8. 多层神经网络代码实战

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本节课中，我们将学习如何利用Python的来实现具有多个隐藏层的图片分类问题。
这是本课程的第三个Python代码实践，通过本节课的实践，你将会一步步的建立一个多层神经网络模型。
此外，通过这次建立的多层神经网络模型，可以将之前的猫分类问题的准确率提升到80%。

本文学习完成后，希望你可以做到：

1. 使用非线性映射单元（例如ReLU）去改善你的模型。
2. 建立一个多个隐藏层的神经网络
3. 创建一个易于调用的模型类

第一步：引入相关的依赖包

```
import numpy as np
import time
import h5py
import matplotlib.pyplot as plt
import scipy
from PIL import Image
from testCases_v2 import *  #提供了一些测试函数所有的数据和方法
from dnn_utils_v2 import sigmoid, sigmoid_backward, relu, relu_backward  #封装好的方法
from dnn_app_utils_v2 import *

%matplotlib inline
plt.rcParams['figure.figsize'] = (5.0, 4.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

%load_ext autoreload
%autoreload 2

np.random.seed(1)
```

其中，sigmoid函数如下：

```
def sigmoid(Z):
    """
    Implements the sigmoid activation in numpy

    Arguments:
    Z -- numpy array of any shape

    Returns:
    A -- output of sigmoid(z), same shape as Z
    cache -- returns Z as well, useful during backpropagation
    """

    A = 1/(1+np.exp(-Z))
    cache = Z

    return A, cache
```

sigmoid_backward函数如下：

```
def sigmoid_backward(dA, cache):
    """
    Implement the backward propagation for a single SIGMOID unit.

    Arguments:
    dA -- post-activation gradient, of any shape
    cache -- 'Z' where we store for computing backward propagation efficiently

    Returns:
    dZ -- Gradient of the cost with respect to Z
    """

    Z = cache

    s = 1/(1+np.exp(-Z))
    dZ = dA * s * (1-s)

    assert (dZ.shape == Z.shape)

    return dZ
```

relu函数如下：

```
def relu(Z):
    """
    Implement the RELU function.

    Arguments:
    Z -- Output of the linear layer, of any shape

    Returns:
    A -- Post-activation parameter, of the same shape as Z
    cache -- a python dictionary containing "A" ; stored for computing the backward pass efficiently
    """

    A = np.maximum(0,Z)

    assert(A.shape == Z.shape)

    cache = Z
    return A, cache
```

relu_backward函数如下：

```
def relu_backward(dA, cache):
    """
    Implement the backward propagation for a single RELU unit.

    Arguments:
    dA -- post-activation gradient, of any shape
    cache -- 'Z' where we store for computing backward propagation efficiently

    Returns:
    dZ -- Gradient of the cost with respect to Z
    """

    Z = cache
    dZ = np.array(dA, copy=True) # just converting dz to a correct object.

    # When z <= 0, you should set dz to 0 as well.
    dZ[Z <= 0] = 0

    assert (dZ.shape == Z.shape)

    return dZ
```

第二步：任务描述

接下来，我们首先简单的描述一下我们需要实现的功能。

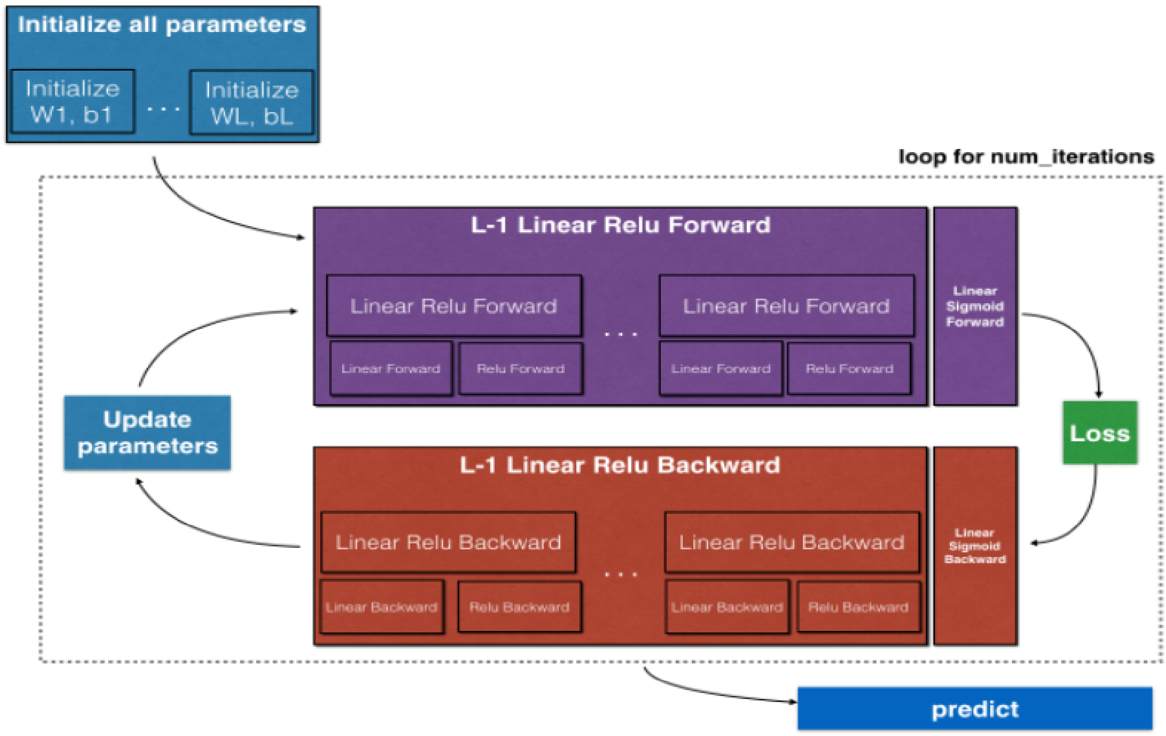
为了最终建立我们的神经网络模型，我们首先需要实现其中相关的一些方法。

接下来，我们将会去依次实现这些需要的方法。

一个神经网络的计算过程如下:

1. 初始化网络参数
2. 前向传播
   2.1 计算一层的中线性求和的部分
   2.2 计算激活函数的部分（ReLU使用L-1次，Sigmod使用1次）
   2.3 结合线性求和与激活函数
3. 计算误差
4. 反向传播
   4.1 线性部分的反向传播公式
   4.2 激活函数部分的反向传播公式
   4.3 结合线性部分与激活函数的反向传播公式
5. 更新参数

整个流程图如下图所示：



第三步：初始化

接下来，我们需要实现初始化函数

对于一个两层的神经网络结构而言，模型结构是线性->ReLU->线性->sigmod函数。

初始化函数如下：

```
def initialize_parameters(n_x, n_h, n_y):
    """
    Argument:
    n_x -- size of the input layer
    n_h -- size of the hidden layer
    n_y -- size of the output layer

    Returns:
    parameters -- python dictionary containing your parameters:
                    W1 -- weight matrix of shape (n_h, n_x)
                    b1 -- bias vector of shape (n_h, 1)
                    W2 -- weight matrix of shape (n_y, n_h)
                    b2 -- bias vector of shape (n_y, 1)
    """

    np.random.seed(1)

    ### START CODE HERE ### (≈ 4 lines of code)
    W1 = np.random.randn(n_h, n_x)*0.01
    b1 = np.zeros((n_h, 1))
    W2 = np.random.randn(n_y, n_h)*0.01
    b2 = np.zeros((n_y, 1))
    ### END CODE HERE ###

    assert(W1.shape == (n_h, n_x))
    assert(b1.shape == (n_h, 1))
    assert(W2.shape == (n_y, n_h))
    assert(b2.shape == (n_y, 1))

    parameters = {"W1": W1,
                  "b1": b1,
                  "W2": W2,
                  "b2": b2}

    return parameters
```

验证一下：

```
parameters = initialize_parameters(3,2,1)
print("W1 = " + str(parameters["W1"]))
print("b1 = " + str(parameters["b1"]))
print("W2 = " + str(parameters["W2"]))
print("b2 = " + str(parameters["b2"]))
```

W1	[[0.01624345 -0.00611756 -0.00528172] [-0.01072969 0.00865408 -0.02301539]]
b1	[[0.] [0.]]
W2	[[0.01744812 -0.00761207]]
b2	[[0.]]

那么，对于一个L层的神经网络而言呢？初始化是什么样的？

假设X的维度为（12288,209）

	Shape of W	Shape of b	Activation	Shape of Activation
Layer 1	$(n^{[1]}, 12288)$	$(n^{[1]}, 1)$	$Z^{[1]} = W^{[1]}X + b^{[1]}$	$(n^{[1]}, 209)$
Layer 2	$(n^{[2]}, n^{[1]})$	$(n^{[2]}, 1)$	$Z^{[2]} = W^{[2]}A^{[1]} + b^{[2]}$	$(n^{[2]}, 209)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Layer L-1	$(n^{[L-1]}, n^{[L-2]})$	$(n^{[L-1]}, 1)$	$Z^{[L-1]} = W^{[L-1]}A^{[L-2]} + b^{[L-1]}$	$(n^{[L-1]}, 209)$
Layer L	$(n^{[L]}, n^{[L-1]})$	$(n^{[L]}, 1)$	$Z^{[L]} = W^{[L]}A^{[L-1]} + b^{[L]}$	$(n^{[L]}, 209)$

第l层的W的维度为(layer_dims[l], layer_dims[l-1])。

而第l层的b的维度为(layer_dims[l], 1)。

因此，初始化函数如下：

```
def initialize_parameters_deep(layer_dims):
    """
    Arguments:
    layer_dims -- python array (list) containing the dimensions of each layer in our network

    Returns:
    parameters -- python dictionary containing your parameters "W1", "b1", ..., "WL", "bL":
                    Wl -- weight matrix of shape (layer_dims[l], layer_dims[l-1])
                    bl -- bias vector of shape (layer_dims[l], 1)
    """

    np.random.seed(3)
    parameters = {}
    L = len(layer_dims)            # number of layers in the network

    for l in range(1, L):
        ### START CODE HERE ### (≈ 2 lines of code)
        parameters['W' + str(l)] = np.random.randn(layer_dims[l], layer_dims[l - 1]) / np.sqrt(layer_dims[l - 1])
        parameters['b' + str(l)] = np.zeros((layer_dims[l], 1))
        ### END CODE HERE ###
        assert(parameters['W' + str(l)].shape == (layer_dims[l], layer_dims[l-1]))
        assert(parameters['b' + str(l)].shape == (layer_dims[l], 1))
    return parameters
```

验证如下：

```
parameters = initialize_parameters_deep([5,4,3])
print("W1 = " + str(parameters["W1"]))
print("b1 = " + str(parameters["b1"]))
print("W2 = " + str(parameters["W2"]))
print("b2 = " + str(parameters["b2"]))
```

W1	[[0.01788628 0.0043651 0.00096497 -0.01863493 -0.00277388] [-0.00354759 -0.00082741 -0.00627001 -0.00043818 -0.00477218] [-0.01313865 0.00884622 0.00881318 0.01709573 0.00050034] [-0.00404677 -0.0054536 -0.01546477 0.00982367 -0.01101068]]
b1	[[0.] [0.] [0.] [0.]]
W2	[[-0.01185047 -0.0020565 0.01486148 0.00236716] [-0.01023785 -0.00712993 0.00625245 -0.00160513] [-0.00768836 -0.00230031 0.00745056 0.01976111]]
b2	[[0.] [0.] [0.]]

第四步：前向传播函数

前向传播中，线性部分计算如下：

```
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 dictionary 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
```

测试一下：

```
A, W, b = linear_forward_test_case()

Z, linear_cache = linear_forward(A, W, b)
print("Z = " + str(Z))
```

Z	[[3.26295337 -1.23429987]]

其中，linear_forward_test_case函数如下：

```
def linear_forward_test_case():
    np.random.seed(1)
    A = np.random.randn(3,2)
    W = np.random.randn(1,3)
    b = np.random.randn(1,1)
    return A, W, b
```

线性激活函数如下：

```python
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 dictionary 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
```

测试一下：

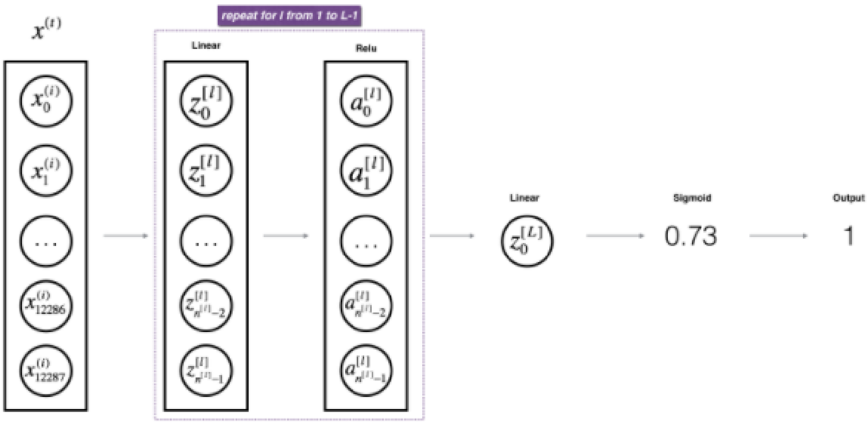
```python
A_prev, W, b = linear_activation_forward_test_case()

A, linear_activation_cache = linear_activation_forward(A_prev, W, b, activation = "sigmoid")
print("With sigmoid: A = " + str(A))

A, linear_activation_cache = linear_activation_forward(A_prev, W, b, activation = "relu")
print("With ReLU: A = " + str(A))
```

With sigmoid: A	[[0.96890023 0.11013289]]
With ReLU: A	[[3.43896131 0.]]

其中，linear_activation_forward_test_case函数如下：

```python
def linear_activation_forward_test_case():
    np.random.seed(2)
    A_prev = np.random.randn(3,2)
    W = np.random.randn(1,3)
    b = np.random.randn(1,1)
    return A_prev, W, b
```

多层模型的前向传播计算模型如下：



函数如下：

```
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_relu_forward() (there are L-1 of them, indexed from 0 to L-2)
                the cache of linear_sigmoid_forward() (there is one, indexed 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
        A, cache = linear_activation_forward(A_prev, parameters['W' + str(l)], parameters['b' + str(l)], "relu")
        caches.append(cache)

    # Implement LINEAR -> SIGMOID. Add "cache" to the "caches" list.
    AL, cache = linear_activation_forward(A, parameters['W' + str(L)], parameters['b' + str(L)], "sigmoid")
    caches.append(cache)
    assert(AL.shape == (1,X.shape[1]))
    return AL, caches
```

测试一下：

```
X, parameters = L_model_forward_test_case()
AL, caches = L_model_forward(X, parameters)

print("AL = " + str(AL))
print("Length of caches list = " + str(len(caches)))
```

AL	[[0.17007265 0.2524272]]
Length of caches list	2

其中，L_model_forward_test_case函数如下：

```
def L_model_forward_test_case():
    np.random.seed(1)
    X = np.random.randn(4,2)
    W1 = np.random.randn(3,4)
    b1 = np.random.randn(3,1)
    W2 = np.random.randn(1,3)
    b2 = np.random.randn(1,1)
    parameters = {"W1": W1,
                  "b1": b1,
                  "W2": W2,
                  "b2": b2}

    return X, parameters
```

第五步：计算代价函数

代价函数计算公式如下：

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

```
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(np.log(AL),Y) + np.multiply(np.log(1 - AL), 1 - Y)) / 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
```

测试一下：

```
Y, AL = compute_cost_test_case()

print("cost = " + str(compute_cost(AL, Y)))
```

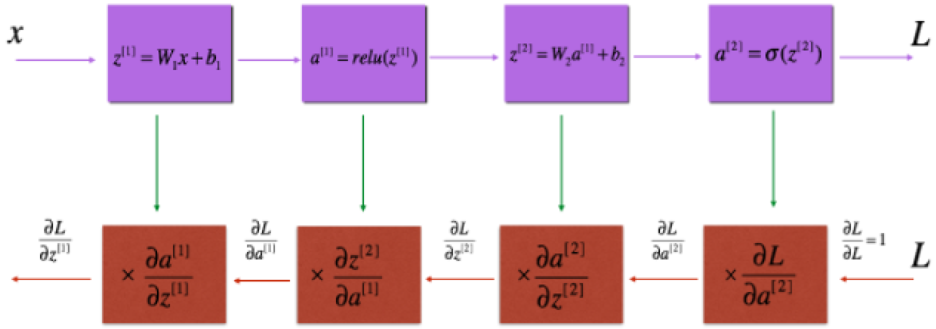
cost	0.41493159961539694

其中，compute_cost_test_case函数如下：

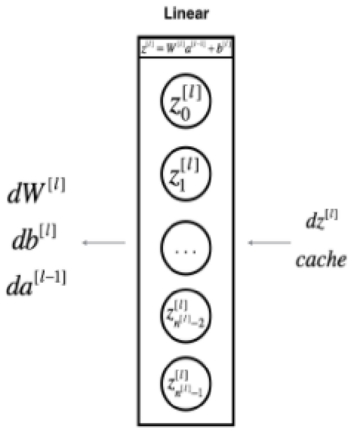
```
1. def compute_cost_test_case():
2.     Y = np.asarray([[1, 1, 1]])
3.     aL = np.array([[.8,.9,0.4]])
4.     return Y, aL
```

第六步：反向传播

神经网络传播结构图如下：



对于线性的部分，反向传播的公式如下：



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

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

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

Figure 4

实现函数如下：

接下来，我们需要计算激活函数的反向传播函数：

```
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
```

测试一下：

```
dZ, linear_cache = linear_backward_test_case()

dA_prev, dW, db = linear_backward(dZ, linear_cache)
print ("dA_prev = "+ str(dA_prev))
print ("dW = " + str(dW))
print ("db = " + str(db))
```

dA_prev	[[0.51822968 -0.19517421] [-0.40506361 0.15255393] [2.37496825 -0.89445391]]
dW	[[-0.10076895 1.40685096 1.64992505]]
db	[[0.50629448]]

其中，linear_backward_test_case函数如下：

```
def linear_backward_test_case():
    np.random.seed(1)
    dZ = np.random.randn(1,2)
    A = np.random.randn(3,2)
    W = np.random.randn(1,3)
    b = np.random.randn(1,1)
    linear_cache = (A, W, b)
    return dZ, linear_cache
```

接下来，我们需要计算激活函数的反向传播函数：

```
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
```

验证一下：

```
AL, linear_activation_cache = linear_activation_backward_test_case()

dA_prev, dW, db = linear_activation_backward(AL, linear_activation_cache, activation = "sigmoid")
print ("sigmoid:")
print ("dA_prev = "+ str(dA_prev))
print ("dW = " + str(dW))
print ("db = " + str(db) + "\n")

dA_prev, dW, db = linear_activation_backward(AL, linear_activation_cache, activation = "relu")
print ("relu:")
print ("dA_prev = "+ str(dA_prev))
print ("dW = " + str(dW))
print ("db = " + str(db))
```

Expected output with sigmoid:

dA_prev	[[0.11017994 0.01105339] [0.09466817 0.00949723] [-0.05743092 -0.00576154]]
dW	[[0.10266786 0.09778551 -0.01968084]]
db	[[-0.05729622]]

Expected output with relu

dA_prev	[[0.44090989 0.] [0.37883606 0.] [-0.2298228 0.]]
dW	[[0.44513824 0.37371418 -0.10478989]]
db	[[-0.20837892]]

其中，linear_activation_backward_test_case函数如下：

```
def linear_activation_backward_test_case():
    np.random.seed(2)
    dA = np.random.randn(1,2)
    A = np.random.randn(3,2)
    W = np.random.randn(1,3)
    b = np.random.randn(1,1)
    Z = np.random.randn(1,2)
    linear_cache = (A, W, b)
    activation_cache = Z
    linear_activation_cache = (linear_cache, activation_cache)

    return dA, linear_activation_cache
```

对于L层神经网络，其反向传播函数如下：

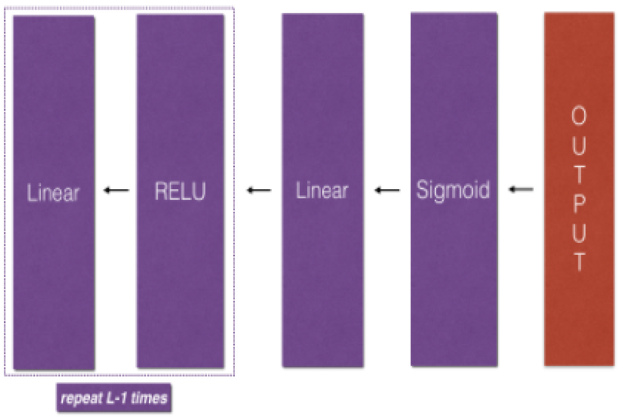


Figure 5 : Backward pass

```
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: "AL, Y, caches". Outputs: "grads["dAL"], grads["dWL"], grads["dbL"]
    ### START CODE HERE ### (approx. 2 lines)
    current_cache = caches[L-1]
    grads["dA" + str(L)], grads["dW" + str(L)], grads["db" + str(L)] = linear_activation_backward(dAL, current_cache, "sigmoid")
    ### END CODE HERE ###

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

    return grads
```

测试一下：

```
AL, Y_assess, caches = L_model_backward_test_case()
grads = L_model_backward(AL, Y_assess, caches)
print ("dW1 = "+ str(grads["dW1"]))
print ("db1 = "+ str(grads["db1"]))
print ("dA1 = "+ str(grads["dA1"]))
```

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. 0.52257901] [0. -0.3269206] [0. -0.32070404] [0. -0.74079187]]

其中，L_model_backward_test_case函数如下：

```
def L_model_backward_test_case():
    np.random.seed(3)
    AL = np.random.randn(1, 2)
    Y = np.array([[1, 0]])

    A1 = np.random.randn(4,2)
    W1 = np.random.randn(3,4)
    b1 = np.random.randn(3,1)
    Z1 = np.random.randn(3,2)
    linear_cache_activation_1 = ((A1, W1, b1), Z1)

    A2 = np.random.randn(3,2)
    W2 = np.random.randn(1,3)
    b2 = np.random.randn(1,1)
    Z2 = np.random.randn(1,2)
    linear_cache_activation_2 = ( (A2, W2, b2), Z2)

    caches = (linear_cache_activation_1, linear_cache_activation_2)

    return AL, Y, caches
```

第七步：更新参数

参数更新公式如下：

$$W^{[l]} = W^{[l]} - \alpha \, dW^{[l]}$$
$$b^{[l]} = b^{[l]} - \alpha \, db^{[l]}$$

实现过程如下：

```
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
```

验证一下：

```
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"]))
```

Expected Output:

W1	[[-0.59562069 -0.09991781 -2.14584584 1.82662008] [-1.76569676 -0.80627147 0.51115557 -1.18258802] [-1.0535704 -0.86128581 0.68284052 2.20374577]]
b1	[[-0.04659241] [-1.28888275] [0.53405496]]
W2	[[-0.55569196 0.0354055 1.32964895]]
b2	[[-0.84610769]]

其中，update_parameters_test_case函数如下：

```
def update_parameters_test_case():
    np.random.seed(2)
    W1 = np.random.randn(3,4)
    b1 = np.random.randn(3,1)
    W2 = np.random.randn(1,3)
    b2 = np.random.randn(1,1)
    parameters = {"W1": W1,
                  "b1": b1,
                  "W2": W2,
                  "b2": b2}
    np.random.seed(3)
    dW1 = np.random.randn(3,4)
    db1 = np.random.randn(3,1)
    dW2 = np.random.randn(1,3)
    db2 = np.random.randn(1,1)
    grads = {"dW1": dW1,
             "db1": db1,
             "dW2": dW2,
             "db2": db2}

    return parameters, grads
```

至此为止，我们已经实现该神经网络中，所有需要的函数。

接下来，我们将这些方法组合在一起，构成一个神经网络类，可以方便的使用。

两层神经网络模型

一个两层的神经网络模型图如下：

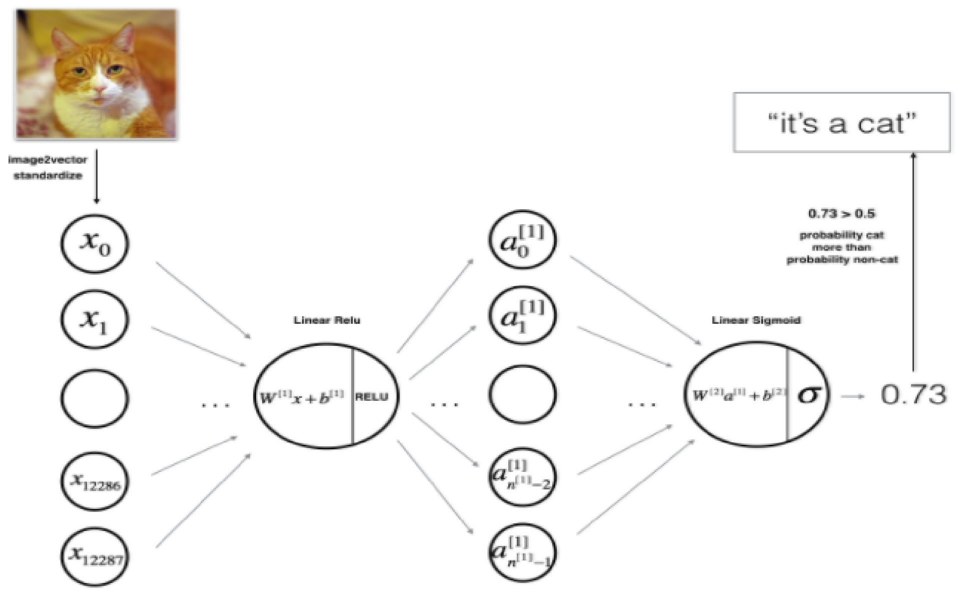


Figure 2: 2-layer neural network.

The model can be summarized as: ***INPUT -> LINEAR -> RELU -> LINEAR -> SIGMOID -> OUTPUT***.

定义常量：

```
n_x = 12288     # num_px * num_px * 3
n_h = 7
n_y = 1
layers_dims = (n_x, n_h, n_y)
```

两层网络模型：

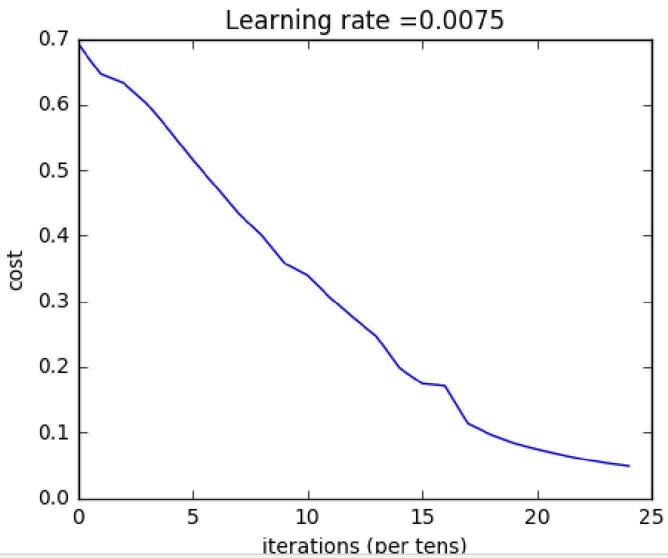
```
def two_layer_model(X, Y, layers_dims, learning_rate = 0.0075, num_iterations = 3000, print_cost=False):
    """
    Implements a two-layer neural network: LINEAR->RELU->LINEAR->SIGMOID.

    Arguments:
    X -- input data, of shape (n_x, number of examples)
    Y -- true "label" vector (containing 0 if cat, 1 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". 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['dWl'] 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 tens)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    return parameters
```

训练一下看看吧：

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

```
Cost after iteration 0: 0.693049735659989
Cost after iteration 100: 0.6464320953428849
Cost after iteration 200: 0.6325140647912678
Cost after iteration 300: 0.6015024920354665
Cost after iteration 400: 0.5601966311605748
Cost after iteration 500: 0.515830477276473
Cost after iteration 600: 0.4754901313943325
Cost after iteration 700: 0.43391631512257495
Cost after iteration 800: 0.40079775362038886
Cost after iteration 900: 0.35807050113237987
Cost after iteration 1000: 0.3394281538366413
Cost after iteration 1100: 0.30527536361962654
Cost after iteration 1200: 0.2749137728213015
Cost after iteration 1300: 0.24681768210614827
Cost after iteration 1400: 0.198507350374661
Cost after iteration 1500: 0.17448318112556593
Cost after iteration 1600: 0.1708076297809661
Cost after iteration 1700: 0.11306524562164737
Cost after iteration 1800: 0.09629426845937163
Cost after iteration 1900: 0.08342617959726878
Cost after iteration 2000: 0.0743907870431909
Cost after iteration 2100: 0.06630748132267938
Cost after iteration 2200: 0.05919329501038176
Cost after iteration 2300: 0.05336140348560564
Cost after iteration 2400: 0.048554785628770226
```



Cost after iteration 0	0.6930497356599888
Cost after iteration 100	0.6464320953428849
...	...
Cost after iteration 2400	0.048554785628770206

看看我们的预测准确度吧：

预测函数的实现如下：

```
def predict(X, y, parameters):
    """
    This function is used to predict the results of a  L-layer neural network.

    Arguments:
    X -- data set of examples you would like to label
    parameters -- parameters of the trained model

    Returns:
    p -- predictions for the given dataset X
    """

    m = X.shape[1]
    n = len(parameters) // 2 # number of layers in the neural network
    p = np.zeros((1,m))

    # Forward propagation
    probas, caches = L_model_forward(X, parameters)


    # convert probas to 0/1 predictions
    for i in range(0, probas.shape[1]):
        if probas[0,i] > 0.5:
            p[0,i] = 1
        else:
            p[0,i] = 0

    print("Accuracy: "  + str(float(np.sum((p == y))/m)))

    return p
```

对于训练集：

```
predictions_train = predict(train_x, train_y, parameters)
```

Accuracy	1.0

对于测试集：

```
predictions_test = predict(test_x, test_y, parameters)
```

Accuracy	0.72

多层神经网络

一个多层的神经网络模型如下：

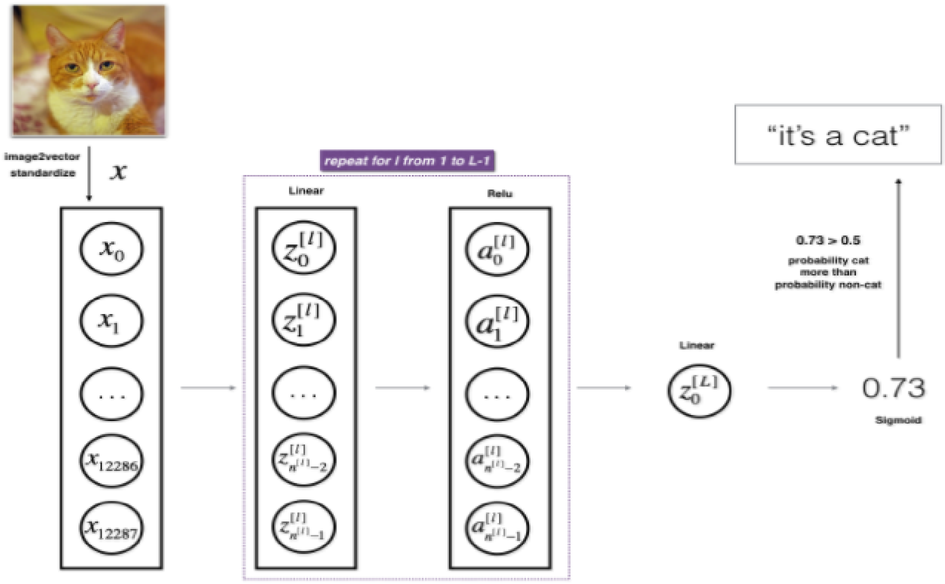


Figure 3: L-layer neural network.

The model can be summarized as: ***[LINEAR -> RELU] × (L-1) -> LINEAR -> SIGMOID***

常量初始化：

```
layers_dims = [12288, 20, 7, 5, 1] #  5-layer model
```

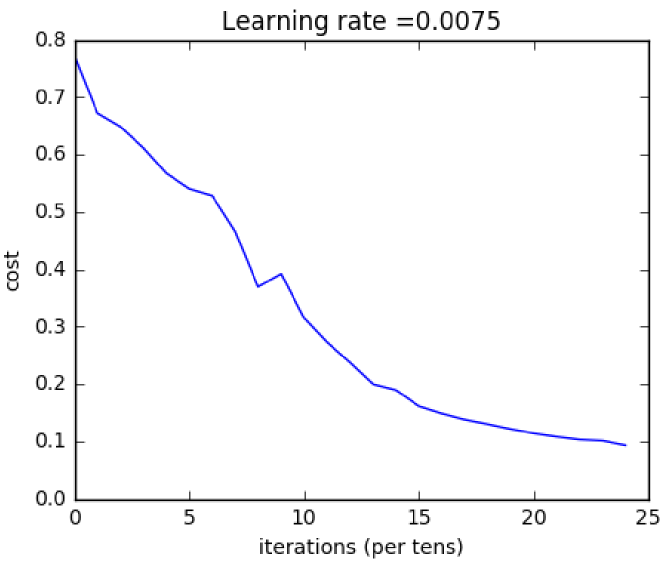
L层神经网络模型：

```
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 (number of examples, num_px * num_px * 3)
    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.
    ### START CODE HERE ###
    parameters = initialize_parameters_deep(layers_dims)
    ### END CODE HERE ###

    # 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 tens)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    return parameters
```

训练一下看看吧：

```
1. parameters = L_layer_model(train_x, train_y, layers_dims, num_iterations = 2500, print_cost = True)
```

```
Cost after iteration 0: 0.771749
Cost after iteration 100: 0.672053
Cost after iteration 200: 0.648263
Cost after iteration 300: 0.611507
Cost after iteration 400: 0.567047
Cost after iteration 500: 0.540138
Cost after iteration 600: 0.527930
Cost after iteration 700: 0.465477
Cost after iteration 800: 0.369126
Cost after iteration 900: 0.391747
Cost after iteration 1000: 0.315187
Cost after iteration 1100: 0.272700
Cost after iteration 1200: 0.237419
Cost after iteration 1300: 0.199601
Cost after iteration 1400: 0.189263
Cost after iteration 1500: 0.161189
Cost after iteration 1600: 0.148214
Cost after iteration 1700: 0.137775
Cost after iteration 1800: 0.129740
Cost after iteration 1900: 0.121225
Cost after iteration 2000: 0.113821
Cost after iteration 2100: 0.107839
Cost after iteration 2200: 0.102855
Cost after iteration 2300: 0.100897
Cost after iteration 2400: 0.092878
```



预测一下呢？

对于训练集：

```
1. pred_train = predict(train_x, train_y, parameters)
```

Train Accuracy	0.985645933014

对于测试集：

```
1. pred_test = predict(test_x, test_y, parameters)
```

Test Accuracy	0.8

结果分析：

接下来，让我们对分类错误的图像进行一下结果分析吧：

```
print_mislabeled_images(classes, test_x, test_y, pred_test)  #显示所有分类错误的图片
```

其中，print_mislabeled_images的实现如下：

```
def print_mislabeled_images(classes, X, y, p):
    """
    Plots images where predictions and truth were different.
    X -- dataset
    y -- true labels
    p -- predictions
    """
    a = p + y
    mislabeled_indices = np.asarray(np.where(a == 1))
    plt.rcParams['figure.figsize'] = (40.0, 40.0) # set default size of plots
    num_images = len(mislabeled_indices[0])
    for i in range(num_images):
        index = mislabeled_indices[1][i]

        plt.subplot(2, num_images, i + 1)
        plt.imshow(X[:,index].reshape(64,64,3), interpolation='nearest')
        plt.axis('off')
        plt.title("Prediction: " + classes[int(p[0,index])].decode("utf-8") + " \n Class: " + classes[y[0,index]].decode("utf-8"))
```

用自己的图片试试吧：

```
## START CODE HERE ##
my_image = "my_image.jpg" # change this to the name of your image file
my_label_y = [1] # the true class of your image (1 -> cat, 0 -> non-cat)
## END CODE HERE ##

fname = "images/" + my_image
image = np.array(ndimage.imread(fname, flatten=False))
my_image = scipy.misc.imresize(image, size=(num_px,num_px)).reshape((num_px*num_px*3,1))
my_predicted_image = predict(my_image, my_label_y, parameters)

plt.imshow(image)
print ("y = " + str(np.squeeze(my_predicted_image)) + ", your L-layer model predicts a \"" + classes[int(np.squeeze(my_predicted_image)),].decode("utf-8") +  "\" picture.")
```

上一篇: 7. 深层神经网络理论学习 (/api/view/blog/59a6ad67e519f50d040000e6)

下一篇: 9.深度学习基础实践理论 (/api/view/blog/5a1ff5cf9112b3493d000000)

5条评论

念师

福利来啦！

本节代码已经整理之Github中，包含所有函数，数据集等。

欢迎大家学习讨论。

附地址：https://github.com/wangzhe0912/missshi_deeplearning_ai

2017-10-16 11:48:04 回复

---

dongzhi

不知 dnn_app_utils_v2 ，testCases_v2.py，dnn_utils_v2.py 在哪里找到，博主GitHub上的代码运行起来的输出结果，貌似有问题，不知是否发现

2017-11-01 11:57:27 回复

---

yizhenfeng2017

运行8multi_hidden_nn的main.py，得出的结果是train：Accuracy: 0.6555023923444976

test：Accuracy: 0.34，跟你上面的结果相差甚远

2017-12-08 07:05:00 回复

---

nel

我也发现了这个问题，在另外一篇CSDN上的文章看到initialize_parameters_deep里是这样写的：

“# 这里参数的初始化与浅层神经网络不同，为了避免梯度爆炸和消失，事实证明，如果此处不使用 “/ np.sqrt(layer_dims[l-1])” 会产生梯度消失

parameters['W' + str(l)] = np.random.randn(layer_dims[l],layer_dims[l-1]) / np.sqrt(layer_dims[l-1])”，

按这个调整过来可以收敛到文中结果了。

2017-12-13 13:50:24 回复

---

nel

另外，L_model_forward最后一行cache掉了一个s..

2017-12-13 13:52:44

念师

非常感谢您认真的回答，我很很快修改文中的错误，谢谢！

2017-12-29 11:41:07

---

ldsfcj

是不是在 update_parameters 和 L_model_forward 中，那个L=len(parameters)我打印了一下输出的结果是8，我的代码中改成了L=int(len(parameters)/2)才是博主的这个结果。因为b,W都要算长度。

2018-01-25 08:35:18 回复

评论内容

提交评论

念师

在想你的365天不断前行

查看熊掌号