Problem4

April 19, 2022

1 Problem 4 - Optimus, Learning and Resource models, Performance-cost tradeoffs(30 points)

Peng et al. proposed Optimus scheduler for deep learning clusters which makes use of a predictive model to estimate the remaining time of a training job. Optimus assumes a parameter-server architecture for distributed training where synchronization between parameter server(s) and workers happen after every training step. The time taken to complete one training step on a worker includes the time for doing forward propagation (i.e., loss computation) and backward propagation (i.e., gradients computation) at the worker, the worker pushing gradients to parameter servers, parameter servers updating parameters, and the worker pulling updated parameters from parameter servers, plus extra communication overhead.

The predictive model proposed in Optimus is based on two sub-models, one to model the training loss as a function of number of steps and the other to model the training speed (training steps per unit time) as a function of resources (number of workers and parameter servers). The training loss model is given by Equation (1) in the paper. It has three parameters 0 , 1 , and 2 that needs to be estimated from the data.

I collaborate with:

Name	Contribution
Aneri Patel	Resnet-18, 20
Kunal Kulkarni	Resnet-32
Shriya Jain	Resnet-44
Xiang Pang	Resnet-56

[ ]:
```python
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.nn.init as init
import torchvision
from torch.autograd import Variable
import torchvision.transforms as transforms
import torch.optim as optim


networks = ['resnet18', 'resnet20', 'resnet32','resnet44','resnet56','resnet50']
```

```
GPU = torch.cuda.get_device_name(0)
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
# print(device,"\n\n")

BATCH_SIZE = 128

train_transforms = transforms.Compose(
    [transforms.ToTensor(),transforms.RandomHorizontalFlip(),torchvision.
     transforms.RandomRotation((-15, +15)),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
test_transforms = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

train_dataset = torchvision.datasets.CIFAR10(root='./data',train=True,␣
 ↪download=True, transform = train_transforms)
test_dataset = torchvision.datasets.CIFAR10(root='./data', train=False,␣
 ↪download=True, transform=test_transforms)

trainloader = torch.utils.data.DataLoader(train_dataset,␣
 ↪batch_size=BATCH_SIZE,shuffle=True, num_workers=2)
testloader = torch.utils.data.
 ↪DataLoader(test_dataset,batch_size=BATCH_SIZE,shuffle=False, num_workers=2)

classes = test_dataset.classes
# print(classes)


import torch
import torch.nn as nn
import torch.nn.functional as F


class Block_Plain(nn.Module):
    def __init__(self, num_layers, in_channels, out_channels,␣
 ↪identity_downsample=None, stride=1):
        assert num_layers in [18, 34, 50, 101, 152], "should be a a valid␣
 ↪architecture"
        super(Block_Plain, self).__init__()
        self.num_layers = num_layers
        if self.num_layers > 34:
            self.expansion = 4
        else:
            self.expansion = 1
            # ResNet50, 101, and 152 include additional layer of 1x1 kernels
        self.conv1 = nn.Conv2d(in_channels, out_channels, kernel_size=1,␣
 ↪stride=1, padding=0)
        self.bn1 = nn.BatchNorm2d(out_channels)
        if self.num_layers > 34:
            self.conv2 = nn.Conv2d(out_channels, out_channels, kernel_size=3,␣
 ↪stride=stride, padding=1)
        else:
            # for ResNet18 and 34, connect input directly to (3x3) kernel (skip␣
 ↪first (1x1))
            self.conv2 = nn.Conv2d(in_channels, out_channels, kernel_size=3,␣
 ↪stride=stride, padding=1)
        self.bn2 = nn.BatchNorm2d(out_channels)
        self.conv3 = nn.Conv2d(out_channels, out_channels * self.expansion,␣
 ↪kernel_size=1, stride=1, padding=0)
        self.bn3 = nn.BatchNorm2d(out_channels * self.expansion)
        self.relu = nn.ReLU()
        self.identity_downsample = identity_downsample

    def forward(self, x):
        identity = x
        if self.num_layers > 34:
            x = self.conv1(x)
            x = self.bn1(x)
            x = self.relu(x)
        x = self.conv2(x)
        x = self.bn2(x)
        x = self.relu(x)
        x = self.conv3(x)
        x = self.bn3(x)

        if self.identity_downsample is not None:
            identity = self.identity_downsample(identity)

        x += identity
        x = self.relu(x)
        return x


class ResNet_Plain(nn.Module):
    def __init__(self, num_layers, block, image_channels, num_classes):
        assert num_layers in [18, 34, 50, 101, 152], f'ResNet{num_layers}:␣
 ↪Unknown architecture! Number of layers has ' \
                                                     f'to be 18, 34, 50, 101,␣
 ↪or 152 '
        super(ResNet_Plain, self).__init__()
        # From table 1 in ResNet paper
        if num_layers < 50:
            self.expansion = 1
        else:
            self.expansion = 4
        if num_layers == 18:
            layers = [2, 2, 2, 2]
        elif num_layers == 34 or num_layers == 50:
            layers = [3, 4, 6, 3]
        elif num_layers == 101:
            layers = [3, 4, 23, 3]
        else:
            layers = [3, 8, 36, 3]

        self.in_channels = 64
        self.conv1 = nn.Conv2d(image_channels, 64, kernel_size=7, stride=2,␣
↪padding=3)
        self.bn1 = nn.BatchNorm2d(64)
        self.relu = nn.ReLU()
        self.maxpool = nn.MaxPool2d(kernel_size=3, stride=2, padding=1)

        # ResNetLayers
        self.layer1 = self.make_layers(num_layers, block, layers[0],␣
↪intermediate_channels=64, stride=1)
        self.layer2 = self.make_layers(num_layers, block, layers[1],␣
↪intermediate_channels=128, stride=2)
        self.layer3 = self.make_layers(num_layers, block, layers[2],␣
↪intermediate_channels=256, stride=2)
        self.layer4 = self.make_layers(num_layers, block, layers[3],␣
↪intermediate_channels=512, stride=2)

        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
        self.fc = nn.Linear(512 * self.expansion, num_classes)

    def forward(self, x):
        x = self.conv1(x)
        x = self.bn1(x)
        x = self.relu(x)
        x = self.maxpool(x)

        x = self.layer1(x)
        x = self.layer2(x)
        x = self.layer3(x)
        x = self.layer4(x)

        x = self.avgpool(x)
        x = x.reshape(x.shape[0], -1)
        x = self.fc(x)
        return x

    def make_layers(self, num_layers, block, num_residual_blocks,␣
 ↪intermediate_channels, stride):
        layers = []

        identity_downsample = nn.Sequential(nn.Conv2d(self.in_channels,␣
 ↪intermediate_channels*self.expansion, kernel_size=1, stride=stride),
                                            nn.
 ↪BatchNorm2d(intermediate_channels*self.expansion))

        layers.append(block(num_layers, self.in_channels,␣
 ↪intermediate_channels, identity_downsample, stride))
        self.in_channels = intermediate_channels * self.expansion # 256

        for i in range(num_residual_blocks - 1):

            layers.append(block(num_layers, self.in_channels,␣
 ↪intermediate_channels)) # 256 -> 64, 64*4 (256) again

        return nn.Sequential(*layers)


class block(nn.Module):
    def __init__(self, filters, subsample=False):
        super().__init__()

        s = 0.5 if subsample else 1.0

        self.conv1 = nn.Conv2d(int(filters*s), filters, kernel_size=3,
                               stride=int(1/s), padding=1, bias=False)
        self.bn1   = nn.BatchNorm2d(filters, track_running_stats=True)
        self.relu1 = nn.ReLU()
        self.conv2 = nn.Conv2d(filters, filters, kernel_size=3, stride=1,␣
 ↪padding=1, bias=False)
        self.bn2   = nn.BatchNorm2d(filters, track_running_stats=True)
        self.relu2 = nn.ReLU()

        # Shortcut downsampling
        self.downsample = nn.AvgPool2d(kernel_size=1, stride=2)

    def shortcut(self, z, x):

        if x.shape != z.shape:
            d = self.downsample(x)
            p = torch.mul(d, 0)
            return z + torch.cat((d, p), dim=1)
        else:
            return z + x

    def forward(self, x, shortcuts=False):
        z = self.conv1(x)
        z = self.bn1(z)
        z = self.relu1(z)

        z = self.conv2(z)
        z = self.bn2(z)

        if shortcuts:
            z = self.shortcut(z, x)

        z = self.relu2(z)

        return z



class ResNet(nn.Module):
    def __init__(self, n, shortcuts=True):
        super().__init__()
        self.shortcuts = shortcuts

        # Input
        self.convIn = nn.Conv2d(3, 16, kernel_size=3, stride=1, padding=1,␣
 ↪bias=False)
        self.bnIn   = nn.BatchNorm2d(16, track_running_stats=True)
        self.relu   = nn.ReLU()

        # Stack1
        self.stack1 = nn.ModuleList([block(16, subsample=False) for _ in␣
 ↪range(n)])

        # Stack2
        self.stack2a = block(32, subsample=True)
        self.stack2b = nn.ModuleList([block(32, subsample=False) for _ in␣
 ↪range(n-1)])

        # Stack3
        self.stack3a = block(64, subsample=True)
        self.stack3b = nn.ModuleList([block(64, subsample=False) for _ in␣
 ↪range(n-1)])

        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
        self.fcOut   = nn.Linear(64, 10, bias=True)
        self.softmax = nn.LogSoftmax(dim=-1)


    def forward(self, x):
        z = self.convIn(x)
        z = self.bnIn(z)
        z = self.relu(z)

        for l in self.stack1: z = l(z, shortcuts=self.shortcuts)

        z = self.stack2a(z, shortcuts=self.shortcuts)
        for l in self.stack2b:
            z = l(z, shortcuts=self.shortcuts)

        z = self.stack3a(z, shortcuts=self.shortcuts)
        for l in self.stack3b:
            z = l(z, shortcuts=self.shortcuts)

        z = self.avgpool(z)
        z = z.view(z.size(0), -1)
        z = self.fcOut(z)
        return self.softmax(z)



def eval_model(val_loader):
    acc = 0
    running_loss = 0.0
    for i, data in enumerate(val_loader, 0):
        inputs, labels = data
        inputs, labels = inputs.to(device), labels.to(device)

        outputs = net(inputs)
        loss = criterion(outputs, labels)
        acc += (torch.sum(labels == outputs.argmax(dim=1))/BATCH_SIZE)
        vf.write('%d,%5d,%.7f,%.7f\n' % (epoch + 1, i + 1, loss.item(),acc/
 ↪(i+1)))
        running_loss += loss.item()
    print('Epoch: %d, Step: %5d Val loss: %.9f, Acc: %.9f' %
        (epoch + 1, i + 1, running_loss / 50,acc/(i+1)))
    running_loss = 0.0


img_channels = 3
num_classes = 10
```

```python
def create_model(n_layers, num_classes=10):
    if n_layers==18:
        net = ResNet_Plain(18, Block_Plain, img_channels, num_classes)
    elif n_layers ==20:
        net = ResNet(3, shortcuts=True)
    elif n_layers ==32:
        net = ResNet(5, shortcuts=True)
    elif n_layers ==44:
        net = ResNet(7, shortcuts=True)
    elif n_layers ==56:
        net = ResNet(9, shortcuts=True)
    # for question 4.2
    elif n_layers==50:
        net = ResNet_Plain(50, Block_Plain, img_channels, num_classes)
    return net



EPOCH = 350

lr = 0.1 # authors cite 0.1
momentum = 0.9
weight_decay = 0.0001
milestones = [82, 123]
gamma = 0.1


# criterion = torch.nn.NLLLoss()

criterion = nn.CrossEntropyLoss()

layers = [18,20,32,44,56,50]
networks = ["resnet"+str(i) for i in layers]

for NETWORK_ID in range(len(layers)):

    print(networks[NETWORK_ID])

    net = create_model(layers[NETWORK_ID]).to(device)
    optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)

#     optimizer = optim.SGD(net.parameters(), lr=lr, momentum=momentum,␣
 ↪weight_decay=weight_decay)
#     scheduler = optim.lr_scheduler.MultiStepLR(optimizer,␣
 ↪milestones=milestones, gamma=gamma)

    f = open(networks[NETWORK_ID]+"_"+GPU+".csv", "w")
    f.write('epoch, step, loss, acc\n')

    vf = open(networks[NETWORK_ID]+"_"+GPU+"_val.csv", "w")
    vf.write('epoch, step, loss, acc\n')

    for epoch in range(EPOCH):
        acc = 0
        running_loss = 0.0
        for i, data in enumerate(trainloader, 0):
            inputs, labels = data
            inputs, labels = inputs.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = net(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            acc += (torch.sum(labels == outputs.argmax(dim=1))/BATCH_SIZE)
            f.write('%d,%5d,%.7f,%.7f\n' % (epoch + 1, i + 1, loss.item(),acc/
 ↪(i+1)))
            running_loss += loss.item()


            if i % 50 == 0: # print every 50 iterations
                print('Epoch: %d, Step: %5d loss: %.9f, Acc: %.9f' %
                (epoch + 1, i + 1, running_loss / 50,acc/(i+1)))
                running_loss = 0.0
                eval_model(testloader)

#          if epoch % 50 == 49:
#              torch.save(net.
 ↪state_dict(),networks[NETWORK_ID]+"_"+GPU+"_"+str(epoch+1)+".pt")

    f.close()
    vf.close()
    print('Finished Training '+ networks[NETWORK_ID])
```

1.1 1

The first step is to generate data for predictive model calibration. You will train Resnet models with different number of layers (18, 20, 32, 44, 56) each with 3 different GPU types (K80, RTX8000, V100).

For these runs you will use CIFAR10, a batch size of 128, and run each job for 350 epochs.

1.2 Read Results

[2]:
```python
import pandas as pd
import numpy as np
import os
```

[3]:
```python
res_path = "./problem4/results/"
for file in os.listdir(res_path):
    if file.endswith(".csv"):
        df = pd.read_csv(res_path + file)
```

[4]:
```python
df
```

[4]:
```
        epoch  step      loss       acc
0           1     1  2.494066  0.109375
1           1     2  2.732457  0.113281
2           1     3  2.677715  0.093750
3           1     4  2.687866  0.105469
4           1     5  2.569639  0.107813
…         …    …        …        …
221195    350    75  1.053012  0.761042
221196    350    76  1.522796  0.761308
221197    350    77  1.956427  0.761161
221198    350    78  1.571791  0.760918
221199    350    79  2.602238  0.752275

[221200 rows x 4 columns]
```

[5]:
```python
from scipy.optimize import curve_fit
```

[6]:
```python
def func(k, b0, b1, b2):
    loss = 1 / (b0 * k + b1) + b2
    return loss
```

[7]:
```python
def get_model_parameters(df):
    df.columns = [s.strip() for s in df.columns]
    x = df["real_step"]
    y = df["loss"]
    popt, pcov = curve_fit(func, x, y, bounds=(0, [np.inf, np.inf, np.inf]))
    # print(popt, pcov)
    return popt, pcov
# popt, pcov = get_model_parameters(df)
# b0, b1, b2 = popt
```

[8]:
```python
def parse_model_name(name):
    name = name.replace(".csv", "")
    model_name = name.split("_")[0]
    gpu_name = name.split("_")[1]
    split = "val" if len(name.split("_")) == 3 else "train"
    return model_name, gpu_name, split
```

```
[82]: res_list = []
res_path = "./problem4/results/"
for file in os.listdir(res_path):
    if file.endswith(".csv"):
        df = pd.read_csv(res_path + file)
        df.columns = [s.strip() for s in df.columns]
        # print(df)
        epoch_steps = max(df[df["epoch"]==1]["step"])
        df["real_step"] = (df["epoch"] - 1) * epoch_steps + df["step"]

        # first step achieve 92 accuracy
        t = df[df["acc"] > 0.92]["real_step"]
        e = df[df["acc"] > 0.92]["epoch"]

        if len(t) > 0:
            t = t.values[0]
            e = e.values[0]
            loss_92acc = df[df["real_step"] == t]["loss"].values[0]
        else:
            t = -1
            e = -1
            loss_92acc = -1
        # print(t)
        # print(epoch_steps)
        # df["real_step"] = (df["epoch"] == 1)
        popt, pcov = get_model_parameters(df)
        model_name, gpu_name, split = parse_model_name(file)
        b0, b1, b2 = popt
        res_list.append({"model": model_name, "gpu": gpu_name, "split": split,␣
 ↪"b0": b0, "b1": b1, "b2": b2, "epoch_to_92acc": e,"step_to_92acc": t,␣
 ↪"loss_92acc": loss_92acc, "epoch_steps": epoch_steps})
res_df = pd.DataFrame.from_records(res_list)
```

```
[83]: res_df
```

```
[83]:      model                 gpu  split            b0            b1  \
0  resnet56  NVIDIA A100-PCIE-40GB    val      0.007232  5.082540e-01
1  resnet18   Tesla V100-PCIE-32GB    val  15074.454974  4.842781e-15
2  resnet50        Quadro RTX 8000  train      0.000237  4.595429e-01
3  resnet56        Quadro RTX 8000    val      0.006419  5.410299e-01
4  resnet50   Tesla V100-PCIE-32GB  train      0.000233  4.650595e-01
5  resnet44   Tesla V100-PCIE-32GB    val      0.006194  6.156885e-01
6  resnet50  NVIDIA A100-PCIE-40GB  train      0.000236  4.631299e-01
```

```
7   resnet18  NVIDIA A100-PCIE-40GB  train      0.000271  5.496289e-01
8   resnet20  NVIDIA A100-PCIE-40GB  train      0.000117  6.774311e-01
9   resnet20   Tesla V100-PCIE-32GB  train      0.000116  6.772954e-01
10  resnet44         Quadro RTX 8000    val      0.005784  5.642377e-01
11  resnet20   Tesla V100-PCIE-32GB    val      0.003309  6.152716e-01
12  resnet56         Quadro RTX 8000  train      0.000181  5.943588e-01
13  resnet44         Quadro RTX 8000  train      0.000164  6.297342e-01
14  resnet32   Tesla V100-PCIE-32GB  train      0.000137  6.529592e-01
15  resnet18         Quadro RTX 8000    val  14190.355527  1.761915e-14
16  resnet50  NVIDIA A100-PCIE-40GB    val  15077.103608  1.228839e-14
17  resnet32         Quadro RTX 8000  train      0.000138  6.542840e-01
18  resnet44  NVIDIA A100-PCIE-40GB    val      0.006523  6.016103e-01
19  resnet32  NVIDIA A100-PCIE-40GB  train      0.000135  6.639689e-01
20  resnet56   Tesla V100-PCIE-32GB    val      0.006986  5.944430e-01
21  resnet20  NVIDIA A100-PCIE-40GB    val      0.002869  6.172305e-01
22  resnet18   Tesla V100-PCIE-32GB  train      0.000276  5.409715e-01
23  resnet18         Quadro RTX 8000  train      0.000274  5.473714e-01
24  resnet32   Tesla V100-PCIE-32GB    val      0.004756  5.696338e-01
25  resnet20         Quadro RTX 8000    val      0.003459  6.028435e-01
26  resnet50         Quadro RTX 8000    val  15963.918072  4.808917e-14
27  resnet32  NVIDIA A100-PCIE-40GB    val      0.004970  5.841725e-01
28  resnet56  NVIDIA A100-PCIE-40GB  train      0.000179  6.156932e-01
29  resnet56   Tesla V100-PCIE-32GB  train      0.000168  6.305453e-01
30  resnet50   Tesla V100-PCIE-32GB    val  29266.171362  7.422585e-07
31  resnet32         Quadro RTX 8000    val      0.005167  5.939095e-01
32  resnet44   Tesla V100-PCIE-32GB  train      0.000163  6.476243e-01
33  resnet44  NVIDIA A100-PCIE-40GB  train      0.000152  6.525351e-01
34  resnet20         Quadro RTX 8000  train      0.000119  6.714442e-01
35  resnet18  NVIDIA A100-PCIE-40GB    val  14406.108425  1.890440e-17

              b2  epoch_to_92acc  step_to_92acc  loss_92acc  epoch_steps
0   5.378531e-01              48           3714    0.310703           79
1   1.489328e+00              -1             -1   -1.000000           79
2   5.166572e-18              35          13295    0.245837          391
3   5.360027e-01              64           4978    0.439552           79
4   6.178933e-18              28          10558    0.258628          391
5   5.165396e-01              60           4662    0.326317           79
6   4.789917e-18              32          12122    0.228549          391
7   1.109550e-20              27          10167    0.227245          391
8   3.629090e-02              58          22288    0.308384          391
9   3.292359e-02              65          25025    0.278525          391
10  5.036776e-01              48           3714    0.314827           79
11  4.710460e-01              98           7664    0.398463           79
12  7.921437e-18              43          16423    0.234778          391
13  3.023622e-17              45          17205    0.227768          391
14  4.390594e-16              40          15251    0.213712          391
15  1.470187e+00              -1             -1   -1.000000           79
```

```
16  1.731670e+00            -1          -1  -1.000000           79
17  1.229320e-14            49       18769   0.211670          391
18  5.284625e-01            40        3082   0.341347           79
19  8.933287e-16            63       24243   0.203317          391
20  5.457043e-01            95        7427   0.436796           79
21  4.385978e-01            90        7032   0.433734           79
22  5.573940e-20            29       10949   0.209562          391
23  2.673371e-20            31       11731   0.171517          391
24  4.845599e-01            87        6795   0.392498           79
25  4.675423e-01            97        7585   0.361966           79
26  1.763151e+00            -1          -1  -1.000000           79
27  4.905964e-01            33        2529   0.410197           79
28  1.386363e-18            40       15250   0.208657          391
29  1.664642e-18            28       10558   0.265990          391
30  1.779010e+00            -1          -1  -1.000000           79
31  5.055491e-01            66        5136   0.368251           79
32  8.308141e-16            43       16423   0.201995          391
33  1.077400e-17            43       16423   0.235092          391
34  3.446392e-02            52       19942   0.288194          391
35  1.435279e+00            -1          -1  -1.000000           79
```

1.2.1 Select Training Split

```
[84]: train_res_df = res_df[res_df["split"] == "train"]
```

```
[85]: train_res_df
```

```
[85]:       model                  gpu  split        b0        b1            b2  \
    2   resnet50        Quadro RTX 8000  train  0.000237  0.459543  5.166572e-18
    4   resnet50    Tesla V100-PCIE-32GB  train  0.000233  0.465060  6.178933e-18
    6   resnet50  NVIDIA A100-PCIE-40GB  train  0.000236  0.463130  4.789917e-18
    7   resnet18  NVIDIA A100-PCIE-40GB  train  0.000271  0.549629  1.109550e-20
    8   resnet20  NVIDIA A100-PCIE-40GB  train  0.000117  0.677431  3.629090e-02
    9   resnet20    Tesla V100-PCIE-32GB  train  0.000116  0.677295  3.292359e-02
    12  resnet56        Quadro RTX 8000  train  0.000181  0.594359  7.921437e-18
    13  resnet44        Quadro RTX 8000  train  0.000164  0.629734  3.023622e-17
    14  resnet32    Tesla V100-PCIE-32GB  train  0.000137  0.652959  4.390594e-16
    17  resnet32        Quadro RTX 8000  train  0.000138  0.654284  1.229320e-14
    19  resnet32  NVIDIA A100-PCIE-40GB  train  0.000135  0.663969  8.933287e-16
    22  resnet18    Tesla V100-PCIE-32GB  train  0.000276  0.540971  5.573940e-20
    23  resnet18        Quadro RTX 8000  train  0.000274  0.547371  2.673371e-20
    28  resnet56  NVIDIA A100-PCIE-40GB  train  0.000179  0.615693  1.386363e-18
    29  resnet56    Tesla V100-PCIE-32GB  train  0.000168  0.630545  1.664642e-18
    32  resnet44    Tesla V100-PCIE-32GB  train  0.000163  0.647624  8.308141e-16
    33  resnet44  NVIDIA A100-PCIE-40GB  train  0.000152  0.652535  1.077400e-17
    34  resnet20        Quadro RTX 8000  train  0.000119  0.671444  3.446392e-02
    epoch_to_92acc  step_to_92acc  loss_92acc  epoch_steps
2               35          13295    0.245837          391
4               28          10558    0.258628          391
6               32          12122    0.228549          391
7               27          10167    0.227245          391
8               58          22288    0.308384          391
9               65          25025    0.278525          391
12              43          16423    0.234778          391
13              45          17205    0.227768          391
14              40          15251    0.213712          391
17              49          18769    0.211670          391
19              63          24243    0.203317          391
22              29          10949    0.209562          391
23              31          11731    0.171517          391
28              40          15250    0.208657          391
29              28          10558    0.265990          391
32              43          16423    0.201995          391
33              43          16423    0.235092          391
34              52          19942    0.288194          391
```

1.3 2

We next study how the learned parameters, 0, 1, and 2, change with the type of GPUs and the size of network. Use a regression model on the data from 15 models to predict the value of these parameters as a function of number of layers in Resnet and GPU type. From these regresssion model predict the training loss curve for Resnet-50. Note that we are effectively doing prediction for a predictive model. To verify how good is this prediction, you will train Resnet-50 on a K80, RTX8000, and V100 for target accuracy of 92% and compare the predicted loss curve with the real measurements. Show this comparison in a graph and calculate the percentage error. From the predicted loss curve get the number of epochs needed to achive 92% accuracy. Observe that there are three curves for three different GPU types, but the number of epochs required to reach a particular accuracy (convergence rate) should be independent of hardware. (8)

[13]:
```python
gpu_kinds = train_res_df["gpu"].unique()
# print(gpu_kinds)
gpu_type_mapping = {t: i for i, t in enumerate(gpu_kinds)}
# print(gpu_type_mapping)
```

[14]:
```python
res_df["gpu_type"] = res_df["gpu"].map(gpu_type_mapping)
```

[15]:
```python
def get_num_layers(model_name):
    num_layers = model_name.replace("resnet", "")
    return int(num_layers)
res_df["num_layers"] = res_df["model"].map(get_num_layers)
res_df.to_csv("./problem4/res_df.csv", index=False)
```

[16]:
```python
res_df = res_df[res_df["split"] == "train"]
```

[17]:
```
train_res_df = res_df[res_df["num_layers"] != 50]
test_res_df = res_df[res_df["num_layers"] == 50]
```

[18]:
```
# b0, b1, b2 = reg(num_layers, )
x0 = train_res_df["num_layers"].values
x1 = train_res_df["gpu_type"].values
X = np.array([x0, x1]).T
y0 = train_res_df["b0"].values
y1 = train_res_df["b1"].values
y2 = train_res_df["b2"].values
Y = np.array([y0, y1, y2]).T
```

[33]:
```
X.shape
```

[33]:
```
(15, 2)
```

[34]:
```
Y.shape
```

[34]:
```
(15, 3)
```

[36]:
```
import numpy as np
from sklearn.datasets import load_linnerud
from sklearn.multioutput import MultiOutputRegressor
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import Ridge
from sklearn.kernel_ridge import KernelRidge
from sklearn.pipeline import make_pipeline
krr = KernelRidge(alpha=1.0)
krr.fit(X, Y)
Y_hat = krr.predict(X)
yy = np.concatenate((Y, Y_hat), axis=1)
df = pd.DataFrame(yy, columns=["b0", "b1", "b2", "b0_hat", "b1_hat", "b2_hat"])
df
```

[36]:
```
          b0        b1            b2    b0_hat    b1_hat    b2_hat
0   0.000271  0.549629  1.109550e-20  0.000126  0.453489  0.008108
1   0.000117  0.677431  3.629090e-02  0.000133  0.479377  0.008108
2   0.000116  0.677295  3.292359e-02  0.000100  0.369129  0.004058
3   0.000181  0.594359  7.921437e-18  0.000189  0.724866  0.000022
4   0.000164  0.629734  3.023622e-17  0.000148  0.569538  0.000017
5   0.000137  0.652959  4.390594e-16  0.000140  0.524457  0.004063
6   0.000138  0.654284  1.229320e-14  0.000108  0.414209  0.000012
7   0.000135  0.663969  8.933287e-16  0.000173  0.634705  0.008113
8   0.000276  0.540971  5.573940e-20  0.000093  0.343241  0.004057
9   0.000274  0.547371  2.673371e-20  0.000061  0.232993  0.000007
10  0.000179  0.615693  1.386363e-18  0.000254  0.945362  0.008122
11  0.000168  0.630545  1.664642e-18  0.000221  0.835114  0.004072
```

```
12  0.000163  0.647624  8.308141e-16  0.000181  0.679786  0.004067
13  0.000152  0.652535  1.077400e-17  0.000214  0.790034  0.008118
14  0.000119  0.671444  3.446392e-02  0.000067  0.258881  0.000008
```

[37]:
```
# b0, b1, b2 = reg(num_layers, )
x0 = test_res_df["num_layers"].values
x1 = test_res_df["gpu_type"].values
test_X = np.array([x0, x1]).T
y0 = test_res_df["b0"].values
y1 = test_res_df["b1"].values
y2 = test_res_df["b2"].values
test_Y = np.array([y0, y1, y2]).T
```

[38]:
```
test_res_df
```

[38]:
```
      model                  gpu  split        b0        b1            b2  \
2  resnet50       Quadro RTX 8000  train  0.000237  0.459543  5.166572e-18
4  resnet50     Tesla V100-PCIE-32GB  train  0.000233  0.465060  6.178933e-18
6  resnet50   NVIDIA A100-PCIE-40GB  train  0.000236  0.463130  4.789917e-18

   epoch_to_92acc  step_to_92acc  loss_92acc  epoch_steps  gpu_type  \
2              35          13295    0.245837          391         0
4              28          10558    0.258628          391         1
6              32          12122    0.228549          391         2

   num_layers
2          50
4          50
6          50
```

[39]:
```
test_X
```

[39]:
```
array([[50,  0],
       [50,  1],
       [50,  2]])
```

[92]:
```
test_res_df["gpu_type"]
```

[92]:
```
2    0
4    1
6    2
Name: gpu_type, dtype: int64
```

[93]:
```
test_Y_hat = krr.predict(test_X)
yy = np.concatenate((test_Y, test_Y_hat), axis=1)
df = pd.DataFrame(yy, columns=["b0", "b1", "b2", "b0_hat", "b1_hat", "b2_hat"])
df["gpu_type"] = test_res_df["gpu_type"].values
```

```
df["num_layers"] = test_res_df["num_layers"].values
df["model"] = test_res_df["model"].values
df["gpu"] = test_res_df["gpu"].values
def get_file_name(model, gpu):
    return model + "_" + gpu + ".csv"
df["file_name"] = get_file_name(df["model"], df["gpu"])
df
```

[93]:

```
         b0        b1            b2    b0_hat    b1_hat    b2_hat  gpu_type  \
0  0.000237  0.459543  5.166572e-18  0.000168  0.647202  0.000019         0
1  0.000233  0.465060  6.178933e-18  0.000201  0.757450  0.004070         1
2  0.000236  0.463130  4.789917e-18  0.000234  0.867698  0.008120         2

   num_layers     model                  gpu  \
0          50  resnet50        Quadro RTX 8000
1          50  resnet50    Tesla V100-PCIE-32GB
2          50  resnet50  NVIDIA A100-PCIE-40GB

                           file_name
0        resnet50_Quadro RTX 8000.csv
1   resnet50_Tesla V100-PCIE-32GB.csv
2  resnet50_NVIDIA A100-PCIE-40GB.csv
```

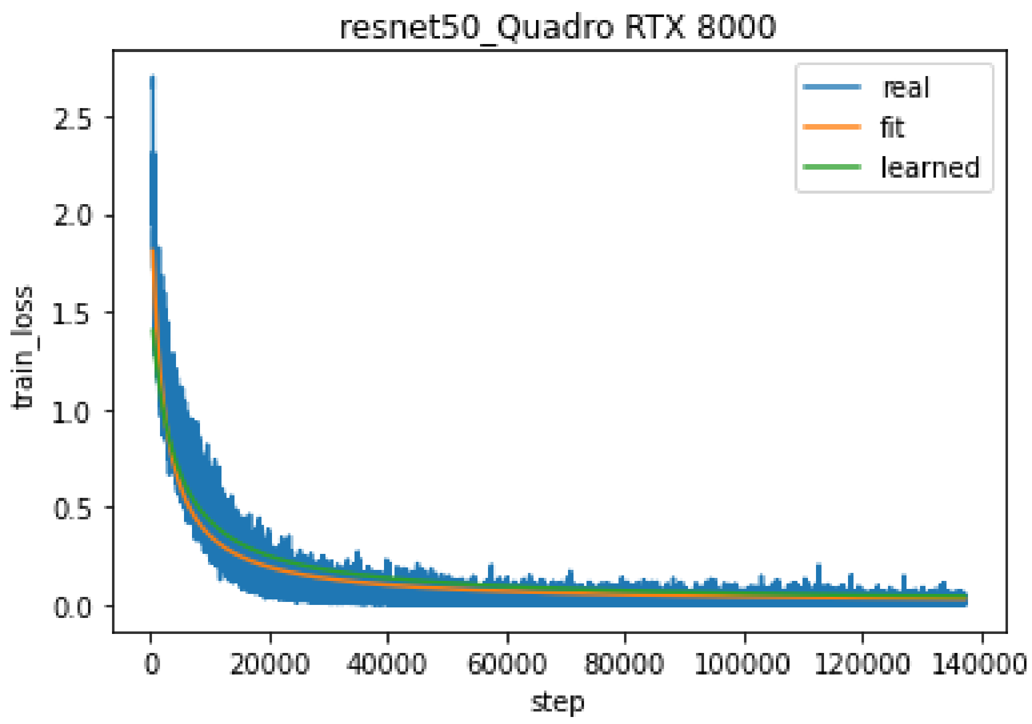
[94]:
```
df.to_csv("./problem4/2.csv", index=False)
```

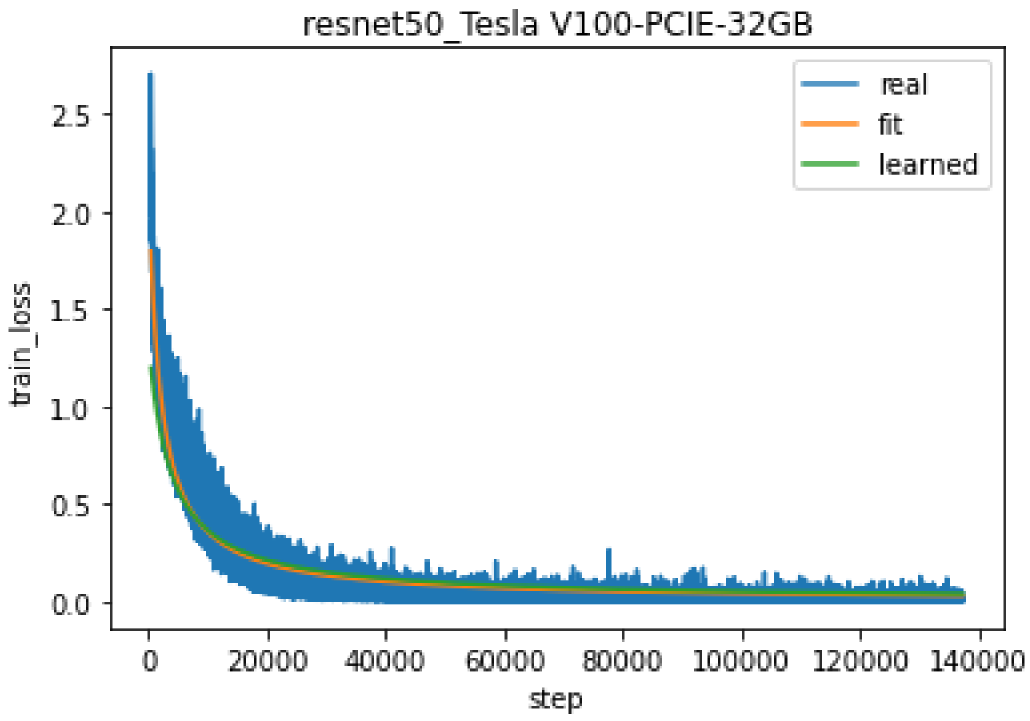
1.3.1 Plot the three curves

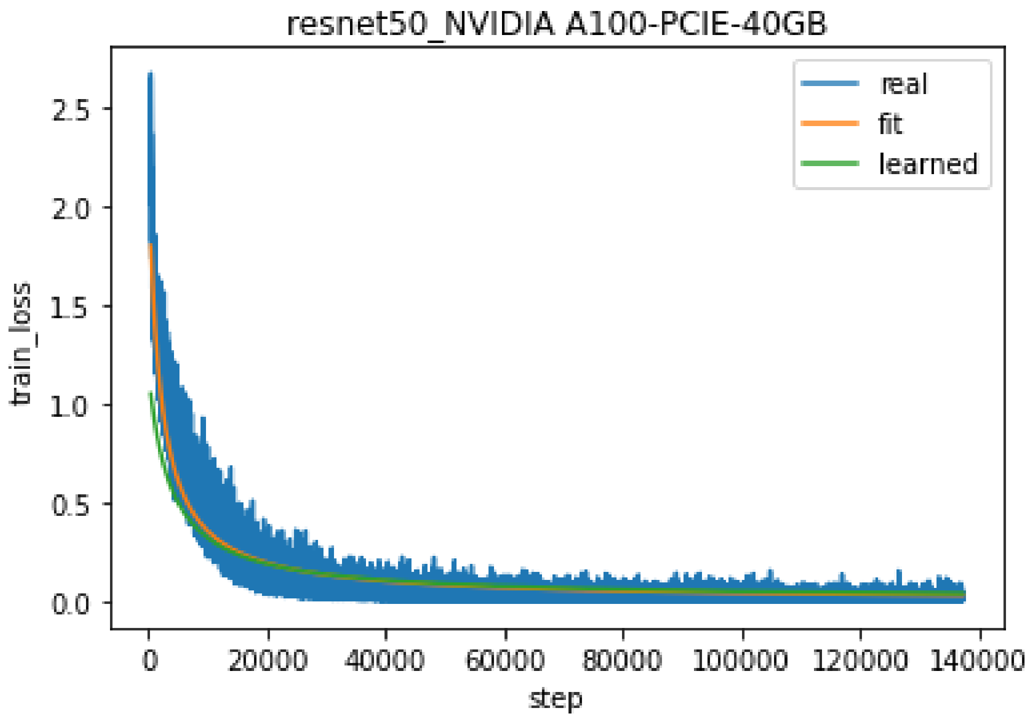
[95]:
```
def func(k, b0, b1, b2):
    loss = 1 / (b0 * k + b1) + b2
    return loss
```

[96]:
```
def get_y(x, params):
    return func(x, *params)
```

[97]:
```
import matplotlib.pyplot as plt
res_path = "./problem4/results/"
for i in range(3):
    fig = plt.figure()
    temp_df = pd.read_csv("./problem4/results/" + df["file_name"][i])
    temp_df.columns = [s.strip() for s in temp_df.columns]

    epoch_steps = max(temp_df["step"])
    temp_df["real_step"] = temp_df["epoch"] * epoch_steps + temp_df["step"]
    real_X = temp_df["real_step"].values
    real_Y = temp_df["loss"].values
    plt.plot(real_X, real_Y, label="real")
    b0 = df["b0"][i]
    b1 = df["b1"][i]
    b2 = df["b2"][i]
    fit_X = real_X
    fit_Y = get_y(fit_X, (b0, b1, b2))
    plt.plot(fit_X, fit_Y, label="fit")

    b0_hat = df["b0_hat"][i]
    b1_hat = df["b1_hat"][i]
    b2_hat = df["b2_hat"][i]
    learned_X = real_X
    learned_Y = get_y(learned_X, (b0_hat, b1_hat, b2_hat))
    plt.plot(learned_X, learned_Y, label="learned")
    plt.xlabel("step")
    plt.ylabel("train_loss")
    plt.title(df["file_name"][i].replace(".csv", ""))
    plt.legend()
    plt.show()
```




resnet50_Tesla V100-PCIE-32GB
real
fit
learned
train_loss
2.5
2.0
1.5
1.0
0.5
0.0
0
20000
40000
60000
80000
100000
120000
140000
step


resnet50_NVIDIA A100-PCIE-40GB
real
fit
learned
train_loss
2.5
2.0
1.5
1.0
0.5
0.0
0
20000
40000
60000
80000
100000
120000
140000
step

1.3.2 Parameter Error

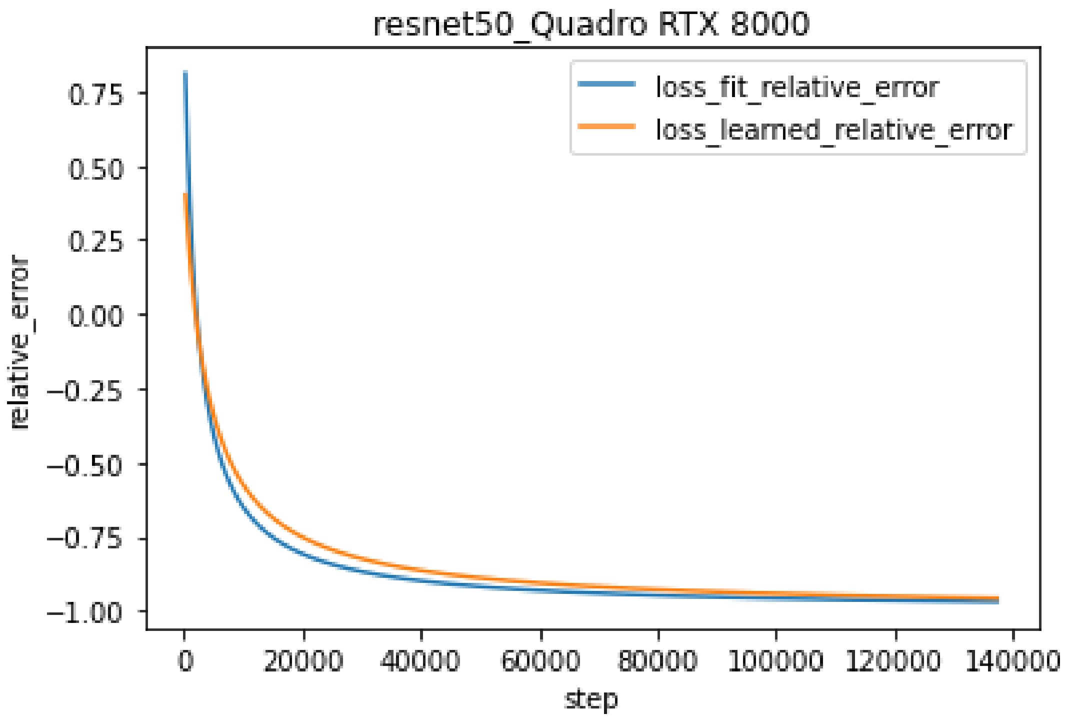
```
[98]: params_list = ["b0", "b1", "b2"]
      for p in params_list:
          df[f"{p}_percentage_error"] = df[f"{p}"] - df[f"{p}_hat"] / df[f"{p}"]
          df[f"{p}_absolut_error"] = df[f"{p}"] - df[f"{p}_hat"]
      df
```

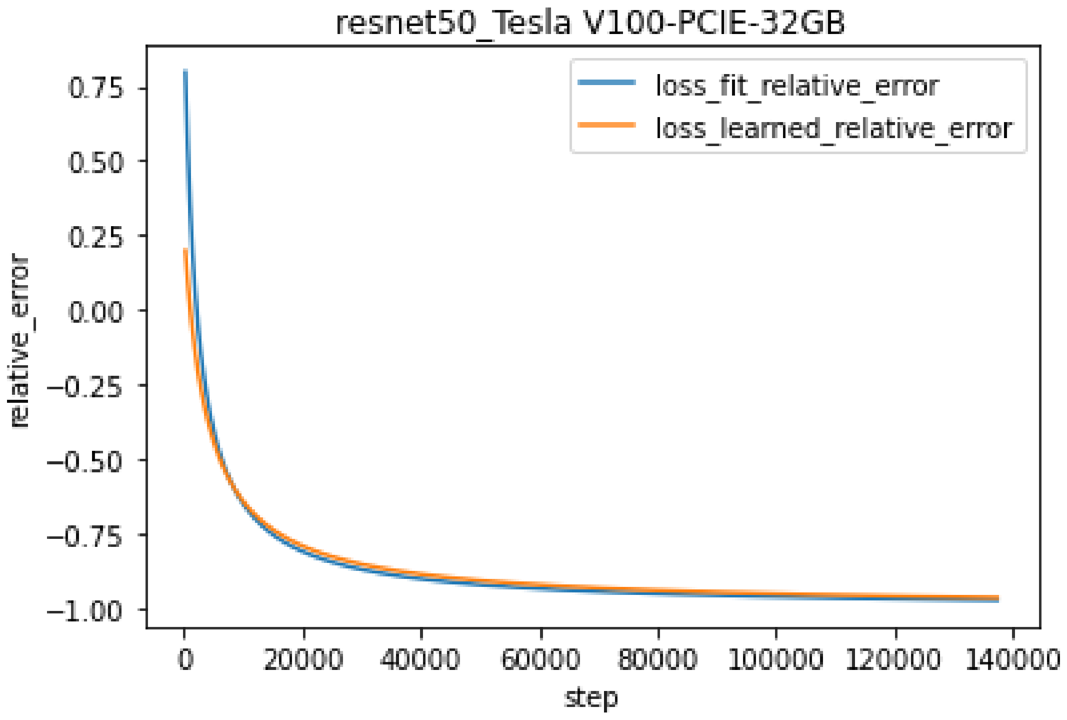
```
[98]:          b0        b1            b2    b0_hat    b1_hat    b2_hat  gpu_type  \
      0  0.000237  0.459543  5.166572e-18  0.000168  0.647202  0.000019         0
      1  0.000233  0.465060  6.178933e-18  0.000201  0.757450  0.004070         1
      2  0.000236  0.463130  4.789917e-18  0.000234  0.867698  0.008120         2

         num_layers     model                   gpu  \
      0          50  resnet50        Quadro RTX 8000
      1          50  resnet50   Tesla V100-PCIE-32GB
      2          50  resnet50  NVIDIA A100-PCIE-40GB

                                 file_name  b0_percentage_error  b0_absolut_error  \
      0        resnet50_Quadro RTX 8000.csv            -0.710173          0.000069
      1   resnet50_Tesla V100-PCIE-32GB.csv            -0.862069          0.000032
      2  resnet50_NVIDIA A100-PCIE-40GB.csv            -0.992541          0.000002

         b1_percentage_error  b1_absolut_error  b2_percentage_error  \
      0            -0.948817         -0.187659        -3.738277e+12
      1            -1.163657         -0.292390        -6.586309e+14
      2            -1.410422         -0.404568        -1.695219e+15

         b2_absolut_error
      0         -0.000019
      1         -0.004070
      2         -0.008120
```

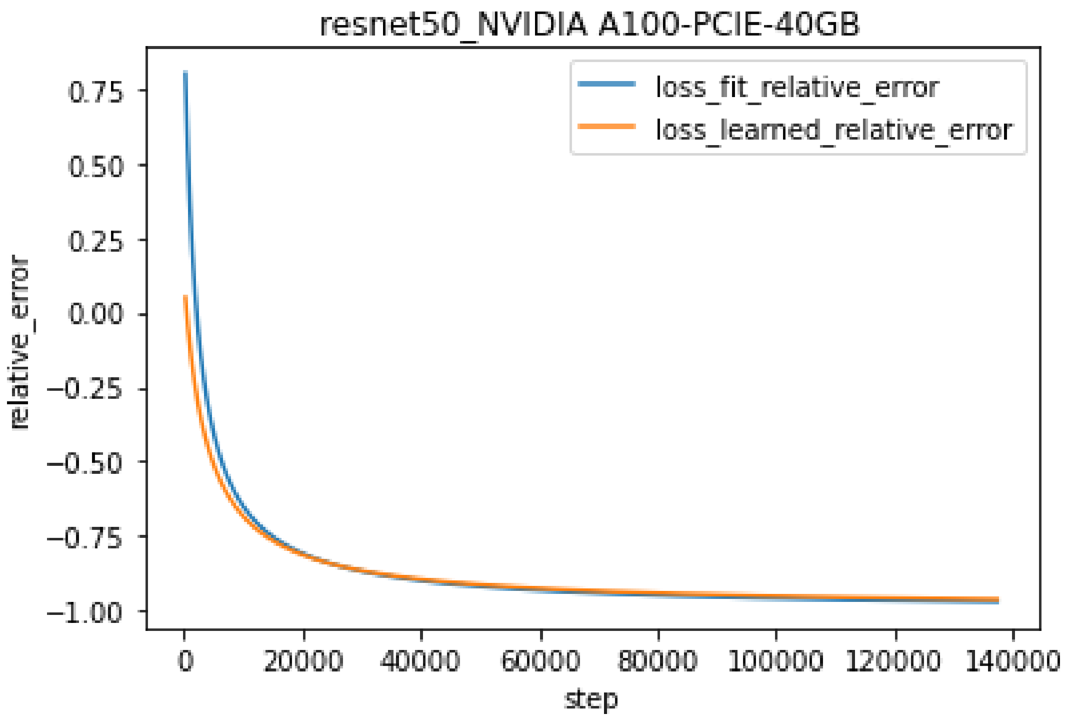
1.3.3 Loss Estimation Percentage Error Over Steps

```
[138]: import matplotlib.pyplot as plt
       res_path = "./problem4/results/"
       for i in range(3):
           fig = plt.figure()
           temp_df = pd.read_csv("./problem4/results/" + df["file_name"][i])
           temp_df.columns = [s.strip() for s in temp_df.columns]

           epoch_steps = max(temp_df["step"])
           temp_df["real_step"] = temp_df["epoch"] * epoch_steps + temp_df["step"]
           real_X = temp_df["real_step"].values
           real_Y = temp_df["loss"].values
```

```
    b0 = df["b0"][i]
    b1 = df["b1"][i]
    b2 = df["b2"][i]
    fit_X = real_X
    fit_Y = get_y(fit_X, (b0, b1, b2))
    fit_percentage_error = fit_Y - real_Y / real_Y
    fit_absolut_error = fit_Y - real_Y

    b0_hat = df["b0_hat"][i]
    b1_hat = df["b1_hat"][i]
    b2_hat = df["b2_hat"][i]
    learned_X = real_X
    learned_Y = get_y(learned_X, (b0_hat, b1_hat, b2_hat))
    learned_percentage_error = learned_Y - real_Y / real_Y
    learned_absolut_error = learned_Y - real_Y

    plt.plot(real_X, fit_percentage_error, label="loss_fit_relative_error")
    # plt.plot(real_X, fit_absolut_error, label="real")
    plt.plot(real_X, learned_percentage_error,␣
↪label="loss_learned_relative_error")
    # plt.plot(real_X, learned_absolut_error, label="learned_absolut_error")
    # plt.plot
    plt.legend()
    plt.title(df["file_name"][i].replace(".csv", ""))
    plt.xlabel("step")
    plt.ylabel("relative_error")
    plt.show()
```

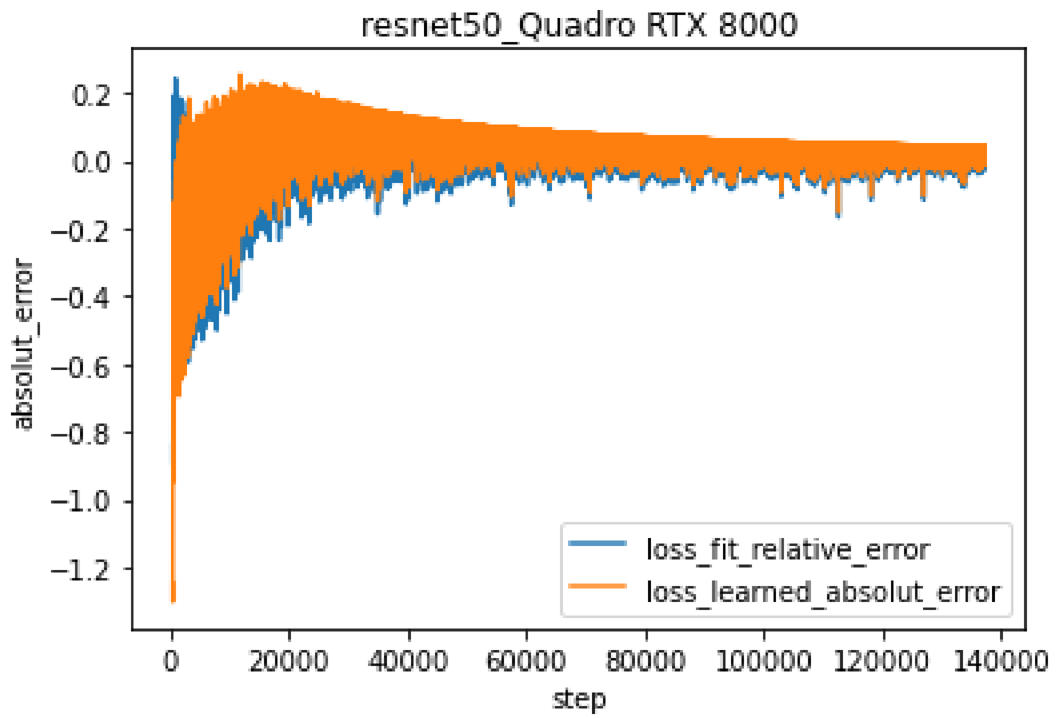

resnet50_Quadro RTX 8000
loss_fit_relative_error
loss_learned_relative_error
relative_error
step
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
20000
40000
60000
80000
100000
120000
140000

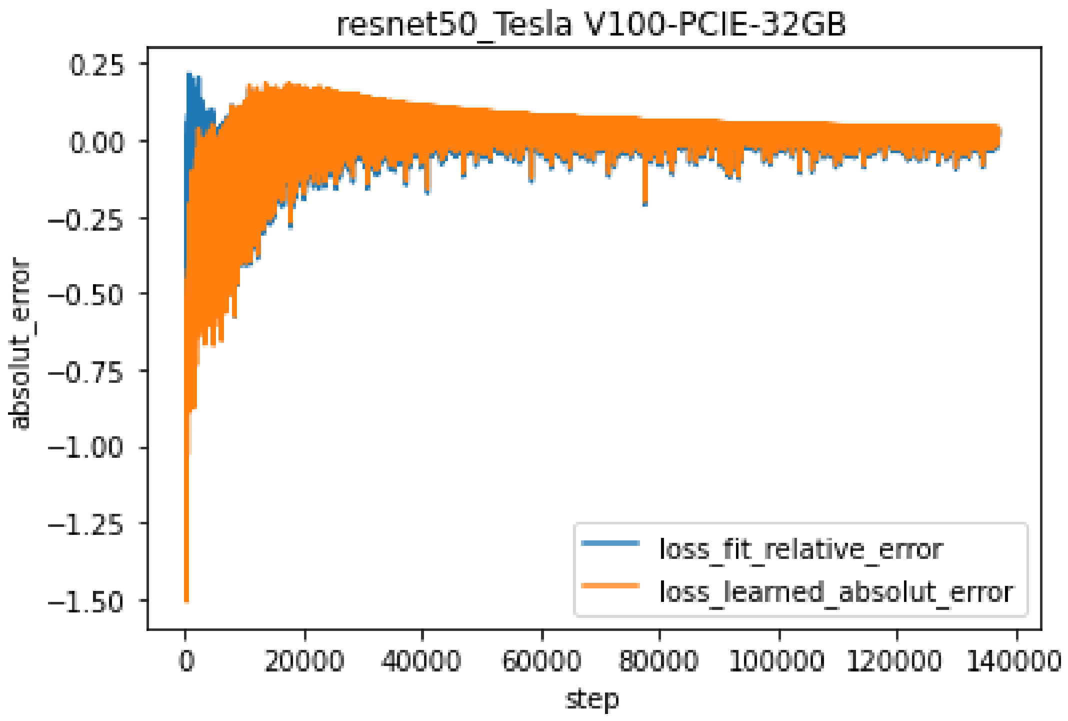

resnet50_Tesla V100-PCIE-32GB
loss_fit_relative_error
loss_learned_relative_error
relative_error
step
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
20000
40000
60000
80000
100000
120000
140000

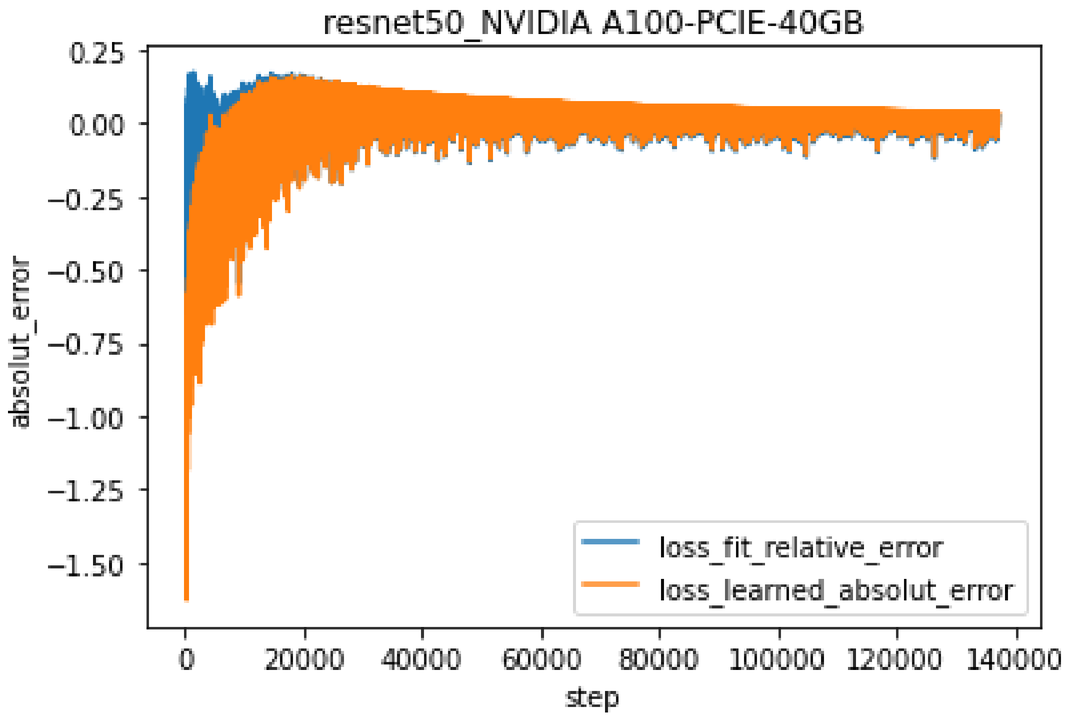


1.3.4 Loss Estimation Absolute Error Over Steps

[139]:
```
import matplotlib.pyplot as plt
res_path = "./problem4/results/"
for i in range(3):
    fig = plt.figure()
    temp_df = pd.read_csv("./problem4/results/" + df["file_name"][i])
    temp_df.columns = [s.strip() for s in temp_df.columns]

    epoch_steps = max(temp_df["step"])
    temp_df["real_step"] = temp_df["epoch"] * epoch_steps + temp_df["step"]
    real_X = temp_df["real_step"].values
    real_Y = temp_df["loss"].values

    b0 = df["b0"][i]
    b1 = df["b1"][i]
    b2 = df["b2"][i]
    fit_X = real_X
    fit_Y = get_y(fit_X, (b0, b1, b2))
    fit_percentage_error = fit_Y - real_Y / real_Y
    fit_absolut_error = fit_Y - real_Y

    b0_hat = df["b0_hat"][i]
    b1_hat = df["b1_hat"][i]
    b2_hat = df["b2_hat"][i]
    learned_X = real_X
    learned_Y = get_y(learned_X, (b0_hat, b1_hat, b2_hat))
    learned_percentage_error = learned_Y - real_Y / real_Y
    learned_absolut_error = learned_Y - real_Y

    plt.plot(real_X, fit_absolut_error, label="loss_fit_relative_error")
    # plt.plot(real_X, fit_absolut_error, label="real")
    plt.plot(real_X, learned_absolut_error, label="loss_learned_absolut_error")
    # plt.plot(real_X, learned_absolut_error, label="learned_absolut_error")
    # plt.plot
    plt.legend()
    plt.title(df["file_name"][i].replace(".csv", ""))
    plt.xlabel("step")
    plt.ylabel("absolut_error")
    plt.show()
```




resnet50_Tesla V100-PCIE-32GB
absolut_error
step
loss_fit_relative_error
loss_learned_absolut_error
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−1.25
−1.50
0
20000
40000
60000
80000
100000
120000
140000


resnet50_NVIDIA A100-PCIE-40GB
absolut_error
step
loss_fit_relative_error
loss_learned_absolut_error
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−1.25
−1.50
0
20000
40000
60000
80000
100000
120000
140000

1.3.5 Comment

We do not know the clear definition of the percentage error. We plot both the relative error and the absolute error over steps.

For fit, it means we use the real loss fitted curve, and calculate the error. For learned, it means we use the curve parameter learning model to get the curve parameters, and calculate the error.

We can notice that the three types of gpu do not have clearn difference in the percentage error.

Epoch to Reach 92% From the predicted loss curve get the number of epochs needed to achive 92% accuracy.

[101]:
```
res_df
```

[101]:
```
       model                  gpu  split            b0            b1  \
0   resnet56  NVIDIA A100-PCIE-40GB    val      0.007232  5.082540e-01
1   resnet18   Tesla V100-PCIE-32GB    val  15074.454974  4.842781e-15
2   resnet50        Quadro RTX 8000  train      0.000237  4.595429e-01
3   resnet56        Quadro RTX 8000    val      0.006419  5.410299e-01
4   resnet50   Tesla V100-PCIE-32GB  train      0.000233  4.650595e-01
5   resnet44   Tesla V100-PCIE-32GB    val      0.006194  6.156885e-01
6   resnet50  NVIDIA A100-PCIE-40GB  train      0.000236  4.631299e-01
7   resnet18  NVIDIA A100-PCIE-40GB  train      0.000271  5.496289e-01
8   resnet20  NVIDIA A100-PCIE-40GB  train      0.000117  6.774311e-01
9   resnet20   Tesla V100-PCIE-32GB  train      0.000116  6.772954e-01
10  resnet44        Quadro RTX 8000    val      0.005784  5.642377e-01
11  resnet20   Tesla V100-PCIE-32GB    val      0.003309  6.152716e-01
12  resnet56        Quadro RTX 8000  train      0.000181  5.943588e-01
13  resnet44        Quadro RTX 8000  train      0.000164  6.297342e-01
14  resnet32   Tesla V100-PCIE-32GB  train      0.000137  6.529592e-01
15  resnet18        Quadro RTX 8000    val  14190.355527  1.761915e-14
16  resnet50  NVIDIA A100-PCIE-40GB    val  15077.103608  1.228839e-14
17  resnet32        Quadro RTX 8000  train      0.000138  6.542840e-01
18  resnet44  NVIDIA A100-PCIE-40GB    val      0.006523  6.016103e-01
19  resnet32  NVIDIA A100-PCIE-40GB  train      0.000135  6.639689e-01
20  resnet56   Tesla V100-PCIE-32GB    val      0.006986  5.944430e-01
21  resnet20  NVIDIA A100-PCIE-40GB    val      0.002869  6.172305e-01
22  resnet18   Tesla V100-PCIE-32GB  train      0.000276  5.409715e-01
23  resnet18        Quadro RTX 8000  train      0.000274  5.473714e-01
24  resnet32   Tesla V100-PCIE-32GB    val      0.004756  5.696338e-01
25  resnet20        Quadro RTX 8000    val      0.003459  6.028435e-01
26  resnet50        Quadro RTX 8000    val  15963.918072  4.808917e-14
27  resnet32  NVIDIA A100-PCIE-40GB    val      0.004970  5.841725e-01
28  resnet56  NVIDIA A100-PCIE-40GB  train      0.000179  6.156932e-01
29  resnet56   Tesla V100-PCIE-32GB  train      0.000168  6.305453e-01
30  resnet50   Tesla V100-PCIE-32GB    val  29266.171362  7.422585e-07
31  resnet32        Quadro RTX 8000    val      0.005167  5.939095e-01
32  resnet44   Tesla V100-PCIE-32GB  train      0.000163  6.476243e-01
```

```
33  resnet44  NVIDIA A100-PCIE-40GB  train      0.000152  6.525351e-01
34  resnet20        Quadro RTX 8000  train      0.000119  6.714442e-01
35  resnet18  NVIDIA A100-PCIE-40GB    val  14406.108425  1.890440e-17

              b2  epoch_to_92acc  step_to_92acc  loss_92acc  epoch_steps
0   5.378531e-01              48           3714    0.310703           79
1   1.489328e+00              -1             -1   -1.000000           79
2   5.166572e-18              35          13295    0.245837          391
3   5.360027e-01              64           4978    0.439552           79
4   6.178933e-18              28          10558    0.258628          391
5   5.165396e-01              60           4662    0.326317           79
6   4.789917e-18              32          12122    0.228549          391
7   1.109550e-20              27          10167    0.227245          391
8   3.629090e-02              58          22288    0.308384          391
9   3.292359e-02              65          25025    0.278525          391
10  5.036776e-01              48           3714    0.314827           79
11  4.710460e-01              98           7664    0.398463           79
12  7.921437e-18              43          16423    0.234778          391
13  3.023622e-17              45          17205    0.227768          391
14  4.390594e-16              40          15251    0.213712          391
15  1.470187e+00              -1             -1   -1.000000           79
16  1.731670e+00              -1             -1   -1.000000           79
17  1.229320e-14              49          18769    0.211670          391
18  5.284625e-01              40           3082    0.341347           79
19  8.933287e-16              63          24243    0.203317          391
20  5.457043e-01              95           7427    0.436796           79
21  4.385978e-01              90           7032    0.433734           79
22  5.573940e-20              29          10949    0.209562          391
23  2.673371e-20              31          11731    0.171517          391
24  4.845599e-01              87           6795    0.392498           79
25  4.675423e-01              97           7585    0.361966           79
26  1.763151e+00              -1             -1   -1.000000           79
27  4.905964e-01              33           2529    0.410197           79
28  1.386363e-18              40          15250    0.208657          391
29  1.664642e-18              28          10558    0.265990          391
30  1.779010e+00              -1             -1   -1.000000           79
31  5.055491e-01              66           5136    0.368251           79
32  8.308141e-16              43          16423    0.201995          391
33  1.077400e-17              43          16423    0.235092          391
34  3.446392e-02              52          19942    0.288194          391
35  1.435279e+00              -1             -1   -1.000000           79
```

[102]:
```
train_res_df = res_df[res_df["split"] == "train"]
```

[103]:
```
train_res_df
```

```
[103]:      model                  gpu  split        b0        b1            b2  \
2   resnet50       Quadro RTX 8000  train  0.000237  0.459543  5.166572e-18
4   resnet50    Tesla V100-PCIE-32GB  train  0.000233  0.465060  6.178933e-18
6   resnet50   NVIDIA A100-PCIE-40GB  train  0.000236  0.463130  4.789917e-18
7   resnet18   NVIDIA A100-PCIE-40GB  train  0.000271  0.549629  1.109550e-20
8   resnet20   NVIDIA A100-PCIE-40GB  train  0.000117  0.677431  3.629090e-02
9   resnet20    Tesla V100-PCIE-32GB  train  0.000116  0.677295  3.292359e-02
12  resnet56         Quadro RTX 8000  train  0.000181  0.594359  7.921437e-18
13  resnet44         Quadro RTX 8000  train  0.000164  0.629734  3.023622e-17
14  resnet32    Tesla V100-PCIE-32GB  train  0.000137  0.652959  4.390594e-16
17  resnet32         Quadro RTX 8000  train  0.000138  0.654284  1.229320e-14
19  resnet32   NVIDIA A100-PCIE-40GB  train  0.000135  0.663969  8.933287e-16
22  resnet18    Tesla V100-PCIE-32GB  train  0.000276  0.540971  5.573940e-20
23  resnet18         Quadro RTX 8000  train  0.000274  0.547371  2.673371e-20
28  resnet56   NVIDIA A100-PCIE-40GB  train  0.000179  0.615693  1.386363e-18
29  resnet56    Tesla V100-PCIE-32GB  train  0.000168  0.630545  1.664642e-18
32  resnet44    Tesla V100-PCIE-32GB  train  0.000163  0.647624  8.308141e-16
33  resnet44   NVIDIA A100-PCIE-40GB  train  0.000152  0.652535  1.077400e-17
34  resnet20         Quadro RTX 8000  train  0.000119  0.671444  3.446392e-02

    epoch_to_92acc  step_to_92acc  loss_92acc  epoch_steps
2               35          13295    0.245837          391
4               28          10558    0.258628          391
6               32          12122    0.228549          391
7               27          10167    0.227245          391
8               58          22288    0.308384          391
9               65          25025    0.278525          391
12              43          16423    0.234778          391
13              45          17205    0.227768          391
14              40          15251    0.213712          391
17              49          18769    0.211670          391
19              63          24243    0.203317          391
22              29          10949    0.209562          391
23              31          11731    0.171517          391
28              40          15250    0.208657          391
29              28          10558    0.265990          391
32              43          16423    0.201995          391
33              43          16423    0.235092          391
34              52          19942    0.288194          391
```

We use the average loss to 92% accuracy as the estimate of loss to reach the accuracy.

```
[59]: threshold = train_res_df["loss_92acc"].mean()
```

```
[104]: threshold
```

```
[104]: 0.23441231666666665
```

[110]:
```
df
```

[110]:
```
         b0        b1            b2    b0_hat    b1_hat    b2_hat  gpu_type  \
0  0.000237  0.459543  5.166572e-18  0.000168  0.647202  0.000019         0
1  0.000233  0.465060  6.178933e-18  0.000201  0.757450  0.004070         1
2  0.000236  0.463130  4.789917e-18  0.000234  0.867698  0.008120         2

   num_layers    model                    gpu  \
0          50  resnet50        Quadro RTX 8000
1          50  resnet50   Tesla V100-PCIE-32GB
2          50  resnet50  NVIDIA A100-PCIE-40GB

                         file_name  b0_percentage_error  b0_absolut_error  \
0        resnet50_Quadro RTX 8000.csv            -0.710173          0.000069
1   resnet50_Tesla V100-PCIE-32GB.csv            -0.862069          0.000032
2  resnet50_NVIDIA A100-PCIE-40GB.csv            -0.992541          0.000002

   b1_percentage_error  b1_absolut_error  b2_percentage_error  \
0            -0.948817         -0.187659        -3.738277e+12
1            -1.163657         -0.292390        -6.586309e+14
2            -1.410422         -0.404568        -1.695219e+15

   b2_absolut_error
0         -0.000019
1         -0.004070
2         -0.008120
```

[112]:
```
test_res_df
```

[112]:
```
      model                    gpu  split        b0        b1            b2  \
2  resnet50        Quadro RTX 8000  train  0.000237  0.459543  5.166572e-18
4  resnet50   Tesla V100-PCIE-32GB  train  0.000233  0.465060  6.178933e-18
6  resnet50  NVIDIA A100-PCIE-40GB  train  0.000236  0.463130  4.789917e-18

   epoch_to_92acc  step_to_92acc  loss_92acc  epoch_steps  gpu_type  \
2              35          13295    0.245837          391         0
4              28          10558    0.258628          391         1
6              32          12122    0.228549          391         2

   num_layers
2          50
4          50
6          50
```

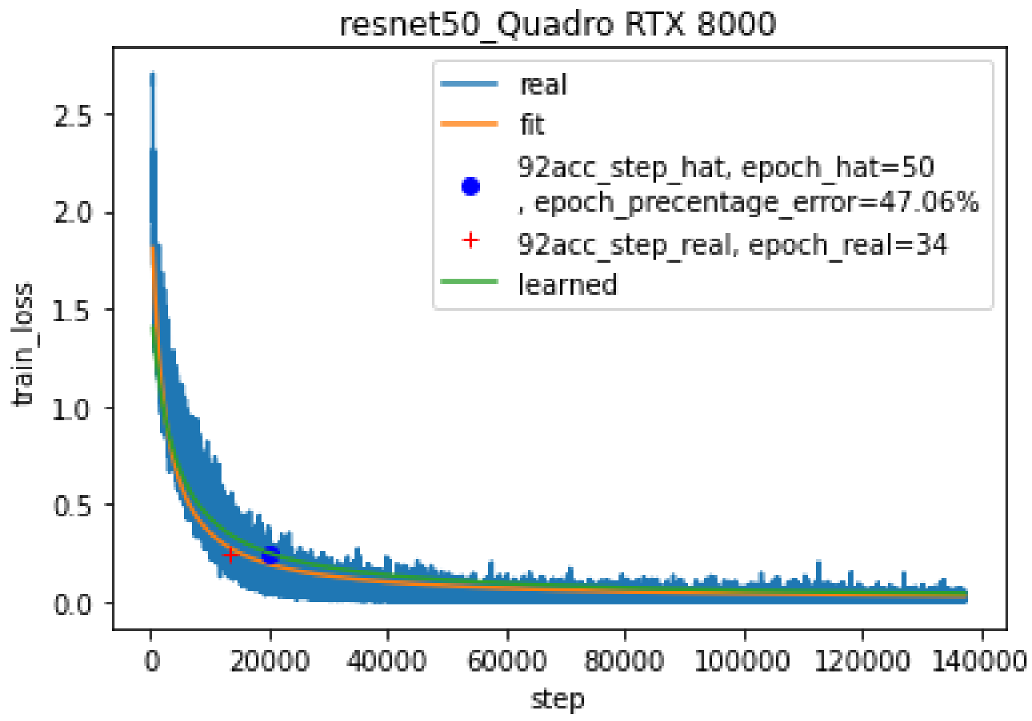
[130]:
```
df
```

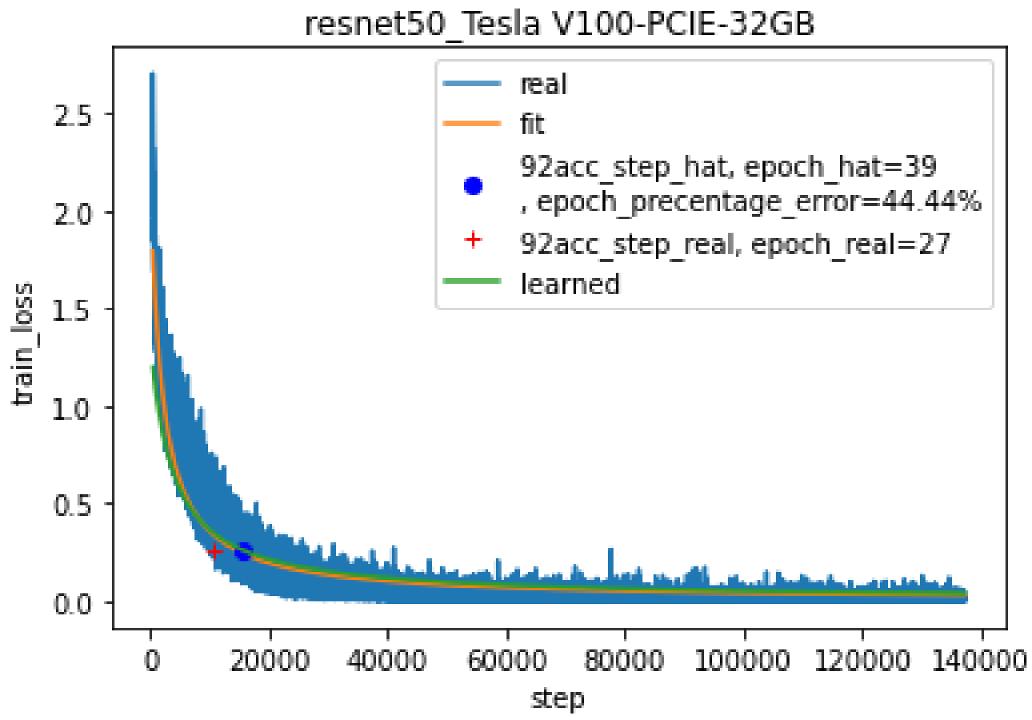
```
[130]:          b0        b1            b2    b0_hat    b1_hat    b2_hat  gpu_type  \
       0  0.000237  0.459543  5.166572e-18  0.000168  0.647202  0.000019         0
       1  0.000233  0.465060  6.178933e-18  0.000201  0.757450  0.004070         1
       2  0.000236  0.463130  4.789917e-18  0.000234  0.867698  0.008120         2

          num_layers     model                    gpu  \
       0          50  resnet50        Quadro RTX 8000
       1          50  resnet50   Tesla V100-PCIE-32GB
       2          50  resnet50  NVIDIA A100-PCIE-40GB

                                 file_name  b0_percentage_error  b0_absolut_error  \
       0        resnet50_Quadro RTX 8000.csv            -0.710173          0.000069
       1   resnet50_Tesla V100-PCIE-32GB.csv            -0.862069          0.000032
       2  resnet50_NVIDIA A100-PCIE-40GB.csv            -0.992541          0.000002

          b1_percentage_error  b1_absolut_error  b2_percentage_error  \
       0            -0.948817         -0.187659        -3.738277e+12
       1            -1.163657         -0.292390        -6.586309e+14
       2            -1.410422         -0.404568        -1.695219e+15

          b2_absolut_error
       0         -0.000019
       1         -0.004070
       2         -0.008120
```

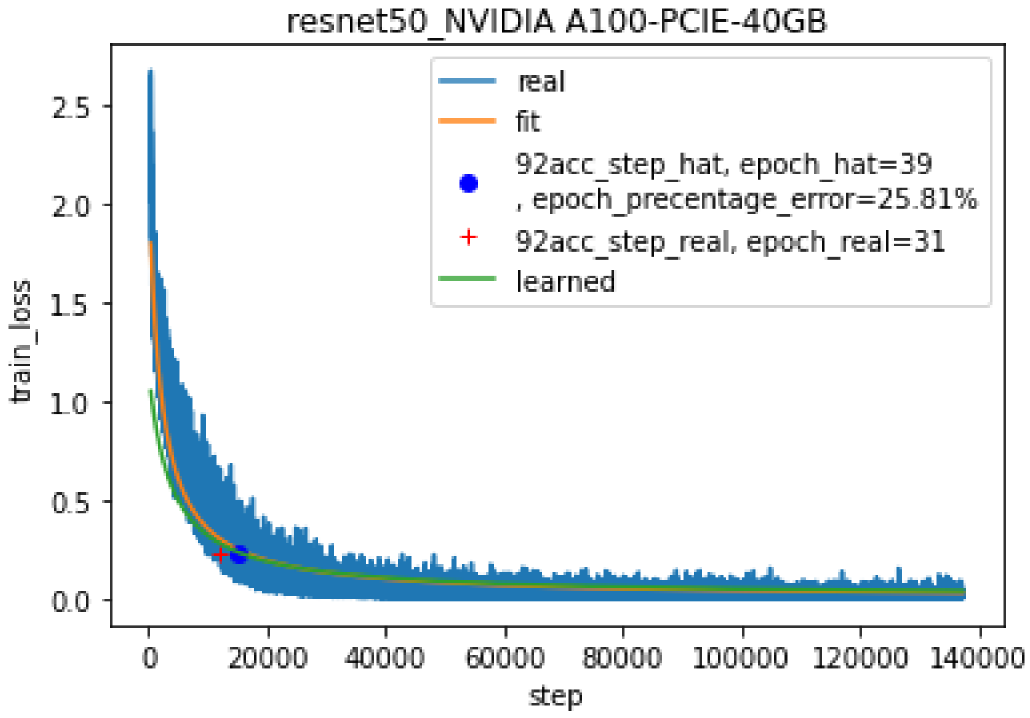
```
[120]: threshold = test_res_df["loss_92acc"].mean()
```

```
[136]: import matplotlib.pyplot as plt
       res_path = "./problem4/results/"
       for i in range(3):
           fig = plt.figure()
           temp_df = pd.read_csv("./problem4/results/" + df["file_name"][i])
           temp_df.columns = [s.strip() for s in temp_df.columns]

           epoch_steps = max(temp_df["step"])
           temp_df["real_step"] = temp_df["epoch"] * epoch_steps + temp_df["step"]
           real_X = temp_df["real_step"].values
           real_Y = temp_df["loss"].values
           plt.plot(real_X, real_Y, label="real")

           b0 = df["b0"][i]
           b1 = df["b1"][i]
           b2 = df["b2"][i]
           fit_X = real_X
           fit_Y = get_y(fit_X, (b0, b1, b2))
           plt.plot(fit_X, fit_Y, label="fit")
```

```
    b0_hat = df["b0_hat"][i]
    b1_hat = df["b1_hat"][i]
    b2_hat = df["b2_hat"][i]
    learned_X = real_X
    learned_Y = get_y(learned_X, (b0_hat, b1_hat, b2_hat))

    step_real = test_res_df["step_to_92acc"].to_list()[i]
    # print(step_real)
    loss_92acc_real = test_res_df["loss_92acc"].to_list()[i]
    # print(step_real)
    # step_hat =
    threshold = test_res_df["loss_92acc"].to_list()[i]
    step_hat = np.where(learned_Y==learned_Y[learned_Y<threshold][0])[0][0]
    num_steps_per_epoch = 391
    epoch_hat = step_hat // num_steps_per_epoch
    epoch_real = step_real // num_steps_per_epoch
    p = "{0:.2f}".format((epoch_hat-epoch_real)/epoch_real * 100)
    plt.plot(step_hat, learned_Y[step_hat], "bo", label=f"92acc_step_hat,␣
↪epoch_hat={epoch_hat} \n, epoch_precentage_error={p}%")
    plt.plot(step_real, loss_92acc_real, "r+", label=f"92acc_step_real,␣
↪epoch_real={epoch_real}")

    plt.plot(learned_X, learned_Y, label="learned")
    plt.xlabel("step")
    plt.ylabel("train_loss")
    plt.title(df["file_name"][i].replace(".csv", ""))
    plt.legend()
    plt.show()
```


resnet50_Quadro RTX 8000
real
fit
92acc_step_hat, epoch_hat=50
, epoch_precentage_error=47.06%
92acc_step_real, epoch_real=34
learned
train_loss
step
0.0
0.5
1.0
1.5
2.0
2.5
0
20000
40000
60000
80000
100000
120000
140000


resnet50_Tesla V100-PCIE-32GB
real
fit
92acc_step_hat, epoch_hat=39
, epoch_precentage_error=44.44%
92acc_step_real, epoch_real=27
learned
train_loss
step
0.0
0.5
1.0
1.5
2.0
2.5
0
20000
40000
60000
80000
100000
120000
140000



1.3.6 Comment

The Learned curve precentage error is not that small, one reason is that we use the the kernel regression which may not extrapolate well, another reason is that the loss curve is not smooth. Actraully, the total epoch is quite small, if we check the results over all the running epoch numbers, it is quite good.

Some discussions with students: For the regression model, I use the GPU type as the categorical feature, and they may use different regression model for different GPU types, the leaned regression model maybe more accurate if we learn the model seperately.

1.3.7 3

Using the predicted number of epochs for Resnet-50 along with the resource-speed model (use Equation (4) in Peng et al. along with its coefficients from the paper) obtain the time to accuracy of Resnet-50 (to reach 92% accuracy) in two different setting (with 2 and 4 parameter servers respectively) as a function of the number of workers. So you will be plotting two curves, one for 2 and one for 4 parameter server case. Each smooth curve will show how the time to achieve 92% accuracy (on the y-axis) scales with number of workers (on the x-axis). (7)

Hint: The theta values are given in the paper. You may re-use them directly

$$f(p,w) = \left(\theta_0 \cdot \frac{M}{w} + \theta_1 + \theta_2 \cdot \frac{w}{p} + \theta_3 \cdot w + \theta_4 \cdot p\right)^{-1} \tag{1}$$

	theta_(1)	theta_(2)	theta_(3)	theta_(4)	theta_(5)	Residual sum of squares for fitting
Async	2.83	3.92	0.00	0.11	-	0.10
Sync	1.02	2.78	4.92	0.00	0.02	0.00

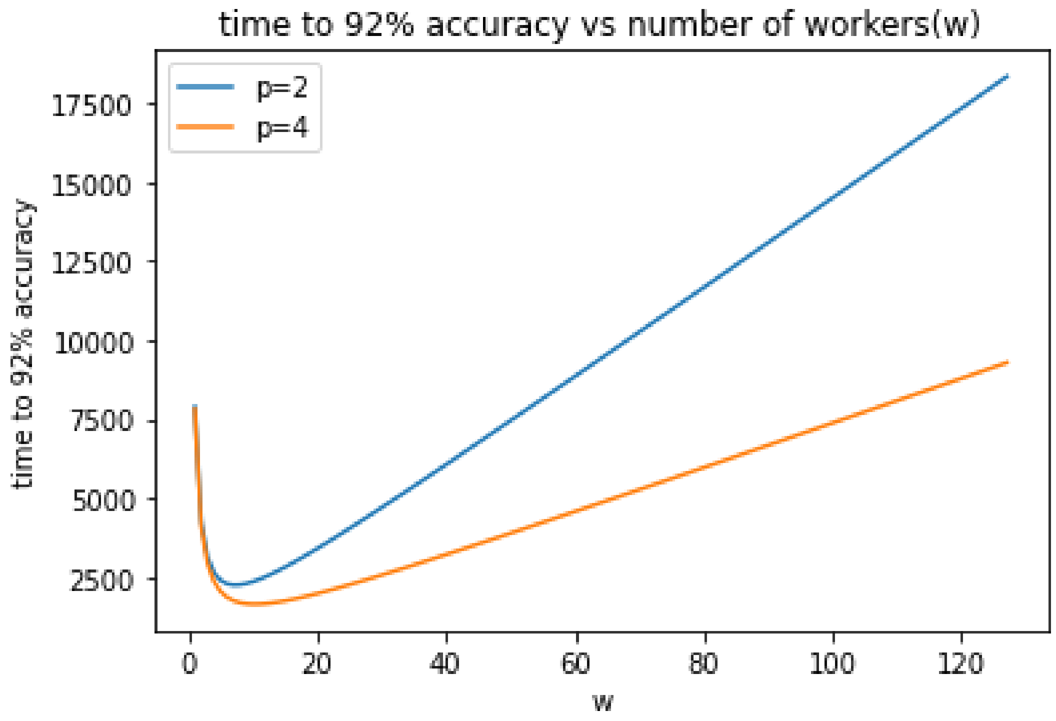
[265]:
```
M = 128

def f_async(w, p):
    theta_0 = 2.83
    theta_1 = 3.92
    theta_2 = 0.00
    theta_3 = 0.11
    # theta_4 = 0.02
    return theta_0 * M / w + theta_1 + theta_2 * w / p + theta_3 * w

def f_sync(w, p):
    theta_0 = 1.02
    theta_1 = 2.78
    theta_2 = 4.92
    theta_3 = 0.00
    theta_4 = 0.02
    return 1 / (theta_0 * M / w + theta_1 + theta_2 * w / p + theta_3 * w +␣
  ↪theta_4 * p)
```

[266]:
```
def get_time(w, p):
    return epoch_hat / f_sync(w, p)

def get_time_p2(w, p=2):
    return epoch_hat / f_sync(w, p)

def get_time_p4(w, p=4):
    return epoch_hat / f_sync(w, p)
```

[267]:
```
w = np.arange(1, M, 1)
t2 = [get_time_p2(w_i) for w_i in w]
t4 = [get_time_p4(w_i) for w_i in w]
```

[268]:
```
# plot
plt.plot(w, t2, label="p=2")
plt.plot(w, t4, label="p=4")
plt.legend()
plt.xlabel("w")
plt.ylabel("time to 92% accuracy")
plt.title("time to 92% accuracy vs number of workers(w)")
```

```
[268]: Text(0.5, 1.0, 'time to 92% accuracy vs number of workers(w)')
```


time to 92% accuracy vs number of workers(w)
p=2
p=4
time to 92% accuracy
w