Statistics and Machine Learning

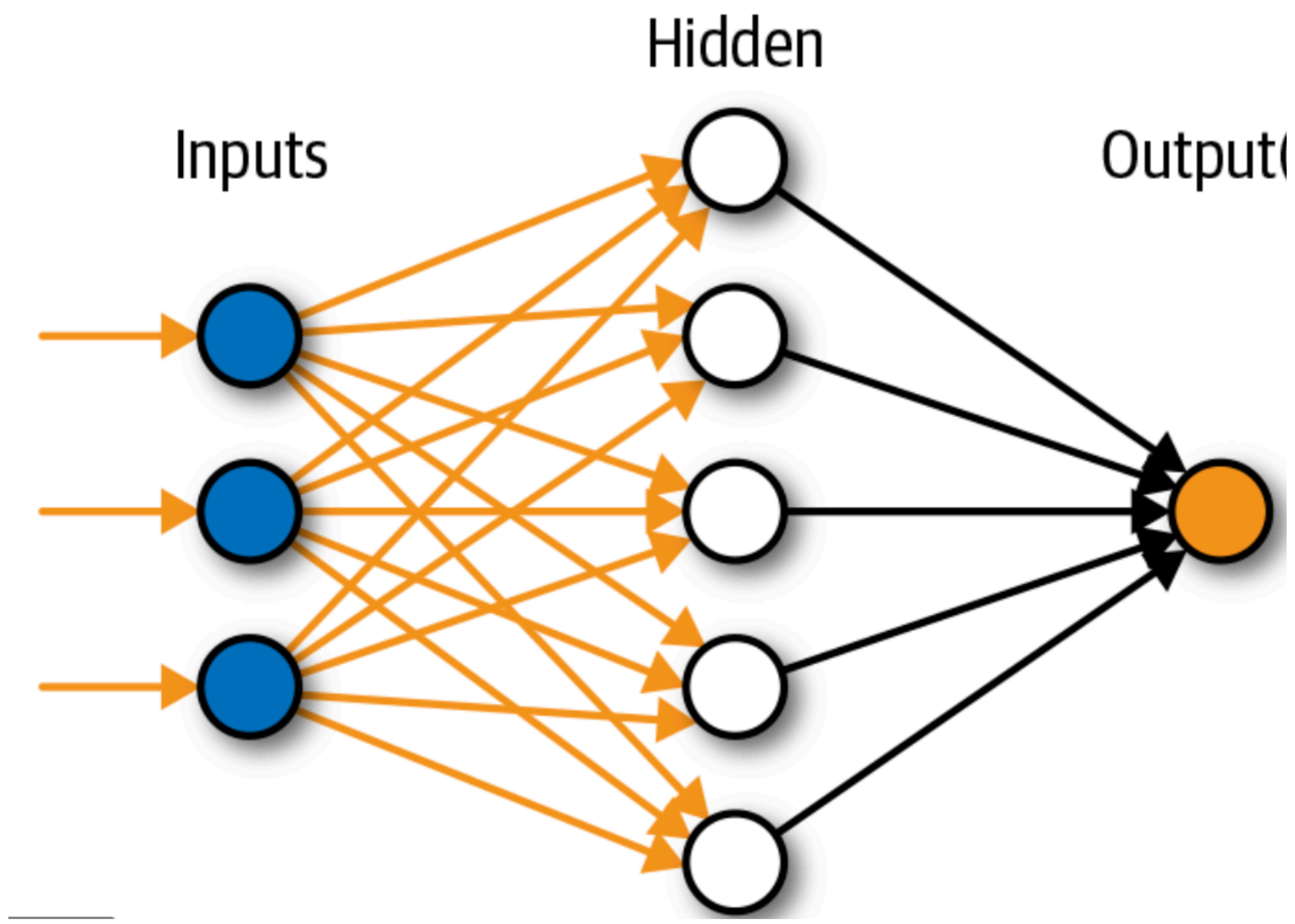
Week 2
01/25 — 01/29
Introduction to Machine Learning

Contents for week 2

- Supervised learning
- Example: digit classification
- Elements of supervised learning
- Why statistics
- Unsupervised learning
- Clustering, principal component analysis, SVM
- Recommender system, natural language processing
- Lab: basic python

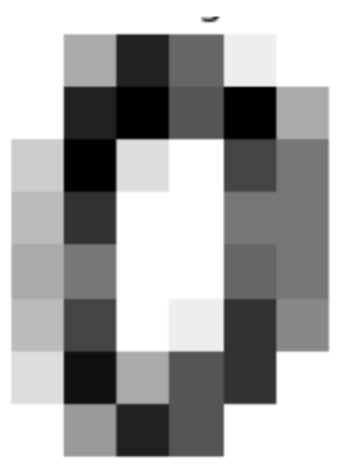
Artificial neuron does the job

Google the keyword "pytorch", "Keras", "tensor flow" to learn more



A horse with 99% confidence

Hand-written digit images



https://scikit-learn.org/stable/auto_examples/classification/plot_digits_classification.html

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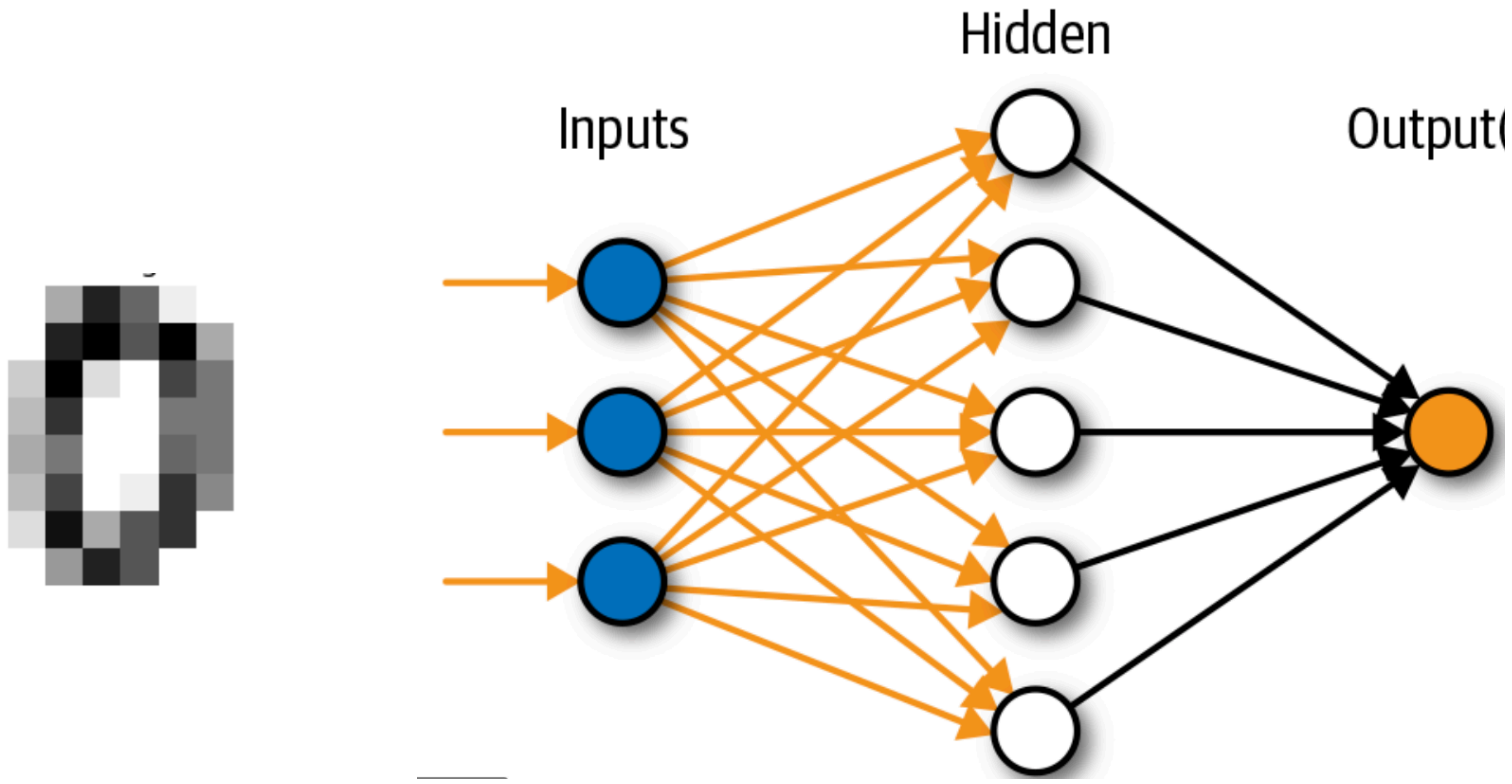

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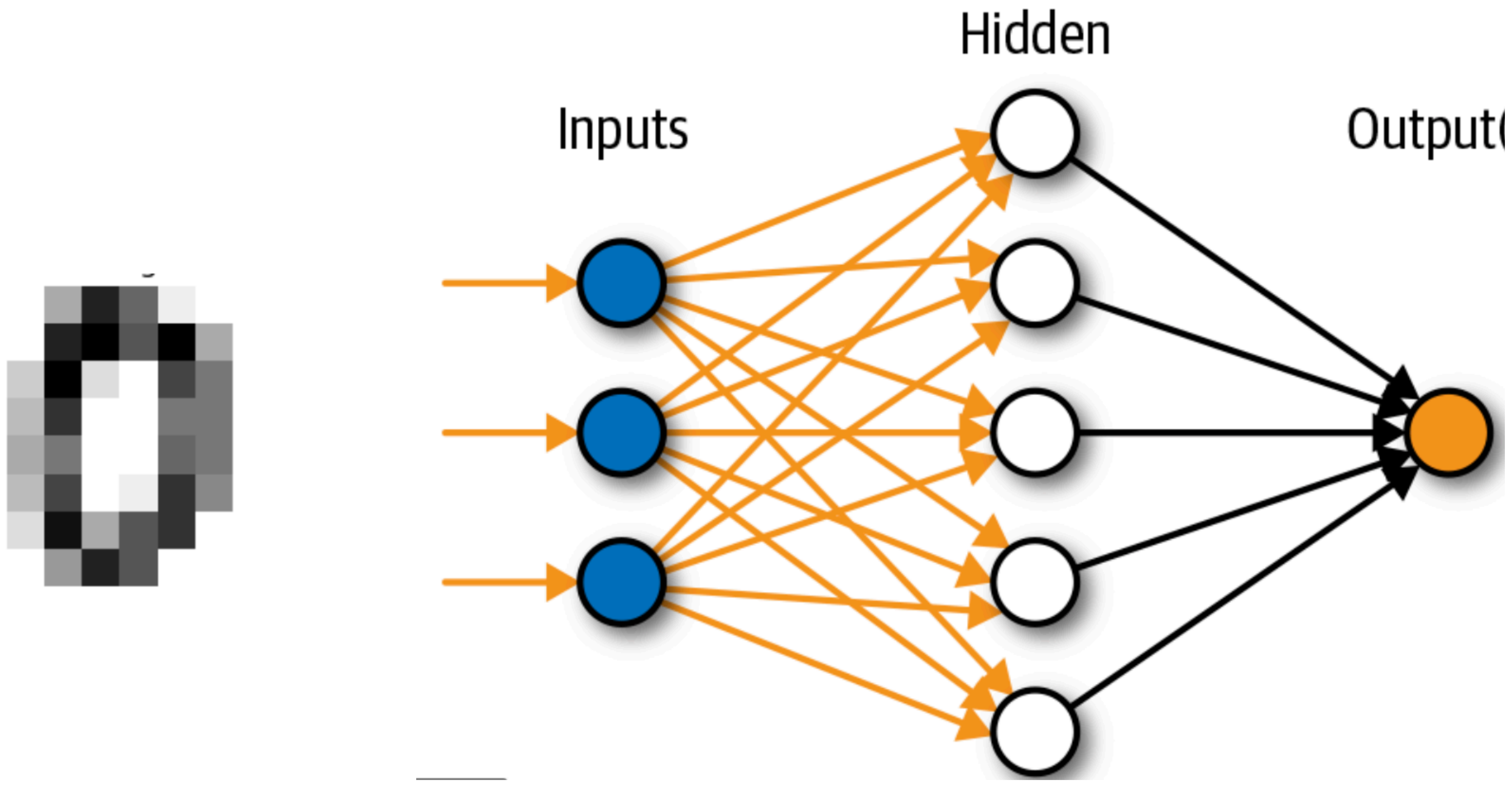

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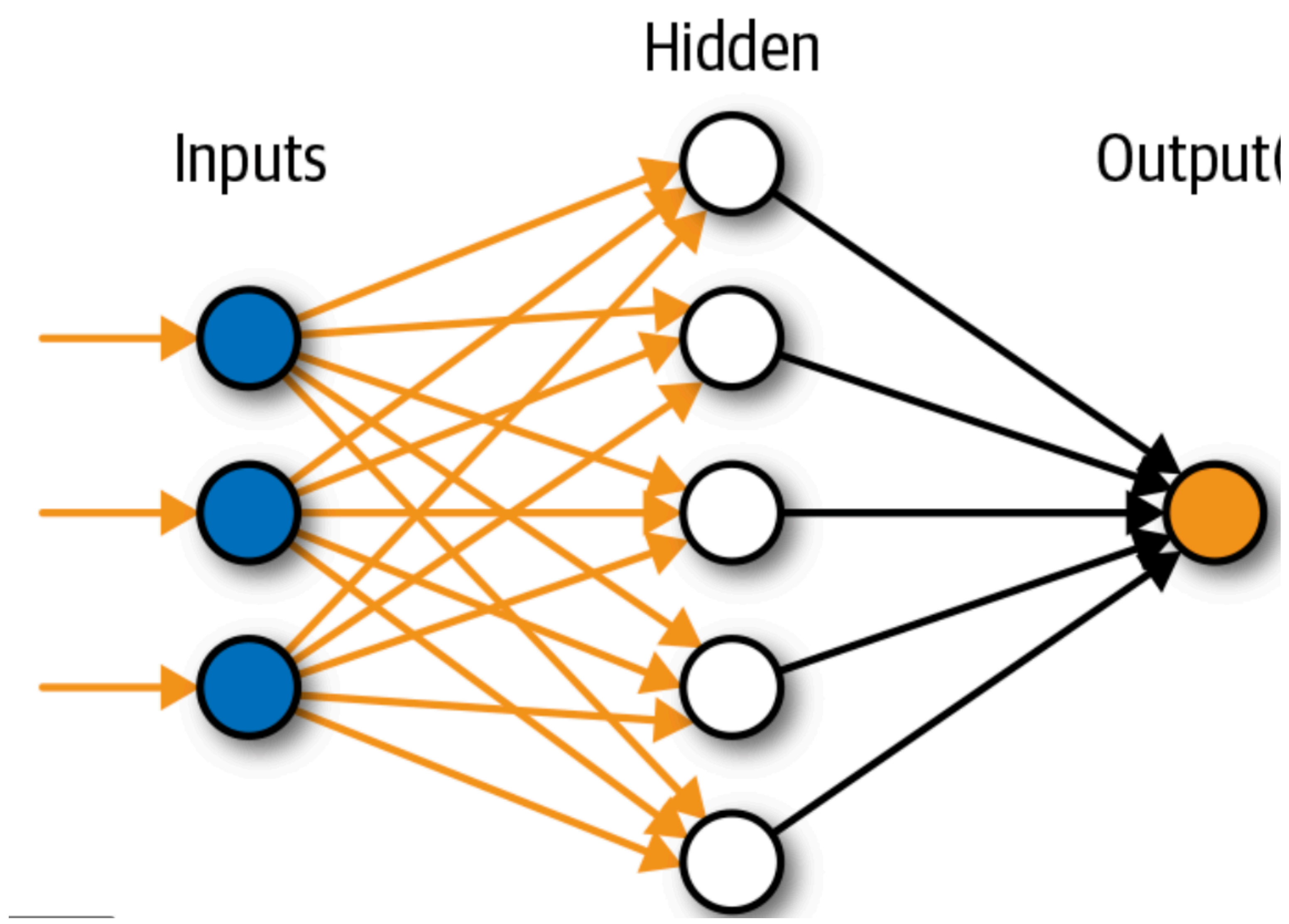

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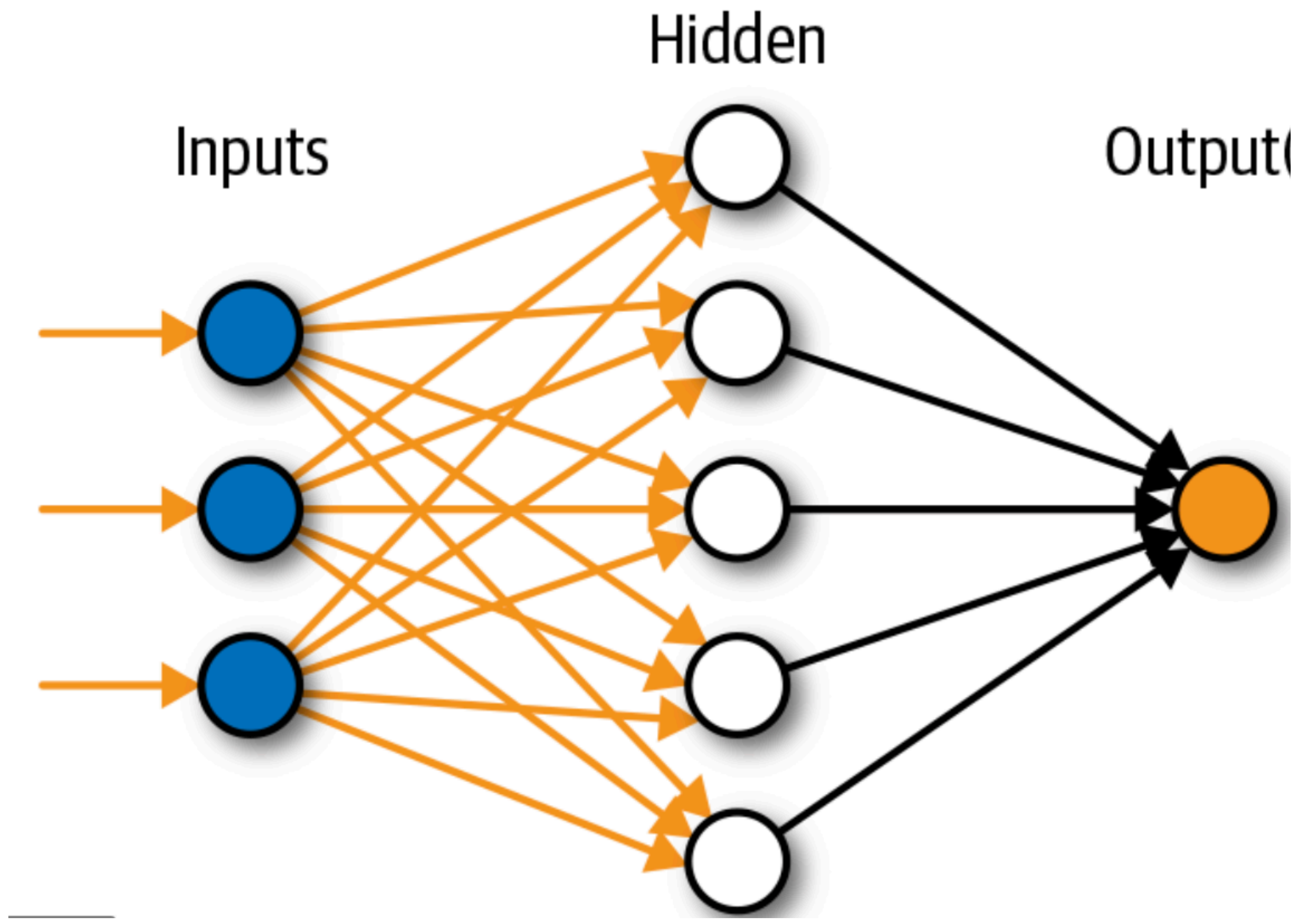

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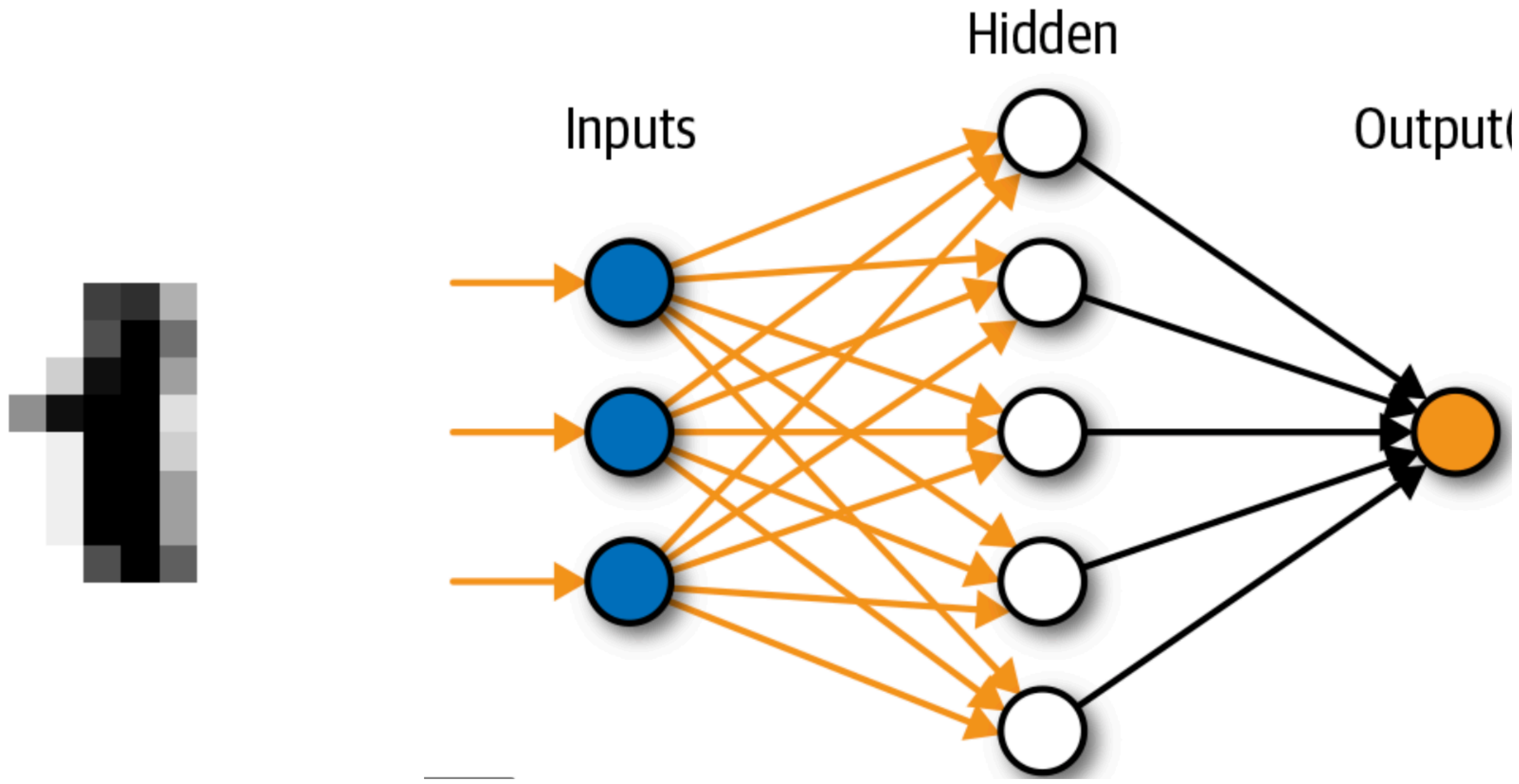

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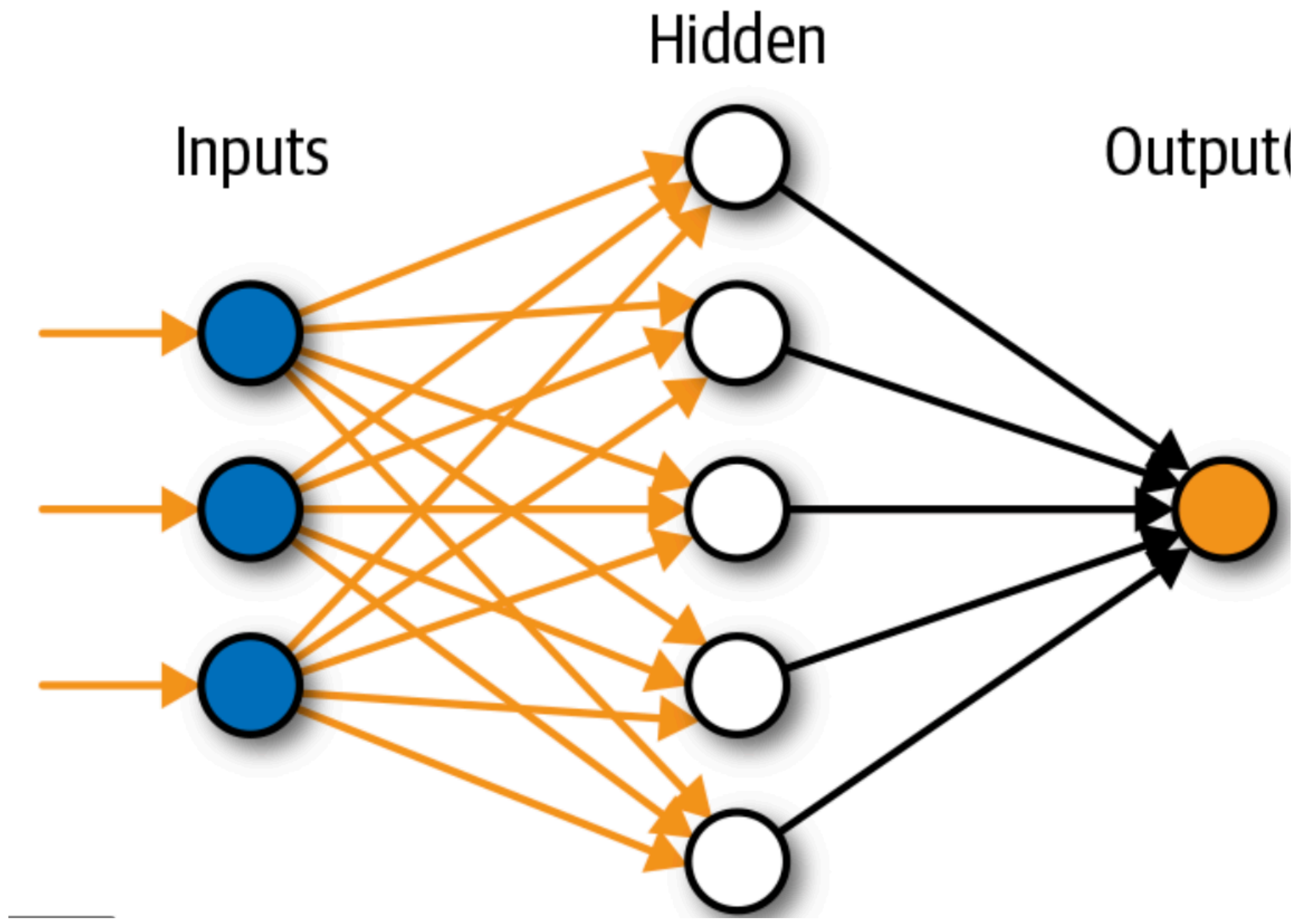

It is 1

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Clarification on datum versus data

Singular versus plural

datum noun

Save Word

da·tum | \ ˈdā-təm , ˈda- , ˈdä- \

Definition of *datum*

1 *plural* **data**\ ˈdā-tə , ˈda- *also* ˈdä- \ **:** something given or admitted especially as a basis for reasoning or inference

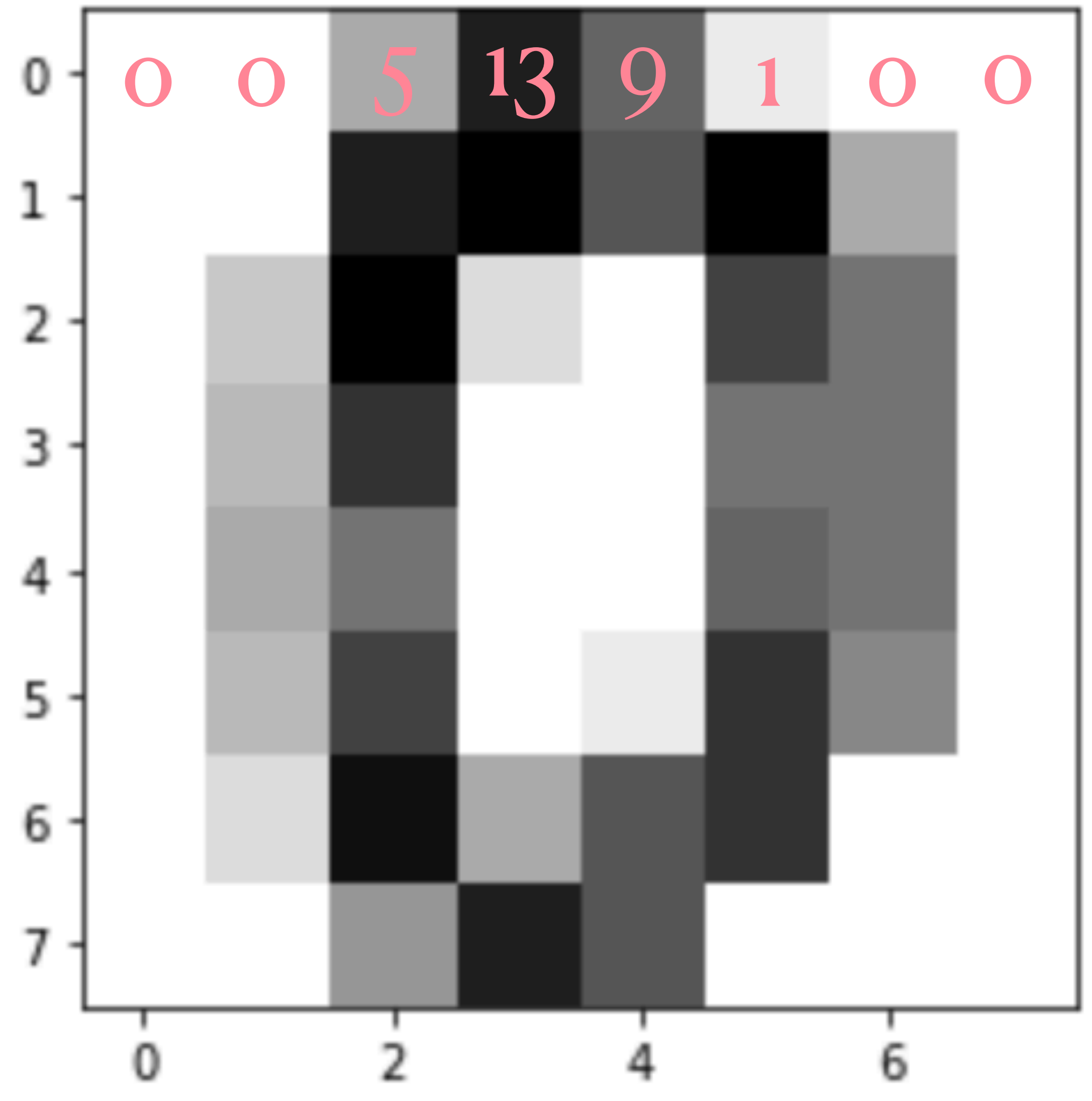
// an important historical *datum*

// This enormous expense—and considerable risk—to pick up a *datum* or two about geriatrics?

— Charles Krauthammer

Model, data set, and loss function

Elements in machine learning




```
digits.images[0]
```

```
array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
       [ 0.,  0., 13., 15., 10., 15.,  5.,  0.],
       [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
       [ 0.,  4., 12.,  0.,  0.,  8.,  8.,  0.],
       [ 0.,  5.,  8.,  0.,  0.,  9.,  8.,  0.],
       [ 0.,  4., 11.,  0.,  1., 12.,  7.,  0.],
       [ 0.,  2., 14.,  5., 10., 12.,  0.,  0.],
       [ 0.,  0.,  6., 13., 10.,  0.,  0.,  0.]])
```

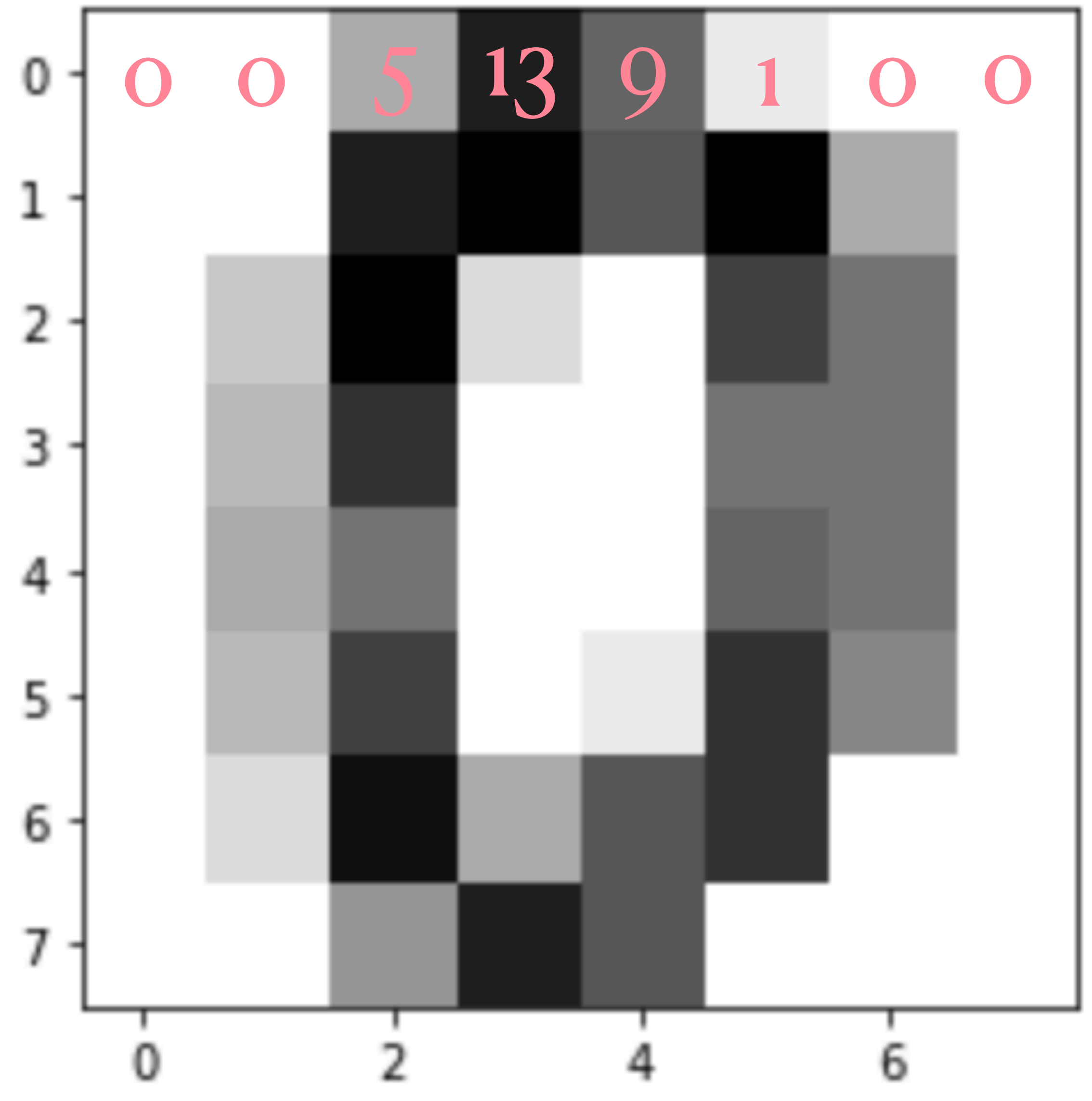
```
# target_names store the label for the digit image

digits.target_names[0]
```

```
0
```

See the code in MNIST_basic.ipynb

Model, data set, and loss function

Elements in machine learning

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The whole thing in the left is a datum. The information contained:

1. Image (8x8, 64 numbers)
2. Label '0'

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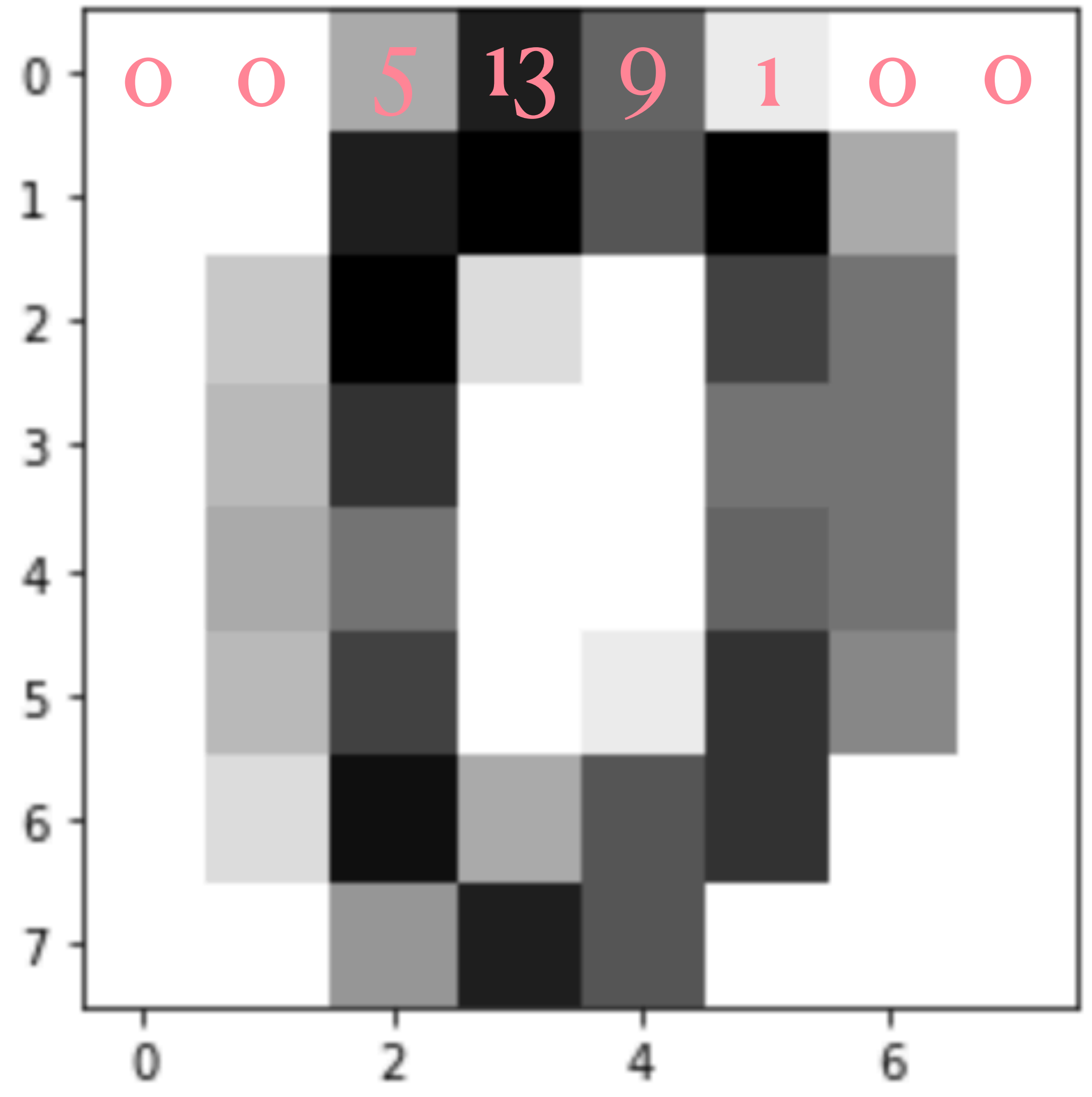
Model, data set, and loss function

Elements in machine learning

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array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
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       [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
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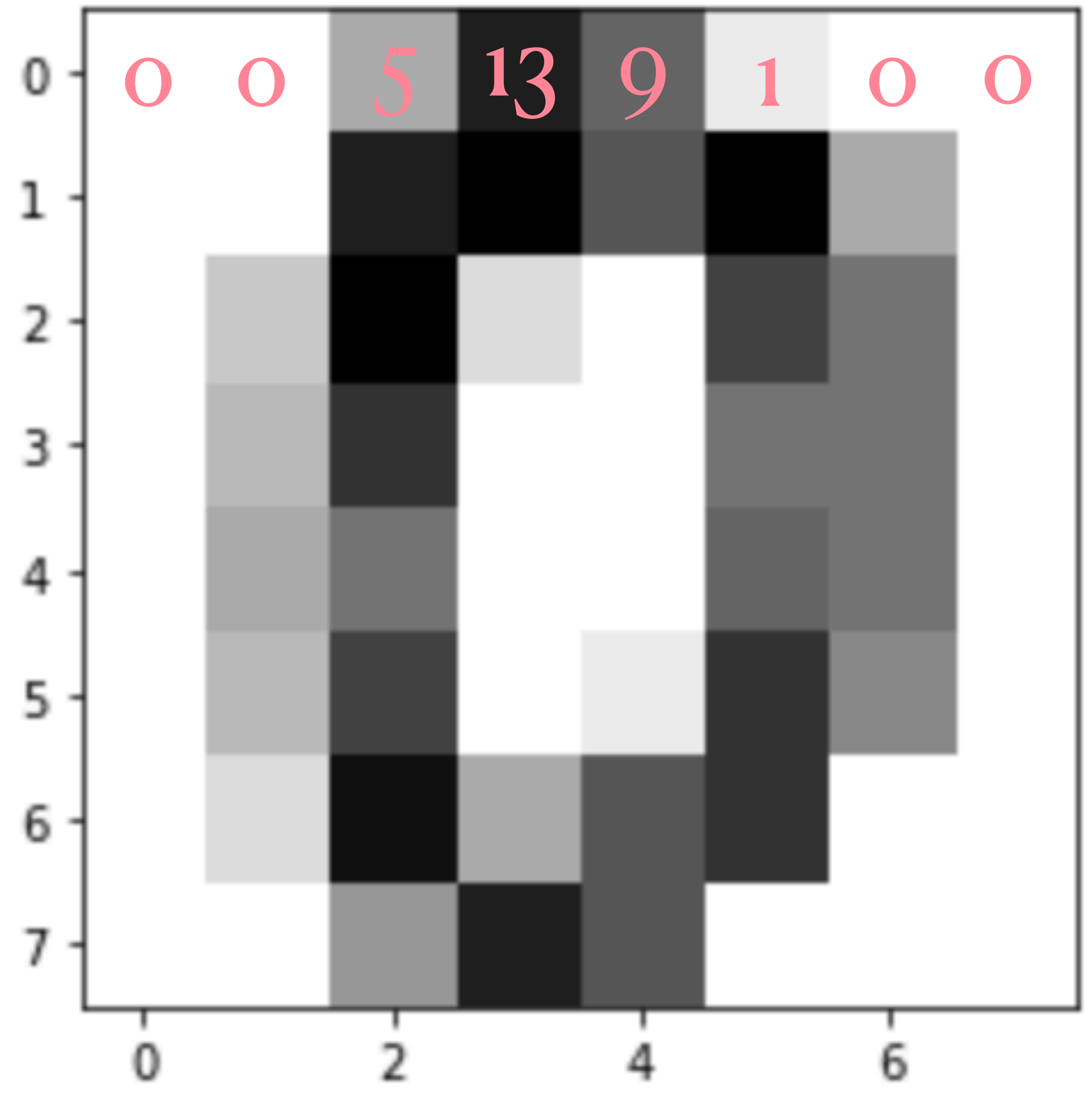
For convenience, we usually do

1. Reshape the image into a 64x1 vector, call it x
2. Call y = 0

See the code in MNIST_basic.ipynb

Model, data set, and loss function

Elements in machine learning

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Model, data set, and loss function

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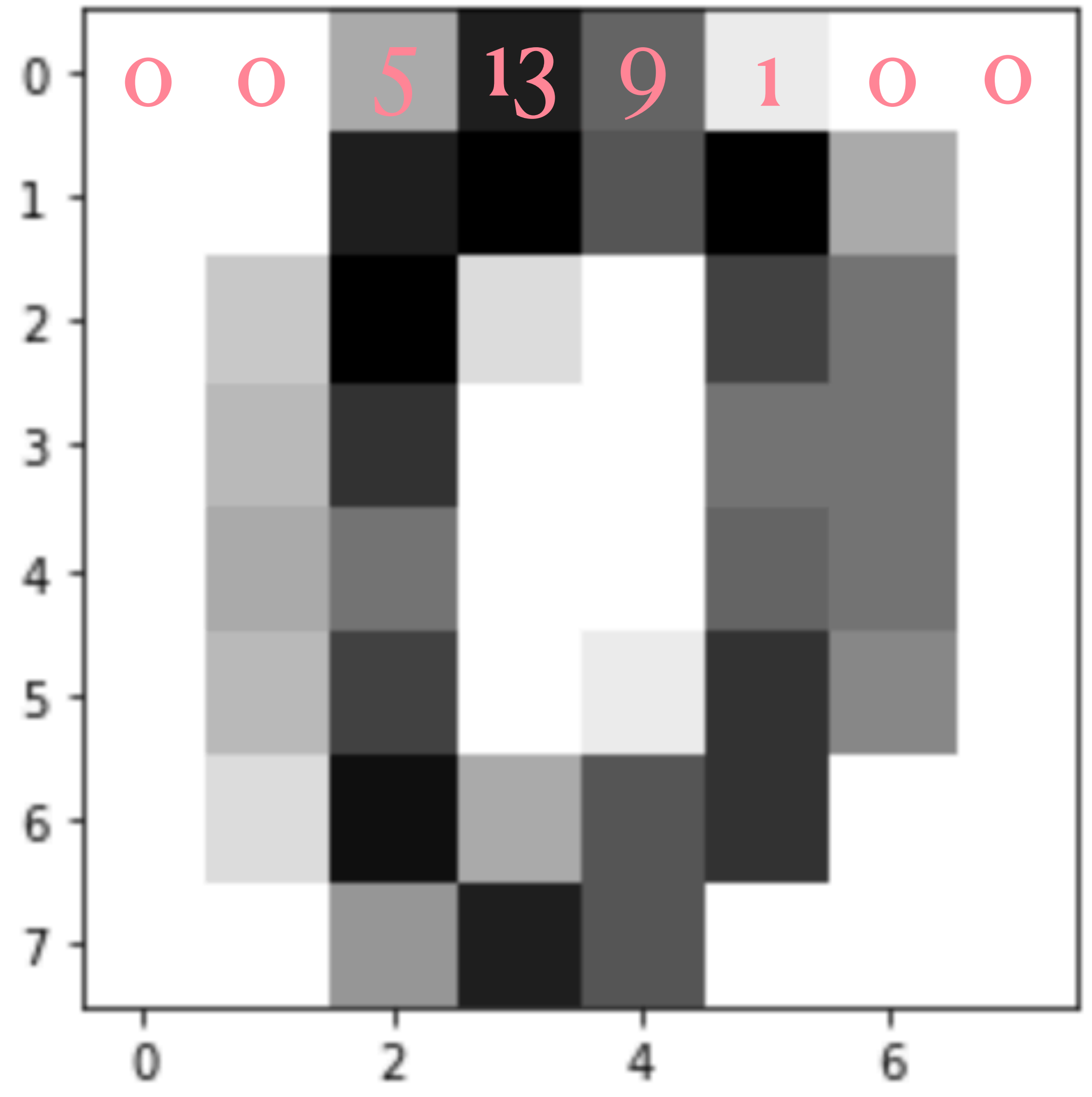


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```

```
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```

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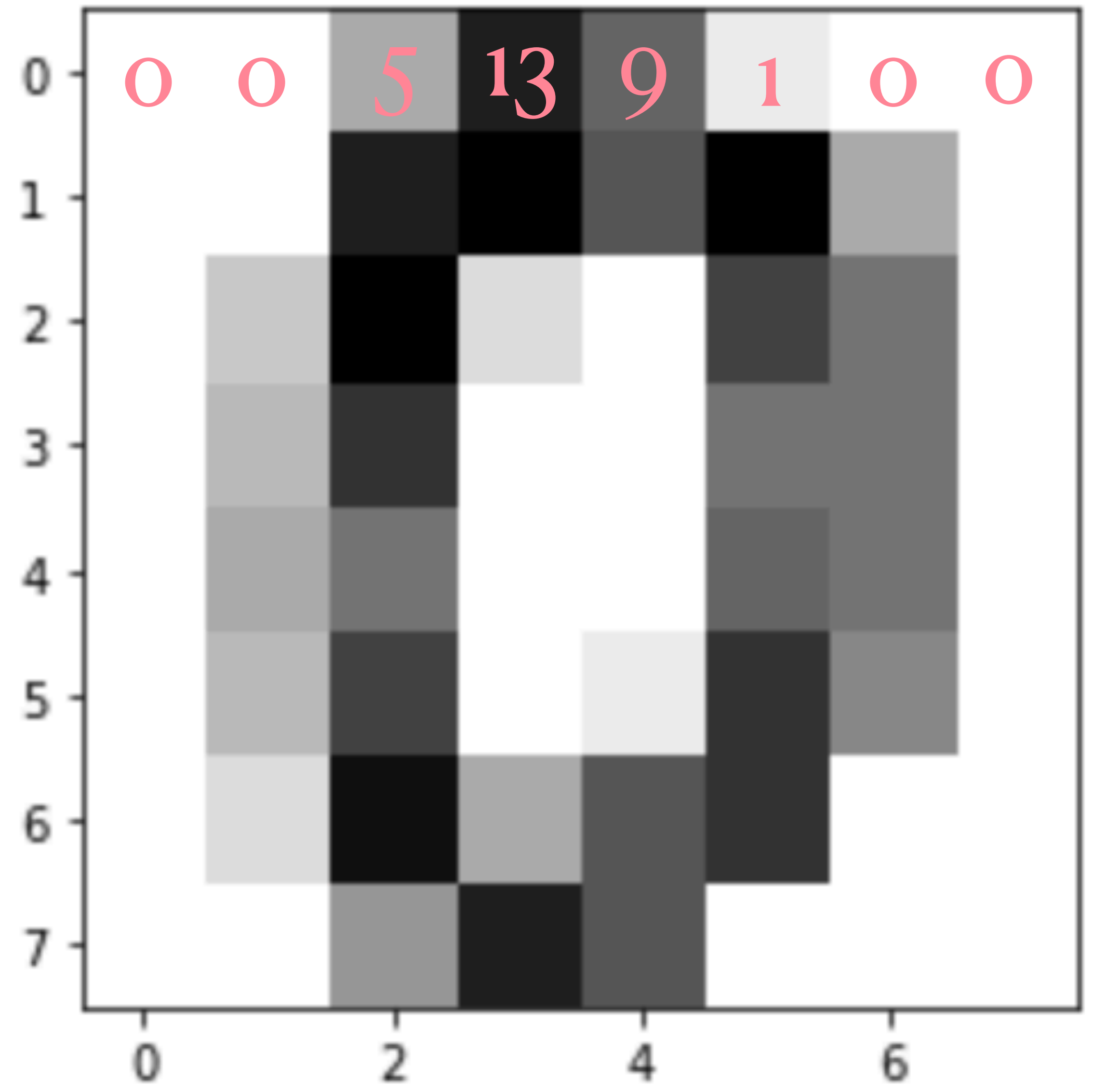
Model, data set, and loss function

Elements in machine learning




```
digits.images[0]
```

```
array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
       [ 0.,  0., 13., 15., 10., 15.,  5.,  0.],
       [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
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```

```
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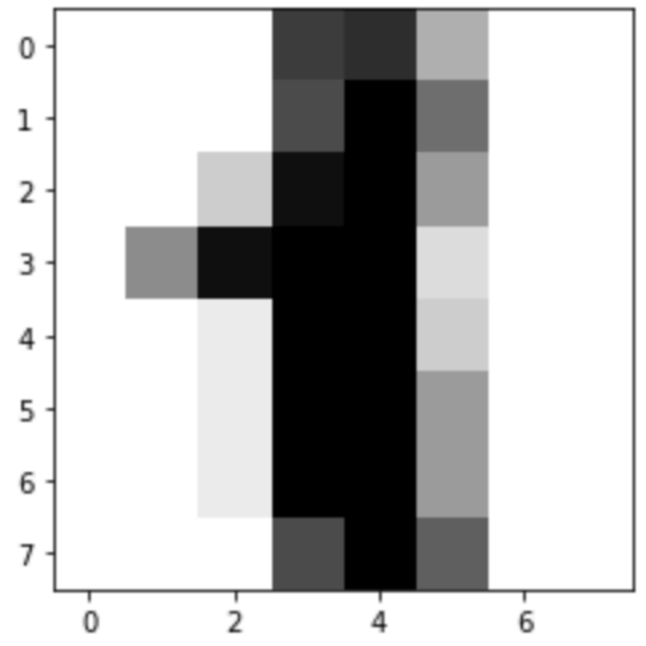
```

< — y



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Model, data set, and loss function

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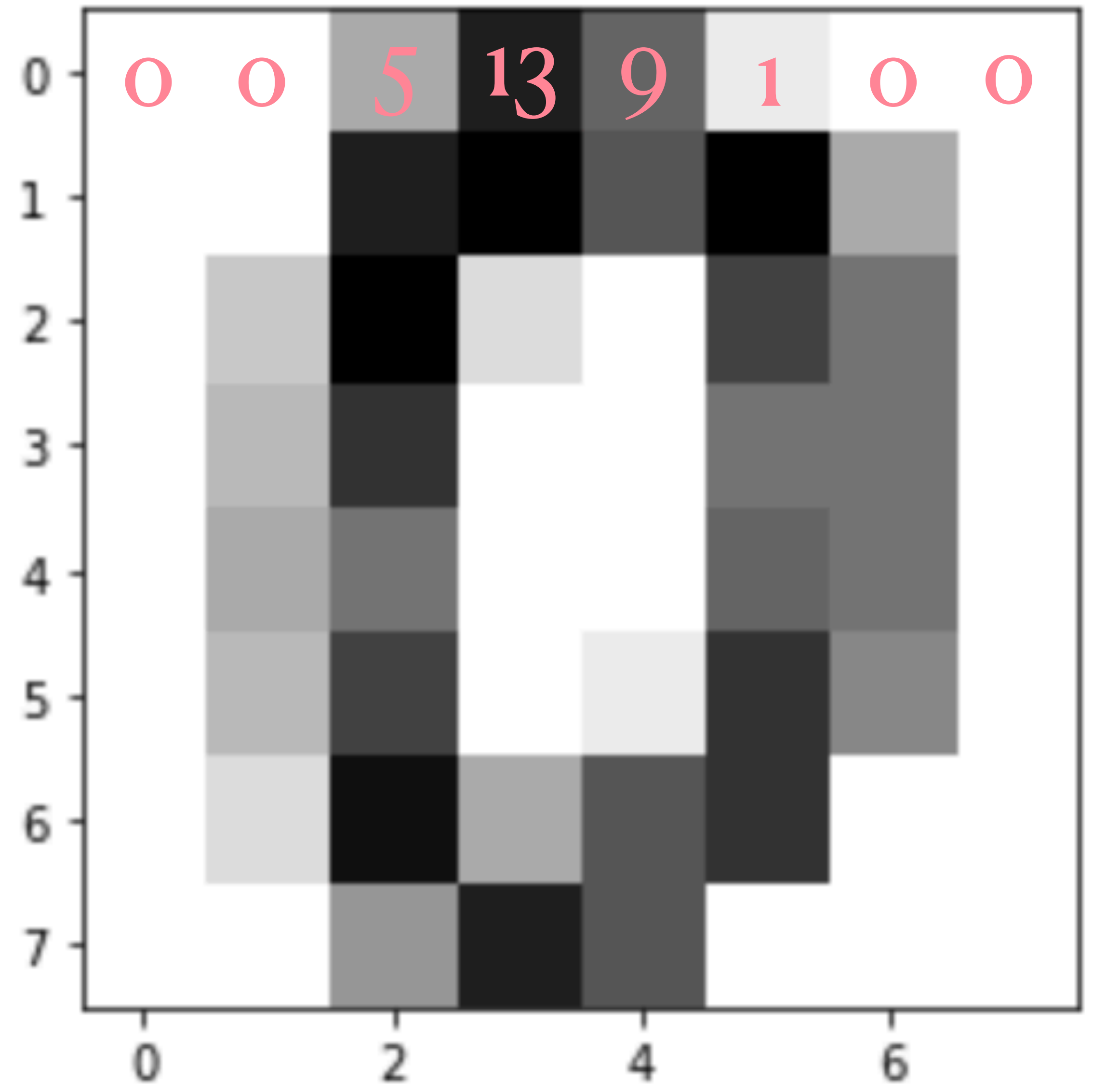


```
digits.images[0]
```

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array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
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< — x

```
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```

```
0
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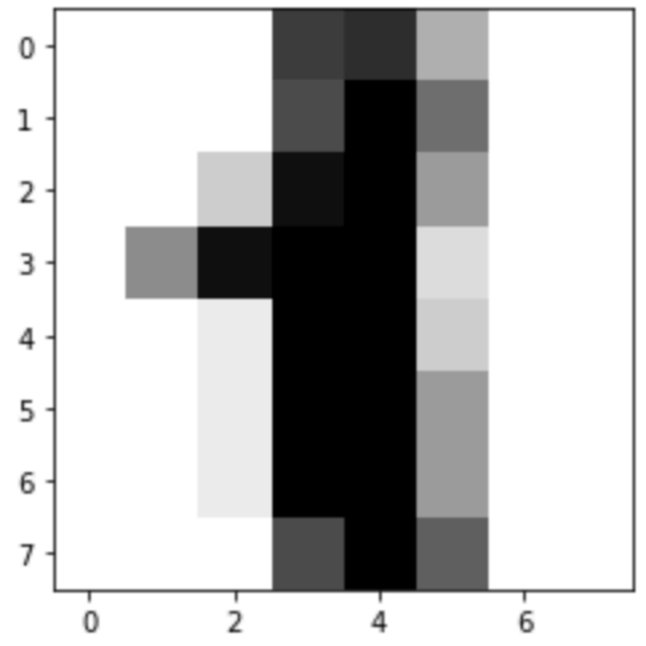

```
digits.images[1]
```

```
array([[ 0.,  0.,  0., 12., 13.,  5.,  0.,  0.],
       [ 0.,  0.,  0., 11., 16.,  9.,  0.,  0.],
       [ 0.,  0.,  3., 15., 16.,  6.,  0.,  0.],
       [ 0.,  7., 15., 16., 16.,  2.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  3.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  6.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  6.,  0.,  0.],
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```
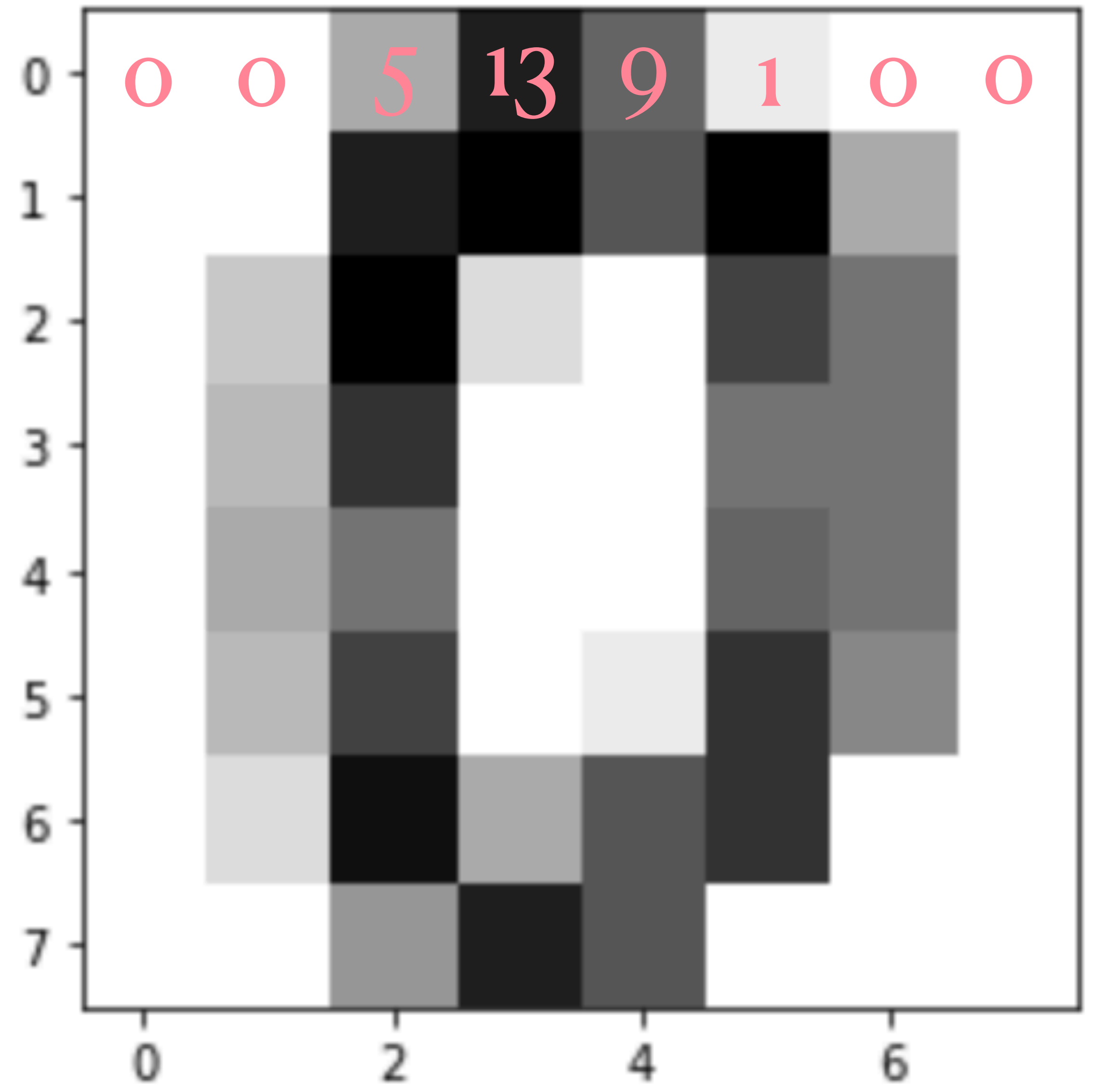

See the code in MNIST_basic.ipynb

Model, data set, and loss function

Elements in machine learning




```
digits.images[0]
```

```
array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
       [ 0.,  0., 13., 15., 10., 15.,  5.,  0.],
       [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
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```

< — x

```
# target_names store the label for the digit image
digits.target_names[0]
```

```
0
```

< — y

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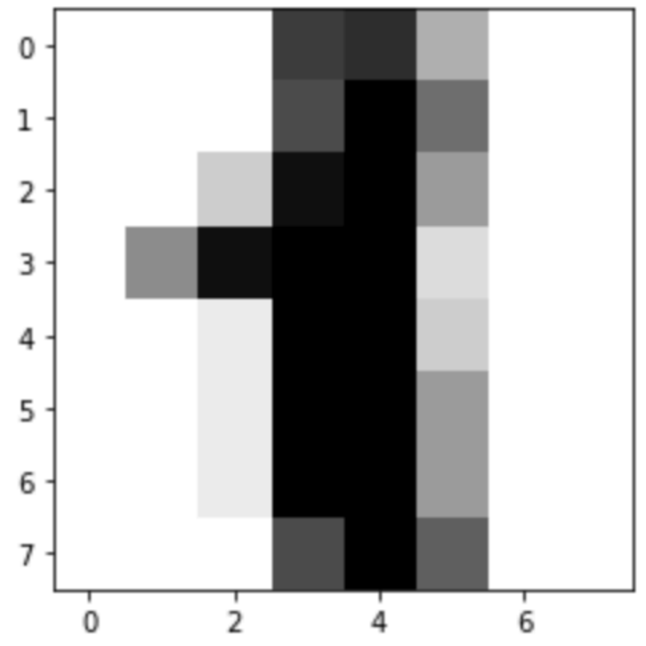

```
digits.images[1]
```

```
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       [ 0.,  0.,  3., 15., 16.,  6.,  0.,  0.],
       [ 0.,  7., 15., 16., 16.,  2.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  3.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  6.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  6.,  0.,  0.],
       [ 0.,  0.,  0., 11., 16., 10.,  0.,  0.]])
```

```
digits.target_names[1]
```

```
1
```

See the code in MNIST_basic.ipynb

Mathematical notation for data set

$$x_i = \begin{pmatrix} x_{i1} \\ x_{i2} \\ \vdots \\ x_{ip} \end{pmatrix}. \qquad (1.1)$$

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$$\mathbf{X} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1p} \\ x_{21} & x_{22} & \dots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{np} \end{pmatrix}$$

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Mathematical notation for data set

$$x_i = \begin{pmatrix} x_{i1} \\ x_{i2} \\ \vdots \\ x_{ip} \end{pmatrix}. \qquad (1.1)$$

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}.$$

$$\mathbf{X} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1p} \\ x_{21} & x_{22} & \dots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{np} \end{pmatrix}$$

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Interpretation: there are n data, each datum contains p features (pixels in MNIST)

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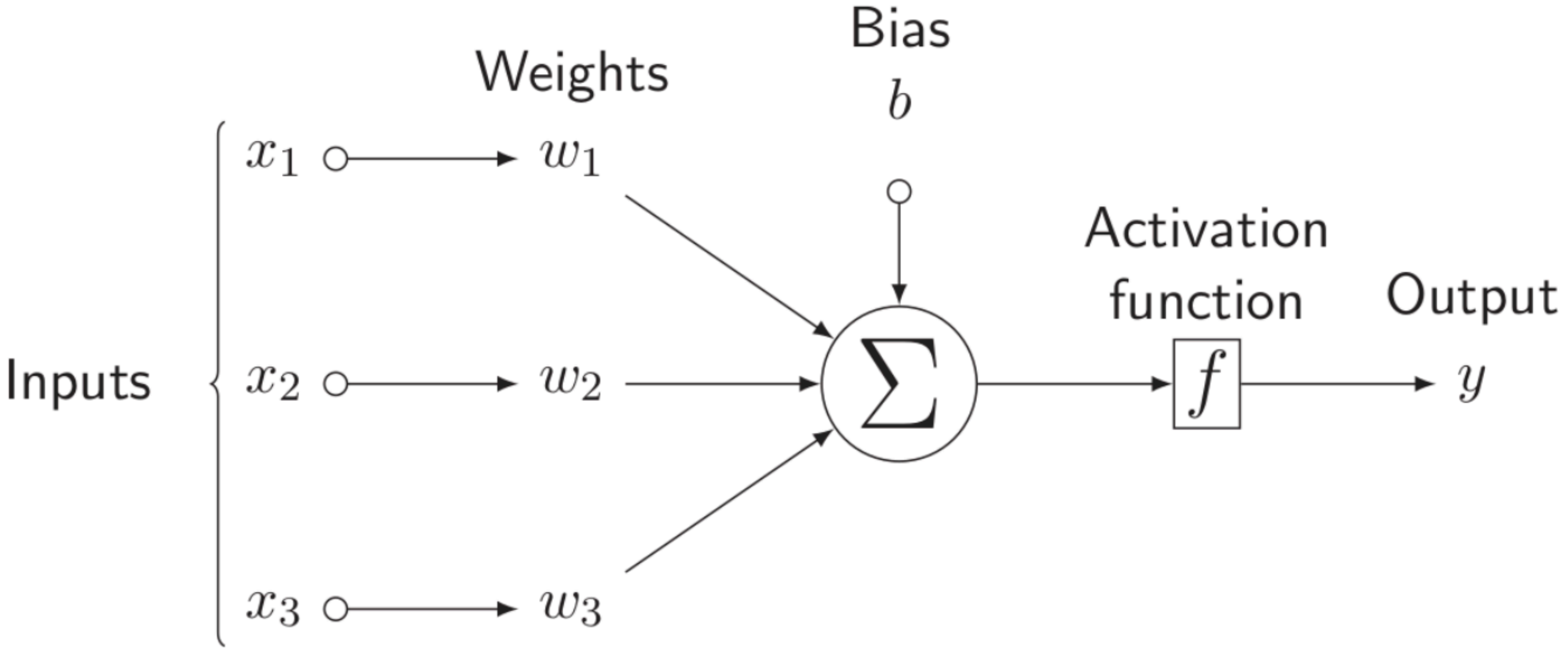
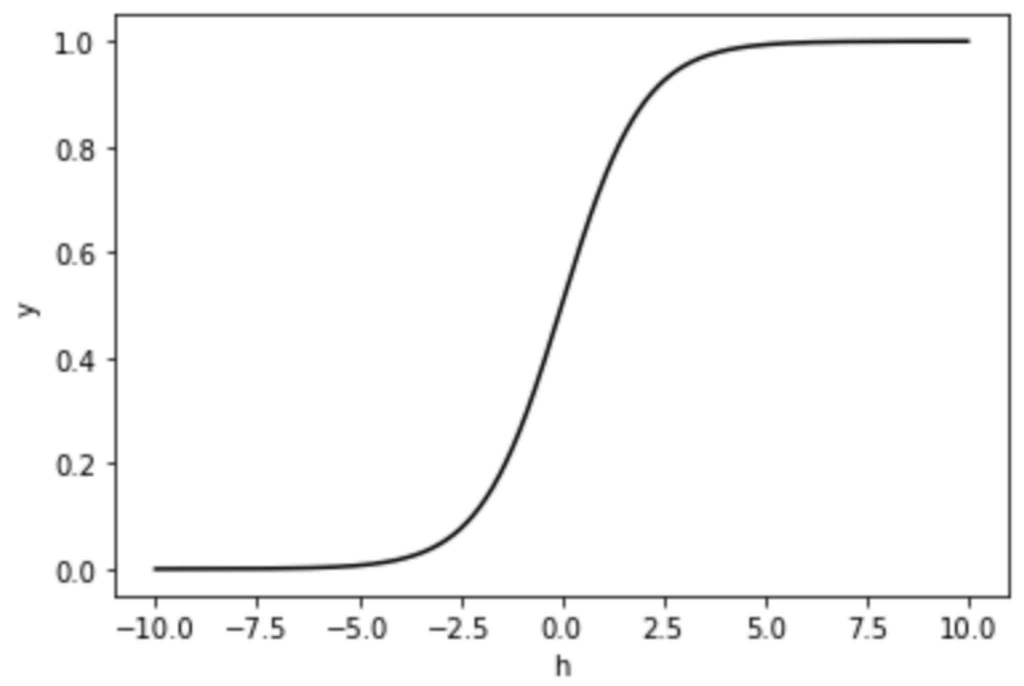
$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}.$$

Interpretation: there are n data, each datum contains p features (pixels in MNIST)

$\boxed{\text{The collection \{X, y\} is a data set.}}$

Model: a mathematical form for $y = f(\mathbf{x} \mid w, b)$



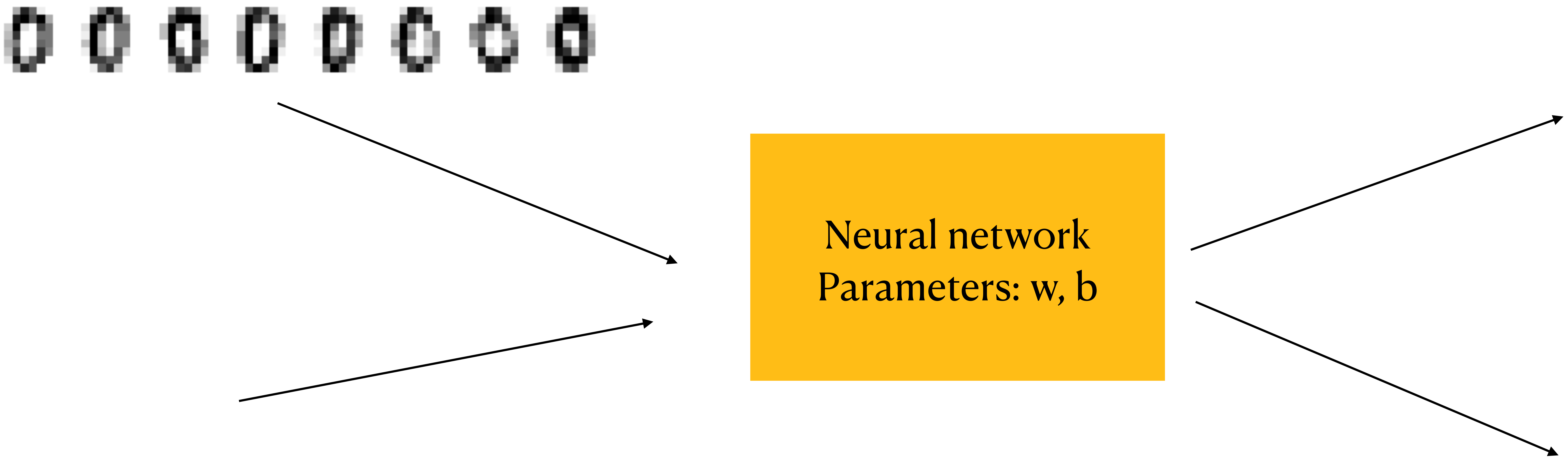


https://tex.stackexchange.com/questions/132444/diagram-of-an-artificial-neural-network

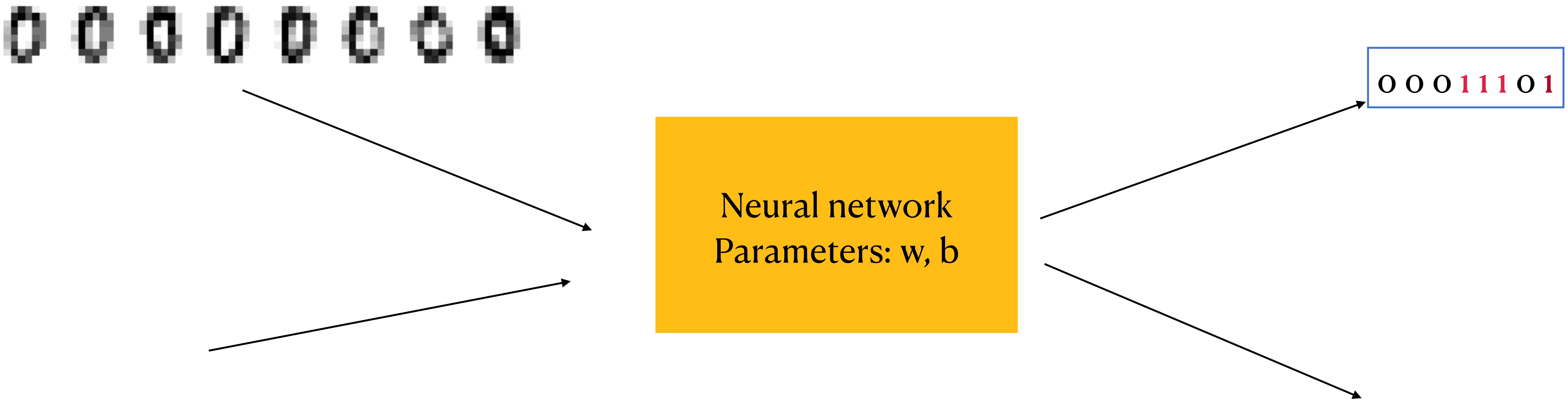
$$h(\mathbf{x}) = b + \sum_i w_i x_i$$

$$f(h) = \frac{1}{1 + e^{-h}}$$

(Qualitative) lose function



(Qualitative) lose function



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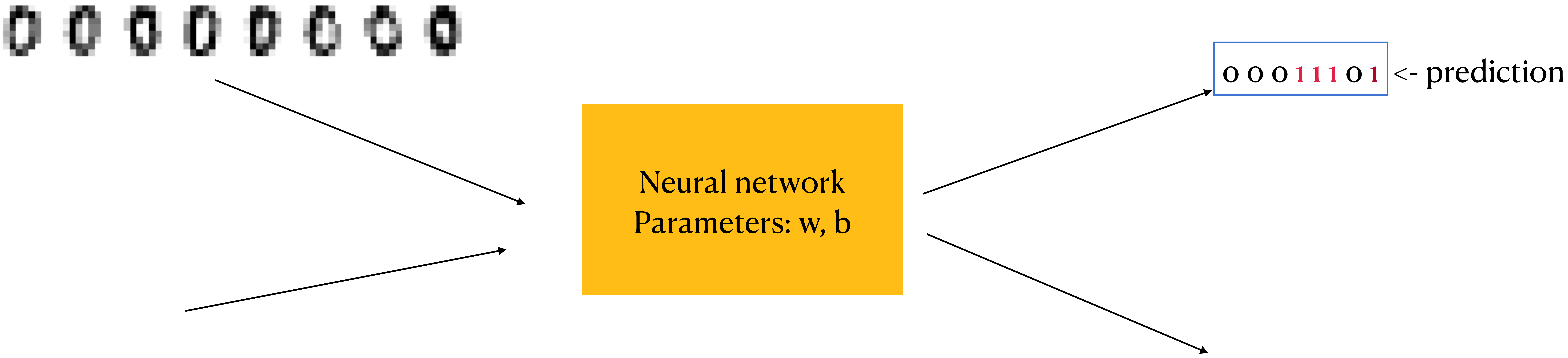
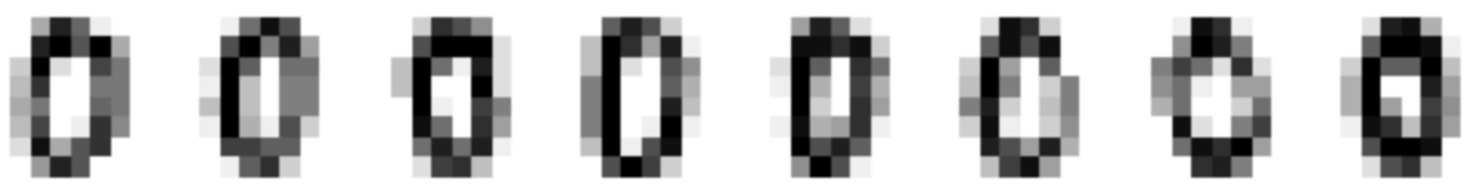


(Qualitative) lose function

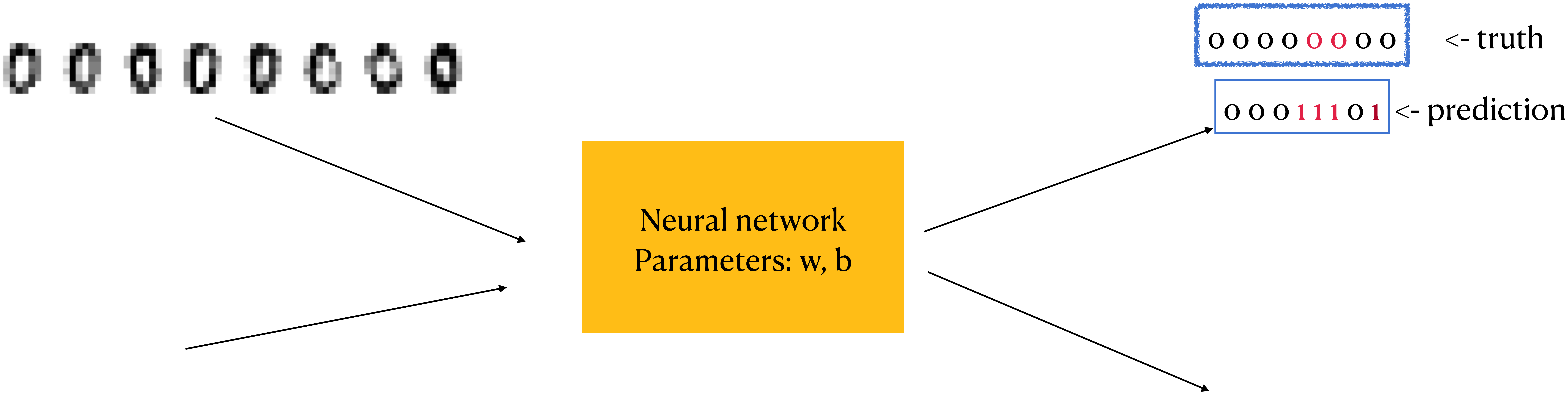
<- truth

0 0 0 1 1 1 0 1 <- prediction



Neural network
Parameters: w, b

(Qualitative) lose function



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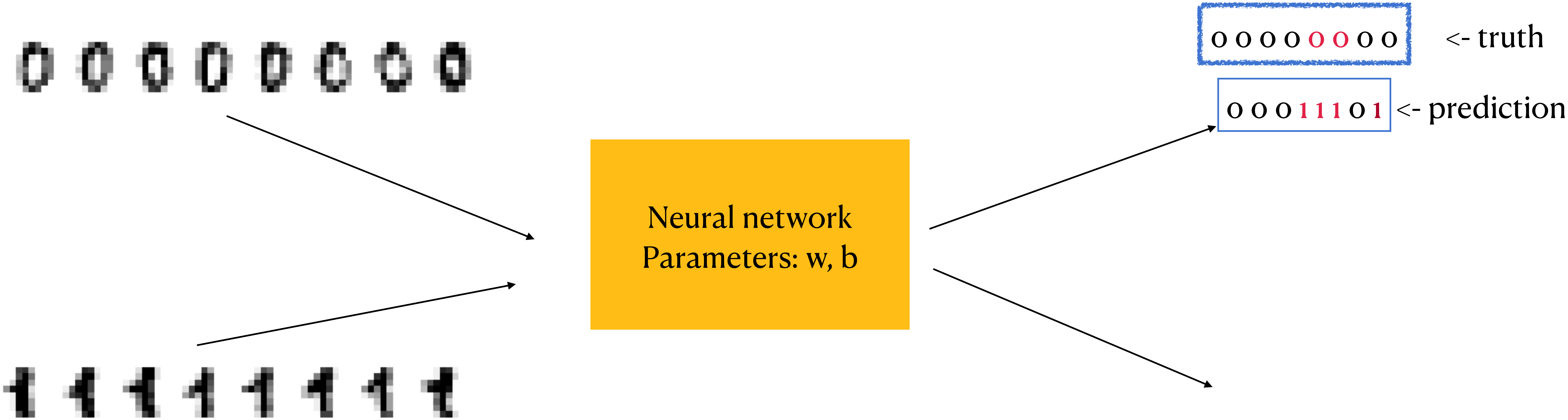

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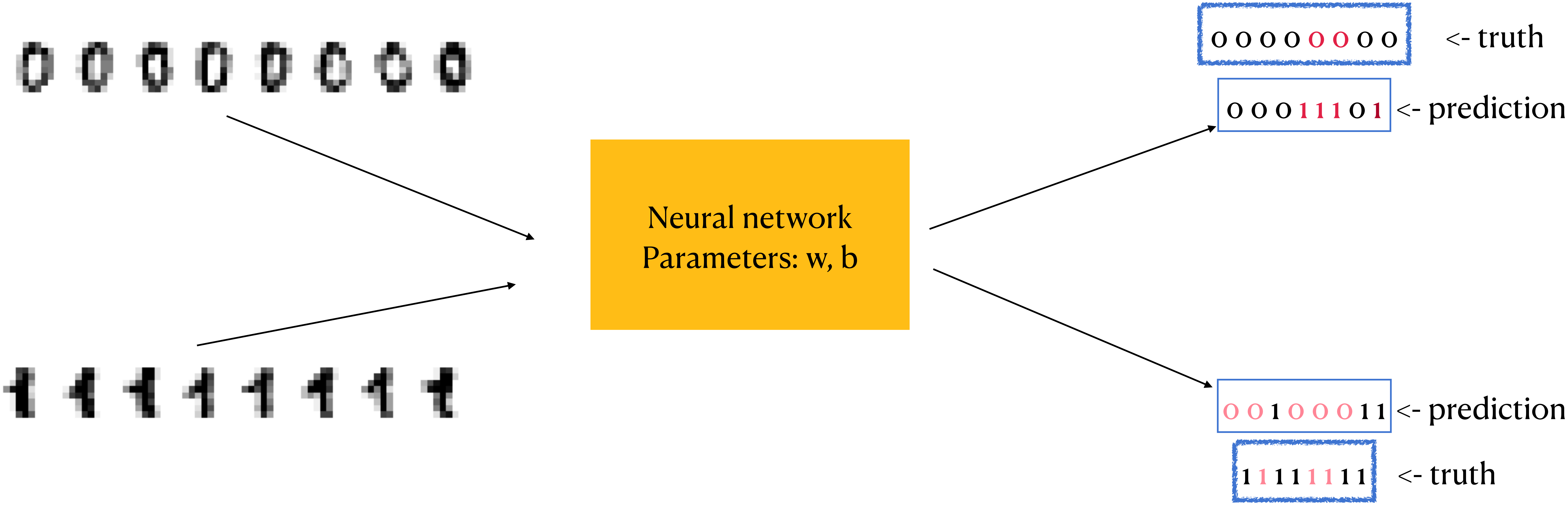
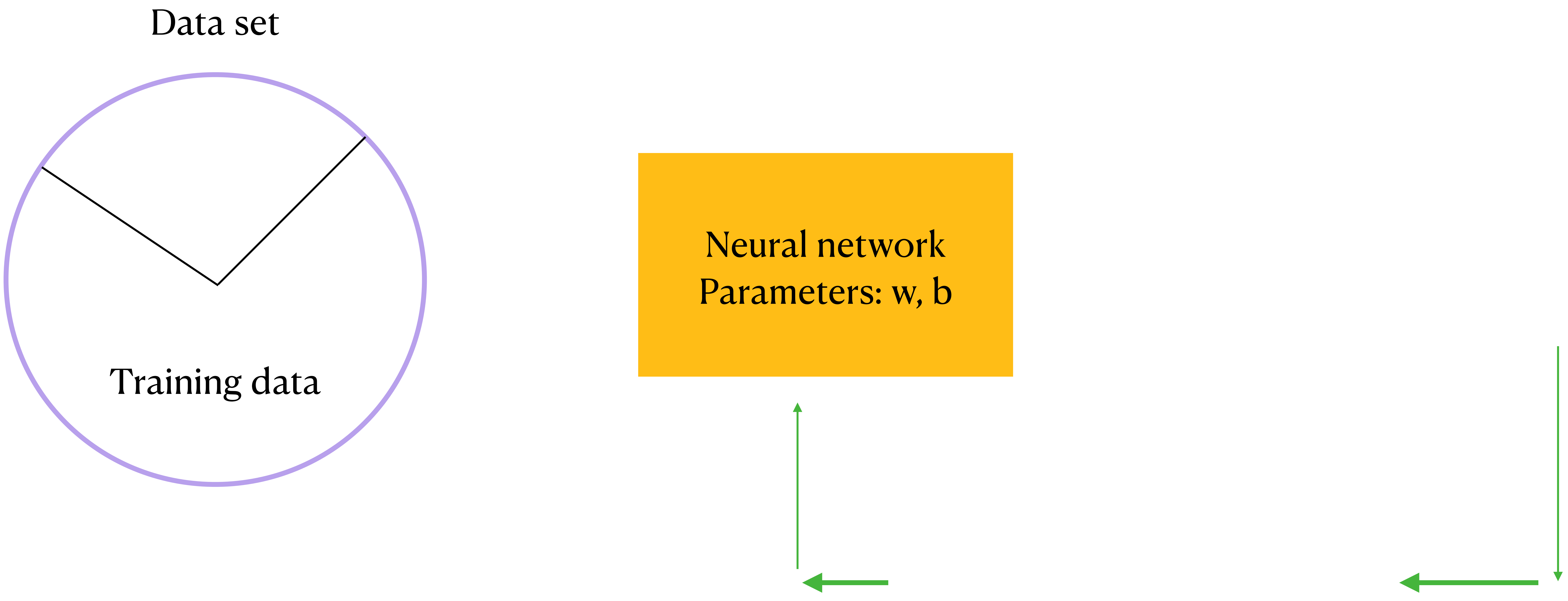


(Qualitative) lose function

Total number of mistakes: 4 + 5 = 9 out of 16 samples

So what is machine learning?

What we want? a capable model, and an unbiased estimate of error rate.



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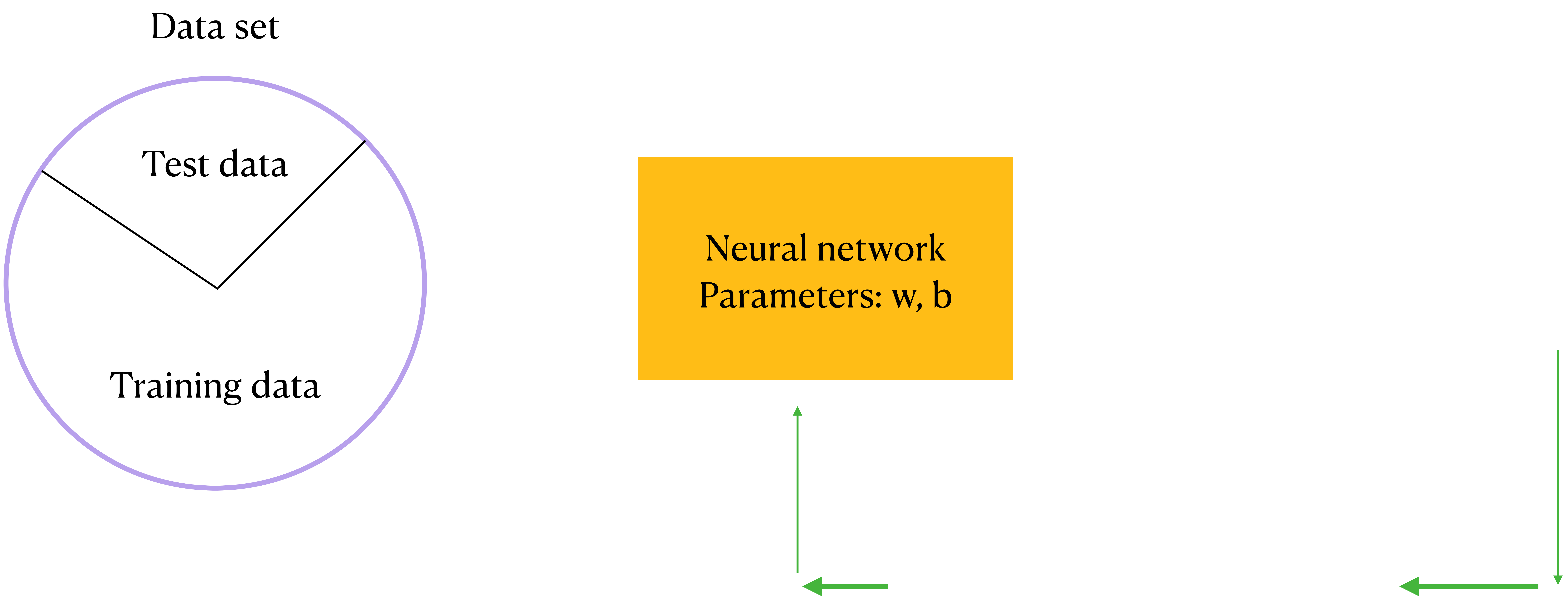

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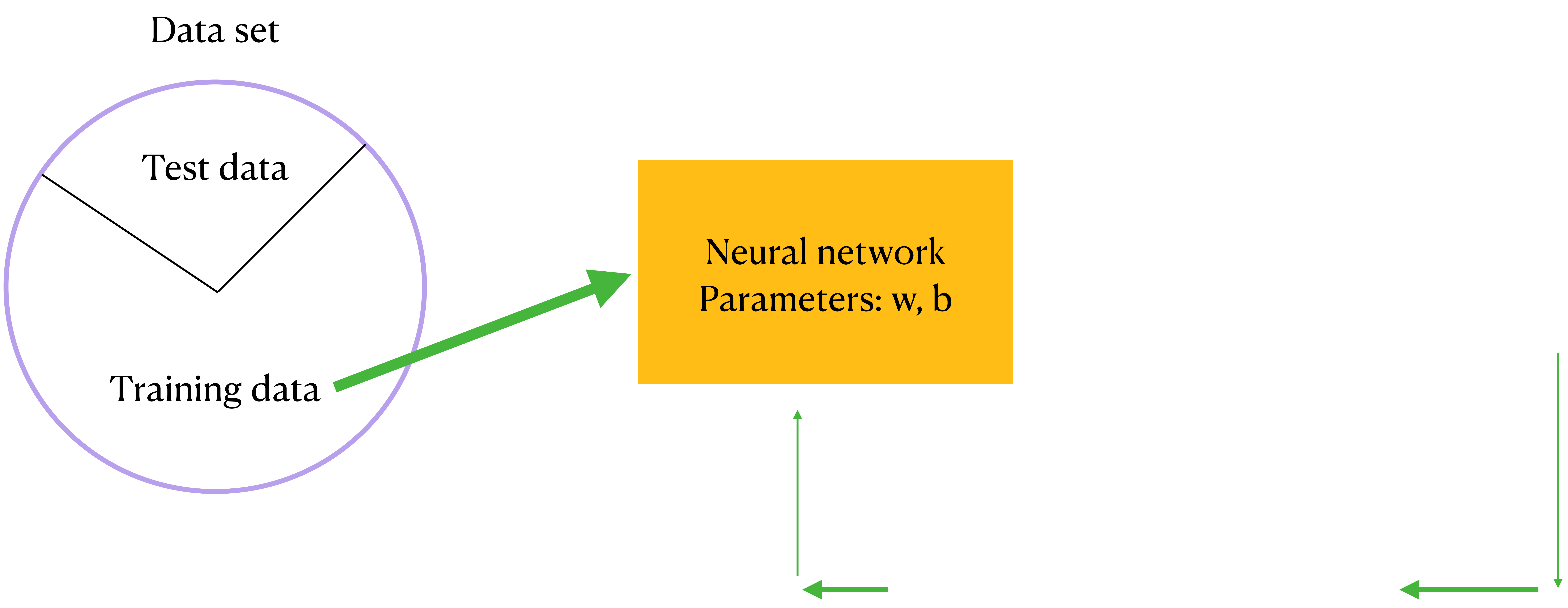

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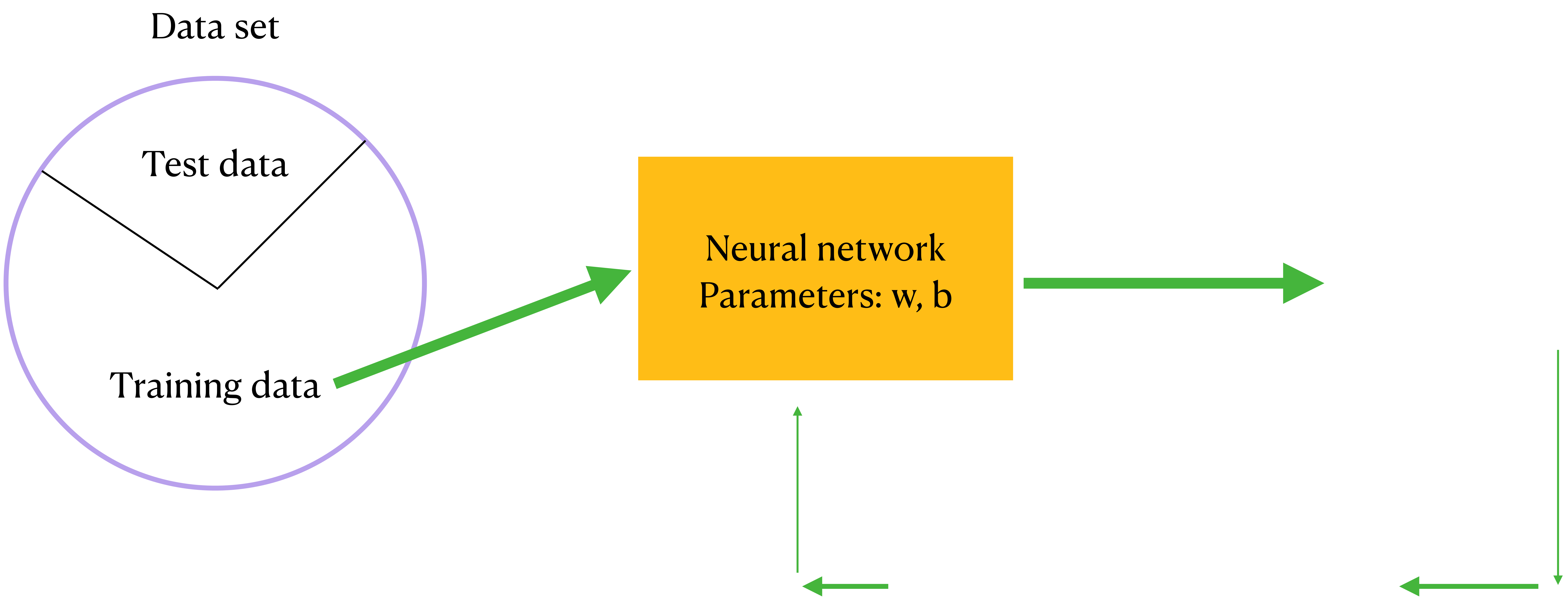

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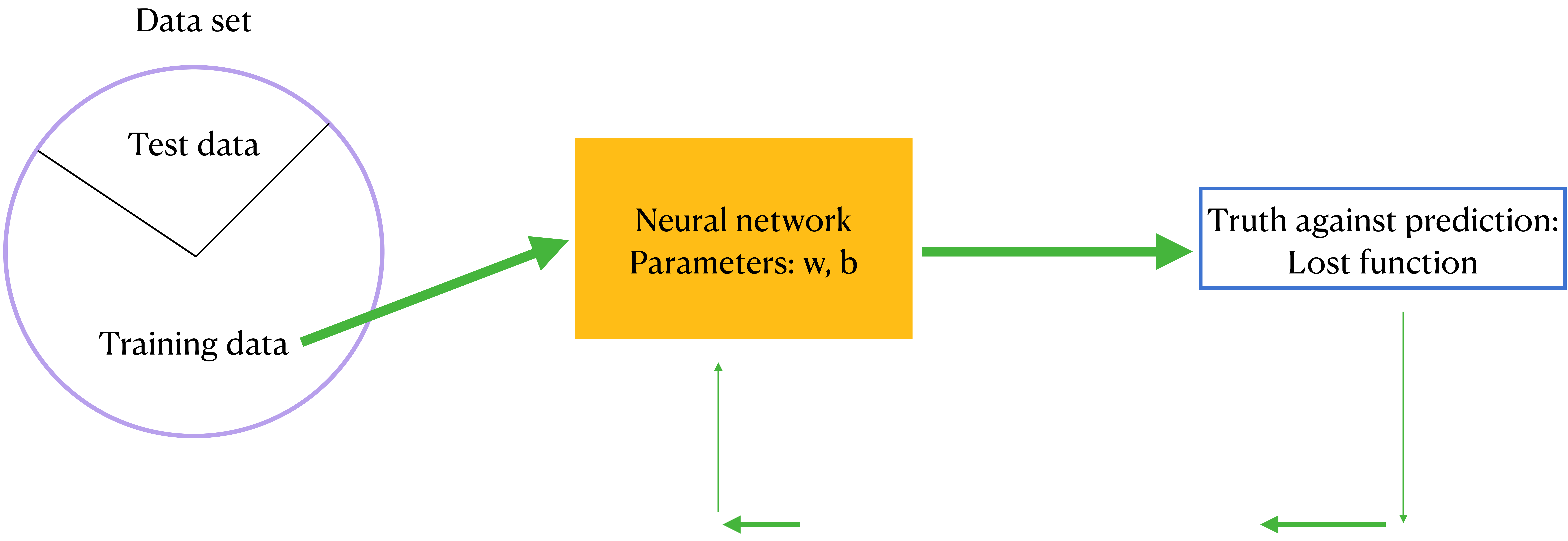

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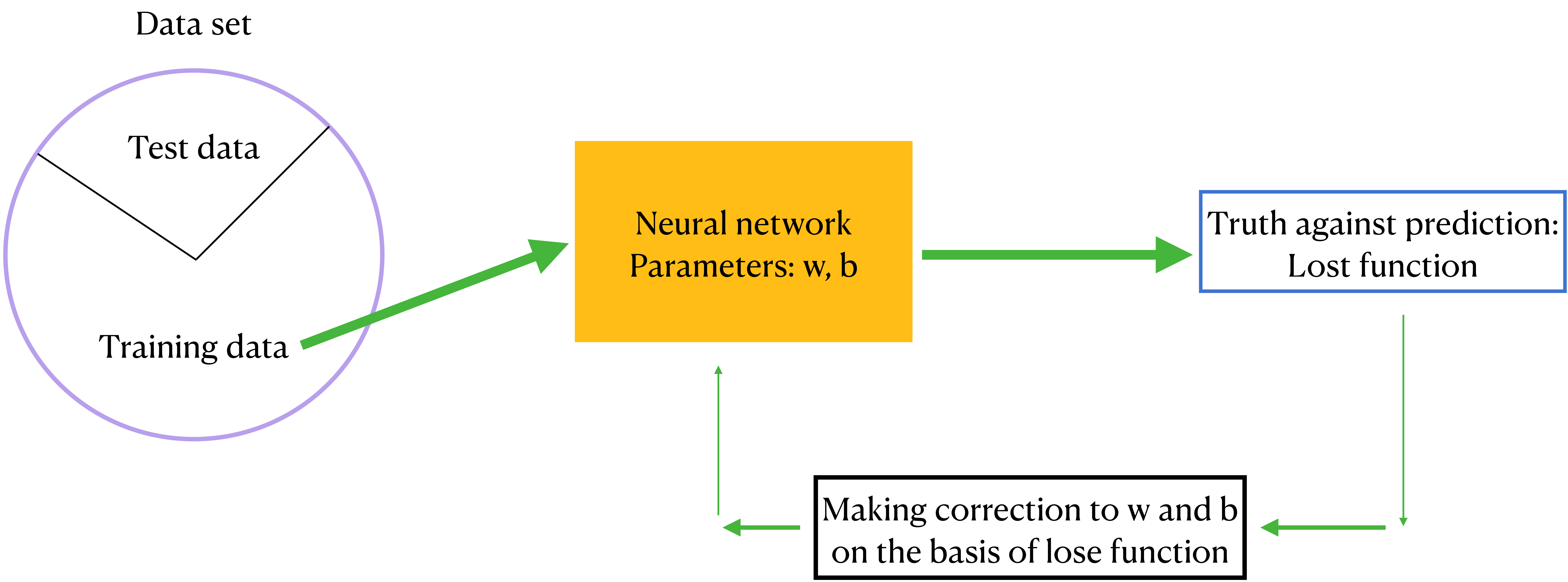

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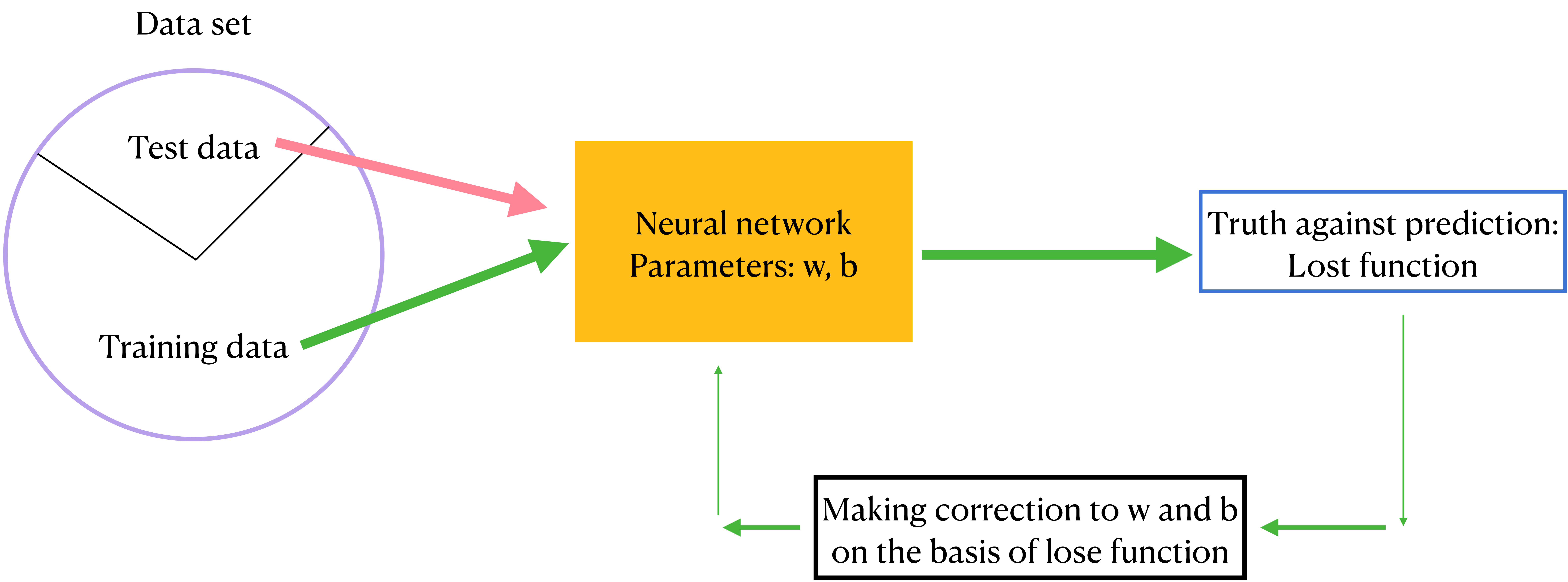

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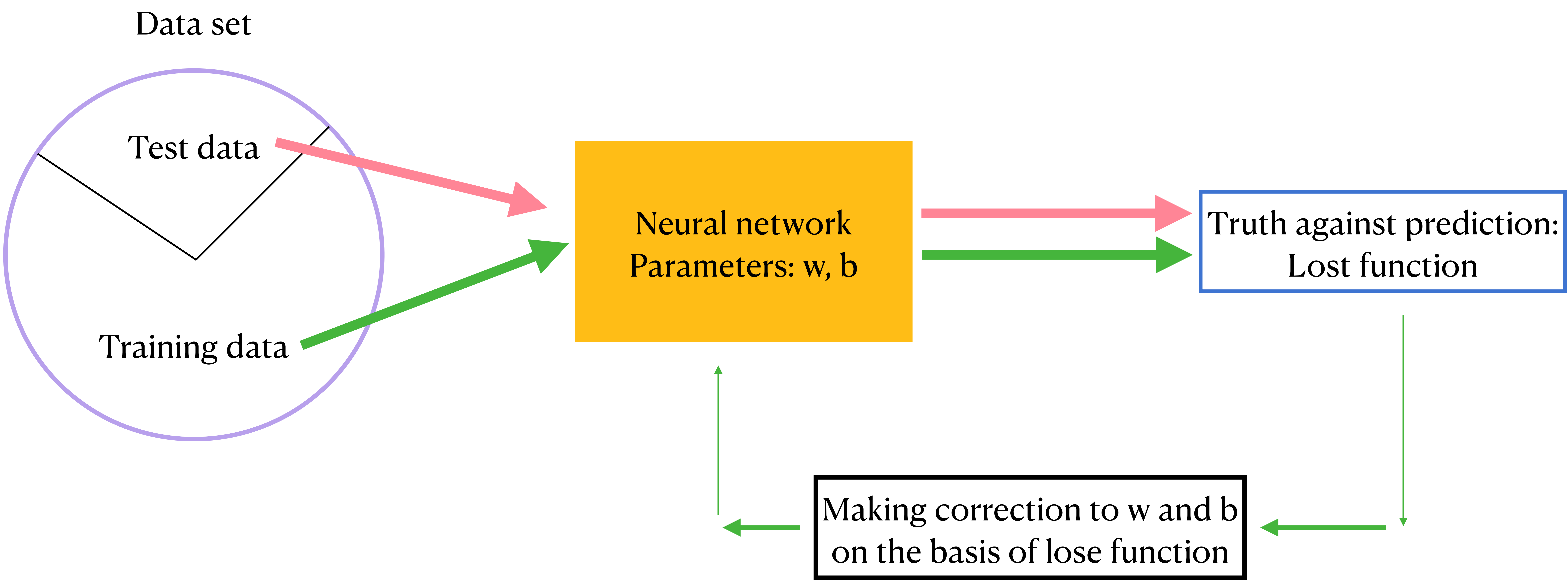

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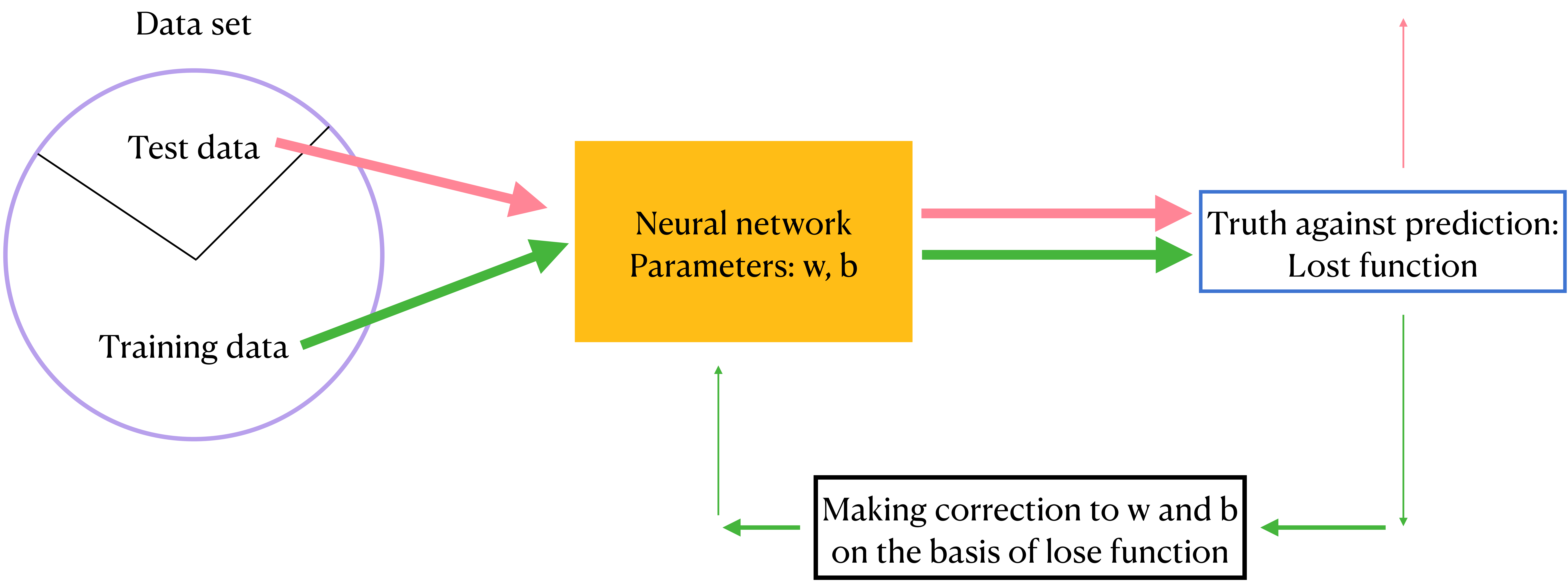

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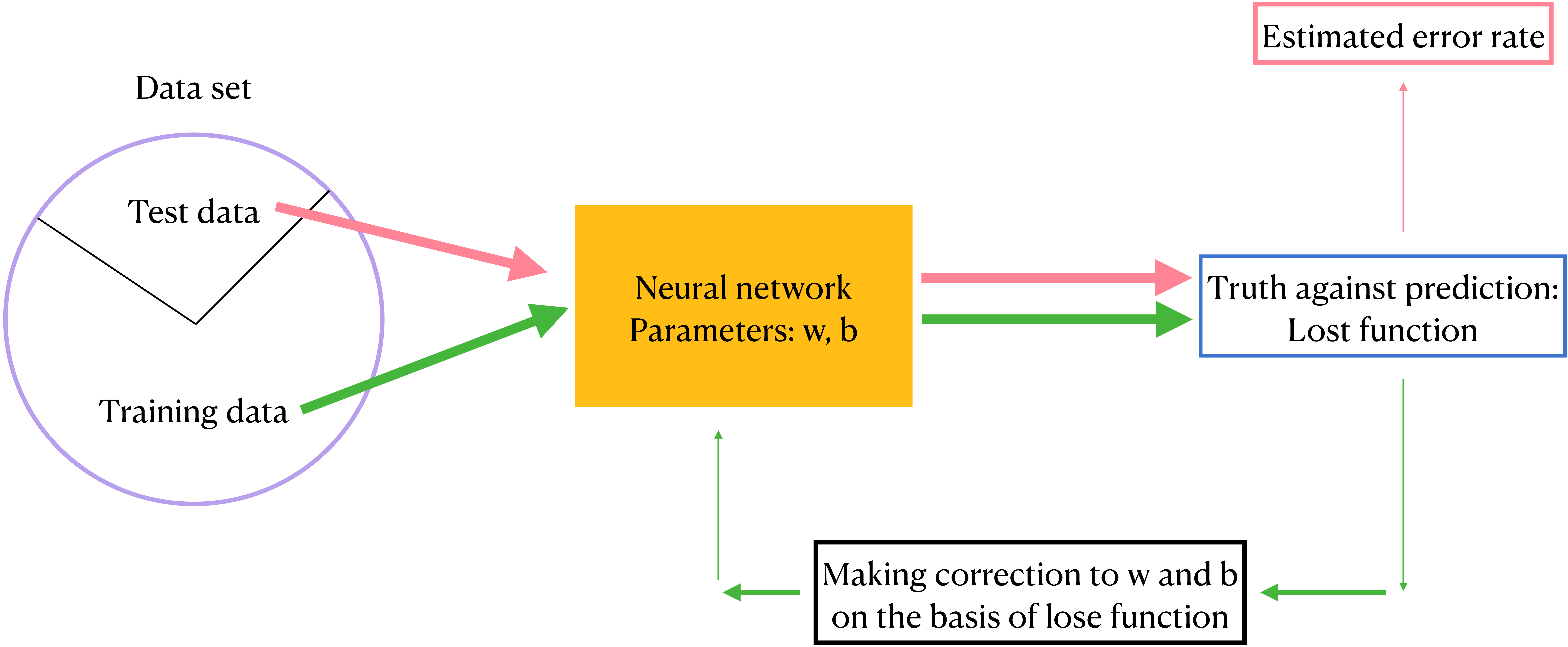

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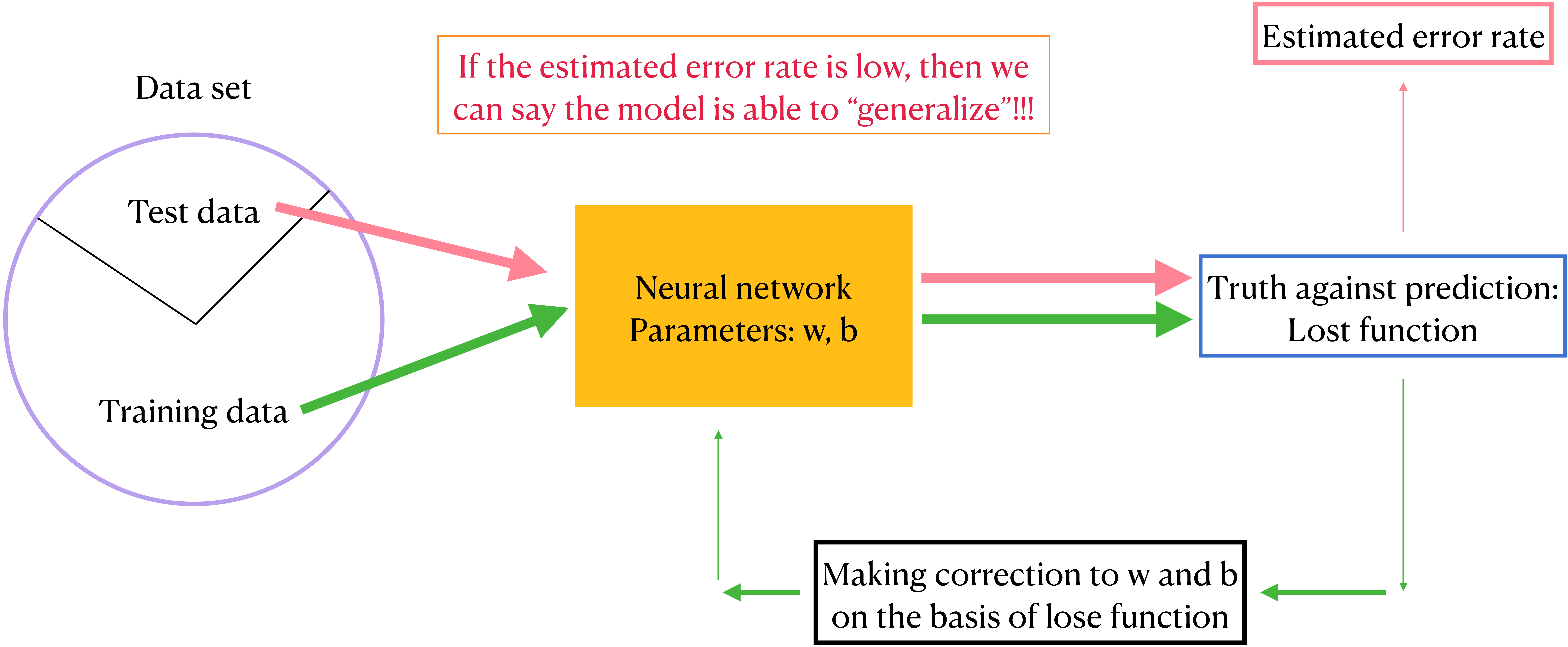

Important notes for supervised learning

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Data set: {X, y}

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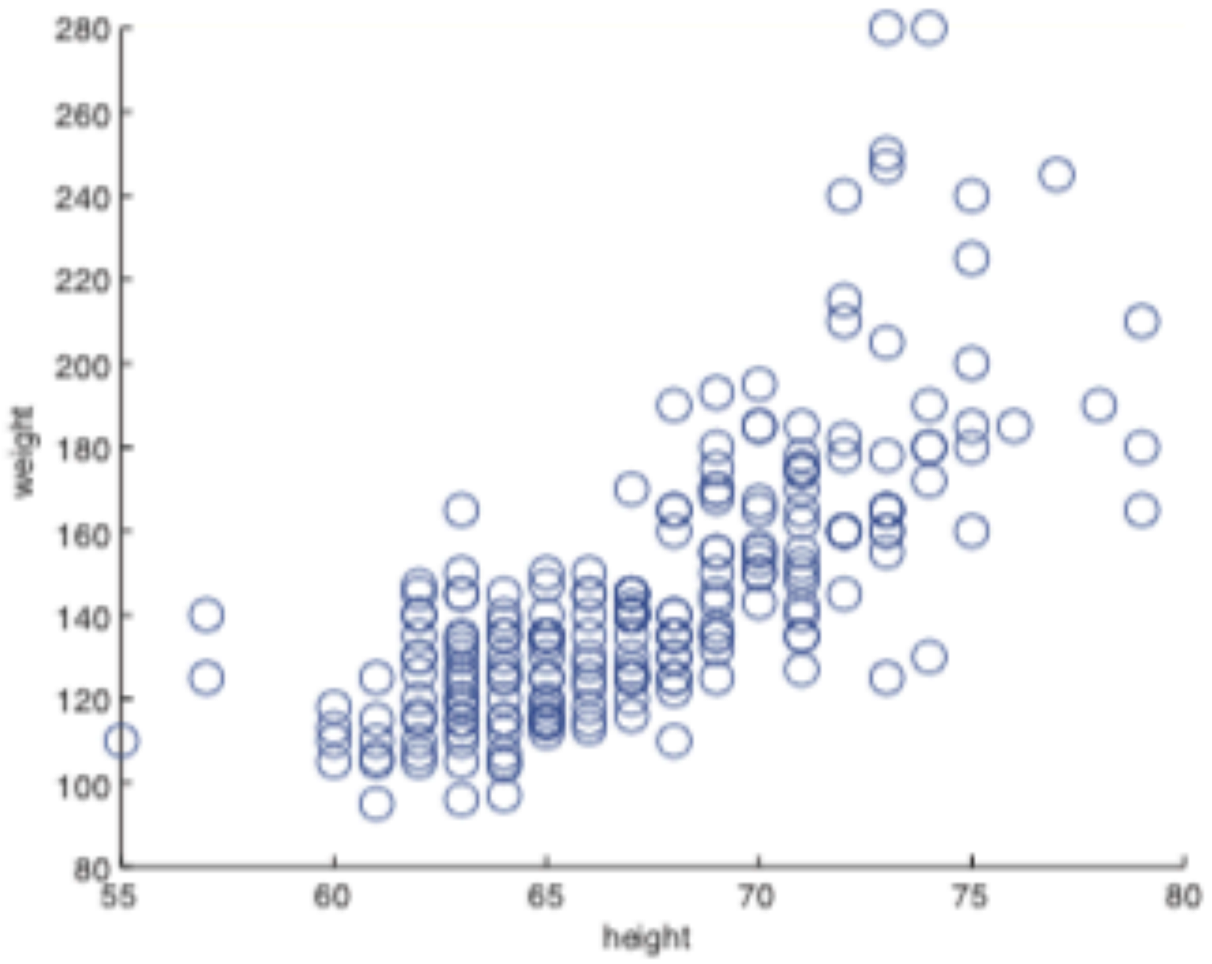
Learning is driven by likelihood.
Metaphor: education with love

Task: given height-weight of a group of students, to separate data into two subgroups



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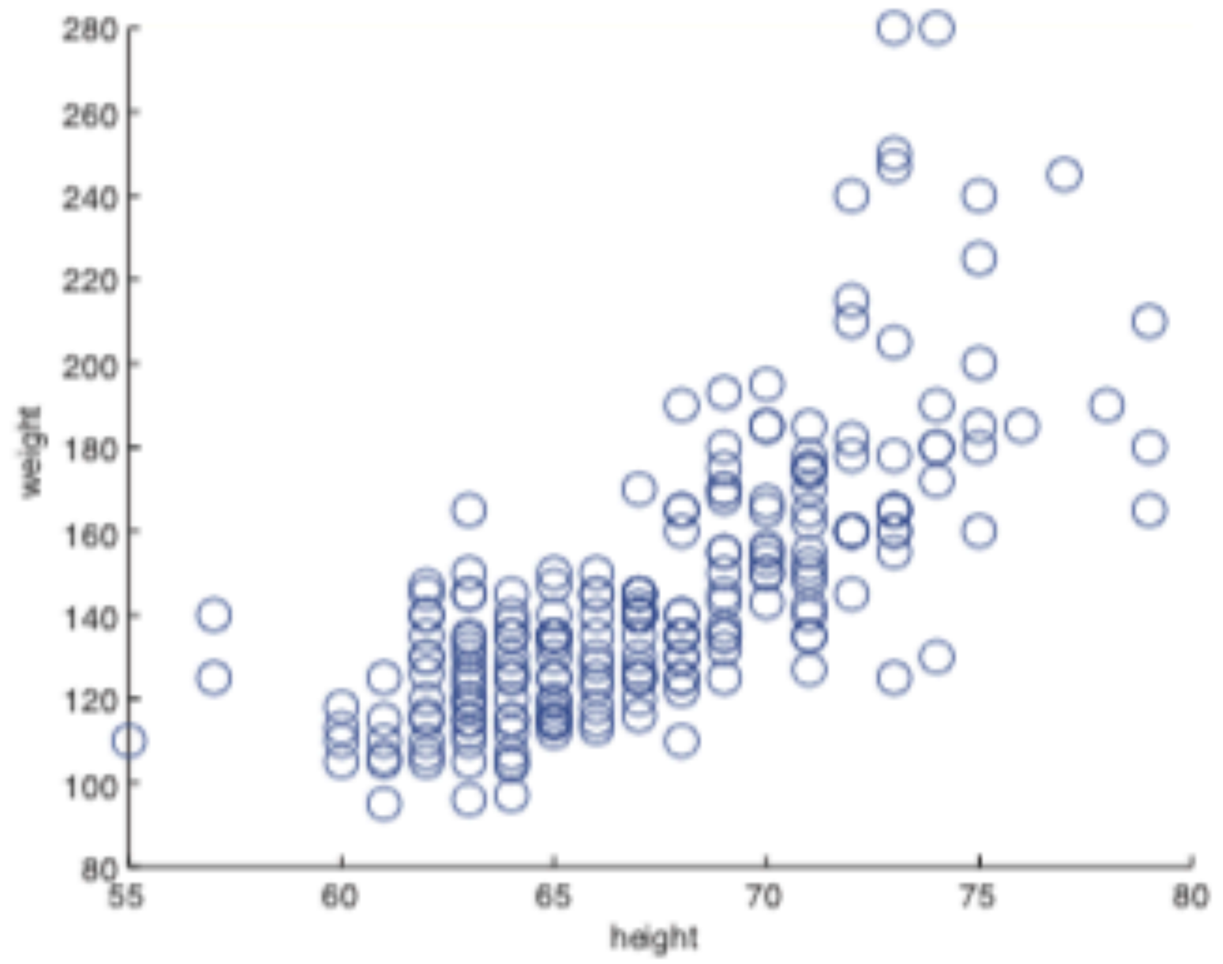

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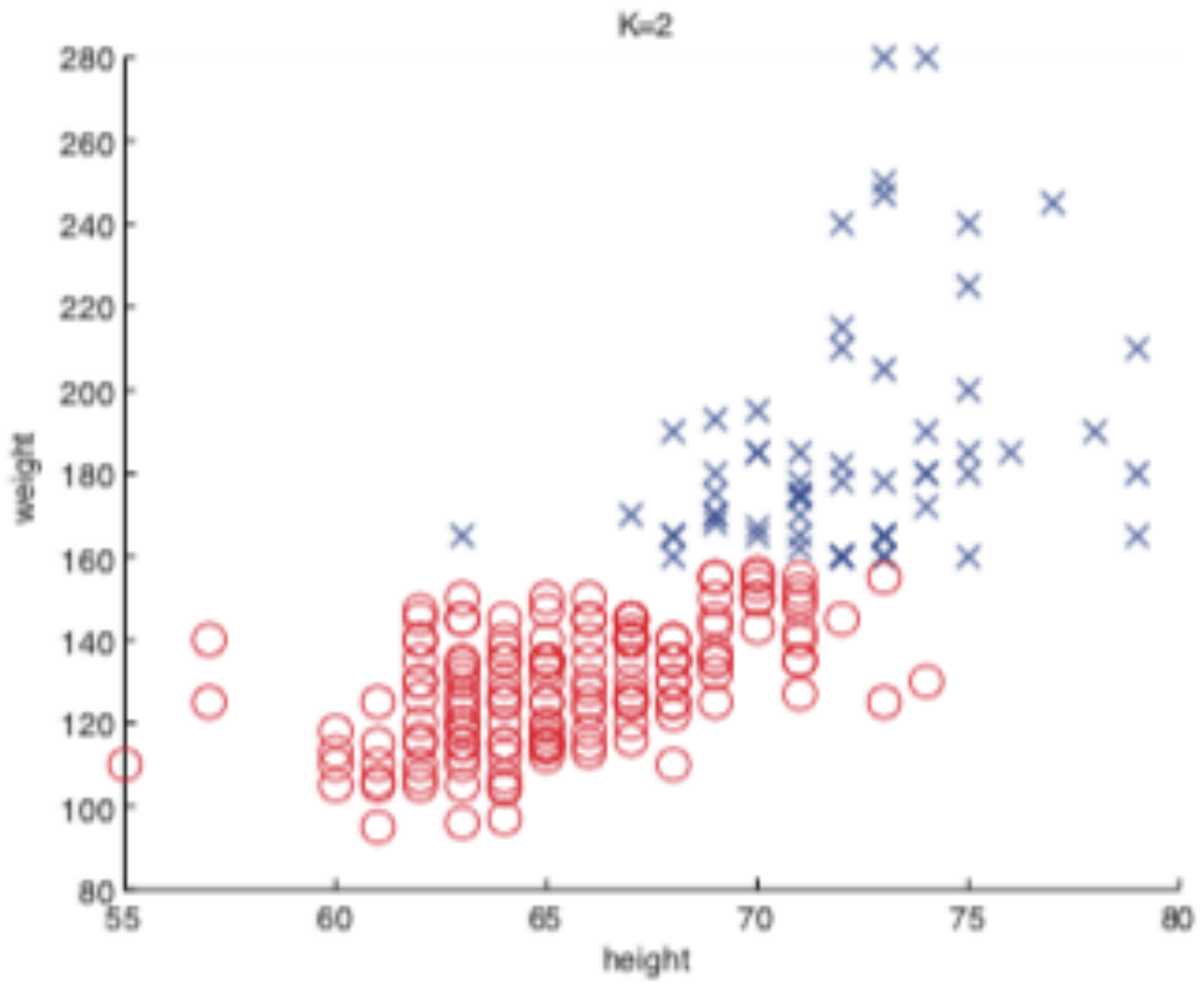

(b)

clustering

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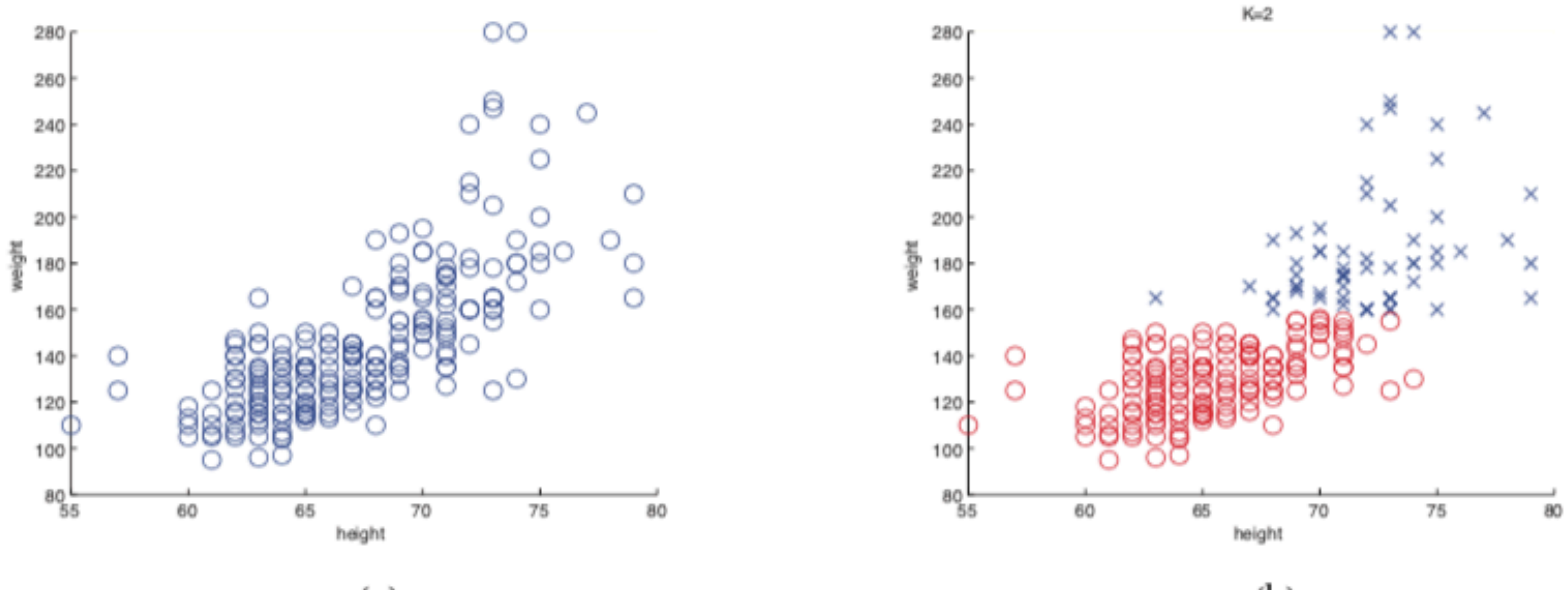


(a) (b)

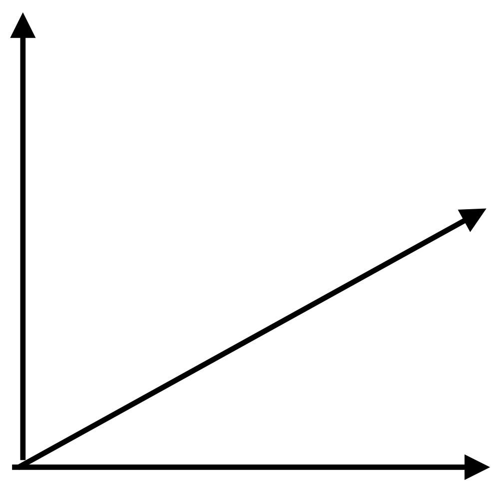
Note: both height and weight are input of a datum, so we don't have a label y for each datum.

high-dimensional space of face images

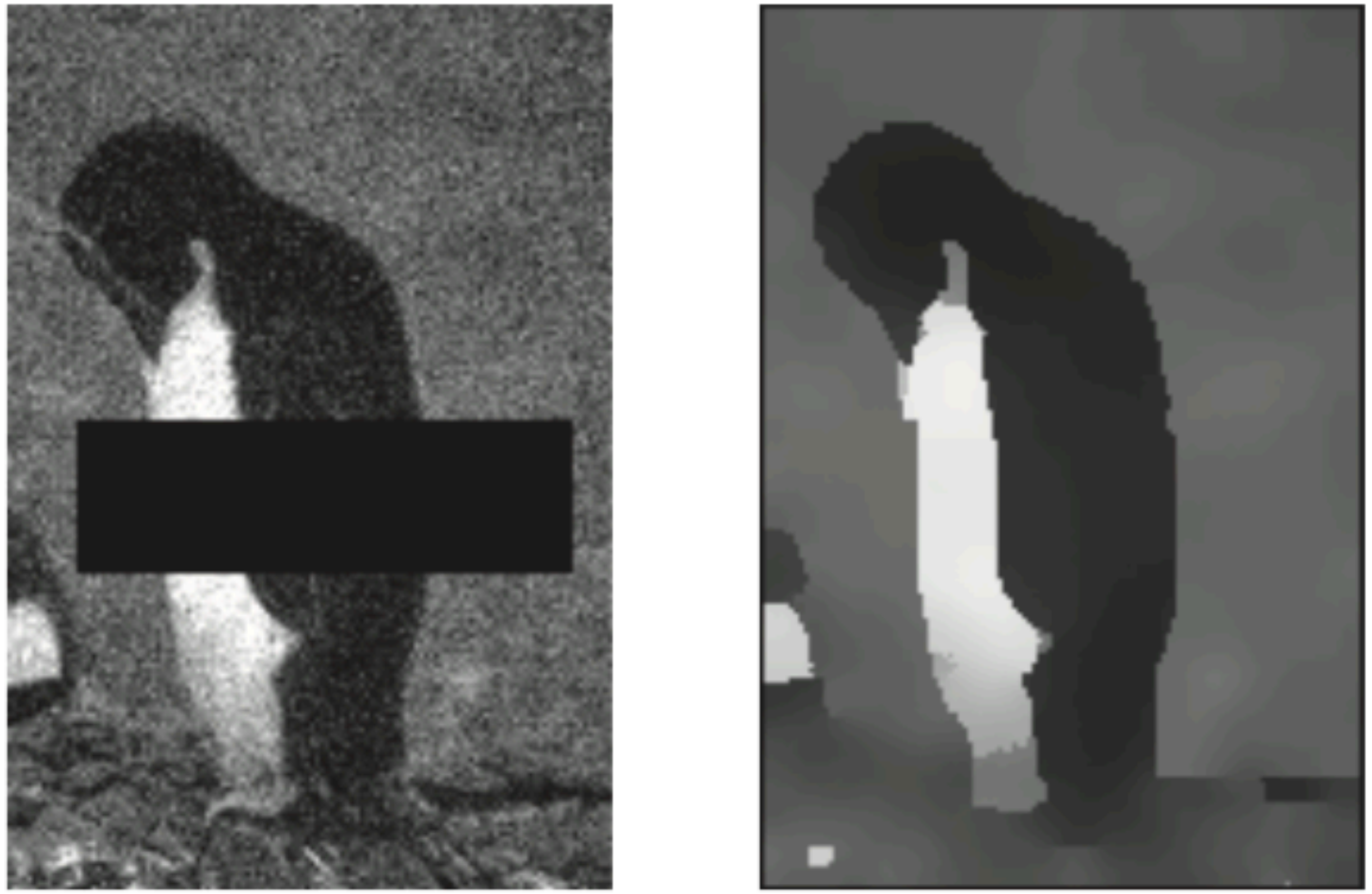
each image is a point in 64 x 64 = 4096 dimensional space

principle-component analysis (PCA)

A face image can be thought of as a vector in high dimensional space. The important features are the projected component onto the principal direction vectors.



missing pixels completion

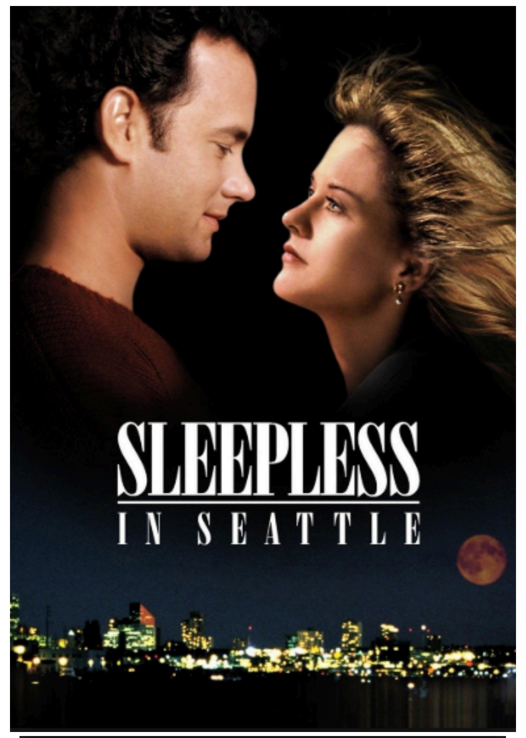


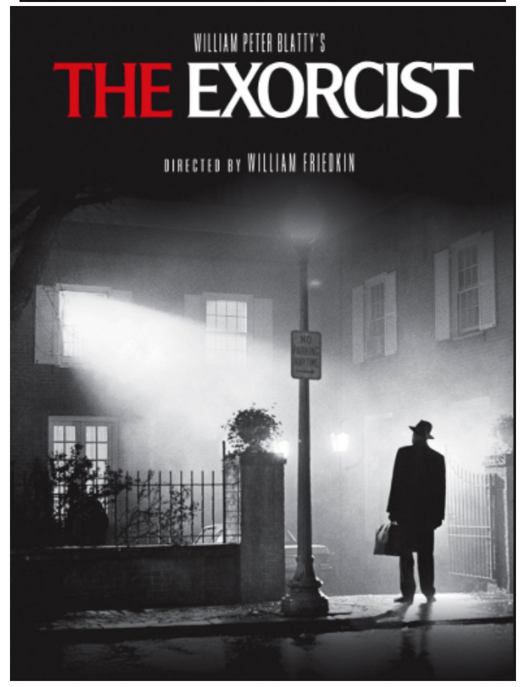
(a) (b)

pixels reconstruction from
statistics of test images

read 1.3.4.1

recommender system,
collaborative filtering





1		?	3	5	?
?	1				2
	4		4	5	?

think about how YouTube generates
the recommending videos to you.

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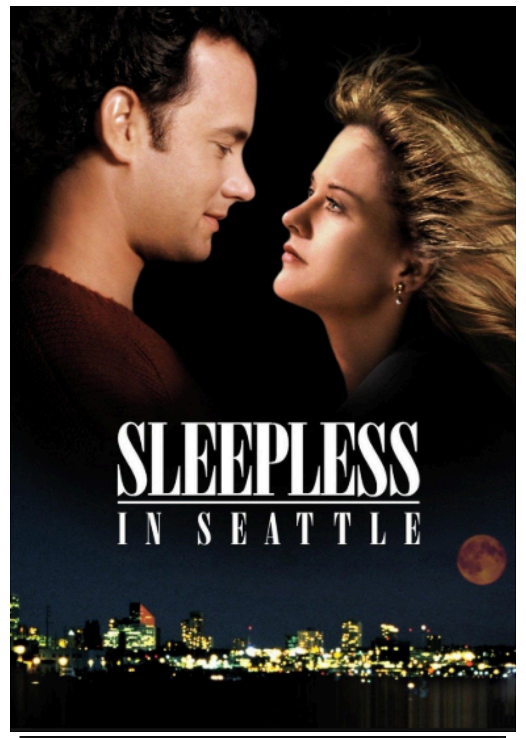

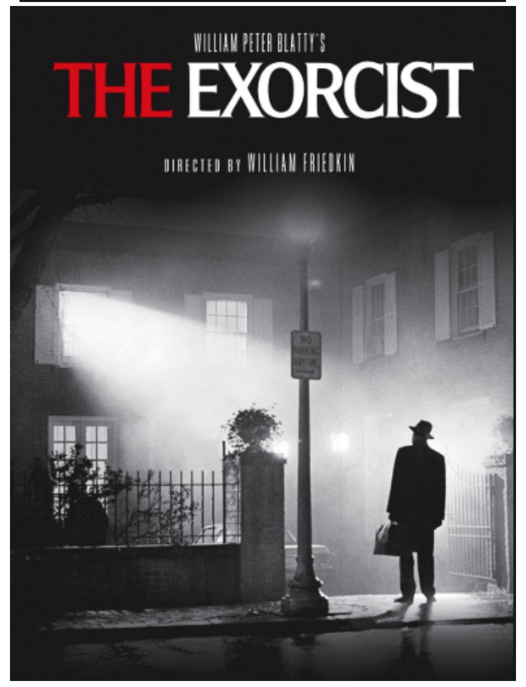

users

movies

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Why the free services from FB, google, twitter is actually profitable for them ...

Data set: e-mails from all google users, wikipedia articles, twitter comments, Ig photos, etc...

Huge neural network

When I _____ my ______ ______ ____________, ____

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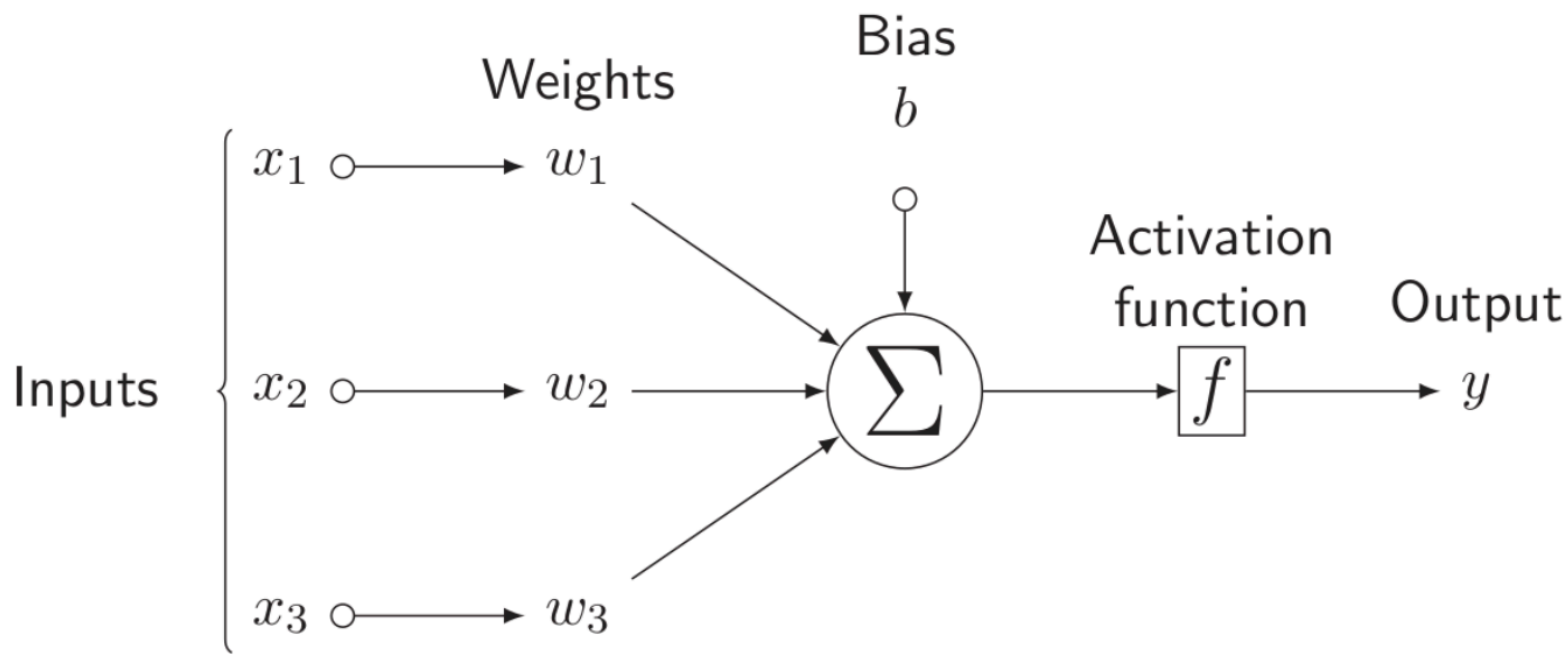
Regression (week 3 & 4) and logistic regression (week 5 &6)



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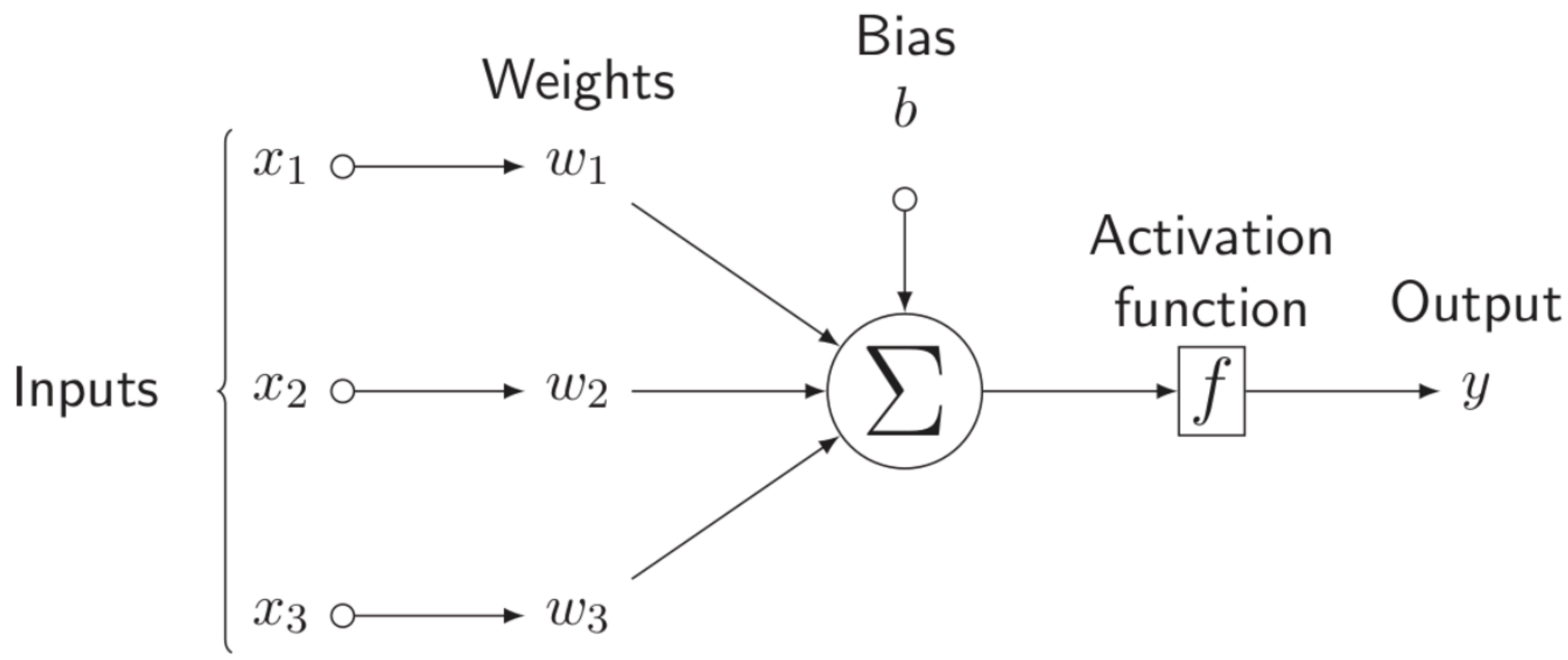

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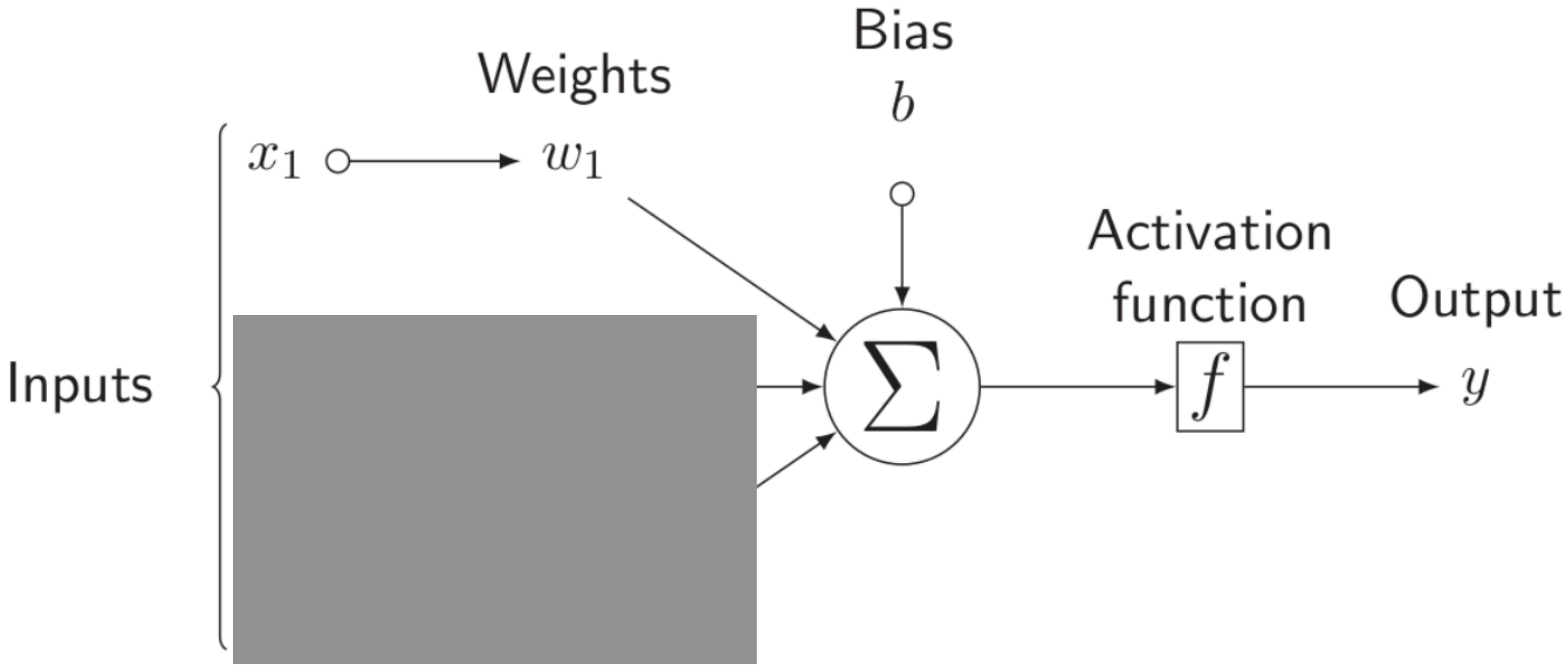

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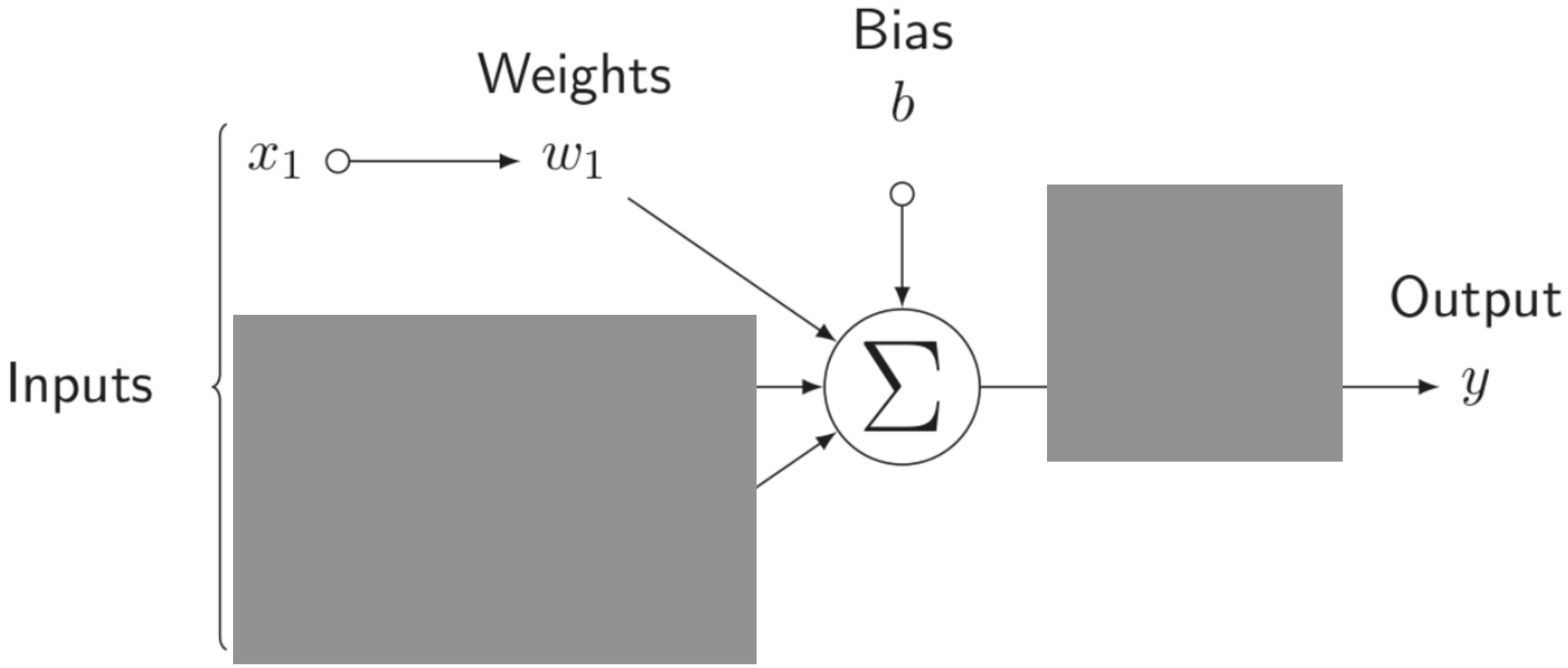

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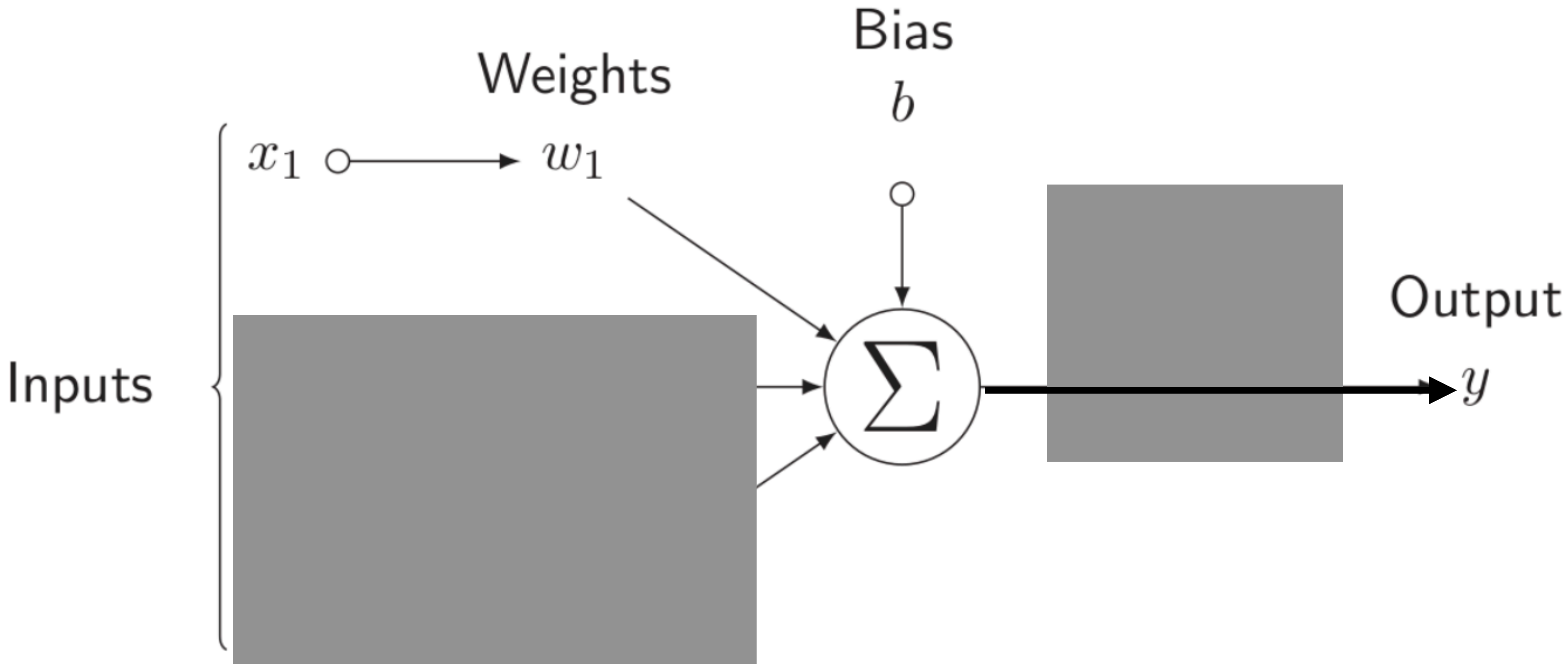

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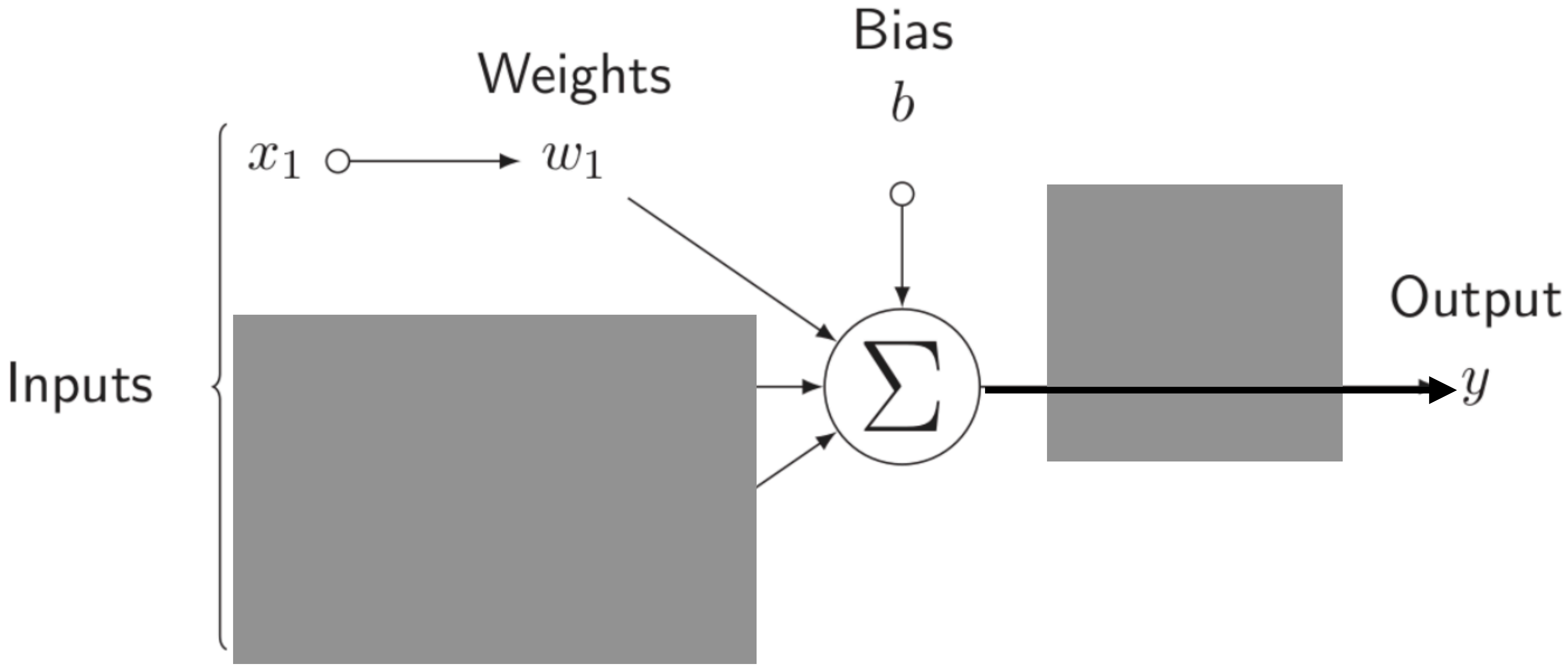

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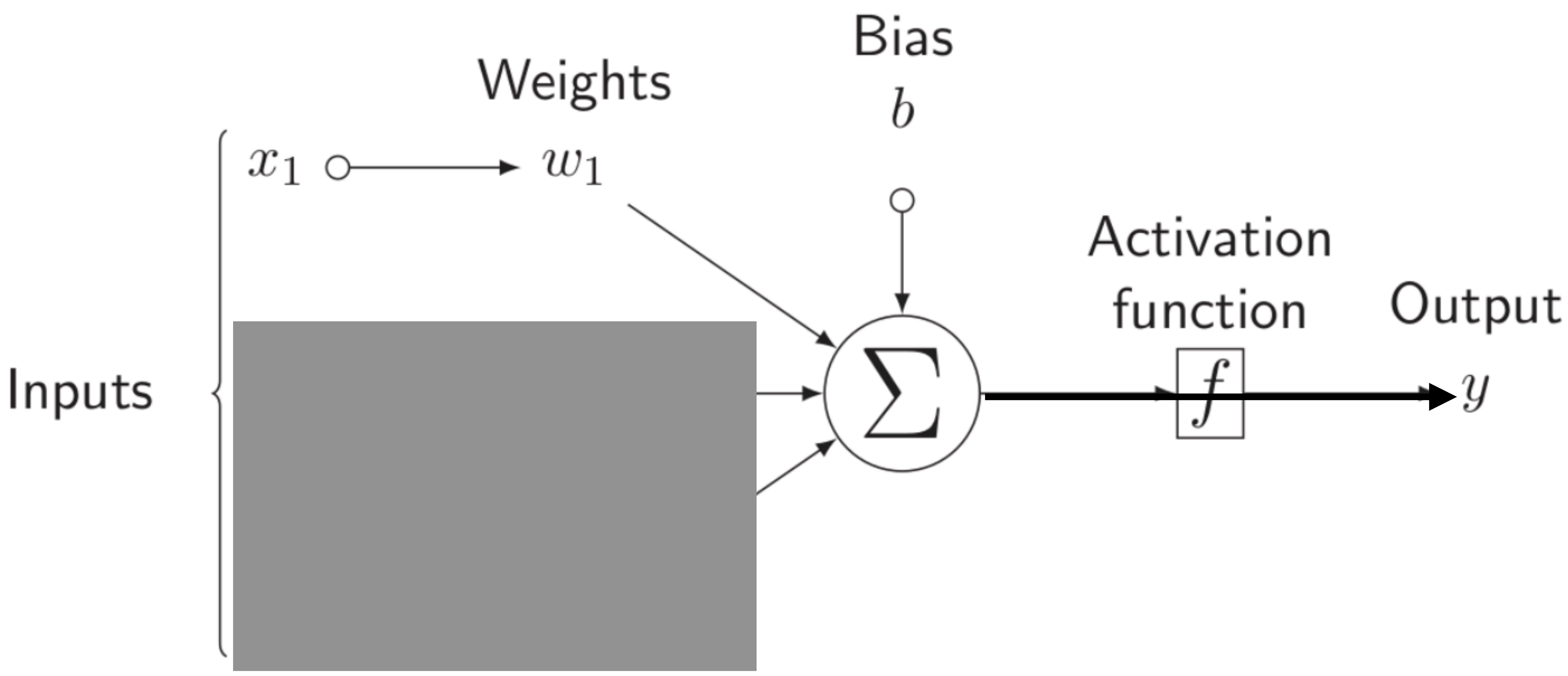

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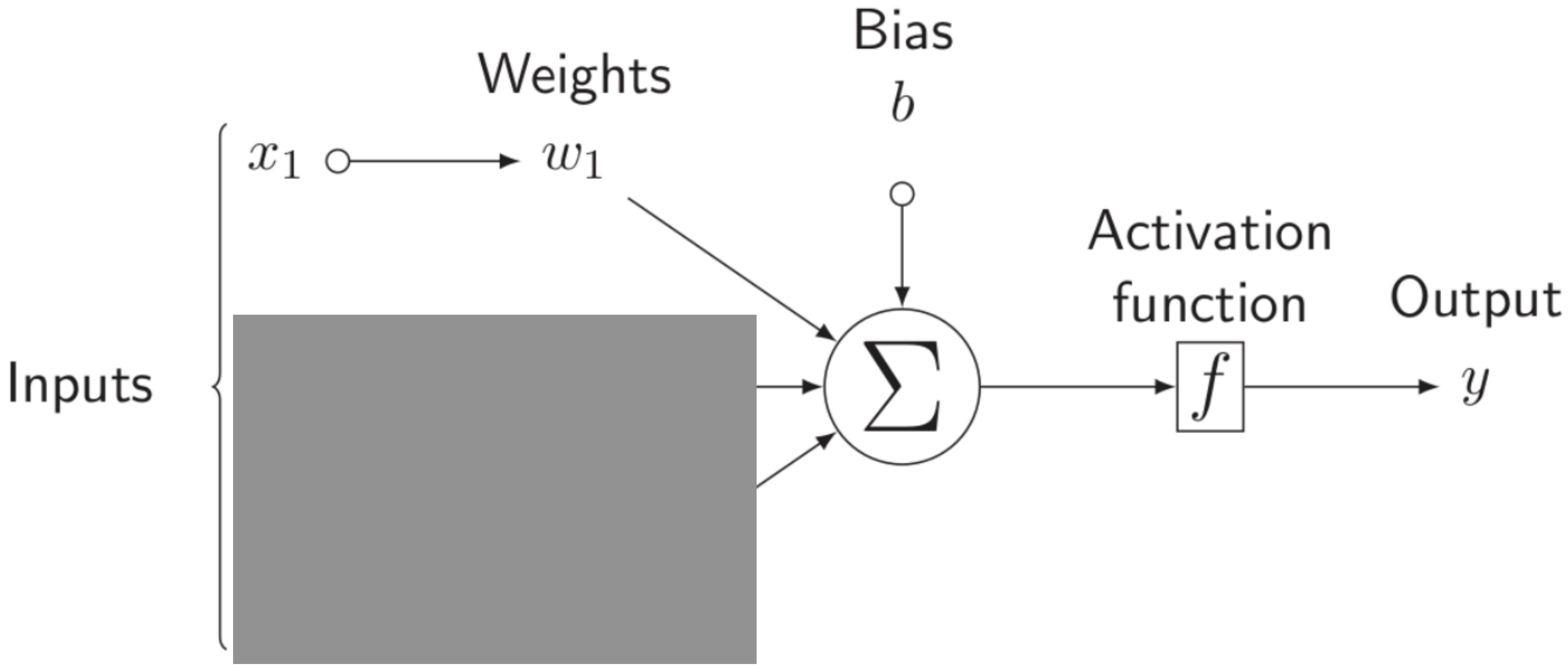

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