```
Homework 1
Monday, January 25, 2021
                                                                   12:08 AM
 Problem 1: Backpropagation (25Pts)
 Assume we have defined a loss function l, now for a given layer \mathbf{y} = f(\mathbf{x}, \mathbf{W}), write \frac{\partial l}{\partial \mathbf{x}} and \frac{\partial l}{\partial \mathbf{W}} as
 functions of \frac{\partial l}{\partial \mathbf{y}}, \mathbf{x}, \mathbf{y}, and \mathbf{W} in the following cases:
 a) \mathbf{y} = \mathbf{x}\mathbf{W}, \mathbf{x} \in \mathbb{R}^{1 \times n}, \mathbf{W} \in \mathbb{R}^{n \times m}
     \frac{\partial l}{\partial x} = \frac{\partial l}{\partial u} \frac{\partial u}{\partial x} = \frac{\partial l}{\partial u} W' \qquad \frac{\partial l}{\partial w} = \frac{\partial l}{\partial u} \frac{\partial u}{\partial w} = x^T \frac{\partial l}{\partial u}
b) \mathbf{y} = \mathbf{x}\mathbf{W}, \mathbf{x} \in \mathbb{C}^{1 \times n}, \mathbf{W} \in \mathbb{C}^{n \times m}
   Pytorch reference on complex derivatives:
   dl = ( dl ) + dl ( dx ) +
      X=a+3b
, a,b ER"
      \frac{\partial y}{\partial x} = \frac{\partial (xw)}{\partial x} = w^{T}, \frac{\partial y}{\partial x^{T}} = 0
   dh = dh . Wat dh = Xat dh
  c) \mathbf{y} = \|\mathbf{x}\mathbf{W}\|_2^2, \mathbf{x} \in \mathbb{R}^{1 \times n}, \mathbf{W} \in \mathbb{R}^{n \times m}
     \frac{\partial l}{\partial x} = \frac{\partial l}{\partial y} 2 (x w) w^{T}
                                                                                                   \frac{\partial l}{\partial \mathbf{W}} = \frac{\partial l}{\partial \mathbf{Y}} 2 \mathbf{x}^{\mathsf{T}} (\mathbf{x} \mathbf{W})
   d) \mathbf{y} = \mathbf{x} \odot \mathbf{w}, \mathbf{y}_k = \mathbf{x}_k \mathbf{w}_k, \mathbf{x} \text{ and } \mathbf{w} \in \mathbb{R}^n
                                                                                                \frac{\partial l}{\partial \mathbf{W}} = \frac{\partial l}{\partial \mathbf{Y}} \odot \mathbf{X}
       \frac{\partial l}{\partial x} = \frac{\partial l}{\partial y} \odot \omega
    e) \mathbf{y} = \mathbf{softmax}(\mathbf{x}), \mathbf{y}_k = \frac{e^{\mathbf{x}_k}}{Z(\mathbf{x})}, Z(\mathbf{x}) = \sum_{i=0}^{n-1} e^{\mathbf{x}_i}, \mathbf{x} \in \mathbb{R}^n
    \frac{\partial l}{\partial x} = \frac{\partial l}{\partial y} \frac{\partial y}{\partial x} Split into cak when i = K \neq i \neq K
     \frac{\partial \mathcal{Z}(f)}{\partial x_i} = \frac{\partial x_i}{\partial x_i} \left( \sum_{i=0}^{N-1} e^{x_i} \right) = e^{x_i}
      \frac{\partial l}{\partial x_i} = \frac{\partial l}{\partial y_k} \frac{\partial y_y}{\partial x_i} = \frac{\partial l}{\partial y_k} \left( \frac{z(x) e^{x_k} - e^{x_k} z(x)}{(z(x))^2} \right)
      \frac{\partial l}{\partial x_i} = \frac{\partial l}{\partial y_k} \frac{\partial y_y}{x_i} = \frac{\partial l}{\partial y_k} \left( \frac{2(x) e^{x_i} - e^{zx_i}}{(2(x))^2} \right)
                                                       =\frac{\partial l}{\partial y_{K}}\left(\frac{e^{x_{i}}}{2(x)}\left[\frac{z(x)-e^{x_{i}}}{2(x)}\right]\right)
                                                        = \frac{d!}{d!!} \left( Sottmax(x_i) \left[ 1 - Sottmax(x_i) \right] \right)
     For i+K:
      \frac{\partial l}{\partial x_i} = \frac{\partial l}{\partial y_K} \frac{\partial y_K}{\partial x_i} = \frac{\partial l}{\partial y_K} \left( \frac{z(x) \cdot \partial - e^{k_K} e^{x_i}}{(z(x))^2} \right)
      \frac{dl}{dx_i} = \frac{\partial l}{\partial y_K} \left( \frac{-e^{x_K} e^{x_i}}{(t(x))^2} \right) = \frac{\partial l}{\partial y_K} \left( - \text{Softmax}(x_K) \cdot \text{Softmax}(x_i) \right)
    Read through the sample script you downloaded. Train the model for 2 epochs, and save the
    weights. This should be done using command line arguments, without modifying the original file.
    Include the bash command you used in your HW submission.
     Bash command: python3 main.py --epochs 2 --no-cuda --save-model
                                                   Image effects of different noise levels
                  \sigma = 0
                                                                                                                \sigma = 0.6
```

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Accuracy for AWGN with a standard deviation of 0

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Accuracy for AWGN with a standard deviation of 0.3

995.

Test set: Average loss: 0.0354, Accuracy: 9872/10000 (99%)

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Test set: Average loss: 0.2217, Accuracy: 9566/10000 (96%)

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Accuracy for AWGN with a standard deviation of 0.6
Test set: Average loss: 1.3472, Accuracy: 5098/10000 (51%)
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62.]]

1. 92. 12. 4. 5. 0. 1. 859. 22. 159. 28. 1. 0. 106. 4.

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58.

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Accuracy for AWGN with a standard deviation of 1.0
Test set: Average loss: 2.2629, Accuracy: 2164/10000 (22%)
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          0. 251. 174.
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```

Code: The matplotlib code for showing the images with various AWGN and the computations for the confusion matrix are on main.py. Setting up and

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```
loading the model is in test_AWGN.py.
               File - /Users/vararevalcmac/Google Drive/School/Machine Learning/ECE281 Computer Vision/Homeworks/Homeworks/I/mage_class
                1 from __future__ import print_function
                2 import argparse
                3 import torch
                4 import torch.nn as nn
                5 import torch.nn.functional as F
                6 import torch.optim as optim
                7 import numpy as np
```

8 import matplotlib.pyplot as plt

13 class AMGN(object):

astype(np.float32))

log-probability

for i in indices:

transpose()

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87

162

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168 169 170

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173 174

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197 198

199

image = test_dataset[0][0]

plt.tight_layout()

transform-transforms.Compose([

transforms.ToTensor(),

model = Net().to(device)

3)

plt.axis('off')

add_noise = AWGN(sigma)

print(transformed_sample)

ax = plt.subplot(1, 4, i + 1)

for i, sigma in enumerate([0.001, 0.3, 0.6, 1.0]):

ax.set_title("\$\sigma = \${}".format(sigma))

fig.suptitle("Image effects of different noise levels")

plt.imshow(transformed_sample.numpy().squeeze(), cmap='gray')

test_loader = torch.utils.data.DataLoader(datasetZ, **test_kwargs)

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File - /Users/vararevalcmac/Google Drive/School/Machine Learning/ECE281 Computer Vision/Homeworks/Homework1/Image_class

dataset1 = datasets.MMIST('../data', train=True, download=True,

train_loader = torch.utils.data.DataLoader(dataset1,**train_kwargs) test_loader = torch.utils.data.DataLoader(datasetZ, **test_kmargs)

transform-transform)

transform-transform)

optimizer = optim.Adadelta(model.parameters(), lr-args.lr)

transforms.Normalize((0.1307,), (0.3081,))

datasetZ = datasets.MNIST('../data', train=False,

transformed_sample = add_noise(image)

print(image.type())

Z1

9 from torchvision import datasets, transforms 18 from torch.optim.lr_scheduler import StepLR

def __init__(self, sigma, vmin=0, vmax=1); assert isinstance(sigma, (int, float)) self.sigma = sigma 17 self.vmin = vmin 18 self.vmax = vmax19 20 def __call__(self, image);

noise = torch.from_numpy(np.random.normal(0.0, self.sigma, image.shape).

```
# Above supports std of 0
23
           # noise = torch.normal(0.0, self.sigma, image.shape)
           autput = image + naise
26
           torch.clip(output, self.vmin, self.vmax, out-output)
27
28
            return output
29
31 class Net(nn.Module):
       def __init__(self):
33
            super(Net, self).__init__()
            self.conv1 = nn.Conv2d(1, 32, 3, 1)
           self.conv2 = nn.Conv2d(32, 64, 3, 1)
35
            self.dropout1 = nn.Dropout(0.25)
36
37
            self.dropout2 = nn.Dropout(0.5)
           self.fc1 = nn.Linear(9216, 128)
39
           self.fc2 = nn.Linear(128, 10)
40
       def forward(self, x):
42
           x = self.comv1(x)
           x = F.relu(x)
44
45
           x = self.comv2(x)
           x = F.relu(x)
           x = F.max_pool2d(x, 2)
           x = self.dropout1(x)
           x = torch.flatten(x, 1)
48
49
           x = self.fcl(x)
           x = F.relu(x)
           x = self.dropout2(x)
           x = self.fcZ(x)
53
           output = F.log_softmax(x, dim=1)
            return output
55
57 def train(args, model, device, train_loader, optimizer, epach):
       for batch_idx, (data, target) in enumerate(train_loader):
           data, target = data,to(device), target,ta(device)
60
61
           optimizer.zero_grad()
62
           output - model(data)
                                          Page 1 of 4
File - /Users/tvarerevalcmac/Google Drive/School/Machine Learning/ECE281 Computer Vision/Homeworks/Homework1/Image_class
            loss = F.nll_loss(output, target)
            loss.backward()
 65
            optimizer.step()
 66
            if batch_idx % args.log_interval — 0:
 67
                 print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                     epoch, batch_idx * len(data), len(train_loader.dataset),
                    188. * batch_idx / len(train_loader), loss.item()))
 69
 70
                 if \ {\tt args.dry\_run};
 71
                    break
 72
 74 def test(model, device, test_loader):
        test_loss = 0
 77
        correct - 0
 78
        confusion_matrix = np.zeros((10,10))
 79
        with torch.no_grad():
            for data, target in test_loader:
 81
                data, target - data.to(device), target.to(device)
                 output = model(data)
 82
 83
                 test_loss += F.nll_loss(output, target, reduction='sum').item() # sum
    up batch loss
 84
                 pred = autput.argmax(dim=1, keepdim=True) # get the index of the max
```

indices = np.array([target.numpy().squeeze(), pred.numpy().squeeze()]).

```
88
                     confusion_matrix[i[0],i[1]] += 1
  90
                 correct += pred.eq(target.view_as(pred)).sum().item()
  91
  92
         test_loss /= len(test_loader.dataset)
  93
  94
         print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} ({:.0f}%)\n'.format(
             test_loss, correct, len(test_loader.dataset),
  95
  96
             100. * correct / len(test_loader.dataset)))
  97
  98
  99
         # suppress: suppress scientific notation
 100
         with np.printoptions(precision=3, suppress=True):
             print(np.array(confusion_matrix))
 161
 102
 103
 184 def main():
         # Training settings
 106
         parser = argparse.ArgumentParser(description='PyTorch MNIST Example')
 167
         parser.add_argument('--batch-size', type=int, default=64, metavar='N'
                             help='input batch size for training (default: 64)')
 108
 109
         parser.add_argument('--test-batch-size', type-int, default-1000, metavar-'N',
 110
                             help='input batch size for testing (default: 1000)')
 111
         parser.add_argument('--epochs', type=int, default=14, metavar='N'
 112
                             help='number of epochs to train (default: 14)')
         parser.add_argument('--lr', type=float, default=1.0, metavar='LR',
 113
 114
                             help='learning rate (default: 1.0)')
         parser.add_argument('--gamma', type=float, default=8.7, metavar='M',
 115
 116
                             help='Learning rate step gamma (default: 0.7)')
 117
         parser.add_argument('--no-cuda', action='store_true', default=False,
 118
                             help='disables CUDA training')
 119
         parser.add_argument('--dry-run', action='store_true', default=False,
 120
                             help='quickly check a single pass')
         parser.add_argument('--seed', type=int, default=1, metavar='S',
 121
 122
                             help='random seed (default: 1)')
                                          Page 2 of 4
File - /Users/ivarerevalomac/Google Drive/School/Machine Learning/ECE281 Computer Vision/Homeworks/Homework1/Image_class
        parser.add_argument('--log-interval', type=int, default=10, metavar='N',
123
124
                             help='how many batches to wait before logging training
        parser.add_argument('--save-model', action='store_true', default=False,
125
                             help='For Saving the current Model')
126
127
        parser.add_argument('--test-AWGN', action='store_true', default=False,
128
                             help='Test AMGN transformation')
129
        parser.add\_argument('--sigma', \ type=float, \ default=0.0, \ metavar='N',
130
                             help='standard deviation of AWGN')
131
        args = parser.parse_args()
132
        use_cuda = not args.no_cuda and torch.cuda.is_available()
133
134
        torch.manual_seed(args.seed)
135
136
        device = torch.device("cuda" if use_cuda else "cpu")
137
138
        train_kwargs = {'batch_size': args.batch_size}
        test_kmargs = {'batch_size': args.test_batch_size}
139
140
141
        if use_cuda:
142
             cuda_kwargs = {'num_workers': 1,
143
                            'pin_memory': True,
                            'shuffle': True}
144
             train_kwargs.update(cuda_kwargs)
145
             test_kwargs.update(cuda_kwargs)
146
147
148
         if args.test_AMGN:
                     n = transforms.(ompase([transforms.ToTensar()])
151
152
             test_dataset = datasets.MNIST('../data', train=False, transform=transform)
153
154
             ##DEBUG STEP
155
             print(type(test_dataset[0][0]))
156
             print(test_dataset[0][0].shape)
            print(type(test_dataset[0][0].numpy()))
157
             print(test_dataset[0][0].numpy().shape)
158
159
             # Display effects of AMGN on first image
160
161
            fig = plt.figure()
```

```
200
201
             scheduler = StepLR(optimizer, step_size=1, gamma=args.gamma)
202
             for epoch in range(1, args.epochs + 1):
203
                 train(args, model, device, train_loader, optimizer, epoch)
204
                 test(model, device, test_loader)
205
                 scheduler.step()
206
207
             if args.save_model:
208
                 torch.save(model.state_dict(), "mnist_cnn.pt")
209
210
| 211 if __name__ — '__main__':
212
213
         main()
                                           Page 4 of 4
File - Ausers/venerevalcmac/Google Drive/School/Machine Laerning/ECE281 Computer Vision/Homeworks/Homework1/Image_class
 1 from __future__ import print_function
 2 import argparse
 3 import torch
 4 import main
 5 from torchvision import datasets, transforms
 9 def run():
       parser = argparse.ArgumentParser(description='PyTorch MNIST Example')
12
       parser.add_argument('--test-batch-size', type=int, default=1800, metavar='N',
13
                            help='input batch size for testing (default: 1808)')
       parser.add\_argument('--no-cuda',\ action='store\_true',\ default=\mathit{True},
14
15
                            help='disables CUDA training')
16
       parser.add_argument('--seed', type=int, default=1, metavar='S',
```

17 help='random seed (default: 1)') 18 parser.add_argument('--log-interval', type=int, default=10, metavar='N', 19 help-'how many batches to wait before logging training status ני 20 parser.add_argument('--test-AMGN', action='store_true', default=False, 21 help='Test AWGN transformation') parser.add_argument('--sigma', type=float, default=0.0, metavar='N', help='standard deviation of AMGN') 22 23 24 25 26 27 args = parser.parse_args() use_cuda = not args.no_cuda and torch.cuda.is_available() 28 29 30 31 torch.manual_seed(args.seed) device = torch.device("cuda" if use_cuda else "cpu") 32 test_kwargs = {'batch_size': args.test_batch_size} 33 34 ## import model from main and import weights model - main.Net().to(device) 36 37 model.load_state_dict(torch.load("mnist_cnr.pt")) # Print model's state_dict 38 print("Model's state_dict:") 39 for param_tensor in model.state_dict(): 40 print(param_tensor, "\t", model.state_dict()[param_tensor].size()) 41 42 for i, sigma in enumerate([0, 0.3, 0.6, 1.0]): 43 transform = transforms.Compose([transforms.ToTensor(), main.AMGN(sigma), transforms.Normalize((0.1307,), (0.3081,))]) 45 test_dataset = datasets.MNIST('../data', train=False, transform=transform) 46 47 test_loader = torch.utils.data.DataLoader(test_dataset, **test_kwargs) 48 49 print(f"\nAccuracy for ANGN with a standard deviation of {sigma}") main.test(model, device, test_loader) 50 53 *if* __name__ — '__main__': run() Page 1 of 1