Carnegie Mellon University
Heinz College

Introduction to Deep Learning

most of the slides here are by George Chen (CMU)

some slides are by Phillip Isola (OpenAI, UC Berkeley)

CMU 95-865 Fall 2017

IMAGENET

Over 10 million images, 1000 object classes

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

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2011: Traditional computer vision achieves accuracy ~74%

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Over 10 million images, 1000 object classes

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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

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Heavily dominated by industry now!

Google
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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

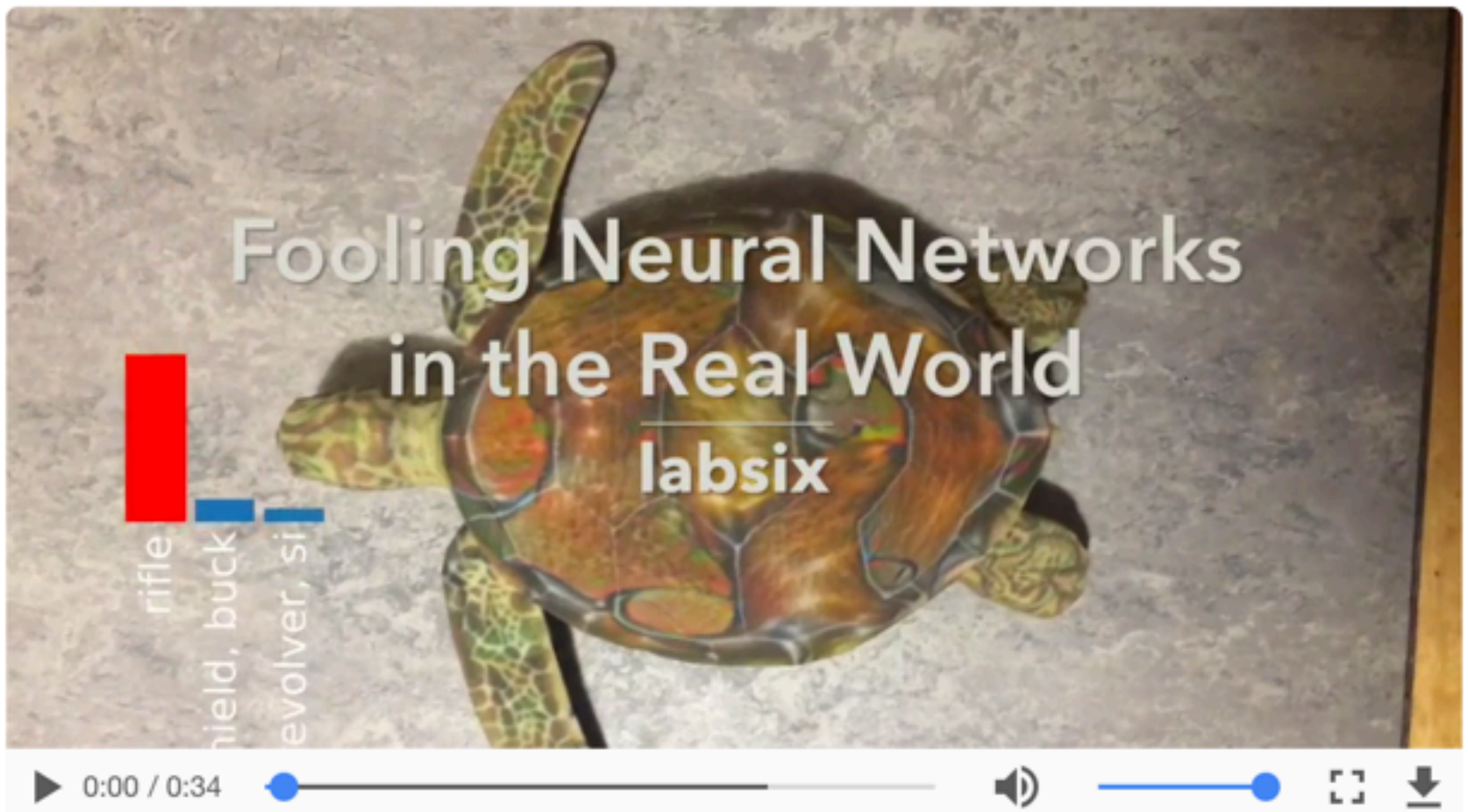
Google DeepMind’s AlphaGo vs Lee Sedol, 2016

Is it all hype?

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

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

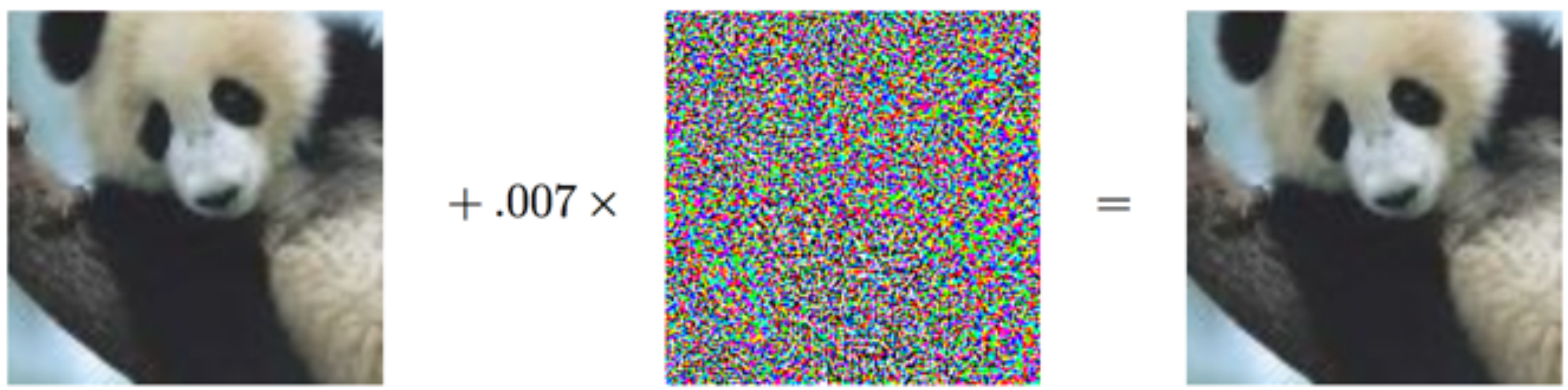
We've developed an approach to generate *3D adversarial objects* that reliably fool neural networks in the real world, no matter how the objects are looked at.



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.)



panda
~58% confidence

adversarial
noise

gibbon
~99% confidence

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

Another AI Winter?

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~1970’s: First AI winter over symbolic AI

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

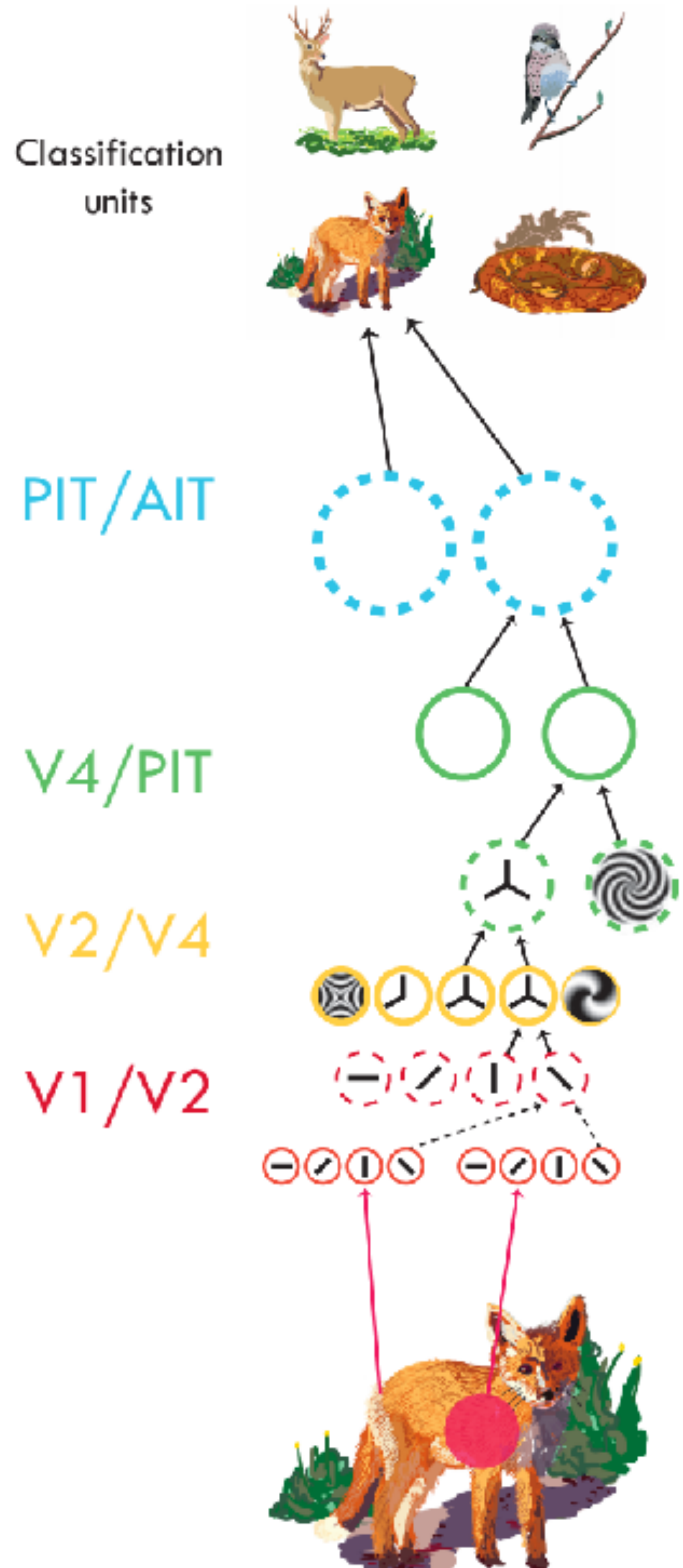
Another AI Winter?

~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

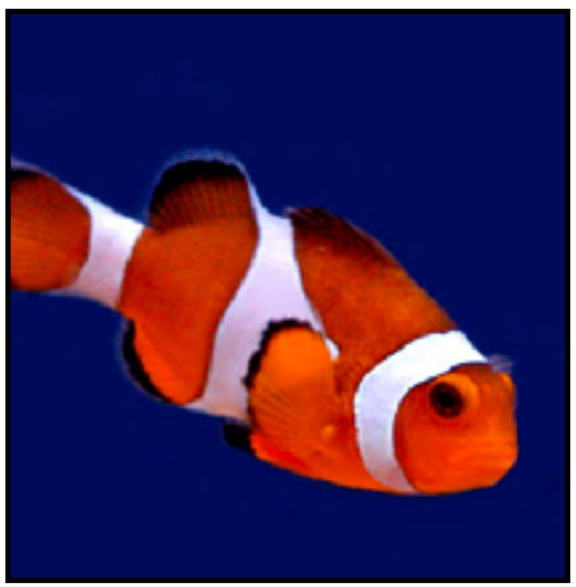
What is deep learning?



Slide by Phillip Isola

Serre, 2014

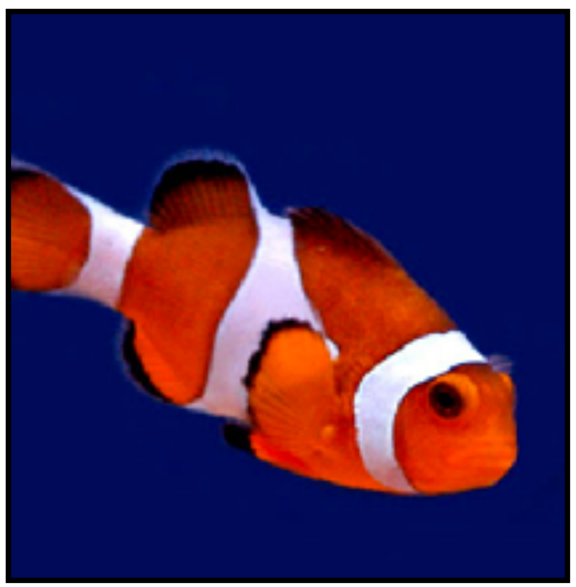
Basic Idea



→ Brain/Machine → "clown fish"

Slide by Phillip Isola

Object Recognition



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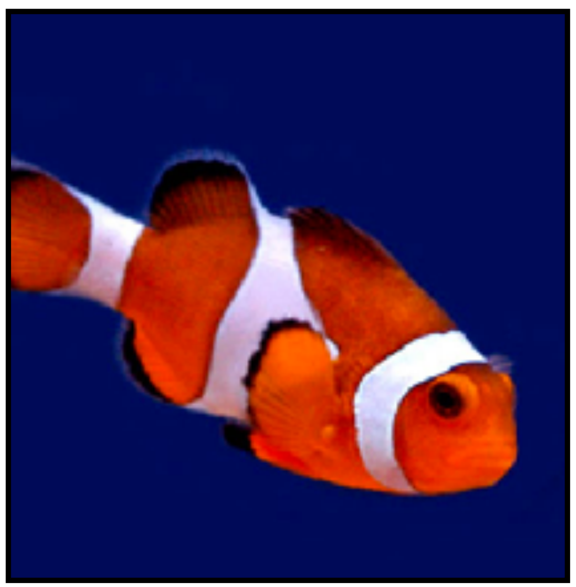

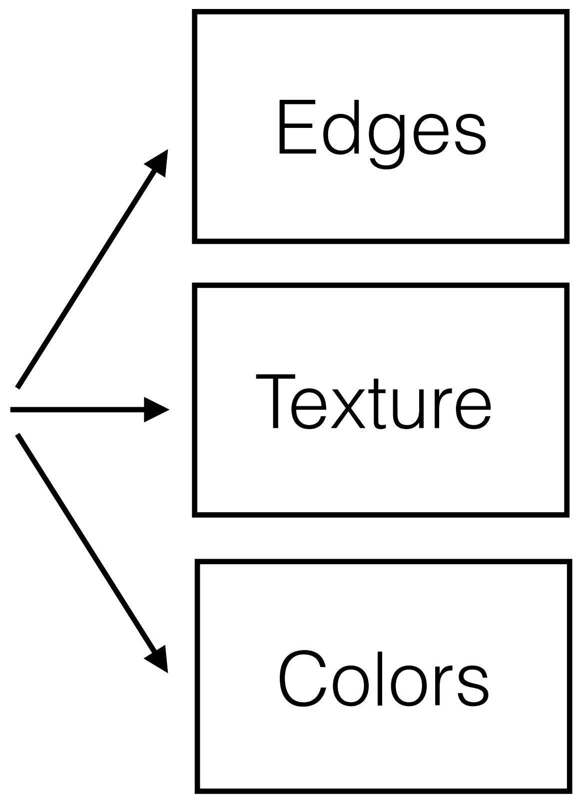

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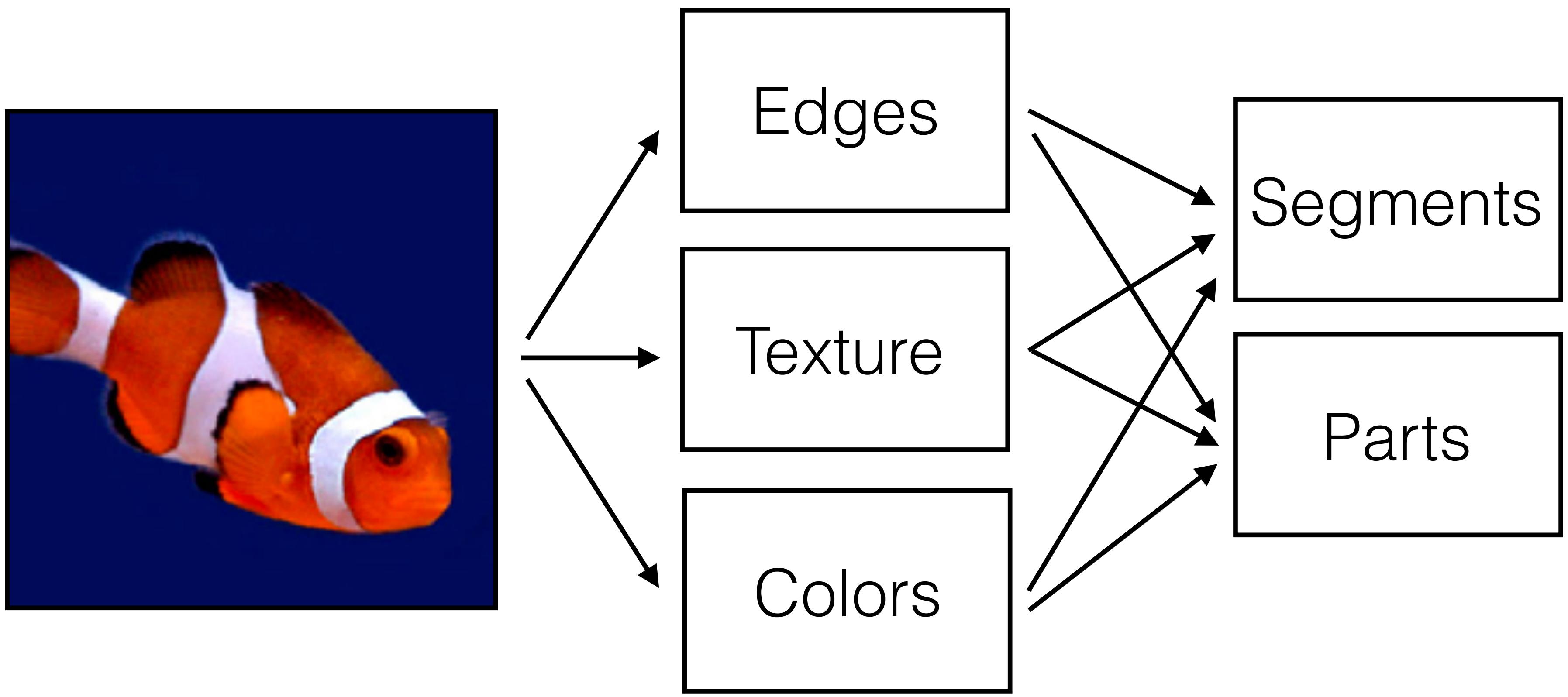

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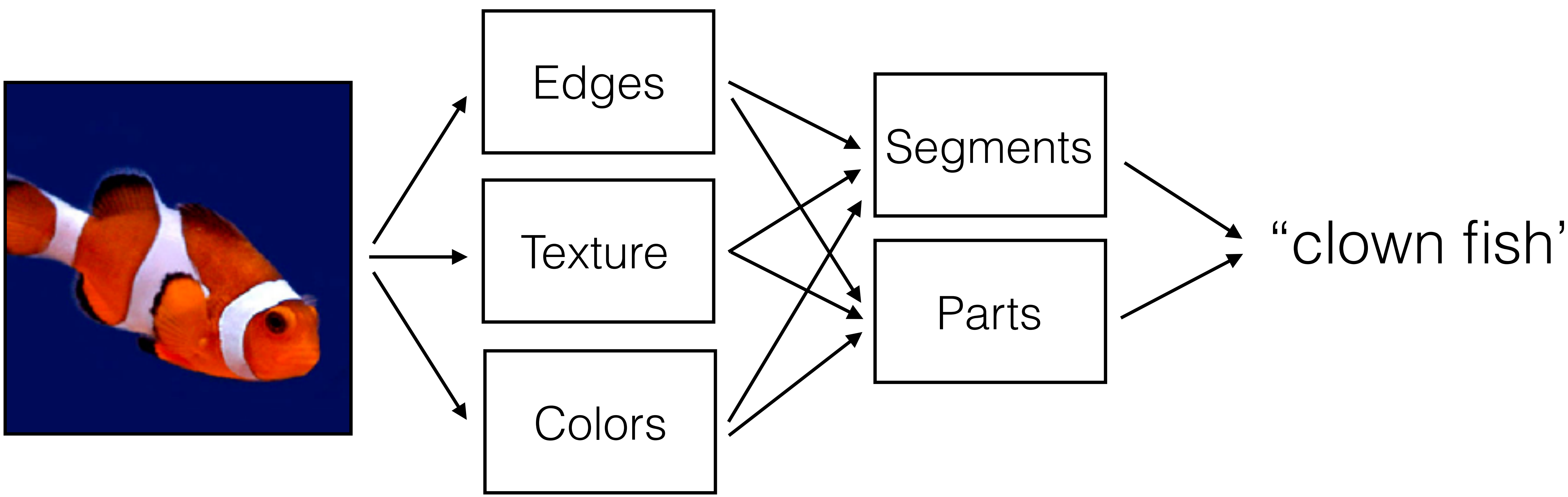

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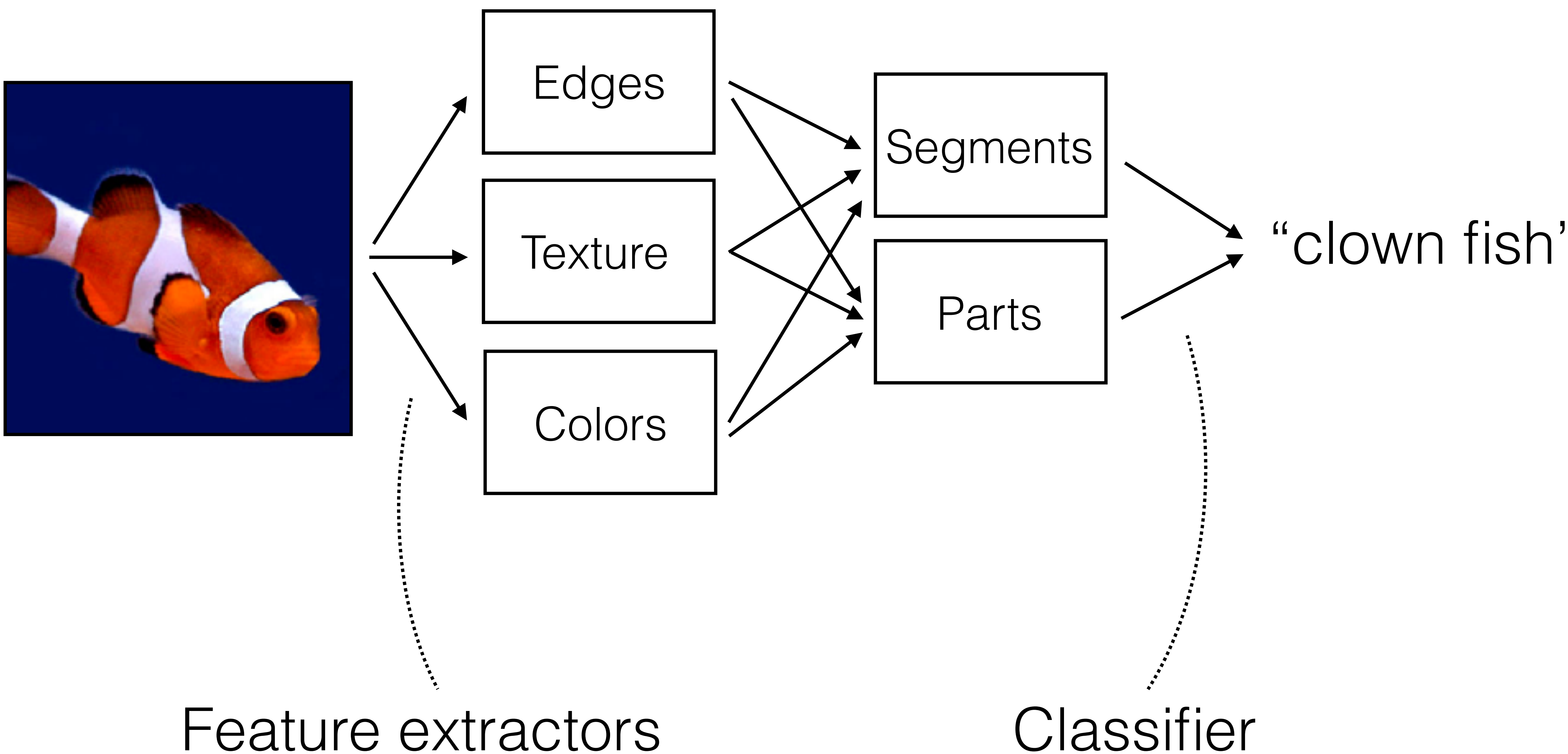

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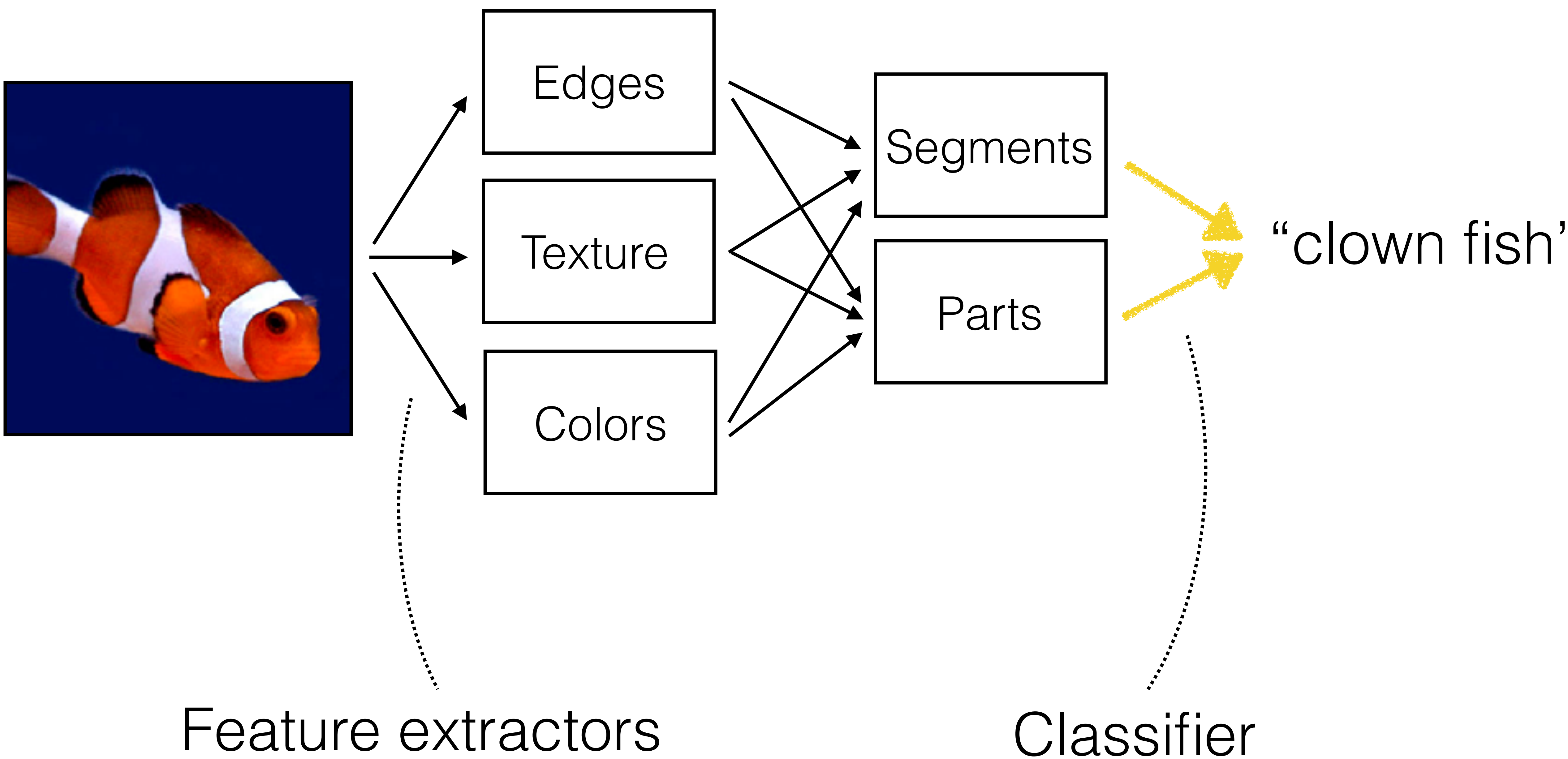
Object Recognition

Learned



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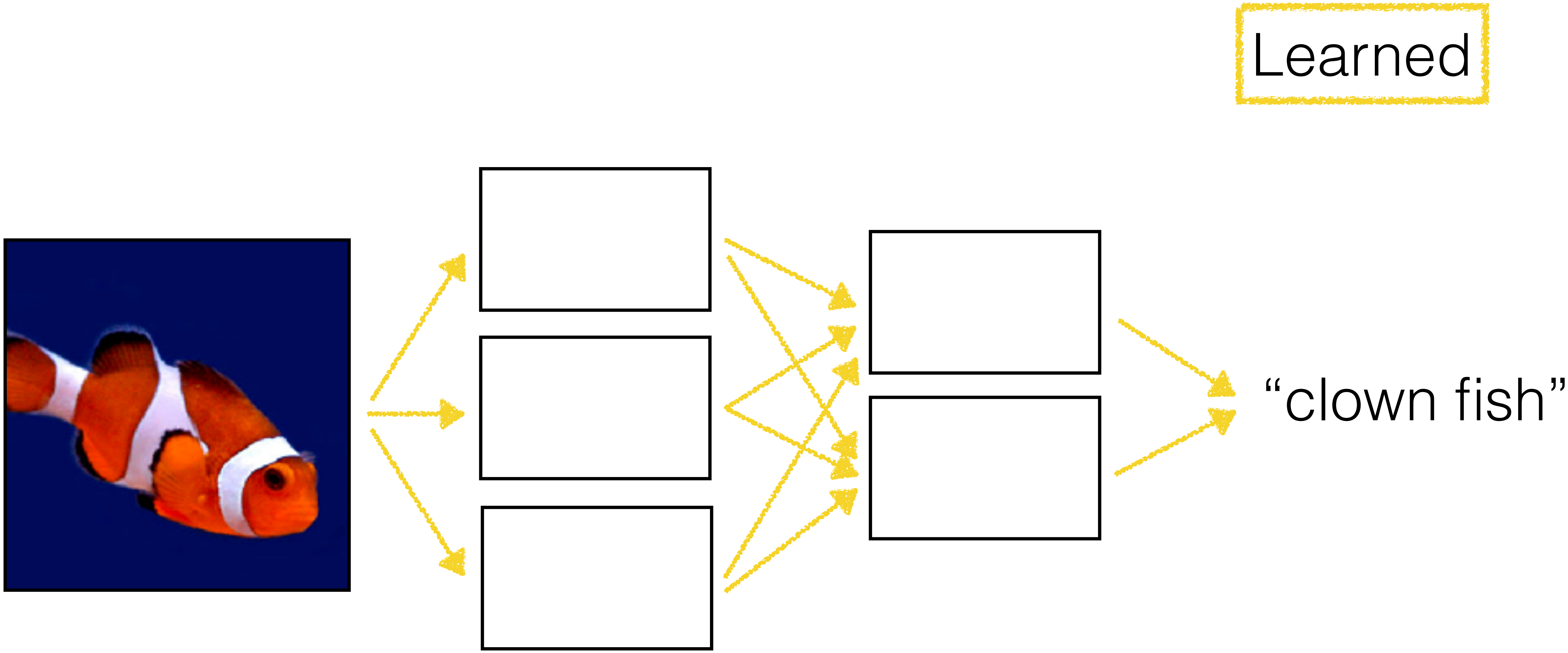
Neural Network



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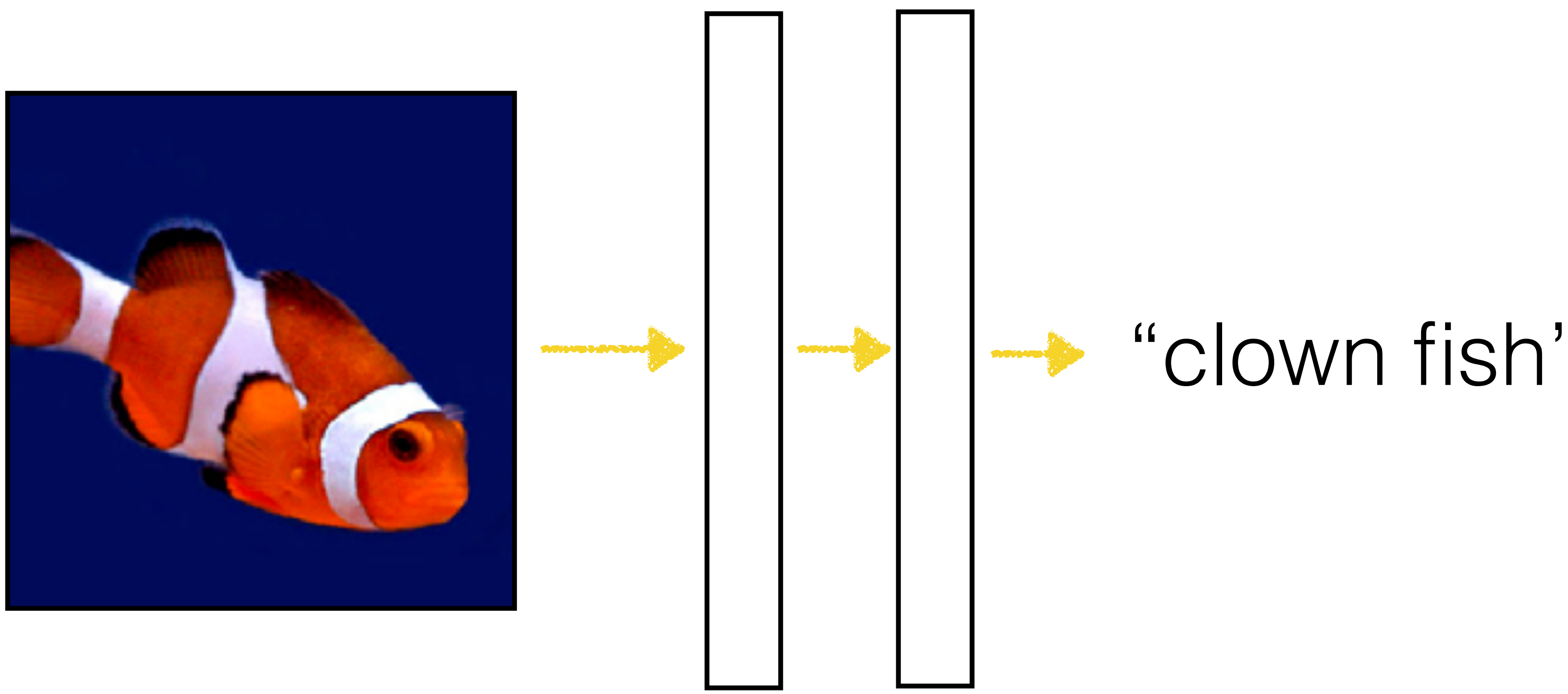
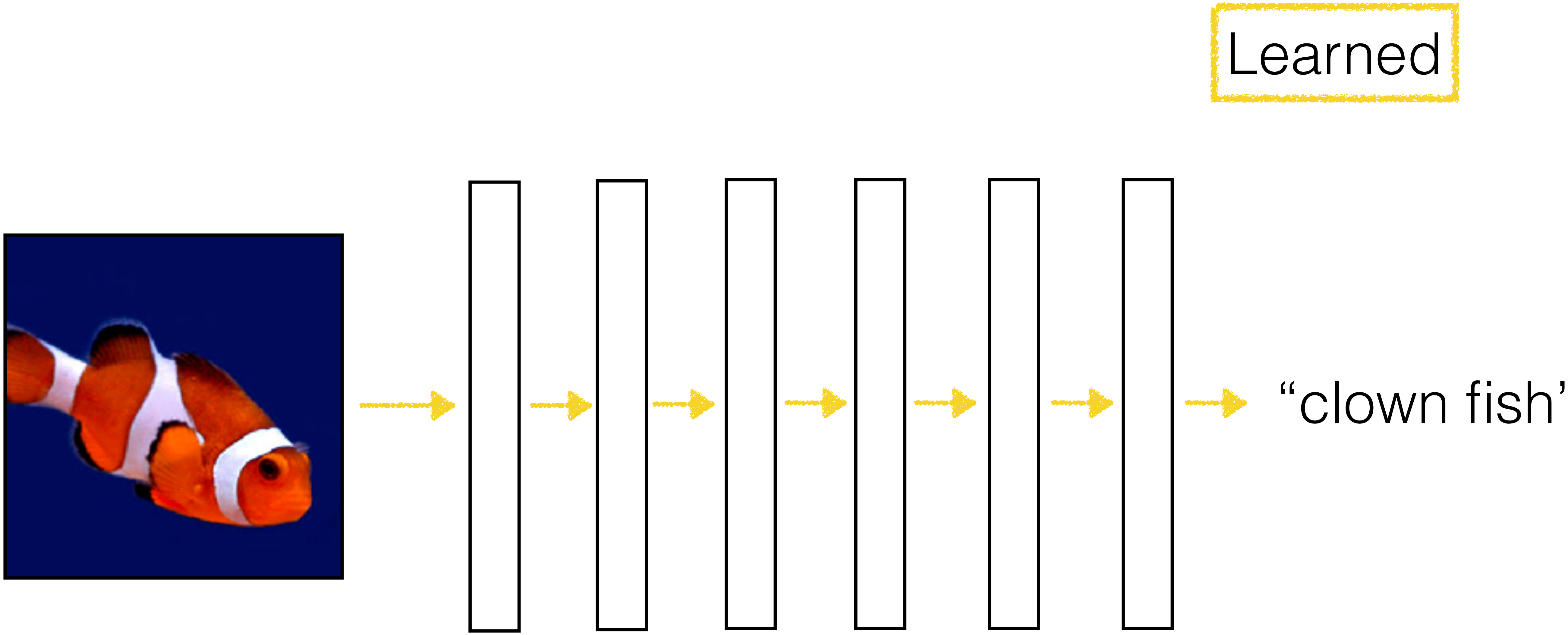


Slide by Phillip Isola

Deep Neural Network



Slide by Phillip Isola

Crumpled Paper Analogy

Analogy: Francois Chollet, photo: George Chen

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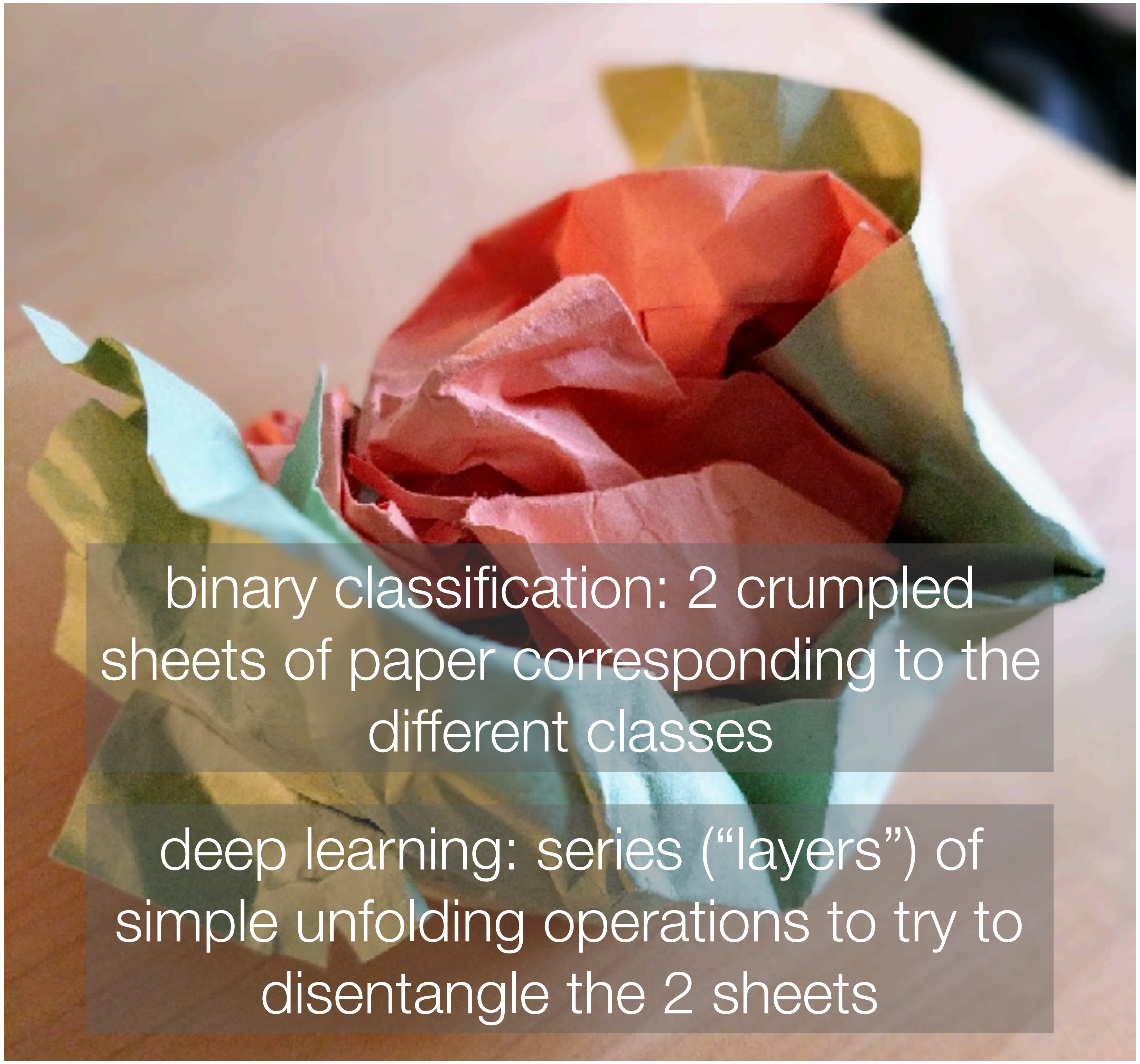

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Structure Present in Data Matters

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The best performing neural network architectures account for the kind of data they process!

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- **Image analysis:** convolutional neural networks (convnets) neatly incorporates intuitive image processing ideas (for example: if a car appears in an image, even if you shift it over by many pixels, it’s still a car)

Structure Present in Data Matters

The best performing neural network architectures account for the kind of data they process!

- **Image analysis:** convolutional neural networks (convnets) neatly incorporates intuitive image processing ideas (for example: if a car appears in an image, even if you shift it over by many pixels, it's still a car)

- **Time series analysis:** recurrent neural networks (RNNs) incorporates ability to remember and forget things over time (note: text naturally comprise of time series as words appear one after another in a meaningful sequence!)

Why Does Deep Learning Work?

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

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CPU's
& Moore's law

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amazon.com

lyft

NETFLIX fitbit

UPMC
LIFE CHANGING MEDICINE

- Better hardware

intel

AMD

CPU’s
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GPU’s

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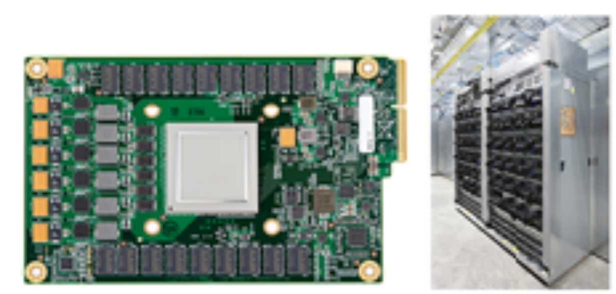

TPU's

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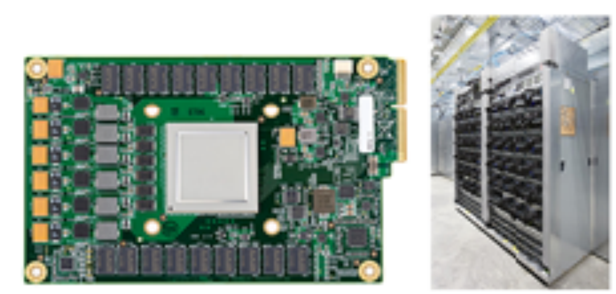

TPU's

- Better algorithms

Handwritten Digit Recognition Example

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

Handwritten Digit Recognition

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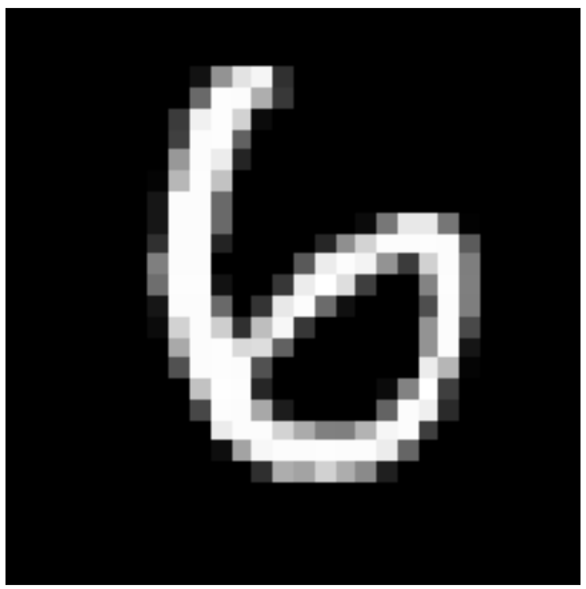
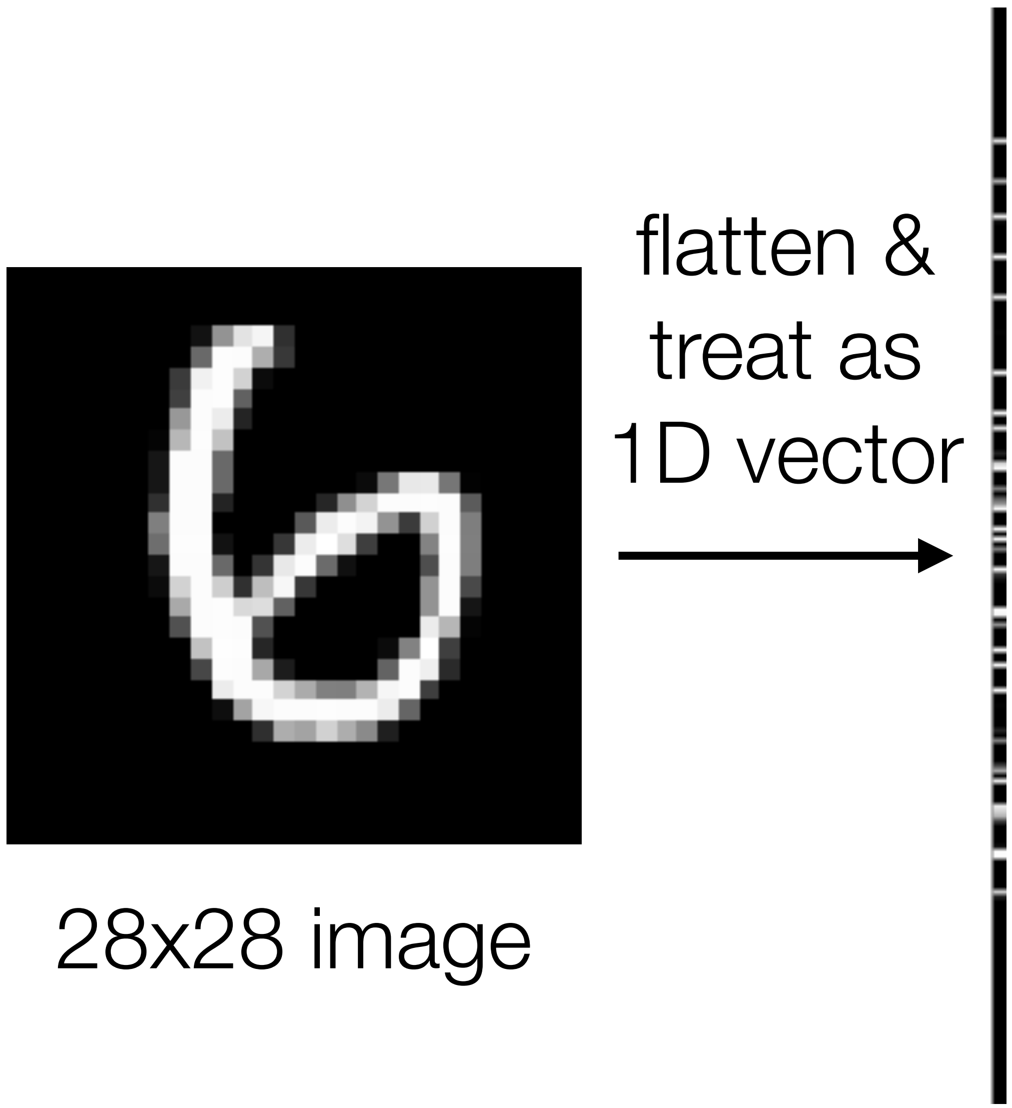


28x28 image

Handwritten Digit Recognition



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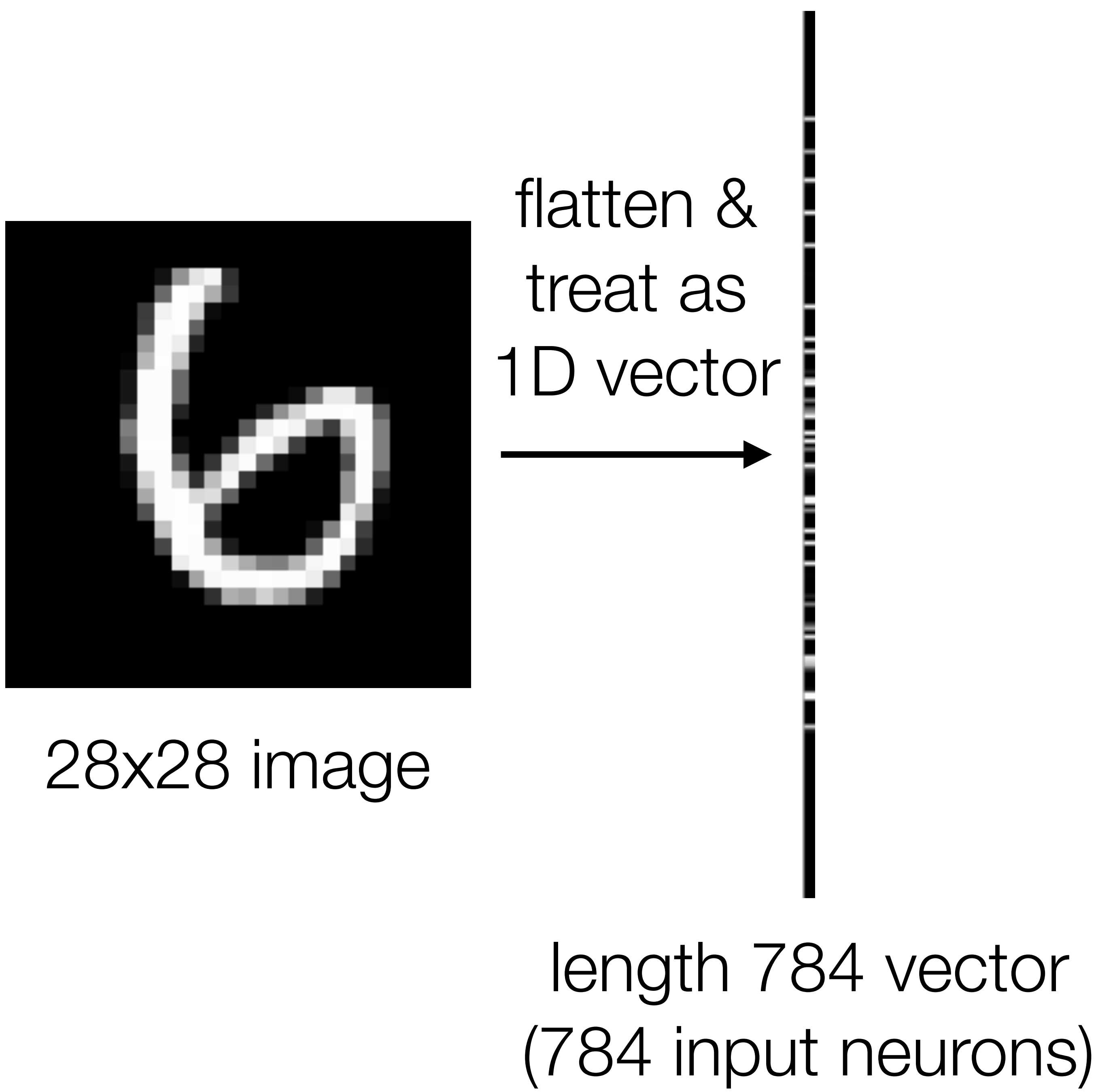

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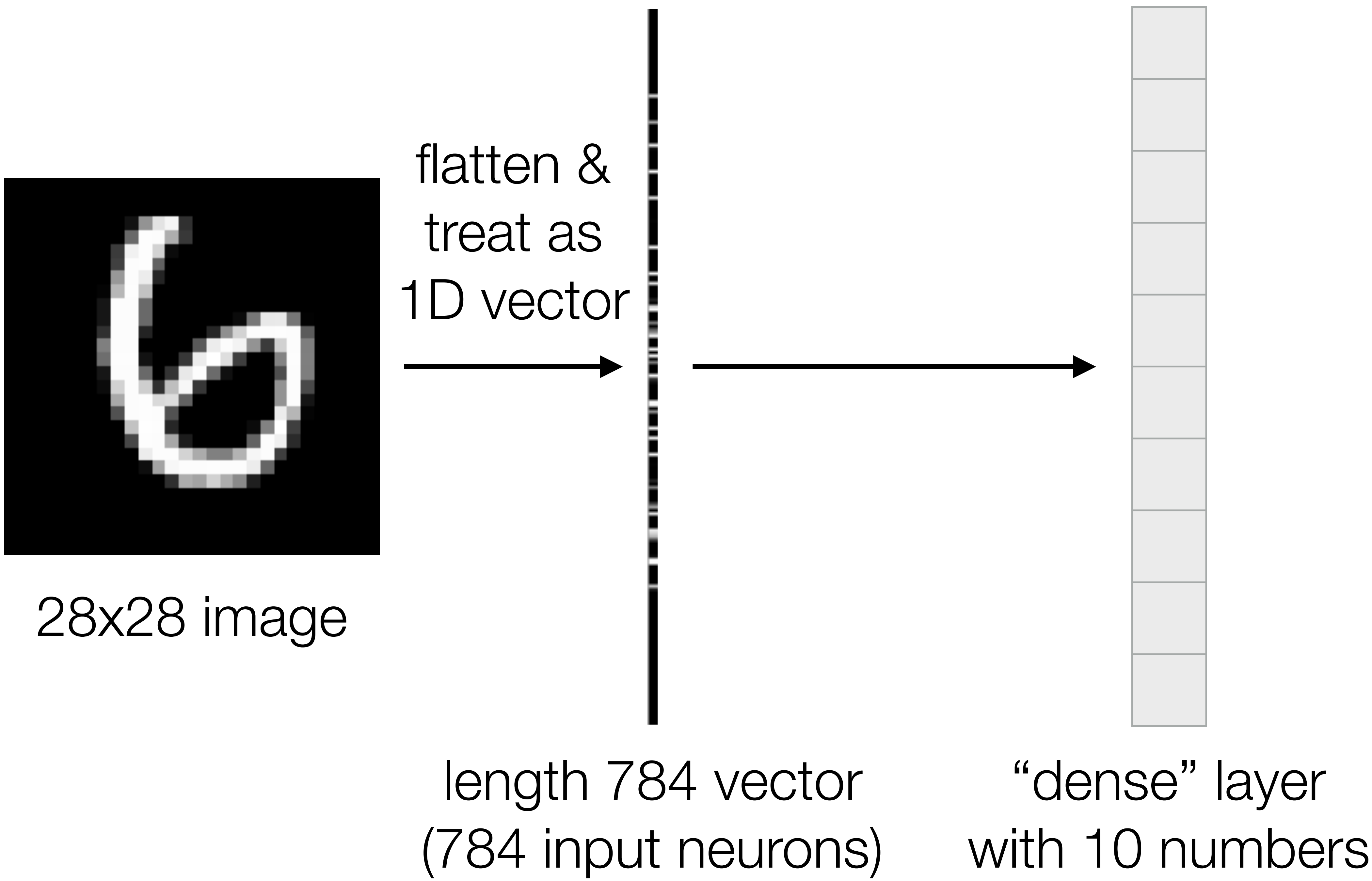

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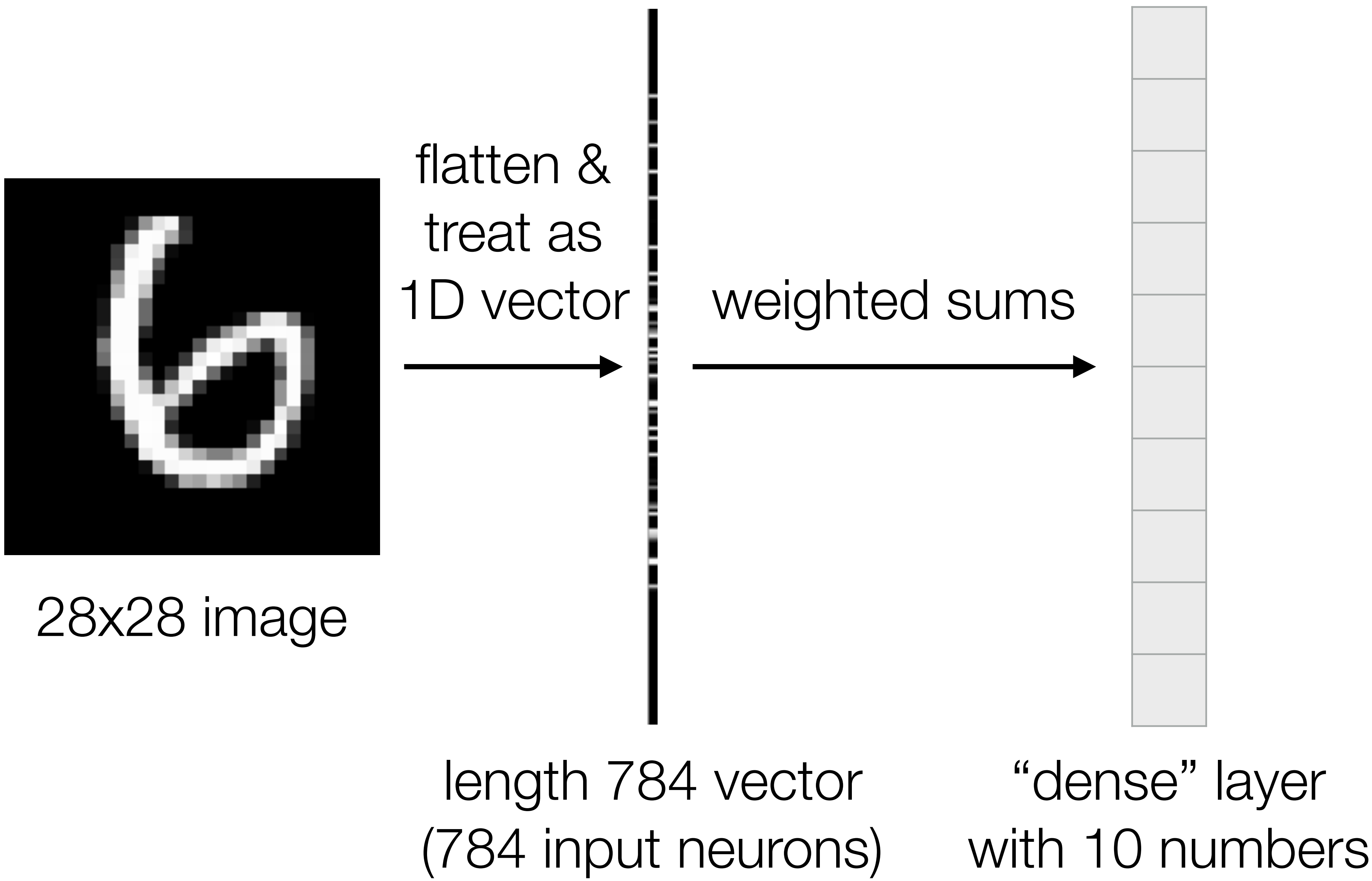

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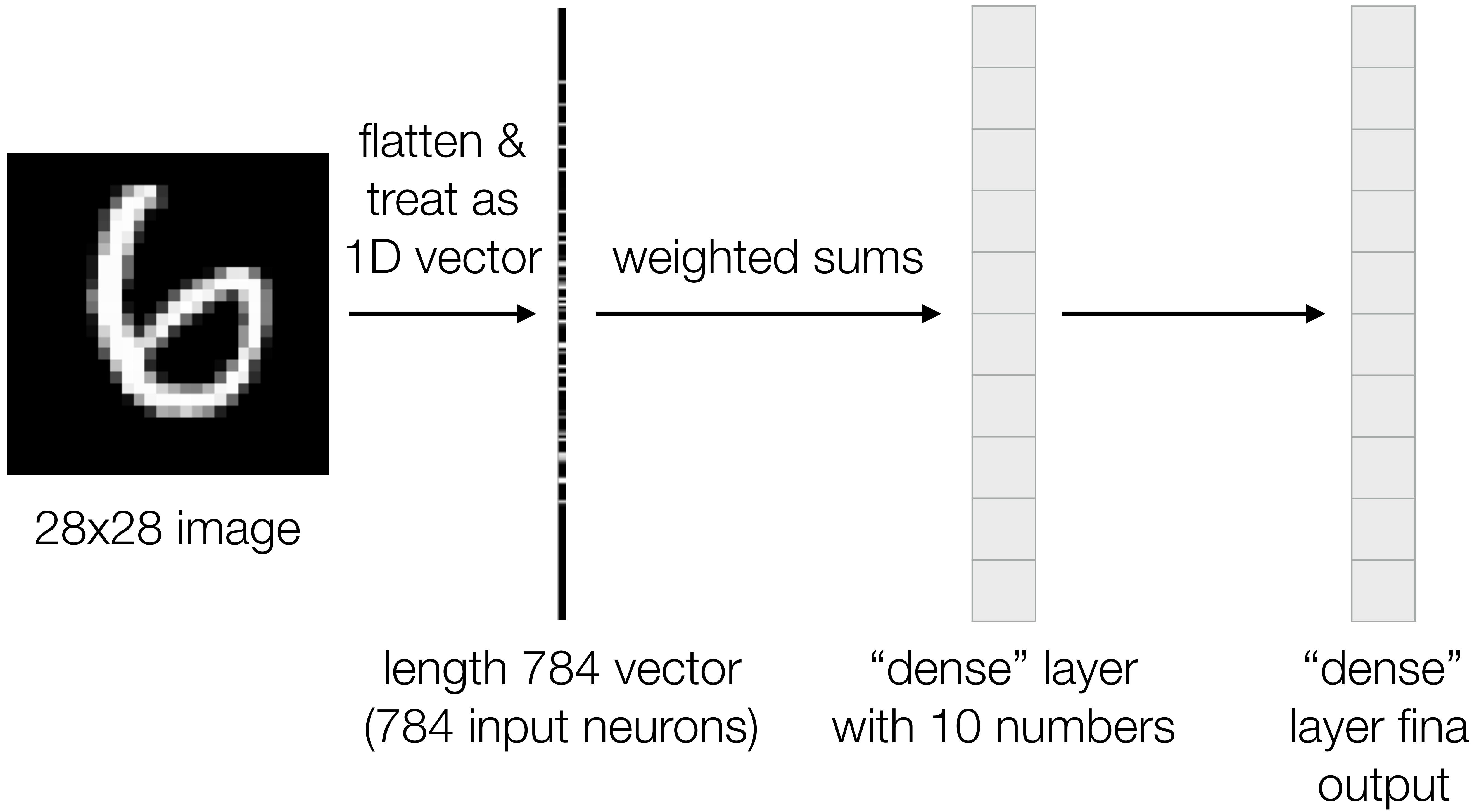

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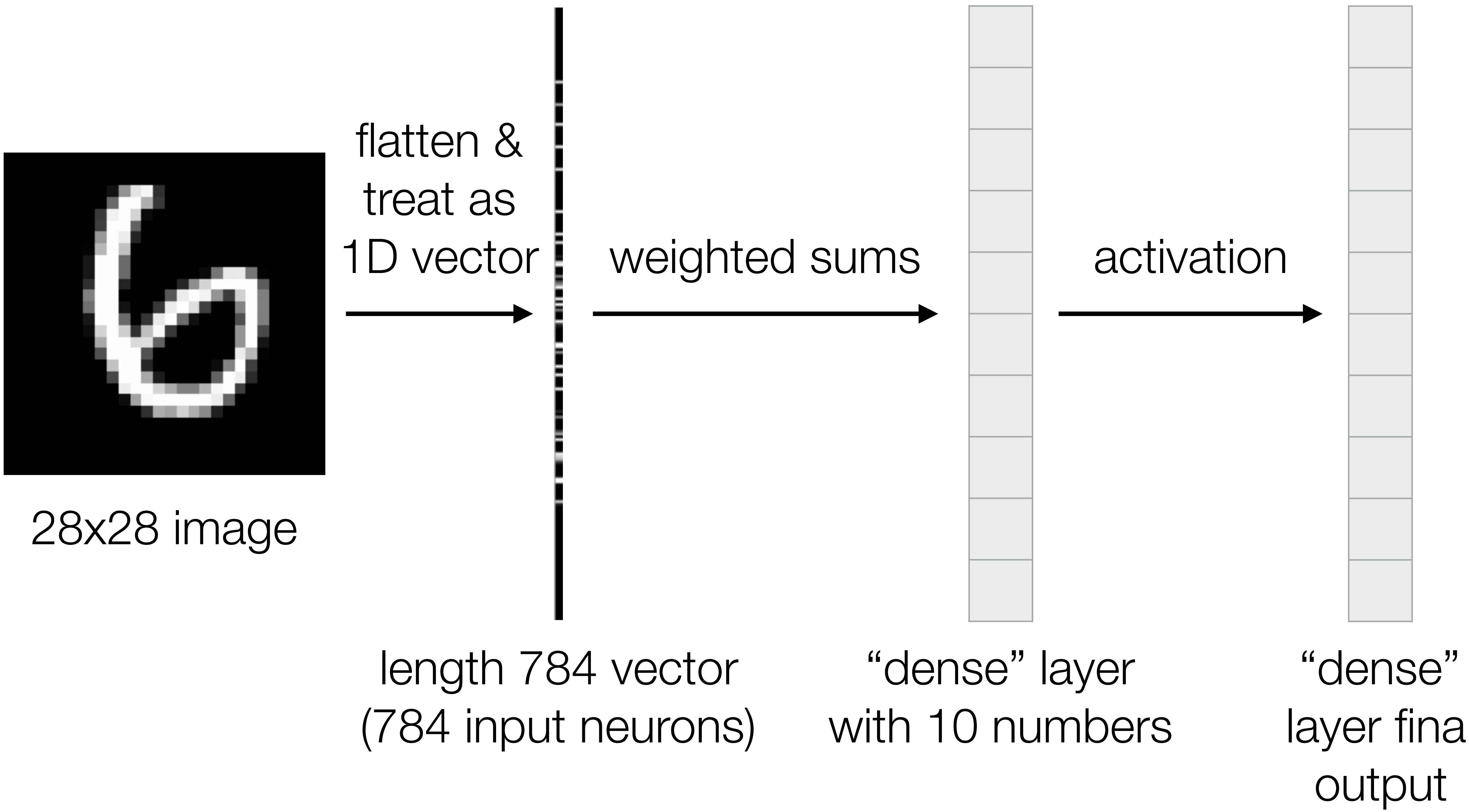

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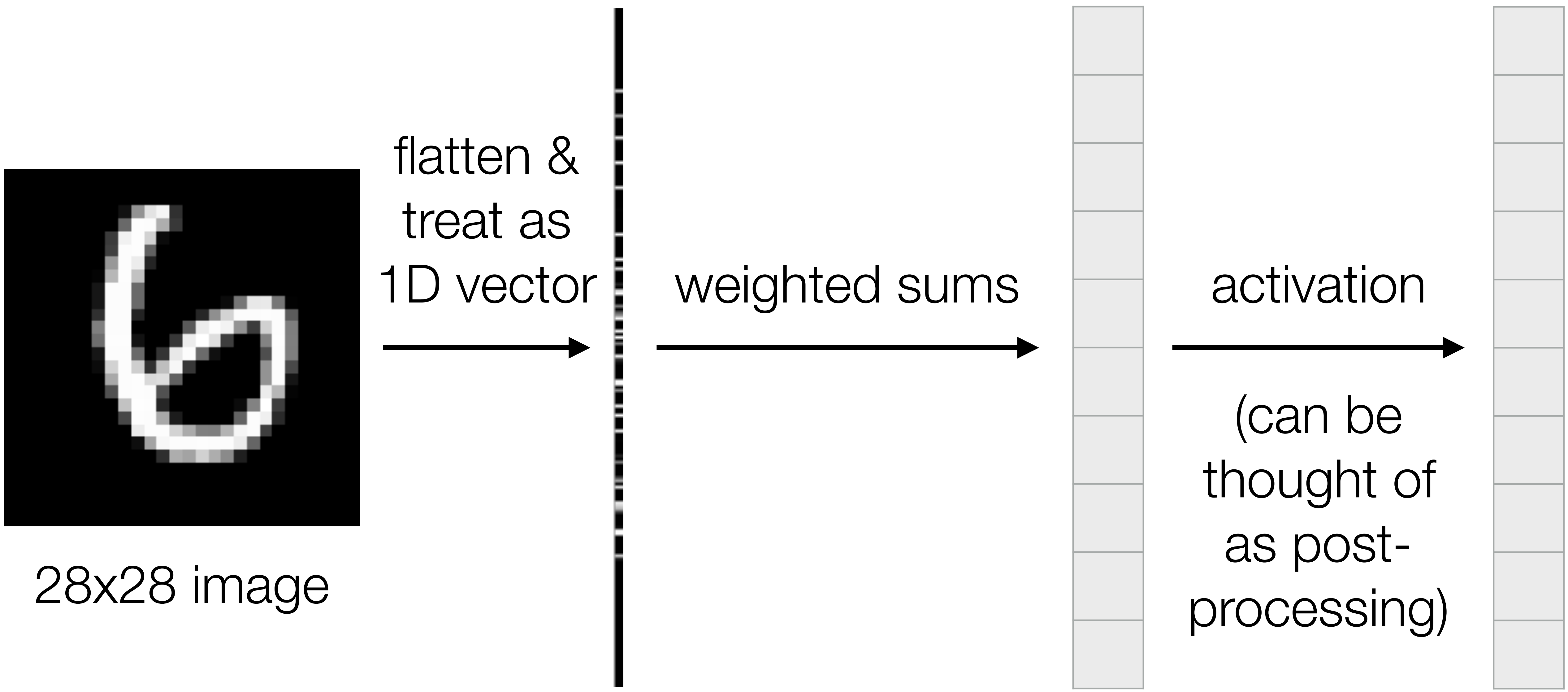

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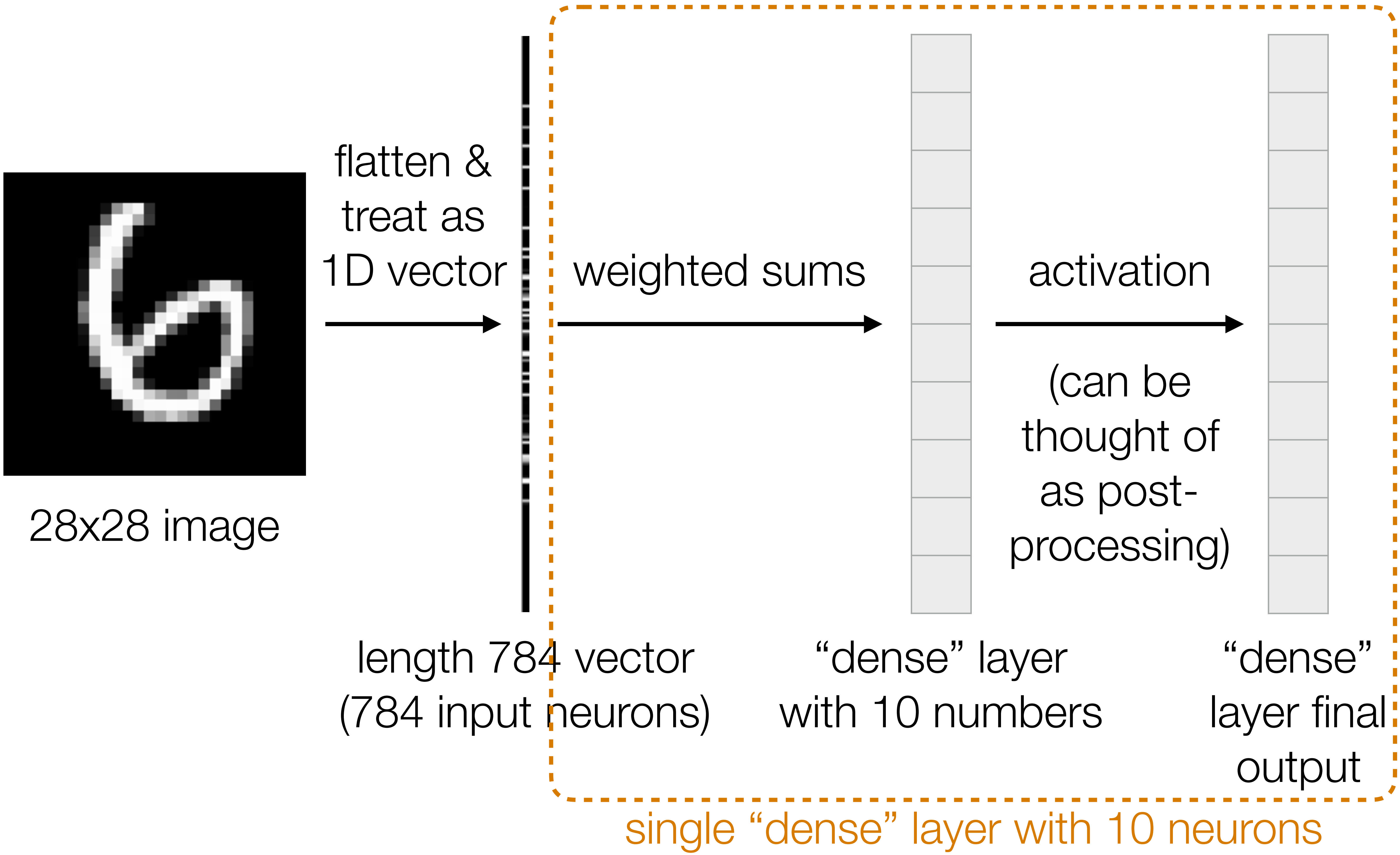

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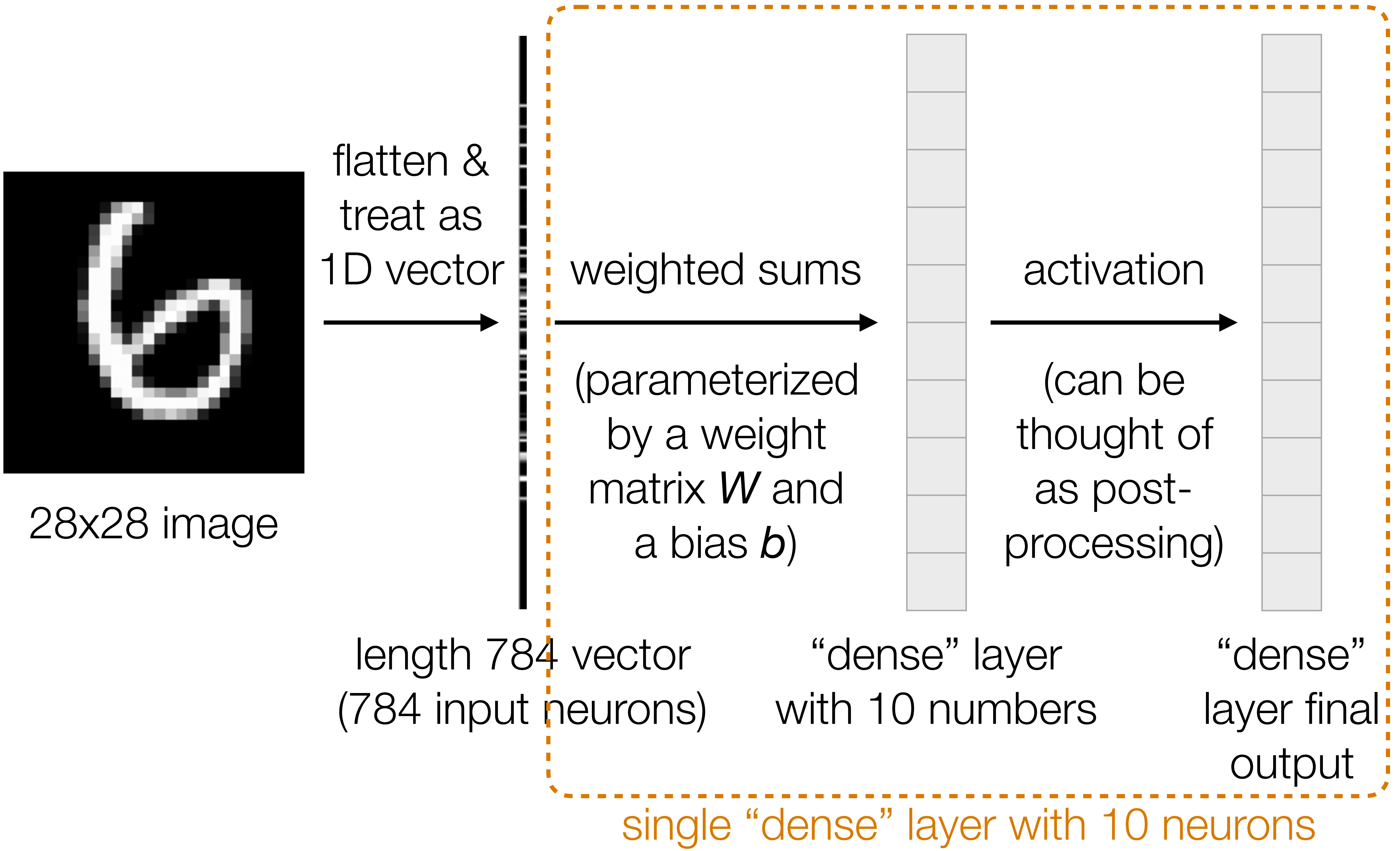

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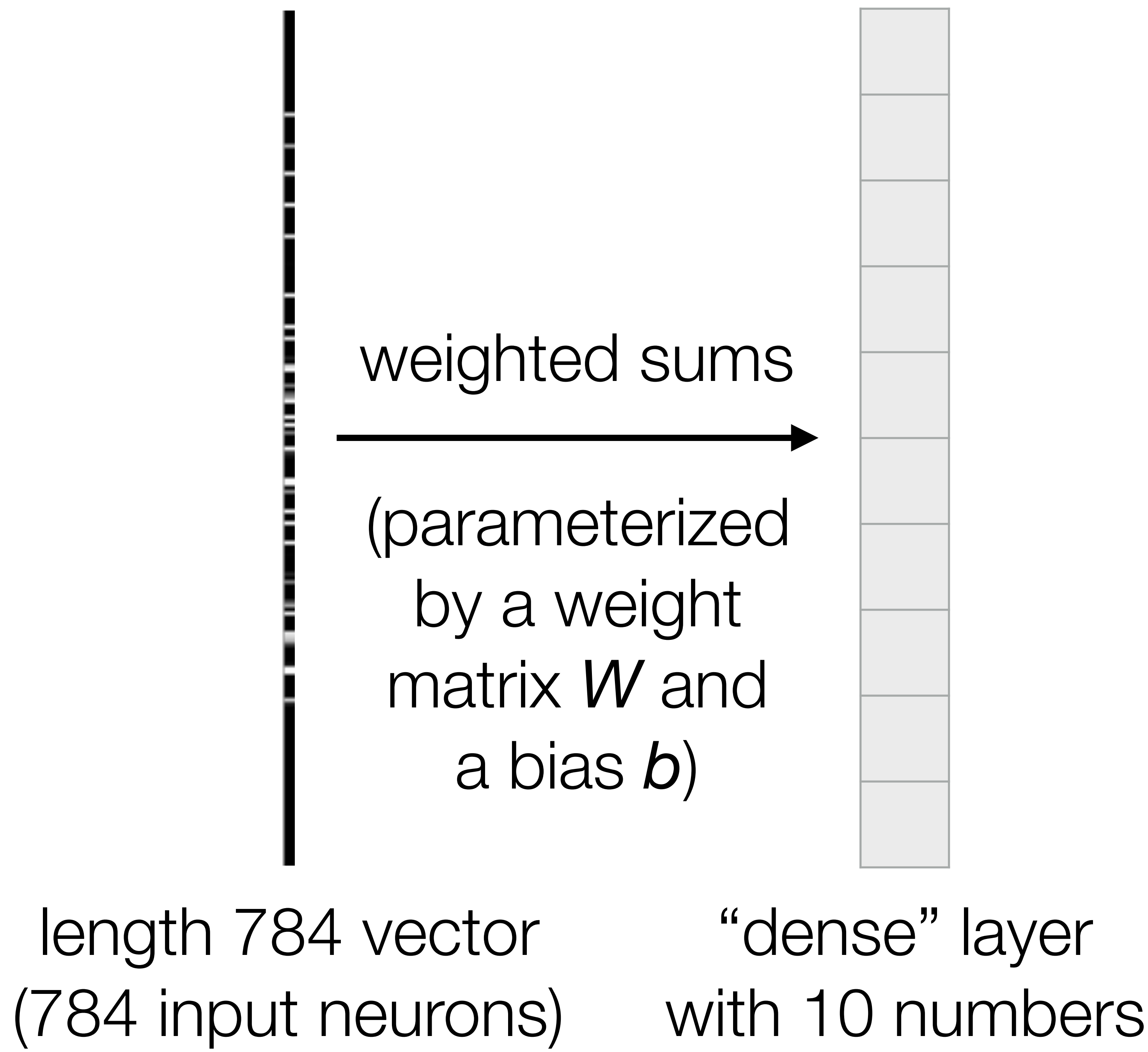

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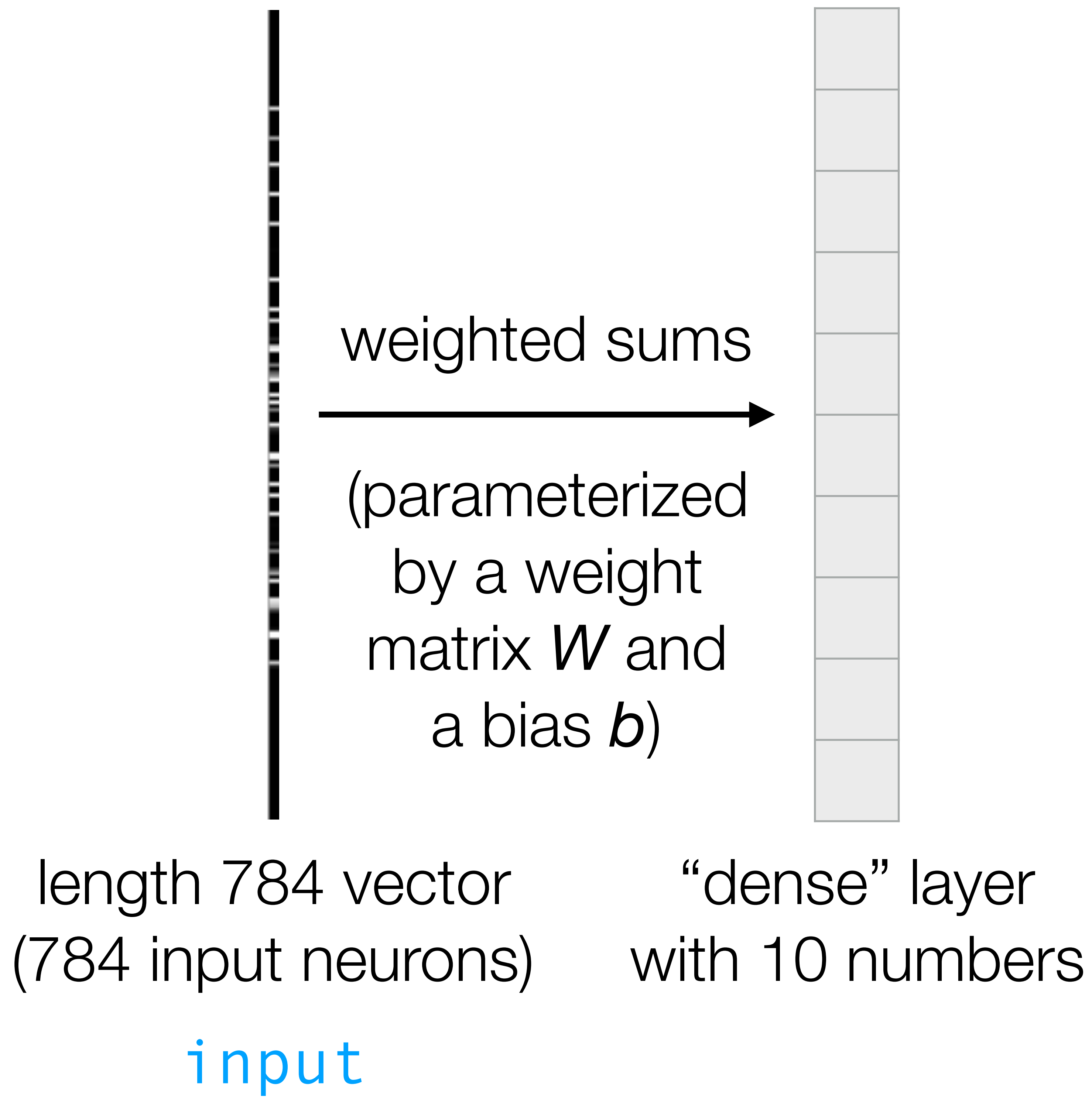

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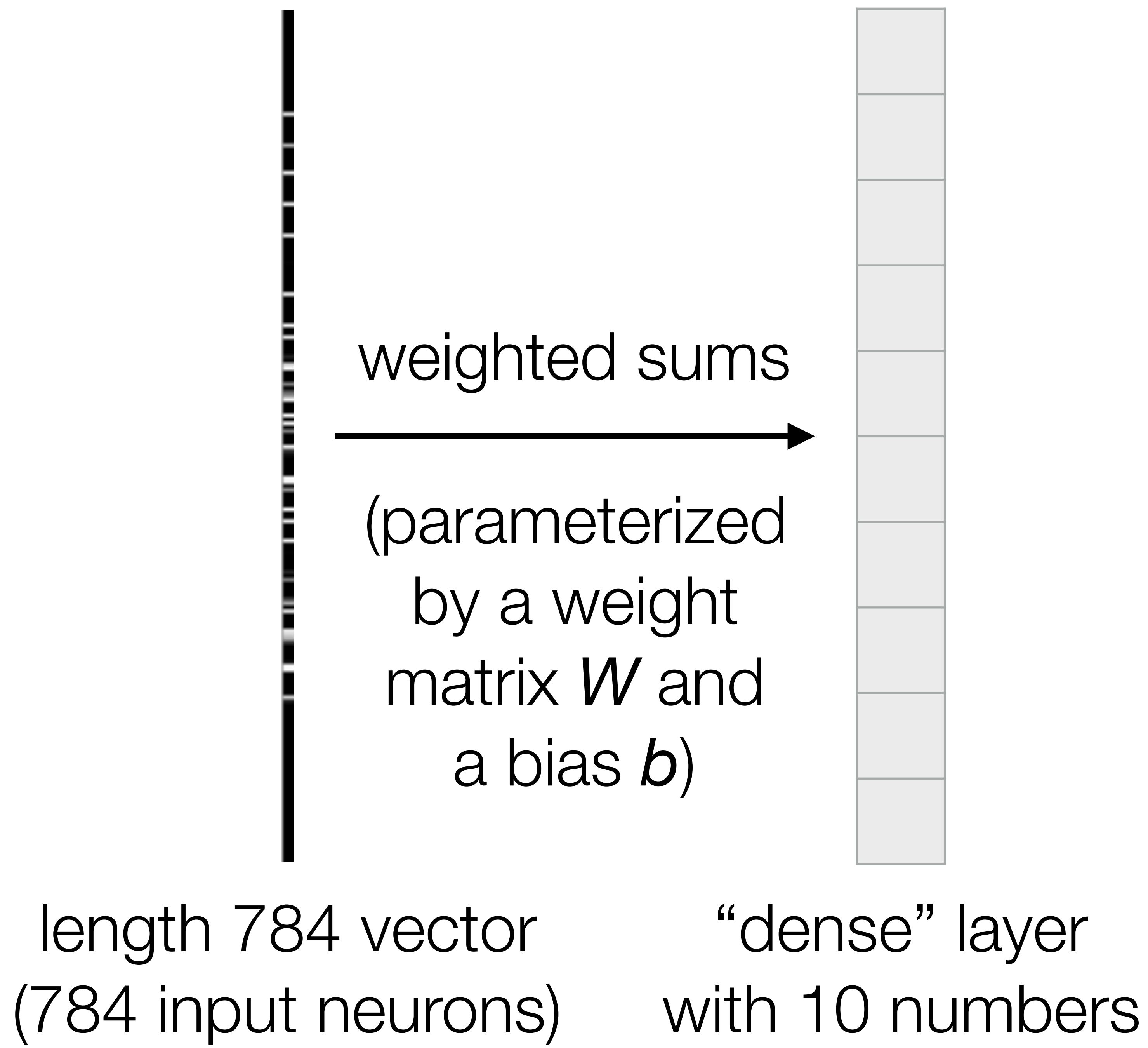
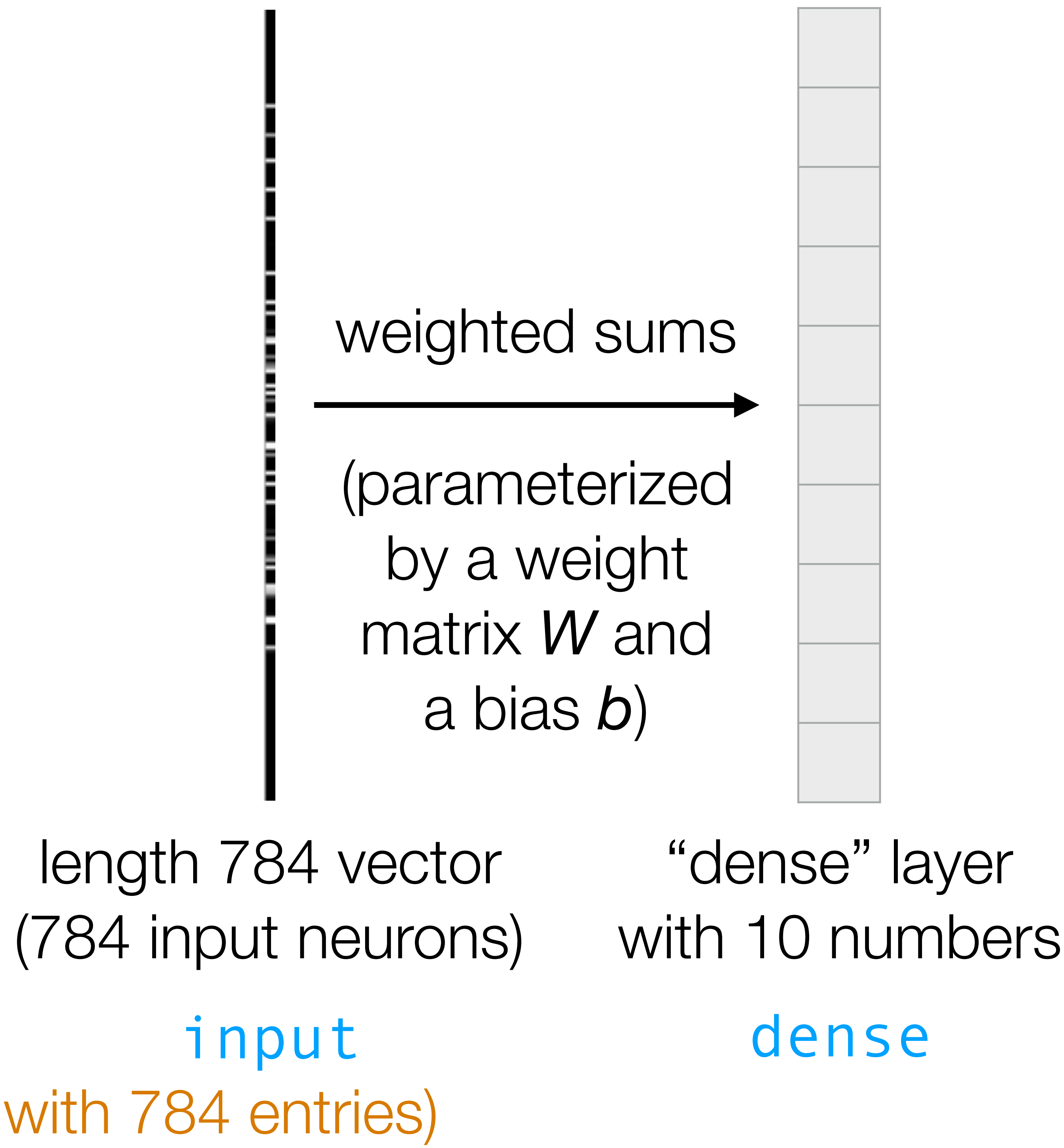


`input`

(1D numpy array with 784 entries)

Handwritten Digit Recognition



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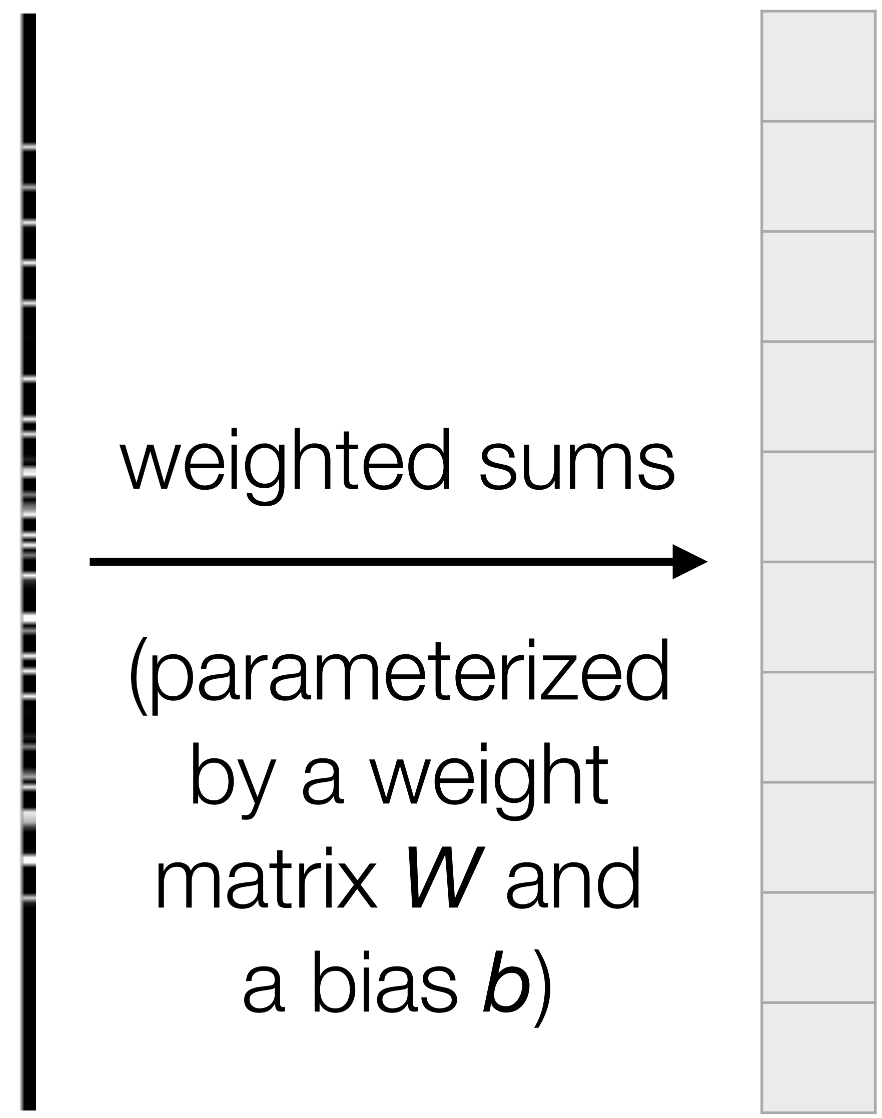


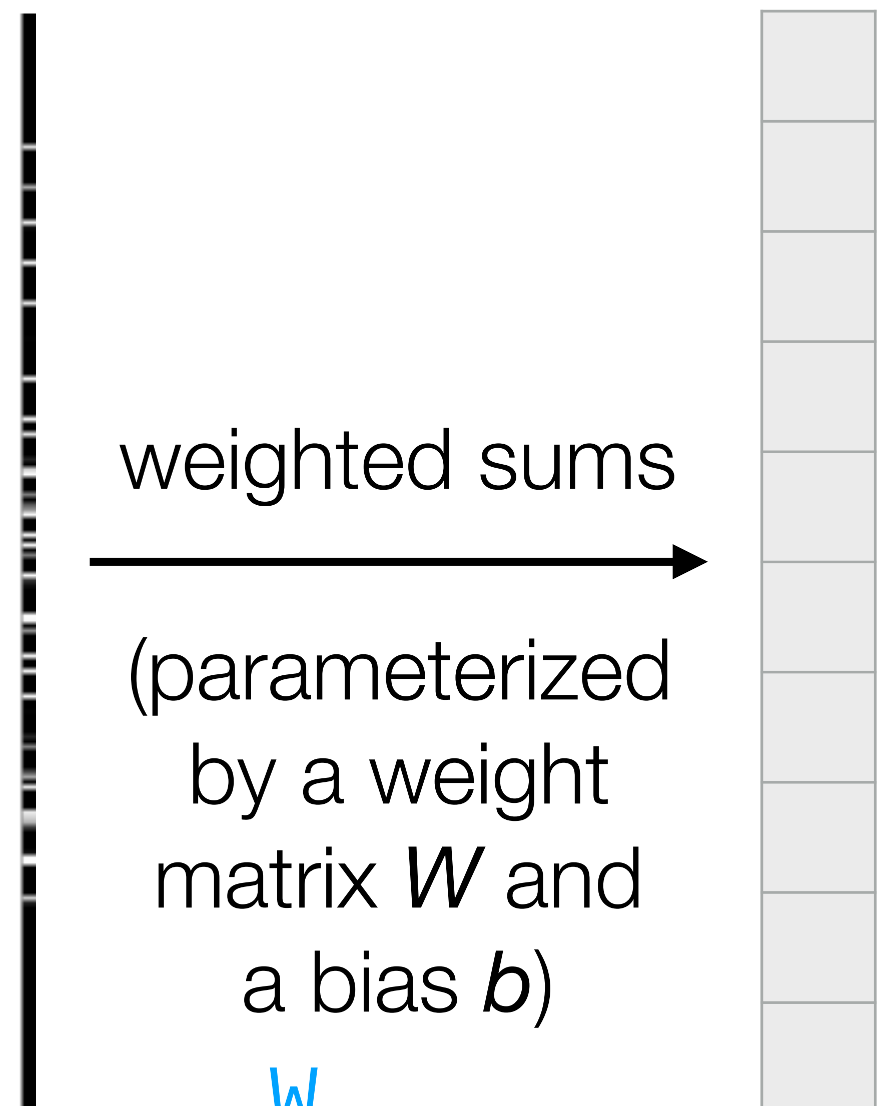
length 784 vector
(784 input neurons)

"dense" layer
with 10 numbers

`input`
(1D numpy array with 784 entries)

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

Handwritten Digit Recognition



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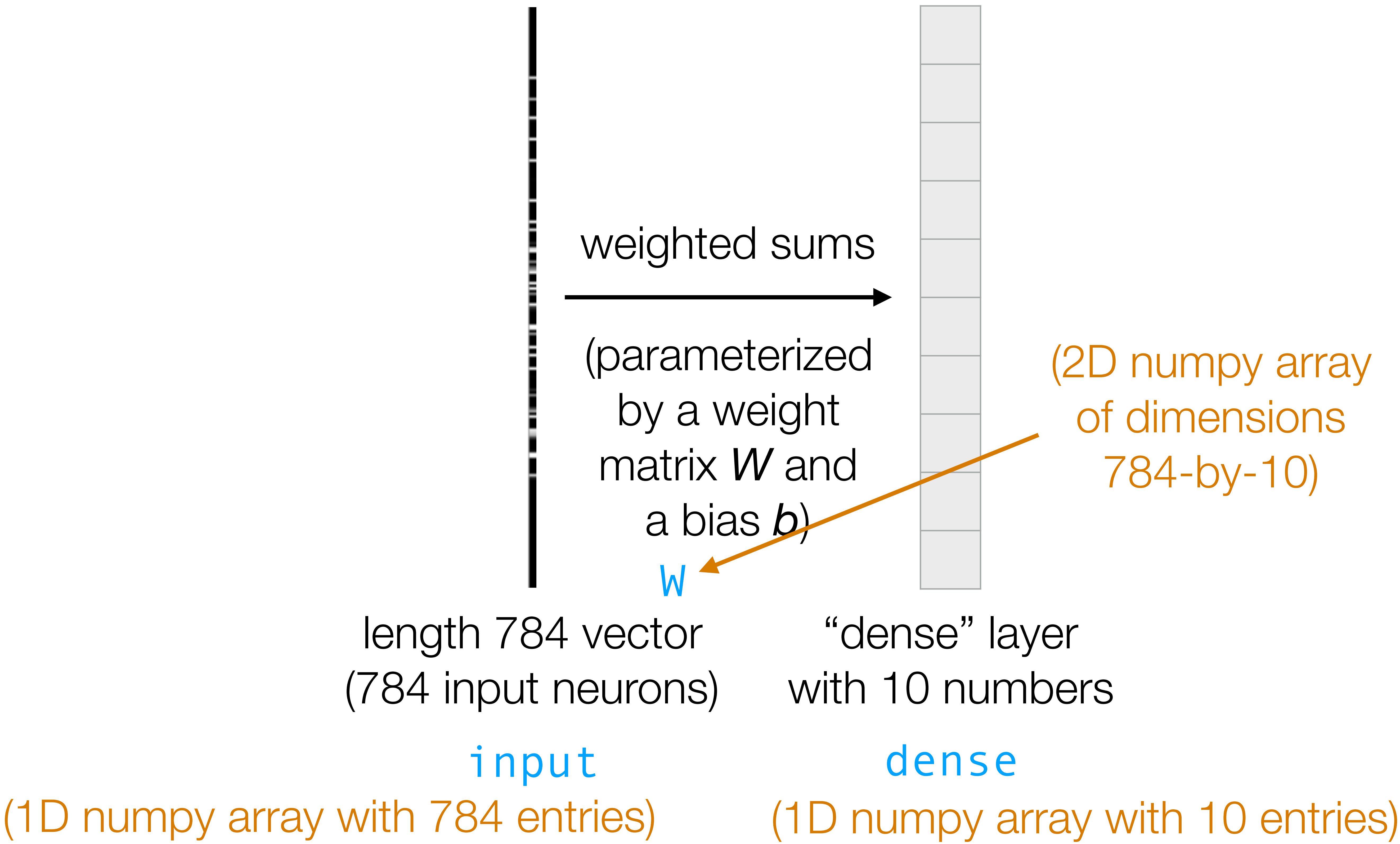

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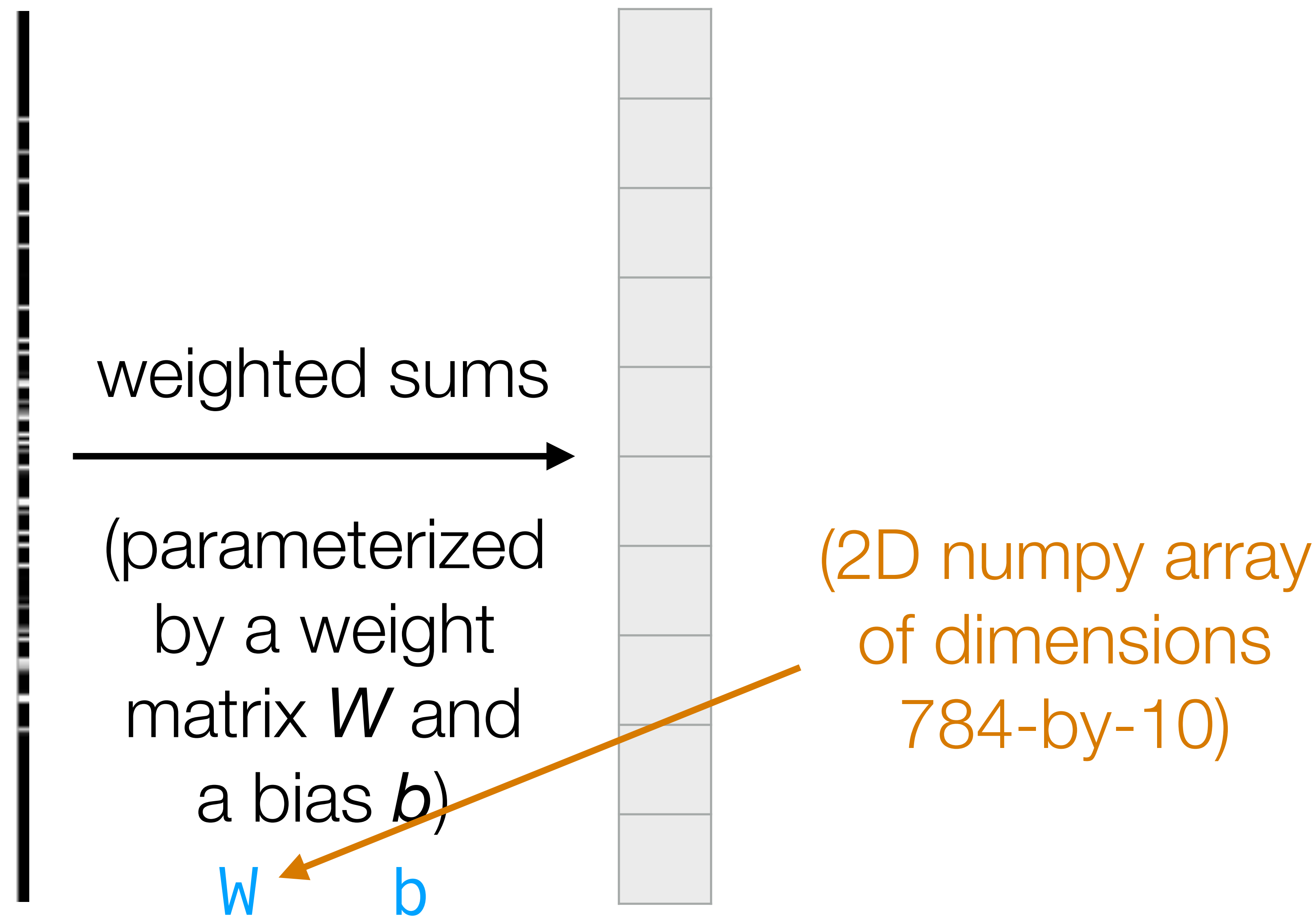

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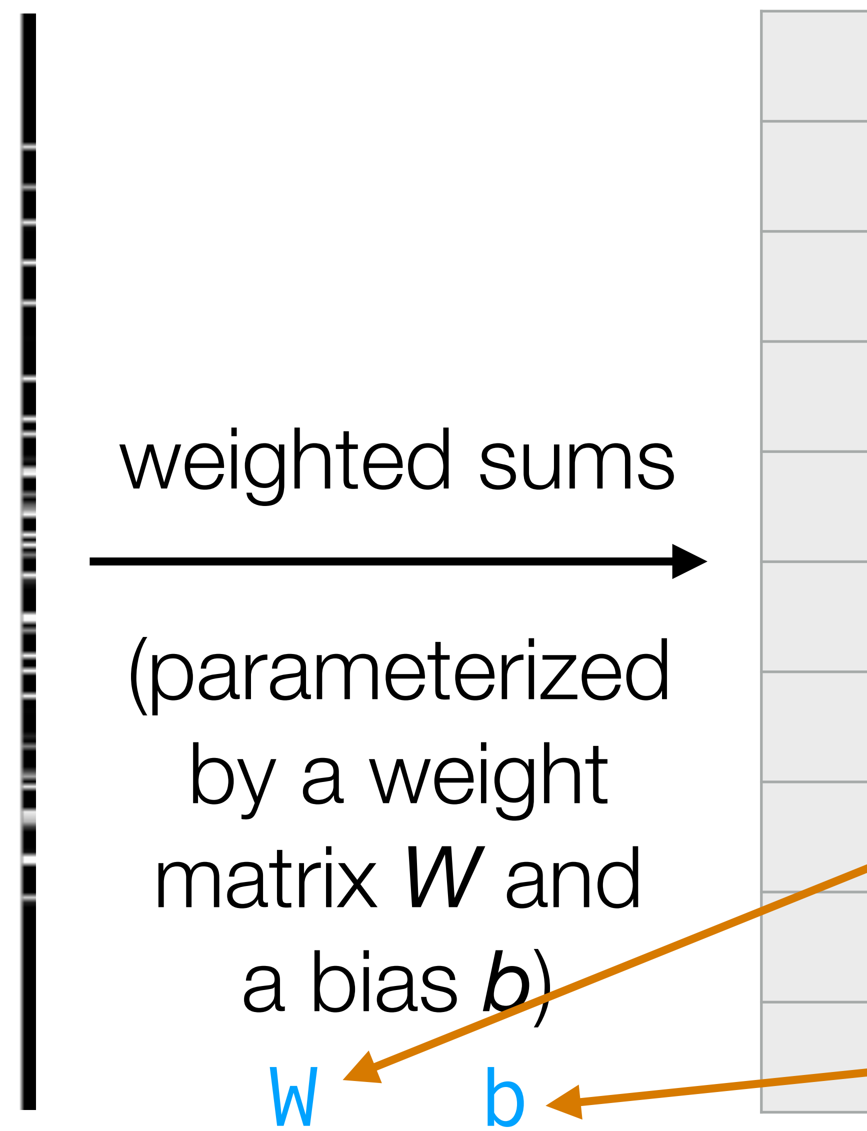


(2D numpy array of dimensions 784-by-10)

(1D numpy array with 10 entries)

length 784 vector (784 input neurons)

“dense” layer with 10 numbers

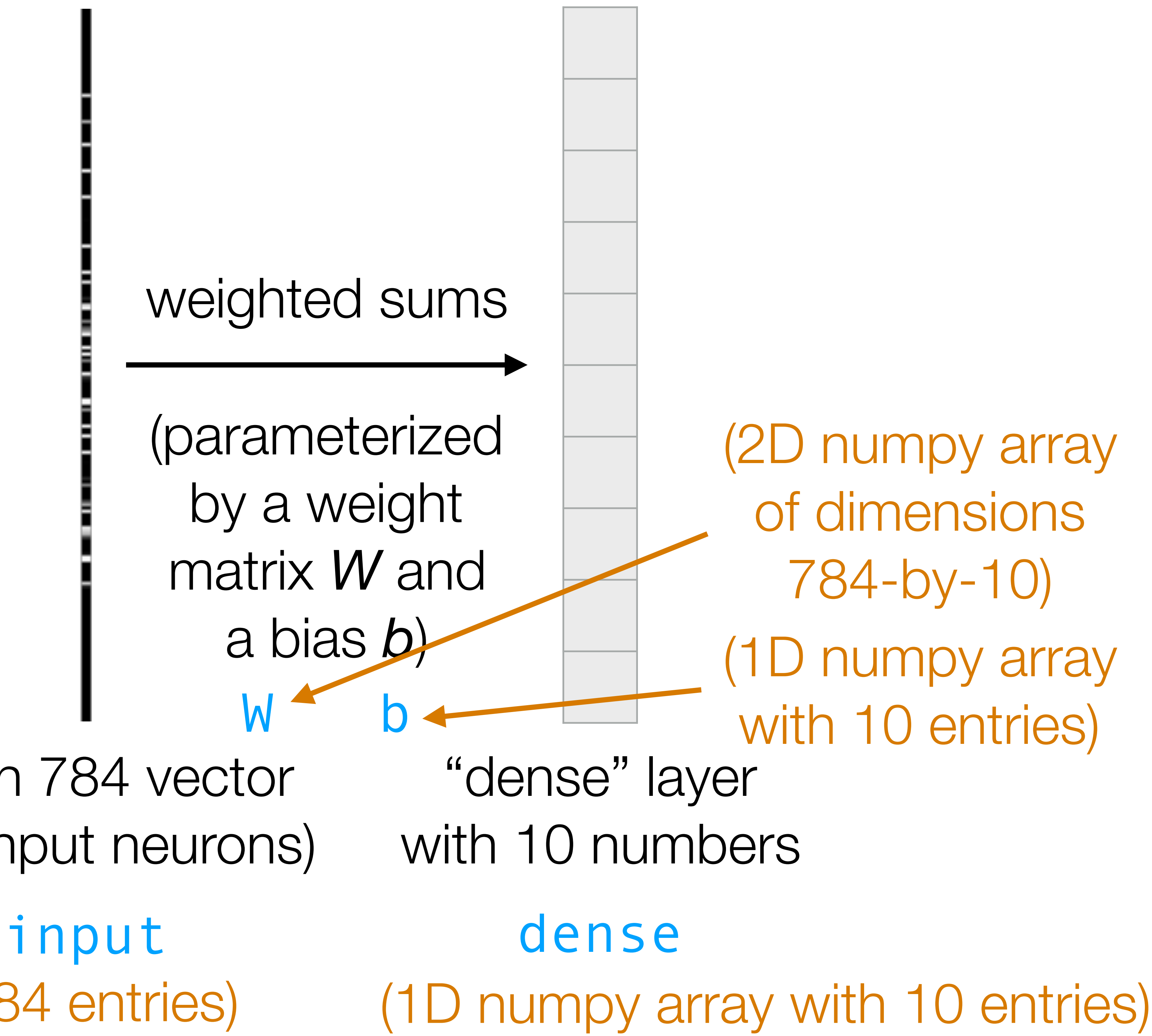
`input`

(1D numpy array with 784 entries)

`dense`

(1D numpy array with 10 entries)

Handwritten Digit Recognition



Handwritten Digit Recognition

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

weighted sums

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

W b

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

(1D numpy array with 10 entries)

n 784 vector
nput neurons)

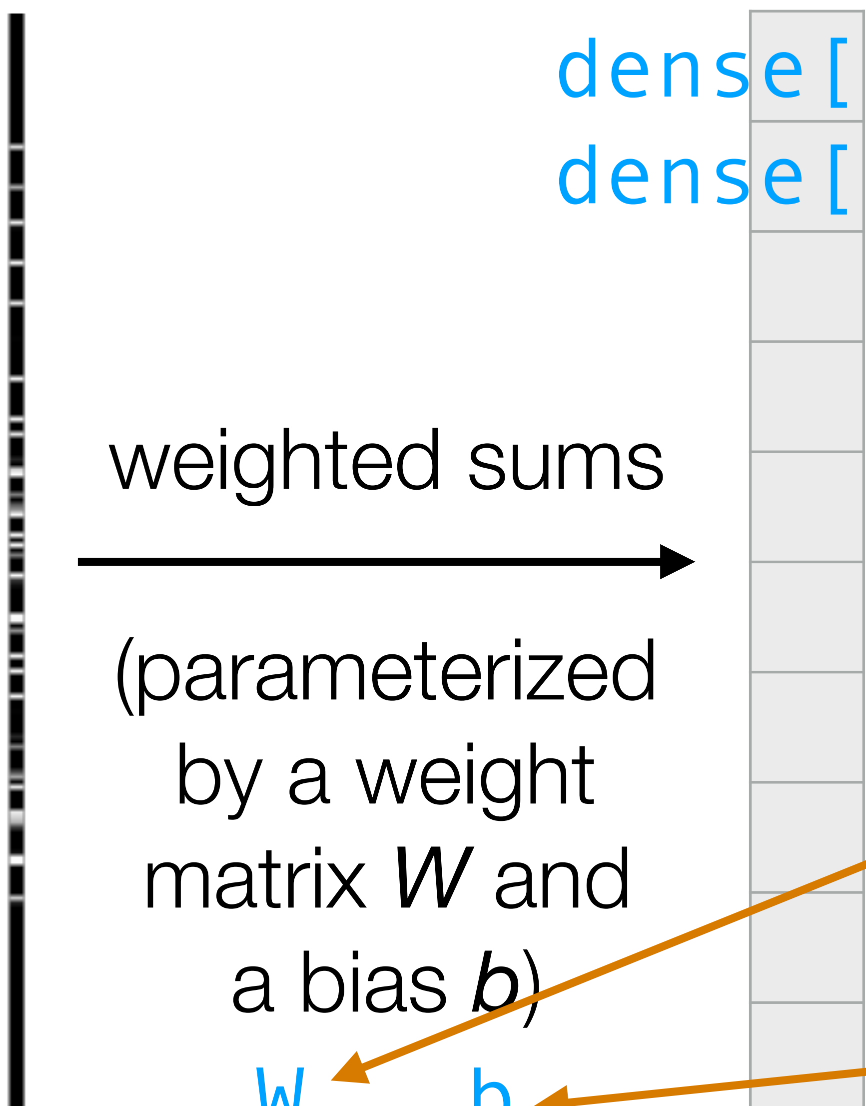
“dense” layer
with 10 numbers

`input`
34 entries)

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

Handwritten Digit Recognition

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



weighted sums

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

`W` `b`

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

(1D numpy array with 10 entries)

n 784 vector
nput neurons)

“dense” layer
with 10 numbers

`input`
84 entries)

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

Handwritten Digit Recognition

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

⋮

weighted sums

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

`W` `b`

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

(1D numpy array with 10 entries)

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nput neurons)

`input`

34 entries)

"dense" layer
with 10 numbers

`dense`

(1D numpy array with 10 entries)

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` `b`

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

(1D numpy array with 10 entries)

n 784 vector
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“dense” layer
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`input`
34 entries)

`dense`
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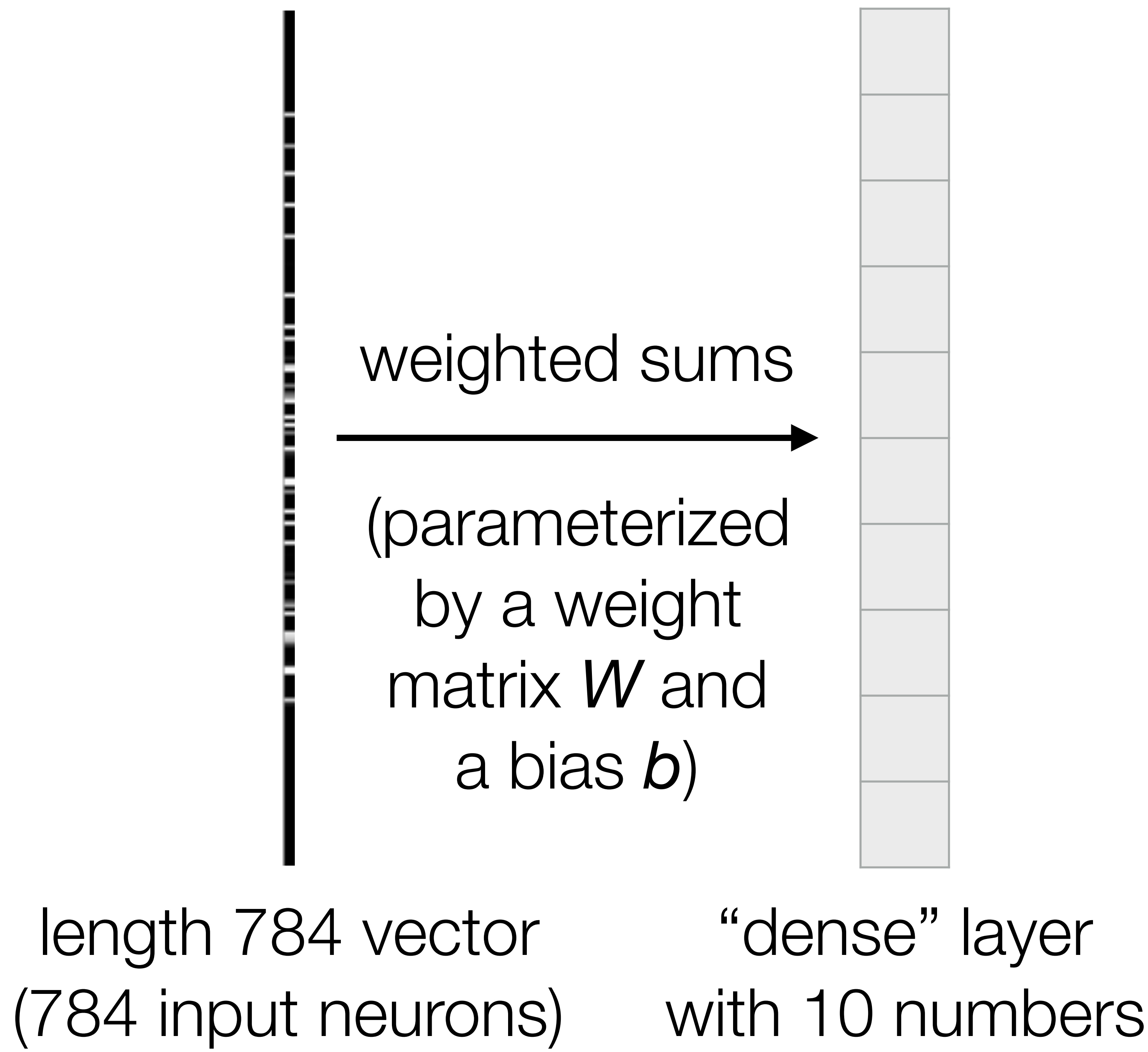

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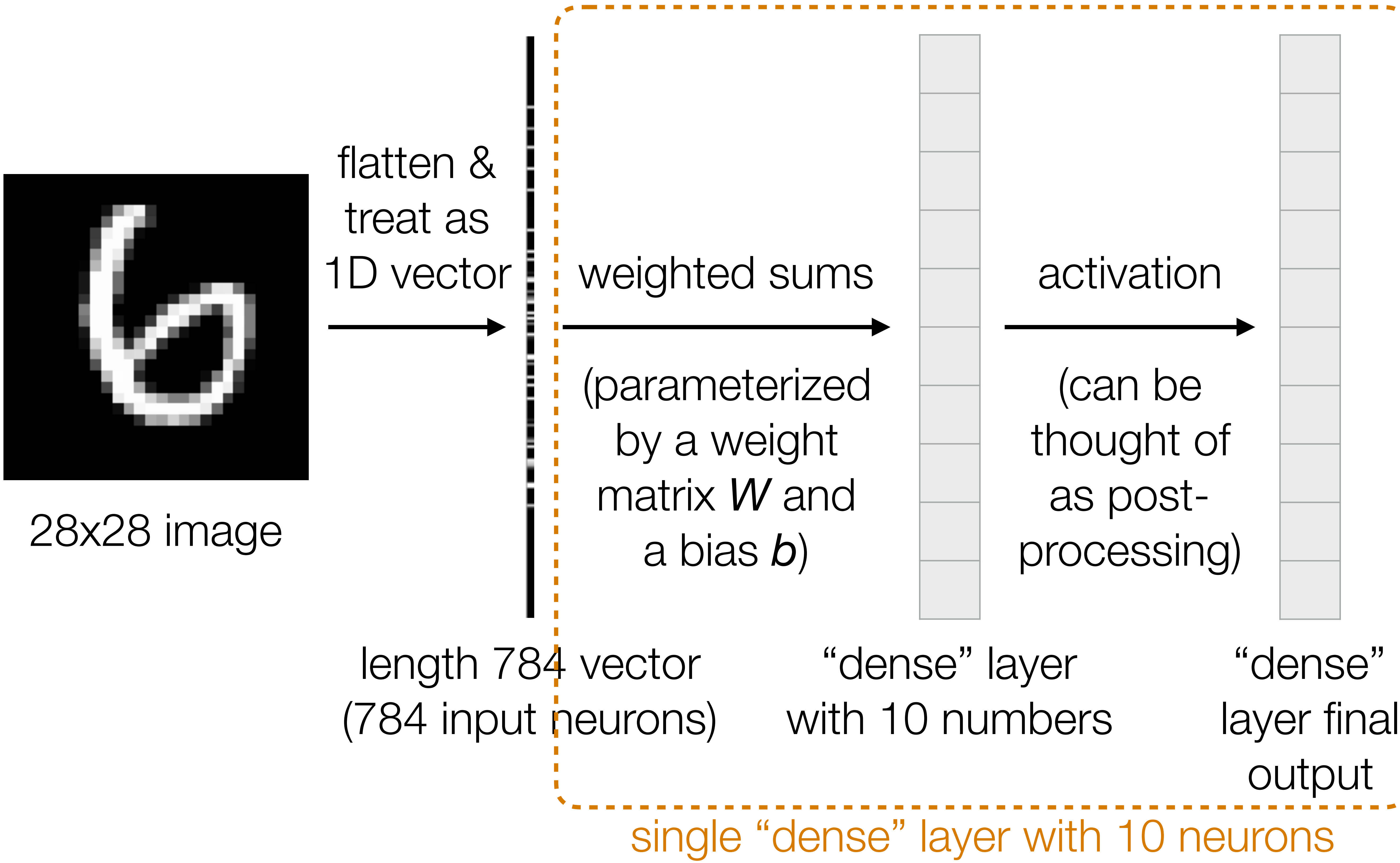

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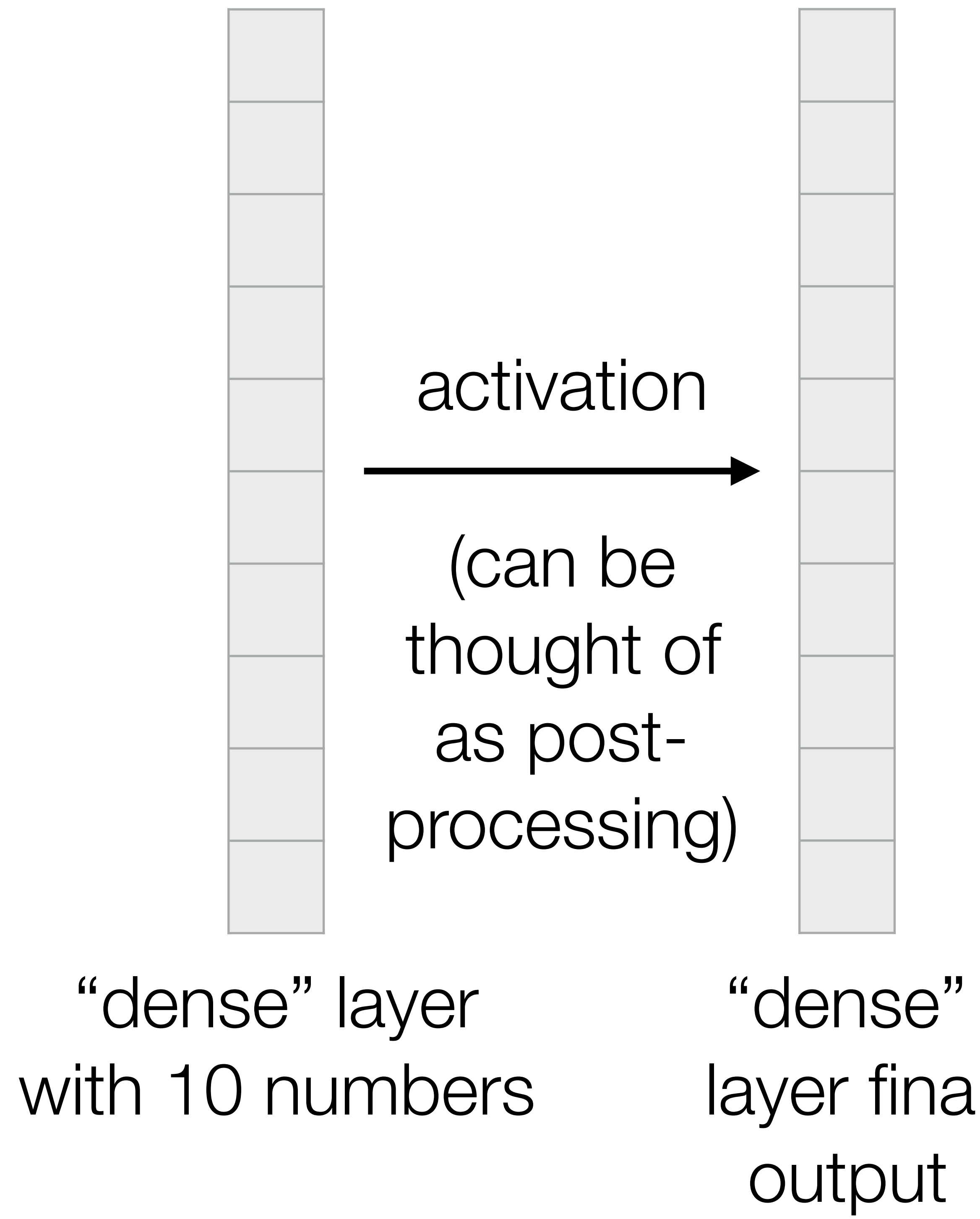
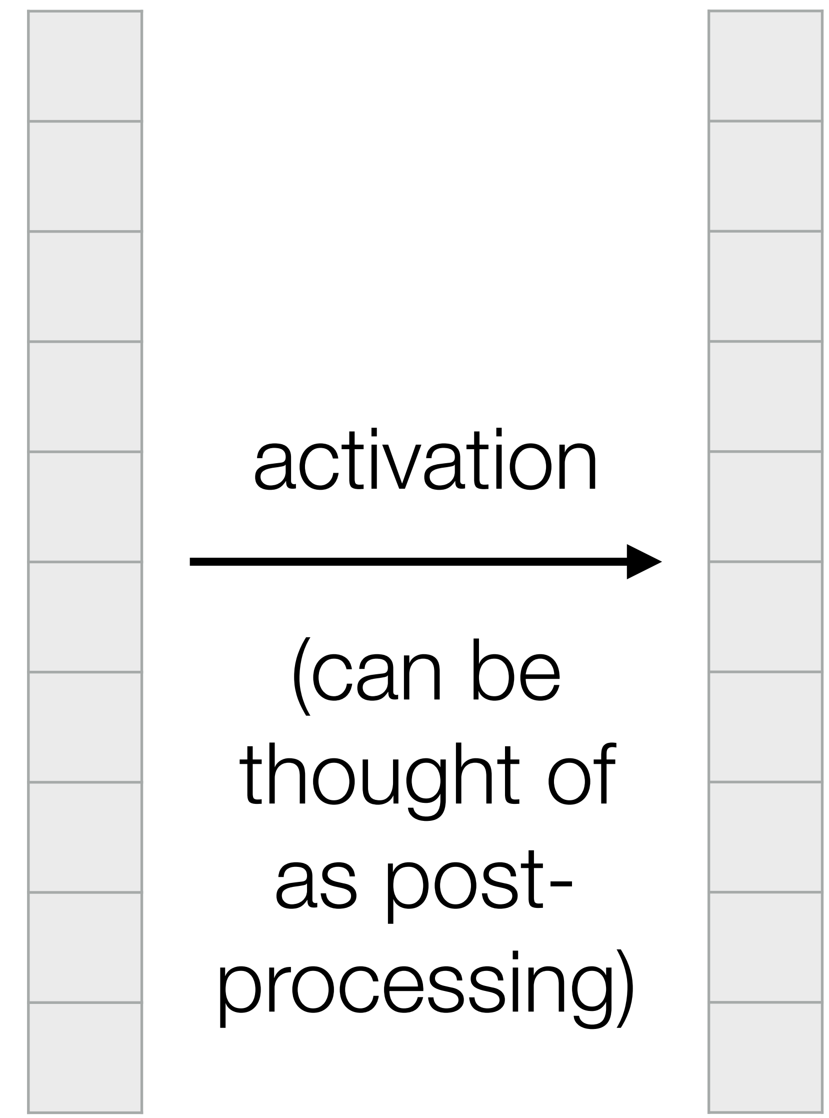


Handwritten Digit Recognition

Many different activation functions possible



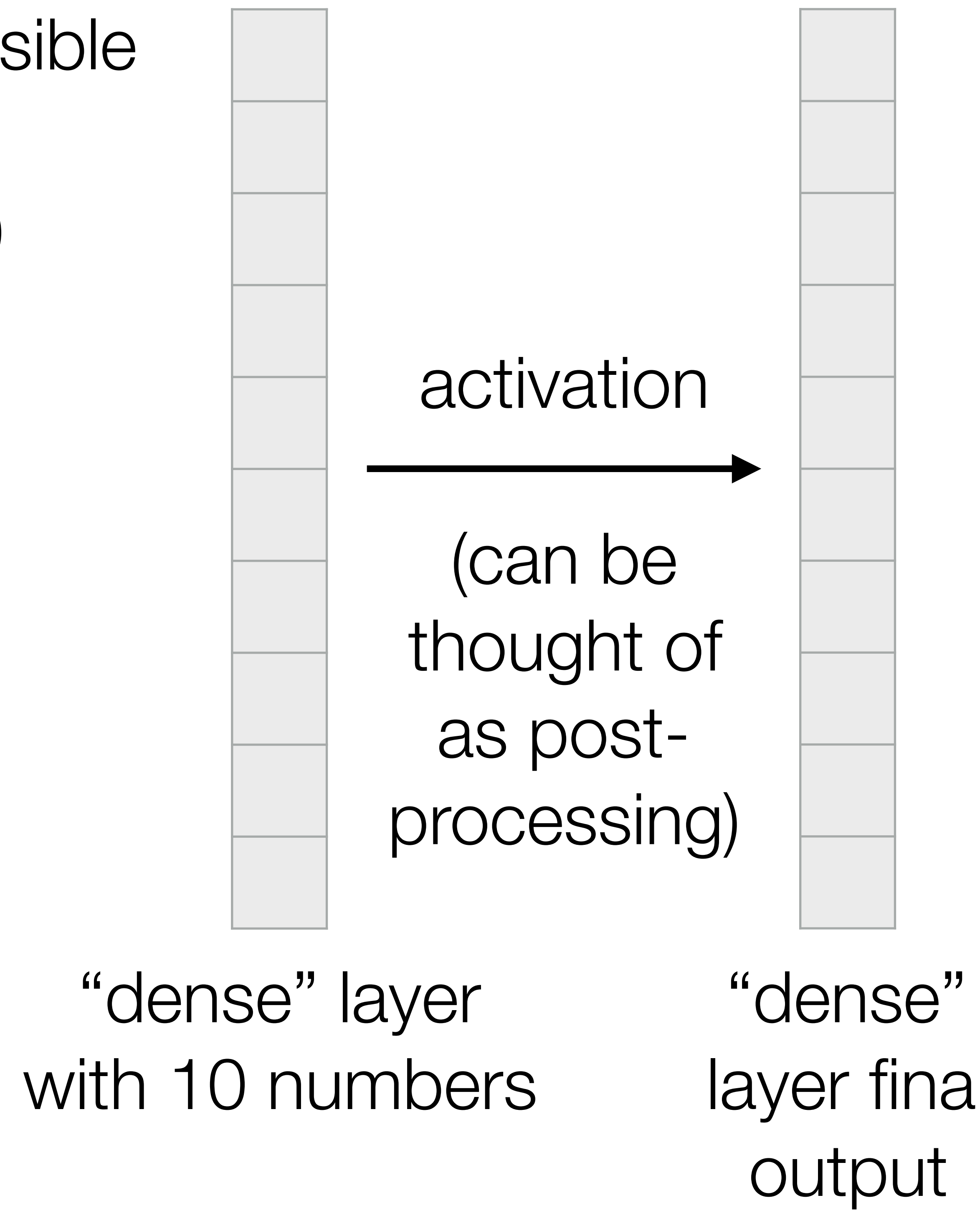
"dense" layer with 10 numbers

"dense" layer final output

Handwritten Digit Recognition

Many different activation functions possible

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



Handwritten Digit Recognition

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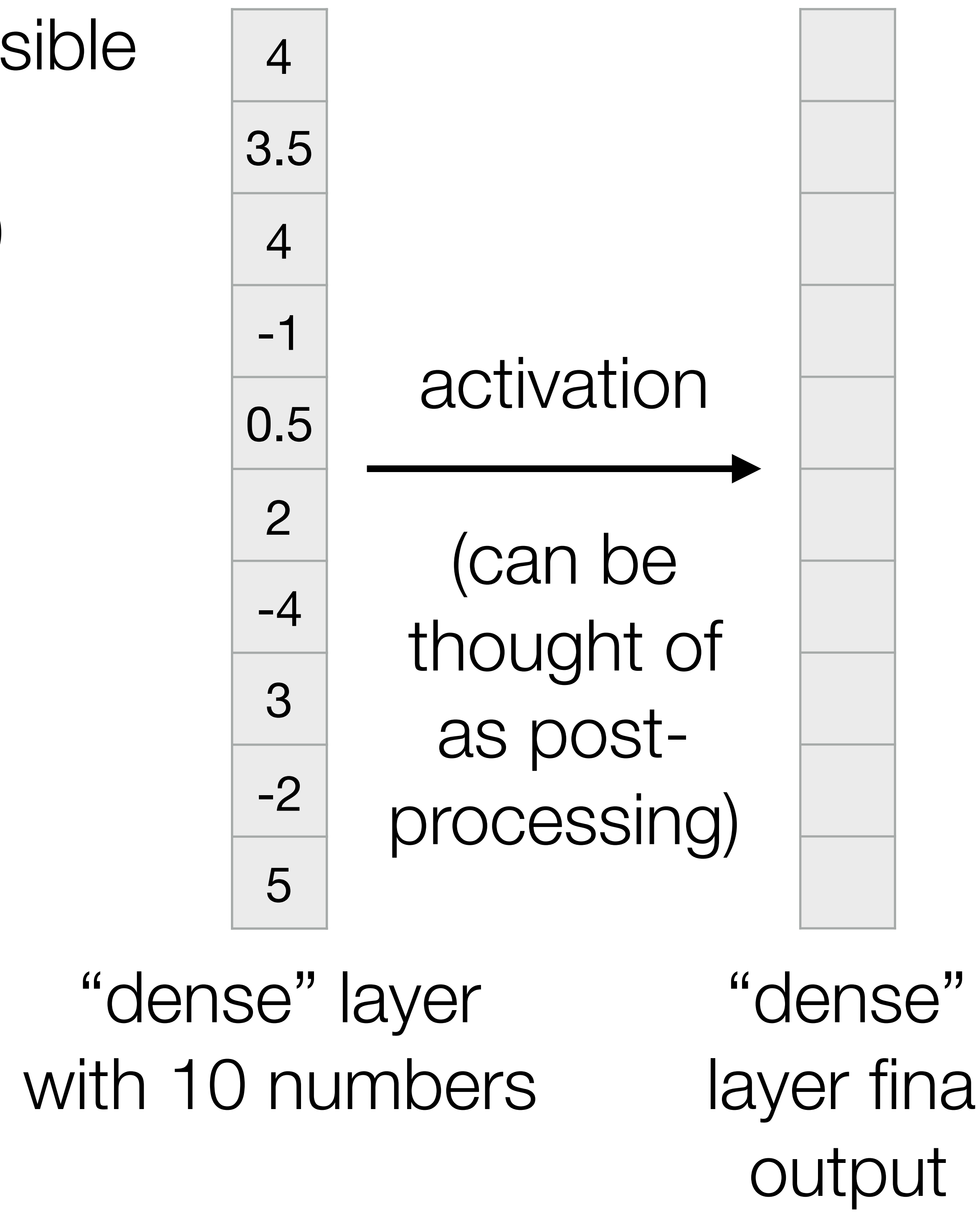
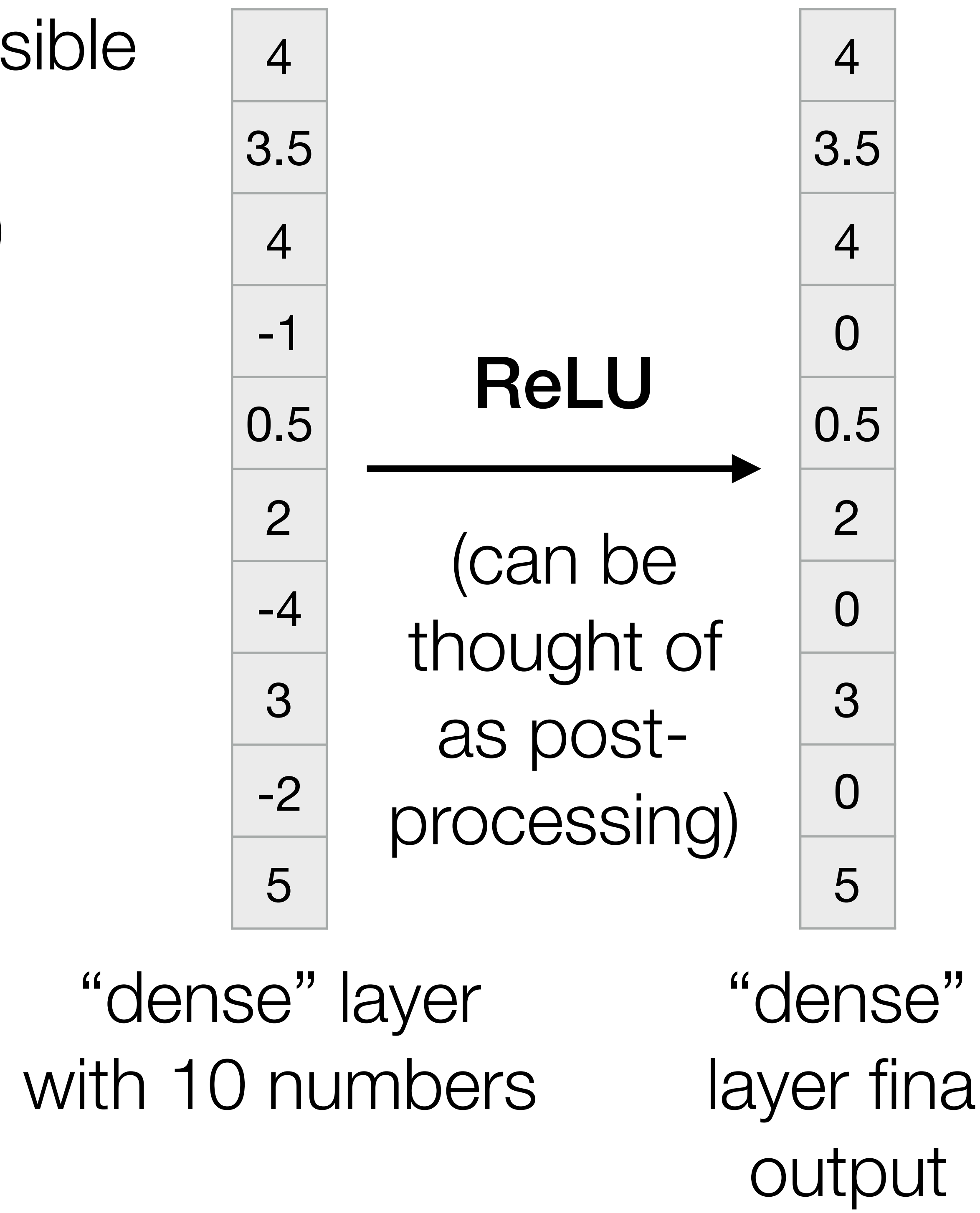


Handwritten Digit Recognition

Many different activation functions possible

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



Handwritten Digit Recognition

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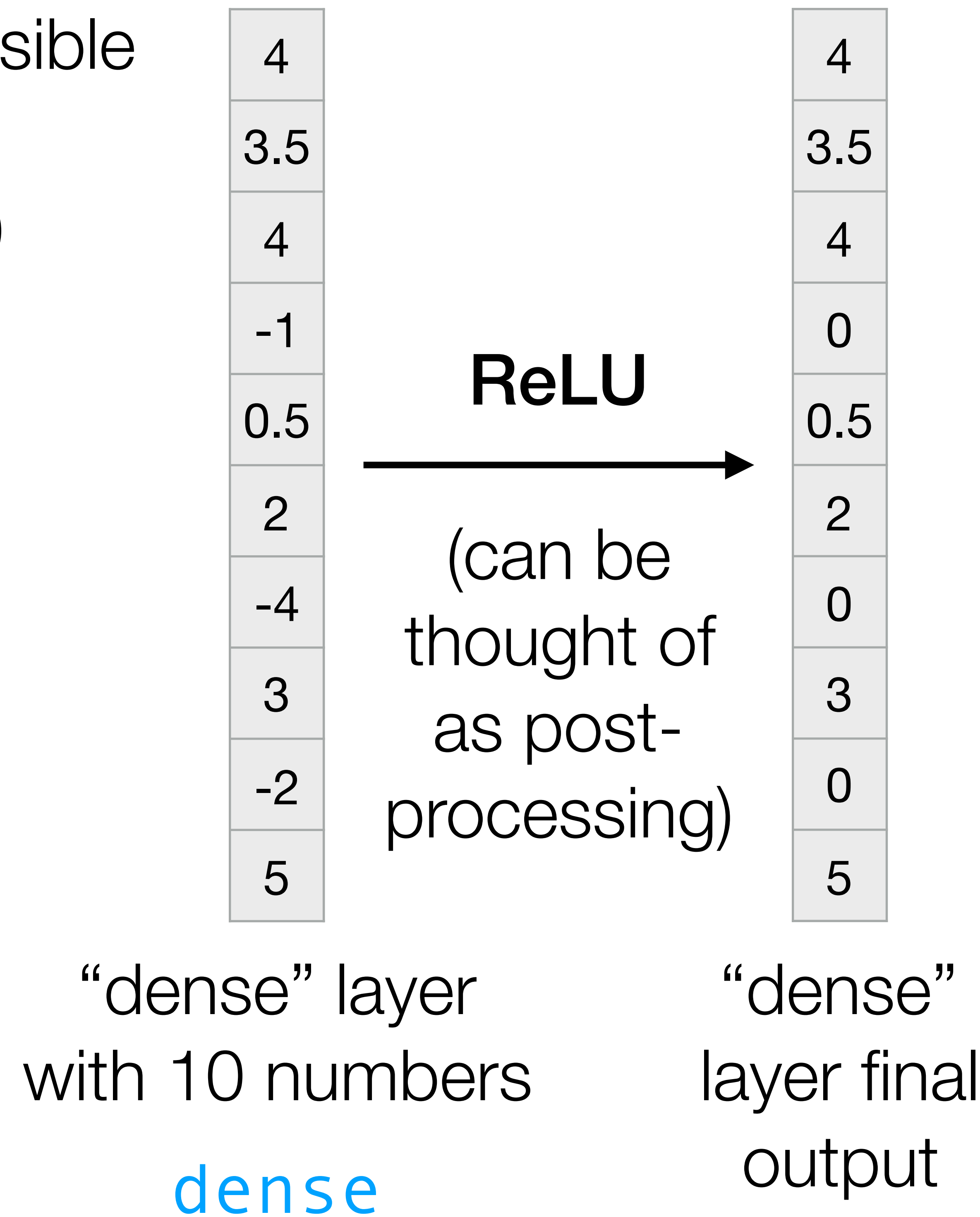

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Example: **Rectified linear unit (ReLU)** zeros out entries that are negative

4		4
3.5		3.5
4		4
-1		0
0.5		0.5
2		2
-4		0
3		3
-2		0
5		5

ReLU

(can be thought of as post-processing)

“dense” layer with 10 numbers

`dense`

“dense” layer final output

`dense_final`

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`)
4	4
3.5	3.5
4	4
-1	0
0.5	0.5
2	2
-4	0
3	3
-2	0
5	5

$\xrightarrow{\textbf{ReLU}}$

(can be thought of as post-processing)

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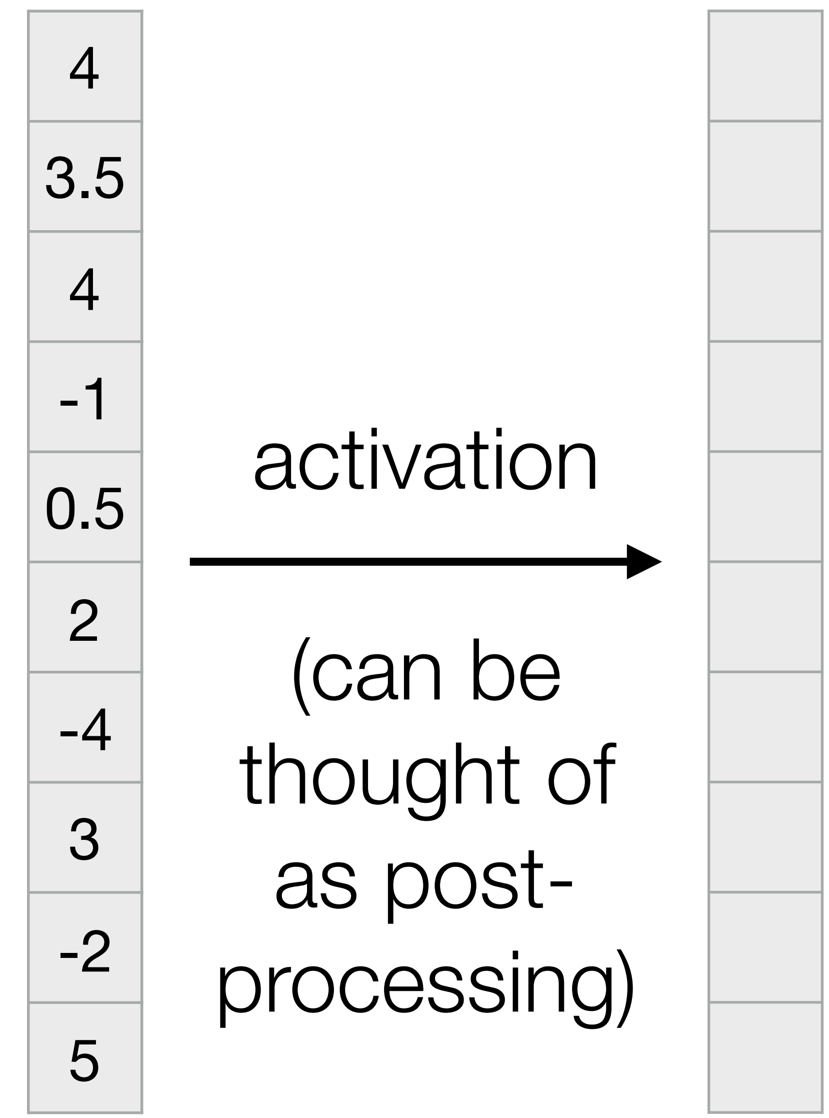

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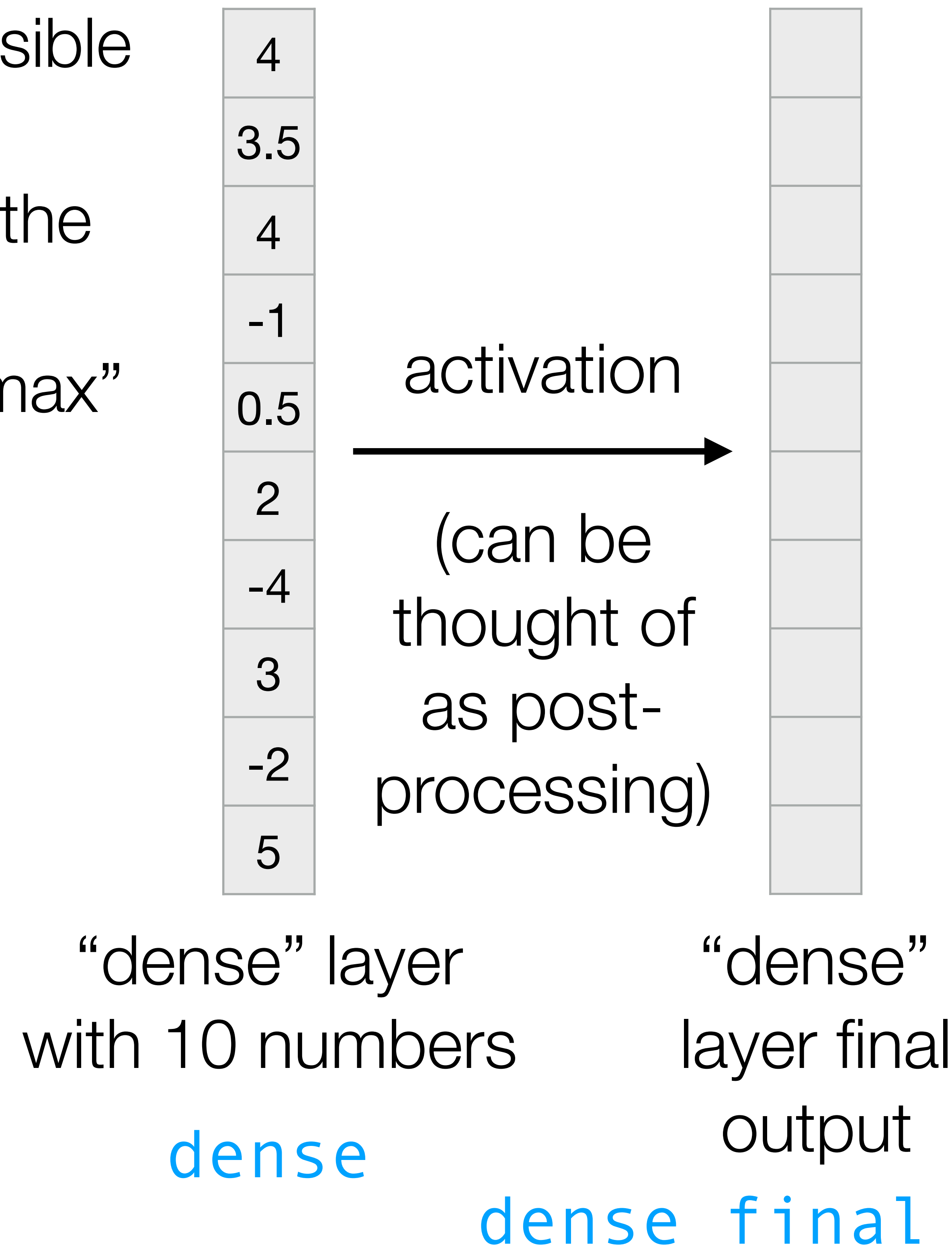
Handwritten Digit Recognition

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)



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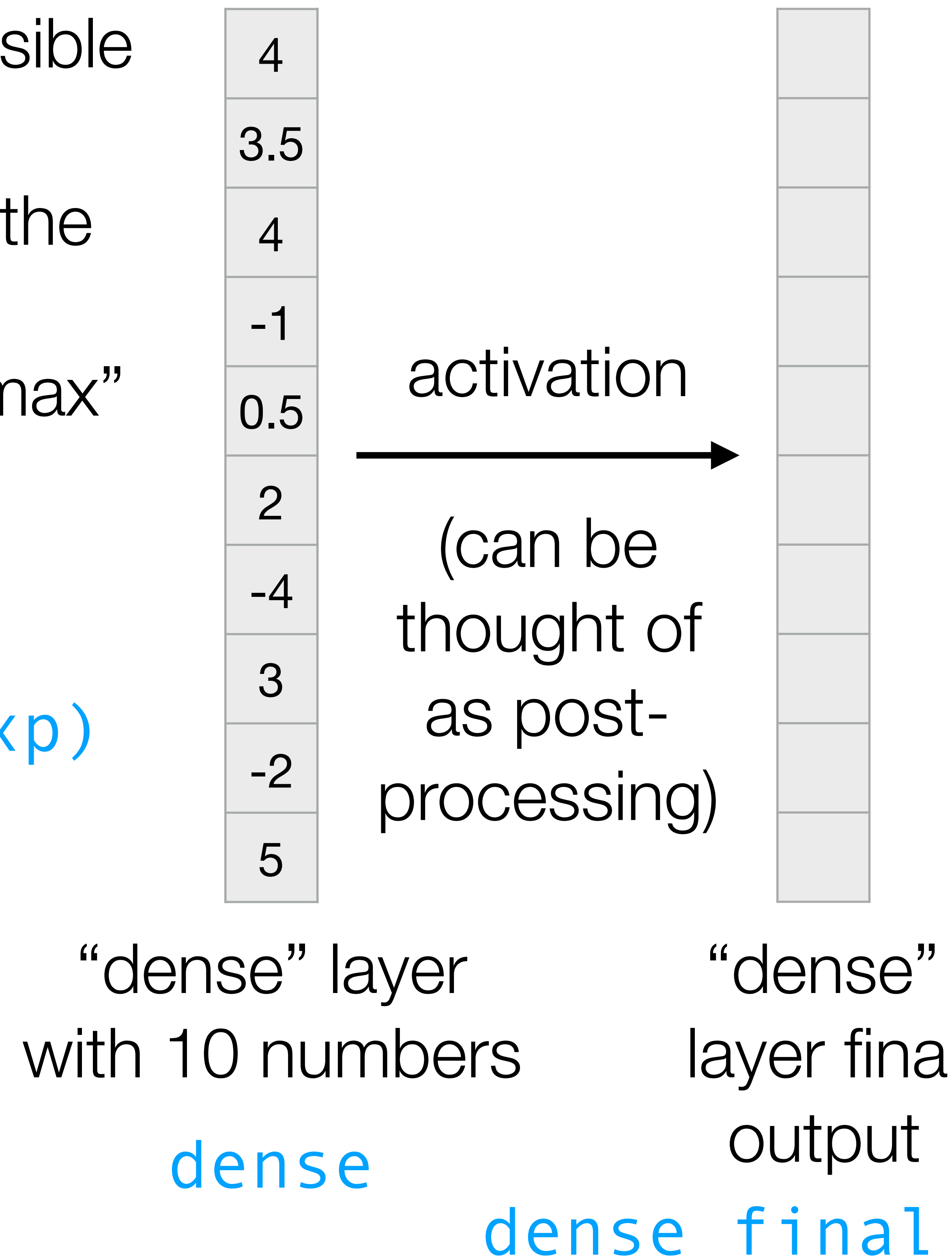
Example: **softmax** turns the entries in the dense layer (prior to activation) into a probability distribution (using the "softmax" transformation)

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



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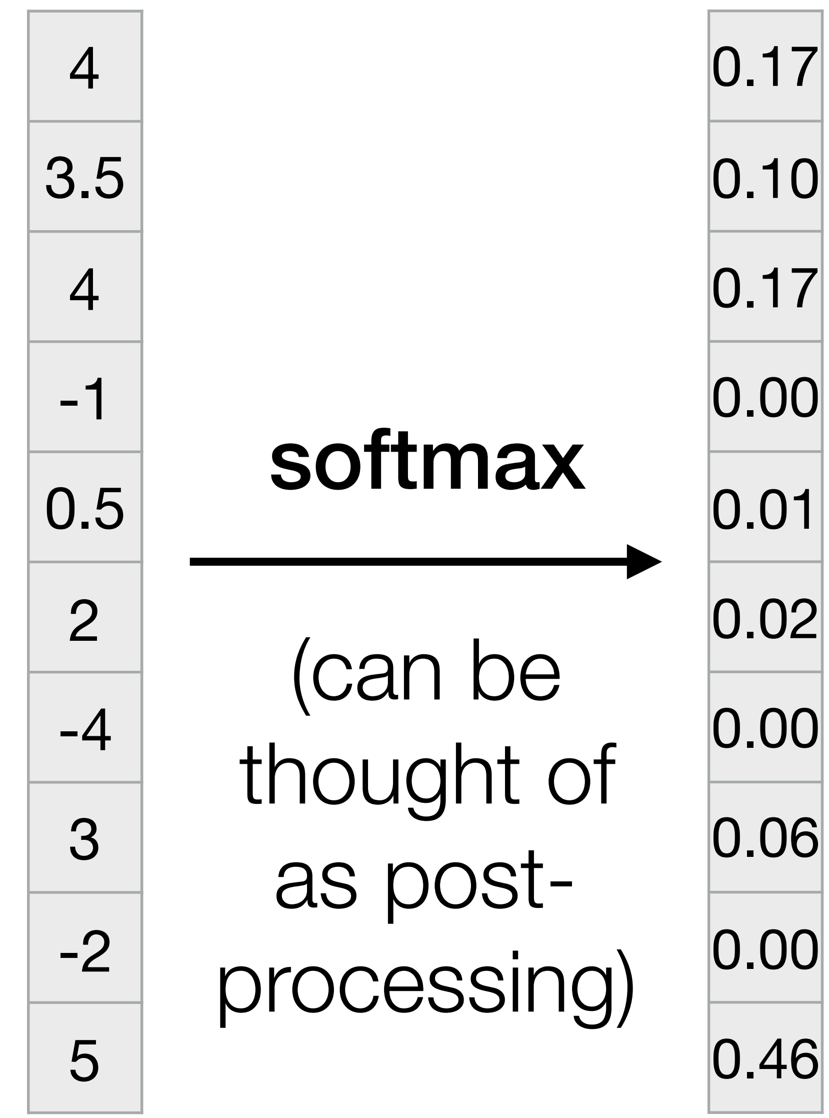

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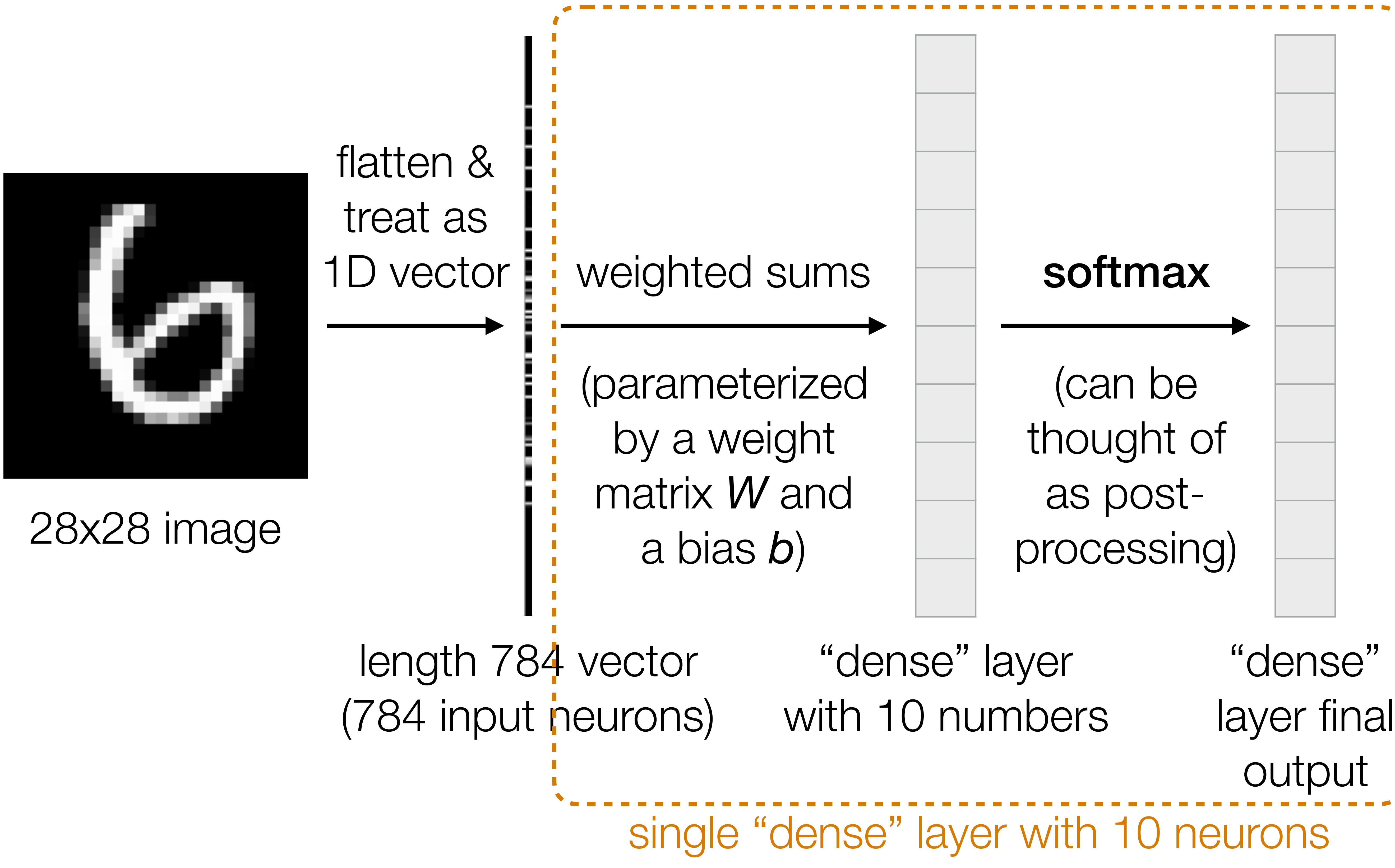
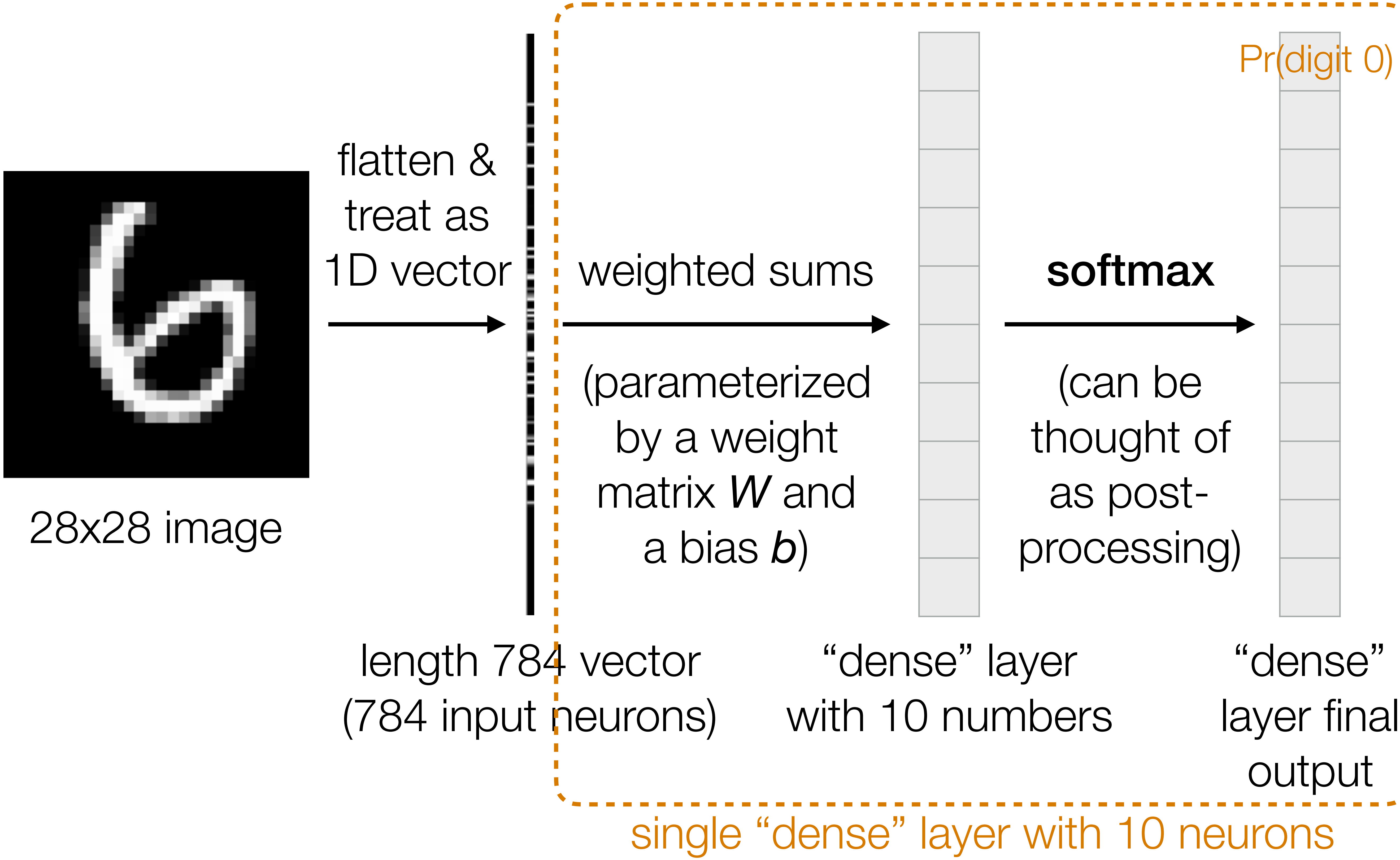
Handwritten Digit Recognition



Handwritten Digit Recognition



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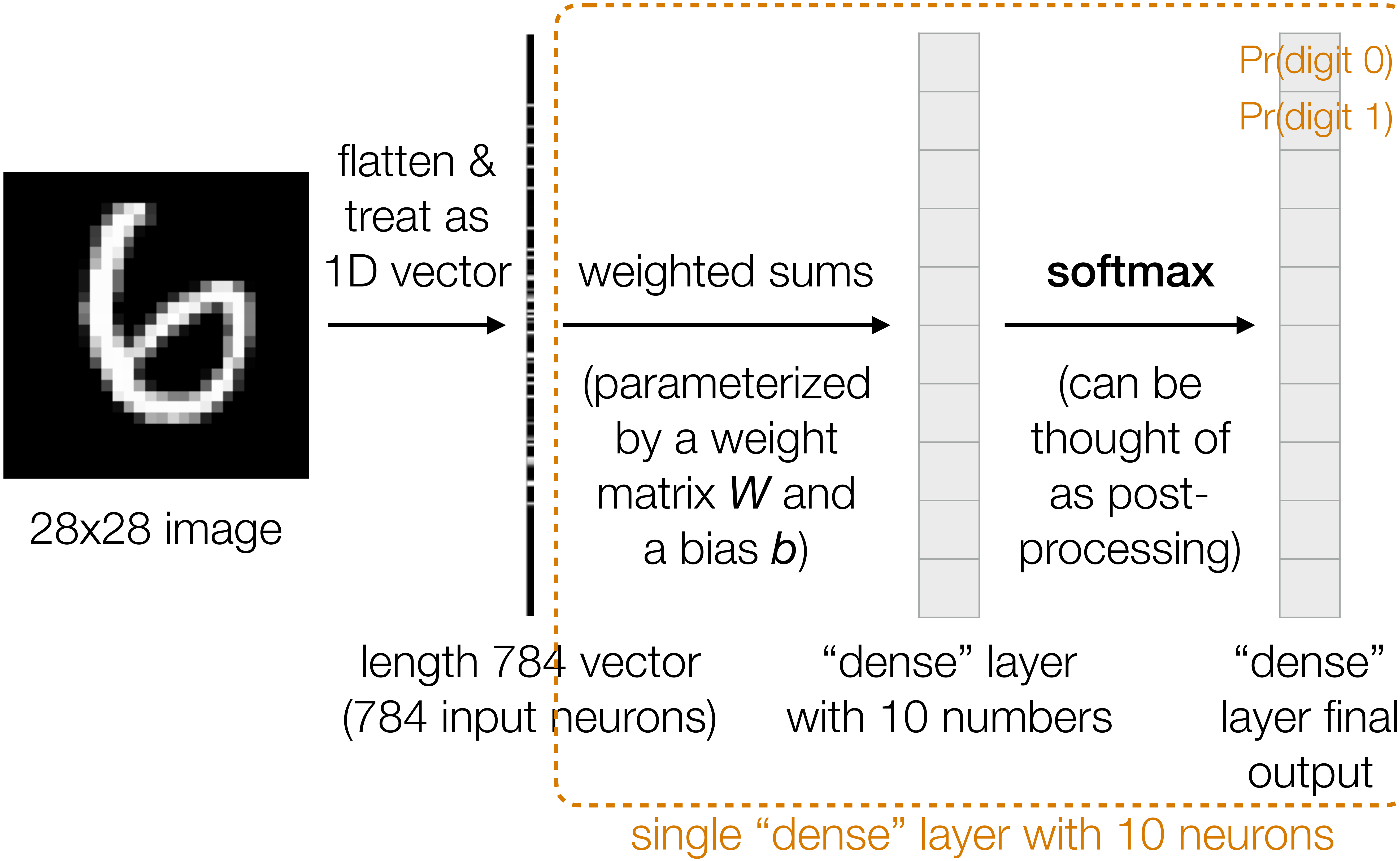

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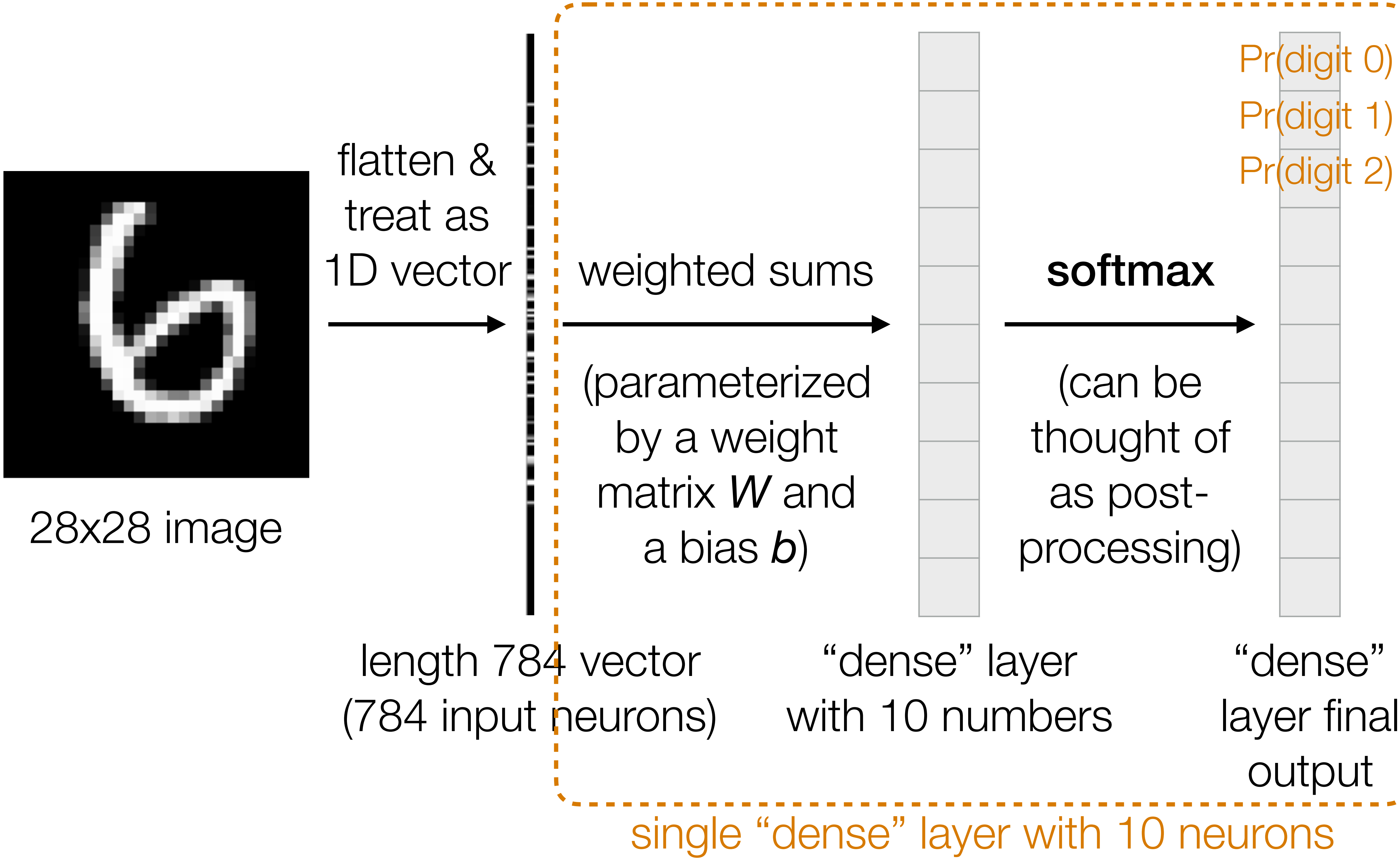

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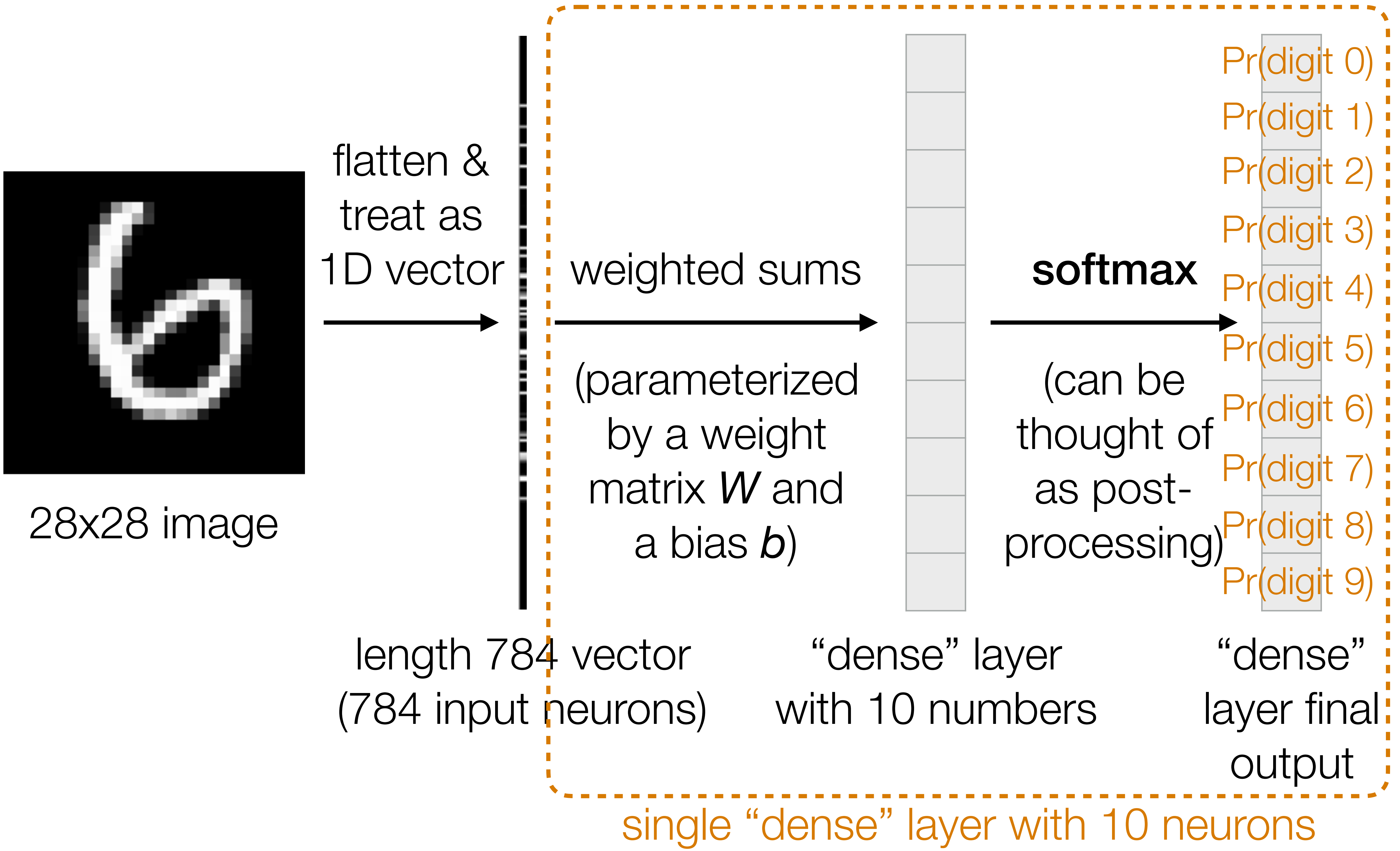

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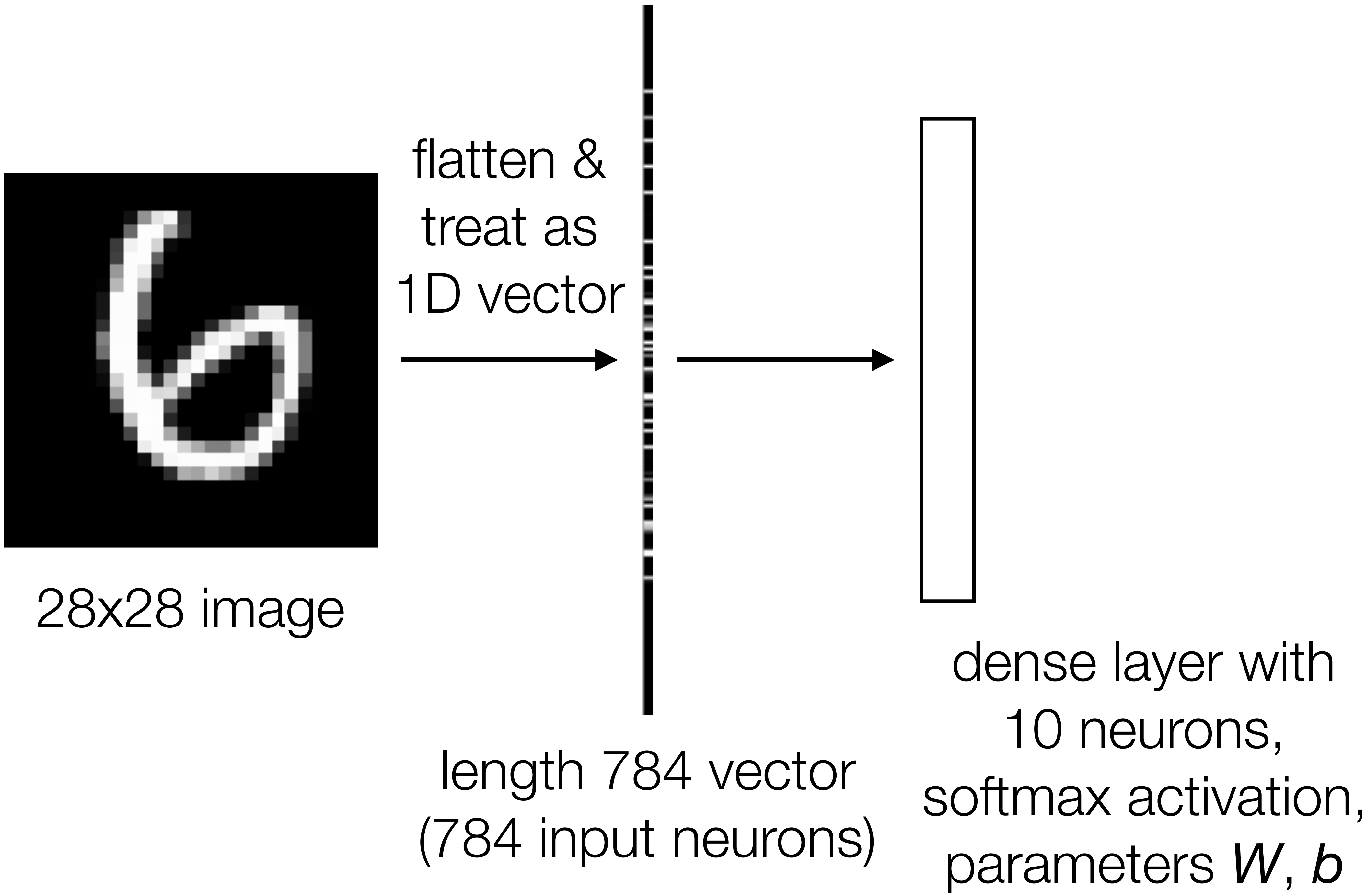

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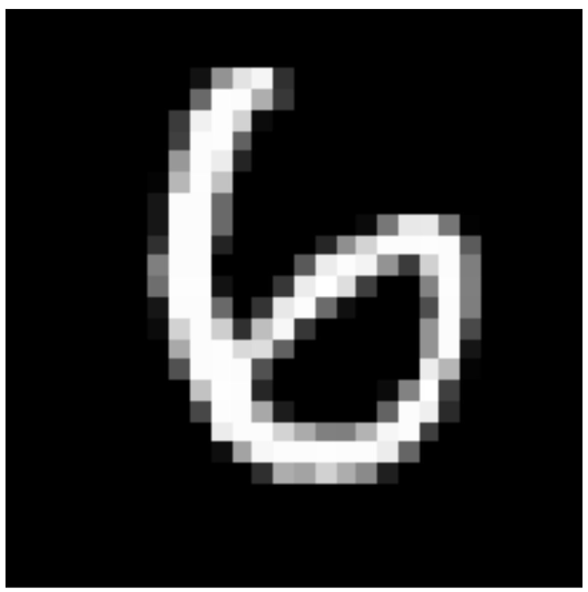


28x28 image

flatten &
treat as
1D vector

length 784 vector
(784 input neurons)

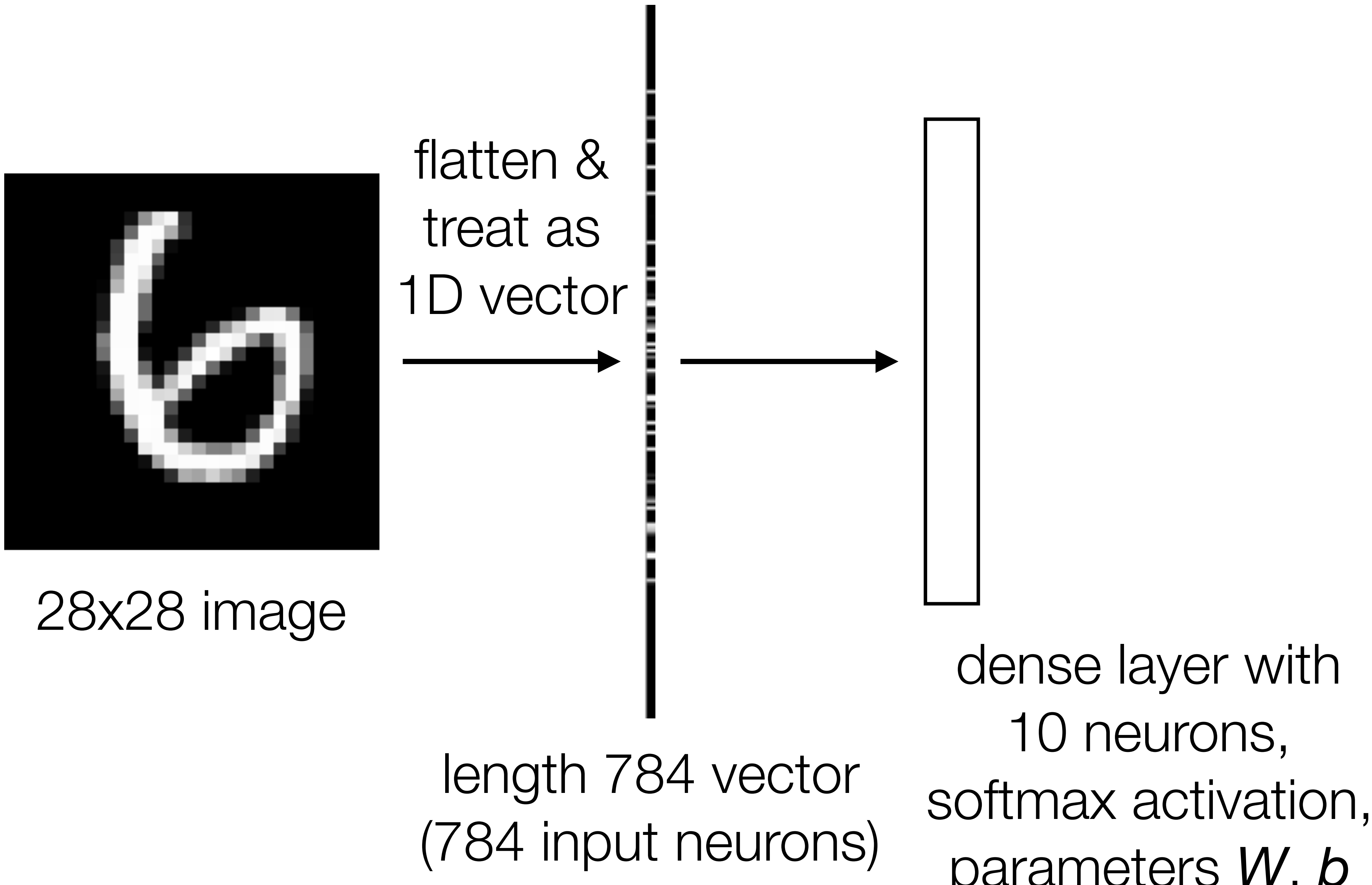
dense layer with
10 neurons,
softmax activation,
parameters *W*, *b*

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*

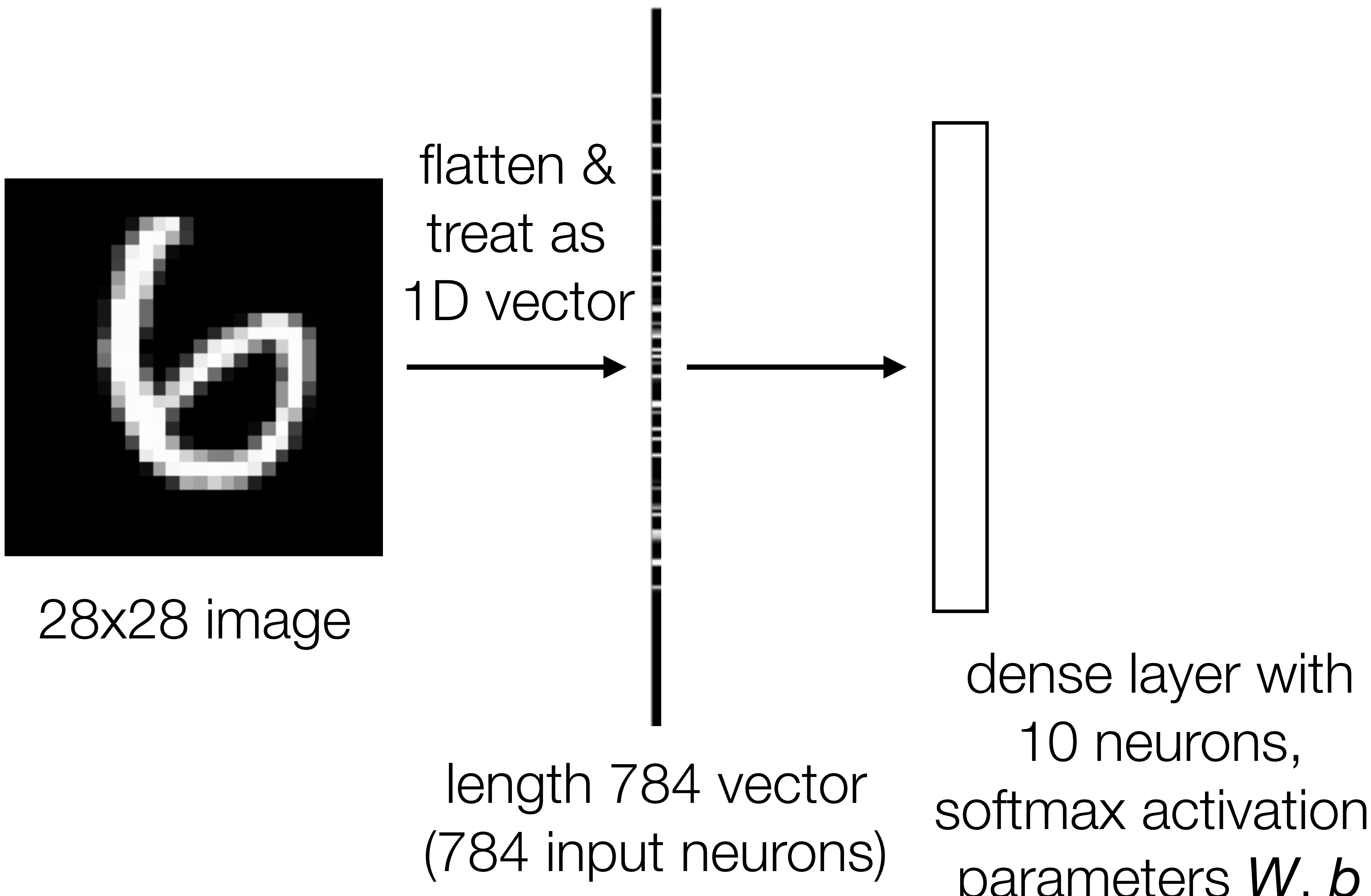
Handwritten Digit Recognition

Demo part 1

Handwritten Digit Recognition

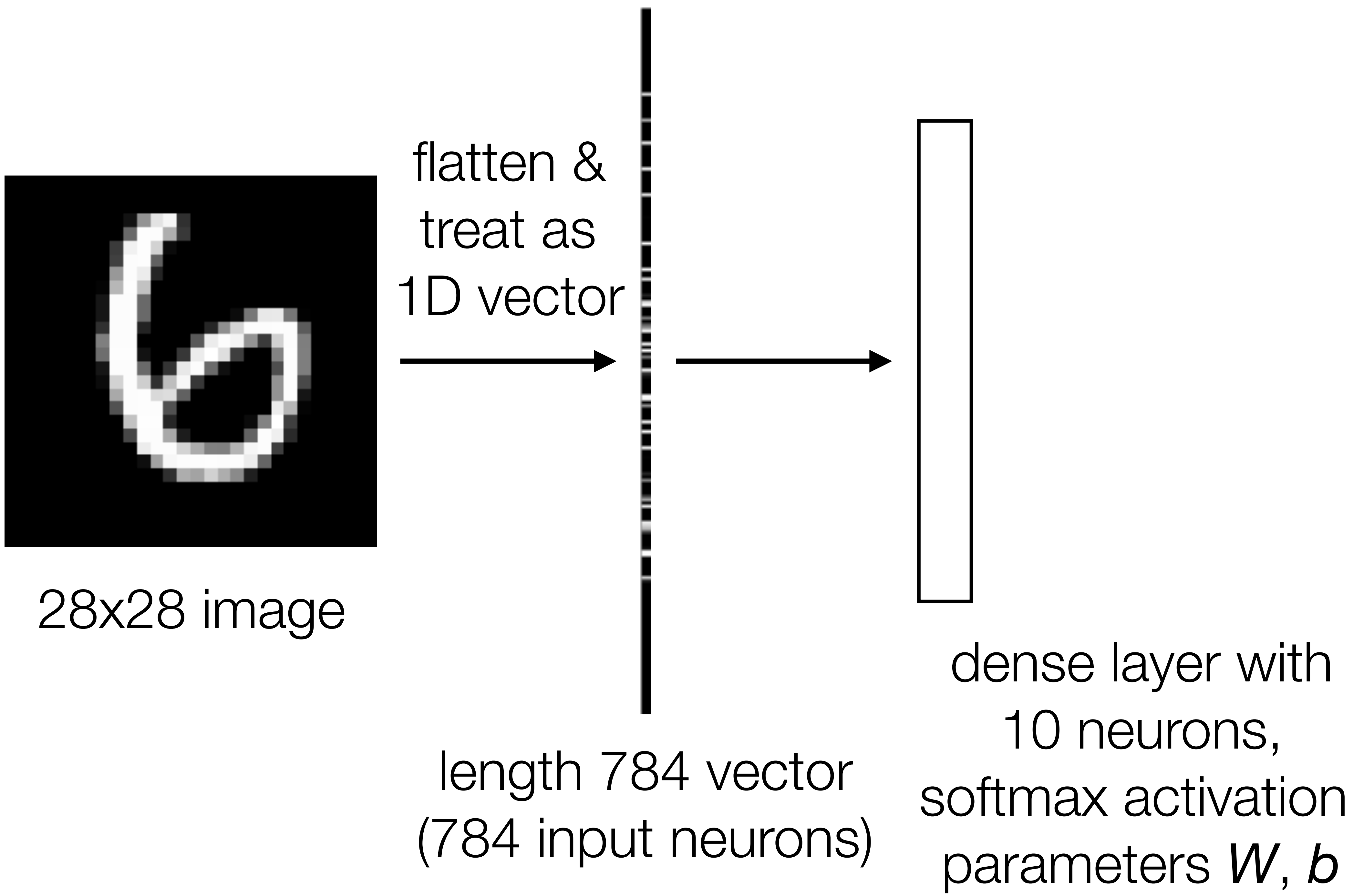


Handwritten Digit Recognition



Handwritten Digit Recognition

Training label: 6



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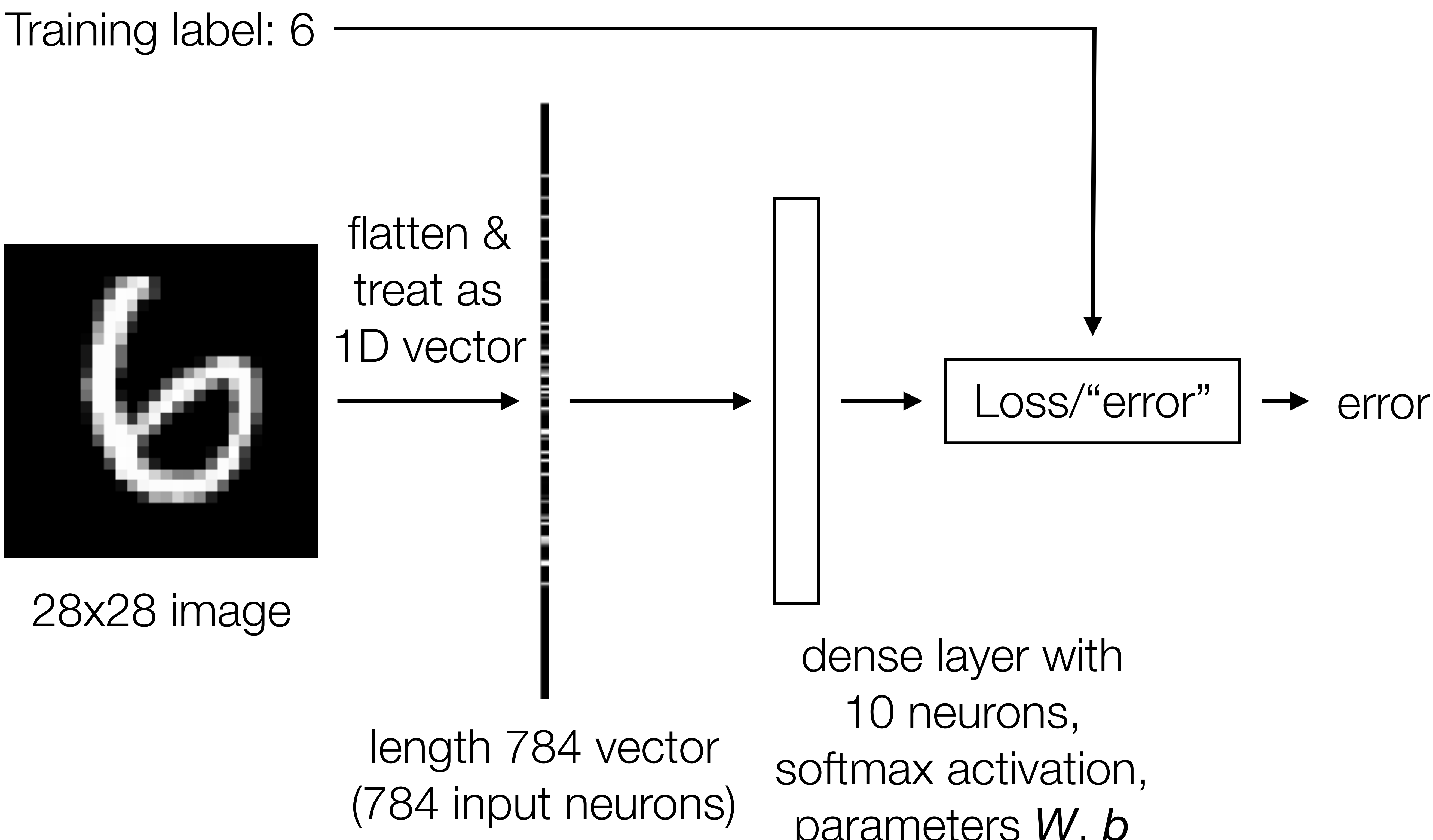

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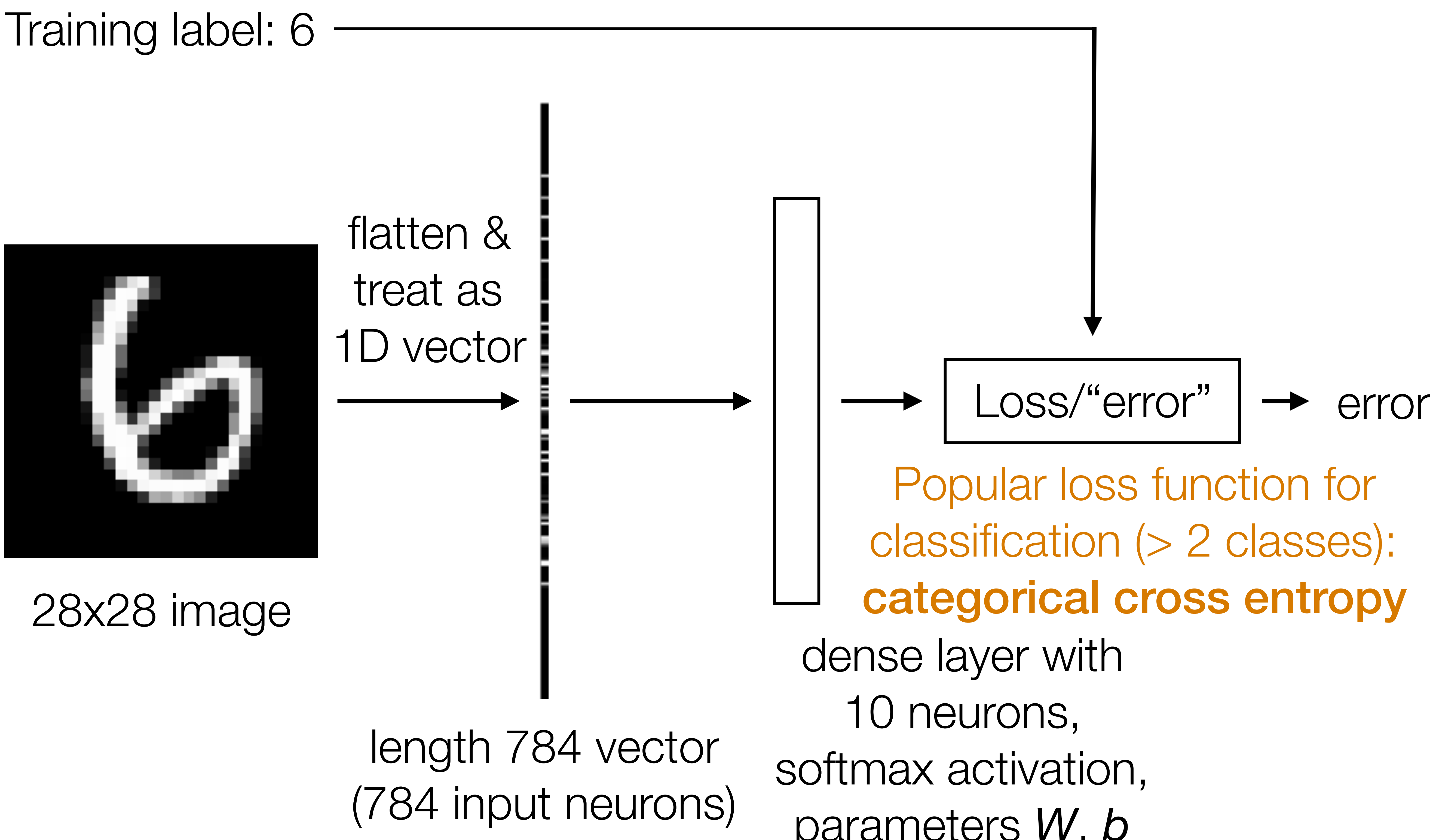

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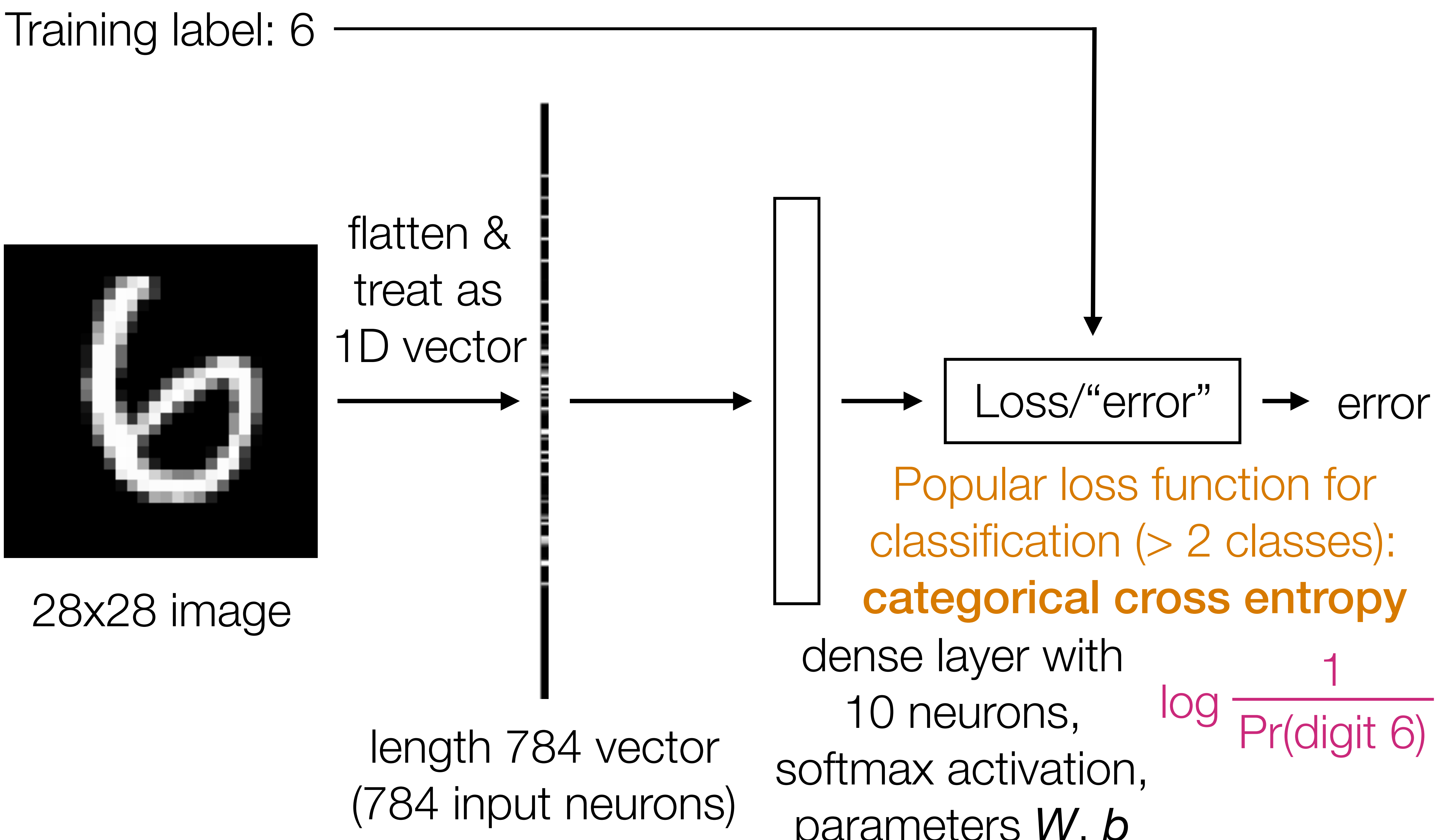

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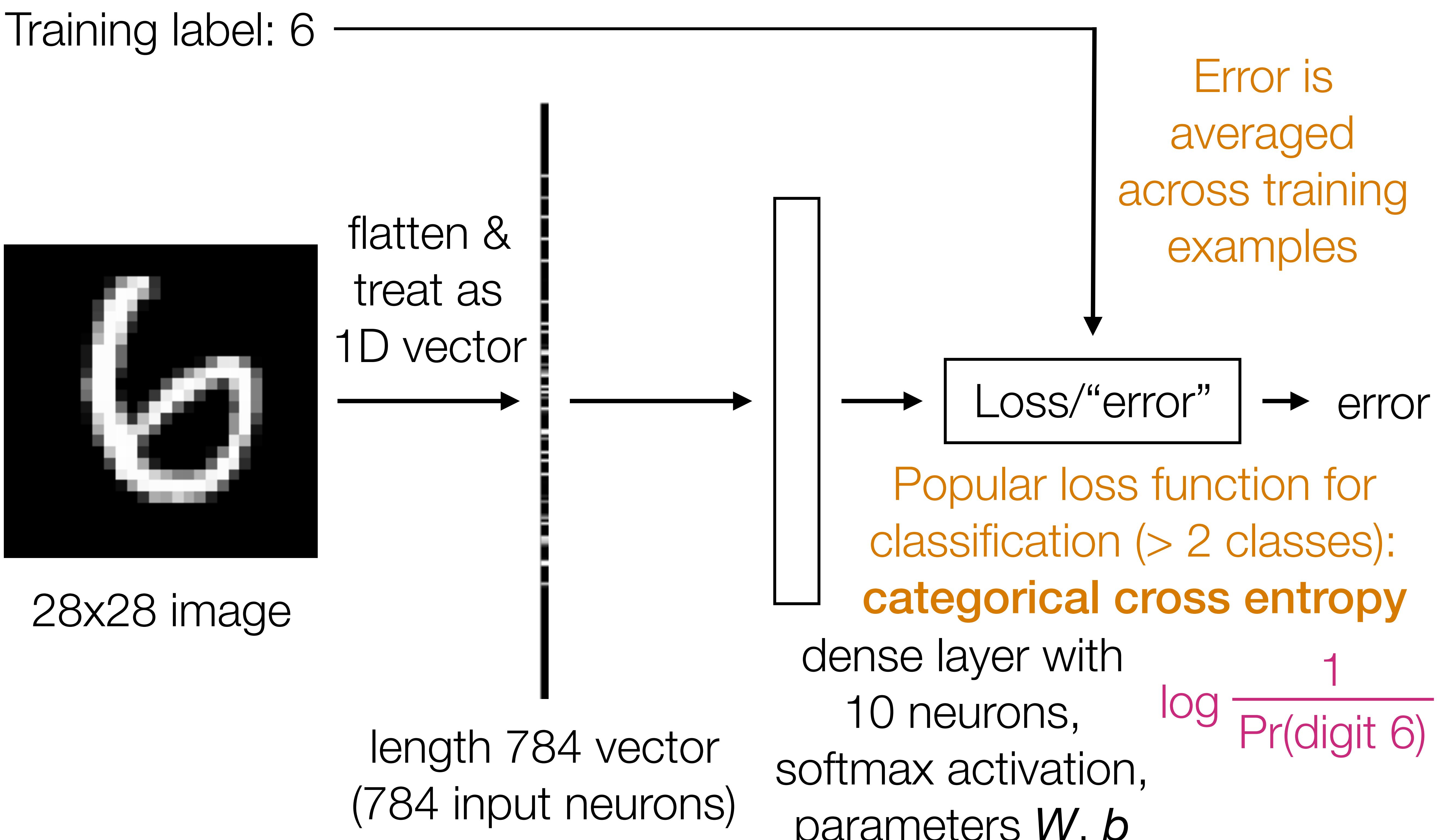

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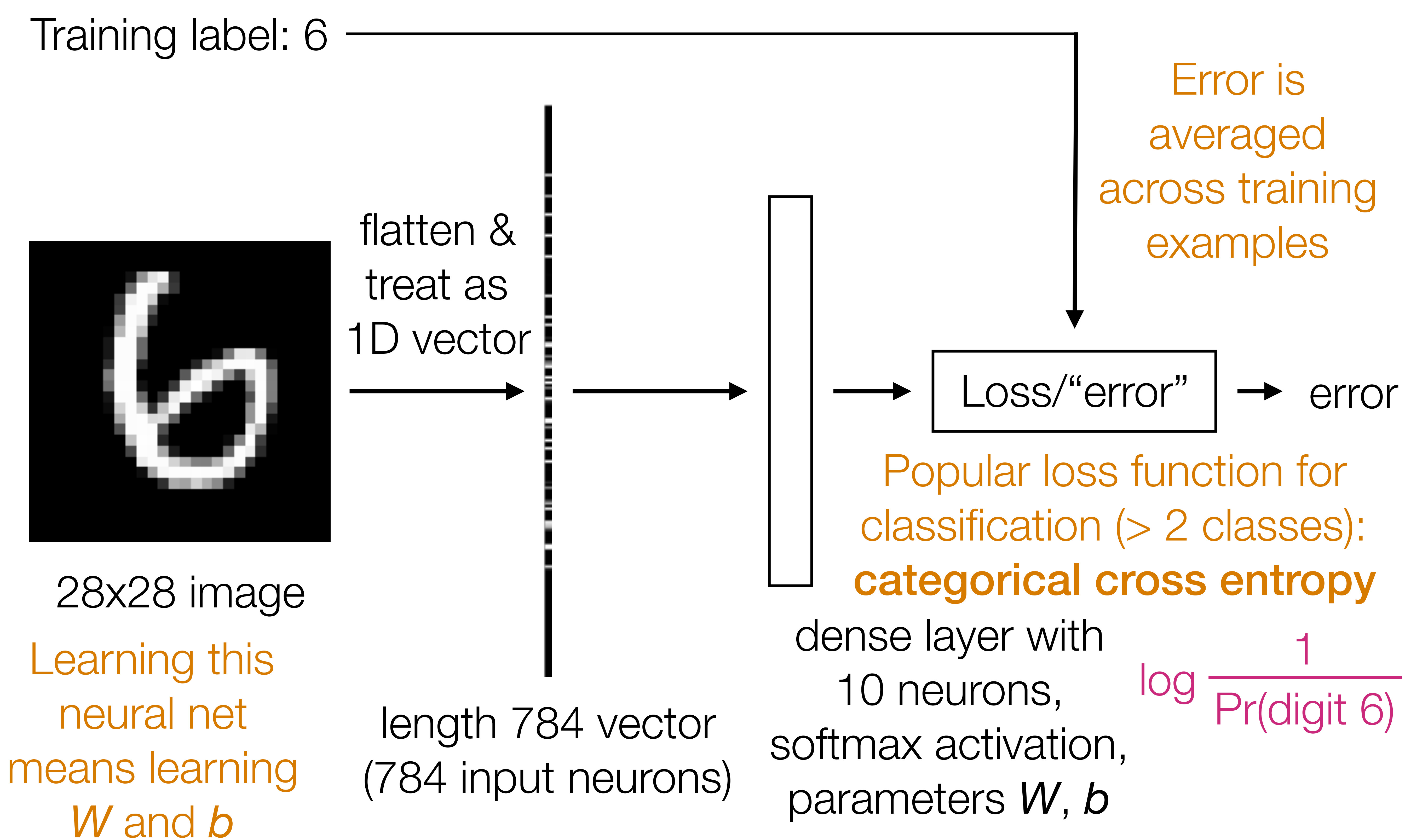
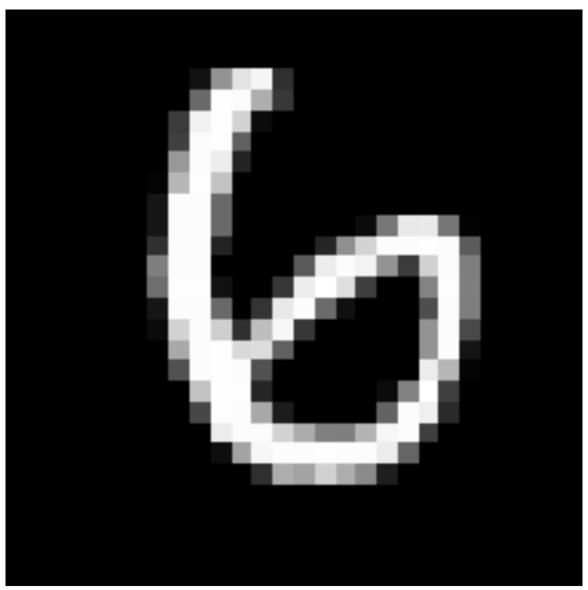


Handwritten Digit Recognition

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*

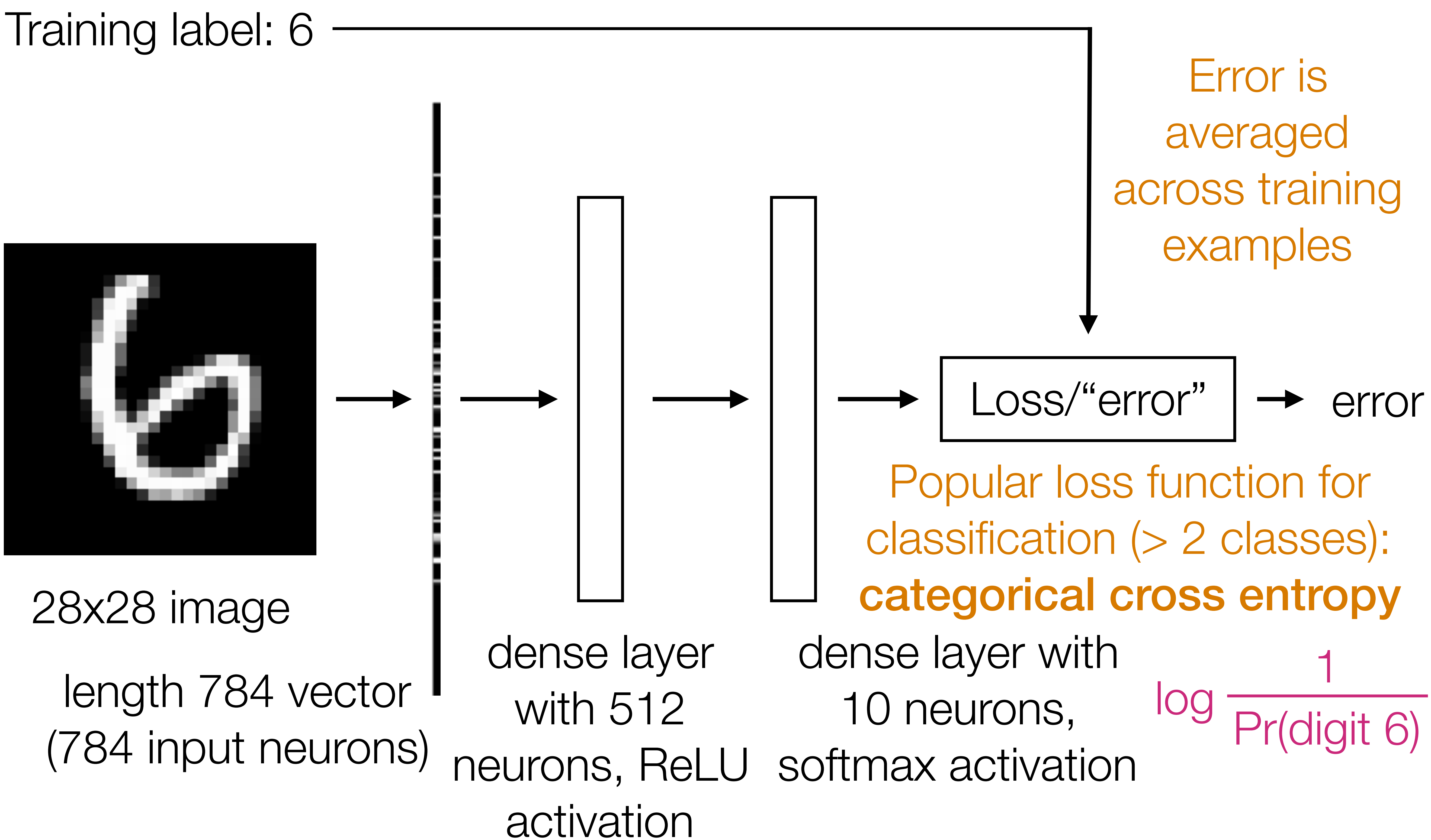
Loss/"error" → error

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



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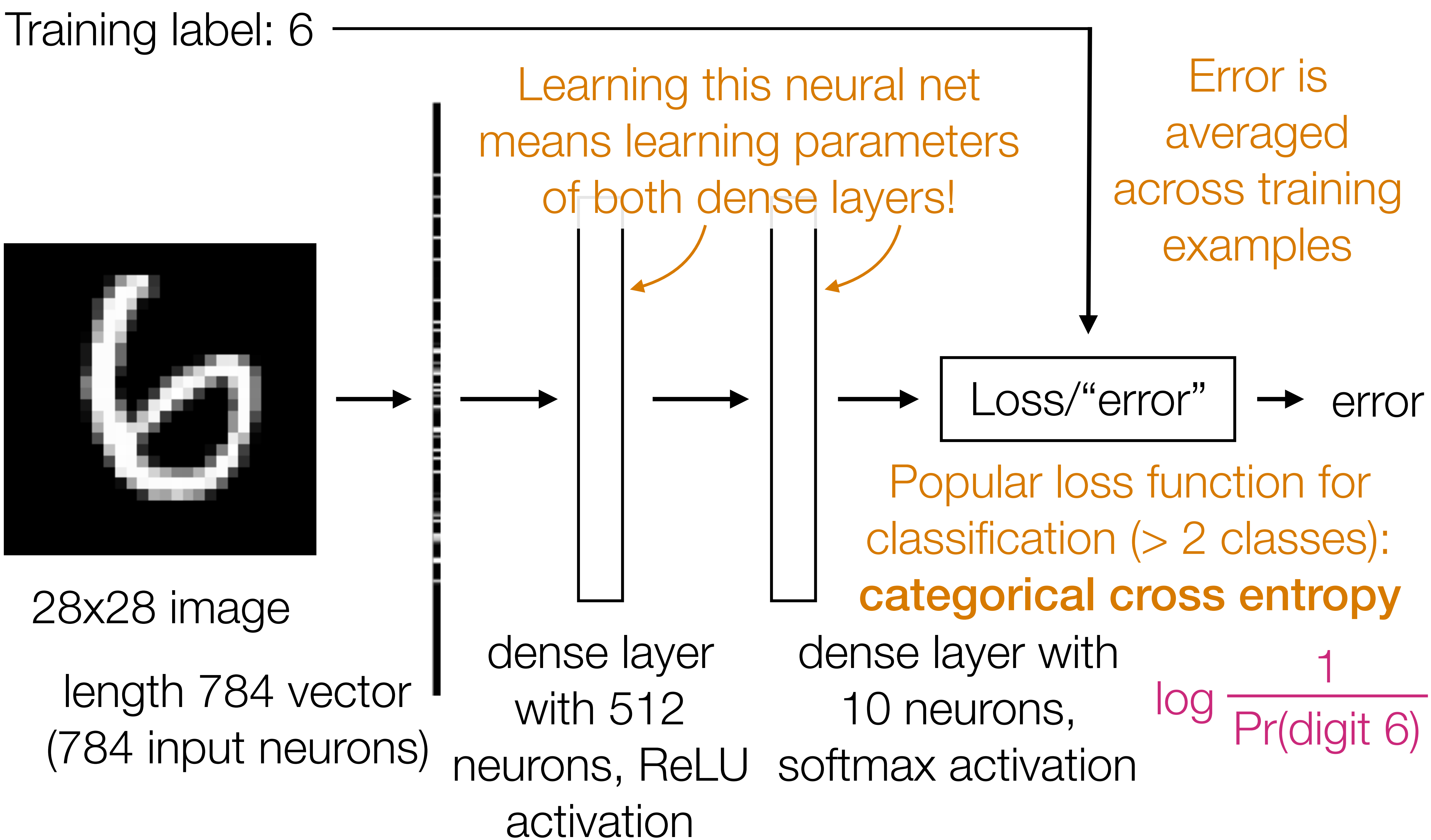

Handwritten Digit Recognition

Demo part 3

Architecting Neural Nets

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- Increasing number of layers (depth) makes neural net more complex

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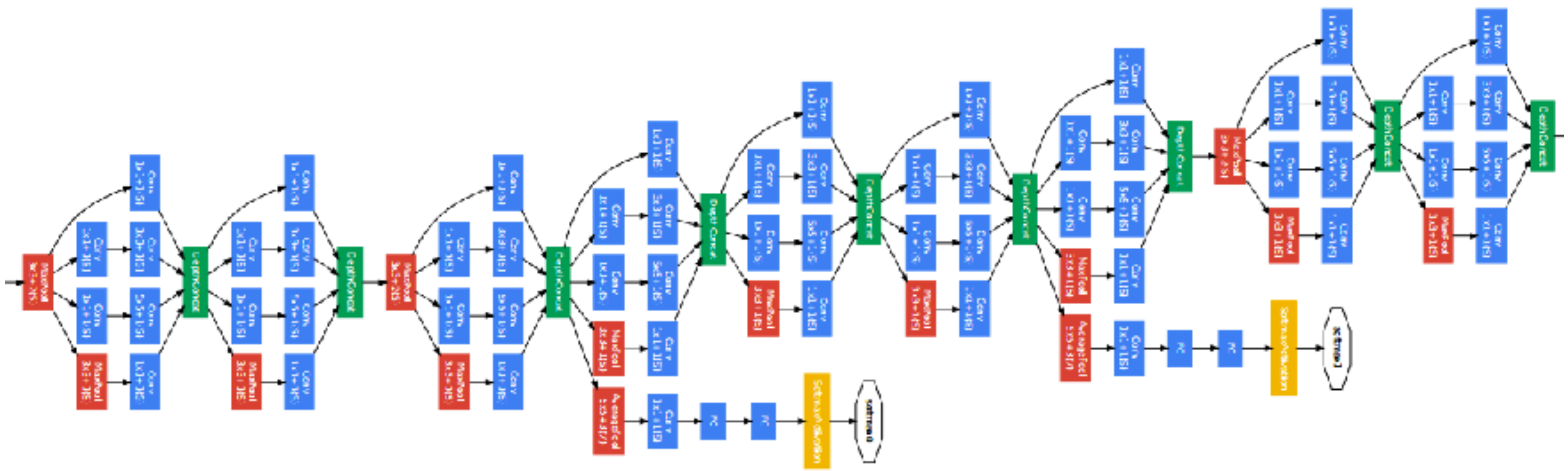
Architecting Neural Nets

- 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

Deep Learning

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  - Tries to get rid of manual feature engineering

- Upcoming: enforce structure using special layers

  - Can think of this as constraining what features are learned