CS 1674: Neural Networks

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Outline

- Motivation Neural Networks
- Perceptron
- Activation Functions
- Training a Neural Network
  - Weight Initialization
  - Forward Propagation
  - Loss Function
  - Regularization
  - Gradient Descent
  - Backpropagation


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What AI courses did you take before this semester?
0
cs1571: Intro to AI
0
cs1675: Intro to Machine Learning
0
cs1678: Intro to Deep Learning
0
cs2731: Intro to Natural Language Processing
0
cs1503: Math Foundations of Machine Learning
0
cs 1671: Human Language Technologies
1
Submissions closed
0
0/100

Many inventions were inspired by Nature ...

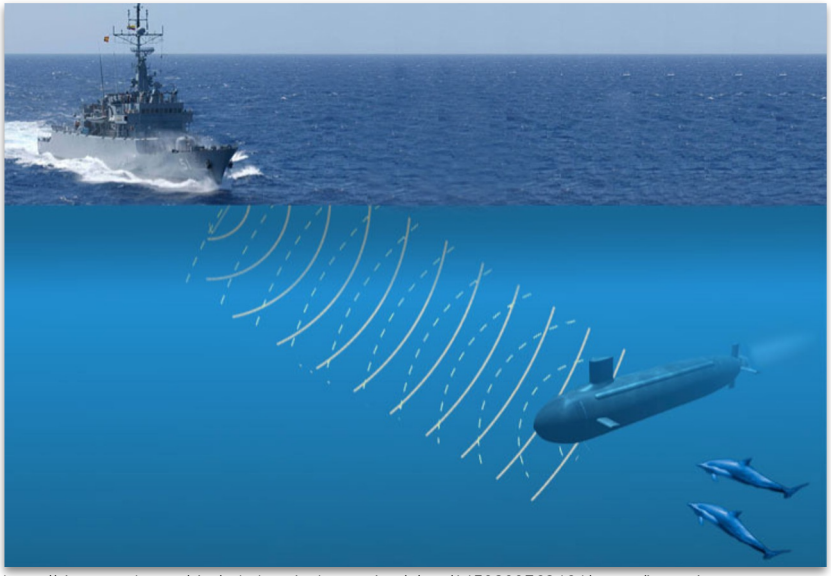
Birds inspired us to fly

https://i.pinimg.com/736x/18/4a/cc/184accf6b4d7980d2c2e8090ff295cd7--animal-tracks-friends.jpg

Slide Credit: Prof. Sandra Avila - UNICAMP

Many inventions were inspired by Nature ...

Dolphins inspired sonar development



https://sites.google.com/site/echolocationkawproject/_/rsrc/1459209762464/sonars/image.jpeg

http://www.dolphinkind.com/images/dolphin_echolocation.jpg

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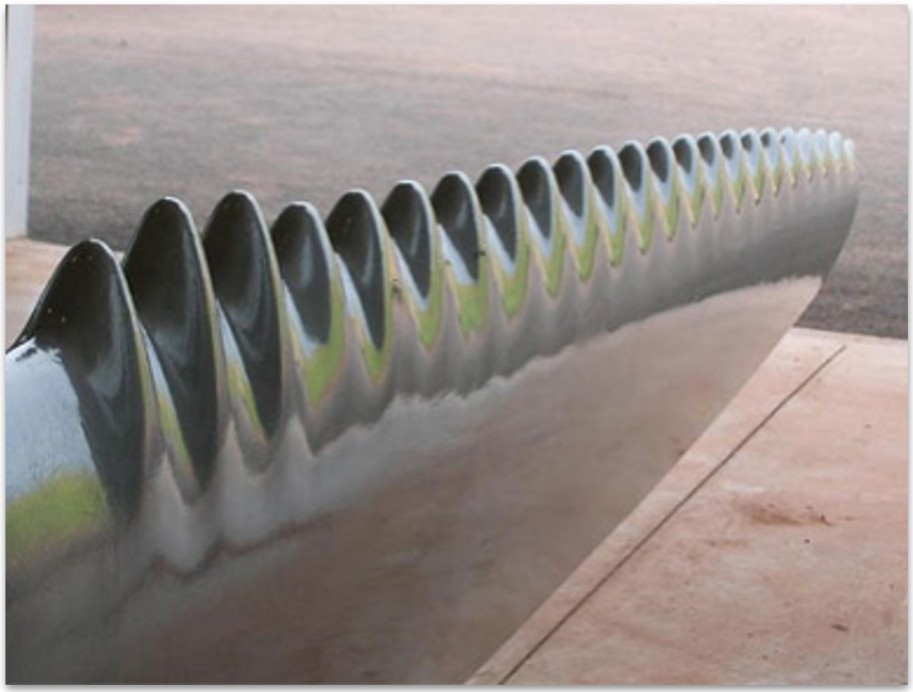
Many inventions were inspired by Nature ...

Humpback whales inspired wind turbines



https://images.app.goo.gl/7muFj7RTQLLRDYdh9

Slide Credit: Prof. Sandra Avila - UNICAMP

It seems logical to look at the brain's architecture for inspiration on how to build an intelligent machine.

Slide Credit: Prof. Sandra Avila - UNICAMP

ILSVRC 2012 — Image Classification task

Rank	Name	Error Rate (%)	Description
1	University of Toronto		Deep Learning
2	University of Tokyo	26.2	Hand-crafted features and learning models
3	University of Oxford	26.9	
4	Xerox/INRIA	27.0	

Object recognition over 1,000,000 images and 1,000 categories (2 GPU)

"ImageNet classification with deep convolutional neural networks". NIPS, 2012.

Slide Credit: Prof. Sandra Avila - UNICAMP

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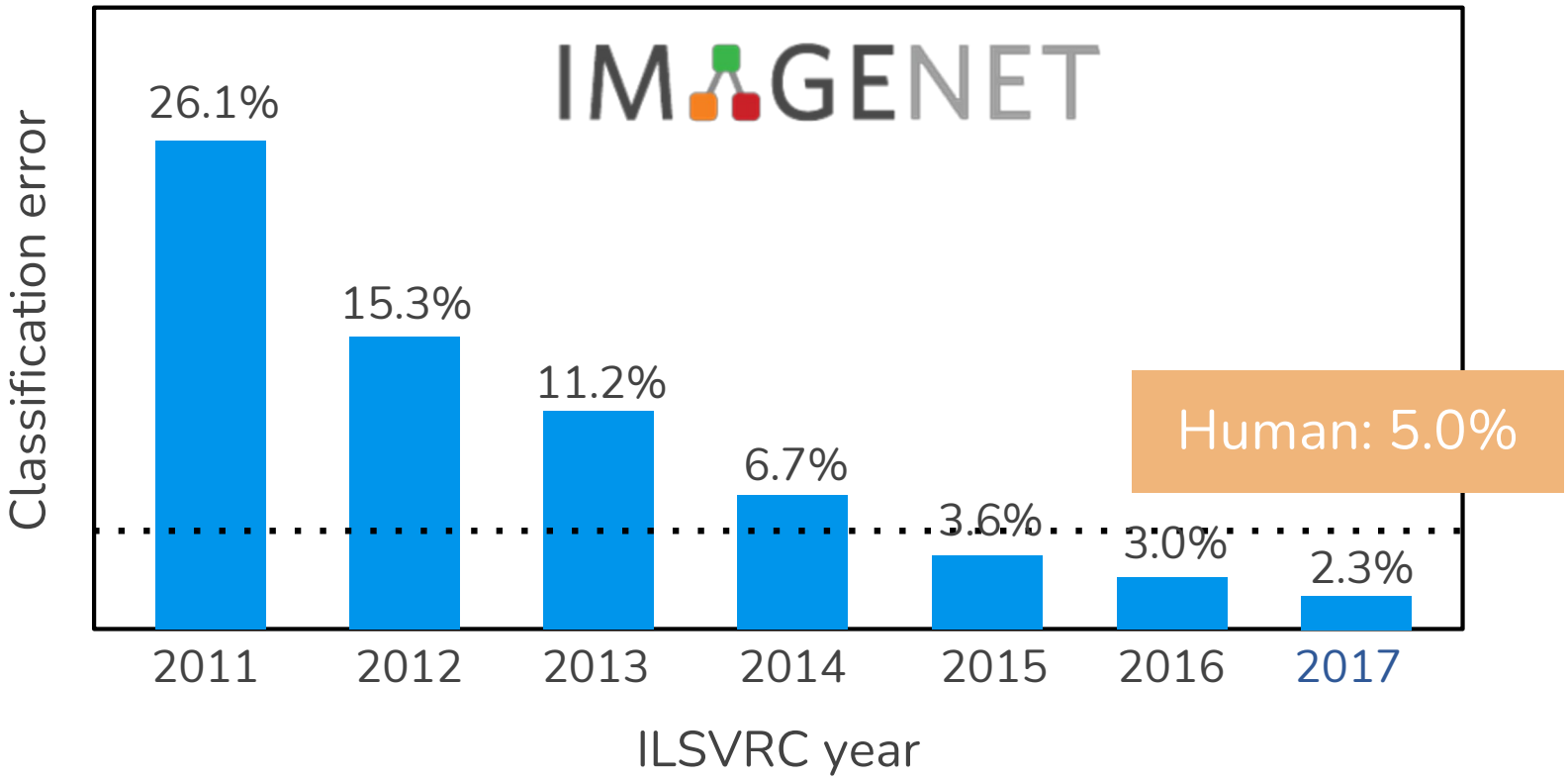

"ImageNet classification with deep convolutional neural networks". NIPS, 2012.

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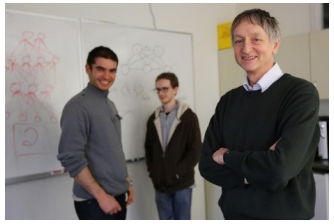
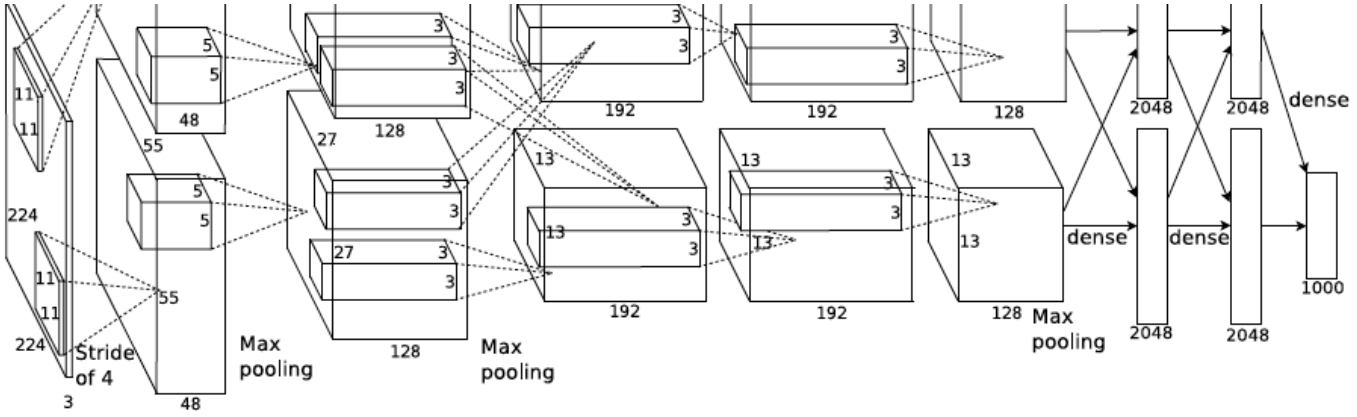
ImageNet Challenge 2012



- AlexNet: Similar framework to LeCun'98 but:
  - Bigger model (7 hidden layers, 650,000 units, 60,000,000 params)
  - More data (10^6 vs. 10^3 images)
  - GPU implementation (50x speedup over CPU)
    - Trained on two GPUs for a week
  - Better regularization for training (DropOut)



A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012

Adapted from Lana Lazebnik

Will this wave die out like the previous ones did?

From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.

Slide Credit: Prof. Sandra Avila - UNICAMP

IMAGENET

www.image-net.org

22K categories and 14M images

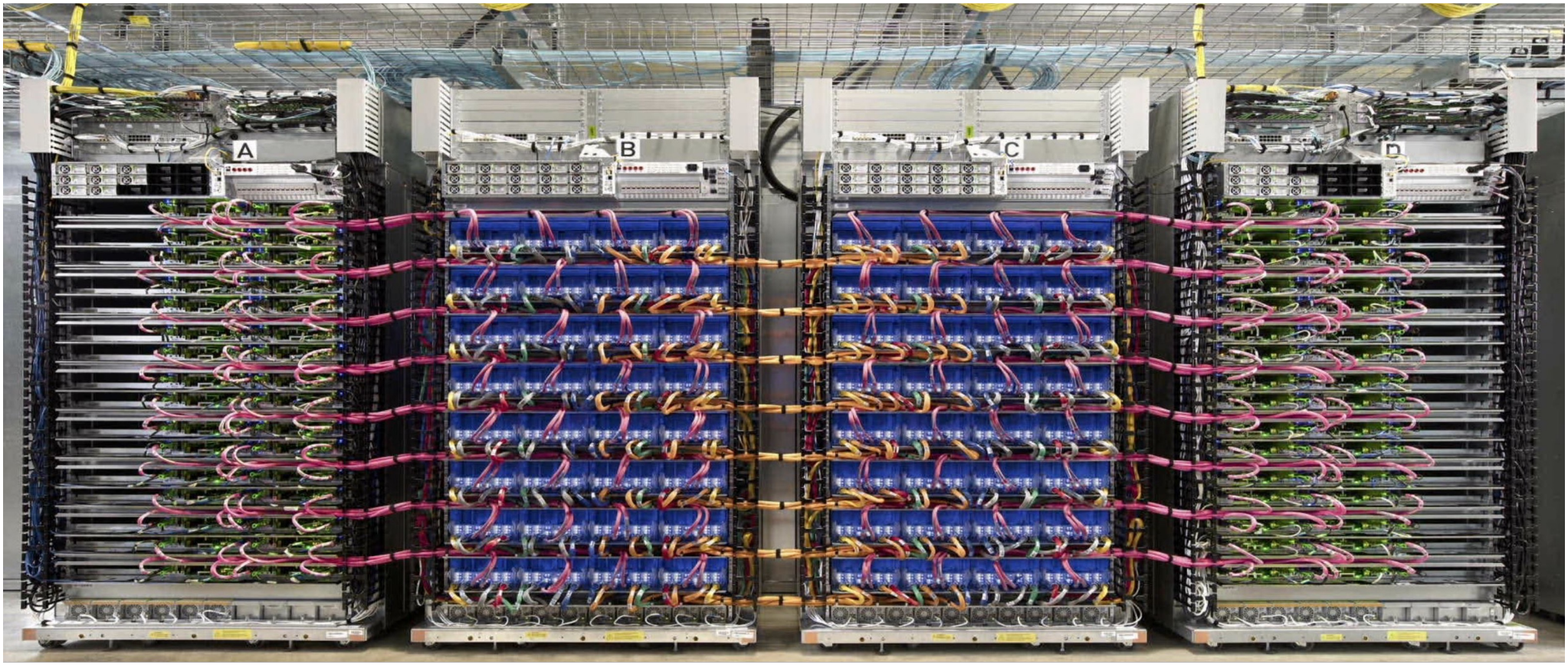
- Animals
  - Bird
  - Fish
  - Mammal
  - Invertebrate
- Plants
  - Tree
  - Flower
- Food
- Materials
- Structures
- Artifact
  - Tools
  - Appliances
  - Structures
- Person
- Scenes
  - Indoor
  - Geological Formations
- Sport Activities

Deng, Dong, Socher, Li, Li, & Fei-Fei, 2009

From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.
2. **Computing power** now makes it possible to train large neural networks in a reasonable amount of time.

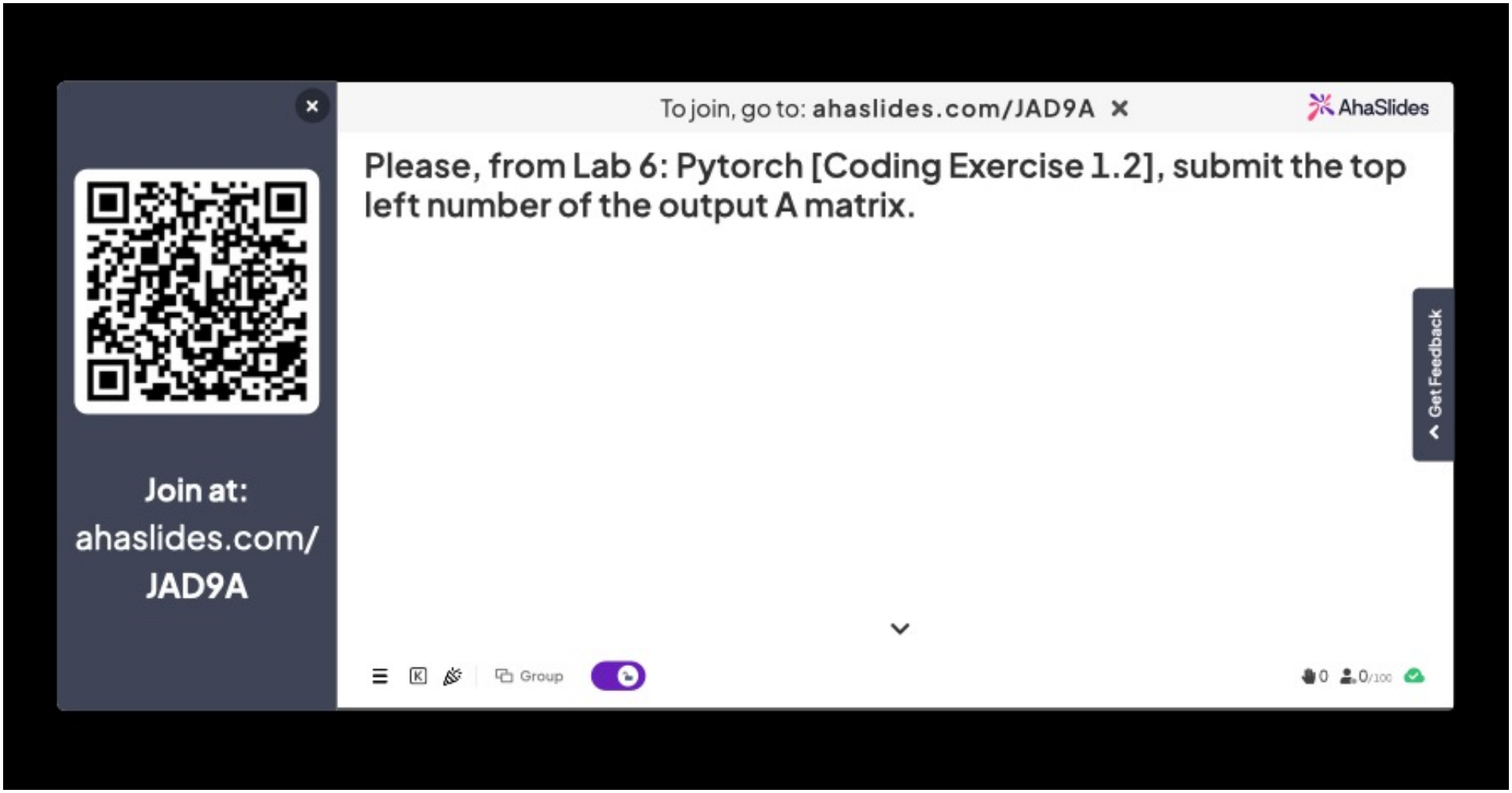
Slide Credit: Prof. Sandra Avila - UNICAMP



http://www.tomshardware.com/news/google-automl-aritifical-intelligence-ai,34533.html

Lab 6: Pytorch

Duration: 20 min


To join, go to: ahaslides.com/JAD9A
AhaSlides
Please, from Lab 6: Pytorch [Coding Exercise 1.2], submit the top left number of the output A matrix.
Join at:
ahaslides.com/
JAD9A
Get Feedback
Group
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Assignment 6: Pytorch

From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.
2. **Computing power** now makes it possible to train large neural networks in a reasonable amount of time.
3. The **training algorithms** have been **improved**.

Slide Credit: Prof. Sandra Avila - UNICAMP

Science AAAS

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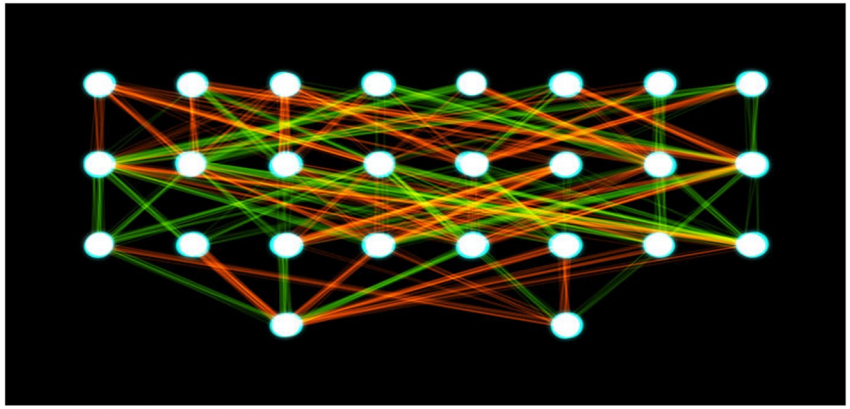


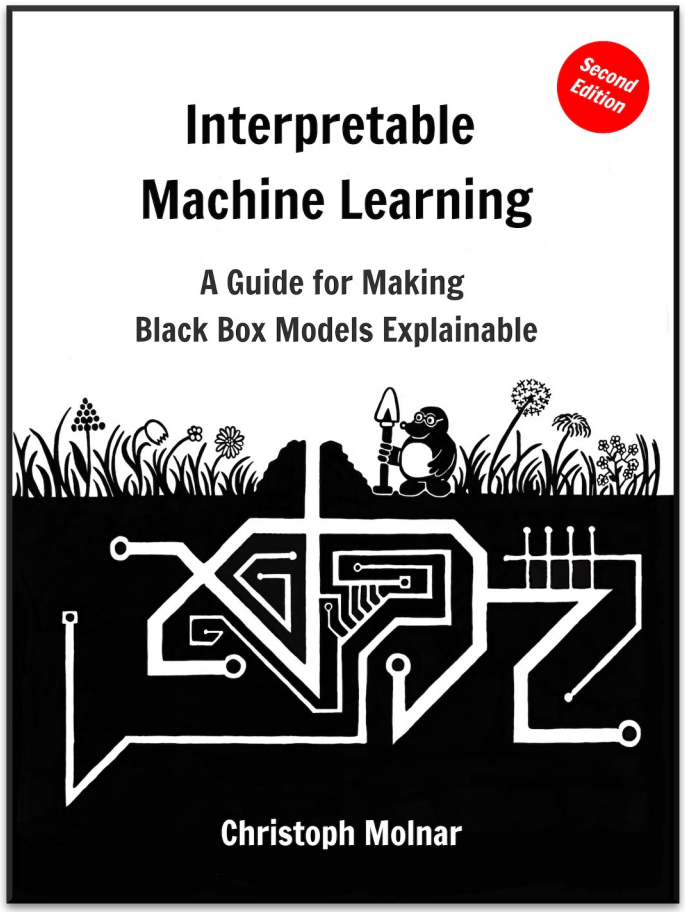
A representation of a neural network. Akritasa/Wikimedia Commons

Brainlike computers are a black box. Scientists are finally peering inside

By Jackie Snow | Mar. 7, 2017 , 3:15 PM

Last month, Facebook announced software that could simply look at a photo and tell, for example, whether it was a picture of a cat or a dog. A related program identifies cancerous

http://www.sciencemag.org/news/2017/03/brainlike-computers-are-black-box-scientists-are-finally-peering-inside



“Interpretable Machine Learning”, 2022

https://christophm.github.io/interpretable-ml-book

Chap. 10 Neural Network Interpretation

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From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.
2. **Computing power** now makes it possible to train large neural networks in a reasonable amount of time.
3. The **training algorithms** have been **improved**.
4. ANNs seem to have entered a virtuous circle of funding and progress.

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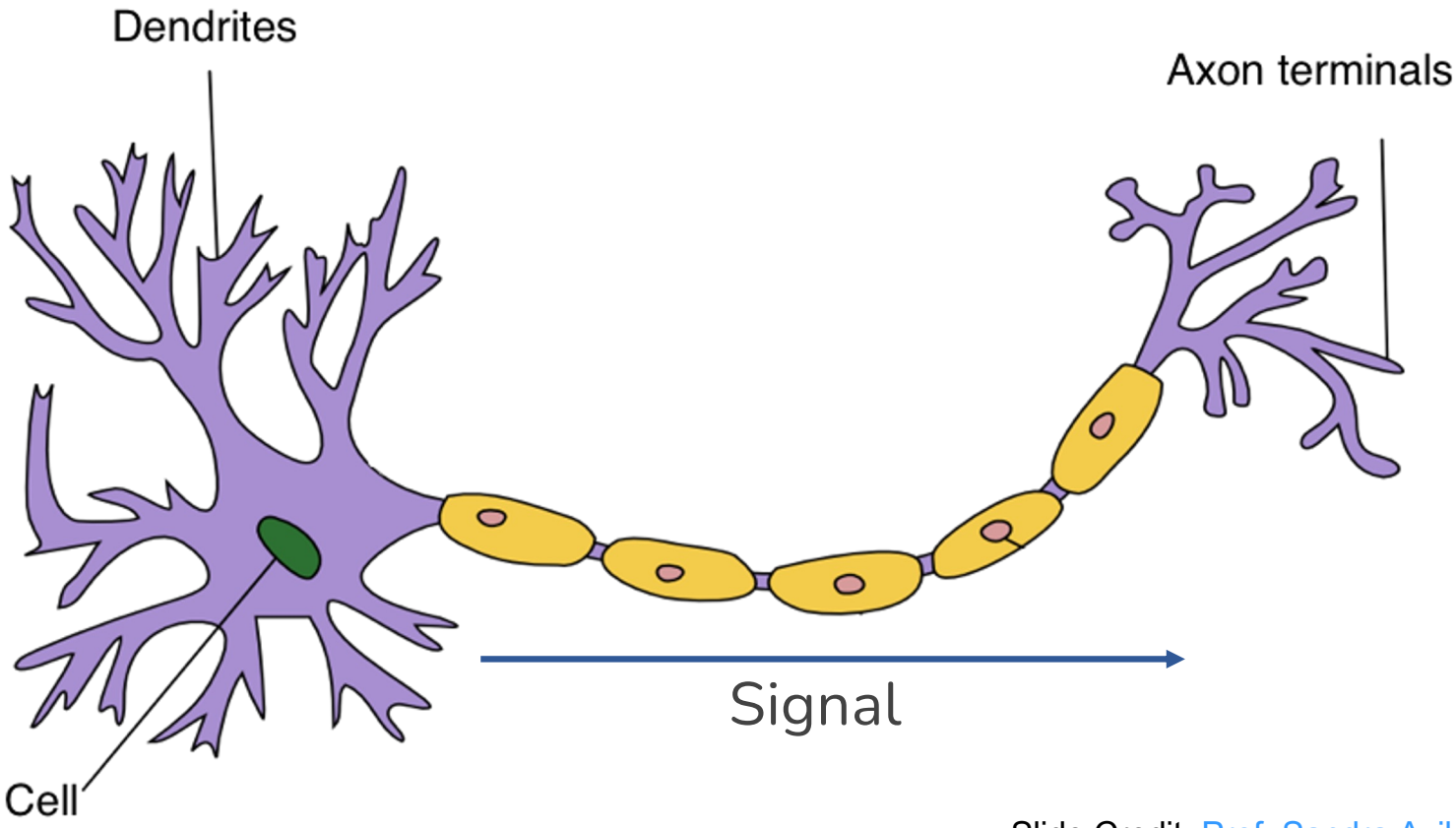
Biological Neurons



http://www.jeremyjordan.me/content/images/2017/06/Neuron_Hand-tuned.png

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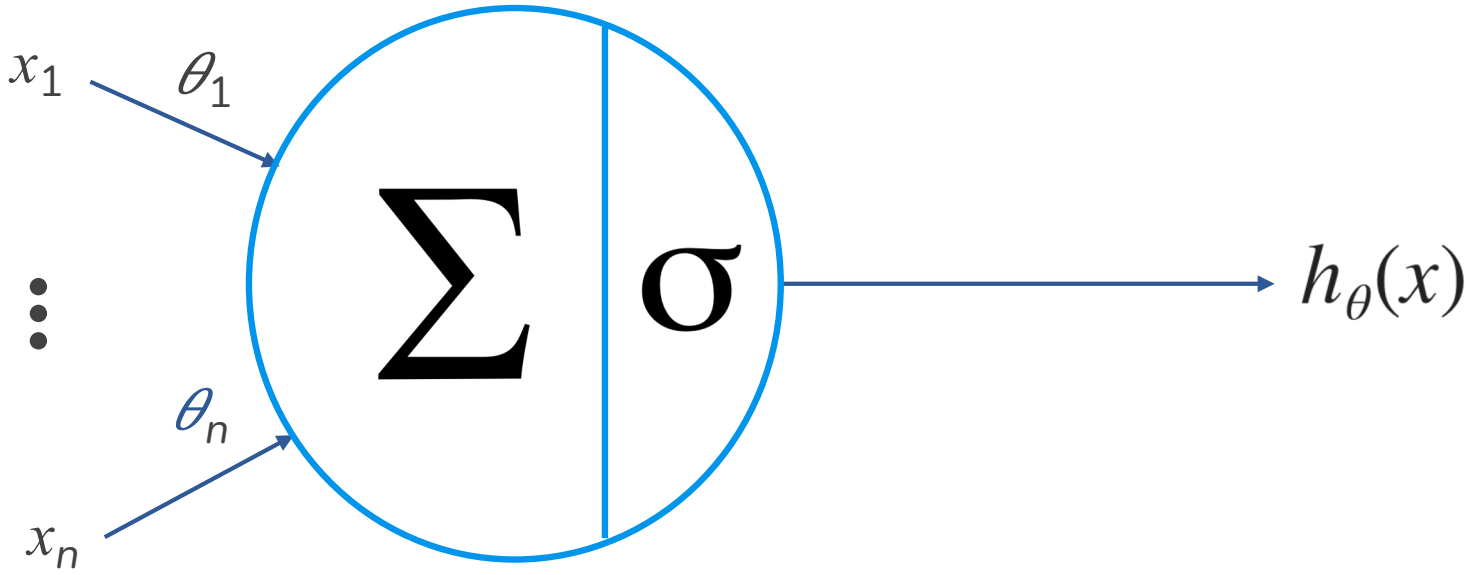
Biological Neurons - Analogy



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The Perceptron

Invented in 1957 by Frank Rosenblatt.

- It is based on a Linear Threshold Unit (LTU):
  - The inputs and output are now **numbers** and each input connection is associated with a **weight**.

- The LTU computes a weighted sum of its inputs then it applies a step function to that sum and outputs the result.

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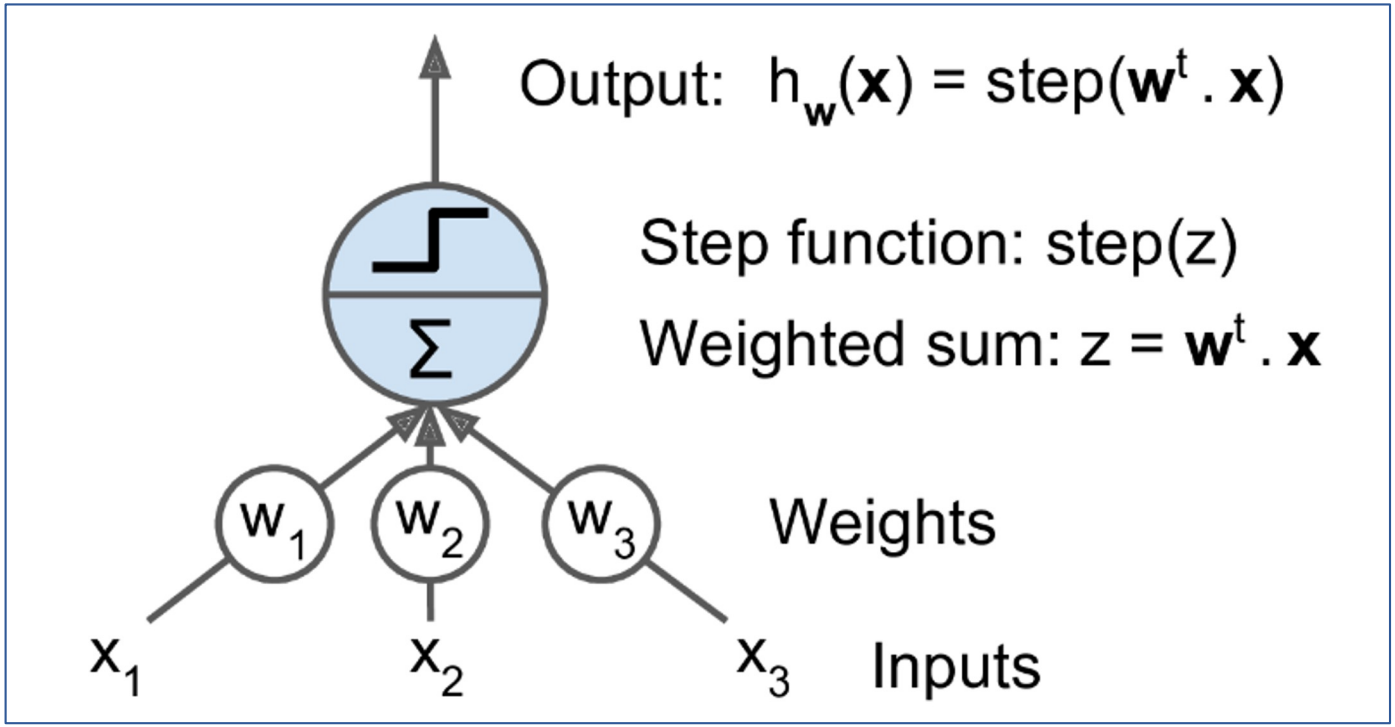
The Perceptron



Linear Threshold Unit

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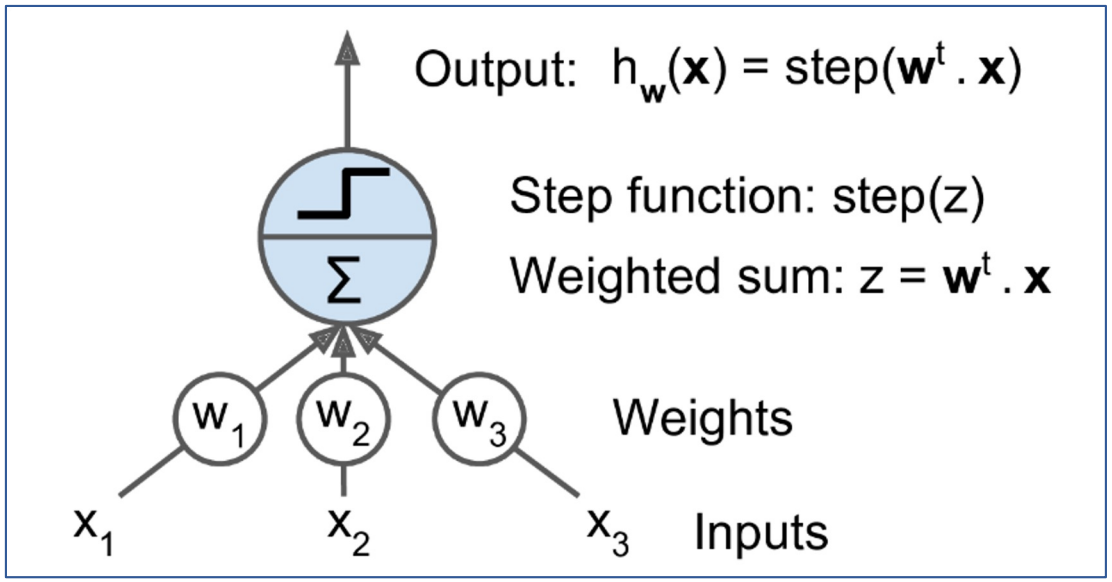
The Perceptron



Linear Threshold Unit

$$\text{heaviside}(z) = \begin{cases} 0 & \text{if } z < 0 \\ 1 & \text{if } z \geq 0 \end{cases}$$

$$\text{sign}(z) = \begin{cases} -1 & \text{if } z < 0 \\ 0 & \text{if } z = 0 \\ +1 & \text{if } z > 0 \end{cases}$$

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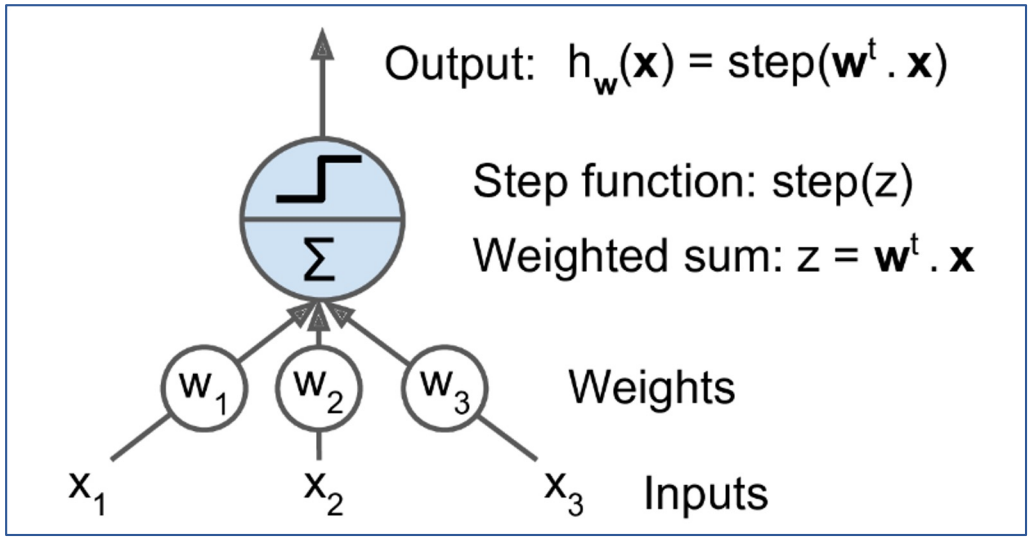
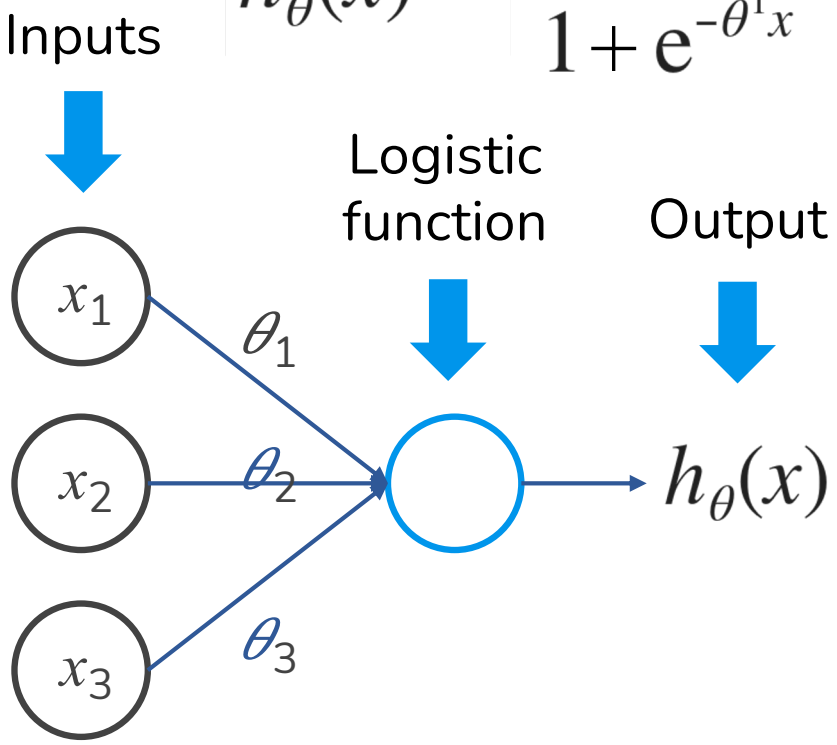
Neuron Model: Logistic Unit



$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$



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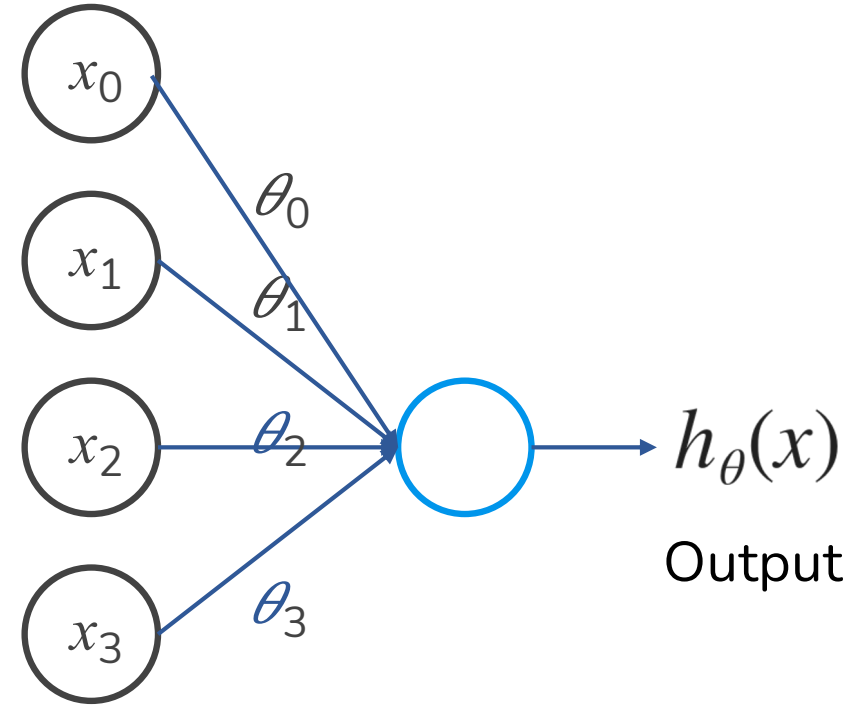
Neuron Model: Logistic Unit



Inputs

Sigmoid (Logistic)
activation function

weights

$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}$$

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

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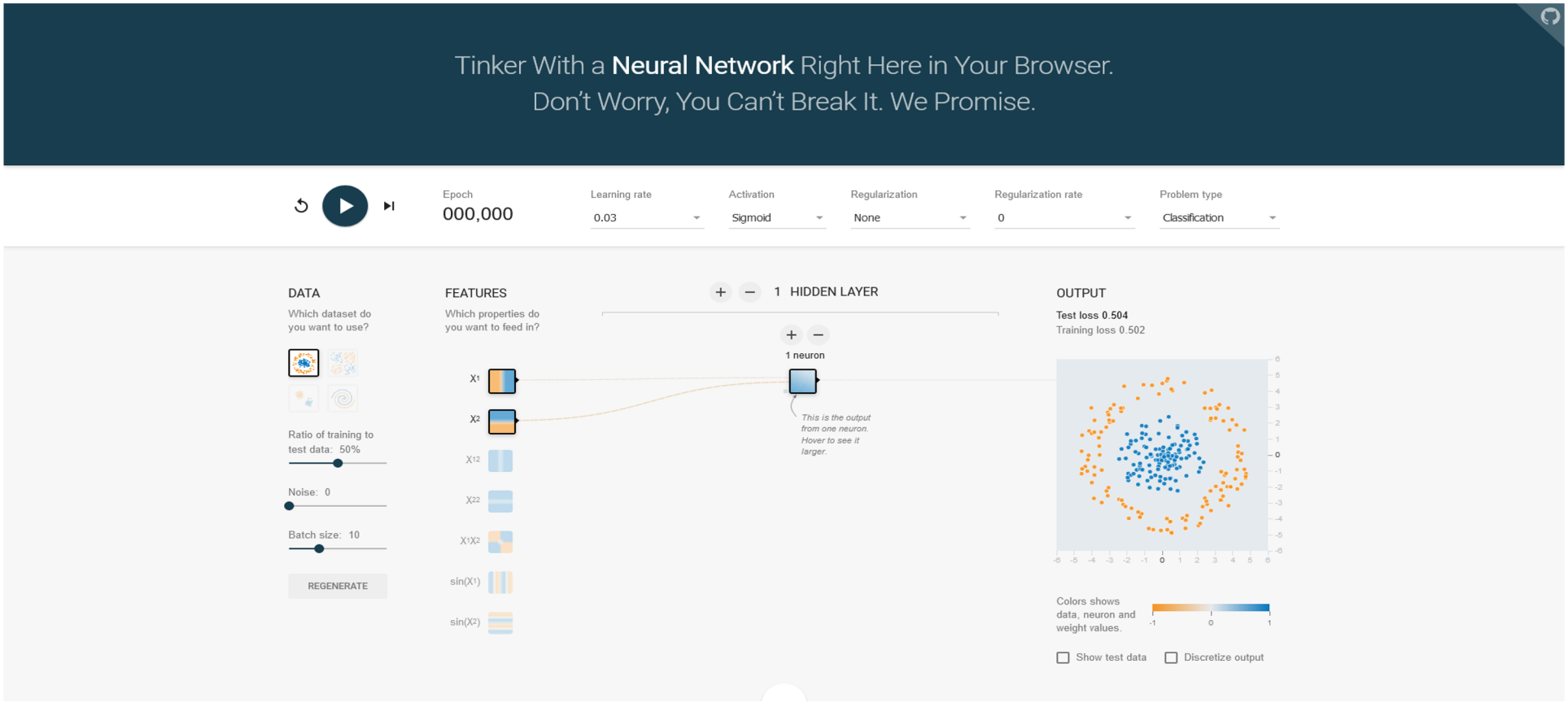
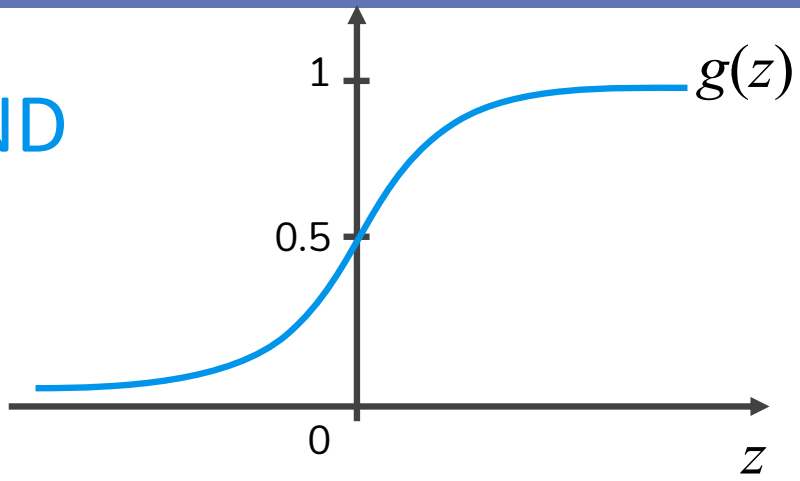
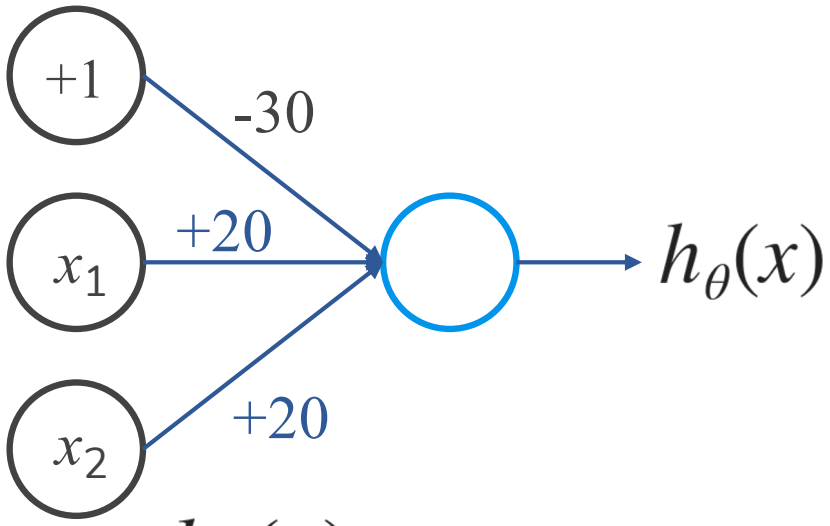
TensorFlow PlayGround



[Example] Simple Example: AND

$x_1, x_2 \in \{0,1\}$ $\quad y = x_1$ AND x_2





$$h_\theta(x) = g(-30 + 20x_1 + 20x_2)$$

x_1	x_2	$h_\theta(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	$g(10) \approx 1$

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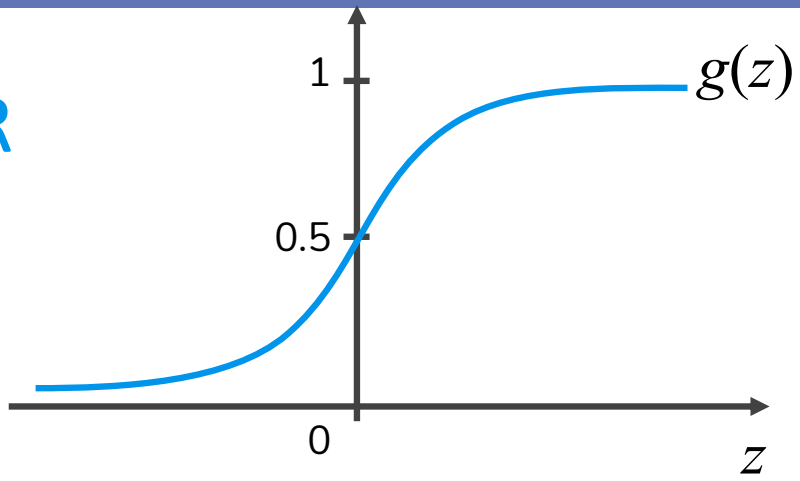
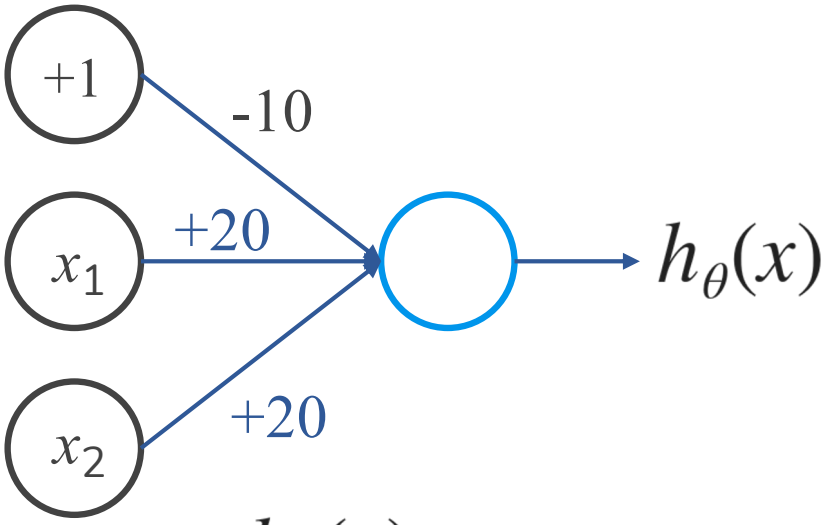
[Example] Simple Example: OR

$x_1, x_2 \in \{0,1\}$ $\quad y = x_1$ OR x_2





$$h_\theta(x) = g(-10 + 20x_1 + 20x_2)$$

x_1	x_2	$h_\theta(x)$
0	0	$g(-10) \approx 0$
0	1	$g(10) \approx 1$
1	0	$g(10) \approx 1$
1	1	$g(30) \approx 1$

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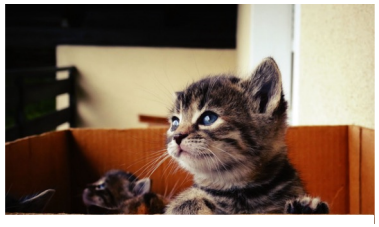
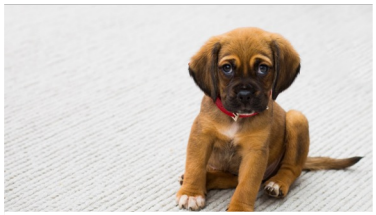
Multi-class Classification?

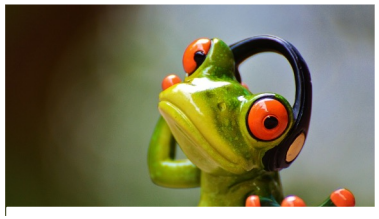
Multi-class Classification



Cat

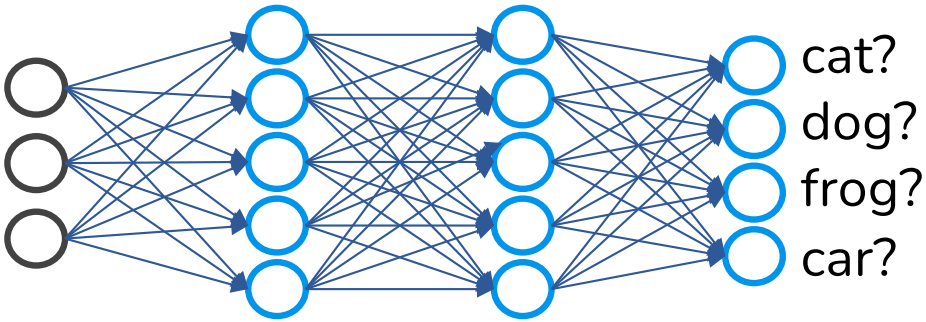


Dog



Frog

Car



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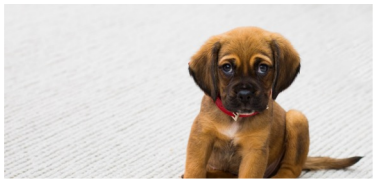
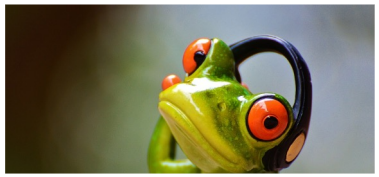
Cat

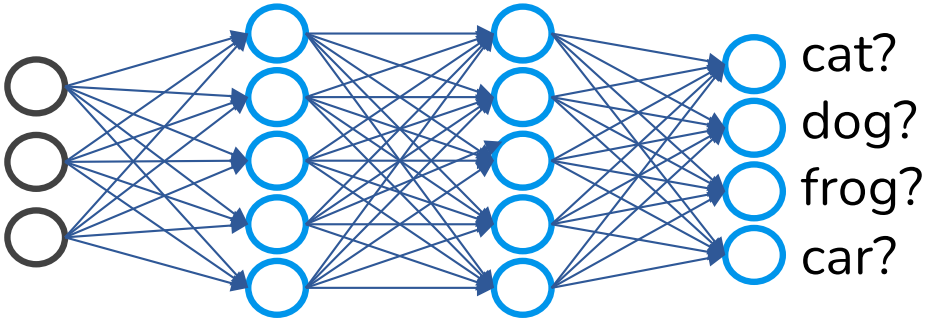


Dog



Frog

Car

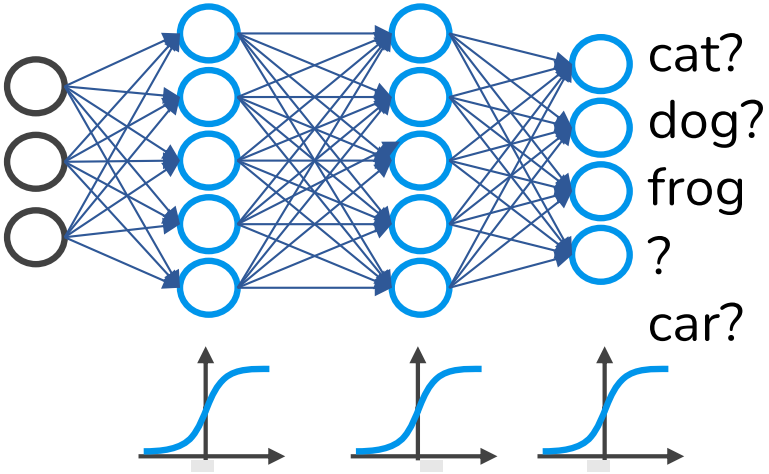


Want $h_\Theta(x) \approx \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$, $h_\Theta(x) \approx \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$, $h_\Theta(x) \approx \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$, $h_\Theta(x) \approx \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$

when cat when dog when frog when car

Softmax Classification

The **output layer** is typically modified **by replacing** the individual activation functions **by a shared softmax** function.



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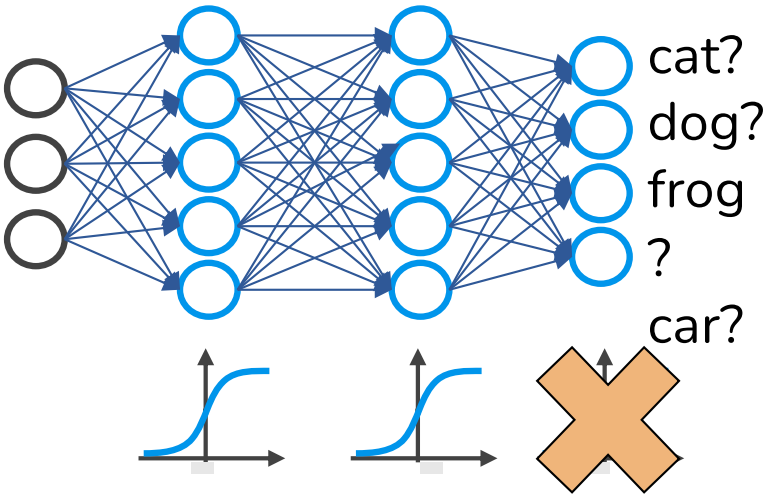

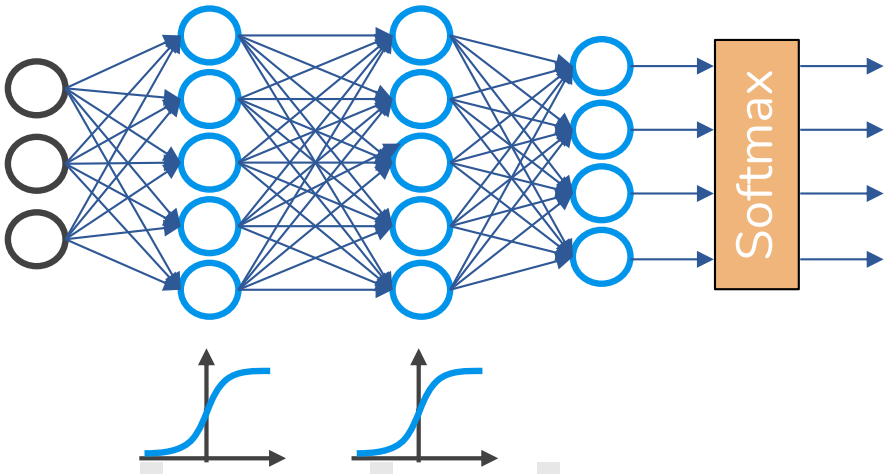

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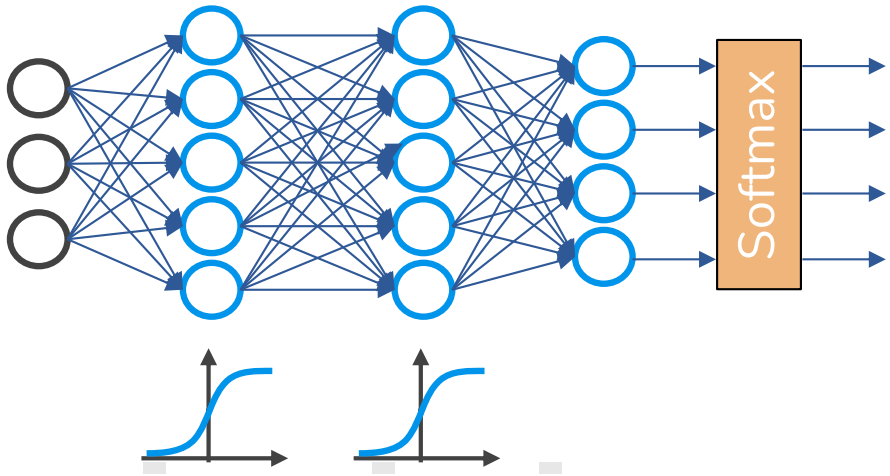
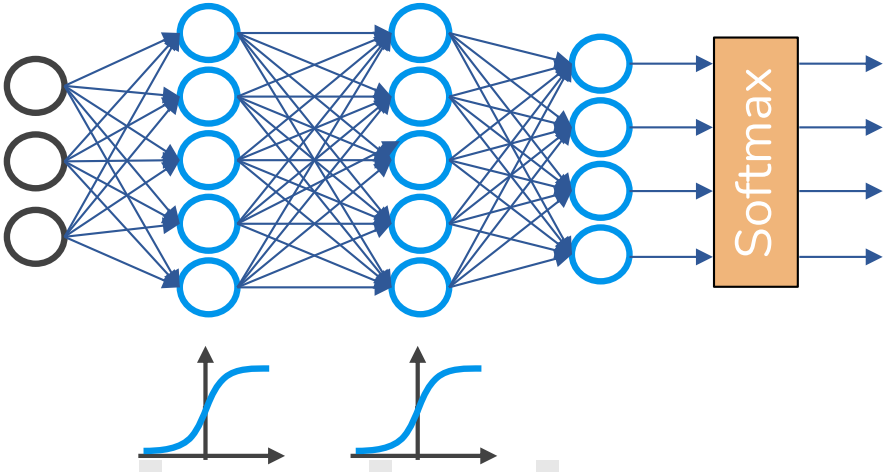


$$f(\mathbf{z})_k = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}$$

Slide Credit: Prof. Sandra Avila - UNICAMP

Softmax Classification



Cat	5.1	164.0	0.87
Dog	3.2	24.5	0.13
Frog	-1.7	0.18	0.00
Car	-2.0	0.13	0.00

$$f(\mathbf{z})_k = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}$$

Slide Credit: Prof. Sandra Avila - UNICAMP

How do we decide whether the neuron should fire or not?

Slide Credit: Prof. Sandra Avila - UNICAMP

We decided to add “activation functions” for this purpose.

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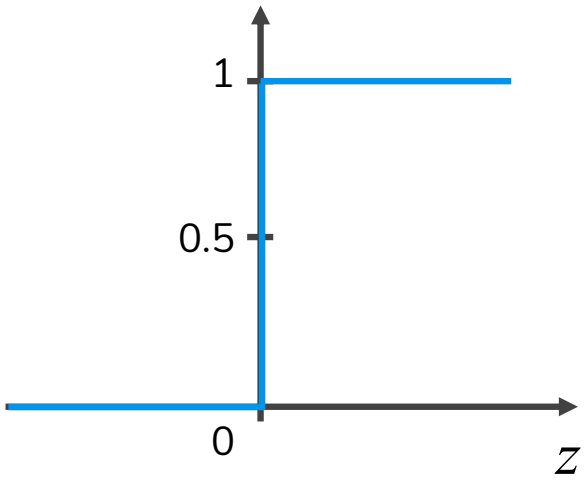
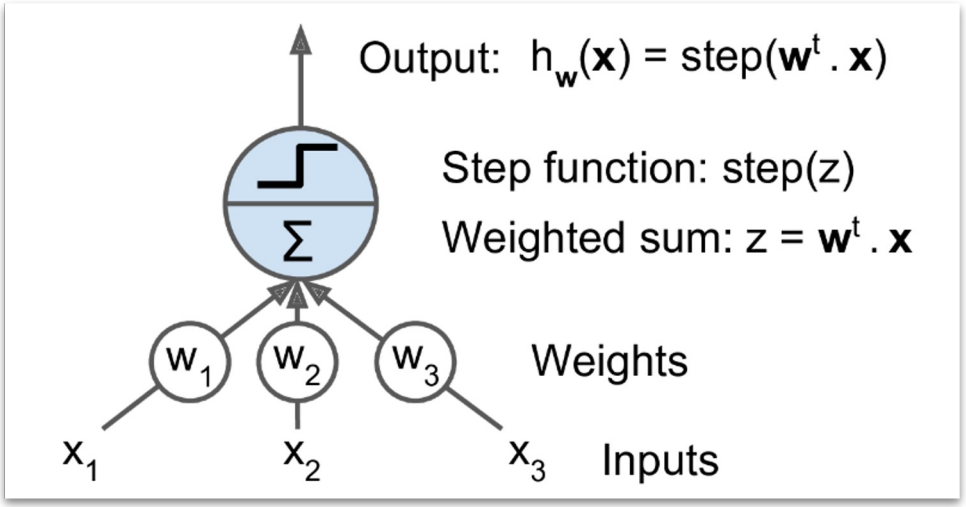
Step Function

Its output is **1 (activated)** when value > 0 (threshold) and outputs a **0 (not activated)** otherwise.





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Step Function: **Problem?**

- Binary classifier (“yes” or “no”, activate or not activate). A Step function could do that for you!

- Multi classifier (class1, class2, class3, etc). What will happen if more than 1 neuron is “activated”?

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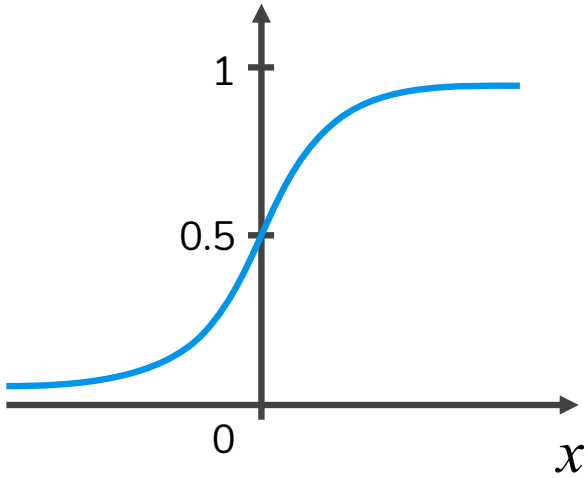
Sigmoid Function

- The output of the activation function is always going to be in range **(0,1)**.
- It is nonlinear in nature.

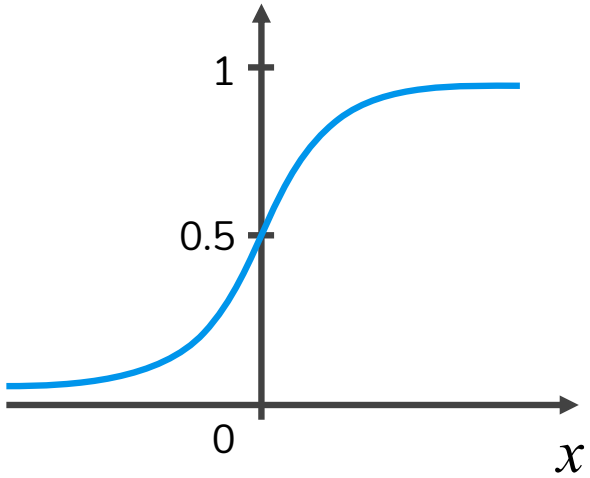


$$\sigma(x) = \frac{1}{1+e^{-x}}$$

Slide Credit: Prof. Sandra Avila - UNICAMP

Sigmoid Function

- The output of the activation function is always going to be in range **(0,1)**.
- It is nonlinear in nature.
- Combinations of this function are also nonlinear! Great!!



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

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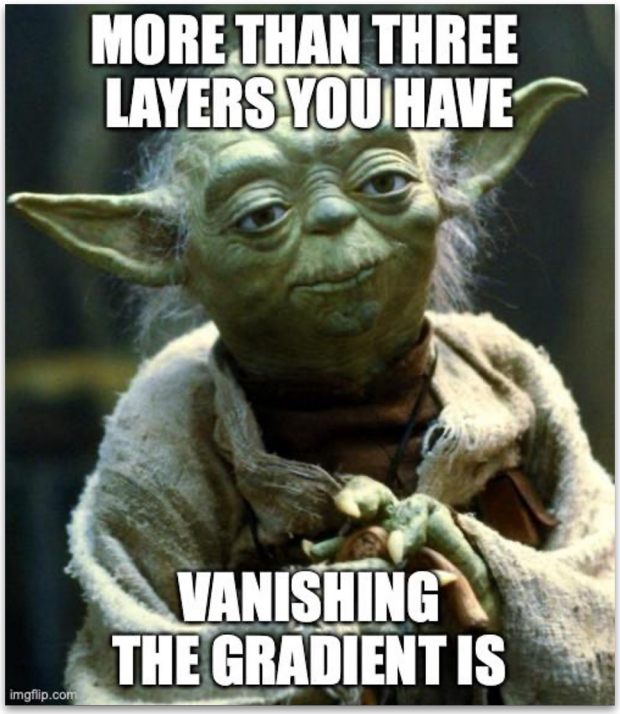
Sigmoid Function: **Problem?**



- Towards either end of the sigmoid function, the $\sigma(x)$ values tend to respond very less to changes in x.
- The problem of "**vanishing gradients**".
  - Cannot make significant change because of the extremely small value.

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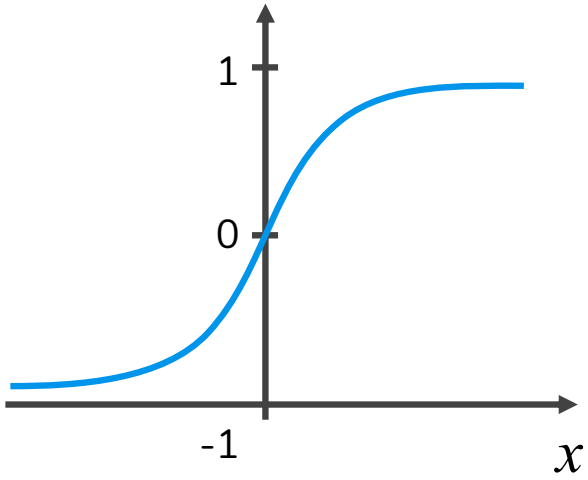
Tanh Function

- The output of the activation function is always going to be in range **(-1,1)**.
- It is nonlinear in nature.
- Combinations of this function are also nonlinear! Great!!



$$tanh(x) = \frac{2}{1+e^{-2x}} - 1$$

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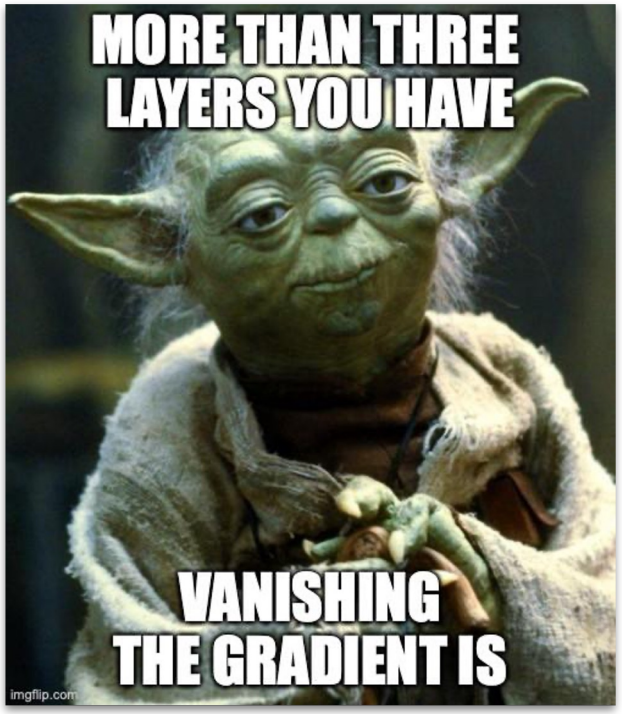
Tanh Function: **Problem?**



- Like sigmoid, tanh also has the vanishing gradient problem.

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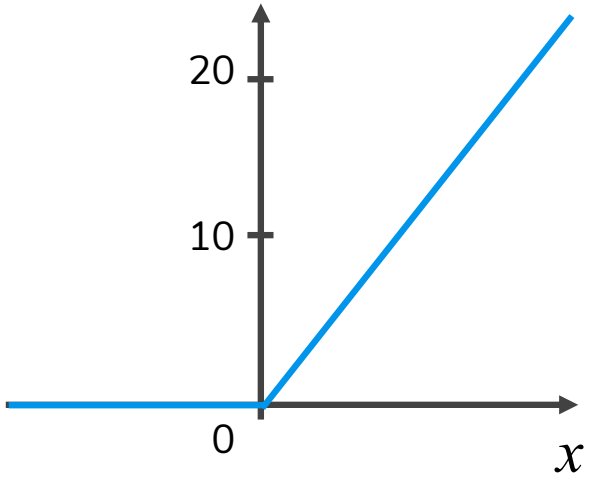
ReLU (Rectified Linear Unit) Function

- It gives an output x if x is positive and 0 otherwise. The range is **[0, inf)**.
- It is nonlinear in nature. Combinations of this function are also nonlinear!
- Sparsity of the activation!



$$\mathrm{ReLU}(x) = max(0,x)$$

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ReLU Function: **Problem?**

- Because of the horizontal line in ReLU (for negative x), the gradient can go towards 0.
- "Dying ReLU problem": several neurons can just die and not respond making a substantial part of the network passive.

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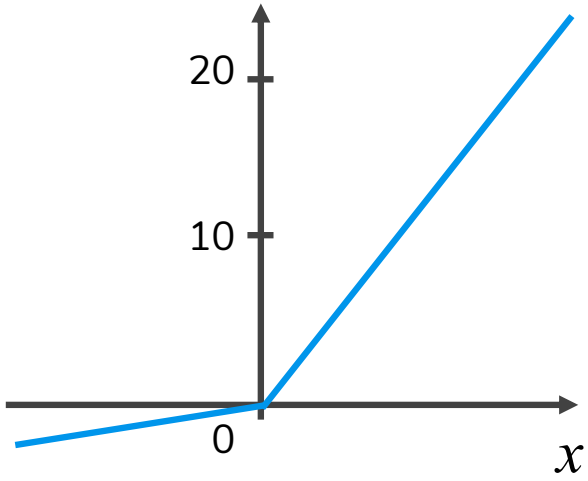
Leaky ReLU Function

- It gives an output x if x is positive and 0 otherwise. The range is **[0, inf)**.
- (Leaky) ReLU is less computationally expensive than *tanh* and *sigmoid* because it involves simpler mathematical operations.



$$\text{Leaky ReLU}(x) = \begin{cases} x \text{ if } x > 0 \\ 0.01x \text{ otherwise} \end{cases}$$

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Ok! Which One Do We Use?

- If you don’t know the nature of the function you are trying to learn, start with ReLU.
- You can use your own custom functions too!

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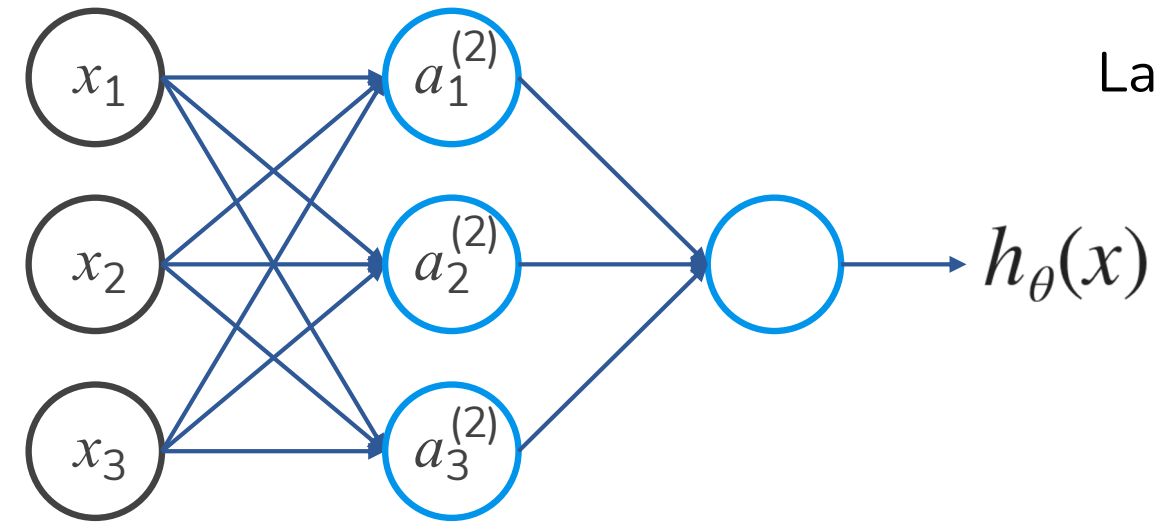
Neural Network

Layer 1 = Input layer

Layer 2 = Hidden layer

Layer 3 = Output layer



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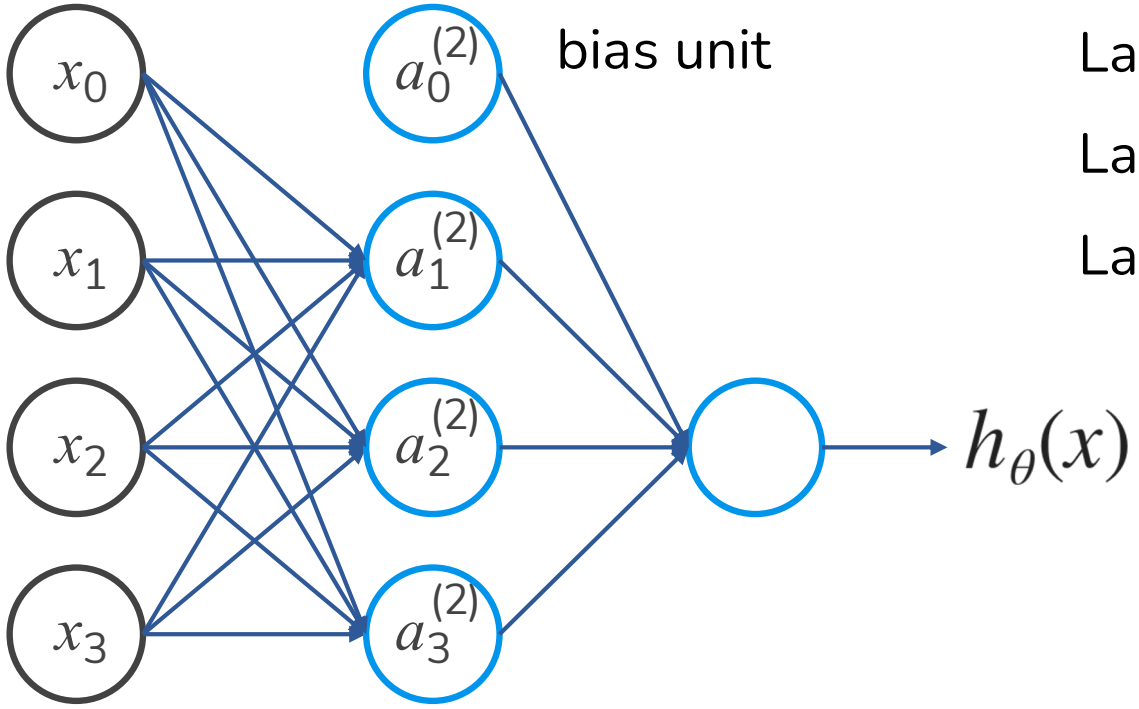
Neural Network



Layer 1 = Input layer

Layer 2 = Hidden layer

Layer 3 = Output layer

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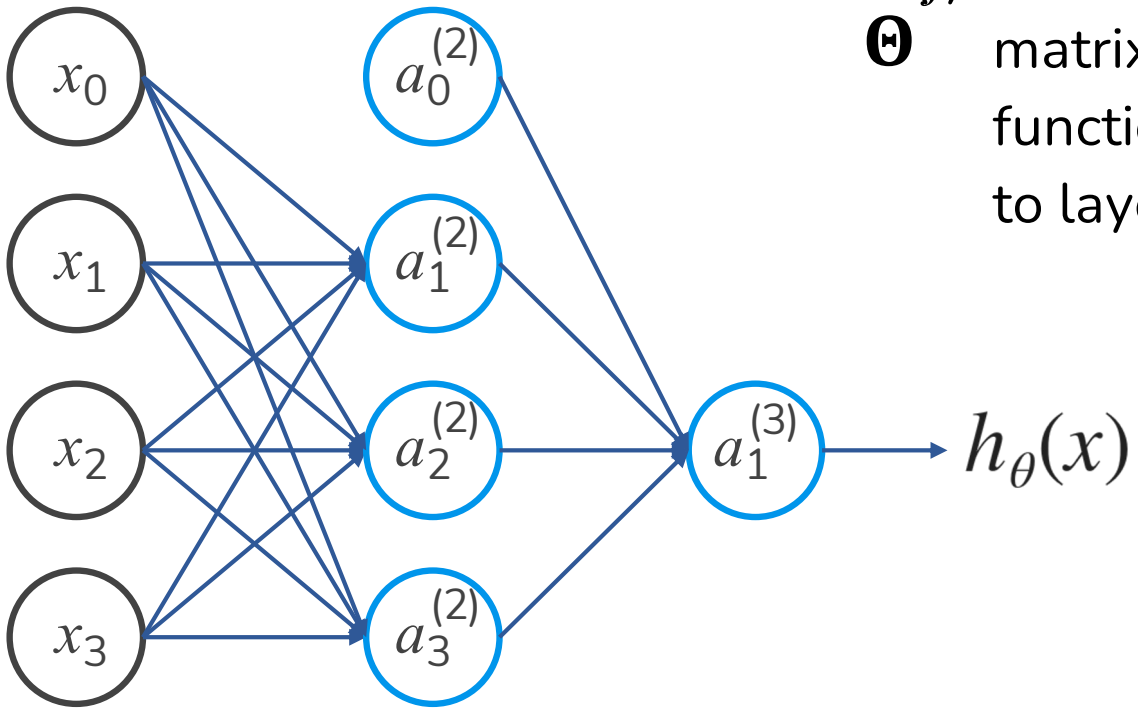
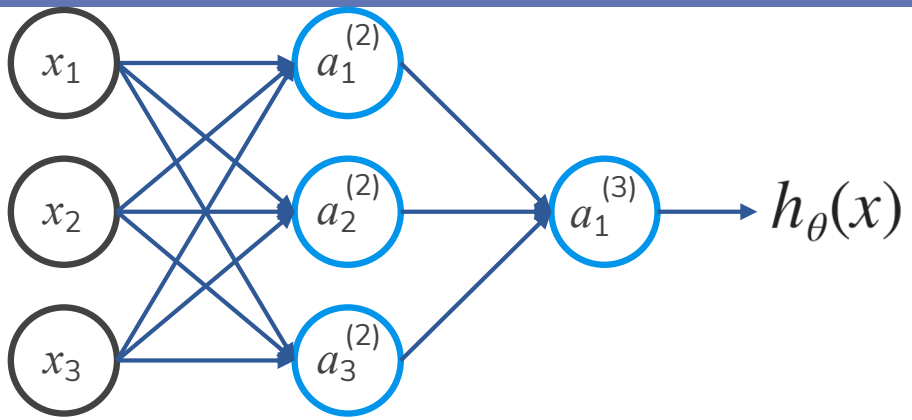
Neural Network

$a_i^{(j)}$ "activation" of unit i in layer j

$\Theta^{(j)}$ matrix of weights controlling function mapping from layer j to layer $j+1$



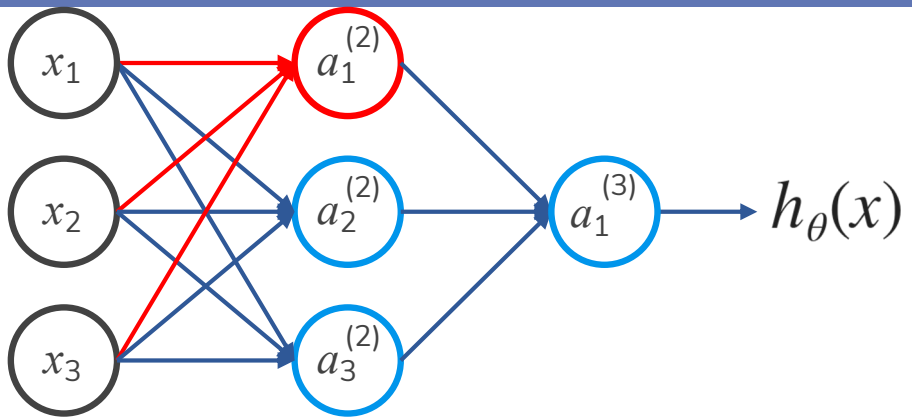
Slide Credit: Prof. Sandra Avila - UNICAMP



$a_i^{(j)}$ "activation" of unit i in layer j

$\Theta^{(j)}$ matrix of weights controlling function mapping from layer j to layer $j+1$

Slide Credit: Prof. Sandra Avila - UNICAMP



$a_i^{(j)}$ "activation" of unit i in layer j

$\Theta^{(j)}$ matrix of weights controlling function mapping from layer j to layer $j+1$

$$a_1^{(2)} = g(\Theta_{10}^{(1)} x_0 + \Theta_{11}^{(1)} x_1 + \Theta_{12}^{(1)} x_2 + \Theta_{13}^{(1)} x_3)$$

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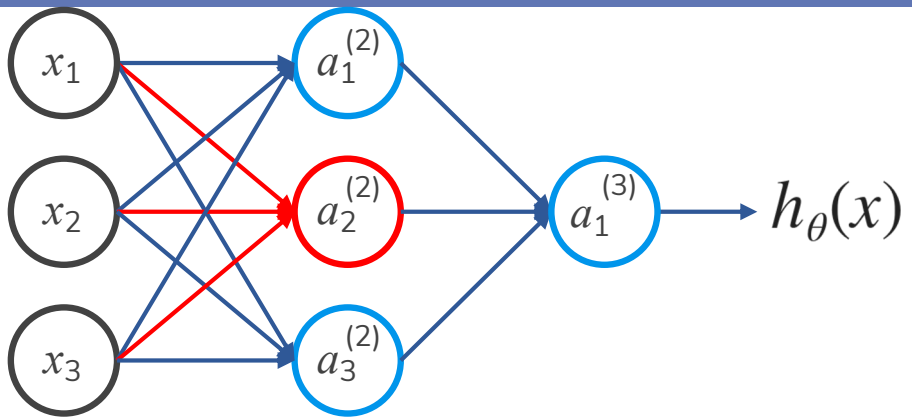

$a_i^{(j)}$ "activation" of unit i in layer j

$\Theta^{(j)}$ matrix of weights controlling function mapping from layer j to layer $j+1$

$$a_1^{(2)} = g(\Theta_{10}^{(1)}x_0 + \Theta_{11}^{(1)}x_1 + \Theta_{12}^{(1)}x_2 + \Theta_{13}^{(1)}x_3)$$

$$a_2^{(2)} = g(\Theta_{20}^{(1)}x_0 + \Theta_{21}^{(1)}x_1 + \Theta_{22}^{(1)}x_2 + \Theta_{23}^{(1)}x_3)$$

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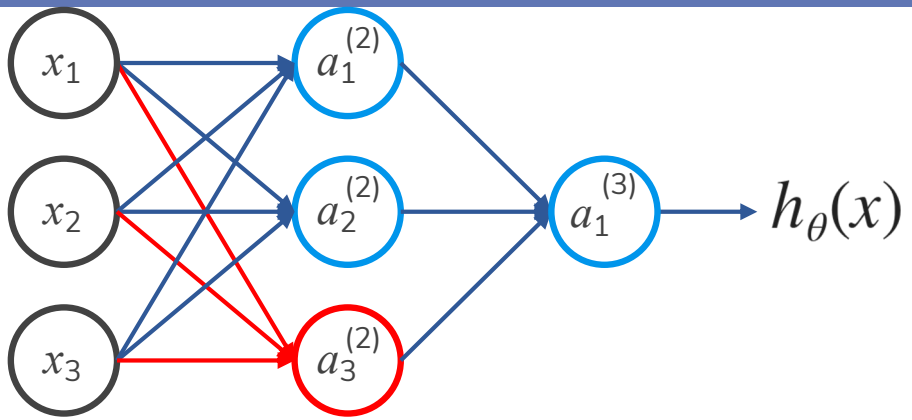

$a_i^{(j)}$ "activation" of unit i in layer j

$\Theta^{(j)}$ matrix of weights controlling function mapping from layer j to layer $j+1$

$$a_1^{(2)} = g(\Theta_{10}^{(1)}x_0 + \Theta_{11}^{(1)}x_1 + \Theta_{12}^{(1)}x_2 + \Theta_{13}^{(1)}x_3)$$

$$a_2^{(2)} = g(\Theta_{20}^{(1)}x_0 + \Theta_{21}^{(1)}x_1 + \Theta_{22}^{(1)}x_2 + \Theta_{23}^{(1)}x_3)$$

$$a_3^{(2)} = g(\Theta_{30}^{(1)}x_0 + \Theta_{31}^{(1)}x_1 + \Theta_{32}^{(1)}x_2 + \Theta_{33}^{(1)}x_3)$$

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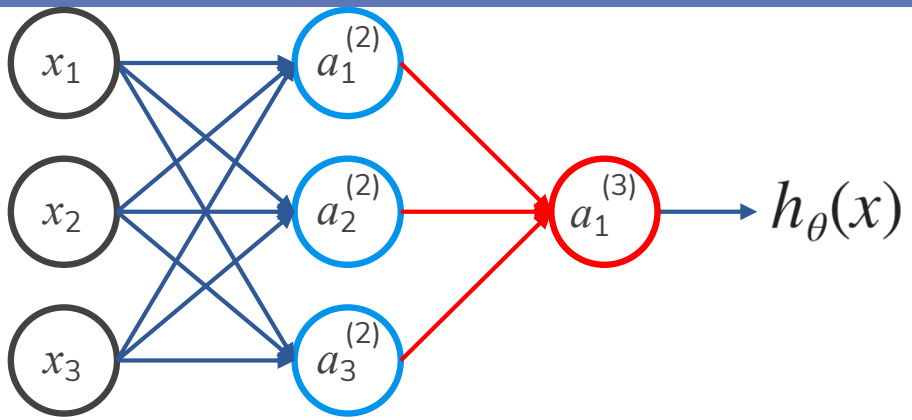


$a_i^{(j)}$ "activation" of unit i in layer j

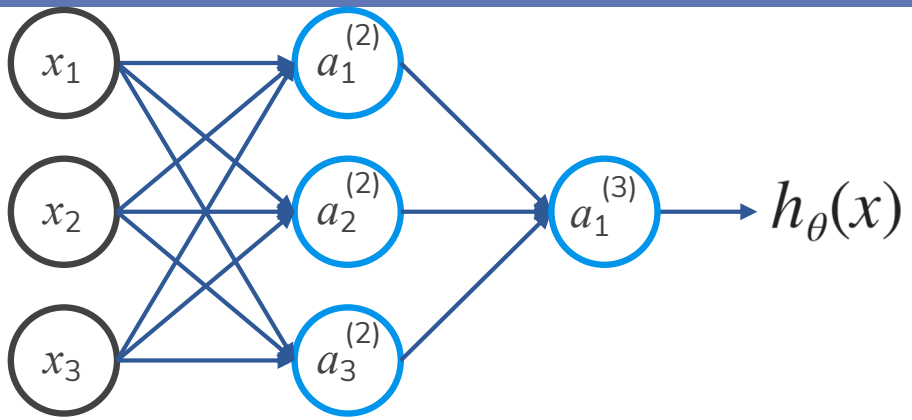
$\Theta^{(j)}$ matrix of weights controlling function mapping from layer j to layer $j+1$

$$a_1^{(2)} = g(\Theta_{10}^{(1)}x_0 + \Theta_{11}^{(1)}x_1 + \Theta_{12}^{(1)}x_2 + \Theta_{13}^{(1)}x_3)$$

$$a_2^{(2)} = g(\Theta_{20}^{(1)}x_0 + \Theta_{21}^{(1)}x_1 + \Theta_{22}^{(1)}x_2 + \Theta_{23}^{(1)}x_3)$$

$$a_3^{(2)} = g(\Theta_{30}^{(1)}x_0 + \Theta_{31}^{(1)}x_1 + \Theta_{32}^{(1)}x_2 + \Theta_{33}^{(1)}x_3)$$

$$h_\Theta(x) = a_1^{(3)} = g(\Theta_{10}^{(2)}a_0^{(2)} + \Theta_{11}^{(2)}a_1^{(2)} + \Theta_{12}^{(2)}a_2^{(2)} + \Theta_{13}^{(2)}a_3^{(2)})$$



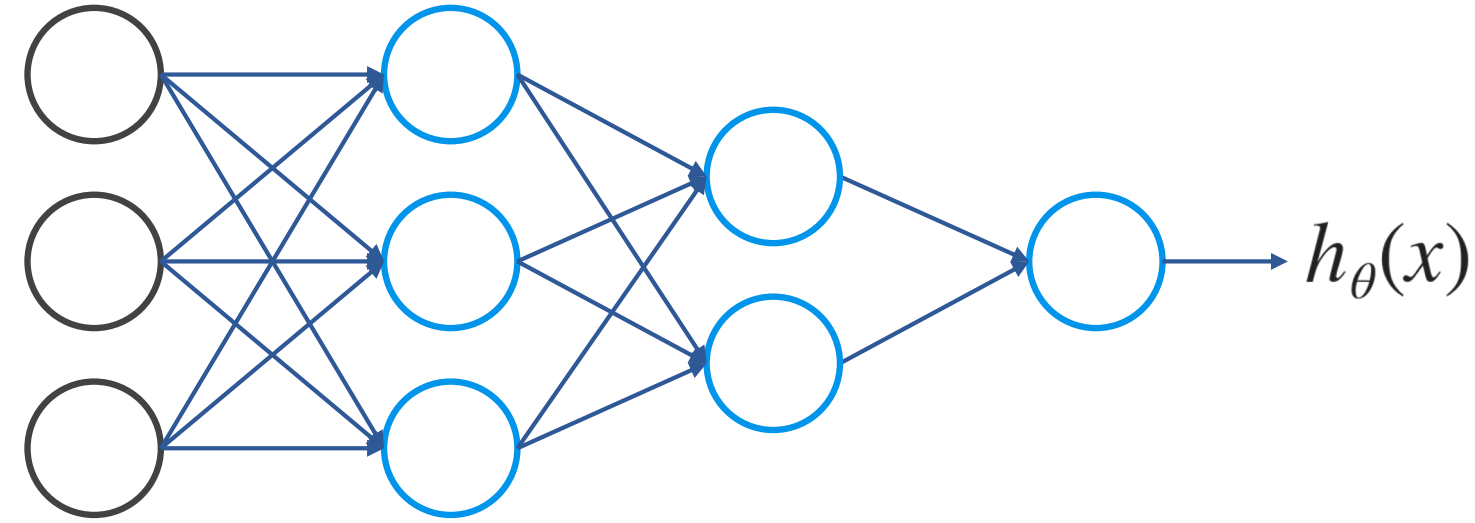
$a_i^{(j)}$ "activation" of unit i in layer j

$\Theta^{(j)}$ matrix of weights controlling function mapping from layer j to layer $j+1$

Feedforward Neural Network (forward propagating)

$$h_\Theta(x) = a_1^{(3)} = g(\Theta_{10}^{(2)} a_0^{(2)} + \Theta_{11}^{(2)} a_1^{(2)} + \Theta_{12}^{(2)} a_2^{(2)} + \Theta_{13}^{(2)} a_3^{(2)})$$

Neural Network Intuition



Complexity

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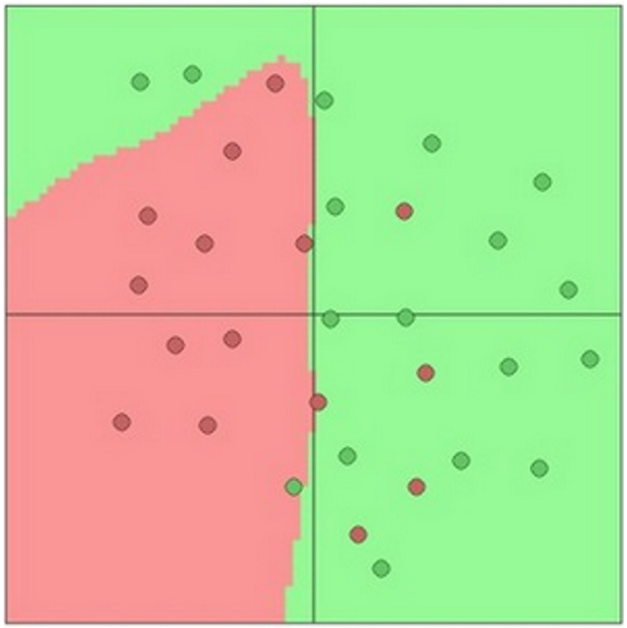
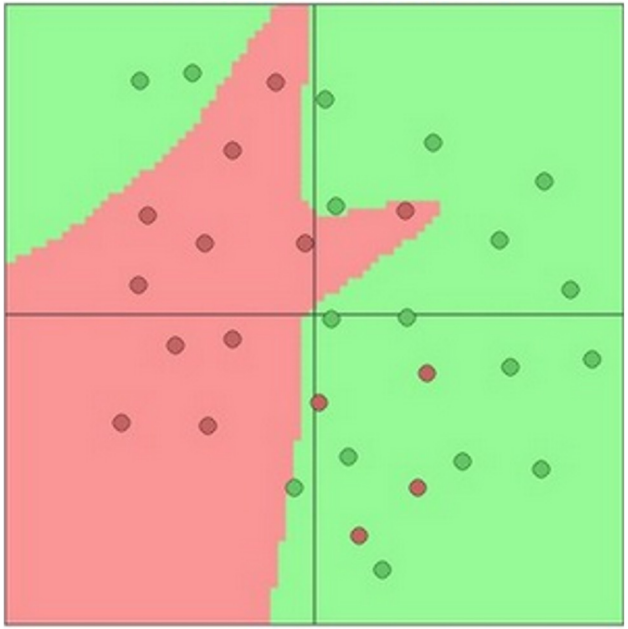
Neural Network Intuition

Toy 2d classification with 2-layer neural network

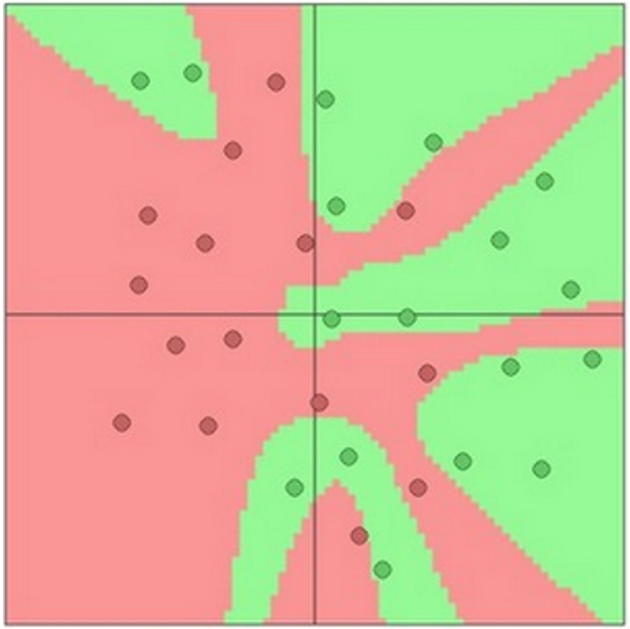
http://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html



3 hidden neurons



6 hidden neurons



20 hidden neurons

http://cs231n.github.io/assets/nn1/layer_sizes.jpeg

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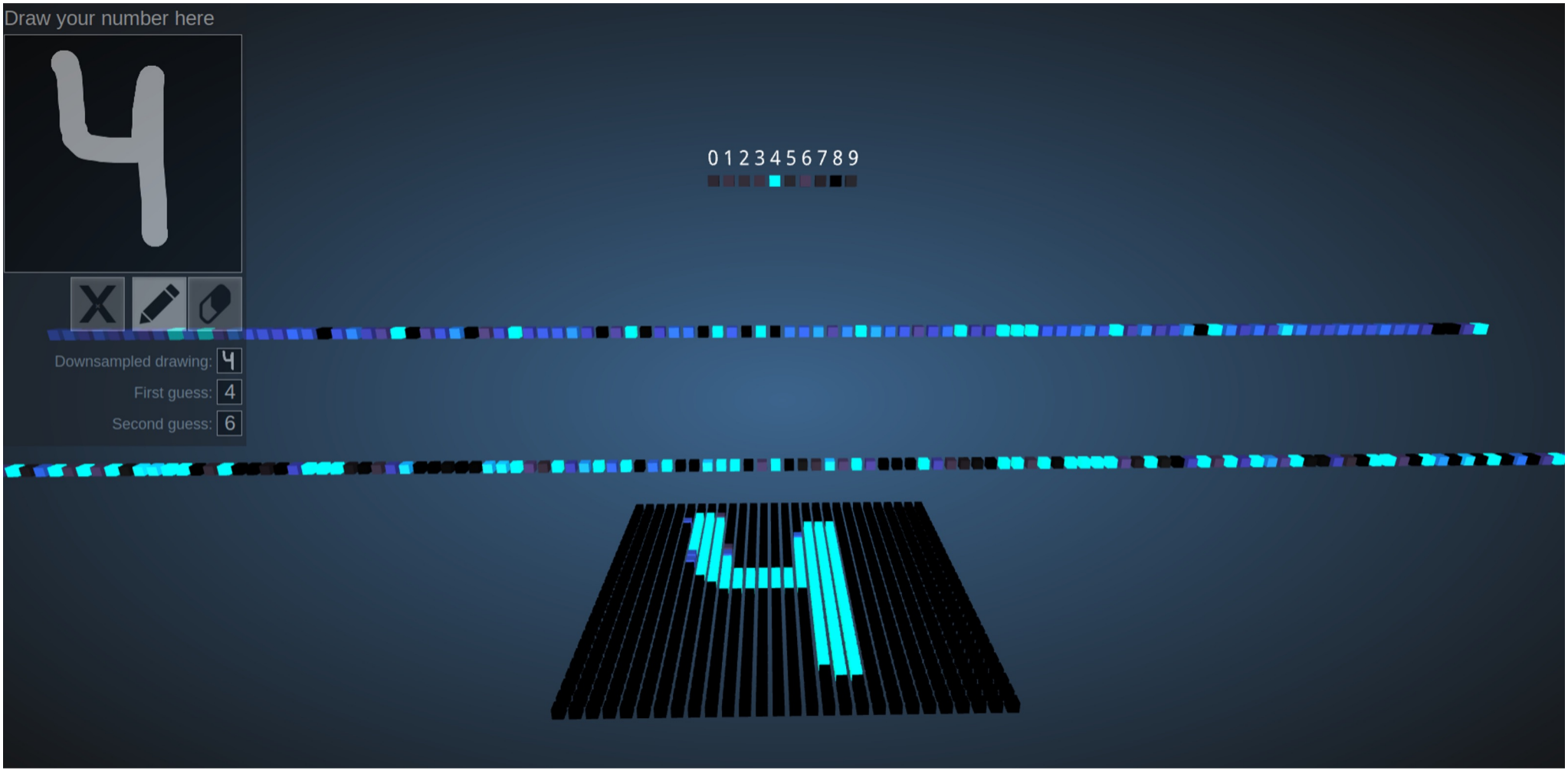
https://adamharley.com/nn_vis/mlp/2d.html



Training a Neural Network

Training a Neural Network

- The first thing we need to do is to "select" an architecture.
- **Input units:** dimensionality of the problem (features x)
- **Output units:** Number of classes
- **Hidden units** (per layer)

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Training a Neural Network

- **Hidden units** (per layer)**:**
  - Usually, the more, the better
  - Good start: a number close to the number of input
  - Default: 1 hidden layer. If you have >1 hidden layer, then it is interesting that you have the **same number of units in every hidden layer**.

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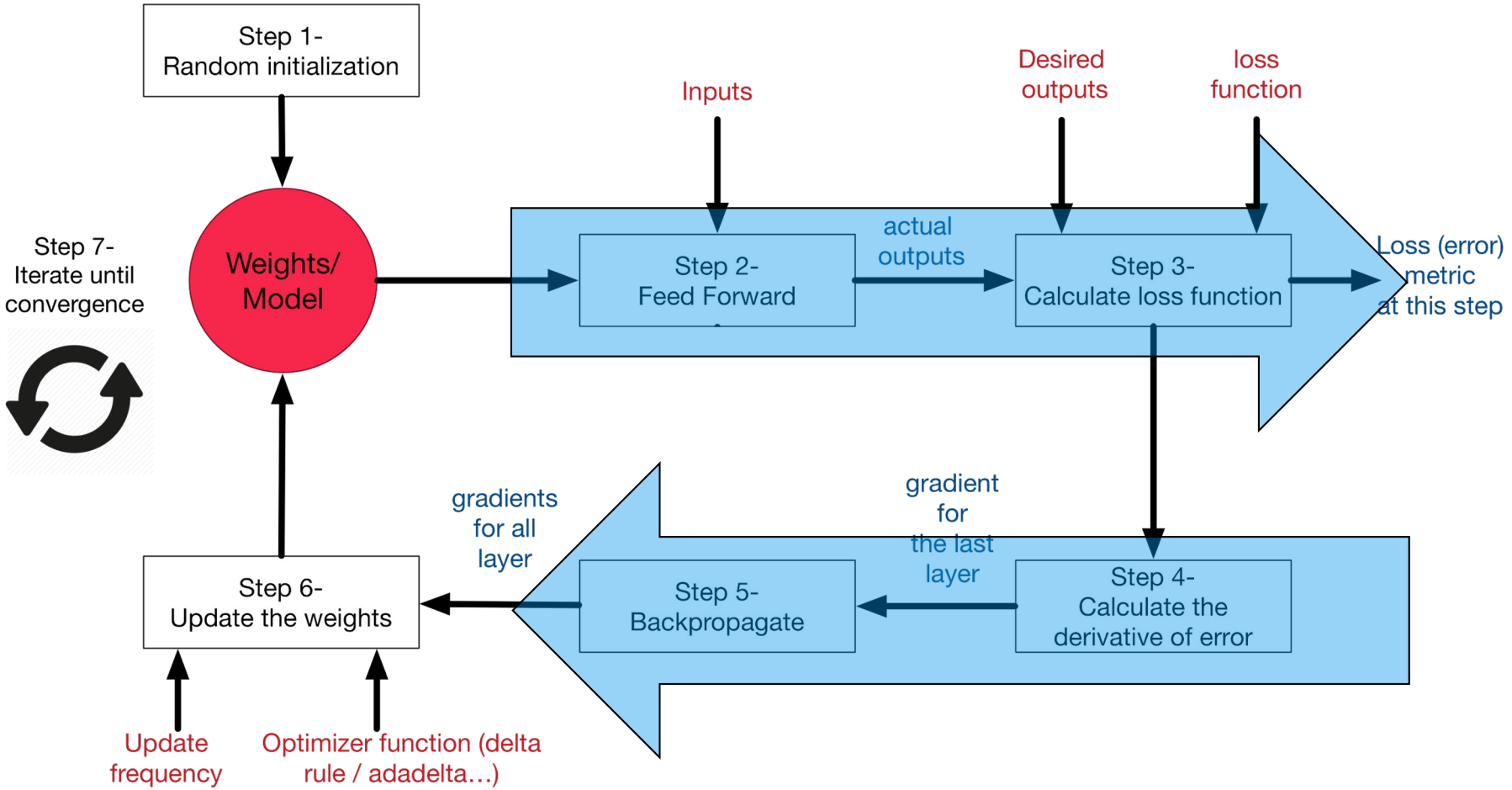
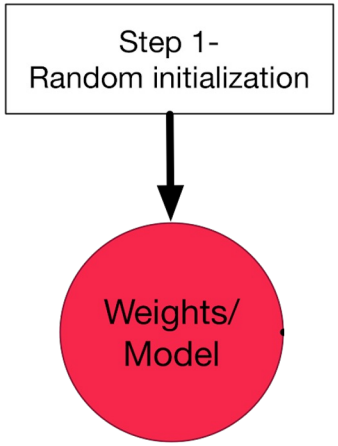
Training a Neural Network



Training a Neural Network



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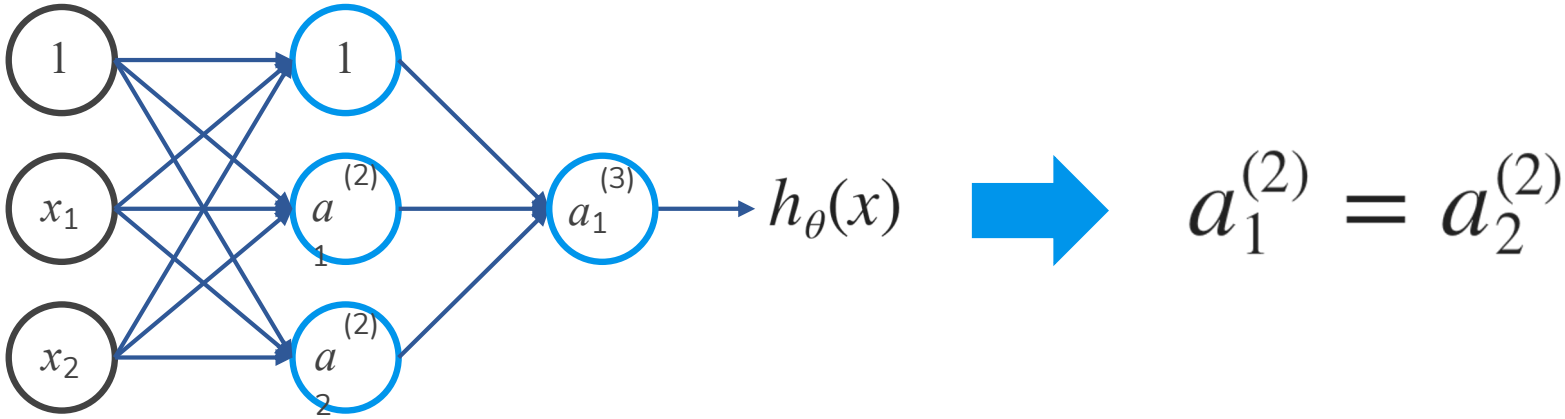
Zero Initialization

Symmetric Weights



$$a_1^{(2)} = a_2^{(2)}$$

After each update, parameters corresponding to inputs going into each of two hidden units are identical.

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Symmetric Breaking

- We must initialize $\boldsymbol{\Theta}$ to a **random value** in $[-\varepsilon, \varepsilon]$ (i.e. $[-\varepsilon \leq \boldsymbol{\Theta} \leq \varepsilon]$)

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Today's Initialization

- Xavier initialization [Glorot & Bengio, 2010]: "Understanding the difficulty of training deep feedforward neural networks", http://proceedings.mlr.press/v9/glorot10a/glorot10a.pdf

```
W = np.random.randn(n)*sqrt(2.0/n)
```

- He initialization [He et al., 2015]: "Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification" https://arxiv.org/pdf/1502.01852

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Today's Initialization

- Xavier initialization [Glorot & Bengio, 2010]:
  n = input + output

- He initialization [He et al., 2015]:
  n = input

```
W = np.random.randn(n)*sqrt(2.0/n)
```

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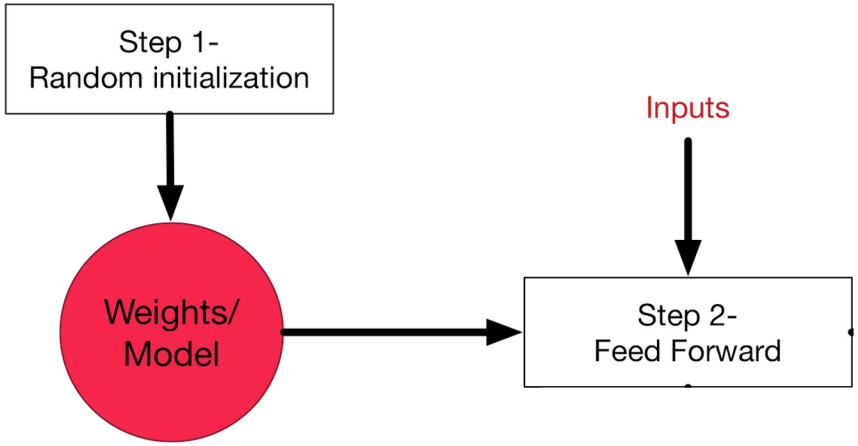
Training a Neural Network



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Forward Propagation

Given one training example (x, y):

$$a^{(1)} = x$$

$$z^{(2)} = \Theta^{(1)} a^{(1)}$$

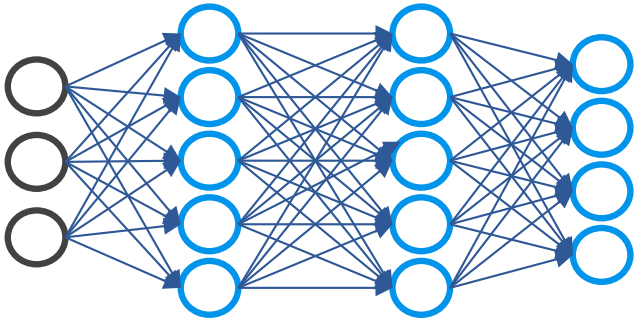
$$a^{(2)} = g(z^{(2)}) \quad (\text{add } a_0^{(2)})$$

$$z^{(3)} = \Theta^{(2)} a^{(2)}$$

$$a^{(3)} = g(z^{(3)}) \quad (\text{add } a_0^{(3)})$$

$$z^{(4)} = \Theta^{(3)} a^{(3)}$$

$$a^{(4)} = h_\Theta(x) = g(z^{(4)})$$



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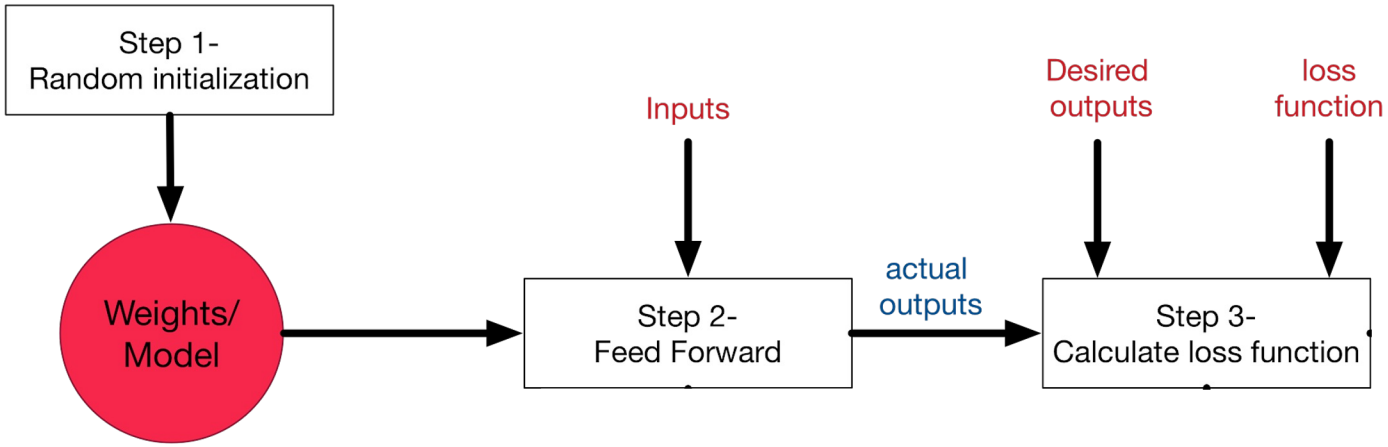
Training a Neural Network



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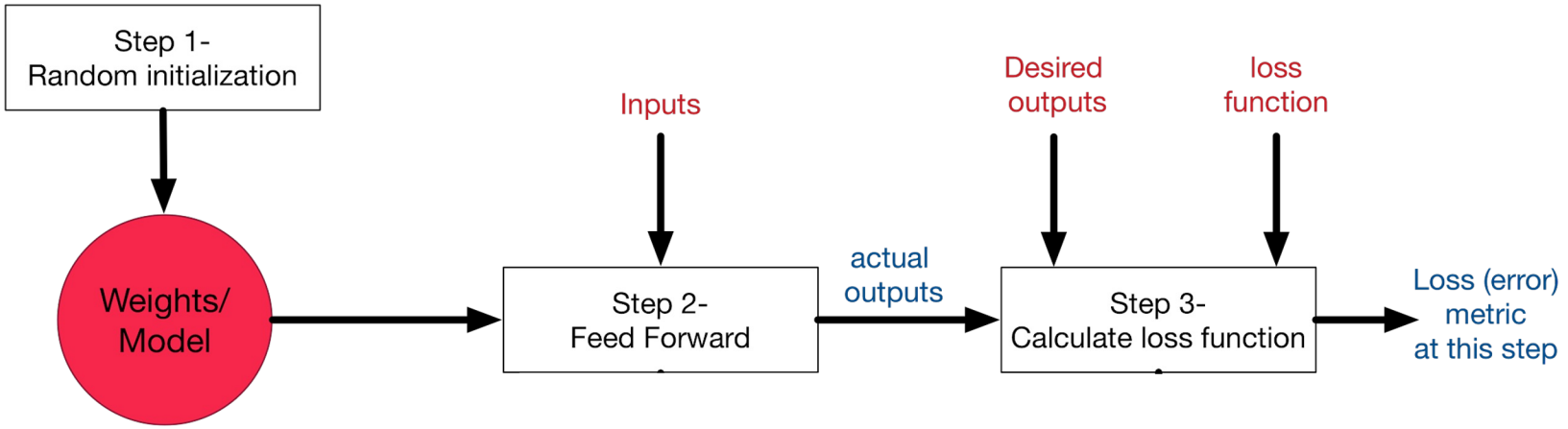
Training a Neural Network



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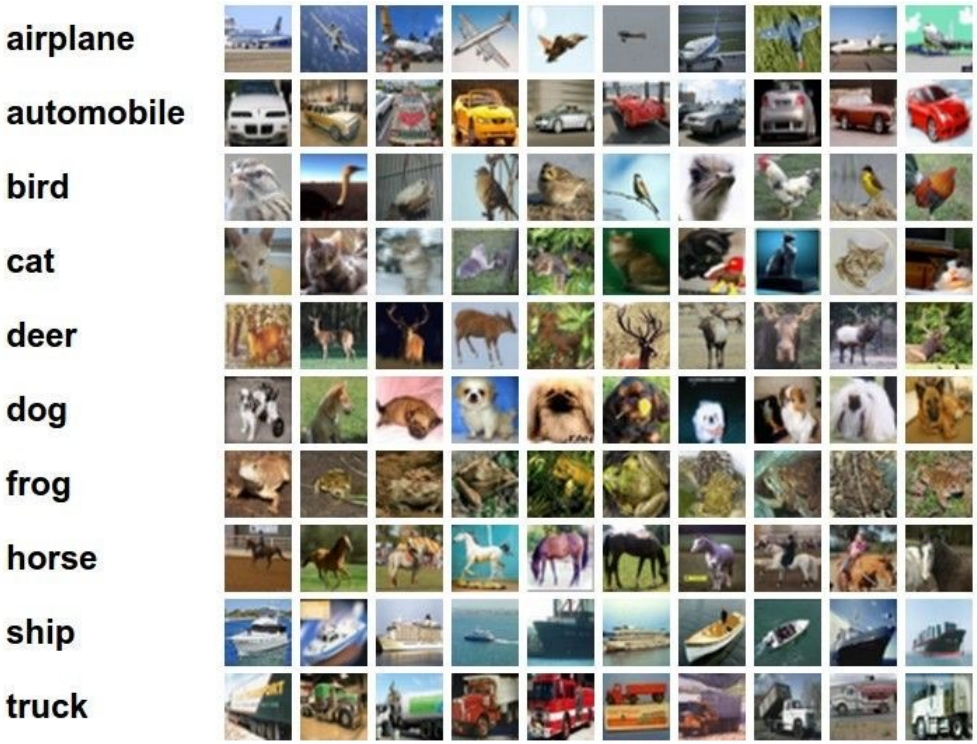
[Loss Function] How do we train deep neural networks?

- The goal is to find such a set of weights that allow the activations/outputs to match the desired output: $f(\boldsymbol{\Theta}, \mathbf{x}_i) \sim y_i$
- Unfortunately, no closed-form solution for weights $\boldsymbol{\Theta}$, but we can express our objective.
- We want to *minimize a* ***loss function*** (a function of the weights in the network), we'll do so iteratively.
- For now, let's simplify and assume there's a single layer of weights in the network.

Classification goal



Example dataset: **CIFAR-10**

10 labels

50,000 training images
each image is **32x32x3**

10,000 test images

Classification scores

$$f(x, \Theta) = \Theta x$$

f(**x**,Θ)

10 numbers, indicating class scores

[32x32x3]
array of numbers 0...1
(3072 numbers total)

Linear classifier

$f(x, \Theta) = \Theta x$ (+b)

3072x1

10x1

10x1

10x3072

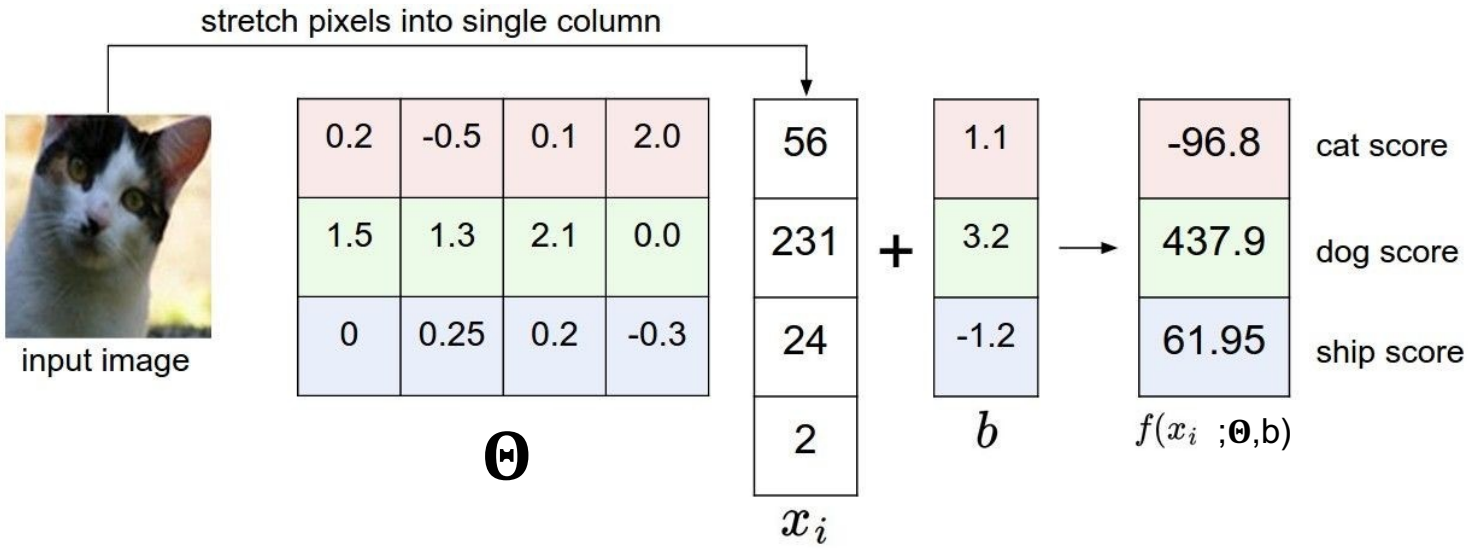
10 numbers, indicating class scores

[32x32x3]
array of numbers 0...1

parameters, or “weights”

Linear classifier

Example with an image with 4 pixels, and 3 classes (cat/dog/ship)



Linear classifier

Going forward: Loss function/Optimization



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

TODO:

1. Define a **loss function** that quantifies our unhappiness with the scores across the training data.

2. Come up with a way of efficiently finding the parameters that minimize the loss function **(optimization)**

Linear classifier

Suppose: 3 training examples, 3 classes. With some Θ. The scores $f(x,\Theta)= \Theta x$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

Adapted from Andrej Karpathy

Linear classifier: Hinge loss

Suppose: 3 training examples, 3 classes. With some W the scores $f(x,\Theta)= \Theta x$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

Hinge loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s =$ $f(x,\Theta)$

the loss has the form:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

Want: $s_{y_i} >= s_j + 1$, for $j != y_i$
i.e. $s_j - s_{y_i} + 1 <= 0$

If true, loss is 0
If false, loss is magnitude of violation

Adapted from Andrej Karpathy

Linear classifier: Hinge loss

Suppose: 3 training examples, 3 classes. With some W the scores $f(x,\Theta)= \Theta x$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9		

Hinge loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s =$ $f(x,\Theta)$

the loss has the form:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

= max(0, 5.1 - 3.2 + 1)
+max(0, -1.7 - 3.2 + 1)
= max(0, 2.9) + max(0, -3.9)
= 2.9 + 0
= 2.9

Linear classifier: Hinge loss

Suppose: 3 training examples, 3 classes. With some W the scores $f(x,\Theta)= \Theta x$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9	0	

Hinge loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s =$ $f(x,\Theta)$

the loss has the form:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

= max(0, 1.3 - 4.9 + 1)
+max(0, 2.0 - 4.9 + 1)
= max(0, -2.6) + max(0, -1.9)
= 0 + 0
= 0

Adapted from Andrej Karpathy

Linear classifier: Hinge loss

Suppose: 3 training examples, 3 classes. With some W the scores f(x,Θ)= Θx are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9	0	12.9

Adapted from Andrej Karpathy

Hinge loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s =$ f(x,Θ)

the loss has the form:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

= max(0, 2.2 - (-3.1) + 1)
+max(0, 2.5 - (-3.1) + 1)
= max(0, 5.3 + 1) + max(0, 5.6 + 1)
= 6.3 + 6.6
= 12.9

Linear classifier: Hinge loss

Suppose: 3 training examples, 3 classes. With some W the scores f(x,Θ)= Θx are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9	0	12.9

Hinge loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s =$ f(x,Θ)

the loss has the form:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

and the full training loss is the **mean over all examples in the training data**:

$$L = \frac{1}{N} \sum_{i=1}^{N} L_i$$

L = (2.9 + 0 + 12.9)/3
= 15.8 / 3 = **5.3**

Adapted from Andrej Karpathy

Linear classifier: Hinge loss

$$f(x, \Theta) = \Theta x$$

$$L = \frac{1}{N} \sum_{i=1}^{N} \sum_{j \neq y_i} \max(0, f(x_i ; \Theta)_j - f(x_i ; \Theta)_{y_i} + 1)$$

$$L(\Theta) = \frac{1}{N} \sum_{i=1}^{N} L_i(f(x_i, \Theta), y_i)$$

Adapted from Andrej Karpathy

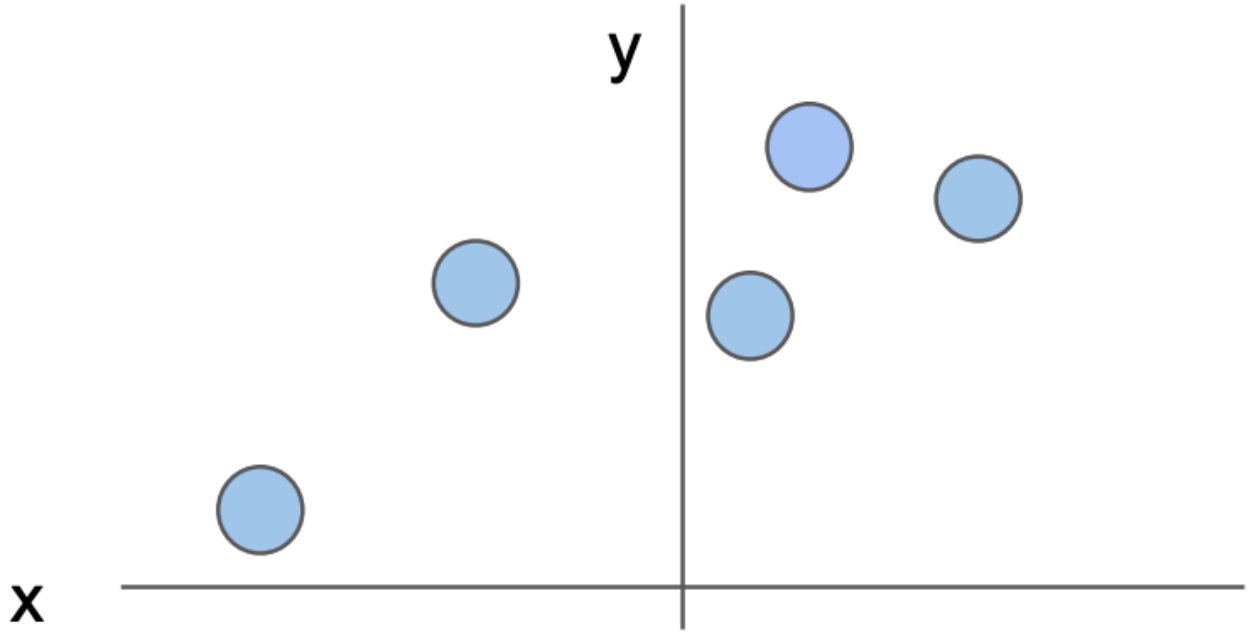
Linear classifier: Regularization

$$L(\theta) = \underbrace{\frac{1}{N}\sum_{i=1}^{N} L_i(f(x_i, \theta), y_i)}$$

Data loss: Model predictions should match training data

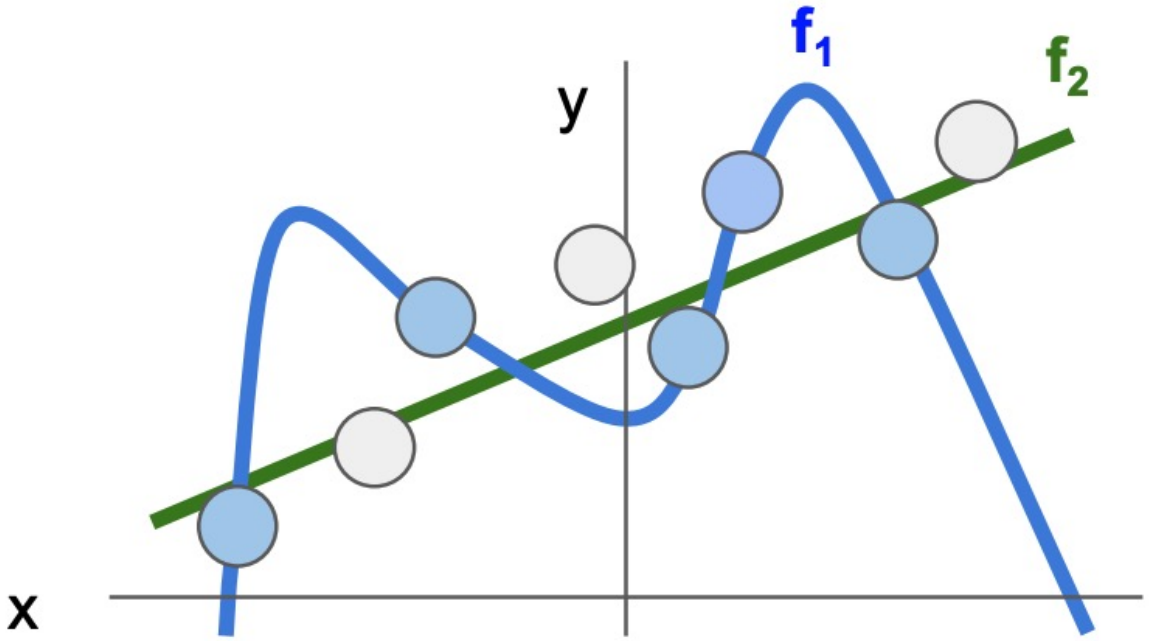
Slide Credit: https://cs231n.stanford.edu/

Linear classifier: Regularization Intuition



Slide Credit: https://cs231n.stanford.edu/

Linear classifier: Regularization – Prefer simpler models



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Linear classifier: Regularization – Overfitting

Slide Credit: Prof. Sandra Avila - UNICAMP

Linear classifier: Regularization

$$L(\Theta) = \underbrace{\frac{1}{N}\sum_{i=1}^{N} L_i(f(x_i, \Theta), y_i)}_{\text{Data loss}} + \underbrace{\lambda R(\Theta)}_{\text{Regularization}}$$

Data loss: Model predictions should match training data

Regularization: Prevent the model from doing *too* well on training data

Slide Credit: https://cs231n.stanford.edu/

Linear classifier: Regularization

$$L(\Theta) = \underbrace{\frac{1}{N}\sum_{i=1}^{N} L_i(f(x_i, \Theta), y_i)}_{\text{Data loss}} + \underbrace{\lambda R(\Theta)}_{\text{Regularization}}$$

Data loss: Model predictions should match training data

Regularization: Prevent the model from doing *too* well on training data

Why Regularization?

- Express preferences over weights
- Make the model simple so it works on test data
- Improve optimization by adding curvature

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Linear classifier: Regularization – Express Preferences

$$x = [1, 1, 1, 1]$$

$$\Theta_1 = [1, 0, 0, 0]$$

$$\Theta_2 = [0.25, 0.25, 0.25, 0.25]$$

$$\Theta_1^T x = \Theta_2^T x = 1$$

L2 Regularization

$$R(\Theta) = \sum_k \sum_l \Theta_{k,l}^2$$

Which of w1 or w2 will the L2 regularizer prefer?

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Linear classifier: Hinge loss

Weight Regularization

λ = regularization strength (hyperparameter)

$$L = \frac{1}{N}\sum_{i=1}^{N}\sum_{j\neq y_i}\max(0, f(x_i; \mathbf{\Theta})_j - f(x_i; \mathbf{\Theta})_{y_i} + 1) + \lambda R(\mathbf{\Theta})$$

In common use:

L2 regularization $R(\mathbf{\Theta}) = \sum_k \sum_l \mathbf{\Theta}_{k,l}^2$

L1 regularization $R(\mathbf{\Theta}) = \sum_k \sum_l |\mathbf{\Theta}_{k,l}|$

Dropout (will see later)

Adapted from Andrej Karpathy

Another loss: Softmax (cross-entropy)

scores = unnormalized log probabilities of the classes

$$P(Y = k|X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$

cat	**3.2**
car	5.1
frog	-1.7

where $s = f(x_i; \boldsymbol{\Theta})$

Want to maximize the log likelihood, or (for a loss function) to minimize the negative log likelihood of the correct class:

$$L_i = -\log P(Y = y_i|X = x_i)$$

maximize

minimize

Another loss: Softmax (cross-entropy)

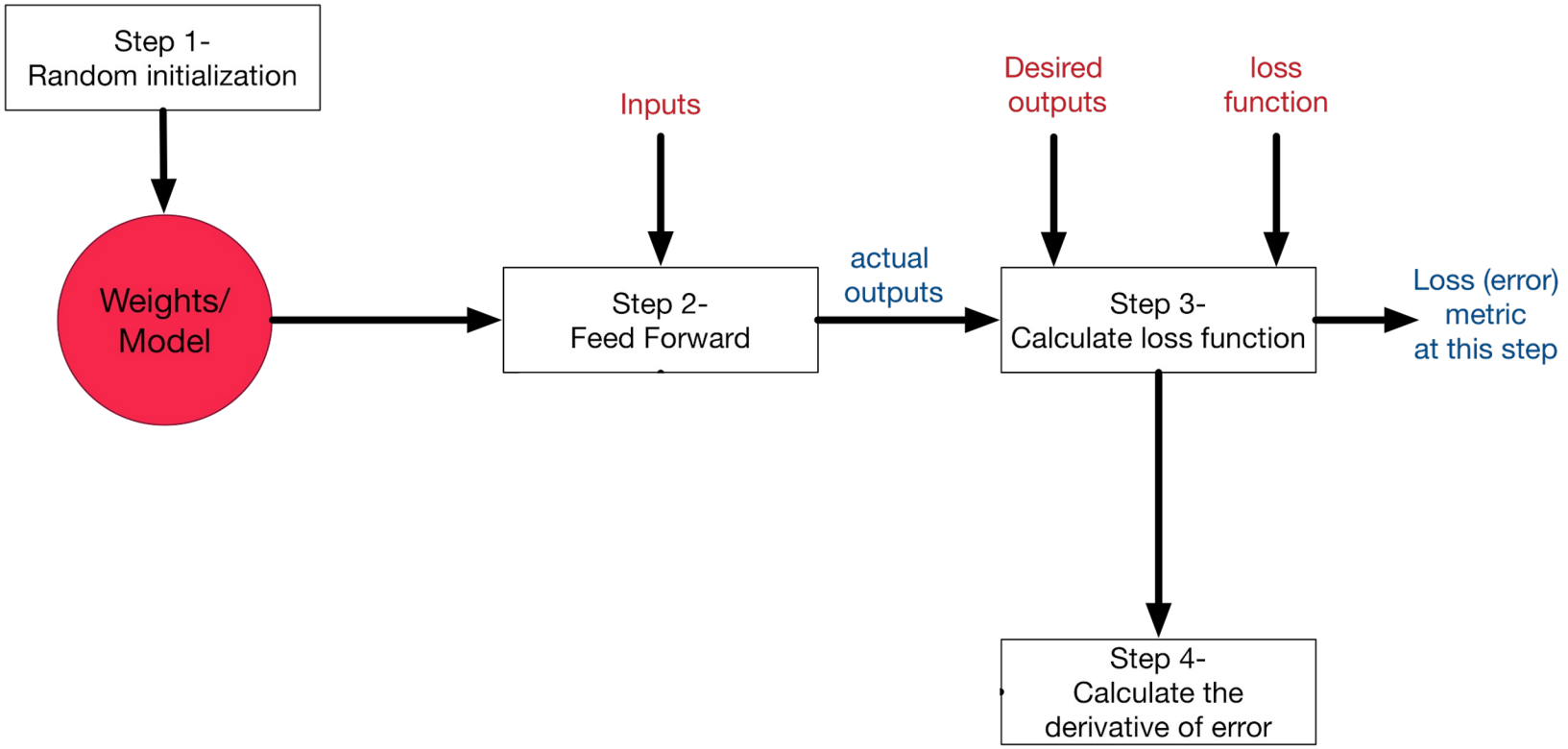
$$L_i = -\log\left(\frac{e^{sy_i}}{\sum_j e^{s_j}}\right)$$

unnormalized probabilities

	unnormalized log probabilities	exp	unnormalized probabilities	normalize	probabilities	
cat	**3.2**		**24.5**		**0.13**	→ L_i = -log(0.13) = **0.89**
car	5.1		164.0		0.87	
frog	-1.7		0.18		0.00	

Adapted from Andrej Karpathy

Training a Neural Network



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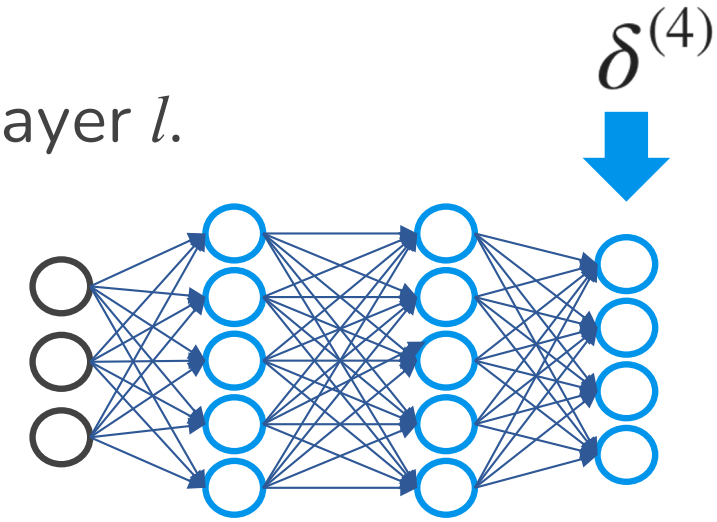
Gradient Computation: Backpropagation Algorithm

Intuition: $\delta_j^{(l)} =$ "error" of node j in layer l.

For each output unit (layer $L = 4$)

$$\delta_j^{(4)} = a_j^{(4)} - y_j$$

$$(h_\Theta(x))_j$$



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Gradient Computation: Backpropagation Algorithm

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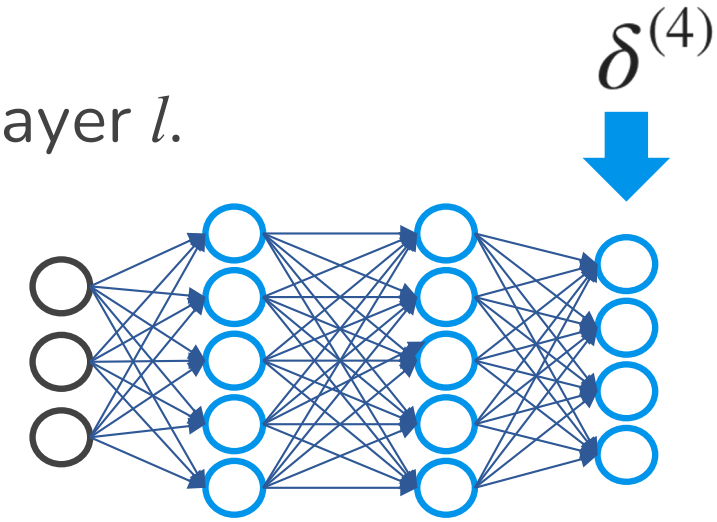

For each output unit (layer $L = 4$)

$$\delta_j^{(4)} = a_j^{(4)} - y_j$$

Vectorizing it, we have:

$$\delta^{(4)} = a^{(4)} - y$$

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Mentimeter

Given the mountain, select the minimum altitude

NM

Menti

Min_loss

Choose a slide to present

How to minimize the loss function?

How to minimize the loss function?

In 1-dimension, the derivative of a function is:

$$\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

f: loss function
x: weights **Θ**
h: small value

In multiple dimensions, the **gradient** is the vector of (partial derivatives):

That is, for $f: \mathbf{R}^n \to \mathbf{R}$, its gradient $\nabla f: \mathbf{R}^n \to \mathbf{R}^n$ is defined at the point $\mathrm{p} = (x_1, \ldots, x_n)$ in *n*-dimensional space as the vector:[b]

$$\nabla f(p) = \begin{bmatrix} \frac{\partial f}{\partial x_1}(p) \\ \vdots \\ \frac{\partial f}{\partial x_n}(p) \end{bmatrix}.$$

The nabla symbol ∇, written as an upside-down triangle and pronounced "del", denotes the vector differential operator.

Adapted from Andrej Karpathy, definition/equation from https://en.wikipedia.org/wiki/Gradient

Computing the gradient numerically

current Θ:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]
loss 1.25347

gradient dΘ:

[?,
?,
?,
?,
?,
?,
?,
?,
?,…]

Computing the gradient numerically

current Θ:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]
loss 1.25347

Θ + h (first dim)**:**

[0.34 + **0.0001**,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]
loss 1.25322

gradient dΘ:

[?,
?,
?,
?,
?,
?,
?,
?,
?,…]

Computing the gradient numerically

current Θ:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]
loss 1.25347

Θ + h (first dim)**:**

[0.34 + **0.0001**,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]
loss 1.25322

gradient dΘ:

[**-2.5**,
?,
?,

(1.25322 - 1.25347)/0.0001
= -2.5

$$\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

?,
?,…]

Computing the gradient numerically

current θ:	**θ + h** (second dim)**:**	**gradient dθ:**
[0.34, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[0.34, -1.11 + **0.0001**, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[-2.5, ?, ?, ?, ?, ?, ?, ?, ?,…]
loss 1.25347	**loss 1.25353**	

Computing the gradient numerically

current Θ:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]
loss 1.25347

Θ + h (second dim)**:**

[0.34,
-1.11 + **0.0001**,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]
loss 1.25353

gradient dΘ:

[-2.5,
0.6,
?,
?,

(1.25353 - 1.25347)/0.0001
= 0.6

$$\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

?,…]

Computing the gradient numerically

current Θ:	**Θ + h** (third dim)**:**	**gradient dΘ:**
[0.34, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[0.34, -1.11, 0.78 + **0.0001**, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[-2.5, 0.6, ?, ?, ?, ?, ?, ?, ?,…]
loss 1.25347	**loss 1.25347**	

Computing the gradient analytically

The loss is just a function of Θ:

$$L = \frac{1}{N}\sum_{i=1}^{N} L_i + \sum_k \Theta_k^2$$

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

$$s = f(x; \Theta) = \Theta x$$

want $\nabla_\Theta L$

Computing the gradient analytically

The loss is just a function of Θ:

$$L = \frac{1}{N}\sum_{i=1}^{N} L_i + \sum_k \Theta_k^2$$

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

$$s = f(x; \Theta) = \Theta x$$

want $\nabla_\Theta L$

Calculus

$\nabla_\Theta L$ = ...

Computing the gradient analytically

current Θ:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]
loss 1.25347

dΘ = ...
(some function of
data and Θ)

gradient dΘ:

[-2.5,
0.6,
0,
0.2,
0.7,
-0.5,
1.1,
1.3,
-2.1,…]

Computing the gradient analytically

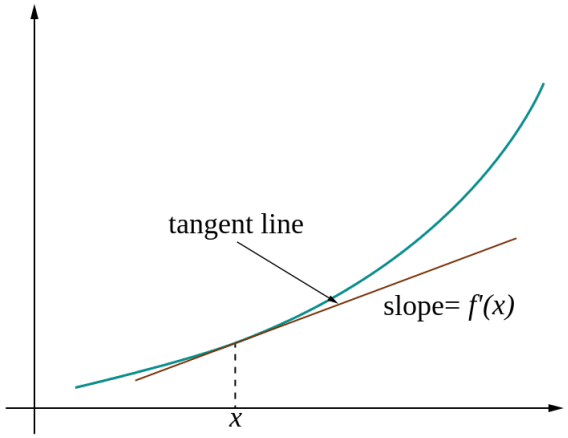
- $f(\mathbf{x}, \boldsymbol{\Theta}) = \text{dot}(\boldsymbol{\Theta}, \mathbf{x}) = \Theta 1 * x1 + \Theta 2 * x2 + \ldots + \Theta D * xD$
- $d\, f(\mathbf{x}, \boldsymbol{\Theta}) / d\, \Theta i = ?$
- $d\, f(\mathbf{x}, \boldsymbol{\Theta}) / d\, \Theta 1 = x1$
- $d\, f(\mathbf{x}, \boldsymbol{\Theta}) / d\, \Theta 2 = x2$

- …

- Gradient of $f(\mathbf{x}, \boldsymbol{\Theta})$ wrt $\boldsymbol{\Theta}$ is [x1 x2 … xD] i.e. $\mathbf{x}$

Loss gradients

- Different notations: $\frac{\partial E_n}{\partial \mathbf{\Theta}_{ji}^{(1)}}$ $\nabla_{\mathbf{\Theta}} L$
- i.e. how does the loss change as a function of the weights
- We want to change weights in a way that makes the loss decrease as fast as possible



Gradient descent

- We'll update weights
- Move in direction opposite to gradient:

$$\Theta^{(\tau+1)} = \Theta^{(\tau)} - \eta \nabla E(\Theta^{(\tau)})$$

Time

Learning rate

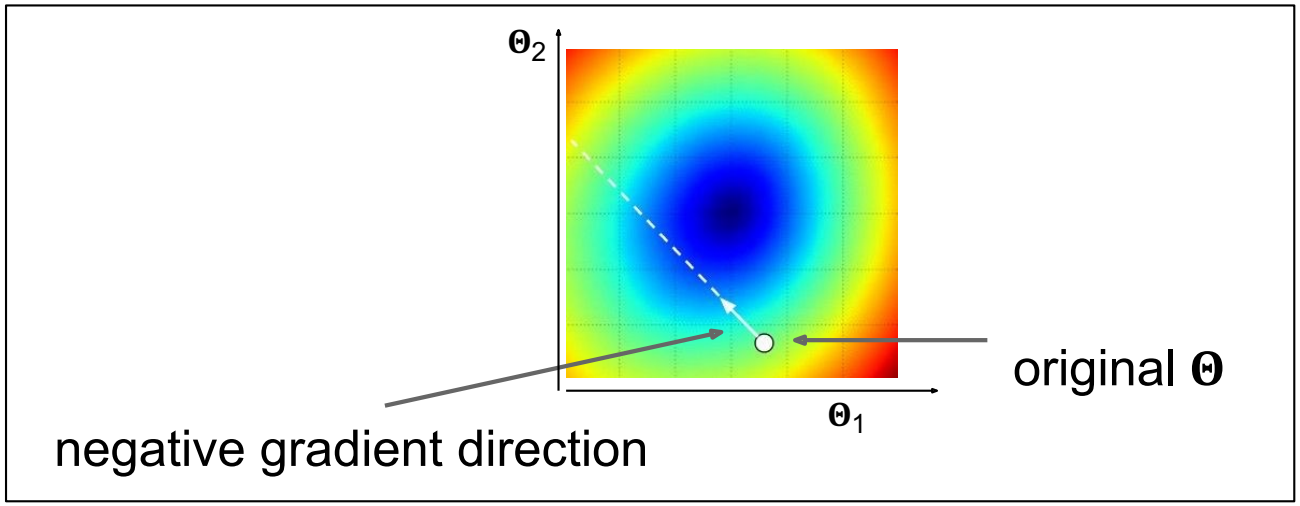
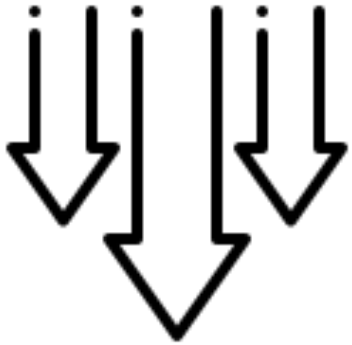


Figure from Andrej Karpathy

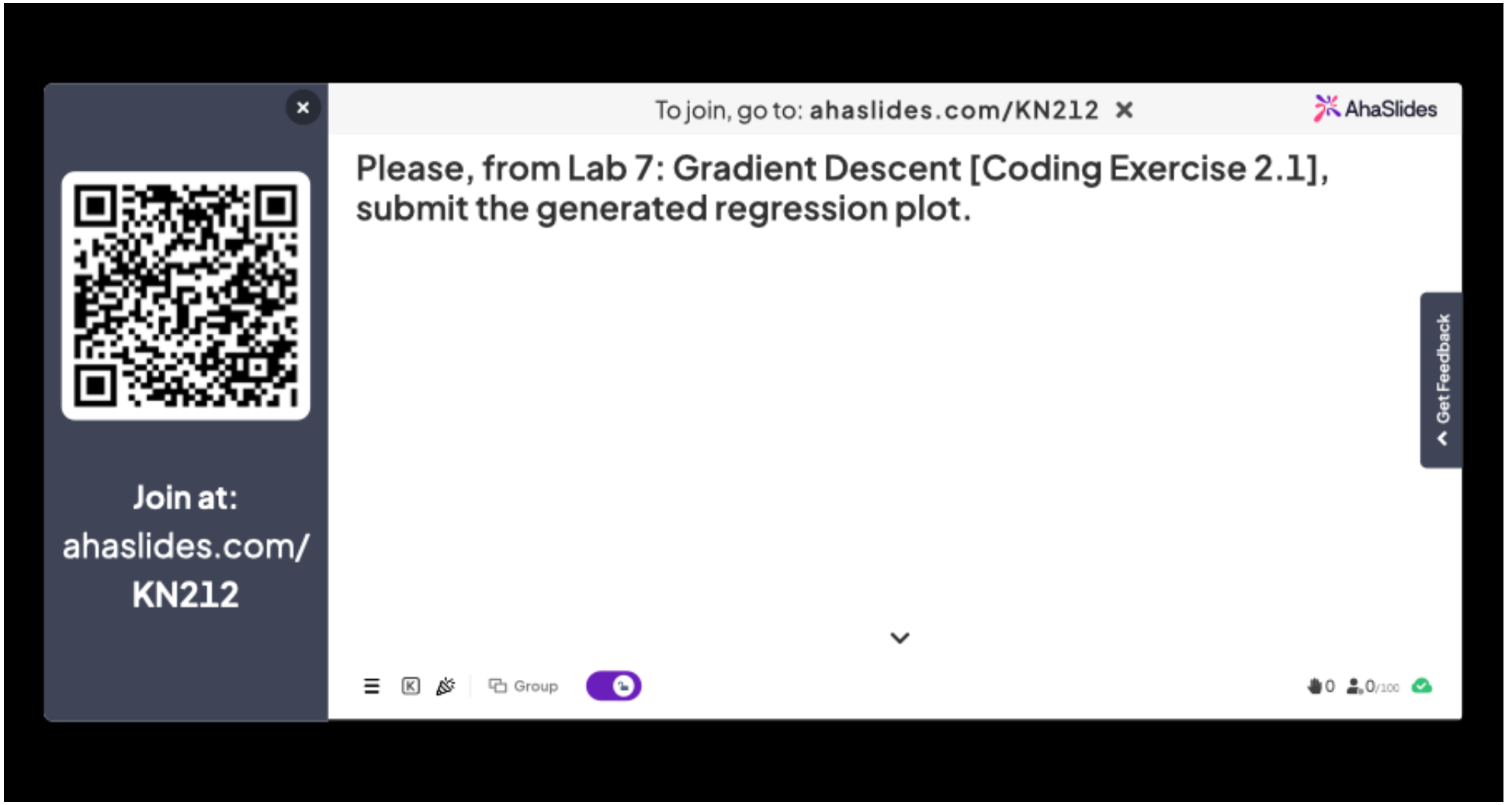
Gradient descent

- Iteratively *subtract* the gradient with respect to the model parameters (Θ)
- I.e. we're moving in a direction opposite to the gradient of the loss
- I.e. we're moving towards *smaller* loss



Lab 7: Gradient Descent

Duration: 10 min


To join, go to: ahaslides.com/KN212
AhaSlides
Please, from Lab 7: Gradient Descent [Coding Exercise 2.1], submit the generated regression plot.
Join at:
ahaslides.com/
KN212
Get Feedback
Group
0
0/100

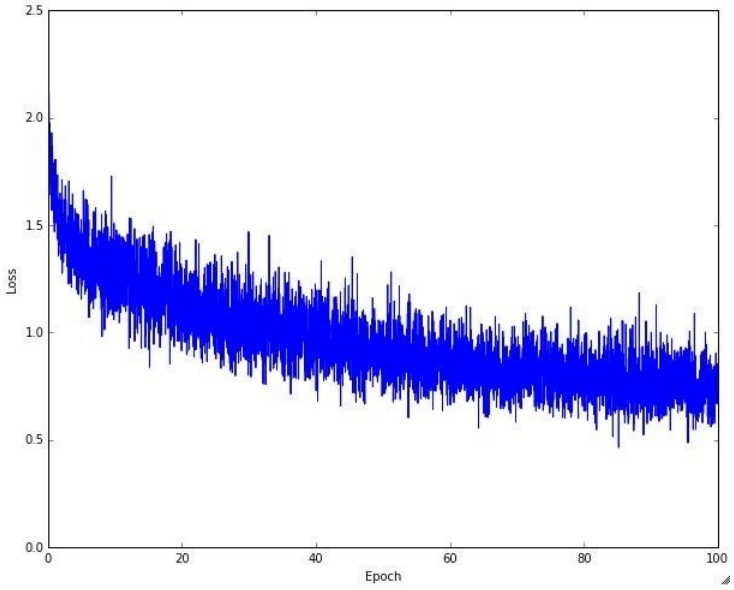
How to compute the loss/gradient?

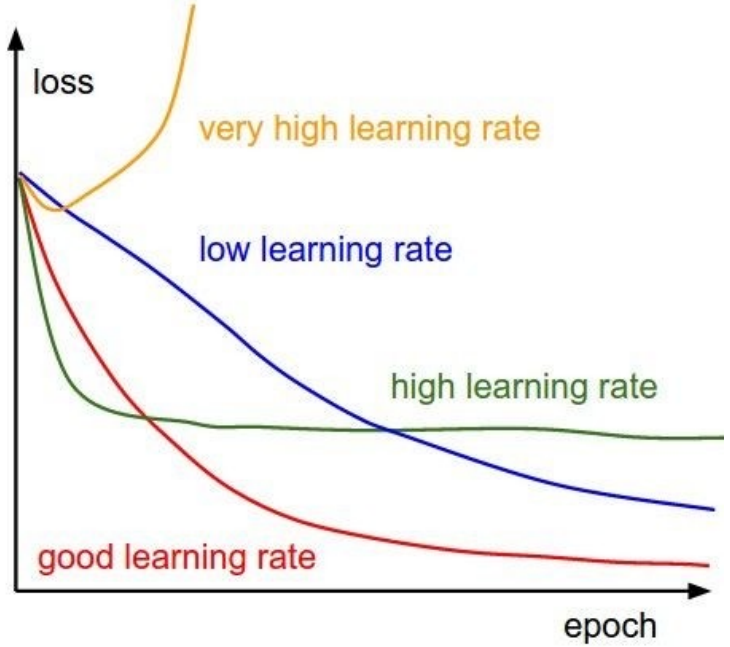
- In classic gradient descent, we compute the gradient from the loss for all training examples

- Mini-batch gradient descent: Only use *some* of the data for each gradient update, cycle through training examples multiple times
  - Each time we've cycled through all of them once is called an 'epoch'
  - Allows faster training (e.g. on GPUs), parallelization
  - Some benefits for learning due to randomness

Learning rate selection

The effects of step size (or “learning rate”)

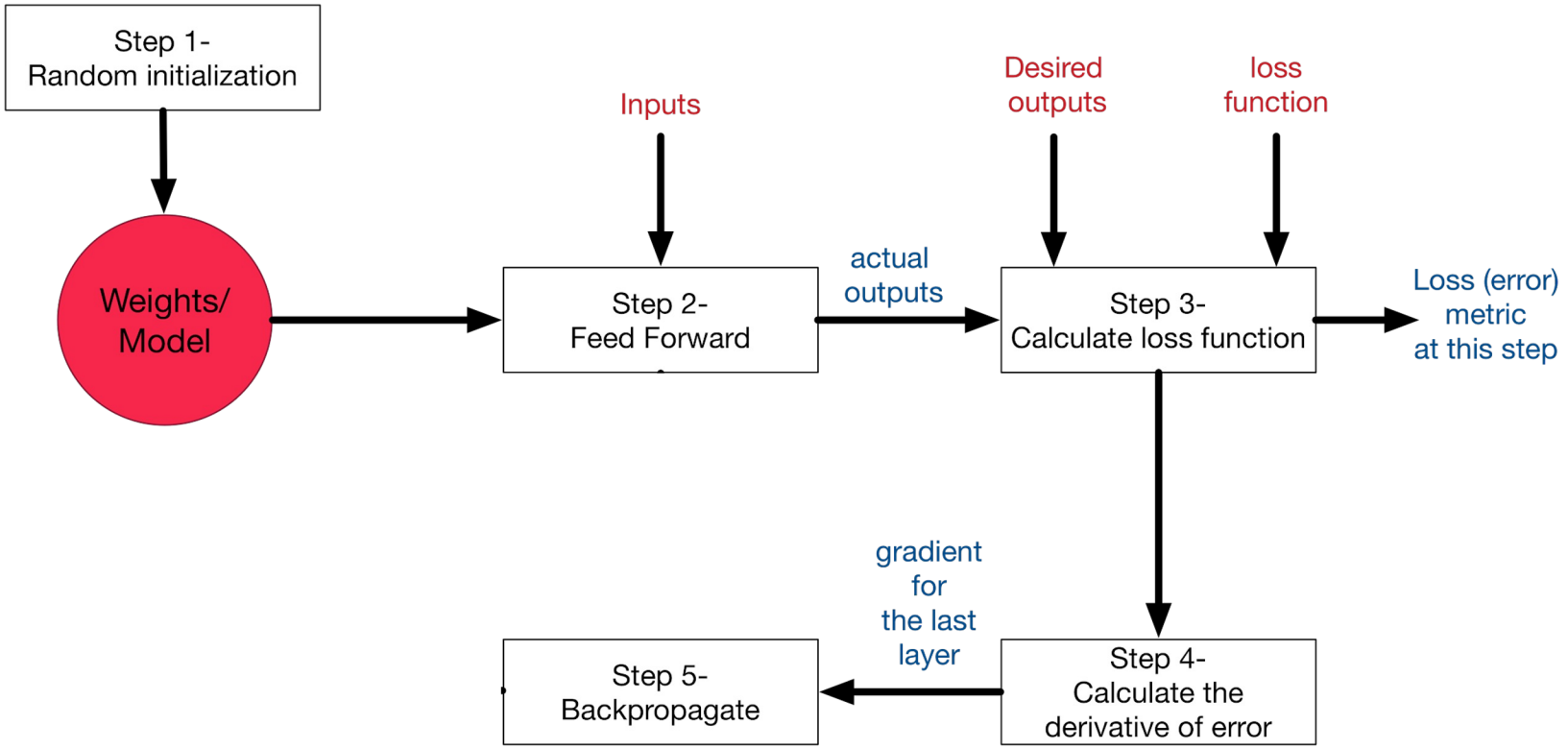




https://www.deeplearning.ai/ai-notes/optimization/

Andrej Karpathy

Training a Neural Network



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Gradient descent in multi-layer nets

- We'll update weights
- Move in direction opposite to gradient:

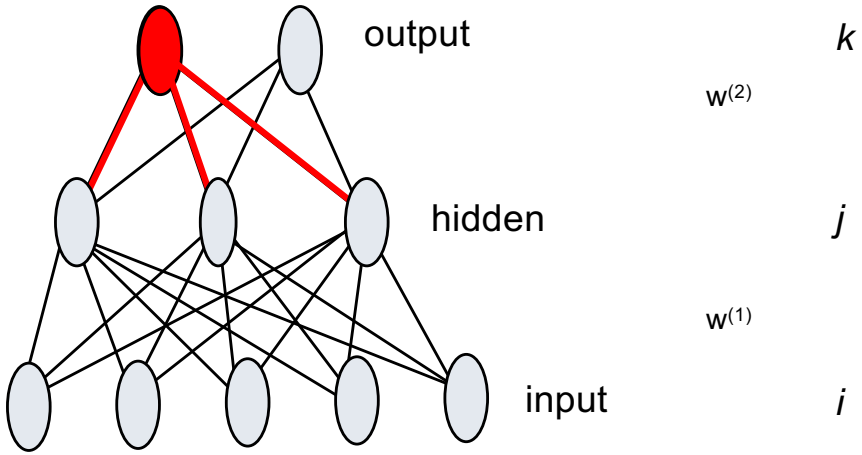
$$\boldsymbol{\Theta}^{(\tau+1)} = \boldsymbol{\Theta}^{(\tau)} - \eta \nabla E(\boldsymbol{\Theta}^{(\tau)})$$

- How to update the weights at all layers?
  - Answer: backpropagation of error from higher layers to lower layers

Backpropagation: Graphic example

- First calculate error of output units and use this to change the top layer of weights.

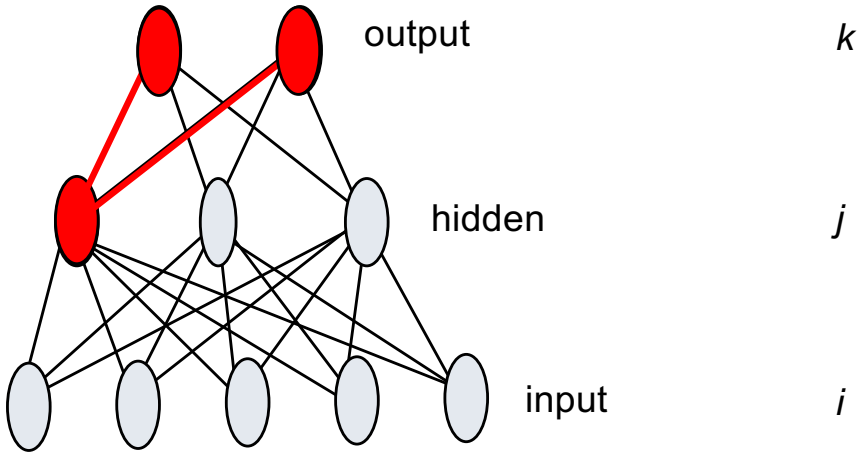
Calculate how to update weights into *j* (update at end of iter)



Adapted from Ray Mooney, equations from Chris Bishop

Backpropagation: Graphic example

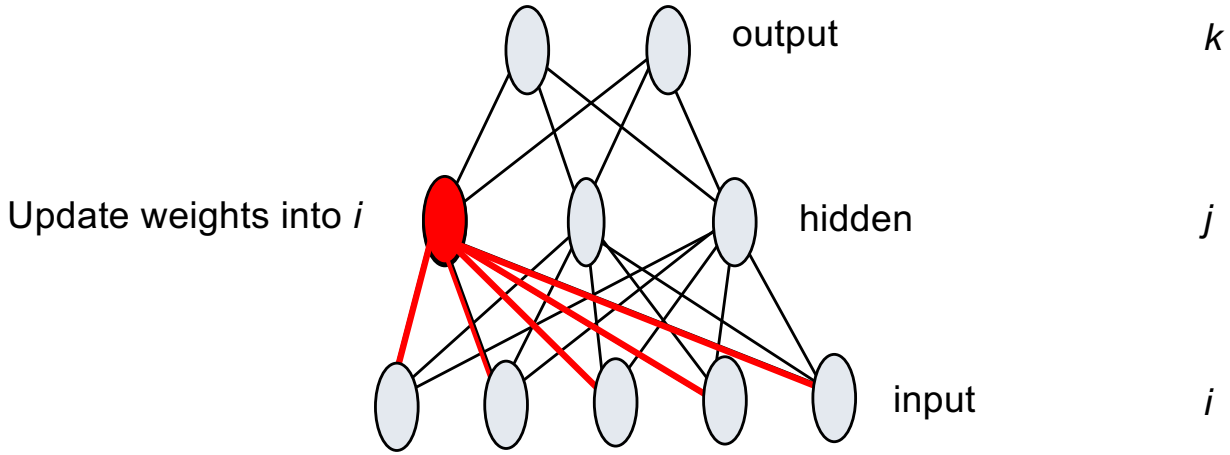
- Next calculate error for hidden units based on errors on the output units it feeds into.



Adapted from Ray Mooney, equations from Chris Bishop

Backpropagation: Graphic example

- Finally update bottom layer of weights based on errors calculated for hidden units.



Adapted from Ray Mooney, equations from Chris Bishop

Backpropagation

A Simple Example

Backpropagation: A Simple Example

$$f(x, y, z) = (x + y)z$$

e.g., $x = -2, y = 5, z = -4$

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Backpropagation: A Simple Example

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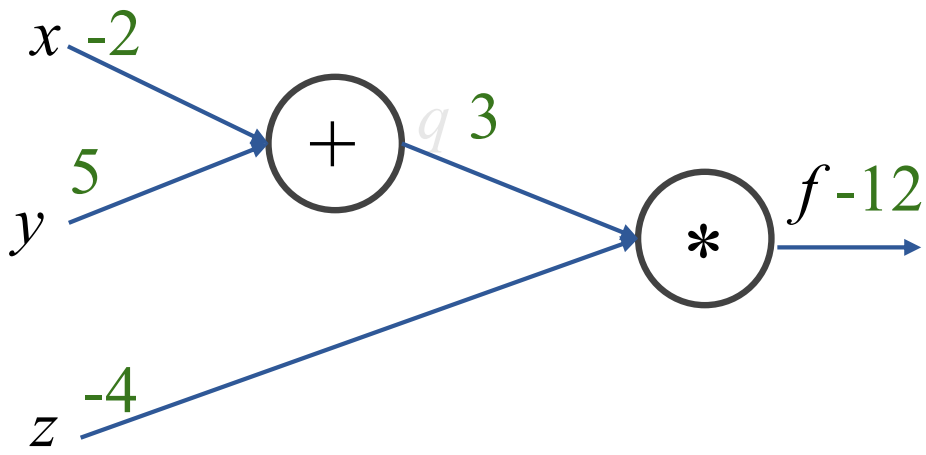

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Backpropagation: A Simple Example

$$f(x, y, z) = (x + y)z$$

e.g., $x = -2, y = 5, z = -4$

$$q = x + y \quad \frac{\partial q}{\partial x} = 1 \quad \frac{\partial q}{\partial y} = 1$$

$$f = qz \quad \frac{\partial f}{\partial q} = z \quad \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$

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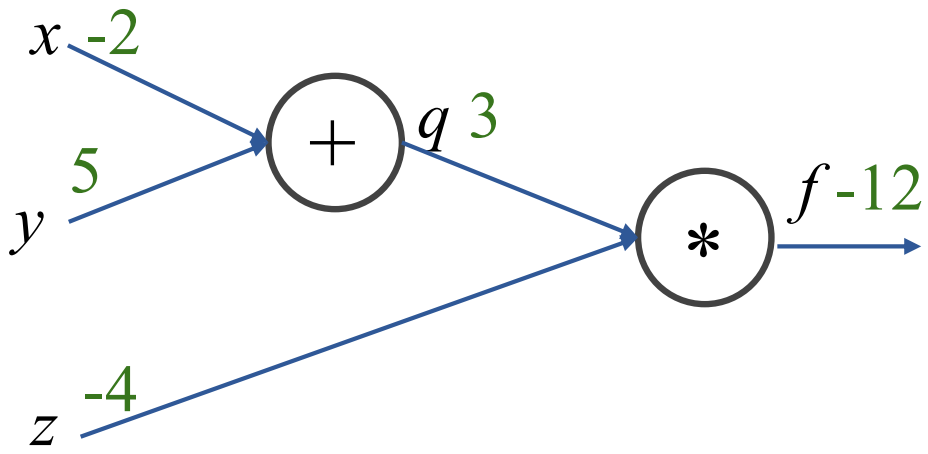

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Backpropagation: A Simple Example

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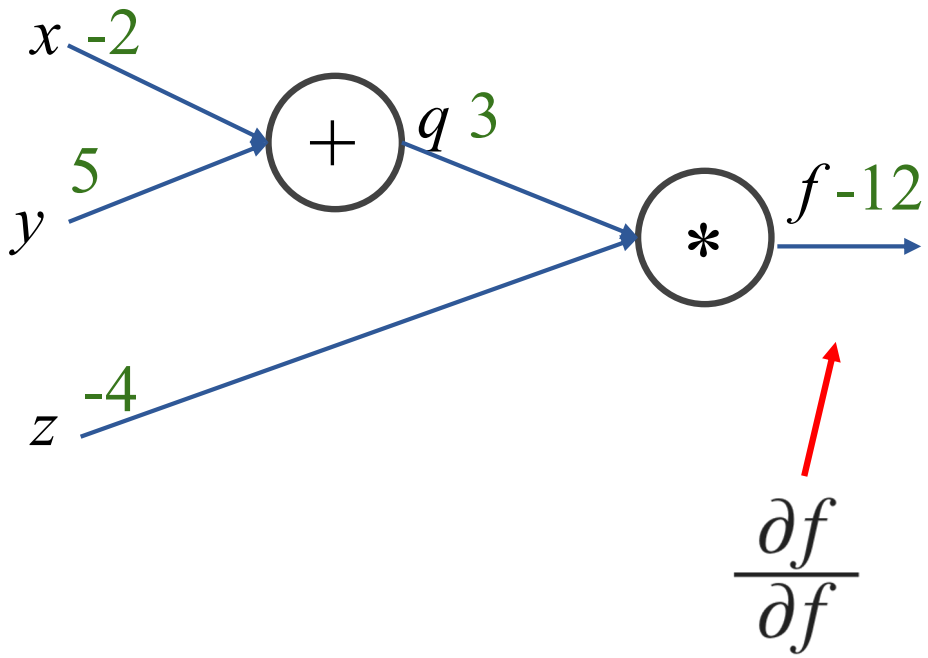

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Backpropagation: A Simple Example

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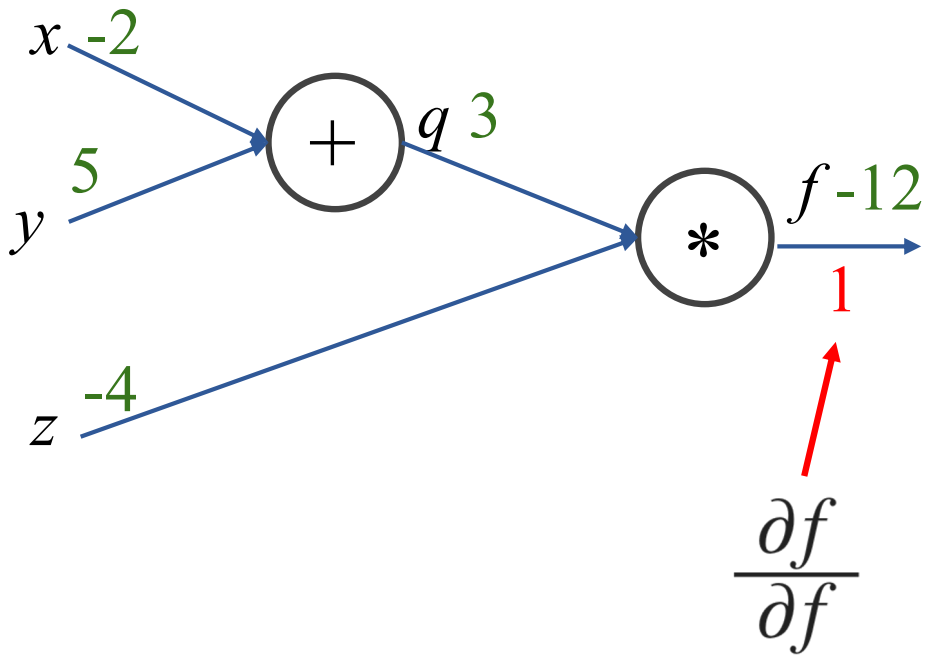
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$

Andrej Karpathy



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Backpropagation: A Simple Example

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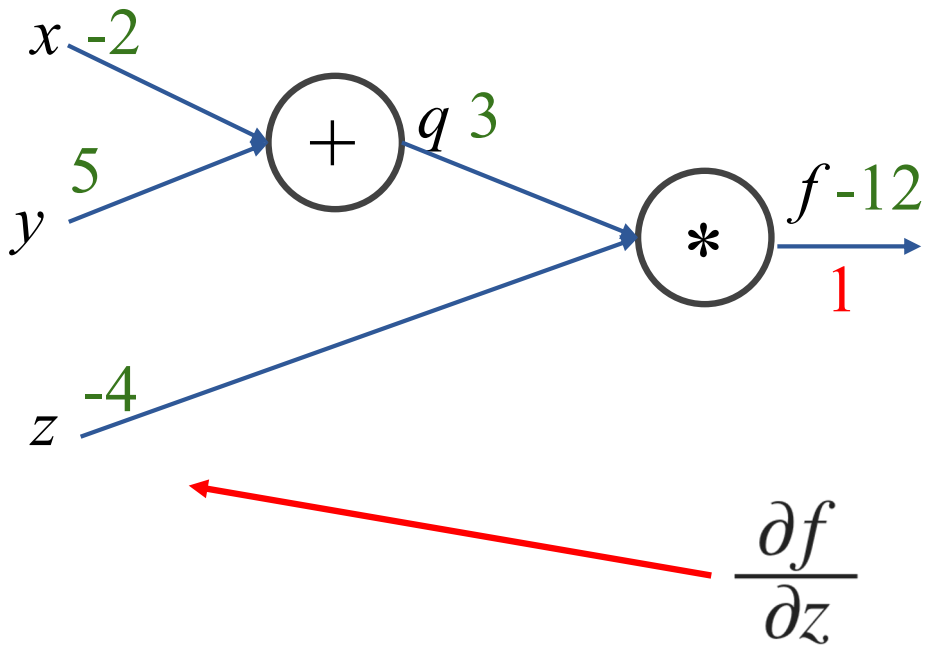
$$f = qz \quad \frac{\partial f}{\partial q} = z \quad \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$

Andrej Karpathy



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$$f(x, y, z) = (x + y)z$$

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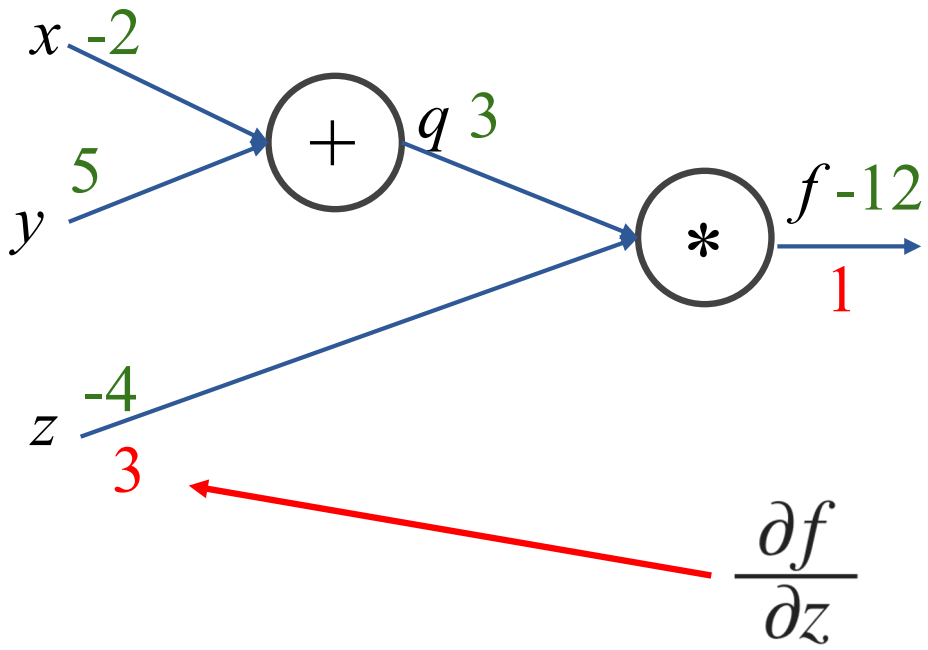
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$

Andrej Karpathy



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Backpropagation: A Simple Example

$f(x, y, z) = (x + y)z$

e.g., $x = -2, y = 5, z = -4$

$$q = x + y \quad \frac{\partial q}{\partial x} = 1 \quad \frac{\partial q}{\partial y} = 1$$

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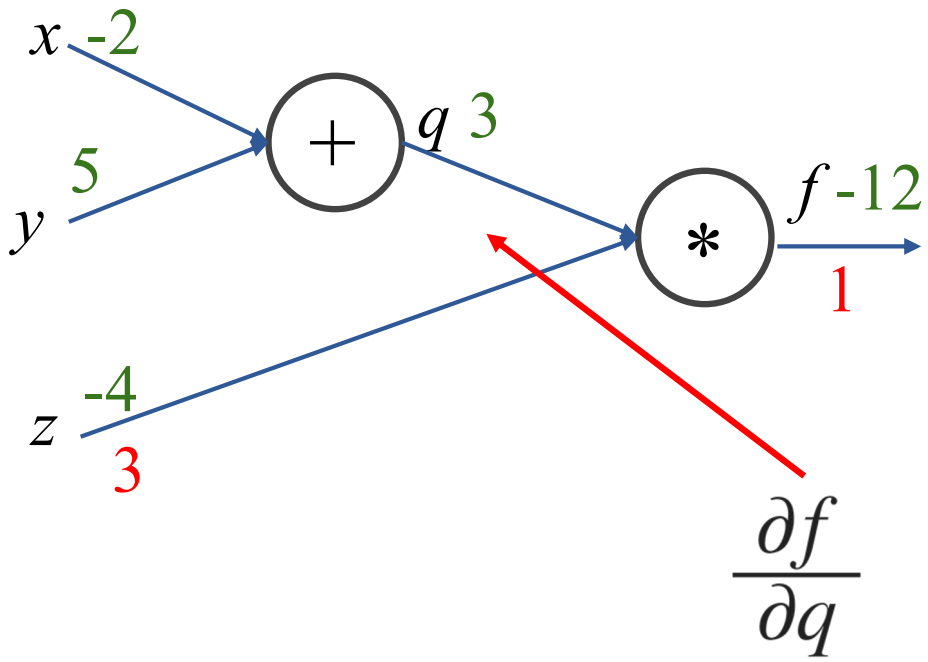

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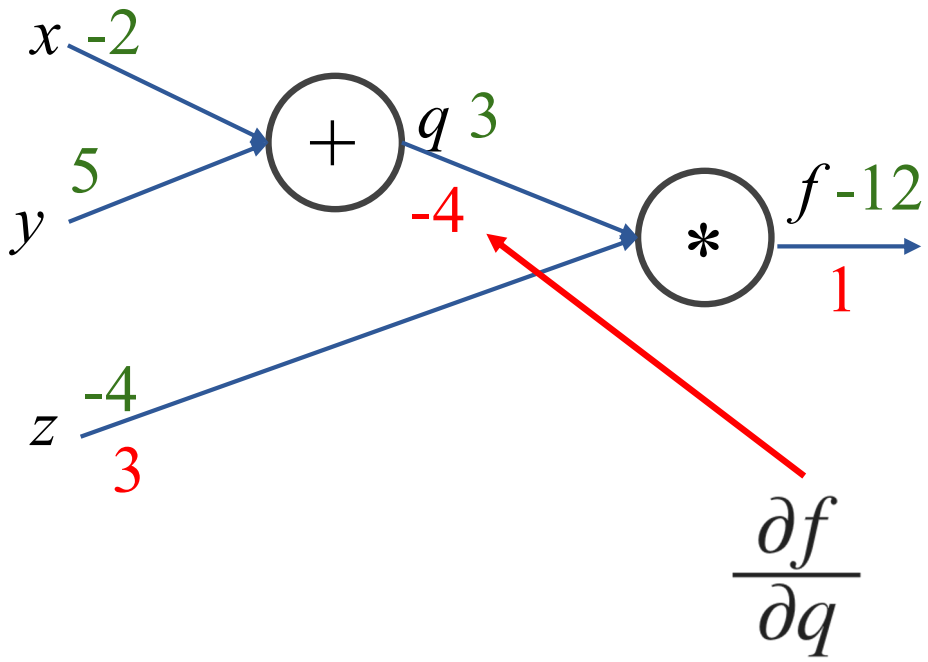

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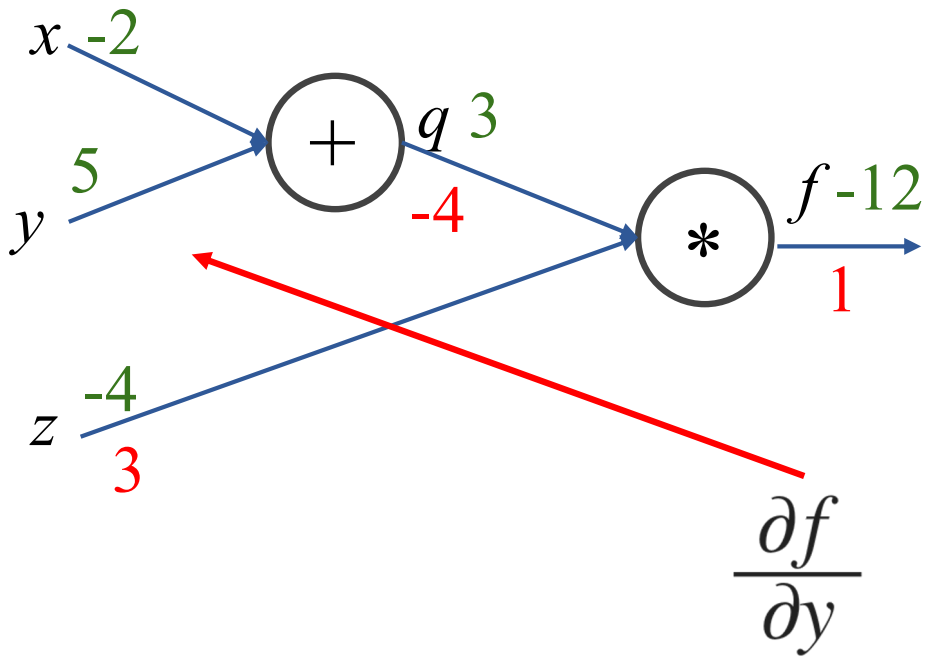

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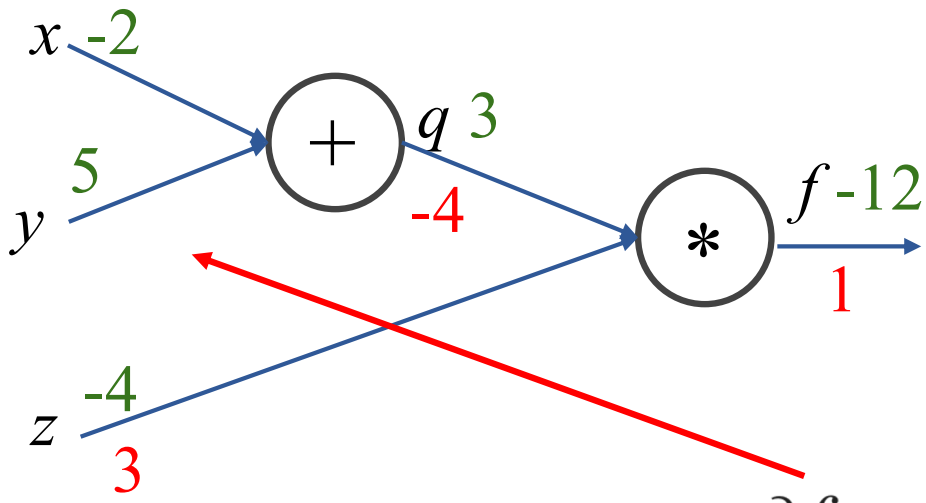

Chain rule

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial y}$$

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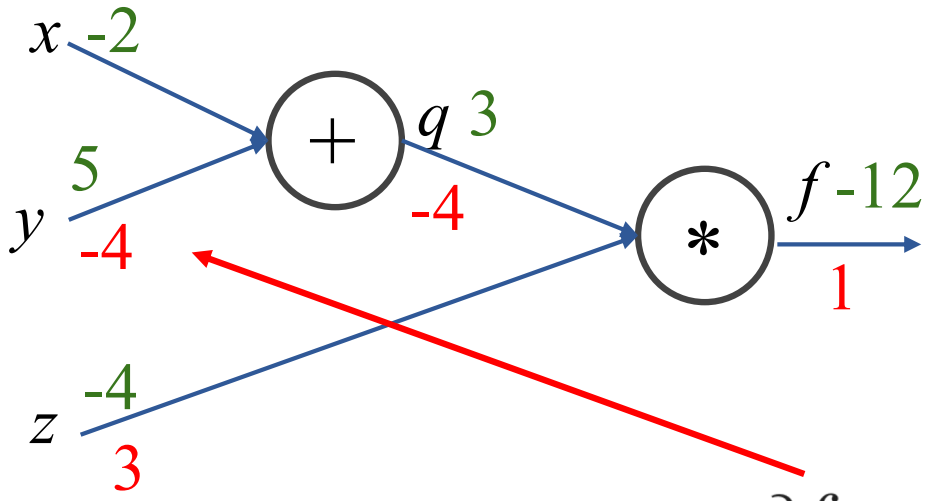

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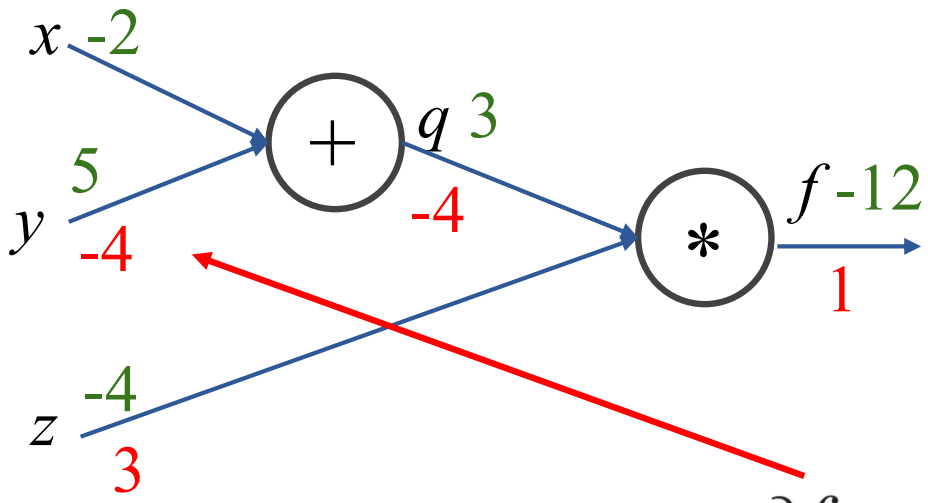

Chain rule

$$\frac{\partial f}{\partial y} = -4 \times 1 = -4$$

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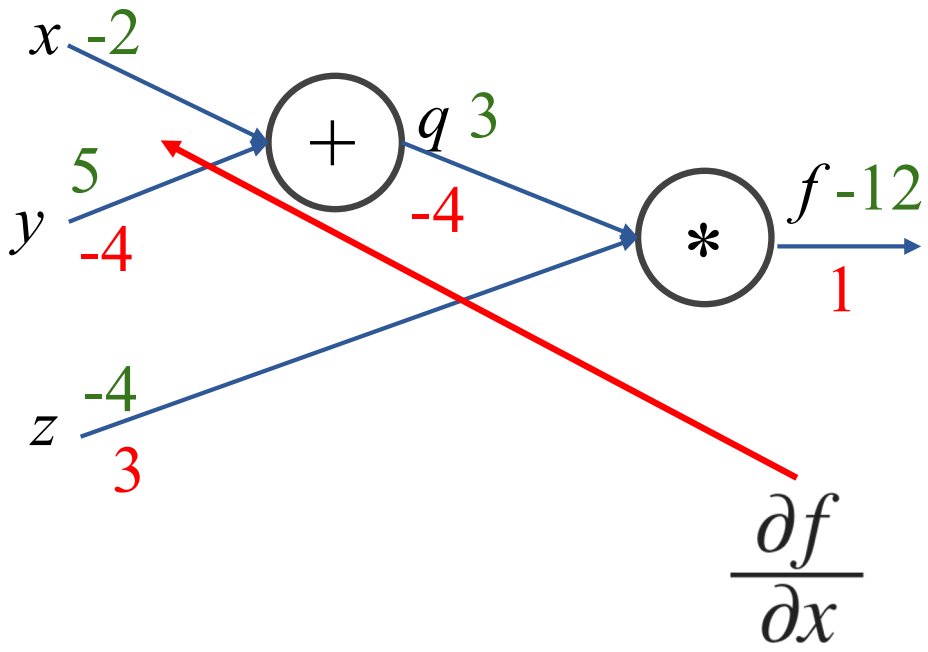

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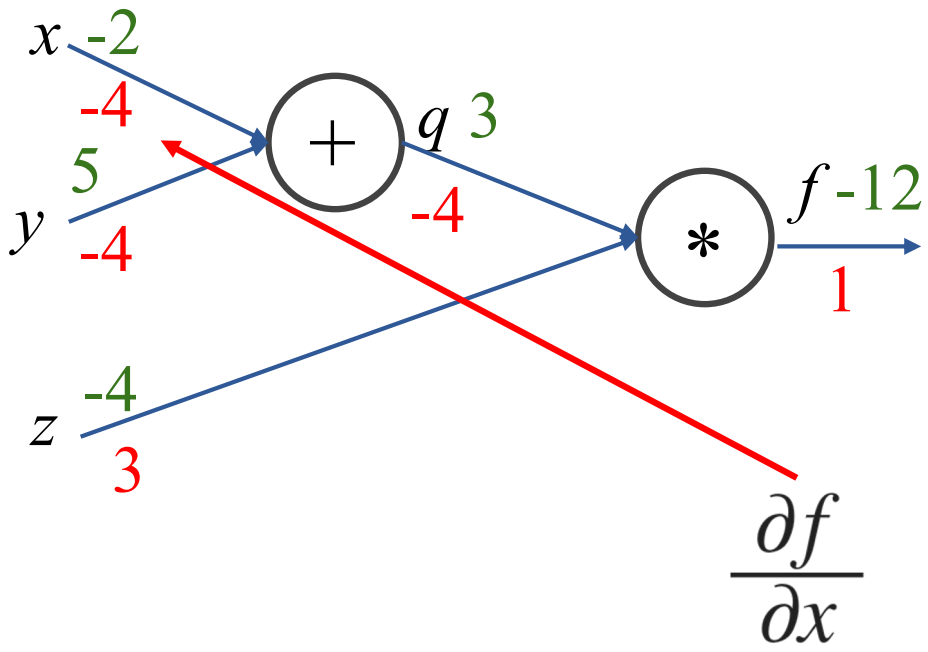

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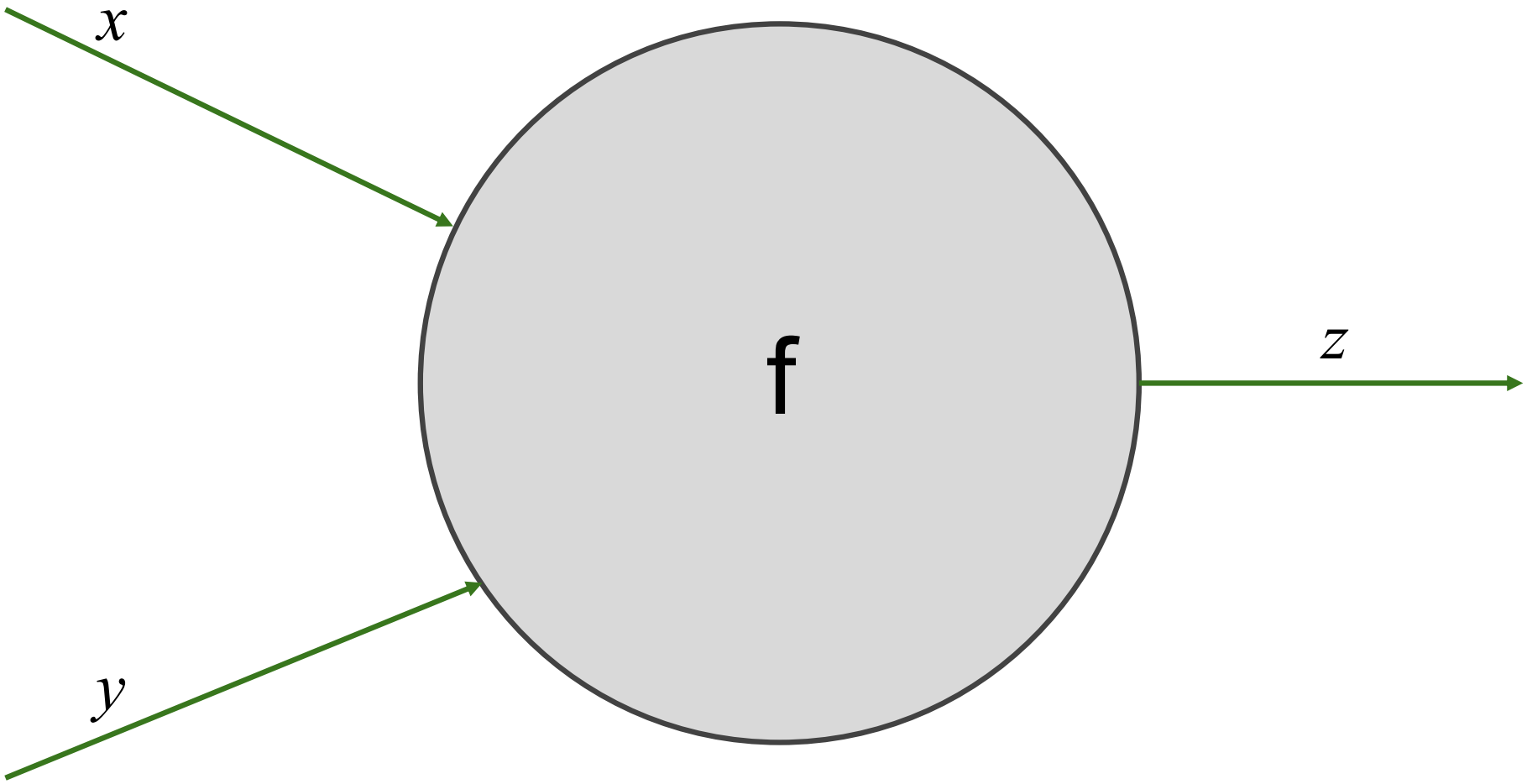

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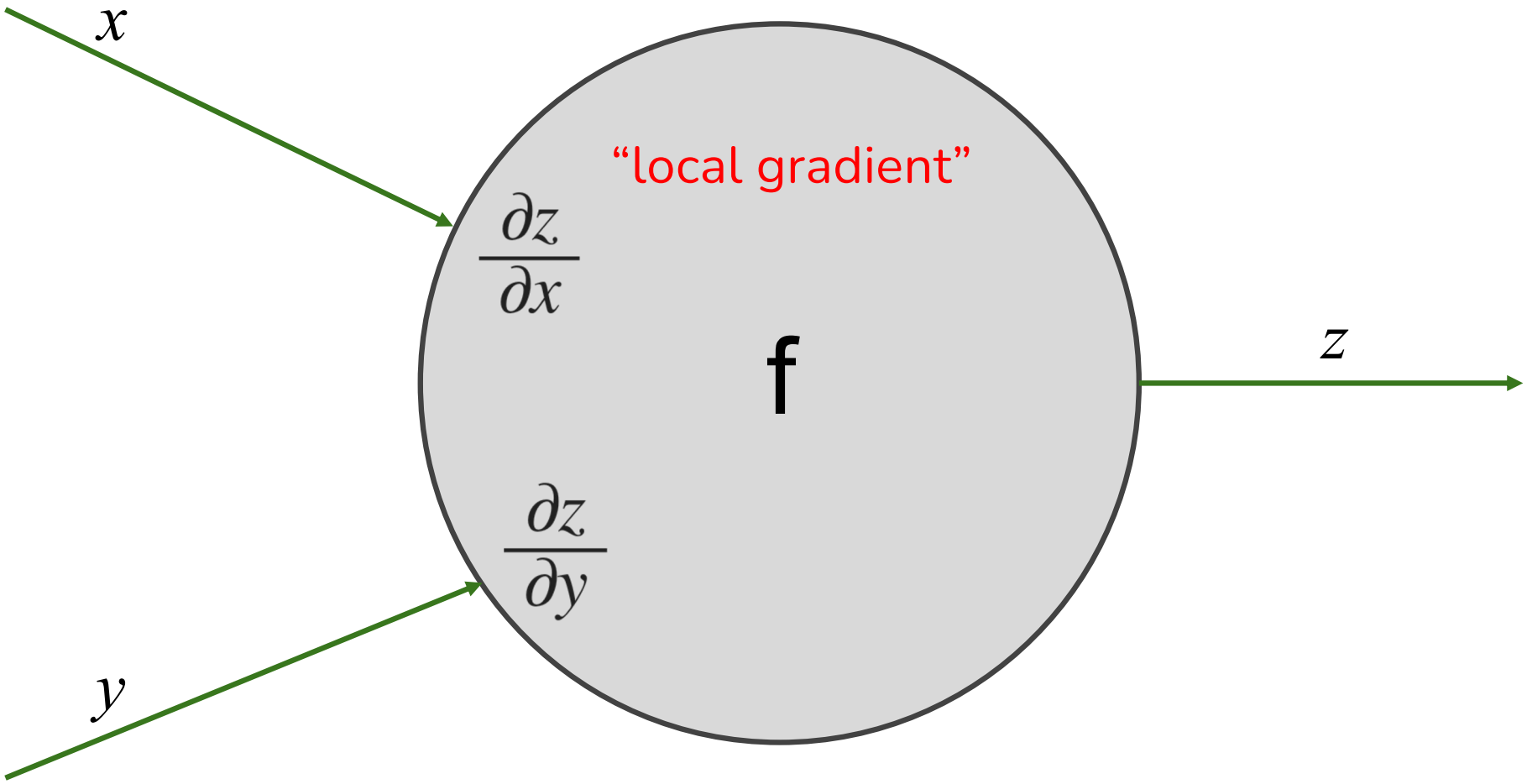

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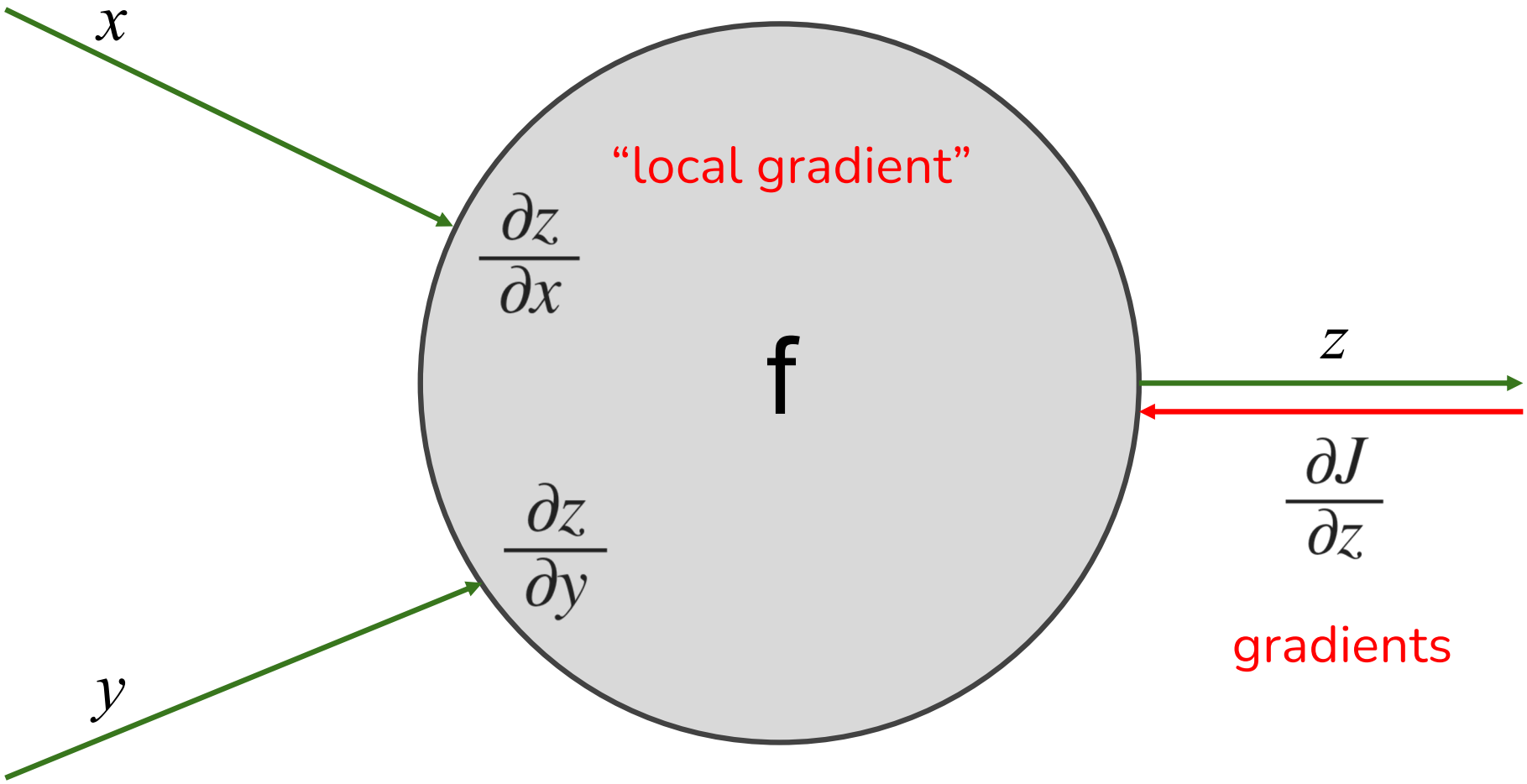

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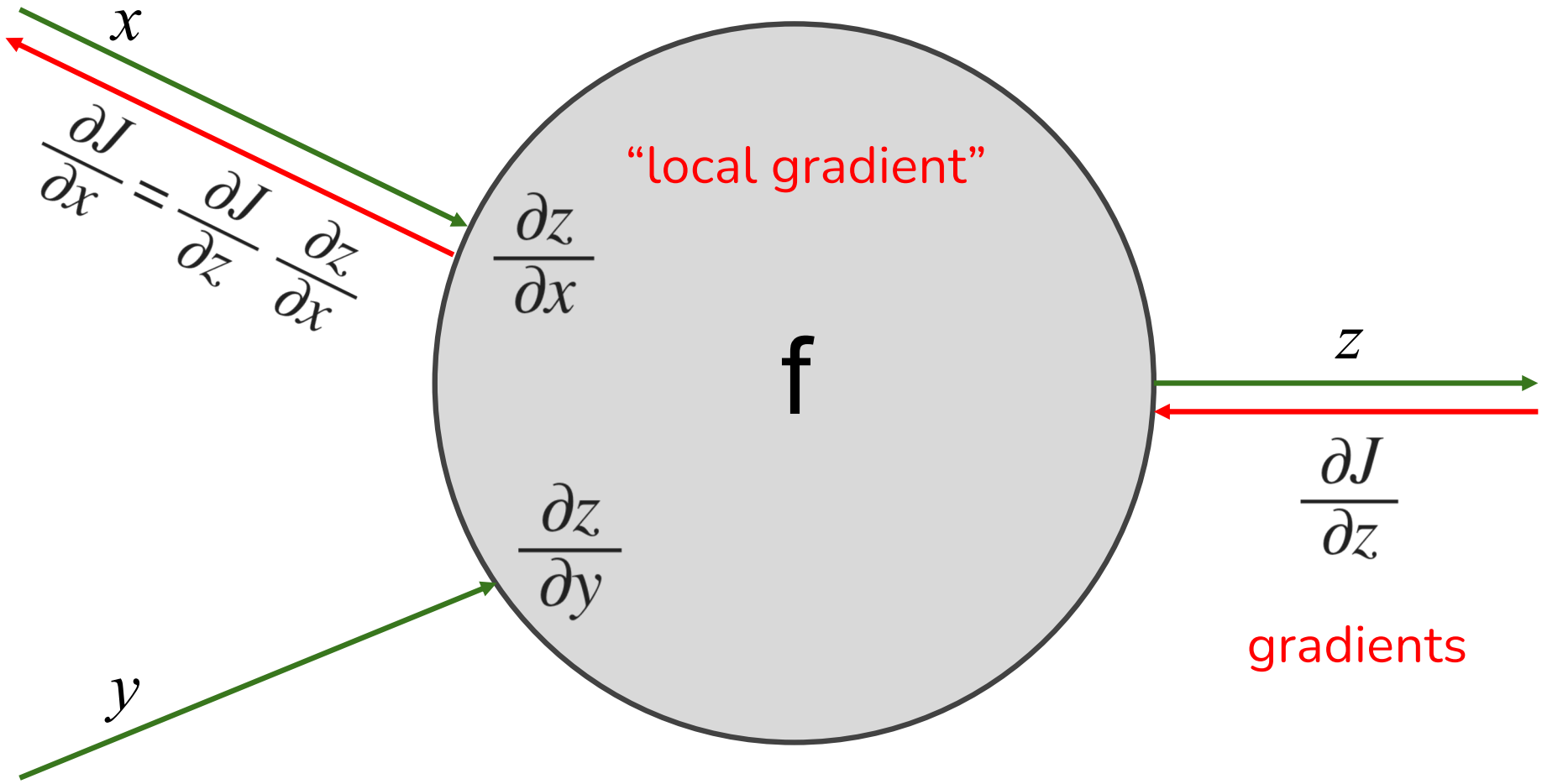

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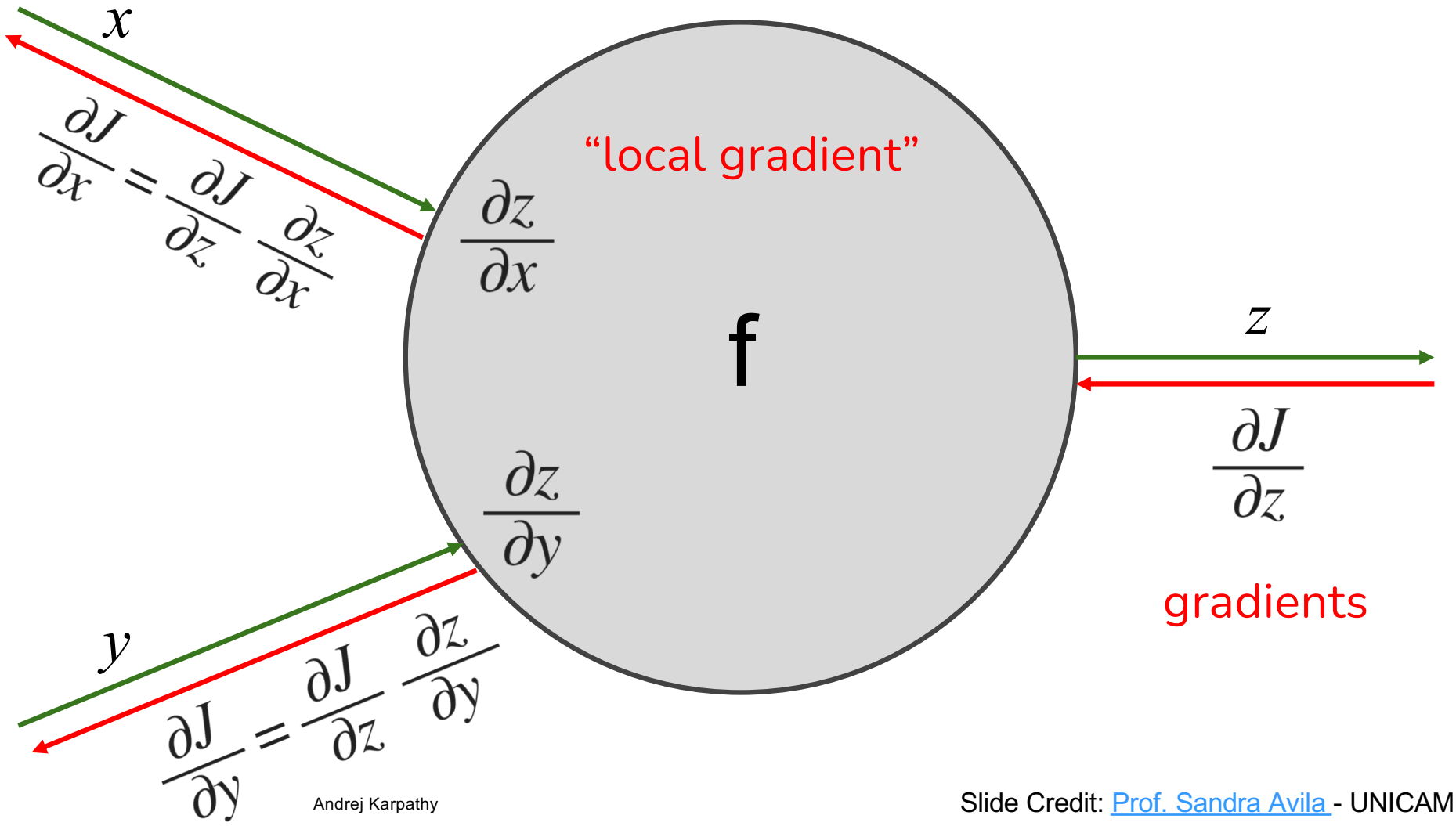

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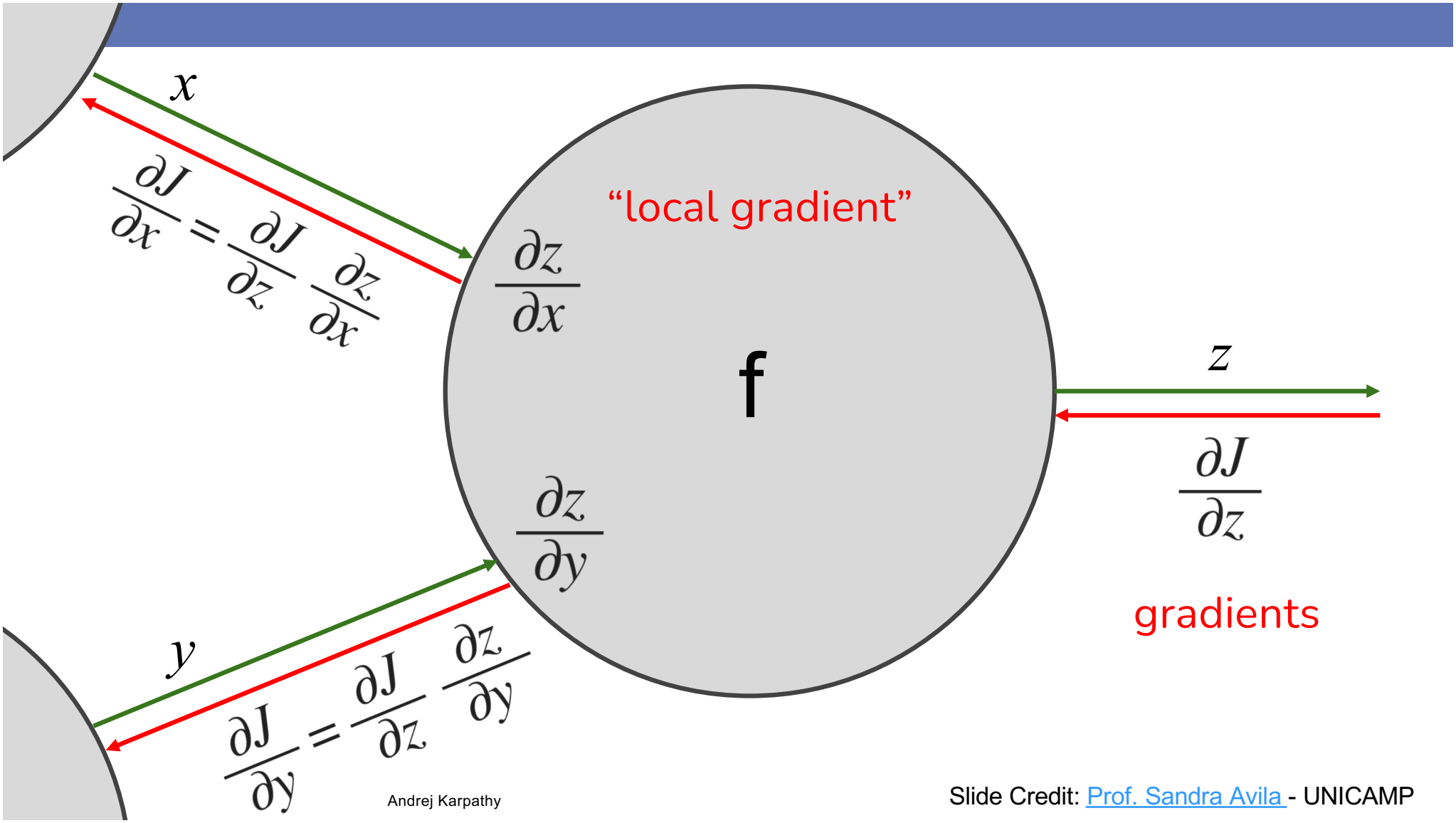

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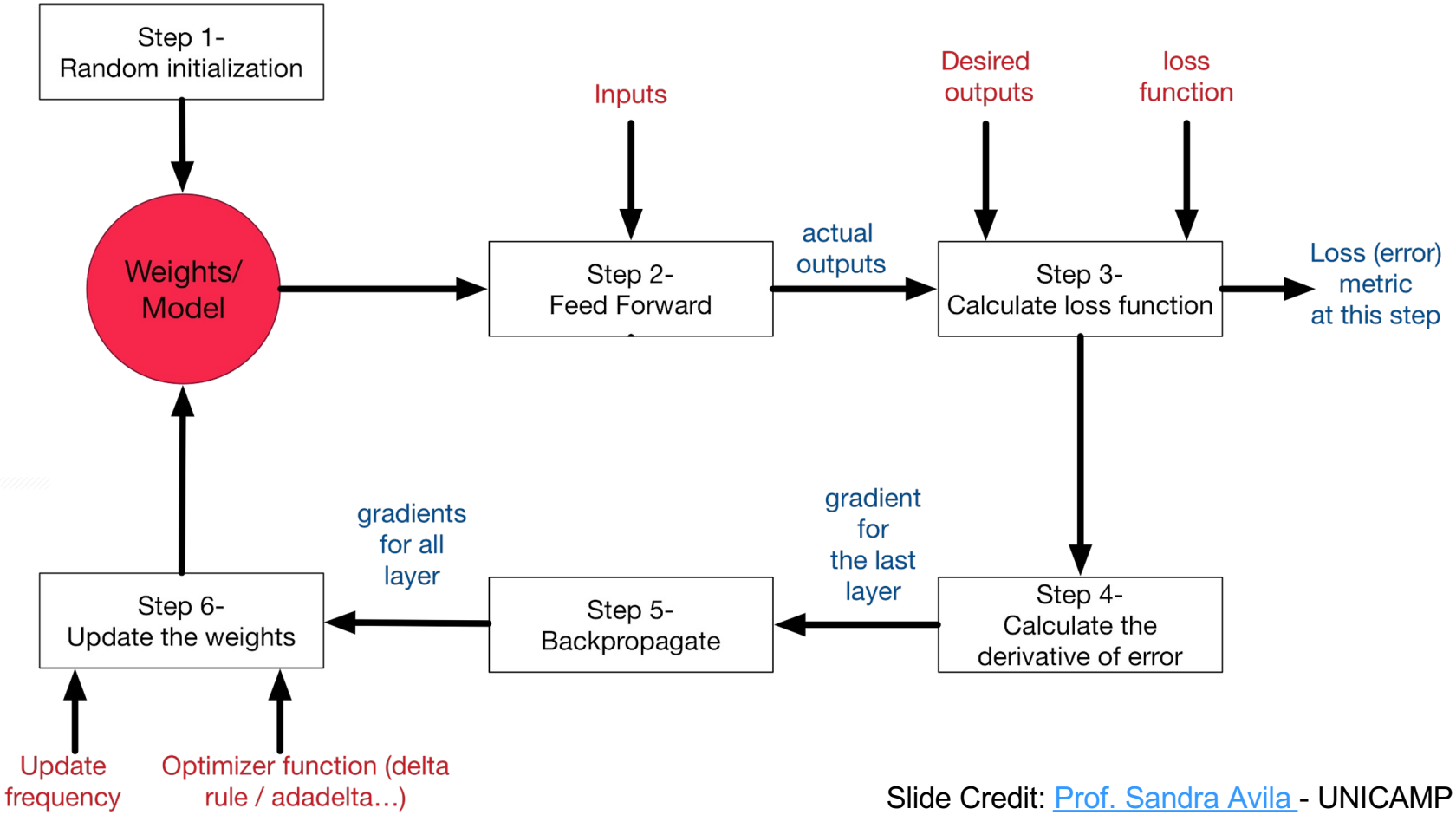
Training a Neural Network



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Gradient Descent

$$E(\Theta) = -\frac{1}{m} \sum_{i=1}^{m} L_i$$

Want $\min_{\Theta} E(\Theta)$:

repeat {

$$\Theta_{ij}^{(l)} := \Theta_{ij}^{(l)} - \alpha \frac{\partial}{\partial \Theta_{ij}^{(l)}} E(\Theta)$$

}

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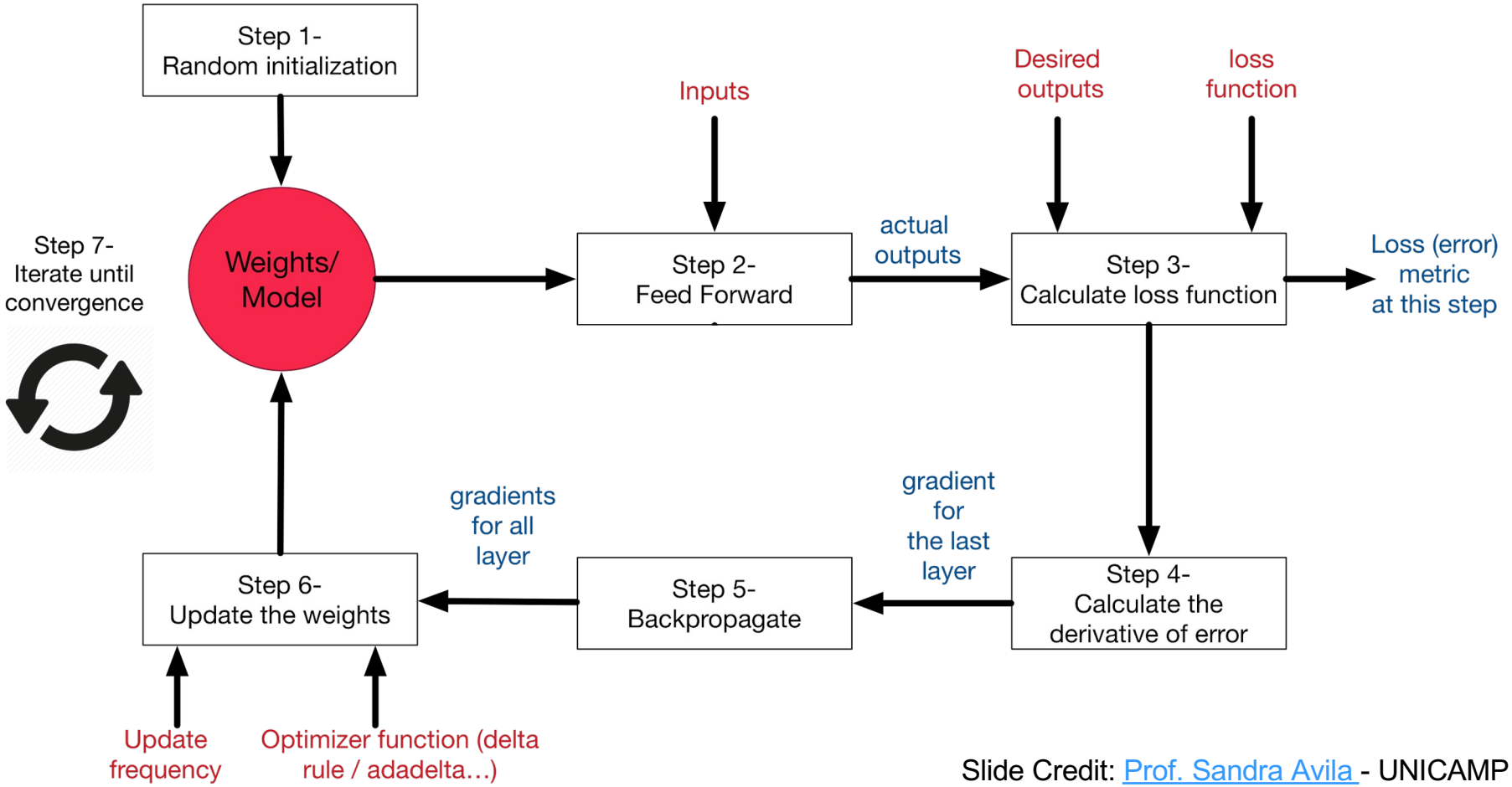
Training a Neural Network



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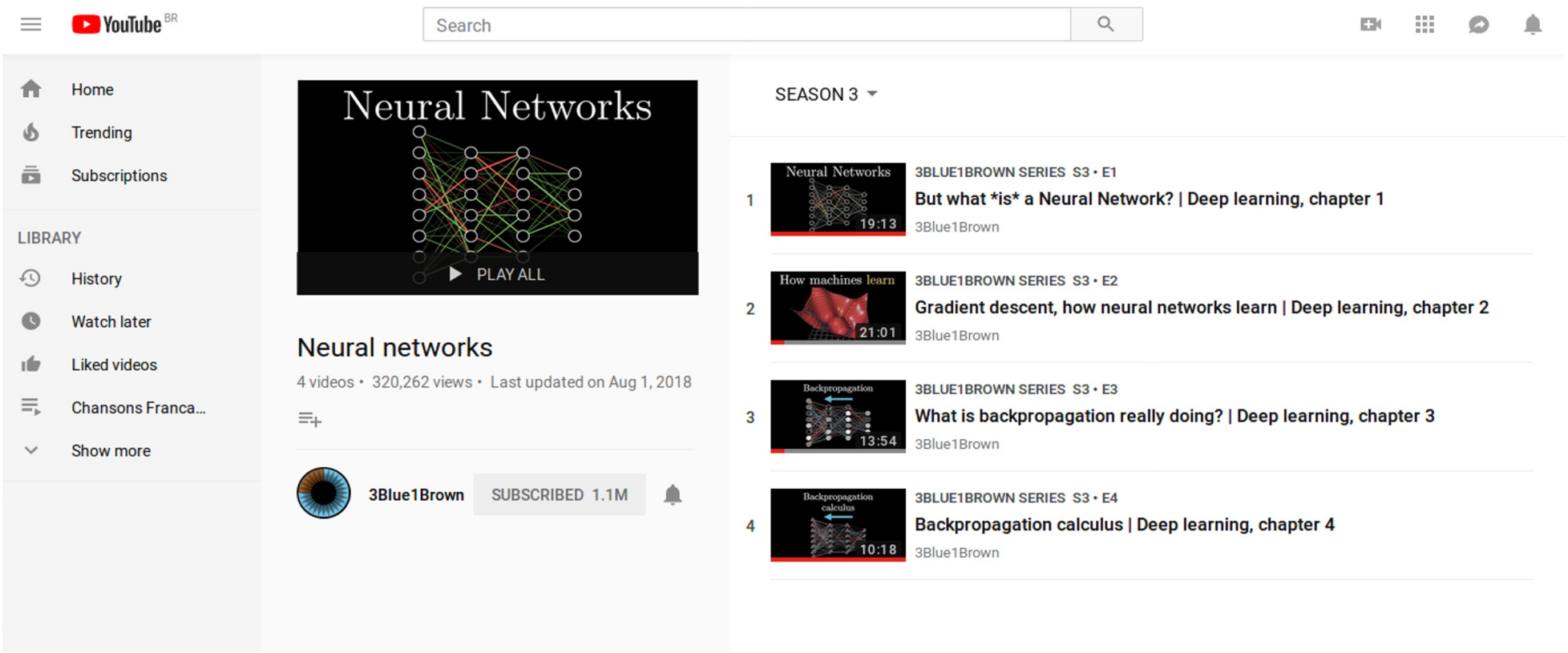
Assignment 6: Data Loaders

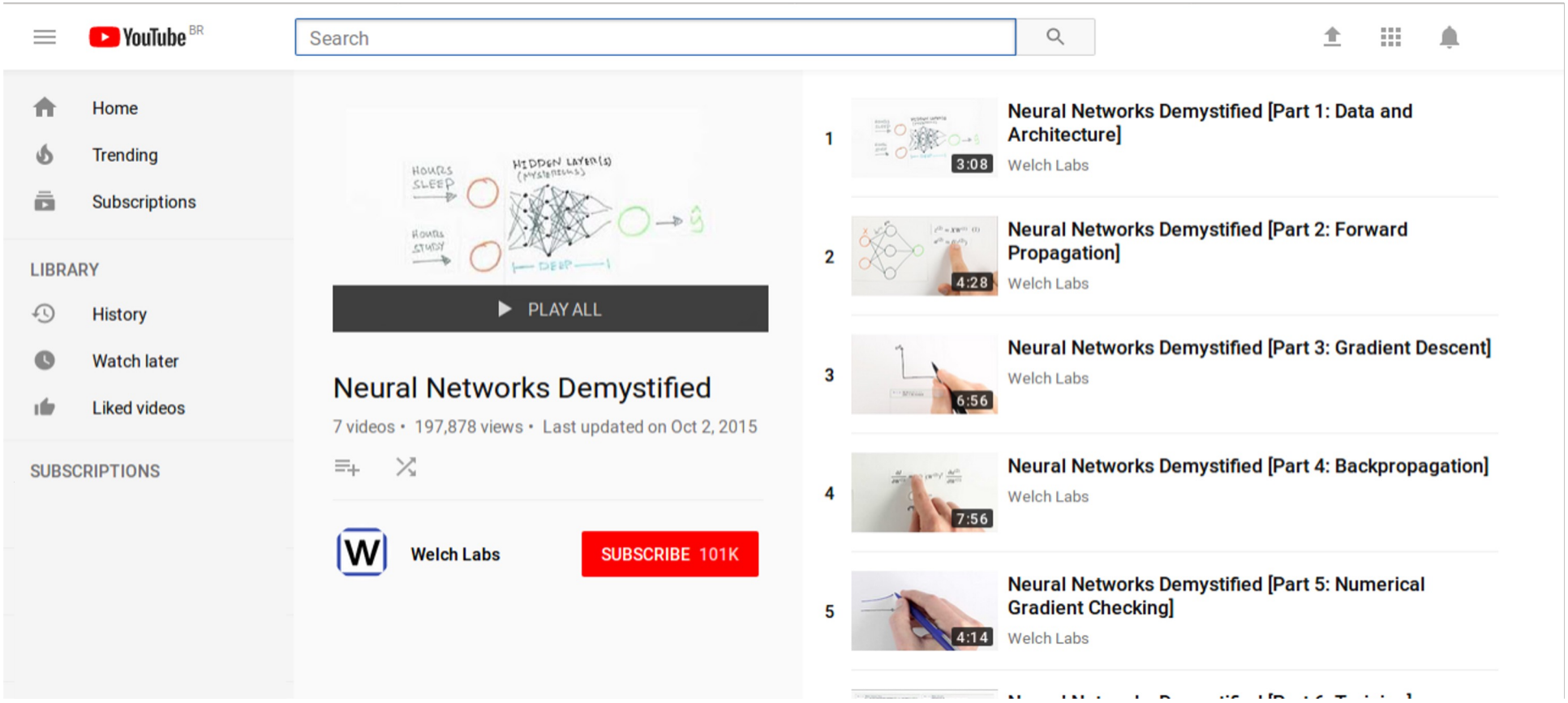
[Extra] Lab 8: Regularization
Section 1

Additional Resources

Neural Networks (3Blue1Brown)

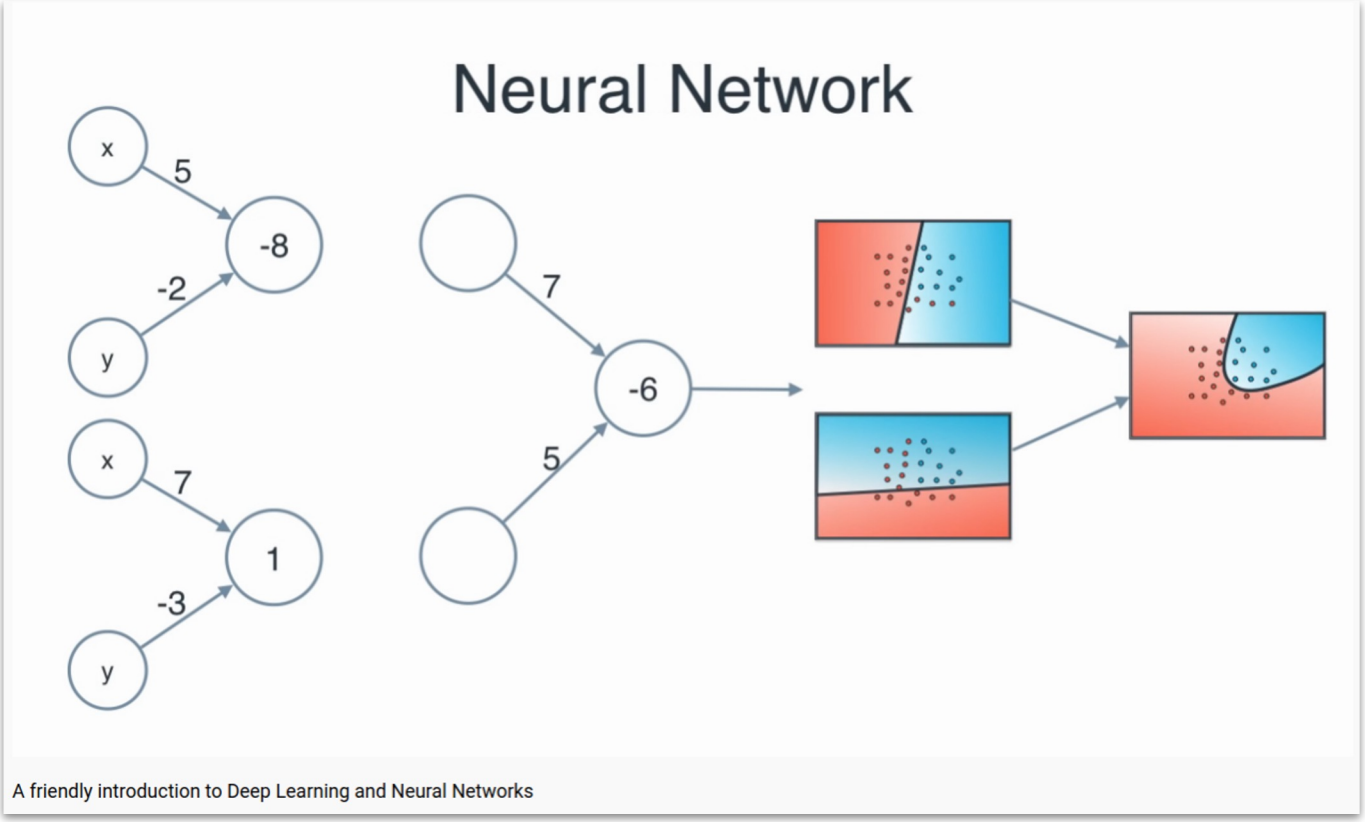


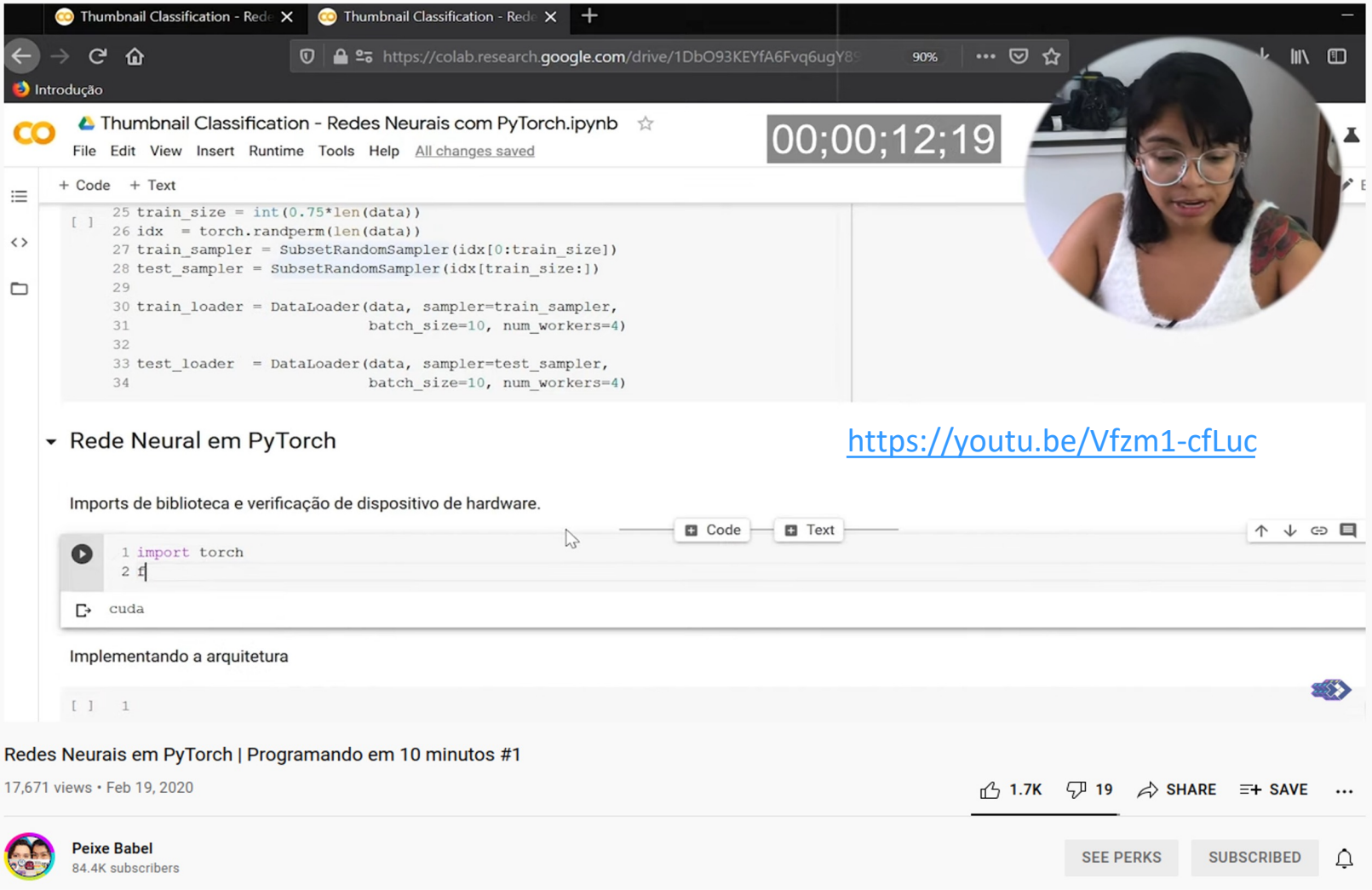
Neural Networks Demystified (in Python)



“A friendly introduction to Neural Networks”

https://youtu.be/BR9h47Jtqyw




Thumbnail Classification - Rede
Thumbnail Classification - Rede
https://colab.research.google.com/drive/1DbO93KEYfA6Fvq6ugY8
90%
Introdução
Thumbnail Classification - Redes Neurais com PyTorch.ipynb
File Edit View Insert Runtime Tools Help All changes saved
00;00;12;19
+ Code + Text
25 train_size = int(0.75*len(data))
26 idx = torch.randperm(len(data))
27 train_sampler = SubsetRandomSampler(idx[0:train_size])
28 test_sampler = SubsetRandomSampler(idx[train_size:])
30 train_loader = DataLoader(data, sampler=train_sampler,
31 batch_size=10, num_workers=4)
33 test_loader = DataLoader(data, sampler=test_sampler,
34 batch_size=10, num_workers=4)
Rede Neural em PyTorch
https://youtu.be/Vfzm1-cfLuc
Imports de biblioteca e verificação de dispositivo de hardware.
Code
Text
1 import torch
2 f
cuda
Implementando a arquitetura
1
Redes Neurais em PyTorch | Programando em 10 minutos #1
17,671 views • Feb 19, 2020
1.7K
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Summary

- We use deep neural networks because of their strong performance in practice

- Training deep neural nets
  - We need an objective function that measures and guides us towards good performance
  - We need a way to minimize the loss function: stochastic gradient descent
  - We need backpropagation to propagate error from end of net towards all layers and change weights at those layers

- Practices for preventing overfitting
  - Regularization