50.039 Theory and Practice of Deep Learning

W6-S3 Introduction to Attacks and Defense on Neural Networks

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About this week (Week 6)

1. What are **attacks** on Neural Networks (NNs)?
2. Why are attacks an **important concept** when studying NNs?
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 (more advanced) attacks and defense, **open questions** in research.

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5. **State-of-the-art** of (more advanced) attacks and defense, **open questions** in research.

In the last episode

Exploiting the intrinsic properties/limits of deep learning models allows for powerful attacks with high efficacy and plausibility.

In some cases, we might be able to attack a model with 100% efficacy and very good plausibility.

- Can we implement **more advanced attacks**?
- Can we **defend** against these attacks?
- Can attackers respond to such **defenses**?

About attacks

Basic attacks (discussed in previous lecture):

0. **(Epsilon Noising Attack)**
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

About attacks (and defense!)

Defense strategies against basic attacks:

1. **Arms-race defense**
2. **Defensive distillation**
3. **Black-boxing your model**
4. **More?**

Restricted

About attacks

Advanced attacks (only discussing the concepts briefly):

1. **Carlini-Wagner attack (targeted, iterated, white-box)**
2. **Surrogate attack (targeted/untargeted, one-shot/iterated, black-box)**
3. **Boundary attack (targeted, iterated, black-box)**

4. **(And, if time allows, a brief state-of-the-art of other remarkable attacks, for curious students!)**

Untargeted Gradient Attack (option #1)

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 #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)

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

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

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)

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

(FGSM attack)

- **Important property:** this also helps to make more plausible samples, as it will, by design, verify $\|\tilde{\boldsymbol{x}} - \boldsymbol{x}\|_\infty \leq \boldsymbol{\epsilon}$.
- (Plausibility constraint, we did not have in the previous attacks!)

```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
    eps_image = torch.clamp(eps_image, 0, 1)

    # Return
    return eps_image
```

Iterative and Targeted FGSM attack

Definition (iterated targeted Fast Gradient Sign Method attack):

The **iterated 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. 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 $\tilde{c}$.

$$\boldsymbol{x_0 = x}$$
$$\boldsymbol{x_{n+1} \leftarrow x_n - \epsilon\, \mathrm{sign}(\nabla_x L(x_n, \theta, \tilde{c}))}$$

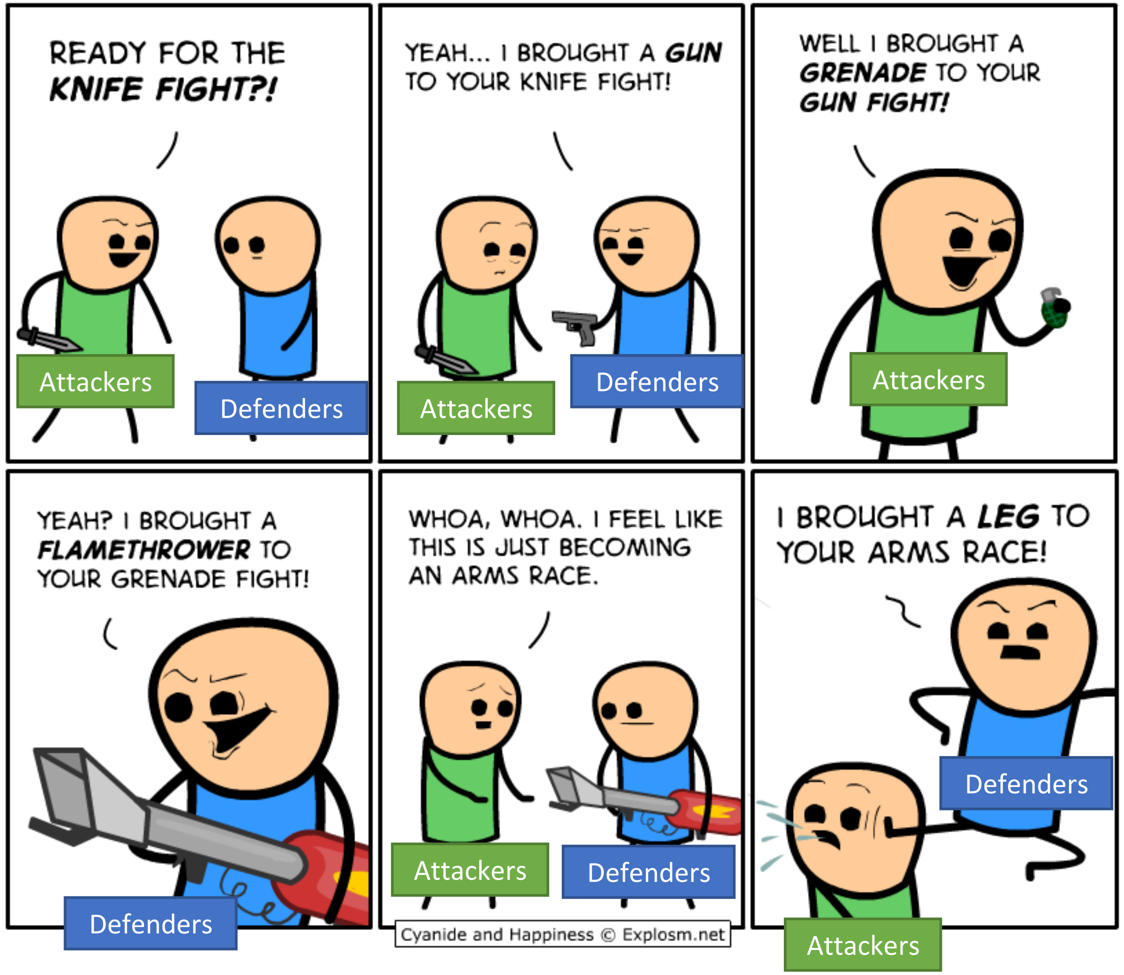
The Madry's (or arms race) defense

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

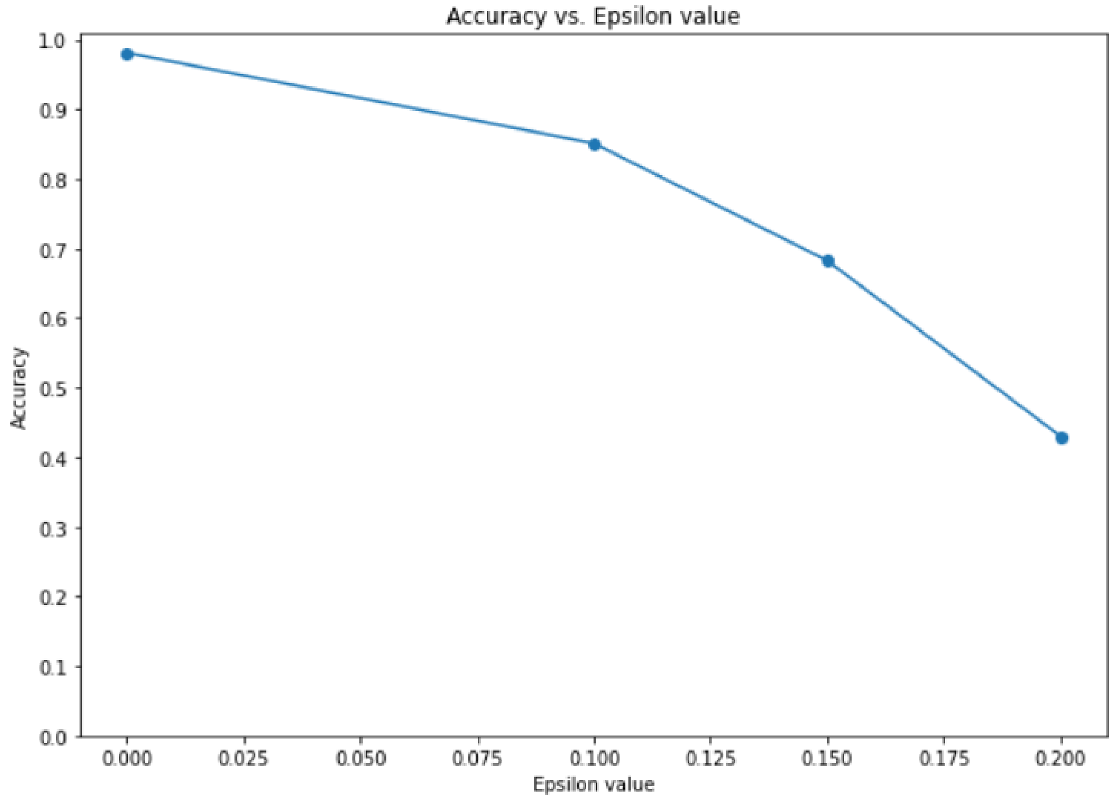
Let us start with our pre-trained model, and the basic FGSM attack (one-shot, untargeted version).

- 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
```



Restricted

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

```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()
```

```python
            """
            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()
```

Restricted

Retraining our model

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

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

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

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

```python
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            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)
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            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

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

    # This will make prints happen every 50 mini-batches
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    # Train over n_iter epochs
    for epoch in range(n_iter):

        # Keep track of the running losses over batches
        running_loss_normal = 0.0
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        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()
```

```python
            """
            2. Mini-batches on generated attack samples
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            # 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
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        # 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()
```

```python
            """
            2. Mini-batches on generated attack samples
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            data_grad = inputs.grad.data

            # Call FGSM Attack with the 0.15 epsilon value
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            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**.

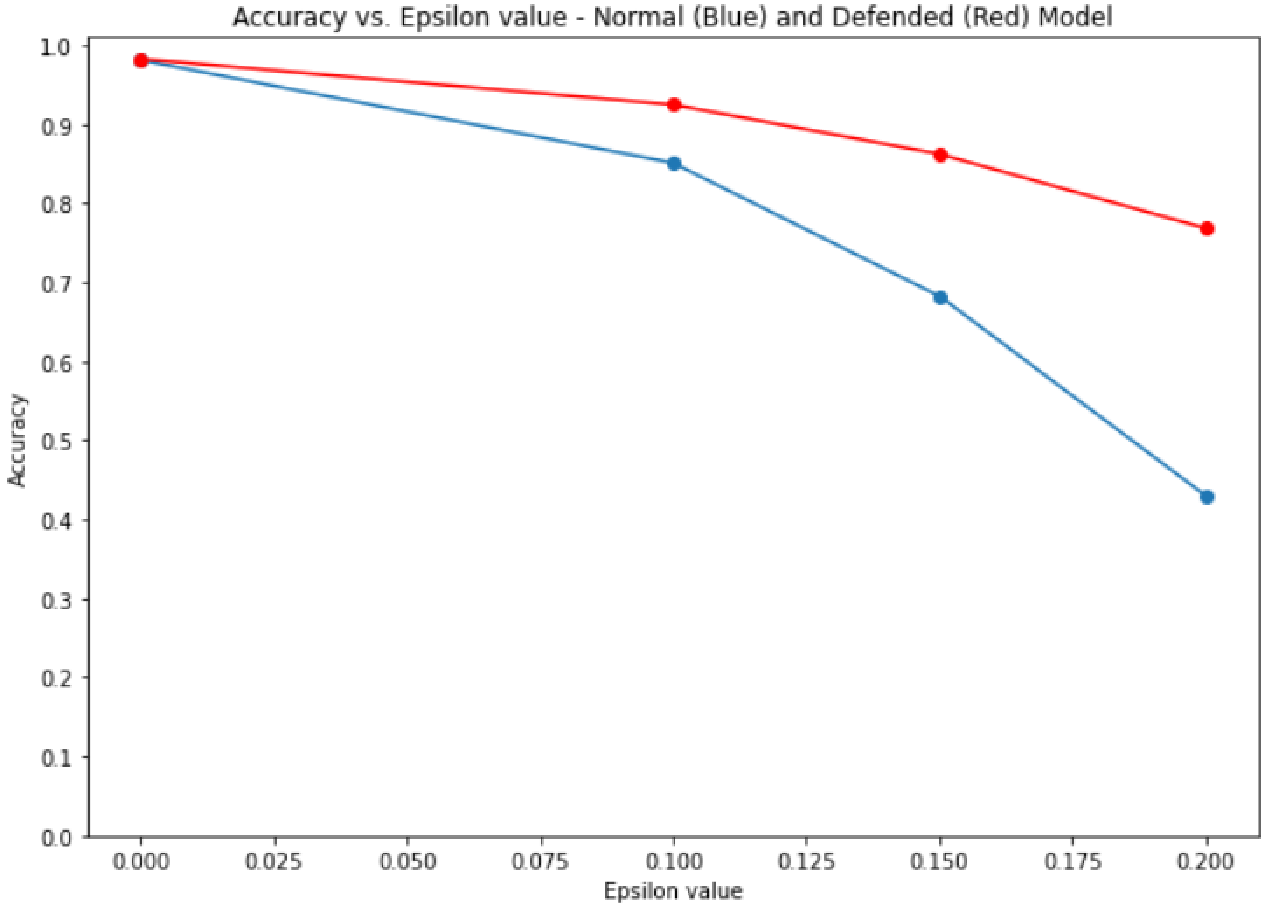
```
retrain(model2, train_loader, optimizer, criterion)
```

```
[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!)**



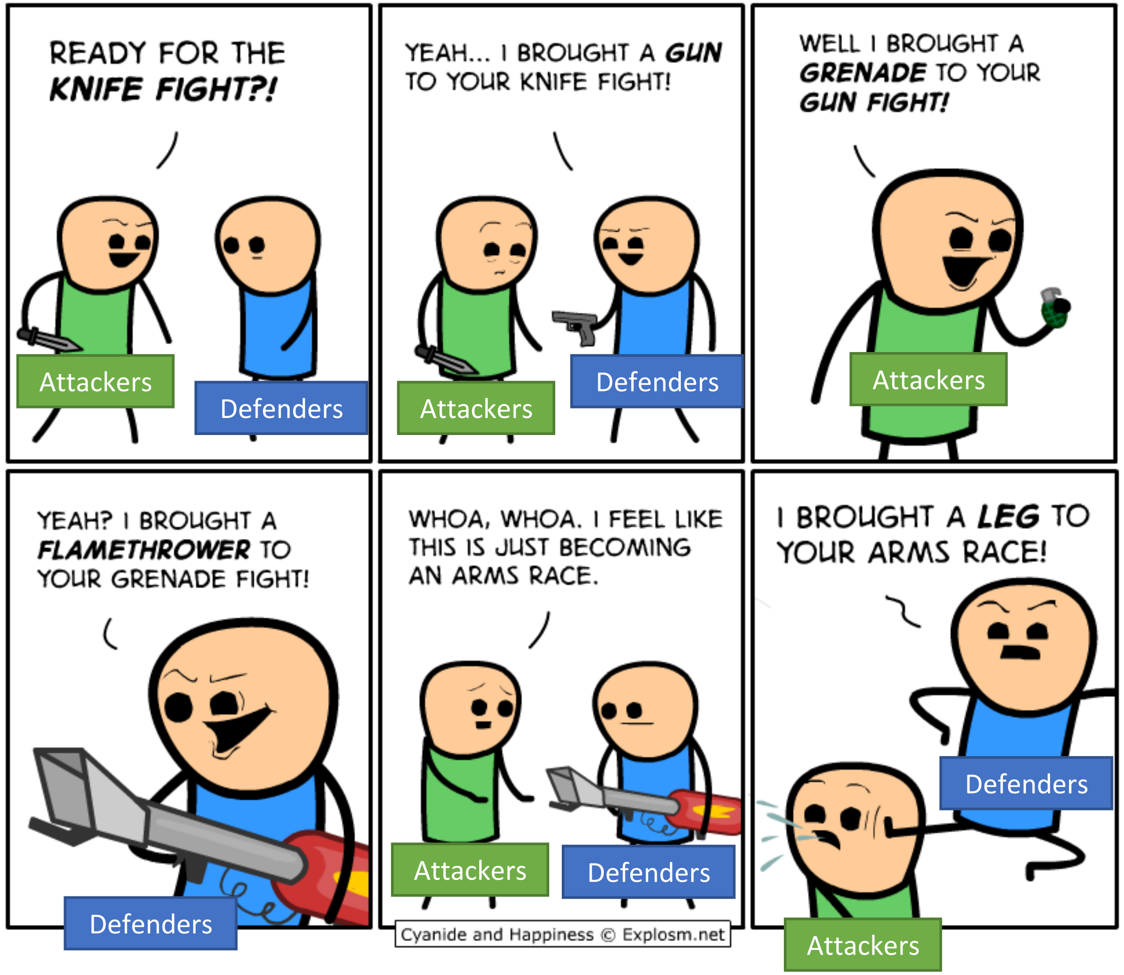
The Madry’s (or arms race) defense

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.

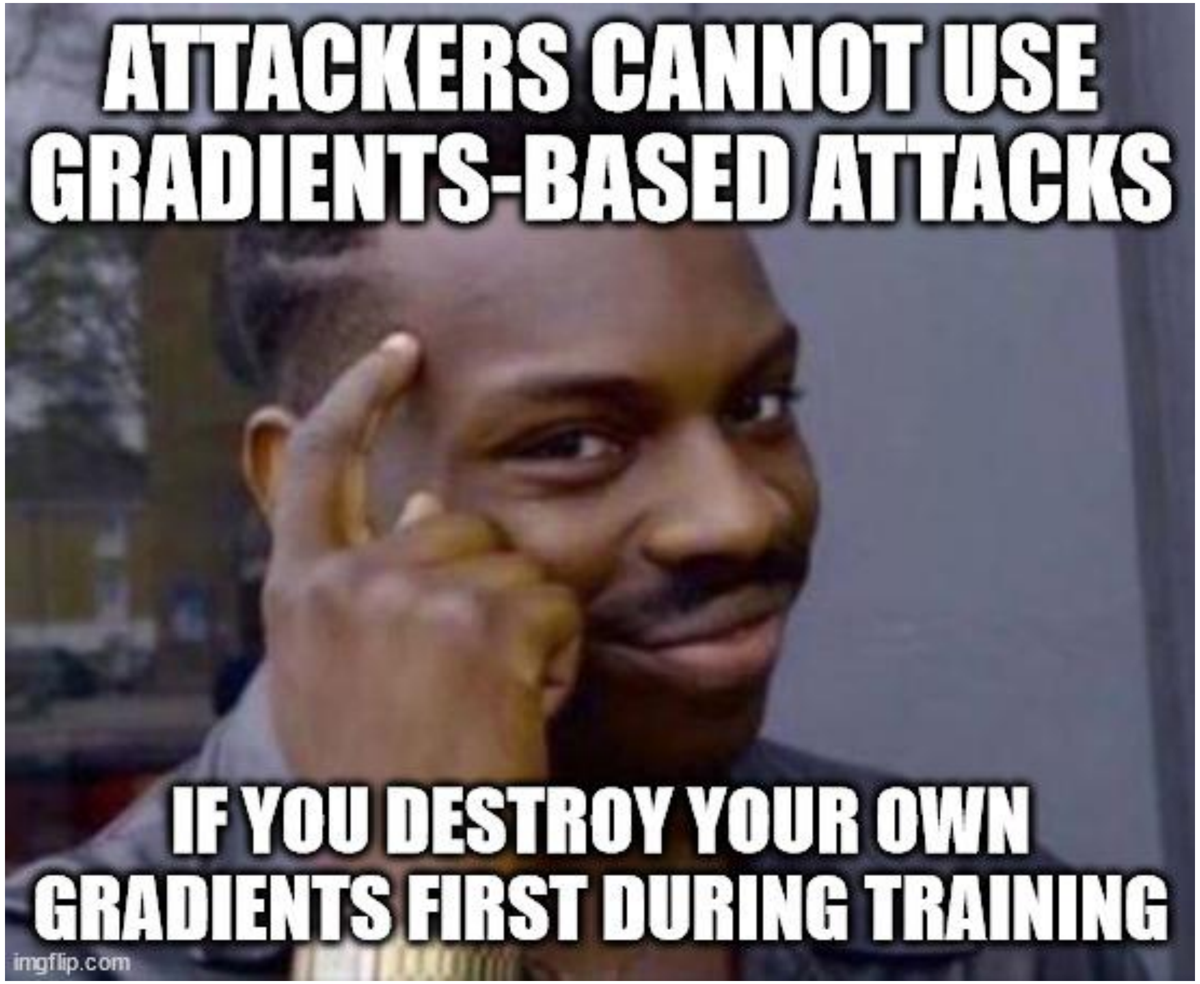
And attackers these days are getting pretty creative with new types of attacks!

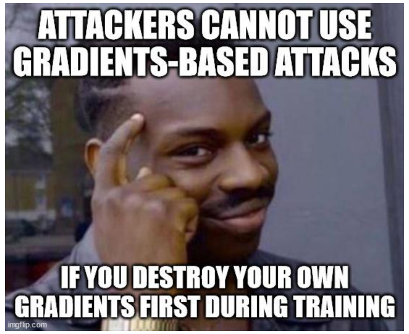
There are even challenges/competitions for coming up with new attacks against "defended" systems! See [Medium1] and [Dong2017].

Defensive distillation

Core idea behind gradient-based defensive distillation.

- Most gradient-based attacks rely on the gradients to compute an attack sample.
- If we were to annihilate these gradients, the attackers would not be able to produce attack samples.





Defensive distillation

Core idea behind gradient-based defensive distillation.

- Most gradient-based attacks rely on the gradients to compute an attack sample.
- If we were to annihilate these gradients, the attackers would not be able to produce attack samples.

- **Important note:** This is a pretty risky strategy, as you need those gradients during the training phase of your model!
- Defensive distillation will however do so, by using some of the softmax function properties.
- Idea comes from [Papernot2015].

Reminder: the softmax function

Definition (softmax function):

The **softmax function** receives a list of values $x = (x_1, \dots, x_N)$ and produces the following outputs $y = (y_1, \dots, y_N)$.

$$\forall i \in [1, N], \quad y_i = \frac{\exp(x_i)}{\sum_{j=1}^{N} \exp(x_j)}$$

Reminder: the softmax function

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$$\forall i \in [1, N], \quad y_i = \frac{\exp(x_i)}{\sum_{j=1}^{N} \exp(x_j)}$$

Definition (softmax function with temperature T):

The **softmax function with temperature** T, receives a list of values $x = (x_1, \dots, x_N)$ and produces the following outputs $y = (y_1, \dots, y_N)$.

$$\forall i \in [1, N], \quad y_i = \frac{\exp\left(\frac{x_i}{T}\right)}{\sum_{j=1}^{N} \exp\left(\frac{x_j}{T}\right)}$$

The softmax function (with temperature T)

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$$\forall i \in [1, N], \quad y_i = \frac{\exp\left(\frac{x_i}{T}\right)}{\sum_{j=1}^{N} \exp\left(\frac{x_j}{T}\right)}$$

Three interesting properties for the softmax with temperature.

1. When $T \to 0$, we have
   - $\forall i \in [1, N], y_i \to 0$,
   - Except for one value k, where $y_k \to 1$.
   - The index value k, corresponds to the largest one among the $(x_i)_{i \in [1,N]}$, that is $k = argmax_{i \in [1,N]}(x_i)$.

The softmax function (with temperature T)

Definition (softmax function with temperature T):

The **softmax function with temperature T**, receives a list of values $x = (x_1, \dots, x_N)$ and produces the following outputs $y = (y_1, \dots, y_N)$.

$$\forall i \in [1, N], \quad y_i = \frac{\exp\left(\frac{x_i}{T}\right)}{\sum_{j=1}^{N} \exp\left(\frac{x_j}{T}\right)}$$

2. When $T \to \infty$, we have
   - $\forall i \in [1, N], y_i \to \frac{1}{N}$.

The softmax function (with temperature T)

Definition (softmax function with temperature T):

The **softmax function with temperature T**, receives a list of values $x = (x_1, \ldots, x_N)$ and produces the following outputs $y = (y_1, \ldots, y_N)$.

$$\forall i \in [1, N], \quad y_i = \frac{\exp\left(\frac{x_i}{\boldsymbol{T}}\right)}{\sum_{j=1}^{N} \exp\left(\frac{x_j}{\boldsymbol{T}}\right)}$$

3. When $T \to \infty$, the gradients will vanish.

The softmax function (with temperature T)

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The **softmax function with temperature** T, receives a list of values $x = (x_1, \dots, x_N)$ and produces the following outputs $y = (y_1, \dots, y_N)$.

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3. When $T \to \infty$, the gradients will vanish.

- Indeed, if f is the softmax function, then its derivative f' will produce the following outputs $z = (z_1, \dots, z_N)$.

$$\forall i \in [1, N], \quad z_i = \frac{1}{T} \cdot \left(\frac{\exp\left(\frac{x_i}{T}\right)}{\sum_{j=1}^{N} \exp\left(\frac{x_j}{T}\right)}\right) \cdot \left(1 - \frac{\exp\left(\frac{x_i}{T}\right)}{\sum_{j=1}^{N} \exp\left(\frac{x_j}{T}\right)}\right)$$

- Using Property 2., this gives

$$\forall i \in [1, N], \lim_{T \to \infty} z_i = \lim_{T \to \infty} \frac{1}{T} \cdot \frac{1}{N} \cdot \left(1 - \frac{1}{N}\right) = 0$$

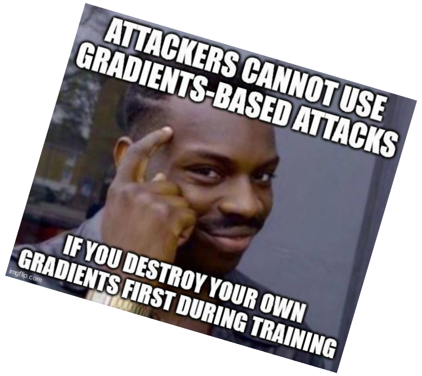
The defensive distillation strategy

Definition (the defensive distillation strategy):

The **defensive distillation strategy** makes use of the last property of the softmax function and its tendency to vanish gradients.

We can make the gradients of our model vanish by using a softmax with a large temperature T, instead of the standard $T = 1$ value.

The defensive distillation strategy



Definition (the defensive distillation strategy):

The **defensive distillation strategy** makes use of the last property of the softmax function and its tendency to vanish gradients.

We can make the gradients of our model vanish by using a softmax with a large temperature T, instead of the standard $T = 1$ value.

This will make the gradients vanish, and they might no longer be usable by the attackers for the gradient and fast gradient sign attacks.

Important: It might however complicate the training of the model! (Remember that we need these gradients to train and backpropagate!)

Model changes

- We will first change the constructor of our model, and add a temperature T.

```python
# Model definition
class Net(nn.Module):
    """
    This is a basic Neural Net for MNIST
    - Two convolutions, into ReLU activations and dropouts after ReLU,
    - Flattening,
    - Fully connected, into ReLU activation and dropout after ReLU,
    - Fully connected, into Log-Softmax.
    """

    def __init__(self):
        super(Net, self).__init__()
        # Conv. 1
        self.conv1 = nn.Conv2d(1, 10, kernel_size = 5)
        # Conv. 2
        self.conv2 = nn.Conv2d(10, 20, kernel_size = 5)
        # Dropout for Conv. layers
        self.conv2_drop = nn.Dropout2d()
        # FC 1
        self.fc1 = nn.Linear(320, 50)
        # FC 2
        self.fc2 = nn.Linear(50, 10)
        # Temperature (set to 1 by default)
        self.T = 1

    def forward(self, x):
        # Conv. 1 + ReLU + Dropout
        x = F.relu(F.max_pool2d(self.conv1(x), 2))
        # Conv. 2 + ReLU + Dropout
        x = F.relu(F.max_pool2d(self.conv2_drop(self.conv2(x)), 2))
        # Flatten
        x = x.view(-1, 320)
        # FC 1 + ReLU + Droupout
        x = F.relu(self.fc1(x))
        x = F.dropout(x, training = self.training)
        # FC 2 + Log-Softmax
        x = self.fc2(x)
        return F.log_softmax(x/self.T, dim = 1)
```

Model changes

- We will first change the constructor of our model, and add a temperature T.

- This temperature is then used in the softmax function of the forward() method.

```python
# Model definition
class Net(nn.Module):
    """
    This is a basic Neural Net for MNIST
    - Two convolutions, into ReLU activations and dropouts after ReLU,
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        x = self.fc2(x)
        return F.log_softmax(x/self.T, dim = 1)
```

Model changes

- We will first change the constructor of our model, and add a temperature T.
- This temperature is then used in the softmax function of the forward() method.
- It can later be changed using model.T = new_value

```python
# Model definition
class Net(nn.Module):
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    - Two convolutions, into ReLU activations and dropouts after ReLU,
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```
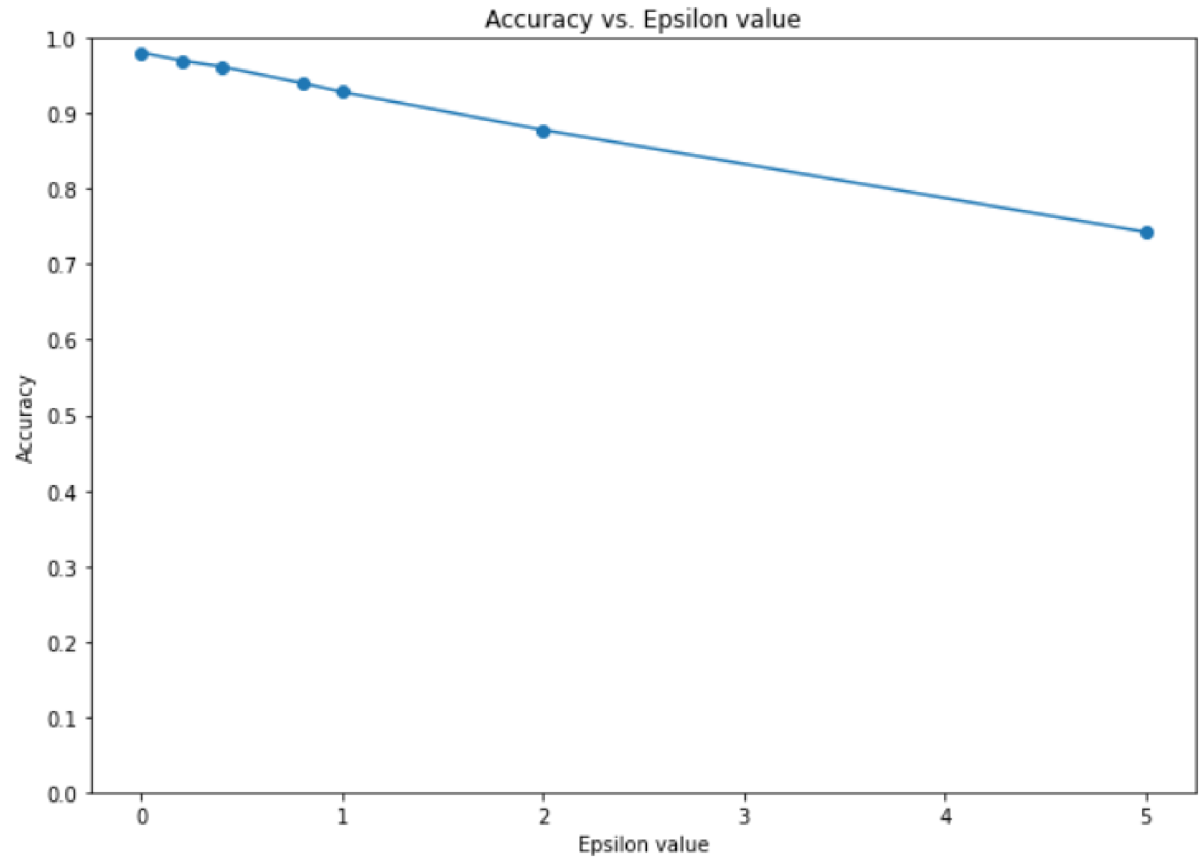

Original model for baseline

- In Notebook 6., we will be using our original model and the Gradient-based attack for reference.

- This is our efficacy vs. epsilon graph for the undefended model.



Defended model

- The defended model, used for comparison will be a copy of the undefended model.

```python
# 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>
```

```python
# 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)
```

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

```
938
```

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

```python
# Setting temperature to 100 for training
model2.T = 100
```

Defended model

- The defended model, used for comparison will be a copy of the undefended model.
- We will then change the temperature to T = 100 (arbitrarily chosen).

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# Load the pretrained model
model2 = Net().to(device)
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Defended model

- The defended model, used for comparison will be a copy of the undefended model.
- We will then change the temperature to T = 100 (arbitrarily chosen).
- And will continue the training of this model on the training set, with this new "high" temperature.

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# Load the pretrained model
model2 = Net().to(device)
pretrained_model = "./mnist_model.data"
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```

```
# Setting temperature to 100 for training
model2.T = 100
```

Defended model

- The defended model, used for comparison will be a copy of the undefended model.
- We will then change the temperature to T = 100 (arbitrarily chosen).
- If we want, we can continue the training of this model, with this new “high” temperature, to check it leads to very little changes in model parameters (gradients are close to zero).

```python
def retrain(model, train_loader, optimizer, criterion, n_iter = 10):

    # 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

        for i, data in enumerate(train_loader):

            # Retrieve input images and labels
            inputs, labels = data
            inputs.requires_grad = True

            # Zeroing gradients
            optimizer.zero_grad()

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

Defended model

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- If we want, we can continue the training of this model, with this new “high” temperature, to check it leads to very little changes in model parameters (gradients are close to zero).

```
retrain(model2, train_loader, optimizer, criterion, n_iter = 50)
```

```
[Epoch 1, Batch    51] Loss: 2.258
[Epoch 1, Batch   101] Loss: 2.256
[Epoch 1, Batch   151] Loss: 2.254
[Epoch 1, Batch   201] Loss: 2.252
[Epoch 1, Batch   251] Loss: 2.250
[Epoch 1, Batch   301] Loss: 2.248
[Epoch 1, Batch   351] Loss: 2.245
[Epoch 1, Batch   401] Loss: 2.243
[Epoch 1, Batch   451] Loss: 2.241
[Epoch 1, Batch   501] Loss: 2.238
[Epoch 1, Batch   551] Loss: 2.236
[Epoch 1, Batch   601] Loss: 2.233
[Epoch 1, Batch   651] Loss: 2.230
[Epoch 1, Batch   701] Loss: 2.227
[Epoch 1, Batch   751] Loss: 2.223
[Epoch 1, Batch   801] Loss: 2.220
[Epoch 1, Batch   851] Loss: 2.216
[Epoch 1, Batch   901] Loss: 2.212
[Epoch 2, Batch    51] Loss: 2.122
[Epoch 2, Batch   101] Loss: 2.114
```

```
# After retraining, set the model in evaluation mode
# (Important, because we have dropout layers!)
model2.eval()
```

Defended model performance

- The high temperature makes the gradients vanish.
- This means that the gradient based attack will now be unable to operate correctly on our defended model!

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

But $\nabla_x L(x, \theta, c) \approx 0$

Implies $\tilde{x} \approx x$

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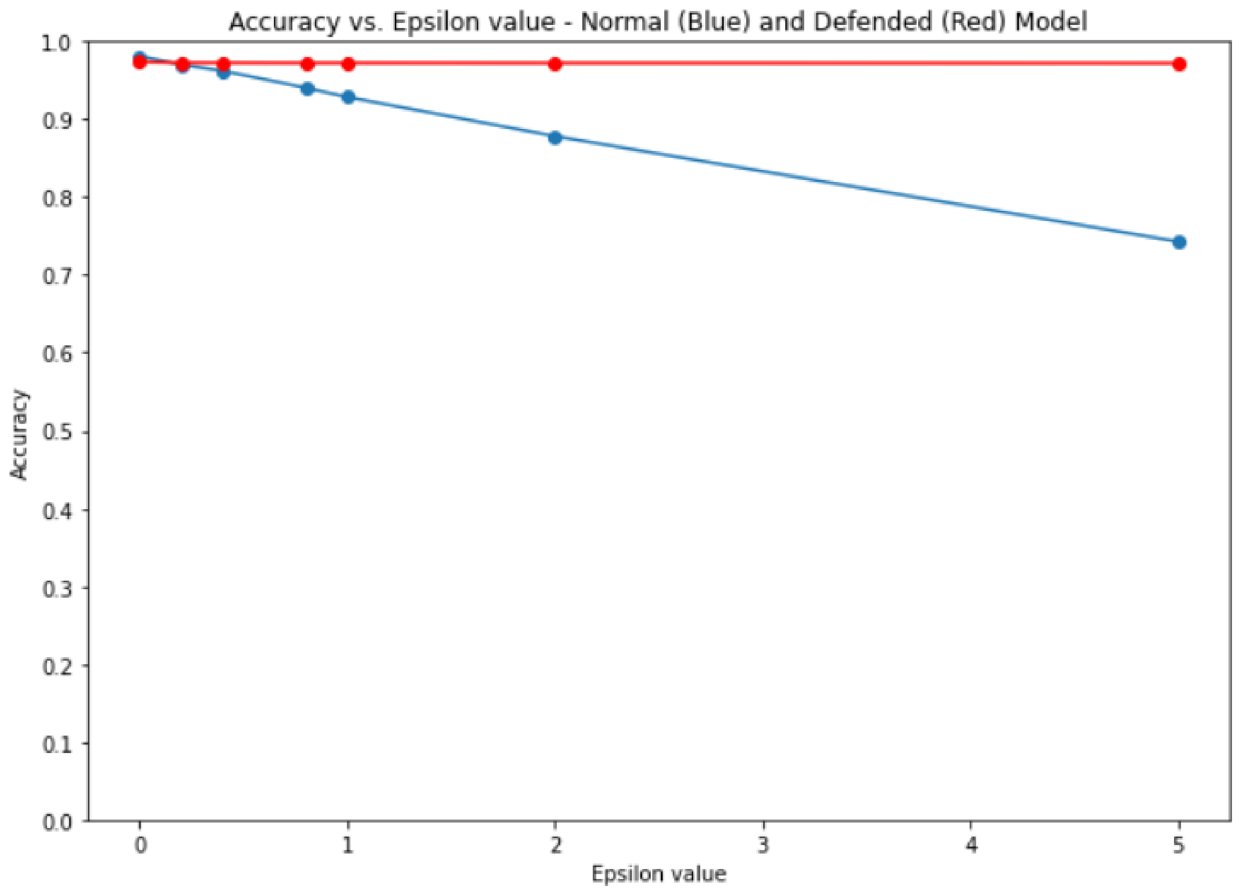

Defended model performance

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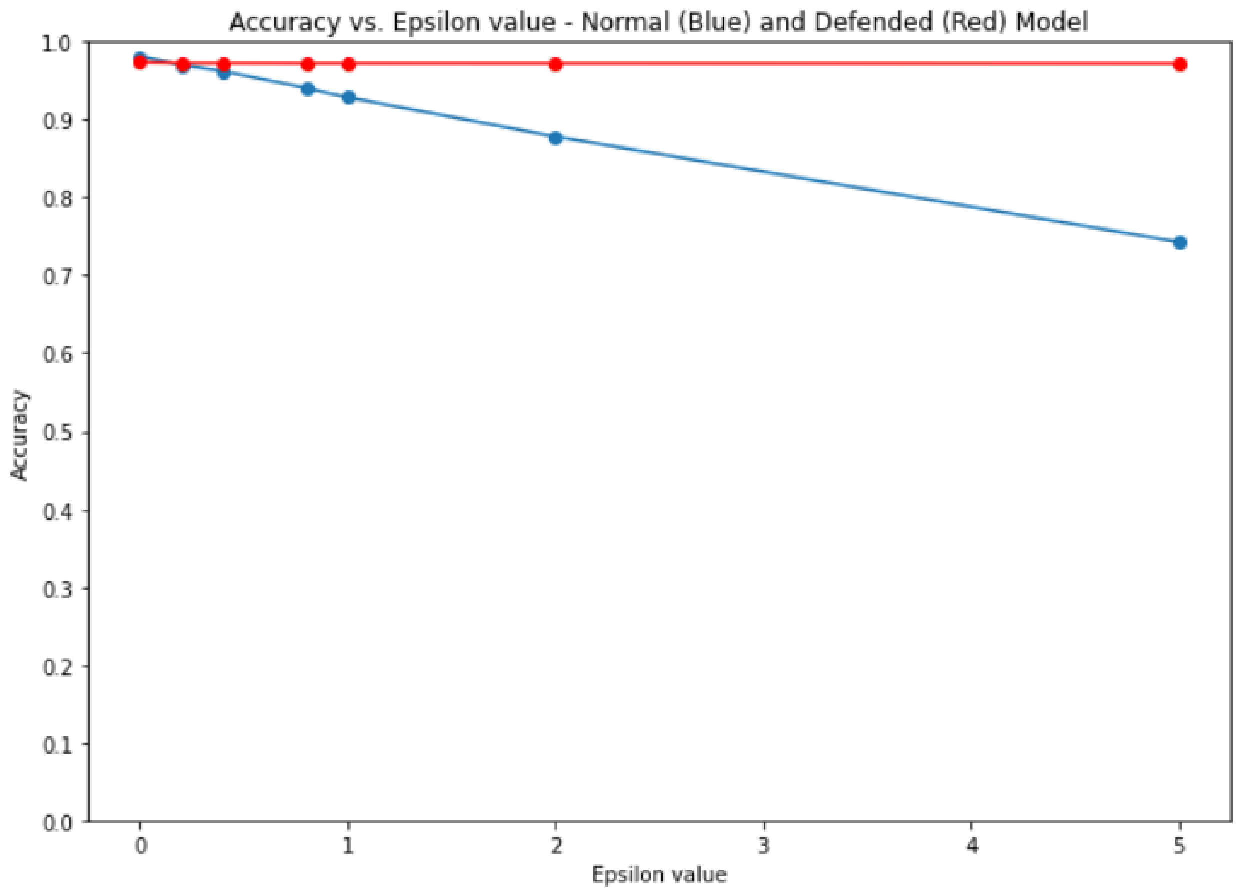
But, $\nabla_x L(x, \theta, c) \approx 0$

implies $\tilde{x} \approx x$

Open question… Will defensive distillation work on the FGSM attack, which only uses the SIGN of the gradient?



The current state of our defenses against white-box models

So far, defenders have only two options to defend against gradient-based attacks.

1. Either train specifically in anticipation for these attacks
(and we have seen it works quite well on FGSM attacks).
2. Or make the gradients vanish to mess with the attackers
(and we have seen it works quite well on gradient-based attacks).

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That should be good enough, right?

I mean, there is now way for attackers to come up with something else, to attack my model, right?

Carlini-Wagner attack (targeted, iterated, white-box)

- The Carlini-Wagner attack is a **targeted**, (**one-shot** or) **iterated**, **white-box** attack [Carlini2017].
- It uses some of the model properties to perform create adversarial samples.
  - It does not use the gradients…
  - It uses the **logits** of the model instead.
  - This means that the defensive distillation or the arms race defense **will not work** against this attack.

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  - It does not use the gradients…
  - It uses the **logits** of the model instead.
  - This means that the defensive distillation or the arms race defense **will not work** against this attack.
- This attack generates samples by solving a **“simple” optimization problem**.
- It also ensures **plausibility** by controlling a norm $||\tilde{x} - x||$ between the generated sample and the original image.

Carlini-Wagner optimization

Objective: generate a sample $\tilde{x}$ with class $\tilde{c}$, from a sample x of class c. Do so by solving the unconstrained multi-objective optimization problem below.

$$\min_{u} \left(\|u - x\|_2 + \alpha \, max(d(u), 0) \right)$$

$$with \; d(u) = \max_{t \neq \tilde{c}} \left(f_t(u) - f_{\tilde{c}}(u) \right)$$

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- The objective to generate the best image u, which minimizes our objective function.
- The first part penalizes images u, which are far from the original image x.
  (this encourages **plausibility**).
- The second part is a positive non-zero value if the image u does not have the target label, and zero otherwise.

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- Indeed, we will have $d(u) > 0$ if and only if
- there exists a class t $\neq \tilde{c}$, such that $f_t(u) - f_{\tilde{c}}(u) > 0$
- Equivalently, this means that image u is not of target class $\tilde{c}$.

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- The first part penalizes images u, which are far from the original image x.
(this encourages **plausibility**).
- The second part is non-zero if the image u does not have the target label.
(this encourages **efficacy**).
- Both important aspects are covered, and α can be arbitrarily set to decide on the importance of each aspect.

Carlini-Wagner optimization

Roughly equivalent formulation #1: generate a sample $\tilde{x}$ with class $\tilde{c}$, from a sample x of class c. Do so by solving the **constrained** optimization problem below.

$$\min_{u} \left(max(d(u), 0)\right)$$

$$with\; d(u) = \max_{t \neq \tilde{c}} \left(f_t(u) - f_{\tilde{c}}(u)\right)$$

$$and\, \|u - x\|_2 \leq \alpha$$

Roughly equivalent formulation #2: generate a sample $\tilde{x}$ with class $\tilde{c}$, from a sample x of class c. Do so by solving the **constrained** optimization problem below.

$$\min_{u} \left(max(d(u), 0)\right)$$

$$with\; d(u) = \max_{t \neq \tilde{c}} \left(f_t(u) - f_{\tilde{c}}(u)\right)$$

$$and\, \|u - x\|_\infty \leq \alpha$$

Carlini-Wagner optimization

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wit

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Note: Solving these optimization problems can prove to be challenging.
Implementation is not necessarily difficult, but cumbersome.
We leave the implementation of these methods out of the scope of this class (Have a look at the papers with code website!)

Interested in implementing advanced algos? Look them up on PapersWithCode first!

Towards Evaluating the Robustness of Neural Networks

Edit social preview

16 Aug 2016 • Nicholas Carlini • David Wagner

Neural networks provide state-of-the-art results for most machine learning tasks. Unfortunately, neural networks are vulnerable to adversarial examples: given an input x and any target classification t, it is possible to find a new input x' that is similar to x but classified as t... (read more)

PDF Abstract

Code

Edit

carlini/nn_robust_attacks	★ 560	TensorFlow
MadryLab/cifar10_challenge	★ 315	TensorFlow
LeMinhThong/blackbox-attack	★ 51	PyTorch
kkew3/pytorch-cw2	★ 38	PyTorch
inspire-group/advml-traffic-sign	★ 16	

See all 22 implementations

https://paperswithcode.com/paper/towards-evaluating-the-robustness-of-neural

Black-boxing your model for defense

Definition (Black-boxing defense):

The **black-boxing defense** refers to the concept of hiding your model parameters to prevent attackers from accessing and using some of these parameters (neither weights, gradients nor logits) in their attacks.

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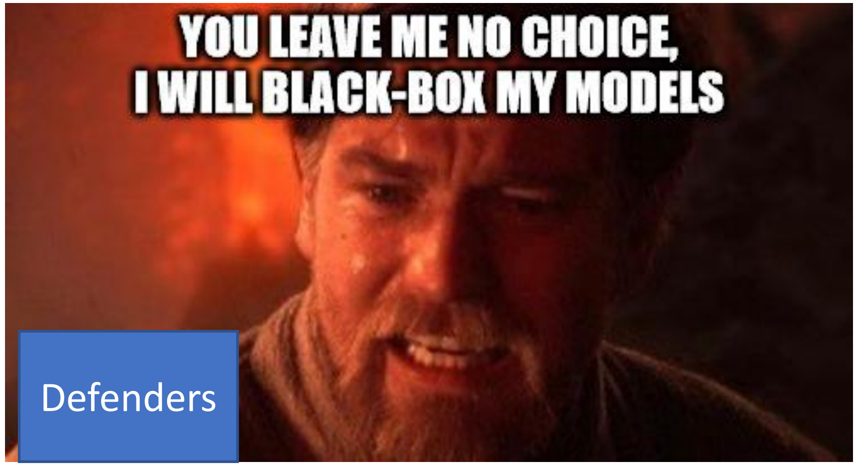
The only thing attackers can do is submit inputs to and get outputs from the model.



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The surrogate attack

Definition (the surrogate attack):

The **surrogate attack** (from [Papernot2017]) is a **black-box** attack.

Its objective is to recreate **a copy g** of the **model f being attacked**.

Then, produce attack samples using your **white-box** attacks we mentioned earlier on your recreated model g. **If they work on g, use them on the model f.**

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Then, produce attack samples using your **white-box** attacks we mentioned earlier on your recreated model g. **If they work on $\boldsymbol{g}$, use them on the model $\boldsymbol{f}$.**

Step 1: training a **surrogate model $\boldsymbol{g}$**

- Use a typical dataset, but do not use the ground truth labels. Instead use the labels produced by the predictions of model f.
- Train the **surrogate model $\boldsymbol{g}$** to match the predictions of the original model f.
- A good loss function would be:

$$L(g(x), f) = \sum_c - \mathrm{f_c(x)log}\big(g_c(x)\big)$$

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Then, produce attack samples using your **white-box** attacks we mentioned earlier on your recreated model g. **If they work on** $\boldsymbol{g}$**, use them on the model** $\boldsymbol{f}$**.**

Step 2: use **white-box** attacks on your **surrogate model** $\boldsymbol{g}$.

- For instance, attack your **surrogate model** $\boldsymbol{g}$ with FGSM.
  If the attack sample $\widetilde{\boldsymbol{x}}$ manages to fool the **surrogate model** $\boldsymbol{g}$, then odds are it will probably work on the original model f as well.
- Ultimately, this depends on how close you managed to make your **surrogate model** $\boldsymbol{g}$ similar to the original model f.

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- For instance, attack your model g with FGSM. If the attack sample $\tilde{x}$

Note: Implementation is not necessarily difficult but has to be done cautiously. Its guided implementation might be part of the next homework! More on this later.

If you are curious, training a surrogate model and attacking it was a Homework in 2023. See attached folder for Homework Notebook (and solutions, maybe)!

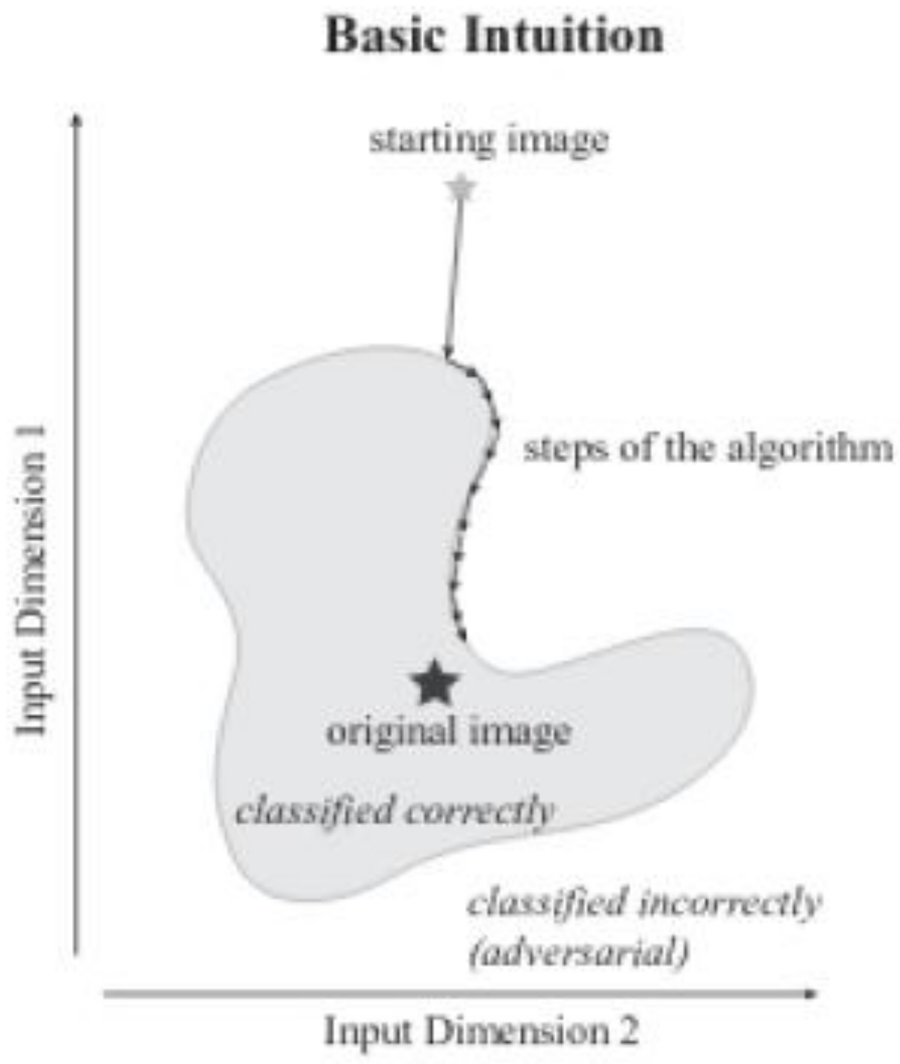
not always essential but helps.

The boundary attack

Definition (the boundary attack):

The **boundary attack** (from [Brendel2018]) is a black-box type of attack, which only requires access to the inputs and outputs of the model under attack f.

It attempts to create an image, which will look plausible, but will be misclassified. It does so by walking on the boundary of the correct prediction region, and attempts to minimize $||\tilde{x} - x||$.



The boundary attack

Step 1: Start with a non-adversarial image x (does not have to belong in the original dataset), which is correctly predicted as c.

Make another image x_0, by (heavily) noising your original image x.

This image x_0 should be misclassified.

Restricted

The boundary attack

Step 2: modify your image x_n for instance by using random noising, with low amplitude.

If the new image x_{n+1} is incorrectly classified and verifies $||x_{n+1} - x|| \leq ||x_n - x||$, then keep x_{n+1}.

Otherwise reuse the previous image, i.e. $x_{n+1} = x_n$.

The boundary attack

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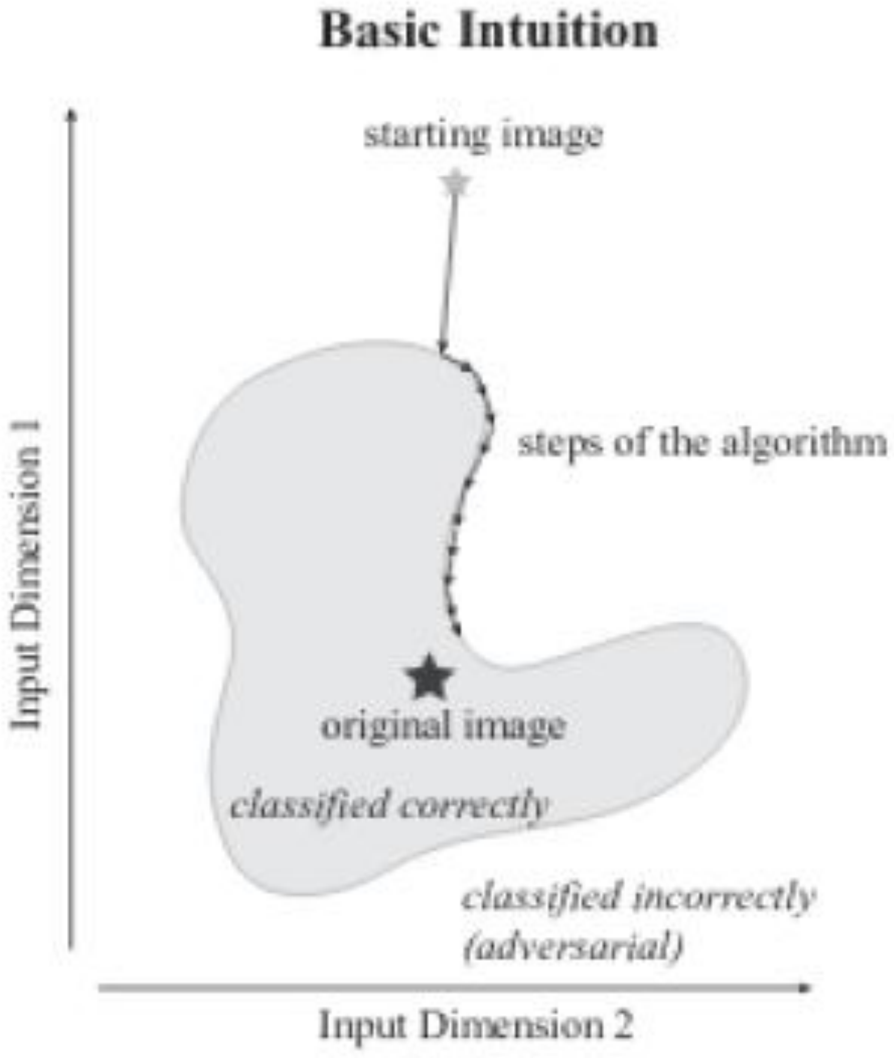
Step 3: repeat step 2, until a maximal number of iterations N is reached.

The boundary attack

Definition (the boundary attack):

The **boundary attack** (from [Brendel2018]) is a black-box type of attack, which only requires access to the inputs and outputs of the model under attack f.

It attempts to create an image, which will look plausible, but will be misclassified. It does so by walking on the boundary of the correct prediction region, and attempts to minimize $||\tilde{x} - x||$



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Step 3: repeat step 2, until a maximal number of iterations N is reached.

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Additional notes

- You can progressively decrease the noise amplitude when generating x_{n+1} from x_n (in a similar fashion as with the learning rate scheduling).
- Add an extra condition, being that your x_n must be of a certain target class $\tilde{c}$ to make it a targeted attack.

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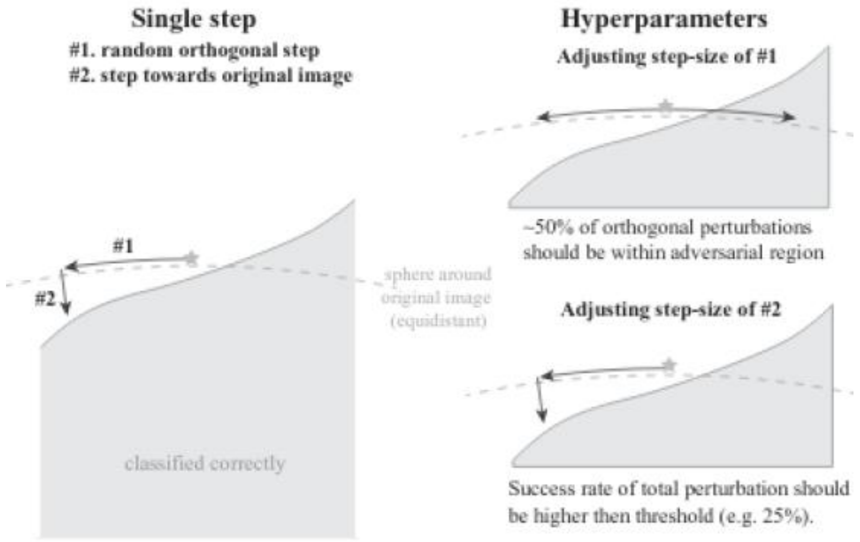
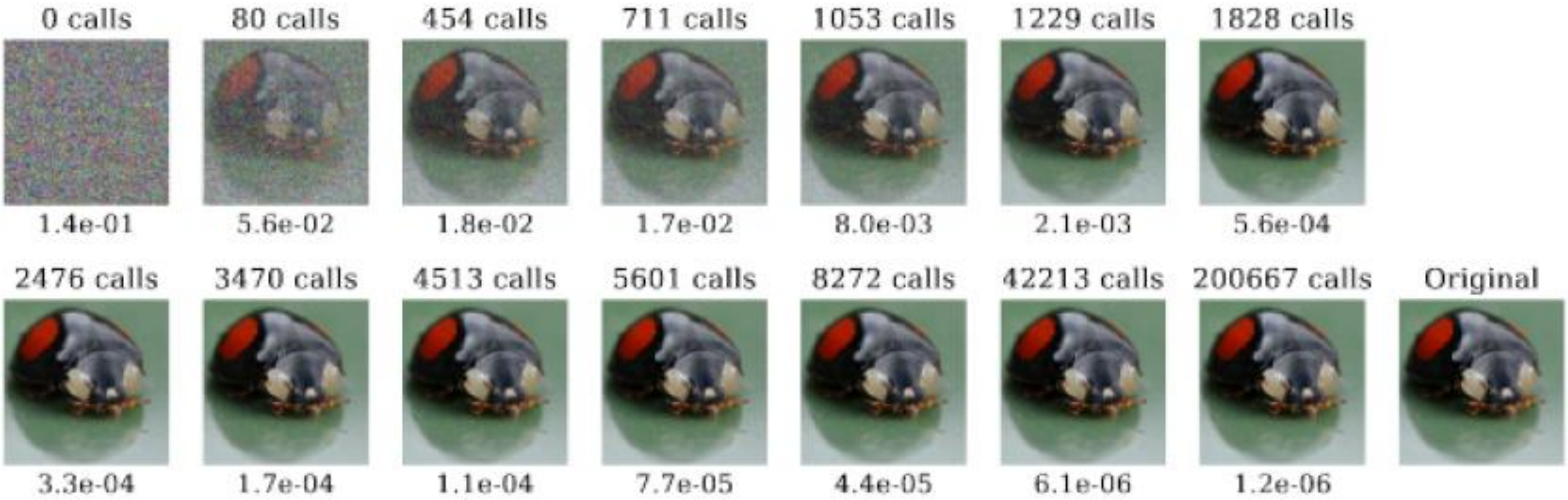
Additional notes

- More advanced methods may even try and guess the local geometry of the boundary to make better iterations on the x_n images.

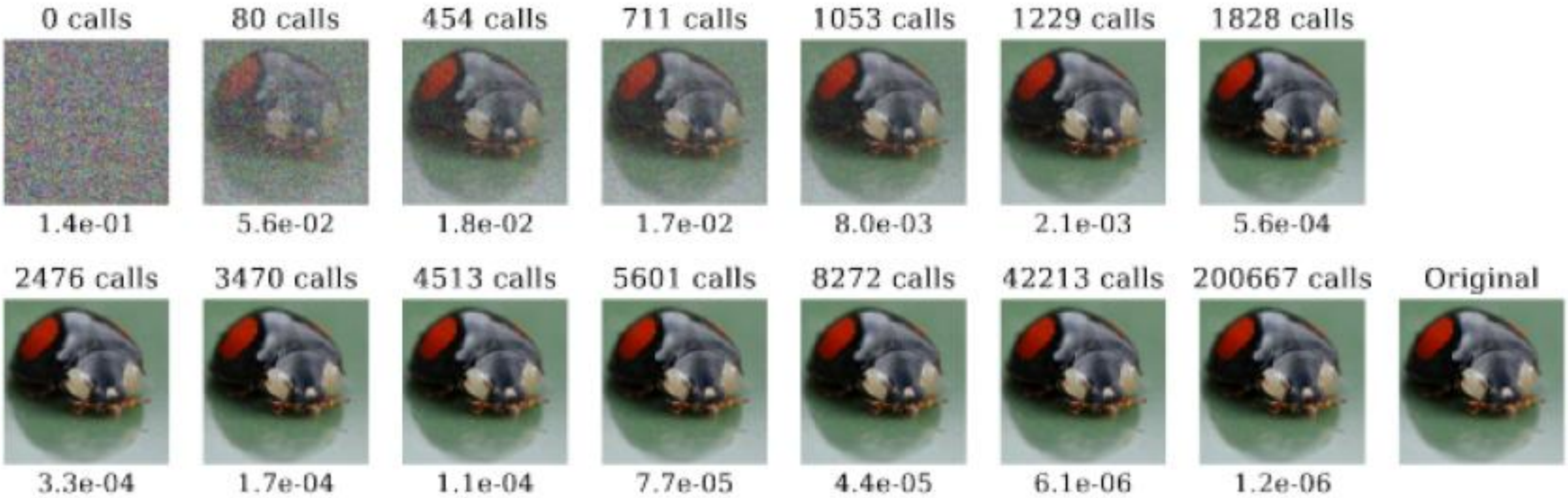


The boundary attack in action



Restricted

The boundary attack in action



Note: Implementation is not necessarily difficult, but cumbersome.
We leave the implementation of these methods out of the scope of this class (Have a look at the papers with code website!)

Black-boxing your model for defense (v2.0!).

Definition (Black-boxing defense, version 2.0!):

The **black-boxing** **defense** refers to the concept of hiding your model parameters to prevent attackers from accessing and using some of these parameters (neither weights, gradients nor logits) in their attacks.

~~The only thing attackers can do is submit inputs and get outputs from the model.~~

To make the model as black as possible, we can forbid the attacker from even ACCESSING THE MODEL!

Defending by ensemble-ing your model

Definition (The ensemble defense):

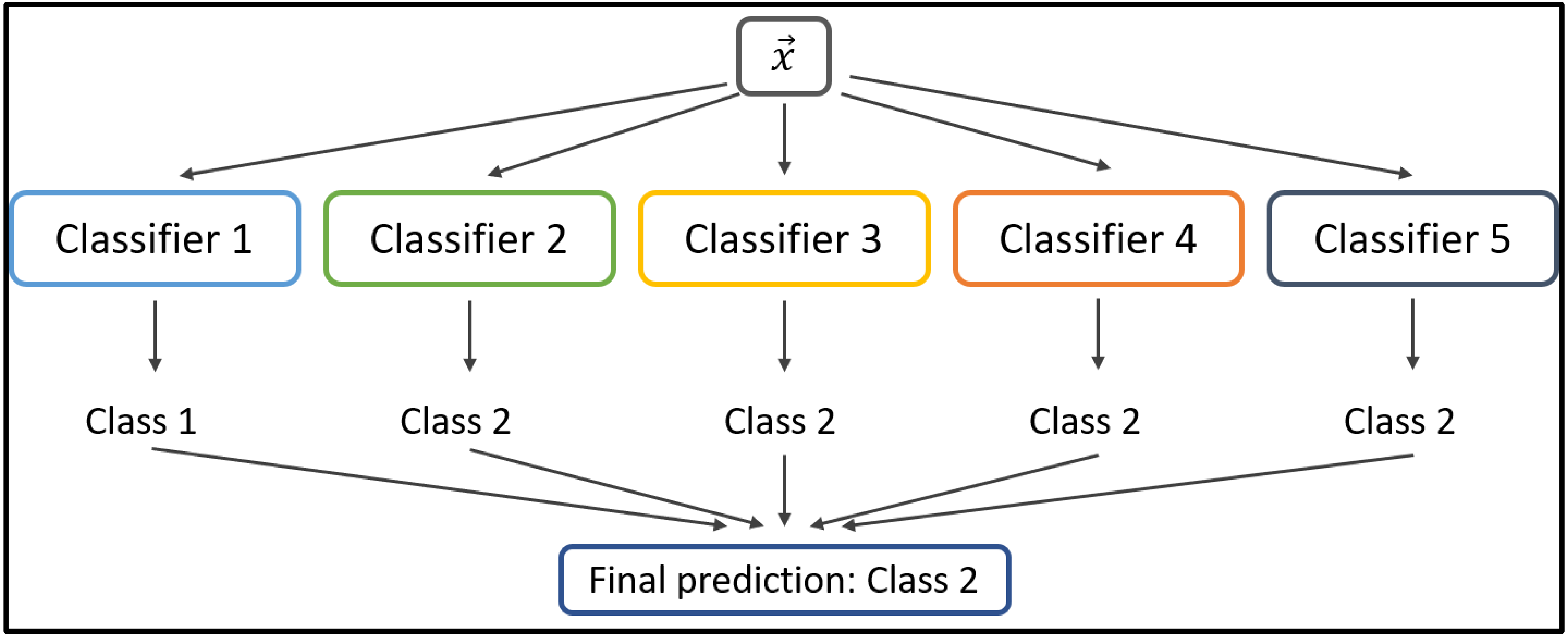
The ensemble **defense** refers to the concept of using multiple models to prevent attackers from making your classifier malfunction.

Each model is trained with a different initialization, hence leading to different weights, gradients, etc.

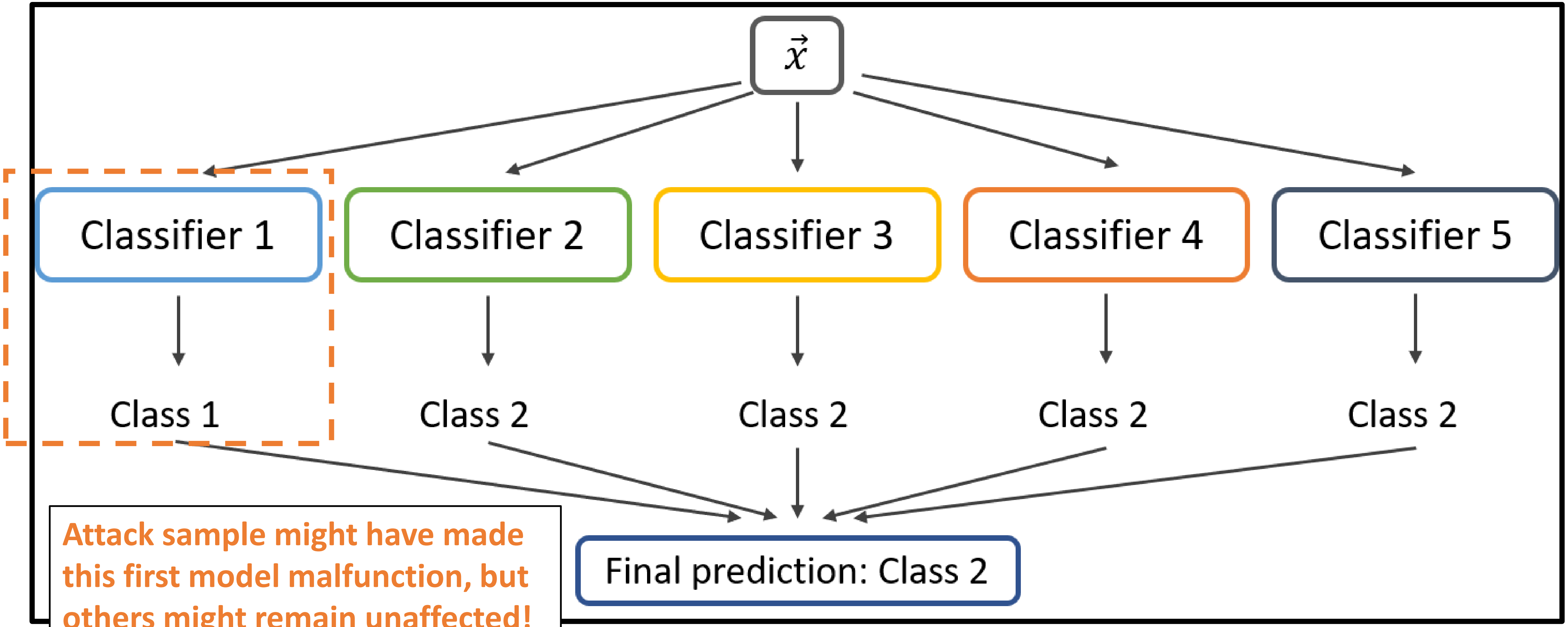
During testing, each image is passed to each different model, and a list of predictions is obtained (one for each model). The label, which appears the most often is the one returned by our ensemble classifier.

This makes the life of attackers extra difficult, as they have to successfully attack multiple models, with the same sample to make the prediction wrong.

Defending by ensemble-ing your model



Defending by ensemble-ing your model



Attack sample might have made this first model malfunction, but others might remain unaffected! (Final decision is still class 2)

Maximal defense

- Nothing more defenders can really do at this point. They have kept their model secret and “ensembled” it.
- The attackers only know that the defender has a model, which is trying to accomplish a certain task, but have no access to it.
- Defenders have even used multiple instances of the model to get an ensemble classifier.
- This covers for attacks that would make one model malfunction.

Attackers obviously lost, right?

On the transferability of attacks

Attackers obviously lost, right?

Well… Yes and no.

- While it may seem very difficult to make an **ensemble**, **hidden** model malfunction…
- Recent papers have shown that attacks might be **transferable** [Liu2017].

- **Note:** this is what we exploited for our **surrogate attack**, in the first place.
- Unfortunately, this means an attack, which makes a certain facial recognition algorithm fail, has great chances to make another mode, even different, fail as well.
- And even more true for models within a same ensemble.

Conclusion (W6S3)

- Training and attacking a model seem to be the two faces of a same coin.
- Being able to do one, unfortunately exposes you to the second one.
- Both attackers and defenders have many options up their sleeve. But attackers seem to have a clear advantage.
- Attackers are able to exploit
  - Intrinsic information from models.
  - But more importantly, fundamental limits of neural networks.
- It is a very active research field, with many more advanced concepts, for obvious reasons, as any “sensitive” application will require some kind of defense.

Learn more about these topics

- [Madry2017] **Madry** et al., “Towards Deep Learning Models Resistant to Adversarial Attacks”, 2017 https://arxiv.org/abs/1706.06083
- [Papernot2015] **Papernot** et al., “Distillation as a Defense to Adversarial Perturbations against Deep Neural Networks”, 2015 https://arxiv.org/abs/1511.04508
- [Dong2017] Dong et al., “Boosting Adversarial Attacks with Momentum”, 2017. https://arxiv.org/abs/1710.06081
- [Carlini2017] **Carlini** and **Wagner**, “Towards Evaluating the Robustness of Neural Networks”, 2017. https://arxiv.org/abs/1608.04644

Learn more about these topics

- [Papernot2017] **Papernot** et al., “Practical Black-Box Attacks against Machine Learning”, 2017. https://arxiv.org/abs/1602.02697
- [Brendel2018] Brendel et al., “Decision-Based Adversarial Attacks: Reliable Attacks Against Black-Box Machine Learning Models”, 2018. https://arxiv.org/abs/1712.04248
- [Liu2017] Liu et al., “Delving into Transferable Adversarial Examples and Black-box Attacks”, 2017. https://arxiv.org/abs/1611.02770

Interested in implementing advanced algos? Look them up on PapersWithCode first!

Towards Evaluating the Robustness of Neural Networks

Edit social preview

16 Aug 2016 • Nicholas Carlini • David Wagner

Neural networks provide state-of-the-art results for most machine learning tasks. Unfortunately, neural networks are vulnerable to adversarial examples: given an input x and any target classification t, it is possible to find a new input x' that is similar to x but classified as t... (read more)

PDF Abstract

Code

Edit

carlini/nn_robust_attacks	★ 560	TensorFlow
MadryLab/cifar10_challenge	★ 315	TensorFlow
LeMinhThong/blackbox-attack	★ 51	PyTorch
kkew3/pytorch-cw2	★ 38	PyTorch
inspire-group/advml-traffic-sign	★ 16	

See all 22 implementations

Tasks

Edit

ADVERSARIAL ATTACK

https://paperswithcode.com/paper/towards-evaluating-the-robustness-of-neural

Learn more about these topics

Out of class, for those of you who are curious

- [Medium1] On the ongoing race of coming up with new attacks. https://medium.com/mlreview/the-intuition-behind-adversarial-attacks-on-neural-networks-71fdd427a33b

- [Medium2]On why security systems using deep learning are potentially under threat. https://medium.com/@chami.soufiane/security-threats-against-machine-learning-based-systems-a-real-concern-2515115c88e4

Learn more about these topics

Out of class, for those of you who are curious

- [YTB1] Generating adversarial patches against YOLOv2, a.k.a. printing patterns to fool AIs and become invisible. https://www.youtube.com/watch?v=MIbFvK2S9g8

- [Stanford] Stanford lecture, by Ian **Goodfellow** @ Stanford on attacks and defense mechanisms for Neural Networks (long!) https://www.youtube.com/watch?v=CIfsB_EYsVI

Learn more about these topics

More fun stuff

- [Eykolt2018] Eykolt et al. “Robust Physical-World Attacks on Deep Learning Models”, 2018.
  Printing stickers to put on your tee-shirts to fool facial recognition systems.
  https://arxiv.org/abs/1707.08945
- [Moosavi-Dezfooli2016] **Moosavi-Dezfooli** et al., “DeepFool: a simple and accurate method to fool deep neural networks”, 2016.
  A toolbox with previously mentioned attacks and more advanced attacks.
  https://arxiv.org/abs/1511.04599
- [Athalye2018] Athalye et al., “Synthesizing Robust Adversarial Examples”, 2018.
  3D printing misclassified stuff.
  https://arxiv.org/abs/1707.07397

Learn more about these topics

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

- **Aleksander Madry: Professor** at **MIT,** Director of the MIT Center for Deployable Machine Learning and a Faculty Co-Lead of the MIT AI Policy Forum.
  http://madry-lab.ml/
  https://people.csail.mit.edu/madry/
  https://scholar.google.ch/citations?user=SupjsEUAAAAJ&hl=en
- **Nicolas Papernot: Assistant Professor** at **University of Toronto**.
  https://www.papernot.fr
  https://scholar.google.com/citations?user=cGxq0cMAAAAJ&hl=en

Learn more about these topics

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- **Nicholas Carlini**: **Research Scientist** at **Google Brain**.
  https://nicholas.carlini.com
  https://scholar.google.com/citations?user=q4qDvAoAAAAJ&hl=en
- **David Wagner**: **Professor** at **UC Berkeley**.
  https://people.eecs.berkeley.edu/~daw/papers
  https://scholar.google.com/citations?user=67kghxAAAAAJ&hl=en