contents

logistic regression as a neural network

binary classification

维度为(64, 64, 3)的图片 ===> img vector: x=维度为(64*64*3=12288, 1)的列向量。($n_x = 12288$)

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

$m = m_{train}$个训练样本：$(x^{(1)}, y^{(1)}), \ldots, (x^{(m)}, y^{(m)})$，$m_{test}$个测试样本。

X表示一个$n_x * m$的训练样本矩阵,在python里就是 `X.shape=(n_x,m)` Y表示一个$1 * m$的向量,在python里是 `Y.shape=(1,m)`

logistic regression

given x, want $\hat{y} = P(y = 1|x), x \in R^{n_x}$

params: $w \in R^{n_x}, b \in R$

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

logistic regression cost function

$(x^(i), y^(i))$ 表示第i个样本。

Loss(error) function只针对一条训练样本：

- square error的loss function:

$$L(\hat{y},y)=1/2*(\hat{y}-y)^2$$

- logistic regression的loss function:

$$L(\hat{y},y)=-(ylog\hat{y}+(1-y)log(1-\hat{y}))$$

if $y=1, L(\hat{y},y)=-log\hat{y}$, want $log\hat{y}$ large, want $\hat{y}$ large

if $y=0, L(\hat{y},y)=-log(1-\hat{y})$, want $\hat{y}$ small

Cost function针对全体训练样本:

$$J(w,b)=1/m\sum_{i=1}^{m}L(\hat{y}^{(i)},y^{(i)})=-1/m\sum_{i=1}^{m}[y^{(i)}log\hat{y}^{(i)}+(1-y^{(i)})log(1-\hat{y}^{(i)})]$$

gradient descent

lr的$J(w,b)$是一个凸函数，所以有全局最优。 因为有全局最优，所以lr的初始化一般是0，不用随机。梯度下降：不断重复$w=w-\alpha\frac{dJ(w)}{dw}$直到收敛。后续，用$dw$来指代$\frac{dJ(w)}{dw}$。梯度下降的公式：

$$w=w-\alpha dw$$

$$b=b-\alpha db$$

derivatives

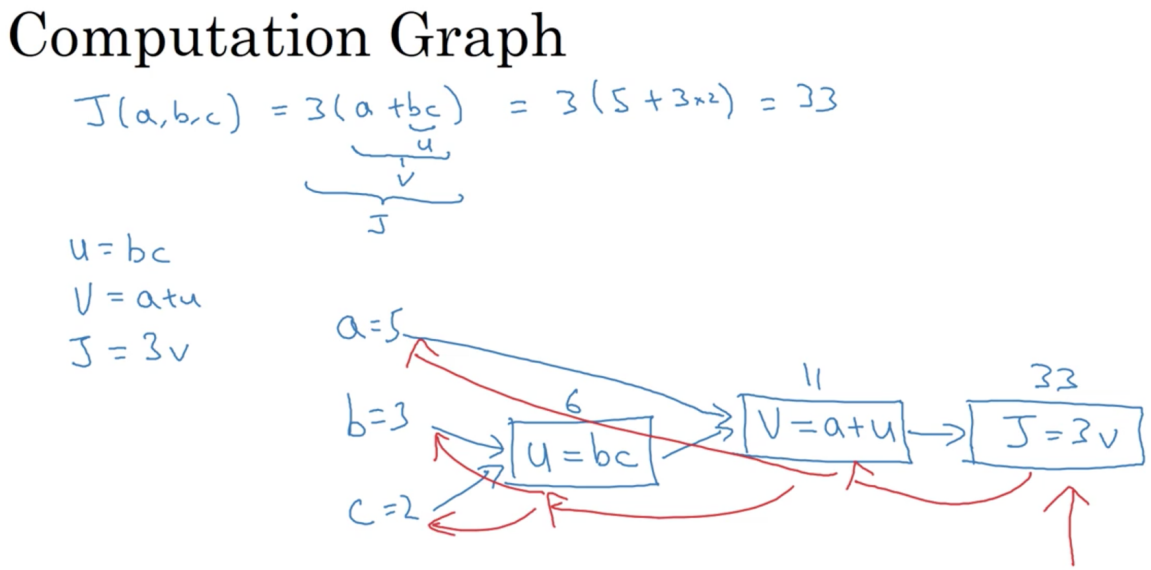
derivative = slope，就是$dy/dx=\Delta y/\Delta x$

more derivative examples

$f(a)=log_e(a)=ln(a), df(a)/da=\frac{1}{a}$

computation graph

正向计算图算出输出，算每个参数的梯度就反向算。



derivatives with a computation graph

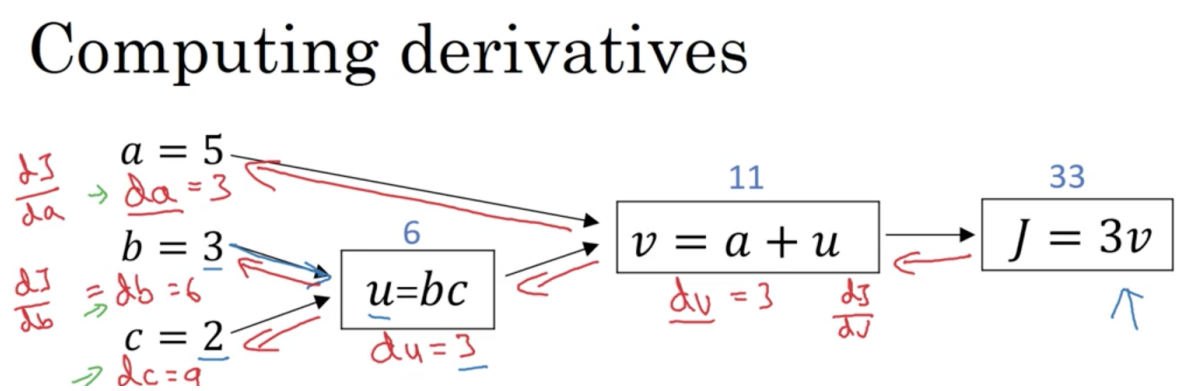
$$J = 3v, v = a + u, u = bc$$

$$\frac{dJ}{dv} = 3, \frac{dv}{da} = 1$$

$$so, \frac{dJ}{da} = \frac{dJ}{dv}\frac{dv}{da} = 3 * 1 = 3$$

$$if\ b = 2, then\ \frac{dJ}{dc} = \frac{dJ}{dv}\frac{dv}{du}\frac{du}{dc} = 3 * 1 * b = 3 * 1 * 2 = 6$$

写代码时，将$\frac{dFinalOutputVar}{dvar}$记为$dvar$(最后输出对这个变量的偏导)

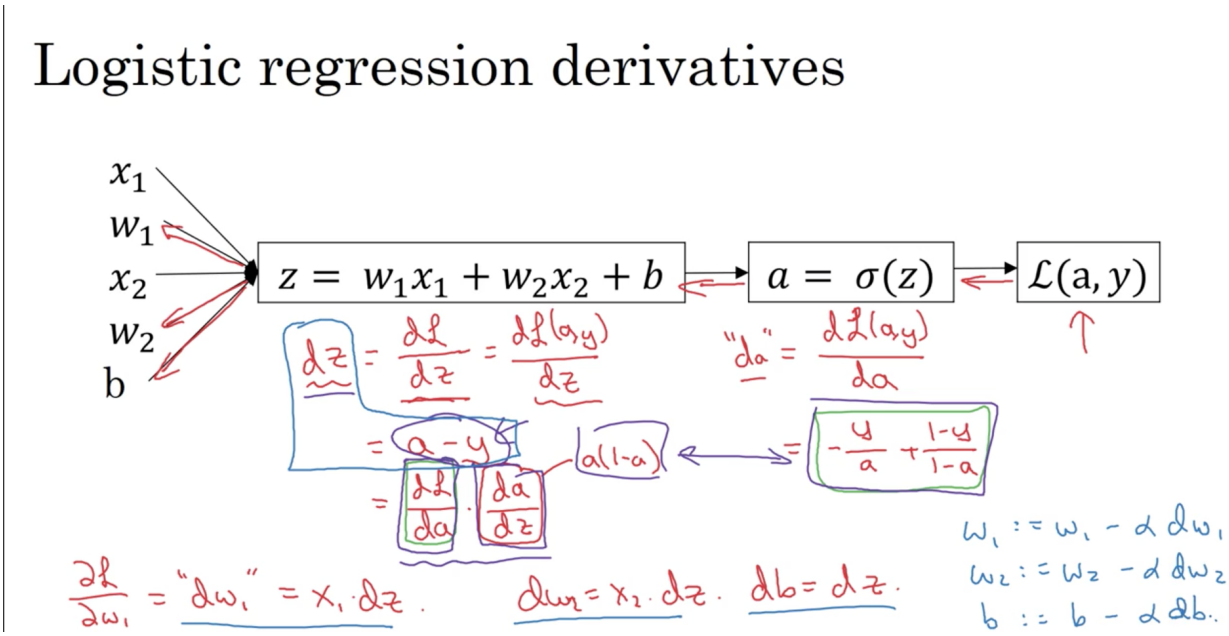


logistic regression gradient descent

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

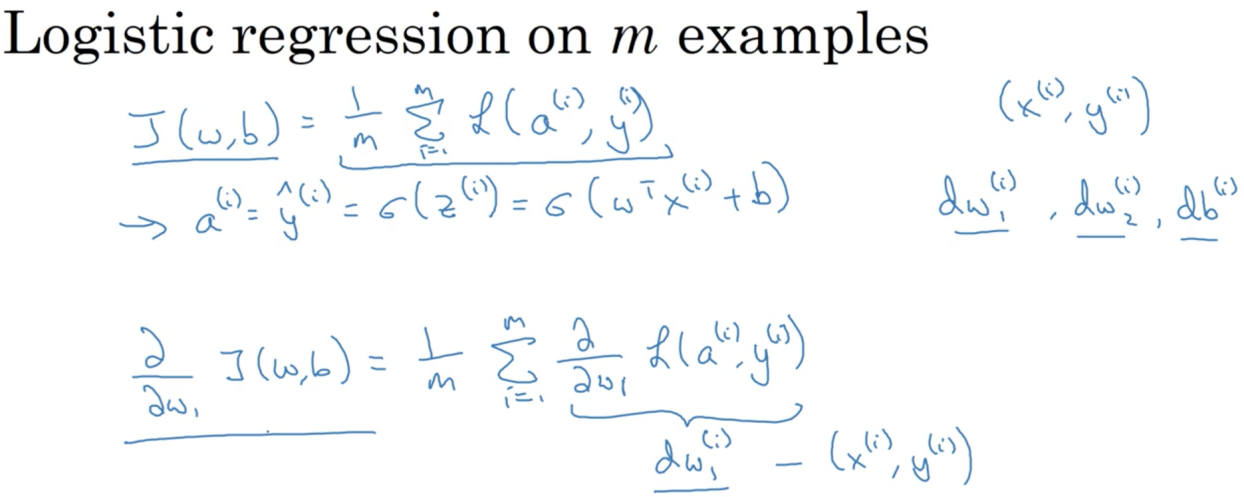
$$\hat{y} = a = \sigma(z)$$

$$L(a, y) = -(ylog(a) + (1 - y)log(1 - a))$$

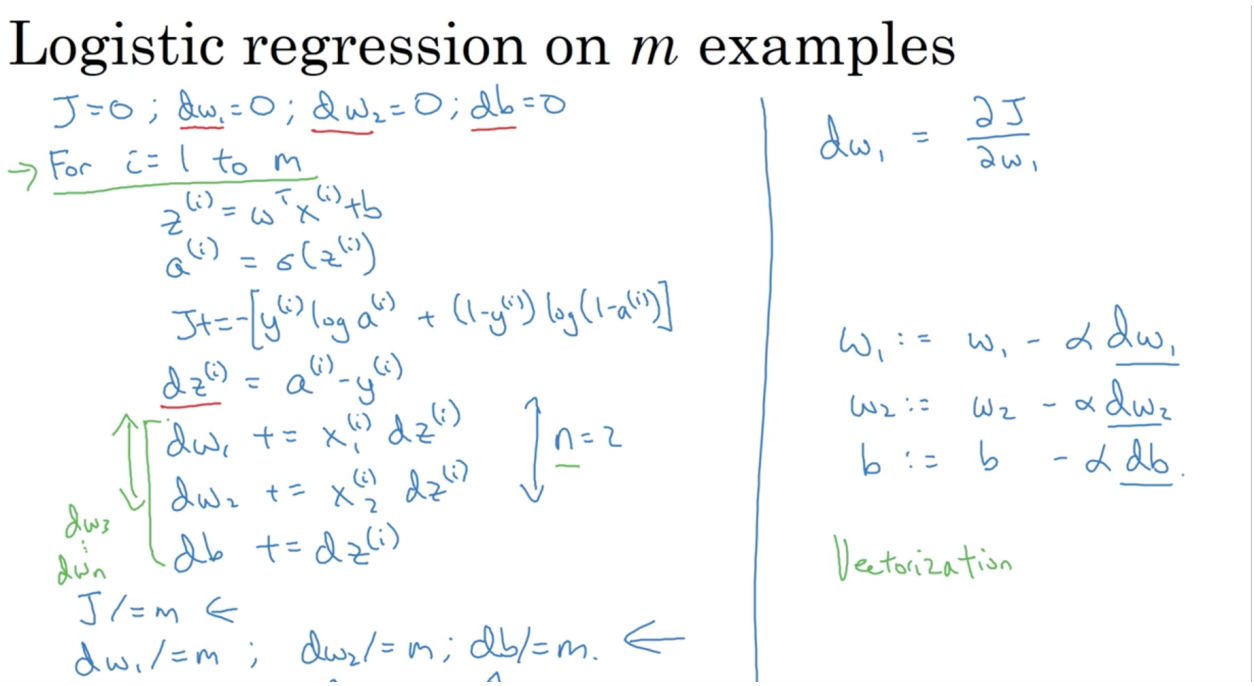


gradient descent on m examples

首先，根据J的公式，可以知道dJ/dw1其实就是对每个样本的dw1求和，然后/m。



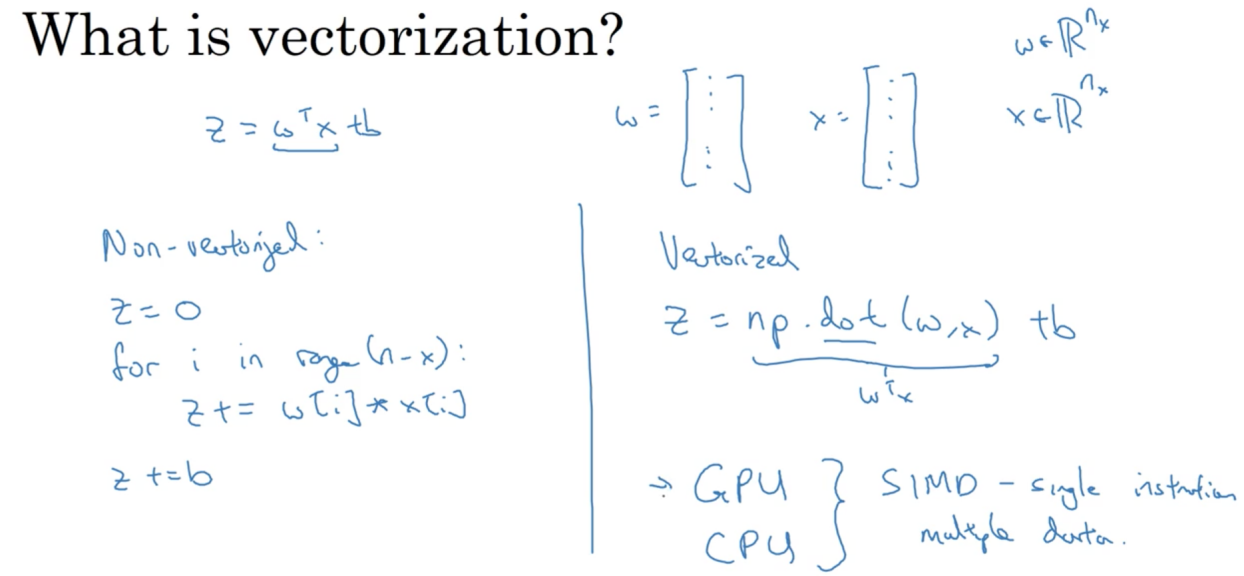
每一次迭代，遍历m个样本，算出J/dw1/dw2/db，然后用这些梯度去更新一次w1/w2/b。



但这的for loop太多了。。所以我们需要vectorization!

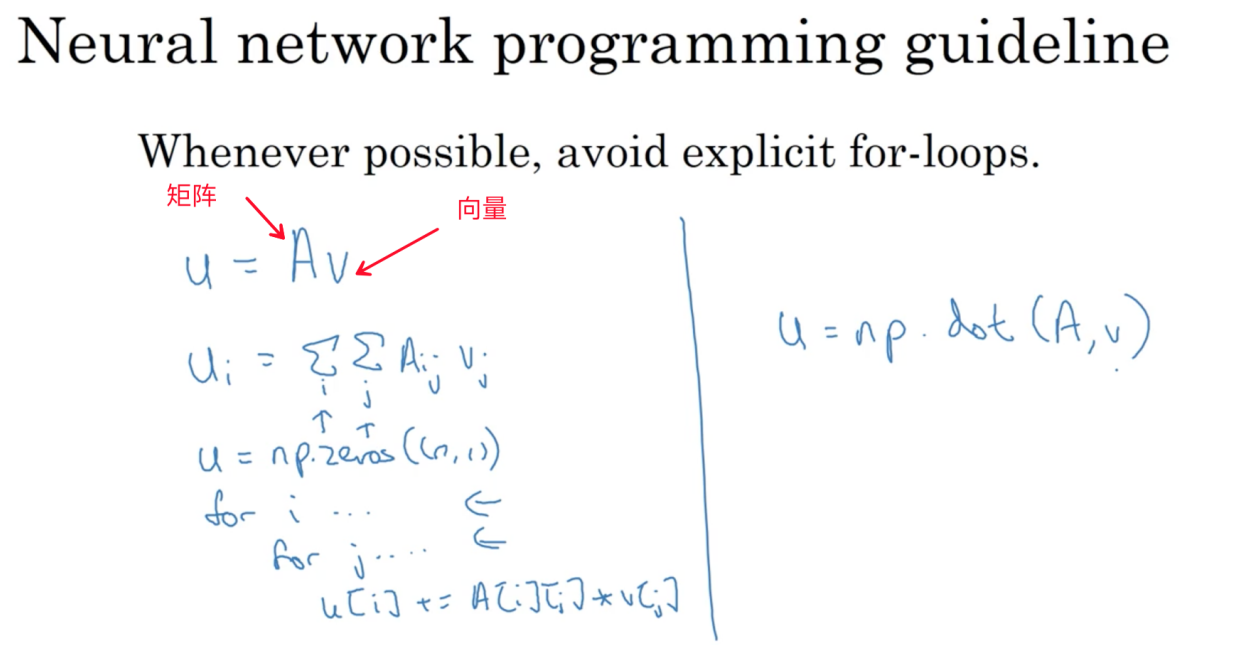
python & vectorization

vectorization



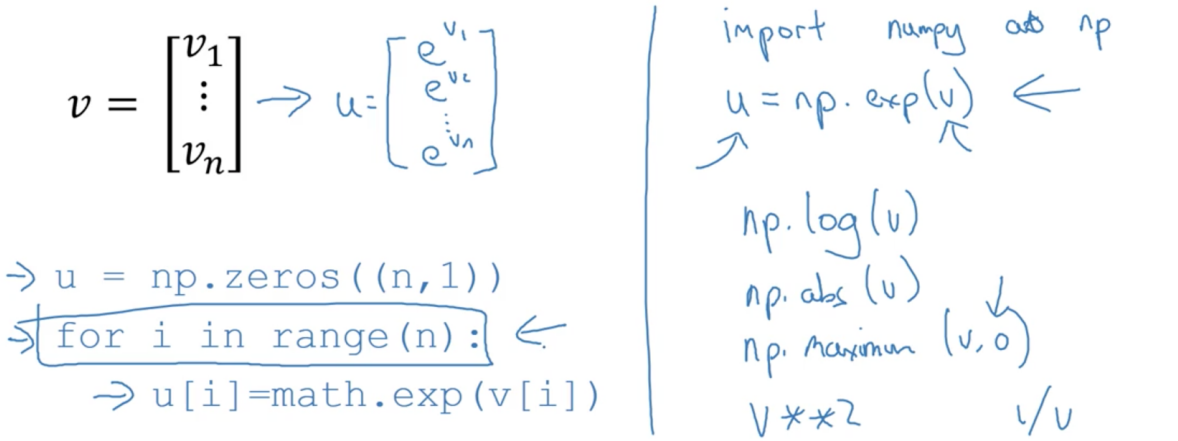
对于两个100w维的向量进行点乘，vectorization(1.5ms) 比for loop(470ms+)快

more examples of vectorization

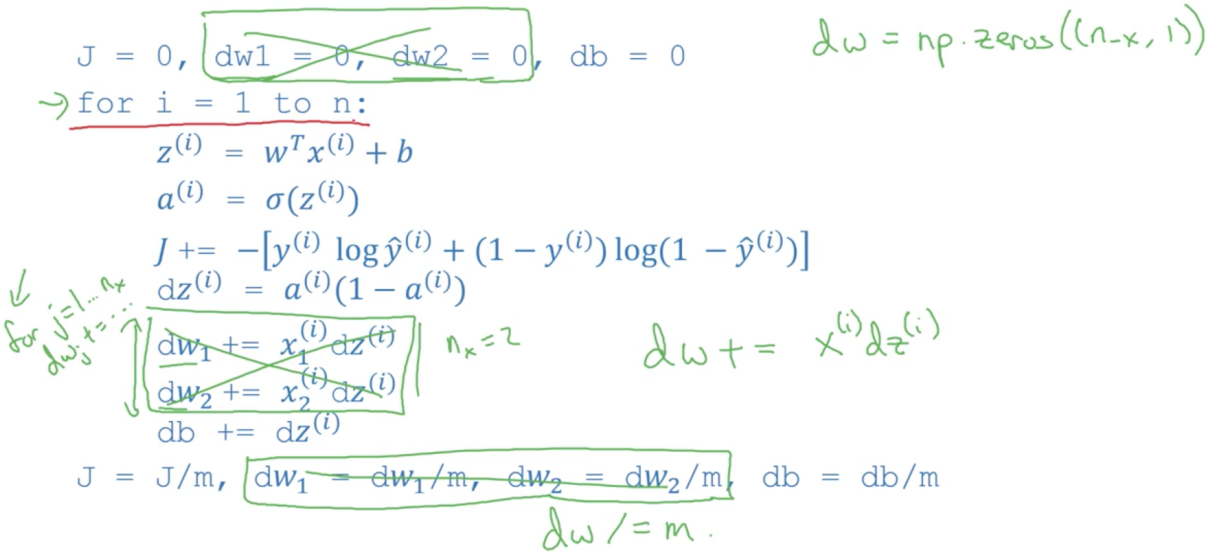


Vectors and matrix valued functions

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



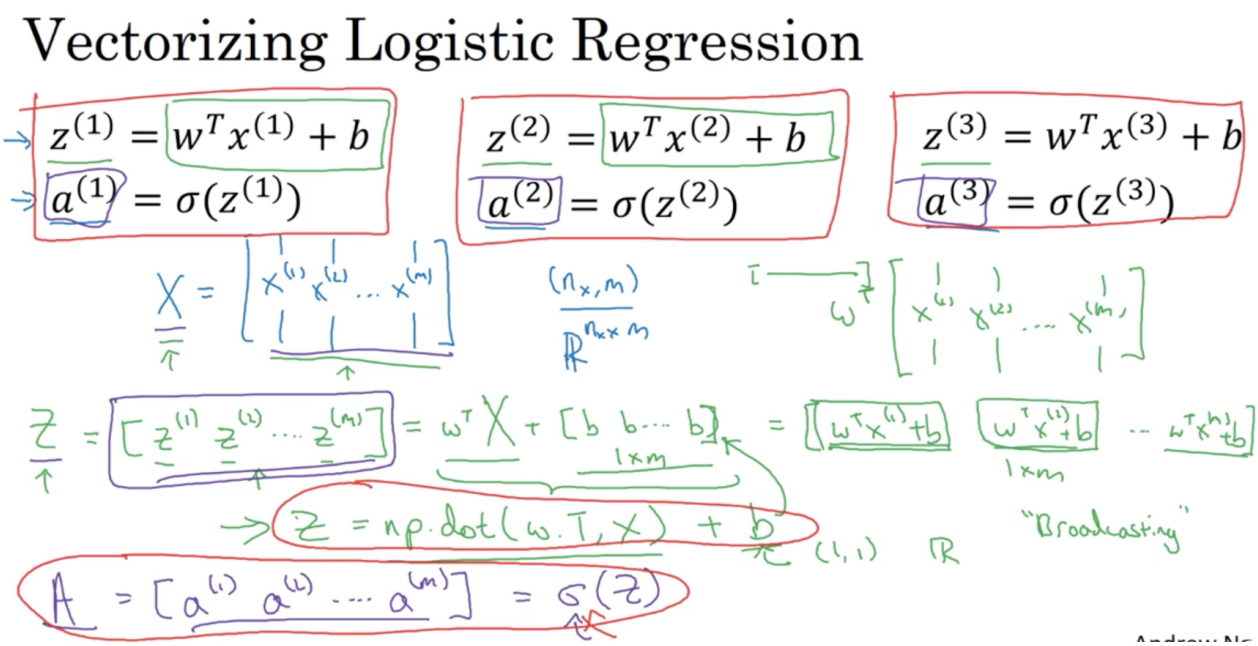
Logistic regression derivatives



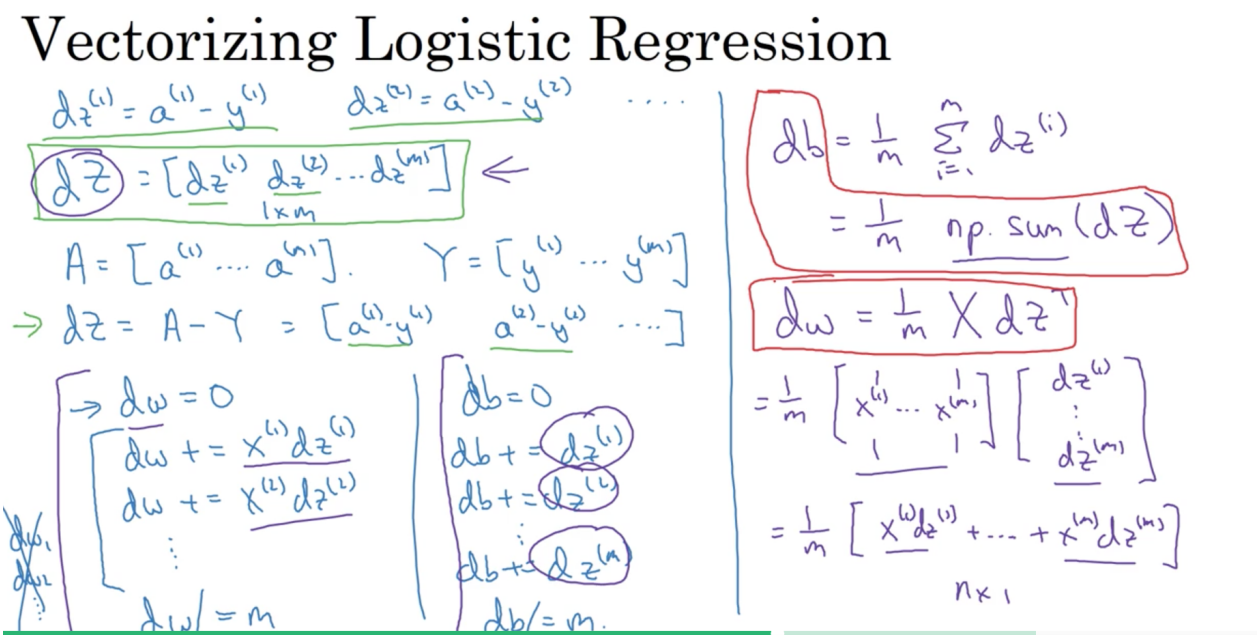
如上图，将n_x维的dw变为一个np.array即可干掉内层的for loop。

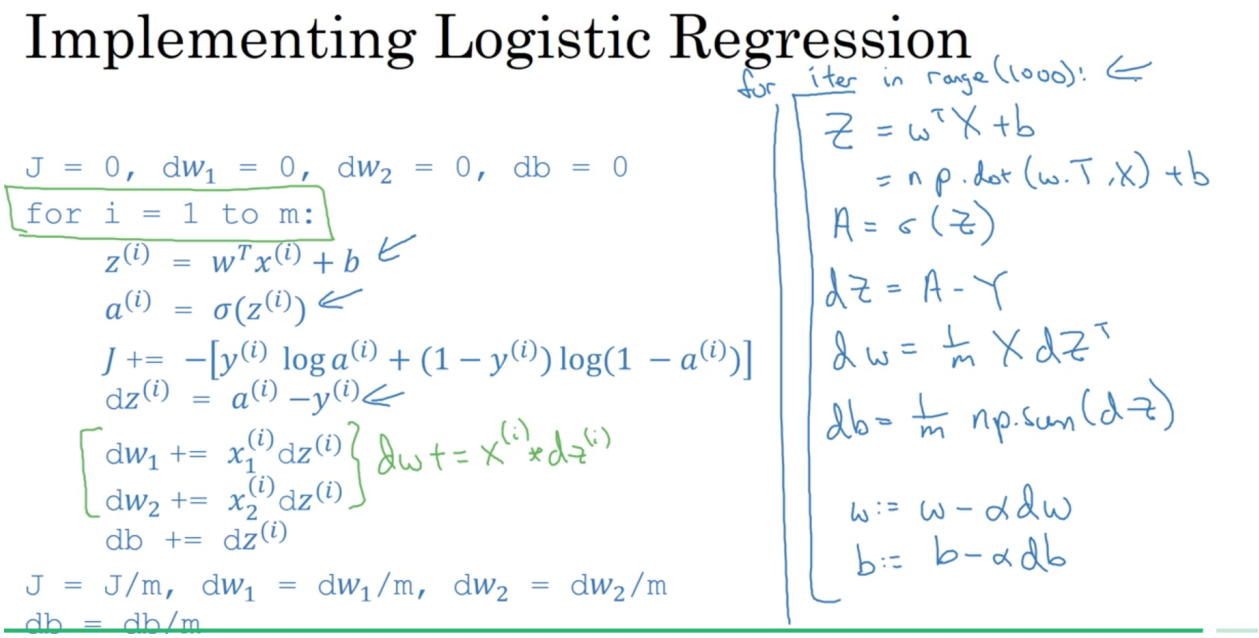
vectorizing logistic regression

可见，整个求Z的过程可以变成一句话，而求A时，需要封装一个基于numpy的sigmoid函数。



vectorizing logistic regression's gradient output

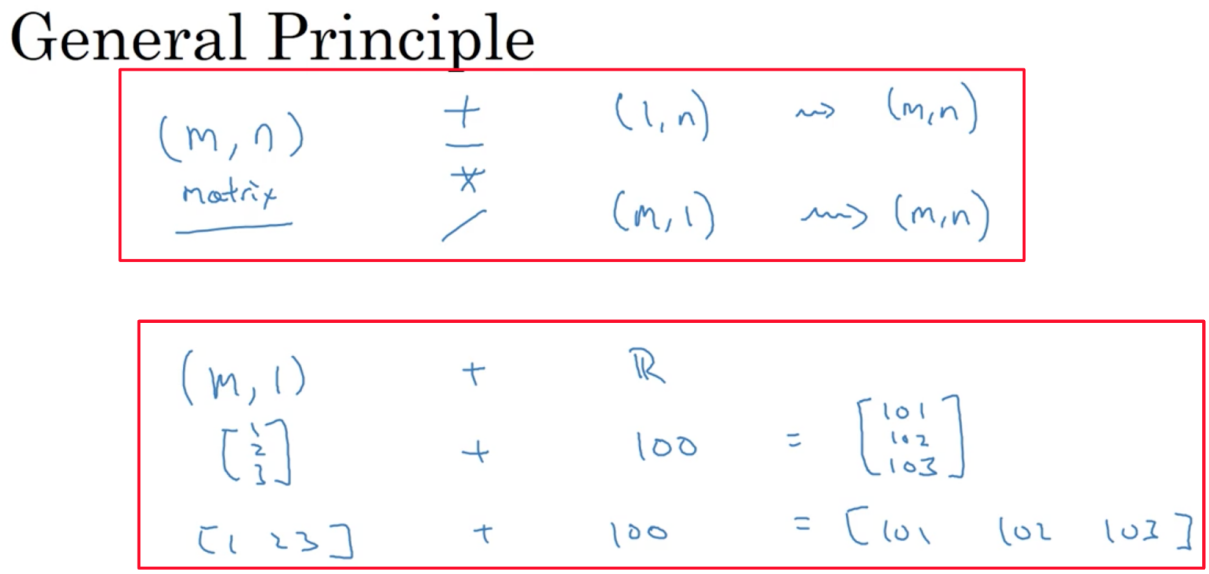




broadcasting in python

```
A = ndarray([[1,2,3,4],[2,3,4,5],[3,4,5,6]]) # 3*4
calc = A.sum(axis=0) # A的每列求和,得到1*4
calc2 = A.sum(axis=1) # A的每行求和,得到3*1
A/calc.reshape(1,4) #得到一个3*4的矩阵，就是broadcasting。其实等价于A/calc，但为了保险，可以调用reshape(1,4)来确保无误
```

小结：



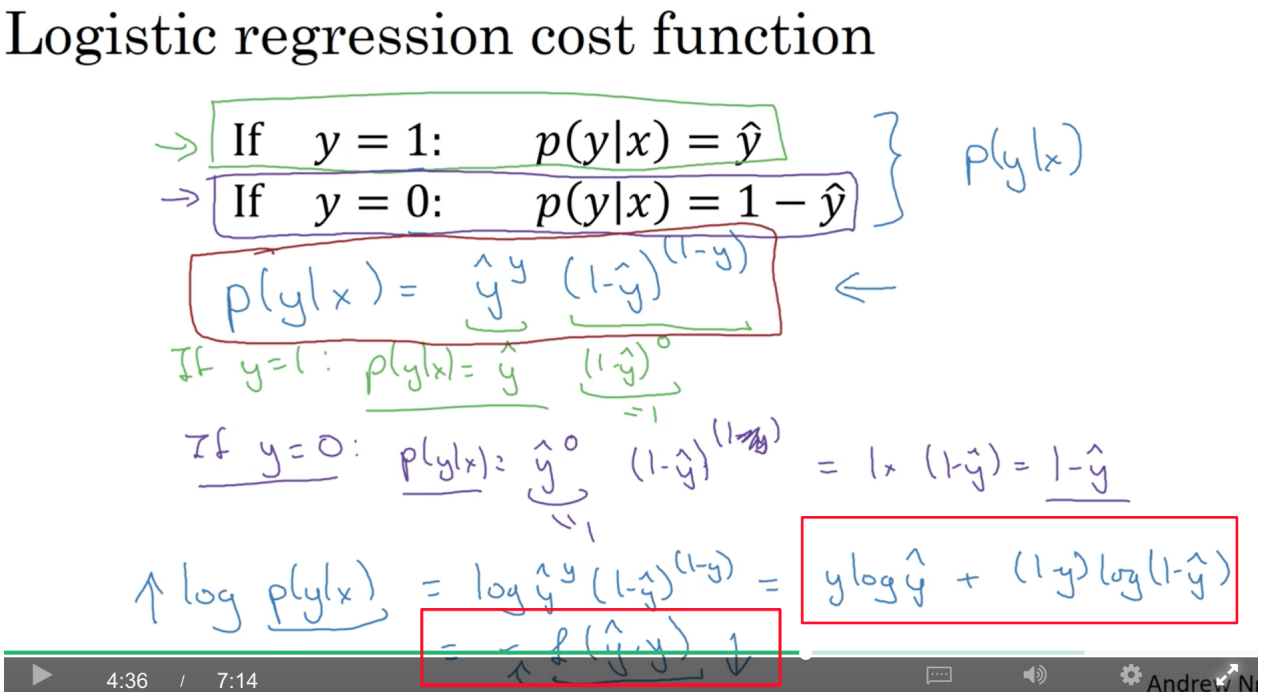
a note on python/numpy vectors

```
a=np.random.randn(5) # a.shape=(5,)是一个vector(rank 1 array)，不是一个矩阵，所以a.T还是(5,)，np.dot(a,a.T)=np.dot(a.T,a

b=np.random.randn(5,1) # a.shape=(5,1)，  a.T.shape=(1,5)，np.dot(a,a.T)是一个5*5的，np.dot(a.T,a)是一个1*1的矩阵（类似a

## 可以加一句：
assert(a.shape == (5, 1))
## 如果不小心搞了个rank 1 array,也可以手动a.reshape((5,1))=a.reshape(5,1)
```

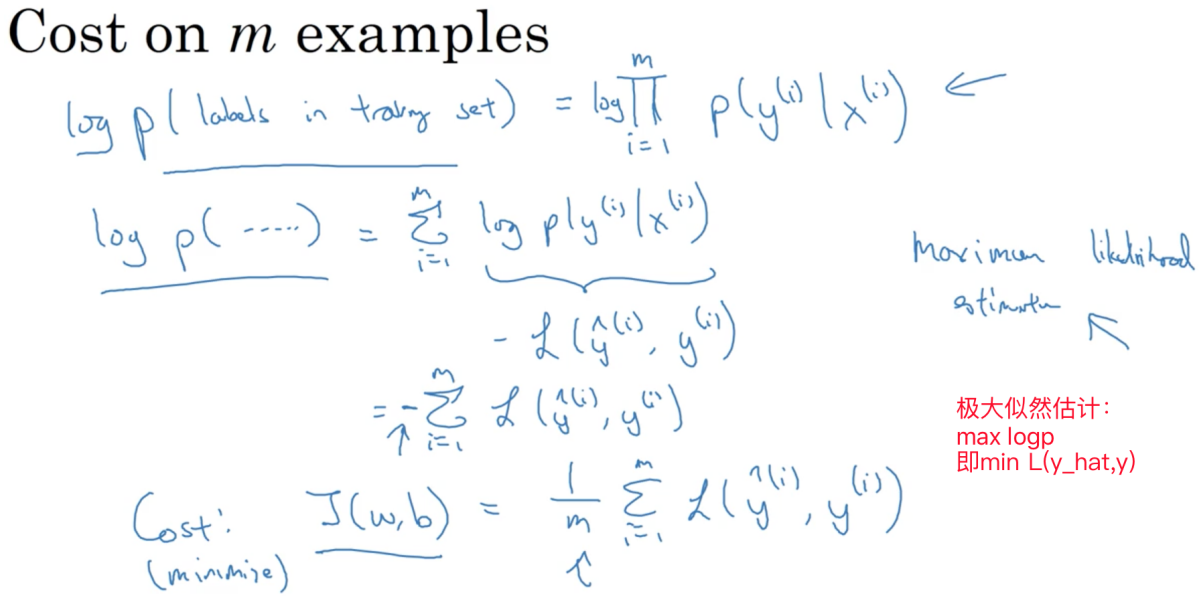
quick tour of jupyter/ipython notebooks

explanation of logistic regression cost function

单个样本的loss function, log越大，loss越小：



如果是iid（独立同分布），那么，m个样本的cost function，其实就叫对数似然。对他求极大似然估计，其实就是对m个样本求每个cost function的min:



极大似然估计：
max logp
即min L(y_hat,y)

programming assignments

squeeze

```
np.squeeze(a, axis=None)
## 删掉维数是一的部分，axis可以是Int/int数组，表示只去掉指定下标的部分，如果该部分维数不是1，会报错
x = np.array([[[0], [1], [2]]])
x.shape=(1,3,1)
np.squeeze(x)=array([0,1,2]) # shape=(3,)
np.squeeze(x, axis=(2,))=array([[0, 1, 2]]) # shape=(1,3)
```

把一个shape是(a,b,c,d)的array转成一个type是(bcd,a)的array:

```
X_flatten = X.reshape(X.shape[0], -1).T
```

图片的预处理：

- Figure out the dimensions and shapes of the problem (m_train, m_test, num_px, ...)
- Reshape the datasets such that each example is now a vector of size (num_px * num_px * 3, 1)
- "Standardize" the data: 对图片而言，所有元素除以255就可以了