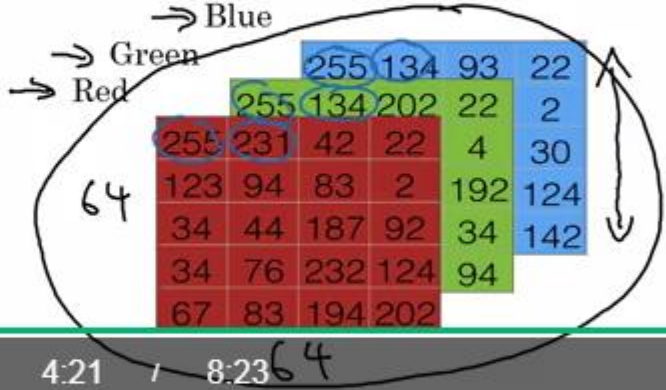
Binary Classification

64

64

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

y



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

$64 \times 64 \times 3 = 12288$

$n = n_x = 12288$

$x \longrightarrow y$

4:21 / 8:23

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Notation

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

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

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

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

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

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

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

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

7:54 / 8:23

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Basics of Neural Network Programming

Logistic Regression

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0:02 / 5:59

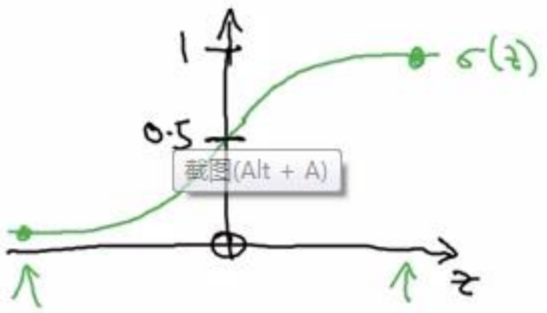
Logistic Regression

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

$x \in \mathbb{R}^{n_x}$ $\qquad 0 \le \hat{y} \le 1$

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

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



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

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

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

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

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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截图(Alt + A)

Basics of Neural Network Programming

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

截图(Alt + A)

$\boxed{\text{Cost}}$ 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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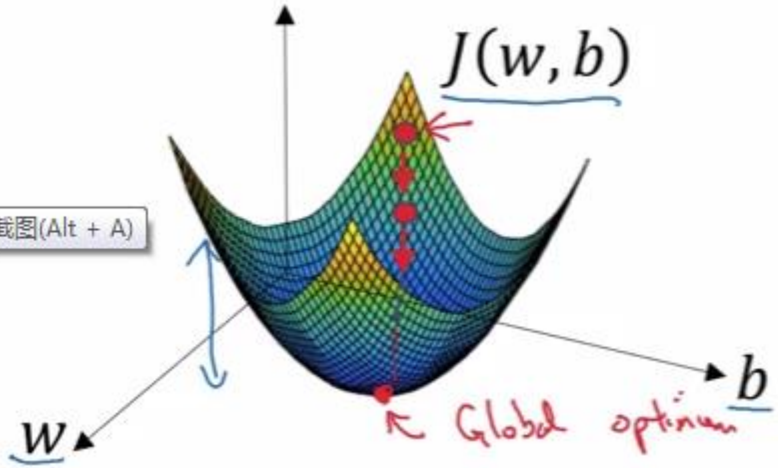
截图(Alt + A)

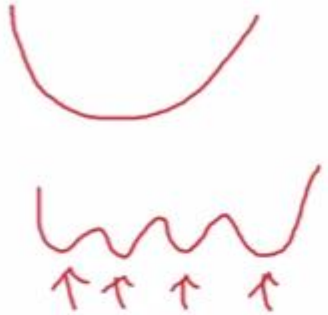
Gradient Descent

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 $J(w,b)$





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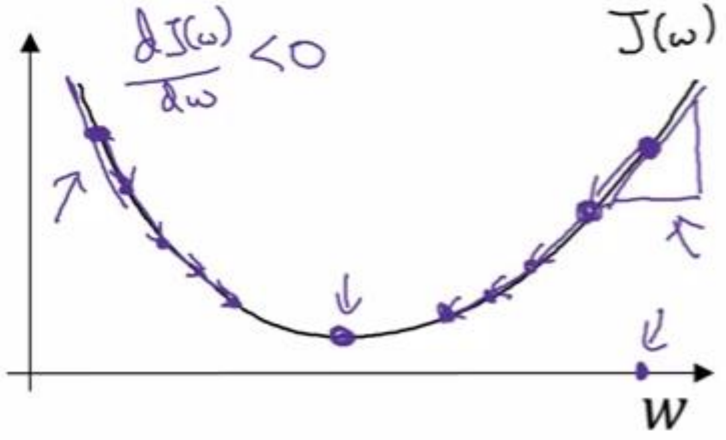
Gradient Descent



learning rate

Repeat {

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

}

"dw"

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

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

J(w, b)

截图(Alt + A)

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

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

∂ "partial derivative"

d J

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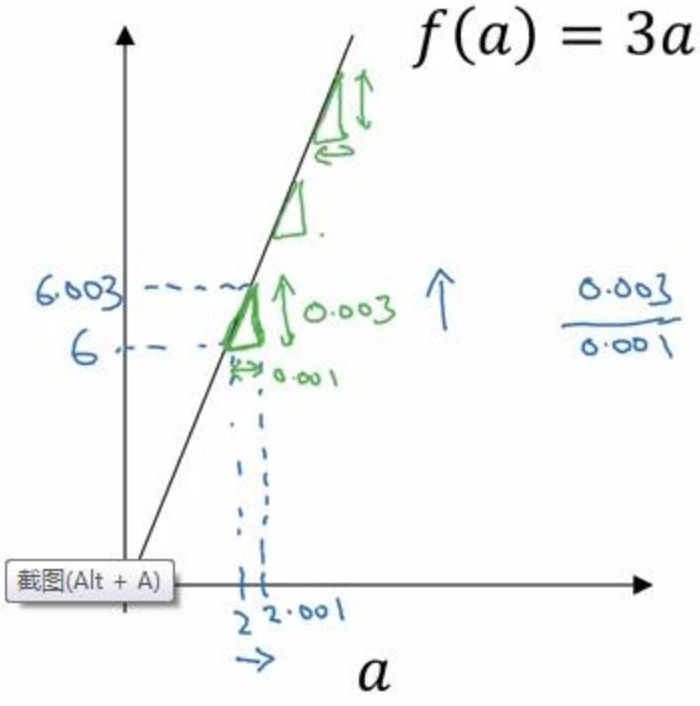
Basics of Neural Network Programming

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
0.000000001

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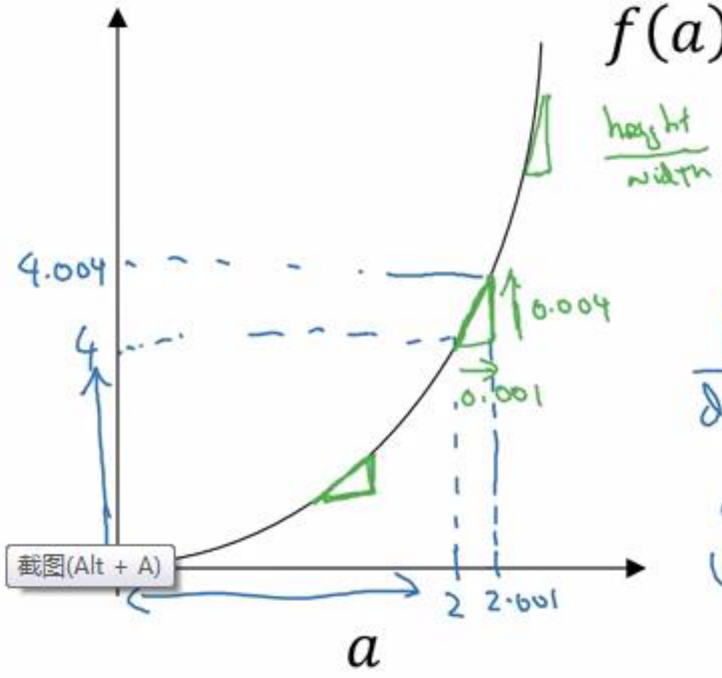
More derivatives examples

Intuition about derivatives

$f(a) = a^2$



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

0.001

$(2a) \times 0.001$

0.001 ←

0.00000....01 ←

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

$a = 2.001$ $\quad f(a) \approx 4.004$ $\quad (4.004\boxed{001})$

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

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

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

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

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

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

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More derivative examples

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

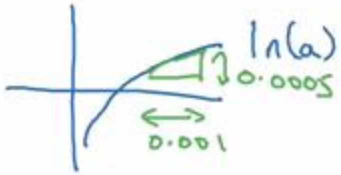
$\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad a = 2.001 \quad f(a) \approx 4.004$

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

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

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

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



$\frac{d}{da} f(a) = \frac{1}{2}$

$0.0005 \longleftrightarrow \underline{0.0005}$

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Basics of Neural Network Programming

Computation Graph

截图(Alt + A) plearning.ai

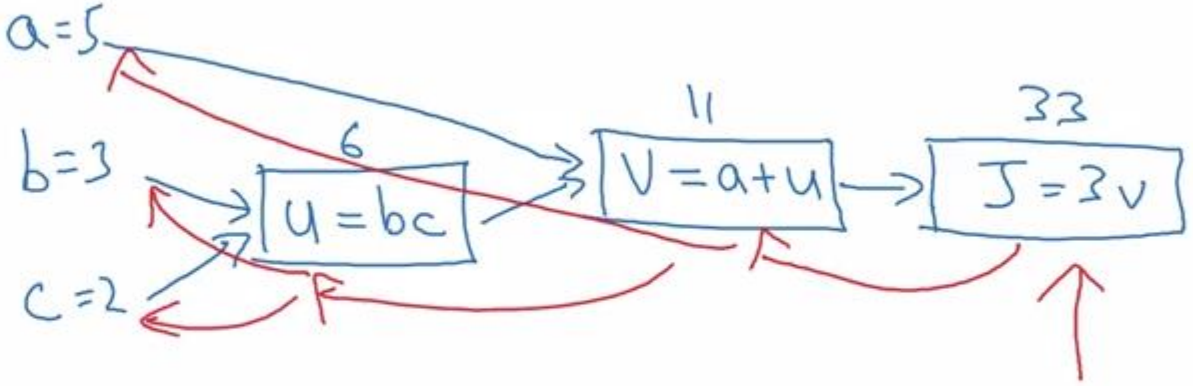
Computation Graph

$$J(a,b,c) = \underbrace{3(\underbrace{a+\underbrace{bc}_{u}}_{v})}_{J} = 3(5+3\times2) = 33$$

$u = bc$

$V = a+u$

$J = 3v$



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截图(Alt + A)

Basics of Neural Network Programming

Derivatives with a Computation Graph

Computing derivatives

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

$a = 5$

$b = 3$ → $u = bc$ (6) → $v = a + u$ (11) → $J = 3v$ (33)

$c = 2$

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

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

$a \to v \to J$

$J = 3v$

$v = 11 \to 11.001$

$J = 33 \to 33.003$

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

3×1

截图(Alt + A)

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

$a = 5 \to 5.001$

$\to v = 11 \to 11.001$

$J = 33 \to 33.003$

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

$dJdvar$

→ "$dvar$"

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

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

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

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

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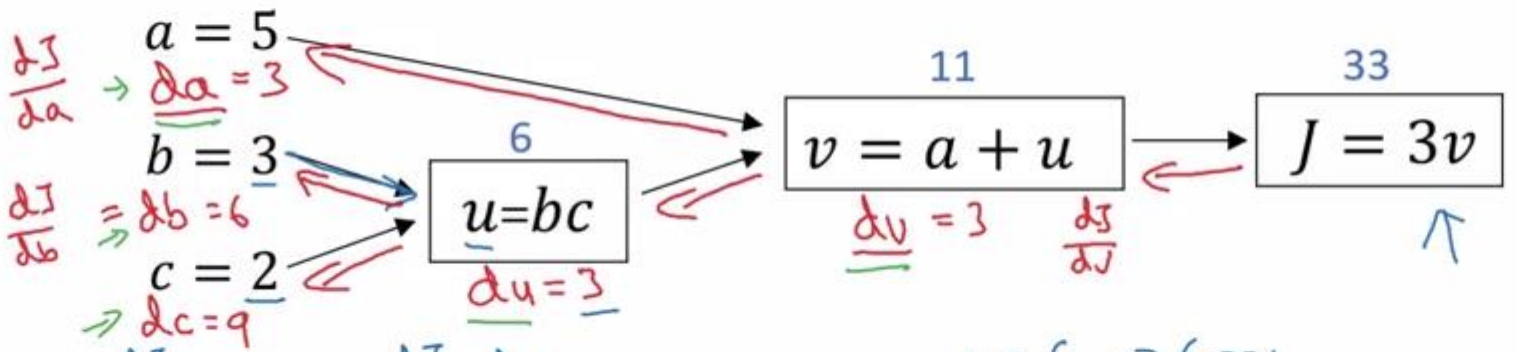
Computing derivatives



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

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

截图(Alt + A)

$$\frac{dJ}{dc} = \underbrace{\frac{dJ}{du}}_{3} \cdot \underbrace{\frac{du}{dc}}_{\times\, 3} = 9$$

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

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

$v = 11.002$
$J = 3v$

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Basics of Neural Network Programming

Logistic Regression
Gradient descent

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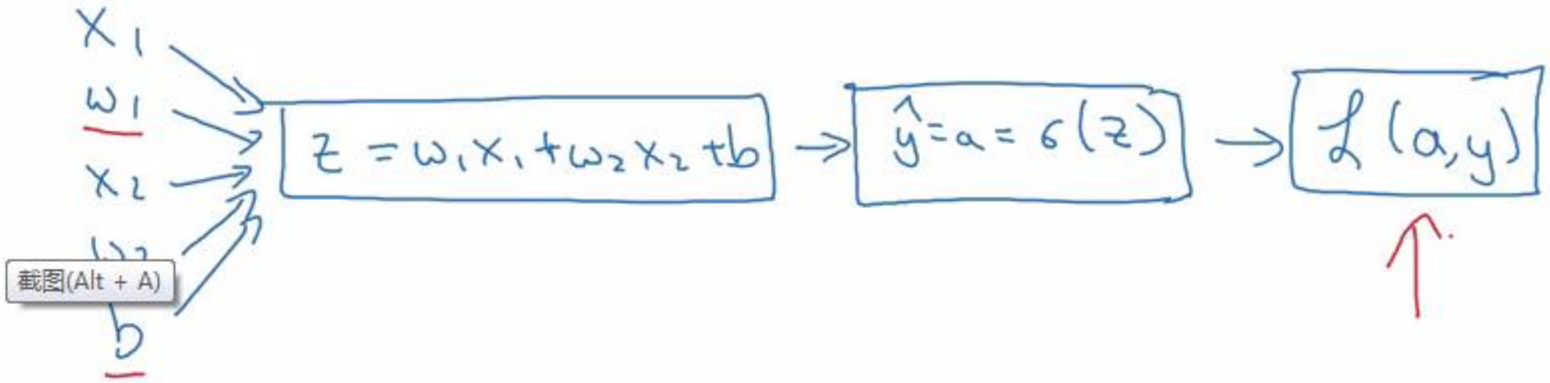
Logistic regression recap

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

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

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



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Logistic regression derivatives

$$\left.\begin{matrix} x_1 \\ w_1 \\ x_2 \\ w_2 \\ b \end{matrix}\right\} \rightarrow \boxed{z = w_1x_1 + w_2x_2 + b} \rightarrow \boxed{a = \sigma(z)} \rightarrow \boxed{\mathcal{L}(a, y)}$$

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

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

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

截图(Alt + 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

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

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

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

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

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

截图(Alt + A)

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Logistic regression on m examples

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

For $i=1$ to m

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

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

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

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

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

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

dw_3

$\vdots$

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

截图(Alt + A)

$n=2$

$J /= m$

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

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

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

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

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

Vectorization

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截图(Alt + A)

Basics of Neural Network Programming

Vectorization

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
```

截图(Alt + A)

Vectorized

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

→ GPU
→ CPU } SIMD - single instruction multiple data.

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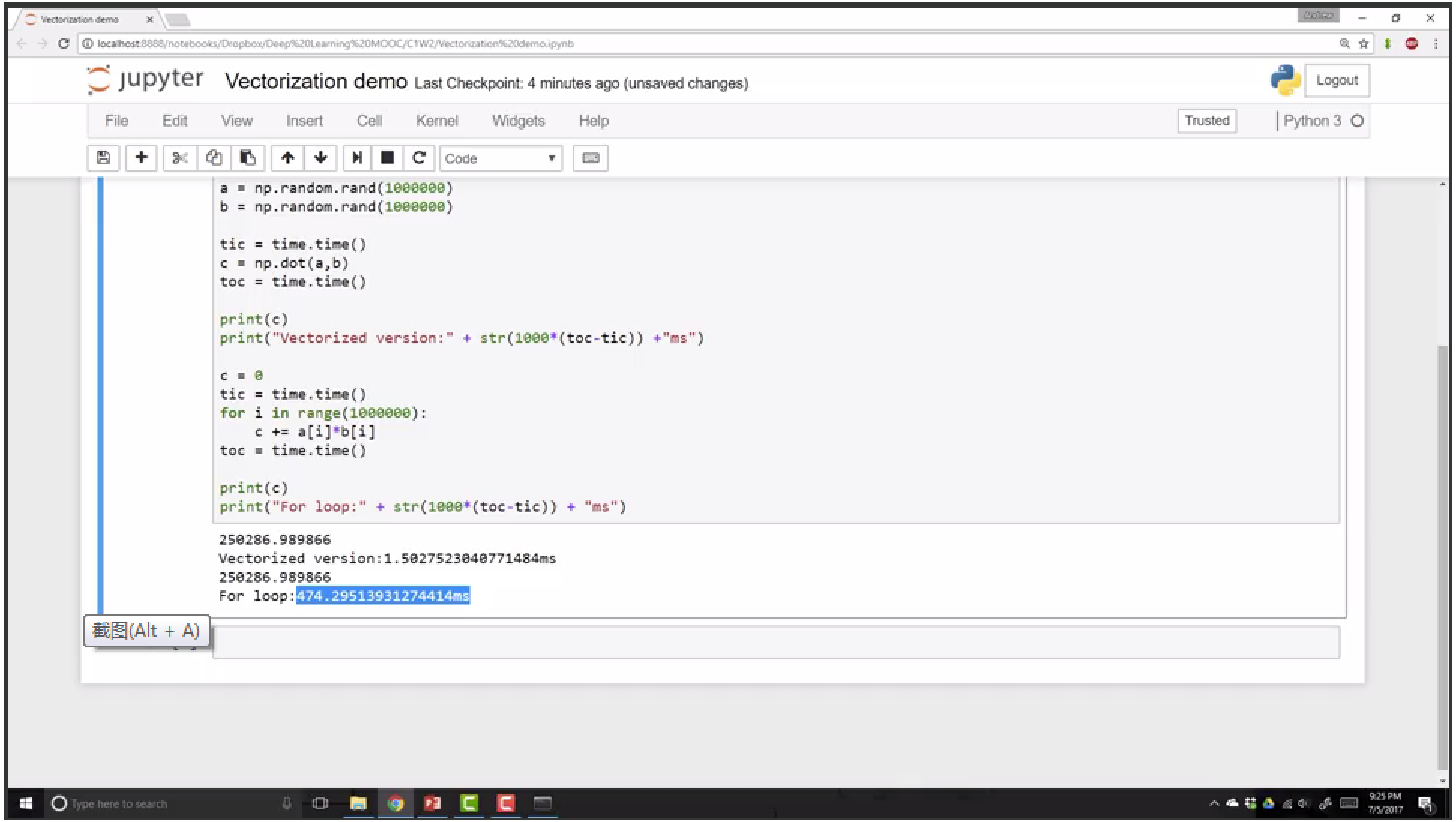
Vectorization demo
localhost:8888/notebooks/Dropbox/Deep%20Learning%20MOOC/C1W2/Vectorization%20demo.ipynb
jupyter
Vectorization demo Last Checkpoint: 4 minutes ago (unsaved changes)
Logout
File
Edit
View
Insert
Cell
Kernel
Widgets
Help
Trusted
Python 3
Code
a = np.random.rand(1000000)
b = np.random.rand(1000000)
tic = time.time()
c = np.dot(a,b)
toc = time.time()
print(c)
print("Vectorized version:" + str(1000*(toc-tic)) +"ms")
c = 0
tic = time.time()
for i in range(1000000):
    c += a[i]*b[i]
toc = time.time()
print(c)
print("For loop:" + str(1000*(toc-tic)) + "ms")
250286.989866
Vectorized version:1.5027523040771484ms
250286.989866
For loop:474.29513931274414ms
截图(Alt + A)
Type here to search

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More vectorization examples

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Neural network programming guideline

Whenever possible, avoid explicit for-loops.

$u = Av$

$u_i = \sum_j A_{ij} v_j$

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

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

截图(Alt + A)

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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])
```

截图(Alt + A)

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

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

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Logistic regression derivatives

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

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

for i = 1 to m:

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

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

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

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

for $j = 1 \ldots n_x$
$dw_j \mathrel{+}= \ldots$

$\boxed{\cancel{dw_1 \mathrel{+}= x_1^{(i)} dz^{(i)}}}$
$\boxed{\cancel{dw_2 \mathrel{+}= x_2^{(i)} dz^{(i)}}}$

$n_x = 2$

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

截图(Alt + A)

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

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

$dw /= m$.

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Basics of Neural Network Programming

Vectorizing Logistic Regression

Vectorizing Logistic Regression

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

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

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

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

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

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

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Basics of Neural Network Programming

Vectorizing Logistic Regression’s Gradient Computation

Vectorizing Logistic Regression

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

$$\boxed{dZ = [dz^{(1)} \; dz^{(2)} \cdots dz^{(m)}]} \Leftarrow$$

$1 \times m$

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

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

$\cancel{dw_1}$, $\cancel{dw_2}$, ...

$\rightarrow dw = 0$

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

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

$\vdots$

$dw /= m$

$db = 0$

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

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

$\vdots$

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

$db /= m.$

$$db = \frac{1}{m} \sum_{i=1}^{m} dz^{(i)} = \frac{1}{m} \, np.sum(dZ)$$

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

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

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

$n \times 1$

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Implementing Logistic Regression

$$
\begin{aligned}
&J = 0,\ dw_1 = 0,\ dw_2 = 0,\ db = 0 \\
&\boxed{\text{for } i = 1 \text{ to } m:} \\
&\quad z^{(i)} = w^T x^{(i)} + b \\
&\quad a^{(i)} = \sigma(z^{(i)}) \\
&\quad J \mathrel{+}= -[y^{(i)} \log a^{(i)} + (1 - y^{(i)}) \log(1 - a^{(i)})] \\
&\quad dz^{(i)} = a^{(i)} - y^{(i)} \\
&\quad \left.\begin{aligned} dw_1 &\mathrel{+}= x_1^{(i)} dz^{(i)} \\ dw_2 &\mathrel{+}= x_2^{(i)} dz^{(i)} \end{aligned}\right\} \ dw \mathrel{+}= x^{(i)} * dz^{(i)} \\
&\quad db \mathrel{+}= dz^{(i)} \\
&J = J/m,\ dw_1 = dw_1/m,\ dw_2 = dw_2/m \\
&db = db/m
\end{aligned}
$$

for iter in range(1000):

$$
\begin{aligned}
Z &= w^T X + b \\
&= np.dot(w.T, X) + b \\
A &= \sigma(Z) \\
dZ &= A - Y \\
dw &= \frac{1}{m} X dZ^T \\
db &= \frac{1}{m} np.sum(dZ) \\
w &:= w - \alpha dw \\
b &:= b - \alpha db
\end{aligned}
$$

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Basics of Neural Network Programming

Broadcasting in Python

00:10 / 11:05

Broadcasting example

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

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

59cal

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

0

1

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))
```

(3,4) / (1,4)

General Principle

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

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

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Basics of Neural Network Programming

A note on python/ numpy vectors

1:23 / 6:49

Python/numpy vectors

```
a = np.random.randn(5)
```

a.shape = (5,)

"rank 1 array"

Don't use

```
a = np.random.randn(5,1)
```

→ a.shape = (5,1) column vector ✓

```
a = np.random.randn(1,5)
```

→ a.shape = (1,5) row vector. ✓

```
assert(a.shape == (5,1))
```

←

a = a.reshape((5,1))

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

If $y=1$: $p(y|x) = \hat{y}$

If $y=0$: $p(\underline{y}|x) = \underline{1-\hat{y}}$

Logistic regression cost function

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

$\} \; p(y|x)$

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

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

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

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

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

Maximum likelihood estimation

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