Deep Neural Network - Application

September 23, 2024

1 Deep Neural Network for Image Classification: Application

By the time you complete this notebook, you will have finished the last programming assignment of Week 4, and also the last programming assignment of Course 1! Go you!

To build your cat/not-a-cat classifier, you'll use the functions from the previous assignment to build a deep network. Hopefully, you'll see an improvement in accuracy over your previous logistic regression implementation.

After this assignment you will be able to:

- Build and train a deep L-layer neural network, and apply it to supervised learning

Let's get started!

1.1 Important Note on Submission to the AutoGrader

Before submitting your assignment to the AutoGrader, please make sure you are not doing the following:

1. You have not added any *extra* `print` statement(s) in the assignment.
2. You have not added any *extra* code cell(s) in the assignment.
3. You have not changed any of the function parameters.
4. You are not using any global variables inside your graded exercises. Unless specifically instructed to do so, please refrain from it and use the local variables instead.
5. You are not changing the assignment code where it is not required, like creating *extra* variables.

If you do any of the following, you will get something like, `Grader Error: Grader feedback not found` (or similarly unexpected) error upon submitting your assignment. Before asking for help/debugging the errors in your assignment, check for these first. If this is the case, and you don't remember the changes you have made, you can get a fresh copy of the assignment by following these instructions.

1.2 Deep Neural Network for Image Classification: Application

==>Để xây dựng bộ phân loại mèo/không phải mèo, bạn sẽ sử dụng các hàm từ bài tập trước để xây dựng mạng lưới sâu.Độ chính xác được cải thiện so với triển khai logisic => điều bạn nhận được: - Xây dựng và đào tạo mạng nơ-ron sâu L-layer và áp dụng vào học có giám sát

1.3 Table of Contents

1 - Packages

Begin by importing all the packages you'll need during this assignment.

- numpy is the fundamental package for scientific computing with Python.
- matplotlib is a library to plot graphs in Python.
- h5py is a common package to interact with a dataset that is stored on an H5 file.
- PIL and scipy are used here to test your model with your own picture at the end.
- `dnn_app_utils` provides the functions implemented in the "Building your Deep Neural Network: Step by Step" assignment to this notebook.
- `np.random.seed(1)` is used to keep all the random function calls consistent. It helps grade your work - so please don't change it!

1.4 [numpy]để tính toán khoa học bằng Python.

- [matplotlib]một thư viện để vẽ đồ thị trong Python.
- [h5py]là một gói phổ biến để tương tác với một tập dữ liệu được lưu trữ trên tệp H5.
- [PIL] and [scipy]được sử dụng ở đây để kiểm tra mô hình của bạn với hình ảnh của chính bạn ở cuối .
- `dnn_app_utils`cung cấp các chức năng được triển khai trong bài tập "Xây dựng mạng lưới thần kinh sâu
- `np.random.seed(1)` giúp chấm điểm

[ ]:
```
### v1.1
```

[1]:
```
import time
import numpy as np
import h5py
import matplotlib.pyplot as plt
import scipy
from PIL import Image
```

```
from scipy import ndimage
from dnn_app_utils_v3 import *
from public_tests 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)
```

2 - Load and Process the Dataset

You'll be using the same "Cat vs non-Cat" dataset as in "Logistic Regression as a Neural Network" (Assignment 2). The model you built back then had 70% test accuracy on classifying cat vs non-cat images. Hopefully, your new model will perform even better!

Problem Statement: You are given a dataset ("data.h5") containing: - a training set of `m_train` images labelled as cat (1) or non-cat (0) - a test set of `m_test` images labelled as cat and non-cat - each image is of shape (num_px, num_px, 3) where 3 is for the 3 channels (RGB).

Let's get more familiar with the dataset. Load the data by running the cell below.

[2]:
```
train_x_orig, train_y, test_x_orig, test_y, classes = load_data()
```

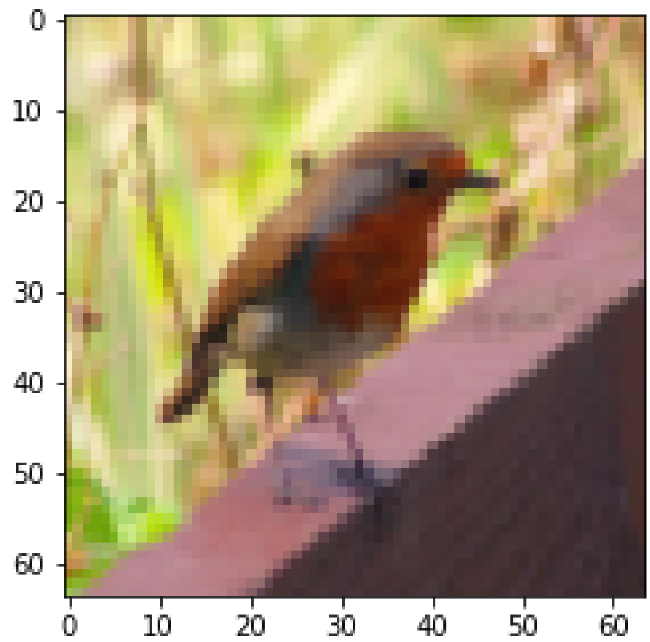
1.5 Bạn sẽ sử dụng cùng một bộ dữ liệu "Mèo so với không phải mèo" như trong "Hồi quy logistic dưới dạng Mạng nơ-ron,có độ chính xác 70%

bạn có 1 tập dataset("data.h5")gồm ### -một tập huấn luyện gồm các hình ảnh `m_train` được gắn nhãn là mèo (1) hoặc không phải mèo (0) ### -một bộ thử nghiệm gồm các hình ảnh `m_test` được gắn nhãn là mèo và không phải mèo ### -mỗi hình ảnh có hình dạng (num_px, num_px, 3) trong đó 3 dành cho 3 kênh (RGB).

The following code will show you an image in the dataset. Feel free to change the index and re-run the cell multiple times to check out other images.

[3]:
```
# Example of a picture
index = 10 #chỉ định vị trí của ảnh trong dataset
plt.imshow(train_x_orig[index])#hiển thị ảnh thứ 10 của tập ảnh gốc
print ("y = " + str(train_y[0,index]) + ". It's a " + classes[train_y[0,index]].
 ↪decode("utf-8") +  " picture.")
#nhãn của ảnh và tên lớp tương ứng được in ra
#mỗi ele trong train y tương ứng với mỗi nhãn trong orig
#chuyển đổi giá trị nhãn thì string và mã hóa utf-8
```

```
y = 0. It's a non-cat picture.
```

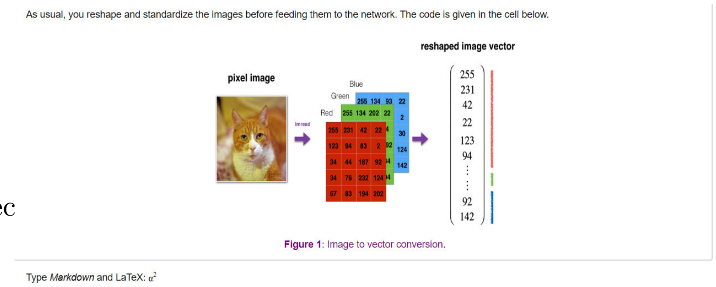


[4]:
```
# Explore your dataset
m_train = train_x_orig.shape[0]
num_px = train_x_orig.shape[1] #lấy chiều rộng or chiều cao (vì ảnh vuông)
m_test = test_x_orig.shape[0]
#lấy số lượng ảnh và gán vào biến ,rồi in thông tin của ảnh  ra
print ("Number of training examples: " + str(m_train))
print ("Number of testing examples: " + str(m_test))
#số lượng
print ("Each image is of size: (" + str(num_px) + ", " + str(num_px) + ",␣
↪3)")#kích thước (rộng ,cao,kênh màu )
print ("train_x_orig shape: " + str(train_x_orig.shape))
print ("train_y shape: " + str(train_y.shape))
print ("test_x_orig shape: " + str(test_x_orig.shape))
print ("test_y shape: " + str(test_y.shape))
#kích thước của mảng chứa nhãn
```

```
Number of training examples: 209
Number of testing examples: 50
Each image is of size: (64, 64, 3)
train_x_orig shape: (209, 64, 64, 3)
train_y shape: (1, 209)
test_x_orig shape: (50, 64, 64, 3)
test_y shape: (1, 50)
```

As usual, you reshape and standardize the images before feeding them to the network. The code is given in the cell below.

Figure 1: Image to vec



1.5.1 quá trình chuyển đổi một ảnh pixel sang một vector

-ảnh gốc là ảnh màu ,tạo từ các điểm ảnh ,mỗi điểm ảnh có giá trị màu đ diện cường độ (đỏ,xanh ,xanh dương) -mỗi ô là 1 pixel ,3 số nguyên đại diện cho màu của mỗi ô -giá trị màu của các pixel sắp theo cột,mỗi cái là 1 vecto

[5]:
```
# thay đổi hình dạng từ mảng 4 chiều thành 2 chiều (kích thước,cao,rộng,kênh)=>(số lượng pixel,sl ảnh)
train_x_flatten = train_x_orig.reshape(train_x_orig.shape[0], -1).T
test_x_flatten = test_x_orig.reshape(test_x_orig.shape[0], -1).T
#-1 tự động tính toán kích thước của sl pixel
#T đổi từ ngang sang dọc

# chuẩn hóa ( chia all pixel cho 255 ) để có feature values between 0 and 1.
train_x = train_x_flatten/255.
test_x = test_x_flatten/255.

print ("train_x's shape: " + str(train_x.shape))
print ("test_x's shape: " + str(test_x.shape))
#in ra
```

```
train_x's shape: (12288, 209)
test_x's shape: (12288, 50)
```

Note: $12,288$ equals $64 \times 64 \times 3$, which is the size of one reshaped image vector.

3 - Model Architecture

3.1 - 2-layer Neural Network

Now that you're familiar with the dataset, it's time to build a deep neural network to distinguish cat images from non-cat images!

You're going to build two different models:

- A 2-layer neural network
- An L-layer deep neural network

Then, you'll compare the performance of these models, and try out some different values for L.

Let's look at the two architectures:

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: $[x_0, x_1, ..., x_{12287}]^T$ is then multiplied by the weight matrix $W^{[1]}$ of size $(n^{[1]}, 12288)$. - Then, add a bias term and take its relu to get the following vector: $[a_0^{[1]}, a_1^{[1]}, ..., a_{n^{[1]}-1}^{[1]}]^T$. - Multiply the resulting vector by $W^{[2]}$ and add the intercept (bias). - Finally, take the sigmoid of the result. If it's greater than 0.5, classify it as a cat.

3.2 - L-layer Deep Neural Network

It's pretty difficult to represent an L-layer deep neural network using the above representation. However, here is a simplified network representation:

Figure 3: L-layer neural network. The model can be summarized as: [LINEAR -> RELU] × (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: $[x_0, x_1, ..., x_{12287}]^T$ 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, 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, take the sigmoid of the final linear unit. If it is greater than 0.5, classify it as a cat.

3.3 - General Methodology

As usual, you'll 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)
3. Use trained parameters to predict labels

Now go ahead and implement those two models!

1.5.2 3.1 - 2-layer Neural Network-build a deep neural network to distinguish cat images from non-cat images!

==> sẽ xây dựng 2 loại flm - A 2-layer neural network - An L-layer deep neural network ==>sau đó so sánh Các bước tiến hành : -một hình ảnh (64x64 pixel) -Hình ảnh được "phẳng hóa" thành một vector gồm 12288 phần tử (mỗi cái là giá trị màu của pixel) ##### +lớp linear:vector nhân với matrix trọng số (W[1]) kích thước (n[2], 12288). ##### +đưa vào hàm kích hoạt hàm ReLU (Rectified Linear Unit).(giữ nguyên dương và âm chuyển thành 0) ##### +next,result nhân với một ma trận trọng số (W[3]) kích thước (1, n[4]) ##### +cuối cùng đưa vào sigmoid ,khoảng từ 0 đến 1, đại diện cho xác suất của hình ảnh là "mèo". ==>kết quả là số thực ,so sánh với 0.5 để đối chiếu mèo hay không

4 - Two-layer Neural Network

Exercise 1 - two_layer_model

Use the helper functions you have implemented in the previous assignment to build a 2-layer neural network with the following structure: *LINEAR -> RELU -> LINEAR -> SIGMOID*. The functions and their inputs are:

[1] 1
[2] 1
[3] 2
[4] 1

```
def initialize_parameters(n_x, n_h, n_y):
    ...
    return parameters
def linear_activation_forward(A_prev, W, b, activation):
    ...
    return A, cache
def compute_cost(AL, Y):
    ...
    return cost
def linear_activation_backward(dA, cache, activation):
    ...
    return dA_prev, dW, db
def update_parameters(parameters, grads, learning_rate):
    ...
    return parameters
```

[6]:
```
### CONSTANTS DEFINING THE MODEL ####
n_x = 12288     # num_px * num_px * 3 #số lượng đặc trưng đầu vào
n_h = 7 #số lượng lớp ẩn
n_y = 1 #giá trị dự đoán
layers_dims = (n_x, n_h, n_y)
learning_rate = 0.0075 #tốc độ thuật toán
```

[ ]:
```
#xây dựng mạng 2 lớp theo linear->relu->linear-> sigmoid
```

[8]:
```
# 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)tạo giá trị ngẫu nhiên
    grads = {} dic lưu value của gradients
```

```
    costs = []                              # to keep track of the cost   hàm mất mát
    m = X.shape[1]                          # number of examples sl mẫu từ đầu vào x
    (n_x, n_h, n_y) = layers_dims   lấy kích thước các layers

    # Initialize parameters dictionary, by calling one of the functions you'd previously implemented
    #( 1 line of code)
    # parameters = ...
    # YOUR CODE STARTS HERE
    khởi tạo các tham số w và b
    parameters = initialize_parameters(n_x, n_h, n_y)   khởi tạo tham số cho neuron
    # YOUR CODE ENDS 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):   lặp num_interations lần

        # Forward propagation: LINEAR -> RELU -> LINEAR -> SIGMOID. Inputs: "X, W1, b1, W2, b2". Output: "A1, cache1, A2, cache2".
        #( 2 lines of code)
        # A1, cache1 = ...
        # A2, cache2 = ...
        # YOUR CODE STARTS HERE
        A1, cache1 = linear_activation_forward(X, W1, b1, activation='relu')
        A2, cache2 = linear_activation_forward(A1, W2, b2, activation='sigmoid')
       thực hiện linear và tiếp nối với relu và sigmoid
        # YOUR CODE ENDS HERE

        # Compute cost
        #( 1 line of code)
        # cost = ...
        # YOUR CODE STARTS HERE
        cost = compute_cost(A2, Y)    tính toán hàm mất mát

        # YOUR CODE ENDS HERE

        # Initializing backward propagation
        dA2 = - (np.divide(Y, A2) - np.divide(1 - Y, 1 - A2))
         tính đạo hàm của hàm mất mát theo giá trị predict
        # Backward propagation. Inputs: "dA2, cache2, cache1". Outputs: "dA1, dW2, db2; also dA0 (not used), dW1, db1".
```

```
        #( 2 lines of code)
        # dA1, dW2, db2 = ...
        # dA0, dW1, db1 = ...
        # YOUR CODE STARTS HERE
        dA1, dW2, db2 =  linear_activation_backward(dA2, cache2,␣
↪activation='sigmoid')
        dA0, dW1, db1 =  linear_activation_backward(dA1, cache1,␣
↪activation='relu')

        # YOUR CODE ENDS 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.
        #(approx. 1 line of code)
        # parameters = ...
        # YOUR CODE STARTS HERE
        parameters = update_parameters(parameters, grads, learning_rate)

        # YOUR CODE ENDS 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 iterations
        if print_cost and i % 100 == 0 or i == num_iterations - 1:
            print("Cost after iteration {}: {}".format(i, np.squeeze(cost)))
        if i % 100 == 0 or i == num_iterations:
            costs.append(cost)

    return parameters, costs

def plot_costs(costs, learning_rate=0.0075):
    plt.plot(np.squeeze(costs))
    plt.ylabel('cost')
    plt.xlabel('iterations (per hundreds)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()
```

thực hiện truyền ngược

lớp thứ 2

lớp thứ 1

lưu vào lại dic

cập nhật các parameters bằng gradient descents

lấy các parameter vừa cập nhật

print values hàm cost sau 100 lần lặp

lưu vào cost

tóm lại:khởi tạo w và b ,sau đó tính linear tiếp đến relu và sigmoids
tính hàm cost sau đó tính đạo hàm của cost theo giá trị predict rồi truyền ngược và cập nhật lại vào w b và cost
==> thuận là kg có đạo hàm

build model với 2 tập trainx và train y qua num lần lặp

[9]:
```
parameters, costs = two_layer_model(train_x, train_y, layers_dims = (n_x, n_h,␣
↪n_y), num_iterations = 2, print_cost=False)

print("Cost after first iteration: " + str(costs[0]))

two_layer_model_test(two_layer_model)
```
kiểm tra hiệu xuất của model :độ chính xác ....

```
Cost after iteration 1: 0.6926114346158595
Cost after first iteration: 0.693049735659989
Cost after iteration 1: 0.6915746967050506
Cost after iteration 1: 0.6915746967050506
Cost after iteration 1: 0.6915746967050506
Cost after iteration 2: 0.6524135179683452
 All tests passed.
```

Expected output:

```
cost after iteration 1 must be around 0.69
```

4.1 - Train the model

If your code passed the previous cell, run the cell below to train your parameters.

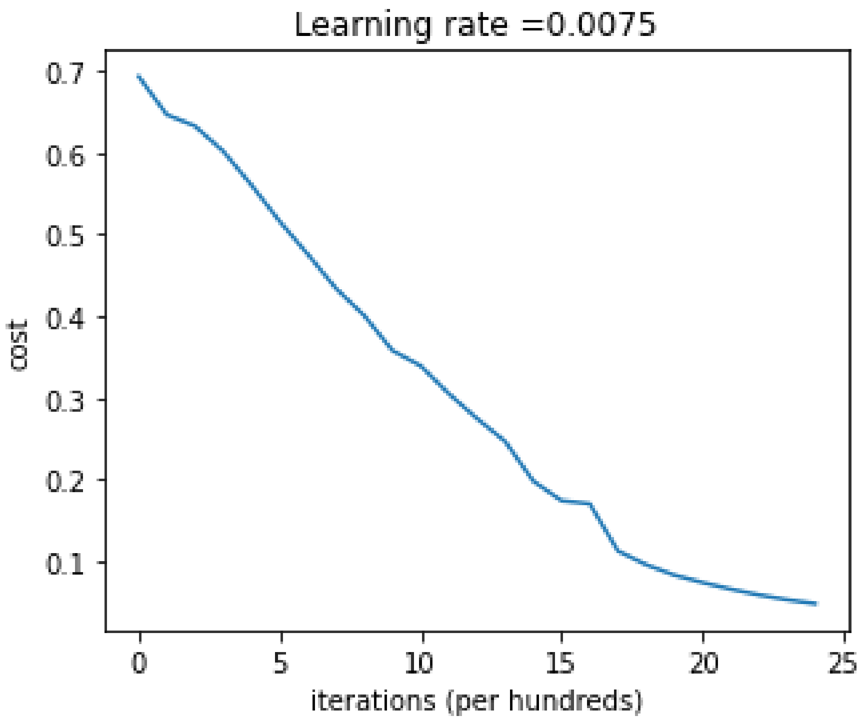
- The cost should decrease on every iteration.
- It may take up to 5 minutes to run 2500 iterations.

[10]:
```
parameters, costs = two_layer_model(train_x, train_y, layers_dims = (n_x, n_h,␣
↪n_y), num_iterations = 2500, print_cost=True)
plot_costs(costs, learning_rate)
```

```
Cost after iteration 0: 0.693049735659989
Cost after iteration 100: 0.6464320953428849
Cost after iteration 200: 0.6325140647912677
Cost after iteration 300: 0.6015024920354665
Cost after iteration 400: 0.5601966311605747
Cost after iteration 500: 0.5158304772764729
Cost after iteration 600: 0.4754901313943325
Cost after iteration 700: 0.43391631512257495
Cost after iteration 800: 0.4007977536203886
Cost after iteration 900: 0.3580705011323798
Cost after iteration 1000: 0.3394281538366413
Cost after iteration 1100: 0.30527536361962654
Cost after iteration 1200: 0.2749137728213015
Cost after iteration 1300: 0.2468176821061484
Cost after iteration 1400: 0.19850735037466102
Cost after iteration 1500: 0.17448318112556638
Cost after iteration 1600: 0.1708076297809692
Cost after iteration 1700: 0.11306524562164715
Cost after iteration 1800: 0.09629426845937156
Cost after iteration 1900: 0.0834261795972687
```

```
Cost after iteration 2000: 0.07439078704319085
Cost after iteration 2100: 0.06630748132267933
Cost after iteration 2200: 0.05919329501038172
Cost after iteration 2300: 0.053361403485605606
Cost after iteration 2400: 0.04855478562877019
Cost after iteration 2499: 0.04421498215868956
```

thể hiện giá trị của hàm cost sau mỗi lần lặp ==>giảm dần cho thấy model học tốt vì cost giảm ,và hiệu quả trong những lần đầu



Expected Output:

Cost after iteration 0

0.6930497356599888

Cost after iteration 100

0.6464320953428849

...

...

Cost after iteration 2499

0.04421498215868956

Nice! You successfully trained the model. Good thing you built a vectorized implementation! Otherwise it might have taken 10 times longer to train this.

Now, you can use the trained parameters to classify images from the dataset. To see your predictions on the training and test sets, run the cell below.

[11]:
```
predictions_train = predict(train_x, train_y, parameters)
```

```
Accuracy: 0.9999999999999998
```

Expected Output:

Accuracy

0.9999999999999998

[12]:
```
predictions_test = predict(test_x, test_y, parameters)
```

```
Accuracy: 0.72
```

Expected Output:

Accuracy

0.72

1.5.3 Congratulations! It seems that your 2-layer neural network has better performance (72%) than the logistic regression implementation (70%, assignment week 2). Let's see if you can do even better with an L-layer model.

Note: You may notice that running the model on fewer iterations (say 1500) gives better accuracy on the test set. This is called "early stopping" and you'll hear more about it in the next course. Early stopping is a way to prevent overfitting.

5 - L-layer Neural Network   triển khai với L layer khác ở trên là 2 layer

Exercise 2 - L_layer_model

Use the helper functions you implemented previously to build an L-layer neural network with the following structure: *[LINEAR -> RELU]×(L-1) -> LINEAR -> SIGMOID*. The functions and their inputs are:

```python
def initialize_parameters_deep(layers_dims):
    ...
    return parameters
def L_model_forward(X, parameters):
    ...
    return AL, caches
def compute_cost(AL, Y):
    ...
    return cost
def L_model_backward(AL, Y, caches):
    ...
    return grads
def update_parameters(parameters, grads, learning_rate):
```

```
    ...
    return parameters
```

[13]:
```
### CONSTANTS ###
layers_dims = [12288, 20, 7, 5, 1] #  4-layer model
```

[14]:
```
# GRADED FUNCTION: L_layer_model

def L_layer_model(X, Y, layers_dims, learning_rate = 0.0075, num_iterations =␣
 ↪3000, print_cost=False):
```
khởi tạo layer
```
    """
    Implements a L-layer neural network: [LINEAR->RELU]*(L-1)->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 -- 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)
    # parameters = ...
    # YOUR CODE STARTS HERE
    parameters = initialize_parameters_deep(layers_dims)

    # YOUR CODE ENDS HERE

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

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

```
        # YOUR CODE ENDS HERE

        # Compute cost.
        #( 1 line of code)
        # cost = ...
        # YOUR CODE STARTS HERE
        cost = compute_cost(AL, Y)

        # YOUR CODE ENDS HERE

        # Backward propagation.
        #( 1 line of code)
        # grads = ...
        # YOUR CODE STARTS HERE
        grads = L_model_backward(AL, Y, caches)

        # YOUR CODE ENDS HERE

        # Update parameters.
        #( 1 line of code)
        # parameters = ...
        # YOUR CODE STARTS HERE
        parameters = update_parameters(parameters, grads, learning_rate)

        # YOUR CODE ENDS HERE

        # Print the cost every 100 iterations
        if print_cost and i % 100 == 0 or i == num_iterations - 1:
            print("Cost after iteration {}: {}".format(i, np.squeeze(cost)))
        if i % 100 == 0 or i == num_iterations:
            costs.append(cost)

    return parameters, costs
```

[15]:
```
parameters, costs = L_layer_model(train_x, train_y, layers_dims, num_iterations␣
↪= 1, print_cost = False)

print("Cost after first iteration: " + str(costs[0]))

L_layer_model_test(L_layer_model)
```

```
Cost after iteration 0: 0.7717493284237686
Cost after first iteration: 0.7717493284237686
Cost after iteration 1: 0.7070709008912569
Cost after iteration 1: 0.7070709008912569
Cost after iteration 1: 0.7070709008912569
```

khác :2 layer chỉ có đầu vào và ra
l layer nhìu lớp
relu cho đầu vào và sigmoid cho ra
còn L thì relu trong nhìu lớp ẩn tích hợp sẵn còn sigmoids cho lớp ra

```
Cost after iteration 2: 0.7063462654190897
 All tests passed.
```

5.1 - Train the model

If your code passed the previous cell, run the cell below to train your model as a 4-layer neural network.

- The cost should decrease on every iteration.
- It may take up to 5 minutes to run 2500 iterations.

[16]:
```
parameters, costs = L_layer_model(train_x, train_y, layers_dims, num_iterations = 2500, print_cost = True)
```

```
Cost after iteration 0: 0.7717493284237686
Cost after iteration 100: 0.6720534400822914
Cost after iteration 200: 0.6482632048575212
Cost after iteration 300: 0.6115068816101356
Cost after iteration 400: 0.5670473268366111
Cost after iteration 500: 0.5401376634547801
Cost after iteration 600: 0.5279299569455267
Cost after iteration 700: 0.4654773771766851
Cost after iteration 800: 0.369125852495928
Cost after iteration 900: 0.39174697434805344
Cost after iteration 1000: 0.31518698886006163
Cost after iteration 1100: 0.2726998441789385
Cost after iteration 1200: 0.23741853400268137
Cost after iteration 1300: 0.19960120532208644
Cost after iteration 1400: 0.18926300388463307
Cost after iteration 1500: 0.16118854665827753
Cost after iteration 1600: 0.14821389662363316
Cost after iteration 1700: 0.13777487812972944
Cost after iteration 1800: 0.1297401754919012
Cost after iteration 1900: 0.12122535068005211
Cost after iteration 2000: 0.11382060668633713
Cost after iteration 2100: 0.10783928526254133
Cost after iteration 2200: 0.10285466069352679
Cost after iteration 2300: 0.10089745445261786
Cost after iteration 2400: 0.09287821526472398
Cost after iteration 2499: 0.08843994344170202
```

Expected Output:

Cost after iteration 0

0.771749

Cost after iteration 100

0.672053

…

…

Cost after iteration 2499

0.088439

[17]:
```
pred_train = predict(train_x, train_y, parameters)
```

```
Accuracy: 0.9856459330143539
```

Expected Output:

Train Accuracy

0.985645933014

[18]:
```
pred_test = predict(test_x, test_y, parameters)
```

```
Accuracy: 0.8
```

Expected Output:

Test Accuracy

0.8

1.5.4 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.

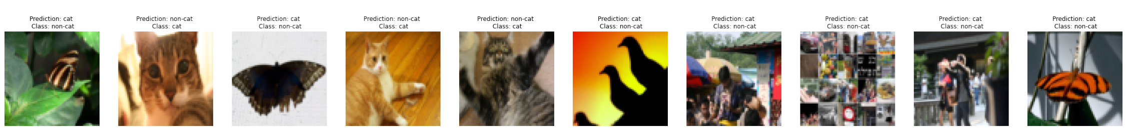
This is pretty good performance for this task. Nice job!

In the next course on "Improving deep neural networks," you'll be able to obtain even higher accuracy by systematically searching for better hyperparameters: learning_rate, layers_dims, or num_iterations, for example.

6 - Results Analysis

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

[19]:
```
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)

1.5.5 Congratulations on finishing this assignment!

You just built and trained a deep L-layer neural network, and applied it in order to distinguish cats from non-cats, a very serious and important task in deep learning. ;)

By now, you've also completed all the assignments for Course 1 in the Deep Learning Specialization. Amazing work! If you'd like to test out how closely you resemble a cat yourself, there's an optional ungraded exercise below, where you can test your own image.

Great work and hope to see you in the next course!

7 - Test with your own image (optional/ungraded exercise)

From this point, if you so choose, you can use your own image to test the output of your model. To do that follow these steps:

1. Click on "File" in the upper bar of this notebook, then click "Open" to go on your Coursera Hub.
2. Add your image to this Jupyter Notebook's directory, in the "images" folder
3. Change your image's name in the following code
4. Run the code and check if the algorithm is right (1 = cat, 0 = non-cat)!

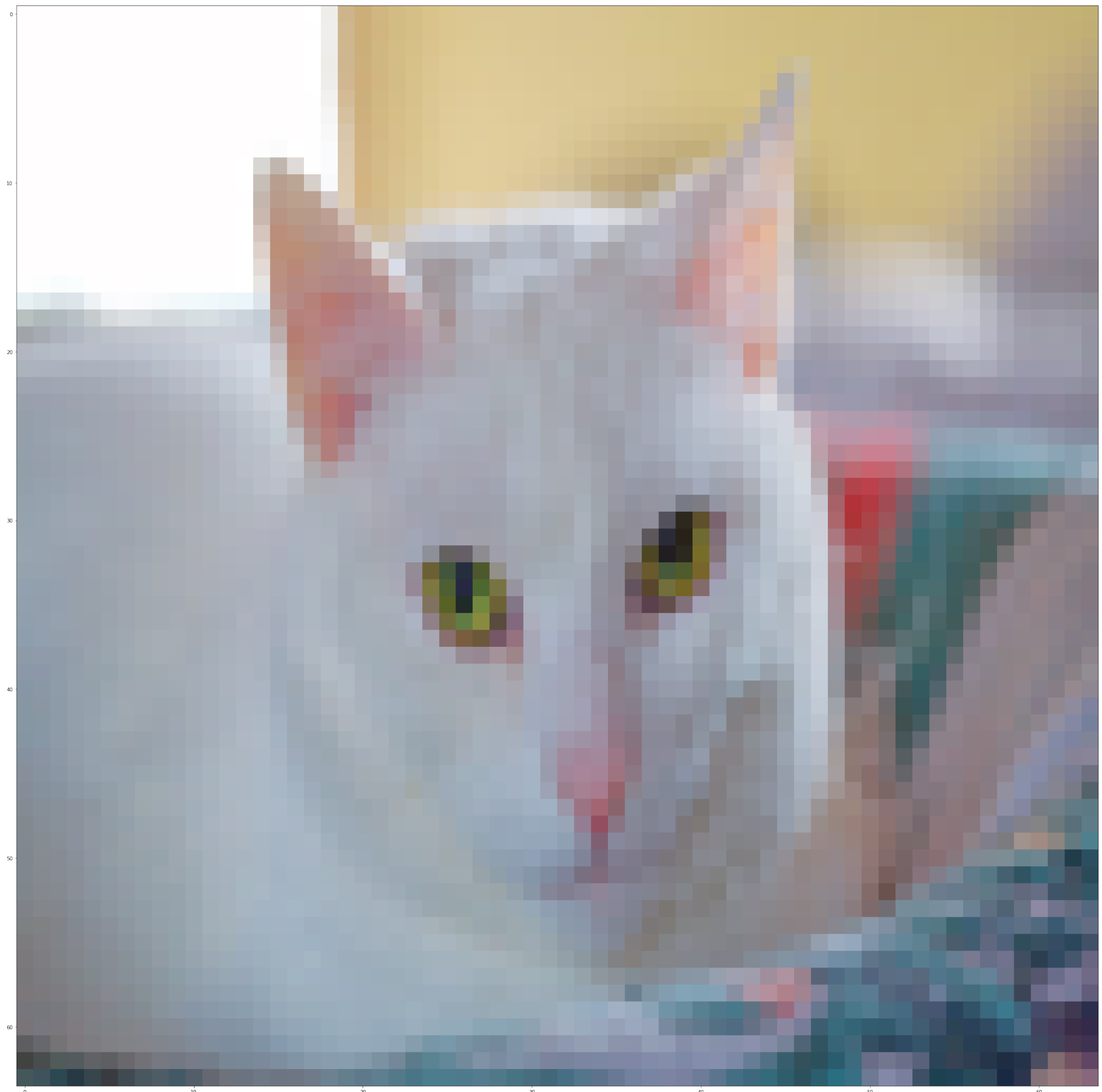
[20]:
```
## START CODE HERE ##
my_image = "my_image.jpg" # change this to the name of your image file
my_label_y = [1] # the true class of your image (1 -> cat, 0 -> non-cat)
## END CODE HERE ##

fname = "images/" + my_image
image = np.array(Image.open(fname).resize((num_px, num_px)))đọc và chuyển đổi thành numpy
plt.imshow(image)
image = image / 255.  chuẩn hóa 0 va 1
image = image.reshape((1, num_px * num_px * 3)).T

my_predicted_image = predict(image, my_label_y, parameters)  dựa đoán dựa trên hàm


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.")
```

```
Accuracy: 1.0
y = 1.0, your L-layer model predicts a "cat" picture.
```



References:

- for auto-reloading external module: http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ipython