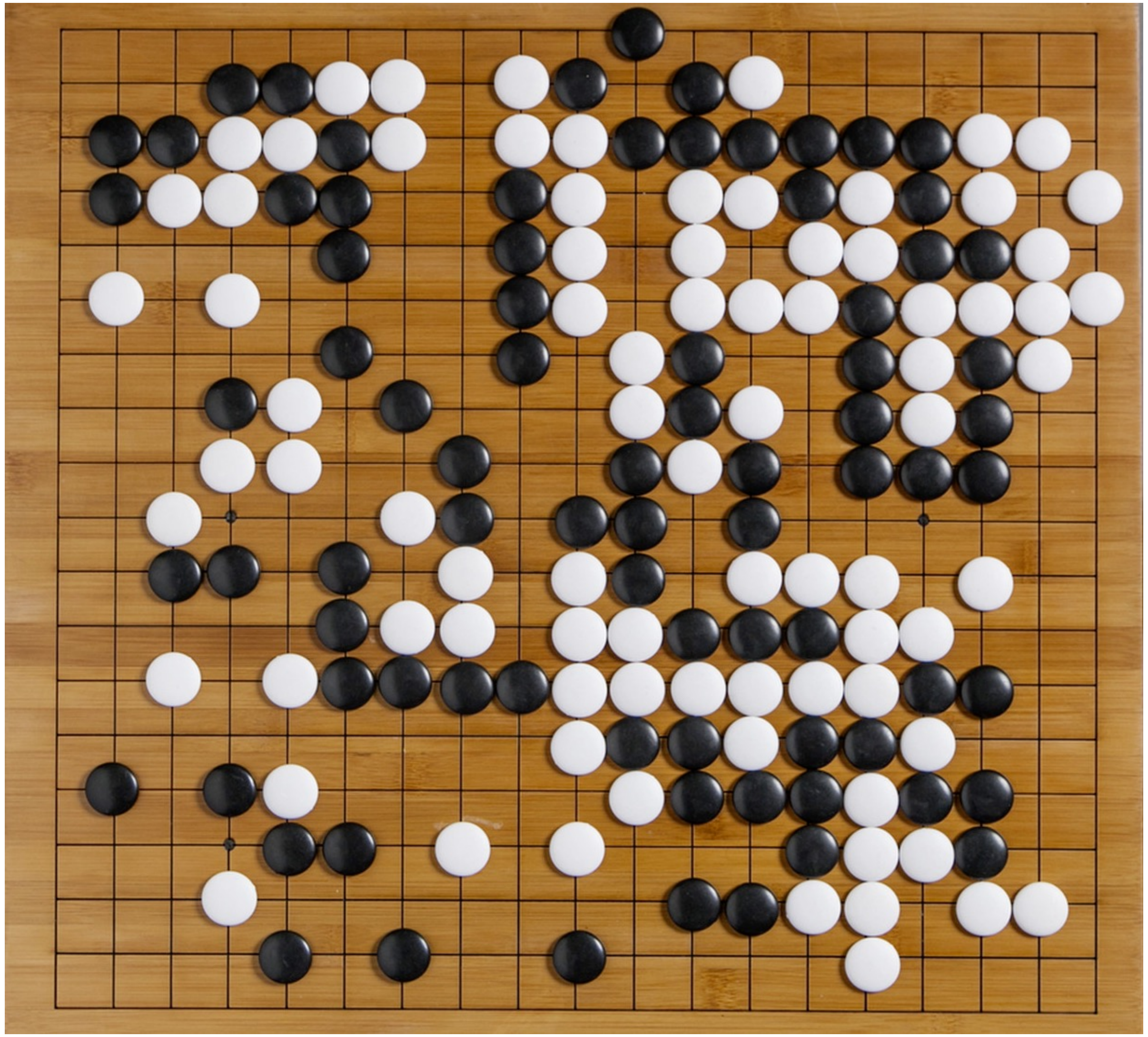
Deep Learning

CS109, Stanford University

Innovations in deep learning



AlphaGO (2016)

Deep learning (neural networks) is the core idea driving the current revolution in AI.

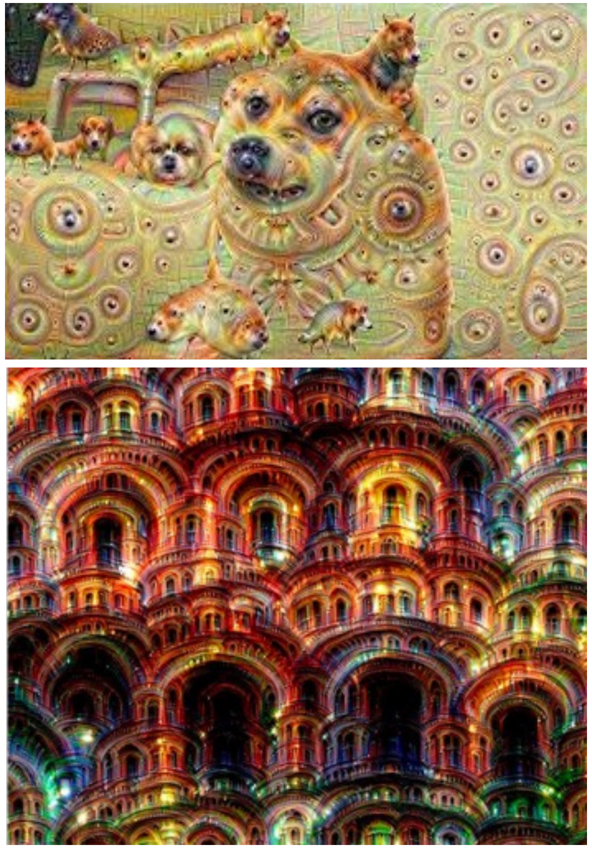
Notes:

- Checkers is the last **solved** game (from game theory, where perfect player outcomes can be fully predicted from any gameboard). https://en.wikipedia.org/wiki/Solved_game
- The first machine learning algorithm defeated a world champion in Chess in 1996. https://en.wikipedia.org/wiki/Deep_Blue_(chess_computer)

Computers making art

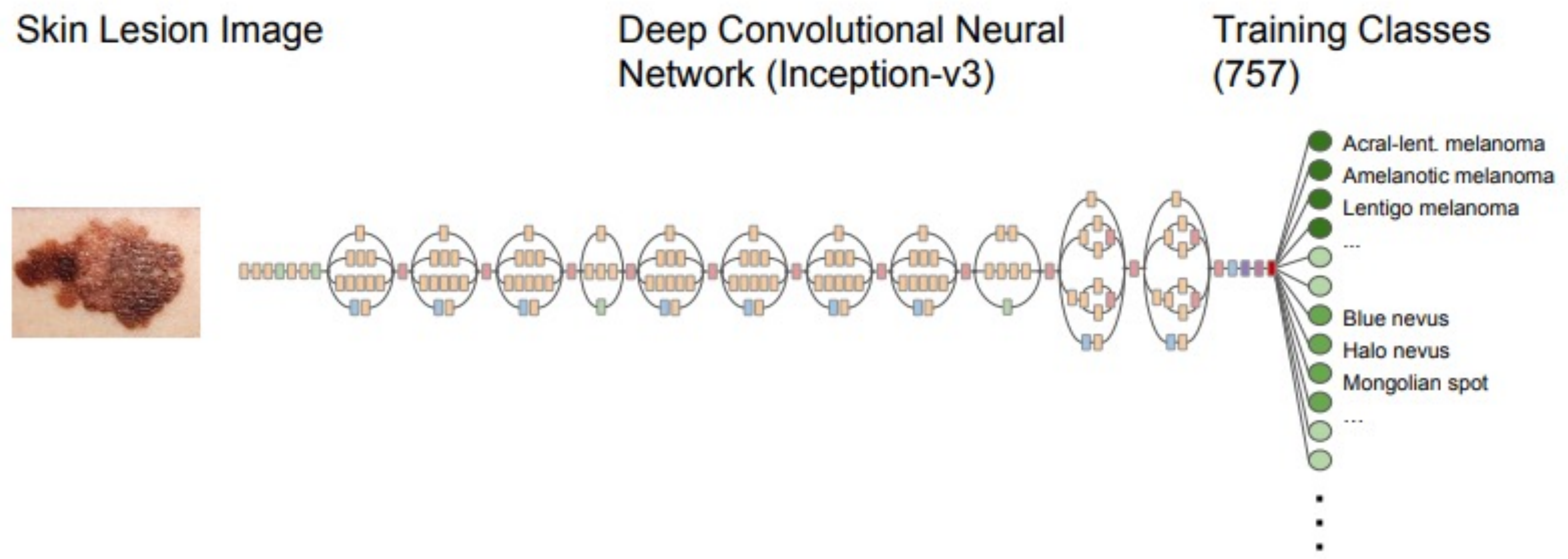
The Next Rembrandt
https://medium.com/@DutchDigital/the-next-rembrandt-bringing-the-old-master-back-to-life-35dfb1653597

A Neural Algorithm of Artistic Style
https://arxiv.org/abs/1508.06576
https://github.com/jcjohnson/neural-style



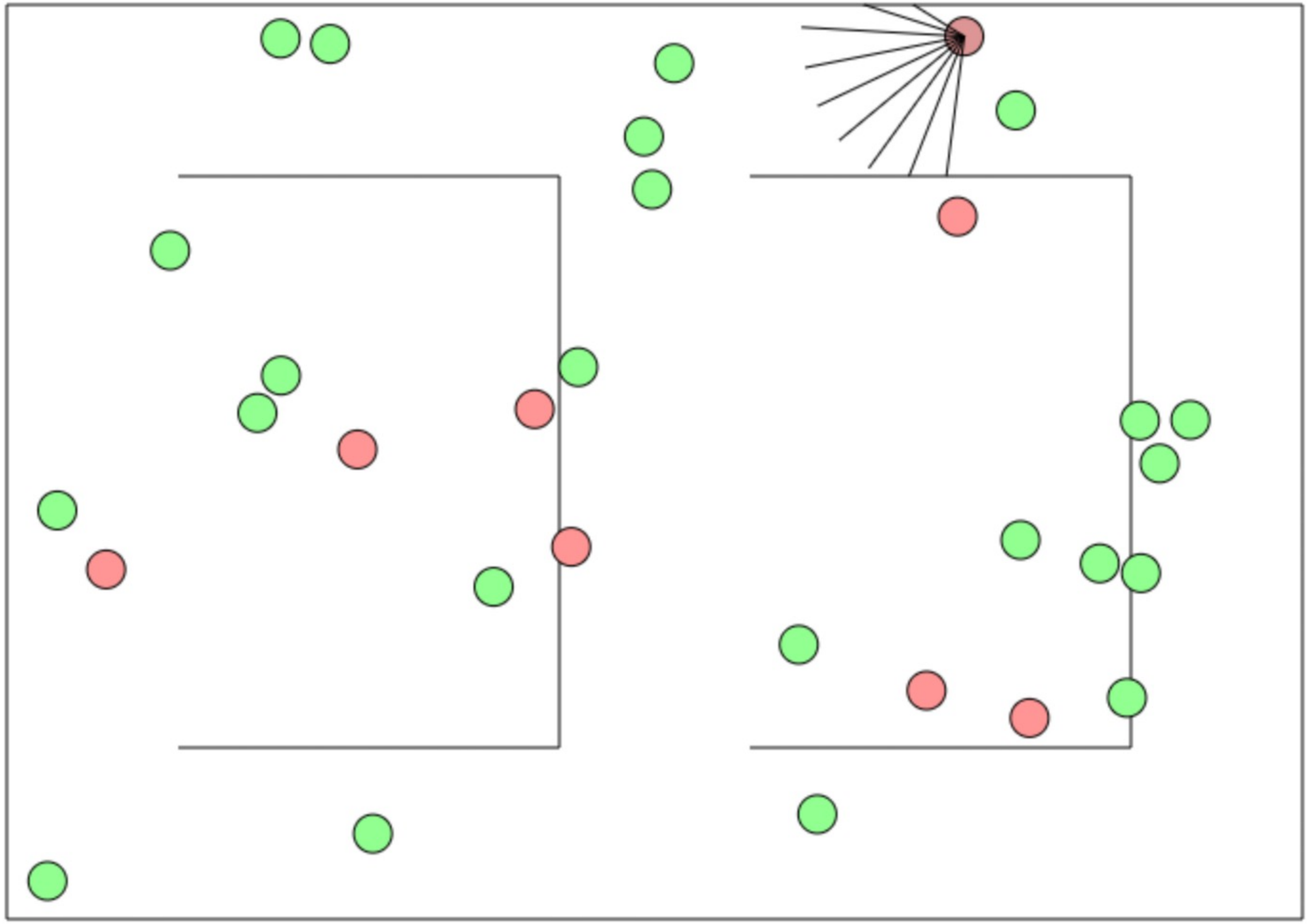
Google Deep Dream
https://ai.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

Detecting skin cancer



Esteva, Andre, et al. "Dermatologist-level classification of skin cancer with deep neural networks." *Nature* 542.7639 (2017): 115-118.

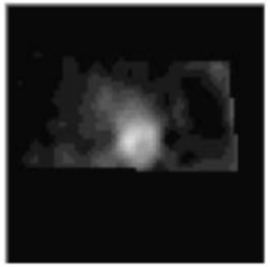
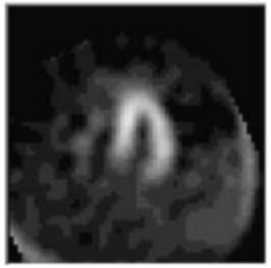
Lets Start Training



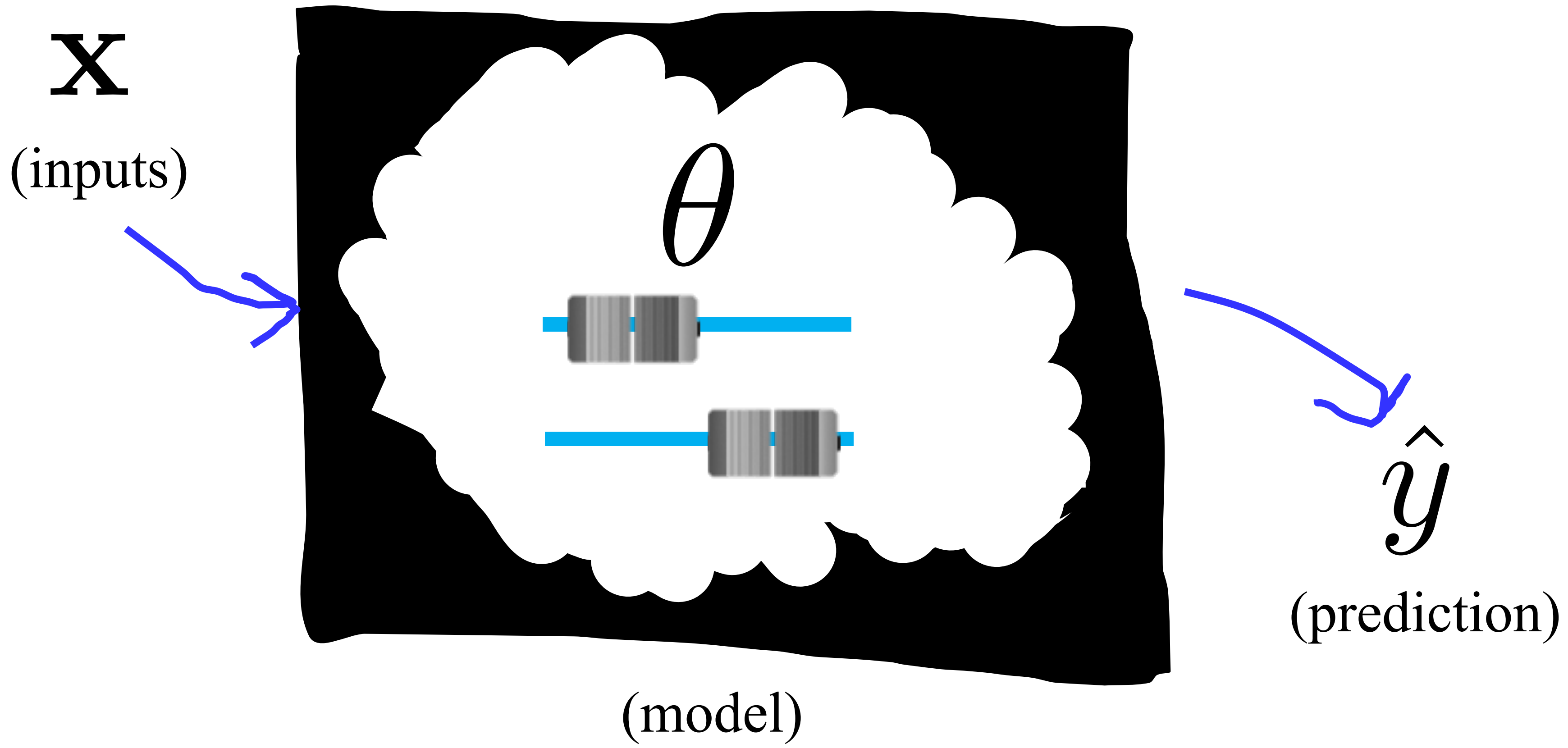
https://cs.stanford.edu/people/karpathy/convnetjs/demo/rldemo.c

Review

Classification Task

	ROI 1	ROI 2		ROI *m*	Output
			…		
Heart 1	0	1		1	0
Heart 2	1	1		1	0
			⋮		⋮
Heart *n*	0	0		0	1

Machine Learning



The Training / Testing Paradigm

The Training / Testing Paradigm

Training

Learn your parameters

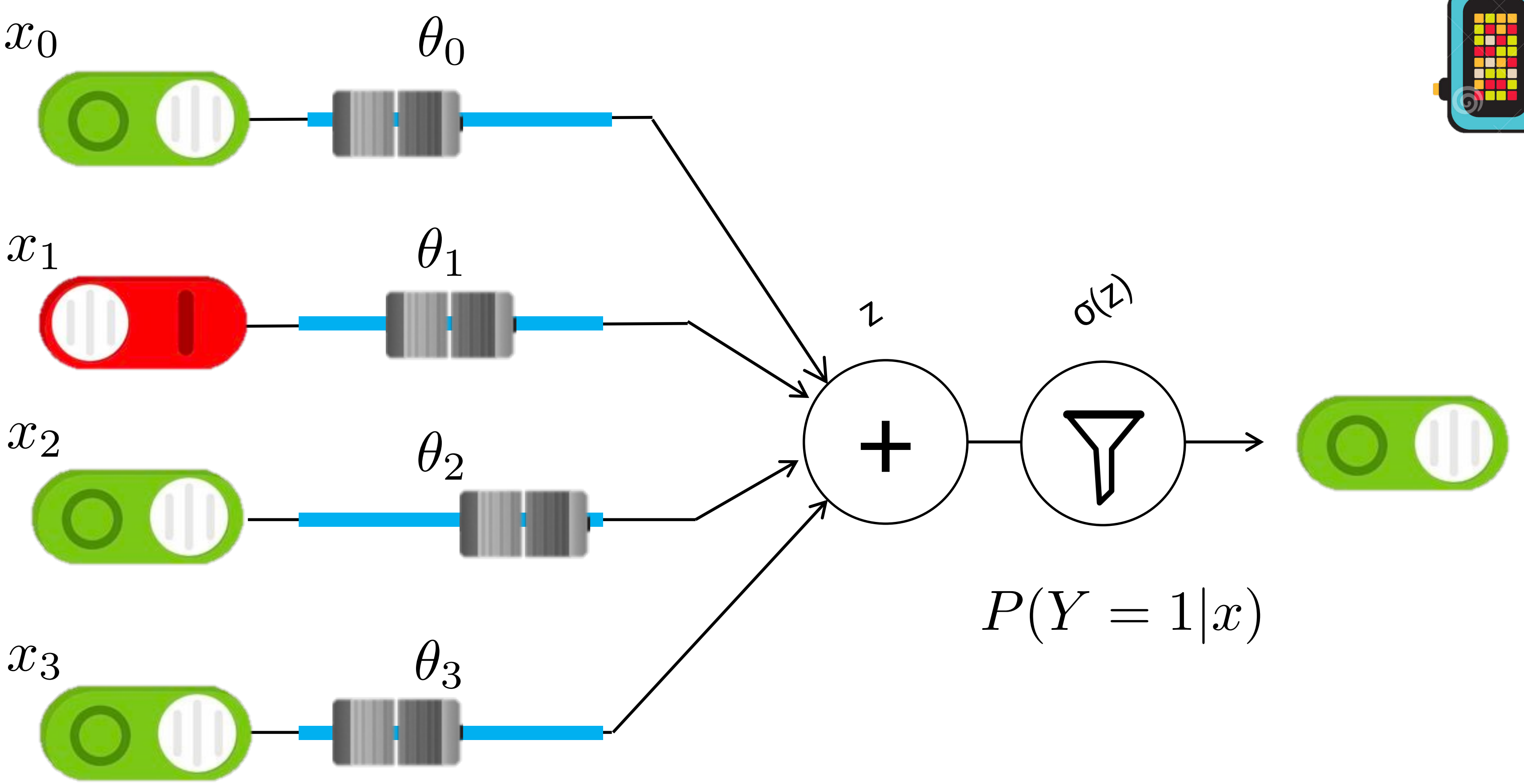
Testing

Make sure that they work

If your model passes testing...

Deployment

Logistic Regression



$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

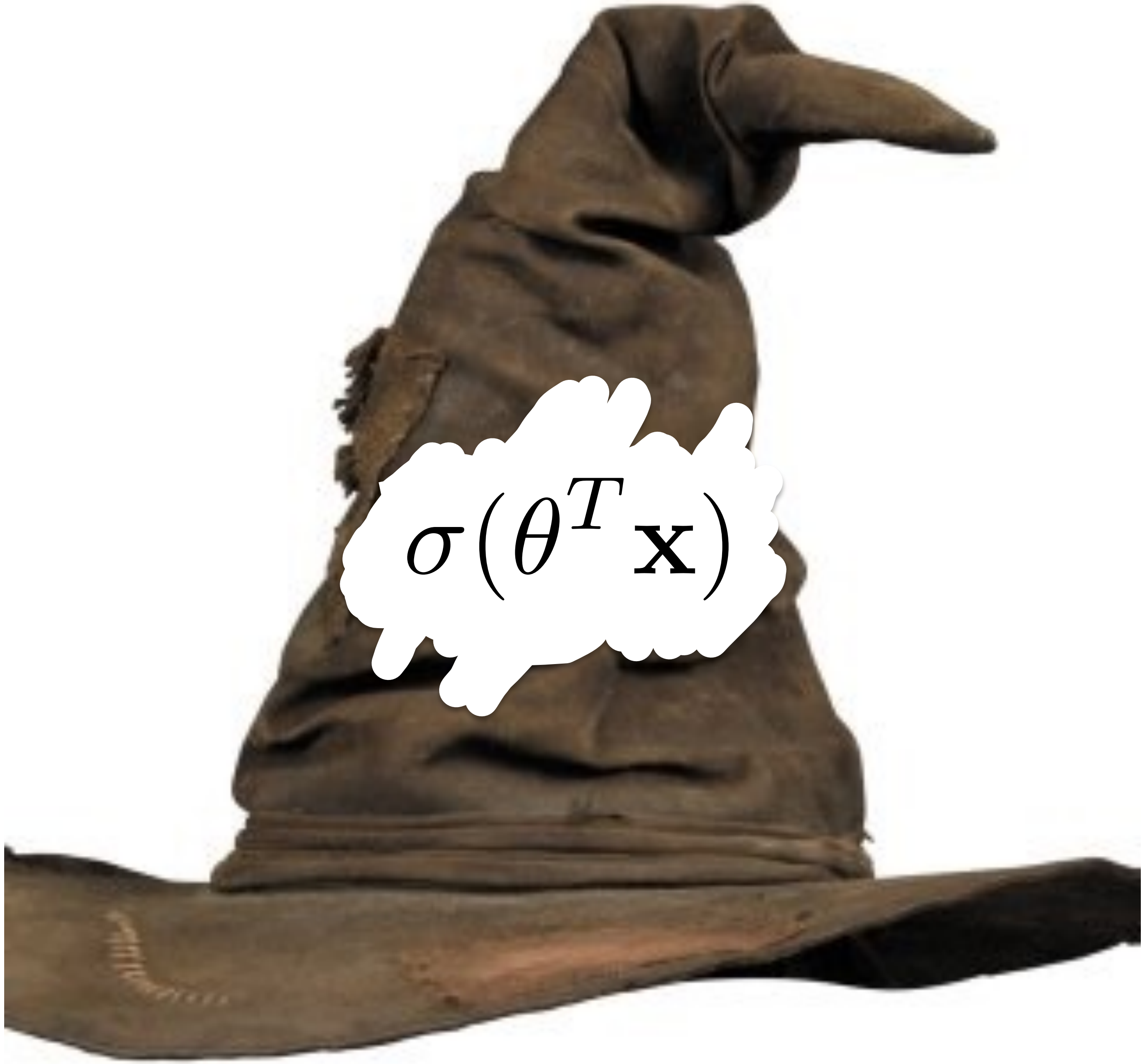
A Journey From Pure Math
into the beyond

Logistic Regression is like the Harry Pottery Sorting Hat

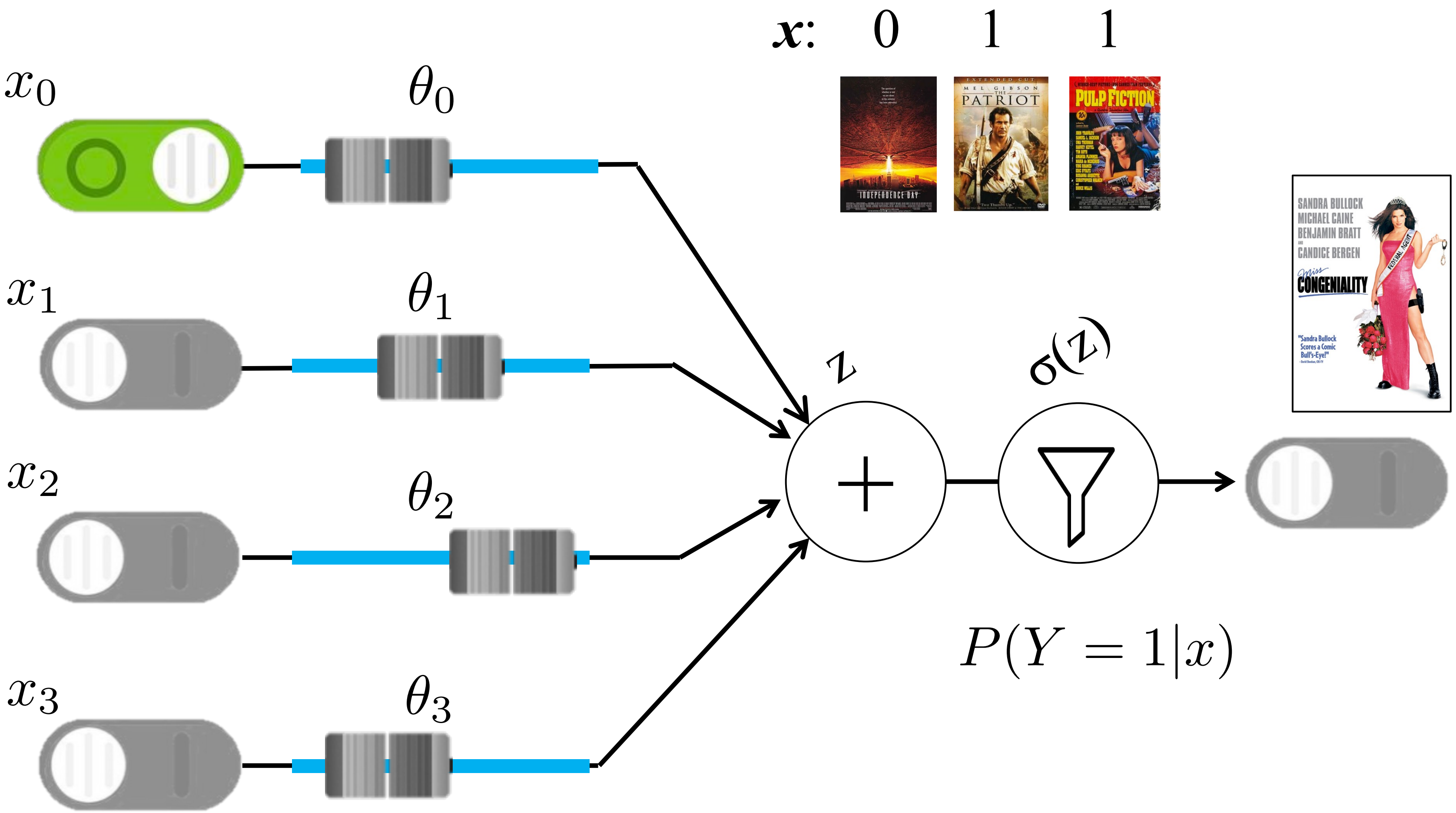
$$P(Y = 1) = 0.91$$

$$\mathbf{X}$$

Logistic Regression is like the Harry Pottery Sorting Hat

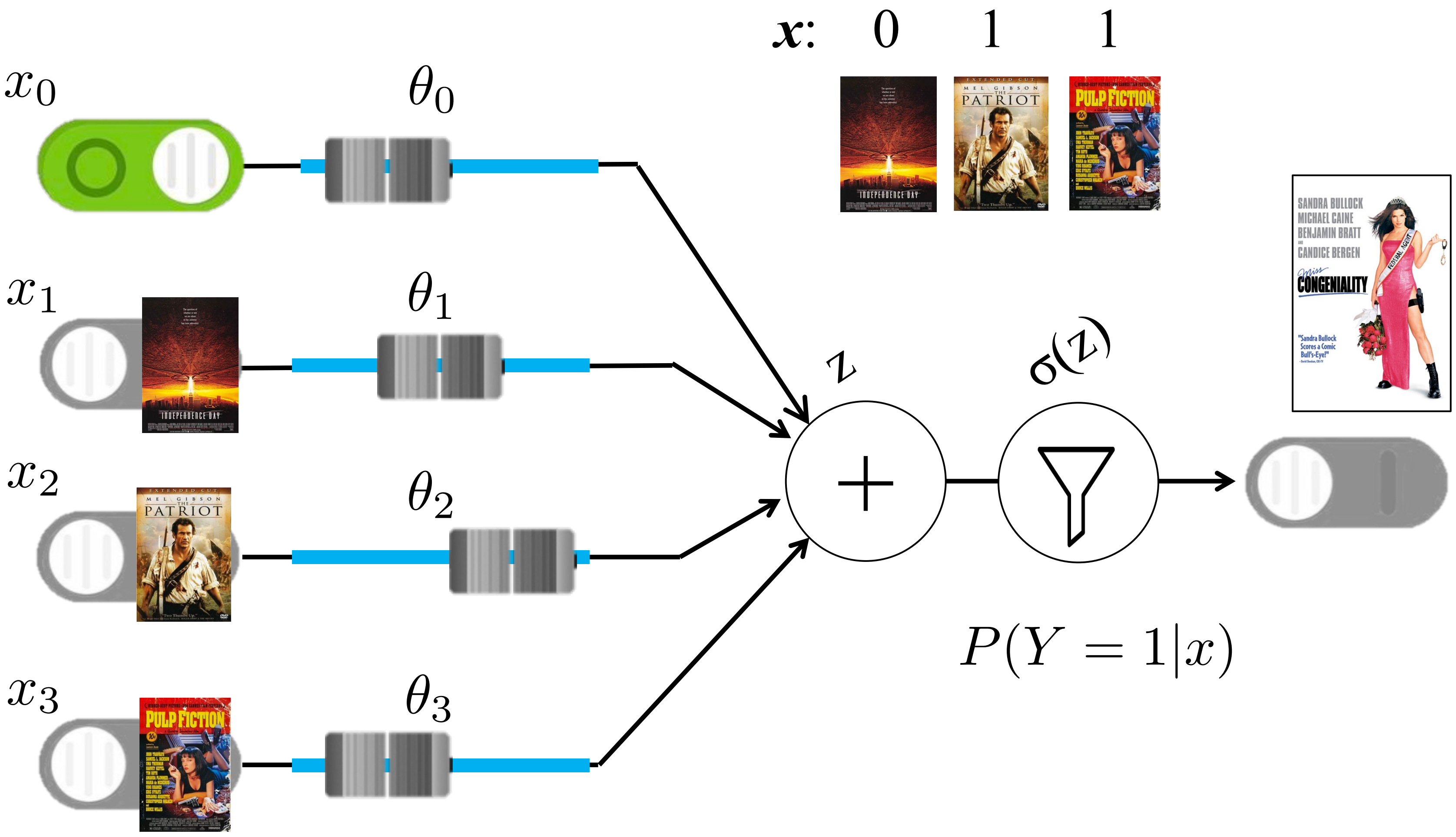


Logistic Regression



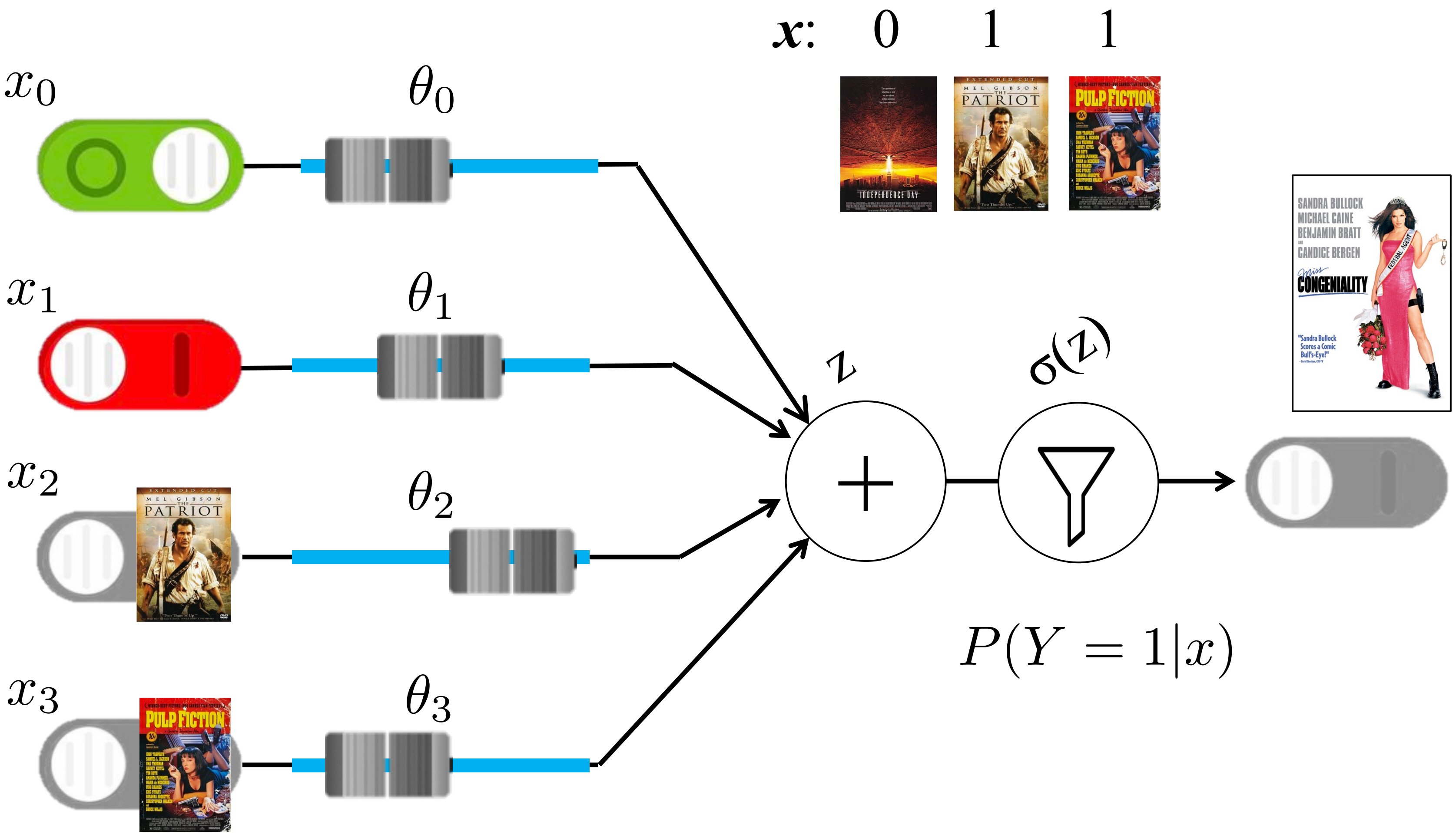
$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

Logistic Regression



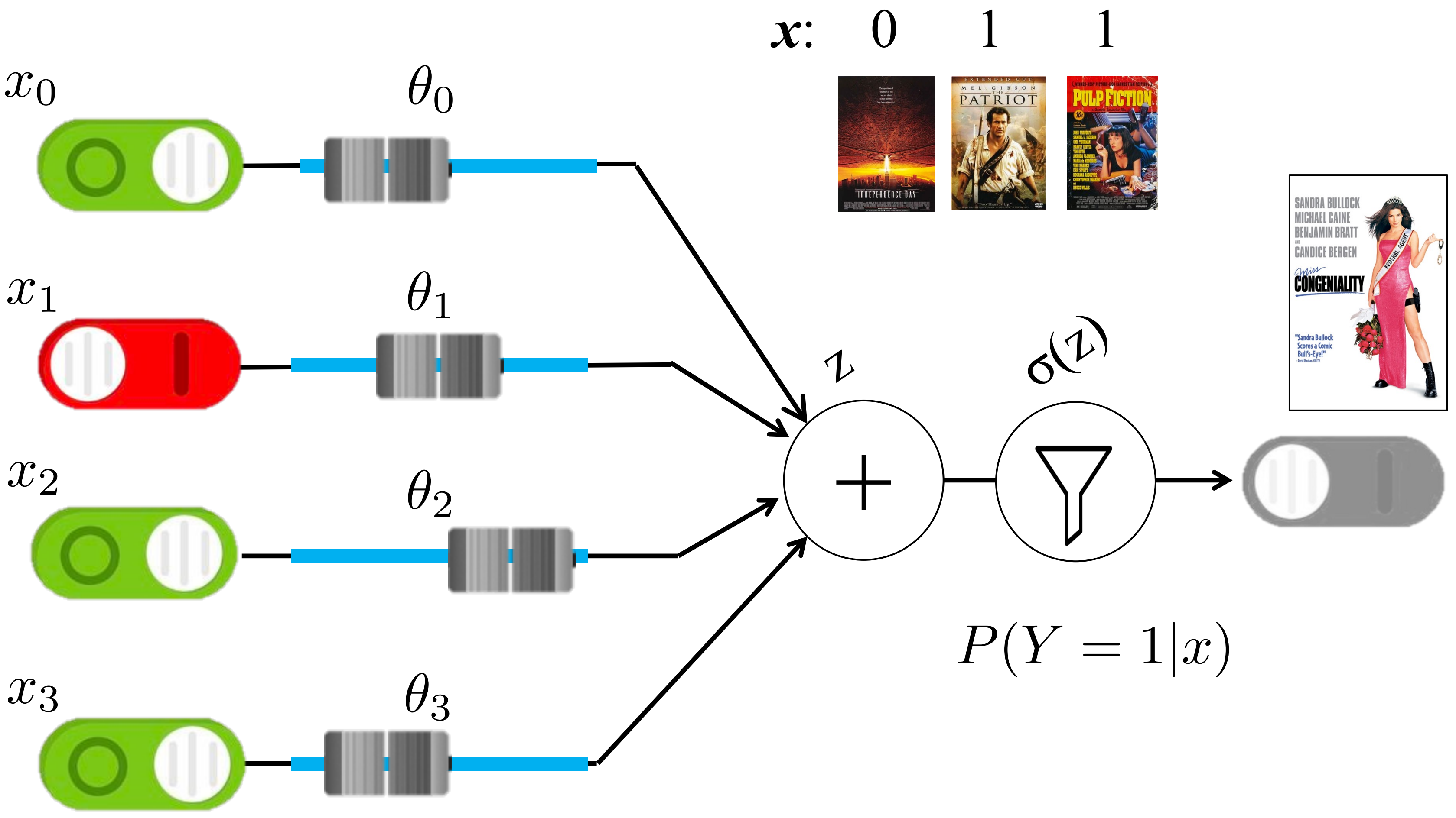
$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

Logistic Regression



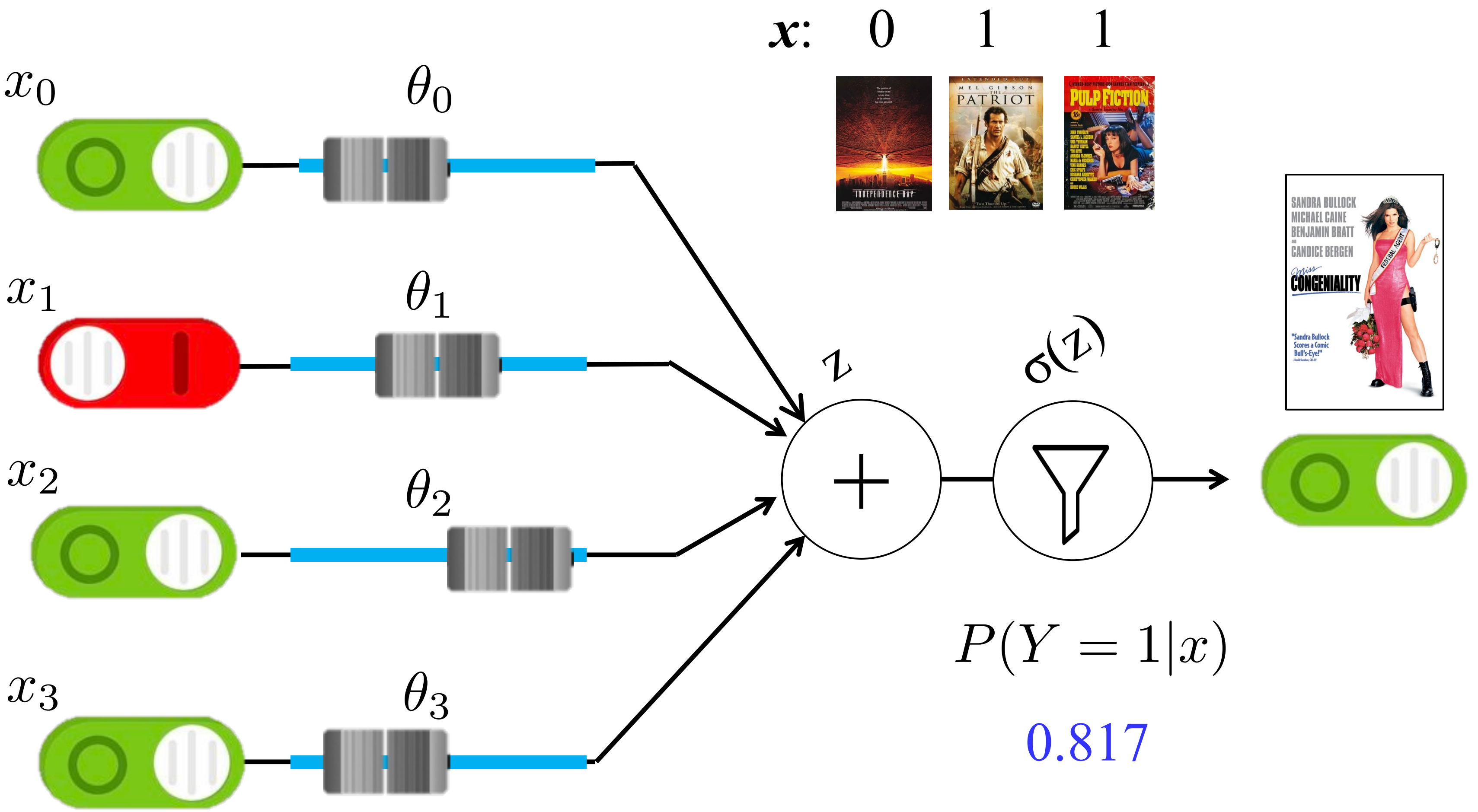
$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

Logistic Regression



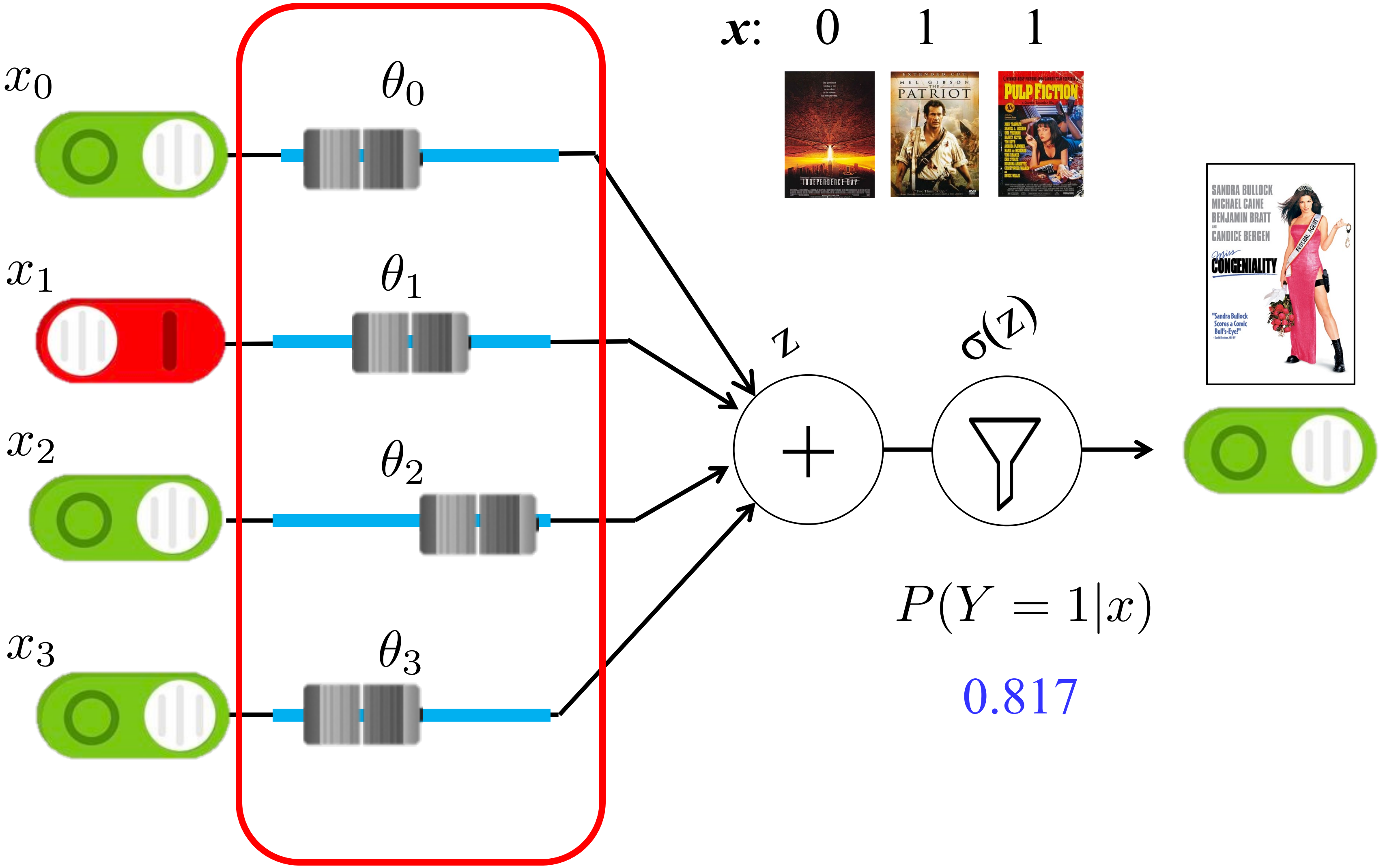
$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

Logistic Regression



$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

Logistic Regression



$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

Math for Logistic Regression

1. Make logistic regression assumption

$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$
$$P(Y = 0|X = \mathbf{x}) = 1 - \sigma(\theta^T \mathbf{x})$$

Often call this $\hat{y}$

2. Calculate the log likelihood for all data

$$LL(\theta) = \sum_{i=1}^{n} y^{(i)} \log \sigma(\theta^T \mathbf{x}^{(i)}) + (1 - y^{(i)}) \log[1 - \sigma(\theta^T \mathbf{x}^{(i)})]$$

3. Get derivative of log likelihood with respect to thetas

$$\frac{\partial LL(\theta)}{\partial \theta_j} = \sum_{i=1}^{n} \left[y^{(i)} - \sigma(\theta^T \mathbf{x}^{(i)}) \right] x_j^{(i)}$$

Logistic Regression Training

Initialize: $\theta_j = 0$ for all $0 \le j \le m$

Repeat many times:

gradient[j] = 0 for all $0 \le j \le m$

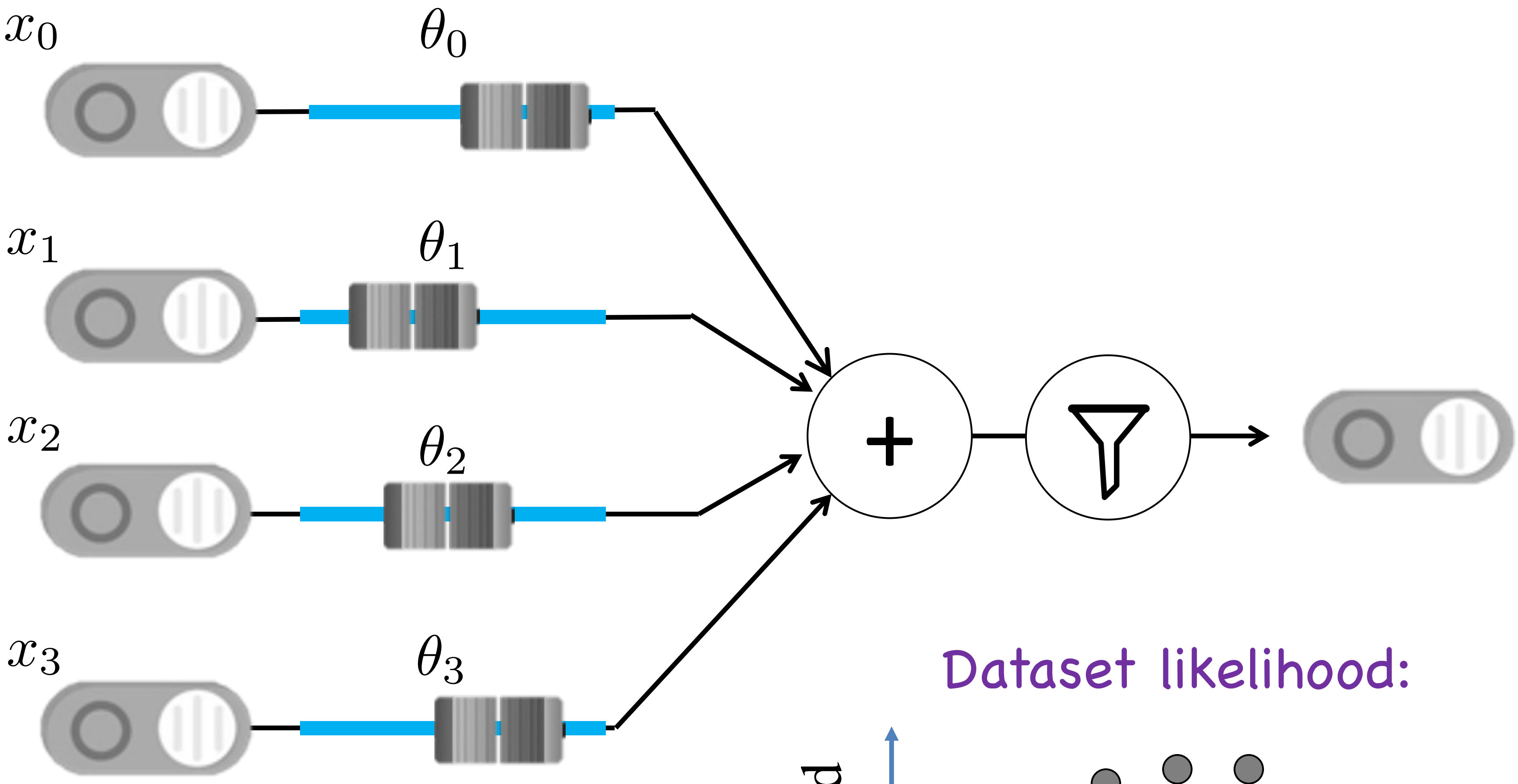
For each parameter j

For each training example (x, y):

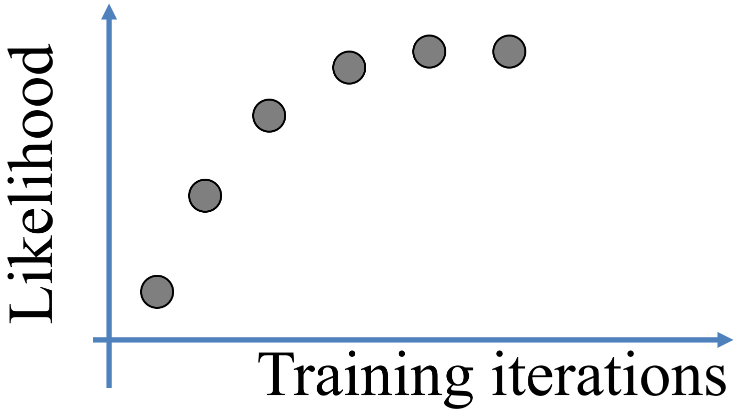
gradient[j] $\mathrel{+}= x_j \left(y - \frac{1}{1 + e^{-\theta^{\mathrm{T}} \mathbf{x}}} \right)$

θ_j += η * gradient[j] for all $0 \le j \le m$

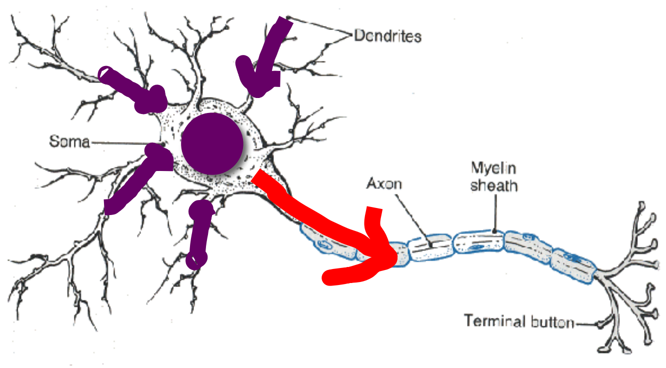
Training

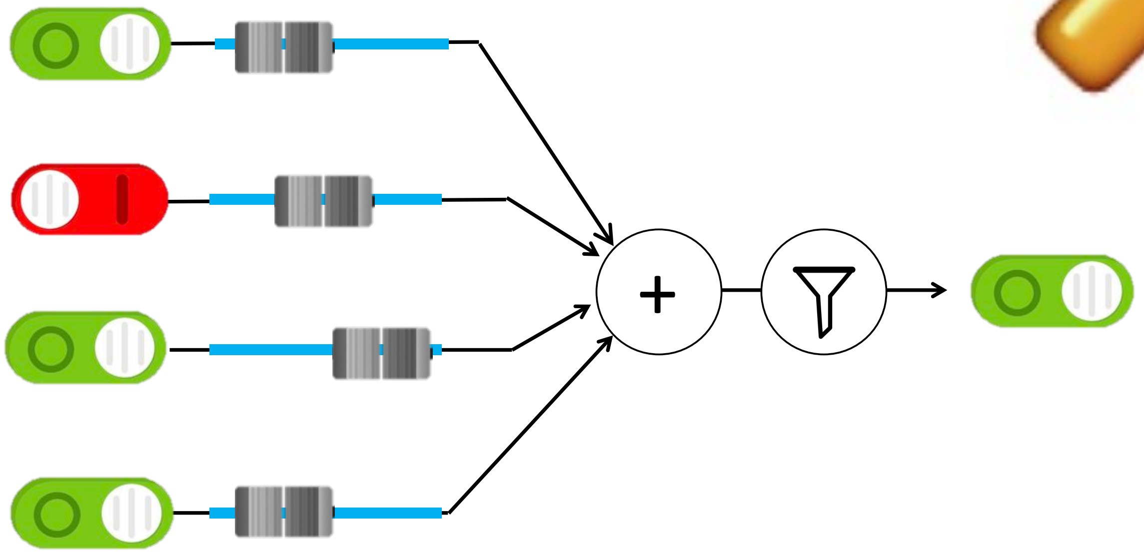


Dataset likelihood:



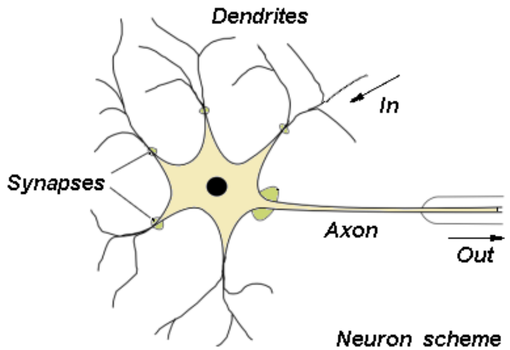
Artificial Neurons

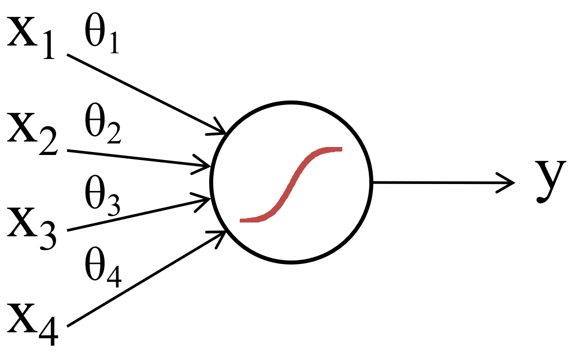




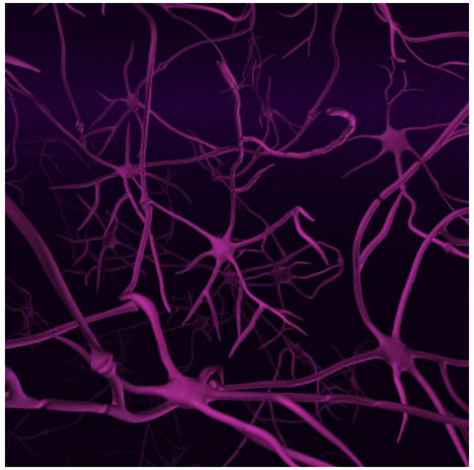
Biological Basis for Neural Networks

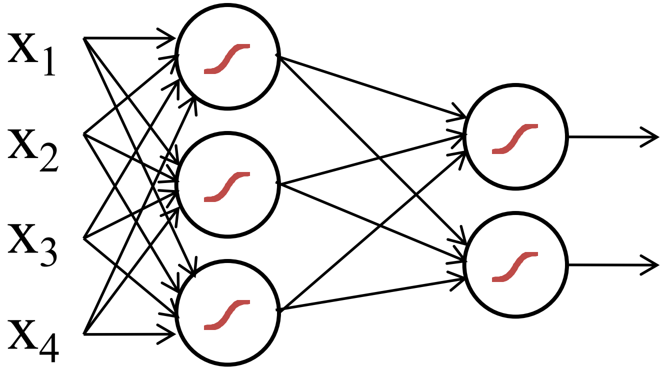
A neuron





Your brain

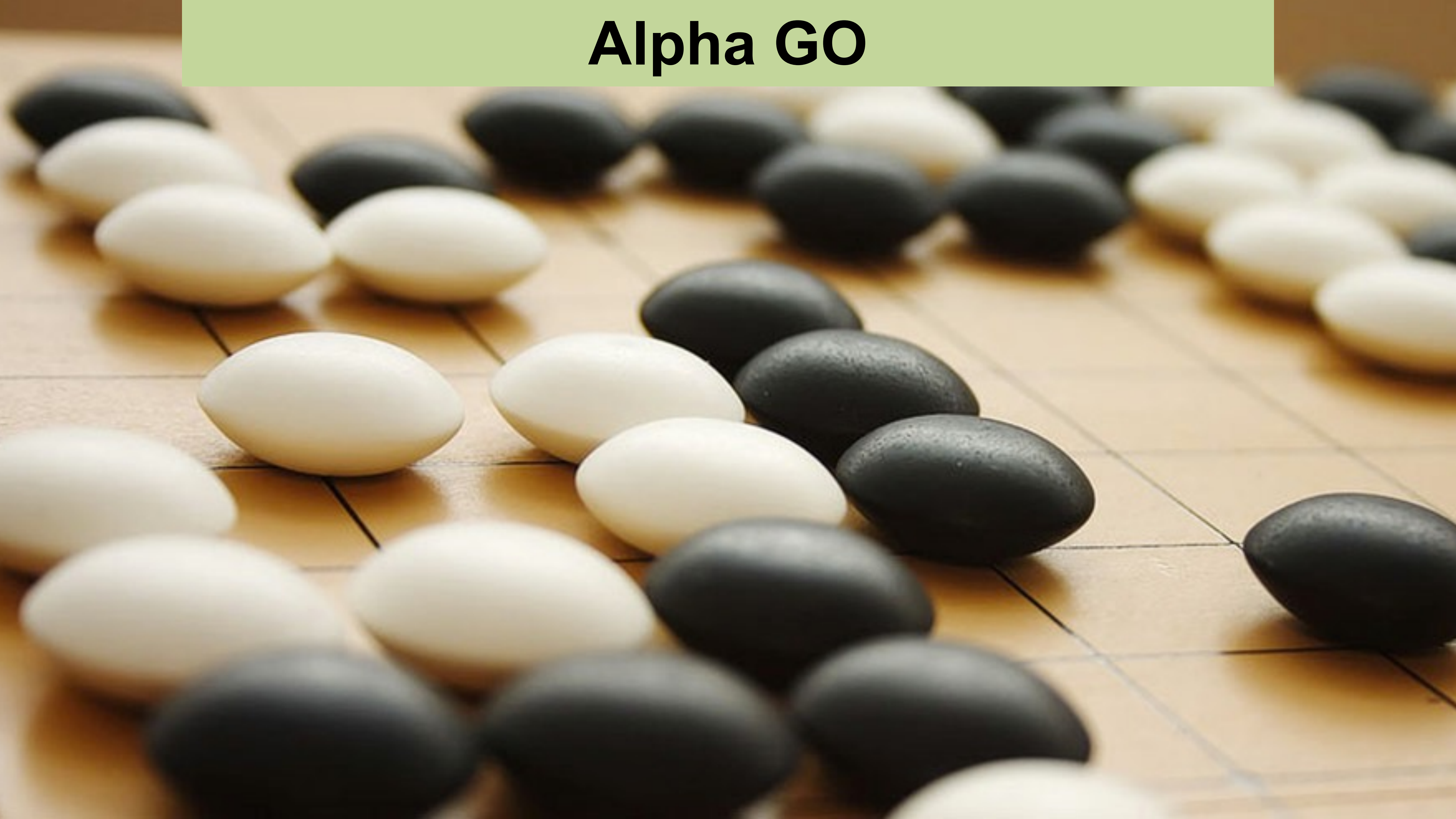




Actually, it's probably someone else's brain

Core idea behind the revolution in AI

Alpha GO



Self Driving Cars

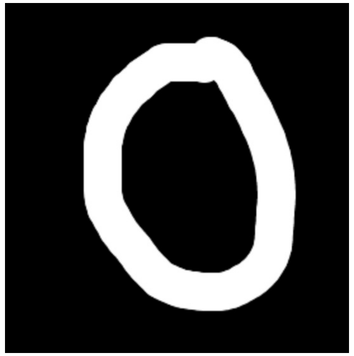
Computers Making Art

(aka Neural Networks)

Deep learning is (at its core) many logistic regression pieces stacked on top of each other.

Digit Recognition Example

Let's make feature vectors from pictures of numbers

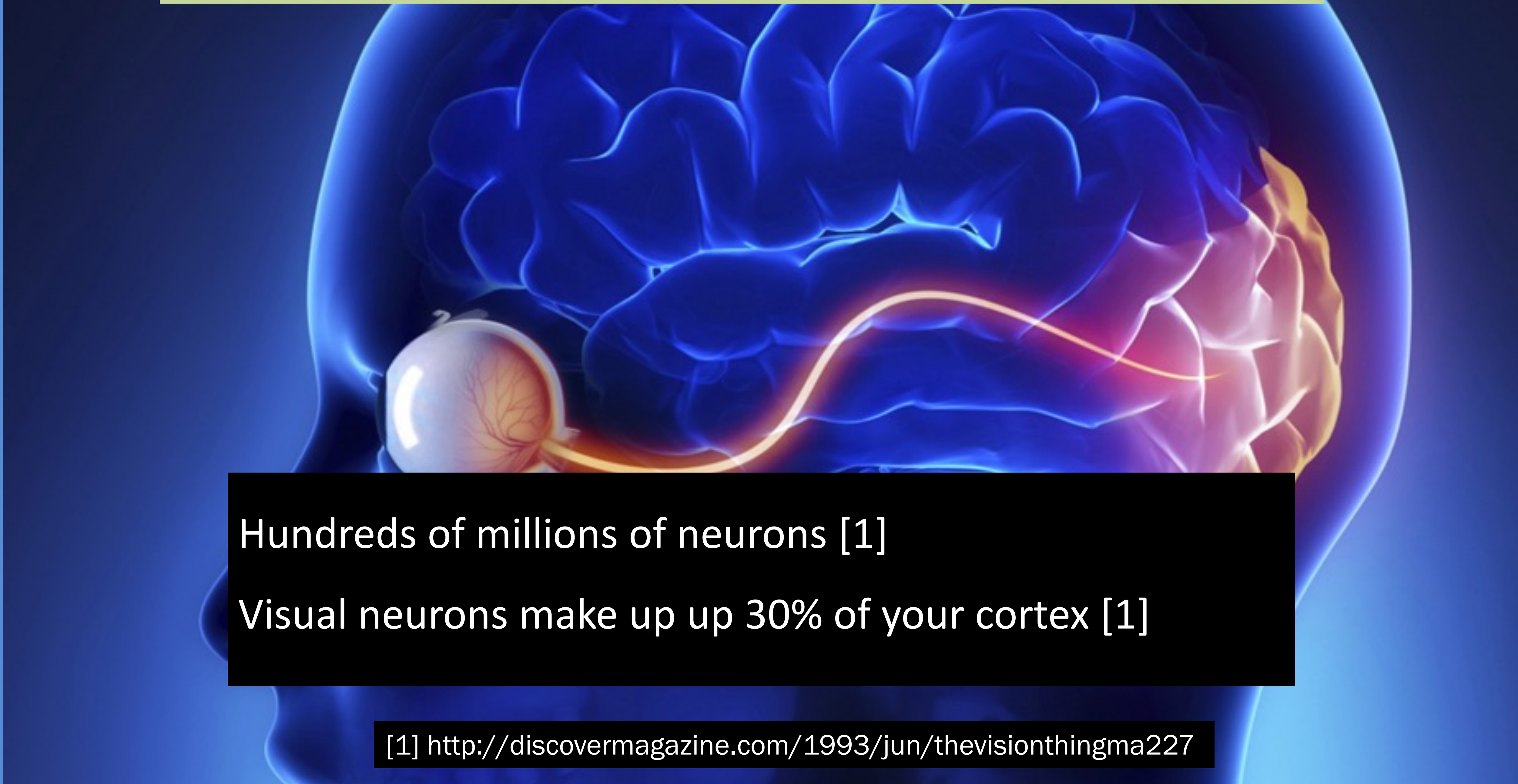


$$\mathbf{x}^{(i)} = [0, 0, 0, 0, \ldots, 1, 0, 0, 1, \ldots 0, 0, 1, 0]$$
$$y^{(i)} = 0$$

$$\mathbf{x}^{(i)} = [0, 0, 1, 1, \ldots, 0, 1, 1, 0, \ldots 0, 1, 0, 0]$$
$$y^{(i)} = 1$$

Computer Vision

Vision in your Brain

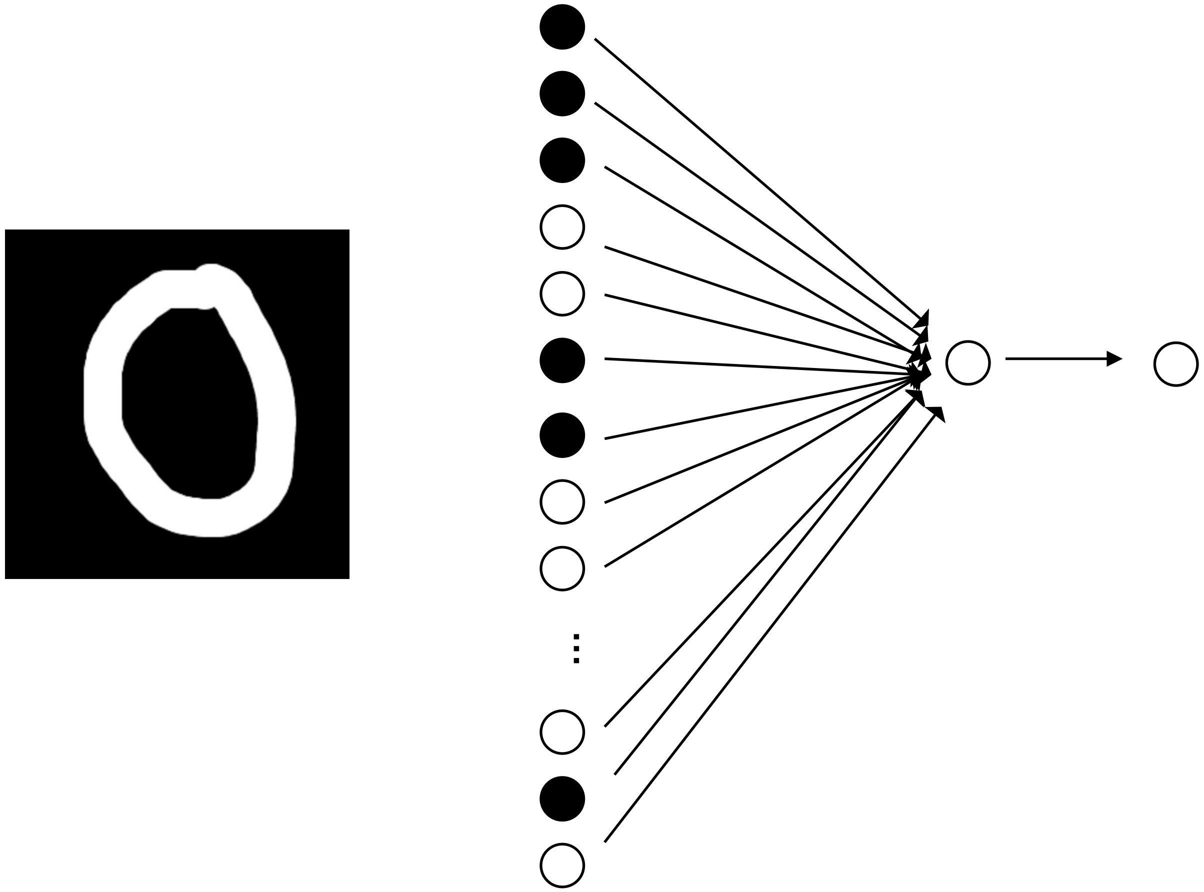


Hundreds of millions of neurons [1]

Visual neurons make up up 30% of your cortex [1]

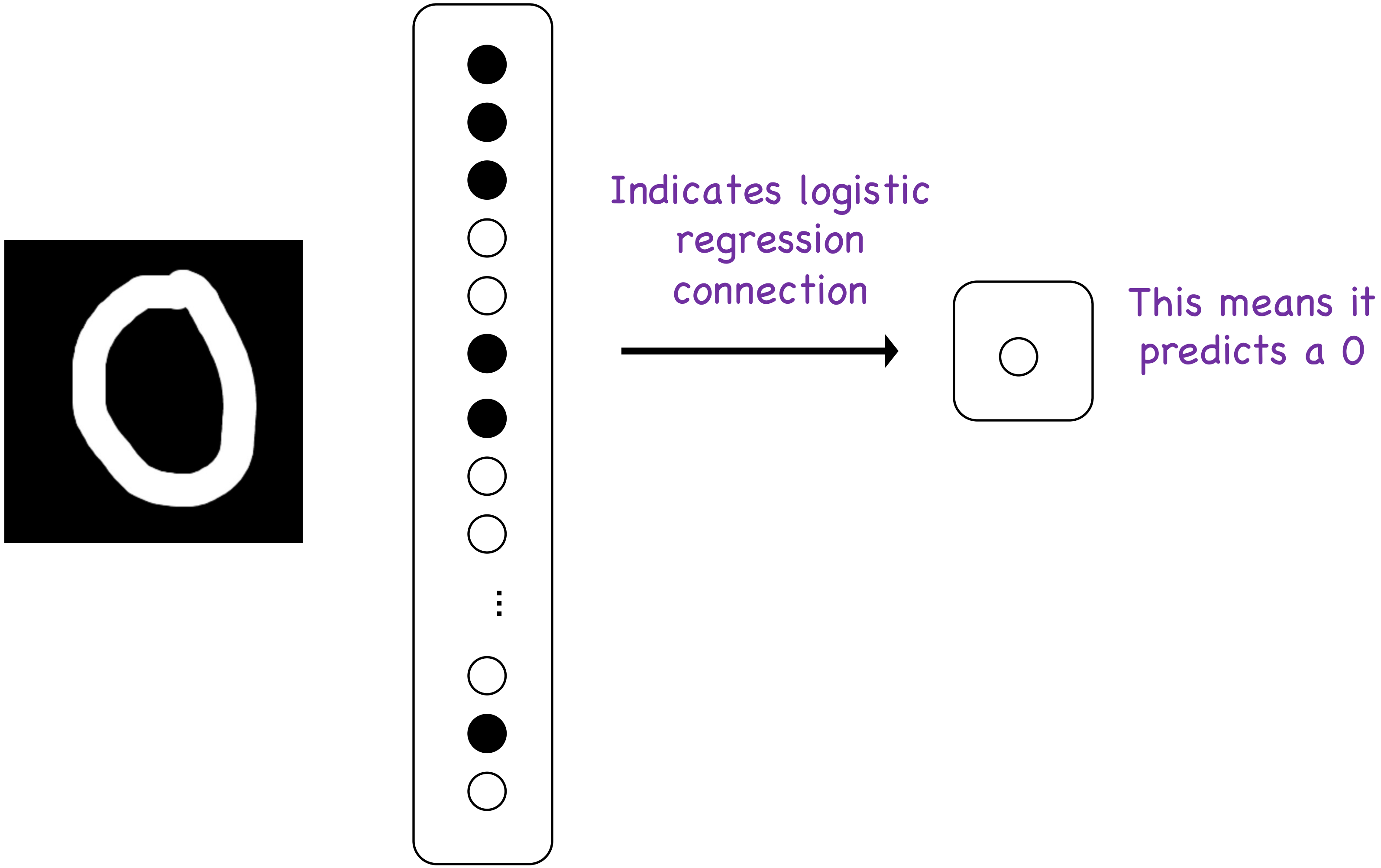
[1] http://discovermagazine.com/1993/jun/thevisionthingma227

Logistic Regression

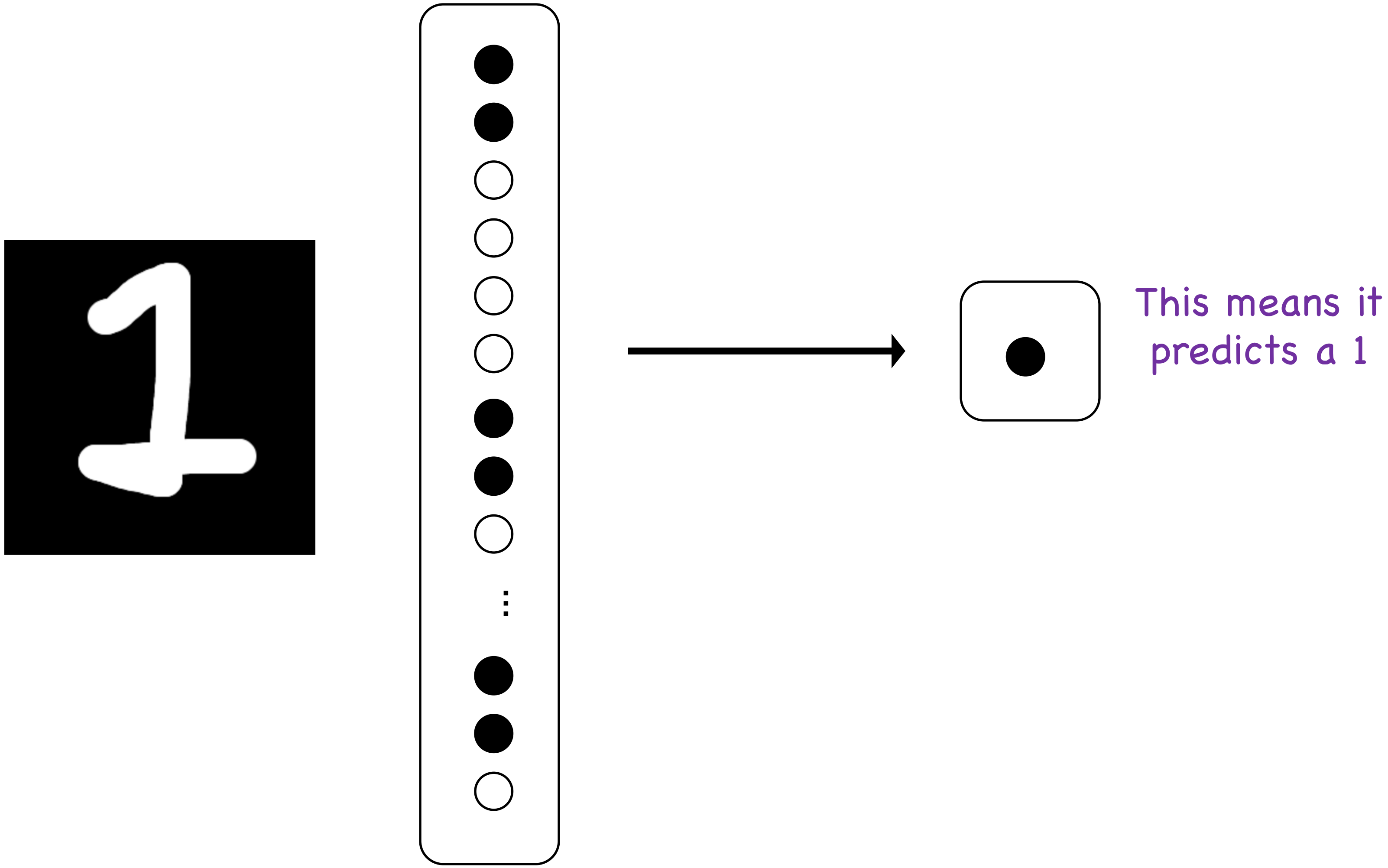


This means it
predicts a 0

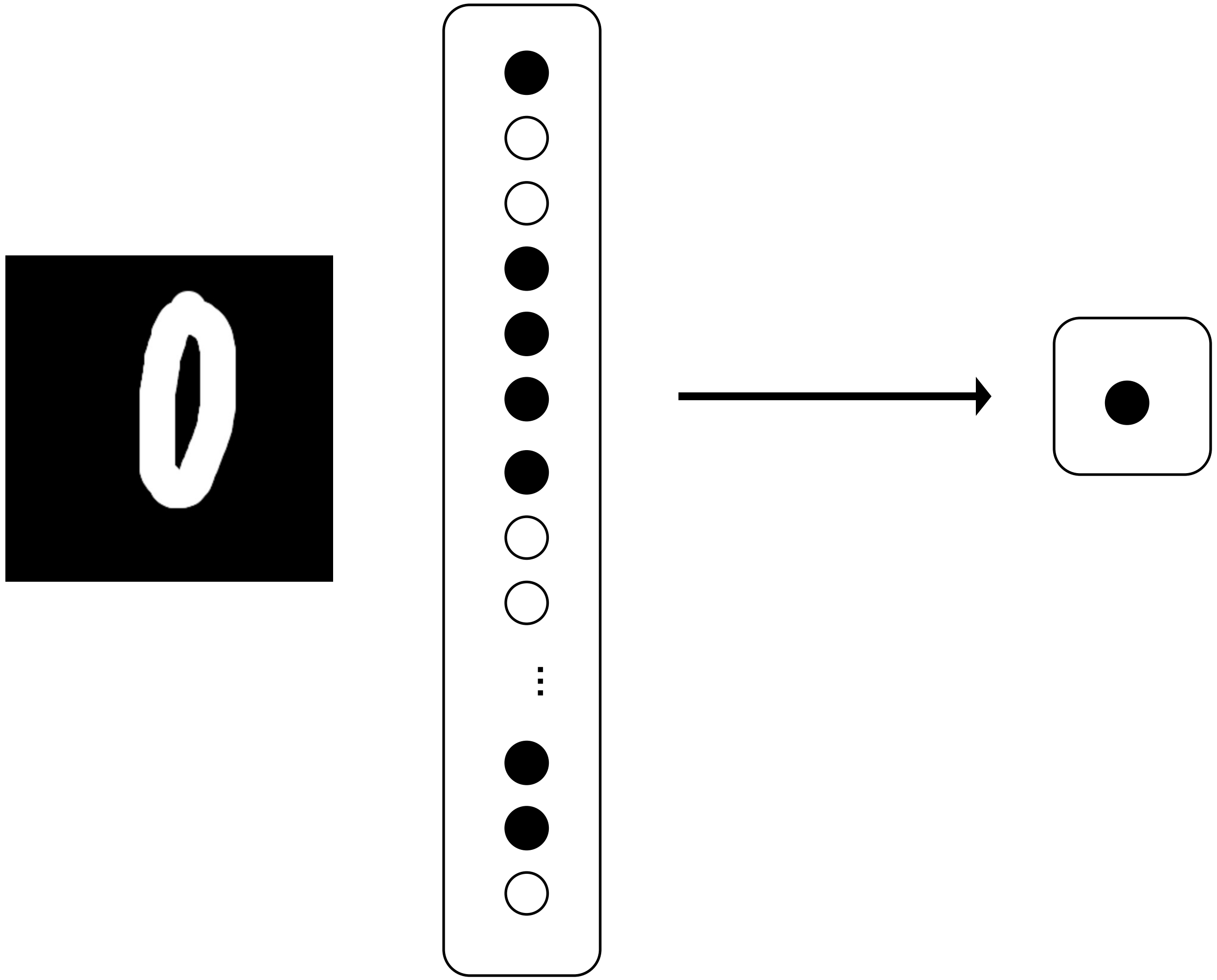
Logistic Regression



Logistic Regression

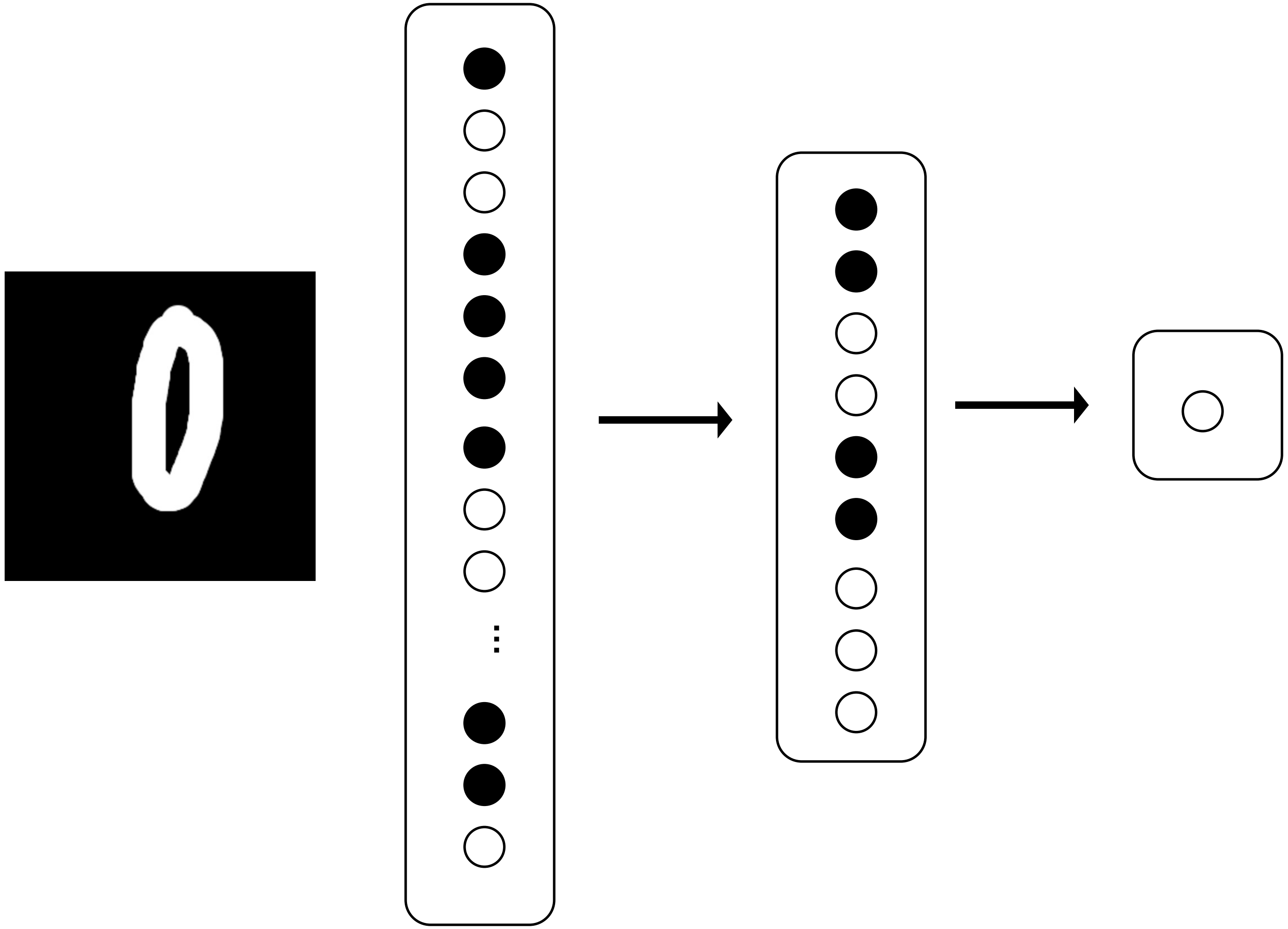


Not So Good



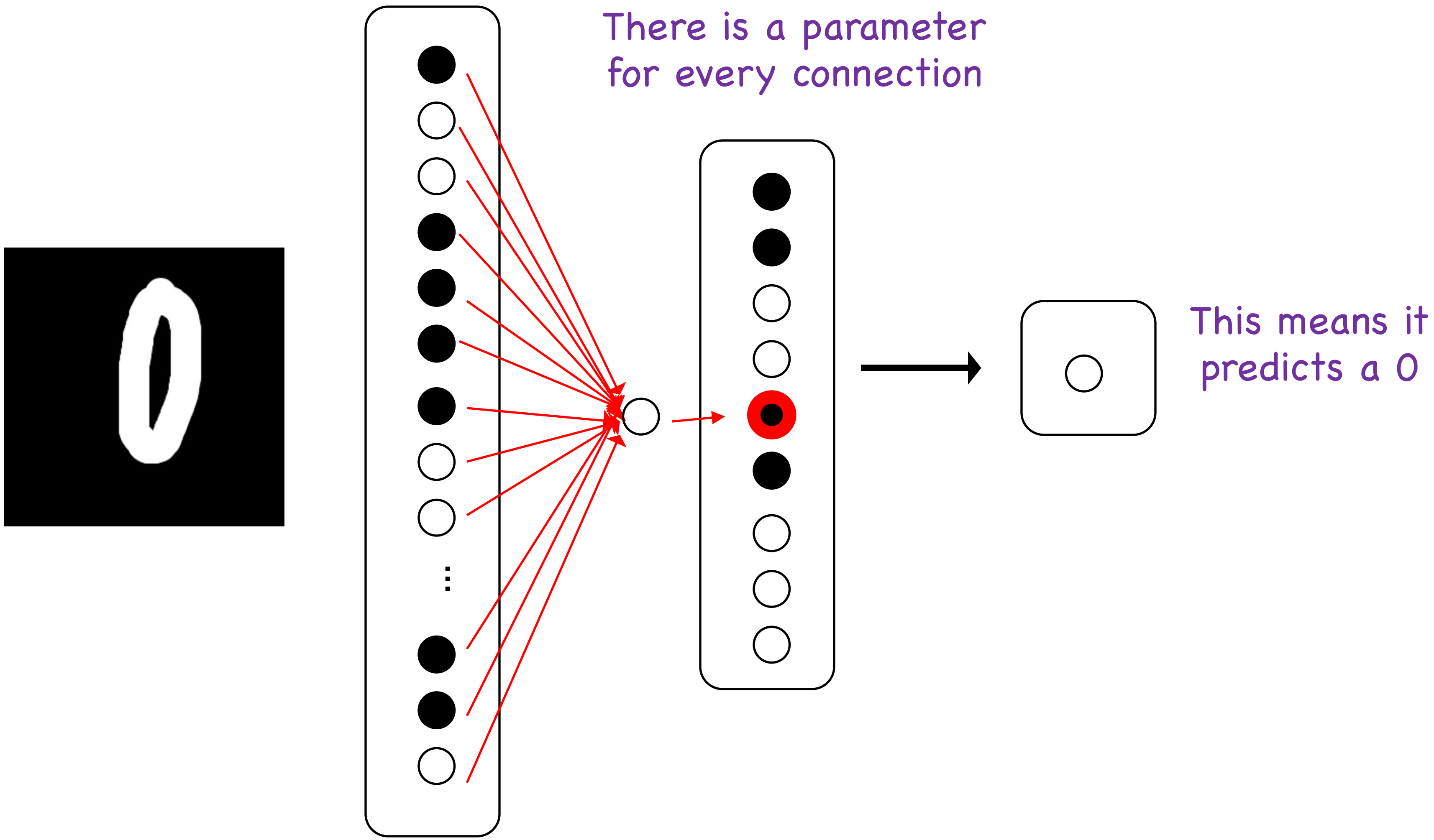
This means it
predicts a 1

We Can Put Neurons Together



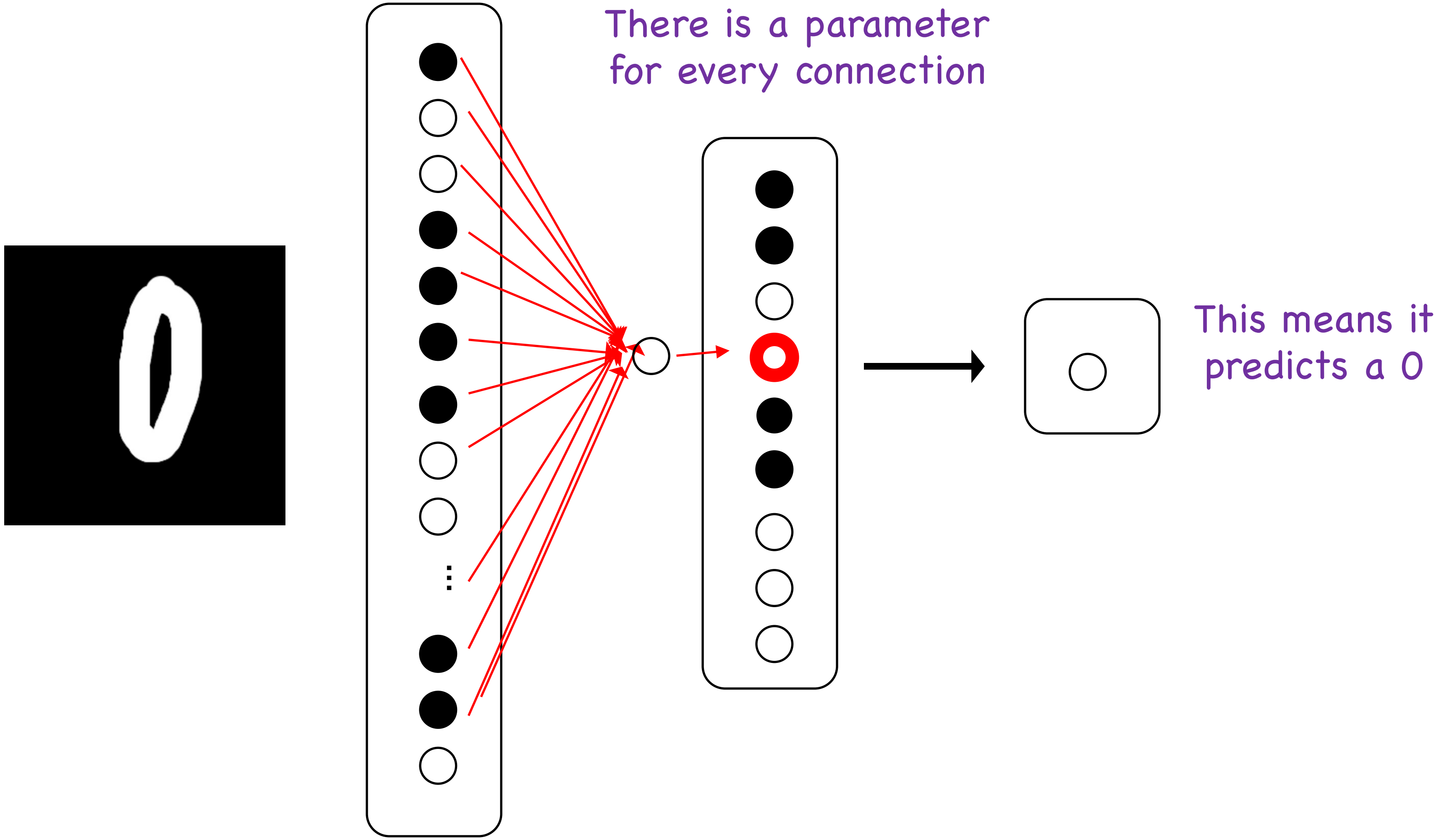
This means it predicts a 0

We Can Put Neurons Together



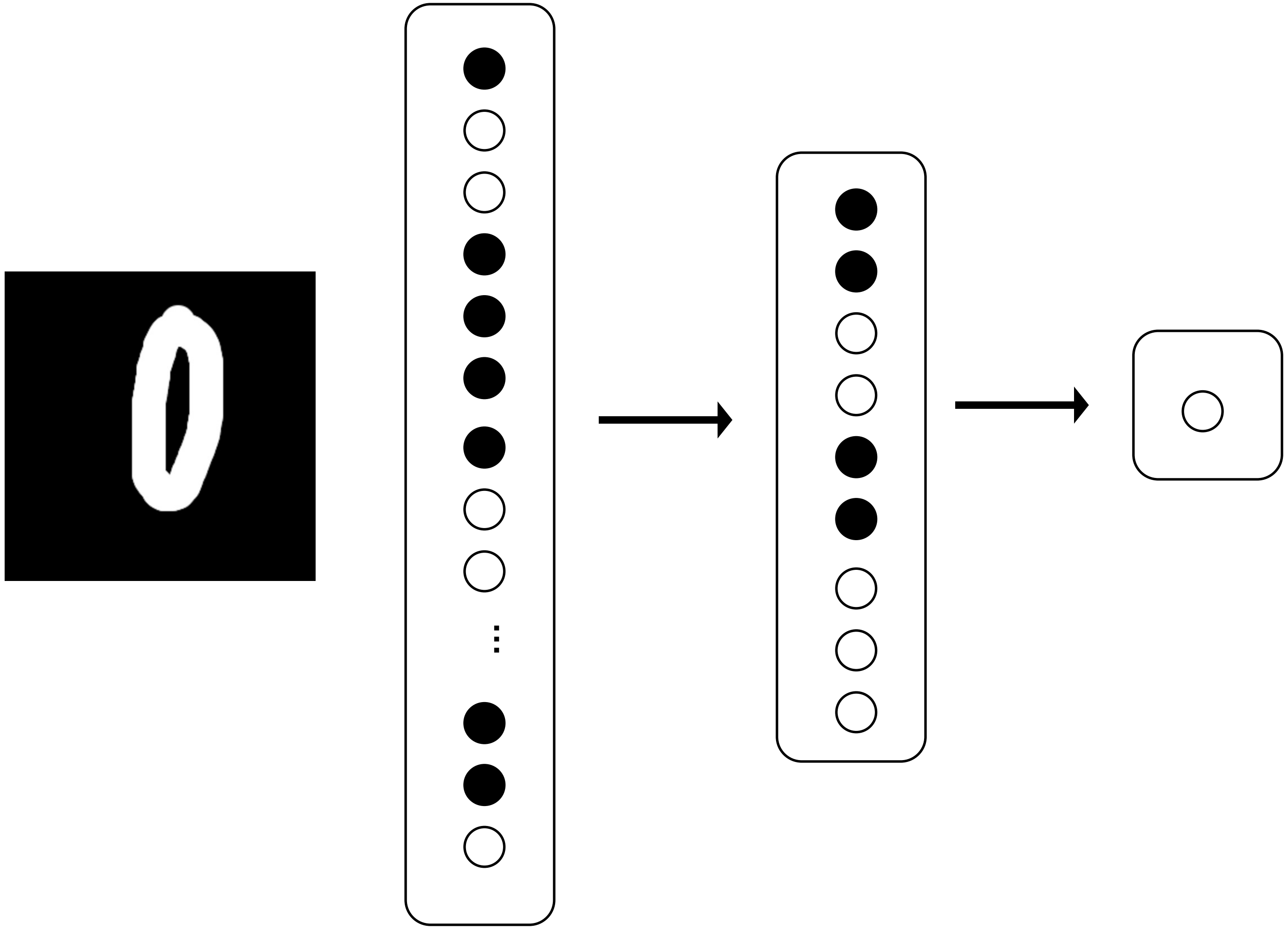
Look at a single "hidden" neuron

We Can Put Neurons Together



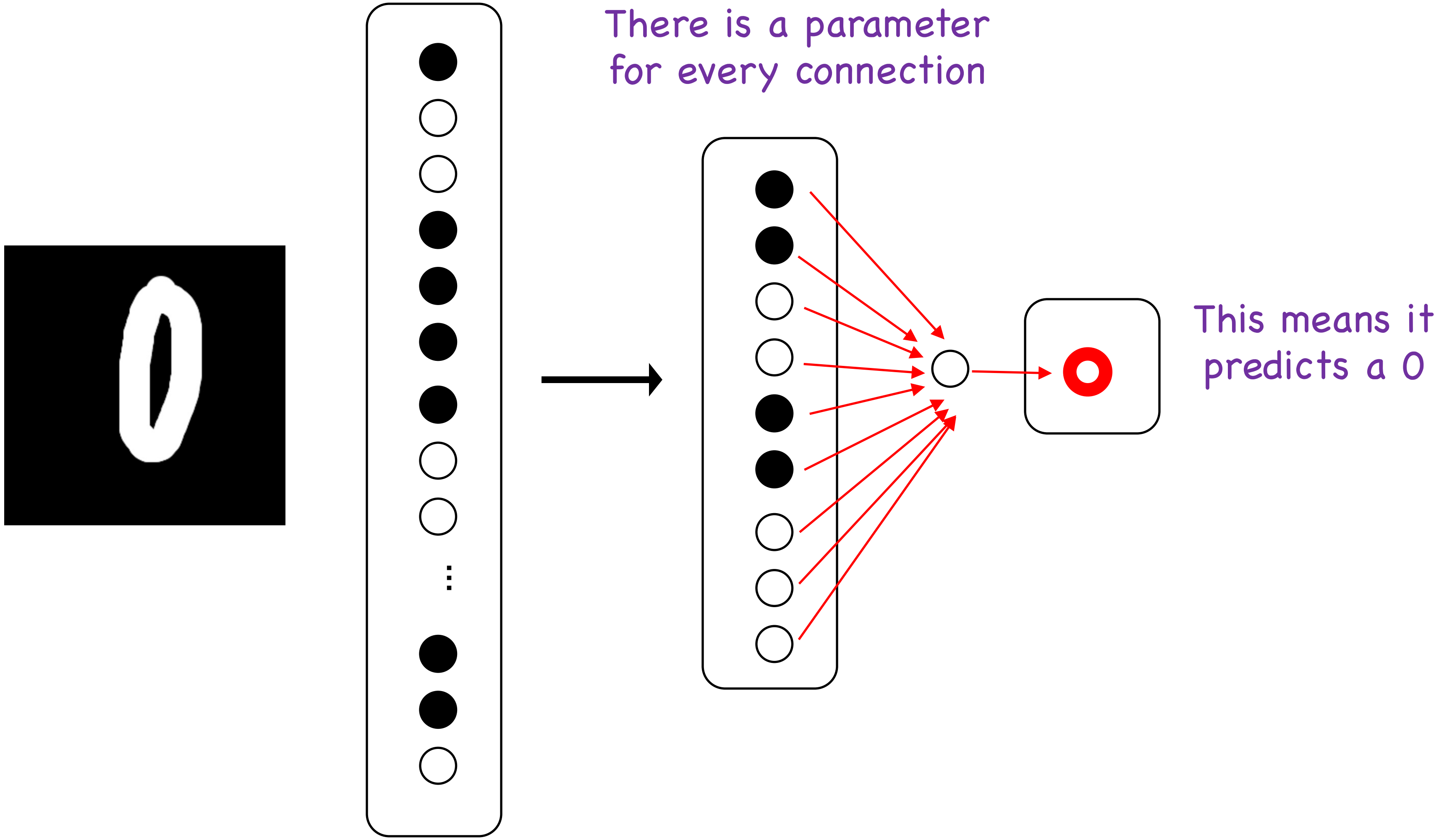
Look at another “hidden” neuron

We Can Put Neurons Together



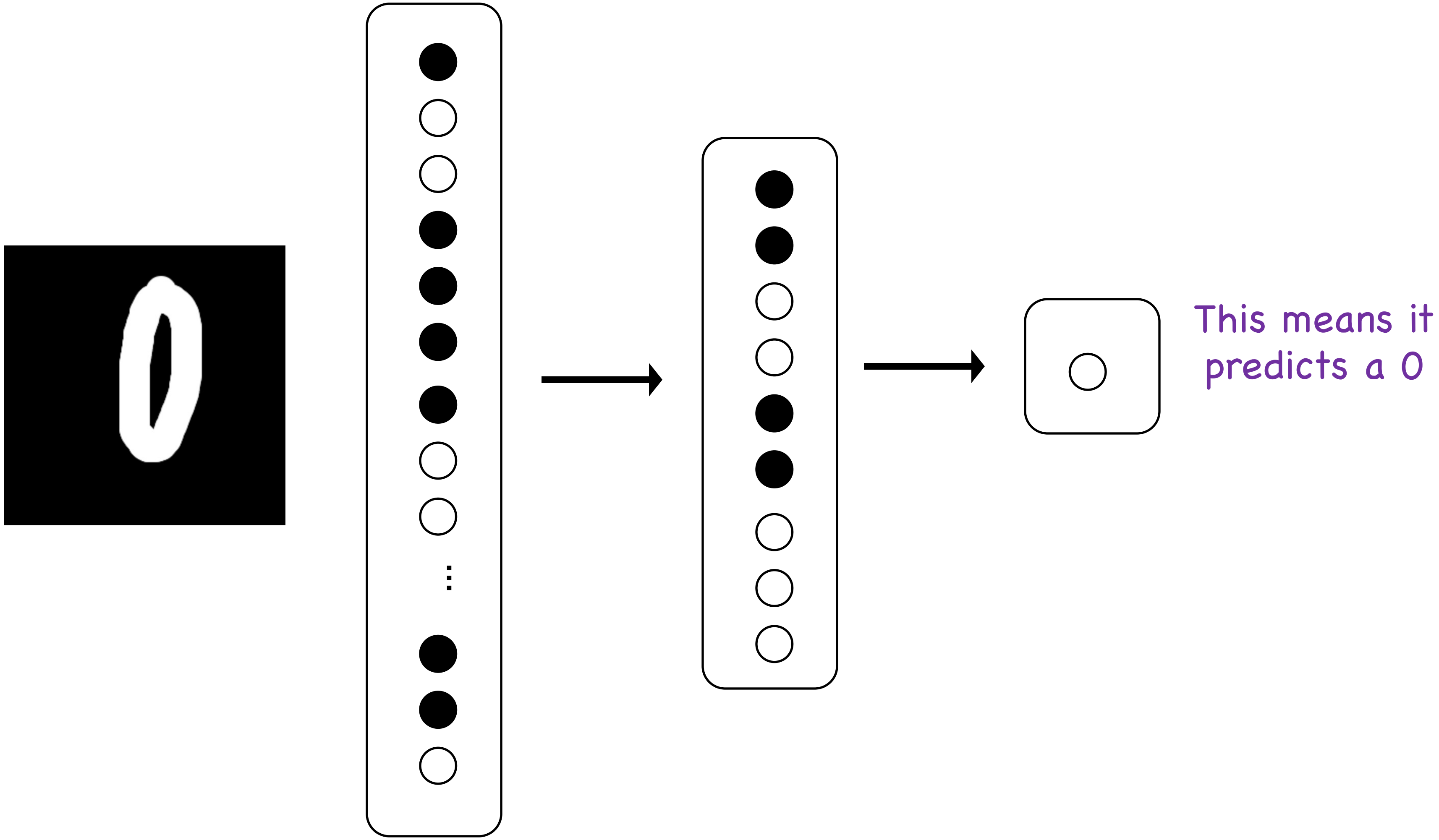
This means it
predicts a 0

We Can Put Neurons Together

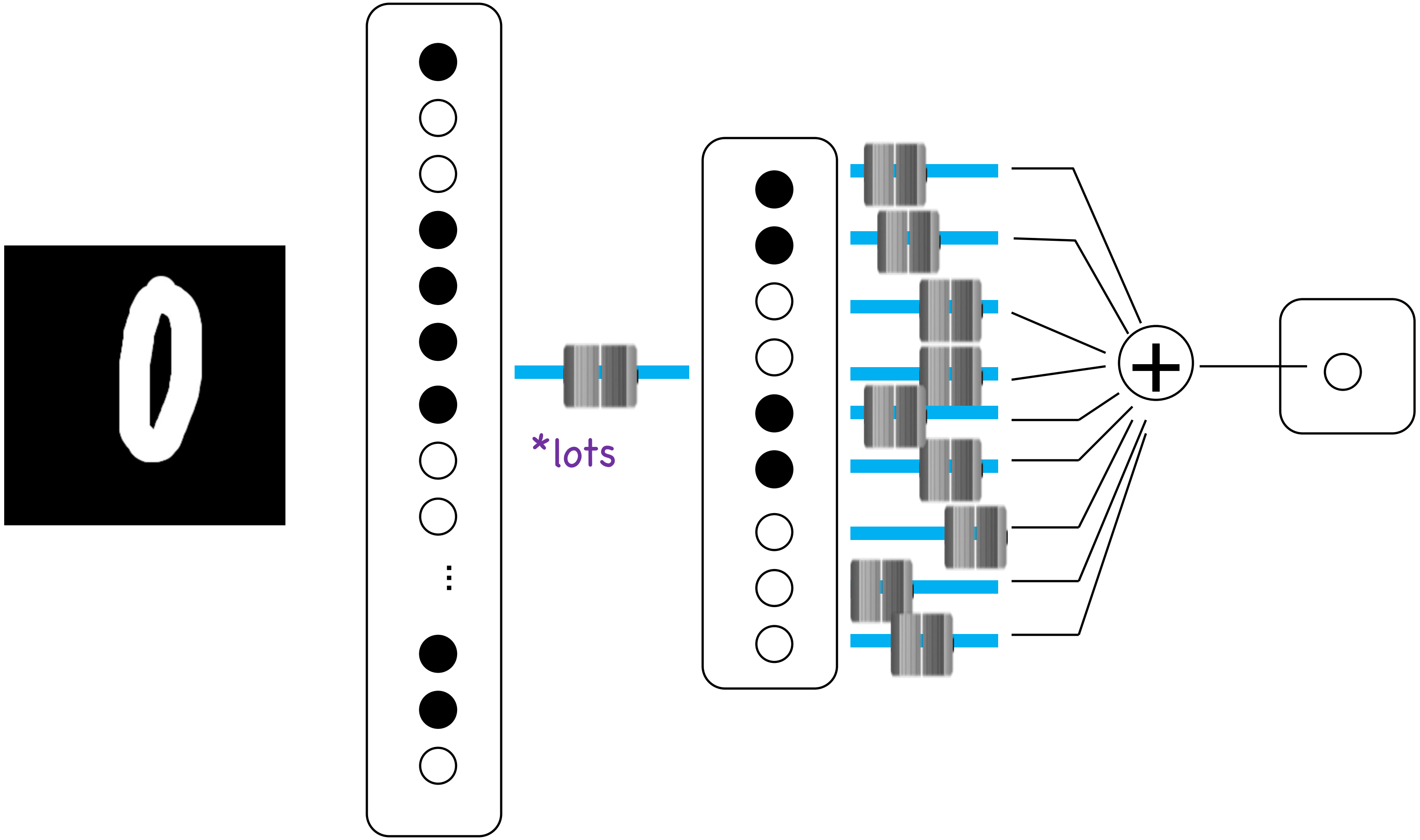


Look at another neuron

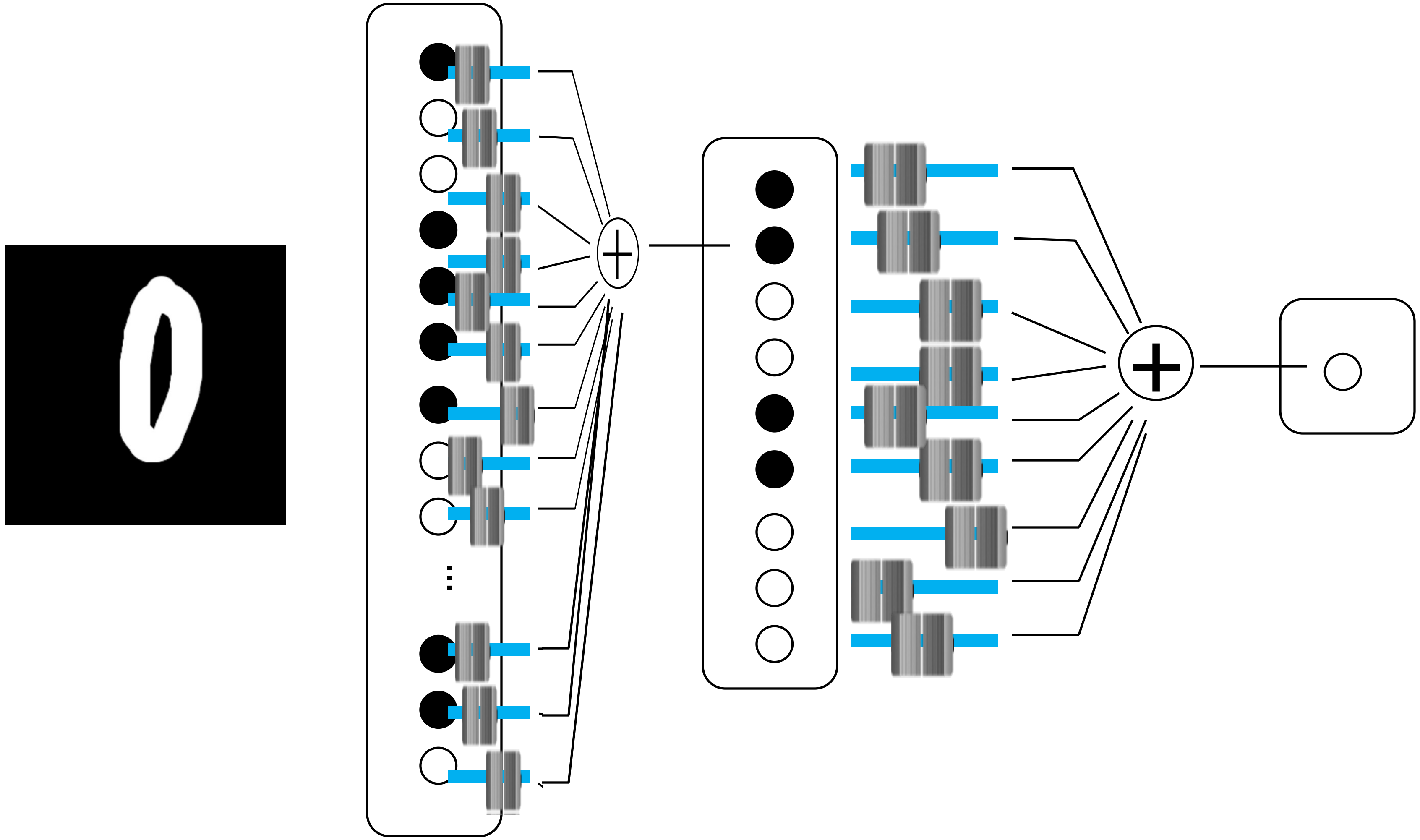
We Can Put Neurons Together



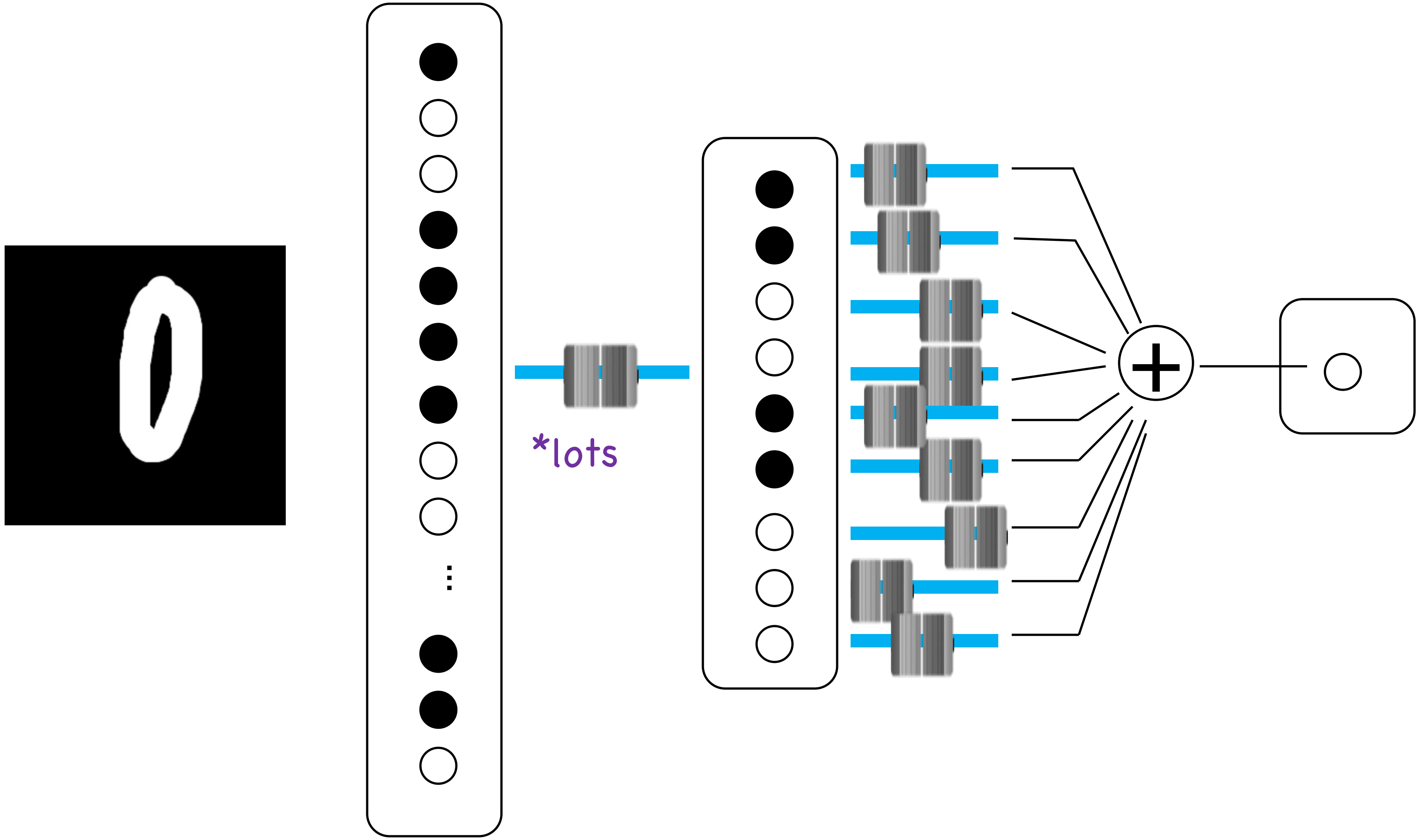
We Can Put Neurons Together



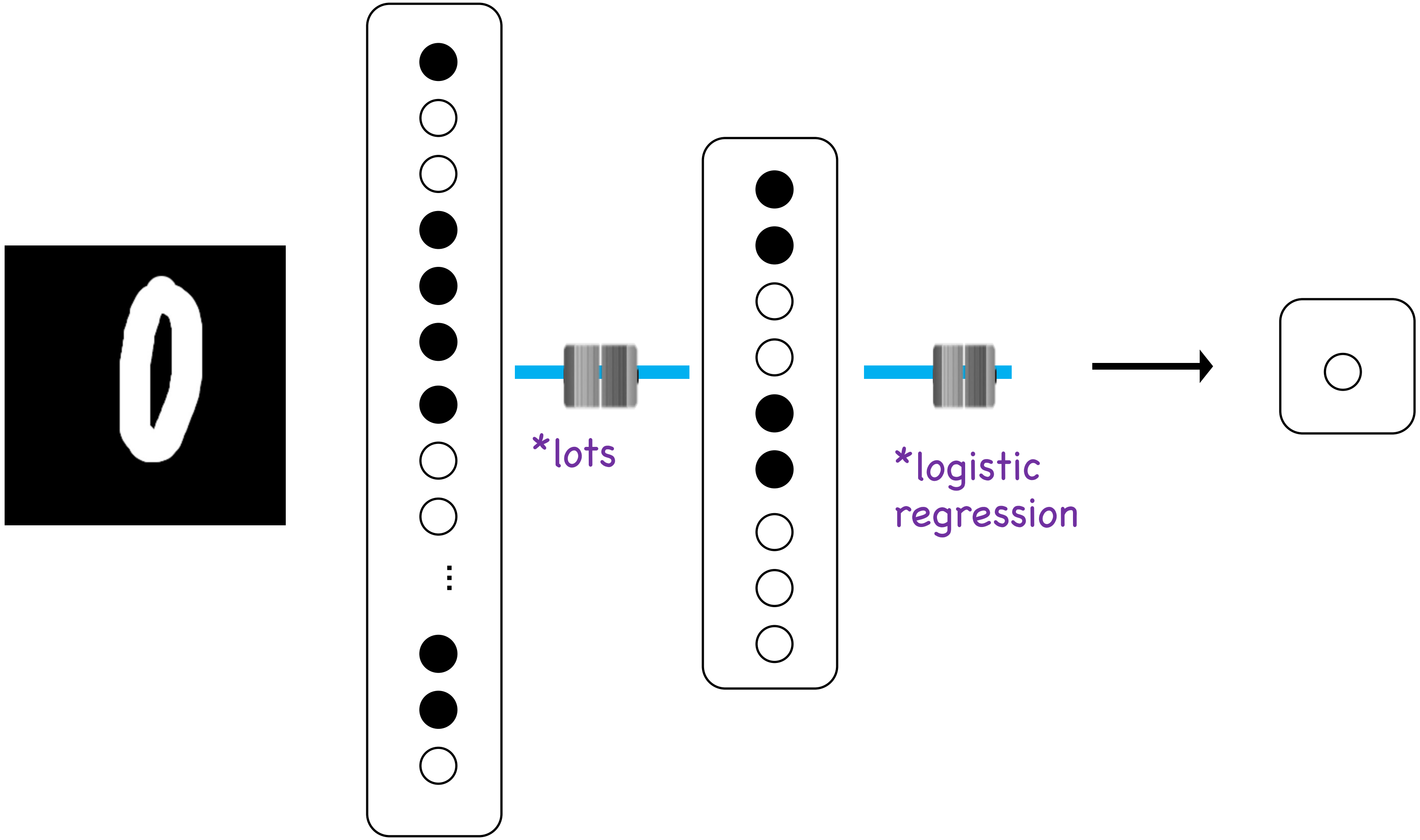
We Can Put Neurons Together



We Can Put Neurons Together



We Can Put Neurons Together



Deep learning

<u>def</u> **Deep learning** is
maximum likelihood estimation with neural networks.

<u>def</u> A **neural network** is
(at its core) many logistic regression pieces stacked on top of each other.

$[1,0, \ldots, 1]$
$\boldsymbol{x}$, input

LOL

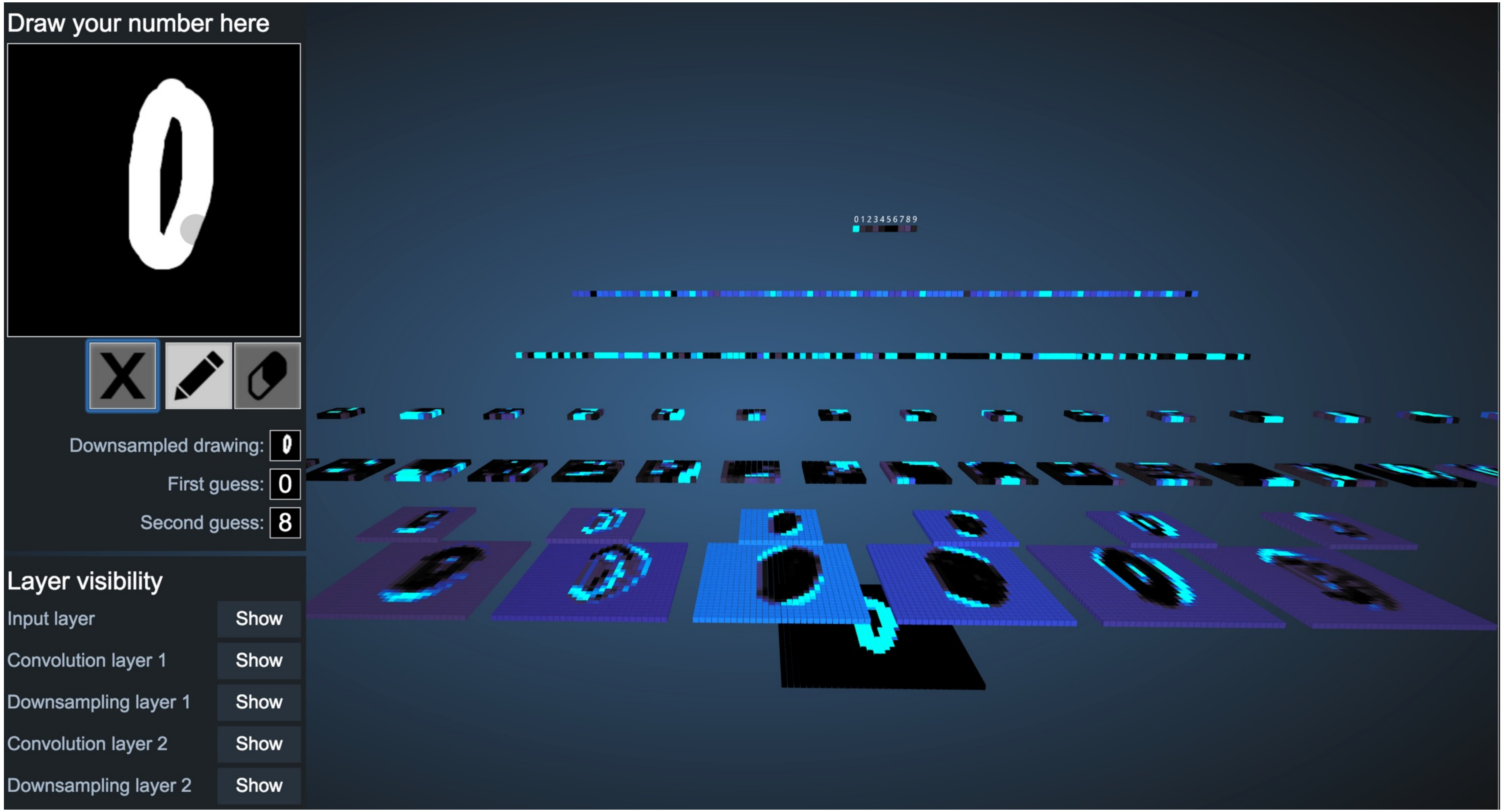
Lots of Logistic (regressions)

$\hat{y}$, output
$P(Y|\boldsymbol{X} = \boldsymbol{x})$

> 0.5?

Yes.
Predict 1

Demonstration



https://web.archive.org/web/20211117115916/https://www.cs.ryerson.ca/~aharley/vis/conv/

Deep learning gets its ***intelligence*** from its thetas (aka its parameters)

How do we train?

MLE of Thetas!

First: Learning Goals…

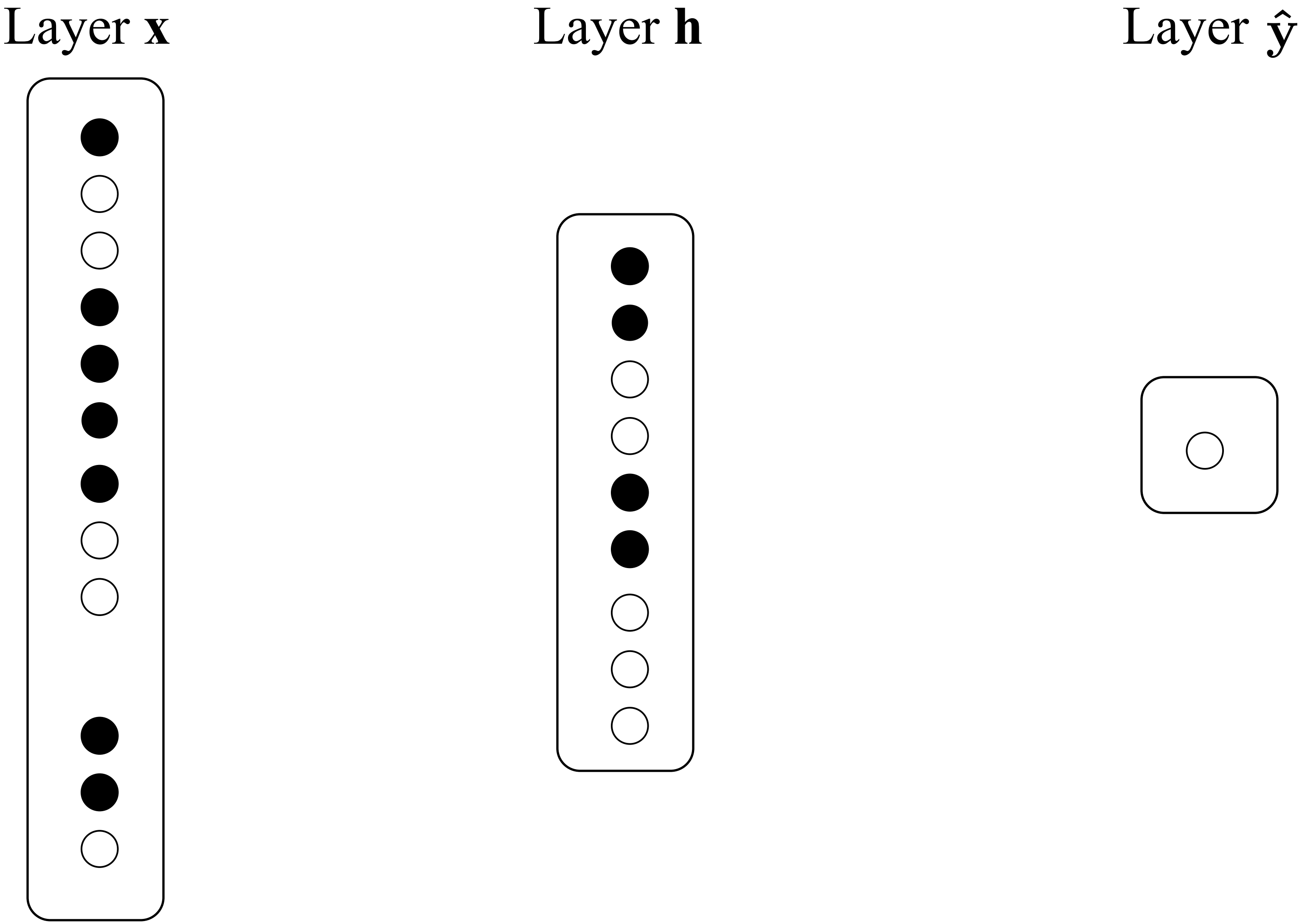
1. Understand Chain Rule as ♡ of Deep Learning

2. Demystify:
Deep Learning is MLE

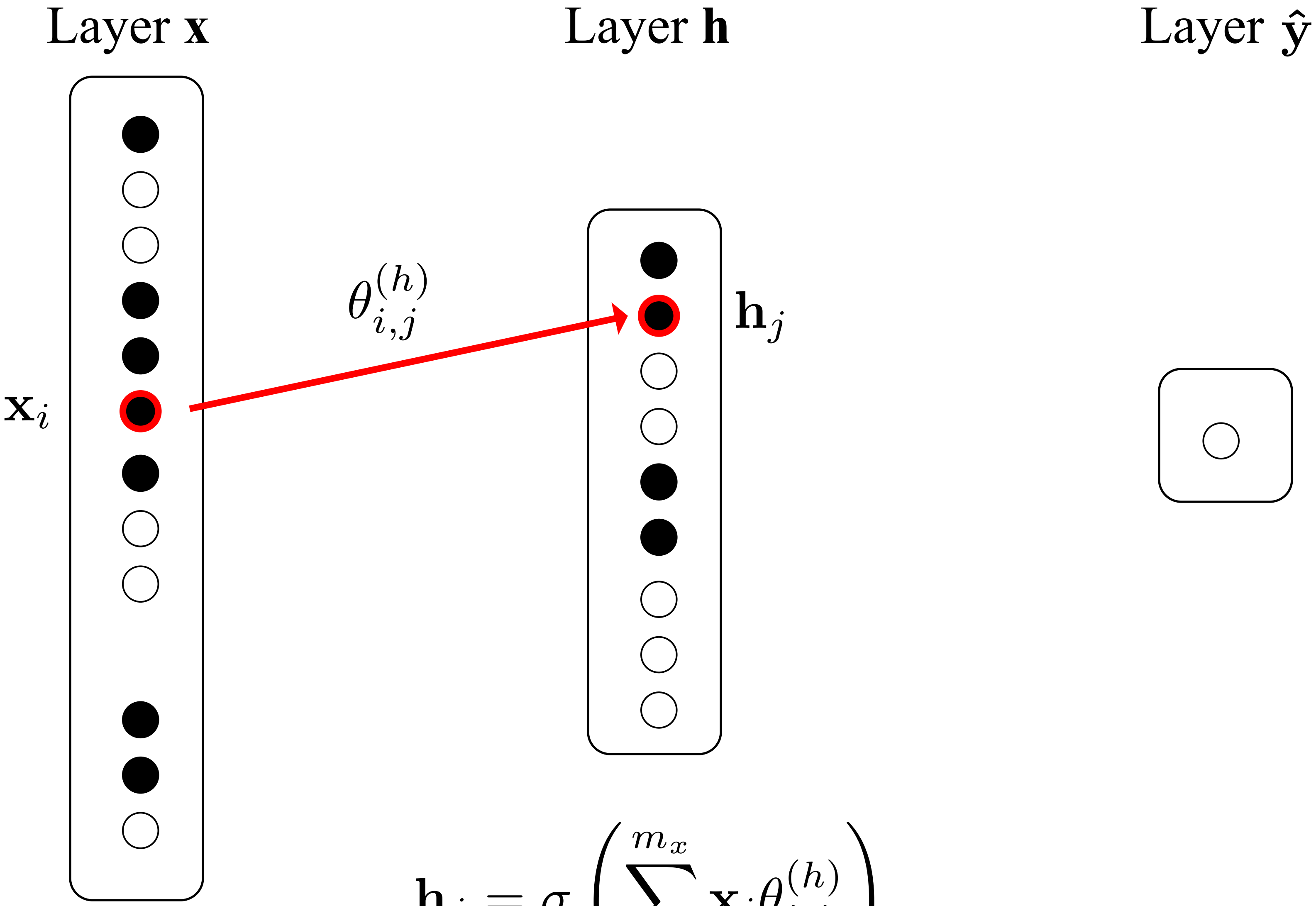
3. Become experts of logistic regression

Math worth knowing:

New Notation

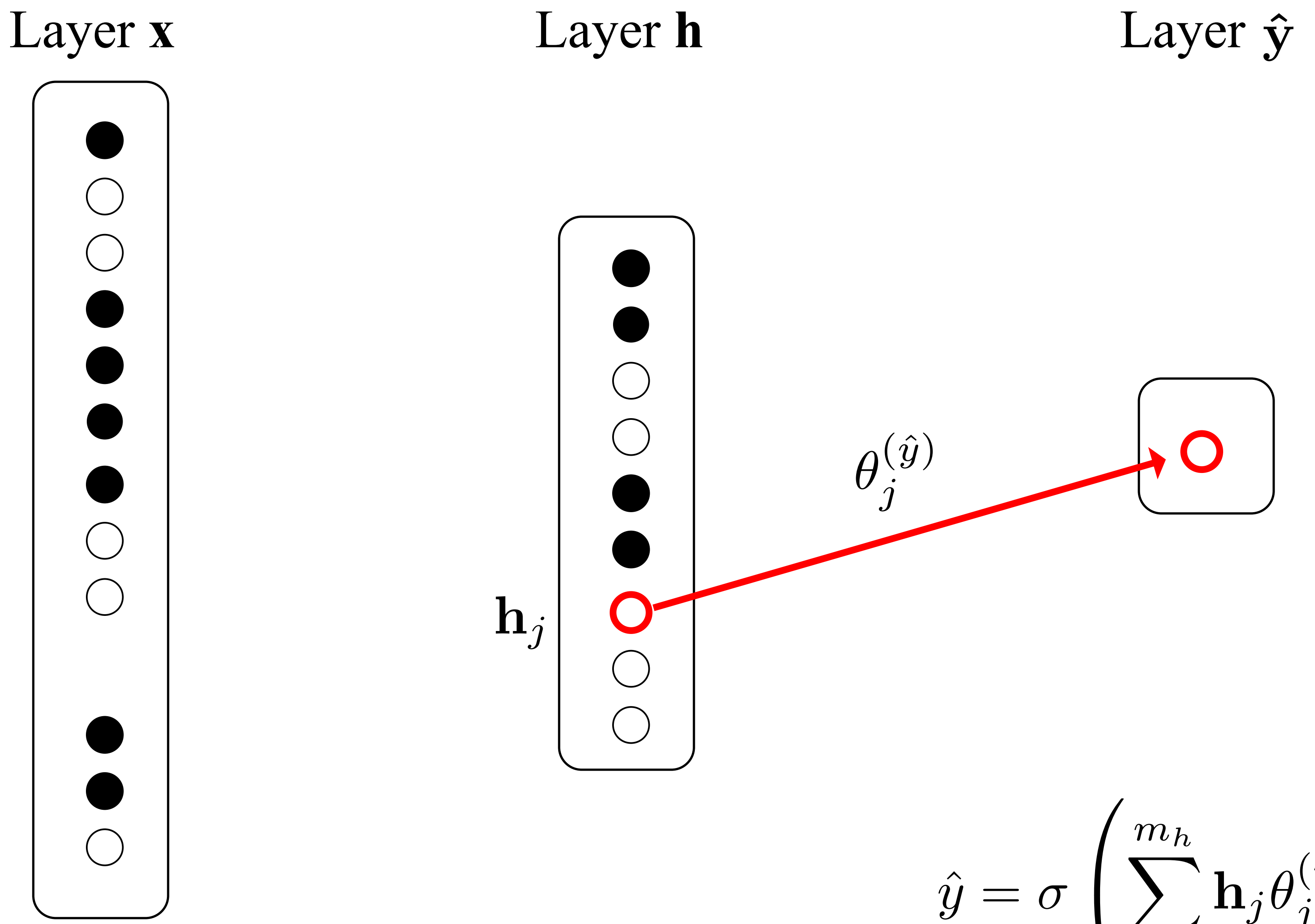


New Notation



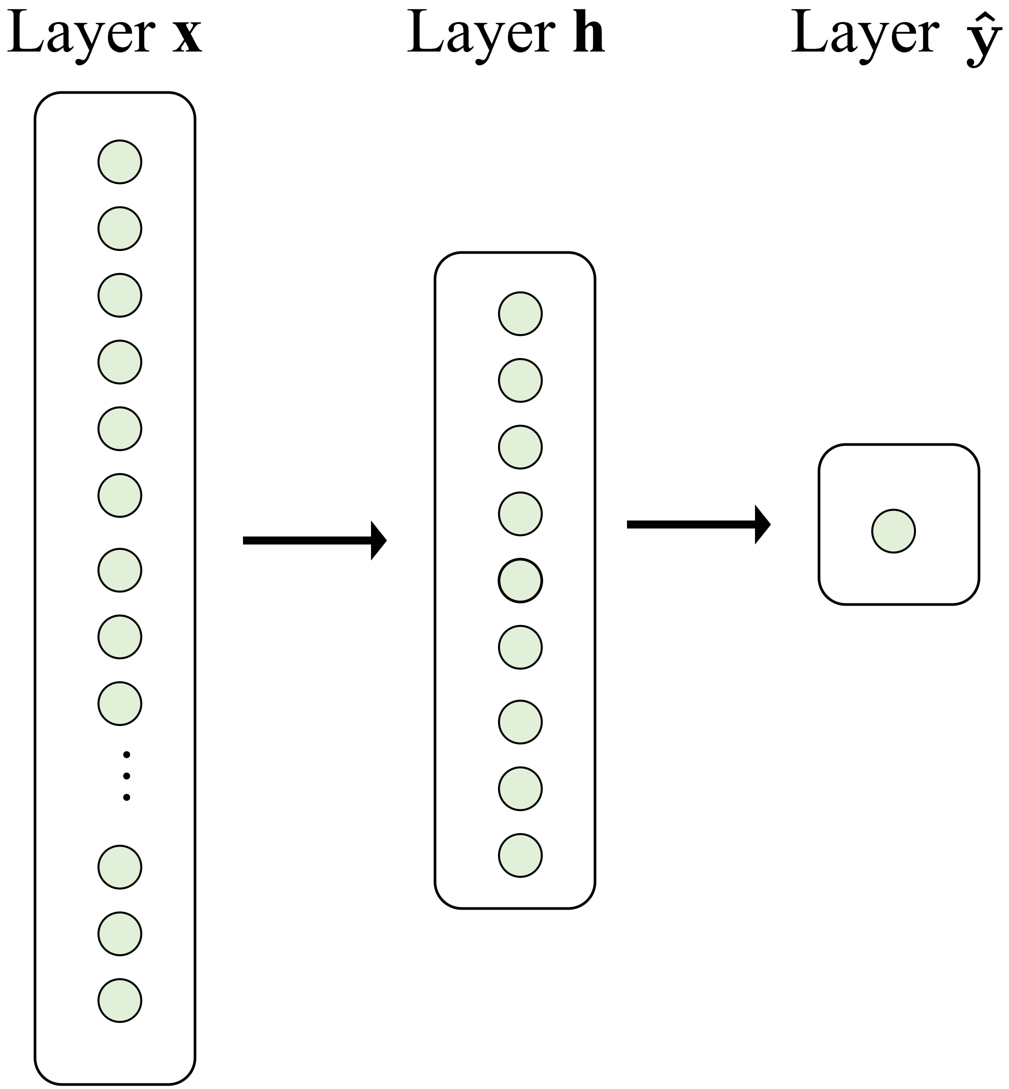
$$\mathbf{h}_j = \sigma\left(\sum_{i=0}^{m_x} \mathbf{x}_i \theta_{i,j}^{(h)}\right)$$

New Notation

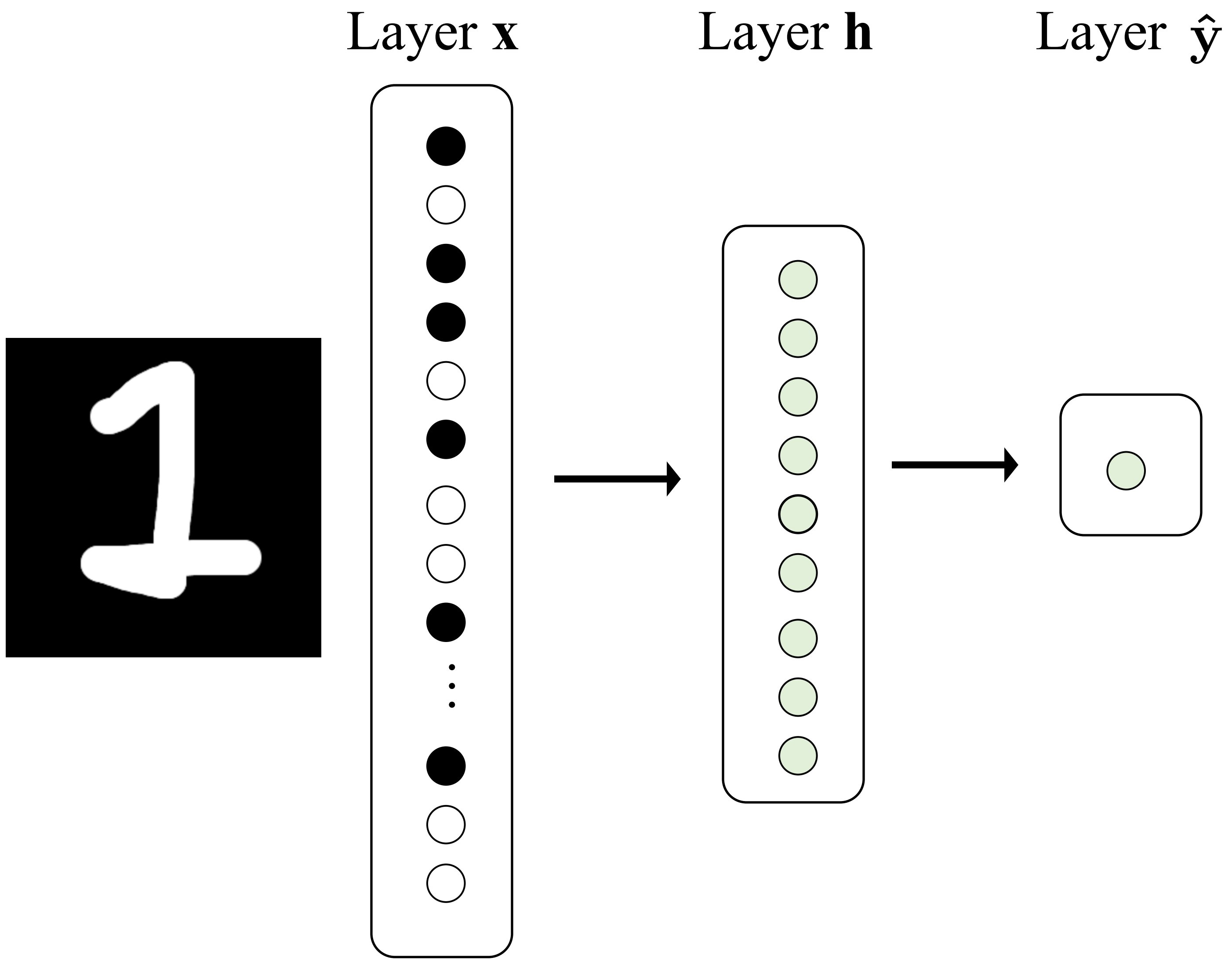


$$\hat{y} = \sigma\left(\sum_{j=0}^{m_h} \mathbf{h}_j \theta_j^{(\hat{y})}\right)$$

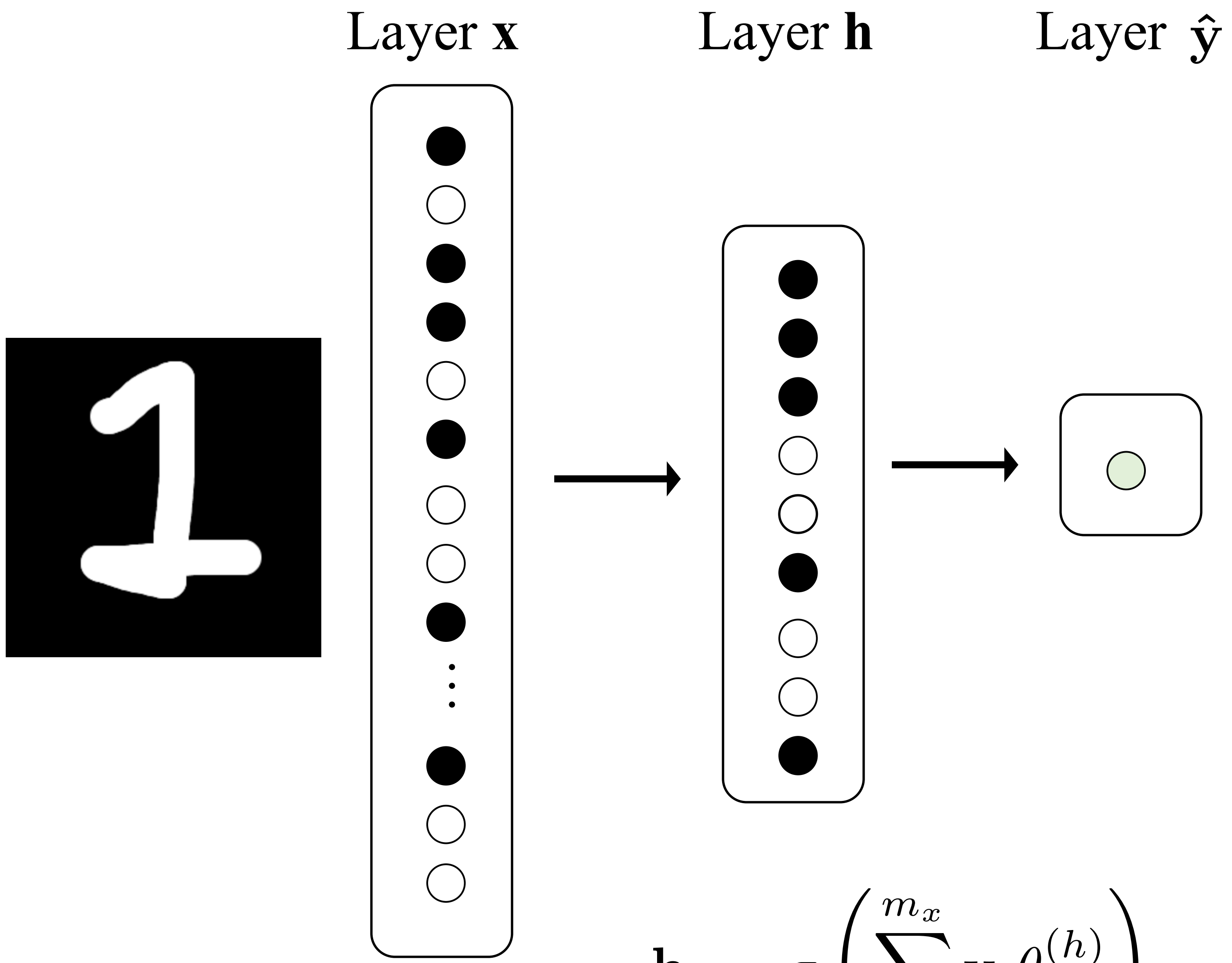
Forward Pass



Forward Pass

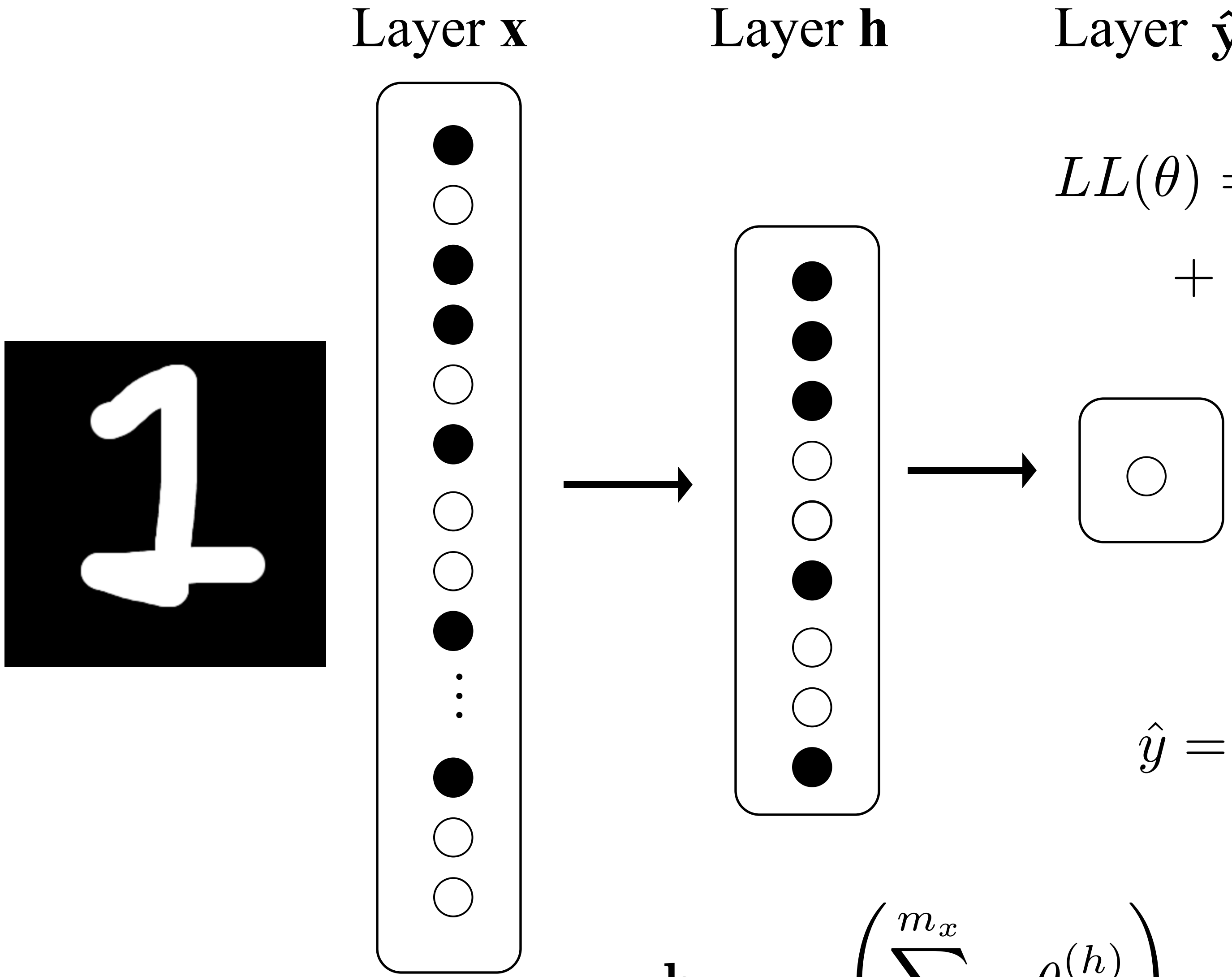


Forward Pass



$$\mathbf{h}_j = \sigma\left(\sum_{i=0}^{m_x} \mathbf{x}_i \theta_{i,j}^{(h)}\right)$$

Forward Pass

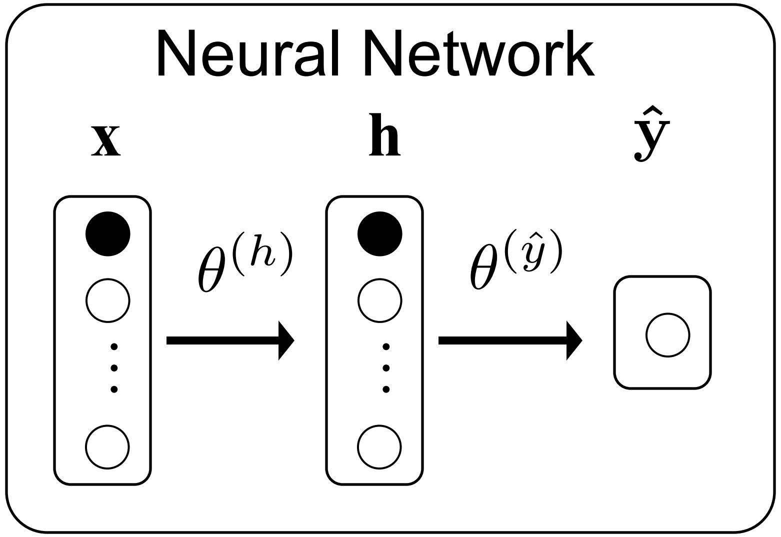


$$LL(\theta) = y \log \hat{y} + (1-y)\log[1-\hat{y}]$$

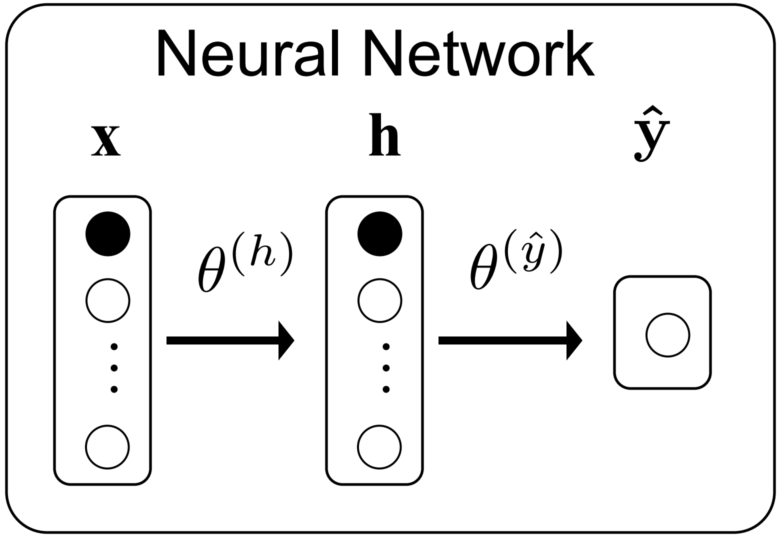
$$\hat{y} = \sigma\left(\sum_{j=0}^{m_h} \mathbf{h}_j \theta_j^{(\hat{y})}\right)$$

$$\mathbf{h}_j = \sigma\left(\sum_{i=0}^{m_x} \mathbf{x}_i \theta_{i,j}^{(h)}\right)$$

All Together



Smoke Check 1



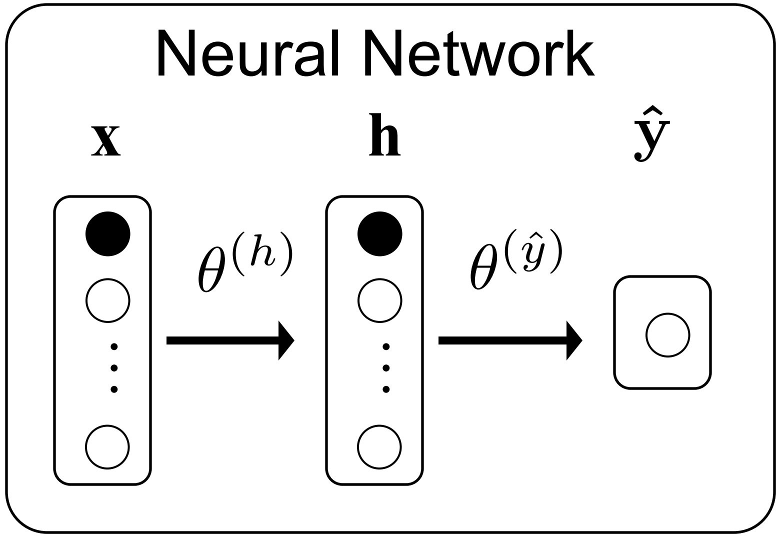
$$|\mathbf{x}| = 40$$

$$|\mathbf{h}| = 20$$

How many parameters in the last layer ?

a) 2 b) 20 c) 40 d) 800

Smoke Check 2



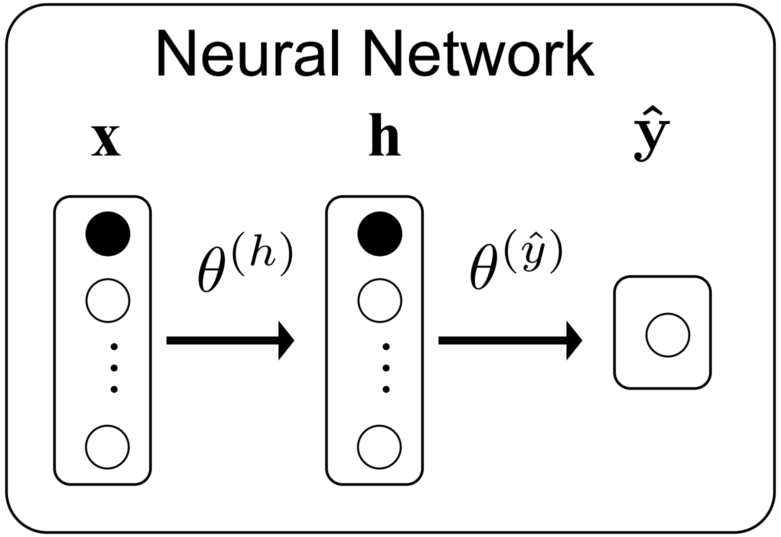
$$|\mathbf{x}| = 40$$

$$|\mathbf{h}| = 20$$

How many parameters in the second layer?

a) 2 b) 20 c) 40 d) 800

Smoke Check 3



$$|\mathbf{x}| = 40$$

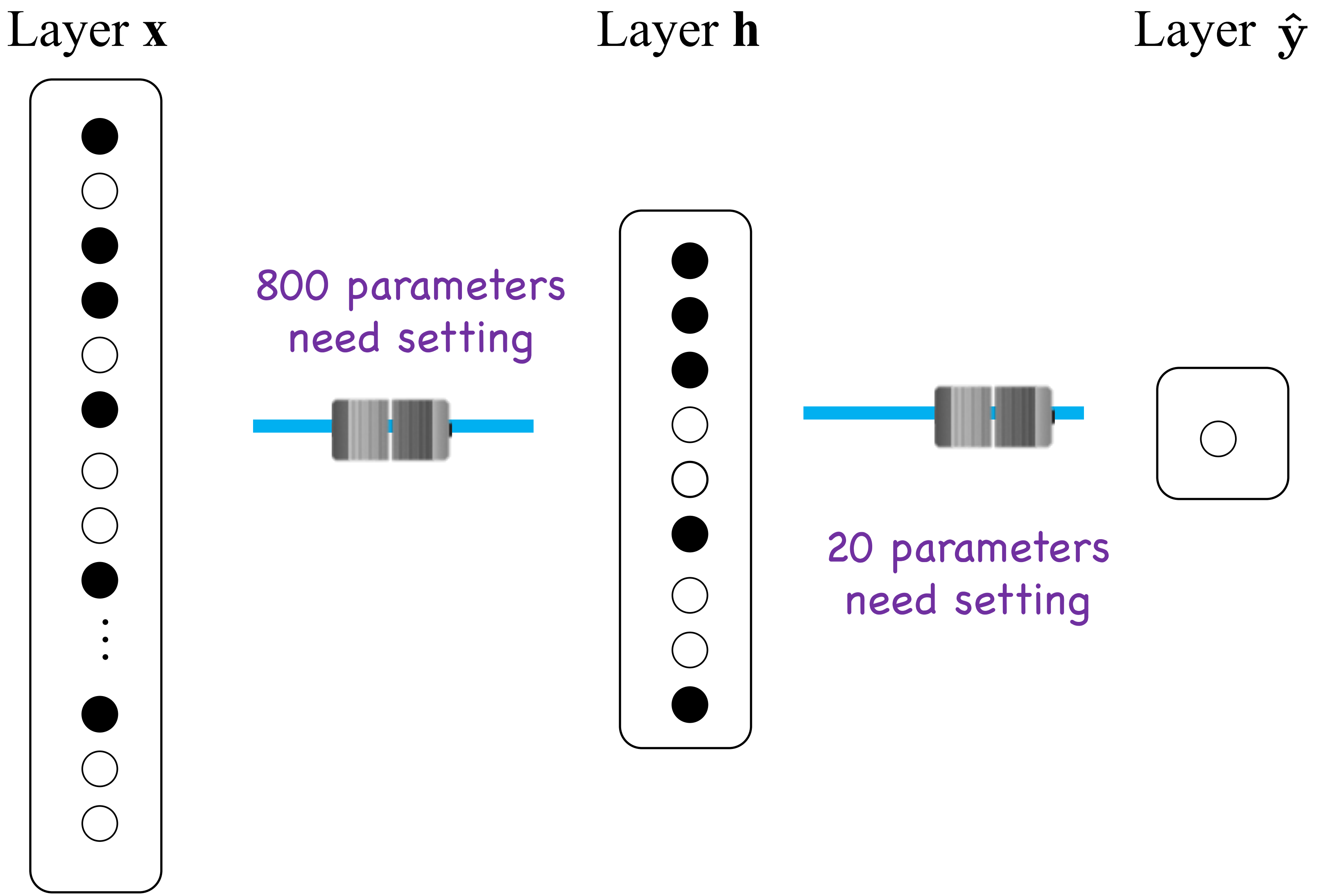
$$|\mathbf{h}| = 20$$

How many parameters in total?

a) 800 b) 20 c) 820 d) 16000

Today: Do Something Brave

Forward Pass



Only Have to Do Three Things

1. Make deep learning assumption

2. Calculate the log probability for all data

3. Get partial derivative of log likelihood with respect to each theta

Smoke Check

3 Get partial derivative of log likelihood with respect to each theta

Why?

Why We Calculate Partial Derivatives

A deep learning model gets its **intelligence** by having **useful thetas**.

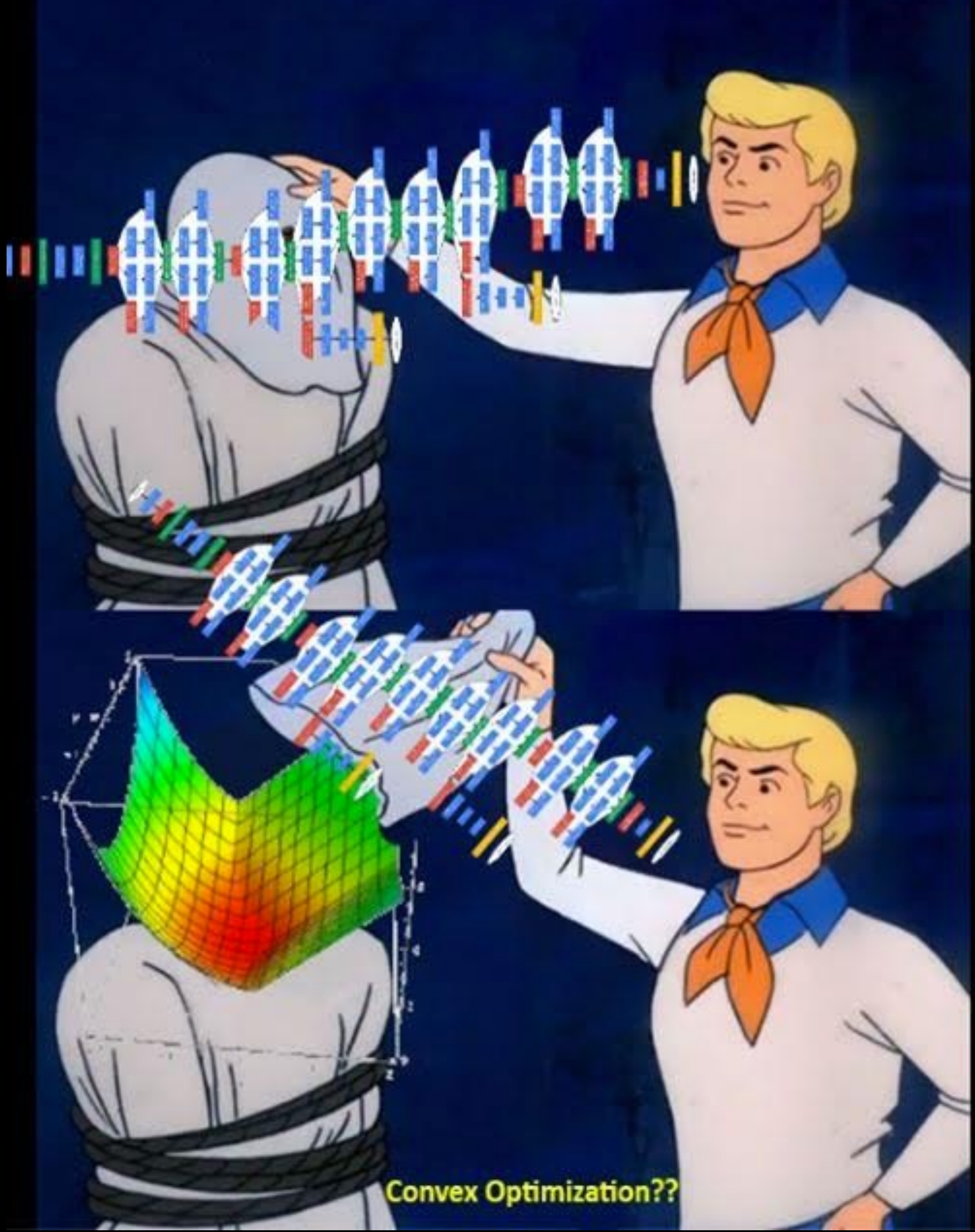
We can find **useful thetas**, by searching for ones that **maximize likelihood** of our training data

We can maximize likelihood using **optimization techniques** (such as gradient ascent).

In order to use **optimization techniques**, we need to calculate the **partial derivative** of likelihood with respect to thetas.

Basically MLE is hard because it has so many details

Thanks to Keith Eicher


Convex Optimization??

Only Have to Do Three Things

1. Make deep learning assumption

$$P(Y = 1|X = \mathbf{x}) = \hat{y}$$
$$P(Y = 0|X = \mathbf{x}) = 1 - \hat{y}$$

2. Calculate the log probability for all data

Same Assumption, Same LL

$$P(Y = 1 | X = \mathbf{x}) = \hat{y} \qquad \hat{y} = \sigma\left(\sum_{j=0}^{m_h} \mathbf{h}_j \theta_j^{(\hat{y})}\right) \qquad \mathbf{h}_j = \sigma\left(\sum_{i=0}^{m_x} \mathbf{x}_i \theta_{i,j}^{(h)}\right)$$

For one datum

$$P(Y = y | \mathbf{X} = \mathbf{x}) = (\hat{y})^y (1 - \hat{y})^{1-y}$$

Feel the Bern!
$Y \sim \text{Bern}(\hat{y})$

For IID data

$$L(\theta) = \prod_{i=1}^{n} P(Y = y^{(i)} | X = \mathbf{x}^{(i)})$$
$$= \prod_{i=1}^{n} (\hat{y}^{(i)})^{y^{(i)}} \cdot \left[1 - (\hat{y}^{(i)})\right]^{(1-y^{(i)})}$$

Take the log

$$LL(\theta) = \sum_{i=1}^{n} y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log[1 - \hat{y}^{(i)}]$$

Only Have to Do Three Things

1. Make deep learning assumption

$$\hat{y} = \sigma\left(\sum_{j=0}^{m_h} \mathbf{h}_j \theta_j^{(\hat{y})}\right)$$

$$P(Y = 1|X = \mathbf{x}) = \hat{y}$$
$$P(Y = 0|X = \mathbf{x}) = 1 - \hat{y}$$

2. Calculate the log probability for all data

$$LL(\theta) = \sum_{i=0}^{n} y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log[1 - \hat{y}^{(i)}]$$

3. Get partial derivative of log likelihood with respect to each theta

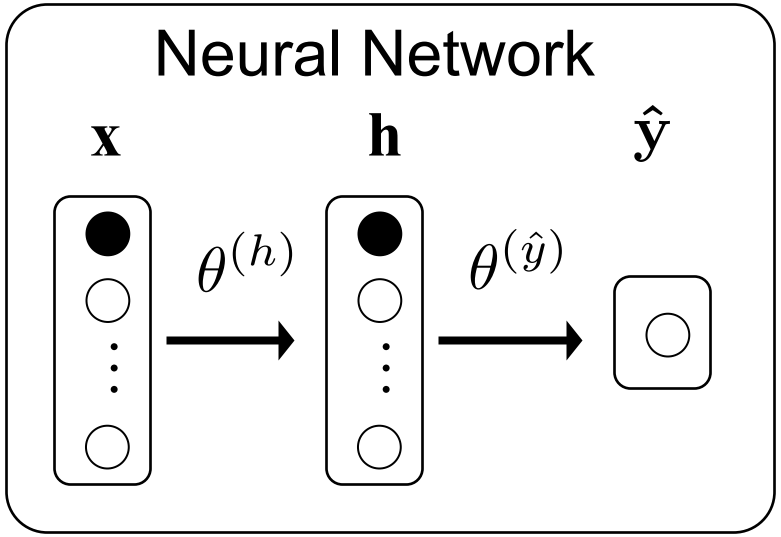
Derivative Goals

Loss with respect to output layer params

$$\frac{\partial LL(\theta)}{\partial \theta_i^{(\hat{y})}}$$

Loss with respect to hidden layer params

$$\frac{\partial LL(\theta)}{\partial \theta_{i,j}^{(h)}}$$



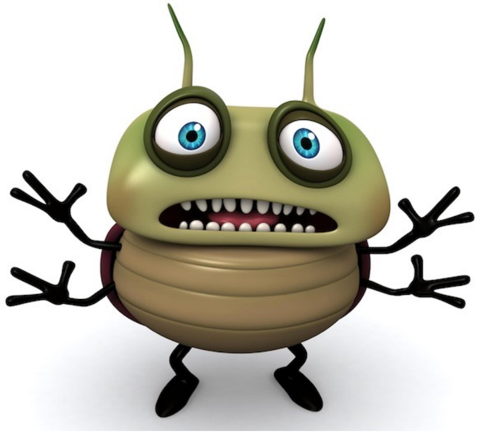
Bad Approach

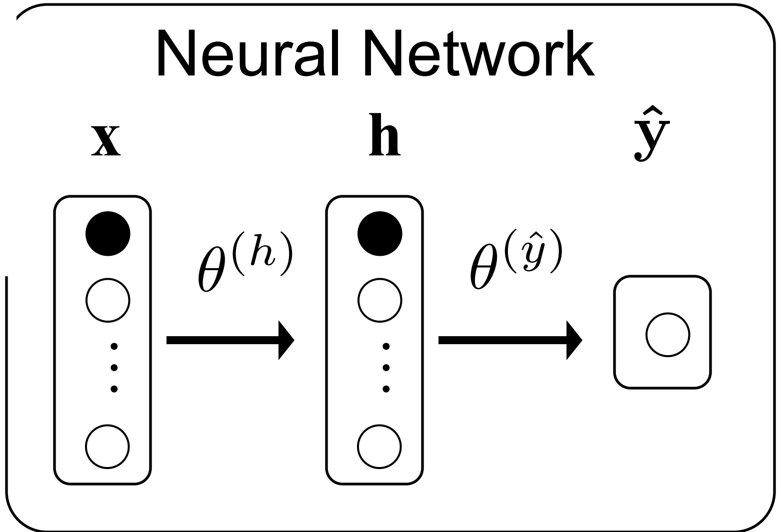
$$LL(\theta) = y \log \hat{y} + (1 - y) \log[1 - \hat{y}]$$

$$\hat{y} = \sigma\left(\sum_{i=0}^{m_h} \mathbf{h}_i \theta_i^{(\hat{\mathbf{y}})}\right)$$

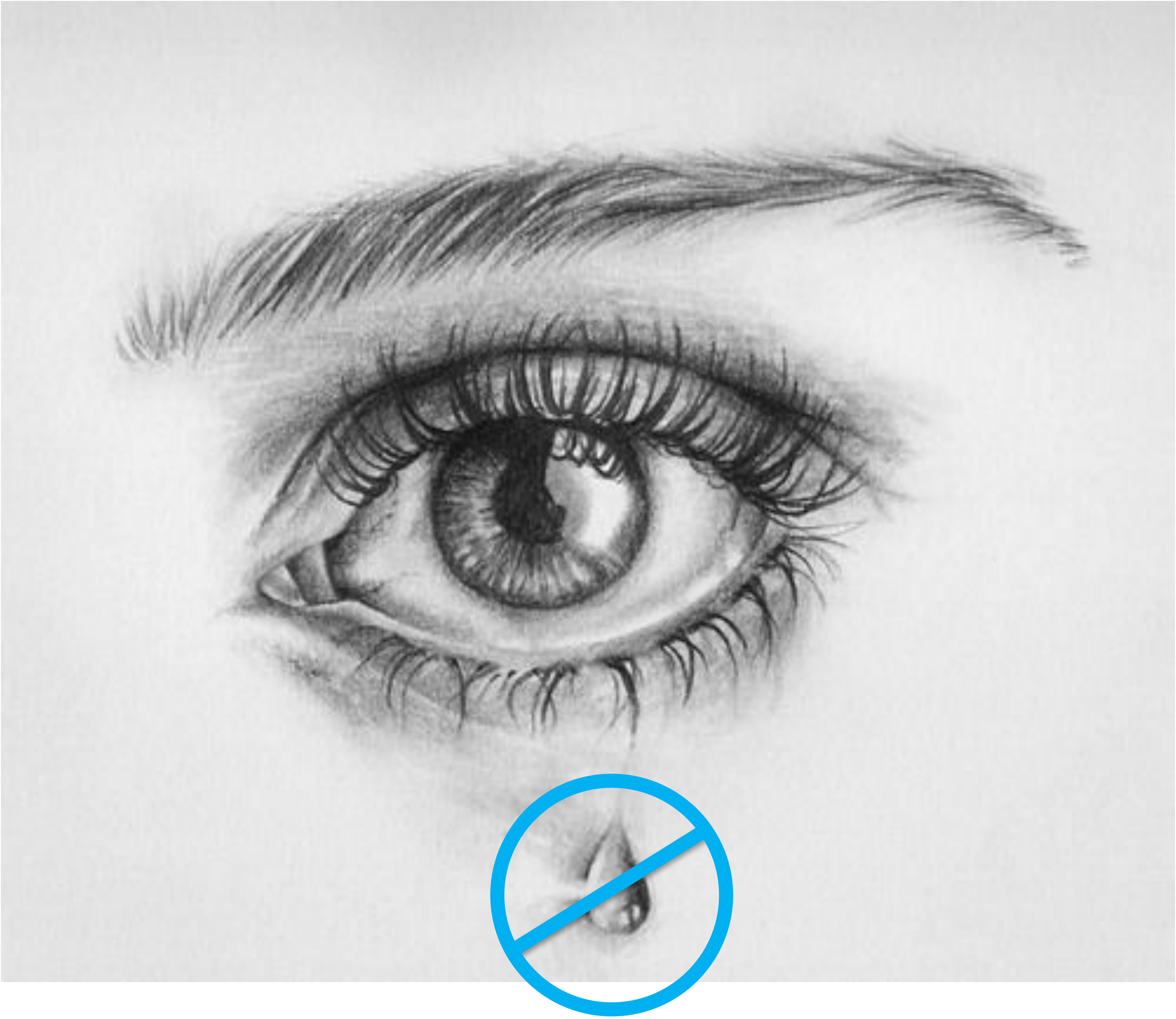
Math bug

$$= \sigma\left(\sum_{i=0}^{m_h} \left[\sigma\left(\sum_{i=0}^{m_x} \mathbf{x}_i \theta_{i,j}^{(\mathbf{h})}\right)\right] \theta_i^{(\hat{\mathbf{y}})}\right)$$





Derivatives Without Tears



Big Idea #1: Chain Rule

Woah Mrs Nicholson, you were right.
Chain rule is useful!

$$\frac{\partial f(z)}{\partial x} = \frac{\partial f(z)}{\partial z} \cdot \frac{\partial z}{\partial x}$$

First use:

$$\frac{\partial LL(\theta)}{\partial \theta_i^{(\hat{y})}} = \frac{\partial LL}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial \theta_i^{(\hat{y})}}$$

Big Idea #2: Sigmoid Derivative

True fact about sigmoid functions

$$\frac{\partial}{\partial z}\sigma(z) = \sigma(z)[1 - \sigma(z)]$$

Big Idea #3: Derivative of Sum

$$LL(\theta) = \sum_{i=0}^{n} y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log[1 - \hat{y}^{(i)}]$$

We only need to calculate the gradient for one training example!

$$\frac{\partial}{\partial x} \sum f(x) = \sum \frac{\partial}{\partial x} f(x)$$

We will pretend we only have one example

$$LL(\theta) = y \log \hat{y} + (1 - y) \log[1 - \hat{y}]$$

We can sum up the gradients of each example to get the correct answer

Recall

Sigmoid has a Beautiful Slope

$$\frac{\partial}{\partial \theta_j} \sigma(\theta^T x)?$$

$$\frac{\partial}{\partial z} \sigma(z) = \sigma(z)[1 - \sigma(z)]$$

where $z = \theta^T x$

$$\frac{\partial}{\partial \theta_j} \sigma(\theta^T x) = \frac{\partial}{\partial z} \sigma(z) \cdot \frac{\partial z}{\partial \theta_j}$$

Chain rule!

$$\frac{\partial}{\partial \theta_j} \sigma(\theta^T x) = \sigma(\theta^T x)[1 - \sigma(\theta^T x)] x_j$$

Plug and chug

Sigmoid, you should be a ski hill

This is ~~Sparta~~!!!!!

Stanford

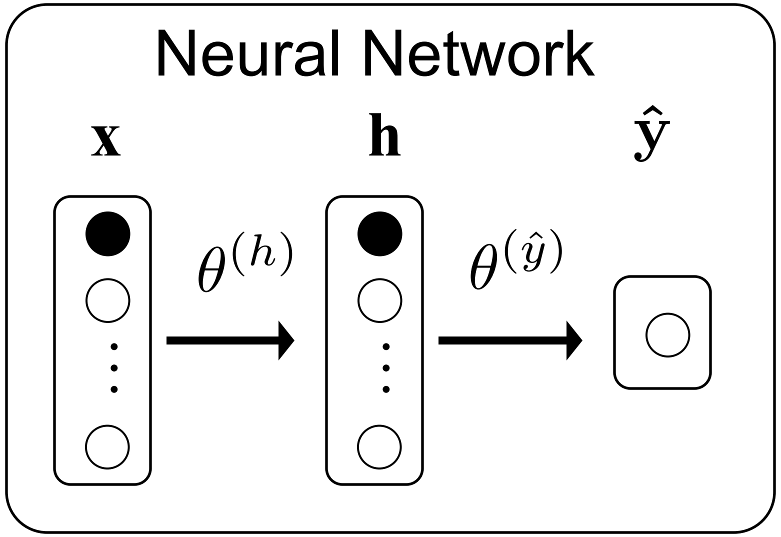
Derivative Goals

Loss with respect to output layer params

$$\frac{\partial LL(\theta)}{\partial \theta_i^{(\hat{y})}}$$

Loss with respect to hidden layer params

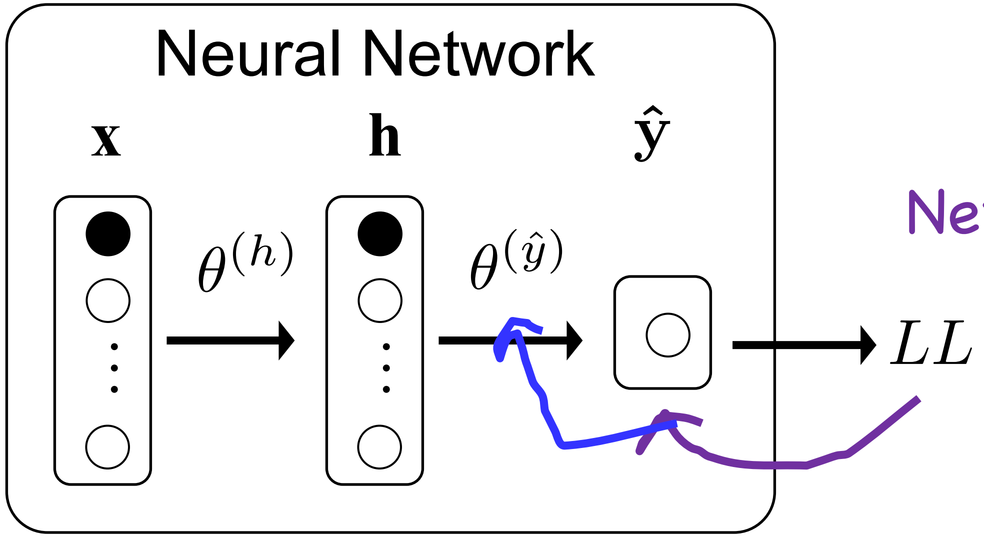
$$\frac{\partial LL(\theta)}{\partial \theta_{i,j}^{(h)}}$$



Chain Rule Example 1

$$\frac{\partial LL(\theta)}{\partial \theta_i^{(\hat{y})}}$$

Goal



Network

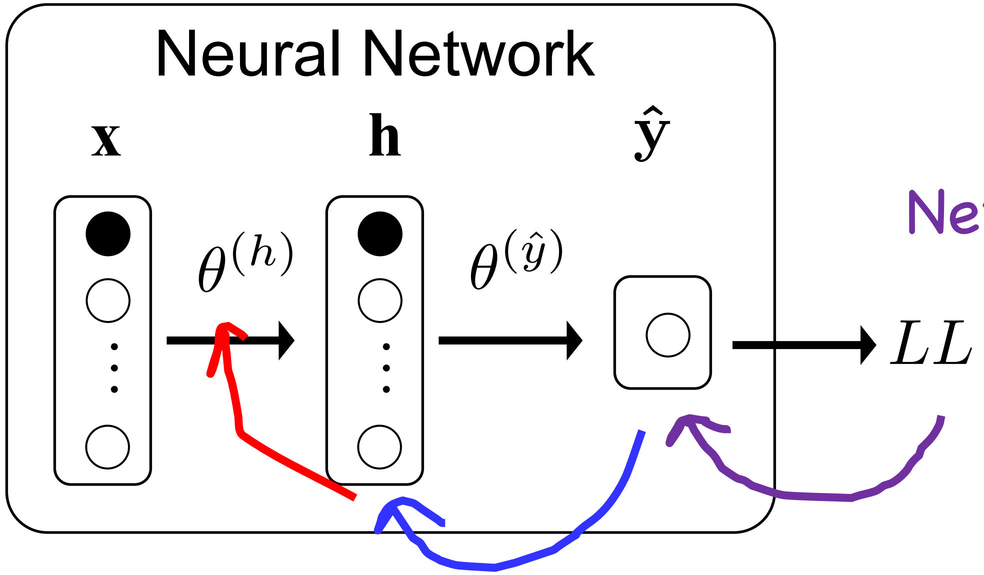
$$\frac{\partial LL(\theta)}{\partial \theta_i^{(\hat{y})}} = \frac{\partial LL}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial \theta_i^{(\hat{y})}}$$

Decomposition

Chain Rule Example 2

$$\frac{\partial LL(\theta)}{\partial \theta^{(h)}_{i,j}}$$

Goal



Network

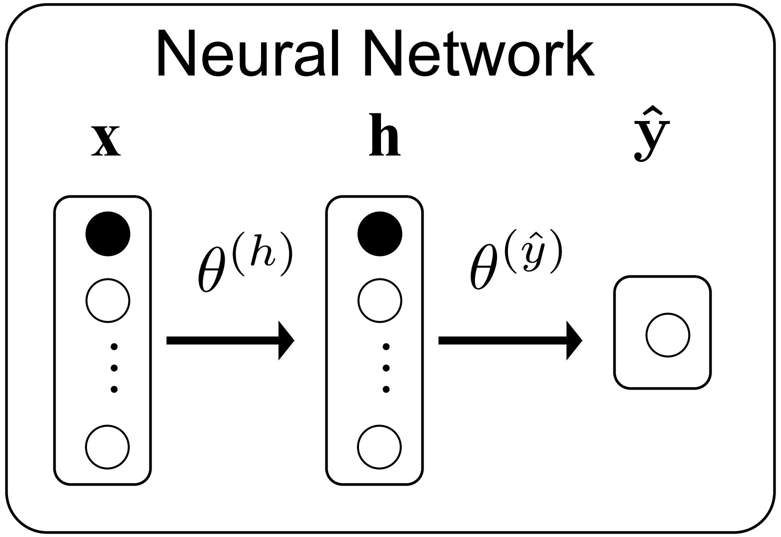
$$\frac{\partial LL(\theta)}{\partial \theta^{(h)}_{i,j}} = \frac{\partial LL}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial \mathbf{h}_j} \cdot \frac{\partial \mathbf{h}_j}{\partial \theta^{(h)}_{i,j}}$$

Decomposition

Decomposition

Gradient of output layer params

$$\frac{\partial LL(\theta)}{\partial \theta_i^{(\hat{y})}} = \frac{\partial LL}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial \theta_i^{(\hat{y})}}$$



Gradient of output layer params

$$\frac{\partial LL(\theta)}{\partial \theta_i^{(\hat{y})}} = \boxed{\frac{\partial LL}{\partial \hat{y}}} \cdot \frac{\partial \hat{y}}{\partial \theta_i^{(\hat{y})}}$$

$$LL(\theta) = y \log \hat{y} + (1-y) \log[1-\hat{y}]$$

$$\frac{\partial LL(\theta)}{\partial \hat{y}} = \frac{y}{\hat{y}} + \frac{(1-y)}{(1-\hat{y})} \cdot \frac{\partial (1-\hat{y})}{\partial \hat{y}}$$

$$\frac{\partial LL(\theta)}{\partial \hat{y}} = \frac{y}{\hat{y}} - \frac{(1-y)}{(1-\hat{y})}$$

Gradient of output layer params

$$\frac{\partial LL(\theta)}{\partial \theta_i^{(\hat{y})}} = \boxed{\frac{\partial LL}{\partial \hat{y}}} \cdot \boxed{\frac{\partial \hat{y}}{\partial \theta_i^{(\hat{y})}}}$$

$$\hat{y} = \sigma\left(\sum_{j=0}^{m_h} \mathbf{h}_j \theta_j^{(\hat{y})}\right) = \sigma(z) \qquad \text{where} \qquad z = \sum_{j=0}^{m_h} \mathbf{h}_j \theta_j^{(\hat{y})}$$

$$\frac{\partial \hat{y}}{\partial \theta_i^{(\hat{y})}} = \hat{y}[1 - \hat{y}] \cdot \frac{\partial}{\partial \theta_i^{(\hat{y})}} \sum_{j=0}^{m_h} \mathbf{h}_j \theta_j^{(\hat{y})}$$

$$= \hat{y}[1 - \hat{y}] \cdot h_i$$

What! That's not scary!

Make it Simple

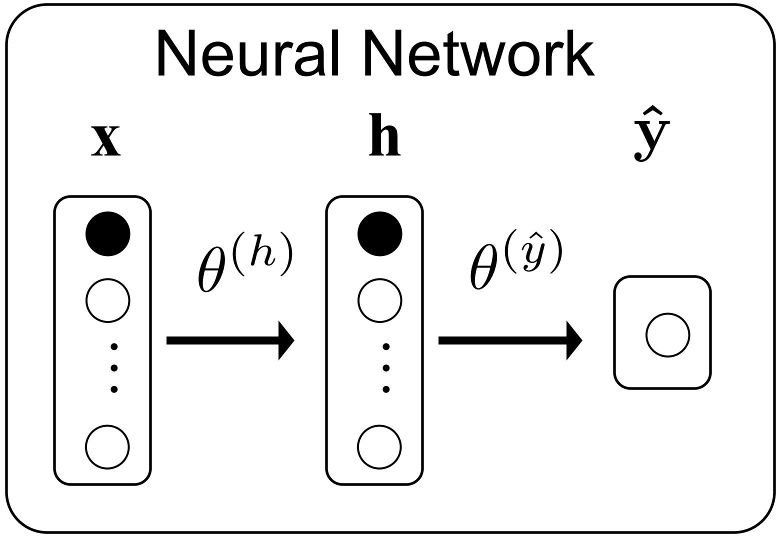
$$\frac{\partial LL(\theta)}{\partial \theta_i^{(\hat{y})}} =$$  $\cdot$ 

 $$= \frac{y}{\hat{y}} - \frac{(1-y)}{(1-\hat{y})}$$

 $$= \hat{y}[1-\hat{y}] \cdot h_i$$

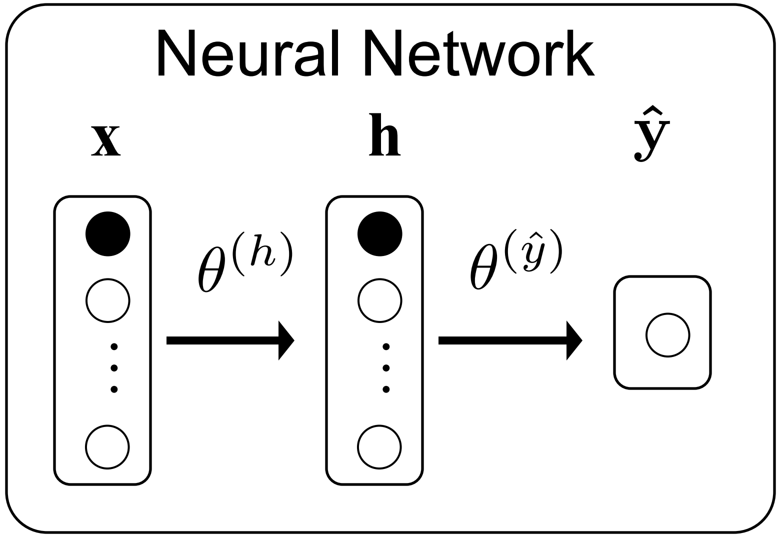
Boom!

$$\frac{\partial LL(\theta)}{\partial \theta^{(h)}_{i,j}}$$



Gradient of hidden layer params

$$\frac{\partial LL(\theta)}{\partial \theta_{i,j}^{(h)}} = \frac{\partial LL}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial \mathbf{h}_j} \cdot \frac{\partial \mathbf{h}_j}{\partial \theta_{i,j}^{(h)}}$$



Gradient of hidden layer params

$$\frac{\partial LL(\theta)}{\partial \theta_{i,j}^{(h)}} = \boxed{\frac{\partial LL}{\partial \hat{y}}} \cdot \boxed{\frac{\partial \hat{y}}{\partial \mathbf{h}_j}} \cdot \frac{\partial \mathbf{h}_j}{\partial \theta_{i,j}^{(h)}}$$

$$\hat{y} = \sigma\left(\sum_{i=0}^{m_h} \mathbf{h}_i \theta_i^{(\hat{y})}\right)$$

$$\frac{\partial \hat{y}}{\partial \mathbf{h}_j} = \hat{y}[1 - \hat{y}]\theta_j^{(\hat{y})}$$

Wait is it over?

Gradient of hidden layer params

$$\frac{\partial LL(\theta)}{\partial \theta^{(h)}_{i,j}} = \boxed{\frac{\partial LL}{\partial \hat{y}}} \cdot \boxed{\frac{\partial \hat{y}}{\partial \mathbf{h}_j}} \cdot \boxed{\frac{\partial \mathbf{h}_j}{\partial \theta^{(h)}_{i,j}}}$$

$$\mathbf{h}_j = \sigma\left(\sum_{k=0}^{m_x} \mathbf{x}_k \theta_{k,j}\right)$$

$$\frac{\partial \mathbf{h}_j}{\partial \theta^{(h)}_{i,j}} = \mathbf{h}_j[1 - \mathbf{h}_j]\mathbf{x}_i$$

That one too?

Make it Simple

$$\frac{\partial LL(\theta)}{\partial \theta_{i,j}^{(h)}} =$$   

$$= \frac{y}{\hat{y}} - \frac{(1-y)}{(1-\hat{y})}$$

$$= \hat{y}[1-\hat{y}]\theta_j^{(\hat{y})}$$

$$= \mathbf{h}_j[1-\mathbf{h}_j]\mathbf{x}_j$$

Congrats. You now know
Backpropagation

Moment of silence

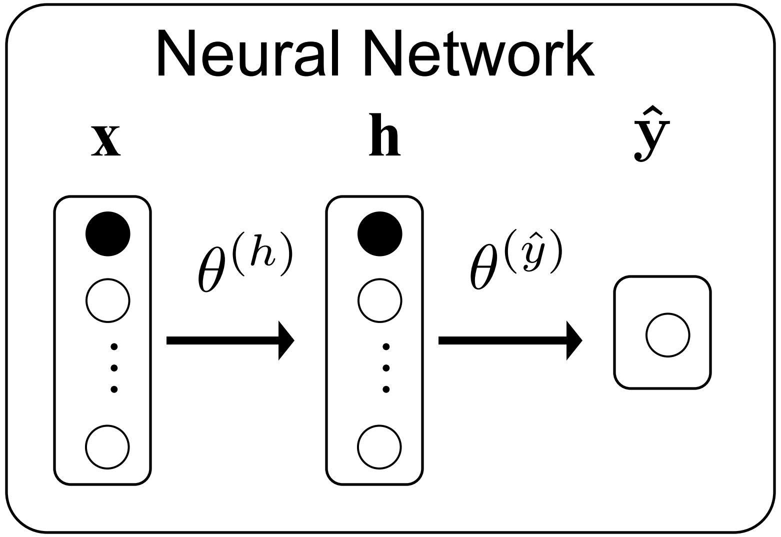
Summary: Simple Calculations For

Loss with respect to output layer params

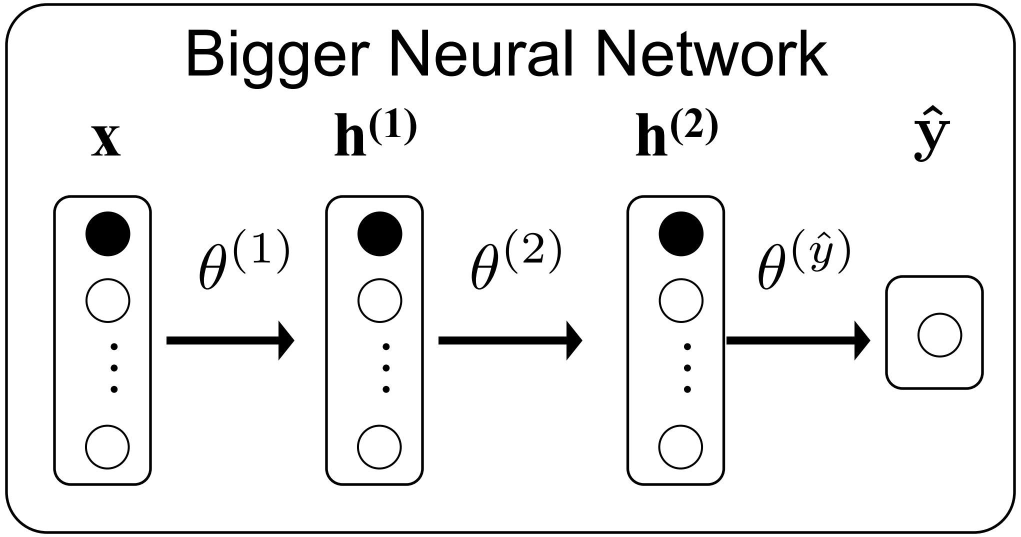
$$\frac{\partial LL(\theta)}{\partial \theta_i^{(\hat{y})}}$$

Loss with respect to hidden layer params

$$\frac{\partial LL(\theta)}{\partial \theta_{i,j}^{(h)}}$$



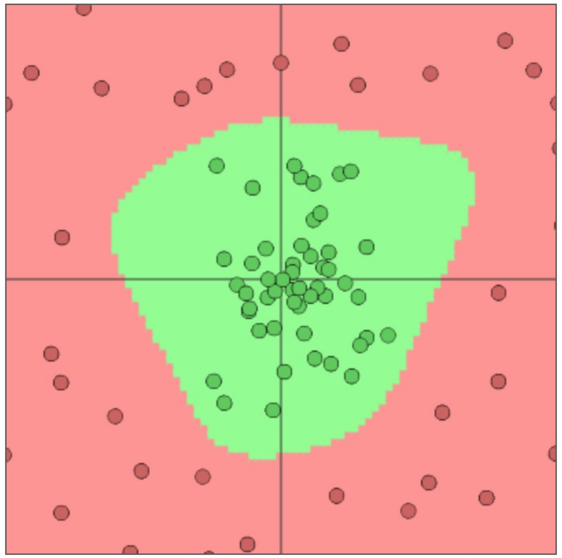
What Would You Do Here?

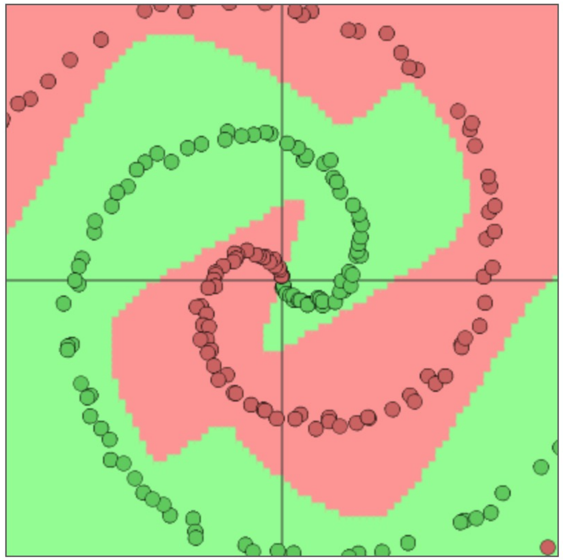


Chain rule:
Game changer for
artificial intelligence

Neural Networks Can Learn Complex Functions

- Some data sets/functions are not separable





  - These are classifiers learned by neural networks

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

Some Extra Ideas!

Multiple Outputs

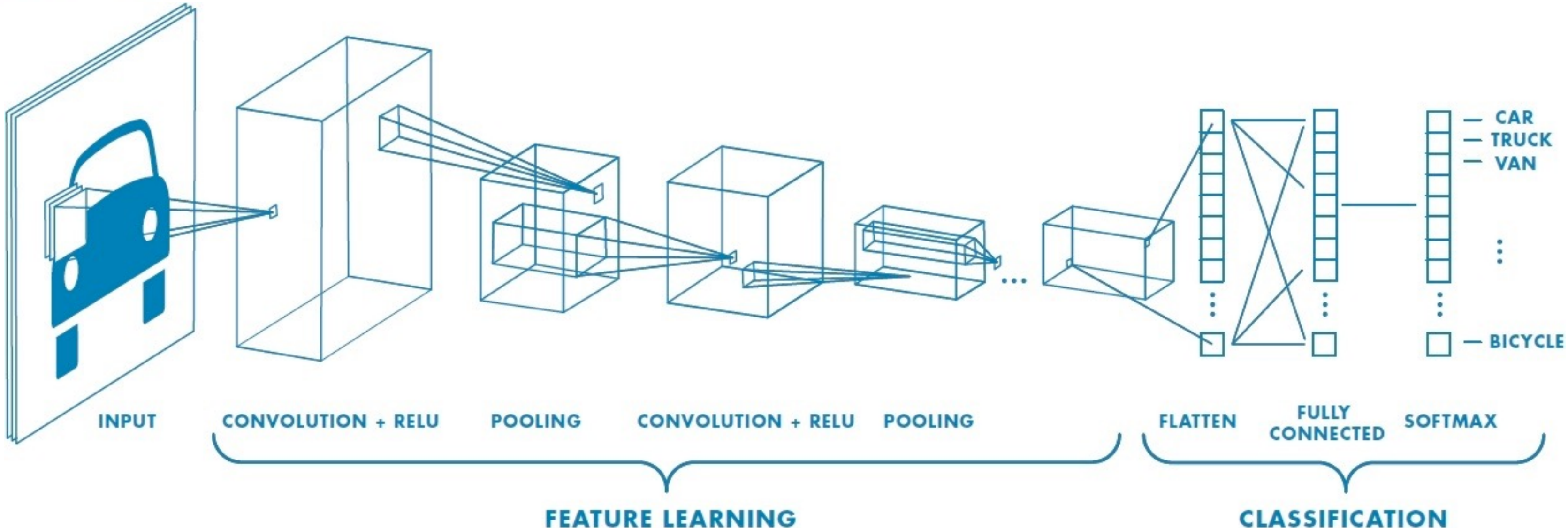
Multiple Output Classification?

Softmax is a generalization of the sigmoid function that squashes a K - dimensional vector $\mathbf{z}$ of arbitrary real values to a K-dimensional vector $\mathrm{softmax}(\mathbf{z})$ of real values in the range [0, 1] that add up to 1.

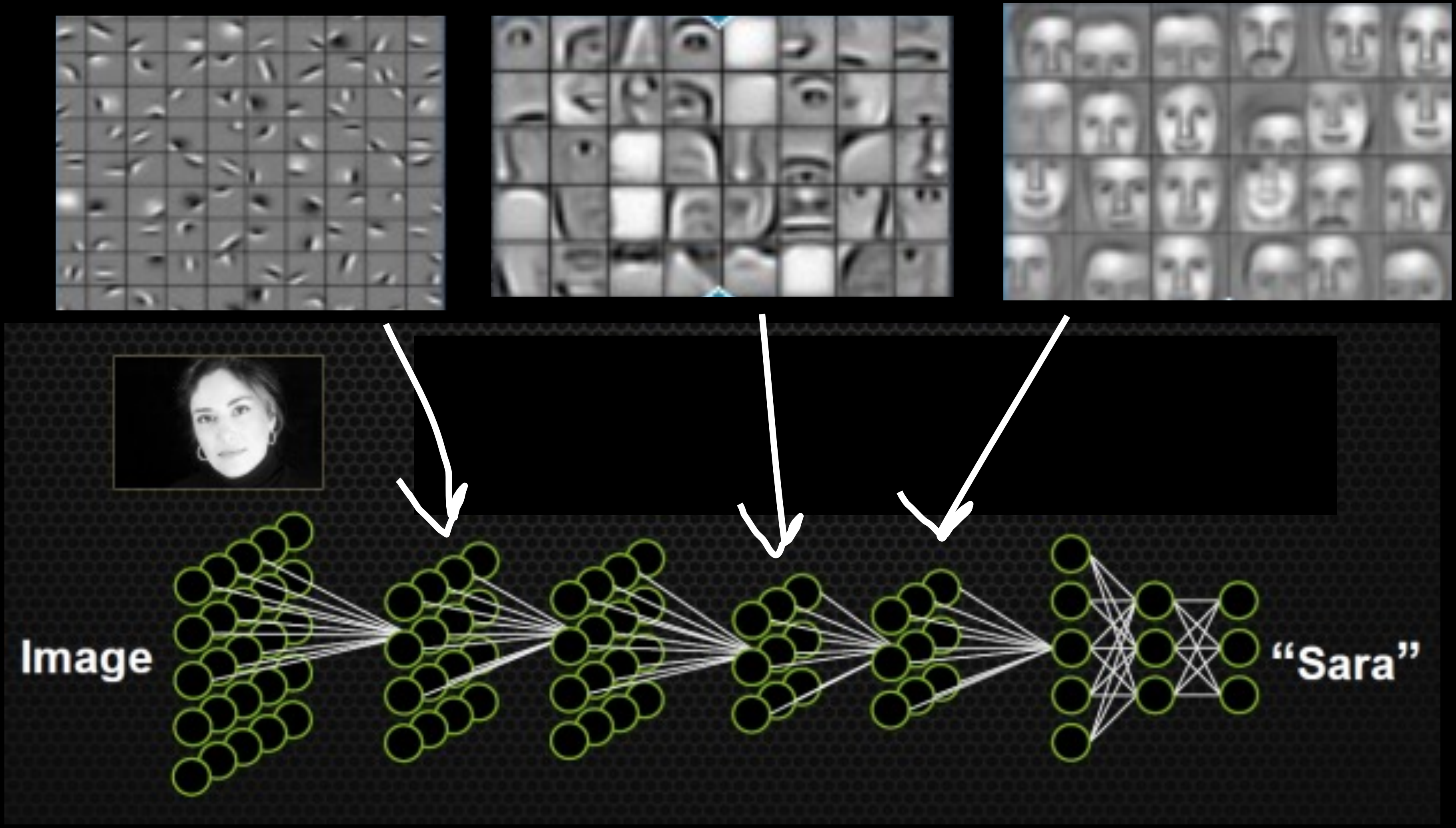
$$P(Y = j|\mathbf{X} = \mathbf{x}) = \mathrm{softmax}(f(\mathbf{x}))_j$$

Shared Weights?

Convolution it turns out if you want to force some of your weights to be shared for different neurons, the math isn't that much harder. This is used a lot for vision (CNN).

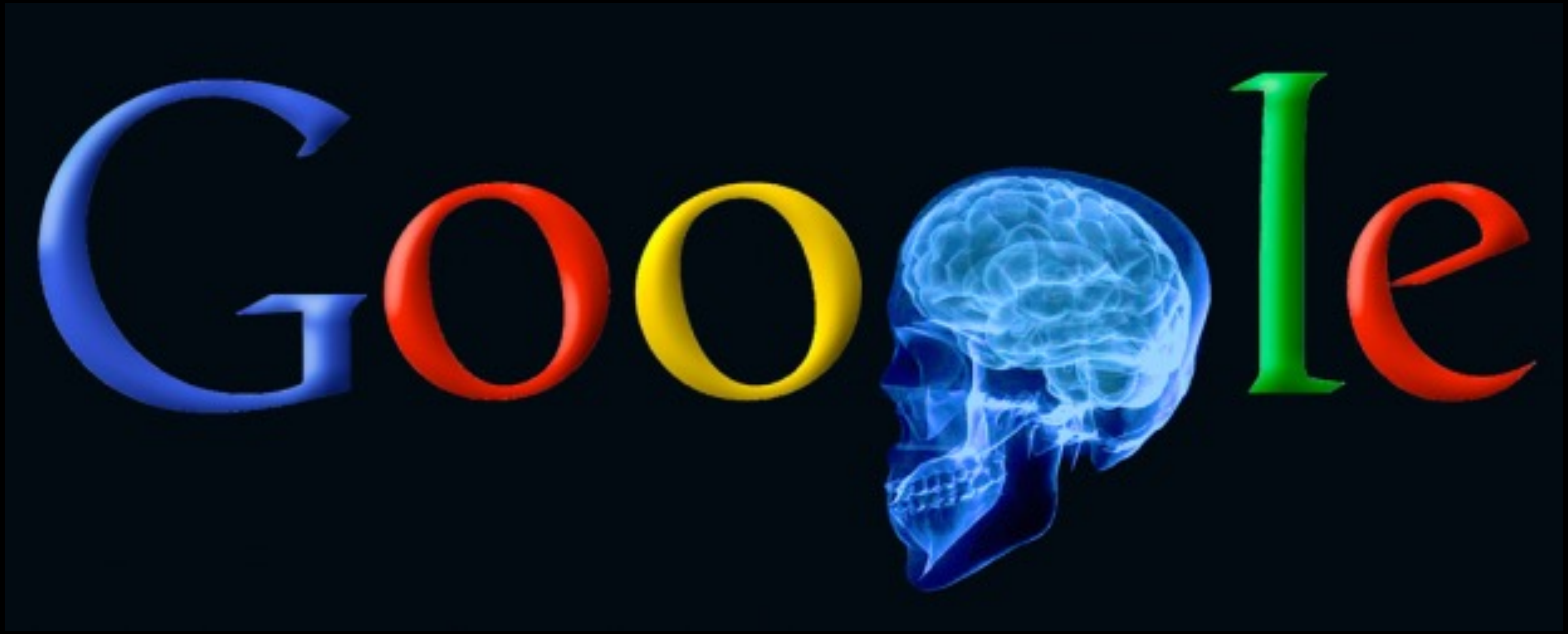


Works for any number of layers



x a b c d e f g LL

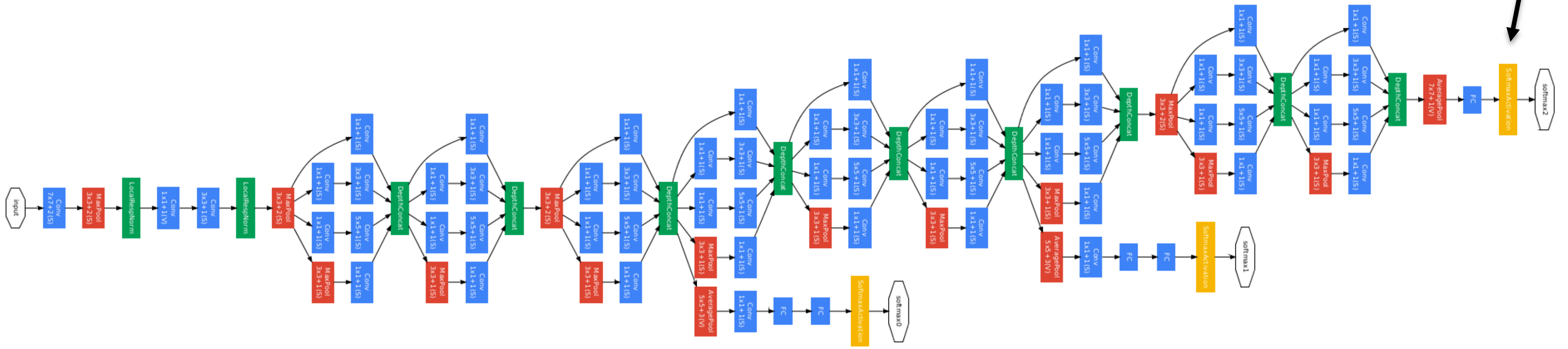
GoogLeNet Brain



1 Trillion Artificial Neurons

GoogLeNet Brain

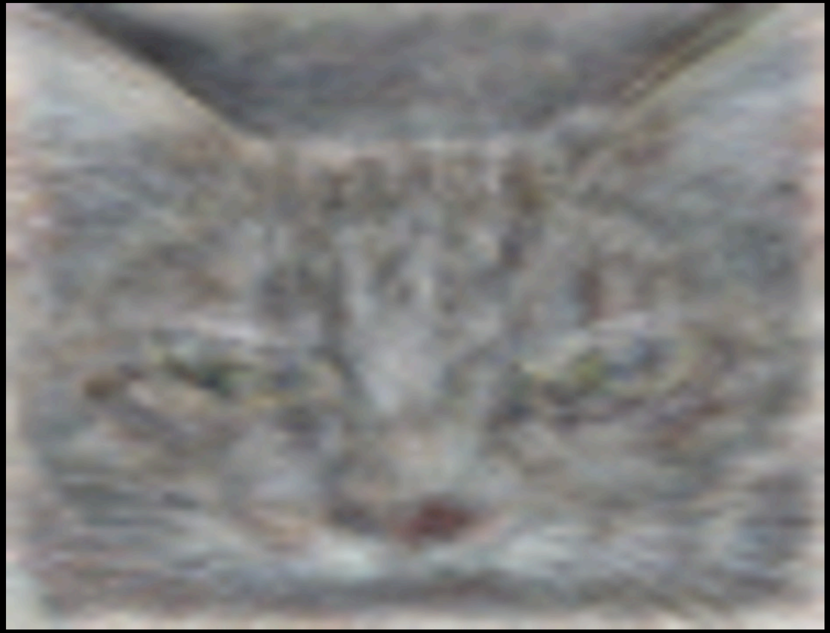
Multiple,
Multi class output



22 layers deep

The Cat Neuron

Top stimuli from the test set

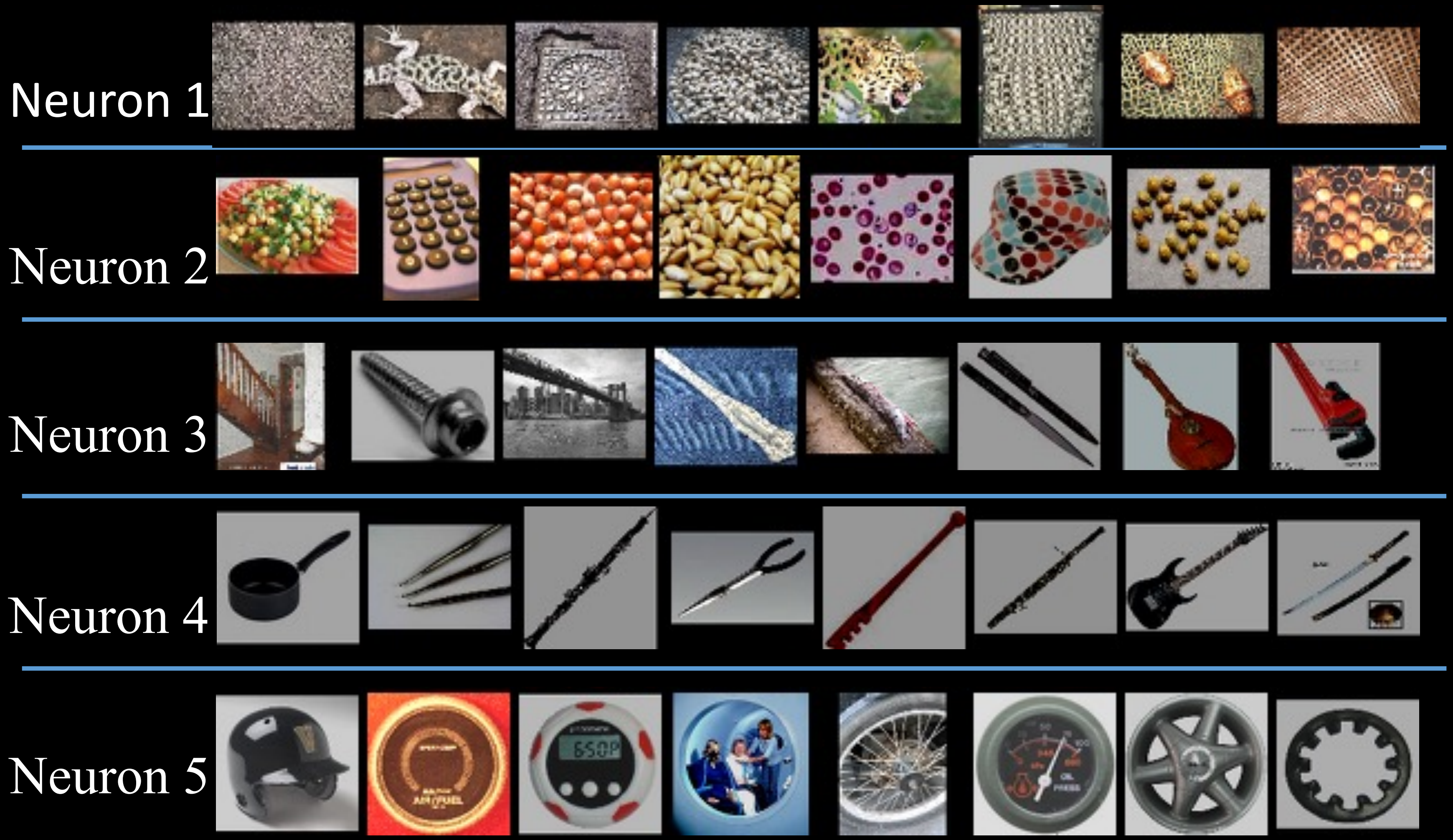


Optimal stimulus
by numerical optimization

Le, et al., *Building high-level features using large-scale unsupervised*

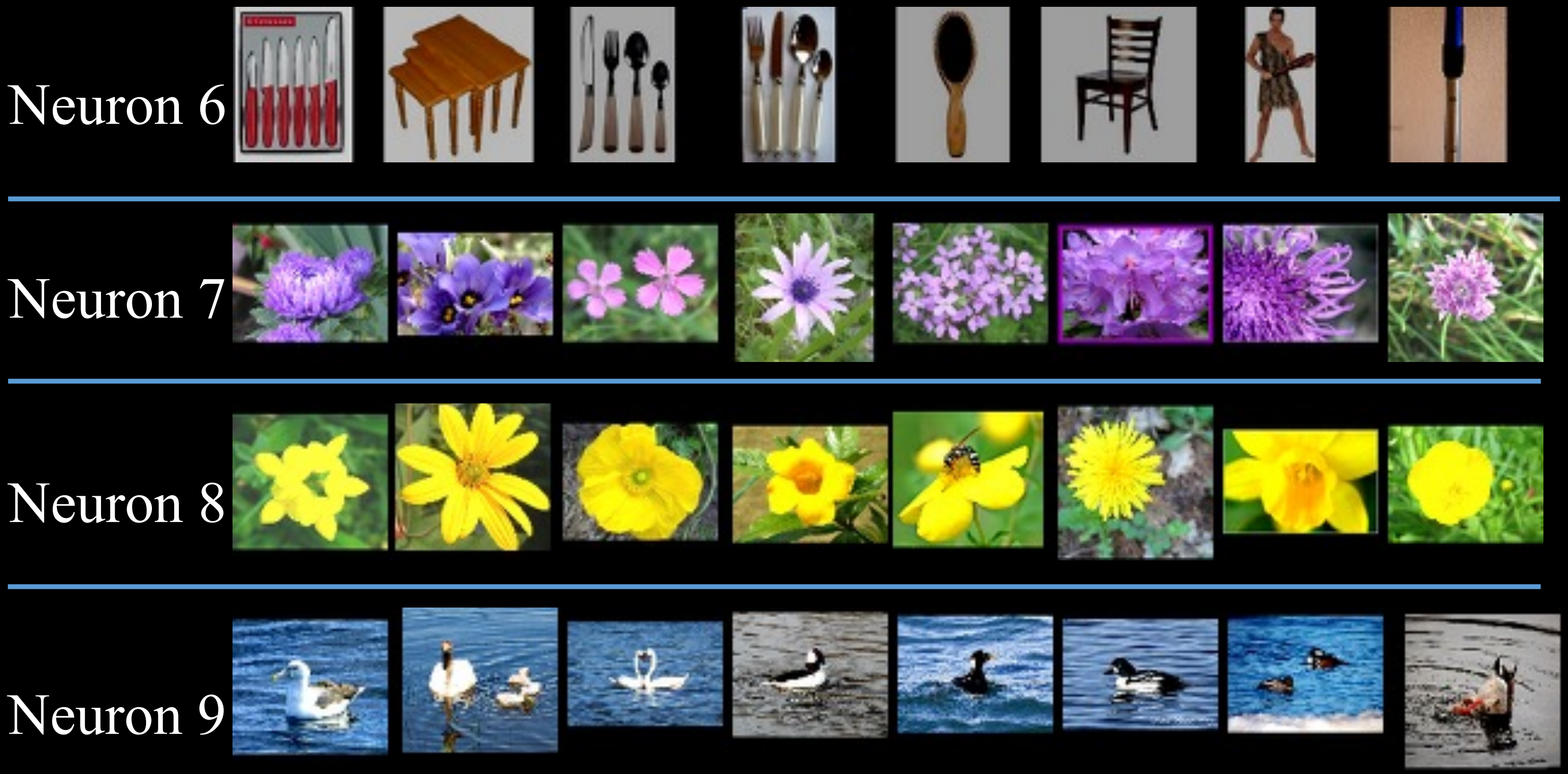

Hire the smartest people in the world
Invent cat detector

Best Neuron Stimuli



Le, et al., *Building high-level features using large-scale unsupervised*

Best Neuron Stimuli



Le, et al., *Building high-level features using large-scale unsupervised*

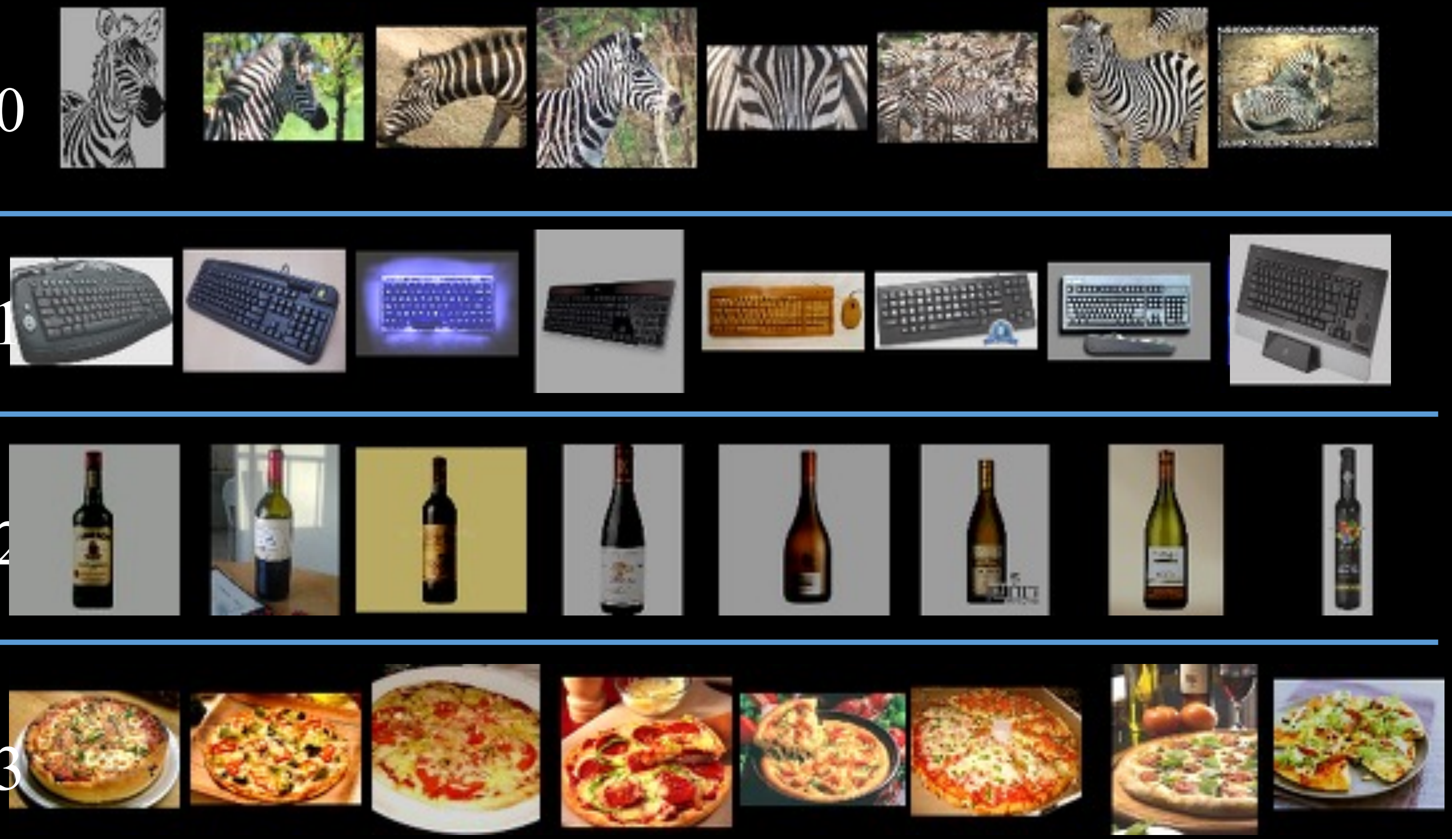
Best Neuron Stimuli

Neuron 10

Neuron 11

Neuron 12

Neuron 13



Le, et al., *Building high-level features using large-scale unsupervised*

ImageNet Classification

22,000 categories

14,000,000 images

Hand-engineered features (SIFT, HOG, LBP),
Spatial pyramid, SparseCoding/Compression

Le, et al., *Building high-level features using large-scale unsupervised*

22,000 is a lot!

…
smoothhound, smoothhound shark, Mustelus mustelus
American smooth dogfish, Mustelus canis
Florida smoothhound, Mustelus norrisi
whitetip shark, reef whitetip shark, Triaenodon obseus
Atlantic spiny dogfish, Squalus acanthias
Pacific spiny dogfish, Squalus suckleyi
hammerhead, hammerhead shark
smooth hammerhead, Sphyrna zygaena
smalleye hammerhead, Sphyrna tudes
shovelhead, bonnethead, bonnet shark, Sphyrna tiburo
angel shark, angelfish, Squatina squatina, monkfish
electric ray, crampfish, numbfish, torpedo
smalltooth sawfish, Pristis pectinatus
guitarfish
roughtail stingray, Dasyatis centroura
butterfly ray
eagle ray
spotted eagle ray, spotted ray, Aetobatus narinari
cownose ray, cow-nosed ray, Rhinoptera bonasus
manta, manta ray, devilfish
Atlantic manta, Manta birostris
devil ray, Mobula hypostoma
grey skate, gray skate, Raja batis
little skate, Raja erinacea
…

Stingray

Mantaray

0.005%	1.5%	?
Random guess	Pre Neural Networks	GoogLeNet

Le, et al., *Building high-level features using large-scale unsupervised*

0.005%	1.5%	43.9%
Random guess	Pre Neural Networks	GoogLeNet

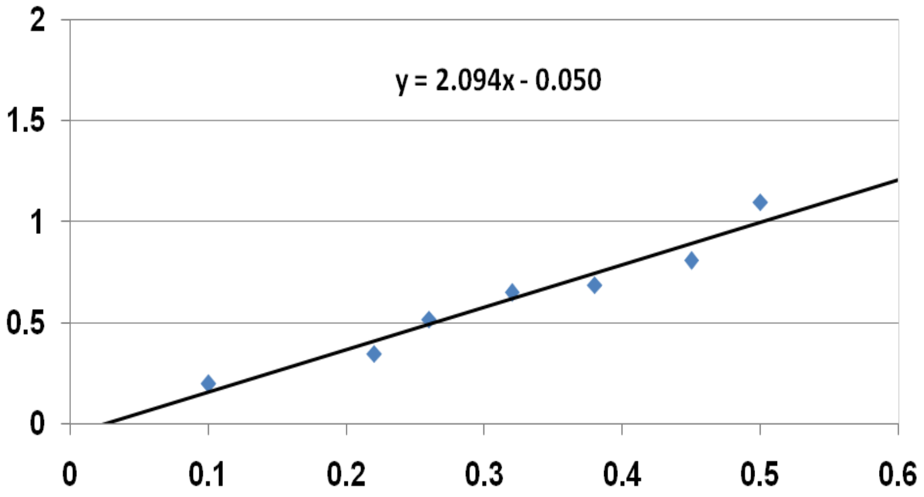
Szegedy et al, Going Deeper With Convolutions, CVPR 2015

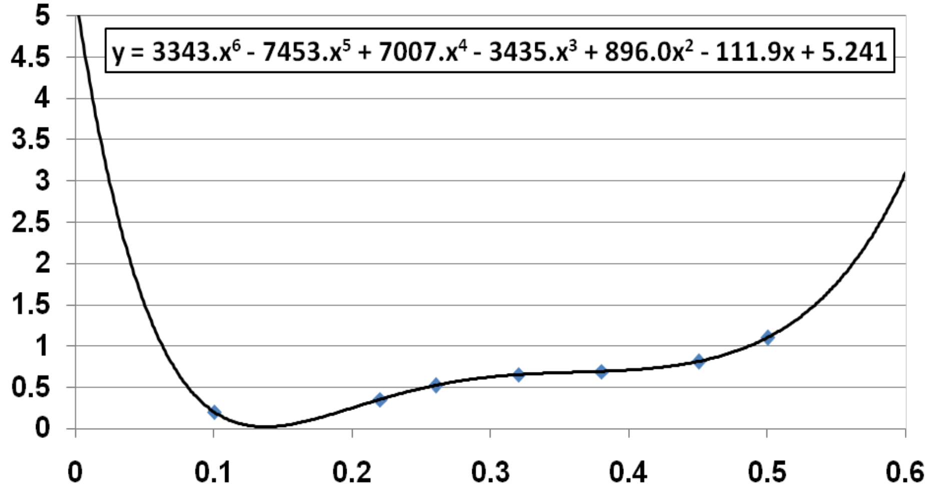
0.005%	1.5%	95.1%
Random guess	Pre Neural Networks	SE-ResNet

How many parameters
is too many?

Good ML = Generalization

- Goal of machine learning: build models that ***generalize*** well to predicting new data
  - “Overfitting”: fitting the training data too well, so we lose generality of model

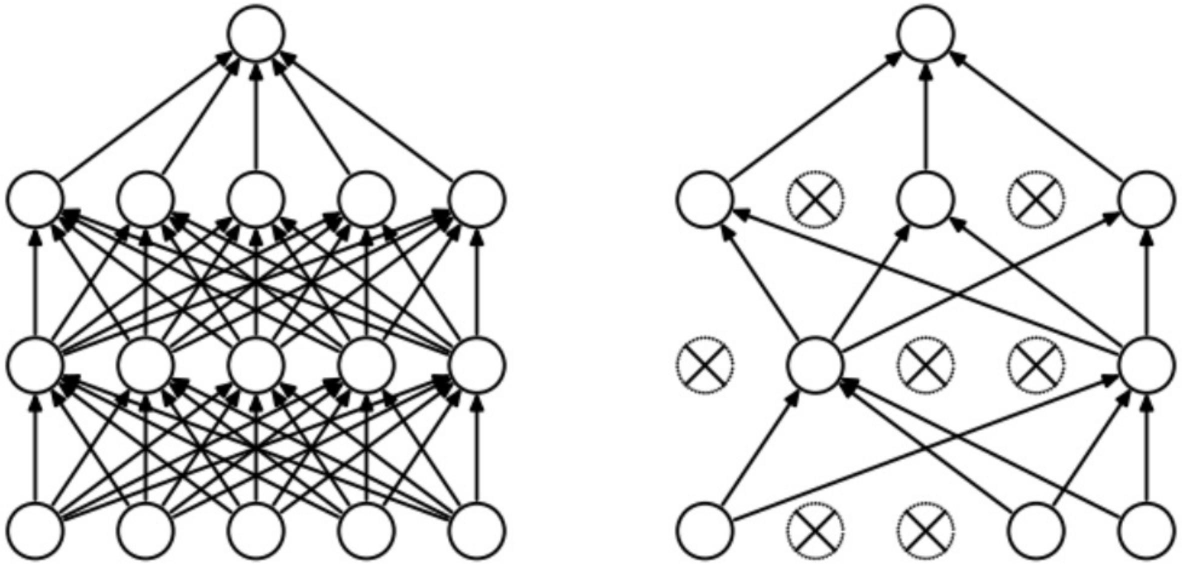




  - Polynomial on the right fits training data perfectly!
  - Which would you rather use to predict a new data point?

Prevent Overfitting?

Dropout when your model is training, randomly turn off your neurons with probability 0.5. It will make your network more robust.



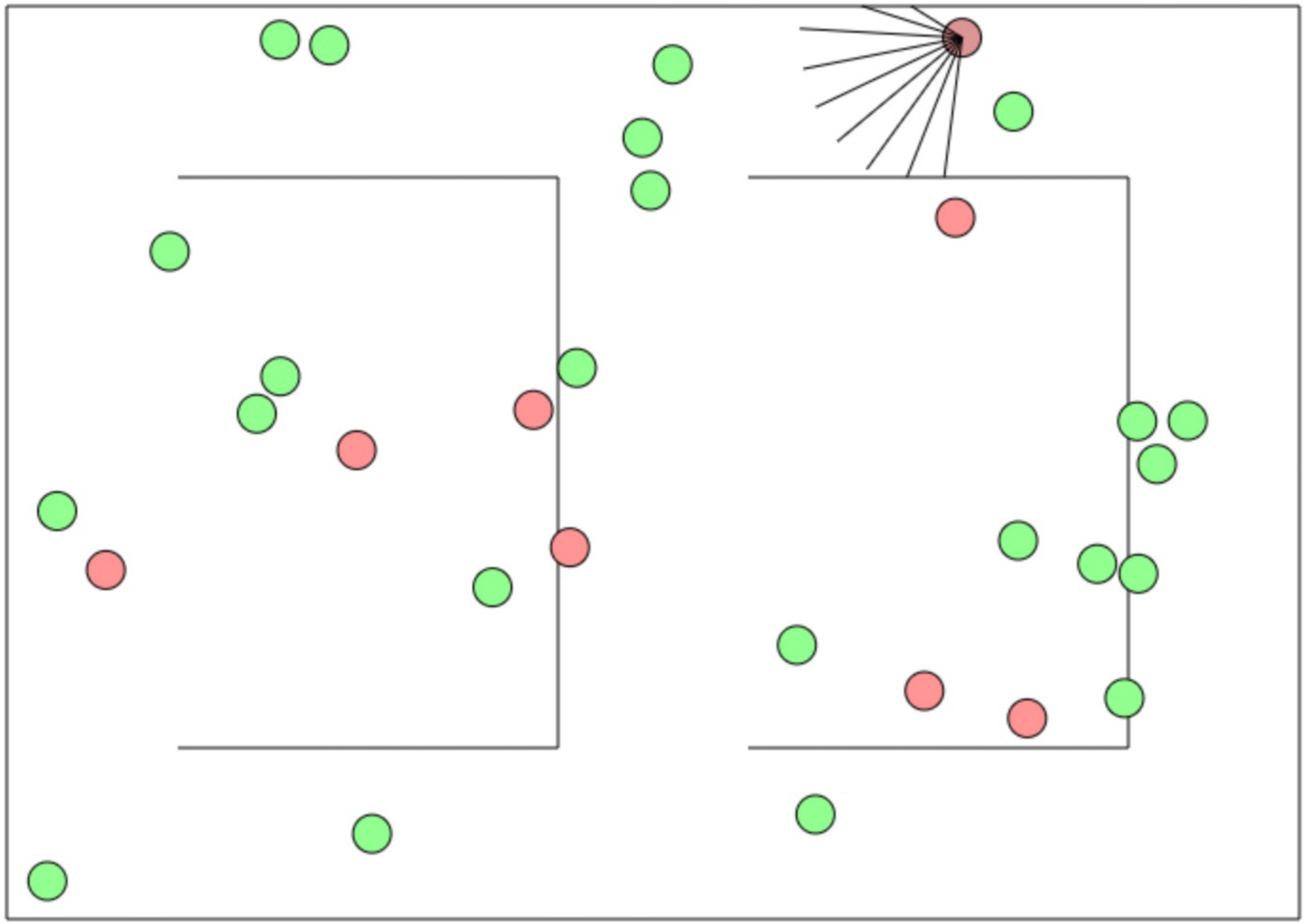
(a) Standard Neural Net (b) After applying dropout.

Not everything is classification

Making Decisions?

Deep Reinforcement Learning
Instead of having the output of a model be a probability you can make it an expectation.

Deep Reinforcement Learning

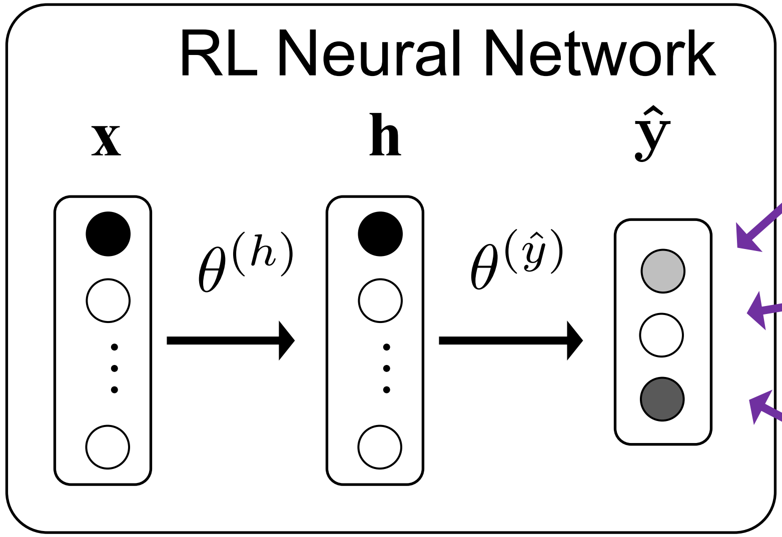


http://cs.stanford.edu/people/karpathy/convnetjs/demo/rldemo.html

Deep Reinforcement Learning

R is a reward and A_i is a legal action

Input is a representation of current state (S)



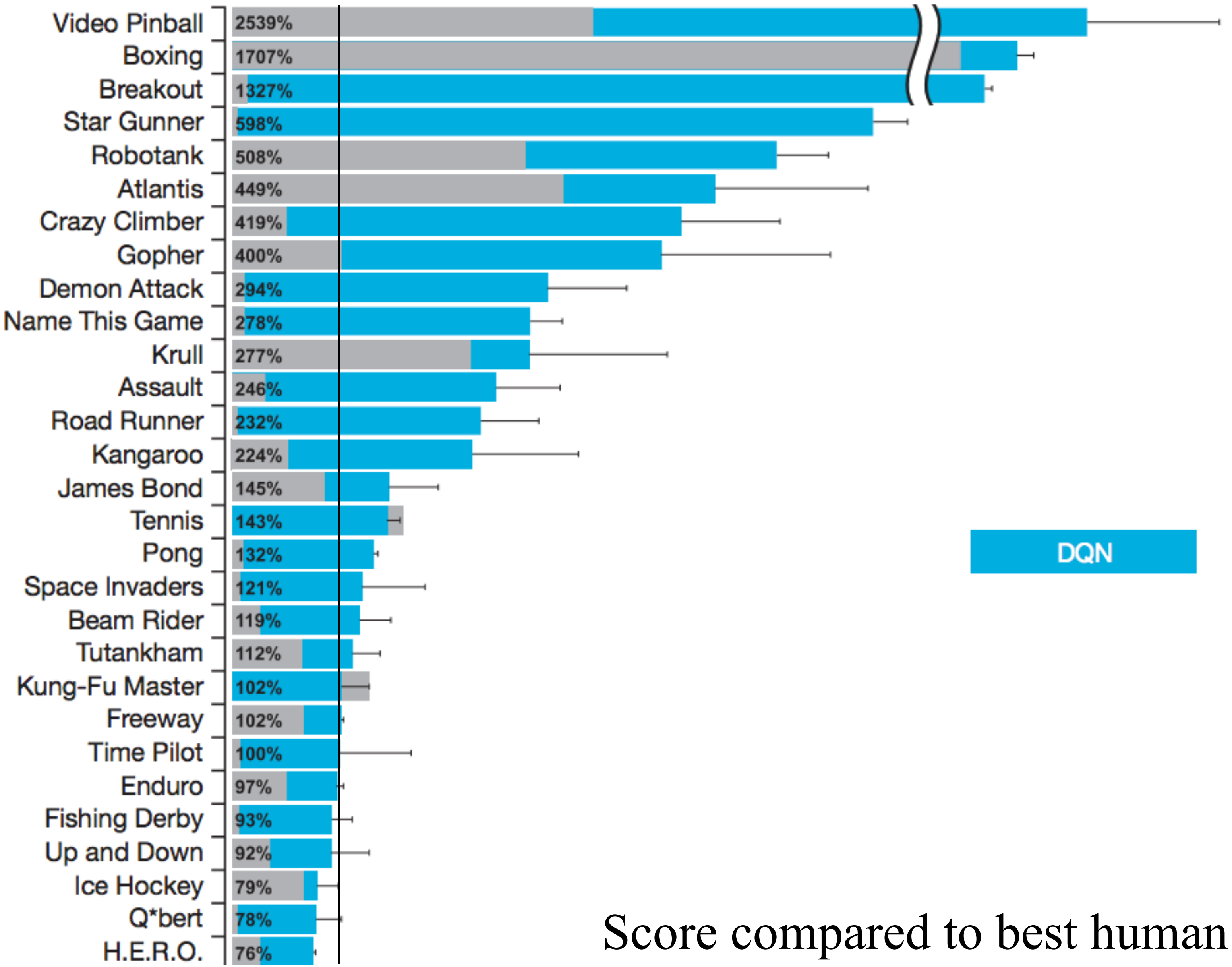
$E[R \mid A_1, S]$

$E[R \mid A_2, S]$

$E[R \mid A_3, S]$

Interpret outputs as expected reward for a given action

Deep Mind Atari Games



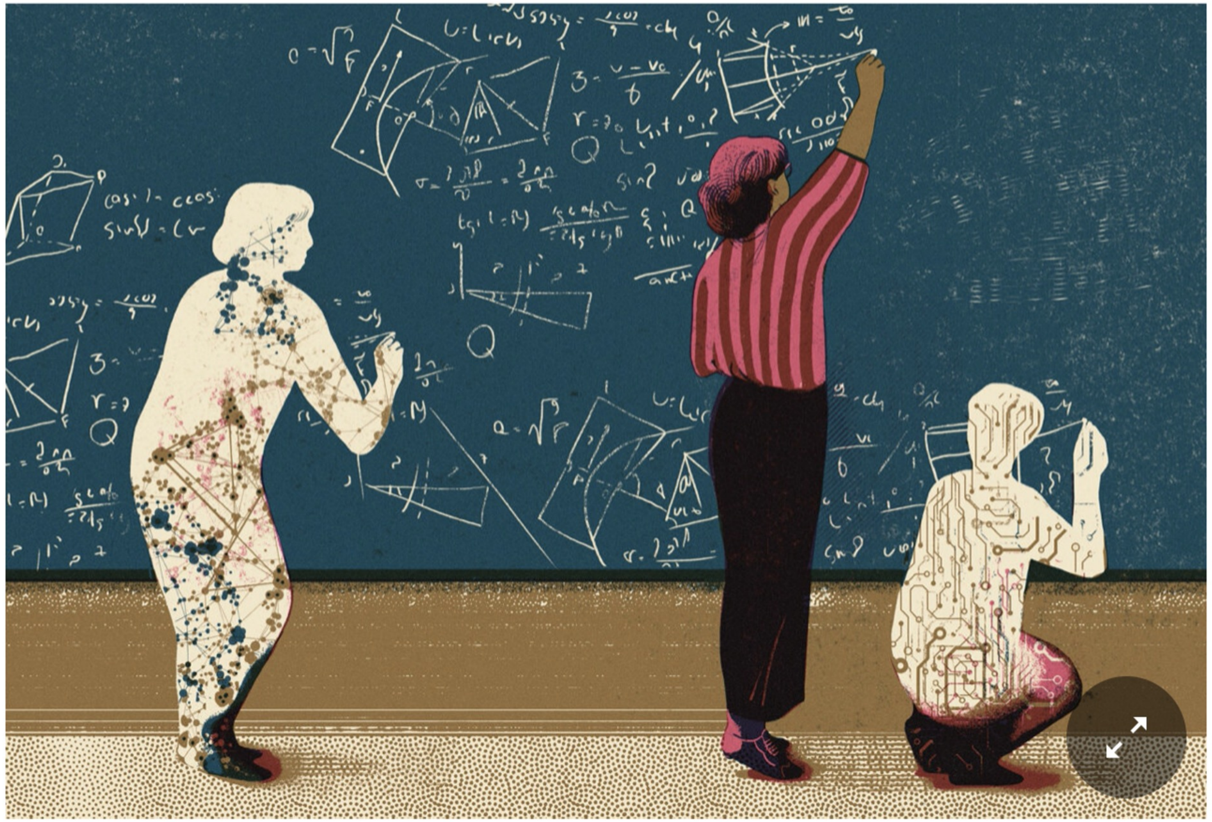
Score compared to best human

The New York Times

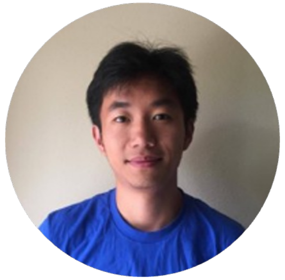
Stanford | News

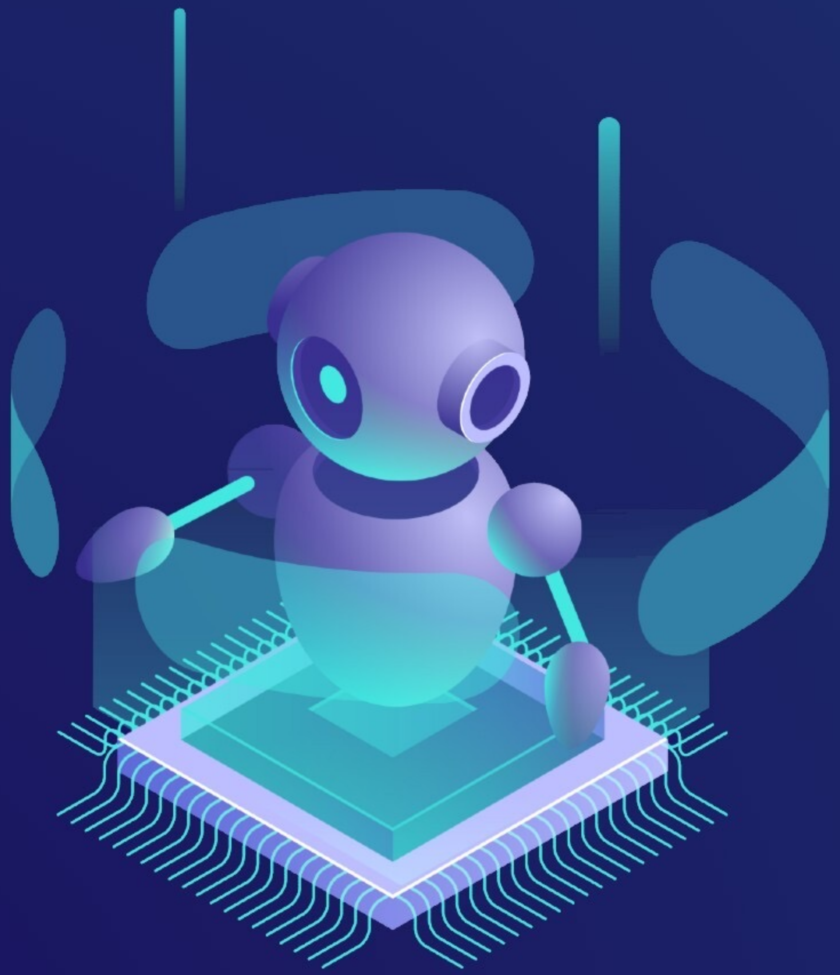
Can A.I. Grade Your Next Test?

Neural networks could give online education a boost by providing automated feedback to students.



https://www.nytimes.com/2021/07/20/technology/ai-education-neural-networks.html





GPT-3