## Kabir Notebook 7

## December 9, 2024

```
[]:
[1]: import torch
     from torch import nn
     import torch.nn.functional as F
     from collections import OrderedDict
     from sklearn.metrics import accuracy_score, precision_score, recall_score,_
     ⇒f1_score, confusion_matrix, classification_report
     import matplotlib.pyplot as plt
     from torchvision import datasets
     import torchvision.transforms as transforms
     from torch.utils.data import DataLoader
     import time
     from IPython.core.magic import register_cell_magic
     import gc
     from torch.amp import autocast, GradScaler
     from torchtnt.utils.data import CudaDataPrefetcher
     @register_cell_magic
     def skip(line, cell):
         return
     device = 'cuda'
    /home/super/.local/lib/python3.11/site-packages/tqdm/auto.py:21: TqdmWarning:
    IProgress not found. Please update jupyter and ipywidgets. See
    https://ipywidgets.readthedocs.io/en/stable/user_install.html
      from .autonotebook import tqdm as notebook_tqdm
[2]: dl = False
     data_path = './data'
     # Load CIFAR-10 dataset with the simple transform
     cifar10_train = datasets.CIFAR10(data_path, train=True, download=dl,__
      ⇔transform=transforms.ToTensor())
     try:
```

```
mean = torch.load('data/mean.pt')
    std = torch.load('data/std.pt')
except FileNotFoundError:
    print("Computing Mean and Std")
    train_imgs = torch.stack([img for img, _ in cifar10_train], dim=3)#.
 ⇔to(device=device)
    view = train_imgs.view(3, -1)#.to(device=device)
    mean = train_imgs.view(3, -1).mean(dim=1)
    std = train_imgs.view(3, -1).std(dim=1)
    transform = transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize(mean, std)
    1)
    torch.save(mean, 'data/mean.pt')
    torch.save(std, 'data/std.pt')
# Define the transform with normalization
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize(mean, std)
])
print("Mean: ", mean)
print("Std: ", std)
cifar10_train = datasets.CIFAR10(data_path, train=True, download=dl,__
 →transform=transform)
cifar10_test = datasets.CIFAR10(data_path, train=False, download=dl,__
 →transform=transform)
```

/tmp/ipykernel\_1721992/2313373535.py:7: FutureWarning: You are using `torch.load` with `weights\_only=False` (the current default value), which uses the default pickle module implicitly. It is possible to construct malicious pickle data which will execute arbitrary code during unpickling (See https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for more details). In a future release, the default value for `weights\_only` will be flipped to `True`. This limits the functions that could be executed during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via `torch.serialization.add\_safe\_globals`. We recommend you start setting `weights\_only=True` for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature.

```
mean = torch.load('data/mean.pt')
/tmp/ipykernel_1721992/2313373535.py:8: FutureWarning: You are using
`torch.load` with `weights_only=False` (the current default value), which uses
```

the default pickle module implicitly. It is possible to construct malicious pickle data which will execute arbitrary code during unpickling (See https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for more details). In a future release, the default value for `weights\_only` will be flipped to `True`. This limits the functions that could be executed during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via `torch.serialization.add\_safe\_globals`. We recommend you start setting `weights\_only=True` for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature.

std = torch.load('data/std.pt')
Mean: tensor([0.4914, 0.4822, 0.4465])
Std: tensor([0.2470, 0.2435, 0.2616])

```
[3]: class Classifier(nn.Module):
         @classmethod
         def compare_results(cls, results1, results2):
             print('Comparing results:')
             comparisons = {
                 'accuracy': 100*(results1['accuracy'] - results2['accuracy'])/
      →results1['accuracy'],
                 'precision': 100*(results1['precision'] - results2['precision'])/
      ⇔results1['precision'],
                 'recall': 100*(results1['recall'] - results2['recall'])/
      →results1['recall'],
                 'f1': 100*(results1['f1'] - results2['f1'])/results1['f1']
             for key, value in comparisons.items():
                 print(f'{key}: {value} %')
         def __init__(self):
             super().__init__()
         def forward(self, x):
             return self.stack(x)
         def predict(self, x):
             with torch.no grad():
                 self.eval()
                 return self.forward(x).argmax(dim=1)
         def train model(
             self,
             epochs,
             train_loader,
             test_loader,
             train_len,
```

```
test_len,
      test_size,
      loss_fn=nn.CrossEntropyLoss(),
      optimizer=torch.optim.SGD,
      optimizer_args = [],
      optimizer_kwargs = {},
      print_epoch=10,
      header_epoch = 15,
      sched_factor = 0.1,
      sched_patience = 5
  ):
      scaler = GradScaler("cuda")
      optimizer = optimizer(self.parameters(), *optimizer_args,_
→**optimizer_kwargs)
      scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer,_
training_time = 0
      train_hist = torch.zeros(epochs, device=device)
      test_hist = torch.zeros(epochs, device=device)
      accuracy_hist = torch.zeros(epochs, device=device)
      cell_width = 20
      header_form_spec = f'^{cell_width}'
      epoch_inspection = {
          "Epoch": 0,
          "Epoch Time (s)": 0,
          "Training Loss": 0,
          "Test Loss ": 0,
          "Overfit (%)": 0,
          "Accuracy (%)": 0,
          "∆ Accuracy (%)": 0,
          "GPU Memory (GiB)": 0
      }
      header_string = "|"
      for key in epoch_inspection.keys():
          header_string += (f"{key:{header_form_spec}}|")
      divider_string = '-'*len(header_string)
      if print_epoch:
          print(f'Training {self.__class__.__name__}\n')
          print(divider_string)
      max_accuracy = torch.zeros(1, device=device)
      for epoch in range(epochs):
          begin_epoch = time.time()
```

```
self.train()
           start_time = time.time()
           train_loss = 0
           for X_batch, Y_batch in train_loader:
               #X_batch, Y_batch = X_batch.to(device, non_blocking=True),_
→ Y_batch.to(device, non_blocking=True)
               optimizer.zero_grad(set_to_none=True)
               with autocast("cuda"):
                   Y_pred = self.forward(X_batch)
                   loss = loss_fn(Y_pred, Y_batch)
               scaler.scale(loss).backward()
               scaler.step(optimizer)
               scaler.update()
               train_loss += loss
           training_time += time.time() - start_time
          train_loss = train_loss/train_len
           train_hist[epoch] = train_loss
           self.eval()
           with torch.no_grad():
              test_loss = torch.zeros(1, device=device)
               correct = torch.zeros(1, device=device)
               for X_test_batch, Y_test_batch in test_loader:
                   #X_test_batch, Y_test_batch = X_test_batch.to(device,_
→non blocking=True), Y test batch.to(device, non blocking=True)
                   out = self.forward(X_test_batch)
                   test_loss += loss_fn(out, Y_test_batch)
                   correct += (out.argmax(dim=1) == Y test batch).sum()
           test_loss = test_loss/test_len
           test_hist[epoch] = test_loss
           accuracy = correct/test_size
           accuracy_hist[epoch] = accuracy
           scheduler.step(accuracy)
           end_epoch = time.time()
           if print_epoch and (epoch % print_epoch == 0 or epoch == epochs -_u
⇒1):
              mem = (torch.cuda.memory_allocated() + torch.cuda.
→memory_reserved())/1024**3
```

```
if header_epoch and epoch % header_epoch == 0:
                  print(header_string)
                  print(divider_string)
              epoch_duration = end_epoch - begin_epoch
              overfit = 100 * (test_loss - train_loss) / train_loss
              d_accuracy = torch.zeros(1) if max_accuracy == 0 else 100 *_
if accuracy > max accuracy:
                  max_accuracy = accuracy
              epoch_inspection['Epoch'] = f'{epoch}'
              epoch_inspection['Epoch Time (s)'] = f'{epoch_duration:4f}'
              epoch_inspection['Training Loss'] = f'{train_loss.item():8f}'
              epoch_inspection['Test Loss '] = f'{test_loss.item():8f}'
              epoch_inspection['Overfit (%)'] = f'{overfit.item():4f}'
              epoch_inspection['Accuracy (%)'] = f'{accuracy.item()*100:4f}'
              epoch_inspection['\Delta Accuracy (%)'] = f'{d_accuracy.item():4f}'
              epoch_inspection["GPU Memory (GiB)"] = f'{mem:2f}'
              for value in epoch_inspection.values():
                  print(f"|{value:^{cell_width}}", end='')
              print('|')
              print(divider_string)
      print(f'\nTraining Time: {training_time} seconds\n')
      self.train_hist = train_hist
      self.test_hist = test_hist
      self.accuracy_hist = accuracy_hist
  def plot_training(self, title='Training Results'):
      plt.plot(self.train_hist.detach().cpu(), label='Training Loss')
      plt.plot(self.test_hist.detach().cpu(), label='Test Loss')
      plt.plot(self.accuracy_hist.detach().cpu(), label='Accuracy')
      plt.title(title)
      plt.xlabel('Epoch')
      plt.ylabel('Loss')
      plt.legend()
      plt.show()
  def get_results(self, Y_test=None, Y_pred=None):
      if Y_test is None:
          Y_test = self.last_test
      if Y_pred is None:
          Y_pred = self.last_pred
      if isinstance(Y_test, torch.Tensor):
```

```
Y_test = Y_test.cpu().detach().numpy()
    if isinstance(Y_pred, torch.Tensor):
        Y_pred = Y_pred.cpu().detach().numpy()
    results = {
        'accuracy': accuracy_score(Y_test, Y_pred),
        'precision': precision_score(Y_test, Y_pred, average='weighted'),
        'recall': recall_score(Y_test, Y_pred, average='weighted'),
        'f1': f1_score(Y_test, Y_pred, average='weighted'),
        'confusion_matrix': confusion_matrix(Y_test, Y_pred),
        'classification_report': classification_report(Y_test, Y_pred)
    self.last_results = results
    return results
def print_results(self, results=None):
    if results is None:
        try:
            results = self.last_results
        except:
            results = self.get_results()
    for key, value in results.items():
        if key in ['confusion_matrix', 'classification_report']:
            print(f'{key.capitalize()}:\n{value}')
        else:
            print(f'{key.capitalize()}: {value}')
```

```
[4]: class ConvImageClassifier(Classifier):
         def __init__(self, input_dim, conv_layers, fc_layers, activation=nn.ReLU):
             super().__init__()
             self.stack = nn.Sequential(OrderedDict(
                 Γ
                     ('conv0', nn.Conv2d(in_channels=3, out_channels=conv_layers[0],__
      ⇔kernel_size=3, padding=1)),
                     ('activation0', activation()),
                     ('maxpool0', nn.MaxPool2d(2)),
                 ]
             ))
             for i in range(1, len(conv_layers)):
                 self.stack.add_module(f'conv{i}', nn.
      →Conv2d(in_channels=conv_layers[i-1], out_channels=conv_layers[i],
      →kernel_size=3, padding=1))
                 self.stack.add module(f'activation(i)', activation())
                 self.stack.add_module(f'maxpool{i}', nn.MaxPool2d(2))
             conv_out = input_dim//(2**len(conv_layers))
             self.stack.add module('flatten', nn.Flatten())
```

```
self.stack.add_module(f'fc0', nn.Linear(conv_out**2*conv_layers[-1],_u
sfc_layers[0]))

for i in range(1, len(fc_layers)):
    self.stack.add_module(f'activation_fc{i}', nn.Tanh())
    self.stack.add_module(f'fc{i}', nn.Linear(fc_layers[i-1],_u
sfc_layers[i]))
```

```
[5]: try:
        del train_loader
        del test_loader
        del model_1a
        del model_1b
        del resnet
        del train_loader_cuda
        del test_loader_cuda
    except:
        pass
    # Reset CUDA context
    start = time.time()
    torch.cuda.empty_cache()
    torch.cuda.reset_peak_memory_stats()
    gc.collect()
    cifar10_train = datasets.CIFAR10(data_path, train=True, download=dl,__

→transform=transform)
    cifar10_test = datasets.CIFAR10(data_path, train=False, download=dl,__
      batch_size = int(2**11)
    workers = 12
    cpu_prefetch = 39
    gpu\_prefetch = 28
    print('begin init train_loader')
    train_loader = DataLoader(
         cifar10 train,
        batch_size=batch_size,
        shuffle=True,
        num_workers=workers,
        prefetch_factor=cpu_prefetch,
        pin_memory=True
    )
```

```
X_batch = next(iter(train_loader))[0]
dtype_size = X_batch.element_size()
print(f"Batch Size: {X_batch.element_size() * X_batch.nelement() / 1024**2}_L
 ⇔MiB")
print('begin init fetcher')
train_loader_cuda = CudaDataPrefetcher(
    data_iterable = train_loader,
    device = torch.device('cuda'),
    num_prefetch_batches=gpu_prefetch
test_loader = DataLoader(cifar10_test, batch_size=len(cifar10_test),__
 →shuffle=True, num_workers=workers, pin_memory=True, prefetch_factor=1)
test_loader_cuda = CudaDataPrefetcher(
    data_iterable = test_loader,
    device = torch.device('cuda'),
    num\_prefetch\_batches=1
model_1a = ConvImageClassifier(
    input_dim = 32,
    conv_layers=[32, 64],
    fc_layers=[32, 10],
    activation=nn.ReLU
).to(device=device)
params = sum(p.numel() for p in model_1a.parameters() if p.requires_grad)
print(f"Total parameters: {params}")
print(model_1a.stack)
model_1a.train_model(
    epochs=200,
    train_loader=train_loader_cuda,
    train len=len(train loader),
    test_loader=test_loader_cuda,
    test_len=len(test_loader),
    test_size = len(cifar10_test),
    loss_fn=nn.CrossEntropyLoss(),
    optimizer=torch.optim.Adam,
    optimizer_kwargs={'lr': 1e-3, 'weight_decay': 1e-2},
    print_epoch=1,
    header_epoch=15,
    #Disable scheduling
    sched_patience = 200
)
del train_loader
```

```
del test_loader
model_1a.plot_training("2 Layer CNN Training Curves")
begin init train_loader
Batch Size: 24.0 MiB
begin init fetcher
Total parameters: 150826
Sequential(
 (conv0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
 (activation0): ReLU()
 (maxpool0): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
 (conv1): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
 (activation1): ReLU()
 (maxpool1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
 (flatten): Flatten(start_dim=1, end_dim=-1)
 (fc0): Linear(in_features=4096, out_features=32, bias=True)
 (activation_fc1): Tanh()
 (fc1): Linear(in_features=32, out_features=10, bias=True)
Training ConvImageClassifier
      Epoch
                      Epoch Time (s) | Training Loss
                                                             Test Loss
    Overfit (%)
                 | Accuracy (%) | Δ Accuracy (%) | GPU Memory
(GiB) |
   ______
                                    0
                        6.879051
                                           1.937800
                                                              1.692992
     -12.633269
                 42.219999
                                     1
                                           0.000000
                                                              4.213852
                       4.994837
                                          1.605037
                                                              1.515875
     -5.555122
                       48.749998
                                         15.466600
                                                              4.916979
                       5.057521
                                    -
        2
                                         1.465897
                                                            1.414413
    -3.512099 | 51.569998 | 5.784616 | 5.618151
```

     	3 -1.791298	   	4.972616 53.240001	 	1.375477 3.238323	   	1.350838 6.319323
       	 4 -1.347484	     	4.927670 55.500001	   	1.308575 4.244927	     	1.290943 7.020495
       	5 -0.904100	   	5.044797 57.049996	   	1.260512 2.792784	   	1.249116 7.721667
       	6 -0.319954	   	4.946557 58.370000	   	1.217713 2.313768	   	1.213817 8.422839
       	 7 -0.537155	   	4.963850 59.389997	   	1.191438 1.747467	   	1.185038 9.124011
       	8 1.377297	   	4.937151 59.560001	   	1.141895 0.286251	   	1.157622 9.825182
       	9 0.949261	     	4.935848 61.479998	 	1.111418 3.223634	     	1.121968 10.526354
 	10 2.569699	     	4.930698 62.089998	     	1.078762 0.992192	     	1.106483 11.227526

   11   2.818901 	   	4.939031 61.820000	   	1.069479 -0.434848		1.099626 11.928698
	   	4.886281 63.379997	   	1.038594 2.077629	   	1.061449 12.629870
13   3.322247 	   	4.995658 63.709998	     	1.013100 0.520671		1.046757 13.331042
14   4.451067 	   	4.999271 64.179999	   	0.998499 0.737719	   	1.042943 14.032214
	   	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
15   4.191998 	     	4.955255 65.099996	     	0.976865 1.433465		1.017815 14.733386
16   6.029279	   	4.942564 64.489996	     	0.963070 -0.937020	   	1.021136 14.733386
17   5.498090	   	5.041818 66.139996	   	0.945570 1.597542	   	0.997559 14.733386

18   4.907250 	   	5.018600 66.490000	   	0.936561 0.529187	   	0.982521 14.733386
19   6.154187	   	4.997144 66.719997	   	0.920925 0.345911	   	0.977600 14.733386
20   7.188182 	     	5.019781 66.649997	     	0.907129 -0.104916	     	0.972335 14.733386
21   8.877600	     	5.009535 66.740000	     	0.895712 0.029981	     	0.975230 14.733386
22   7.808997 	     	5.038126 67.089999	     	0.891375 0.524421	     	0.960982 14.733386
	   	5.222510 67.780000	   	0.878327 1.028471	   	0.942524 14.733386
24   12.014804	   	5.124631 66.719997	   	0.869255 -1.563888	   	0.973694 14.733386
	   	5.112703 67.009997	   	0.867551 -1.136032	   	0.953081 14.733386

26   9.714802 	   	5.065426 68.000001	   	0.851950 0.324581	 	0.934716 14.733386
   27   13.385069 	   	5.058987 67.490000	     	0.834209 -0.750002	   	0.945868 14.733386
	   	5.017909 68.759996	     	0.846333 1.117640	   	0.925520 14.733386
29   10.340587	   	5.092650 69.000000	     	0.823023 0.349046	   	0.908128 14.733386
   Epoch   Overfit (%) (GiB)	   	Epoch Time (s) Accuracy (%)	     	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
30   12.075120	   	4.918151 68.349999	   	0.822712 -0.942030	   	0.922056 14.733386
31   10.827121	   	4.989425 69.330001	     	0.818894 0.478262	   	0.907556 14.733386
    32   10.779591	   	4.983510 69.180000	   	0.813875 -0.216358	   	0.901607 14.733386

33   14.035186 	   	5.009483 68.919998	   	0.798466 -0.591378	   	0.910532 14.733386
34   12.324631 	   	4.931305 69.239998	   	0.800569 -0.129818	   	0.899236 14.733386
35   13.245255 	     	5.006773 69.479996	   	0.788863 0.216349	     	0.893350 14.733386
36   12.487496 	     	4.997746 69.229996	     	0.796416 -0.359815	     	0.895868 14.733386
37   12.208151 	     	5.044682 69.309998	     	0.796336 -0.244672	     	0.893554 14.733386
38   13.201449 	     	5.000170 69.849998	     	0.779699 0.532530	     	0.882630 14.733386
	     	4.996383 70.029998	   	0.775605 0.257695	     	0.881047 14.733386
	   	5.043076 69.940001	   	0.776948 -0.128512	   	0.884165 14.733386

   41   15.430255 	   	5.041635 69.239998	   	0.773695 -1.128088		0.893078 14.733386
	   	5.058732 70.269996	   	0.770552 0.342708	   	0.878690 14.733386
43   15.384832 	   	5.043230 70.139998	     	0.754261 -0.184997		0.870302 14.733386
44   16.213068 	   	4.998542 70.080000	   	0.752734 -0.270380	   	0.874776 14.733386
Epoch   Overfit (%)  GiB)	     	Epoch Time (s) Accuracy (%)	     	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
	   	5.019987 71.209997	   	0.743835 1.337699		0.855158 14.733386
46   16.937983	   	5.004228 70.440000	     	0.745706 -1.081304	   	0.872013 14.733386
	   	5.011259 71.039999	   	0.743847 -0.238728	   	0.855449 14.733386

   48   17.444962 		4.993983 70.899999	   	0.735898 -0.435329	   	0.864275 14.733386
49   19.066174 	   	5.076868 70.220000	   	0.732867 -1.390251	   	0.872597 14.733386
50   17.815176 	   	5.019500 70.419997	     	0.735458 -1.109395	     	0.866482 14.733386
51   18.082968 	     	4.996568 70.519996	   	0.731122 -0.968967	     	0.863331 14.733386
52   17.829021 	     	4.973970 71.109998	     	0.723913 -0.140428	     	0.852979 14.733386
	   	4.986421 70.980000	   	0.720687 -0.322983	     	0.850710 14.733386
	   	5.057110 70.099998	   	0.717377 -1.558769	   	0.881610 14.733386
	   	5.026342 70.459998	   	0.717588 -1.053222	   	0.856848 14.733386

   56   23.733633 	 	5.025057 69.510001	   	0.713417 -2.387300	   	0.882737 14.733386
	   	5.034989 71.660000	   	0.713721 0.631938	   	0.839316 14.733386
58   21.328808 	   	5.013689 70.669997	     	0.704705 -1.381528	   	0.855010 14.733386
   59   19.513639 	   	5.026370 71.270001	   	0.708809 -0.544235	   	0.847124 14.733386
	   	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
	   	4.995232 70.379996	     	0.709052 -1.786218	   	0.869824 14.733386
	   	5.050303 70.469999	   	0.712813 -1.660621	   	0.855380 14.733386
	   	5.017296 70.400000	   	0.701495 -1.758304	   	0.868435 14.733386

63   19.931078 	   	5.017220 71.590000	   	0.701392 -0.097683	   	0.841186 14.733386
	   	5.014618 72.029996	   	0.691178 0.516321	     	0.828895 14.733386
	   	5.022207 71.590000	   	0.691030 -0.610850	   	0.834924 14.733386
66   25.537222 	     	5.087819 71.079999	   	0.679771 -1.318890	   	0.853366 14.733386
67   19.596493 	     	5.001268 72.139996	   	0.692515 0.152715	   	0.828224 14.733386
68   19.918194 	     	4.985179 72.349995	     	0.684203 0.291099	     	0.820484 14.733386
69   23.128300	   	4.998172 71.329999	   	0.680681 -1.409809	   	0.838111 14.733386
	   	4.971375 71.399999	   	0.687074 -1.313057	   	0.845096 14.733386

	   	5.033550 71.980000	   	0.677085 -0.511397		0.833596 14.733386
	     	5.027353 71.669996	     	0.674671 -0.939875	   	0.835942 14.733386
	   	5.011705 71.109998	   	0.674149 -1.713887	   	0.846878 14.733386
	   	5.005163 72.249997	     	0.669994 -0.138215	   	0.822554 14.733386
Epoch   Overfit (%) (GiB)	   	Epoch Time (s) Accuracy (%)	     	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
75   25.052343 	     	5.051726 72.450000	     	0.661650 0.138223		0.827408 14.733386
	   	5.025922 71.599996	     	0.671461 -1.173228	   	0.837118 14.733386
	   	5.002988 71.619999	   	0.672062 -1.145619	   	0.834897 14.733386

   78   26.343037 	   	5.037694 71.029997	   	0.674381 -1.959977	   	0.852034 14.733386
	   	5.008406 71.689999	   	0.673514 -1.049001	   	0.835284 14.733386
80   22.542067 	     	5.023103 72.329998	   	0.664724 -0.165634	     	0.814567 14.733386
81   26.091066 	     	5.032135 71.520001	     	0.660016 -1.283643	     	0.832222 14.733386
82   25.713850 	     	5.014982 72.069997	     	0.658289 -0.524504	     	0.827561 14.733386
83   26.368765 	     	4.990252 72.169995	   	0.657215 -0.386480	     	0.830514 14.733386
	   	5.049405 72.529995	   	0.646537 0.110415	   	0.816893 14.733386
	   	5.018591 72.700000	   	0.647542 0.234392	   	0.815600 14.733386

   86   25.488043 	   	5.033751 72.389996	   	0.647618 -0.426415	 	0.812683 14.733386
87   26.231840 	     	5.045481 72.779995	     	0.646377 0.110035	   	0.815934 14.733386
	   	4.996143 72.670001	     	0.648928 -0.151133	   	0.810473 14.733386
89   26.543398 	     	5.029956 73.259997	     	0.639077 0.659525	   	0.808710 14.733386
	   	Epoch Time (s) Accuracy (%)	     	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
90   29.526297	     	5.110249 71.480000	   	0.641995 -2.429699	   	0.831552 14.733386
91   27.022100	   	4.982387 71.929997	     	0.649811 -1.815452	   	0.825403 14.733386
92 27.902637	   	4.985412 72.479999	   	0.635004 -1.064699	   	0.812187 14.733386

93   26.830687 	   	5.036469 72.169995	   	0.644235 -1.487854	   	0.817088 14.733386
94   29.515427 	   	5.012946 71.819997	   	0.632602 -1.965603	     	0.819317 14.733386
95   33.269829	   	5.045994 70.599997	     	0.633972 -3.630904	     	0.844893 14.733386
96   30.598265 	   	4.988159 71.309996	     	0.644581 -2.661755	     	0.841811 14.733386
97   27.524033	   	5.099520 72.079998	   	0.642988 -1.610700	   	0.819964 14.733386
98   37.142879	   	5.076290 70.159996	   	0.630325 -4.231507	   	0.864446 14.733386
99   34.734249	   	5.029150 69.690001	   	0.642412 -4.873050	   	0.865549 14.733386
100   30.120871	   	5.074078 71.419996	 	0.639341 -2.511605	     	0.831916 14.733386

   101   31.982470 		5.076982 70.739996	   	0.641404 -3.439805	   	0.846540 14.733386
102   25.839453 	   	5.054729 72.939998	   	0.635157 -0.436800	   	0.799278 14.733386
103   31.170256	   	5.141601 72.029996	     	0.625099 -1.678954	   	0.819944 14.733386
104   31.387720 	   	5.070658 72.420001	   	0.622841 -1.146596	   	0.818336 14.733386
	   	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
105   29.384373 	   	5.019599 72.560000	     	0.628627 -0.955497	   	0.813345 14.733386
106   32.085606	   	5.024177 71.630001	     	0.626152 -2.224947	   	0.827057 14.733386
107   31.783247	   	5.013819 71.639997	   	0.629211 -2.211303	   	0.829194 14.733386

108   32.902443 	   	4.982967 71.789998	   	0.627714 -2.006552	   	0.834247 14.733386
109   30.716171	   	5.065071 72.819996	   	0.623302 -0.600603	     	0.814757 14.733386
110   31.602104	   	5.052822 72.520000	   	0.620189 -1.010098	     	0.816181 14.733386
	   	5.039487 71.509999	   	0.620462 -2.388750	     	0.830820 14.733386
	   	5.014404 72.859997	   	0.628477 -0.546002	   	0.807500 14.733386
113   32.736797	   	5.031634 72.799999	   	0.607373 -0.627899	   	0.806208 14.733386
	   	5.058440 71.499997	   	0.613070 -2.402402	   	0.832420 14.733386
115   33.077972	     	5.137480 72.349995	   	0.615059 -1.242154	     	0.818509 14.733386

   116   33.198799 	   	5.018563 72.399998	   	0.609816 -1.173901		0.812268 14.733386
	   	5.109816 72.839999	   	0.607323 -0.573298	   	0.806634 14.733386
118   33.439774 	   	5.038103 72.499996	     	0.607644 -1.037402	   	0.810839 14.733386
119   35.660679	   	5.046576 71.880001	   	0.606106 -1.883697	   	0.822247 14.733386
Epoch   Overfit (%) (GiB)	   	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
120   31.503040	   	5.127125 73.170000	     	0.604725 -0.122846	   	0.795232 14.733386
121   33.107285	   	5.092554 72.639996	     	0.603490 -0.846303	   	0.803289 14.733386
122   33.076607	   	5.157858 72.589999	   	0.607773 -0.914548	   	0.808804 14.733386

123   33.502678	 	5.063401 72.380000	   	0.606742 -1.201197	   	0.810017 14.733386
124   31.636356	   	5.077441 73.249996	   	0.600606 -0.013652	   	0.790615 14.733386
125   32.233276	   	5.053849 72.359997	   	0.614245 -1.228502	     	0.812236 14.733386
126   33.992432 	   	5.084872 72.589999	     	0.599685 -0.914548	     	0.803532 14.733386
127   36.170300	   	5.167486 72.490001	     	0.599114 -1.051046	     	0.815815 14.733386
128   34.085697	   	5.089398 72.829998	   	0.602681 -0.586950	     	0.808109 14.733386
129   33.262379	   	5.076684 73.109996	   	0.600694 -0.204752	   	0.800499 14.733386
130   36.840973	   	5.027541 71.969998	   	0.597062 -1.760851	   	0.817026 14.733386

   131   34.879238 	 	5.041021 72.869998	   	0.594622 -0.532349	 	0.802022 14.733386
	   	5.119192 71.880001	     	0.598600 -1.883697	   	0.819156 14.733386
133   34.609364 	   	5.096864 73.139995	   	0.595433 -0.163803	   	0.801509 14.733386
134   37.861038 	   	5.065614 72.679996	     	0.587363 -0.791702	   	0.809745 14.733386
Epoch   Overfit (%) (GiB)	   	Epoch Time (s) Accuracy (%)	     	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
135   34.924698 	   	5.141582 73.619998	     	0.584925 0.491401		0.789208 14.733386
	   	5.089416 71.779996	   	0.588752 -2.499323	   	0.831994 14.733386
137   35.581394	   	5.073261 72.209996	   	0.602229 -1.915243	   	0.816510 14.733386

138   36.976452 	   	5.051284 72.749996	   	0.588933 -1.181746	   	0.806700 14.733386
139   33.132214 	   	5.172863 73.219997	     	0.596244 -0.543332	     	0.793793 14.733386
140   35.722385 	   	5.030095 72.749996	   	0.589227 -1.181746	   	0.799713 14.733386
141   37.097630	   	5.064724 72.929996	   	0.587496 -0.937247	   	0.805443 14.733386
142   36.550980	     	5.317110 72.659999		0.589445 -1.303991	     	0.804893 14.733386
143   38.193150 	     	5.075824 72.189999	     	0.595370 -1.942405	     	0.822761 14.733386
144   37.697517 	     	5.127365 72.229999	     	0.595650 -1.888072	     	0.820195 14.733386
	   	5.070822 73.519999	   	0.589687 -0.135831	   	0.787928 14.733386

   146   42.182186 	   	5.024504 71.639997	   	0.584502 -2.689488		0.831057 14.733386
	   	5.040956 72.999996	   	0.586660 -0.842165	   	0.796234 14.733386
148   36.290077	   	5.033256 73.579997	     	0.580001 -0.054334	   	0.790484 14.733386
149   42.540440 	   	5.084164 71.969998	   	0.583147 -2.241238	   	0.831220 14.733386
	   	Epoch Time (s) Accuracy (%)	     	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
150   34.768665 	   	5.084607 72.340000	   	0.597433 -1.738655	   	0.805152 14.733386
151   37.786106	   	5.077116 72.889996	     	0.578795 -0.991581	   	0.797499 14.733386

     	153 38.517136	   	5.031142 72.829998	   	0.578993 -1.073078	   	0.802004 14.733386
       	154 40.675404	   	5.084552 72.499996	     	0.580315 -1.521327	     	0.816360 14.733386
       	155 38.971237	     	5.067575 72.380000	     	0.578752 -1.684321	     	0.804299 14.733386
       	156 37.144699	   	5.113379 73.429996	   	0.579363 -0.258084	   	0.794566 14.733386
       	157 38.051037	   	5.017329 73.069996	   	0.578061 -0.747082	   	0.798019 14.733386
       	158 39.837406	   	5.101545 72.529995	   	0.575089 -1.480579	   	0.804189 14.733386
       	159 36.858311	   	5.028152 73.569995	   	0.571383 -0.067920	   	0.781985 14.733386
      	160 40.800018	     	5.082304 72.259998	     	0.580265 -1.847323	     	0.817013 14.733386

   161   40.162014 	   	5.036721 72.319996	   	0.578746 -1.765826		0.811182 14.733386
	     	5.045552 72.439998	     	0.588903 -1.602824	   	0.808974 14.733386
163   40.077641 	   	5.086725 72.369999	     	0.584779 -1.697907	   	0.819144 14.733386
164   39.984184 	     	5.100532 72.950000	     	0.570557 -0.910076	   	0.798689 14.733386
	   	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
165   44.997696	   	5.097234 72.149998	     	0.566995 -1.996740	   	0.822130 14.733386
	   	5.046937 73.299998	   	0.571805 -0.434664	   	0.786729 14.733386
167   40.899544	   	5.059964 72.649997	   	0.572341 -1.317577	   	0.806426 14.733386

168   38.978401 	   	5.083268 72.819996	   	0.578109 -1.086663	   	0.803447 14.733386
169   40.377739	   	5.034514 72.499996	   	0.575779 -1.521327	     	0.808265 14.733386
170   46.976452	   	5.096079 71.059996	     	0.571691 -3.477318	     	0.840251 14.733386
171   39.395245 	   	5.090700 72.749996	     	0.577162 -1.181746	     	0.804536 14.733386
172   40.235794	   	5.041945 72.889996	   	0.570497 -0.991581	   	0.800041 14.733386
173   37.342800	   	5.052004 73.259997	   	0.574199 -0.488998	   	0.788621 14.733386
174   39.534668	   	5.052775 73.420000	   	0.572699 -0.271662	   	0.799113 14.733386
175   42.482597	   	5.074750 72.109997	     	0.567056 -2.051074	   	0.807956 14.733386

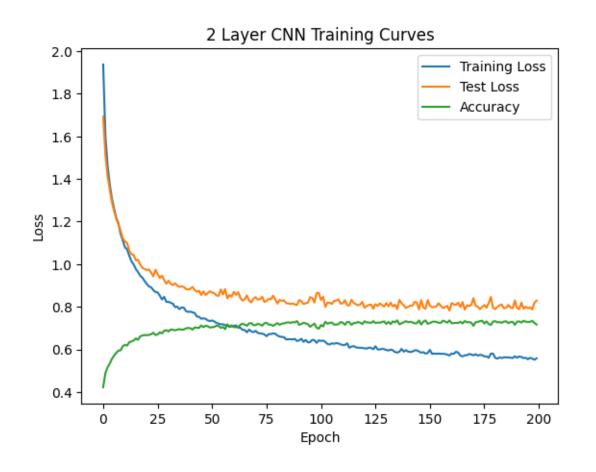
   176   40.365253 		5.063622 73.119998	   	0.566776 -0.679163	 	0.795557 14.733386
	   	5.112973 71.889997	   	0.560236 -2.349906	   	0.817368 14.733386
178   45.909477 	   	5.141950 71.459997	     	0.579844 -2.933986		0.846047 14.733386
179   37.004822 	   	5.097329 73.069996	     	0.579943 -0.747082	   	0.794550 14.733386
	   	Epoch Time (s) Accuracy (%)	     	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
180   40.968742 	   	5.048506 73.219997	     	0.560042 -0.543332	   	0.789484 14.733386
181   43.626152 	   	5.058635 72.679996	     	0.556483 -1.276828	   	0.799255 14.733386
182   43.621426	   	5.078006 72.779995	   	0.561945 -1.140997	   	0.807073 14.733386

183   44.903713 	 	5.123325 72.469997	   	0.559224 -1.562076		0.810336 14.733386
184   40.937675	     	5.105889 73.049998	   	0.562512 -0.774245	   	0.792792 14.733386
185   41.383297	     	5.135925 73.170000	     	0.562172 -0.611243	   	0.794817 14.733386
186   43.891663 	     	5.117503 72.289997	   	0.562027 -1.806575	     	0.808710 14.733386
187   42.078255	   	5.105713 72.819996	   	0.560768 -1.086663	     	0.796730 14.733386
188   41.871277 	   	5.096840 72.889996	   	0.558971 -0.991581	     	0.793019 14.733386
189   46.185753	     	5.079002 71.509999	     	0.567355 -2.866067	     	0.829393 14.733386
190   41.629650	   	5.047444 72.979999	   	0.560887 -0.869328	   	0.794382 14.733386

   191   39.289711 	   	5.137882 73.119998	   	0.566190 -0.679163		0.788644 14.733386
192   45.213093 	   	5.176906 72.579998	   	0.564188 -1.412659	   	0.819275 14.733386
193   41.452759	     	5.095566 73.390001	     	0.558991 -0.312410	   	0.790708 14.733386
194   42.800682 	   	5.114154 72.979999	   	0.560496 -0.869328	   	0.800392 14.733386
Epoch   Overfit (%) (GiB)	   	Epoch Time (s) Accuracy (%)	     	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
195   43.317894 	     	5.104700 72.819996	     	0.553329 -1.086663		0.793020 14.733386
196   42.219360	   	5.060708 72.920001	     	0.560255 -0.950824	   	0.796791 14.733386
197   41.452240	   	5.068001 73.390001	   	0.556775 -0.312410	   	0.787571 14.733386

198		5.114279		0.551170		0.818402
48.484344	1	72.380000	1	-1.684321	1	14.733386
199	1	5.161066	1	0.557756	1	0.828847
48.603931		71.619999		-2.716650		14.733386

Training Time: 465.7891447544098 seconds



```
[7]: try:
         del train_loader
         del test_loader
         del model_1a
         del model_1b
         del resnet
         del train_loader_cuda
         del test_loader_cuda
     except:
         pass
     # Reset CUDA context
     start = time.time()
     torch.cuda.empty_cache()
     torch.cuda.reset_peak_memory_stats()
     gc.collect()
     cifar10_train = datasets.CIFAR10(data_path, train=True, download=dl,_u
      →transform=transform)
     cifar10_test = datasets.CIFAR10(data_path, train=False, download=dl,__
      →transform=transform)
     batch_size = int(2**11)
     workers = 12
     cpu_prefetch = 39
     gpu_prefetch = 28
     print('begin init train_loader')
     train_loader = DataLoader(
         cifar10_train,
         batch_size=batch_size,
         shuffle=True,
         num_workers=workers,
         prefetch_factor=cpu_prefetch,
        pin_memory=True
     )
     X_batch = next(iter(train_loader))[0]
     dtype_size = X_batch.element_size()
     print(f"Batch Size: {X_batch.element_size() * X_batch.nelement() / 1024**2}_L
      →MiB")
     print('begin init fetcher')
     train_loader_cuda = CudaDataPrefetcher(
```

```
data_iterable = train_loader,
    device = torch.device('cuda'),
    num_prefetch_batches=gpu_prefetch
test_loader = DataLoader(cifar10_test, batch_size=len(cifar10_test),_u
 →shuffle=True, num_workers=workers, pin_memory=True, prefetch_factor=1)
test loader cuda = CudaDataPrefetcher(
    data_iterable = test_loader,
    device = torch.device('cuda'),
    num_prefetch_batches=1
)
model_1b = ConvImageClassifier(
    input_dim = 32,
    conv_layers=[32, 64, 128],
    fc_layers=[32, 10],
    activation=nn.ReLU
).to(device=device)
params = sum(p.numel() for p in model_1b.parameters() if p.requires_grad)
print(f"Total parameters: {params}")
print(model_1b.stack)
model_1b.train_model(
    epochs=200,
    train_loader=train_loader_cuda,
    train_len=len(train_loader),
    test_loader=test_loader_cuda,
    test_len=len(test_loader),
    test_size = len(cifar10_test),
    optimizer = torch.optim.Adam,
    optimizer_kwargs={'lr': 4e-4, 'weight_decay': 1e-2}, #Increase alpha to 2
 →next time
    loss_fn=nn.CrossEntropyLoss(),
    print_epoch=1,
    #Disable scheduling
    sched_patience = 200
del train_loader
del test_loader
model_1b.plot_training("3 Layer CNN Training Curves")
begin init train_loader
Batch Size: 24.0 MiB
begin init fetcher
Sequential(
  (conv0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
```

```
(activation0): ReLU()
 (maxpool0): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
 (conv1): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
 (activation1): ReLU()
 (maxpool1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil mode=False)
 (conv2): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
 (activation2): ReLU()
 (maxpool2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
 (flatten): Flatten(start_dim=1, end_dim=-1)
 (fc0): Linear(in_features=2048, out_features=32, bias=True)
 (activation_fc1): Tanh()
 (fc1): Linear(in_features=32, out_features=10, bias=True)
Training ConvImageClassifier
      Epoch | Epoch Time (s) | Training Loss
   Overfit (%)
               | Accuracy (%) | Δ Accuracy (%) | GPU Memory
                     6.599083
                                0
                                     2.123456
                                                       1.948487
                                0.000000 | 4.397570
   -8.239858 | 30.339998
  ______
                     5.095938
                                 1
                                      1.884181
                                                        1.808225
               36.960000
                                21.819387
   -4.031254
                                                       5.098743
._____
       2
                      5.104386
                                 1.763717
                                                       1.702580
    -3.466377
               41.149998
                                 11.336574
                                                       5.799916
       3
                     5.259627
                                1.671804
                                                       1.621082
                                6.585669
    -3.033968
                     43.860000
                                                 6.501088
```

   4   -2.492332 	   	5.091378 45.389998	   	1.603726 3.488367	   	1.563755 7.202260
5   5   -1.828888	   	5.196554 47.219998	   	1.546524 4.031724	   	1.518240 7.903431
	     	5.055001 47.829998	   	1.505353 1.291825	     	1.491611 8.604603
	     	5.300217 47.700000	     	1.466276 -0.271791	     	1.470768 9.305775
8   -0.038194 	     	5.158196 50.019997	     	1.436028 4.578716	     	1.435479 10.006947
   9   -0.598020	   	5.092443 51.370001	   	1.406422 2.698928	   	1.398012 10.708119
10   -0.469776	   	5.108890 52.129996	   	1.377094 1.479453	   	1.370624 11.409291
	   	5.151833 52.759999	   	1.352459 1.208523	   	1.352640 12.110463

12   -0.549647 		5.107094 53.729999	   	1.329279 1.838514	   	1.321973 12.811635
13   -0.467534 	   	5.113696 54.240000	     	1.310188 0.949193	   	1.304062 13.512806
14   0.117547 	   	5.095271 55.339998	     	1.286842 2.028019	   	1.288354 14.213978
Epoch   Overfit (%) (GiB)	   	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
15   0.374658	   	5.078908 55.229998	   	1.272123 -0.198772	   	1.276889 14.915150
16   0.692424 	   	5.201680 56.049997	     	1.258695 1.282975	   	1.267410 14.915150
17   0.898146	   	5.199535 56.430000	     	1.244539 0.677972	   	1.255717 14.915150
18   0.344559	   	5.049537 57.080001	   	1.226315 1.151871		1.230540 14.915150

19   0.657372 	   	5.060830 57.639998		1.211456 0.981075	   	1.219420 14.915150
20   0.328824 	   	5.101258 58.309996	   	1.194798 1.162384	     	1.198727 14.915150
21   0.917526	   	5.119519 58.340001	   	1.180924 0.051458	     	1.191759 14.915150
22   1.014699 	     	5.043655 58.649999	   	1.173767 0.531364	     	1.185677 14.915150
23   1.207450	     	5.075843 58.849996	     	1.161882 0.341002	     	1.175911 14.915150
24   1.113444 	     	5.146863 59.700000	     	1.150066 1.444357	     	1.162871 14.915150
25   1.375481 	     	5.158943 59.990001	   	1.138020 0.485763	     	1.153674 14.915150
	   	5.087031 60.240000	   	1.123744 0.416736	   	1.139605 14.915150

   27   3.088480 	   	5.090375 59.689999	   	1.116595 -0.913018	   	1.151081 14.915150
   28   1.439053 	   	5.113190 60.899997	   	1.110461 1.095611	   	1.126441 14.915150
29   3.575929	     	5.114990 60.310000	   	1.096704 -0.968796	   	1.135921 14.915150
   Epoch   Overfit (%) (GiB)	     	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
   30   1.917087 	   	5.186446 61.430001	     	1.088094 0.870287	   	1.108954 14.915150
   31   4.133659 	   	5.093885 60.749996	   	1.077307 -1.106960	   	1.121839 14.915150
32   2.107863 	   	5.126390 62.000000	   	1.076997 0.927884	   	1.099699 14.915150
	   	5.127231 61.299998	   	1.064820 -1.129037	   	1.102011 14.915150

34   3.555117 	   	5.073361 62.140000	   	1.051656 0.225805	   	1.089044 14.915150
	     	5.091969 63.190001	   	1.046859 1.689735	     	1.067175 14.915150
36   2.728457 	   	5.078733 63.459998	   	1.033740 0.427278	     	1.061945 14.915150
37   3.369730	     	5.084619 63.519996	     	1.026881 0.094545	     	1.061484 14.915150
38   3.568783 	     	5.107906 63.290000	     	1.016998 -0.362085	     	1.053293 14.915150
	     	5.128337 63.589996	   	1.009513 0.110201	     	1.045956 14.915150
40   3.138276	   	5.097540 64.639997	   	0.998343 1.651205	     	1.029674 14.915150
	   	5.108642 64.609998	   	0.990487 -0.046409	   	1.027441 14.915150

42   5.080703 		5.131843 64.289999	 	0.980696 -0.541458		1.030523 14.915150
43   7.134252 	   	5.013742 63.379997	   	0.982274 -1.949258	   	1.052352 14.915150
44   4.024603 	   	5.081797 65.050000	     	0.978605 0.634286	   	1.017990 14.915150
	     	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
45   6.555111 	   	5.021367 64.709997	     	0.966912 -0.522679	   	1.030294 14.915150
46   5.338353 	   	5.044518 65.270001	   	0.958193 0.338203	   	1.009344 14.915150
47   5.718028	   	5.089929 65.130001	     	0.951124 -0.214493	   	1.005510 14.915150
	   	5.070228 65.899998	   	0.944371 0.965217	   	0.995486 14.915150

49   6.944112 	   	5.104623 64.840001	   	0.945438 -1.608493	   	1.011090 14.915150
	   	5.083852 66.219997	   	0.937149 0.485583	   	0.984229 14.915150
	   	5.122586 66.249996	   	0.925459 0.045302	   	0.984319 14.915150
	     	5.096201 65.990001	     	0.922812 -0.392446	     	0.978621 14.915150
53   8.277654 	     	5.131413 65.520000	     	0.921411 -1.101881	     	0.997682 14.915150
	   	5.056648 67.030001	   	0.908973 1.177365	     	0.960075 14.915150
	   	5.029018 67.140001	   	0.903034 0.164106	     	0.963079 14.915150
	   	5.040206 67.420000	     	0.902585 0.417037	     	0.951875 14.915150

   57   6.130551 	   	5.028303 67.170000	   	0.893709 -0.370809	   	0.948499 14.915150
   58   8.351196 	     	5.011108 66.469997	     	0.891331 -1.409081	   	0.965768 14.915150
   59   6.756923 	   	5.085455 67.379999	   	0.889393 -0.059331	   	0.949489 14.915150
   Epoch   Overfit (%) (GiB)	     	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
	   	5.060808 67.750001	     	0.885069 0.489471	   	0.935363 14.915150
	   	5.040805 68.099999	   	0.877112 0.516603	   	0.930217 14.915150
62   7.948235 	     	5.088319 67.890000	   	0.869066 -0.308369	   	0.938141 14.915150
	   	5.085271 67.809999	   	0.873677 -0.425845	   	0.937699 14.915150

64   6.338306 	   	5.123614 68.500000	   	0.868866 0.587373	   	0.923938 14.915150
65   7.809257	   	5.134030 68.110001	   	0.859185 -0.569342	     	0.926281 14.915150
66   8.024608 	   	5.078809 68.129998	   	0.857151 -0.540149	   	0.925934 14.915150
67   8.264010	   	5.098463 68.229997	   	0.854254 -0.394165	   	0.924849 14.915150
	   	5.111977 68.629998	   	0.859365 0.189778	   	0.935850 14.915150
	   	5.039732 68.009996	   	0.840639 -0.903397	   	0.929612 14.915150
	   	5.085504 69.000000	   	0.838153 0.539125	   	0.907637 14.915150
	     	5.067537 67.820001		0.843908 -1.710144	     	0.929506 14.915150

   72   9.561942 	   	5.057573 68.529999	   	0.835999 -0.681160	   	0.915937 14.915150
	   	5.074442 69.199997	     	0.837075 0.289851	   	0.904336 14.915150
74   10.233088 	   	5.095749 68.949997	   	0.832735 -0.361271	   	0.917949 14.915150
	     	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
	   	5.059535 69.690001	     	0.821980 0.708098	   	0.893973 14.915150
	   	5.055362 69.389999	   	0.817010 -0.430481	   	0.903975 14.915150
	     	5.104808 69.499999	     	0.819375 -0.272638	   	0.889156 14.915150
	   	5.068392 69.229996	   	0.813133 -0.660073	   	0.900651 14.915150

   79   12.335466 	   	5.061541 68.930000	   	0.808862 -1.090545	   	0.908639 14.915150
80   10.847201 	   	5.071167 69.510001	   	0.806705 -0.258287	     	0.894210 14.915150
81   10.492674 	   	5.105503 69.369996	   	0.804085 -0.459184	   	0.888455 14.915150
82   12.024125 	     	5.102875 69.349998	   	0.801373 -0.487879	     	0.897731 14.915150
83   10.056890	     	5.091874 70.269996		0.801492 0.832250	     	0.882098 14.915150
84   13.987577 	     	5.102546 68.909997	     	0.796571 -1.935391	     	0.907992 14.915150
	   	5.091497 70.429999	   	0.793067 0.227697	   	0.872336 14.915150
	   	5.108479 69.870001	   	0.786681 -0.795112	   	0.880855 14.915150

87   11.219831 	 	5.188274 70.489997	   	0.782331 0.085188	   	0.870107 14.915150
88   12.024100	   	5.092411 70.300001	   	0.778280 -0.269536	   	0.871861 14.915150
89   13.743012 	     	5.157857 70.120001	   	0.779800 -0.524891	   	0.886968 14.915150
Epoch   Overfit (%) (GiB)	     	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
90   14.110626	     	5.120567 69.830000	     	0.777302 -0.936298	   	0.886984 14.915150
91   12.974070	   	5.096100 70.400000	     	0.774991 -0.127674	   	0.875539 14.915150
92   11.032430 	     	5.158041 70.469999	   	0.780365 -0.028369	   	0.866458 14.915150
93   17.167654	   	5.121035 68.439996	   	0.781344 -2.908215	   	0.915482 14.915150

94   12.485970 	   	5.098719 70.099998	   	0.782252 -0.553269	   	0.879924 14.915150
	   	5.121605 70.739996	   	0.769990 0.354660	     	0.859838 14.915150
96   14.056423	   	5.093006 70.559996	   	0.763771 -0.254453	   	0.871130 14.915150
97   14.216483 	     	5.114752 69.999999	   	0.765917 -1.046081	     	0.874804 14.915150
98   13.809715 	     	5.081268 70.349997	   	0.765277 -0.551314	     	0.870959 14.915150
99   13.208964 	     	5.104732 70.539999	     	0.758171 -0.282722	     	0.858317 14.915150
100   12.756919	   	5.126863 71.359998	   	0.755749 0.876451	   	0.852160 14.915150
	   	5.160976 70.319998	   	0.756665 -1.457399	   	0.870397 14.915150

102   15.462502 		5.071728 70.480001	   	0.754289 -1.233180	 	0.870921 14.915150
103   13.864575 	   	5.068205 70.940000	   	0.752413 -0.588562	   	0.856732 14.915150
104   13.224454 	   	5.067548 71.039999	     	0.750012 -0.448430	   	0.849197 14.915150
	   	Epoch Time (s) Accuracy (%)	     	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
105   16.169134 	   	5.069998 70.489997	     	0.740821 -1.219172	   	0.860605 14.915150
106   13.943147 	   	5.074821 71.129996	     	0.751605 -0.322313	   	0.856403 14.915150
107   13.491354 	   	5.041211 71.069998	   	0.748542 -0.406391	   	0.849530 14.915150
108   15.037781	   	5.067728 71.219999	   	0.735770 -0.196187	   	0.846414 14.915150

109   13.499506 	   	5.120624 71.359998	   	0.735236 0.000000	   	0.834490 14.915150
110   15.473345 	   	5.120245 71.099997	   	0.736660 -0.364352	     	0.850646 14.915150
111   18.609299	   	5.119845 69.569999	   	0.743295 -2.508407	   	0.881617 14.915150
112   14.571980	   	5.103891 71.499997	   	0.732732 0.196187	   	0.839506 14.915150
113   15.984736 	   	5.176232 71.480000		0.722651 -0.027968	     	0.838164 14.915150
114   17.338436 	   	5.130633 71.389997	     	0.720923 -0.153847	     	0.845920 14.915150
115   16.536243 	   	5.117654 70.980000	     	0.726849 -0.727268	     	0.847043 14.915150
		5.059834 71.700001	   	0.722787 0.279725	   	0.836406 14.915150

117   17.208736 	 	5.077767 71.789998	   	0.716625 0.125519	   	0.839947 14.915150
118   16.445593 	   	5.042213 72.219998	   	0.711941 0.598969	   	0.829023 14.915150
119   17.613676	     	5.109068 71.770000	   	0.710683 -0.623092	   	0.835860 14.915150
	     	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
120   16.298500 	   	5.136141 72.139996	     	0.708005 -0.110775	   	0.823399 14.915150
121   16.242987 	   	5.081880 72.119999	   	0.707609 -0.138464	   	0.822545 14.915150
122   21.204630 	     	5.100162 70.879996	     	0.703986 -1.855444	   	0.853264 14.915150
123   13.671699	   	5.043020 72.099996	   	0.721448 -0.166162	   	0.820083 14.915150

124   16.185585 	   	5.151543 72.329998	   	0.705544 0.152313	   	0.819741 14.915150
125   17.851221 	     	5.112077 72.279996	     	0.697202 -0.069131	     	0.821662 14.915150
126   17.294765	     	5.074937 71.759999	     	0.706385 -0.788054	     	0.828553 14.915150
127   18.335752 	     	5.112021 71.829998	     	0.712020 -0.691275	     	0.842574 14.915150
128   19.994738 	     	5.068683 71.429998	     	0.701907 -1.244298	     	0.842251 14.915150
129   17.327799	     	5.106611 71.730000	     	0.703883 -0.829529	     	0.825850 14.915150
130   18.496904 	     	5.161842 72.149998	     	0.693148 -0.248859	     	0.821358 14.915150
131   20.580921	   	5.114609 71.469998	   	0.692579 -1.188994	   	0.835119 14.915150

132   19.033396 	 	5.234236 72.380000		0.694519 0.069131		0.826709 14.915150
133   19.689714 	   	5.167754 72.240001	   	0.683442 -0.193423	   	0.818009 14.915150
134   20.512833 	   	5.169732 72.119999	   	0.686514 -0.359217	   	0.827337 14.915150
	     	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
135   19.662561 	   	5.170857 72.240001	     	0.685092 -0.193423	   	0.819798 14.915150
136   19.349766 	   	5.165364 72.450000	   	0.681307 0.096711	   	0.813139 14.915150
137   22.380207 	   	5.184544 71.980000	   	0.676408 -0.648724	   	0.827789 14.915150
	   	5.041432 72.209996	   	0.682127 -0.331269	   	0.816983 14.915150

139   20.595865 	   	5.188199 72.950000	   	0.672820 0.690130	   	0.811393 14.915150
140   20.519125 	     	5.134880 72.719997	   	0.672488 -0.315288	     	0.810476 14.915150
141   19.227417 	     	5.105504 72.899997	   	0.675568 -0.068543	     	0.805462 14.915150
142   20.412378 	     	5.120533 72.969997	     	0.671230 0.027412	     	0.808244 14.915150
143   22.280344 	   	5.068957 72.499996	   	0.665354 -0.644101	   	0.813597 14.915150
144   21.313772	   	5.135123 72.920001	   	0.667591 -0.068516	   	0.809880 14.915150
145   21.067223	   	5.082710 72.700000	   	0.663192 -0.370011	   	0.802908 14.915150
146   20.678925	 	5.110504 72.799999	     	0.666857 -0.232970	     	0.804756 14.915150

   147   23.743467 	   	5.176138 72.689998	   	0.662117 -0.383718	 	0.819327 14.915150
	     	5.138168 71.569997	     	0.666574 -1.918597	   	0.826696 14.915150
149   20.634020 	   	5.160818 73.249996	     	0.664240 0.383718	   	0.801299 14.915150
	     	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
	   	5.115169 73.039997	     	0.659333 -0.286688	   	0.801870 14.915150
151   25.935585 	     	5.125012 72.270000	     	0.653944 -1.337878	   	0.823548 14.915150
152   21.247782 	   	5.116081 73.100001	   	0.655704 -0.204771	   	0.795027 14.915150
	   	5.120463 72.240001	   	0.658052 -1.378832	   	0.818986 14.915150

154   22.198418 	   	5.186667 73.359996	   	0.649822 0.150171	   	0.794072 14.915150
155   22.971737 	   	5.152768 73.039997	   	0.646464 -0.436204	     	0.794968 14.915150
156   22.672680	     	5.118167 73.259997	   	0.651932 -0.136312	     	0.799742 14.915150
157   22.436533 	     	5.073302 72.939998	     	0.654624 -0.572517	     	0.801499 14.915150
158   23.836645 	     	5.136588 73.219997	     	0.644021 -0.190839	     	0.797534 14.915150
159   23.307957	     	5.128449 73.100001	     	0.647507 -0.354410	     	0.798428 14.915150
160   23.543064 	   	5.112539 73.240000	     	0.641143 -0.163572	     	0.792088 14.915150
	   	5.120852 72.719997	   	0.643312 -0.872409	   	0.809783 14.915150

162   23.984808 	 	5.094538 73.299998	   	0.641172 -0.081786	 	0.794955 14.915150
163   23.424995 	   	5.057532 73.679996	   	0.635318 0.436204	   	0.784141 14.915150
164   24.227589 	   	5.093210 73.759997	     	0.631926 0.108579	   	0.785027 14.915150
Epoch   Overfit (%) (GiB)	     	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
165   26.197598 	   	5.111727 73.299998	     	0.631431 -0.623643	   	0.796851 14.915150
166   24.473181 	   	5.123473 73.460001	   	0.634222 -0.406719	   	0.789436 14.915150
167   23.732395 	   	5.107878 73.579997	     	0.634861 -0.244035	   	0.785529 14.915150
168   28.073561	   	5.150738 72.909999	   	0.629582 -1.152383	   	0.806329 14.915150

169   25.637213 	   	5.091628 73.670000	   	0.628832 -0.122013	   	0.790047 14.915150
170   23.062716 	   	5.073217 73.909998	   	0.635245 0.203364	     	0.781749 14.915150
171   28.592190 	   	5.121365 72.889996	   	0.632413 -1.380060	   	0.813234 14.915150
172   25.663792 	     	5.029716 73.299998	     	0.631198 -0.825328	     	0.793187 14.915150
173   23.415546 	     	5.140740 73.589998	     	0.633403 -0.432958	     	0.781718 14.915150
174   25.323292 	     	5.088692 73.569995	   	0.627700 -0.460023	     	0.786654 14.915150
	   	5.156265 73.490000	   	0.625505 -0.568256	   	0.783891 14.915150
176   26.000751	   	5.202651 73.490000	   	0.622379 -0.568256	   	0.784202 14.915150

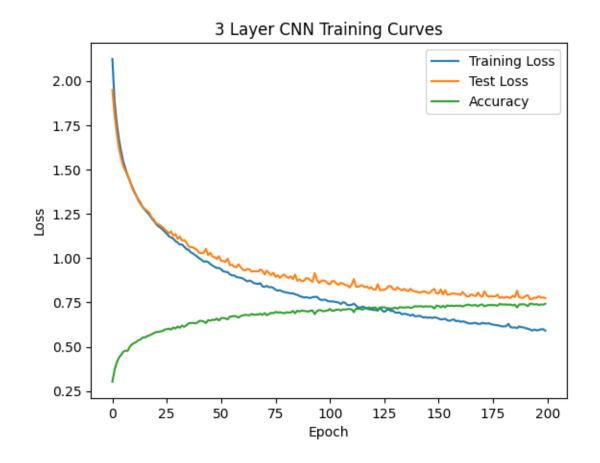
177   27.505703 	 	5.100004 73.149997	   	0.622683 -1.028279	 	0.793957 14.915150
178   25.300802 	   	5.156939 74.180001	     	0.618830 0.365313	   	0.775399 14.915150
179   26.931622 	   	5.132620 73.839998	     	0.615692 -0.458348	   	0.781508 14.915150
Epoch   Overfit (%) (GiB)	     	Epoch Time (s) Accuracy (%)	     	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
180   26.147738 	   	5.125704 73.939997	     	0.614744 -0.323543	   	0.775486 14.915150
181   26.707546 	   	5.205902 73.859996	   	0.616690 -0.431390	   	0.781392 14.915150
182   23.686480 	   	5.122013 73.759997	     	0.629987 -0.566196	   	0.779209 14.915150
	   	5.205942 73.829997	   	0.611550 -0.471831	   	0.774581 14.915150

184   29.599031 	 	5.180202 73.390001	   	0.608123 -1.064977	   	0.788122 14.915150
185   28.057093	   	5.212535 73.789996	     	0.609963 -0.525755	     	0.781101 14.915150
186   34.980904 	   	5.164953 72.209996	     	0.605180 -2.655709	     	0.816878 14.915150
187   26.719515 	   	5.107094 73.890001	     	0.615284 -0.390942	     	0.779685 14.915150
188   27.181515 	   	5.131805 73.939997	     	0.610408 -0.323543	     	0.776326 14.915150
189   27.448435 	   	5.131907 74.009997	     	0.609715 -0.229178	     	0.777072 14.915150
190   30.120705	   	5.079273 73.699999	     	0.605033 -0.647078	     	0.787273 14.915150
191   31.473764	   	5.156400 72.920001	   	0.601853 -1.698572	   	0.791279 14.915150

192   28.601042 	   	5.183256 74.379998	   	0.597795 0.269611	 	0.768771 14.915150
193   30.235384 	     	5.132535 74.210000	     	0.591397 -0.228554	   	0.770208 14.915150
	     	5.130533 73.850000	     	0.598124 -0.712555	   	0.777528 14.915150
	     	Epoch Time (s) Accuracy (%)	   	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
	   	5.087523 74.100000	     	0.592661 -0.376444	   	0.776363 14.915150
196   32.188976 	   	5.129474 73.569995	   	0.594608 -1.089007	   	0.786006 14.915150
197   29.724390 	     	5.143143 73.920000	     	0.599006 -0.618444	   	0.777057 14.915150
	   	5.106315 73.749995	   	0.599403 -0.847006	   	0.778661 14.915150

```
| 199 | 5.109549 | 0.591137 | 0.773772
| 30.895559 | 74.309999 | -0.094111 | 14.915150
```

Training Time: 472.81531620025635 seconds



```
[4]: #after last bn but before last weight

class ResBlock(nn.Module):
    def __init__(self, in_chans, out_chans, nonlinearity = 'relu', stride=1,__
    dropout = 0.4):
        super().__init__()
```

```
self.conv1 = nn.Conv2d(in_chans, out_chans, kernel_size=3, padding=1,__
 ⇔bias=False, stride=stride)
        self.batch_norm1 = nn.BatchNorm2d(num_features=out_chans)
        self.conv2 = nn.Conv2d(out chans, out chans, kernel size=3, padding=1,...
 ⇒bias=False, stride=stride)
        self.batch_norm2 = nn.BatchNorm2d(num_features=out_chans)
        self.dropout = nn.Dropout(dropout)
        self.shortcut = nn.Conv2d(in_chans, out_chans, kernel_size=1, stride=1,__
 ⇒bias=False) if in_chans != out_chans else nn.Identity()
        torch.nn.init.kaiming_normal_(self.conv1.weight,_
 →nonlinearity=nonlinearity)
        torch.nn.init.constant_(self.batch_norm1.weight, 0.5)
        torch.nn.init.zeros_(self.batch_norm1.bias)
        torch.nn.init.kaiming_normal_(self.conv2.weight,__
 →nonlinearity=nonlinearity)
        torch.nn.init.zeros_(self.batch_norm2.bias)
    def forward(self, x):
        out = self.batch norm1(x)
        out = F.relu(out)
        out = self.conv1(out)
        out = self.batch_norm2(out)
        out = F.relu(out)
        out = self.dropout(out)
        out = self.conv2(out)
        out += self.shortcut(x)
        return out
class ResNet(Classifier):
    def __init__(self, input_dim = 32, n_blocks = 10, conv_channels = [32,16],__

fc_channels = [32, 10], dropout_p=0.4, dropout_h=0.4, nonlinearity='relu'):
        super().__init__()
        # Add initial convolutions
        self.h1 = nn.Sequential()
        for i in range(len(conv_channels)):
            self.h1.add module(
                name=f'conv{i}',
                module=nn.Conv2d(
                    in_channels = 3 if i == 0 else conv_channels[i-1],
                    out_channels=conv_channels[i],
                    kernel_size=3,
                    padding=1
                )
            self.h1.add_module(
```

```
name=f'activation{i}',
               module=nn.ReLU()
           )
       self.h1.add_module(
          name=f'maxpool',
           module=nn.MaxPool2d(2)
      )
       #output of h1 before maxpool is 16 32x32 images. After maxpool, 16
\hookrightarrow 16x16 images
      # h1_in: torch.Size([1024, 3, 32, 32])
       # res_block_in: torch.Size([1024, 16, 16, 16])
       # h2_in: torch.Size([1024, 64])
       #Add Resblocks
      res_block_in = conv_channels[0]//2
      self.resblocks = nn.Sequential(
           *[
               ResBlock(
                   in_chans=conv_channels[-1],
                   out_chans=conv_channels[-1],
                   nonlinearity=nonlinearity,
                   dropout=dropout p
               ) for _ in range(n_blocks)
          ]
       )
       #output of resblocks is 16 16x16 images
       # Add final layers
      self.h2 = nn.Sequential()
       self.h2.add_module(
           name='final_batch_norm',
          module=nn.BatchNorm2d(
               num_features=conv_channels[-1]
           )
       )
       self.h2.add_module(
           name='final_relu',
           module=nn.ReLU()
      self.h2.add_module(
           name = 'dropout_head',
           module=nn.Dropout(dropout_h)
       self.h2.add_module(
           name = 'gap',
           module=nn.AvgPool2d(2)
```

```
self.h2.add_module(
        name = 'flatten',
        module=nn.Flatten()
    )
    #output is 16 8x8 images
    # 16 comes from conv_channels[-1]
    # 8x8 comes from input dim // 4
    fc_in = conv_channels[-1] * (input_dim//4)**2
    for i in range(len(fc_channels)):
        self.h2.add_module(
            name=f'fc{i}',
            module=nn.Linear(
                in_features=fc_in if i == 0 else fc_channels[i-1],
                out_features=fc_channels[i]
            )
        if i < len(fc_channels) - 1:</pre>
            self.h2.add_module(
                name = f'fc_activation{i}',
                module=nn.ReLU()
            )
    self.h2.add_module('softmax', nn.Softmax(dim=1))
def forward(self, x):
    #print(f"h1_in: {x.shape}")
    out = self.h1(x)
    #print(f"res_block_in: {out.shape}")
    out = self.resblocks(out)
    #print(f"h2_in: {out.shape}")
    out = self.h2(out)
    return out
```

```
[5]: from torch.profiler import profile, record_function, ProfilerActivity
try:
    del train_loader
    del test_loader
    del model_1a
    del model_1b
    del resnet
    del train_loader_cuda
    del test_loader_cuda
    except:
    pass
```

```
# Reset CUDA context
start = time.time()
torch.cuda.empty_cache()
torch.cuda.reset_peak_memory_stats()
gc.collect()
cifar10_train = datasets.CIFAR10(data_path, train=True, download=dl,__
 →transform=transform)
cifar10_test = datasets.CIFAR10(data_path, train=False, download=dl,__
 →transform=transform)
batch_size = int(2**11)
workers = 12
cpu_prefetch = 39
gpu_prefetch = 28
print('begin init train_loader')
train_loader = DataLoader(
    cifar10_train,
    batch_size=batch_size,
    shuffle=True,
    num_workers=workers,
    prefetch_factor=cpu_prefetch,
    pin_memory=True
)
X_batch = next(iter(train_loader))[0]
dtype_size = X_batch.element_size()
print(f"Batch Size: {X_batch.element_size() * X_batch.nelement() / 1024**2}__
 →MiB")
print('begin init fetcher')
train_loader_cuda = CudaDataPrefetcher(
    data_iterable = train_loader,
    device = torch.device('cuda'),
   num_prefetch_batches=gpu_prefetch
test_loader = DataLoader(cifar10_test, batch_size=len(cifar10_test),__
 →shuffle=True, num_workers=workers, pin_memory=True, prefetch_factor=1)
test_loader_cuda = CudaDataPrefetcher(
    data_iterable = test_loader,
    device = torch.device('cuda'),
   num_prefetch_batches=1
```

```
resnet = ResNet(
    input_dim = 32,
    conv_channels=[16,16],
    n_blocks = 10,
    fc_channels=[16,10],
    dropout_h = 0.6,
    dropout_p = 0.4
).to(device=device)
print(f"Init time: {(time.time() - start):.2f} seconds")
params = sum(p.numel() for p in resnet.parameters() if p.requires_grad)
print(f"Total parameters: {params}")
resnet.train_model(
    epochs=200,
    train_loader=train_loader_cuda,
    train_len=len(train_loader),
    test_loader=test_loader_cuda,
    test_len=len(test_loader),
    test_size=len(cifar10_test),
    loss_fn=nn.CrossEntropyLoss(),
    optimizer = torch.optim.Adam,
    optimizer_kwargs={'lr': 2e-3, 'weight_decay': 7e-3},
    print_epoch = 1,
    sched_factor = 0.6,
    sched_patience = 15
)
resnet.plot_training("ResNet Training Curves")
begin init train_loader
Batch Size: 24.0 MiB
begin init fetcher
Init time: 4.00 seconds
Total parameters: 66090
Training ResNet
      Epoch | Epoch Time (s) | Training Loss |
                                                                    Test Loss
    Overfit (%) | Accuracy (%) | \Delta Accuracy (%) | GPU Memory
    0 | 7.758229 | 2.262175 | 2.303453
1.824688 | 9.999999 | 0.000000 | 4.617005
1
```

l 						
1   8.505051 	   	5.941853 10.349999	   	2.131489 3.500000	   	2.312773 5.320131
2   9.820173	   	5.965214 18.820000	   	2.039086 81.835754	   	2.239328 6.021304
	   	5.957030 32.960001	   	1.999411 75.132843	   	2.137333 6.722476
	   	5.937284 47.529998	   	1.963828 44.205090	   	2.014531 7.423647
	   	5.978225 46.619999	   	1.935574 -1.914578	   	2.026971 8.124819
	   	5.998431 46.309999	   	1.916032 -2.566800	   	2.005815 8.825991
7   1.637028	   	5.885165 55.320001	   	1.904790 16.389654	   	1.935971 9.527163
8   1.899396	   	5.937993 55.729997	   	1.893218 0.741136	   	1.929178 10.228335

9 0.490889	   	5.912222 59.649998	   	1.880680 7.033916	   	1.889912 10.929507
10 2.963132	   	5.891649 54.809999	   	1.870847 -8.113996	   	1.926282 11.630679
11 6.643737	   	5.917224 47.759998	     	1.862037 -19.932943	   	1.985746 12.331851
12 6.210001	   	5.954925 50.389999	     	1.852967 -15.523887	   	1.968036 13.033022
13 2.376869	   	5.949610 58.849996	     	1.850348 -1.341159	   	1.894329 13.734194
  14 2.553910	   	5.927939 58.950001	     	1.838039 -1.173507	   	1.884981 14.435366
 Epoch Overfit (%) GiB)				Training Loss Δ Accuracy (%)		
15 4.408997	   	5.978298 55.689996	   	1.835852 -6.638729		1.916794 15.136538

l 						
16   8.774986 	     	5.931443 46.829998	     	1.831612 -21.492037	   	1.992336 15.136538
17   2.640804	     	5.936951 60.289997	     	1.830642 1.072924	   	1.878986 15.136538
18   0.481930	   	6.016370 63.940001	     	1.825897 6.054079	   	1.834697 15.136538
	   	5.955230 58.520001	     	1.824874 -8.476695	     	1.879447 15.136538
20   3.877305 	   	5.945711 58.429998	     	1.819507 -8.617457	   	1.890054 15.136538
	   	5.960409 56.019998	     	1.816705 -12.386617	   	1.909476 15.136538
	   	5.979871 54.909998	     	1.816134 -14.122619	   	1.913466 15.136538
	   	5.943759 58.359998	   	1.814242 -8.726934	   	1.888312 15.136538

l 						
24   6.616277	   	5.989490 53.270000	   	1.812754 -16.687519	   	1.932691 15.136538
25   2.282714	   	5.976249 61.919999	     	1.811979 -3.159214	   	1.853341 15.136538
	   	5.926868 57.969999	     	1.805859 -9.336880	   	1.890505 15.136538
27   1.124280	   	5.957161 64.550000	     	1.808381 0.954019	   	1.828712 15.136538
28   3.866507	   	5.978532 58.649999	   	1.808984 -9.140203	     	1.878929 15.136538
29   4.350254 	   	5.943629 58.569998	     	1.806721 -9.264141	   	1.885318 15.136538
Epoch   Overfit (%) (GiB)		<del>-</del>		Training Loss Δ Accuracy (%)		
30   9.197787	   	5.946413 48.940000	   	1.802864 -24.182804	   	1.968687 15.136538

	   	5.973595 65.279996	   	1.804069 1.130900	   	1.820951 15.136538
32   1.988929 	   	5.941212 63.870001	     	1.800107 -2.159920	   	1.835910 15.136538
	   	5.957007 52.329999	     	1.798617 -19.837620	   	1.939540 15.136538
34   1.438882 	   	5.956561 64.569998	   	1.798999 -1.087620	   	1.824884 15.136538
	   	6.000816 53.549999	   	1.799080 -17.968748	   	1.926372 15.136538
36   2.922882	   	5.929878 61.909997	   	1.797763 -5.162376	   	1.850310 15.136538
37   3.880836	   	5.952627 60.339999	   	1.798736 -7.567398	   	1.868542 15.136538
	   	5.983609 59.729999	   	1.794371 -8.501835	   	1.869053 15.136538

	   	5.951901 60.249996	   	1.791374 -7.705270	   	1.866068 15.136538
   40   5.861915 	   	6.068545 56.849998	   	1.793264 -12.913601	   	1.898383 15.136538
41   1.779197 	   	6.035099 64.849997	     	1.790199 -0.658701	   	1.822050 15.136538
	     	5.953965 60.039997	     	1.793583 -8.026960	   	1.866762 15.136538
	   	6.000158 57.660002	     	1.793789 -11.672788	   	1.888961 15.136538
	   	6.012037 62.459999	     	1.788270 -4.319849	   	1.844360 15.136538
				Training Loss Δ Accuracy (%)		
	   	6.064523 61.769998	   	1.786979 -5.376836	   	1.848547 15.136538

<u> </u>						
46   7.348784 	   	6.086365 54.629999	   	1.789465 -16.314335	   	1.920969 15.136538
	   	5.946903 58.359998	     	1.786739 -10.600488	   	1.878974 15.136538
	   	5.962193 65.450001	   	1.780643 0.260423	   	1.818045 15.136538
	   	5.993754 67.890000	   	1.766896 3.728036	   	1.795054 15.136538
	   	5.979029 65.309995	   	1.765290 -3.800272	   	1.812099 15.136538
	   	5.931840 63.080001	   	1.769414 -7.084990		1.837127 15.136538
52   3.113217 	   	5.952838 64.399999	   	1.767406 -5.140670	   	1.822430 15.136538
	   	5.972234 66.929996	   	1.765201 -1.414059	   	1.797711 15.136538

<u> </u>						
54   1.494045 	   	5.964084 67.729998	   	1.764875 -0.235679	     	1.791243 15.136538
55   2.859046 	   	5.955197 65.169996	   	1.766104 -4.006487	     	1.816597 15.136538
56   6.151809		6.029804 58.849996	   	1.763746 -13.315663	   	1.872248 15.136538
57   1.685915 		5.953676 67.839998	   	1.762739 -0.073652	   	1.792457 15.136538
58   3.382094 		5.990416 64.569998	   	1.761238 -4.890267	   	1.820805 15.136538
	   	5.994577 65.230000	   	1.761105 -3.918103	   	1.813354 15.136538
Epoch   Overfit (%) (GiB)		<del>-</del>		Training Loss Δ Accuracy (%)		
60   6.825368	   	6.018641 59.749997	   	1.758287 -11.989988	   	1.878296 15.136538

l 						
		6.037763 65.740001	   	1.745997 -3.166886	   	1.808743 15.136538
62   0.964996 	     	5.997109 71.319997	     	1.739772 5.052286	   	1.756561 15.136538
63   2.968363 	     	5.976972 68.320000	     	1.739508 -4.206390	   	1.791143 15.136538
	   	6.112227 61.369997	   	1.732286 -13.951206	   	1.857396 15.136538
	   	5.984481 70.529997	   	1.726140 -1.107684	   	1.763518 15.136538
66   3.147723 	   	6.100321 69.150001	   	1.728138 -3.042620	   	1.782535 15.136538
67   5.902898 	     	5.998295 63.919997	     	1.725812 -10.375772	   	1.827685 15.136538
	   	6.043867 65.810001	   	1.727304 -7.725739	   	1.807588 15.136538

69 4.924157	   	6.017951 66.399997	   	1.723430 -6.898486	   	1.808294 15.136538
70 2.425069	   	6.035763 70.190001	   	1.725271 -1.584404	   	1.767110 15.136538
71 3.783398	   	5.997301 68.059999	     	1.720044 -4.570946	   	1.785120 15.136538
72 4.661331	   	6.033640 66.780001	     	1.718865 -6.365671	   	1.798987 15.136538
73 1.233708	   	6.025136 72.560000	     	1.722847 1.738647	   	1.744101 15.136538
74 6.532368	   	6.044716 63.679999	     	1.716789 -12.238149	   	1.828936 15.136538
Epoch Overfit (%) GiB)				Training Loss Δ Accuracy (%)		
75 4.480049		6.046995 66.319996	   	1.724921 -8.599786	   	1.802198 15.136538

l 						
   76   3.791047 	   	6.073751 67.979997	   	1.722809 -6.312021	   	1.788122 15.136538
    77   4.254255 	     	5.978110 68.110001	     	1.715931 -6.132854	   	1.788931 15.136538
    78   2.981410 	     	6.042846 70.389998	     	1.714050 -2.990632	   	1.765153 15.136538
    79   5.875241 	     	5.989166 65.799999	     	1.709710 -9.316429	   	1.810159 15.136538
    80   6.630245 	   	6.026500 63.989997	     	1.713593 -11.810920	   	1.827208 15.136538
81   6.280786 	   	6.064908 64.289999	   	1.713212 -11.397466	   	1.820815 15.136538
   82   2.457978 	   	6.053454 71.099997	   	1.713486 -2.012133	   	1.755603 15.136538
   83   4.686906	   	6.030574 67.890000	   	1.709514 -6.436053	   	1.789637 15.136538

84 4.484475	   	6.010733 67.530000	     	1.713726 -6.932194	   	1.790577 15.136538
85 1.686579	   	5.997445 72.700000	   	1.712908 0.192943	   	1.741797 15.136538
86 5.101524	   	6.078503 67.109996	     	1.707408 -7.689139	   	1.794512 15.136538
 87 5.046287	   	6.048886 66.710001	     	1.713436 -8.239338	   	1.799901 15.136538
88 7.842492	   	6.026438 61.939996	   	1.711424 -14.800554	   	1.845643 15.136538
89 2.983910	   	6.002117 71.410000	   	1.707037 -1.774415	   	1.757974 15.136538
Epoch Overfit (%) GiB)				Training Loss Δ Accuracy (%)		
90 3.804483	   	5.973038 69.150001	   	1.710023 -4.883080	   	1.775080 15.136538

l 						
91   2.142406 	   	6.030484 72.649997	   	1.706634 -0.068779	   	1.743197 15.136538
92   8.859737 	     	6.044240 60.549998	     	1.706756 -16.712519	   	1.857970 15.136538
93   4.667165 	     	6.025276 67.949998	   	1.709503 -6.533702	   	1.789289 15.136538
94   1.249039	     	6.065005 73.869997	     	1.709287 1.609350	   	1.730637 15.136538
95   7.642605	   	6.063215 62.809998	   	1.706813 -14.972248	   	1.837258 15.136538
96   2.349999	   	6.046596 72.299999	   	1.709644 -2.125353	   	1.749821 15.136538
97   3.357140	     	6.041147 70.229995	     	1.707956 -4.927578	   	1.765295 15.136538
98   3.342478	   	6.140745 70.159996	   	1.705159 -5.022339		1.762154 15.136538

	   	5.942571 64.919996	   	1.704508 -12.115881	   	1.816739 15.136538
100   2.868941 	   	5.976495 71.859998	   	1.704234 -2.720996	   	1.753127 15.136538
101   8.514546 	   	6.089538 61.739999	     	1.705383 -16.420738	   	1.850588 15.136538
   102   2.381902 	   	6.001499 72.499996	     	1.704032 -1.854611	   	1.744620 15.136538
103   5.437298 	   	6.000335 67.570001	   	1.703446 -8.528491	   	1.796068 15.136538
104   8.410723 	   	5.989391 61.839998	     	1.702863 -16.285366	   	1.846086 15.136538
				Training Loss Δ Accuracy (%)		
105   4.693377	   	6.053767 68.210000	   	1.704828 -7.662106	   	1.784842 15.136538

   106   6.841868 	   	5.995612 63.989997	   	1.704311 -13.374848	   	1.820918 15.136538
107   5.168544 	     	6.119347 67.799997	     	1.703072 -8.217138	   	1.791096 15.136538
   108   5.101415 	     	5.988535 68.229997	     	1.702467 -7.635035	   	1.789317 15.136538
   109   6.018831 	     	6.011374 65.700001	     	1.704103 -11.059965	     	1.806670 15.136538
   110   2.752946 	   	6.016177 71.799999	   	1.705480 -2.802217	   	1.752431 15.136538
111   3.003156 	   	6.034240 73.249996	   	1.686944 -0.839314	   	1.737605 15.136538
	   	6.049294 74.759996	   	1.681191 1.204818	   	1.718573 15.136538
   113   2.188763	   	6.035938 75.009996	   	1.682705 0.334403	   	1.719535 15.136538

l						
114   2.272208	   	6.005780 74.759996	     	1.682150 -0.333289	   	1.720372 15.136538
	   	6.040393 70.400000	     	1.683993 -6.145842	   	1.763142 15.136538
116   3.181357	   	6.026464 73.899996	     	1.679085 -1.479802	   	1.732503 15.136538
	   	6.116028 73.769999	     	1.679812 -1.653109	   	1.728820 15.136538
118   2.576033	   	6.095558 74.169999	     	1.680922 -1.119846	   	1.724223 15.136538
119   3.472963	   	6.083001 73.119998	   	1.678301 -2.519661	   	1.736588 15.136538
		_		Training Loss Δ Accuracy (%)		
120   2.503350	   	6.071417 74.419999	   	1.680773 -0.786557	   	1.722848 15.136538

<u> </u>						
121   1.859566	     	6.101312 75.769997	     	1.682564 1.013200	   	1.713852 15.136538
122   2.919064 	     	6.108806 73.869997	   	1.682129 -2.507588	   	1.731231 15.136538
123   1.255068	     	6.083366 76.769996	   	1.681966 1.319782	   	1.703076 15.136538
	     	6.085177 76.580000	   	1.679816 -0.247487	   	1.698992 15.136538
	   	6.054791 71.819997	   	1.680250 -6.447830		1.748276 15.136538
	   	6.054725 74.149996	   	1.681701 -3.412791		1.729124 15.136538
127   6.096926	   	6.105957 67.839998	   	1.682942 -11.632145	   	1.785550 15.136538
128   6.379204	   	6.027437 67.739999	   	1.680754 -11.762403		1.787973 15.136538

129 3.626660	   	6.026318 72.439998	   	1.681985 -5.640221	   	1.742985 15.136538
130 2.170037	   	6.067482 74.799997	     	1.681037 -2.566106	   	1.717516 15.136538
131 4.271327	   	6.053882 71.630001	     	1.680817 -6.695317	   	1.752610 15.136538
132 4.757300	   	6.073949 70.599997	     	1.681933 -8.036992	   	1.761947 15.136538
133 2.943421	   	6.100069 73.749995	     	1.679813 -3.933829	   	1.729257 15.136538
134 3.971707	   	6.060847 72.179997	   	1.681197 -5.978897	   	1.747969 15.136538
Epoch Overfit (%) GiB)	     	Epoch Time (s) Accuracy (%)	     	Training Loss Δ Accuracy (%)	   	Test Loss GPU Memory
135 3.101143	   	6.092427 73.869997	   	1.676345 -3.777515	   	1.728331 15.136538

l 						
136   1.952925 	   	6.111445 75.689995	   	1.677436 -1.406800	   	1.710195 15.136538
137   5.944660 	   	6.154238 68.439996	     	1.680783 -10.850594	     	1.780700 15.136538
138   5.203455 	     	6.104064 69.580001	     	1.680163 -9.365631	   	1.767590 15.136538
   139   2.667443 	   	6.064308 74.210000	     	1.679928 -3.334630	   	1.724739 15.136538
   140   1.469260 	   	6.095605 77.579999	   	1.670509 1.055104	   	1.695053 15.136538
	   	6.075877 78.099996	   	1.665254 0.670272		1.685887 15.136538
   142   2.531463 	   	6.111793 76.239997	   	1.662272 -2.381561	   	1.704352 15.136538
143   2.318458	   	6.030466 76.569998	   	1.663150 -1.959024	   	1.701710 15.136538

l 						
144   1.957377 	   	6.110031 76.959997	   	1.664230 -1.459665	   	1.696805 15.136538
145   2.480386 		6.130999 76.400000	   	1.662143 -2.176692	   	1.703371 15.136538
   146   4.186393 	   	6.076478 73.600000	     	1.659864 -5.761838	   	1.729352 15.136538
    147   1.133810 	     	6.191991 79.029995	     	1.659926 1.190780	   	1.678746 15.136538
   148   1.406648 	   	6.065806 78.039998	     	1.664576 -1.252686	   	1.687991 15.136538
    149   2.584342	   	6.120574 76.519996	     	1.660582 -3.176008	   	1.703497 15.136538
Epoch Overfit (%) (GiB)				Training Loss Δ Accuracy (%)		
    150   1.861263	   	6.083641 77.609998	   	1.660676 -1.796783	   	1.691585 15.136538

151 3.929745	   	6.159505 74.030000	     	1.661676 -6.326706	     	1.726976 15.136538
152 0.888861	   	6.116043 78.789997	     	1.662686 -0.303680	     	1.677465 15.136538
153 0.512795	     	6.153685 79.769999	     	1.661415 0.936358	     	1.669934 15.136538
154 3.710041	   	6.083883 74.159998	     	1.660522 -7.032721	     	1.722128 15.136538
155 2.913857	   	6.110673 75.610000	     	1.661754 -5.214992	     	1.710175 15.136538
156 1.717822	   	6.137404 77.899998	     	1.660498 -2.344240	     	1.689023 15.136538
157 1.327353	   	6.167748 78.389996	     	1.659847 -1.729977	     	1.681879 15.136538
    158   4.399757	   	6.080560 73.509997	   	1.659312 -7.847564	   	1.732317 15.136538

159 3.496686	   	6.110744 74.640000	   	1.659585 -6.430988	   	1.717616 15.136538
160 2.843304	   	6.144540 75.439996	   	1.661628 -5.428110	   	1.708873 15.136538
161 3.634423	   	6.116296 74.469995	     	1.661444 -6.644106	   	1.721828 15.136538
162 2.119488		6.133440 76.919997	     	1.659592 -3.572774	   	1.694767 15.136538
163 1.395393	   	6.133320 78.200001	   	1.661856 -1.968156	   	1.685046 15.136538
164 2.211732	   	6.137462 76.719999	   	1.661753 -3.823492	   	1.698507 15.136538
 Epoch Overfit (%) GiB)		_		Training Loss Δ Accuracy (%)		
165 3.010189	   	6.100959 75.489998	   	1.660505 -5.365427	   	1.710490 15.136538

l 						
   166   4.311771 	   	6.162635 73.479998	     	1.660260 -7.885171	   	1.731846 15.136538
167   2.146534 	     	6.242150 77.279997	     	1.659401 -3.121477	     	1.695021 15.136538
168   3.783221 	     	6.126612 73.850000	     	1.662474 -7.421335	     	1.725369 15.136538
    169   2.099681 	     	6.159417 77.079999	     	1.660429 -3.372194	     	1.695292 15.136538
170   1.606785	     	6.097894 78.639996	     	1.653447 -1.416576	   	1.680014 15.136538
171   17277208	     	6.127400 79.850000	     	1.648021 0.100290	   	1.669070 15.136538
172   1.451743 	     	6.093162 79.439998	     	1.646899 -0.513466	     	1.670808 15.136538
    173   2.161102	   	6.118891 78.469998	     	1.646340 -1.728244	   	1.681919 15.136538

<u> </u>						
174   1.345276	   	6.095659 79.749995	   	1.646992 -0.125241	   	1.669149 15.136538
175   1.793243	   	6.131203 78.799999	     	1.648076 -1.314967	   	1.677630 15.136538
176   1.935102	   	6.111234 78.560001	     	1.649875 -1.615528	   	1.681801 15.136538
177   4.357234 	   	6.161559 74.390000	     	1.647128 -6.837821	   	1.718898 15.136538
178   0.780025	   	6.125992 80.739999	     	1.647206 1.114588	     	1.660054 15.136538
179   1.803398	   	6.156801 79.189998	     	1.645703 -1.919744	   	1.675382 15.136538
Epoch   Overfit (%) (GiB)		<del>-</del>		Training Loss Δ Accuracy (%)		
180   3.203148		6.101541 76.969999	   	1.646676 -4.669309	   	1.699421 15.136538

I						
181   1.476050	   	6.070375 79.560000	   	1.646551 -1.461480	   	1.670855 15.136538
182   2.840550	   	6.133426 77.370000	   	1.645668 -4.173890	   	1.692414 15.136538
183   1.611929 	     	6.103067 79.369998	     	1.646507 -1.696806	     	1.673047 15.136538
184   2.609001	     	6.220975 77.609998	     	1.645006 -3.876642	     	1.687924 15.136538
	   	6.173976 79.539996	   	1.645559 -1.486255	   	1.670266 15.136538
   186   1.939509 	   	6.171250 78.759998	   	1.644896 -2.452317	   	1.676799 15.136538
   187   1.374997 	   	6.168568 79.879999	   	1.644711 -1.065147	   	1.667325 15.136538
	   	6.133537 77.759999	   	1.644299 -3.690859	   	1.690048 15.136538

   189   2.287131 	   	6.135493 78.410000	   	1.645682 -2.885805	   	1.683321 15.136538
190   1,559951 	   	6.136440 79.189998	   	1.646676 -1.919744	   	1.672363 15.136538
   191   3.170348 	   	6.104340 76.800001	     	1.644953 -4.879859	   	1.697103 15.136538
    192   1.924519 	   	6.190171 79.119998	     	1.642390 -2.006441	   	1.673998 15.136538
   193   2.467033 	   	6.137682 78.109998	     	1.644042 -3.257371	   	1.684601 15.136538
    194   1.525608	   	6.132952 79.549998	     	1.644127 -1.473868	   	1.669210 15.136538
Epoch  Overfit (%)  (GiB)				Training Loss Δ Accuracy (%)		
   195   1.499475	   	6.213376 80.070001	   	1.641013 -0.829822	   	1.665620 15.136538

196 1.953695		6.159393 80.039996	   	1.635479 -0.866984	   	1.667431 15.136538
197 1.689192	   	6.220014 80.129999	   	1.636976 -0.755511	   	1.664628 15.136538
198 1.452788	   	6.141409 80.409998	   	1.638255 -0.408721	   	1.662055 15.136538
199 1.792761	     	6.201807 79.899997	     	1.636783 -1.040379	   	1.666127 15.136538
··						

Training Time: 667.1745541095734 seconds

