Tutorial 7b - Adversarial Examples

This notebook demonstrates how easy it is to create adversarial examples. Let's start by training some models to classify the digits in the MNIST data set. We'll work with one fully-connected neural network and one convolutional network to show the generality of our approach.

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

from torchvision import datasets, transforms
import matplotlib.pyplot as plt

mnist_images = datasets.MNIST('data', train=True, download=True, transform=transforms.ToTensor())

class FCNet(nn.Module):
    def __init__(self):
        super(FCNet, self).__init__()
        self.layer1 = nn.Linear(28 * 28, 50)
        self.layer2 = nn.Linear(50, 20)
        self.layer3 = nn.Linear(20, 10)
    def forward(self, img):
        flattened = img.view(-1, 28 * 28)
        activation1 = F.relu(self.layer1(flattened))
        activation2 = F.relu(self.layer2(activation1))
        output = self.layer3(activation2)
        return output

class ConvNet(nn.Module):
    def __init__(self):
        super(ConvNet, self).__init__()
        self.conv1 = nn.Conv2d(1, 5, 5, padding=2)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(5, 10, 5, padding=2)
        self.fc1 = nn.Linear(10 * 7 * 7, 32)
        self.fc2 = nn.Linear(32, 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, 10 * 7 * 7)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        x = x.squeeze(1)
        return x
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to data/MNIST/raw/tra
100%    9912422/9912422 [00:00<00:00, 24117411.16it/s]
Extracting data/MNIST/raw/train-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to data/MNIST/raw/tra
100%    28881/28881 [00:00<00:00, 185396.55it/s]
Extracting data/MNIST/raw/train-labels-idx1-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to data/MNIST/raw/t10k
100%    1648877/1648877 [00:00<00:00, 6390588.70it/s]
Extracting data/MNIST/raw/t10k-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to data/MNIST/raw/t10k
100%    4542/4542 [00:00<00:00, 43862.89it/s]
```

```
def train(model, data, batch_size=64, lr=0.001, num_iters=1000, print_every=100):
    train_loader = torch.utils.data.DataLoader(data, batch_size=batch_size)
    optimizer = optim.Adam(model.parameters(), lr=lr)
    criterion = nn.CrossEntropyLoss()

    total_loss = 0
    n = 0

    while True:
        for imgs, labels in iter(train_loader):
            out = model(imgs)
            loss = criterion(out, labels)
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()
            total_loss += loss.item()
            n += 1

            if n % print_every == 0:
                print("Iter %d. Avg.Loss: %f" % (n, total_loss/print_every))
                total_loss = 0
            if n > num_iters:
                return
```

```
fc_model = FCNet()
train(fc_model, mnist_images, num_iters=1000)
```

```
Iter 100. Avg.Loss: 1.372479
Iter 200. Avg.Loss: 0.561812
Iter 300. Avg.Loss: 0.462339
Iter 400. Avg.Loss: 0.360247
Iter 500. Avg.Loss: 0.367673
Iter 600. Avg.Loss: 0.329149
Iter 700. Avg.Loss: 0.327951
Iter 800. Avg.Loss: 0.320968
Iter 900. Avg.Loss: 0.275103
Iter 1000. Avg.Loss: 0.224888
```

```
cnn_model = ConvNet()
train(cnn_model, mnist_images, num_iters=1000)
```

```
Iter 100. Avg.Loss: 1.535319
Iter 200. Avg.Loss: 0.494825
Iter 300. Avg.Loss: 0.351819
Iter 400. Avg.Loss: 0.252105
Iter 500. Avg.Loss: 0.240497
Iter 600. Avg.Loss: 0.191622
Iter 700. Avg.Loss: 0.197972
Iter 800. Avg.Loss: 0.185336
Iter 900. Avg.Loss: 0.159352
Iter 1000. Avg.Loss: 0.132964
```

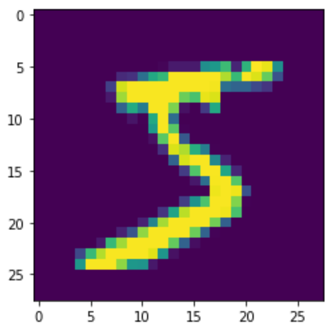
Targetted Adversarial Attack

The purpose of an adversarial attack is to perturb an input (usually an image x) so that a neural network f misclassifies the perturbed image $x + \epsilon$. In a targeted attack, we want the network f to misclassify the perturbed image into a class of our choosing.

Let's begin with this image. We will perturb the image so our model thinks that the image is of the digit 3, when in fact it is of the digit 5.

```
image = mnist_images[0][0]
target_label = 3
model = fc_model

plt.imshow(image[0])
```

```
<matplotlib.image.AxesImage at 0x7fdeb5c97fd0>
```



Our approach is as follows:

- We will create a random noise ϵ that is the same size as the image.
- We will use an optimizer to tune the values of ϵ to make the neural network misclassify $x + \epsilon$ to our target class

The second step might sound a little mysterious, but is actually very similar to tuning the weights of a neural network!

First, let's create some noise values. In order for PyTorch to be able to tune these values using an optimizer, we need to set `requires_grad=True`:

```
noise = torch.randn(1, 28, 28) * 0.01
noise.requires_grad = True
```

Now, we will tune the noise:

```
optimizer = optim.Adam([noise], lr=0.01, weight_decay=1)
criterion = nn.CrossEntropyLoss()

for i in range(1000):
        adv_image = torch.clamp(image + noise, 0, 1)
        out = model(adv_image.unsqueeze(0))
        loss = criterion(out, torch.Tensor([target_label]).long())
        loss.backward()
        optimizer.step()
        optimizer.zero_grad()
```

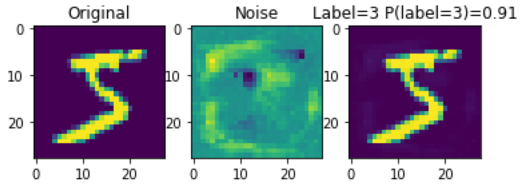
To keep the pixel values in `noise` small, we use a fairly large `weight_decay`. We use the `CrossEntropyLoss`, but maximize the neural network prediction of our `target_label`.

Notice also that the `adv_image` is clamped so that the pixel values are kept in the range [0, 1].

Now, let's see the resulting image:

```
adv_image = torch.clamp(image + noise, 0, 1)
adv_label = torch.argmax(model(adv_image), dim=1).item()
adv_percent = torch.softmax(model(adv_image), dim=1)[0,target_label].item()

plt.subplot(1, 3, 1)
plt.title("Original")
plt.imshow(image[0])

plt.subplot(1, 3, 2)
plt.title("Noise")
plt.imshow(noise[0].detach().numpy())

plt.subplot(1, 3, 3)
plt.title("Label=%d P(label=%d)=%.2f" % (adv_label, target_label, adv_percent))
plt.imshow(adv_image.detach().numpy()[0])
```

```
<matplotlib.image.AxesImage at 0x7fdeb4f65c90>
```

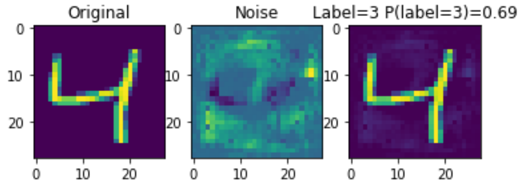


The image on the right still looks like a "5" to a human. However, the neural network misclassifies the image.

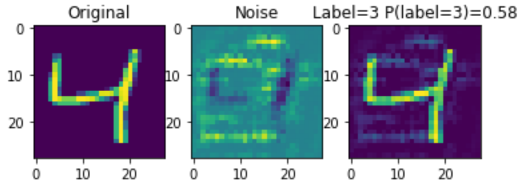
The same steps can be used to create an adversarial attack for other images, and for other model architectures.

```
def create_adversarial_example(model, image, target_label):
    noise = torch.randn(1, 28, 28)
    noise.requires_grad = True

    optimizer = optim.Adam([noise], lr=0.01, weight_decay=1)
    criterion = nn.CrossEntropyLoss()

    for i in range(1000):
        adv_image = torch.clamp(image + noise, 0, 1)
        out = model(adv_image.unsqueeze(0))
        loss = criterion(out, torch.Tensor([target_label]).long())
        loss.backward()
        optimizer.step()
        optimizer.zero_grad()


    adv_image = torch.clamp(image + noise, 0, 1)
```

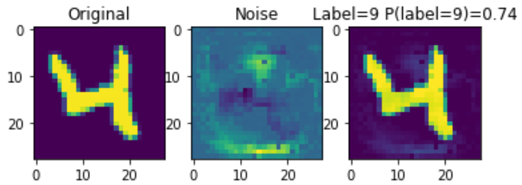
```
create_adversarial_example(fc_model, mnist_images[2][0], 3)
```




```
create_adversarial_example(cnn_model, mnist_images[2][0], 3)
```




```
create_adversarial_example(fc_model, mnist_images[20][0], 9)
```




```
create_adversarial_example(cnn_model, mnist_images[20][0], 6)
```