EN2550_190621M_Exercise10

May 18, 2022

0.1 Exercise-10

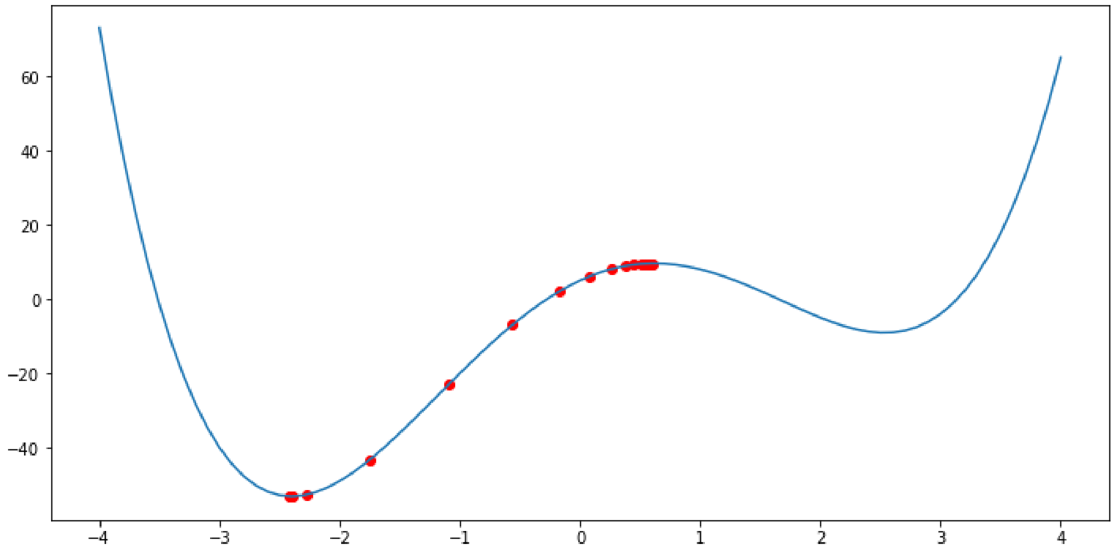
0.2 Index No - 190621M

0.3 Name - K. Thanushan

[ ]:
```python
import numpy as np
import matplotlib.pyplot as plt

def f(x):
    w = np.array([1,-1,-12,15,5])
    M = np.size(w)-1
    return np.sum([x**i*w[M-i] for i in range(0,M+1)], axis=0)

def g(x):
    w = np.array([1,-1,-12,15,5])
    M = np.size(w)-1
    return np.sum([i*x**(i-1)*w[M-i] for i in range(0,M+1)], axis=0)

alpha = 0.02
x = 0.6
x_hist = np.array(x)
fx_hist = np.array(f(x))
for i in range(20):
    x = x - alpha*g(x)
    x_hist= np.append(x_hist, x)
    fx_hist= np.append(fx_hist, f(x))

print('x= ',x,'f(x) = ',f(x))

fig = plt.figure(figsize = (12,6))
ax = plt.subplot(1,1,1)
delta = 0.1
x_ = np.arange(-4,4+delta,delta)
ax.plot(x_,f(x_))
ax.scatter(x_hist,fx_hist, c='r')
```

```
x=  -2.4003994283530288 f(x) =  -53.11840483760499
```

[ ]: <matplotlib.collections.PathCollection at 0x107f819c100>



Setting the initial value is very important because setting the correct initial value helps gradient descent to identify the correct minimum value. If the value is not selected exactly, the gradient descent will guide to the wrong answer.

Learning rate should be selected accurately, if the learning rate is very large, gradient descent will overshoot and the minimum value cannot be accurately found. If the learning rate is very small the gradient descent will be slow and the wrong minimum value is found. Therefore, the correct value for the learning rate should be selected.

[ ]:
```
import ssl
ssl._create_default_https_context = ssl._create_unverified_context
```

[ ]:
```
import numpy as np
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
from tensorflow.keras.datasets import cifar10, mnist

(x_train, y_train), (x_test, y_test) = cifar10.load_data( )
# ( x_train , y _ t r a i n ) , ( x _ t e s t , y _ t e s t ) = mnist .␣
↪load_data ( )
print( "x_train => " , x_train.shape)

Ntr = x_train.shape[0]
Nte = x_test.shape[0]
Din = 3072 # CIFAR10
# Din = 784 # MINIST
```

```
x_train = x_train[range(Ntr), : ]
x_test = x_test[range(Nte), :]
y_train = y_train[range(Ntr)]
y_test =y_test[range(Nte)]



# Utility function for displaying
def display(y_train, y_test, y_train_pred, y_test_pred, loss_history, w, showim␣
↪= True):
    plt.plot(loss_history)


     # For diapaying the weights matrix w as an image. 32*32*3 assumption is␣
↪there
    if showim:
        f, axarr = plt.subplots(2, 5)
        f.set_size_inches(16, 6)
        for i in range(10):
            img = w[:, i].reshape(32, 32, 3)# CIFAR10
            # img = w1[:, i].reshape(28, 28)# MNIST
            img = (img - np.amin(img))/(np.amax(img) - np.amin(img))
            axarr[i//5, i%5].imshow(img)
        plt.show()

    train_acc = np.mean(np.abs(np.argmax(y_train, axis=1) == np.
↪argmax(y_train_pred, axis=1)))
    print("train_acc = ", train_acc)

    test_acc = np.mean(np.abs(np.argmax(y_test, axis=1) == np.
↪argmax(y_test_pred, axis=1)))
    print("test_acc = ", test_acc)
```

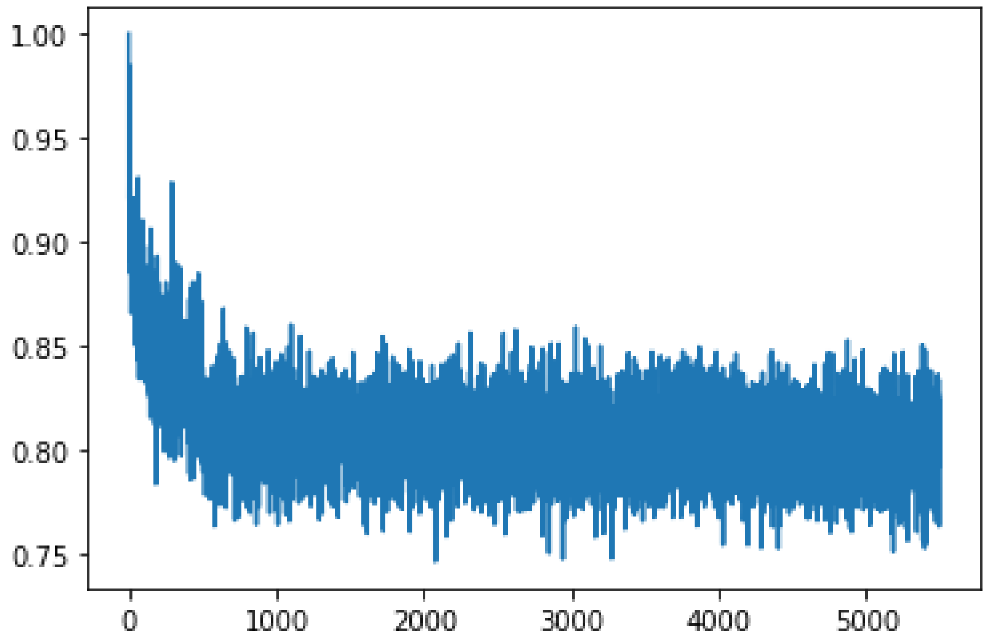
```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==============================] - 259s 2us/step
x_train =>  (50000, 32, 32, 3)
```

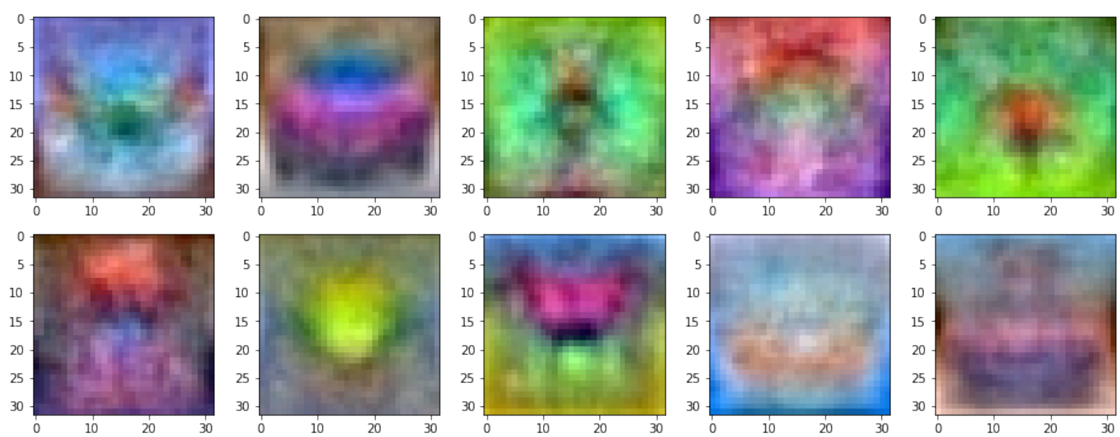
[ ]:
```
K = len(np.unique(y_train))
y_train = tf.keras.utils.to_categorical(y_train,num_classes=K)
y_test = tf.keras.utils.to_categorical(y_test,num_classes=K)
x_train = np.reshape(x_train,(Ntr,Din))
x_test = np.reshape(x_test,(Nte,Din))
x_train = x_train.astype(np.float32)
x_test = x_test.astype(np.float32)
x_train/= 255.
x_test/= 255.
```

[ ]:
```
std = 1e-5
w = std*np.random.randn(Din, K)
b = np.zeros(K)
lr = 1e-3
lr_decay = 0.1
epochs = 11
batch_size = 100
loss_history = []
rng = np.random.default_rng(seed = 0)

for e in range(epochs):
    indices = np.arange(Ntr)
    rng.shuffle(indices)
    for batch in range(Ntr//batch_size):
        batch_indices = indices[batch*batch_size:(batch+1)*batch_size]
        x = x_train[batch_indices] #Extract a bath of 100
        y = y_train[batch_indices]

        #Forward pass
        y_pred = x@w + b
        loss = 1./batch_size*np.square(y_pred - y).sum()
        loss_history.append(loss)

        #Backward pass
        dy_pred = 1./batch_size*2.0*(y_pred - y)
        dw = x.T @ dy_pred
        db = dy_pred.sum(axis=0)*1
        w = w - lr*dw #dw is partial derivative of L with respect to w
        b = b - lr*db

    if e % 5 == 0:
        print('Iteration %d / %d: loss %f' %(e, epochs, loss))
    if e % 10 == 0:
        lr *= lr_decay
```

```
Iteration 0 / 11: loss 0.813446
Iteration 5 / 11: loss 0.802915
Iteration 10 / 11: loss 0.804667
```

[ ]:
```
y_train_pred = x_train.dot(w) + b
y_test_pred = x_test.dot(w) + b
display(y_train, y_test, y_train_pred, y_test_pred, loss_history, w, showim =␣
↪True)
```





```
train_acc =  0.39566
test_acc =  0.388
```