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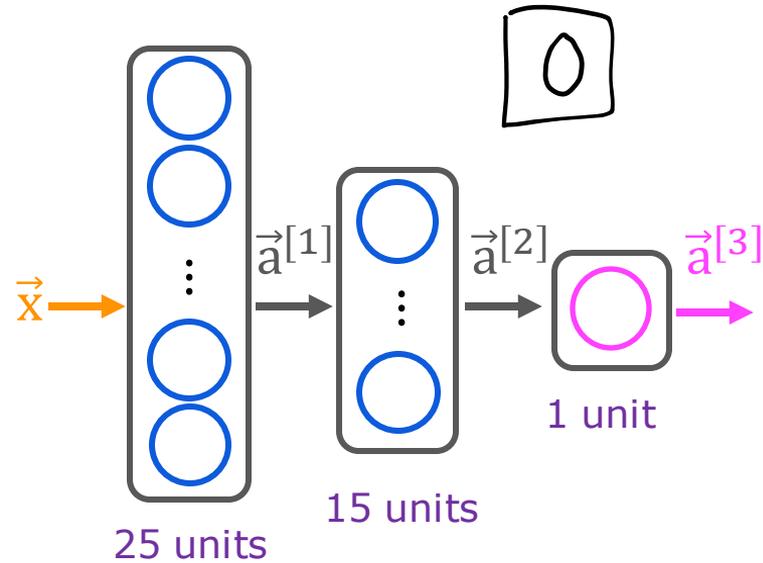
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Neural Network Training

TensorFlow
implementation

Train a Neural Network in TensorFlow



Given set of (x,y) examples
How to build and train this in code?

```
import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense

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

from tensorflow.keras.losses import BinaryCrossentropy
```

```
model.compile(loss=BinaryCrossentropy())
```

```
model.fit(X,Y,epochs=100)
```

*epochs: number of steps
in gradient descent*

Model Training Steps

①

specify how to compute output given input x and parameters w, b (define model)

$$f_{\vec{w}, b}(\vec{x}) = ?$$

②

specify loss and cost

$$L(f_{\vec{w}, b}(\vec{x}), y) \quad \text{1 example}$$

$$J(\vec{w}, b) = \frac{1}{m} \sum_{i=1}^m L(f_{\vec{w}, b}(\vec{x}^{(i)}), y^{(i)})$$

③

Train on data to minimize $J(\vec{w}, b)$

logistic regression

```
z = np.dot(w, x) + b  
  
f_x = 1 / (1 + np.exp(-z))
```

logistic loss

```
loss = -y * np.log(f_x)  
       -(1-y) * np.log(1-f_x)
```

```
w = w - alpha * dj_dw  
b = b - alpha * dj_db
```

neural network

```
model = Sequential([  
    Dense(...)  
    Dense(...)  
    Dense(...)])
```

binary cross entropy

```
model.compile(  
    loss=BinaryCrossentropy())
```

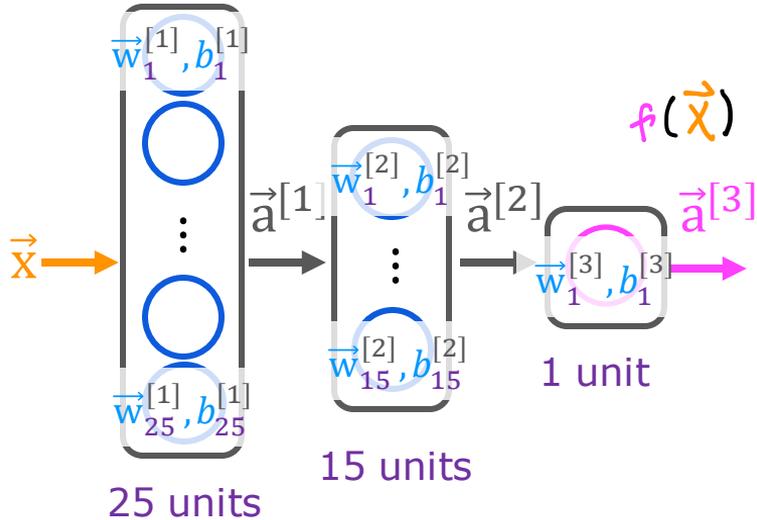
```
model.fit(X, y, epochs=100)
```

1. Create the model

define the model

$$f(\vec{x}) = ?$$

$$\vec{w}^{[1]}, \vec{b}^{[1]} \quad \vec{w}^{[2]}, \vec{b}^{[2]} \quad \vec{w}^{[3]}, \vec{b}^{[3]}$$



```
import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
```

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

2. Loss and cost functions

Mnist digit
classification problem

binary classification

$$L(f(\vec{x}), y) = -y \log(f(\vec{x})) - (1 - y) \log(1 - f(\vec{x}))$$

compare prediction vs. target

logistic loss

also known as binary cross entropy

```
model.compile(loss= BinaryCrossentropy())
```

regression

(predicting numbers
and not categories) mean squared error

```
model.compile(loss= MeanSquaredError())
```

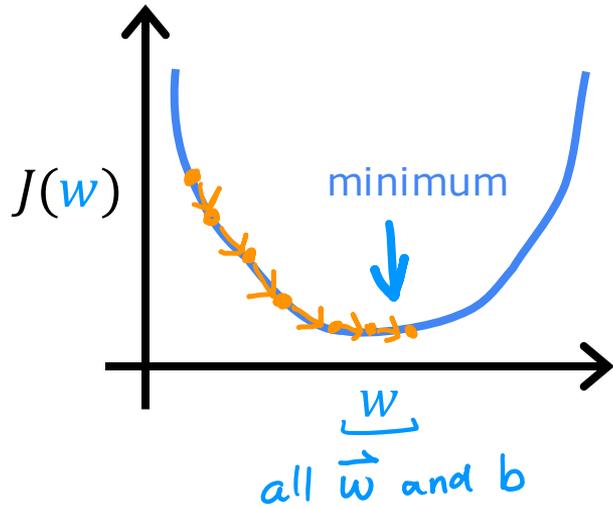
$$J(\mathbf{W}, \mathbf{B}) = \frac{1}{m} \sum_{i=1}^m L(f(\vec{x}^{(i)}), y^{(i)})$$

$w^{[1]}, w^{[2]}, w^{[3]}$ $\vec{b}^{[1]}, \vec{b}^{[2]}, \vec{b}^{[3]}$ $f_{\mathbf{W}, \mathbf{B}}(\vec{x})$

```
from tensorflow.keras.losses import  
BinaryCrossentropy
```

```
from tensorflow.keras.losses import  
MeanSquaredError
```

3. Gradient descent



repeat {

$$w_j^{[l]} = w_j^{[l]} - \alpha \frac{\partial}{\partial w_j} J(\vec{w}, b)$$

$$b_j^{[l]} = b_j^{[l]} - \alpha \frac{\partial}{\partial b} J(\vec{w}, b)$$

} Compute derivatives
for gradient descent
using "backpropagation"

```
model.fit(X, y, epochs=100)
```

Neural network libraries

Use code libraries instead of coding "from scratch"



TensorFlow



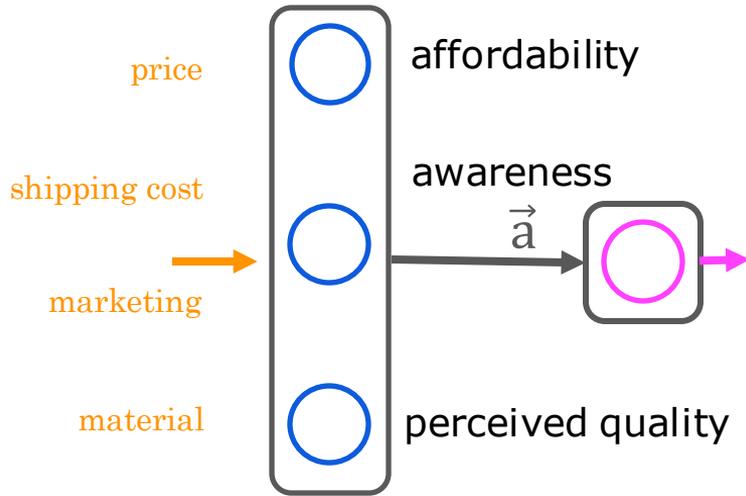
PyTorch

Good to understand the implementation

Activation Functions

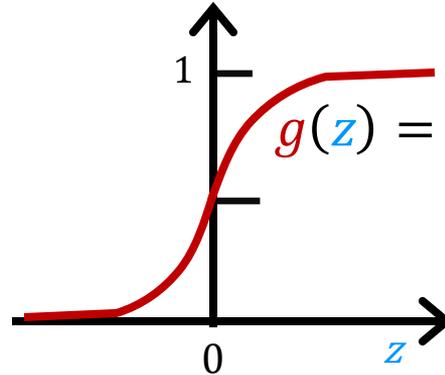
Alternatives to the
sigmoid activation

Demand Prediction Example



$$a_2^{[1]} = g(\overbrace{\vec{w}_2^{[1]} \cdot \vec{x} + b_2^{[1]}}^z)$$

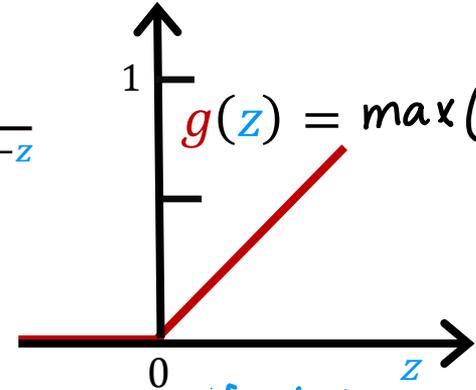
Sigmoid



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

$$0 < g(z) < 1$$

ReLU Rectified Linear Unit



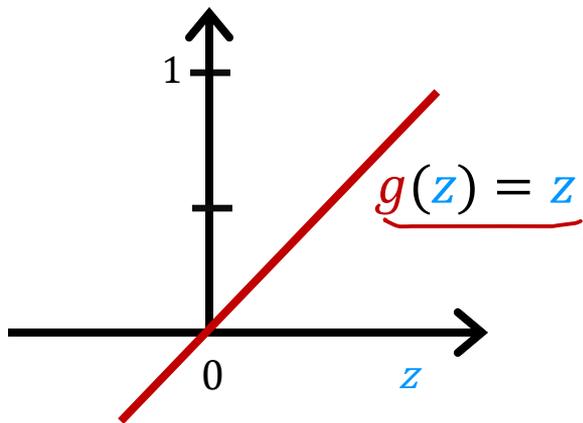
$$\text{if } z < 0 \\ g(z) \text{ is } 0$$

$$\text{if } z \geq 0 \\ g(z) \text{ is } z$$

Examples of Activation Functions

"No activation function"

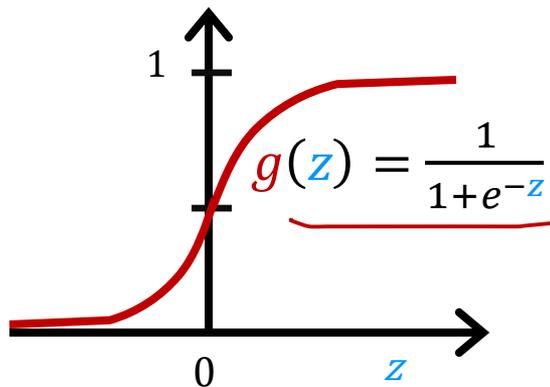
Linear activation function



$$a = g(z) = \underbrace{\vec{w} \cdot \vec{x} + b}_z$$

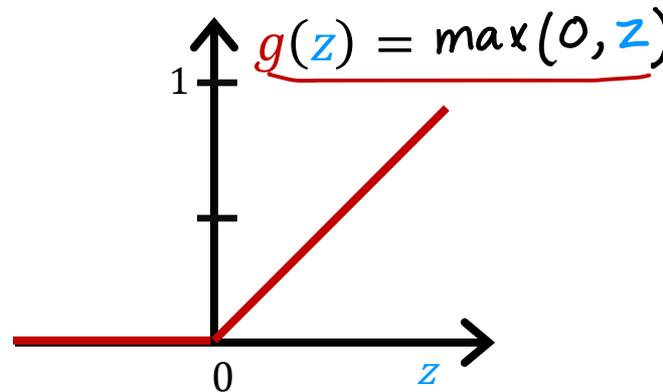
$$a_2^{[1]} = g(\vec{w}_2^{[1]} \cdot \vec{x} + b_2^{[1]})$$

Sigmoid



$$0 < g(z) < 1$$

ReLU Rectified Linear Unit



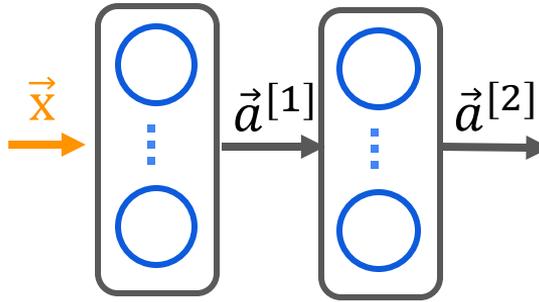
if $z < 0$

$g(z)$ is 0

if $z \geq 0$

$g(z)$ is z

Output Layer



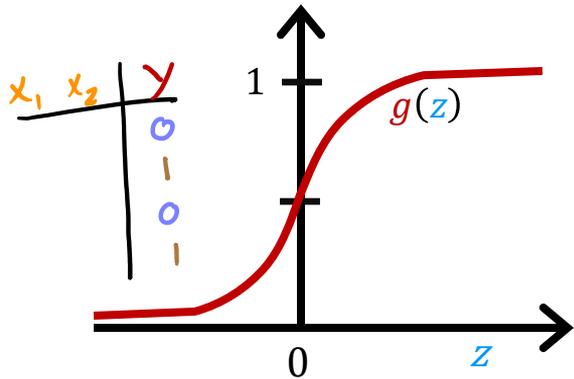
$$\vec{a}^{[3]} = f(\vec{x})$$

$$f(\vec{x}) = a_1^{[3]} = g(z_1^{[3]})$$

Choosing $g(z)$ for output layer?

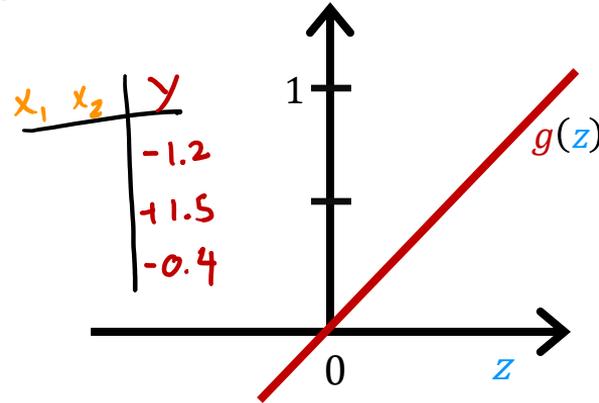
Binary classification

Sigmoid
y=0/1



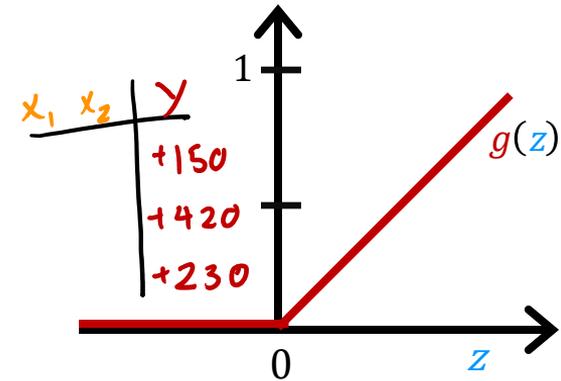
Regression

Linear activation function
y = +/-

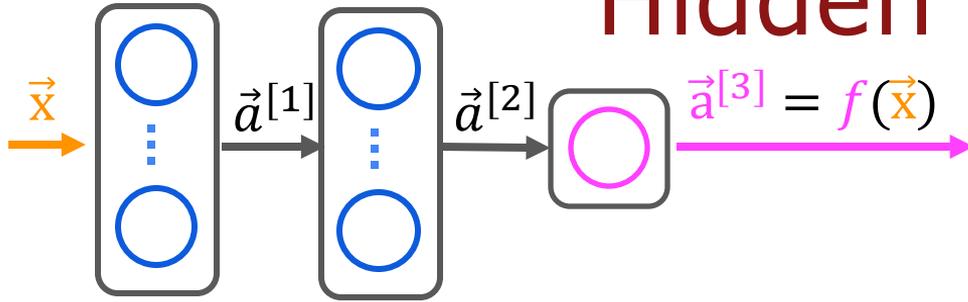


Regression

ReLU
Y = 0 or +

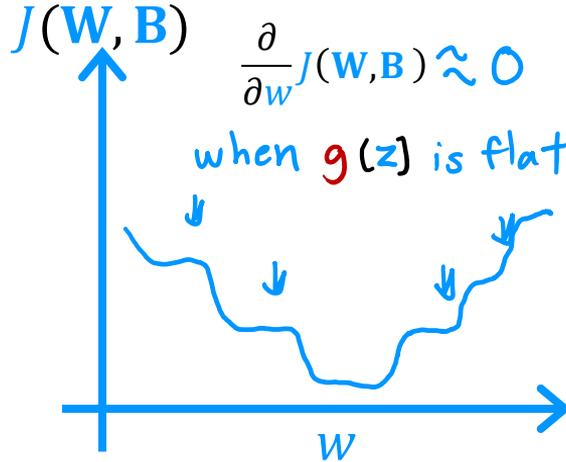
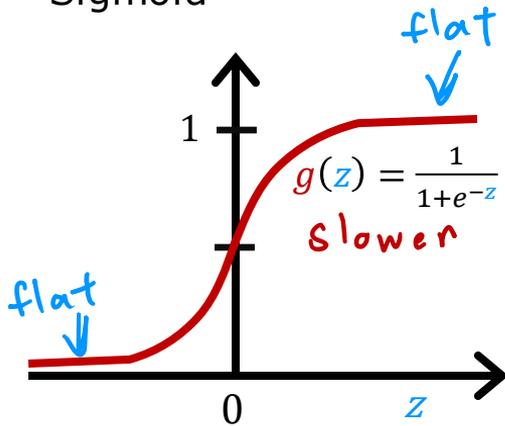


Hidden Layer



Choosing $g(z)$ for hidden layer

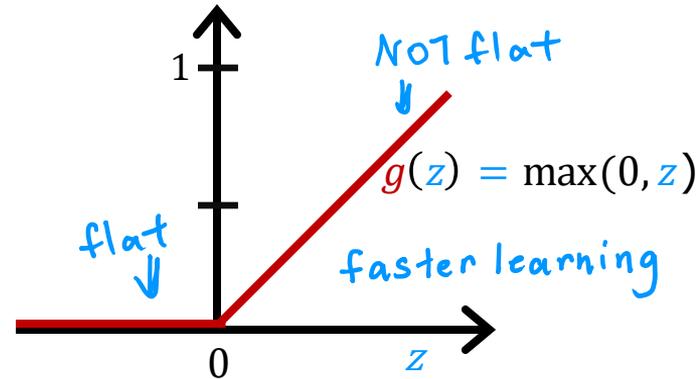
Sigmoid



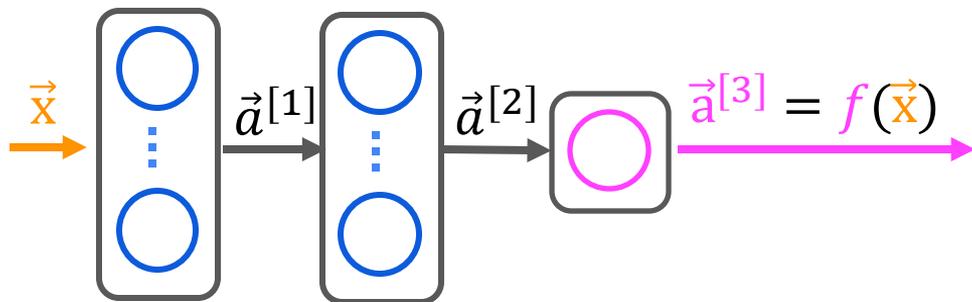
most common choice

ReLU

faster



Choosing Activation Summary



ReLU hidden layers

```
from tf.keras.layers import Dense
model = Sequential([
    Dense(units=25, activation='relu'), layer1
    Dense(units=15, activation='relu'), layer2
    Dense(units=1, activation='sigmoid') layer3
])
```

or 'linear'
or 'relu'

binary classification

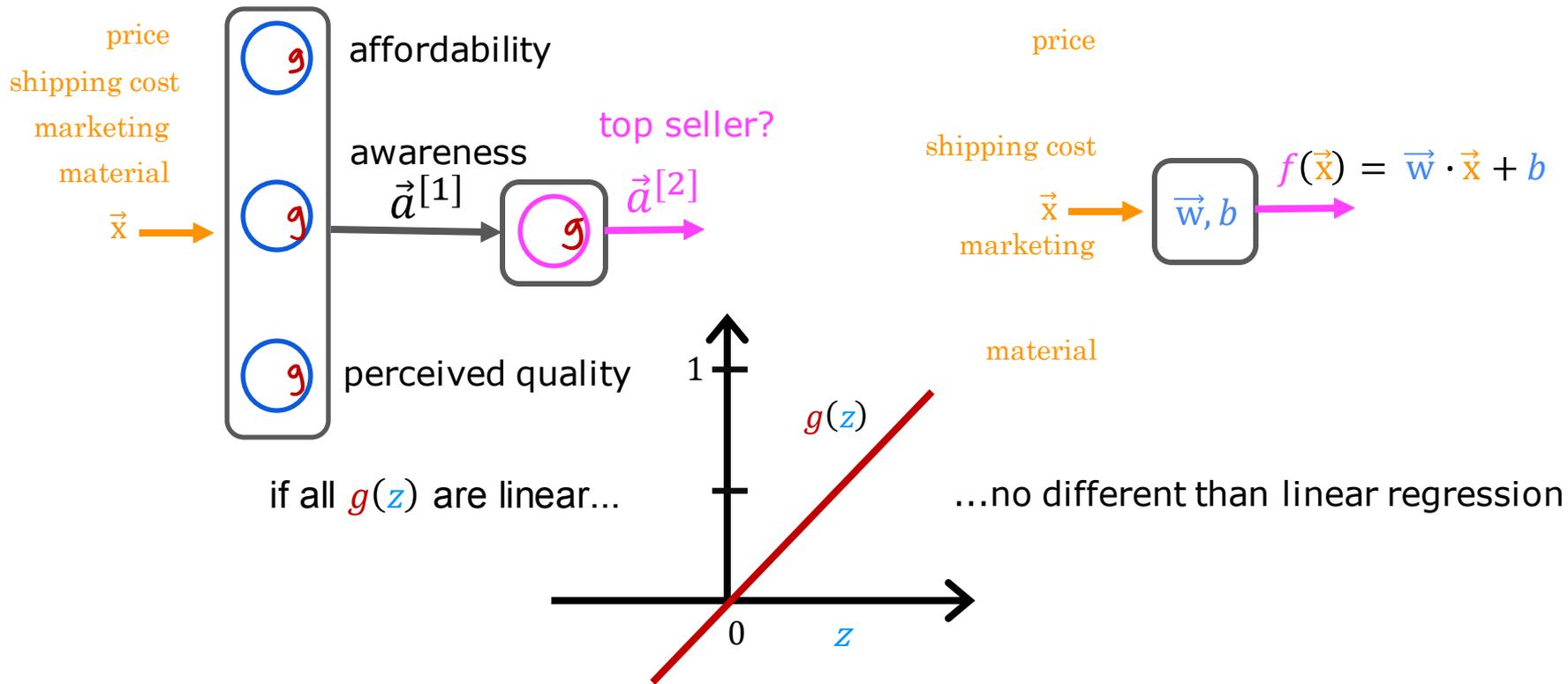
activation='sigmoid'

regression y negative/
activation='linear' positive

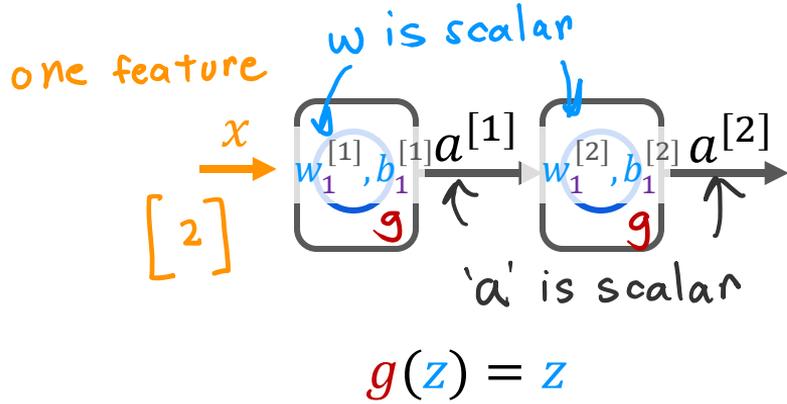
regression $y \geq 0$

activation='relu'

Why do we need activation functions?



Linear Example



$$a^{[1]} = w_1^{[1]} x + b_1^{[1]}$$

$$a^{[2]} = w_1^{[2]} a^{[1]} + b_1^{[2]}$$

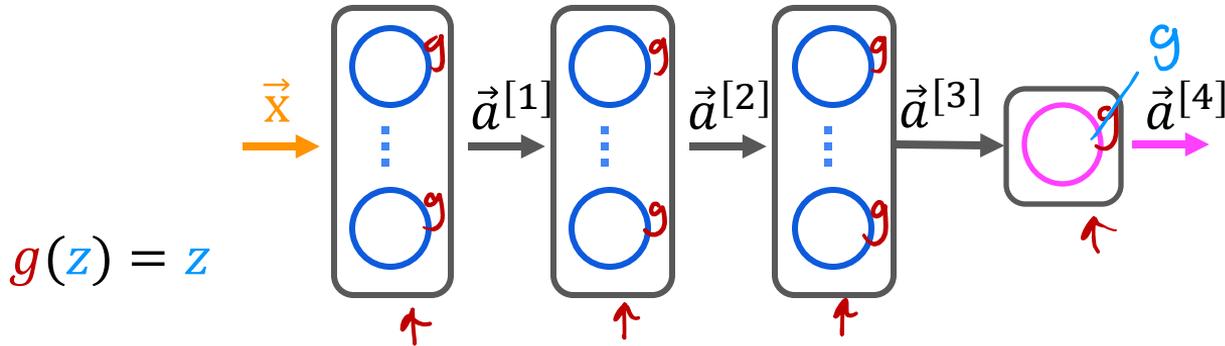
$$= w_1^{[2]} (w_1^{[1]} x + b_1^{[1]}) + b_1^{[2]}$$

$$\vec{a}^{[2]} = (\underbrace{\vec{w}_1^{[2]} \vec{w}_1^{[1]}}_w) x + \underbrace{w_1^{[2]} b_1^{[1]} + b_1^{[2]}}_b$$

$$\vec{a}^{[2]} = w x + b$$

$$f(x) = wx + b \quad \text{linear regression}$$

Example



$$g(z) = z$$

$$\vec{a}^{[4]} = \vec{w}_1^{[4]} \cdot \vec{a}^{[3]} + b_1^{[4]}$$

all linear (including output)
↳ equivalent to linear regression

$$\vec{a}^{[4]} = \frac{1}{1 + e^{-(\vec{w}_1^{[4]} \cdot \vec{a}^{[3]} + b_1^{[4]})}}$$

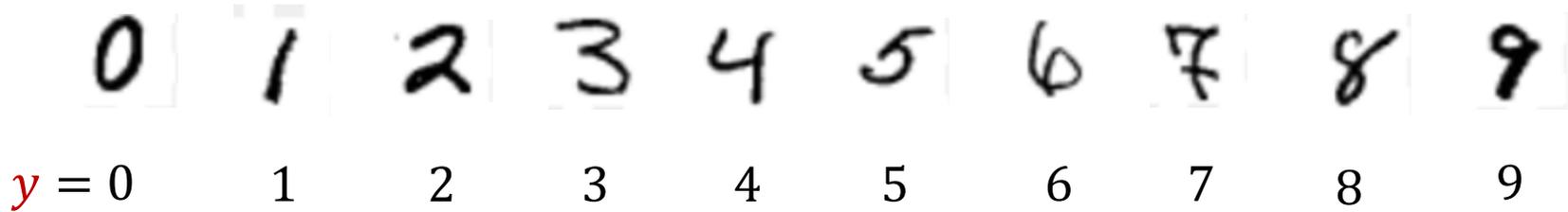
output activation is sigmoid
(hidden layers still linear)
↳ equivalent to logistic regression

Don't use linear activations in hidden layers (use ReLU)

Multiclass Classification

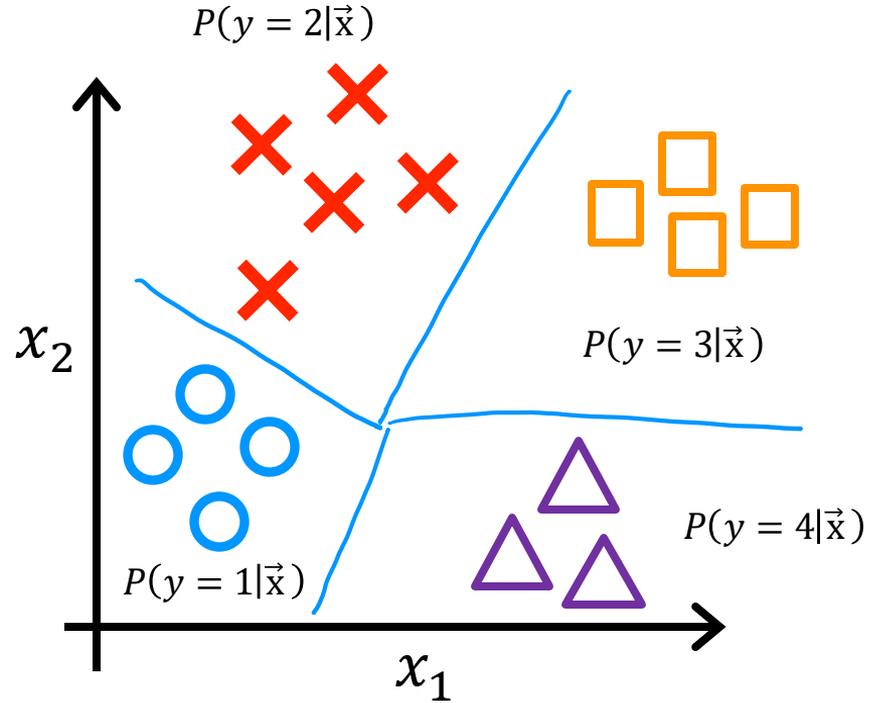
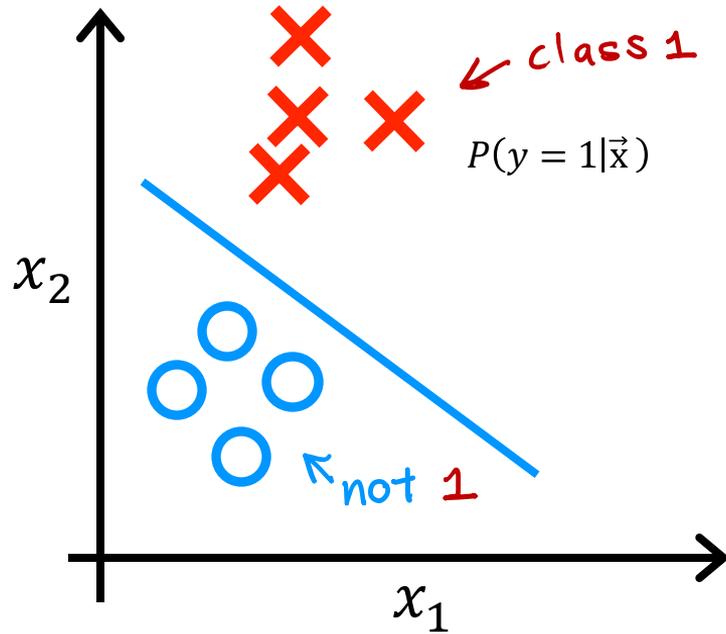
Multiclass

MNIST example



multiclass classification problem:
target y can take on more than two possible values

Multiclass classification example



Multiclass Classification

Softmax

Logistic regression

(2 possible output values)

$$z = \vec{w} \cdot \vec{x} + b$$

$$\times a_1 = g(z) = \frac{1}{1+e^{-z}} = P(y=1|\vec{x}) \quad 0.71$$

$$\circ a_2 = 1 - a_1 = P(y=0|\vec{x}) \quad 0.29$$

Softmax regression

(N possible outputs) $y=1,2,3,\dots,N$

$$z_j = \vec{w}_j \cdot \vec{x} + b_j \quad j = 1, \dots, N$$

parameters w_1, w_2, \dots, w_N
 b_1, b_2, \dots, b_N

$$a_j = \frac{e^{z_j}}{\sum_{k=1}^N e^{z_k}} = P(y=j|\vec{x})$$

note: $a_1 + a_2 + \dots + a_N = 1$

Softmax regression (4 possible outputs) $y=1,2,3,4$

$$\times z_1 = \vec{w}_1 \cdot \vec{x} + b_1$$

$$\circ z_2 = \vec{w}_2 \cdot \vec{x} + b_2$$

$$\square z_3 = \vec{w}_3 \cdot \vec{x} + b_3$$

$$\triangle z_4 = \vec{w}_4 \cdot \vec{x} + b_4$$

$$a_1 = \frac{e^{z_1}}{e^{z_1} + e^{z_2} + e^{z_3} + e^{z_4}} \\ \times \quad \circ \quad \square \quad \triangle \\ = P(y=1|\vec{x}) \quad 0.30$$

$$a_2 = \frac{e^{z_2}}{e^{z_1} + e^{z_2} + e^{z_3} + e^{z_4}} \\ = P(y=2|\vec{x}) \quad 0.20$$

$$a_3 = \frac{e^{z_3}}{e^{z_1} + e^{z_2} + e^{z_3} + e^{z_4}} \\ = P(y=3|\vec{x}) \quad 0.15$$

$$a_4 = \frac{e^{z_4}}{e^{z_1} + e^{z_2} + e^{z_3} + e^{z_4}} \\ = P(y=4|\vec{x}) \quad 0.35$$

Cost

Logistic regression

$$z = \vec{w} \cdot \vec{x} + b$$

$$a_1 = g(z) = \frac{1}{1 + e^{-z}} = P(y = 1|\vec{x})$$

$$a_2 = 1 - a_1 = P(y = 0|\vec{x})$$

$$\text{loss} = \underbrace{-y \log a_1}_{\text{if } y=1} - \underbrace{(1-y) \log(1-a_1)}_{\text{if } y=0}$$

$$J(\vec{w}, b) = \text{average loss}$$

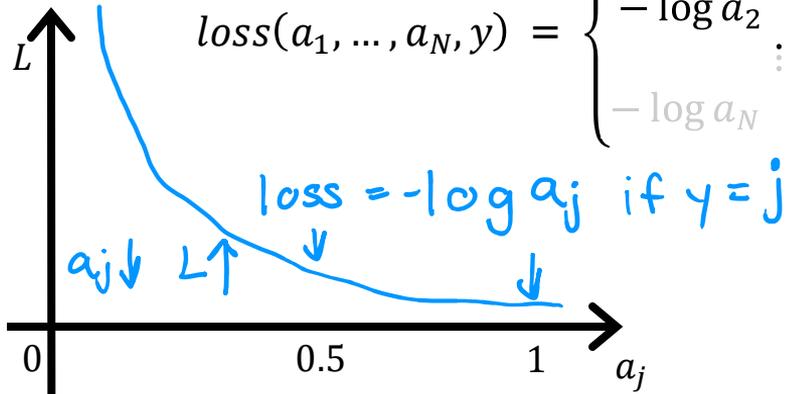
Softmax regression

$$a_1 = \frac{e^{z_1}}{e^{z_1} + e^{z_2} + \dots + e^{z_N}} = P(y = 1|\vec{x})$$

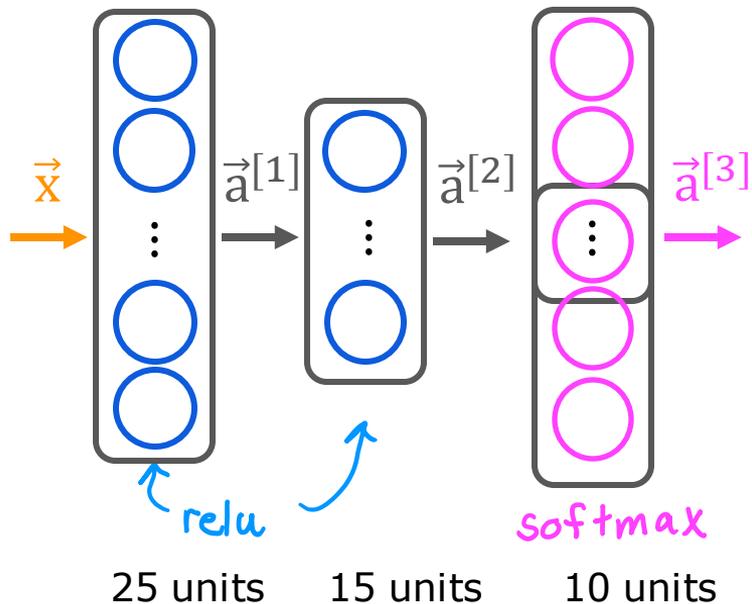
$$\vdots$$
$$a_N = \frac{e^{z_N}}{e^{z_1} + e^{z_2} + \dots + e^{z_N}} = P(y = N|\vec{x})$$

Crossentropy loss

$$\text{loss}(a_1, \dots, a_N, y) = \begin{cases} -\log a_1 & \text{if } y = 1 \\ -\log a_2 & \text{if } y = 2 \\ \vdots \\ -\log a_N & \text{if } y = N \end{cases}$$



Neural Network with Softmax output



$$z_1 = \vec{w}_1^1 \cdot \vec{a}^{[2]} + b_1$$

$$a_1 = \frac{e^{z_1^1}}{e^{z_1^1} + \dots + e^{z_{10}^1}}$$

$$= P(y = 1 | \vec{x})$$

⋮

$$z_{10} = \vec{w}_{10}^1 \cdot \vec{a}^{[2]} + b_{10}$$

$$a_{10} = \frac{e^{z_{10}^1}}{e^{z_1^1} + \dots + e^{z_{10}^1}}$$

$$= P(y = 10 | \vec{x})$$

logistic regression

$$a_1^{[3]} = g(z_1^{[3]}) \quad a_2^{[3]} = g(z_2^{[3]})$$

softmax

$$\vec{a}^{[3]} = (a_1^{[3]}, \dots, a_{10}^{[3]}) = g(z_1^{[3]}, \dots, z_{10}^{[3]})$$

MNIST with softmax

① specify the model

$$f_{\vec{w},b}(\vec{x}) = ?$$

```
import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
model = Sequential([
    Dense(units=25, activation='relu')
    Dense(units=15, activation='relu')
    Dense(units=10, activation='softmax')
])
```

② specify loss and cost

$$L(f_{\vec{w},b}(\vec{x}), y)$$

```
from tensorflow.keras.losses import
    SparseCategoricalCrossentropy

model.compile(loss= SparseCategoricalCrossentropy() )
model.fit(X, Y, epochs=100)
```

③ Train on data to minimize $J(\vec{w}, b)$

Note: better (recommended) version later.

Multi-label Classification



Is there a car?

yes
no
yes

$$y = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

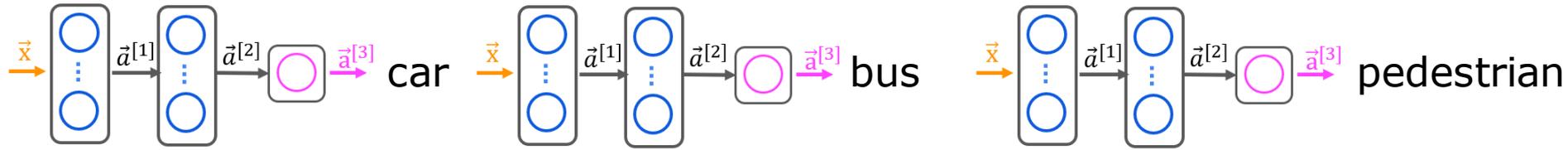
no
no
yes

$$y = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

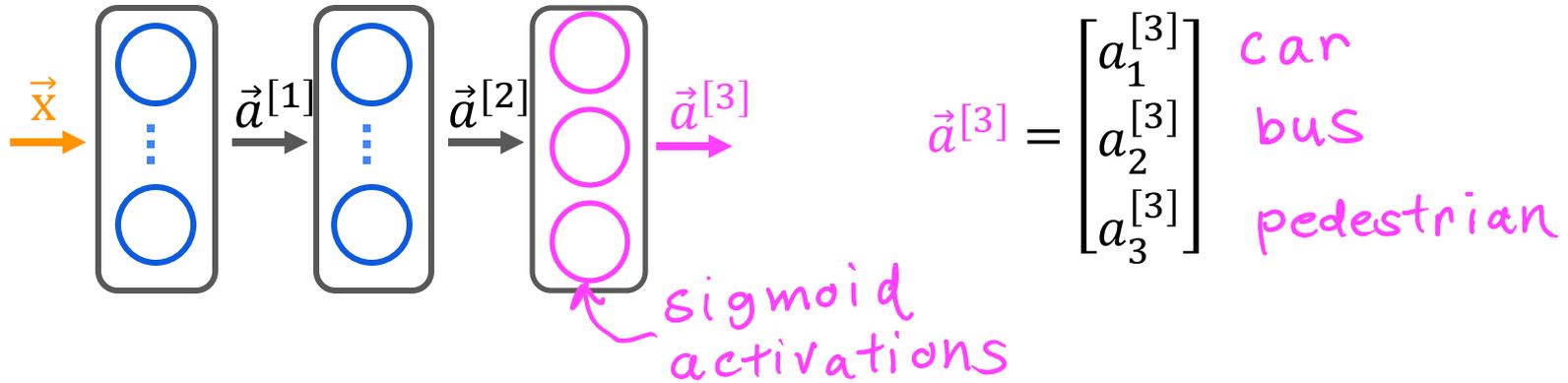
yes
yes
no

$$y = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

Multiple classes



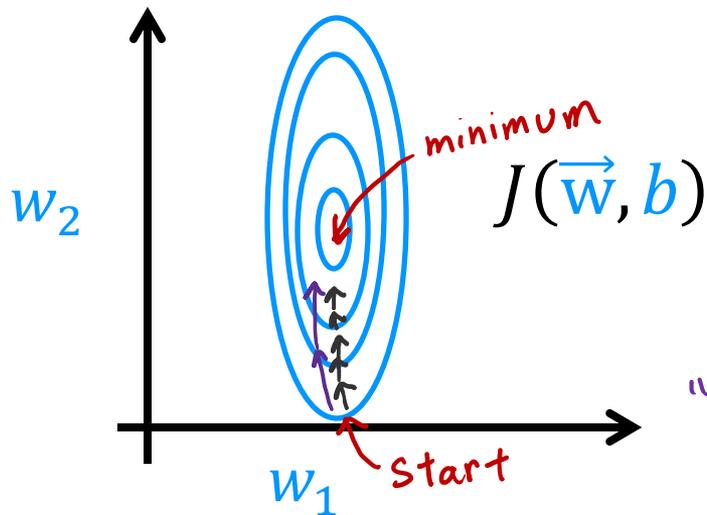
Alternatively, train one neural network with three outputs



Gradient Descent

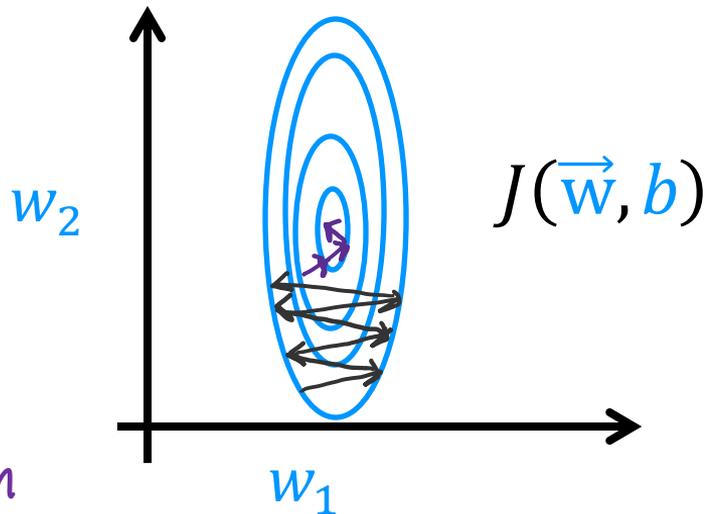
$$w_j = w_j - \alpha \frac{\partial}{\partial w_j} J(\vec{w}, b)$$

α learning rate



Go faster – increase α

"Adam" algorithm



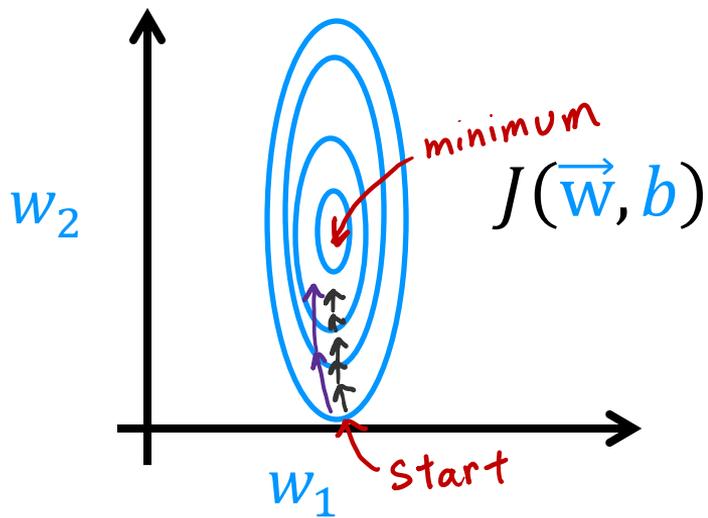
Go slower – decrease α

Adam Algorithm Intuition

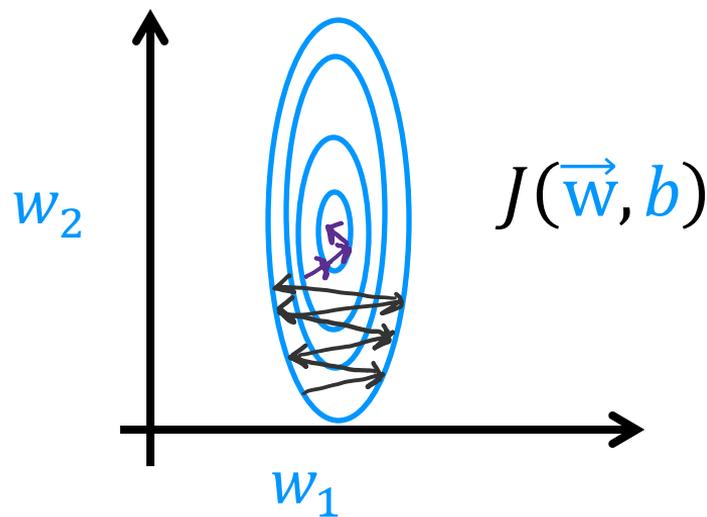
Adam: Adaptive Moment estimation *not just one α*

$$\begin{aligned}w_1 &= w_1 - \alpha_1 \frac{\partial}{\partial w_1} J(\vec{w}, b) \\&\vdots \\w_{10} &= w_{10} - \alpha_{10} \frac{\partial}{\partial w_{10}} J(\vec{w}, b) \\b &= b - \alpha_{11} \frac{\partial}{\partial b} J(\vec{w}, b)\end{aligned}$$

Adam Algorithm Intuition



If w_j (or b) keeps moving in same direction, increase α_j .



If w_j (or b) keeps oscillating, reduce α_j .

MNIST Adam

model

```
model = Sequential([
    tf.keras.layers.Dense(units=25, activation='sigmoid')
    tf.keras.layers.Dense(units=15, activation='sigmoid')
    tf.keras.layers.Dense(units=10, activation='linear')
])
```

compile

$$\alpha = 10^{-3} = 0.001$$

```
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=1e-3),
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True))
```

fit

```
model.fit(X, Y, epochs=100)
```