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 pr
evious 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)

    Returns:
    Z -- the input of the activation function, also called pre-activa
tion 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 lay
er.

    Arguments:
    dA -- post-activation gradient for current layer l
    cache -- tuple of values (linear_cache, activation_cache) we stor
e 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 (o
f the previous layer l-1), same shape as A_prev
    dW -- Gradient of the loss with respect to W (current layer l), s
ame shape as W
    db -- Gradient of the loss with respect to b (current layer l), s
ame 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.

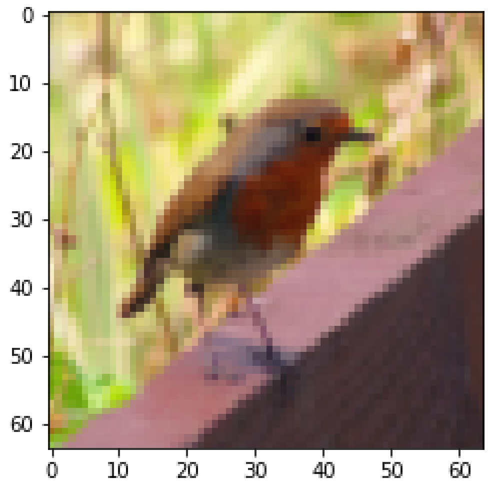
In [19]:
```
def load_data(train_file, test_file):
    # Load the training data
    train_dataset = h5py.File(train_file, 'r')

    # 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.shape[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:

```python
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]:

```python
### CONSTANTS DEFINING THE MODEL ####
n_x = 12288     # num_px * num_px * 3
n_h = 7
n_y = 1
layers_dims = (n_x, n_h, n_y)
```

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
```

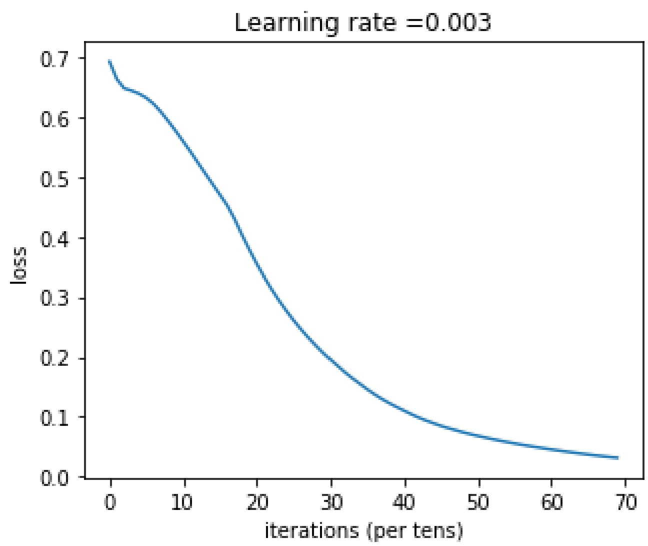
```
        ### START CODE HERE ### (≈ 1 line of code)

        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 [154]:
```
parameters = two_layer_model(train_x, train_y, layers_dims = (n_x, n_h, n_y), learning_rate=0.003, num_iterations = 7000, print_loss=True)
```

```
Loss after iteration 0: 0.69304973566
Loss after iteration 100: 0.66358362054
Loss after iteration 200: 0.648272816823
Loss after iteration 300: 0.644370511753
Loss after iteration 400: 0.639397427608
Loss after iteration 500: 0.632374537296
Loss after iteration 600: 0.6222656789
Loss after iteration 700: 0.608749048358
Loss after iteration 800: 0.593317668528
Loss after iteration 900: 0.577051173035
Loss after iteration 1000: 0.559815202387
Loss after iteration 1100: 0.54260614129
Loss after iteration 1200: 0.524435258075
Loss after iteration 1300: 0.50629684946
Loss after iteration 1400: 0.488534059566
Loss after iteration 1500: 0.470691257416
Loss after iteration 1600: 0.452698521786
Loss after iteration 1700: 0.430112987407
Loss after iteration 1800: 0.40371365539
Loss after iteration 1900: 0.379037148229
Loss after iteration 2000: 0.355524892053
Loss after iteration 2100: 0.334077833925
Loss after iteration 2200: 0.31377615142
Loss after iteration 2300: 0.295163988192
Loss after iteration 2400: 0.277980886773
Loss after iteration 2500: 0.26172341494
Loss after iteration 2600: 0.24673638906
Loss after iteration 2700: 0.232723655169
Loss after iteration 2800: 0.219602225882
Loss after iteration 2900: 0.207130090975
Loss after iteration 3000: 0.1956742445
Loss after iteration 3100: 0.184661640146
Loss after iteration 3200: 0.173723977661
Loss after iteration 3300: 0.163918461958
Loss after iteration 3400: 0.154874149793
Loss after iteration 3500: 0.145669560808
Loss after iteration 3600: 0.137200381502
Loss after iteration 3700: 0.129435190953
Loss after iteration 3800: 0.122515828644
Loss after iteration 3900: 0.11610318636
Loss after iteration 4000: 0.110072191657
Loss after iteration 4100: 0.10406774094
Loss after iteration 4200: 0.0984590798725
Loss after iteration 4300: 0.0935180956028
Loss after iteration 4400: 0.0890586140023
Loss after iteration 4500: 0.0847087401318
Loss after iteration 4600: 0.0808851905079
Loss after iteration 4700: 0.0774511672646
Loss after iteration 4800: 0.0739222258769
Loss after iteration 4900: 0.070827789301
Loss after iteration 5000: 0.0679165909286
Loss after iteration 5100: 0.0651693765764
Loss after iteration 5200: 0.062481603939
Loss after iteration 5300: 0.0599379765221
Loss after iteration 5400: 0.0575760866184
Loss after iteration 5500: 0.0553193553812
Loss after iteration 5600: 0.0531034948389
```

```
Loss after iteration 5700: 0.0510428466166
Loss after iteration 5800: 0.0490311649651
Loss after iteration 5900: 0.0470733380646
Loss after iteration 6000: 0.045215782521
Loss after iteration 6100: 0.0434024427312
Loss after iteration 6200: 0.0416500470376
Loss after iteration 6300: 0.0399726228339
Loss after iteration 6400: 0.0383499390173
Loss after iteration 6500: 0.0368139336141
Loss after iteration 6600: 0.0353062856631
Loss after iteration 6700: 0.0338848414523
Loss after iteration 6800: 0.032537506473
Loss after iteration 6900: 0.0312628723581
```



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 [155]:
```
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 [175]:
```
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(float(np.sum((p == y)/float(m)))))
    return p
```

In [176]:
```
predictions_train = predict(train_x, train_y, parameters)
```

```
Accuracy: 1.0
```

In [173]:
```
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.

Values of Hyperparameters tried:

1. Learning rate = 0.005, Epochs = 2000, Training loss = 0.187, Testing accuracy: 70%
2. Learning rate = 0.005, Epochs = 3000, Training loss = 0.073, Testing accuracy: 72%
3. Learning rate = 0.005, Epochs = 4000, Training loss = 0.036, Testing accuracy: 72%
4. Learning rate = 0.001, Epochs = 2000, Training loss = 0.617, Testing accuracy: 34%
5. Learning rate = 0.001, Epochs = 3000, Training loss = 0.56, Testing accuracy: 34%
6. Learning rate = 0.001, Epochs = 4000, Training loss = 0.5, Testing accuracy: 34%
7. Learning rate = 0.01, Epochs = 2000, Training loss = 0.05, Testing accuracy: 72%
8. Learning rate = 0.01, Epochs = 3000, Training loss = 0.01, Testing accuracy: 72%
9. Learning rate = 0.01, Epochs = 4000, Training loss = 0.008, Testing accuracy: 72%
10. Learning rate = 0.05, Epochs = 2000, Training loss = 0.58, Testing accuracy: 46%
11. Learning rate = 0.01, Epochs = 3000, Training loss = 0.36, Testing accuracy: 56%
12. Learning rate = 0.03, Epochs = 2000, Training loss = 0.0058, Testing accuracy: 72%
13. Learning rate = 0.03, Epochs = 3000, Training loss = 0.0024, Testing accuracy: 72%
14. Learning rate = 0.003, Epochs = 4000, Training loss = 0.11, Testing accuracy: 76%
15. Learning rate = 0.003, Epochs = 7000, Training loss = 0.047, Testing accuracy: 76%
16. Learning rate = 0.003, Epochs = 8000, Training loss = 0.021, Testing accuracy: 74%
17. Learning rate = 0.002, Epochs = 4000, Training loss = 0.24, Testing accuracy: 76%
18. Learning rate = 0.002, Epochs = 6000, Training loss = 0.113, Testing accuracy: 74%
19. Learning rate = 0.002, Epochs = 8000, Training loss = 0.06, Testing accuracy: 74%
20. Learning rate = 0.0025, Epochs = 6000, Training loss = 0.07, Testing accuracy: 74%
21. Learning rate = 0.0025, Epochs = 8000, Training loss = 0.03, Testing accuracy: 72%

Optimal hyperparameters found

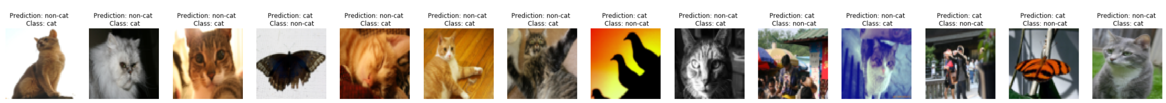
1. Learning rate = 0.003
2. Epochs = 7000

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 [177]:
```
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 [178]:
```
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 [179]:
```
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 [180]:
```
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 [181]:
```
train_file = "data/train_imdb.txt"
test_file = "data/test_imdb.txt"
train_dataset, test_dataset = load_data(train_file, test_file)
```

In [182]:
```
# 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 [183]:
```
# 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 [184]:
```
# 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 [185]:
```
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 [186]:
```
# 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 [187]:
```
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 [188]:
```
X = np.array(X.todense()).astype(float)
X_test = np.array(X_test.todense()).astype(float)
y = np.array(y)
```

Model

In [189]:
```
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
)
```

```
/home/arpitdec5/.local/lib/python2.7/site-packages/sklearn/model_sele
ction/_split.py:2178: FutureWarning: From version 0.21, test_size wil
l always complement train_size unless both are specified.
  FutureWarning)
```

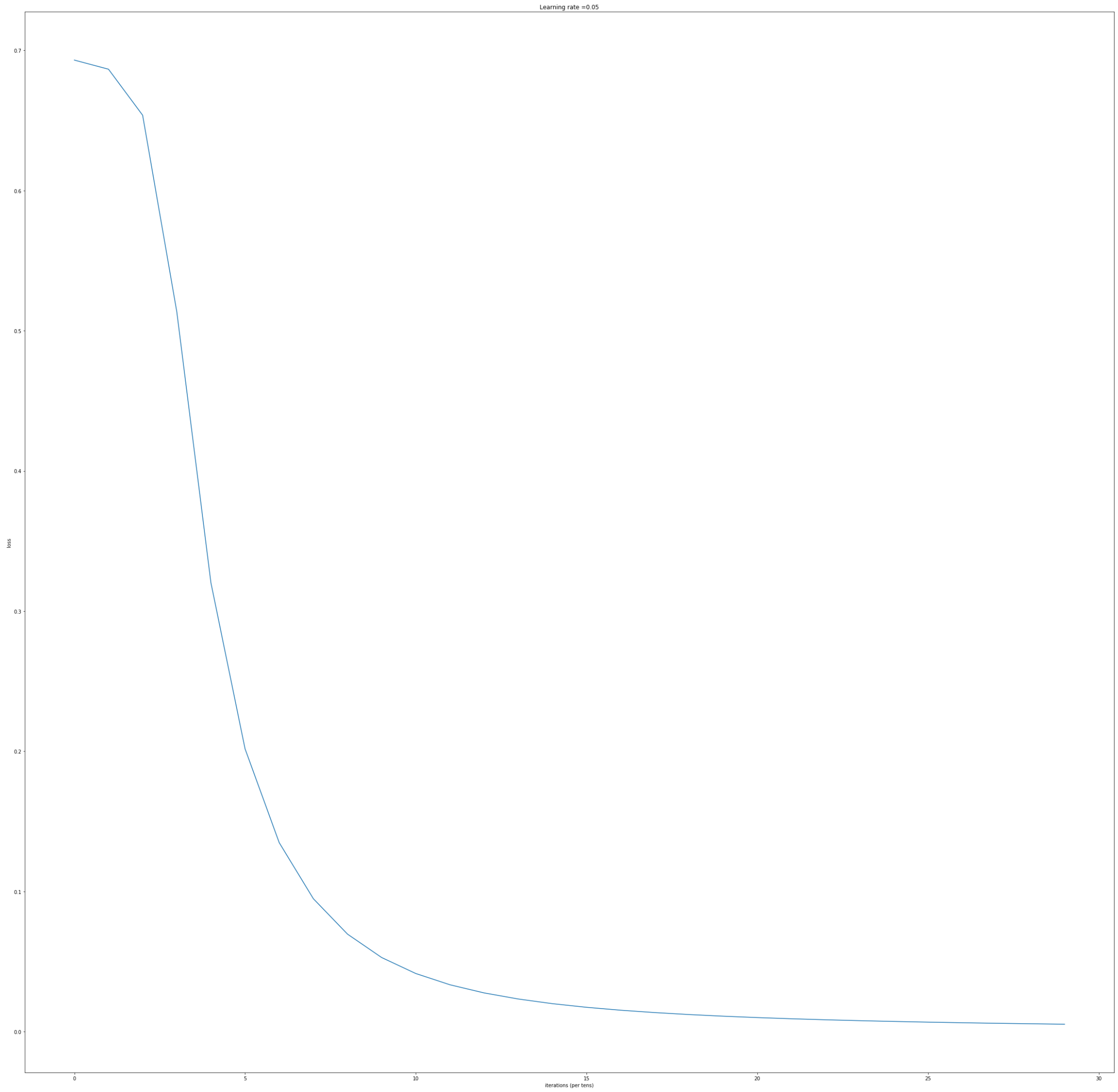
In [190]:
```
# This is just to correct the shape of the arrays as required by the
 two_layer_model
X_train = X_train.T
X_val = X_val.T
y_train = y_train.reshape(1,-1)
y_val = y_val.reshape(1,-1)
```

In [191]:
```
### 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 [192]:
```
parameters = two_layer_model(X_train, y_train, layers_dims = (n_x, n_
h, n_y), learning_rate=0.05, num_iterations = 3000, print_loss=True)
```

```
Loss after iteration 0: 0.693079416169
Loss after iteration 100: 0.686569463673
Loss after iteration 200: 0.653746782902
Loss after iteration 300: 0.513637888328
Loss after iteration 400: 0.320195643458
Loss after iteration 500: 0.201724848093
Loss after iteration 600: 0.134819976219
Loss after iteration 700: 0.0948401309064
Loss after iteration 800: 0.0695863625855
Loss after iteration 900: 0.0528916264559
Loss after iteration 1000: 0.041486399968
Loss after iteration 1100: 0.0334640145333
Loss after iteration 1200: 0.027650556749
Loss after iteration 1300: 0.0233134006421
Loss after iteration 1400: 0.0199911510628
Loss after iteration 1500: 0.0173876238095
Loss after iteration 1600: 0.0153066762094
Loss after iteration 1700: 0.0136146620512
Loss after iteration 1800: 0.0122180889721
Loss after iteration 1900: 0.0110502249368
Loss after iteration 2000: 0.010062214655
Loss after iteration 2100: 0.00921766338755
Loss after iteration 2200: 0.00848910281476
Loss after iteration 2300: 0.00785537317867
Loss after iteration 2400: 0.00730000461864
Loss after iteration 2500: 0.00681003094208
Loss after iteration 2600: 0.00637506645976
Loss after iteration 2700: 0.00598679650114
Loss after iteration 2800: 0.00563846787071
Loss after iteration 2900: 0.0053244913391
```



Predict the review for our movies!

In [193]:
```
predictions_train = predict(X_train, y_train, parameters)
```

```
Accuracy: 1.0
```

In [194]:
```
predictions_val = predict(X_val, y_val, parameters)
```

```
Accuracy: 0.850746268657
```

Results Analysis

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

In [195]:
```
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 [196]:
```
print_mislabeled_reviews(X_val.T, y_val, predictions_val)
```

```
actors attempt beauty believable big bit charismatic claims definitel
y delivery did didnt disappointing disaster entertained fact film fin
e group job line looked lost miss offensive performance playing plays
plot project recommend rent scenes screen seen strong talent wish wri
ting
Prediction: 0
 Class: 1
acting add annoying bad change character dicaprio did director does e
yes film filmmakers films glad going good great half hand hardly impr
essive just kate learned lesson love mean million movie opinion oscar
performance possible really romance romantic second ship shouldnt sin
gle sit stories story sure talented think thinking time times titanic
try watching win wonderful wont worst
Prediction: 0
 Class: 1
anna appearance away bad better bible big black blue book boys build
capture cat catch chaos charles child city comic connected cops cult
deal didnt doesnt earth edge exactly extreme far favorite fictional f
ine finished followed fond form fun gang gas genius giant god going g
ood got government green guy guys half happening happens hard havent
having heroes hey hospital include japanese join just kind know known
like liked line looks lot make match monster movie mysterious naked n
amed names new nice oh order paid past people place places police pow
er problem project puts quickly red remains right seconds seeing seri
es set sexy soon sorts special starts story taking thanks thats there
s theyre thing tom unfortunately use using villains violence want who
s woman world yeah year youd
Prediction: 0
 Class: 1
able action add admit adult ahead anna bit black boy characters cinem
atography come deserves disappointed disappointment does dont doubt d
ownright elements end entirely expect expecting fear film forget genr
e girls guys hopes imagination instead intense knew leave lesbian lev
el like little looking lot love managed memorable mid movie ok perfor
mances play pleasure prepared read real realized really received roma
nce school secret shot shown soon stars story straight sudden teenage
rs theyre think time times trying unexpected watching way white women
wont wrong years youll
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
based got involved movie moving mystery oscar review script slow star
Prediction: 1
 Class: 0
actually ahead better box budget burning character charlie come damn
development did didnt dont enjoy eye fake far film flick forced genre
good guinea guts hand hear heard horror hours interested just know li
ke listen looks lot low making men minutes movie naturally offer pain
ful pretty really recommend say scene scenes second seen set sharp sh
ort simply snuff story think thought throwing told torture trying ult
imately unless various watching ways went woman worst
```

```
Prediction: 0
 Class: 1
cause early effort government heavy past people problems production p
ropaganda short spending sudden time truly using war window
Prediction: 1
 Class: 0
ability acting actor ages anti better cheap cinema complete confused
day decent direction disappointed disappointment does dont dull dvd e
xplanation film finally finding flat gate good got great guess intrig
uing kind lead like liked love main meet mouth movie performance plot
poor premise remind required result rip saw say store story tell thou
ght took tv wanted way week written
Prediction: 1
 Class: 0
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
better body cast central cinema come coming comments company computer
decides die entertaining exist failed fall fan film films genius gets
getting going great hard hey highly hollywood house idea interested j
udging latest lesson lessons like make making man member money movie
movies near potential premise puts review reviews role scenes seen se
t shock soon stupid taken takes type unless unrelated wish wow writer
writing yes zero
Prediction: 1
 Class: 0
admit almighty attempt big bruce carrey cast cheesy comedy dont end e
njoyable fan feel funny gets gone havent help hilarious ill im jim ju
st know let light like movie movies music note poor positive really r
est reviews saying seen shows somewhat start steve thinking want writ
ers youre
Prediction: 0
 Class: 1
action age body brain building certainly computer crazy damme daughte
r dead entertaining especially fan fi fights folks genius goes going
goldberg good government guess hes humor just keeps king lame later l
atest like manages mean named new original particularly perfect power
pretty pro reason run sci sequel shoot site snake soldiers sort step
super takes thriller train usual van war white working wrong year yea
rs youre
Prediction: 1
 Class: 0
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
bunch doesnt feel got laugh laughed left like loud make masterpiece m
ovie ok purpose smile times viewer worth
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
charlie dont eye fake film final harder hot im know like look looks r
eal said say scene scenes sure tell thing truth
Prediction: 0
 Class: 1
actually ago american begin begins big bring buy century circumstance
s couple does doesnt effects emotional flicks follows happen highly h
ome house husband impact john life like man masterpiece mysterious ol
d outside plot recommended simple special story strange supposedly th
ings turn unknown went woman world
Prediction: 0
 Class: 1
absolutely add bad best better boat book brought cases classic clear
cliché close course critics deserves didnt disappointed exactly excit
ement family felt field film finally giving grew hard hear hero heroe
s home ill im instead know latest like line mind missing musical name
s nature non offensive old particularly past poor professional race r
eal reality reviewer ridiculous right rock sadly said scene scenes sc
ore sense shot shots shows smile sound spot starting supposed taking
talking theres theyve thrill time took town versions water wonderful
years yes
Prediction: 1
 Class: 0
ability able accident action actresses actually aspect away bad belie
ve better bit blood brothers cause cgi charlie crap crime cut days de
al death disturbing does doesnt dont effects especially eyes fact fak
e favorite film films footage forget funny happens hope horror im ins
tead leaving like look lot make makers making marry money movie movie
s overall people plot point porn probably pull rape rating real sayin
g says scene scenes seen series shocking snuff sound stand stars suck
ed sucks super supposed sure talent talking thing thinking time tried
visual visuals want wanted wasnt watch wouldnt
Prediction: 0
 Class: 1
achieve acting approach art artistic background box brief cast cheap
cinema close come cons considered consists contemporary country deali
ng deals deserves director fact fan fit good half hard history hope h
ot huge job just knows like make manage masterpiece meant media membe
rs money movie naked near office ones opinion perfect perfectly provi
de purpose real roles short single small success talent theatrical th
ing time touching tried usual waiting women word work
Prediction: 1
 Class: 0
acting actors admit annoying arent art bad ball beginning best better
big billy bits book calling camera case character characters cinemati
c come coming cons crouse cusack david definitely dialogue did didnt
direct directed does doesnt dont early end ending entertaining expect
ing extremely far feel film filmed films flat forth free fun game gam
es gets getting girl going good guy half help heres hes hour house il
l im inner involved isnt james john just keeps lesson let level like
lindsay line lines little look looked lose mamet mantegna mark maybe
mean men middle mind minutes moves movie narration nature new ones op
ening pick play precious pretty problem quality questions read readin
g real realize really result ring roll room scene second shes sort so
```

```
und sounds speaking standard start stick story strange stuff supposed
theatre theyre things true want wants watch way weird whats words wor
k wouldnt write
Prediction: 0
 Class: 1
accept ago army away bad begins body bucks budget chase comes couple
dolph door energy especially exist explained feel feeling fight fight
ing films flash flick follow forward goes good happens hell human ide
a ideas involved isnt just key lacks like long looks low lukas make m
an master member merely middle movie movies needless new order place
plays potential previous satan say scene scenes secret sense sort sta
rs story study sucks supposed sure takes theres thrown time undergrou
nd wish wont years york youll
Prediction: 1
 Class: 0
absolutely acted art audience bad bar beginning came chinese come com
ing comments course deep didnt director doing drawn end ending entert
aining essentially experience faces fact fantastic far feel festival
film final following forget fresh fun gonna government half happy har
d hidden hollywood hour hours im immediately incredibly intelligent i
ntriguing judging just land late life likable long looked lot loved m
ake making match meaning mention natural new number pain painful poin
t post probably problem promising reading really reason reviews right
russian said saw say sense sharp simply society sounds spent started
state talking thank theatre thought time took try utter utterly view
want wanted warned way week whats whatsoever words working years yes
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
actors ask blood cares character conclusion content crap crew damn da
y disturbing effort ends episode exception family fan fate gets going
gore great gross hopes horror hour imagine lot mindless new performan
ces pointless producers production reason season sense series shock s
tories story tend thinking utter values violence work worse
Prediction: 1
 Class: 0
absolutely acting bits casting cheap close come comments completely c
ouldve did direction edge end film gone humor intense literally littl
e loved mediocre movie number perfect phone points read rest ring sca
ry script second spot story thrill time years
Prediction: 0
 Class: 1
ann cause characters comedy compared computer connection considered d
ay days did dont end entertainment ex fight film films flight future
george given going got hand having help hes home human including inst
ead isnt issue just kids kill killed know lesson life like live losin
g lost love make making man matter maybe meets money necessary people
pictures plan plays plot prior project rich school sets shows stars s
tep street streets stupid technology tender theyre things think throw
n treasure used using vote wall wants war wasnt woman work world writ
ten years young
```

```
Prediction: 0
 Class: 1
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
film forgotten late little long makers money movie night present subt
le time todays tv
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 word from previous words and is failing to learn from the sentence as a whole.

In [ ]: