deep Learning_c1_week1&2

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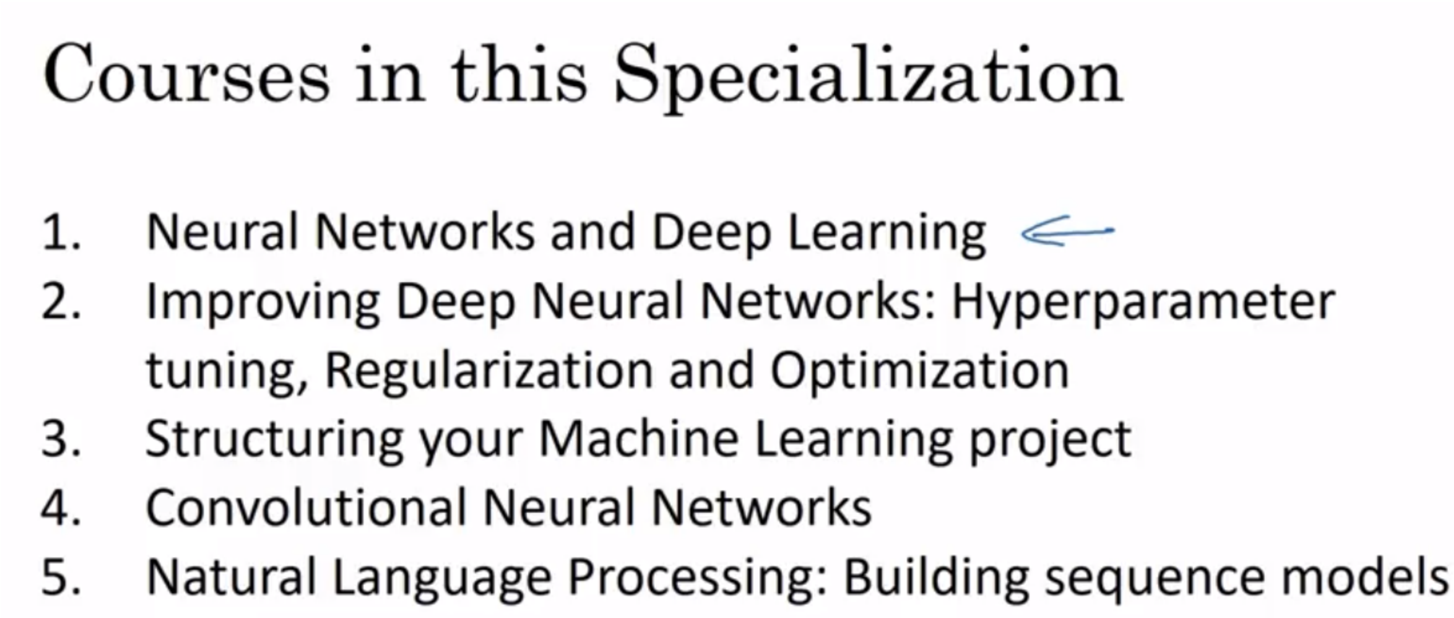
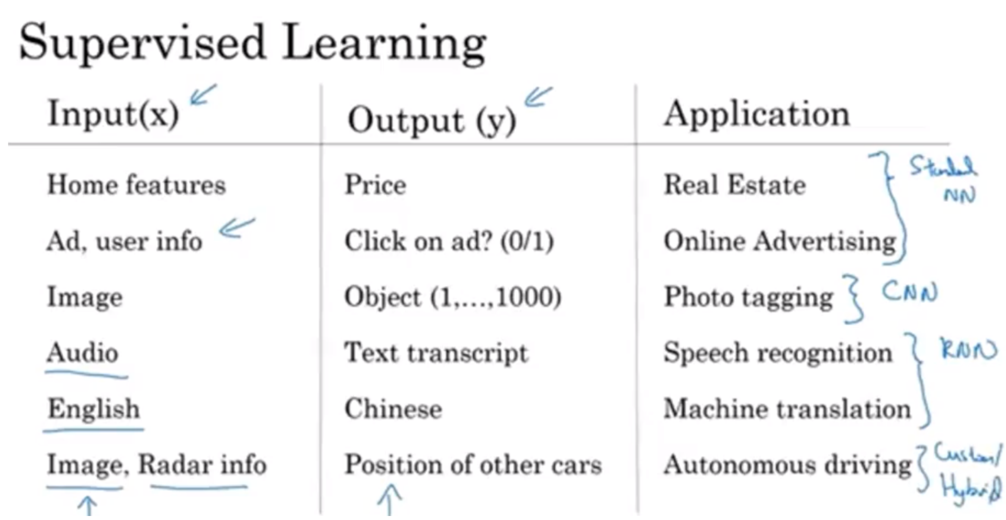
content of courses :

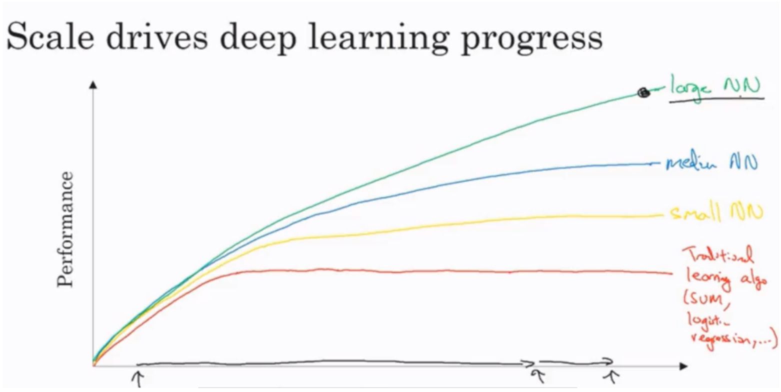


hi Andrew Ng, I'm back~

Introduction:

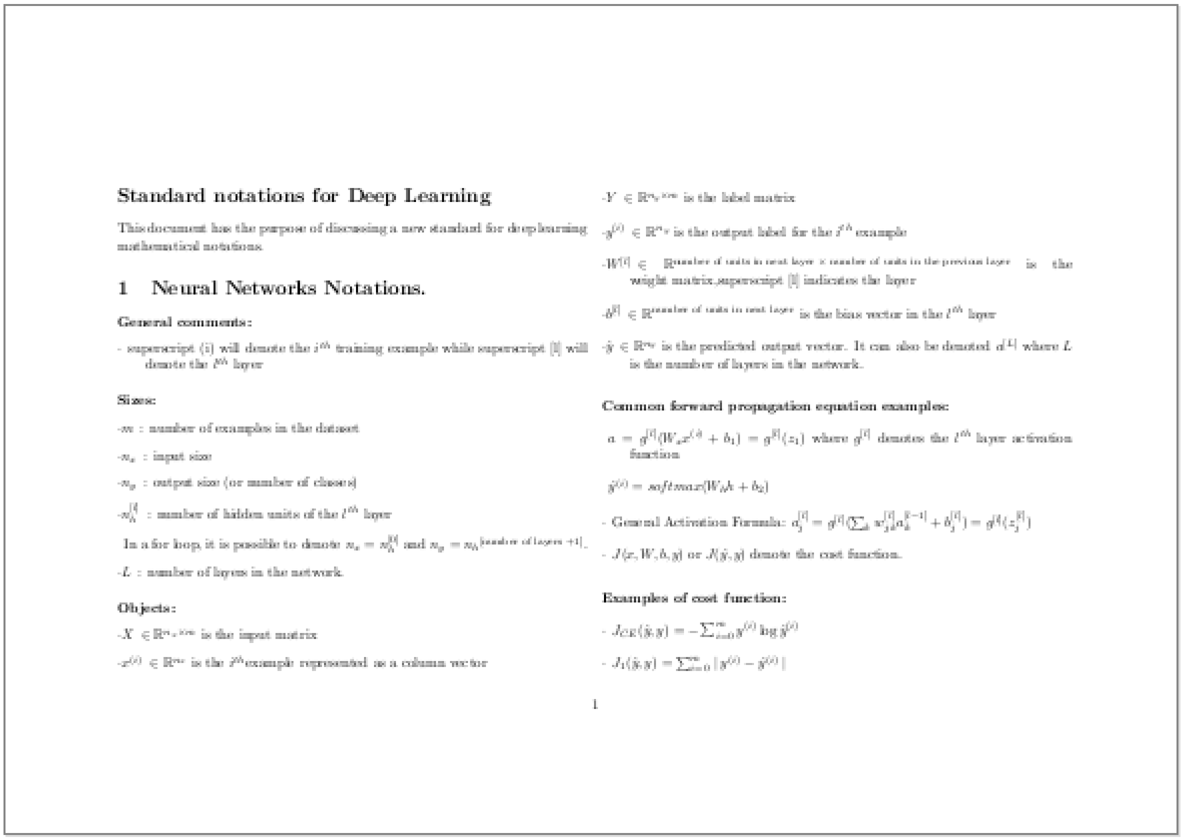
- applications e.g.,
  - 

  - implements in both structured data/ unstructured data
- why NN go bananas nowadays
  - boosting data!
  - hardware improvement!
  - algorithm help reduce computation. (e.g., sigmoid function 👉 Relu function)
  - see the performance compared with traditional machine learning in Big Data

- 

Logistic Regression in NN

- as usual, notation first:



Standard notations for Deep Learning

This document has the purpose of discussing a new standard for deep learning mathematical notations.

1 Neural Networks Notations.

General comments:

- superscript (i) will denote the i^{th} training example while superscript [l] will denote the l^{th} layer

Sizes:

-m : number of examples in the dataset

-n_x : input size

-n_y : output size (or number of classes)

-$n_h^{[l]}$: number of hidden units of the l^{th} layer

In a for loop, it is possible to denote $n_x = n_h^{[0]}$ and $n_y = n_h^{[\text{number of layers}+1]}$.

-L : number of layers in the network.

Objects:

-$X \in \mathbb{R}^{n_x \times m}$ is the input matrix

-$x^{(i)} \in \mathbb{R}^{n_x}$ is the i^{th} example represented as a column vector

-$Y \in \mathbb{R}^{n_y \times m}$ is the label matrix

-$y^{(i)} \in \mathbb{R}^{n_y}$ is the output label for the i^{th} example

-$W^{[l]} \in \mathbb{R}^{\text{number of units in next layer} \times \text{number of units in the previous layer}}$ is the weight matrix, superscript [l] indicates the layer

-$b^{[l]} \in \mathbb{R}^{\text{number of units in next layer}}$ is the bias vector in the l^{th} layer

-$\hat{y} \in \mathbb{R}^{n_y}$ is the predicted output vector. It can also be denoted $a^{[L]}$ where L is the number of layers in the network.

Common forward propagation equation examples:

$a = g^{[l]}(W_x x^{(i)} + b_1) = g^{[l]}(z_1)$ where $g^{[l]}$ denotes the l^{th} layer activation function

$\hat{y}^{(i)} = softmax(W_h h + b_2)$

- General Activation Formula: $a_j^{[l]} = g^{[l]}(\sum_k w_{jk}^{[l]} a_k^{[l-1]} + b_j^{[l]}) = g^{[l]}(z_j^{[l]})$

- $J(x, W, b, y)$ or $J(\hat{y}, y)$ denote the cost function.

Examples of cost function:

- $J_{CE}(\hat{y}, y) = -\sum_{i=0}^{m} y^{(i)} \log \hat{y}^{(i)}$

- $J_1(\hat{y}, y) = \sum_{i=0}^{m} | y^{(i)} - \hat{y}^{(i)} |$

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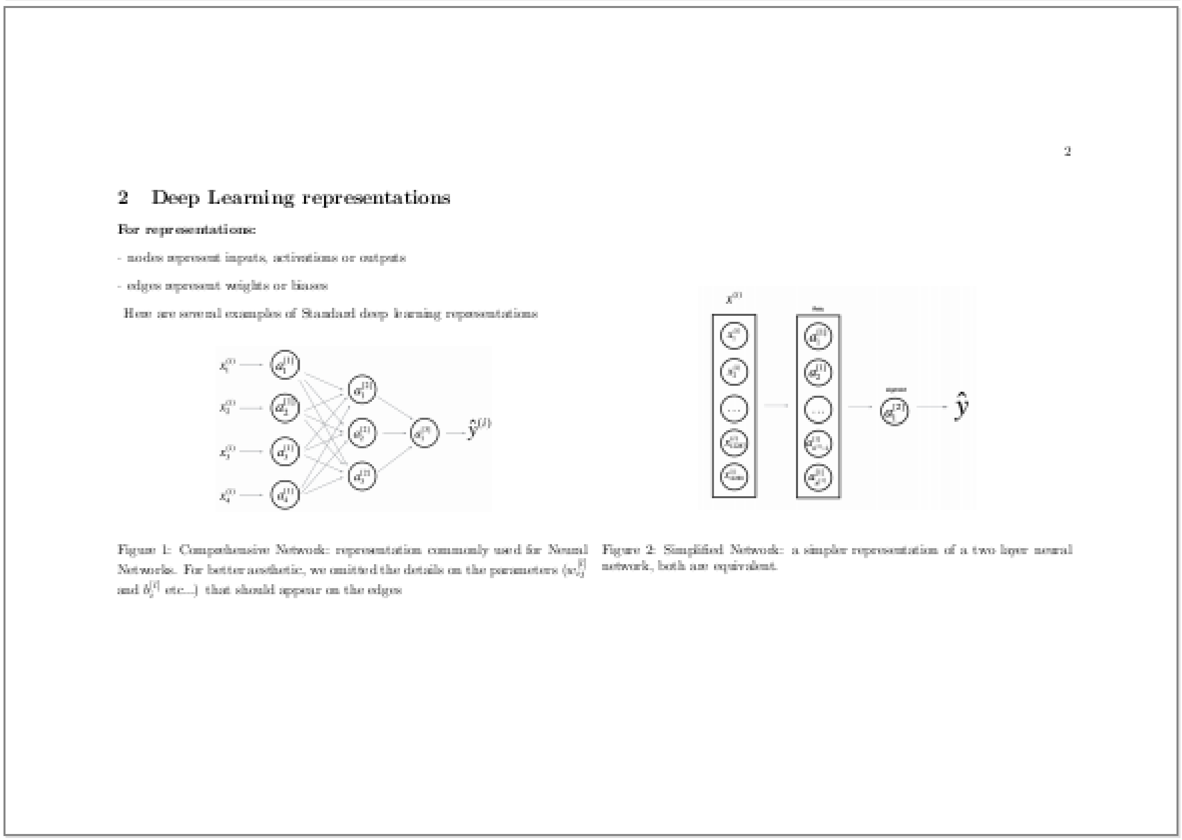

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2 Deep Learning representations

For representations:

- nodes represent inputs, activations or outputs

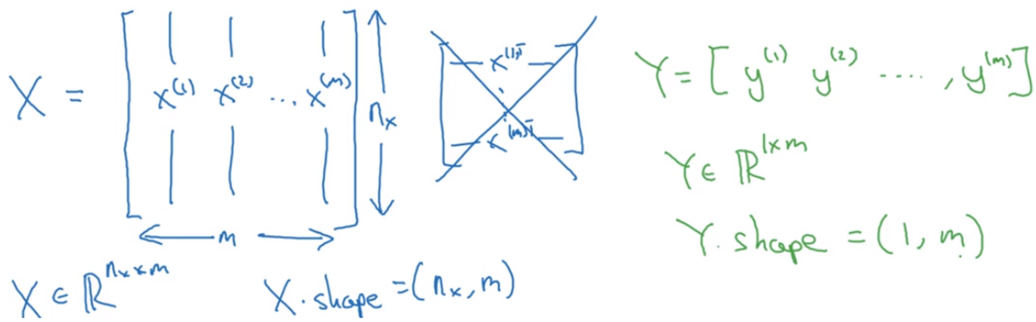
- edges represent weights or biases

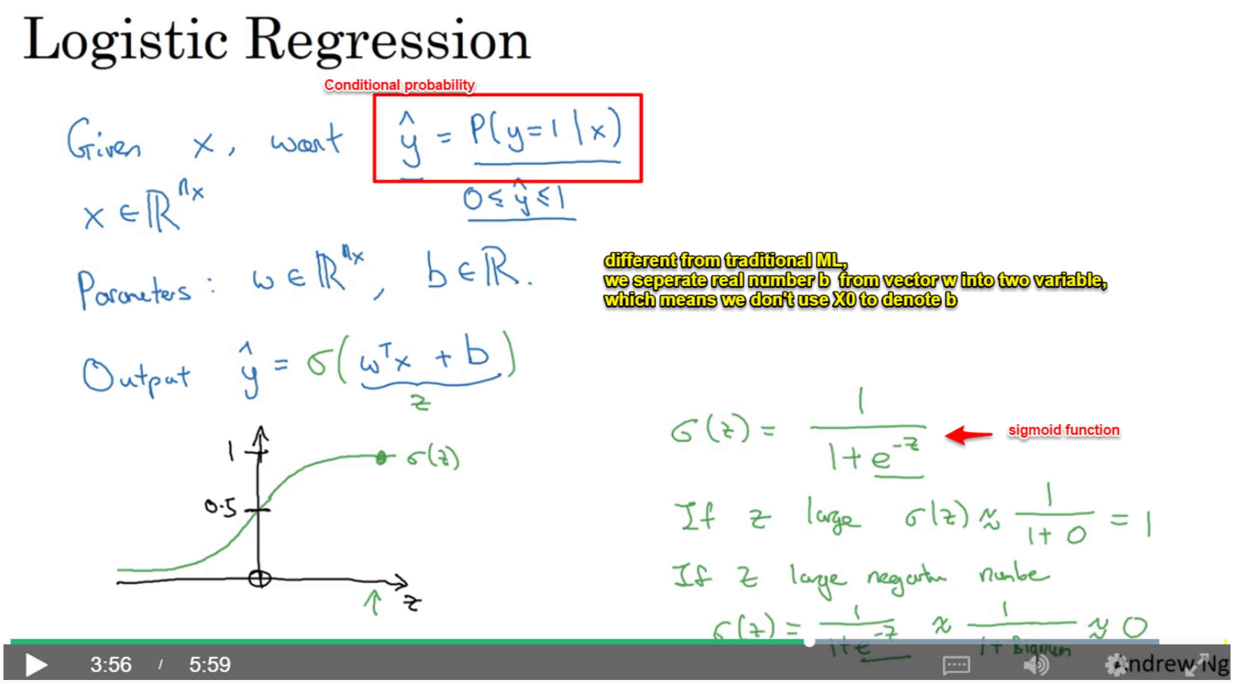
Here are several examples of Standard deep learning representations

Figure 1: Comprehensive Network: representation commonly used for Neural Networks. For better aesthetic, we omitted the details on the parameters ($w_{ij}^{[l]}$ and $b_i^{[l]}$ etc...) that should appear on the edges

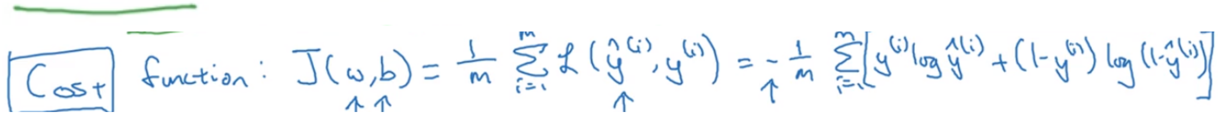
Figure 2: Simplified Network: a simpler representation of a two layer neural network, both are equivalent.

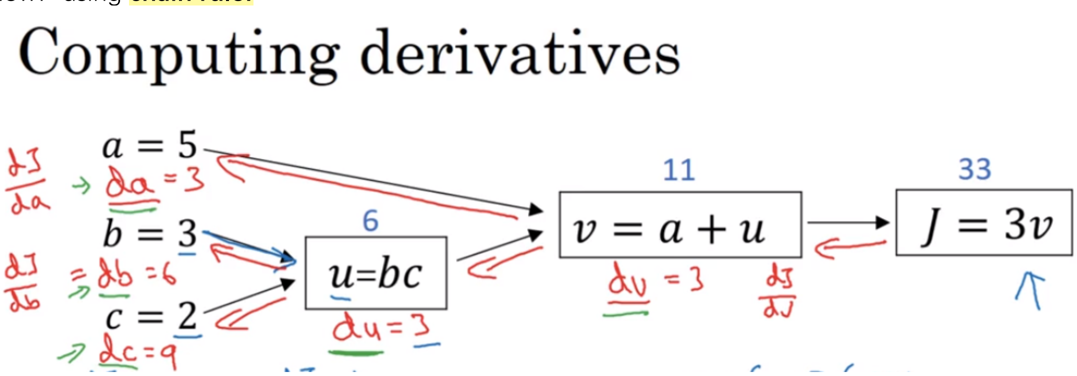
- caution! In Python, our data shape is **different** from Matlab. (the vector is transposed.)

- 

- **Review Logistic Regression and see things new in neural network.**
  - hypothesis:
    - 

  - loss function & cost function(same)
    - 

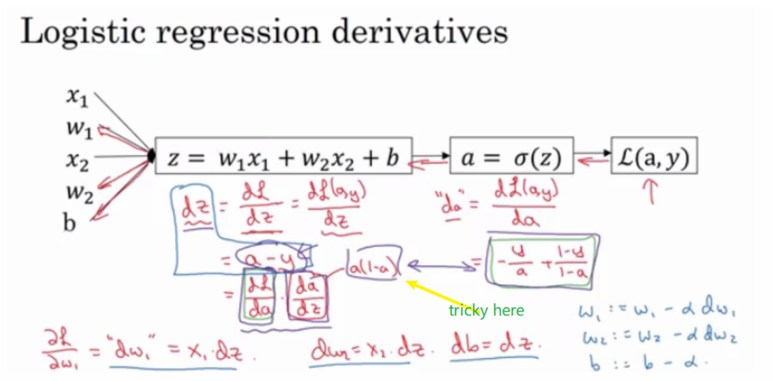
    - 

- Intuition of backward propagation
  - task: to compute parameters' derovatives
  - how? using **chain rule!**
  - 

  - coding habit: use "**dvar"** as the derivatives of those output variables. e.g., use "da, db, dc" to denote the derivatives of a,b,c above.
- **Whole algorithm(forward propagation+backward propagation)**

```
#forward propagation(Pseudo code)
Z=W.T * X+b
A=sigmoid(Z) #y-hat, our hypothesis      sigmoid(Z)=1/(1+e^(-Z))
Loss(A,Y)=-!/m*(Y*Log(A)+(1-Y)*Log(1-Y))
```

```
#backward propagation(Pseudo code)
dZ=A-Y
dW=(X.T *dZ)/m
db=sum(dZ)/m
```

- 

- details:

$$\frac{dL}{dz} = \frac{dz}{da} \times \frac{da}{dz}$$

$$\therefore \frac{dz}{da} = -\frac{y}{a} + \frac{1-y}{1-a}.$$

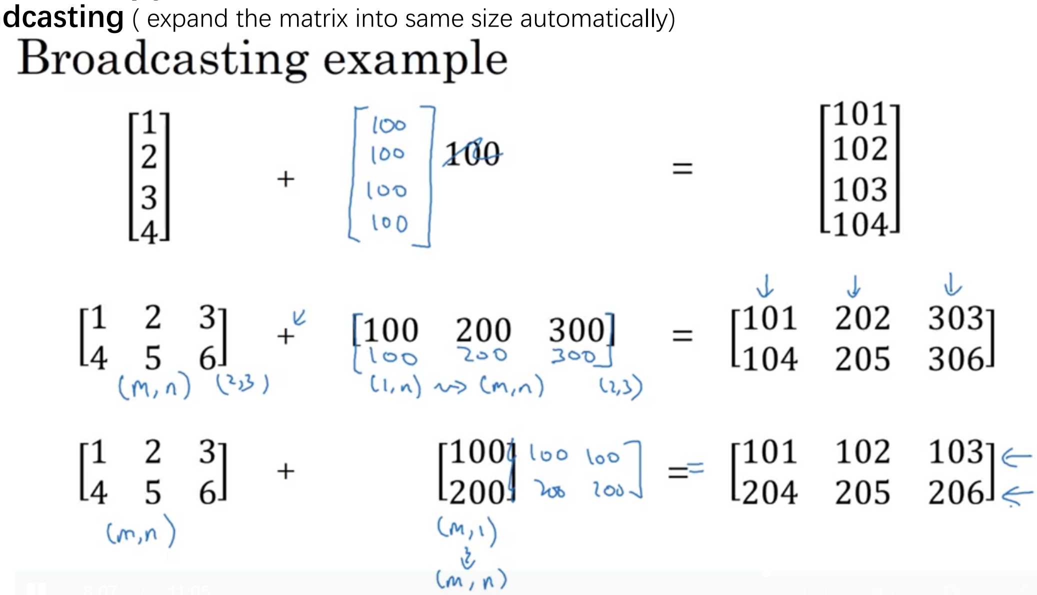
$$\frac{da}{dz} = \frac{e^{-z}}{(1+e^{-z})^2} = \frac{1}{1+e^{-z}} \cdot \frac{e^{-z}}{1+e^{-z}}$$

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

$$\therefore \frac{dL}{dz} = a(1-a) \times \left(\frac{-y}{a} + \frac{(1-y)}{1-a}\right)$$

$$= a-y$$

- **concept of Numpy**
  - **broadcasting** (expand the matrix into same size automatically)



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-
    - flexible enough but sometime cause subtle bugs TAT.
  - **Coding habits in Numpy**
    - specify the shape of a vector, don't use "rank 1 array" which looks like this: `(m,)`
    - don't be shy to use:
      - `assert(a.shape == (5,1))` to check if your matrix shape is the required one.
      - reshape matrix to `(m, n) #the size you want.`
  - **Axis**
    - `obj.sum(axis = 0)` sums the columns while `obj.sum(axis = 1)` sums the rows.
  - **get help from document**
    - write `np.exp?` (for example) to get quick access to the documentation.
  - **normalize**
    - **1.4 - Normalizing rows**

      Another common technique we use in Machine Learning and Deep Learning is to normalize our data. It often leads to a better performance because gradient descent converges faster after normalization. Here, by normalization we mean changing x to $\frac{x}{\|x\|}$ (dividing each row vector of x by its norm).

      For example, if

      $$x = \begin{bmatrix} 0 & 3 & 4 \\ 2 & 6 & 4 \end{bmatrix} \tag{3}$$

      then

      $$\|x\| = np.linalg.norm(x, axis = 1, keepdims = True) = \begin{bmatrix} 5 \\ \sqrt{56} \end{bmatrix} \tag{4}$$

      the self product of row

      and

      $$x\_normalized = \frac{x}{\|x\|} = \begin{bmatrix} 0 & \frac{3}{5} & \frac{4}{5} \\ \frac{2}{\sqrt{56}} & \frac{6}{\sqrt{56}} & \frac{4}{\sqrt{56}} \end{bmatrix} \tag{5}$$
  - **L1 & L2 Loss**
    - $$L_1(\hat{y}, y) = \sum_{i=0}^{m} |y^{(i)} - \hat{y}^{(i)}|$$

```
loss_1 = sum(abs(y-yhat))
```

    - $$L_2(\hat{y}, y) = \sum_{i=0}^{m} (y^{(i)} - \hat{y}^{(i)})^2$$

```
loss_2 = np.dot(yhat-y,yhat-y)
```

  - **reshape & flatten images**
    - A trick when you want to flatten a matrix X of shape (a,b,c,d) to a matrix X_flatten of shape (b∗c∗d, a) is to use:

      ```
      X_flatten = X.reshape(X.shape[0], -1).T      # X.T is the transpose of X
      ```

Assignment: Classify Cat or Non-Cat!

- **Step by step**

- **data preview and preprocess**
  - get intuition of your data, i.e. know what their size are.
  - **regularization:**
    - instead of std=(x-μ)/sqrt(σ) , here we just divide every row of the dataset by 255 (the maximum value of a pixel channel).
- **function prepare:**

```
def sigmoid(z):
    s = 1/(1+np.exp(-z))
    return s
```

- **Initialization**
  - use *np.zeros((n,m))*
- **Forward and Backward Propagation to optimize parameters**
- **Make Prediction**