Logistic Regression with a Neural Network mindset

Build a logistic regression classifier to recognize cats.

Process

- Build the general architecture of a learning algorithm, including:

  - Initializing parameters

  - Calculating the cost function and its gradient

  - Using an optimization algorithm (gradient descent)

- Gather all three functions above into a main model function, in the right order.

−Analyse the results and conclude

Packages Used

- [numpy](www.numpy.org) is the fundamental package for scientific computing with Python.

- [h5py](http://www.h5py.org) is a common package to interact with a dataset that is stored on an H5 file.

- [matplotlib](http://matplotlib.org) is a famous library to plot graphs in Python.

- [PIL](http://www.pythonware.com/products/pil/) and [scipy](https://www.scipy.org/) are used here to test model with your own picture at the end.

Overview of the Problem set

given a dataset ("data.h5") containing:

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

  - a test set of m_test images labeled as cat or non-cat

  - each image is of shape (num_px, num_px, 3) where 3 is for the 3 channels (RGB). Thus, each image is square (height = num_px) and (width = num_px).

AIM

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

Pre processing

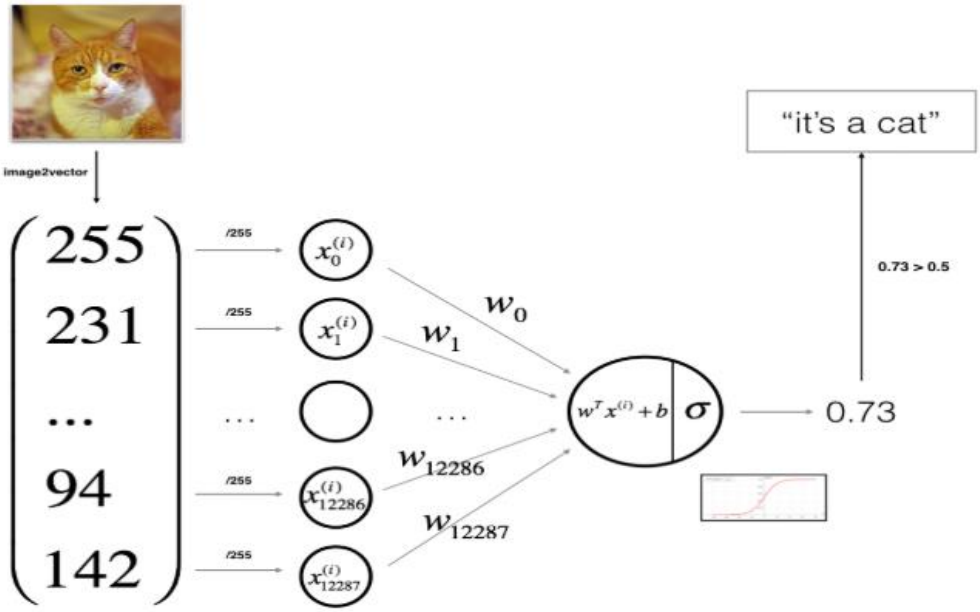
- Reshaping the training and test data sets so that images of size (num_px, num_px, 3) are flattened into single vectors of shape (num_px $*$ num_px $*$ 3, 1)

```
# Reshape the training and test examples


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


print ("train_set_x_flatten shape: " + str(train_set_x_flatten.shape))
print ("train_set_y shape: " + str(train_set_y.shape))
print ("test_set_x_flatten shape: " + str(test_set_x_flatten.shape))
print ("test_set_y shape: " + str(test_set_y.shape))
print ("sanity check after reshaping: " + str(train_set_x_flatten[0:5,0]))
```

- Center and standardize your dataset, meaning that you substract the mean of the whole numpy array from each example, and then divide each example by the standard deviation of the whole numpy array. But for picture datasets, it is simpler and more convenient and works almost as well to just divide every row of the dataset by 255 (the maximum value of a pixel channel)

```
train_set_x = train_set_x_flatten/255.
test_set_x = test_set_x_flatten/255.
```

General Architecture of the learning algorithm



Mathematical expression of the algorithm:

For one example $x^{(i)}$:

$$z^{(i)} = w^T x^{(i)} + b$$
$$\hat{y}^{(i)} = a^{(i)} = sigmoid(z^{(i)})$$
$$\mathcal{L}(a^{(i)}, y^{(i)}) = -y^{(i)} \log(a^{(i)}) - (1 - y^{(i)}) \log(1 - a^{(i)})$$

The cost is then computed by summing over all training examples:

$$J = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(a^{(i)}, y^{(i)})$$

Building the parts of our algorithm

The main steps for building a Neural Network are:

1. Define the model structure (such as number of input features)
2. Initialize the model's parameters
3. Loop:
    - Calculate current loss (forward propagation)
    - Calculate current gradient (backward propagation)
    - Update parameters (gradient descent)

You often build 1-3 separately and integrate them into one function we call model().-

-defining Sigmoid Function

$$sigmoid(w^T x + b) = \frac{1}{1+e^{-(w^T x+b)}}$$

```
# sigmoid

def sigmoid(z):
    """
    Compute the sigmoid of z

    Arguments:
    z -- A scalar or numpy array of any size.

    Return:
    s -- sigmoid(z)
    """


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


    return s
```

-Initializing Parameters with 0

```
def initialize_with_zeros(dim):
    """
    This function creates a vector of zeros of shape (dim, 1) for w and initializes b to 0.

    Argument:
    dim -- size of the w vector we want (or number of parameters in this case)

    Returns:
    w -- initialized vector of shape (dim, 1)
    b -- initialized scalar (corresponds to the bias)
    """


    w = np.zeros((dim,1))
    b = np.zeros(1)


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

    return w, b
```

Forward and Backward propagation

Forward Propagation:

- You get X
- You compute $A = \sigma(w^T X + b) = (a^{(1)}, a^{(2)}, \ldots, a^{(m-1)}, a^{(m)})$
- You calculate the cost function: $J = -\frac{1}{m}\sum_{i=1}^{m} y^{(i)} \log(a^{(i)}) + (1 - y^{(i)}) \log(1 - a^{(i)})$

Here are the two formulas you will be using:

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

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

Optimization

The goal is to learn w and b by minimizing the cost function J. For a parameter θ, the update rule is $\theta = \theta - \alpha\, d\theta$, where α is the learning rate.

Prediction

Use w and b to predict the labels for a dataset X. Implement the `predict()` function. There are two steps to computing predictions:

1. Calculate $\hat{Y} = A = \sigma(w^T X + b)$
2. Convert the entries of a into 0 (if activation <= 0.5) or 1 (if activation > 0.5), stores the predictions in a vector `Y_prediction`.

Merge all Functions into a Model

Implement the model function.Following notation is used:

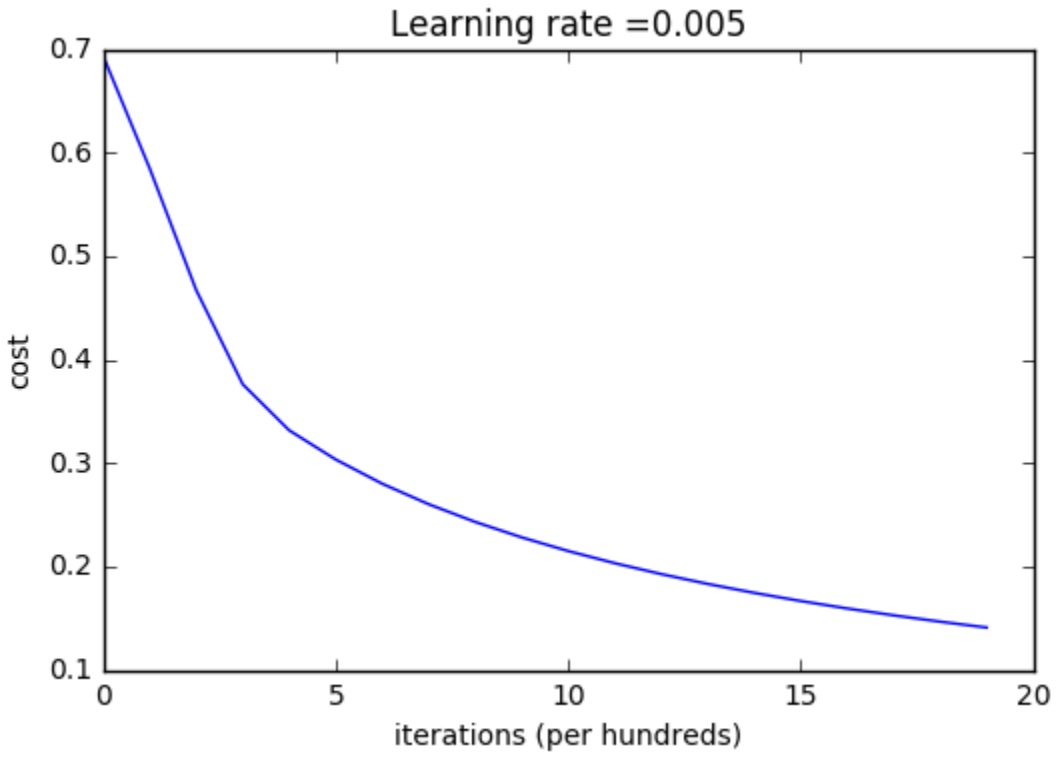
```
- Y_prediction_test for your predictions on the test set
- Y_prediction_train for your predictions on the train set
- w, costs, grads for the outputs of optimize()
```

Run the model

```
d = model(train_set_x, train_set_y, test_set_x, test_set_y, num_iterations = 2000, learning_rate = 0.005, print_cost = True)
```

```
Cost after iteration 0: 0.693147
Cost after iteration 100: 0.584508
Cost after iteration 200: 0.466949
Cost after iteration 300: 0.376007
Cost after iteration 400: 0.331463
Cost after iteration 500: 0.303273
Cost after iteration 600: 0.279880
Cost after iteration 700: 0.260042
Cost after iteration 800: 0.242941
Cost after iteration 900: 0.228004
Cost after iteration 1000: 0.214820
Cost after iteration 1100: 0.203078
Cost after iteration 1200: 0.192544
Cost after iteration 1300: 0.183033
Cost after iteration 1400: 0.174399
Cost after iteration 1500: 0.166521
Cost after iteration 1600: 0.159305
Cost after iteration 1700: 0.152667
Cost after iteration 1800: 0.146542
Cost after iteration 1900: 0.140872
train accuracy: 99.04306220095694 %
test accuracy: 70.0 %
```

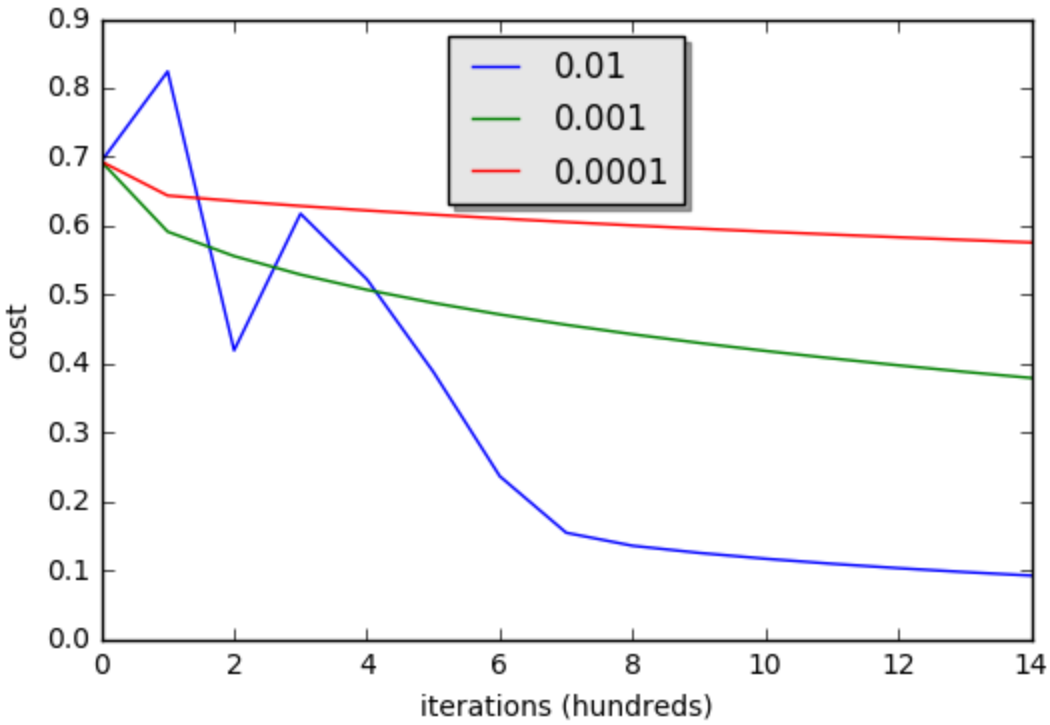
Plotting Learning curve



Trying different values of learning rates

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

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

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

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

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

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

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

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

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

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



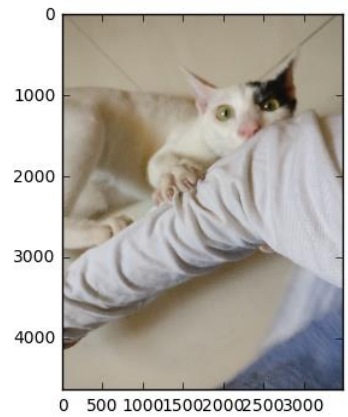
It can be seen that

- Different learning rates give different costs and thus different predictions results.
- If the learning rate is too large (0.01), the cost may oscillate up and down. It may even diverge (though in this example, using 0.01 still eventually ends up at a good value for the cost).
- A lower cost doesn't mean a better model. You have to check if there is possibly overfitting. It happens when the training accuracy is a lot higher than the test accuracy.

Trying my own Cats Image

```
## Trying your won image
my_image = "kitkat3.jpg"   # change this to the name of your image file


# preprocess the image to fit your algorithm.
fname = "images/" + my_image
image = np.array(ndimage.imread(fname, flatten=False))
my_image = scipy.misc.imresize(image, size=(num_px,num_px)).reshape((1, num_px*num_px*3)).T
my_predicted_image = predict(d["w"], d["b"], my_image)

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

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



Results

1) Training accuracy is close to 100%. Model is working and has high enough capacity to fit the training data.

2) Test error is 68%, which is not bad given the small size of dataset used and given that logistic regression is a linear classifier.

3)The model is clearly overfitting on the training data and hence we should be using techniques like regularization to reduce it.