Includes and network parameters

```
import time
import shutil
import numpy as np
import torch
import torch.nn as nn
from torch.utils.data import TensorDataset, DataLoader
import matplotlib.pyplot as plt
from matplotlib import rcParams
```

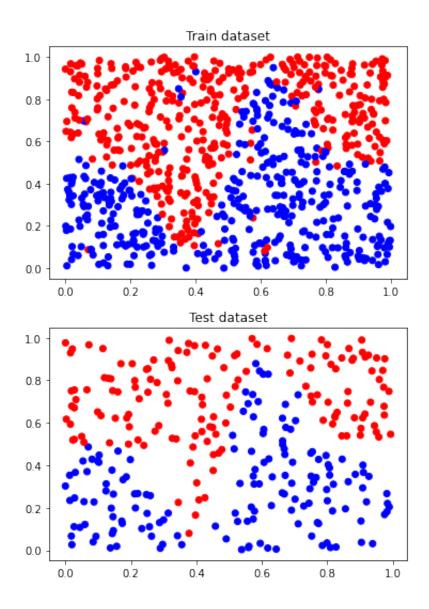
```
# Network parameters
num_neurons : TYPE list
            DESCRIPTION. list of neurons in each layer.
                This should have a minimum length of 3.
                First element represents the dimension of input vector.
                Last element represents the dimension of the output vector.
                middle elements represent the number of neurons in hidden layers.
activations: TYPE, option list where each element can be either 'relu' or 'sigmoic
            DESCRIPTION. The default is ['relu'].
            If len(activations)==1:
                same activation function is applied across all hidden layers.
            else:
                len(activations) should be equal to the number of hidden layers.
1 1 1
num_neurons = [2,20,10,10,2] # list of neurons in each layer of NN.
activations = ['relu'] # represents the activation function used at the hidden laye
# optimizer parameters
lr = 0.01
lr_step = [500]
weight_decay = 1e-3
# training parameters
num_epochs = 200
batch_size = 256
print_freq = 10
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

Create and plot data set

Do not change this cell!

```
# D0 NOT change this cell.
ns = 800
np.random.seed(0)
X_train = np.random.rand(ns,2)
x1 = X_train[:,0]
x2 = X_train[:,1]
```

```
y_{train} = ((np.exp(-((x1-0.5)*6)**2)*2*((x1-0.5)*6)+1)/2-x2)>0
idx = np.random.choice(range(ns), size=(int(ns*0.03),))
y_{train}[idx] = \sim y_{train}[idx]
ns = 300
np.random.seed(1)
X_val = np.random.rand(ns,2)
x1 = X_val[:,0]
x2 = X_val[:,1]
y_val = ((np.exp(-((x1-0.5)*6)**2)*2*((x1-0.5)*6)+1)/2-x2)>0
def plot(X,y,title="Dataset"):
    colors = np.where(y==0, 'r', 'b')
    plt.figure()
    plt.scatter(X[:,0],X[:,1],color=colors)
    plt.title(title)
    plt.show()
plot(X_train,y_train,"Train dataset")
plot(X_val,y_val,"Test dataset")
```



▼ Load data set into Torch dataloader

```
X_train_tensor = torch.Tensor(X_train) # transform to torch tensor
y_train_tensor = torch.Tensor(y_train)

train_dataset = TensorDataset(X_train_tensor,y_train_tensor) # create your datset
train_loader = DataLoader(train_dataset,batch_size=batch_size,shuffle=True,drop_las

X_val_tensor = torch.Tensor(X_val) # transform to torch tensor
y_val_tensor = torch.Tensor(y_val)

val_dataset = TensorDataset(X_val_tensor,y_val_tensor) # create your datset
val_loader = DataLoader(val_dataset,batch_size=batch_size,shuffle=True,drop_last=Fa
```

Model: Feedforward neural network

```
class LinearNN(nn.Module):
   def __init__(self,num_neurons,activations=['relu']):
        Parameters
        _____
        num neurons : TYPE list
            DESCRIPTION. list of neurons in each layer.
                This should have a minimum length of 3.
                First element represents the dimension of input vector.
                Last element represents the dimension of the output vector.
                middle elements represent the number of neurons in hidden layers.
        activations: TYPE, optional list.
            DESCRIPTION. The default is ['relu'].
            If len(activations)==1:
                same activation function is applied across all hidden layers.
            else:
                len(actiavtions) should be equal to the number of hidden layers.
        Returns
        None.
        1.1.1
        super(LinearNN, self).__init__()
        assert isinstance(num_neurons,list)
```

```
assert np.all([isinstance(neurons,int) for neurons in num_neurons])
assert np.all([neurons>=1 for neurons in num_neurons])
assert len(num neurons)>=3
if activations is not None:
    assert isinstance(activations,(list))
    assert (len(activations)==len(num_neurons)-2) or (len(activations)==1)
def activation_layer(act_func):
    Parameters
    act_func : TYPE should be one from {'relu', 'sigmoid', 'tanh'}.
        DESCRIPTION.
    Raises
    NotImplementedError
        DESCRIPTION.
    Returns
    _____
    TYPF
        DESCRIPTION.
    if act_func=='relu':
        return nn.ReLU(inplace=True)
    elif act_func=='sigmoid':
        return nn.Sigmoid()
    elif act func=='tanh':
        return nn.Tanh()
    else:
        raise NotImplementedError
layers = []
for idx,_ in enumerate(num_neurons[:-1]):
    layers.append(nn.Linear(in_features=num_neurons[idx],
                            out_features=num_neurons[idx+1],
                            bias=True))
    if idx!=len(num_neurons)-2: # add activation for all layers except the
```

Define training function

```
def train(train_loader, model, criterion, optimizer, epoch):
    batch_time = AverageMeter()
   data time = AverageMeter()
    losses = AverageMeter()
   top1 = AverageMeter()
   # switch to train mode
   model.train()
   end = time.time()
    for i, (input, target) in enumerate(train loader):
        # measure data loading time
        data_time.update(time.time() - end)
        target = target.to(device)
        input var = torch.autograd.Variable(input).to(device)
        target_var = torch.autograd.Variable(target).to(device)
        # target_var = torch.squeeze(target_var)
        # compute output
        output = model(input_var)
        # compute loss
```

```
loss = criterion(output, target_var.long())
    # measure accuracy and record loss
    prec1 = accuracy(output.data, target)
    losses.update(loss.item(), input.size(0))
    top1.update(prec1[0][0], input.size(0))
    # compute gradient and do SGD step
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
    # measure elapsed time
    batch time.update(time.time() - end)
    end = time.time()
    if i % print freq == 0:
        curr_lr = optimizer.param_groups[0]['lr']
        print('Epoch: [{0}/{1}][{2}/{3}]\t'
              'LR: {4}\t'
              'Loss {loss.val:.4f} ({loss.avg:.4f})\t'
              'Train Acc {top1.val:.3f} ({top1.avg:.3f})'.format(
               epoch, num_epochs, i, len(train_loader), curr_lr,
               loss=losses, top1=top1))
print(' * Train Acc {top1.avg:.3f}'.format(top1=top1))
# compute and return train loss and accuracy
train loss = losses.avg
train_acc = top1.avg
return train_loss, train_acc
```

Define validation and prediction functions

```
def validate(val_loader, model, criterion):
    batch_time = AverageMeter()
    losses = AverageMeter()
    top1 = AverageMeter()

# switch to evaluate mode
    model.eval()
```

```
end = time.time()
    for i, (input, target) in enumerate(val_loader):
        target = target.to(device)
        input_var = torch.autograd.Variable(input, volatile=True).to(device)
        target_var = torch.autograd.Variable(target, volatile=True).to(device)
        # compute output
        output = model(input_var)
        # loss = criterion(output, target_var[:,None])
        loss = criterion(output, target_var.long())
        # measure accuracy and record loss
        prec1 = accuracy(output.data, target)
        losses.update(loss.item(), input.size(0))
        top1.update(prec1[0][0], input.size(0))
        # measure elapsed time
        batch_time.update(time.time() - end)
        end = time.time()
        if i % print freq == 0:
            print('Test: [{0}/{1}]\t'
                  'Loss {loss.val:.4f} ({loss.avg:.4f})\t'
                  'Prec@1 {top1.val:.3f} ({top1.avg:.3f})'.format(
                   i, len(val loader), loss=losses,
                   top1=top1))
    print(' * Test Acc {top1.avg:.3f}'.format(top1=top1))
    return top1.avg
def predict(dataloader, model):
   y_pred = []
   y_{true} = []
   x = 1
   with torch.no grad():
        for i, (input, target) in enumerate(dataloader):
            # target = target.to(device)
            input_var = torch.autograd.Variable(input, volatile=True).to(device)
            # target_var = torch.autograd.Variable(target, volatile=True).to(device
            # compute output
            output = model(input_var)
```

```
labels = torch.argmax(output,axis=1)
    y_pred.extend(list(labels.data.detach().cpu().numpy()))
    y_true.extend(list(target.numpy()))
    x.extend(list(input_var.data.detach().cpu().numpy()))
return np.array(x),np.array(y_true),np.array(y_pred)
```

Function to plot the decision boundary of the neural network

```
def plot_decision_boundary(model):
    h = 0.005
    x_min, x_max = 0,1
    y_min, y_max = 0,1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                          np.arange(y_min, y_max, h))
    x1 = xx.ravel()
    x2 = yy.ravel()
    y = ((np.exp(-((x1-0.5)*6)**2)*2*((x1-0.5)*6)+1)/2-x2)>0
    X_train_tensor = torch.Tensor(np.c_[xx.ravel(), yy.ravel()]) # transform to tor
    y_train_tensor = torch.Tensor(y)
    dataset = TensorDataset(X_train_tensor,y_train_tensor) # create your datset
    dataloader = DataLoader(dataset,batch_size=batch_size,shuffle=False,drop_last=F
    x,y_true,y_pred = predict(dataloader,model)
    Z = y_pred.reshape(xx.shape)
    plt.figure()
    plt.contourf(x[:,0].reshape(xx.shape), x[:,1].reshape(xx.shape), Z, cmap=plt.cn
    plt.axis('tight')
    # scatter plot of data points with colors corresponding to the correct labels.
    ns = 500
    np.random.seed(0)
    X_test = np.random.rand(ns,2)
    x1 = X \text{ test}[:,0]
    x2 = X_{test}[:,1]
    y_{\text{test}} = ((np.exp(-((x1-0.5)*6)**2)*2*((x1-0.5)*6)+1)/2-x2)>0
    colors = np.where(y test==0, 'r', 'b')
    plt.scatter(x1,x2,color=colors)
    # plt.scatter(x[:,0],x[:,1],colors=)
    plt.show()
```

Functions to track the model performance and save the desired model state

```
def save_checkpoint(state, is_best, filename='checkpoint.pth.tar'):
    torch.save(state, filename)
    if is best:
        shutil.copyfile(filename, 'model_best.pth.tar')
class AverageMeter(object):
    """Computes and stores the average and current value"""
    def __init__(self):
        self.reset()
    def reset(self):
        self_val = 0
        self_avg = 0
        self.sum = 0
        self.count = 0
    def update(self, val, n=1):
        self.val = val
        self.sum += val * n
        self.count += n
        self.avg = self.sum / self.count
def accuracy(output, target, topk=(1,)):
    """Computes the precision@k for the specified values of k"""
    maxk = max(topk)
    batch size = target.size(0)
    _, pred = output.topk(maxk, 1, True, True)
    pred = pred.t()
    correct = pred.eq(target.view(1, -1).expand as(pred))
    res = []
    for k in topk:
        correct_k = correct[:k].view(-1).float().sum(0, keepdim=True)
        res.append(correct_k.mul_(100.0 / batch_size))
    return res
```

Create model instance; define loss function and optimizer

```
torch.manual_seed(999)
model = linear_nn(num_neurons,activations).to(device)

# define loss function (criterion) and optimizer
# criterion = nn.BCEWithLogitsLoss().to(device)
criterion = nn.CrossEntropyLoss().to(device)

optimizer = torch.optim.Adam(model.parameters(),lr=lr,weight_decay=weight_decay)
```

Train model and validate

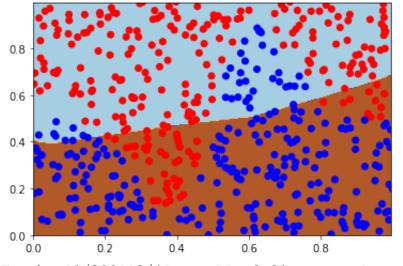
```
train_losses·=·[]
train_accuracies ·= ·[]
test_accuracies ·= ·[]
best prec1·=·0
for epoch in range(num_epochs):
····if·epoch·in·lr_step:
·····for·param group·in·optimizer.param groups:
·····param group['lr']·*=·0.1
····#·train·for·one·epoch
····#·train·for·one·epoch
····train_loss,·train_acc·=·train(train_loader,·model,·criterion,·optimizer,·epoch)
....train_losses.append(train_loss)
····train_accuracies.append(train_acc)
····#·evaluate·on·validation·set
\cdots \# \cdot prec1 = 0
....prec1.=.validate(val_loader,.model,.criterion)
····test accuracies.append(prec1)
····#·remember·best·prec@1·and·save·checkpoint
····is_best·=·prec1·>·best_prec1
····best_prec1·=·max(prec1, ·best_prec1)
....save_checkpoint({
·····'epoch': epoch ·+·1,
.....'state_dict': model.state_dict(),
.....'best_prec1': best_prec1,
······'optimizer': optimizer.state_dict(),
....}, is_best, filename="checkpoint.pth.tar")
```

```
····print("-----")
····if·epoch%print_freq==0:
....plot_decision_boundary(model)
plot decision boundary(model)
```

Epoch: [0/200][0/4] LR: 0.01 Loss 0.6985 (0.6985) Train Acc 51.5 * Train Acc 52.750 Test: [0/2] Loss 0.6820 (0.6820) Prec@1 83.594 (83.594) * Test Acc 83.000

<ipython-input-7-56ce71016660>:12: UserWarning: volatile was removed and now h input var = torch.autograd.Variable(input, volatile=True).to(device) <ipython-input-7-56ce71016660>:13: UserWarning: volatile was removed and now h target var = torch.autograd.Variable(target, volatile=True).to(device)

<ipython-input-7-56ce71016660>:48: UserWarning: volatile was removed and now h input var = torch.autograd.Variable(input, volatile=True).to(device)



Epoch: [1/200][0/4] LR: 0.01 Loss 0.6831 (0.6831) Train Acc 81.2 * Train Acc 78.250

Test: [0/2] Loss 0.6595 (0.6595) Prec@1 77.344 (77.344)

* Test Acc 75.333

._____

Epoch: [2/200][0/4] LR: 0.01 Loss 0.6630 (0.6630) Train Acc 73.0 * Train Acc 75.875 Test: [0/2] Loss 0.6293 (0.6293) Prec@1 78.125 (78.125)

* Test Acc 78.667

Epoch: [3/200][0/4] LR: 0.01 Loss 0.6298 (0.6298) Train Acc 74.6 * Train Acc 76.500

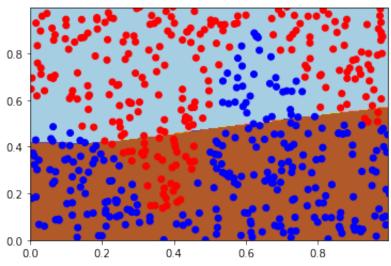
Test: [0/2] Loss 0.5832 (0.5832) Prec@1 77.344 (77.344)

* Test Acc 78.333

Epoch: [4/200][0/4] LR: 0.01 Loss 0.5832 (0.5832) Train Acc 75.0 * Train Acc 76.500

A E101 /A E101\

```
Test: [U/2] Loss U.DIVI (U.DIVI) Precel /9.000 (/9.000)
* Test Acc 80.333
_____
Epoch: [5/200][0/4] LR: 0.01 Loss 0.5337 (0.5337) Train Acc 75.7
* Train Acc 77.625
Test: [0/2] Loss 0.4754 (0.4754) Prec@1 82.422 (82.422)
* Test Acc 82.667
Epoch: [6/200][0/4] LR: 0.01 Loss 0.4728 (0.4728) Train Acc 82.4
* Train Acc 79.500
Test: [0/2] Loss 0.4169 (0.4169) Prec@1 83.984 (83.984)
* Test Acc 83.667
_____
Epoch: [7/200][0/4] LR: 0.01 Loss 0.4718 (0.4718) Train Acc 79.2
* Train Acc 80.750
Test: [0/2] Loss 0.4137 (0.4137) Prec@1 83.984 (83.984)
* Test Acc 85.333
_____
Epoch: [8/200][0/4] LR: 0.01 Loss 0.4030 (0.4030) Train Acc 85.5
* Train Acc 82.125
Test: [0/2] Loss 0.3937 (0.3937) Prec@1 84.375 (84.375)
* Test Acc 85.333
-----
Epoch: [9/200][0/4] LR: 0.01 Loss 0.4551 (0.4551) Train Acc 79.2
* Train Acc 80.750
Test: [0/2] Loss 0.3609 (0.3609) Prec@1 87.109 (87.109)
* Test Acc 86.000
Epoch: [10/200][0/4] LR: 0.01 Loss 0.4544 (0.4544) Train Acc 80.0
* Train Acc 81.500
Test: [0/2] Loss 0.3511 (0.3511) Prec@1 85.938 (85.938)
* Test Acc 85.667
```

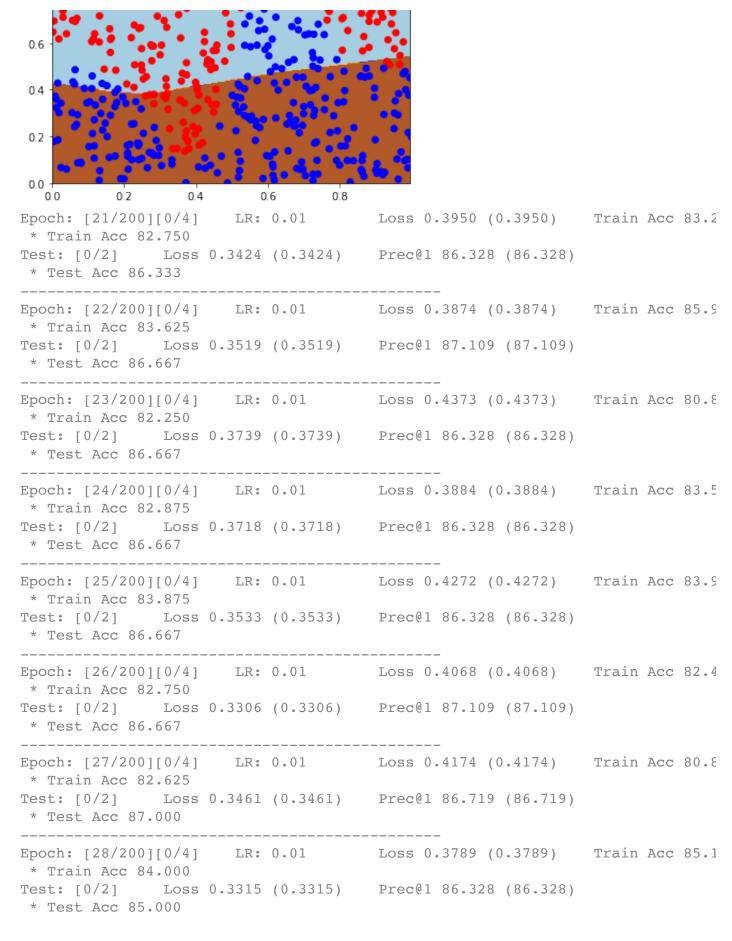


Epoch: [11/200][0/4] LR: 0.01 Loss 0.4563 (0.4563) Train Acc 82.0 * Train Acc 81.625

Test: [0/2] Loss 0.3819 (0.3819) Prec@1 84.375 (84.375)

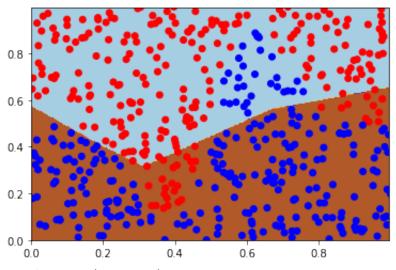
```
* Test Acc 86.333
_____
Epoch: [12/200][0/4] LR: 0.01 Loss 0.4123 (0.4123) Train Acc 81.6
* Train Acc 82.500
Test: [0/2] Loss 0.3636 (0.3636) Prec@1 86.328 (86.328)
* Test Acc 86.667
_____
Epoch: [13/200][0/4] LR: 0.01 Loss 0.4833 (0.4833) Train Acc 80.0
* Train Acc 82.125
Test: [0/2] Loss 0.3691 (0.3691) Prec@1 85.938 (85.938)
* Test Acc 86.333
_____
Epoch: [14/200][0/4] LR: 0.01
                             Loss 0.4464 (0.4464) Train Acc 80.8
* Train Acc 82.375
Test: [0/2] Loss 0.3491 (0.3491) Prec@1 88.281 (88.281)
* Test Acc 87.333
Epoch: [15/200][0/4] LR: 0.01 Loss 0.4394 (0.4394) Train Acc 80.4
* Train Acc 81.875
Test: [0/2] Loss 0.3434 (0.3434) Prec@1 88.281 (88.281)
* Test Acc 87.000
_____
Epoch: [16/200][0/4] LR: 0.01
                             Loss 0.4237 (0.4237) Train Acc 82.0
* Train Acc 81.375
Test: [0/2] Loss 0.3487 (0.3487) Prec@1 87.500 (87.500)
* Test Acc 86.667
_____
Epoch: [17/200][0/4] LR: 0.01 Loss 0.4092 (0.4092) Train Acc 82.0
* Train Acc 83.375
Test: [0/2] Loss 0.3718 (0.3718) Prec@1 85.547 (85.547)
* Test Acc 84.667
-----
Epoch: [18/200][0/4] LR: 0.01 Loss 0.4691 (0.4691) Train Acc 80.8
* Train Acc 81.375
Test: [0/2] Loss 0.3514 (0.3514) Prec@1 87.109 (87.109)
* Test Acc 86.667
_____
Epoch: [19/200][0/4] LR: 0.01 Loss 0.3969 (0.3969) Train Acc 82.0
* Train Acc 81.000
Test: [0/2] Loss 0.3477 (0.3477) Prec@1 87.109 (87.109)
* Test Acc 85.000
Epoch: [20/200][0/4] LR: 0.01 Loss 0.4609 (0.4609) Train Acc 78.5
* Train Acc 81.875
Test: [0/2] Loss 0.3456 (0.3456) Prec@1 87.500 (87.500)
* Test Acc 87.000
```





```
Epoch: [29/200][0/4] LR: 0.01 Loss 0.4062 (0.4062) Train Acc 82.4
* Train Acc 82.250
Test: [0/2] Loss 0.3159 (0.3159) Prec@1 88.281 (88.281)
* Test Acc 86.667
_____
Epoch: [30/200][0/4] LR: 0.01 Loss 0.4190 (0.4190) Train Acc 83.9
* Train Acc 83.500
Test: [0/2] Loss 0.3421 (0.3421) Prec@1 86.719 (86.719)
* Test Acc 86.333
0.2
0.0
        0.2
               0.4
                     0.6
                           0.8
Epoch: [31/200][0/4] LR: 0.01 Loss 0.4032 (0.4032) Train Acc 83.9
* Train Acc 84.000
Test: [0/2] Loss 0.3291 (0.3291) Prec@1 87.891 (87.891)
* Test Acc 87.000
Epoch: [32/200][0/4] LR: 0.01 Loss 0.4202 (0.4202) Train Acc 82.4
* Train Acc 84.250
Test: [0/2] Loss 0.3620 (0.3620) Prec@1 82.422 (82.422)
* Test Acc 84.333
_____
Epoch: [33/200][0/4] LR: 0.01 Loss 0.4116 (0.4116) Train Acc 82.4
* Train Acc 82.125
Test: [0/2] Loss 0.3392 (0.3392) Prec@1 84.766 (84.766)
* Test Acc 85.000
Epoch: [34/200][0/4] LR: 0.01 Loss 0.4168 (0.4168) Train Acc 82.4
* Train Acc 84.500
Test: [0/2] Loss 0.3234 (0.3234) Prec@1 86.719 (86.719)
* Test Acc 86.333
_____
Epoch: [35/200][0/4] LR: 0.01 Loss 0.3590 (0.3590) Train Acc 86.7
* Train Acc 84.750
Test: [0/2] Loss 0.3336 (0.3336) Prec@1 84.375 (84.375)
* Test Acc 84.333
```

```
Epoch: [36/200][0/4] LR: 0.01 Loss 0.3884 (0.3884) Train Acc 83.2
* Train Acc 82.375
Test: [0/2] Loss 0.3301 (0.3301) Prec@1 85.938 (85.938)
* Test Acc 86.667
_____
Epoch: [37/200][0/4] LR: 0.01 Loss 0.3337 (0.3337) Train Acc 87.5
* Train Acc 85.000
Test: [0/2] Loss 0.3401 (0.3401) Prec@1 89.453 (89.453)
* Test Acc 88.667
_____
Epoch: [38/200][0/4] LR: 0.01 Loss 0.3774 (0.3774) Train Acc 85.9
* Train Acc 85.500
Test: [0/2] Loss 0.3371 (0.3371) Prec@1 83.984 (83.984)
* Test Acc 83.333
_____
Epoch: [39/200][0/4] LR: 0.01 Loss 0.4059 (0.4059) Train Acc 82.4
* Train Acc 83.375
Test: [0/2] Loss 0.3326 (0.3326) Prec@1 86.328 (86.328)
* Test Acc 86.667
_____
Epoch: [40/200][0/4] LR: 0.01 Loss 0.3531 (0.3531) Train Acc 88.2
* Train Acc 85.250
Test: [0/2] Loss 0.3345 (0.3345) Prec@1 84.375 (84.375)
* Test Acc 85.667
```



Epoch: [41/200][0/4] LR: 0.01 Loss 0.3988 (0.3988) Train Acc 83.2

* Train Acc 84.625

Test: [0/2] Loss 0.3034 (0.3034) Prec@1 85.938 (85.938)

* Test Acc 85.000

Epoch: [42/200][0/4] LR: 0.01 Loss 0.3236 (0.3236) Train Acc 88.2

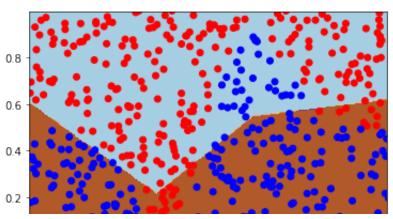
* Train Acc 85.750

Test: [0/2] Loss 0.3217 (0.3217) Prec@1 84.375 (84.375)

* Test Acc 85.667

Epoch: [43/200][0/4] LR: 0.01 Loss 0.3836 (0.3836) Train Acc 86.3

```
* Train Acc 85.625
Test: [0/2] Loss 0.3284 (0.3284) Prec@1 84.375 (84.375)
* Test Acc 85.000
_____
Epoch: [44/200][0/4] LR: 0.01 Loss 0.3232 (0.3232) Train Acc 85.9
* Train Acc 85.000
Test: [0/2] Loss 0.3267 (0.3267) Prec@1 85.938 (85.938)
* Test Acc 87.000
_____
Epoch: [45/200][0/4] LR: 0.01 Loss 0.3142 (0.3142) Train Acc 88.2
* Train Acc 85.750
Test: [0/2] Loss 0.3149 (0.3149) Prec@1 87.109 (87.109)
* Test Acc 87.000
Epoch: [46/200][0/4] LR: 0.01 Loss 0.3162 (0.3162) Train Acc 87.5
* Train Acc 86.000
Test: [0/2] Loss 0.3169 (0.3169) Prec@1 84.766 (84.766)
* Test Acc 84.667
_____
Epoch: [47/200][0/4] LR: 0.01 Loss 0.3247 (0.3247) Train Acc 86.3
* Train Acc 86.250
Test: [0/2] Loss 0.3140 (0.3140) Prec@1 84.766 (84.766)
* Test Acc 85.000
_____
Epoch: [48/200][0/4] LR: 0.01 Loss 0.3255 (0.3255) Train Acc 87.1
* Train Acc 85.375
Test: [0/2] Loss 0.3155 (0.3155) Prec@1 86.719 (86.719)
* Test Acc 87.000
_____
Epoch: [49/200][0/4] LR: 0.01 Loss 0.3221 (0.3221) Train Acc 87.5
* Train Acc 86.125
Test: [0/2] Loss 0.3120 (0.3120) Prec@1 85.938 (85.938)
* Test Acc 86.667
_____
Epoch: [50/200][0/4] LR: 0.01 Loss 0.3203 (0.3203) Train Acc 87.5
* Train Acc 85.375
Test: [0/2] Loss 0.2990 (0.2990) Prec@1 86.719 (86.719)
* Test Acc 87.333
```

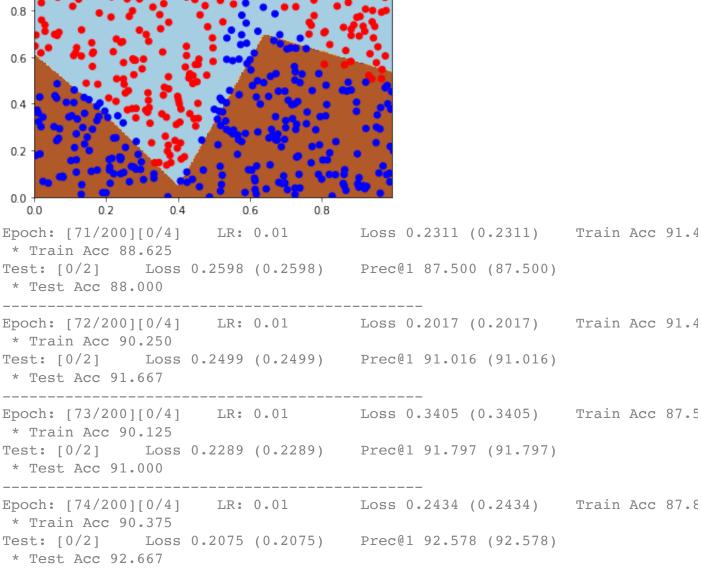


0.0			1.4.	
0.0	0.2 0.4		0.6 0.8	
0/2	cc 86.375] Loss c 88.000	0.2820	(0.2820)	Pred
Train A st: [0/2	/200][0/4] .cc 86.000] Loss			
 och: [53	c 85.333 / /200][0/4]	 LR:	0.01	Loss
	cc 87.250] Loss c 87.667	0.2890	(0.2890)	Pred
* Train A	/200][0/4] .cc 87.375			
est: [0/2 * Test Ac			(0.2824)	
* Train A est: [0/2	/200][0/4] .cc 85.500] Loss			
	/200][0/4]	 LR:	0.01	Loss
est: [0/2 * Test Ac			,	
poch: [57 * Train A	/200][0/4] .cc 87.250	LR:	0.01	Loss
Test Ac				
* Train A est: [0/2 * Test Ac		0.2654	(0.2654)	Prec
poch: [59 * Train A	/200][0/4] .cc 88.375	LR:	0.01	Loss
Test Ac] Loss c 86.667			
	/200][0/4] .cc 88.750		0.01	

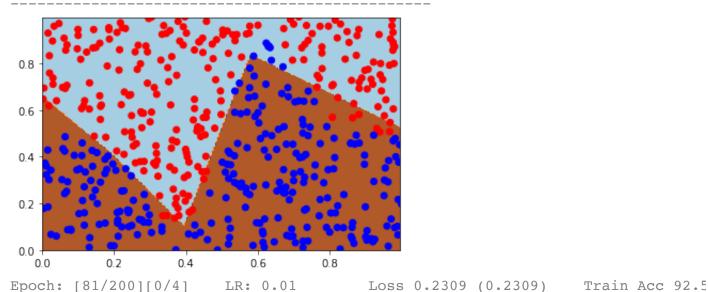
Test: [0/2] Loss 0.2734 (0.2734) Prec@1 87.500 (87.500)
* Test Acc 88.667

0.2 0.0 0.4 0.6 0.8 0.0 0.2 Loss 0.2987 (0.2987) Train Acc 89.4 Epoch: [61/200][0/4] LR: 0.01 * Train Acc 87.875 Test: [0/2] Loss 0.2847 (0.2847) Prec@1 90.625 (90.625) * Test Acc 91.333 _____ Epoch: [62/200][0/4] LR: 0.01 Loss 0.2657 (0.2657) Train Acc 91.0 * Train Acc 88.625 Test: [0/2] Loss 0.2421 (0.2421) Prec@1 88.281 (88.281) * Test Acc 87.000 Epoch: [63/200][0/4] LR: 0.01 Loss 0.2714 (0.2714) Train Acc 87.5 * Train Acc 89.500 Test: [0/2] Loss 0.2764 (0.2764) Prec@1 86.328 (86.328) * Test Acc 87.333 Epoch: [64/200][0/4] LR: 0.01 Loss 0.2966 (0.2966) Train Acc 89.4 * Train Acc 89.000 Test: [0/2] Loss 0.2550 (0.2550) Prec@1 90.625 (90.625) * Test Acc 90.667 _____ Epoch: [65/200][0/4] LR: 0.01 Loss 0.2593 (0.2593) Train Acc 90.6 * Train Acc 88.750 Test: [0/2] Loss 0.2340 (0.2340) Prec@1 89.844 (89.844) * Test Acc 89.333 _____ Epoch: [66/200][0/4] LR: 0.01 Loss 0.2323 (0.2323) Train Acc 92.5 * Train Acc 90.375 Test: [0/2] Loss 0.2509 (0.2509) Prec@1 87.891 (87.891) * Test Acc 88.000 Epoch: [67/200][0/4] LR: 0.01 Loss 0.2620 (0.2620) Train Acc 91.0 * Train Acc 90.750 Test: [0/2] Loss 0.2198 (0.2198) Prec@1 92.578 (92.578)

```
* Test Acc 91.000
_____
Epoch: [68/200][0/4] LR: 0.01 Loss 0.2527 (0.2527) Train Acc 92.1
* Train Acc 91.125
Test: [0/2] Loss 0.2512 (0.2512) Prec@1 89.062 (89.062)
* Test Acc 89.333
_____
Epoch: [69/200][0/4] LR: 0.01 Loss 0.2756 (0.2756) Train Acc 88.6
* Train Acc 89.250
Test: [0/2] Loss 0.2324 (0.2324) Prec@1 91.406 (91.406)
* Test Acc 91.667
_____
Epoch: [70/200][0/4] LR: 0.01 Loss 0.2216 (0.2216) Train Acc 91.7
* Train Acc 90.625
Test: [0/2] Loss 0.2327 (0.2327) Prec@1 90.234 (90.234)
* Test Acc 90.000
```



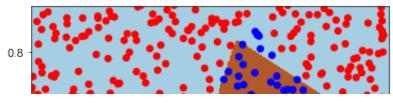
```
_____
Epoch: [75/200][0/4] LR: 0.01 Loss 0.2588 (0.2588) Train Acc 90.2
* Train Acc 91.375
Test: [0/2] Loss 0.1999 (0.1999) Prec@1 91.797 (91.797)
* Test Acc 92.000
Epoch: [76/200][0/4] LR: 0.01 Loss 0.2279 (0.2279) Train Acc 91.7
* Train Acc 90.750
Test: [0/2] Loss 0.2308 (0.2308) Prec@1 90.234 (90.234)
* Test Acc 90.000
_____
Epoch: [77/200][0/4] LR: 0.01 Loss 0.3019 (0.3019) Train Acc 87.8
* Train Acc 90.875
Test: [0/2] Loss 0.2012 (0.2012) Prec@1 92.188 (92.188)
* Test Acc 92.000
_____
Epoch: [78/200][0/4] LR: 0.01 Loss 0.2712 (0.2712) Train Acc 90.2
* Train Acc 91.500
Test: [0/2] Loss 0.1954 (0.1954) Prec@1 92.578 (92.578)
* Test Acc 92.000
_____
Epoch: [79/200][0/4] LR: 0.01 Loss 0.2237 (0.2237) Train Acc 94.1
* Train Acc 92.750
Test: [0/2] Loss 0.2235 (0.2235) Prec@1 90.625 (90.625)
* Test Acc 90.667
_____
Epoch: [80/200][0/4] LR: 0.01 Loss 0.2457 (0.2457) Train Acc 91.0
* Train Acc 91.875
Test: [0/2] Loss 0.2159 (0.2159) Prec@1 91.406 (91.406)
* Test Acc 91.667
```

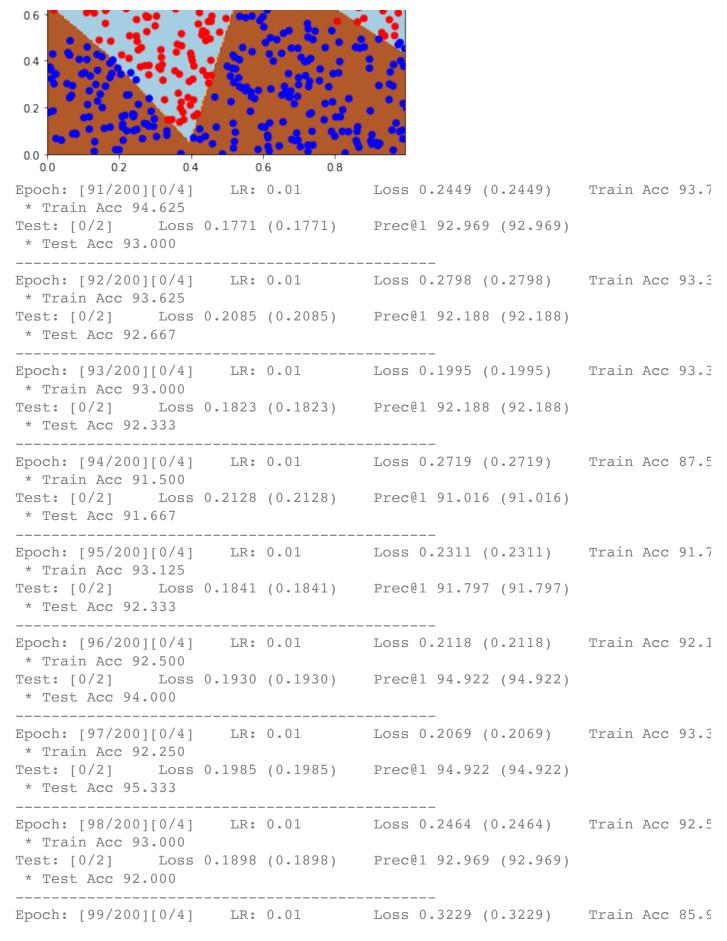


* Train Acc 93.000
Test: [0/2] Loss 0.1937 (0.1937) Prec@1 92.188 (92.188)

* Test Acc 92.333

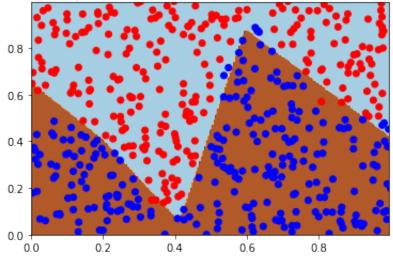
```
Epoch: [82/200][0/4] LR: 0.01 Loss 0.2288 (0.2288) Train Acc 91.4
* Train Acc 92.625
Test: [0/2] Loss 0.2010 (0.2010) Prec@1 93.359 (93.359)
* Test Acc 92.333
_____
Epoch: [83/200][0/4] LR: 0.01 Loss 0.2317 (0.2317) Train Acc 93.7
* Train Acc 93.000
Test: [0/2] Loss 0.1862 (0.1862) Prec@1 92.578 (92.578)
* Test Acc 91.667
_____
Epoch: [84/200][0/4] LR: 0.01
                              Loss 0.2331 (0.2331) Train Acc 92.9
* Train Acc 92.875
Test: [0/2] Loss 0.1901 (0.1901) Prec@1 93.750 (93.750)
* Test Acc 92.333
Epoch: [85/200][0/4] LR: 0.01 Loss 0.2234 (0.2234) Train Acc 94.1
* Train Acc 92.500
Test: [0/2] Loss 0.1790 (0.1790) Prec@1 93.750 (93.750)
* Test Acc 92.667
_____
Epoch: [86/200][0/4] LR: 0.01 Loss 0.2092 (0.2092) Train Acc 92.1
* Train Acc 93.125
Test: [0/2] Loss 0.2544 (0.2544) Prec@1 86.719 (86.719)
* Test Acc 88.333
_____
Epoch: [87/200][0/4] LR: 0.01 Loss 0.2562 (0.2562) Train Acc 90.2
* Train Acc 90.875
Test: [0/2] Loss 0.1953 (0.1953) Prec@1 91.797 (91.797)
* Test Acc 92.000
_____
Epoch: [88/200][0/4] LR: 0.01 Loss 0.2375 (0.2375) Train Acc 91.0
* Train Acc 90.625
Test: [0/2] Loss 0.1911 (0.1911) Prec@1 94.531 (94.531)
* Test Acc 93.333
_____
Epoch: [89/200][0/4] LR: 0.01 Loss 0.2631 (0.2631) Train Acc 92.1
* Train Acc 92.625
Test: [0/2] Loss 0.1955 (0.1955) Prec@1 93.359 (93.359)
* Test Acc 94.000
Epoch: [90/200][0/4] LR: 0.01 Loss 0.1982 (0.1982) Train Acc 92.9
* Train Acc 93.250
Test: [0/2] Loss 0.1783 (0.1783) Prec@1 94.141 (94.141)
* Test Acc 94.333
```





```
* Train Acc 90.125
Test: [0/2] Loss 0.2559 (0.2559) Prec@1 88.672 (88.672)
* Test Acc 87.667
Epoch: [100/200][0/4] LR: 0.01
                                Loss 0.3159 (0.3159) Train Acc 85.1
* Train Acc 90.375
Test: [0/2] Loss 0.1631 (0.1631) Prec@1 93.750 (93.750)
* Test Acc 93.333
0.8
0.4
0.0
                            0.8
        0.2
                      0.6
               0.4
Epoch: [101/200][0/4] LR: 0.01 Loss 0.2095 (0.2095) Train Acc 91.7
* Train Acc 91.750
Test: [0/2] Loss 0.1544 (0.1544) Prec@1 92.969 (92.969)
* Test Acc 93.000
Epoch: [102/200][0/4] LR: 0.01 Loss 0.2062 (0.2062) Train Acc 94.5
* Train Acc 92.750
Test: [0/2] Loss 0.1914 (0.1914) Prec@1 92.188 (92.188)
* Test Acc 92.667
_____
Epoch: [103/200][0/4] LR: 0.01 Loss 0.2126 (0.2126) Train Acc 91.7
* Train Acc 92.375
Test: [0/2] Loss 0.1773 (0.1773) Prec@1 92.578 (92.578)
* Test Acc 93.000
Epoch: [104/200][0/4] LR: 0.01 Loss 0.1794 (0.1794) Train Acc 95.7
* Train Acc 93.625
Test: [0/2] Loss 0.1691 (0.1691) Prec@1 94.141 (94.141)
* Test Acc 93.000
_____
Epoch: [105/200][0/4] LR: 0.01 Loss 0.2334 (0.2334) Train Acc 93.7
* Train Acc 93.875
Test: [0/2] Loss 0.1536 (0.1536) Prec@1 95.312 (95.312)
* Test Acc 94.000
.....
Epoch: [106/200][0/4] LR: 0.01 Loss 0.2093 (0.2093) Train Acc 94.1
* Train Acc 93.875
```

```
Test: [0/2] Loss 0.1983 (0.1983) Prec@1 91.406 (91.406)
* Test Acc 92.000
_____
Epoch: [107/200][0/4] LR: 0.01 Loss 0.1906 (0.1906) Train Acc 92.5
* Train Acc 92.250
Test: [0/2] Loss 0.1407 (0.1407) Prec@1 94.922 (94.922)
* Test Acc 94.000
_____
Epoch: [108/200][0/4] LR: 0.01 Loss 0.2046 (0.2046) Train Acc 94.5
* Train Acc 93.375
Test: [0/2] Loss 0.2218 (0.2218) Prec@1 90.625 (90.625)
* Test Acc 91.000
_____
Epoch: [109/200][0/4] LR: 0.01 Loss 0.2761 (0.2761) Train Acc 91.7
* Train Acc 93.000
Test: [0/2] Loss 0.1738 (0.1738) Prec@1 91.406 (91.406)
* Test Acc 92.000
Epoch: [110/200][0/4] LR: 0.01 Loss 0.2502 (0.2502) Train Acc 88.6
* Train Acc 90.750
Test: [0/2] Loss 0.1766 (0.1766) Prec@1 93.750 (93.750)
* Test Acc 94.333
```



Epoch: [111/200][0/4] LR: 0.01 Loss 0.1669 (0.1669) Train Acc 94.5

* Train Acc 92.250

Test: [0/2] Loss 0.2485 (0.2485) Prec@1 87.500 (87.500)

* Test Acc 87.333

Epoch: [112/200][0/4] LR: 0.01 Loss 0.2313 (0.2313) Train Acc 89.0

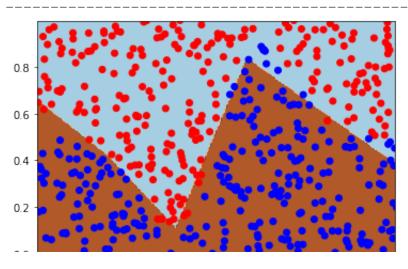
* Train Acc 88.875

Test: [0/2] Loss 0.1682 (0.1682) Prec@1 92.969 (92.969)

* Test Acc 93.333

Epoch: [113/200][0/4] LR: 0.01 Loss 0.2760 (0.2760) Train Acc 90.6

* Test Acc 95.000			
Epoch: [114/200][0/4] LR: * Train Acc 92.875 Test: [0/2] Loss 0.1655 * Test Acc 95.000	0.01		Train Acc 95.3
		Loss 0.2300 (0.2300)	Train Acc 94.1
Epoch: [116/200][0/4] LR: * Train Acc 91.000 Test: [0/2] Loss 0.2540 * Test Acc 88.667			Train Acc 91.0
Epoch: [117/200][0/4] LR: * Train Acc 90.375 Test: [0/2] Loss 0.1669 * Test Acc 93.000			Train Acc 90.2
Epoch: [118/200][0/4] LR: * Train Acc 93.125 Test: [0/2] Loss 0.1640 * Test Acc 93.333			Train Acc 91.7
Epoch: [119/200][0/4] LR: * Train Acc 92.625 Test: [0/2] Loss 0.1498 * Test Acc 93.667			Train Acc 92.9
Epoch: [120/200][0/4] LR: * Train Acc 92.875 Test: [0/2] Loss 0.1736 * Test Acc 94.333			Train Acc 91.7



0.0 0.2	0.4	0.6 0.8		
Epoch: [121/20 * Train Acc 9		: 0.01	Loss 0.2542 (0.2542)	Train Acc 9
	Loss 0.169	9 (0.1699)	Prec@1 93.750 (93.750)	
Epoch: [122/20 * Train Acc 9	00][0/4] LR 93.000		Loss 0.1860 (0.1860)	Train Acc 9
Test: [0/2] * Test Acc 93		8 (0.1388)	Prec@1 94.531 (94.531)	
Epoch: [123/20 * Train Acc 9		: 0.01	Loss 0.2100 (0.2100)	Train Acc 9
* Test Acc 94	1.667		Prec@1 94.531 (94.531)	
			Loss 0.2182 (0.2182)	Train Acc 9
	Loss 0.156	9 (0.1569)	Prec@1 94.531 (94.531)	
Epoch: [125/20 * Train Acc 9		: 0.01	Loss 0.1824 (0.1824)	Train Acc 9
	Loss 0.173	7 (0.1737)	Prec@1 95.312 (95.312)	
Epoch: [126/20 * Train Acc		: 0.01	Loss 0.2122 (0.2122)	Train Acc 9
	Loss 0.164		Prec@1 91.797 (91.797)	
Epoch: [127/20 * Train Acc	00][0/4] LR	: 0.01	Loss 0.1731 (0.1731)	Train Acc 9
Cest: [0/2] * Test Acc 93	Loss 0.151		Prec@1 95.312 (95.312)	
Epoch: [128/20 * Train Acc 9	00][0/4] LR		Loss 0.1642 (0.1642)	Train Acc 9
Pest: [0/2] * Test Acc 92	Loss 0.150		Prec@1 92.969 (92.969)	
poch: [129/20** Train Acc 9	00][0/4] LR		Loss 0.2348 (0.2348)	Train Acc 9
Cest: [0/2] * Test Acc 92	Loss 0.207		Prec@1 91.797 (91.797)	
Epoch: [130/20 * Train Acc 9	00][0/4] LR		Loss 0.2080 (0.2080)	Train Acc 9
Test: [0/2] * Test Acc 92		2 (0.1632)	Prec@1 92.578 (92.578)	

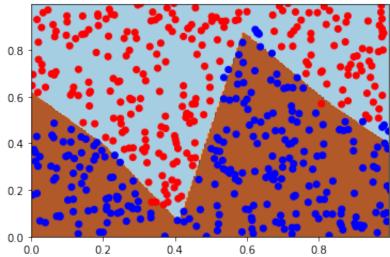
0.2 0.2 0.6 0.8 0.0 Epoch: [131/200][0/4] LR: 0.01 Loss 0.2349 (0.2349) Train Acc 91.7 * Train Acc 90.875 Test: [0/2] Loss 0.2854 (0.2854) Prec@1 83.984 (83.984) * Test Acc 83.667 Epoch: [132/200][0/4] LR: 0.01 Loss 0.2978 (0.2978) Train Acc 85.1 * Train Acc 88.000 Test: [0/2] Loss 0.1985 (0.1985) Prec@1 91.797 (91.797) * Test Acc 92.333 ._____ Epoch: [133/200][0/4] LR: 0.01 Loss 0.2997 (0.2997) Train Acc 89.0 * Train Acc 90.125 Test: [0/2] Loss 0.2181 (0.2181) Prec@1 90.234 (90.234) * Test Acc 88.000 _____ Epoch: [134/200][0/4] LR: 0.01 Loss 0.2108 (0.2108) Train Acc 92.1 * Train Acc 91.000 Test: [0/2] Loss 0.2256 (0.2256) Prec@1 91.797 (91.797) * Test Acc 92.000 Epoch: [135/200][0/4] LR: 0.01 Loss 0.2784 (0.2784) Train Acc 87.8 * Train Acc 88.000 Test: [0/2] Loss 0.2309 (0.2309) Prec@1 87.500 (87.500) * Test Acc 87.667 _____ Epoch: [136/200][0/4] LR: 0.01 Loss 0.3065 (0.3065) Train Acc 86.7 * Train Acc 88.125 Test: [0/2] Loss 0.1431 (0.1431) Prec@1 94.141 (94.141) * Test Acc 93.333 Epoch: [137/200][0/4] LR: 0.01 Loss 0.1887 (0.1887) Train Acc 92.9 * Train Acc 92.125 Test: [0/2] Loss 0.1718 (0.1718) Prec@1 92.969 (92.969) * Test Acc 93.333

```
Epoch: [138/200][0/4] LR: 0.01 Loss 0.1924 (0.1924) Train Acc 94.9
* Train Acc 93.750
Test: [0/2] Loss 0.1838 (0.1838) Prec@1 94.141 (94.141)
* Test Acc 95.000
_____
Epoch: [139/200][0/4] LR: 0.01 Loss 0.1694 (0.1694) Train Acc 94.9
* Train Acc 93.875
Test: [0/2] Loss 0.1718 (0.1718) Prec@1 93.750 (93.750)
* Test Acc 94.000
_____
Epoch: [140/200][0/4] LR: 0.01 Loss 0.2138 (0.2138) Train Acc 92.1
* Train Acc 93.250
Test: [0/2] Loss 0.1732 (0.1732) Prec@1 93.750 (93.750)
* Test Acc 94.000
0.2
         0.2
               0.4
                      0.6
                            0.8
Epoch: [141/200][0/4] LR: 0.01 Loss 0.2254 (0.2254) Train Acc 92.5
* Train Acc 94.125
Test: [0/2] Loss 0.1582 (0.1582) Prec@1 94.531 (94.531)
* Test Acc 94.000
Epoch: [142/200][0/4] LR: 0.01 Loss 0.1883 (0.1883) Train Acc 92.5
* Train Acc 93.875
Test: [0/2] Loss 0.1633 (0.1633) Prec@1 95.703 (95.703)
* Test Acc 95.333
Epoch: [143/200][0/4] LR: 0.01 Loss 0.2159 (0.2159) Train Acc 93.3
* Train Acc 94.125
Test: [0/2] Loss 0.1945 (0.1945) Prec@1 93.359 (93.359)
* Test Acc 94.333
Epoch: [144/200][0/4] LR: 0.01 Loss 0.2090 (0.2090) Train Acc 92.9
* Train Acc 92.500
Test: [0/2] Loss 0.1378 (0.1378) Prec@1 93.750 (93.750)
* Test Acc 93.000
```

Froch • [1/5/200][0//] T.D. 0 01

Togg N 1022 /N 10221 Train Acc 02 5

```
Thoeir [143/500][0.44] Tr. 0.01 TOB 0.1753 (0.1753)
                                                    TIGITI DOC 14.0
* Train Acc 93.625
Test: [0/2] Loss 0.1408 (0.1408) Prec@1 92.969 (92.969)
* Test Acc 93.333
Epoch: [146/200][0/4] LR: 0.01 Loss 0.1997 (0.1997) Train Acc 95.7
* Train Acc 93.125
Test: [0/2] Loss 0.1442 (0.1442) Prec@1 94.141 (94.141)
* Test Acc 93.667
_____
Epoch: [147/200][0/4] LR: 0.01 Loss 0.2138 (0.2138) Train Acc 92.9
* Train Acc 93.375
Test: [0/2] Loss 0.1537 (0.1537) Prec@1 95.312 (95.312)
* Test Acc 95.333
Epoch: [148/200][0/4] LR: 0.01 Loss 0.2596 (0.2596) Train Acc 92.1
* Train Acc 94.125
Test: [0/2] Loss 0.1394 (0.1394) Prec@1 96.094 (96.094)
* Test Acc 95.667
.....
Epoch: [149/200][0/4] LR: 0.01 Loss 0.2196 (0.2196) Train Acc 94.1
* Train Acc 94.250
Test: [0/2] Loss 0.1614 (0.1614) Prec@1 93.750 (93.750)
* Test Acc 94.667
Epoch: [150/200][0/4] LR: 0.01 Loss 0.1910 (0.1910) Train Acc 93.3
* Train Acc 92.750
Test: [0/2] Loss 0.1438 (0.1438) Prec@1 95.312 (95.312)
* Test Acc 95.333
```



Epoch: [151/200][0/4] LR: 0.01 Loss 0.2042 (0.2042) Train Acc 94.9

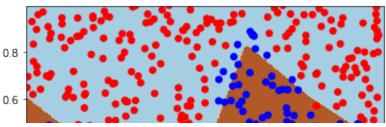
* Train Acc 93.750

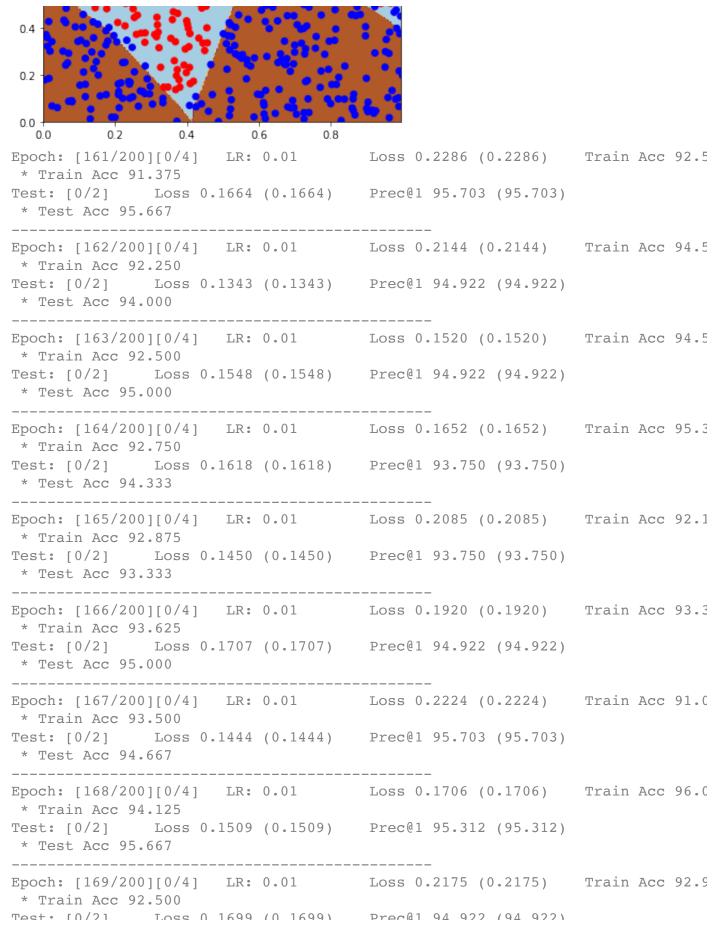
Test: [0/2] Loss 0.1388 (0.1388) Prec@1 96.094 (96.094)

* Test Acc 95.333

Epoch: [152/200][0/4] LR: 0.01 Loss 0.2171 (0.2171) Train Acc 93.7

```
* Train ACC 95.000
Test: [0/2] Loss 0.1498 (0.1498) Prec@1 95.312 (95.312)
* Test Acc 95.000
_____
Epoch: [153/200][0/4] LR: 0.01 Loss 0.1870 (0.1870) Train Acc 94.1
* Train Acc 93.750
Test: [0/2] Loss 0.2010 (0.2010) Prec@1 90.234 (90.234)
* Test Acc 90.333
-----
Epoch: [154/200][0/4] LR: 0.01
                             Loss 0.1872 (0.1872) Train Acc 93.7
* Train Acc 91.000
Test: [0/2] Loss 0.1505 (0.1505) Prec@1 94.531 (94.531)
* Test Acc 93.667
-----
Epoch: [155/200][0/4] LR: 0.01 Loss 0.2420 (0.2420) Train Acc 87.5
* Train Acc 89.375
Test: [0/2] Loss 0.2146 (0.2146) Prec@1 90.234 (90.234)
* Test Acc 91.000
_____
Epoch: [156/200][0/4] LR: 0.01 Loss 0.1973 (0.1973) Train Acc 92.5
* Train Acc 90.250
Test: [0/2] Loss 0.1585 (0.1585) Prec@1 94.141 (94.141)
* Test Acc 93.333
_____
Epoch: [157/200][0/4] LR: 0.01 Loss 0.2145 (0.2145) Train Acc 91.7
* Train Acc 89.625
Test: [0/2] Loss 0.1835 (0.1835) Prec@1 92.578 (92.578)
* Test Acc 92.333
_____
Epoch: [158/200][0/4] LR: 0.01 Loss 0.2387 (0.2387) Train Acc 92.5
* Train Acc 91.125
Test: [0/2] Loss 0.1578 (0.1578) Prec@1 92.578 (92.578)
* Test Acc 92.333
_____
Epoch: [159/200][0/4] LR: 0.01 Loss 0.2176 (0.2176) Train Acc 91.4
* Train Acc 92.375
Test: [0/2] Loss 0.1748 (0.1748) Prec@1 93.750 (93.750)
* Test Acc 94.333
Epoch: [160/200][0/4] LR: 0.01 Loss 0.2122 (0.2122) Train Acc 92.5
* Train Acc 93.125
Test: [0/2] Loss 0.1581 (0.1581) Prec@1 92.969 (92.969)
* Test Acc 93.667
```

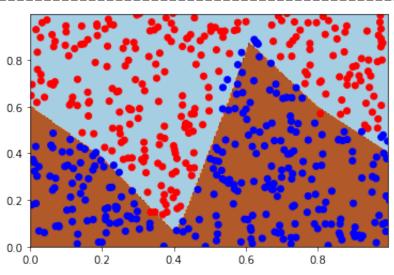




```
TODG: [0/8] HODD 0:1000 (0:1000) TECOCE 03:028 (03:028)
* Test Acc 95.667
-----
Epoch: [170/200][0/4] LR: 0.01
                              Loss 0.2174 (0.2174) Train Acc 93.3
* Train Acc 94.750
Test: [0/2] Loss 0.1414 (0.1414) Prec@1 94.922 (94.922)
* Test Acc 94.667
0.4
0.0
                    0.6
                           0.8
        0.2
              0.4
Epoch: [171/200][0/4] LR: 0.01 Loss 0.1552 (0.1552) Train Acc 95.7
* Train Acc 94.250
Test: [0/2] Loss 0.1675 (0.1675) Prec@1 94.531 (94.531)
* Test Acc 95.000
_____
Epoch: [172/200][0/4] LR: 0.01 Loss 0.2422 (0.2422) Train Acc 91.7
* Train Acc 93.250
Test: [0/2] Loss 0.1458 (0.1458) Prec@1 94.922 (94.922)
* Test Acc 94.333
_____
Epoch: [173/200][0/4] LR: 0.01 Loss 0.1571 (0.1571) Train Acc 95.3
* Train Acc 94.500
Test: [0/2] Loss 0.1622 (0.1622) Prec@1 93.359 (93.359)
* Test Acc 94.333
Epoch: [174/200][0/4] LR: 0.01 Loss 0.2177 (0.2177) Train Acc 93.7
* Train Acc 94.375
Test: [0/2] Loss 0.1571 (0.1571) Prec@1 94.922 (94.922)
* Test Acc 95.333
_____
Epoch: [175/200][0/4] LR: 0.01 Loss 0.2299 (0.2299) Train Acc 93.7
* Train Acc 94.625
Test: [0/2] Loss 0.1554 (0.1554) Prec@1 95.312 (95.312)
* Test Acc 95.000
._____
Epoch: [176/200][0/4] LR: 0.01 Loss 0.1691 (0.1691) Train Acc 94.9
* Train Acc 93.500
Test: [0/2] Loss 0.1642 (0.1642) Prec@1 95.312 (95.312)
```

```
^ TEST ACC 90.333
```

_____ Epoch: [177/200][0/4] LR: 0.01 Loss 0.1581 (0.1581) Train Acc 96.0 * Train Acc 94.750 Test: [0/2] Loss 0.1382 (0.1382) Prec@1 95.312 (95.312) * Test Acc 94.000 _____ Epoch: [178/200][0/4] LR: 0.01 Loss 0.2244 (0.2244) Train Acc 92.9 * Train Acc 94.375 Test: [0/2] Loss 0.1600 (0.1600) Prec@1 94.141 (94.141) * Test Acc 94.333 Epoch: [179/200][0/4] LR: 0.01 Loss 0.1752 (0.1752) Train Acc 94.9 * Train Acc 94.000 Test: [0/2] Loss 0.1501 (0.1501) Prec@1 94.141 (94.141) * Test Acc 94.667 _____ Epoch: [180/200][0/4] LR: 0.01 Loss 0.1420 (0.1420) Train Acc 96.4 * Train Acc 93.750 Test: [0/2] Loss 0.1357 (0.1357) Prec@1 93.750 (93.750) * Test Acc 94.000



Epoch: [181/200][0/4] LR: 0.01 Loss 0.1961 (0.1961) Train Acc 94.5

* Train Acc 94.000

Test: [0/2] Loss 0.1513 (0.1513) Prec@1 92.969 (92.969)

* Test Acc 93.000

Epoch: [182/200][0/4] LR: 0.01 Loss 0.2542 (0.2542) Train Acc 90.6

* Train Acc 93.125

Test: [0/2] Loss 0.1334 (0.1334) Prec@1 94.531 (94.531)

* Test Acc 94.667

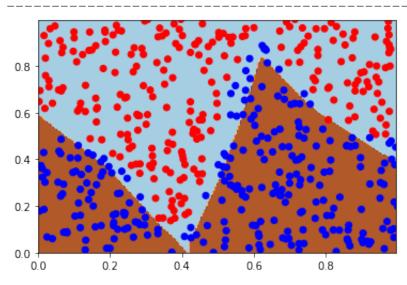
Epoch: [183/200][0/4] LR: 0.01 Loss 0.1895 (0.1895) Train Acc 93.3

* Train Acc 94.000

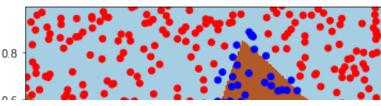
Test: [0/2] Loss 0.1548 (0.1548) Prec@1 94.922 (94.922)

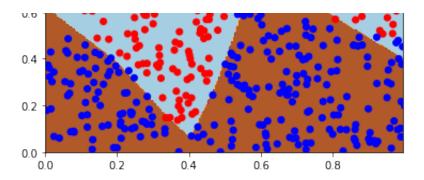
* Test Acc 94.667

_____ Epoch: [184/200][0/4] LR: 0.01 Loss 0.1913 (0.1913) Train Acc 94.5 * Train Acc 93.875 Test: [0/2] Loss 0.1211 (0.1211) Prec@1 94.922 (94.922) * Test Acc 94.000 _____ Epoch: [185/200][0/4] LR: 0.01 Loss 0.2075 (0.2075) Train Acc 92.9 * Train Acc 93.125 Test: [0/2] Loss 0.1865 (0.1865) Prec@1 91.406 (91.406) * Test Acc 90.333 Epoch: [186/200][0/4] LR: 0.01 Loss 0.2068 (0.2068) Train Acc 91.7 * Train Acc 92.125 Test: [0/2] Loss 0.1512 (0.1512) Prec@1 93.750 (93.750) * Test Acc 93.333 _____ Epoch: [187/200][0/4] LR: 0.01 Loss 0.2364 (0.2364) Train Acc 91.0 * Train Acc 91.875 Test: [0/2] Loss 0.2172 (0.2172) Prec@1 90.234 (90.234) * Test Acc 89.667 _____ Epoch: [188/200][0/4] LR: 0.01 Loss 0.1660 (0.1660) Train Acc 94.9 * Train Acc 91.250 Test: [0/2] Loss 0.1723 (0.1723) Prec@1 92.969 (92.969) * Test Acc 93.000 Epoch: [189/200][0/4] LR: 0.01 Loss 0.2113 (0.2113) Train Acc 90.6 * Train Acc 90.750 Test: [0/2] Loss 0.2103 (0.2103) Prec@1 90.625 (90.625) * Test Acc 90.333 Epoch: [190/200][0/4] LR: 0.01 Loss 0.2030 (0.2030) Train Acc 92.9 * Train Acc 92.625 Test: [0/2] Loss 0.1417 (0.1417) Prec@1 94.531 (94.531) * Test Acc 93.667



```
Epoch: [191/200][0/4] LR: 0.01 Loss 0.2216 (0.2216) Train Acc 91.7
* Train Acc 92.000
Test: [0/2] Loss 0.2124 (0.2124) Prec@1 91.016 (91.016)
* Test Acc 91.667
_____
Epoch: [192/200][0/4] LR: 0.01 Loss 0.2258 (0.2258) Train Acc 92.1
* Train Acc 92.625
Test: [0/2] Loss 0.1648 (0.1648) Prec@1 92.578 (92.578)
* Test Acc 93.000
_____
Epoch: [193/200][0/4] LR: 0.01 Loss 0.2372 (0.2372) Train Acc 90.2
* Train Acc 91.125
Test: [0/2] Loss 0.1942 (0.1942) Prec@1 92.188 (92.188)
* Test Acc 91.667
_____
Epoch: [194/200][0/4] LR: 0.01 Loss 0.2520 (0.2520) Train Acc 89.8
* Train Acc 91.500
Test: [0/2] Loss 0.1792 (0.1792) Prec@1 92.578 (92.578)
* Test Acc 93.000
Epoch: [195/200][0/4] LR: 0.01 Loss 0.1848 (0.1848) Train Acc 92.5
* Train Acc 88.750
Test: [0/2] Loss 0.1971 (0.1971) Prec@1 92.578 (92.578)
* Test Acc 93.000
_____
Epoch: [196/200][0/4] LR: 0.01
                             Loss 0.2719 (0.2719) Train Acc 91.4
* Train Acc 89.750
Test: [0/2] Loss 0.1479 (0.1479) Prec@1 94.141 (94.141)
* Test Acc 94.667
_____
Epoch: [197/200][0/4] LR: 0.01 Loss 0.1864 (0.1864) Train Acc 93.3
* Train Acc 92.000
Test: [0/2] Loss 0.1382 (0.1382) Prec@1 94.531 (94.531)
* Test Acc 95.000
_____
Epoch: [198/200][0/4] LR: 0.01 Loss 0.1945 (0.1945) Train Acc 94.5
* Train Acc 94.250
Test: [0/2] Loss 0.1652 (0.1652) Prec@1 94.531 (94.531)
* Test Acc 94.333
_____
Epoch: [199/200][0/4] LR: 0.01 Loss 0.2113 (0.2113) Train Acc 93.3
* Train Acc 94.375
Test: [0/2] Loss 0.1478 (0.1478) Prec@1 92.578 (92.578)
* Test Acc 93.333
```

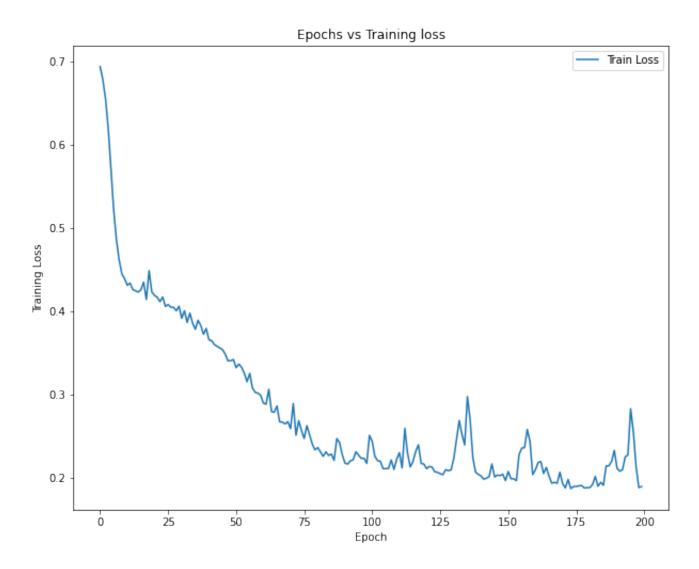




▼ a)

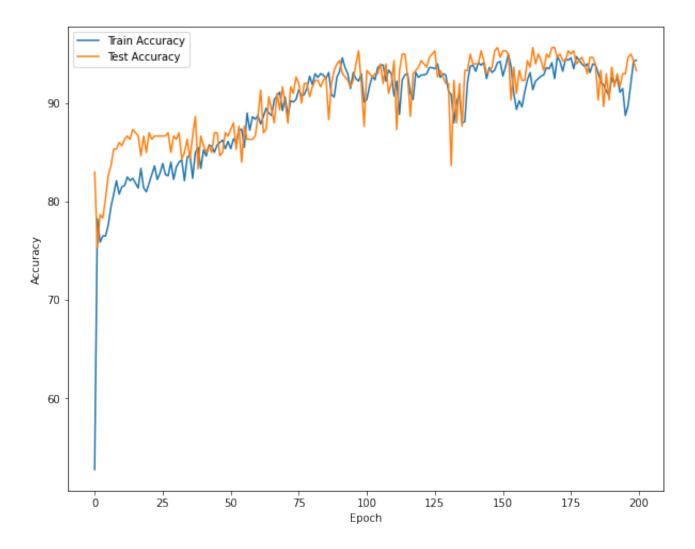
```
rcParams['figure.figsize'] = 10, 8  # adjust the size of the plot
rcParams['xtick.labelsize'] = 10  # adjust font size for x-axis ticks
rcParams['ytick.labelsize'] = 10  # adjust font size for y-axis ticks
rcParams['legend.fontsize'] = 10  # adjust font size for legend

plt.plot(train_losses, label='Train Loss')
plt.xlabel('Epoch')
plt.ylabel('Training Loss')
plt.title('Epochs vs Training loss')
plt.legend()
plt.show()
```



```
rcParams['figure.figsize'] = 10, 8  # adjust the size of the plot
rcParams['xtick.labelsize'] = 10  # adjust font size for x-axis ticks
rcParams['ytick.labelsize'] = 10  # adjust font size for y-axis ticks
rcParams['legend.fontsize'] = 10  # adjust font size for legend

plt.plot(train_accuracies, label='Train Accuracy')
plt.plot(test_accuracies, label='Test Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



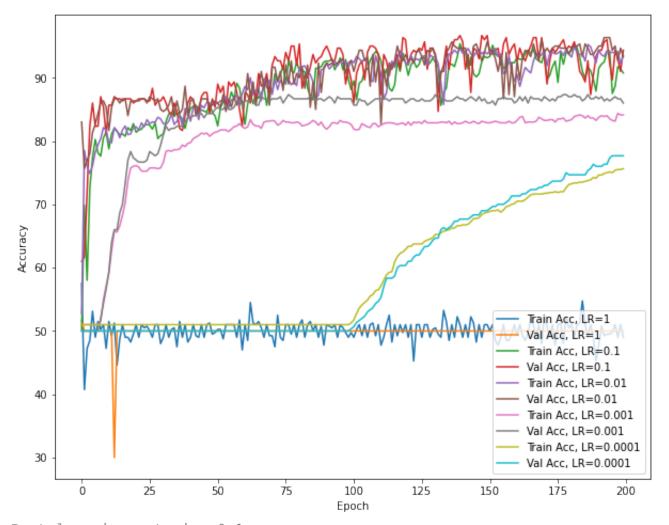
▼ b)

```
lrs = [1, 0.1, 0.01, 0.001, 0.0001]
train_losses = []
train_accuracies = []
val accuracies = []
best val acc = 0
best_lr = 0
for lr in lrs:
   # create new model and optimizer with the current learning rate
   torch.manual_seed(999)
   model = linear_nn(num_neurons, activations).to(device)
    criterion = nn.CrossEntropyLoss().to(device)
    optimizer = torch.optim.Adam(model.parameters(), lr=lr, weight_decay=weight_dec
   # train the model for num_epochs and record the accuracy
    train_acc, val_acc = [], []
    for epoch in range(num_epochs):
        train_loss, train_acc_epoch = train(train_loader, model, criterion, optimiz
        val_acc_epoch = validate(val_loader, model, criterion)
        train_acc.append(train_acc_epoch)
        val acc.append(val acc epoch)
        # update best validation accuracy and learning rate
        if val_acc_epoch > best_val_acc:
            best_val_acc = val_acc_epoch
            best lr = lr
   # store the accuracy for the current learning rate
   train losses.append(train loss)
   train accuracies.append(train acc)
   val_accuracies.append(val_acc)
```

```
# plot the training and validation accuracy curves for each learning rate
for i, lr in enumerate(lrs):
    plt.plot(train_accuracies[i], label='Train Acc, LR={}'.format(lr))
    plt.plot(val_accuracies[i], label='Val Acc, LR={}'.format(lr))

plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

print("Best learning rate is:", best_lr)



Best learning rate is: 0.1

Based on the validation accuracy, we determined that the best learning rate is 0.1. It is possible that different learning rates may perform better or worse depending on the specific problem and dataset being used, but in this case, based on the given code and data, 0.1 appears to be the best choice.

→ C)

```
def linear_nn_one_layer():
    model = LinearNN(num_neurons=[2, 100, 2], activations=['relu'])
    return model
# Create new model
model new = linear nn one layer()
# Define optimizer for new model
optimizer_new = torch.optim.Adam(model_new.parameters(), lr=lr, weight_decay=weight
# Train new model
train_losses_new = []
train_accuracies_new = []
test_accuracies_new = []
best_prec1_new = 0
for epoch in range(num_epochs):
    if epoch in lr step:
        for param_group in optimizer_new.param_groups:
            param_group['lr'] *= 0.1
    # train for one epoch
    train_loss, train_acc = train(train_loader, model_new, criterion, optimizer_new
    train_losses_new.append(train_loss)
    train_accuracies_new.append(train_acc)
    # evaluate on validation set
    prec1_new = validate(val_loader, model_new, criterion)
    test_accuracies_new.append(prec1_new)
    # remember best prec@1 and save checkpoint
    is_best_new = prec1_new > best_prec1_new
```

best_prec1_new = max(prec1_new, best_prec1_new)

```
# Print final training and testing accuracies and number of parameters
print('Model with 3 hidden layers:')
print('Train Accuracy: {:.2f}%'.format(train_accuracies[-1]))
print('Test Accuracy: {:.2f}%'.format(test_accuracies[-1]))
print('Number of parameters: {}'.format(sum(p.numel() for p in model.parameters()))

print('Model with 1 hidden layer:')
print('Train Accuracy: {:.2f}%'.format(train_accuracies_new[-1]))
print('Test Accuracy: {:.2f}%'.format(test_accuracies_new[-1]))
print('Number of parameters: {}'.format(sum(p.numel() for p in model_new.parameters))
```

* Train Acc 81.250		,	
Test: [0/2] Loss 0.4958	(0.4958)	Prec@1 86.328 (86.328)	
* Test Acc 86.667	, ,	,	
Epoch: [188/200][0/4] LR:	0.0001	Loss 0.4951 (0.4951)	Train Acc 83.9
* Train Acc 81.250			
Test: [0/2] Loss 0.4970	(0.4970)	Prec@1 85.547 (85.547)	
* Test Acc 86.667			
Epoch: [189/200] [0/4] LR:	0.0001	Loss 0.5143 (0.5143)	Train Acc 83.
* Train Acc 81.500	(
Test: [0/2] Loss 0.4929	(0.4929)	Prec@1 86.719 (86.719)	
* Test Acc 86.667	0.0001		T : A 70 /
Epoch: [190/200] [0/4] LR:	0.0001	LOSS 0.5164 (0.5164)	Irain Acc /9.0
* Train Acc 81.625 Test: [0/2] Loss 0.4909	(0.4000)	Drocel 96 710 (96 710)	
* Test Acc 86.667	(0.4909)	Frec@1 80.719 (80.719)	
Epoch: [191/200] [0/4] LR:	0 0001	Loss 0 5104 (0 5104)	Train Acc 70 1
* Train Acc 81.750	0.0001	2033 0:3134 (0:3134)	TIGITI ACC 7512
Test: [0/2] Loss 0.4893	(0.4893)	Prec@1 87.500 (87.500)	
* Test Acc 86.667	, ,	, ,	
Epoch: [192/200][0/4] LR:	0.0001	Loss 0.5144 (0.5144)	Train Acc 83.
* Train Acc 81.750			
Test: [0/2] Loss 0.4790	(0.4790)	Prec@1 88.672 (88.672)	
* Test Acc 86.667			
Epoch: [193/200] [0/4] LR:	0.0001	Loss 0.4839 (0.4839)	Train Acc 86.7
* Train Acc 81.750			
Test: [0/2] Loss 0.4877	(0.4877)	Prec@1 85.547 (85.547)	
* Test Acc 86.667	0.0001	1 0 5207 (0 5207)	T
Epoch: [194/200] [0/4] LR:	0.0001	Loss 0.5207 (0.5207)	Irain Acc 81.0
* Train Acc 81.750 Test: [0/2] Loss 0.4751	(0.4751)	Drace1 97 E00 (97 E00)	
* Test Acc 86.667	(0.4/31)	Prec(g1 87.300 (87.300)	
Epoch: [195/200] [0/4] LR:	0.0001	Loss 0.5154 (0.5154)	Train Acc 81.6
* Train Acc 81.625	0.0001	2000 01010 . (010101)	
Test: [0/2] Loss 0.4777	(0.4777)	Prec@1 88.672 (88.672)	

* Test Acc 86.667				
Epoch: [196/200][0/4] LR:	0.0001	Loss 0.4885 (0.4885)	Train Acc 84	1.7
* Train Acc 81.625				
Test: [0/2] Loss 0.4816	(0.4816)	Prec@1 86.719 (86.719)		
* Test Acc 86.667				
Epoch: [197/200] [0/4] LR:	0.0001	Loss 0.5235 (0.5235)	Train Acc 80).{
* Train Acc 81.625				
Test: [0/2] Loss 0.4784	(0.4784)	Prec@1 87.891 (87.891)		
* Test Acc 86.667				
Epoch: [198/200] [0/4] LR:	0.0001	Loss 0.5057 (0.5057)	Train Acc 82	2.{
* Train Acc 81.750	()	-		
Test: [0/2] Loss 0.4802	(0.4802)	Prec@1 87.891 (87.891)		
* Test Acc 86.333	0.0004	1 0 4054 (0 4054)	-	
Epoch: [199/200] [0/4] LR:	0.0001	LOSS 0.4861 (0.4861)	Train Acc 84	+ •
* Train Acc 81.750	(0.4006)	D 01 05 330 (05 330)		
Test: [0/2] Loss 0.4826	(0.4826)	Prec@1 86.328 (86.328)		
* Test Acc 86.000				
Model with 3 hidden layers:				
Train Accuracy: 78.00%				
Test Accuracy: 80.33%				
Number of parameters: 402 Model with 1 hidden layer:				
Train Accuracy: 81.75%				
Test Accuracy: 86.00%				
Number of parameters: 502				
Number of parameters. 302				

The model with 1 hidden layer containing 100 neurons performs better than the model with 3 hidden layers. The test accuracy of the model with 1 hidden layer is higher than that of the model with 3 hidden layers. Additionally, the model with 1 hidden layer has more parameters than the model with 3 hidden layers, indicating that it is more expressive and can capture more complex patterns in the data. Therefore, the shallow model with 1 hidden layer is better than the deep model with 3 hidden layers in this case.

X

Colab paid products - Cancel contracts here

√ 4s completed at 10:56 PM