# Week2 Report

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#### Abstract

This time, I put my effort on coding, setting environment of python, and spend efforts on using VS Code which treats me most friendly.

To sum up what I have down this week, it can be concluded as below:

- 1. Reset the operation system for 3 times, because I have so messed up installing the extentions
  - 2. Learning to use VS Code to code everything, python, c++, markdown, and latex
  - 3. Find the homework of Deeplearning and code them.

Summary: I hate this week

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## 1 Homework First

### 1.1 Building basic functions with numpy

Numpy is the main package for scientific computing in Python. It is maintained by a large community (www.numpy.org). In this exercise you will learn several key numpy functions such as np.exp, np.log, and np.reshape. You will need to know how to use these functions for future assignments.

 $sigmoid(x) = \frac{1}{1+e^{-x}}$  (also known as the logistic function)

```
import numpy as np
#Exercise_1: Implement the sigmoid function using numpy.

def sigmod(x):
    s=1/(1+np.exp(x))
    return s

x=np.array([1,2,3])
print ("sigmod is "+str(sigmod(x)))
```

## 1.2 Sigmoid gradient

Implement the function sigmoid\_grad to compute the gradient of the sigmoid function with respect to its input x. The formula is:

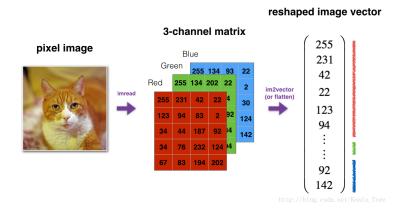
```
sigmoid_derivative(x) = \sigma(x) = \sigma'(x) (1 - \sigma(x))
```

```
def sigmoid_derivative(x):
    s=sigmod(x)
    ds=s*(1-s)
    return ds
print("sigmoid_derivative is "+str(sigmoid_derivative(x)))
```

#### 1.3 Reshaping arrays

Two common numpy functions used in deep learning are np.shape and np.reshape().

- X.shape is used to get the shape (dimension) of a matrix/vector X.
- X.reshape() is used to reshape X into some other dimension.



#### [htbp]

```
def image2vector(image):
    res = image.reshape((image.shape[0] * image.shape[1] * image.shape[2], 1))
image = np.array([[[ 0.67826139,  0.29380381],
        [ 0.90714982, 0.52835647], [ 0.4215251, 0.45017551]],
       [[ 0.92814219, 0.96677647],
          0.85304703,
                        0.52351845]
        [ 0.19981397,
                        0.27417313]],
       [[ 0.60659855,
                        0.00533165],
        [ 0.10820313, 0.49978937],
[ 0.34144279, 0.94630077]]])
print("image reshaped like this "+"\n"+str(image2vector(image)))
##### And result returns:
image2vector(image) = [[ 0.67826139]
 [ 0.29380381]
 [ 0.90714982]
 [ 0.52835647]
 [ 0.4215251 ]
 [ 0.45017551]
 [ 0.92814219]
 [ 0.96677647]
 [ 0.85304703]
 [ 0.52351845]
 [ 0.19981397]
 [ 0.27417313]
 [ 0.60659855]
 [ 0.00533165]
 [ 0.10820313]
 [ 0.49978937]
 [ 0.34144279]
 [ 0.94630077]]
```

### 1.4 Broadcasting

A very important concept to understand in numpy is broadcasting. It is very useful for performing mathematical operations between arrays of different shapes. For the full details on broadcasting, you can read the official broadcasting documentation.

#### 1.5 Implement the L1 and L2 loss functions

Implement the numpy vectorized version of the L1 loss. You may find the function abs(x) (absolute value of x) useful.

```
import numpy as np
def L1(yhat, y):
    loss = np.sum(np.abs(y - yhat))
    return loss
yhat = np.array([.9, 0.2, 0.1, .4, .9])
y = np.array([1, 0, 0, 1, 1])
print("L1 = " + str(L1(yhat,y)))
#########---L1---#######
def L2(yhat, y):
    loss =np.sum(np.power((y - yhat), 2))
    return loss
yhat = np.array([.9, 0.2, 0.1, .4, .9])
y = np.array([1, 0, 0, 1, 1])
print("L2 = " + str(L2(yhat,y)))
```

### 2 Logistic Regression with a Neural Network mindset

#### Abstract

- numpy is the fundamental package for scientific computing with Python.
- h5py is a common package to interact with a dataset that is stored on an H5 file.
- matplotlib is a famous library to plot graphs in Python.
- PIL and scipy are used here to test your model with your own picture at the end.

```
### Fllows are packages
import numpy as np
{\color{red} {\tt import}} \ {\color{blue} {\tt matplotlib.pyplot}} \ {\color{blue} {\tt as}} \ {\color{blue} {\tt plt}}
import h5py
import scipy
from PIL import Image
from scipy import ndimage
from lr_utils import load_dataset
### Load Data
### load_dataset
train_set_x_orig, train_set_y, test_set_x_orig, test_set_y, classes = load_dataset
index = 25
plt.imshow(train_set_x_orig[index])
print ("y = " + str(train_set_y[:, index]) + ", it's a '" + classes[np.squeeze(
                                                 train_set_y[:, index])].decode("utf-8") +
                                                    "' picture.")
```

```
#####Fllows are lr_utils.py
import numpy as np
import h5py
def load_dataset():
   train_dataset = h5py.File('datasets/train_catvnoncat.h5', "r")
   train_set_x_orig = np.array(train_dataset["train_set_x"][:]) # your train set
                                            features
   train_set_y_orig = np.array(train_dataset["train_set_y"][:]) # your train set
                                             labels
   test_dataset = h5py.File('datasets/test_catvnoncat.h5', "r")
   test_set_x_orig = np.array(test_dataset["test_set_x"][:]) # your test set
                                             features
   test_set_y_orig = np.array(test_dataset["test_set_y"][:]) # your test set
   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,
```

# 3 Summary

The vedios are easy to get through, and the new concepts to be understand are not that difficult, but to program it is really challenging.

However, the most challenging part is to build the proper environment, and make sure your OS is in healthy condition.