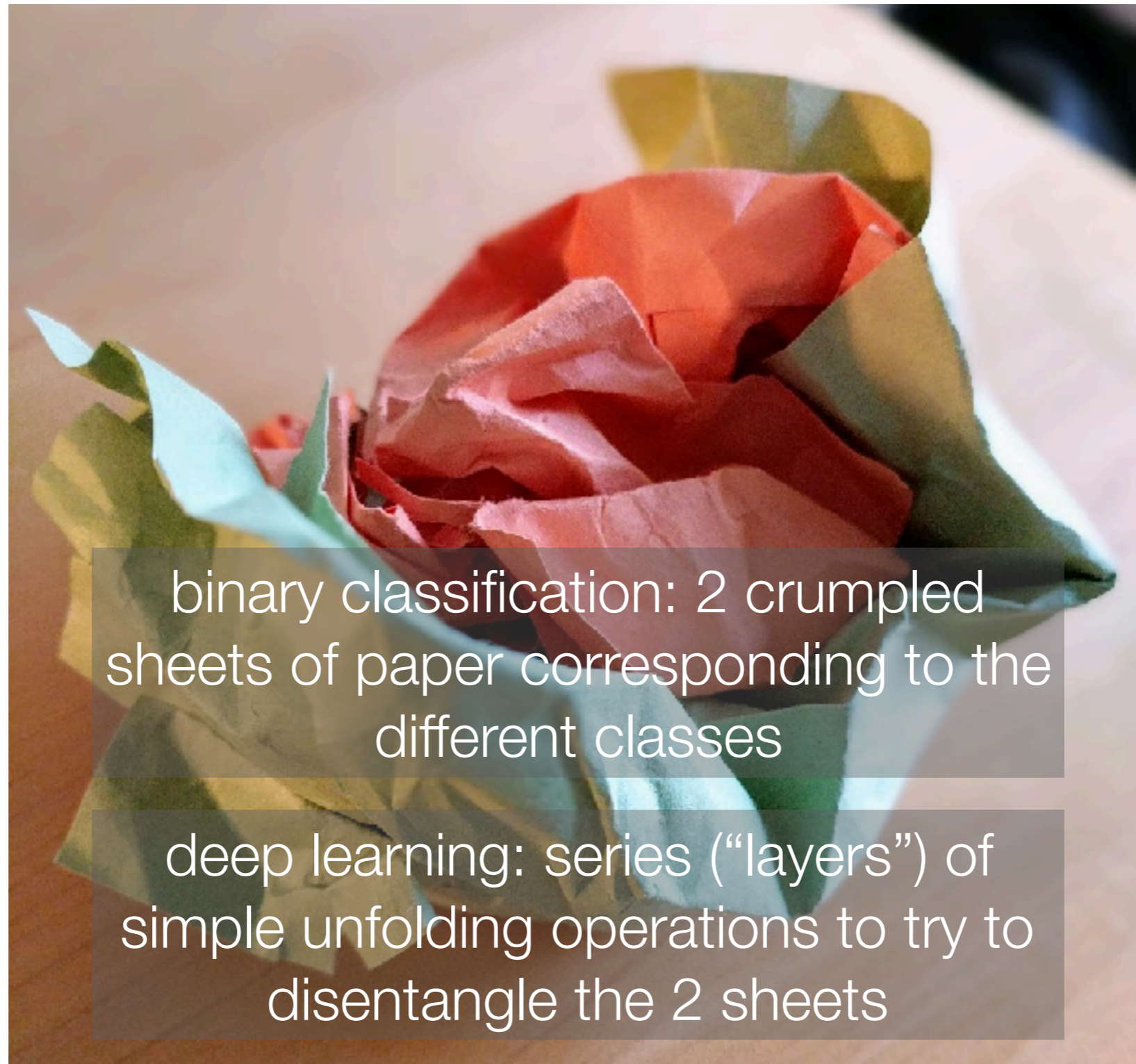


Neural Nets & Deep Learning

George Chen

(some neural net & deep learning slides are by Phillip Isola)

Crumpled Paper Analogy

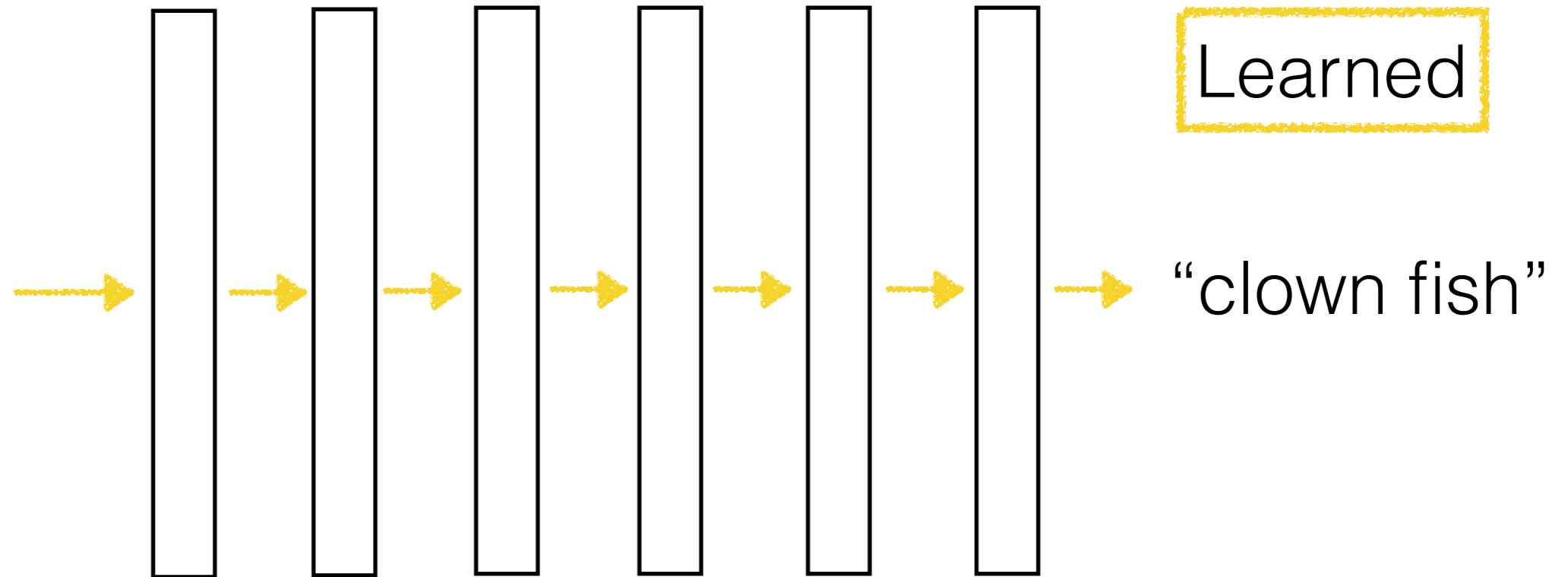
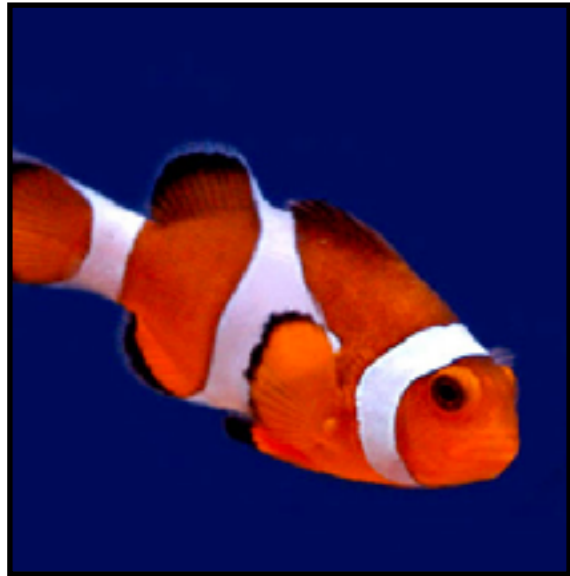


binary classification: 2 crumpled sheets of paper corresponding to the different classes

deep learning: series (“layers”) of simple unfolding operations to try to disentangle the 2 sheets

Analogy: Francois Chollet, photo: George Chen

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

Why Does Deep Learning Work?

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

- Big data



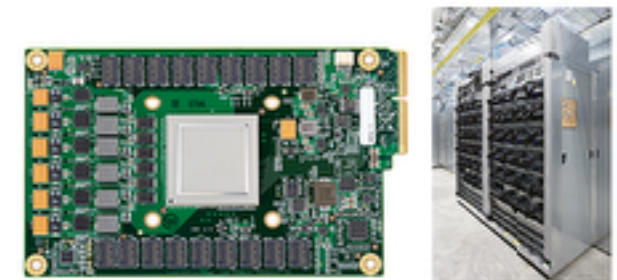
- Better hardware



CPU's
& Moore's law



GPU's



TPU's

- Better algorithms

Structure Present in Data Matters

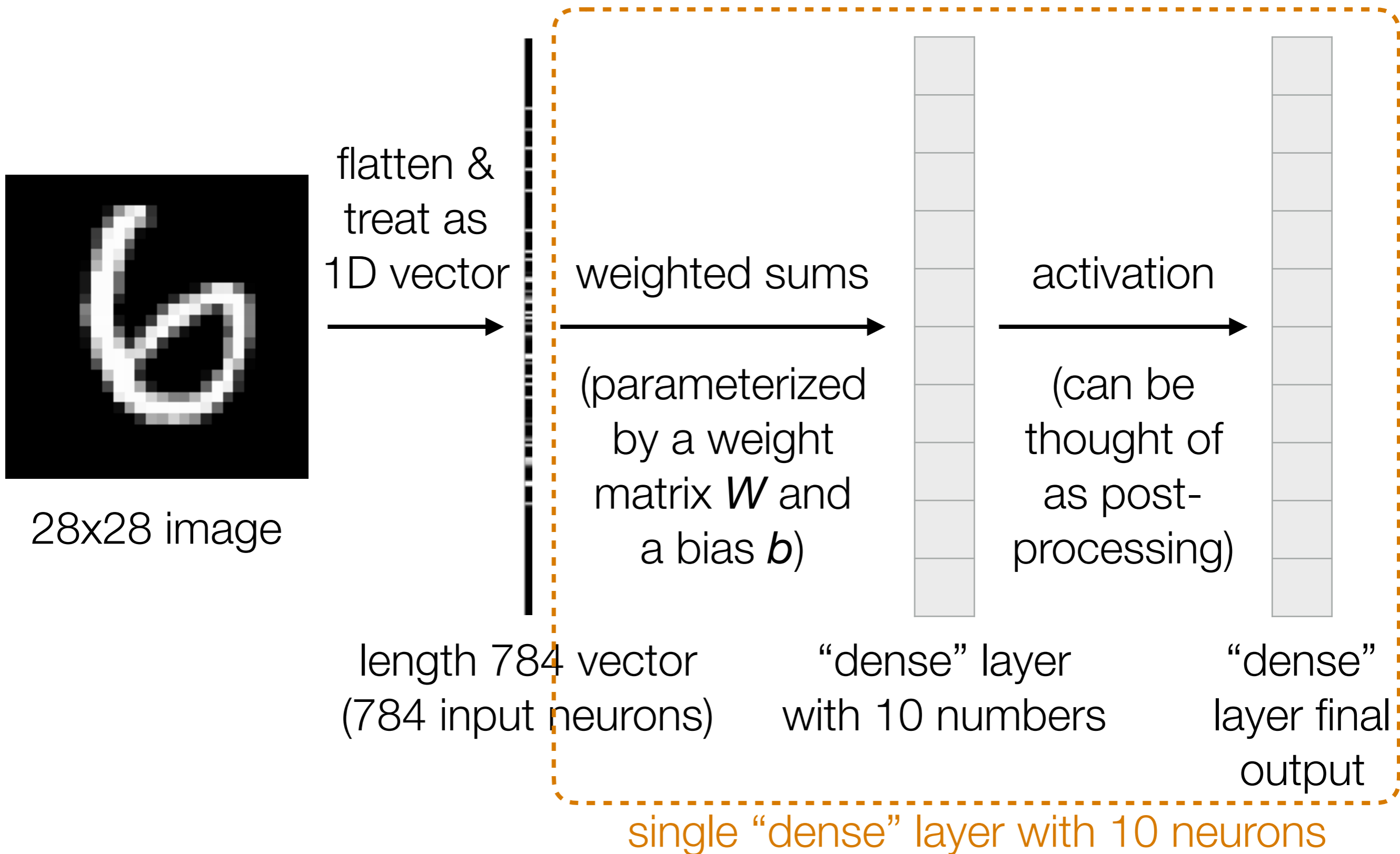
Neural nets aren't doing black magic

- **Image analysis:** convolutional neural networks (convnets) neatly incorporates basic image processing structure
- **Time series analysis:** recurrent neural networks (RNNs) incorporates ability to remember and forget things over time
 - Note: text is a time series
 - Note: video is a time series

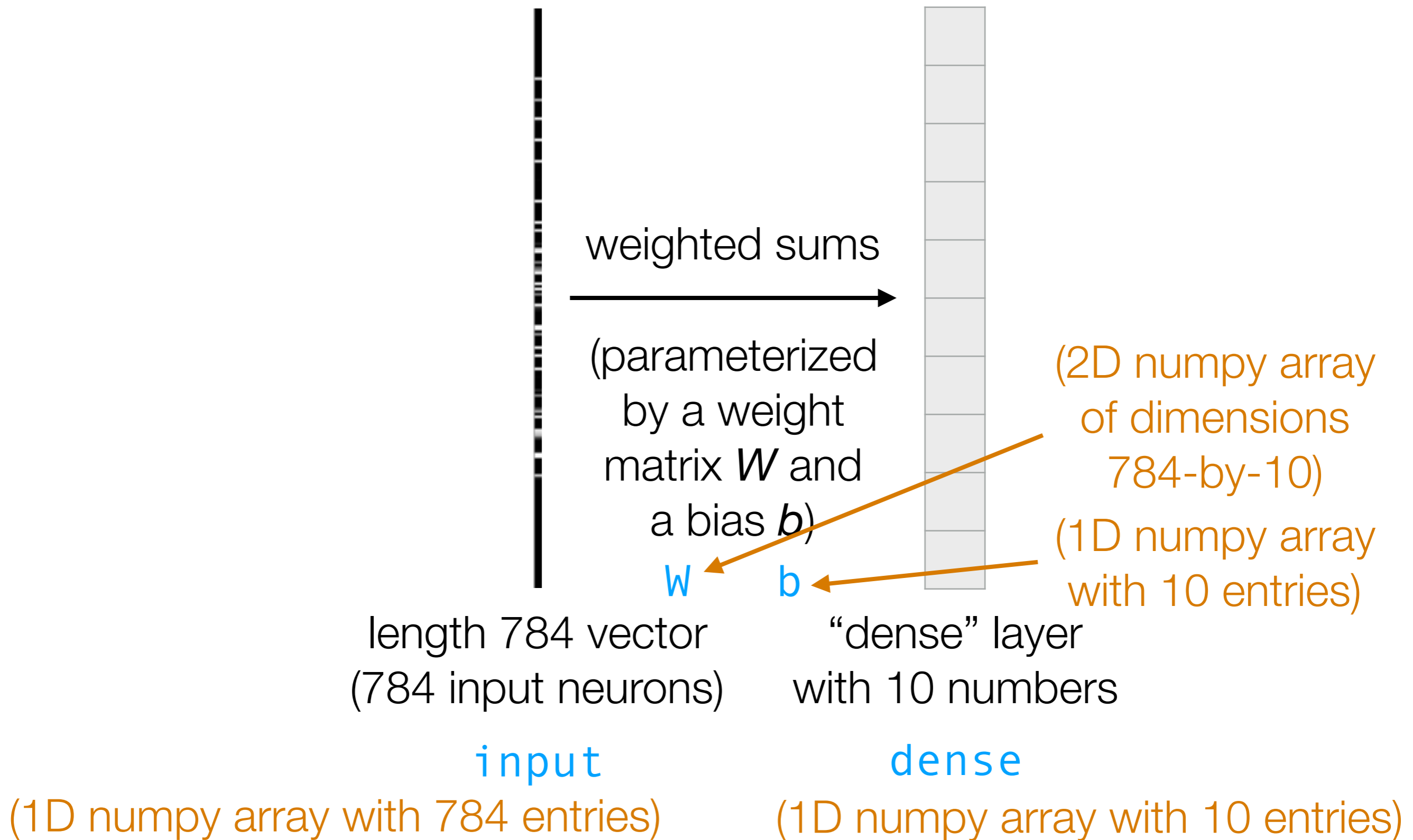
Handwritten Digit Recognition Example

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

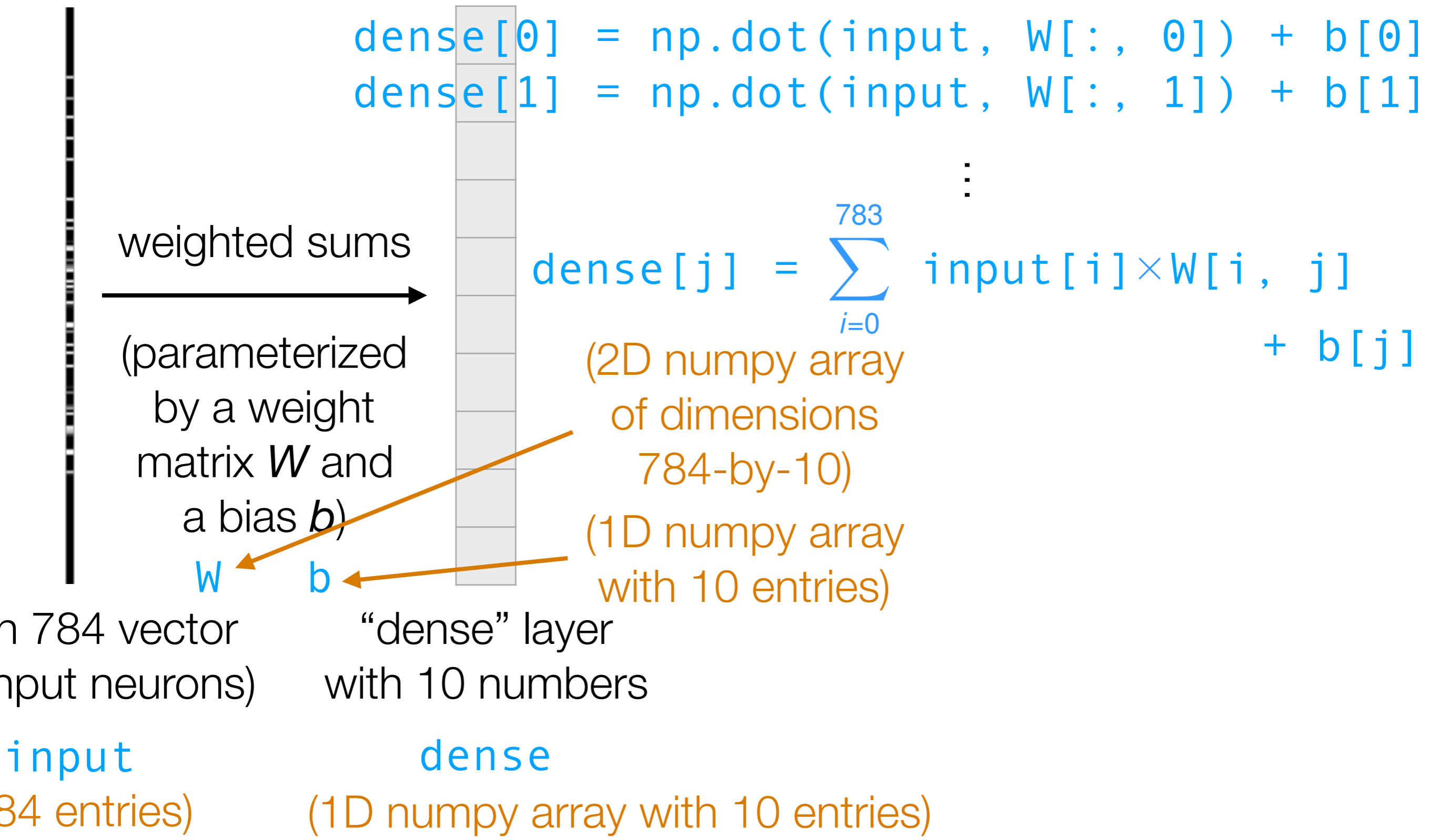
Handwritten Digit Recognition



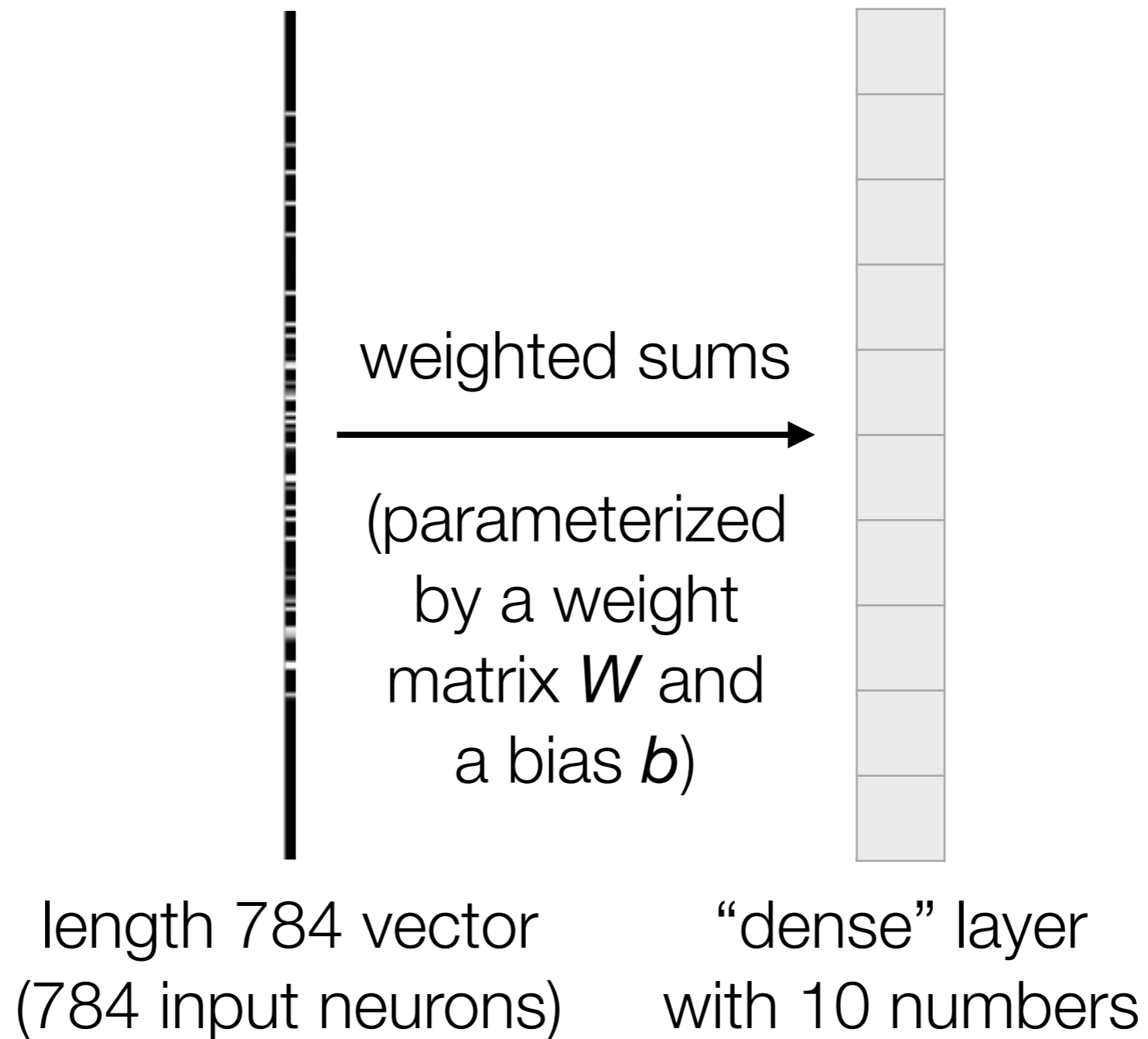
Handwritten Digit Recognition



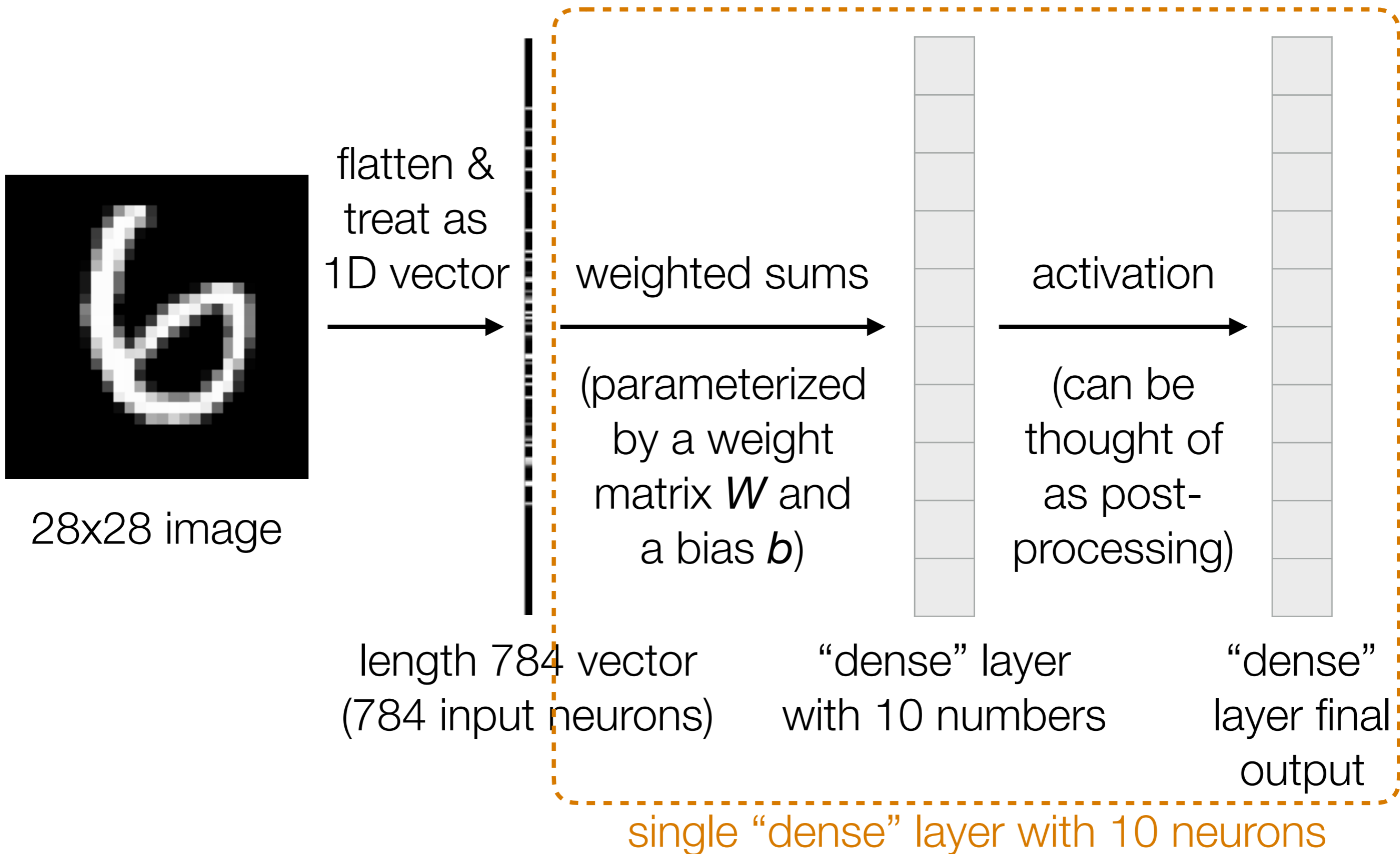
Handwritten Digit Recognition



Handwritten Digit Recognition



Handwritten Digit Recognition



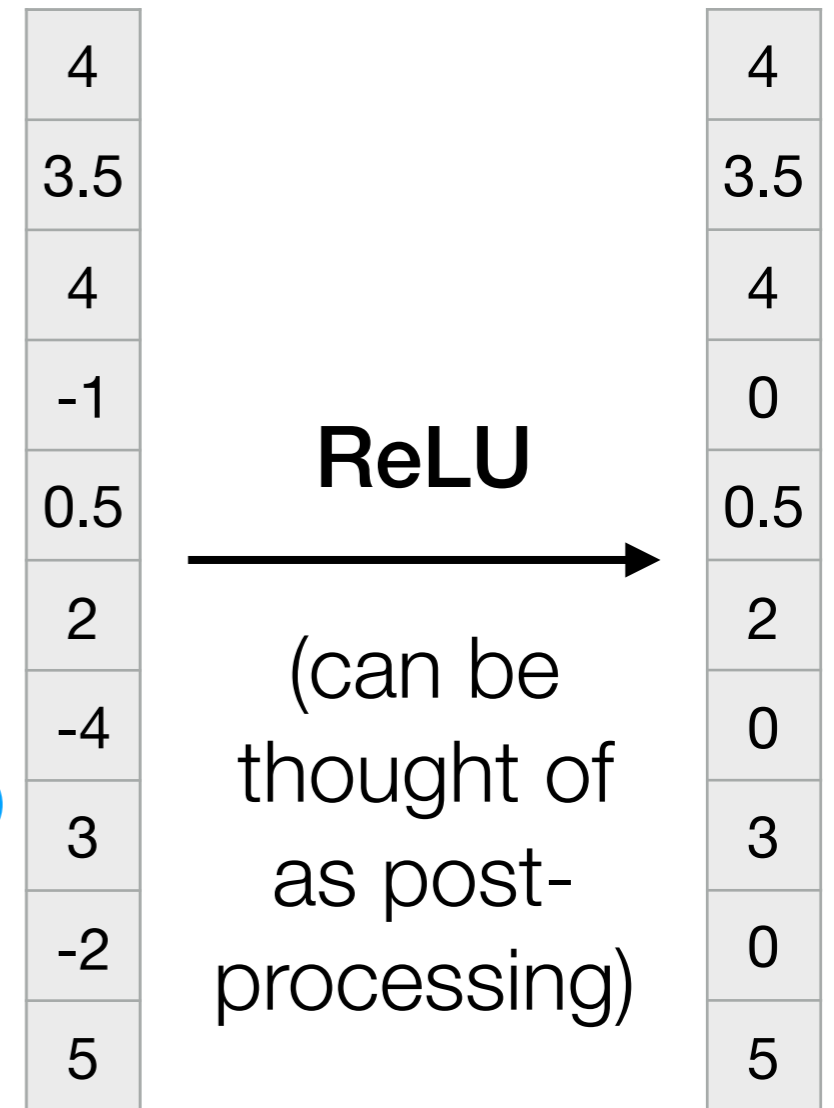
Handwritten Digit Recognition

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`

“dense”
layer final
output

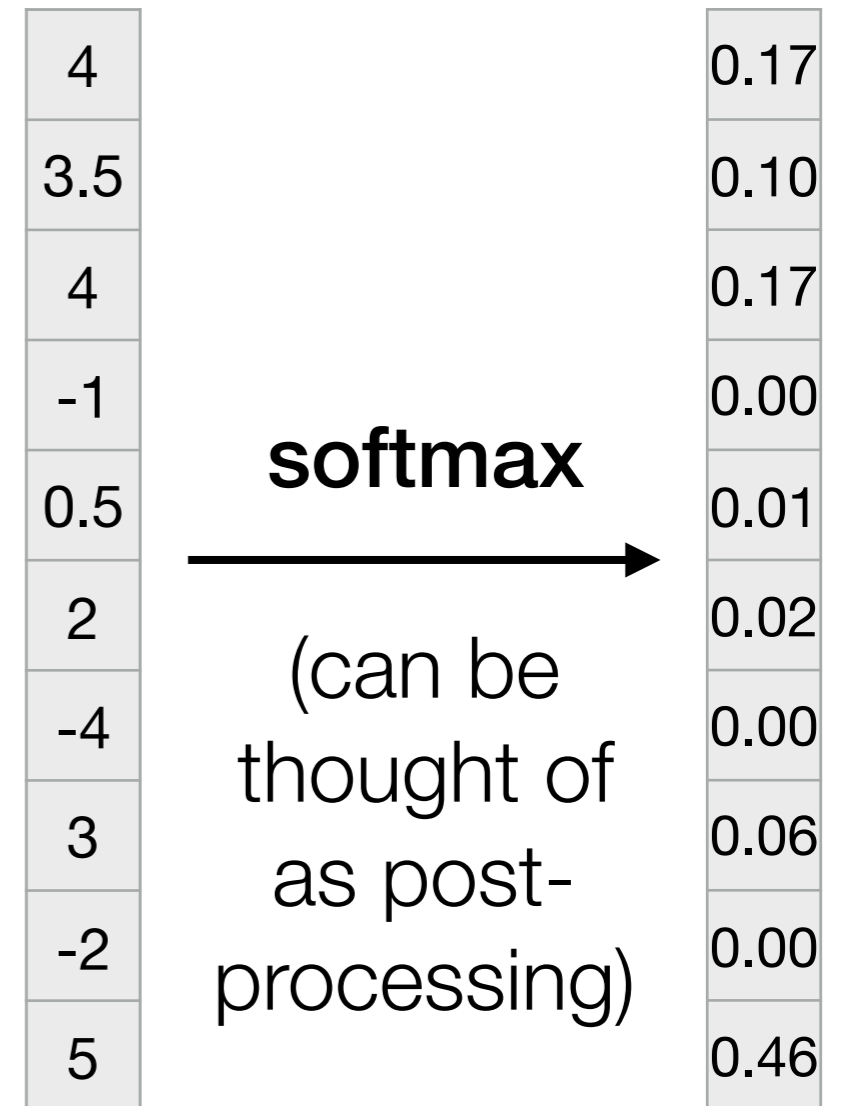
`dense_final`

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
```



(can be thought of as post-processing)

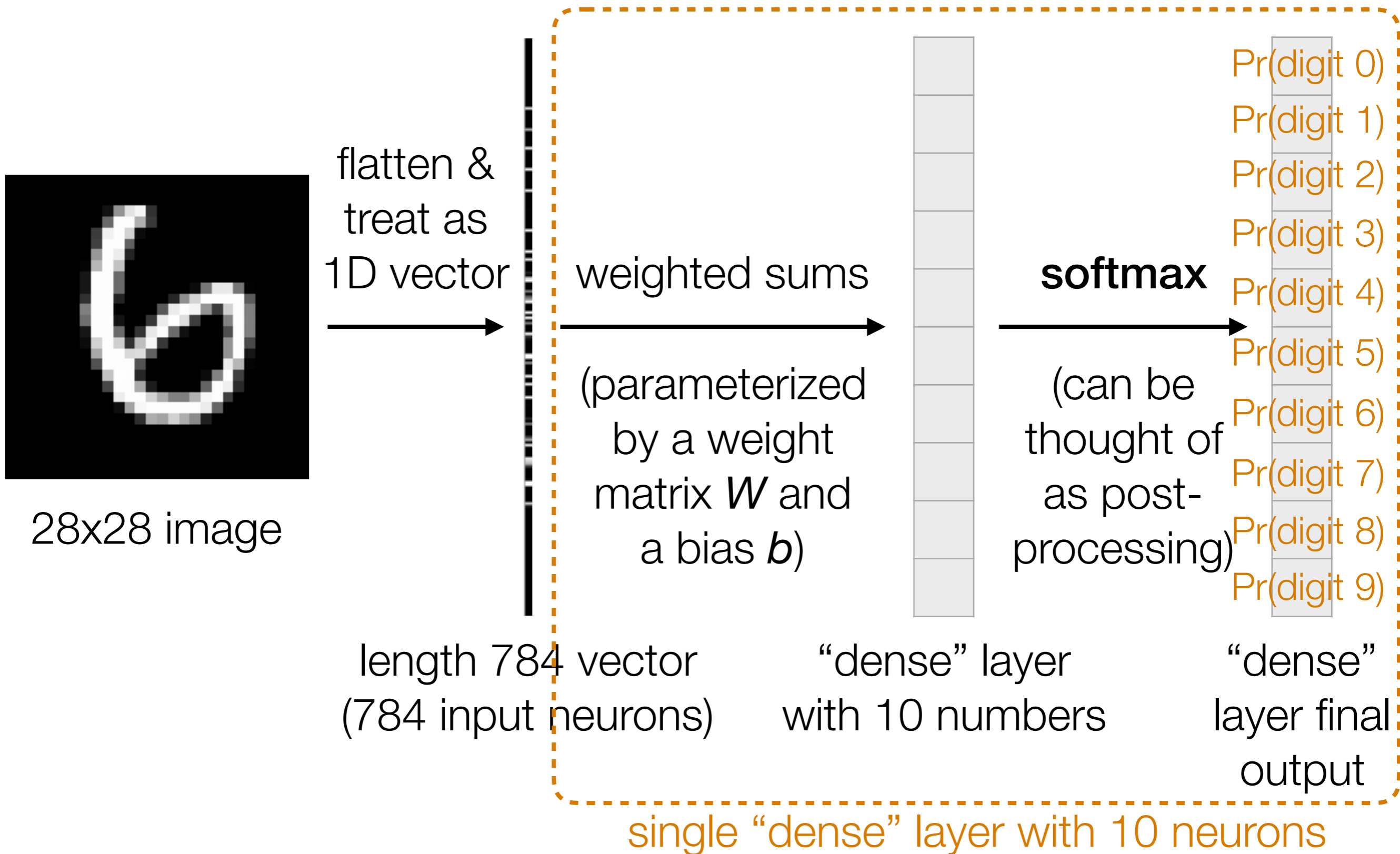
“dense” layer with 10 numbers

“dense” layer final output

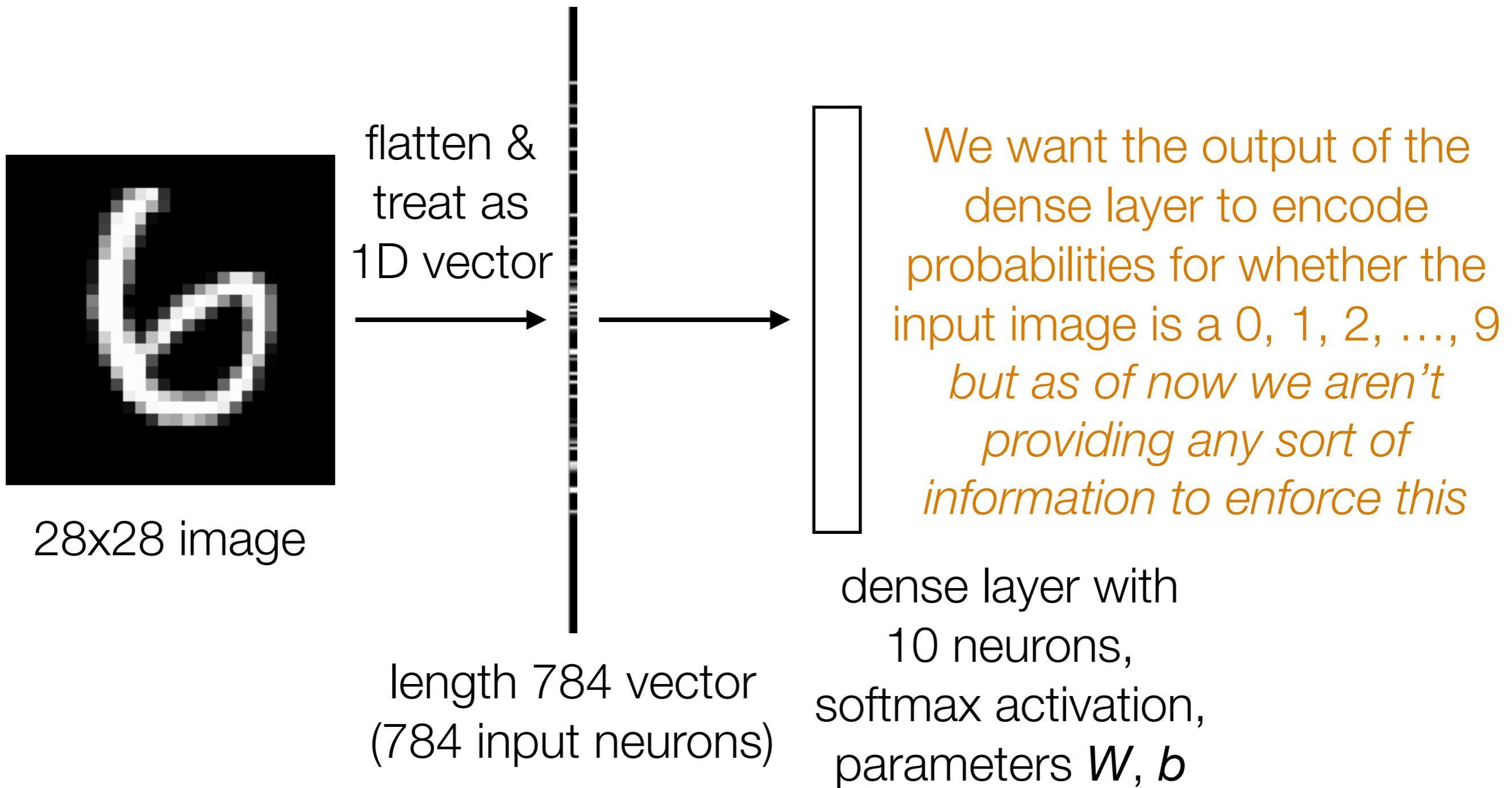
`dense`

`dense_final`

Handwritten Digit Recognition



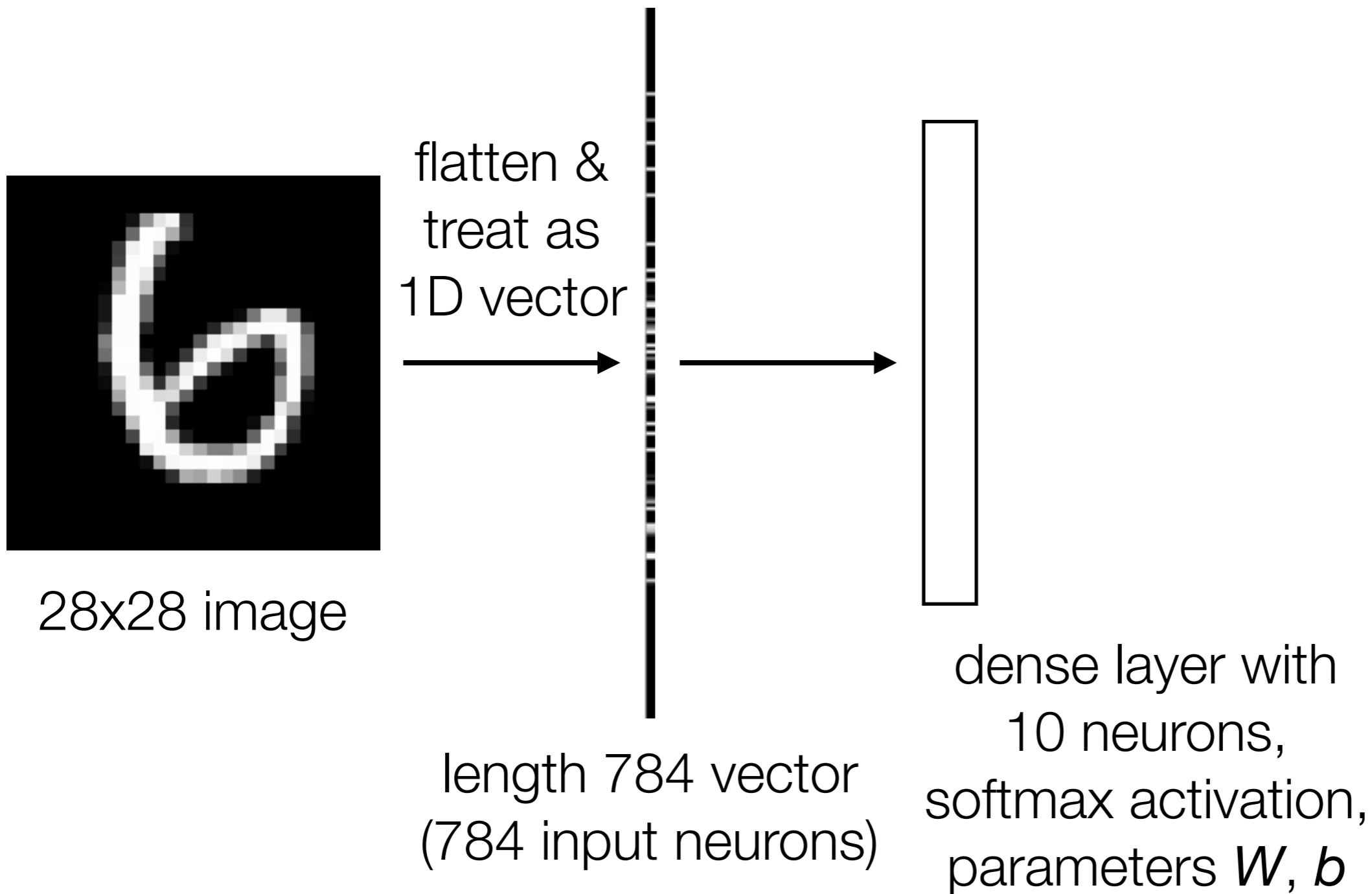
Handwritten Digit Recognition



Handwritten Digit Recognition

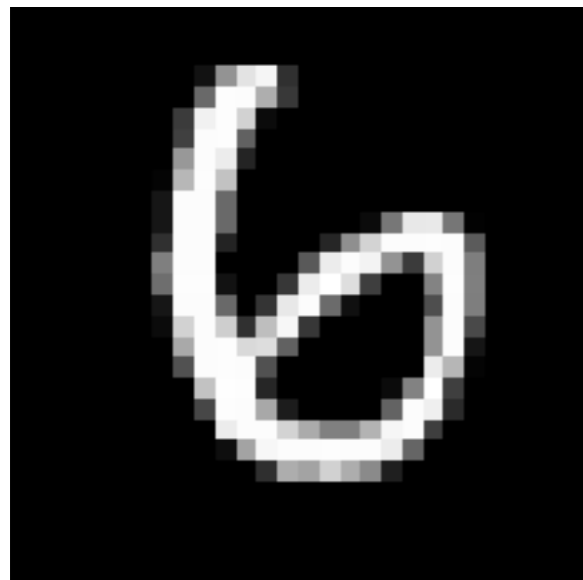
Demo part 1

Handwritten Digit Recognition



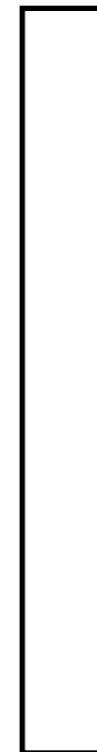
Handwritten Digit Recognition

Training label: 6



28x28 image

flatten &
treat as
1D vector



Loss/"error"



Error is averaged across training examples

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

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

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

Learning this neural net means learning W and b

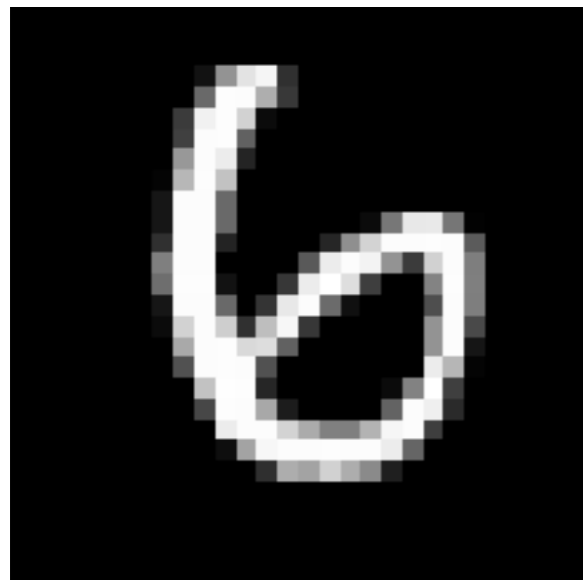
length 784 vector (784 input neurons)

Handwritten Digit Recognition

Demo part 2

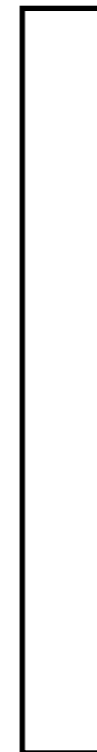
Handwritten Digit Recognition

Training label: 6



28x28 image

flatten &
treat as
1D vector



Loss/"error"



Error is averaged across training examples

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

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

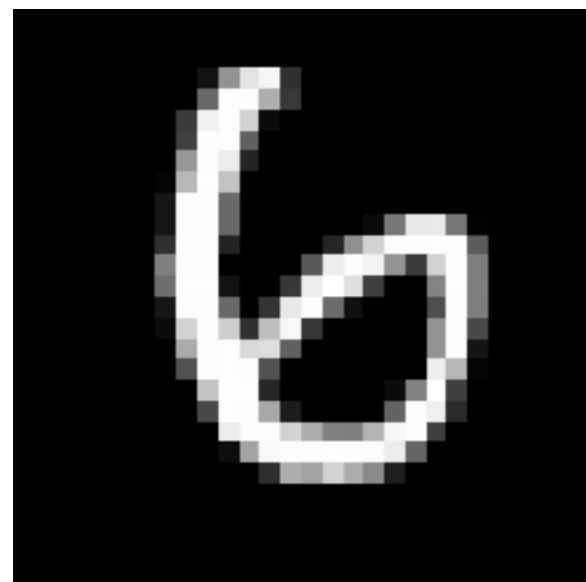
$$\log \frac{1}{\text{Pr}(\text{digit } 6)}$$

Learning this neural net means learning W and b

length 784 vector (784 input neurons)

Handwritten Digit Recognition

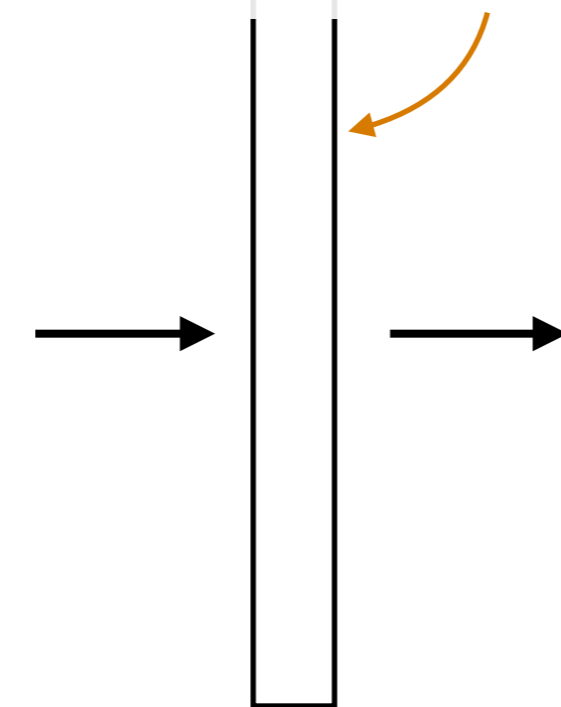
Training label: 6



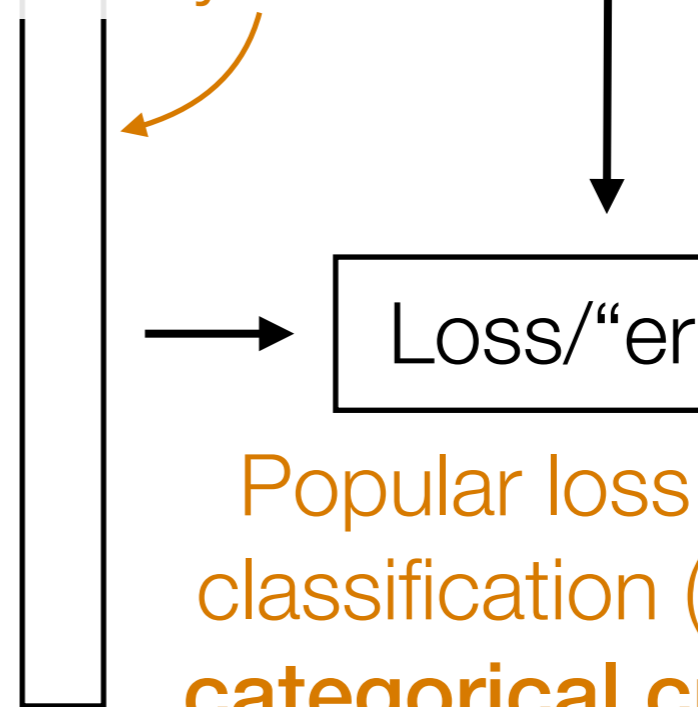
28x28 image

length 784 vector
(784 input neurons)

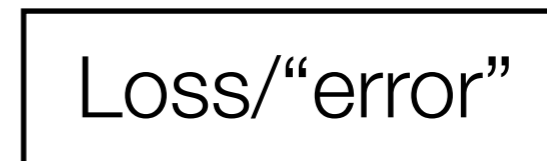
Learning this neural net means learning parameters of both dense layers!



dense layer with 512 neurons, ReLU activation



dense layer with 10 neurons, softmax activation



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

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

Error is averaged across training examples

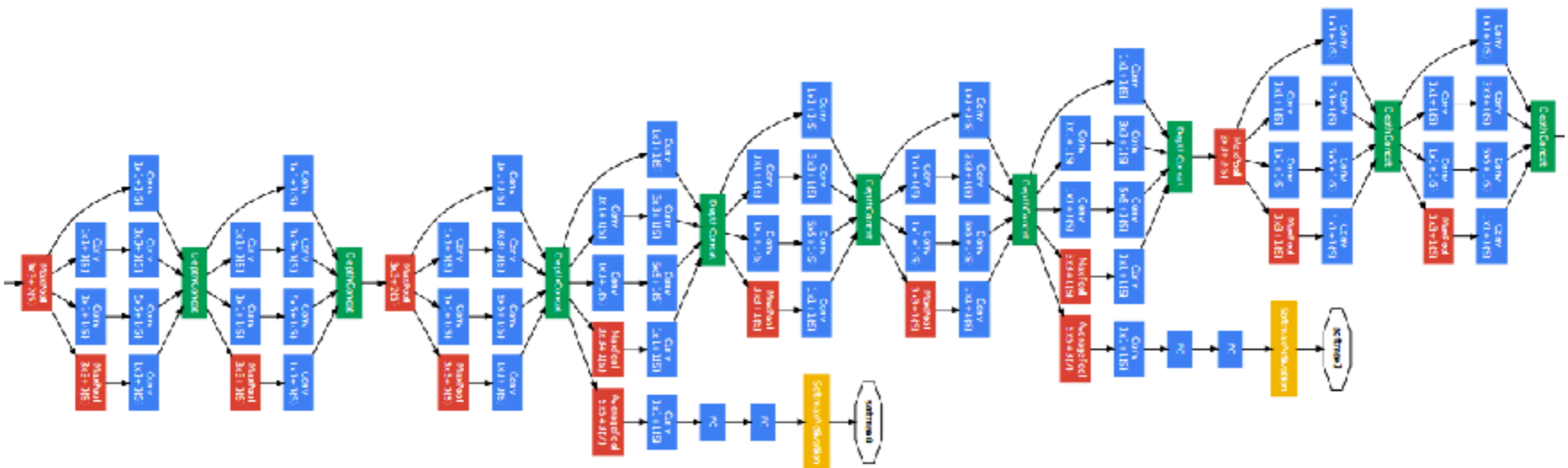
error

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)



GoogLeNet 2014