Notebook

Binary Image Classification using Logistic regression

overview

in Binary Classification your are provided with attribute and you have to predict whether the tuple belongs to tha
example for an image

you have to predict whether it belongs to that class(yhat = 1) or not (yhat = 0) in this case the class label is a ca

and we are going to this with logistic regression the basic idea behind logistic regression is a follows

given x you have to find $\hat{y}$ = P$(y = 1|x)$
wheer P$(y = 1|x)$ is the probability of class label y to be 1 given x

so we will start by looking at our dataset but before that we need to import the important modules

theses are

- numpy
- matplotlib
- PIL and SciPy for reading image data
- h5py for loading h5 files

```
import numpy as np
import matplotlib.pyplot as plt
import os
from PIL import Image
from scipy import ndimage
import h5py
import scipy
import PIL
```

```
import warnings

warnings.filterwarnings("ignore")
```

our data is in the form of h5 files so we need to first create a method to load this dataset into proper format usi

```
train_data = h5py.File('/content/train_catvnoncat.h5' , "r" )
train_set_x_real = np.array(train_data['train_set_x'][:])
train_set_y_real = np.array(train_data['train_set_y'][:])

test_data = h5py.File("/content/test_catvnoncat.h5" , "r")
```

```
test_set_x_real = np.array(test_data["test_set_x"][:])
test_set_y_real = np.array(test_data["test_set_y"][:])

classes = np.array(test_data["list_classes"][:])

train_set_y_real = train_set_y_real.reshape(1, train_set_y_real.shape[0])
test_set_y_real = test_set_y_real.reshape(1, test_set_y_real.shape[0])
```

so now our data set is loaded

- train_set_x_real
- train_set_y_real
- test_set_x_real
- test_set_y_real

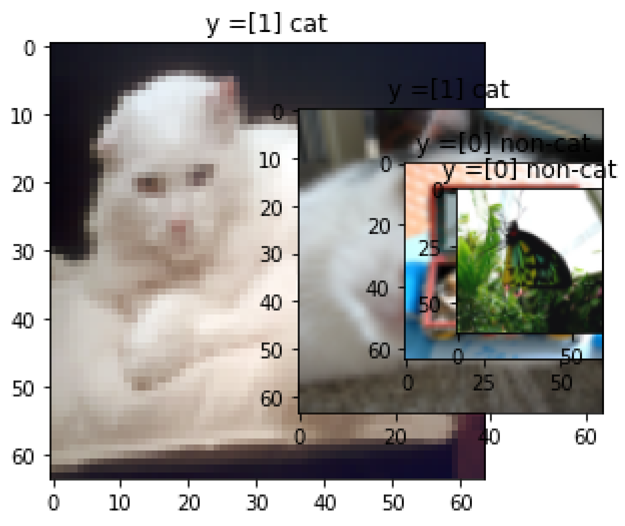
now lets look at some example images

```
index = 13

fig = plt.figure()
x = 1
for i in range(index , index+4):
    ax = fig.add_subplot(1 , x, x)
    ax.imshow(train_set_x_real[i])
    ax.set_title("y =" + str(train_set_y_real[:,i]) +" "+ classes[np.squeeze(train_set_y_real[:,i])
    x+= 1

fig.tight_layout(pad=10)
fig.show()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:11: UserWarning: tight_layout not app
  # This is added back by InteractiveShellApp.init_path()
```



now lets move further

first look at the shape of our images and datasets

```
print("# images in our training set = " + str(train_set_x_real.shape[0]))
print("# images in our testing set = " + str(test_set_x_real.shape[0]))
print("# pixels in each channel (R,G,B) = " + str(train_set_x_real.shape[1]))
print("shape of training images = " + str(train_set_x_real.shape))
print("shape of training labels = " + str(train_set_y_real.shape))
print("shape of testing images = " + str(test_set_x_real.shape))
print("shape of testing labels = " + str(test_set_y_real.shape))
```

```
# images in our training set = 209
```

so we can see that each image is of the shape $(64, 64, 3)$ but we need to convert it into a vector o $(64 * 64 * 3, 1)$

this is called flattening the image so lets do it

so for our whole training set with shape $(209, 64, 64, 3)$ we have convert it into the shape $(64 * 64 * 3, 209)$ for our testing set

```python
train_set_x_real = train_set_x_real.reshape(train_set_x_real.shape[0] , -1).T
test_set_x_real = test_set_x_real.reshape(test_set_x_real.shape[0] , -1).T
```

now lets look at the shape

```python
print("shape of training set = " + str(train_set_x_real.shape))
print("shape of testing set = " + str(test_set_x_real.shape) )
```

```
shape of training set = (12288, 209)
shape of testing set = (12288, 50)
```

logistic regression consist of two processes *forward propagation* and *backward propagation*

forward propagation

it computes yhat using the equation

$$\hat{y} = \sigma(z)$$

where $z = w^T . x + b$,
w is the weight matrix and b is the bias
and $\sigma(x)$ is the sigmoid function that is $\sigma(x) = \frac{1}{1+e^{-x}}$
and compute cost using

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

where J is the cost and

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

backward propagation

computes derivatives for gradient descent to update and optimise the parameters w and b

$$\frac{\partial J}{\partial w} = \frac{1}{m} X(A - Y)^T$$
$$\frac{\partial J}{\partial b} = \frac{1}{m} \sum_{i=1}^{m} (a^{(i)} - y^{(i)})$$

where J is the total cost

first lets create the sigmoid function

```python
def sigmoid(z):
    """
    computes sigmoid of z
    """
    result = 1 / (1 + np.exp(-z))
    return result

#test
sigmoid(54)
```

```
1.0
```

now first we need to initialize the weight and bias with zeroes

```python
def initialize_params(dims):
    """
    dims = size of w
    """
    w = np.zeros((dims , 1))
    b = 0
    return w , b
```

```python
def propagate(w , b, X , Y):
    """
    w - wieght
    b - bias
    X - training data
    Y - training labels

    retrun
    J - total cost
    dw - derivative of J w.r.t.  'w'
    db - derivative of J w.r.t.  'b"

    """
    m = X.shape[0]

    ## forward prop
    A = sigmoid(np.dot(w.T , X) + b)

    cost = -(np.sum(Y*np.log(A) + (1-Y)*np.log(1-A)))/ m

    ## backward prop
    dw = (np.dot(X , (A-Y).T))/m
    db = (np.sum(A - Y))/m

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

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

    return grads , cost


```

now lets create the function for gradient descent which will optimize our parameters

as follows

$$w = w - \alpha * dw$$
$$b = b - \alpha * db$$

where α is the learning rate and this process iterate multiple times

```python
def optimize_parameters(w , b, X , Y , num_iteration = 2000 , learning_rate = 0.05):
    """
    return - grads , parama optimized , cost reduced
    """
    costs  = []
    for i in range(num_iteration):
        grads , cost = propagate(w , b, X,Y)
        dw = grads["dw"]
        db = grads["db"]

        w = w - learning_rate*dw
        w = w - learning_rate*db

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

    params = {"w" : w , "b":b}
    grads = {"dw" : dw , "db" : db}

    return params , grads , costs

```

```
w, b, X, Y = np.array([[1.],[2.]]), 2., np.array([[1.,2.,-1.],[3.,4.,-3.2]]), np.array([[1,0,1]])
params, grads, costs = optimize_parameters(w, b, X, Y, num_iteration= 100, learning_rate = 0.009)
costs
```

```
[8.70231797909183]
```

now lets create the predict method to predict the labels for our testing set

```
def predict(w , b, X):
    m = X.shape[1]
    y_preds = np.zeros((1, m))
    w = w.reshape(X.shape[0] , 1)

    A = sigmoid(np.dot(w.T , X) + b)

    for i in range(A.shape[1]):
        y_preds[0, i] = np.round(A[0, i])

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

    return y_preds
```

so now all our methods are ready now lets combine this to form our model

```
def log_reg_model(X_train , Y_train , X_test , Y_test , num_iteration = 2000 , learning_rate = 0.05
    dim = X_train.shape[0]
    w , b = initialize_params(dim)

    params , grads , costs = optimize_parameters(w, b, X_train , Y_train , num_iteration , learning_
    w = params["w"]
    b = params["b"]

    y_pred_test = predict(w , b, X_test)
    y_pred_train = predict(w , b, X_train)

    test_accuracy = 100 - np.mean(np.abs(y_pred_test - Y_test)) * 100
    train_accuracy = 100 - np.mean(np.abs(y_pred_train - Y_train)) * 100

    print("train accuracy = " + str(train_accuracy) +"%")
    print("test accuracy = " + str(test_accuracy) + "%")

    cache = {
        "w": w,
        "b":b,
        "costs": costs,
        "y_prediction_test": y_pred_test,
        "y_prediction_train": y_pred_train,
        "learning_rate":learning_rate,
        "num_iteration" : num_iteration
    }

    return cache
```

so now our model is ready we can now apply it to our data set

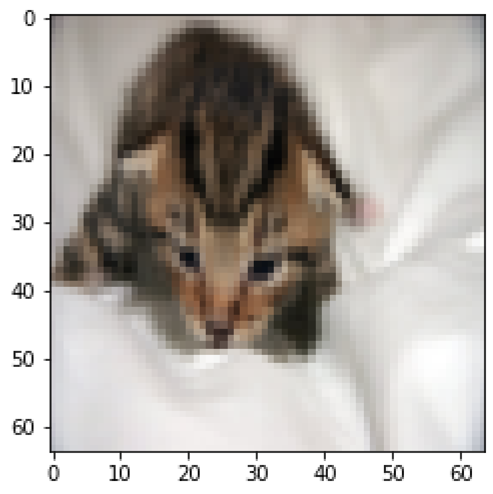
```
cache = log_reg_model(train_set_x_real , train_set_y_real , test_set_x_real , test_set_y_real)
```

```
train accuracy = 100.0%
test accuracy = 72.0%
```

now lets look at the prediction of opur model

```
num_px = 64
index = 1
plt.imshow(test_set_x_real[:, index].reshape(num_px , num_px , 3))
print("y = "+ str(test_set_y_real[0,index]) + " prediction = " + str(cache["y_prediction_test"][0,ir
```

```
y = 1 prediction = 1.0
```

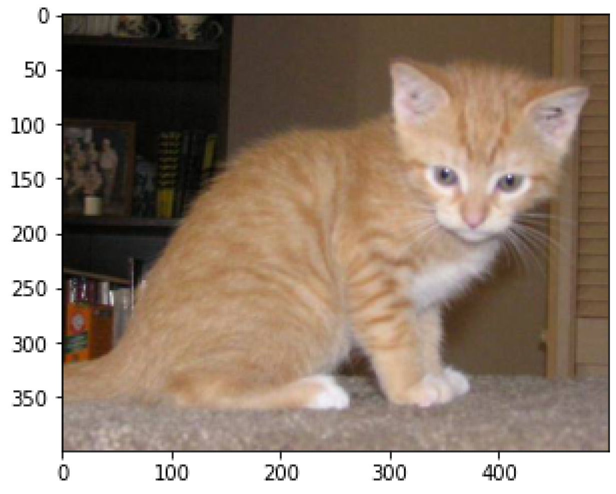


now lets test our model on a random image

```
my_image = "/content/dataset/test_set/cats/cat.4003.jpg"
image = np.array(plt.imread(my_image))
#my_image = scipy.misc.imresize(image, size=(num_px,num_px)).reshape((1, num_px*num_px*3)).T
my_image = np.array(Image.fromarray(image).resize((num_px , num_px))).reshape((1 , num_px *num_px *
my_predicted_image = predict(cache["w"], cache["b"], my_image)

plt.imshow(image)
print("predicted  = " + str(my_predicted_image))
```

```
predicted  = [[1.]]
```



lets create a flatten image method which will help us to flatten and resize any external image according to mod

```
def flatten(path):
    image = np.array(plt.imread(path))
    im_flatten = np.array(Image.fromarray(image).resize((num_px , num_px))).reshape((1 , num_px *nur

    return image , im_flatten
```

now this is it our model using logistic regression is ready

```
! nbconvert Binary Image Classification using Logistic regression.ipynb
```

```
/bin/bash: nbconvert: command not found
```