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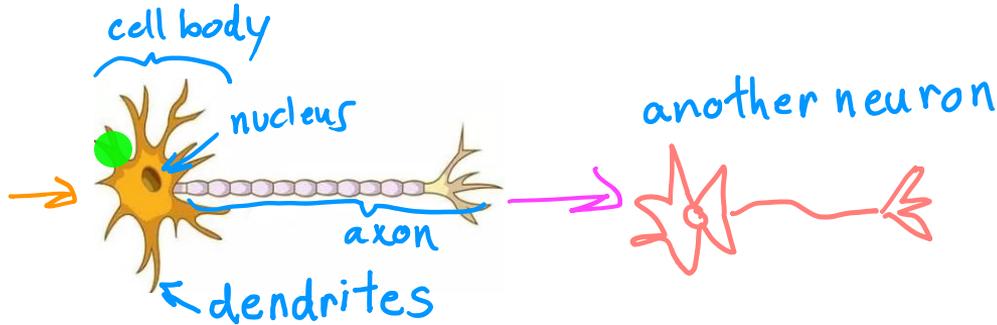
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Neural Networks

Biological neuron

inputs

outputs



Simplified mathematical model of a neuron

inputs

outputs

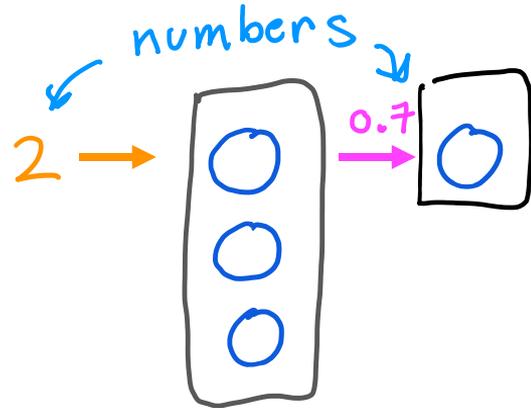
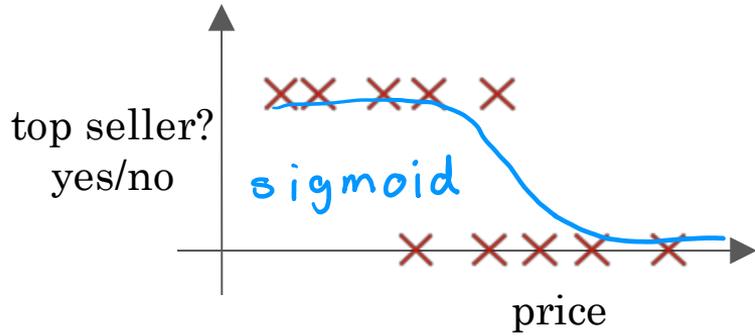


image source: <https://biologydictionary.net/sensory-neuron/>

Demand Prediction



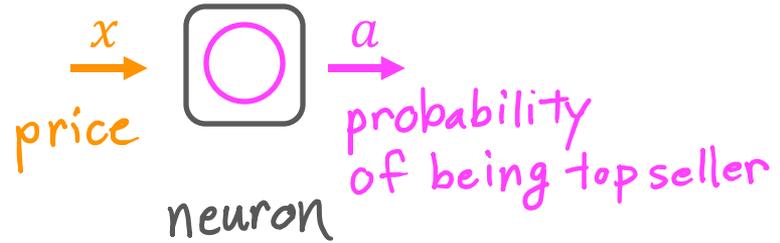
$x = \text{price}$

input

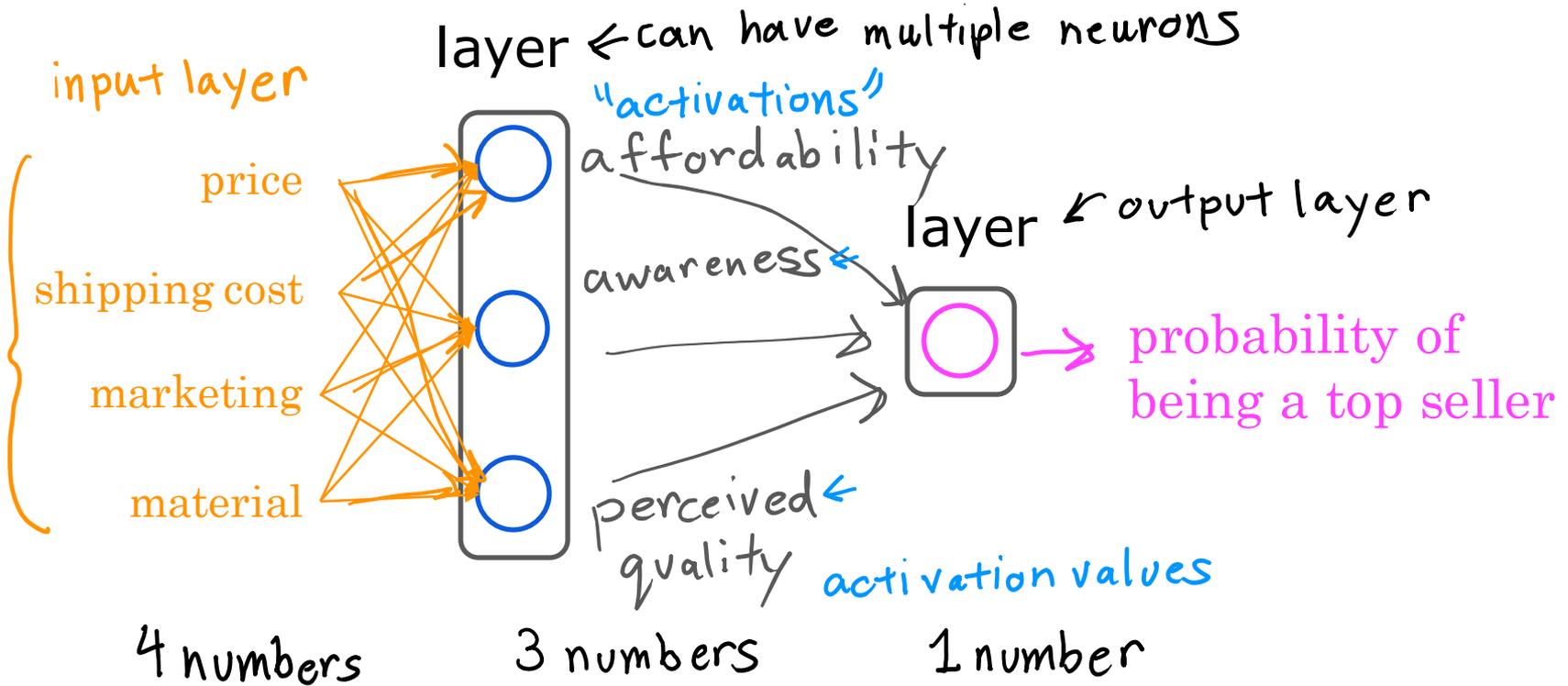
activation

$$a = f(x) = \frac{1}{1 + e^{-(wx+b)}}$$

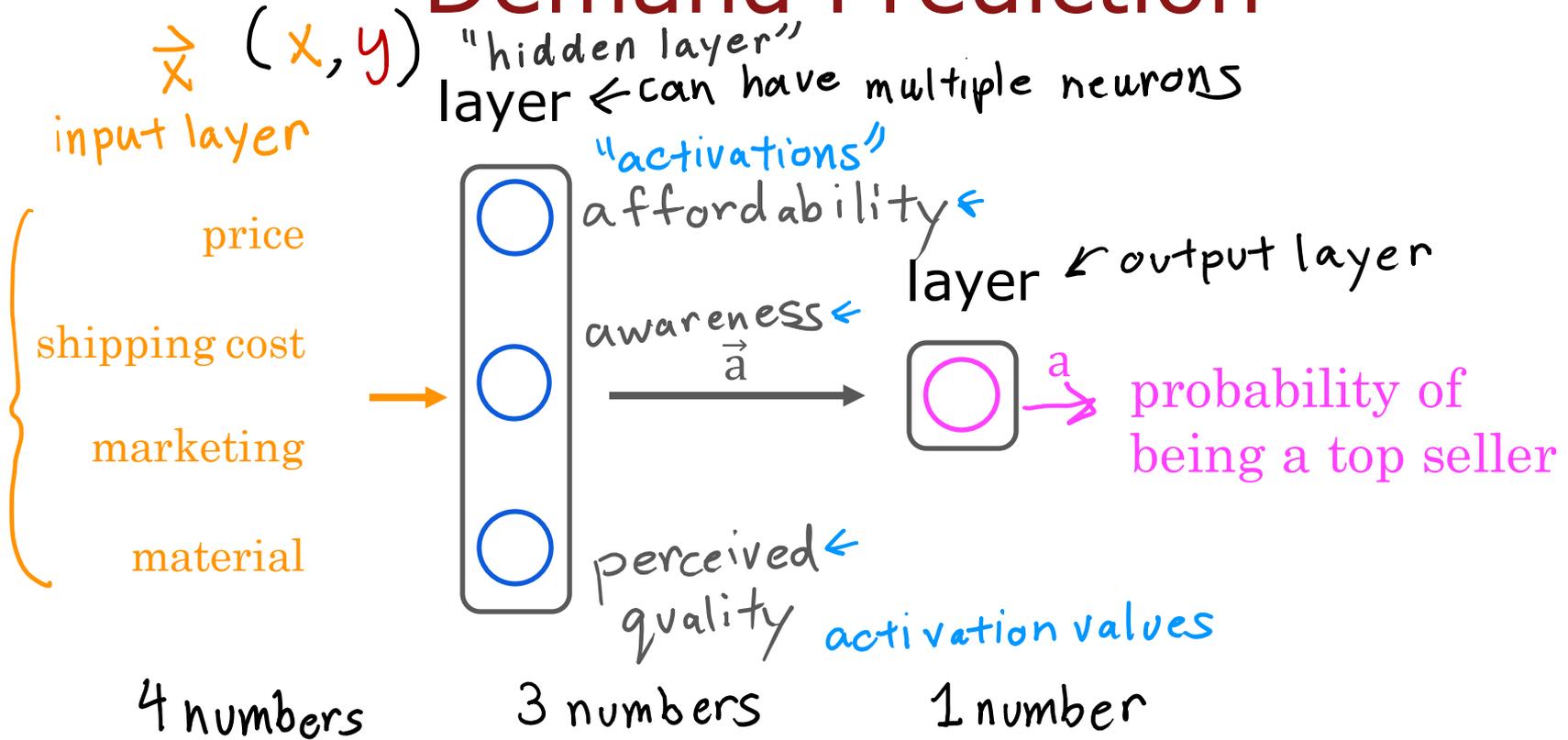
output



Demand Prediction



Demand Prediction



Demand Prediction



feature engineering
 $x_1 x_2$

$\vec{x} = (x, y)$

"hidden layer"
layer ← can have multiple neurons

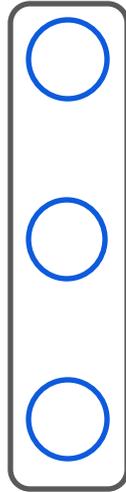
input layer

price

shipping cost

marketing

material



"activations"

affordability ←

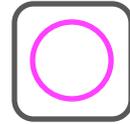
awareness ←

perceived
quality ←

activation values

3 numbers

layer ← output layer

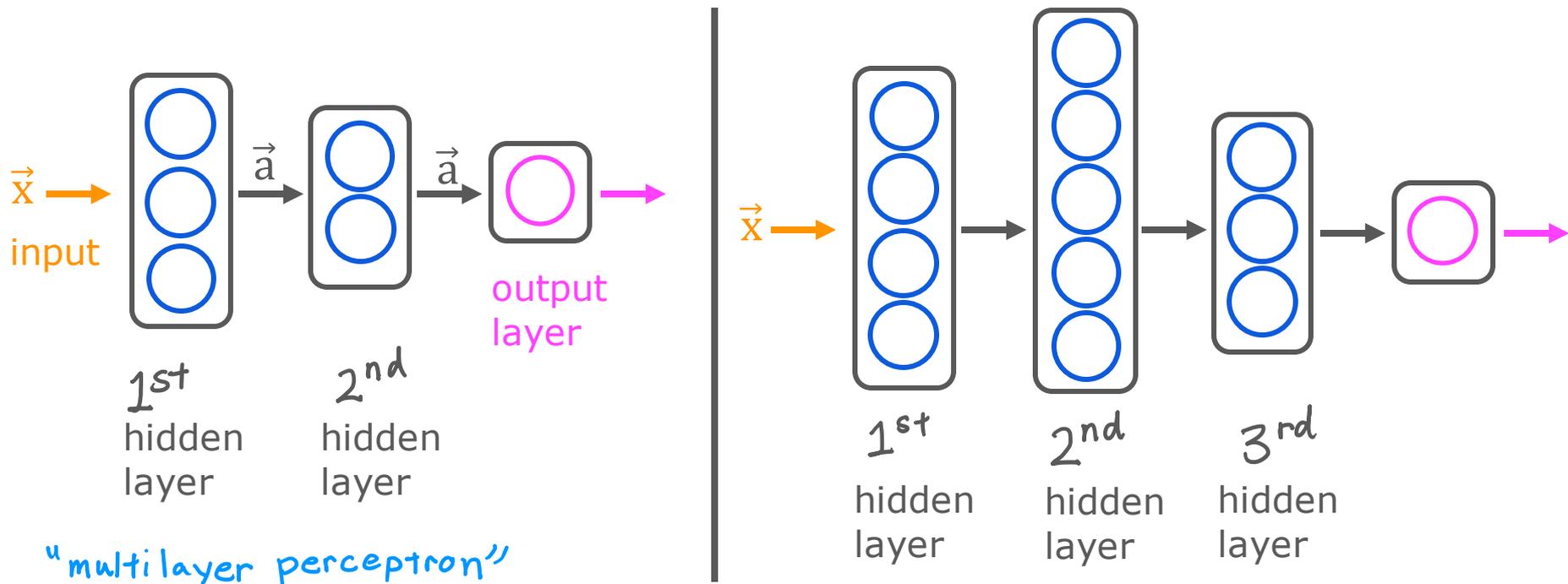


probability of
being a top seller

1 number

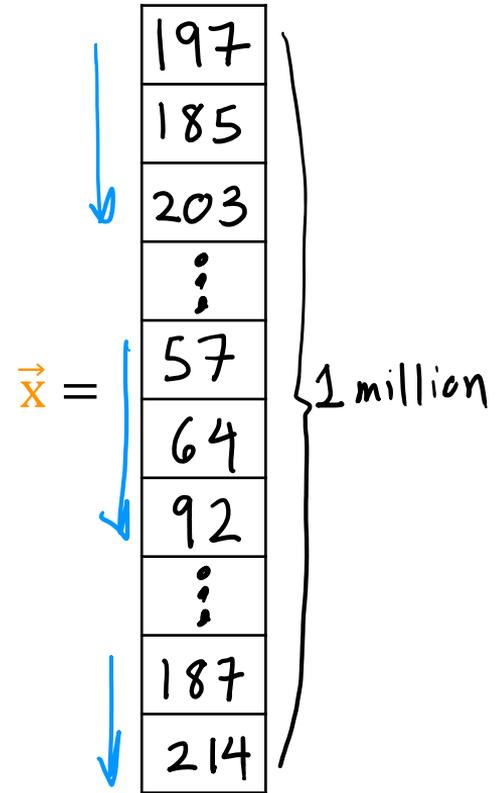
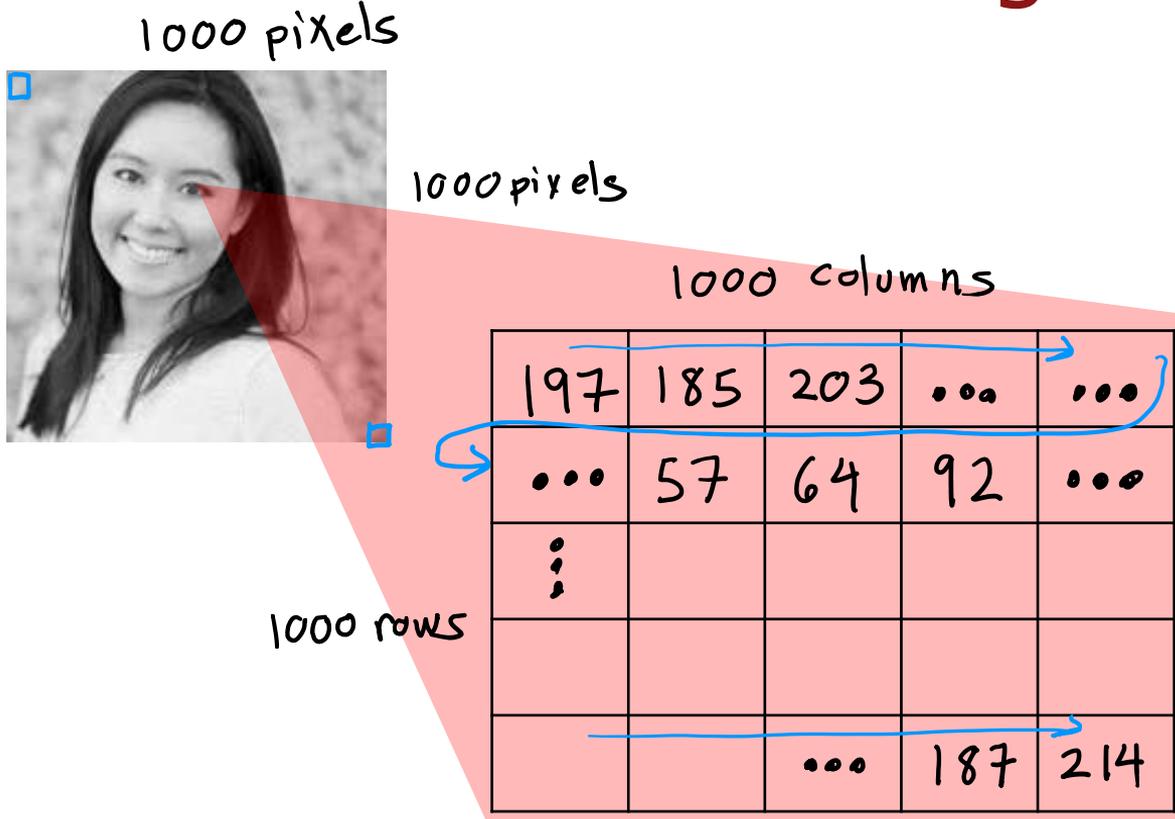
4 numbers

Multiple hidden layers

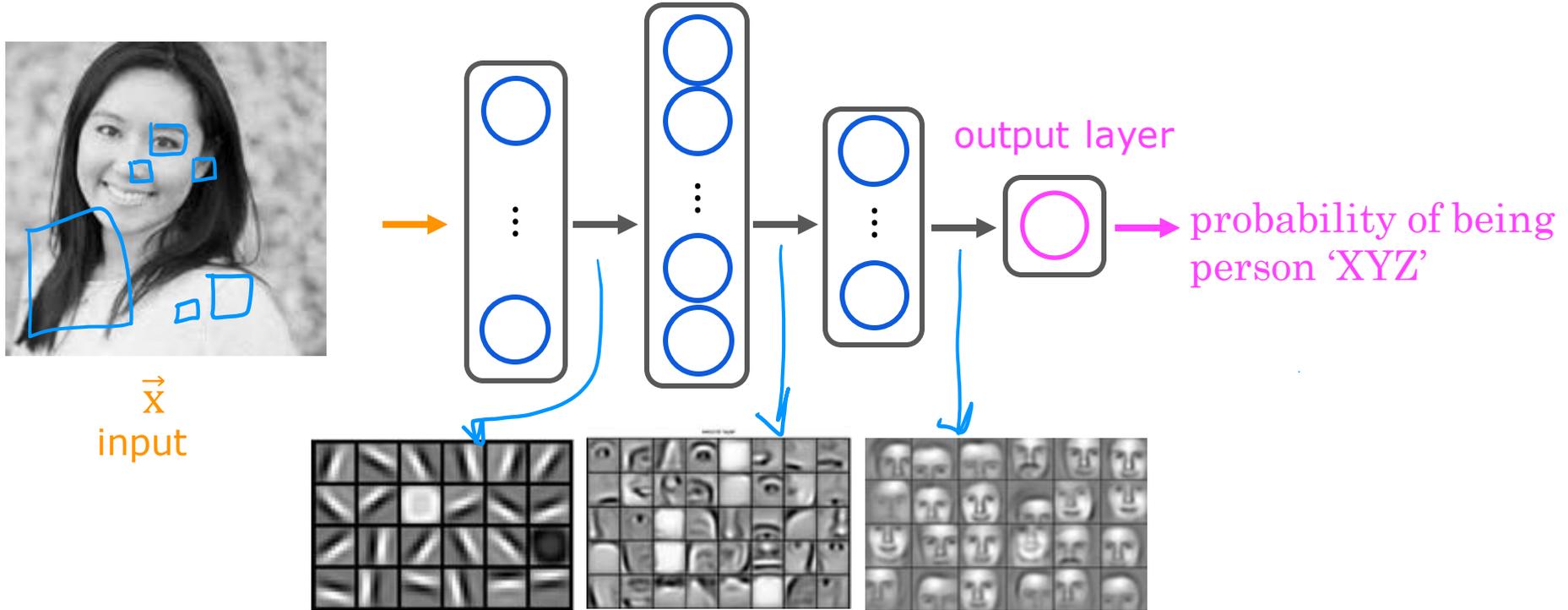


neural network architecture

Face recognition

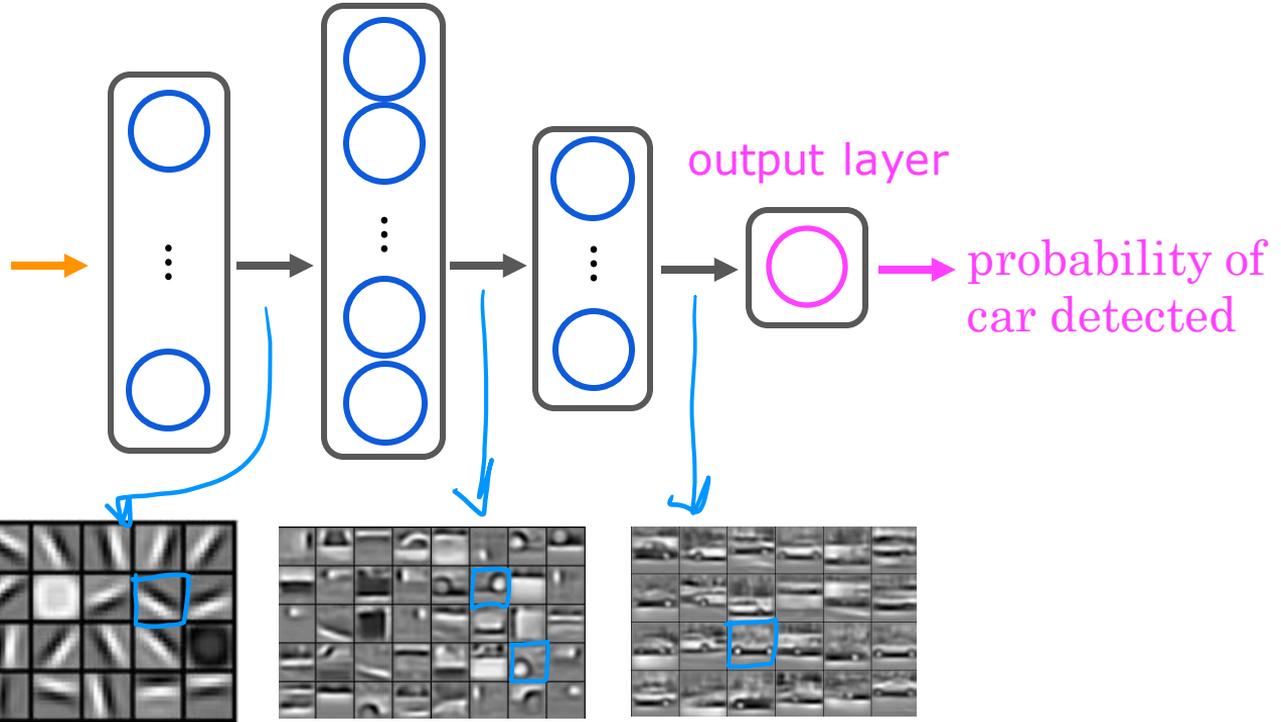


Face recognition



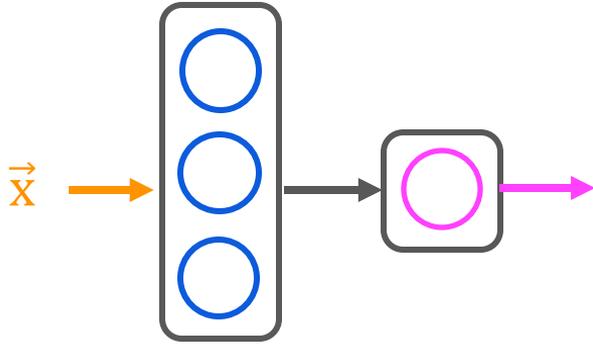
source: Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations by Honglak Lee, Roger Grosse, Ranganath Andrew Y. Ng

Car classification



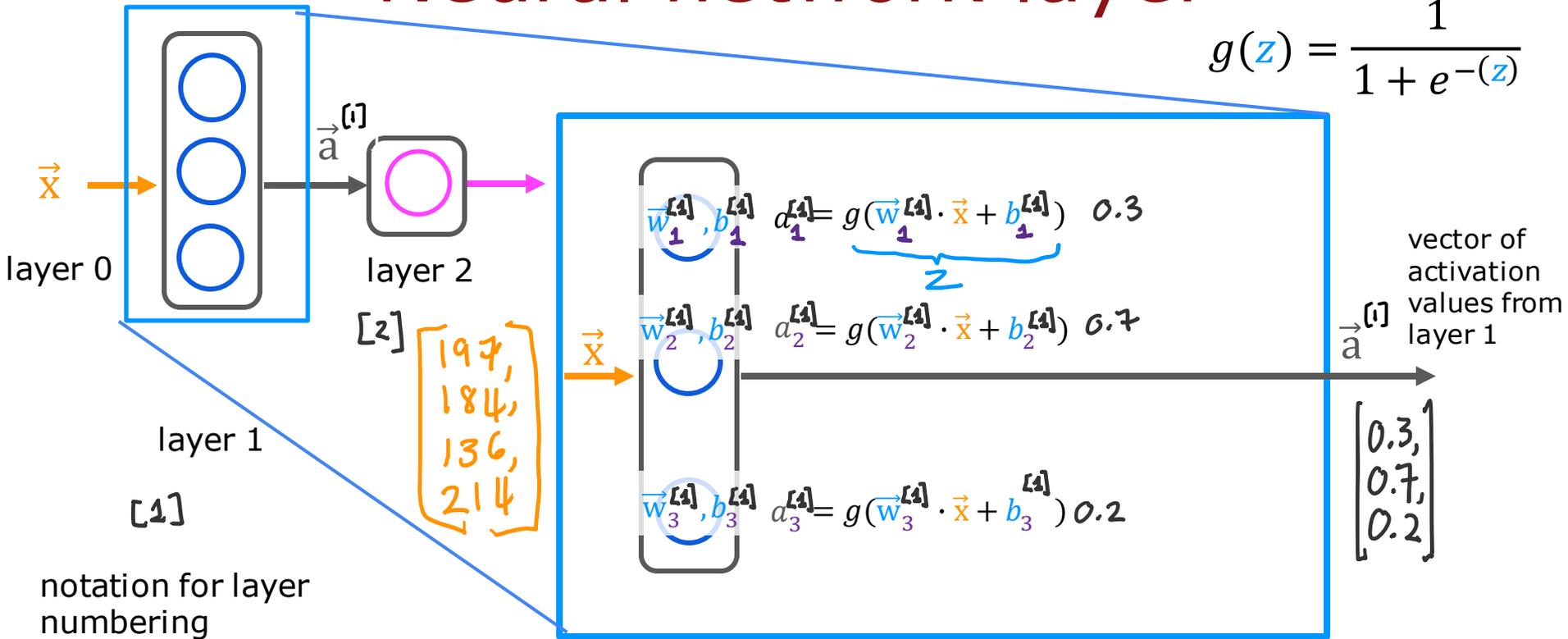
source: Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations by Honglak Lee, Roger Grosse, Ranganath Andrew Y. Ng

Neural network layer

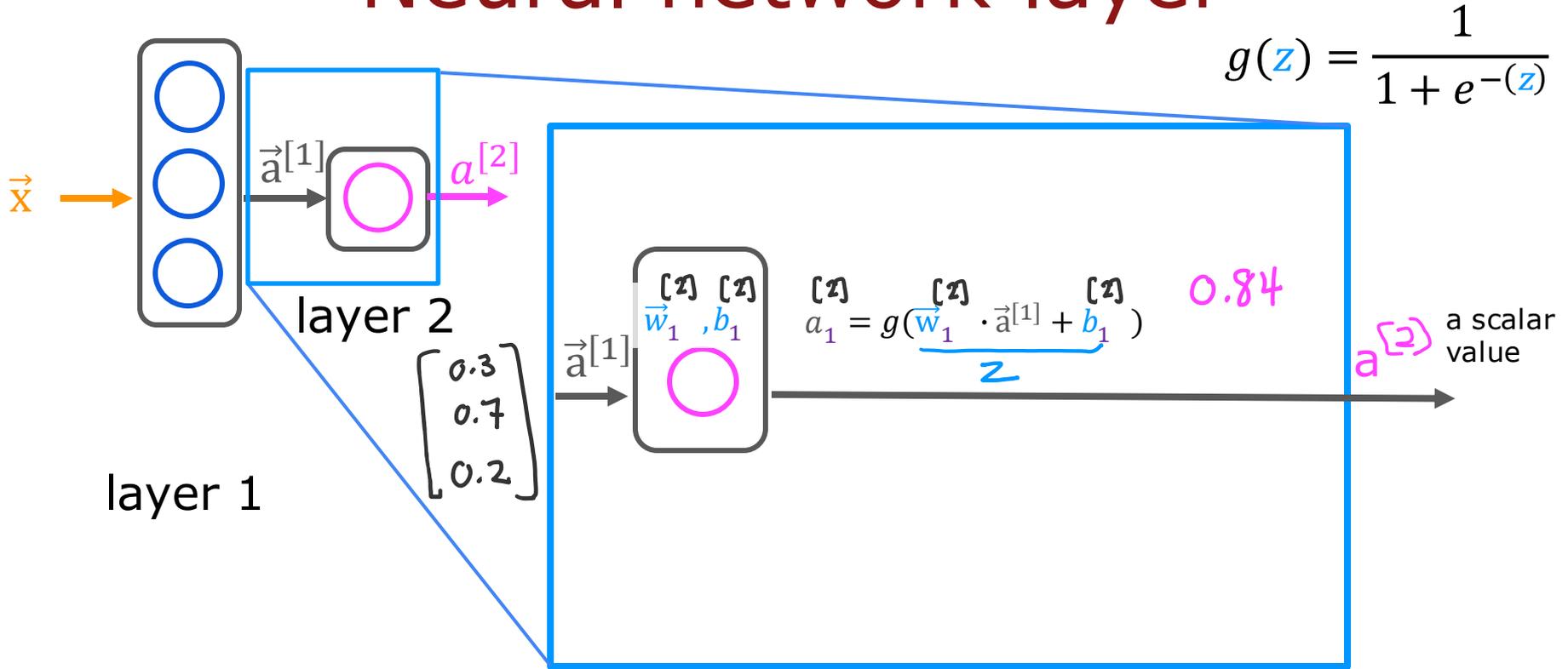


Neural network layer

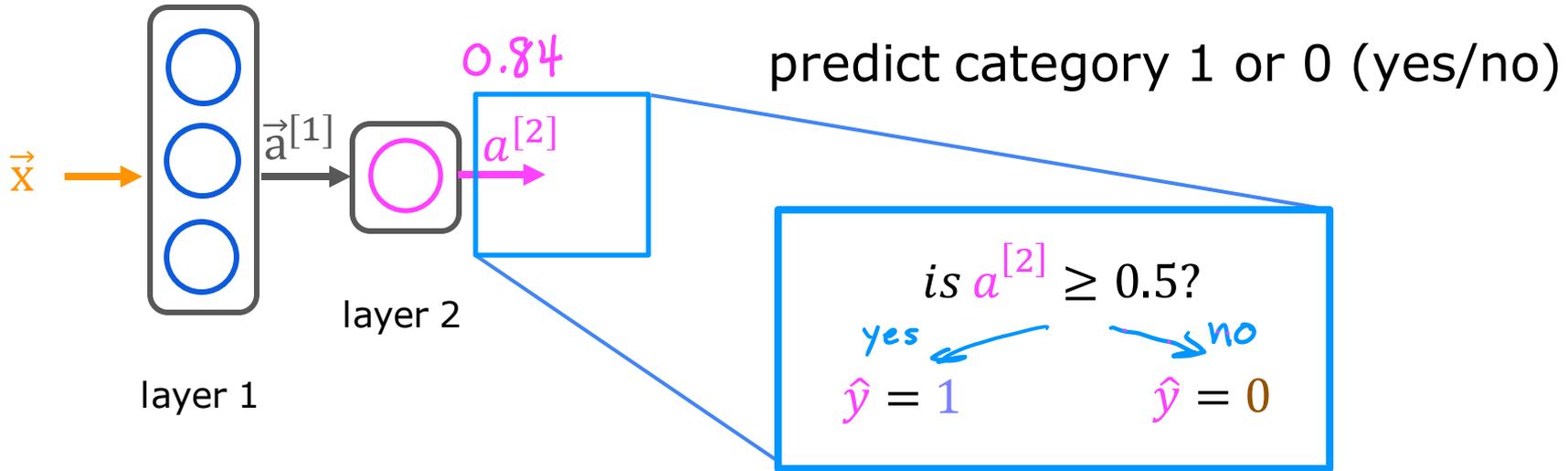
$$g(z) = \frac{1}{1 + e^{-z}}$$



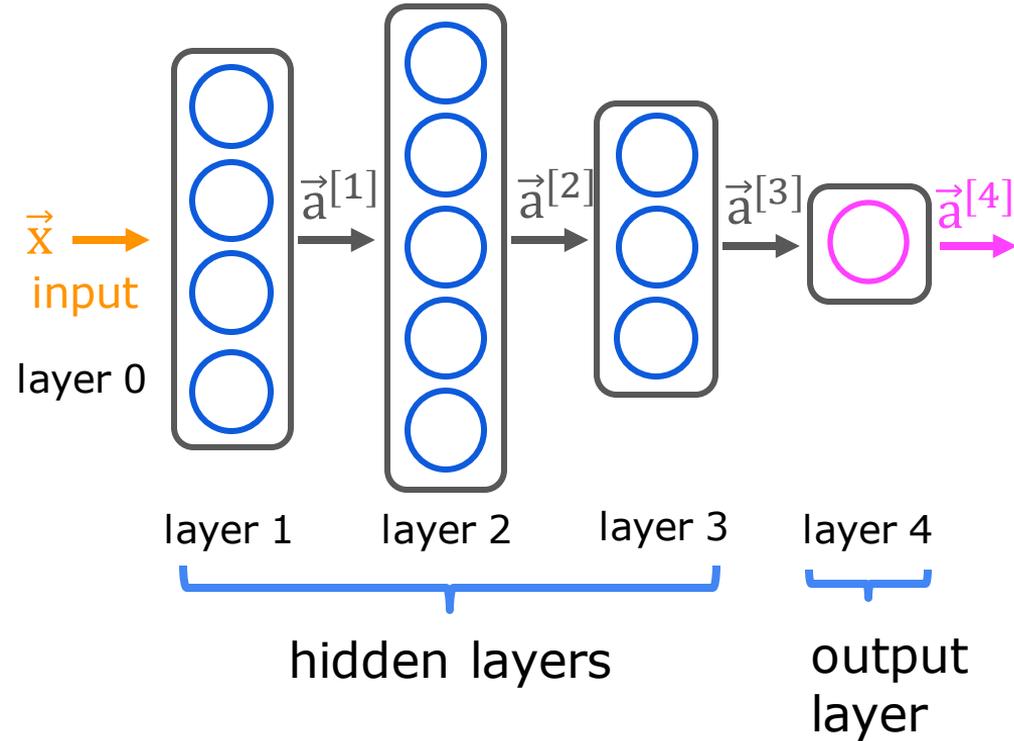
Neural network layer



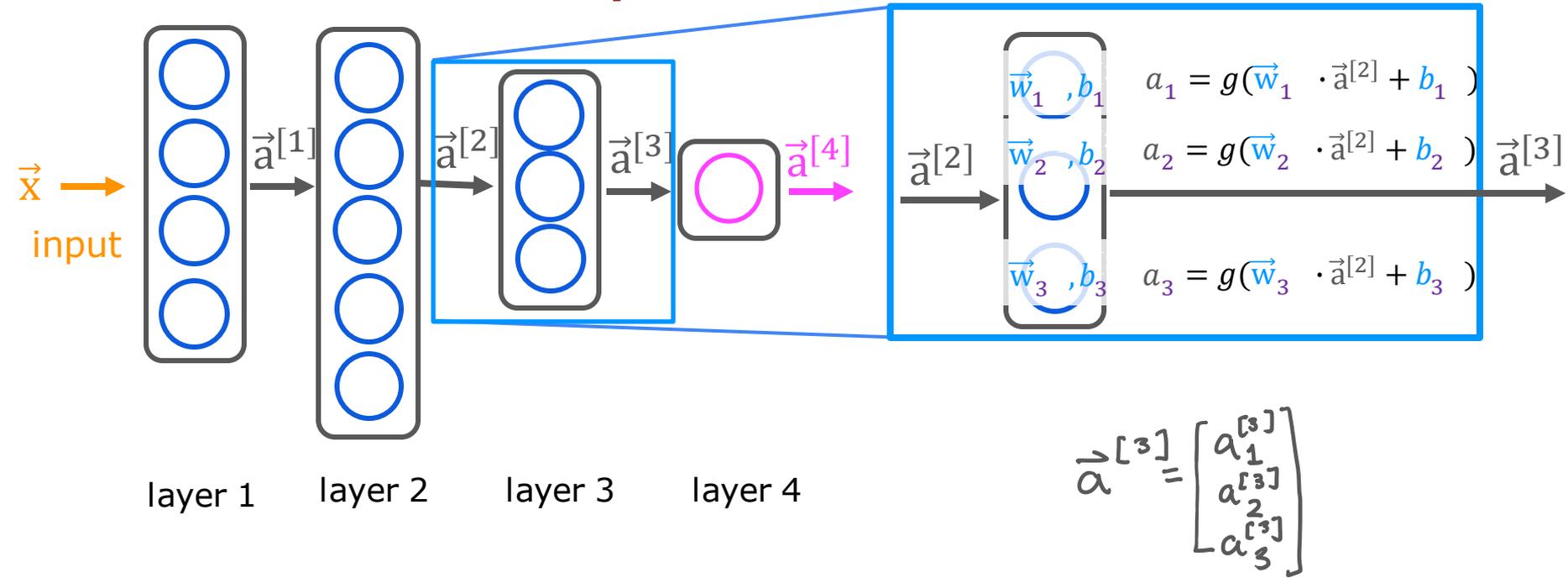
Neural network layer



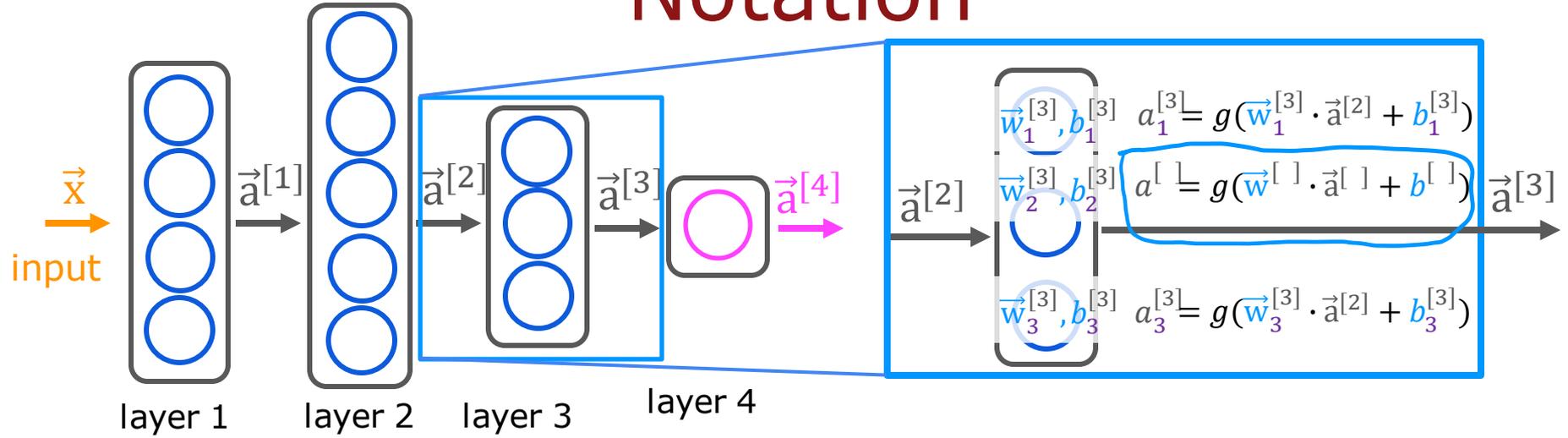
More complex neural network



More complex neural network

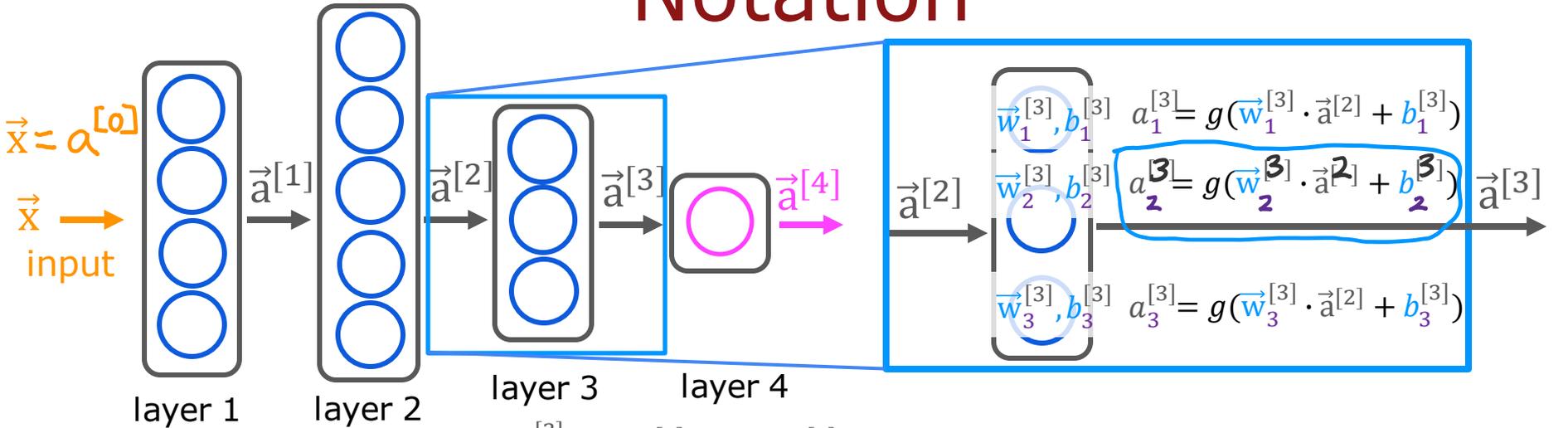


Notation



Question:
Can you fill in the superscripts and subscripts for the second neuron?

Notation



Activation value of layer l , unit (neuron) j

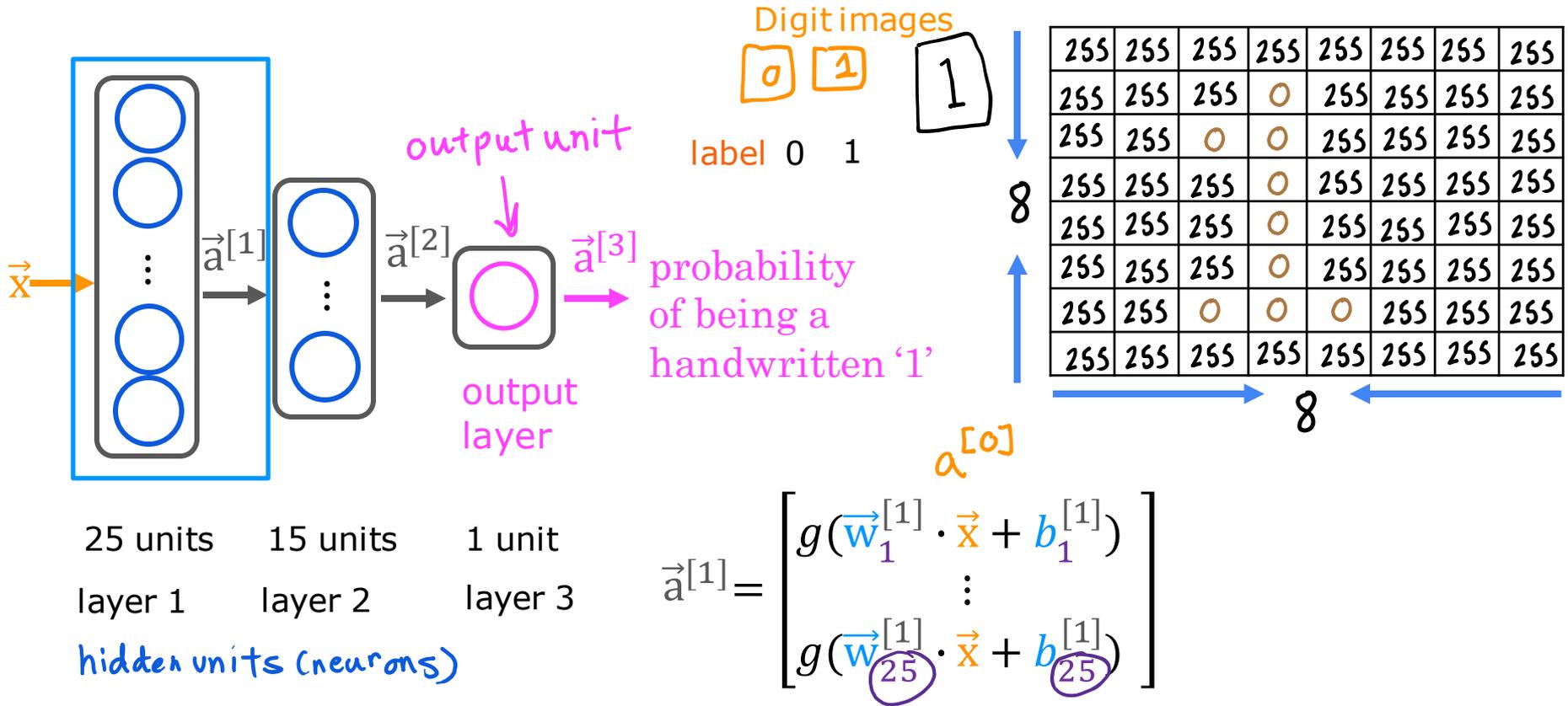
$$a_j^{[l]} = g(\vec{w}_j^{[l]} \cdot \vec{a}^{[l-1]} + b_j^{[l]})$$

output of layer $l - 1$ (previous layer)

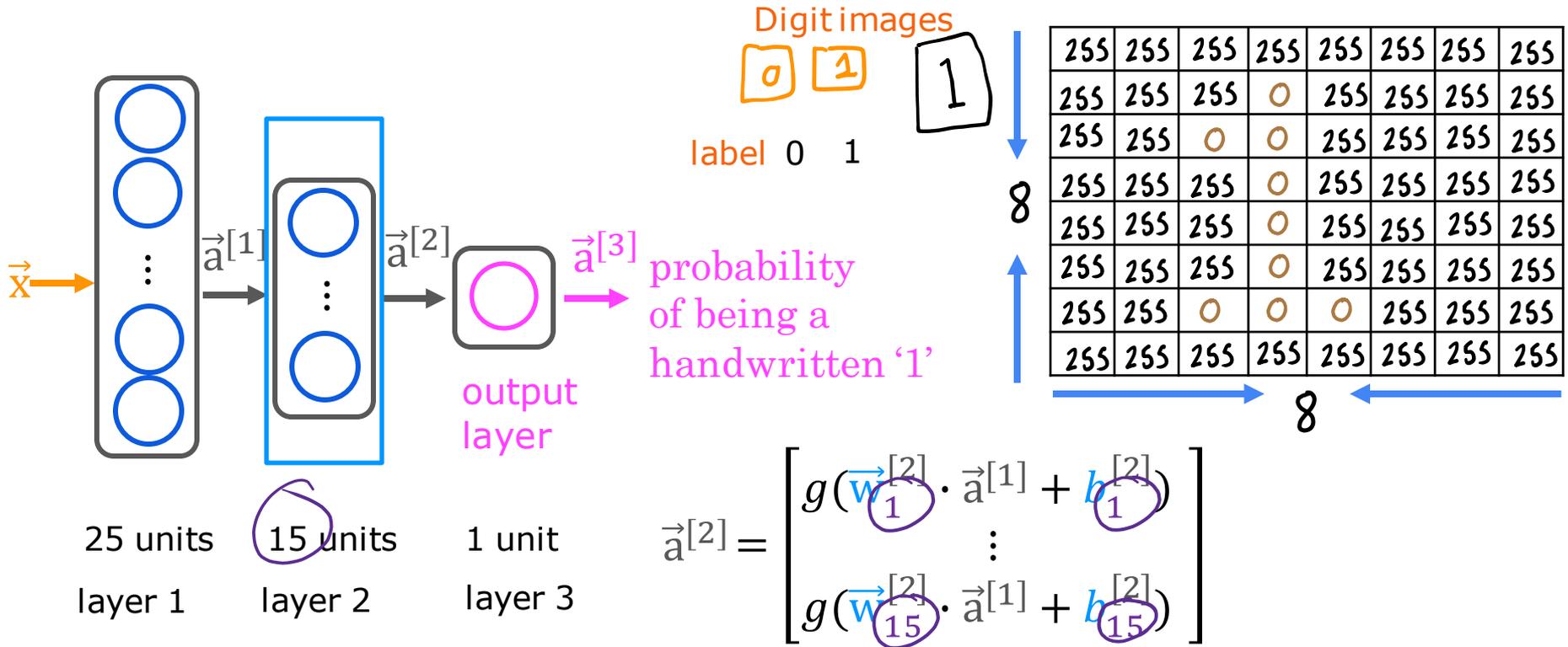
sigmoid "activation function"

Parameters w & b of layer l , unit j

Handwritten digit recognition

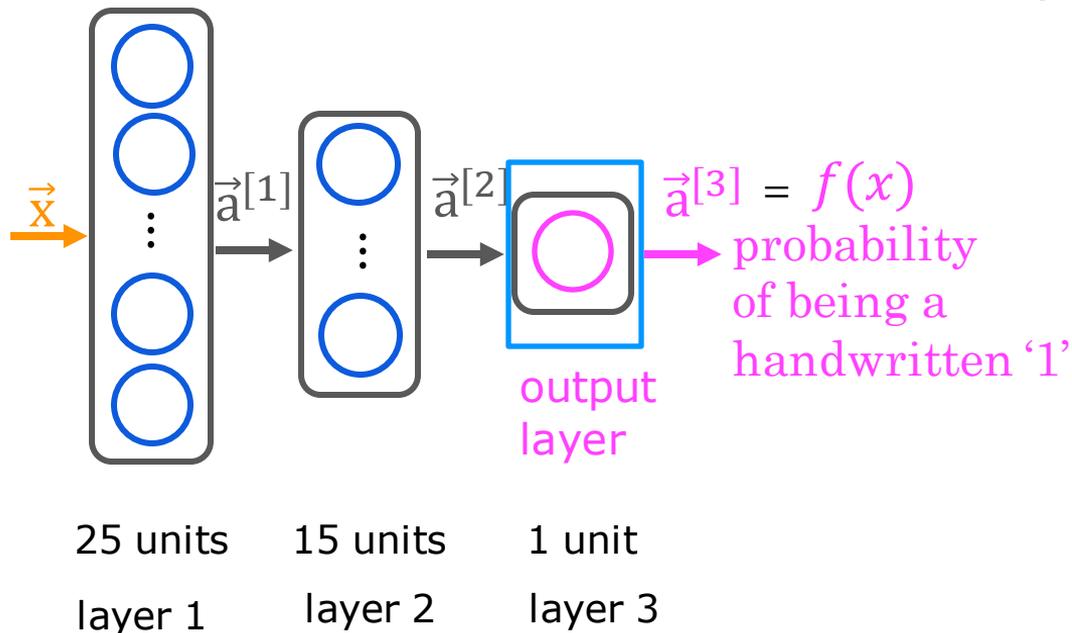


Handwritten digit recognition



Handwritten digit recognition

forward propagation



$$\vec{a}^{[3]} = \left[g \left(\vec{w}_1^{[3]} \cdot \vec{a}^{[2]} + b_1^{[3]} \right) \right]$$

$$\text{is } a_1^{[3]} \geq 0.5?$$

yes

$$\hat{y} = 1$$

image is digit 1

no



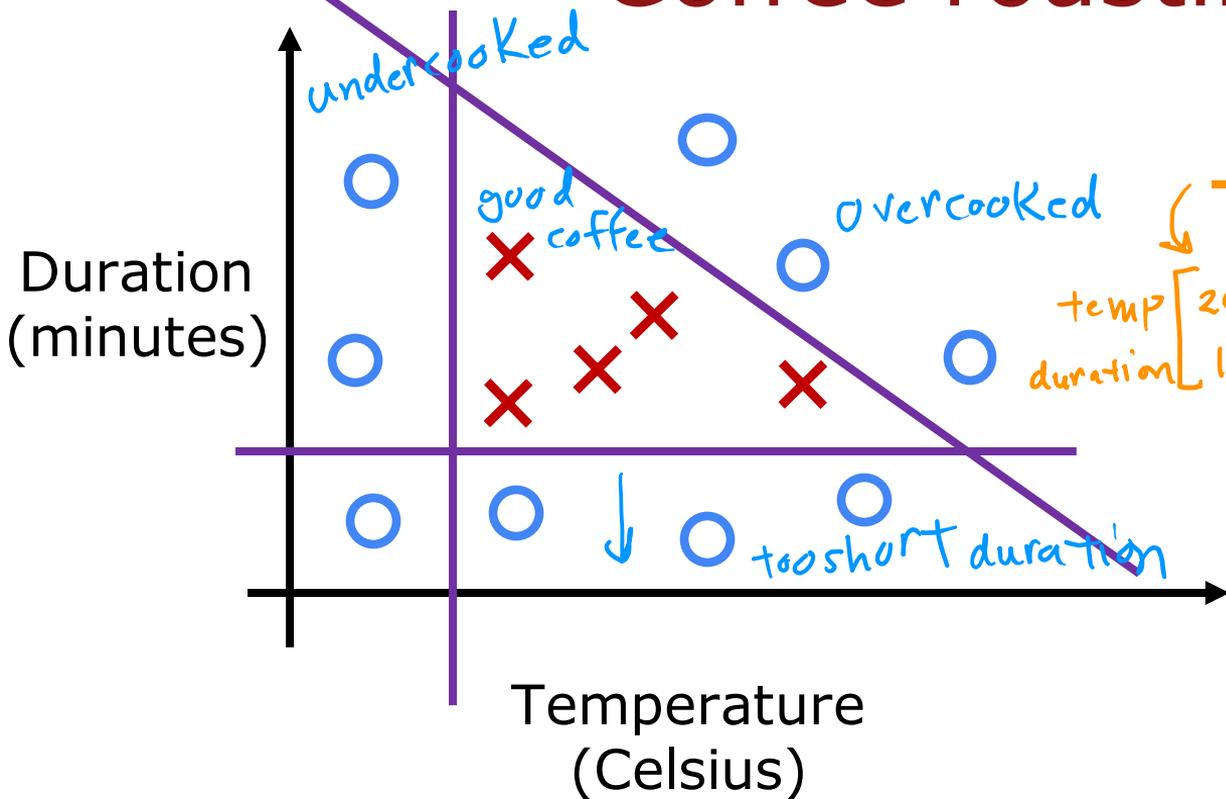
$$\hat{y} = 0$$

image isn't digit 1

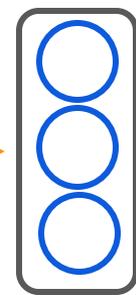
TensorFlow implementation

Inference in Code

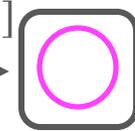
Coffee roasting



\vec{x}
temp [200]
duration [17]

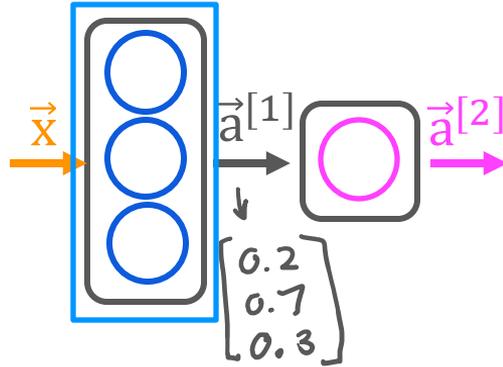


$\vec{a}^{[1]}$



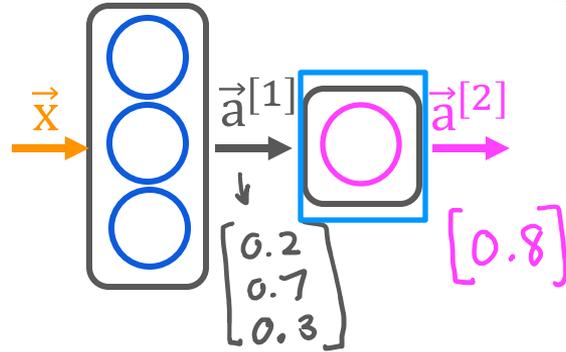
$\vec{a}^{[2]}$

is $a_1^{[2]} \geq 0.5$?
yes $\hat{y} = 1$
no $\hat{y} = 0$



```
x = np.array([[200.0, 17.0]])  
layer_1 = Dense(units=3, activation='sigmoid')  
a1 = layer_1(x)
```

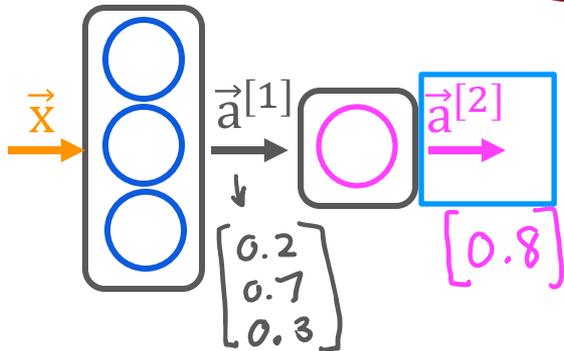
Build the model using TensorFlow



```
x = np.array([[200.0, 17.0]])  
layer_1 = Dense(units=3, activation='sigmoid')  
a1 = layer_1(x)
```

```
layer_2 = Dense(units=1, activation='sigmoid')  
a2 = layer_2(a1)
```

Build the model using TensorFlow



```
x = np.array([[200.0, 17.0]])  
layer_1 = Dense(units=3, activation='sigmoid')  
a1 = layer_1(x)
```

```
layer_2 = Dense(units=1, activation='sigmoid')  
a2 = layer_2(a1)
```

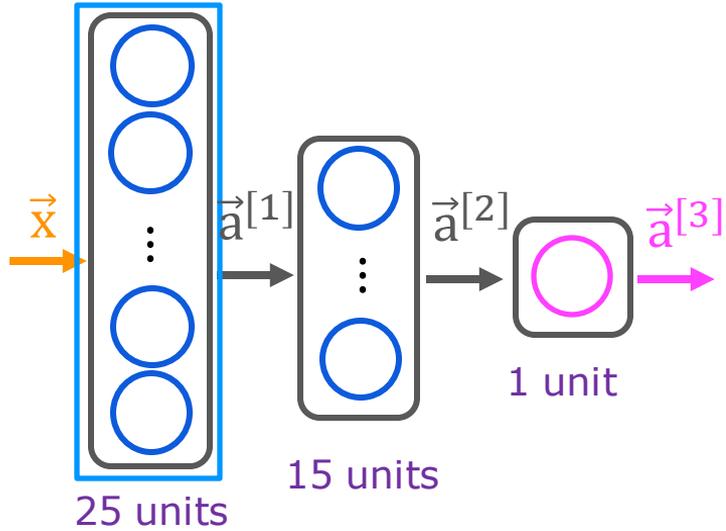
is $a_1^{[2]} \geq 0.5$?

yes $\hat{y} = 1$ ✗

no $\hat{y} = 0$ ○

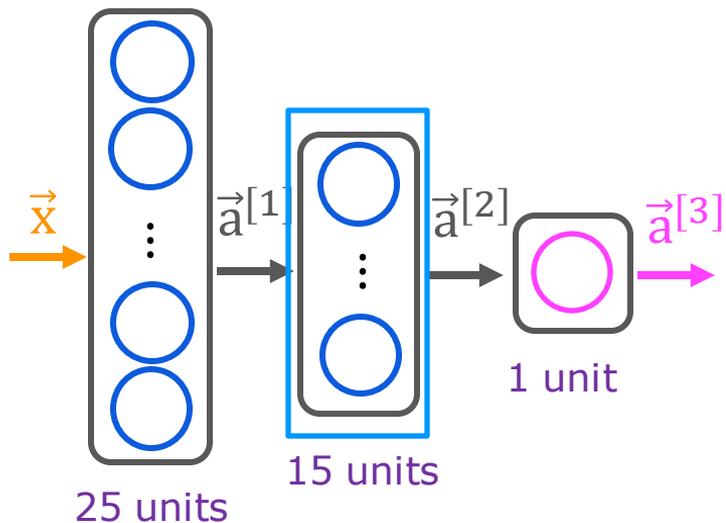
```
if a2 >= 0.5:  
    yhat = 1  
else:  
    yhat = 0
```

Model for digit classification



```
x = np.array([[0.0, ...245, ...240...0]])  
layer_1 = Dense(units=25, activation='sigmoid')  
a1 = layer_1(x)
```

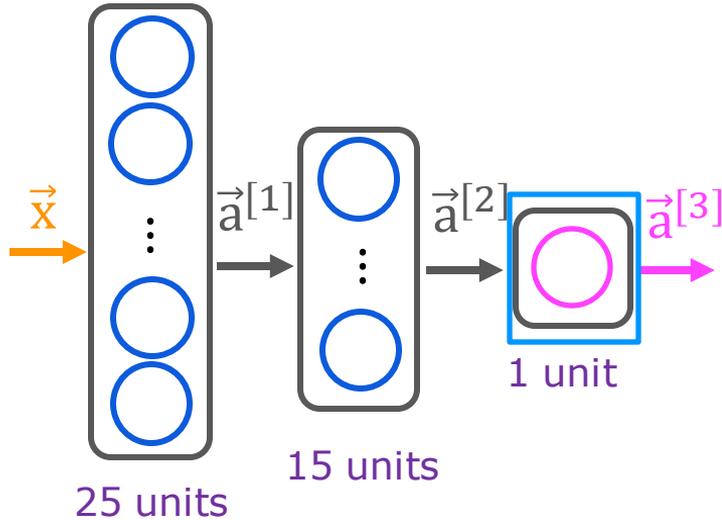
Model for digit classification



```
x = np.array([[0.0, ...245, ...240...0]])  
layer_1 = Dense(units=25, activation='sigmoid')  
a1 = layer_1(x)
```

```
layer_2 = Dense(units=15, activation='sigmoid')  
a2 = layer_2(a1)
```

Model for digit classification

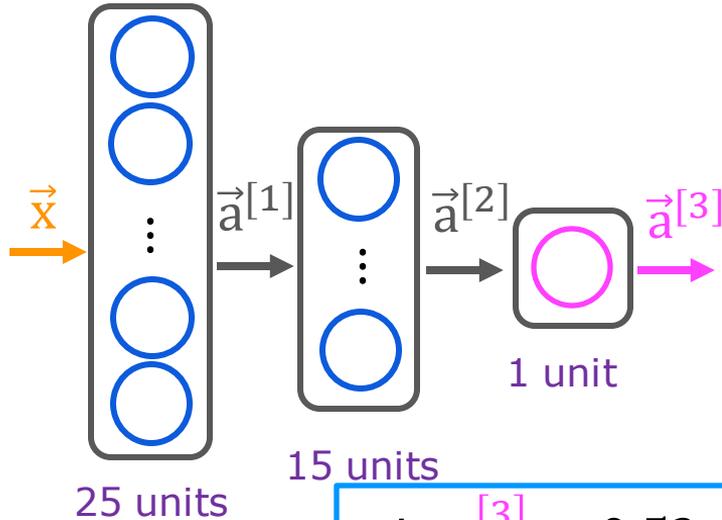


```
x = np.array([[0.0, ...245, ...240...0]])  
layer_1 = Dense(units=25, activation='sigmoid')  
a1 = layer_1(x)
```

```
layer_2 = Dense(units=15, activation='sigmoid')  
a2 = layer_2(a1)
```

```
layer_3 = Dense(units=1, activation='sigmoid')  
a3 = layer_3(a2)
```

Model for digit classification



```
x = np.array([[0.0, ..., 245, ..., 240, ..., 0]])  
layer_1 = Dense(units=25, activation='sigmoid')  
a1 = layer_1(x)
```

```
layer_2 = Dense(units=15, activation='sigmoid')  
a2 = layer_2(a1)
```

```
layer_3 = Dense(units=1, activation='sigmoid')  
a3 = layer_3(a2)
```

is $a_1^{[3]} \geq 0.5$?

$\hat{y} = 1$

✗

$\hat{y} = 0$

○

```
if a3 >= 0.5:  
    yhat = 1  
else:  
    yhat = 0
```

Feature vectors

temperature (Celsius)	duration (minutes)	Good coffee? (1/0)
200.0	17.0	1
425.0	18.5	0
...

```
x = np.array([[200.0, 17.0]])  
[[200.0, 17.0]]
```

Why?

Note about numpy arrays

2 rows $\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$ 3 columns
2 x 3 matrix

```
x = np.array([[1, 2, 3],  
              [4, 5, 6]])
```

```
[[1, 2, 3],  
 [4, 5, 6]]
```

2D array

2 x 3

4 rows $\begin{bmatrix} 0.1 & 0.2 \\ -3 & -4 \\ -0.5 & -0.6 \\ 7 & 8 \end{bmatrix}$

```
x = np.array([[0.1, 0.2],  
              [-3.0, -4.0, ],  
              [-0.5, -0.6, ],  
              [7.0, 8.0, ]])
```

4 x 2

1 x 2

2 columns

4 x 2 matrix

```
[[0.1, 0.2],  
 [-3.0, -4.0, ],  
 [-0.5, -0.6, ],  
 [7.0, 8.0, ]]
```

2 x 1

Note about numpy arrays

`x = np.array([[200, 17]])` $[200 \quad 17]$ 1×2

`x = np.array([[200],
[17]])` $\begin{bmatrix} 200 \\ 17 \end{bmatrix}$ 2×1

`x = np.array([200,17])`

1D
"vector"

Feature vectors

temperature (Celsius)	duration (minutes)	Good coffee? (1/0)
200.0	17.0	1
425.0	18.5	0
...

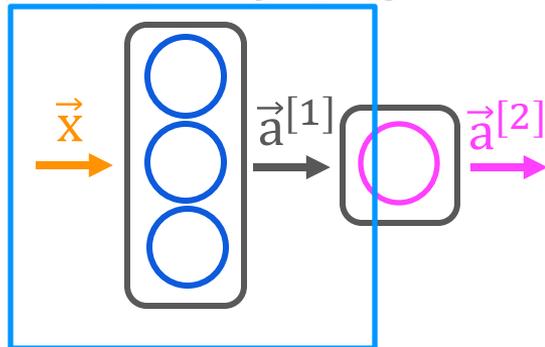
`x = np.array([[200.0, 17.0]])` ←

`[[200.0, 17.0]]`

1 x 2

`[200.0 17.0]`

Activation vector



```
x = np.array([[200.0, 17.0]])  
layer_1 = Dense(units=3, activation='sigmoid')  
a1 = layer_1(x)
```

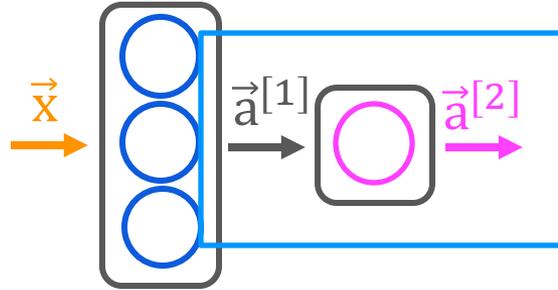
→ $[0.2, 0.7, 0.3]$ 1 x 3 matrix

```
tf.Tensor([[0.2 0.7 0.3]], shape=(1, 3), dtype=float32)
```

```
a1.numpy()
```

```
array([[1.4661001, 1.125196 , 3.2159438]], dtype=float32)
```

Activation vector



```
layer_2 = Dense(units=1, activation='sigmoid')  
a2 = layer_2(a1)
```

\leftarrow $[[0.8]]$ \leftarrow

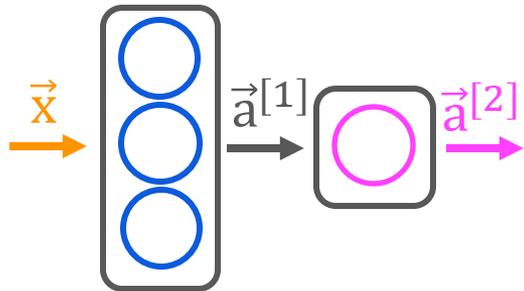
1 x 1

```
tf.Tensor([[0.8]], shape=(1, 1), dtype=float32)
```

```
a2.numpy()
```

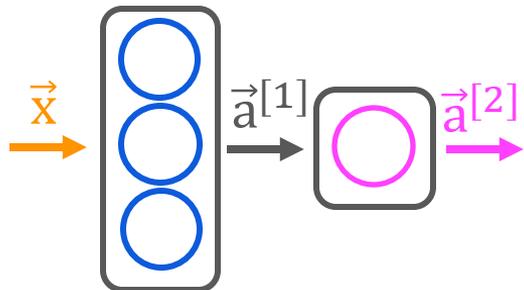
```
array([[0.8]], dtype=float32)
```

What you saw earlier



```
→ x = np.array([[200.0, 17.0]])  
→ layer_1 = Dense(units=3, activation="sigmoid")  
→ a1 = layer_1(x)  
  
→ layer_2 = Dense(units=1, activation="sigmoid")  
→ a2 = layer_2(a1)
```

Building a neural network architecture



```
layer_1 = Dense(units=3, activation="sigmoid")  
layer_2 = Dense(units=1, activation="sigmoid")  
model = Sequential([layer_1, layer_2])
```

layer1
layer2

```
x = np.array([[200.0, 17.0],  
              [120.0, 5.0],  
              [425.0, 20.0],  
              [212.0, 18.0]])
```

4 x 2

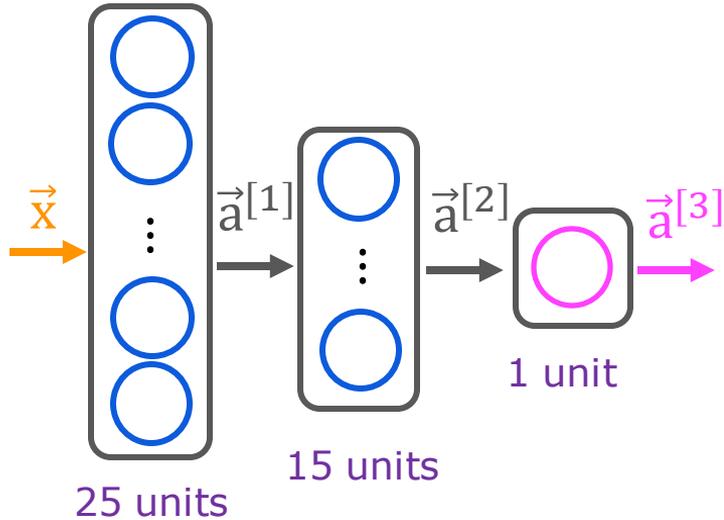
targets `y = np.array([1,0,0,1])`

```
model.compile(...)  
model.fit(x,y)
```

```
model.predict(x_new)
```

		y
200	17	1
120	5	0
425	20	0
212	18	1

Digit classification model



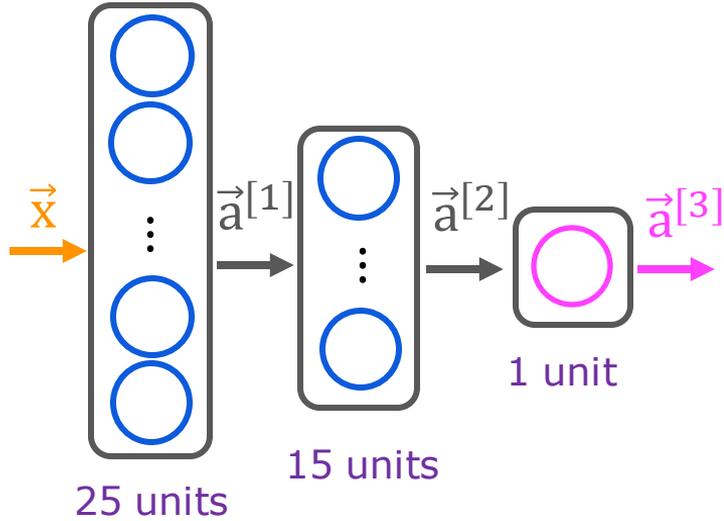
```
layer_1 = Dense(units=25, activation="sigmoid")
layer_2 = Dense(units=15, activation="sigmoid")
layer_3 = Dense(units=1, activation="sigmoid")
model = Sequential([layer_1, layer_2, layer_3])
model.compile(...)

x = np.array([[0..., 245, ..., 17],
              [0..., 200, ..., 184]])
y = np.array([1,0])

model.fit(x,y)

model.predict(x_new)
```

Digit classification model



```
model = Sequential([  
    Dense(units=25, activation="sigmoid"),  
    Dense(units=15, activation="sigmoid"),  
    Dense(units=1, activation="sigmoid")])
```

```
model.compile(...)
```

```
x = np.array([[0..., 245, ..., 17],  
              [0..., 200, ..., 184]])
```

```
y = np.array([1,0])
```

```
model.fit(x,y)
```

```
model.predict(x_new)
```