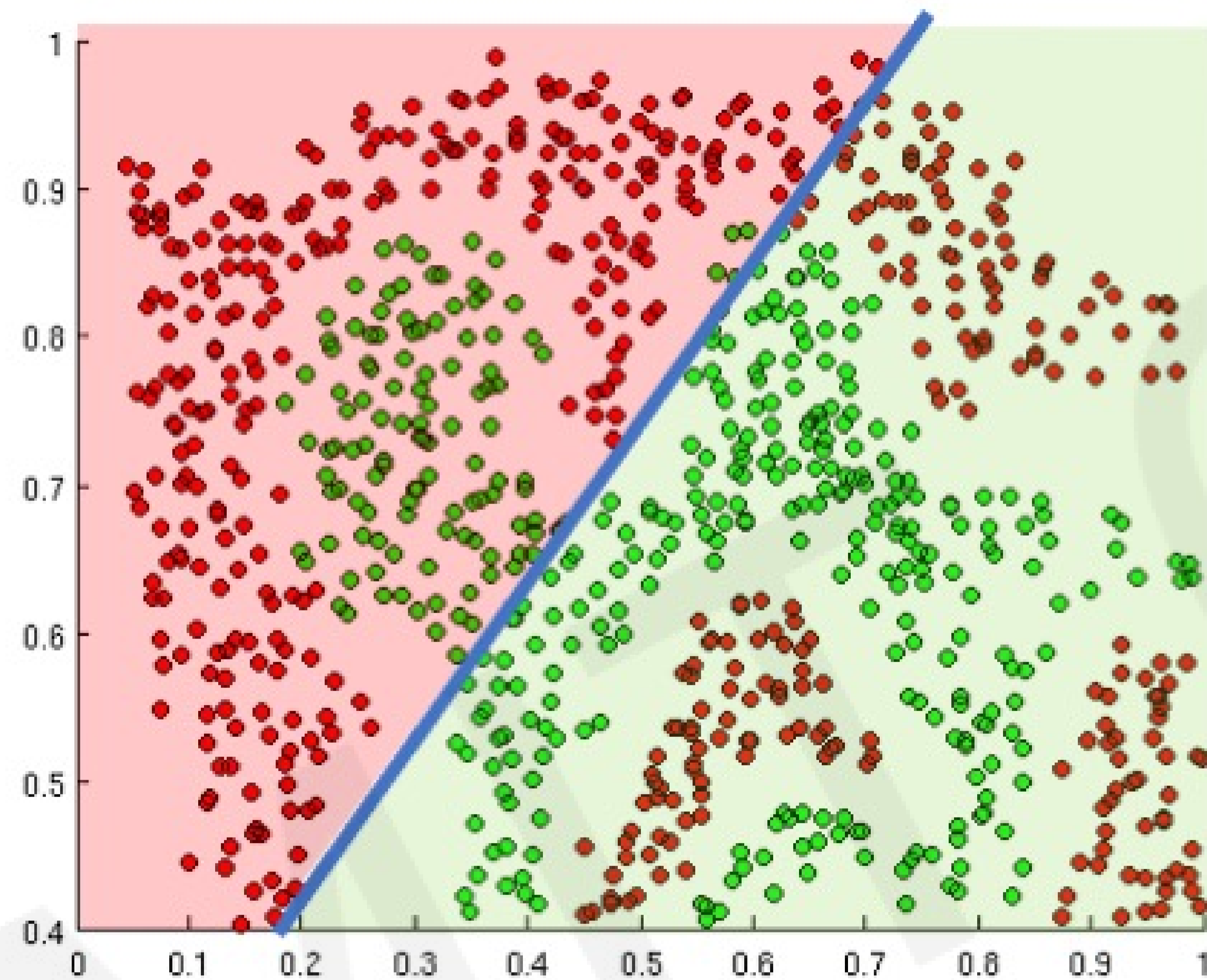
The purpose of activation functions is to *introduce non-linearities* into the network



What if we wanted to build a neural network to distinguish green vs red points?

Importance of Activation Functions

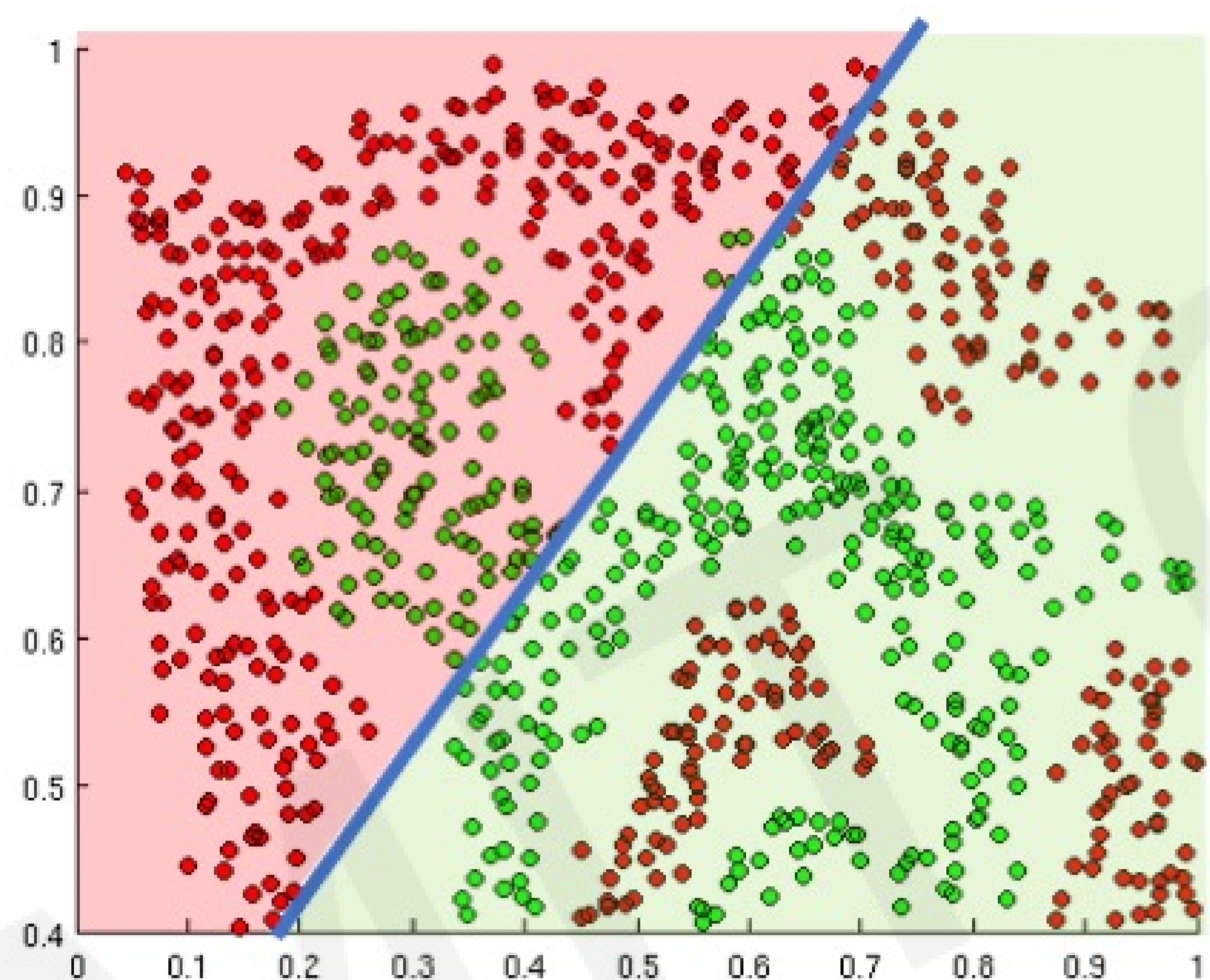
The purpose of activation functions is to *introduce non-linearities* into the network



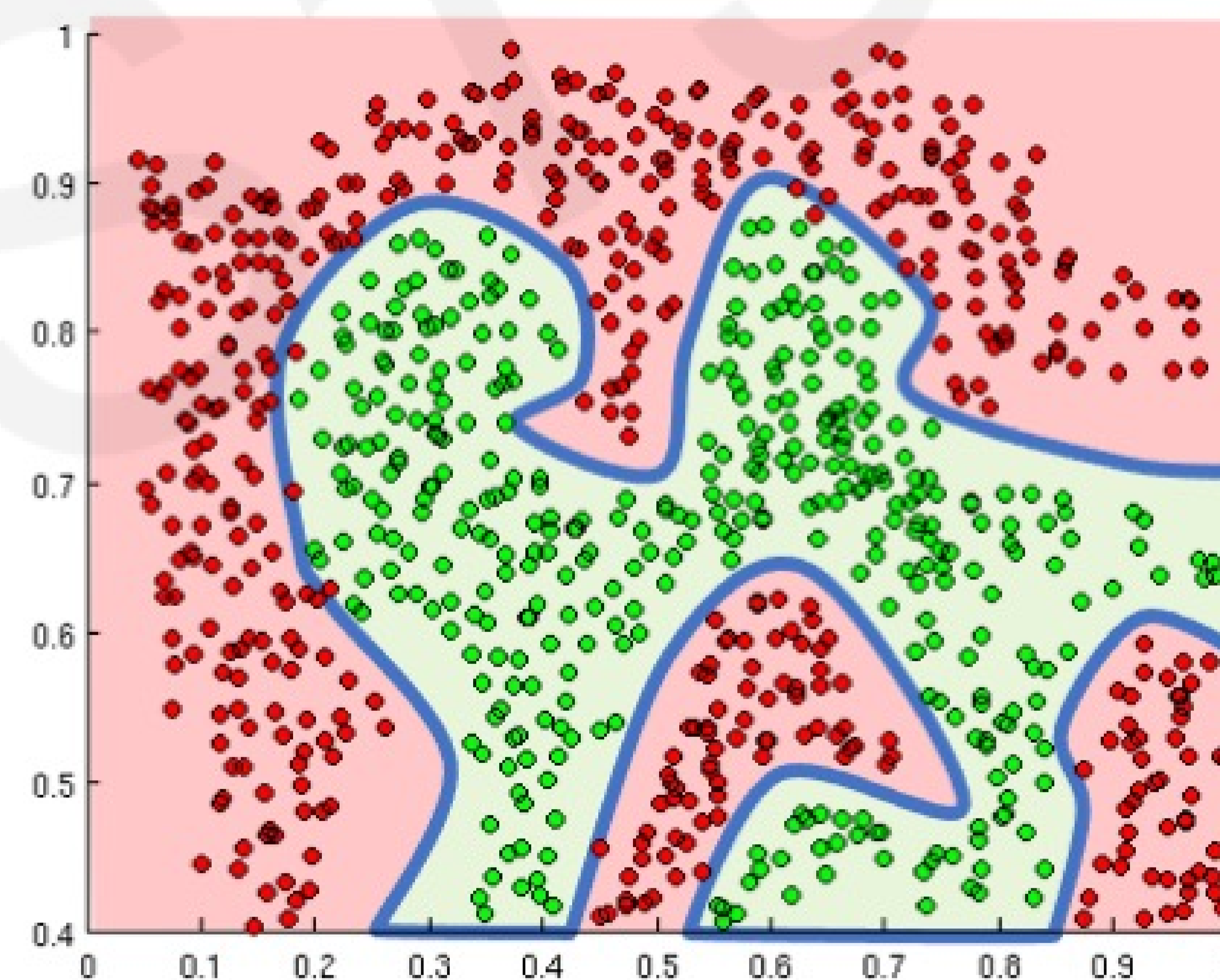
Linear activation functions produce linear decisions no matter the network size

Importance of Activation Functions

The purpose of activation functions is to *introduce non-linearities* into the network

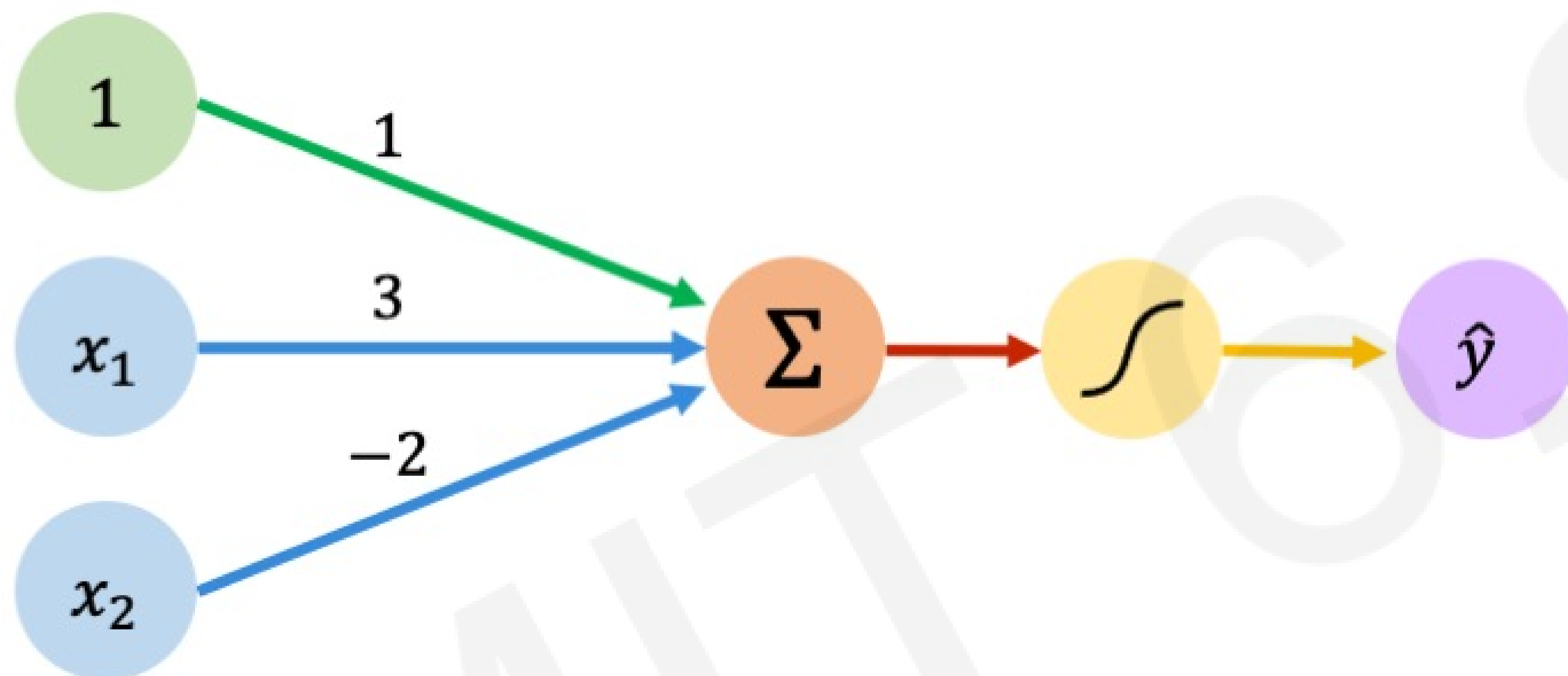


Linear activation functions produce linear decisions no matter the network size



Non-linearities allow us to approximate arbitrarily complex functions

The Perceptron: Example

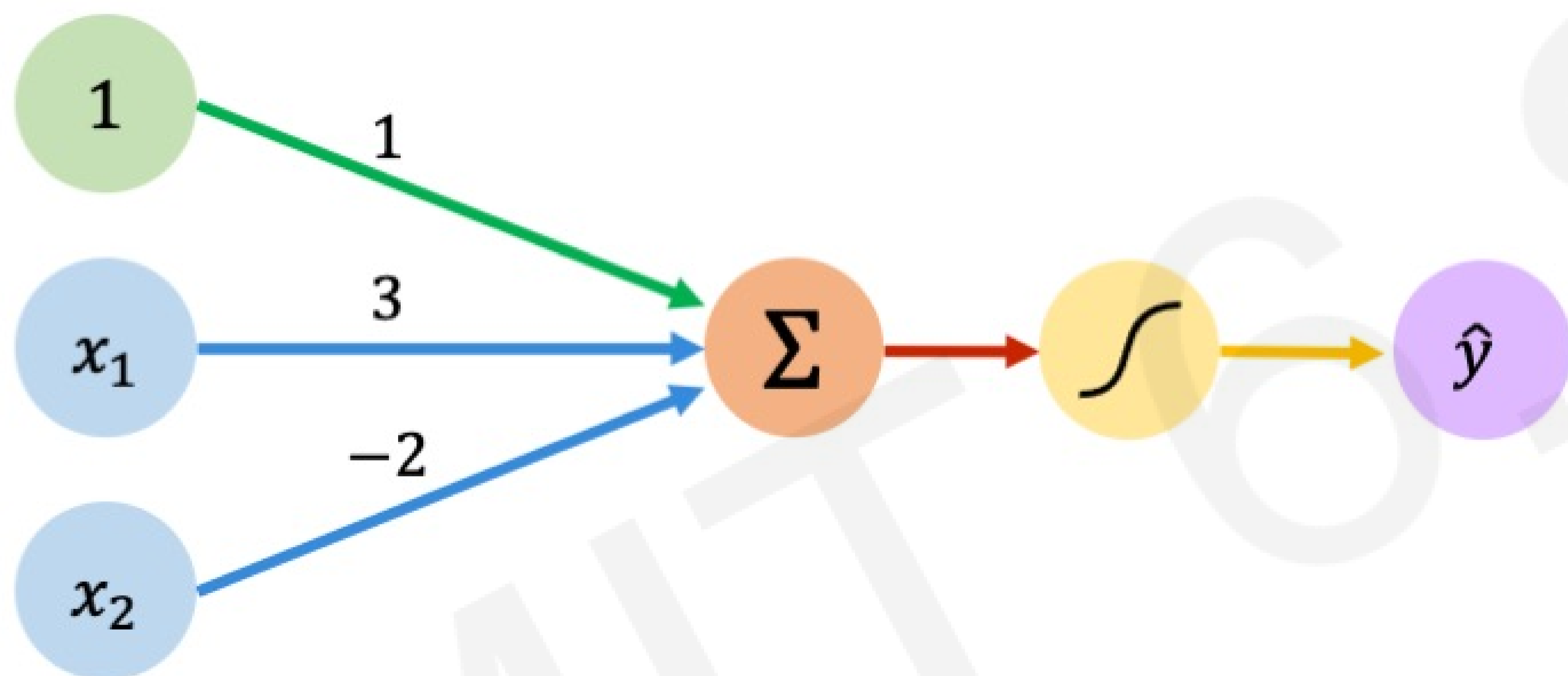


We have: $w_0 = 1$ and $\mathbf{W} = \begin{bmatrix} 3 \\ -2 \end{bmatrix}$

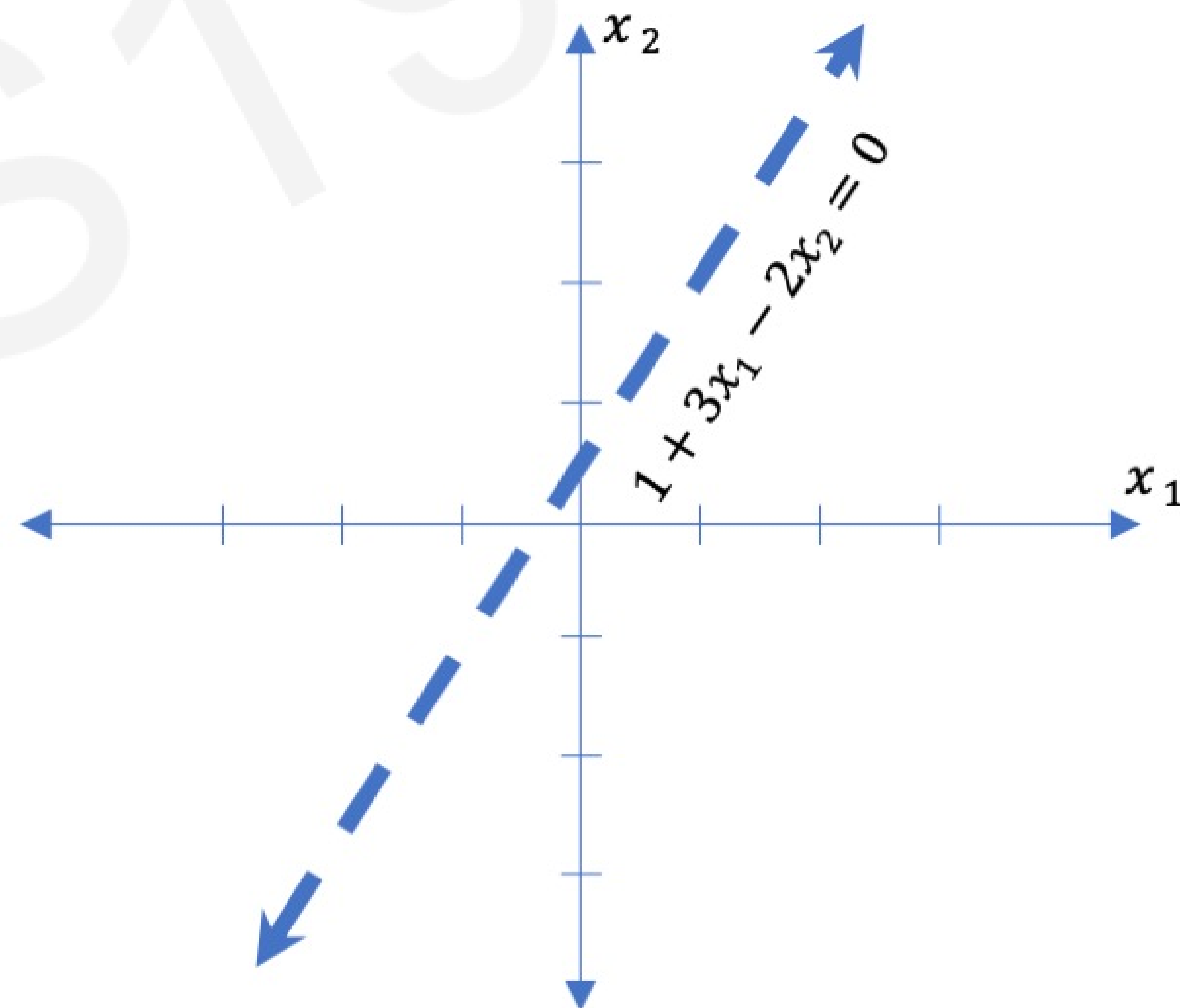
$$\begin{aligned}\hat{y} &= g(w_0 + \mathbf{X}^T \mathbf{W}) \\ &= g\left(1 + \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^T \begin{bmatrix} 3 \\ -2 \end{bmatrix}\right) \\ \hat{y} &= g(1 + 3x_1 - 2x_2)\end{aligned}$$

This is just a line in 2D!

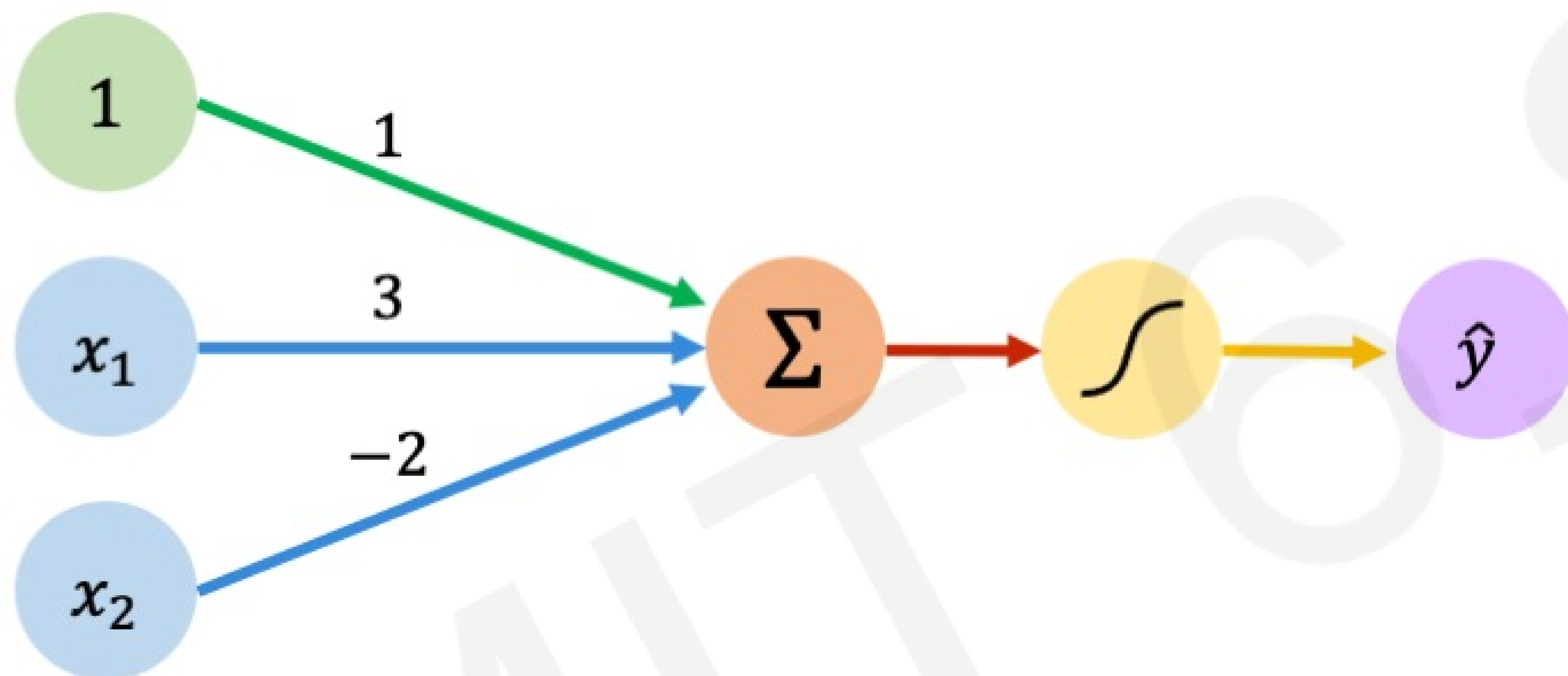
The Perceptron: Example



$$\hat{y} = g(1 + 3x_1 - 2x_2)$$

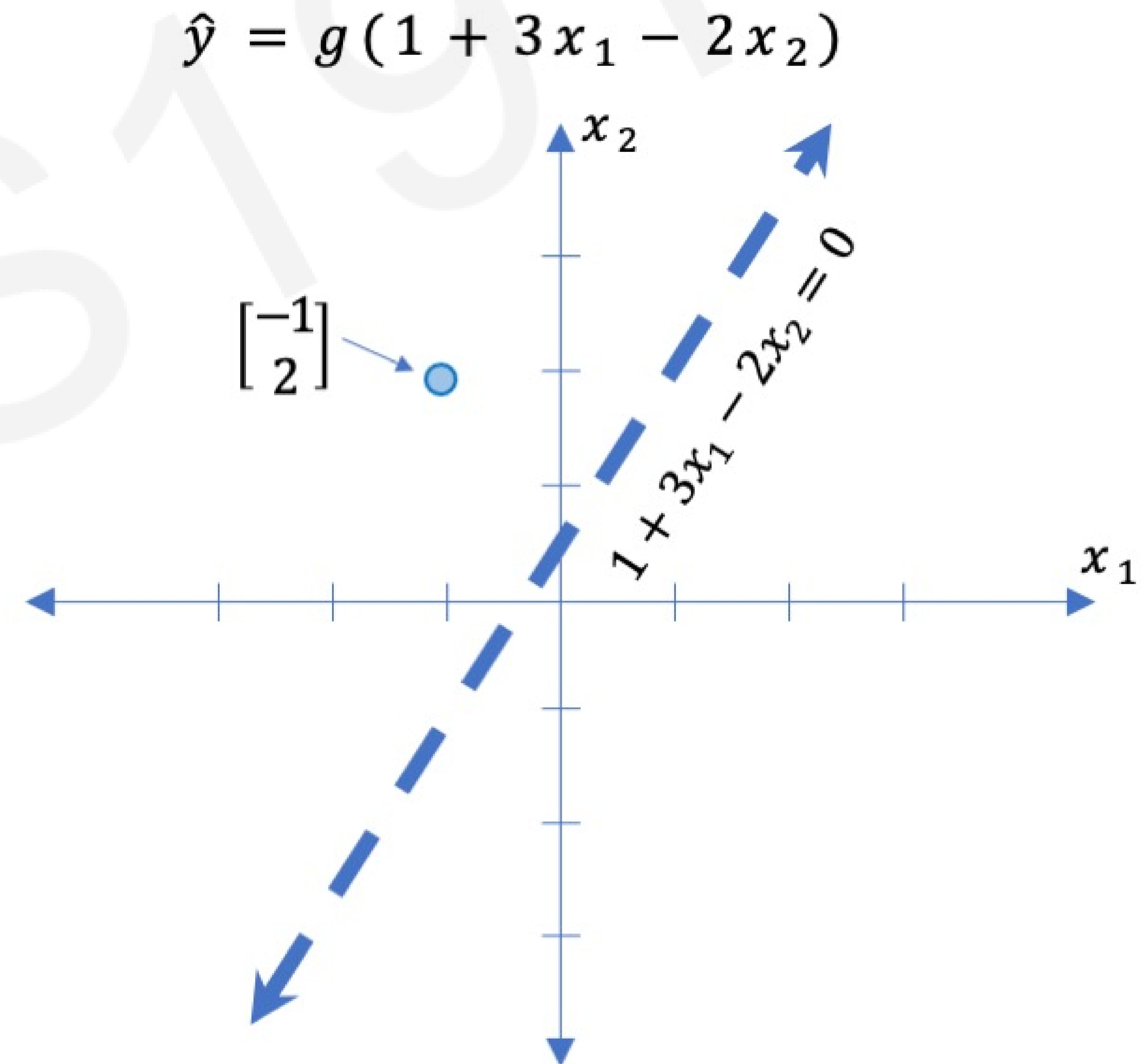


The Perceptron: Example

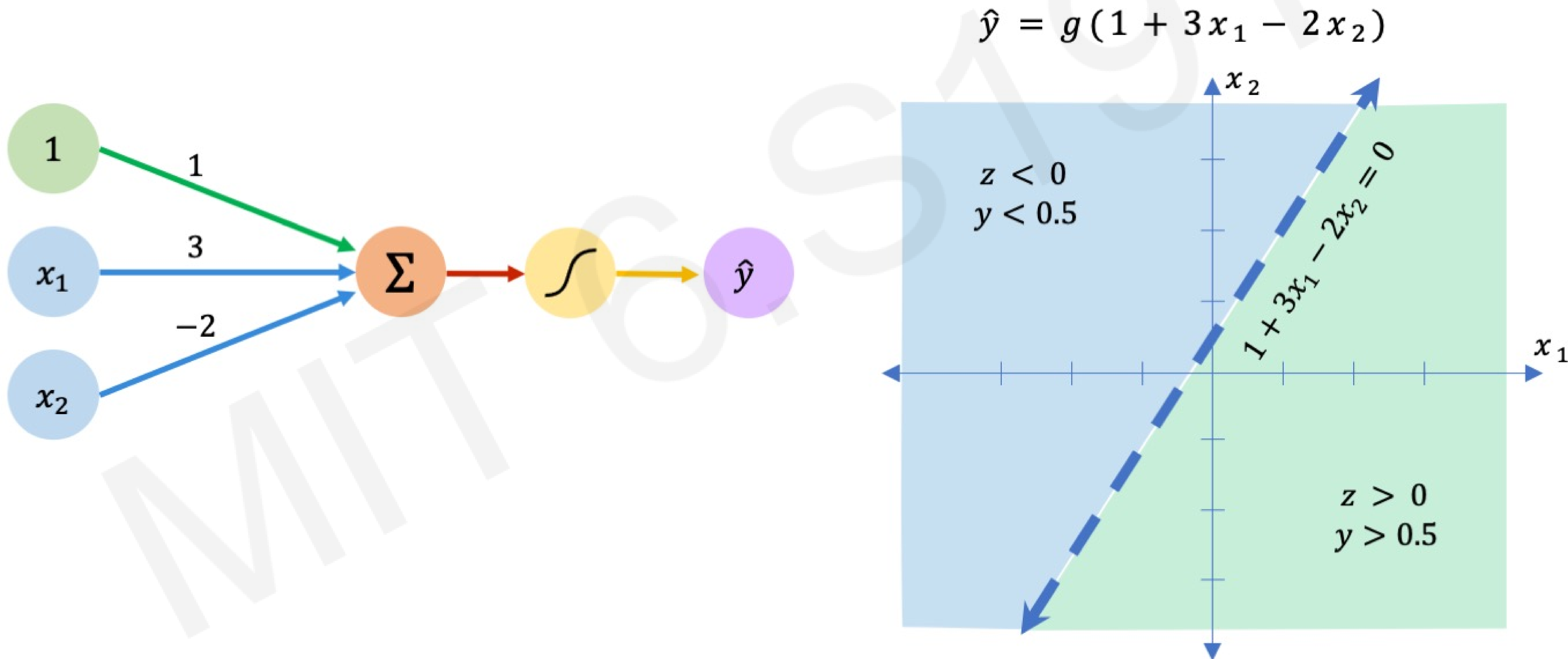


Assume we have input: $\mathbf{X} = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$

$$\begin{aligned}\hat{y} &= g(1 + (3 * -1) - (2 * 2)) \\ &= g(-6) \approx 0.002\end{aligned}$$



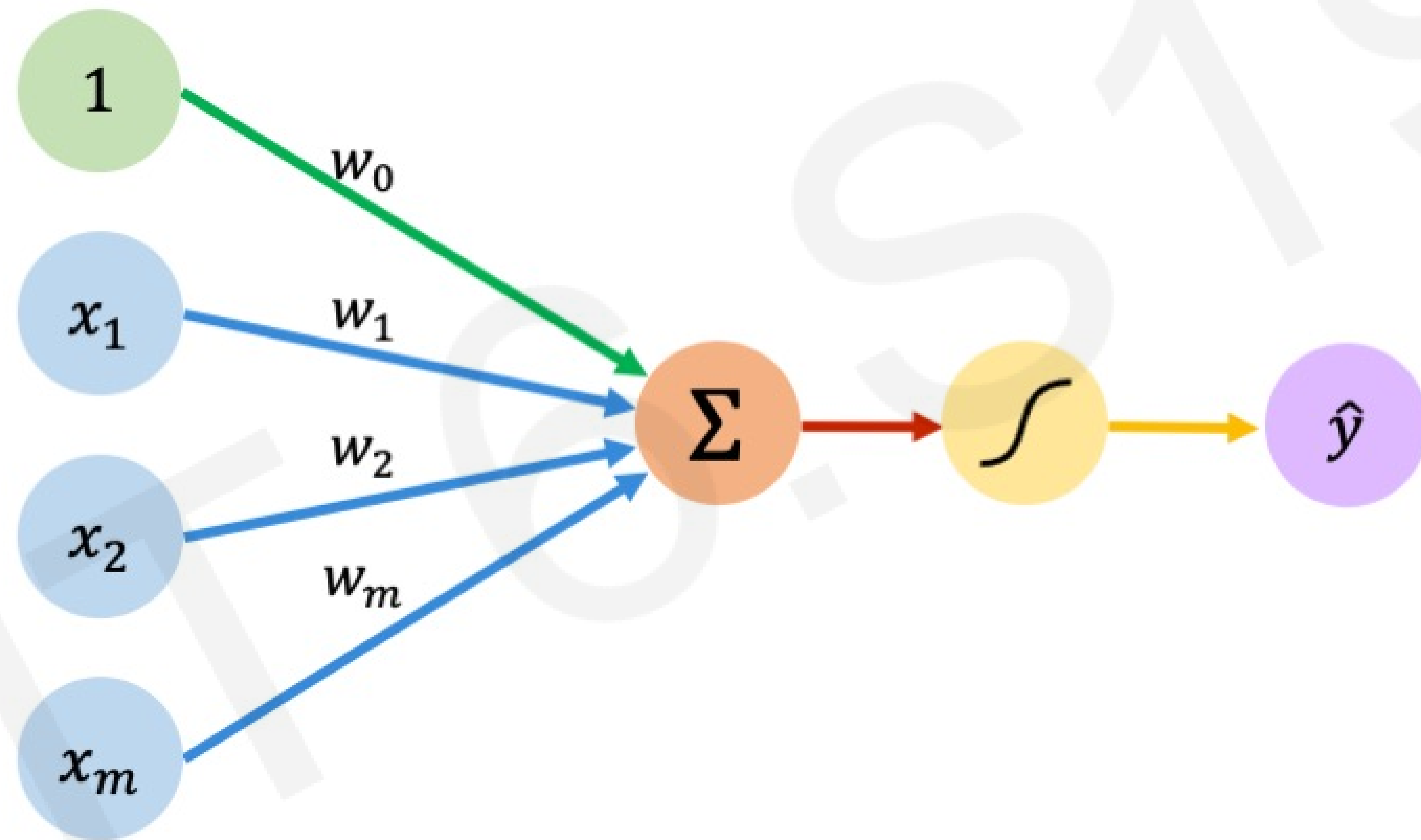
The Perceptron: Example



Building Neural Networks with Perceptrons

The Perceptron: Simplified

$$\hat{y} = g(w_0 + \mathbf{X}^T \mathbf{W})$$



Inputs

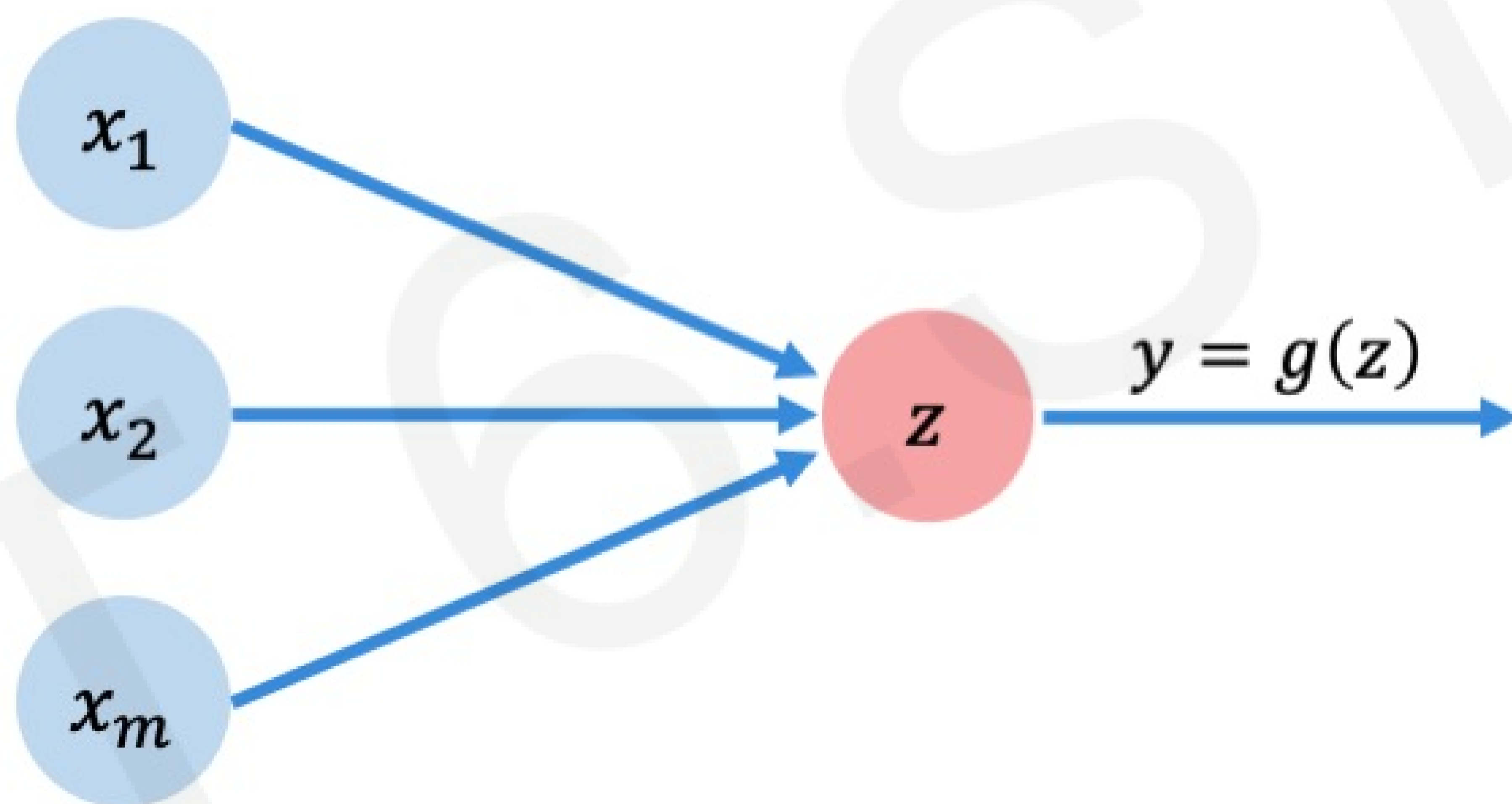
Weights

Sum

Non-Linearity

Output

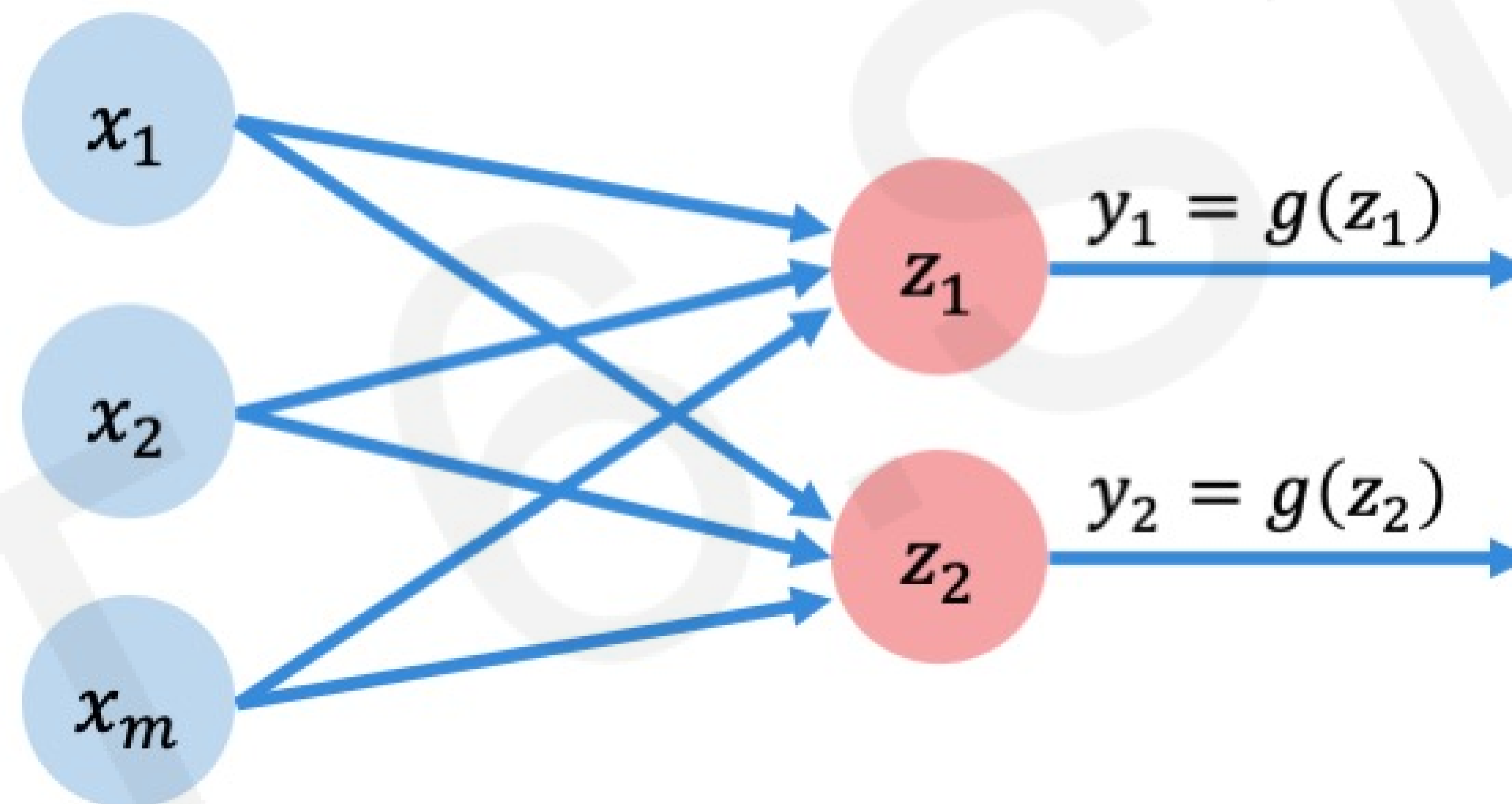
The Perceptron: Simplified



$$z = w_0 + \sum_{j=1}^m x_j w_j$$

Multi Output Perceptron

Because all inputs are densely connected to all outputs, these layers are called **Dense** layers



$$z_i = w_{0,i} + \sum_{j=1}^m x_j w_{j,i}$$

Dense layer from scratch



```
class MyDenseLayer(tf.keras.layers.Layer):
    def __init__(self, input_dim, output_dim):
        super(MyDenseLayer, self).__init__()

        # Initialize weights and bias
        self.W = self.add_weight([input_dim, output_dim])
        self.b = self.add_weight([1, output_dim])

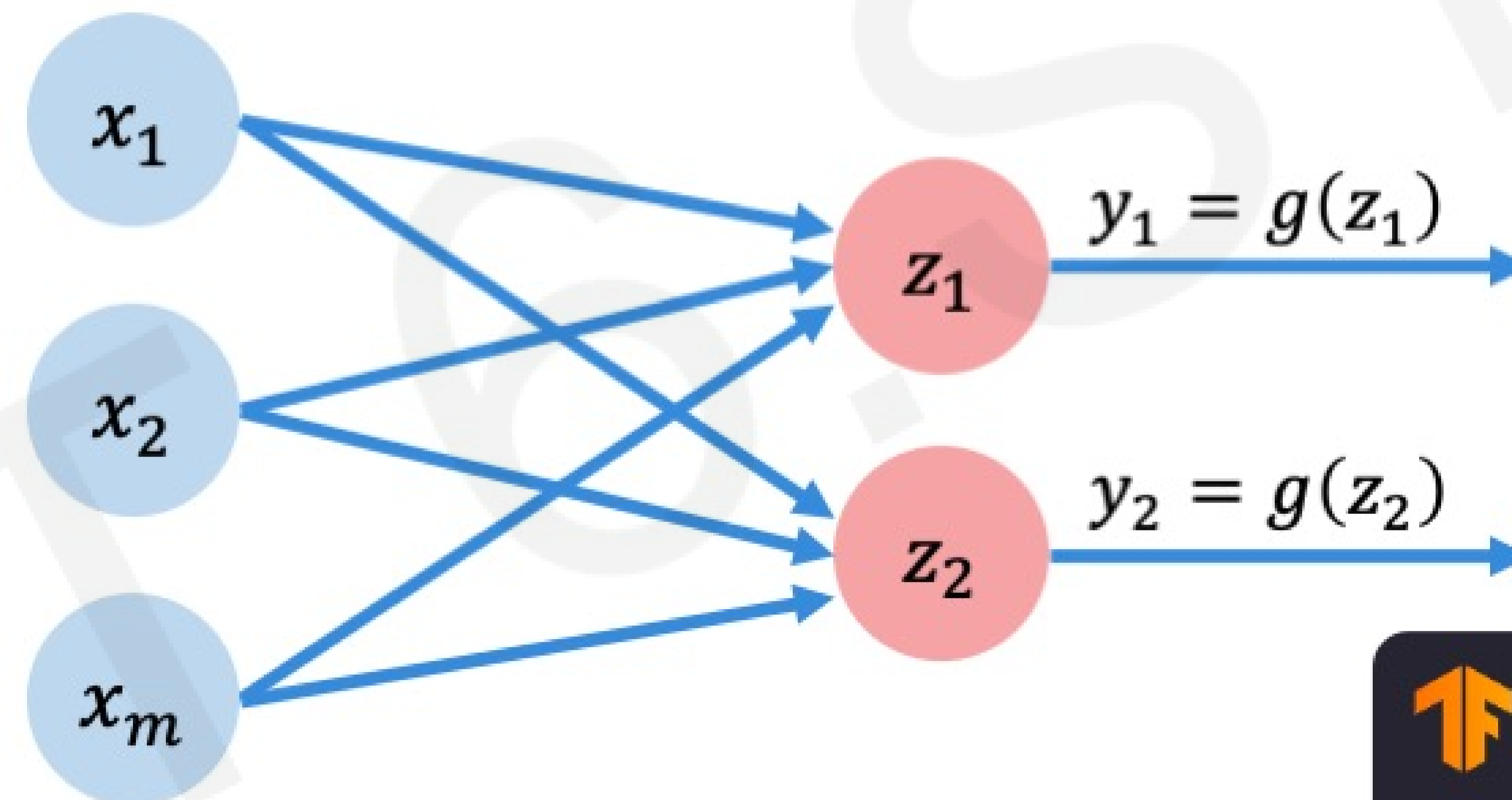
    def call(self, inputs):
        # Forward propagate the inputs
        z = tf.matmul(inputs, self.W) + self.b

        # Feed through a non-linear activation
        output = tf.math.sigmoid(z)

        return output
```

Multi Output Perceptron

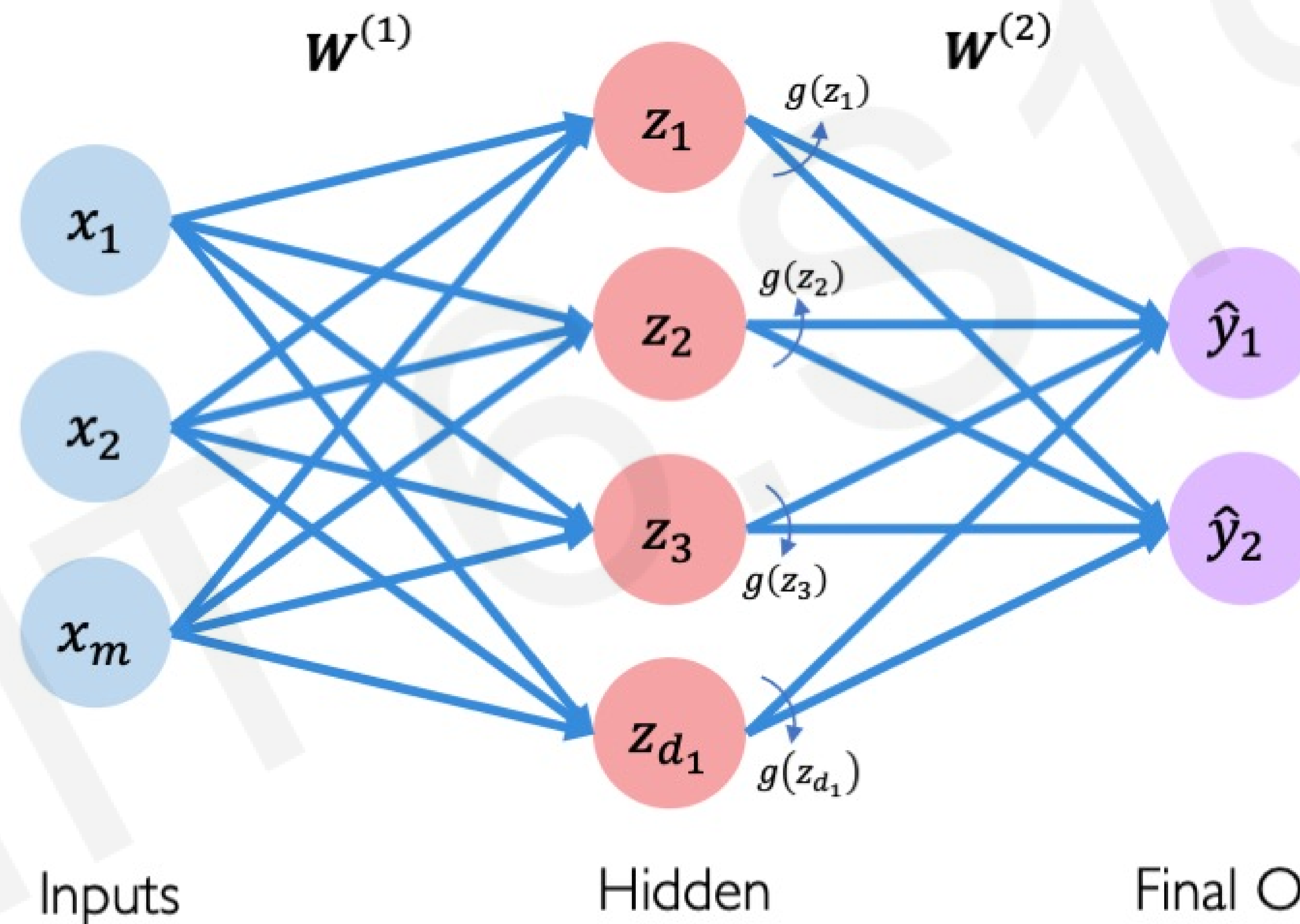
Because all inputs are densely connected to all outputs, these layers are called **Dense** layers



```
import tensorflow as tf  
  
layer = tf.keras.layers.Dense(  
    units=2)
```

$$z_i = w_{0,i} + \sum_{j=1}^m x_j w_{j,i}$$

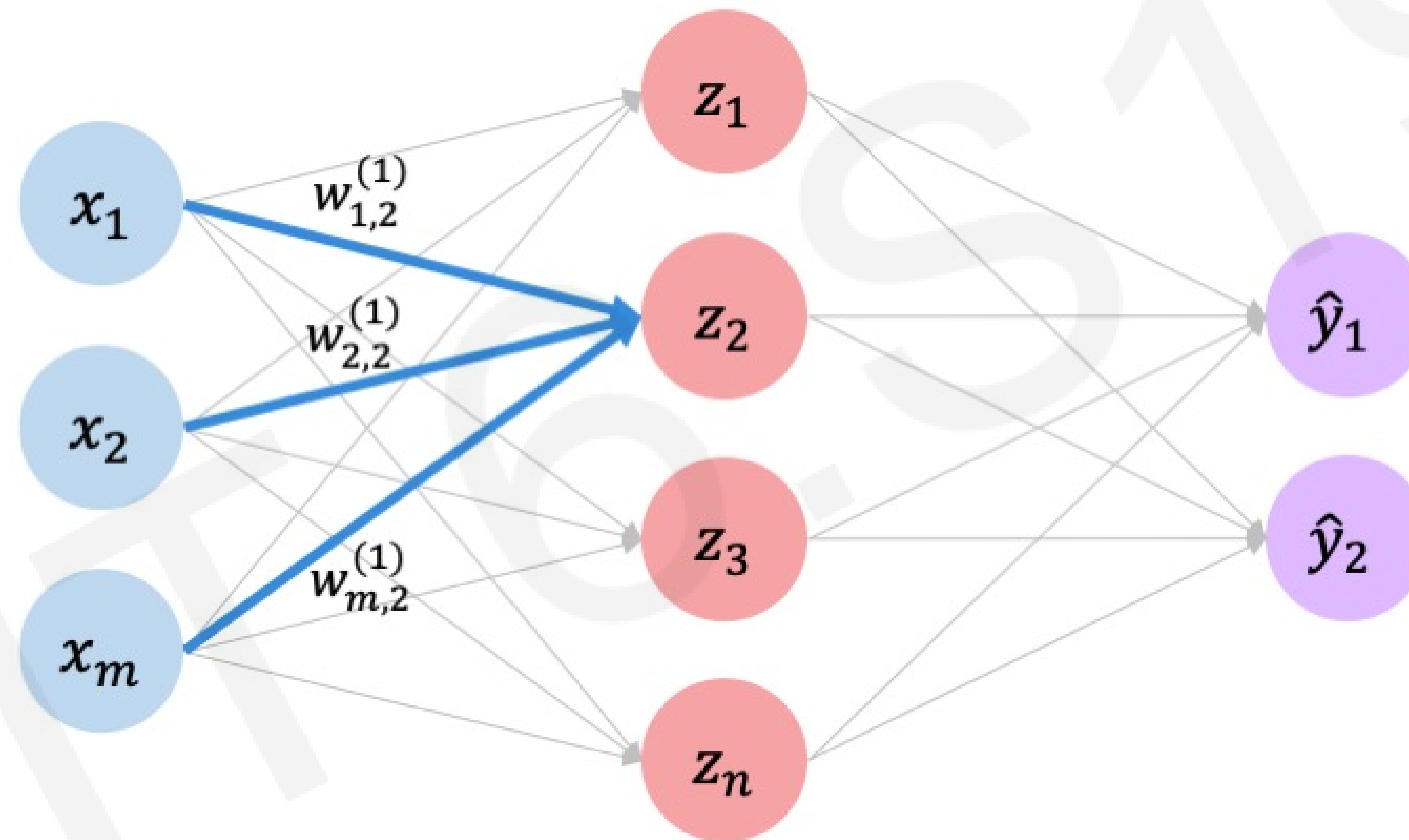
Single Layer Neural Network



$$z_i = w_{0,i}^{(1)} + \sum_{j=1}^m x_j w_{j,i}^{(1)}$$

$$\hat{y}_i = g \left(w_{0,i}^{(2)} + \sum_{j=1}^{d_1} g(z_j) w_{j,i}^{(2)} \right)$$

Single Layer Neural Network



$$\begin{aligned} z_2 &= w_{0,2}^{(1)} + \sum_{j=1}^m x_j w_{j,2}^{(1)} \\ &= w_{0,2}^{(1)} + x_1 w_{1,2}^{(1)} + x_2 w_{2,2}^{(1)} + x_m w_{m,2}^{(1)} \end{aligned}$$

Multi Output Perceptron

x_1

x_2

x_m

Inputs

\times

z_1

z_2

z_3

z_n

Hidden

\times

\hat{y}_1

\hat{y}_2

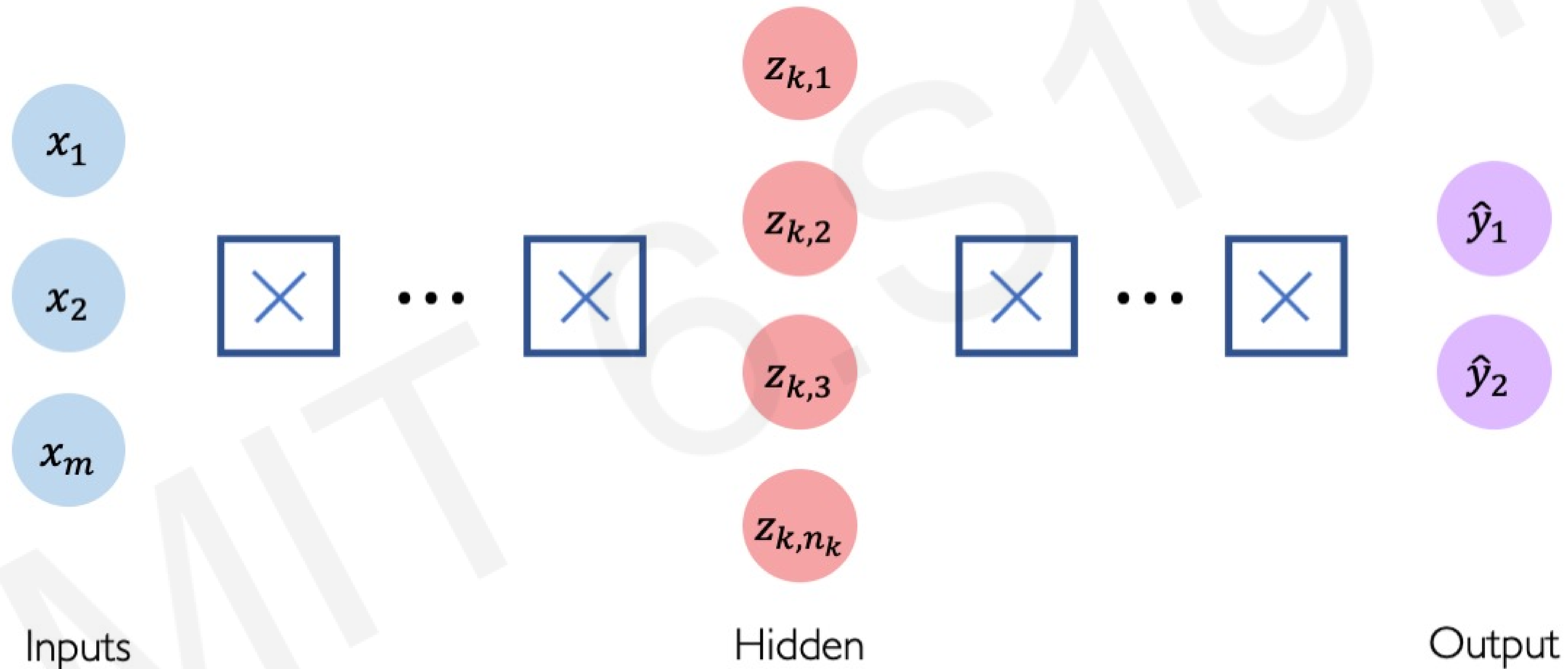
Output



```
import tensorflow as tf
```

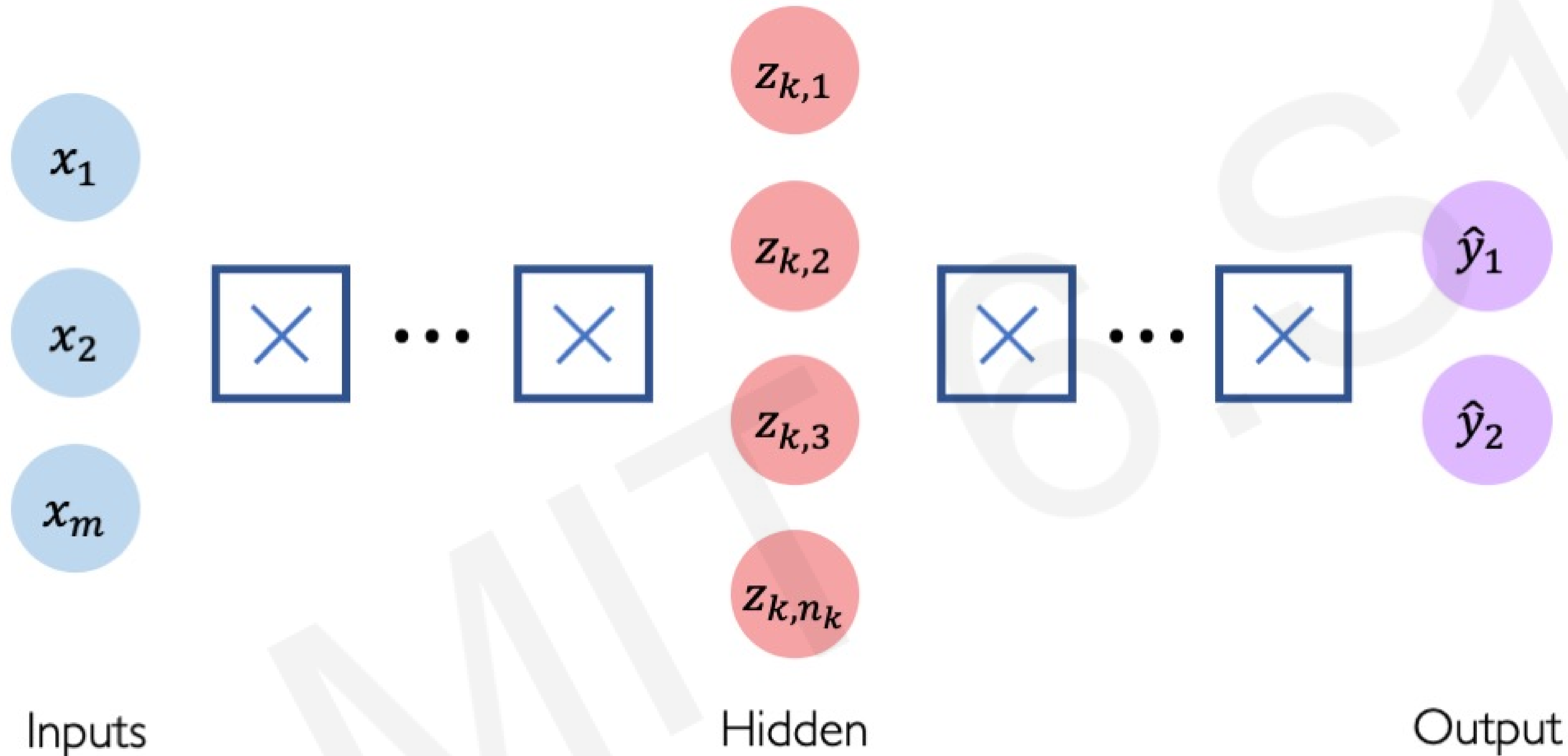
```
model = tf.keras.Sequential([  
    tf.keras.layers.Dense(n),  
    tf.keras.layers.Dense(2)  
])
```

Deep Neural Network



$$z_{k,i} = w_{0,i}^{(k)} + \sum_{j=1}^{n_{k-1}} g(z_{k-1,j}) w_{j,i}^{(k)}$$

Deep Neural Network



```
↑  
import tensorflow as tf  
  
model = tf.keras.Sequential([  
    tf.keras.layers.Dense(n1),  
    tf.keras.layers.Dense(n2),  
    :  
    tf.keras.layers.Dense(2)  
])
```

$$z_{k,i} = w_{0,i}^{(k)} + \sum_{j=1}^{n_{k-1}} g(z_{k-1,j}) w_{j,i}^{(k)}$$

Applying Neural Networks

Example Problem

Will I pass this class?

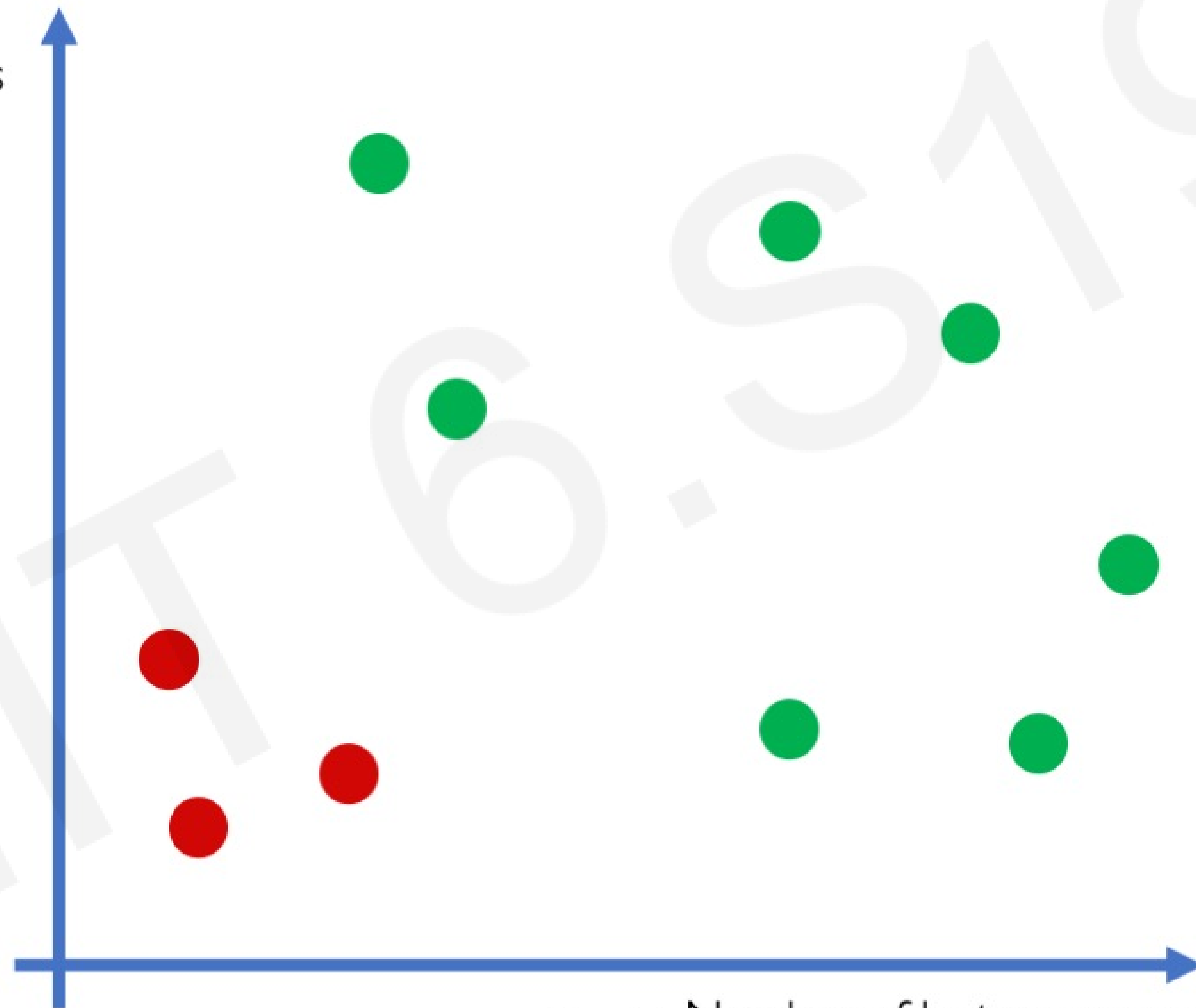
Let's start with a simple two feature model

x_1 = Number of lectures you attend

x_2 = Hours spent on the final project

Example Problem: Will I pass this class?

x_2 = Hours spent on the final project



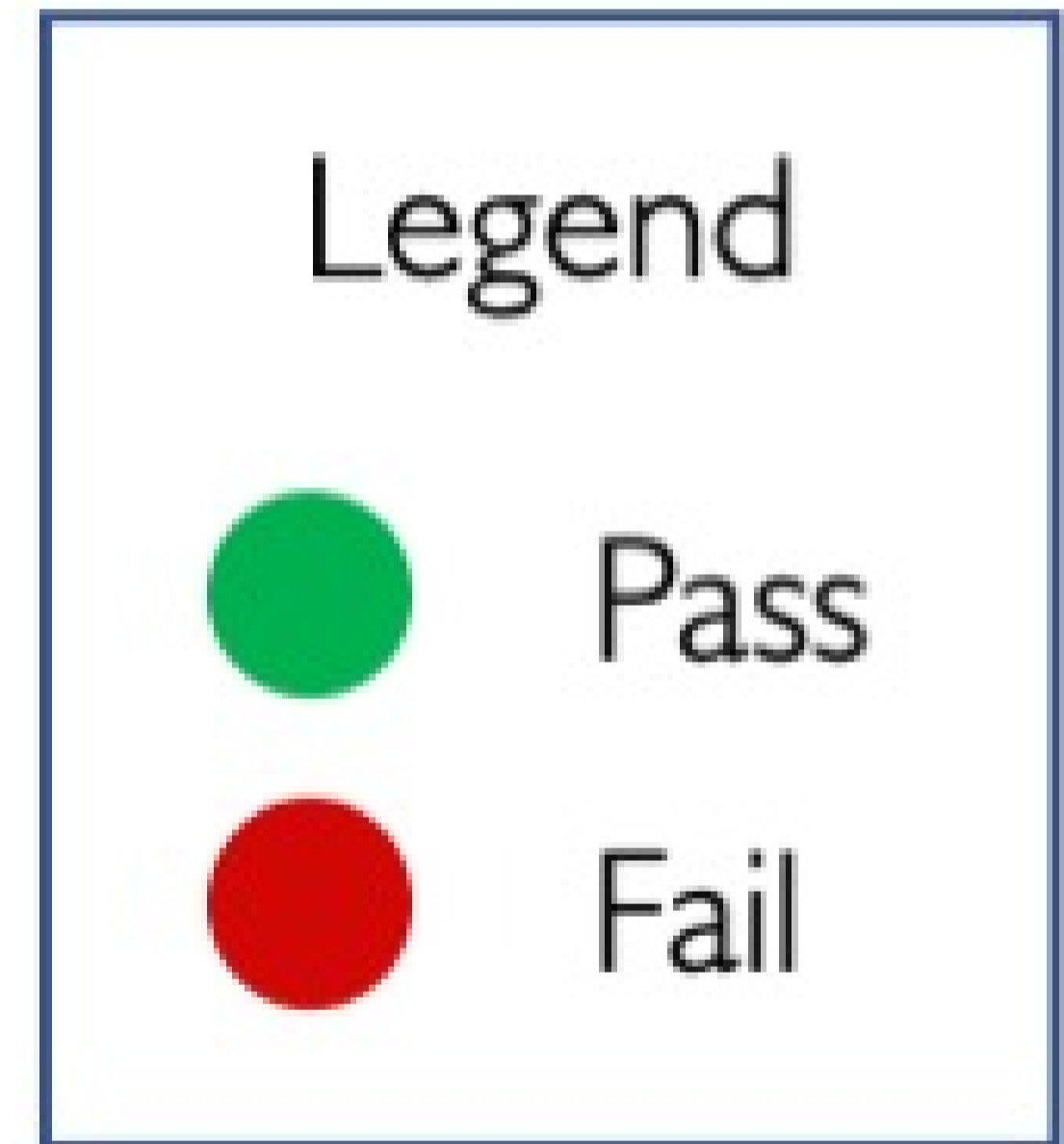
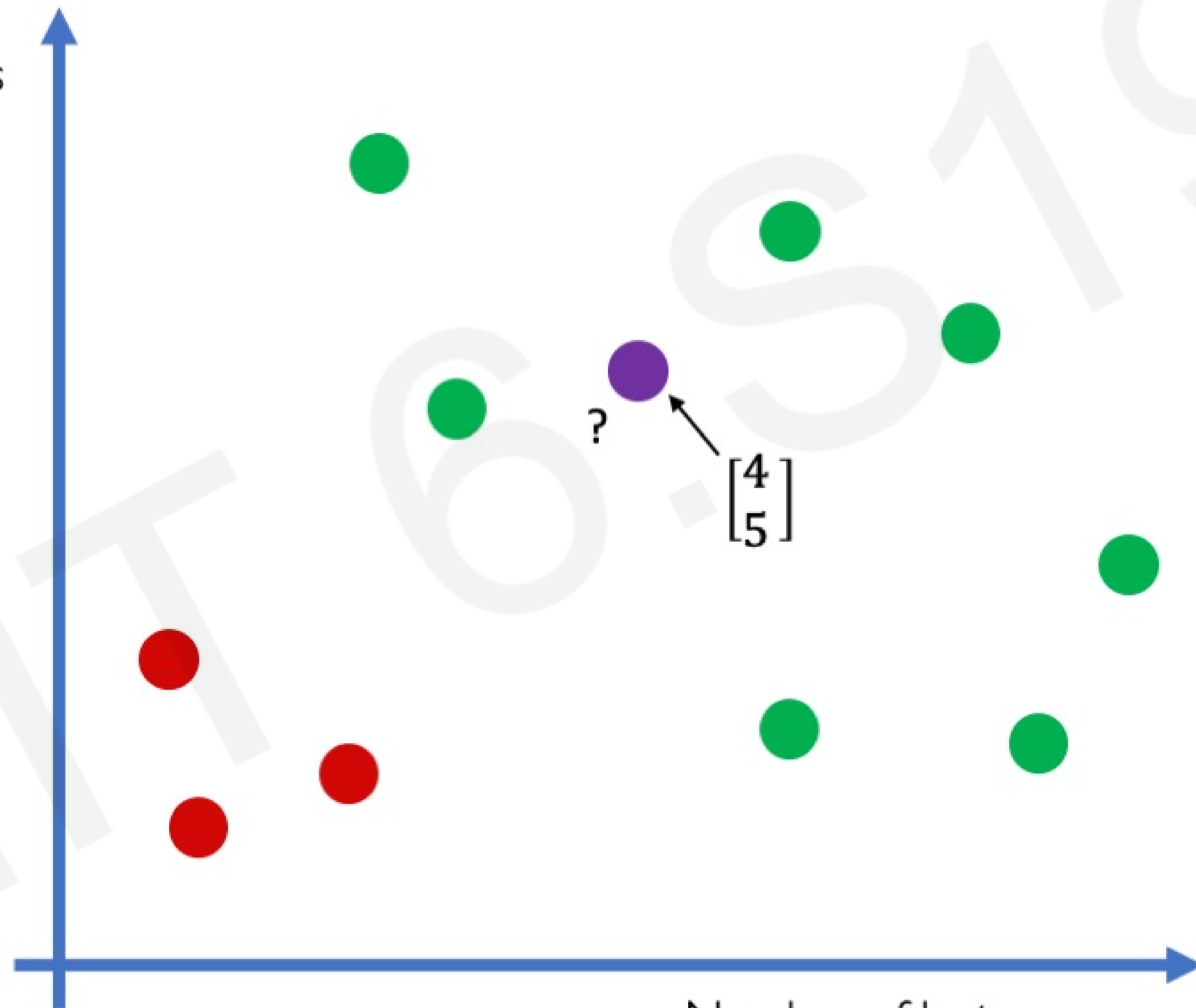
x_1 = Number of lectures you attend

Legend

- Pass
- Fail

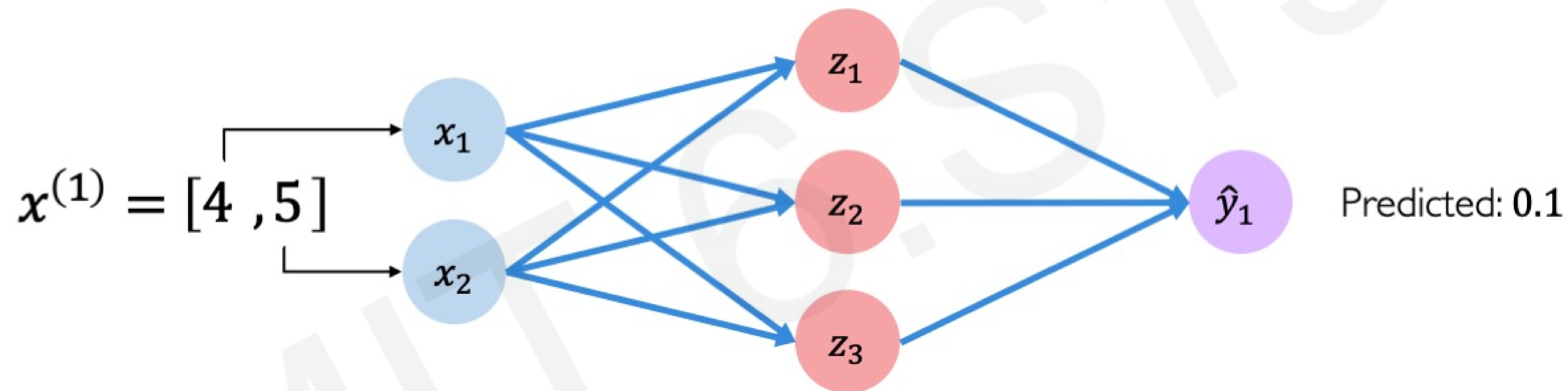
Example Problem: Will I pass this class?

x_2 = Hours spent on the final project

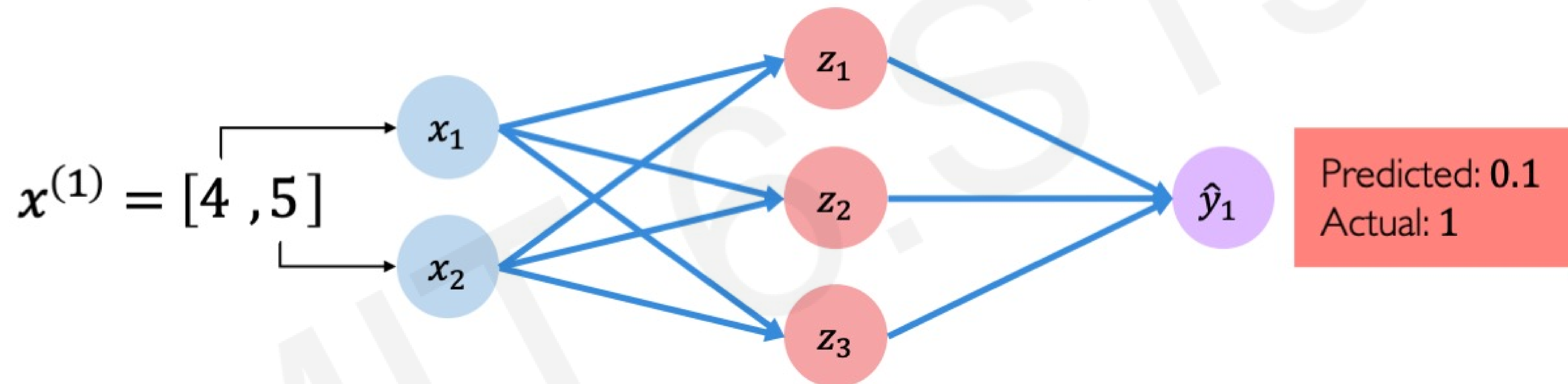


x_1 = Number of lectures you attend

Example Problem: Will I pass this class?

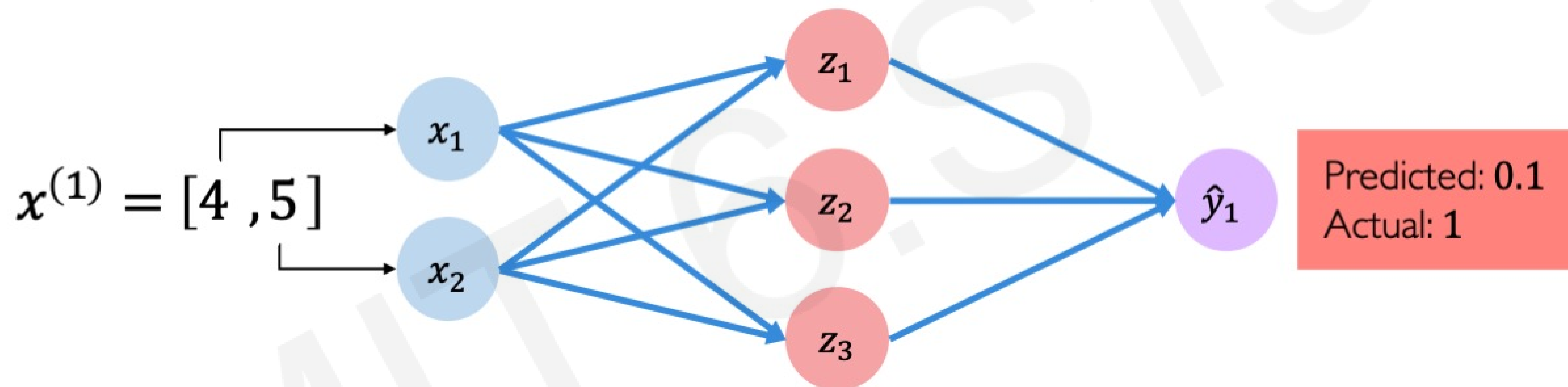


Example Problem: Will I pass this class?



Quantifying Loss

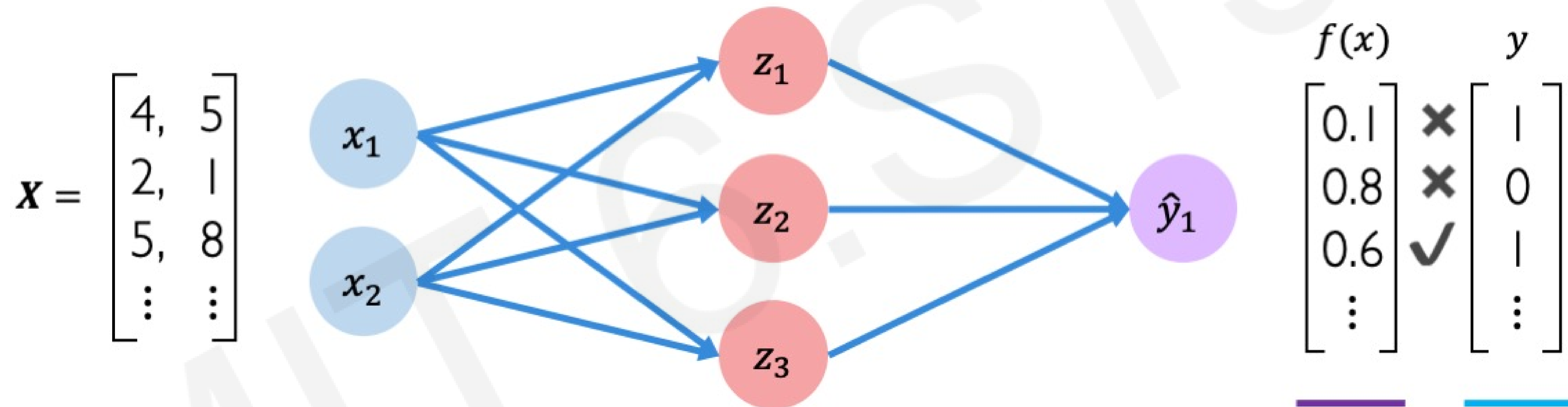
The **loss** of our network measures the cost incurred from incorrect predictions



$$\mathcal{L}(\underbrace{f(x^{(i)}; \mathbf{W})}_{\text{Predicted}}, \underbrace{y^{(i)}}_{\text{Actual}})$$

Empirical Loss

The **empirical loss** measures the total loss over our entire dataset



- Also known as:
- Objective function
 - Cost function
 - Empirical Risk

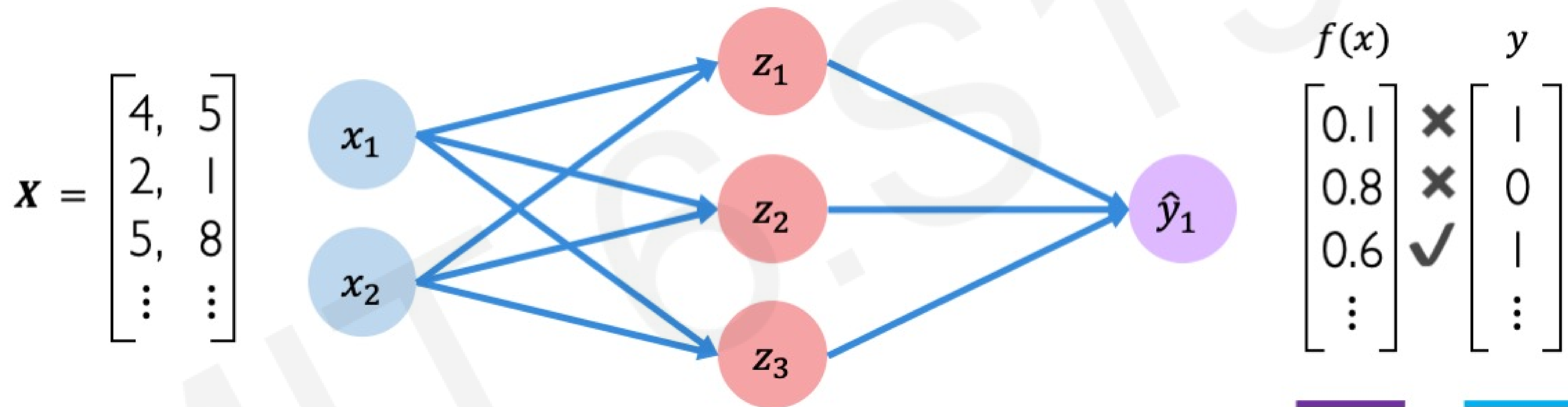
$$J(\mathbf{W}) = \frac{1}{n} \sum_{i=1}^n \mathcal{L}(\underbrace{f(x^{(i)}; \mathbf{W})}_{\text{Predicted}}, \underbrace{y^{(i)}}_{\text{Actual}})$$

Predicted

Actual

Binary Cross Entropy Loss

Cross entropy loss can be used with models that output a probability between 0 and 1



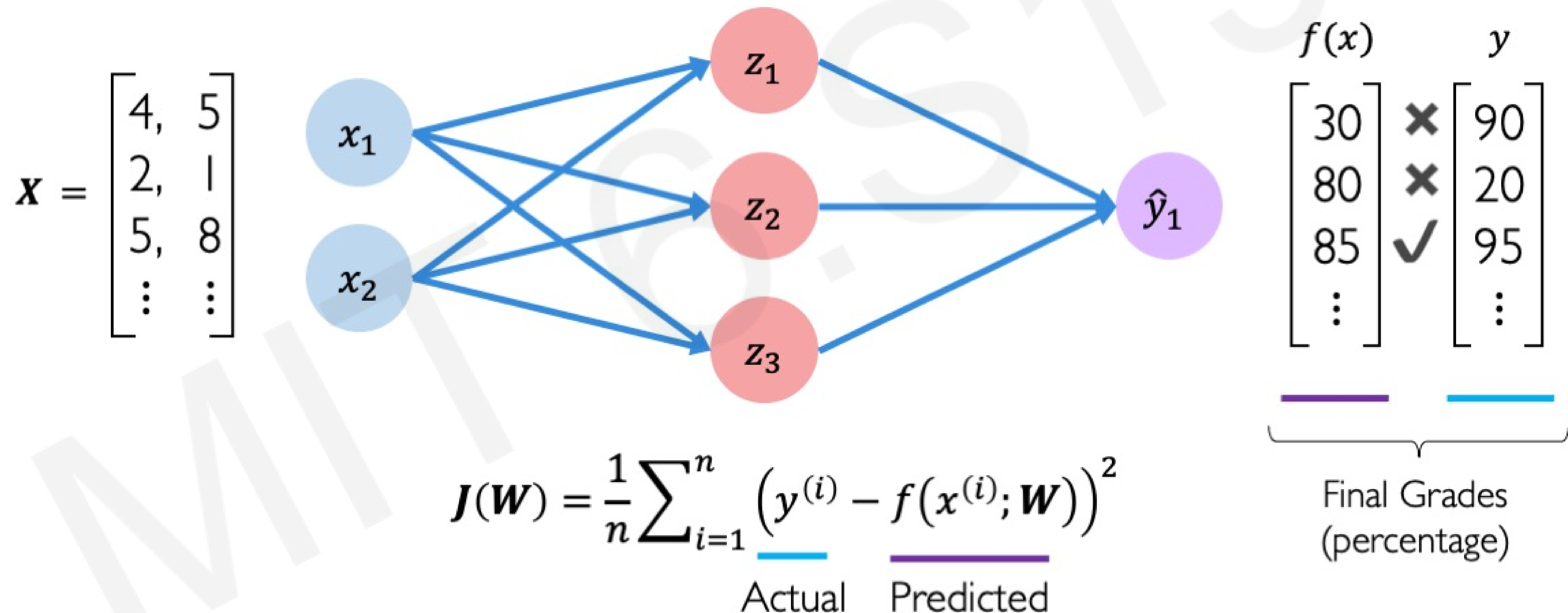
$$J(\mathbf{W}) = -\frac{1}{n} \sum_{i=1}^n \underbrace{y^{(i)}}_{\text{Actual}} \log \left(\underbrace{f(x^{(i)}; \mathbf{W})}_{\text{Predicted}} \right) + (1 - \underbrace{y^{(i)}}_{\text{Actual}}) \log \left(1 - \underbrace{f(x^{(i)}; \mathbf{W})}_{\text{Predicted}} \right)$$



```
loss = tf.reduce_mean( tf.nn.softmax_cross_entropy_with_logits(y, predicted) )
```

Mean Squared Error Loss

Mean squared error loss can be used with regression models that output continuous real numbers



```
loss = tf.reduce_mean( tf.square(tf.subtract(y, predicted)) )  
loss = tf.keras.losses.MSE( y, predicted )
```

Training Neural Networks

Loss Optimization

We want to find the network weights that *achieve the lowest loss*

$$\mathbf{W}^* = \operatorname{argmin}_{\mathbf{W}} \frac{1}{n} \sum_{i=1}^n \mathcal{L}(f(x^{(i)}; \mathbf{W}), y^{(i)})$$

$$\mathbf{W}^* = \operatorname{argmin}_{\mathbf{W}} J(\mathbf{W})$$

Loss Optimization

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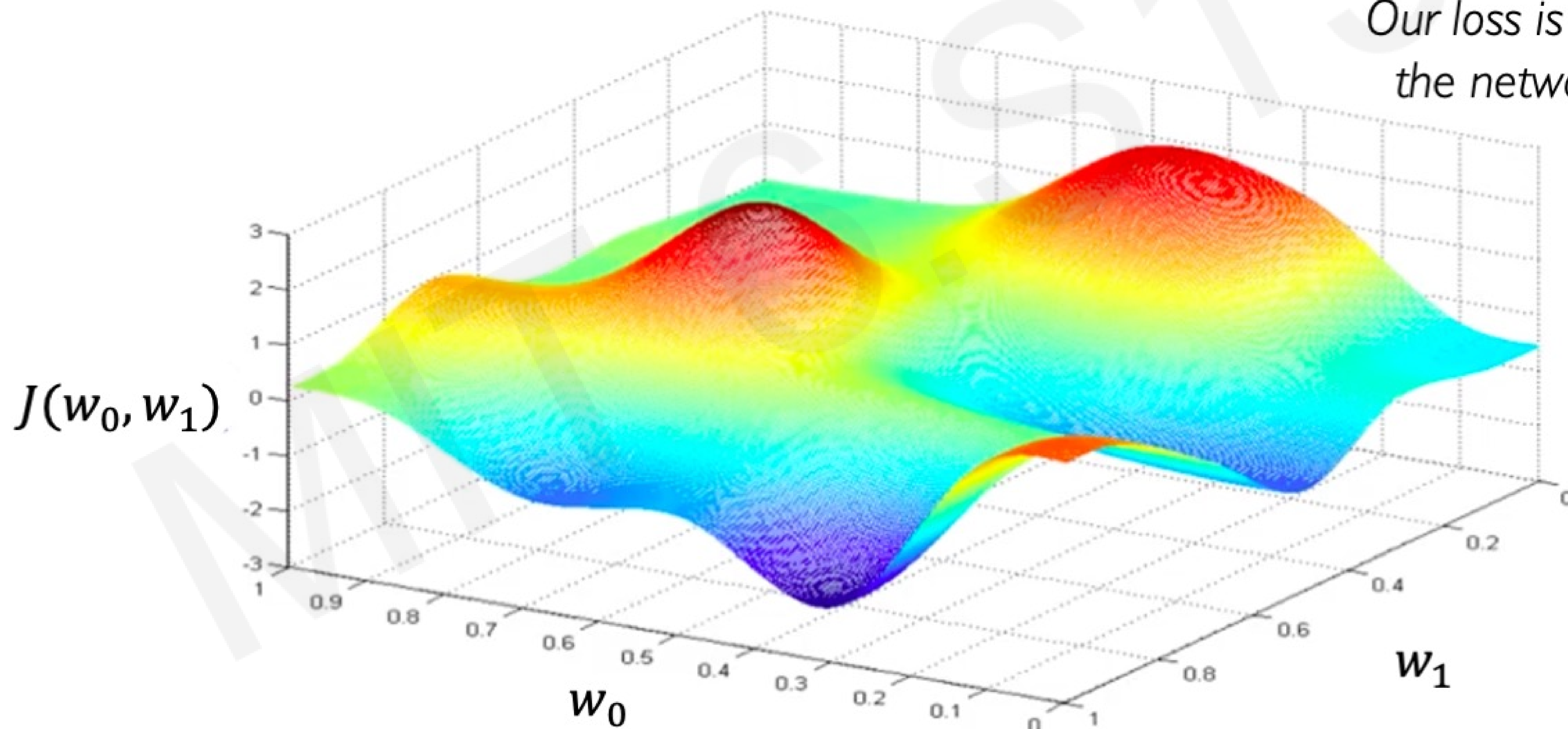
Remember:

$$\mathbf{W} = \{\mathbf{W}^{(0)}, \mathbf{W}^{(1)}, \dots\}$$

Loss Optimization

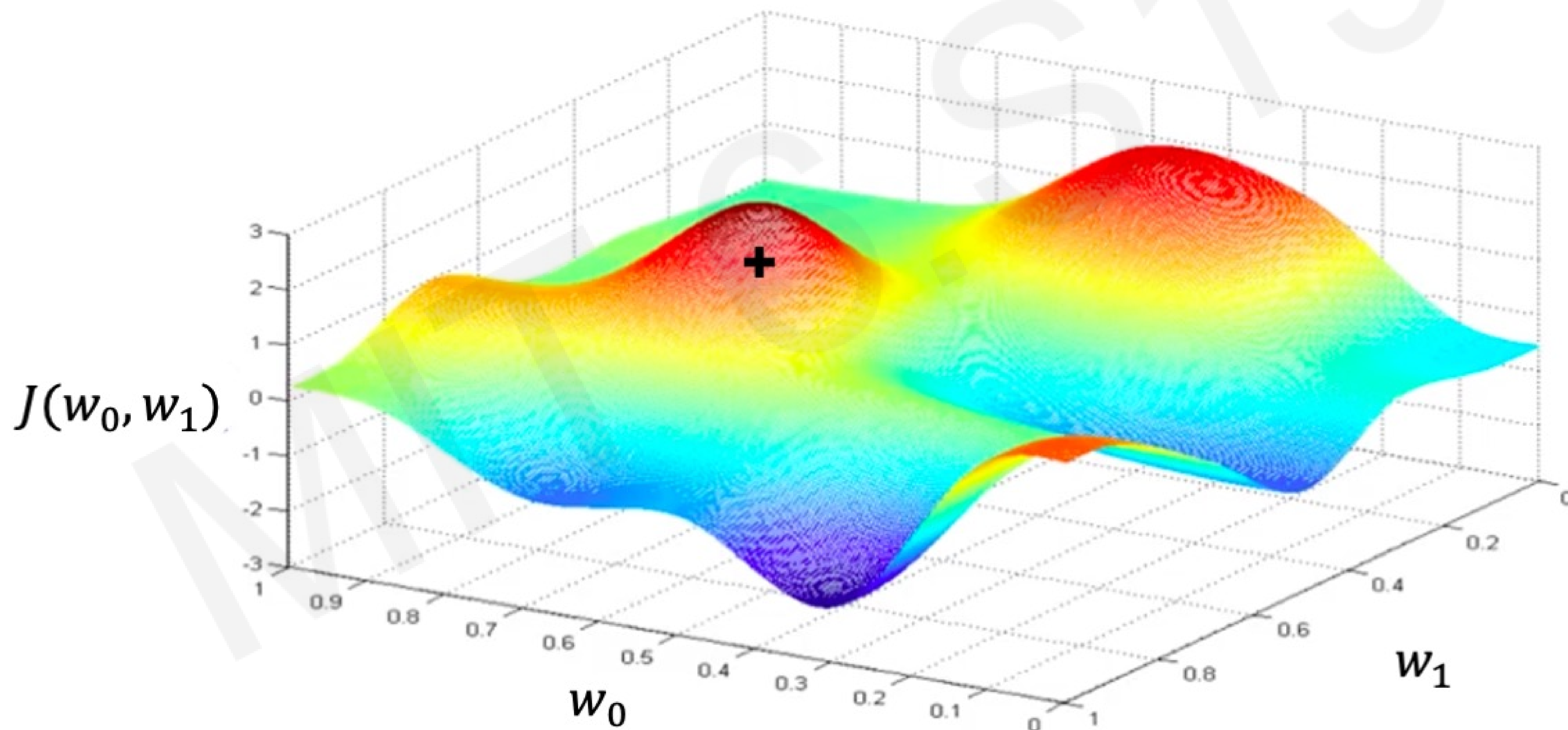
$$W^* = \operatorname{argmin}_W J(W)$$

Remember:
*Our loss is a function of
the network weights!*



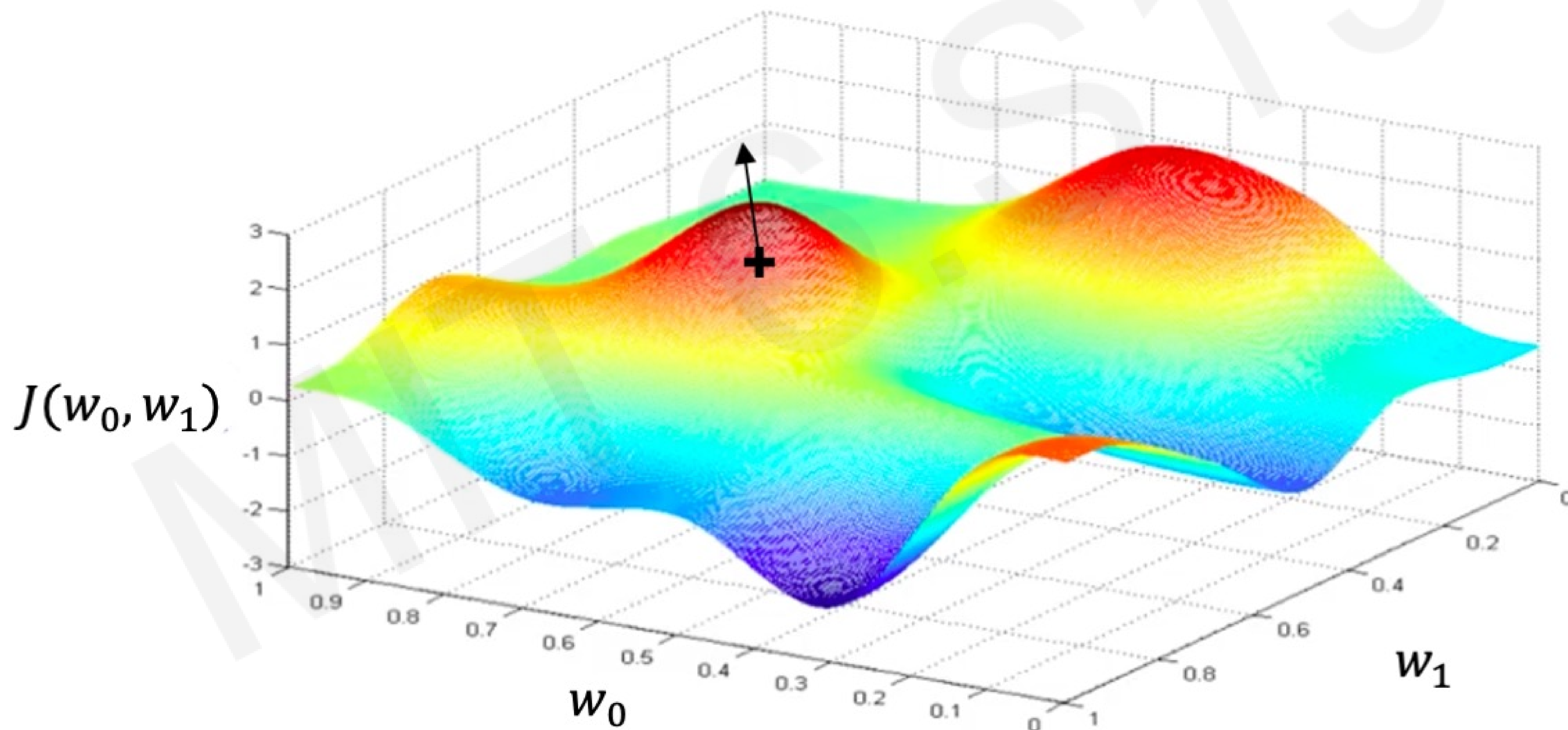
Loss Optimization

Randomly pick an initial (w_0, w_1)



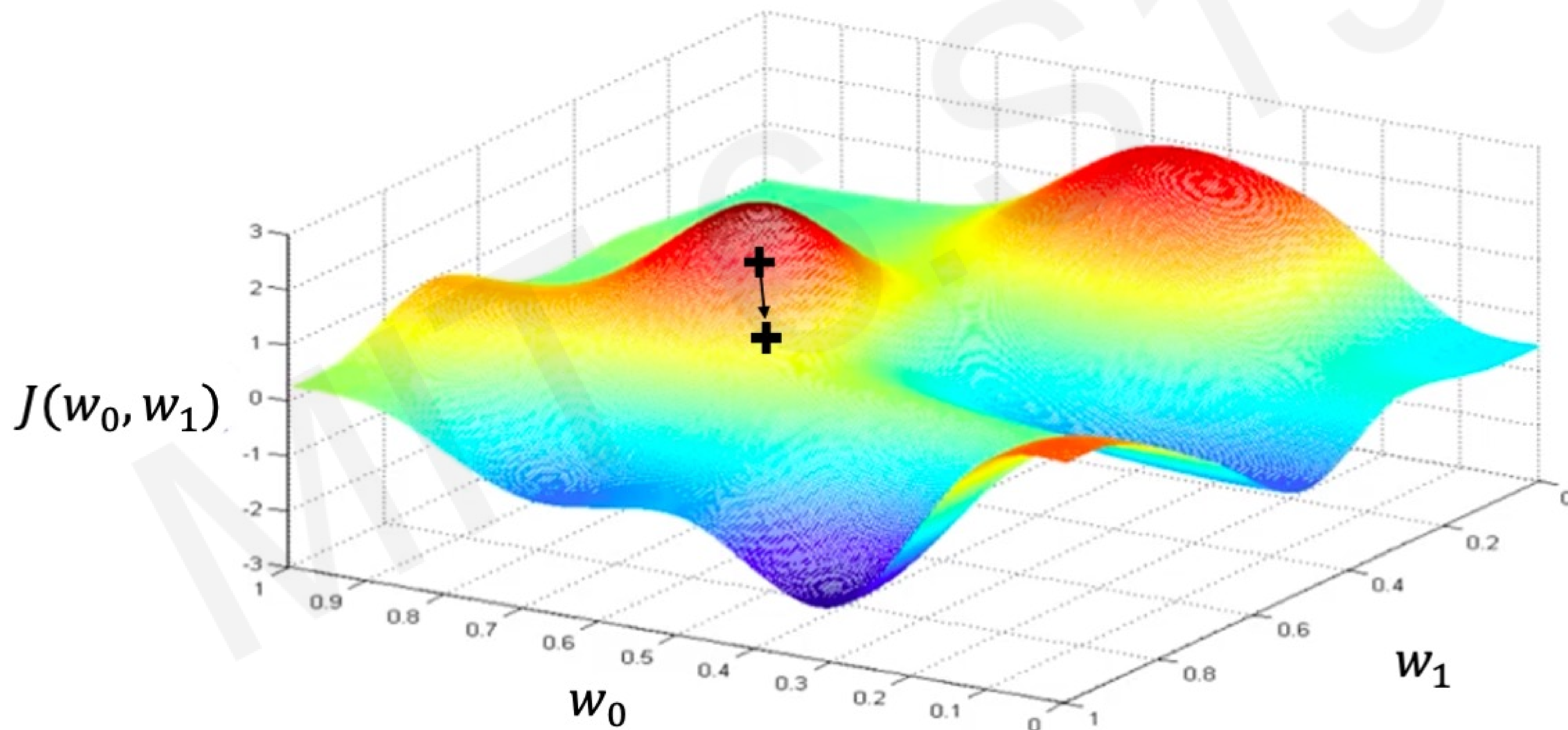
Loss Optimization

Compute gradient, $\frac{\partial J(W)}{\partial W}$



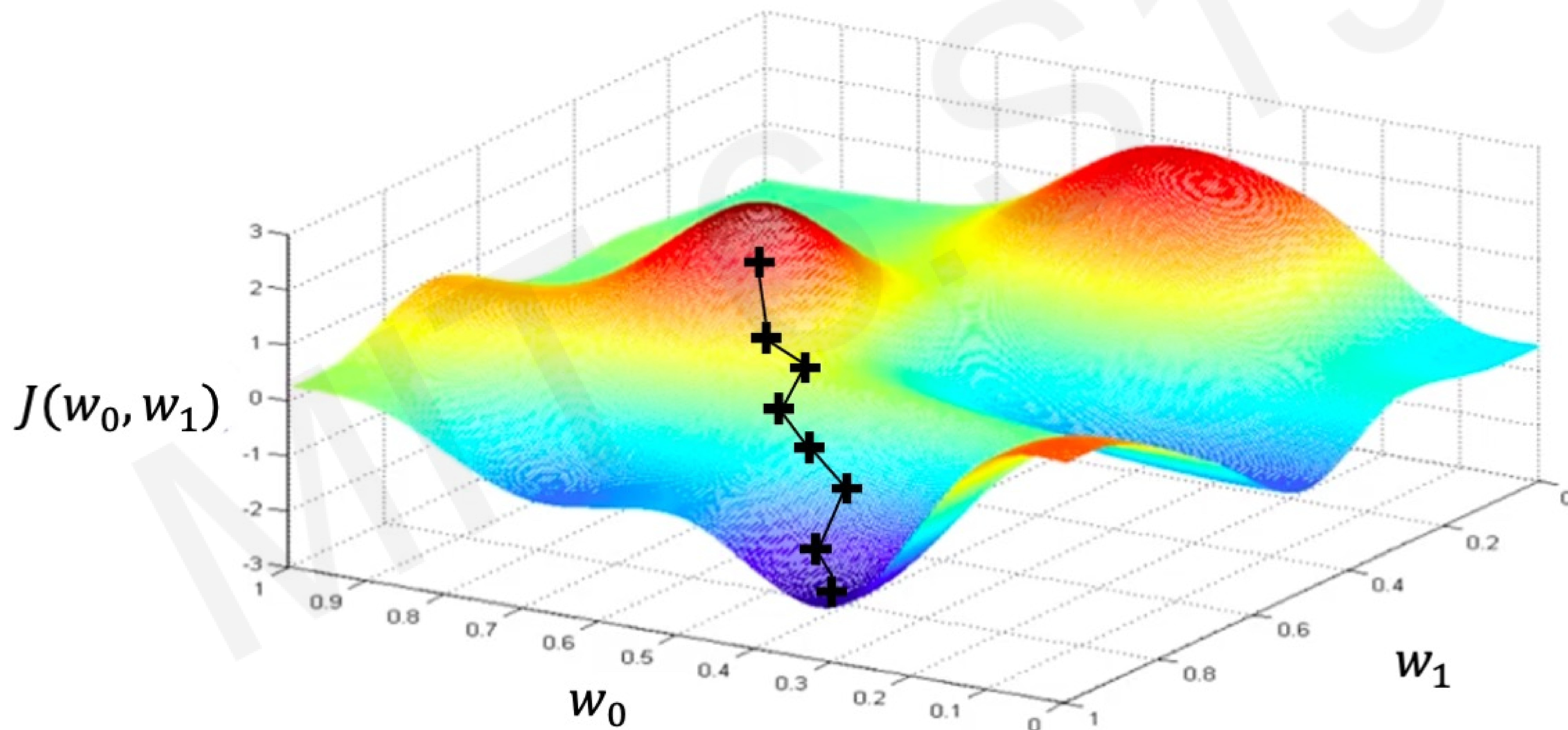
Loss Optimization

Take small step in opposite direction of gradient



Gradient Descent

Repeat until convergence



Gradient Descent

Algorithm

1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
4. Update weights, $\mathbf{W} \leftarrow \mathbf{W} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
5. Return weights

Gradient Descent



Algorithm

1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(W)}{\partial W}$
4. Update weights, $\mathbf{W} \leftarrow \mathbf{W} - \eta \frac{\partial J(W)}{\partial W}$
5. Return weights

```
import tensorflow as tf

weights = tf.Variable([tf.random.normal()])

while True: # loop forever
    with tf.GradientTape() as g:
        loss = compute_loss(weights)
        gradient = g.gradient(loss, weights)

    weights = weights - lr * gradient
```



Gradient Descent

Algorithm

1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(W)}{\partial W}$
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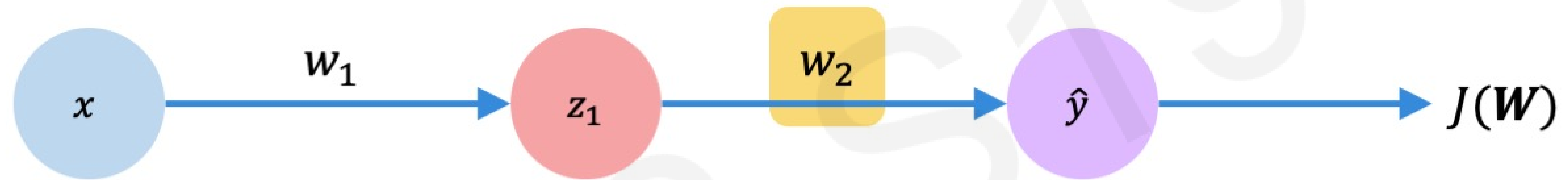
    weights = weights - lr * gradient
```

Computing Gradients: Backpropagation



How does a small change in one weight (ex. w_2) affect the final loss $J(\mathbf{W})$?

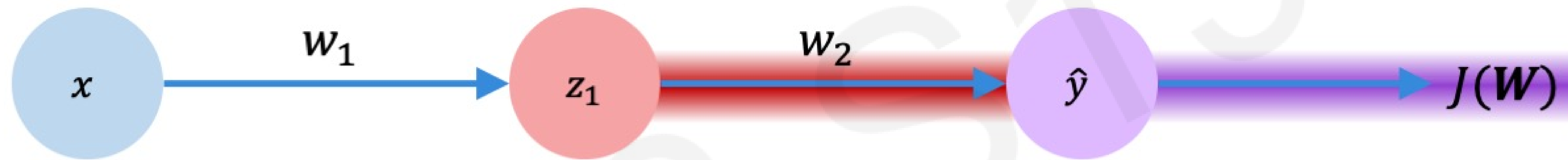
Computing Gradients: Backpropagation



$$\frac{\partial J(W)}{\partial w_2} =$$

Let's use the chain rule!

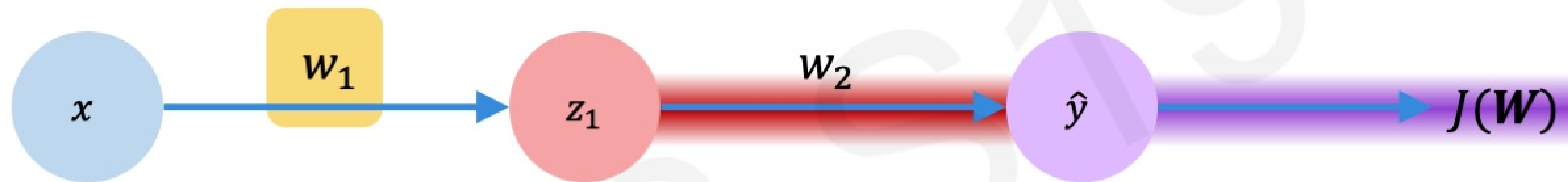
Computing Gradients: Backpropagation



$$\frac{\partial J(W)}{\partial w_2} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial w_2}$$

The equation shows the chain rule for backpropagation. The term $\frac{\partial J(W)}{\partial \hat{y}}$ is underlined in purple, and $\frac{\partial \hat{y}}{\partial w_2}$ is underlined in red.

Computing Gradients: Backpropagation

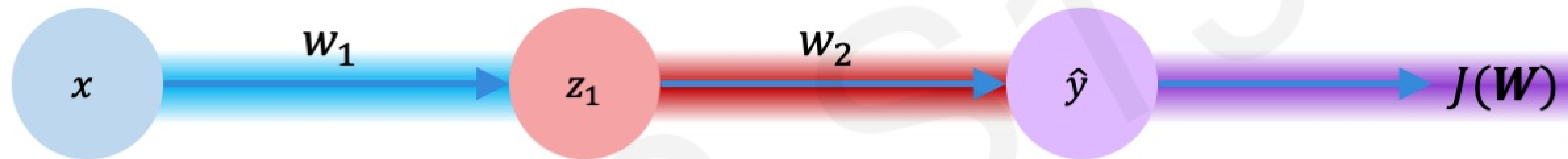


$$\frac{\partial J(W)}{\partial w_1} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial w_1}$$

Apply chain rule!

Apply chain rule!

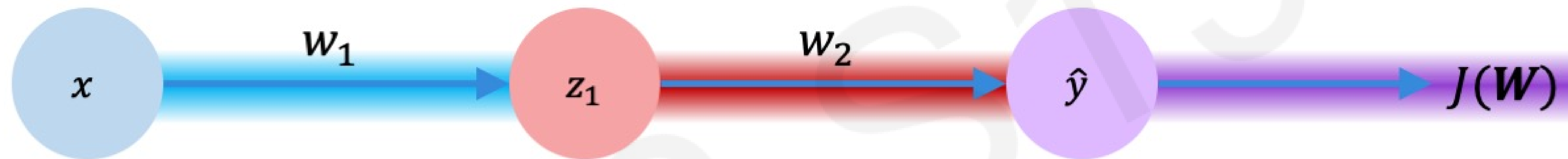
Computing Gradients: Backpropagation



$$\frac{\partial J(W)}{\partial w_1} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial z_1} * \frac{\partial z_1}{\partial w_1}$$

The terms in the equation are color-coded: $\frac{\partial J(W)}{\partial \hat{y}}$ is purple, $\frac{\partial \hat{y}}{\partial z_1}$ is red, and $\frac{\partial z_1}{\partial w_1}$ is blue.

Computing Gradients: Backpropagation



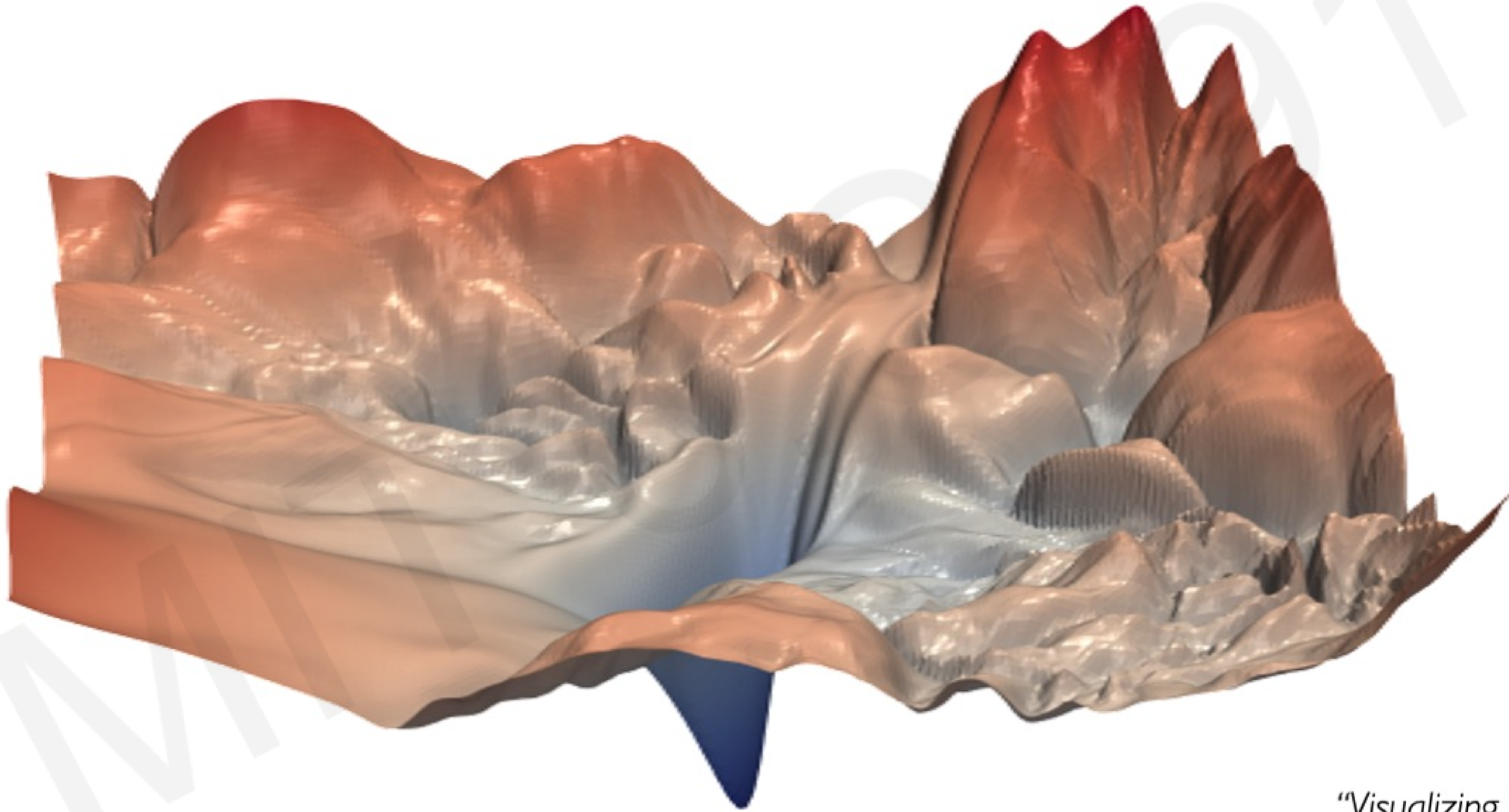
$$\frac{\partial J(W)}{\partial w_1} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial z_1} * \frac{\partial z_1}{\partial w_1}$$

(Purple bar under $\frac{\partial J(W)}{\partial \hat{y}}$, Red bar under $\frac{\partial \hat{y}}{\partial z_1}$, Blue bar under $\frac{\partial z_1}{\partial w_1}$)

Repeat this for **every weight in the network** using gradients from later layers

Neural Networks in Practice: Optimization

Training Neural Networks is Difficult



"Visualizing the loss landscape of neural nets". Dec 2017.

Loss Functions Can Be Difficult to Optimize

Remember:

Optimization through gradient descent

$$\mathbf{W} \leftarrow \mathbf{W} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$$

Loss Functions Can Be Difficult to Optimize

Remember:

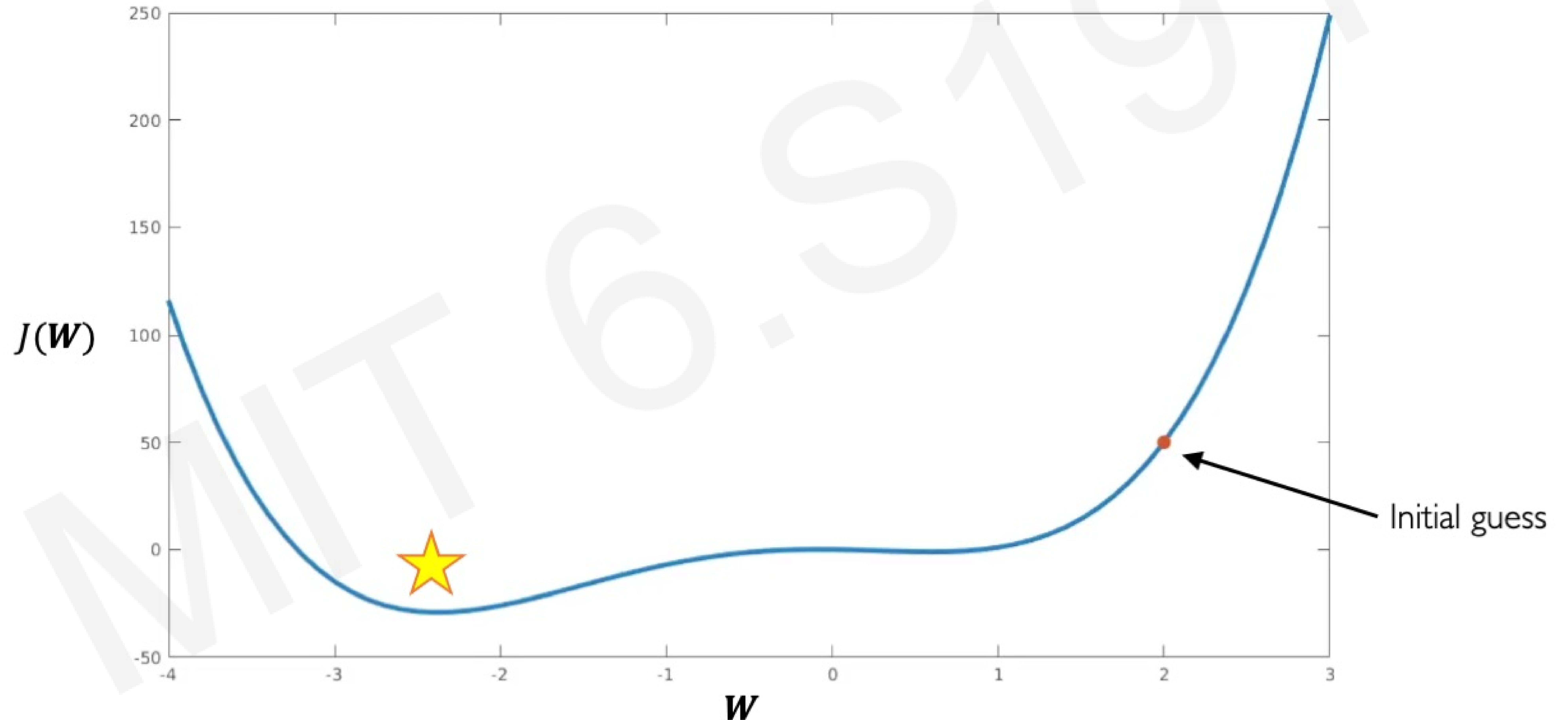
Optimization through gradient descent

$$\mathbf{W} \leftarrow \mathbf{W} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$$

How can we set the learning rate?

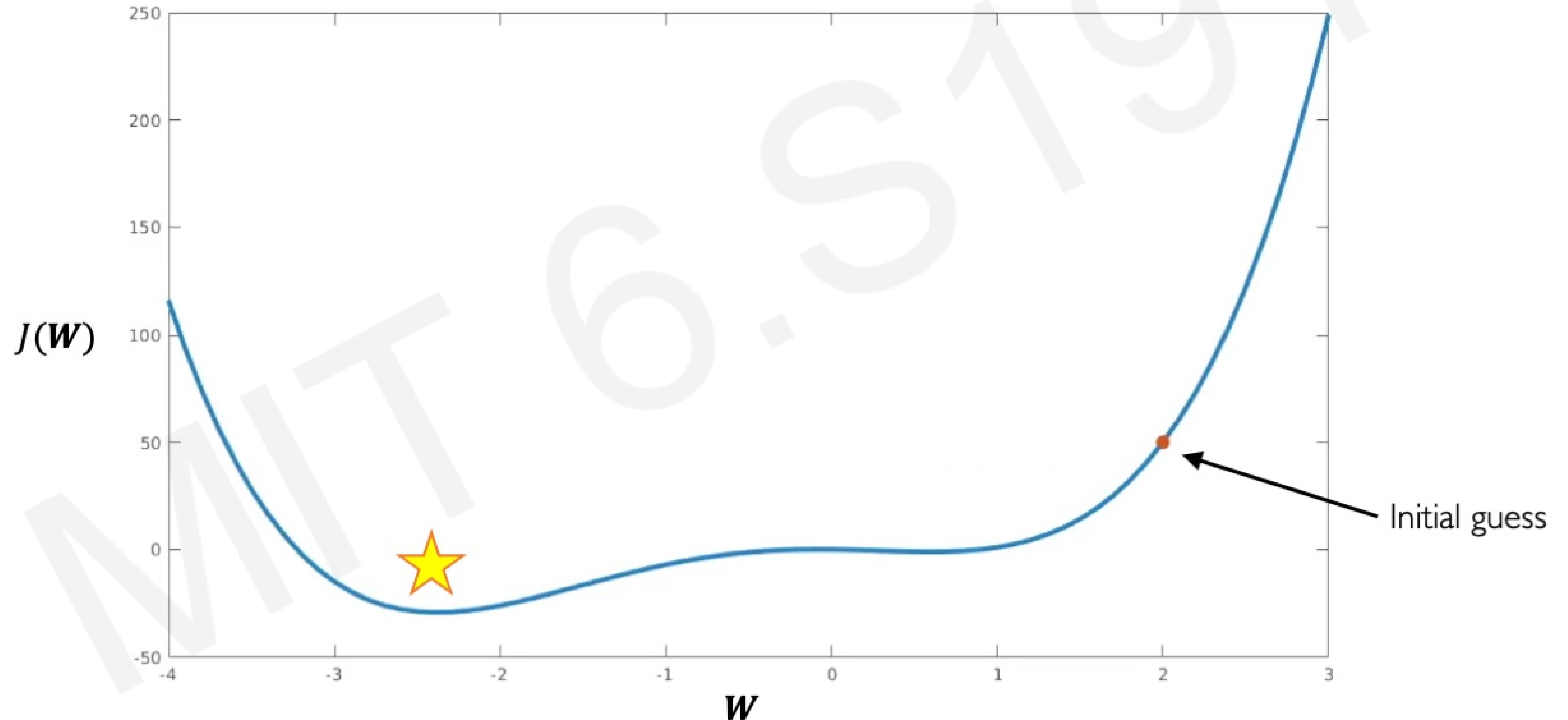
Setting the Learning Rate

Small learning rate converges slowly and gets stuck in false local minima



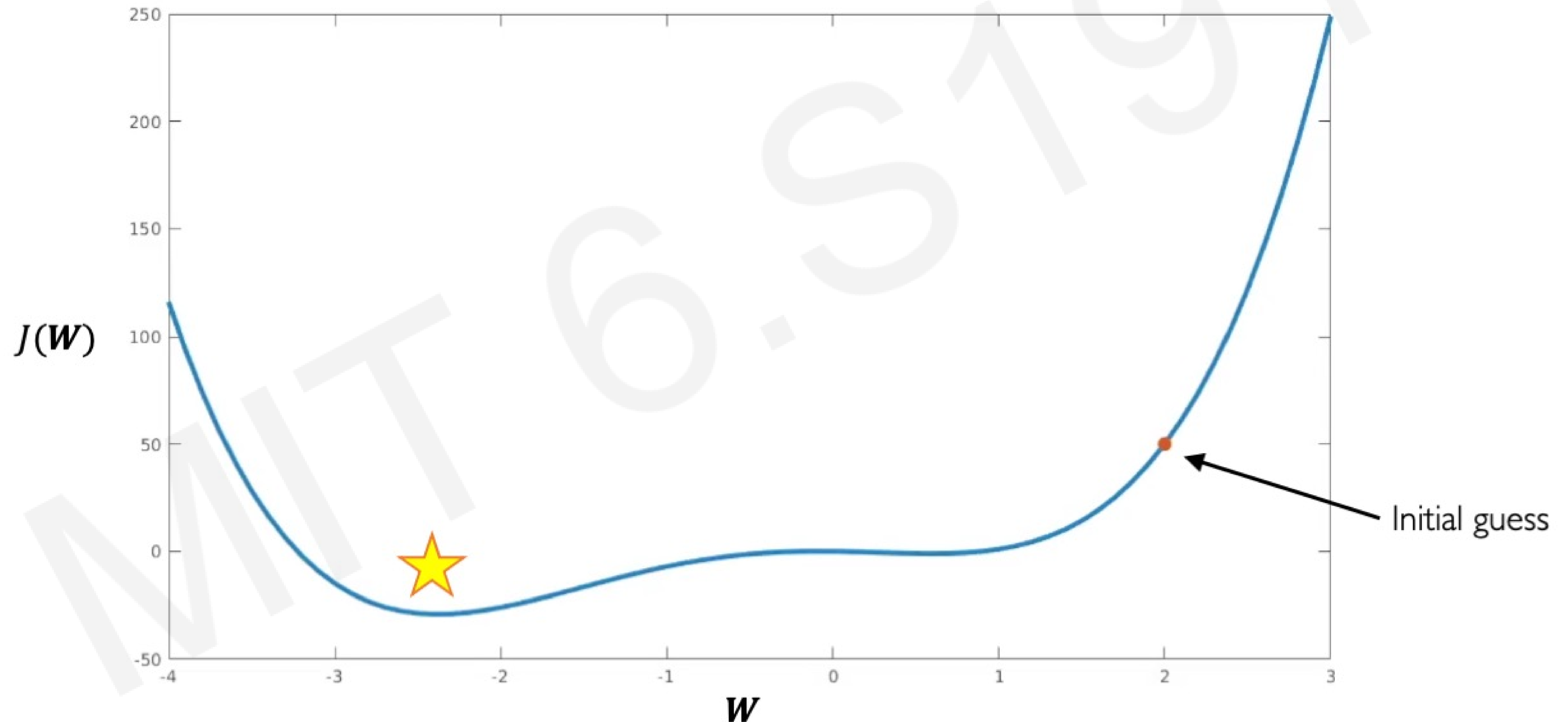
Setting the Learning Rate

Large learning rates overshoot, become unstable and diverge



Setting the Learning Rate

Stable learning rates converge smoothly and avoid local minima



How to deal with this?

Idea 1:

Try lots of different learning rates and see what works “just right”

How to deal with this?

Idea 1:

Try lots of different learning rates and see what works “just right”

Idea 2:




Do something smarter!

Design an adaptive learning rate that “adapts” to the landscape

Adaptive Learning Rates

- Learning rates are no longer fixed
- Can be made larger or smaller depending on:
 - how large gradient is
 - how fast learning is happening
 - size of particular weights
 - etc...

Gradient Descent Algorithms

Algorithm	TF Implementation	Reference
• SGD	 <code>tf.keras.optimizers.SGD</code>	Kiefer & Wolfowitz. "Stochastic Estimation of the Maximum of a Regression Function." 1952.
• Adam	 <code>tf.keras.optimizers.Adam</code>	Kingma et al. "Adam: A Method for Stochastic Optimization." 2014.
• Adadelta	 <code>tf.keras.optimizers.Adadelta</code>	Zeiler et al. "ADADELTA: An Adaptive Learning Rate Method." 2012.
• Adagrad	 <code>tf.keras.optimizers.Adagrad</code>	Duchi et al. "Adaptive Subgradient Methods for Online Learning and Stochastic Optimization." 2011.
• RMSProp	 <code>tf.keras.optimizers.RMSProp</code>	

Additional details: <http://ruder.io/optimizing-gradient-descent/>

Putting it all together



```
import tensorflow as tf

model = tf.keras.Sequential([...])

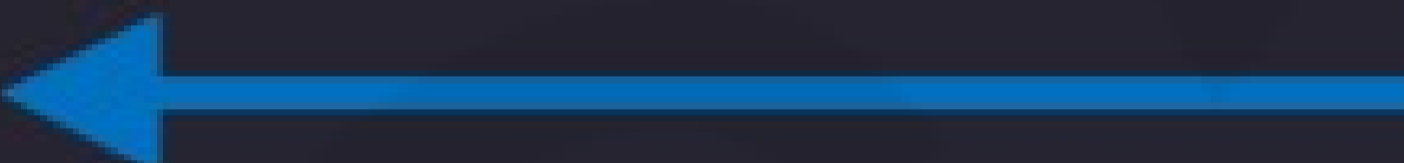
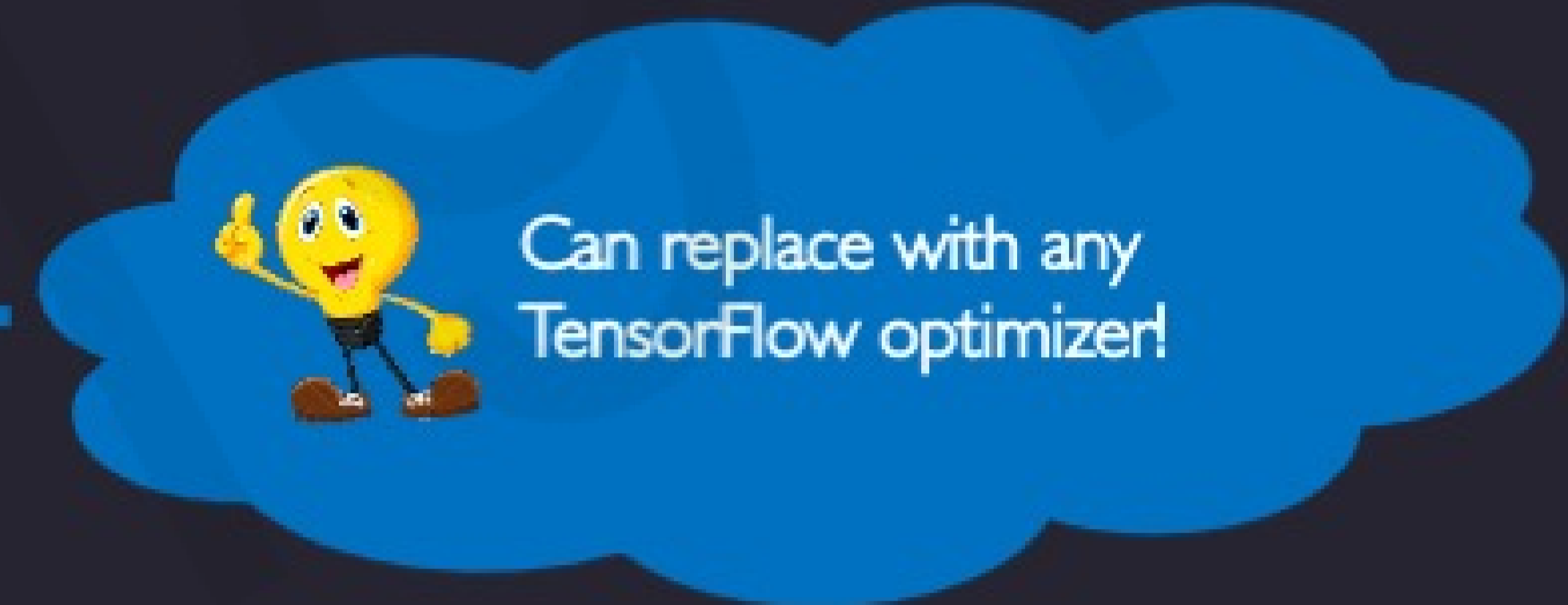
# pick your favorite optimizer
optimizer = tf.keras.optimizer.SGD()

while True: # loop forever

    # forward pass through the network
    prediction = model(x)

    with tf.GradientTape() as tape:
        # compute the loss
        loss = compute_loss(y, prediction)

    # update the weights using the gradient
    grads = tape.gradient(loss, model.trainable_variables)
    optimizer.apply_gradients(zip(grads, model.trainable_variables))
```

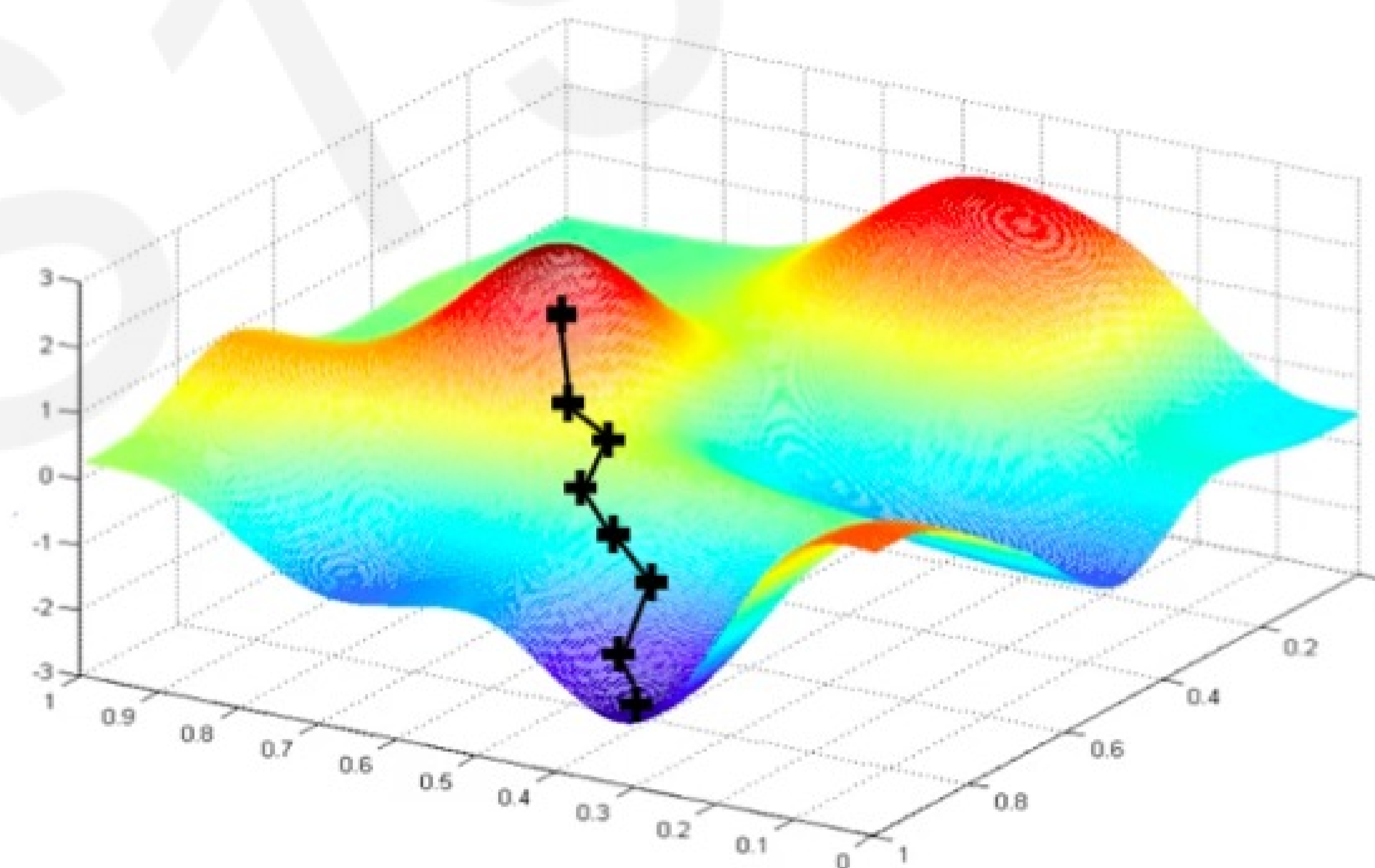


Neural Networks in Practice: Mini-batches

Gradient Descent

Algorithm

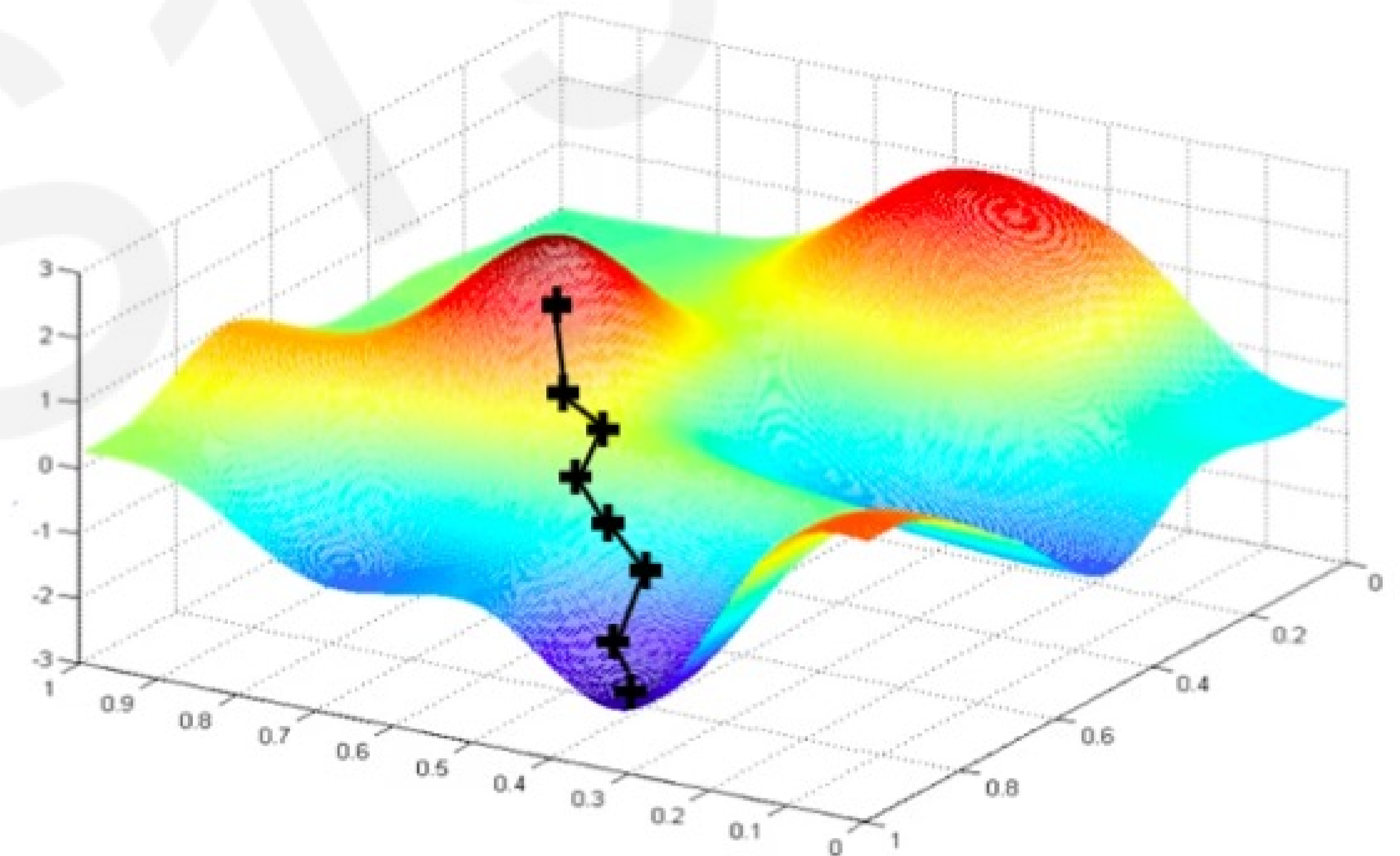
1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
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4. Update weights, $\mathbf{W} \leftarrow \mathbf{W} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
5. Return weights



Gradient Descent

Algorithm

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3. Compute gradient, $\frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
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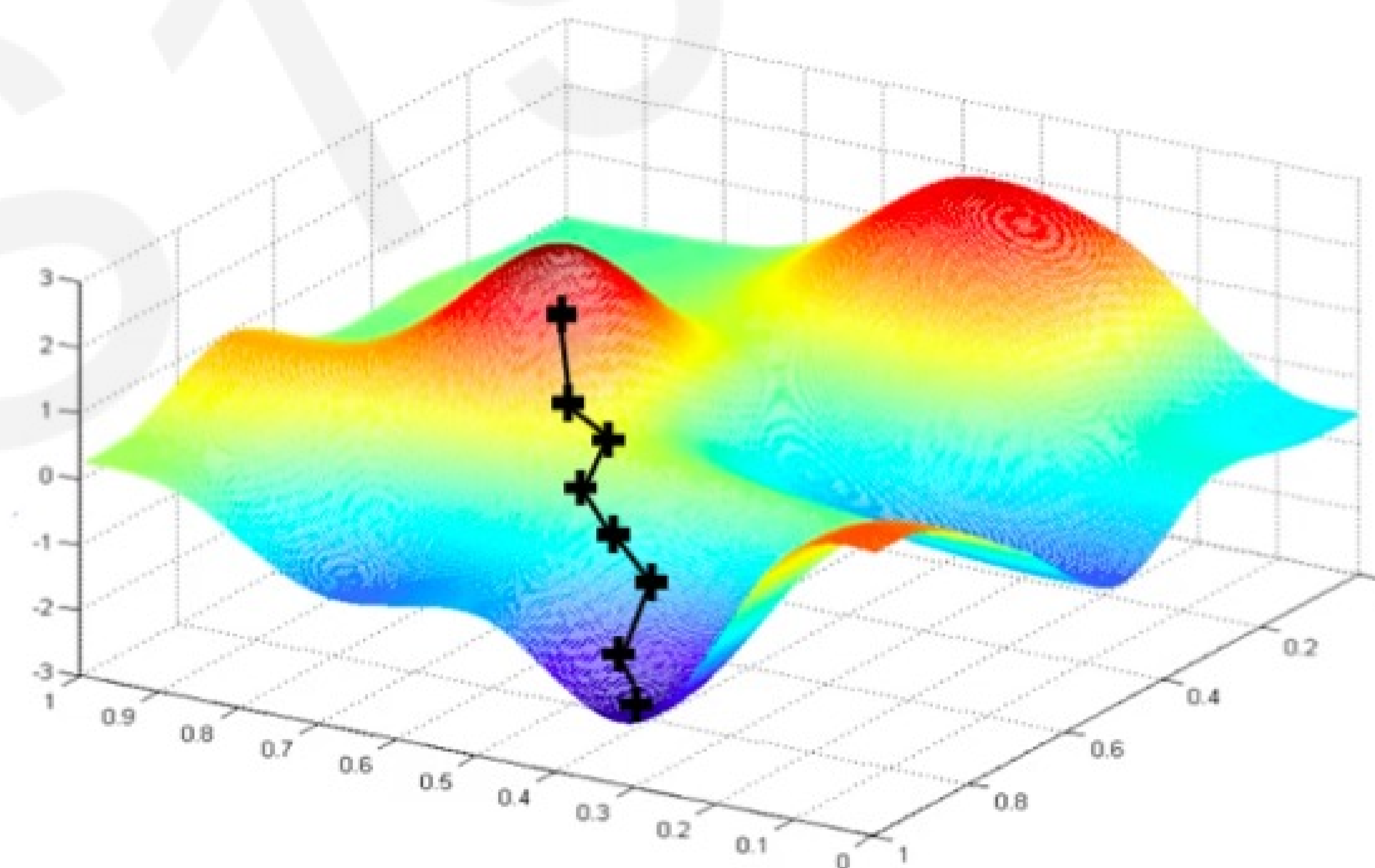


Can be very
computationally
intensive to compute!

Stochastic Gradient Descent

Algorithm

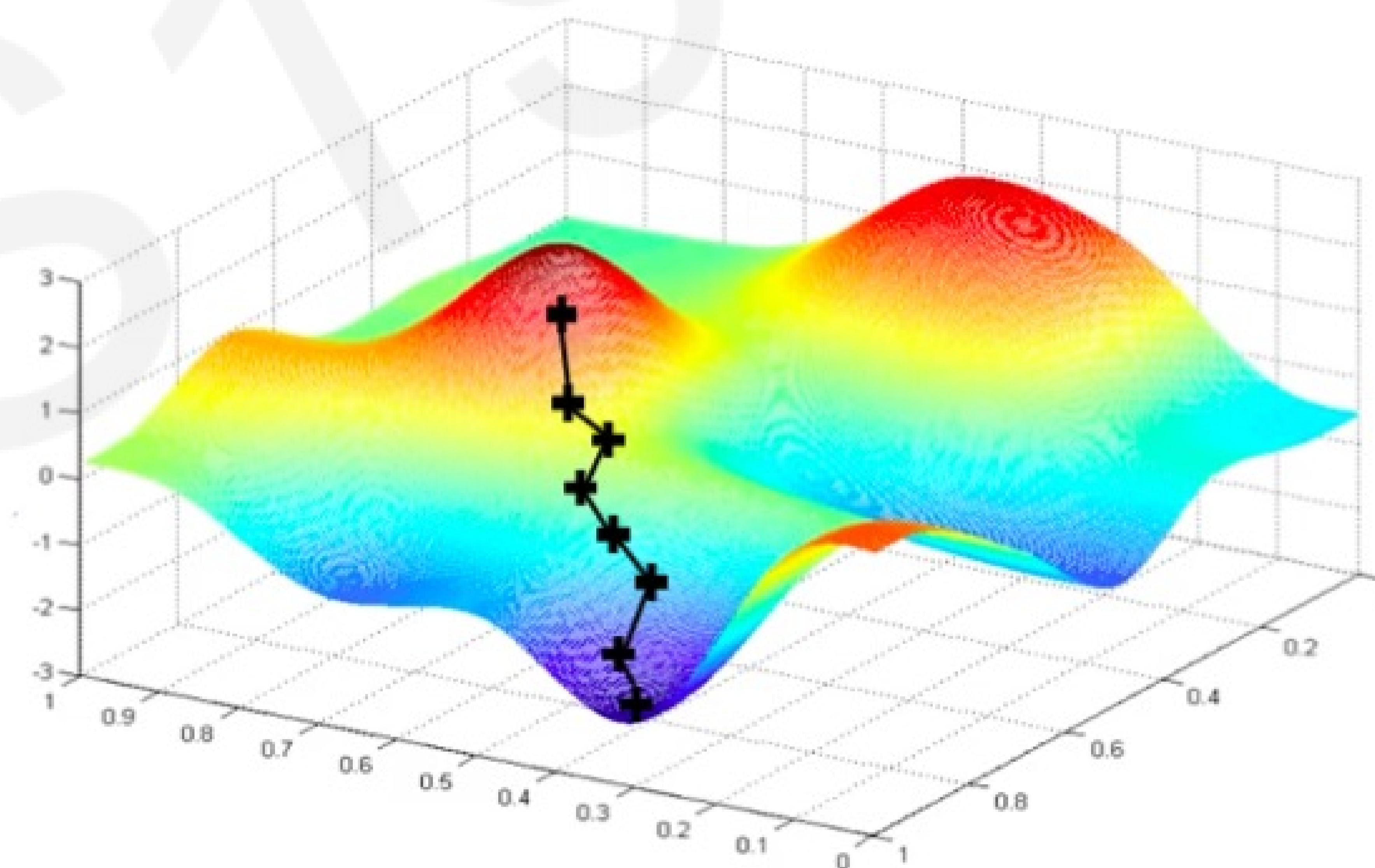
1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Pick single data point i
4. Compute gradient, $\frac{\partial J_i(\mathbf{W})}{\partial \mathbf{W}}$
5. Update weights, $\mathbf{W} \leftarrow \mathbf{W} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
6. Return weights



Stochastic Gradient Descent

Algorithm

1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Pick single data point i
4. Compute gradient, $\frac{\partial J_i(\mathbf{W})}{\partial \mathbf{W}}$
5. Update weights, $\mathbf{W} \leftarrow \mathbf{W} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
6. Return weights

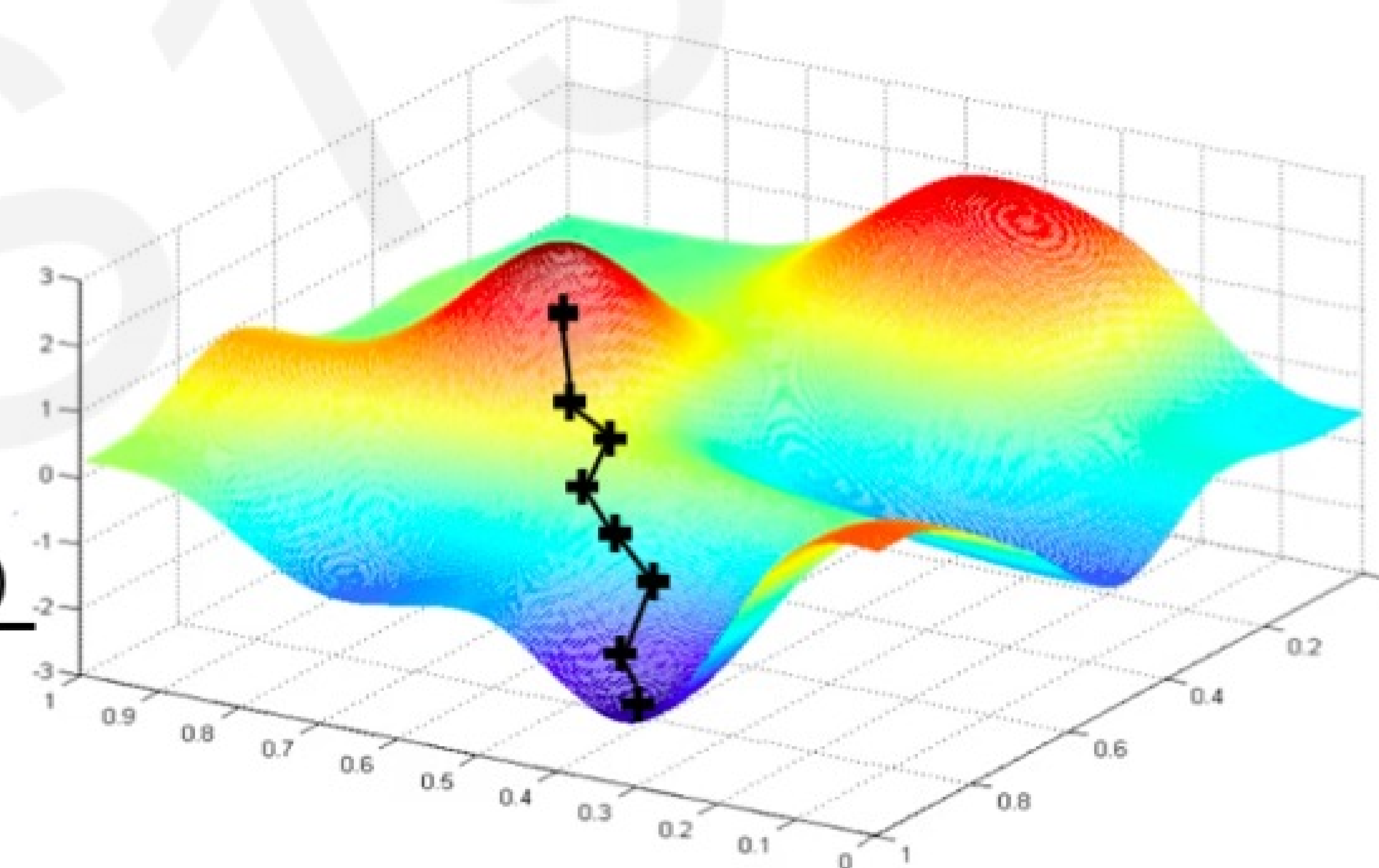


Easy to compute but
very noisy (stochastic)!

Stochastic Gradient Descent

Algorithm

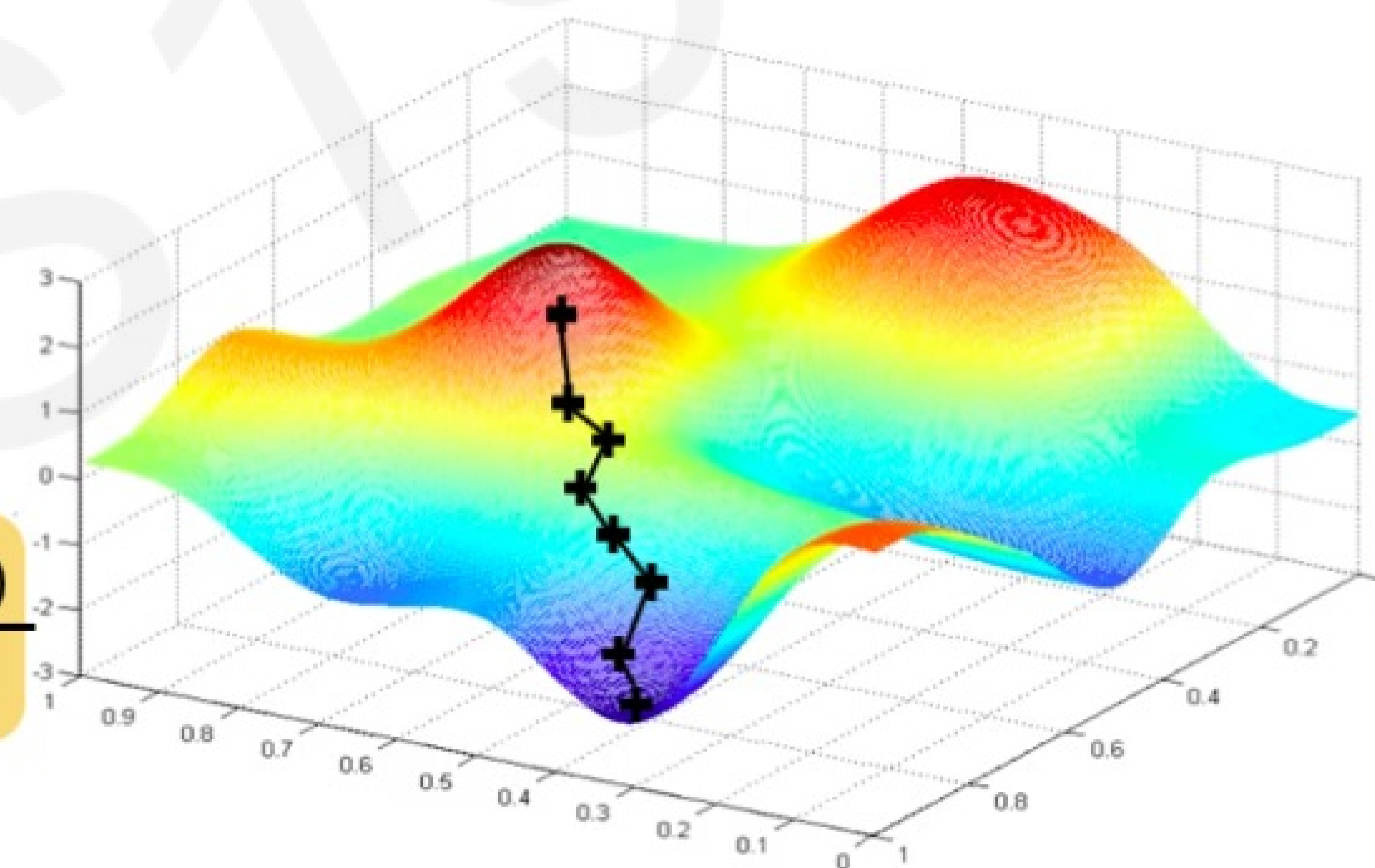
1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Pick batch of B data points
4. Compute gradient, $\frac{\partial J(\mathbf{W})}{\partial \mathbf{W}} = \frac{1}{B} \sum_{k=1}^B \frac{\partial J_k(\mathbf{W})}{\partial \mathbf{W}}$
5. Update weights, $\mathbf{W} \leftarrow \mathbf{W} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
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Stochastic Gradient Descent

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6. Return weights



Fast to compute and a much better estimate of the true gradient!

Mini-batches while training

More accurate estimation of gradient

Smother convergence
Allows for larger learning rates

Mini-batches while training

More accurate estimation of gradient

Smother convergence

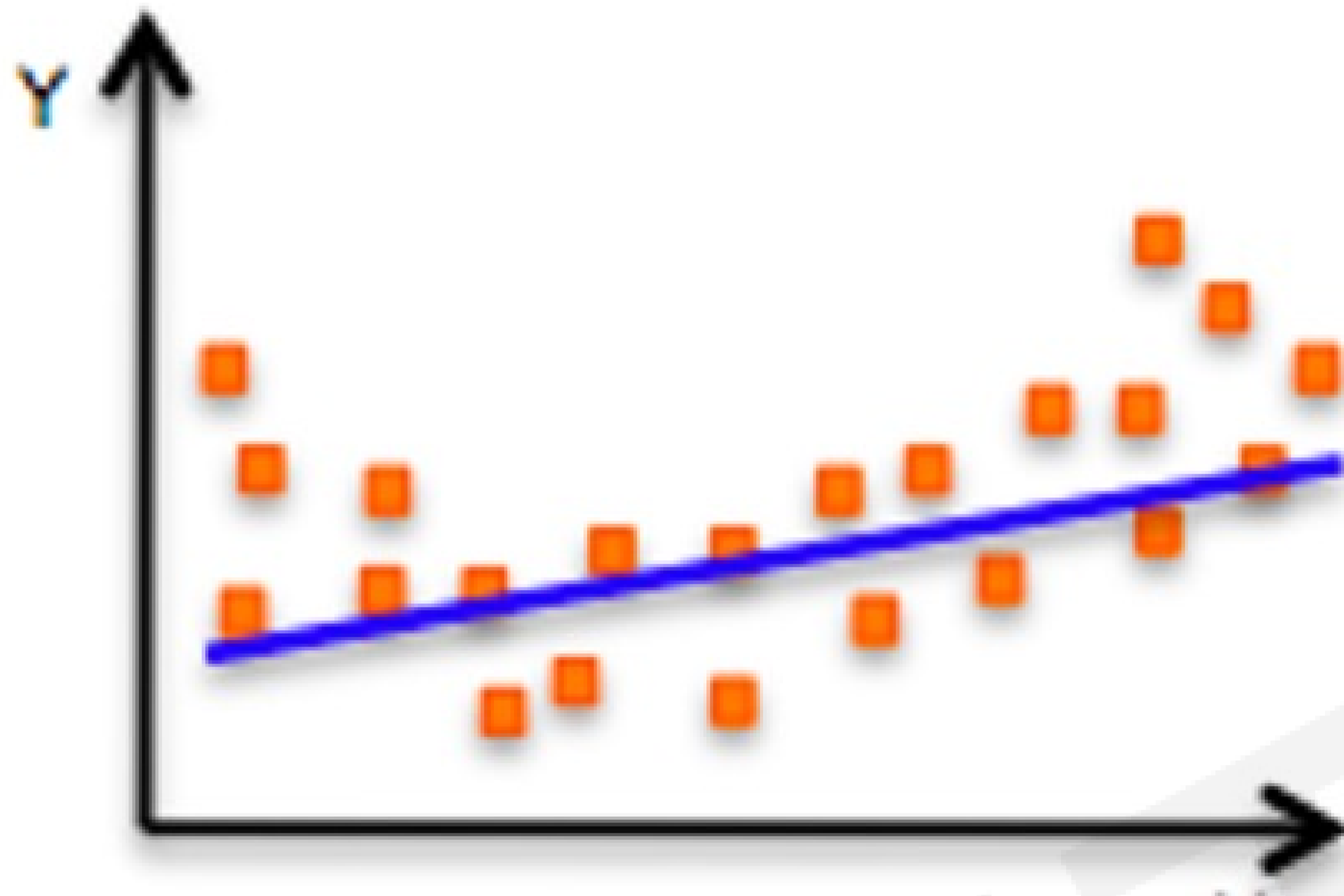
Allows for larger learning rates

Mini-batches lead to fast training!

Can parallelize computation + achieve significant speed increases on GPU's

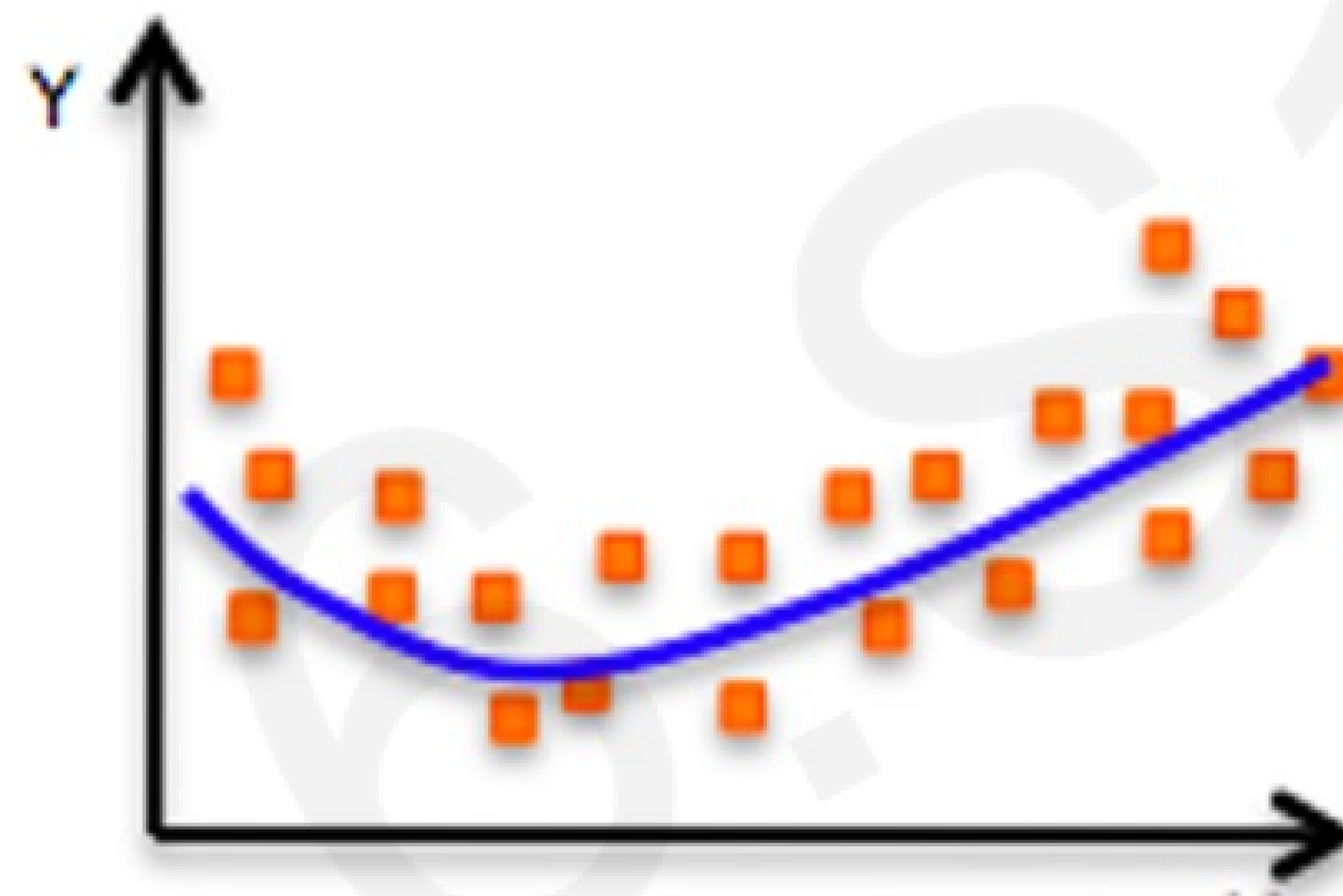
Neural Networks in Practice: Overfitting

The Problem of Overfitting

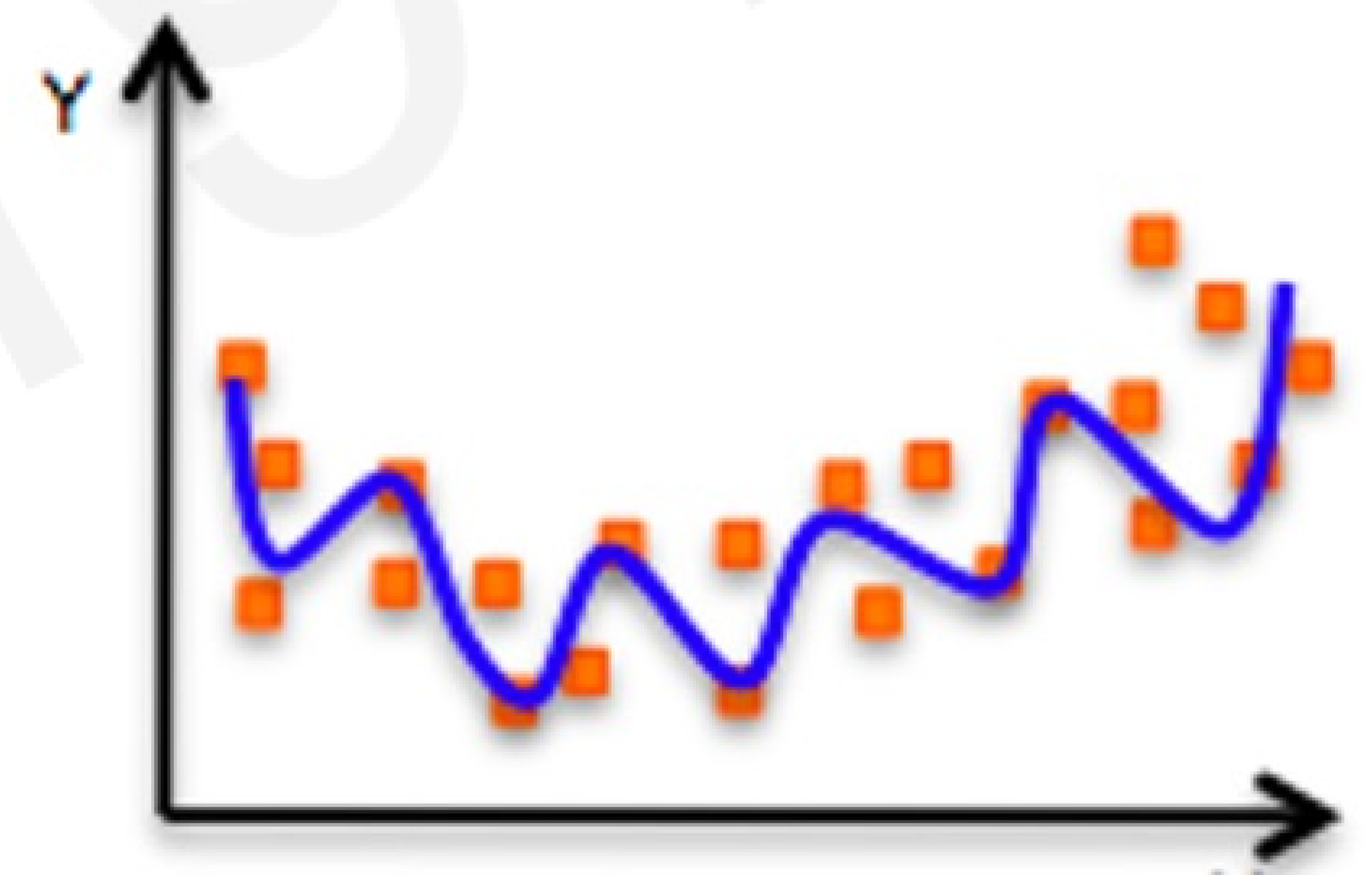


Underfitting

Model does not have capacity to fully learn the data



Ideal fit



Overfitting

Too complex, extra parameters, does not generalize well

Regularization

What is it?

Technique that constrains our optimization problem to discourage complex models

Regularization

What is it?

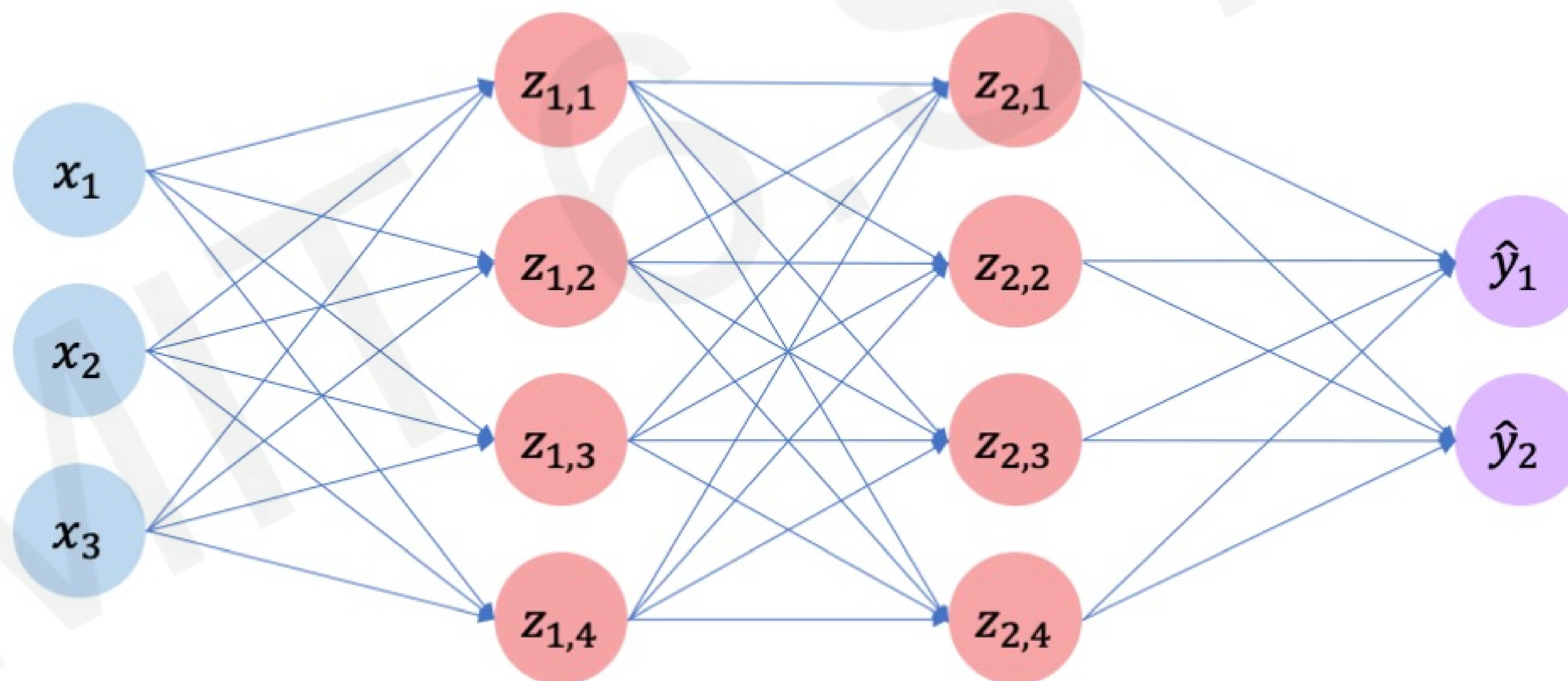
Technique that constrains our optimization problem to discourage complex models

Why do we need it?

Improve generalization of our model on unseen data

Regularization I: Dropout

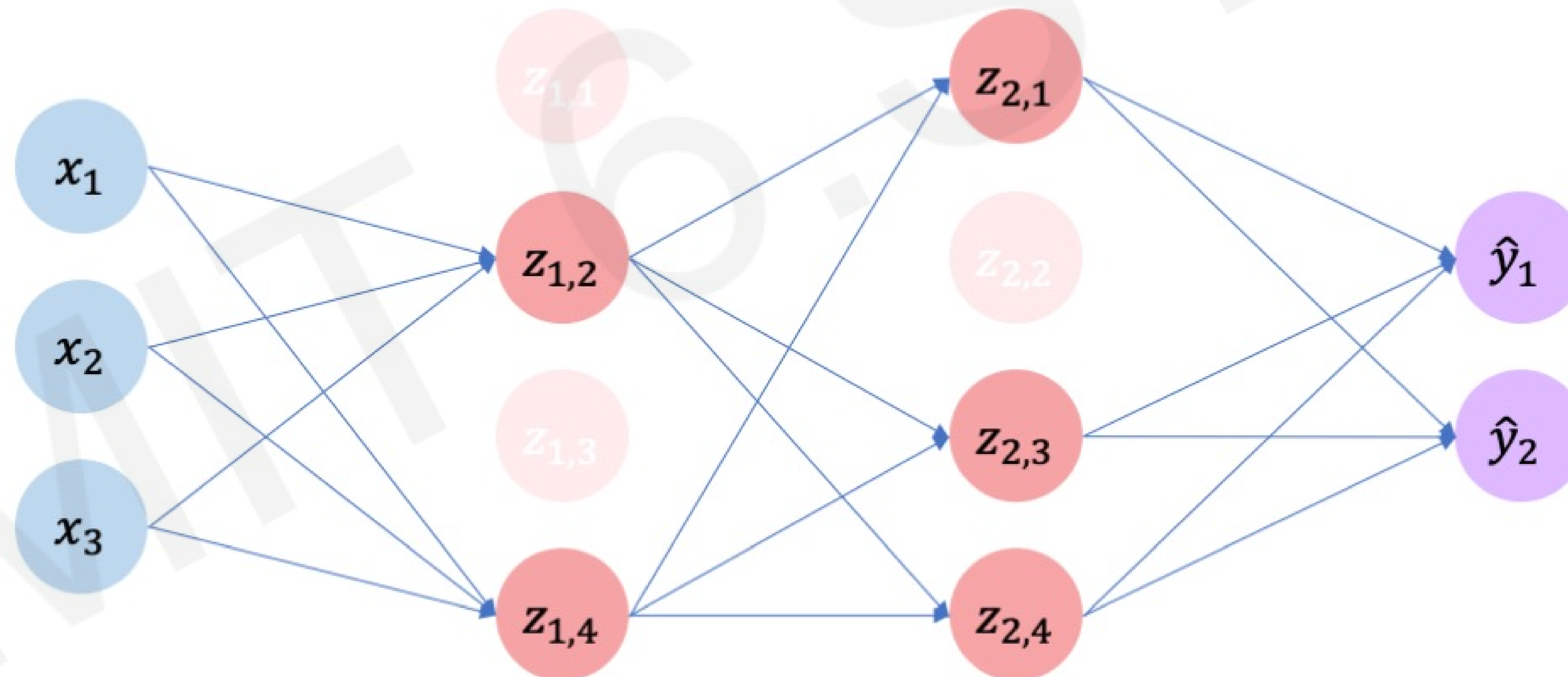
- During training, randomly set some activations to 0



Regularization I: Dropout

- During training, randomly set some activations to 0
 - Typically 'drop' 50% of activations in layer
 - Forces network to not rely on any 1 node

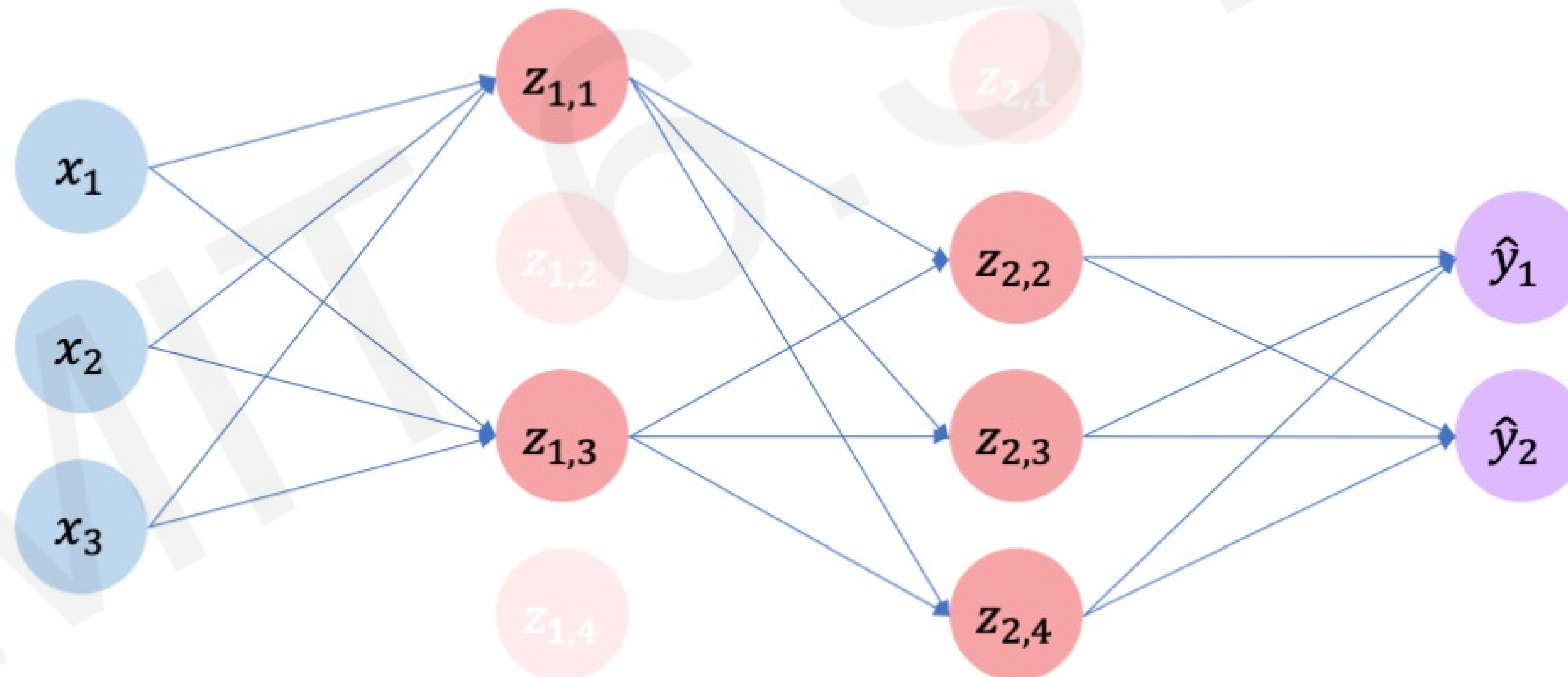
```
 tf.keras.layers.Dropout(p=0.5)
```



Regularization I: Dropout

- During training, randomly set some activations to 0
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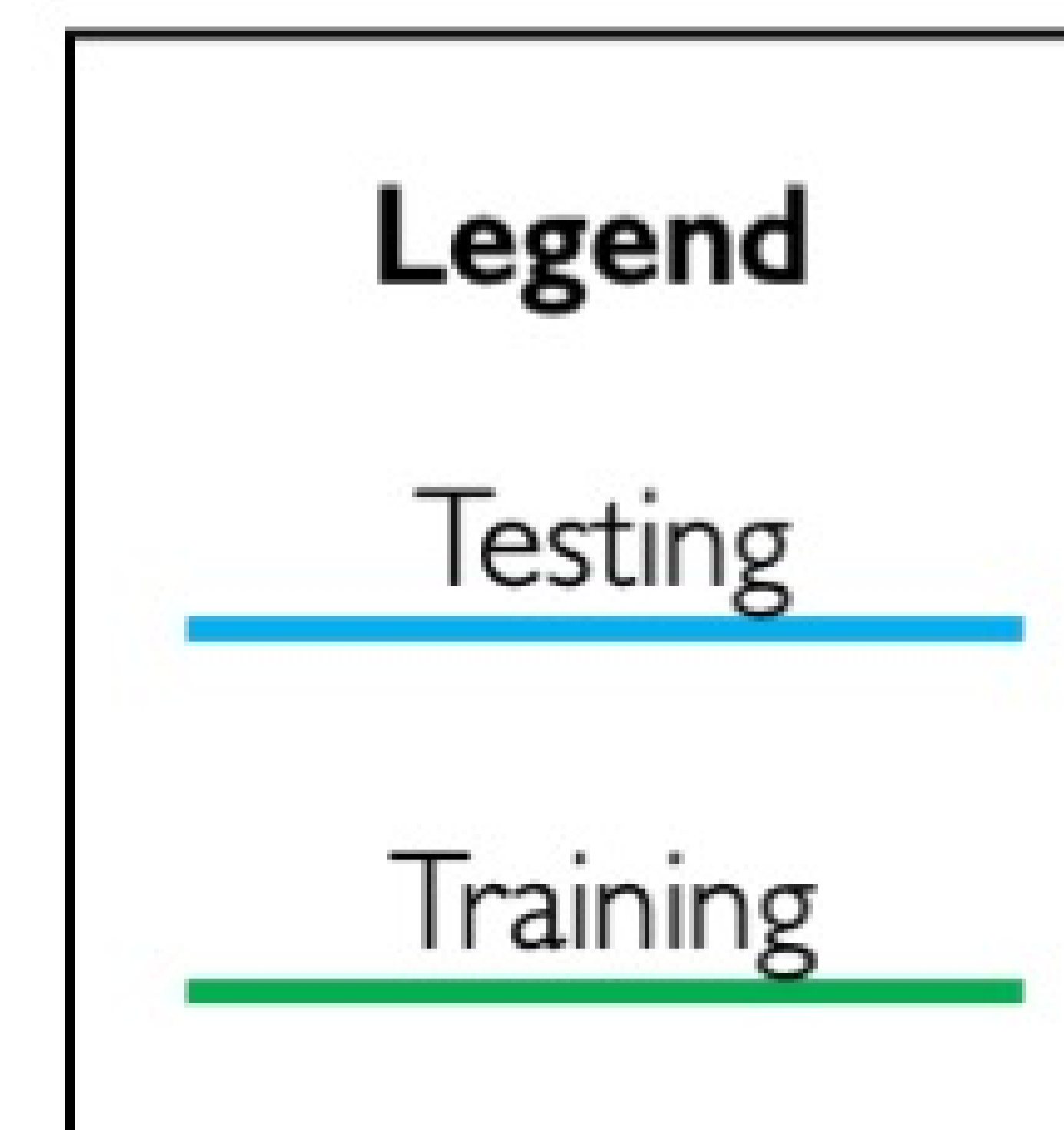
Regularization 2: Early Stopping

- Stop training before we have a chance to overfit



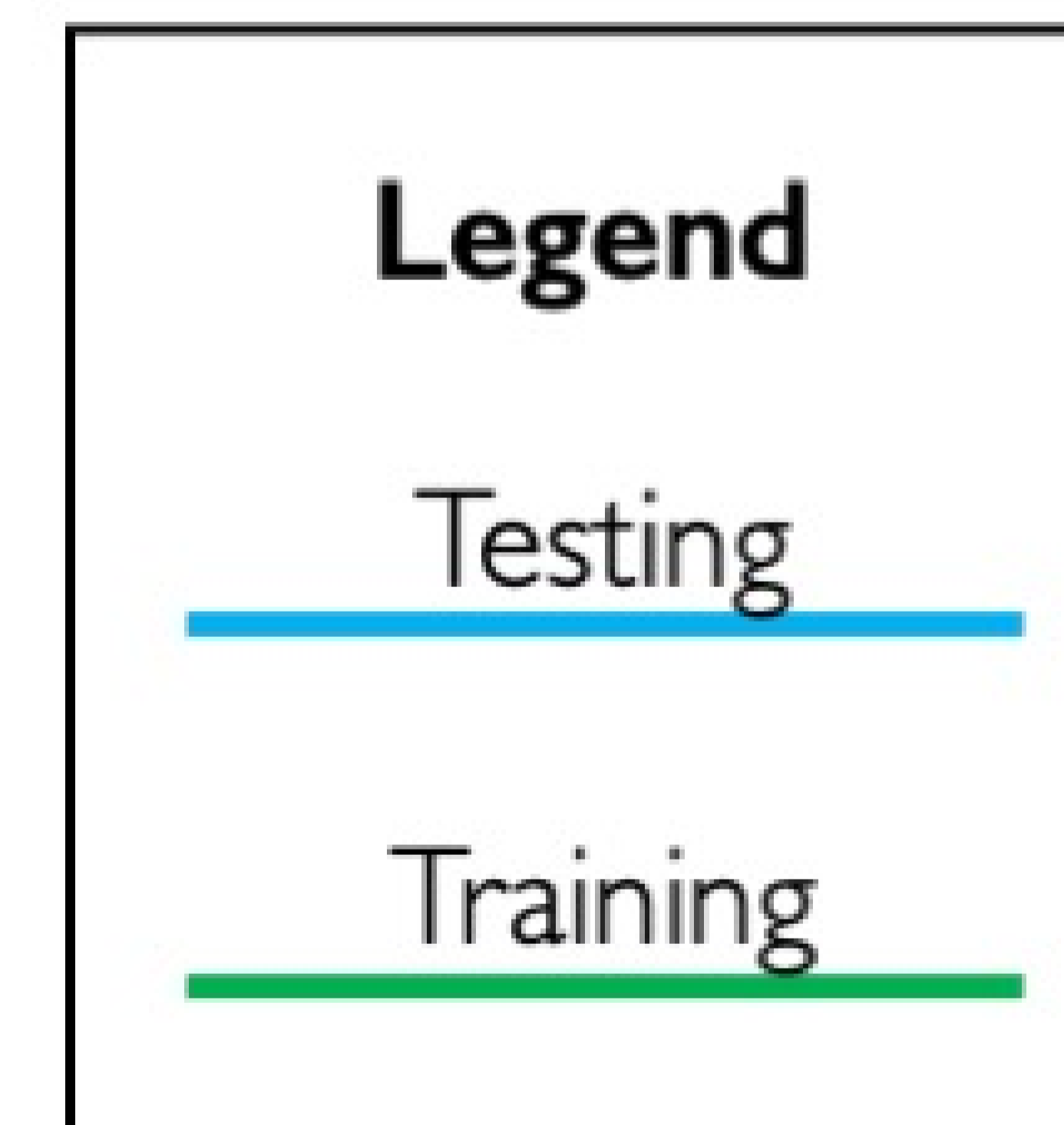
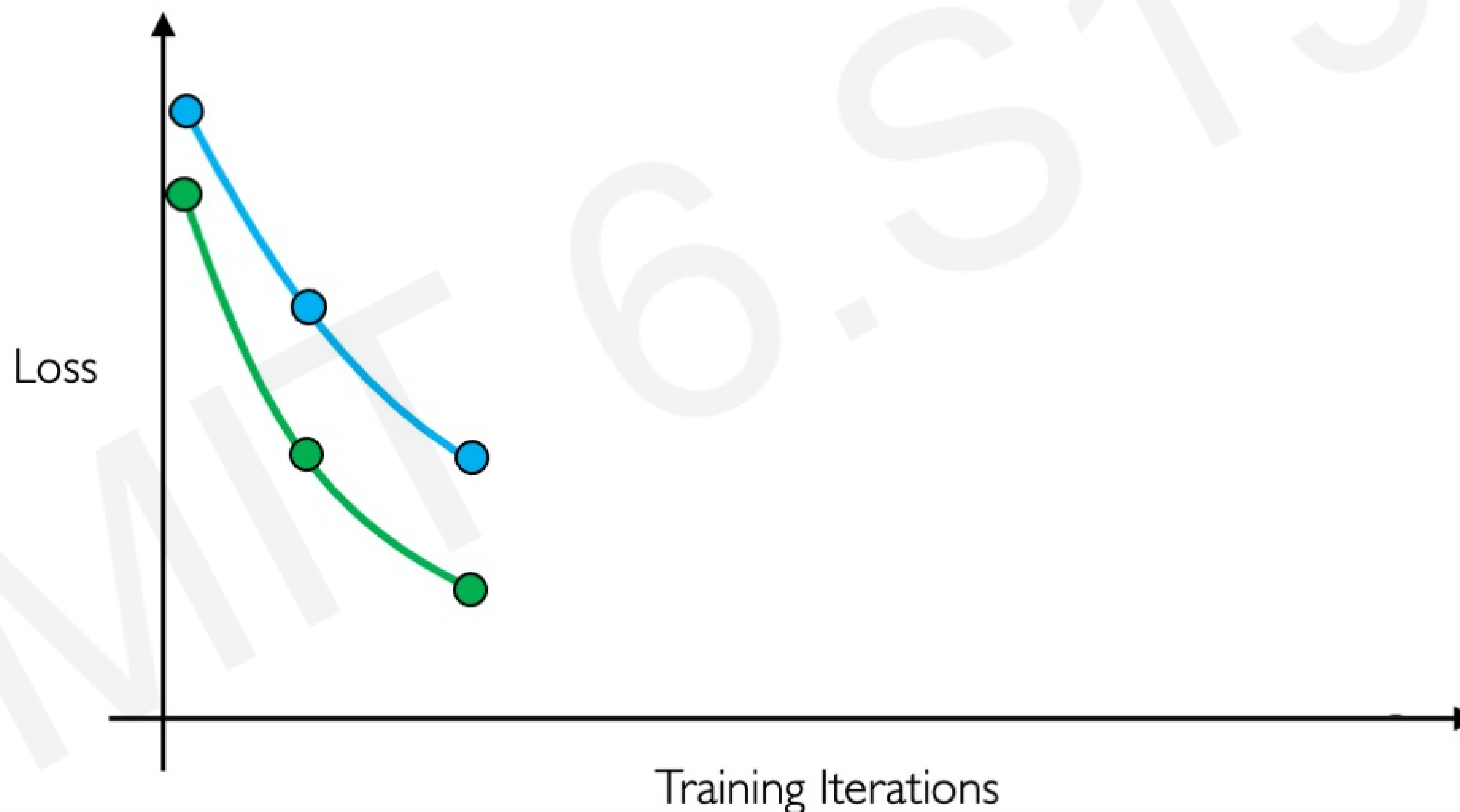
Regularization 2: Early Stopping

- Stop training before we have a chance to overfit



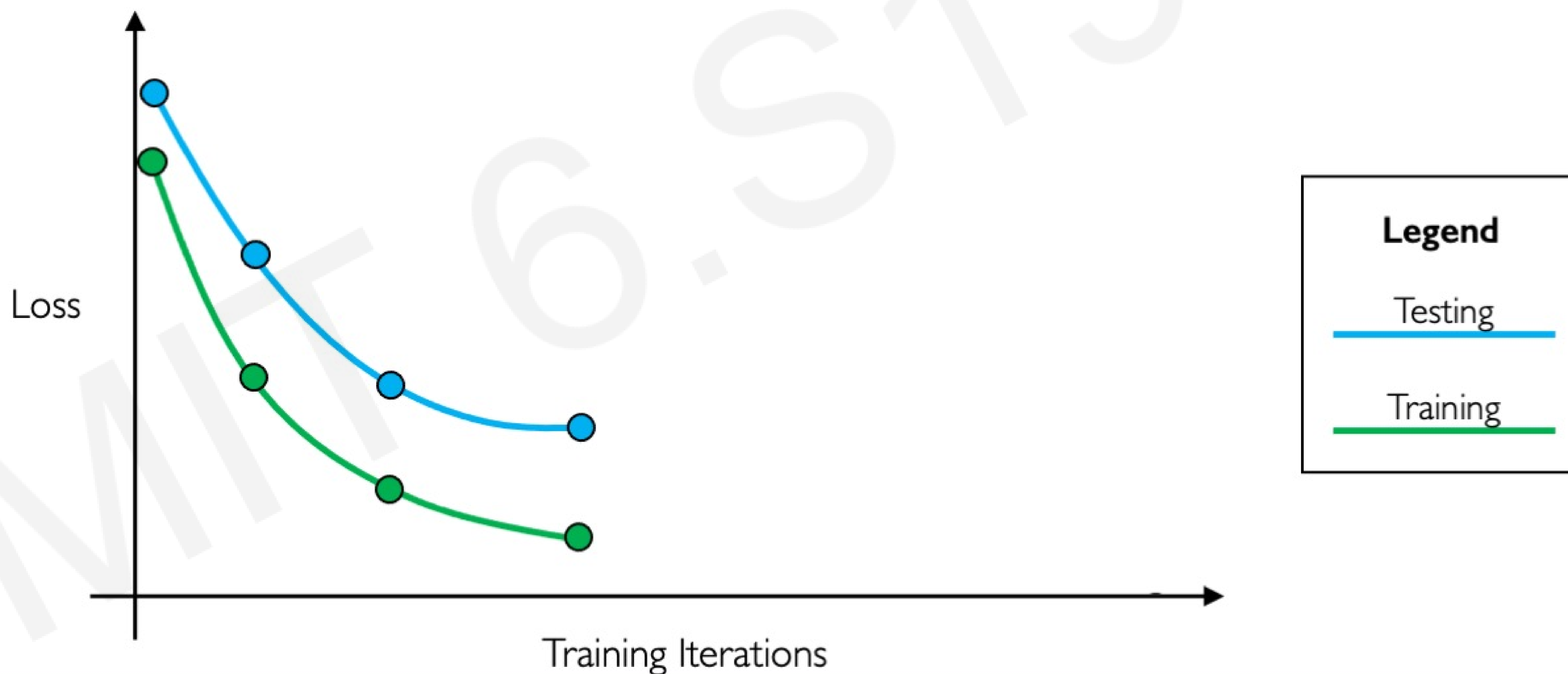
Regularization 2: Early Stopping

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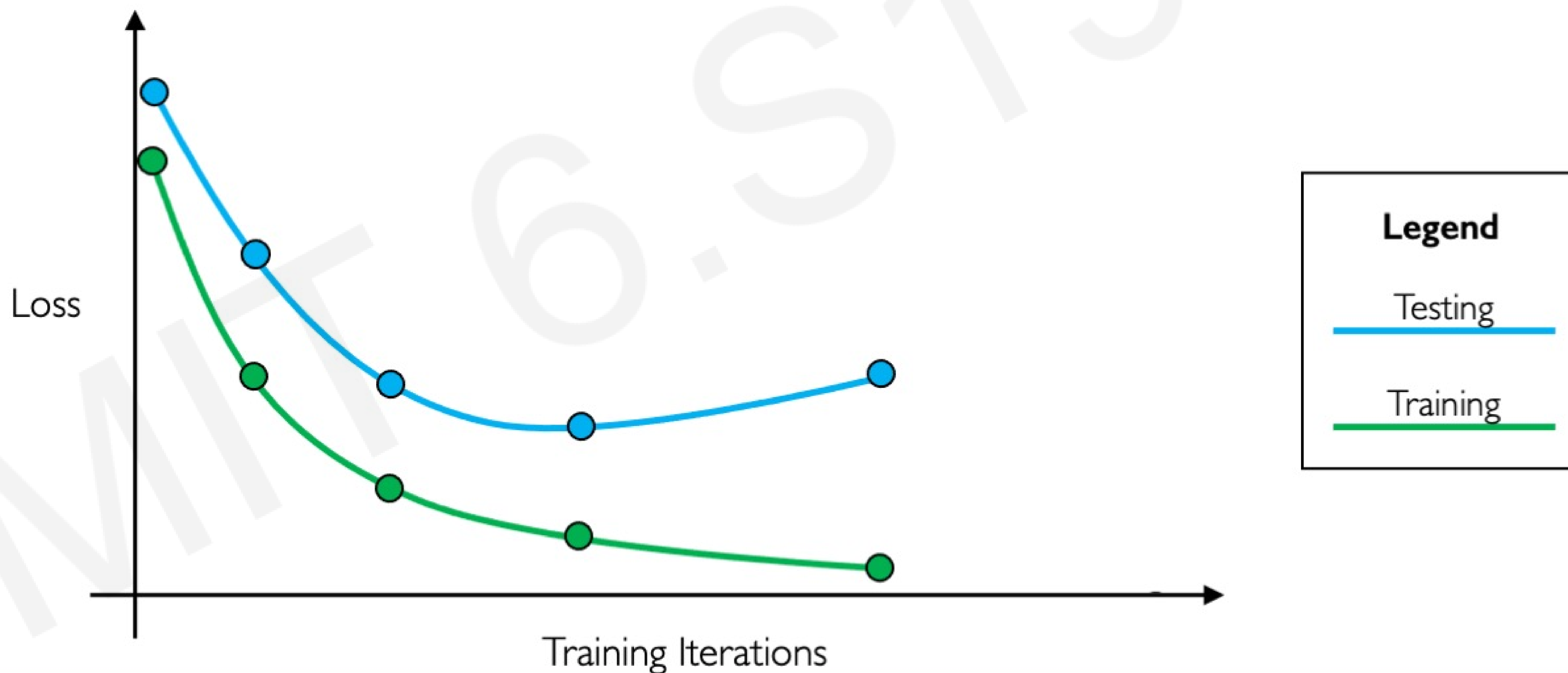
Regularization 2: Early Stopping

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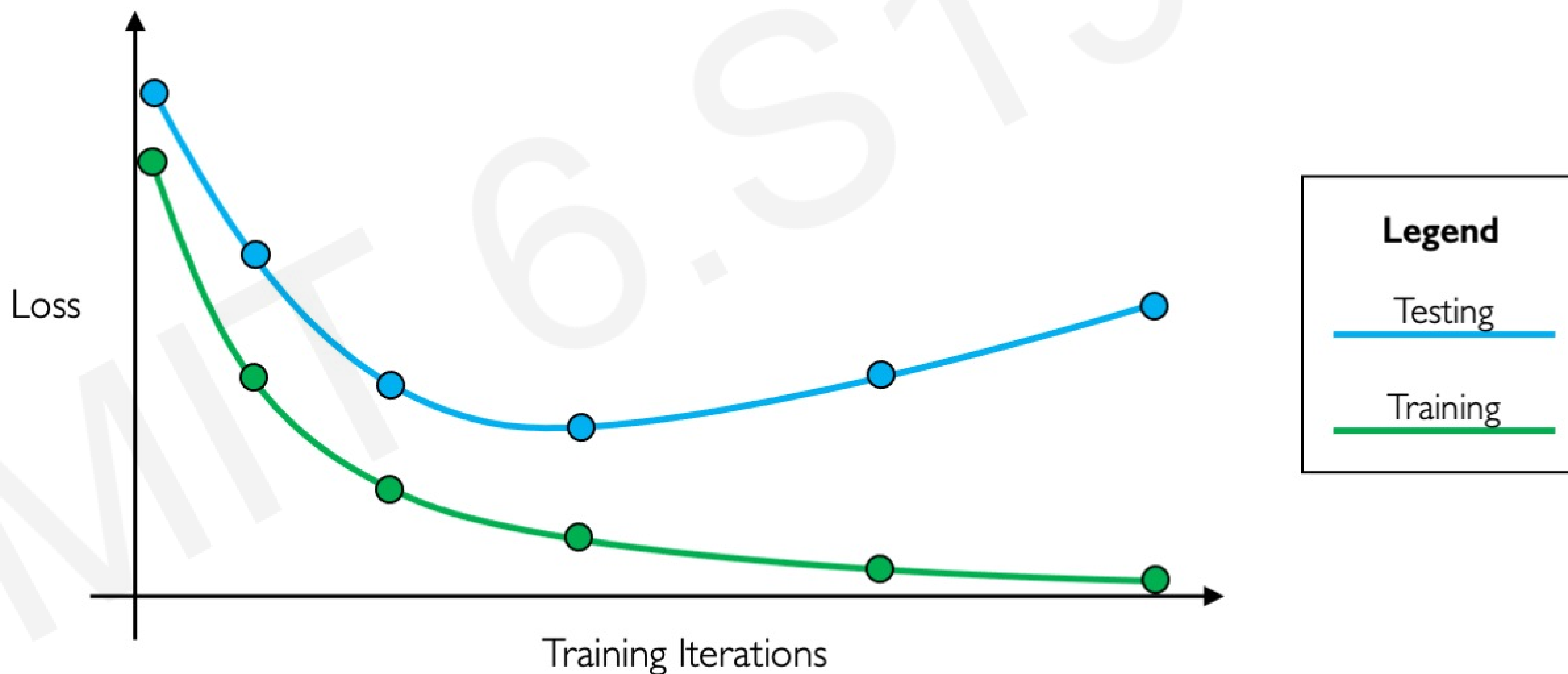
Regularization 2: Early Stopping

- Stop training before we have a chance to overfit



Regularization 2: Early Stopping

- Stop training before we have a chance to overfit



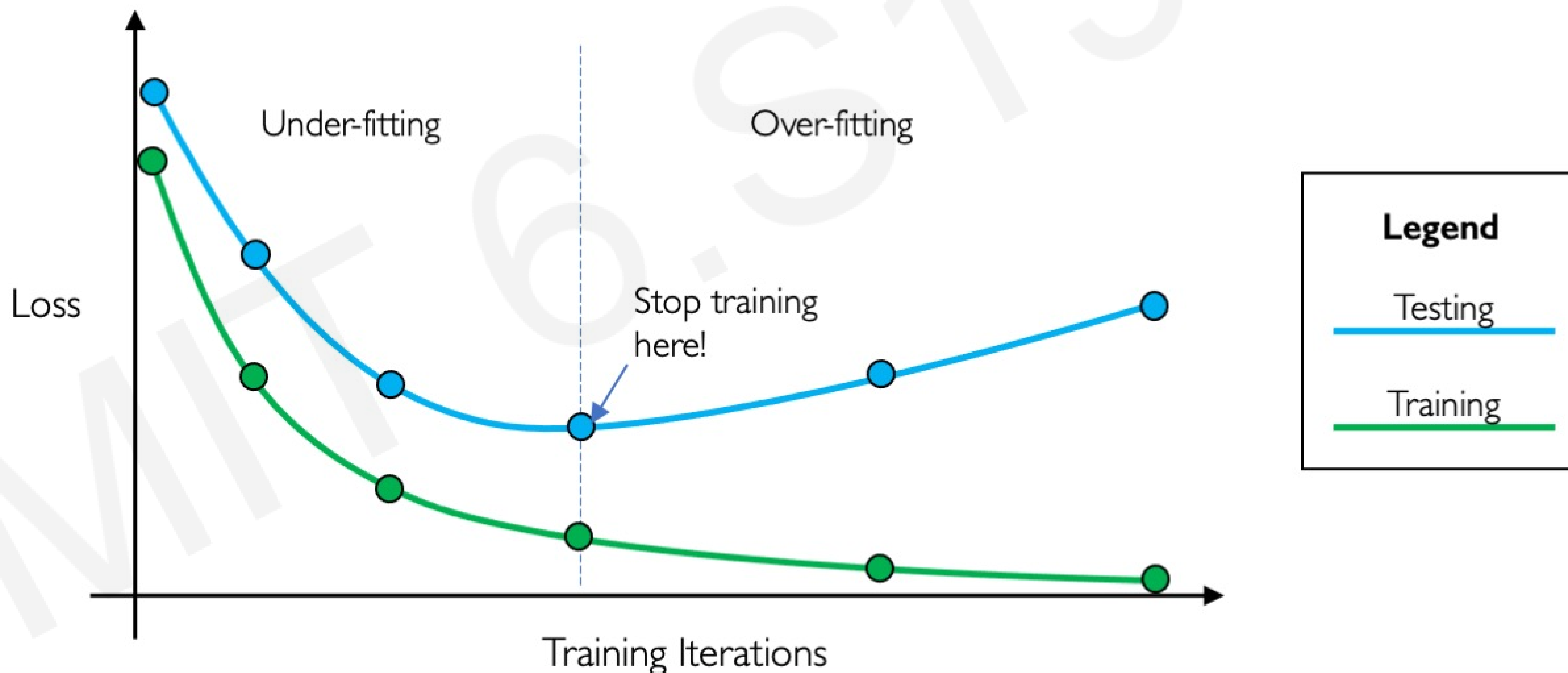
Regularization 2: Early Stopping

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Regularization 2: Early Stopping

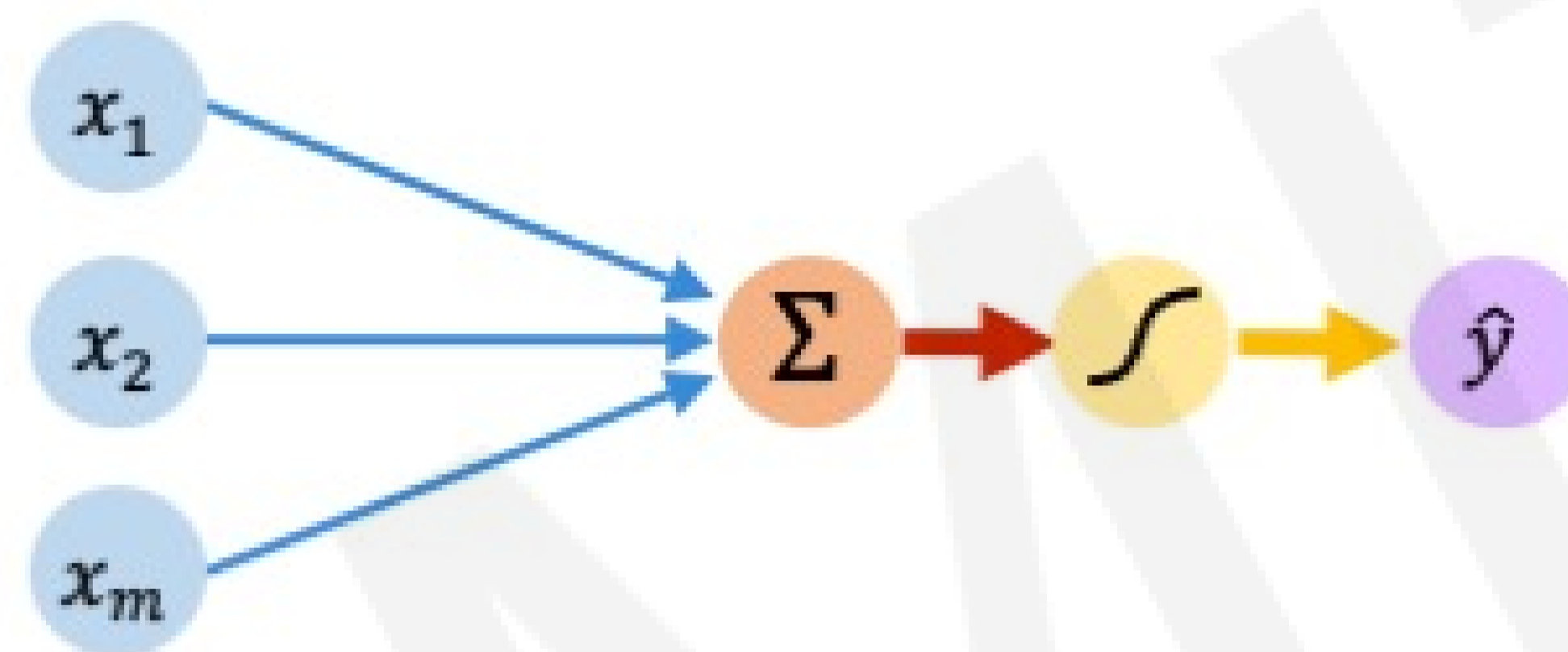
- Stop training before we have a chance to overfit



Core Foundation Review

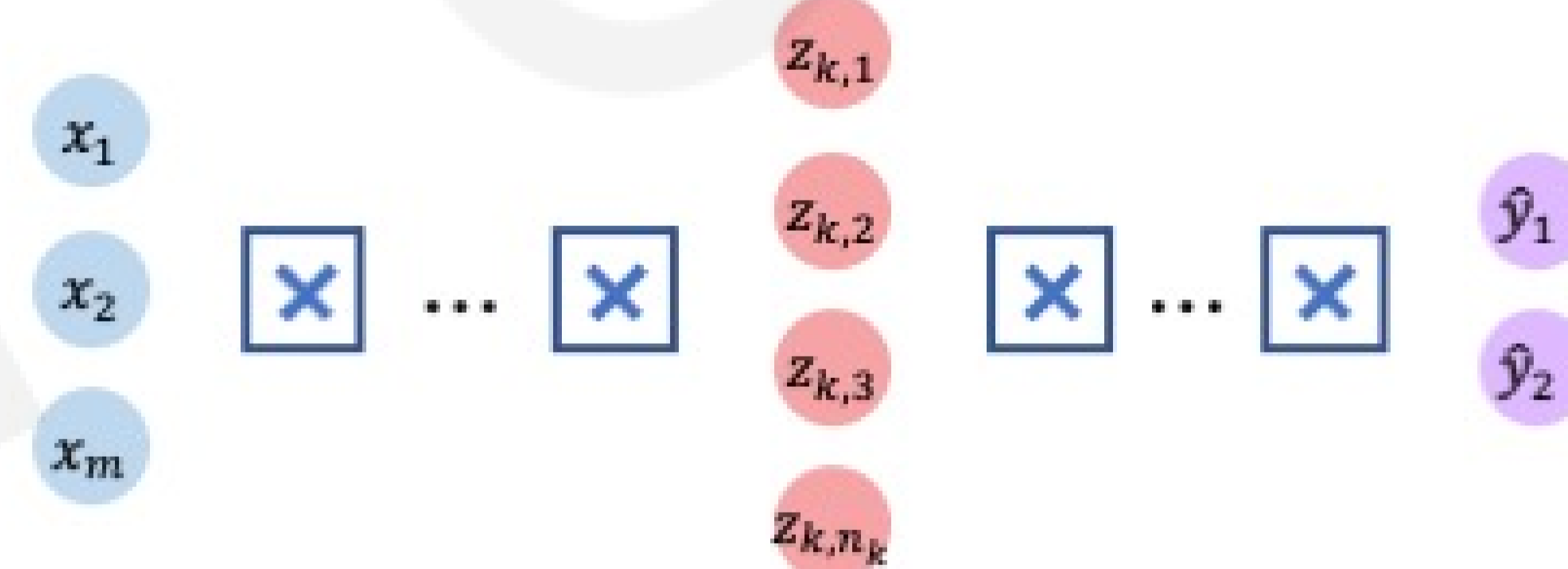
The Perceptron

- Structural building blocks
- Nonlinear activation functions



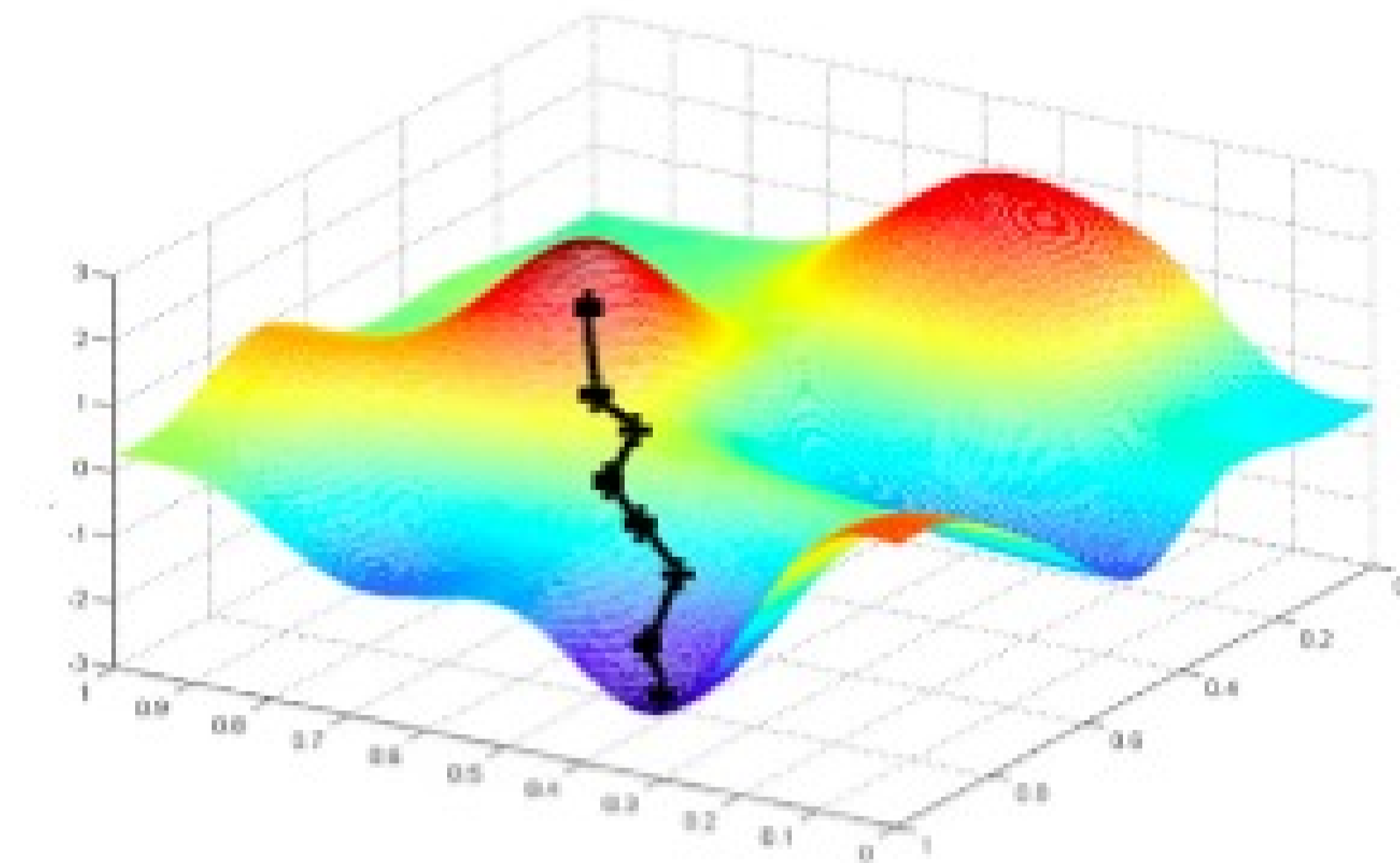
Neural Networks

- Stacking Perceptrons to form neural networks
- Optimization through backpropagation



Training in Practice

- Adaptive learning
- Batching
- Regularization



6.S191: Introduction to Deep Learning

Lab 1: Introduction to TensorFlow and Music Generation with RNNs

Link to download labs:

<http://introtodeeplearning.com#schedule>

1. Open the lab in Google Colab
2. Start executing code blocks and filling in the #TODOs
3. Need help? Come to the class Gather.Town!

