94-775 Lecture 10: Introduction to Neural Nets and Deep Learning

George Chen

A few slides are by Phillip Isola

Comments on the Final Project

- Final project presentation times will be **randomized**
  - Unless your team really, really wants to present next Tuesday
- Minis are short, and we understand that there isn't that much time to do the project
  - Analysis: prioritize easier things first
  - Negative results are fine provided that **you've correctly put together a well-thought out experiment**

IMAGENET

Over 10 million images, 1000 object classes

2011: Traditional computer vision achieves accuracy ~74%

2012: Initial deep neural network approach accuracy ~84%

2015 onwards: Deep learning achieves accuracy 96%+

Russakovsky et al. ImageNet Large Scale Visual Recognition Challenge. IJCV 2015.

Deep Learning Takeover

Academia:

- Top computer vision conferences (CVPR, ICCV, ECCV) are now nearly all about deep learning
- Top machine learning conferences (ICML, NIPS) have *heavily* been taken over by deep learning

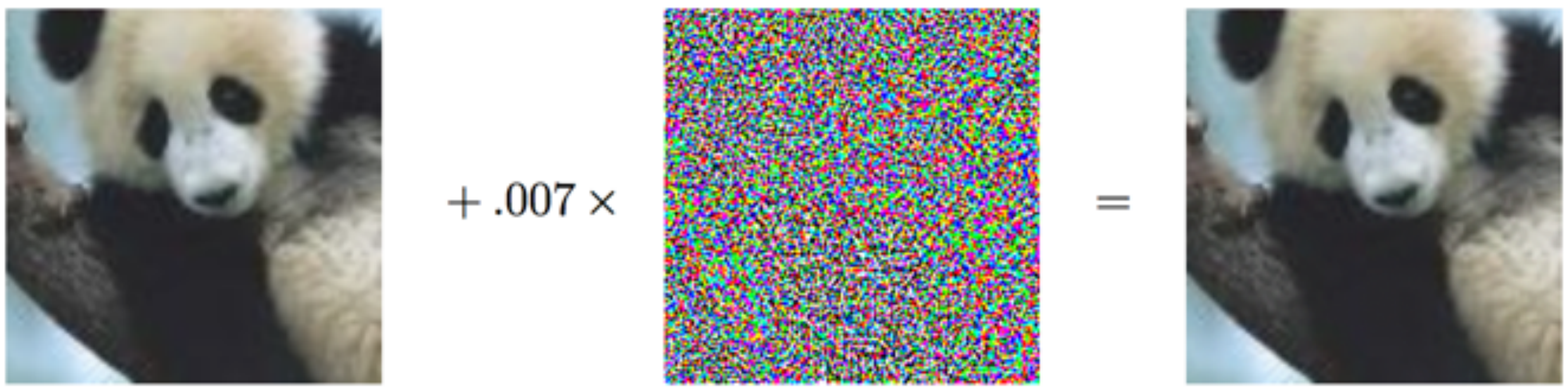
Heavily dominated by industry now!

Extremely useful in practice:

- Near human level image classification (including handwritten digit recognition)
- Near human level speech recognition
- Improvements in machine translation, text-to-speech
- Self-driving cars
- *Better* than humans at playing Go

Google DeepMind’s AlphaGo vs Lee Sedol, 2016

Is it all hype?



panda
~58% confidence

adversarial
noise

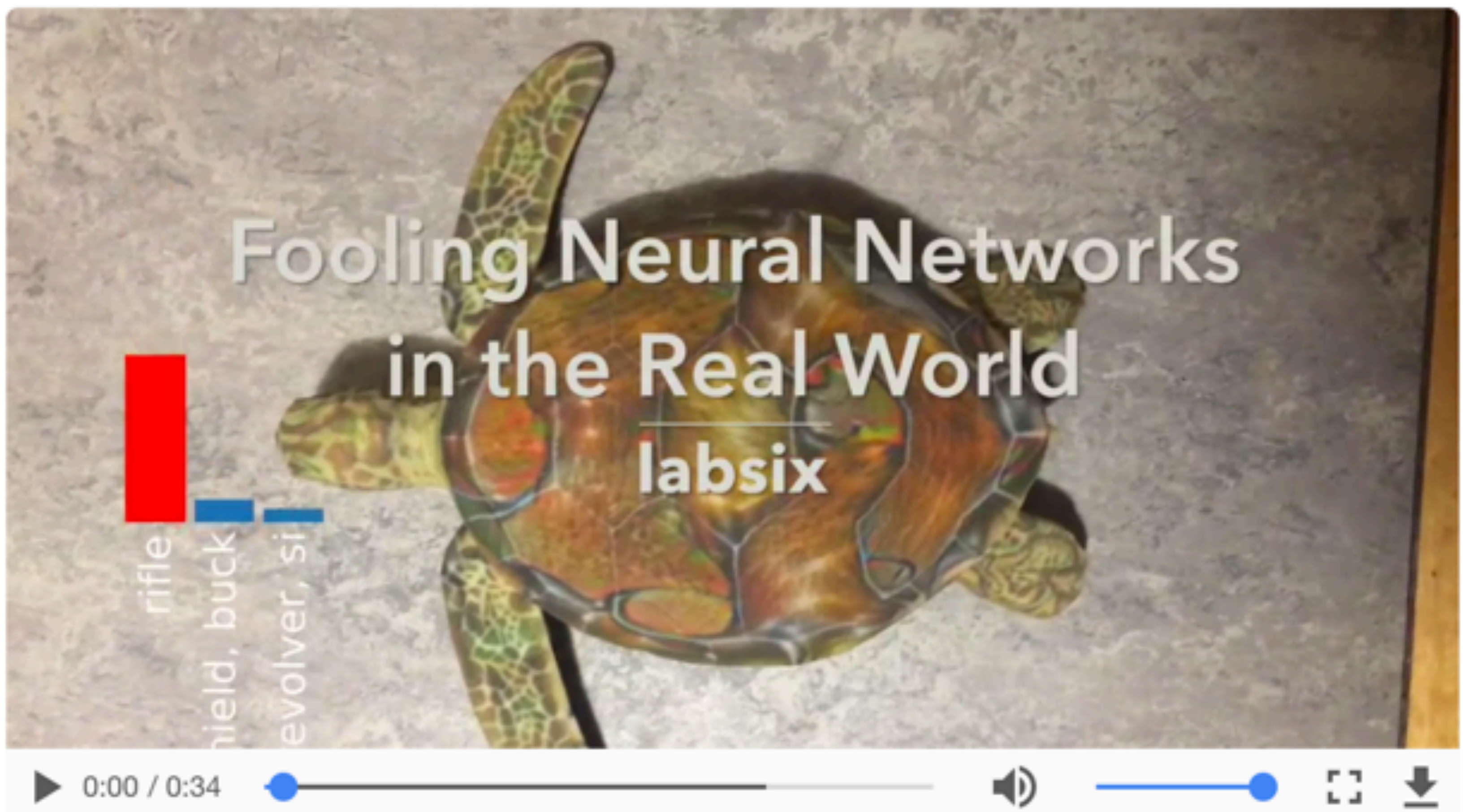
gibbon
~99% confidence

Source: Goodfellow, Shlens, and Szegedy. Explaining and Harnessing Adversarial Examples. ICLR 2015.

Fooling Neural Networks in the Physical World with 3D Adversarial Objects

31 Oct 2017 · 3 min read — shared on Hacker News, Lobsters, Reddit, Twitter

We've developed an approach to generate *3D adversarial objects* that reliably fool neural networks in the real world, no matter how the objects are looked at.



Neural network based classifiers reach near-human performance in many tasks, and they're used in high risk, real world systems. Yet, these same neural networks are particularly vulnerable to *adversarial examples*, carefully perturbed inputs that cause

Source: labsix

Source: Gizmodo article "This Neural Network's Hilariously Bad Image Descriptions Are Still Advanced AI". September 16, 2015. (They're using the NeuralTalk image-to-caption software.)

Another AI Winter?

~1970's: First AI winter over symbolic AI

~1980's: Second AI winter over "expert systems"

Every time: Lots of hype, explosion in funding, then bubble bursts

About membership

Medium

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Michael Jordan Follow

Michael I. Jordan is a Professor in the Department of Electrical Engineering and Computer Sciences and the Department of Statistics at UC Berkeley.

Apr 18 · 16 min read

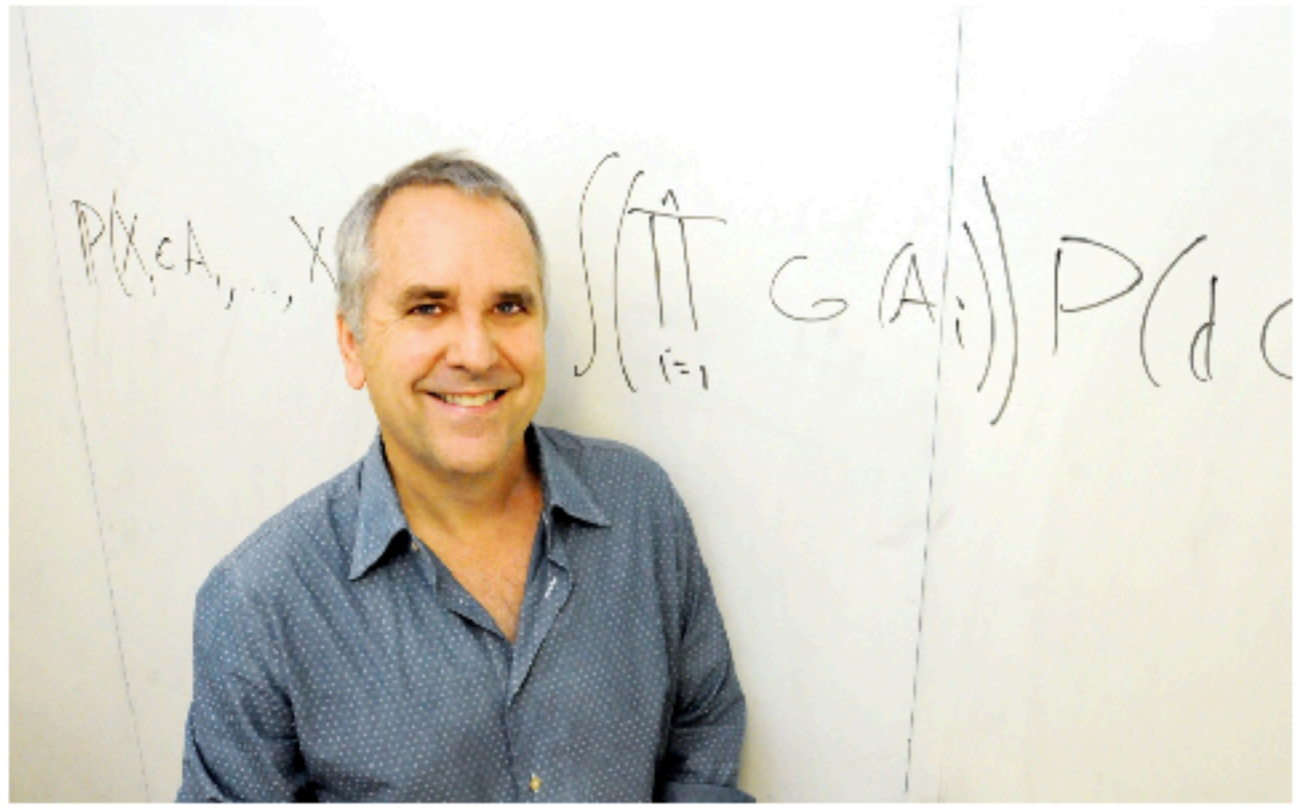


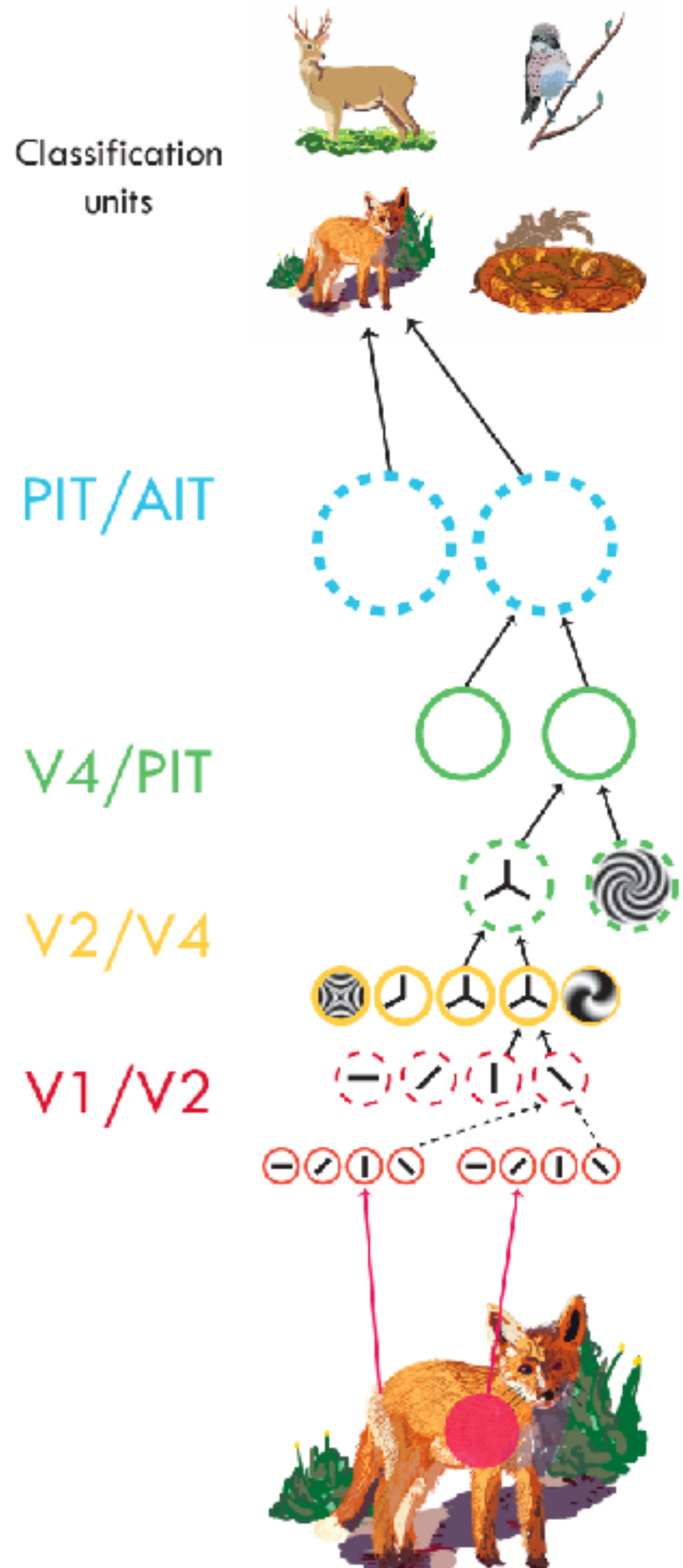
Photo credit: Peg Skorpinski

Artificial Intelligence—The Revolution Hasn't Happened Yet

Artificial Intelligence (AI) is the mantra of the current era. The phrase is intoned by technologists, academicians, journalists and venture capitalists

https://medium.com/@mijordan3/artificial-intelligence-the-revolution-hasnt-happened-yet-5e1d5812e1e7

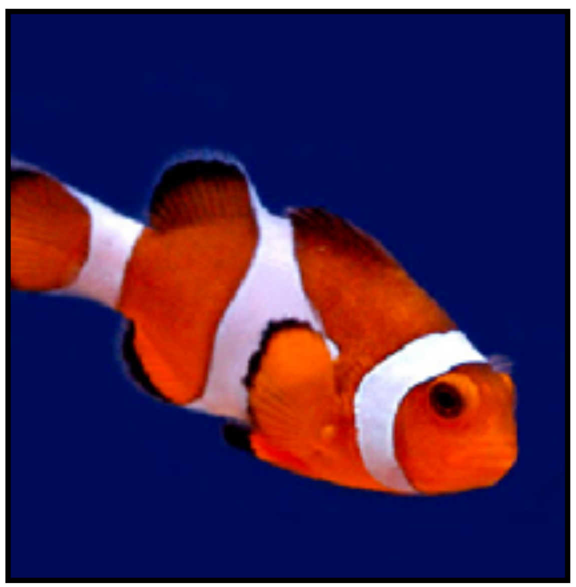
What is deep learning?



Slide by Phillip Isola

Serre, 2014

Basic Idea



→ Brain/Machine → "clown fish"

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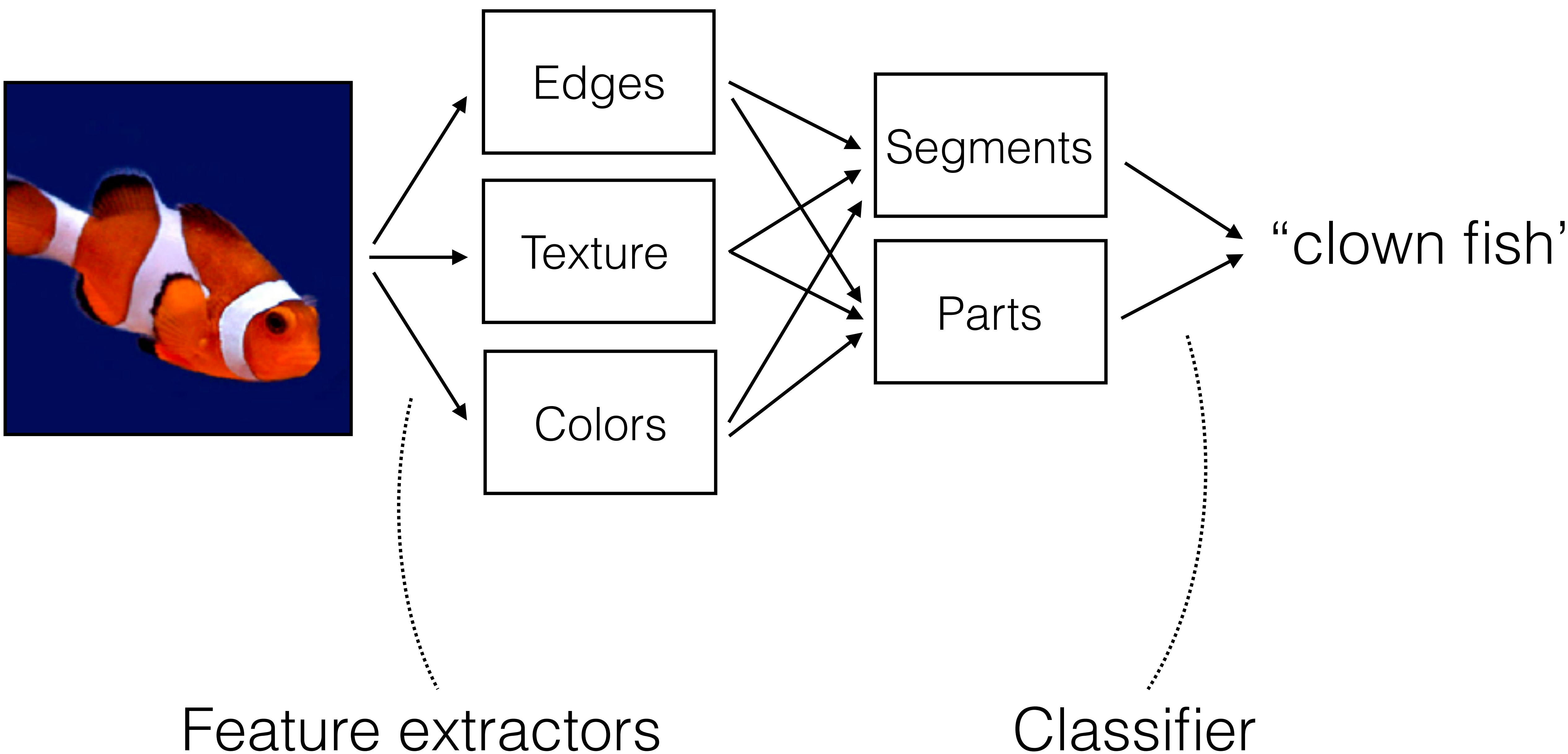
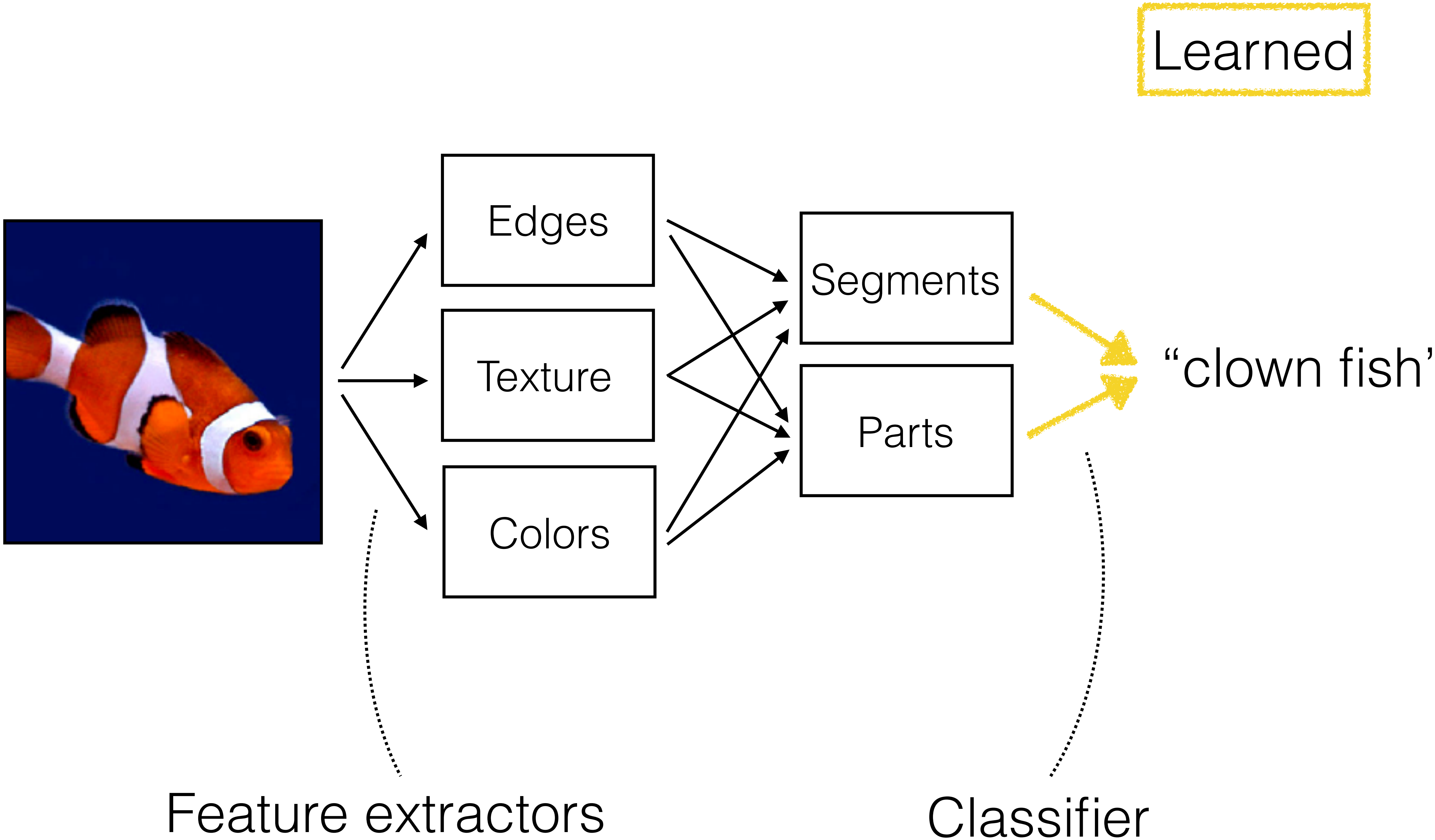
Object Recognition



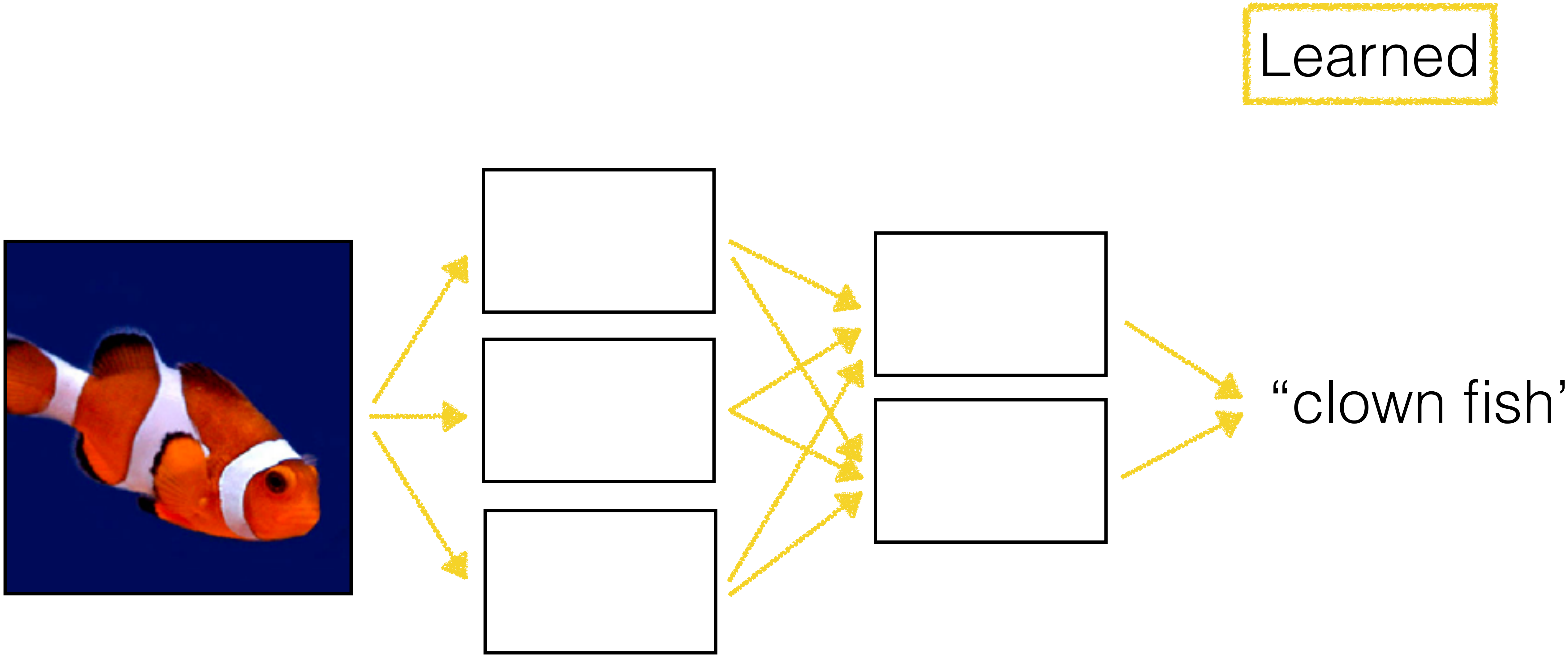
Slide by Phillip Isola

Object Recognition



Slide by Phillip Isola

Neural Network



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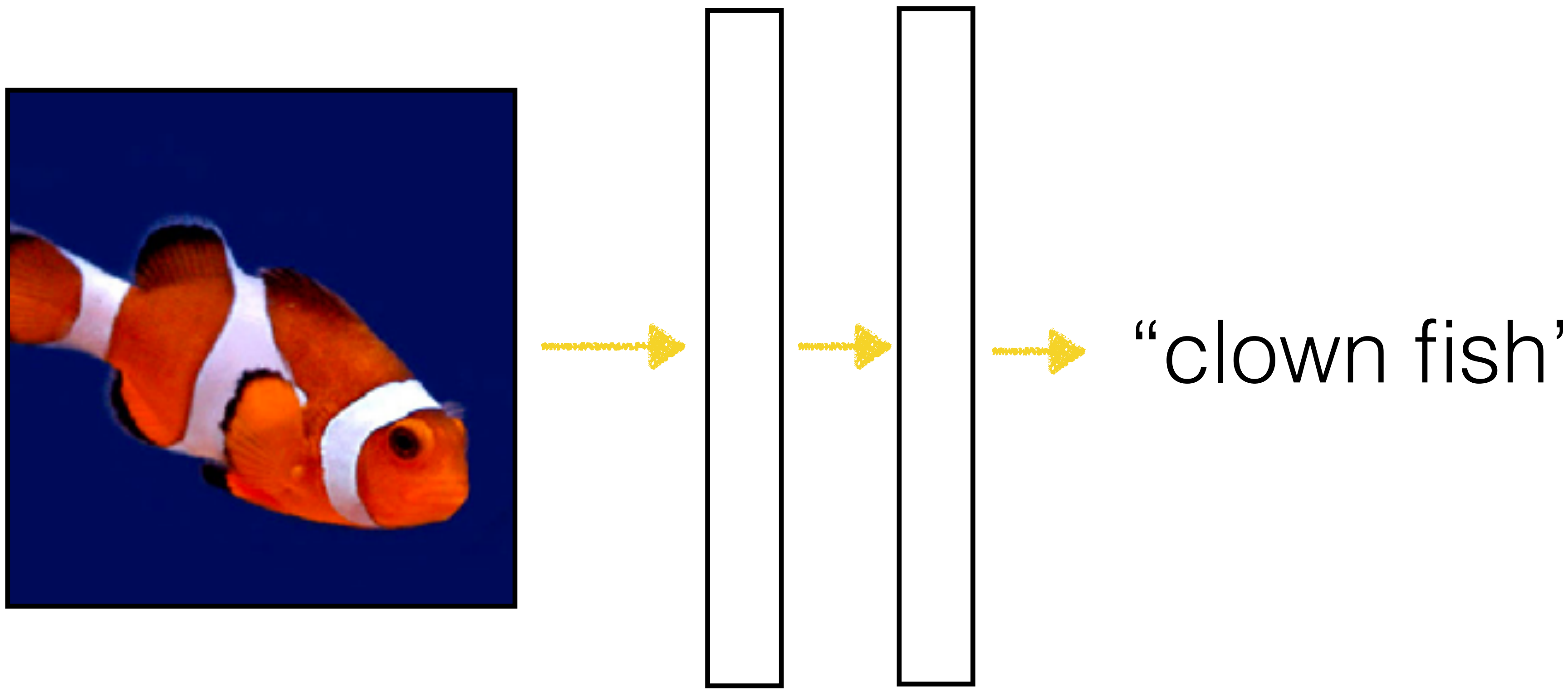
Neural Network

Learned



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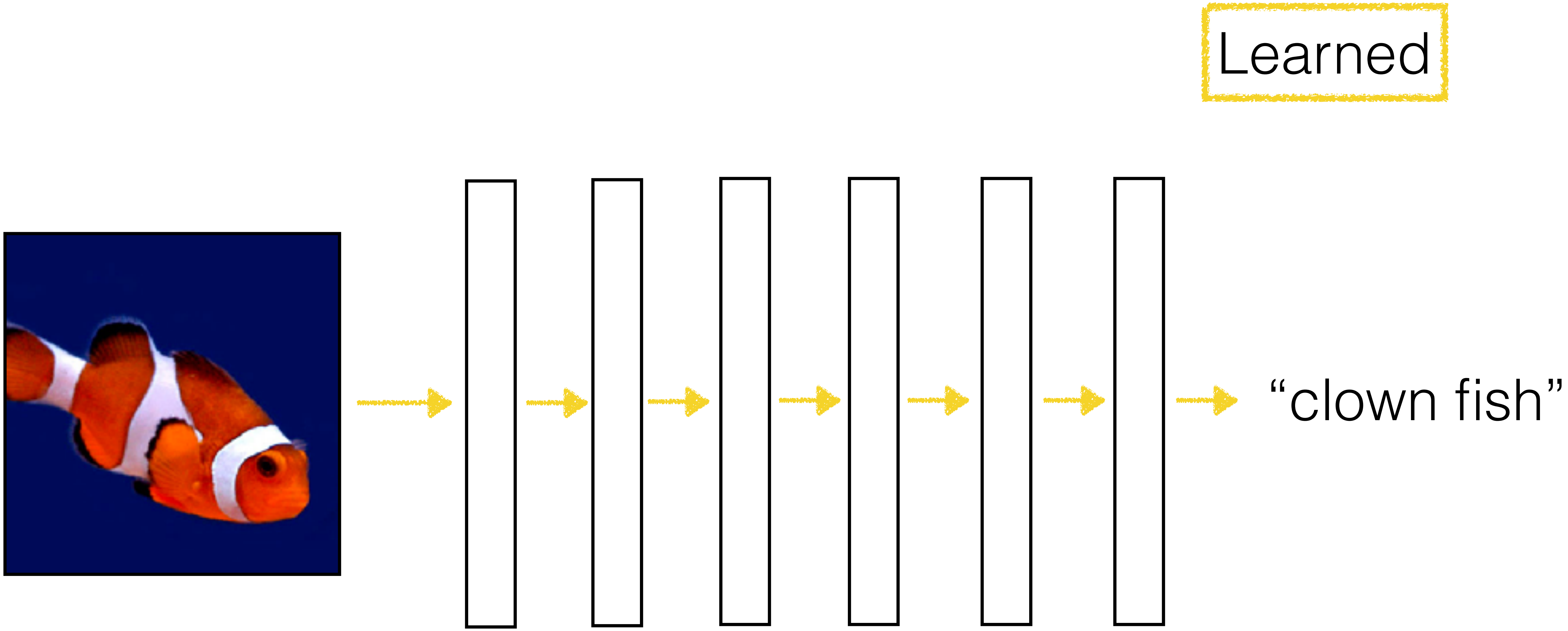
Deep Neural Network



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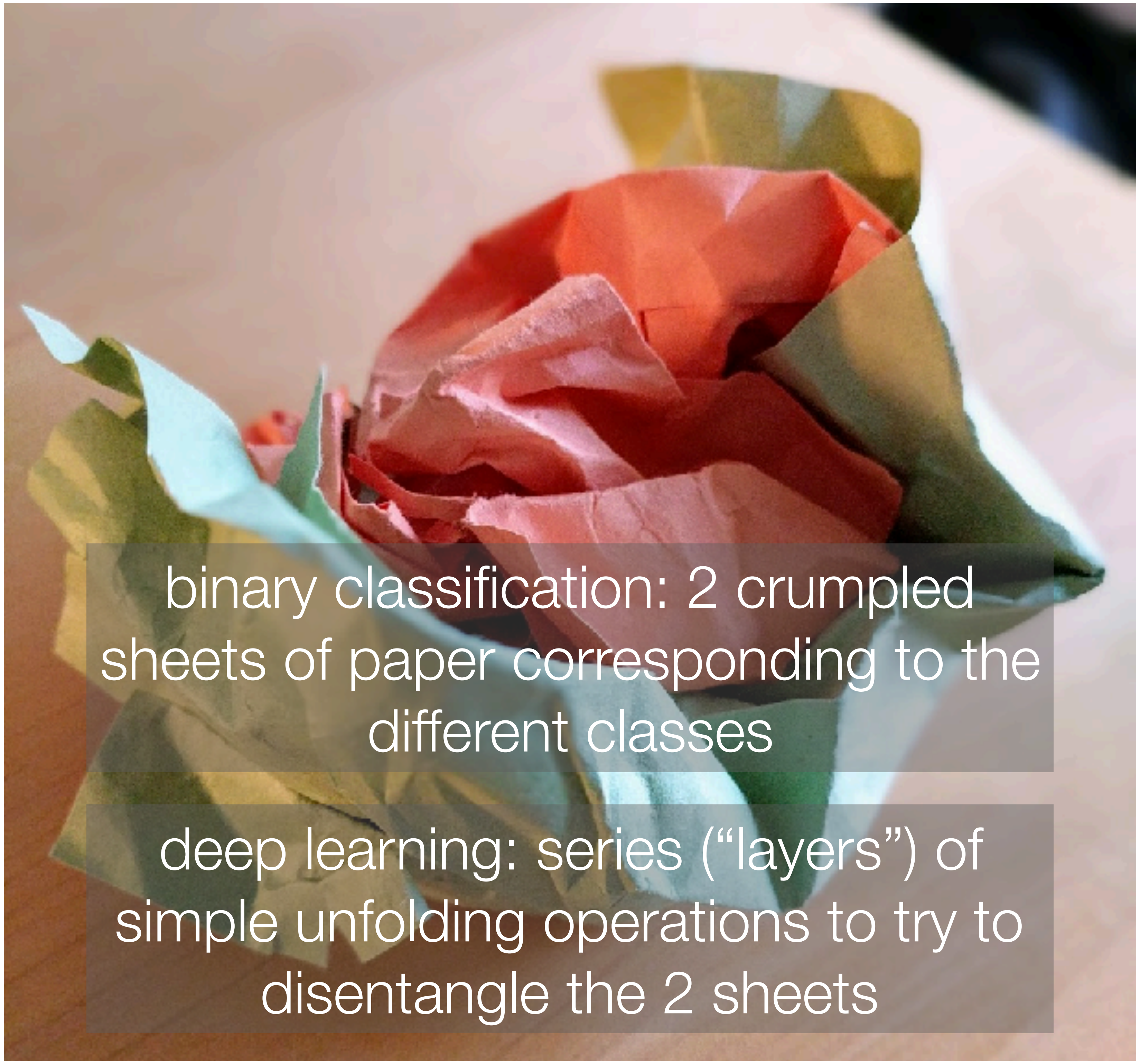
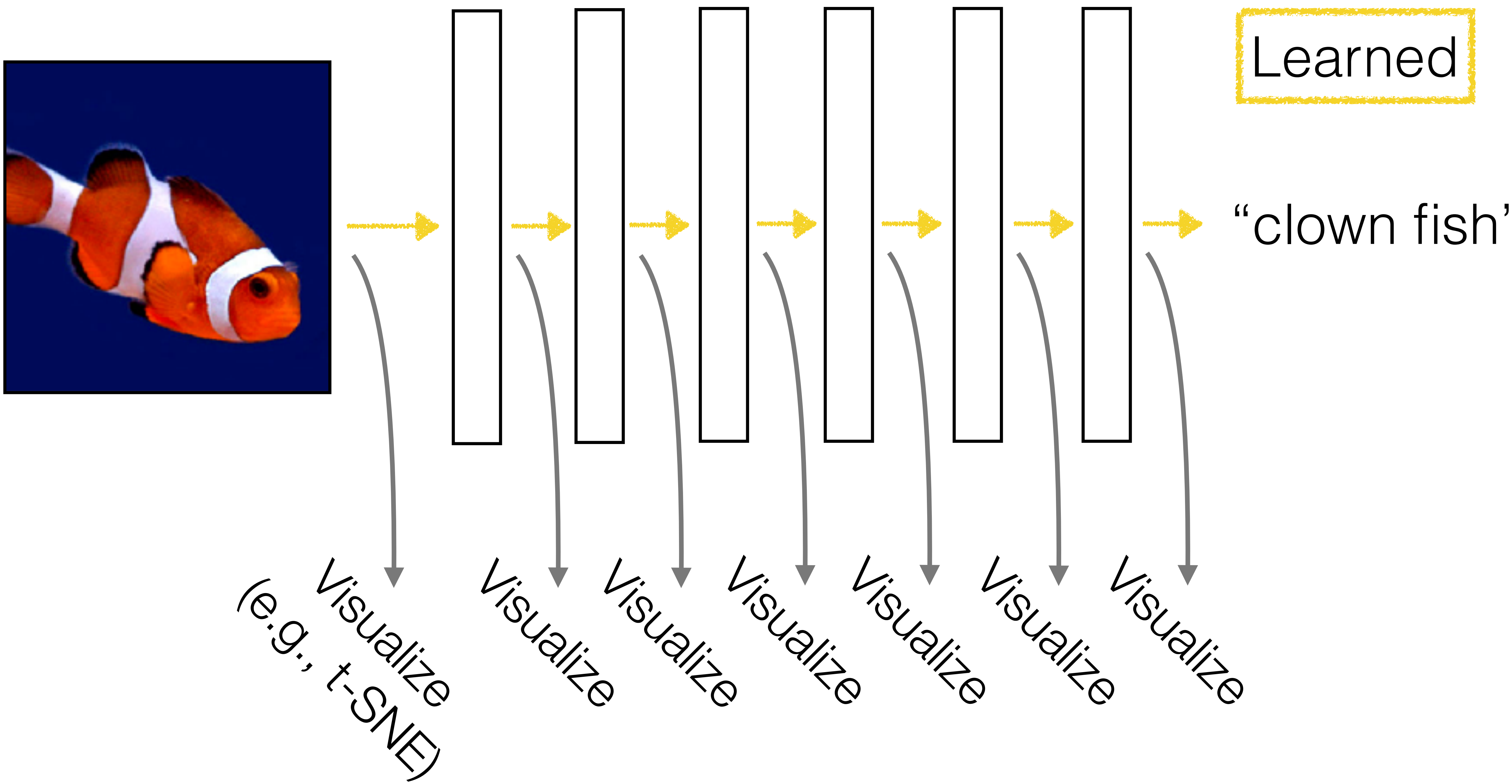
Crumpled Paper Analogy



Analogy: Francois Chollet, photo: George Chen

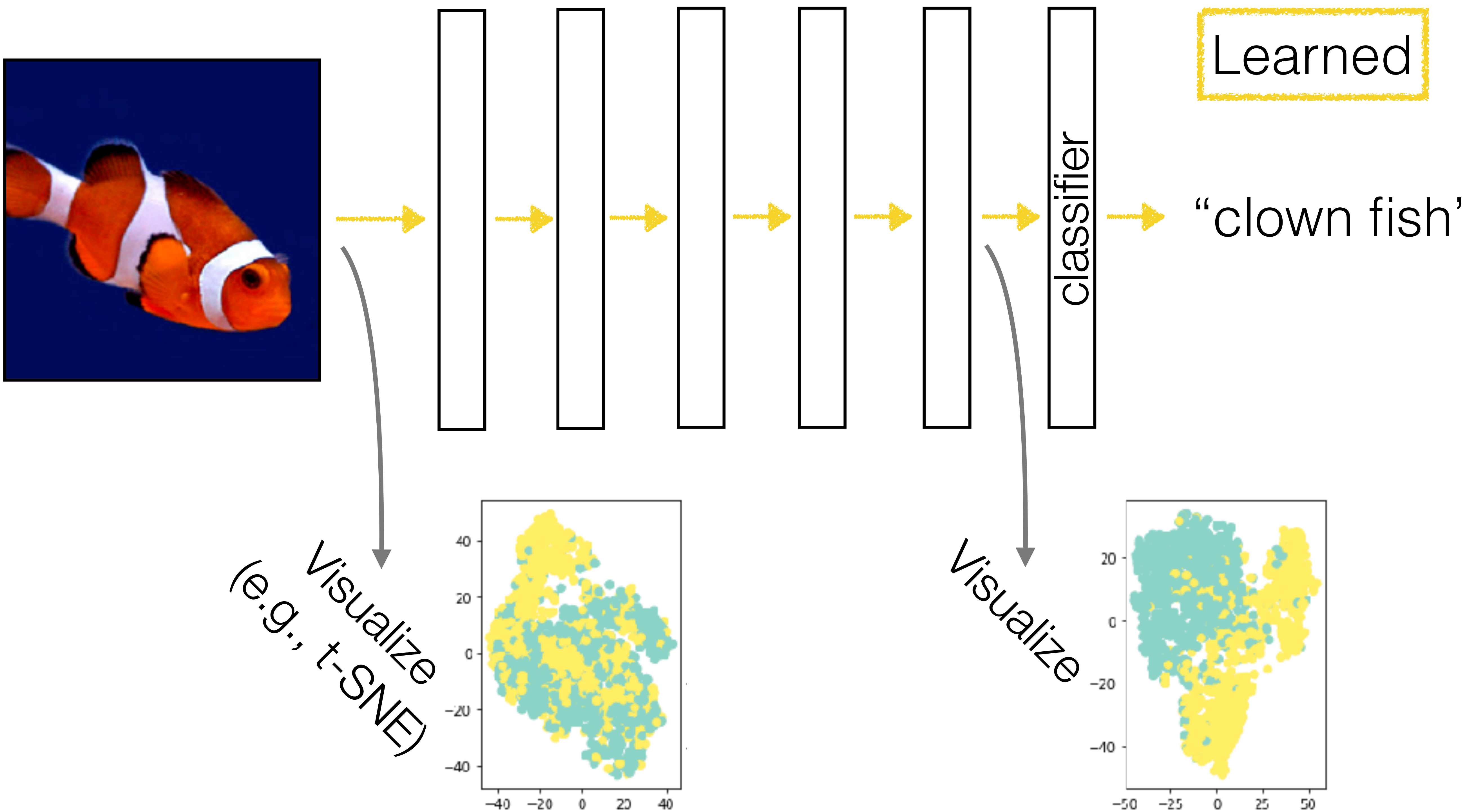
Representation Learning

Each layer's output is *another way we could represent the input data*



Representation Learning

Each layer's output is *another way we could represent the input data*



Why Does Deep Learning Work?

Actually the ideas behind deep learning are old (~1980's)

- Big data

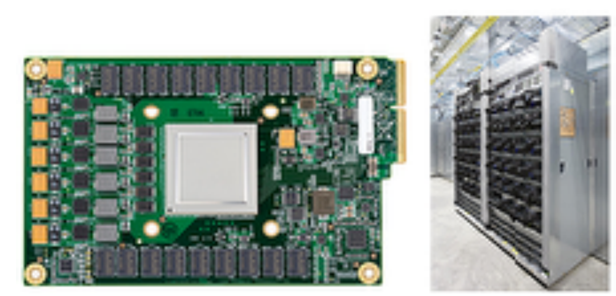
amazon.com NETFLIX fitbit UPMC LIFE CHANGING MEDICINE

- Better hardware

intel AMD

CPU's
& Moore's law

GPU's



TPU's

- Better algorithms

Structure Present in Data Matters

Neural nets aren't doing black magic

- **Image analysis:** convolutional neural networks (convnets) neatly <u>incorporates basic image processing structure</u>

- **Time series analysis:** recurrent neural networks (RNNs) <u>incorporates ability to remember and forget things over time</u>

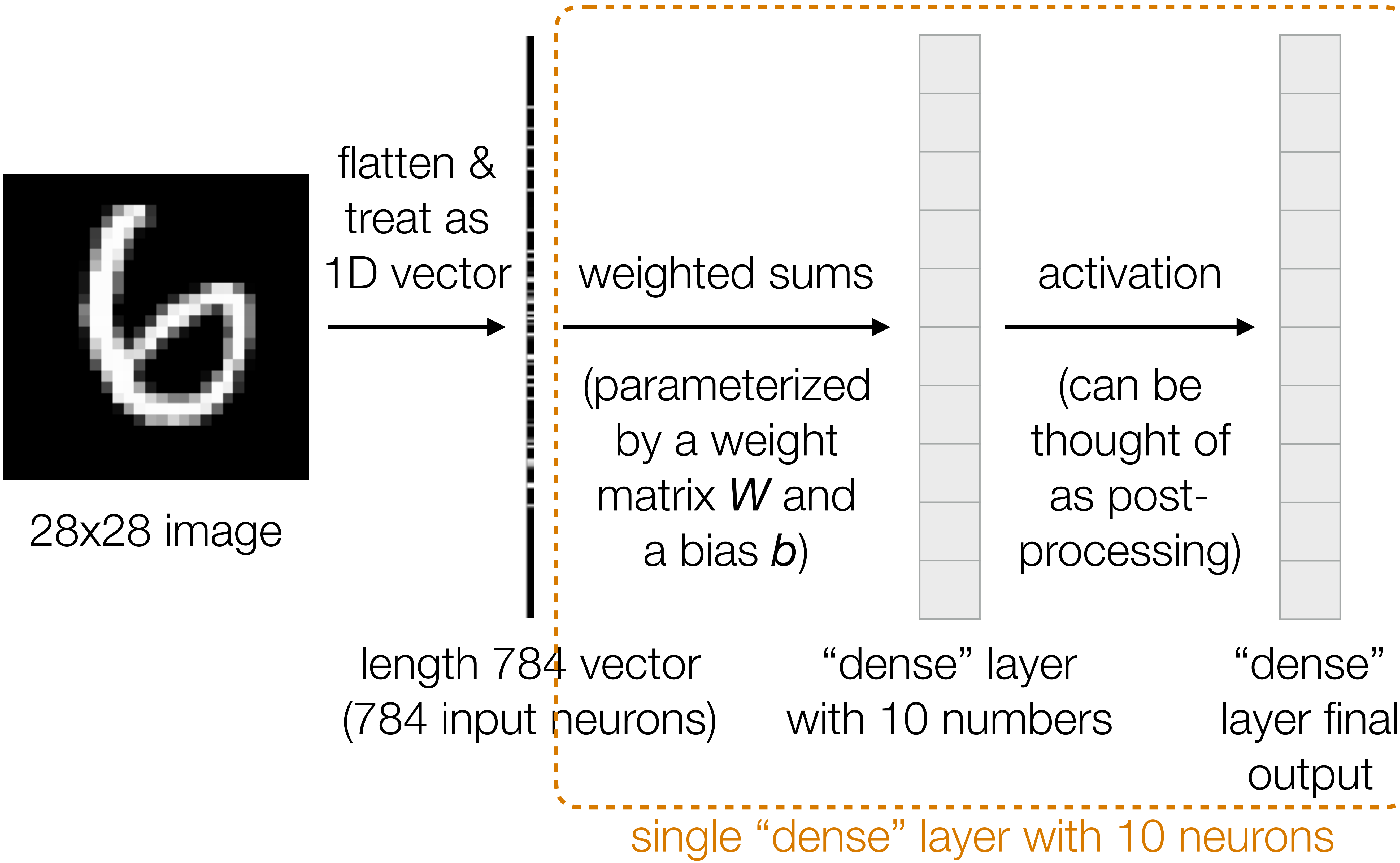
  - Note: text is a time series

  - Note: video is a time series

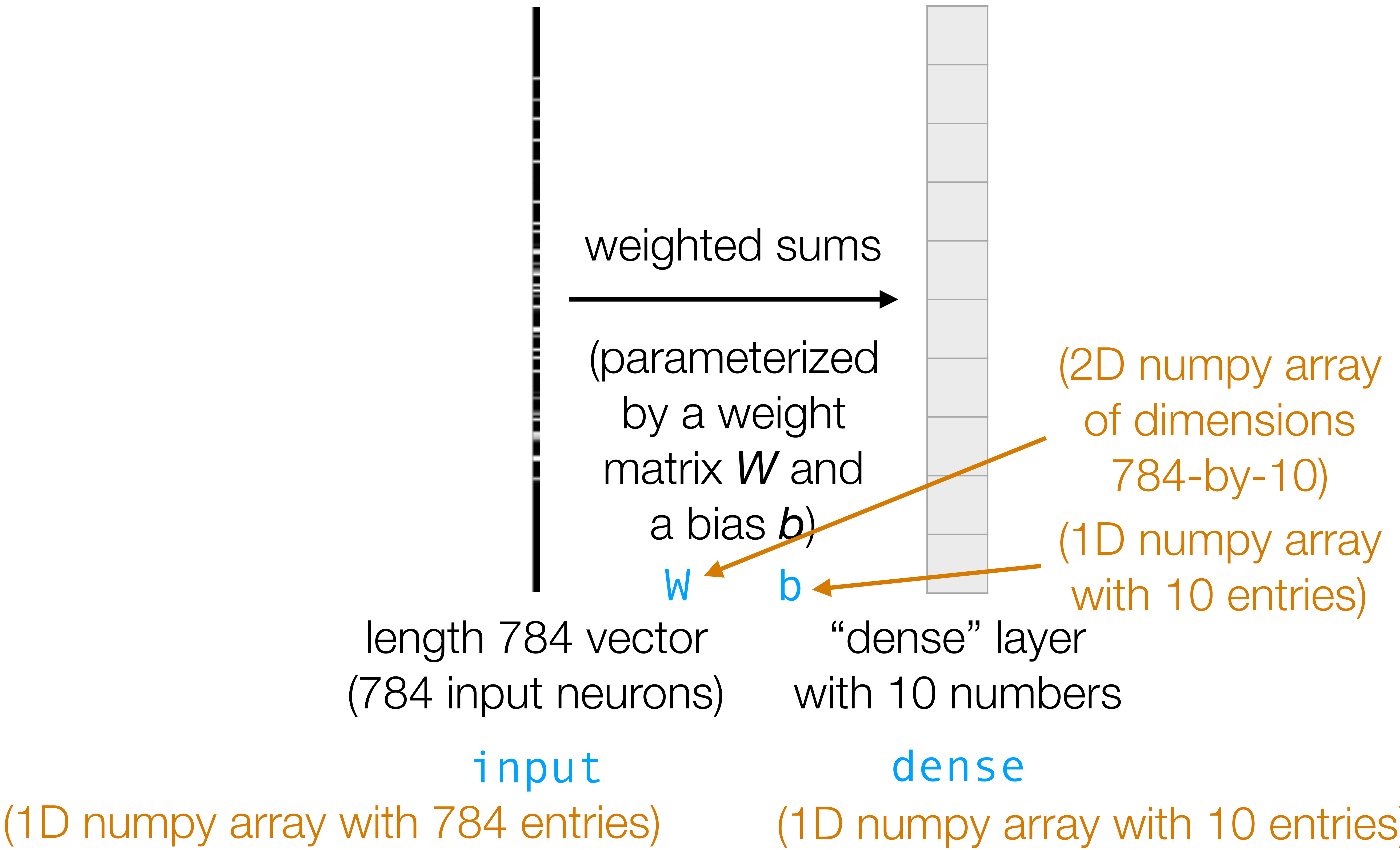
Handwritten Digit Recognition Example

Walkthrough of building a 1-layer and then a 2-layer neural net

Handwritten Digit Recognition



Handwritten Digit Recognition



Handwritten Digit Recognition

```
dense[0] = np.dot(input, W[:, 0]) + b[0]
dense[1] = np.dot(input, W[:, 1]) + b[1]
```

⋮

$$\texttt{dense[j]} = \sum_{i=0}^{783} \texttt{input[i]} \times \texttt{W[i, j]} + \texttt{b[j]}$$

weighted sums

(parameterized by a weight matrix *W* and a bias *b*)

`W` (2D numpy array of dimensions 784-by-10)

`b` (1D numpy array with 10 entries)

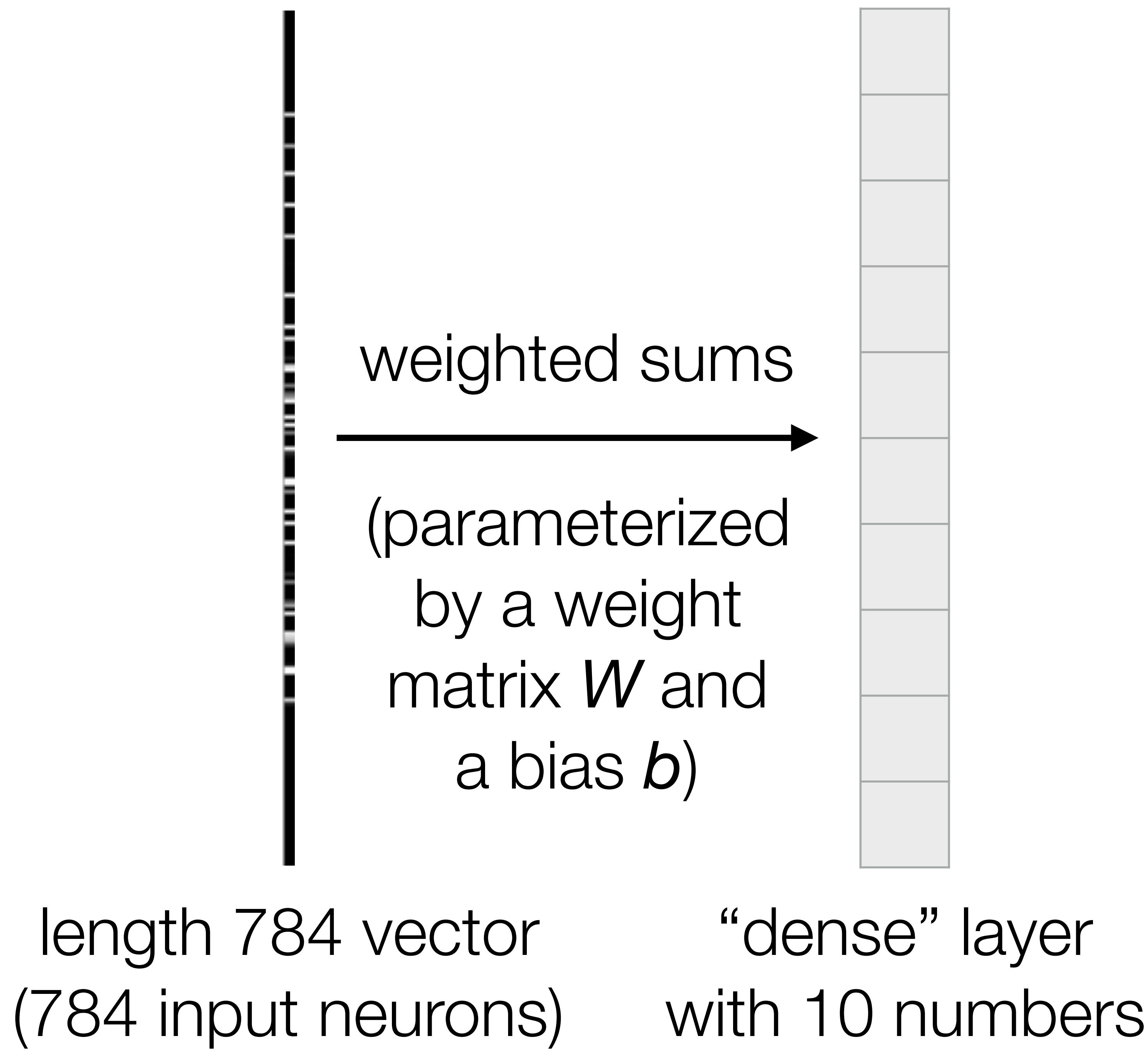
n 784 vector
nput neurons)

`input`
84 entries)

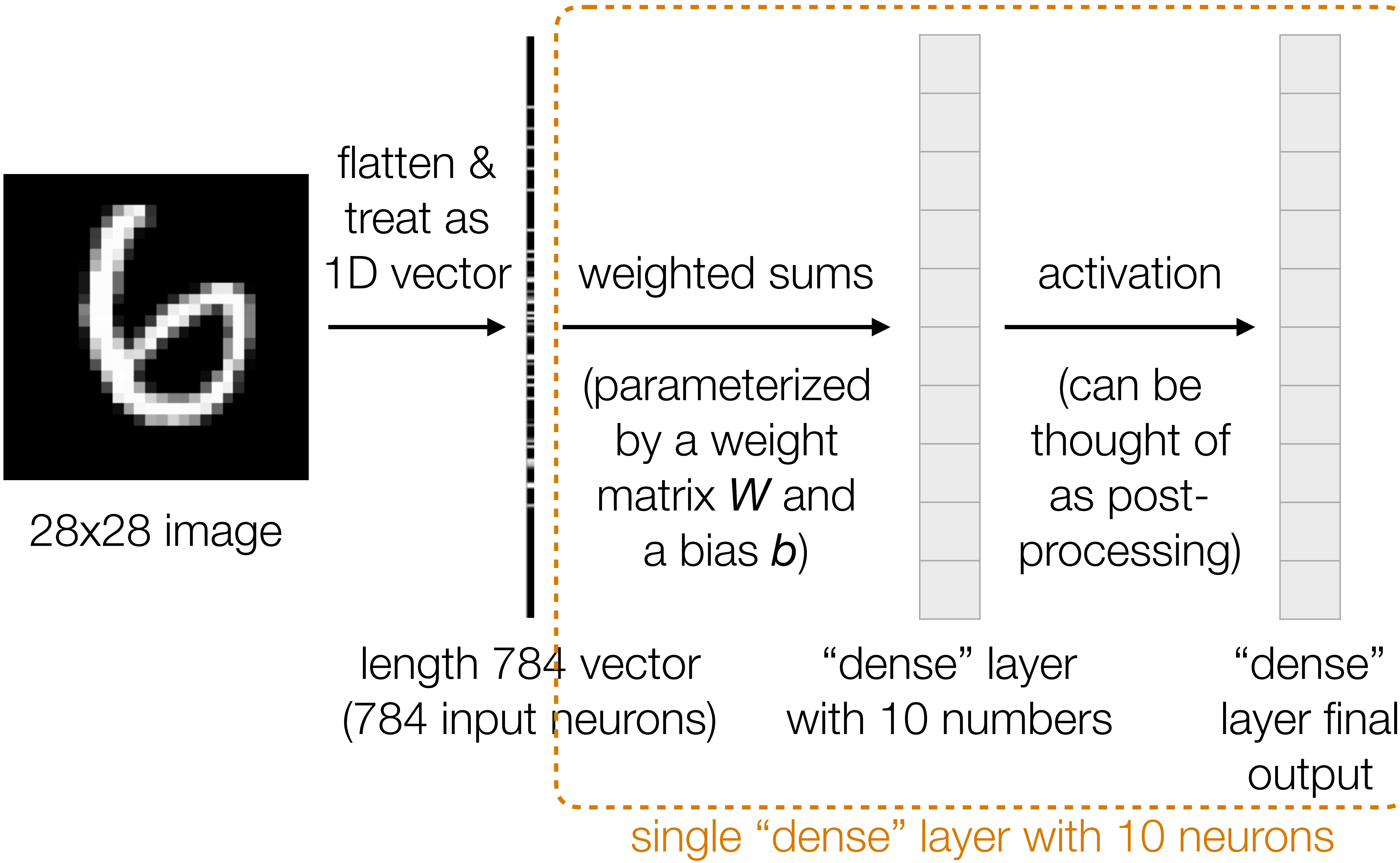
“dense” layer
with 10 numbers

`dense`
(1D numpy array with 10 entries)

Handwritten Digit Recognition



Handwritten Digit Recognition



Handwritten Digit Recognition

Many different activation functions possible

Example: **Rectified linear unit (ReLU)** zeros out entries that are negative

```
dense_final = np.maximum(0, dense)
```

“dense” layer with 10 numbers (`dense`)	**ReLU** → (can be thought of as post-processing)	“dense” layer final output (`dense_final`)
4		4
3.5		3.5
4		4
-1		0
0.5		0.5
2		2
-4		0
3		3
-2		0
5		5

“dense” layer with 10 numbers

`dense`

“dense” layer final output

`dense_final`

Handwritten Digit Recognition

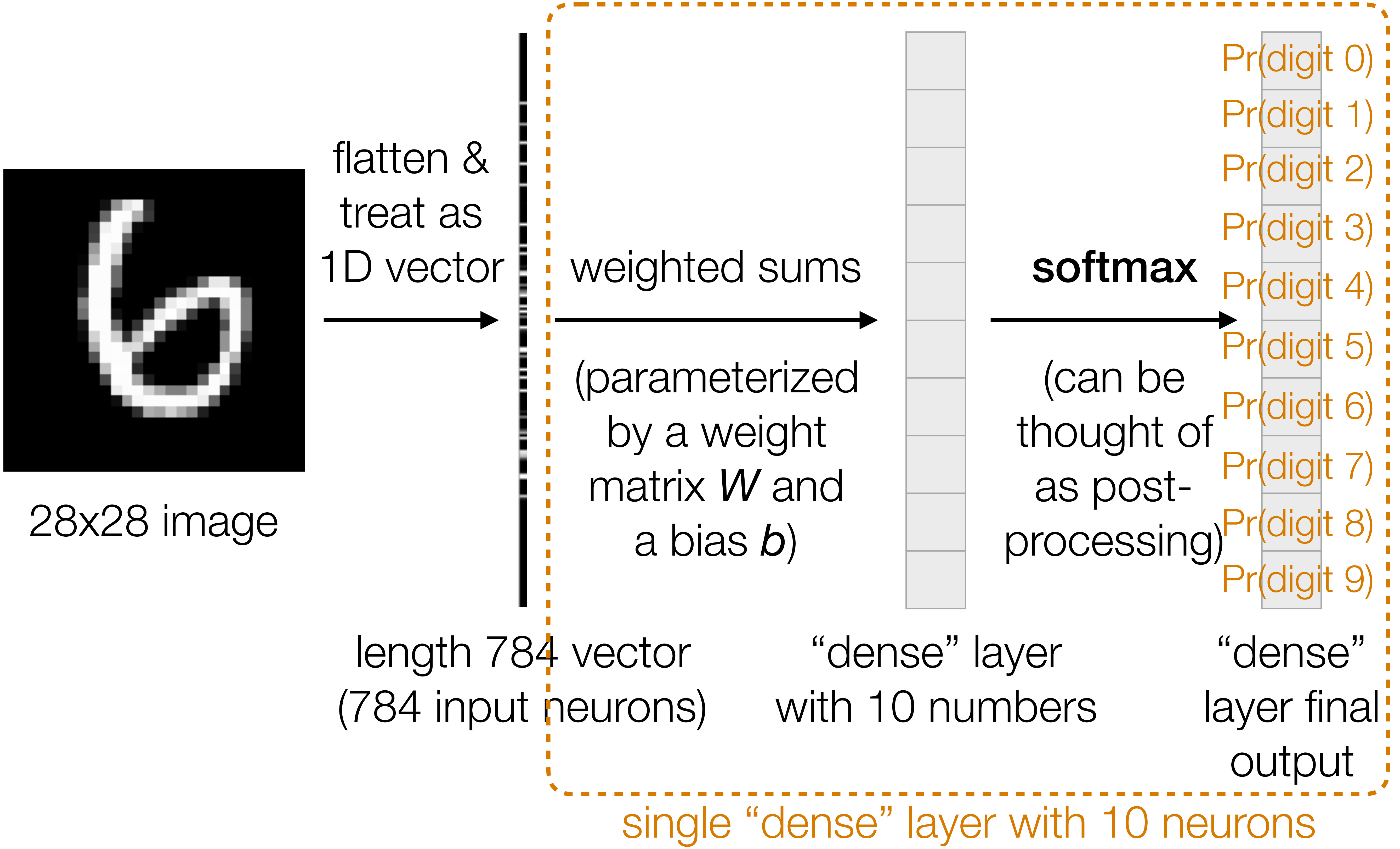
Many different activation functions possible

Example: **softmax** turns the entries in the dense layer (prior to activation) into a probability distribution (using the "softmax" transformation)

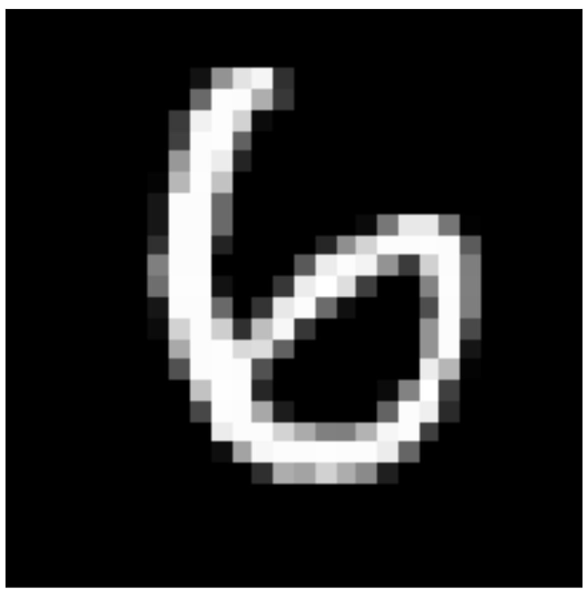
```
dense_exp = np.exp(dense)
dense_exp /= np.sum(dense_exp)
dense_final = dense_exp
```

"dense" layer with 10 numbers `dense`	**softmax** → (can be thought of as post-processing)	"dense" layer final output `dense_final`
4		0.17
3.5		0.10
4		0.17
-1		0.00
0.5		0.01
2		0.02
-4		0.00
3		0.06
-2		0.00
5		0.46

Handwritten Digit Recognition



Handwritten Digit Recognition



28x28 image

flatten & treat as 1D vector

length 784 vector (784 input neurons)

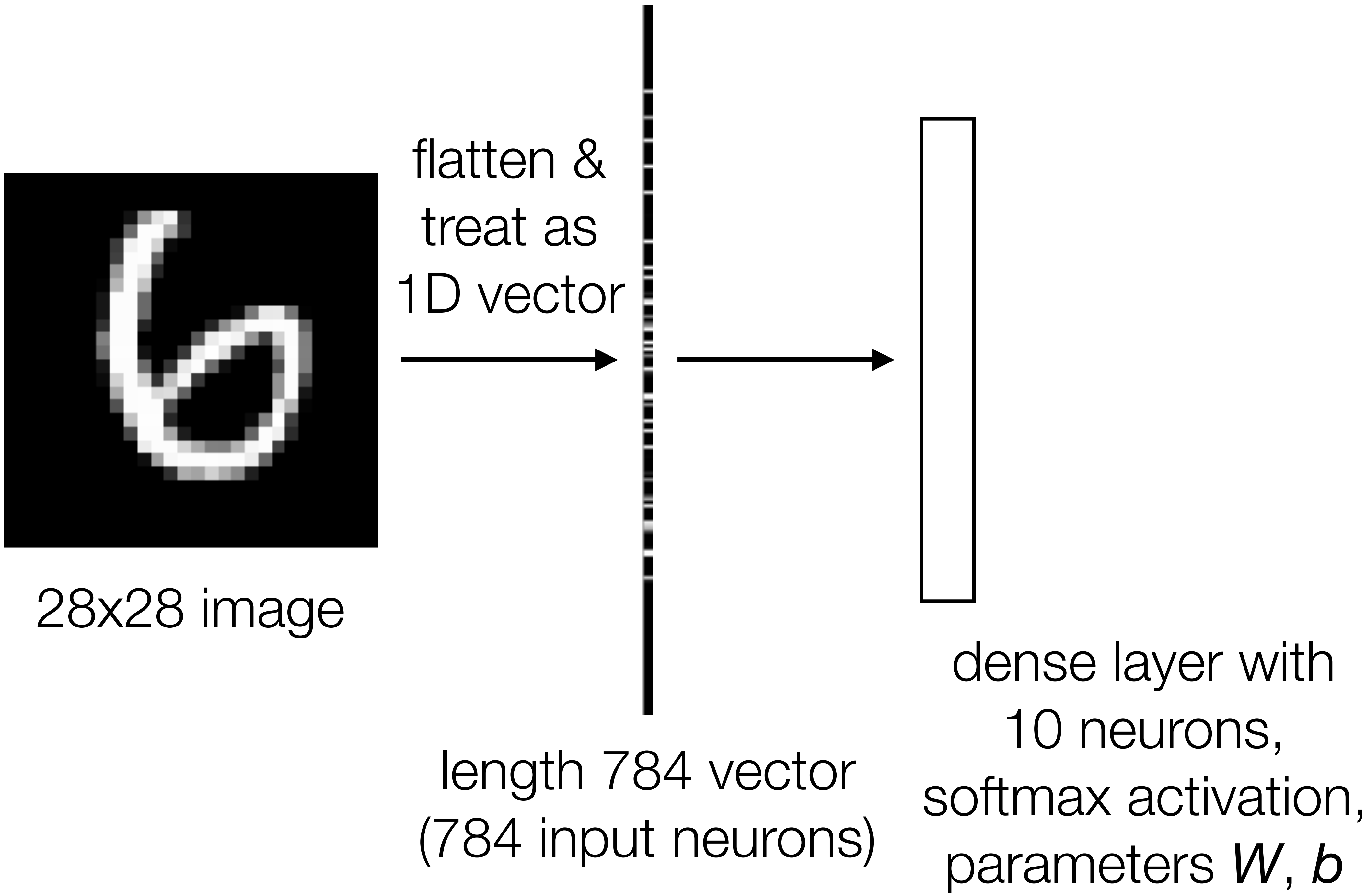
dense layer with 10 neurons, softmax activation, parameters *W*, *b*

We want the output of the dense layer to encode probabilities for whether the input image is a 0, 1, 2, …, 9 *but as of now we aren't providing any sort of information to enforce this*

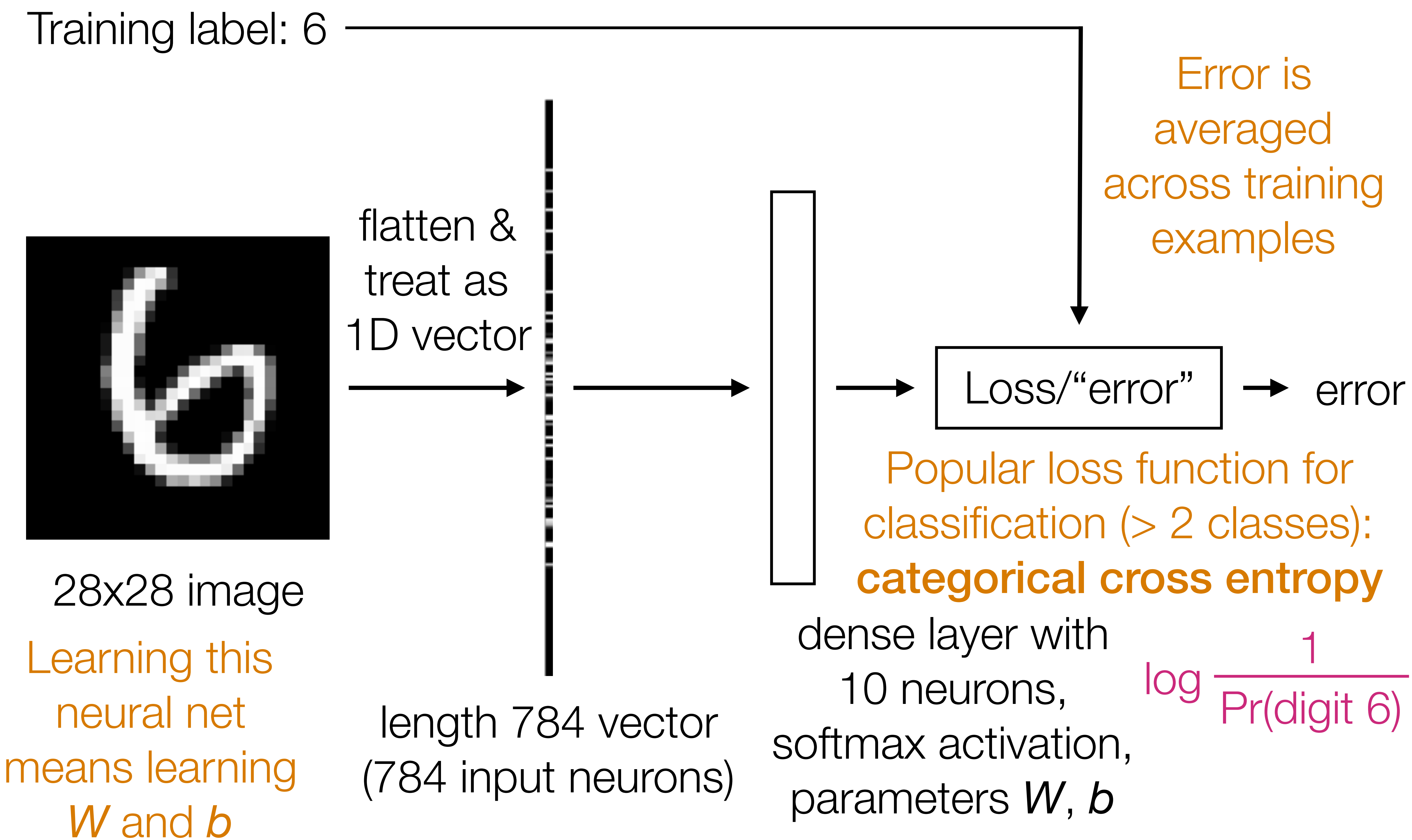
Handwritten Digit Recognition

Demo part 1

Handwritten Digit Recognition



Handwritten Digit Recognition

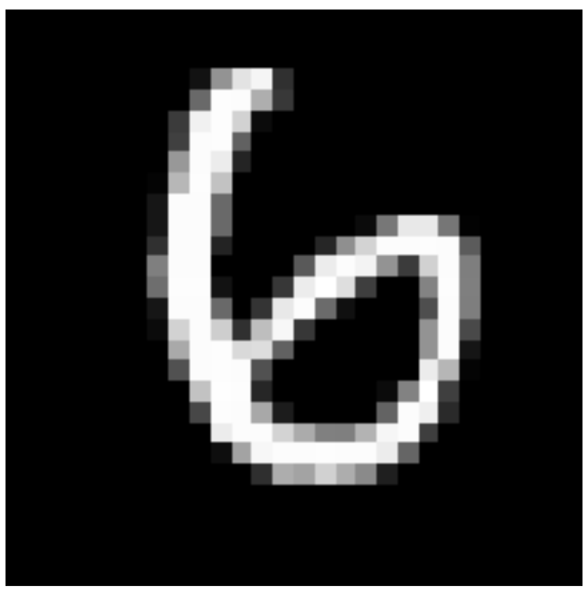


Handwritten Digit Recognition

Demo part 2

Handwritten Digit Recognition

Training label: 6



28x28 image

Learning this neural net means learning *W* and *b*

flatten & treat as 1D vector

length 784 vector (784 input neurons)

dense layer with 10 neurons, softmax activation, parameters *W*, *b*

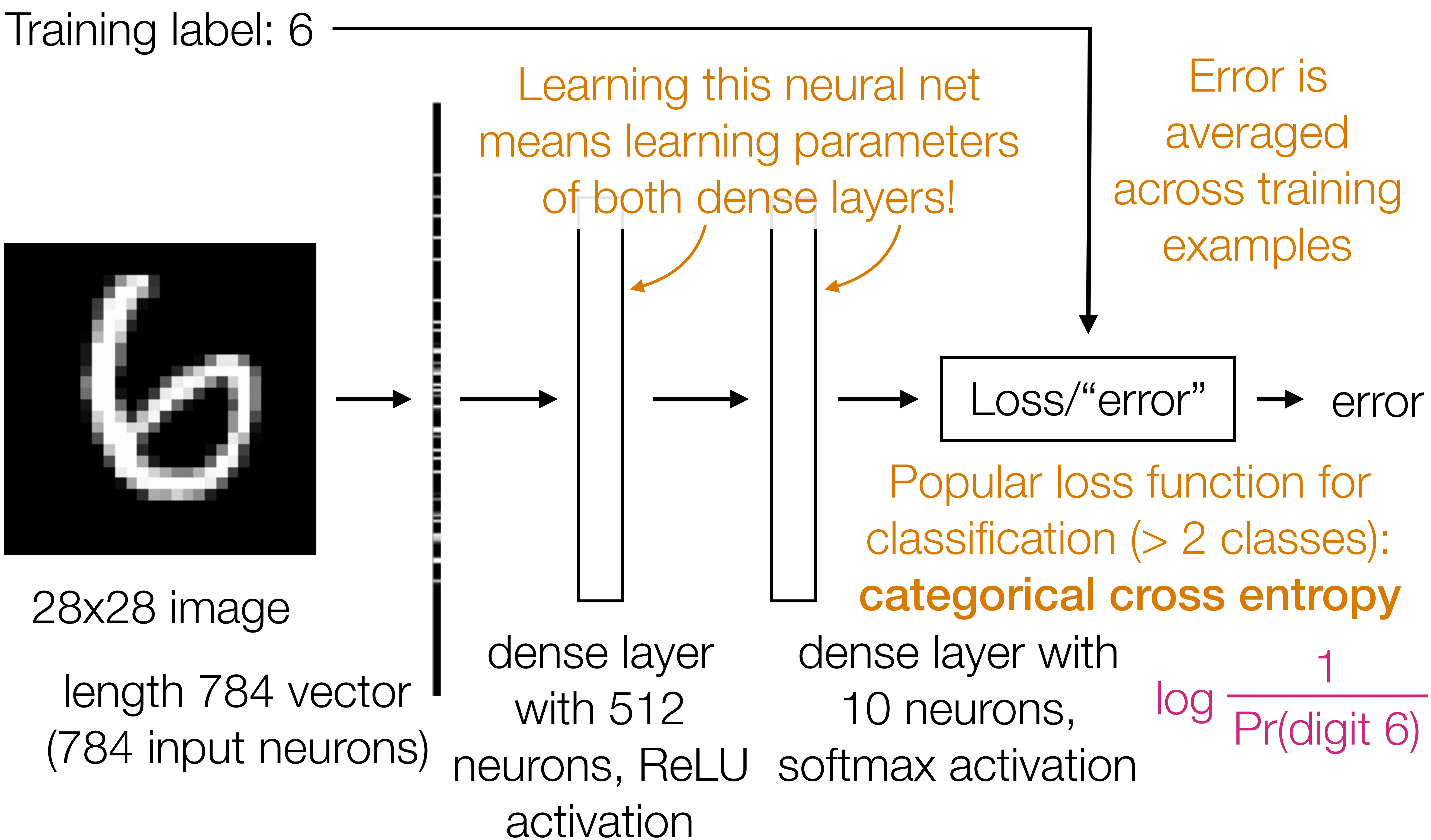
Loss/“error” → error

Error is averaged across training examples

Popular loss function for classification (> 2 classes): **categorical cross entropy**

$$\log \frac{1}{\Pr(\text{digit } 6)}$$

Handwritten Digit Recognition



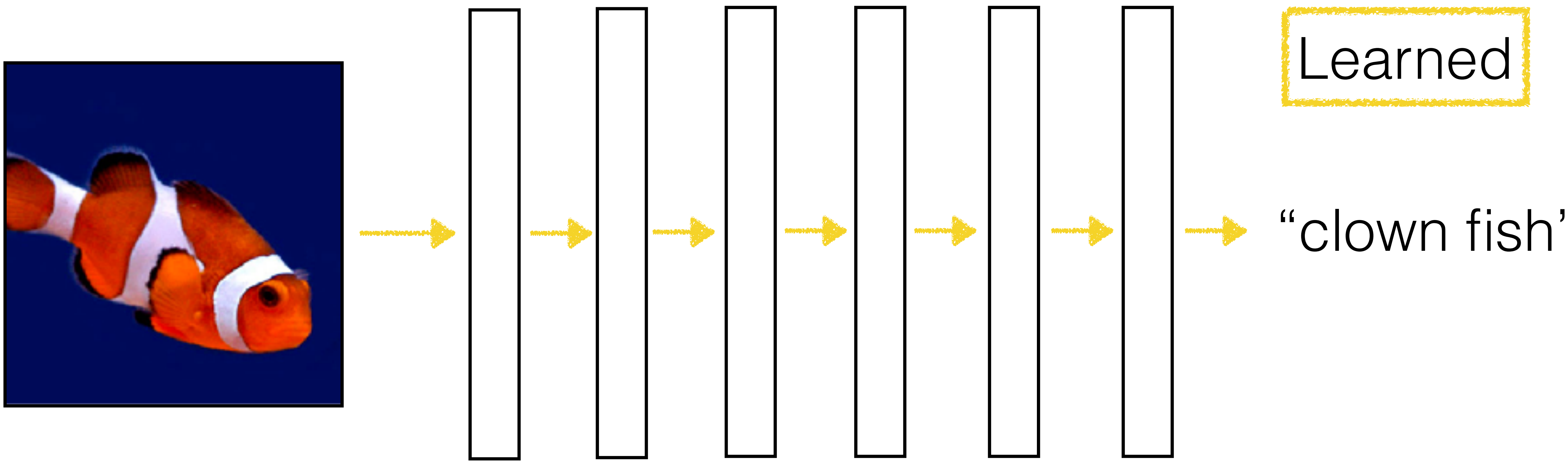
Handwritten Digit Recognition

Demo part 3

Architecting Neural Nets

- Increasing number of layers (depth) makes neural net more complex
  - Can approximate more functions
  - More parameters needed
    - More training data may be needed
- Designing neural net architectures is a bit of an art
  - How to select the number of neurons for intermediate layers?
  - Very common in practice: modify existing architectures that are known to work well (e.g., VGG-16 for computer vision/image processing)

Deep Learning



- Inspired by biological neural nets *but otherwise not the same at all* (biological neural nets do *not* work like deep nets)
- Learns a layered representation
  - Tries to get rid of manual feature engineering
  - Need to design constraints for what features are learned to account for structure in data (e.g., images, text, …)