Basic Instructions

1. Enter your Name and UID in the provided space.
2. Do the assignment in the notebook itself
3. you are free to use Google Colab

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In the first part, you will implement all the functions required to build a two layer neural network. In the next part, you will use these functions for image and text classification. Provide your code at the appropriate placeholders.

1. Packages

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

2. Layer Initialization

Exercise: Create and initialize the parameters of the 2-layer neural network. Use random initialization for the weight matrices and zero initialization for the biases.

In [2]:
```
def initialize_parameters(n_x, n_h, n_y):
    """
    Argument:
    n_x -- size of the input layer
    n_h -- size of the hidden layer
    n_y -- size of the output layer

    Returns:
    parameters -- python dictionary containing your parameters:
                    W1 -- weight matrix of shape (n_h, n_x)
                    b1 -- bias vector of shape (n_h, 1)
                    W2 -- weight matrix of shape (n_y, n_h)
                    b2 -- bias vector of shape (n_y, 1)
    """

    np.random.seed(1)

    ### START CODE HERE ### (≈ 4 lines of code)

    W1 = np.random.randn(n_h, n_x) * 0.01
    b1 = np.zeros(shape=(n_h, 1))
    W2 = np.random.randn(n_y, n_h) * 0.01
    b2 = np.zeros(shape=(n_y, 1))

    ### END CODE HERE ###

    assert(W1.shape == (n_h, n_x))
    assert(b1.shape == (n_h, 1))
    assert(W2.shape == (n_y, n_h))
    assert(b2.shape == (n_y, 1))

    parameters = {"W1": W1,
                  "b1": b1,
                  "W2": W2,
                  "b2": b2}

    return parameters
```

In [3]:
```
parameters = initialize_parameters(3,2,1)
print("W1 = " + str(parameters["W1"]))
print("b1 = " + str(parameters["b1"]))
print("W2 = " + str(parameters["W2"]))
print("b2 = " + str(parameters["b2"]))
```

```
W1 = [[ 0.01624345 -0.00611756 -0.00528172]
 [-0.01072969  0.00865408 -0.02301539]]
b1 = [[0.]
 [0.]]
W2 = [[ 0.01744812 -0.00761207]]
b2 = [[0.]]
```

Expected output:

W1	[[0.01624345 -0.00611756 -0.00528172] [-0.01072969 0.00865408 -0.02301539]]
b1	[[0.] [0.]]
W2	[[0.01744812 -0.00761207]]
b2	[[0.]]

3. Forward Propagation

Now that you have initialized your parameters, you will do the forward propagation module. You will start by implementing some basic functions that you will use later when implementing the model. You will complete three functions in this order:

- LINEAR
- LINEAR -> ACTIVATION where ACTIVATION will be either ReLU or Sigmoid.

The linear module computes the following equation:

$$Z = WA + b \tag{4}$$

3.1 Exercise: Build the linear part of forward propagation.

In [4]:
```
def linear_forward(A, W, b):
    """
    Implement the linear part of a layer's forward propagation.

    Arguments:
    A -- activations from previous layer (or input data): (size of previous layer, number of examples)
    W -- weights matrix: numpy array of shape (size of current layer, size of previous layer)
    b -- bias vector, numpy array of shape (size of the current layer, 1)

    Returns:
    Z -- the input of the activation function, also called pre-activation parameter
    cache -- a python dictionary containing "A", "W" and "b" ; stored for computing the backward pass efficiently
    """

    ### START CODE HERE ### (≈ 1 line of code)

    Z = np.dot(W, A) + b

    ### END CODE HERE ###

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

    return Z, cache
```

In [5]:
```
np.random.seed(1)

A = np.random.randn(3,2)
W = np.random.randn(1,3)
b = np.random.randn(1,1)

Z, linear_cache = linear_forward(A, W, b)
print("Z = " + str(Z))
```

```
Z = [[ 3.26295337 -1.23429987]]
```

Expected output:

Z	[[3.26295337 -1.23429987]]

3.2 - Linear-Activation Forward

In this notebook, you will use two activation functions:

- **Sigmoid**: $\sigma(Z) = \sigma(WA + b) = \frac{1}{1+e^{-(WA+b)}}$. Write the code for the `sigmoid` function. This function returns **two** items: the activation value " a " and a " `cache` " that contains " Z " (it's what we will feed in to the corresponding backward function). To use it you could just call:

```
A, activation_cache = sigmoid(Z)
```

- **ReLU**: The mathematical formula for ReLu is $A = RELU(Z) = max(0, Z)$. Write the code for the `relu` function. This function returns **two** items: the activation value " A " and a " `cache` " that contains " Z " (it's what we will feed in to the corresponding backward function). To use it you could just call: ``` python A, activation_cache = relu(Z)

Exercise:

- Implement the activation functions
- Build the linear activation part of forward propagation. Mathematical relation is: $A = g(Z) = g(WA_{prev} + b)$

In [6]:
```
def sigmoid(Z):
    """
    Implements the sigmoid activation in numpy

    Arguments:
    Z -- numpy array of any shape

    Returns:
    A -- output of sigmoid(z), same shape as Z
    cache -- returns Z, useful during backpropagation
    """
    ### START CODE HERE ### (≈ 2 line of code)

    A = 1.0 / (1.0 + np.exp(-Z))
    cache = Z

    ### END CODE HERE ###

    return A, cache

def relu(Z):
    """
    Implement the RELU function.

    Arguments:
    Z -- Output of the linear layer, of any shape

    Returns:
    A -- Post-activation parameter, of the same shape as Z
    cache --  returns Z, useful during backpropagation
    """

    ### START CODE HERE ### (≈ 2 line of code)

    A = np.maximum(0, Z)
    cache = Z

    ### END CODE HERE ###

    assert(A.shape == Z.shape)
    return A, cache
```

In [7]:
```
def linear_activation_forward(A_prev, W, b, activation):
    """
    Implement the forward propagation for the LINEAR->ACTIVATION laye
r

    Arguments:
    A_prev -- activations from previous layer (or input data): (size
 of previous layer, number of examples)
    W -- weights matrix: numpy array of shape (size of current layer,
size of previous layer)
    b -- bias vector, numpy array of shape (size of the current laye
r, 1)
    activation -- the activation to be used in this layer, stored as
 a text string: "sigmoid" or "relu"

    Returns:
    A -- the output of the activation function, also called the post-
activation value
    cache -- a python dictionary containing "linear_cache" and "activ
ation_cache";
             stored for computing the backward pass efficiently
    """

    if activation == "sigmoid":
        # Inputs: "A_prev, W, b". Outputs: "A, activation_cache".
        ### START CODE HERE ### (≈ 2 lines of code)

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

        ### END CODE HERE ###

    elif activation == "relu":
        # Inputs: "A_prev, W, b". Outputs: "A, activation_cache".
        ### START CODE HERE ### (≈ 2 lines of code)

        Z, linear_cache = linear_forward(A_prev, W, b)
        A, activation_cache = relu(Z)

        ### END CODE HERE ###

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

    return A, cache
```

In [8]:
```
np.random.seed(2)
A_prev = np.random.randn(3,2)
W = np.random.randn(1,3)
b = np.random.randn(1,1)

A, linear_activation_cache = linear_activation_forward(A_prev, W, b,
activation = "sigmoid")
print("With sigmoid: A = " + str(A))

A, linear_activation_cache = linear_activation_forward(A_prev, W, b,
activation = "relu")
print("With ReLU: A = " + str(A))
```

```
With sigmoid: A = [[0.96890023 0.11013289]]
With ReLU: A = [[3.43896131 0.        ]]
```

Expected output:

**With sigmoid: A **	[[0.96890023 0.11013289]]
**With ReLU: A **	[[3.43896131 0.]]

4 - Loss function

Now you will implement forward and backward propagation. You need to compute the loss, because you want to check if your model is actually learning.

Exercise: Compute the cross-entropy loss J, using the following formula:

$$-\frac{1}{m}\sum_{i=1}^{m}(y^{(i)}\log\left(a^{(i)}\right)+(1-y^{(i)})\log\left(1-a^{(i)}\right)) \tag{7}$$

In [9]:
```
# GRADED FUNCTION: compute_loss

def compute_loss(A, Y):
    """
    Implement the loss function defined by equation (7).

    Arguments:
    A -- probability vector corresponding to your label predictions,
 shape (1, number of examples)
    Y -- true "label" vector (for example: containing 0 if non-cat, 1
if cat), shape (1, number of examples)

    Returns:
    loss -- cross-entropy loss
    """

    m = Y.shape[1]

    # Compute loss from aL and y.
    ### START CODE HERE ### (≈ 1 lines of code)

    loss = (-1.0 / m) * np.sum((Y * np.log(A)) + ((1.0 - Y) * np.log(
1.0 - A)))

    ### END CODE HERE ###

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

    return loss
```

In [10]:
```
Y = np.asarray([[1, 1, 1]])
A = np.array([[.8,.9,0.4]])

print("loss = " + str(compute_loss(A, Y)))
```

```
loss = 0.41493159961539694
```

Expected Output:

loss 0.41493159961539694

5 - Backward propagation module

Just like with forward propagation, you will implement helper functions for backpropagation. Remember that back propagation is used to calculate the gradient of the loss function with respect to the parameters.

Now, similar to forward propagation, you are going to build the backward propagation in two steps:

- LINEAR backward
- LINEAR -> ACTIVATION backward where ACTIVATION computes the derivative of either the ReLU or sigmoid activation

5.1 - Linear backward

In [11]:
```
# GRADED FUNCTION: linear_backward

def linear_backward(dZ, cache):
    """
    Implement the linear portion of backward propagation for a single layer (layer l)

    Arguments:
    dZ -- Gradient of the loss with respect to the linear output (of current layer l)
    cache -- tuple of values (A_prev, W, b) coming from the forward propagation in the current layer

    Returns:
    dA_prev -- Gradient of the loss with respect to the activation (of the previous layer l-1), same shape as A_prev
    dW -- Gradient of the loss with respect to W (current layer l), same shape as W
    db -- Gradient of the loss with respect to b (current layer l), same shape as b
    """
    A_prev, W, b = cache
    m = A_prev.shape[1]

    ### START CODE HERE ### (≈ 3 lines of code)

    dA_prev = np.dot(W.T, dZ)
    dW = np.dot(dZ, A_prev.T)
    db = np.array([np.sum(dZ, axis = 1)]).T

    ### END CODE HERE ###

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

    return dA_prev, dW, db
```

In [12]:
```
np.random.seed(1)
dZ = np.random.randn(1,2)
A = np.random.randn(3,2)
W = np.random.randn(1,3)
b = np.random.randn(1,1)
linear_cache = (A, W, b)

dA_prev, dW, db = linear_backward(dZ, linear_cache)
print ("dA_prev = "+ str(dA_prev))
print ("dW = " + str(dW))
print ("db = " + str(db))
```

```
dA_prev = [[ 0.51822968 -0.19517421]
 [-0.40506361  0.15255393]
 [ 2.37496825 -0.89445391]]
dW = [[-0.2015379   2.81370193  3.2998501 ]]
db = [[1.01258895]]
```

Expected Output:

dA_prev	[[0.51822968 -0.19517421] [-0.40506361 0.15255393] [2.37496825 -0.89445391]]
dW	[[-0.2015379 2.81370193 3.2998501]]
db	[[1.01258895]]

5.2 - Linear Activation backward

Next, you will create a function that merges the two helper functions: **`linear_backward`** and the backward step for the activation **`linear_activation_backward`**.

Before implementing `linear_activation_backward`, you need to implement two backward functions for each activations:

- **`sigmoid_backward`**: Implements the backward propagation for SIGMOID unit. You can call it as follows:

  `dZ = sigmoid_backward(dA, activation_cache)`

- **`relu_backward`**: Implements the backward propagation for RELU unit. You can call it as follows:

  `dZ = relu_backward(dA, activation_cache)`

If $g(.)$ is the activation function, `sigmoid_backward` and `relu_backward` compute

$$dZ^{[l]} = dA^{[l]} * g'(Z^{[l]}) \tag{11}$$

.

Exercise:

- Implement the backward functions for the relu and sigmoid activation layer.
- Implement the backpropagation for the *LINEAR->ACTIVATION* layer.

In [13]:
```
def relu_backward(dA, cache):
    """
    Implement the backward propagation for a single RELU unit.

    Arguments:
    dA -- post-activation gradient, of any shape
    cache -- 'Z' where we store for computing backward propagation ef
ficiently

    Returns:
    dZ -- Gradient of the loss with respect to Z
    """

    Z = cache
    dZ = np.array(dA, copy=True) # just converting dz to a correct ob
ject.

    ### START CODE HERE ### (≈ 1 line of code)

    dZ = dA * np.where(Z <= 0, 0, 1)

    ### END CODE HERE ###

    assert (dZ.shape == Z.shape)

    return dZ

def sigmoid_backward(dA, cache):
    """
    Implement the backward propagation for a single SIGMOID unit.

    Arguments:
    dA -- post-activation gradient, of any shape
    cache -- 'Z' where we store for computing backward propagation ef
ficiently

    Returns:
    dZ -- Gradient of the loss with respect to Z
    """

    Z = cache

    ### START CODE HERE ### (≈ 2 line of code)

    sigmoid_derivative = sigmoid(Z)[0] * (1.0 - sigmoid(Z)[0])
    dZ = dA * sigmoid_derivative

    ### END CODE HERE ###

    assert (dZ.shape == Z.shape)

    return dZ
```

In [14]:
```
# GRADED FUNCTION: linear_activation_backward

def linear_activation_backward(dA, cache, activation):
    """
    Implement the backward propagation for the LINEAR->ACTIVATION layer.

    Arguments:
    dA -- post-activation gradient for current layer l
    cache -- tuple of values (linear_cache, activation_cache) we store for computing backward propagation efficiently
    activation -- the activation to be used in this layer, stored as a text string: "sigmoid" or "relu"

    Returns:
    dA_prev -- Gradient of the loss with respect to the activation (of the previous layer l-1), same shape as A_prev
    dW -- Gradient of the loss with respect to W (current layer l), same shape as W
    db -- Gradient of the loss with respect to b (current layer l), same shape as b
    """
    linear_cache, activation_cache = cache

    if activation == "relu":
        ### START CODE HERE ### (≈ 2 lines of code)

        dZ = relu_backward(dA, activation_cache)
        dA_prev, dW, db = linear_backward(dZ, linear_cache)

        ### END CODE HERE ###

    elif activation == "sigmoid":
        ### START CODE HERE ### (≈ 2 lines of code)

        dZ = sigmoid_backward(dA, activation_cache)
        dA_prev, dW, db = linear_backward(dZ, linear_cache)

        ### END CODE HERE ###

    return dA_prev, dW, db
```

In [15]:
```
np.random.seed(2)
dA = np.random.randn(1,2)
A = np.random.randn(3,2)
W = np.random.randn(1,3)
b = np.random.randn(1,1)
Z = np.random.randn(1,2)
linear_cache = (A, W, b)
activation_cache = Z
linear_activation_cache = (linear_cache, activation_cache)

dA_prev, dW, db = linear_activation_backward(dA, linear_activation_ca
che, activation = "sigmoid")
print ("sigmoid:")
print ("dA_prev = "+ str(dA_prev))
print ("dW = " + str(dW))
print ("db = " + str(db) + "\n")

dA_prev, dW, db = linear_activation_backward(dA, linear_activation_ca
che, activation = "relu")
print ("relu:")
print ("dA_prev = "+ str(dA_prev))
print ("dW = " + str(dW))
print ("db = " + str(db))
```

```
sigmoid:
dA_prev = [[ 0.11017994  0.01105339]
 [ 0.09466817  0.00949723]
 [-0.05743092 -0.00576154]]
dW = [[ 0.20533573  0.19557101 -0.03936168]]
db = [[-0.11459244]]

relu:
dA_prev = [[ 0.44090989  0.        ]
 [ 0.37883606  0.        ]
 [-0.2298228  -0.        ]]
dW = [[ 0.89027649  0.74742835 -0.20957978]]
db = [[-0.41675785]]
```

Expected output with sigmoid:

dA_prev	[[0.11017994 0.01105339] [0.09466817 0.00949723] [-0.05743092 -0.00576154]]
dW	[[0.20533573 0.19557101 -0.03936168]]
db	[[-0.11459244]]

Expected output with relu:

dA_prev	[[0.44090989 0.] [0.37883606 0.] [-0.2298228 0.]]
dW	[[0.89027649 0.74742835 -0.20957978]]
db	[[-0.41675785]]

6 - Update Parameters

In this section you will update the parameters of the model, using gradient descent:

$$W^{[1]} = W^{[1]} - \alpha \, dW^{[1]} \tag{16}$$
$$b^{[1]} = b^{[1]} - \alpha \, db^{[1]} \tag{17}$$
$$W^{[2]} = W^{[2]} - \alpha \, dW^{[2} \tag{16}$$
$$b^{[2]} = b^{[2]} - \alpha \, db^{[2]} \tag{17}$$

where α is the learning rate. After computing the updated parameters, store them in the parameters dictionary.

Exercise: Implement `update_parameters()` to update your parameters using gradient descent.

Instructions: Update parameters using gradient descent.

In [16]:
```
# GRADED FUNCTION: update_parameters

def update_parameters(parameters, grads, learning_rate):
    """
    Update parameters using gradient descent

    Arguments:
    parameters -- python dictionary containing your parameters
    grads -- python dictionary containing your gradients, output of L
_model_backward

    Returns:
    parameters -- python dictionary containing your updated parameter
s
                  parameters["W" + str(l)] = ...
                  parameters["b" + str(l)] = ...
    """
    # Update rule for each parameter. Use a for loop.
    ### START CODE HERE ### (≈ 4 lines of code)

    for key in parameters:
        parameters[key] = parameters[key] - (learning_rate * grads[
"d" + str(key)])

    ### END CODE HERE ###
    return parameters
```

In [17]:
```
np.random.seed(2)
W1 = np.random.randn(3,4)
b1 = np.random.randn(3,1)
W2 = np.random.randn(1,3)
b2 = np.random.randn(1,1)
parameters = {"W1": W1,
              "b1": b1,
              "W2": W2,
              "b2": b2}
np.random.seed(3)
dW1 = np.random.randn(3,4)
db1 = np.random.randn(3,1)
dW2 = np.random.randn(1,3)
db2 = np.random.randn(1,1)
grads = {"dW1": dW1,
         "db1": db1,
         "dW2": dW2,
         "db2": db2}
parameters = update_parameters(parameters, grads, 0.1)

print ("W1 = "+ str(parameters["W1"]))
print ("b1 = "+ str(parameters["b1"]))
print ("W2 = "+ str(parameters["W2"]))
print ("b2 = "+ str(parameters["b2"]))
```

```
W1 = [[-0.59562069 -0.09991781 -2.14584584  1.82662008]
 [-1.76569676 -0.80627147  0.51115557 -1.18258802]
 [-1.0535704  -0.86128581  0.68284052  2.20374577]]
b1 = [[-0.04659241]
 [-1.28888275]
 [ 0.53405496]]
W2 = [[-0.55569196  0.0354055   1.32964895]]
b2 = [[-0.84610769]]
```

Expected Output:

W1	[[-0.59562069 -0.09991781 -2.14584584 1.82662008] [-1.76569676 -0.80627147 0.51115557 -1.18258802] [-1.0535704 -0.86128581 0.68284052 2.20374577]]
b1	[[-0.04659241] [-1.28888275] [0.53405496]]
W2	[[-0.55569196 0.0354055 1.32964895]]
b2	[[-0.84610769]]

7 - Conclusion

Congrats on implementing all the functions required for building a deep neural network!

We know it was a long assignment but going forward it will only get better. The next part of the assignment is easier.

Part 2:

In the next part you will put all these together to build a two-layer neural networks for image classification.

In [18]:
```
%matplotlib inline
plt.rcParams['figure.figsize'] = (5.0, 4.0) # set default size of plo
ts
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

%load_ext autoreload
%autoreload 2

np.random.seed(1)
```

Dataset

Problem Statement: You are given a dataset ("data/train_catvnoncat.h5", "data/test_catvnoncat.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 completing the function and run the cell below.

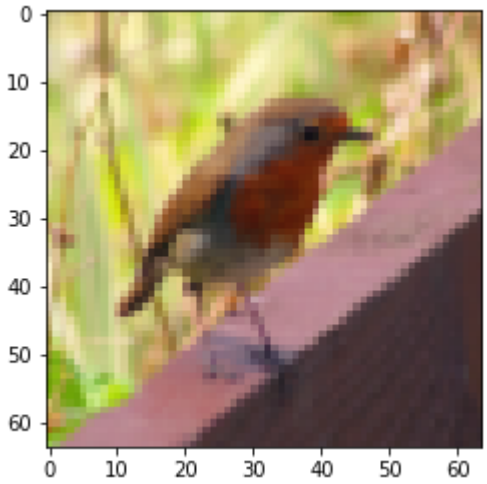
In [19]:
```
def load_data(train_file, test_file):
    # Load the training data
    train_dataset = h5py.File(train_file, 'r')

    # Separate features(x) and labels(y) for training set
    train_set_x_orig = np.array(train_dataset['train_set_x'])
    train_set_y_orig = np.array(train_dataset['train_set_y'])

    # Load the test data
    test_dataset = h5py.File(test_file, 'r')

    # Separate features(x) and labels(y) for training set
    test_set_x_orig = np.array(test_dataset['test_set_x'])
    test_set_y_orig = np.array(test_dataset['test_set_y'])

    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.sha
pe[0]))

    return train_set_x_orig, train_set_y_orig, test_set_x_orig, test_
set_y_orig, classes
```

In [20]:
```
train_file="data/train_catvnoncat.h5"
test_file="data/test_catvnoncat.h5"
train_x_orig, train_y, test_x_orig, test_y, classes = load_data(train
_file, test_file)
```

The following code will show you an image in the dataset. Feel free to change the index and re-run the cell multiple times to see other images.

In [21]:
```
# Example of a picture
index = 10
plt.imshow(train_x_orig[index])
print ("y = " + str(train_y[0,index]) + ". It's a " + classes[train_y
[0,index]].decode("utf-8") +  " picture.")
```

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



In [22]:
```
# 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.

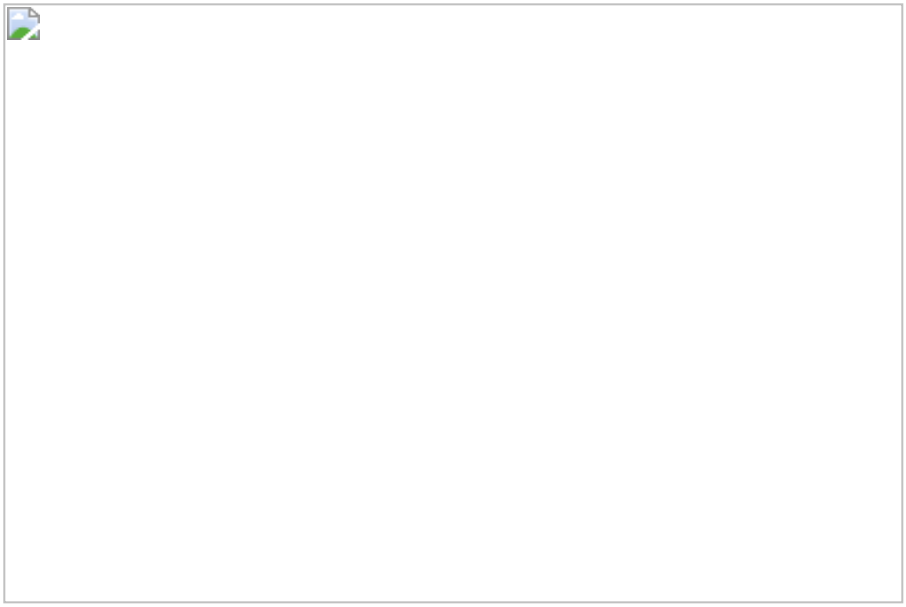


Figure 1: Image to vector conversion.

In [23]:
```
# 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)
```

3 - Architecture of your model

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

2-layer neural network

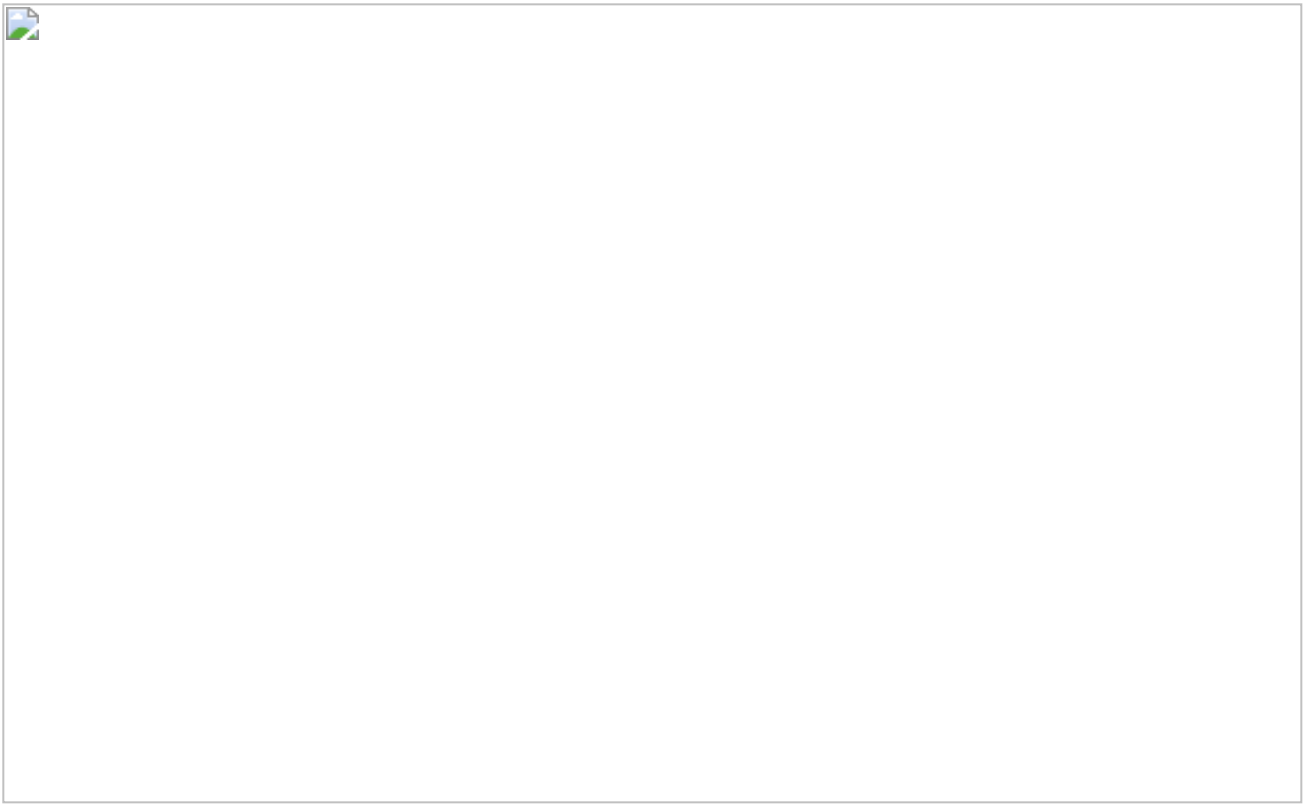


Figure 2: 2-layer neural network.
The model can be summarized as: ***INPUT -> LINEAR -> RELU -> LINEAR -> SIGMOID -> OUTPUT***.

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: $[x_0, x_1, \ldots, x_{12287}]^T$ is then multiplied by the weight matrix $W^{[1]}$ of size $(n^{[1]}, 12288)$.
- You then add a bias term and take its relu to get the following vector: $[a_0^{[1]}, a_1^{[1]}, \ldots, a_{n^{[1]}-1}^{[1]}]^T$.
- You multiply the resulting vector by $W^{[2]}$ and add your intercept (bias).
- Finally, you take the sigmoid of the result. If it is greater than 0.5, you classify it to be a cat.

General methodology

As usual you will follow the Deep Learning methodology to build the model:

```
1. Initialize parameters / Define hyperparameters
2. Loop for num_iterations:
    a. Forward propagation
    b. Compute loss function
    c. Backward propagation
    d. Update parameters (using parameters, and grads from backprop)
```

Question: Use the helper functions you have implemented in the previous assignment to build a 2-layer neural network with the following structure: *LINEAR -> RELU -> LINEAR -> SIGMOID*. The functions you may need and their inputs are:

```
def initialize_parameters(n_x, n_h, n_y):
    ...
    return parameters
def linear_activation_forward(A_prev, W, b, activation):
    ...
    return A, cache
def compute_loss(AL, Y):
    ...
    return loss
def linear_activation_backward(dA, cache, activation):
    ...
    return dA_prev, dW, db
def update_parameters(parameters, grads, learning_rate):
    ...
    return parameters
```

In [24]:
```
### CONSTANTS DEFINING THE MODEL ####
n_x = 12288     # num_px * num_px * 3
n_h = 14
n_y = 1
layers_dims = (n_x, n_h, n_y)
```

In [25]:
```
def two_layer_model(X, Y, layers_dims, learning_rate = 0.0075, num_it
erations = 3000, print_loss=False):
    """
    Implements a two-layer neural network: LINEAR->RELU->LINEAR->SIGM
OID.

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

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

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

    # Initialize parameters dictionary, by calling one of the functio
ns you'd previously implemented
    ### START CODE HERE ### (≈ 1 line of code)

    parameters = initialize_parameters(n_x, n_h, n_y)

    ### END CODE HERE ###

    # Get W1, b1, W2 and b2 from the dictionary parameters.
    W1 = parameters["W1"]
    b1 = parameters["b1"]
    W2 = parameters["W2"]
    b2 = parameters["b2"]

    # Loop (gradient descent)

    for i in range(0, num_iterations):

        # Forward propagation: LINEAR -> RELU -> LINEAR -> SIGMOID. I
nputs: "X, W1, b1, W2, b2". Output: "A1, cache1, A2, cache2".
        ### START CODE HERE ### (≈ 2 lines of code)

        A1, cache1 = linear_activation_forward(X, W1, b1, "relu")
        A2, cache2 = linear_activation_forward(A1, W2, b2, "sigmoid")

        ### END CODE HERE ###

        # Compute loss
```

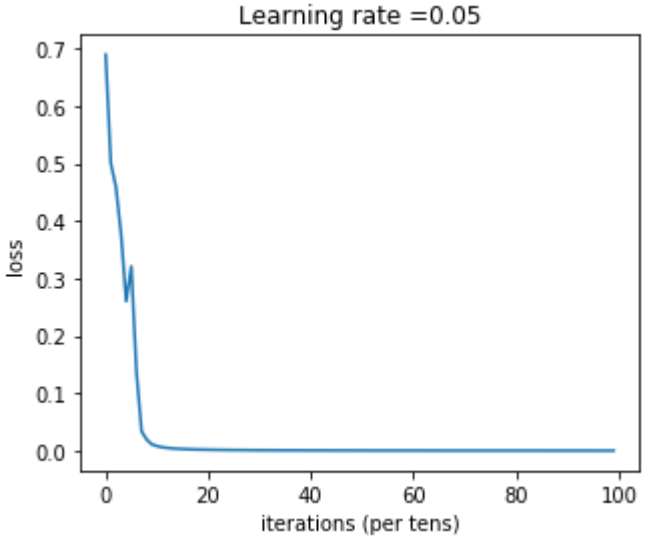
```
        ### START CODE HERE ### (≈ 1 line of code)

        loss = compute_loss(A2, Y)

        ### END CODE HERE ###

        # Initializing backward propagation
        dA2 = - (np.divide(Y, A2) - np.divide(1 - Y, 1 - A2))/m

        # Backward propagation. Inputs: "dA2, cache2, cache1". Output
s: "dA1, dW2, db2; also dA0 (not used), dW1, db1".
        ### START CODE HERE ### (≈ 2 lines of code)

        dA1, dW2, db2 = linear_activation_backward(dA2, cache2, "sigm
oid")
        dA0, dW1, db1 = linear_activation_backward(dA1, cache1, "rel
u")

        ### END CODE HERE ###

        # Set grads['dWl'] to dW1, grads['db1'] to db1, grads['dW2']
 to dW2, grads['db2'] to db2
        ### START CODE HERE ### (≈ 4 lines of code)

        grads['dW1'] = dW1
        grads['db1'] = db1
        grads['dW2'] = dW2
        grads['db2'] = db2

        ### END CODE HERE ###


        # Update parameters.
        ### START CODE HERE ### (approx. 1 line of code)

        parameters = update_parameters(parameters, grads, learning_ra
te)

        ### END CODE HERE ###

        # Retrieve W1, b1, W2, b2 from parameters
        W1 = parameters["W1"]
        b1 = parameters["b1"]
        W2 = parameters["W2"]
        b2 = parameters["b2"]

        # Print the loss every 100 training example
        if print_loss and i % 100 == 0:
            print("Loss after iteration {}: {}".format(i, np.squeeze(
loss)))
        if print_loss and i % 100 == 0:
            losses.append(loss)

    # plot the loss

    plt.plot(np.squeeze(losses))
    plt.ylabel('loss')
```

```
    plt.xlabel('iterations (per tens)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    return parameters
```

In [26]:
```
parameters = two_layer_model(train_x, train_y, layers_dims = (n_x, n_
h, n_y), learning_rate=0.05, num_iterations = 10000, print_loss=True)
```

```
Loss after iteration 0: 0.6897576016609726
Loss after iteration 100: 0.5005103970842145
Loss after iteration 200: 0.4591366577945993
Loss after iteration 300: 0.3770052403577409
Loss after iteration 400: 0.2602361949176332
Loss after iteration 500: 0.3210213987659625
Loss after iteration 600: 0.1367893333118584
Loss after iteration 700: 0.03359939981401825
Loss after iteration 800: 0.019386051135145306
Loss after iteration 900: 0.011123321804135526
Loss after iteration 1000: 0.008085966068735755
Loss after iteration 1100: 0.00616150541674634
Loss after iteration 1200: 0.004954980443160653
Loss after iteration 1300: 0.00412527939969342
Loss after iteration 1400: 0.003518870206173741
Loss after iteration 1500: 0.003061308333436289
Loss after iteration 1600: 0.002695432614851714
Loss after iteration 1700: 0.0024031455850395153
Loss after iteration 1800: 0.0021657663882503936
Loss after iteration 1900: 0.0019666545525735507
Loss after iteration 2000: 0.0017992090366167263
Loss after iteration 2100: 0.001655080585719804
Loss after iteration 2200: 0.001532728059038323
Loss after iteration 2300: 0.0014249424774429758
Loss after iteration 2400: 0.001330553593243608
Loss after iteration 2500: 0.0012475240882572054
Loss after iteration 2600: 0.0011727019519600752
Loss after iteration 2700: 0.0011056301663001271
Loss after iteration 2800: 0.0010457423870421556
Loss after iteration 2900: 0.0009915468122138715
Loss after iteration 3000: 0.0009420018320298385
Loss after iteration 3100: 0.0008970140989984581
Loss after iteration 3200: 0.0008562810059245188
Loss after iteration 3300: 0.0008191135281381895
Loss after iteration 3400: 0.0007838555609432737
Loss after iteration 3500: 0.0007514969459309871
Loss after iteration 3600: 0.00072130352396622
Loss after iteration 3700: 0.0006940840997760265
Loss after iteration 3800: 0.0006683430107462324
Loss after iteration 3900: 0.0006445101616427947
Loss after iteration 4000: 0.0006216714796829128
Loss after iteration 4100: 0.0006006068158078043
Loss after iteration 4200: 0.0005805519119852851
Loss after iteration 4300: 0.0005624372861389752
Loss after iteration 4400: 0.000544874474057781
Loss after iteration 4500: 0.0005284500979268323
Loss after iteration 4600: 0.0005126917618333164
Loss after iteration 4700: 0.0004979762636994264
Loss after iteration 4800: 0.0004839012712583636
Loss after iteration 4900: 0.0004704411023058348
Loss after iteration 5000: 0.0004577937384031588
Loss after iteration 5100: 0.00044598465731073695
Loss after iteration 5200: 0.000434483744664138
Loss after iteration 5300: 0.00042370844082581825
Loss after iteration 5400: 0.00041317897226191474
Loss after iteration 5500: 0.00040323771454891236
Loss after iteration 5600: 0.0003937562023728228
```

```
Loss after iteration 5700: 0.00038471579365848414
Loss after iteration 5800: 0.00037595275712624574
Loss after iteration 5900: 0.00036760741482198296
Loss after iteration 6000: 0.0003595729085302991
Loss after iteration 6100: 0.00035198469616855397
Loss after iteration 6200: 0.0003445832426314159
Loss after iteration 6300: 0.0003373602065832987
Loss after iteration 6400: 0.00033068899324190223
Loss after iteration 6500: 0.0003239920313130308
Loss after iteration 6600: 0.00031765736222179417
Loss after iteration 6700: 0.0003115783929520816
Loss after iteration 6800: 0.0003057224589431675
Loss after iteration 6900: 0.00029993244270315185
Loss after iteration 7000: 0.0002944885737968172
Loss after iteration 7100: 0.00028914155377593584
Loss after iteration 7200: 0.0002839942043889244
Loss after iteration 7300: 0.00027908092680975884
Loss after iteration 7400: 0.000274293450219458
Loss after iteration 7500: 0.00026967461711512 93
Loss after iteration 7600: 0.0002650832886613369
Loss after iteration 7700: 0.000260715518831069
Loss after iteration 7800: 0.00025645957286575847
Loss after iteration 7900: 0.00025236328424961763
Loss after iteration 8000: 0.00024841922018241933
Loss after iteration 8100: 0.00024452882527081494
Loss after iteration 8200: 0.00024080196463993798
Loss after iteration 8300: 0.00023716749264069868
Loss after iteration 8400: 0.00023362080160555117
Loss after iteration 8500: 0.00023017178793499434
Loss after iteration 8600: 0.00022674664520046123
Loss after iteration 8700: 0.00022350176459231887
Loss after iteration 8800: 0.00022032494572542867
Loss after iteration 8900: 0.00021725972894868126
Loss after iteration 9000: 0.00021420638106666774
Loss after iteration 9100: 0.00021129988994003632
Loss after iteration 9200: 0.0002084057777612922
Loss after iteration 9300: 0.00020564002586125055
Loss after iteration 9400: 0.00020292603428197505
Loss after iteration 9500: 0.00020024855521877112
Loss after iteration 9600: 0.00019767906292175353
Loss after iteration 9700: 0.00019516551929647815
Loss after iteration 9800: 0.00019268843950658336
Loss after iteration 9900: 0.00019024278192427018
```



Expected Output:

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

Good thing you built a vectorized implementation! Otherwise it might have taken 10 times longer to train this.

Now, you can use the trained parameters to classify images from the dataset.

Exercise:

- Implement the forward function
- Implement the predict function below to make prediction on test_images

In [27]:
```
def two_layer_forward(X, parameters):
    """
    Implement forward propagation for the [LINEAR->RELU]*(L-1)->LINEA
R->SIGMOID computation

    Arguments:
    X -- data, numpy array of shape (input size, number of examples)
    parameters -- output of initialize_parameters_deep()

    Returns:
    AL -- last post-activation value
    caches -- list of caches containing:
                every cache of linear_relu_forward() (there are L-1 o
f them, indexed from 0 to L-2)
                the cache of linear_sigmoid_forward() (there is one,
 indexed L-1)
    """

    caches = []
    A = X

    # Implement LINEAR -> RELU. Add "cache" to the "caches" list.
    ### START CODE HERE ### (approx. 3 line of code)

    W1, b1 = parameters["W1"], parameters["b1"]
    A1, cache1 = linear_activation_forward(A, W1, b1, "relu")
    caches.append(cache1)

    ### END CODE HERE ###

    # Implement LINEAR -> SIGMOID. Add "cache" to the "caches" list.
    ### START CODE HERE ### (approx. 3 line of code)

    W2, b2 = parameters["W2"], parameters["b2"]
    A2, cache2 = linear_activation_forward(A1, W2, b2, "sigmoid")
    caches.append(cache2)

    ### END CODE HERE ###

    assert(A2.shape == (1,X.shape[1]))

    return A2, caches
```

In [28]:
```
def predict(X, y, parameters):
    """
    This function is used to predict the results of a  L-layer neural network.

    Arguments:
    X -- data set of examples you would like to label
    parameters -- parameters of the trained model

    Returns:
    p -- predictions for the given dataset X
    """

    m = X.shape[1]
    n = len(parameters) // 2 # number of layers in the neural network
    p = np.zeros((1,m))

    # Forward propagation
    ### START CODE HERE ### (≈ 1 lines of code)

    probas, caches = two_layer_forward(X, parameters)

    ### END CODE HERE ###

    # convert probas to 0/1 predictions
    for i in range(0, probas.shape[1]):
        ### START CODE HERE ### (≈ 4 lines of code)

        if(probas[0][i] > 0.5):
            p[0][i] = 1
        else:
            p[0][i] = 0

        ### END CODE HERE ###

    print("Accuracy: "  + str(np.sum((p == y)/m)))
    return p
```

In [29]:
```
predictions_train = predict(train_x, train_y, parameters)
```

```
Accuracy: 0.9999999999999998
```

In [30]:
```
predictions_test = predict(test_x, test_y, parameters)
```

```
Accuracy: 0.76
```

Exercise: Identify the hyperparameters in the model and For each hyperparameter

- Briefly explain its role
- Explore a range of values and describe their impact on (a) training loss and (b) test accuracy
- Report the best hyperparameter value found.

Note: Provide your results and explanations in the report for this question.

Hyperparameters The hyperparameters are:

1. Learning rate - It is used for updating the parameters of the neural network that is the weights and biases of the neural network. It controls the amount of update that needs to take place so that we are able to reach the minima of the loss function.
2. Epochs - It represents the number of times the network sees the data and adjusts its parameters for optimal learning.
3. Number of hidden neurons in the hidden layer - The number of neurons in the hidden layer where each neuron is learning some properties of the input data and able to establish a relationship between input and output.

Values of Hyperparameters tried:

1. Learning rate = 0.0075, Epochs = 2500, Hidden neurons = 7, Training loss = 0.0485, Testing accuracy: 72%
2. Learning rate = 0.0075, Epochs = 3000, Hidden neurons = 7, Training loss = 0.03, Testing accuracy: 72%
3. Learning rate = 0.01, Epochs = 8000, Hidden neurons = 7, Training loss = 0.0023, Testing accuracy: 72%
4. Learning rate = 0.01, Epochs = 10000, Hidden neurons = 7, Training loss = 0.001, Testing accuracy: 72%
5. Learning rate = 0.1, Epochs = 10000, Hidden neurons = 7, Training loss = 0.24, Testing accuracy: 62%
6. Learning rate = 0.001, Epochs = 10000, Hidden neurons = 7, Training loss = 0.16, Testing accuracy: 74%
7. Learning rate = 0.01, Epochs = 10000, Hidden neurons = 14, Training loss = 0.0015, Testing accuracy: 74%
8. Learning rate = 0.01, Epochs = 10000, Hidden neurons = 21, Training loss = 0.0014, Testing accuracy: 74%
9. Learning rate = 0.01, Epochs = 10000, Hidden neurons = 28, Training loss = 0.0014, Testing accuracy: 74%
10. Learning rate = 0.01, Epochs = 10000, Hidden neurons = 35, Training loss = 0.0014, Testing accuracy: 74%
11. Learning rate = 0.03, Epochs = 8000, Hidden neurons = 14, Training loss = 0.0004, Testing accuracy: 76%
12. Learning rate = 0.05, Epochs = 8000, Hidden neurons = 14, Training loss = 0.0002, Testing accuracy: 76%
13. Learning rate = 0.07, Epochs = 8000, Hidden neurons = 14, Training loss = 0.006, Testing accuracy: 72%
14. Learning rate = 0.05, Epochs = 8000, Hidden neurons = 28, Training loss = 0.0002, Testing accuracy: 74%
15. Learning rate = 0.05, Epochs = 8000, Hidden neurons = 21, Training loss = 0.001, Testing accuracy: 68%
16. Learning rate = 0.05, Epochs = 10000, Hidden neurons = 14, Training loss = 0.0001, Testing accuracy: 76%

Optimal hyperparameters found

1. Learning rate = 0.05
2. Epochs = 10000
3. Number of hidden neurons = 14

Results Analysis

First, let's take a look at some images the 2-layer model labeled incorrectly. This will show a few mislabeled images.

In [31]:
```
def print_mislabeled_images(classes, X, y, p):
    """
    Plots images where predictions and truth were different.
    X -- dataset
    y -- true labels
    p -- predictions
    """
    a = p + y
    mislabeled_indices = np.asarray(np.where(a == 1))
    plt.rcParams['figure.figsize'] = (40.0, 40.0) # set default size
 of plots
    num_images = len(mislabeled_indices[0])
    for i in range(num_images):
        index = mislabeled_indices[1][i]

        plt.subplot(2, num_images, i + 1)
        plt.imshow(X[:,index].reshape(64,64,3), interpolation='neares
t')
        plt.axis('off')
        plt.title("Prediction: " + classes[int(p[0,index])].decode("u
tf-8") + " \n Class: " + classes[y[0,index]].decode("utf-8"))
```

In [32]:
```
print_mislabeled_images(classes, test_x, test_y, predictions_test)
```

Exercise: Identify a few types of images that tends to perform poorly on the model

Answer The model performs poorly when the cat is at certain angle or rotated at some angle, which makes it classify it as a non-cat class.

Now, lets use the same architecture to predict sentiment of movie reviews. In this section, most of the implementation is already provided. The exercises are mainly to understand what the workflow is when handling the text data.

In [33]:
```
import re
```

Dataset

Problem Statement: You are given a dataset ("train_imdb.txt", "test_imdb.txt") containing:

```
- a training set of m_train reviews
- a test set of m_test reviews
- the labels for the training examples are such that the first 50% belong to
class 1 (positive) and the rest 50% of the data belong to class 0(negative)
```

Let's get more familiar with the dataset. Load the data by completing the function and run the cell below.

In [34]:
```
def load_data(train_file, test_file):
    train_dataset = []
    test_dataset = []

    # Read the training dataset file line by line
    for line in open(train_file, 'r'):
        train_dataset.append(line.strip())

    for line in open(test_file, 'r'):
        test_dataset.append(line.strip())
    return train_dataset, test_dataset
```

In [35]:
```
train_file = "data/train_imdb.txt"
test_file = "data/test_imdb.txt"
train_dataset, test_dataset = load_data(train_file, test_file)
```

In [36]:
```
# This is just how the data is organized. The first 50% data is posit
ive and the rest 50% is negative for both train and test splits.
y = [1 if i < len(train_dataset)*0.5 else 0 for i in range(len(train_
dataset))]
```

As usual, lets check our dataset

In [37]:
```
# Example of a review
index = 10
print(train_dataset[index])
print ("y = " + str(y[index]))
```

```
I liked the film. Some of the action scenes were very interesting, te
nse and well done. I especially liked the opening scene which had a s
emi truck in it. A very tense action scene that seemed well done.<br
/><br />Some of the transitional scenes were filmed in interesting wa
ys such as time lapse photography, unusual colors, or interesting ang
les. Also the film is funny is several parts. I also liked how the ev
il guy was portrayed too. I'd give the film an 8 out of 10.
y = 1
```

In [38]:
```
# Explore your dataset
m_train = len(train_dataset)
m_test = len(test_dataset)

print ("Number of training examples: " + str(m_train))
print ("Number of testing examples: " + str(m_test))
```

```
Number of training examples: 1001
Number of testing examples: 201
```

Pre-Processing

From the example review, you can see that the raw data is really noisy! This is generally the case with the text data. Hence, Preprocessing the raw input and cleaning the text is essential. Please run the code snippet provided below.

Exercise: Explain what pattern the model is trying to capture using re.compile in your report.

Answer

1. re.compile() removes special characters like ', . " etc and makes all characters in lowercase. It is learning properties from words.

In [39]:
```
REPLACE_NO_SPACE = re.compile("(\.)|(\;)|(\:)|(\!)|(\')|(\?)|(\,)|(\"
)|(\()|(\))|(\[)|(\])|(\d+)")
REPLACE_WITH_SPACE = re.compile("(<br\s*/><br\s*/>)|(\-)|(\/)")
NO_SPACE = ""
SPACE = " "

def preprocess_reviews(reviews):

    reviews = [REPLACE_NO_SPACE.sub(NO_SPACE, line.lower()) for line
in reviews]
    reviews = [REPLACE_WITH_SPACE.sub(SPACE, line) for line in review
s]

    return reviews

train_dataset_clean = preprocess_reviews(train_dataset)
test_dataset_clean = preprocess_reviews(test_dataset)
```

In [40]:
```
# Example of a clean review
index = 10
print(train_dataset_clean[index])
print ("y = " + str(y[index]))
```

```
i liked the film some of the action scenes were very interesting tens
e and well done i especially liked the opening scene which had a semi
truck in it a very tense action scene that seemed well done some of t
he transitional scenes were filmed in interesting ways such as time l
apse photography unusual colors or interesting angles also the film i
s funny is several parts i also liked how the evil guy was portrayed
too id give the film an  out of
y = 1
```

Vectorization

Now lets create a feature vector for our reviews based on a simple bag of words model. So, given an input text, we need to create a numerical vector which is simply the vector of word counts for each word of the vocabulary. Run the code below to get the feature representation.

In [41]:
```
from sklearn.feature_extraction.text import CountVectorizer

cv = CountVectorizer(binary=True, stop_words="english", max_features=
2000)
cv.fit(train_dataset_clean)
X = cv.transform(train_dataset_clean)
X_test = cv.transform(test_dataset_clean)
```

CountVectorizer provides a sparse feature representation by default which is reasonable because only some words occur in individual example. However, for training neural network models, we generally use a dense representation vector.

In [42]:
```
X = np.array(X.todense()).astype(float)
X_test = np.array(X_test.todense()).astype(float)
y = np.array(y)
```

Model

In [43]:
```
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split

X_train, X_val, y_train, y_val = train_test_split(
    X, y, train_size = 0.80
)
```

In [44]:
```
# This is just to correct the shape of the arrays as required by the
 two_layer_model
X_train = X_train.T
X_val = X_val.T
y_train = y_train.reshape(1,-1)
y_val = y_val.reshape(1,-1)
```

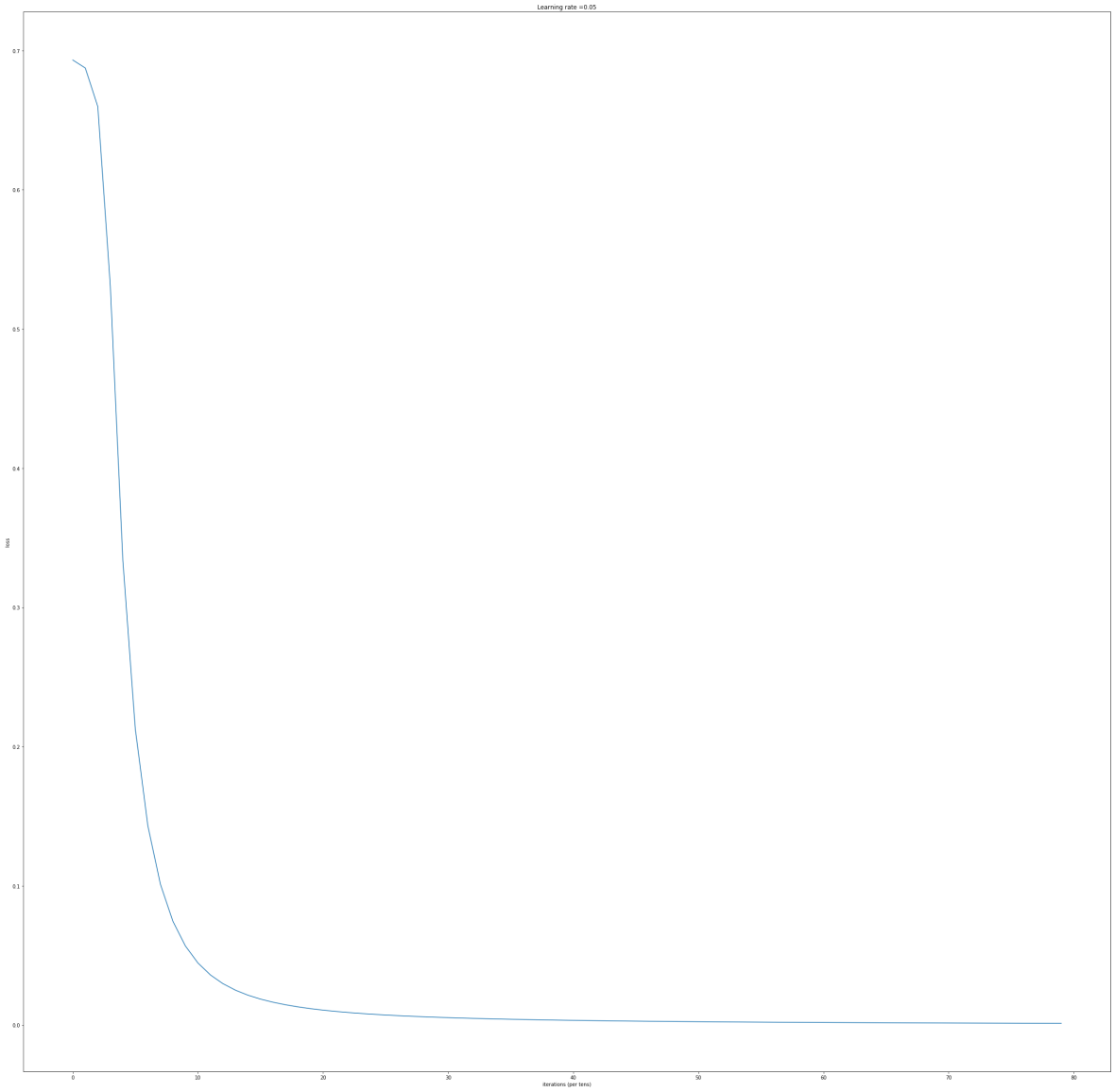
In [45]:
```
### CONSTANTS DEFINING THE MODEL ####
n_x = X_train.shape[0]
n_h = 200
n_y = 1
layers_dims = (n_x, n_h, n_y)
```

We will use the same two layer model that you completed in the previous section for training.

In [46]:
```
parameters = two_layer_model(X_train, y_train, layers_dims = (n_x, n_
h, n_y), learning_rate=0.05, num_iterations = 8000, print_loss=True)
```

```
Loss after iteration 0: 0.6931669649893015
Loss after iteration 100: 0.6874292042033144
Loss after iteration 200: 0.6597144317222486
Loss after iteration 300: 0.5307636749107454
Loss after iteration 400: 0.33384385320577264
Loss after iteration 500: 0.21244588141292753
Loss after iteration 600: 0.1432223796712702
Loss after iteration 700: 0.1012999651610651
Loss after iteration 800: 0.07461707348889567
Loss after iteration 900: 0.05686657164001318
Loss after iteration 1000: 0.04466704096581919
Loss after iteration 1100: 0.03605012060334668
Loss after iteration 1200: 0.029786383758999974
Loss after iteration 1300: 0.02510388722392519
Loss after iteration 1400: 0.02151296119183033
Loss after iteration 1500: 0.018698094499721974
Loss after iteration 1600: 0.01644791728269799
Loss after iteration 1700: 0.014618365747086927
Loss after iteration 1800: 0.013109001697082156
Loss after iteration 1900: 0.011847392036098811
Loss after iteration 2000: 0.010780610240406023
Loss after iteration 2100: 0.00986935036416729
Loss after iteration 2200: 0.009083581769610953
Loss after iteration 2300: 0.00840042761096894
Loss after iteration 2400: 0.007802044824301254
Loss after iteration 2500: 0.007274414436432064
Loss after iteration 2600: 0.006806288279798432
Loss after iteration 2700: 0.006388675281828682
Loss after iteration 2800: 0.006014175577462164
Loss after iteration 2900: 0.005676757154986056
Loss after iteration 3000: 0.005371445121802232
Loss after iteration 3100: 0.005094070251632812
Loss after iteration 3200: 0.004841157104235913
Loss after iteration 3300: 0.0046097427310416985
Loss after iteration 3400: 0.004397296332357337
Loss after iteration 3500: 0.004201693990906421
Loss after iteration 3600: 0.004021092220400464
Loss after iteration 3700: 0.003853911842859966
Loss after iteration 3800: 0.003698766249870028
Loss after iteration 3900: 0.00355446728665987
Loss after iteration 4000: 0.003419959359915118
Loss after iteration 4100: 0.0032943206456596207
Loss after iteration 4200: 0.003176746220331223
Loss after iteration 4300: 0.0030665140854806727
Loss after iteration 4400: 0.0029629760236383317
Loss after iteration 4500: 0.002865578254987389
Loss after iteration 4600: 0.002773812253176744
Loss after iteration 4700: 0.002687210789110669
Loss after iteration 4800: 0.002605367878703423
Loss after iteration 4900: 0.0025279200145005448
Loss after iteration 5000: 0.0024545351238028728
Loss after iteration 5100: 0.002384915376330747
Loss after iteration 5200: 0.002318791177946547
Loss after iteration 5300: 0.002255918584538012
Loss after iteration 5400: 0.00219606712248068
Loss after iteration 5500: 0.0021390333023998324
Loss after iteration 5600: 0.0020846280352281965
```

```
Loss after iteration 5700: 0.0020326853311540822
Loss after iteration 5800: 0.001983044164082544
Loss after iteration 5900: 0.0019355662348153116
Loss after iteration 6000: 0.0018901141467163895
Loss after iteration 6100: 0.0018465684297981693
Loss after iteration 6200: 0.0018048137628808225
Loss after iteration 6300: 0.0017647458339610923
Loss after iteration 6400: 0.0017262679448169678
Loss after iteration 6500: 0.0016892930624617546
Loss after iteration 6600: 0.0016537342918131592
Loss after iteration 6700: 0.0016195178504683594
Loss after iteration 6800: 0.0015865693746847272
Loss after iteration 6900: 0.0015548264690664285
Loss after iteration 7000: 0.0015242249057224905
Loss after iteration 7100: 0.0014947045762600591
Loss after iteration 7200: 0.0014662124823130618
Loss after iteration 7300: 0.0014386974913165446
Loss after iteration 7400: 0.0014121121200015214
Loss after iteration 7500: 0.0013864107085018946
Loss after iteration 7600: 0.0013615523074070818
Loss after iteration 7700: 0.0013374967842876557
Loss after iteration 7800: 0.0013142086558700122
Loss after iteration 7900: 0.001291652831771192
```



Predict the review for our movies!

In [47]:
```
predictions_train = predict(X_train, y_train, parameters)
```

```
Accuracy: 0.9999999999999998
```

In [48]:
```
predictions_val = predict(X_val, y_val, parameters)
```

```
Accuracy: 0.8756218905472635
```

Results Analysis

Let's take a look at some examples the 2-layer model labeled incorrectly

In [49]:
```
def print_mislabeled_reviews(X, y, p):
    """
    Plots images where predictions and truth were different.
    X -- dataset
    y -- true labels
    p -- predictions
    """
    a = p + y
    mislabeled_indices = np.asarray(np.where(a == 1))
    plt.rcParams['figure.figsize'] = (40.0, 40.0) # set default size
 of plots
    num_reviews = len(mislabeled_indices[0])
    for i in range(num_reviews):
        index = mislabeled_indices[1][i]

        print((" ").join(cv.inverse_transform(X[index])[0]))
        print("Prediction: " + str(int(p[0,index])) + " \n Class: " +
str(y[0,index]))
```

In [50]:
```
print_mislabeled_reviews(X_val.T, y_val, predictions_val)
```

```
agree apart awful best close come day decided didnt directors general
ly good great greatest ive james like lord masterpiece masters match
money movie movies oscar people sadly said say seen st star tim time
titanic trilogy truly world wrong
Prediction: 0
 Class: 1
adult apart best bit bizarre carry caught changed clear comes didnt d
irector documentary edward especially fact fan feelings film films gi
rlfriend havent hes impressed include industry infamous interesting i
ve jr just king knew life like long loud make man mediocre mixed movi
e movies need needed paul people pretty really run say seen somewhat
sort talent tears terrible theatre theyre time totally try week wood
woods worked worst wouldnt youre
Prediction: 0
 Class: 1
avoid away best blair body does ending entire father fellow female fi
lm flick gang girls lets like makes minutes movie old plays pointless
running scene school shot showing somewhat stuck tedious utterly year
Prediction: 1
 Class: 0
acting attempt attempts camera cinematography complete did director d
oes effective entertainment experience extremely fact film films girl
s goes good henry high imagery including innocent intelligent interes
ting later lesbian long make nature nudity number paris school sex sl
owly stories story study sweet todays trip try went
Prediction: 0
 Class: 1
actually amusing bit building cameo casting david day desperate didnt
director filled film finds follows funny gay girl good guy hes hope i
snt jokes left let like look looks lucky make makes movie painful pic
tures playing plays pretty really reason remember rest scene script s
hes sort sounds talented tom turn wasted watch way ways wonder young
Prediction: 1
 Class: 0
animal dont hours life love planet script series video wait
Prediction: 1
 Class: 0
actors alive based childhood documentary got kill know man mission mo
nster movie people personality played rate real scenes set seven turn
used women work
Prediction: 0
 Class: 1
absolutely acting amusing atmosphere awful bunch career certain chara
cter charm cheesy cinematography conclusion count creepy eccentric en
ded face female flick gets getting gives gore gross hero horror large
ly life likable looks making murder numbers officer people performanc
e period pieces place police poor pretty reading real ridiculous righ
t score script set sex soon ugly
Prediction: 0
 Class: 1
acting away beautifully biggest burt came character drinking fact fai
lure fast fell general help hoping job movie movies night notice play
ed promising real right screen single state thats walk way
Prediction: 1
 Class: 0
action attempt audience bad black bruce calling character check clich
éd compared create day decided dialog dont drawn dvd effects film giv
```

```
en good great holes imdb just knew latest line lot lots mediocre mix
modern morning movie new night notice people perfect plot possibly qu
ite ready really reviews sadly saw smart smith somewhat special spect
acular story terrible think todays true viewing works written
Prediction: 1
 Class: 0
academy actors average best bit blown career changing character chara
cters completely connected considered cruise crying deep didnt doesnt
dont easy emotions enjoy enjoyable episode events fair far film finis
h flaws forced friends good great hate help high honestly hours im ju
st life like little long love meaningful movie music pace people perf
ormance play playing plot pointless police poor quality relationships
seemingly self share significant start stories stuff tells thats ther
es think thought tom total turns unique wasnt watch whilst wife worse
written wrong
Prediction: 1
 Class: 0
actors ago believe better bit characters contains crazy dvd ed felt g
erman good hard havent head high level like live look lot maybe missi
ng movie movies nasty really saw say scenes seen short sick story tha
ts thing uk version violence years
Prediction: 0
 Class: 1
bar beat bed beginning best certainly characters death director eye f
ilm good guess hour intriguing late leads line main make meet missed
movie negative night opening particular plot professional read review
separate sets sleep stories thats unfortunately view ways wild
Prediction: 1
 Class: 0
actually ago bad better book church course does enjoyable familiar fi
lm forgotten forward good hadnt heard hour instantly job know laid le
t long minute minutes missed mr nearly overall quick read really scho
ol second sense short simply story tales thats thing time trilogy wat
ched worked write years
Prediction: 0
 Class: 1
care catch comes detective diamond elizabeth end ends film flick forc
es gas given going got griffith hand help hes horse involving kinds l
atest life longer lovely lower make maybe meets nasty opportunity par
tner parts play power really serial slasher spirit team theyre thing
time villains wasted worthy years
Prediction: 1
 Class: 0
billy character christopher comedy completely couple decided did ente
rtainment extremely felt film flick good hardly jokes julia just lady
laughs like little looking love loved loves mindless movie night ok p
ast plays poor redeeming roberts romantic said self shown shows smart
space strong sure thats thing thought value watch watching wife youre
Prediction: 1
 Class: 0
act acting action bad boring car climax crime effort enjoyable entert
aining especially fairly film films finish friends fun good got guy h
elp hero innocence liked long looks lord makes movie normally perform
ance played plays plot powerful prove quite right run saw smith star
steve thought tough unknown watch way
Prediction: 0
 Class: 1
```

```
actor actually adults bringing calls cast child children doing era ey
es famous focus fun given guess guy history host interesting john jul
ia kenneth kind king like martin movie natural news park police provi
ded question really say seeing short shouldnt simply smith sort story
thought true version voice voices woman work worth wouldnt young
Prediction: 0
 Class: 1
action adventure adventures bad camp character characters check crew
decided doc elements familiar fan fans feel feeling film good hero he
roes im james jones just know long lot major minutes movie movies mus
ic number ones promise provided really resulting savage say seeing so
mewhat spirit star thats theres throw time trying unfortunate way
Prediction: 0
 Class: 1
action anderson appear appears away bit bizarre boy brilliant caught
child childhood christian come constant country course create credit
day days decided device director directors discover dramatic ends exa
ctly face fact faith far feeling film flying genius given gives going
great happen having hero idea important just keeps land like living l
uck magic makers making men missed modern old ones opportunity order
people place plot poor probably prove quite really revealing sky smil
e sort spending stick story subtle support surely tale tells theme th
ings think time times try turns uses want work
Prediction: 1
 Class: 0
action actually answer blair camera chaos check clearly day definitel
y did directors disgusting end favorite field film flat forced happen
happens history horror hot ladies latest laughing like look make man
minute minutes movie movies night open opening previous producer proj
ect random rent ride say scenes seat set shoot shot shots sit somewha
t stolen talking times trash victims vision watch watched way witch w
ow
Prediction: 1
 Class: 0
arent attractive came cast certain comments date delivered disappoint
ed dont douglas enjoyable expect fan fun funny great greatest hope id
ea isnt know like material movie movies people performances pleasant
read really review stars talented time title unfortunate usually watc
hing
Prediction: 0
 Class: 1
able animal art believable best bit blue boring character david dialo
g did dumb eyes female film fun got impressive kept la lady light lik
e love match music nice oh picked plenty plot point pretty realized r
ich robert says seeing sets shots strong stuff supposed things thinki
ng throw version viewing wasnt window wondering
Prediction: 1
 Class: 0
away better bit bought boy carried case comes complete day deserves d
iscovers doggie dont drama dvd ending expect fact film final funny ge
ts girl good humor instead involving just kid kind like little lookin
g lot man manage minutes missing money needs nice obviously old overa
ll pass performer picture problems quality really rent rest sentiment
al son soon spending story street suspense thought treatment tv usual
ly wang way
Prediction: 0
 Class: 1
```

```
acting animals best better die dont entire episode episodes funny goo
d horrible ice just killing know life like movie obviously plot pro p
roblem really remember right scene scenes season second series shocki
ng suspense think torture turns victims watch women wonderful worst
Prediction: 0
 Class: 1
```

Exercise: Provide explanation as to why these examples were misclassified below.

Type your answer here

The main aim of the model is to predict the sentiment. As each word is taken individually, the model is failing to learn the sentiment of the current input or word from previous words and is failing to learn from the sentence as a whole.

In [ ]: