# **Assignment 3: AI Security** Graded Student LANA CHLOE LIM **Total Points** 21 / 20 pts Question 1 **Counting Correctly** 4 / 4 pts + 0 pts Correct Question 2 Seeing Close or Seeing Far (CIFAR) 4 / 4 pts + 0 pts Incorrect Question 3 **Unlearning that Look 1** / 0 pts + 2 pts Correct ● +1 pt Attempt at machine unlearning. Some issues with visualization. Question 4 Report 12 / 12 pts → + 12 pts Attempt at all questions.

+ 0 pts No attempt at questions.

# Q1 Counting Correctly

4 Points

Upload your copy of part1.ipynb. Make sure that it contains the outputs of your run.

# ECE 117 Assignment 3: Part 1

Training an MNIST model. Goal is to achieve 90+% accuracy.

In [ ]:

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

from torchvision import datasets, transforms

import tqdm

import matplotlib.pyplot as plt

In []: device = torch.device("cuda" if torch.cuda.is\_available() else "cpu")
 print(f"Using {device} device")

Using cuda device

In [ ]: transform = transforms.Compose([transforms.ToTensor()])

train\_data = datasets.MNIST("./data", train=True, download=True, transform=transform) test\_data = datasets.MNIST("./data", train=False, download=True,

transform=transform)

Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyt Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyt

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Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/ Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyt Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyt 1648877/1648877 [00:00<00:00, 7700409 100% Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to ./data/MNIST Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte 100%| 4542/4542 [00:00<00:00, 5005393.79it/s] Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/ In []: train\_loader = torch.utils.data.DataLoader(train\_data, batch\_size=32, shuffle=True) test\_loader = torch.utils.data.DataLoader(test\_data, batch\_size=32, shuffle=False) In []: # This is provided as a baseline model but feel free to adjust this. class CNN(nn.Module): def \_\_init\_\_(self): super(CNN, self).\_\_init\_\_() self.conv1 = nn.Conv2d(1, 32, 3, 1)self.conv2 = nn.Conv2d(32, 64, 3, 1)self.dropout1 = nn.Dropout(0.25)self.dropout2 = nn.Dropout(0.5) self.fc1 = nn.Linear(9216, 128)self.fc2 = nn.Linear(128, 10)def forward(self, x): x = self.conv1(x)x = F.relu(x)x = self.conv2(x)x = F.relu(x) $x = F.max_pool2d(x, 2)$ x = self.dropout1(x)x = torch.flatten(x, 1)

```
x = self.fc1(x)
x = F.relu(x)
x = self.dropout2(x)
x = self.fc2(x)
output = F.log_softmax(x, dim=1)
return output
```

```
In []: model = CNN().to(device)

i_max = 5000

criterion = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001, weight_decay=0.0001)
```

```
In []: @torch.no_grad()
    def get_accuracy(model, data_loader, device):
        correct = 0
        total = 0

    for inputs, labels in data_loader:
        inputs = inputs.to(device)
        labels = labels.to(device)

        outputs = model(inputs)
        _, predicted = torch.max(outputs, dim=1)

        total += labels.shape[0]
        correct += int((predicted == labels).sum())

    return correct / total
```

```
In []: progress = tqdm.tqdm(total=i_max, desc="Training")

i = 0

while i < i_max:
    for inputs, labels in train_loader:
    # ========= Forward Pass ========
    # model's training forward pass

# move the images and labels to the GPU

# predict the output of the model

# calculate the loss with respect to the output

model.train()
```

```
inputs = inputs.to(device)
    labels = labels.to(device)
    outputs = model(inputs)
    loss = criterion(outputs, labels)
    # ====== Backwards Pass =======
    # zero the optimizer's gradient
    # perform backpropagation on the loss function
    # call .step() on the optimizer
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
    i += 1
    progress.update(1)
    if i % 100 == 0:
      train_acc = get_accuracy(model, train_loader, device)
      test_acc = get_accuracy(model, test_loader, device)
      progress.write(f"Iter {i} Train Acc {train_acc:.4f} Test Acc
{test_acc:.4f}")
    if i \ge i max:
      break
torch.save(model.state_dict(), "./model.pth")
```

```
Training: 100% | 500/500 [01:24<00:00, 5.94it/s]
Training: 0% | 15/5000 [00:00<00:35, 142.25it/s] [A
Training: 1%|
                | 30/5000 [00:00<00:34, 143.31it/s] [A
Training: 1%
                46/5000 [00:00<00:33, 148.95it/s] [A
Training: 1% | 40/5000 [00:00<00:33, 140:55123] [A
Training: 2%
                 79/5000 [00:00<00:31, 157.56it/s] [A
Training: 2%|| | 95/5000 [00:00<00:32, 150.99it/s] [A
 [A
Training: 2%
                   | 100/5000 [00:11<00:32, 150.99it/s] [A
Training: 2%
                   | 111/5000 [00:11<18:09, 4.49it/s] [A
Training: 3%
                   | 128/5000 [00:11<12:16, 6.61it/s] [A
Iter 100 Train Acc 0.8329 Test Acc 0.8403
```

Training: 3% | | 144/5000 [00:11<08:37, 9.38it/s] [A

Training:	3%	161/5000 [00:11<06:00, 13.41it/s] [A
Training:	4%	177/5000 [00:11<04:21, 18.48it/s] [A
Training:	4%	193/5000 [00:11<03:12, 24.98it/s] [A
[A		
Training:	4%	200/5000 [00:21<03:12, 24.98it/s] [A
Training:	4%	209/5000 [00:21<17:01, 4.69it/s] [A

Iter 200 Train Acc 0.8976 Test Acc 0.9027

Training:	4% ■	220/5000 [00:21<13:19, 5.98it/s] [A
Training:	5%	231/5000 [00:22<10:14, 7.75it/s] [A
Training:	5%	245/5000 [00:22<07:14, 10.94it/s] [A
Training:	5%	261/5000 [00:22<04:58, 15.86it/s] [A
Training:	6%	275/5000 [00:22<03:40, 21.46it/s] [A
Training:	6%	292/5000 [00:22<02:35, 30.36it/s] [A
[A		
Training:	6%	300/5000 [00:31<02:34, 30.36it/s] [A
Training:	6%	306/5000 [00:31<16:50, 4.64it/s] [A
Training:	6%	323/5000 [00:31<11:23, 6.84it/s] [A

Iter 300 Train Acc 0.9270 Test Acc 0.9316

Training:	7% I	338/5000 [00:32<08:10, 9.51it/s] [A
Training:	7% I	351/5000 [00:32<06:10, 12.55it/s] [A
Training:	7% I	363/5000 [00:32<04:43, 16.35it/s] [A
Training:	8%	375/5000 [00:32<03:37, 21.27it/s] [A
Training:	8%	387/5000 [00:32<02:48, 27.36it/s] [A
Training:	8%	400/5000 [00:32<02:08, 35.84it/s] [A
[A		
Training:	8%	400/5000 [00:42<02:08, 35.84it/s] [A
Training:	8%	412/5000 [00:42<19:21, 3.95it/s] [A
Training:	9%	429/5000 [00:42<12:24, 6.14it/s] [A

Iter 400 Train Acc 0.9334 Test Acc 0.9386

Training: 9%	445/5000 [00:42<08:26, 8.99it/s] [A
Training: 9%	463/5000 [00:42<05:39, 13.38it/s] [A
Training: 10%	478/5000 [00:42<04:08, 18.20it/s] [A
Training: 10%	494/5000 [00:42<03:00, 25.02it/s] [A
[A	
Training: 10%	500/5000 [00:52<02:59, 25.02it/s] [A
Training: 10%	509/5000 [00:52<16:30, 4.53it/s] [A
Training: 11%	527/5000 [00:52<11:06, 6.71it/s] [A

Iter 500 Train Acc 0.9415 Test Acc 0.9428

```
      Training:
      11%|
      | 544/5000 [00:53<07:46, 9.56it/s] [A</td>

      Training:
      11%|
      | 560/5000 [00:53<05:36, 13.21it/s] [A</td>

      Training:
      12%|
      | 577/5000 [00:53<03:59, 18.44it/s] [A</td>

      Training:
      12%|
      | 594/5000 [00:53<02:53, 25.33it/s] [A</td>

      [A
      | 600/5000 [01:03<02:53, 25.33it/s] [A</td>

      Training:
      12%|
      | 610/5000 [01:03<15:21, 4.76it/s] [A</td>

      Training:
      12%|
      | 624/5000 [01:03<11:21, 6.42it/s] [A</td>
```

Iter 600 Train Acc 0.9471 Test Acc 0.9529

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      Training:
      13% | ■
      | 640/5000 [01:03<08:01, 9.05it/s] [A</td>

      Training:
      13% | ■
      | 657/5000 [01:03<05:36, 12.90it/s] [A</td>

      Training:
      14% | ■
      | 675/5000 [01:03<03:55, 18.40it/s] [A</td>

      Training:
      14% | ■
      | 691/5000 [01:03<02:53, 24.78it/s] [A</td>

      [A
      | 700/5000 [01:13<02:53, 24.78it/s] [A</td>

      Training:
      14% | ■
      | 707/5000 [01:13<15:00, 4.77it/s] [A</td>

      Training:
      14% | ■
      | 724/5000 [01:13<10:28, 6.80it/s] [A</td>
```

Iter 700 Train Acc 0.9490 Test Acc 0.9537

Iter 800 Train Acc 0.9489 Test Acc 0.9526

Iter 900 Train Acc 0.9567 Test Acc 0.9580

Training: 19% | 938/5000 [01:34<07:11, 9.41it/s] [A

#### Iter 1000 Train Acc 0.9565 Test Acc 0.9557

Training: 21% | 1028/5000 [01:44<07:48, 8.47it/s] [A Training: 21% | 1041/5000 [01:44<05:43, 11.53it/s] [A Training: 21% | 1054/5000 [01:44<04:12, 15.62it/s] [A Training: 21% | 1066/5000 [01:44<03:11, 20.54it/s] [A Training: 22% | 1080/5000 [01:45<02:19, 28.00it/s] [A Training: 22% | 1093/5000 [01:45<01:47, 36.38it/s] [A [A Training: 22% | 1100/5000 [01:54<01:47, 36.38it/s] [A Training: 22% | 1106/5000 [01:54<15:31, 4.18it/s] [A Training: 22% | 1122/5000 [01:54<10:18, 6.27it/s] [A

#### Iter 1100 Train Acc 0.9598 Test Acc 0.9593

#### Iter 1200 Train Acc 0.9635 Test Acc 0.9626

Iter 1300 Train Acc 0.9648 Test Acc 0.9673

Training: 27% | 1336/5000 [02:16<06:25, 9.50it/s] [A

Iter 1400 Train Acc 0.9664 Test Acc 0.9648

Training: 29% | 1432/5000 [02:27<08:43, 6.81it/s] [A Training: 29% 1449/5000 [02:27<06:05, 9.73it/s] [A | 1465/5000 [02:27<04:22, 13.46it/s] [A Training: 29% Training: 30% | 1481/5000 [02:27<03:10, 18.47it/s] [A Training: 30% | 1497/5000 [02:27<02:19, 25.06it/s] [A ΓΑ Training: 30% | 1500/5000 [02:37<02:19, 25.06it/s] [A Training: 30% | 1513/5000 [02:37<12:20, 4.71it/s] [A Training: 31% | 1530/5000 [02:37<08:33, 6.75it/s] [A

Iter 1500 Train Acc 0.9679 Test Acc 0.9706

Training: 31% | | 1546/5000 [02:37<06:07, 9.41it/s] [A Training: 31% | | 1563/5000 [02:37<04:18, 13.29it/s] [A Training: 32% | | 1579/5000 [02:37<03:08, 18.17it/s] [A Training: 32% | | 1595/5000 [02:37<02:18, 24.55it/s] [A [A Training: 32% | | 1600/5000 [02:47<02:18, 24.55it/s] [A Training: 32% | | 1610/5000 [02:47<12:10, 4.64it/s] [A Training: 33% | 1627/5000 [02:47<08:24, 6.68it/s] [A

Iter 1600 Train Acc 0.9666 Test Acc 0.9682

Iter 1700 Train Acc 0.9681 Test Acc 0.9681

 Training: 34%|
 | 1719/5000 [02:58<09:06, 6.01it/s] [A</td>

 Training: 35%|
 | 1736/5000 [02:58<06:09, 8.83it/s] [A</td>

 Training: 35%|
 | 1753/5000 [02:58<04:15, 12.71it/s] [A</td>

Iter 1800 Train Acc 0.9666 Test Acc 0.9663

Training: 37% | 1828/5000 [03:08<06:05, 8.69it/s] [A Training: 37% | 1840/5000 [03:08<04:36, 11.44it/s] [A Training: 37% | 1852/5000 [03:08<03:27, 15.14it/s] [A Training: 37% | 1865/5000 [03:08<02:33, 20.40it/s] [A Training: 38% | 1877/5000 [03:08<01:57, 26.58it/s] [A Training: 38% | 1889/5000 [03:08<01:31, 33.97it/s] [A ΓΑ Training: 38% | 1900/5000 [03:18<01:31, 33.97it/s] [A Training: 38% | 1901/5000 [03:18<13:14, 3.90it/s] [A Training: 38% | 1917/5000 [03:18<08:36, 5.97it/s] [A

Iter 1900 Train Acc 0.9703 Test Acc 0.9703

Training: 39% | 1933/5000 [03:18<05:47, 8.83it/s] [A Training: 39% | 1950/5000 [03:18<03:54, 12.98it/s] [A | 1966/5000 [03:19<02:46, 18.21it/s] [A Training: 39% Training: 40% | 1982/5000 [03:19<02:00, 24.98it/s] [A Training: 40% | 1998/5000 [03:19<01:29, 33.59it/s] [A ΓΑ Training: 40% | 2000/5000 [03:29<01:29, 33.59it/s] [A Training: 40% 2013/5000 [03:29<10:42, 4.65it/s] [A Training: 41% 2030/5000 [03:29<07:19, 6.75it/s] [A

Iter 2000 Train Acc 0.9702 Test Acc 0.9672

 Training: 41%|
 | 2046/5000 [03:29<05:12, 9.46it/s] [A</td>

 Training: 41%|
 | 2062/5000 [03:29<03:42, 13.18it/s] [A</td>

 Training: 42%|
 | 2077/5000 [03:29<02:43, 17.82it/s] [A</td>

 Training: 42%|
 | 2092/5000 [03:29<02:01, 23.96it/s] [A</td>

 Training: 42%|
 | 2100/5000 [03:39<02:01, 23.96it/s] [A</td>

 Training: 42%|
 | 2107/5000 [03:39<10:57, 4.40it/s] [A</td>

 Training: 42%|
 | 2124/5000 [03:40<07:28, 6.41it/s] [A</td>

Iter 2100 Train Acc 0.9715 Test Acc 0.9708

Training: 43% | 2141/5000 [03:40<05:11, 9.19it/s] [A

Iter 2200 Train Acc 0.9725 Test Acc 0.9705

Iter 2300 Train Acc 0.9714 Test Acc 0.9670

Training: 47% | 2335/5000 [04:01<05:08, 8.63it/s] [A
Training: 47% | 2351/5000 [04:01<03:40, 12.01it/s] [A
Training: 47% | 2368/5000 [04:02<02:35, 16.90it/s] [A
Training: 48% | 2385/5000 [04:02<01:51, 23.36it/s] [A
Training: 48% | 2400/5000 [04:12<01:51, 23.36it/s] [A
Training: 48% | 2401/5000 [04:12<09:13, 4.69it/s] [A
Training: 48% | 2418/5000 [04:12<06:25, 6.70it/s] [A

Iter 2400 Train Acc 0.9694 Test Acc 0.9683

Iter 2500 Train Acc 0.9754 Test Acc 0.9759

 Training: 51%|
 | 2527/5000 [04:22<06:14, 6.60it/s] [A</td>

 Training: 51%|
 | 2540/5000 [04:22<04:37, 8.88it/s] [A</td>

 Training: 51%|
 | 2552/5000 [04:22<03:28, 11.74it/s] [A</td>

 Training:
 51%
 | 2564/5000 [04:22<02:36, 15.59it/s] [A</td>

 Training:
 52%
 | 2578/5000 [04:22<01:52, 21.55it/s] [A</td>

 Training:
 52%
 | 2591/5000 [04:22<01:24, 28.48it/s] [A</td>

 [A
 | 2600/5000 [04:32<01:24, 28.48it/s] [A</td>

 Training:
 52%
 | 2604/5000 [04:32<09:38, 4.14it/s] [A</td>

 Training:
 52%
 | 2622/5000 [04:32<06:07, 6.47it/s] [A</td>

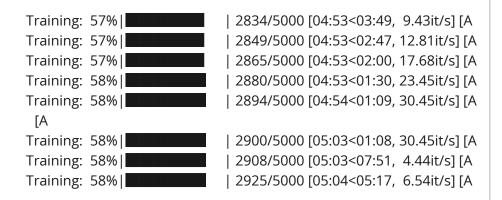
Iter 2600 Train Acc 0.9742 Test Acc 0.9737



Iter 2700 Train Acc 0.9763 Test Acc 0.9754



Iter 2800 Train Acc 0.9738 Test Acc 0.9725



Iter 2900 Train Acc 0.9757 Test Acc 0.9724

Training: 59%	2940/5000 [05:04<03:46, 9.08it/s] [A
Training: 59%	2957/5000 [05:04<02:36, 13.05it/s] [A

Training: 59% | 2974/5000 [05:04<01:50, 18.39it/s] [A Training: 60% | 2991/5000 [05:04<01:19, 25.40it/s] [A [A Training: 60% | 3000/5000 [05:14<01:18, 25.40it/s] [A Training: 60% | 3007/5000 [05:14<06:59, 4.75it/s] [A Training: 60% | 3024/5000 [05:14<04:51, 6.78it/s] [A

Iter 3000 Train Acc 0.9746 Test Acc 0.9728

Training: 61% | 3040/5000 [05:14<03:27, 9.43it/s] [A
Training: 61% | 3058/5000 [05:14<02:23, 13.53it/s] [A
Training: 62% | 3075/5000 [05:14<01:42, 18.73it/s] [A
Training: 62% | 3091/5000 [05:14<01:16, 25.09it/s] [A
Training: 62% | 3100/5000 [05:24<01:15, 25.09it/s] [A
Training: 62% | 3107/5000 [05:24<06:32, 4.82it/s] [A
Training: 62% | 3123/5000 [05:24<04:38, 6.75it/s] [A

Iter 3100 Train Acc 0.9661 Test Acc 0.9669

 Training: 63%|
 | 3139/5000 [05:24<03:17, 9.41it/s] [A</td>

 Training: 63%|
 | 3155/5000 [05:25<02:21, 13.06it/s] [A</td>

 Training: 63%|
 | 3172/5000 [05:25<01:39, 18.29it/s] [A</td>

 Training: 64%|
 | 3188/5000 [05:25<01:13, 24.72it/s] [A</td>

 [A
 | 3200/5000 [05:35<01:12, 24.72it/s] [A</td>

 Training: 64%|
 | 3203/5000 [05:35<06:29, 4.62it/s] [A</td>

 Training: 64%|
 | 3220/5000 [05:35<04:27, 6.65it/s] [A</td>

Iter 3200 Train Acc 0.9764 Test Acc 0.9734

 Training:
 65%|
 | 3237/5000 [05:35<03:06, 9.46it/s] [A</td>

 Training:
 65%|
 | 3254/5000 [05:35<02:11, 13.31it/s] [A</td>

 Training:
 65%|
 | 3270/5000 [05:35<01:35, 18.17it/s] [A</td>

 Training:
 66%|
 | 3287/5000 [05:35<01:08, 25.00it/s] [A</td>

 Training:
 66%|
 | 3300/5000 [05:44<01:08, 25.00it/s] [A</td>

 Training:
 66%|
 | 3303/5000 [05:44<05:34, 5.07it/s] [A</td>

 Training:
 66%|
 | 3319/5000 [05:45<03:57, 7.09it/s] [A</td>

Iter 3300 Train Acc 0.9759 Test Acc 0.9730

 Training: 67% |
 | 3334/5000 [05:45<02:51, 9.71it/s] [A</td>

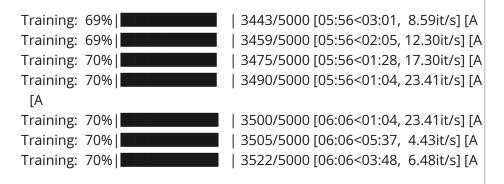
 Training: 67% |
 | 3348/5000 [05:45<02:07, 12.93it/s] [A</td>

 Training: 67% |
 | 3361/5000 [05:45<01:36, 16.94it/s] [A</td>

 Training: 67% |
 | 3374/5000 [05:45<01:13, 22.12it/s] [A</td>

Training: 68%	3386/5000 [05:45<00:57, 28.15it/s] [A
Training: 68%	3398/5000 [05:45<00:45, 35.56it/s] [A
[A	
Training: 68%	3400/5000 [05:56<00:44, 35.56it/s] [A
Training: 68%	3410/5000 [05:56<06:59, 3.79it/s] [A
Training: 69%	3427/5000 [05:56<04:27, 5.87it/s] [A

Iter 3400 Train Acc 0.9768 Test Acc 0.9734



Iter 3500 Train Acc 0.9777 Test Acc 0.9754



Iter 3600 Train Acc 0.9789 Test Acc 0.9758

Iter 3700 Train Acc 0.9771 Test Acc 0.9734

Training: 75%	3730/5000 [06:27<03:02, 6.94it/s] [ <i>A</i>
Training: 75%	3747/5000 [06:27<02:07, 9.84it/s] [ <i>f</i>
Training: 75%	3764/5000 [06:27<01:29, 13.80it/s] [
Training: 76%	3781/5000 [06:27<01:03, 19.10it/s] [

Training: 76%	3798/5000 [06:28<00:46, 26.05it/s] [
Training: 76%	3800/5000 [06:37<00:46, 26.05it/s] [
Training: 76%	3814/5000 [06:37<04:04, 4.85it/s] [/
Training: 77%	3831/5000 [06:37<02:49, 6.89it/s]
Iter 3800 Train Acc 0.9781 Test A	cc 0.9753
ΓΛ	
[A Training: 77%	3847/5000 [06:38<02:00, 9.55it/s] [ <i>A</i>
Training: 77%	3865/5000 [06:38<01:23, 13.66it/s] [
Training: 77%	3883/5000 [06:38<01:23, 13:06it/s] [
Training: 78%	3900/5000 [06:38<00:42, 26.03it/s] [
[A	3300/3000 [00.30 \00.42, 20.0318/3] [
Training: 78%	3900/5000 [06:48<00:42, 26.03it/s] [
Training: 78%	3916/5000 [06:48<03:40, 4.92it/s] [/
lter 3900 Train Acc 0.9776 Test A	cc 0.9747
Training: 79%	3933/5000 [06:48<02:33, 6.96it/s] [/
Training: 79%	3949/5000 [06:48<01:49, 9.62it/s] [/
Training: 79%	3966/5000 [06:48<01:16, 13.48it/s] [
Training: 80%	3982/5000 [06:48<00:55, 18.35it/s] [
Training: 80%	3997/5000 [06:48<00:41, 24.32it/s] [
[A	
Training: 80%	4000/5000 [06:58<00:41, 24.32it/s] [
Training: 80%	4012/5000 [06:58<03:27, 4.75it/s] [ <i>f</i>
lter 4000 Train Acc 0.9774 Test A	cc 0.9746
Training: 80%	4024/5000 [06:58<02:37, 6.21it/s] [/
Training: 81%	4035/5000 [06:58<01:59, 8.05it/s] [/
Training: 81%	4046/5000 [06:58<01:30, 10.59it/s] [
Training: 81%	4057/5000 [06:58<01:07, 13.99it/s] [
Training: 81%	4068/5000 [06:58<00:50, 18.45it/s]
Training: 82%	4079/5000 [06:58<00:38, 24.04it/s]
Training: 82%	4090/5000 [06:59<00:29, 30.75it/s]
[A	L   44.00 /5000 507.00 /00.00 00 757.1
Training: 82%	4100/5000 [07:08<00:29, 30.75it/s]
Training: 82%	4101/5000 [07:08<04:03, 3.69it/s]
Training: 82%	4117/5000 [07:08<02:30, 5.85it/s]
H	0.0760
Iter 4100 Train Acc 0.9791 Test A	CC U.9/68
Turining at 0200 I	L 4420/F000 F07 00 -04 45 - 0.05***
Training: 83%	4130/5000 [07:08<01:45, 8.25it/s]

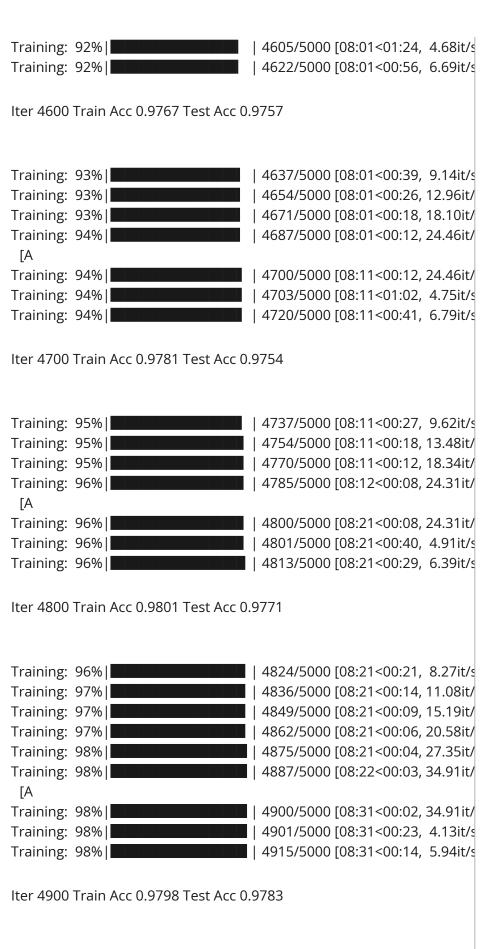
| 4147/5000 [07:08<01:07, 12.57it/s]

| 4164/5000 [07:08<00:45, 18.36it/s]

Training: 83%

Training: 83%

Training: 84%	4180/5000 [07:08<00:32, 25.43it/s]
Training: 84%	4197/5000 [07:08<00:22, 35.06it/s]
[A	
Training: 84%	4200/5000 [07:18<00:22, 35.06it/s]
Training: 84%	4213/5000 [07:18<02:42, 4.85it/s]
lter 4200 Train Acc 0.9775 Test Acc	0.9767
Training: 85%	4229/5000 [07:18<01:52, 6.86it/s]
Training: 85%	4246/5000 [07:19<01:16, 9.82it/s]
Training: 85%	4263/5000 [07:19<00:53, 13.86it/s]
Training: 86%	4280/5000 [07:19<00:37, 19.29it/s]
Training: 86%	4296/5000 [07:19<00:27, 25.94it/s]
[A	
Training: 86%	4300/5000 [07:29<00:26, 25.94it/s]
Training: 86%	4312/5000 [07:29<02:22, 4.82it/s]
Iter 4300 Train Acc 0.9747 Test Acc	0.9718
Training: 87%	4329/5000 [07:29<01:37, 6.88it/s]
Training: 87%	4345/5000 [07:29<01:08, 9.56it/s]
Training: 87%	4362/5000 [07:29<00:47, 13.47it/s]
Training: 88%	4378/5000 [07:29<00:33, 18.39it/s]
Training: 88%	4395/5000 [07:29<00:23, 25.30it/s]
[A Training: 88%	4400/5000 [07:39<00:23, 25.30it/s]
Training: 88%	4411/5000 [07:39<00:23, 23:30it/s]
Training: 89%	4428/5000 [07:39<02:02, 4.81t/3]
1141111116. 0370	4420/3000 [07.33 101.23, 0.00103]
Iter 4400 Train Acc 0.9802 Test Acc	0 9753
itel 4400 Irain Acc 0.3002 rest Acc	. 0.9733
Training: 89%	4442/5000 [07:39<01:00, 9.18it/s]
Training: 89%	4457/5000 [07:39<00:43, 12.60it/s]
Training: 89%	4474/5000 [07:39<00:29, 17.86it/s]
Training: 90%	4491/5000 [07:39<00:20, 24.79it/s]
[A	
Training: 90%	4500/5000 [07:50<00:20, 24.79it/s]
Training: 90%	4507/5000 [07:50<01:51, 4.43it/s]
Training: 90%	4524/5000 [07:50<01:14, 6.35it/s]
lter 4500 Train Acc 0.9789 Test Acc	0.9745
Training: 91%	4540/5000 [07:50<00:52, 8.83it/s]
Training: 91%	4556/5000 [07:50<00:36, 12.24it/s]
Training: 91%	4572/5000 [07:51<00:25, 16.85it/
Training: 92%	4589/5000 [07:51<00:17, 23.37it/
[A	
Training: 92%	4600/5000 [08:01<00:17, 23.37it/



Training: 99% | 4930/5000 [08:32<00:08, 8.63it/s Training: 99% | 4947/5000 [08:32<00:04, 12.81it/s Training: 99% | 4964/5000 [08:32<00:01, 18.40it/s Training: 100% | 4981/5000 [08:32<00:00, 25.71it Training: 100% | 4997/5000 [08:32<00:00, 34.34it]

```
[A
                                                  | 5000/5000 [08:42<00:00, 34.34it
             Training: 100%
              Iter 5000 Train Acc 0.9803 Test Acc 0.9763
   In [ ]:
              model.load_state_dict(torch.load("./model.pth"))
              model.eval()
Out [14]:
              CNN(
              (conv1): Conv2d(1, 32, kernel_size=(3, 3), stride=(1, 1))
              (conv2): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1))
              (dropout1): Dropout(p=0.25, inplace=False)
              (dropout2): Dropout(p=0.5, inplace=False)
              (fc1): Linear(in_features=9216, out_features=128, bias=True)
              (fc2): Linear(in_features=128, out_features=10, bias=True)
             )
   In []:
              correct = 0
              total = 0
              with torch.no_grad():
                for image, label in test_loader:
                  image = image.to(device)
                  label = label.to(device)
                  pred = model(image)
                  _, pred = torch.max(pred, dim=1)
                  total += label.shape[0]
                  correct += int((pred == label).sum())
                print(f"Accuracy: {correct / total * 100:.2f}%")
             Accuracy: 98.69%
```

# Q2 Seeing Close or Seeing Far (CIFAR) 4 Points

Upload your copy of part2.ipynb. Make sure that it contains the outputs of your run.

## ECE 117 - Assignment 3: Part 2

The goal of this part of the assignment is to implement the adversarial examples attack, FGSM.

In []: import numpy as np import torch from torch import nn, utils import torch.nn.functional as F from torchvision import datasets, transforms import matplotlib.pyplot as plt

In [ ]: device = torch.device("cuda" if torch.cuda.is\_available() else "cpu")
 print(f"Device: {device}")

Device: cuda

In []: transform = transforms.Compose([transforms.ToTensor()])

train\_dataset = datasets.CIFAR10(root='./data', train=True,
download=True, transform=transform)
train\_loader = utils.data.DataLoader(train\_dataset,
batch\_size=128, shuffle=True, num\_workers=2)

test\_dataset = datasets.CIFAR10(root='./data', train=False, download=True, transform=transform) test\_loader = utils.data.DataLoader(test\_dataset, batch\_size=128, shuffle=True, num\_workers=2)

Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to

100%| 170498071/170498071 [00:13<00:00, 129

Extracting ./data/cifar-10-python.tar.gz to ./data Files already downloaded and verified

```
In [ ]:
          class CNN(nn.Module):
            def __init__(self):
              super().__init__()
              self.network = nn.Sequential(
                nn.Conv2d(3, 32, kernel_size=3, stride=1, padding=1),
                nn.ReLU(),
                nn.BatchNorm2d(32),
                nn.Conv2d(32, 32, kernel_size=3, stride=2, padding=1),
                nn.ReLU(),
                nn.BatchNorm2d(32),
                nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1),
                nn.ReLU(),
                nn.BatchNorm2d(64),
                nn.Conv2d(64, 64, kernel_size=3, stride=2, padding=1),
                nn.ReLU(),
                nn.BatchNorm2d(64),
                nn.Conv2d(64, 64, kernel_size=3, stride=1, padding=1),
                nn.ReLU(),
                nn.BatchNorm2d(64),
                nn.Conv2d(64, 128, kernel_size=3, stride=2, padding=1),
                nn.ReLU(),
                nn.BatchNorm2d(128),
                nn.Flatten(),
                nn.Linear(128 * 4 * 4, 10))
            def forward(self, x):
              x = self.network(x)
              return x
            def size(self):
              parameters = self.parameters()
              size = 0
              for parameter in parameters:
                size += np.prod(parameter.shape)
              return size
In []:
          # Download pretrained CIFAR-10 model.
          !pip install wget
          import wget
          weights_file = wget.download("https://github.com/kuanhenglin/ai-secur
          workshop/blob/f08ced8a4afb7de1120bfdbf468888c7be10fdd8/cifar10_
          raw=true")
          Collecting wget
          Downloading wget-3.2.zip (10 kB)
          Preparing metadata (setup.py) ... [?25l [?25hdone
          Building wheels for collected packages: wget
          Building wheel for wget (setup.py) ... [?25] [?25hdone
          Created wheel for wget: filename=wget-3.2-py3-none-any.whl size=965
```

```
Stored in directory: /root/.cache/pip/wheels/8b/f1/7f/5c94f0a7a505ca1
Successfully built wget
Installing collected packages: wget
Successfully installed wget-3.2
network = CNN()
network.load_state_dict(torch.load(weights_file,
map_location=device))
network.to(device)
network.eval()
CNN(
 (network): Sequential(
  (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (1): ReLU()
  (2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_
  (3): Conv2d(32, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
  (4): ReLU()
  (5): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_
  (6): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (7): ReLU()
  (8): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_
  (9): Conv2d(64, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
  (10): ReLU()
  (11): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track
  (12): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (13): ReLU()
  (14): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track
  (15): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
  (16): ReLU()
  (17): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, trace
  (18): Flatten(start_dim=1, end_dim=-1)
  (19): Linear(in_features=2048, out_features=10, bias=True)
 )
)
@torch.no_grad()
def evaluate(loader, network):
  network.eval()
  accuracies = []
  for inputs, labels in loader:
    inputs = inputs.to(device)
    labels = labels.to(device)
    outputs = network(inputs)
    accuracy = (torch.max(outputs, dim=1)[1] ==
labels).to(torch.float32).mean() # accuracy
    accuracies.append(accuracy.cpu().numpy())
  return np.mean(accuracies)
```

In []:

Out [7]:

In []:

```
In []: accuracy = evaluate(test_loader, network)
print(f"Test accuracy: {str(accuracy * 100):.6}%")
```

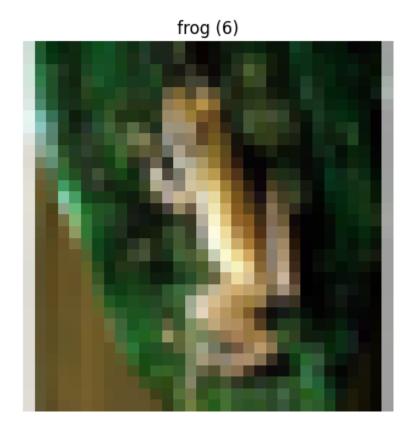
Test accuracy: 86.728%

#### **Adversarial Attack**

```
In []: def display_torch_image(image, label=None):
    if label is not None:
        plt.title(f"{classes[label]} ({label})")
    plt.axis("off")
    plt.imshow(torch.moveaxis(image, 0, -1).cpu(), vmin=0, vmax=1)
```

```
In [ ]:
          def display_attacked(image, image_attacked, noise, label,
          label_attacked):
            fig, axes = plt.subplots(1, 3, figsize=(15, 5))
            axes[0].axis("off")
            axes[0].set_title(f"{classes[label]} ({label})", fontsize=16)
            axes[0].text(33.25, 16.5, "$+$", fontsize=24)
            axes[0].imshow(torch.moveaxis(image, 0, -1).cpu(), vmin=0,
          vmax=1)
            axes[1].axis("off")
            axes[1].set_title(f"noise (amplified 5x)", fontsize=16)
            axes[1].text(32.75, 16, "$=$", fontsize=24)
            axes[1].imshow(torch.moveaxis(noise, 0, -1).cpu(), vmin=0,
          vmax=1)
            axes[2].axis("off")
            axes[2].set_title(f"{classes[label_attacked]} ({label_attacked})",
          fontsize=16)
             axes[2].imshow(torch.moveaxis(image_attacked, 0, -1).cpu(),
          vmin=0, vmax=1)
```

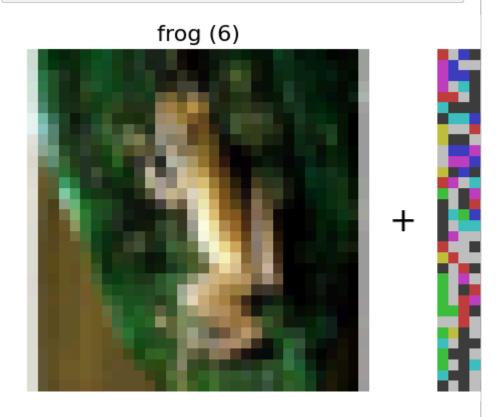
```
In []: batch_data = next(iter(train_loader))
    image = batch_data[0][0].to(device)
    label = batch_data[1][0].to(device)
    with torch.no_grad():
        prediction = network(image.unsqueeze(dim=0)).max(dim=1)[1]
    [0].cpu().numpy()
        display_torch_image(image, label=prediction)
```



Fast Gradient Sign Attack (FGSM)

The goal of this part is to demonstrate a misclasification a baseline epsilon is provided but your goal is to provide the best hyperparameter.

In []: adversarial\_attack(network, image, label, epsilon=0.1, sign=True)



### Q3 Unlearning that Look 0 Points

Optional. Upload your copy of part3.ipynb. Make sure that it contains the outputs of your run.

# ECE 117 - Assignment 3: Part 3

The goal of this part of the assignment is to implement machine unlearning via fine-tuning.

```
In [1]:
          import os
          import requests
          import numpy as np
          import matplotlib.pyplot as plt
          from sklearn import linear_model, model_selection
          import torch
          from torch import nn
          import torch.nn.functional as F
          from torch import optim
          from torch.utils.data import DataLoader
          import torchvision
          from torchvision import datasets, transforms
          from torchvision.utils import make_grid
          from torchvision.models import resnet18
          import tqdm
          DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
          print("Running on device:", DEVICE.upper())
          RNG = torch.Generator().manual_seed(42)
```

Running on device: CUDA

```
In [2]: normalize = transforms.Compose([transforms.ToTensor()])

train_set = torchvision.datasets.FashionMNIST(
    root="./data", train=True, download=True,
    transform=normalize
)
train_loader = DataLoader(train_set, batch_size=128,
    shuffle=True, num_workers=2)

held_out = torchvision.datasets.FashionMNIST(
    root="./data", train=False, download=True,
    transform=normalize
)
test_set, val_set = torch.utils.data.random_split(held_out, [0.5,
```

```
test loader = DataLoader(test set, batch size=128, shuffle=False,
num_workers=2)
val_loader = DataLoader(val_set, batch_size=128, shuffle=False,
num workers=2)
forget_class = 0
forget_idx, retain_idx = [], []
for i, target in enumerate(train_set.targets):
if target == forget class:
  forget_idx.append(i)
 else:
  retain_idx.append(i)
forget_set = torch.utils.data.Subset(train_set, forget_idx)
retain_set = torch.utils.data.Subset(train_set, retain_idx)
forget_loader = torch.utils.data.DataLoader(
  forget_set, batch_size=128, shuffle=True, num_workers=2
)
retain_loader = torch.utils.data.DataLoader(
  retain_set, batch_size=128, shuffle=True, num_workers=2,
generator=RNG
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.c
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.c
100%|
                          | 26421880/26421880 [00:02<00:00, 11699
Extracting ./data/FashionMNIST/raw/train-images-idx3-ubyte.gz to ./dat
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.c
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.c
100%|
                          | 29515/29515 [00:00<00:00, 211831.00it/s
Extracting ./data/FashionMNIST/raw/train-labels-idx1-ubyte.gz to ./data/
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.c
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.
100%| 4422102/4422102 [00:01<00:00, 3924497]
Extracting ./data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz to ./data/
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.c
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.
                         | 5148/5148 [00:00<00:00, 20029941.55it/s
100%
```

0.5], generator=RNG)

```
In [3]:
           # This is provided as a baseline model but feel free to adjust this.
           class CNN(nn.Module):
              def __init__(self):
                super(CNN, self).__init__()
                self.conv1 = nn.Conv2d(1, 6, 5)
                self.pool = nn.MaxPool2d(2, 2)
                self.conv2 = nn.Conv2d(6, 16, 5)
                self.fc1 = nn.Linear(16 * 4 * 4, 120)
                self.fc2 = nn.Linear(120, 84)
                self.fc3 = nn.Linear(84, 10)
              def forward(self, x):
                x = self.pool(F.relu(self.conv1(x)))
                x = self.pool(F.relu(self.conv2(x)))
                x = x.view(-1, 16 * 4 * 4)
                x = F.relu(self.fc1(x))
                x = F.relu(self.fc2(x))
                x = self.fc3(x)
                return x
```

```
In [4]: model = CNN().to(DEVICE)

i_max = 6400

criterion = torch.nn.CrossEntropyLoss()
 optimizer = torch.optim.Adam(model.parameters(), Ir=0.001,
 weight_decay=0.0001)
```

```
In [5]:

@torch.no_grad()
def get_accuracy(model, data_loader, device):
    correct = 0
    total = 0

for inputs, labels in data_loader:
    inputs = inputs.to(DEVICE)
    labels = labels.to(DEVICE)

    outputs = model(inputs)
    _, predicted = torch.max(outputs, dim=1)

    total += labels.shape[0]
    correct += int((predicted == labels).sum())
```

```
In []:
            # First, train a baseline FashionMNIST CNN
            progress = tqdm.tqdm(total=i_max, desc="Training")
            i = 0
            while i < i_max:
              for inputs, labels in train_loader:
                # modify training loop
                model.train()
                inputs = inputs.to(DEVICE)
                labels = labels.to(DEVICE)
                outputs = model(inputs)
                loss = criterion(outputs, labels)
                optimizer.zero_grad()
                loss.backward()
                optimizer.step()
                i += 1
                progress.update(1)
                if i % 100 == 0:
                   train_acc = get_accuracy(model, train_loader, DEVICE)
                   test_acc = get_accuracy(model, test_loader, DEVICE)
                   progress.write(f"Iter {i} Train Acc {train_acc:.4f} Test Acc
            {test_acc:.4f}")
                if i \ge i_max:
                   break
            torch.save(model.state_dict(), "./model.pth")
In [12]:
            test_accuracy = get_accuracy(model, test_loader, DEVICE)
            print(f"Test Accuracy: {test_accuracy}")
            Test Accuracy: 0.8972
In [57]:
            # Machine unlearning via fine-tuning
            i max = 500
```

progress = tqdm.tqdm(total=i\_max, desc="Training")

```
i = 0
while i < i max:
  for inputs, labels in retain_set:
    # modify loop to fine-tune model
    model.train()
    inputs, labels = inputs.to(DEVICE),
torch.tensor(labels).to(DEVICE)
    optimizer.zero grad()
    outputs = model(inputs)
    loss = criterion(outputs[0], labels)
    loss.backward()
    optimizer.step()
    i += 1
    progress.update(1)
    if i % 100 == 0:
      train_acc = get_accuracy(model, train_loader, DEVICE)
      test_acc = get_accuracy(model, test_loader, DEVICE)
      progress.write(f"Iter {i} Train Acc {train_acc:.4f} Test Acc
{test_acc:.4f}")
    if i >= i max:
      break
torch.save(model.state_dict(), "./model-unlearned.pth")
Training: 100% | 500/500 [02:09<00:00, 3.87it/s]
Training: 29% | 144/500 [00:08<00:26, 13.25it/s]
Iter 100 Train Acc 0.7911 Test Acc 0.7760
Training: 50% | 249/500 [00:17<00:18, 13.38it/s]
Iter 200 Train Acc 0.7936 Test Acc 0.7806
Training: 72%
                              360/500 [00:24<00:09, 14.89it/s]
Iter 300 Train Acc 0.7749 Test Acc 0.7638
Training: 94%
                               471/500 [00:32<00:02, 14.39it/s]
Iter 400 Train Acc 0.7918 Test Acc 0.7806
Training: 100%
                                 | 500/500 [00:40<00:00, 14.39it/s]
Iter 500 Train Acc 0.7738 Test Acc 0.7604
```

```
In [58]: model_retain = CNN().to(DEVICE)

i_max = 500

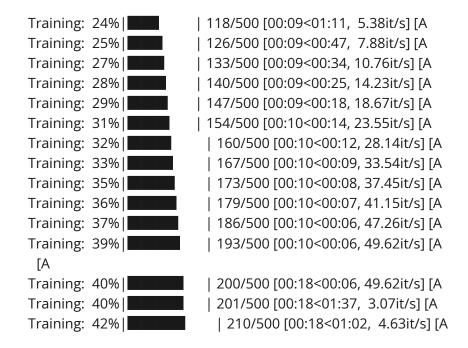
criterion_retain = torch.nn.CrossEntropyLoss()
optimizer_retain = torch.optim.Adam(model.parameters(),
Ir=0.001, weight_decay=0.0001)

In [59]: # Train only purely the retain set to benchmark
```

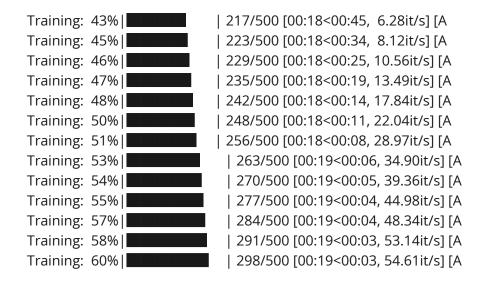
```
progress = tqdm.tqdm(total=i_max, desc="Training")
i = 0
while i < i_max:
  for inputs, labels in retain_loader:
    model_retain.train()
    inputs = inputs.to(DEVICE)
    labels = labels.to(DEVICE)
    outputs = model_retain(inputs)
    loss = criterion_retain(outputs, labels)
    optimizer_retain.zero_grad()
    loss.backward()
    optimizer_retain.step()
    i += 1
    progress.update(1)
    if i % 100 == 0:
       train_acc = get_accuracy(model_retain, retain_loader,
DEVICE)
      test_acc = get_accuracy(model, test_loader, DEVICE)
       progress.write(f"Iter {i} Train Acc {train_acc:.4f} Test Acc
{test_acc:.4f}")
    if i >= i max:
      break
torch.save(model.state_dict(), "./model-retain.pth")
```

Training:	7%	36/500 [00:00<00:07, 58.85it/s] [A
Training:	9%	43/500 [00:00<00:07, 60.57it/s] [A
Training:	10%	50/500 [00:00<00:07, 61.09it/s] [A
Training:	11%	57/500 [00:01<00:07, 59.19it/s] [A
Training:	13%	64/500 [00:01<00:07, 59.89it/s] [A
Training:	14%	71/500 [00:01<00:06, 61.45it/s] [A
Training:	16%	78/500 [00:01<00:06, 61.72it/s] [A
Training:	17%	85/500 [00:01<00:06, 59.62it/s] [A
Training:	18%	92/500 [00:01<00:06, 62.03it/s] [A
Training:	20%	99/500 [00:01<00:06, 59.65it/s] [A
[A		
Training:	20%	100/500 [00:09<00:06, 59.65it/s] [A
Training:	21%	106/500 [00:09<02:11, 3.00it/s] [A
Training:	22%	112/500 [00:09<01:36, 4.02it/s] [A

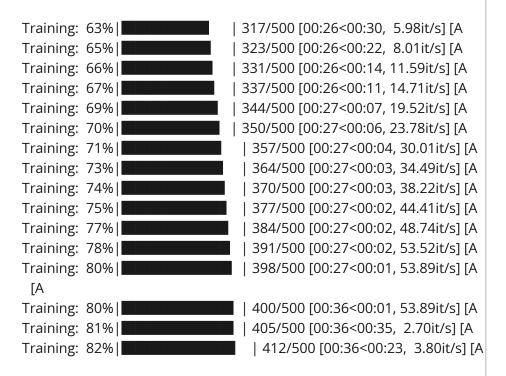
Iter 100 Train Acc 0.0931 Test Acc 0.7604



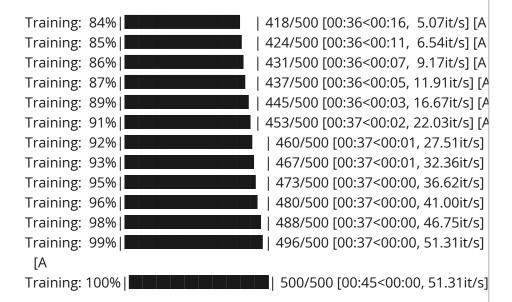
Iter 200 Train Acc 0.0931 Test Acc 0.7604



Iter 300 Train Acc 0.0931 Test Acc 0.7604



Iter 400 Train Acc 0.0931 Test Acc 0.7604



Iter 500 Train Acc 0.0931 Test Acc 0.7604

```
In [60]: def compute_losses(net, loader):
    criterion = nn.CrossEntropyLoss(reduction="none")
    all_losses = []
```

```
for inputs, targets in loader:
    inputs, targets = inputs.to(DEVICE), targets.to(DEVICE)

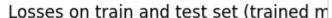
logits = net(inputs)
    losses = criterion(logits, targets).numpy(force=True)
    for l in losses:
        all_losses.append(l)

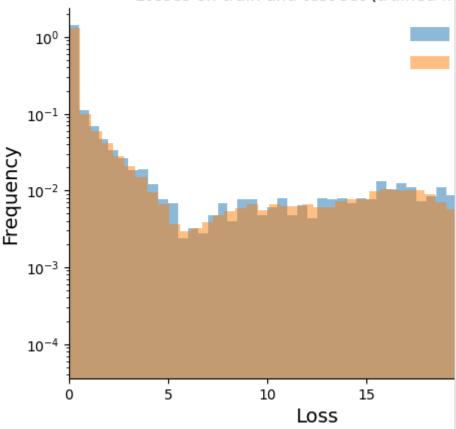
return np.array(all_losses)

train_losses = compute_losses(model, train_loader)
    test_losses = compute_losses(model, test_loader)
```

#### In [61]:

```
# plot losses on train and test set
plt.title("Losses on train and test set (trained model)")
plt.hist(test_losses, density=True, alpha=0.5, bins=50, label="Test
set")
plt.hist(train_losses, density=True, alpha=0.5, bins=50,
label="Train set")
plt.xlabel("Loss", fontsize=14)
plt.ylabel("Frequency", fontsize=14)
plt.xlim((0, np.max(test_losses)))
plt.yscale("log")
plt.legend(frameon=False, fontsize=14)
ax = plt.gca()
ax.spines["top"].set_visible(False)
ax.spines["right"].set_visible(False)
plt.show()
```





# In [62]: def simple\_mia(sample\_loss, members, n\_splits=10, random\_state=0): unique\_members = np.unique(members) if not np.all(unique\_members == np.array([0, 1])): raise ValueError("members should only have 0 and 1s") attack\_model = linear\_model.LogisticRegression() cv = model\_selection.StratifiedShuffleSplit( n\_splits=n\_splits, random\_state=random\_state ) return model\_selection.cross\_val\_score( attack\_model, sample\_loss, members, cv=cv, scoring="accuracy" )

```
In [63]: forget_losses = compute_losses(model, forget_loader)

# Since we have more forget losses than test losses, sub-sample them, to have a class-balanced dataset.

np.random.shuffle(forget_losses)
forget_losses = forget_losses[: len(test_losses)]

samples_mia = np.concatenate((test_losses, forget_losses)).reshape((-1, 1))
```

```
labels_mia = [0] * len(test_losses) + [1] * len(forget_losses)
mia_scores = simple_mia(samples_mia, labels_mia)
print(
   f"The MIA has an accuracy of {mia_scores.mean():.3f} on forgotten vs unseen images"
)
```

The MIA has an accuracy of 0.919 on forgotten vs unseen images

```
In [64]: # Benchmark model purely on the retain set.

ft_forget_losses = compute_losses(model_retain, forget_loader)
ft_test_losses = compute_losses(model_retain, test_loader)

# make sure we have a balanced dataset for the MIA
#assert len(ft_test_losses) == len(ft_forget_losses)

ft_samples_mia = np.concatenate((ft_test_losses,
ft_forget_losses)).reshape((-1, 1))
labels_mia = [0] * len(ft_test_losses) + [1] * len(ft_forget_losses)
```

```
In [53]: ft_mia_scores = simple_mia(ft_samples_mia, labels_mia)

print(
    f"The MIA has an accuracy of {ft_mia_scores.mean():.3f} on forgotten vs unseen images"
)
```

The MIA has an accuracy of 0.769 on forgotten vs unseen images

```
In [65]: # Compare the results to determine the efficacy of the machine-unlearning implementation

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 6))

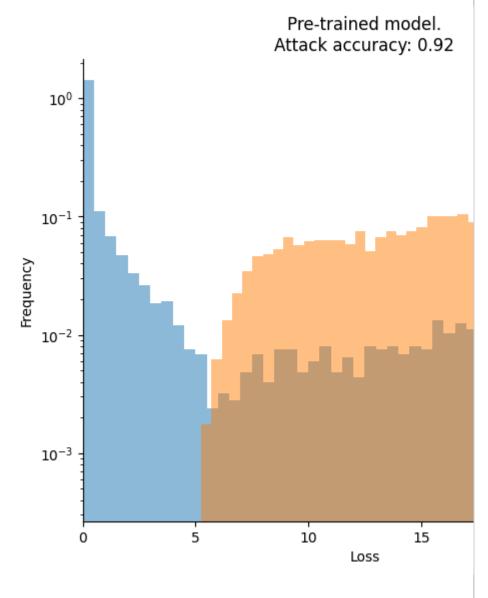
ax1.set_title(f"Pre-trained model.\nAttack accuracy:
{mia_scores.mean():0.2f}")

ax1.hist(test_losses, density=True, alpha=0.5, bins=50, label="Test set")

ax1.hist(forget_losses, density=True, alpha=0.5, bins=50, label="Forget set")

ax2.set_title(
    f"Unlearned by fine-tuning.\nAttack accuracy:
{ft_mia_scores.mean():0.2f}"
```

```
ax2.hist(ft_test_losses, density=True, alpha=0.5, bins=50,
label="Test set")
ax2.hist(ft_forget_losses, density=True, alpha=0.5, bins=50,
label="Forget set")
ax1.set_xlabel("Loss")
ax2.set_xlabel("Loss")
ax1.set_ylabel("Frequency")
ax1.set_yscale("log")
ax2.set_yscale("log")
ax1.set_xlim((0, np.max(test_losses)))
ax2.set_xlim((0, np.max(test_losses)))
for ax in (ax1, ax2):
  ax.spines["top"].set_visible(False)
  ax.spines["right"].set_visible(False)
ax1.legend(frameon=False, fontsize=14)
plt.show()
```



#### Q4 Report

#### 12 Points

Make sure to include report.pdf containing all of the responses to questions in the assignment. Make sure to respond to questions in parts 1, 2 & 3. Part 3 coding is optional but questions are required.

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