

# CSC 7570-001 AI Assisted Cyber Security (Fall 2023)

(Assignment 5 - Adversarial Solutions )

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## Lab A - Adversarial Attack on Malware Classifier

### 1 Adversarial Attack: Questions and Solution

#### 1.1 Q1: Did the model correctly classify it?

**Answer:** Yes, the model correctly classify the **Gatak sample** with 100 % confidence, this is shown in Fig. 1

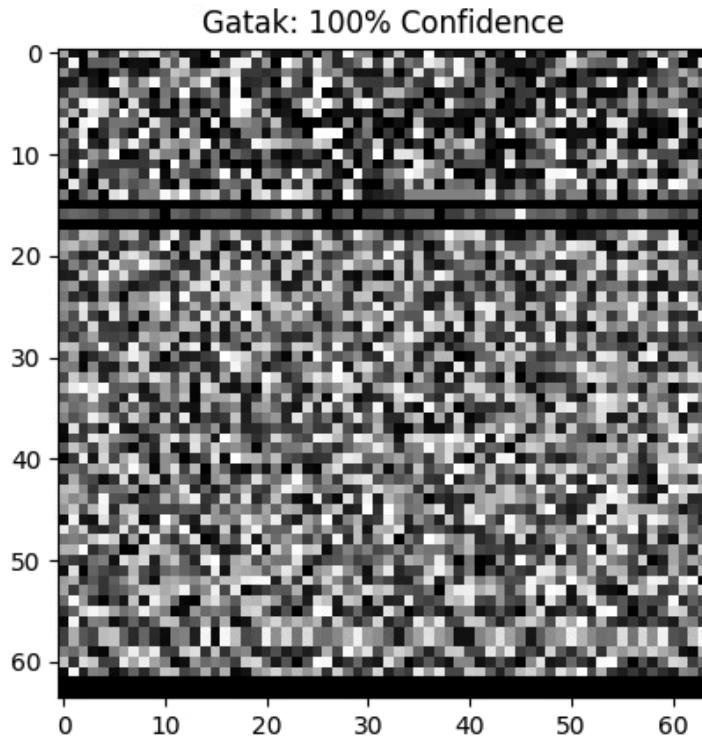


Figure 1: Screenshot of Classifying the base Gatak sample

#### 1.2 The adversarial pattern

Shown below is the plot after uncommenting line 91 for "plt.show()" in the FGSM\_attack.py file.

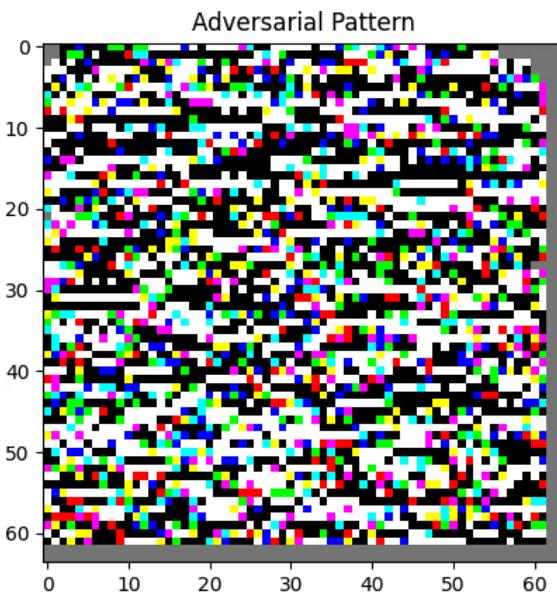


Figure 2: Screenshot of the adversarial pattern

### 1.3 Making an adversarial sample by adjusting the Epsilon.

#### 1.3.1 Q3: Did the model calssify the adversarial sample correclly?

**Answer:** No, with **Epsilon = 0.15** the model wrongly classify the image as **Remnit** malware family. See Figure 3 for the screenshot.

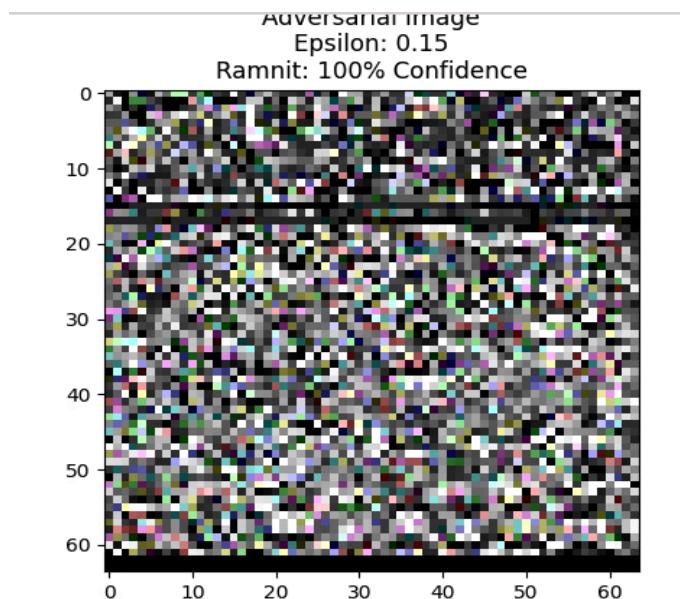


Figure 3: Screenshot of the adversarial classification with Epsilon = 0.15

#### 1.3.2 Multiple Testing with Espilon=0.15:

After running the test more than once, the model always produce the **Remnit** family prediction with the same confidence of 100 %

## 2 Fine-tuning the Adversarial Attack

The goal of an adversarial image is to maximize disruption to the model while minimizing visible changes to the image.

### 2.1 epsilon value at 0.05, 0.25, 0.30

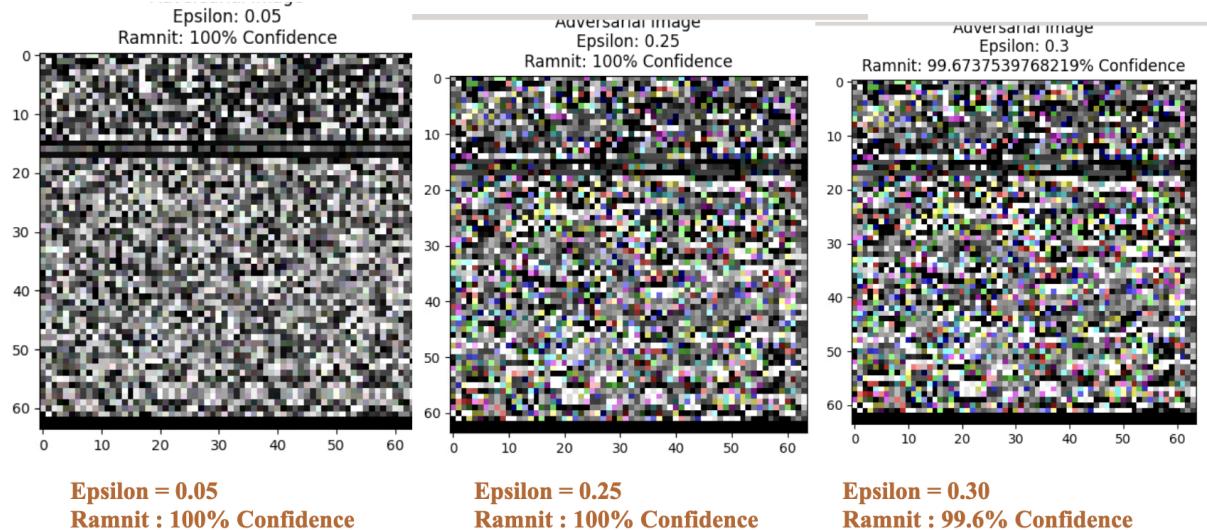


Figure 4: Screenshot of Epsilon = 0.05, 0.25, 0.30

### 2.2 epsilon value at 0.40, 0.50, 0.65

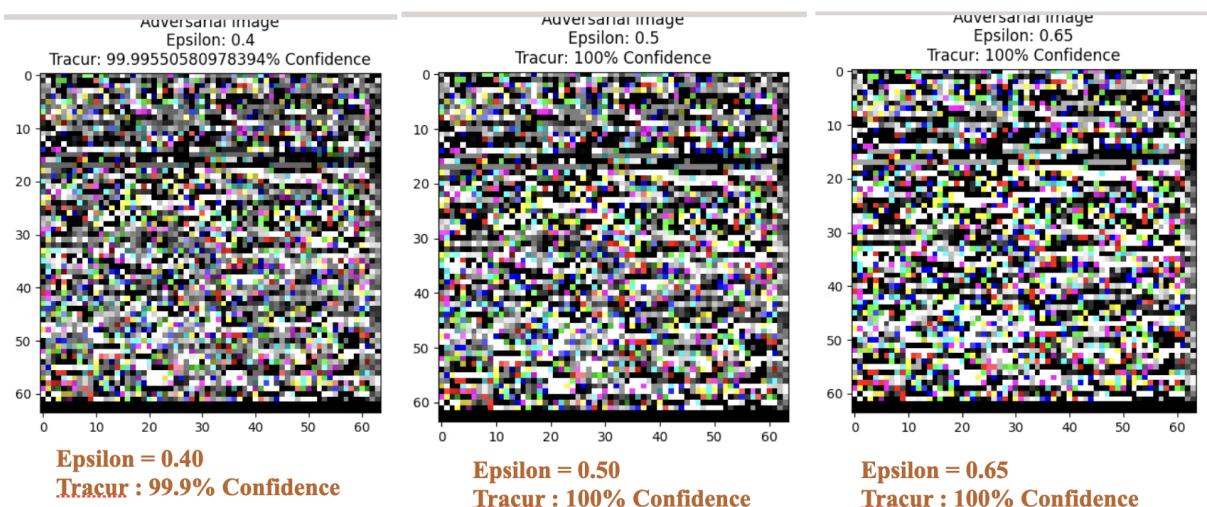


Figure 5: Screenshot of Epsilon = 0.40, 0.50, 0.65

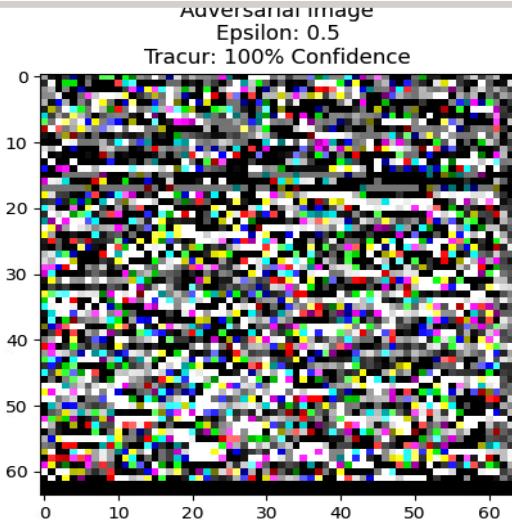


Figure 6: Screenshot of Epsilon = 0.50

### 2.3 epsilon value at 0.85, 0.92, 0.99

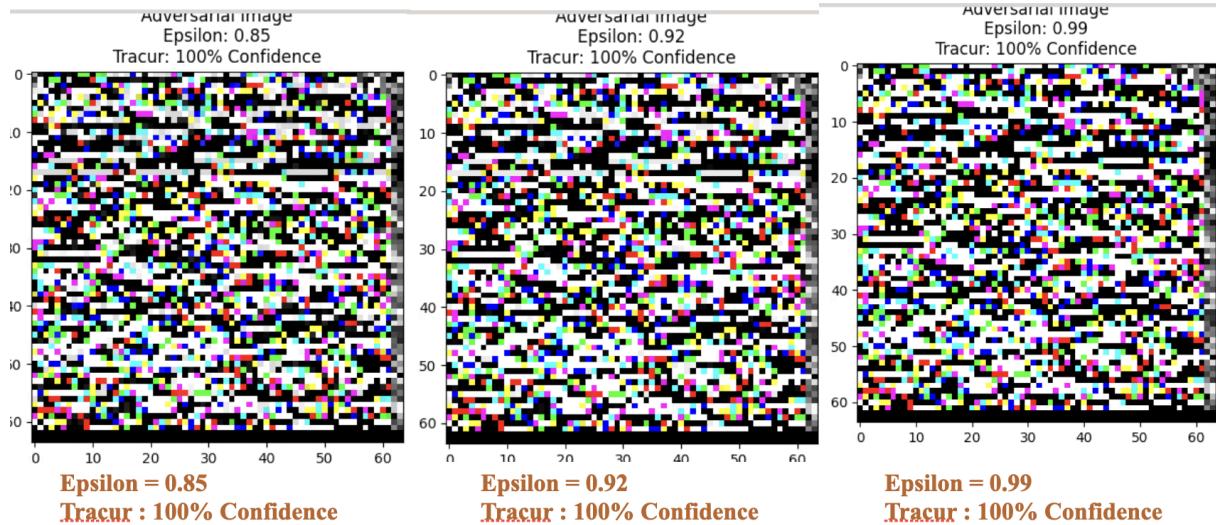


Figure 7: Screenshot of Epsilon = 0.85, 0.92, 0.99

#### 2.3.1 Best Value of Epilon

In my experiment the best values for epilon with 100% confidence includes:

1. 0.25 for **Ramnit** family, see fig. 4
2. 0.50 for **Tracur** family see 5 and 6
3. 0.85, 0.92, 0.99 for **Tracur** family, see fig. 7

**Q 3.2:** Yes, there is a visual difference in the adversarial sample and the original as the epsilon value increases.

**Q 3.3:** Yes, the model misclassify my adversarial sample to **Ramnit** family and **Tracur** family at epsilon = 0.50, 0.85, 0.92, 0.99 with 100% confidence

### 3 Lab B. Adversarial Training

#### Lab A - Adversarial Attack on Malware Classifier

##### 3.1 Model accuracy on regular inputs

- Accuracy on regular input = 91.5%. Attached is the screenshot in fig. 8

```
    ////////////////////////////////////////////////// - 1s 84ms/step - loss: 0.2315 - accuracy: 0.9200
Epoch 50/50
7/7 [=====] - 1s 89ms/step - loss: 0.2519 - accuracy: 0.9250
Found 1584 images belonging to 8 classes.
7/7 [=====] - 0s 30ms/step - loss: 0.8403 - accuracy: 0.8400
trained, regular data: 0.8399999737739563

7/7 [=====] - 0s 30ms/step - loss: 1.2671 - accuracy: 0.7450
trained, adversarial data 0.7450000047683716

Report:
Untrained model, regular data: 91.50000214576721 %
```

Figure 8: Model's accuracy on regular malware sample images

##### 3.2 Plots of some of the non-adversarial malware samples

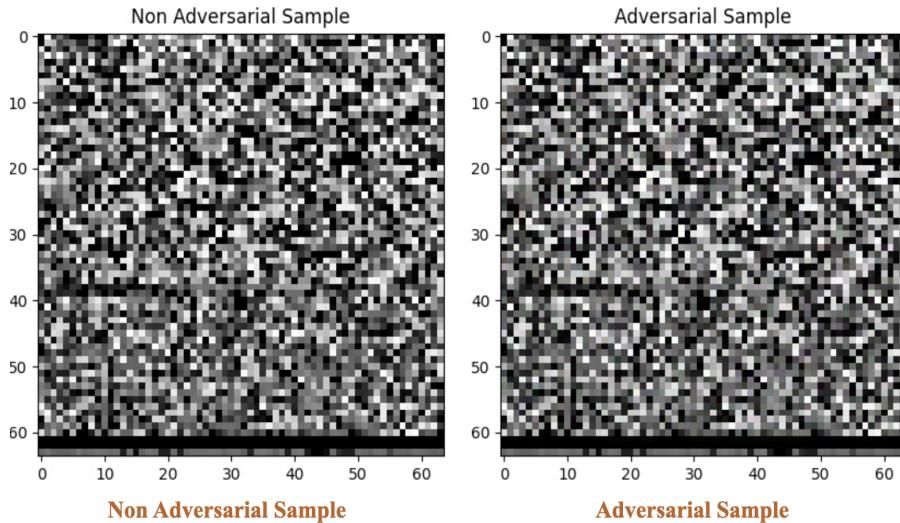


Figure 9: Adversarial and Non-adversarial sample

###### 3.2.1 Untrained model accuracy on the adversarial inputs

- Untrained model's accuracy = 86.00%. Attached is the screenshot in fig. 10.

```
trained, regular data: 0.8700000047683716

7/7 [=====] - 0s 27ms/step - loss: 1.6567 - accuracy: 0.7400
trained, adversarial data 0.7400000095367432

Report:
Untrained model, regular data: 86.00000143051147 %
```

Figure 10: untrained model's accuracy on the adversarial inputs

### 3.3 Model's accuracy on adversarial samples

- model's accuracy on adversarial = 74.50%.

```
trained, adversarial data 0.7450000047683716

Report:
Untrained model, regular data: 87.00000047683716 %
Trained model, adversarial data: 74.50000047683716 %
```

Figure 11: model's accuracy on adversarial samples

### 3.4 model's accuracy on regular malware samples

- model's accuracy on regular malware sample = 87.99%.

```
Report:
Untrained model, regular data: 86.00000143051147 %
Trained model, adversarial data: 73.00000190734863 %
Trained model, regular data: 87.9999952316284 %
```

Figure 12: model's accuracy on regular malware samples

### 3.5 model's accuracy with New set of Adversarial samples of Epsilon =0.005

- Accuracy on adversarial sample (espilon =0.005) = 86.00%.

```
Report:
Untrained model, regular data: 86.00000143051147 %
Trained model, adversarial data: 86.00000143051147 %
Trained model, regular data: 87.9999952316284 %
```

Figure 13: model's accuracy = 86 % epsilon=0.005

### 3.6 model's accuracy with New set of Adversarial samples of Epsilon =0.1

```
Report:  
Untrained model, regular data: 86.50000095367432 %  
Trained model, adversarial data: 14.000000059604645 %  
Trained model, regular data: 86.50000095367432 %
```

Figure 14: trained model's accuracy = 14.00 % epsilon=0.1

- The trained model accuracy on adversarial sample with (espilon =0.1) = 14.00%.

**Answer:** with larger epsilon value such as  $\epsilon = 0.1$ , our model performs poorly with 14 % accuracy, hence our model can't sufficiently defend against those adversarial samples.

### 3.7 Train model with large Epsilon =0.1 and Attack model with small Epsilon = 0.005

- The trained model accuracy for adversarial samples = 77.99%.
- The trained model accuracy for regular sample = 68.99%.

```
Report:  
Untrained model, regular data: 91.00000262260437 %  
Trained model, adversarial data: 77.99999713897705 %  
Trained model, regular data: 68.9999976158142 %
```

Figure 15: trained model'swith with epsilon=0.1 vs attack epsilon = 0.005

• **Q 7.3 Answer: YES**, With larger epsilon value  $\epsilon = 0.1$  for the training model. The accuracy of model on regular dropped from 86.5 % to 68.99 %.

• **Q-7.4:** Is adversarial training on this model a good protection against fast gradient sign method attacks? **Why or why not?**

#### 3.7.1 Answer: 7.4

**YES**, adversarial training on this model could be effective against **fast gradient sign method attacks**, as the model exhibits higher accuracy on adversarial samples of 77.99% for train epsilon = 0.1 and 86% for training epsilon =0.1.

The improvement to suggests that the model has learned to better handle **perturbations** introduced by such attacks, making it a potentially robust defense. However, a more comprehensive evaluation and testing on a diverse set of adversarial scenarios are recommended for a conclusive assessment.