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Basics of Neural Network Programming

Binary Classification

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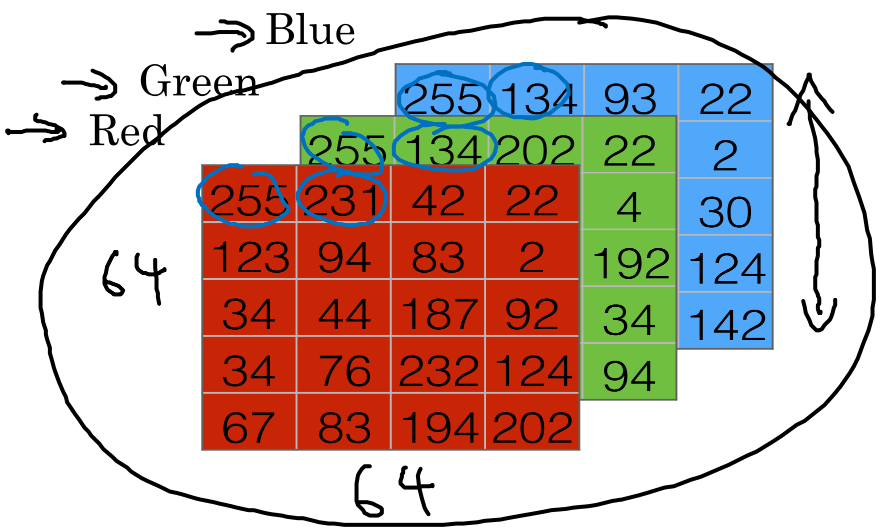
Binary Classification

64

64

$\rightarrow$ 1 (cat) vs 0 (non cat)

y



$$x = \begin{bmatrix} 255 \\ 231 \\ \vdots \\ \vdots \\ 255 \\ 134 \\ \vdots \end{bmatrix}$$

$64 \times 64 \times 3 = 12288$

$n = n_x = 12288$

$x \longrightarrow y$

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Notation

$(x, y) \qquad x \in \mathbb{R}^{n_x}, \; y \in \{0, 1\}$

m training examples : $\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(m)}, y^{(m)})\}$

$M = M_{train} \qquad M_{test} = \#\text{test examples.}$

$$X = \underbrace{\begin{bmatrix} | & | & & | \\ x^{(1)} & x^{(2)} & \ldots & x^{(m)} \\ | & | & & | \end{bmatrix}}_{m} \Bigg\updownarrow n_x \qquad \cancel{\begin{bmatrix} - & x^{(1)T} & - \\ & \vdots & \\ - & x^{(m)T} & - \end{bmatrix}}$$

$X \in \mathbb{R}^{n_x \times m} \qquad X.\text{shape} = (n_x, m)$

$Y = [y^{(1)} \; y^{(2)} \; \ldots, y^{(m)}]$

$Y \in \mathbb{R}^{1 \times m}$

$Y.\text{shape} = (1, m)$

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Basics of Neural Network Programming

Logistic Regression

Logistic Regression

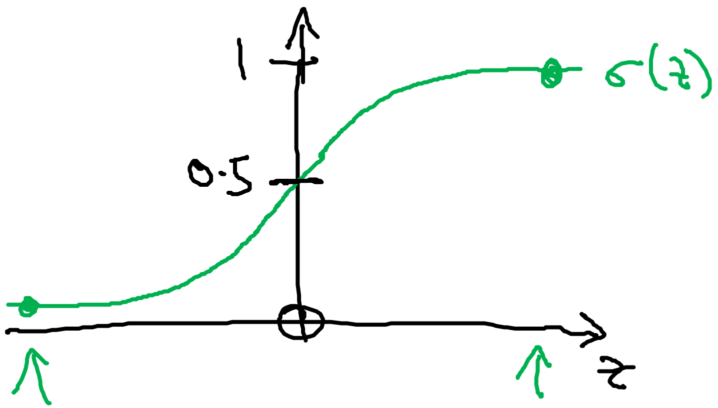
Given x, want $\hat{y} = P(y=1 \mid x)$

$0 \le \hat{y} \le 1$

$x \in \mathbb{R}^{n_x}$

Parameters: $\boxed{w} \in \mathbb{R}^{n_x}$, $\boxed{b} \in \mathbb{R}$.

Output $\hat{y} = \sigma(\underbrace{w^T x + b}_{z})$



$x_0 = 1$, $x \in \mathbb{R}^{n_x+1}$

$\hat{y} = \sigma(\theta^T x)$

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \vdots \\ \theta_{n_x} \end{bmatrix} \begin{array}{l} \} \; b \leftarrow \\ \left.\begin{array}{l} \\ \\ \\ \\ \end{array}\right\} w \leftarrow \end{array}$$

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

If z large $\sigma(z) \approx \frac{1}{1+0} = 1$

If z large negative number

$$\sigma(z) = \frac{1}{1+e^{-z}} \approx \frac{1}{1+\text{Bignum}} \approx 0$$

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Logistic Regression cost function

Logistic Regression cost function

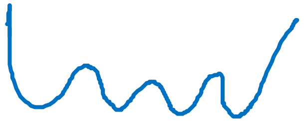
$\rightarrow \hat{y}^{(i)} = \sigma(w^T x^{(i)} + b)$, where $\sigma(z^{(i)}) = \frac{1}{1+e^{-z^{(i)}}}$

$z^{(i)} = w^T x^{(i)} + b$

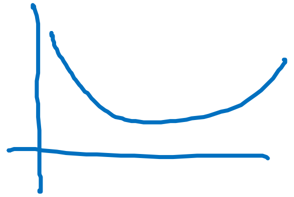
Given $\{(x^{(1)}, y^{(1)}), \ldots, (x^{(m)}, y^{(m)})\}$, want $\hat{y}^{(i)} \approx y^{(i)}$.

$x^{(i)}$ $y^{(i)}$ $z^{(i)}$ i-th example.

$\boxed{\text{Loss}}$ (error) function: $\mathcal{L}(\hat{y}, y) = \frac{1}{2}(\hat{y} - y)^2$



$$\boxed{\mathcal{L}(\hat{y}, y)} = -\left(\boxed{y \log \hat{y}} + (1-y)\log(1-\hat{y})\right) \leftarrow$$



If $y=1$: $\mathcal{L}(\hat{y}, y) = -\log \hat{y} \leftarrow$ Want $\log \hat{y}$ large, want $\hat{y}$ large.

If $y=0$: $\mathcal{L}(\hat{y}, y) = -\log(1-\hat{y}) \leftarrow$ Want $\log 1-\hat{y}$ large .... want $\hat{y}$ small

$\boxed{\text{Cost}}$ function: $J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\log \hat{y}^{(i)} + (1-y^{(i)})\log(1-\hat{y}^{(i)})\right]$

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Basics of Neural Network Programming

Gradient Descent

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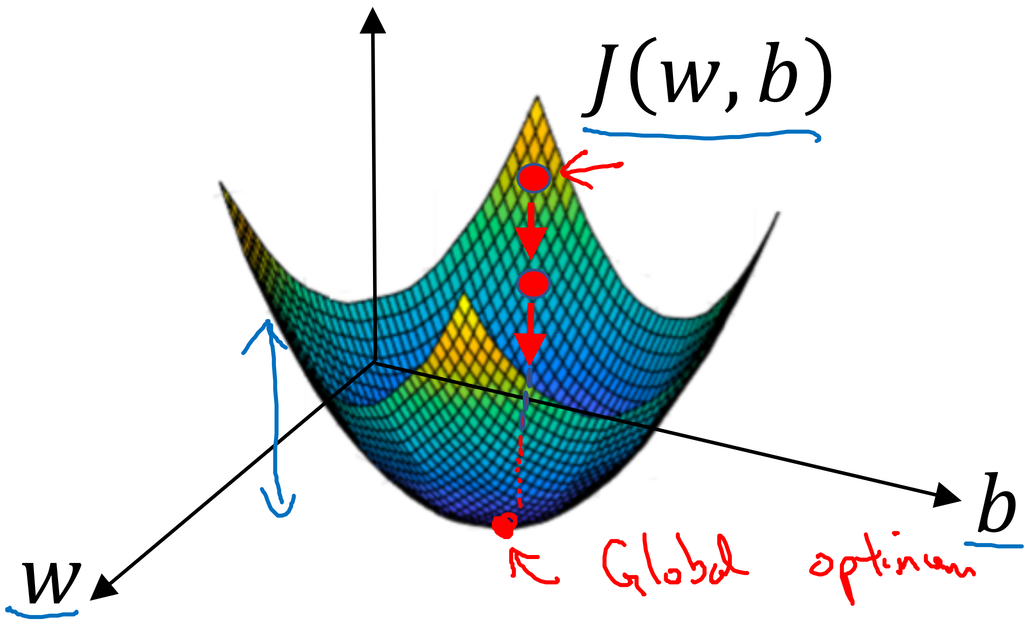
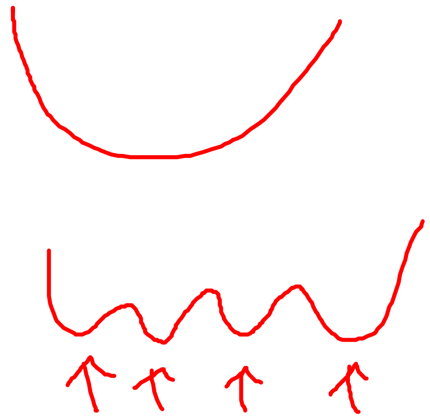
Gradient Descent

Recap: $\hat{y} = \sigma(w^T x + b), \ \sigma(z) = \frac{1}{1+e^{-z}}$

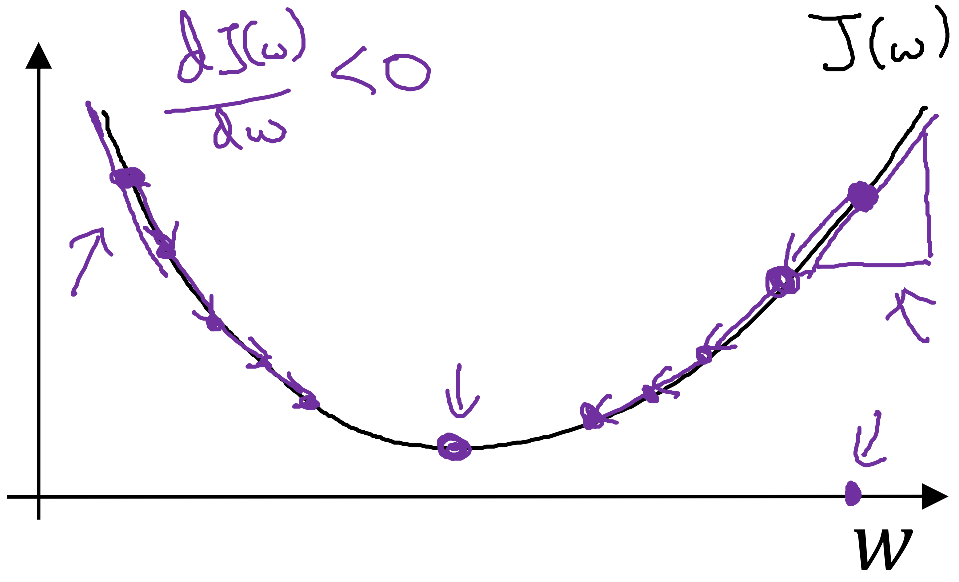
$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\boxed{\hat{y}^{(i)}}, \boxed{y^{(i)}}) = -\frac{1}{m}\sum_{i=1}^{m} y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)})$$

Want to find w, b that minimize $J(w,b)$





Gradient Descent



learning rate

Repeat {

$$w := w - \alpha \boxed{\frac{dJ(w)}{dw}}$$

}

"dw"

$$w := w - \alpha \, dw$$

$$\frac{dJ(w)}{dw} = ?$$

$J(w,b)$

$$w := w - \alpha \boxed{\frac{dJ(w,b)}{dw}} \quad \boxed{\frac{\partial J(w,b)}{\partial w}} \rightarrow dw$$

$$b := b - \alpha \boxed{\frac{dJ(w,b)}{db}} \quad \boxed{\frac{\partial J(w,b)}{\partial b}} \rightarrow db$$

∂ "partial derivative"

d J

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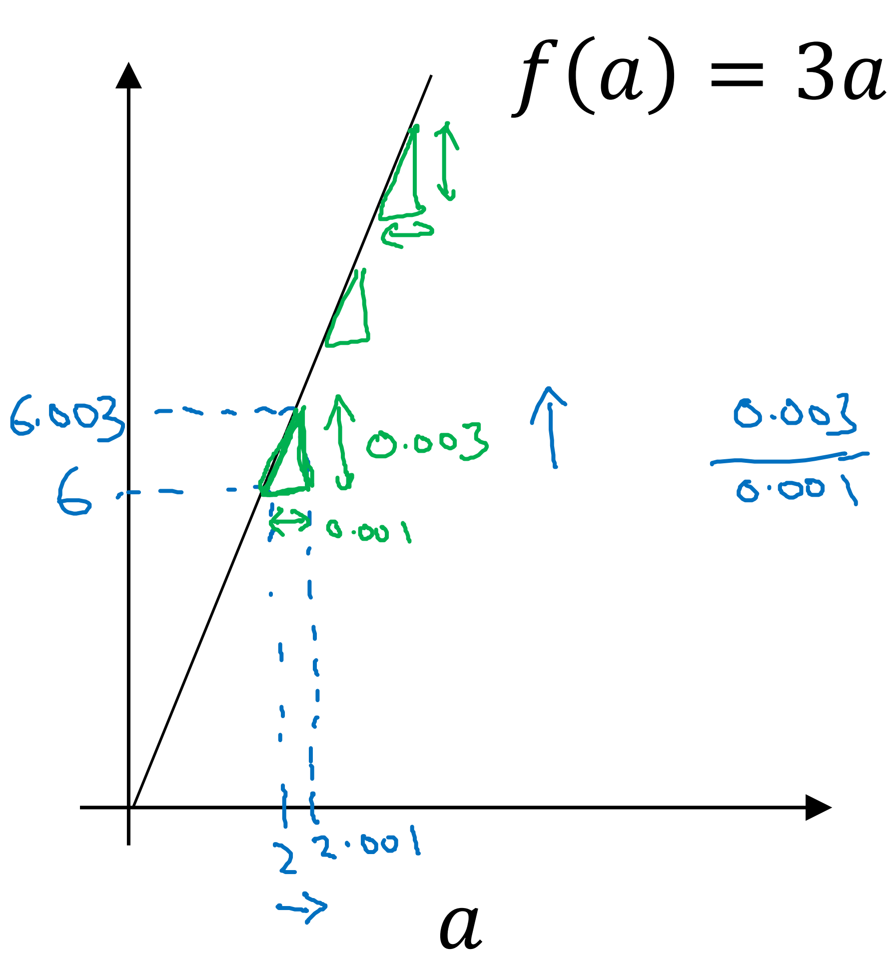
Derivatives

Intuition about derivatives



$\frac{0.003}{0.001}$ $\frac{\text{height}}{\text{width}}$

$a = 2$ $f(a) = 6$

$a = 2.001$ $f(a) = 6.003$

slope (derivative) of $f(a)$ at $a=2$ is 3

$a=5$ $f(a)=15$

$a = 5.001$ $f(a) = 15.003$

slope at $a=5$ is also 3

$$\frac{d f(a)}{da} = 3 = \frac{d}{da} f(a)$$

0.001
0.00000001
0.000000000001

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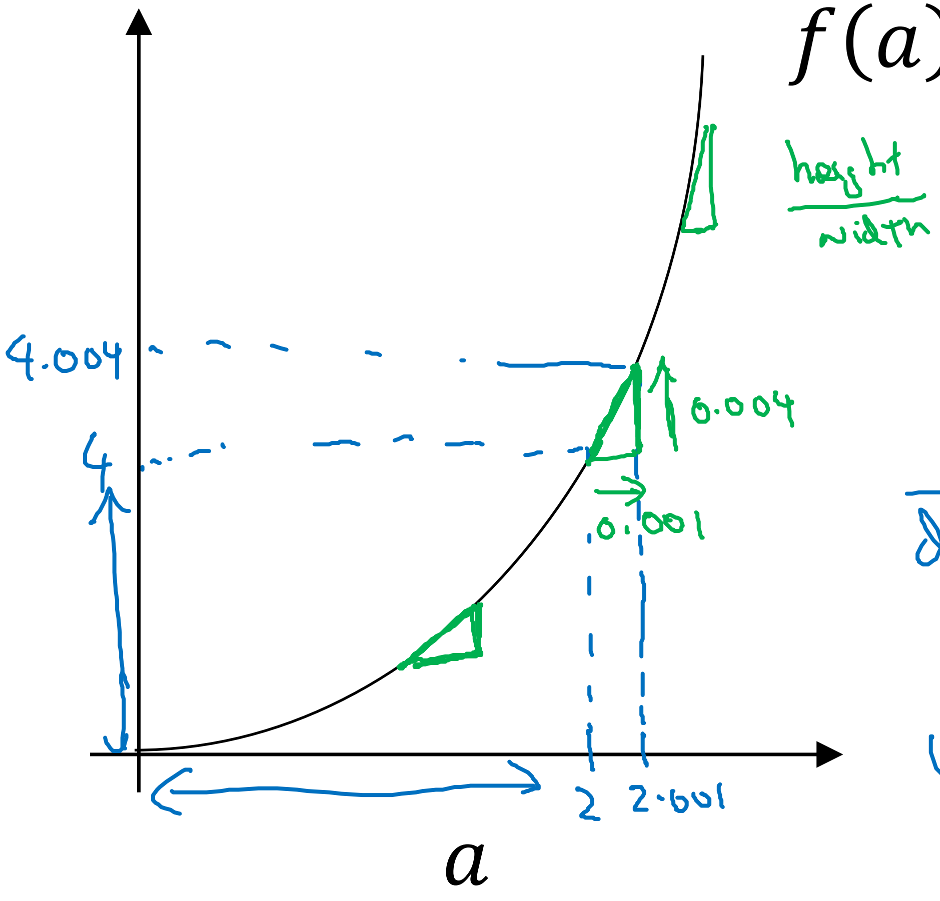
More derivatives examples

Intuition about derivatives

0.001
$0.00000\ldots01$

$$f(a) = a^2$$



$$\frac{d}{da} a^2 = 2a$$

0.001

$(2a) \times 0.001$

$a = 2 \qquad f(a) = 4$

$a = 2.001 \qquad f(a) \approx 4.004$

$(4.004\boxed{001})$

slope (derivative) of $f(a)$ at $a=2$ is 4.

$$\boxed{\frac{d}{da} f(a) = 4} \text{ when } \boxed{a = 2}.$$

$a = 5 \qquad f(a) = 25$

$a = 5.001 \qquad f(a) \approx 25.010$

$$\boxed{\frac{d}{da} f(a) = 10} \text{ when } \boxed{a = 5}$$

$$\frac{d}{da} f(a) = \frac{d}{da} a^2 = \boxed{2a}$$

More derivative examples

$f(a) = a^2$ $\qquad$ $\frac{d}{da}f(a) = \underbrace{2a}_{4}$ $\qquad$ $a = 2$ $\quad$ $f(a) = 4$

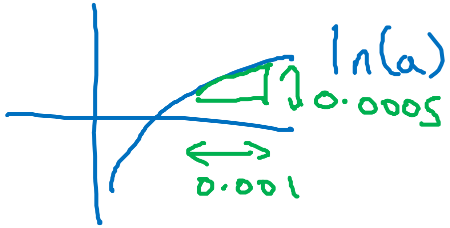
$a = 2.001$ $\quad$ $f(a) \approx 4.004$

$f(a) = a^3$ $\qquad$ $\frac{d}{da}f(a) = \underbrace{3a^2}_{3 \times 2^2 = 12}$ $\qquad$ $a = 2$ $\quad$ $f(a) = 8$

$a = \underline{2.001}$ $\quad$ $f(a) \approx 8.\underline{012}$

$f(a) = \log_e(a)$ $\qquad$ $\frac{d}{da}f(a) = \underline{\frac{1}{a}}$ $\qquad$ $a = 2$ $\quad$ $f(a) \approx 0.69315$

$\ln(a)$ $\qquad\qquad\qquad\qquad$ $a = 2.\underline{001}$ $\quad$ $\underline{f(a)} \approx 0.69365$



$\frac{d}{da}f(a) = \boxed{\frac{1}{2}}$ $\qquad$ $0.0005 \leftrightarrow \underline{0.0005}$

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Computation Graph

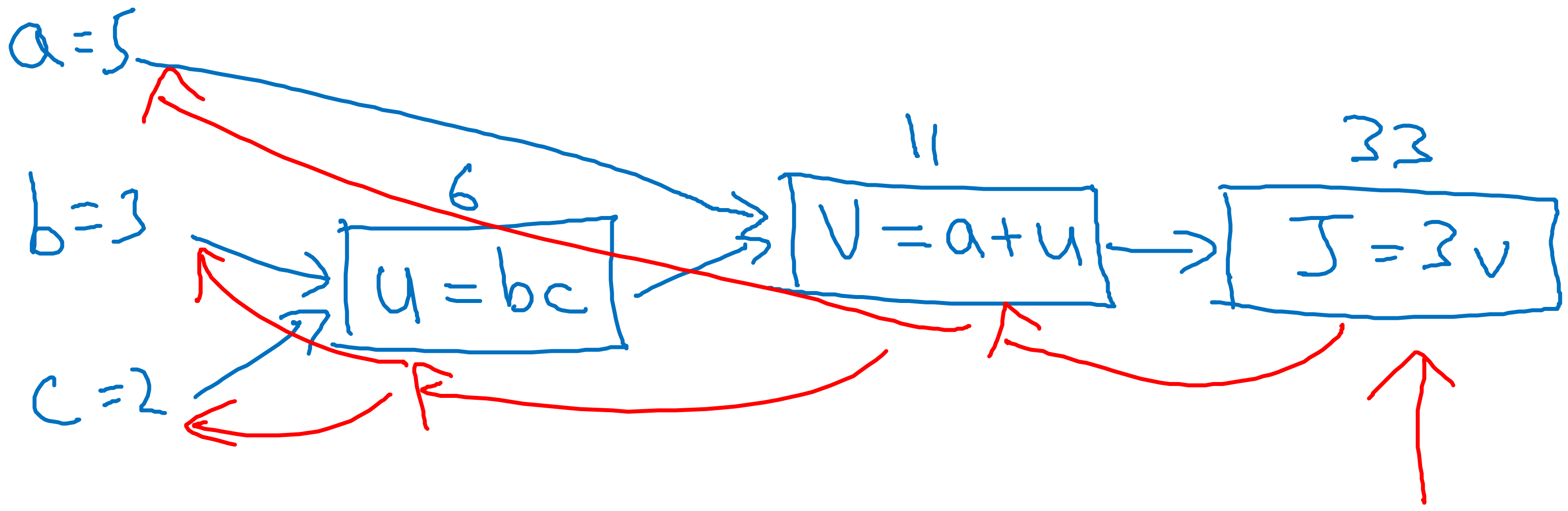
Computation Graph

$$J(a,b,c) = \underbrace{3(\underbrace{a+\underbrace{bc}_{u}}_{v})}_{J} = 3(5+3\times 2) = 33$$

$u = bc$

$v = a + u$

$J = 3v$



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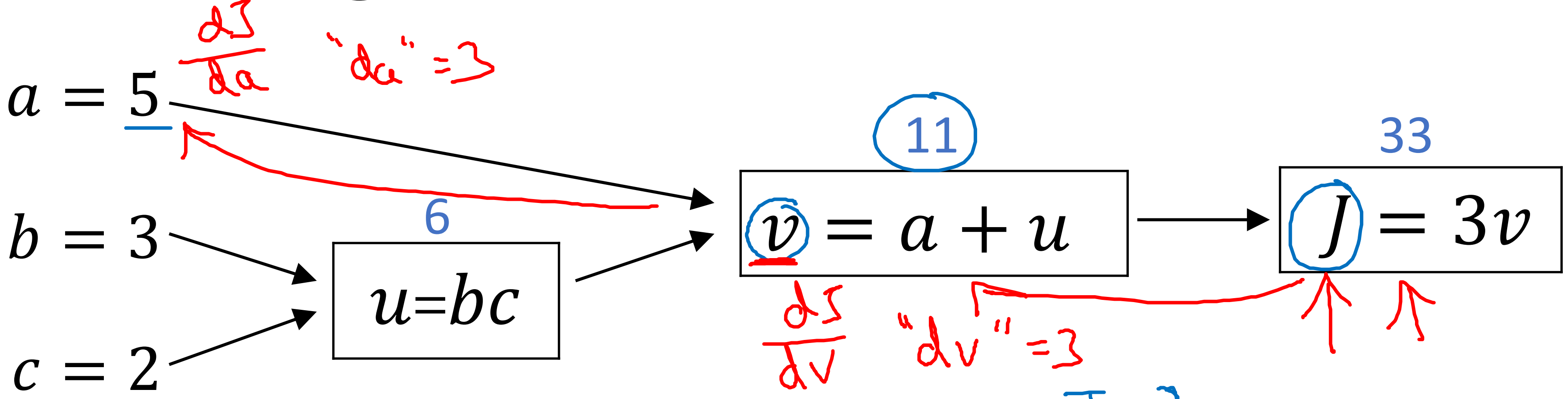
Derivatives with a Computation Graph

Computing derivatives



$$\boxed{\frac{dJ}{dv} = ? = 3}$$

$$\frac{dJ}{da} = 3 = \frac{dJ}{dv}\frac{dv}{da}$$

3×1

$$\boxed{\frac{dv}{da} = 1}$$

$a \rightarrow v \rightarrow J$

$J = 3v$

$v = 11 \rightarrow 11.001$

$J = 33 \rightarrow 33.003$

$a = 5 \rightarrow 5.001$

$\rightarrow v = 11 \rightarrow 11.001$

$J = 33 \rightarrow 33.003$

$$\boxed{\frac{d\,\text{FinalOutputVar}}{d\,\text{var}}}$$

dJdvar

"dvar"

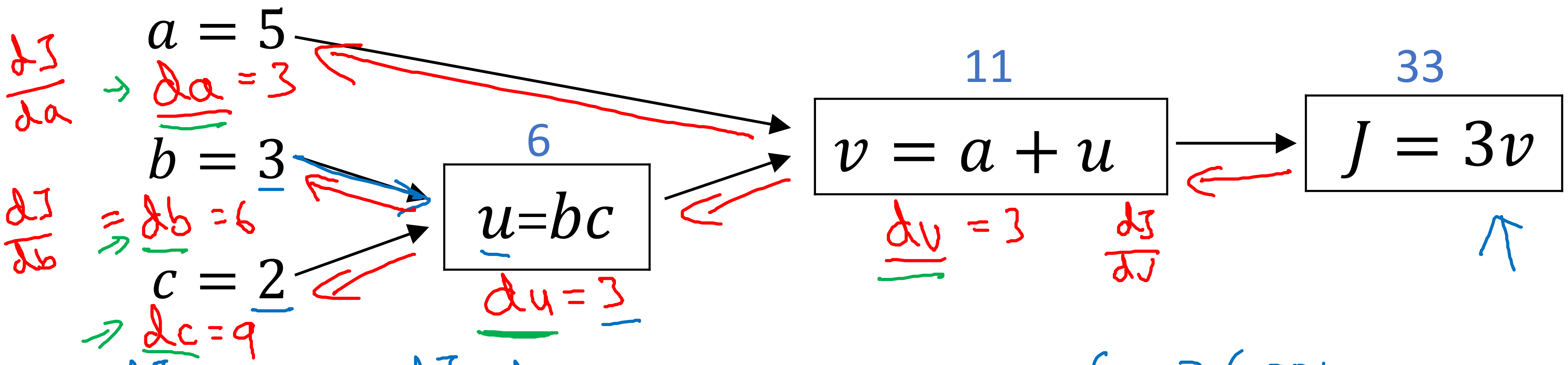
$$\boxed{f(a) = 3a}$$

$$\frac{df(a)}{da} = \frac{df}{da} = 3$$

$$\boxed{J = 3v}$$

$$\frac{dJ}{dv} = 3$$

Computing derivatives



$$\underline{\frac{dJ}{du}} = 3 = \underbrace{\frac{dJ}{dv}}_{3} \cdot \underbrace{\frac{dv}{du}}_{1}$$

$$\frac{dJ}{db} = \underbrace{\boxed{\frac{dJ}{du}}}_{\to 3} \cdot \underbrace{\frac{du}{db}}_{=2} = \underline{6}$$

$$\frac{dJ}{da} = \boxed{\frac{dJ}{du}} \cdot \frac{du}{da} = 9$$

$$3 \times 3$$

$u = 6 \rightarrow 6.001$
$v = 11 \rightarrow 11.001$
$J = 33 \rightarrow 33.003$

$b = 3 \rightarrow 3.001$
$u = b \cdot c = 6 \rightarrow 6.002$ $\qquad c = 2$
$J = 33.006$ $\qquad .006$

$v = 11.002$
$J = 3v$

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Basics of Neural Network Programming

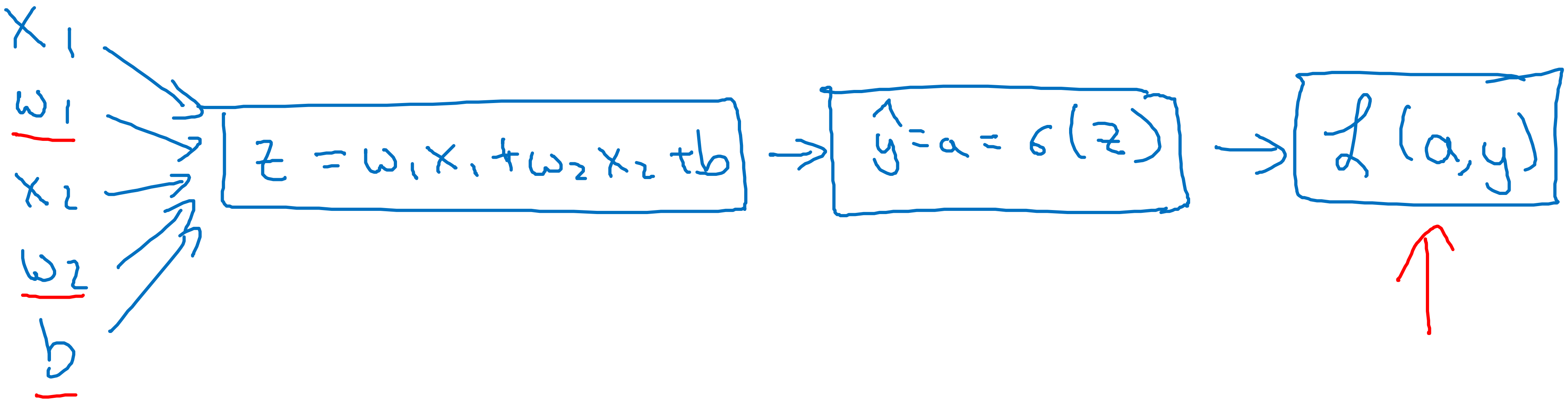
Logistic Regression Gradient descent

Logistic regression recap

$$z = w^T x + b$$

$$\hat{y} = a = \sigma(z)$$

$$\mathcal{L}(a, y) = -(y \log(a) + (1 - y) \log(1 - a))$$



Logistic regression derivatives

x_1, w_1, x_2, w_2, b

$$z = w_1 x_1 + w_2 x_2 + b \longrightarrow a = \sigma(z) \longrightarrow \mathcal{L}(a, y)$$

$$\text{“}dz\text{”} = \frac{d\mathcal{L}}{dz} = \frac{d\mathcal{L}(a,y)}{dz} = a - y = \frac{d\mathcal{L}}{da} \cdot \frac{da}{dz}$$

$$\frac{da}{dz} = a(1-a)$$

$$\text{“}da\text{”} = \frac{d\mathcal{L}(a,y)}{da} = -\frac{y}{a} + \frac{1-y}{1-a}$$

$$\frac{\partial \mathcal{L}}{\partial w_1} = \text{“}dw_1\text{”} = x_1 \cdot dz. \qquad dw_2 = x_2 \cdot dz. \qquad db = dz.$$

$$w_1 := w_1 - \alpha\, dw_1$$

$$w_2 := w_2 - \alpha\, dw_2$$

$$b := b - \alpha\, db.$$

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Basics of Neural Network Programming

Gradient descent on m examples

Logistic regression on m examples

$$\underline{J(w,b)} = \underbrace{\frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(a^{(i)}, y^{(i)})}$$

$$(x^{(i)}, y^{(i)})$$

$$\rightarrow a^{(i)} = \hat{y}^{(i)} = \sigma(z^{(i)}) = \sigma(w^T x^{(i)} + b)$$

$$\underline{dw_1^{(i)}},\ \underline{dw_2^{(i)}},\ \underline{db^{(i)}}$$

$$\underline{\frac{\partial}{\partial w_1} J(w,b)} = \frac{1}{m}\sum_{i=1}^{m} \underbrace{\frac{\partial}{\partial w_1}\mathcal{L}(a^{(i)}, y^{(i)})}_{\underline{dw_1^{(i)}}}$$

$$- \ (x^{(i)}, y^{(i)})$$

Logistic regression on m examples

$J = 0;\ dw_1 = 0;\ dw_2 = 0;\ db = 0$

For $i = 1$ to m

$$z^{(i)} = w^T x^{(i)} + b$$

$$a^{(i)} = \sigma(z^{(i)})$$

$$J += -\left[y^{(i)} \log a^{(i)} + (1 - y^{(i)}) \log(1 - a^{(i)})\right]$$

$$dz^{(i)} = a^{(i)} - y^{(i)}$$

$$dw_1 += x_1^{(i)} dz^{(i)}$$

$$dw_2 += x_2^{(i)} dz^{(i)}$$

$$db += dz^{(i)}$$

$n = 2$

dw_3

$\vdots$

dw_n

$J /= m$

$dw_1 /= m;\ dw_2 /= m;\ db /= m.$

$$dw_1 = \frac{\partial J}{\partial w_1}$$

$$w_1 := w_1 - \alpha\, dw_1$$

$$w_2 := w_2 - \alpha\, dw_2$$

$$b := b - \alpha\, db$$

Vectorization

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Vectorization

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What is vectorization?

$$z = \underbrace{w^T x} + b$$

$w = \begin{bmatrix} \vdots \\ \vdots \end{bmatrix}$ $x = \begin{bmatrix} \vdots \\ \vdots \end{bmatrix}$ $w \in \mathbb{R}^{n_x}$ $x \in \mathbb{R}^{n_x}$

Non-vectorized:

```
z = 0
for i in range(n-x):
    z += w[i] * x[i]
z += b
```

Vectorized

$$z = \underbrace{np.dot(w, x)}_{w^T x} + b$$

$\left.\begin{array}{l} \rightarrow \text{GPU} \\ \rightarrow \text{CPU} \end{array}\right\}$ SIMD - single instruction multiple data.

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More vectorization examples

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Neural network programming guideline

Whenever possible, avoid explicit for-loops.

$u = Av$

$u_i = \sum_i \sum_j A_{ij} v_j$

```
u = np.zeros((n,1))
for i ...
    for j ...
        u[i] += A[i][j] * v[j]
```

```
u = np.dot(A,v)
```

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Vectors and matrix valued functions

Say you need to apply the exponential operation on every element of a matrix/vector.

$$v = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix} \rightarrow u = \begin{bmatrix} e^{v_1} \\ e^{v_2} \\ \vdots \\ e^{v_n} \end{bmatrix}$$

```
u = np.zeros((n,1))
for i in range(n):
    u[i]=math.exp(v[i])
```

```
import numpy as np
u = np.exp(v)

np.log(v)
np.abs(v)
np.maximum(v, 0)
v**2          1/v
```

Logistic regression derivatives

$J = 0$, $\boxed{\cancel{dw1 = 0, dw2 = 0}}$, $db = 0$

$dw = np.zeros((n\_x, 1))$

$\rightarrow$ for i = 1 to n:

$z^{(i)} = w^T x^{(i)} + b$

$a^{(i)} = \sigma(z^{(i)})$

$J \mathrel{+}= -[y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)})]$

$dz^{(i)} = a^{(i)}(1 - a^{(i)})$

for $j = 1 \dots n_x$

$dw_j \mathrel{+}= \dots$

$\boxed{\cancel{dw_1 \mathrel{+}= x_1^{(i)} dz^{(i)}}}$

$\boxed{\cancel{dw_2 \mathrel{+}= x_2^{(i)} dz^{(i)}}}$

$n_x = 2$

$dw \mathrel{+}= x^{(i)} dz^{(i)}$

$db \mathrel{+}= dz^{(i)}$

$J = J/m$, $\boxed{\cancel{dw_1 = dw_1/m, dw_2 = dw_2/m}}$, $db = db/m$

$dw /= m.$

$\rightarrow$ from 2 for loops -->1 for loop

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Basics of Neural Network Programming

Vectorizing Logistic Regression

Vectorizing Logistic Regression

$z^{(1)} = \boxed{w^T x^{(1)} + b}$ $\quad$ $z^{(2)} = \boxed{w^T x^{(2)} + b}$ $\quad$ $z^{(3)} = w^T x^{(3)} + b$

$\boxed{a^{(1)}} = \sigma(z^{(1)})$ $\quad$ $\boxed{a^{(2)}} = \sigma(z^{(2)})$ $\quad$ $\boxed{a^{(3)}} = \sigma(z^{(3)})$

$$X = \begin{bmatrix} | & | & & | \\ x^{(1)} & x^{(2)} & \cdots & x^{(m)} \\ | & | & & | \end{bmatrix} \qquad (n_x, m) \qquad \mathbb{R}^{n_x \times m}$$

$$[\text{———}]\, w^T \begin{bmatrix} | & | & & | \\ x^{(1)} & x^{(2)} & \cdots & x^{(m)} \\ | & | & & | \end{bmatrix}$$

$$Z = \boxed{[z^{(1)}\ z^{(2)} \cdots z^{(m)}]} = \underbrace{w^T X + \underbrace{[b\ b \cdots b]}_{1 \times m}} = [\boxed{w^T x^{(1)} + b}\ \boxed{w^T x^{(2)} + b}\ \cdots\ w^T x^{(m)} + b]$$

$1 \times m$

$\rightarrow$ Z = np.dot(w.T, X) + b $\quad (1,1) \quad \mathbb{R}$ $\quad$ "Broadcasting"

$$A = [a^{(1)}\ a^{(2)} \cdots a^{(m)}] = \sigma(Z)$$

chỉ cần 2 câu lệnh trong NumPy

What are the dimensions of matrix X in this video?-->(n_x, m)

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Vectorizing Logistic Regression's Gradient Computation

Vectorizing Logistic Regression

$dz^{(1)} = a^{(1)} - y^{(1)}$ $\quad$ $dz^{(2)} = a^{(2)} - y^{(2)}$ $\quad \ldots\ldots$

$\boxed{dZ = [dz^{(1)} \ dz^{(2)} \ \ldots \ dz^{(m)}]}$ $\leftarrow$

$1 \times m$

$A = [a^{(1)} \ \ldots \ a^{(m)}]$, $\quad Y = [y^{(1)} \ \ldots \ y^{(m)}]$

$\rightarrow dZ = A - Y = [a^{(1)} - y^{(1)} \quad a^{(2)} - y^{(2)} \quad \ldots]$

$\rightarrow dw = 0$

$dw \mathrel{+}= x^{(1)} dz^{(1)}$

$dw \mathrel{+}= x^{(2)} dz^{(2)}$

$\vdots$

$dw \mathrel{/}= m$

$\cancel{dw_1}$

$\cancel{dw_2}$

$\vdots$

$db = 0$

$db \mathrel{+}= dz^{(1)}$

$db \mathrel{+}= dz^{(2)}$

$\vdots$

$db \mathrel{+}= dz^{(m)}$

$db \mathrel{/}= m$.

$db = \frac{1}{m} \sum_{i=1}^{m} dz^{(i)}$

$= \frac{1}{m} \text{np.sum}(dZ)$ in Numpy

$\boxed{dw = \frac{1}{m} X \, dZ^T}$

$= \frac{1}{m} \begin{bmatrix} | & & | \\ x^{(1)} & \ldots & x^{(m)} \\ | & & | \end{bmatrix} \begin{bmatrix} dz^{(1)} \\ \vdots \\ dz^{(m)} \end{bmatrix}$

$= \frac{1}{m} [x^{(1)} dz^{(1)} + \ldots + x^{(m)} dz^{(m)}]$

$n \times 1$

Implementing Logistic Regression

$J = 0,\ dw_1 = 0,\ dw_2 = 0,\ db = 0$

$\boxed{\text{for i = 1 to m:}}$

$z^{(i)} = w^T x^{(i)} + b$

$a^{(i)} = \sigma(z^{(i)})$

$J \mathrel{+}= -[y^{(i)} \log a^{(i)} + (1 - y^{(i)}) \log(1 - a^{(i)})]$

$dz^{(i)} = a^{(i)} - y^{(i)}$

$dw_1 \mathrel{+}= x_1^{(i)} dz^{(i)}$

$dw_2 \mathrel{+}= x_2^{(i)} dz^{(i)}$

$dw \mathrel{+}= x^{(i)} * dz^{(i)}$

$db \mathrel{+}= dz^{(i)}$

$J = J/m,\ dw_1 = dw_1/m,\ dw_2 = dw_2/m$

$db = db/m$

for iter in range(1000):

in NumPy

$Z = w^T X + b$

$= np.dot(w.T, X) + b$

$A = \sigma(Z)$

A = sigmoid(np.dot(w.T, X) + b)

$dZ = A - Y$

$dw = \frac{1}{m} X dZ^T$

dw = (1 / m) * np.dot(X, (A - Y).T)

$db = \frac{1}{m} np.sum(dZ)$

db = (1 / m) * np.sum(A - Y)

= 1 / m*(np.sum(dZ))

$w := w - \alpha dw$

w = w - learning_rate*dw

$b := b - \alpha db$

b = b - learning_rate * db

How do you compute **the derivative of b** in one line of code in Python numpy?

cost = (- 1 / m) * np.sum(Y * np.log(A) + (1 - Y) * (np.log(1 - A)))

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Broadcasting in Python

Broadcasting example

Which of the following **numpy** line of code would **sum** the values in a matrix A **vertically?** **A.sum(axis = 0)**

Calories from Carbs, Proteins, Fats in 100g of different foods:

$$
\begin{array}{r}
\\ \text{Carb} \\ \text{Protein} \\ \text{Fat}
\end{array}
\begin{array}{c}
\begin{array}{cccc} \text{Apples} & \text{Beef} & \text{Eggs} & \text{Potatoes} \end{array} \\
\begin{bmatrix} 56.0 & 0.0 & 4.4 & 68.0 \\ 1.2 & 104.0 & 52.0 & 8.0 \\ 1.8 & 135.0 & 99.0 & 0.9 \end{bmatrix}
\end{array}
= A \quad (3,4)
$$

axis = 0 -->sum vertically

0

1

59 cal

$\frac{56}{59} \approx 94.9\%$

Calculate % of calories from Carb, Protein, Fat. Can you do this without explicit for-loop?

```
cal = A.sum(axis = 0)
percentage = 100*A/(cal.reshape(1,4))
```

(cal.reshape(1,4)) -->to make sure a (1,4) matrix

(3,4) / (1,4)

Broadcasting example

$$\begin{bmatrix}1\\2\\3\\4\end{bmatrix} + \cancel{100}\ \begin{bmatrix}100\\100\\100\\100\end{bmatrix} = \begin{matrix}101\\102\\103\\104\end{matrix}$$

$$\underset{(m,n)\ \ (2,3)}{\begin{bmatrix}1 & 2 & 3\\4 & 5 & 6\end{bmatrix}} + \underset{(1,n) \rightsquigarrow (m,n)\ \ (2,3)}{\begin{bmatrix}100 & 200 & 300\\100 & 200 & 300\end{bmatrix}} = \begin{matrix}101 & 202 & 303\\104 & 205 & 306\end{matrix}$$

$$\underset{(m,n)}{\begin{bmatrix}1 & 2 & 3\\4 & 5 & 6\end{bmatrix}} + \underset{(m,1) \to (m,n)}{\begin{bmatrix}100 & 100 & 100\\200 & 200 & 200\end{bmatrix}} = \begin{matrix}101 & 102 & 103\\204 & 205 & 206\end{matrix}$$

General Principle

$$\underset{\text{matrix}}{(m, n)} \quad \begin{matrix} + \\ - \\ * \\ / \end{matrix} \quad \begin{matrix} (1, n) \rightsquigarrow (m, n) \\ (m, 1) \rightsquigarrow (m, n) \end{matrix}$$

$$(m, 1) \quad + \quad \mathbb{R}$$

$$\begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} + 100 = \begin{bmatrix} 101 \\ 102 \\ 103 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 & 3 \end{bmatrix} + 100 = \begin{bmatrix} 101 & 102 & 103 \end{bmatrix}$$

Matlab/Octave: bsxfun

deeplearning.ai

Basics of Neural Network Programming

Explanation of logistic regression cost function (Optional)

Logistic regression cost function

$\hat{y} = \sigma(w^T x + b)$ where $\sigma(z) = \frac{1}{1+e^{-z}}$

Interpret $\hat{y} = P(y=1 \mid x)$

If $y=1$: $P(y \mid x) = \hat{y}$

If $y=0$: $P(y \mid x) = 1 - \hat{y}$

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Logistic regression cost function

$$\boxed{\text{If} \quad y = 1: \qquad p(y|x) = \hat{y}}$$
$$\boxed{\text{If} \quad y = 0: \qquad p(y|x) = 1 - \hat{y}}$$

$p(y|x)$

$$\boxed{p(y|x) = \hat{y}^{y} (1-\hat{y})^{(1-y)}}$$

If $y=1$: $p(y|x) = \hat{y} \quad \underbrace{(1-\hat{y})^{0}}_{=1}$

If $y=0$: $p(y|x) = \underbrace{\hat{y}^{0}}_{=1} \quad (1-\hat{y})^{(1-y)} = 1 \times (1-\hat{y}) = 1-\hat{y}$

$\uparrow \log p(y|x) = \log \hat{y}^{y} (1-\hat{y})^{(1-y)} = y \log \hat{y} + (1-y) \log (1-\hat{y})$

$= -\mathcal{L}(\hat{y}, y) \downarrow$

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Cost on m examples

$$\underline{\log p(\text{labels in training set})} = \log \prod_{i=1}^{m} p(y^{(i)} \mid x^{(i)})$$

$$\underline{\log p(\ldots\ldots)} = \sum_{i=1}^{m} \underbrace{\log p(y^{(i)} \mid x^{(i)})}_{-\mathcal{L}(\hat{y}^{(i)},\, y^{(i)})}$$

Maximum likelihood estimation

$$= -\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

Cost: $\underline{J(w,b)} = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$

(minimize)