



# Deep Learning Workshop

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17<sup>th</sup> October 2022

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- Topic 6: How Deep Learning is changing /will change the world?

# Who am I?

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UNIVERSITAT  
POLITÈCNICA  
DE VALÈNCIA



Maastricht  
University



B.Sc. Biotechnology

M.Sc.  
Computational Biology



Universitat  
Pompeu Fabra  
Barcelona

ETH zürich



P.hD. @ BbgLab  
Computational Biology  
EMIBA



hynts

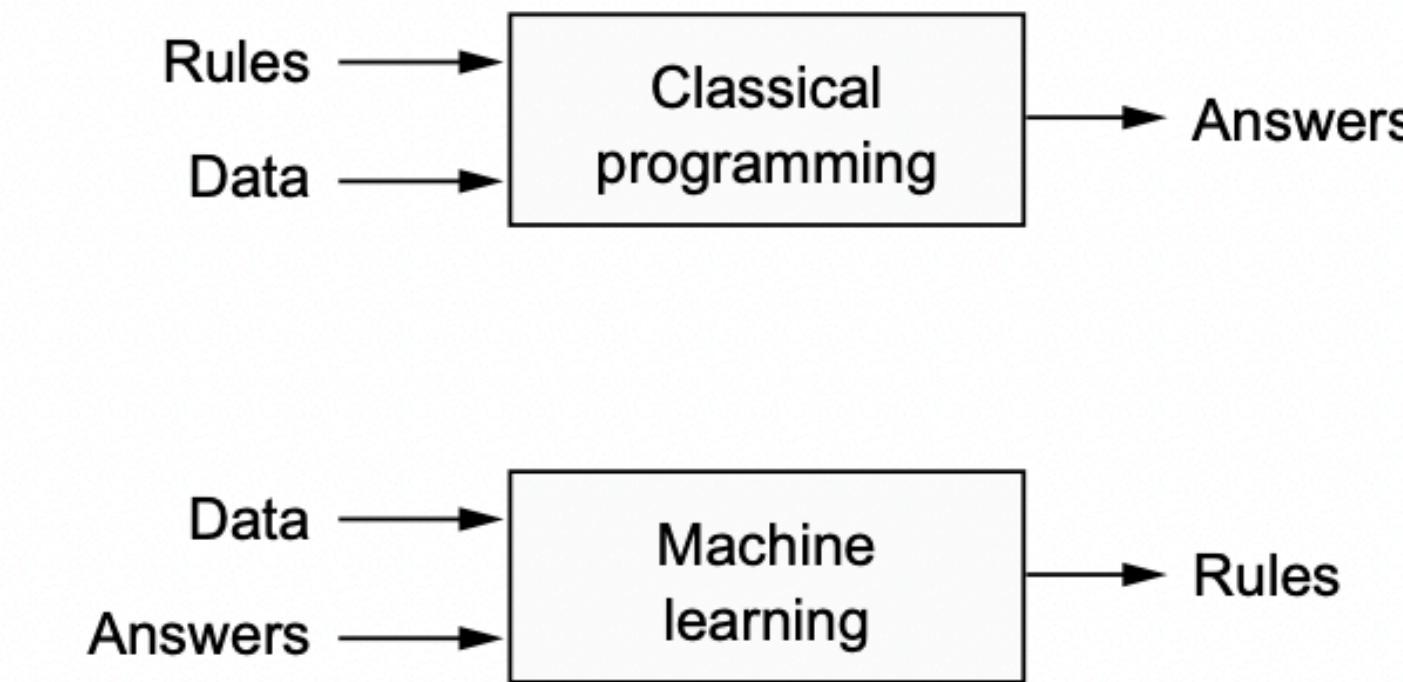
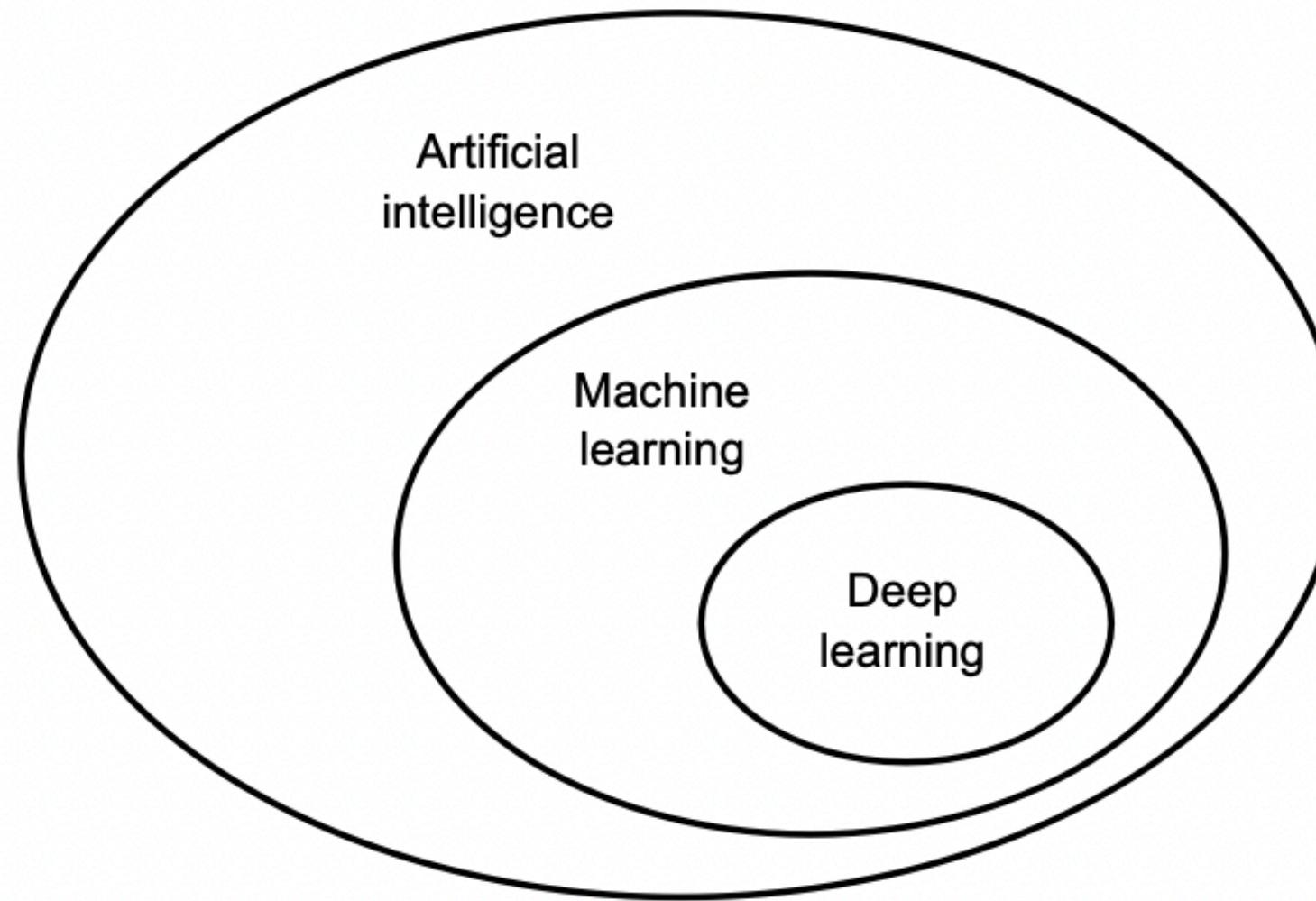
Hynts Analytics



# What is Deep Learning?

# Differences between symbolic AI and Machine Learning

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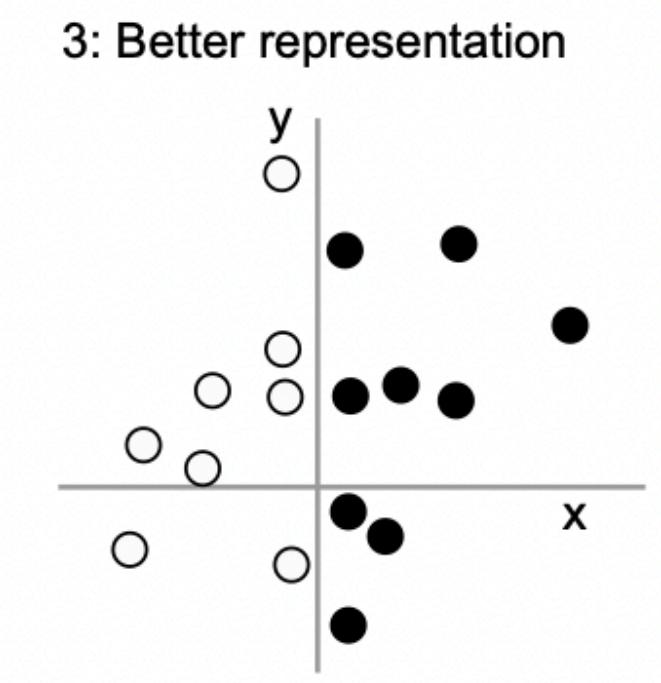
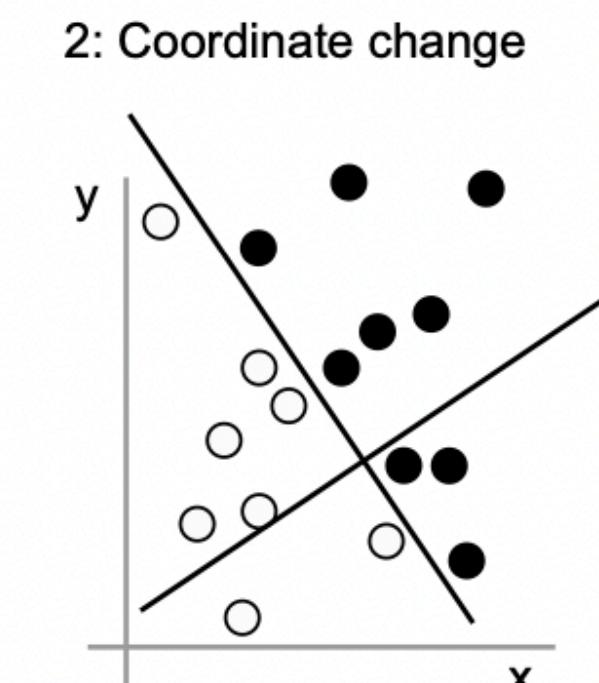
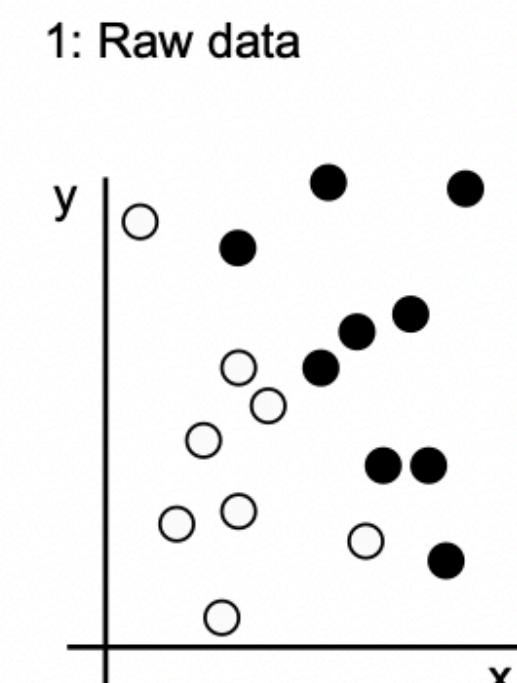
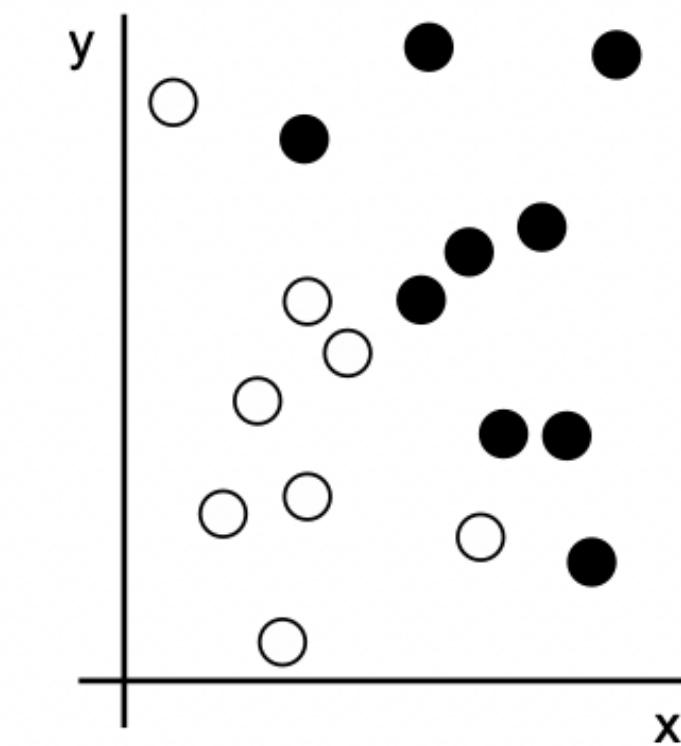


- AI: Effort to automate intellectual tasks normally performed by humans
- ~ 1950-1980 Symbolic AI. Rules + Data → Answers
- ML: Data + Answers → Rules

# ML Recap

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- ML: Data + Answers → Rules
- What do we need:
  1. Input data points
  2. Examples of the expected output
  3. A way to measure whether the algorithm is doing a good job
- Transform data into meaningful outputs  
(Learning from exposure to known examples)
- Meaningfully transform data: learn representations



# Limitations of ML. What makes DL different?

---

Easier Problem-solving

Automation of feature engineering

3	4	2	1	9	5	6	2	1	8
8	9	1	2	5	0	0	6	6	4
6	7	0	1	6	3	6	3	7	0
3	7	7	9	4	6	6	1	8	2
2	9	3	4	3	9	8	7	2	5
1	5	9	8	3	6	5	7	2	3
9	3	1	9	1	5	8	0	8	4
5	6	2	6	8	5	8	8	9	9
3	7	7	0	9	4	8	5	4	3
7	9	6	4	7	0	6	9	2	3

SVM,  
Decision Trees...

Neural Nets

# Limitations of ML. What makes DL different?

Easier Problem-solving

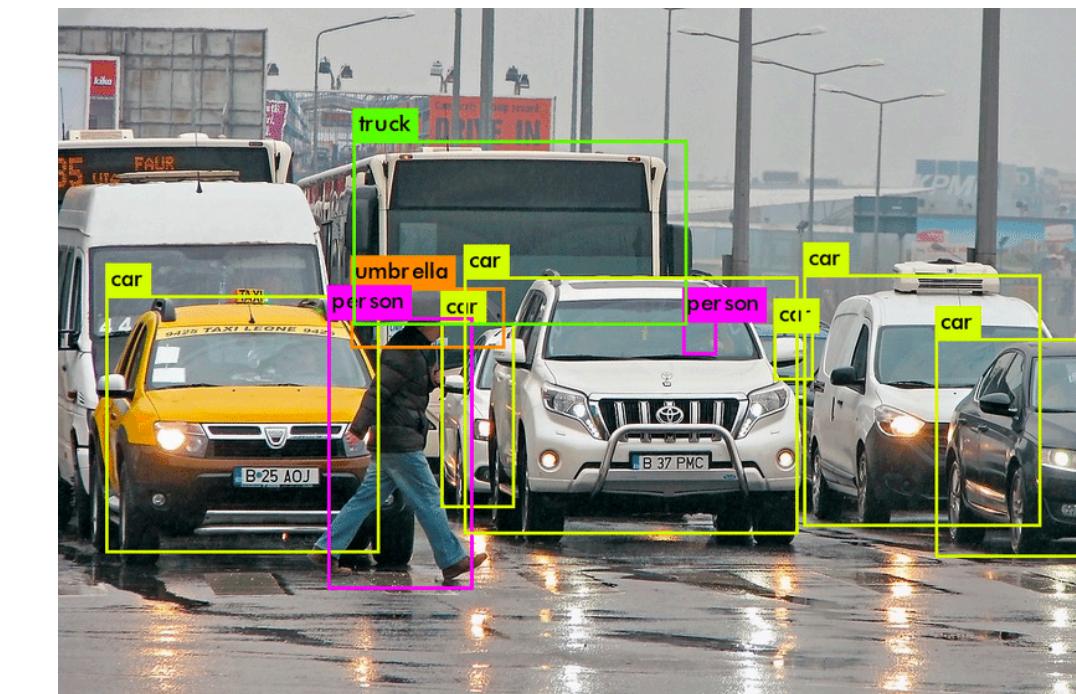
Automation of feature engineering



SVM,  
Decision Trees...

Neural Nets

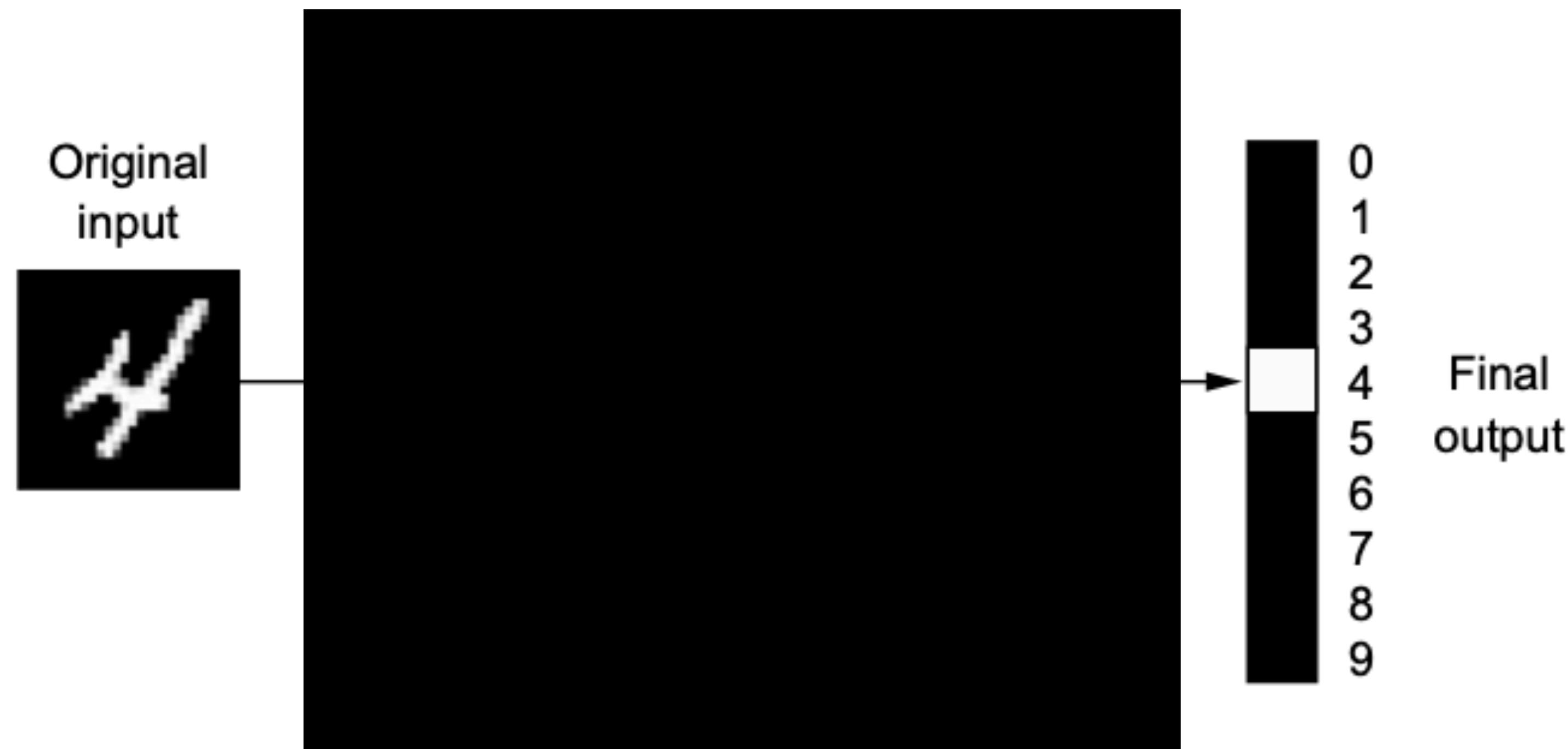
Better performance for many problems



# A first glance at Deep Learning

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## Neural Networks



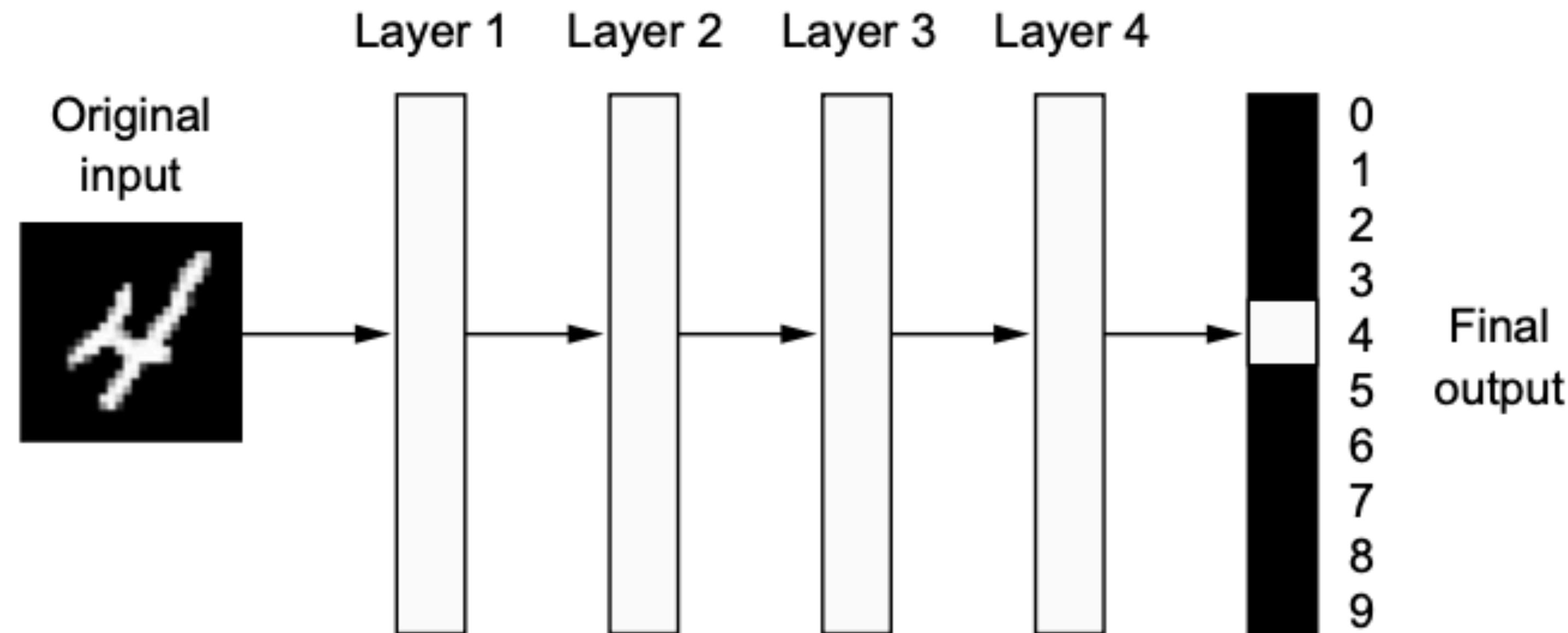
# A first glance at Deep Learning

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Neural Networks

Hidden Layers

Deep (Depth):  
Successive Layers

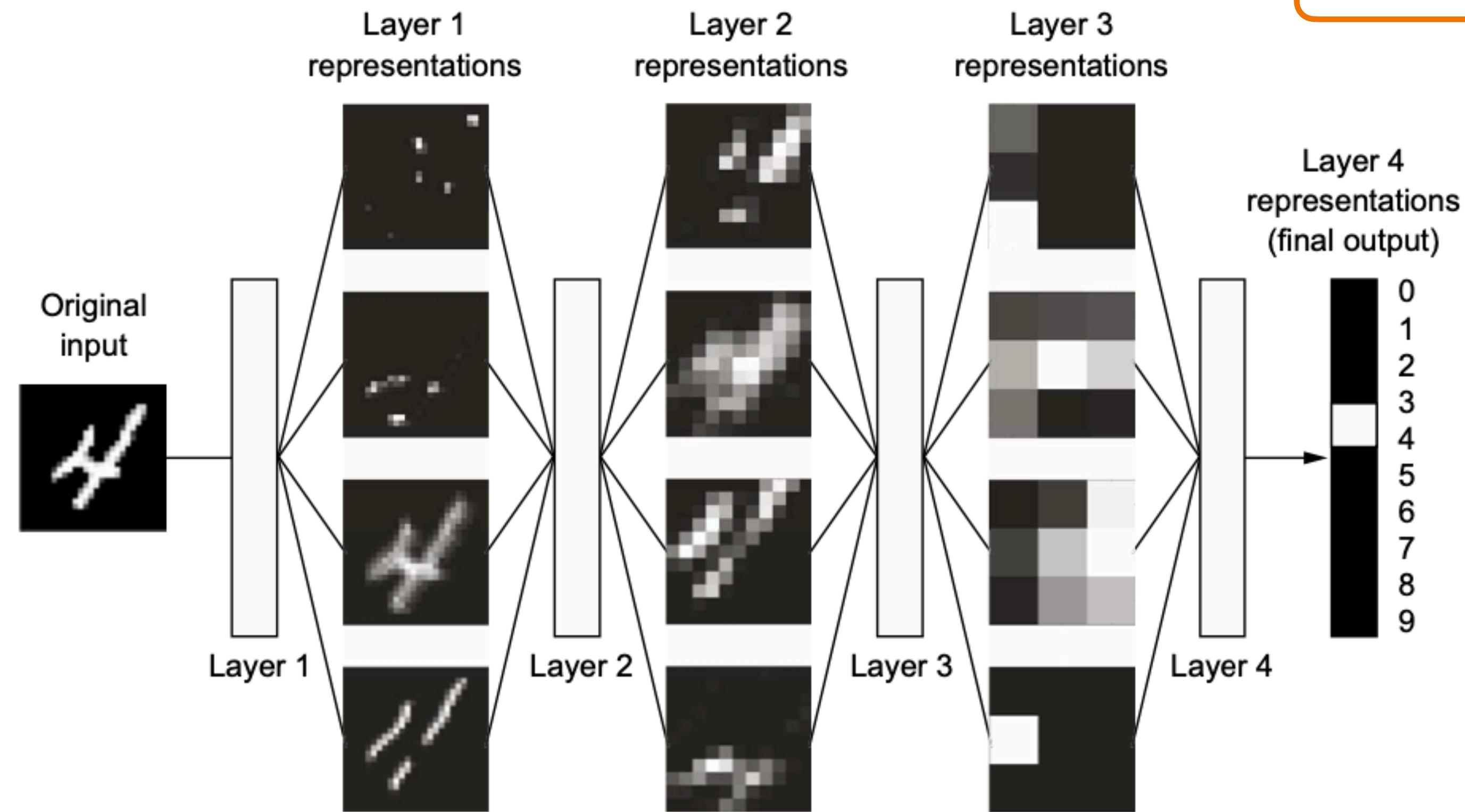


# A first glance at Deep Learning

Neural Networks

Hidden Layers

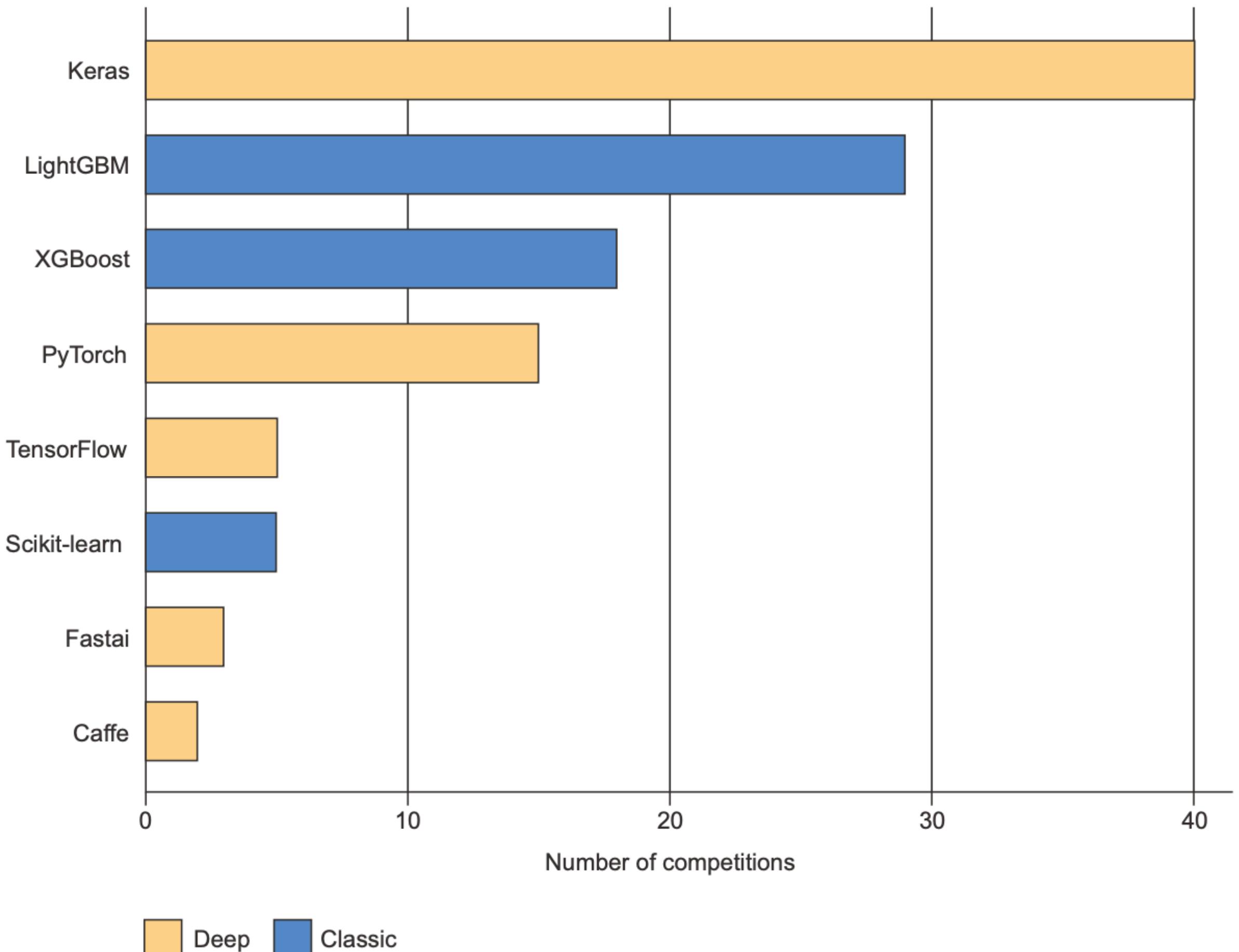
*Multistage (several layers)  
way to learn data  
representations*



# What deep learning has achieved so far?

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- Near-human-level image classification
- Near-human-level speech transcription
- Near-human-level handwriting transcription
- Dramatically improved machine translation
- Dramatically improved text-to-speech conversion
- Google assistant - Alexa
- Near-human-level autonomous driving
- Superhuman game-playing (AlphaGo, Alphazero, AlphaStar, etc...)



# Why Deep Learning and why now?

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- CNNs were well understood already in 1990.  
Why did this not happen earlier?

## 1. Hardware:

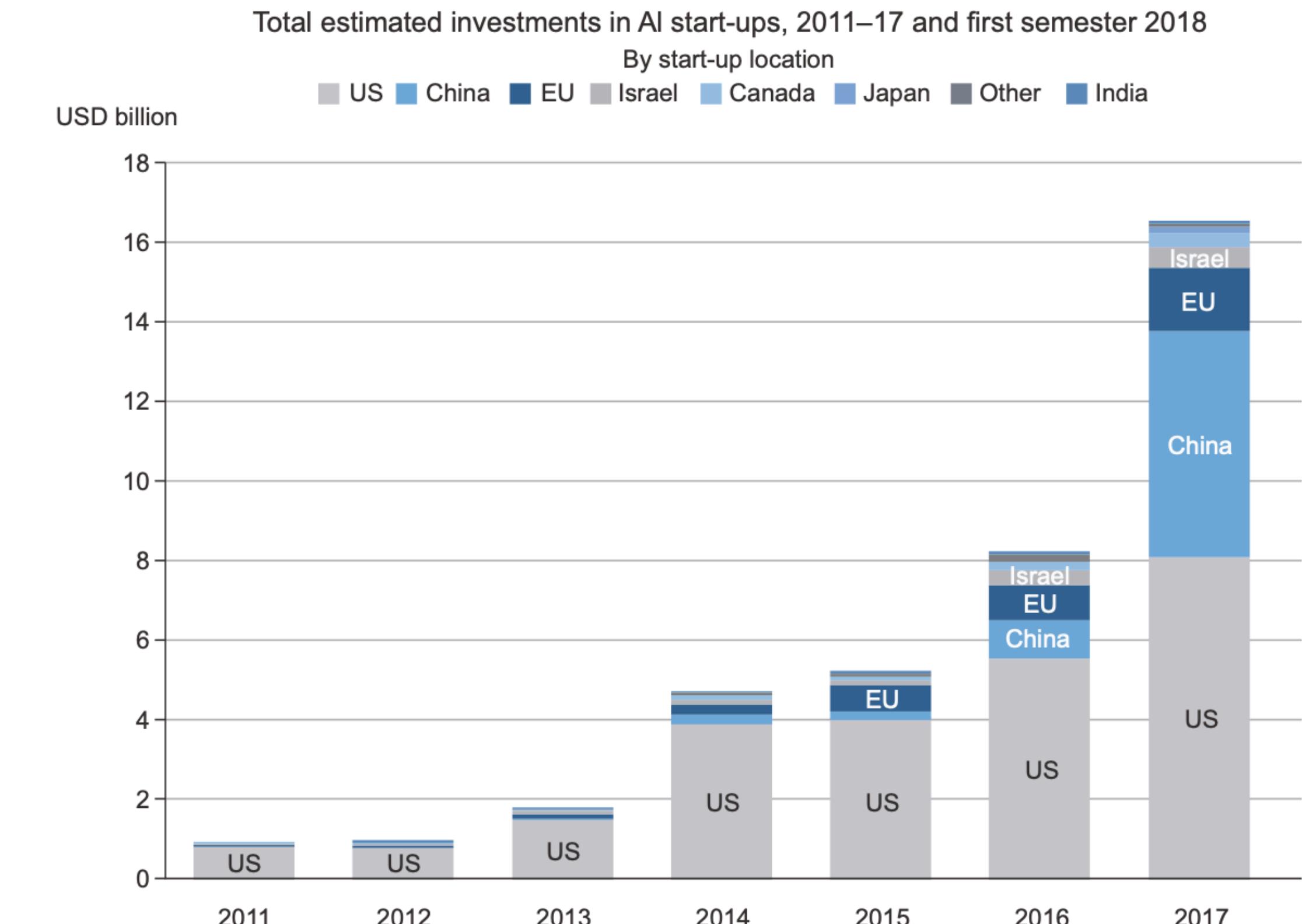
- Development of GPUs, TPUs

## 2. Data (ImageNet)

- Kaggle competitions

## 3. Algorithmic advances

- Extensive research





# The building blocks of Neural Networks

# Back to the hand-written digits

---



Label: 3



Label: 3



Label: 3

Could you write a  
program that takes the pixels  
as input and tells you the  
number?

# Back to the hand-written digits

---



Label: 3



Label: 3



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# Back to the hand-written digits

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Label: 3



Label: 3

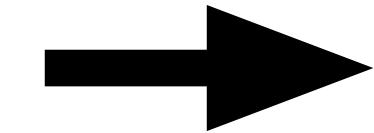


Label: 3

Could you write a  
program that takes the pixels  
as input and tells you the  
number?



Label: 3



0  
1  
2  
**3**  
4  
5  
6  
7  
8  
9

Neural Network  
to recognize hand-  
written digits

# What is a neuron?

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Neural Networks

What are neurons?

How are they linked  
together?

# What is a neuron?

---

Neural Networks

What are neurons?

How are they linked  
together?

0.8

A thing that holds a number  
between 0 and 1

# What is a neuron?

# Neural Networks

# What are neurons?

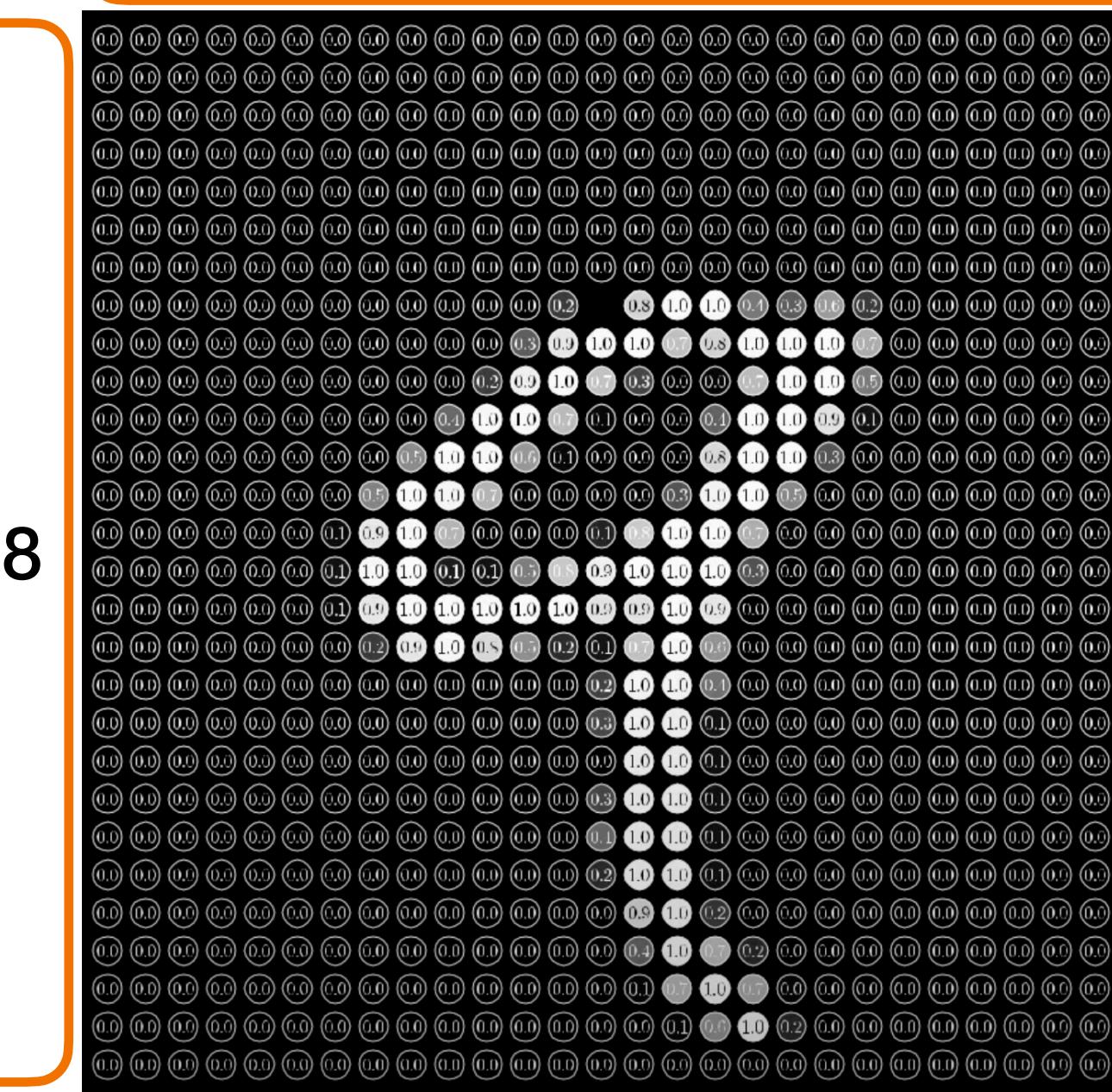
# How are they linked together?

0.8

A thing that holds a number  
between 0 and 1

2

28



# What is a neuron?

Neural Networks

What are neurons?

How are they linked together?

28

A thing that holds a number between 0 and 1

0.8

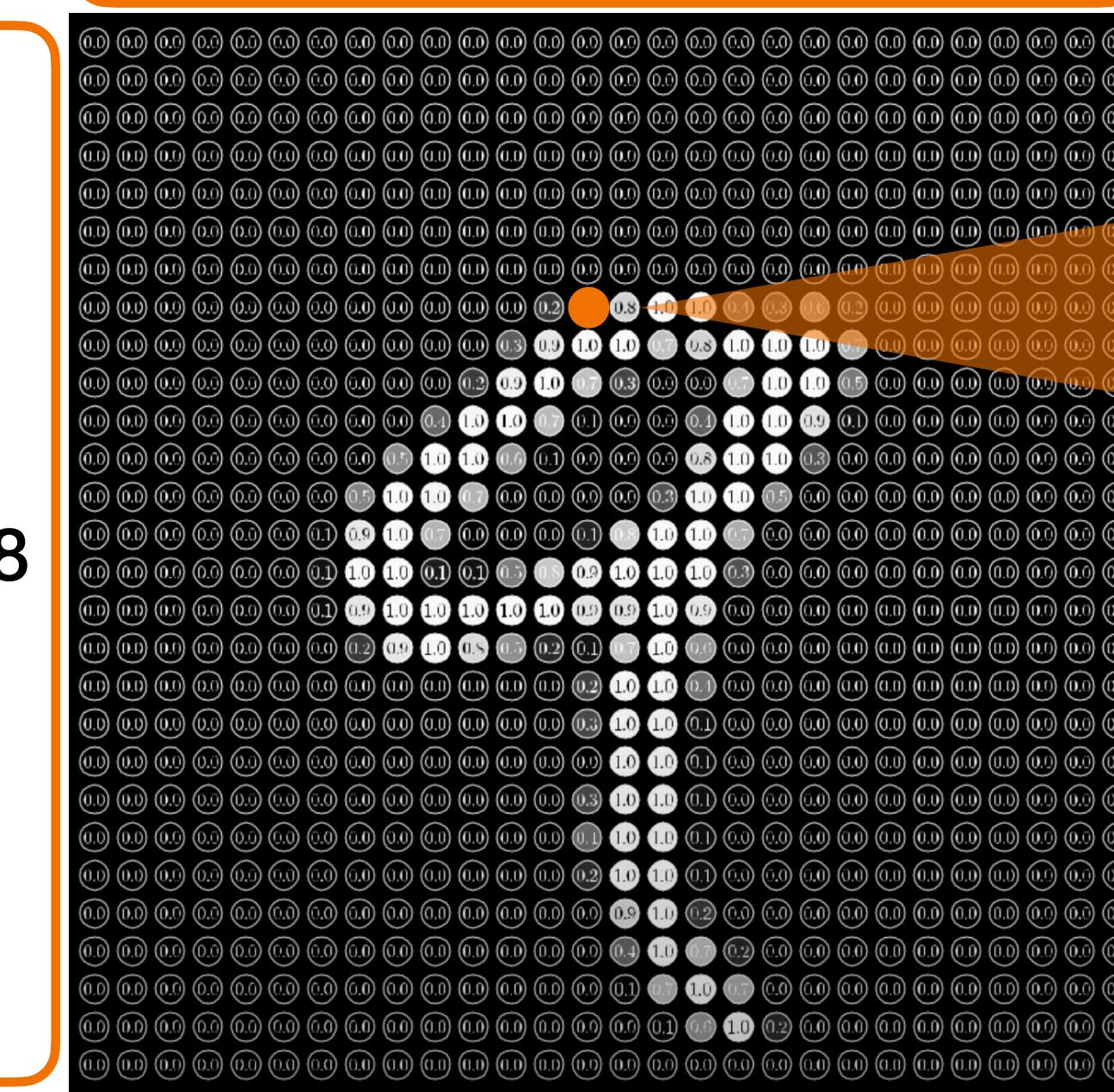
28

$28 \times 28 = 784$

0.9

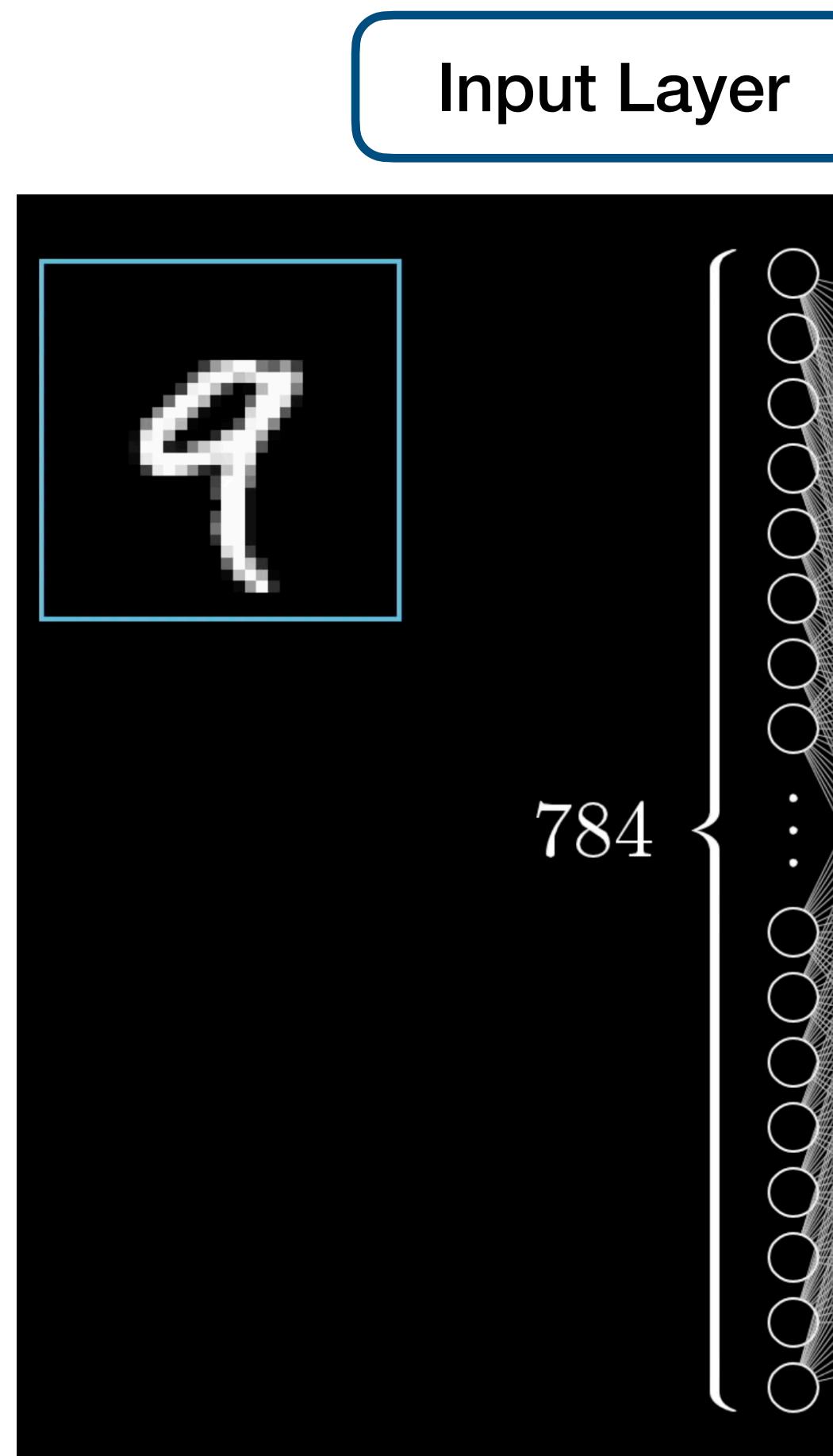
Activation

0.1



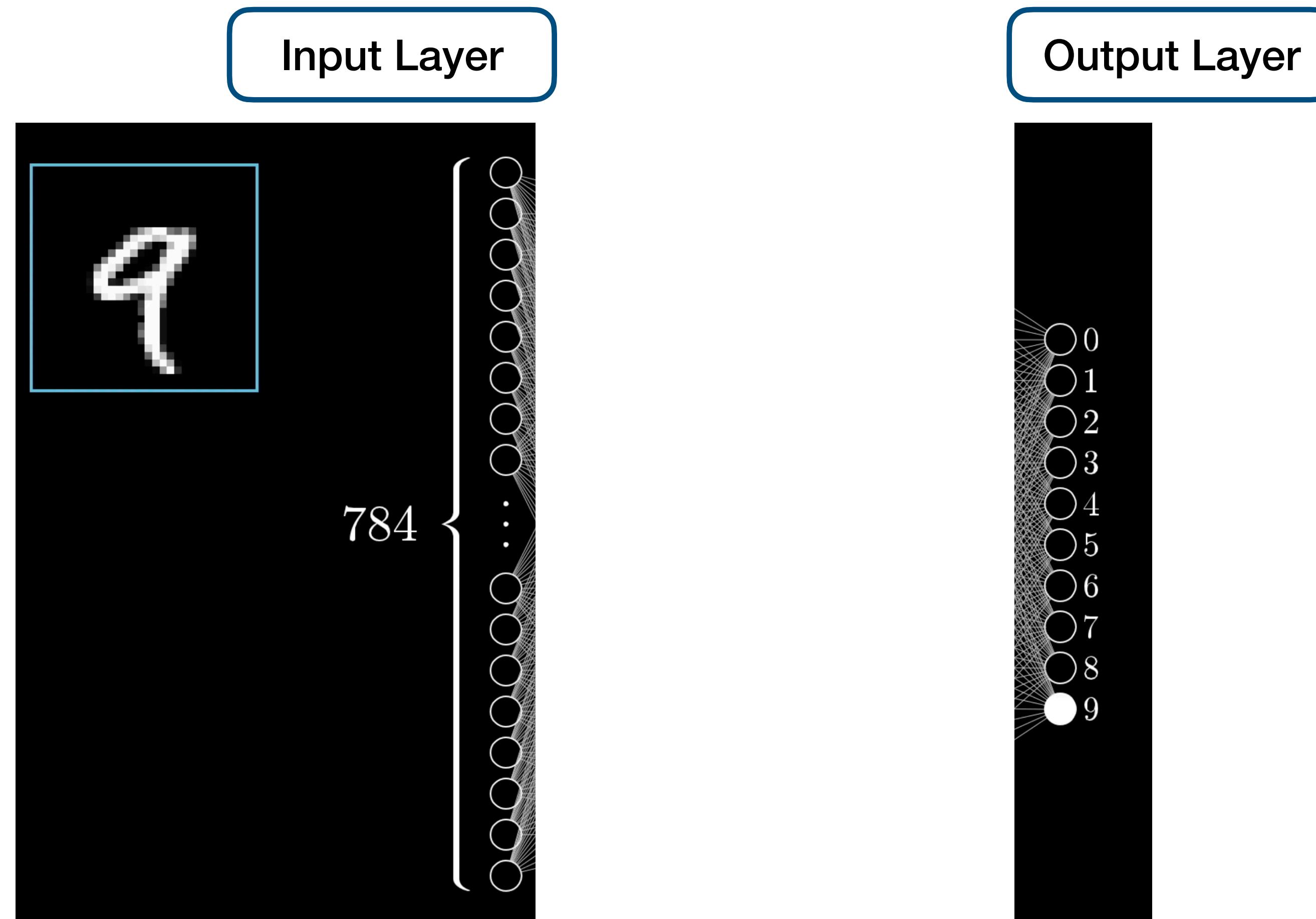
# Layers of Neurons lead to the Neural network structure

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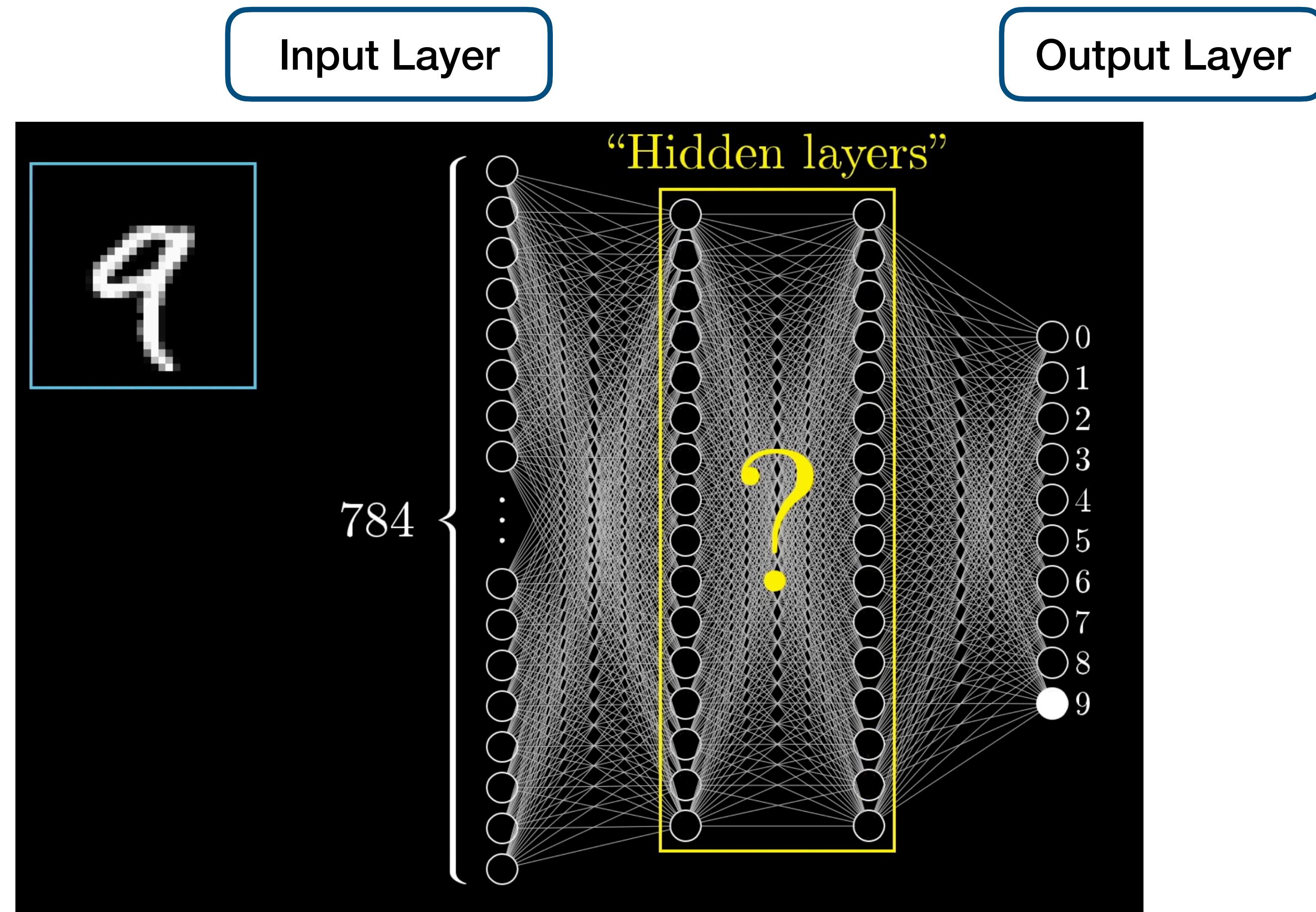
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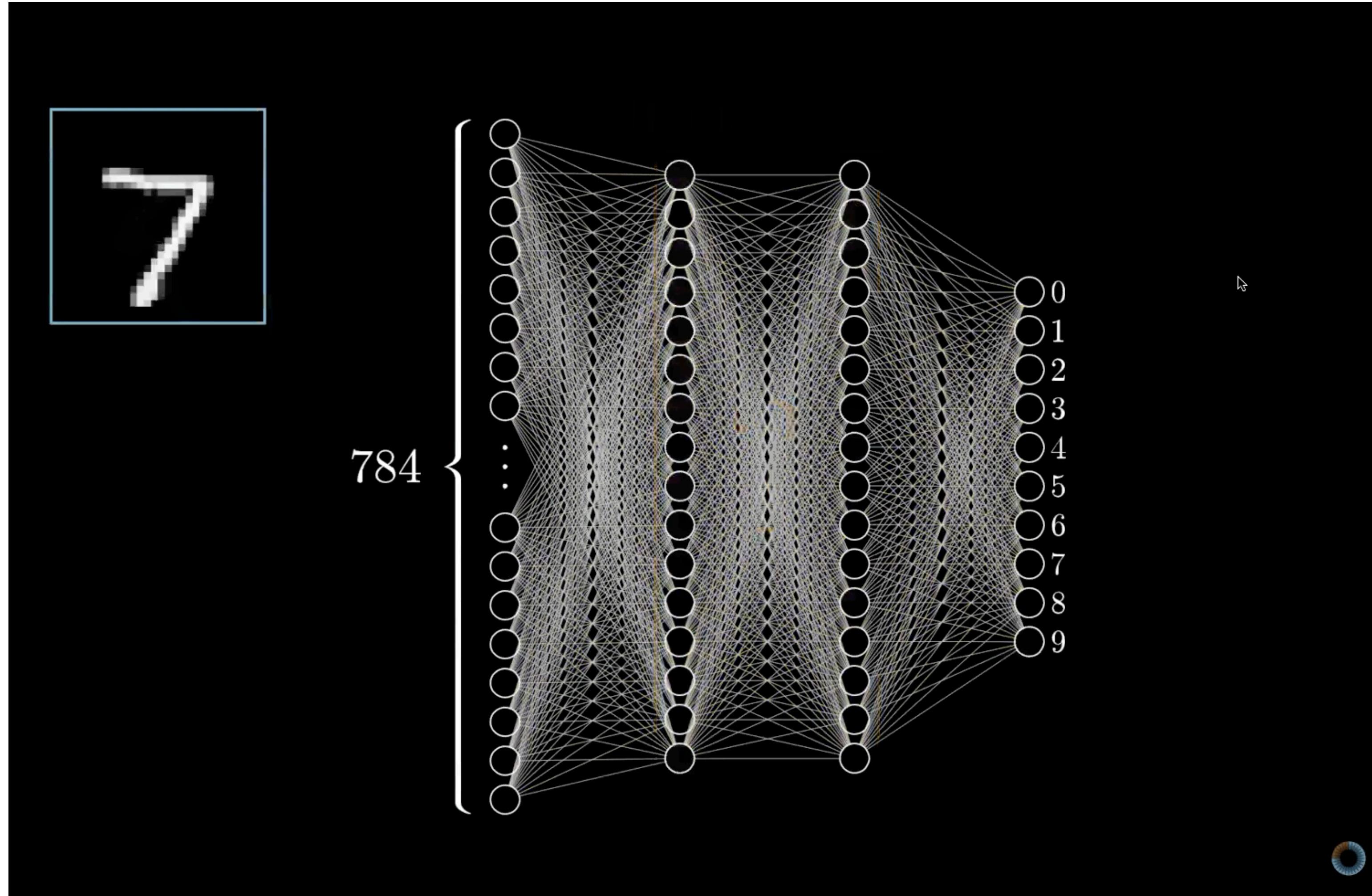
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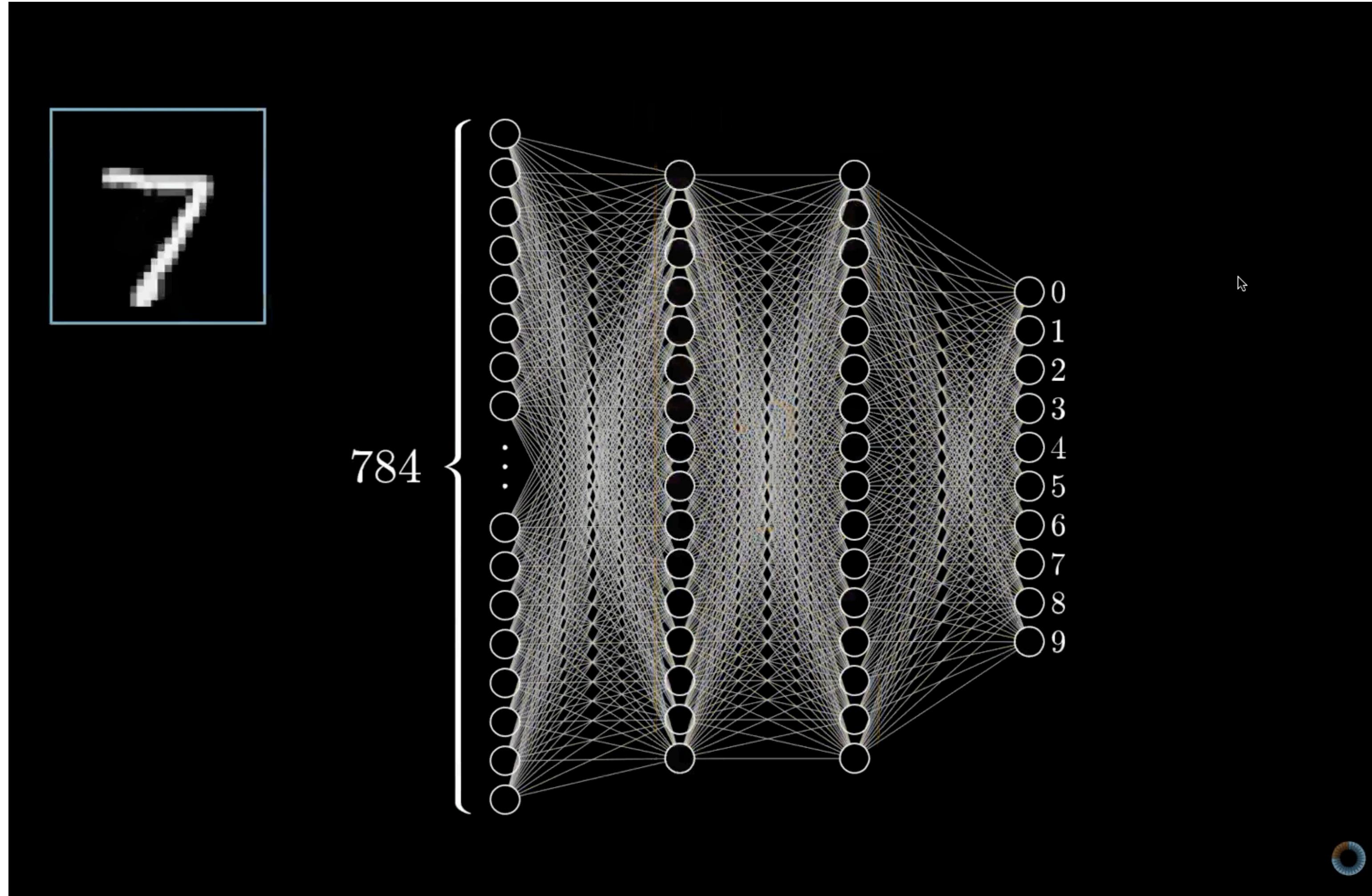
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# Layers of Neurons lead to the Neural network structure

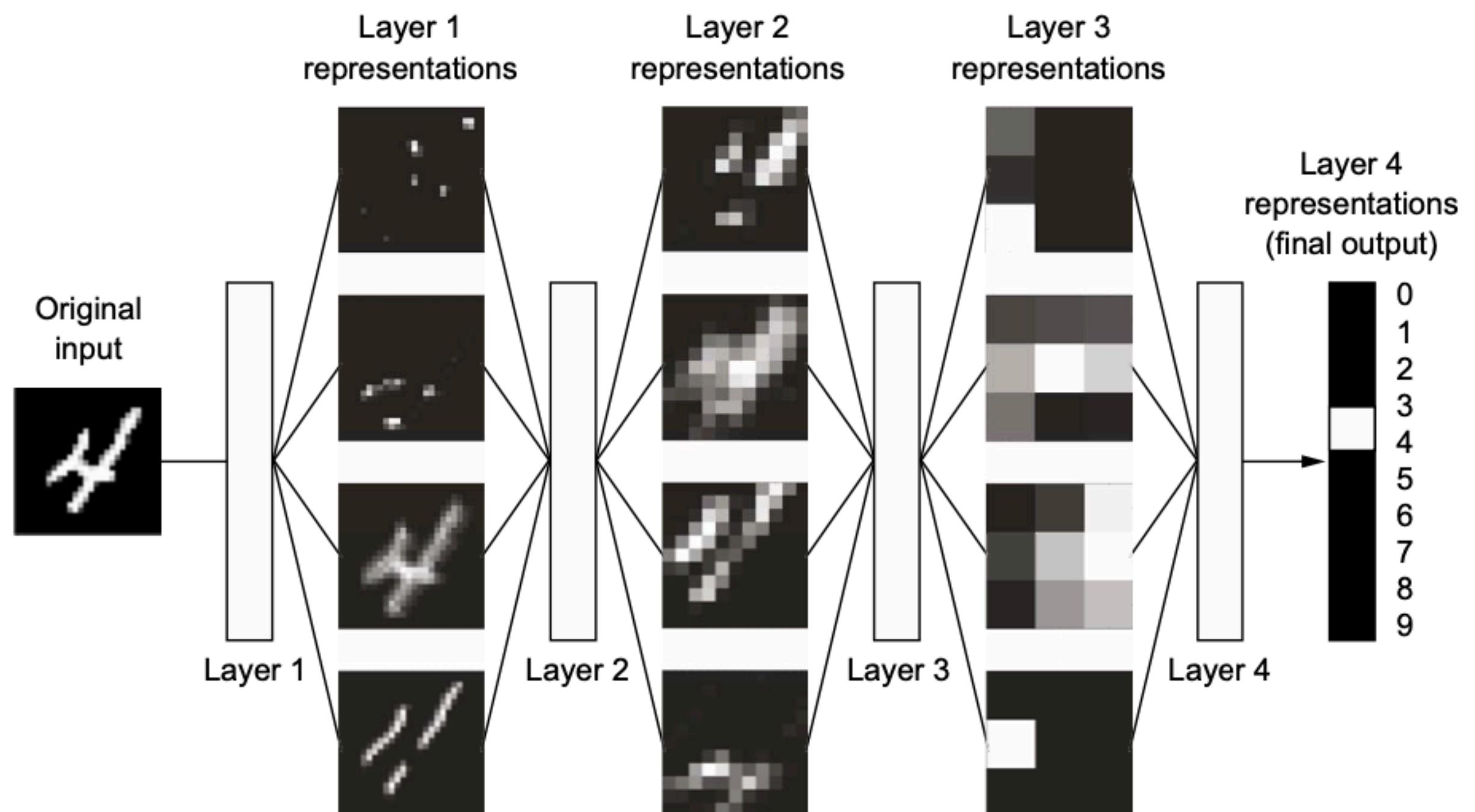
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# Why layers?

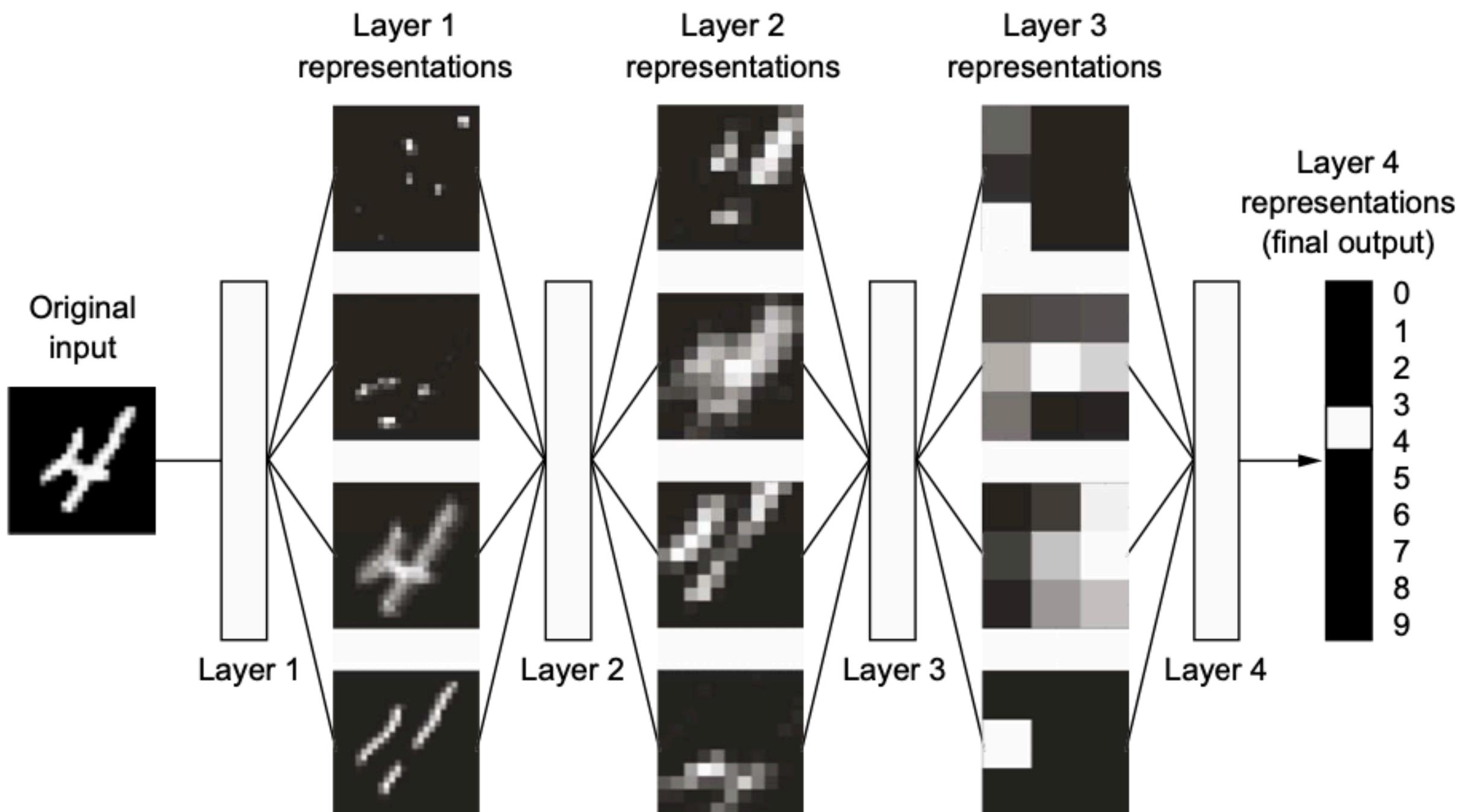
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Find data representations



# Why layers?

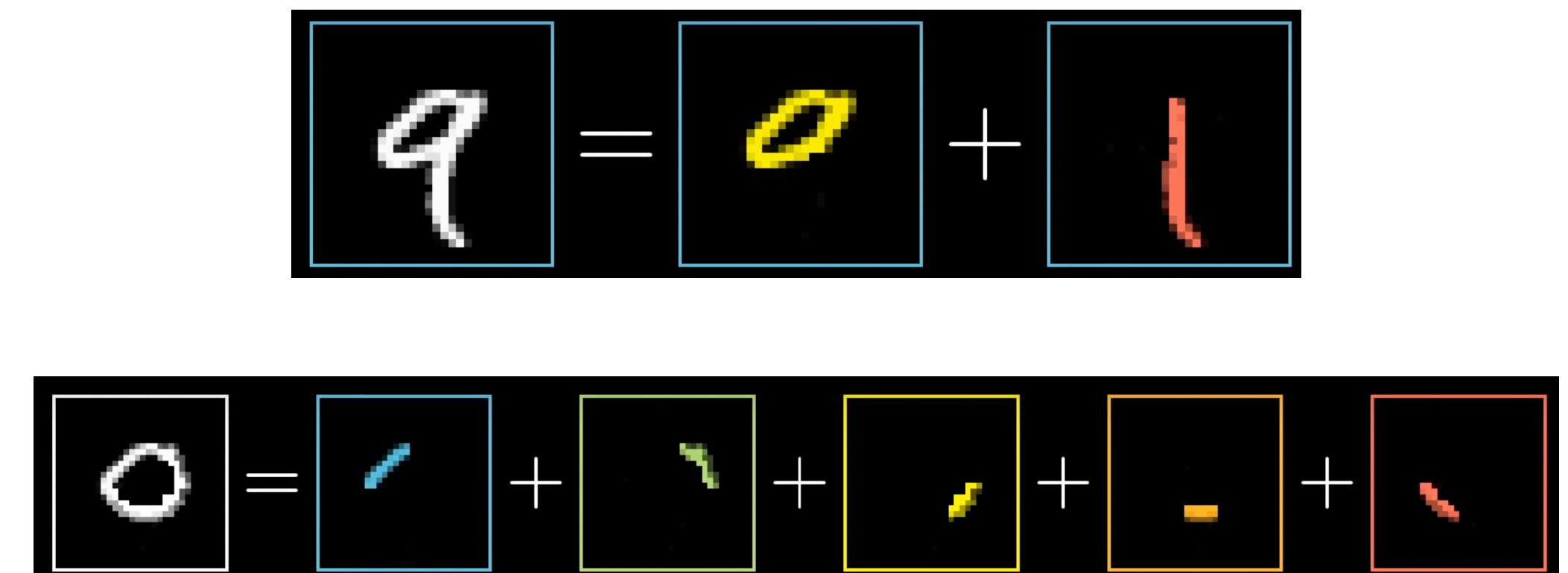
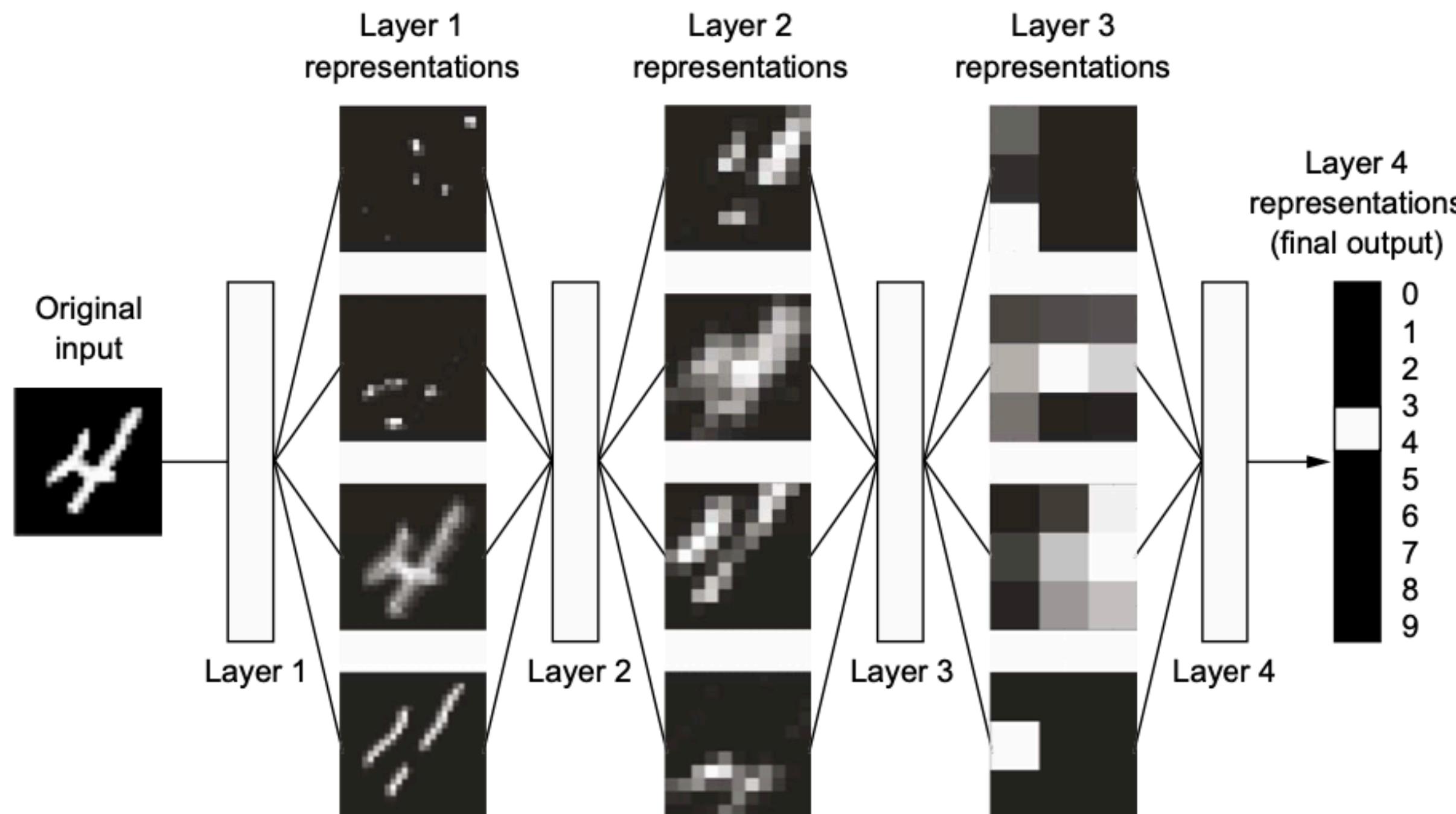
Find data representations



$$\begin{aligned} \text{Digit } 4 &= \text{Feature } 1 + \text{Feature } 2 \\ \text{Digit } 0 &= \text{Feature } 1 + \text{Feature } 2 + \text{Feature } 3 + \text{Feature } 4 + \text{Feature } 5 \end{aligned}$$

# Why layers?

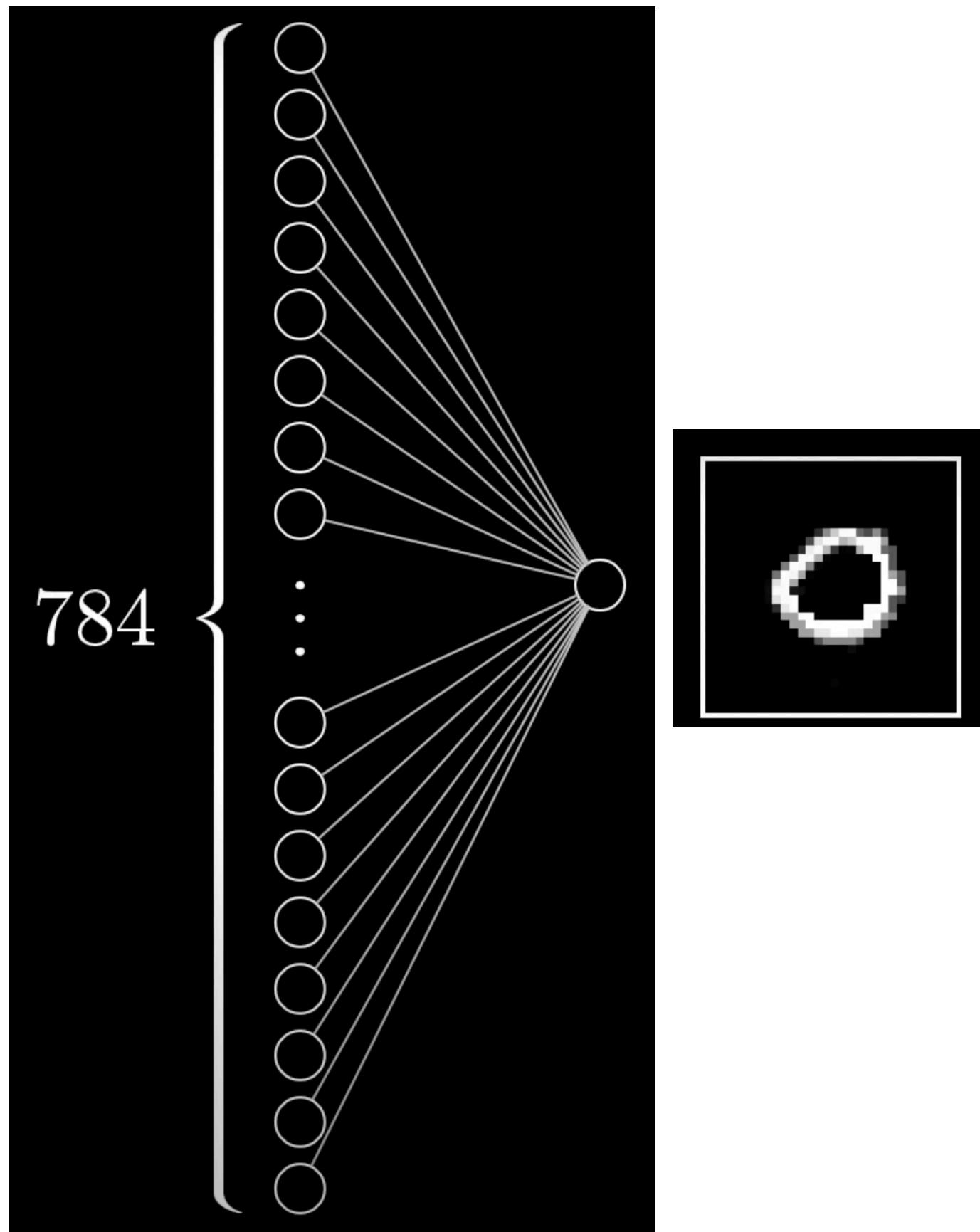
Find data representations



How connections in one layer may determine the activations in the next layer?

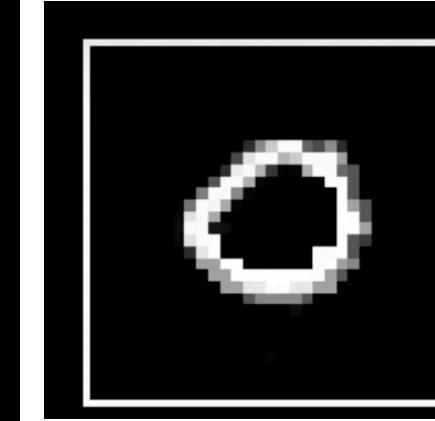
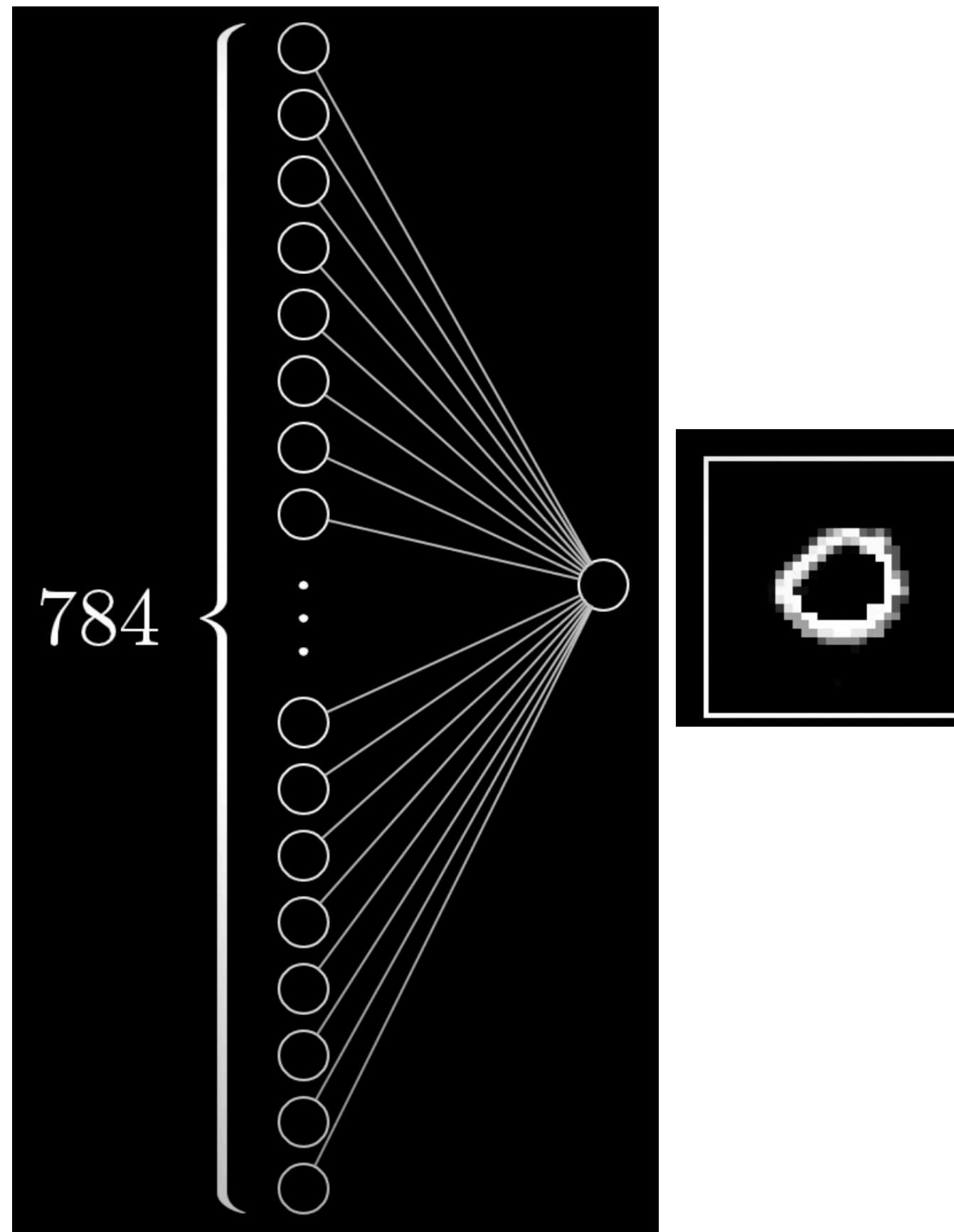
# The parameters of the Network (Weights and Biases)

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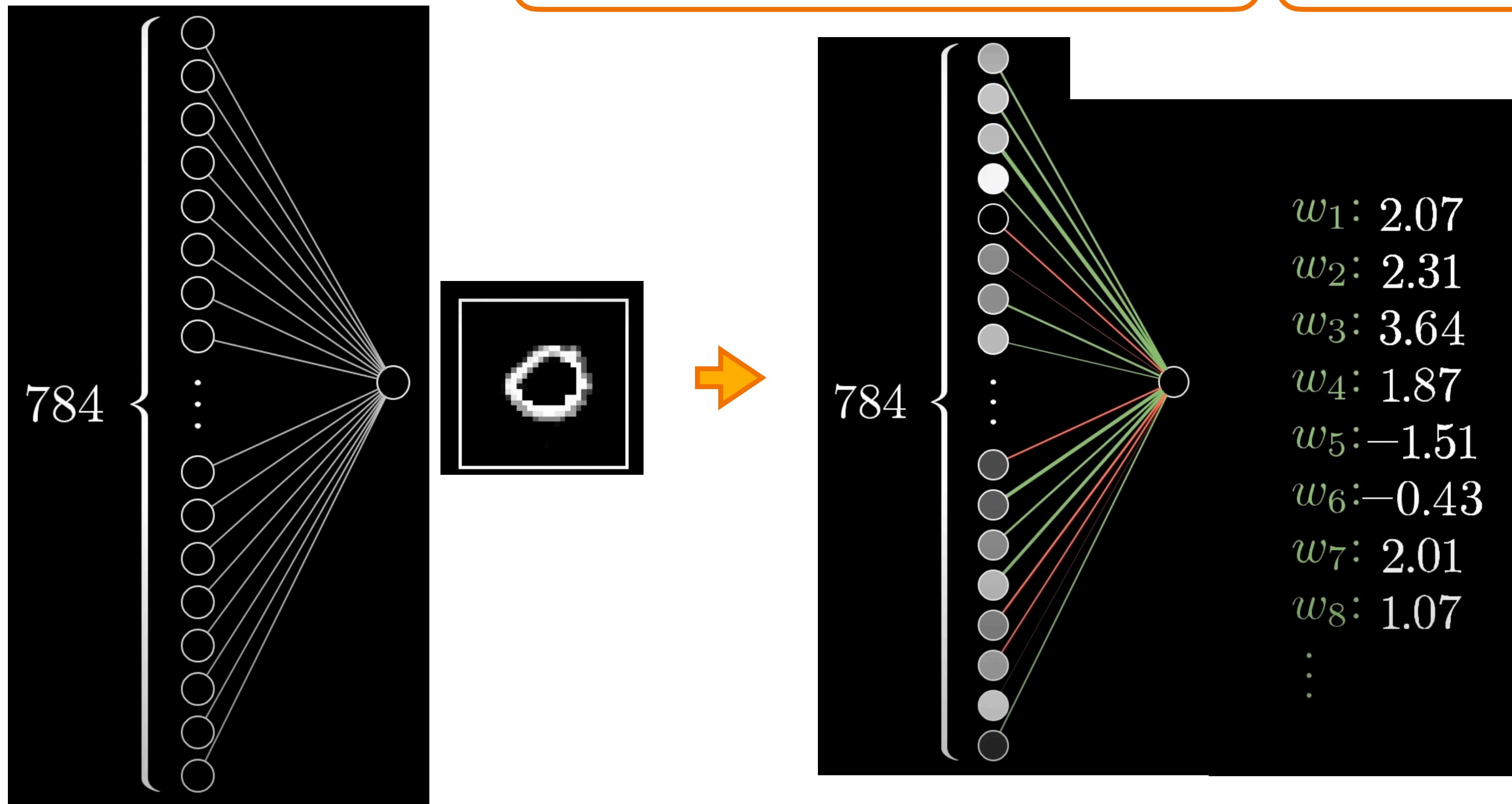
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Which pixels are more important to recognize the circle?

What parameters does the network need to detect that circle?

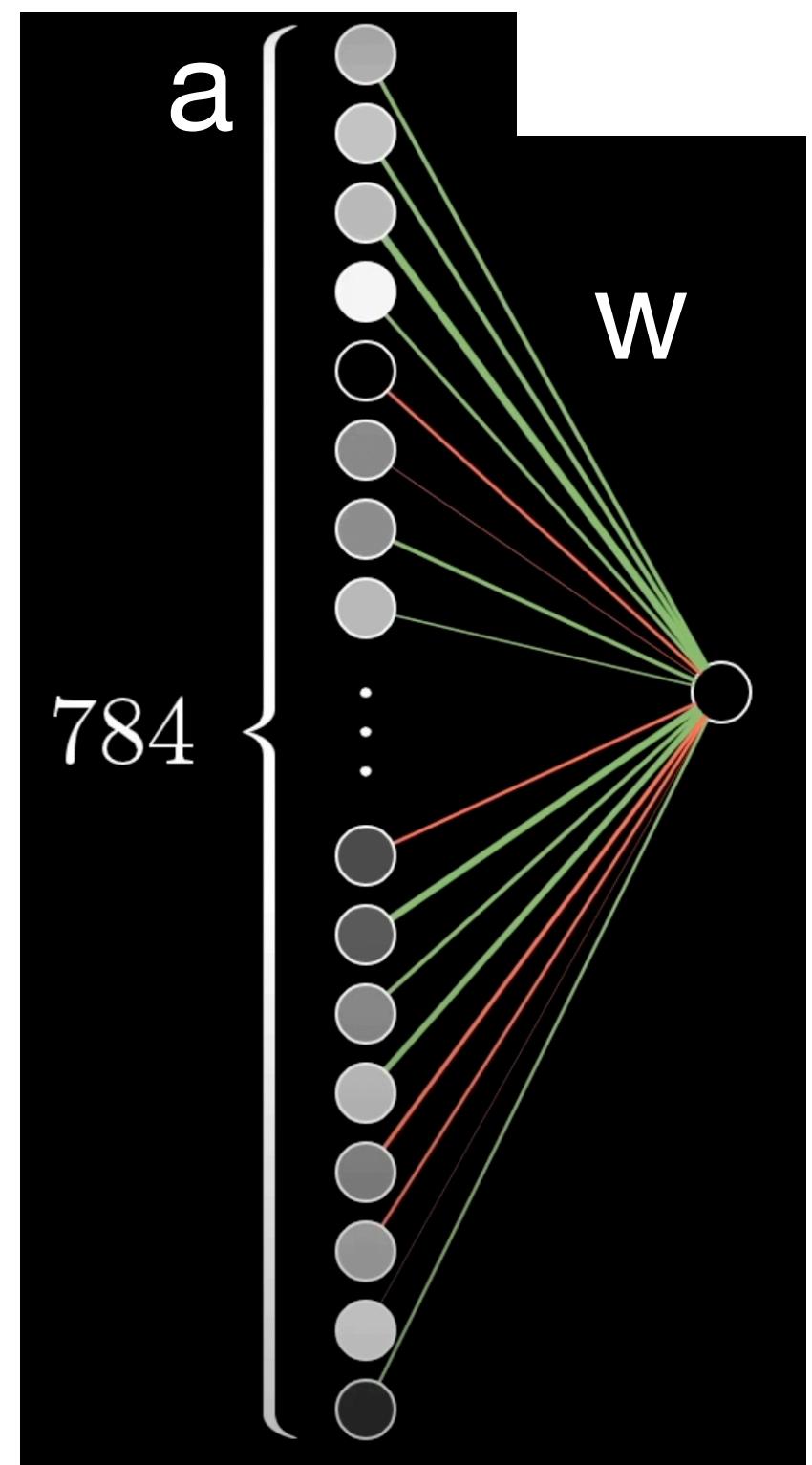
# The parameters of the Network (Weights and Biases)



For every connection we have what we call weights

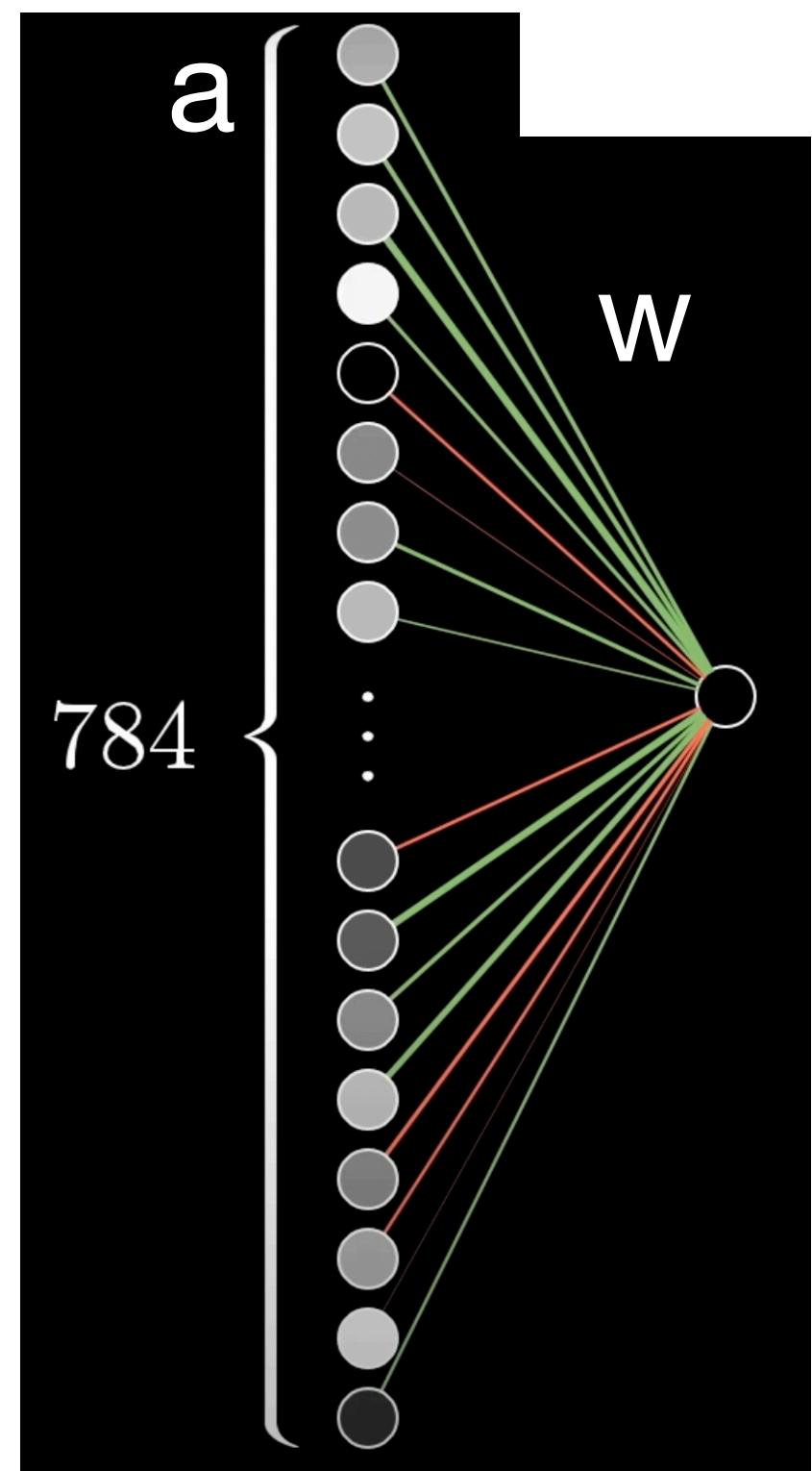
# The parameters of the Network (Weights and Biases)

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# The parameters of the Network (Weights and Biases)

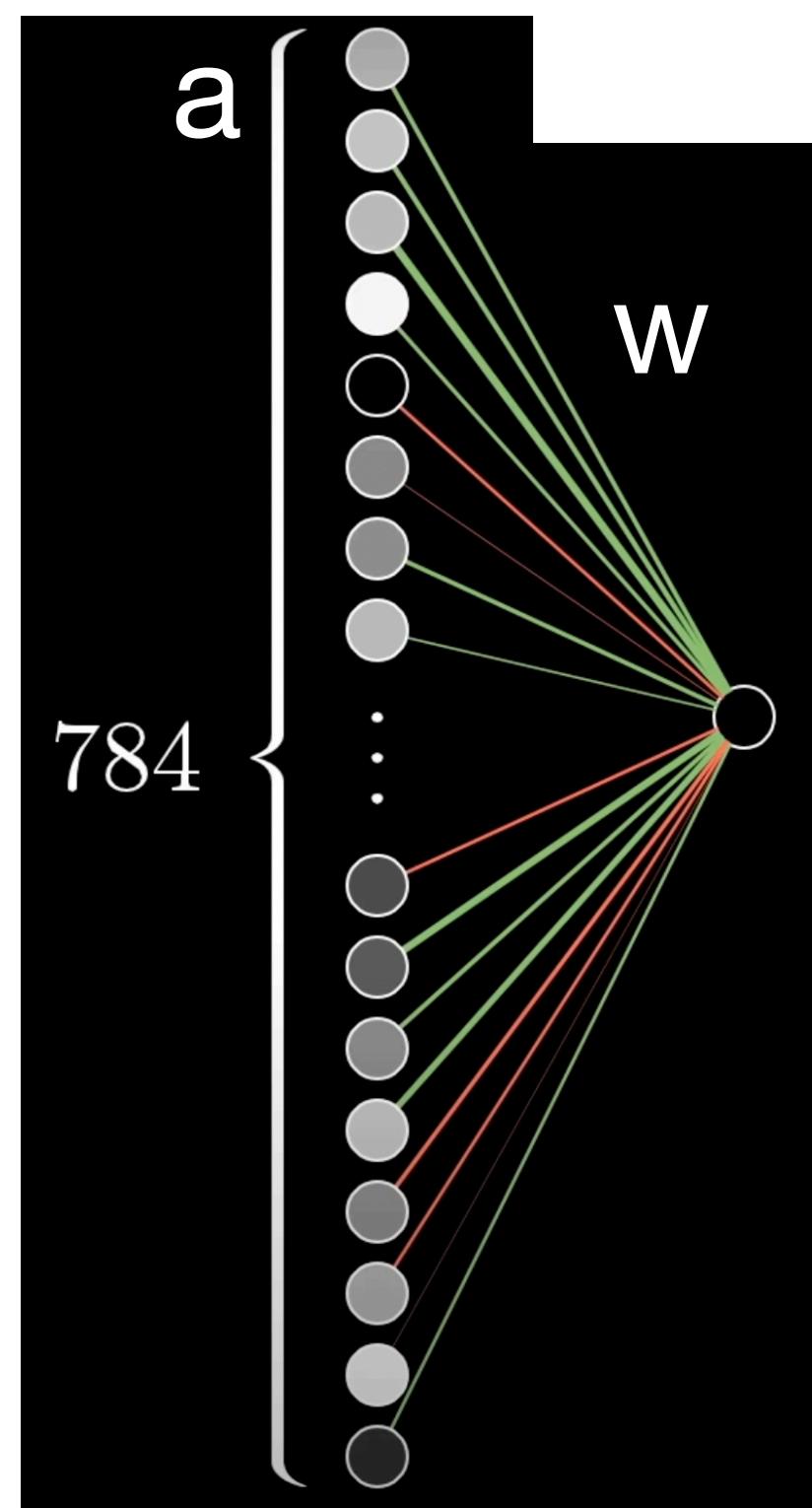
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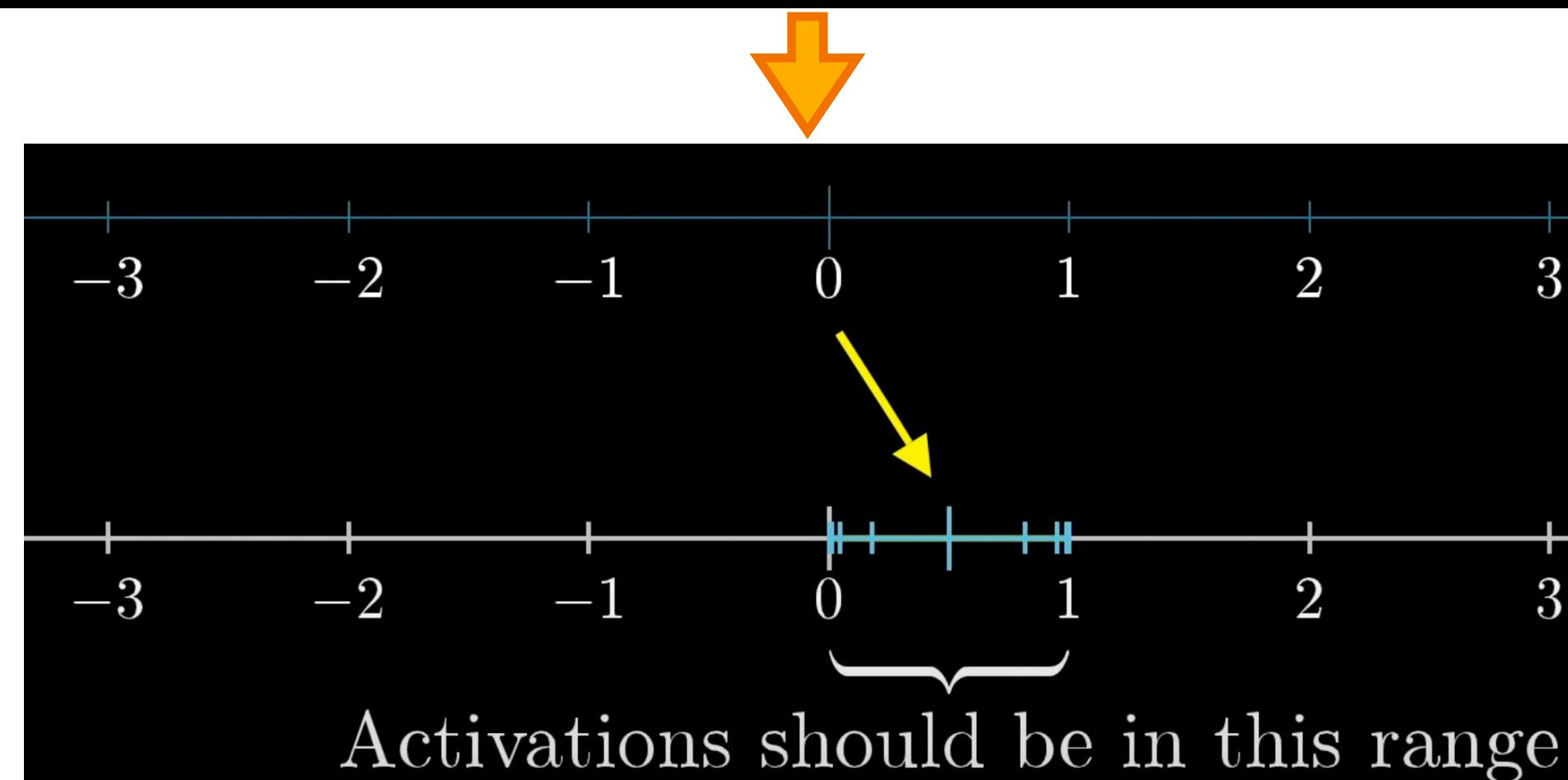
$$w_1 a_1 + w_2 a_2 + w_3 a_3 + w_4 a_4 + \dots + w_n a_n$$

But we need to combine  
the activations and the  
weights

# The parameters of the Network (Weights and Biases)



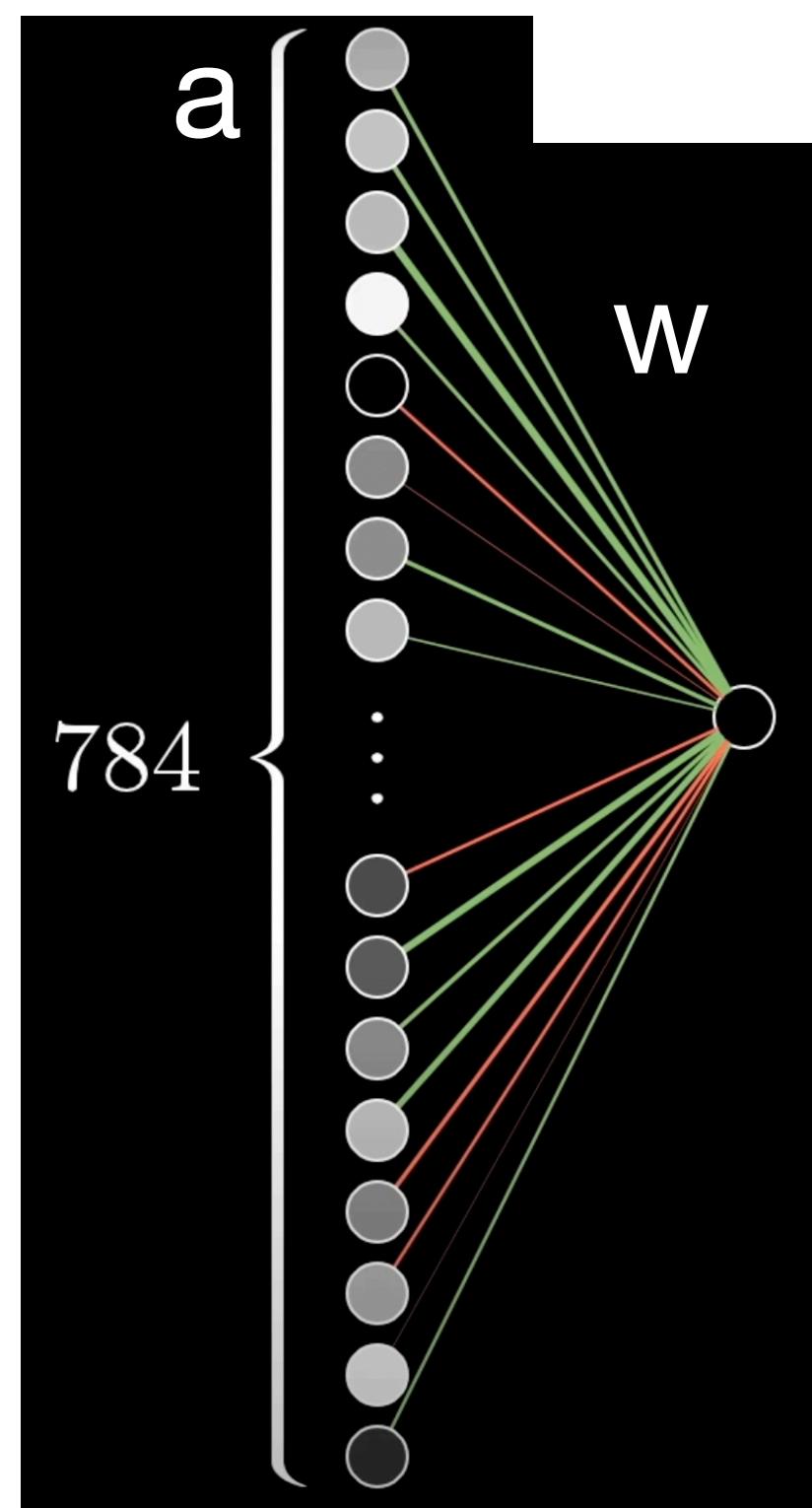
$$w_1 a_1 + w_2 a_2 + w_3 a_3 + w_4 a_4 + \dots + w_n a_n$$



But we need to combine the activations and the weights

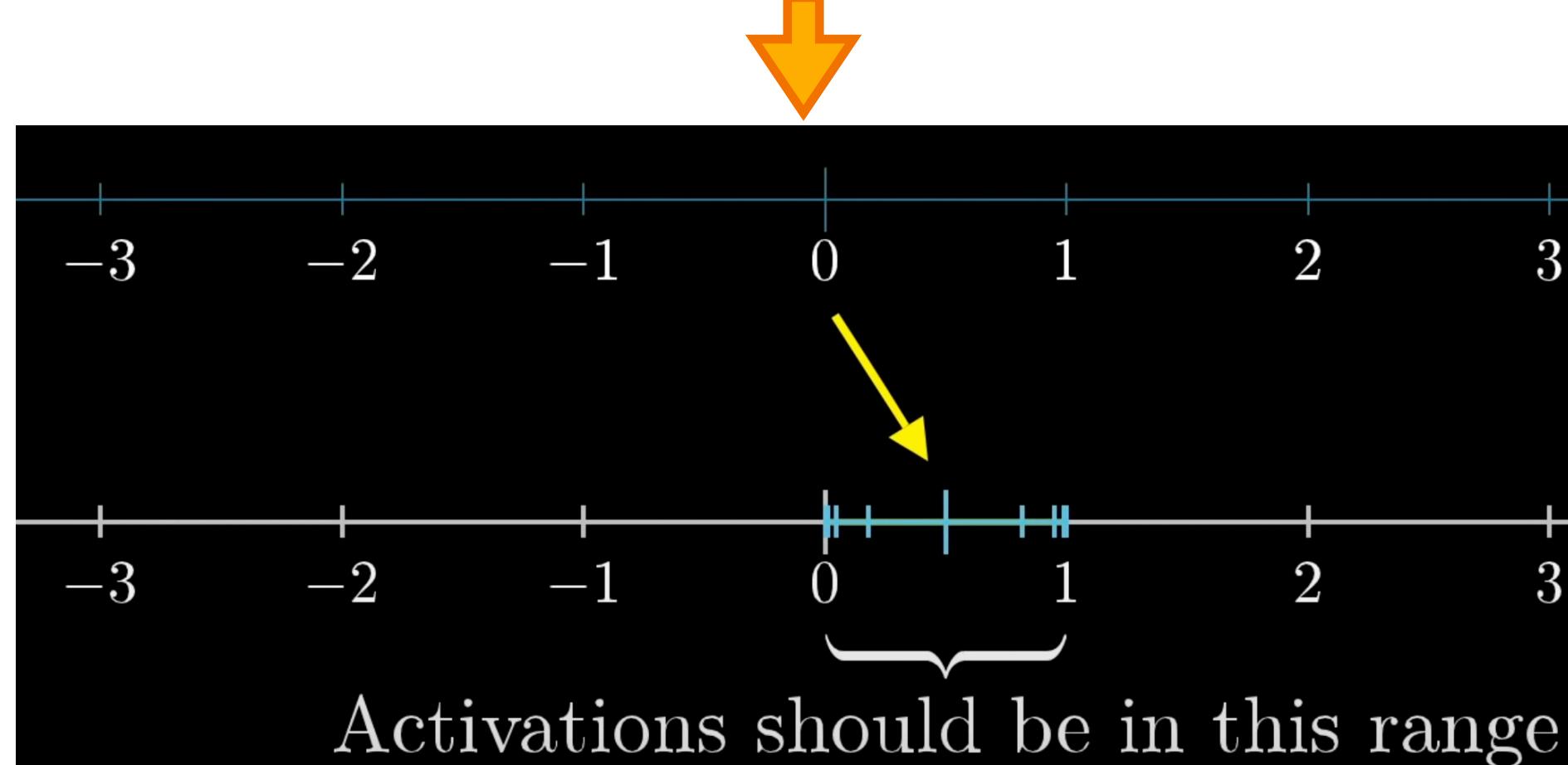
We also need values between 0 and 1 for the activation of our new neuron therefore we need an additional step

# The parameters of the Network (Weights and Biases)



$$w_1 a_1 + w_2 a_2 + w_3 a_3 + w_4 a_4 + \dots + w_n a_n$$

But we need to combine the activations and the weights

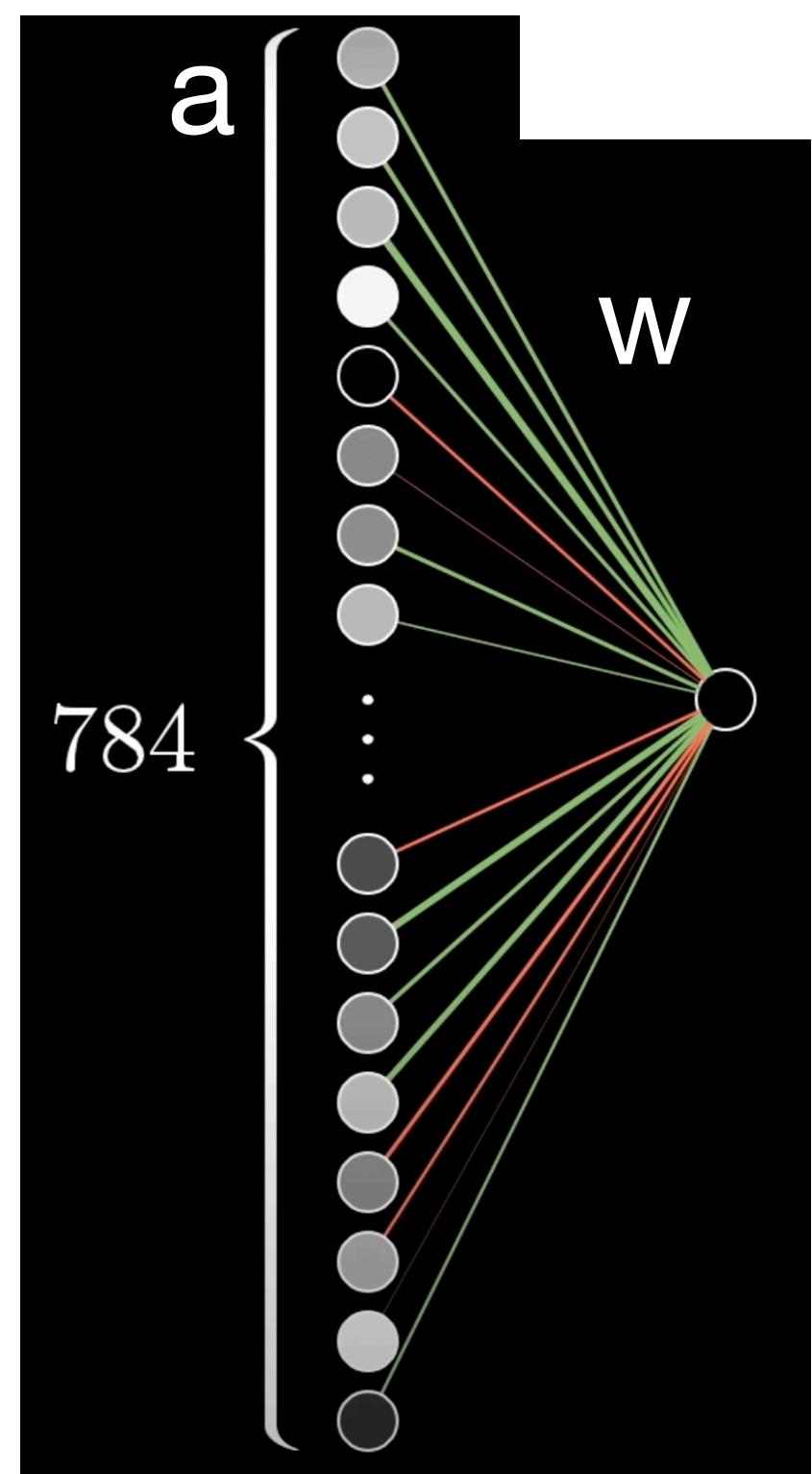


Activations should be in this range

Sigmoid  
↓  
 $\sigma(w_1 a_1 + w_2 a_2 + w_3 a_3 + \dots + w_n a_n)$

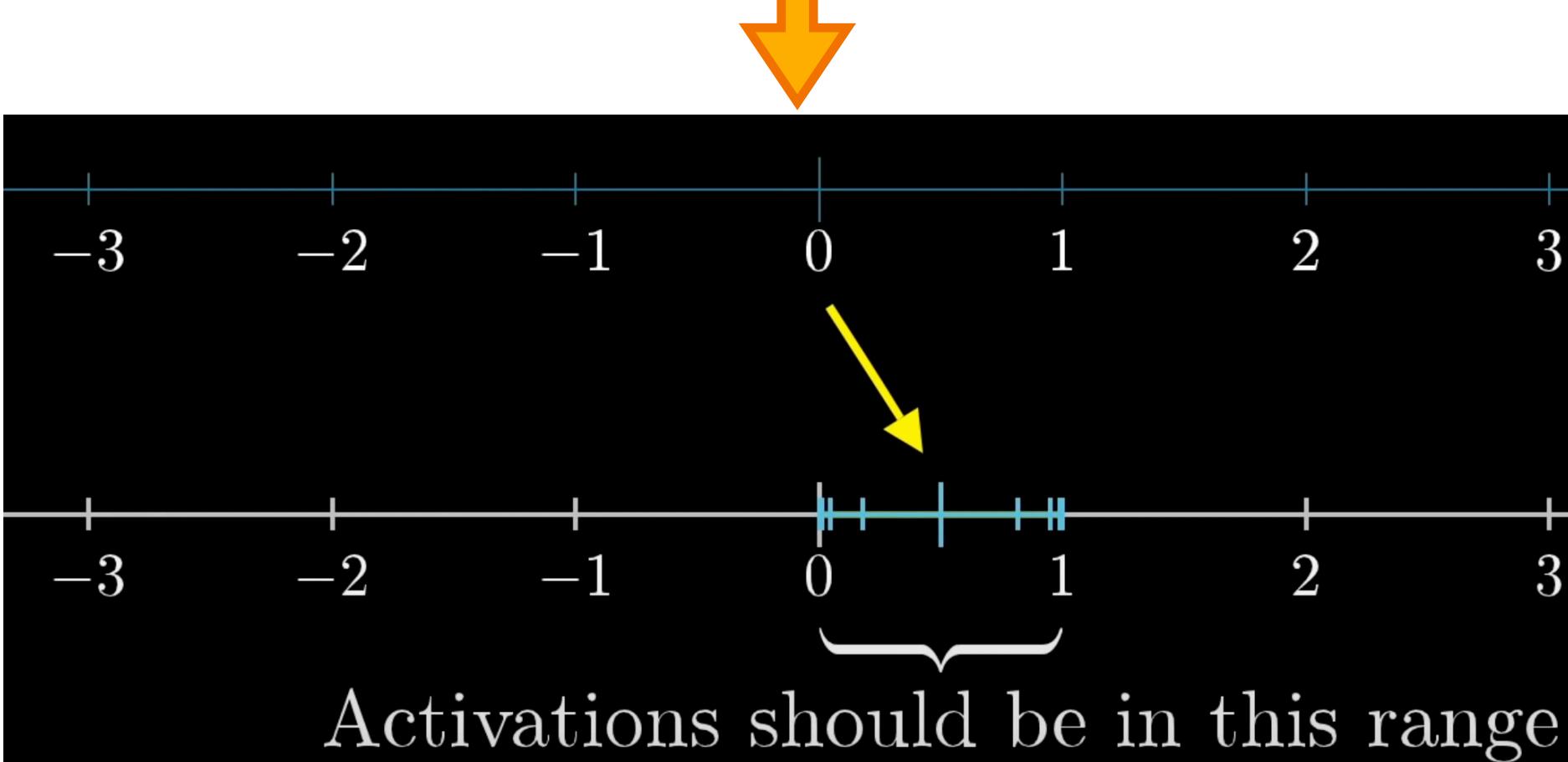
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# The parameters of the Network (Weights and Biases)



$$w_1 a_1 + w_2 a_2 + w_3 a_3 + w_4 a_4 + \dots + w_n a_n$$

But we need to combine the activations and the weights



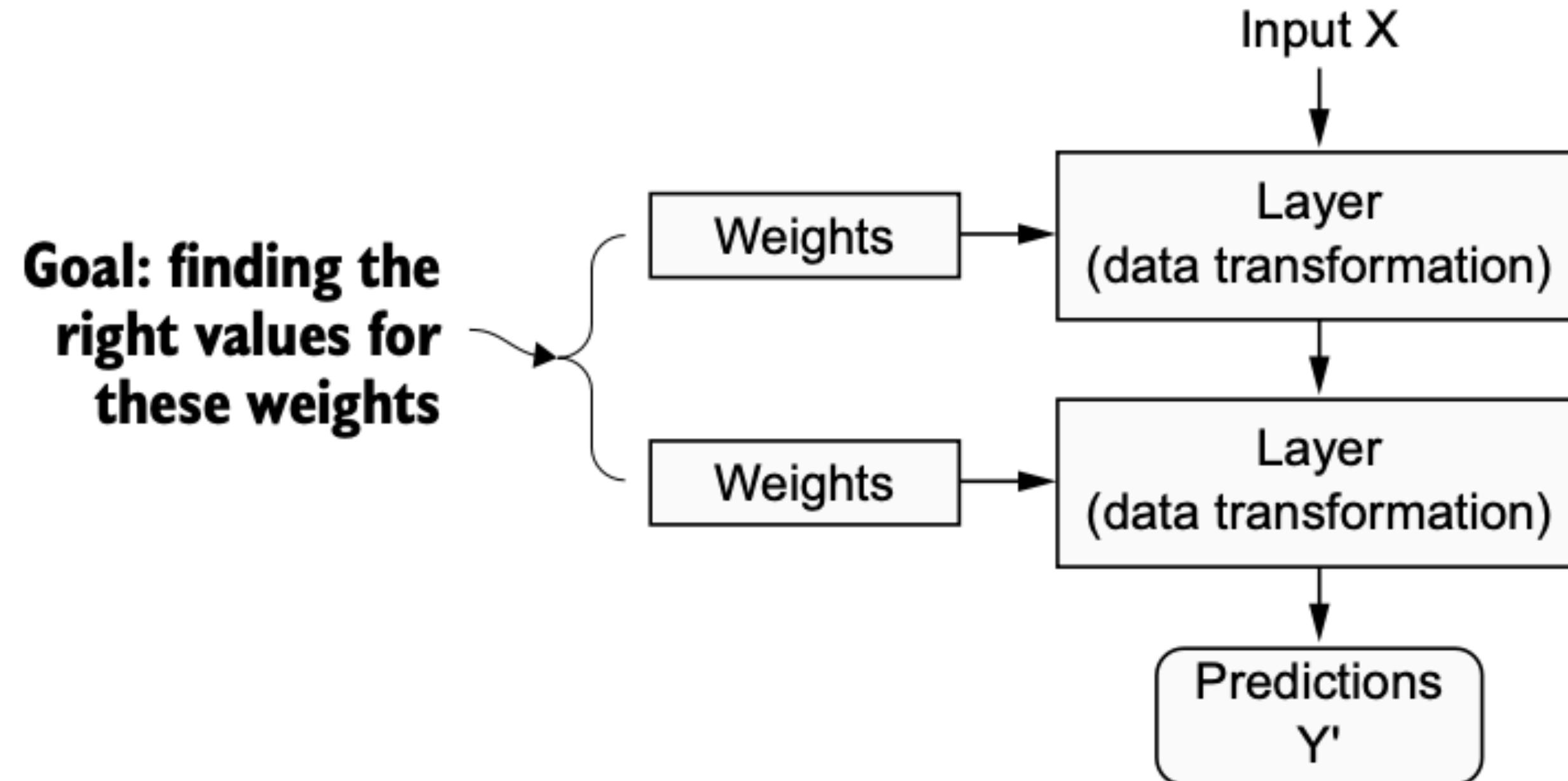
Sigmoid  
 $\downarrow$   
 $\sigma(w_1 a_1 + w_2 a_2 + w_3 a_3 + \dots + w_n a_n)$

How positive is this?

Neural Networks also present a bias parameter (How high the Weighted sum needs to be before the neuron becomes active)

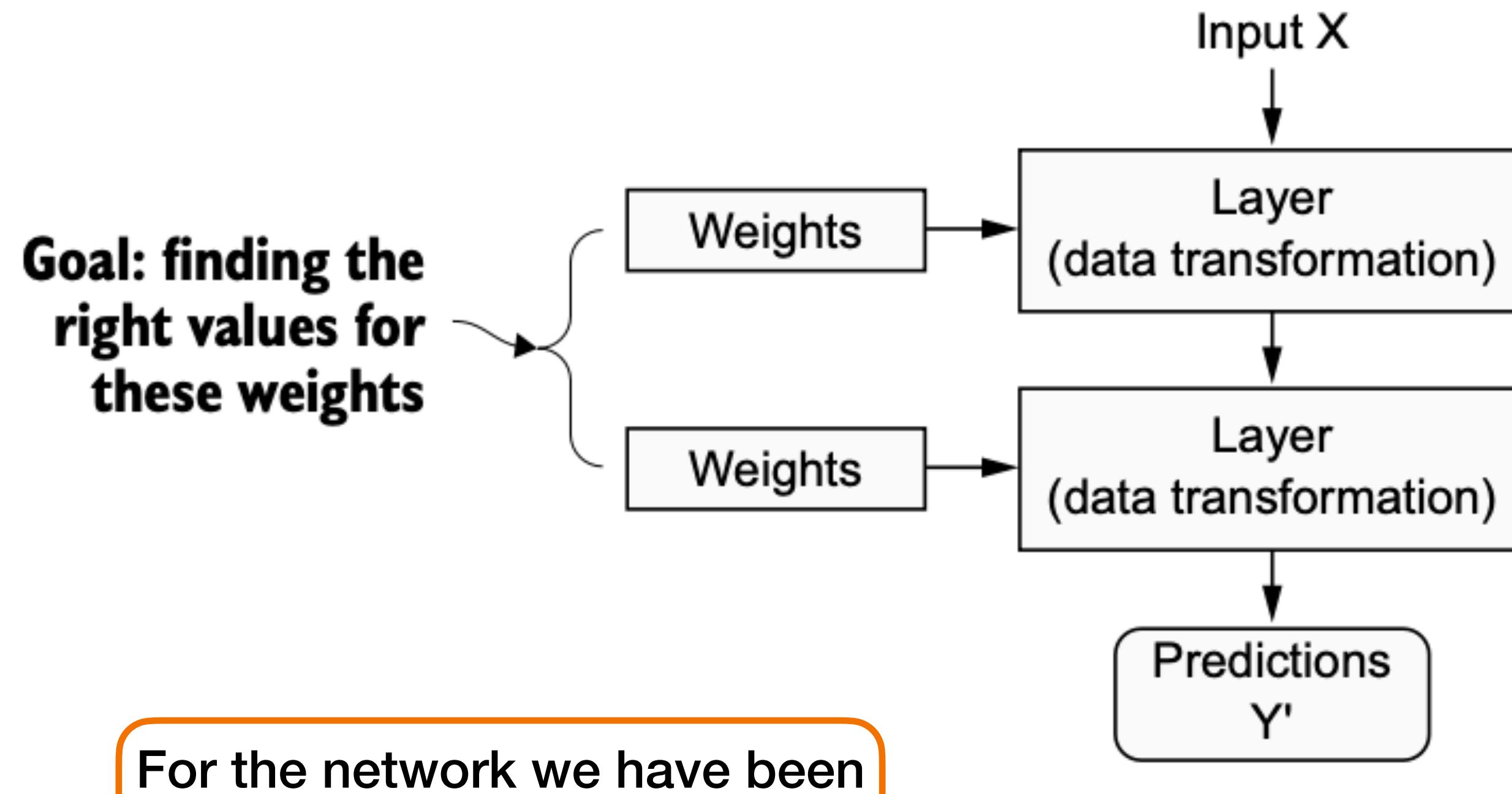
# Recap

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# Recap

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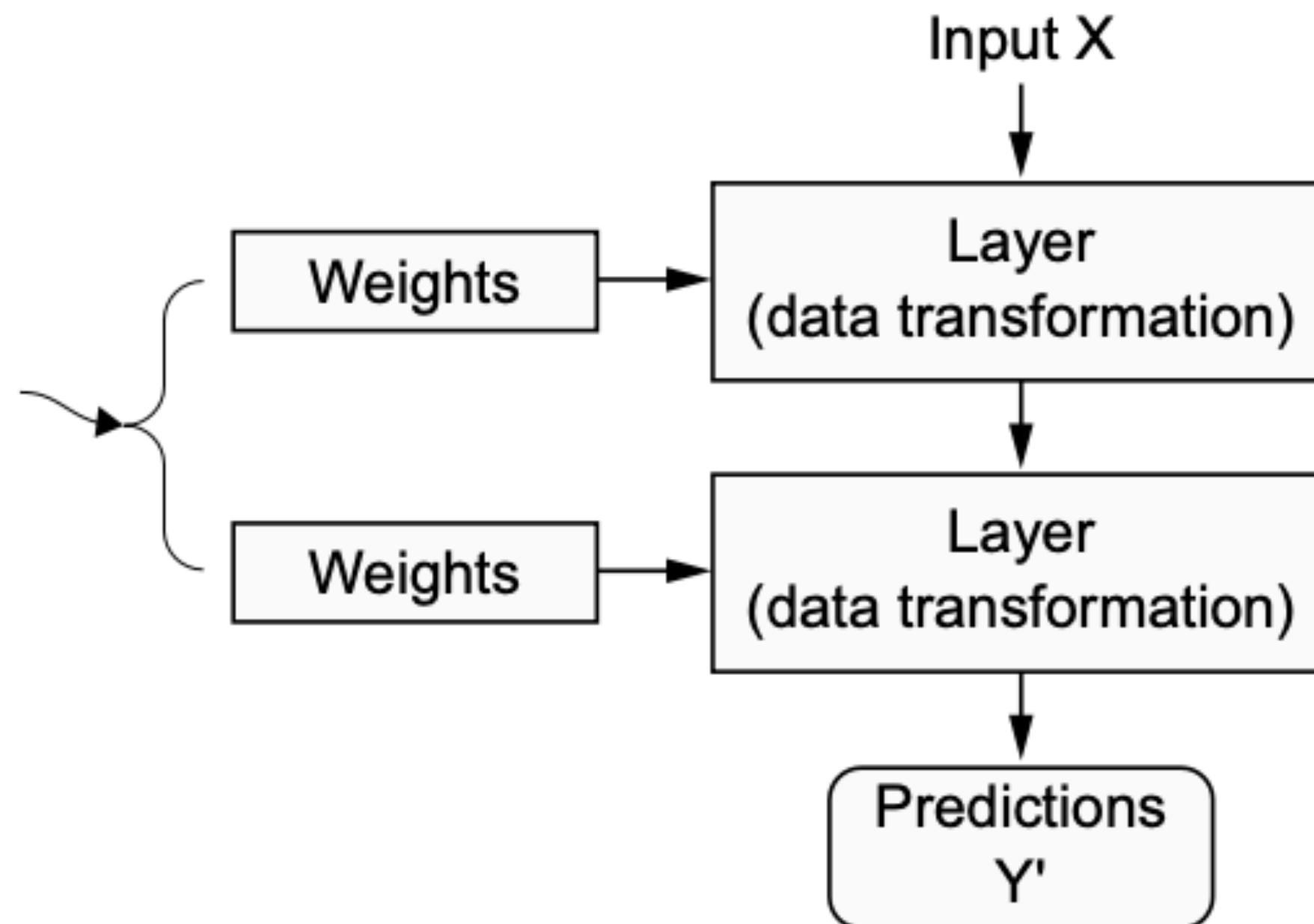


For the network we have been using we have  $> 13\text{ K}$  weights and biases

# Recap

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**Goal: finding the right values for these weights**



## New Neuron Definition

Is a function that squeezes all the activations from the neurons in the previous layers and their corresponding weights to a value between 0 and 1

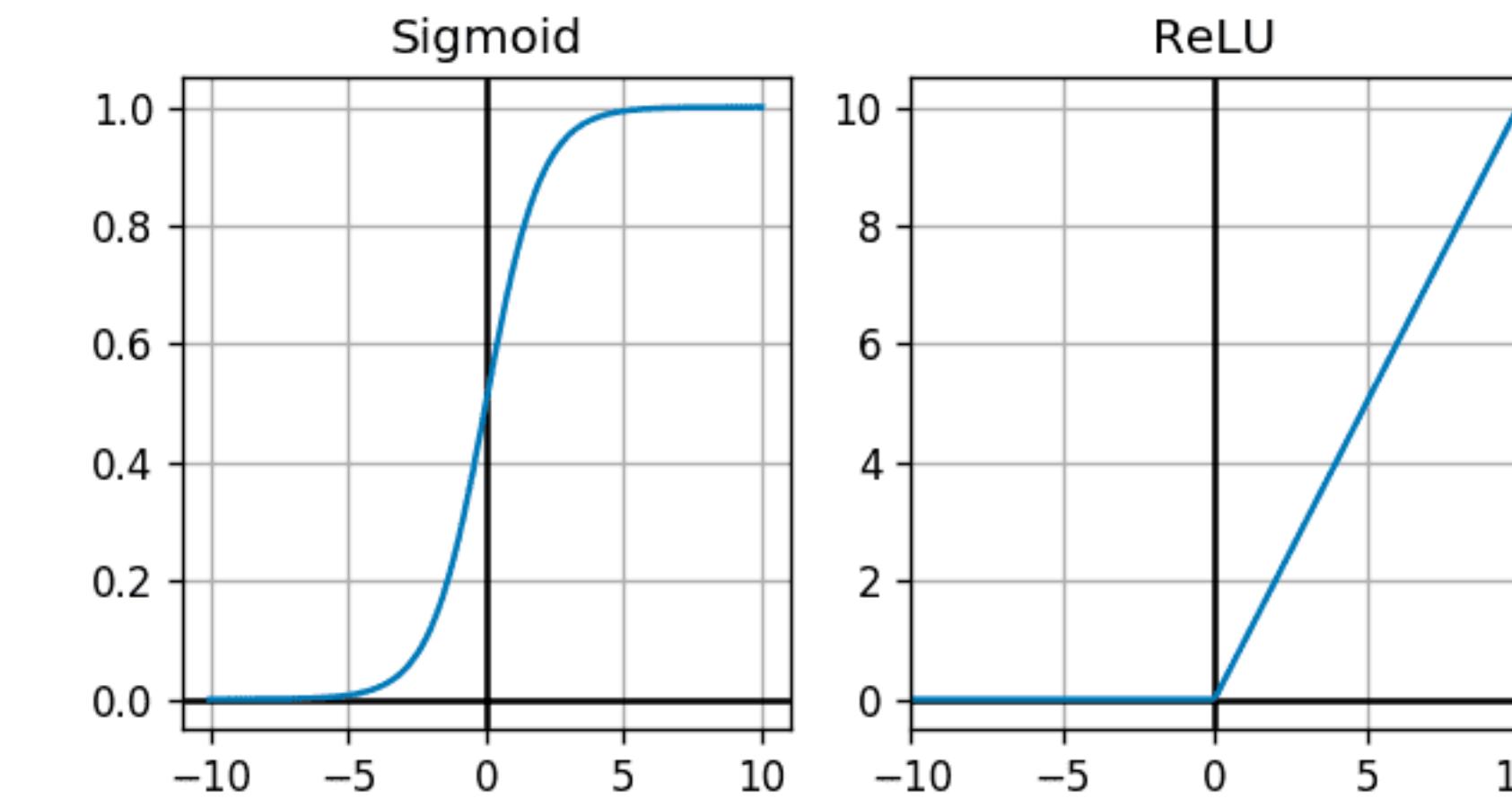
$$\mathbf{a}^{(1)} = \sigma(\mathbf{W}\mathbf{a}^{(0)} + \mathbf{b})$$

# Note on Neurons and Activation Functions

Sorry I was not able to explain activation functions well enough during the class. When using ReLU activation, neurons are not upper-bounded, that is, they can take values between 0 and  $x$ .  $X$  being any positive number.

This is different from what I explicitly said in class. However, I thought it to be the best way to have a clear definition of a neuron for the time being. Bear in mind that this definition can change if a different activation function is used.

Therefore, sorry for not explaining that in a little bit more detail. I add some websites where you can learn more about the differences, which are the things I should have said but I did not have off the top of my head. If you have any additional questions let me know.



<https://stats.stackexchange.com/questions/126238/what-are-the-advantages-of-relu-over-sigmoid-function-in-deep-neural-networks#:~:text=Efficiency%3A%20ReLU%20is%20faster%20to,factor%2C%20but%20constants%20can%20matter>

<https://wandb.ai/ayush-thakur/dl-question-bank/reports/ReLU-vs-Sigmoid-Function-in-Deep-Neural-Networks--VmldzoyMDk0Mzl>

<https://www.datasciencecentral.com/deep-learning-advantages-of-relu-over-sigmoid-function-in-deep/>



# How do Neural Networks learn?

# What are we gonna learn?

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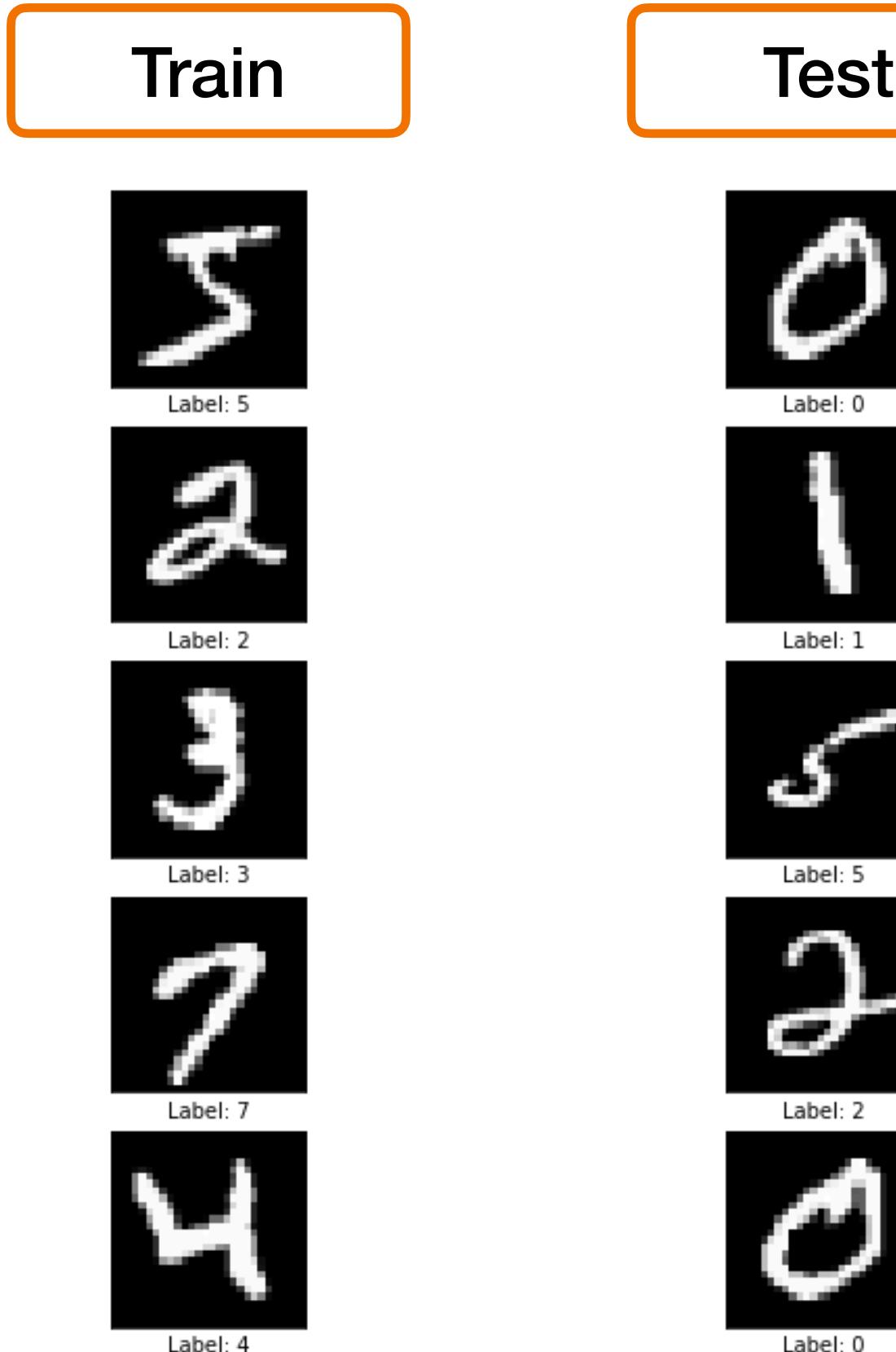
- 1. Forward Pass**
- 2. Backward Pass**
- 3. Update Weights**

# What are we gonna learn?

---

- 1. Forward Pass**
- 2. Backward Pass**
- 3. Update Weights**

- The objective is two-fold:
- To train the network to recognize images of numbers
  - To have a model able to generalize for images beyond that training data



How accurately does the network classify those new images?

# The first step: Randomly initialize the parameters of the network

---

Weights

Biases

$$a^{(1)} = \sigma(Wa^{(0)} + b)$$

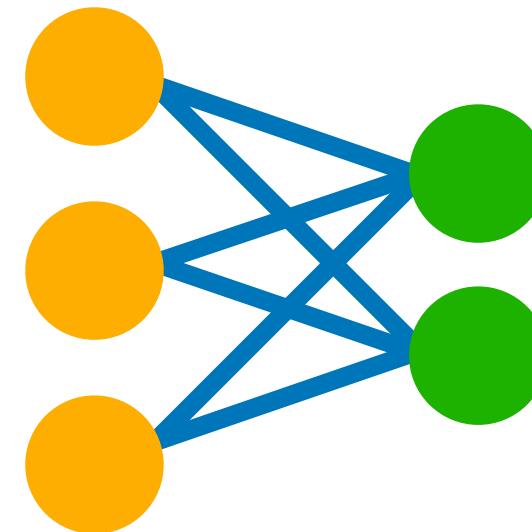
# The first step: Randomly initialize the parameters of the network

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Weights      Biases

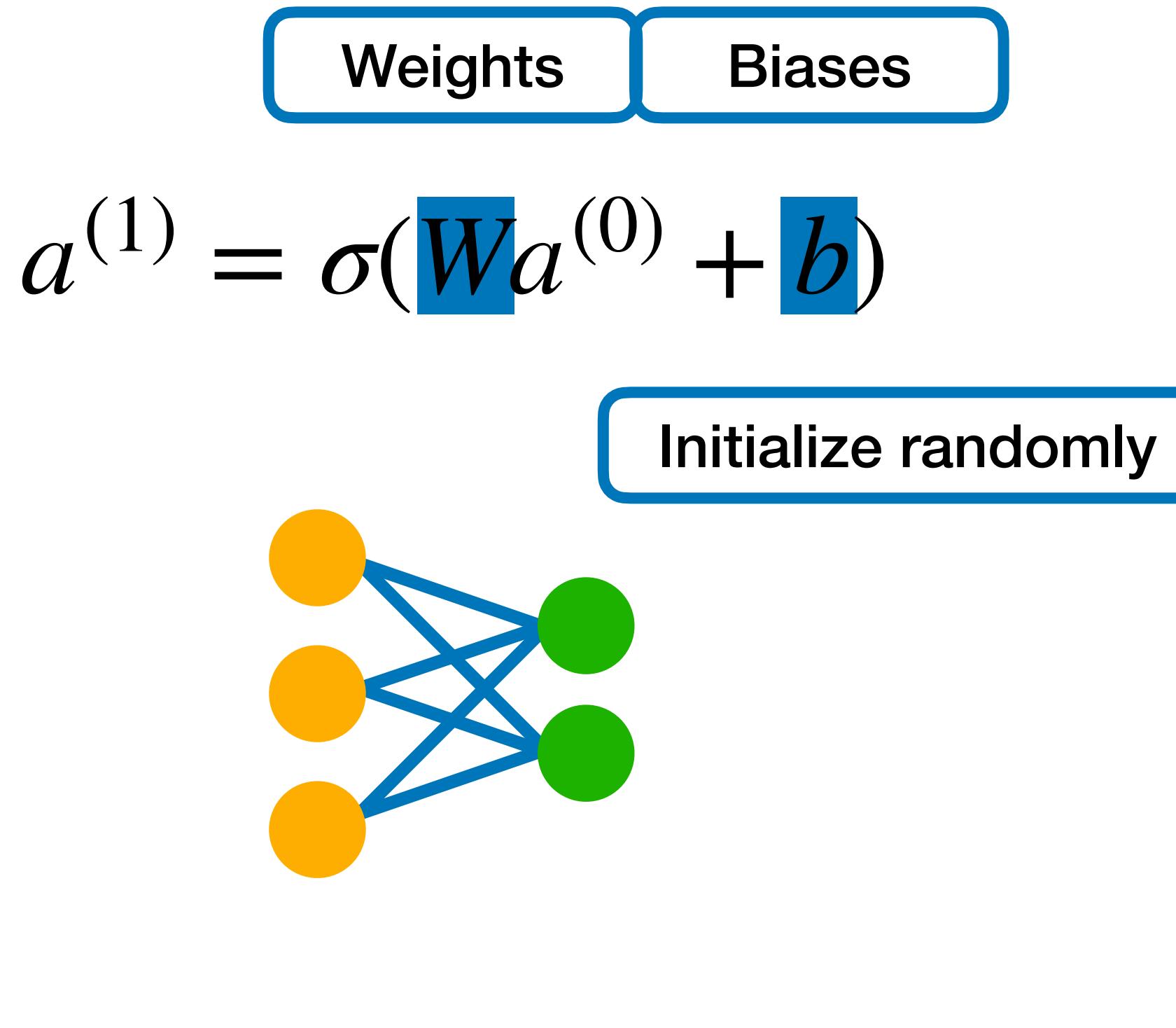
$$a^{(1)} = \sigma(Wa^{(0)} + b)$$

Initialize randomly



# The first step: Randomly initialize the parameters of the network

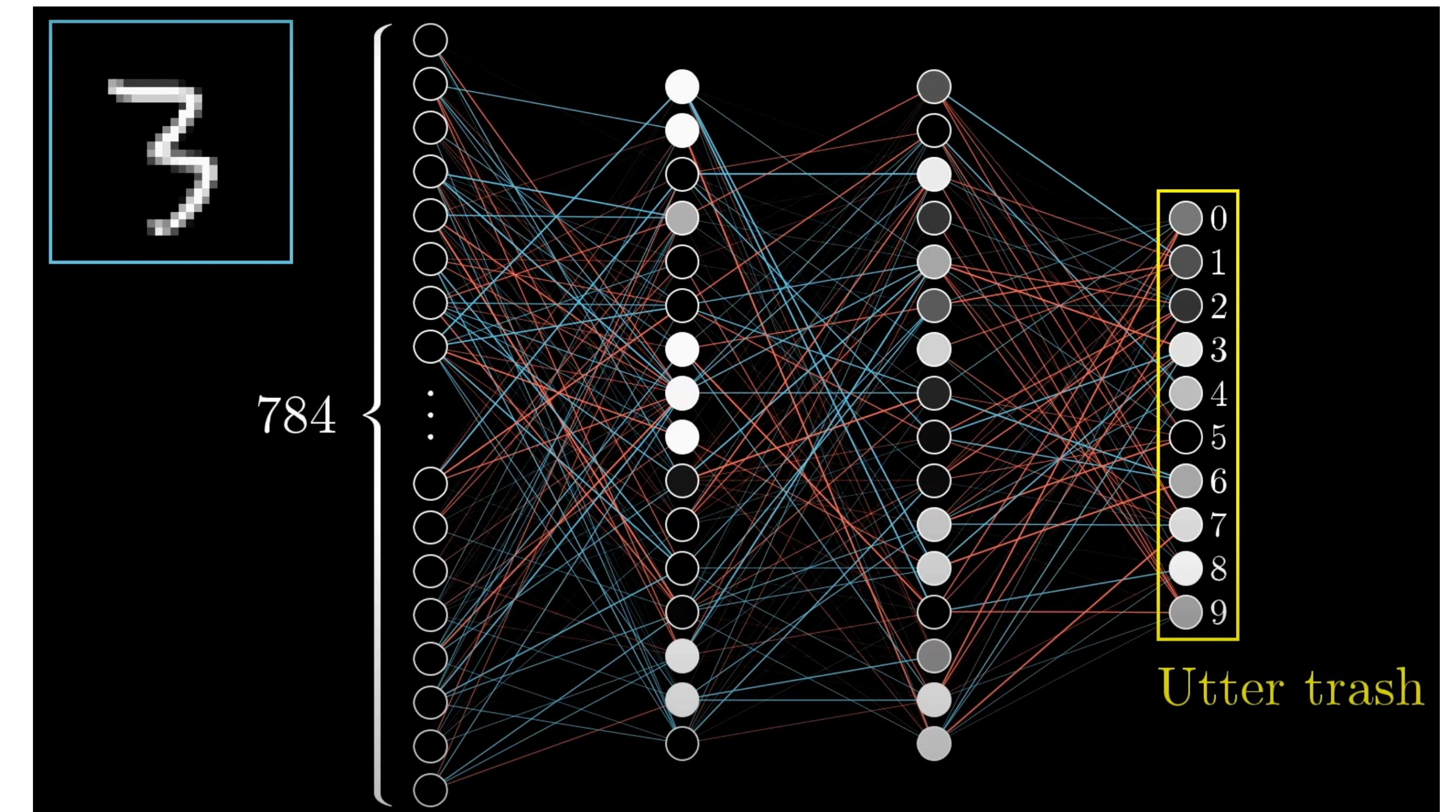
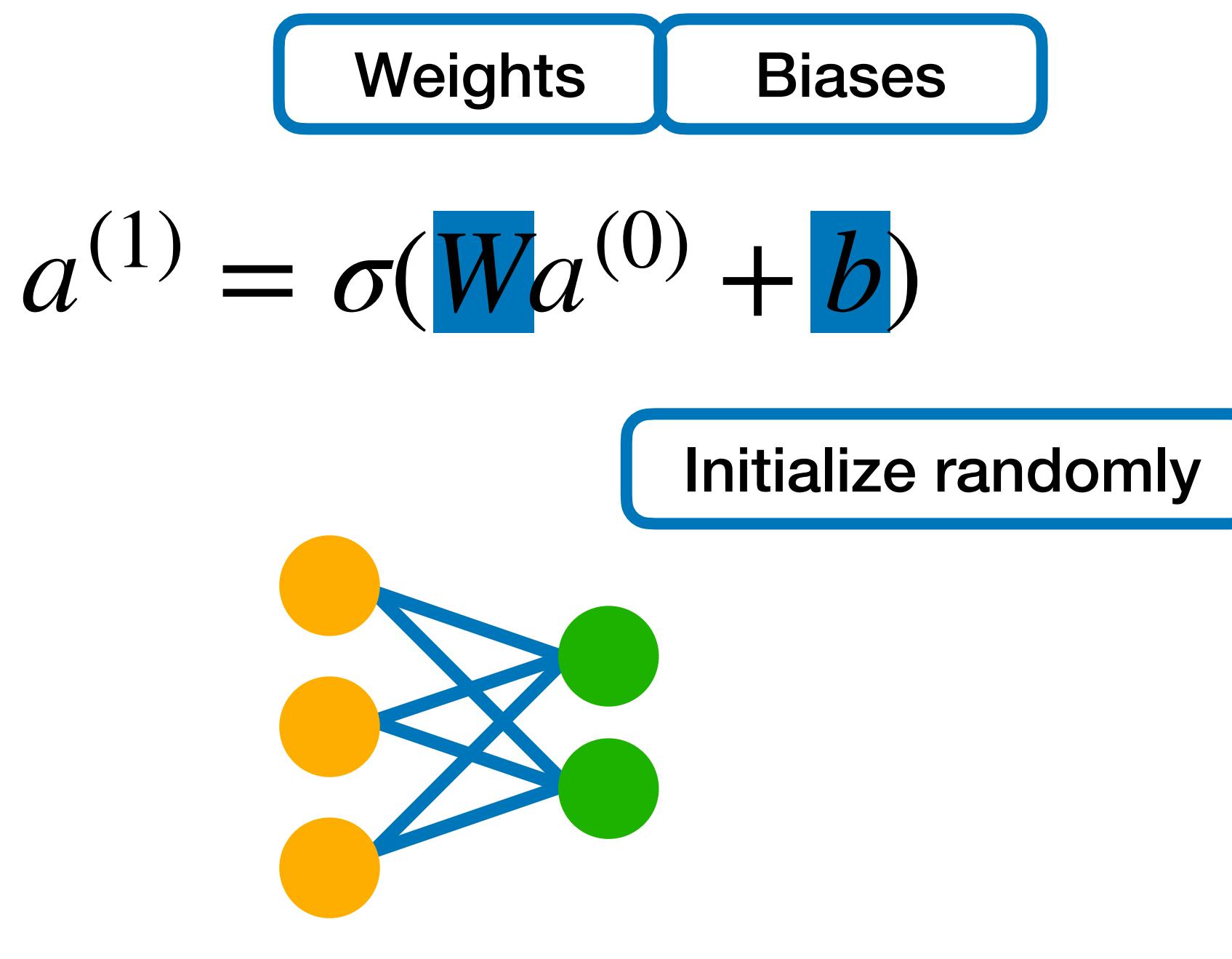
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What do you think  
will happen?

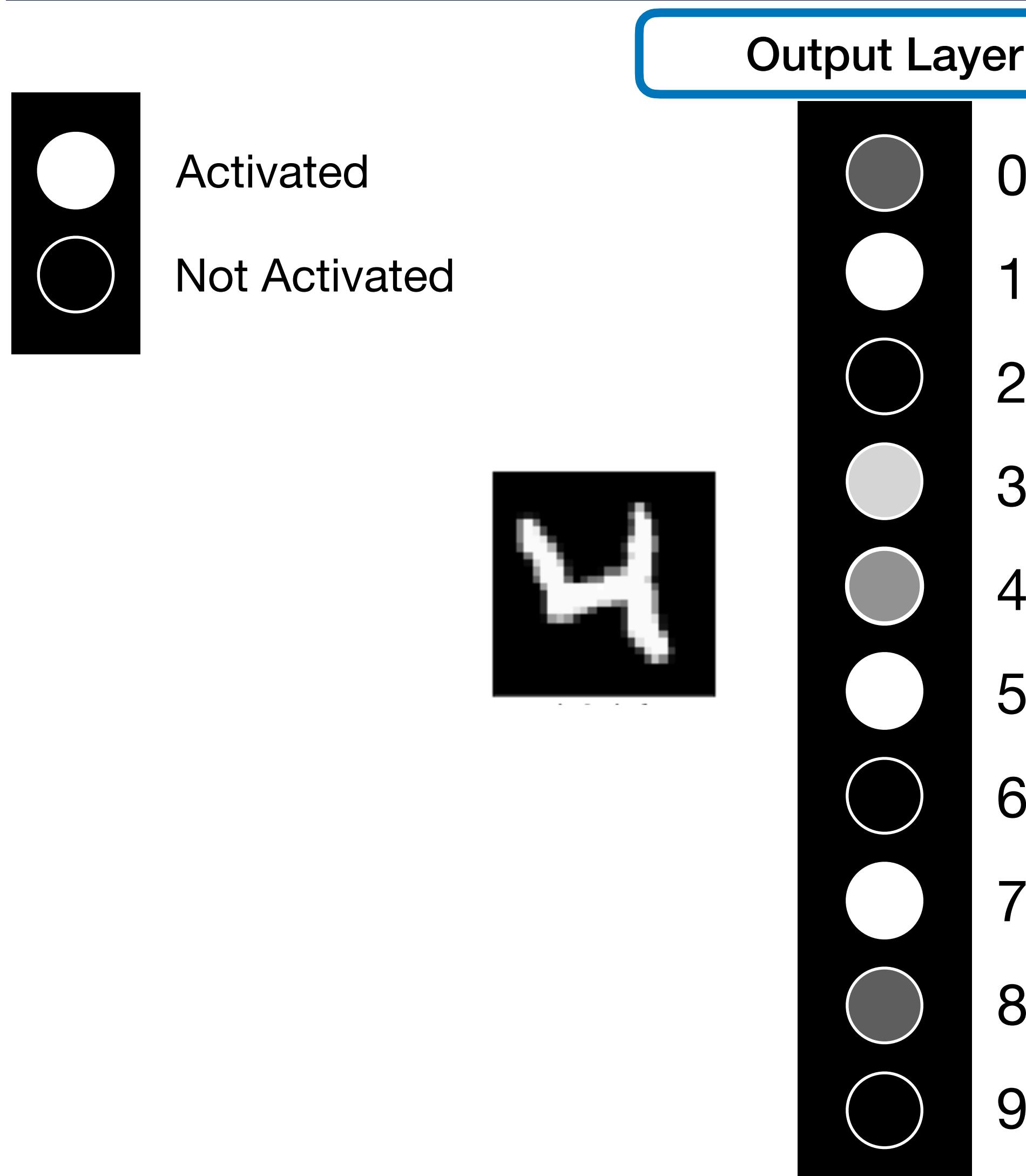
# First step: Randomly initialize the parameters of the network

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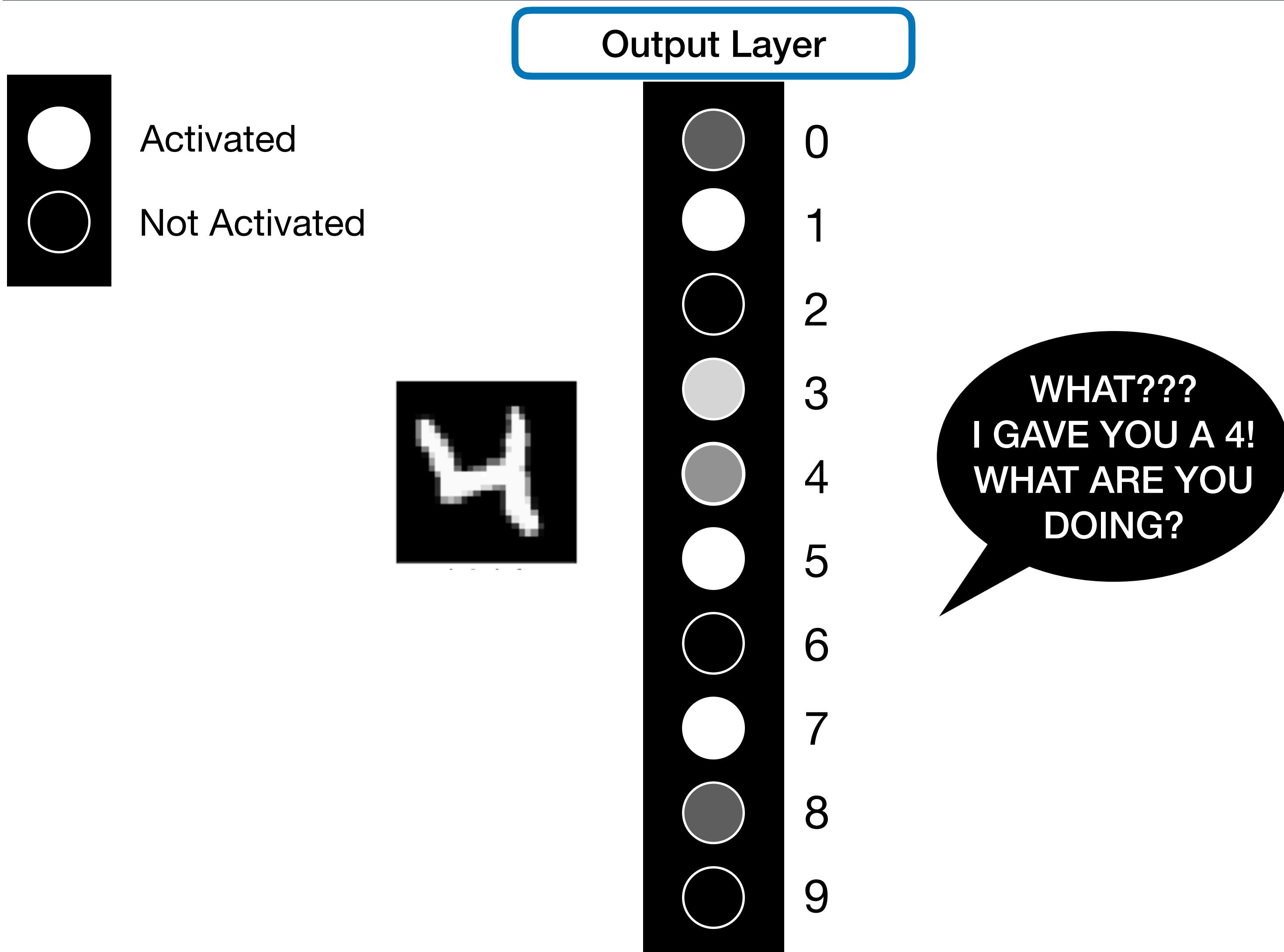


# Second step: Tell the computer that is doing it wrong

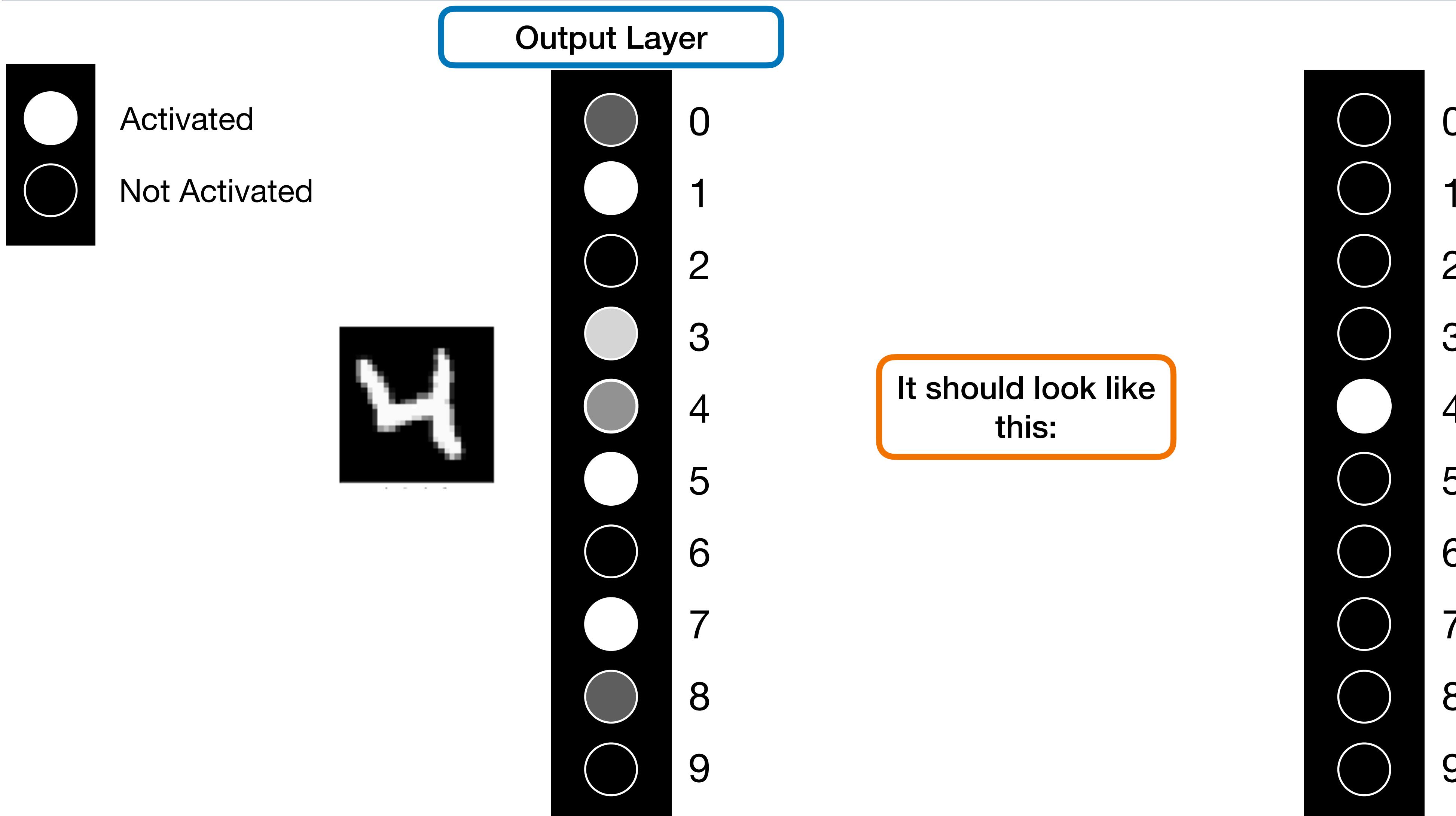
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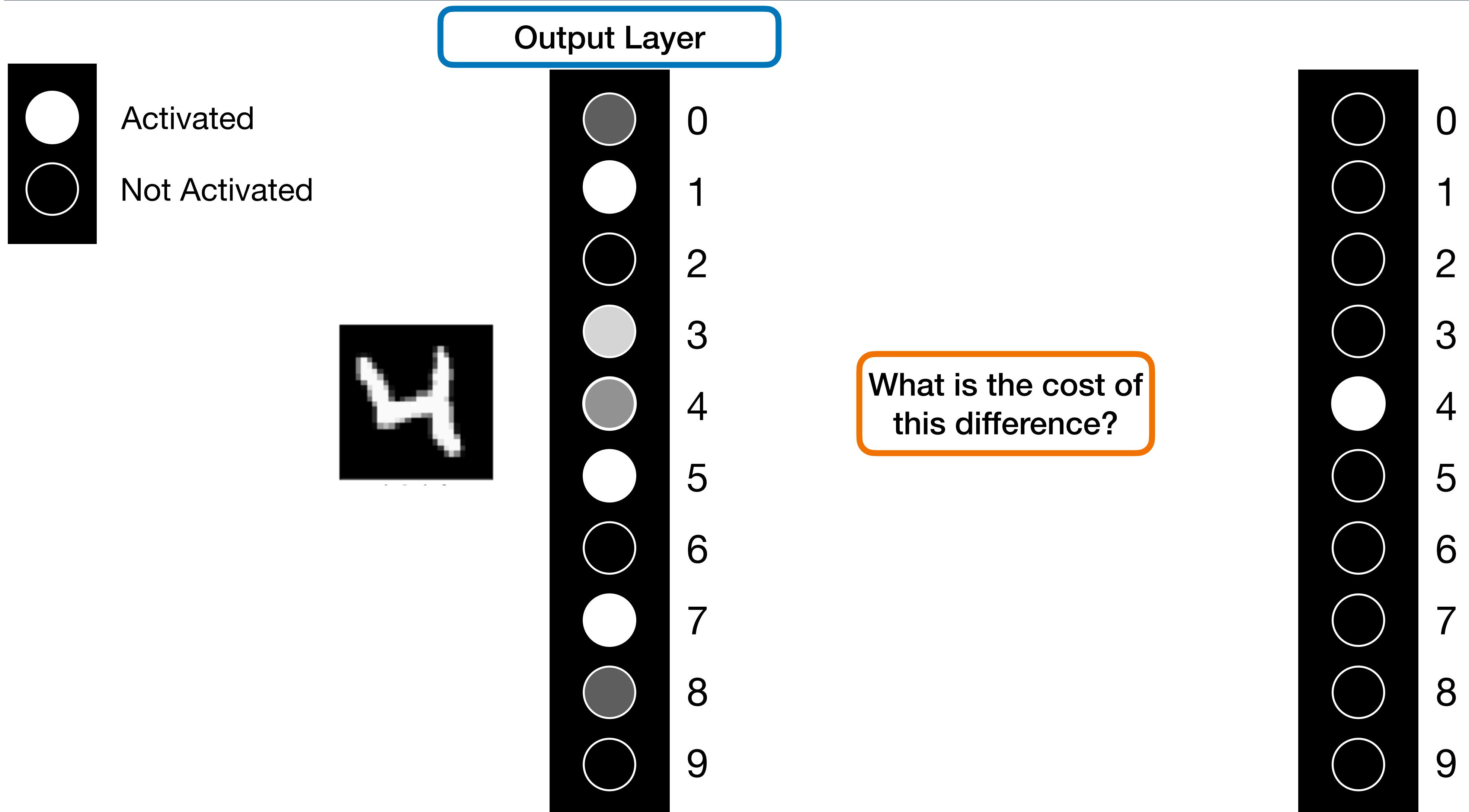
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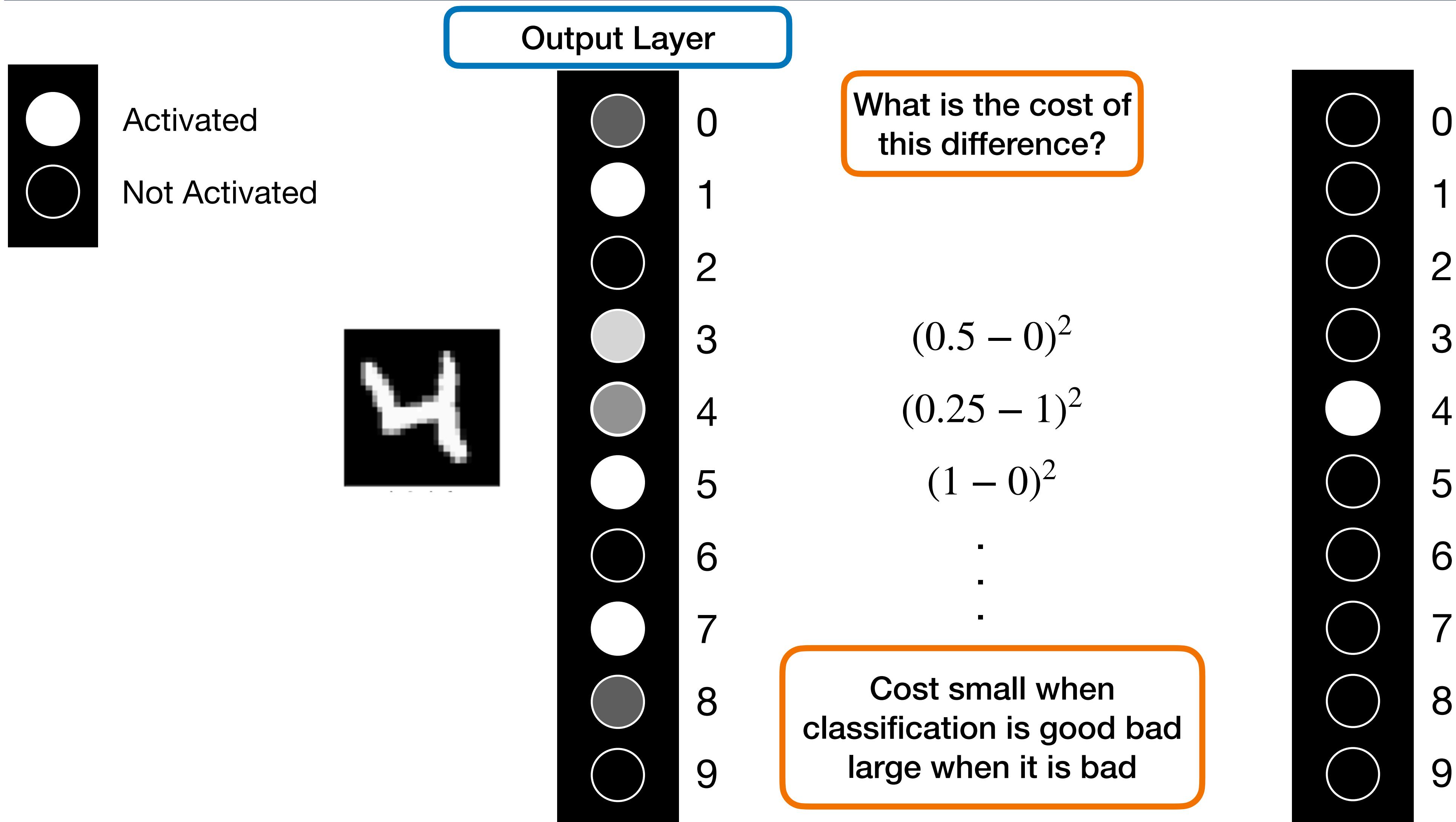
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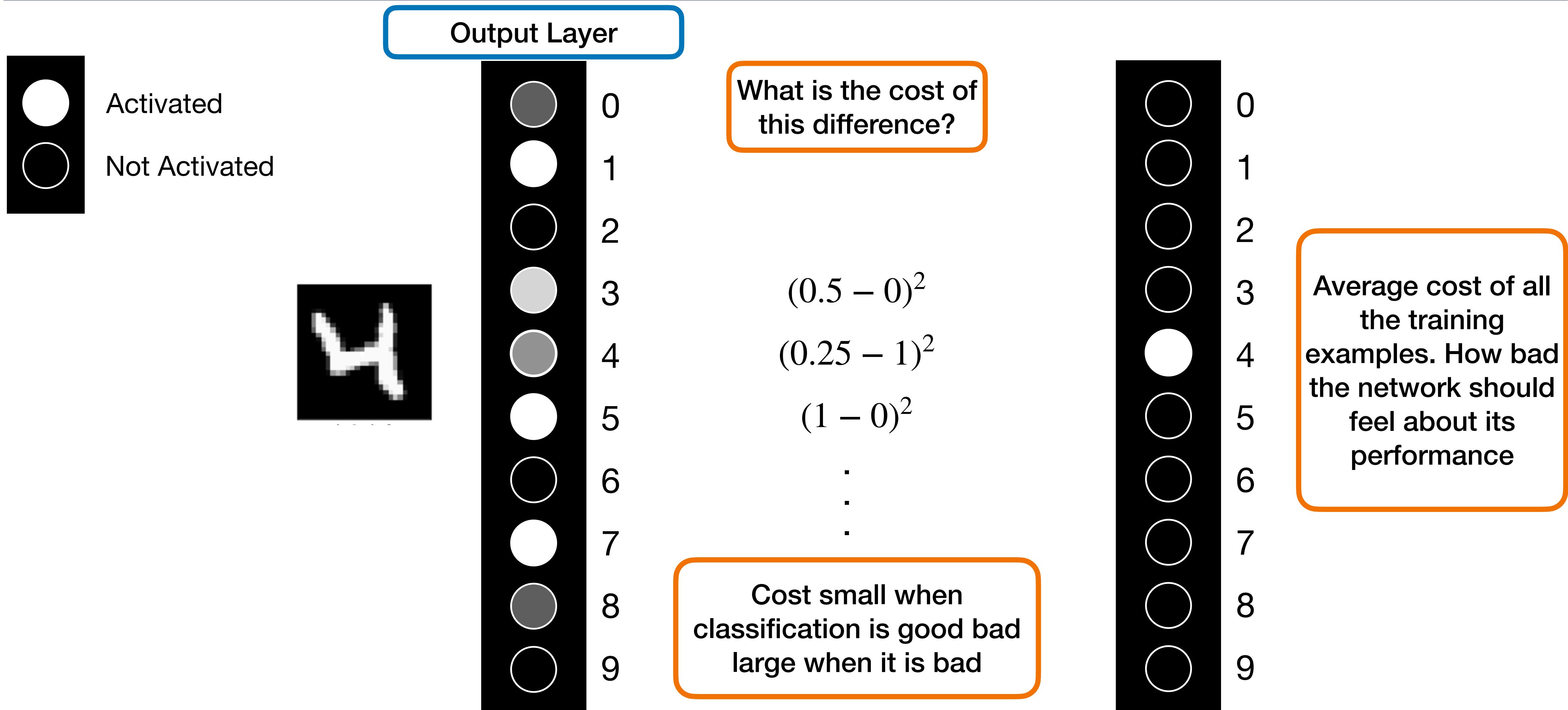
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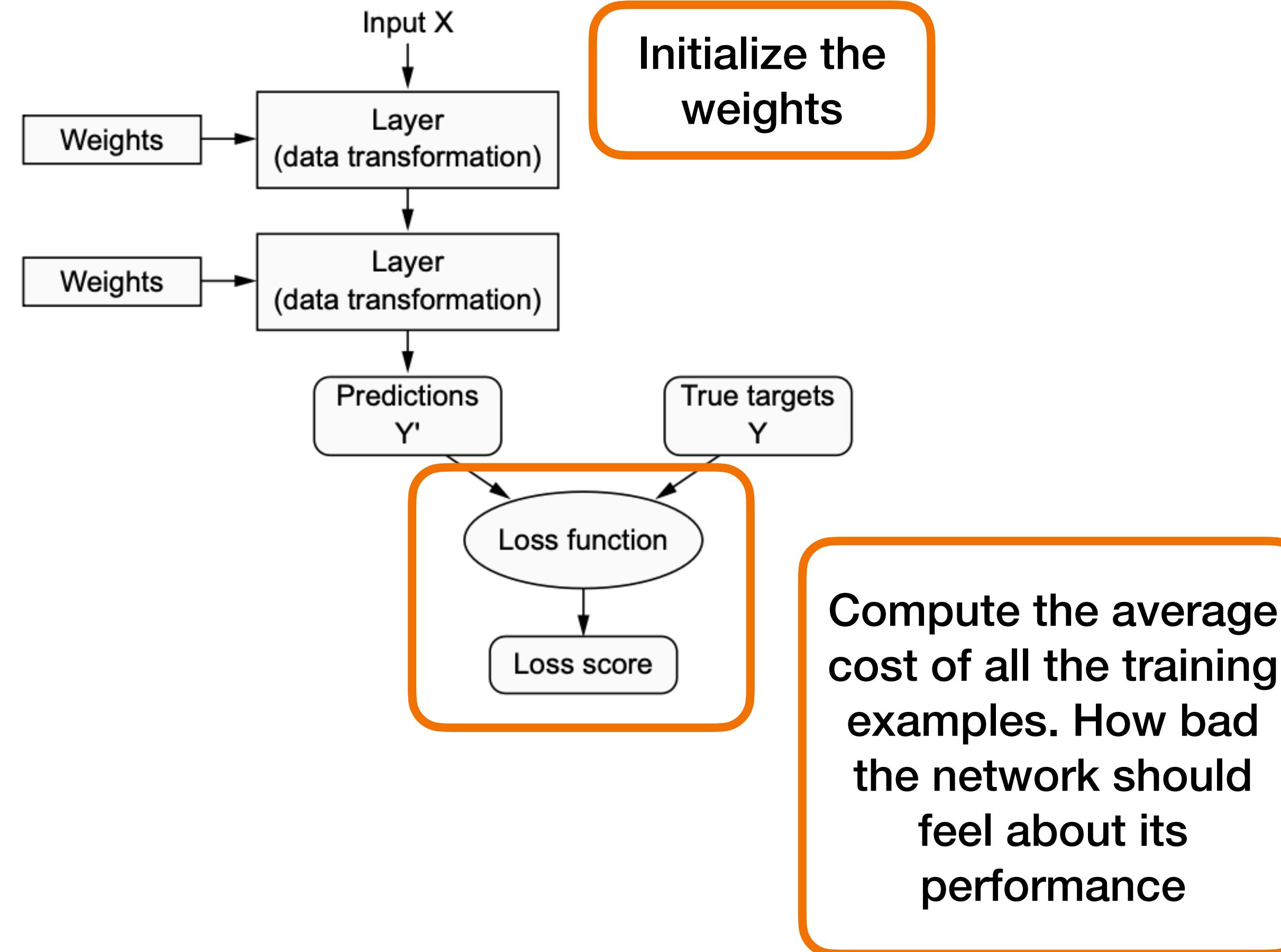
# Second step: Tell the computer that is doing it wrong



# Small Recap: We found a number to tell how the model is doing

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## Forward Pass



How do we improve the network (weights and biases) now that we know how is it doing it?

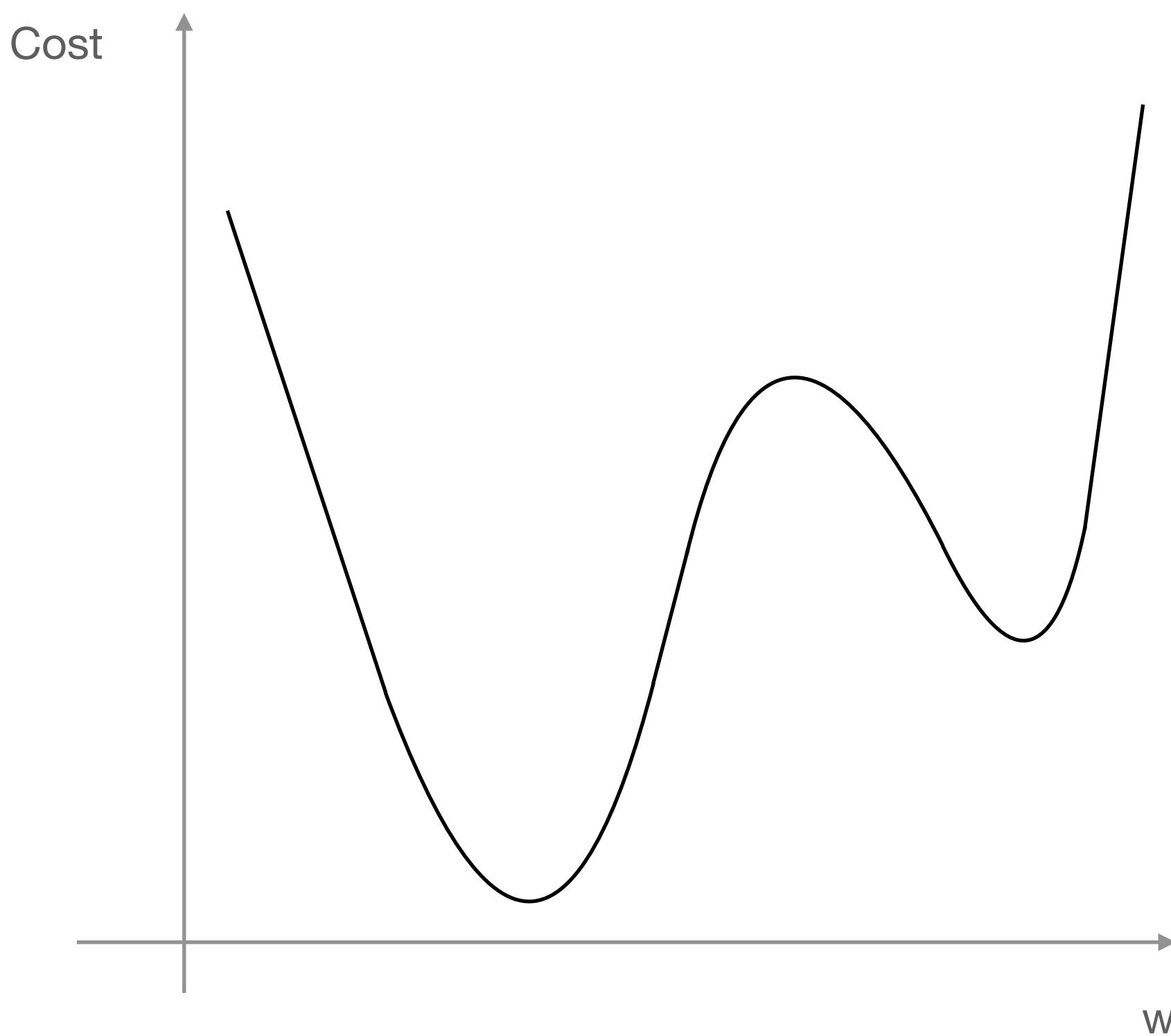
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How do we propagate this cost backwards?

# How do we propagate this cost backwards?

---

**First, we need to look at the cost function**

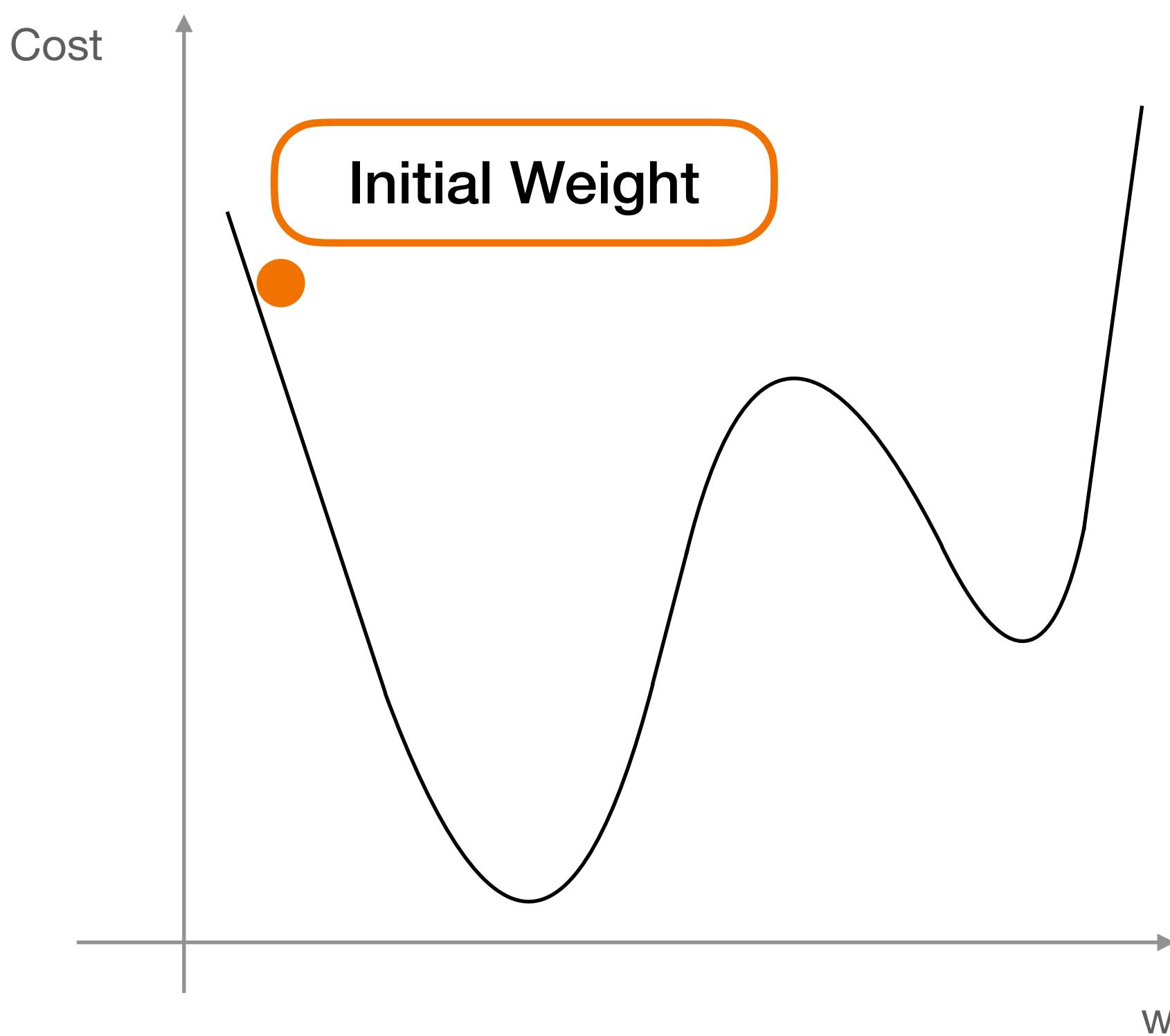


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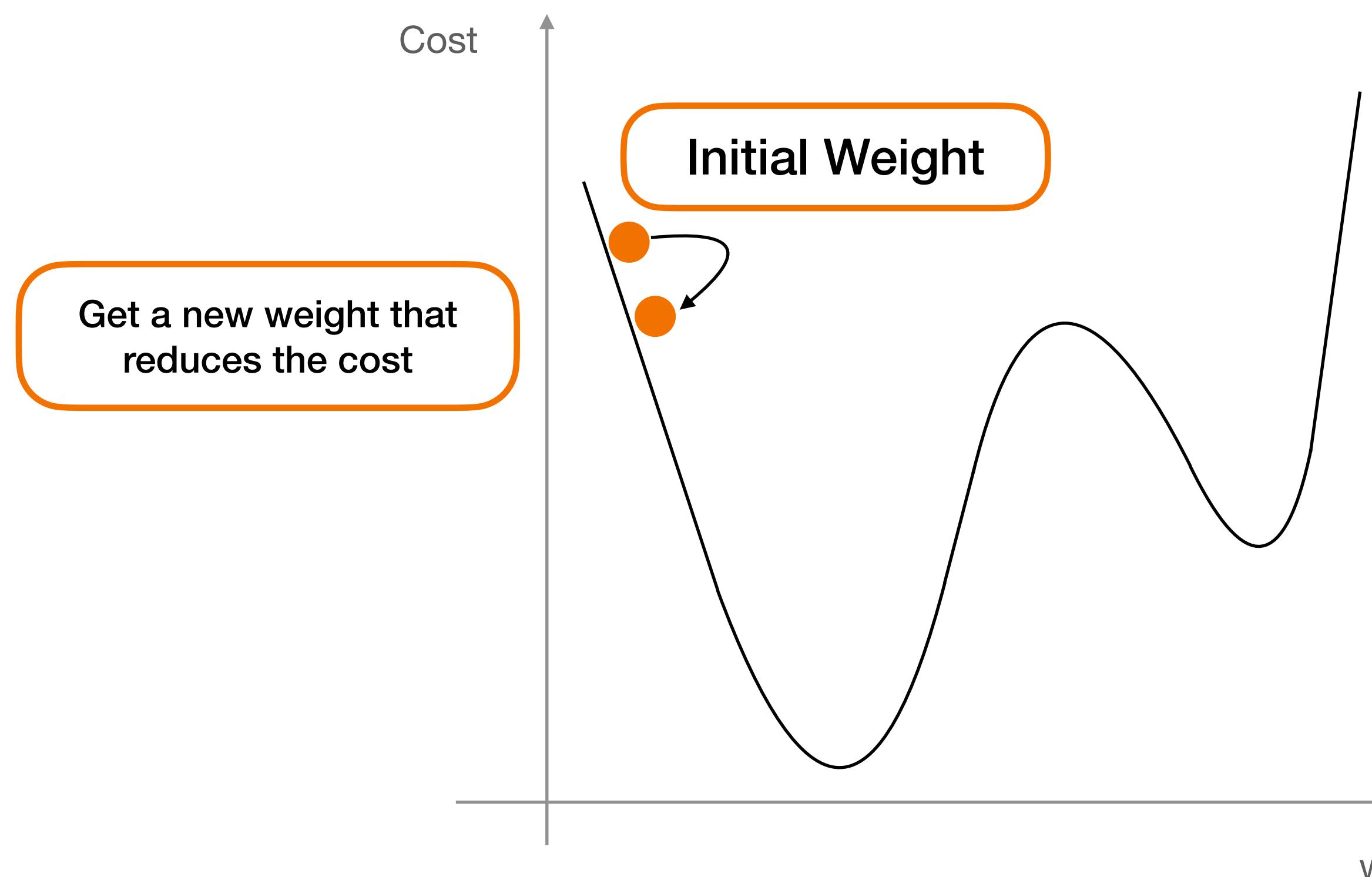
Objective: Reduce the cost



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First, we need to look at the cost function

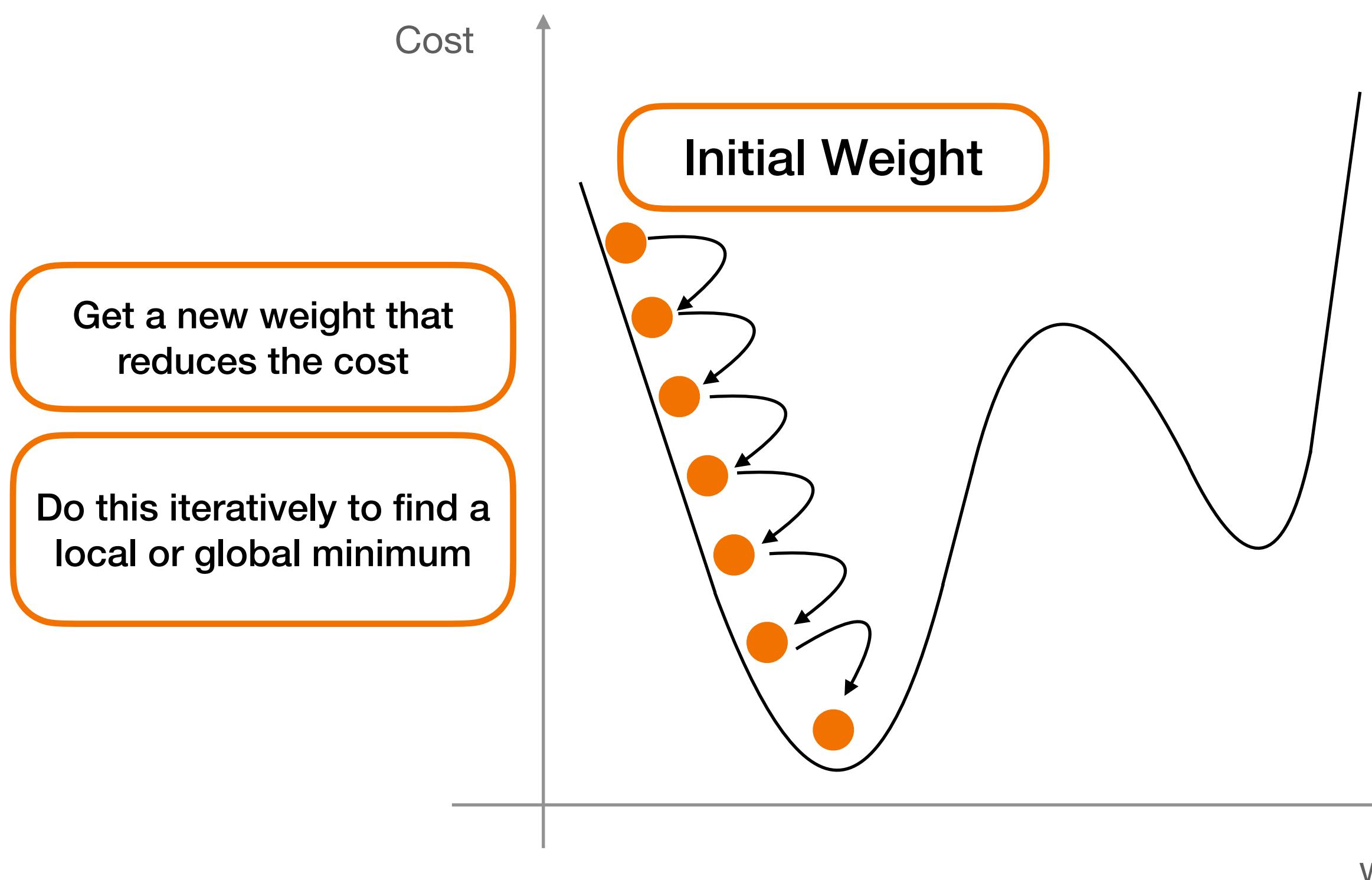
Objective: Reduce the cost



# How do we propagate this cost backwards?

First, we need to look at the cost function

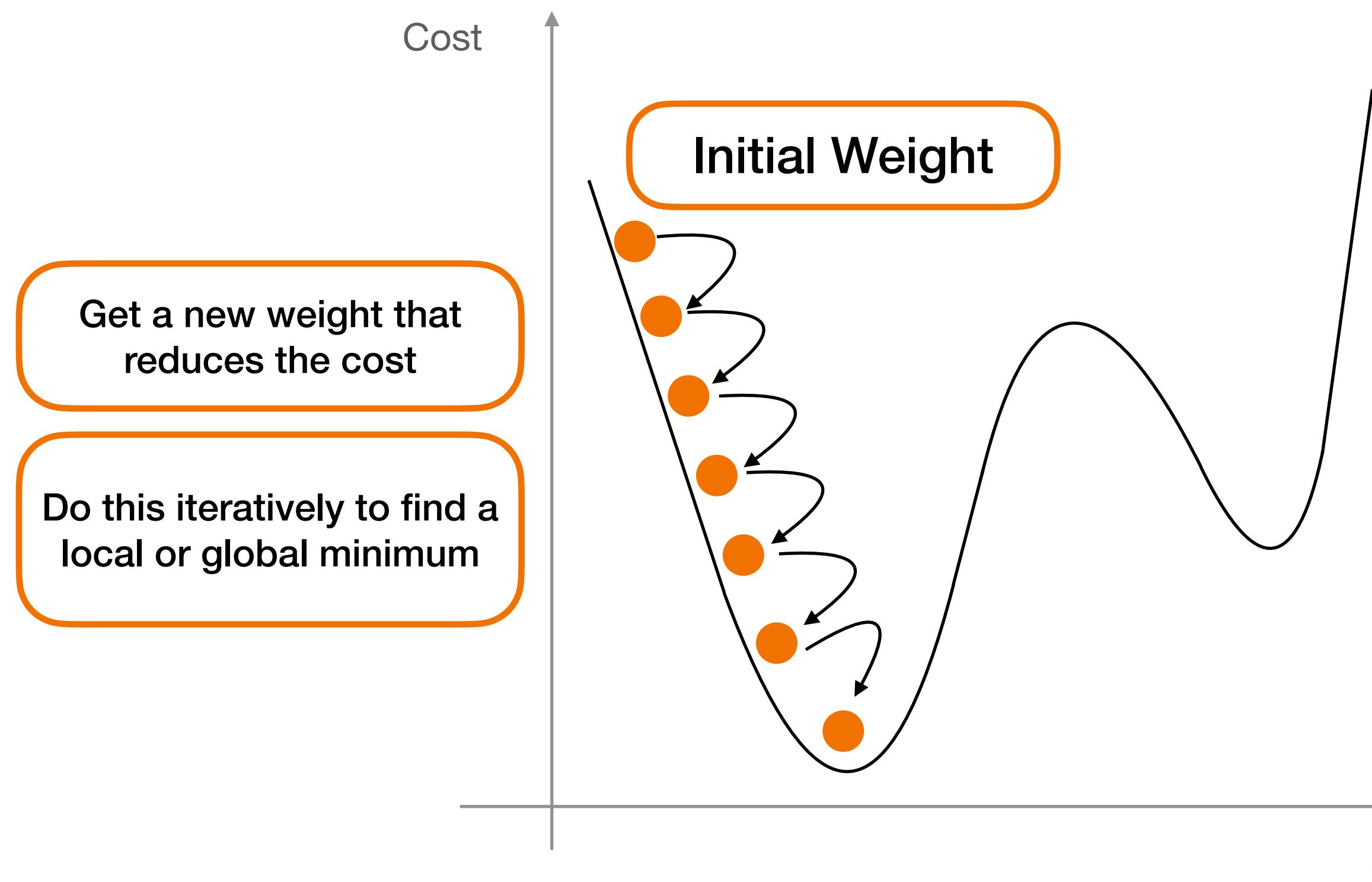
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First, we need to look at the cost function

Objective: Reduce the cost

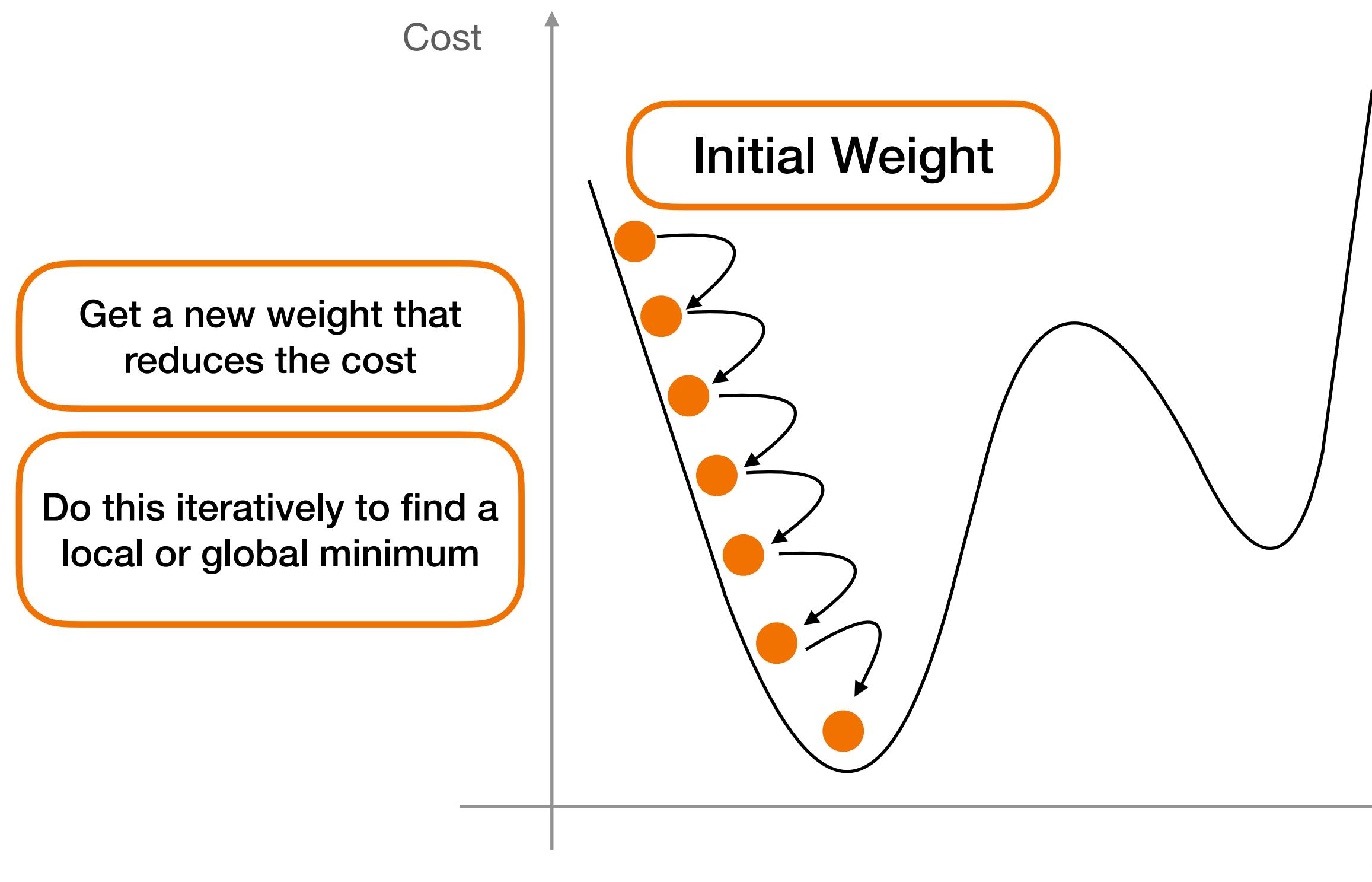


Essentially you increase or decrease the weight to reduce the cost function

# How do we propagate this cost backwards?

First, we need to look at the cost function

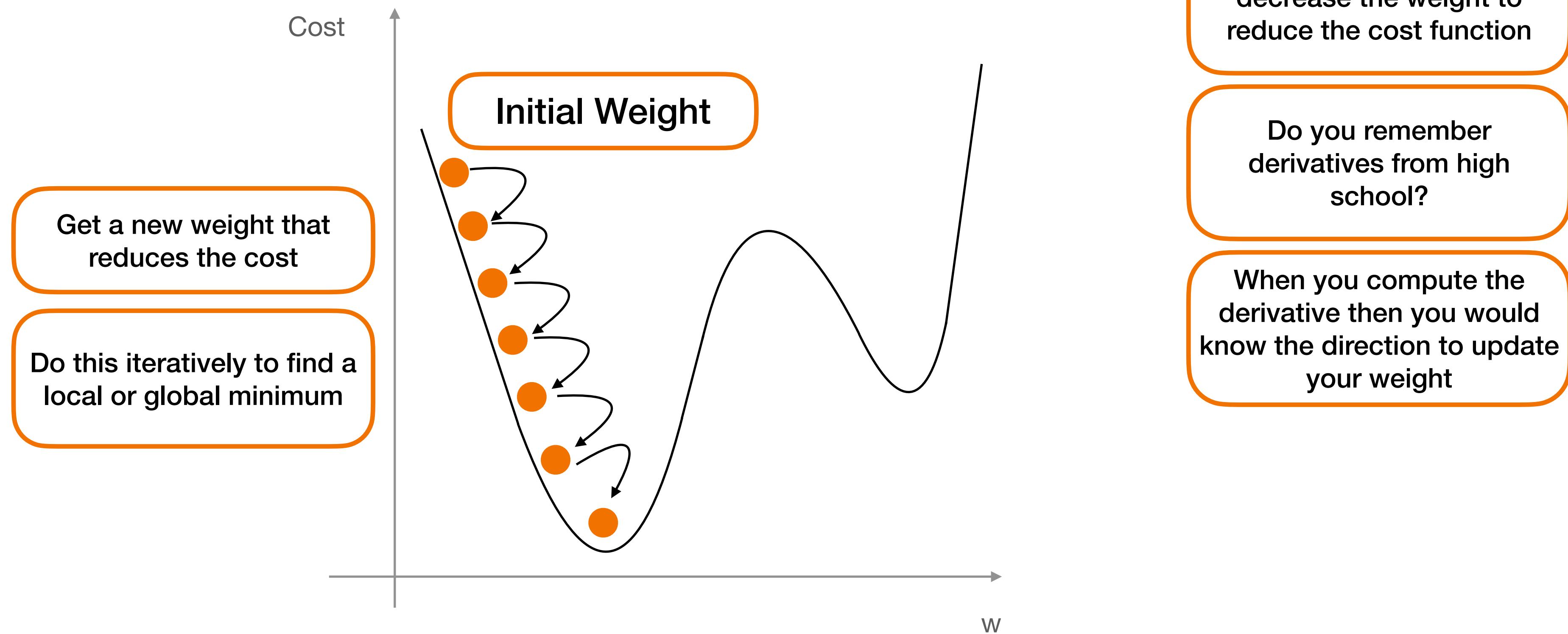
Objective: Reduce the cost



# How do we propagate this cost backwards?

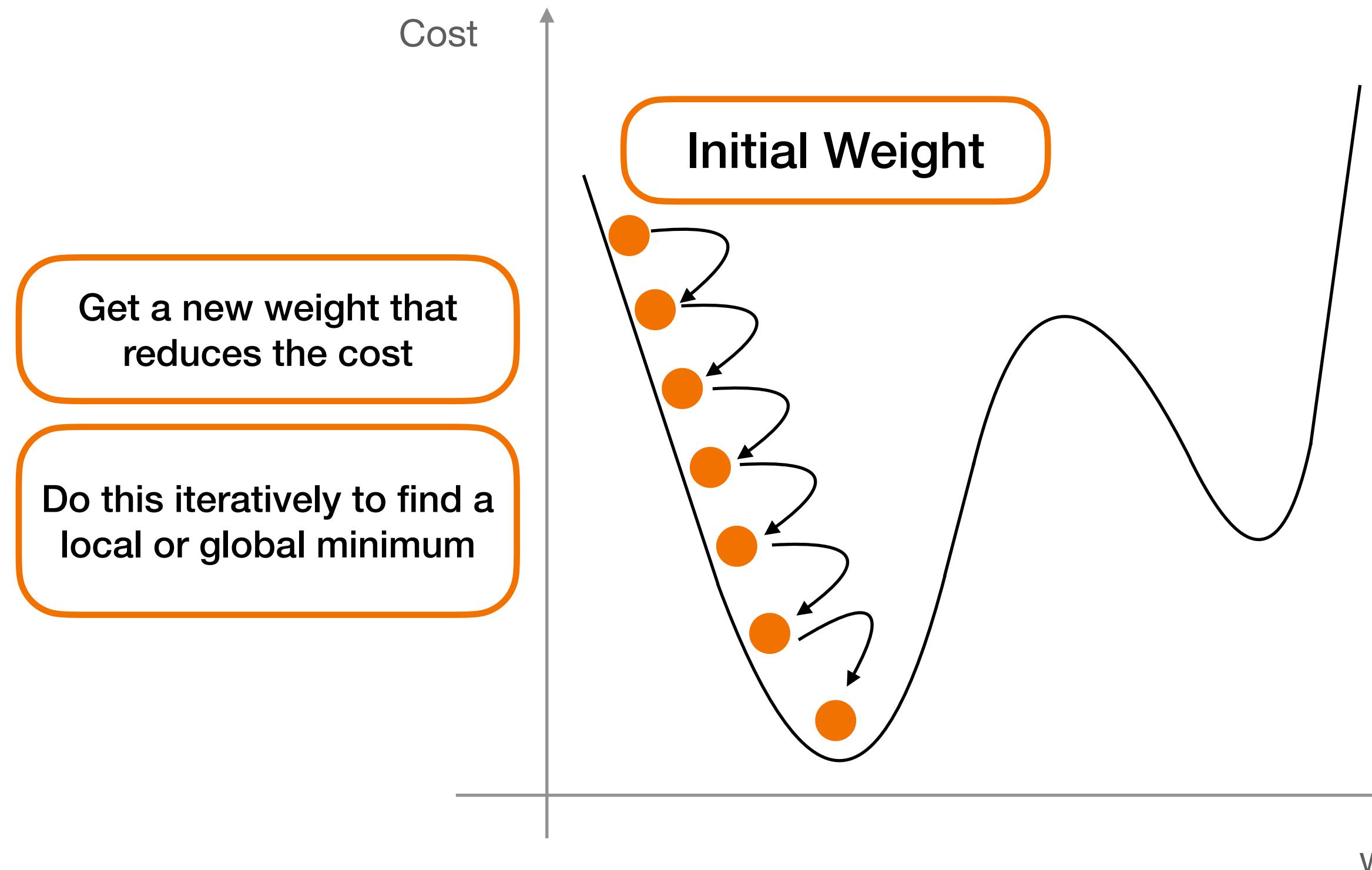
First, we need to look at the cost function

Objective: Reduce the cost



# How do we propagate this cost backwards?

First, we need to look at the cost function



Objective: Reduce the cost

Essentially you increase or decrease the weight to reduce the cost function

Do you remember derivatives from high school?

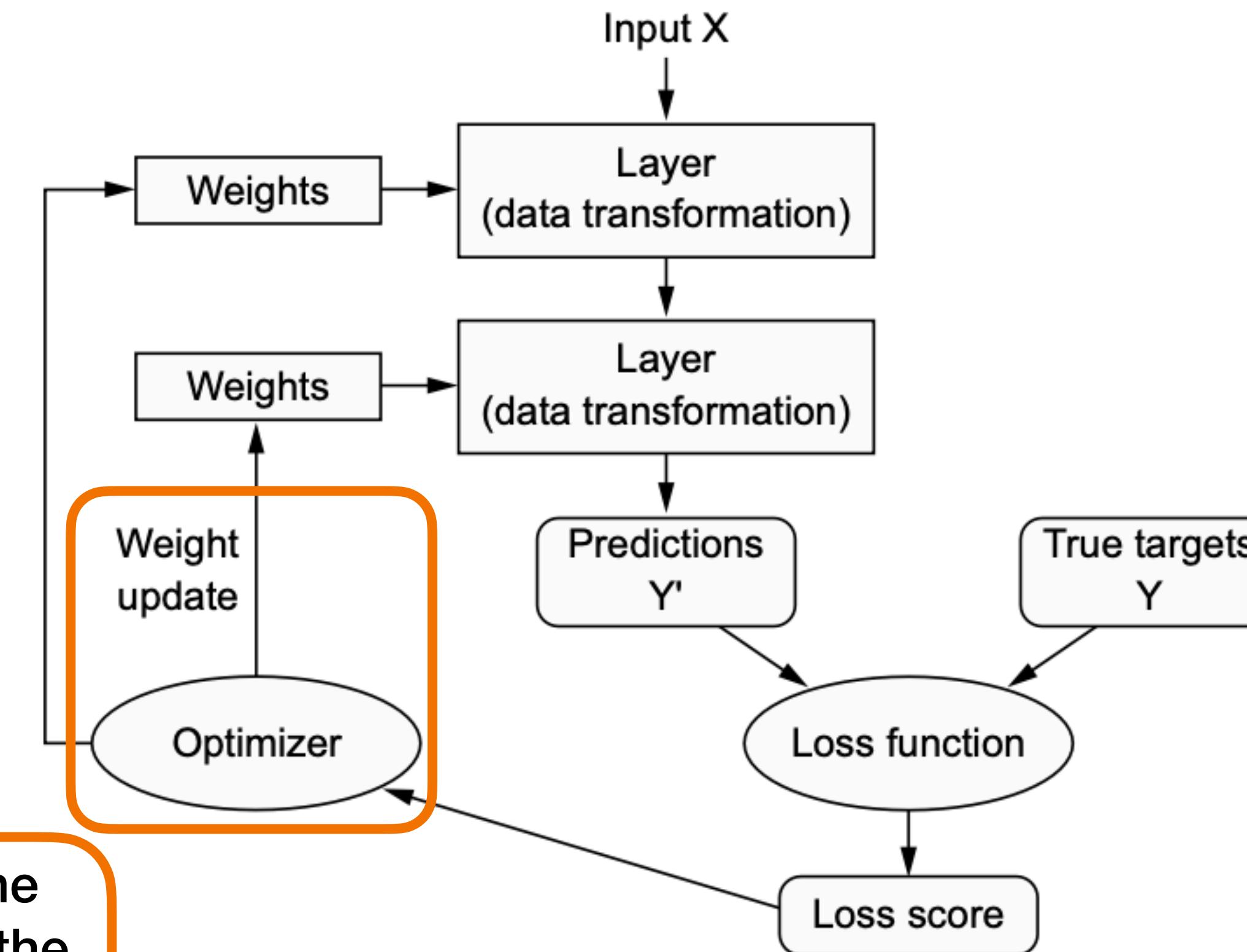
When you compute the derivative then you would know the direction to update your weight

As we have a lot of weights:  
Multidimensional function,  
we use the Gradient

Gradient Descent

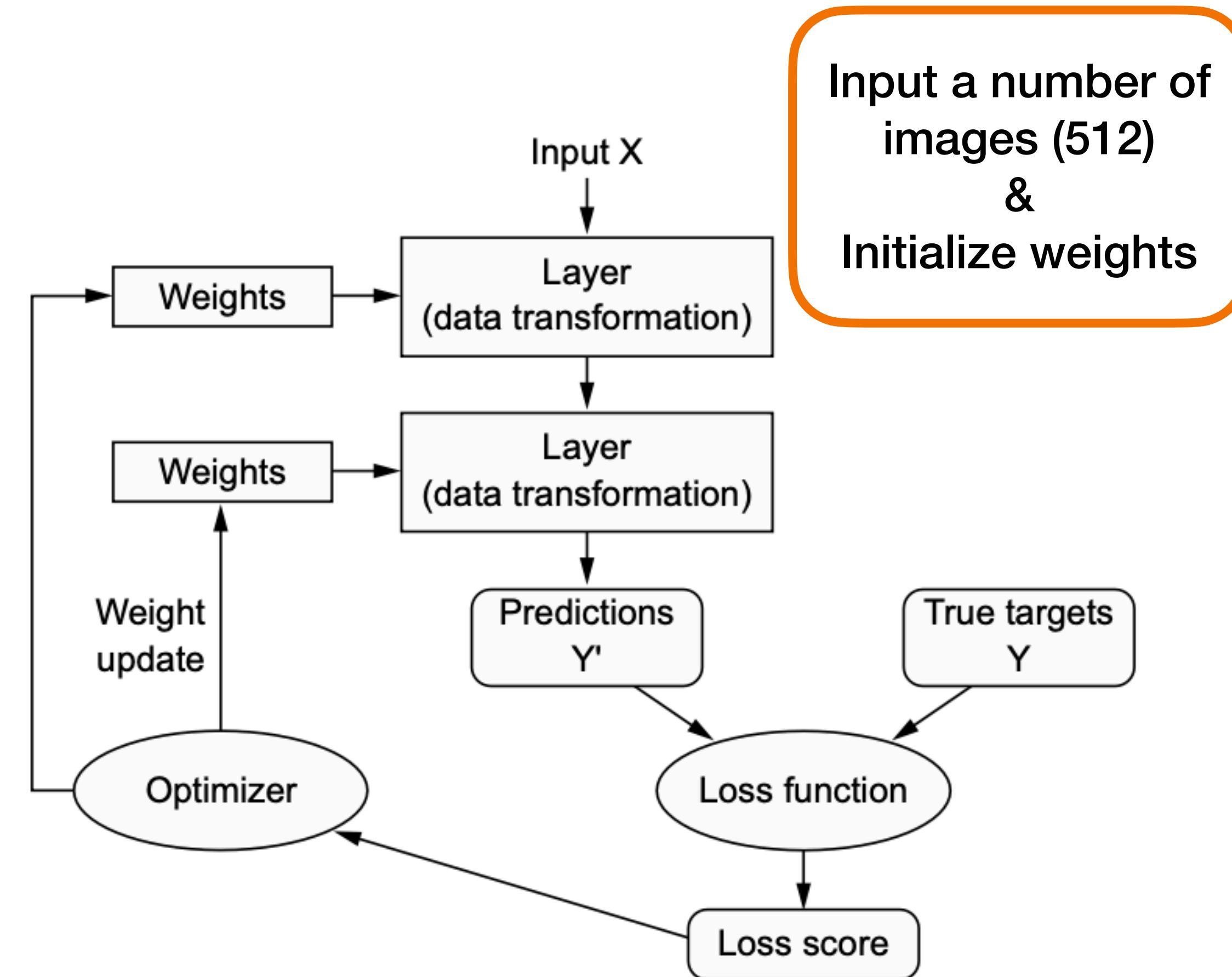
# How do we propagate this cost backwards?

## Backward Pass & Weight Update

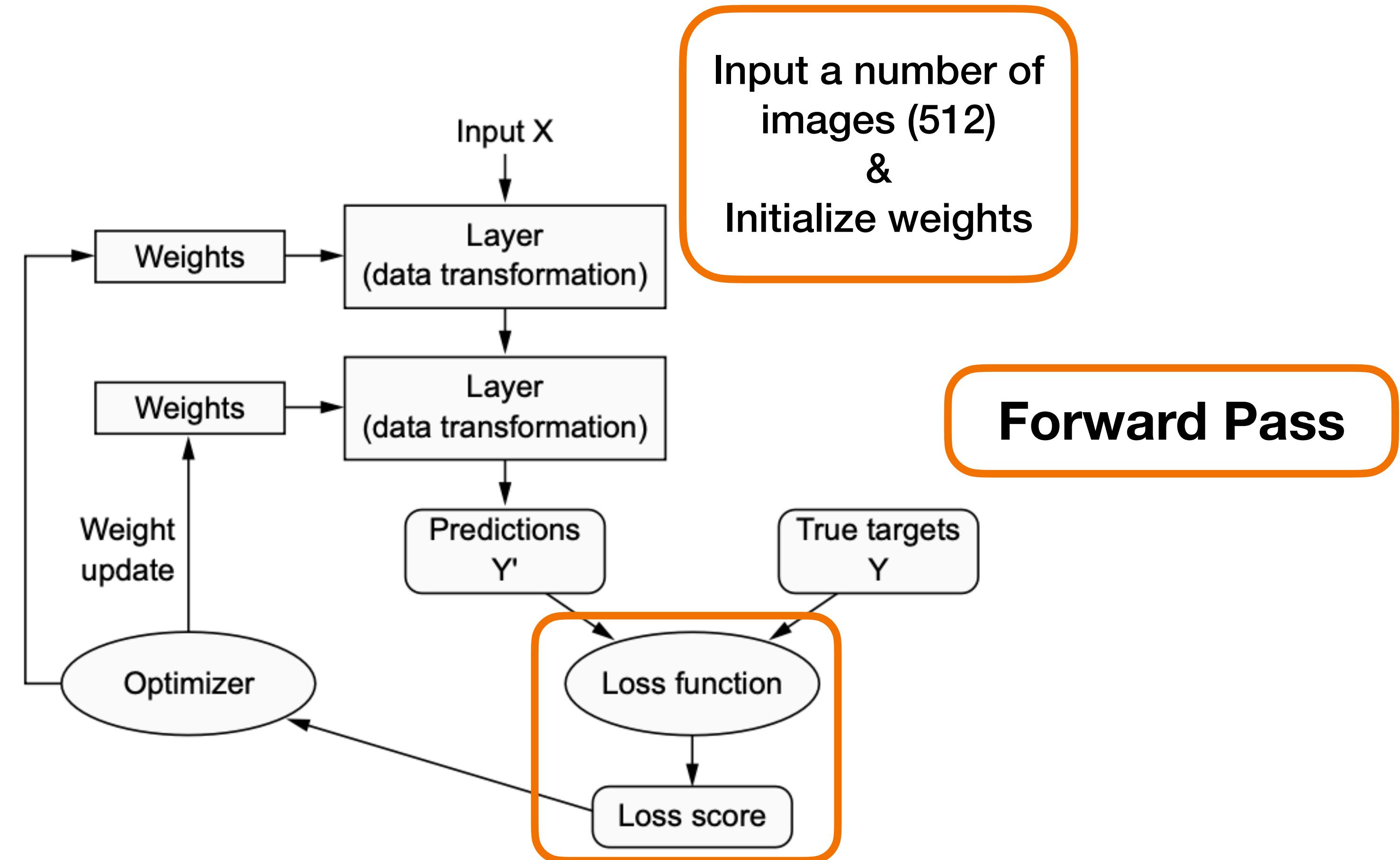


The algorithm to compute the gradients for every weight in the network efficiently is called backpropagation

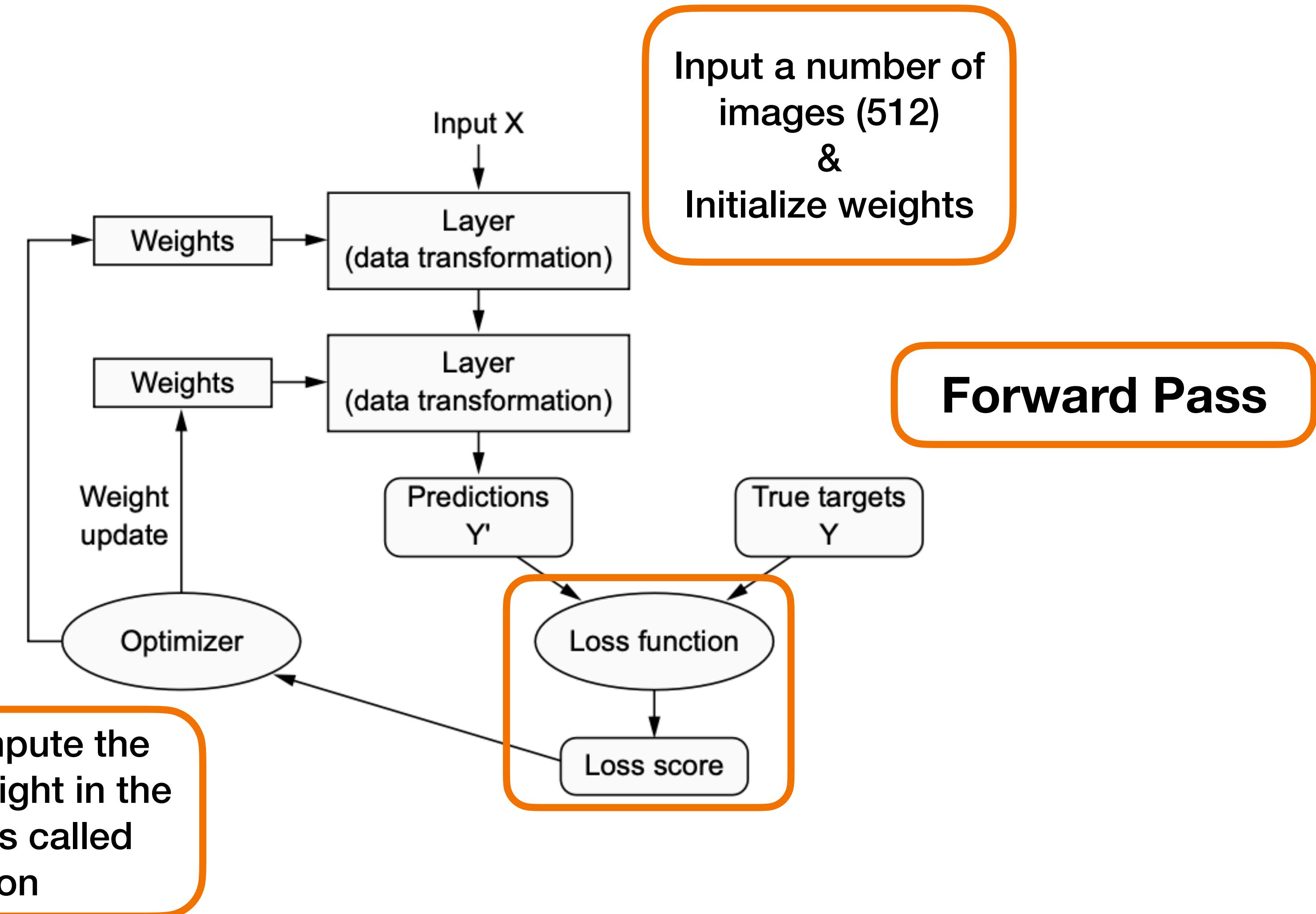
# In reality: Stochastic Gradient Descent



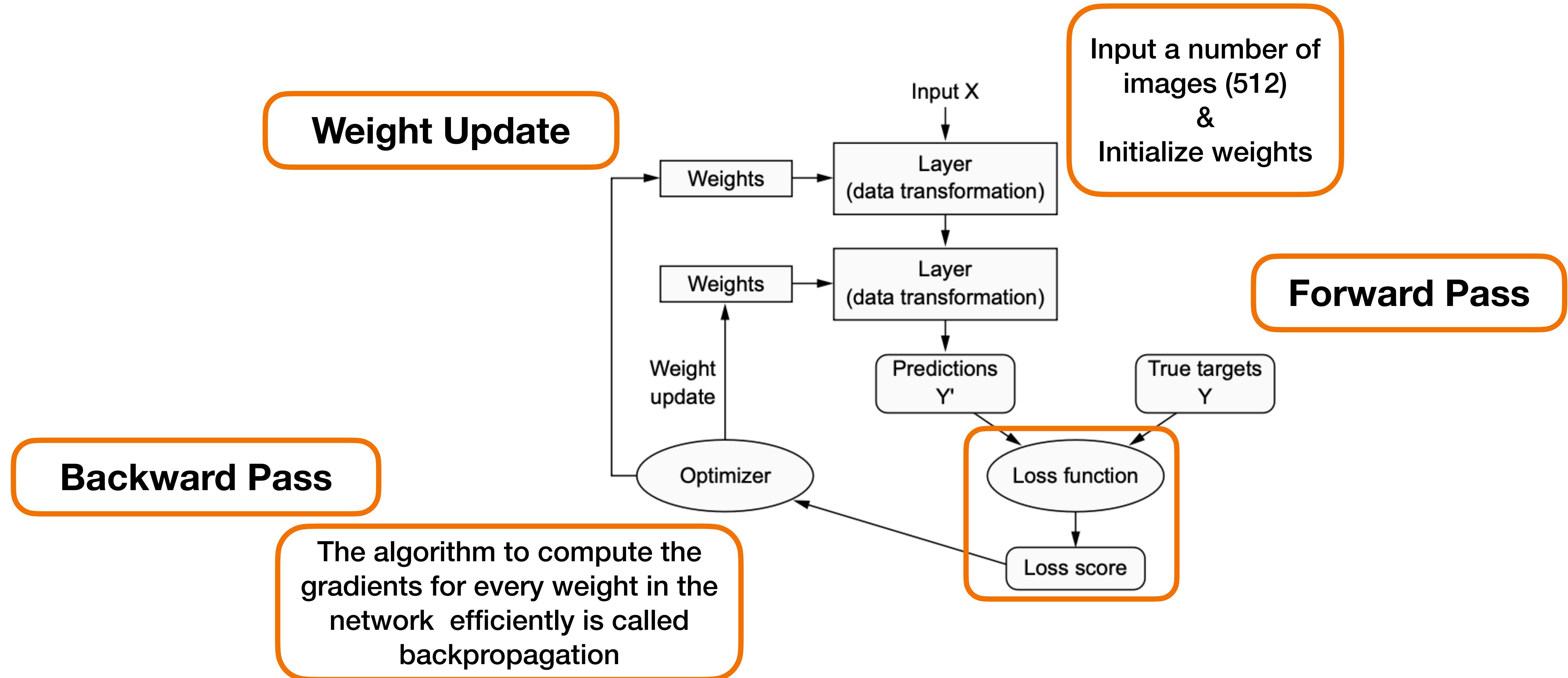
# In reality: Stochastic Gradient Descent



# In reality: Stochastic Gradient Descent



# In reality: Stochastic Gradient Descent





# Introduction to Keras. The MNIST dataset

# What is Keras?

---



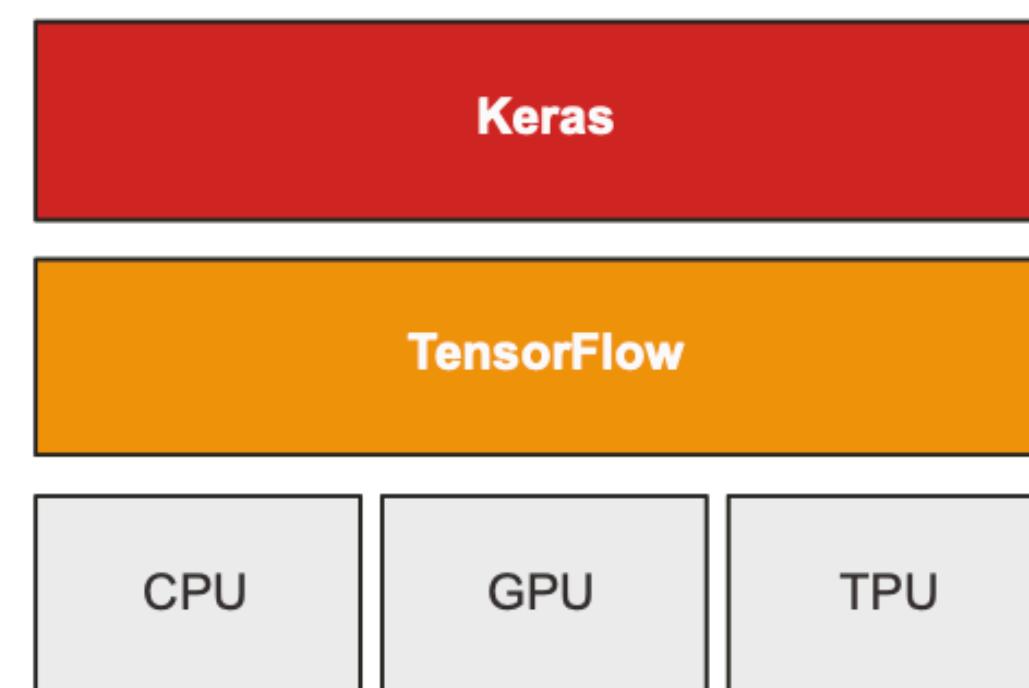
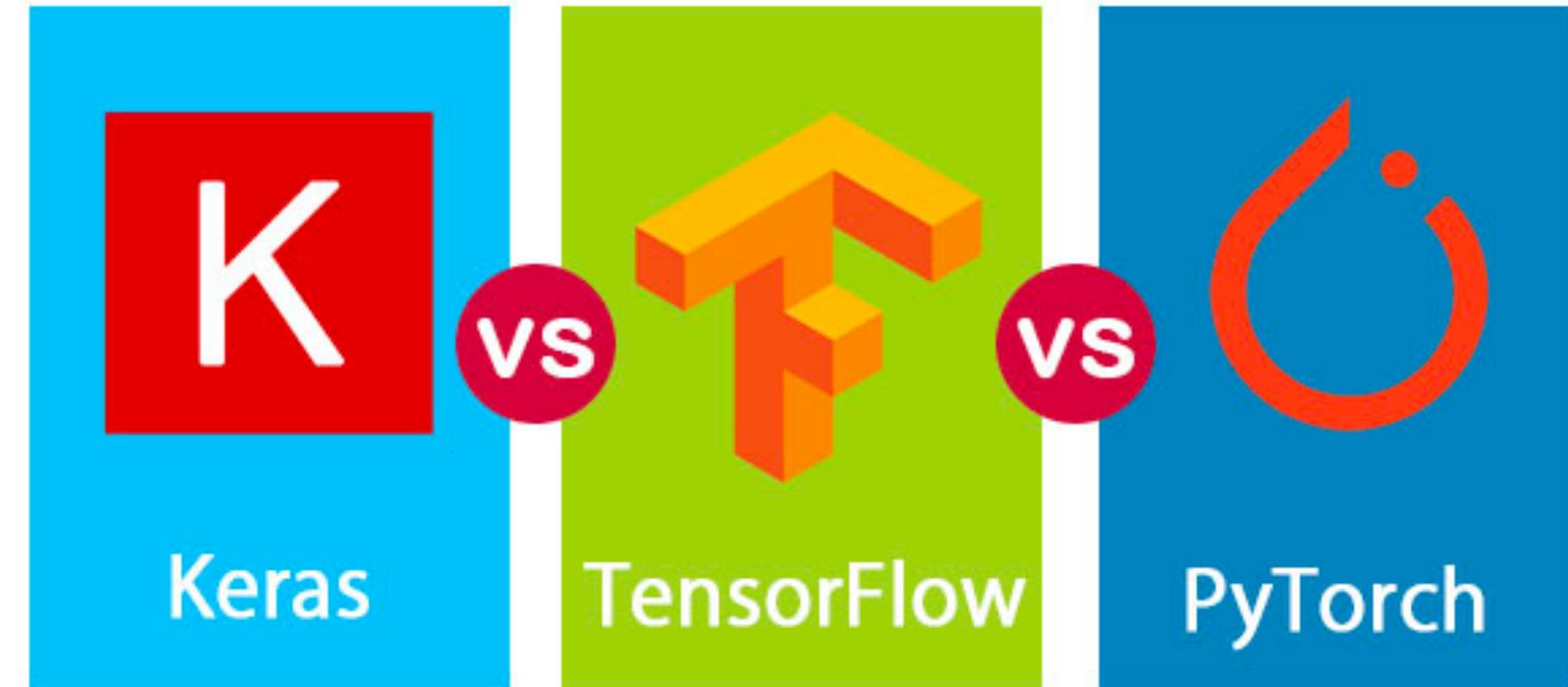
```
>>> from sklearn.datasets import make_regression
>>> from sklearn.ensemble import GradientBoostingRegressor
>>> from sklearn.model_selection import train_test_split
>>> X, y = make_regression(random_state=0)
>>> X_train, X_test, y_train, y_test = train_test_split(
...     X, y, random_state=0)
>>> reg = GradientBoostingRegressor(random_state=0)
>>> reg.fit(X_train, y_train)
GradientBoostingRegressor(random_state=0)
>>> reg.predict(X_test[1:2])
array([-61...])
>>> reg.score(X_test, y_test)
0.4...
```

# What is Keras?

---



```
>>> from sklearn.datasets import make_regression
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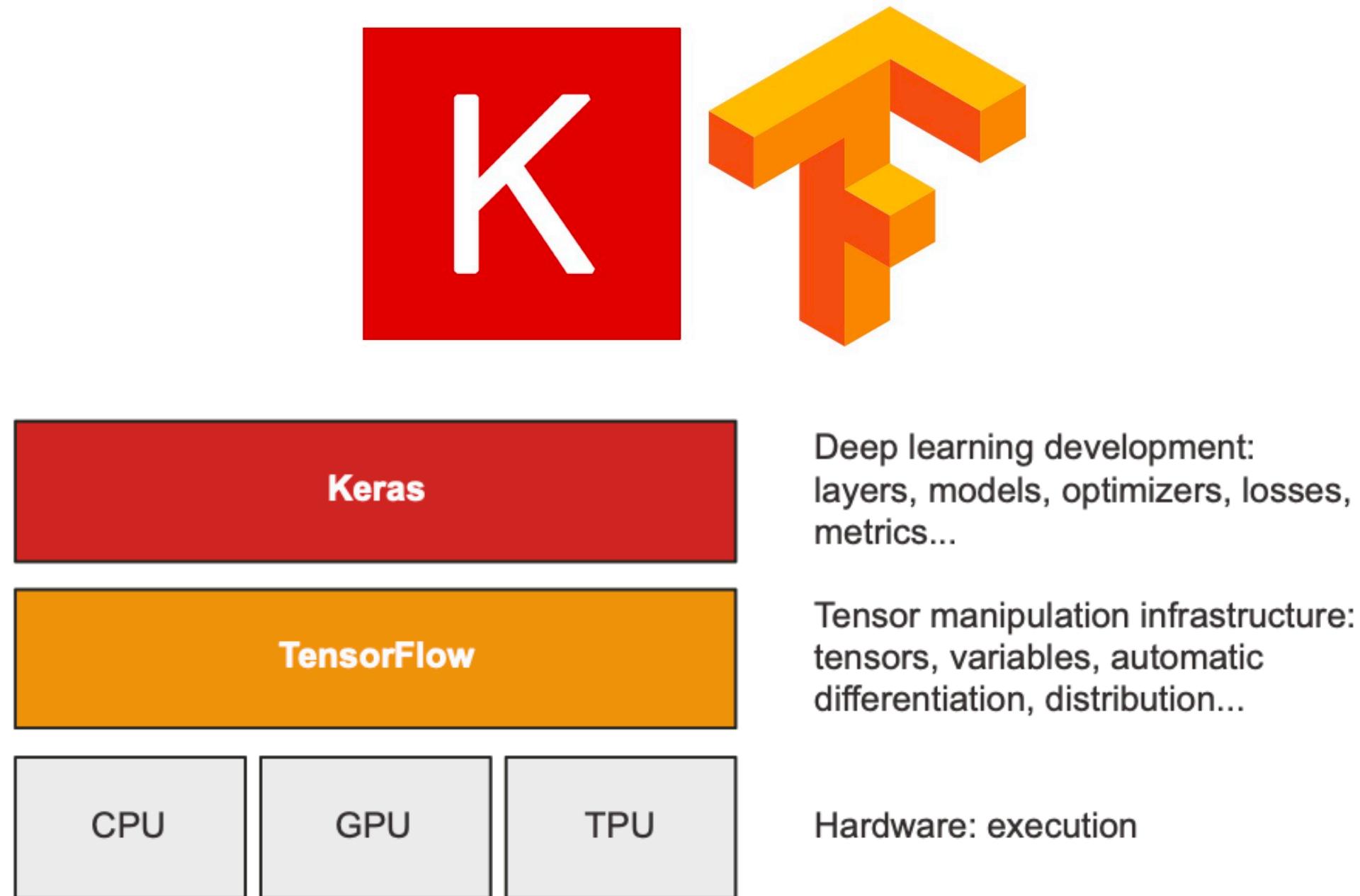
Deep learning development:  
layers, models, optimizers, losses,  
metrics...

Tensor manipulation infrastructure:  
tensors, variables, automatic  
differentiation, distribution...

Hardware: execution

# Why Keras & Tensorflow? The best way to start

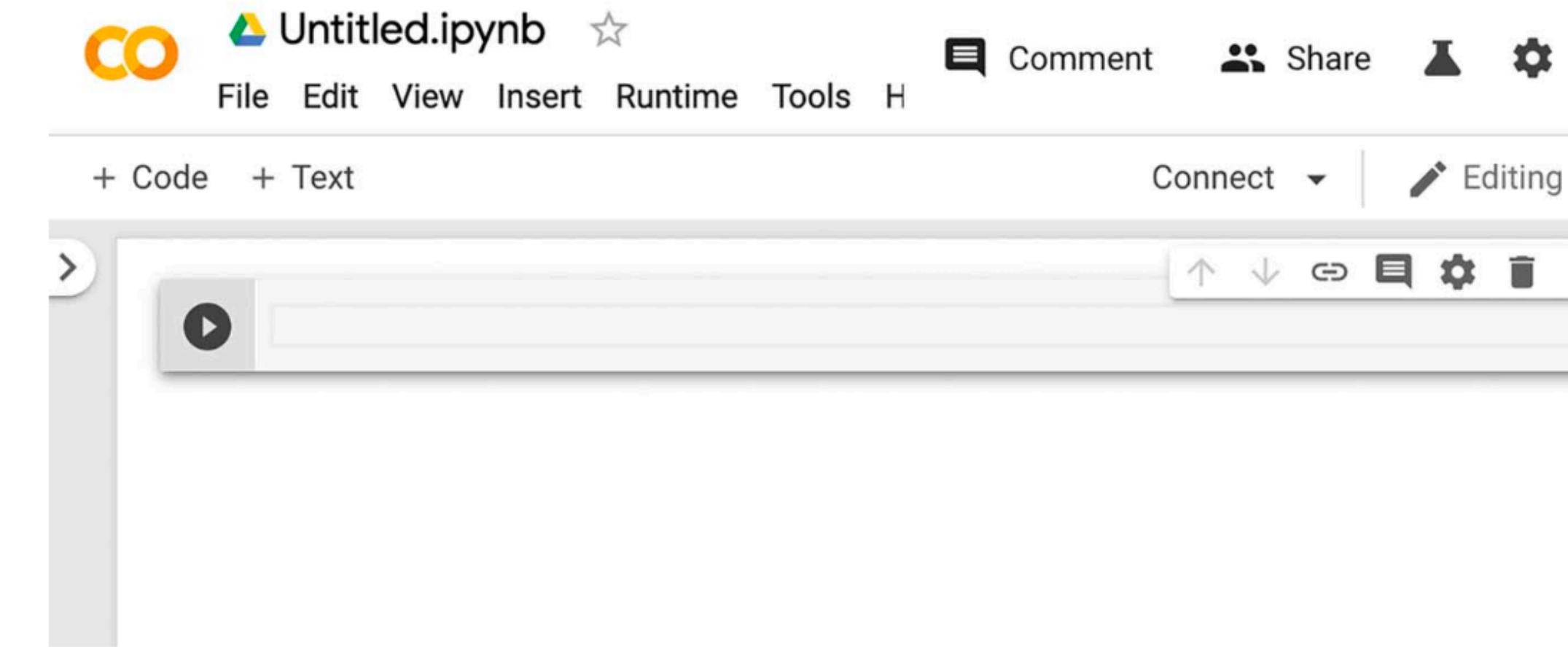
---



- Tensorflow:
  - Computes gradients Automatically
  - Runs on GPUs
  - Easy to parallelize
- Keras is easy to use and allows you to build NN in a straightforward manner

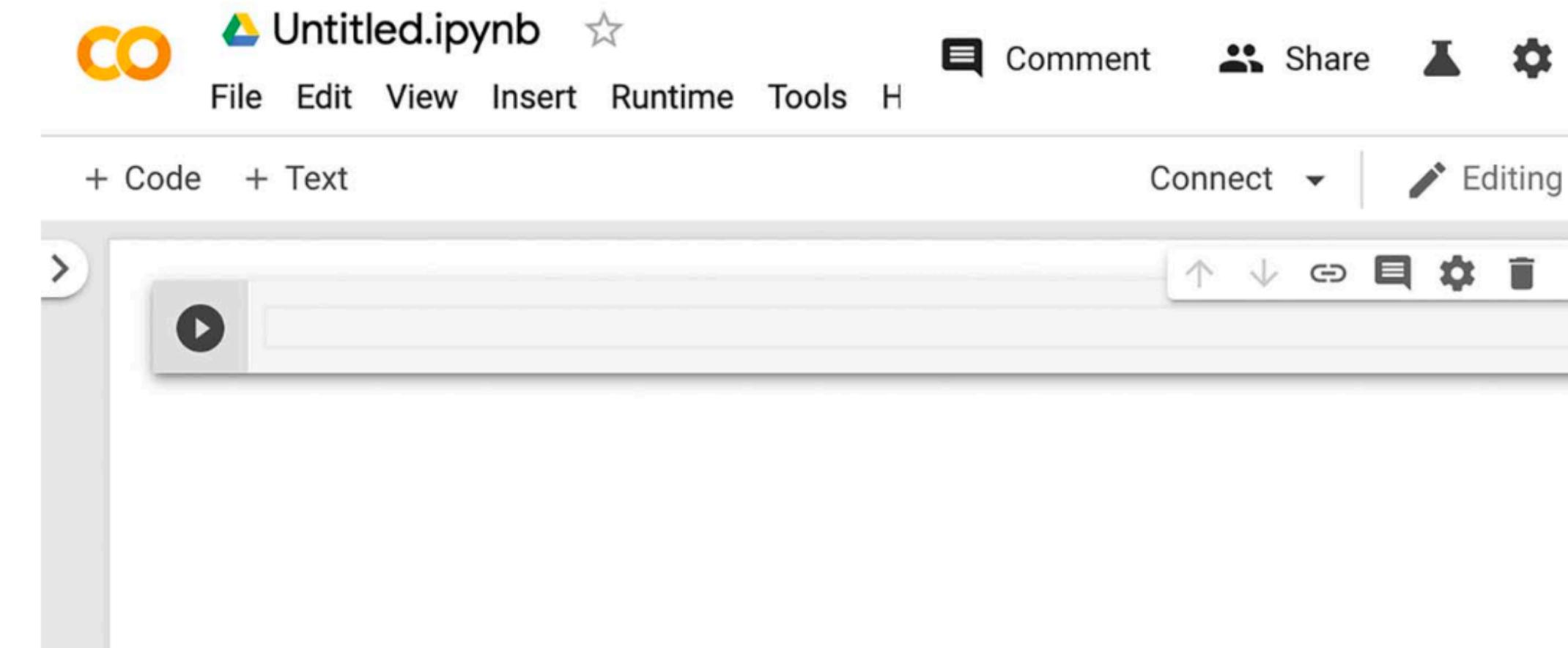
# The best way to start coding Neural networks

---



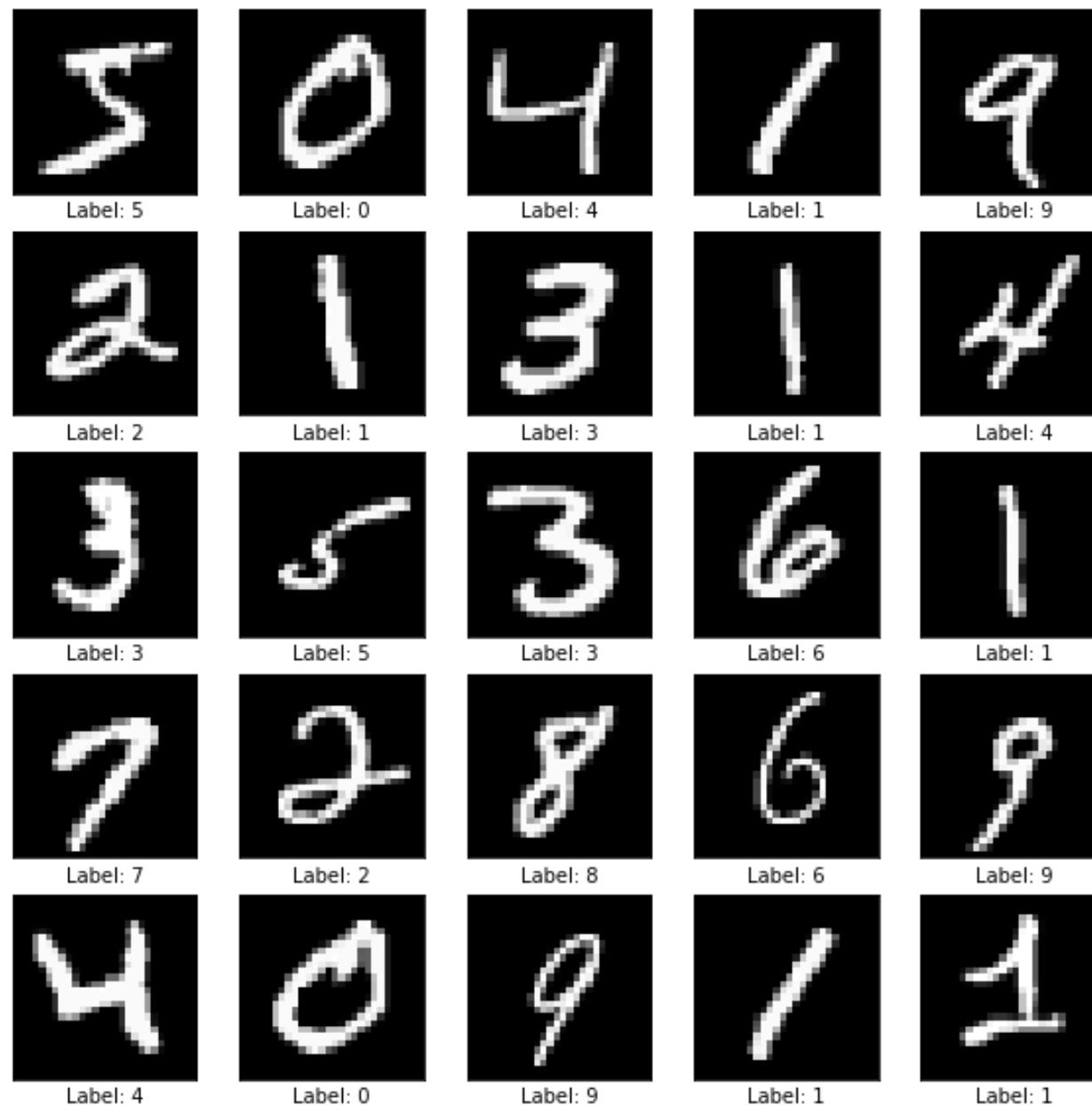
# The best way to start coding Neural networks

---



Let's build our first Neural Network!

# Open Colab, Load Keras, and load the MNIST dataset



Load Keras

```
from tensorflow.keras.datasets import mnist  
from tensorflow import keras  
from tensorflow.keras import layers
```

Load Dataset

```
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
```

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz>  
11490434/11490434 [=====] - 0s 0us/step

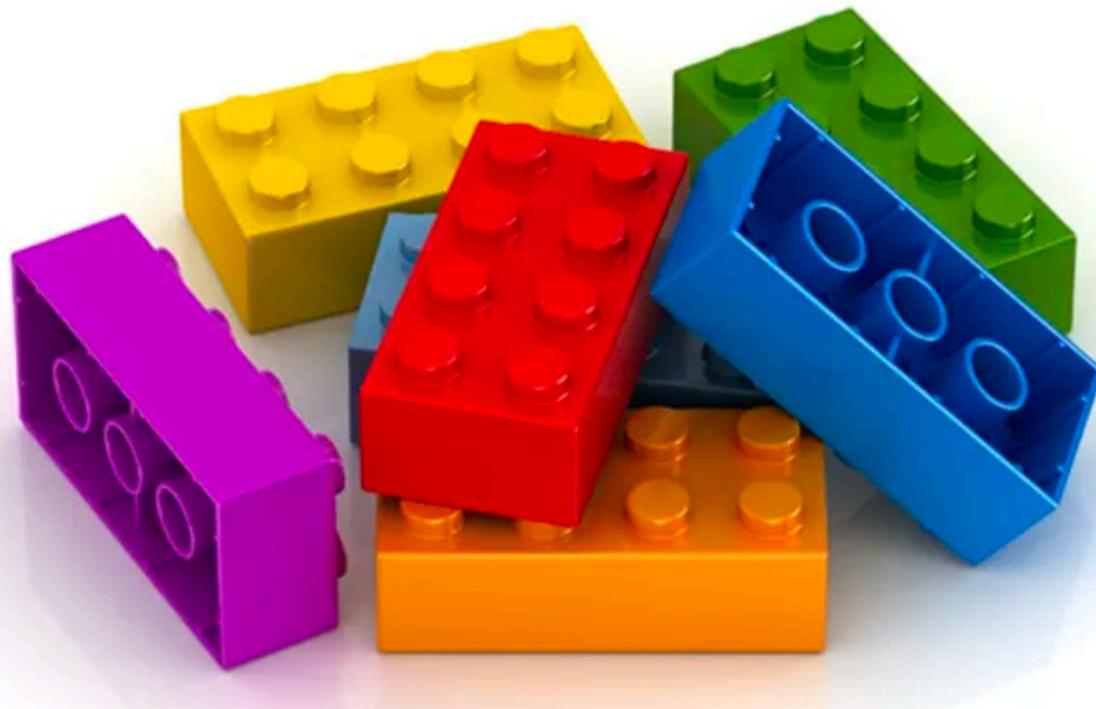
```
train_images.shape, test_images.shape
```

```
((60000, 28, 28), (10000, 28, 28))
```

# Keras building blocks: Layers (Build the structure)

---

- Layers are the building blocks of deep learning
- You can think of them as the LEGO bricks of deep learning (Keras uses this analogy to stack layers)



## Core layers

- Input object
- Dense layer
- Activation layer
- Embedding layer
- Masking layer
- Lambda layer

## Convolution layers

- Conv1D layer
- Conv2D layer

## Layer activations

- relu function
- sigmoid function
- softmax function
- softplus function
- softsign function
- tanh function
- selu function
- elu function
- exponential function

```
model = keras.Sequential([
    layers.Dense(784, activation='sigmoid'),
    layers.Dense(16, activation='sigmoid'),
    layers.Dense(16, activation='sigmoid'),
    layers.Dense(10, activation='softmax'),
])
```

# Keras building blocks: Compile (Tell it how to learn)

---

- **Loss Function** (Tell the computer how good/bad is doing it): Objective function to be minimized during training.
- **Optimizer**: Updates to the network. A version of SGD (Stochastic Gradient Descent)
- **Metrics**: Measure of success to monitor during training, i.e. Accuracy.

```
model.compile(  
    optimizer="rmsprop",  
    loss="sparse_categorical_crossentropy",  
    metrics=[ 'accuracy' ]  
)
```

# Keras building blocks: Compile (Tell it how to learn)

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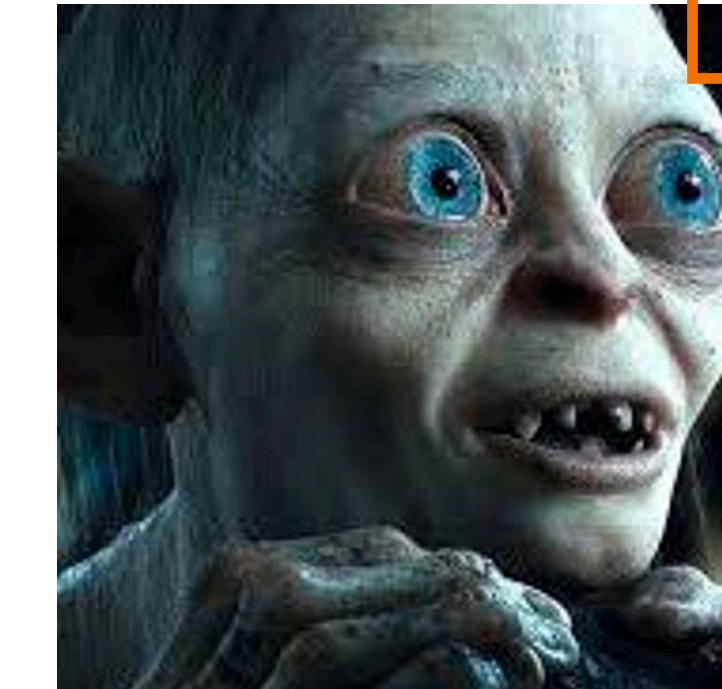
$$\text{Loss} = - \sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i$$

# Keras building blocks: Compile (Tell it how to learn)

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)
```

$$\text{Loss} = - \sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i$$



## Loss Function

The network will do anything to lower the loss (Example of well-being and fake news). Choose wisely

# Keras building blocks: Fit (Make it learn)

---

- **The Data** (Inputs & Targets) to train on. Numpy arrays or a TensorFlow Dataset object
- **Number of Epochs**: Number of times the training loop should iterate over the data.
- **Batch Size**: Number of training examples considered to compute the gradients for one weight update.

```
model.fit(  
    train_images,  
    train_labels,  
    epochs=10,  
    batch_size=128)
```

# Keras building blocks: Fit (Make it learn)

---

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    epochs=10,  
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```

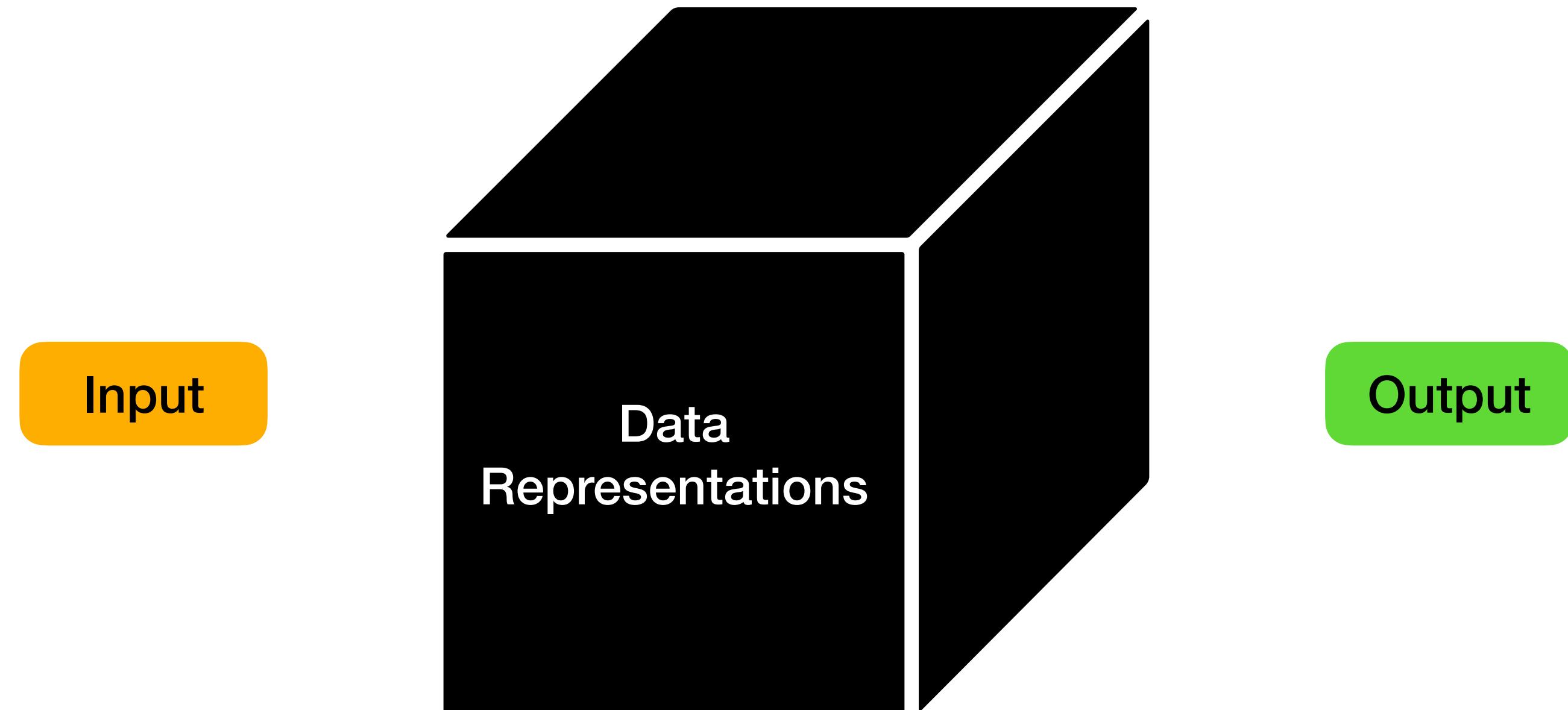
We are able to recognize hand-written digits with  
~96% Accuracy!



# Types of Neural Networks and their applications

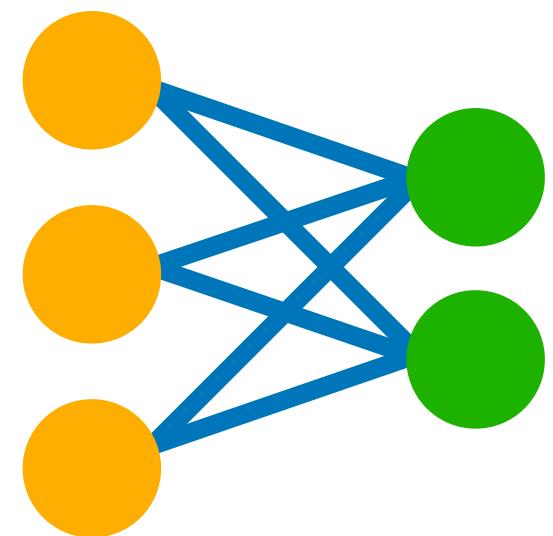
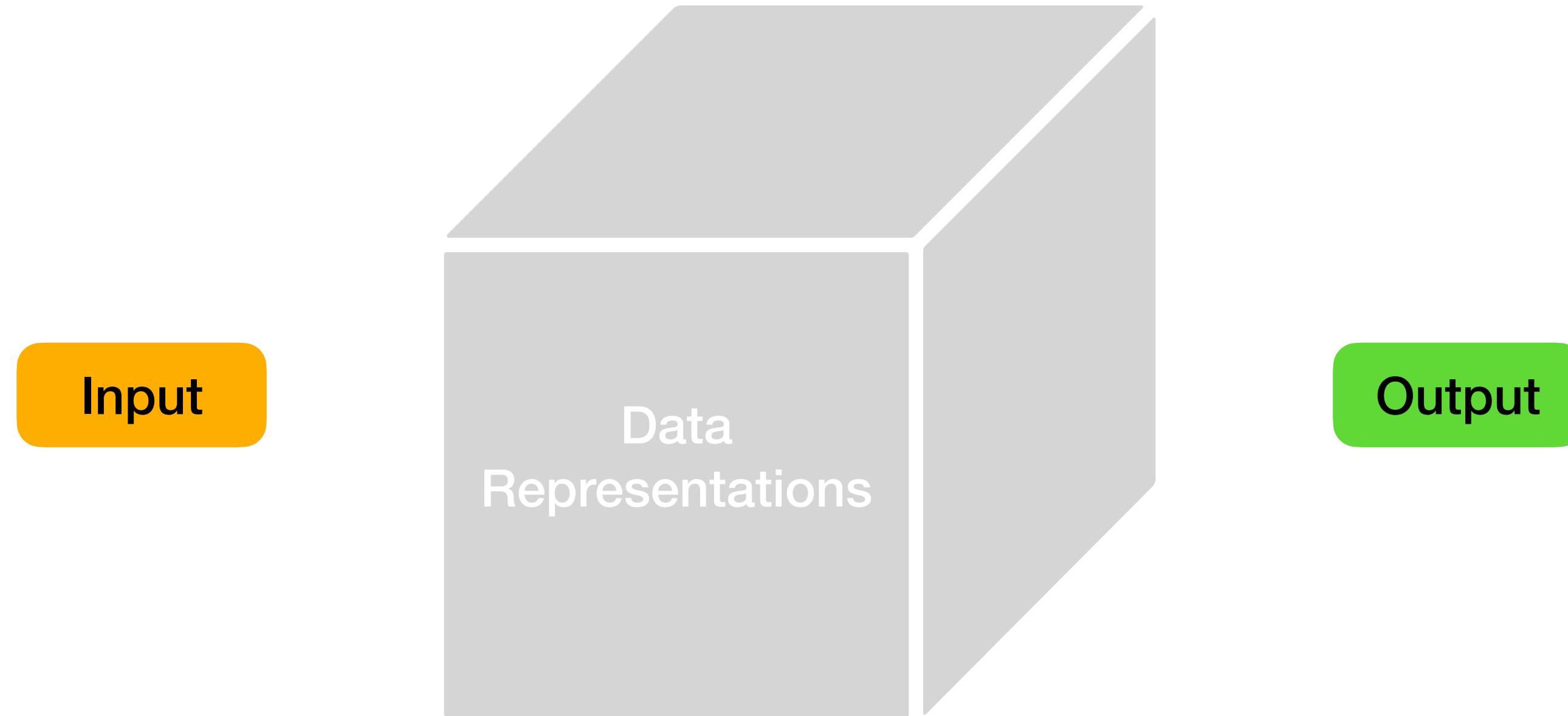
# Building upon the same idea

---



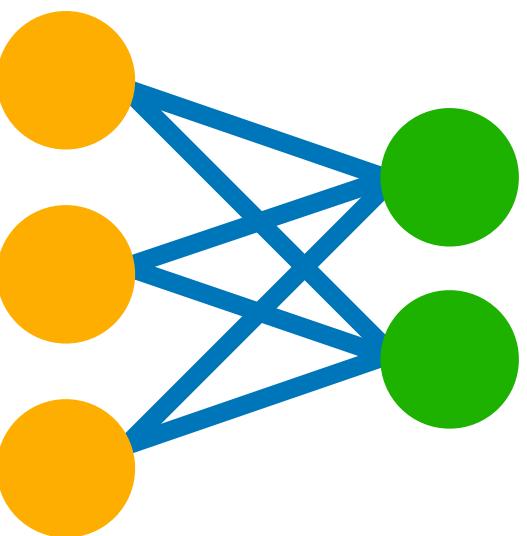
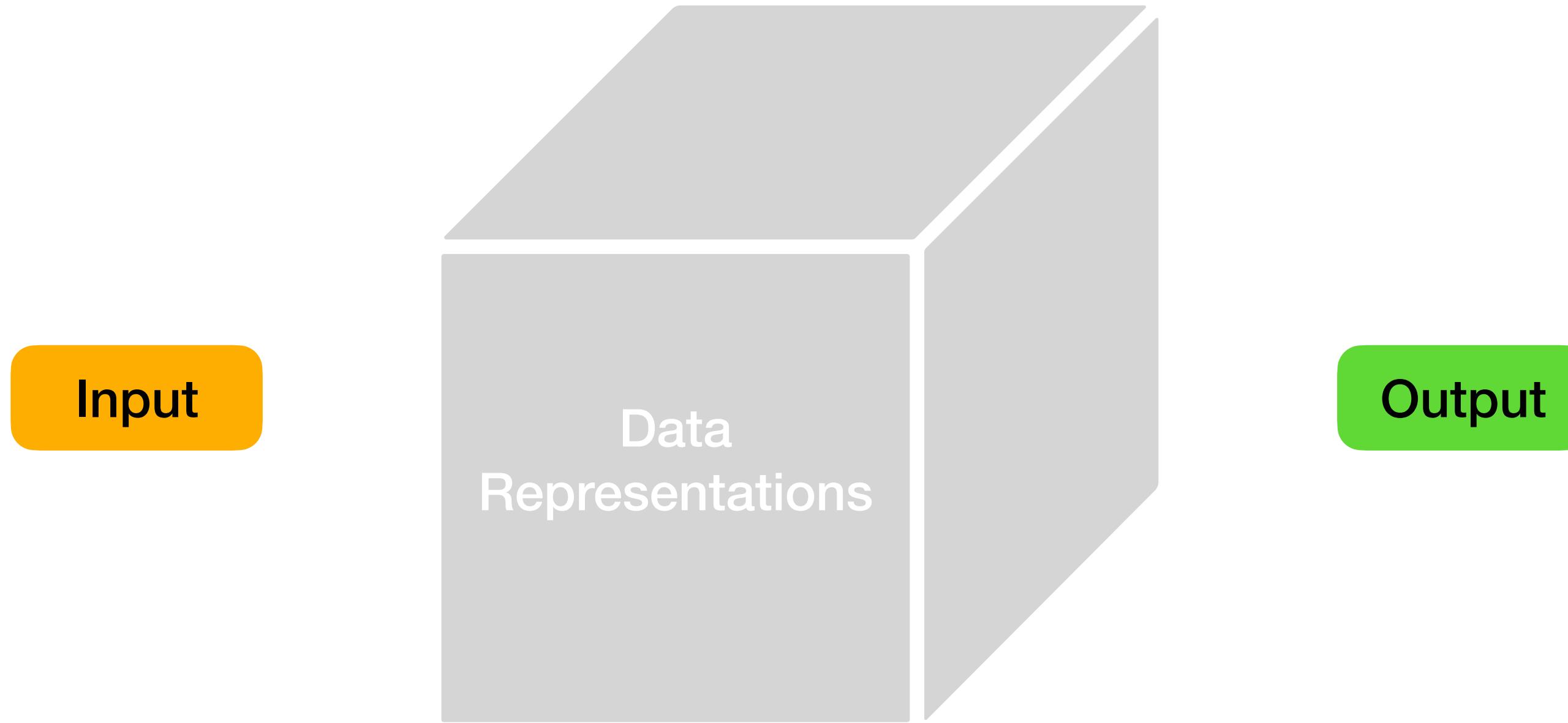
# Building upon the same idea

---



# Building upon the same idea

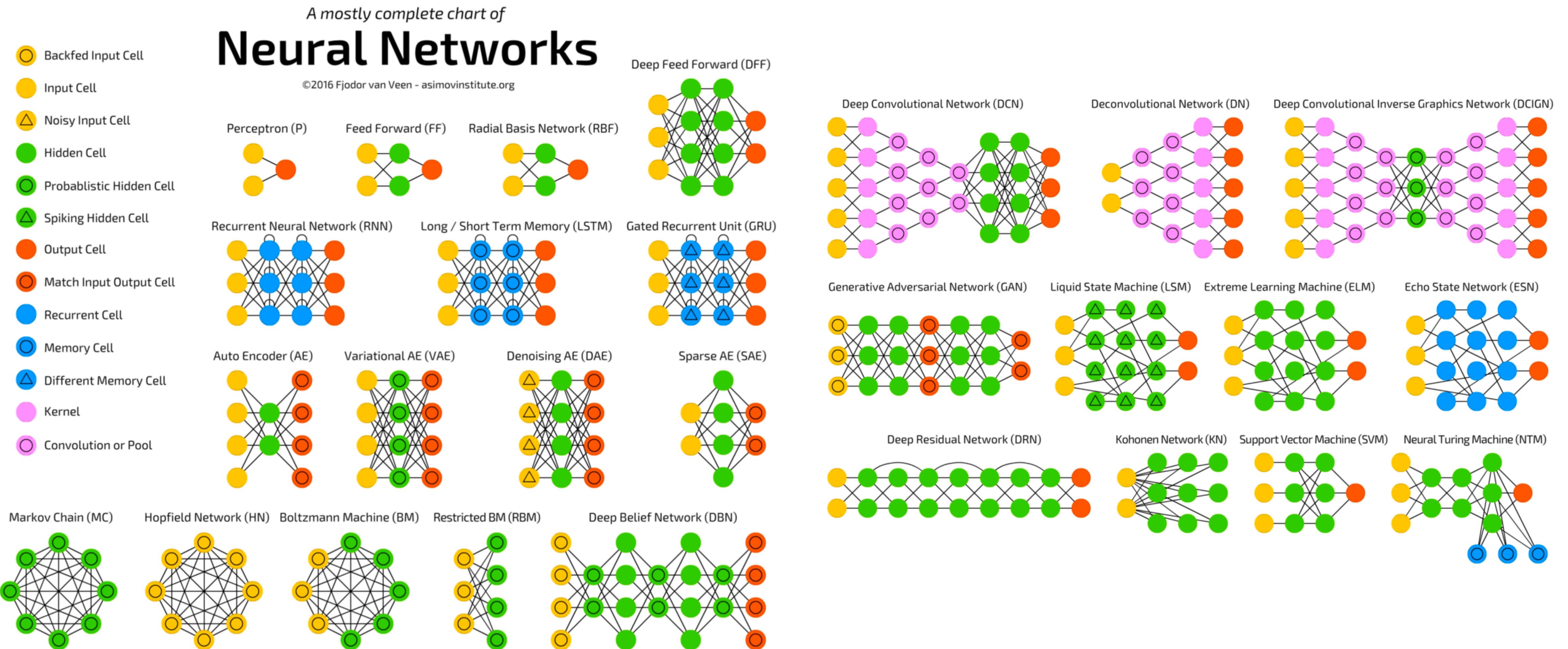
---



However, what we saw was  
only one type of Neural Network

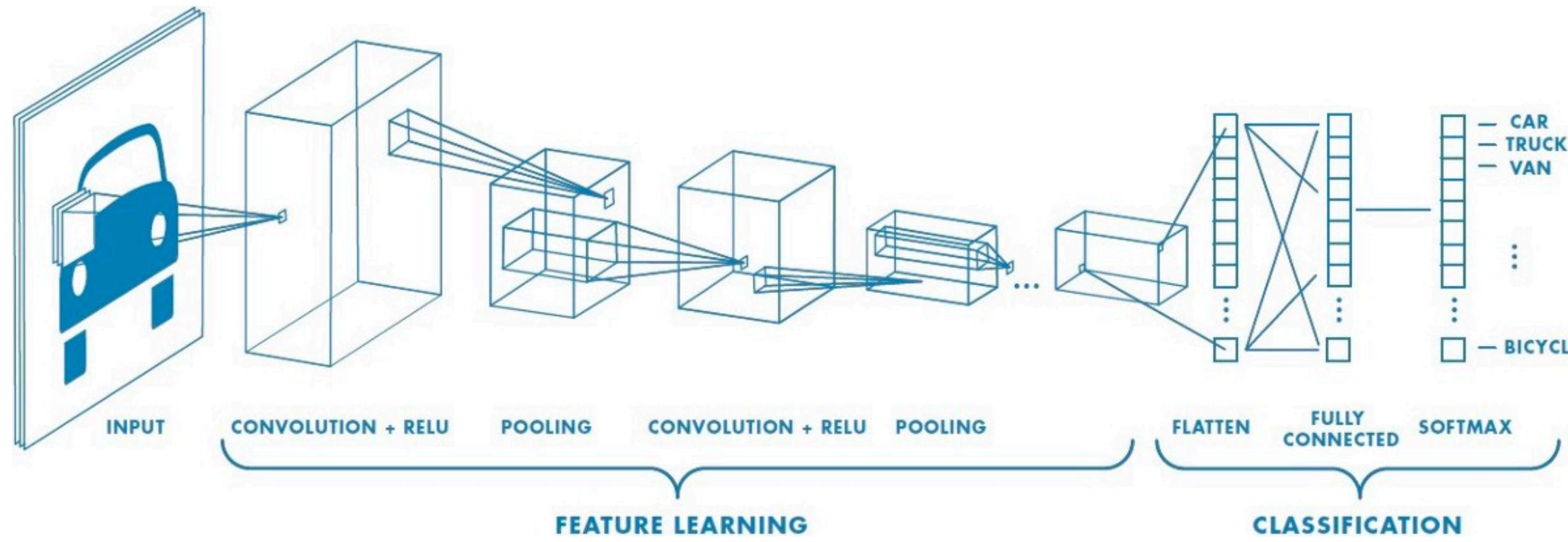
# It's a huge field

---

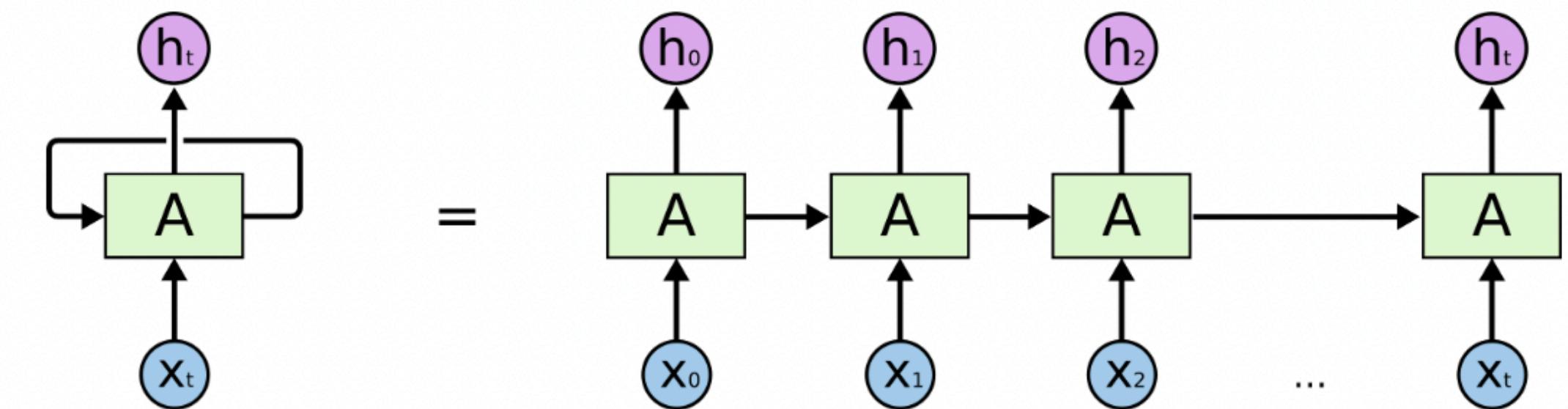


# Let's talk and try to code two of the most important ones

## Convolutional Neural Networks (CNNs)



## Recurrent Neural Networks (RNNs)



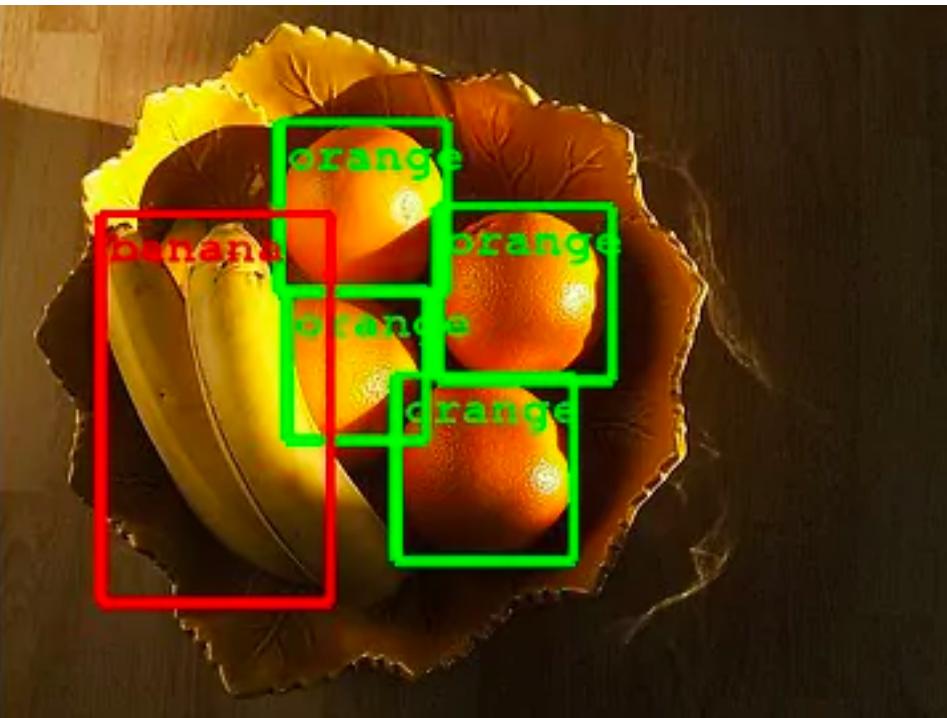
An unrolled recurrent neural network.

## Computer Vision

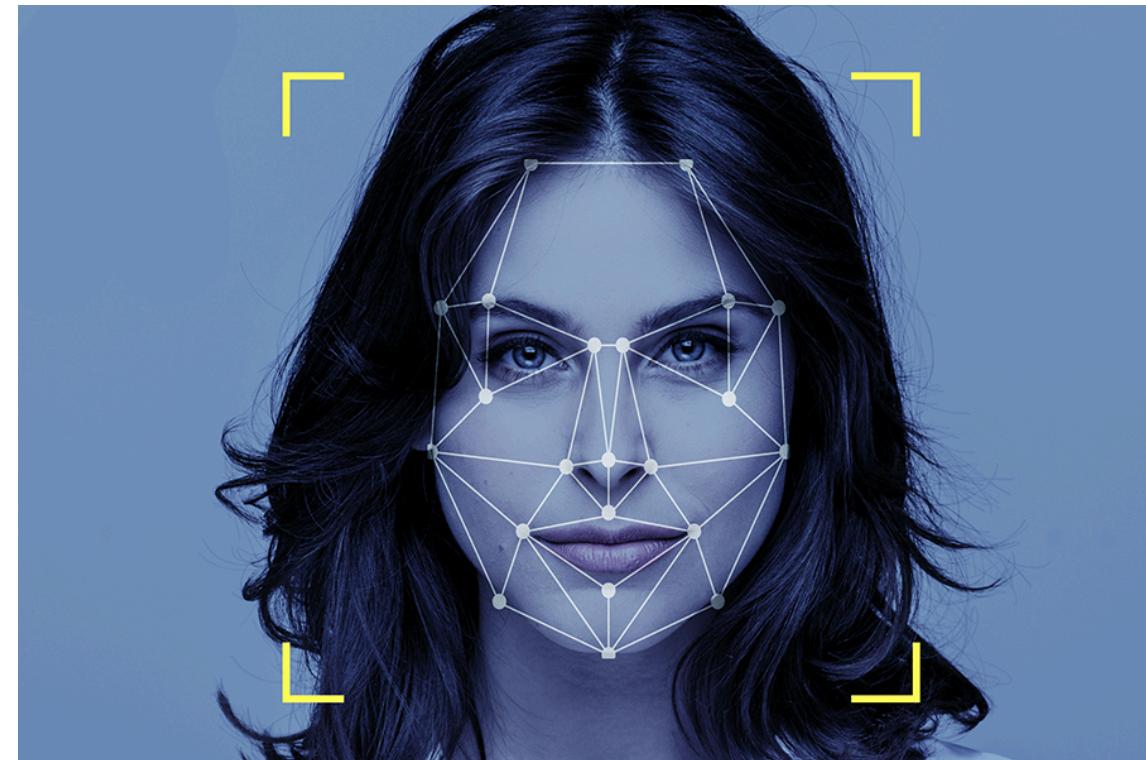
## Natural Language Process (NLP)

# Applications of Convolutional Neural Networks (CNNs)

Image Recognition & Optical Character Recognition



Face Recognition on social media



Object detection for self-driving cars

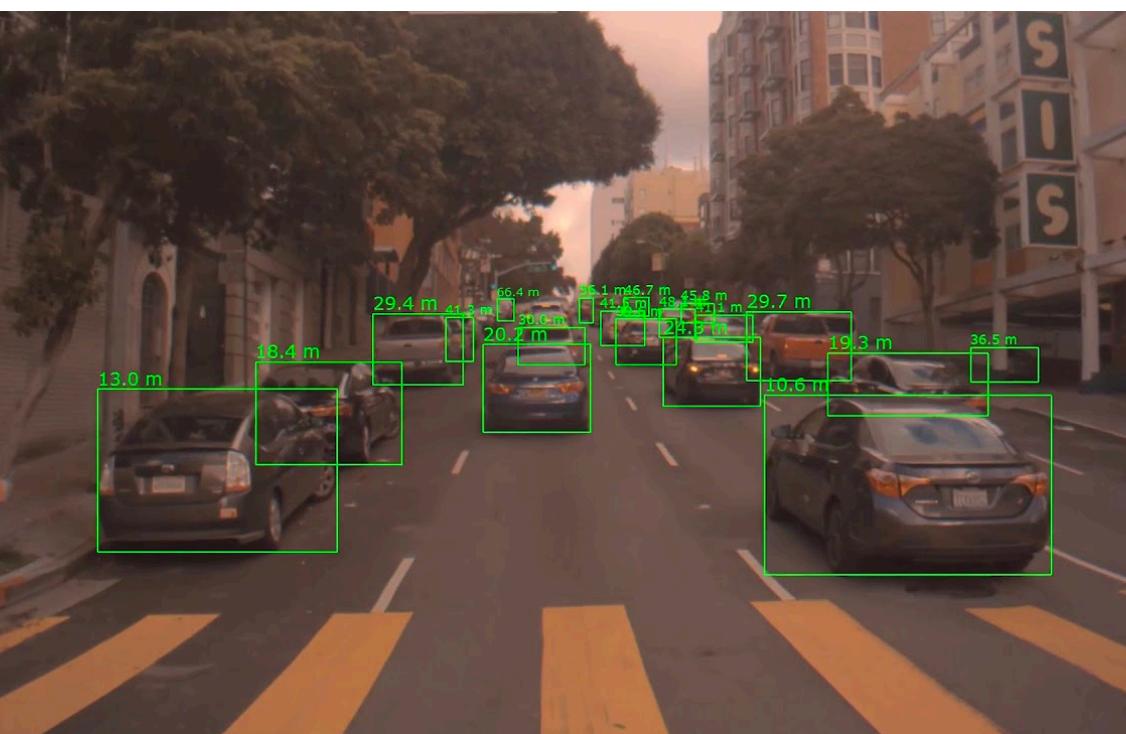
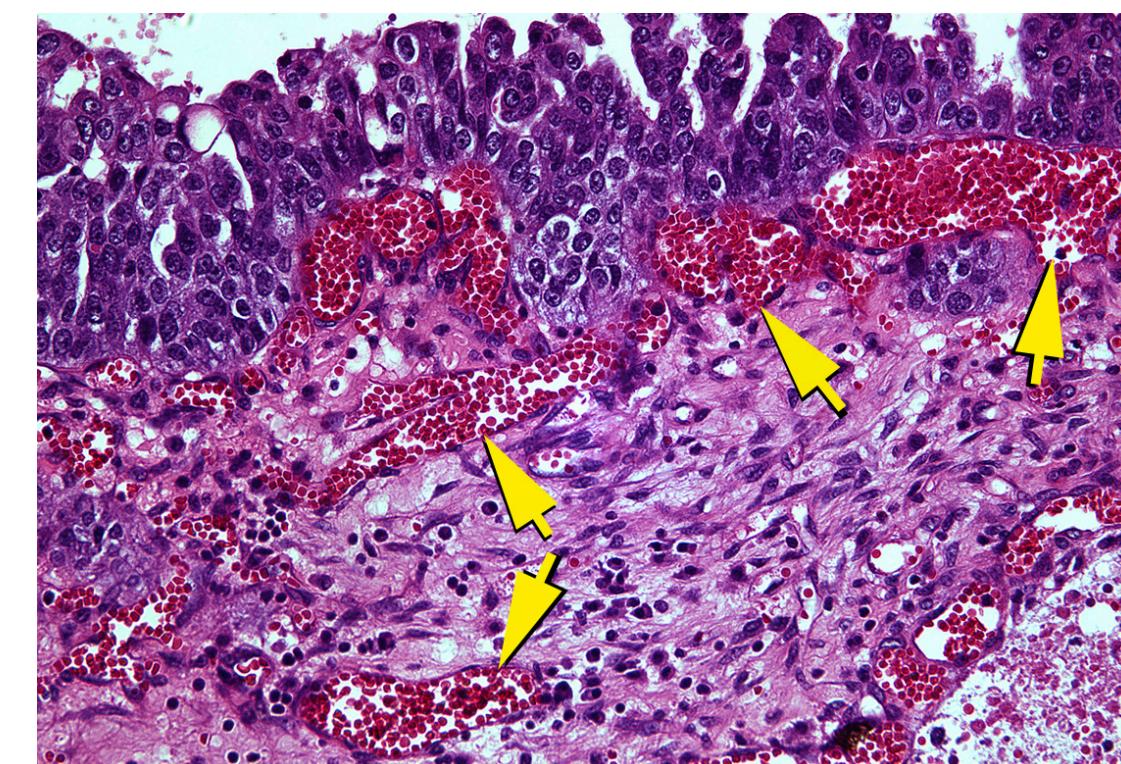


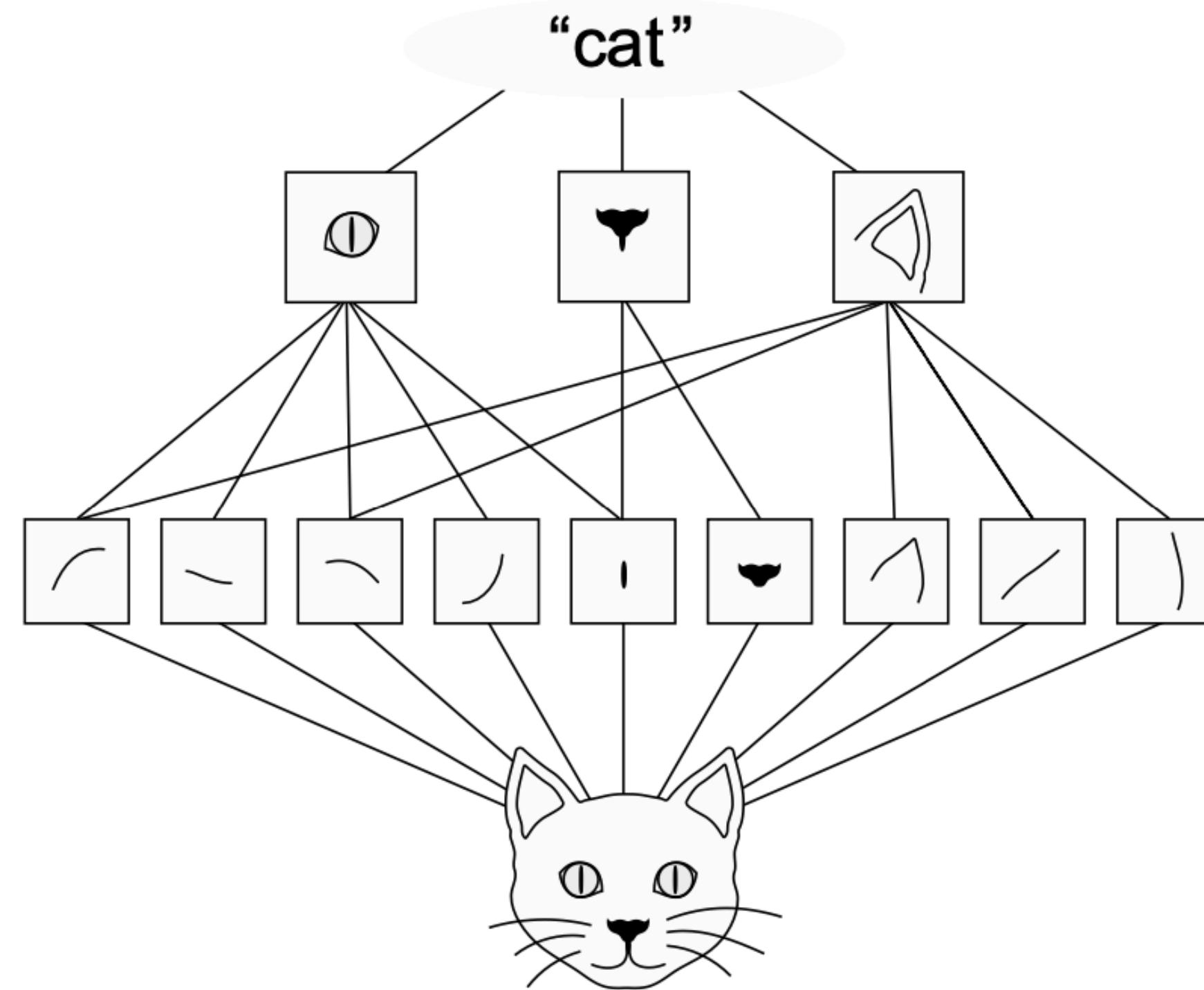
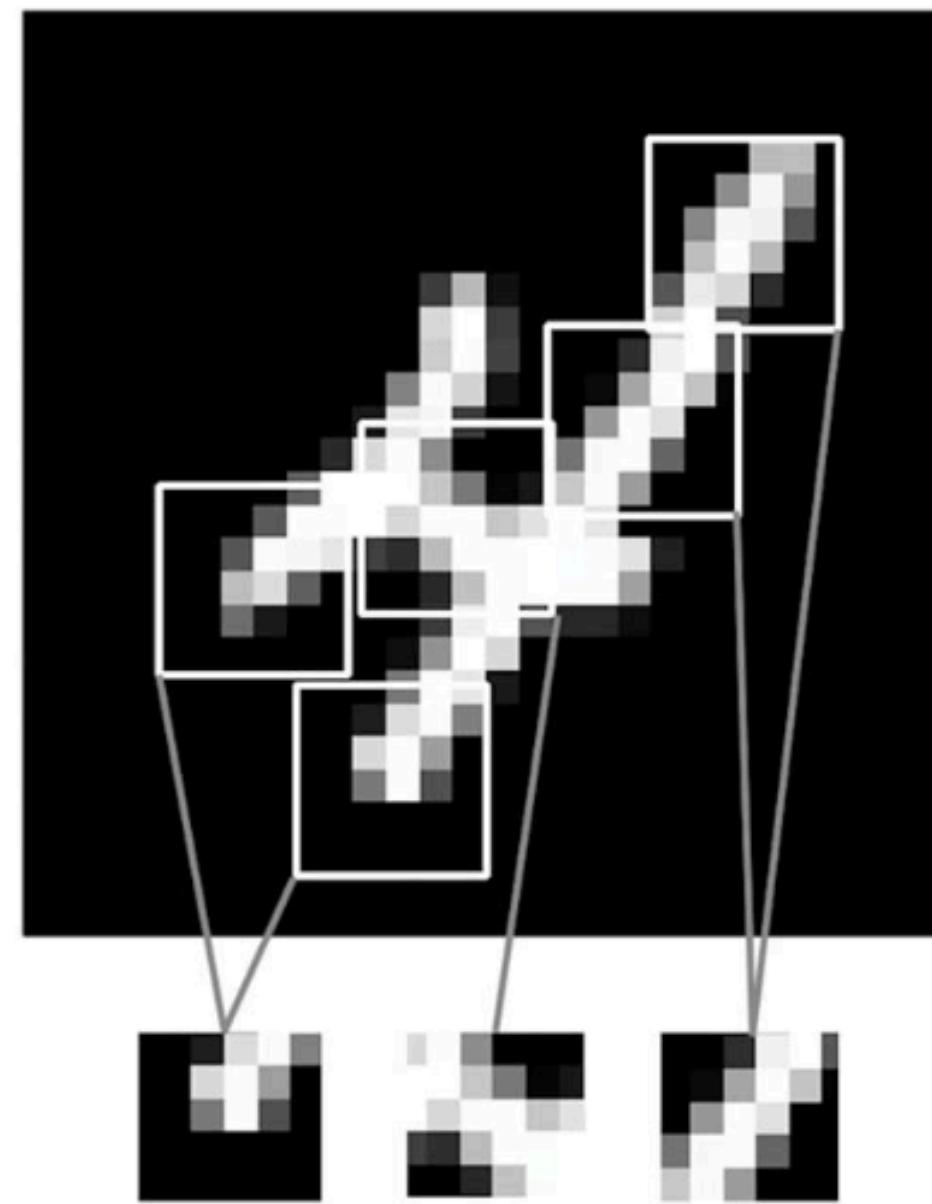
Image analysis in healthcare



# A bit of understanding to the Network

---

Images can be broken into local patterns such as edges, textures, and so on

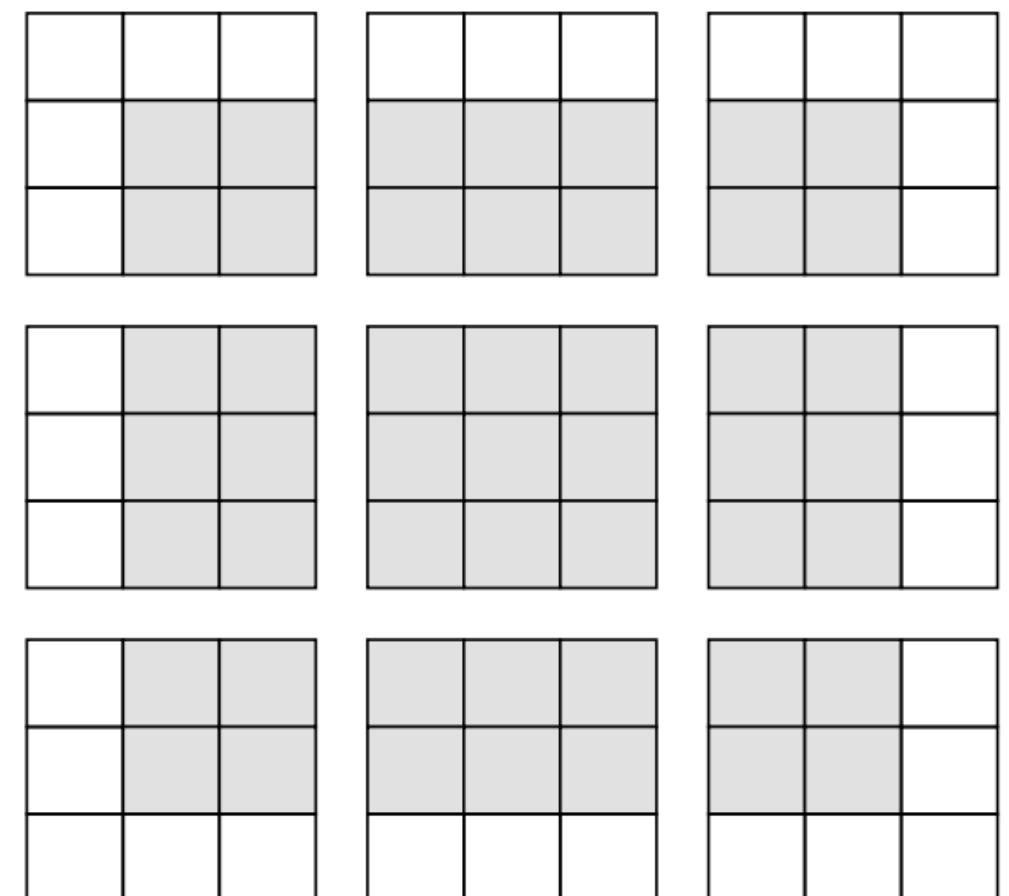
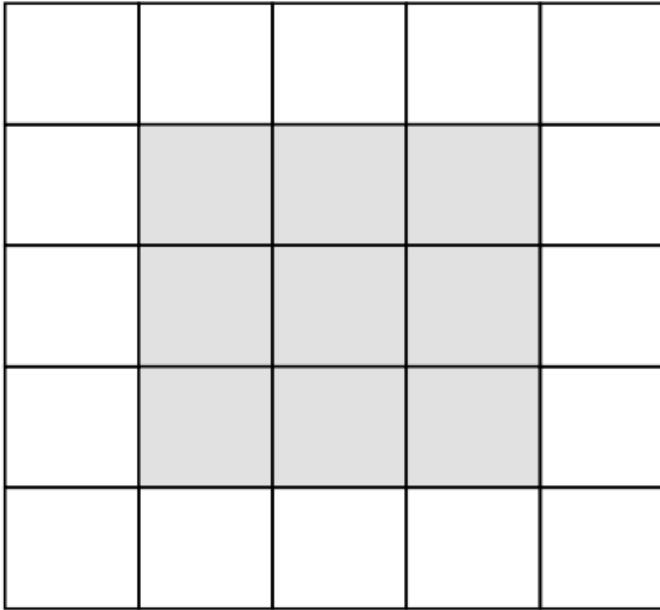


# A bit of understanding of the Network

---

In this case, the parameters (weights) of the network are filters

Locations of 3x3 patches in a 5x5 input feature image

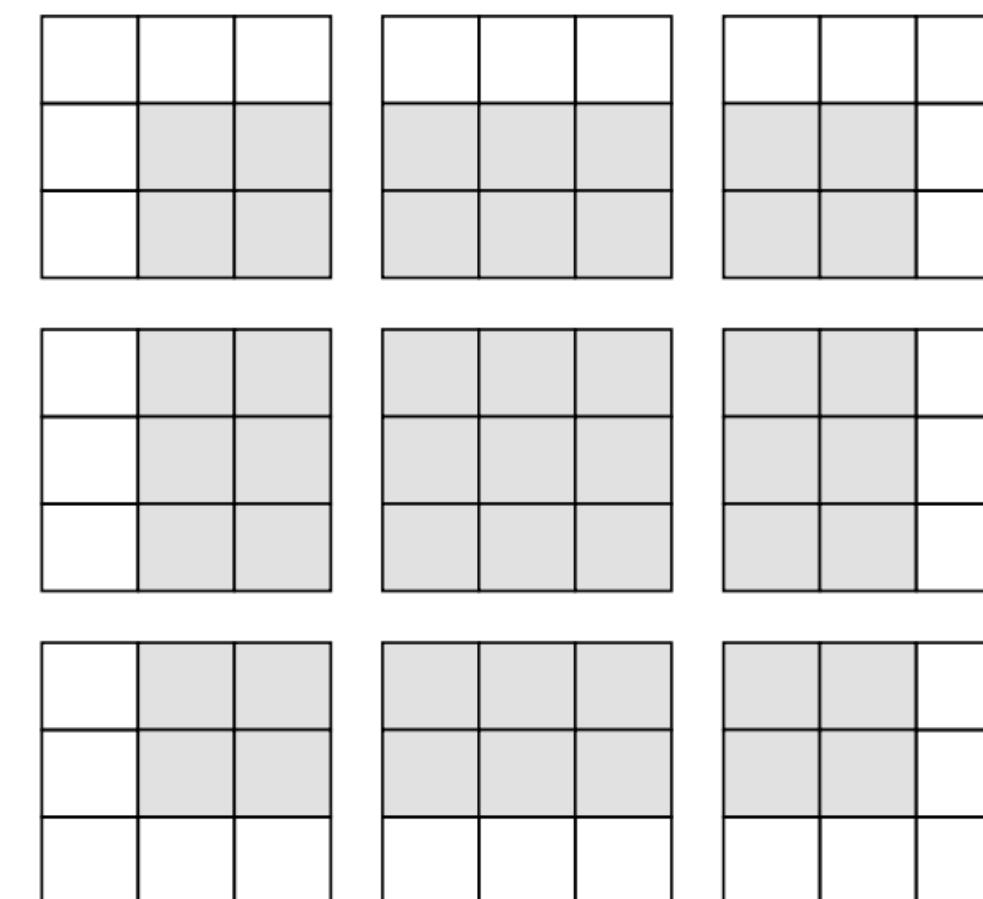
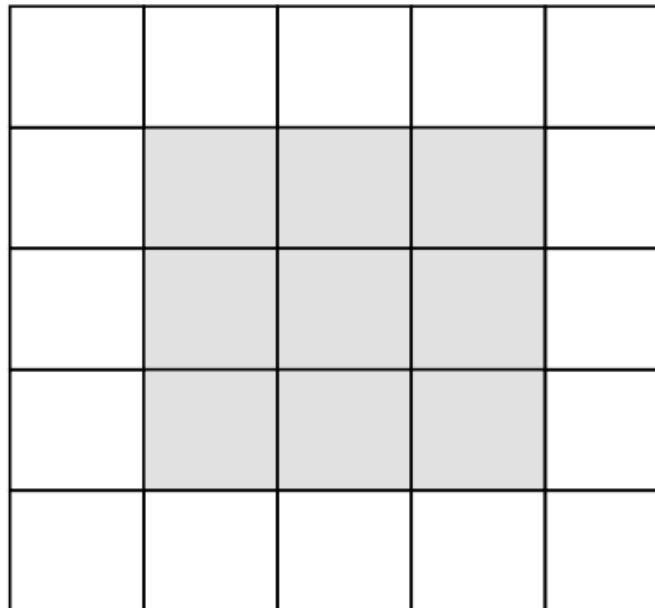


# A bit of understanding of the Network

---

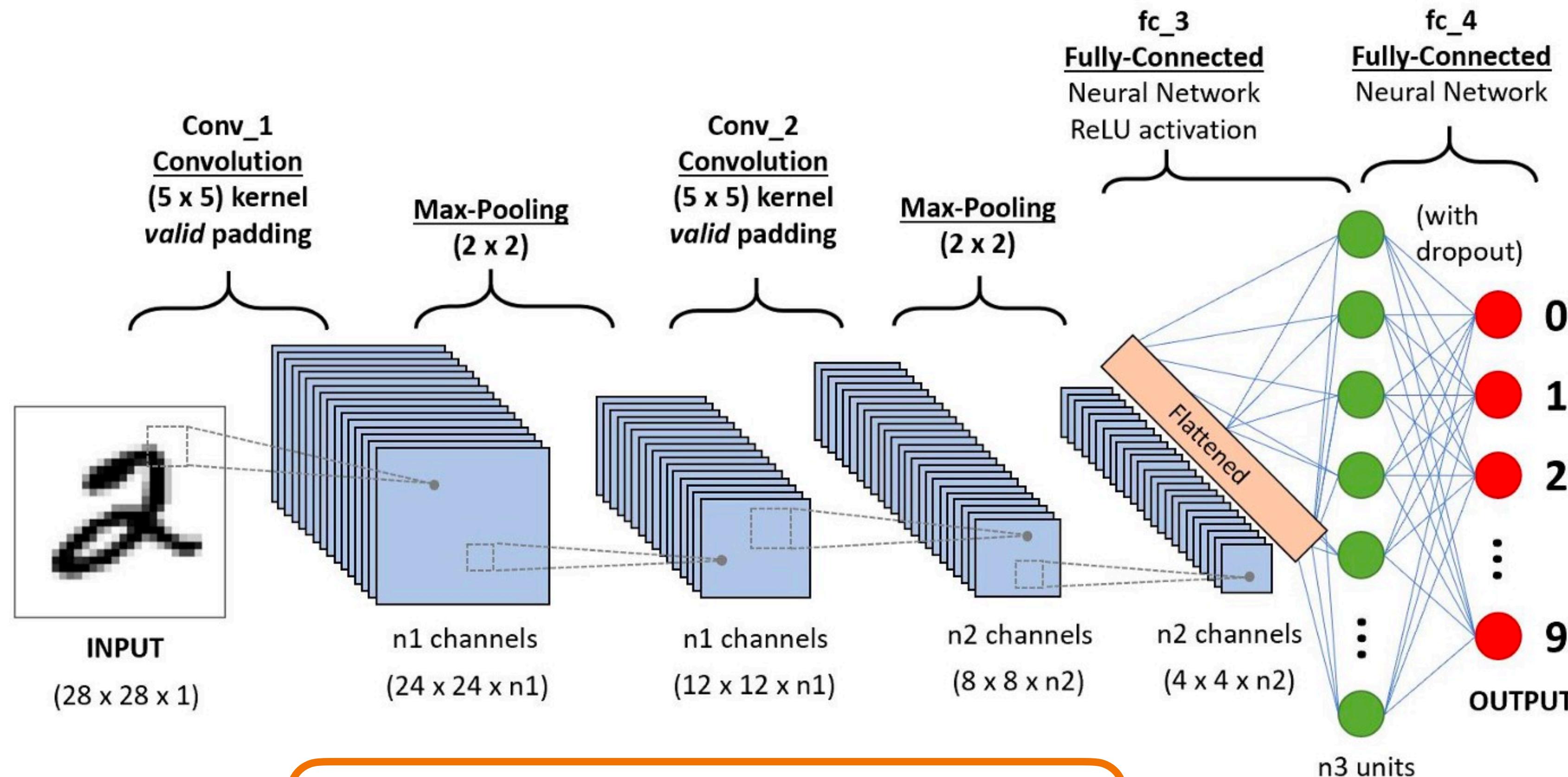
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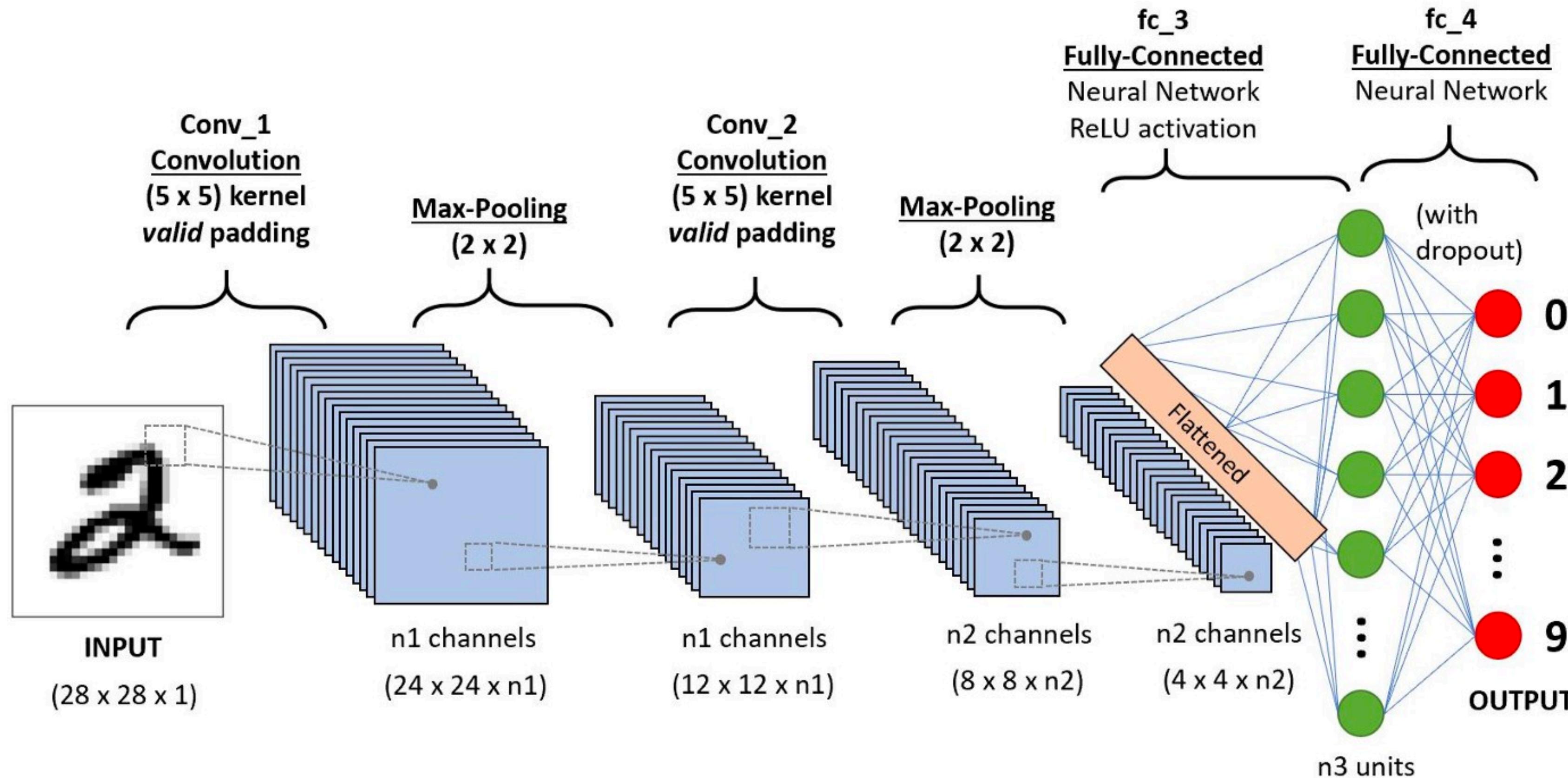
Input	Kernel	Output													
<table border="1" style="margin: auto;"><tr><td>0</td><td>1</td><td>2</td></tr><tr><td>3</td><td>4</td><td>5</td></tr><tr><td>6</td><td>7</td><td>8</td></tr></table>	0	1	2	3	4	5	6	7	8	*	<table border="1" style="margin: auto;"><tr><td>0</td><td>1</td></tr><tr><td>2</td><td>3</td></tr></table>	0	1	2	3
0	1	2													
3	4	5													
6	7	8													
0	1														
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		=													
		<table border="1" style="margin: auto;"><tr><td>19</td><td>25</td></tr><tr><td>37</td><td>43</td></tr></table>	19	25	37	43									
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# A bit of understanding of the Network



# A bit of understanding of the Network

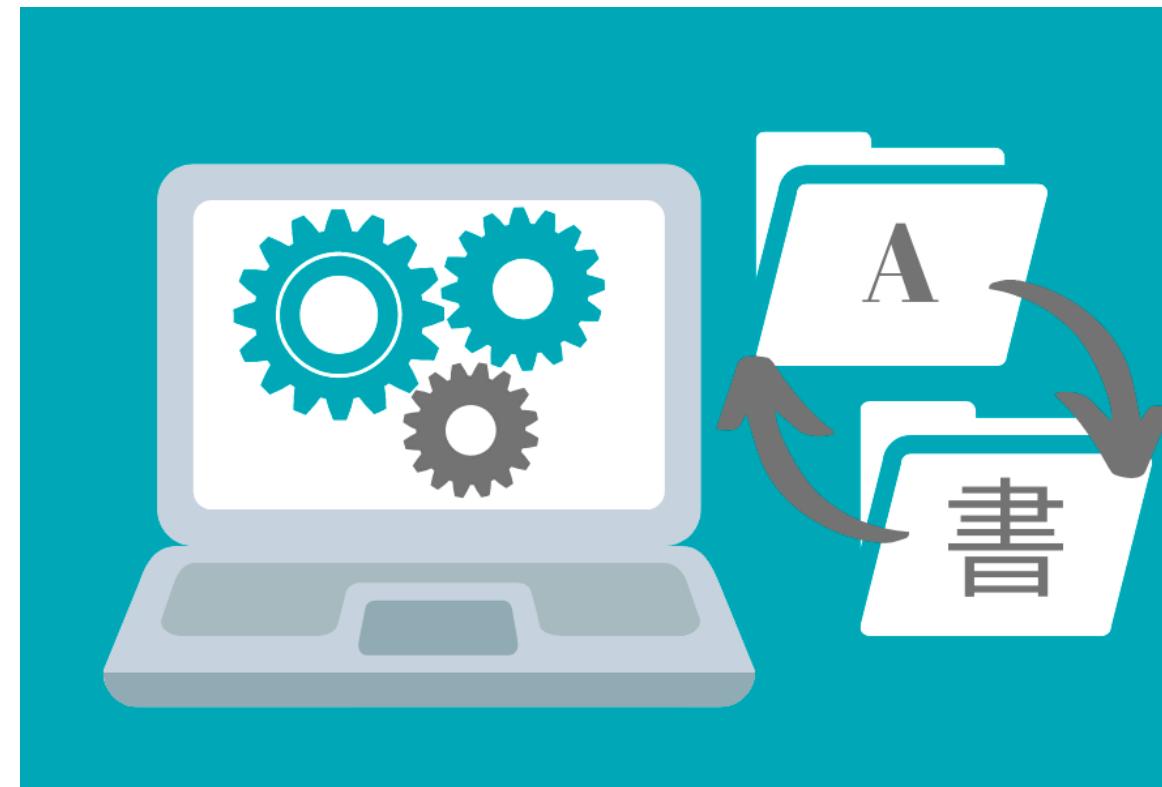
---



Let's build a CNN!

# Applications of Recurrent Neural Networks (RNNs)

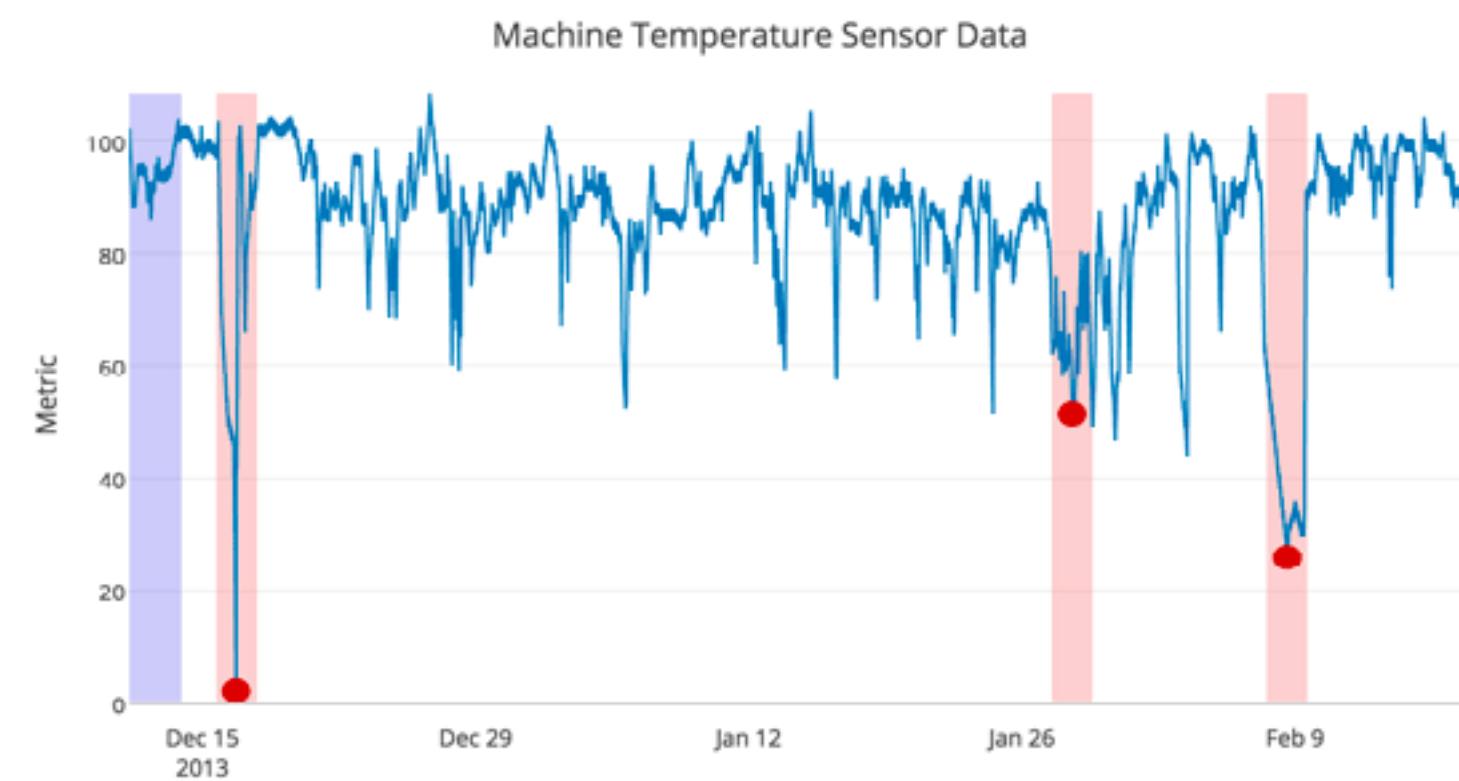
## Machine Translation



## Stock prediction



## Time series anomaly detection



## Speech Recognition



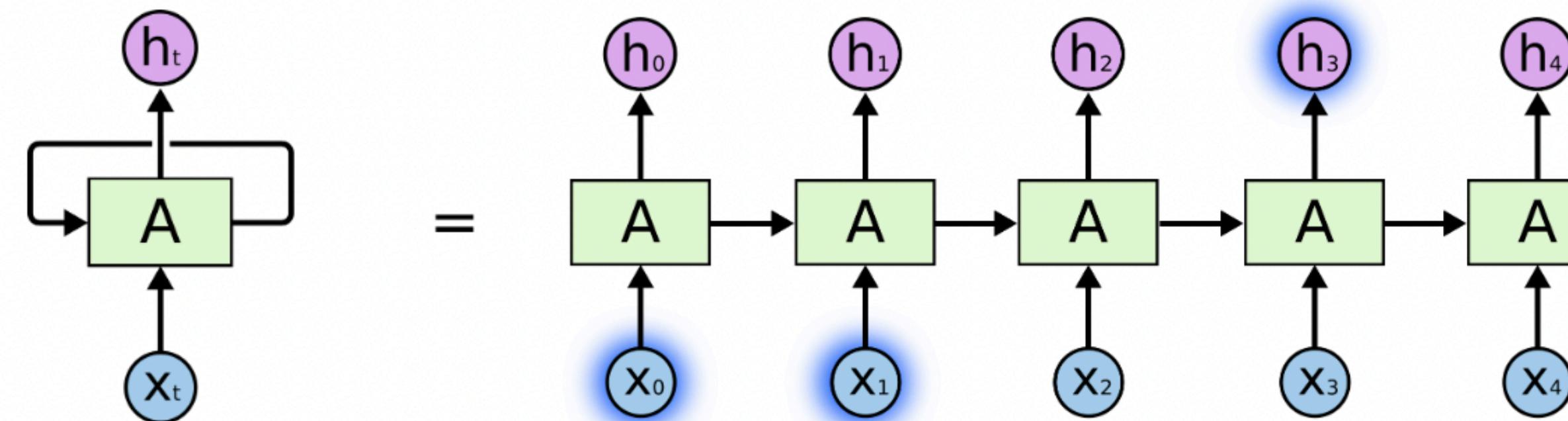
# A glimpse of how the network works (RNNs)

---

Densely connected networks and CNNs have no memory. Inputs are processed independently. However, that is not the case of RNNs.

# A glimpse of how the network works (RNNs)

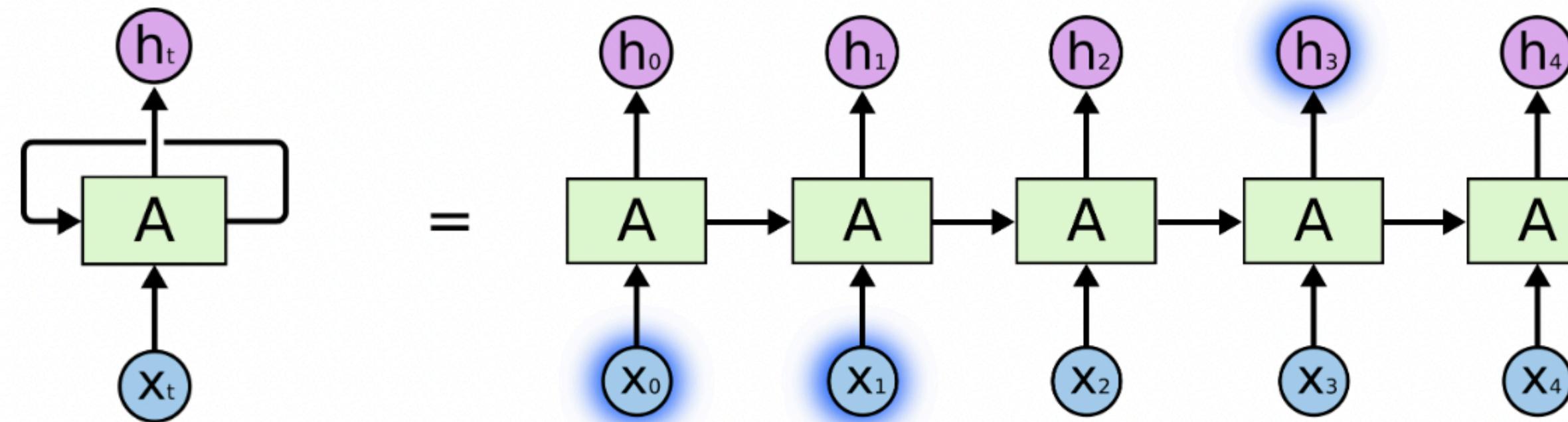
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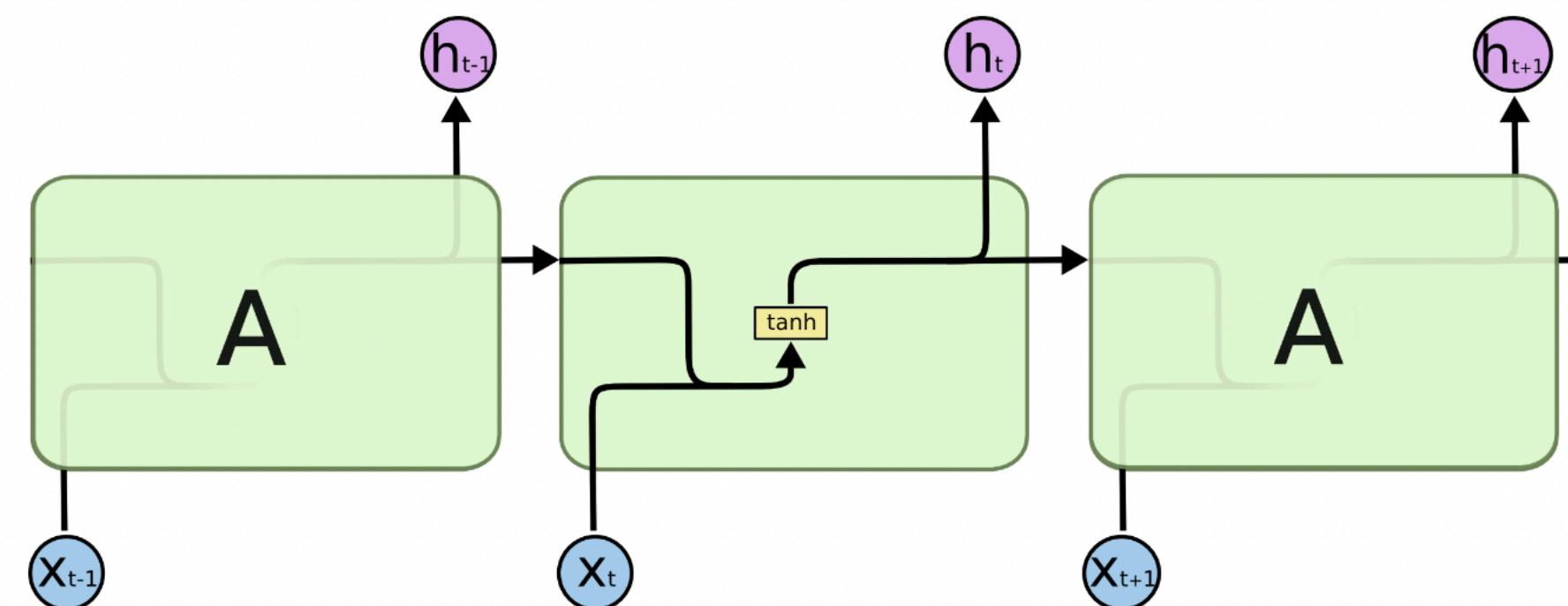
They retain information from previous neurons

# A glimpse of how the network works (RNNs)

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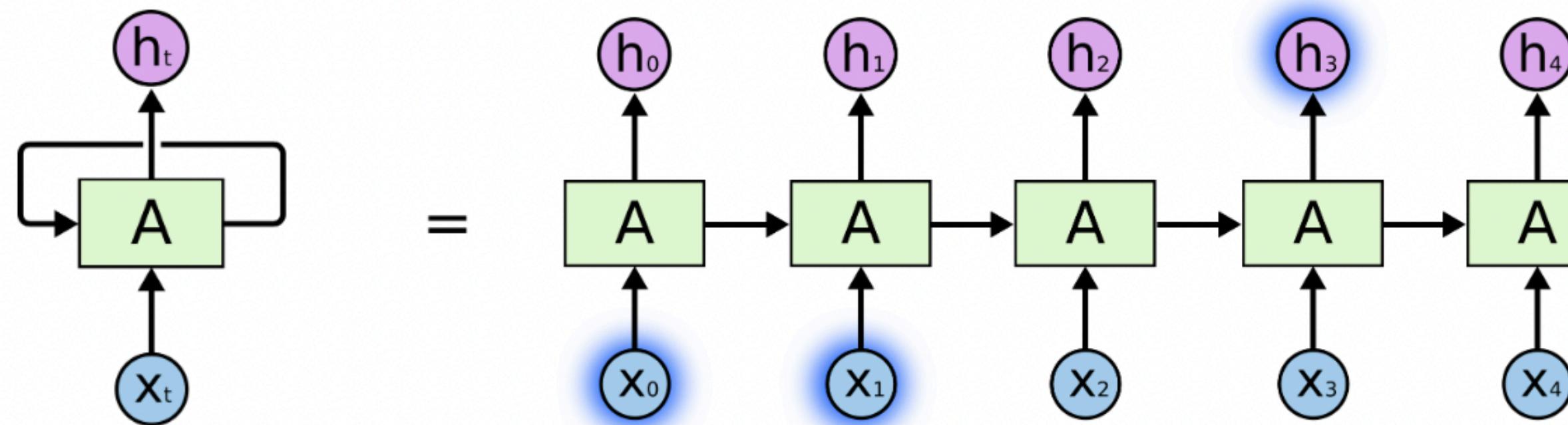
They retain information from previous neurons



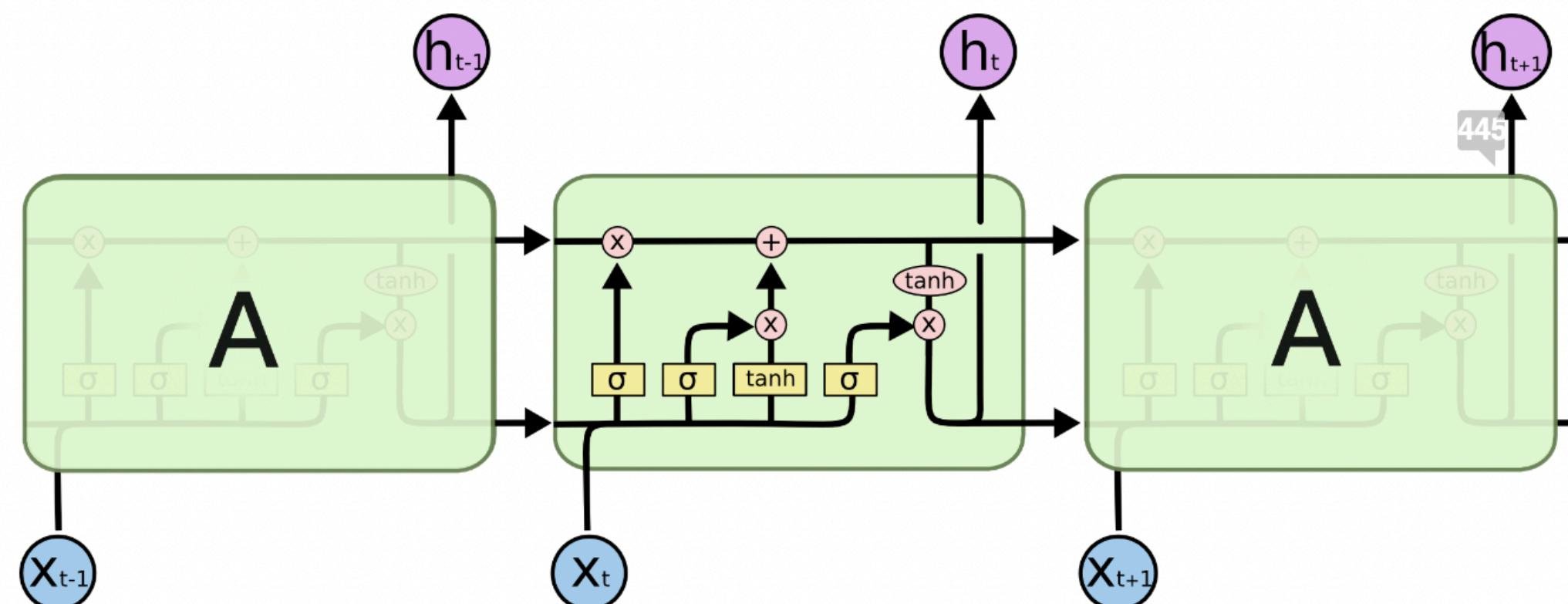
They keep the state of the previous neuron

# A glimpse of how the network works (LSTMs)

Densely connected networks and CNNs have no memory. Inputs are processed independently. However, that is not the case of RNNs.



They retain information from previous neurons



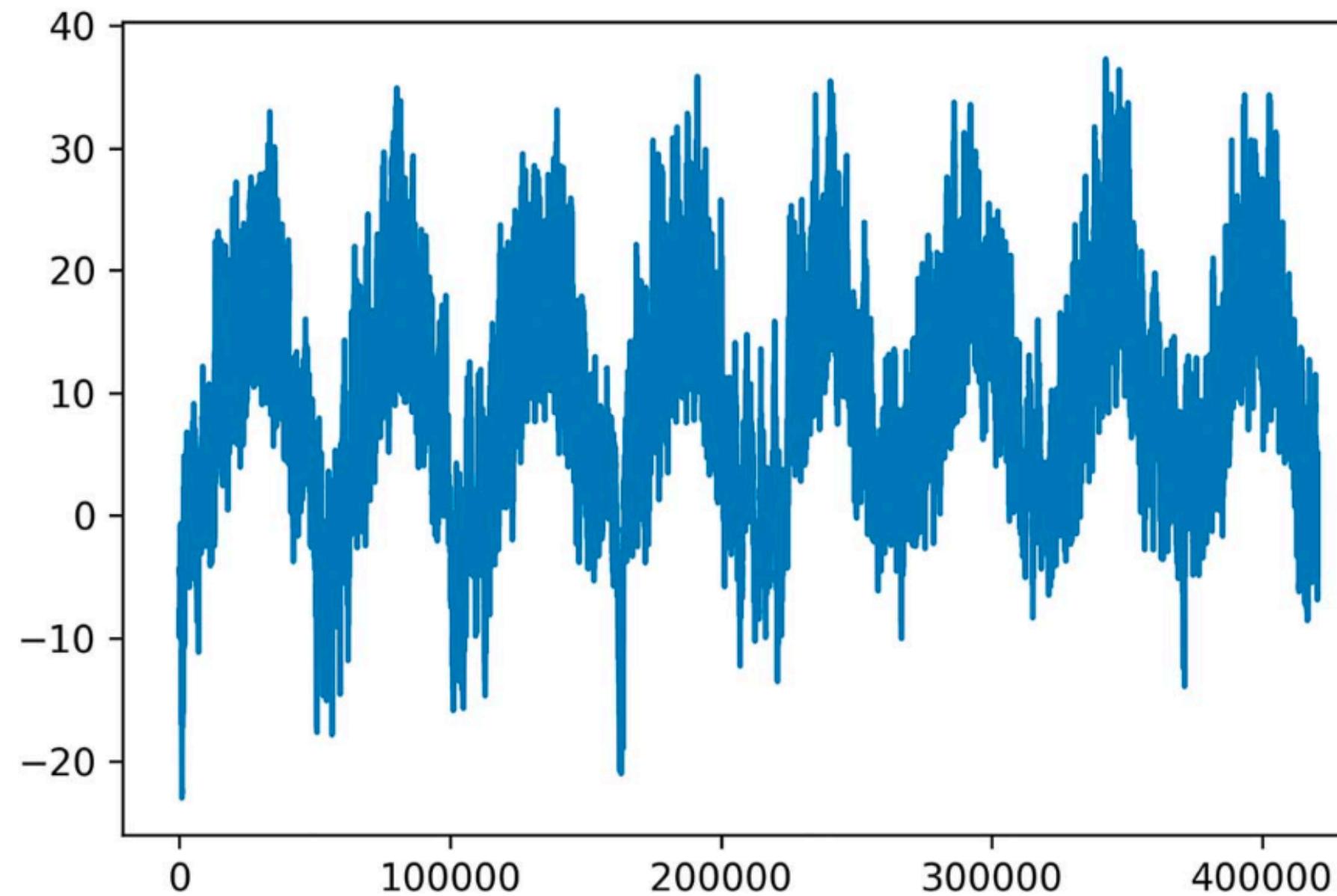
They keep the state of the previous neuron

# A practical example (LSTMs): Temperature Forecasting

---

Time series forecasting

Temperature Forecasting  
example



```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))  
x = layers.LSTM(16)(inputs)  
outputs = layers.Dense(1)(x)  
model = keras.Model(inputs, outputs)
```



# How Deep Learning is changing / will change the world?

# Some examples using novel networks that are revolutionizing the AI world

---



New AI Model Translates 200 Languages, Making Technology Accessible to More People

July 6, 2022

Meta AI Introduces 'Make-A-Video': An Artificial Intelligence System That Generates Videos From Text

By **Ashish kumar** - October 3, 2022

<https://makeavideo.studio/>

# Some examples using novel networks that are revolutionizing the AI world

---



New AI Model Translates 200 Languages, Making Technology Accessible to More People

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Meta AI Introduces 'Make-A-Video': An Artificial Intelligence System That Generates Videos From Text

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<https://makeavideo.studio/>



Discovering novel algorithms with AlphaTensor

October 5, 2022

INTELIGENCIA ARTIFICIAL

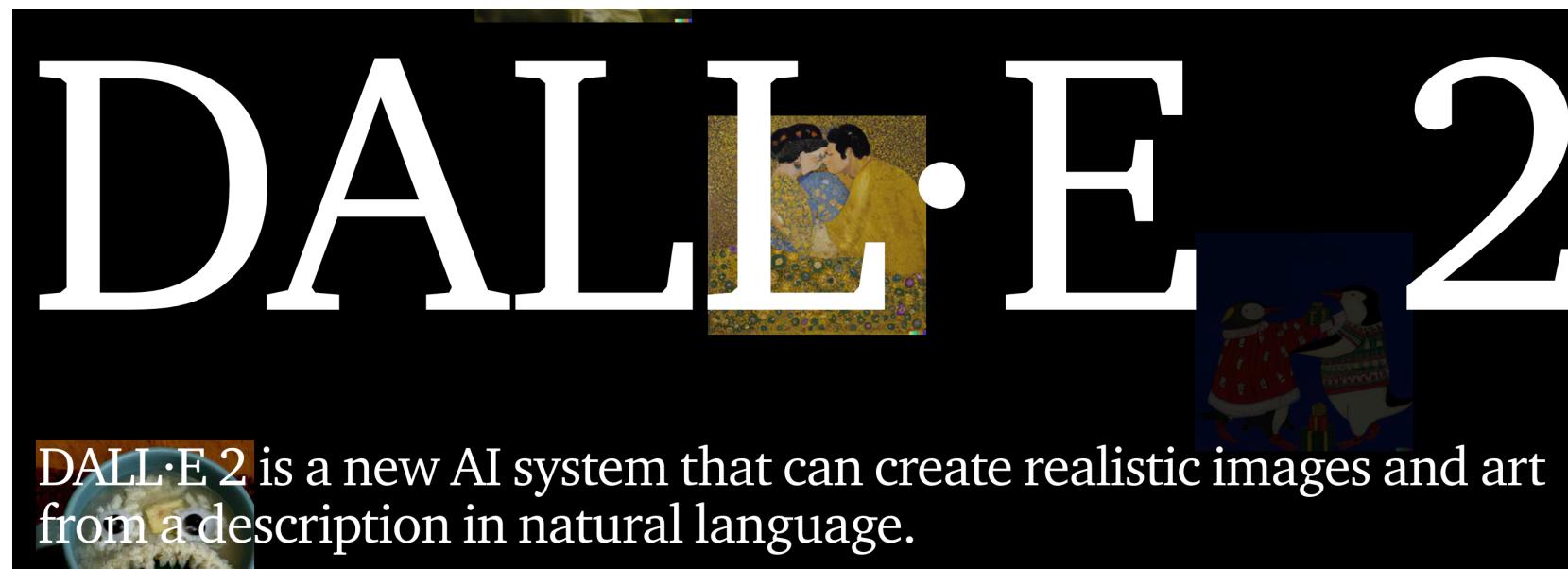
Una IA de DeepMind halla una nueva forma de multiplicar números y acelerar los ordenadores

Article | **Open Access** | Published: 15 July 2021

**Highly accurate protein structure prediction with AlphaFold**

# Some examples using novel networks that are revolutionizing the AI world

---



A beautiful landscape in the mountains, in the middle of the trees, with snow around and a big husky laying around

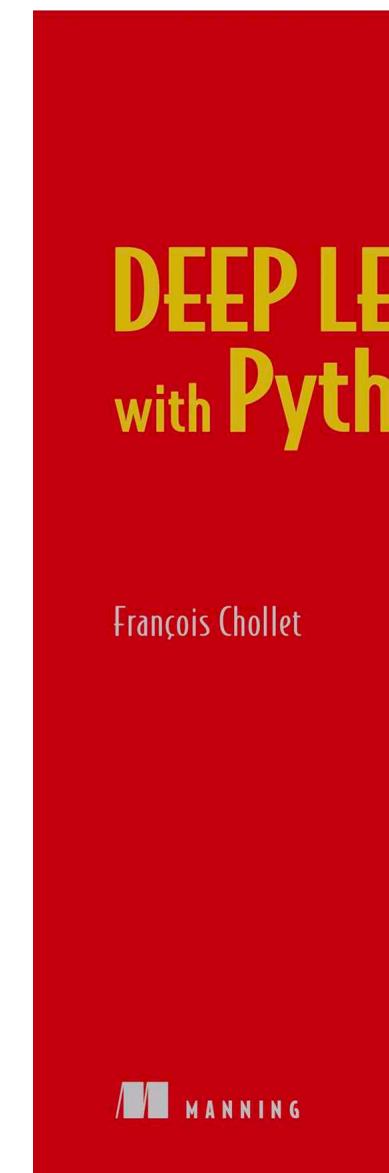
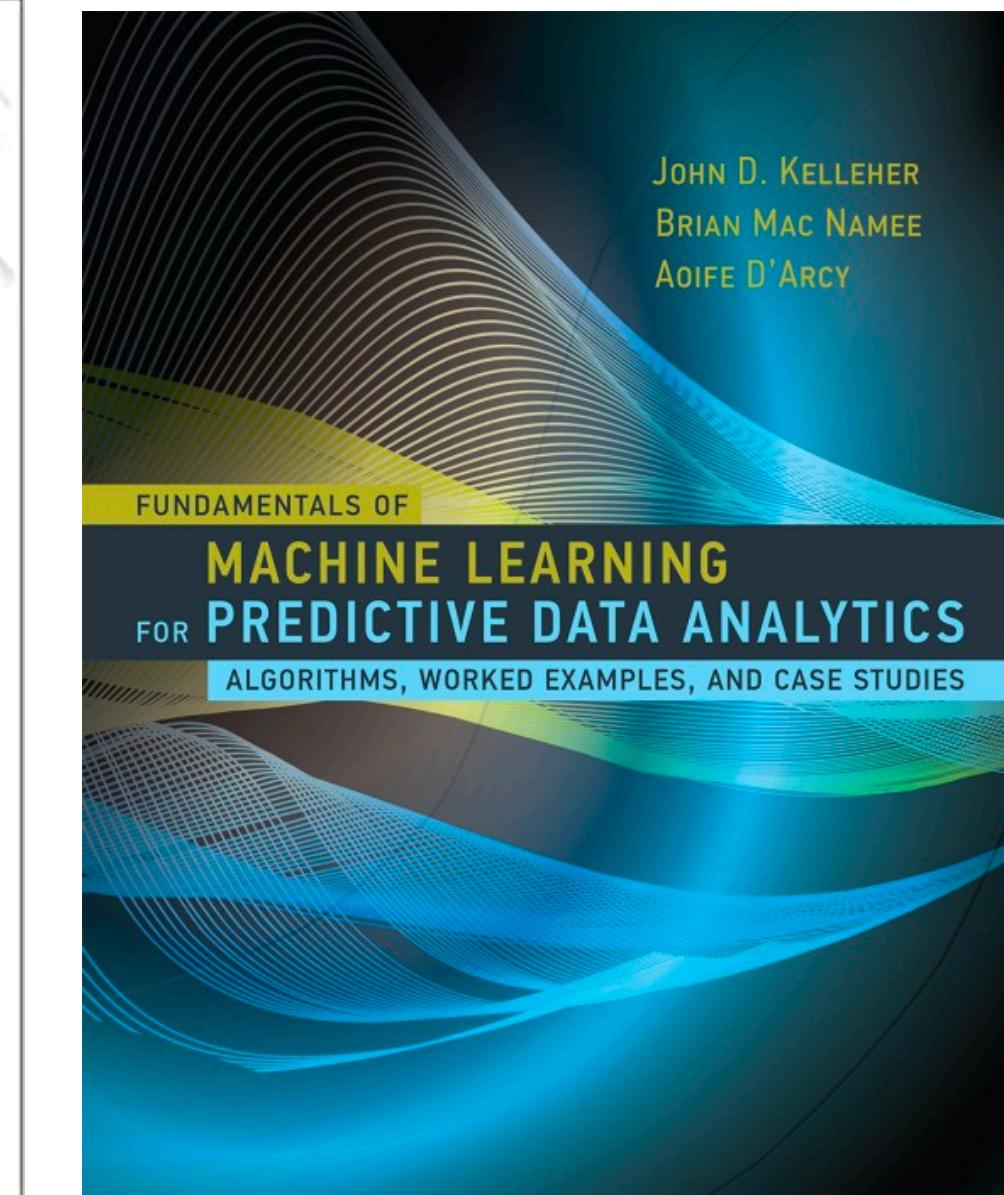
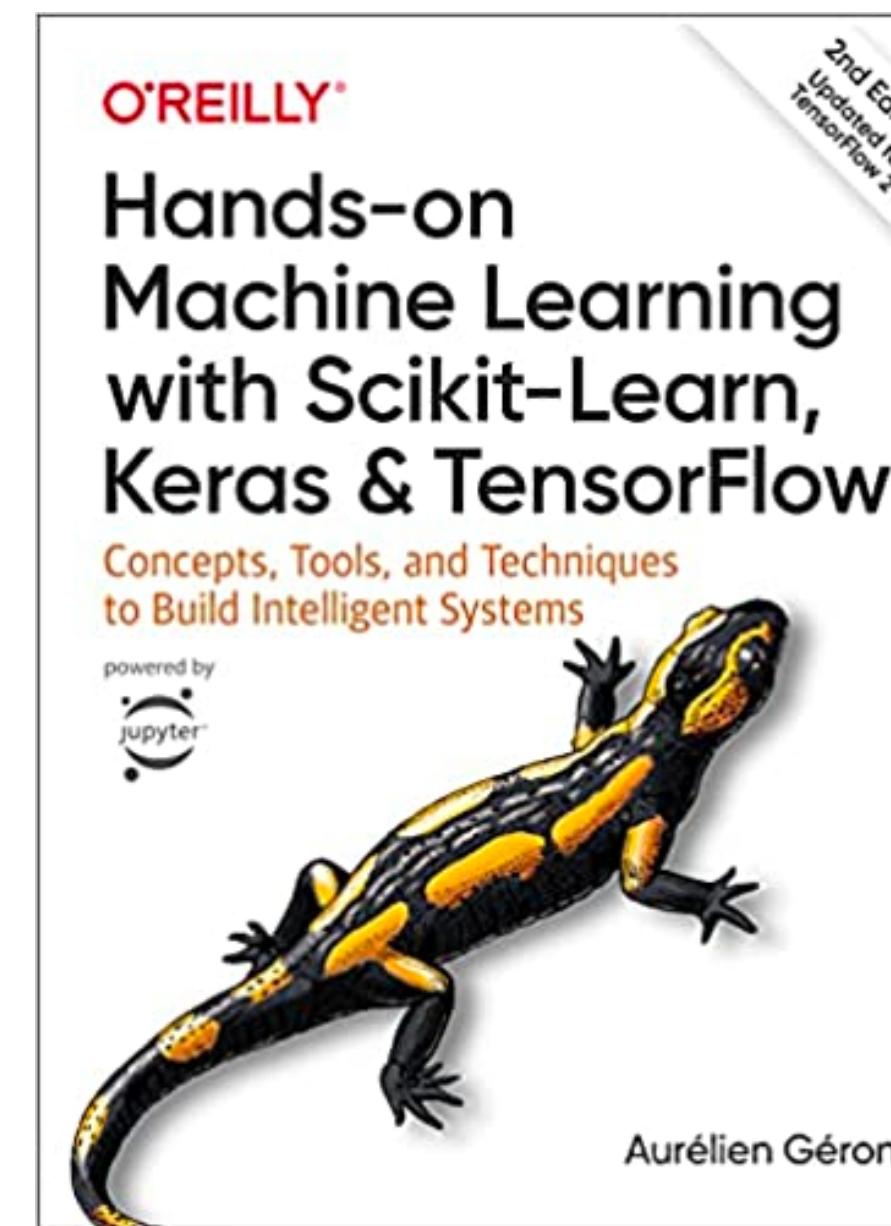
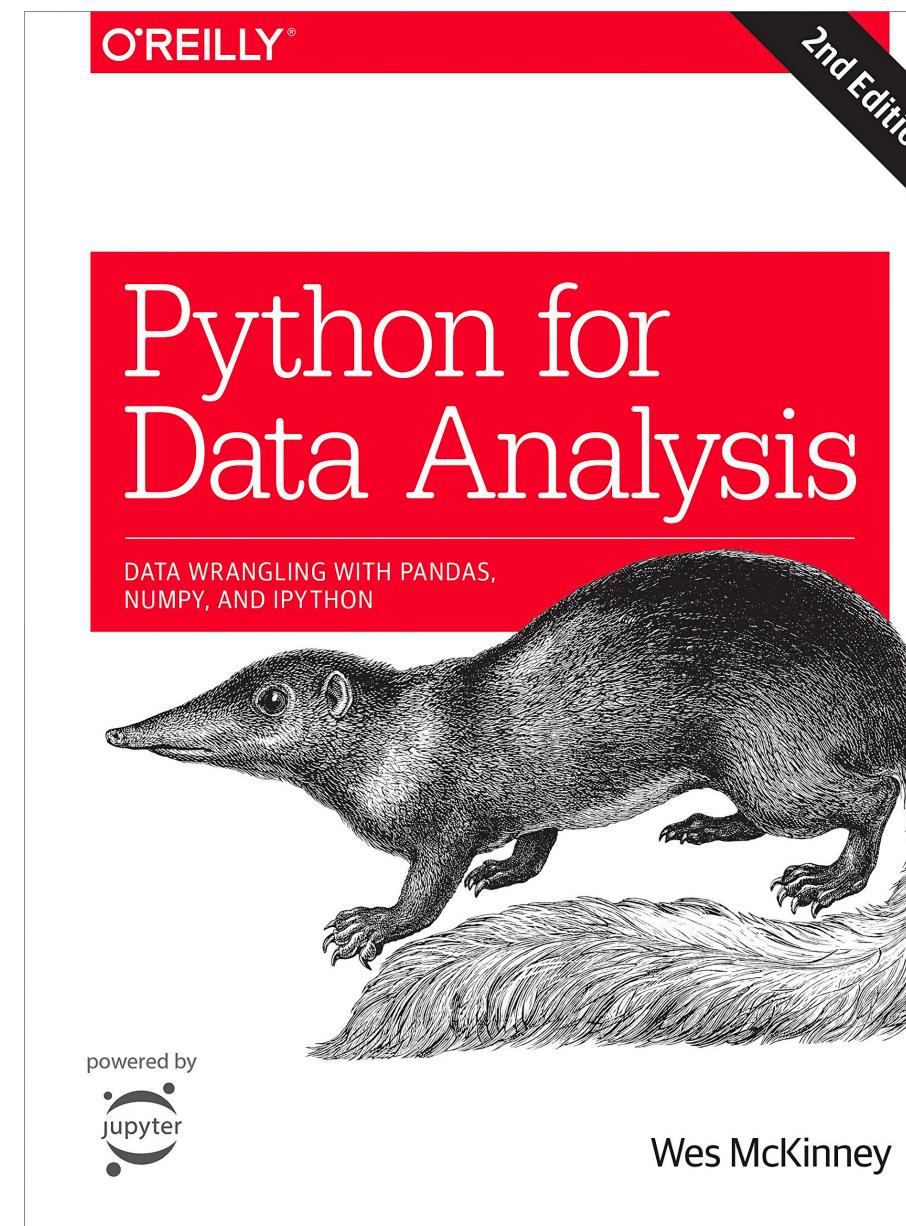




# Last words

# Free Books to learn Python, ML & DL

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3Blue1Brown in YouTube

# You are in the right place at the right moment (My Opinion)

---

- Computational analytical skills are in demand
- Companies need people who can make sense of their data and give them an edge with that.
- AI, ML, and DL are booming, and being able to apply such techniques will be increasingly important
- Math knowledge is not “strictly” necessary, instead having a general understanding and being able to build solutions on the cloud will be the key to the future (my take)
- ML engineer / Data engineer > Data Scientist



# Thank you!



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## Feel Free to contact me!

- Linkedin: Jose Bonet Giner
- Personal mail: [pepebogi5@gmail.com](mailto:pepebogi5@gmail.com)
- Company website: [hyntsanalytics.com](http://hyntsanalytics.com)
- Blog: [pepesjourney.com](http://pepesjourney.com)
- Twitter: [pepeb\\_5](https://twitter.com/pepeb_5)

The hynts logo consists of the word "hynts" in a lowercase sans-serif font. The letter "n" has a small orange dot positioned above its middle vertical stroke.