Image_Classification_using_MLP

November 9, 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 | 27.19 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
```

[4]:
```
import warnings
warnings.filterwarnings('ignore')
```

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).

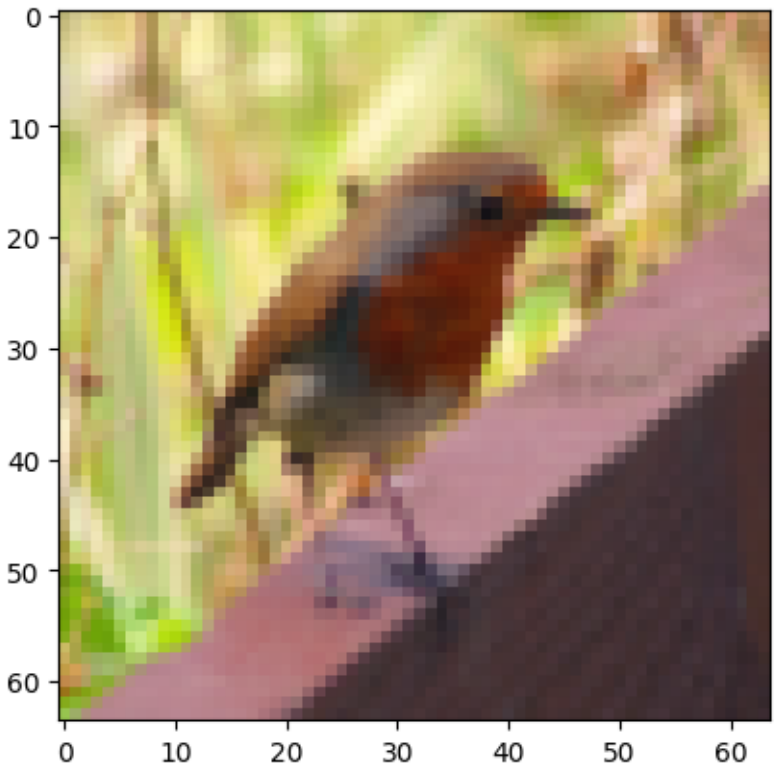
You will build a simple image-recognition algorithm that can correctly classify pictures as cat or non-cat.

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

[5]:
```
# Loading the data (cat/non-cat)
train_set_x_orig, train_set_y, test_set_x_orig, test_set_y, classes =␣
↪load_dataset()
```

[6]:
```
# 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.
```



[7]:
```
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
```

[8]:
```
# 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.

[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 (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().

[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)
    """

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

    ### END CODE HERE ###

    return s
```

[11]:
```
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.

[12]:
```
# 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
```

[13]:
```
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:

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

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

[25]:
```
# 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[0]

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

    # BACKWARD PROPAGATION (TO FIND GRAD)
    ### START CODE HERE ### ( 2 lines of code)
    dw = (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
```

[26]:
```
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 = [[-1.13158355  1.63708175]]
db = 0.13316341249958227
cost = 2.638279395102516
```

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.

[27]:
```
# 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 ###
        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
```

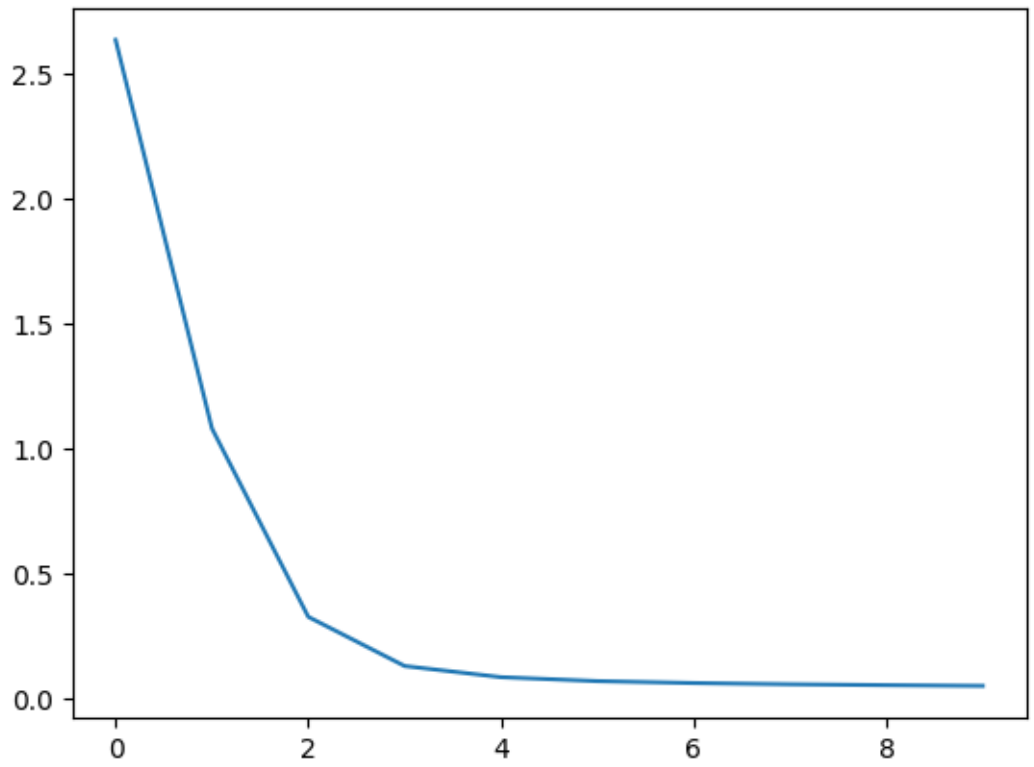
[28]:
```
params, grads, costs = optimize(w, b, X, Y, num_iterations= 1000, learning_rate
 ↪= 0.009, print_cost = False)

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

```
w = [[ 2.27089741 -0.55623518]]
b = 1.2977395794272832
dw = [[-0.04852213  0.01387587]]
db = -0.00415666345349916
```

[29]:
```
import matplotlib.pyplot as plt
plt.plot(costs)
```

[29]:
```
[<matplotlib.lines.Line2D at 0x797878500970>]
```



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).

[30]:
```
# 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(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
```

[31]:
```
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.

[32]:
```
# 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, 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)
    ### 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.

[33]:
```
d = model(train_set_x, train_set_y, test_set_x, test_set_y, num_iterations =␣
↪20000, learning_rate = 0.05, print_cost = True)
```

```
Cost after iteration 0: 0.693147
Cost after iteration 100: 1.025272
Cost after iteration 200: 10.755509
Cost after iteration 300: 0.379580
Cost after iteration 400: 10.127811
Cost after iteration 500: 0.145073
Cost after iteration 600: 0.059949
Cost after iteration 700: 0.023127
Cost after iteration 800: 0.016407
Cost after iteration 900: 0.013258
Cost after iteration 1000: 0.011368
Cost after iteration 1100: 0.010074
Cost after iteration 1200: 0.009114
Cost after iteration 1300: 0.008364
Cost after iteration 1400: 0.007757
Cost after iteration 1500: 0.007251
Cost after iteration 1600: 0.006823
Cost after iteration 1700: 0.006454
Cost after iteration 1800: 0.006131
Cost after iteration 1900: 0.005847
Cost after iteration 2000: 0.005593
Cost after iteration 2100: 0.005366
Cost after iteration 2200: 0.005160
Cost after iteration 2300: 0.004973
Cost after iteration 2400: 0.004801
Cost after iteration 2500: 0.004644
Cost after iteration 2600: 0.004499
Cost after iteration 2700: 0.004364
Cost after iteration 2800: 0.004239
Cost after iteration 2900: 0.004123
Cost after iteration 3000: 0.004013
Cost after iteration 3100: 0.003911
Cost after iteration 3200: 0.003815
Cost after iteration 3300: 0.003724
Cost after iteration 3400: 0.003639
Cost after iteration 3500: 0.003558
```

```
Cost after iteration 3600: 0.003482
Cost after iteration 3700: 0.003409
Cost after iteration 3800: 0.003340
Cost after iteration 3900: 0.003274
Cost after iteration 4000: 0.003211
Cost after iteration 4100: 0.003151
Cost after iteration 4200: 0.003094
Cost after iteration 4300: 0.003039
Cost after iteration 4400: 0.002987
Cost after iteration 4500: 0.002937
Cost after iteration 4600: 0.002888
Cost after iteration 4700: 0.002842
Cost after iteration 4800: 0.002797
Cost after iteration 4900: 0.002754
Cost after iteration 5000: 0.002713
Cost after iteration 5100: 0.002673
Cost after iteration 5200: 0.002635
Cost after iteration 5300: 0.002598
Cost after iteration 5400: 0.002562
Cost after iteration 5500: 0.002527
Cost after iteration 5600: 0.002493
Cost after iteration 5700: 0.002461
Cost after iteration 5800: 0.002429
Cost after iteration 5900: 0.002398
Cost after iteration 6000: 0.002369
Cost after iteration 6100: 0.002340
Cost after iteration 6200: 0.002312
Cost after iteration 6300: 0.002285
Cost after iteration 6400: 0.002258
Cost after iteration 6500: 0.002233
Cost after iteration 6600: 0.002208
Cost after iteration 6700: 0.002183
Cost after iteration 6800: 0.002159
Cost after iteration 6900: 0.002136
Cost after iteration 7000: 0.002114
Cost after iteration 7100: 0.002092
Cost after iteration 7200: 0.002070
Cost after iteration 7300: 0.002049
Cost after iteration 7400: 0.002029
Cost after iteration 7500: 0.002009
Cost after iteration 7600: 0.001989
Cost after iteration 7700: 0.001970
Cost after iteration 7800: 0.001952
Cost after iteration 7900: 0.001934
Cost after iteration 8000: 0.001916
Cost after iteration 8100: 0.001898
Cost after iteration 8200: 0.001881
Cost after iteration 8300: 0.001864
```

```
Cost after iteration 8400: 0.001848
Cost after iteration 8500: 0.001832
Cost after iteration 8600: 0.001816
Cost after iteration 8700: 0.001801
Cost after iteration 8800: 0.001786
Cost after iteration 8900: 0.001771
Cost after iteration 9000: 0.001756
Cost after iteration 9100: 0.001742
Cost after iteration 9200: 0.001728
Cost after iteration 9300: 0.001714
Cost after iteration 9400: 0.001701
Cost after iteration 9500: 0.001688
Cost after iteration 9600: 0.001675
Cost after iteration 9700: 0.001662
Cost after iteration 9800: 0.001649
Cost after iteration 9900: 0.001637
Cost after iteration 10000: 0.001625
Cost after iteration 10100: 0.001613
Cost after iteration 10200: 0.001601
Cost after iteration 10300: 0.001590
Cost after iteration 10400: 0.001578
Cost after iteration 10500: 0.001567
Cost after iteration 10600: 0.001556
Cost after iteration 10700: 0.001545
Cost after iteration 10800: 0.001535
Cost after iteration 10900: 0.001524
Cost after iteration 11000: 0.001514
Cost after iteration 11100: 0.001504
Cost after iteration 11200: 0.001494
Cost after iteration 11300: 0.001484
Cost after iteration 11400: 0.001474
Cost after iteration 11500: 0.001465
Cost after iteration 11600: 0.001455
Cost after iteration 11700: 0.001446
Cost after iteration 11800: 0.001437
Cost after iteration 11900: 0.001428
Cost after iteration 12000: 0.001419
Cost after iteration 12100: 0.001410
Cost after iteration 12200: 0.001402
Cost after iteration 12300: 0.001393
Cost after iteration 12400: 0.001385
Cost after iteration 12500: 0.001377
Cost after iteration 12600: 0.001368
Cost after iteration 12700: 0.001360
Cost after iteration 12800: 0.001352
Cost after iteration 12900: 0.001345
Cost after iteration 13000: 0.001337
Cost after iteration 13100: 0.001329
```

```
Cost after iteration 13200: 0.001322
Cost after iteration 13300: 0.001314
Cost after iteration 13400: 0.001307
Cost after iteration 13500: 0.001299
Cost after iteration 13600: 0.001292
Cost after iteration 13700: 0.001285
Cost after iteration 13800: 0.001278
Cost after iteration 13900: 0.001271
Cost after iteration 14000: 0.001264
Cost after iteration 14100: 0.001258
Cost after iteration 14200: 0.001251
Cost after iteration 14300: 0.001244
Cost after iteration 14400: 0.001238
Cost after iteration 14500: 0.001231
Cost after iteration 14600: 0.001225
Cost after iteration 14700: 0.001219
Cost after iteration 14800: 0.001213
Cost after iteration 14900: 0.001206
Cost after iteration 15000: 0.001200
Cost after iteration 15100: 0.001194
Cost after iteration 15200: 0.001188
Cost after iteration 15300: 0.001182
Cost after iteration 15400: 0.001177
Cost after iteration 15500: 0.001171
Cost after iteration 15600: 0.001165
Cost after iteration 15700: 0.001160
Cost after iteration 15800: 0.001154
Cost after iteration 15900: 0.001148
Cost after iteration 16000: 0.001143
Cost after iteration 16100: 0.001138
Cost after iteration 16200: 0.001132
Cost after iteration 16300: 0.001127
Cost after iteration 16400: 0.001122
Cost after iteration 16500: 0.001117
Cost after iteration 16600: 0.001111
Cost after iteration 16700: 0.001106
Cost after iteration 16800: 0.001101
Cost after iteration 16900: 0.001096
Cost after iteration 17000: 0.001091
Cost after iteration 17100: 0.001087
Cost after iteration 17200: 0.001082
Cost after iteration 17300: 0.001077
Cost after iteration 17400: 0.001072
Cost after iteration 17500: 0.001067
Cost after iteration 17600: 0.001063
Cost after iteration 17700: 0.001058
Cost after iteration 17800: 0.001054
Cost after iteration 17900: 0.001049
```

```
Cost after iteration 18000: 0.001045
Cost after iteration 18100: 0.001040
Cost after iteration 18200: 0.001036
Cost after iteration 18300: 0.001031
Cost after iteration 18400: 0.001027
Cost after iteration 18500: 0.001023
Cost after iteration 18600: 0.001019
Cost after iteration 18700: 0.001014
Cost after iteration 18800: 0.001010
Cost after iteration 18900: 0.001006
Cost after iteration 19000: 0.001002
Cost after iteration 19100: 0.000998
Cost after iteration 19200: 0.000994
Cost after iteration 19300: 0.000990
Cost after iteration 19400: 0.000986
Cost after iteration 19500: 0.000982
Cost after iteration 19600: 0.000978
Cost after iteration 19700: 0.000974
Cost after iteration 19800: 0.000971
Cost after iteration 19900: 0.000967
train accuracy: 100.0 %
test accuracy: 66.0 %
```

Expected Output:

Cost after iteration 0

0.693147

⋮

⋮

Train Accuracy

99.04306220095694 %

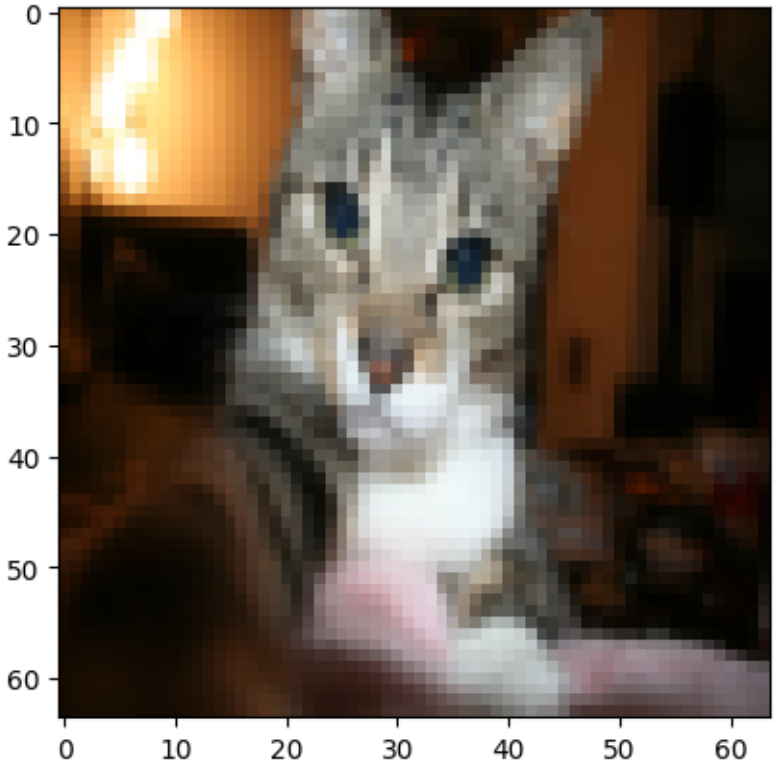
Test Accuracy

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.

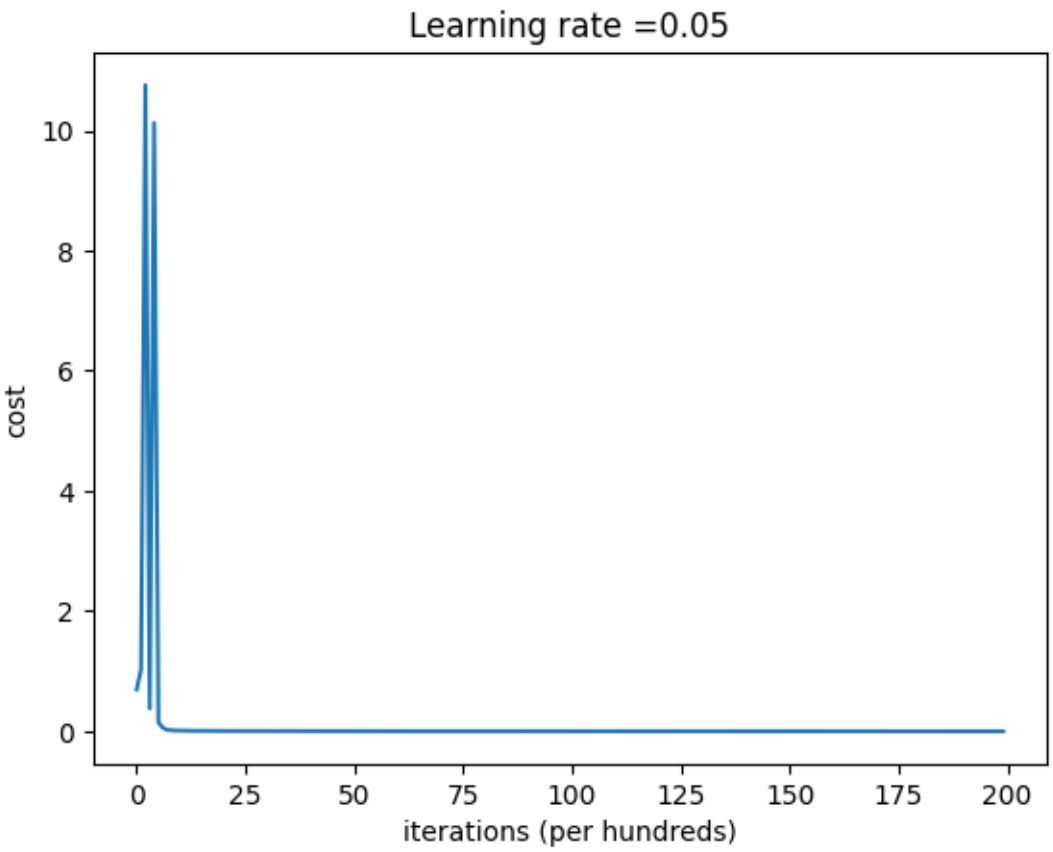
[34]:
```
# Example of a picture that was wrongly classified.
index = 25
plt.imshow(test_set_x[index, :].reshape((num_px, num_px, 3)))
print ("y = " + str(test_set_y[index, 0]) + ", you predicted that it is a \"" +␣
 ↪classes[int(d["Y_prediction_test"][index][0])].decode("utf-8") +  "\"␣
 ↪picture.")
```

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



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

[35]:
```
# 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.