Deep Learning and its Applications - ECE480

Introduction to Deep Learning

Lecturer: Associate Prof. Dimitrios Rafailidis

https://blog.boardinfinity.com/deep-learning-dive-into-the-world-of-machine-learning/

Course structure

- Εφαρμογή τεχνικών deep learning σε πραγματικά δεδομένα της εταιρείας Hive Streaming!

- Δεν υπάρχει γραπτή εξέταση στο μάθημα, ο βαθμός θα βασίζεται σε τελική εργασία. Η εργασία θα είναι ατομική ή ομαδική με 2 φοιτητές. Η εργασία θα αποτελείται από δύο μέρη. Το πρώτο μέρος αφορά την ανάλυση πραγματικών δεδομένων και το δεύτερο μέρος την μοντελοποίηση και εφαρμογή τεχνικών deep learning. Η προθεσμία της ενδιάμεσης υποβολής του πρώτου μέρους είναι 15 Απριλίου. Η τελική υποβολή και των δύο μερών είναι 17 Ιουνίου στο draf@uth.gr και stefanos.antaris@hivestreaming.com.

- Tutorials and group meetings witth S. Antaris - HiveStreaming online. Links will be announceed soon
- Lectures (Αμφ.2-101)
- Tutorials and group meetings (online)

Course schedule

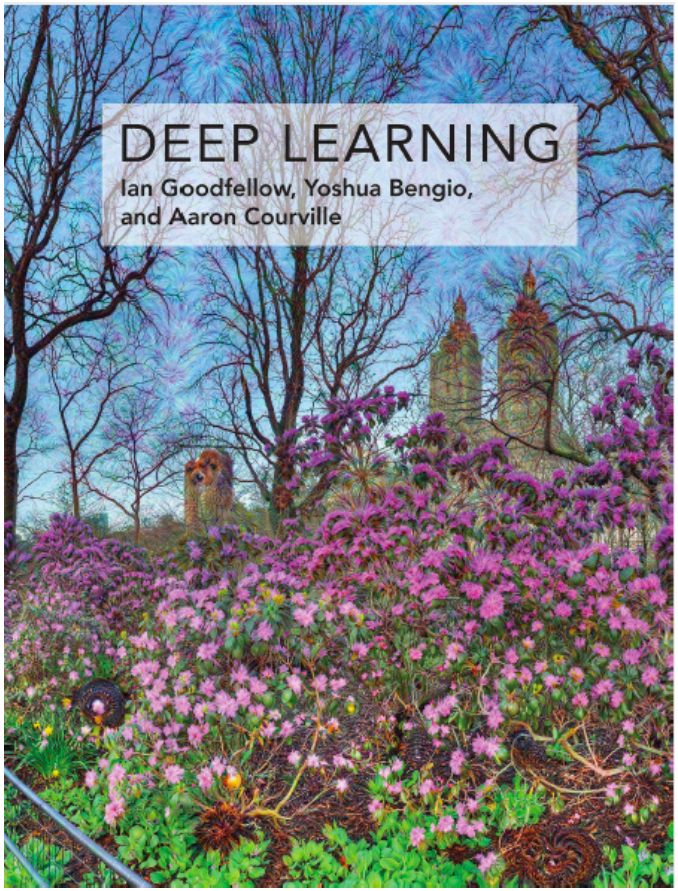
- 3 March: Introduction - Αμφ.2-101
- 4 March: Tutorial I – online
- 10 March: Assignment description – online
- 11 March: Tutorial II – online
- 17 March: Group meeting I – online
- 18 March: Group meeting I – online
- 24-25 March: -
- 31 March: Deep sequential learning - Αμφ.2-101
- 1 April: Tutorial III – online
- 7 April: Group meeting II – online
- 8 April: Group meeting II – online
- 14 April: CNNs - Αμφ.2-101
- 15 April: Deep generative models - Αμφ.2-101
- 5 May: Tutorial IV – online
- 6 May: Introduction to reinforcement learning - Αμφ.2-101
- 12 May: Group meeting III – online
- 13 May: Group meeting III – online
- 19 May: Deep reinforcement learning - Αμφ.2-101
- 20 May: -
- 26 May: Group meeting IV – online
- 27 May: Group meeting IV – online

Course material

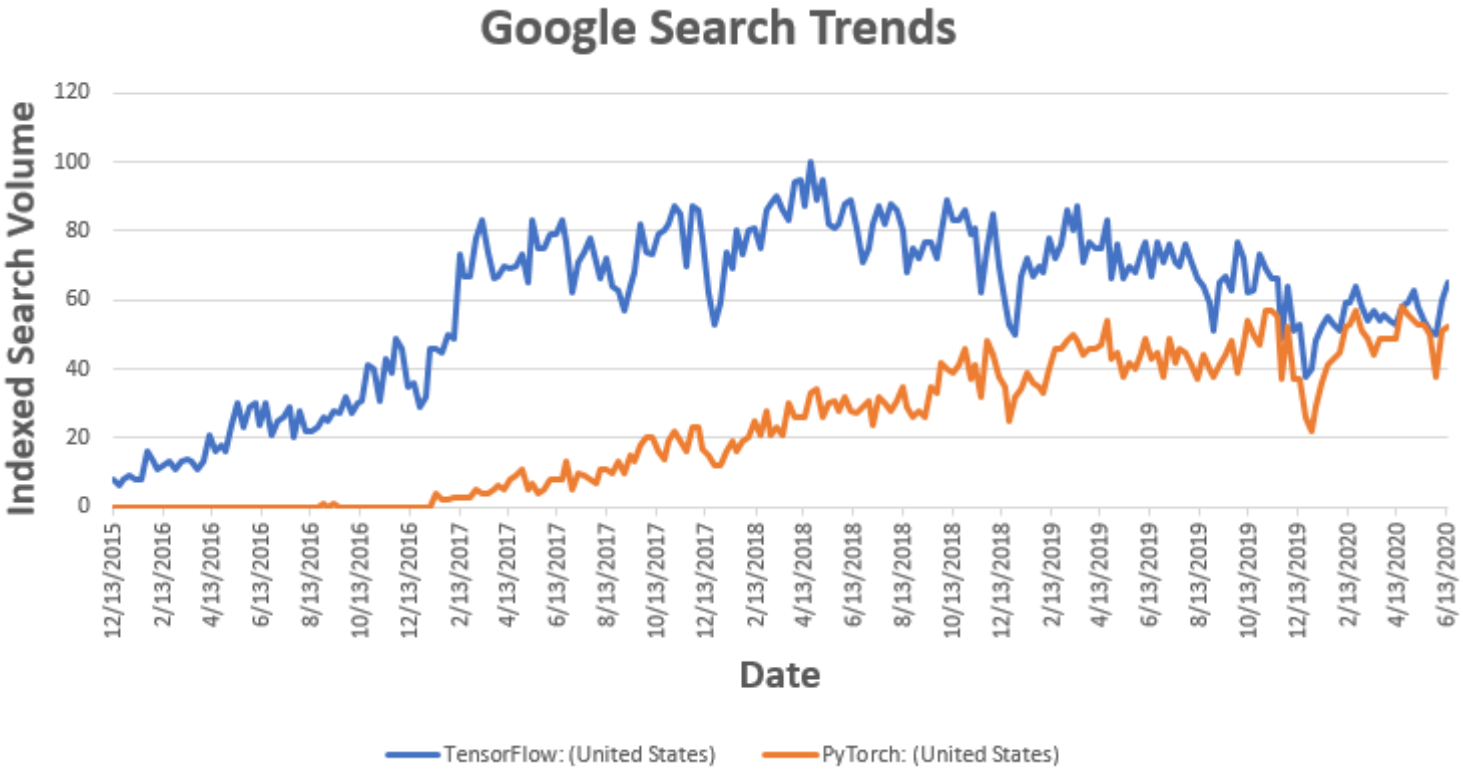
This course follows:

- MIT 6.S191: Introduction to Deep Learning by Alexander Amini and Ava Soleimany
- COMP3547: Reinforcement Learning by Chris G. Willcocks

Suggested book:
Goodfellow et al. 2016



Pytorch tutorials



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

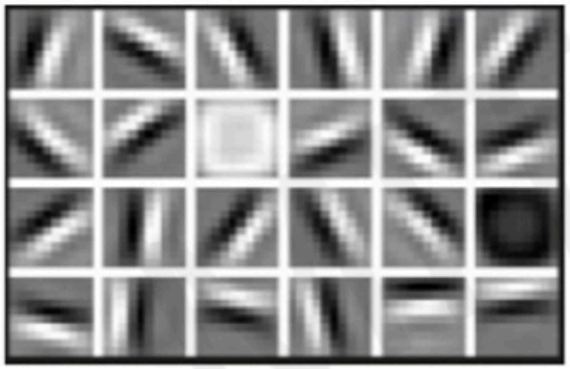
Why deep learning and Why now?

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?

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 resurgence?

1. Big Data
- Larger Datasets
- Easier Collection & Storage

IMAGENET

WIKIPEDIA The Free Encyclopedia

2. Hardware
- Graphics Processing Units (GPUs)
- Massively Parallelizable

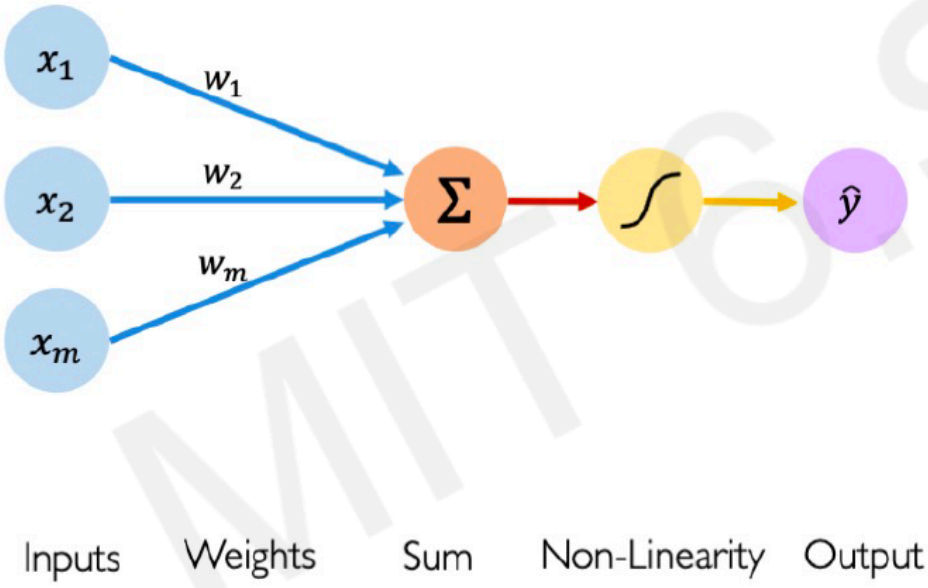
3. Software
- Improved Techniques
- New Models
- Toolboxes

TensorFlow

The Perceptron

The structural building block of deep learning

The Perceptron: Forward Propagation



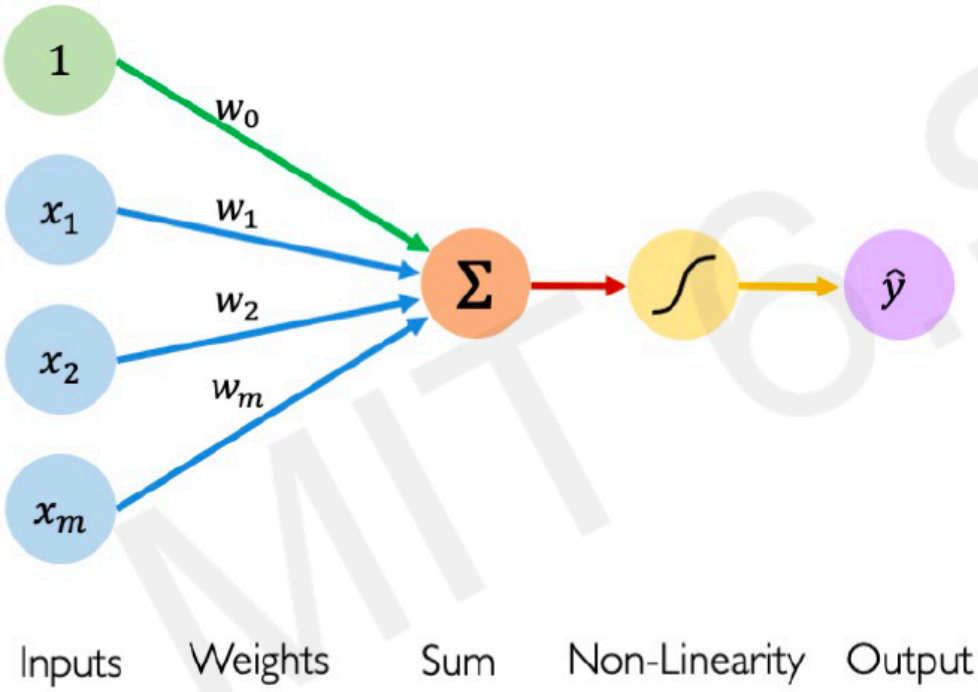
Output

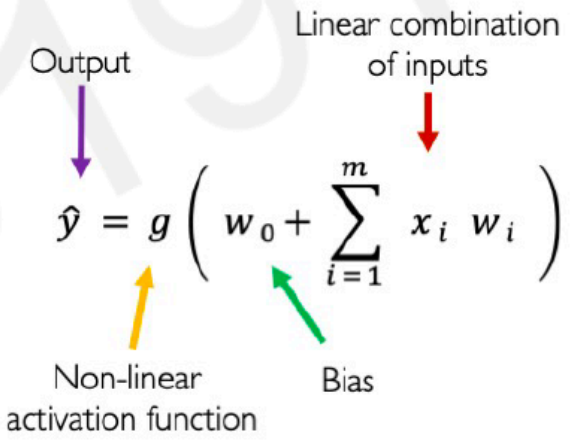
Linear combination of inputs

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

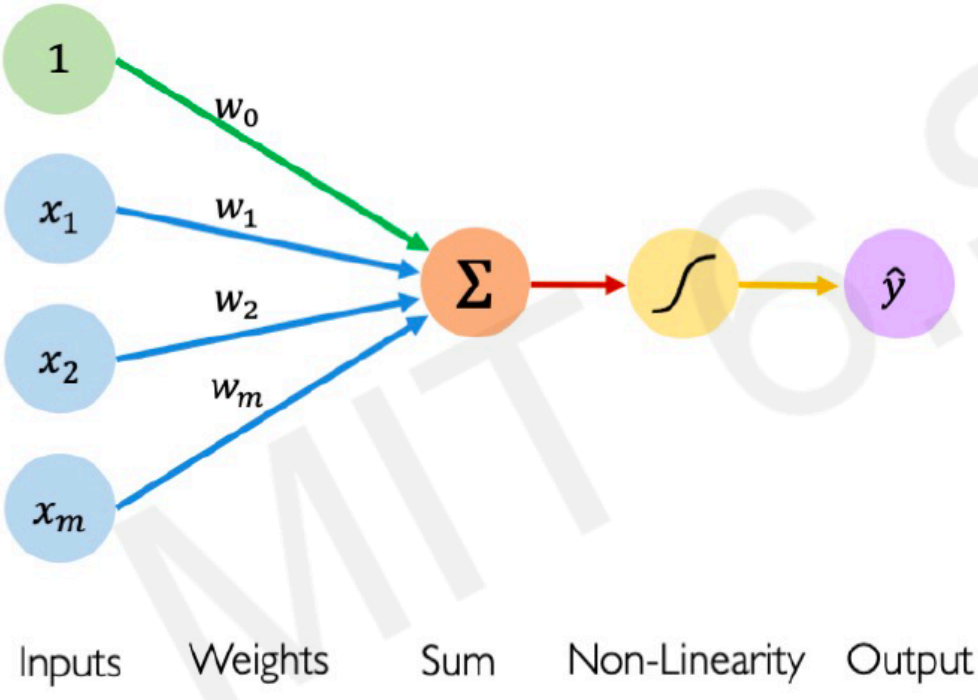
Non-linear activation function

The Perceptron: Forward Propagation





The Perceptron: Forward Propagation

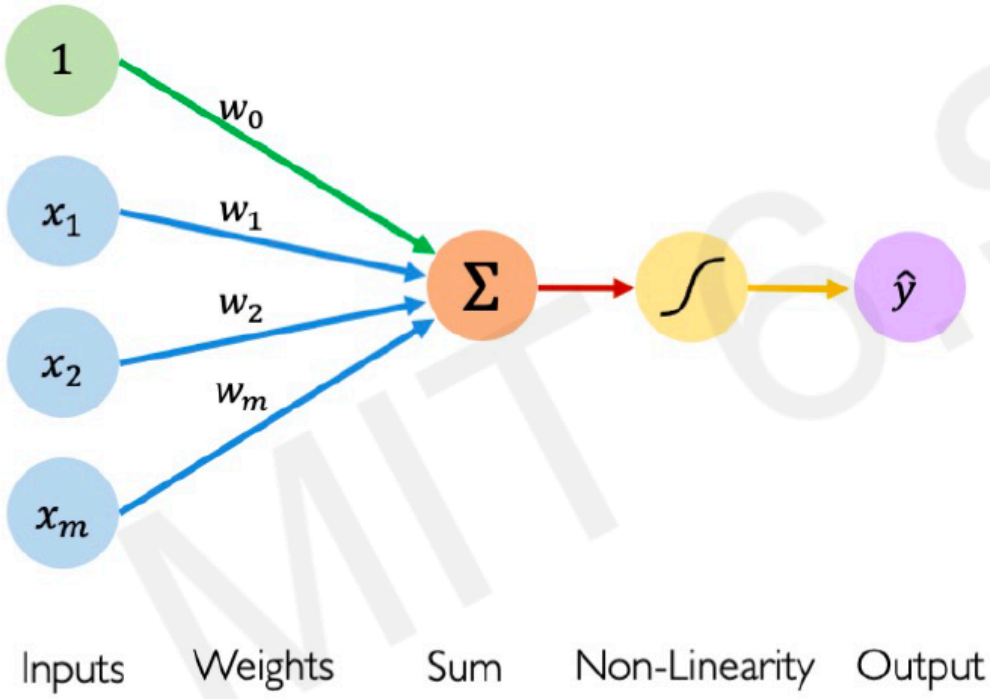


$$\hat{y} = g\left(w_0 + \sum_{i=1}^{m} x_i\, w_i\right)$$

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

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

The Perceptron: Forward Propagation

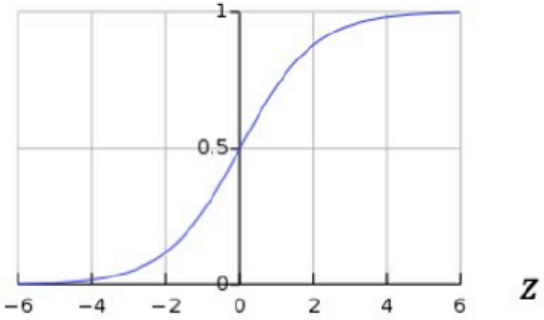


Activation Functions

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

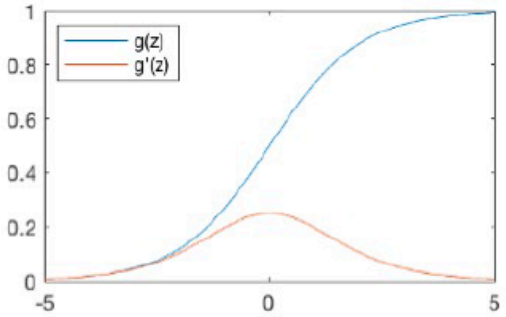
- Example: sigmoid function

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



Common activation functions

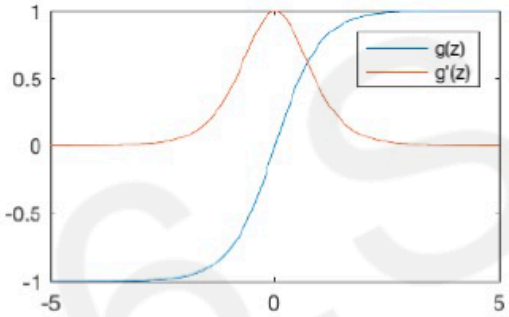
Sigmoid Function



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

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

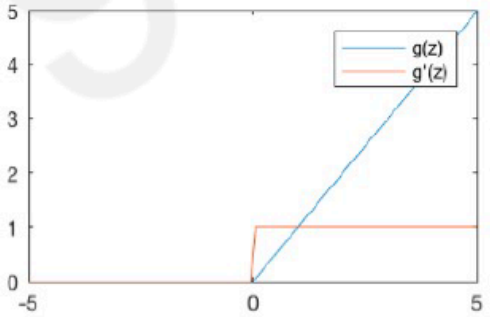
Hyperbolic Tangent



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

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

Rectified Linear Unit (ReLU)

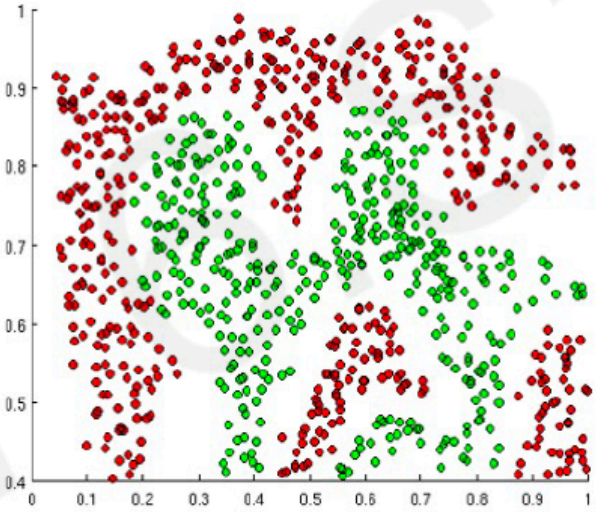


$$g(z) = \max(0, z)$$

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

Importance of activation functions

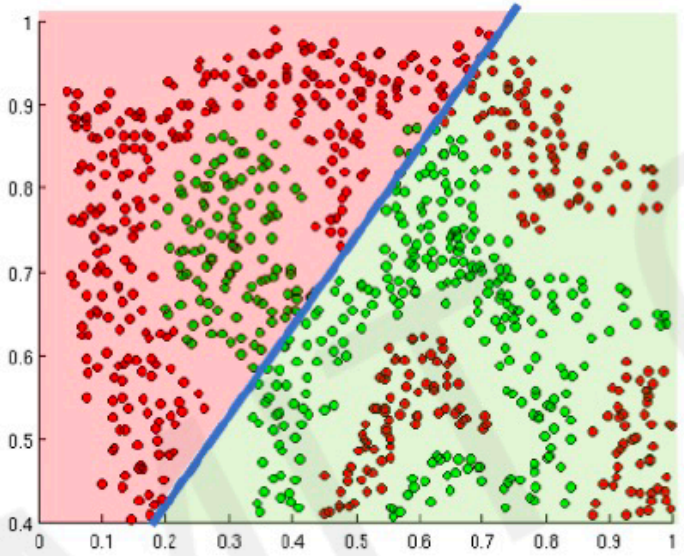
The purpose of activation functions is to ***introduce non-linearities*** *into the network*



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

Importance of activation functions

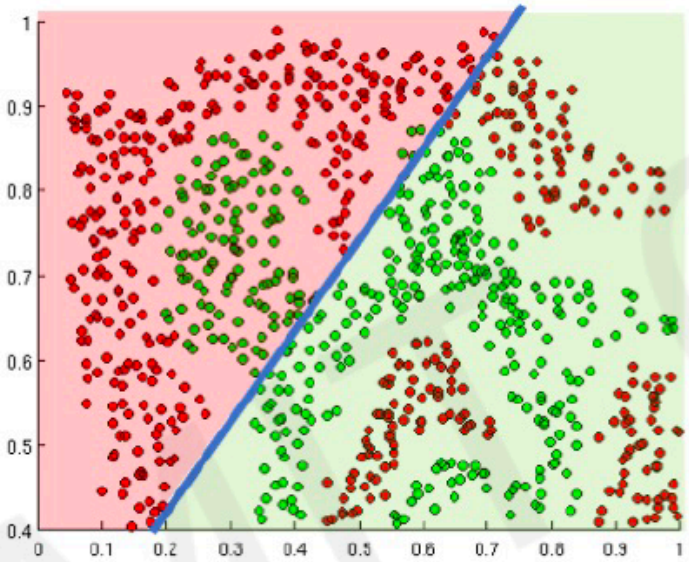
*The purpose of activation functions is to **introduce non-linearities** into the network*



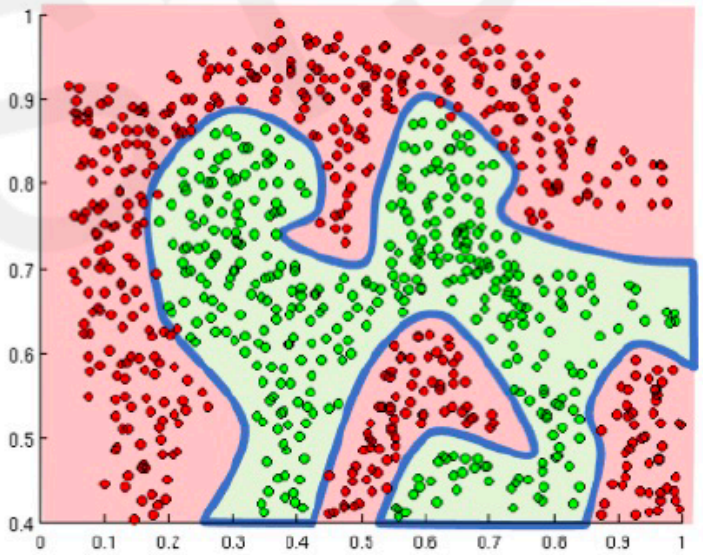
Linear activation functions produce linear decisions no matter the network size

Importance of activation functions

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

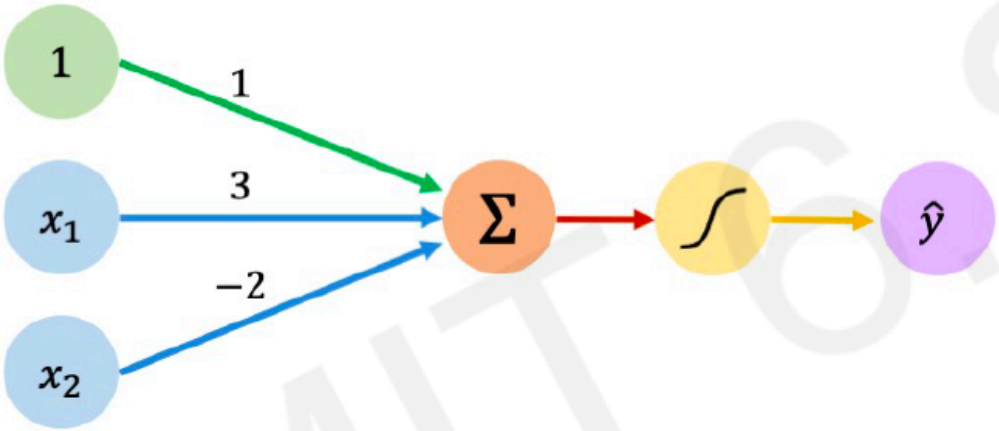


Linear activation functions produce linear decisions no matter the network size



Non-linearities allow us to approximate arbitrarily complex functions

The perceptron: example



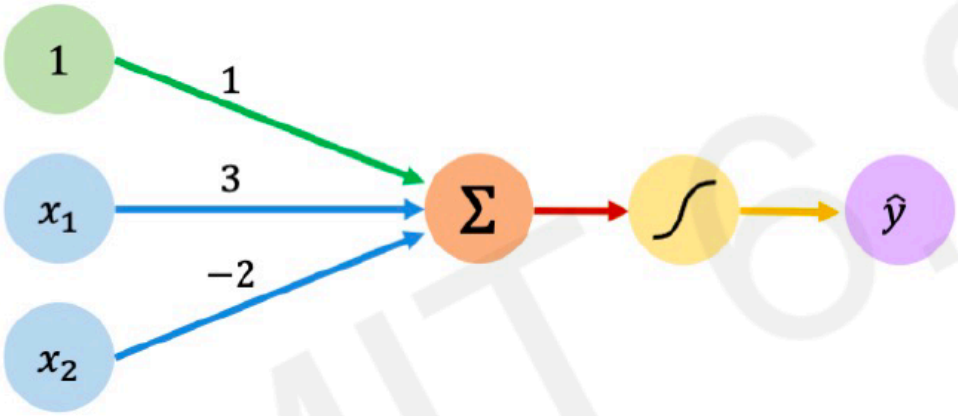
We have: $w_0 = 1$ and $\boldsymbol{W} = \begin{bmatrix} 3 \\ -2 \end{bmatrix}$

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

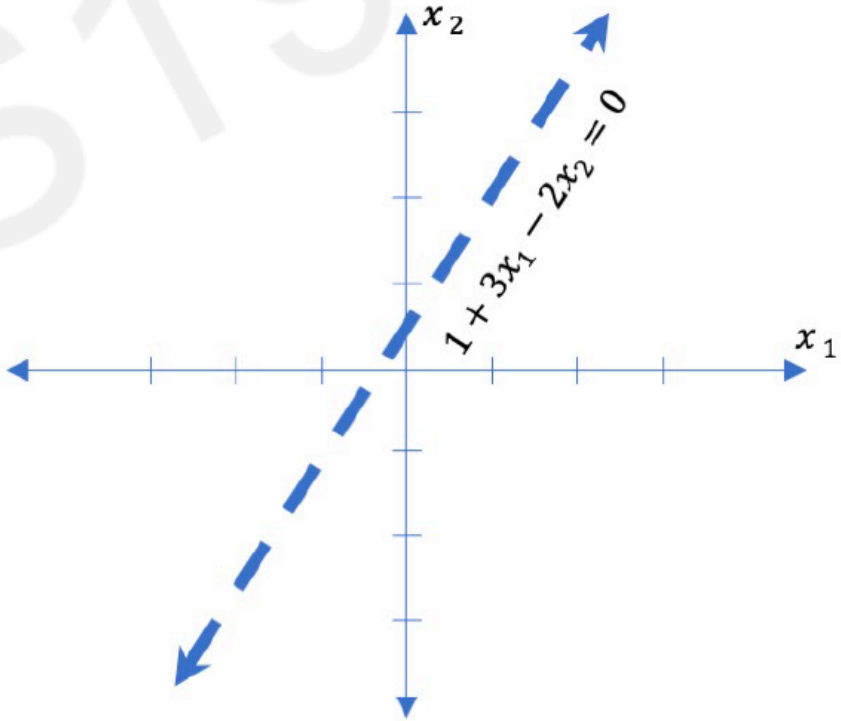
$$= g\left(1 + \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^T \begin{bmatrix} 3 \\ -2 \end{bmatrix}\right)$$

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

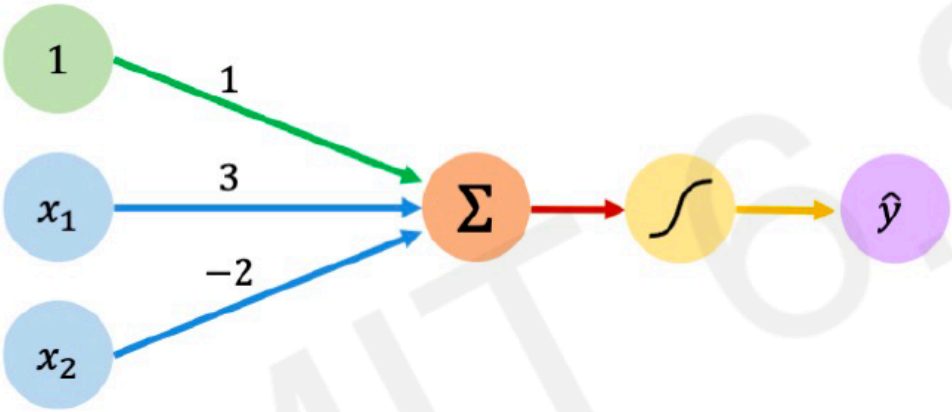
The perceptron: example



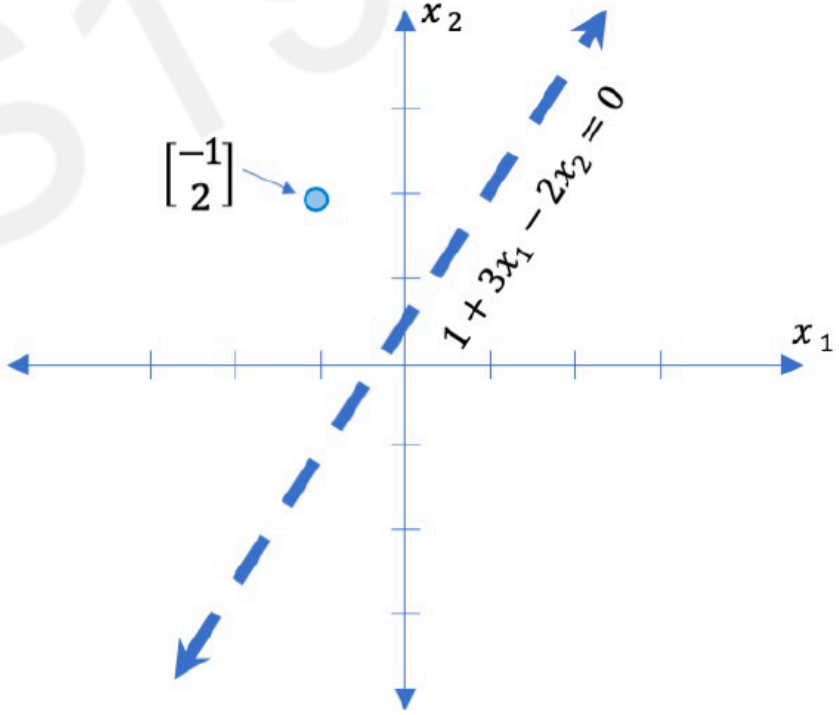
$$\hat{y} = g(1 + 3x_1 - 2x_2)$$



The perceptron: example



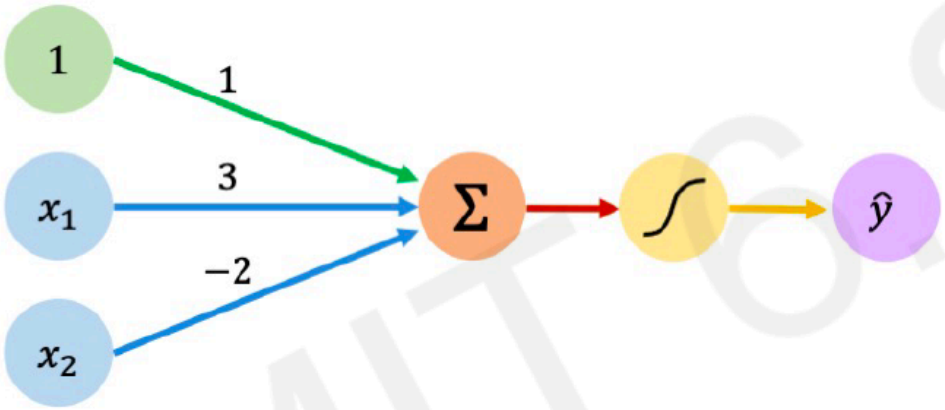
$$\hat{y} = g(1 + 3x_1 - 2x_2)$$

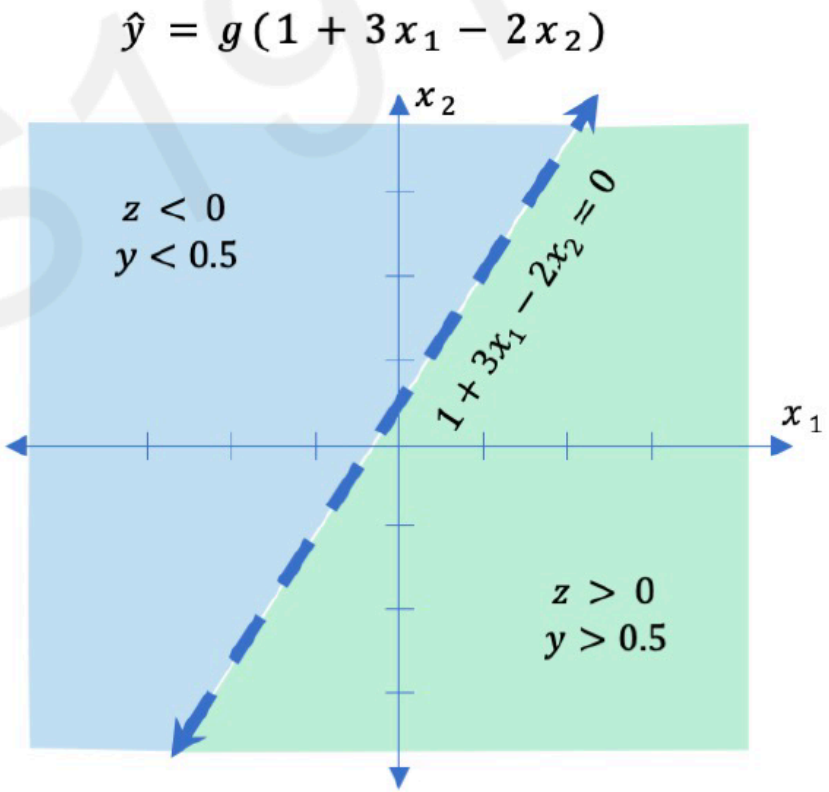


Assume we have input: $\boldsymbol{X} = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$

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

The perceptron: example

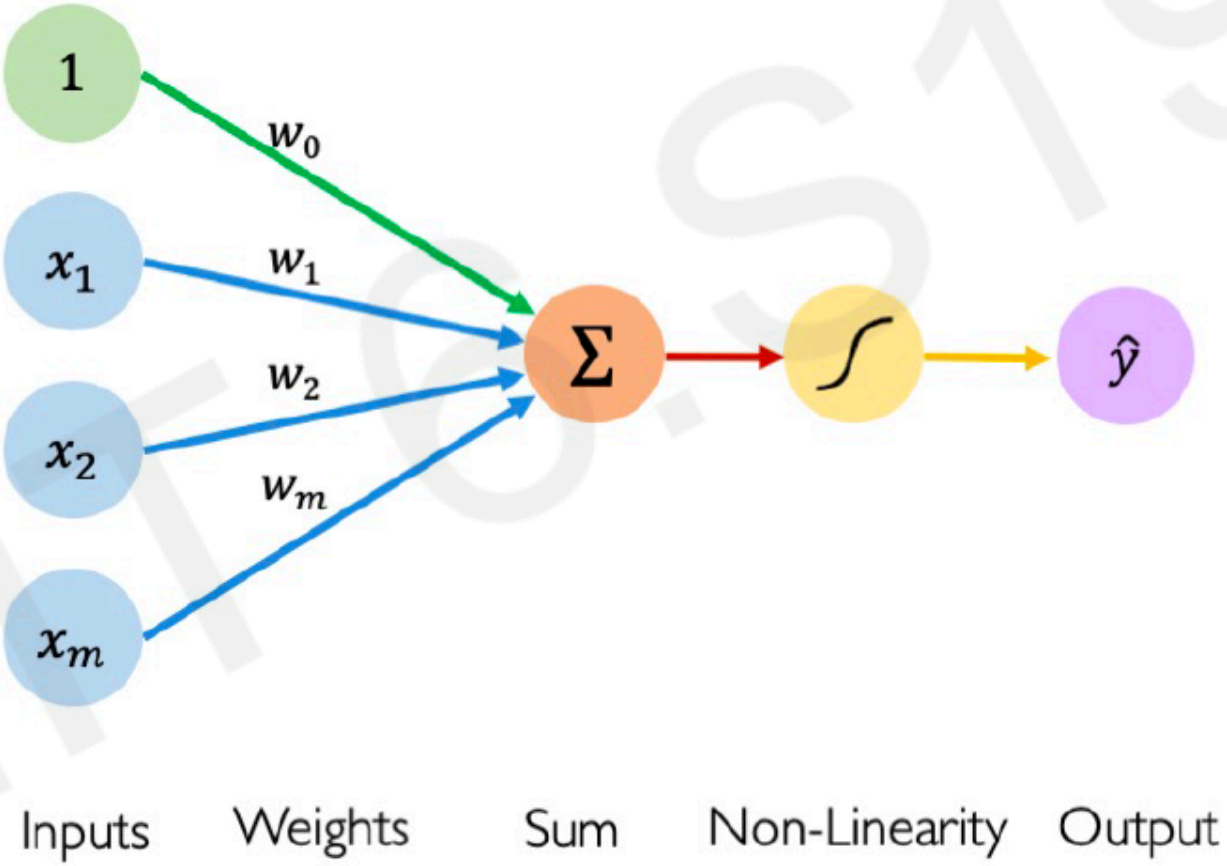




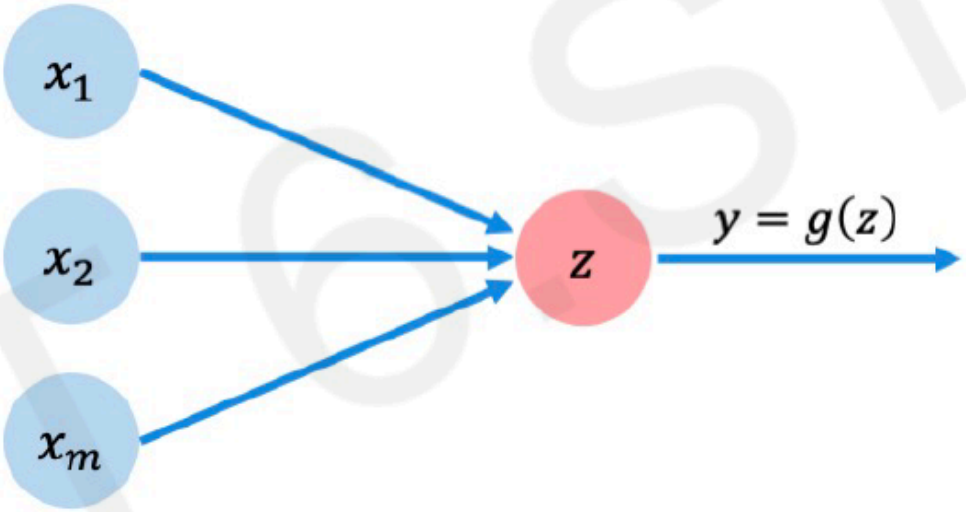
Building Neural Networks with Perceptrons

The perceptron: simplified

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



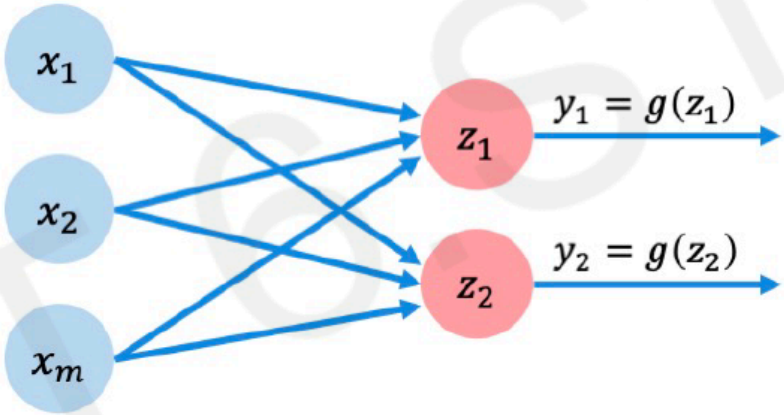
The perceptron: simplified



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

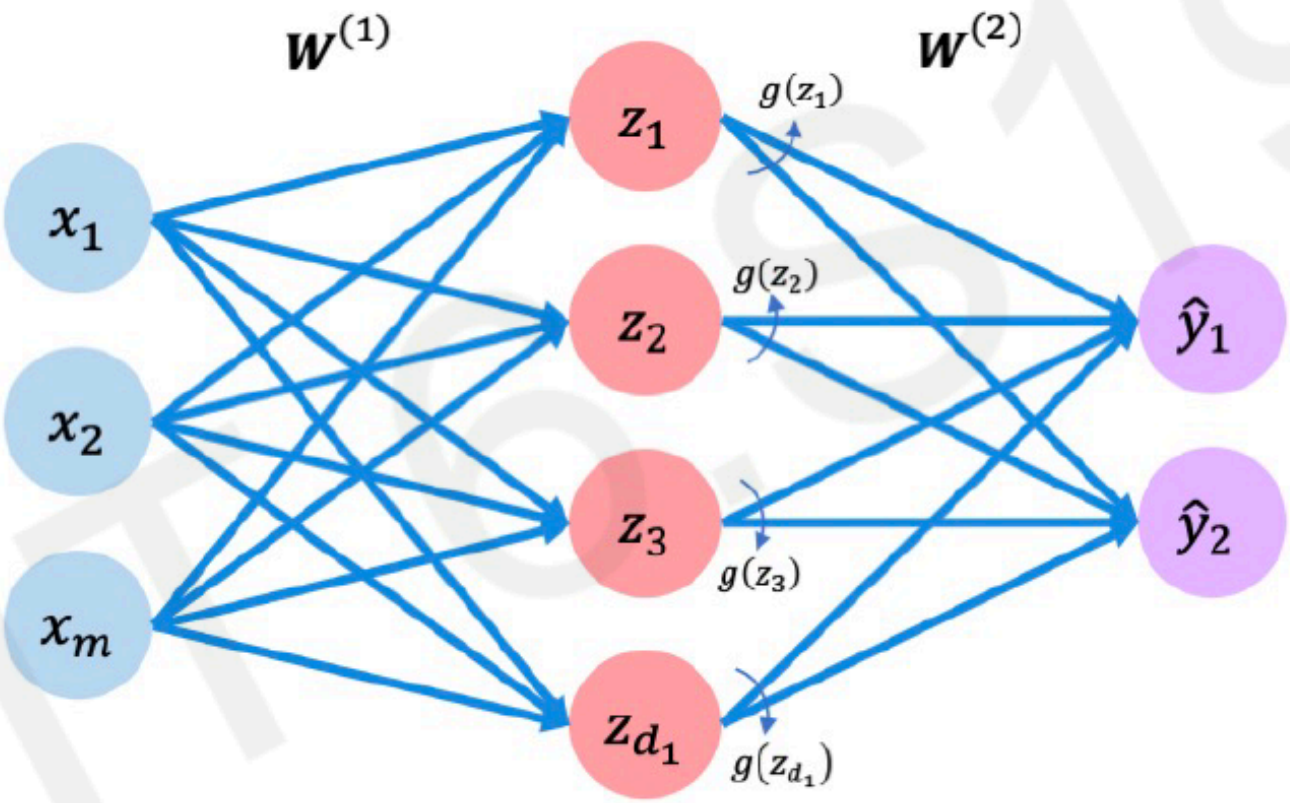
Multi output perceptron

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



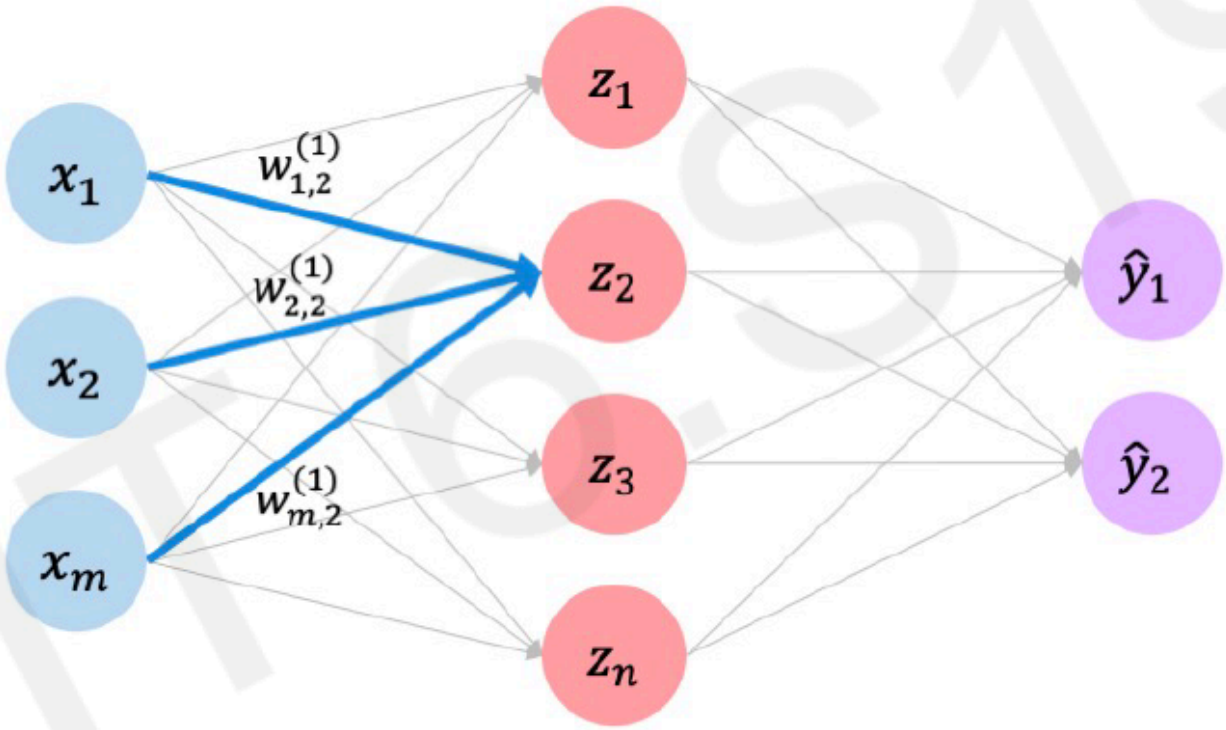
$$z_i = w_{0,i} + \sum_{j=1}^{m} x_j \, w_{j,i}$$

Single layer neural network



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

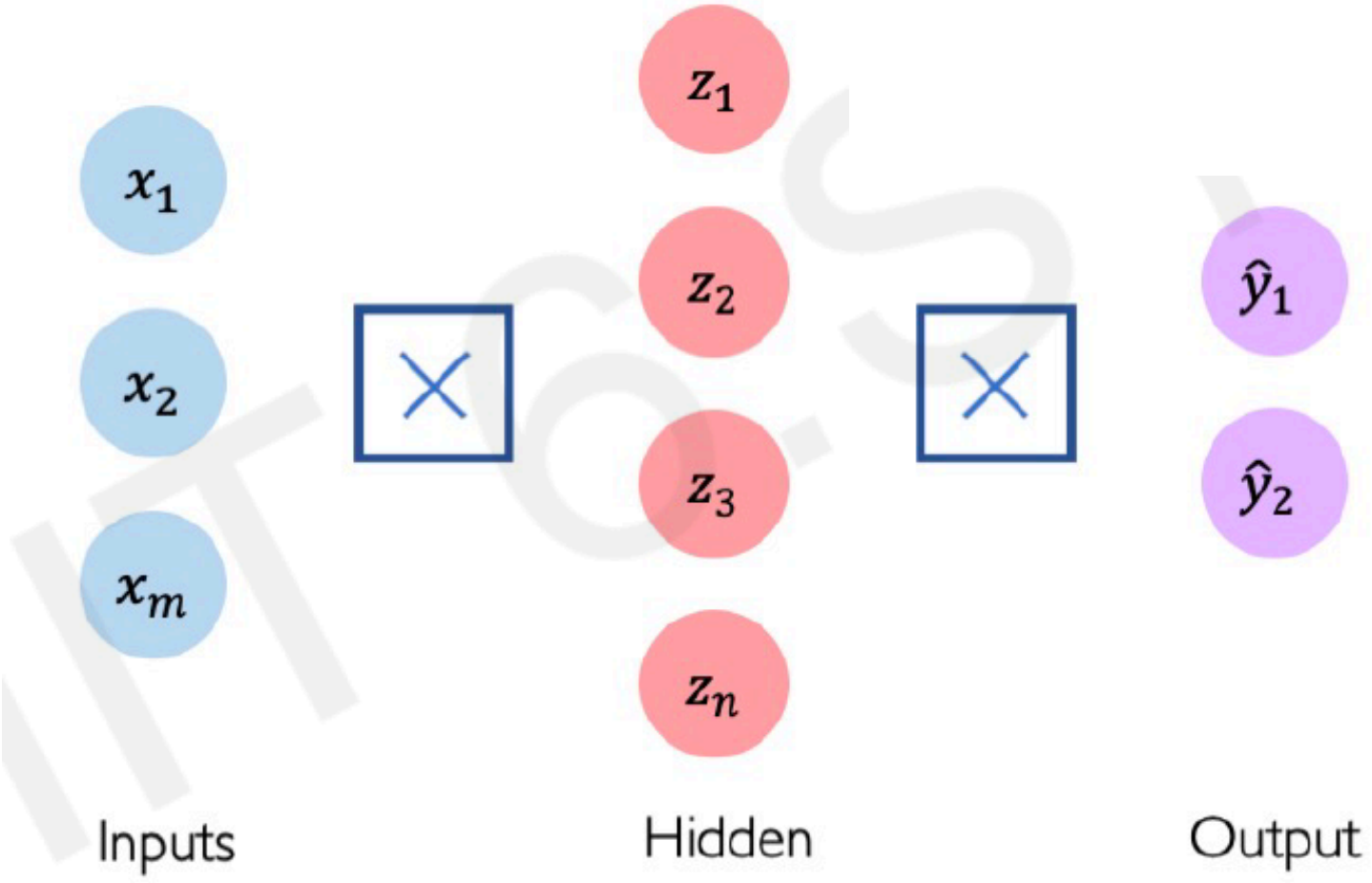
Single layer neural network



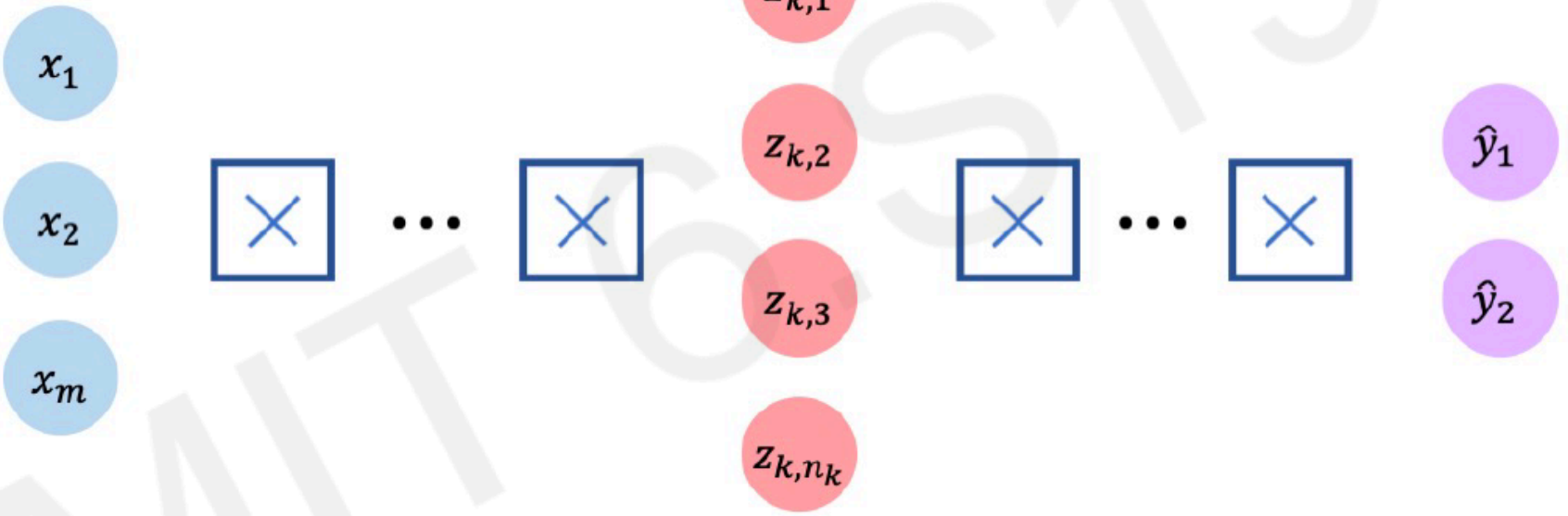
$$z_2 = w_{0,2}^{(1)} + \sum_{j=1}^{m} x_j \, w_{j,2}^{(1)}$$

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

Multi output perceptron



Deep neural network



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

Applying Neural Networks

Example problem

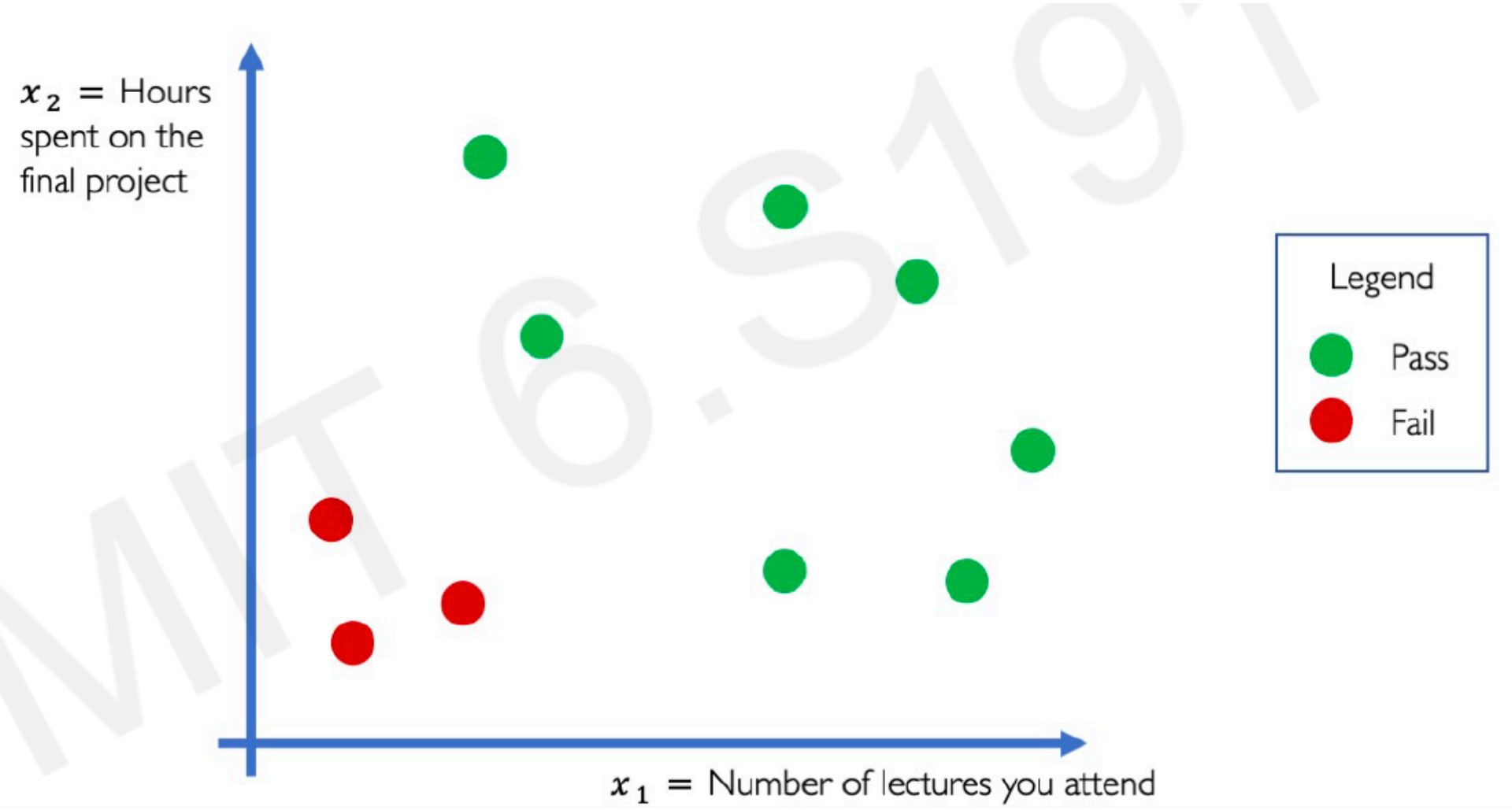
Will I pass this class?

Let's start with a simple two feature model

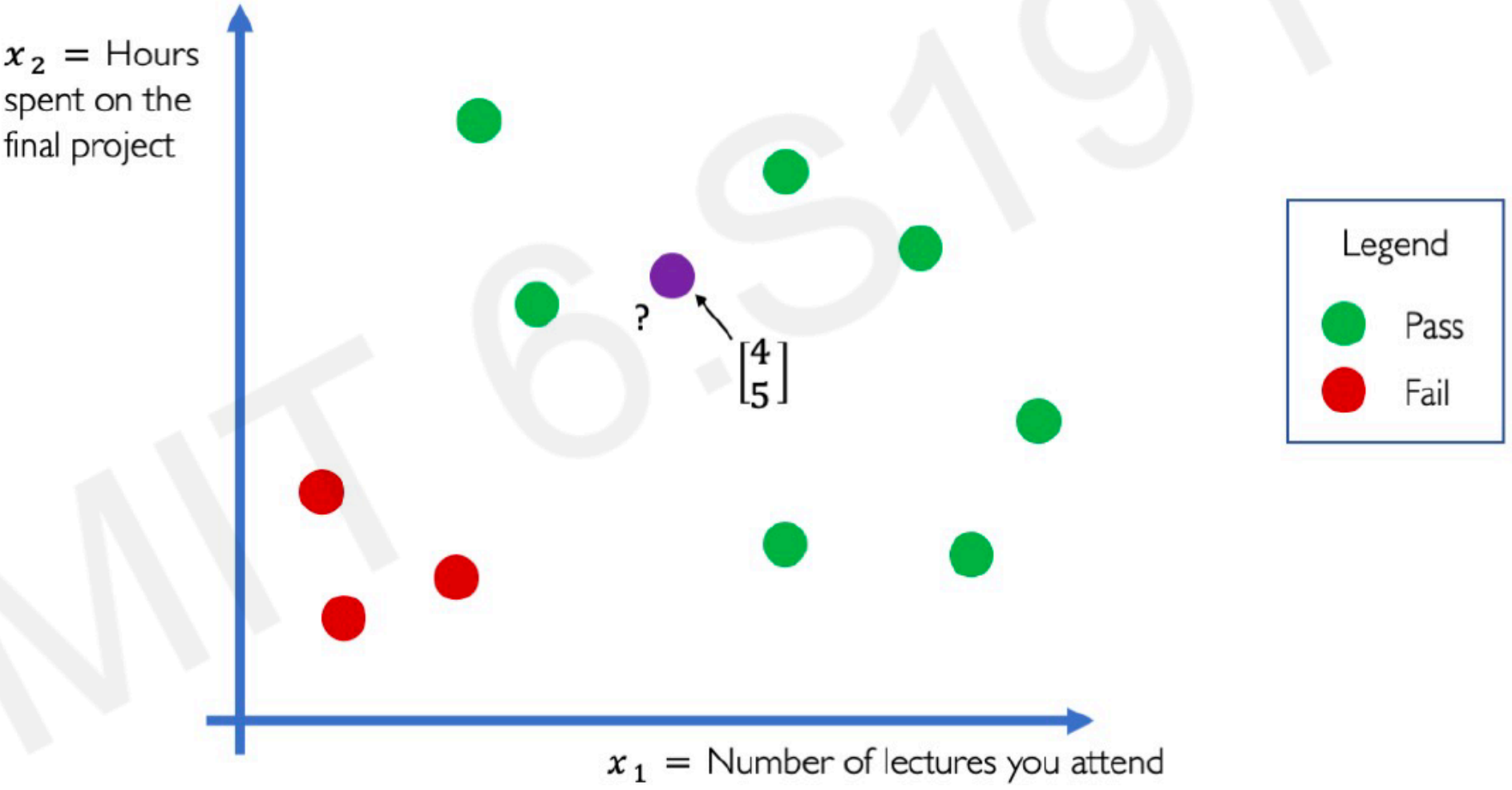
x_1 = Number of lectures you attend

x_2 = Hours spent on the final project

Example problem: will I pass this class?



Example problem: will I pass this class?



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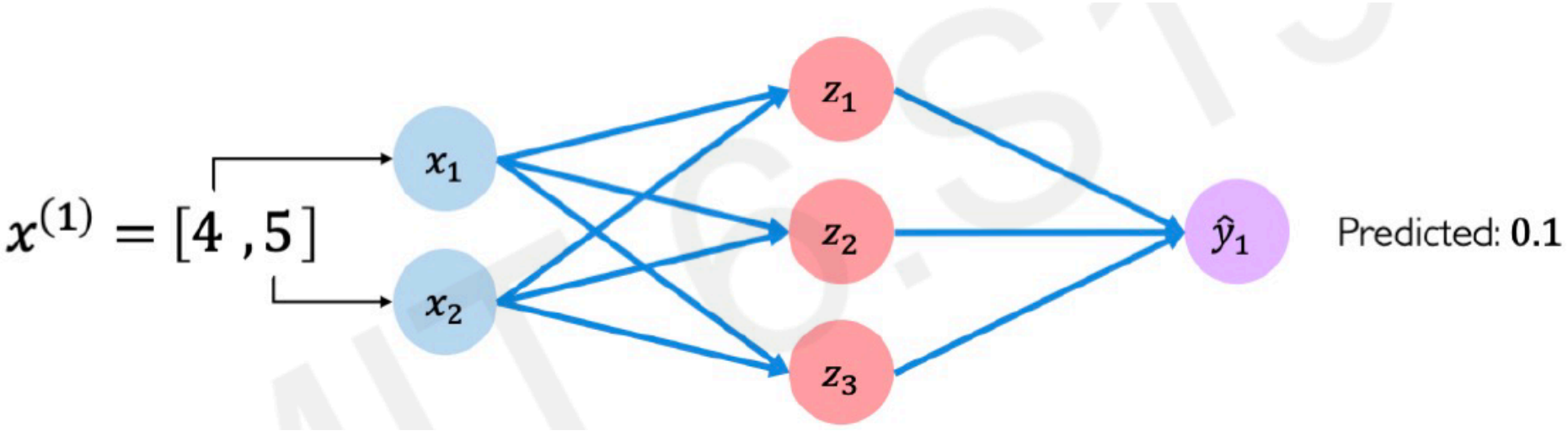

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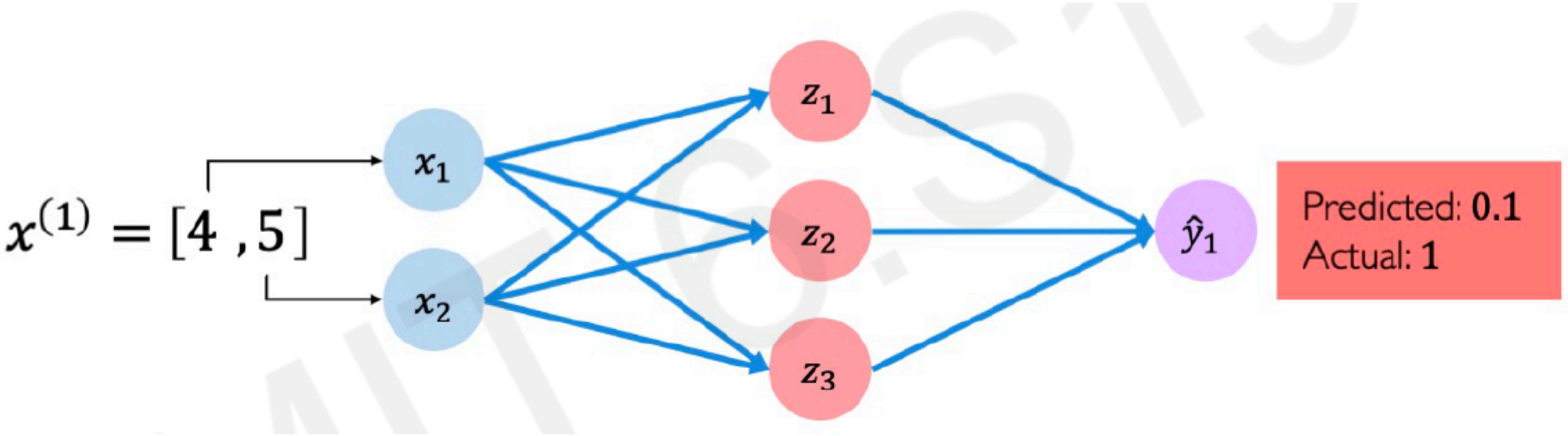
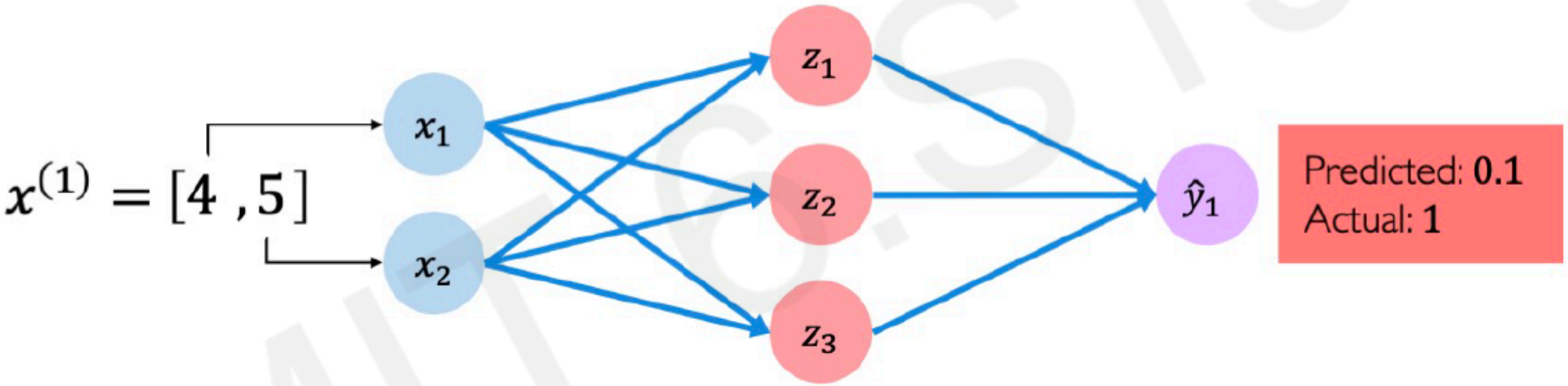


Quantifying loss

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

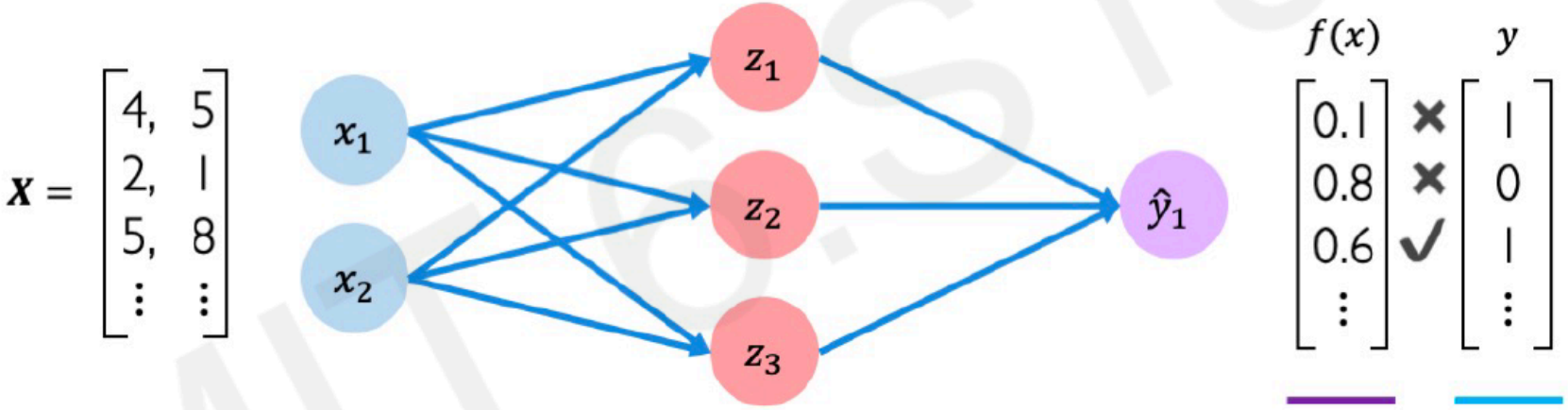


$$\mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

Predicted Actual

Empirical loss

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



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

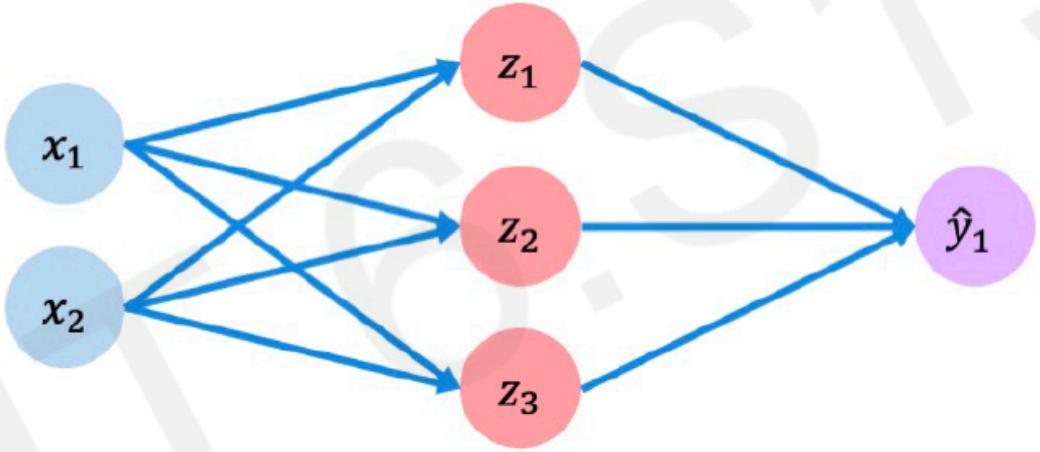
$$J(\boldsymbol{W}) = \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

Predicted Actual

Binary cross entropy loss

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

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



$f(x)$ $\quad$ y

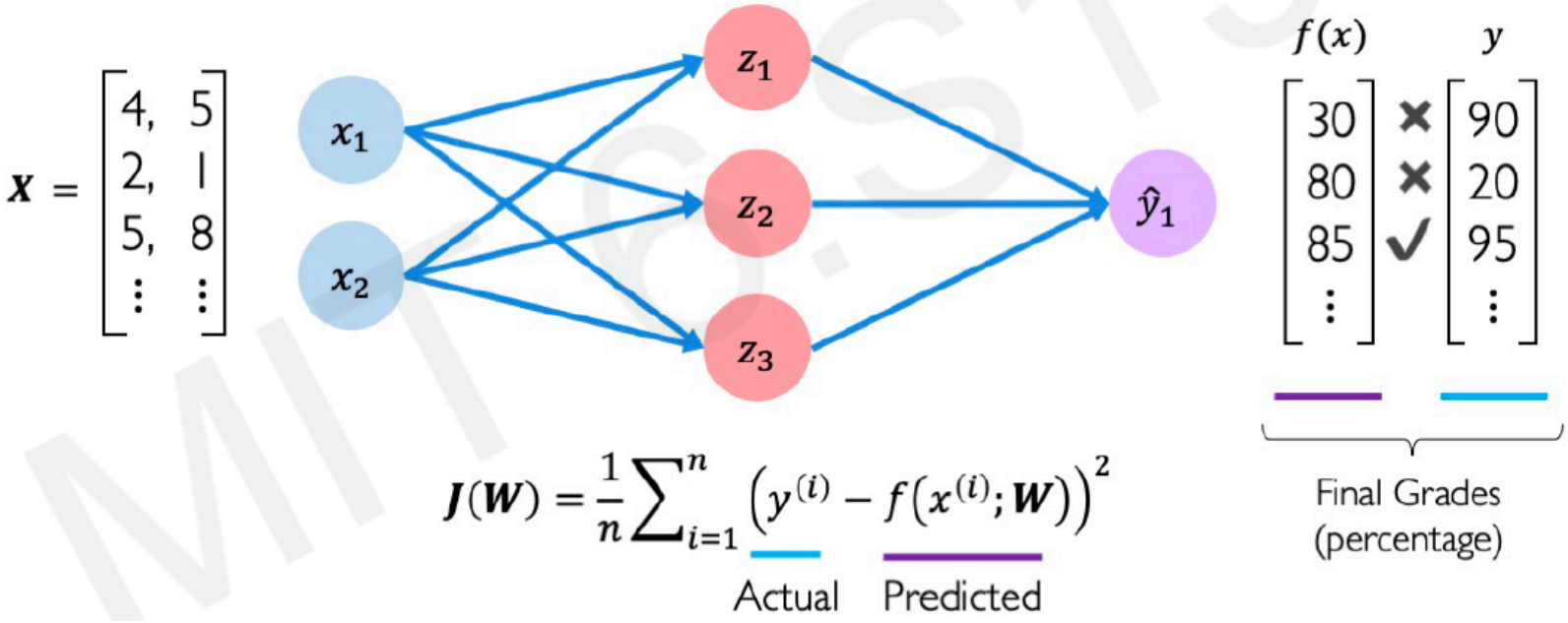
$$\begin{bmatrix} 0.1 \\ 0.8 \\ 0.6 \\ \vdots \end{bmatrix} \times \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix}$$

$$J(\boldsymbol{W}) = -\frac{1}{n}\sum_{i=1}^{n} y^{(i)} \log\left(f\left(x^{(i)}; \boldsymbol{W}\right)\right) + \left(1 - y^{(i)}\right) \log\left(1 - f\left(x^{(i)}; \boldsymbol{W}\right)\right)$$

Actual $\quad$ Predicted $\quad$ Actual $\quad$ Predicted

Mean squared error loss

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



Training Neural Networks

Loss optimization

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

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

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

Loss optimization

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

Remember:

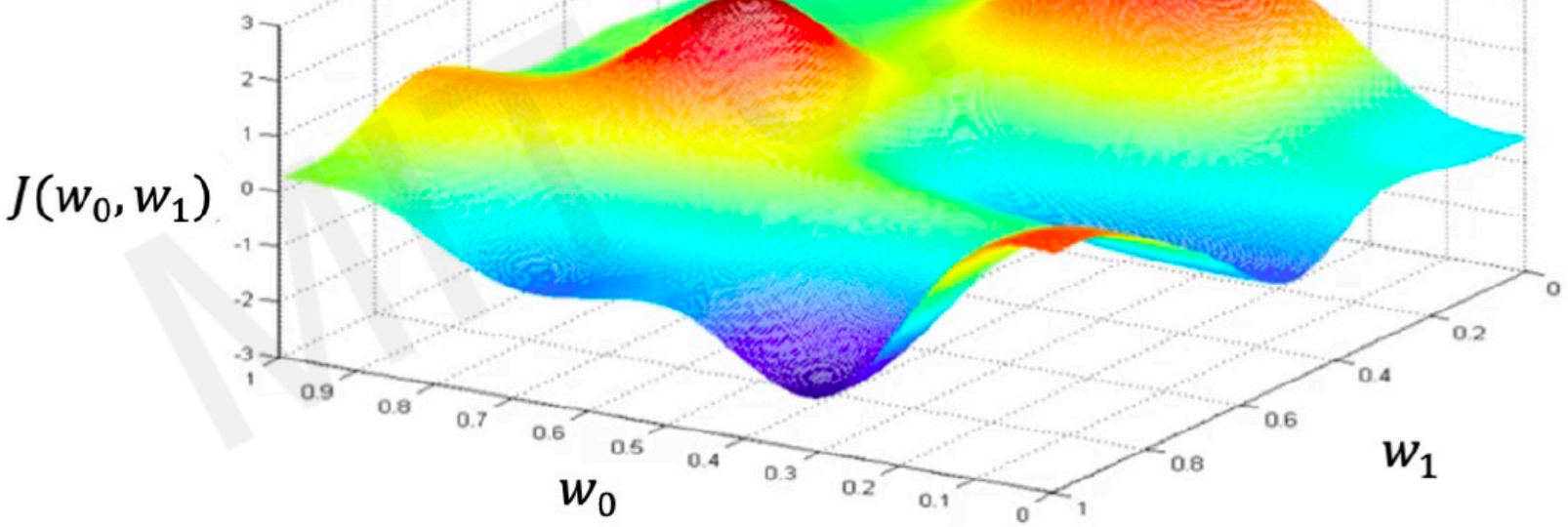
$$\boldsymbol{W} = \left\{\boldsymbol{W}^{(0)}, \boldsymbol{W}^{(1)}, \dots\right\}$$

Loss optimization

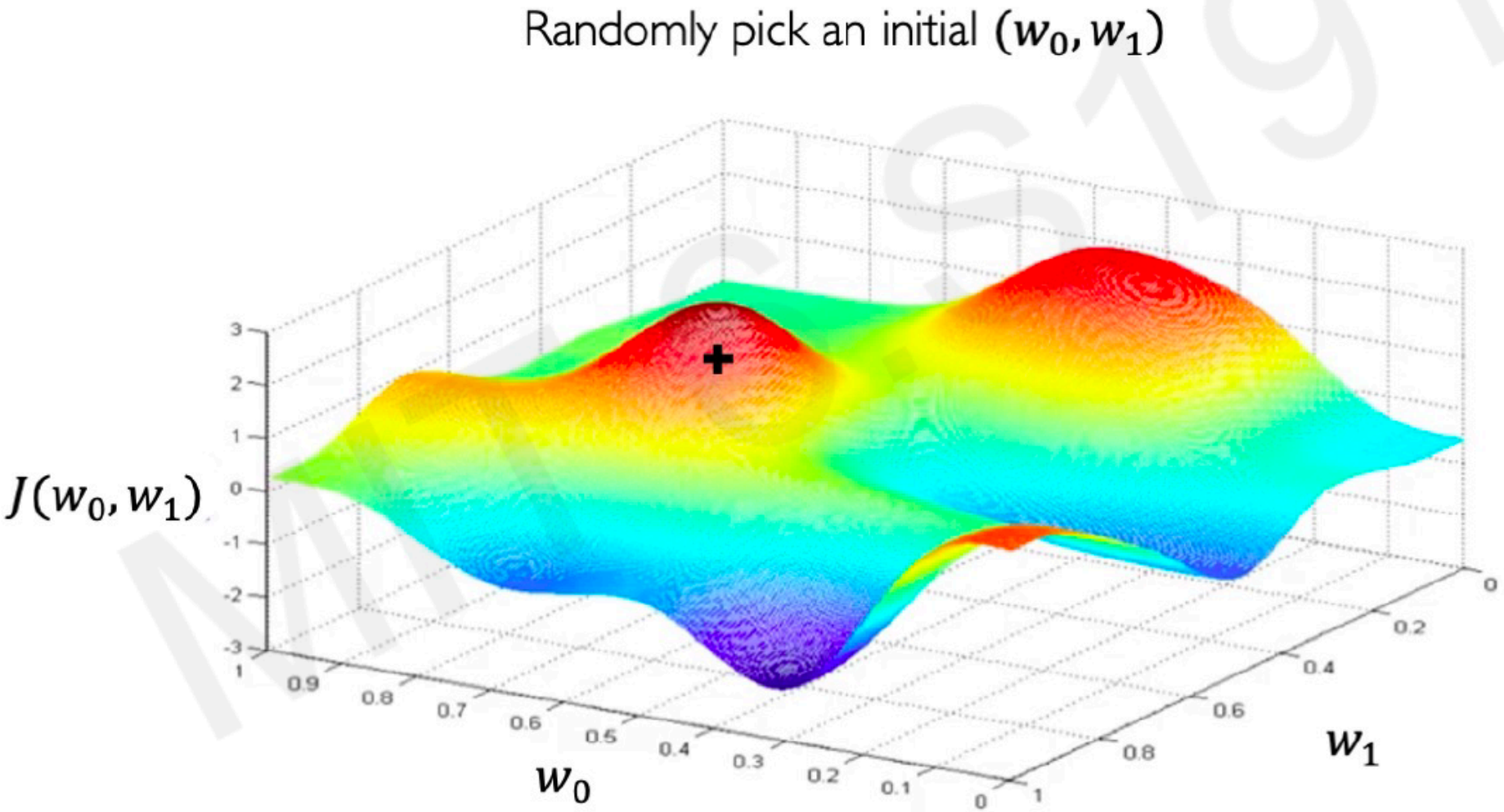
$$W^* = \underset{w}{\text{argmin}}\, J(W)$$

Remember:

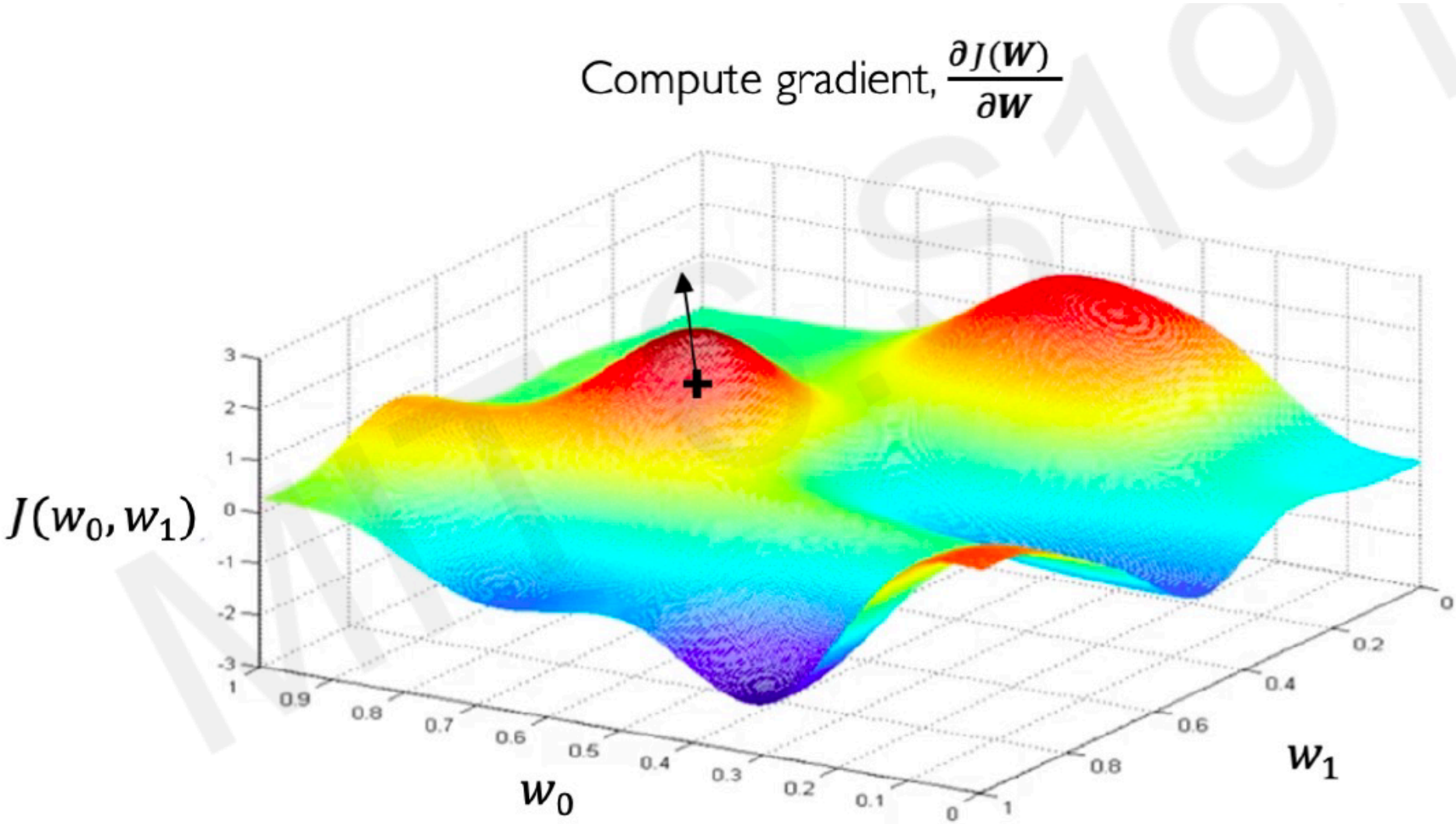
Our loss is a function of the network weights!



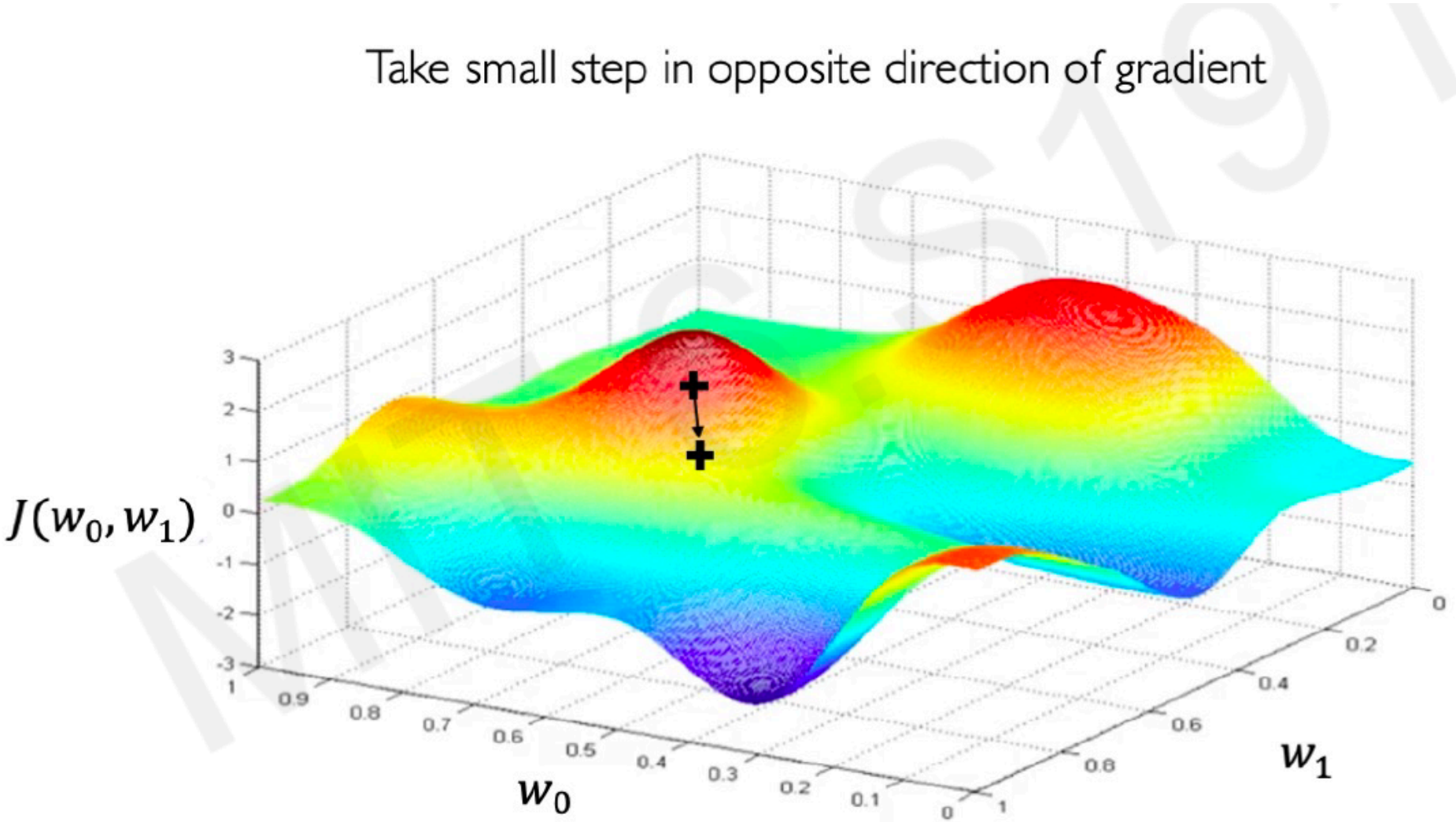
Loss optimization



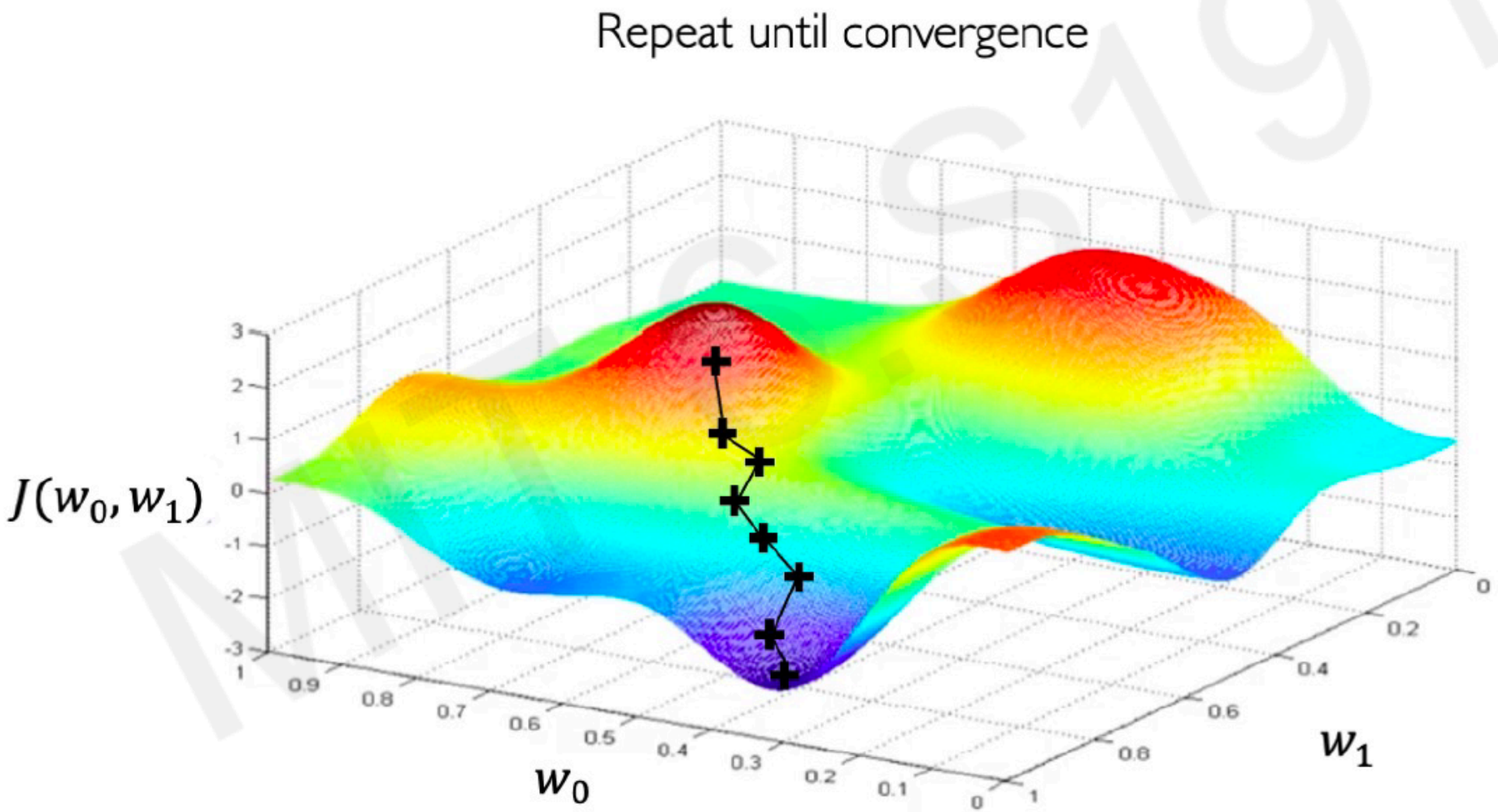
Loss optimization



Loss optimization



Gradient descent



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

Computing gradients: backpropagation

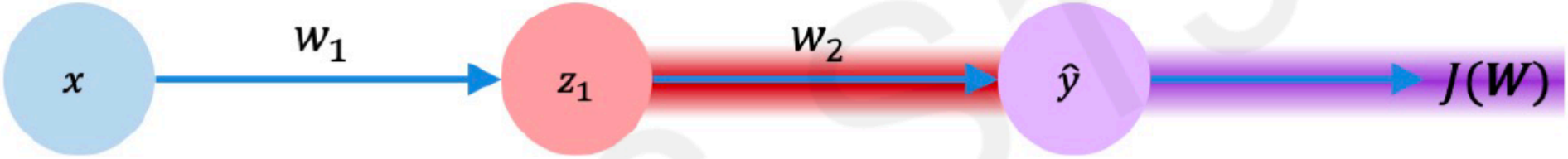
How does a small change in one weight (ex. $\boldsymbol{w_2}$) affect the final loss $J(\boldsymbol{W})$?

Computing gradients: backpropagation

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

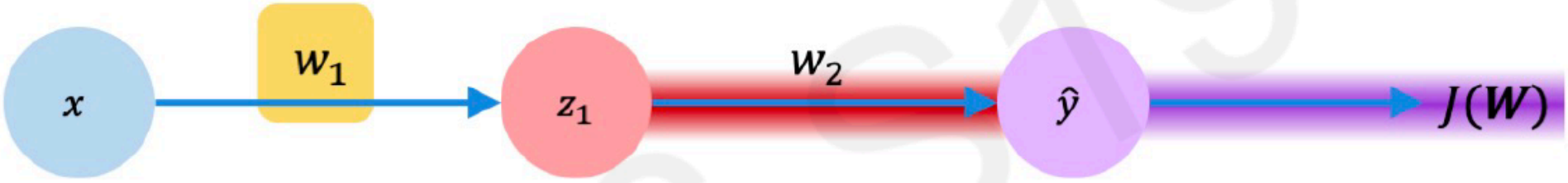
Let's use the chain rule!

Computing gradients: backpropagation



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

Computing gradients: backpropagation

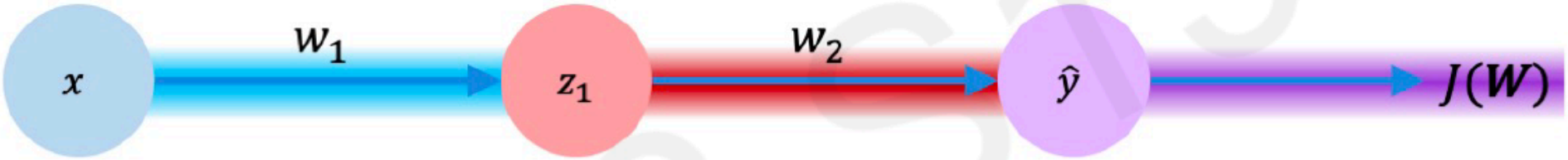


$$\frac{\partial J(W)}{\partial w_1} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial w_1}$$

Apply chain rule!

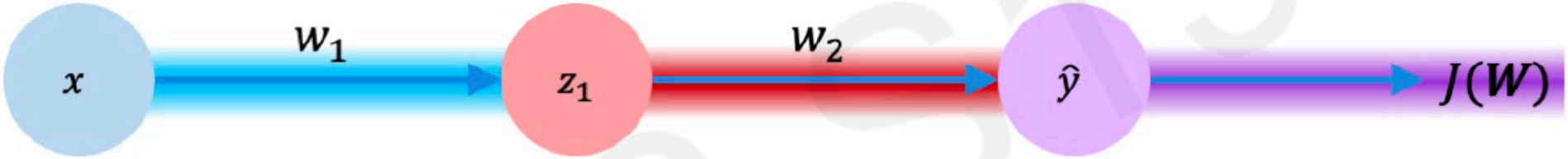
Apply chain rule!

Computing gradients: backpropagation



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

Computing gradients: backpropagation

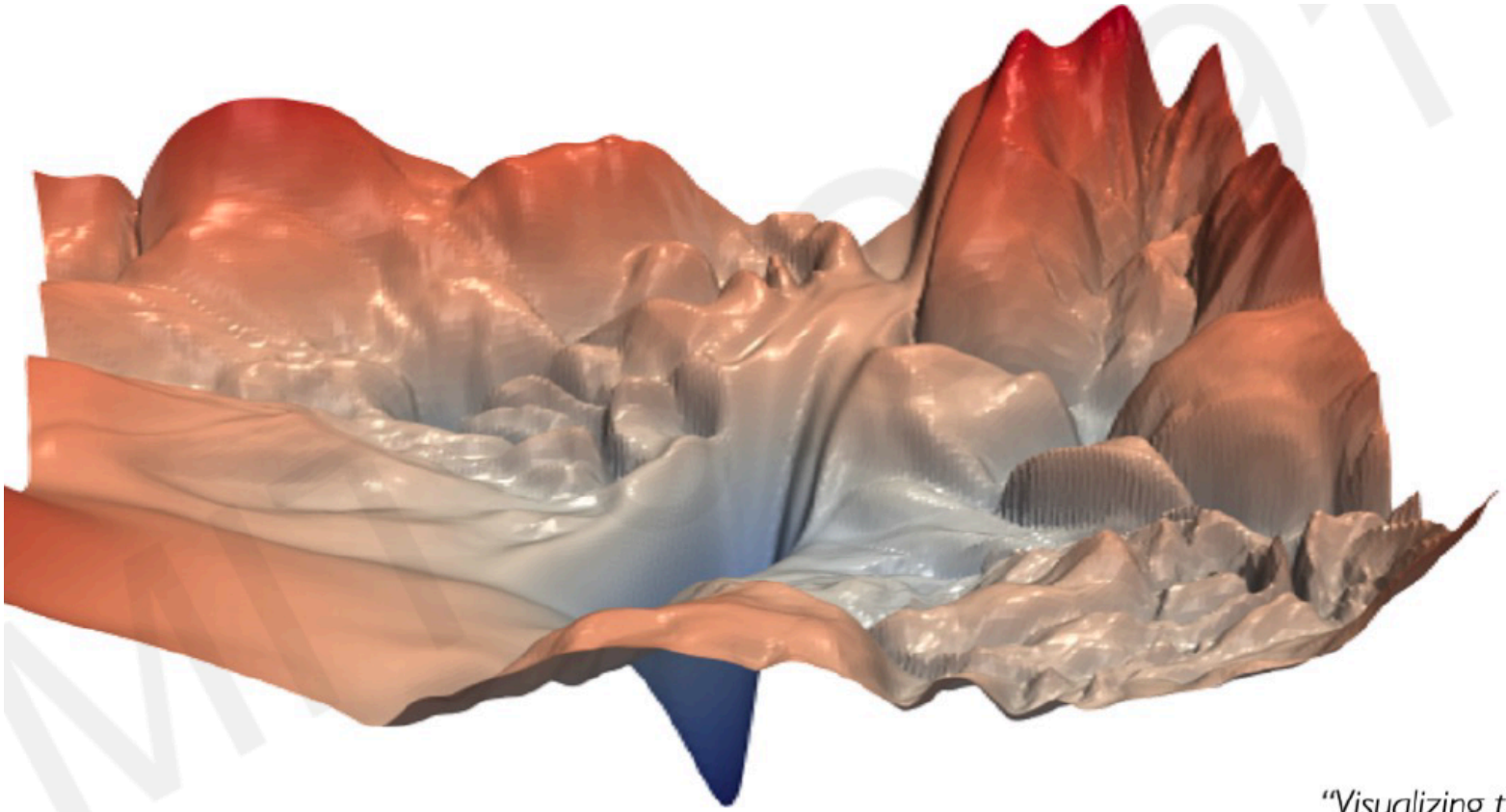


$$\frac{\partial J(W)}{\partial w_1} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial z_1} * \frac{\partial z_1}{\partial w_1}$$

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 function can be difficult to optimize

Remember:

Optimization through gradient descent

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

Loss function can be difficult to optimize

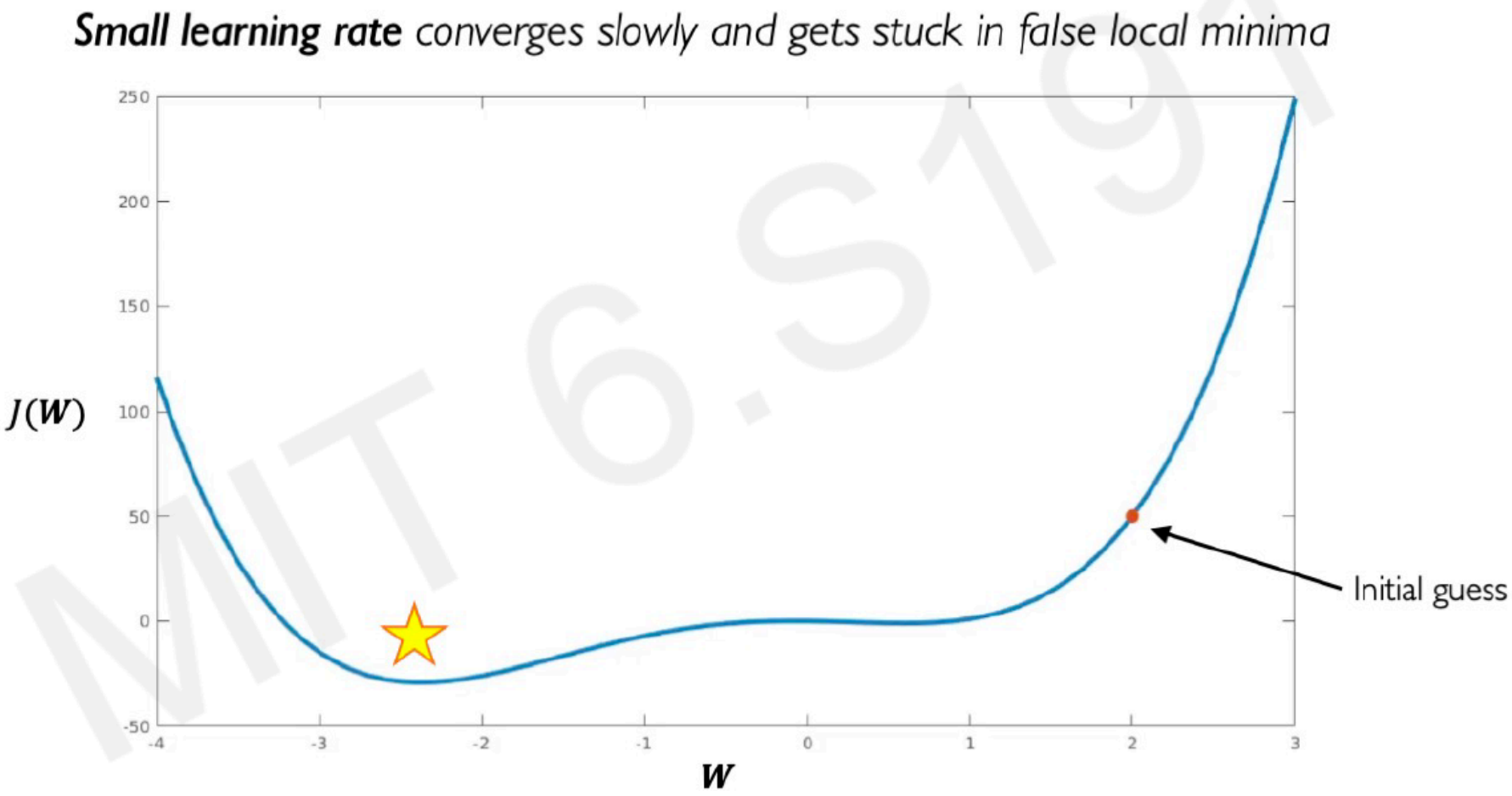
Remember:

Optimization through gradient descent

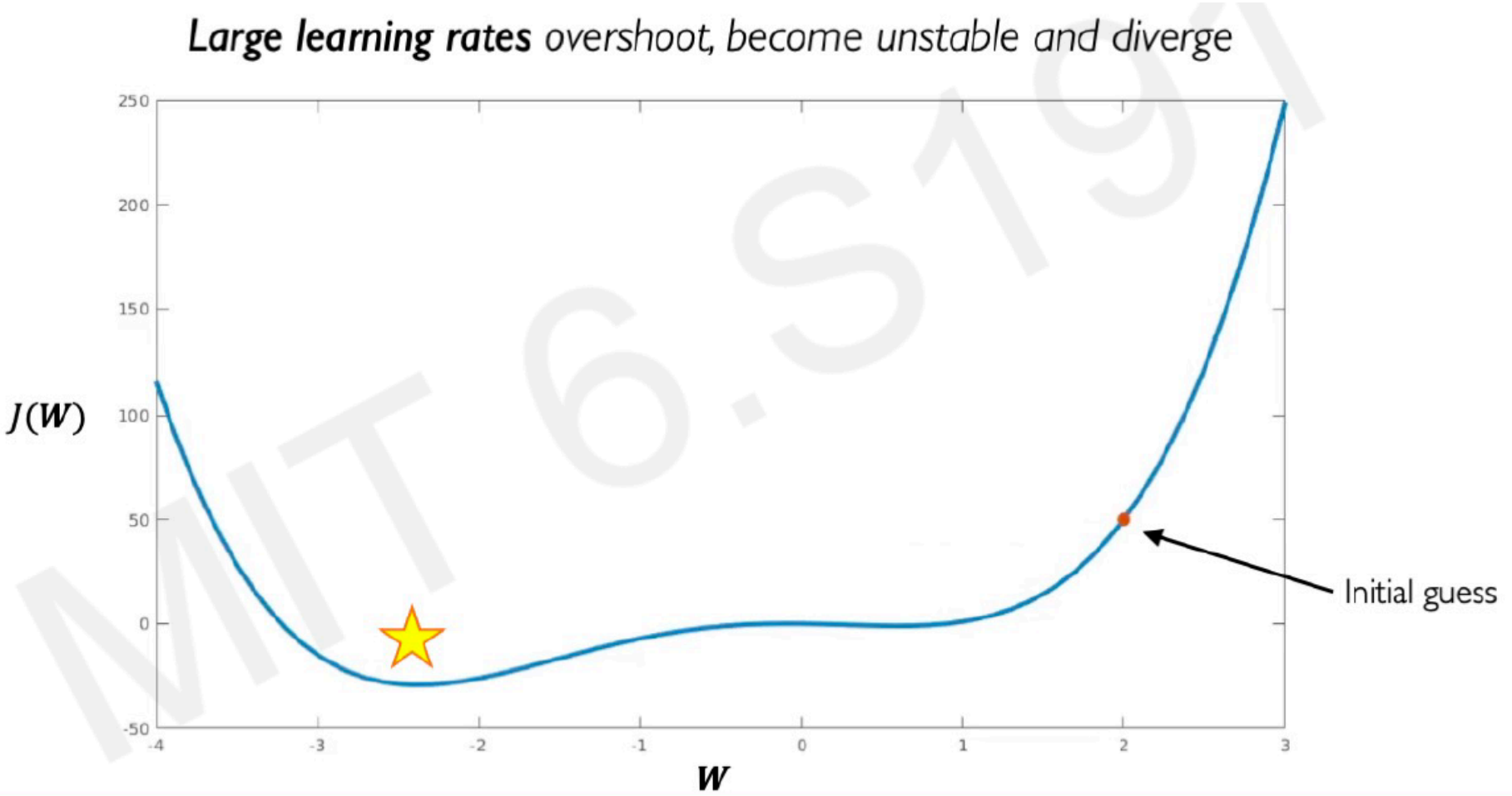
$$\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$$

How can we set the learning rate?

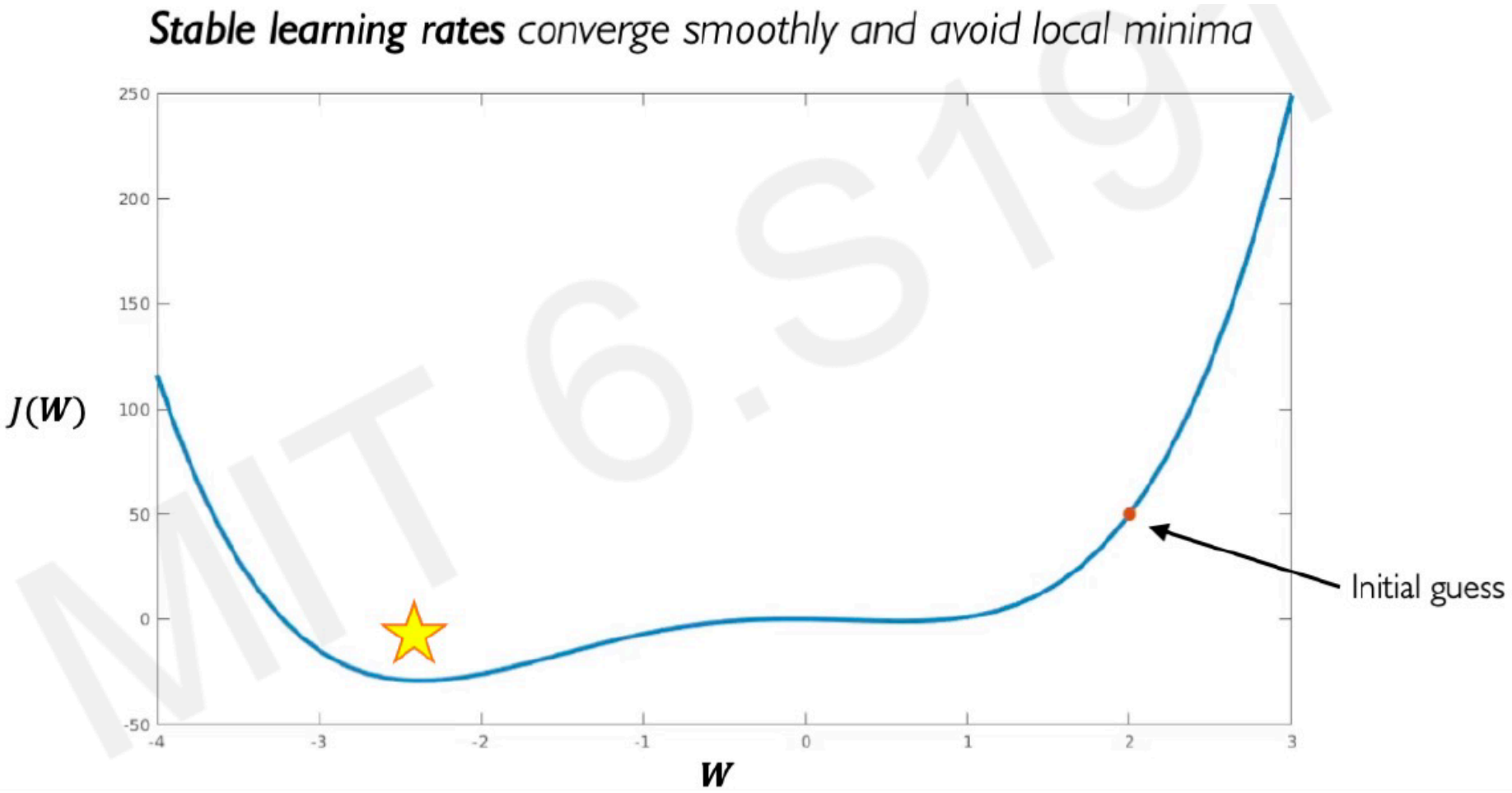
Setting the learning rate



Setting the learning rate



Setting the learning rate



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

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

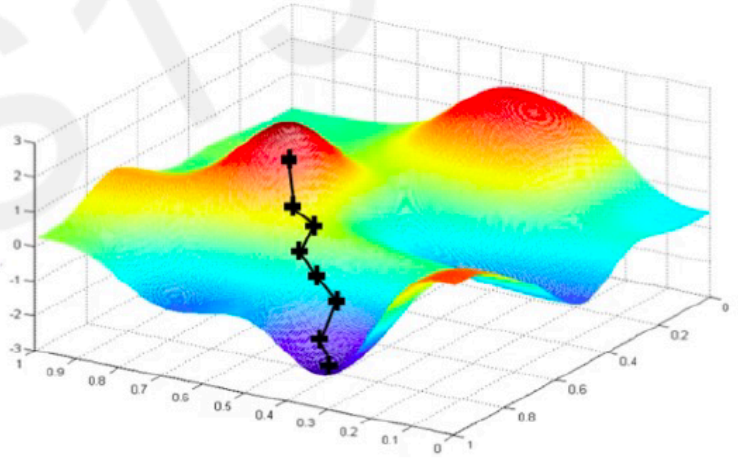
Neural Networks in Practice: Mini-batches

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

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

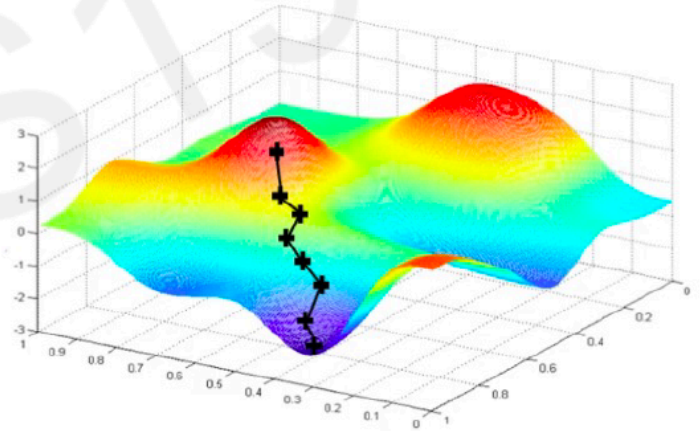


Stochastic gradient descent

Algorithm

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

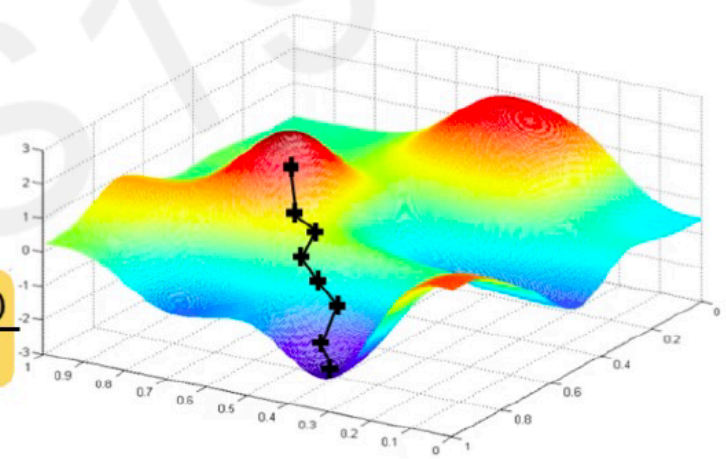
Easy to compute but **very noisy** (stochastic)!



Mini-batches while training

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, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}} = \frac{1}{B}\sum_{k=1}^{B} \frac{\partial J_k(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
6. Return weights



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

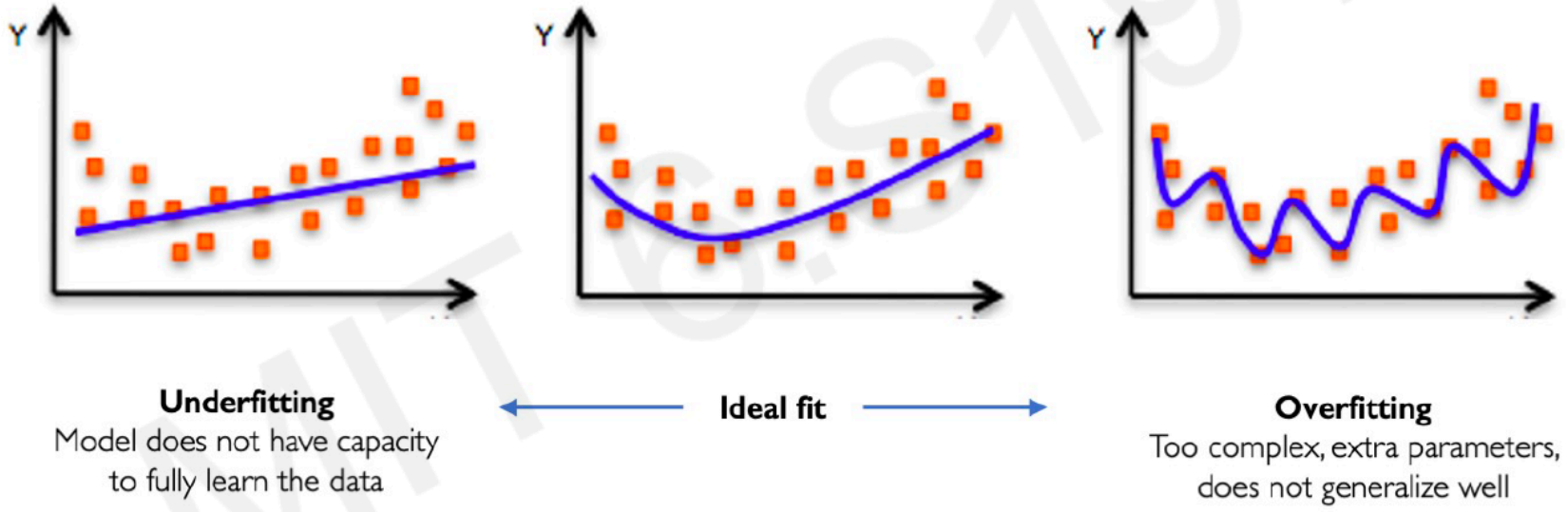
More accurate estimation of gradient

Smoother convergence

Allows for larger learning rates

Neural Networks in Practice: Overfitting

The problem of overfitting



Regularization

What is it?

Technique that constrains our optimization problem to discourage complex models

Regularization

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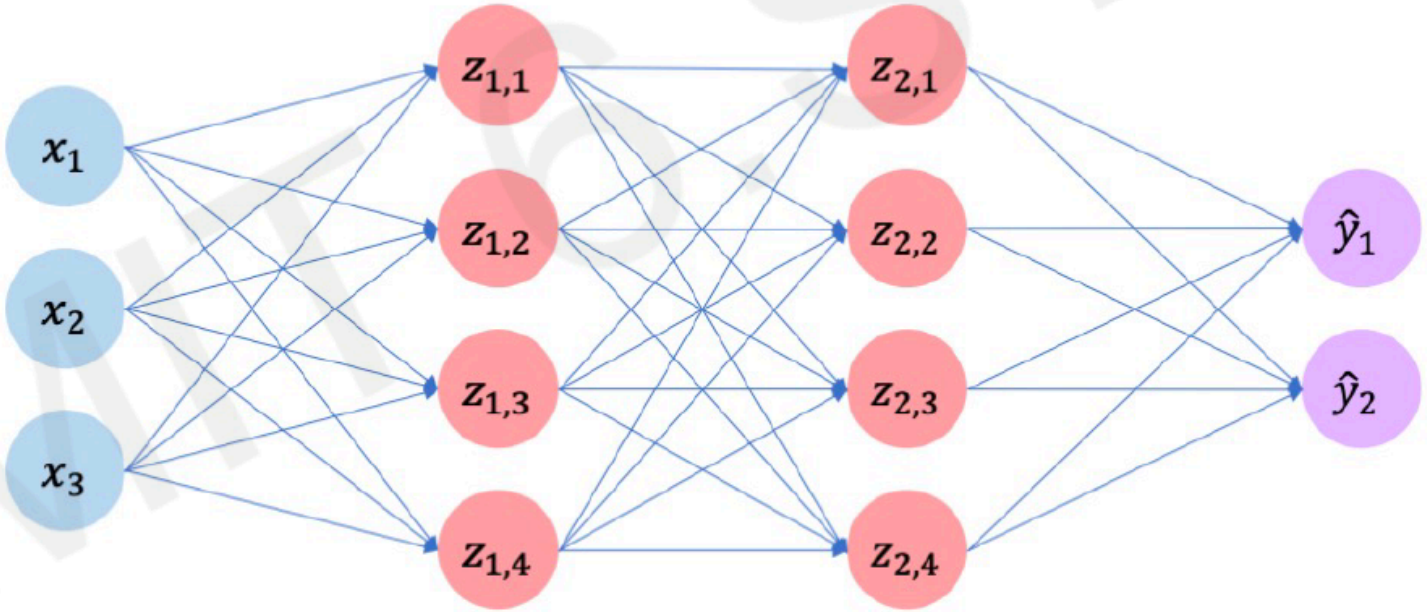
Technique that constrains our optimization problem to discourage complex models

Why do we need it?

Improve generalization of our model on unseen data

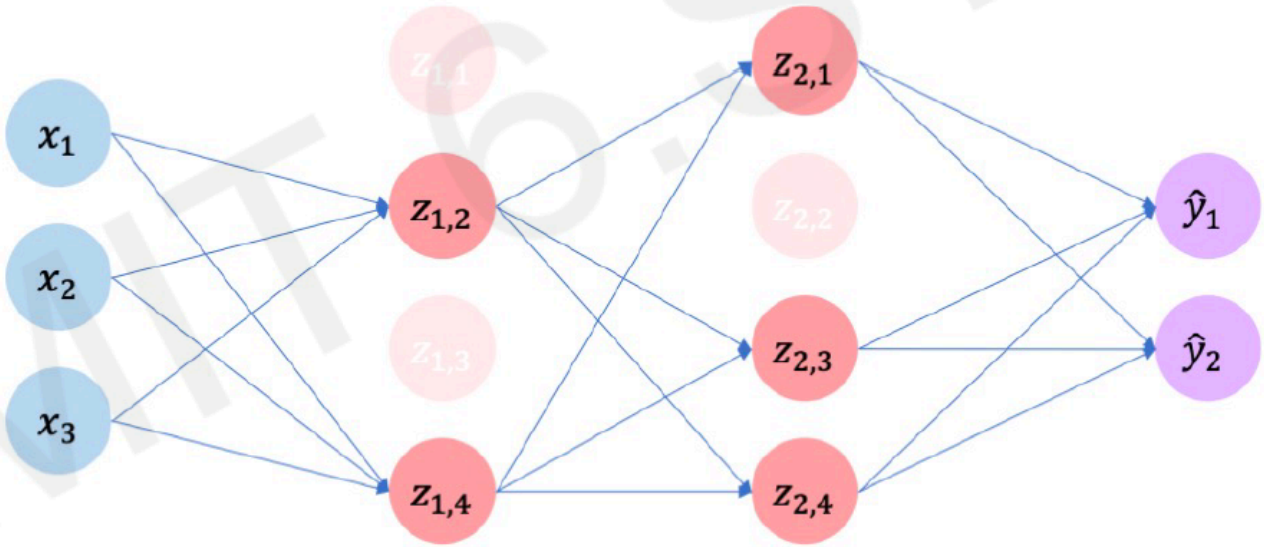
Regularization I: dropout

- 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



Regularization II: early stopping

- Stop training before we have a chance to overfit

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- Stop training before we have a chance to overfit