Week 4 - prog ex:

笔记本: DL 1 - NN and DL
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Welcome to your third programming exercise of the deep learning specialization. You will implement all the building blocks of a neural network and use these building blocks in the next assignment to build a neural network of any architecture you want. By completing this assignment you will:

- Develop an intuition of the over all structure of a neural network.

- Write functions (e.g. forward propagation, backward propagation, logistic loss, etc...) that would help you decompose your code and ease the process of building a neural network.

- Initialize/update parameters according to your desired structure.

Building your Deep Neural Network: Step by Step

Welcome to your week 4 assignment (part 1 of 2)! You have previously trained a 2-layer Neural Network (with a single hidden layer). This week, you will build a deep neural network, with as many layers as you want!

- In this notebook, you will implement all the functions required to build a deep neural network.
- In the next assignment, you will use these functions to build a deep neural network for image classification.

After this assignment you will be able to:

- Use non-linear units like ReLU to improve your model
- Build a deeper neural network (with more than 1 hidden layer)
- Implement an easy-to-use neural network class

Notation:

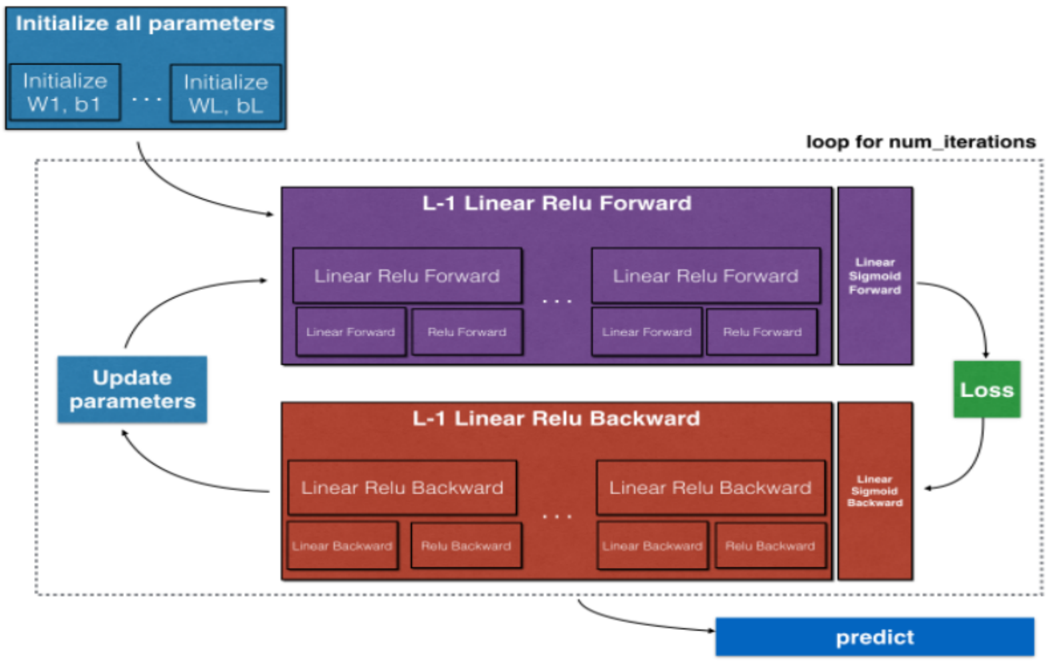
- Superscript $[l]$ denotes a quantity associated with the l^{th} layer.
    - Example: $a^{[L]}$ is the L^{th} layer activation. $W^{[L]}$ and $b^{[L]}$ are the L^{th} layer parameters.
- Superscript (i) denotes a quantity associated with the i^{th} example.
    - Example: $x^{(i)}$ is the i^{th} training example.
- Lowerscript i denotes the i^{th} entry of a vector.
    - Example: $a^{[l]}_i$ denotes the i^{th} entry of the l^{th} layer's activations).

Let's get started!

2 - Outline of the Assignment

To build your neural network, you will be implementing several "helper functions". These helper functions will be used in the next assignment to build a two-layer neural network and an L-layer neural network. Each small helper function you will implement will have detailed instructions that will walk you through the necessary steps. Here is an outline of this assignment, you will:

- Initialize the parameters for a two-layer network and for an L-layer neural network.
- Implement the forward propagation module (shown in purple in the figure below).
    - Complete the LINEAR part of a layer's forward propagation step (resulting in $Z^{[l]}$).
    - We give you the ACTIVATION function (relu/sigmoid).
    - Combine the previous two steps into a new [LINEAR->ACTIVATION] forward function.
    - Stack the [LINEAR->RELU] forward function L-1 time (for layers 1 through L-1) and add a [LINEAR->SIGMOID] at the end (for the final layer L). This gives you a new L_model_forward function.
- Compute the loss.
- Implement the backward propagation module (denoted in red in the figure below).
    - Complete the LINEAR part of a layer's backward propagation step.
    - We give you the gradient of the ACTIVATE function (relu_backward/sigmoid_backward)
    - Combine the previous two steps into a new [LINEAR->ACTIVATION] backward function.
    - Stack [LINEAR->RELU] backward L-1 times and add [LINEAR->SIGMOID] backward in a new L_model_backward function
- Finally update the parameters.



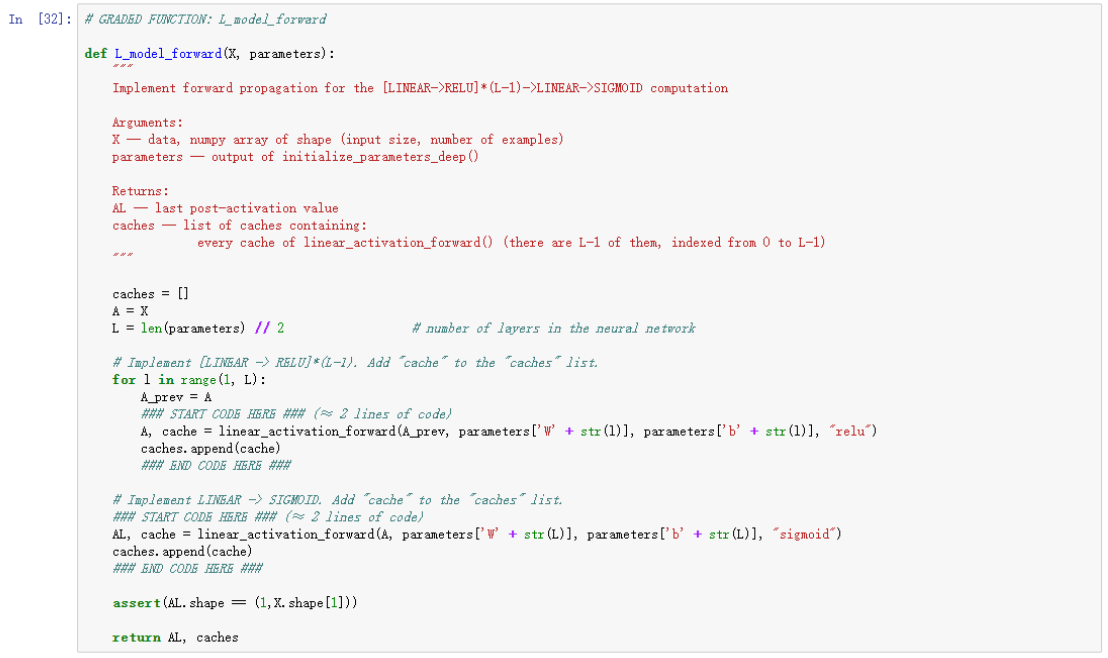
forward

In [8]:

```python
# GRADED FUNCTION: linear_forward

def linear_forward(A, W, b):
    """
    Implement the linear part of a layer's forward propagation.

    Arguments:
    A -- activations from previous layer (or input data): (size of previous layer, number of examples)
    W -- weights matrix: numpy array of shape (size of current layer, size of previous layer)
    b -- bias vector, numpy array of shape (size of the current layer, 1)

    Returns:
    Z -- the input of the activation function, also called pre-activation parameter
    cache -- a python tuple containing "A", "W" and "b" ; stored for computing the backward pass efficiently
    """

    ### START CODE HERE ### (≈ 1 line of code)
    Z = np.dot(W, A) + b
    ### END CODE HERE ###

    assert(Z.shape == (W.shape[0], A.shape[1]))
    cache = (A, W, b)

    return Z, cache
```

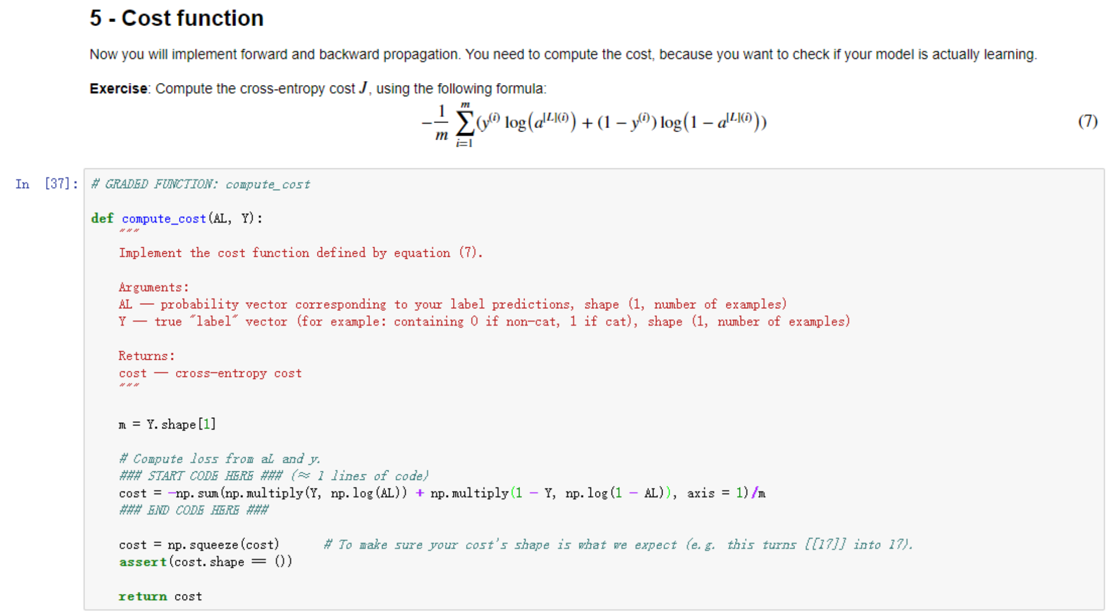
In [10]:

```python
# GRADED FUNCTION: linear_activation_forward

def linear_activation_forward(A_prev, W, b, activation):
    """
    Implement the forward propagation for the LINEAR->ACTIVATION layer

    Arguments:
    A_prev -- activations from previous layer (or input data): (size of previous layer, number of examples)
    W -- weights matrix: numpy array of shape (size of current layer, size of previous layer)
    b -- bias vector, numpy array of shape (size of the current layer, 1)
    activation -- the activation to be used in this layer, stored as a text string: "sigmoid" or "relu"

    Returns:
    A -- the output of the activation function, also called the post-activation value
    cache -- a python tuple containing "linear_cache" and "activation_cache";
             stored for computing the backward pass efficiently
    """

    if activation == "sigmoid":
        # Inputs: "A_prev, W, b". Outputs: "A, activation_cache".
        ### START CODE HERE ### (≈ 2 lines of code)
        Z, linear_cache = linear_forward(A_prev, W, b)
        A, activation_cache = sigmoid(Z)
        ### END CODE HERE ###

    elif activation == "relu":
        # Inputs: "A_prev, W, b". Outputs: "A, activation_cache".
        ### START CODE HERE ### (≈ 2 lines of code)
        Z, linear_cache = linear_forward(A_prev, W, b)
        A, activation_cache = relu(Z)
        ### END CODE HERE ###

    assert (A.shape == (W.shape[0], A_prev.shape[1]))
    cache = (linear_cache, activation_cache)

    return A, cache
```



```
In [32]: # GRADED FUNCTION: L_model_forward

         def L_model_forward(X, parameters):
             """
             Implement forward propagation for the [LINEAR->RELU]*(L-1)->LINEAR->SIGMOID computation

             Arguments:
             X -- data, numpy array of shape (input size, number of examples)
             parameters -- output of initialize_parameters_deep()

             Returns:
             AL -- last post-activation value
             caches -- list of caches containing:
                         every cache of linear_activation_forward() (there are L-1 of them, indexed from 0 to L-1)
             """

             caches = []
             A = X
             L = len(parameters) // 2                  # number of layers in the neural network

             # Implement [LINEAR -> RELU]*(L-1). Add "cache" to the "caches" list.
             for l in range(1, L):
                 A_prev = A
                 ### START CODE HERE ### (≈ 2 lines of code)
                 A, cache = linear_activation_forward(A_prev, parameters['W' + str(l)], parameters['b' + str(l)], "relu")
                 caches.append(cache)
                 ### END CODE HERE ###

             # Implement LINEAR -> SIGMOID. Add "cache" to the "caches" list.
             ### START CODE HERE ### (≈ 2 lines of code)
             AL, cache = linear_activation_forward(A, parameters['W' + str(L)], parameters['b' + str(L)], "sigmoid")
             caches.append(cache)
             ### END CODE HERE ###

             assert(AL.shape == (1,X.shape[1]))

             return AL, caches
```

cost



5 - Cost function

Now you will implement forward and backward propagation. You need to compute the cost, because you want to check if your model is actually learning.

Exercise: Compute the cross-entropy cost J, using the following formula:

$$-\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)}\log\left(a^{[L](i)}\right) + (1-y^{(i)})\log\left(1-a^{[L](i)}\right)\right) \tag{7}$$

```
In [37]: # GRADED FUNCTION: compute_cost

         def compute_cost(AL, Y):
             """
             Implement the cost function defined by equation (7).

             Arguments:
             AL -- probability vector corresponding to your label predictions, shape (1, number of examples)
             Y -- true "label" vector (for example: containing 0 if non-cat, 1 if cat), shape (1, number of examples)

             Returns:
             cost -- cross-entropy cost
             """

             m = Y.shape[1]

             # Compute loss from aL and y.
             ### START CODE HERE ### (≈ 1 lines of code)
             cost = -np.sum(np.multiply(Y, np.log(AL)) + np.multiply(1 - Y, np.log(1 - AL)), axis = 1)/m
             ### END CODE HERE ###

             cost = np.squeeze(cost)      # To make sure your cost's shape is what we expect (e.g. this turns [[17]] into 17).
             assert(cost.shape == ())

             return cost
```

backward

6.1 - Linear backward

For layer l, the linear part is: $Z^{[l]} = W^{[l]}A^{[l-1]} + b^{[l]}$ (followed by an activation).

Suppose you have already calculated the derivative $dZ^{[l]} = \frac{\partial \mathcal{L}}{\partial Z^{[l]}}$. You want to get $(dW^{[l]}, db^{[l]}, dA^{[l-1]})$.

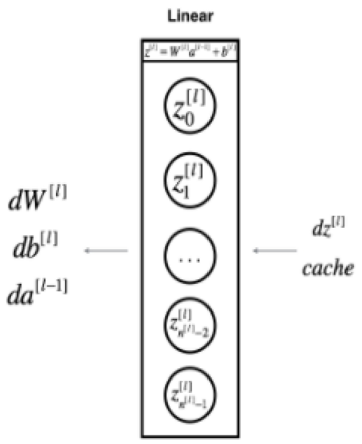


Figure 4

The three outputs $(dW^{[l]}, db^{[l]}, dA^{[l-1]})$ are computed using the input $dZ^{[l]}$.Here are the formulas you need:

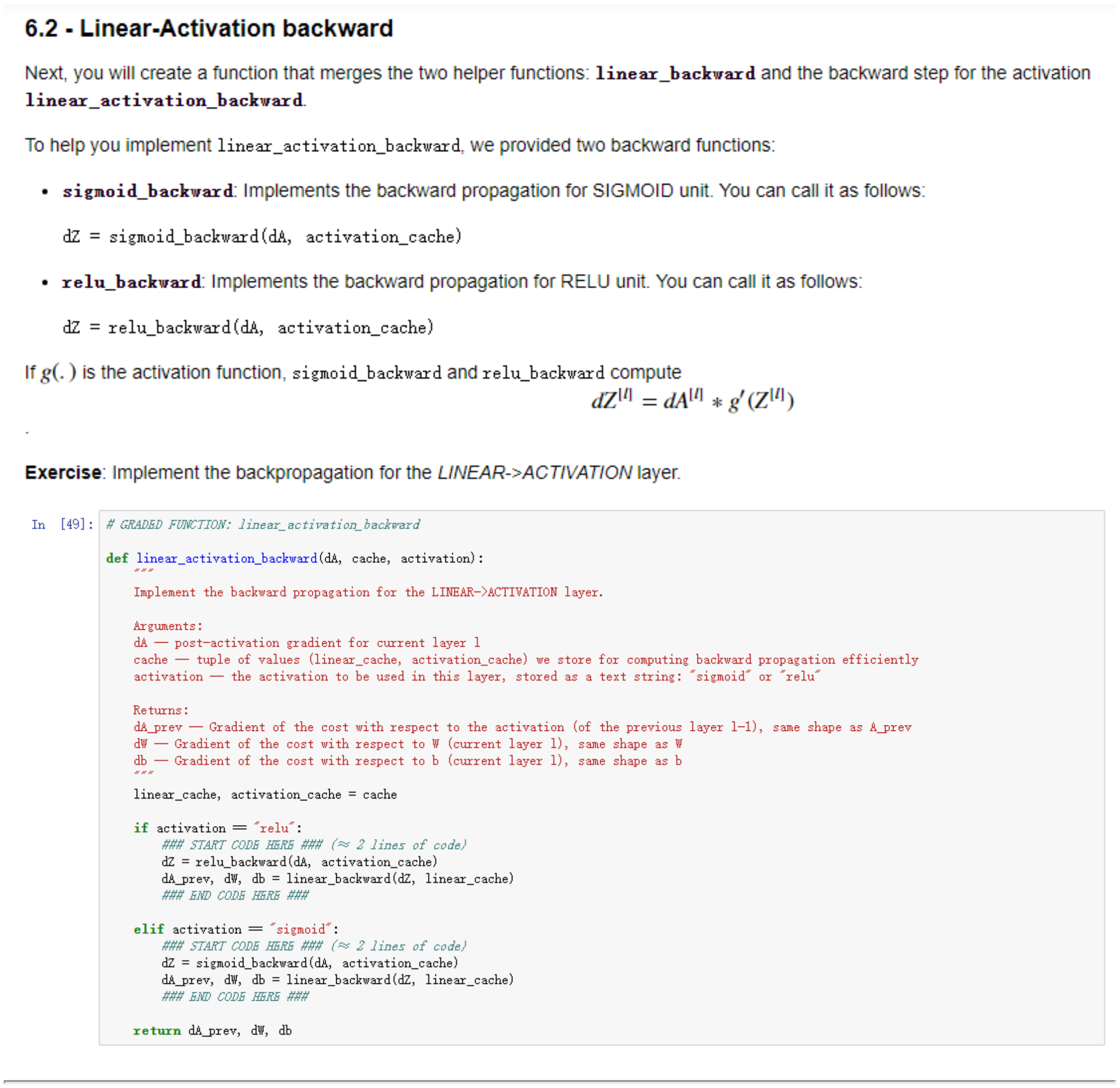
$$dW^{[l]} = \frac{\partial \mathcal{J}}{\partial W^{[l]}} = \frac{1}{m} dZ^{[l]} A^{[l-1]T}$$

$$db^{[l]} = \frac{\partial \mathcal{J}}{\partial b^{[l]}} = \frac{1}{m} \sum_{i=1}^{m} dZ^{[l](i)}$$

$$dA^{[l-1]} = \frac{\partial \mathcal{L}}{\partial A^{[l-1]}} = W^{[l]T} dZ^{[l]}$$

[43]:

```python
# GRADED FUNCTION: linear_backward

def linear_backward(dZ, cache):
    """
    Implement the linear portion of backward propagation for a single layer (layer l)

    Arguments:
    dZ -- Gradient of the cost with respect to the linear output (of current layer l)
    cache -- tuple of values (A_prev, W, b) coming from the forward propagation in the current layer

    Returns:
    dA_prev -- Gradient of the cost with respect to the activation (of the previous layer l-1), same shape as A_prev
    dW -- Gradient of the cost with respect to W (current layer l), same shape as W
    db -- Gradient of the cost with respect to b (current layer l), same shape as b
    """
    A_prev, W, b = cache
    m = A_prev.shape[1]

    ### START CODE HERE ### (≈ 3 lines of code)
    dW = np.dot(dZ, A_prev.T)/m
    db = np.sum(dZ, axis = 1, keepdims = True) / m
    dA_prev = np.dot(W.T, dZ)
    ### END CODE HERE ###

    assert (dA_prev.shape == A_prev.shape)
    assert (dW.shape == W.shape)
    assert (db.shape == b.shape)

    return dA_prev, dW, db
```



6.2 - Linear-Activation backward

Next, you will create a function that merges the two helper functions: **`linear_backward`** and the backward step for the activation **`linear_activation_backward`**.

To help you implement `linear_activation_backward`, we provided two backward functions:

- **`sigmoid_backward`**: Implements the backward propagation for SIGMOID unit. You can call it as follows:

  ```
  dZ = sigmoid_backward(dA, activation_cache)
  ```

- **`relu_backward`**: Implements the backward propagation for RELU unit. You can call it as follows:

  ```
  dZ = relu_backward(dA, activation_cache)
  ```

If $g(.)$ is the activation function, `sigmoid_backward` and `relu_backward` compute

$$dZ^{[l]} = dA^{[l]} * g'(Z^{[l]})$$

.

Exercise: Implement the backpropagation for the *LINEAR->ACTIVATION* layer.

In [49]:
```
# GRADED FUNCTION: linear_activation_backward

def linear_activation_backward(dA, cache, activation):
    """
    Implement the backward propagation for the LINEAR->ACTIVATION layer.

    Arguments:
    dA -- post-activation gradient for current layer l
    cache -- tuple of values (linear_cache, activation_cache) we store for computing backward propagation efficiently
    activation -- the activation to be used in this layer, stored as a text string: "sigmoid" or "relu"

    Returns:
    dA_prev -- Gradient of the cost with respect to the activation (of the previous layer l-1), same shape as A_prev
    dW -- Gradient of the cost with respect to W (current layer l), same shape as W
    db -- Gradient of the cost with respect to b (current layer l), same shape as b
    """
    linear_cache, activation_cache = cache

    if activation == "relu":
        ### START CODE HERE ### (≈ 2 lines of code)
        dZ = relu_backward(dA, activation_cache)
        dA_prev, dW, db = linear_backward(dZ, linear_cache)
        ### END CODE HERE ###

    elif activation == "sigmoid":
        ### START CODE HERE ### (≈ 2 lines of code)
        dZ = sigmoid_backward(dA, activation_cache)
        dA_prev, dW, db = linear_backward(dZ, linear_cache)
        ### END CODE HERE ###

    return dA_prev, dW, db
```

whole

6.3 - L-Model Backward

Now you will implement the backward function for the whole network. Recall that when you implemented the `L_model_forward` function, at each iteration, you stored a cache which contains (X,W,b, and z). In the back propagation module, you will use those variables to compute the gradients. Therefore, in the `L_model_backward` function, you will iterate through all the hidden layers backward, starting from layer L. On each step, you will use the cached values for layer l to backpropagate through layer l. Figure 5 below shows the backward pass.

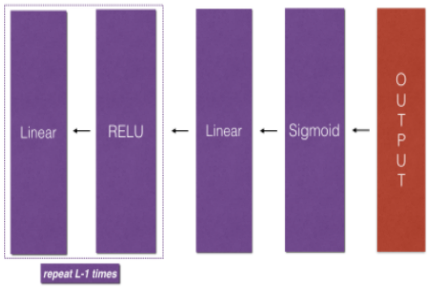


Figure 5 : Backward pass

Initializing backpropagation: To backpropagate through this network, we know that the output is, $A^{[L]} = \sigma(Z^{[L]})$. Your code thus needs to compute `dAL` $= \frac{\partial \mathcal{L}}{\partial A^{[L]}}$. To do so, use this formula (derived using calculus which you don't need in-depth knowledge of):

```
dAL = - (np.divide(Y, AL) - np.divide(1 - Y, 1 - AL)) # derivative of cost with respect to AL
```

You can then use this post-activation gradient `dAL` to keep going backward. As seen in Figure 5, you can now feed in `dAL` into the LINEAR->SIGMOID backward function you implemented (which will use the cached values stored by the L_model_forward function). After that, you will have to use a `for` loop to iterate through all the other layers using the LINEAR->RELU backward function. You should store each dA, dW, and db in the grads dictionary. To do so, use this formula :

$$grads["dW" + str(l)] = dW^{[l]} \tag{15}$$

For example, for $l = 3$ this would store $dW^{[l]}$ in `grads["dW3"]`.

dAL is of n_y * m

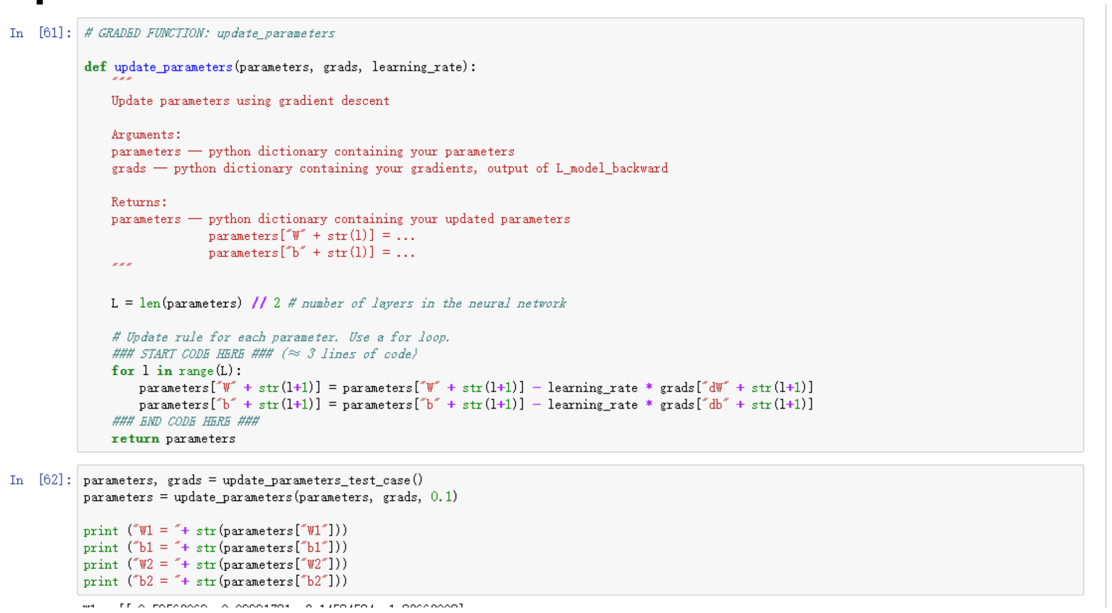
Exercise: Implement backpropagation for the *[LINEAR->RELU]* × *(L-1) -> LINEAR -> SIGMOID* model.

In [55]:
```
# GRADED FUNCTION: L_model_backward

def L_model_backward(AL, Y, caches):
    """
    Implement the backward propagation for the [LINEAR->RELU] * (L-1) -> LINEAR -> SIGMOID group

    Arguments:
    AL -- probability vector, output of the forward propagation (L_model_forward())
    Y -- true "label" vector (containing 0 if non-cat, 1 if cat)
    caches -- list of caches containing:
                every cache of linear_activation_forward() with "relu" (it's caches[l], for l in range(L-1) i.e l = 0...L-2)
                the cache of linear_activation_forward() with "sigmoid" (it's caches[L-1])

    Returns:
    grads -- A dictionary with the gradients
             grads["dA" + str(l)] = ...
             grads["dW" + str(l)] = ...
             grads["db" + str(l)] = ...
    """
    grads = {}
    L = len(caches) # the number of layers
    m = AL.shape[1]
    Y = Y.reshape(AL.shape) # after this line, Y is the same shape as AL

    # Initializing the backpropagation
    ### START CODE HERE ### (1 line of code)
    dAL = -(np.divide(Y, AL) - np.divide(1 - Y, 1 - AL))
    ### END CODE HERE ###

    # Lth layer (SIGMOID -> LINEAR) gradients. Inputs: "dAL, current_cache". Outputs: "grads["dAL-1"], grads["dWL"], grads["dbL"]
    ### START CODE HERE ### (approx. 2 lines)
    current_cache = caches[L-1]
    grads["dA" + str(L-1)], grads["dW" + str(L)], grads["db" + str(L)] = linear_activation_backward(dAL, current_cache, "sigmoid")
    ### END CODE HERE ###

    # Loop from l=L-2 to l=0
    for l in reversed(range(L-1)):
        # lth layer: (RELU -> LINEAR) gradients.
        # Inputs: "grads["dA" + str(l + 1)], current_cache". Outputs: "grads["dA" + str(l)] , grads["dW" + str(l + 1)] , grads["db" + str(l + 1
        ### START CODE HERE ### (approx. 5 lines)
        current_cache = caches[l]
        dA_prev_temp, dW_temp, db_temp = linear_activation_backward(grads["dA" + str(l+1)], current_cache, "relu")
        grads["dA" + str(l)] = dA_prev_temp
        grads["dW" + str(l + 1)] = dW_temp
        grads["db" + str(l + 1)] = db_temp
        ### END CODE HERE ###

    return grads
```

In [56]:
```
AL, Y_assess, caches = L_model_backward_test_case()
grads = L_model_backward(AL, Y_assess, caches)
print_grads(grads)
```

```
dW1 = [[ 0.41010002  0.07807203  0.13798444  0.10502167]
 [ 0.          0.          0.          0.        ]
 [ 0.05283652  0.01005865  0.01777766  0.0135308 ]]
db1 = [[-0.22007063]
 [ 0.        ]
 [-0.02835349]]
dA1 = [[ 0.12913162 -0.44014127]
 [-0.14175655  0.48317296]
 [ 0.01663708 -0.05670698]]
```

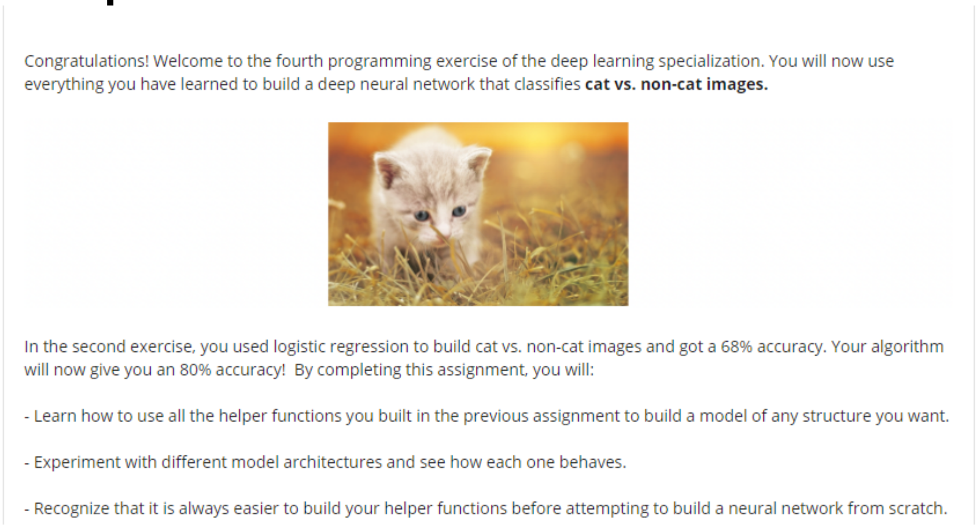
update



```
In [61]: # GRADED FUNCTION: update_parameters

         def update_parameters(parameters, grads, learning_rate):
             """
             Update parameters using gradient descent

             Arguments:
             parameters -- python dictionary containing your parameters
             grads -- python dictionary containing your gradients, output of L_model_backward

             Returns:
             parameters -- python dictionary containing your updated parameters
                           parameters["W" + str(l)] = ...
                           parameters["b" + str(l)] = ...
             """

             L = len(parameters) // 2 # number of layers in the neural network

             # Update rule for each parameter. Use a for loop.
             ### START CODE HERE ### (≈ 3 lines of code)
             for l in range(L):
                 parameters["W" + str(l+1)] = parameters["W" + str(l+1)] - learning_rate * grads["dW" + str(l+1)]
                 parameters["b" + str(l+1)] = parameters["b" + str(l+1)] - learning_rate * grads["db" + str(l+1)]
             ### END CODE HERE ###
             return parameters
```

```
In [62]: parameters, grads = update_parameters_test_case()
         parameters = update_parameters(parameters, grads, 0.1)

         print ("W1 = "+ str(parameters["W1"]))
         print ("b1 = "+ str(parameters["b1"]))
         print ("W2 = "+ str(parameters["W2"]))
         print ("b2 = "+ str(parameters["b2"]))
```

Next part -> cat classification



Congratulations! Welcome to the fourth programming exercise of the deep learning specialization. You will now use everything you have learned to build a deep neural network that classifies **cat vs. non-cat images.**

In the second exercise, you used logistic regression to build cat vs. non-cat images and got a 68% accuracy. Your algorithm will now give you an 80% accuracy! By completing this assignment, you will:

- Learn how to use all the helper functions you built in the previous assignment to build a model of any structure you want.

- Experiment with different model architectures and see how each one behaves.

- Recognize that it is always easier to build your helper functions before attempting to build a neural network from scratch.

3.1 - 2-layer neural network

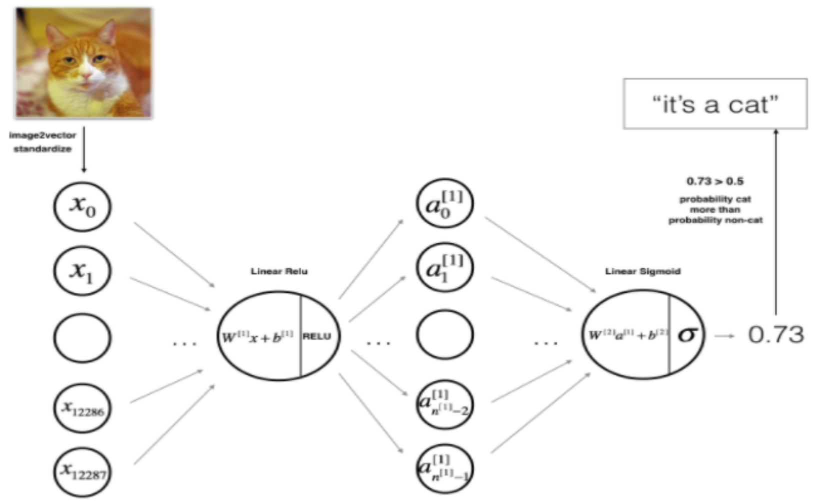


Figure 2: 2-layer neural network.
The model can be summarized as: ***INPUT -> LINEAR -> RELU -> LINEAR -> SIGMOID -> OUTPUT***.

Detailed Architecture of figure 2:

- The input is a (64,64,3) image which is flattened to a vector of size $(12288, 1)$.
- The corresponding vector: $[x_0, x_1, \dots, x_{12287}]^T$ is then multiplied by the weight matrix $W^{[1]}$ of size $(n^{[1]}, 12288)$.
- You then add a bias term and take its relu to get the following vector: $[a_0^{[1]}, a_1^{[1]}, \dots, a_{n^{[1]}-1}^{[1]}]^T$.
- You then repeat the same process.
- You multiply the resulting vector by $W^{[2]}$ and add your intercept (bias).
- Finally, you take the sigmoid of the result. If it is greater than 0.5, you classify it to be a cat.

3.2 - L-layer deep neural network

It is hard to represent an L-layer deep neural network with the above representation. However, here is a simplified network representation:

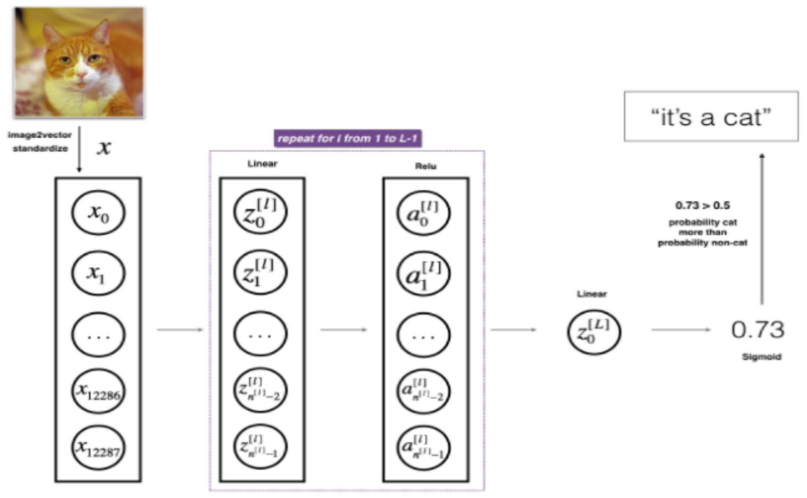
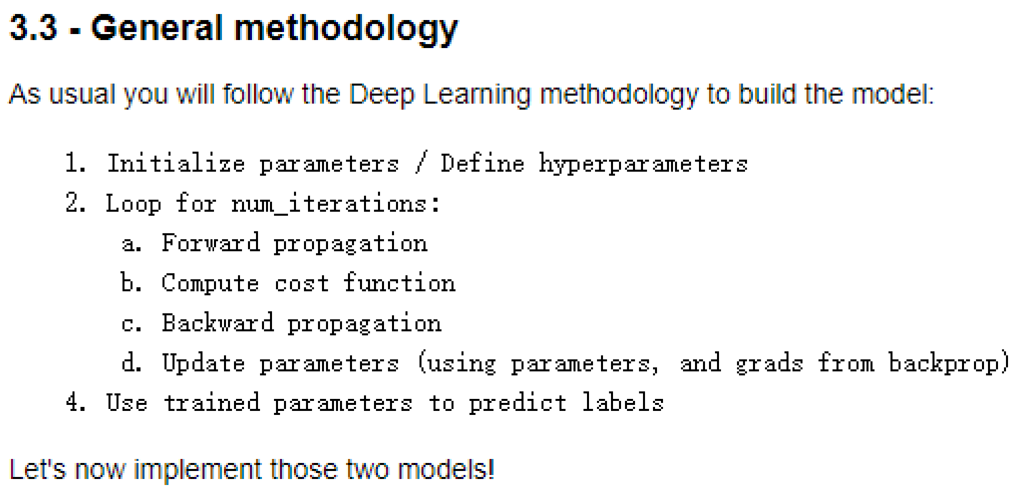


Figure 3: L-layer neural network.
The model can be summarized as: ***[LINEAR -> RELU] $\times$ (L-1) -> LINEAR -> SIGMOID***

Detailed Architecture of figure 3:

- The input is a (64,64,3) image which is flattened to a vector of size (12288,1).
- The corresponding vector: $[x_0, x_1, \dots, x_{12287}]^T$ is then multiplied by the weight matrix $W^{[1]}$ and then you add the intercept $b^{[1]}$. The result is called the linear unit.
- Next, you take the relu of the linear unit. This process could be repeated several times for each $(W^{[l]}, b^{[l]})$ depending on the model architecture.
- Finally, you take the sigmoid of the final linear unit. If it is greater than 0.5, you classify it to be a cat.



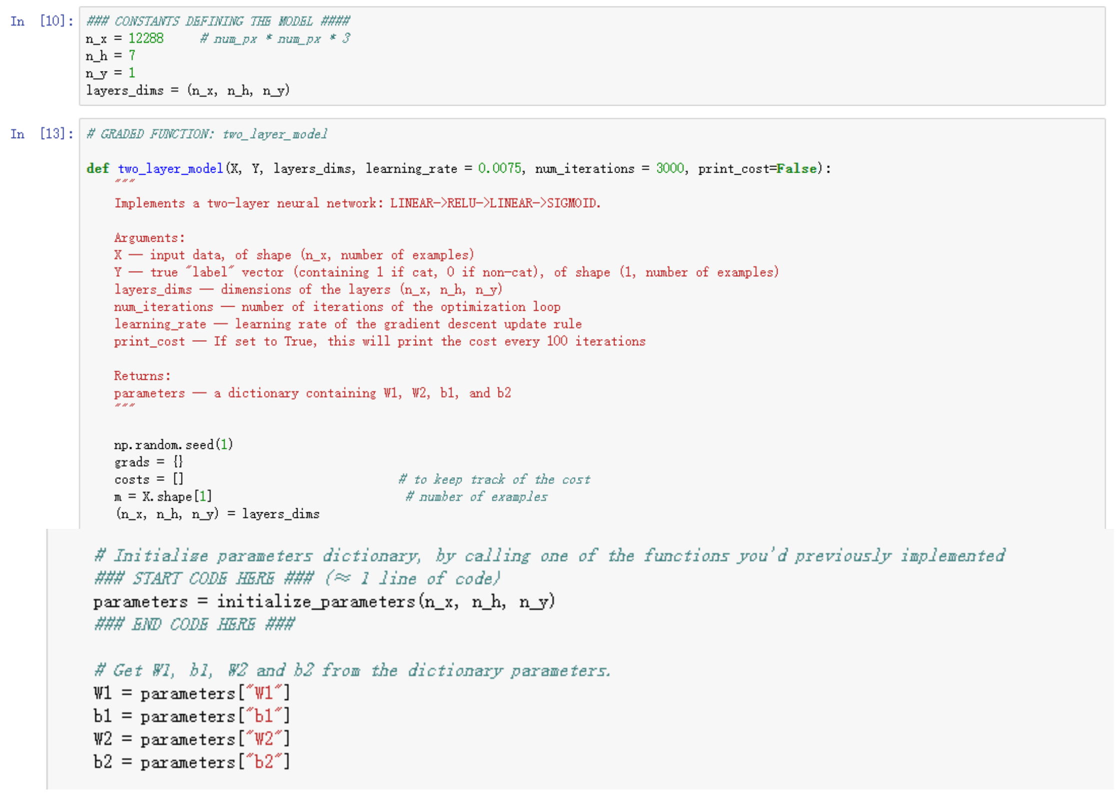
3.3 - General methodology

As usual you will follow the Deep Learning methodology to build the model:

```
1. Initialize parameters / Define hyperparameters
2. Loop for num_iterations:
    a. Forward propagation
    b. Compute cost function
    c. Backward propagation
    d. Update parameters (using parameters, and grads from backprop)
4. Use trained parameters to predict labels
```

Let's now implement those two models!

As a whole:

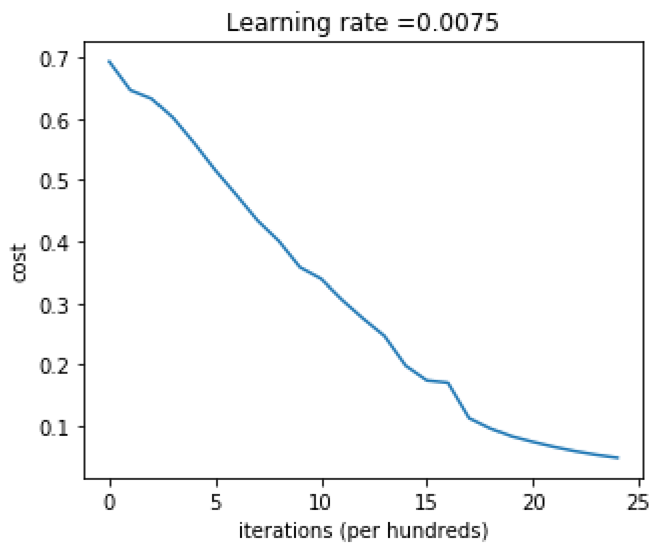


In [10]:
```python
### CONSTANTS DEFINING THE MODEL ####
n_x = 12288     # num_px * num_px * 3
n_h = 7
n_y = 1
layers_dims = (n_x, n_h, n_y)
```

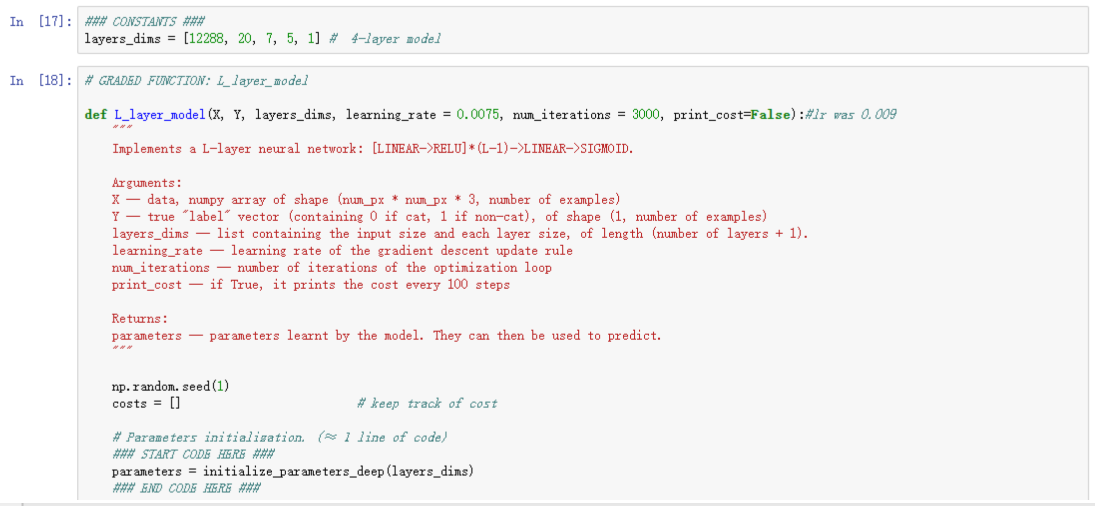
In [13]:
```python
# GRADED FUNCTION: two_layer_model

def two_layer_model(X, Y, layers_dims, learning_rate = 0.0075, num_iterations = 3000, print_cost=False):
    """
    Implements a two-layer neural network: LINEAR->RELU->LINEAR->SIGMOID.

    Arguments:
    X -- input data, of shape (n_x, number of examples)
    Y -- true "label" vector (containing 1 if cat, 0 if non-cat), of shape (1, number of examples)
    layers_dims -- dimensions of the layers (n_x, n_h, n_y)
    num_iterations -- number of iterations of the optimization loop
    learning_rate -- learning rate of the gradient descent update rule
    print_cost -- If set to True, this will print the cost every 100 iterations

    Returns:
    parameters -- a dictionary containing W1, W2, b1, and b2
    """

    np.random.seed(1)
    grads = {}
    costs = []                              # to keep track of the cost
    m = X.shape[1]                           # number of examples
    (n_x, n_h, n_y) = layers_dims

    # Initialize parameters dictionary, by calling one of the functions you'd previously implemented
    ### START CODE HERE ### (≈ 1 line of code)
    parameters = initialize_parameters(n_x, n_h, n_y)
    ### END CODE HERE ###

    # Get W1, b1, W2 and b2 from the dictionary parameters.
    W1 = parameters["W1"]
    b1 = parameters["b1"]
    W2 = parameters["W2"]
    b2 = parameters["b2"]
    # Loop (gradient descent)

    for i in range(0, num_iterations):

        # Forward propagation: LINEAR -> RELU -> LINEAR -> SIGMOID. Inputs: "X, W1, b1, W2, b2". Output: "A1, cache1, A2, cache2".
        ### START CODE HERE ### (≈ 2 lines of code)
        A1, cache1 = linear_activation_forward(X, W1, b1, "relu")
        A2, cache2 = linear_activation_forward(A1, W2, b2, "sigmoid")
        ### END CODE HERE ###

        # Compute cost
        ### START CODE HERE ### (≈ 1 line of code)
        cost = compute_cost(A2, Y)
        ### END CODE HERE ###

        # Initializing backward propagation
        dA2 = - (np.divide(Y, A2) - np.divide(1 - Y, 1 - A2))

        # Backward propagation. Inputs: "dA2, cache2, cache1". Outputs: "dA1, dW2, db2; also dA0 (not used), dW1, db1".
        ### START CODE HERE ### (≈ 2 lines of code)
        dA1, dW2, db2 = linear_activation_backward(dA2, cache2, "sigmoid")
        dA0, dW1, db1 = linear_activation_backward(dA1, cache1, "relu")
        ### END CODE HERE ###

        # Set grads['dW1'] to dW1, grads['db1'] to db1, grads['dW2'] to dW2, grads['db2'] to db2
        grads['dW1'] = dW1
        grads['db1'] = db1
        grads['dW2'] = dW2
        grads['db2'] = db2

        # Update parameters.
        ### START CODE HERE ### (approx. 1 line of code)
        parameters = update_parameters(parameters, grads, learning_rate)
        ### END CODE HERE ###

        # Retrieve W1, b1, W2, b2 from parameters
        W1 = parameters["W1"]
        b1 = parameters["b1"]
        W2 = parameters["W2"]
        b2 = parameters["b2"]

        # Print the cost every 100 training example
        if print_cost and i % 100 == 0:
            print("Cost after iteration {}: {}".format(i, np.squeeze(cost)))
        if print_cost and i % 100 == 0:
            costs.append(cost)

    # plot the cost

    plt.plot(np.squeeze(costs))
    plt.ylabel('cost')
    plt.xlabel('iterations (per hundreds)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    return parameters
```

Run the cell below to train your parameters. See if your model runs. The cost should be decreasing. It may take up to 5 minutes to run 2500 iterations. Check if the "Cost after iteration 0" matches the expected output below, if not click on the square (⬛) on the upper bar of the notebook to stop the cell and try to find your error.

```
[*]: parameters = two_layer_model(train_x, train_y, layers_dims = (n_x, n_h, n_y), num_iterations = 2500, print_cost=True)
```

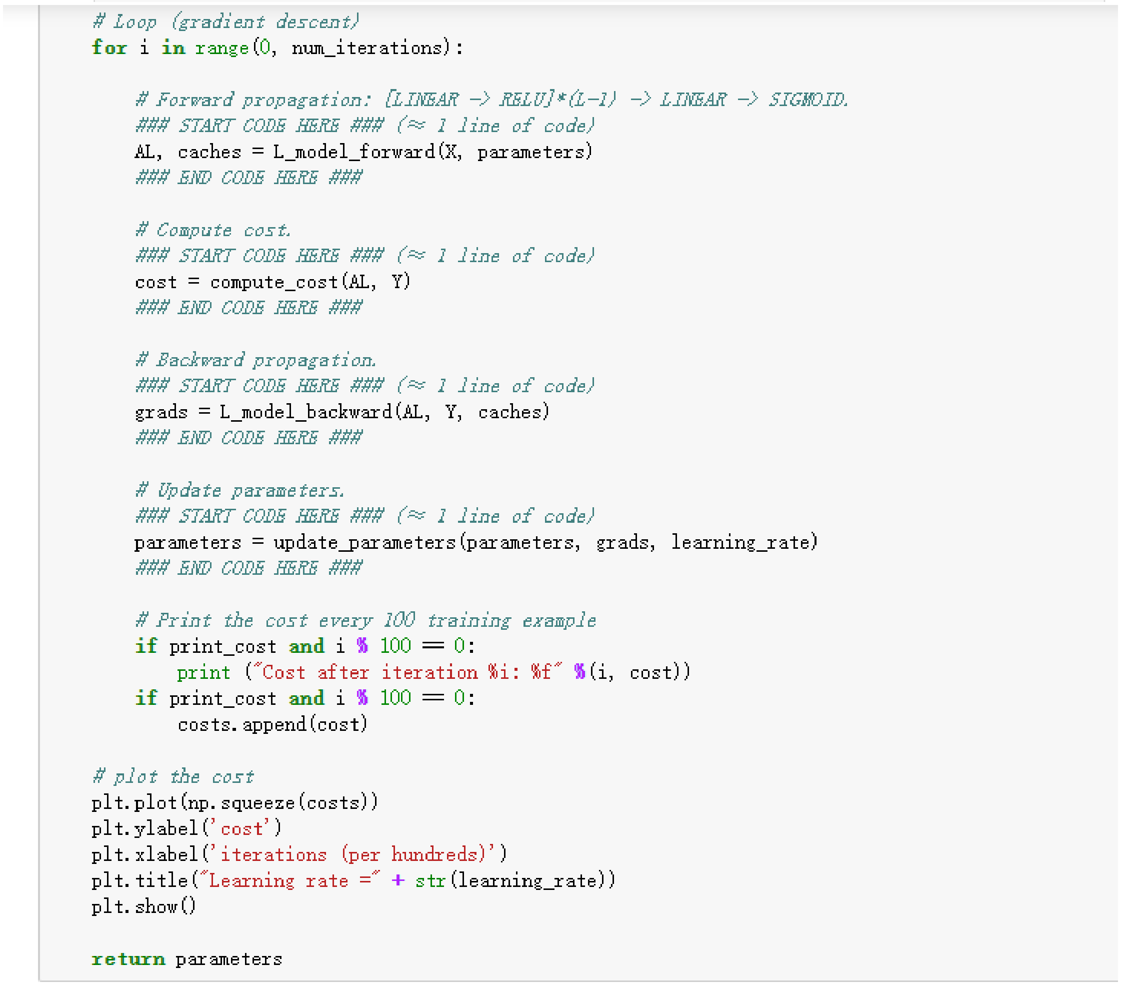


multi: (similar)



In [17]:
```python
### CONSTANTS ###
layers_dims = [12288, 20, 7, 5, 1] #  4-layer model
```

In [18]:
```python
# GRADED FUNCTION: L_layer_model

def L_layer_model(X, Y, layers_dims, learning_rate = 0.0075, num_iterations = 3000, print_cost=False):#lr was 0.009
    """
    Implements a L-layer neural network: [LINEAR->RELU]*(L-1)->LINEAR->SIGMOID.

    Arguments:
    X -- data, numpy array of shape (num_px * num_px * 3, number of examples)
    Y -- true "label" vector (containing 0 if cat, 1 if non-cat), of shape (1, number of examples)
    layers_dims -- list containing the input size and each layer size, of length (number of layers + 1).
    learning_rate -- learning rate of the gradient descent update rule
    num_iterations -- number of iterations of the optimization loop
    print_cost -- if True, it prints the cost every 100 steps

    Returns:
    parameters -- parameters learnt by the model. They can then be used to predict.
    """

    np.random.seed(1)
    costs = []                         # keep track of cost

    # Parameters initialization. (≈ 1 line of code)
    ### START CODE HERE ###
    parameters = initialize_parameters_deep(layers_dims)
    ### END CODE HERE ###
```



```python
    # Loop (gradient descent)
    for i in range(0, num_iterations):

        # Forward propagation: [LINEAR -> RELU]*(L-1) -> LINEAR -> SIGMOID.
        ### START CODE HERE ### (≈ 1 line of code)
        AL, caches = L_model_forward(X, parameters)
        ### END CODE HERE ###

        # Compute cost.
        ### START CODE HERE ### (≈ 1 line of code)
        cost = compute_cost(AL, Y)
        ### END CODE HERE ###

        # Backward propagation.
        ### START CODE HERE ### (≈ 1 line of code)
        grads = L_model_backward(AL, Y, caches)
        ### END CODE HERE ###

        # Update parameters.
        ### START CODE HERE ### (≈ 1 line of code)
        parameters = update_parameters(parameters, grads, learning_rate)
        ### END CODE HERE ###

        # Print the cost every 100 training example
        if print_cost and i % 100 == 0:
            print ("Cost after iteration %i: %f" %(i, cost))
        if print_cost and i % 100 == 0:
            costs.append(cost)

    # plot the cost
    plt.plot(np.squeeze(costs))
    plt.ylabel('cost')
    plt.xlabel('iterations (per hundreds)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    return parameters
```

Expected Output:

Test Accuracy	0.8

Congrats! It seems that your 4-layer neural network has better performance (80%) than your 2-layer neural network (72%) on the same test set.

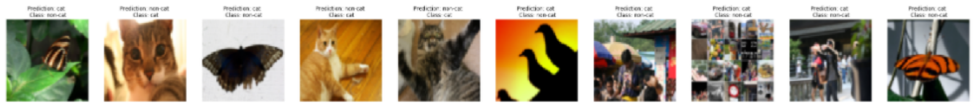
This is good performance for this task. Nice job!

Though in the next course on "Improving deep neural networks" you will learn how to obtain even higher accuracy by systematically searching for better hyperparameters (learning_rate, layers_dims, num_iterations, and others you'll also learn in the next course).

6) Results Analysis

First, let's take a look at some images the L-layer model labeled incorrectly. This will show a few mislabeled images.

```
In [22]: print_mislabeled_images(classes, test_x, test_y, pred_test)
```



A few types of images the model tends to do poorly on include:

- Cat body in an unusual position
- Cat appears against a background of a similar color
- Unusual cat color and species
- Camera Angle
- Brightness of the picture
- Scale variation (cat is very large or small in image)