Deep Neural Network for Image Classification: Application ¶

When you finish this, you will have finished the last programming assignment of Week 4, and also the last programming assignment of this course!

You will use use the functions you'd implemented in the previous assignment to build a deep network, and apply it to cat vs non-cat classification. Hopefully, you will see an improvement in accuracy relative to your previous logistic regression implementation.

After this assignment you will be able to:

- Build and apply a deep neural network to supervised learning.

Let's get started!

1 - Packages

Let's first import all the packages that you will need during this assignment.

- numpy (www.numpy.org) is the fundamental package for scientific computing with Python.
- matplotlib (http://matplotlib.org) is a library to plot graphs in Python.
- h5py (http://www.h5py.org) is a common package to interact with a dataset that is stored on an H5 file.
- PIL (http://www.pythonware.com/products/pil/) and scipy (https://www.scipy.org/) 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 will help us grade your work.

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

In [2]:
```
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

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 efficient
ly
    """

    A = np.maximum(0,Z)

    assert(A.shape == Z.shape)

    cache = Z
    return A, cache
```

```python
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


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


def load_data():
    train_dataset = h5py.File('/root/datasets/train_catvnoncat.h5', "r")
    train_set_x_orig = np.array(train_dataset["train_set_x"][:]) # your train set features
    train_set_y_orig = np.array(train_dataset["train_set_y"][:]) # your train set labels

    test_dataset = h5py.File('/root/datasets/test_catvnoncat.h5', "r")
    test_set_x_orig = np.array(test_dataset["test_set_x"][:]) # your test set features
    test_set_y_orig = np.array(test_dataset["test_set_y"][:]) # your test set labels

    classes = np.array(test_dataset["list_classes"][:]) # the list of classes

    train_set_y_orig = train_set_y_orig.reshape((1, train_set_y_orig.shape[0]))
    test_set_y_orig = test_set_y_orig.reshape((1, test_set_y_orig.shape[0]))

    return train_set_x_orig, train_set_y_orig, test_set_x_orig, test_set_y_orig, classes


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)
```

```
    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))

    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


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(1)
    parameters = {}
    L = len(layer_dims)            # number of layers in the network

    for l in range(1, L):
        parameters['W' + str(l)] = np.random.randn(layer_dims[l], layer_dims[l-1]) / np.sqrt(layer
_dims[l-1]) #*0.01
        parameters['b' + str(l)] = np.zeros((layer_dims[l], 1))

        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

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 examp
les)
    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 p
ass efficiently
    """

    Z = W.dot(A) + b

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

    return Z, cache


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".
        Z, linear_cache = linear_forward(A_prev, W, b)
        A, activation_cache = sigmoid(Z)

    elif activation == "relu":
        # Inputs: "A_prev, W, b". Outputs: "A, activation_cache".
        Z, linear_cache = linear_forward(A_prev, W, b)
        A, activation_cache = relu(Z)

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

    return A, cache


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' + st
r(l)], activation = "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)], a
ctivation = "sigmoid")
    caches.append(cache)

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

    return AL, caches


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 example
s)
    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.
    cost = (1./m) * (-np.dot(Y,np.log(AL).T) - np.dot(1-Y, np.log(1-AL).T))

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

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

    return cost


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 lay
er

    Returns:
    dA_prev -- Gradient of the cost with respect to the activation (of the previous layer l-1), sa
me 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]

    dW = 1./m * np.dot(dZ,A_prev.T)
    db = 1./m * np.sum(dZ, axis = 1, keepdims = True)
    dA_prev = np.dot(W.T,dZ)

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

    return dA_prev, dW, db


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 prop
agation 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), sa
me 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":
        dZ = relu_backward(dA, activation_cache)
        dA_prev, dW, db = linear_backward(dZ, linear_cache)

    elif activation == "sigmoid":
        dZ = sigmoid_backward(dA, activation_cache)
        dA_prev, dW, db = linear_backward(dZ, linear_cache)

    return dA_prev, dW, db


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" (there are (L-1) or them, i
ndexes from 0 to L-2)
                the cache of linear_activation_forward() with "sigmoid" (there is one, index 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
    dAL = - (np.divide(Y, AL) - np.divide(1 - Y, 1 - AL))

    # Lth layer (SIGMOID -> LINEAR) gradients. Inputs: "AL, Y, caches". Outputs: "grads["dAL"], gr
ads["dWL"], grads["dbL"]
    current_cache = caches[L-1]
    grads["dA" + str(L)], grads["dW" + str(L)], grads["db" + str(L)] =
linear_activation_backward(dAL, current_cache, activation = "sigmoid")

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

    return grads

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.
    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)]

    return parameters

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 results
    #print ("predictions: " + str(p))
    #print ("true labels: " + str(y))
    print("Accuracy: "  + str(np.sum((p == y)/m)))

    return p

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: " + clas
ses[y[0,index]].decode("utf-8"))
```

In [3]:
```
%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 - Dataset

You will use the same "Cat vs non-Cat" dataset as in "Logistic Regression as a Neural Network" (Assignment 2). The model you had built had 70% test accuracy on classifying cats vs non-cats images. Hopefully, your new model will perform a 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).
```

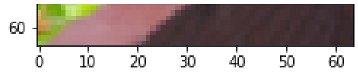
Let's get more familiar with the dataset. Load the data by running the cell below.

In [4]:
```
train_x_orig, train_y, test_x_orig, test_y, classes = load_data()
```

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 see other images.

In [5]:
```
# Example of a picture
index = 10
plt.imshow(train_x_orig[index])
print ("y = " + str(train_y[0,index]) + ". It's a " + classes[train_y[0,index]].decode("utf-8") +
 " picture.")
```

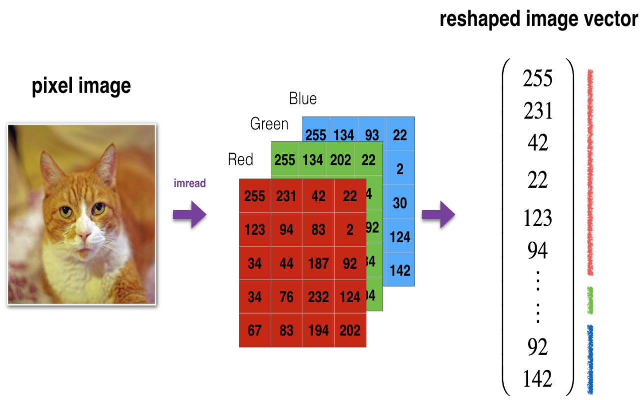
```
y = 0. It's a non-cat picture.
```



In [6]:
```
# Explore your dataset
m_train = train_x_orig.shape[0]
num_px = train_x_orig.shape[1]
m_test = test_x_orig.shape[0]

print ("Number of training examples: " + str(m_train))
print ("Number of testing examples: " + str(m_test))
print ("Each image is of size: (" + str(num_px) + ", " + str(num_px) + ", 3)")
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))
```

```
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.



In [8]:
```
# Reshape the training and test examples
train_x_flatten = train_x_orig.reshape(train_x_orig.shape[0], -1).T   # The "-1" makes reshape fla
tten the remaining dimensions
test_x_flatten = test_x_orig.reshape(test_x_orig.shape[0], -1).T

# Standardize data to have 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))
```

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

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

3 - Architecture of your model

Now that you are familiar with the dataset, it is time to build a deep neural network to distinguish cat images from non-cat images.

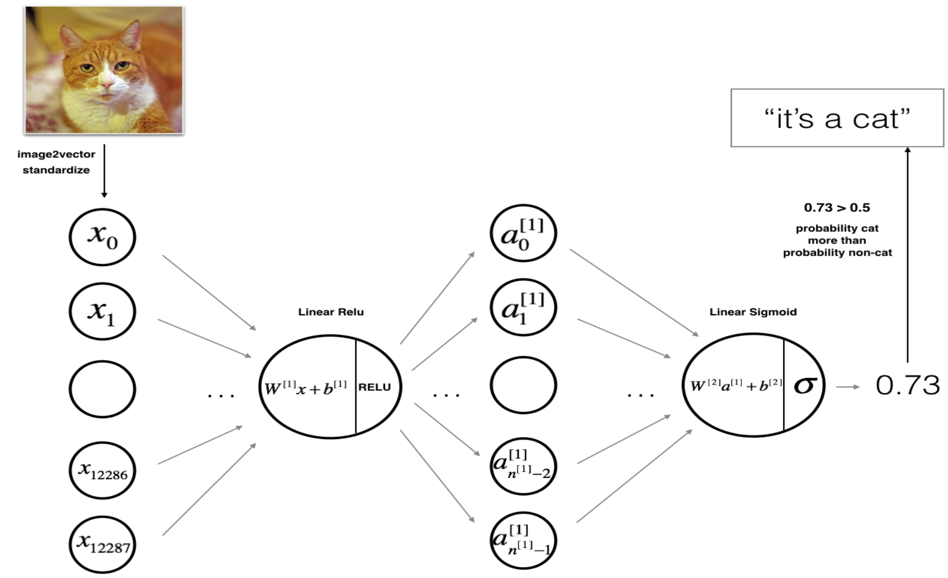
You will build two different models:

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

You will then compare the performance of these models, and also try out different values for L.

Let's look at the two architectures.

3.1 - 2-layer neural network

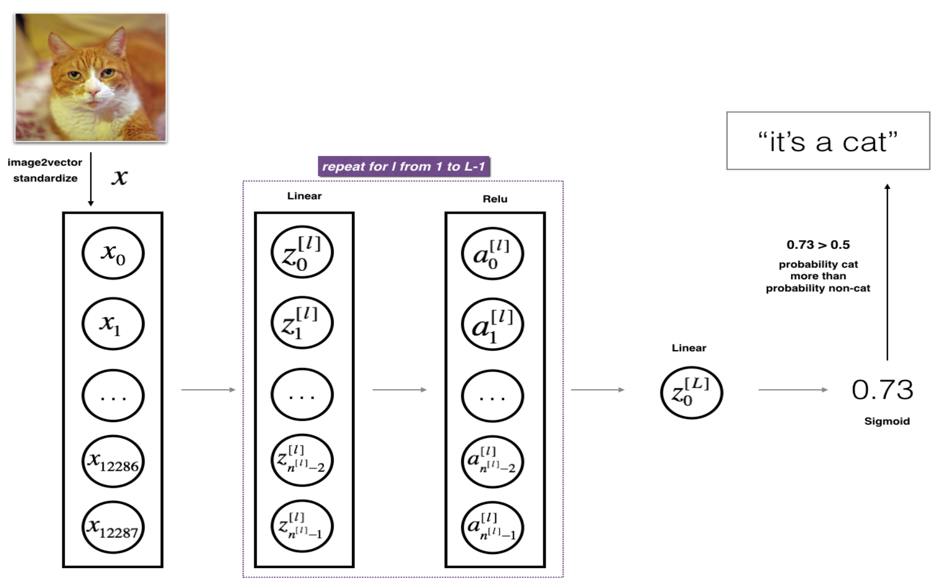


:

- 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 $(n^{[1]}, 12288)$.
- You then add a bias term and take its relu to get the following vector: $[a_0^{[1]}, a_1^{[1]}, ..., a_{n^{[1]}-1}^{[1]}]^T$.
- 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:



:

- 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, 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!

4 - Two-layer neural network

Question: 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 you may need and their inputs are:

```
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
```

In [9]:
```
### 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 [10]:
```
# GRADED FUNCTION: two_layer_model

def two_layer_model(X, Y, layers_dims, learning_rate = 0.0075, num_iterations = 3000, print_cost=F
alse):
    """
    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 implement
ed
    ### 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.
```

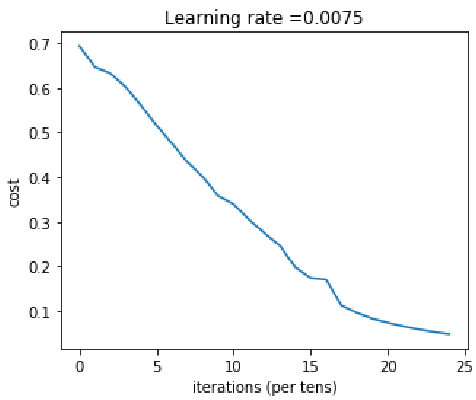
```
    W1 = parameters["W1"]
    b1 = parameters["b1"]
    W2 = parameters["W2"]
    b2 = parameters["b2"]

    # 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['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 tens)')
    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.

In [11]:
```
parameters = two_layer_model(train_x, train_y, layers_dims = (n_x, n_h, n_y), num_iterations = 250
0, 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: 0.5158304772764729
Cost after iteration 600: 0.47549013139433255
Cost after iteration 700: 0.4339163151225749
Cost after iteration 800: 0.4007977536203888
```

```
Cost after iteration 900: 0.3580705011323798
Cost after iteration 1000: 0.3394281538366412
Cost after iteration 1100: 0.30527536361962637
Cost after iteration 1200: 0.27491377282130147
Cost after iteration 1300: 0.24681768210614838
Cost after iteration 1400: 0.19850735037466094
Cost after iteration 1500: 0.17448318112556654
Cost after iteration 1600: 0.17080762978096337
Cost after iteration 1700: 0.11306524562164727
Cost after iteration 1800: 0.09629426845937146
Cost after iteration 1900: 0.08342617959726863
Cost after iteration 2000: 0.0743907870431908
Cost after iteration 2100: 0.0663074813226793
Cost after iteration 2200: 0.05919329501038169
Cost after iteration 2300: 0.05336140348560555
Cost after iteration 2400: 0.04855478562877018
```



Expected Output:

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

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.

In [12]:
```
predictions_train = predict(train_x, train_y, parameters)
```

```
Accuracy: 1.0
```

Expected Output:

Accuracy	1.0

In [13]:
```
predictions_test = predict(test_x, test_y, parameters)
```

```
Accuracy: 0.72
```

Expected Output:

Accuracy	0.72

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 we will talk about it in the next course. Early stopping is a way to prevent overfitting.

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.

5 - L-layer Neural Network

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

```
def initialize_parameters_deep(layer_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
```

In [14]:
```
### CONSTANTS ###
layers_dims = [12288, 20, 7, 5, 1] #  5-layer model
```

In [15]:
```
# GRADED FUNCTION: L_layer_model

def L_layer_model(X, Y, layers_dims, learning_rate = 0.0075, num_iterations = 3000, print_cost=Fal
se):#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))
```

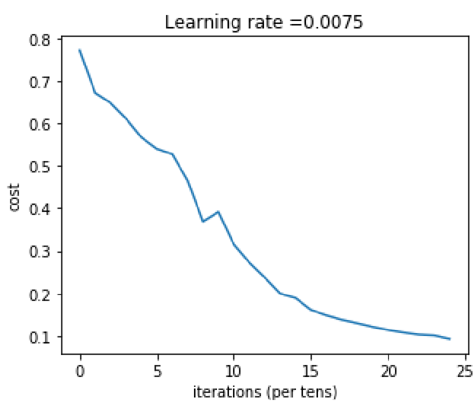
```
        if print_cost and i % 100 == 0:
            costs.append(cost)

    # 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
```

You will now train the model as a 5-layer neural network.

Run the cell below to train your model. The cost should decrease on every iteration. 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.

In [16]:
```
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
```



Expected Output:

Cost after iteration 0	0.771749
Cost after iteration 100	0.672053
...	...
Cost after iteration 2400	0.092878

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

```
Accuracy: 0.985645933014
```

Train Accuracy	0.985645933014

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

```
Accuracy: 0.8
```

Expected Output:

Test Accuracy	0.8

Congrats! It seems that your 5-layer neural network has better performance (80%) than your 2-layer neural network (72%) on the same test set.

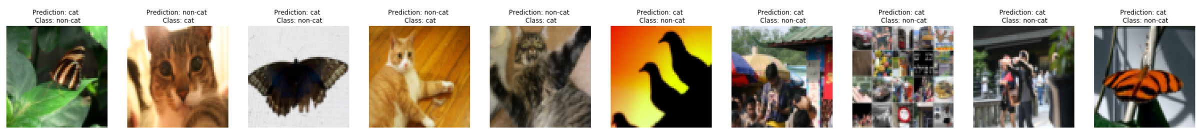
This is good performance for this task. Nice job!

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 [19]:
```
print_mislabeled_images(classes, test_x, test_y, pred_test)
```



A few type 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)

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

Congratulations on finishing this assignment. You can use your own image and see the output of your model. To do that:

```
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)!
```

In [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(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 \"" + class
es[int(np.squeeze(my_predicted_image)),].decode("utf-8") +  "\" picture.")
```

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


200
300
400
500