Computer Vision in Python

Day 2, Part 2/4

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About this lecture

1. What are **attacks** on Neural Networks (NNs) and what is **Adversarial Machine Learning**?
2. Why are attacks an **important concept** when studying NNs and what are the important lessons to be learnt from Adversarial ML?
3. What are the different **types of attacks** and what is the intuition behind basic attacks?
4. How to **defend** against such attacks?
5. **State-of-the-art** of attacks and defense, **open questions** in research, ethical discussions.

In the last episode

Noising samples is sometimes good enough to produce adversarial samples and make a trained Neural Network malfunction.

- This exploits the intrinsic properties/limits of Neural Networks.
- The problem, however, is that noising is **too random**, and is often not guaranteed to work.

Can we implement **more advanced attacks**, with higher **success rates**?

- Can we **"target"** these attacks to produce adversarial samples with expected effects on Neural Networks?
- And later, can we **defend** against these attacks?

Some more taxonomy on attacks

Definition (untargeted attack):

The objective of an **untargeted attack** is to produce an attack sample, which will simply be misclassified.

Noising was an **untargeted attack**, as we attempted to modify a sample in such a way that it would classified as anything but its ground truth label.

Definition (targeted attack):

The objective of a **targeted attack** is to produce an attack sample, which will be misclassified as a specific class.

As such, **targeted attacks** are often **more complex** than **untargeted ones**.

E.g., modify a picture of a **dog (original label)** so it is misclassified as a **cat (target label)**.

Some more taxonomy on attacks

Definition (black-box attack):

A **black-box attack** does not exploit any properties of the model.

Black-box attacks assume that they can **only try inputs and access the outputs of the model under attack**.

Noising was therefore a **black-box** and **untargeted attack**.

Definition (white-box attack):

A **white-box attack** attempts to exploit properties of the model, e.g. its gradients, logits, weights, etc.

White-box attacks therefore assume that the model as a whole can be accessed, including its **weights** and **gradients**.

White-box attacks attempt to **learn** how the model works, to make it malfunction in a certain way.

Some more taxonomy on attacks

Definition (one-shot attack):

A **one-shot attack** attempts to produce a single attack sample, and if this attack fails, it simply retries on a different sample.

Noising was therefore a **one-shot attack**. It attempted to noise a sample to have it misclassified.

However, if this attempt failed, it simply tried on another sample.

Definition (iterated attack):

An **iterated attack** attempts to produce an attack sample, like the one-shot attacks.

However, it will try to **adjust the said sample** until it either

- **makes the model malfunction (in an expected way)**,
- or **reaches a maximal number of allowed iterations**.

The iterated attacks are often more robust and efficient.

About attacks

Adversarial Machine Learning can be very creative and is currently a very active research field. In this lecture, and in the interest of time, we will only cover some of the basic ones.

- What matters is to understand the intuition behind these basic attacks, more specifically how we might use information about the model to tailor our attacks and enhance their efficacy.
- In the next lecture, we will then discuss some more advanced attack techniques, for general knowledge.
- To summarize, keep in mind that the potential for attacks is quite unlimited and researchers have been very creative…!

About attacks

Basic attacks (to be discussed today):

1. **Untargeted**, **one-shot**, **white-box** gradient attack
2. **Untargeted**, **one-shot**, **white-box** fast gradient sign attack
3. **Untargeted**, **iterated**, **white-box** fast gradient sign attack
4. **Targeted**, **one-shot**, **white-box** fast gradient sign attack
5. **Targeted**, **iterated**, **white-box** fast gradient sign attack

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4. **Targeted**, **one-shot**, **white-box** fast **gradient** sign attack
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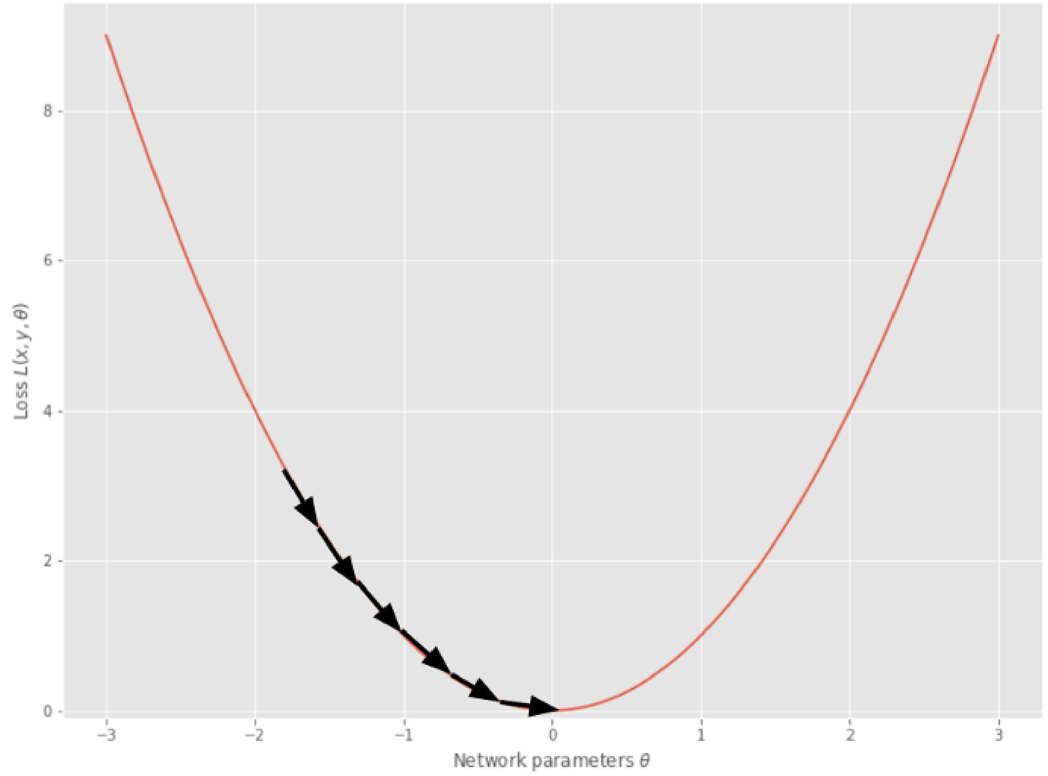
Note: "Gradient" seems to be the important keyword here, but why and how are gradients used for attacks?

A reminder on gradient descent

When **training** a neural network, we attempt to adjust the parameters of a model θ, to minimize a loss function $L(x, \theta, y)$.

- We typically use an optimizer, which implements some version of the **gradient descent** algorithm.

$$\theta \leftarrow \theta - \alpha \nabla_{\theta} L(x, \theta, y)$$



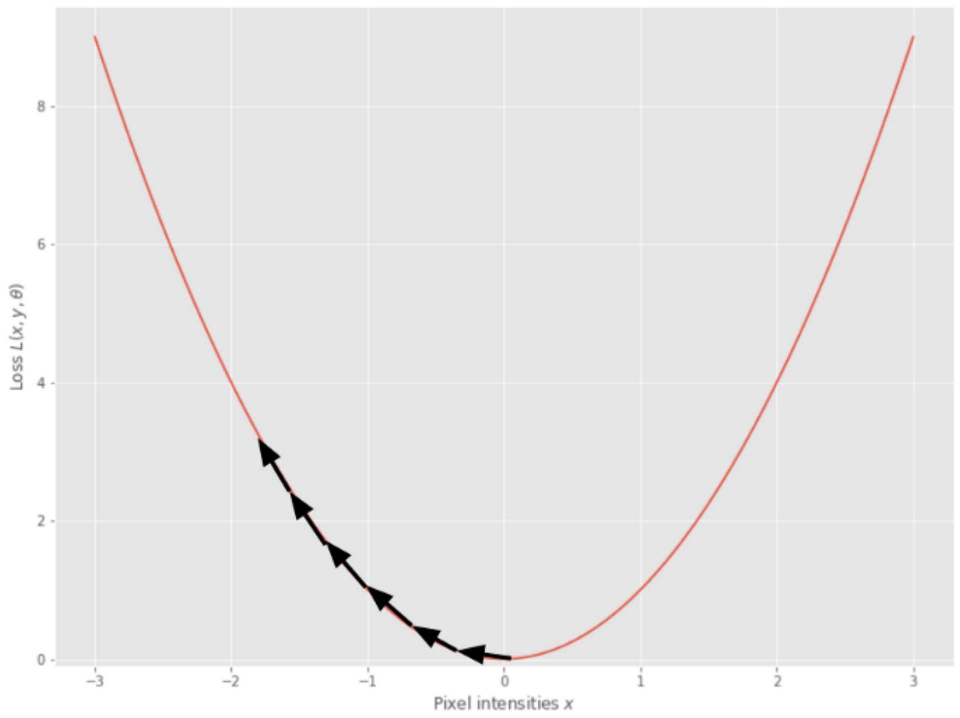
In a sense, gradients tell us how to improve the model performance by adjusting its parameters meaningfully.

Using Gradient Ascent to Attack

A possible approach to “smarter” attacks would then **turn this process on its head**.

- If we held the parameters of the model θ as constants and differentiated the loss with respect to some input sample x,
- We could then modify a sample x and create a new “somewhat similar” sample $\tilde{x}$, in a such a way that the expected loss of the model would increase.

- To do so, we would simply have to use some **gradient ascent** on this sample x.



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$$\theta \leftarrow \theta - \alpha \nabla_\theta L(x, \theta, y)$$

(Gradient **descent** on **parameters**, a.k.a. **"training"** a model)

Using Gradient Ascent to Attack

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- To do so, we would simply have to use some **gradient ascent** on this sample x.

$$\theta \leftarrow \theta - \alpha \nabla_{\theta} L(x, \theta, y)$$

(Gradient **descent** on **parameters**, a.k.a. **"training"** a model)

$$\tilde{x} \leftarrow x + \alpha \nabla_{x} L(x, \theta, y)$$

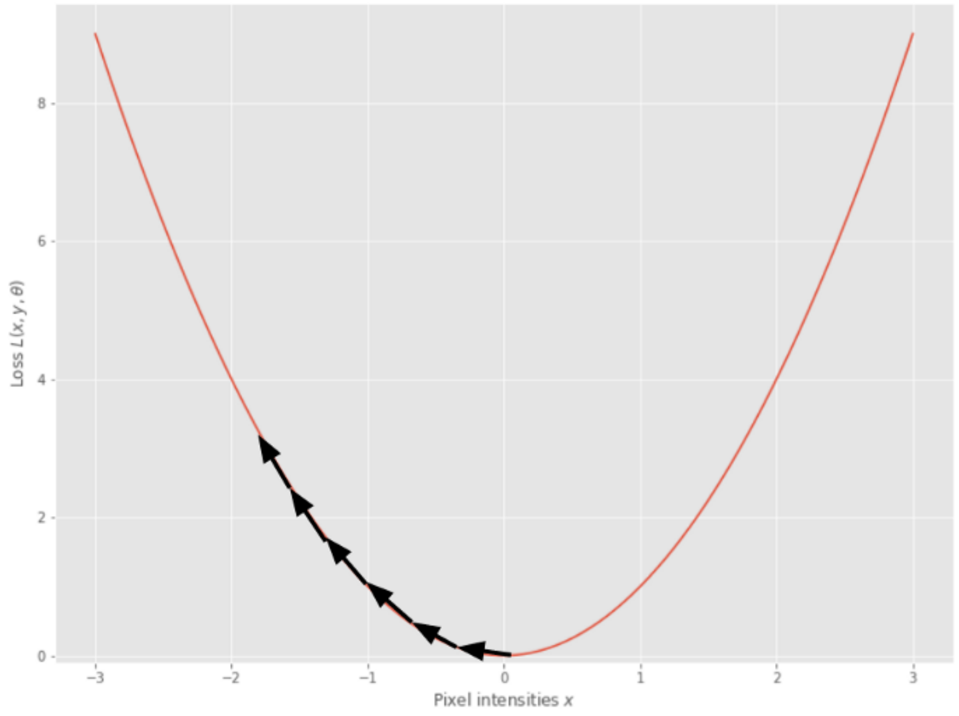
(Gradient **ascent** on a **sample**, a.k.a. "**attacking**" a model)

A note on losses, softmax and gradients

Most gradient-based attacks can operate on the gradients computed from the loss function $L(x, \theta, c)$, for instance, to move away from the original class c.

- To do so, by **increasing the loss** for said sample x and class c, using **gradient ascent** on the loss.

$$\tilde{x} \leftarrow x + \alpha \nabla_x L(x, \theta, c)$$

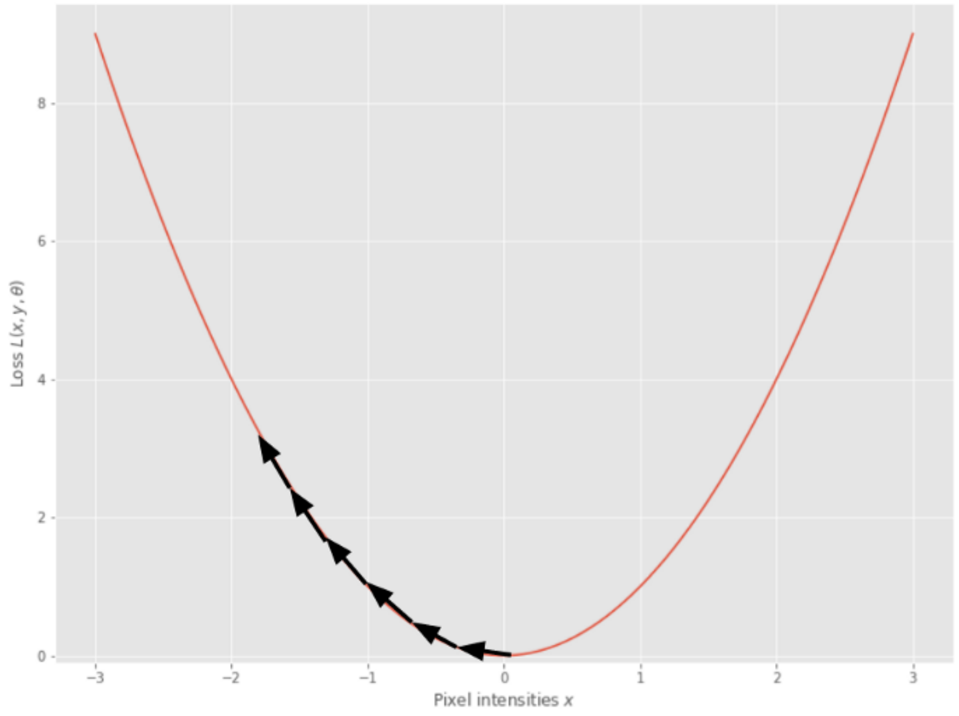


A note on losses, softmax and gradients

Some papers however mention that it would be preferable to use the logits $f_c(x)$ to **minimize the value of these logits ($\approx$ final vector before softmax and argmax decision)**.

- In that case, we would use **gradient descent** to minimize the probability of class c to be chosen!

$$\tilde{x} \leftarrow x - \alpha \nabla_x f_c(x)$$



Note: this second approach (logits) often works better, because of the softmax might end up messing up the gradients sometimes (to be seen later).

Untargeted Gradient Attack

Definition (untargeted gradient attack):

The **untargeted gradient attack** takes a single sample x, of original class $c \in C$ and attempts to produce a sample $\tilde{x}$ of class $\tilde{c} \in C$, with $\tilde{c} \neq c$.

$$c = argmax_{i \in C}\left(f_i(x)\right)$$

And then two options…

Restricted

Untargeted Gradient Attack (option #1)

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$$c = argmax_{i \in C}\left(f_i(x)\right)$$

And then two options…

- **Option #1:** Look for the most probable class $c \in C$ and use gradient **ascent** to move the sample **away from its original class**, with step ϵ.

$$\tilde{x} \leftarrow x + \epsilon \nabla_x L(x, \theta, c)$$

The attack is successful if

$$\tilde{c} = argmax_{i \in C}\left(f_i(\tilde{x})\right) \neq c$$

Untargeted Gradient Attack (option #2, not implemented in notebooks)

Definition (untargeted gradient attack):

The **untargeted gradient attack** takes a single sample x, of original class $c \in C$ and attempts to produce a sample $\tilde{x}$ of class $\tilde{c} \in C$, with $\tilde{c} \neq c$.

$$c = argmax_{i \in C}\left(f_i(x)\right)$$

And then two options…

- **Option #2:** Look for the least probable class $c^* \in C$ and use gradient **descent** to move the sample **in the direction of the least probable class**, with step ϵ.

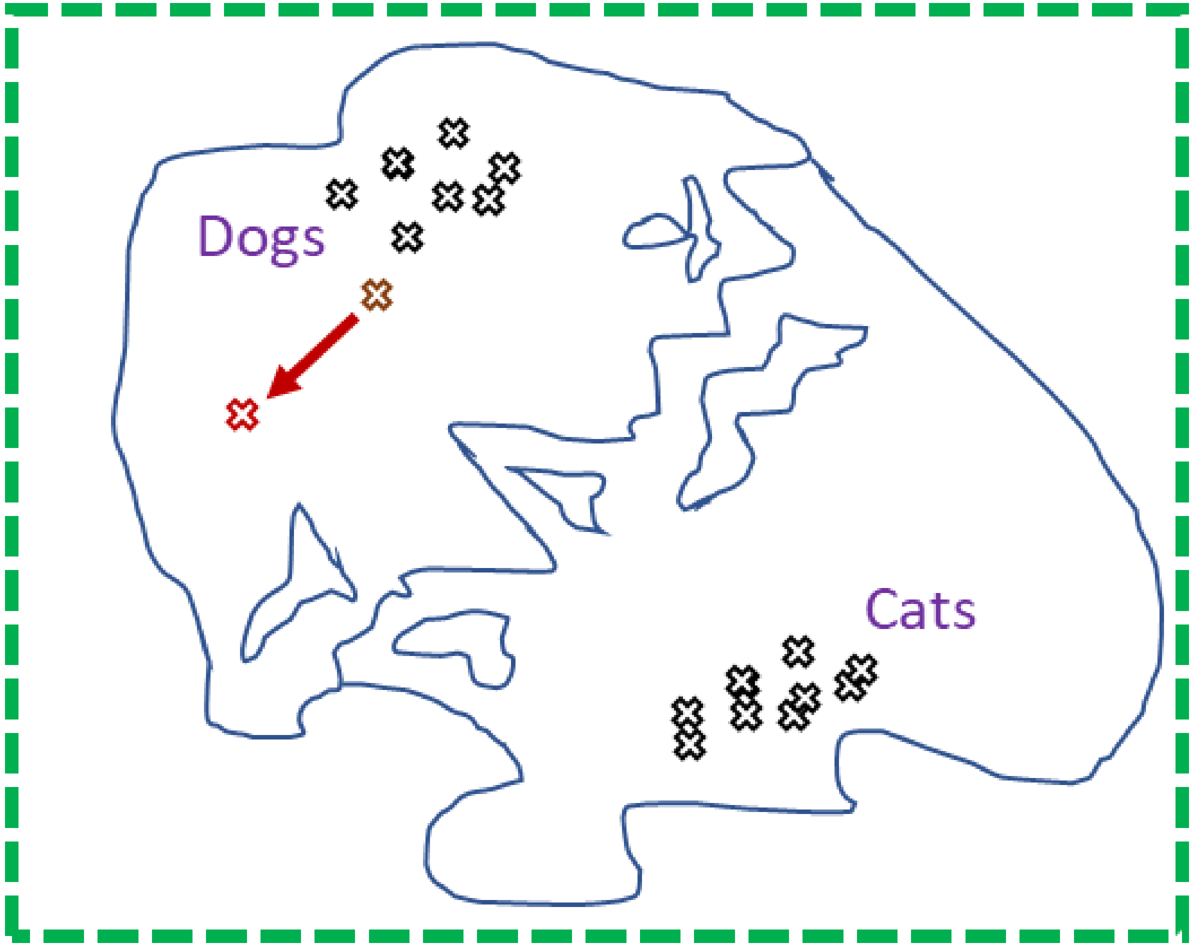
$$c^* = argmin_{i \in C}\left(f_i(x)\right)$$
$$\tilde{x} \leftarrow x - \epsilon \nabla_x L(x, \theta, c^*)$$

The attack is successful if

$$\tilde{c} = argmax_{i \in C}\left(f_i(\tilde{x})\right) \neq c$$

Why gradient attack works better than randomly noising

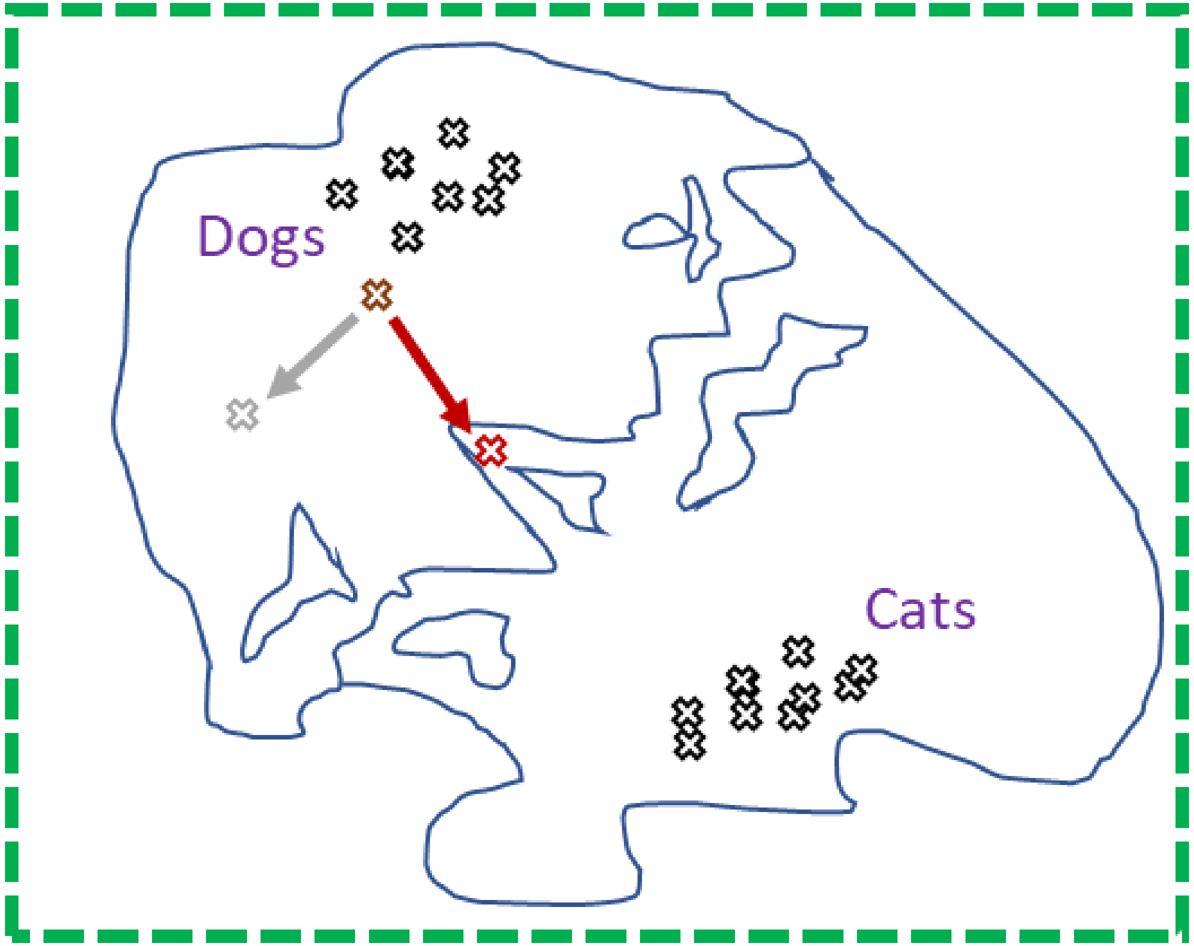
- When randomly noising a **sample** to make an **attack sample**, we move **randomly** in the feature map.



Why gradient attack works better than randomly noising

- When randomly noising a **sample** to make an **attack sample**, we move randomly in the feature map.

- When using gradient attack, we move in **a more meaningful direction**, which might help our **original sample** become **misclassified**.



Untargeted gradient attack code

The **untargeted gradient attack (option #1)** takes a single sample x, of original class $c \in C$ and attempts to produce a sample $\tilde{x}$ of class $\tilde{c} \in C$, with $\tilde{c} \neq c$.

- It uses gradient ascent to move the original sample **away from the most probable class** (i.e. its original one) to generate an attack sample.

```
1  def ugm_attack(image, epsilon, data_grad):
2  
3      # Create the attack image by adjusting
4      # each pixel of the input image
5      eps_image = image + epsilon*data_grad
6  
7      # Clipping eps_image to maintain pixel
8      # values into the [0, 1] range
9      eps_image = torch.clamp(eps_image, 0, 1)
10 
11     # Return
12     return eps_image
```

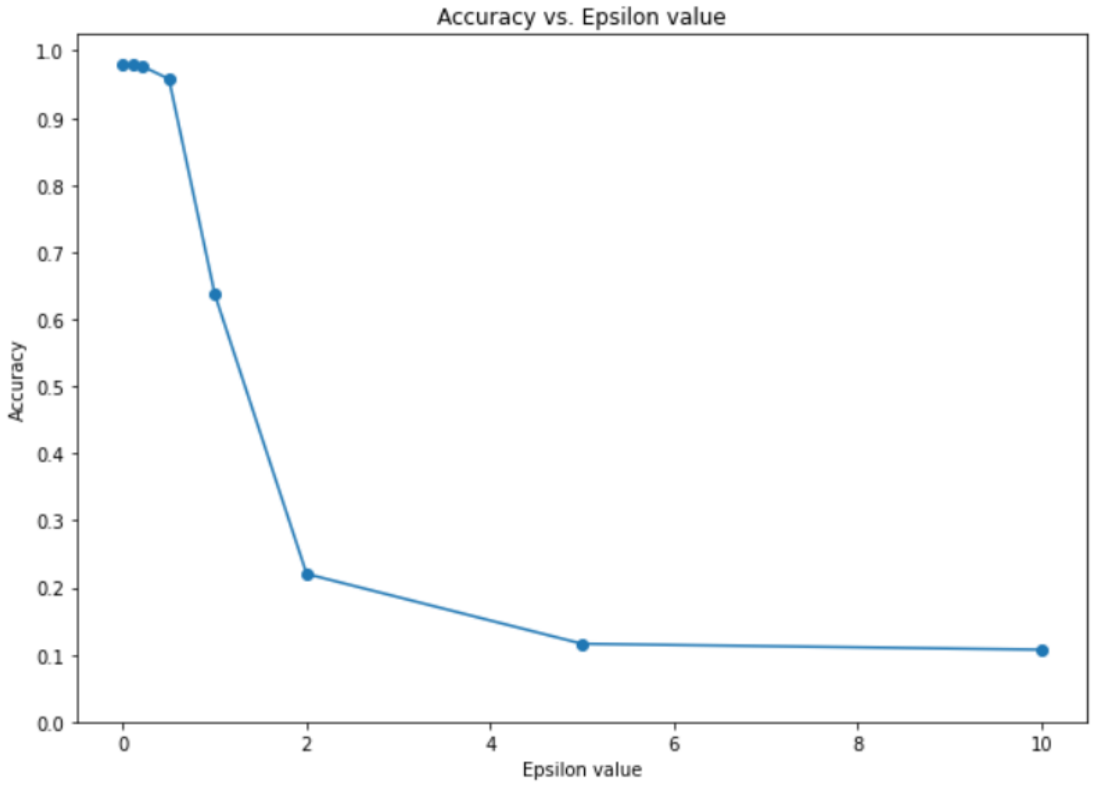
Line 5 easily implements

$$\tilde{x} \leftarrow x + \epsilon \nabla_x L(x, \theta, c)$$

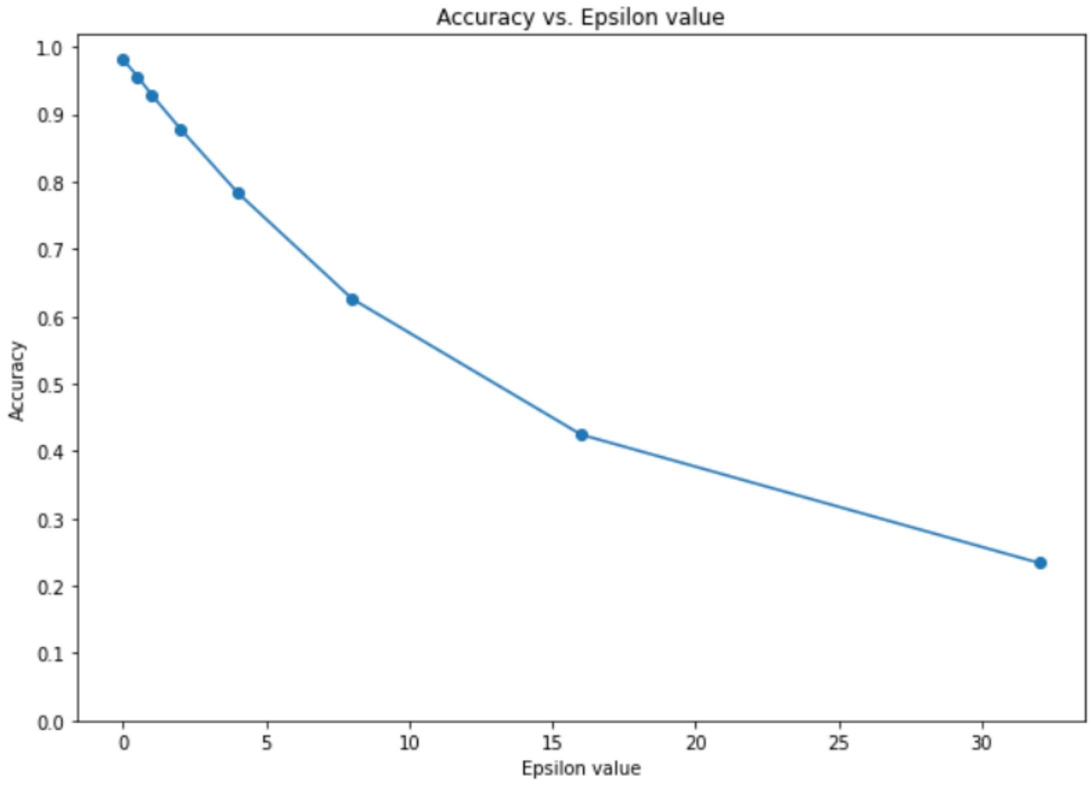
(Taken from notebook 2.)

Untargeted gradient vs. epsilon noising

- Epsilon Noising Method



- Untargeted Gradient Method



Untargeted gradient vs. epsilon noising

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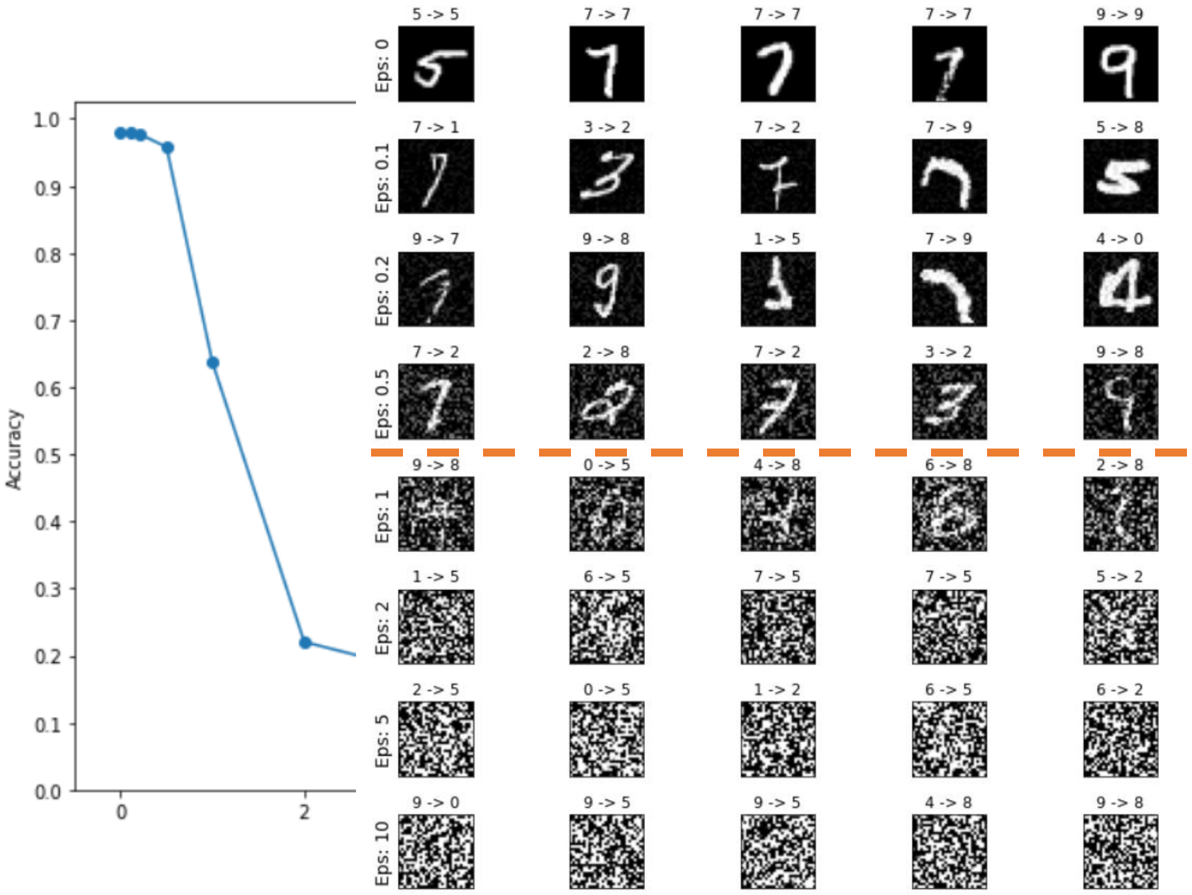
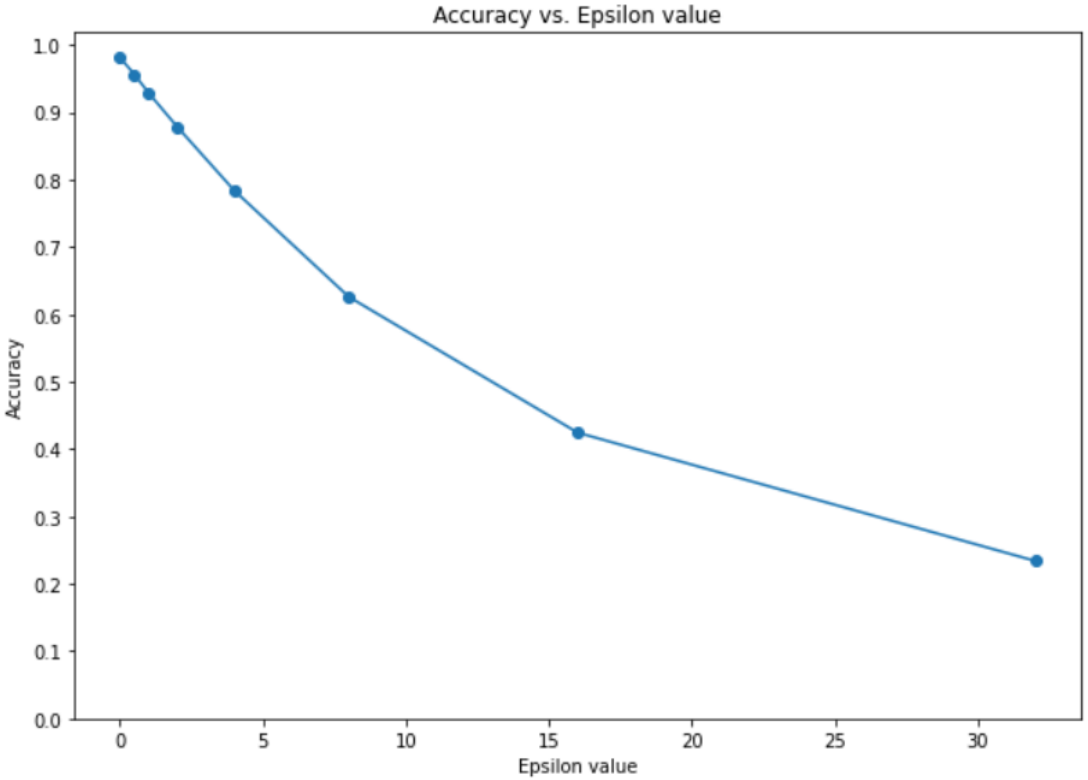


- Untargeted Gradient Method



Untargeted gradient vs. epsilon noising

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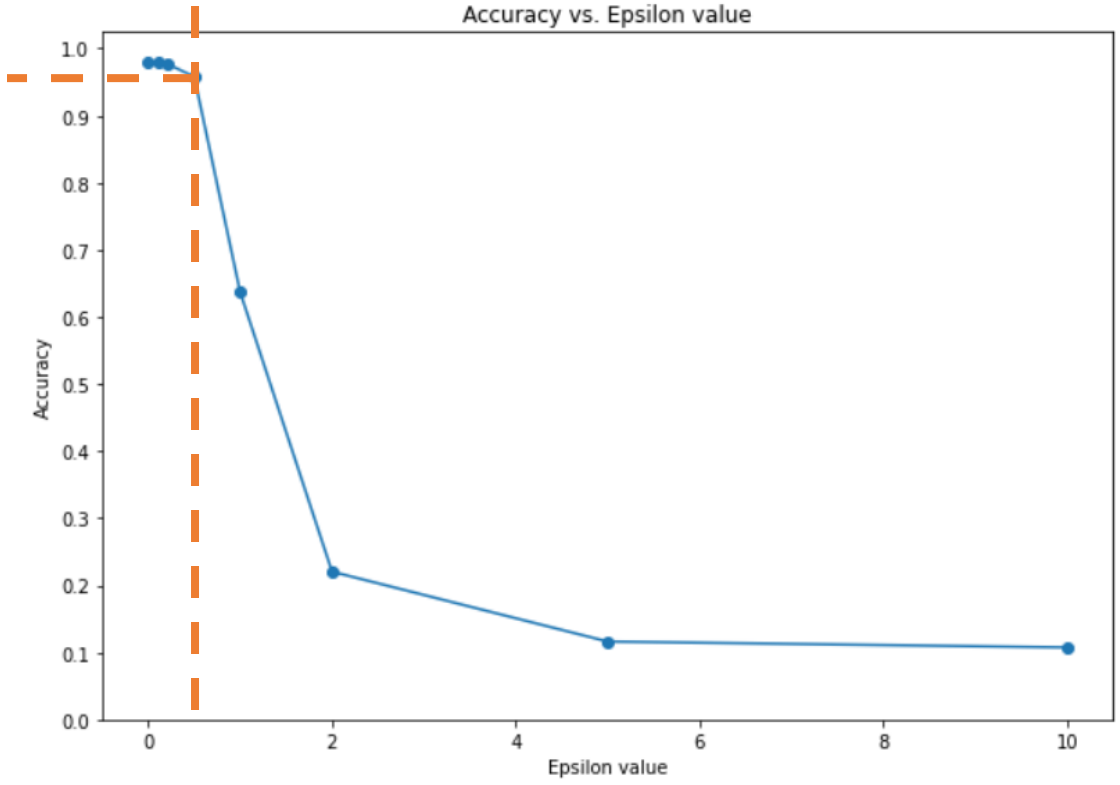
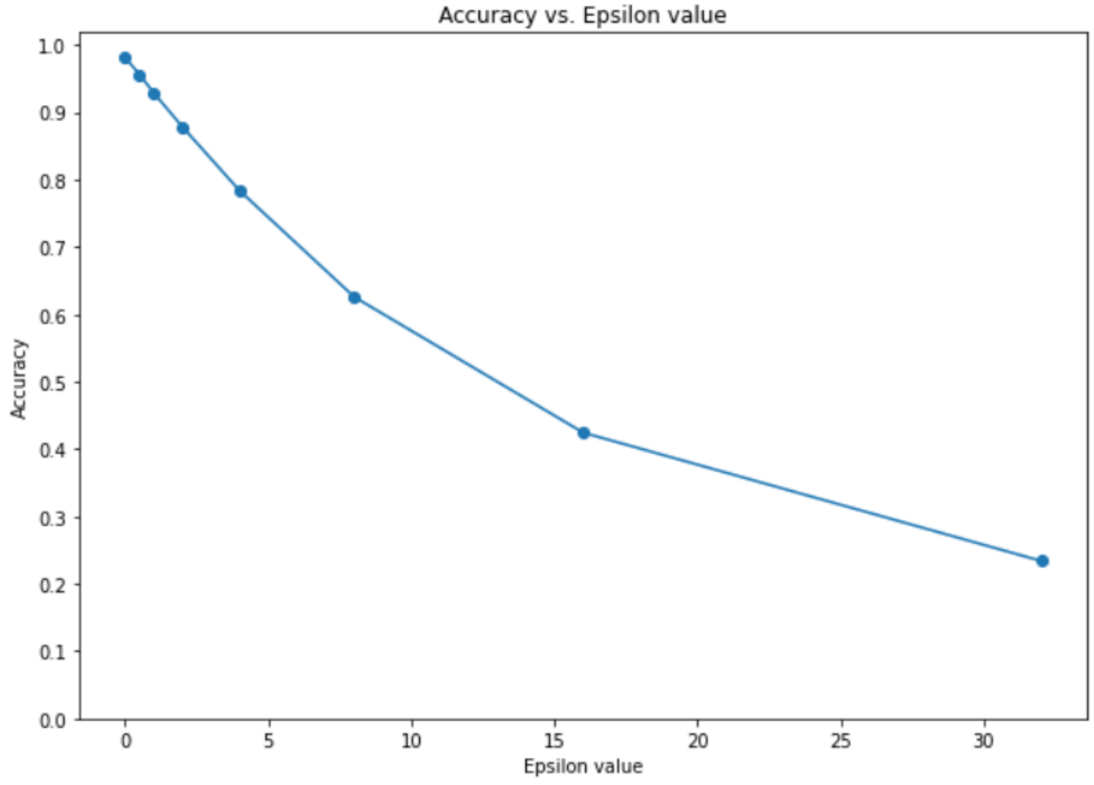


- Untargeted Gradient Method



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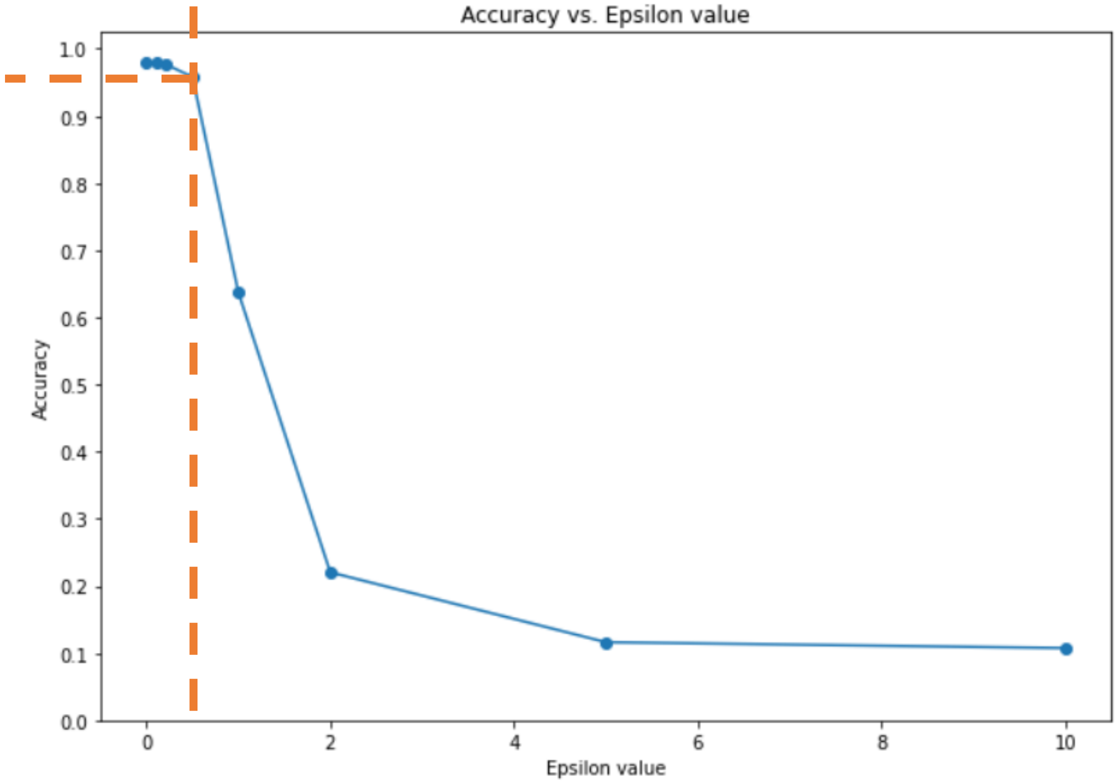
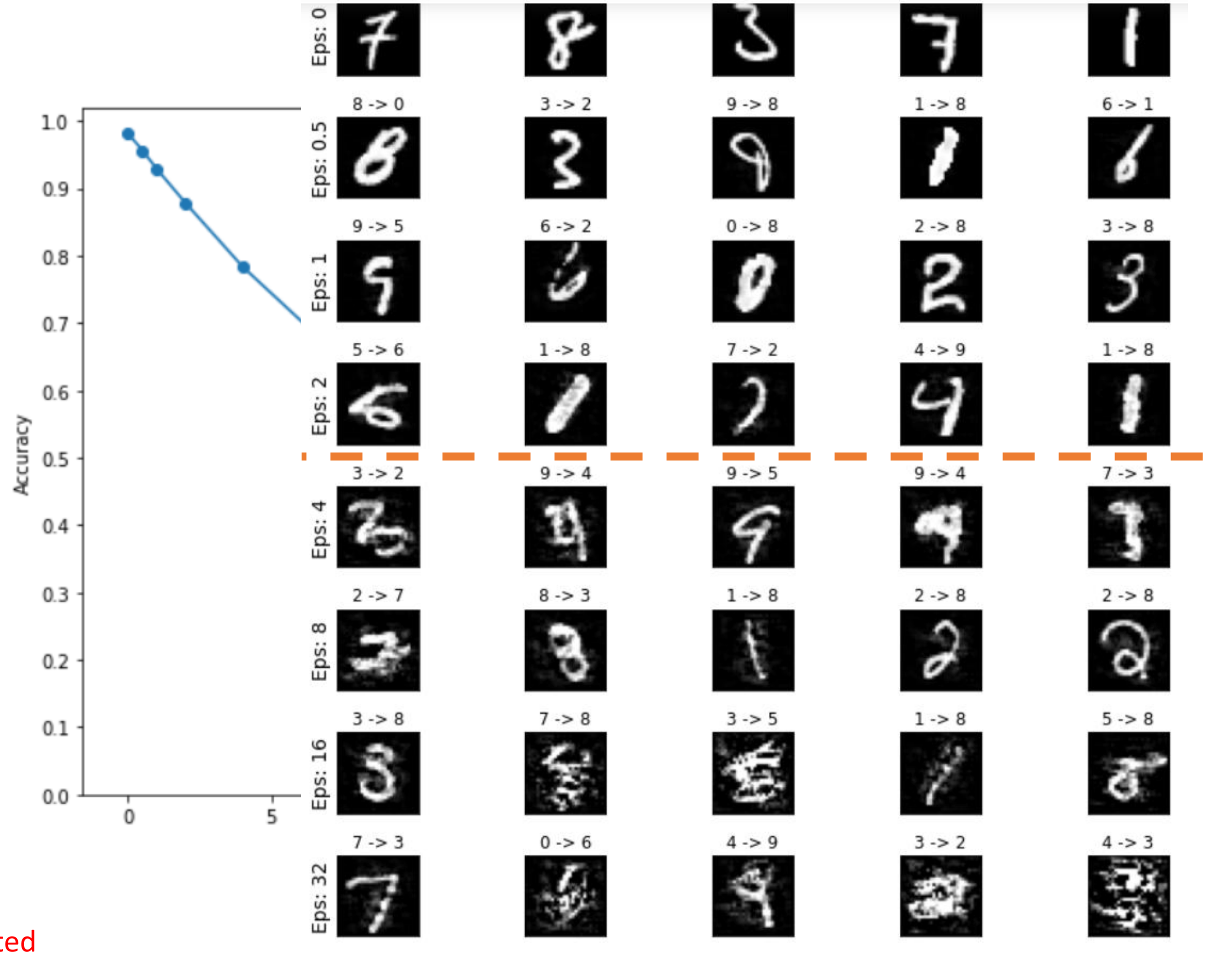


- Untargeted Gradient Method



Untargeted gradient vs. epsilon noising

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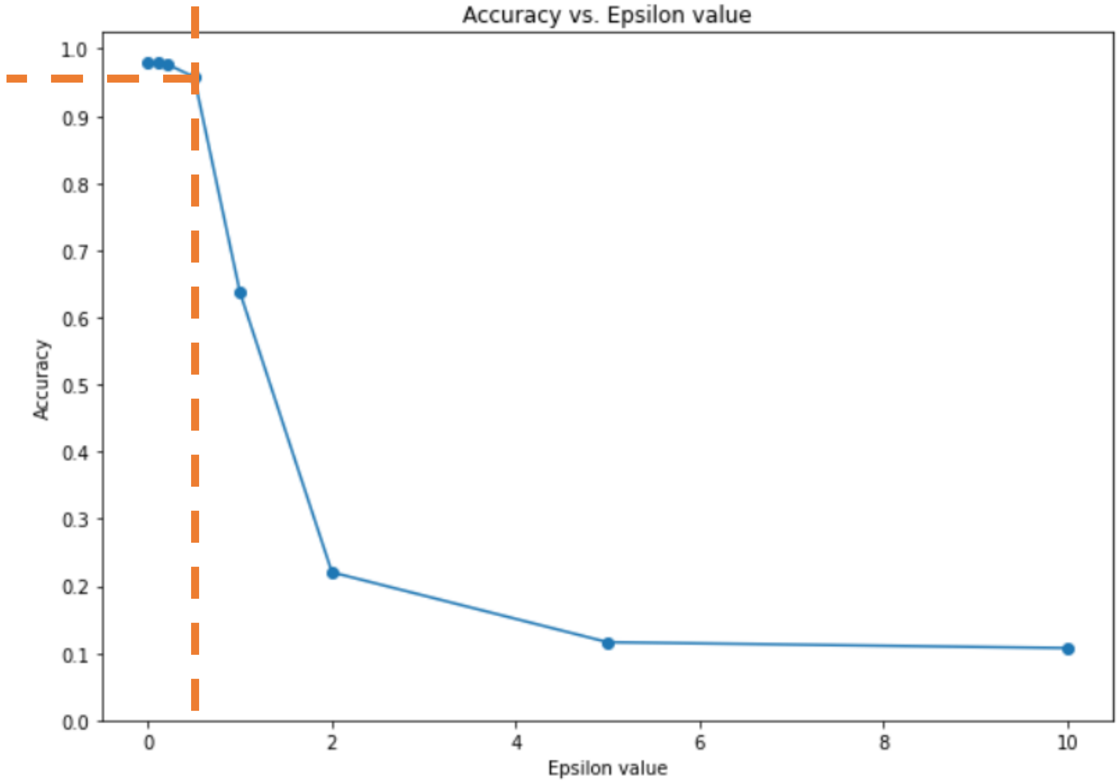

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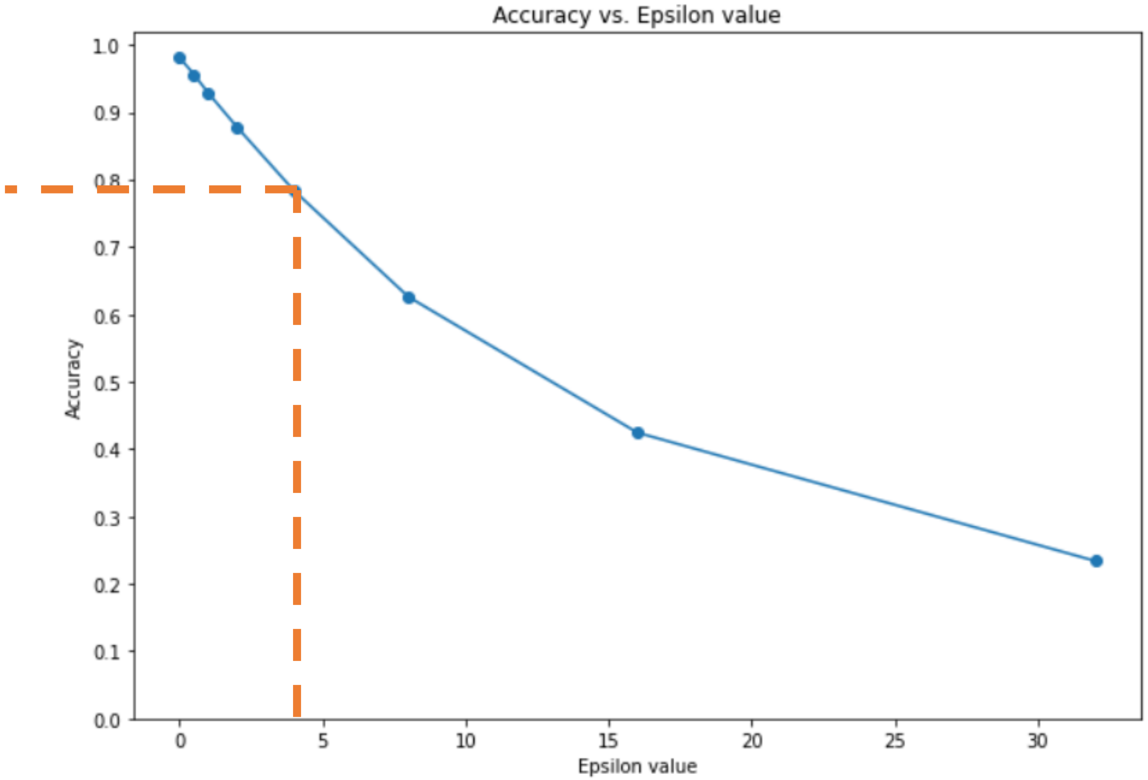
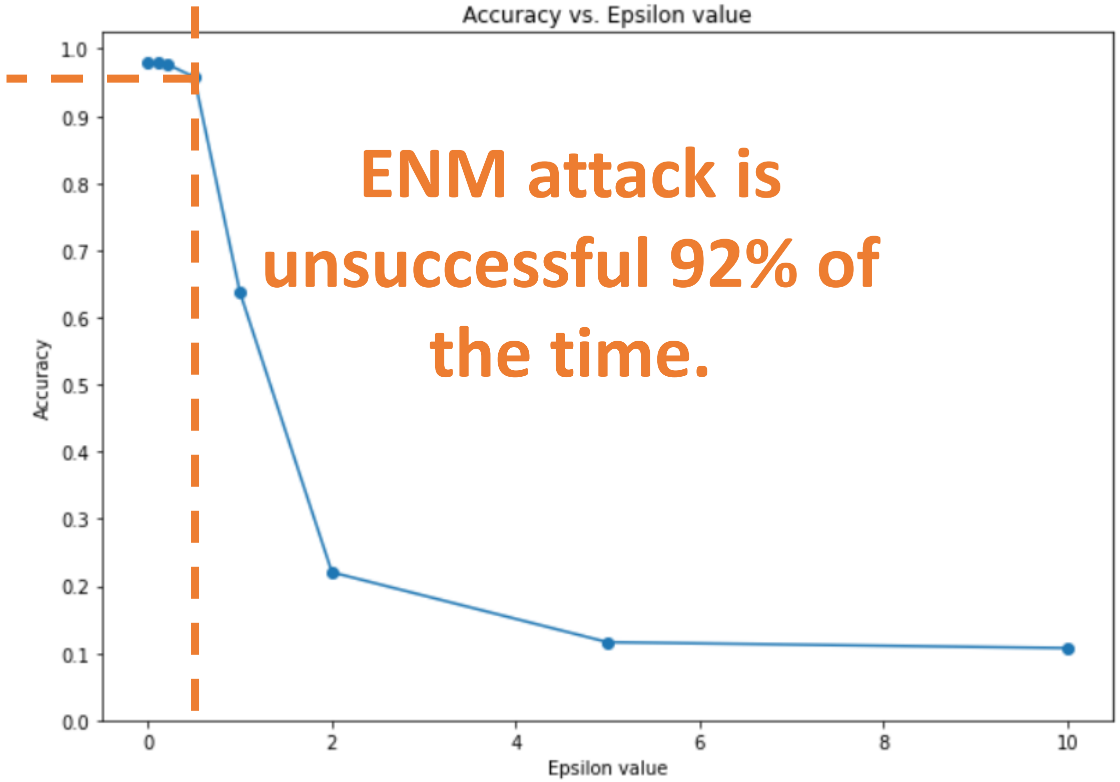


Untargeted gradient vs. epsilon noising

- Epsilon Noising Method



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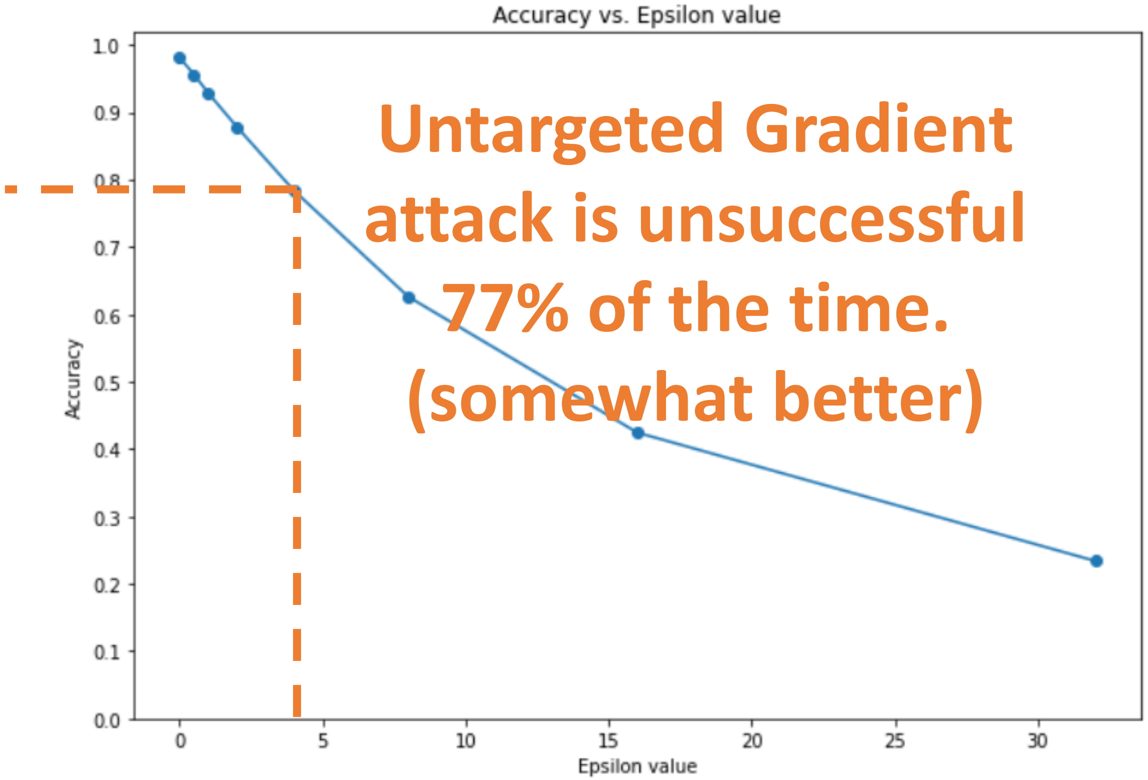
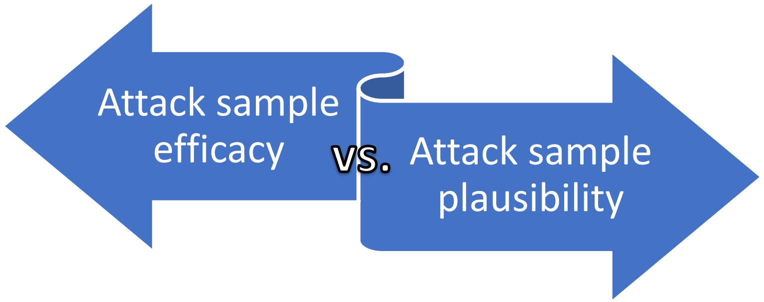


Untargeted gradient attack recap

- Like the Epsilon Noising Method from lecture 1, the Untargeted Gradient Method is an attack which is subject to the same **tradeoff** we identified earlier.



- However, **it performs better than the Epsilon Noising Method, as it is able to produce plausible attack samples that seem to fool the models more often** (~92% vs. ~77%, failure rates).

Untargeted gradient attack recap

This being said, it suffers from several problems:

- Its **efficacy is still rather low** (fails $\sim 77\%$ of the time).

Untargeted gradient attack recap

This being said, it suffers from several problems:

- Its **efficacy is still rather low** (fails $\sim 77\%$ of the time).
- It is a **one-shot** attack, which does not necessarily make sense.
  - The gradient descent algorithms takes multiple steps (batches + epochs) during training to converge…
  - Why would a single step of gradient attack be enough?
  - We should repeat the gradient attack multiple times (i.e. make it **iterated**).

Untargeted gradient attack recap

This being said, it suffers from several problems:

- Its **efficacy is still rather low** (fails $\sim 77\%$ of the time).
- It is a **one-shot** attack, which does not necessarily make sense.
- It is **untargeted**.
    - It attempts to invalidate the sample by moving away from its original label,
    - or in the direction of the least probable class.
    - This seems to indicate we can orient the direction in which we move and therefore **target** classes…

Untargeted gradient attack recap

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- It is **untargeted**.
- Its **plausibility is not too great.**
- (It has a **heavy computational cost**, as it requires the gradients from the model to be applied on a sample.)

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- It is **untargeted**.
- Its **plausibility is not too great.**
- (It has a **heavy computational cost**, as it requires the gradients from the model to be applied on a sample.)

Our next attack, the **Fast Gradient Sign Method** attempts to solve this heavy computational issue and help make more plausible samples.

Fast Gradient Sign Method (FGSM)

Definition (Fast Gradient Sign Method attack):

The **Fast Gradient Sign Method attack** only uses the **sign** of the gradient to create an attack sample.

$$\tilde{x} \leftarrow x + \epsilon \nabla_x L(x, \theta, c)$$

(Gradient attack)

$$\tilde{\boldsymbol{x}} \leftarrow \boldsymbol{x} + \boldsymbol{\epsilon}\, \mathbf{sign}(\boldsymbol{\nabla}_{\boldsymbol{x}} L(x, \theta, c))$$

(FGSM attack)

```python
def fgsm_attack(image, epsilon, data_grad):
    # Get element-wise signs of each element of the data gradient
    data_grad_sign = data_grad.sign()

    # Create the attack image by adjusting each pixel of the input image
    eps_image = image + epsilon*data_grad_sign

    # Clipping eps_image to maintain pixel values into the [0, 1] range
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(FGSM attack)

Important property: this also helps to make more plausible samples, as it will, by design, verify $\|\tilde{x} - x\|_\infty \leq \epsilon$.

- (**Plausibility constraint** that we did not have it in the previous attacks!)

```python
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    # Return
    return eps_image
```

Remember

- $\boldsymbol{L^0}$ **norm:** bounds the total number of pixels in $\tilde{x}$ that can be modified with respect to x (though they can be modified by any amount).
- $\boldsymbol{L^1}$ **norm:** bounds the average absolute distance between the values of pixels in $\tilde{x}$ and the corresponding pixels in x.
- $\boldsymbol{L^2}$ **norm:** bounds the total squared distance between the values of pixels in $\tilde{x}$ and the corresponding pixels in x. Often referred to as the Euclidean distance.
- $\boldsymbol{L^\infty}$ **norm:** bounds the maximum difference between any pixel in $\tilde{x}$ and the corresponding pixel in x. Often referred to as max norm.

$$\|\tilde{x} - x\|_\infty = \max_{i,j}\left(\left|\tilde{x}_{i,j} - x_{i,j}\right|\right)$$

Preferred one!

Testing the FGSM attack

The FGSM attack works just fine, and it might even make the **model completely malfunction!**

- In the noising approach, the model had to guess randomly and ended up getting a 10% accuracy for large values of epsilon.
- Here, the FGSM will strongly push the model to malfunction, eventually leading to a **0%** accuracy.

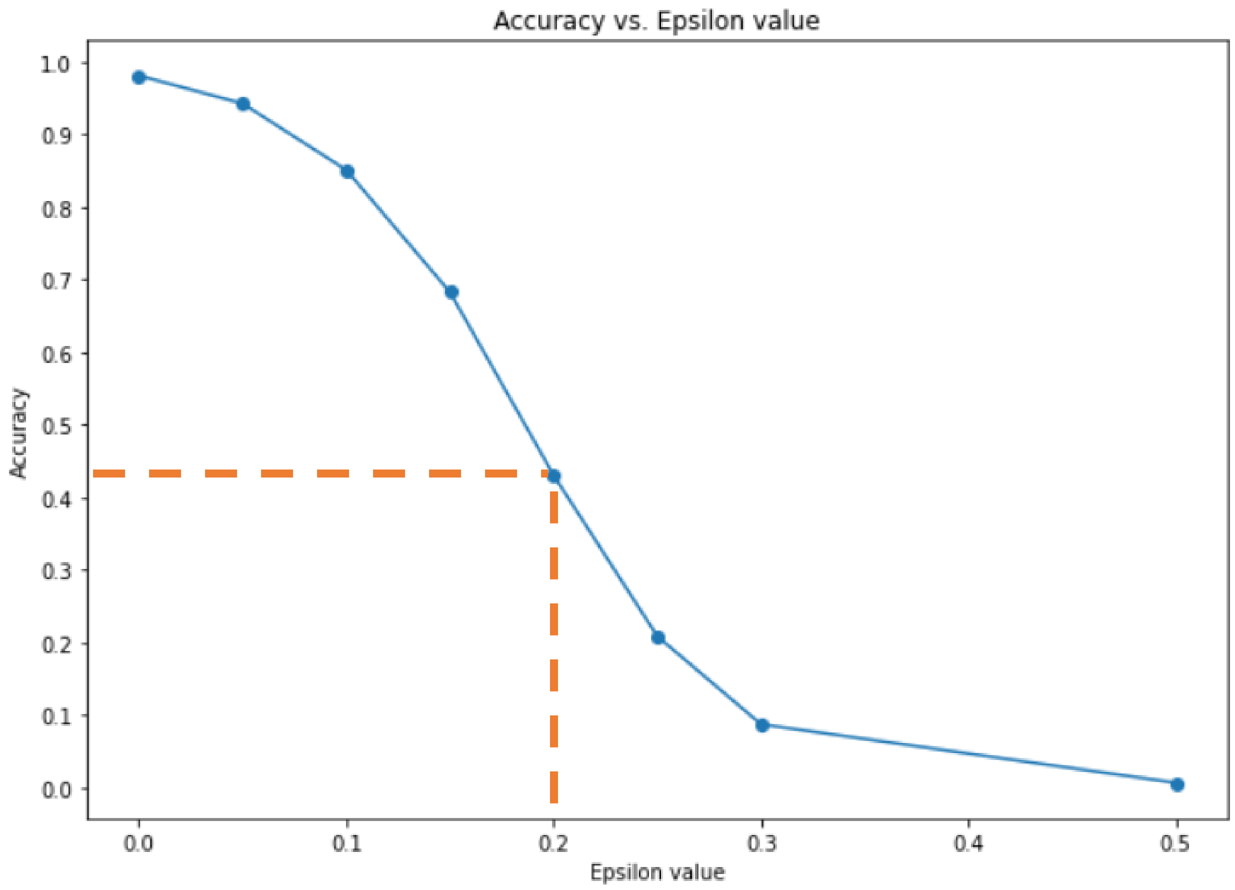
```
epsilons = [0, .05, .1, .15, .2, .25, .3, .5]
accuracies = []
examples = []

# Run test() function for each epsilon
for eps in epsilons:
    acc, ex = test(model, device, test_loader, eps)
    accuracies.append(acc)
    examples.append(ex)
```

```
Epsilon: 0 - Test Accuracy = 9810/10000 = 0.981
Epsilon: 0.05 - Test Accuracy = 9426/10000 = 0.9426
Epsilon: 0.1 - Test Accuracy = 8510/10000 = 0.851
Epsilon: 0.15 - Test Accuracy = 6826/10000 = 0.6826
Epsilon: 0.2 - Test Accuracy = 4301/10000 = 0.4301
Epsilon: 0.25 - Test Accuracy = 2082/10000 = 0.2082
Epsilon: 0.3 - Test Accuracy = 869/10000 = 0.0869
Epsilon: 0.5 - Test Accuracy = 63/10000 = 0.0063
```

From Notebook 3.

Testing the FGSM attack



Restricted

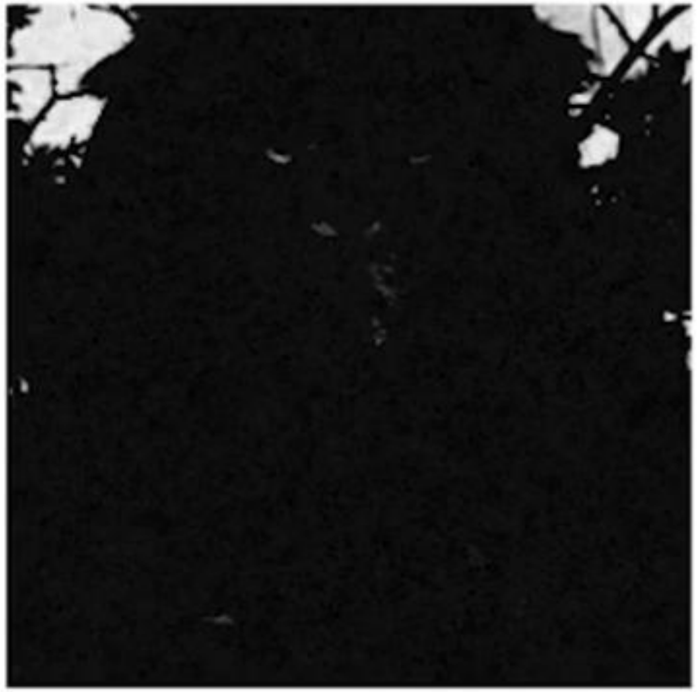
lion

golden retriever

Original: 291

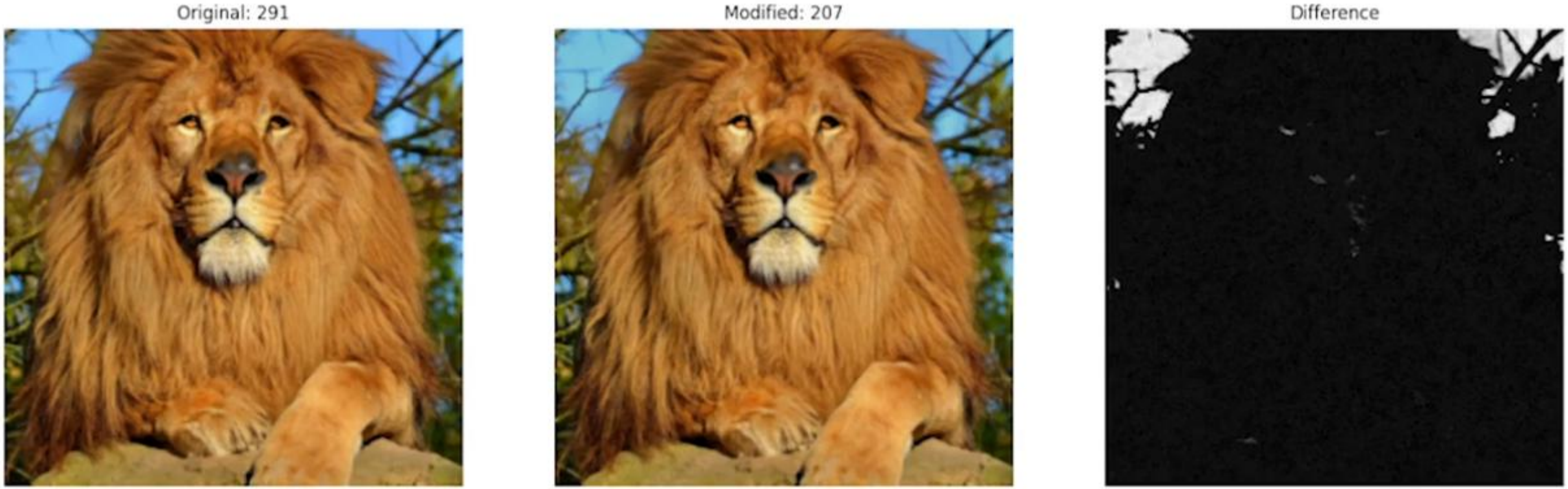
Modified: 207

Difference



lion

golden
retriever



Background pixels were changed and this led to an entirely different classification result?! This indicates that our model probably has a wrong classification logic somewhere…

From [Goodfellow2015].

Some more taxonomy on attacks

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A **one-shot attack** attempts to produce a single attack sample, and if this attack fails, it simply retries on a different sample.

Noising was therefore a **one-shot attack**. It attempted to noise a sample to have it misclassified.

However, if this attempt failed, it simply tried on another sample.

Definition (iterated attack):

An **iterated attack** attempts to produce an attack sample, like the one-shot attacks.

However, it will try to **adjust the said sample** until it either

- **makes the model malfunction in an expected way**,
- or **reaches a maximal number of allowed iterations**.

The iterated attacks are often more robust and efficient.

Iterative FGSM attack (from [Kurakin2016])

Definition (iterative Fast Gradient Sign Method attack):

The **iterative Fast Gradient Sign Method attack** will repeat the FGSM attack until it reaches a maximal number of iterations or makes the model malfunction.

$$\boldsymbol{x_0 = x}$$
$$\boldsymbol{x_{n+1} \leftarrow x_n + \epsilon\, \mathbf{sign}(\nabla_{x_n} L(x_n, \theta, c))}$$

Core idea behind iterating: gradient descent was used for several iterations to <u>train</u> our model, so why should our <u>attacks</u> be using only one iteration of gradient ascent?

Some more taxonomy on attacks

Definition (untargeted attack):

The objective of an **untargeted attack** is to produce an attack sample, which will simply be misclassified.

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Definition (targeted attack):

The objective of a **targeted attack** is to produce an attack sample, which will be misclassified as a specific class.

As such, **targeted attacks** are often **more complex** than **untargeted ones**.

E.g., modify a picture of a **dog (original label)**, so it is misclassified as a **cat (target label)**.

Targeted FGSM attack

Definition (targeted Fast Gradient Sign Method attack):

The **targeted Fast Gradient Sign Method attack** will use the FGSM attack but will use the gradients of a targeted class $\tilde{c}$.

This follows the same logic as moving towards the least probable class as in Gradient attack option #2, but you can use it with any class of your choice $\tilde{c}$ instead of the least probable one.

This attack uses gradient descent to move the sample towards the targeted class $\tilde{c}$.

$$\tilde{x} \leftarrow x - \epsilon \, \mathbf{sign}(\nabla_x L(x, \theta, \tilde{c}))$$

Untargeted gradient attack recap

This being said, it suffers from several problems:

- Its **efficacy is still rather low** (fails ~77% of the time).
- It is a **one-shot** attack, which does not necessarily make sense.
- It is **untargeted**.
- Its **plausibility is not too great.**
- (It has a **heavy computational cost**, as it requires the gradients from the model to be applied on a sample.)

Iterative and Targeted FGSM attack

Definition (iterative targeted Fast Gradient Sign Method attack):

The **iterative targeted Fast Gradient Sign Method attack** will use the FGSM attack but will use the gradients of a targeted class $\tilde{c}$.

This follows the same logic as moving towards the least probable class as in Gradient attack option #2, but you can use it with any class of your choice $\tilde{c}$ instead of the least probable one. This attack uses gradient descent to move the sample towards the targeted class $\tilde{c}$.

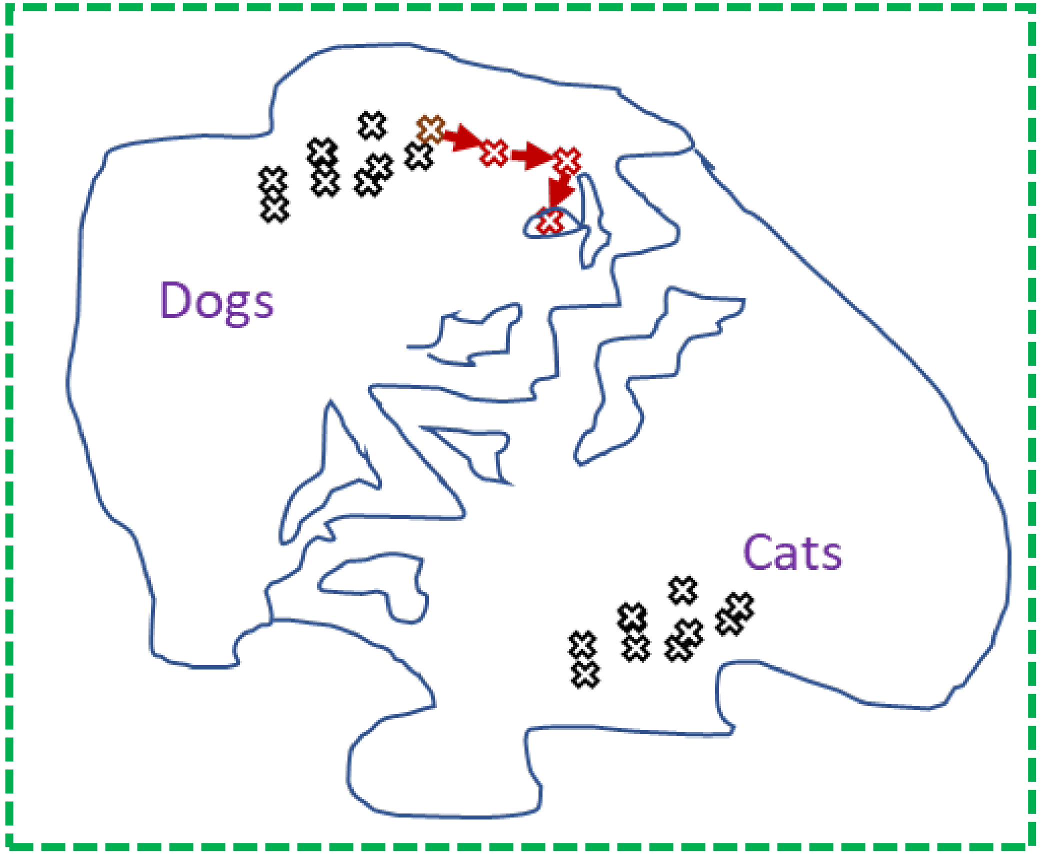
This is repeated until it reaches a maximal number of iterations or makes the model malfunction with targeted class $\tilde{c}$.

$$x_0 = x$$

$$x_{n+1} \leftarrow x_n - \epsilon \, \mathrm{sign}(\nabla_x L(x_n, \theta, \tilde{c}))$$

Why gradient attack works better than randomly noising

- When randomly noising a **sample** to make an **attack sample**, we move randomly in the feature map.
- When using a gradient-type attack, we move in a more meaningful direction, which might help our **original sample** become **misclassified**.
- **Iterating** allows for smaller steps and **better plausibility** in general (smaller changes in original image).



```python
def itfgsm_attack(image, epsilon, model, orig_class, target_class, iter_num = 10):

    # Convert target class to a LongTensor with one element
    # (Expected format for the F.nll_loss later on)
    target_class_var = Variable(torch.from_numpy(np.asarray([target_class])))
    target_class_torch = target_class_var.type(torch.LongTensor)
    worked = False

    for i in range(iter_num):
        # Zero out previous gradients
        image.grad = None
        # Forward pass
        out = model(image)
        # Calculate loss
        pred_loss = F.nll_loss(out, target_class_torch)

        # Do backward pass and retain graph
        #pred_loss.backward()
        pred_loss.backward(retain_graph = True)

        # Add noise to processed image
        eps_image = image - epsilon*torch.sign(image.grad.data)
        eps_image.retain_grad()

        # Clipping eps_image to maintain pixel values into the [0, 1] range
        eps_image = torch.clamp(eps_image, 0, 1)

        # Forward pass
        new_output = model(eps_image)
        # Get prediction
        _, new_label = new_output.data.max(1)

        # Check if the new_label matches target, if so stop
        if new_label == target_class_torch:
            worked = True
            break
        else:
            image = eps_image
            image.retain_grad()

    return eps_image, worked, i
```

From Notebook 4.

Testing the ITFGSM attack

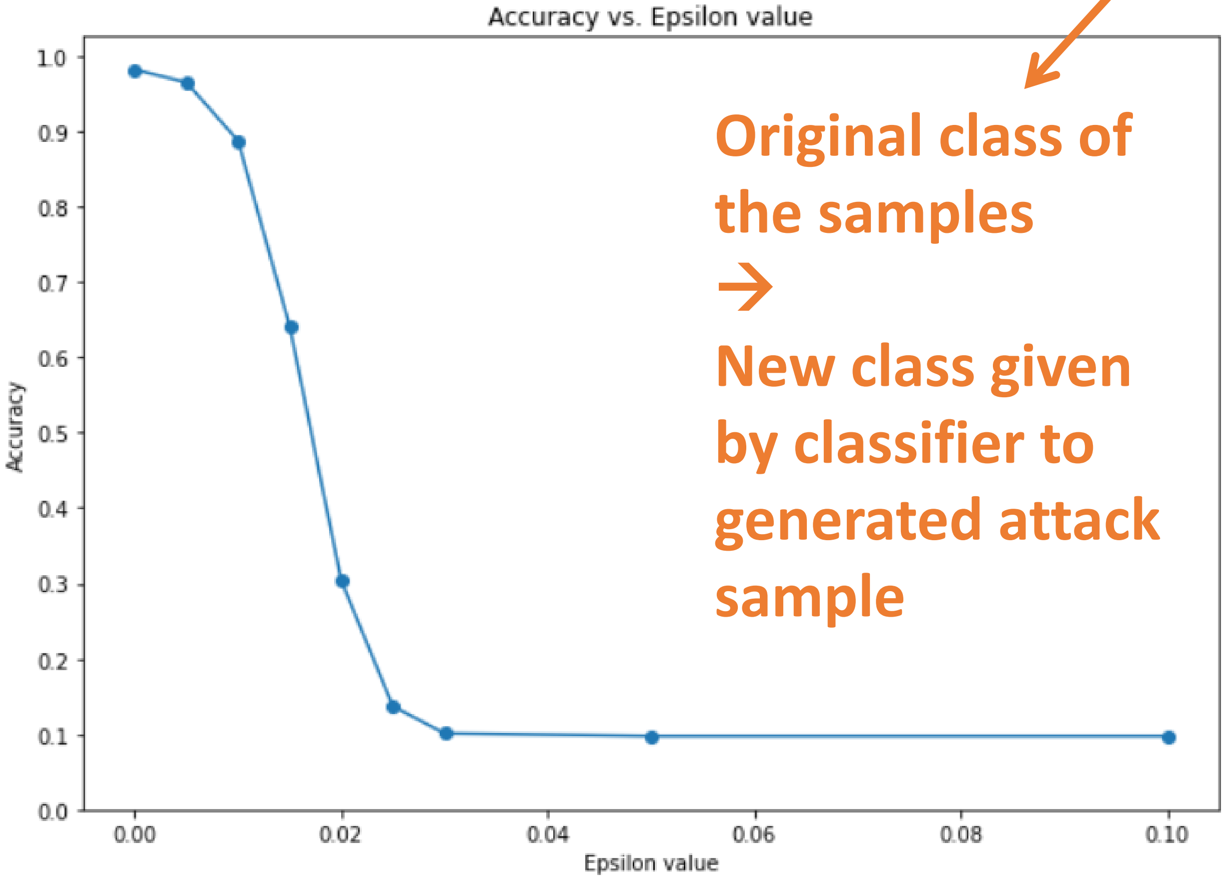
```
def test(model, device, test_loader, epsilon):

    # Target class
    target_class = 8

    # Counter for correct values (used for accuracy)
    correct_counter = 0

    # List of successful adversarial samples
    adv_examples_list = []

    # Loop over all examples in test set
    for image, label in test_loader:

        # If the initial label is already matching the target class,
        # do not bother attacking, skip current image
        if target_class == label.item():
            correct_counter += 1
            continue

        # Send the data and label to the device
        image, label = image.to(device), label.to(device)

        # Set requires_grad attribute of tensor to force torch to
        # keep track of the gradients of the image
        # (Needed for the ugm_attack() function!)
        image.requires_grad = True

        # Pass the image through the model
        output = model(image)
        # Get the index of the max log-probability
        init_pred = output.max(1, keepdim = True)[1]

        # If the initial prediction is wrong, do not bother attacking, skip current image
        if init_pred.item() != label.item():
            continue

        # Call TFGSM Attack
        eps_image, worked, iterations = itfgsm_attack(image, epsilon, model, label, target_class)
```

If sample is already of the target class, attack cannot happen…

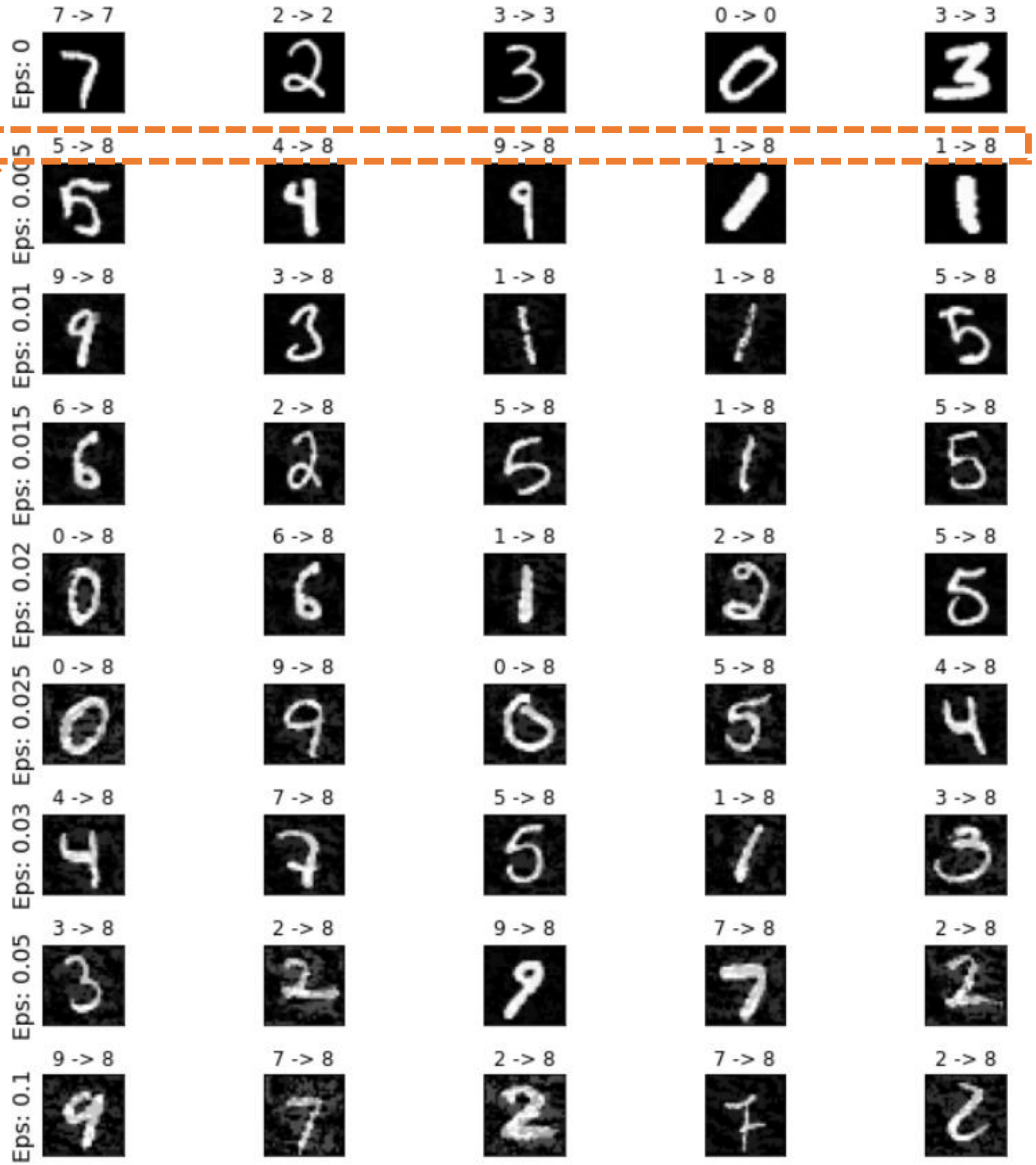
We cannot modify a picture of an 8 so that it becomes misclassified as an 8! Skip these.

Restricted

Testing the ITFGSM attack



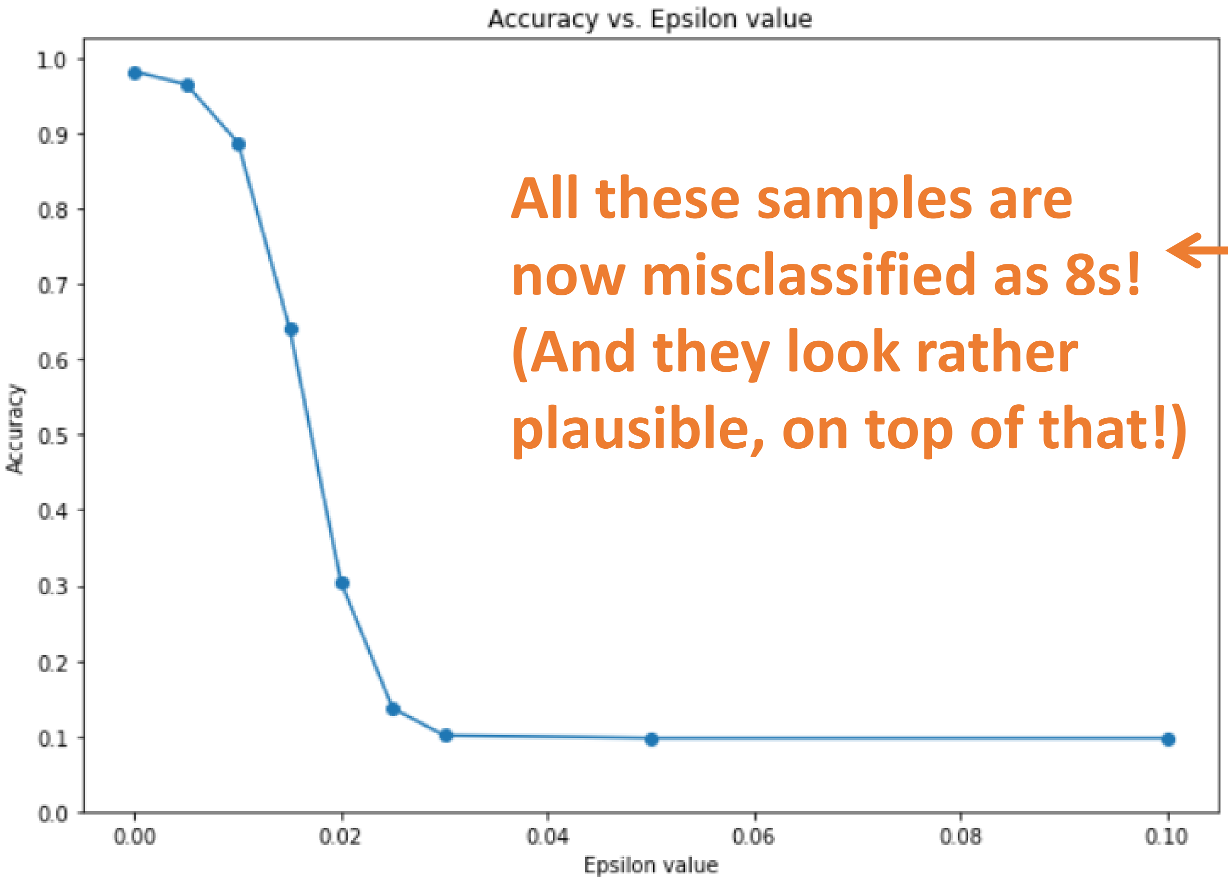
Original class of the samples → New class given by classifier to generated attack sample



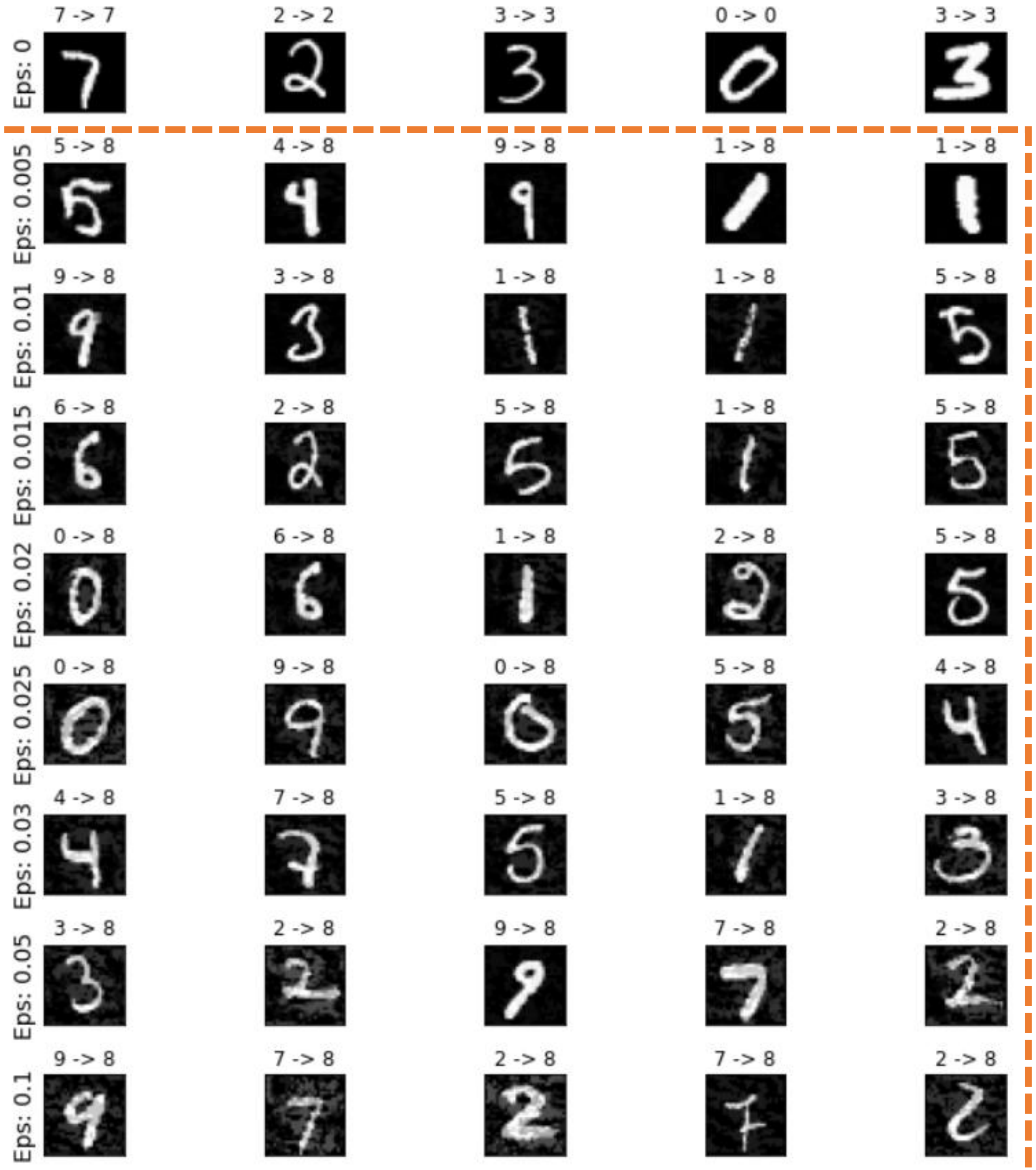
Restr

Restr

Testing the ITFGSM attack

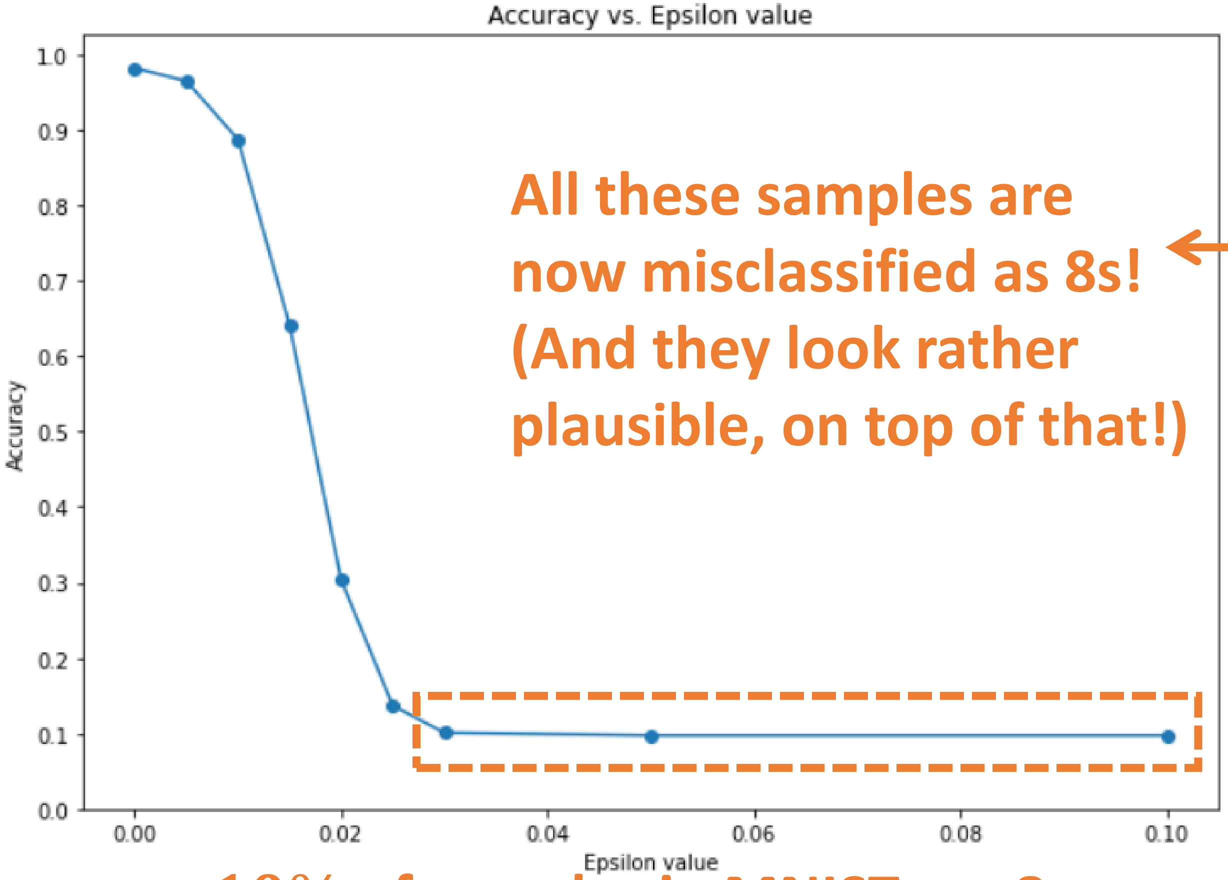


All these samples are now misclassified as 8s! (And they look rather plausible, on top of that!)

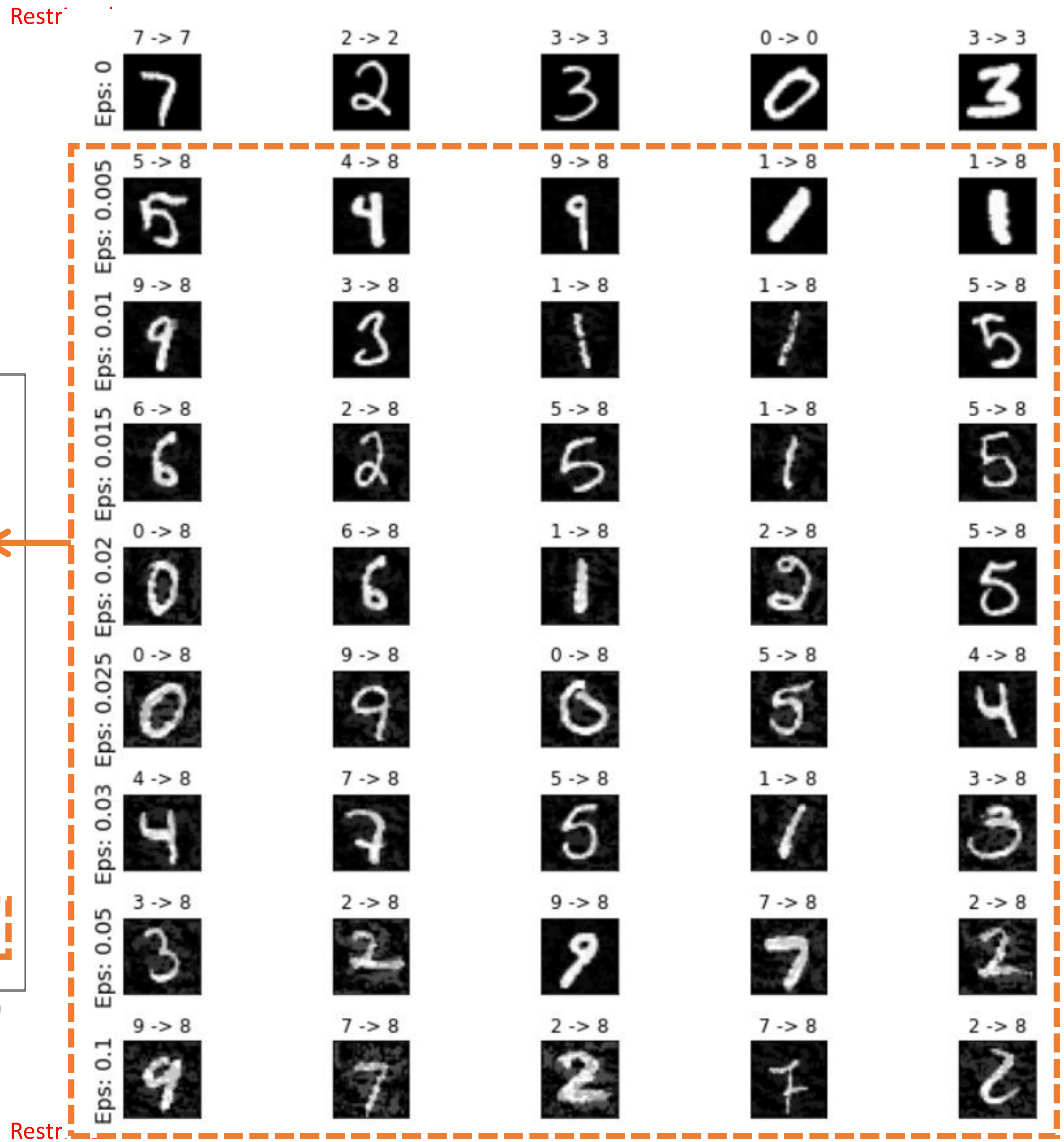


Restr

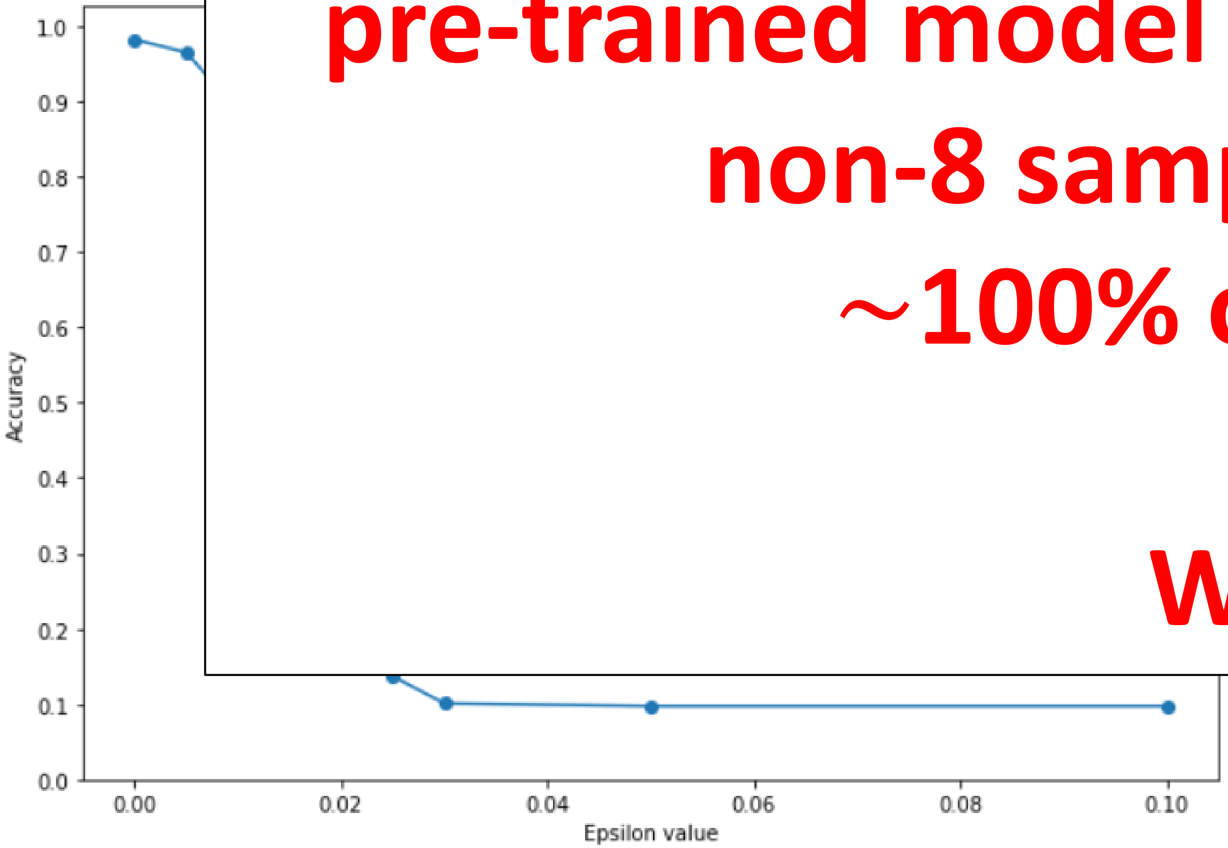
Testing the ITFGSM attack



All these samples are now misclassified as 8s! (And they look rather plausible, on top of that!)



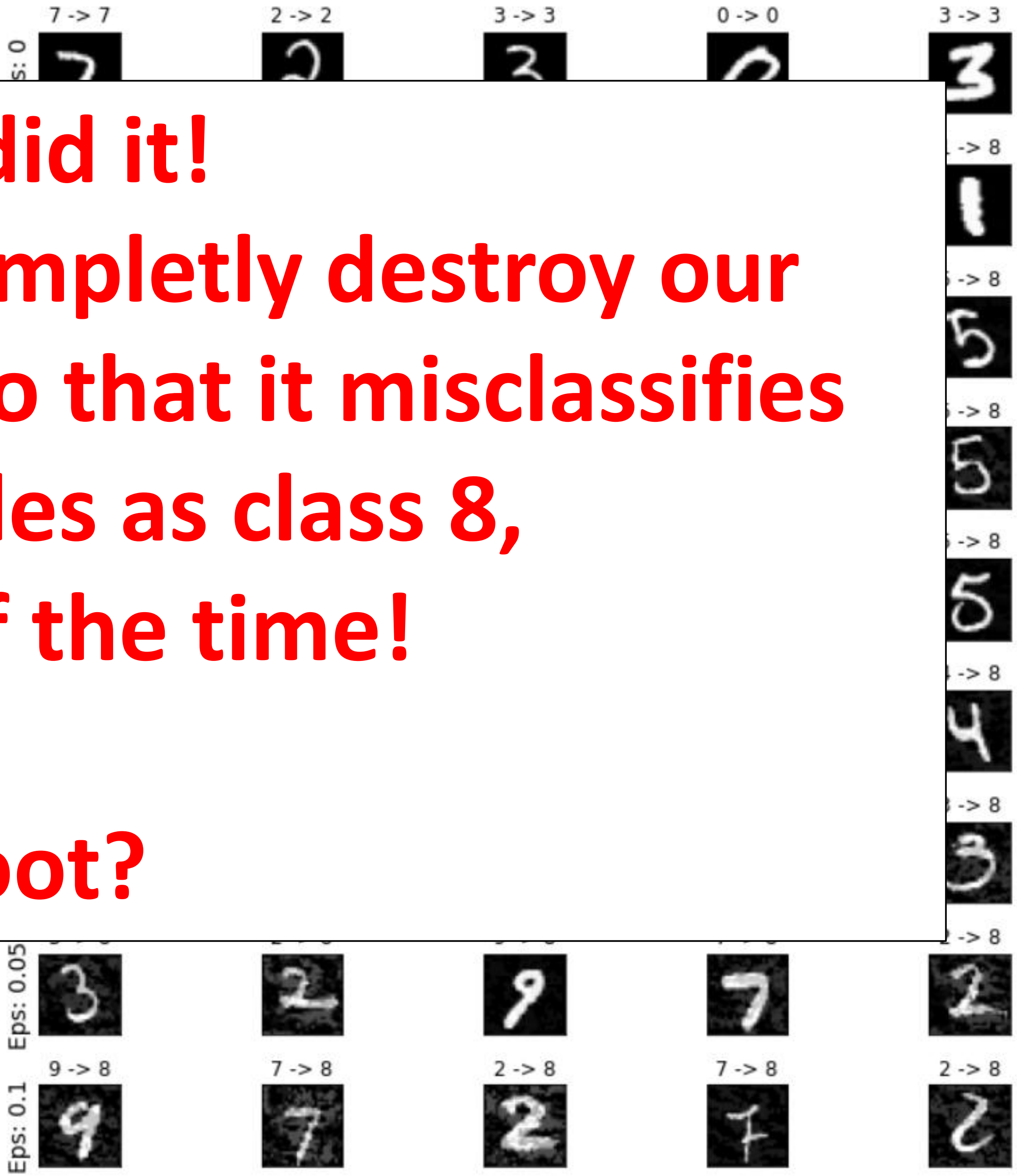
~10% of samples in MNIST are 8s and cannot be attacked



We did it!

We managed to completly destroy our pre-trained model so that it misclassifies non-8 samples as class 8, ~100% of the time!

Woot?



(Wait, actually, that is scary, I never EVER want to trust a Neural Network again…!)

Remember, there is more... Reason #2: Defense

Definition (Defense on Neural Networks):

In adversarial machine learning, **defense** refers to machine learning techniques that attempt to **protect models from being attacked** by malicious attempts.

Important: defense mechanisms often rely on an understanding of how attacks work.

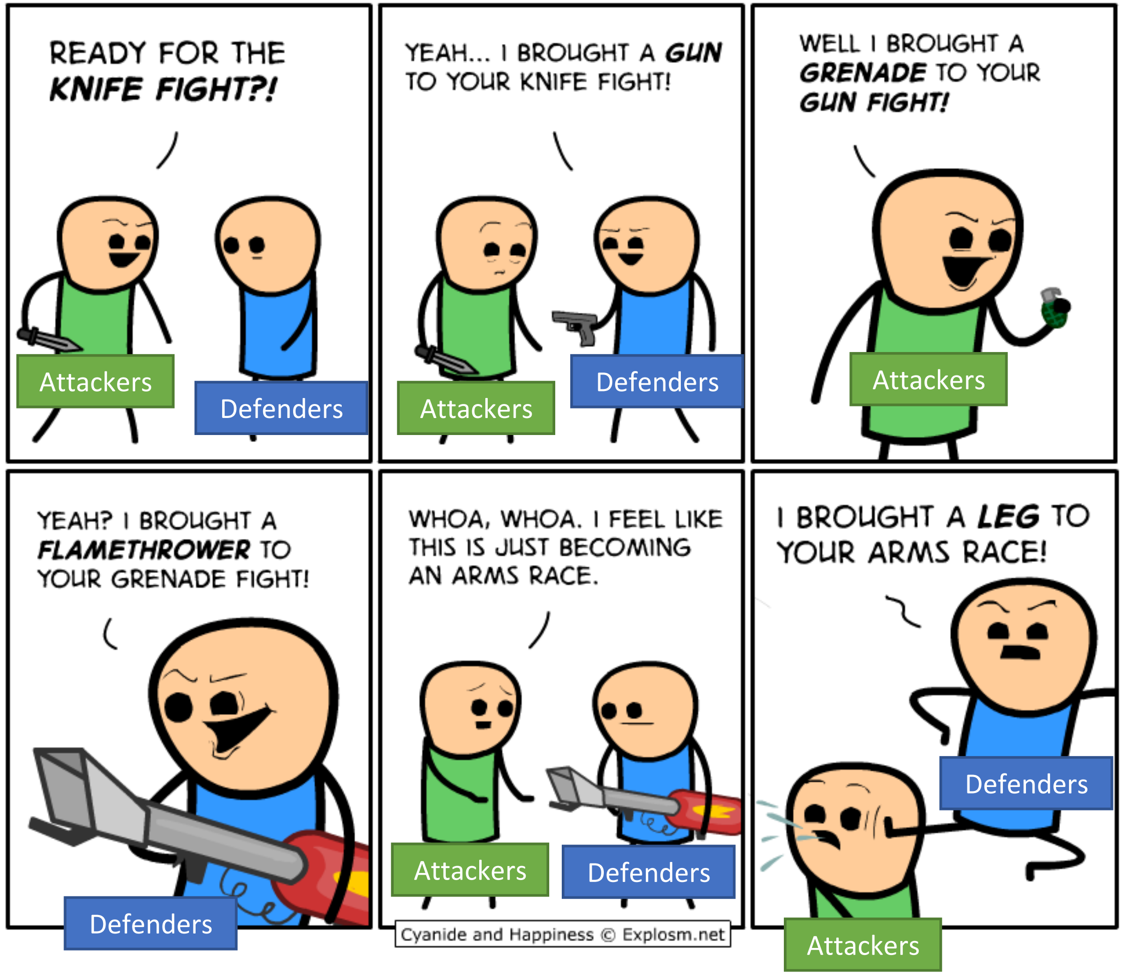
The Madry's (or arms race) defense

Definition (the Madry's or arms race defense):

The **arms race defense strategy**, is the most basic defense strategy.

If we know the type of attack that is coming, we can generate our own attack samples and train our model to correctly classify some of these attack samples.

Doing so, we therefore anticipate for future attacks of this type.



Source: https://explosm.net/comics/3939/

Note: this is also known as the **Madry's defense** [Madry2017].

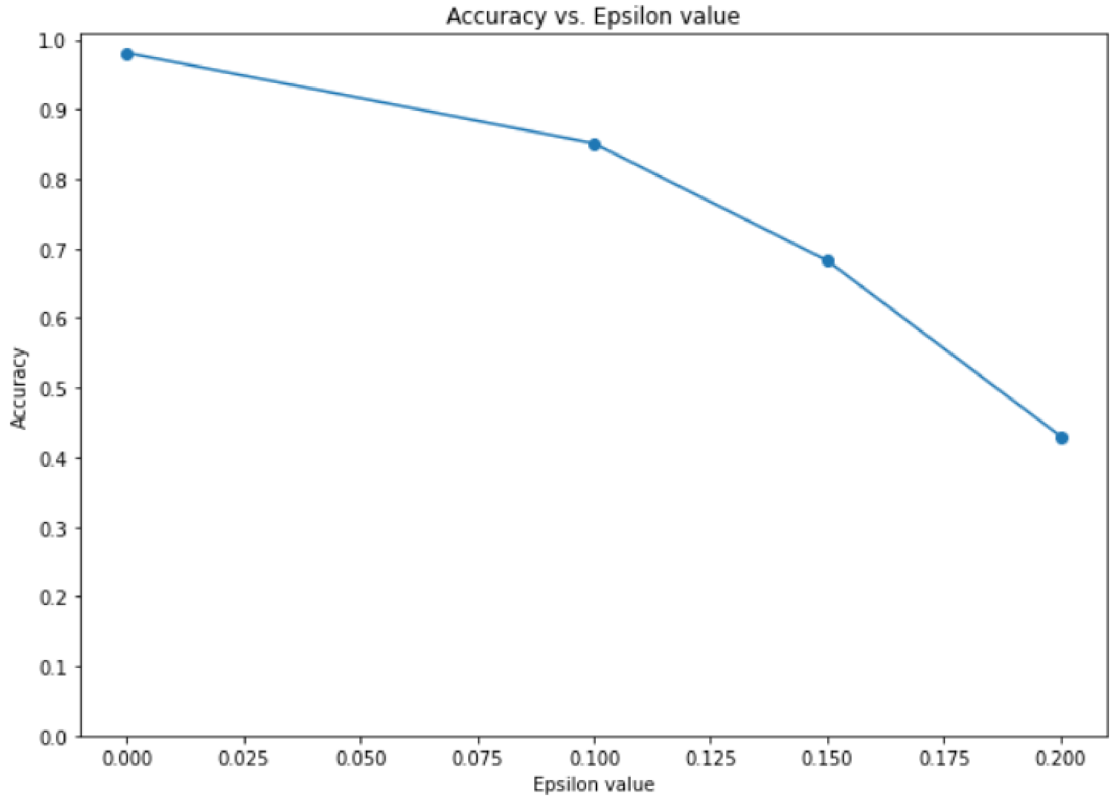
The arms race defense

Let us start with our pre-trained model, and the basic FGSM attack (one-shot, untargeted version).

- Our model is not prepared to face this type of attacks and will suffer badly from it.

```python
epsilons = [0, .1, .15, .2]
accuracies = []
examples = []

# Run test() function for each epsilon
for eps in epsilons:
    acc, ex = test(model, device, test_loader, eps)
    accuracies.append(acc)
    examples.append(ex)
```

```
Epsilon: 0 - Test Accuracy = 9810/10000 = 0.981
Epsilon: 0.1 - Test Accuracy = 8510/10000 = 0.851
Epsilon: 0.15 - Test Accuracy = 6826/10000 = 0.6826
Epsilon: 0.2 - Test Accuracy = 4301/10000 = 0.4301
```



The arms race defense

Our next step would then be to continue the training of our model, integrating samples that have been generated using said FGSM attack.

- **Intuition:** in a sense, the arms race defense is a sort of **data augmentation technique**, that helps make the model more robust to attacks of the FGSM type.

The arms race defense

- For demonstration, we will create a second model, using the same pre-trained weights.
- We will also retrieve the training dataset and make its dataloader (train_loader), with mini-batches.
- We will then continue the training of this model, using CrossEntropy as our loss and a basic SGD as our optimizer.

```
# Load the pretrained model
model2 = Net().to(device)
pretrained_model = "./mnist_model.data"
model2.load_state_dict(torch.load(pretrained_model, map_location = 'cpu'))
```

```
<All keys matched successfully>
```

```
# MNIST dataset and dataloader
# (For testing only, we will use a pre-trained model)
ds2 = datasets.MNIST('./data', train = True, download = True, transform = tf)
train_loader = torch.utils.data.DataLoader(ds2, batch_size = 64, shuffle = True)
```

```
print(len(train_loader))
```

```
938
```

```
# Define a loss function and an optimizer for training
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model2.parameters(), lr = 0.001, momentum = 0.9)
```

From Notebook 5.!

Retraining our model

```
def retrain(model, train_loader, optimizer, criterion, n_iter = 5):

    # This will make prints happen every 50 mini-batches
    mod_val = 50

    # Train over n_iter epochs
    for epoch in range(n_iter):

        # Keep track of the running losses over batches
        running_loss_normal = 0.0
        running_loss_attack = 0.0

        for i, data in enumerate(train_loader):
            """
            1. Mini-batches on normal samples
            """
            # Retrieve input images and labels
            inputs, labels = data
            inputs.requires_grad = True

            # Zeroing gradients
            optimizer.zero_grad()

            # Forward, Loss, Backprop
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()

            # Keep track of running loss (normal samples)
            running_loss_normal += loss.item()

            """
            2. Mini-batches on generated attack samples
            """

            # Collect gradients of image
            data_grad = inputs.grad.data

            # Call FGSM Attack with the 0.15 epsilon value
            epsilon = .15
            eps_image = fgsm_attack(inputs, epsilon, data_grad)

            # Re-classify the epsilon image
            output2 = model(eps_image)
            # Get the index of the max log-probability
            eps_pred = output2.max(1, keepdim = True)[1]

            # Loss, Backprop, Optimize
            loss2 = criterion(output2, labels)
            loss2.backward()
            optimizer.step()

            # Keep track of running loss (attack samples)
            running_loss_attack += loss2.item()
```

Retraining our model

```
def retrain(model, train_loader, optimizer, criterion, n_iter = 5):

    # This will make prints happen every 50 mini-batches
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            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()

            # Keep track of running loss (normal samples)
            running_loss_normal += loss.item()
```

```
            """
            2. Mini-batches on generated attack samples
            """

            # Collect gradients of image
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            # Call FGSM Attack with the 0.15 epsilon value
            epsilon = .15
            eps_image = fgsm_attack(inputs, epsilon, data_grad)

            # Re-classify the epsilon image
            output2 = model(eps_image)
            # Get the index of the max log-probability
            eps_pred = output2.max(1, keepdim = True)[1]

            # Loss, Backprop, Optimize
            loss2 = criterion(output2, labels)
            loss2.backward()
            optimizer.step()

            # Keep track of running loss (attack samples)
            running_loss_attack += loss2.item()
```

Just like in "normal" training we are going to train on the training samples (this uses our train_loader, not the test one!)

Retraining our model

```
def retrain(model, train_loader, optimizer, criterion, n_iter = 5):

    # This will make prints happen every 50 mini-batches
    mod_val = 50

    # Train over n_iter epochs
    for epoch in range(n_iter):

        # Keep track of the running losses over batches
        running_loss_normal = 0.0
        running_loss_attack = 0.0

        for i, data in enumerate(train_loader):
            """
            1. Mini-batches on normal samples
            """
            # Retrieve input images and labels
            inputs, labels = data
            inputs.requires_grad = True

            # Zeroing gradients
            optimizer.zero_grad()

            # Forward, Loss, Backprop
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()

            # Keep track of running loss (normal samples)
            running_loss_normal += loss.item()
```

```
            """
            2. Mini-batches on generated attack samples
            """

            # Collect gradients of image
            data_grad = inputs.grad.data

            # Call FGSM Attack with the 0.15 epsilon value
            epsilon = .15
            eps_image = fgsm_attack(inputs, epsilon, data_grad)

            # Re-classify the epsilon image
            output2 = model(eps_image)
            # Get the index of the max log-probability
            eps_pred = output2.max(1, keepdim = True)[1]

            # Loss, Backprop, Optimize
            loss2 = criterion(output2, labels)
            loss2.backward()
            optimizer.step()

            # Keep track of running loss (attack samples)
            running_loss_attack += loss2.item()
```

And in the second part, we will do the same, but will transform the samples using our attack function and train on this sample.

Retraining our model

```python
def retrain(model, train_loader, optimizer, criterion, n_iter = 5):

    # This will make prints happen every 50 mini-batches
    mod_val = 50

    # Train over n_iter epochs
    for epoch in range(n_iter):

        # Keep track of the running losses over batches
        running_loss_normal = 0.0
        running_loss_attack = 0.0

        for i, data in enumerate(train_loader):
            """
            1. Mini-batches on normal samples
            """
            # Retrieve input images and labels
            inputs, labels = data
            inputs.requires_grad = True

            # Zeroing gradients
            optimizer.zero_grad()

            # Forward, Loss, Backprop
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()

            # Keep track of running loss (normal samples)
            running_loss_normal += loss.item()

            """
            2. Mini-batches on generated attack samples
            """

            # Collect gradients of image
            data_grad = inputs.grad.data

            # Call FGSM Attack with the 0.15 epsilon value
            epsilon = .15
            eps_image = fgsm_attack(inputs, epsilon, data_grad)

            # Re-classify the epsilon image
            output2 = model(eps_image)
            # Get the index of the max log-probability
            eps_pred = output2.max(1, keepdim = True)[1]

            # Loss, Backprop, Optimize
            loss2 = criterion(output2, labels)
            loss2.backward()
            optimizer.step()

            # Keep track of running loss (attack samples)
            running_loss_attack += loss2.item()
```

In addition (not shown here), we will display the running losses for both the normal and attack samples.

The arms race defense

Retraining will not necessarily affect the loss on normal samples (it will keep on decreasing, possibly overfitting, but this should not change the accuracy performance of the model on normal samples).

- **What is important:** We are able to train to **recognize attack samples and our model progressively becomes better at classifying those correctly**.

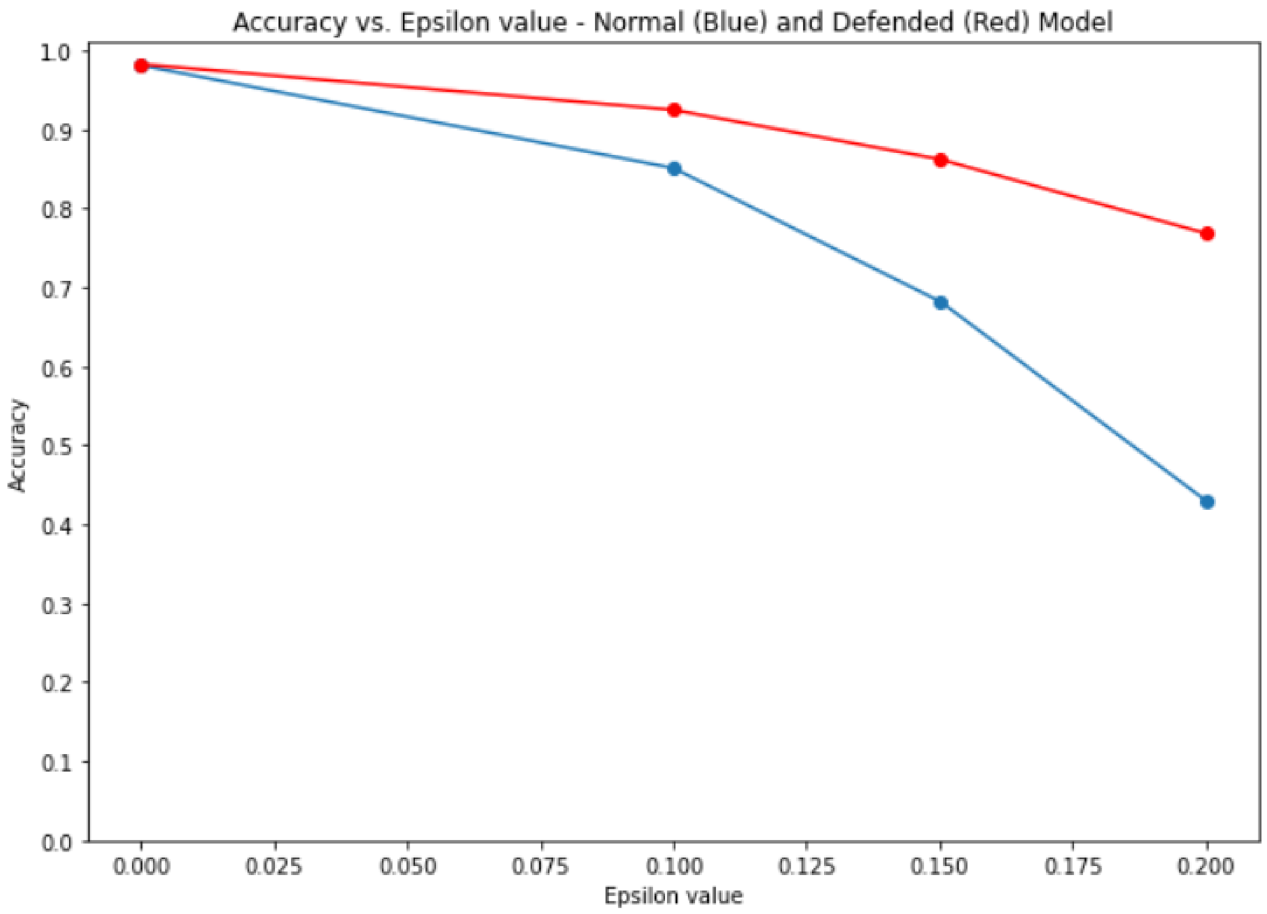
```
retrain(model2, train_loader, optimizer, criterion)
```

```
[Epoch 1, Batch    51] Normal Loss: 0.296 - Attack Loss: 0.941
[Epoch 1, Batch   101] Normal Loss: 0.257 - Attack Loss: 0.877
[Epoch 1, Batch   151] Normal Loss: 0.244 - Attack Loss: 0.857
[Epoch 1, Batch   201] Normal Loss: 0.234 - Attack Loss: 0.831
[Epoch 1, Batch   251] Normal Loss: 0.226 - Attack Loss: 0.817
[Epoch 1, Batch   301] Normal Loss: 0.220 - Attack Loss: 0.798
[Epoch 1, Batch   351] Normal Loss: 0.219 - Attack Loss: 0.789
[Epoch 1, Batch   401] Normal Loss: 0.216 - Attack Loss: 0.776
[Epoch 1, Batch   451] Normal Loss: 0.216 - Attack Loss: 0.769
[Epoch 1, Batch   501] Normal Loss: 0.214 - Attack Loss: 0.761
[Epoch 1, Batch   551] Normal Loss: 0.213 - Attack Loss: 0.755
[Epoch 1, Batch   601] Normal Loss: 0.212 - Attack Loss: 0.753
[Epoch 1, Batch   651] Normal Loss: 0.211 - Attack Loss: 0.749
[Epoch 1, Batch   701] Normal Loss: 0.209 - Attack Loss: 0.744
[Epoch 1, Batch   751] Normal Loss: 0.209 - Attack Loss: 0.739
[Epoch 1, Batch   801] Normal Loss: 0.209 - Attack Loss: 0.733
[Epoch 1, Batch   851] Normal Loss: 0.208 - Attack Loss: 0.729
[Epoch 1, Batch   901] Normal Loss: 0.207 - Attack Loss: 0.725
[Epoch 2, Batch    51] Normal Loss: 0.187 - Attack Loss: 0.626
[Epoch 2, Batch   101] Normal Loss: 0.184 - Attack Loss: 0.634
[Epoch 2, Batch   151] Normal Loss: 0.191 - Attack Loss: 0.625
[Epoch 2, Batch   201] Normal Loss: 0.191 - Attack Loss: 0.628
[Epoch 2, Batch   251] Normal Loss: 0.189 - Attack Loss: 0.628
[Epoch 2, Batch   301] Normal Loss: 0.188 - Attack Loss: 0.628
[Epoch 2, Batch   351] Normal Loss: 0.189 - Attack Loss: 0.629
[Epoch 2, Batch   401] Normal Loss: 0.187 - Attack Loss: 0.629
[Epoch 2, Batch   451] Normal Loss: 0.187 - Attack Loss: 0.626
[Epoch 2, Batch   501] Normal Loss: 0.187 - Attack Loss: 0.625
[Epoch 2, Batch   551] Normal Loss: 0.187 - Attack Loss: 0.621
[Epoch 2, Batch   601] Normal Loss: 0.186 - Attack Loss: 0.618
[Epoch 2, Batch   651] Normal Loss: 0.185 - Attack Loss: 0.616
[Epoch 2, Batch   701] Normal Loss: 0.186 - Attack Loss: 0.614
[Epoch 2, Batch   751] Normal Loss: 0.186 - Attack Loss: 0.614
[Epoch 2, Batch   801] Normal Loss: 0.186 - Attack Loss: 0.614
[Epoch 2, Batch   851] Normal Loss: 0.186 - Attack Loss: 0.611
[Epoch 2, Batch   901] Normal Loss: 0.186 - Attack Loss: 0.610
[Epoch 3, Batch    51] Normal Loss: 0.176 - Attack Loss: 0.584
[Epoch 3, Batch   101] Normal Loss: 0.178 - Attack Loss: 0.594
[Epoch 3, Batch   151] Normal Loss: 0.181 - Attack Loss: 0.591
[Epoch 3, Batch   201] Normal Loss: 0.181 - Attack Loss: 0.590
[Epoch 3, Batch   251] Normal Loss: 0.180 - Attack Loss: 0.585
[Epoch 3, Batch   301] Normal Loss: 0.179 - Attack Loss: 0.582
[Epoch 3, Batch   351] Normal Loss: 0.179 - Attack Loss: 0.581
[Epoch 3, Batch   401] Normal Loss: 0.179 - Attack Loss: 0.577
```

The arms race defense

Training on the attack samples then makes the model a bit more robust to this type of attacks.

- In **blue**, you have the **original undefended model**. In **red**, the **defended model**.
- **Conclusion: Both of them have the same baseline accuracy, but the second model seems to resist more to the FGSM attacks (Can be improved with more training than just 5 iterations!)**



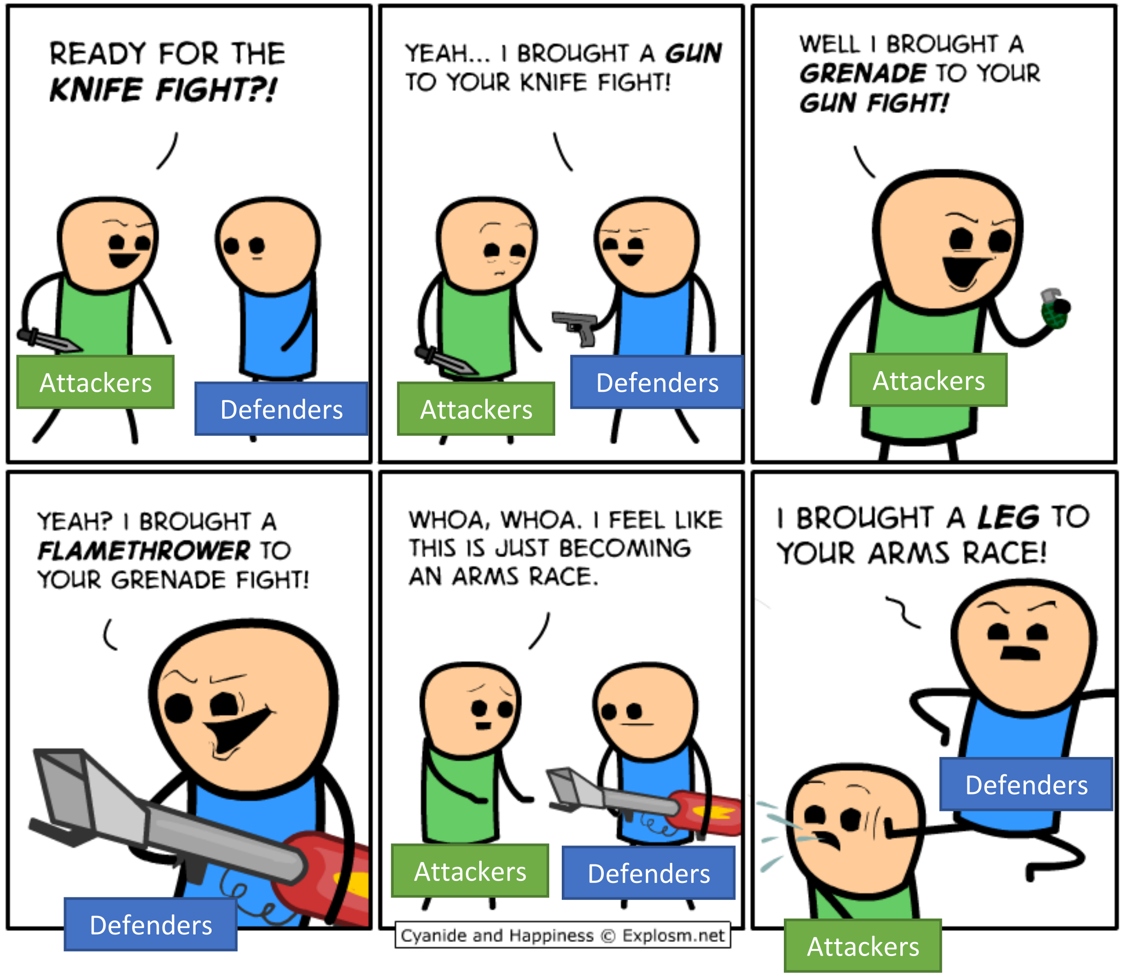
The Madry's (or arms race) defense

Definition (the Madry's or arms race defense):

The **arms race defense strategy**, is the most basic defense strategy.

If we know the type of attack that is coming, we can generate our own attack samples and train our model to correctly classify some of these attack samples.

Doing so, we therefore anticipate for future attacks of this type.



Source: https://explosm.net/comics/3939/

Note: this is also known as the **Madry's defense** [Madry2017].

The arms race defense

While this is the most intuitive approach and might work on the type of attacks you train your model for…

- This defense strategy will ultimately be defeated by attackers, who just have to implement a new type of attack…
- And your model simply will not know how to handle it.

- For instance, here, we defended against FGSM, but the Gradient attack remains undefended.

The arms race defense

While this is the most intuitive approach and might work on the type of attacks you train your model for…

- This defense strategy will ultimately be defeated by attackers, who just have to implement a new type of attack…
- And your model simply will not know how to handle it.

- For instance, here, we defended against FGSM, but the Gradient attack remains undefended.

And attackers these days are getting pretty creative with new types of attacks!

There are even challenges/competitions for coming up with new attacks against "defended" systems!

See [Medium1] and [Dong2017].

Conclusion (W6S2)

- Using gradient-based attacks can help produce attacks with higher success rates.
- Using Fast Gradient Sign Method gives an extra plausibility constraint, in the form of a max norm constraint between the original image and attack image.
- This can lead to a devastating attack!
- Iterations were used during training, so might as well use them in attacks as well.
- Iterating greatly helps with plausibility.
- Iterated FGSM can technically lead to a full failure of our pre-trained model…!
- Defense is very much needed, often via arms race defense, but with limited effects!

Let us call it a break for now

We will continue on the next lecture with the video data type and its uses.

Restricted

Learn more about these topics

Out of class, for those of you who are curious

- [Goodfellow2015] **Goodfellow** et al., “**Explaining and Harnessing Adversarial Examples**“, 2015. https://arxiv.org/abs/1412.6572
- [Kurakin2016] **Kurakin** et al. “**Adversarial examples in the physical world**”, 2016. https://arxiv.org/abs/1607.02533
- Implementing more advanced gradient ascent, e.g. FGSM with gradient ascent and momentum as in [Dong2017] Y. Dong et al. “**Boosting Adversarial Attacks with Momentum**”, 2017. https://arxiv.org/abs/1710.06081

Learn more about these topics

Tracking important names (Track their works and follow them on Scholar, Twitter, or whatever works for you!)

- **Alexei Kurakin: Researcher** at **Google Brain**.
  http://kurakin.me/
  https://scholar.google.com/citations?user=nCh4qyMAAAAJ&hl=en
- **Ian Goodfellow: (Former?) director** at **Apple** and **PhD** from **Stanford**, wrote a book that is considered the Bible of Deep Learning, and inventor of Generative Adversarial Networks (for later).
  https://www.iangoodfellow.com/
  https://www.deeplearningbook.org/
  https://scholar.google.ca/citations?user=iYN86KEAAAAJ&hl=en

Learn more about these topics

Tracking important names (Track their works and follow them on Scholar, Twitter, or whatever works for you!)

- **Samy Bengio: Senior Director** at **Apple, inventor** of **PyTorch** (!), (and brother of Yoshua Bengio).
  https://bengio.abracadoudou.com
  https://scholar.google.com/citations?user=Vs-MdPcAAAAJ&hl=fr