Image_Classification_using_MLP

September 18, 2023

1 Logistic Regression with a Neural Network

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 so will also hone your intuitions about deep learning.

[1]:
```
!git clone https://github.com/SanVik2000/EE5179-Final.git
```

```
Cloning into 'EE5179-Final'…
remote: Enumerating objects: 188, done.
remote: Counting objects: 100% (129/129), done.
remote: Compressing objects: 100% (82/82), done.
remote: Total 188 (delta 50), reused 93 (delta 35), pack-reused 59
Receiving objects: 100% (188/188), 48.06 MiB | 25.72 MiB/s, done.
Resolving deltas: 100% (71/71), done.
```

[2]:
```
import numpy as np
import matplotlib.pyplot as plt
import h5py
import scipy
from PIL import Image
from scipy import ndimage

%matplotlib inline
```

[3]:
```
def load_dataset():
    train_dataset = h5py.File('/content/EE5179-Final/Tutorial-2/
↪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('/content/EE5179-Final/Tutorial-2/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
```

1.1 1 - Overview of the Problem set

Problem Statement: You are given a dataset containing: * a training set of images labeled as cat (y=1) or non-cat (y=0) * a test set of 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).

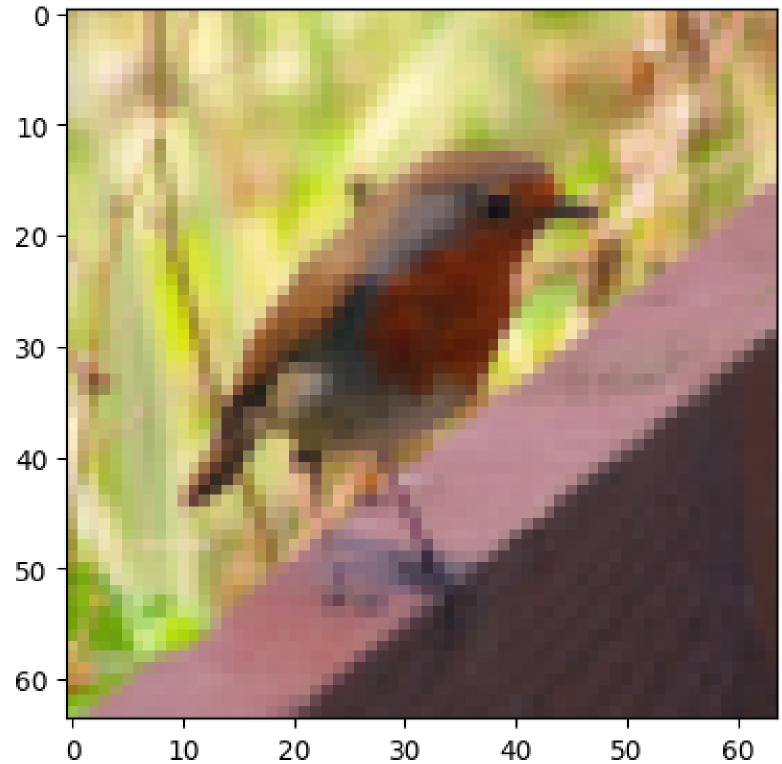
You will build a simple image-recognition algorithm that can correctly classify pictures as cat or non-cat.

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

[4]:
```
# Loading the data (cat/non-cat)
train_set_x_orig, train_set_y, test_set_x_orig, test_set_y, classes =␣
↪load_dataset()
```

[5]:
```
# Example of a picture
index =10
plt.imshow(train_set_x_orig[index])
print ("y = " + str(train_set_y[0, index]) + ", it's a '" + classes[np.
↪squeeze(train_set_y[:, index])].decode("utf-8") +  "' picture.")
```

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



[6]:

```
m_train = train_set_x_orig.shape[0]
m_test =  test_set_x_orig.shape[0]
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)
```

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).

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
```

[7]:

```
# Reshape the training and test examples

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

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

Expected Output:

train_set_x_flatten shape

(209, 12288)

train_set_y shape

(209, 1)

test_set_x_flatten shape

(50, 12288)

test_set_y shape

(50, 1)

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.

[8]:
```
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 (m_train, num_px * num_px * 3) - "Standardize" the data

1.2 2 - 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 $x^{(i)}$:

$$z^{(i)} = x^{(i)} w^T + b \tag{1}$$

$$\hat{y}^{(i)} = a^{(i)} = sigmoid(z^{(i)}) \tag{2}$$

$$\mathcal{L}(a^{(i)}, y^{(i)}) = -y^{(i)} \log(a^{(i)}) - (1-y^{(i)}) \log(1-a^{(i)}) \tag{3}$$

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

1.3 3 - 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()`.

1.3.1 3.1 - Helper functions

Exercise: Using your code from "Task02", implement `sigmoid()`. As you've seen in the figure above, you need to compute $sigmoid(xw^T + b) = \frac{1}{1+e^{-(xw^T+b)}}$ to make predictions. Use np.exp().

[9]:
```python
# 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)
    """

    ### START CODE HERE ### ( 1 line of code)
    s=1/(1+np.exp(-z))
    ### END CODE HERE ###

    return s
```

[10]:
```python
print ("sigmoid([0, 2]) = " + str(sigmoid(np.array([0,2]))))
```

```
sigmoid([0, 2]) = [0.5        0.88079708]
```

Expected Output:

sigmoid([0, 2])

[0.5 0.88079708]

1.3.2 3.2 - 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.

[11]:
```python
# GRADED FUNCTION: initialize_with_zeros

def initialize_with_zeros(dim):
    """
    This function creates a vector of zeros of shape (1, dim) 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)
    """

    ### START CODE HERE ### ( 1 line of code)
    w=np.zeros((1, dim))
    b=0
    ### END CODE HERE ###

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

    return w, b
```

[12]:
```
dim = 2
w, b = initialize_with_zeros(dim)
print ("w = " + str(w))
print ("b = " + str(b))
```

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

Expected Output:

** w **

[[0. 0.]]

** b **

0

For image inputs, w will be of shape (1, num_px × num_px × 3).

1.3.3 3.3 - Forward and Backward propagation

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

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

Hints:

Forward Propagation: - You get X - You compute $A = \sigma(Xw^T + b) = (a^{(1)}, a^{(2)}, ..., a^{(m-1)}, a^{(m)})$ - 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:

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

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

[15]:
```python
# 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 (1, num_px * num_px * 3)
    b -- bias, a scalar
    X -- data of size (number of examples, num_px * num_px * 3)
    Y -- true "label" vector (containing 0 if non-cat, 1 if cat) of size␣
 ↪(number of examples, 1)

    Return:
    cost -- negative log-likelihood cost for logistic regression
    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
    """

    m = X.shape[1]

    # FORWARD PROPAGATION (FROM X TO COST)
    ### START CODE HERE ### ( 2 lines of code)
    A = sigmoid(np.matmul(X,w.T)+b)
    cost =  -np.sum(np.multiply(Y, np.log(A))+np.multiply((1-Y), np.log(1-A)))/m
    ### END CODE HERE ###

    # BACKWARD PROPAGATION (TO FIND GRAD)
    ### START CODE HERE ### ( 2 lines of code)
    dw = np.matmul((A-Y).T,X)/m
    db = np.sum(A-Y)/m
    ### END CODE HERE ###

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

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

    return grads, cost
```

[16]:
```python
w, b, X, Y = np.array([[1.,2.]]), 2., np.array([[1.,2.],[-1.,3.],[4.,-3.2]]), np.array([[1],[0],[1]])
print("W Shape : " , w.shape)
print("X Shape : " , X.shape)
print("Y Shape : " , Y.shape, "\n")

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

```
W Shape :  (1, 2)
X Shape :  (3, 2)
Y Shape :  (3, 1)

dw = [[-1.69737532  2.45562263]]
db = 0.1997451187493734
cost = 3.9574190926537742
```

Expected Output:

** dw **

[[0.99845601] [2.39507239]]

** db **

0.00145557813678

** cost **

5.801545319394553

1.3.4 3.4 - 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 \$ = - d \$, where α is the learning rate.

[28]:
```python
# GRADED FUNCTION: optimize

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

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

```
    Y -- true "label" vector (containing 0 if non-cat, 1 if cat), of shape␣
↪(number of examples, 1)
    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.
    """

    costs = []

    for i in range(num_iterations):


        # Cost and gradient calculation ( 1-4 lines of code)
        ### START CODE HERE ###
        if i==0: w,b= initialize_with_zeros(X.shape[1])
        grads, cost = propagate(w, b, X, Y)
        ### END CODE HERE ###

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

        # update rule ( 2 lines of code)
        ### START CODE HERE ###
        w = w-learning_rate*dw
        b = b-learning_rate*db
        ### END CODE HERE ###

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

        # Print the cost every 100 training iterations
        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
```

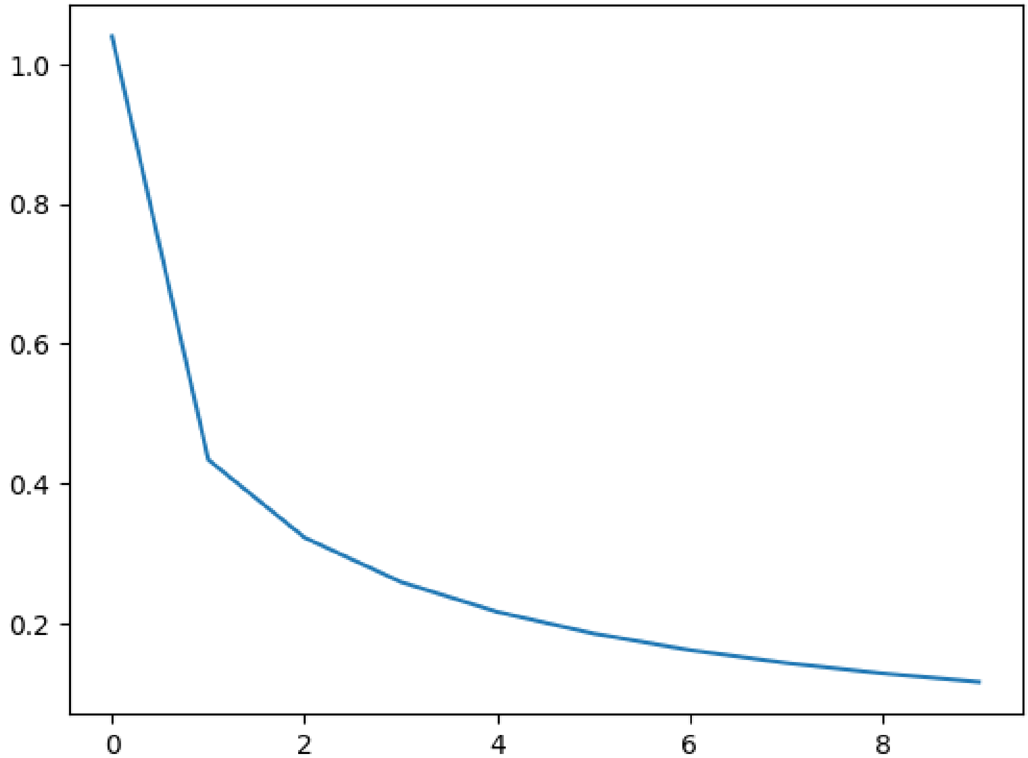
[29]:
```
params, grads, costs = optimize(w, b, X, Y, num_iterations= 1000, learning_rate␣
↪= 0.009, print_cost = False)

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

```
w = [[ 2.08802245 -0.25248079]]
b = 0.4331529888995371
dw = [[-0.10009527  0.00595985]]
db = -0.017685768767477607
```

[30]:
```
import matplotlib.pyplot as plt
plt.plot(costs)
```

[30]:
```
[<matplotlib.lines.Line2D at 0x7a94c00f2c20>]
```



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 are two steps to computing predictions:

1. Calculate $\hat{Y} = A = \sigma(Xw^T + b)$
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).

[31]:
```
# 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 (1, num_px * num_px * 3)
    b -- bias, a scalar
    X -- data of size (number of examples, num_px * num_px * 3)

    Returns:
```

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

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

    # Compute vector "A" predicting the probabilities of a cat being present in␣
↪the picture
    ### START CODE HERE ### (  1 line of code)
    A =  sigmoid(np.matmul(X, w.T)+b)# Dimentions = (m, 1)
    ### END CODE HERE ###

    #### VECTORISED IMPLEMENTATION ####
    Y_prediction = (A >= 0.5) * 1.0

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

    return Y_prediction
```

[32]:
```
w = np.array([[2.46915585, -0.59357113]])
b = 1.322892868548117
X = np.array([[1.,-1.1],[-3.2,1.2],[2.,0.1]])
print ("predictions = " + str(predict(w, b, X)))
```

```
predictions = [[1.]
 [0.]
 [1.]]
```

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

1.4 4 - 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.

[33]:
```
# 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 (m_train,␣
↪num_px * num_px * 3)
    Y_train -- training labels represented by a numpy array (vector) of shape␣
↪(m_train, 1)
    X_test -- test set represented by a numpy array of shape (m_test, num_px *␣
↪num_px * 3)
    Y_test -- test labels represented by a numpy array (vector) of shape␣
↪(m_test, 1)
    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.
    """

    ### START CODE HERE ###

    # initialize parameters with zeros (  1 line of code)
    w, b = initialize_with_zeros(X_train.shape[1])

    # Gradient descent (  1 line of code)
    parameters, grads, costs = optimize(w, b, X_train, Y_train, num_iterations,␣
↪learning_rate)

    # 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)
    ### END CODE HERE ###

    # Print train/test Errors
    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.

[45]:
```
d = model(train_set_x, train_set_y, test_set_x, test_set_y, num_iterations =␣
 ↪50000, learning_rate = 0.05, print_cost = True)
```

```
train accuracy: 100.0 %
test accuracy: 70.0 %
```

Expected Output:

Cost after iteration 0

0.693147

⋮

⋮

Train Accuracy

99.04306220095694 %

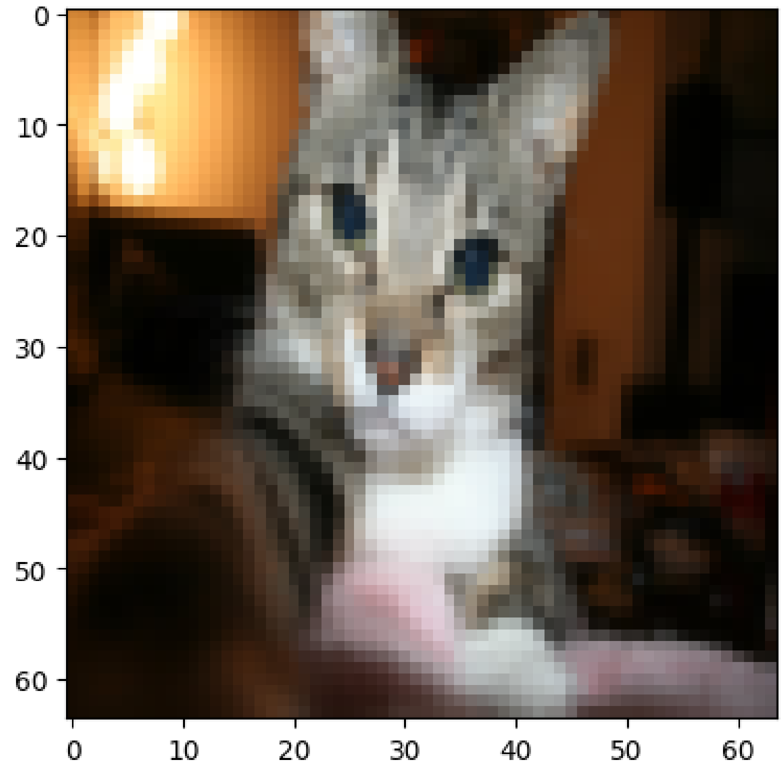
Test Accuracy

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 68%. It is actually not bad for this simple model, given the small dataset we used and that logistic regression is a linear classifier.

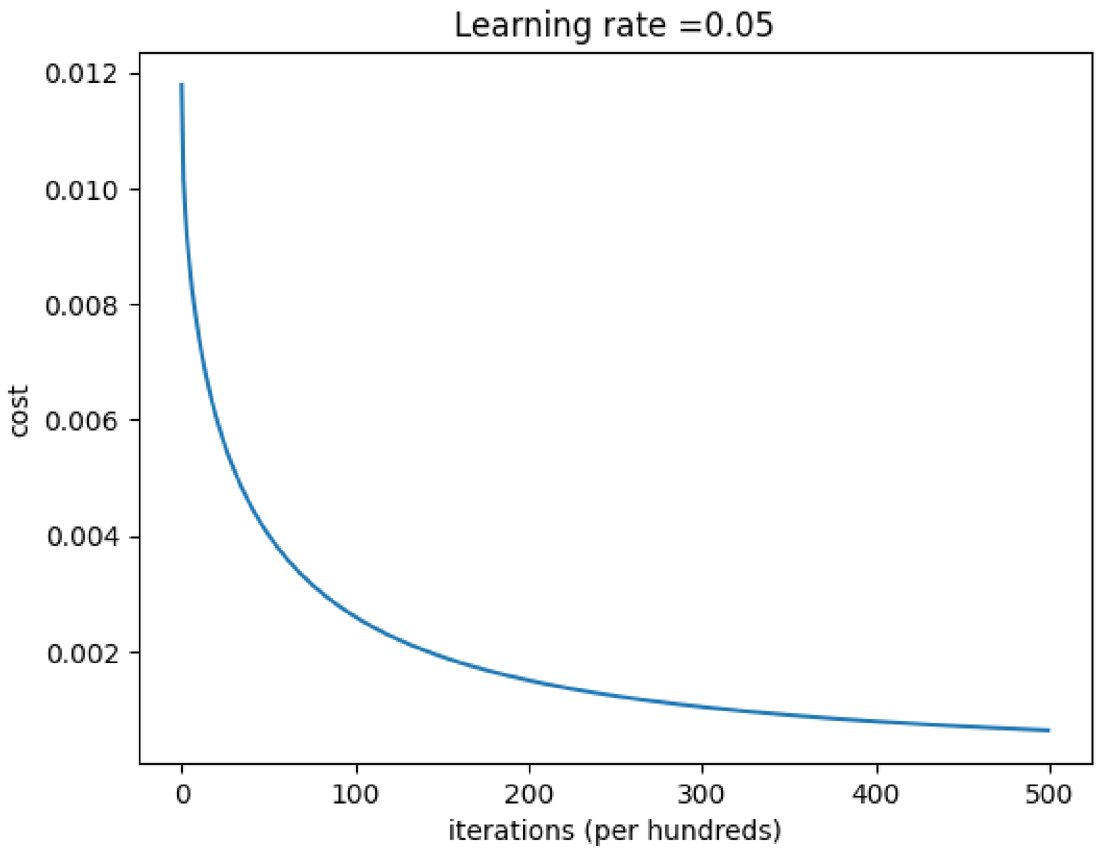
[46]:
```
# Example of a picture that was wrongly classified.
index = 25
plt.imshow(test_set_x[index, :].reshape((num_px, num_px, 3)))
print ("y = " + str(test_set_y[index, 0]) + ", you predicted that it is a \"" +␣
 ↪classes[int(d["Y_prediction_test"][index][0])].decode("utf-8") +  "\"␣
 ↪picture.")
```

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



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

[47]:
```
# 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.