Deep Neural Network - Application

January 13, 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 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!

[ ]:
```
### 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).

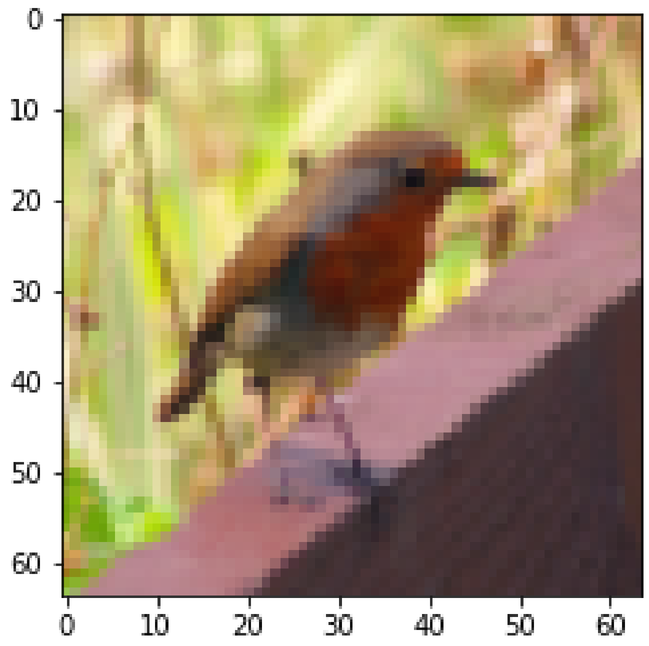
Let's get more familiar with the dataset. Load the data by running the cell below.

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

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
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.
```



[4]:
```
# 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.

Figure 1: Image to vector conversion.

[5]:
```
# Reshape the training and test examples
train_x_flatten = train_x_orig.reshape(train_x_orig.shape[0], -1).T   # The␣
 ↪"-1" makes reshape flatten 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)
```

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!

## 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:

```
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
n_h = 7
n_y = 1
layers_dims = (n_x, n_h, n_y)
learning_rate = 0.0075
```

[7]:
```
# GRADED FUNCTION: two_layer_model

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

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

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

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

    # Initialize parameters dictionary, by calling one of the functions you'd␣
↪previously implemented
    #( 1 line of code)
    # parameters = ...
    # YOUR CODE STARTS HERE
    parameters = initialize_parameters(n_x, n_h, n_y)
    # 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):

        # 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")

        # YOUR CODE ENDS HERE

        # Compute cost
        #( 1 line of code)
        # cost = ...
        # YOUR CODE STARTS HERE
        cost = compute_cost(A2, Y)

        # YOUR CODE ENDS 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".
        #( 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()
```

[8]:
```
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)
```

```
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
```

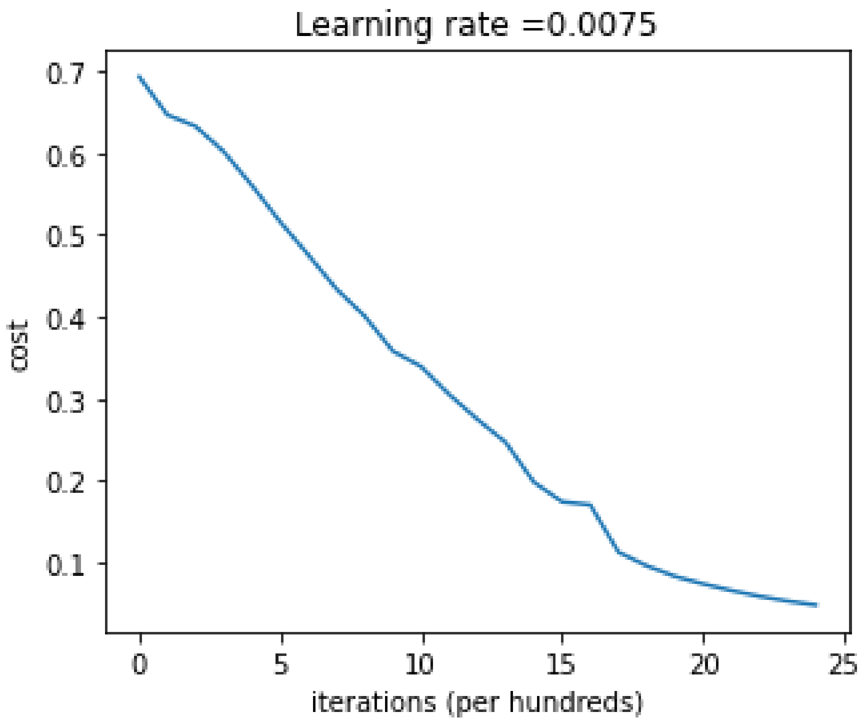
### 4.1 - Train the model

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.

[9]:
```
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
```



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.

[10]:
```
predictions_train = predict(train_x, train_y, parameters)
```

```
Accuracy: 0.9999999999999998
```

Expected Output:

Accuracy

0.9999999999999998

[11]:
```
predictions_test = predict(test_x, test_y, parameters)
```

```
Accuracy: 0.72
```

Expected Output:

Accuracy

0.72

1.2.1 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

### 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:

```
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
```

[12]:
```
### CONSTANTS ###
layers_dims = [12288, 20, 7, 5, 1] #  4-layer model
```

[13]:
```
# GRADED FUNCTION: L_layer_model
```

```
def L_layer_model(X, Y, layers_dims, learning_rate = 0.0075, num_iterations =␣
↪3000, print_cost=False):
    """
    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
```

[14]:
```
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
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.

[15]:
```
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

[16]:
```
pred_train = predict(train_x, train_y, parameters)
```

```
Accuracy: 0.9856459330143539
```

Expected Output:

Train Accuracy

0.985645933014

[17]:
```
pred_test = predict(test_x, test_y, parameters)
```

```
Accuracy: 0.8
```

Expected Output:

Test Accuracy

0.8

1.2.2 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.

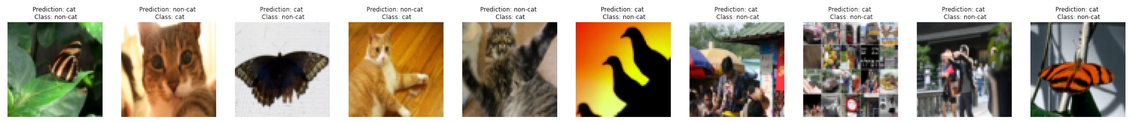
This is pretty good performance for this task. Nice job!

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.

[18]:
```
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)

1.2.3 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!

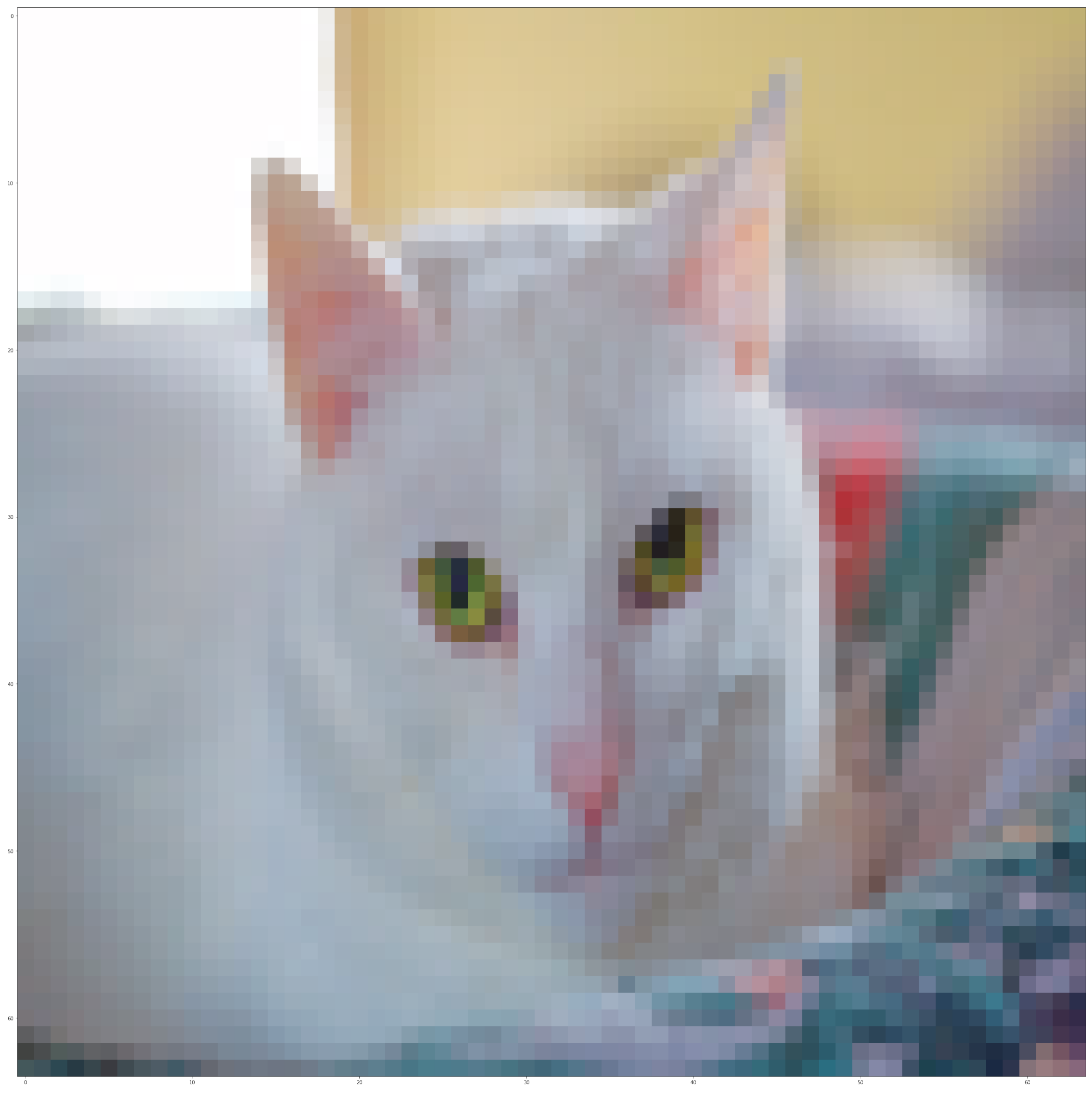
## 7 - Test with your own image (optional/ungraded exercise) ##

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)!

[19]:
```
## 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)))
plt.imshow(image)
image = image / 255.
image = image.reshape((1, num_px * num_px * 3)).T

my_predicted_image = predict(image, my_label_y, parameters)


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

Logistic Regression with a Neural Network mindset

Welcome to your first (required) programming assignment! You will build a logistic regression classifier to recognize cats. This assignment will step you through how to do this with a Neural Network mindset, and will also hone your intuitions about deep learning.

Instructions:

- Do not use loops (for/while) in your code, unless the instructions explicitly ask you to do so.
- Use `np.dot(X,Y)` to calculate dot products.

You will learn to:

- Build the general architecture of a learning algorithm, including:
  - Initializing parameters
  - Calculating the cost function and its gradient
  - Using an optimization algorithm (gradient descent)
- Gather all three functions above into a main model function, in the right order.

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 (https://www.coursera.org/learn/neural-networks-deep-learning/supplement/iLwon/h-ow-to-refresh-your-workspace).

Table of Contents

1 - Packages

First, let's run the cell below to import all the packages that you will need during this assignment.

- numpy (https://numpy.org/doc/1.20/) is the fundamental package for scientific computing with Python.
- h5py (http://www.h5py.org) is a common package to interact with a dataset that is stored on an H5 file.
- matplotlib (http://matplotlib.org) is a famous library to plot graphs in Python.
- PIL (https://pillow.readthedocs.io/en/stable/) and scipy (https://www.scipy.org/) are used here to test your model with your own picture at the end.

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

In [2]:
```
import numpy as np
import copy
import matplotlib.pyplot as plt
import h5py
import scipy
from PIL import Image
from scipy import ndimage
from lr_utils import load_dataset
from public_tests import *

%matplotlib inline
%load_ext autoreload
%autoreload 2
```

2 - Overview of the Problem set

Problem Statement: You are given a dataset ("data.h5") containing:

```
- a training set of m_train images labeled as cat (y=1) or non-cat (y=0)
- a test set of m_test images labeled as cat or non-cat
- each image is of shape (num_px, num_px, 3) where 3 is for the 3 channels (RGB). Thus, each image is square (height = num_px) and (width = num_px).
```

You will build a simple image-recognition algorithm that can correctly classify pictures as cat or non-cat.

Let's get more familiar with the dataset. Load the data by running the following code.

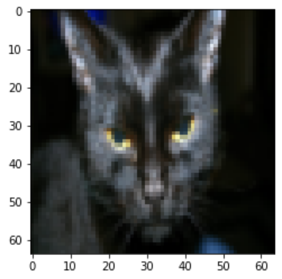
In [3]:
```
# Loading the data (cat/non-cat)
train_set_x_orig, train_set_y, test_set_x_orig, test_set_y, classes = load_dataset()
```

We added "_orig" at the end of image datasets (train and test) because we are going to preprocess them. After preprocessing, we will end up with train_set_x and test_set_x (the labels train_set_y and test_set_y don't need any preprocessing).

Each line of your train_set_x_orig and test_set_x_orig is an array representing an image. You can visualize an example by running the following code. Feel free also to change the `index` value and re-run to see other images.

In [4]:
```
# Example of a picture
index = 25
plt.imshow(train_set_x_orig[index])
print ("y = " + str(train_set_y[:, index]) + ", it's a '" + classes[np.squeeze(train_set_y[:, index])].decode("utf-8") +  "' picture.")
```

```
y = [1], it's a 'cat' picture.
```



Many software bugs in deep learning come from having matrix/vector dimensions that don't fit. If you can keep your matrix/vector dimensions straight you will go a long way toward eliminating many bugs.

Exercise 1

Find the values for:

```
- m_train (number of training examples)
- m_test (number of test examples)
- num_px (= height = width of a training image)
```

Remember that `train_set_x_orig` is a numpy-array of shape (m_train, num_px, num_px, 3). For instance, you can access `m_train` by writing `train_set_x_orig.shape[0]`.

In [5]:
```
#a = np.shape(train_set_x_orig)
#print(a)
#b = np.shape(test_set_x_orig)
#print(b)
#print(len(a))
```

In [6]:
```
#(≈ 3 lines of code)
# m_train =
# m_test =
# num_px =
# YOUR CODE STARTS HERE
m_train = train_set_x_orig.shape[0]
m_test = test_set_x_orig.shape[0]
num_px = train_set_x_orig.shape[2]

# YOUR CODE ENDS HERE

print ("Number of training examples: m_train = " + str(m_train))
print ("Number of testing examples: m_test = " + str(m_test))
print ("Height/Width of each image: num_px = " + str(num_px))
print ("Each image is of size: (" + str(num_px) + ", " + str(num_px) + ", 3)")
print ("train_set_x shape: " + str(train_set_x_orig.shape))
print ("train_set_y shape: " + str(train_set_y.shape))
print ("test_set_x shape: " + str(test_set_x_orig.shape))
print ("test_set_y shape: " + str(test_set_y.shape))
```

```
Number of training examples: m_train = 209
Number of testing examples: m_test = 50
Height/Width of each image: num_px = 64
Each image is of size: (64, 64, 3)
train_set_x shape: (209, 64, 64, 3)
train_set_y shape: (1, 209)
test_set_x shape: (50, 64, 64, 3)
test_set_y shape: (1, 50)
```

Expected Output for m_train, m_test and num_px:

m_train	209
m_test	50
num_px	64

For convenience, you should now reshape images of shape (num_px, num_px, 3) in a numpy-array of shape (num_px ∗ num_px ∗ 3, 1). After this, our training (and test) dataset is a numpy-array where each column represents a flattened image. There should be m_train (respectively m_test) columns.

Exercise 2

Reshape the training and test data sets so that images of size (num_px, num_px, 3) are flattened into single vectors of shape (num_px ∗ num_px ∗ 3, 1).

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

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

In [7]:
```
np.shape(train_set_x_orig[5])
```
Out[7]:
```
(64, 64, 3)
```

In [8]:
```
# Reshape the training and test examples
#(≈ 2 lines of code)
# train_set_x_flatten = ...
# test_set_x_flatten = ...
# YOUR CODE STARTS HERE

#train_set_x_flatten =
train_set_x_flatten = train_set_x_orig.reshape(train_set_x_orig.shape[0], -1).T
test_set_x_flatten = test_set_x_orig.reshape(test_set_x_orig.shape[0], -1).T

# train_set_x_flatten = train_set_y.reshape(train_set_y.shape[1]*train_set_y.shape[2]*train_set_y.shape[3], 1).T
# test_set_x_flatten = test_set_y.reshape(test_set_y.shape[1]*test_set_y.shape[2]*test_set_y.shape[3], 1).T
# YOUR CODE ENDS HERE

# Check that the first 10 pixels of the second image are in the correct place
assert np.alltrue(train_set_x_flatten[0:10, 1] == [196, 192, 190, 193, 186, 182, 188, 179, 174, 213]), "Wrong solution. Use (X.shape[0], -1).T."
assert np.alltrue(test_set_x_flatten[0:10, 1] == [115, 110, 111, 137, 129, 129, 155, 146, 145, 159]), "Wrong solution. Use (X.shape[0], -1).T."

print ("train_set_x_flatten shape: " + str(train_set_x_flatten.shape))
print ("train_set_y shape: " + str(train_set_y.shape))
print ("test_set_x_flatten shape: " + str(test_set_x_flatten.shape))
print ("test_set_y shape: " + str(test_set_y.shape))
```

```
train_set_x_flatten shape: (12288, 209)
train_set_y shape: (1, 209)
test_set_x_flatten shape: (12288, 50)
test_set_y shape: (1, 50)
```

Expected Output:

train_set_x_flatten shape	(12288, 209)
train_set_y shape	(1, 209)
test_set_x_flatten shape	(12288, 50)
test_set_y shape	(1, 50)

To represent color images, the red, green and blue channels (RGB) must be specified for each pixel, and so the pixel value is actually a vector of three numbers ranging from 0 to 255.

One common preprocessing step in machine learning is to center and standardize your dataset, meaning that you substract the mean of the whole numpy array from each example, and then divide each example by the standard deviation of the whole numpy array. But for picture datasets, it is simpler and more convenient and works almost as well to just divide every row of the dataset by 255 (the maximum value of a pixel channel).

Let's standardize our dataset.

In [9]:
```
train_set_x = train_set_x_flatten / 255.
test_set_x = test_set_x_flatten / 255.
```

What you need to remember:

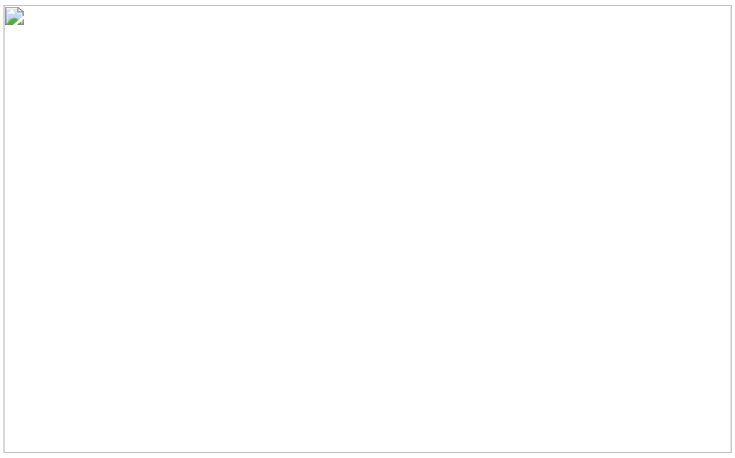
Common steps for pre-processing a new dataset are:

- Figure out the dimensions and shapes of the problem (m_train, m_test, num_px, ...)
- Reshape the datasets such that each example is now a vector of size (num_px * num_px * 3, 1)
- "Standardize" the data

3 - General Architecture of the learning algorithm

It's time to design a simple algorithm to distinguish cat images from non-cat images.

You will build a Logistic Regression, using a Neural Network mindset. The following Figure explains why **Logistic Regression is actually a very simple Neural Network!**



Mathematical expression of the algorithm:

For one example $x^{(i)}$:

$$z^{(i)} = w^T x^{(i)} + b \tag{1}$$
$$\hat{y}^{(i)} = a^{(i)} = sigmoid(z^{(i)}) \tag{2}$$
$$\mathcal{L}(a^{(i)}, y^{(i)}) = - y^{(i)} \log(a^{(i)}) - (1-y^{(i)}) \log(1-a^{(i)}) \tag{3}$$

The cost is then computed by summing over all training examples:

$$J = \frac{1}{m} \sum_{i=1}^m \mathcal{L}(a^{(i)}, y^{(i)}) \tag{6}$$

Key steps: In this exercise, you will carry out the following steps:

```
- Initialize the parameters of the model
- Learn the parameters for the model by minimizing the cost  
- Use the learned parameters to make predictions (on the test set)
- Analyse the results and conclude
```

4 - Building the parts of our algorithm

The main steps for building a Neural Network are:

1. Define the model structure (such as number of input features)
2. Initialize the model's parameters
3. Loop:
   - Calculate current loss (forward propagation)
   - Calculate current gradient (backward propagation)
   - Update parameters (gradient descent)

You often build 1-3 separately and integrate them into one function we call `model()` .

4.1 - Helper functions

Exercise 3 - sigmoid

Using your code from "Python Basics", implement `sigmoid()` . As you've seen in the figure above, you need to compute $sigmoid(z) = \frac{1}{1 + e^{-z}}$ for $z = w^T x + b$ to make predictions. Use np.exp().

In [10]:
```
# GRADED FUNCTION: sigmoid

def sigmoid(z):
    """
    Compute the sigmoid of z

    Arguments:
    z -- A scalar or numpy array of any size.

    Return:
    s -- sigmoid(z)
    """

    #(≈ 1 line of code)
    # s = ...
    # YOUR CODE STARTS HERE
    s = 1/(1+np.exp(-z))

    # YOUR CODE ENDS HERE

    return s
```

In [11]:
```
print ("sigmoid([0, 2]) = " + str(sigmoid(np.array([0,2]))))

sigmoid_test(sigmoid)
```

```
sigmoid([0, 2]) = [0.5        0.88079708]
All tests passed!
```

```
In [12]: x = np.array([0.5, 0, 2.0])
         output = sigmoid(x)
         print(output)
```

```
[0.62245933 0.5        0.88079708]
```

4.2 - Initializing parameters

Exercise 4 - initialize_with_zeros

Implement parameter initialization in the cell below. You have to initialize w as a vector of zeros. If you don't know what numpy function to use, look up np.zeros() in the Numpy library's documentation.

```
In [13]: # GRADED FUNCTION: initialize_with_zeros

         def initialize_with_zeros(dim):
             """
             This function creates a vector of zeros of shape (dim, 1) for w and initializes b to 0.

             Argument:
             dim -- size of the w vector we want (or number of parameters in this case)

             Returns:
             w -- initialized vector of shape (dim, 1)
             b -- initialized scalar (corresponds to the bias) of type float
             """

             # (≈ 2 lines of code)
             # w = ...
             # b = ...
             # YOUR CODE STARTS HERE
             w = np.zeros((dim, 1))
             b = 0.0

             # YOUR CODE ENDS HERE

             return w, b
```

```
In [14]: dim = 2
         w, b = initialize_with_zeros(dim)

         assert type(b) == float
         print ("w = " + str(w))
         print ("b = " + str(b))

         initialize_with_zeros_test_1(initialize_with_zeros)
         initialize_with_zeros_test_2(initialize_with_zeros)
```

```
w = [[0.]
 [0.]]
b = 0.0
First test passed!
Second test passed!
```

4.3 - Forward and Backward propagation

Now that your parameters are initialized, you can do the "forward" and "backward" propagation steps for learning the parameters.

Exercise 5 - propagate

Implement a function `propagate()` that computes the cost function and its gradient.

Hints:

Forward Propagation:

- You get X
- You compute $A = \sigma(w^T X + b) = (a^{(1)}, a^{(2)}, \ldots, a^{(m-1)}, a^{(m)})$
- You calculate the cost function: $J = -\frac{1}{m}\sum_{i=1}^{m}(y^{(i)}\log(a^{(i)}) + (1-y^{(i)})\log(1-a^{(i)}))$

Here are the two formulas you will be using:

$$\frac{\partial J}{\partial w} = \frac{1}{m}X(A-Y)^T \tag{7}$$

$$\frac{\partial J}{\partial b} = \frac{1}{m}\sum_{i=1}^{m}(a^{(i)}-y^{(i)}) \tag{8}$$

```
In [ ]:
```

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

def propagate(w, b, X, Y):
    """
    Implement the cost function and its gradient for the propagation explained above

    Arguments:
    w -- weights, a numpy array of size (num_px * num_px * 3, 1)
    b -- bias, a scalar
    X -- data of size (num_px * num_px * 3, number of examples)
    Y -- true "label" vector (containing 0 if non-cat, 1 if cat) of size (1, number of examples)

    Return:
    grads -- dictionary containing the gradients of the weights and bias
            (dw -- gradient of the loss with respect to w, thus same shape as w)
            (db -- gradient of the loss with respect to b, thus same shape as b)
    cost -- negative log-likelihood cost for logistic regression

    Tips:
    - Write your code step by step for the propagation. np.log(), np.dot()
    """

    m = X.shape[1]

    # FORWARD PROPAGATION (FROM X TO COST)
    #(≈ 2 lines of code)
    # compute activation
    # A = ...
    # compute cost by using np.dot to perform multiplication.
    # And don't use loops for the sum.
    # cost = ...
    # YOUR CODE STARTS HERE
    A = sigmoid(np.dot(np.transpose(w), X) + b)
    cost = (-1/m)*np.sum((Y*np.log(A)+(1-Y)*np.log(1-A)))
    # YOUR CODE ENDS HERE

    # BACKWARD PROPAGATION (TO FIND GRAD)
    #(≈ 2 lines of code)
    # dw = ...
    # db = ...
    # YOUR CODE STARTS HERE
    dw = (1/m)*np.dot(X, np.transpose(A-Y))
    db = (1/m)*np.sum(A-Y)
    # YOUR CODE ENDS HERE
    cost = np.squeeze(np.array(cost))


    grads = {"dw": dw,
             "db": db}

    return grads, cost
```

In [16]:
```
w =  np.array([[1.], [2]])
b = 1.5
X = np.array([[1., -2., -1.], [3., 0.5, -3.2]])
Y = np.array([[1, 1, 0]])
grads, cost = propagate(w, b, X, Y)

assert type(grads["dw"]) == np.ndarray
assert grads["dw"].shape == (2, 1)
assert type(grads["db"]) == np.float64


print ("dw = " + str(grads["dw"]))
print ("db = " + str(grads["db"]))
print ("cost = " + str(cost))

propagate_test(propagate)
```

```
dw = [[ 0.25071532]
 [-0.06604096]]
db = -0.1250040450043965
cost = 0.15900537707692405
All tests passed!
```

Expected output

```
dw = [[ 0.25071532]
 [-0.06604096]]
db = -0.1250040450043965
cost = 0.15900537707692405
```

4.4 - Optimization

- You have initialized your parameters.
- You are also able to compute a cost function and its gradient.
- Now, you want to update the parameters using gradient descent.

Exercise 6 - optimize

Write down the optimization function. The goal is to learn w and b by minimizing the cost function J. For a parameter θ, the update rule is $\theta = \theta - \alpha \; d\theta$, where α is the learning rate.

In [17]:
```
# GRADED FUNCTION: optimize

def optimize(w, b, X, Y, num_iterations=100, learning_rate=0.009, print_cost=False):
    """
    This function optimizes w and b by running a gradient descent algorithm

    Arguments:
    w -- weights, a numpy array of size (num_px * num_px * 3, 1)
    b -- bias, a scalar
    X -- data of shape (num_px * num_px * 3, number of examples)
    Y -- true "label" vector (containing 0 if non-cat, 1 if cat), of shape (1, number of examples)
    num_iterations -- number of iterations of the optimization loop
    learning_rate -- learning rate of the gradient descent update rule
    print_cost -- True to print the loss every 100 steps

    Returns:
    params -- dictionary containing the weights w and bias b
    grads -- dictionary containing the gradients of the weights and bias with respect to the cost function
    costs -- list of all the costs computed during the optimization, this will be used to plot the learning curve.

    Tips:
    You basically need to write down two steps and iterate through them:
        1) Calculate the cost and the gradient for the current parameters. Use propagate().
        2) Update the parameters using gradient descent rule for w and b.
    """

    w = copy.deepcopy(w)
    b = copy.deepcopy(b)

    costs = []

    for i in range(num_iterations):
        # (≈ 1 lines of code)
        # Cost and gradient calculation
        # grads, cost = ...
        # YOUR CODE STARTS HERE
        grads, cost = propagate(w, b, X, Y)

        # YOUR CODE ENDS HERE

        # Retrieve derivatives from grads
        dw = grads["dw"]
        db = grads["db"]

        # update rule (≈ 2 lines of code)
        # w = ...
        # b = ...
        # YOUR CODE STARTS HERE
        w = w-learning_rate*dw
        b = b-learning_rate*db

        # YOUR CODE ENDS HERE

        # Record the costs
        if i % 100 == 0:
            costs.append(cost)

            # Print the cost every 100 training iterations
            if print_cost:
                print ("Cost after iteration %i: %f" %(i, cost))

    params = {"w": w,
              "b": b}

    grads = {"dw": dw,
             "db": db}

    return params, grads, costs
```

In [18]:
```
params, grads, costs = optimize(w, b, X, Y, num_iterations=100, learning_rate=0.009, print_cost=False)

print ("w = " + str(params["w"]))
print ("b = " + str(params["b"]))
print ("dw = " + str(grads["dw"]))
print ("db = " + str(grads["db"]))
print("Costs = " + str(costs))

optimize_test(optimize)
```

```
w = [[0.80956046]
 [2.0508202 ]]
b = 1.5948713189708588
dw = [[ 0.17860505]
 [-0.04840656]]
db = -0.08888460336847771
Costs = [array(0.15900538)]
All tests passed!
```

Exercise 7 - predict

The previous function will output the learned w and b. We are able to use w and b to predict the labels for a dataset X. Implement the `predict()` function. There are two steps to computing predictions:

1. Calculate $\hat{Y} = A = \sigma(w^T X + b)$
2. Convert the entries of a into 0 (if activation <= 0.5) or 1 (if activation > 0.5), stores the predictions in a vector `Y_prediction`. If you wish, you can use an `if` / `else` statement in a `for` loop (though there is also a way to vectorize this).

In [19]:
```
# GRADED FUNCTION: predict

def predict(w, b, X):
    '''
    Predict whether the label is 0 or 1 using learned logistic regression parameters (w, b)

    Arguments:
    w -- weights, a numpy array of size (num_px * num_px * 3, 1)
    b -- bias, a scalar
    X -- data of size (num_px * num_px * 3, number of examples)

    Returns:
    Y_prediction -- a numpy array (vector) containing all predictions (0/1) for the examples in X
    '''

    m = X.shape[1]
    Y_prediction = np.zeros((1, m))
    w = w.reshape(X.shape[0], 1)

    # Compute vector "A" predicting the probabilities of a cat being present in the picture
    #(≈ 1 line of code)
    # A = ...
    # YOUR CODE STARTS HERE
    A = sigmoid(np.dot(np.transpose(w), X)+b)

    # YOUR CODE ENDS HERE

    for i in range(A.shape[1]):

        # Convert probabilities A[0,i] to actual predictions p[0,i]
        #(≈ 4 lines of code)
        # if A[0, i] > ____ :
        #     Y_prediction[0,i] =
        # else:
        #     Y_prediction[0,i] =
        # YOUR CODE STARTS HERE
        if A[0, i] > 0.5:
            Y_prediction[0, i] = 1
        else:
            Y_prediction[0, i] = 0

        # YOUR CODE ENDS HERE

    return Y_prediction
```

In [20]:
```
w = np.array([[0.1124579], [0.23106775]])
b = -0.3
X = np.array([[1., -1.1, -3.2],[1.2, 2., 0.1]])
print ("predictions = " + str(predict(w, b, X)))

predict_test(predict)
```

```
predictions = [[1. 1. 0.]]
All tests passed!
```

What to remember:

You've implemented several functions that:

- Initialize (w,b)
- Optimize the loss iteratively to learn parameters (w,b):
  - Computing the cost and its gradient
  - Updating the parameters using gradient descent
- Use the learned (w,b) to predict the labels for a given set of examples

5 - Merge all functions into a model

You will now see how the overall model is structured by putting together all the building blocks (functions implemented in the previous parts) together, in the right order.

Exercise 8 - model

Implement the model function. Use the following notation:

```
- Y_prediction_test for your predictions on the test set
- Y_prediction_train for your predictions on the train set
- parameters, grads, costs for the outputs of optimize()
```

In [21]:
```python
# GRADED FUNCTION: model

def model(X_train, Y_train, X_test, Y_test, num_iterations=2000, learning_rate=0.5, print_cost=False):
    """
    Builds the logistic regression model by calling the function you've implemented previously

    Arguments:
    X_train -- training set represented by a numpy array of shape (num_px * num_px * 3, m_train)
    Y_train -- training labels represented by a numpy array (vector) of shape (1, m_train)
    X_test -- test set represented by a numpy array of shape (num_px * num_px * 3, m_test)
    Y_test -- test labels represented by a numpy array (vector) of shape (1, m_test)
    num_iterations -- hyperparameter representing the number of iterations to optimize the parameters
    learning_rate -- hyperparameter representing the learning rate used in the update rule of optimize()
    print_cost -- Set to True to print the cost every 100 iterations

    Returns:
    d -- dictionary containing information about the model.
    """
    # (≈ 1 line of code)
    # initialize parameters with zeros
    # and use the "shape" function to get the first dimension of X_train
    # w, b = ...
    w, b = initialize_with_zeros(X_train.shape[0])

    #(≈ 1 line of code)
    # Gradient descent
    # params, grads, costs = ...
    params, grads, costs = optimize(w, b, X_train, Y_train, num_iterations, learning_rate, print_cost)

    # Retrieve parameters w and b from dictionary "params"
    # w = ...
    # b = ...

    w = params["w"]
    b = params["b"]

    # Predict test/train set examples (≈ 2 lines of code)
    # Y_prediction_test = ...
    # Y_prediction_train = ...

    # YOUR CODE STARTS HERE
    Y_prediction_test = predict(w, b, X_test)
    Y_prediction_train = predict(w, b, X_train)
    # YOUR CODE ENDS HERE

    # Print train/test Errors
    if print_cost:
        print("train accuracy: {} %".format(100 - np.mean(np.abs(Y_prediction_train - Y_train)) * 100))
        print("test accuracy: {} %".format(100 - np.mean(np.abs(Y_prediction_test - Y_test)) * 100))


    d = {"costs": costs,
         "Y_prediction_test": Y_prediction_test,
         "Y_prediction_train" : Y_prediction_train,
         "w" : w,
         "b" : b,
         "learning_rate" : learning_rate,
         "num_iterations": num_iterations}

    return d
```

In [22]:
```python
from public_tests import *

model_test(model)
```

```
All tests passed!
```

If you pass all the tests, run the following cell to train your model.

In [23]:
```python
logistic_regression_model = model(train_set_x, train_set_y, test_set_x, test_set_y, num_iterations=2000, learning_rate=0.005, print_cost=True)
```

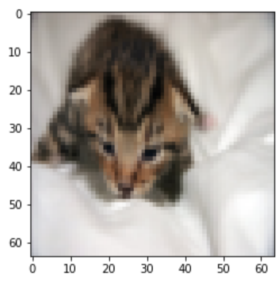
```
Cost after iteration 0: 0.693147
Cost after iteration 100: 0.584508
Cost after iteration 200: 0.466949
Cost after iteration 300: 0.376007
Cost after iteration 400: 0.331463
Cost after iteration 500: 0.303273
Cost after iteration 600: 0.279880
Cost after iteration 700: 0.260042
Cost after iteration 800: 0.242941
Cost after iteration 900: 0.228004
Cost after iteration 1000: 0.214820
Cost after iteration 1100: 0.203078
Cost after iteration 1200: 0.192544
Cost after iteration 1300: 0.183033
Cost after iteration 1400: 0.174399
Cost after iteration 1500: 0.166521
Cost after iteration 1600: 0.159305
Cost after iteration 1700: 0.152667
Cost after iteration 1800: 0.146542
Cost after iteration 1900: 0.140872
train accuracy: 99.04306220095694 %
test accuracy: 70.0 %
```

Comment: Training accuracy is close to 100%. This is a good sanity check: your model is working and has high enough capacity to fit the training data. Test accuracy is 70%. It is actually not bad for this simple model, given the small dataset we used and that logistic regression is a linear classifier. But no worries, you'll build an even better classifier next week!

Also, you see that the model is clearly overfitting the training data. Later in this specialization you will learn how to reduce overfitting, for example by using regularization. Using the code below (and changing the `index` variable) you can look at predictions on pictures of the test set.

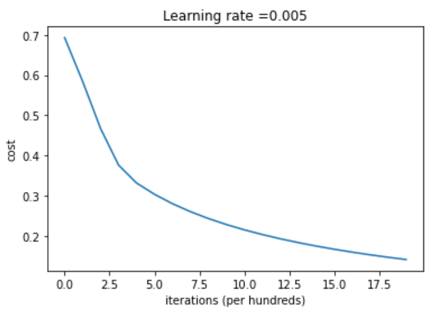
In [24]:
```
# Example of a picture that was wrongly classified.
index = 1
plt.imshow(test_set_x[:, index].reshape((num_px, num_px, 3)))
print ("y = " + str(test_set_y[0,index]) + ", you predicted that it is a \"" + classes[int(logistic_regression_model['Y_prediction_test'][0,inde
x])].decode("utf-8") +  "\" picture.")
```

```
y = 1, you predicted that it is a "cat" picture.
```



Let's also plot the cost function and the gradients.

In [25]:
```
# Plot learning curve (with costs)
costs = np.squeeze(logistic_regression_model['costs'])
plt.plot(costs)
plt.ylabel('cost')
plt.xlabel('iterations (per hundreds)')
plt.title("Learning rate =" + str(logistic_regression_model["learning_rate"]))
plt.show()
```



Interpretation: You can see the cost decreasing. It shows that the parameters are being learned. However, you see that you could train the model even more on the training set. Try to increase the number of iterations in the cell above and rerun the cells. You might see that the training set accuracy goes up, but the test set accuracy goes down. This is called overfitting.

6 - Further analysis (optional/ungraded exercise)

Congratulations on building your first image classification model. Let's analyze it further, and examine possible choices for the learning rate α.

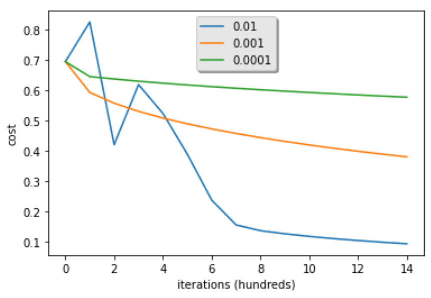
Choice of learning rate

Reminder: In order for Gradient Descent to work you must choose the learning rate wisely. The learning rate α determines how rapidly we update the parameters. If the learning rate is too large we may "overshoot" the optimal value. Similarly, if it is too small we will need too many iterations to converge to the best values. That's why it is crucial to use a well-tuned learning rate.

Let's compare the learning curve of our model with several choices of learning rates. Run the cell below. This should take about 1 minute. Feel free also to try different values than the three we have initialized the `learning_rates` variable to contain, and see what happens.

In [26]:
```python
learning_rates = [0.01, 0.001, 0.0001]
models = {}

for lr in learning_rates:
    print ("Training a model with learning rate: " + str(lr))
    models[str(lr)] = model(train_set_x, train_set_y, test_set_x, test_set_y, num_iterations=1500, learning_rate=lr, print_cost=False)
    print ('\n' + "-------------------------------------------------------" + '\n')

for lr in learning_rates:
    plt.plot(np.squeeze(models[str(lr)]["costs"]), label=str(models[str(lr)]["learning_rate"]))

plt.ylabel('cost')
plt.xlabel('iterations (hundreds)')

legend = plt.legend(loc='upper center', shadow=True)
frame = legend.get_frame()
frame.set_facecolor('0.90')
plt.show()
```

```
Training a model with learning rate: 0.01

-------------------------------------------------------

Training a model with learning rate: 0.001

-------------------------------------------------------

Training a model with learning rate: 0.0001

-------------------------------------------------------
```



Interpretation:

- Different learning rates give different costs and thus different predictions results.
- If the learning rate is too large (0.01), the cost may oscillate up and down. It may even diverge (though in this example, using 0.01 still eventually ends up at a good value for the cost).
- A lower cost doesn't mean a better model. You have to check if there is possibly overfitting. It happens when the training accuracy is a lot higher than the test accuracy.
- In deep learning, we usually recommend that you:
    - Choose the learning rate that better minimizes the cost function.
    - If your model overfits, use other techniques to reduce overfitting. (We'll talk about this in later videos.)

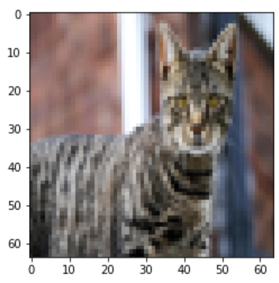
7 - Test with your own image (optional/ungraded exercise)

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 [28]:
```python
# change this to the name of your image file
my_image = "cat1.jpg"

# We preprocess the image to fit your algorithm.
fname = "images/" + my_image
image = np.array(Image.open(fname).resize((num_px, num_px)))
plt.imshow(image)
image = image / 255.
image = image.reshape((1, num_px * num_px * 3)).T
my_predicted_image = predict(logistic_regression_model["w"], logistic_regression_model["b"], image)

print("y = " + str(np.squeeze(my_predicted_image)) + ", your algorithm predicts a \"" + classes[int(np.squeeze(my_predicted_image)),].decode("utf-8") +  "\" picture.")
```

```
y = 1.0, your algorithm predicts a "cat" picture.
```



What to remember from this assignment:

1. Preprocessing the dataset is important.
2. You implemented each function separately: initialize(), propagate(), optimize(). Then you built a model().
3. Tuning the learning rate (which is an example of a "hyperparameter") can make a big difference to the algorithm. You will see more examples of this later in this course!

Finally, if you'd like, we invite you to try different things on this Notebook. Make sure you submit before trying anything. Once you submit, things you can play with include:

```
- Play with the learning rate and the number of iterations
- Try different initialization methods and compare the results
- Test other preprocessings (center the data, or divide each row by its standard deviation)
```

Bibliography:

- http://www.wildml.com/2015/09/implementing-a-neural-network-from-scratch/ (http://www.wildml.com/2015/09/implementing-a-neural-network-from-scratch/)
- https://stats.stackexchange.com/questions/211436/why-do-we-normalize-images-by-subtracting-the-datasets-image-mean-and-not-the-c (https://stats.stackexchange.com/questions/211436/why-do-we-normalize-images-by-subtracting-the-datasets-image-mean-and-not-the-c)