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Class: MBATech CE

Sem: 6

Roll No: N049

In [2]:

```
#Experiment 5
#Effect of Learning Rates and optimizers on accuracy of DNN
```

Importing Libraries:

In [3]:

```
from sklearn.datasets import make_blobs #total number of points equally divided among clu
sters, no. of samples per cluster
from matplotlib import pyplot #for plotting the curves/graphs to identify relationship
from numpy import where #for returning the indices of elements in an input array where co
ndition satisfies
```

In [5]:

```
X,y=make_blobs(n_samples=1000, centers=3, n_features=2, cluster_std=2, random_state=2)
```

In [6]:

```
#make_blobs collect 1000 data points which are randomly located , with standard deviation
of 2
```

In [7]:

```
X[1], y[1]
#X is label of the training sample
#y is the output of the training sample
```

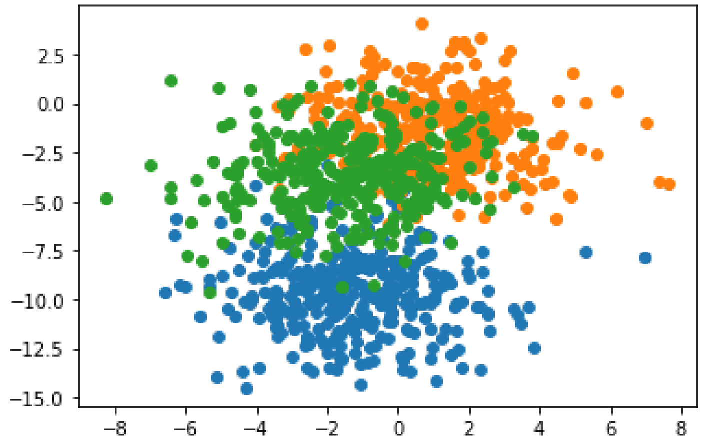
Out[7]:

```
(array([-1.48958879, -3.47915742]), 2)
```

Drawing Scatter Plot:

In [8]:

```
for class_v in range(3):
  class_r=where(y==class_v)
  pyplot.scatter(X[class_r,0], X[class_r,1])
```



In [ ]:

In [ ]:

```
#there are 3 values for y (0,1,2)
#first feature is plotted on x axis
#second feature is plotted on y axis
```

In [9]:

```
from keras.utils import to_categorical #for converting categorical data into matrix havin
g binary values
y=to_categorical(y)
```

In [10]:

```
y[10]
```

Out[10]:

```
array([0., 1., 0.], dtype=float32)
```

In [ ]:

```
#1 in the output shows, which label is active
```

In [11]:

```
n_train=500 #training 500 samples out of 1000 for training
train_x, test_x=X[:n_train,:], X[n_train:,:]
train_y, test_y=y[:n_train],y[n_train:]
#training for two features as x and y
```

In [ ]:

```
#500 samples, 2 columns which represent the training data i.e number of features
```

In [12]:

```
train_y.shape
```

Out[12]:

```
(500, 3)
```

Model Architecture:

In [13]:

```
from keras.layers import Dense #Dense function is imported to feed all outputs from the p
revious layer to all its Neurons of Dense Layer
from keras.models import Sequential
model = Sequential() #a sequential model of neural network is built by passing a list of
layers to the sequential constructor
model.add(Dense(50,input_dim=2,activation='relu',kernel_initializer='he_uniform'))
model.add(Dense(3,activation='softmax'))
```

In [ ]:

```
#We take 50 samples as neurons in the input layer, with 2 features
#There are 3 features in the fist hidden layer
#softmax function is used for activation as it converts vector of K real values into a ve
ctor of K real values such that their sum is equal to 1
```

Compiling the Model:

In [14]:

```
from keras.optimizers import SGD #(stochastic gradient)
opt=SGD(lr=0.001) #learning rate is set to 0.001
model.compile(loss='categorical_crossentropy', optimizer=opt, metrics=['accuracy'])
#we use categorical crossentropy for calculating the loss, as to train the Neural Network
```

```
to output a probability over the C classes for each image
```

Fitting the Model:

In [15]:

```
history=model.fit(train_x,train_y,validation_data=(test_x,test_y),epochs=200,verbose=0)
```

In [ ]:

```
#after compiling the model, the model is fitted
#this model (training data) is validated with the testing data
#we are running it for 200 epochs
#verbose refers to
```

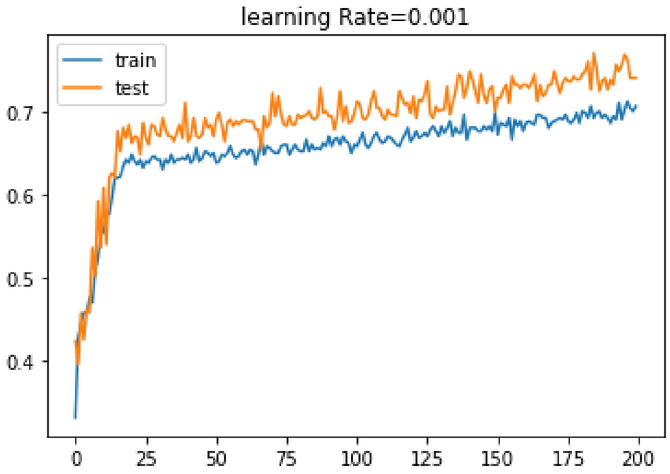
Plotting the Learning Curve:

In [17]:

```
pyplot.plot(history.history['accuracy'],label='train') #we calculate the accuracy of the
training model
pyplot.plot(history.history['val_accuracy'],label='test') #and then validate that accurac
y from the testing model
pyplot.title('learning Rate=0.001')
pyplot.legend()
```

Out[17]:

```
<matplotlib.legend.Legend at 0x7ff2c1a5de50>
```



In [18]:

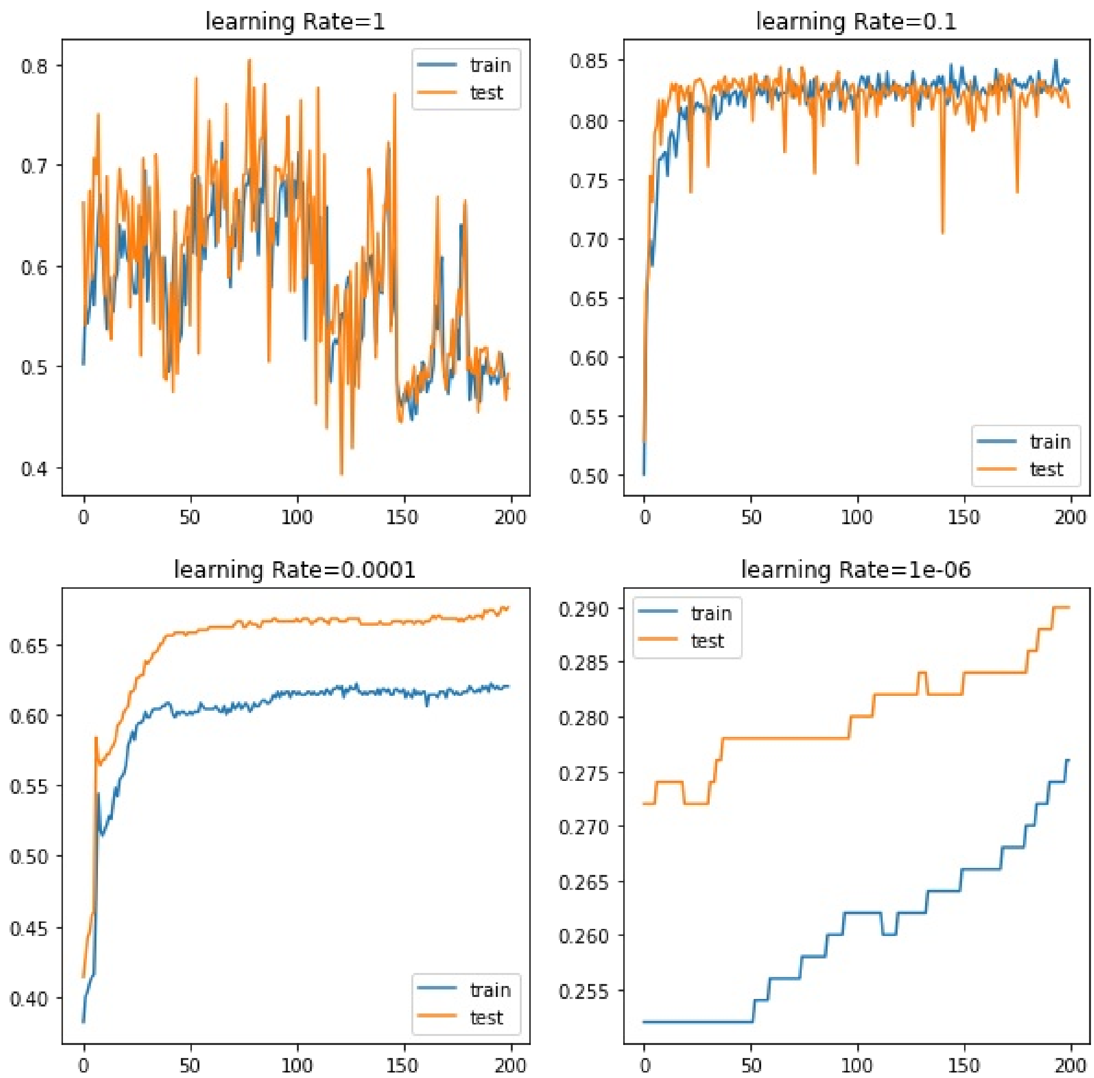
```
def pre_data():
  X,y=make_blobs(n_samples=1000, centers=3, n_features=2, cluster_std=2, random_state=2)
  y=to_categorical(y)
  train_x,test_x=X[:n_train,:], X[n_train:,:]
  train_y,test_y=y[:n_train],y[n_train:]
  return train_x,train_y,test_x,test_y
```

In [19]:

```
def fit_model(train_x,train_y,test_x,test_y,lrate):
  model = Sequential()
  model.add(Dense(50,input_dim=2,activation='relu',kernel_initializer='he_uniform'))
  model.add(Dense(3,activation='softmax'))
  opt=SGD(lr=lrate)
  model.compile(loss='categorical_crossentropy', optimizer=opt, metrics=['accuracy'])
  history=model.fit(train_x,train_y,validation_data=(test_x,test_y),epochs=200,verbose=0
)
  pyplot.plot(history.history['accuracy'],label='train')
  pyplot.plot(history.history['val_accuracy'],label='test')
  pyplot.title('learning Rate='+str(lrate))
  pyplot.legend()
```

In [20]:

```
train_x,train_y,test_x,test_y=pre_data()
learning_rates=[1,0.1,0.0001,0.000001]
pyplot.figure(figsize=(10,10))
for i in range(len(learning_rates)):
  plot_no=220+(i+1)
  pyplot.subplot(plot_no)
  fit_model(train_x,train_y,test_x,test_y,learning_rates[i])
```



Conlusion: 1) For different learning rates, we obtained that for lr=0.1, it is giving us good accuracy. much better than other three learning rates.

Momentum:

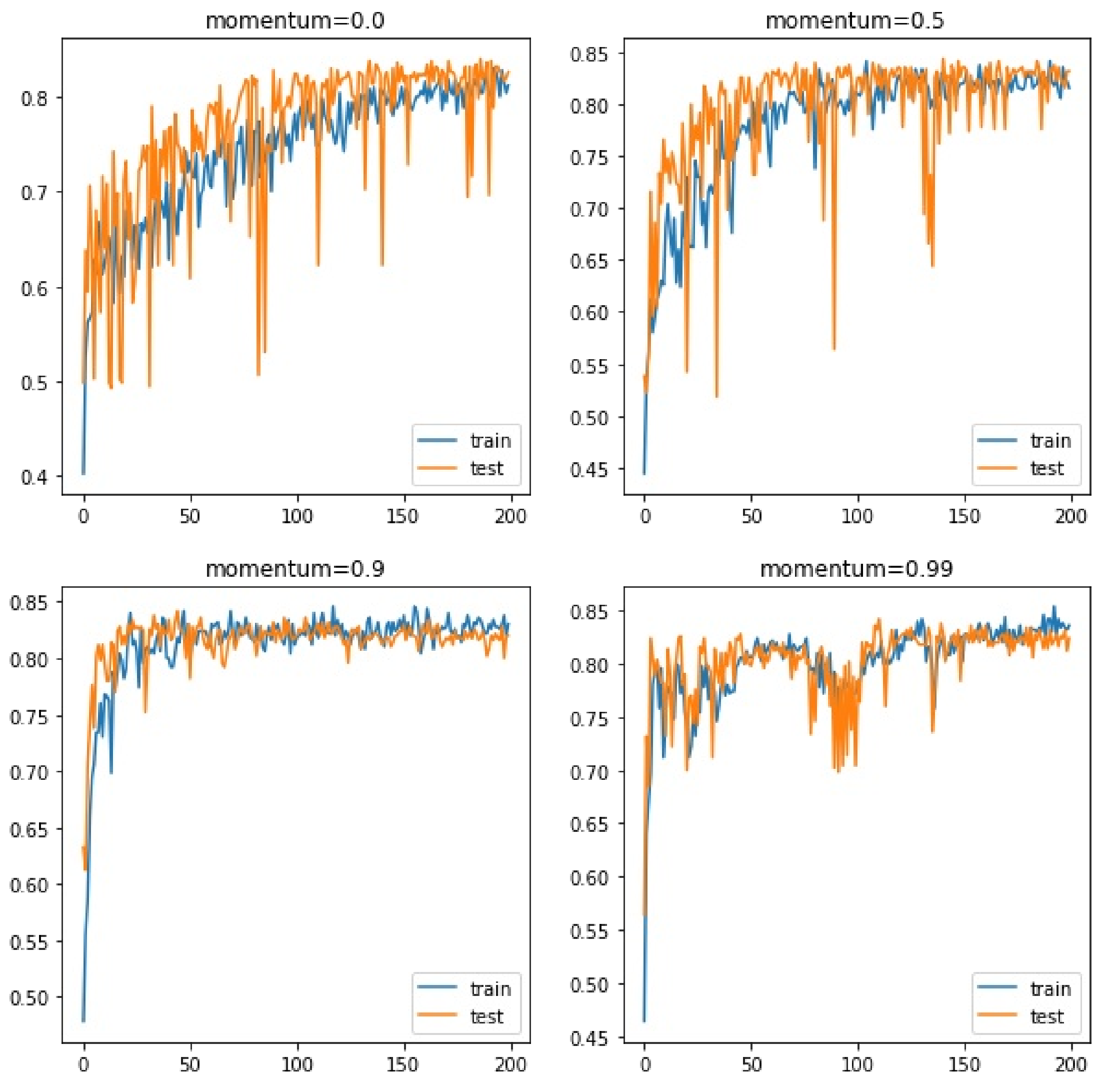
In [21]:

```
def fit_model(train_x,train_y,test_x,test_y,mom):
  model = Sequential()
  model.add(Dense(50,input_dim=2,activation='relu',kernel_initializer='he_uniform'))
  model.add(Dense(3,activation='softmax'))
  opt=SGD(lr=0.01, momentum=mom)
  model.compile(loss='categorical_crossentropy', optimizer=opt, metrics=['accuracy'])
  history=model.fit(train_x,train_y,validation_data=(test_x,test_y),epochs=200,verbose=0
)
  pyplot.plot(history.history['accuracy'],label='train')
  pyplot.plot(history.history['val_accuracy'],label='test')
  pyplot.title('momentum='+str(mom))
  pyplot.legend()
```

In [22]:

```
mom_values=[0.0,0.5,0.9,0.99]
```

```python
pyplot.figure(figsize=(10,10))
for i in range(len(mom_values)):
  plot_no=220+(i+1)
  pyplot.subplot(plot_no)
  fit_model(train_x,train_y,test_x,test_y,mom_values[i])
```



In [ ]:

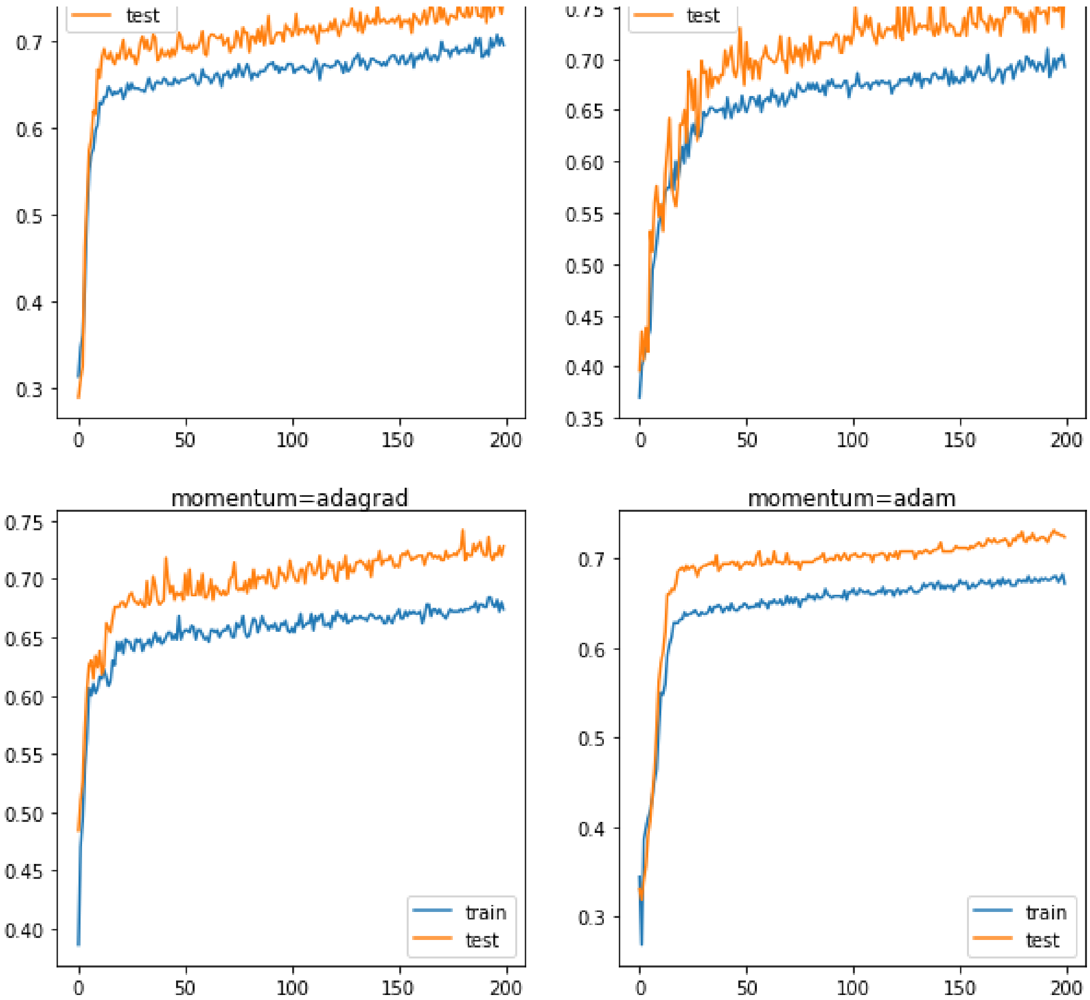
```python
#0.9 gives the best result
```

In [23]:

```python
def fit_model(train_x,train_y,test_x,test_y,optr):
  model = Sequential()
  model.add(Dense(50,input_dim=2,activation='relu',kernel_initializer='he_uniform'))
  model.add(Dense(3,activation='softmax'))
  model.compile(loss='categorical_crossentropy', optimizer=opt, metrics=['accuracy'])
  history=model.fit(train_x,train_y,validation_data=(test_x,test_y),epochs=200,verbose=0
)
  pyplot.plot(history.history['accuracy'],label='train')
  pyplot.plot(history.history['val_accuracy'],label='test')
  pyplot.title('momentum='+str(optr),pad=-80)
  pyplot.legend()
```

In [24]:

```python
optr=['sgd','rmsprop','adagrad','adam'] #using different optimizers to find best one
pyplot.figure(figsize=(10,10))
for i in range(len(optr)):
  plot_no=220+(i+1)
  pyplot.subplot(plot_no)
  fit_model(train_x,train_y,test_x,test_y,optr[i])
```



Conclusion: 1) For the given dataset, the stochastic gradient 2) Rmsprop and adam are giving same, but adam gives the best since it's less oscillating

FINAL CONCLUSION:

1. **For given data set, if SGD is used for different values of learning rates, it gives best value for learning rate = 0.1**
2. **For given data set, if SGD is used for learning rate = 0.01, momentum = 0.9, the training and testing accuracies converge very fast and testing accuracy comes best faster, out of all the given values.**
3. **For given data set, out of all the provided optimizers, adam is giving the best accuracy.**