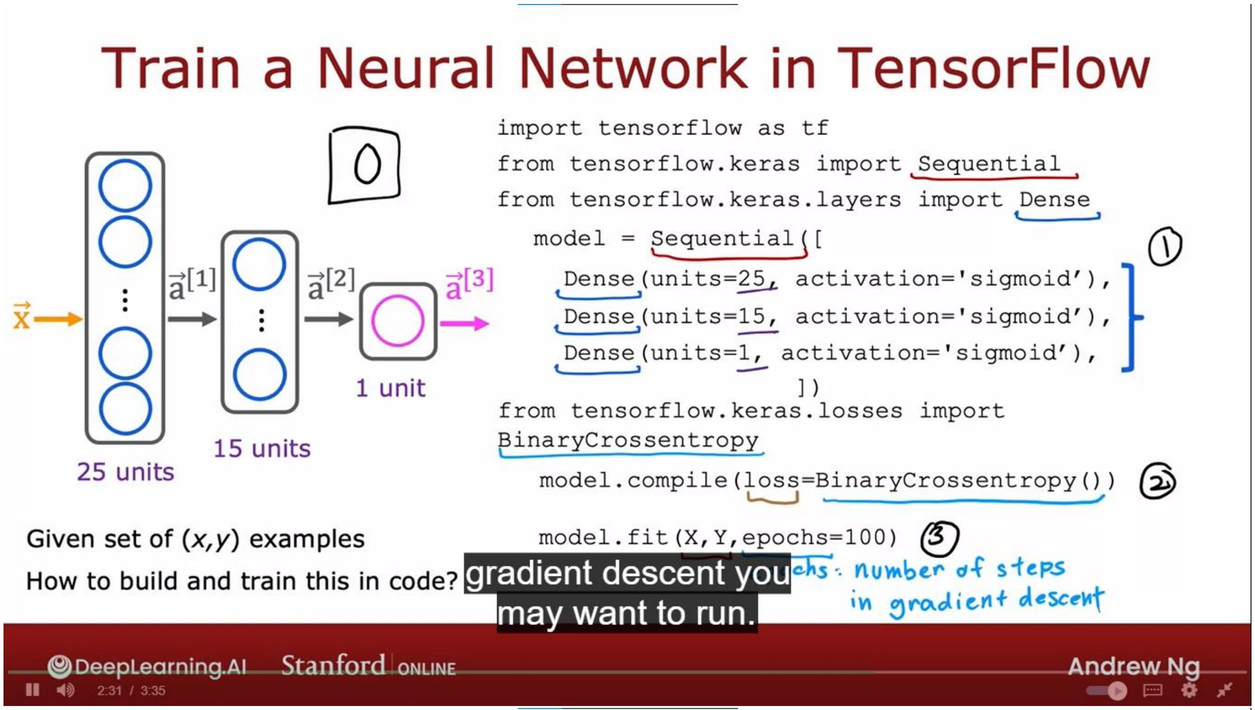
Train a Neural Network in TensorFlow
0
x
a[1]
a[2]
a[3]
25 units
15 units
1 unit
import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
model = Sequential([
Dense(units=25, activation='sigmoid'),
Dense(units=15, activation='sigmoid'),
Dense(units=1, activation='sigmoid'),
])
1
from tensorflow.keras.losses import
BinaryCrossentropy
model.compile(loss=BinaryCrossentropy())
2
model.fit(X,Y,epochs=100)
3
epochs: number of steps
in gradient descent
Given set of (x,y) examples
How to build and train this in code?
gradient descent you
may want to run.
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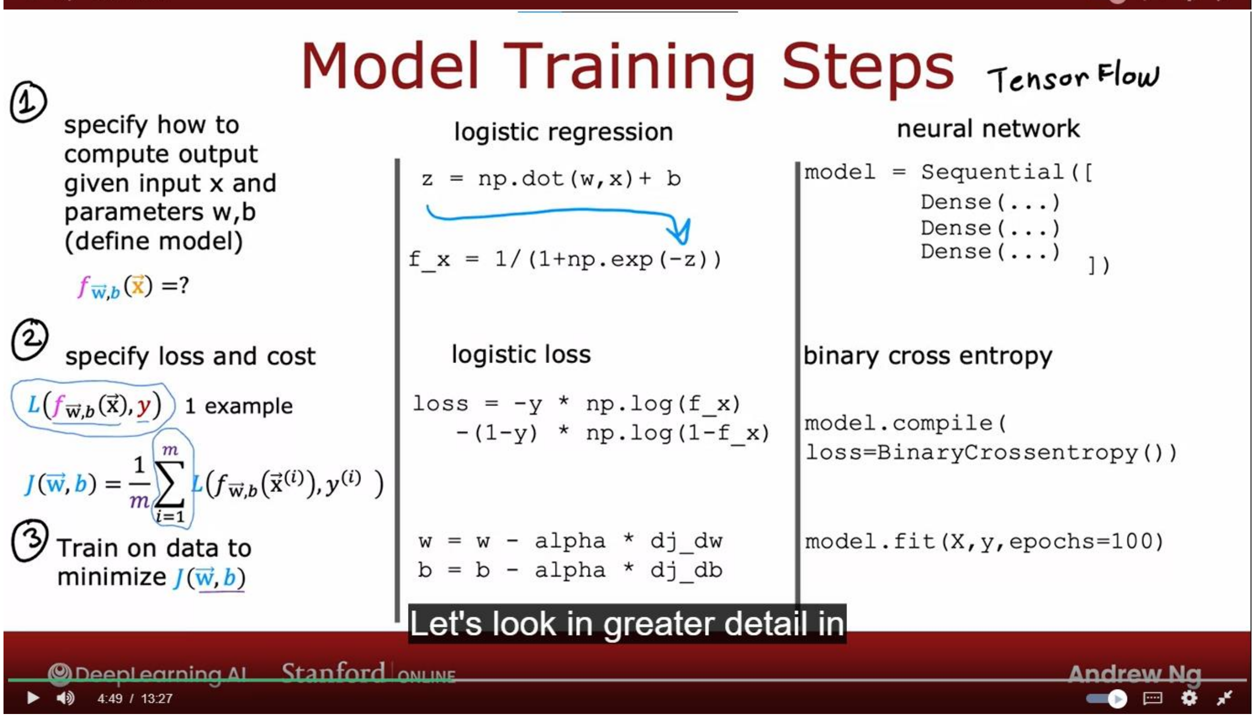
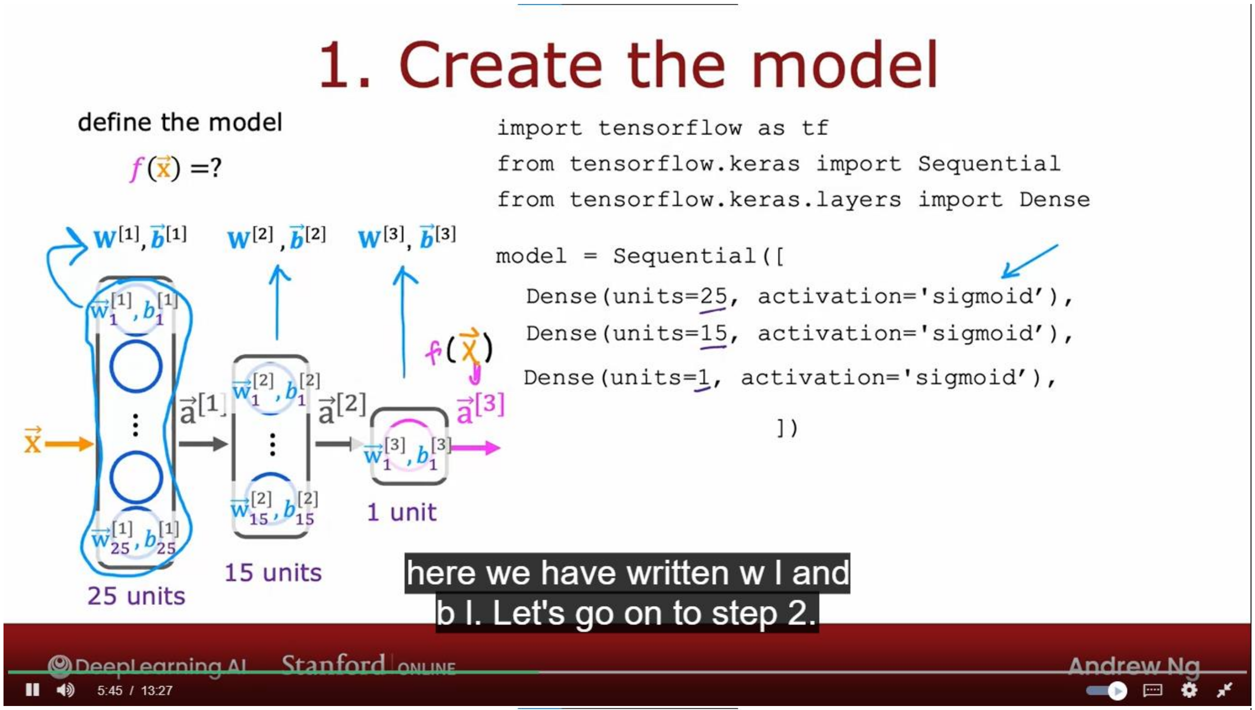
Stanford ONLINE
Andrew Ng
2:31 / 3:35


Model Training Steps
TensorFlow
1
specify how to
compute output
given input x and
parameters w,b
(define model)
f_w,b(x) =?
2
specify loss and cost
L(f_w,b(x), y) 1 example
J(w,b) = 1/m Σ_{i=1}^{m} L(f_w,b(x^(i)), y^(i))
3
Train on data to
minimize J(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)
Let's look in greater detail in
DeepLearning.AI
Stanford ONLINE
Andrew Ng
4:49 / 13:27


1. Create the model
define the model
f(x) =?
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'),
])
W[1], b[1]
W[2], b[2]
W[3], b[3]
f(x)
x
a[1]
a[2]
a[3]
25 units
15 units
1 unit
here we have written w l and
b l. Let's go on to step 2.
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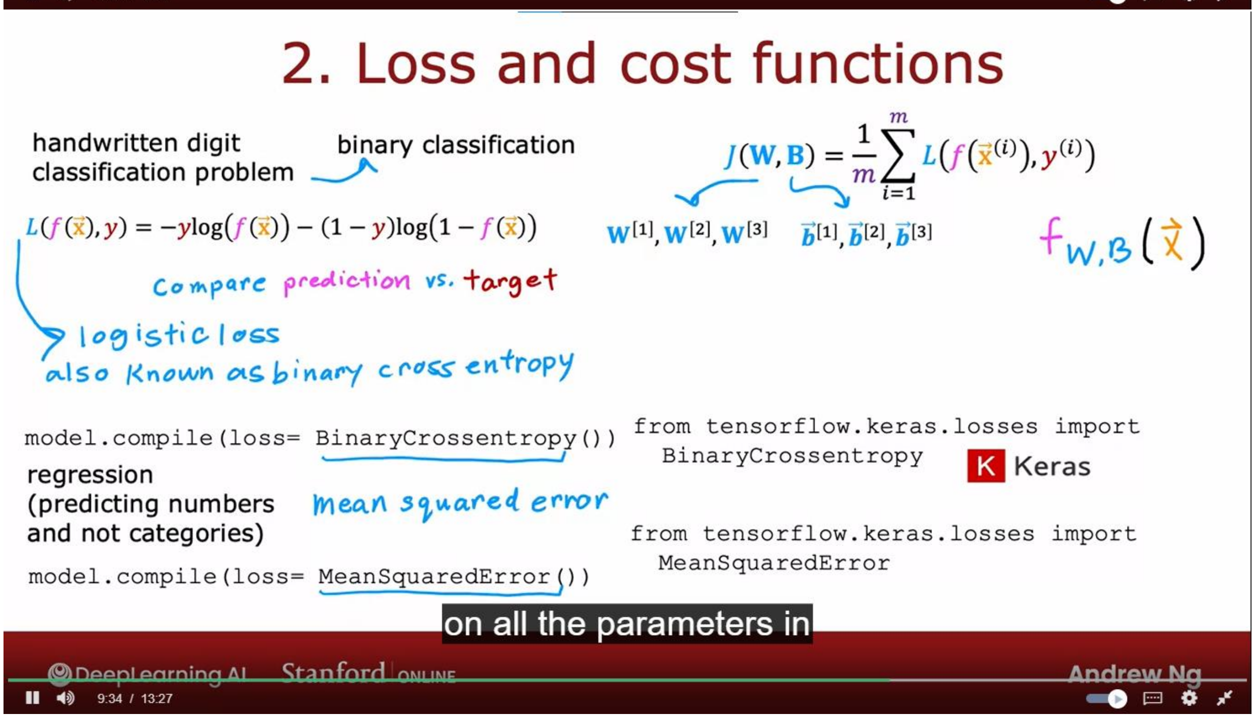
5:45 / 13:27


2. Loss and cost functions
handwritten digit
classification problem
binary classification
J(W,B) = 1/m Σ L(f(x(i)), y(i))
W[1], W[2], W[3]
b[1], b[2], b[3]
f W,B (x)
L(f(x),y) = −ylog(f(x)) − (1 − y)log(1 − f(x))
compare prediction vs. target
logistic loss
also known as binary cross entropy
model.compile(loss= BinaryCrossentropy())
from tensorflow.keras.losses import
BinaryCrossentropy
Keras
regression
(predicting numbers
and not categories)
mean squared error
from tensorflow.keras.losses import
MeanSquaredError
model.compile(loss= MeanSquaredError())
on all the parameters in
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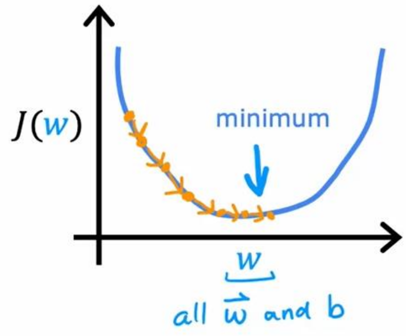
9:34 / 13:27

3. Gradient descent



repeat {

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

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

} Compute derivatives for gradient descent using "back propagation"

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

In fact, what you see later
is that TensorFlow can use

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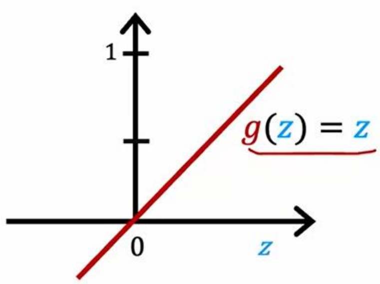
Examples of Activation Functions

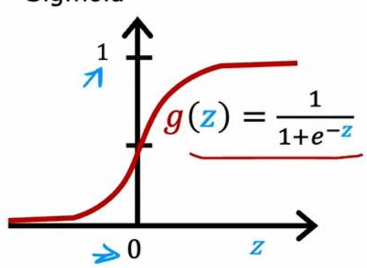
$$a_2^{[1]} = g(\overbrace{\vec{\mathrm{w}}_2^{[1]} \cdot \vec{\mathrm{x}} + b_2^{[1]}}^{z})$$

"No activation function" — Linear activation function



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

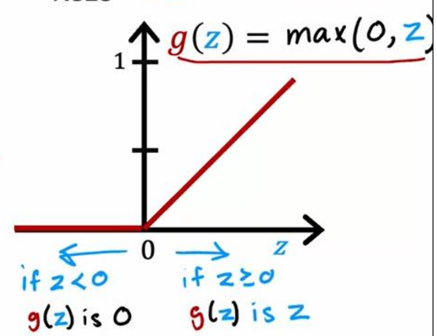
Sigmoid



$0 < g(z) < 1$

Later: softmax activation

ReLU Rectified Linear Unit



a rich variety of
powerful neural networks.

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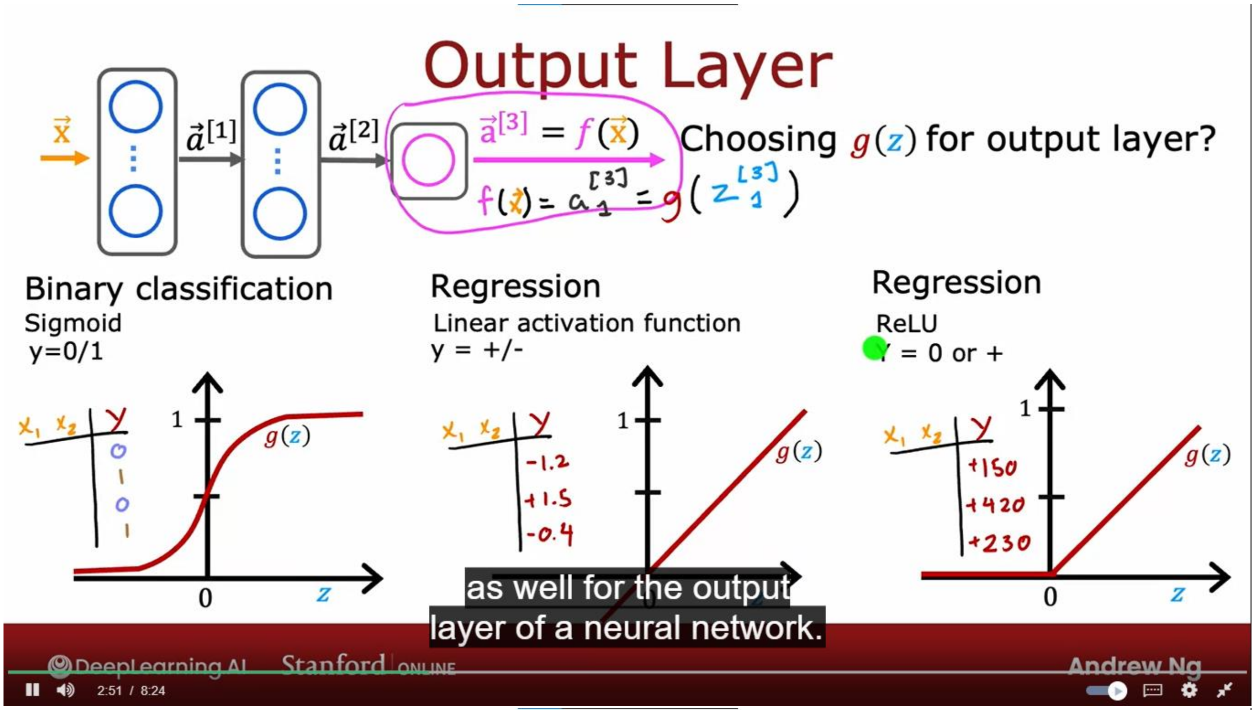
5:10 / 5:29


Output Layer
$\vec{x}$
$\vec{a}^{[1]}$
$\vec{a}^{[2]}$
$\vec{a}^{[3]} = f(\vec{x})$
$f(\vec{x}) = a_1^{[3]} = g(z_1^{[3]})$
Choosing $g(z)$ for output layer?
Binary classification
Sigmoid
y=0/1
Regression
Linear activation function
y = +/-
Regression
ReLU
y = 0 or +
x_1 x_2 y
0
1
0
1
-1.2
+1.5
-0.4
+150
+420
+230
$g(z)$
z
as well for the output
layer of a neural network.
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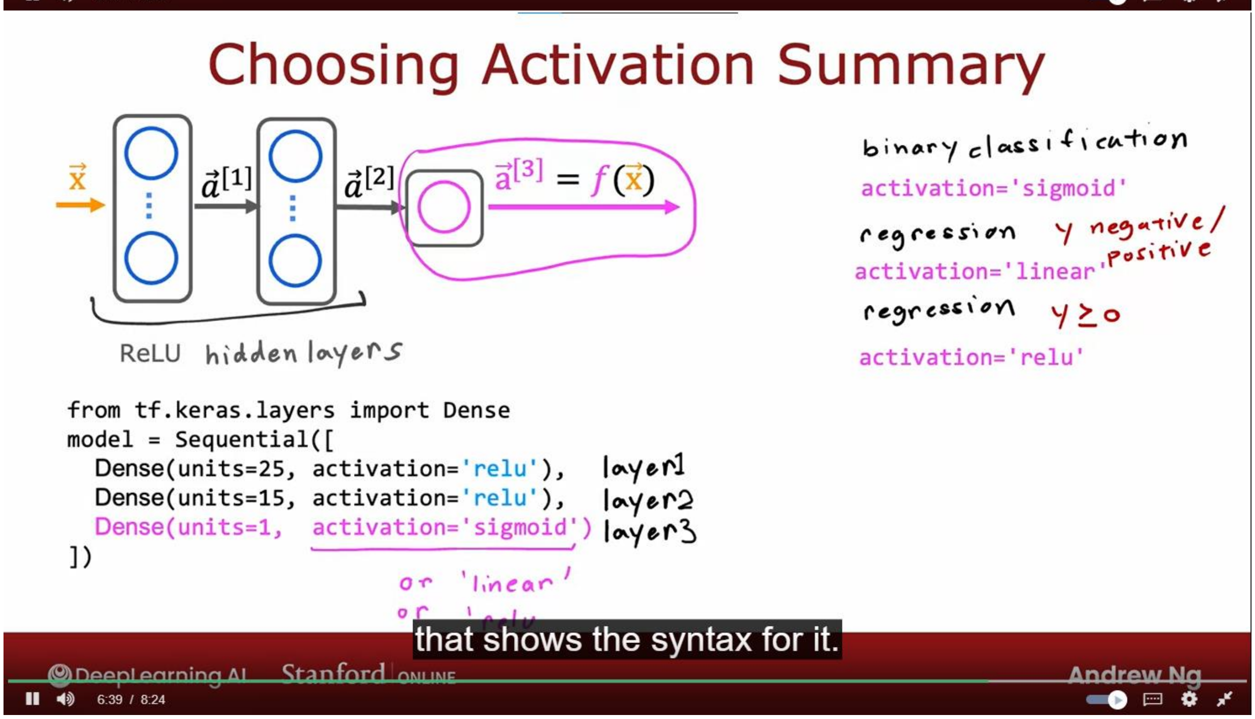
2:51 / 8:24


Choosing Activation Summary
$\vec{x}$
$\vec{a}^{[1]}$
$\vec{a}^{[2]}$
$\vec{a}^{[3]} = f(\vec{x})$
ReLU hidden layers
binary classification
activation='sigmoid'
regression y negative/positive
activation='linear'
regression y ≥ 0
activation='relu'
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'
that shows the syntax for it.
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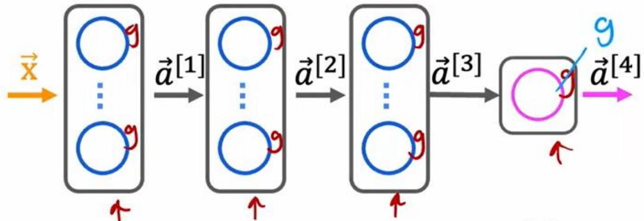
6:39 / 8:24

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

in the hidden layers
of the neural network.

Logistic regression
(2 possible output values)

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

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

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

Softmax regression
(N possible outputs) $y = 1, 2, 3, \ldots, N$

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

parameters $w_1, w_2, \ldots, w_N$
$b_1, b_2, \ldots, b_N$

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

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

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

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

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

× ○ □ △

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

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

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

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

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

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

thing as logistic regression.

Cost

Logistic regression

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

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

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

$\text{loss} = -y \underbrace{\log a_1}_{\text{if } y=1} - (1-y) \underbrace{\overbrace{\log(1 - a_1)}^{a_2}}_{\text{if } y=0}$

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

Softmax regression

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

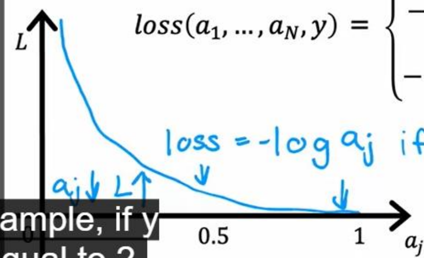
$\vdots$

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

Crossentropy loss

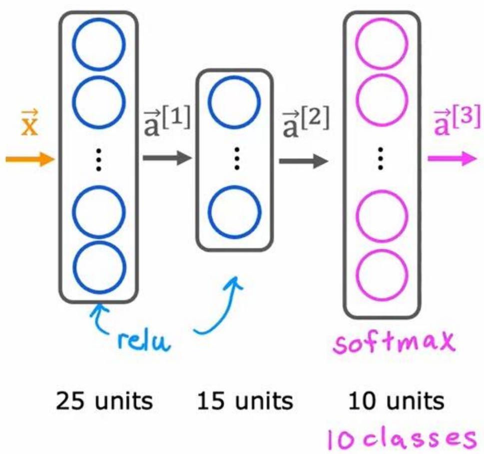
$$loss(a_1, \ldots, a_N, y) = \begin{cases} -\log a_1 & \text{if } y = 1 \\ -\log a_2 & \text{if } y = 2 \\ \vdots & \\ -\log a_N & \text{if } y = N \end{cases}$$

loss = $-\log a_j$ if $y = j$



For example, if y was equal to 2,

Neural Network with Softmax output



$z_1^{[3]} = \vec{w}_1^{[3]} \cdot \vec{a}^{[2]} + b_1^{[3]} \qquad a_1^{[3]} = \dfrac{e^{z_1^{[3]}}}{e^{z_1^{[3]}} + \cdots + e^{z_{10}^{[3]}}}$

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

$\vdots$

$z_{10}^{[3]} = \vec{w}_{10}^{[3]} \cdot \vec{a}^{[2]} + b_{10}^{[3]} \qquad a_{10}^{[3]} = \dfrac{e^{z_{10}^{[3]}}}{e^{z_1^{[3]}} + \cdots + e^{z_{10}^{[3]}}}$

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

logistic regression

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

softmax

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

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() )
```

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

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

you can train a neural network on
a multi class classification problem.

Numerical Roundoff Errors

More numerically accurate implementation of logistic loss:

$1 + \frac{1}{10{,}000}$ $\quad 1 - \frac{1}{10{,}000}$

Logistic regression:

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

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

'linear'

Original loss

$$loss = -y\log(a) - (1-y)\log(1-a)$$

```
model.compile(loss=BinaryCrossEntropy() )
model.compile(loss=BinaryCrossEntropy(from_logits=True) )
```

More accurate loss (in code)

$$loss = -y\log\left(\frac{1}{1+e^{-z}}\right) - (1-y)\log\left(1-\frac{1}{1+e^{-z}}\right)$$

logit: z

worse when it comes to softmax.

More numerically accurate implementation of softmax

Softmax regression

$$(a_1, \dots, a_{10}) = g(z_1, \dots, z_{10})$$

$$\text{Loss} = L(\vec{a}, y) = \begin{cases} -\log a_1 & \text{if } y = 1 \\ \vdots \\ -\log a_{10} & \text{if } y = 10 \end{cases}$$

```
model = Sequential([
  Dense(units=25, activation='relu'),
  Dense(units=15, activation='relu'),
  Dense(units=10, activation='softmax')
          ])
```

'linear'

~~model.compile(loss=SparseCategoricalCrossEntropy()~~)

More Accurate

$$L(\vec{a}, y) = \begin{cases} -\log \dfrac{e^{z_1}}{e^{z_1} + \cdots + e^{z_{10}}} & \text{if } y = 1 \\ \vdots \\ -\log \dfrac{e^{z_{10}}}{e^{z_1} + \cdots + e^{z_{10}}} & \text{if } y = 10 \end{cases}$$

```
model.compile(loss=SparseCategoricalCrossEntropy(from_logits=True))
```

and this whole computation of

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MNIST (more numerically accurate)

model

```
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='linear') ])
```

loss

```
from tensorflow.keras.losses import
  SparseCategoricalCrossentropy
model.compile(...,loss=SparseCategoricalCrossentropy(from_logits=True) )
```

fit

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

predict

```
logits = model(X)
```

← not $a_1 \dots a_{10}$
is $z_1 \dots z_{10}$

```
f_x = tf.nn.softma
```

It is instead of putting
z_1 through z_10.

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8:27 / 9:11

logistic regression (more numerically accurate)

model
```
model = Sequential([
  Dense(units=25, activation='sigmoid'),
  Dense(units=15, activation='sigmoid'),
  Dense(units=1, activation='linear')
                  ])
from tensorflow.keras.losses import
  BinaryCrossentropy
```

loss
```
model.compile(..., BinaryCrossentropy(from_logits=True))
```

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

fit
```
logit = model(X)
```
z

predict
```
f_x = tf.nn.sigmoid(logit)
```

to actually get the probability.

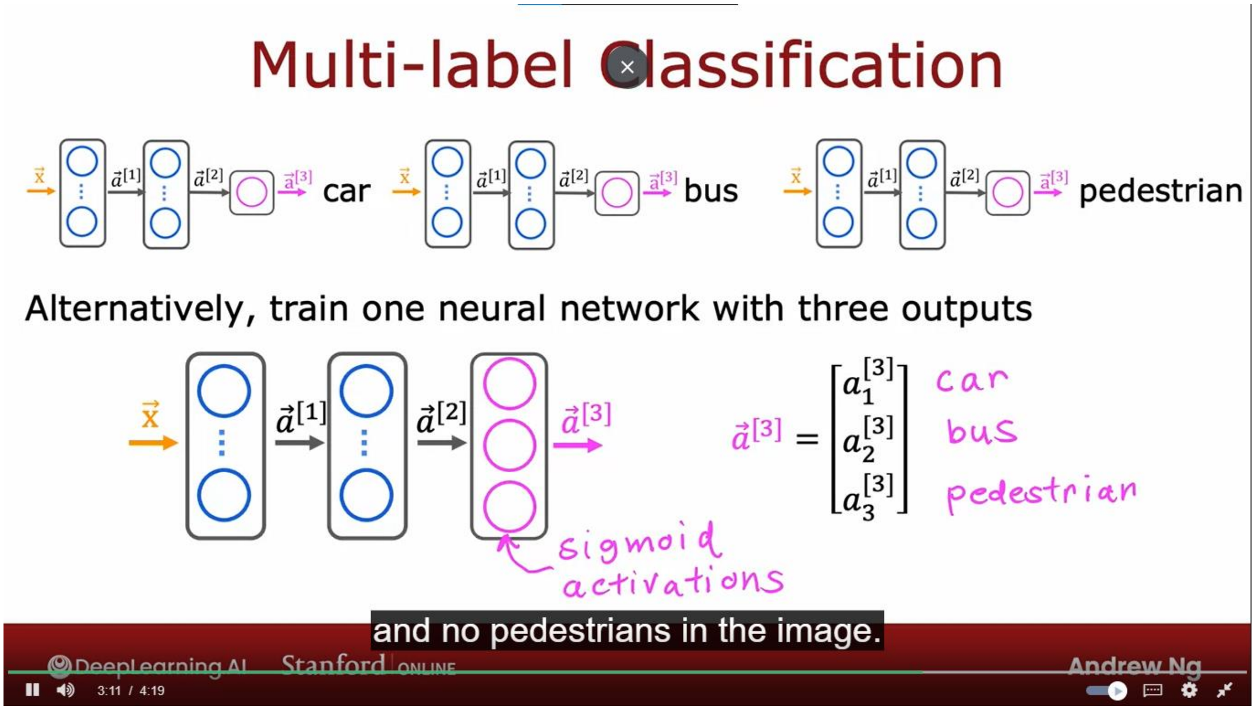
Multi-label Classification

$\vec{x}$

Is there a car?	yes	no	yes
Is there a bus?	no	no	yes
Is there a pedestrian	yes	yes	no

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

The second one to detect buses and


Multi-label Classification
car
bus
pedestrian
Alternatively, train one neural network with three outputs
$\vec{a}^{[3]} = \begin{bmatrix} a_1^{[3]} \\ a_2^{[3]} \\ a_3^{[3]} \end{bmatrix}$
car
bus
pedestrian
sigmoid activations
and no pedestrians in the image.
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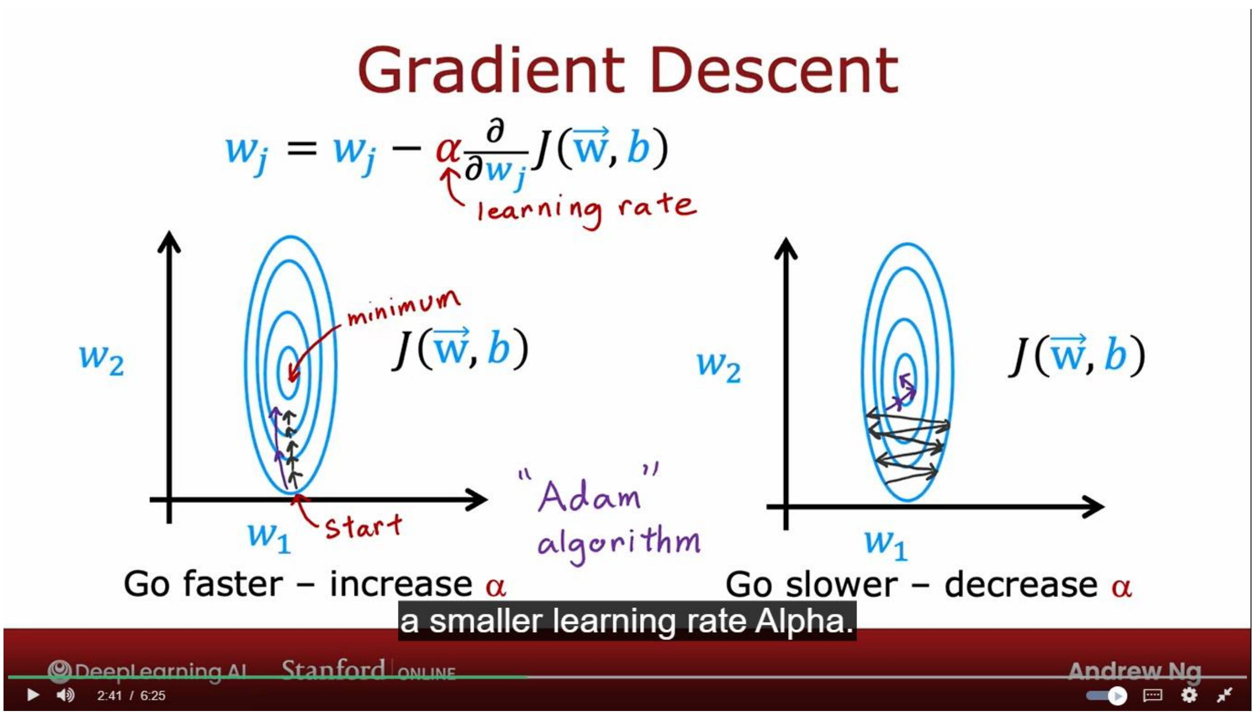
3:11 / 4:19


Gradient Descent
$w_j = w_j - \alpha \frac{\partial}{\partial w_j} J(\vec{w}, b)$
learning rate
minimum
$J(\vec{w}, b)$
w_2
w_1
start
"Adam" algorithm
Go faster – increase α
Go slower – decrease α
a smaller learning rate Alpha.
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2:41 / 6:25

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

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

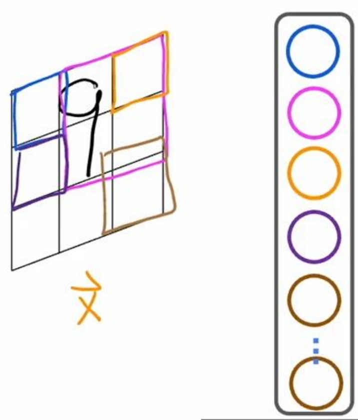
```
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=1e-3),
  loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True))
```

fit

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

see what gives you the
fastest learning performance.

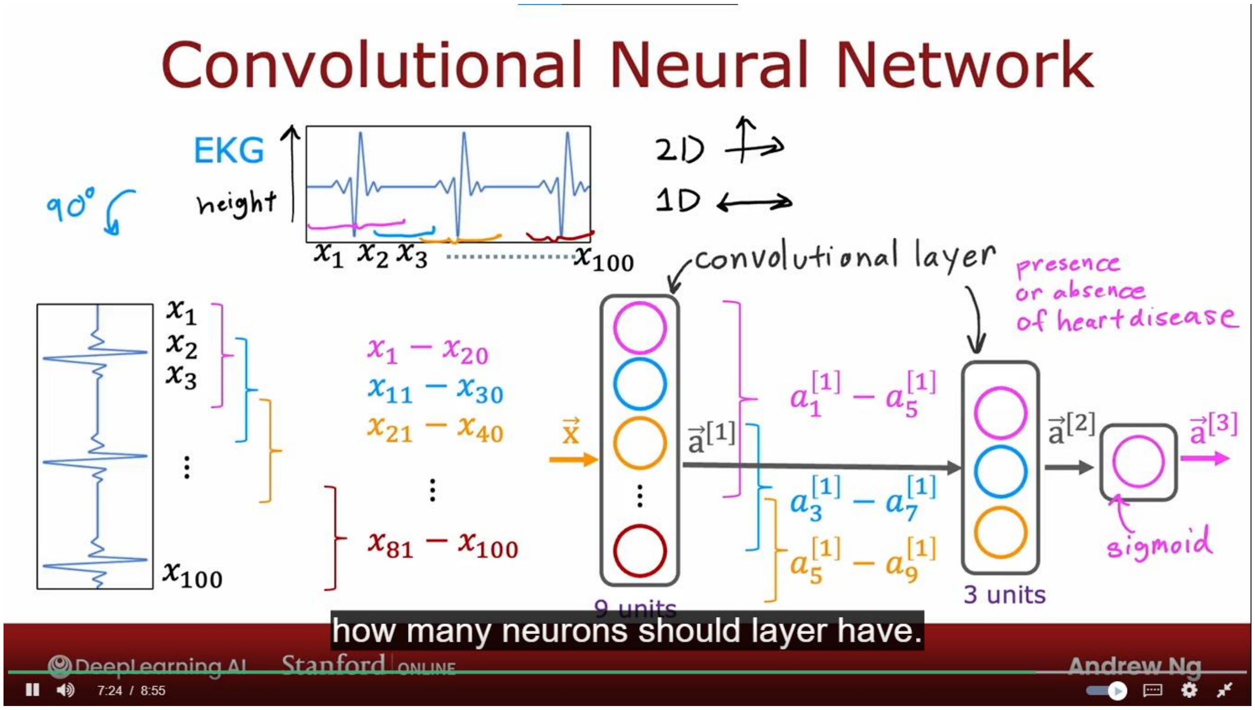
Convolutional Layer



Each neuron only looks at
part of the previous layer's outputs.

Why?
- Faster computation
- Need less training data
  (less prone to
  overfitting)

of how to get convolutional layers
to work and popularized their use.


Convolutional Neural Network
EKG
height
90°
2D
1D
x_1 x_2 x_3 .... x_{100}
x_1
x_2
x_3
x_{100}
$x_1 - x_{20}$
$x_{11} - x_{30}$
$x_{21} - x_{40}$
$x_{81} - x_{100}$
$\vec{x}$
convolutional layer
$\vec{a}^{[1]}$
$a_1^{[1]} - a_5^{[1]}$
$a_3^{[1]} - a_7^{[1]}$
$a_5^{[1]} - a_9^{[1]}$
9 units
3 units
$\vec{a}^{[2]}$
$\vec{a}^{[3]}$
presence or absence of heart disease
sigmoid
how many neurons should layer have.
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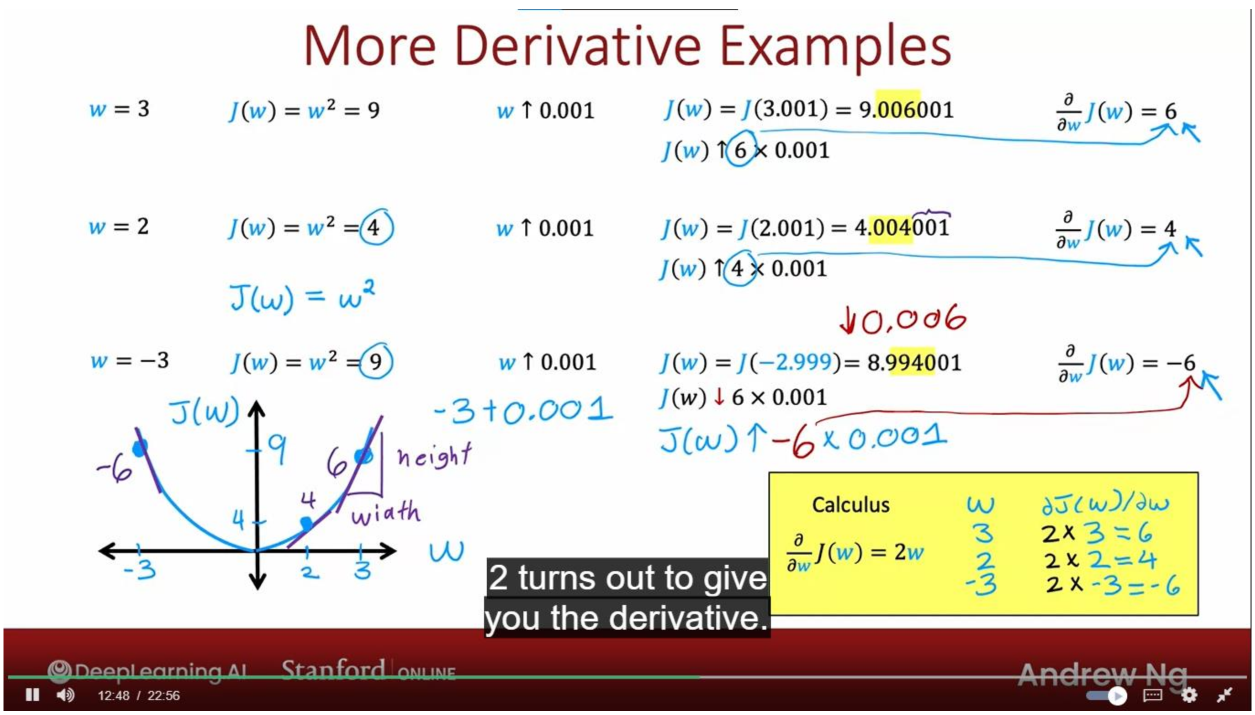
7:24 / 8:55


More Derivative Examples
$w = 3$
$J(w) = w^2 = 9$
$w \uparrow 0.001$
$J(w) = J(3.001) = 9.006001$
$J(w) \uparrow 6 \times 0.001$
$\frac{\partial}{\partial w} J(w) = 6$
$w = 2$
$J(w) = w^2 = 4$
$J(w) = w^2$
$w \uparrow 0.001$
$J(w) = J(2.001) = 4.004001$
$J(w) \uparrow 4 \times 0.001$
$\frac{\partial}{\partial w} J(w) = 4$
$\downarrow 0.006$
$w = -3$
$J(w) = w^2 = 9$
$w \uparrow 0.001$
$J(w) = J(-2.999) = 8.994001$
$J(w) \downarrow 6 \times 0.001$
$J(w) \uparrow -6 \times 0.001$
$\frac{\partial}{\partial w} J(w) = -6$
$-3 + 0.001$
J(w)
9
4
-6
6
height
width
w
-3
2
3
Calculus
$\frac{\partial}{\partial w} J(w) = 2w$
w
$\partial J(w)/\partial w$
3 2 x 3 = 6
2 2 x 2 = 4
-3 2 x -3 = -6
2 turns out to give you the derivative.
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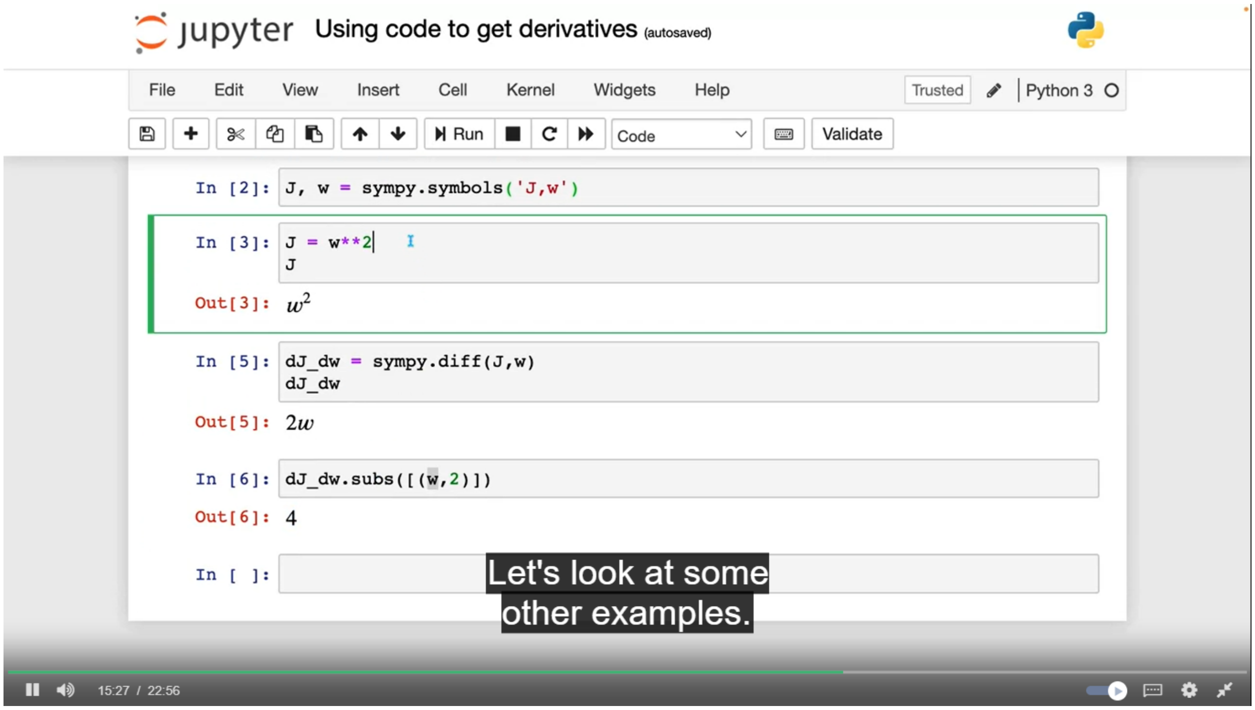
12:48 / 22:56


jupyter Using code to get derivatives (autosaved)
File Edit View Insert Cell Kernel Widgets Help
Trusted
Python 3
Run
Code
Validate
In [2]: J, w = sympy.symbols('J,w')
In [3]: J = w**2
J
Out[3]: w^2
In [5]: dJ_dw = sympy.diff(J,w)
dJ_dw
Out[5]: 2w
In [6]: dJ_dw.subs([(w,2)])
Out[6]: 4
In [ ]:
Let's look at some
other examples.
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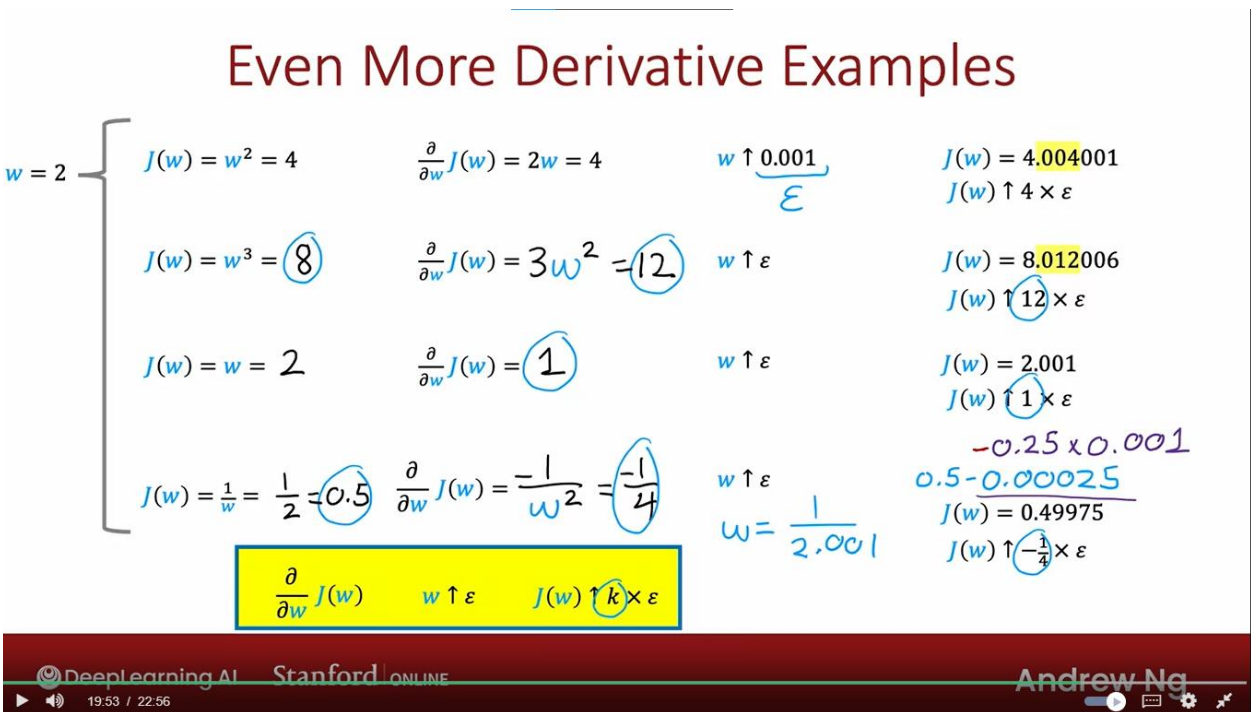
Even More Derivative Examples
w = 2
J(w) = w² = 4
∂/∂w J(w) = 2w = 4
w ↑ 0.001
ε
J(w) = 4.004001
J(w) ↑ 4 × ε
J(w) = w³ = 8
∂/∂w J(w) = 3w² = 12
w ↑ ε
J(w) = 8.012006
J(w) ↑ 12 × ε
J(w) = w = 2
∂/∂w J(w) = 1
w ↑ ε
J(w) = 2.001
J(w) ↑ 1 × ε
-0.25 x 0.001
0.5 - 0.00025
J(w) = 1/w = 1/2 = 0.5
∂/∂w J(w) = -1/w² = -1/4
w ↑ ε
w = 1/2.001
J(w) = 0.49975
J(w) ↑ -1/4 × ε
∂/∂w J(w)   w ↑ ε   J(w) ↑ k × ε
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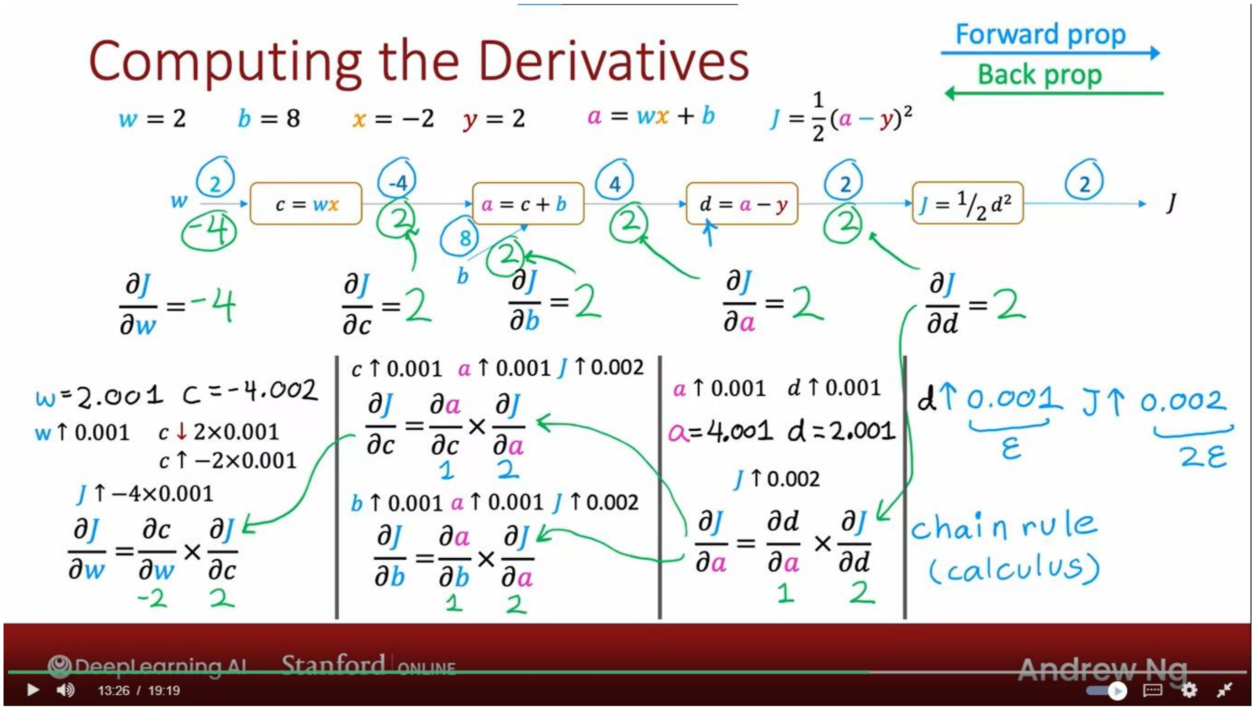
Computing the Derivatives
Forward prop
Back prop
w = 2   b = 8   x = −2   y = 2   a = wx + b   J = 1/2 (a − y)²
c = wx
a = c + b
d = a − y
J = ½ d²
w 2 −4 ; −4 2 ; 8 b 2 ; 4 2 ; 2 2 ; 2 J
∂J/∂w = −4   ∂J/∂c = 2   ∂J/∂b = 2   ∂J/∂a = 2   ∂J/∂d = 2
w=2.001 c=−4.002
w ↑ 0.001   c ↓ 2×0.001
c ↑ −2×0.001
J ↑ −4×0.001
∂J/∂w = ∂c/∂w × ∂J/∂c
−2 2
c ↑ 0.001 a ↑ 0.001 J ↑ 0.002
∂J/∂c = ∂a/∂c × ∂J/∂a
1 2
b ↑ 0.001 a ↑ 0.001 J ↑ 0.002
∂J/∂b = ∂a/∂b × ∂J/∂a
1 2
a ↑ 0.001 d ↑ 0.001
a=4.001 d=2.001
J ↑ 0.002
∂J/∂a = ∂d/∂a × ∂J/∂d
1 2
d↑ 0.001 J↑ 0.002
ε 2ε
chain rule
(calculus)
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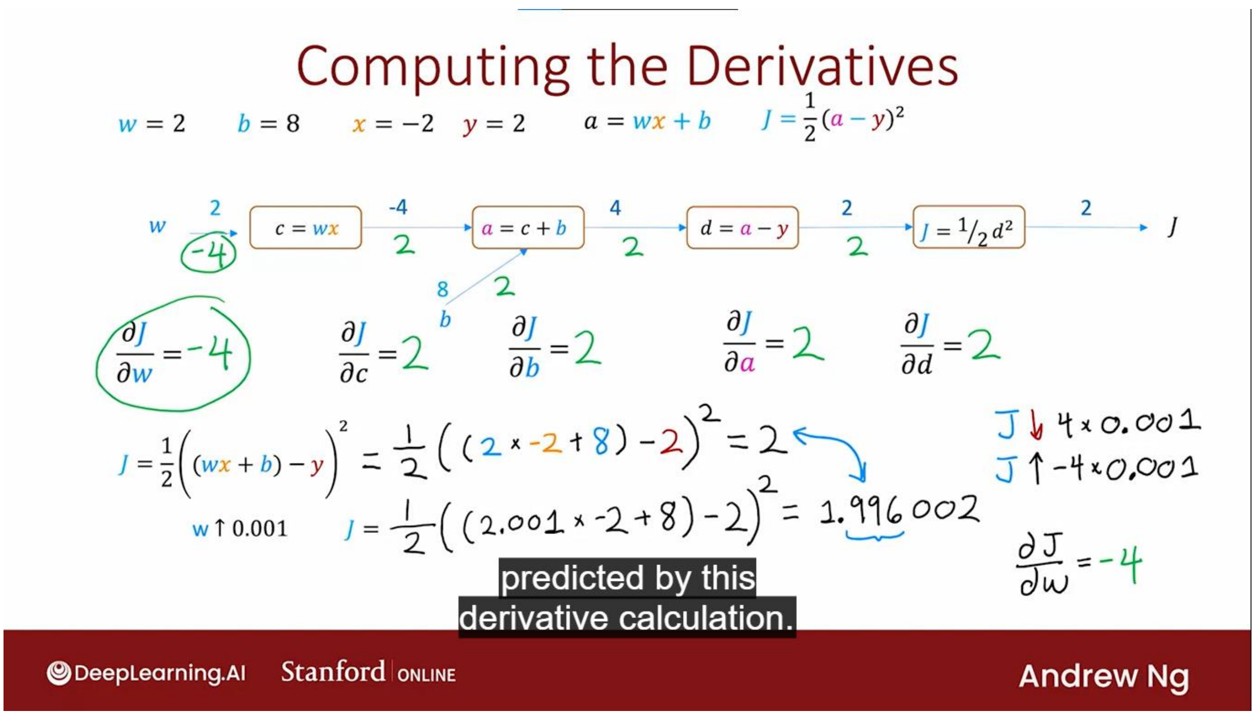
Computing the Derivatives
w = 2   b = 8   x = −2   y = 2   a = wx + b   J = 1/2 (a − y)²
c = wx
a = c + b
d = a − y
J = ½ d²
w 2 −4 ; −4 2 ; 8 b 2 ; 4 2 ; 2 2 ; 2 J
∂J/∂w = −4   ∂J/∂c = 2   ∂J/∂b = 2   ∂J/∂a = 2   ∂J/∂d = 2
J = 1/2 ((wx + b) − y)² = 1/2 ((2 × −2 + 8) − 2)² = 2
w ↑ 0.001   J = 1/2 ((2.001 × −2 + 8) − 2)² = 1.996002
J ↓ 4 × 0.001
J ↑ −4 × 0.001
∂J/∂w = −4
predicted by this
derivative calculation.
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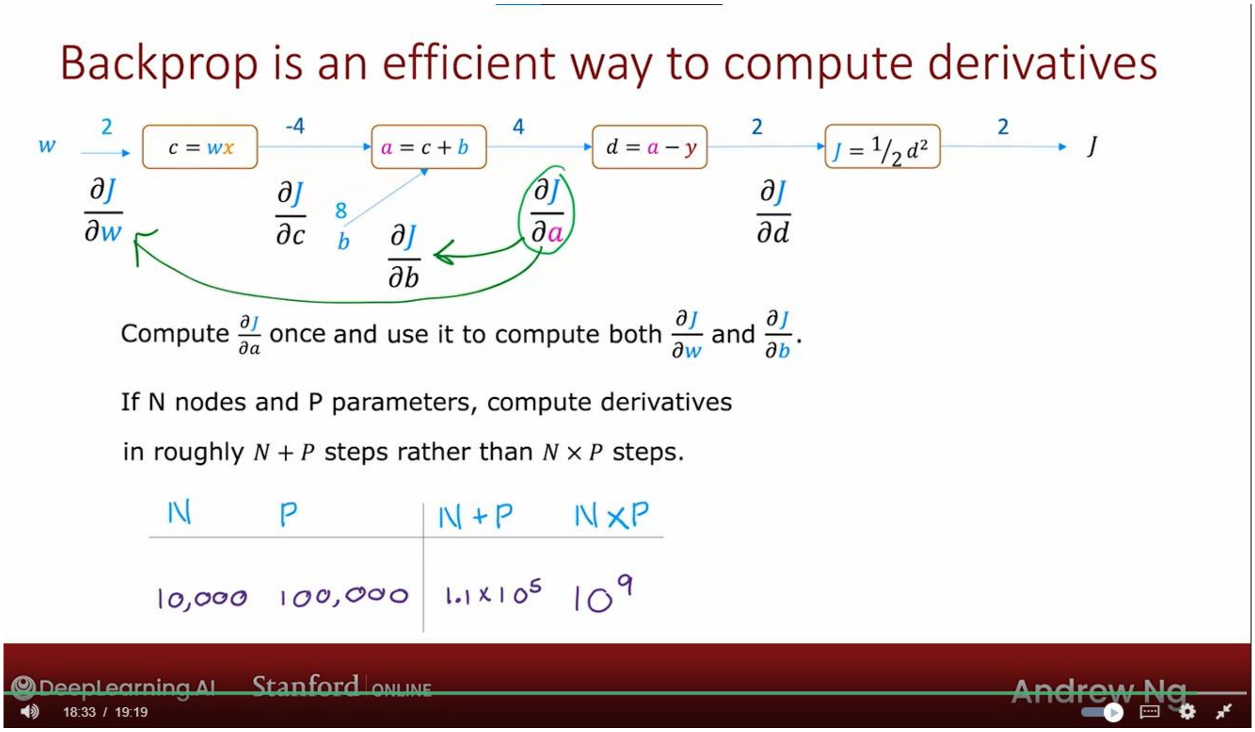
Backprop is an efficient way to compute derivatives
w 2 c = wx -4 a = c + b 4 d = a − y 2 J = 1/2 d² 2 J
8 b
∂J/∂w ∂J/∂c ∂J/∂b ∂J/∂a ∂J/∂d
Compute ∂J/∂a once and use it to compute both ∂J/∂w and ∂J/∂b.
If N nodes and P parameters, compute derivatives
in roughly N + P steps rather than N × P steps.
N P N+P N×P
10,000 100,000 1.1×10⁵ 10⁹
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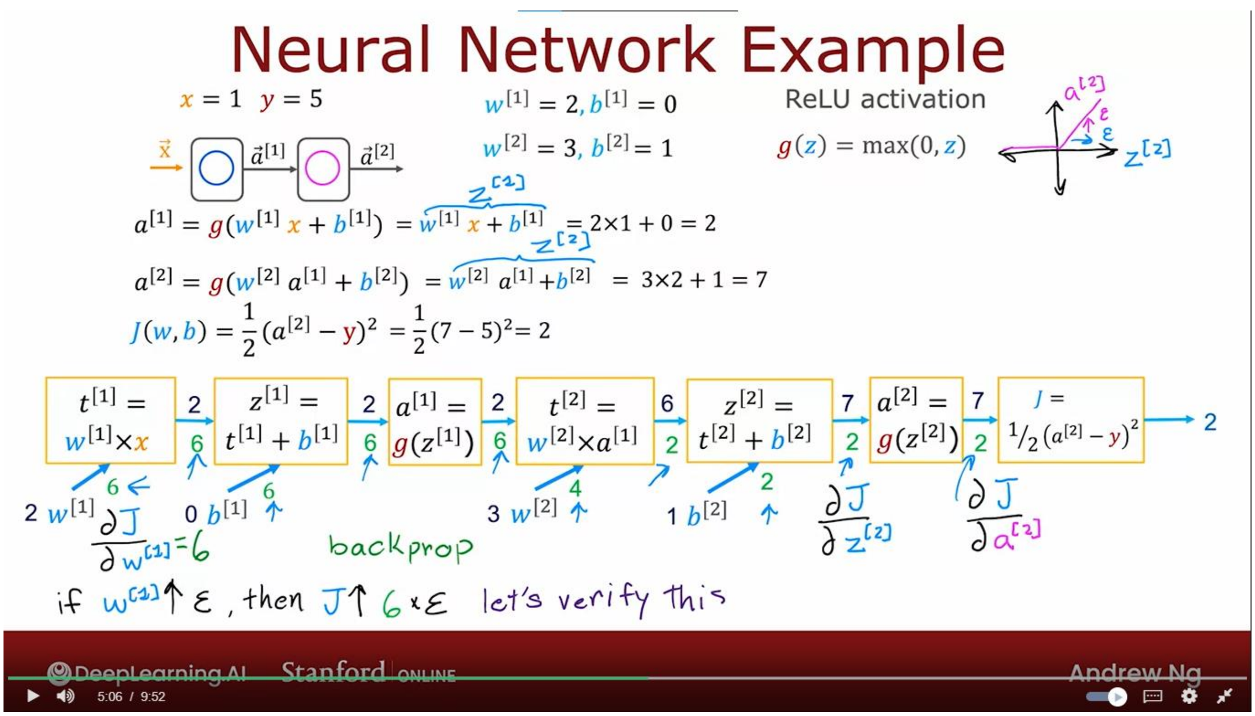
Neural Network Example
x = 1 y = 5
w[1] = 2, b[1] = 0
w[2] = 3, b[2] = 1
ReLU activation
g(z) = max(0, z)
a[2] ε z[2]
x a[1] a[2]
a[1] = g(w[1] x + b[1]) = w[1] x + b[1] = 2×1 + 0 = 2
z[1]
a[2] = g(w[2] a[1] + b[2]) = w[2] a[1] + b[2] = 3×2 + 1 = 7
z[2]
J(w, b) = 1/2 (a[2] − y)² = 1/2 (7 − 5)² = 2
t[1] = w[1]×x 2 6
z[1] = t[1] + b[1] 2 6
a[1] = g(z[1]) 2 6
t[2] = w[2]×a[1] 6 2
z[2] = t[2] + b[2] 7 2
a[2] = g(z[2]) 7 2
J = 1/2 (a[2] − y)² 2
2 w[1] 6 ∂J/∂w[1] = 6
0 b[1] 6
3 w[2] 4
1 b[2] 2
∂J/∂z[2] ∂J/∂a[2]
backprop
if w[1] ↑ ε, then J ↑ 6×ε let's verify this
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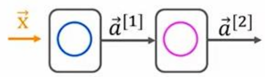
Neural Network Example

$x = 1$ $y = 5$ $w^{[1]} = 2, b^{[1]} = 0$ ReLU activation



$w^{[2]} = 3, b^{[2]} = 1$ $g(z) = \max(0, z)$

$$a^{[1]} = g(w^{[1]}x + b^{[1]}) = w^{[1]}x + b^{[1]} = \cancel{2}^{\,2.001}\times 1 + 0 = \cancel{2}\ 2.001$$

$$a^{[2]} = g(w^{[2]}a^{[1]} + b^{[2]}) = w^{[2]}a^{[1]} + b^{[2]} = 3\times\cancel{2}^{\,2.001} + 1 = \cancel{7}\ 7.003$$

$$J(w,b) = \frac{1}{2}(a^{[2]} - y)^2 = \frac{1}{2}(\cancel{7}^{\,7.003} - 5)^2 = \cancel{2}\quad 2\boxed{.006}005$$

$$\frac{(2.003)^2}{2}$$

$w^{[1]} \uparrow 0.001$

$J \uparrow 6 \times 0.001$

$$\frac{\partial J}{\partial w^{[1]}} = 6$$

$$\frac{\partial J}{\partial w^{[1]}} \quad \frac{\partial J}{\partial b^{[1]}}$$

$$\frac{\partial J}{\partial w^{[2]}} \quad \frac{\partial J}{\partial b^{[2]}}$$

N nodes □→□→□

P parameters

$w_1, b_1, w_2, b_2 \ldots$

inefficient way

$N \times P$

efficient way (backprop)

$N + P$