Welcome to „Introduction to Deep Learning“

We will start at 9am.

The slides can be downloaded form:

https://github.com/auliyafitri/Intro-to-Deep-Learning-Seminar/slides

or

https://tinyurl.com/dl-intro-slides

Introduction to Deep Learning
Part I - Basics

June 16, 2021

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- > Explainable Artificial Intelligence
- > Uncertainties in Neural Networks

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- > Data Fusion

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Curriculum

A: Theoretical introduction – Morning
I. Introduction and basics
II. Advanced concepts
III. Practical application

B. Hands-on seminar – Afternoon
Run prepared Jupyter Notebooks online on Binder, or locally on your own laptop.

Curriculum

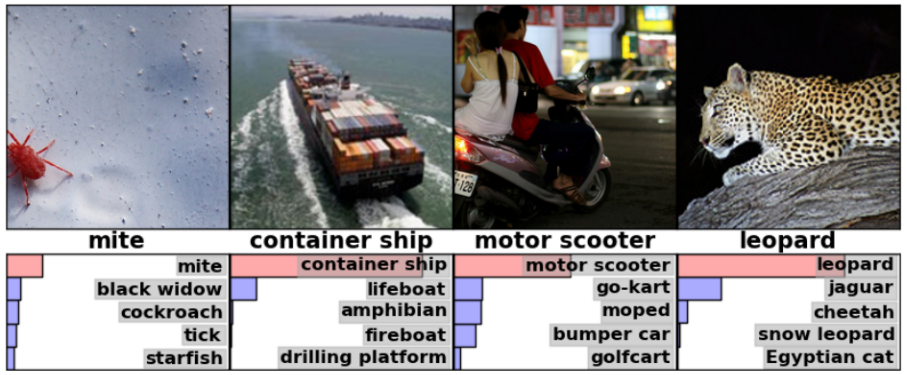
I. Introduction and basics

- Application examples
- Machine learning background
- Neural network concepts
- Training procedure

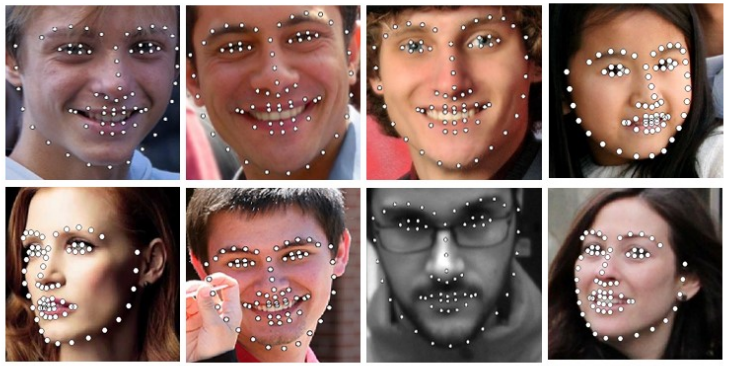
Inspired by lectures from Paris Saclay and MIT; images taken from these, if not noted otherwise

Application examples

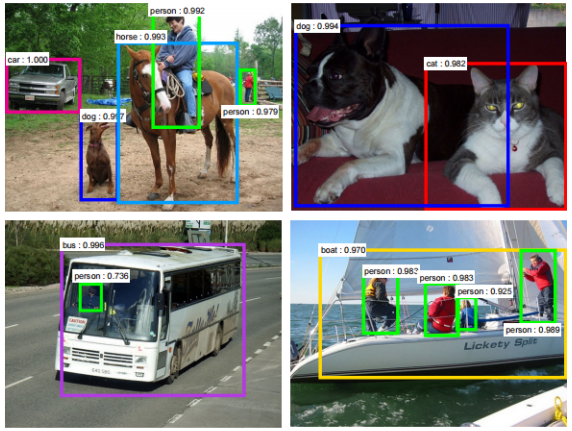
Application Examples
Vision



[Krizhevsky 2012]



[Facial landmark detection CUHK 2014]



[Faster R-CNN - Ren 2015]

[NVIDIA dev blog]

Application Examples
Natural Language Processing (NLP)

Facebook AI, 2020

Application Examples
Natural Language Processing (NLP)

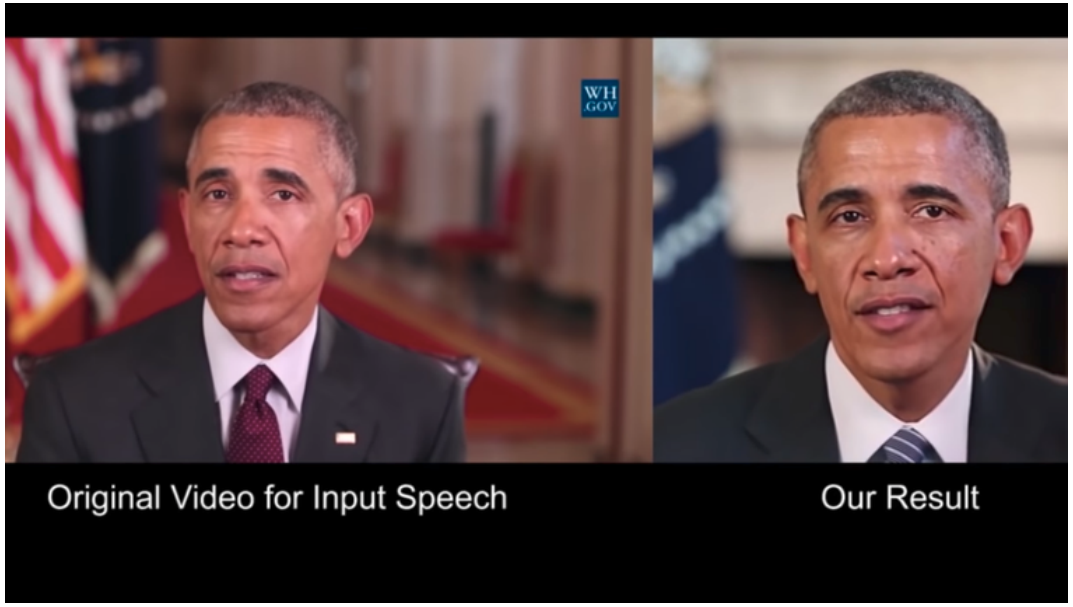
[Google Inbox Smart Reply]

[Amazon Echo / Alexa]

Application Examples
Generative models

StackGAN v2 [Zhang 2017]

Application Examples
Generative Models

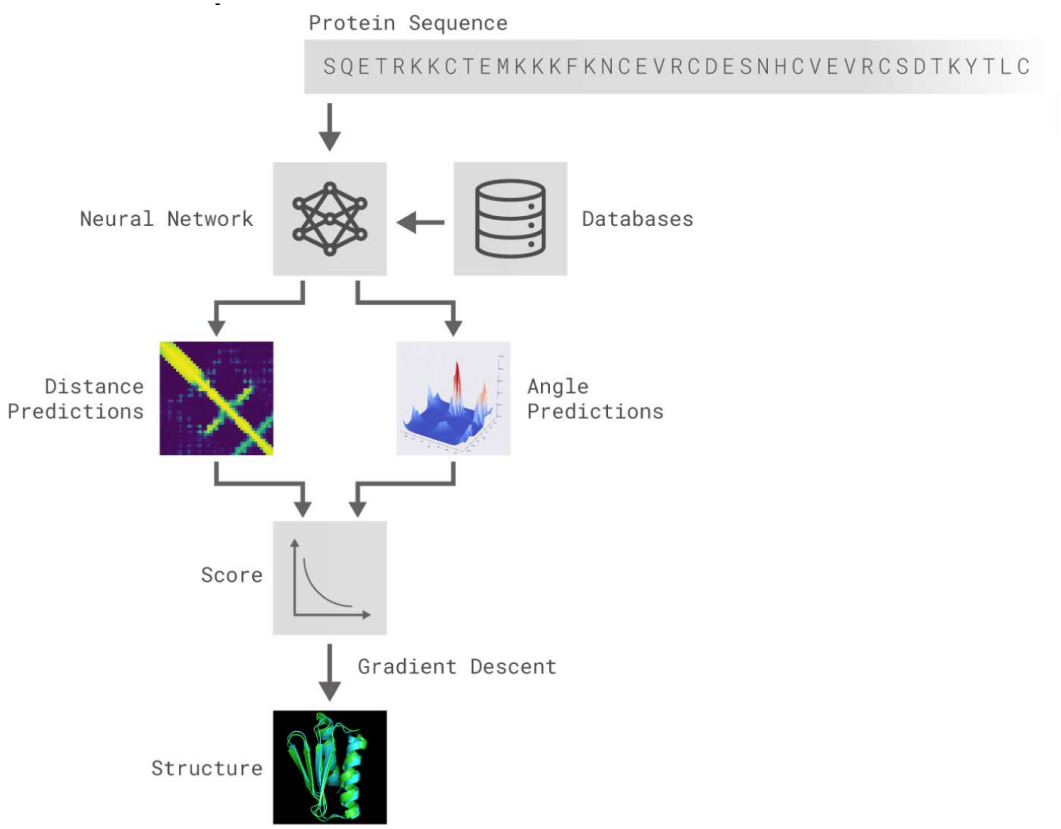


https://www.youtube.com/watch?v=g5wLaJYBAm4

Suwajanakorn, Supasorn, Steven M. Seitz, and Ira Kemelmacher-Shlizerman. "Synthesizing obama: learning lip sync from audio."

Application Examples
Other sciences

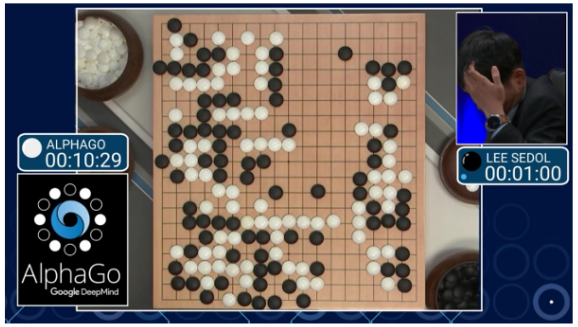
AlphaFol

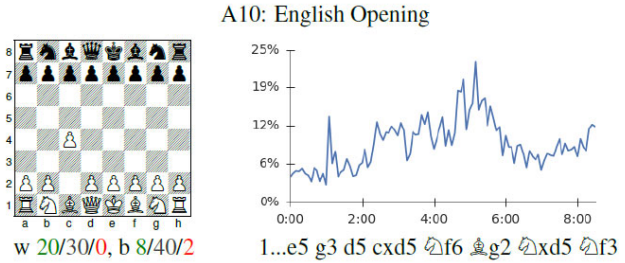


Deepmind, 2020

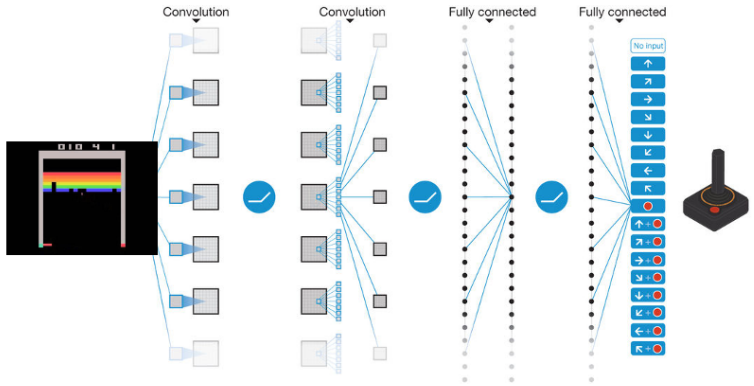
https://deepmind.com/blog/article/AlphaFold-Using-AI-for-scientific-discovery

Application Examples
Game AI

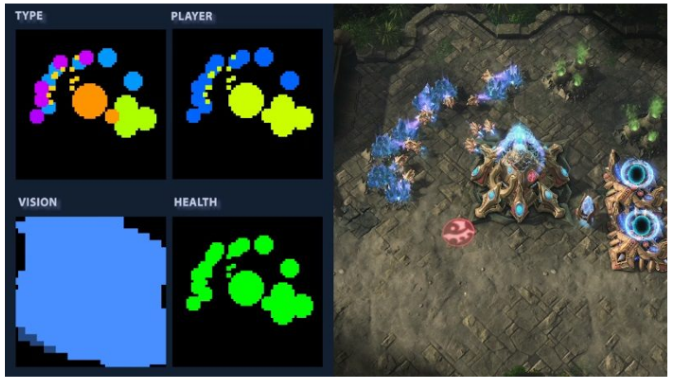




[Deepmind AlphaGo / Zero 2017]



[Atari Games - DeepMind 2016]



[Starcraft 2 for AI research]

Machine learning background

Machine learning background

Artificial Intelligence

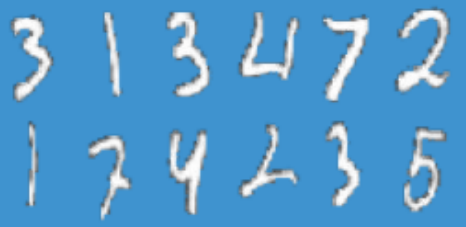
Any technique that enables computers to mimic human behavior

Machine Learning

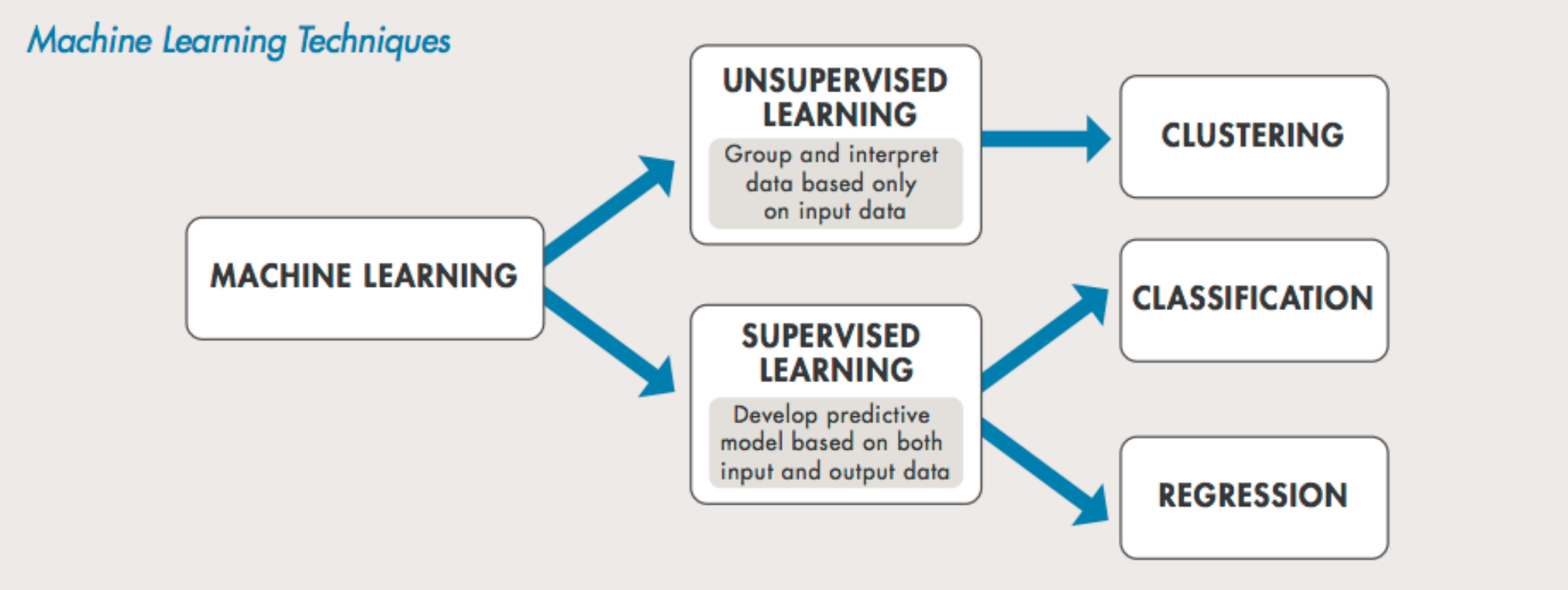
Ability to learn without explicitly being programmed

Deep Learning

Extract patterns from data using neural networks

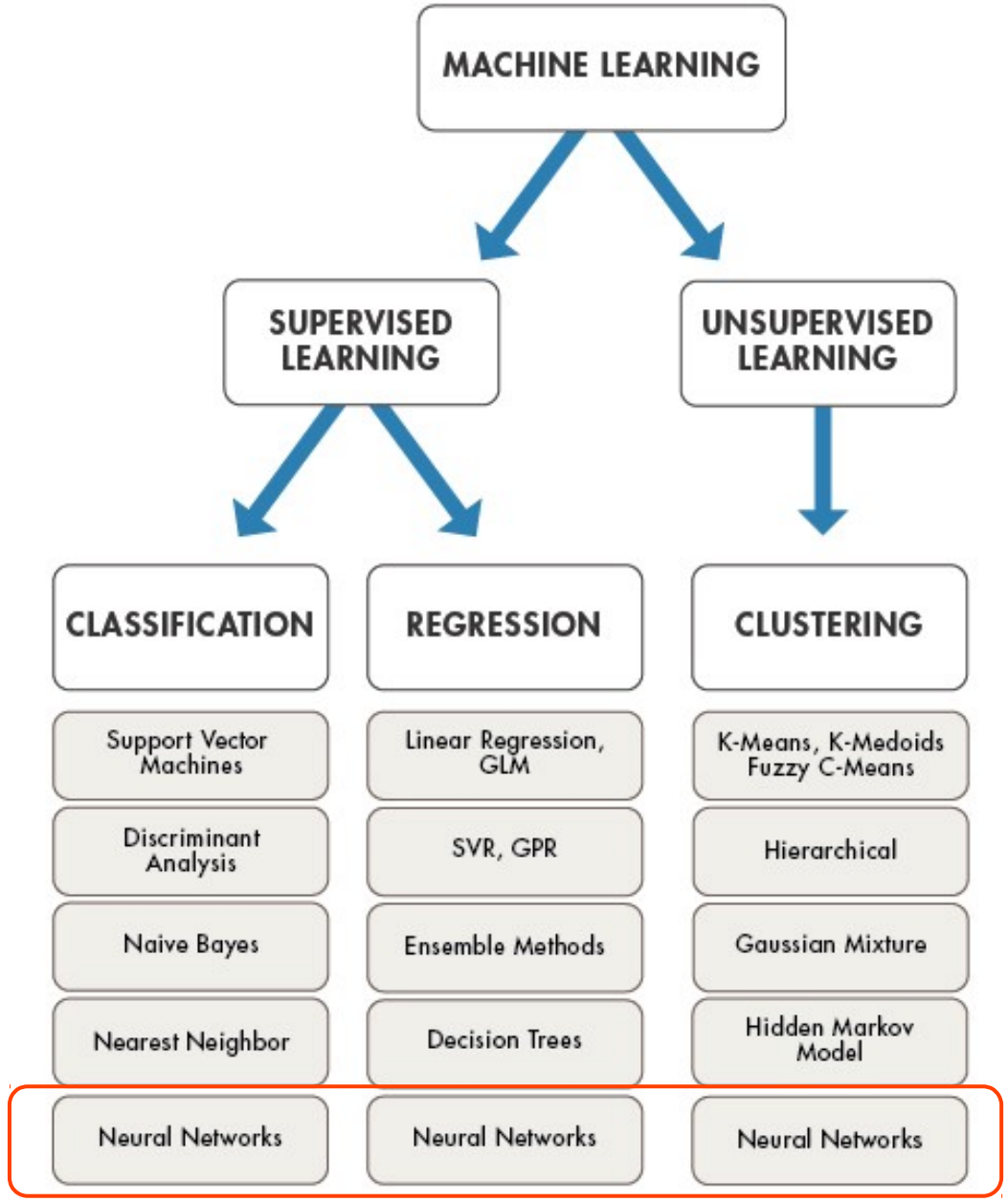


Machine learning background



https://vitalflux.com/dummies-notes-supervised-vs-unsupervised-learning/

Machine learning background



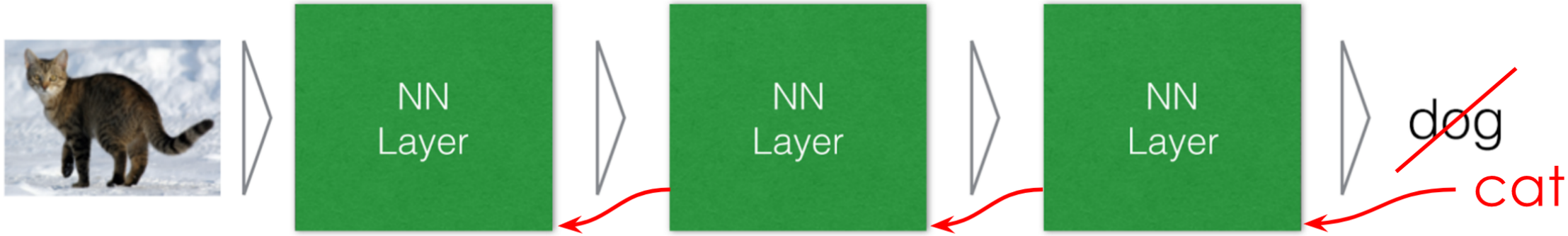
https://medium.com/technology-nineleaps/popular-machine-learning-algorithms-a574e3835ebb

Machine learning background
“Traditional“ ML system

Data independent

Supervised Learning

Machine learning background
Deep learning system



Supervised
Learning

Machine learning background
Deep learning system

Why deep learning now?

1. Big Data

- Larger Datasets
- Easier Collection & Storage

IMAGENET

WIKIPEDIA The Free Encyclopedia

2. Hardware

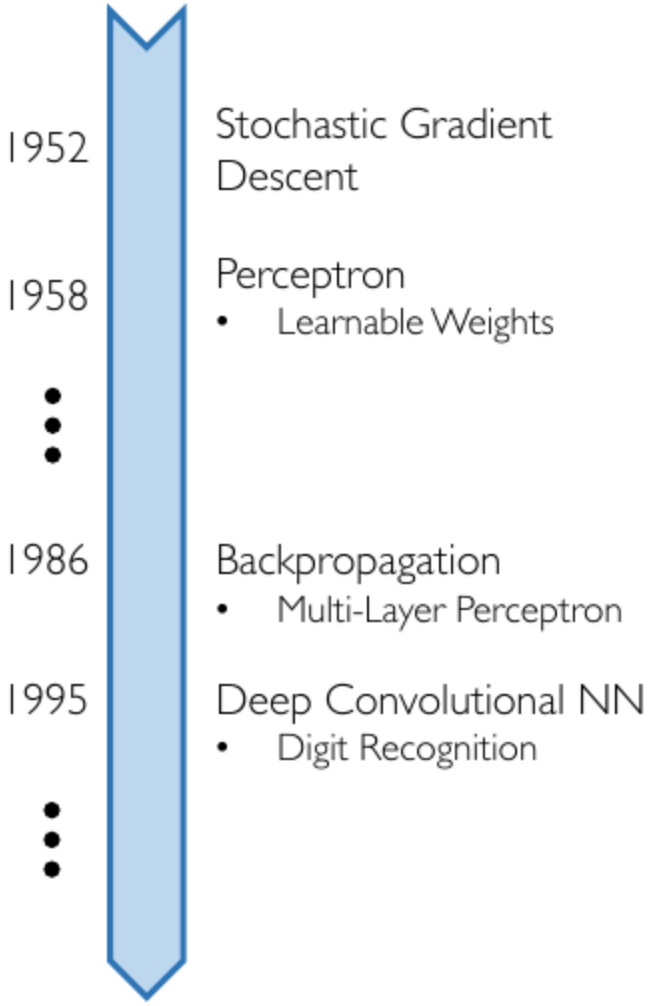
- Graphics Processing Units (GPUs)
- Massively Parallelizable

3. Software

- Improved Techniques
- New Models
- Toolboxes

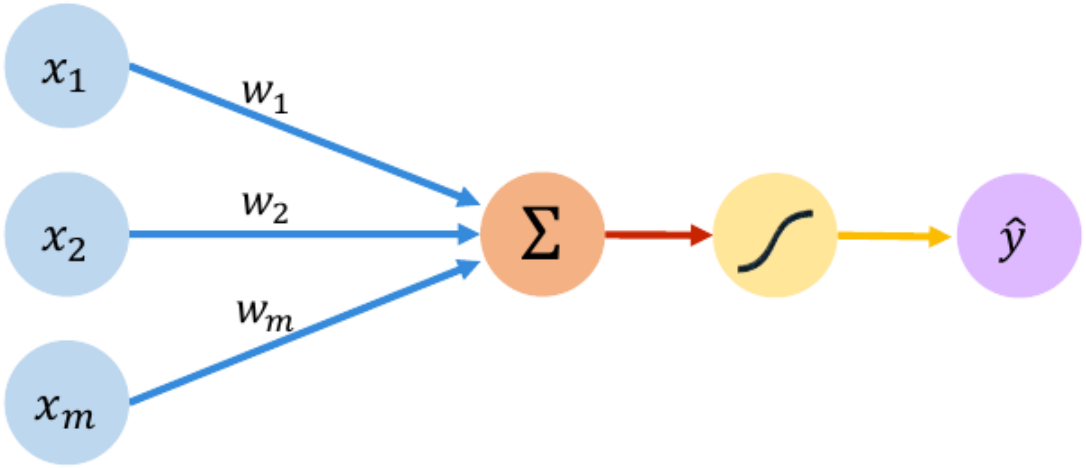
TensorFlow

PyTorch



Neural network concepts

Neural network concepts
A single neuron (perceptron)



Inputs Weights Sum Non-Linearity Output

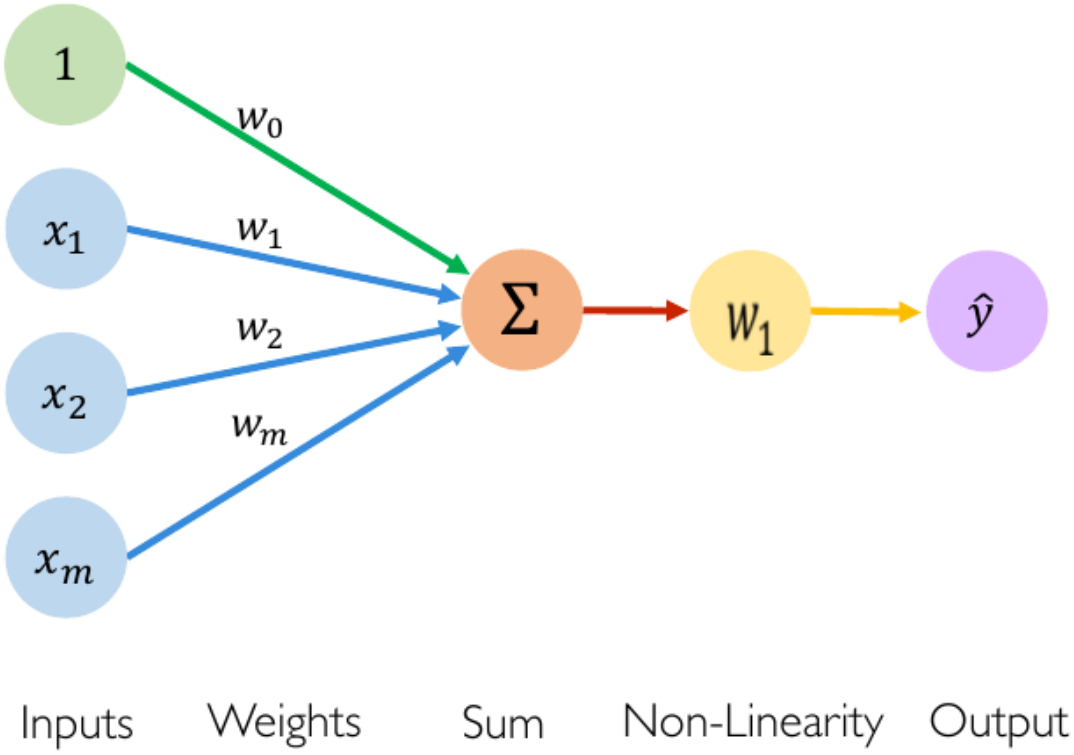
Linear combination of inputs

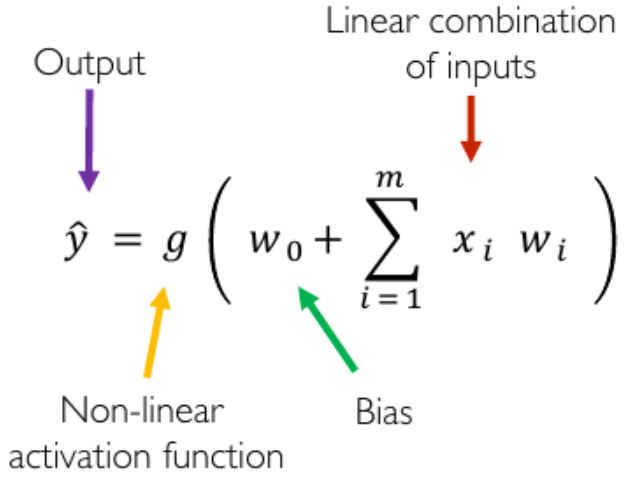
Output

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

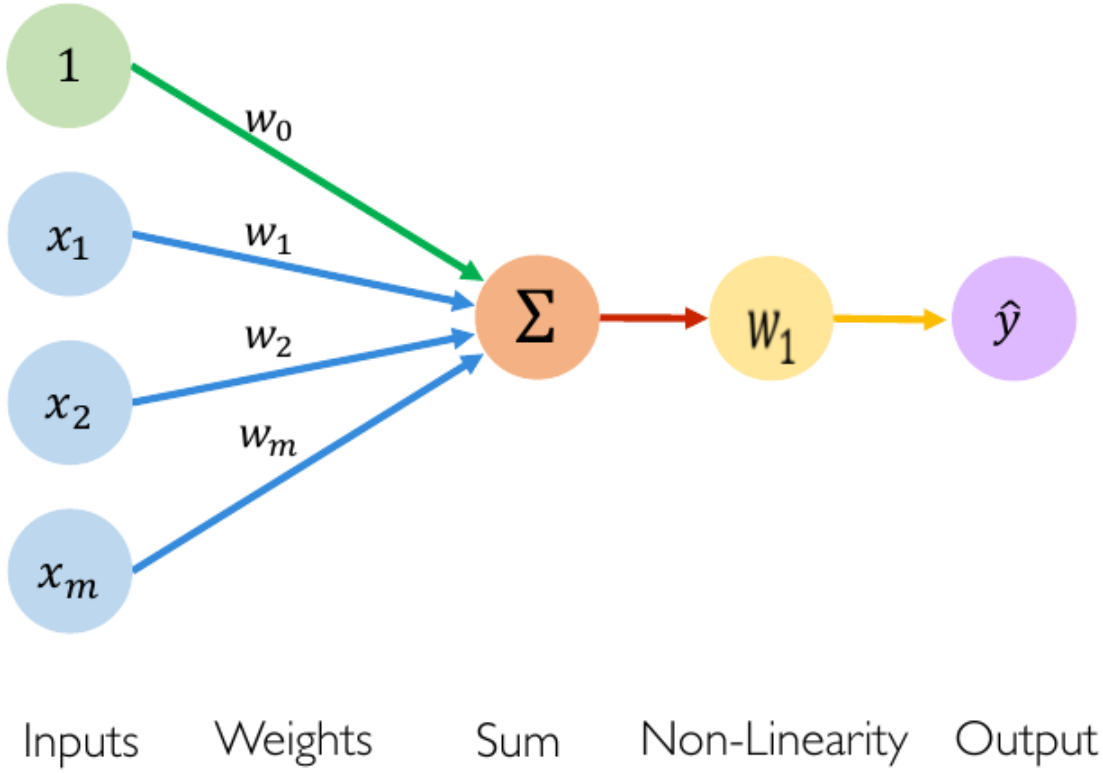
Non-linear activation function

Neural network concepts
A single neuron (perceptron)





Neural network concepts
A single neuron (perceptron)

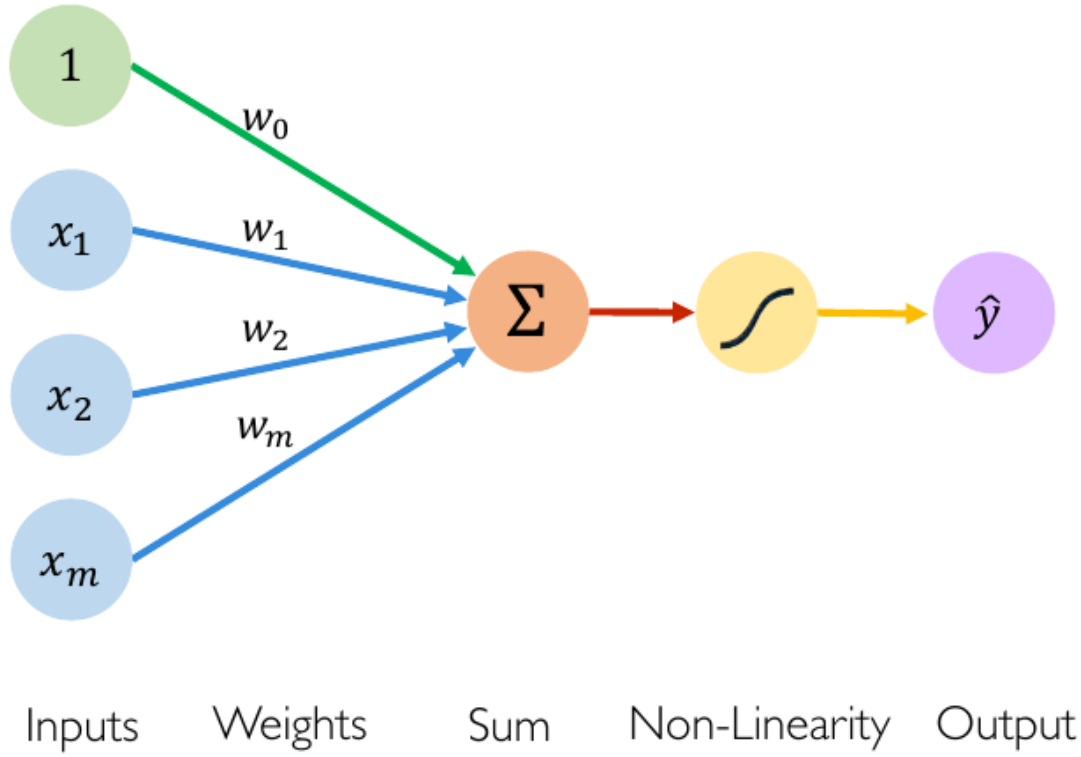


$$\hat{y} = g\left(w_0 + \sum_{i=1}^{m} x_i\, w_i\right)$$

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

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

Neural network concepts
A single neuron (perceptron)

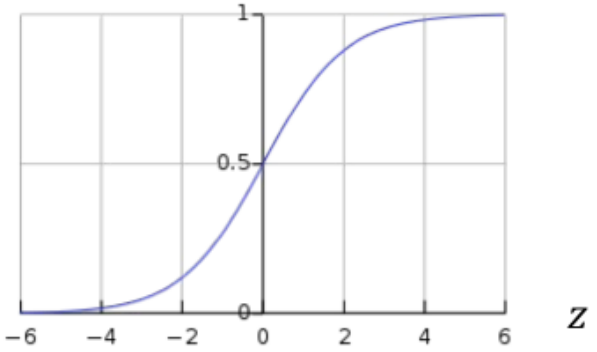


Activation Functions

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

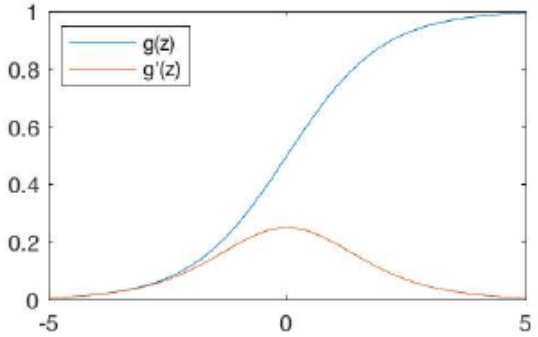
- Example: sigmoid function

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



Neural network concepts
Activation functions

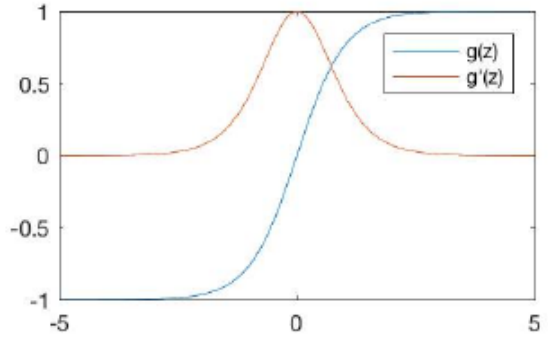
Sigmoid Function



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

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

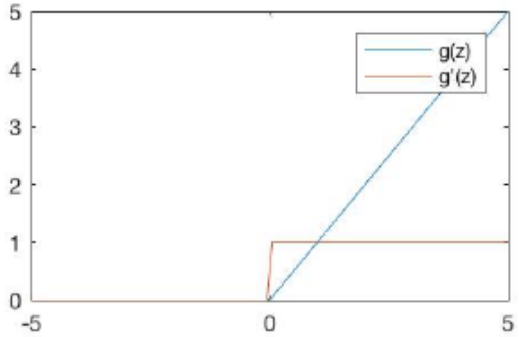
Hyperbolic Tangent



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

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

Rectified Linear Unit (ReLU)



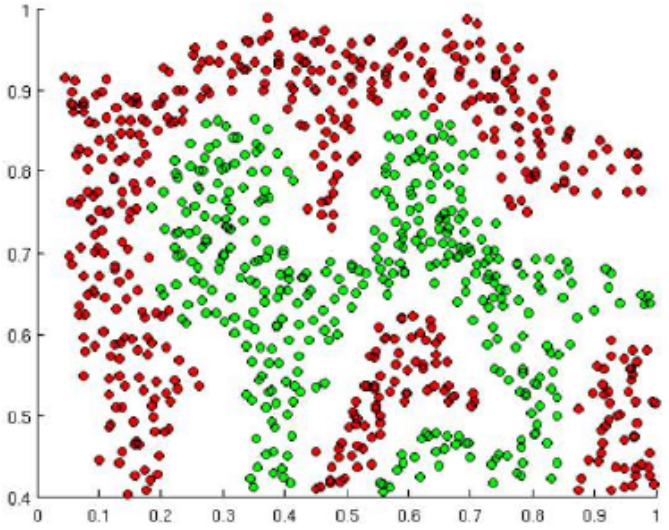
$$g(z) = \max(0, z)$$

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

NOTE: All activation functions are non-linear

Neural network concepts
Activation functions

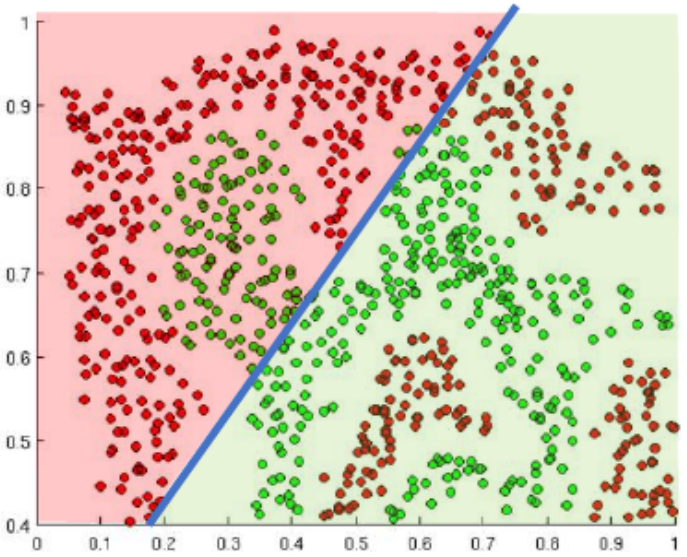
*The purpose of activation functions is to **introduce non-linearities** into the network*



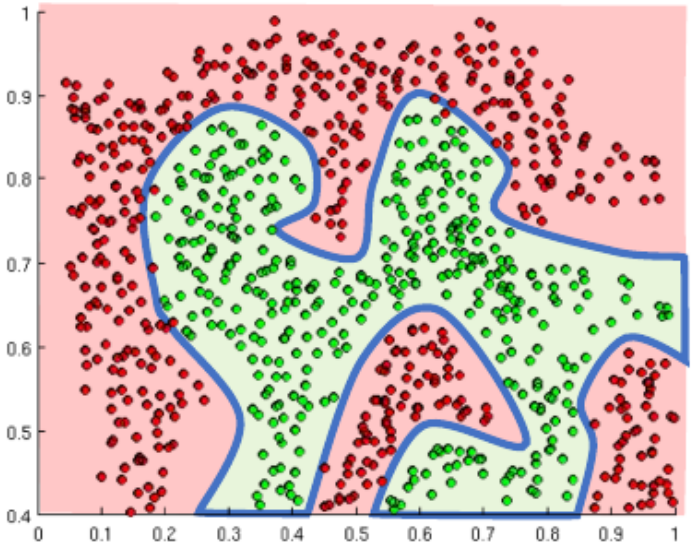
What if we wanted to build a Neural Network to distinguish green vs red points?

Neural network concepts
Activation functions

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

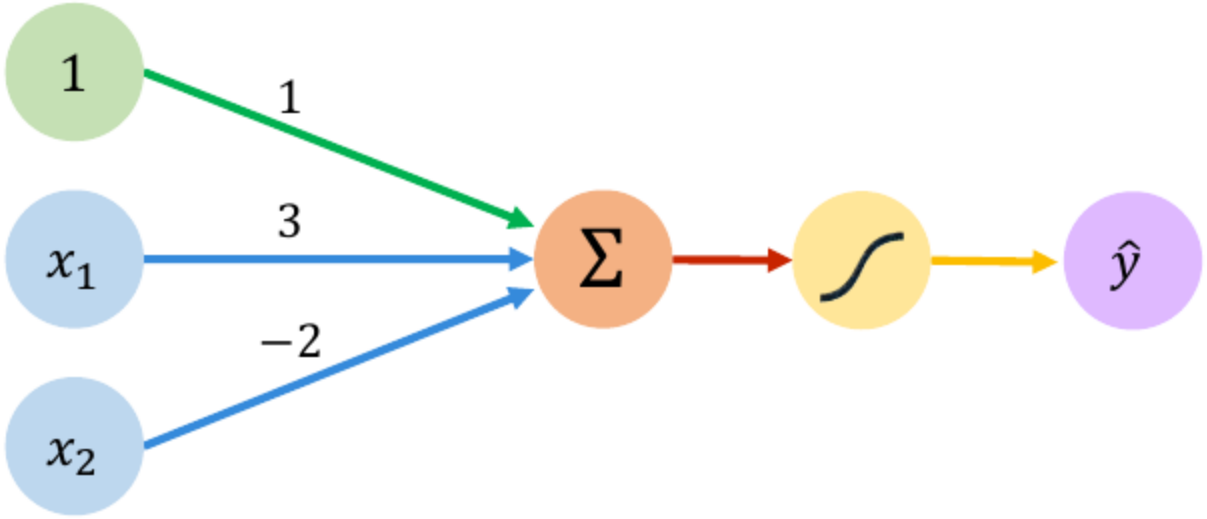


Linear Activation functions produce linear decisions no matter the network size



Non-linearities allow us to approximate arbitrarily complex functions

Neural network concepts
A single neuron (perceptron) - Example



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

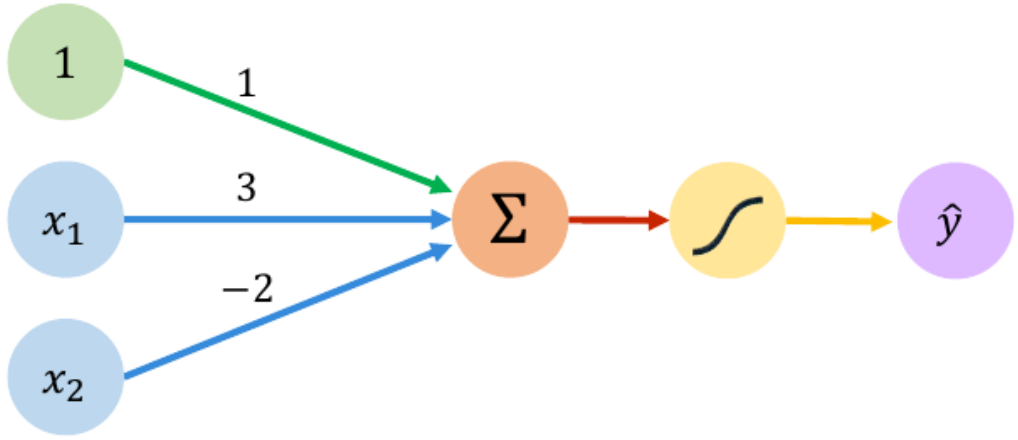
$$\hat{y} = g(w_0 + \boldsymbol{X}^T \boldsymbol{W})$$

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

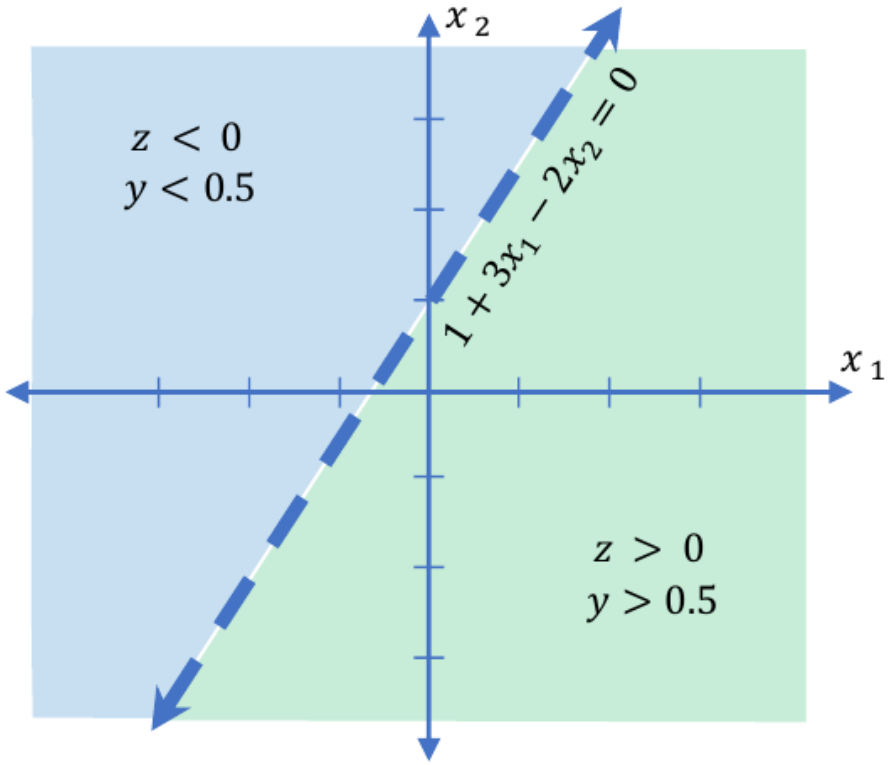
$$\hat{y} = g(\underbrace{1 + 3x_1 - 2x_2}_{\text{This is just a line in 2D!}})$$

Neural network concepts

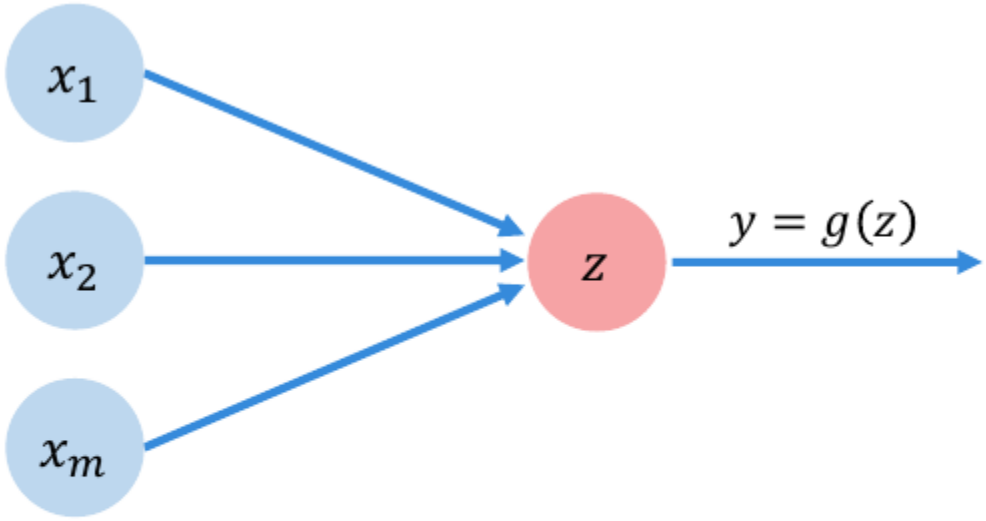
A single neuron (perceptron) - Example



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

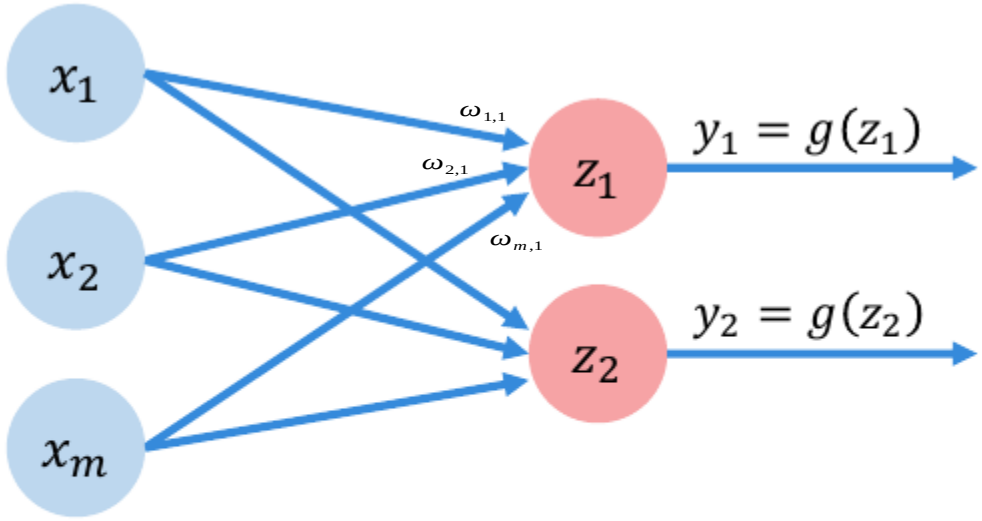


Neural network concepts
Simplified neuron



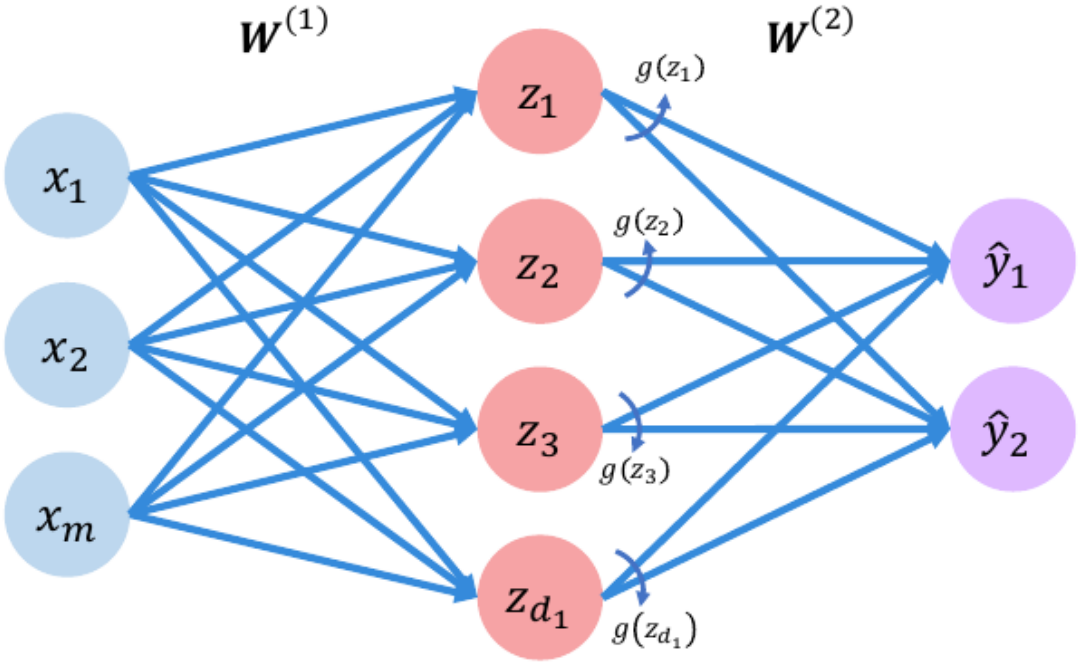
$$z = w_0 + \sum_{j=1}^{m} x_j w_j$$

Neural network concepts
Multi-output neuron



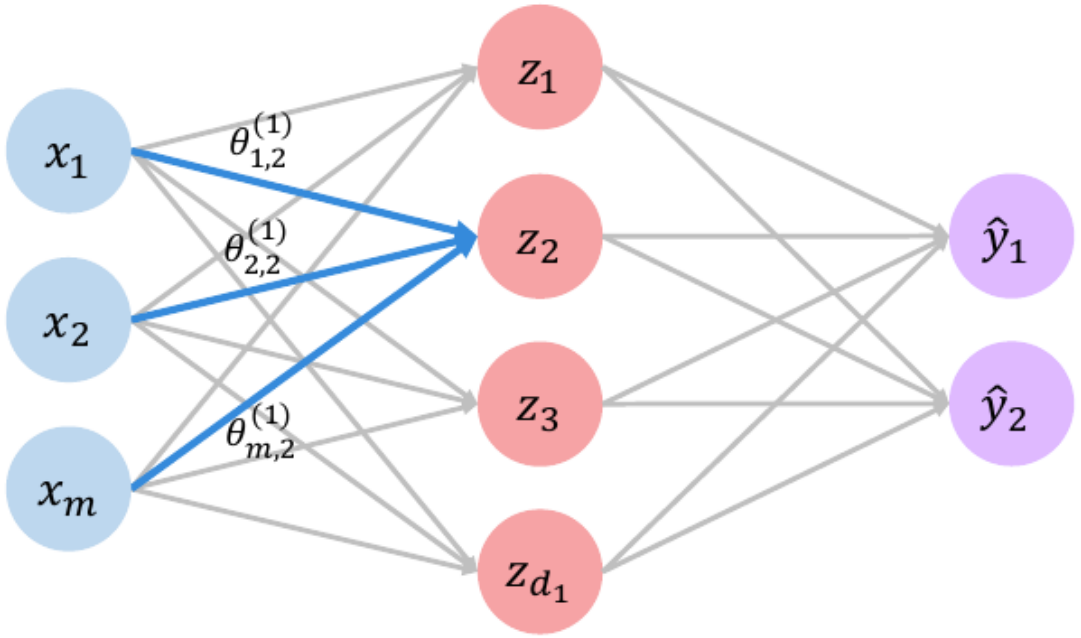
$$z_i = w_{0,i} + \sum_{j=1}^{m} x_j \, w_{j,i}$$

Neural network concepts
A single-layer neural network



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

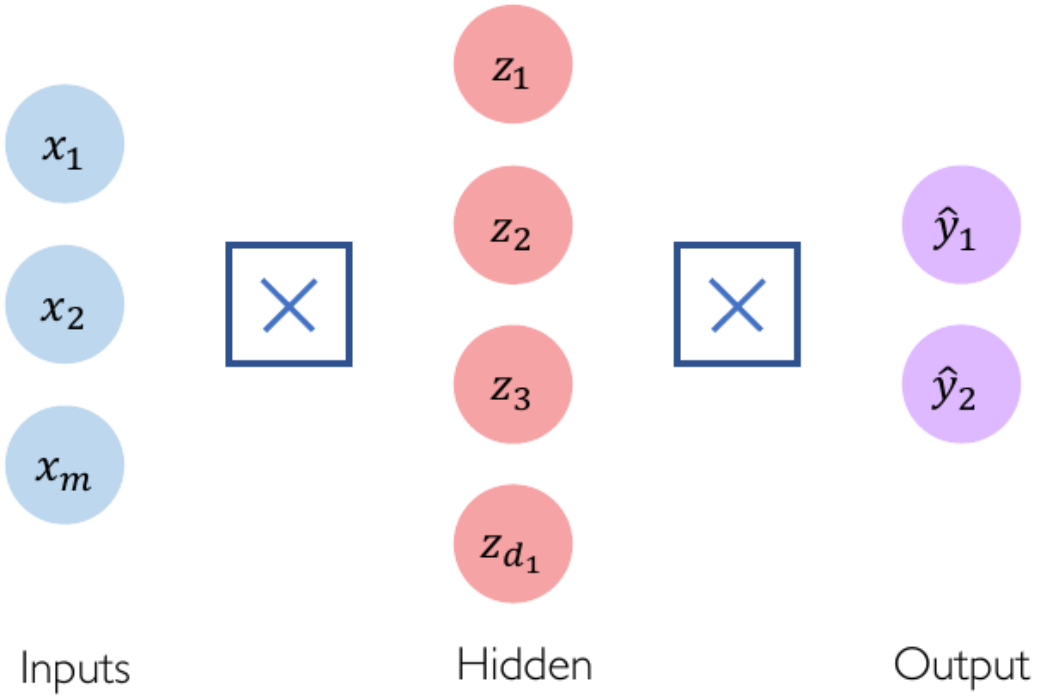
Neural network concepts
A single-layer neural network



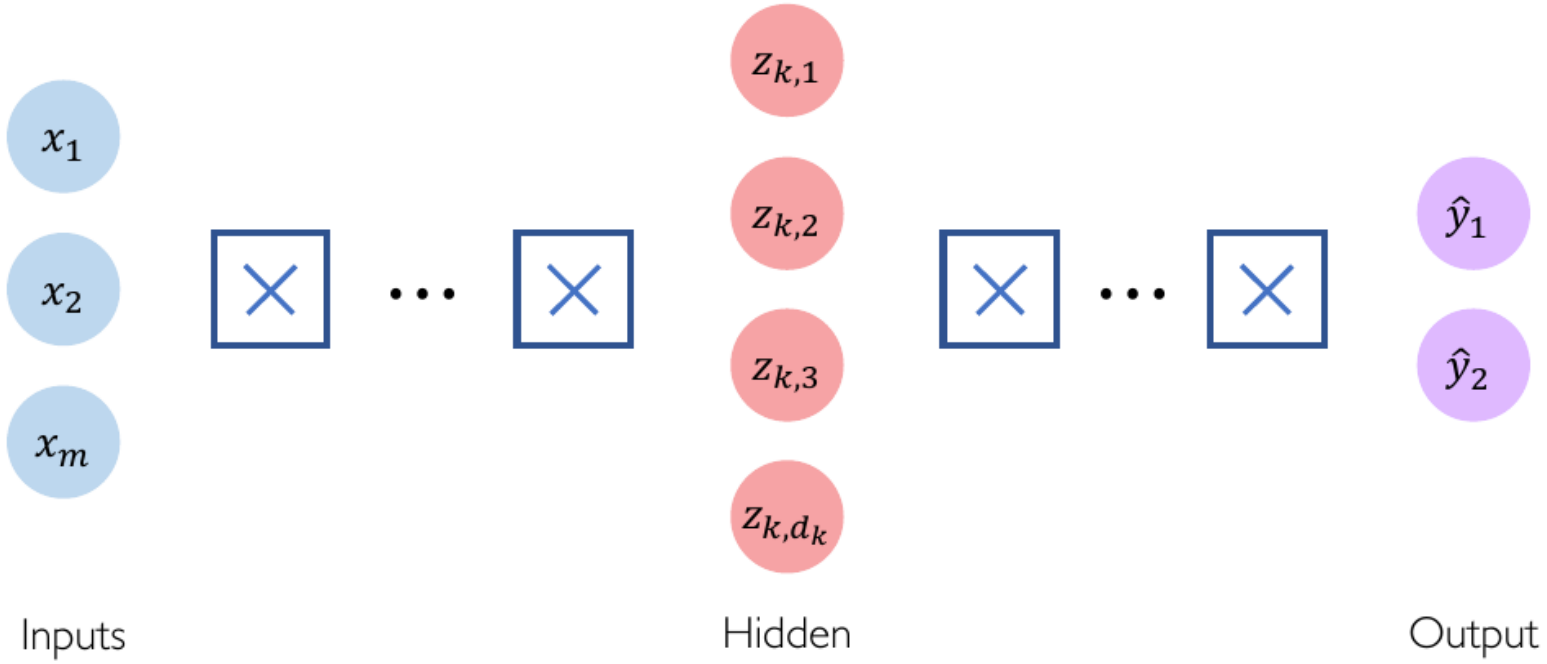
$$z_2 = w_{0,2}^{(1)} + \sum_{j=1}^{m} x_j \, w_{j,2}^{(1)}$$

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

Neural network concepts
A single-layer neural network



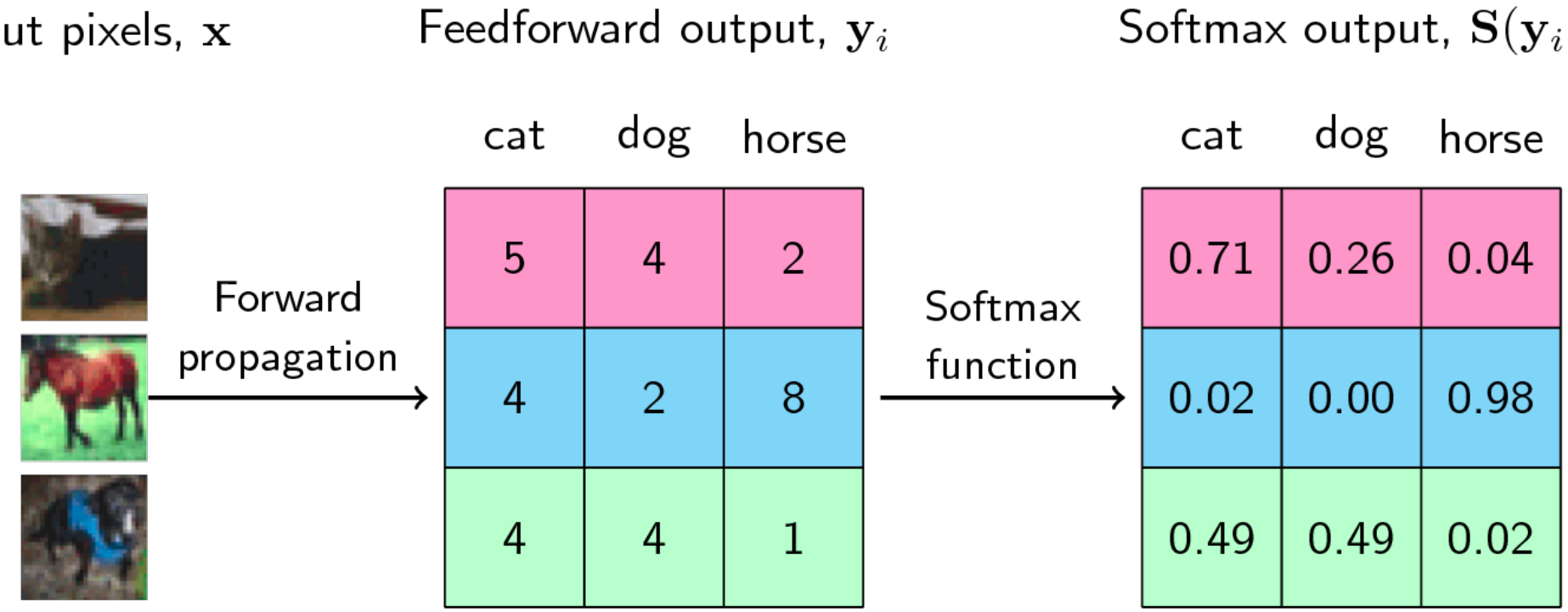
Neural network concepts
Deep neural network



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

Neural network concepts
Softmax activation

$$S(f_{y_i}) = \frac{e^{f_{y_i}}}{\sum_j e^{f_j}}$$

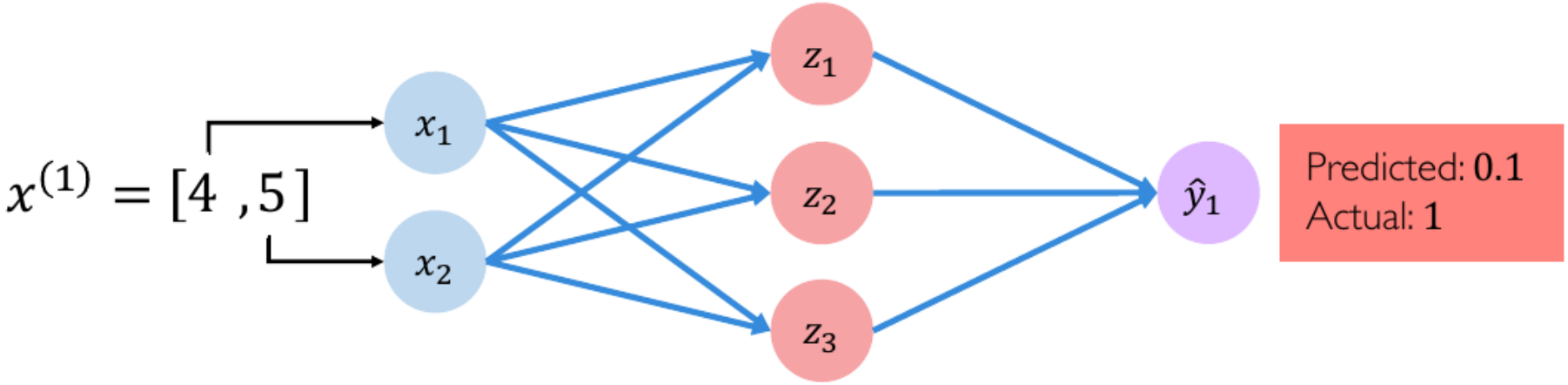


https://ljvmiranda921.github.io/notebook/2017/08/13/softmax-and-the-negative-log-likelihood/

Training procedure

Training procedure
Loss function

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



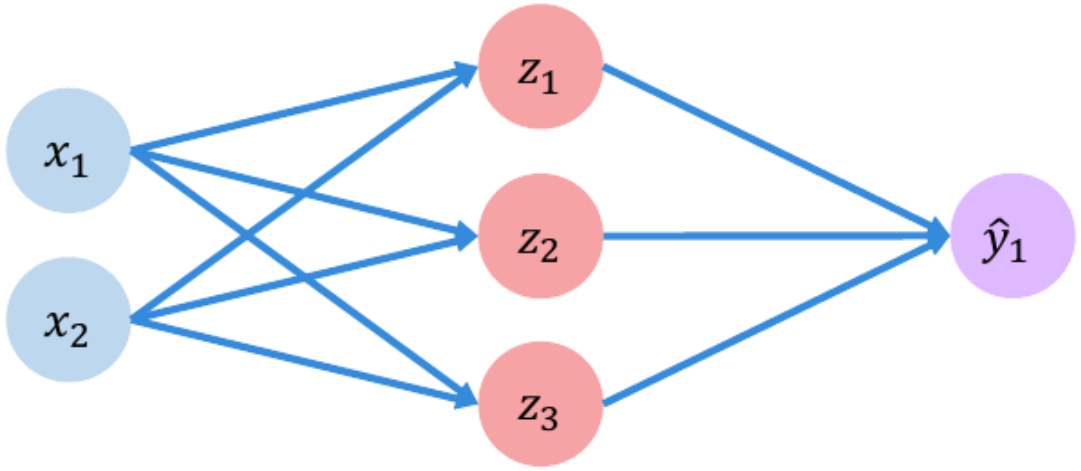
$$\mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

Predicted Actual

Training procedure
Loss function

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

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



$$f(x) = \begin{bmatrix} 0.1 \\ 0.8 \\ 0.6 \\ \vdots \end{bmatrix} \qquad y = \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix}$$

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

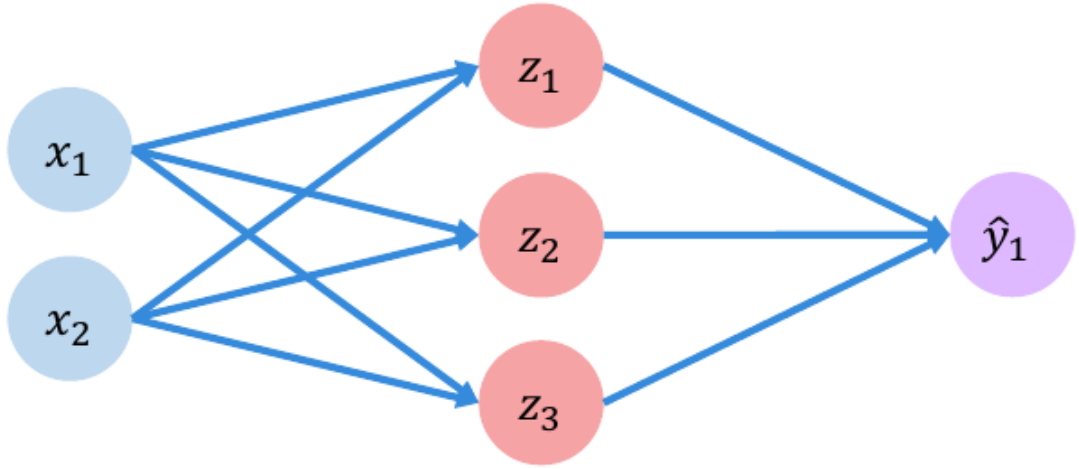
$$\boldsymbol{J}(\boldsymbol{W}) = \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

Predicted Actual

Training procedure
Binary cross-entropy loss

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

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



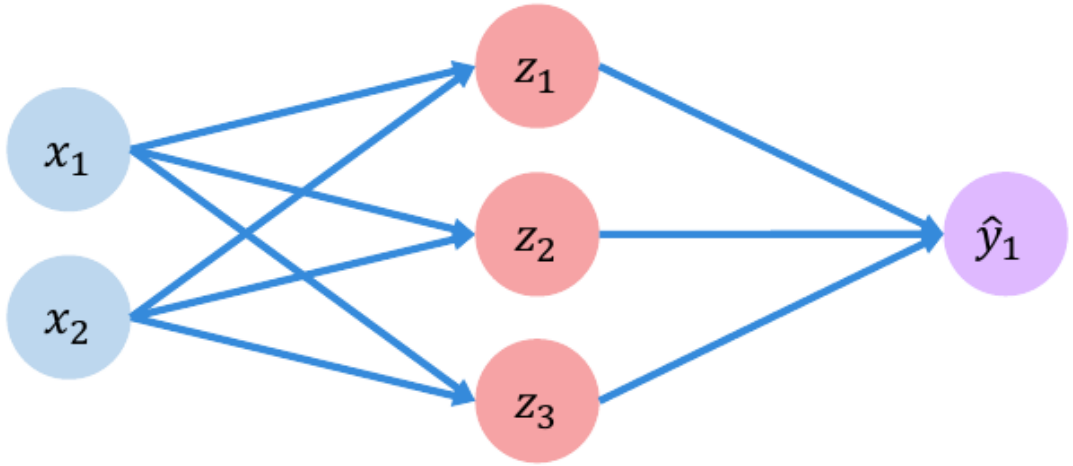
$$f(x) = \begin{bmatrix} 0.1 \\ 0.8 \\ 0.6 \\ \vdots \end{bmatrix} \qquad y = \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix}$$

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

Training procedure
Mean squared error loss

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

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



$$f(x) \qquad y$$

$$\begin{bmatrix} 30 \\ 80 \\ 85 \\ \vdots \end{bmatrix} \qquad \begin{bmatrix} 90 \\ 20 \\ 95 \\ \vdots \end{bmatrix}$$

Final Grades (percentage)

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

Actual Predicted

Training procedure
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:

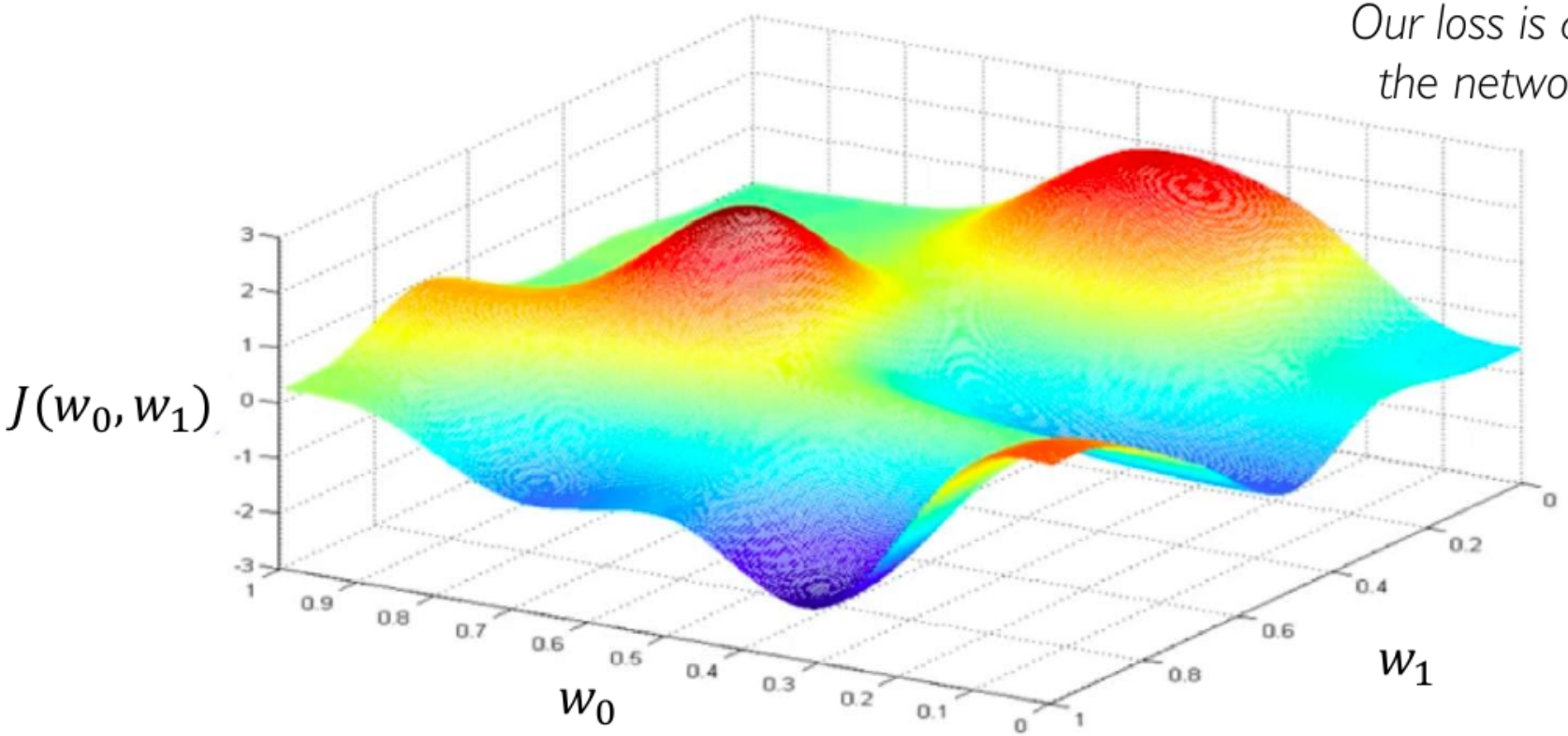
$$\boldsymbol{W} = \{\boldsymbol{W}^{(0)}, \boldsymbol{W}^{(1)}, \dots\}$$

Training procedure
Loss optimization

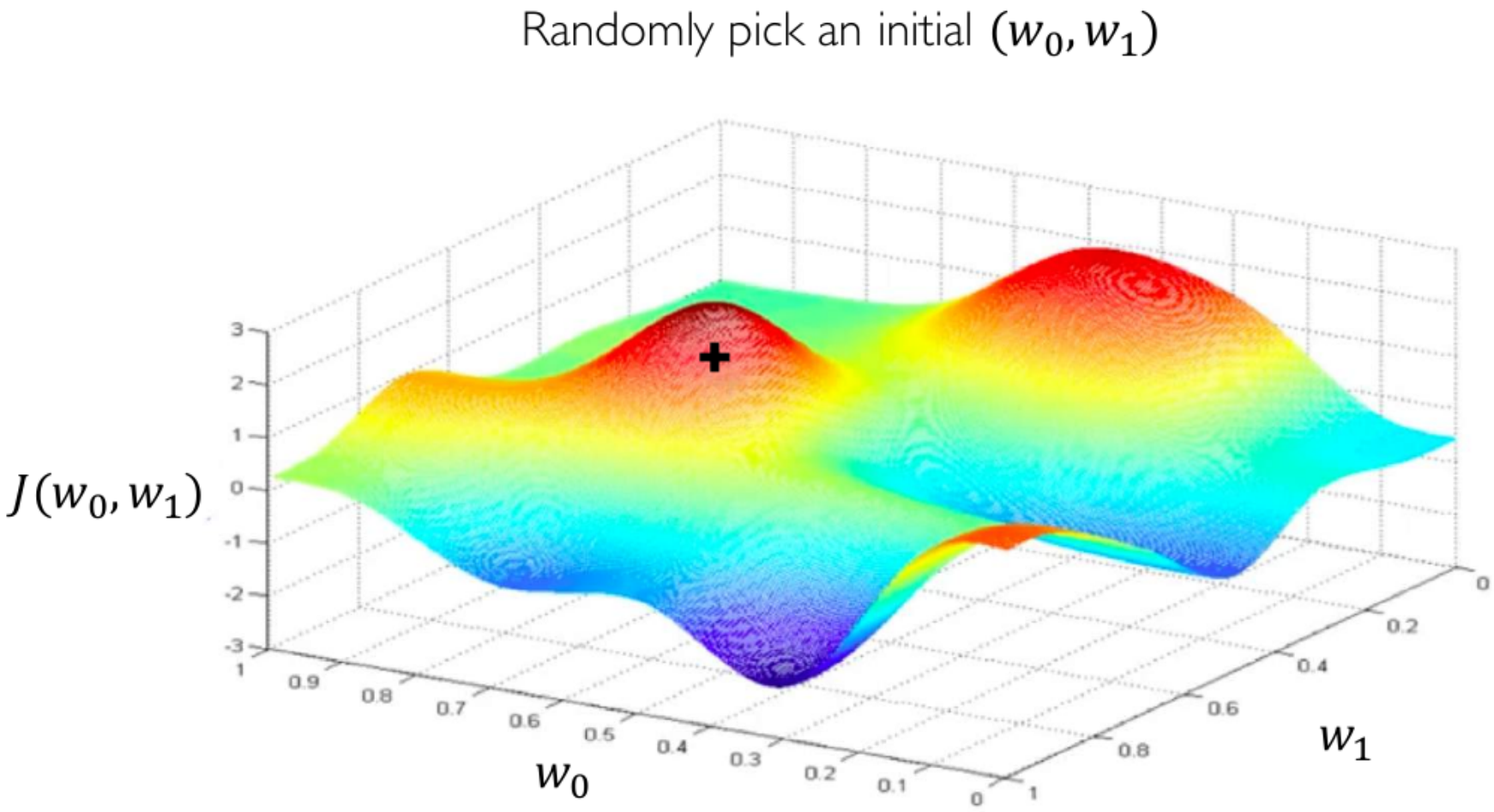
$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{\operatorname{argmin}}\, J(\boldsymbol{W})$$

Remember:

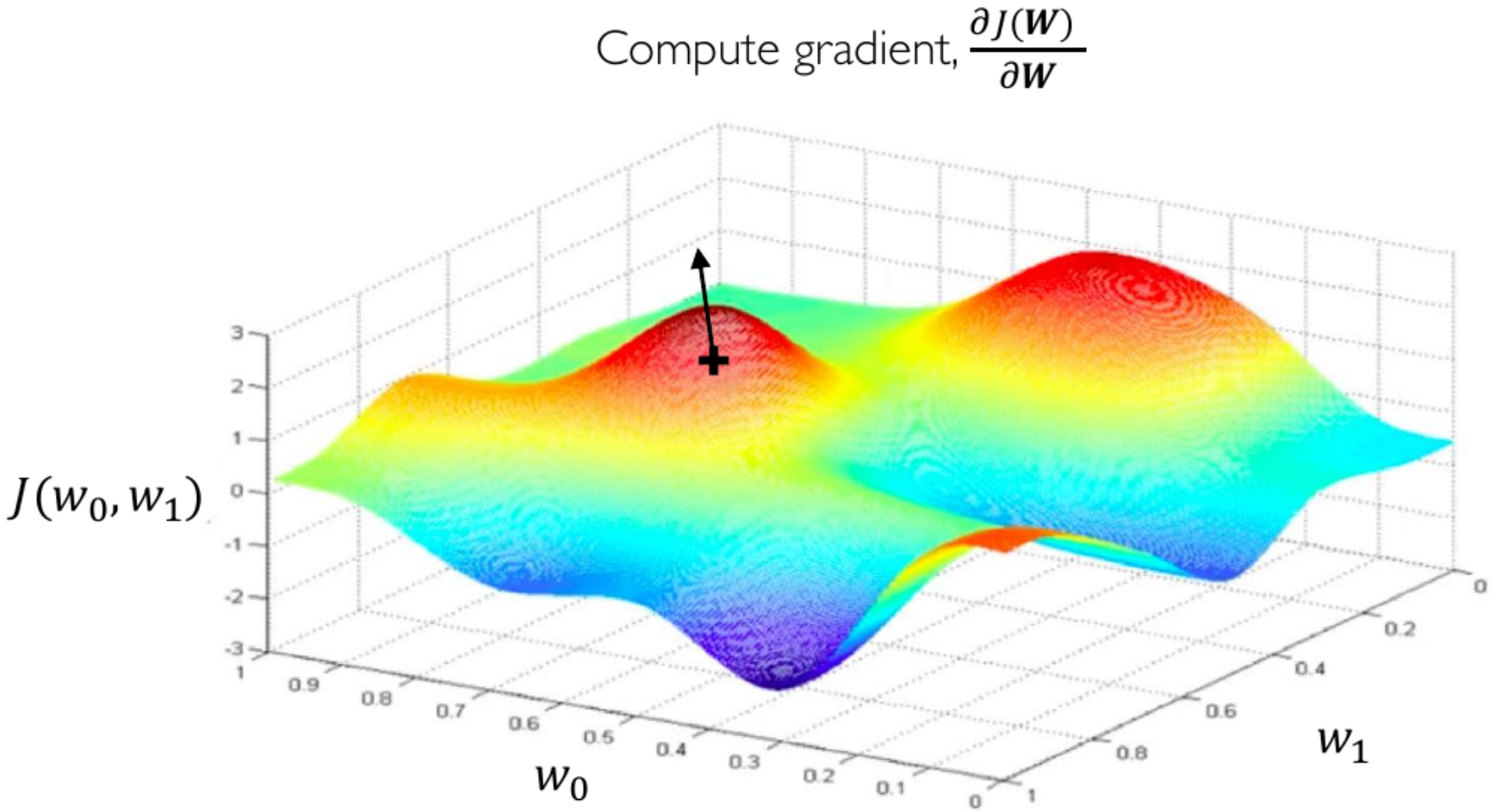
Our loss is a function of the network weights!



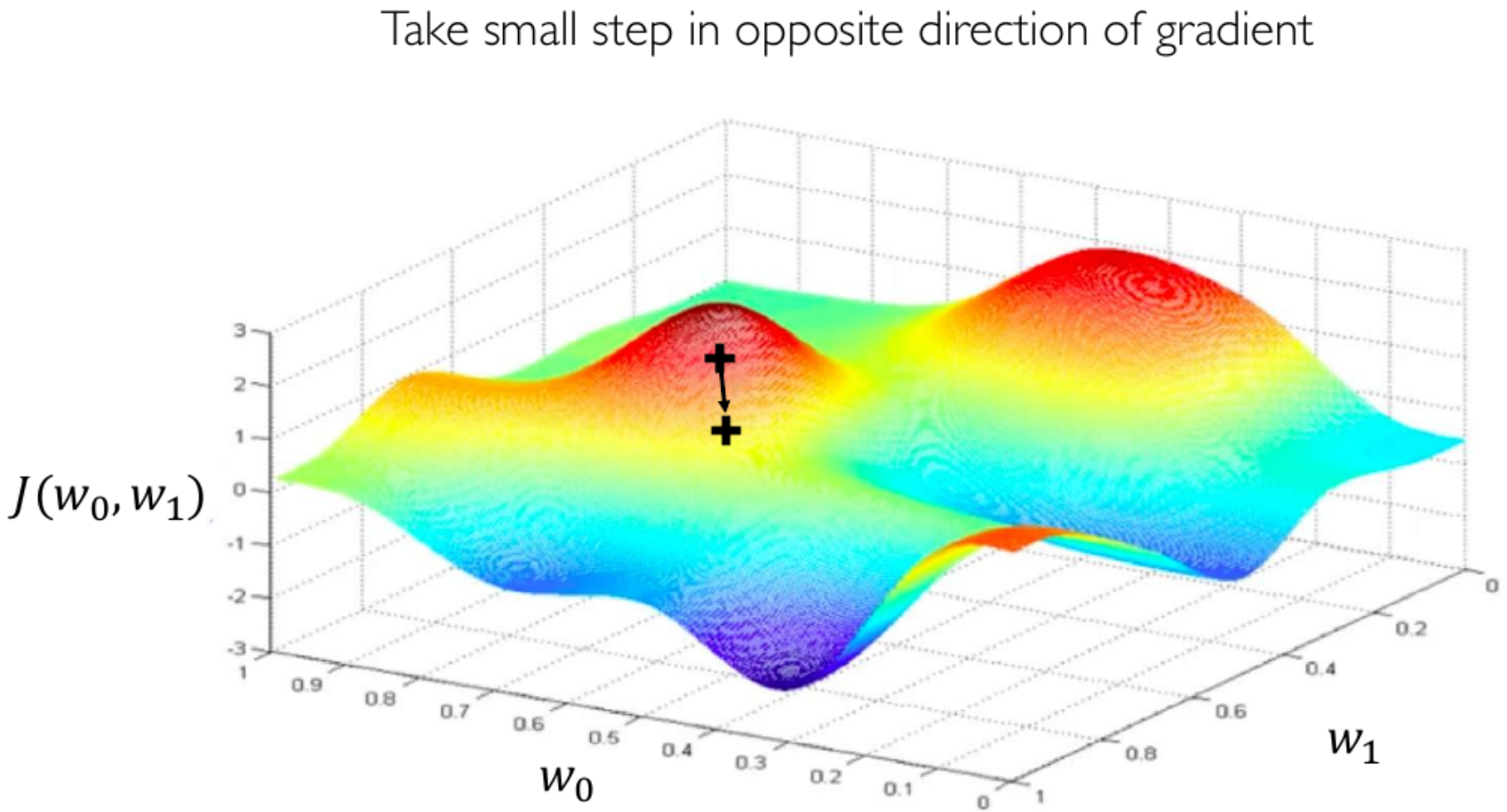
Training procedure
Gradient descent



Training procedure
Gradient descent

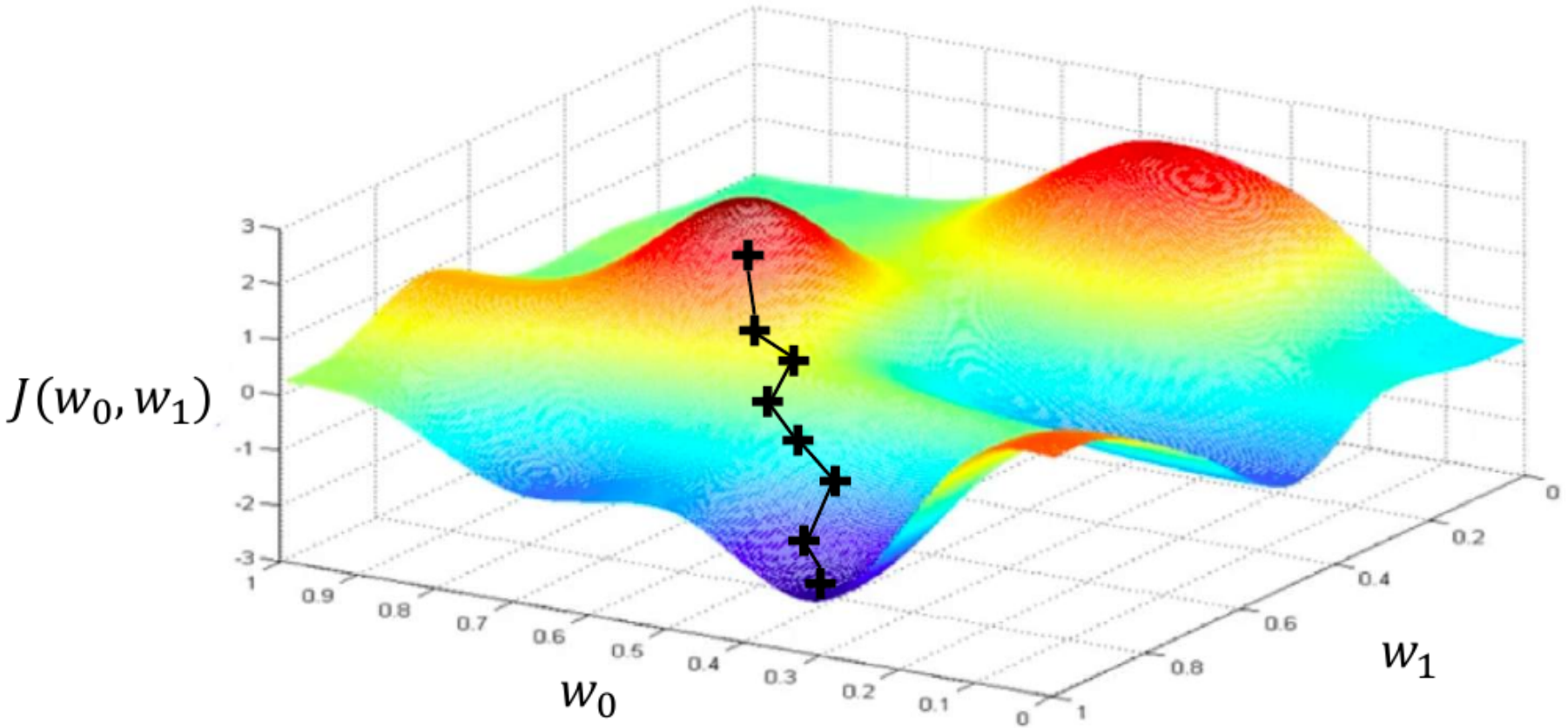


Training procedure
Gradient descent



Training procedure
Gradient descent

Repeat until convergence

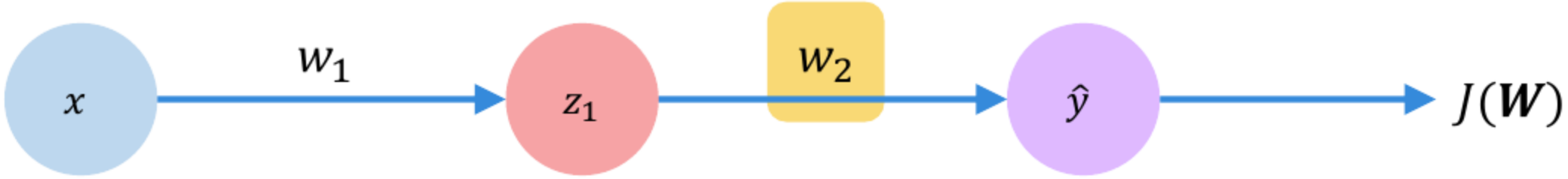


Training procedure
Gradient descent

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

Training procedure
Backpropagation



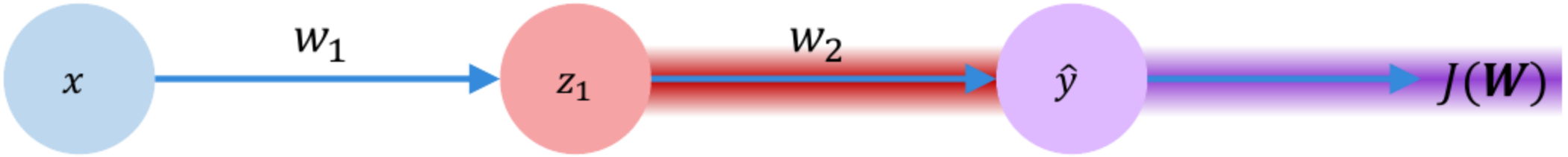
How does a small change in one weight (ex. $\boldsymbol{w_2}$) affect the final loss $\boldsymbol{J(W)}$?

Training procedure
Backpropagation

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

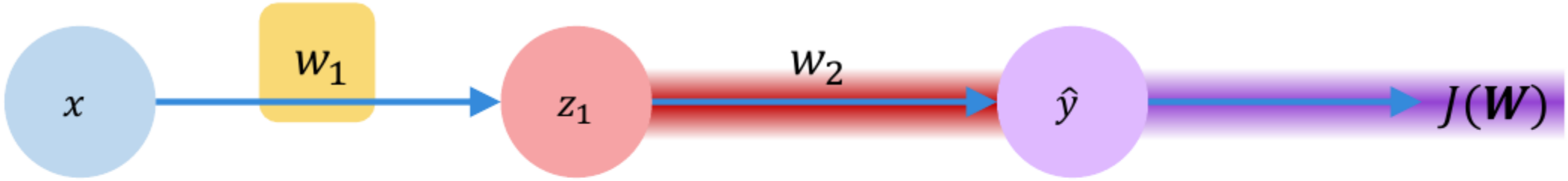
Let's use the chain rule!

Training procedure
Backpropagation



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

Training procedure
Backpropagation

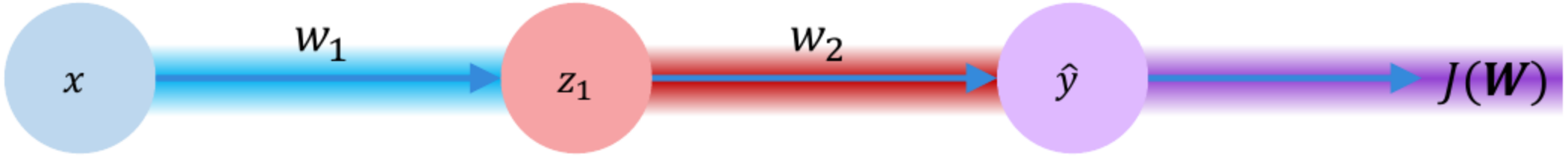


$$\frac{\partial J(\boldsymbol{W})}{\partial w_1} = \frac{\partial J(\boldsymbol{W})}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial w_1}$$

Apply chain rule!

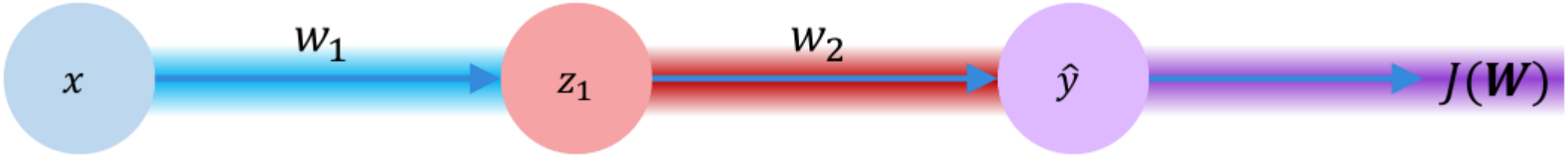
Apply chain rule!

Training procedure
Backpropagation



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

Training procedure
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*

Curriculum

Next: II. Advanced concepts

- Regularization
- Convolutional Neural Networks