Reference

Coursera deep learning series by Andrew NG

Logistic Regression with a Neural Network mindset

- Do not use loops (for/while) in your code, unless the instructions explicitly ask you to do so.
- 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.

1 - Packages

- 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.

In [26]:
```
import numpy as np
import matplotlib.pyplot as plt
import h5py
import scipy
from PIL import Image
from scipy import ndimage
from lr_utils import load_dataset

%matplotlib inline
```

2 - Overview of the Problem set

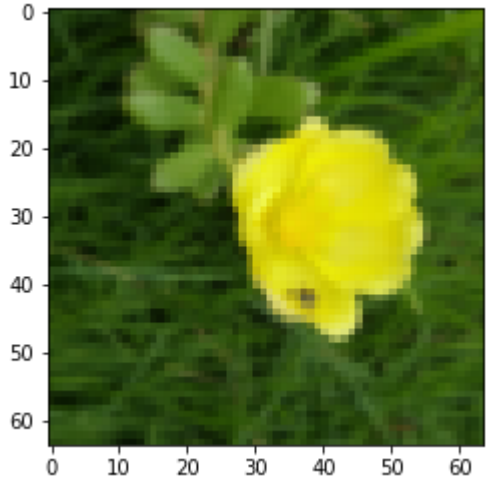
- A training set of m_train images labeled as cat (y=1) or non-cat (y=0)

- 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).
- **Note that each element of 'classes' is 'numpy.bytes_'**. It is necessary to convert them to string type before printing. For example, we may use .decode("utf-8") to convert, as shown in the example below.

In [27]:
```
train_set_x_orig, train_set_y, test_set_x_orig, test_set_y, classes = load_dataset()
```

In [28]:
```
index = 157
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-
print(train_set_y[:,index])
print(type(classes))
print(classes)
print(type(train_set_y))
print(train_set_y.shape)
print('The index value is', np.squeeze(train_set_y[:,index]))
print(type(classes[np.squeeze(train_set_y[:,index])]))
# print(train_set_y)
```

```
y = [0], it's a 'non-cat' picture.
[0]
<class 'numpy.ndarray'>
[b'non-cat' b'cat']
<class 'numpy.ndarray'>
(1, 209)
The index value is 0
<class 'numpy.bytes_'>
```



Exercise: 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 [29]:
```
m_train = train_set_y.shape[1]
m_test = test_set_y.shape[1]
num_px = train_set_x_orig.shape[1]

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)
```

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: 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 [30]:
```
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

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))
print ("sanity check after reshaping: " + str(train_set_x_flatten[0:5,0]))
```

```
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)
sanity check after reshaping: [17 31 56 22 33]
```

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)**.

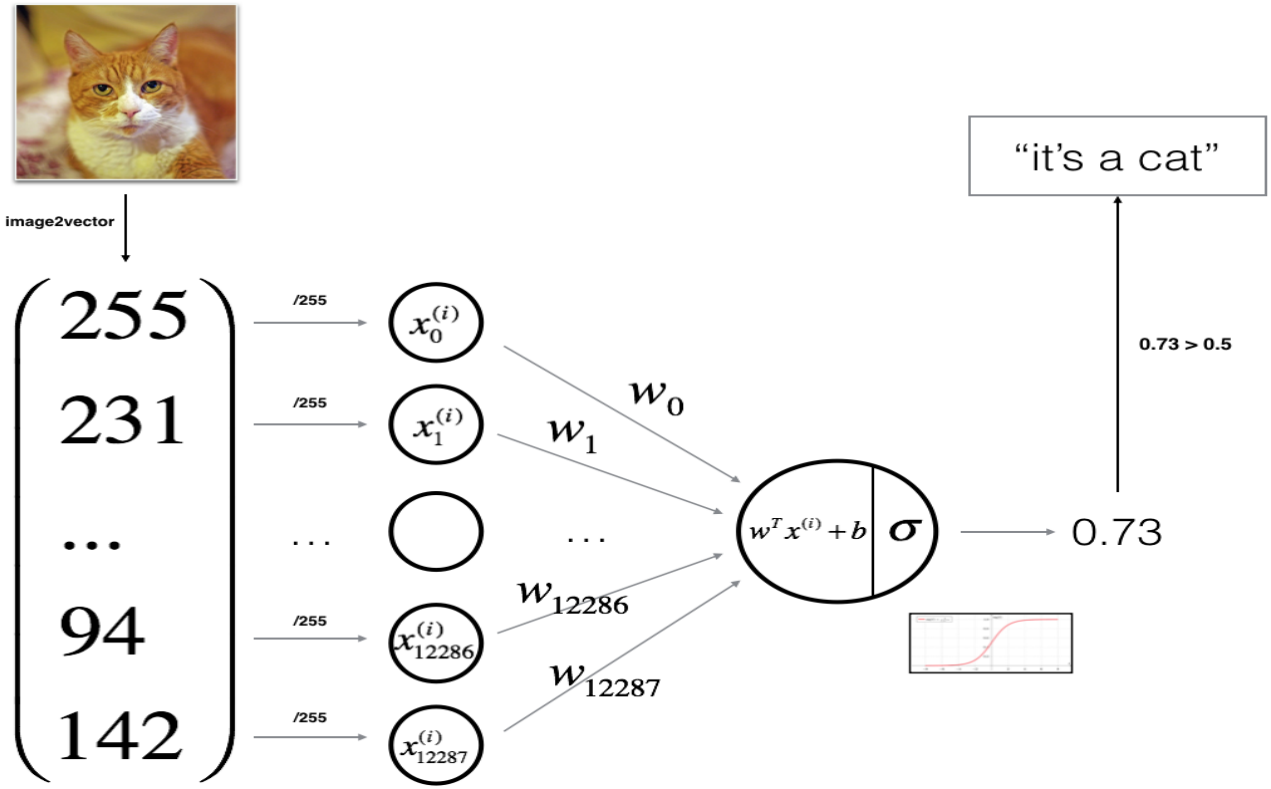
In [31]:
```
train_set_x = train_set_x_flatten / 255.
test_set_x = test_set_x_flatten / 255.
```

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!**

I cannot use absolute path such as 'C:...' for the image file possible due to security reason.



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: Using your code from "Python Basics", implement `sigmoid()` . As you've seen in the figure above, you need to compute $sigmoid(w^T x + b)$ to make predictions.

In [32]:
```
def sigmoid(z):

    s = 1 / (1 + np.exp(-z))

    return s
```

In [33]:
```
print ("sigmoid(0) = " + str(sigmoid(0)))
print ("sigmoid(9.2) = " + str(sigmoid(9.2)))
```

```
sigmoid(0) = 0.5
sigmoid(9.2) = 0.9998989708060922
```

4.2 - Initializing parameters

Exercise: 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 [34]:
```
def initialize_with_zeros(dim):

    w = np.zeros(shape=(dim, 1)) #Normally we don't initialize with zero in deep learning.
    b = 0

    assert(w.shape == (dim, 1))
    assert(isinstance(b, float) or isinstance(b, int))

    return w, b
```

In [35]:
```
dim = 2
w, b = initialize_with_zeros(dim)
print ("w = " + str(w))
print ("b = " + str(b))
```

```
w = [[0.]
 [0.]]
b = 0
```

4.3 - Forward and Backward propagation

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

Hints:

Forward Propagation:

- You get X
- You compute $A = \sigma(w^T X + b) = (a^{(0)}, a^{(1)}, \ldots, a^{(m-1)}, a^{(m)})$
- 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 [36]:
```
def propagate(w, b, X, Y):

    m = X.shape[1]

    A = sigmoid(np.dot(w.T, X) + b)  # compute activation
    cost = (- 1 / m) * np.sum(Y * np.log(A) + (1 - Y) * (np.log(1 - A)))  # compute cost

    dw = (1 / m) * np.dot(X, (A - Y).T)
    db = (1 / m) * np.sum(A - Y)

    assert(dw.shape == w.shape)
    assert(db.dtype == float)
    cost = np.squeeze(cost)
    assert(cost.shape == ())

    grads = {"dw": dw,
             "db": db}
    #This is just for grouping purpose only.

    return grads, cost
```

In [37]:
```
w, b, X, Y = np.array([[1], [2]]), 2, np.array([[1,2], [3,4]]), np.array([[1, 0]])
#Need a clear understanding of np shapes to assign examples as above.

grads, cost = propagate(w, b, X, Y)
print ("dw = " + str(grads["dw"]))
print ("db = " + str(grads["db"]))
print ("cost = " + str(cost))
print(w.shape)
# print(b.shape)
print(X.shape)
print(Y.shape)
```

```
dw = [[0.99993216]
 [1.99980262]]
db = 0.49993523062470574
cost = 6.000064773192205
(2, 1)
(2, 2)
(1, 2)
```

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: 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 [38]:
```
def optimize(w, b, X, Y, num_iterations, learning_rate, print_cost = False):

    costs = []

    for i in range(num_iterations): #Normally we cannot vectorize the number of interation


        # Cost and gradient calculation (≈ 1-4 lines of code)
        grads, cost = propagate(w, b, X, Y)

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

        # update rule (≈ 2 lines of code)
        w = w - learning_rate * dw  # need to broadcast
        b = b - learning_rate * db

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

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

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

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

    return params, grads, costs
```

In [39]:
```
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"]))
```

```
w = [[0.1124579 ]
 [0.23106775]]
b = 1.5593049248448891
dw = [[0.90158428]
 [1.76250842]]
db = 0.4304620716786828
```

Exercise: 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 is 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 [40]:
```
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)

    A = sigmoid(np.dot(w.T, X) + b)

    for i in range(A.shape[1]):
        # Convert probabilities a[0,i] to actual predictions p[0,i]
        Y_prediction[0, i] = 1 if A[0, i] > 0.5 else 0

    assert(Y_prediction.shape == (1, m))

    return Y_prediction
```

In [41]:
```
print("predictions = " + str(predict(w, b, X)))
```

```
predictions = [[1. 1.]]
```

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: Implement the model function. Use the following notation:

- Y_prediction for your predictions on the test set
- Y_prediction_train for your predictions on the train set
- w, costs, grads for the outputs of optimize()

In [42]:
```
def model(X_train, Y_train, X_test, Y_test, num_iterations=2000, learning_rate=0.5, print_cost=False):

    w, b = initialize_with_zeros(X_train.shape[0])

    parameters, grads, costs = optimize(w, b, X_train, Y_train, num_iterations, learning_rate, print_cost)

    # Retrieve parameters w and b from dictionary "parameters"
    w = parameters["w"]
    b = parameters["b"]

    # Predict test/train set examples (≈ 2 lines of code)
    Y_prediction_test = predict(w, b, X_test)
    Y_prediction_train = predict(w, b, X_train)

    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
```

Run the following cell to train your model.

In [43]:
```
d = model(train_set_x, train_set_y, test_set_x, test_set_y, num_iterations = 2000, learning_rate = 0.005, print_
```

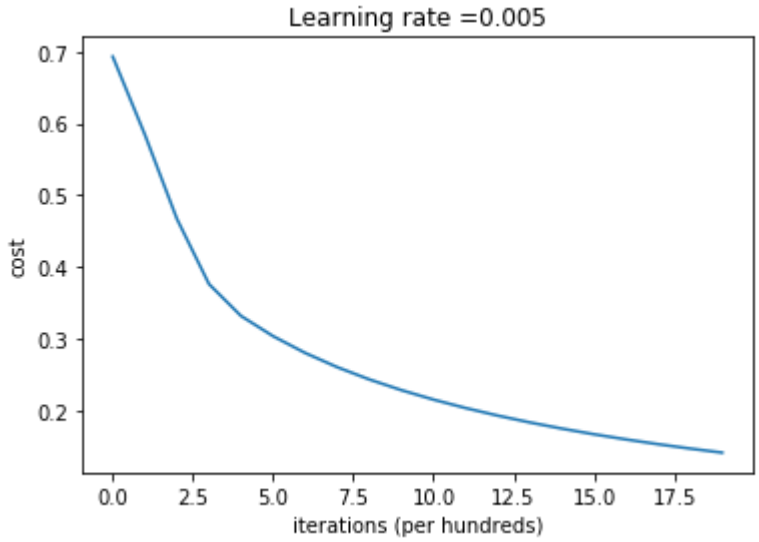
```
Cost after iteration 0: 0.693147
Cost after iteration 100: 0.584508
Cost after iteration 200: 0.466949
Cost after iteration 300: 0.376007
Cost after iteration 400: 0.331463
Cost after iteration 500: 0.303273
Cost after iteration 600: 0.279880
Cost after iteration 700: 0.260042
Cost after iteration 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 error is 68%. It is actually not bad for this simple model, given the small dataset we used and that logistic regression is a linear classifier.

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.

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

In [19]:
```
# Plot learning curve (with costs)
costs = np.squeeze(d['costs'])
plt.plot(costs)
plt.ylabel('cost')
plt.xlabel('iterations (per hundreds)')
plt.title("Learning rate =" + str(d["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)

Let's analyze it further, and examine possible choices for the learning rate α.

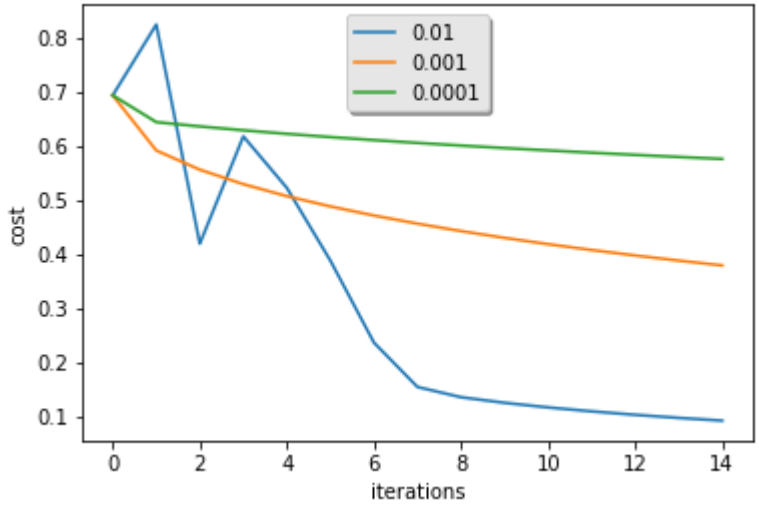
Choice of learning rate

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 [20]:
```
learning_rates = [0.01, 0.001, 0.0001]
models = {}
for i in learning_rates:
    print ("learning rate is: " + str(i))
    models[str(i)] = model(train_set_x, train_set_y, test_set_x, test_set_y, num_iterations = 1500, learning_rate
    print ('\n' + "-------------------------------------------------------" + '\n')

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

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

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

```
learning rate is: 0.01
train accuracy: 99.52153110047847 %
test accuracy: 68.0 %

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

learning rate is: 0.001
train accuracy: 88.99521531100478 %
test accuracy: 64.0 %

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

learning rate is: 0.0001
train accuracy: 68.42105263157895 %
test accuracy: 36.0 %

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



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

In [24]:
```
import matplotlib.pyplot
import skimage.transform

my_image = "images/cat_in_iran.jpg"   # change this to the name of your image file

image = np.array(matplotlib.pyplot.imread(my_image))
my_image = scipy.misc.imresize(image, size=(num_px, num_px)).reshape((1, num_px * num_px * 3)).T

my_predicted_image = predict(d["w"], d["b"], my_image)

plt.imshow(image)
print("y = " + str(np.squeeze(my_predicted_image)) + ", your algorithm predicts a \"" + classes[int(np.squeeze(my
```

```
C:\Users\ljyan\Anaconda3\lib\site-packages\ipykernel_launcher.py:7: DeprecationWarning: `imresize` is deprec
ated!
`imresize` is deprecated in SciPy 1.0.0, and will be removed in 1.2.0.
Use ``skimage.transform.resize`` instead.
  import sys

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