Introduction to Deep Learning

Alexander Amini

MIT Introduction to Deep Learning

January 5, 2026

"Seeing" the progress of deep learning throughout the years

2015
Goodfellow et al.

2018
Karras, Laine, Aila.

2020
MIT Intro to Deep Learning

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Language has transformed the way that we interact with deep learning

2022
ChatGPT launches (GPT-3)

2023
The GPT-4 "wow" moment

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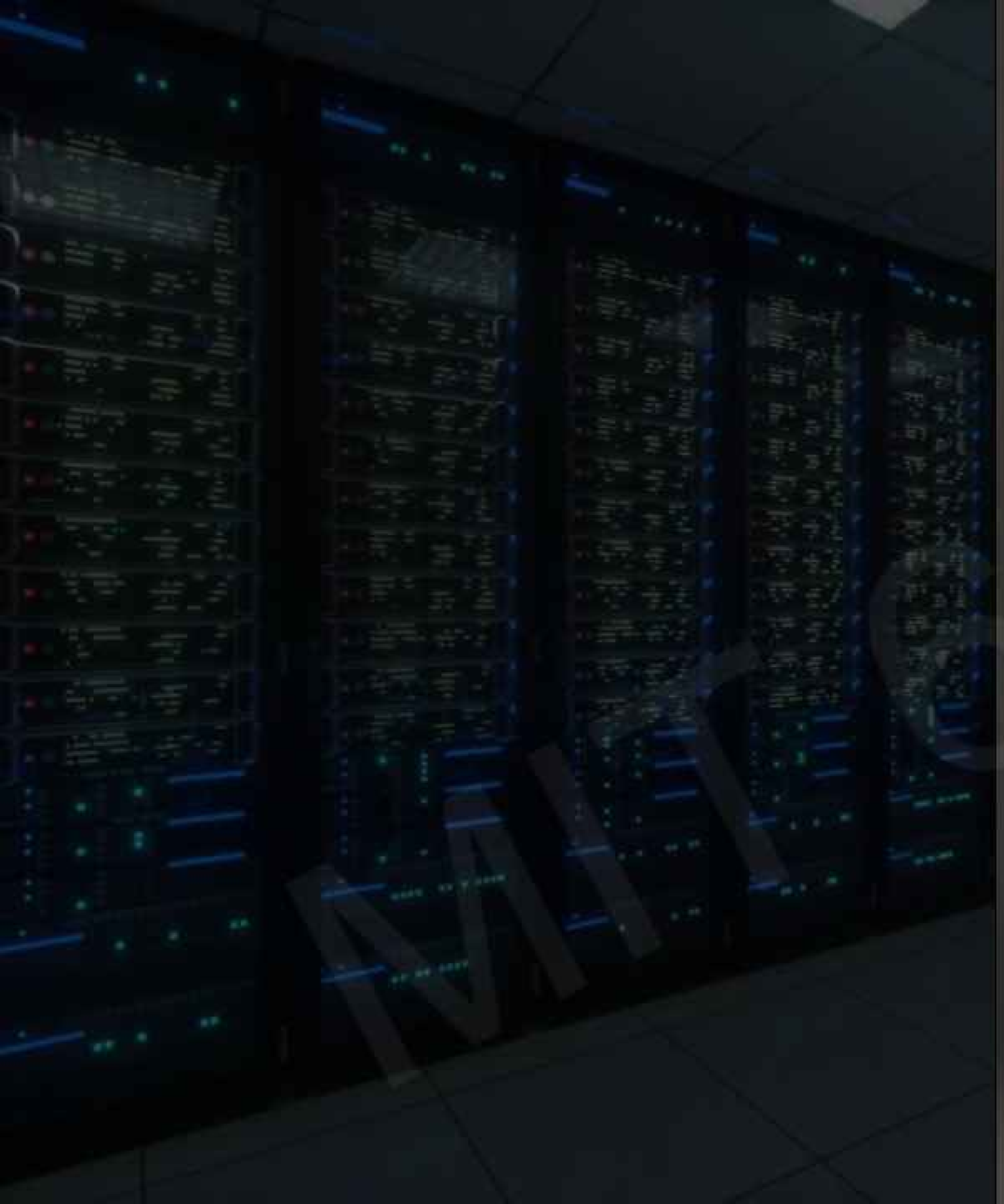

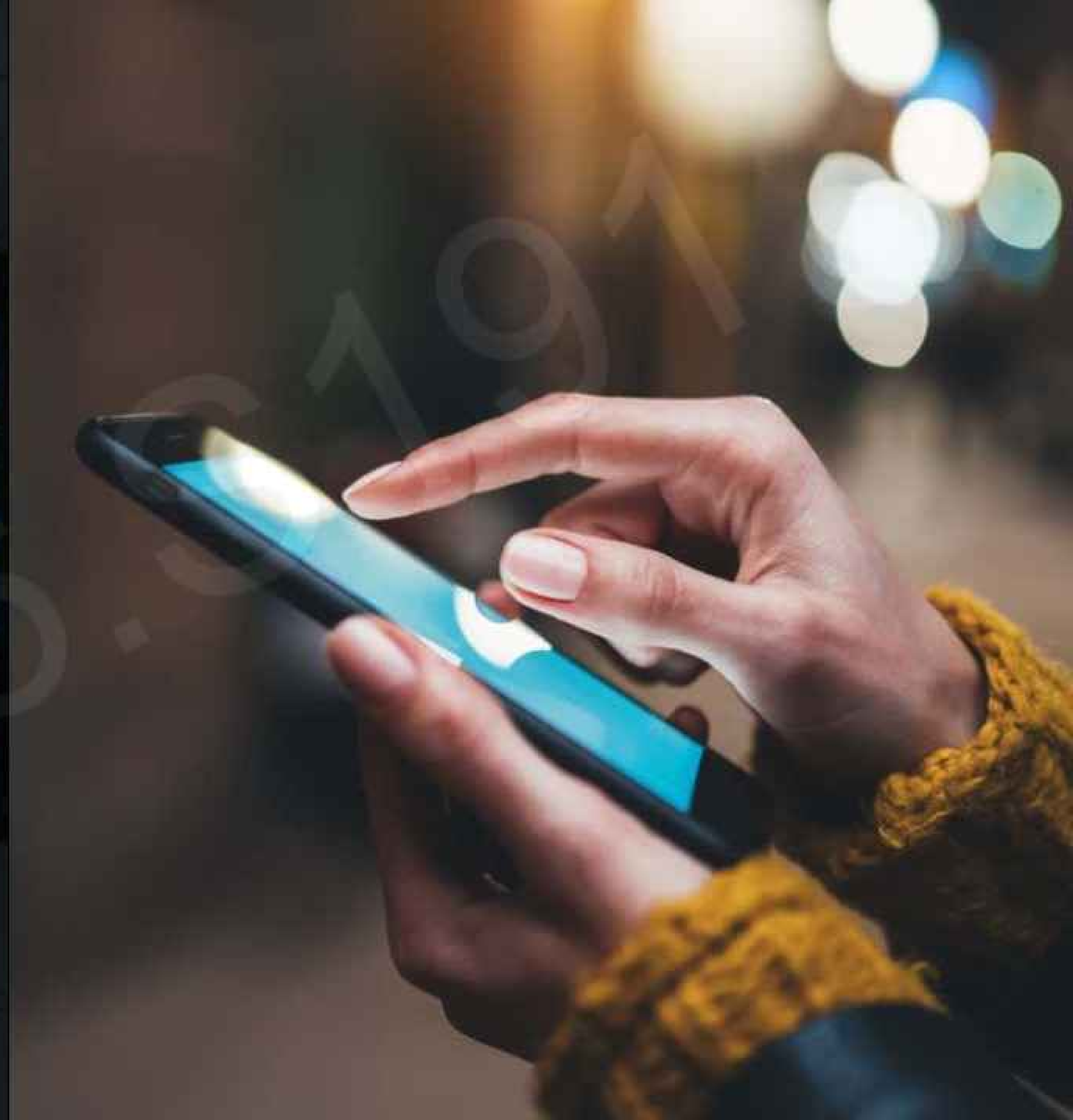

Paul Couvert
@itsPaulAi

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That's pretty crazy when you think about it

One of the biggest “wow” moments with ChatGPT was the update from GPT-3.5 to GPT-4.

And now this open-source model with only 2.6B parameters that can run locally on your phone... is BETTER than the original GPT-4.

Unbelievable.

Benchmarking LFM2-2.6B-Exp vs. GPT-4

Benchmark	**LFM2-2.6B-Exp** (Liquid AI)	**GPT-4 (Original)**
IFEval (Strict Instruction Following)	**88.13**	79.0
Multi-IF (Complex Instructions)	**73.05**	65.0
IFBench (Formatting Accuracy)	**44.40**	24.0
GPQA (PhD-level Reasoning)	**41.31**	35.7
MMLU-Pro (Hard Expert Knowledge)	53.87	**63.7**
AIME25 (Olympiad-level Math)	**22.67**	15.0

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4:27 PM · Dec 25, 2025 · **253.5K** Views

80 178 2.5K 1.1K

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

Teaching computers how to **learn a task** directly from **raw data**

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Lecture Schedule

Intro to Deep Learning
Lecture 1
Jan. 5, 2026
[Slides] [Video] *coming soon!*

Deep Sequence Modeling
Lecture 2
Jan. 5, 2026
[Slides] [Video] *coming soon!*

Deep Learning in Python; Music Generation
Software Lab 1
[Code] *coming soon!*

Deep Computer Vision
Lecture 3
Jan. 6, 2026
[Slides] [Video] *coming soon!*

Deep Generative Modeling
Lecture 4
Jan. 6, 2026
[Slides] [Video] *coming soon!*

Facial Detection Systems
Software Lab 2
[Paper] [Code] *coming soon!*

Deep Reinforcement Learning
Lecture 5
Jan. 7, 2026
[Slides] [Video] *coming soon!*

New Frontiers
Lecture 6
Jan. 7, 2026
[Slides] [Video] *coming soon!*

Fine-Tune an LLM, You Must!
Software Lab 3
[Code] *coming soon!*

AI for Science
Lecture 7
Jan. 8, 2026
[Info] [Slides] [Video] *coming soon!*

Secrets to Massively Parallel Training
Lecture 8
Jan. 8, 2026
[Info] [Slides] [Video] *coming soon!*

Final Project
Work on final projects

Guest Lecture
Lecture 9
Jan. 9, 2026
[Slides] [Video] *coming soon!*

Guest Lecture
Lecture 10
Jan. 9, 2026
[Slides] [Video] *coming soon!*

Project Presentations
Pitch your ideas, awards, and celebration!

- Jan 5 – Jan 9, 2026
- Lecture Breakdown
- Labs: TensorFlow & PyTorch
- Competitions
- Final Projects + Prizes!

Software Labs: TensorFlow *and* PyTorch

TensorFlow

PyTorch

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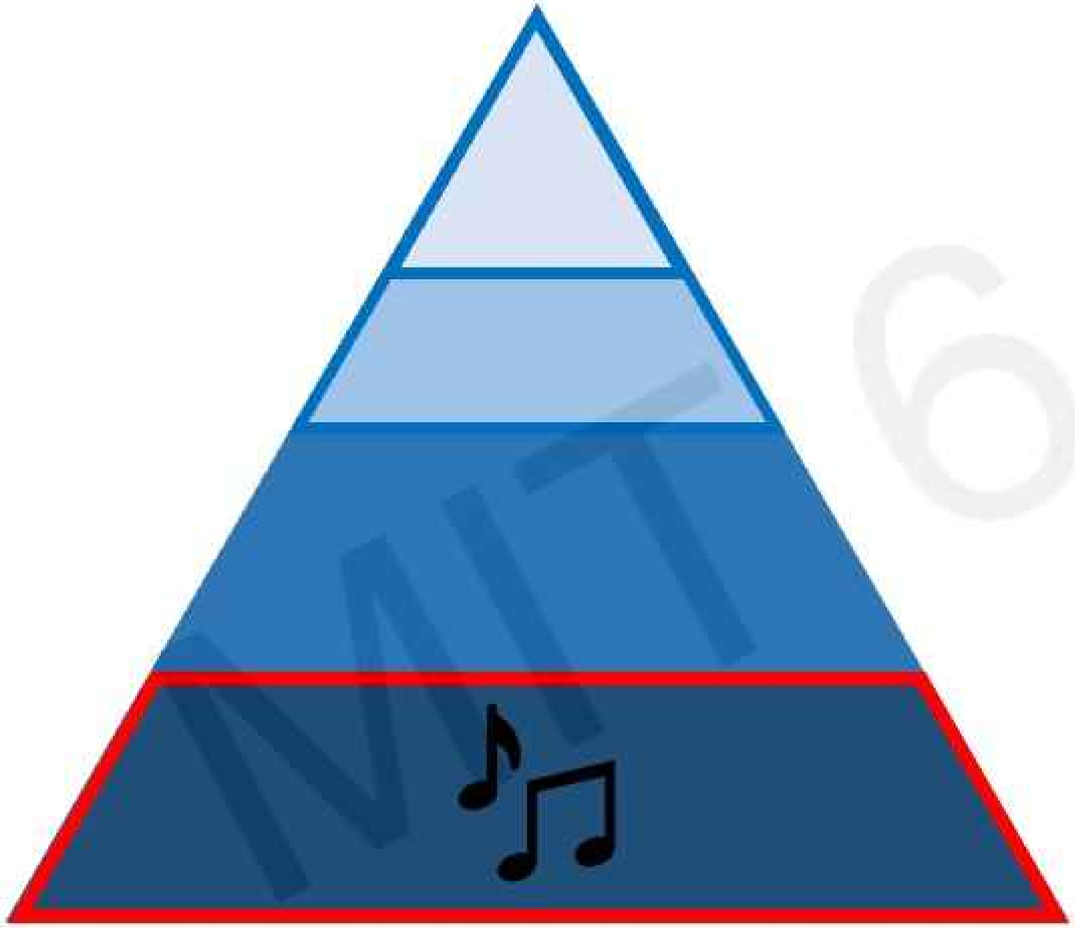
Labs and Prizes

All due Thursday 1/8 at 11:59pm ET. Instructions: bit.ly/6s191-syllabus



Music Generation

Build a neural network that can learn the genre of Irish folk songs and use it to generate brand new songs!

Prize:

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Labs and Prizes

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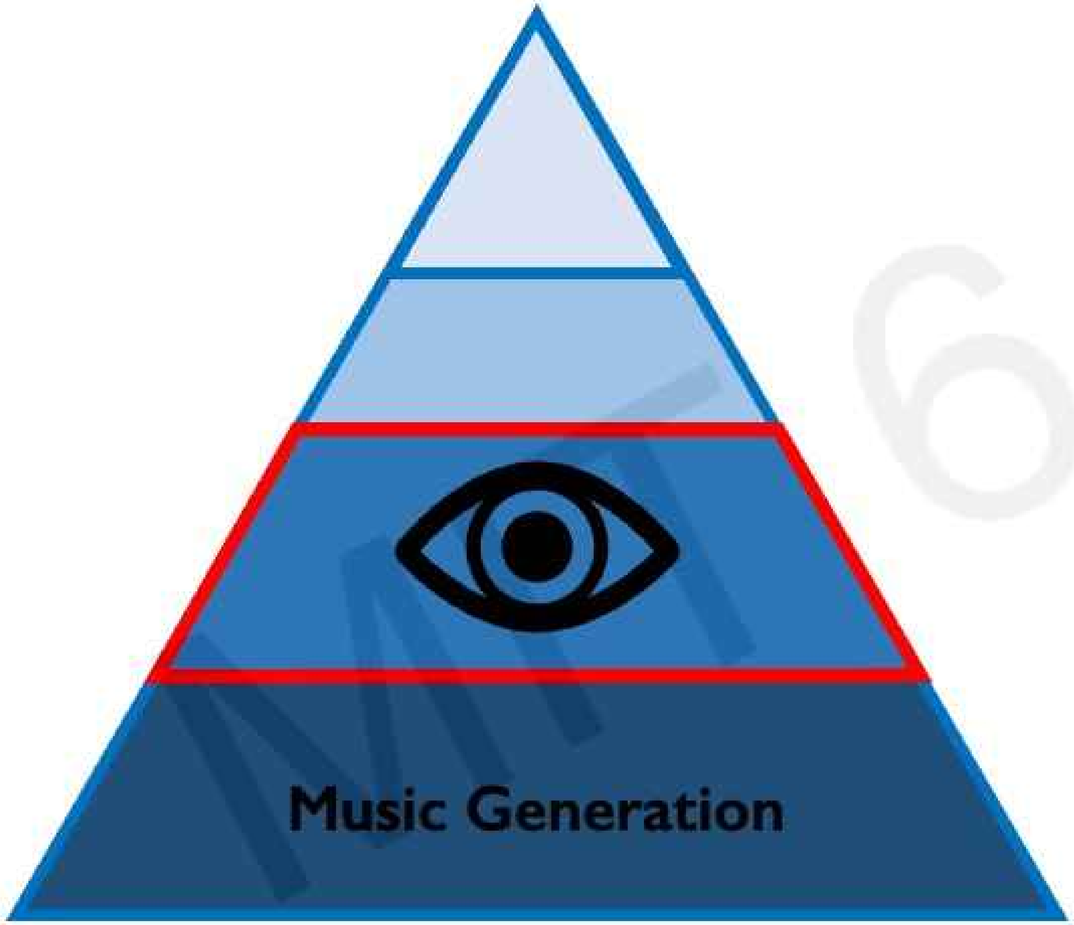

Computer Vision

Build a neural network that can detect and mitigate biases in computer vision facial recognition systems!

Prize:

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Labs and Prizes

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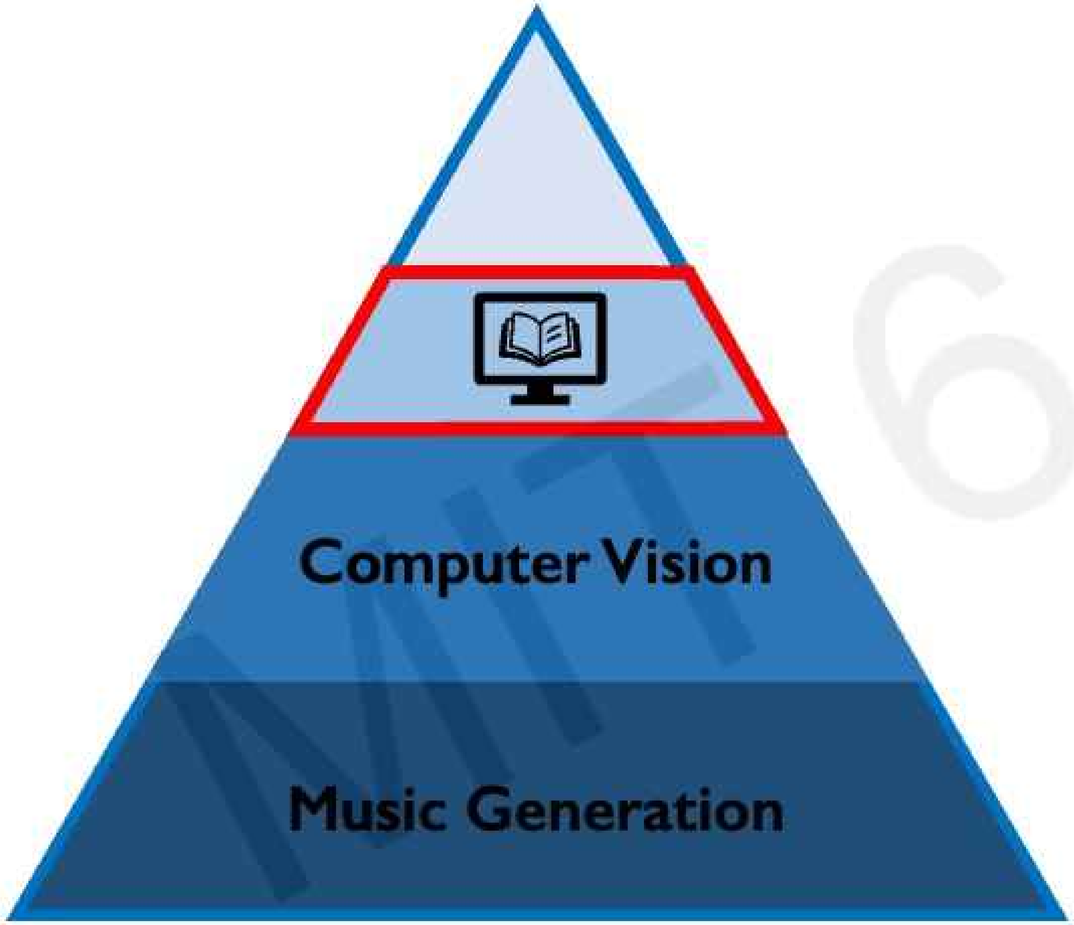

Large Language Models

Finetune the Gemma large language model (LLM) in a mystery style and evaluate with an AI judge!

Prize:

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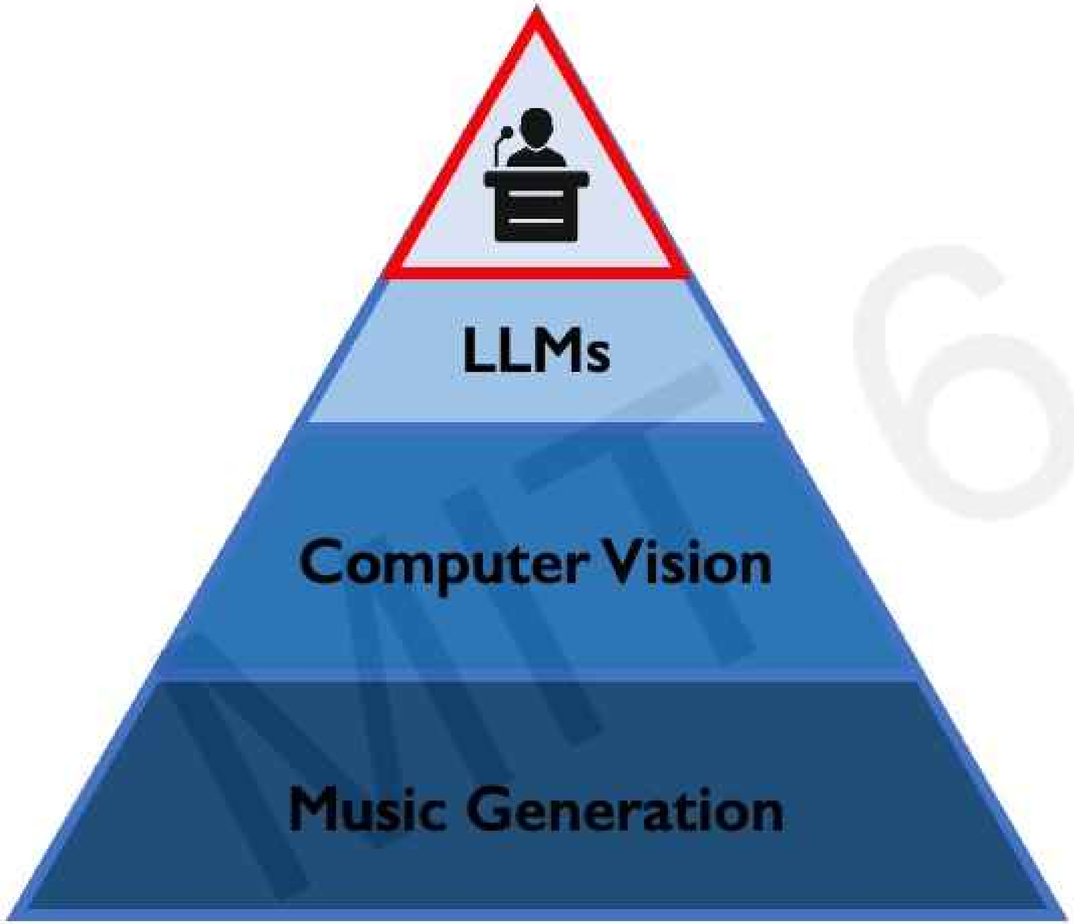
Project Pitch Competition

Friday 1/9. Instructions: bit.ly/6s191-syllabus



Project Pitch Competition

Present a novel deep learning research idea or application (5 minutes, strict)

Presentations on **Friday, Jan 9**

Submit groups by **Wed 1/07 11:59pm ET**

Submit slides by **Thu 1/08 11:59pm ET**

Instructions: bit.ly/6s191-syllabus

Prizes:

Gold:
NVIDIA 3070 GPU

Silver:
Smartwatch

Bronze:
HD Monitor

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Program Support

- All lectures will be held in person in 32-123
- Software labs + office hours in 32-123
- Piazza: piazza.com/mit/spring2026/6s191
  - Course announcements & asking questions
- Program Website: introtodeeplearning.com
  - Lecture schedule
  - Slides and lecture recordings
  - Software labs
- Syllabus: bit.ly/6s191-syllabus
- Labs: github.com/MITDeepLearning/introtodeeplearning
- Email us: introtodeeplearning-staff@mit.edu

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Program Staff

Alexander Amini
Lead Instructor

Ava Amini
Lead Instructor

Anisha Parsan
Lead TA

Shrika Eddula
Lead TA

Program TAs & EECS Sponsor

Victory

Daniela Rus
Director of CSAIL

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Why Deep Learning and Why Now?

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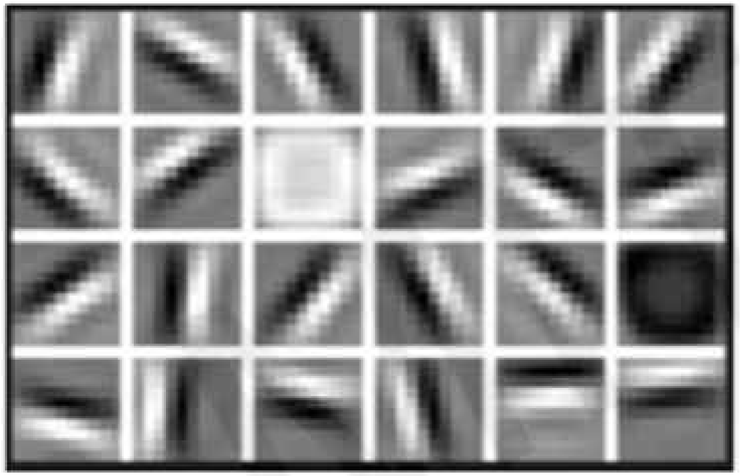
Why Deep Learning?

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?

1952 Stochastic Gradient Descent

1958 Perceptron
- Learnable Weights

⋮

1986 Backpropagation
- Multi-Layer Perceptron

1995 Deep Convolutional NN
- Digit Recognition

⋮

Neural Networks date back decades, so why the dominance?

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

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The Perceptron

The structural building block of deep learning

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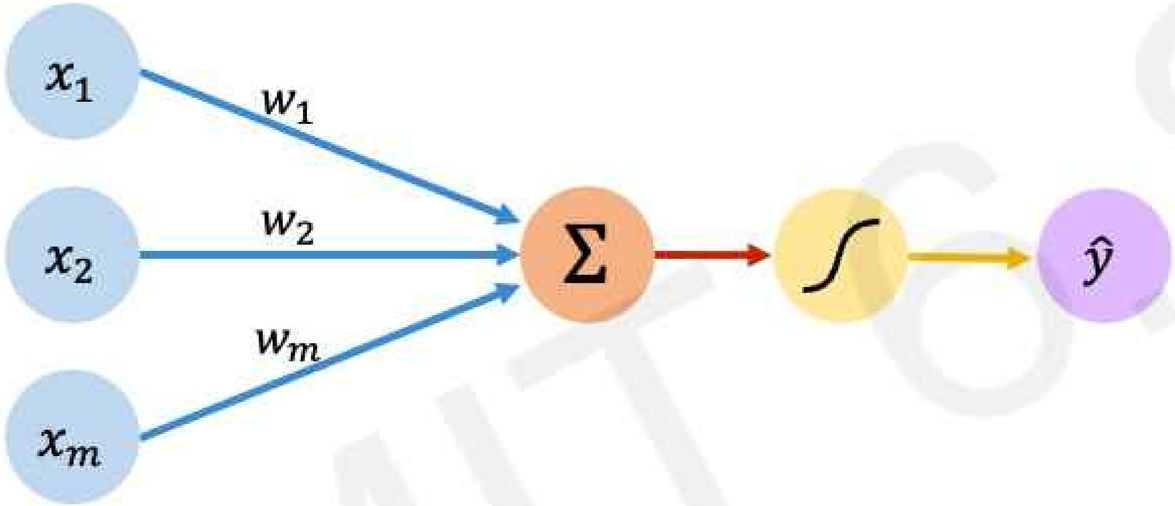
The Perceptron: Forward Propagation



Inputs Weights Sum Non-Linearity Output

Output

Linear combination of inputs

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

Non-linear activation function

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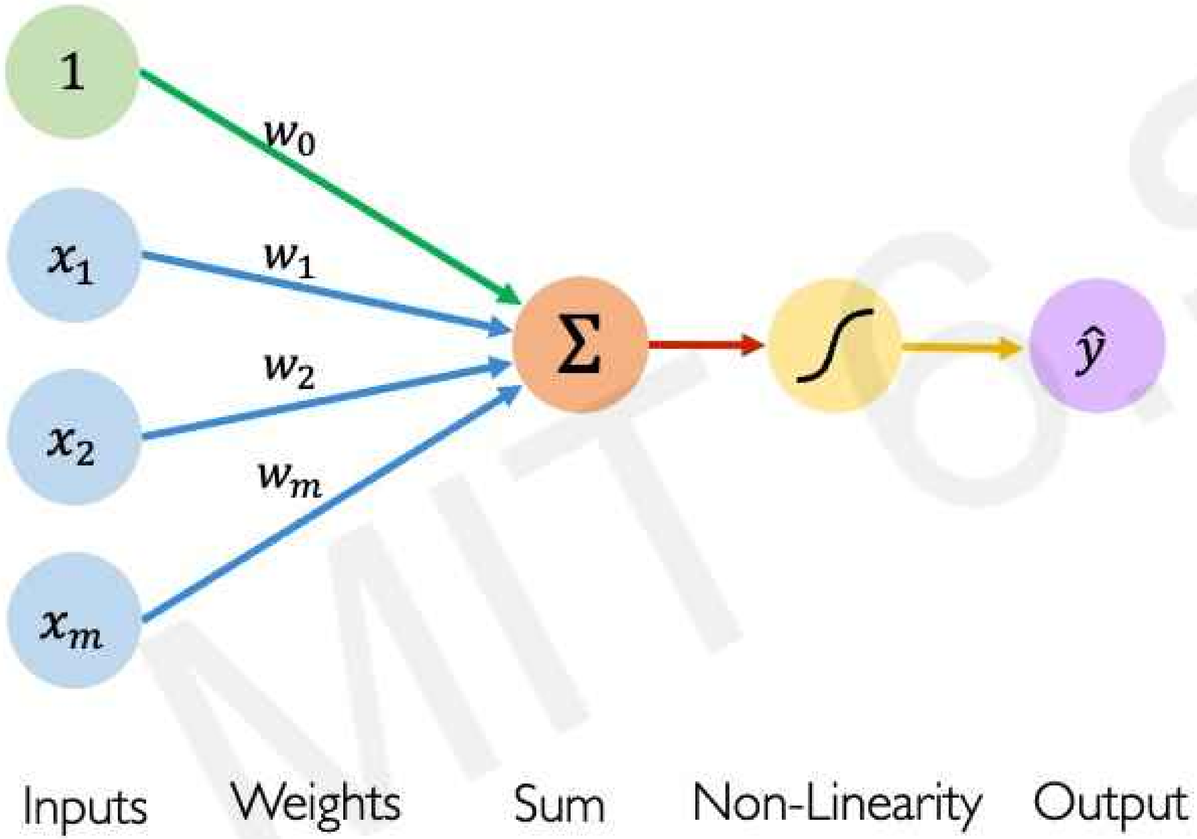
The Perceptron: Forward Propagation



Output

Linear combination of inputs

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

Non-linear activation function

Bias

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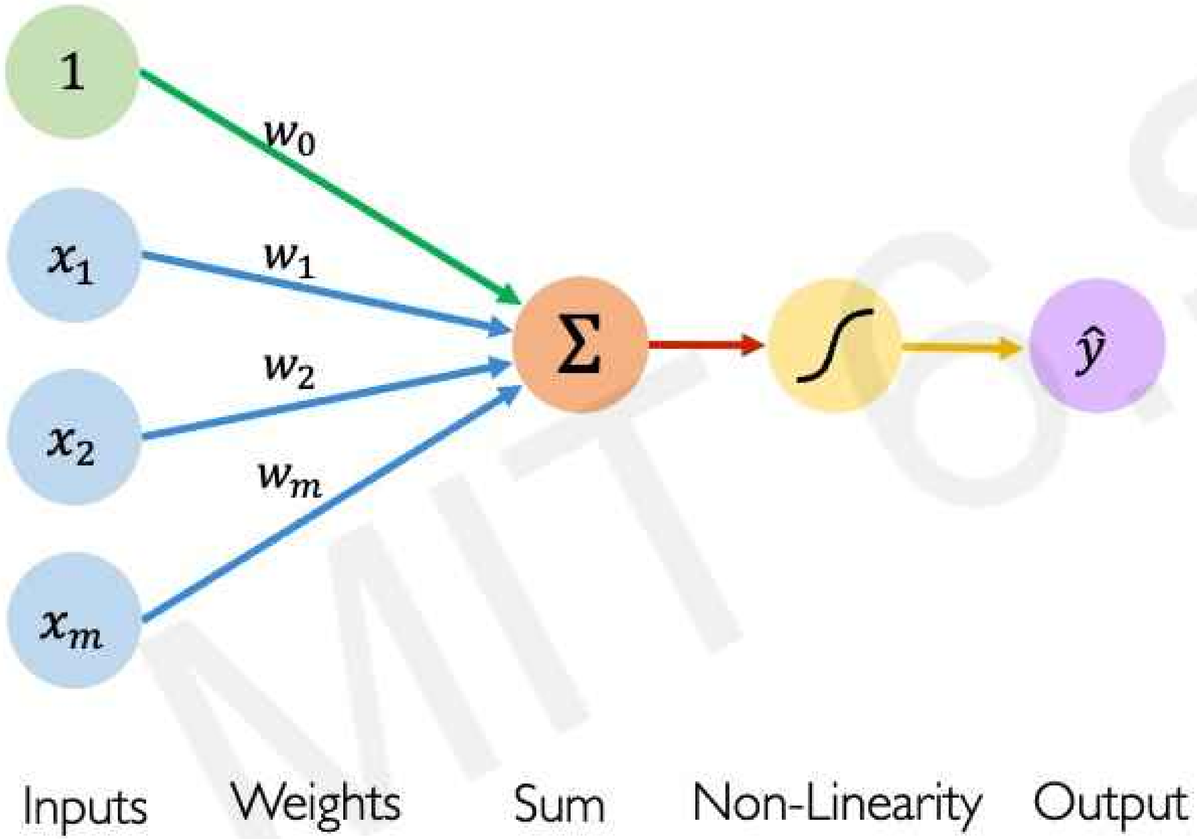
The Perceptron: Forward Propagation



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

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

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

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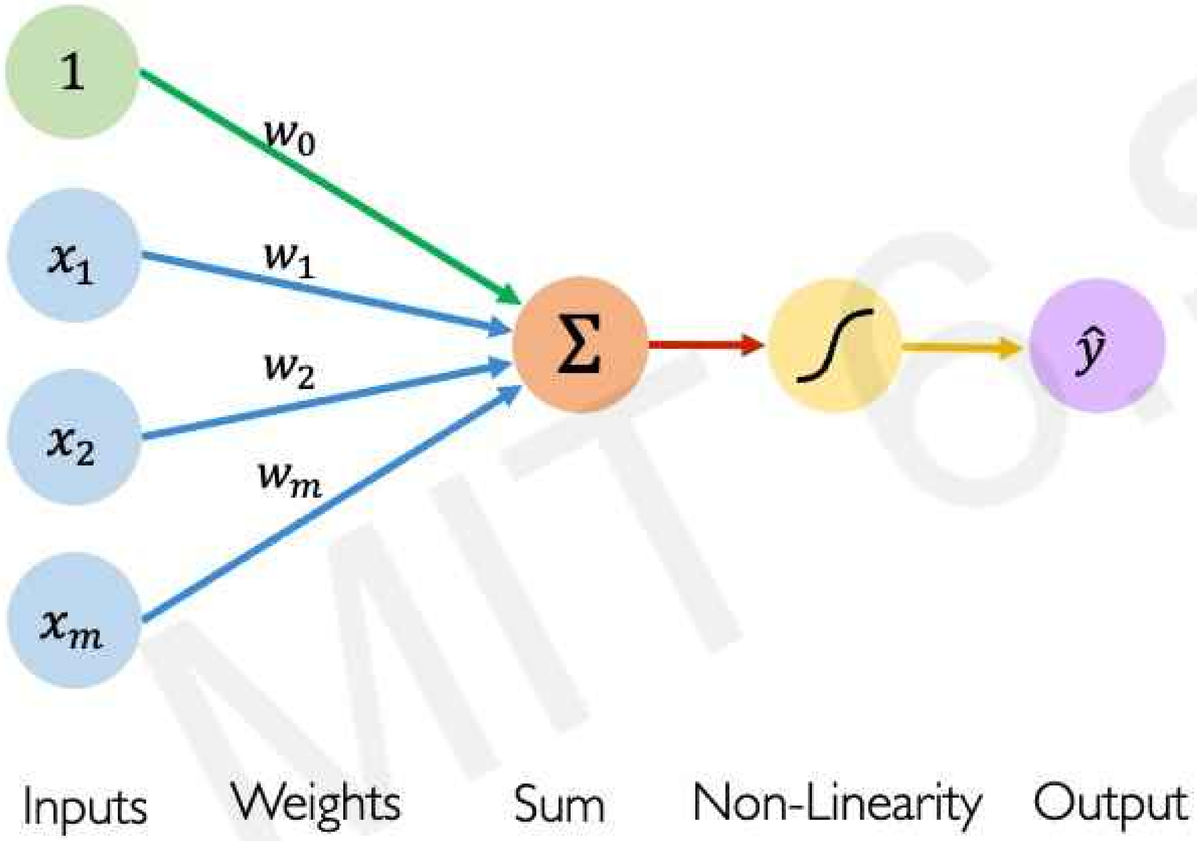
The Perceptron: Forward Propagation

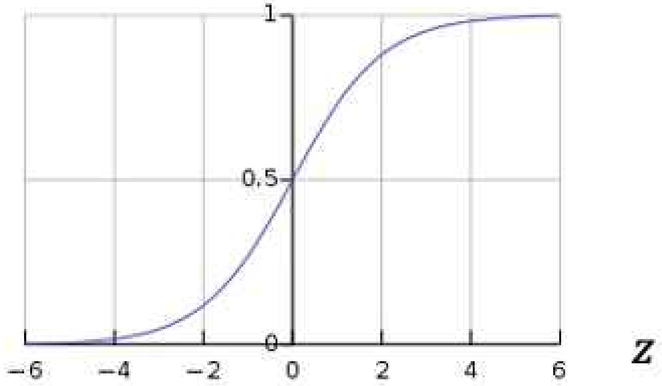


Activation Functions

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

- Example: sigmoid function

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



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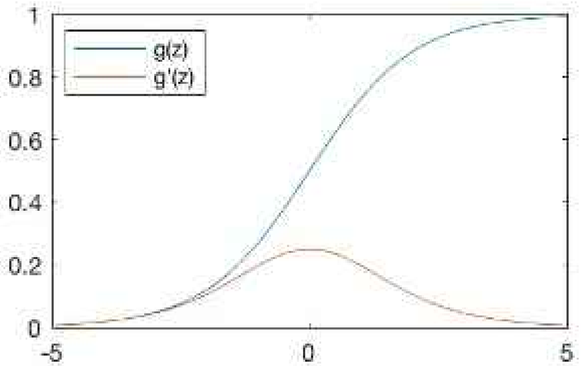
Common Activation Functions

Sigmoid Function



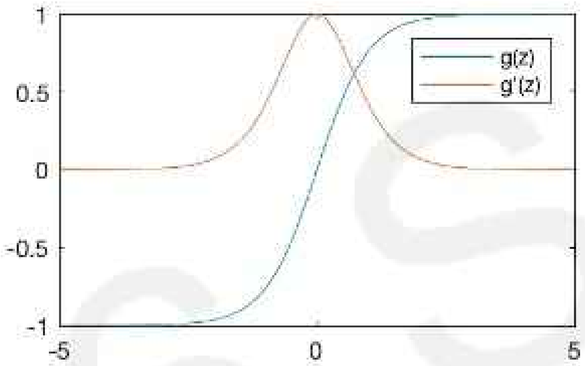
$$g(z) = \frac{1}{1 + e^{-z}}$$

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

```
tf.math.sigmoid(z)
```

```
torch.sigmoid(z)
```

Hyperbolic Tangent



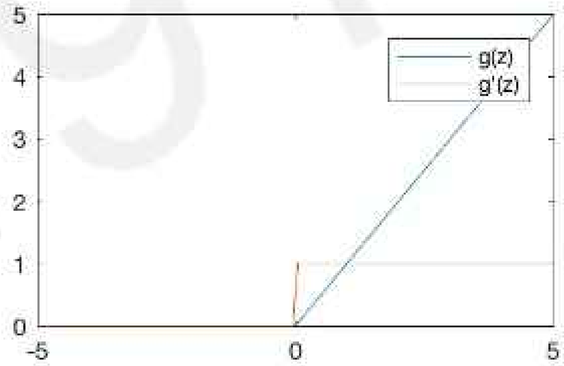
$$g(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

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

```
tf.math.tanh(z)
```

```
torch.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)
```

```
torch.nn.ReLU(z)
```

TensorFlow code blocks

NOTE: All activation functions are non-linear

PyTorch code blocks

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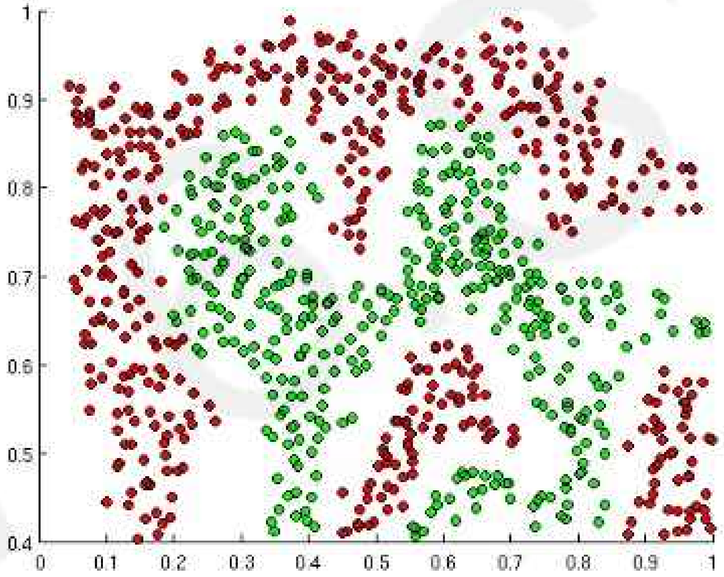
Importance of Activation Functions

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?

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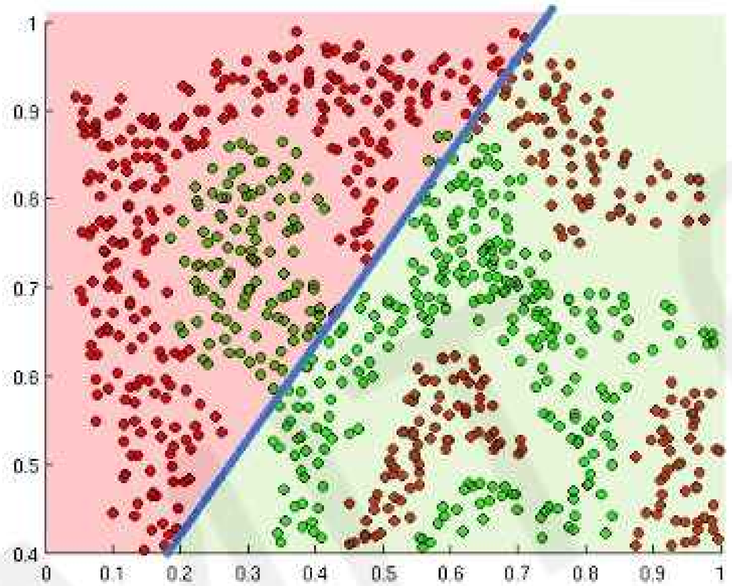
Importance of Activation Functions

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



Linear activation functions produce linear decisions no matter the network size

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Importance of Activation Functions

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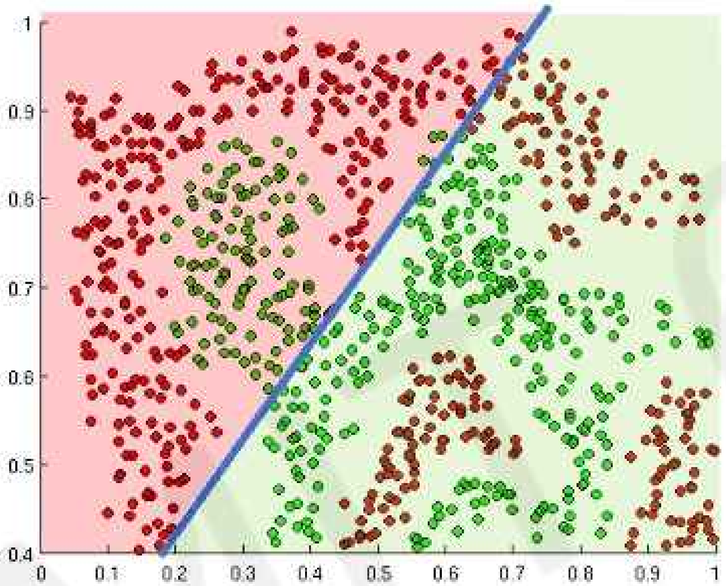
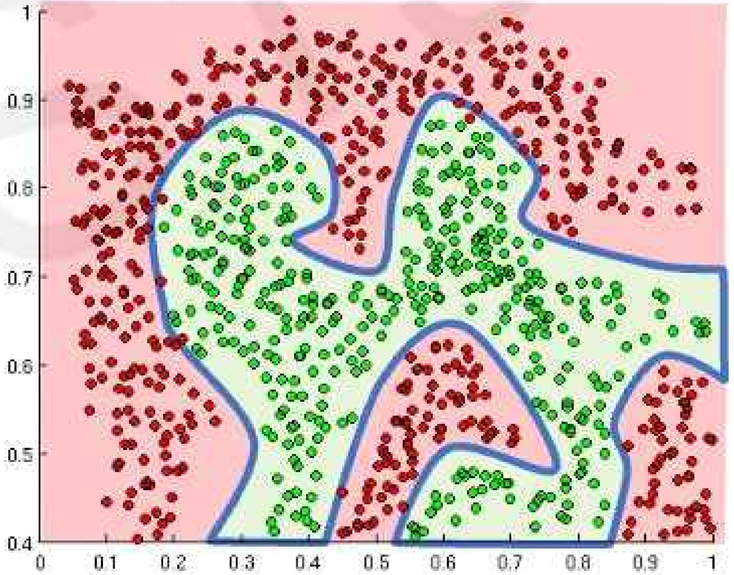
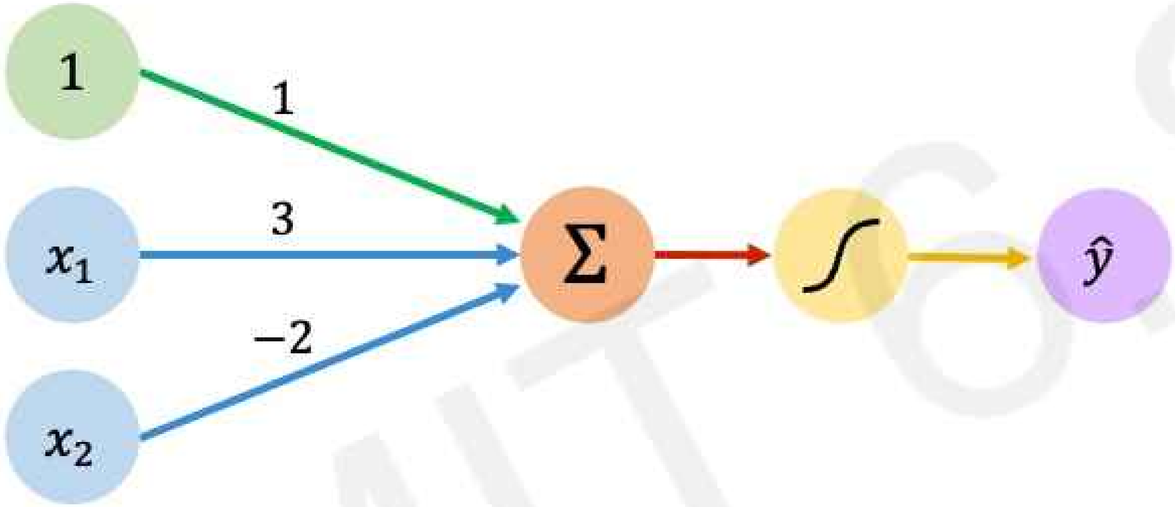


Linear activation functions produce linear decisions no matter the network size



Non-linearities allow us to approximate arbitrarily complex functions

The Perceptron: Example



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

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

$$= g\left(1 + \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^T \begin{bmatrix} 3 \\ -2 \end{bmatrix}\right)$$

$$\hat{y} = g(\underbrace{1 + 3x_1 - 2x_2}_{\text{This is just a line in 2D!}})$$

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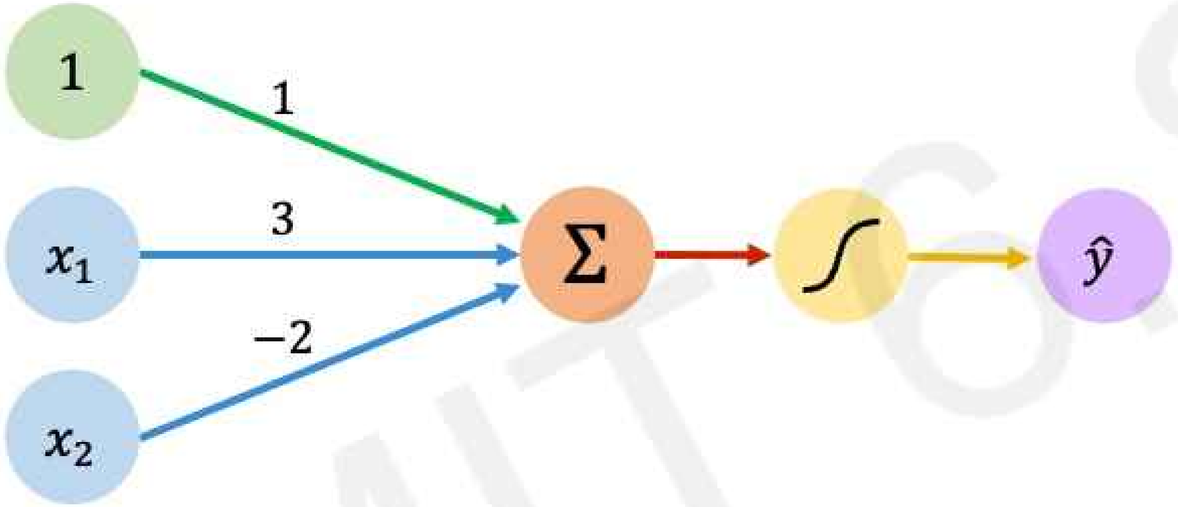
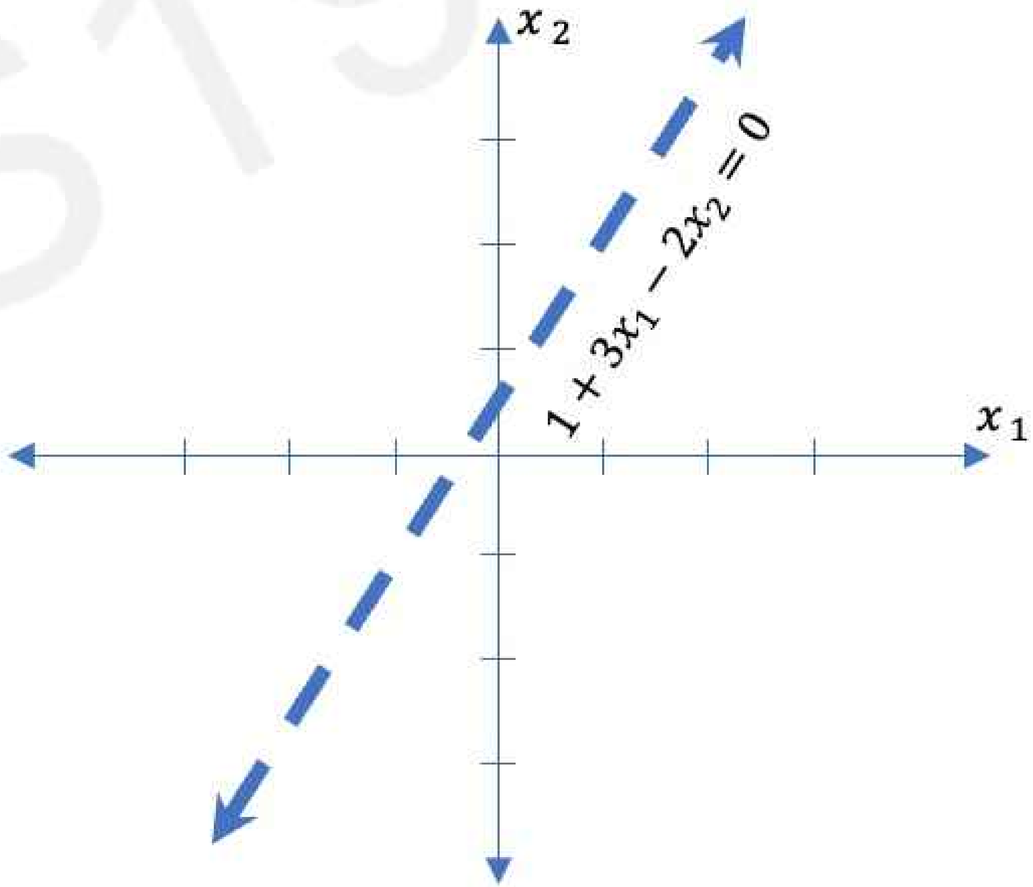
The Perceptron: Example

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





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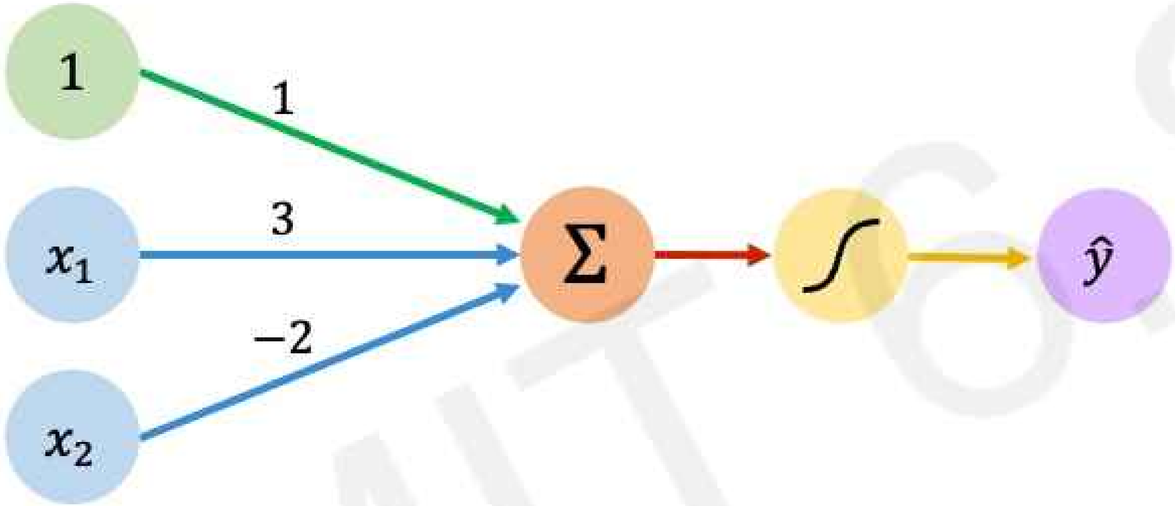
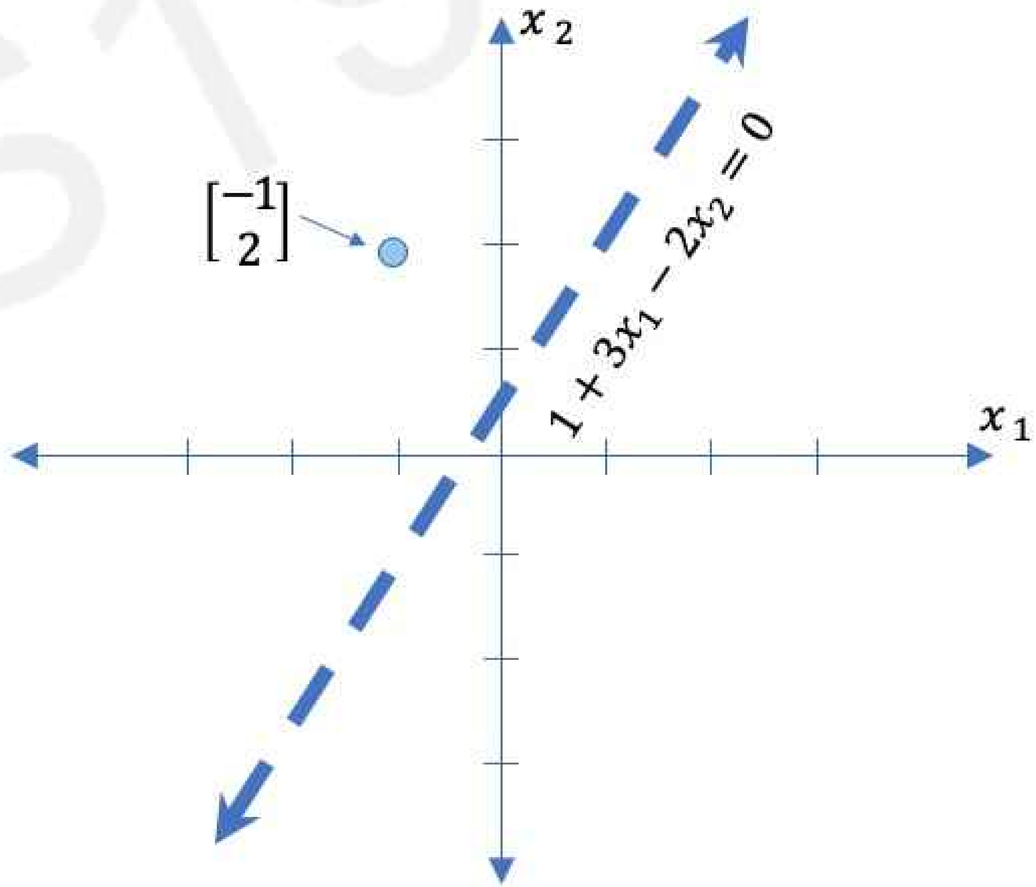
The Perceptron: Example



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



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

$$\hat{y} = g\big(1 + (3 * -1) - (2 * 2)\big)$$
$$= g(-6) \approx 0.002$$

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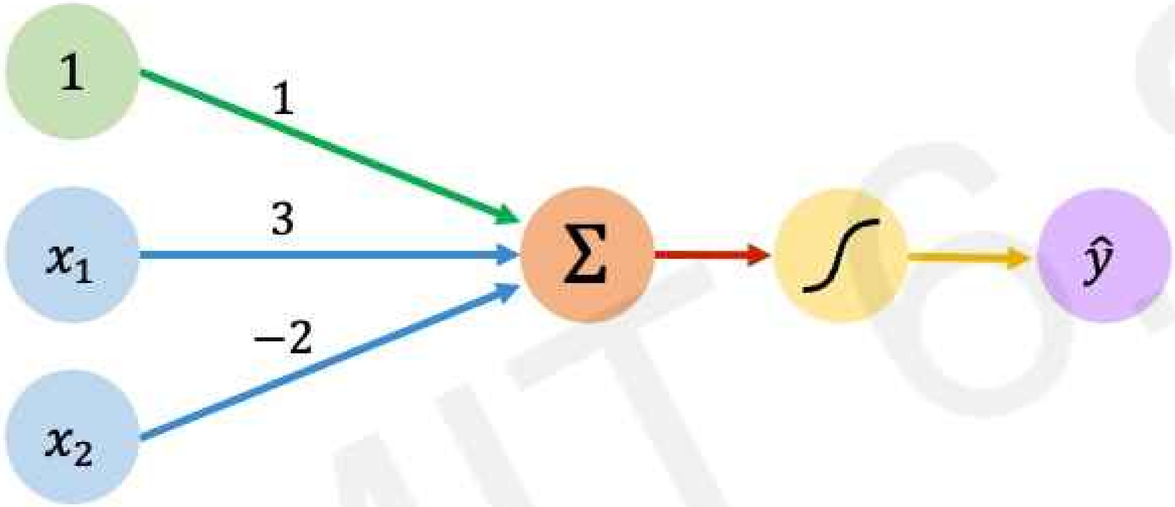
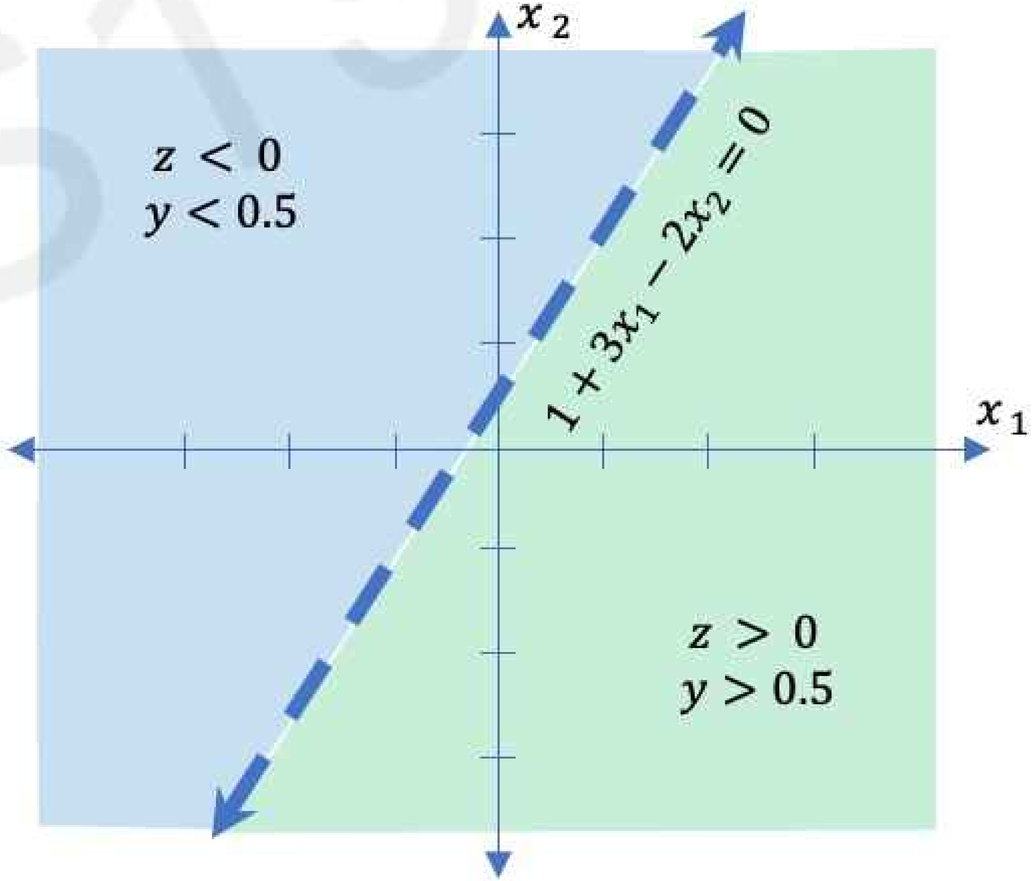
The Perceptron: Example



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



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Building Neural Networks with Perceptrons

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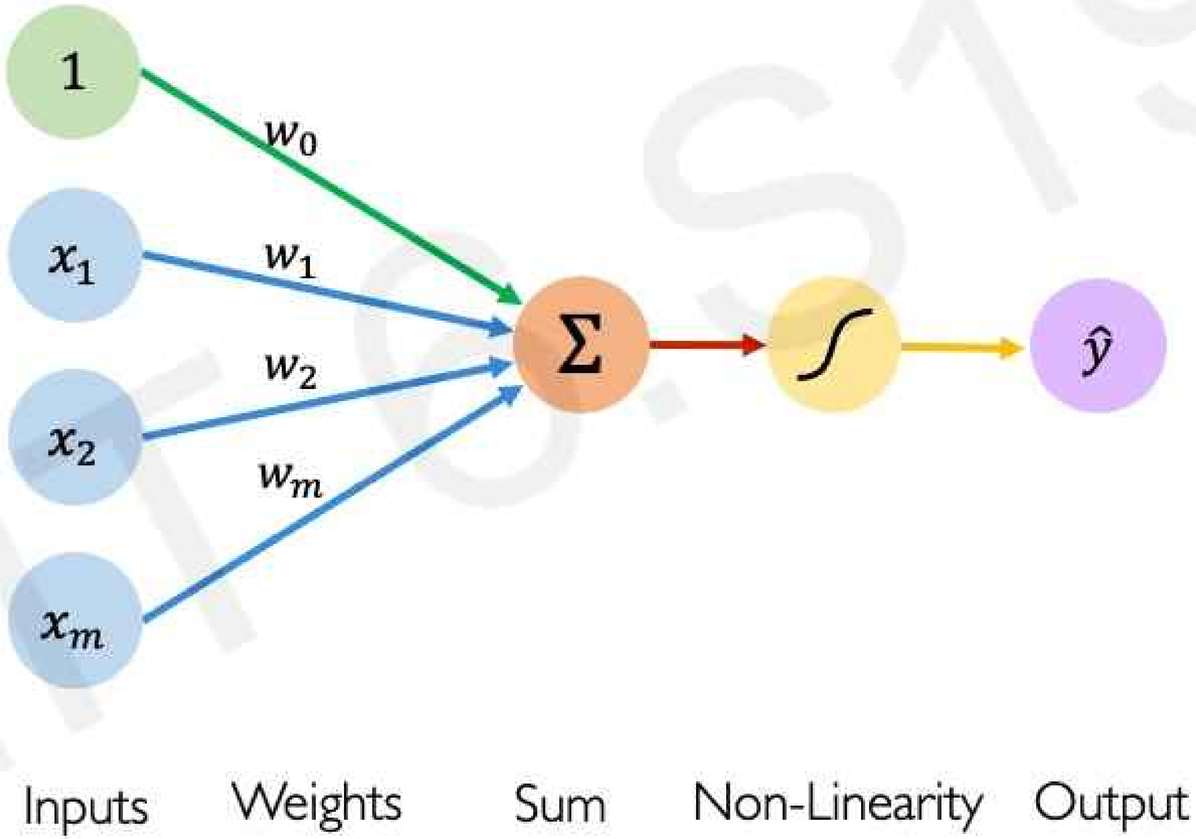
The Perceptron: Simplified

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



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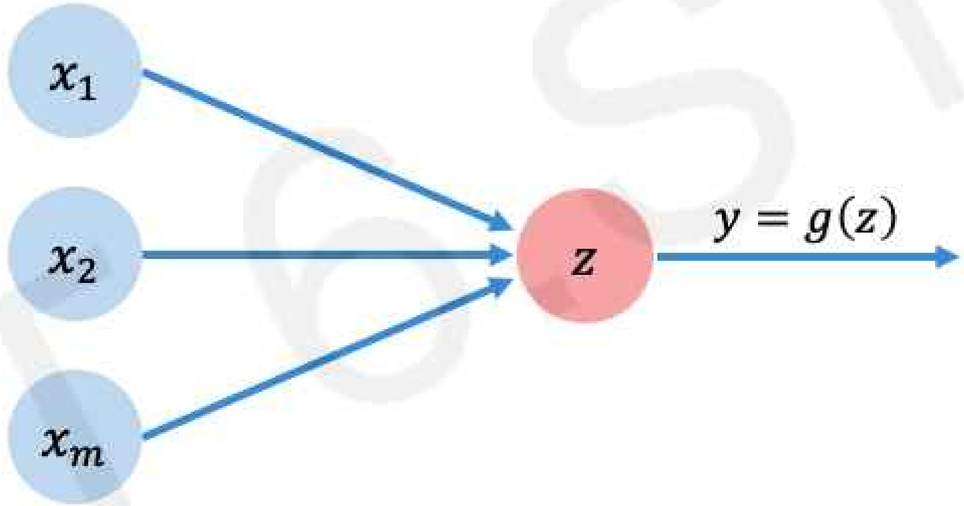
The Perceptron: Simplified



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

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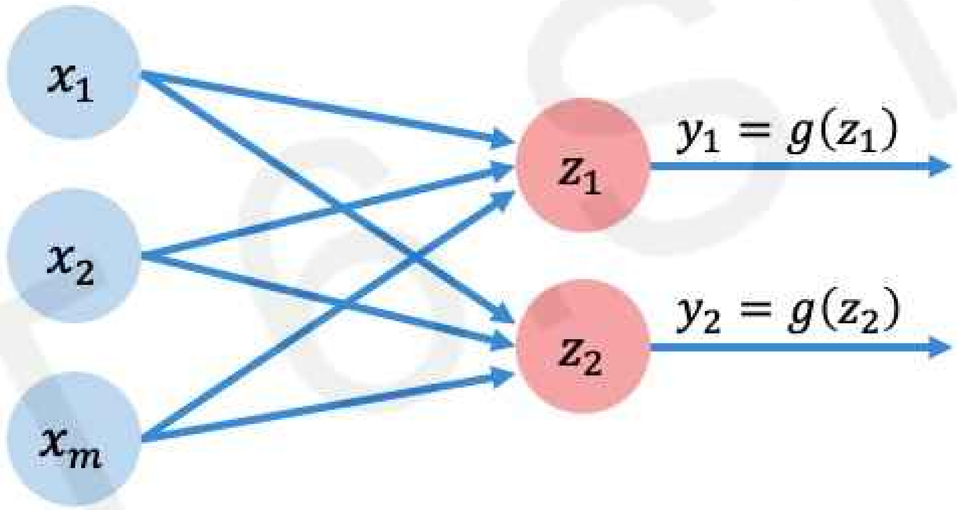
Multi Output Perceptron

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



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

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Dense layer from scratch

```tf
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
```

```pt
class MyDenseLayer(nn.Module):
  def __init__(self, input_dim, output_dim):
    super(MyDenseLayer, self).__init__()

    # Initialize weights and bias
    self.W = nn.Parameter(torch.randn(input_dim,
        output_dim, requires_grad=True)
    self.b = nn.Parameter(torch.randn(1, output_dim,
        requires_grad=True)

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

    # Feed through a non-linear activation
    output = torch.sigmoid(z)
    return output
```

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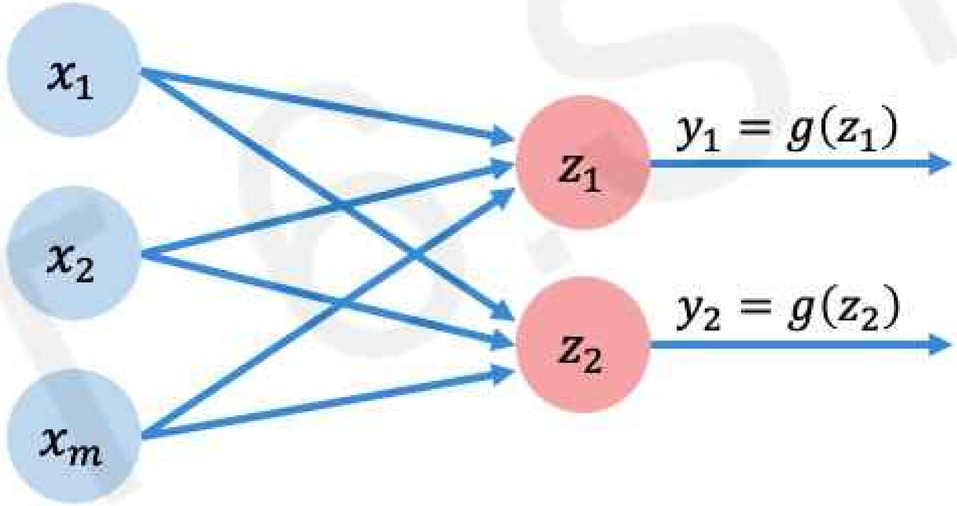
Multi Output Perceptron

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




```tensorflow
import tensorflow as tf

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

```torch
import torch.nn as nn

layer = nn.Linear(in_features=m,
    out_features=2)
```

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

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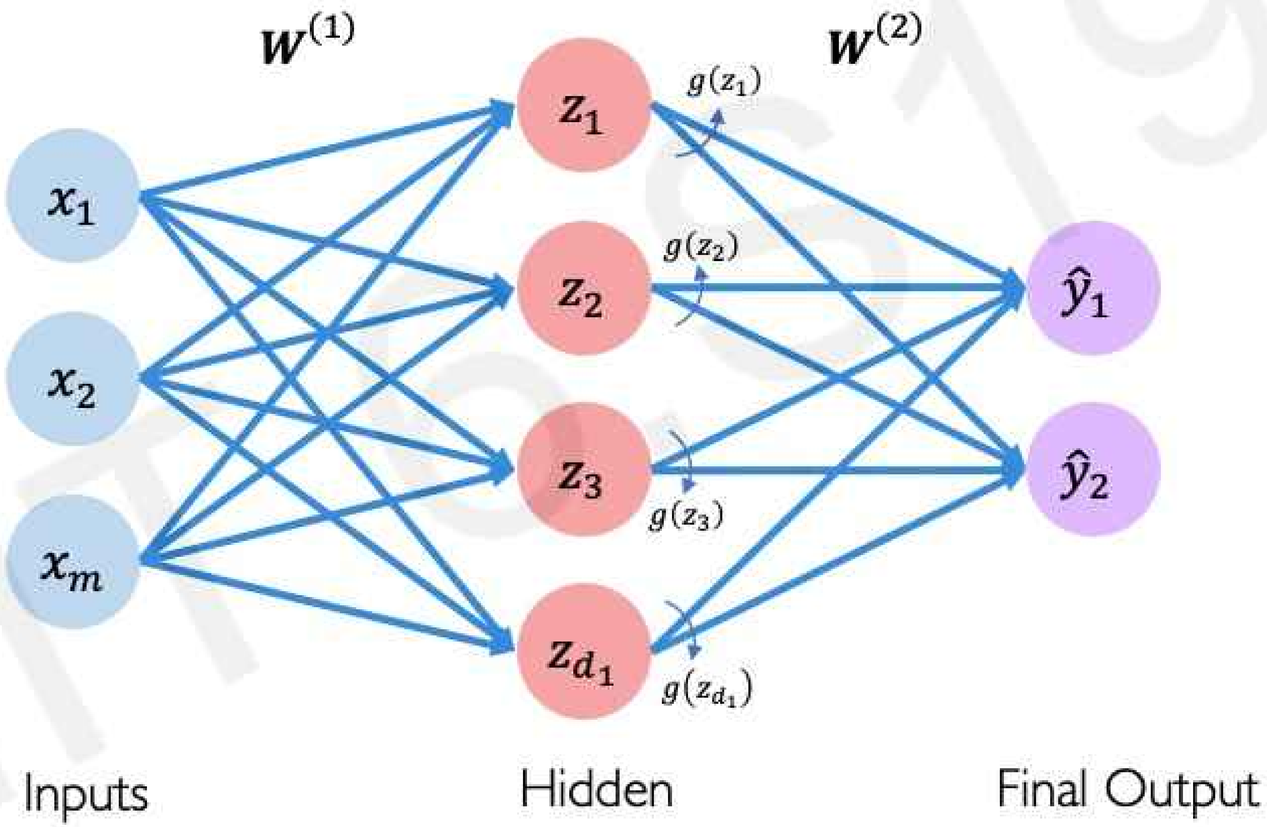
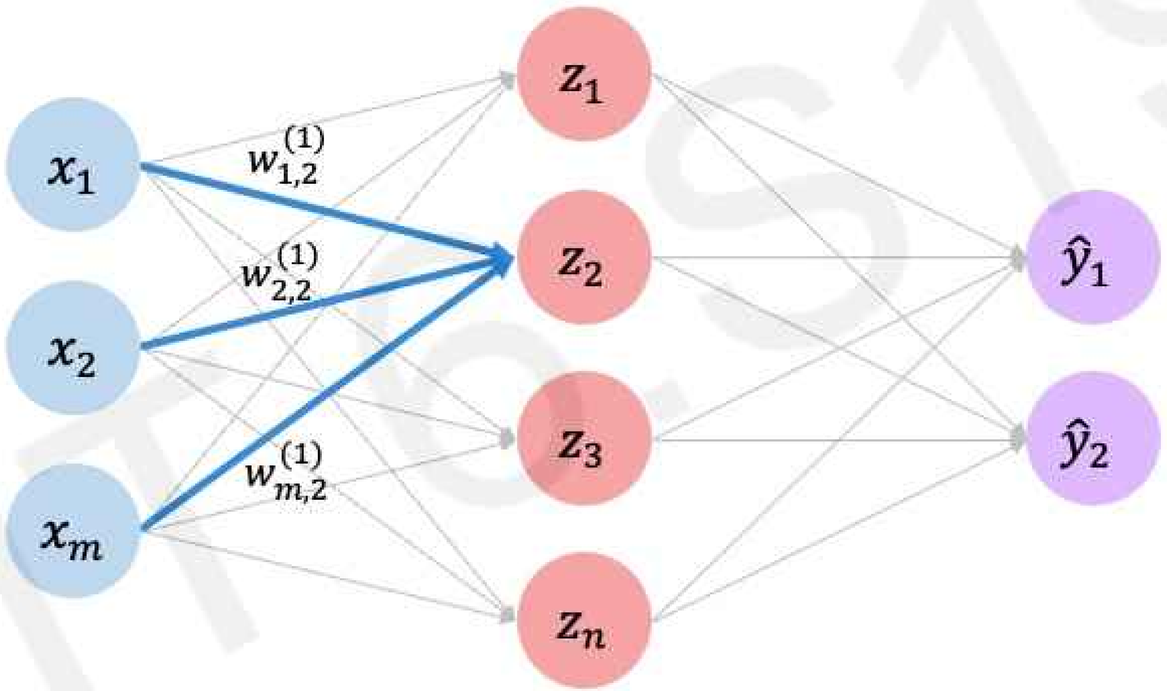
Single Layer Neural Network



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

Single Layer Neural Network



$$z_2 = w_{0,2}^{(1)} + \sum_{j=1}^{m} x_j \, w_{j,2}^{(1)}$$

$$= w_{0,2}^{(1)} + x_1 \, w_{1,2}^{(1)} + x_2 \, w_{2,2}^{(1)} + x_m \, w_{m,2}^{(1)}$$

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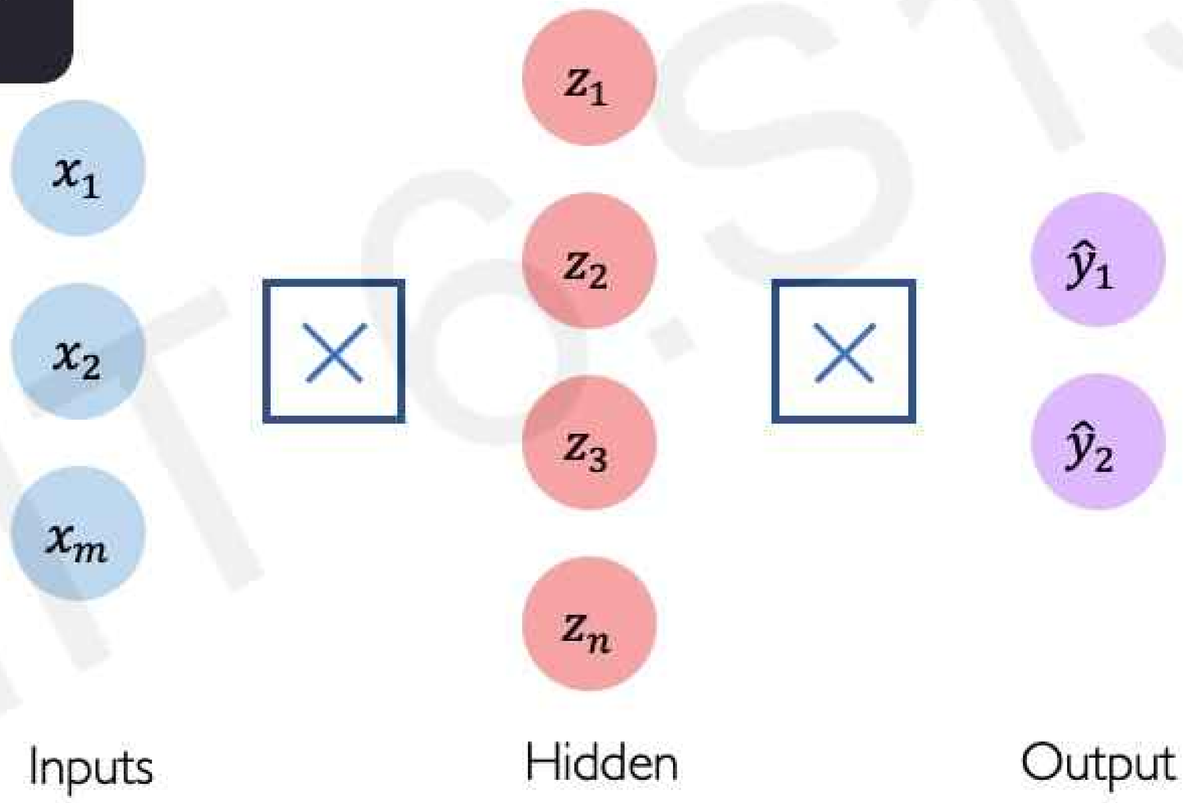
Multi Output Perceptron

```python
import tensorflow as tf

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

```python
from torch import nn

model = nn.Sequential(
    nn.Linear(m, n),
    nn.ReLU(),
    nn.Linear(n, 2)
)
```



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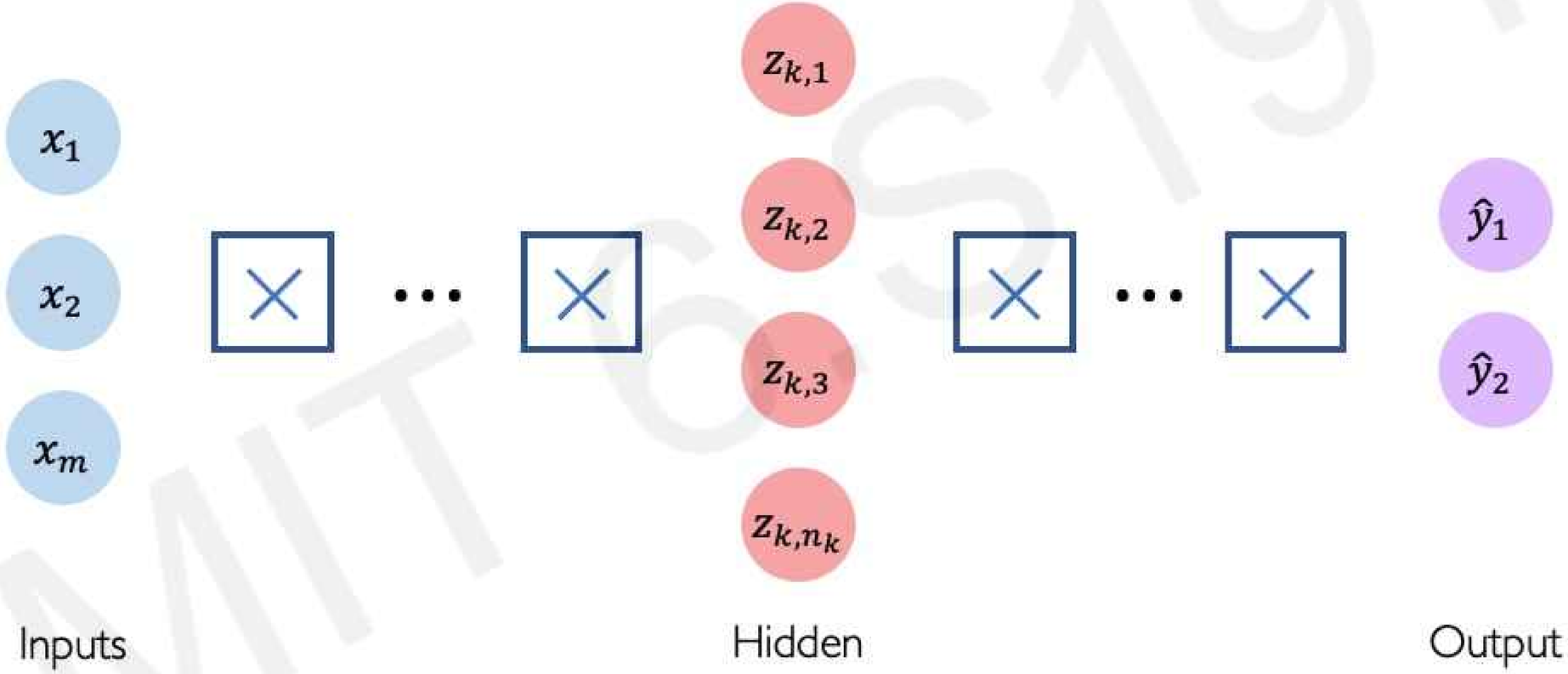
Deep Neural Network



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

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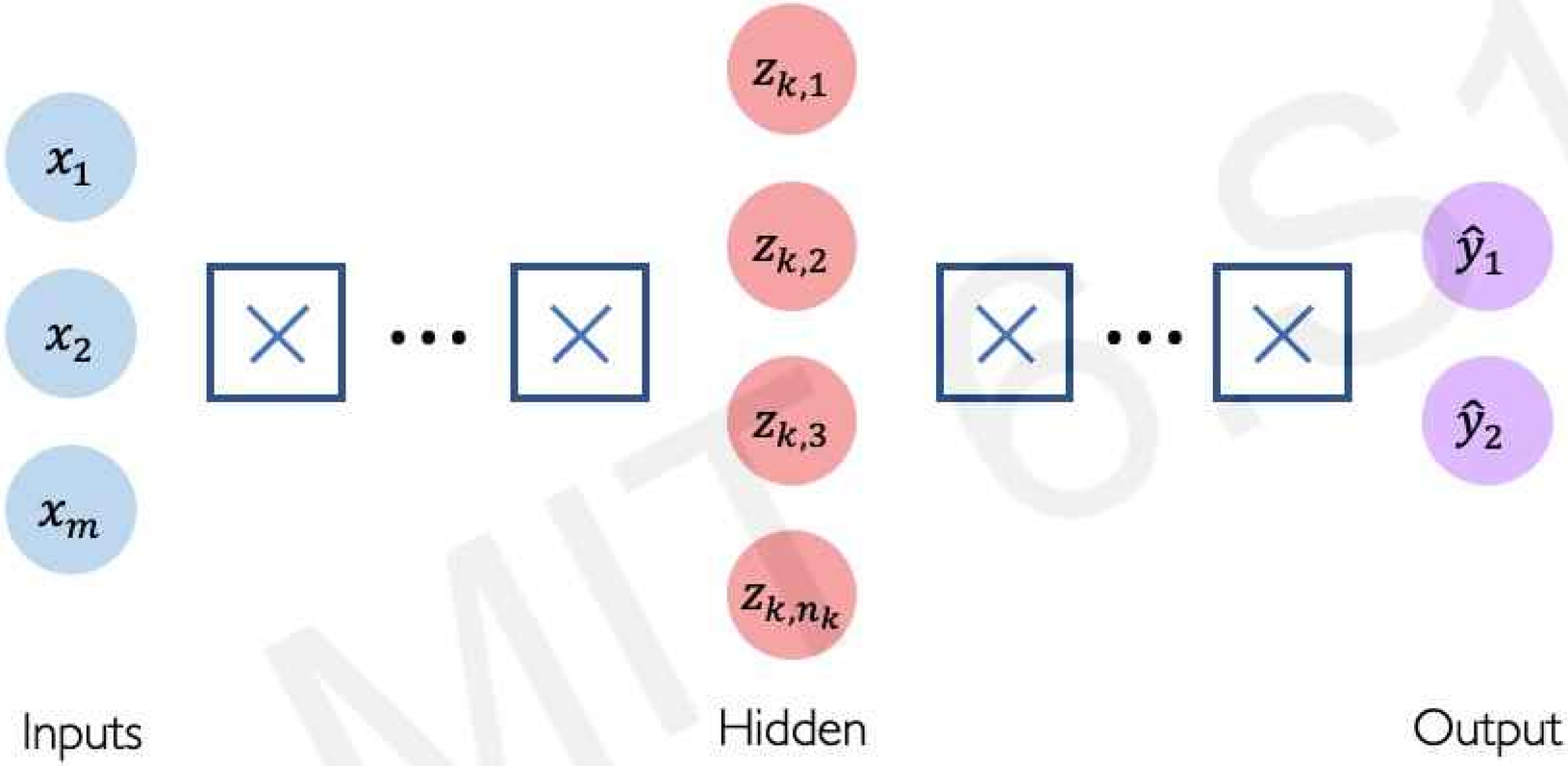
Deep Neural Network



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

```python
import tensorflow as tf

model = tf.keras.Sequential([
  tf.keras.layers.Dense(n1),
  tf.keras.layers.Dense(n2),
  ⋮
  tf.keras.layers.Dense(2)
])
```

```python
from torch import nn

model = nn.Sequential(
  nn.Linear(m, n1),
  nn.ReLU(),
⋮
  nn.ReLU(),
  nn.Linear(nK, 2)
)
```

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Applying Neural Networks

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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

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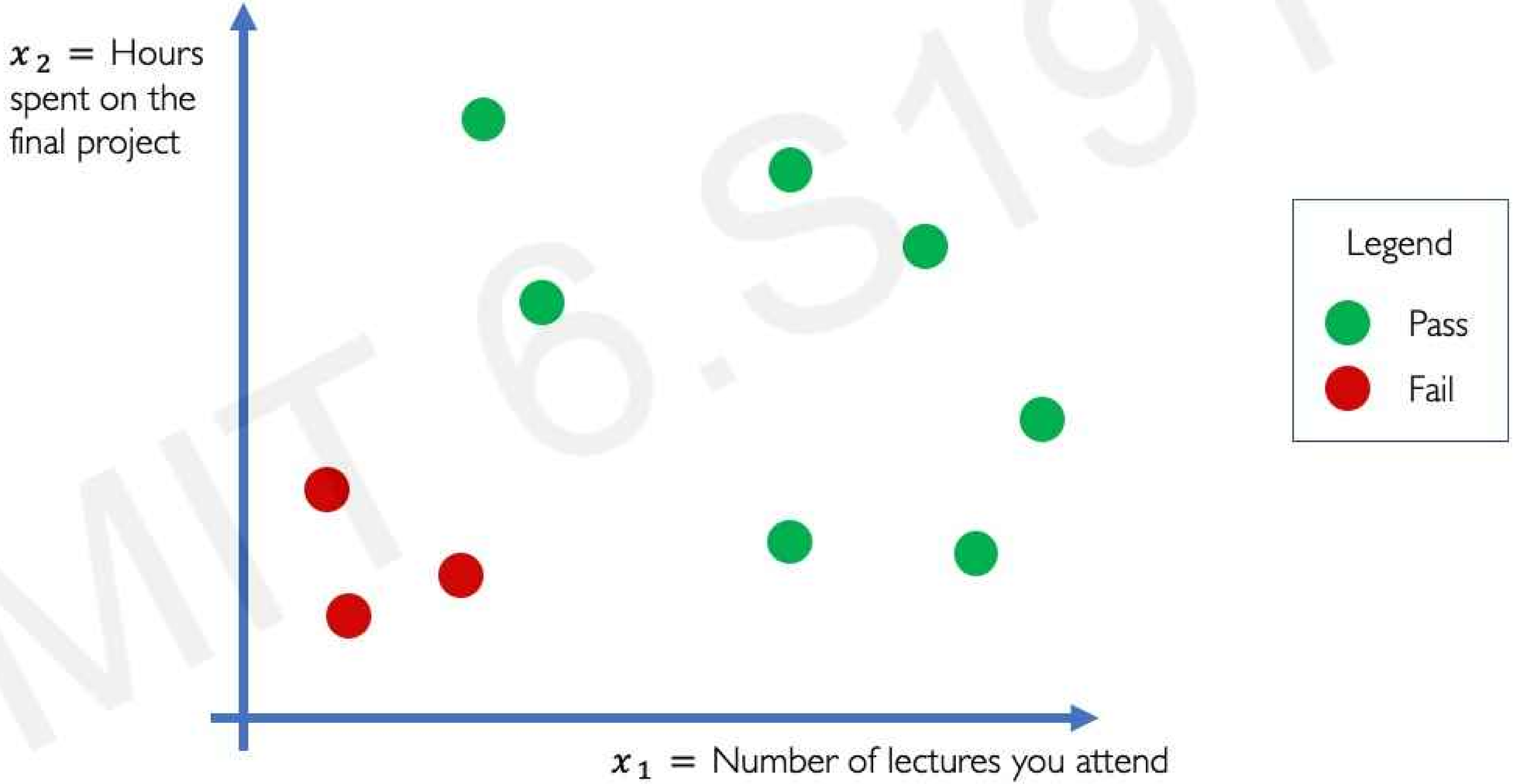
Example Problem: Will I pass this class?



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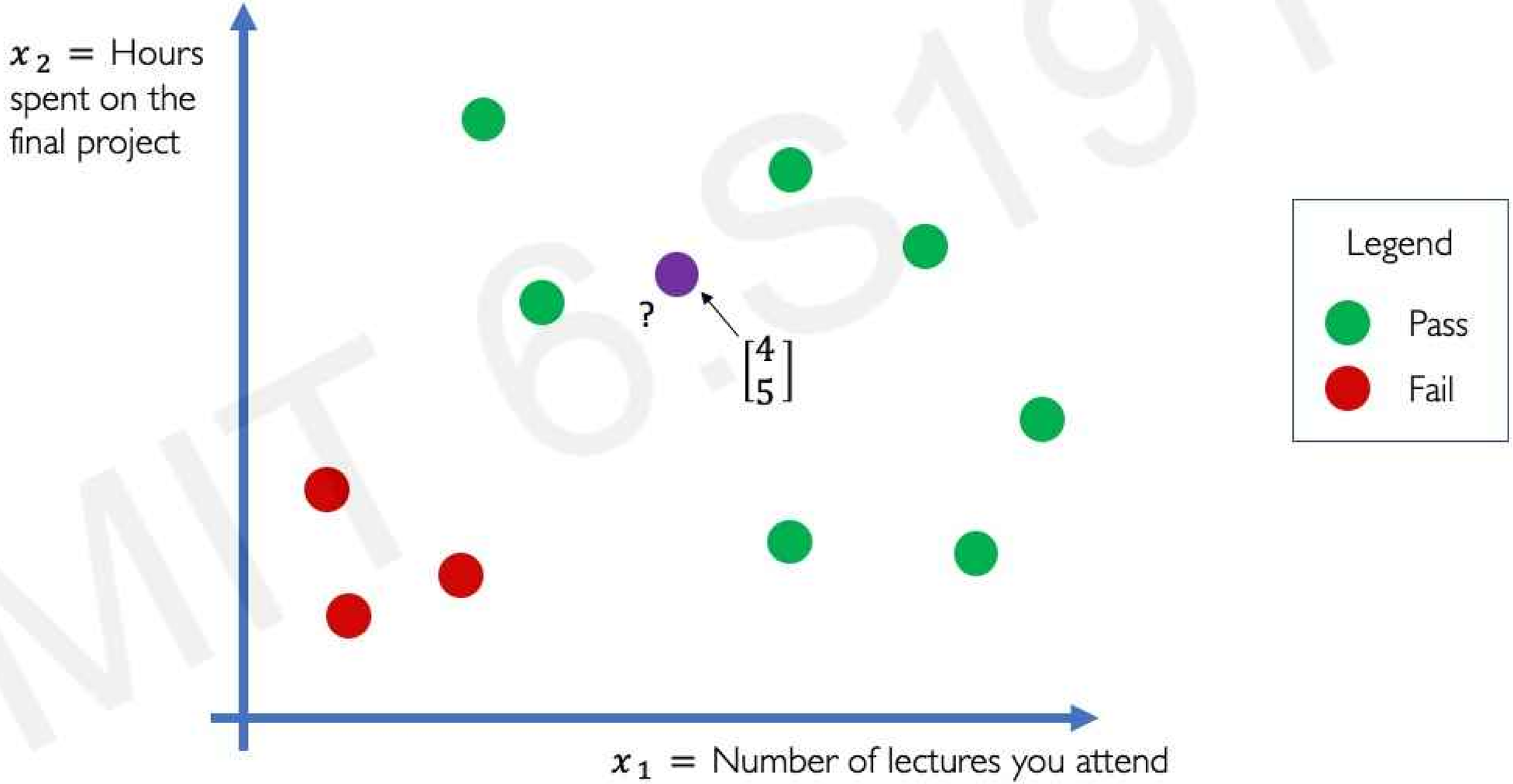
Example Problem: Will I pass this class?



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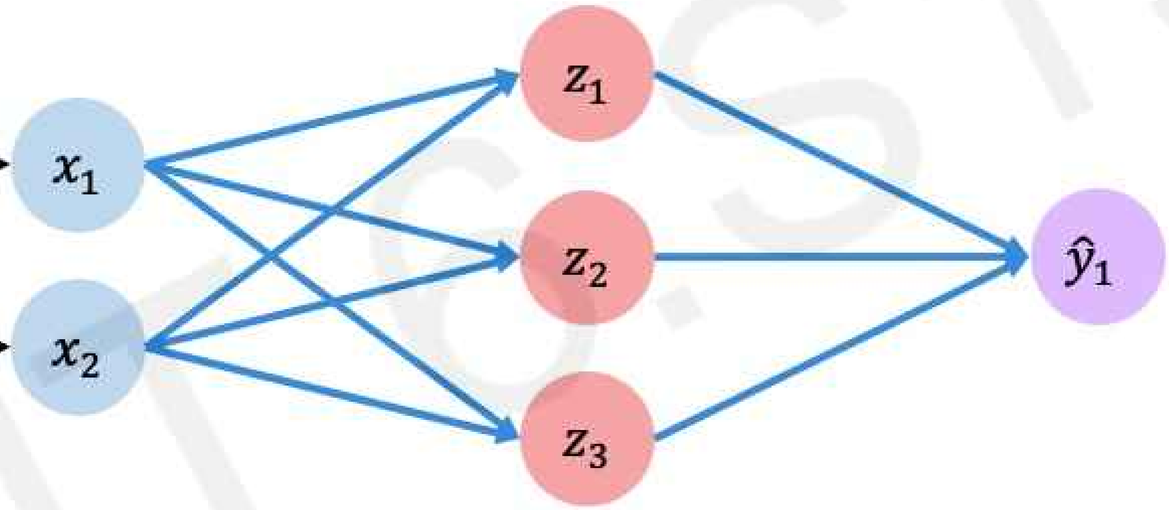
Example Problem: Will I pass this class?

$$x^{(1)} = [4\ ,5\,]$$



Predicted: **0.1**

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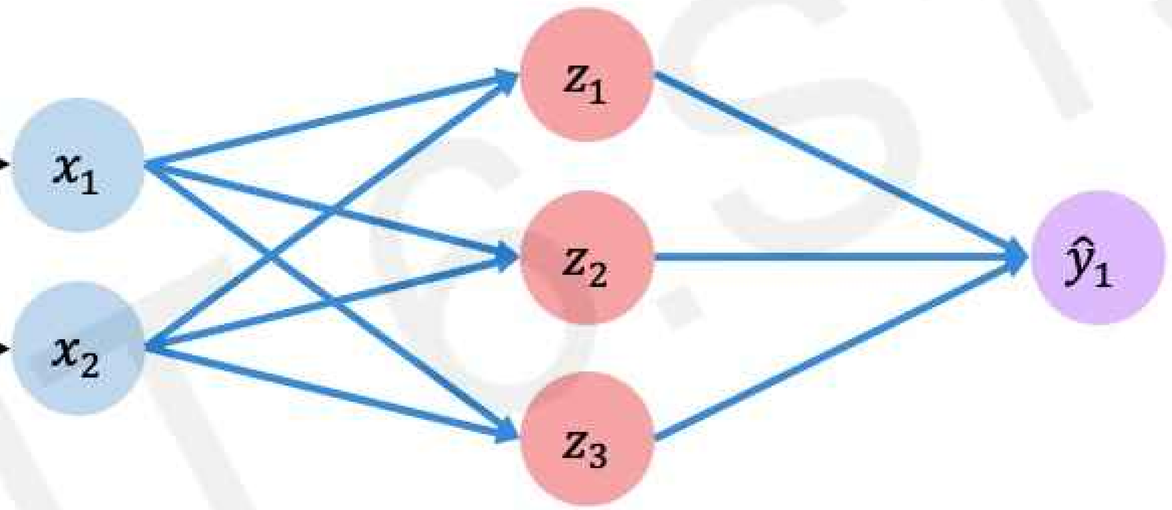
Example Problem: Will I pass this class?

$$x^{(1)} = [4\ ,5\,]$$



Predicted: 0.1
Actual: 1

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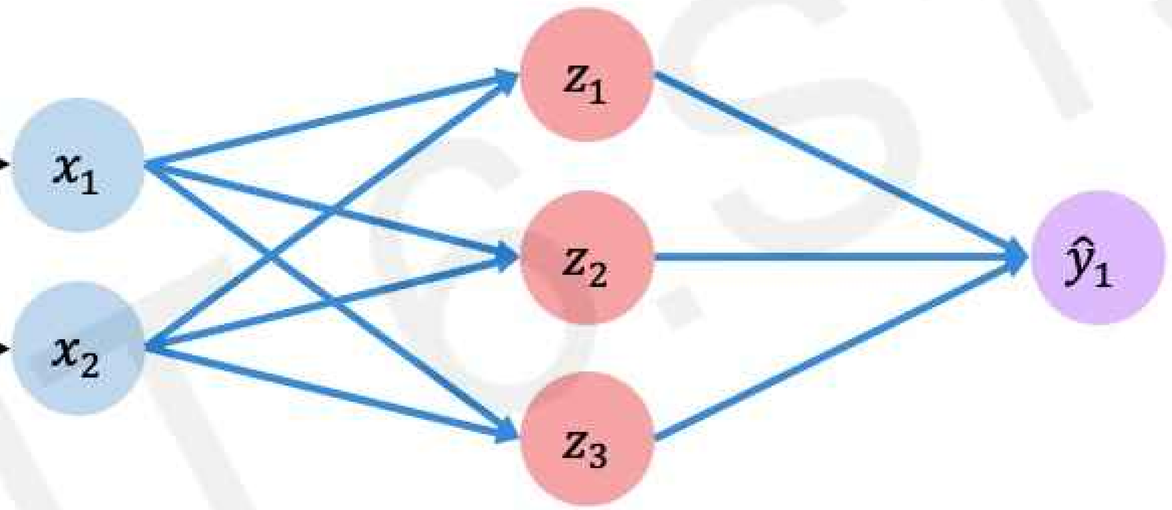
Quantifying Loss

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

$$x^{(1)} = [4\ ,5]$$



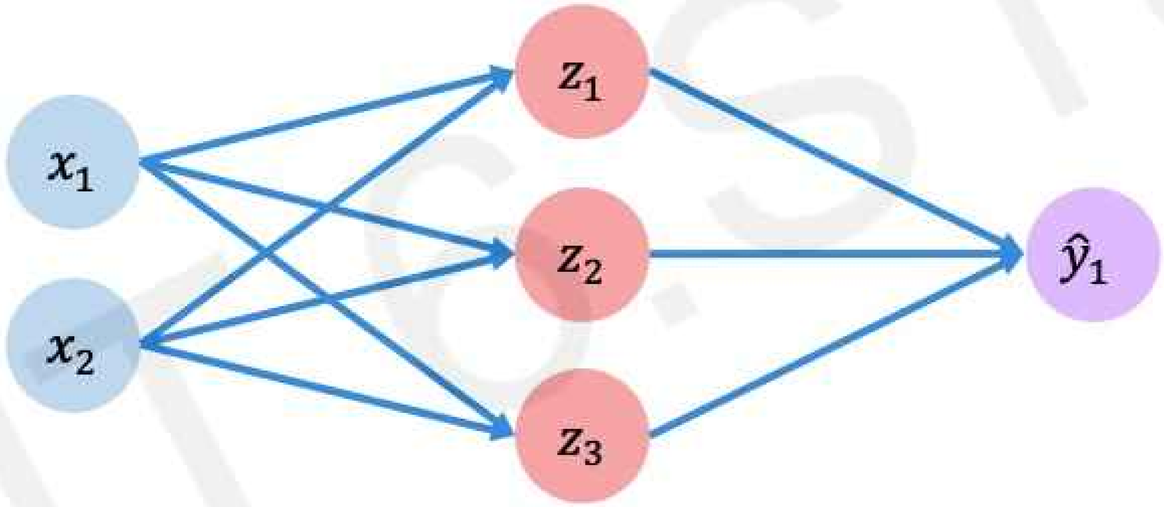
Predicted: **0.1**
Actual: **1**

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

Empirical Loss

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

$$\boldsymbol{X} = \begin{bmatrix} 4, & 5 \\ 2, & 1 \\ 5, & 8 \\ \vdots & \vdots \end{bmatrix}$$



$$\begin{array}{ccc} f(x) & & y \\ \begin{bmatrix} 0.1 \\ 0.8 \\ 0.6 \\ \vdots \end{bmatrix} & \begin{matrix} \times \\ \times \\ \checkmark \\ \\ \end{matrix} & \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix} \end{array}$$

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

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

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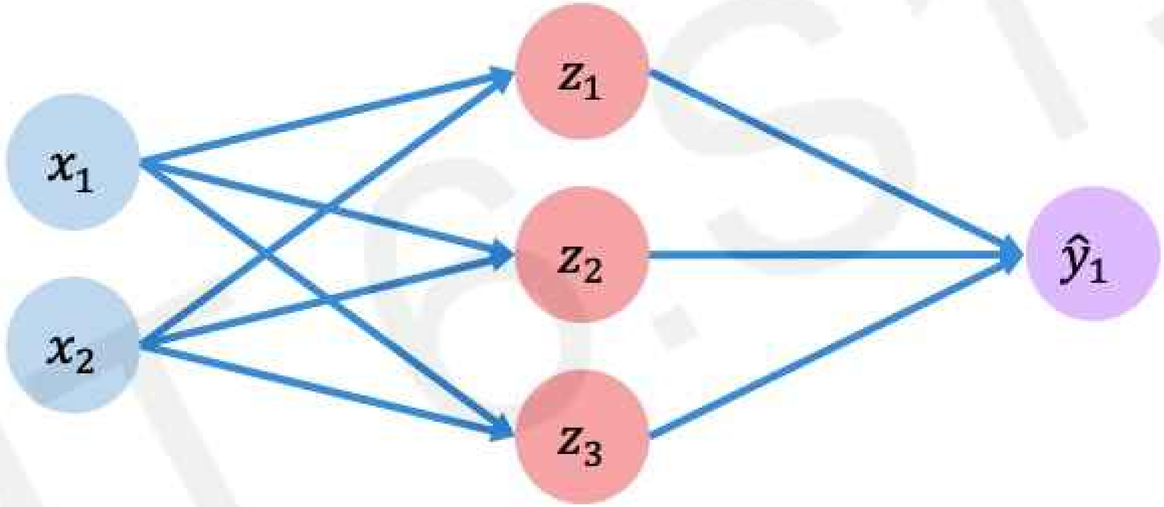
Binary Cross Entropy Loss

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

$$\boldsymbol{X} = \begin{bmatrix} 4, & 5 \\ 2, & 1 \\ 5, & 8 \\ \vdots & \vdots \end{bmatrix}$$



$$\begin{array}{ccc} f(x) & & y \\ \begin{bmatrix} 0.1 \\ 0.8 \\ 0.6 \\ \vdots \end{bmatrix} & \begin{matrix} \times \\ \times \\ \checkmark \\ \end{matrix} & \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix} \end{array}$$

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

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

```
loss = torch.nn.functional.cross_entropy( predicted, y )
```

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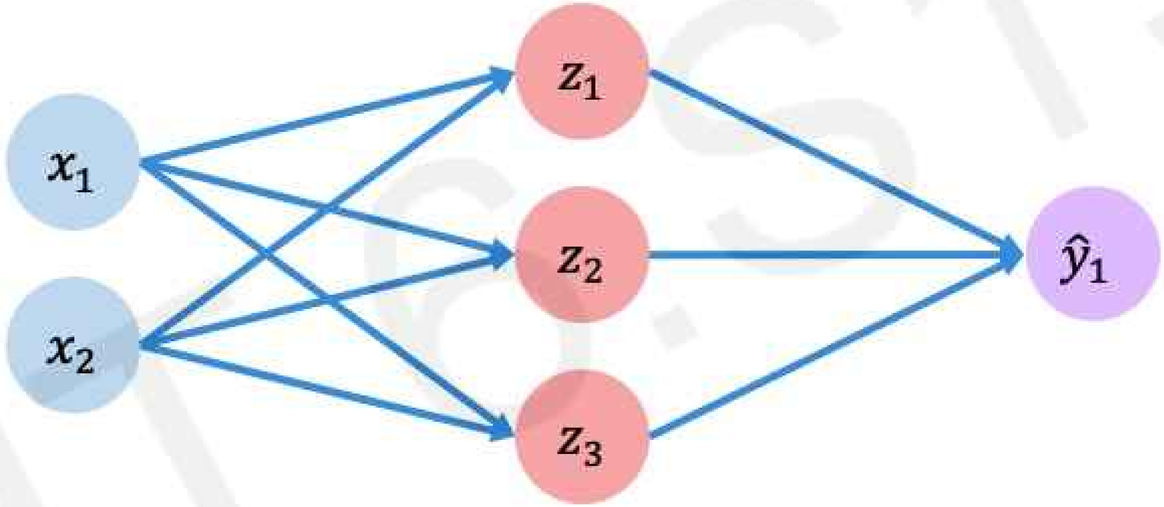
Mean Squared Error Loss

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

$$\boldsymbol{X} = \begin{bmatrix} 4, & 5 \\ 2, & 1 \\ 5, & 8 \\ \vdots & \vdots \end{bmatrix}$$



$$\begin{array}{ccc} f(x) & & y \\ \begin{bmatrix} 30 \\ 80 \\ 85 \\ \vdots \end{bmatrix} & \begin{matrix} \times \\ \times \\ \checkmark \\ \\ \end{matrix} & \begin{bmatrix} 90 \\ 20 \\ 95 \\ \vdots \end{bmatrix} \end{array}$$

Final Grades (percentage)

$$J(\boldsymbol{W}) = \frac{1}{n}\sum_{i=1}^{n}\left(\underbrace{y^{(i)}}_{\text{Actual}} - \underbrace{f\left(x^{(i)};\boldsymbol{W}\right)}_{\text{Predicted}}\right)^2$$

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

```
loss = torch.nn.functional.mse_loss(
        predicted, y )
```

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Training Neural Networks

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Loss Optimization

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

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

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

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Loss Optimization

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

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

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

Remember:

$$\boldsymbol{W} = \left\{\boldsymbol{W}^{(0)}, \boldsymbol{W}^{(1)}, \dots\right\}$$

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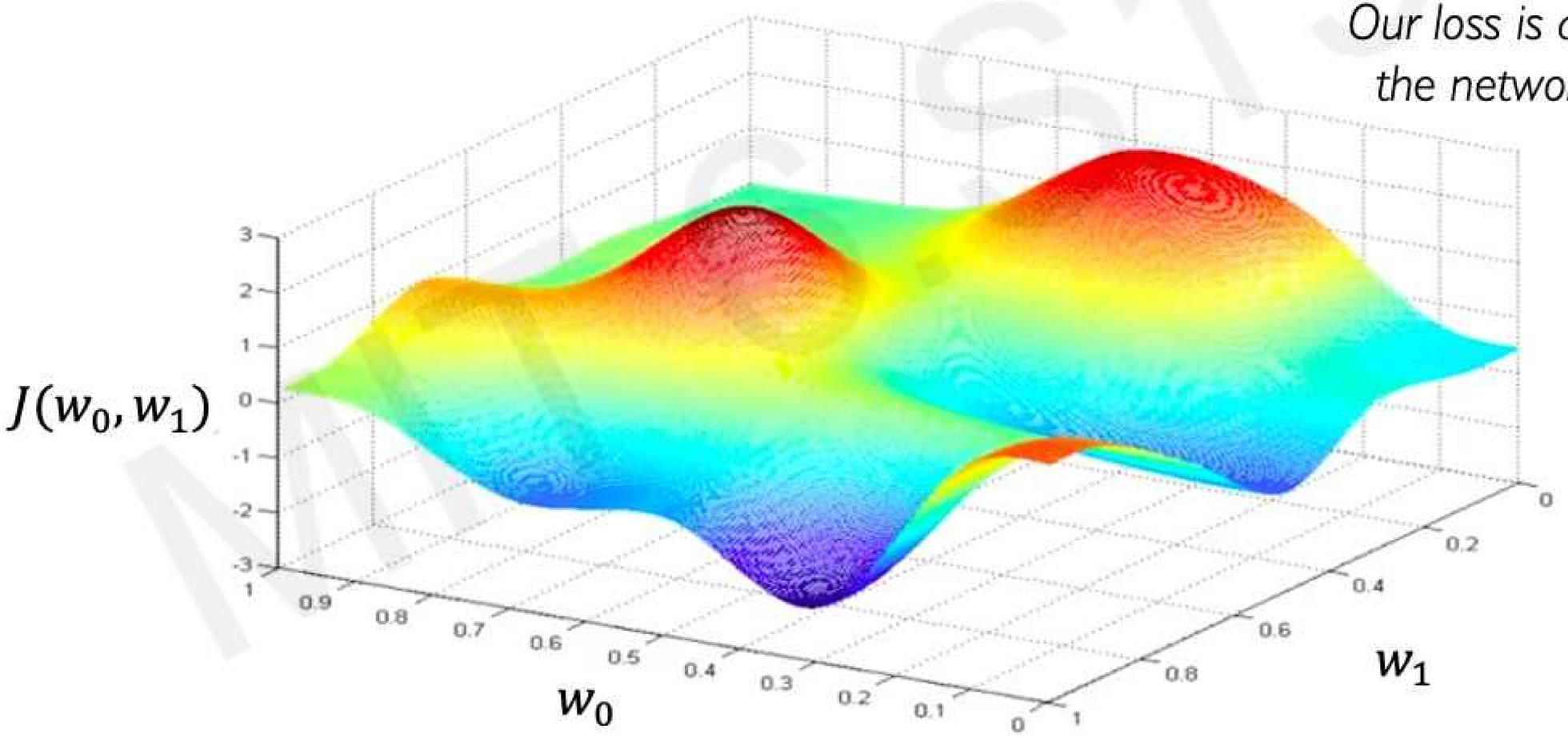
Loss Optimization

$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{\operatorname{argmin}}\, J(\boldsymbol{W})$$

Remember:

Our loss is a function of the network weights!



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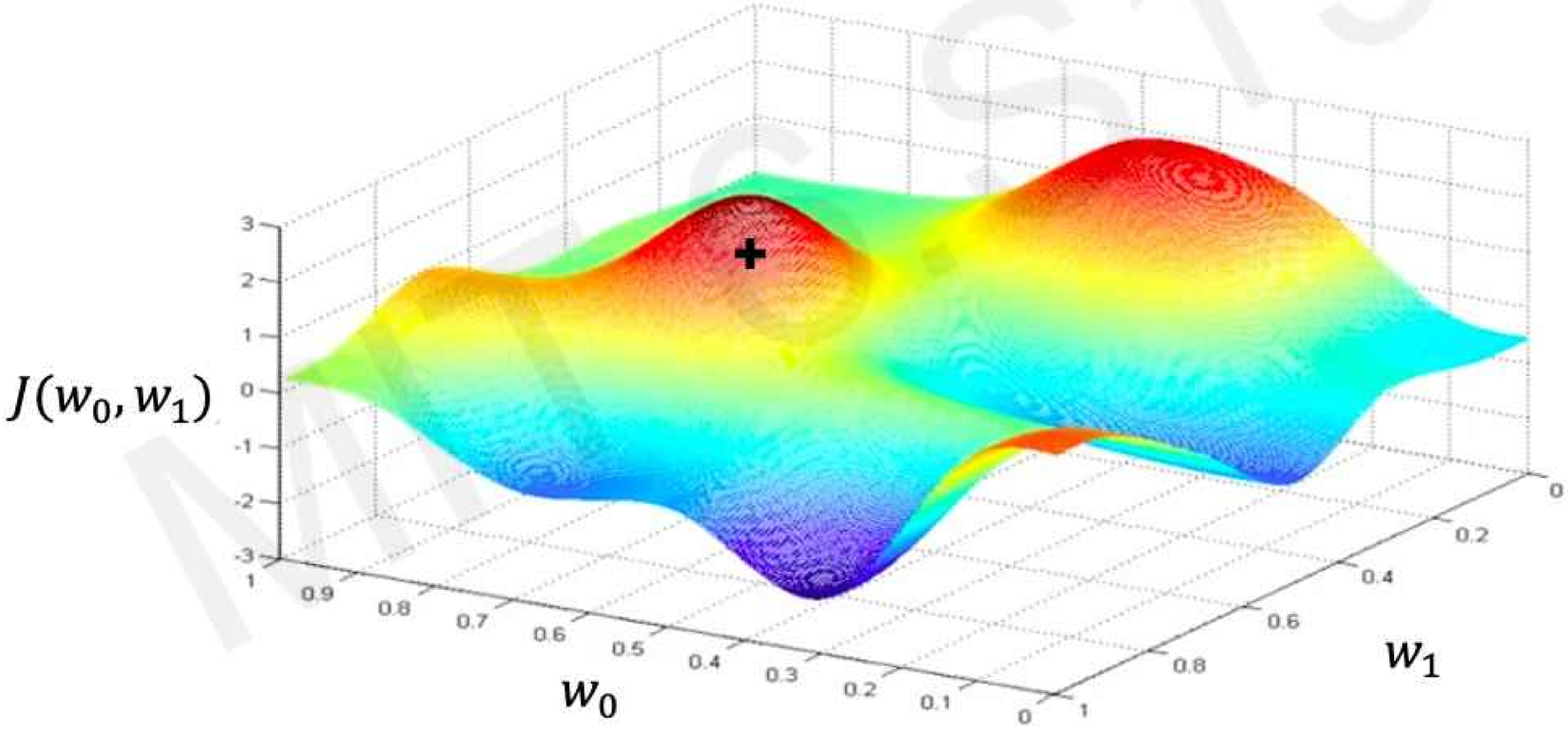
Loss Optimization

Randomly pick an initial (w_0, w_1)



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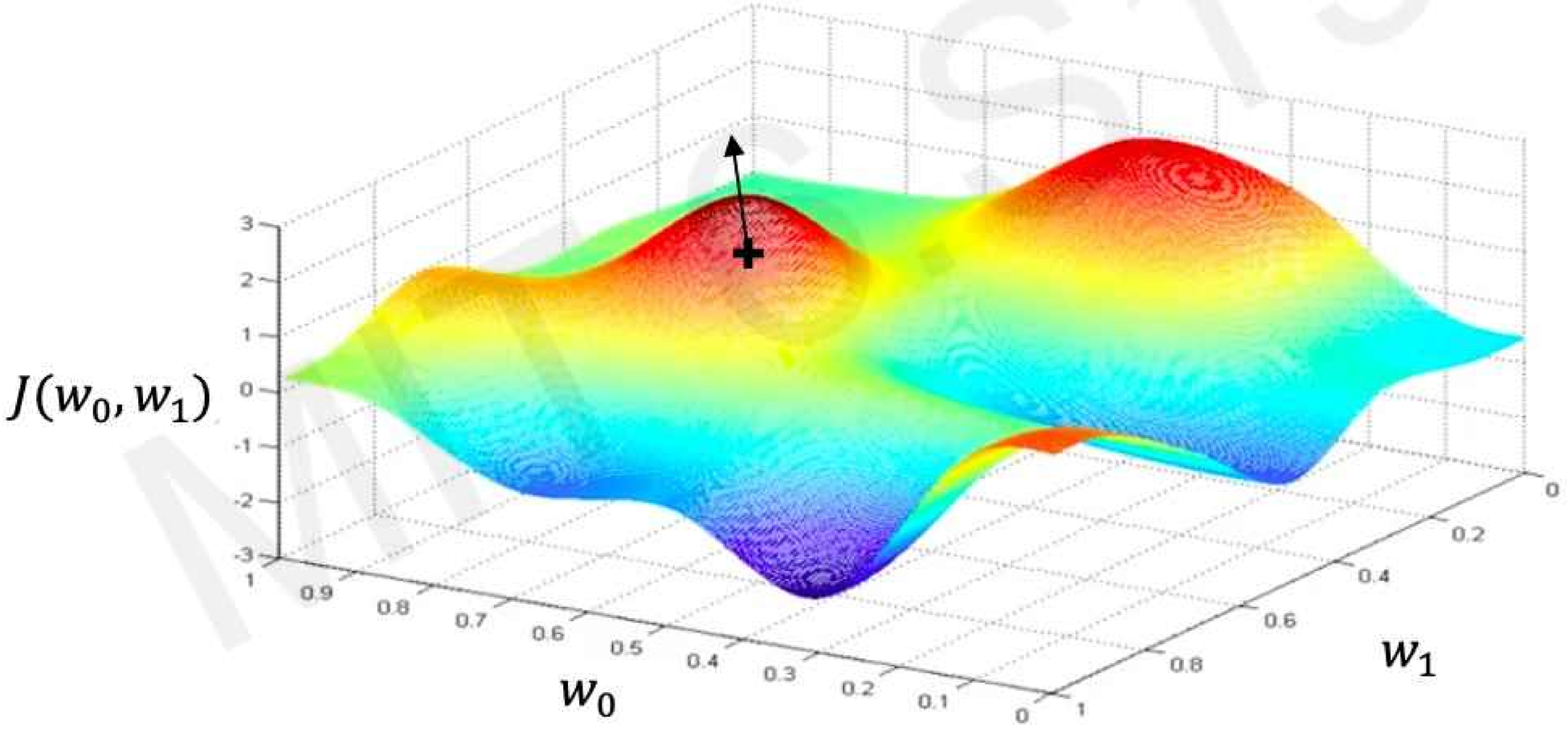
Loss Optimization

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



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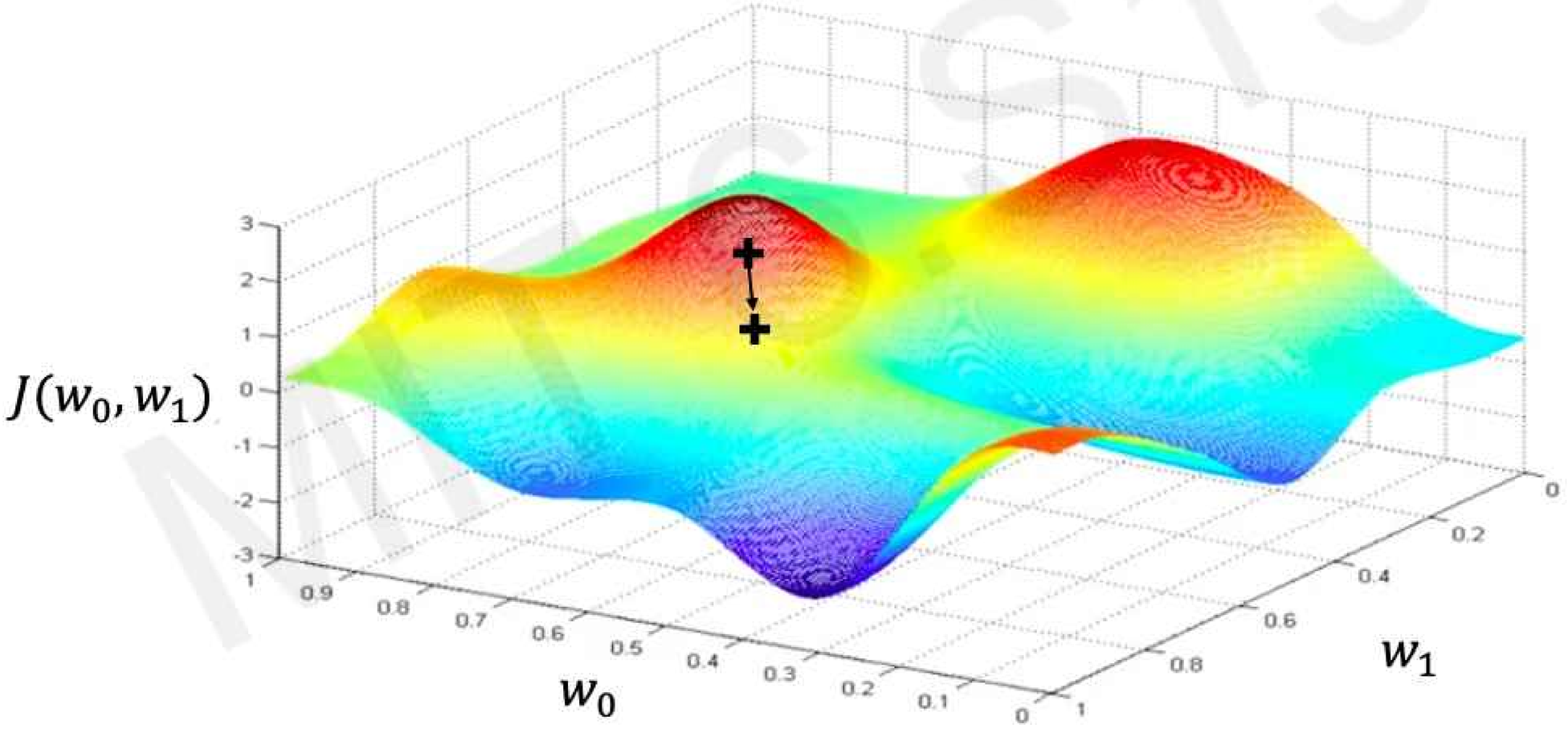
Loss Optimization

Take small step in opposite direction of gradient



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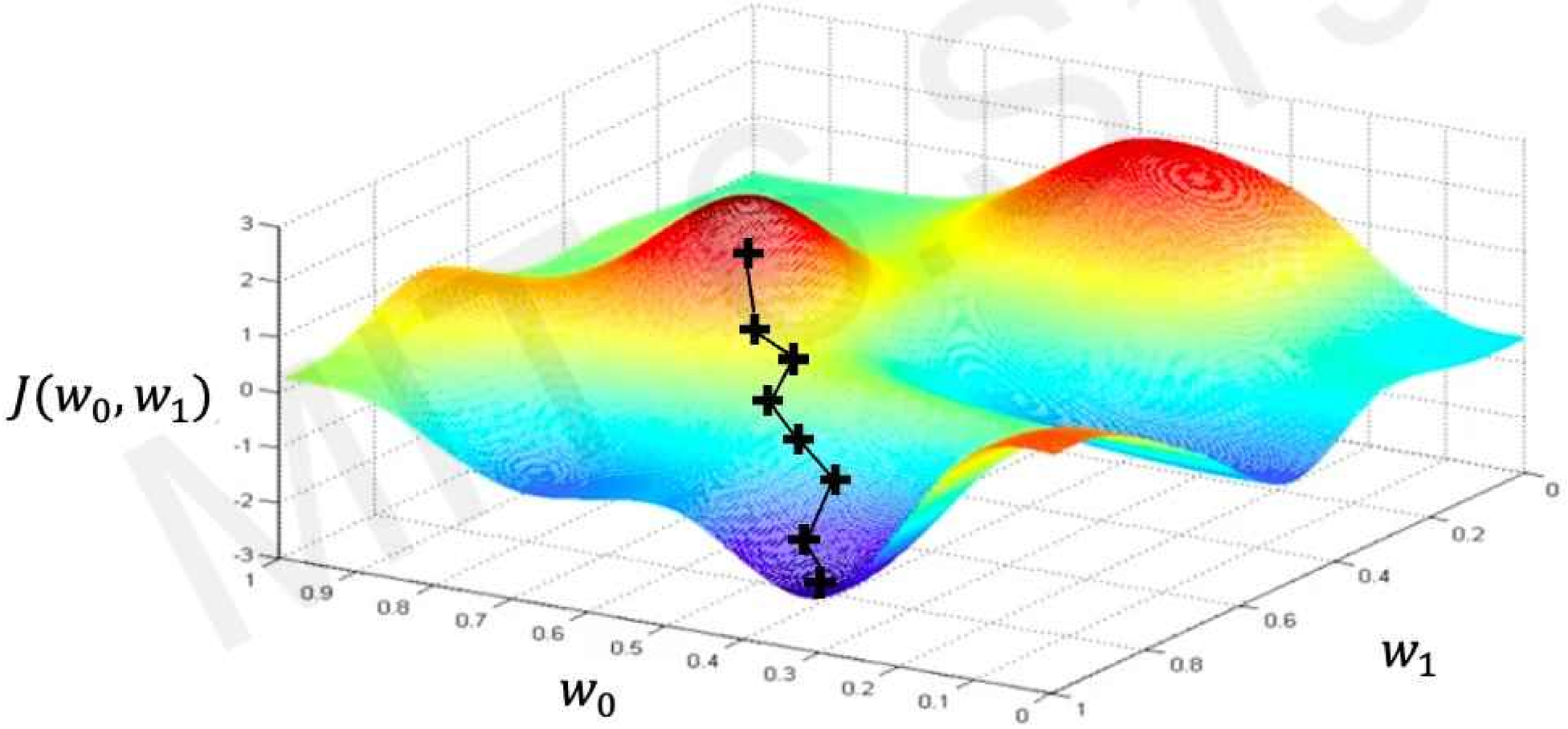
Gradient Descent

Repeat until convergence



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Gradient Descent

Algorithm

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

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Gradient Descent

Algorithm

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

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Gradient Descent

Algorithm

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

    weights = weights - lr * gradient
```

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Computing Gradients: Backpropagation

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

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Computing Gradients: Backpropagation

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

Let's use the chain rule!

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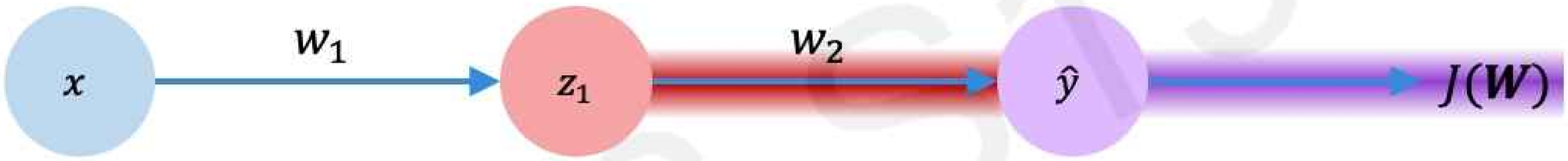
Computing Gradients: Backpropagation



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

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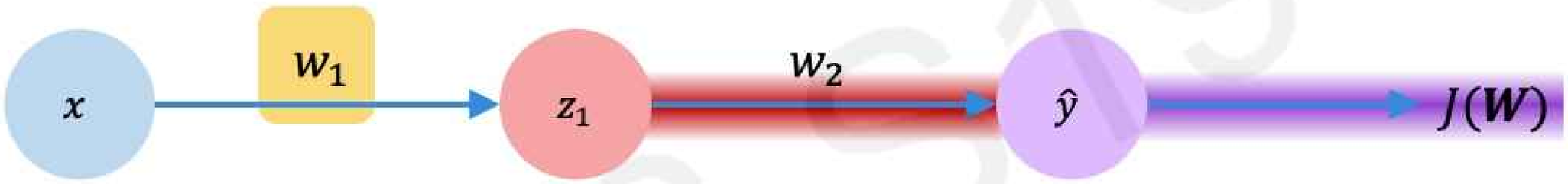
Computing Gradients: Backpropagation



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

Apply chain rule!

Apply chain rule!

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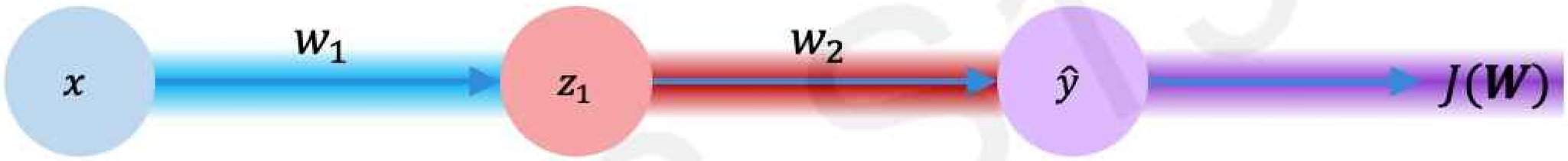
Computing Gradients: Backpropagation



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

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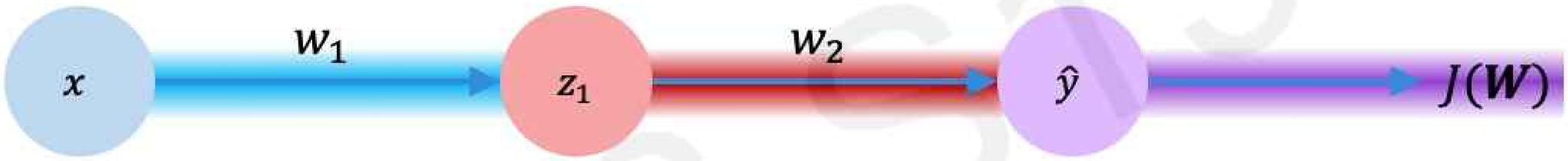
Computing Gradients: Backpropagation



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

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

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Neural Networks in Practice: Optimization

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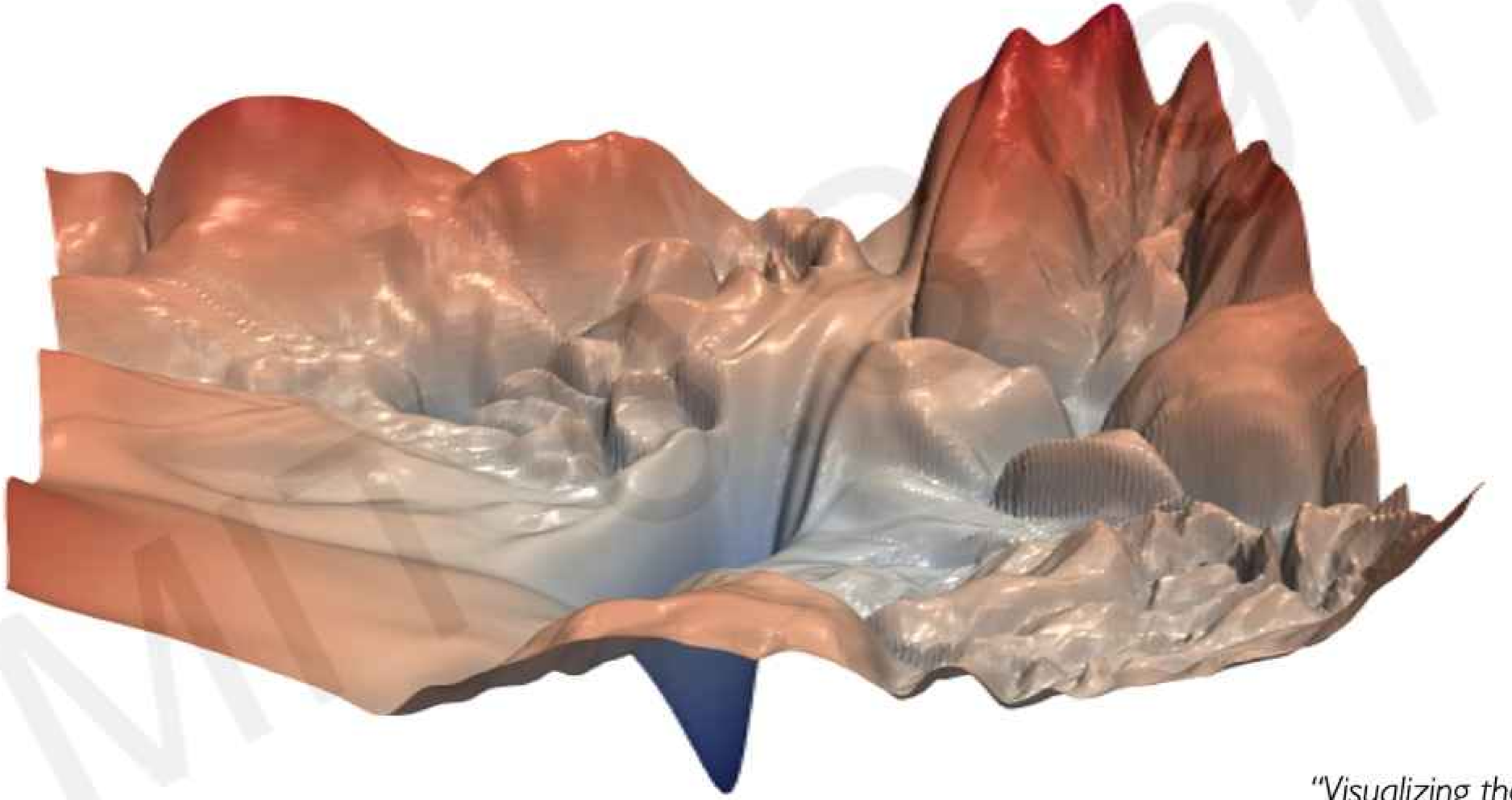
Training Neural Networks is Difficult



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

Loss Functions Can Be Difficult to Optimize

Remember:

Optimization through gradient descent

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

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Loss Functions Can Be Difficult to Optimize

Remember:

Optimization through gradient descent

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

How can we set the learning rate?

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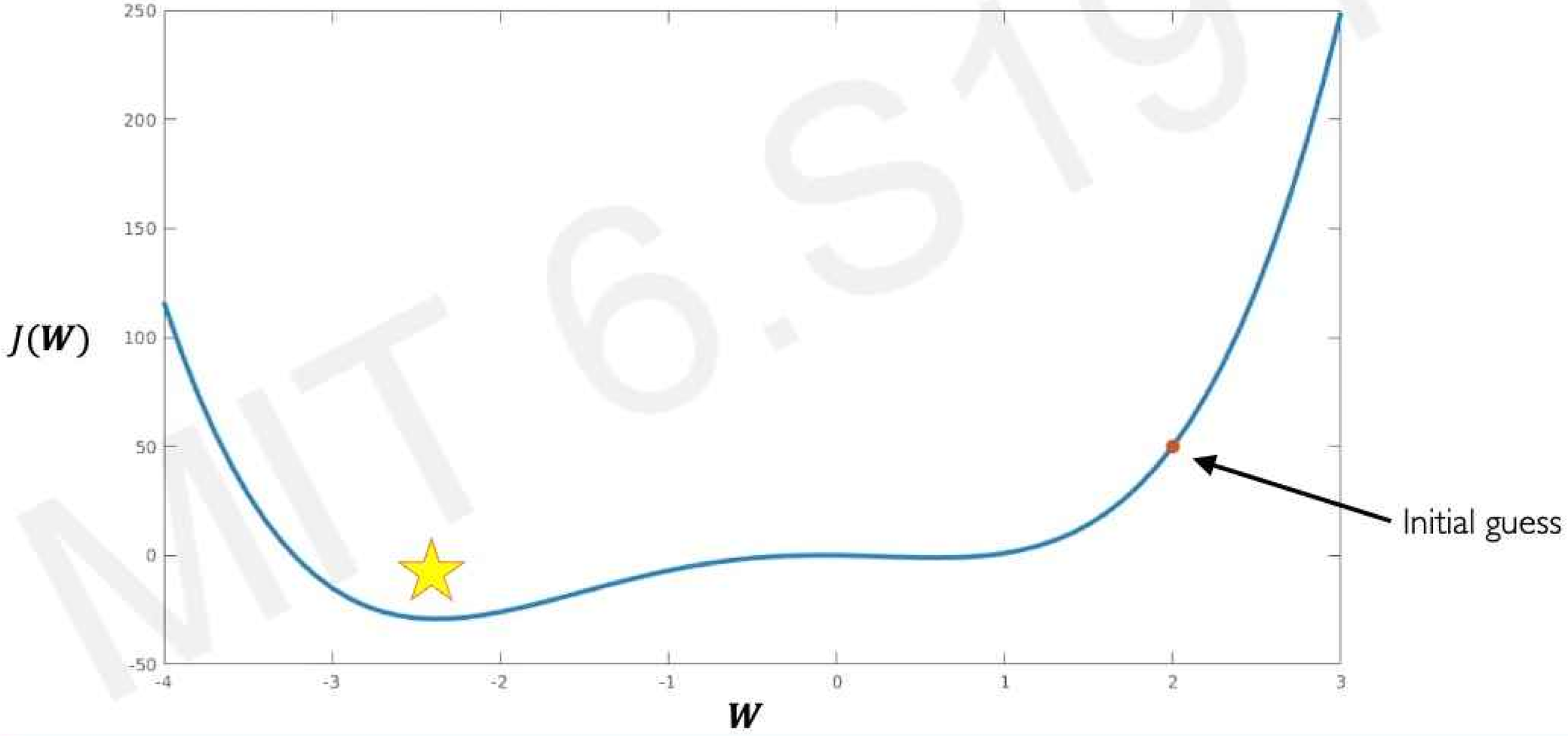
Setting the Learning Rate

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



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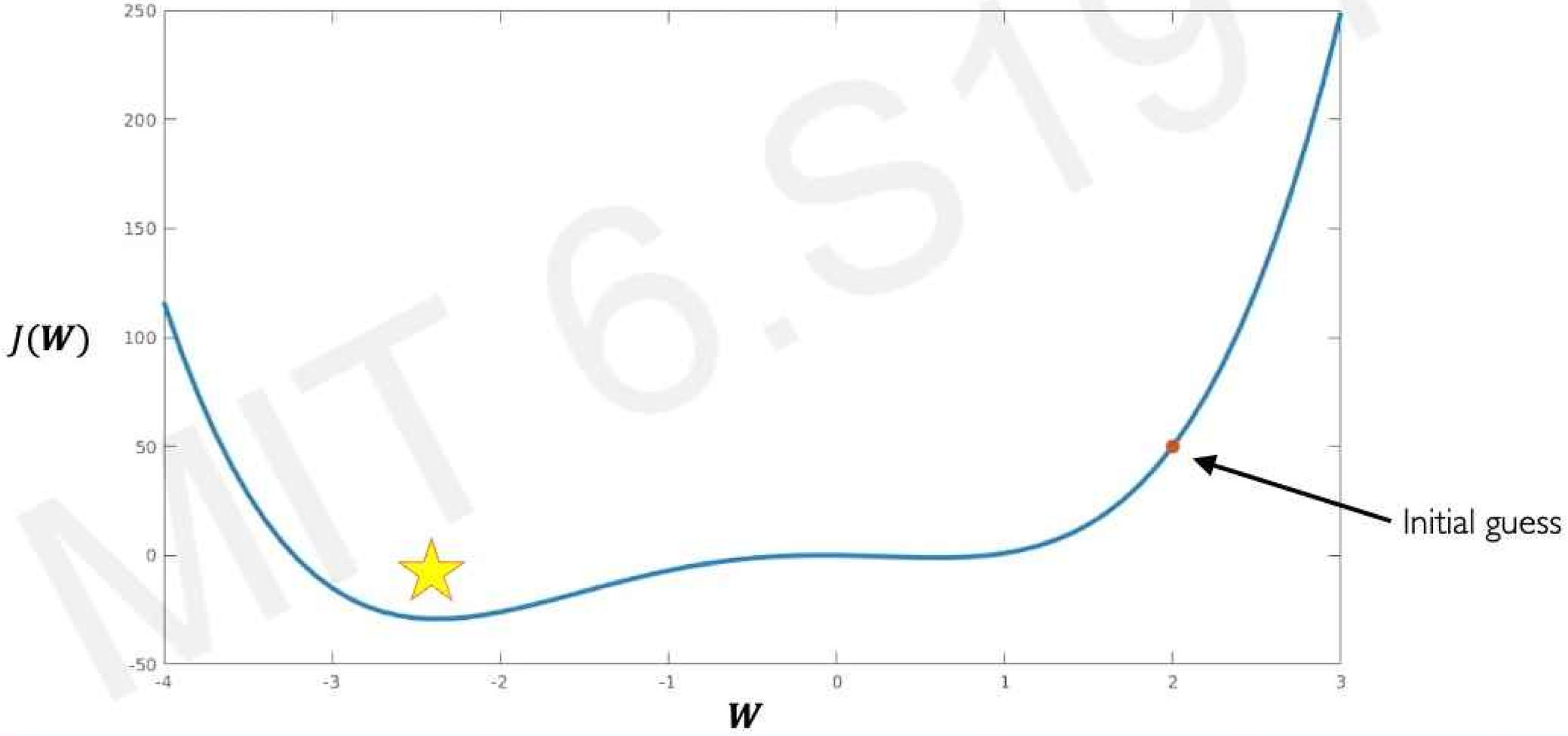
Setting the Learning Rate

Large learning rates *overshoot, become unstable and diverge*



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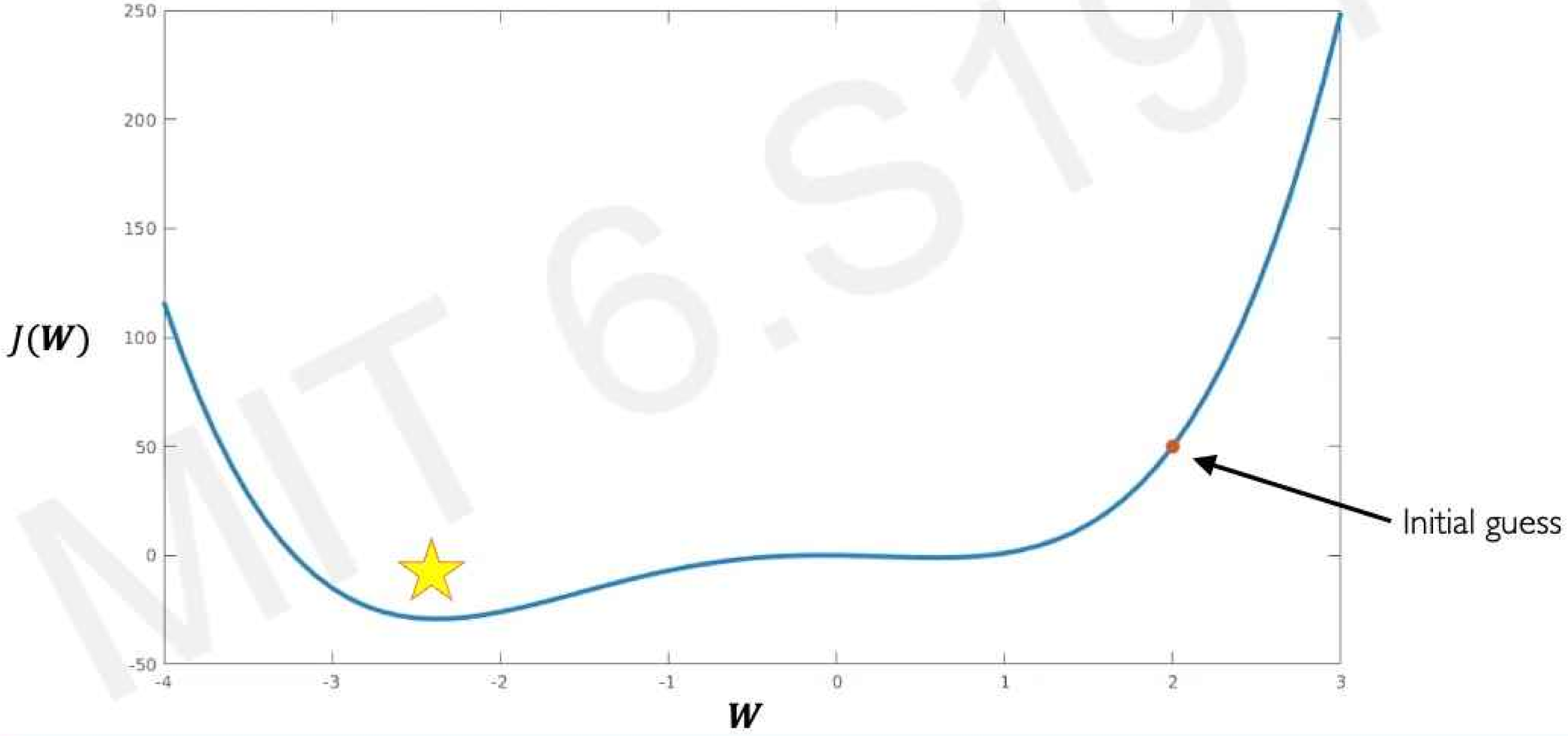
Setting the Learning Rate

Stable learning rates *converge smoothly and avoid local minima*



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How to deal with this?

Idea 1:

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

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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

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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...

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Gradient Descent Algorithms

Algorithm	TF Implementation	Torch Implementation	Reference
• SGD	`tf.keras.optimizers.SGD`	`torch.optim.SGD`	Kiefer & Wolfowitz, 1952.
• Adam	`tf.keras.optimizers.Adam`	`torch.optim.Adam`	Kingma et al., 2014.
• Adadelta	`tf.keras.optimizers.Adadelta`	`torch.optim.Adadelta`	Zeiler et al., 2012.
• Adagrad	`tf.keras.optimizers.Adagrad`	`torch.optim.Adagrad`	Duchi et al., 2011.
• RMSProp	`tf.keras.optimizers.RMSProp`	`torch.optim.RMSProp`	

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

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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)))
```

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Neural Networks in Practice: Mini-batches

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Gradient Descent

Algorithm

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2. Loop until convergence:
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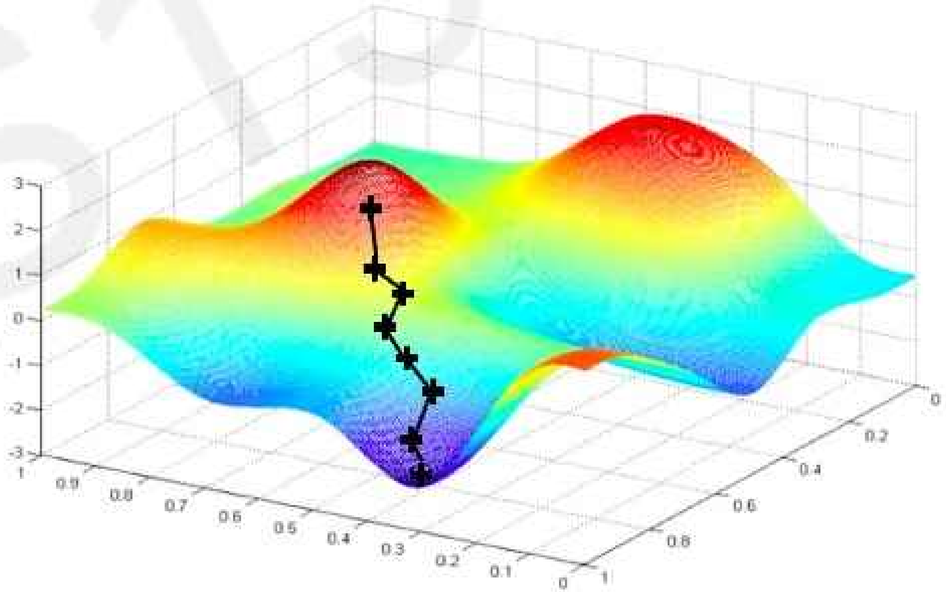

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Gradient Descent

Algorithm

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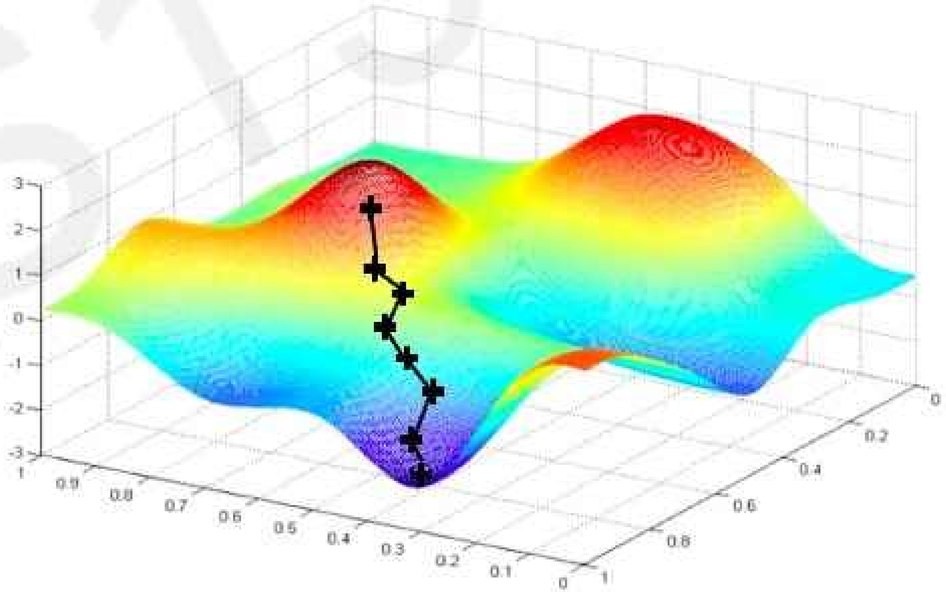

Can be very **computationally intensive** to compute!

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Stochastic Gradient Descent

Algorithm

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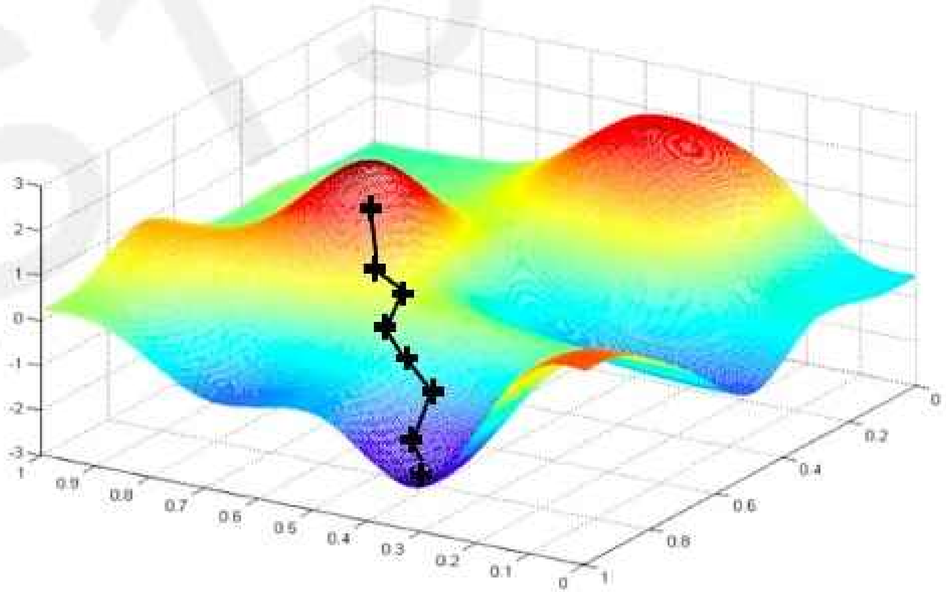

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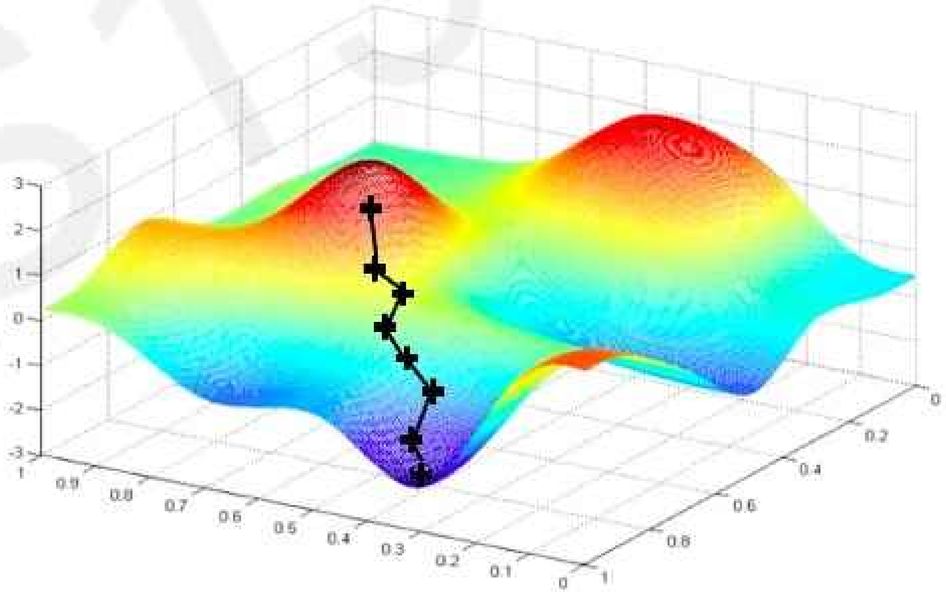

Easy to compute but **very noisy** (stochastic)!

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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, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}} = \frac{1}{B}\sum_{k=1}^{B} \frac{\partial J_k(\boldsymbol{W})}{\partial \boldsymbol{W}}$
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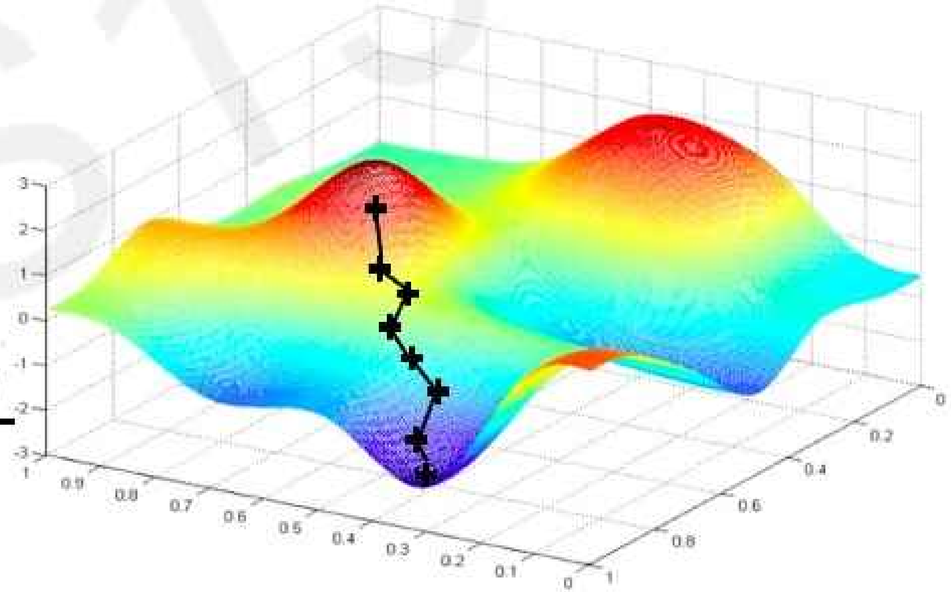

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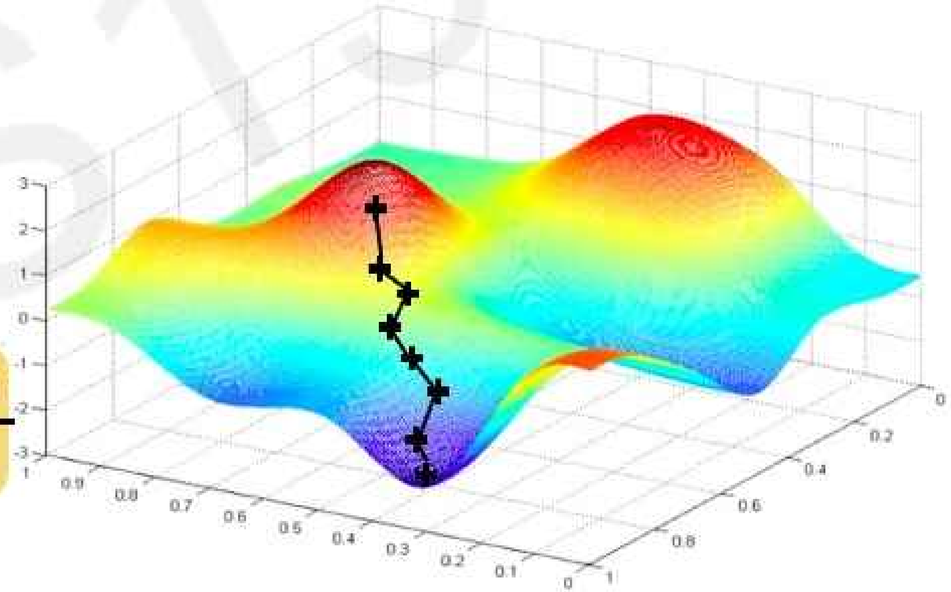

Fast to compute and a much better estimate of the true gradient!

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Mini-batches while training

More accurate estimation of gradient

Smoother convergence

Allows for larger learning rates

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Mini-batches while training

More accurate estimation of gradient

Smoother convergence

Allows for larger learning rates

Mini-batches lead to fast training!

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

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Neural Networks in Practice: Overfitting

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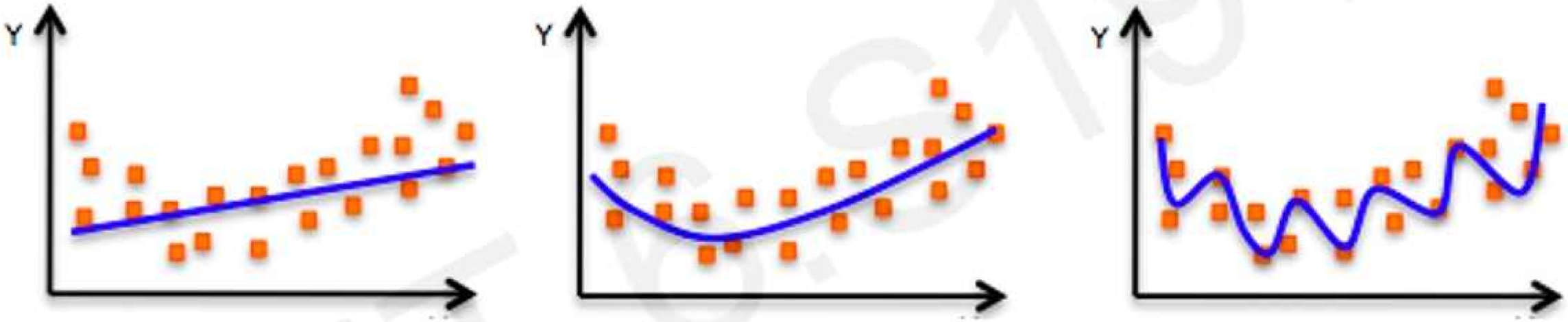
The Problem of Overfitting



Underfitting
Model does not have capacity to fully learn the data

Ideal fit

Overfitting
Too complex, extra parameters, does not generalize well

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Regularization

What is it?

Technique that constrains our optimization problem to discourage complex models

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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

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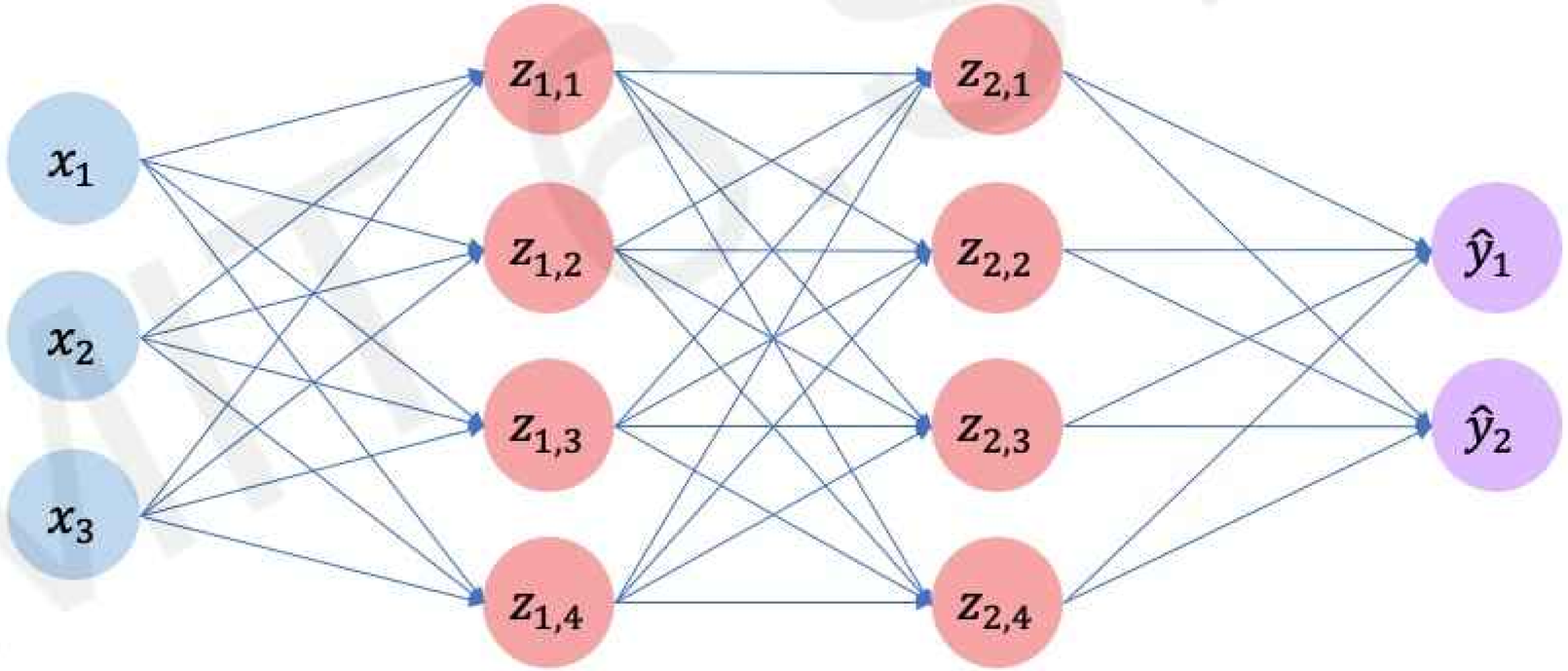
Regularization 1: Dropout

- During training, randomly set some activations to 0



Regularization 1: 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)
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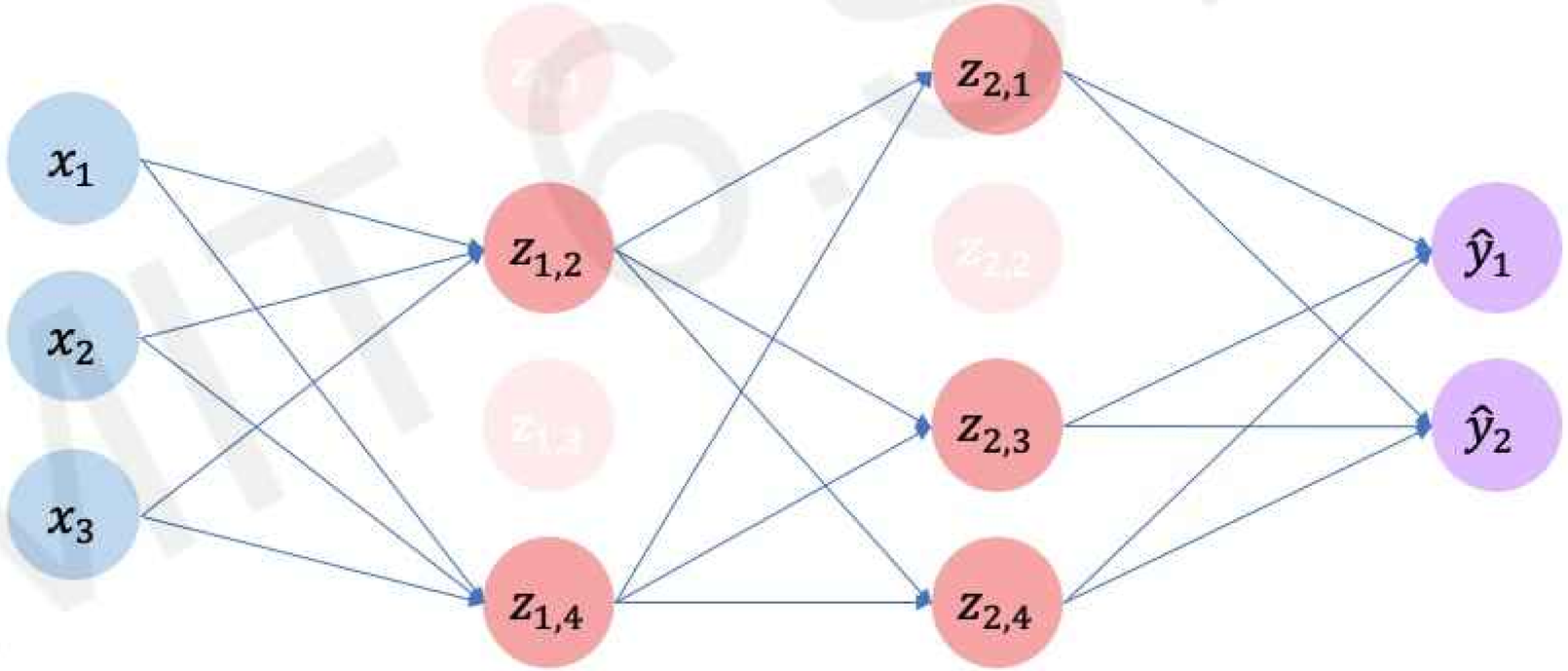
```



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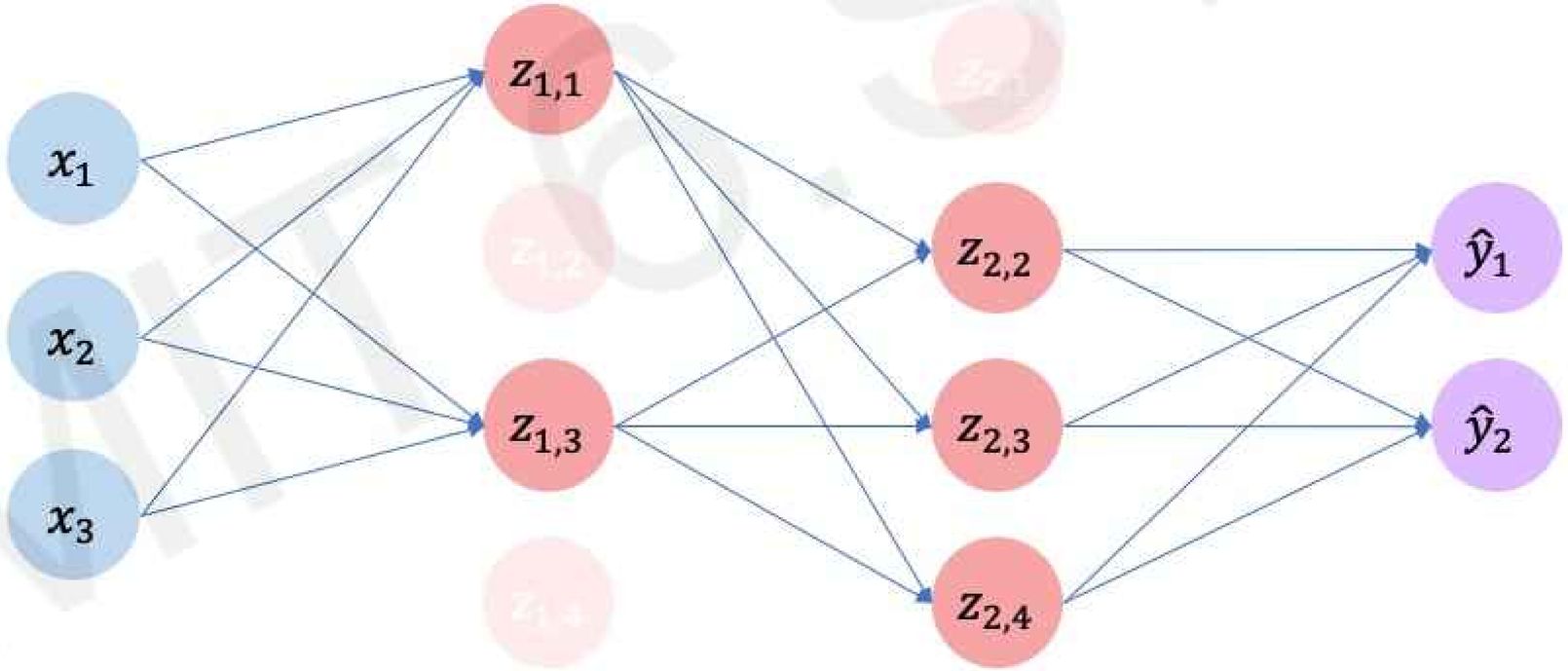

Regularization 2: Early Stopping

- Stop training before we have a chance to overfit

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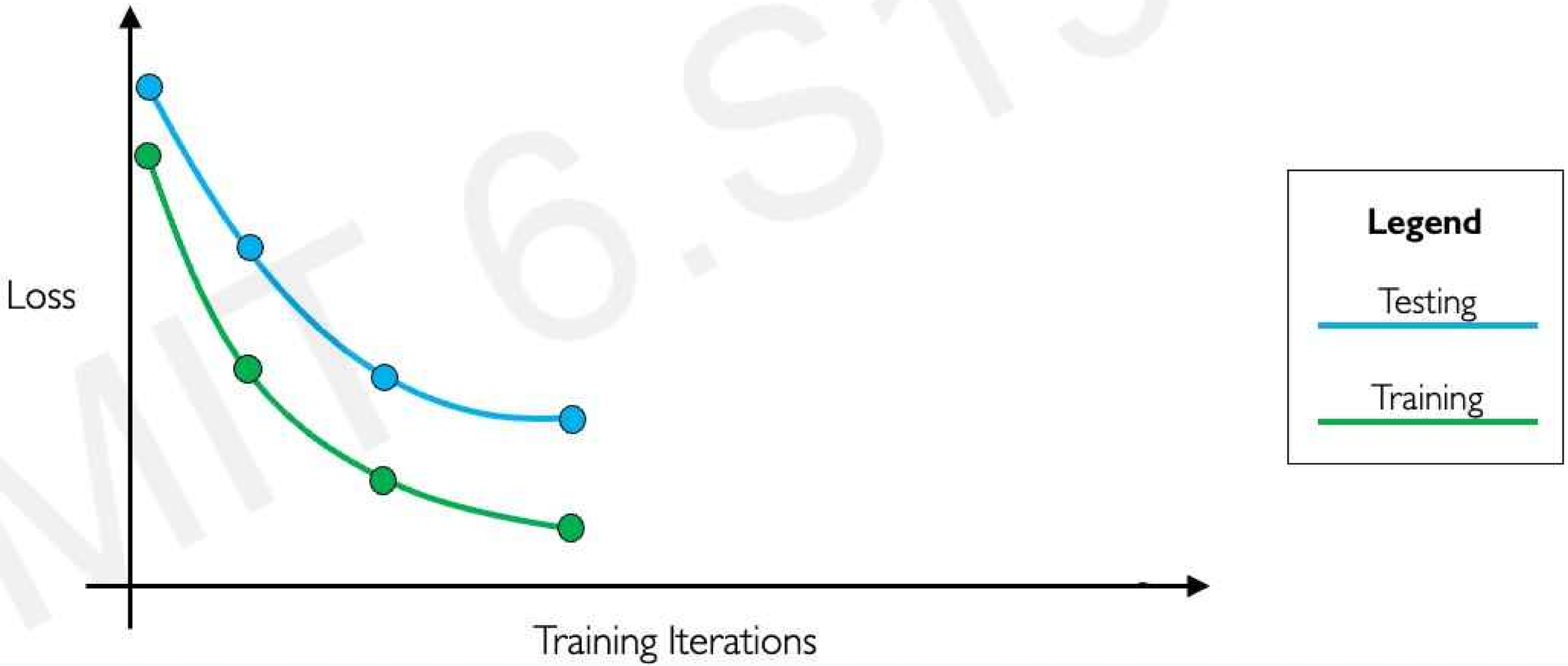

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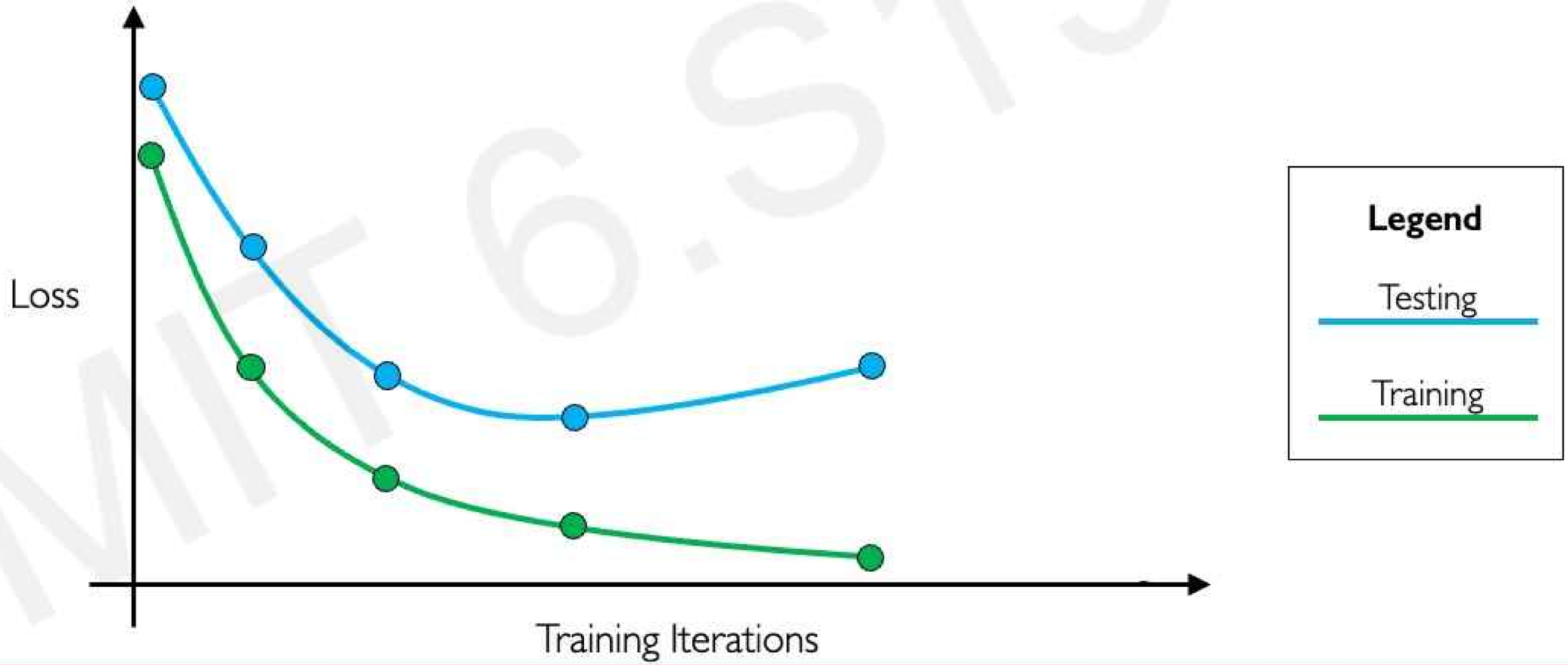

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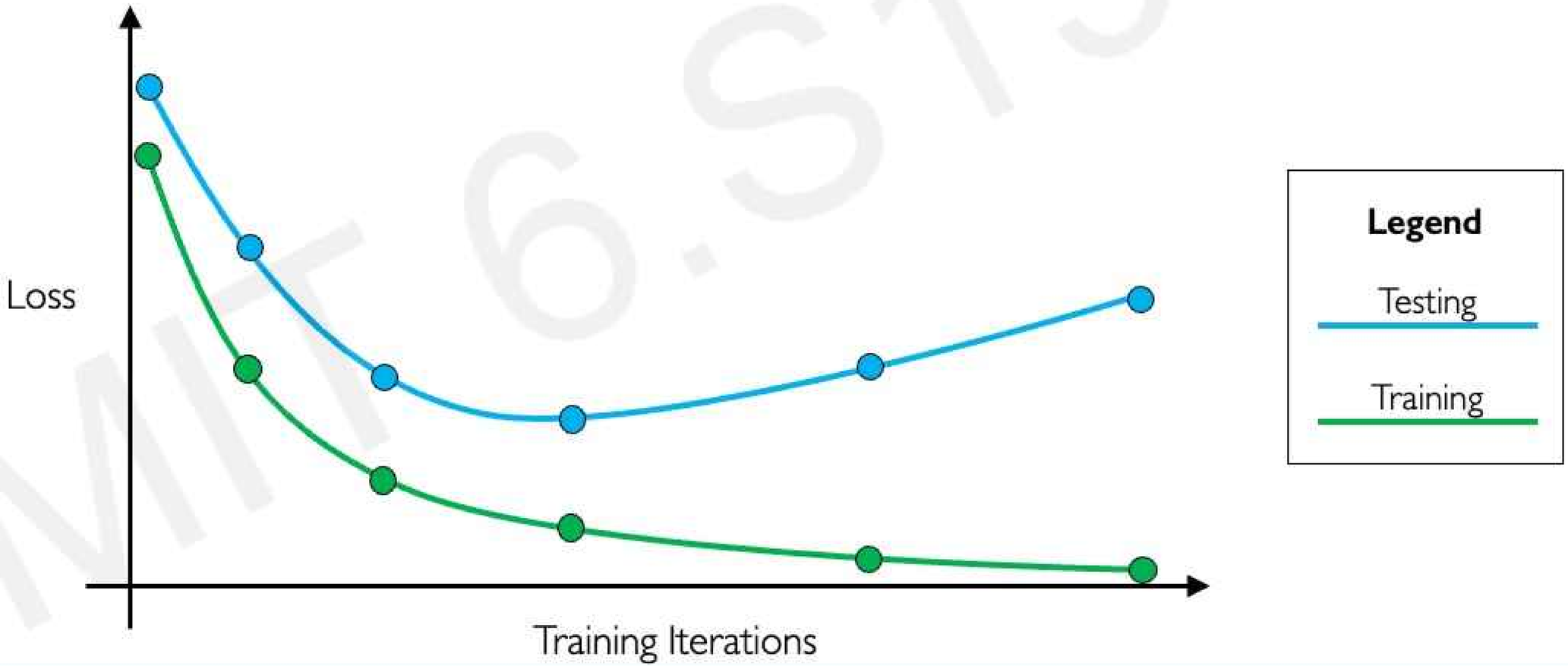

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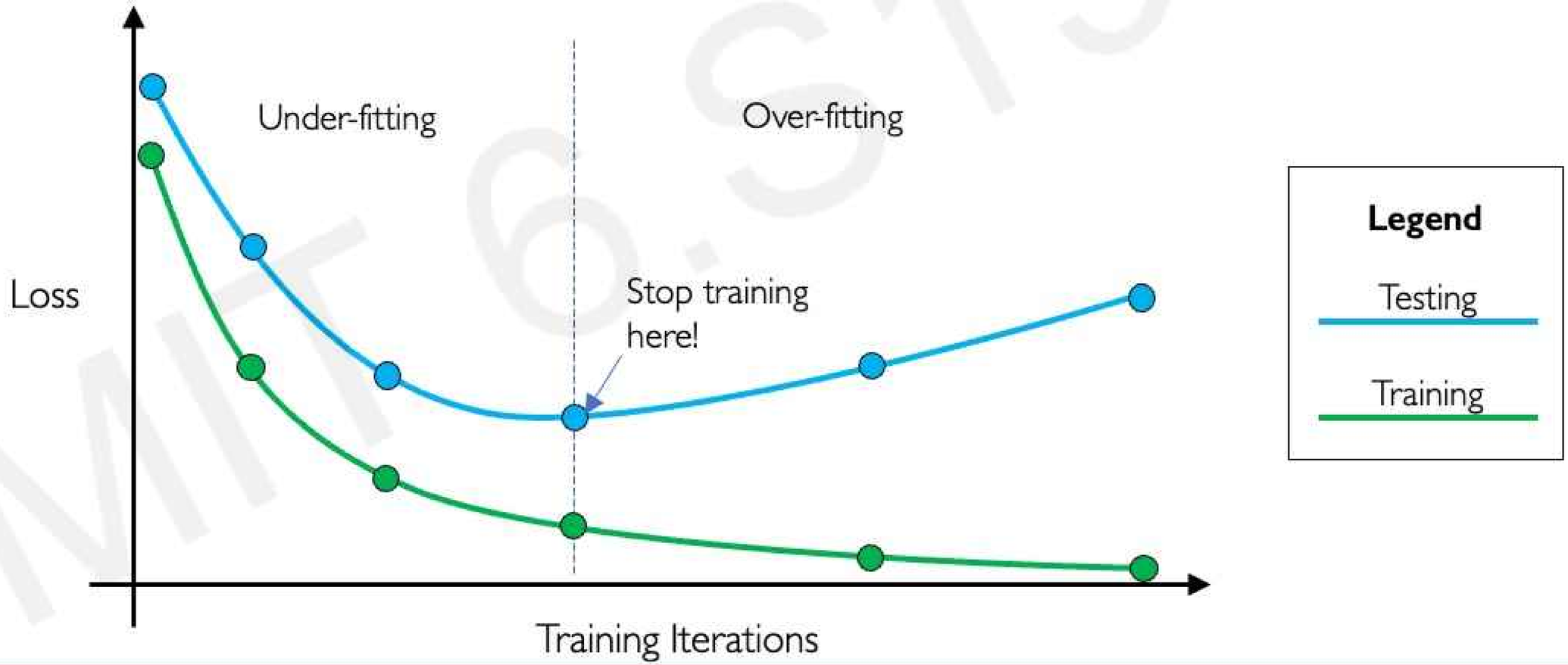

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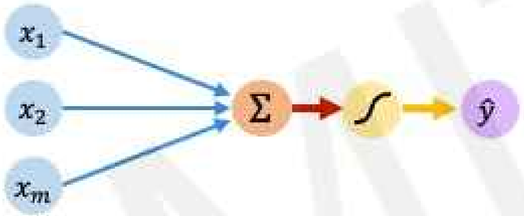
Core Foundation Review

The Perceptron

- Structural building blocks
- Nonlinear activation functions

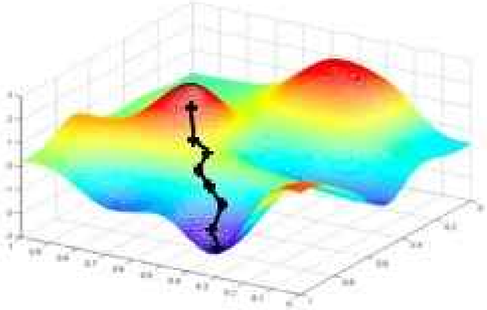


Neural Networks

- Stacking Perceptrons to form neural networks
- Optimization through backpropagation

Training in Practice

- Adaptive learning
- Batching
- Regularization



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MIT Introduction to Deep Learning

Lab 1: Introduction to Deep Learning in Python 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 32-123!

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