group-project-SEResNet-1

July 13, 2019

In [9]:
```
import torch
import pandas as pd
import numpy as np
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms, utils
from torch.utils.data.sampler import SubsetRandomSampler

import matplotlib.pyplot as plt

import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torchvision

device = torch.device('cuda:0')
```

In [10]:
```
class PUBG_imglike_dataset(Dataset):
    def __init__(self, csv_file, transform=None):
        self.frame = pd.read_csv(csv_file)
        self.transform = transform

    def __len__(self):
        return len(self.frame)

    def __getitem__(self, idx):
        def transfrom2imglike(input):
            output = np.zeros((3,32,32))
            temp = np.array(input)
            for x in range(23):
                for y in range(23):
                    if(x == y):
                        output[0][x][y] = temp[x]
                        output[1][x][y] = temp[x]
                        output[2][x][y] = temp[x]
            return output
        # get one line in csv
        player_id = self.frame.iloc [idx, 0]
```

```
            player_stats = self.frame.iloc [idx, [x for x in range(3, 27) if x != 15]].valu
            player_stats = torch.tensor(transfrom2imglike(player_stats))
            win_place_perc = torch.tensor(self.frame.iloc [idx, 28])
            if self.transform:
                player_stats = self.transform(player_stats)
            sample = {
                "player_id": player_id,
                "player_stats": player_stats,
                "win_place_perc": win_place_perc
            }
            return sample

    def get_dataset(csv_file, train_dataset_size_ratio, batch_size):
        dataset = PUBG_imglike_dataset(csv_file)
        #  `torch.utils.data.random_split` meets server problem and lead to CRASH
        # see also:
        # - a denied fix PR for this problem: https://github.com/pytorch/pytorch/pull/9237
        #train_dataset, test_dataset = torch.utils.data.random_split(dataset, [train_size,
        dataset_size = len(dataset)
        indices = list(range(dataset_size))
        split = int(np.floor((1-train_dataset_size_ratio) * dataset_size))
        train_indices, val_indices = indices[split:], indices[:split]

        train_sampler = SubsetRandomSampler(train_indices)
        valid_sampler = SubsetRandomSampler(val_indices)

        train_loader = torch.utils.data.DataLoader(dataset, batch_size=batch_size, sampler=
        test_loader = torch.utils.data.DataLoader(dataset, batch_size=batch_size, sampler=v
        print("load dataset: train dataset: {}, test dataset: {}.".format(len(train_loader)
        return (train_loader, test_loader)

    # load dataset
    csv_file = 'train_small.csv'
    train_dataset_size_ratio = 0.9
    batch_size = 128
    train_loader, test_loader = get_dataset(csv_file, train_dataset_size_ratio, batch_size)
```

```
load dataset: train dataset: 1152, test dataset: 128.
```

```
In [11]: def show_curve(ys, title):
            x = np.array(range(len(ys)))
            y = np.array(ys)
            plt.plot(x, y, c='b')
            plt.axis()
            plt.title('{} curve'.format(title))
            plt.xlabel('epoch')
            plt.ylabel('{}'.format(title))
            plt.show()
```

```
In [12]: def train(model, train_loader, loss_func, optimizer, device):
             total_loss = 0
             # train the model using minibatch
             for i, data in enumerate(train_loader):
                 stats, prec = data['player_stats'], data['win_place_perc']
                 stats, prec = stats.to(torch.float32).to(device), prec.to(device)

                 # forward
                 outputs = model(stats)
                 loss = loss_func(outputs, prec)

                 # backward and optimize
                 optimizer.zero_grad()
                 loss.backward()
                 optimizer.step()

                 total_loss += loss.item()

                 #if (i + 1) % 10 == 0:
                 #    print ("Step [{}/{}] Train Loss: {:.4f}".format(i+1, len(train_loader), lo
             #print ("Train Loss: {:.4f}".format(loss.item()))
             return total_loss / len(train_loader)

         def evaluate(model, val_loader, device):

             model.eval()
             with torch.no_grad():
                 loss = 0
                 total = 0

                 for i, data in enumerate(val_loader):
                     stats, prec = data['player_stats'], data['win_place_perc']
                     stats, prec = stats.to(torch.float32).to(device), prec.to(device)

                     outputs = model(stats)


                     loss += (torch.abs(torch.t(outputs) - prec)).sum()
                     total += prec.size(0)


                 accuracy = loss / total
                 #print('Test Loss: {:.4f}'.format(accuracy))
                 return accuracy

         def fit(model, num_epochs, optimizer, device):
             loss_func = nn.MSELoss()
             model.to(device)
```

```
    if device == torch.device('cuda'):
        model = torch.nn.DataParallel(model)
        cudnn.benchmark = True
    loss_func.to(device)
    losses = []
    accs = []

    for epoch in range(num_epochs):


        # train step
        loss = train(model, train_loader, loss_func, optimizer, device)
        losses.append(loss)

        # evaluate step
        accuracy = evaluate(model, test_loader, device)
        accs.append(accuracy)

        # print loss
        if (epoch+1) % 10 == 0:
            print("Epoch {}/{}".format(epoch+1, num_epochs))
            print("Train Loss: {:.4f}".format(loss))
            print('Test Loss: {:.4f}'.format(accuracy))

    show_curve(losses, "train loss")
    show_curve(accs, "test loss")
```

In [13]:
```
from torch import nn
def conv3x3(in_channels, out_channels, stride=1):
    return nn.Conv2d(in_channels, out_channels, kernel_size=3,
                     stride=stride, padding=1, bias=False)

class ResNet(nn.Module):
    def __init__(self, block, layers, num_classes=10):
        """
        block: ResidualBlock or other block
        layers: a list with 3 positive num.
        """
        super(ResNet, self).__init__()
        self.in_channels = 16
        self.conv = conv3x3(3, 16)
        self.bn = nn.BatchNorm2d(16)
        self.relu = nn.ReLU(inplace=True)
        # layer1: image size 32
        self.layer1 = self.make_layer(block, 16, num_blocks=layers[0])
        # layer2: image size 32 -> 16
        self.layer2 = self.make_layer(block, 32, num_blocks=layers[1], stride=2)
        # layer1: image size 16 -> 8
```

```
        self.layer3 = self.make_layer(block, 64, num_blocks=layers[2], stride=2)
        # global avg pool: image size 8 -> 1
        self.avg_pool = nn.AvgPool2d(8)

        self.fc = nn.Linear(64, num_classes)

    def make_layer(self, block, out_channels, num_blocks, stride=1):
        """
        make a layer with num_blocks blocks.
        """

        downsample = None
        if (stride != 1) or (self.in_channels != out_channels):
            # use Conv2d with stride to downsample
            downsample = nn.Sequential(
                conv3x3(self.in_channels, out_channels, stride=stride),
                nn.BatchNorm2d(out_channels))

        # first block with downsample
        layers = []
        layers.append(block(self.in_channels, out_channels, stride, downsample))

        self.in_channels = out_channels
        # add num_blocks - 1 blocks
        for i in range(1, num_blocks):
            layers.append(block(out_channels, out_channels))

        # return a layer containing layers
        return nn.Sequential(*layers)

    def forward(self, x):
        out = self.conv(x)
        out = self.bn(out)
        out = self.relu(out)
        out = self.layer1(out)
        out = self.layer2(out)
        out = self.layer3(out)
        out = self.avg_pool(out)
        # view: here change output size from 4 dimensions to 2 dimensions
        out = out.view(out.size(0), -1)
        out = self.fc(out)
        return out

class SELayer(nn.Module):
    def __init__(self, channel, reduction=16):
        super(SELayer, self).__init__()
        # The output of AdaptiveAvgPool2d is of size H x W, for any input size.
        self.avg_pool = nn.AdaptiveAvgPool2d((1, 1))
```

```
            """
            To-Do: add code here
            """
            self.fc1 = nn.Linear(channel, channel // reduction)
            self.relu = nn.ReLU(inplace=True)
            self.fc2 = nn.Linear(channel // reduction,channel)
            self.sigmoid = nn.Sigmoid()
        def forward(self, x):
            """
            To-Do: add code here
            """
            out = self.avg_pool(x)
            out = out.view(out.size(0),-1)
            out = self.fc1(out)
            out = self.relu(out)
            out = self.fc2(out)
            out = self.sigmoid(out)
            out = out.view(out.size(0),out.size(1),1,1)
            return out * x

    class SEResidualBlock(nn.Module):
        def __init__(self, in_channels, out_channels, stride=1, downsample=None, reduction=
            super(SEResidualBlock, self).__init__()
            self.conv1 = conv3x3(in_channels, out_channels, stride)
            self.bn1 = nn.BatchNorm2d(out_channels)
            self.relu = nn.ReLU(inplace=True)
            self.conv2 = conv3x3(out_channels, out_channels)
            self.bn2 = nn.BatchNorm2d(out_channels)
            self.se = SELayer(out_channels, reduction)
            self.downsample = downsample

        def forward(self, x):

            residual = x
            """
            To-Do: add code here
            """
            if self.downsample:
                residual = self.downsample(x)

            out = self.conv1(x)
            out = self.bn1(out)
            out = self.relu(out)
            out = self.conv2(out)
            out = self.bn2(out)
            out = self.se(out)
            out += residual
            out = self.relu(out)
```

```
                return out

In [14]: se_resnet = ResNet(SEResidualBlock, [2, 2, 2], 1)
         print(se_resnet)

ResNet(
  (conv): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  (bn): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace)
  (layer1): Sequential(
    (0): SEResidualBlock(
      (conv1): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (se): SELayer(
        (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
        (fc1): Linear(in_features=16, out_features=1, bias=True)
        (relu): ReLU(inplace)
        (fc2): Linear(in_features=1, out_features=16, bias=True)
        (sigmoid): Sigmoid()
      )
    )
    (1): SEResidualBlock(
      (conv1): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (se): SELayer(
        (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
        (fc1): Linear(in_features=16, out_features=1, bias=True)
        (relu): ReLU(inplace)
        (fc2): Linear(in_features=1, out_features=16, bias=True)
        (sigmoid): Sigmoid()
      )
    )
  )
  (layer2): Sequential(
    (0): SEResidualBlock(
      (conv1): Conv2d(16, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (se): SELayer(
        (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
```

```
      (fc1): Linear(in_features=32, out_features=2, bias=True)
      (relu): ReLU(inplace)
      (fc2): Linear(in_features=2, out_features=32, bias=True)
      (sigmoid): Sigmoid()
    )
    (downsample): Sequential(
      (0): Conv2d(16, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): SEResidualBlock(
    (conv1): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
    (conv2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (se): SELayer(
      (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
      (fc1): Linear(in_features=32, out_features=2, bias=True)
      (relu): ReLU(inplace)
      (fc2): Linear(in_features=2, out_features=32, bias=True)
      (sigmoid): Sigmoid()
    )
  )
)
(layer3): Sequential(
  (0): SEResidualBlock(
    (conv1): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (se): SELayer(
      (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
      (fc1): Linear(in_features=64, out_features=4, bias=True)
      (relu): ReLU(inplace)
      (fc2): Linear(in_features=4, out_features=64, bias=True)
      (sigmoid): Sigmoid()
    )
    (downsample): Sequential(
      (0): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): SEResidualBlock(
    (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
```

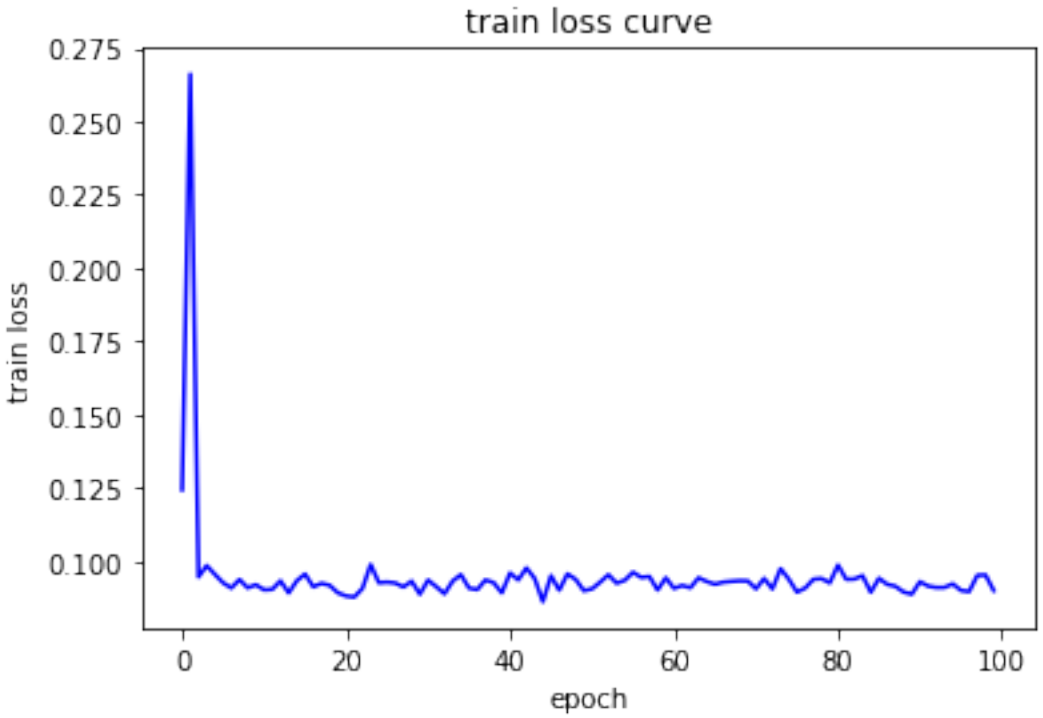
```
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (se): SELayer(
        (avg_pool): AdaptiveAvgPool2d(output_size=(1, 1))
        (fc1): Linear(in_features=64, out_features=4, bias=True)
        (relu): ReLU(inplace)
        (fc2): Linear(in_features=4, out_features=64, bias=True)
        (sigmoid): Sigmoid()
      )
    )
  )
  (avg_pool): AvgPool2d(kernel_size=8, stride=8, padding=0)
  (fc): Linear(in_features=64, out_features=1, bias=True)
)
```

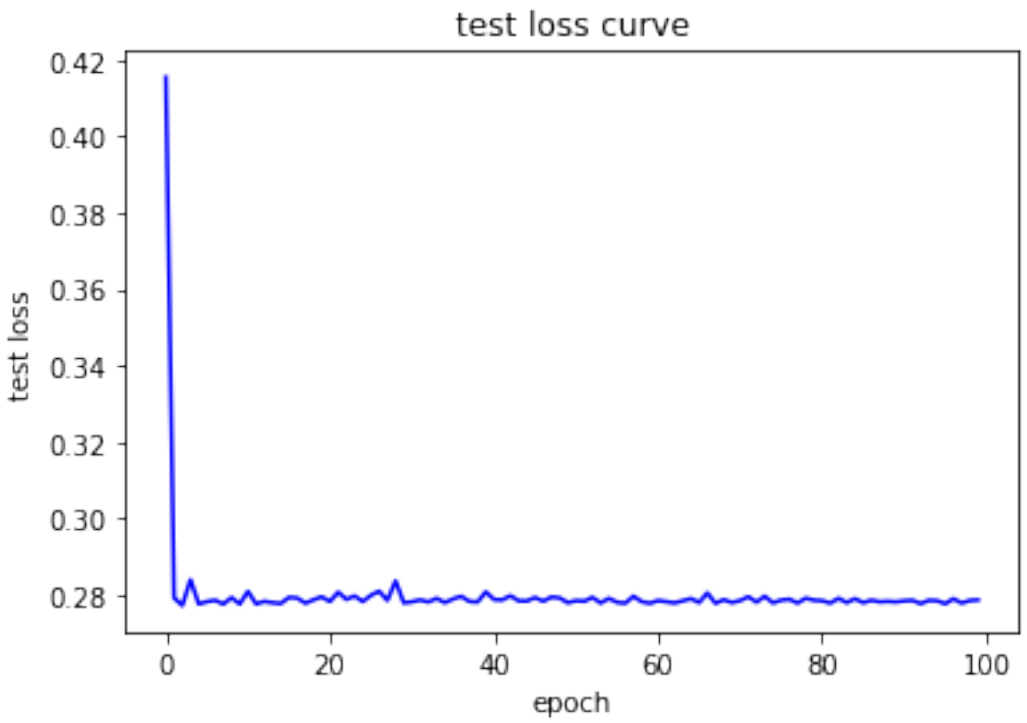
```
In [15]: # training setting
         # hyper parameters
         num_epochs = 100
         lr = 0.01
         image_size = 32

         # Device configuration, cpu, cuda:0/1/2/3 available
         device = torch.device('cuda:0')

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

```
In [9]: fit(se_resnet, num_epochs, optimizer, device)
```

```
Epoch 10/100
Train Loss: 0.0919
Test Loss: 0.2777
Epoch 20/100
Train Loss: 0.0892
Test Loss: 0.2795
Epoch 30/100
Train Loss: 0.0887
Test Loss: 0.2780
Epoch 40/100
Train Loss: 0.0891
Test Loss: 0.2808
Epoch 50/100
Train Loss: 0.0899
Test Loss: 0.2780
Epoch 60/100
Train Loss: 0.0943
Test Loss: 0.2779
Epoch 70/100
```

```
Train Loss: 0.0932
Test Loss: 0.2780
Epoch 80/100
Train Loss: 0.0925
Test Loss: 0.2787
Epoch 90/100
Train Loss: 0.0887
Test Loss: 0.2782
Epoch 100/100
Train Loss: 0.0899
Test Loss: 0.2787
```

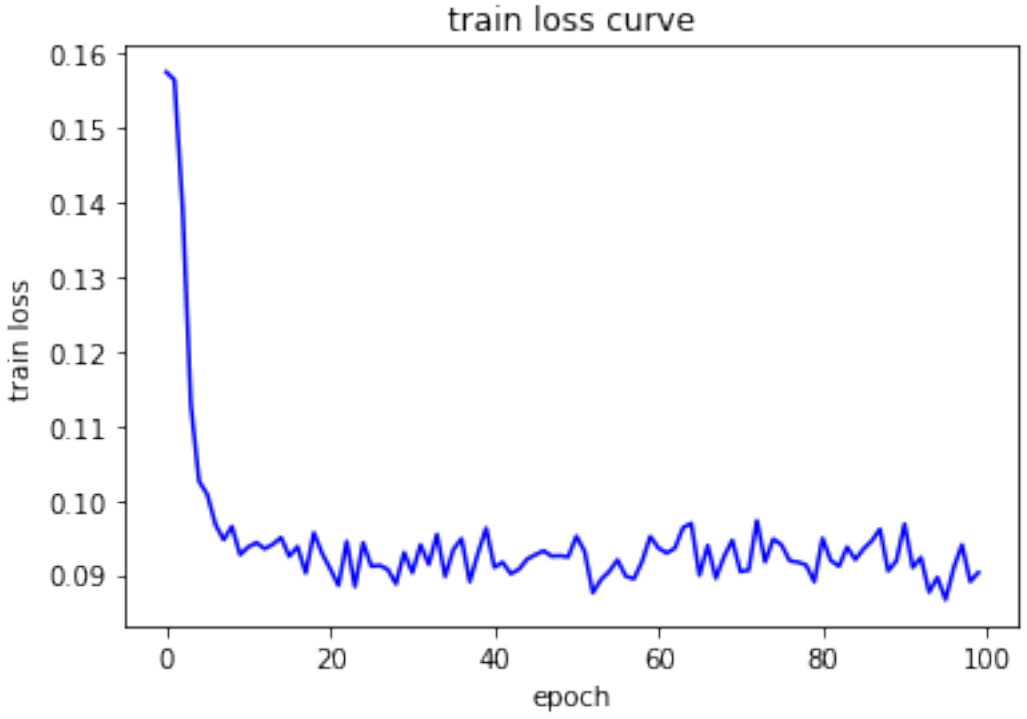


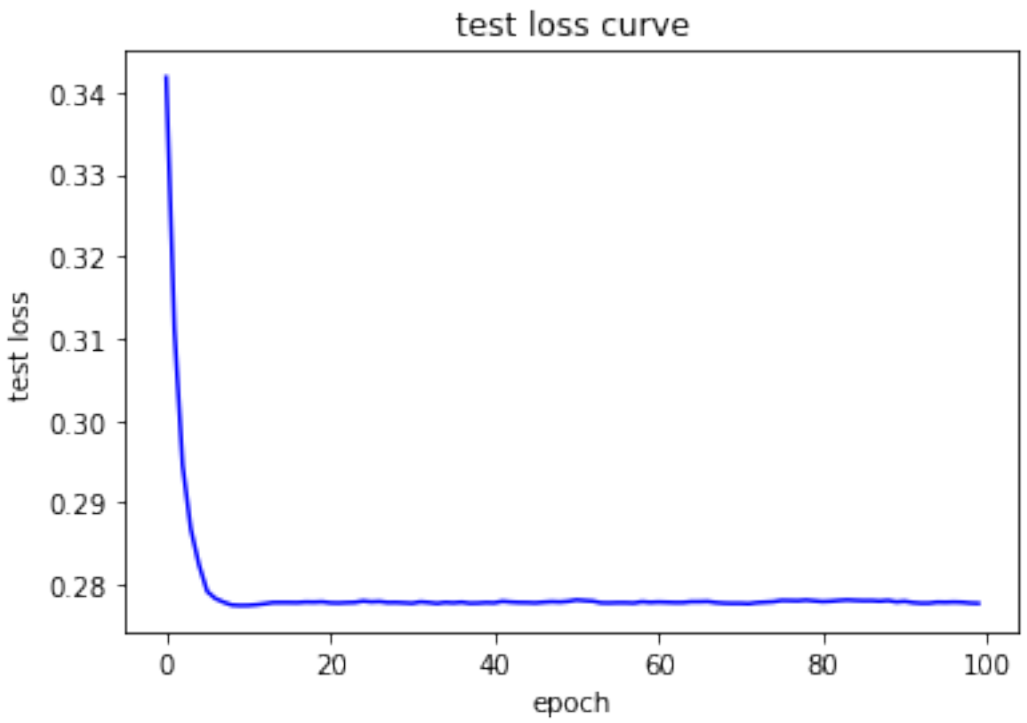


In [17]:
```
# training setting
# hyper parameters
num_epochs = 100
lr = 0.01
image_size = 32

# Device configuration, cpu, cuda:0/1/2/3 available
device = torch.device('cuda:3')

optimizer = torch.optim.SGD(se_resnet.parameters(), lr=lr)
fit(se_resnet, num_epochs, optimizer, device)
```

```
Epoch 10/100
Train Loss: 0.0927
Test Loss: 0.2775
Epoch 20/100
Train Loss: 0.0929
Test Loss: 0.2779
Epoch 30/100
Train Loss: 0.0930
Test Loss: 0.2778
Epoch 40/100
Train Loss: 0.0963
Test Loss: 0.2778
```

```
Epoch 50/100
Train Loss: 0.0924
Test Loss: 0.2780
Epoch 60/100
Train Loss: 0.0952
Test Loss: 0.2778
Epoch 70/100
Train Loss: 0.0946
Test Loss: 0.2777
Epoch 80/100
Train Loss: 0.0891
Test Loss: 0.2780
Epoch 90/100
Train Loss: 0.0919
Test Loss: 0.2779
Epoch 100/100
Train Loss: 0.0903
Test Loss: 0.2777
```

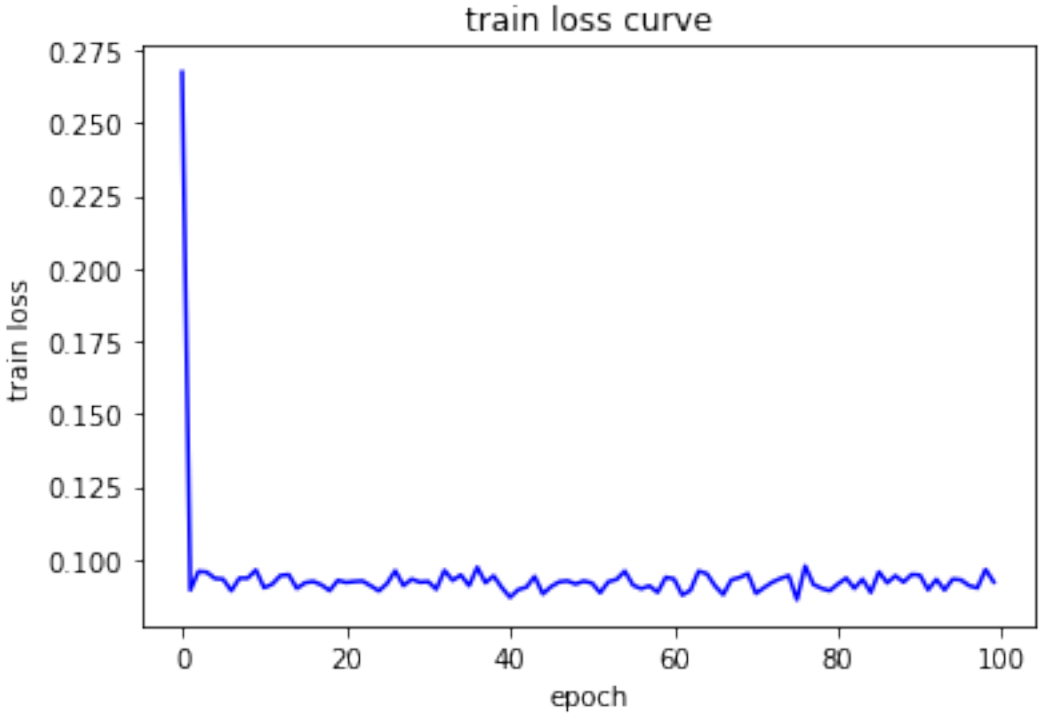


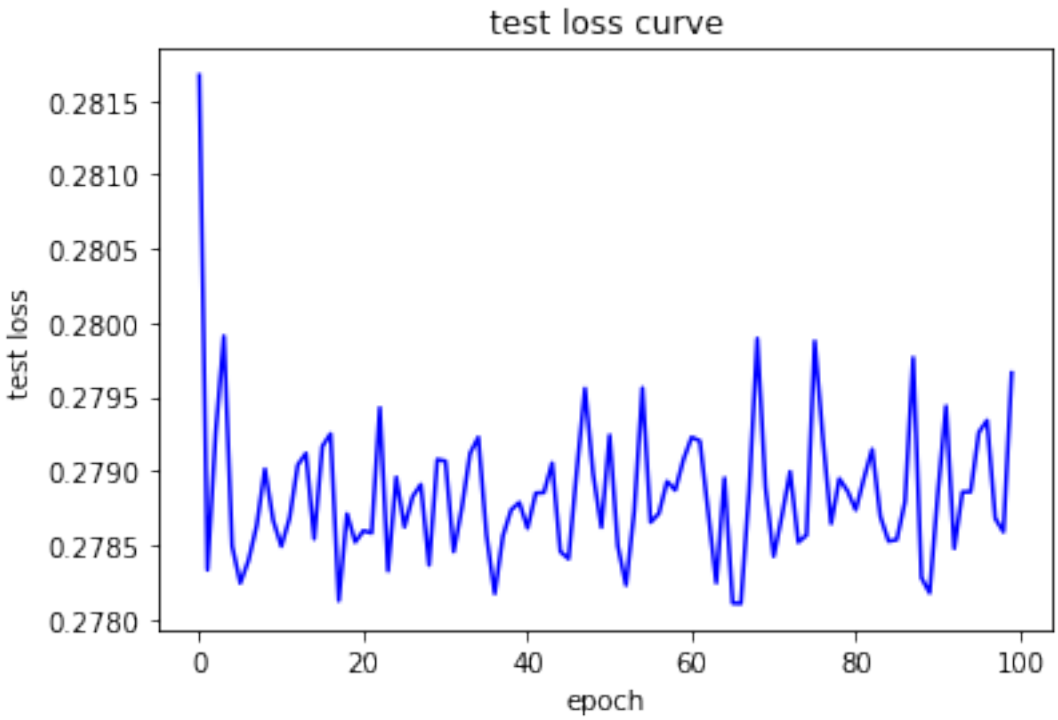


In [18]:
```
# training setting
# hyper parameters
num_epochs = 100
lr = 0.01
image_size = 32

# Device configuration, cpu, cuda:0/1/2/3 available
device = torch.device('cuda:3')

optimizer = torch.optim.Adam(se_resnet.parameters(), lr=lr)
fit(se_resnet, num_epochs, optimizer, device)
```

```
Epoch 10/100
Train Loss: 0.0964
Test Loss: 0.2787
Epoch 20/100
Train Loss: 0.0928
Test Loss: 0.2785
Epoch 30/100
Train Loss: 0.0921
Test Loss: 0.2791
Epoch 40/100
Train Loss: 0.0903
Test Loss: 0.2788
```

```
Epoch 50/100
Train Loss: 0.0925
Test Loss: 0.2786
Epoch 60/100
Train Loss: 0.0938
Test Loss: 0.2791
Epoch 70/100
Train Loss: 0.0951
Test Loss: 0.2789
Epoch 80/100
Train Loss: 0.0892
Test Loss: 0.2789
Epoch 90/100
Train Loss: 0.0948
Test Loss: 0.2782
Epoch 100/100
Train Loss: 0.0922
Test Loss: 0.2797
```





In [ ]: [U+901A][U+8FC7][U+6BD4][U+8F83]test loss, SGD[U+4F18][U+5316][U+5668][U+7684][U+8868][

In [19]:
```
from torch.optim import lr_scheduler
def fit2(model, num_epochs, optimizer, device):
    loss_func = nn.MSELoss()
    model.to(device)
    if device == torch.device('cuda'):
        model = torch.nn.DataParallel(model)
        cudnn.benchmark = True
    loss_func.to(device)
    losses = []
    accs = []

    scheduler = lr_scheduler.StepLR(optimizer,step_size=100,gamma=0.1)

    for epoch in range(num_epochs):


        # train step
        loss = train(model, train_loader, loss_func, optimizer, device)
        losses.append(loss)

        # evaluate step
        accuracy = evaluate(model, test_loader, device)
```

```
                accs.append(accuracy)
                # change the learning rate by scheduler
                scheduler.step()

                # print loss
                if (epoch+1) % 10 == 0:
                    print("Epoch {}/{}".format(epoch+1, num_epochs))
                    print("Train Loss: {:.4f}".format(loss))
                    print('Test Loss: {:.4f}'.format(accuracy))

            show_curve(losses, "train loss")
            show_curve(accs, "test loss")

        # training setting
        # hyper parameters
        num_epochs = 400
        lr = 0.01
        image_size = 32

        # Device configuration, cpu, cuda:0/1/2/3 available
        device = torch.device('cuda:3')

        optimizer = torch.optim.SGD(se_resnet.parameters(), lr=lr)
        fit2(se_resnet, num_epochs, optimizer, device)
```

```
Epoch 10/400
Train Loss: 0.0949
Test Loss: 0.2791
Epoch 20/400
Train Loss: 0.0900
Test Loss: 0.2788
Epoch 30/400
Train Loss: 0.0921
Test Loss: 0.2787
Epoch 40/400
Train Loss: 0.0930
Test Loss: 0.2789
Epoch 50/400
Train Loss: 0.0923
Test Loss: 0.2788
Epoch 60/400
Train Loss: 0.0918
Test Loss: 0.2786
Epoch 70/400
Train Loss: 0.0940
Test Loss: 0.2785
Epoch 80/400
Train Loss: 0.0940
```

```
Test Loss: 0.2788
Epoch 90/400
Train Loss: 0.0927
Test Loss: 0.2788
Epoch 100/400
Train Loss: 0.0941
Test Loss: 0.2787
Epoch 110/400
Train Loss: 0.0894
Test Loss: 0.2787
Epoch 120/400
Train Loss: 0.0928
Test Loss: 0.2787
Epoch 130/400
Train Loss: 0.0916
Test Loss: 0.2787
Epoch 140/400
Train Loss: 0.0913
Test Loss: 0.2788
Epoch 150/400
Train Loss: 0.0908
Test Loss: 0.2788
Epoch 160/400
Train Loss: 0.0886
Test Loss: 0.2788
Epoch 170/400
Train Loss: 0.0938
Test Loss: 0.2788
Epoch 180/400
Train Loss: 0.0931
Test Loss: 0.2788
Epoch 190/400
Train Loss: 0.0922
Test Loss: 0.2788
Epoch 200/400
Train Loss: 0.0910
Test Loss: 0.2788
Epoch 210/400
Train Loss: 0.0969
Test Loss: 0.2788
Epoch 220/400
Train Loss: 0.0923
Test Loss: 0.2788
Epoch 230/400
Train Loss: 0.0891
Test Loss: 0.2788
Epoch 240/400
Train Loss: 0.0921
```

```
Test Loss: 0.2788
Epoch 250/400
Train Loss: 0.0905
Test Loss: 0.2788
Epoch 260/400
Train Loss: 0.0929
Test Loss: 0.2788
Epoch 270/400
Train Loss: 0.0912
Test Loss: 0.2788
Epoch 280/400
Train Loss: 0.0938
Test Loss: 0.2788
Epoch 290/400
Train Loss: 0.0935
Test Loss: 0.2788
Epoch 300/400
Train Loss: 0.0927
Test Loss: 0.2788
Epoch 310/400
Train Loss: 0.0973
Test Loss: 0.2788
Epoch 320/400
Train Loss: 0.0935
Test Loss: 0.2788
Epoch 330/400
Train Loss: 0.0891
Test Loss: 0.2788
Epoch 340/400
Train Loss: 0.0896
Test Loss: 0.2788
Epoch 350/400
Train Loss: 0.0900
Test Loss: 0.2788
Epoch 360/400
Train Loss: 0.0881
Test Loss: 0.2788
Epoch 370/400
Train Loss: 0.0913
Test Loss: 0.2788
Epoch 380/400
Train Loss: 0.0902
Test Loss: 0.2788
Epoch 390/400
Train Loss: 0.0913
Test Loss: 0.2788
Epoch 400/400
Train Loss: 0.0907
```

```
Test Loss: 0.2788
```