Question 2:

It was asked to impelment back propogation algorithm from scratch(Using Numpy) on MNIST Dataset.

Approach:

First I tried to implement Stochastic Gradient descent(SGD) from scratch, In SGD we update model weight after every forward propogation of each sample in Training set.I have used sum of square differene as my Error Function, I have trained my model for 20 epoch and for total 2000 sample....I have stored error after every iteration and then plotted Cost function vs Iteration plot. As expected it is clearly visible from plot that SGD is not at all smooth. That is because it responds to the effects of each and every sample ,this can be a benefit if we stuckedin between local minima.....SGD will come out of it and try to converge at optimal minima.

Then as asked in Question I have tried to implement Batch gradient descent....very first thing I like to mentioned that ,it is clearly visible from results that to reach optimal point for minima we need to perform so many iteration as compared to SGD. What make batch grad descent different from SGD is here we update weight after every epoch(after passing all sample from training data ,we accumulate error and back propogate average of that error)

Finally one more thing I would like to mentioned that when I implement SGD from scratch I got reliable result(Confusion matrix Looks good),But when I implement Batch gradient descent I need to perform so many iteration but still result what I am getting is not like SGD.

In [0]:

```
import keras
from keras.datasets import mnist
import matplotlib.pyplot as PLT
import numpy as NP
import seaborn as SNS
```

- From Keras I have Imported MNIST Dataset

In [0]:

```
(X_TRAIN,Y_TRAIN),(X_TEST,Y_TEST)=mnist.load_data()
```

- We have 60K sample as Training Data and 10K sample as Test data.

In [25]:

```
print("Type Of TRAIN DATA: {}".format(type(X_TRAIN)))
print("SHAPE OF TRAIN DATA : {}".format(X_TRAIN.shape))
print("Type Of TEST DATA: {}".format(type(X_TEST)))
print("SHAPE OF TEST DATA : {}".format(X_TEST.shape))
```

```
Type Of TRAIN DATA: <class 'numpy.ndarray'>
SHAPE OF TRAIN DATA : (60000, 28, 28)
Type Of TEST DATA: <class 'numpy.ndarray'>
SHAPE OF TEST DATA : (10000, 28, 28)
```

- Normalizing Train and Test DATA

In [0]:

```
X_TRAIN = X_TRAIN/255.0
X_TEST = X_TEST/255.0
```

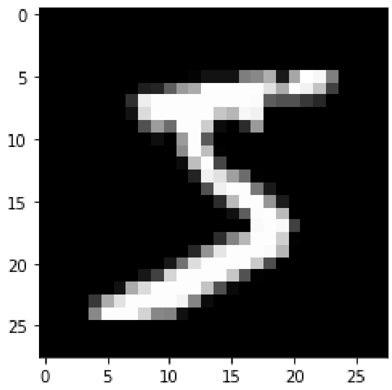
- Just Printing very first Train smaple point and label correspond to it.

In [27]:

```
PLT.imshow(X_TRAIN[0],'gray')
```

Out[27]:

```
<matplotlib.image.AxesImage at 0x7f827a7580b8>
```



- Converting Labels into One hot encoding.

In [0]:

```
Y_TEST = keras.utils.to_categorical(Y_TEST,num_classes=10,dtype='int32')
Y_TRAIN = keras.utils.to_categorical(Y_TRAIN,num_classes=10,dtype='int32')
```

In [29]:

```
Y_TRAIN[0]
```

Out[29]:

```
array([0, 0, 0, 0, 0, 1, 0, 0, 0, 0], dtype=int32)
```

Weight Initialization:

In [0]:

```
WT_1 = NP.random.normal(0,1,(784,150))

WT_2 = NP.random.normal(0,1,(150,100))
WT_3 = NP.random.normal(0,1,(100,50))
WT_4 = NP.random.normal(0,1,(50,10))
```

MODEL : 3 hidden layer

Layer 1: 150 neurons

Layer 2 : 100 neurons

Layer 3: 50 neurons

Activation function: Sigmoid.

Optimizer: SGD

Output LAyer: 10 neuron of Sigmoid.

Implementing SGD:

In [0]:

```
import timeit
start_time = timeit.default_timer()

ERR=[]
VALUE=0
for epoc in range(0,20):
```

```
  #print(epoc)
  #if VALUE!=0:
   # VALUE =VALUE/100
    #ERR.append(VALUE)
  VALUE=0
  for sample in range(0,2000):

    IP = NP.reshape(X_TRAIN[sample],(784,1))
    Z1 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_1),IP)))
    Z2 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_2),Z1)))
    Z3 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_3),Z2)))
    Z4 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_4),Z3)))


    LOCAL_ERROR = Z4-Y_TRAIN[sample].reshape(10,1)
    VALUE=VALUE+0.5*NP.sum(((LOCAL_ERROR)**2))
    ERR.append(VALUE)

    TEMP1 =NP.zeros((50,10))
    for i in range(0,10):
      TEMP1[:,i] = Z4[i]*(1-Z4[i])
    DIF_Z4_W4 = TEMP1*Z3
    UP_WT_4 = WT_4-(0.2)*(NP.transpose(LOCAL_ERROR)*DIF_Z4_W4)



    B=NP.dot(NP.transpose(LOCAL_ERROR),NP.transpose((WT_4*TEMP1)))
    TEMP2 =NP.zeros((100,50))
    for i in range(0,50):
      TEMP2[:,i] = Z3[i]*(1-Z3[i])
    UP_WT_3 = WT_3-(0.2)*B*(TEMP2*Z2)



    C=NP.dot(B,NP.transpose(TEMP2*WT_3))
    TEMP3 =NP.zeros((150,100))
    for i in range(0,100):
      TEMP3[:,i] = Z2[i]*(1-Z2[i])
    UP_WT_2=WT_2-(0.2)*C*(TEMP3*Z1)



    D=NP.dot(C,NP.transpose((TEMP3*WT_2)))
    TEMP4 =NP.zeros((784,150))
    for i in range(0,150):
      TEMP4[:,i] = Z1[i]*(1-Z1[i])
    UP_WT_1=WT_1-(0.2)*D*(TEMP4*NP.reshape(X_TRAIN[sample],(784,1)))
    WT_1 = UP_WT_1
    WT_2 = UP_WT_2
    WT_3 = UP_WT_3
    WT_4 = UP_WT_4


elapsed = timeit.default_timer() - start_time
```

In [102]:

```
print(f"Time Required To run Cell : {elapsed}")
```

```
Time Required To run Cell : 134.76489311000114
```

In [103]:

```
len(ERR)
```

Out[103]:

```
40000
```

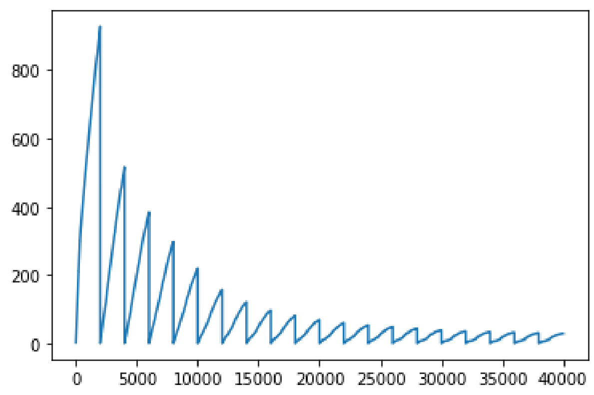
COST VS iteration

In [104]:

```
X=list(range(1,40001))
PLT.plot(X,ERR)
```

Out[104]:

```
[<matplotlib.lines.Line2D at 0x7fa0f4a10208>]
```



In [0]:

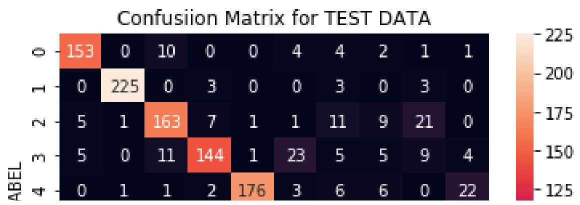
```
# FFN
# PREDICTION
PRED_LABEL=[]
ACTUAL_LABEL=[]
Y=[]
for sample in range(0,2000):
  IP = NP.reshape(X_TEST[sample],(784,1))
  Z1 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_1),IP)))
  Z2 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_2),Z1)))
  Z3 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_3),Z2)))
  Z4 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_4),Z3)))
  PRED_LABEL.append(NP.argmax(Z4))
  ACTUAL_LABEL.append(NP.argmax(Y_TEST[sample]))
  #print(NP.argmax(Z4),NP.argmax(Y_TEST[sample]))
```

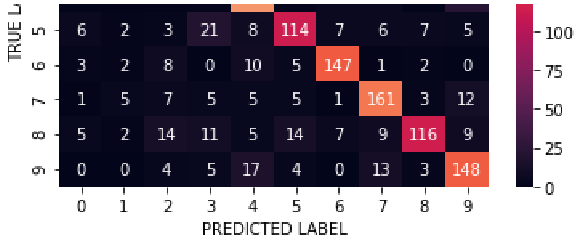
In [0]:

```
# This Function will take input as PRED_LABEL and ACTUAL LABEL return Confusion MATRIX.
def CONFUSION_MATRIX(PRED_LABEL,Y_TEST):
    from sklearn.metrics import confusion_matrix
    import seaborn as sns
    import matplotlib.pyplot as plt
    import pandas as pd
    import numpy as np
    plt.figure()
    cm = confusion_matrix(np.array(Y_TEST),np.array(PRED_LABEL))
   # class_label = ['0','1','2','3','4','5','6','7','8','9']
    DATA = pd.DataFrame(cm)#, index = class_label, columns = class_label)
    sns.heatmap(DATA , annot = True, fmt = "d")
    plt.title("Confusiion Matrix for TEST DATA")
    plt.xlabel("PREDICTED LABEL")
    plt.ylabel("TRUE LABEL")
    plt.show()
```

In [109]:

```
CONFUSION_MATRIX(PRED_LABEL,ACTUAL_LABEL)
```





Implementing Batch Gradient Descent

In [0]:

```
WT_1 = NP.random.normal(0,1,(784,150))

WT_2 = NP.random.normal(0,1,(150,100))
WT_3 = NP.random.normal(0,1,(100,50))
WT_4 = NP.random.normal(0,1,(50,10))
```

FIRST APPROACH: 20K epoch of 2000 sample

In [32]:

```
# 20K epoch of 2000 sample

import timeit
start_time = timeit.default_timer()
ERR=[]
VALUE=0
LOCAL_ERROR= NP.zeros((10,1))
LES= NP.zeros((10,1))
for epoc in range(0,20000):
  print(epoc)
  VALUE=0
  LOCAL_ERROR= NP.zeros((10,1))
  LES= NP.zeros((10,1))
  for sample in range(0,2000):

    IP = NP.reshape(X_TRAIN[sample],(784,1))
    Z1 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_1),IP)))
    Z2 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_2),Z1)))
    Z3 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_3),Z2)))
    Z4 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_4),Z3)))


    LOCAL_ERROR = LOCAL_ERROR+(Z4-Y_TRAIN[sample].reshape(10,1))
    LES=LES+(LOCAL_ERROR)**2
    #VALUE=VALUE+0.5*NP.sum(((LOCAL_ERROR)**2))
    #ERR.append(VALUE)
  LOCAL_ERROR=(1/2000)*LOCAL_ERROR
  VALUE=VALUE+(1/4000)*NP.sum(LES)
  ERR.append(VALUE)
  TEMP1 =NP.zeros((50,10))
  for i in range(0,10):
    TEMP1[:,i] = Z4[i]*(1-Z4[i])
  DIF_Z4_W4 = TEMP1*Z3
  UP_WT_4 = WT_4-(0.2)*(NP.transpose(LOCAL_ERROR)*DIF_Z4_W4)



  B=NP.dot(NP.transpose(LOCAL_ERROR),NP.transpose((WT_4*TEMP1)))
  TEMP2 =NP.zeros((100,50))
  for i in range(0,50):
    TEMP2[:,i] = Z3[i]*(1-Z3[i])
  UP_WT_3 = WT_3-(0.2)*B*(TEMP2*Z2)



  C=NP.dot(B,NP.transpose(TEMP2*WT_3))
  TEMP3 =NP.zeros((150,100))
  for i in range(0,100):
    TEMP3[:,i] = Z2[i]*(1-Z2[i])
```

```
    TEMP3[:,i] = Z2[i]*(1-Z2[i])
  UP_WT_2=WT_2-(0.2)*C*(TEMP3*Z1)



  D=NP.dot(C,NP.transpose((TEMP3*WT_2)))
  TEMP4 =NP.zeros((784,150))
  for i in range(0,150):
    TEMP4[:,i] = Z1[i]*(1-Z1[i])
  UP_WT_1=WT_1-(0.2)*D*(TEMP4*NP.reshape(X_TRAIN[sample],(784,1)))
  WT_1 = UP_WT_1
  WT_2 = UP_WT_2
  WT_3 = UP_WT_3
  WT_4 = UP_WT_4

elapsed = timeit.default_timer() - start_time
print(f"Time Required To run Cell : {elapsed}")
```

```
Time Required To run Cell : 4948.687527753
```

In [14]:

```
len(ERR)
```

Out[14]:

```
40000
```

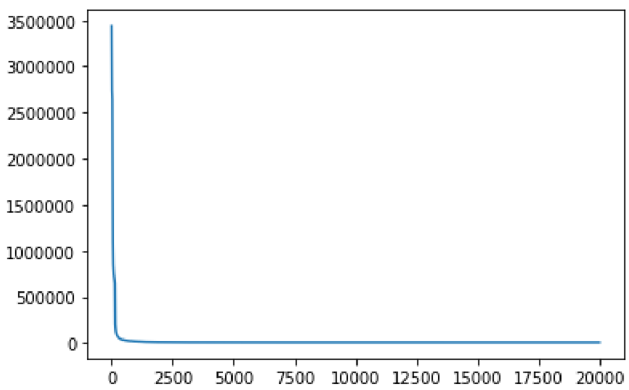
Cost vs Epoch

In [35]:

```
X=list(range(1,20001))
PLT.plot(X,ERR)
```

Out[35]:

```
[<matplotlib.lines.Line2D at 0x7f827aa16f28>]
```



In [0]:

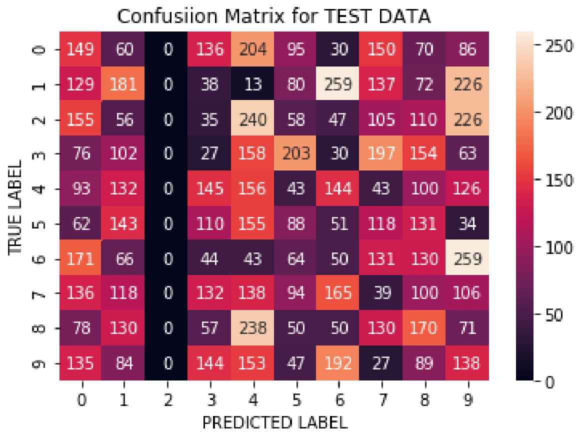
```
# FFN
# PREDICTION
PRED_LABEL=[]
ACTUAL_LABEL=[]
Y=[]
for sample in range(0,10000):
  IP = NP.reshape(X_TEST[sample],(784,1))
  Z1 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_1),IP)))
  Z2 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_2),Z1)))
  Z3 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_3),Z2)))
  Z4 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_4),Z3)))
  PRED_LABEL.append(NP.argmax(Z4))
  ACTUAL_LABEL.append(NP.argmax(Y_TEST[sample]))
  #print(NP.argmax(Z4),NP.argmax(Y_TEST[sample]))

# This Function will take input as PRED_LABEL and ACTUAL LABEL return Confusion MATRIX.
```

```
def CONFUSION_MATRIX(PRED_LABEL,Y_TEST):
    from sklearn.metrics import confusion_matrix
    import seaborn as sns
    import matplotlib.pyplot as plt
    import pandas as pd
    import numpy as np
    plt.figure()
    cm = confusion_matrix(np.array(Y_TEST),np.array(PRED_LABEL))
   # class_label = ['0','1','2','3','4','5','6','7','8','9']
    DATA = pd.DataFrame(cm)#, index = class_label, columns = class_label)
    sns.heatmap(DATA , annot = True, fmt = "d")
    plt.title("Confusiion Matrix for TEST DATA")
    plt.xlabel("PREDICTED LABEL")
    plt.ylabel("TRUE LABEL")
    plt.show()
```

In [22]:

```
CONFUSION_MATRIX(PRED_LABEL,ACTUAL_LABEL)
```



SEcond APPROACH: 2K epoch of 2000 sample

In [0]:

```
WT_1 = NP.random.normal(0,1,(784,150))

WT_2 = NP.random.normal(0,1,(150,100))
WT_3 = NP.random.normal(0,1,(100,50))
WT_4 = NP.random.normal(0,1,(50,10))
```

In [38]:

```
# 2K epoch of 2000 sample
import timeit
start_time = timeit.default_timer()
ERR=[]
VALUE=0
LOCAL_ERROR= NP.zeros((10,1))
LES= NP.zeros((10,1))
for epoc in range(0,2000):
  print(epoc)
  VALUE=0
  LOCAL_ERROR= NP.zeros((10,1))
  LES= NP.zeros((10,1))
  for sample in range(0,2000):

    IP = NP.reshape(X_TRAIN[sample],(784,1))
    Z1 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_1),IP)))
    Z2 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_2),Z1)))
    Z3 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_3),Z2)))
    Z4 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_4),Z3)))


    LOCAL_ERROR = LOCAL_ERROR+(Z4-Y_TRAIN[sample].reshape(10,1))
    LES=LES+(LOCAL_ERROR)**2
```

```
    #VALUE=VALUE+0.5*NP.sum(((LOCAL_ERROR)**2))
    #ERR.append(VALUE)
  LOCAL_ERROR=(1/2000)*LOCAL_ERROR
  VALUE=VALUE+(1/4000)*NP.sum(LES)
  ERR.append(VALUE)
  TEMP1 =NP.zeros((50,10))
  for i in range(0,10):
    TEMP1[:,i] = Z4[i]*(1-Z4[i])
  DIF_Z4_W4 = TEMP1*Z3
  UP_WT_4 = WT_4-(0.2)*(NP.transpose(LOCAL_ERROR)*DIF_Z4_W4)



  B=NP.dot(NP.transpose(LOCAL_ERROR),NP.transpose((WT_4*TEMP1)))
  TEMP2 =NP.zeros((100,50))
  for i in range(0,50):
    TEMP2[:,i] = Z3[i]*(1-Z3[i])
  UP_WT_3 = WT_3-(0.2)*B*(TEMP2*Z2)



  C=NP.dot(B,NP.transpose(TEMP2*WT_3))
  TEMP3 =NP.zeros((150,100))
  for i in range(0,100):
    TEMP3[:,i] = Z2[i]*(1-Z2[i])
  UP_WT_2=WT_2-(0.2)*C*(TEMP3*Z1)



  D=NP.dot(C,NP.transpose((TEMP3*WT_2)))
  TEMP4 =NP.zeros((784,150))
  for i in range(0,150):
    TEMP4[:,i] = Z1[i]*(1-Z1[i])
  UP_WT_1=WT_1-(0.2)*D*(TEMP4*NP.reshape(X_TRAIN[sample],(784,1)))
  WT_1 = UP_WT_1
  WT_2 = UP_WT_2
  WT_3 = UP_WT_3
  WT_4 = UP_WT_4

elapsed = timeit.default_timer() - start_time
print(f"Time Required To run Cell : {elapsed}")
```

```
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
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24
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26
27
28
29
30
31
32
33
34
```

```
1958
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1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
Time Required To run Cell : 506.99901070300075
```

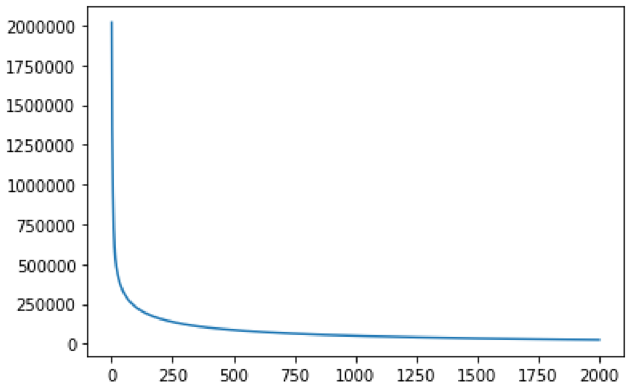
Cost Vs Iteration

In [39]:

```
X=list(range(1,2001))
PLT.plot(X,ERR)
```

Out[39]:

```
[<matplotlib.lines.Line2D at 0x7f827a747fd0>]
```



In [40]:

```
# PREDICTION
PRED_LABEL=[]
ACTUAL_LABEL=[]
Y=[]
for sample in range(0,10000):
  IP = NP.reshape(X_TEST[sample],(784,1))
  Z1 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_1),IP)))
  Z2 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_2),Z1)))
  Z3 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_3),Z2)))
  Z4 = 1/(1+NP.exp(-NP.dot(NP.transpose(WT_4),Z3)))
  PRED_LABEL.append(NP.argmax(Z4))
  ACTUAL_LABEL.append(NP.argmax(Y_TEST[sample]))
  #print(NP.argmax(Z4),NP.argmax(Y_TEST[sample]))

# This Function will take input as PRED_LABEL and ACTUAL LABEL return Confusion MATRIX.
def CONFUSION_MATRIX(PRED_LABEL,Y_TEST):
    from sklearn.metrics import confusion_matrix
    import seaborn as sns
    import matplotlib.pyplot as plt
    import pandas as pd
    import numpy as np
    plt.figure()
    cm = confusion_matrix(np.array(Y_TEST),np.array(PRED_LABEL))
   # class_label = ['0','1','2','3','4','5','6','7','8','9']
    DATA = pd.DataFrame(cm)#, index = class_label, columns = class_label)
    sns.heatmap(DATA , annot = True, fmt = "d")
    plt.title("Confusiion Matrix for TEST DATA")
    plt.xlabel("PREDICTED LABEL")
    plt.ylabel("TRUE LABEL")
    plt.show()
CONFUSION_MATRIX(PRED_LABEL,ACTUAL_LABEL)
```