



Center for Research in Applied
Cryptography and Cyber Security

DEFENCE AGAINST ADVERSARIAL EXAMPLES

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Problem Description

Building high accuracy DNN models which are sufficiently resistant to adversarial attacks



Background and Goal

- ✓ An adversarial example is an instance with small, intentional feature perturbations that cause a machine learning model to make a false prediction.
- ✓ The goal is to Find a way to train 'secured' models such that this sort of attacks should not affect them.
- ✓ Project based on the article <u>Bridging machine learning and cryptography in defence against adversarial attacks</u>

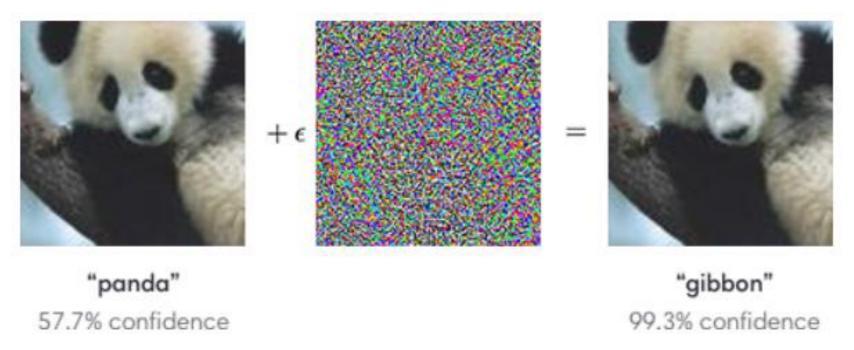


Figure 1: example of an adversarial image

Set-Up

- ✓ Mnist and Fashion-Mnist datasets
- ✓ Using well-known neural nets

1. Securing Models

Approach: training models on encrypted images.

Encryption techniques:

- ✓ Permutation
- ✓ AES in ECB, CBC and CTR modes

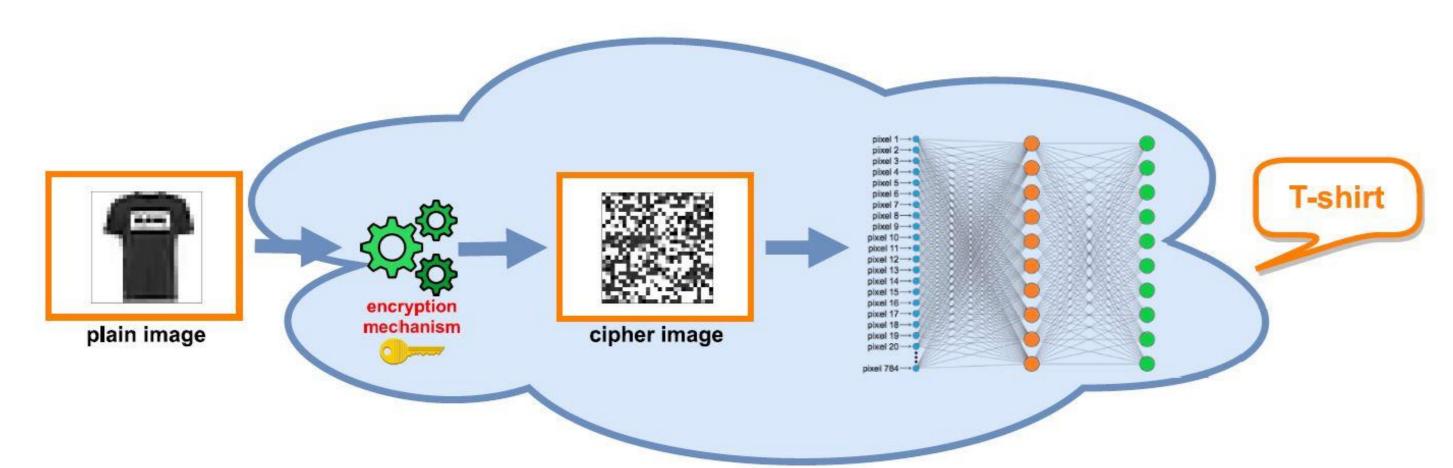


Figure 2: architecture for securing models

2. Cutting Loose Ends

Eliminated the models that did not learn well. Learning encrypted images is not very intuitive, as can be seen in figure 3.

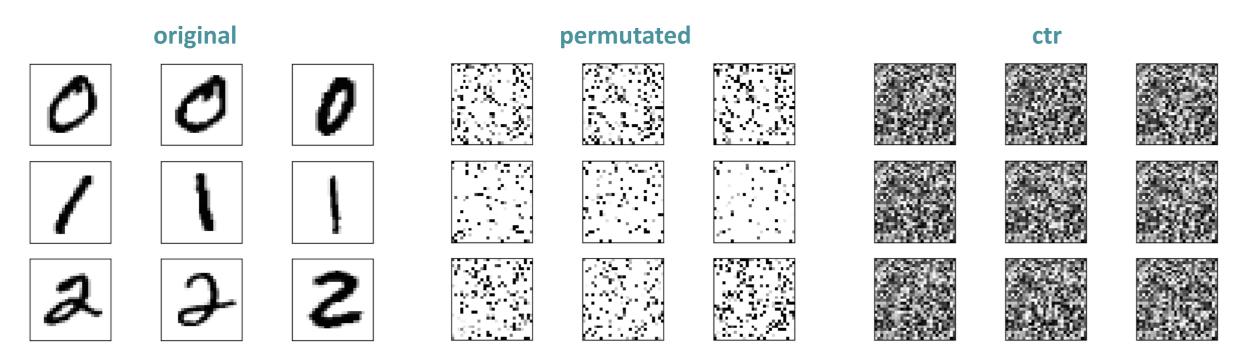


Figure 3: Sample of the encrypted images. Interesting to see how for the human eye it's not easy to distinguish between various classes but a DNN model classifies quite well, as can be seen in table 1

3. Attacking

Attacks:

- ✓ Carlini & Wagner, CW
- ✓ Fast Gradient Sign Method, FGSM

'gray-box' scenario, i.e. the attacker knows the architecture of the model but has no access to the private key.

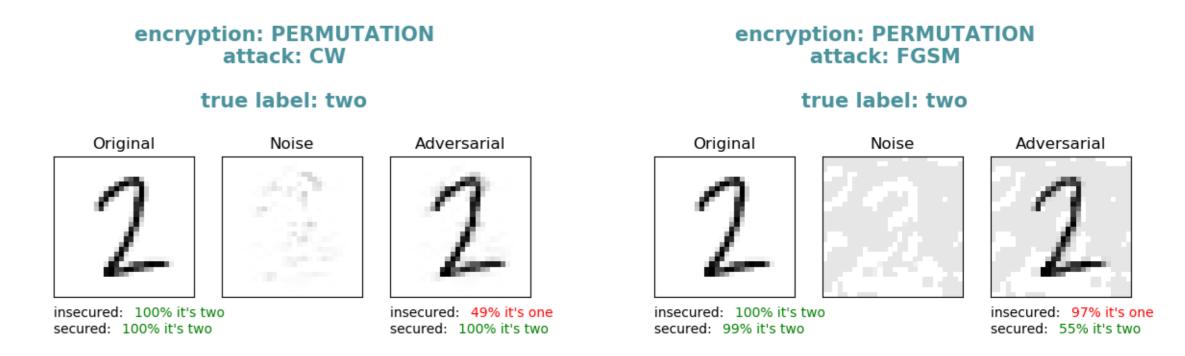


Figure 4: visualization of a CW and FGSM attack

Results

There's a slight tradeoff between accuracy on the original images and the accuracy on the adversarial images, but overall, accuracies are good. See table 1 for the detailed results.

Classification error (%) on the first 1000 test samples								
		mnist		fashion_mnist				
		original	iginal adversarial images		original	adversarial images		
	model	images	attack	gray-box	images	attack	gray-box	
UNENCRYPTED			CW I ₂	100.00		CW I ₂	100.00	
	Α	1.49	CW I ₀	100.00	8.30	CW I ₀	100.00	
			CW I _∞	100.00		CW I _∞	100.00	
	В	2.10	FGSM	39.50	9.50	FGSM	77.20	
PERMUTATED			CW I ₂	4.50		CW I ₂	12.70	
	Α	3.70	CW I ₀	7.30	12.30	CW I ₀	12.50	
			CW I _∞	5.40		CW I _∞	12.90	
	В	4.20	FGSM	8.60	12.00	FGSM	29.80	
AES · ECB	Α	18.40	CW I ₂	irrela	54.60	CW I ₂	irrela	
	В	19.30	FGSM	irrelevant	55.30	FGSM	irrelevant	
AES · CBC	Α	67.60	CW I ₂	irrela	71.50	CW I ₂	irrela	
	В	87.40	FGSM	irrelevant	90.30	FGSM	irrelevant	
AES · CTR	Α	3.70	CW I ₂	4.20	17.40	CW I ₂	17.20	
	В	2.70	FGSM	4.90	16.70	FGSM	26.50	

Table 1: table containing all the results

Success with Permutation, Coincidence?

To verify that the learning ability of a permutation model does not result from high density in small images, we trained models on padded images. See table 2 for results.

Padding done with white pixels					
	image size	error rate			
	28x28	3.70			
mnist	40x40	3.40			
	60x60	3.30			
	28x28	12.30			
fashion_mnist	40x40	14.40			
	60x60	10.80			

Table 2: results for training permutated data, various image dimensions

Future Work

- ✓ Improve accuracy on AES-ECB model
- ✓ Nicholas Carlini (the 'C' in CW attack) believes we still might defeat these defenses. (we contacted him)
- ✓ Test on more complicated datasets; i.e. Cifar-10







