

Paper Review - TFHM : A Traffic Feature Hiding Scheme Based on Generative Adversarial Networks



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TFHM : A Traffic Feature Hiding Scheme Based on Generative Adversarial Networks

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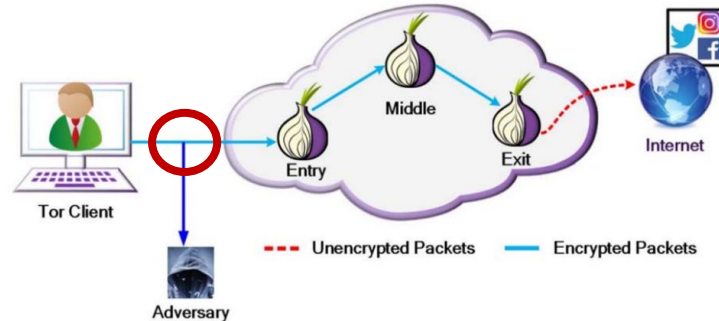
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TFHM : A Traffic Feature Hiding Scheme Based on Generative Adversarial Networks

Problem

- Privacy leakage (encrypted traffic)
- Difficult to implement traffic features hiding mechanisms



TFHM : A Traffic Feature Hiding Scheme Based on Generative Adversarial Networks

Motivation

- Current defense schemes lack dynamics
- Most schemes lose defense ability

Contribution

- A dynamic traffic feature hiding technology for traffic analysis (TFHM)

TFHM : A Traffic Feature Hiding Scheme Based on Generative Adversarial Networks

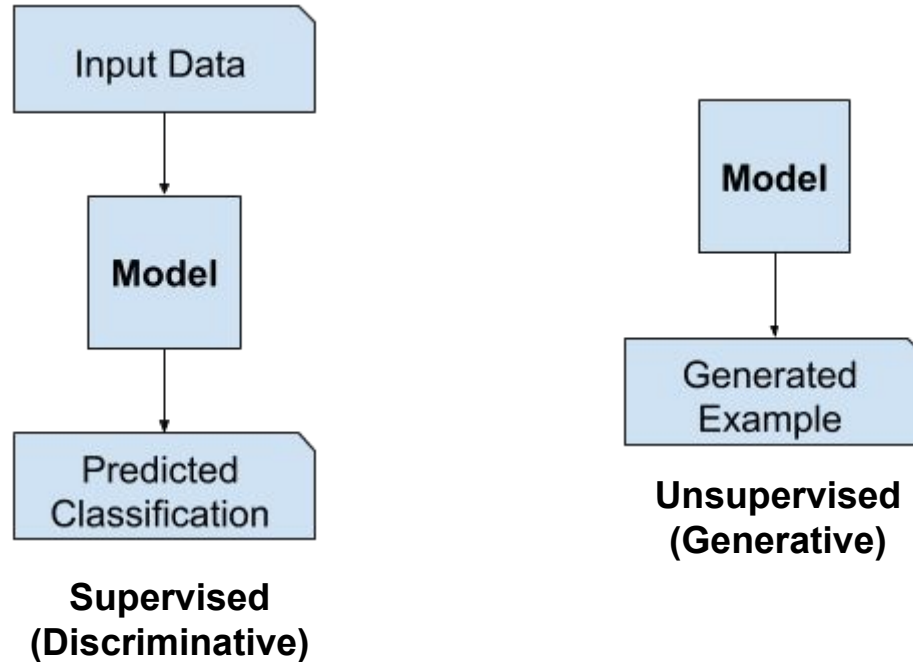
Background

- Adversarial Examples (AML)
- Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GAN)

- **GAN**
 - Generative modeling
 - Unsupervised learning
 - Based on minimax game-theory
 - Generate or output new examples

Generative Adversarial Network (GAN) - Explained



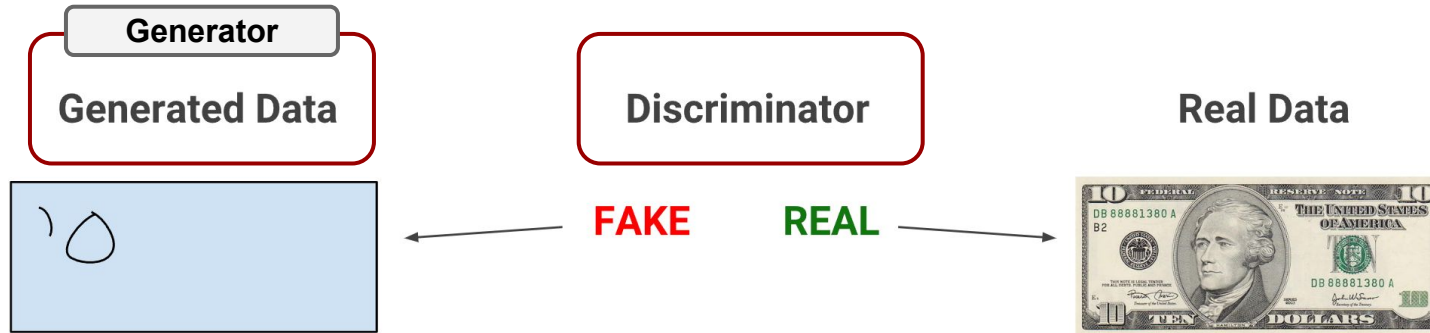
Generative Adversarial Network (GAN)

- Overview of GAN Structure

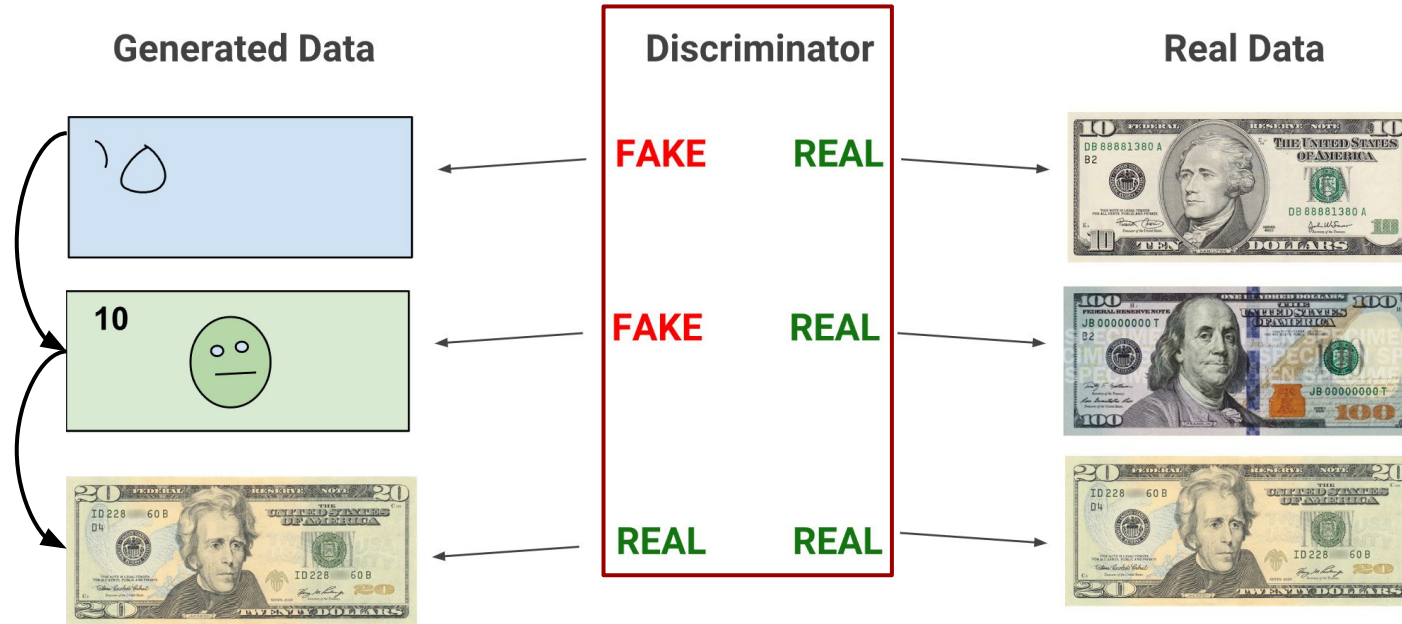


Generative Adversarial Networks (GAN)

- Overview of GAN Structure



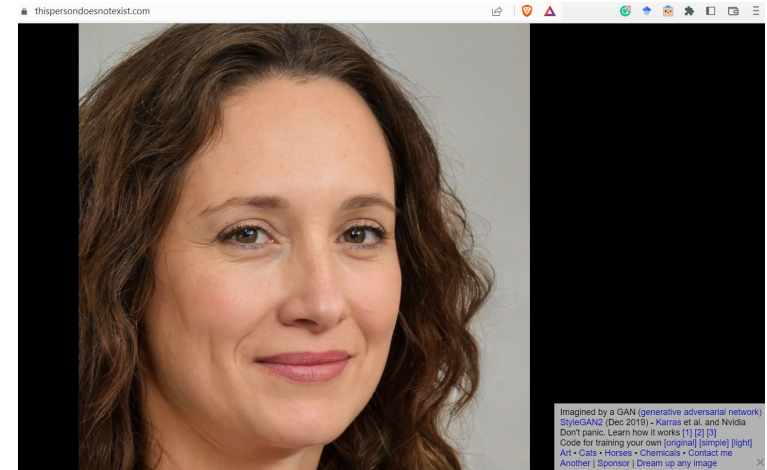
Generative Adversarial Networks (GAN)



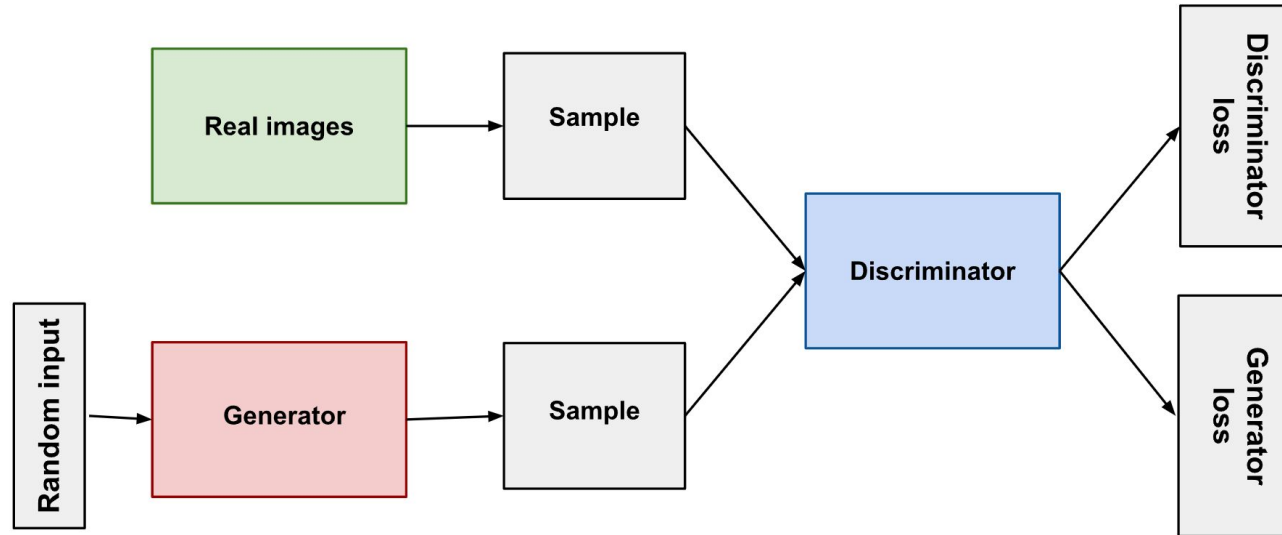
Generative Adversarial Networks (GAN)



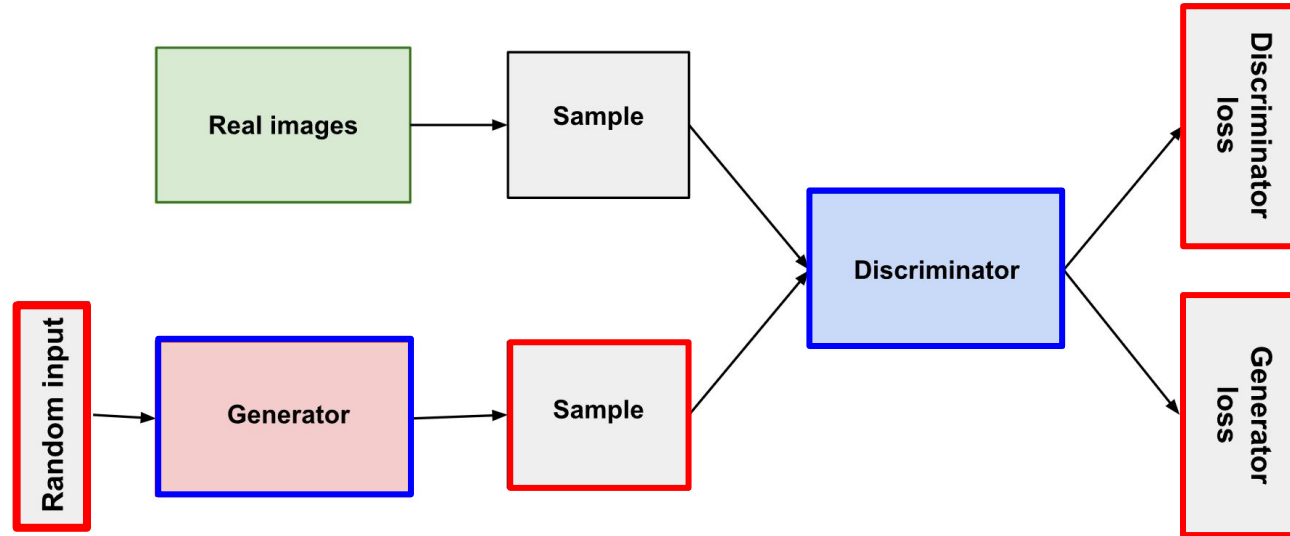
Brundage, Miles, et al. "The malicious use of artificial intelligence: Forecasting, prevention, and mitigation." *arXiv preprint arXiv:1802.07228* (2018).



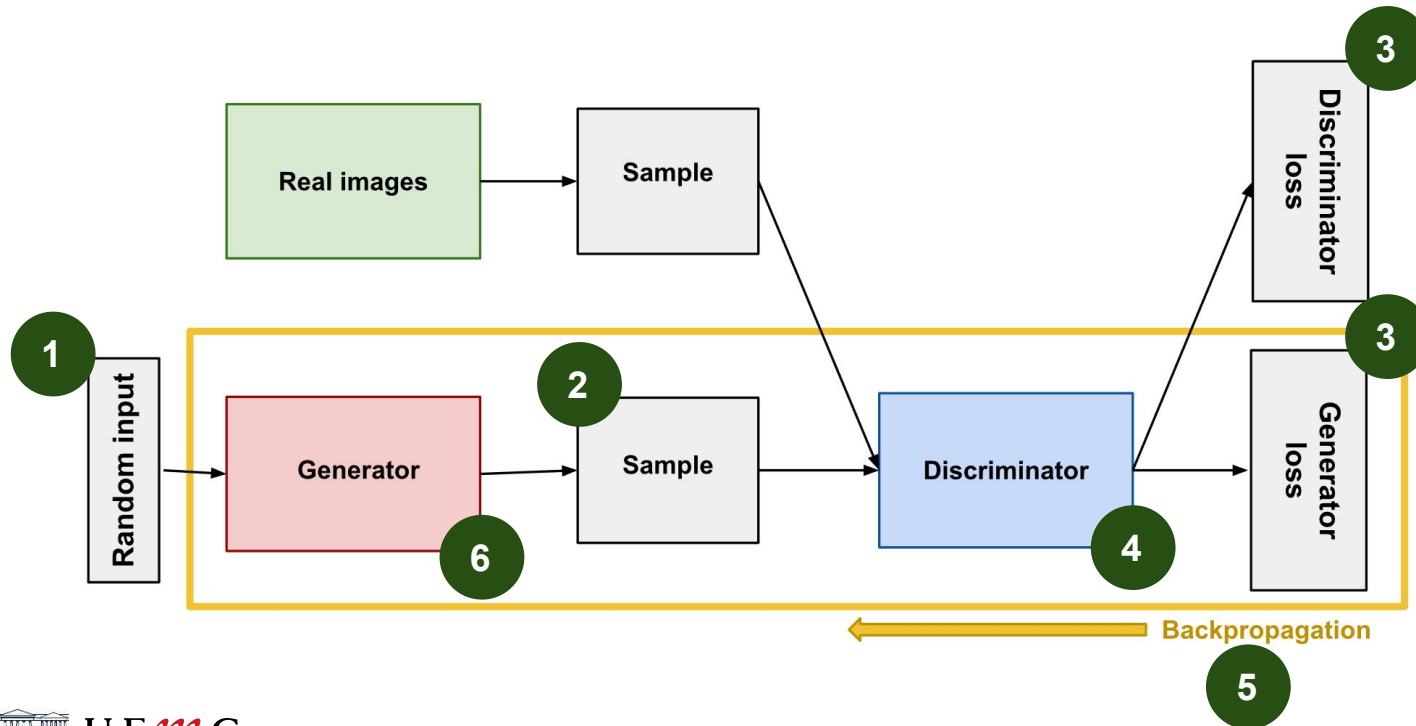
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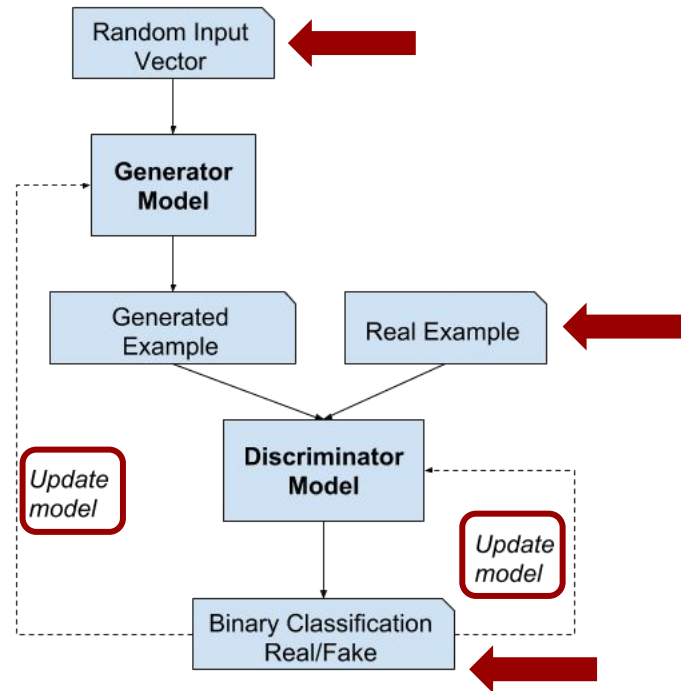
Generative Adversarial Network (GAN)



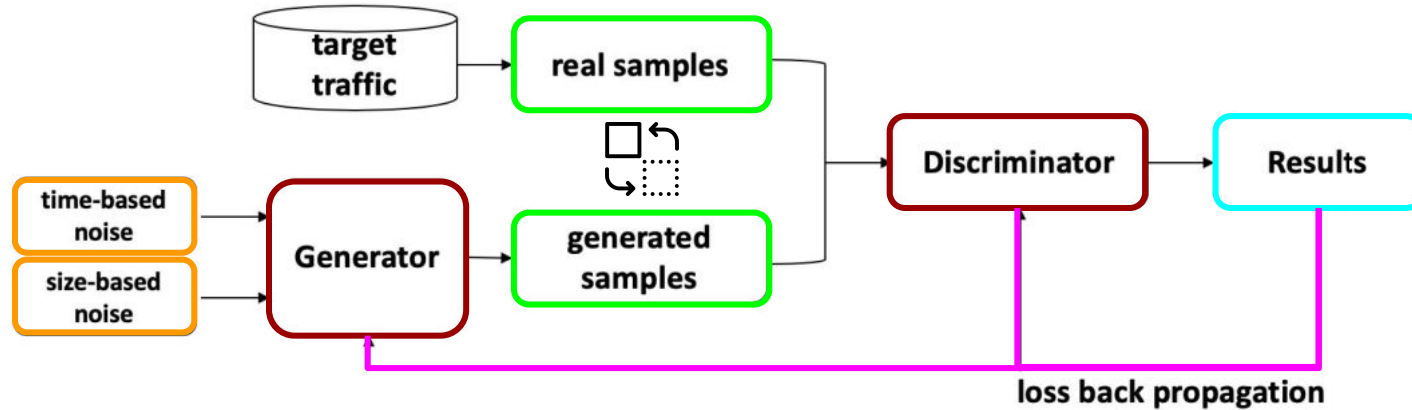
Generative Adversarial Network (GAN)



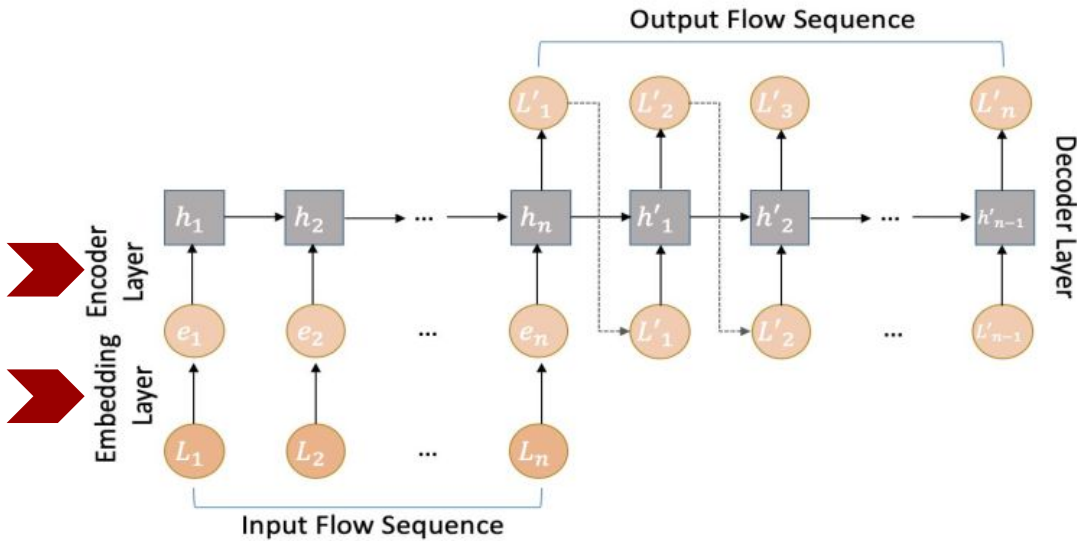
Generative Adversarial Network (GAN)



Generative Adversarial Networks (GAN)



Generative Adversarial Network (GAN)



Generator model structure

Seq2Seq model

3 layer (Embedding, encoder, decoder)

Generative Adversarial Network (GAN)

Discriminator model structure

Multilayer fully connected network

SIGMOD classification

Generative Adversarial Network (GAN)

Model solution

Minimax game-theory

Algorithm 1 Traffic feature hiding based on GAN

Input: Traffic features from the training set, where is one flow feature including packet sizes sequence and IPDs sequence.

Output: A trained traffic feature generator.

```

1: function TRAINALGORITHM
2:   Initialize a generator  $G$  with parameters and a discriminator  $D$  with parameters, maximum number of iterations  $MAXEPOCH$ .
3:   Current iteration number,  $epoch \leftarrow 1$ .
4:   while  $epoch < MAXEPOCH$  do
5:     for  $i = 0 \rightarrow step$  do
6:        $x \leftarrow$  a batch of  $m$  training samples from.
7:        $z \leftarrow$  a batch of  $m$  generated samples from random noise
8:        $z' \leftarrow$  sample data generated by the generation model based on seq-2-seq
9:       Update the generator with Adam algorithm by descending the generator's loss:
10:       $J_G = -E_m[D_\omega G_\theta(z)]$ 
11:      Use the discriminator network to distinguish the generated samples and real samples.
12:      Update the discriminator with Adam algorithm by descending the discriminator's loss:
13:       $J_D = E_m[D_\omega G_\theta(z)] - D_\omega(x) + \lambda(|||)$ 
14:     end for
15:   end while
16:   return
17: end function

```

Generative Adversarial Networks (GAN)

Threat model and dataset

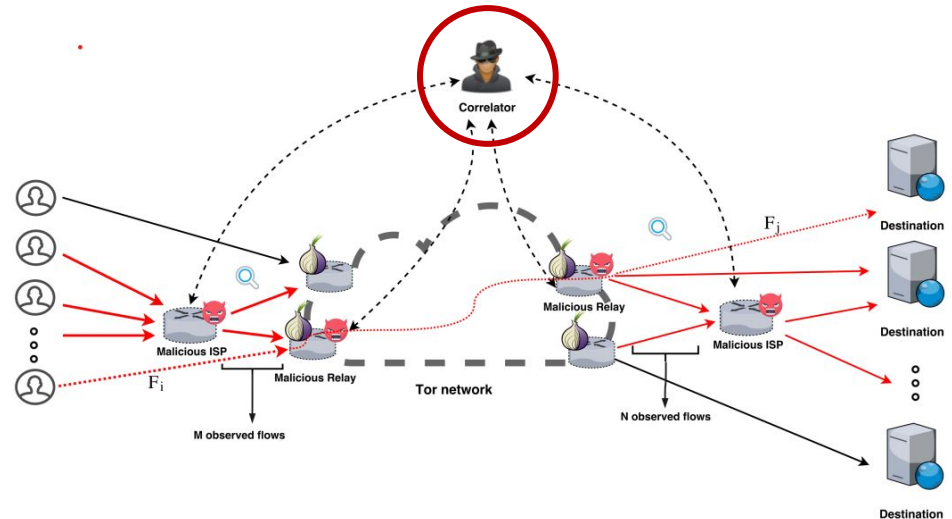
- DeepCorr**

Inter-packet delay
Packet size

<https://github.com/SPIN-UMass/DeepCorr>

Requirements

tensorflow
tqdm
pickle
numpy



Generative Adversarial Networks (GAN)

Results

ACCURACY OF ATTACKS WITH WITHOUT TFHM

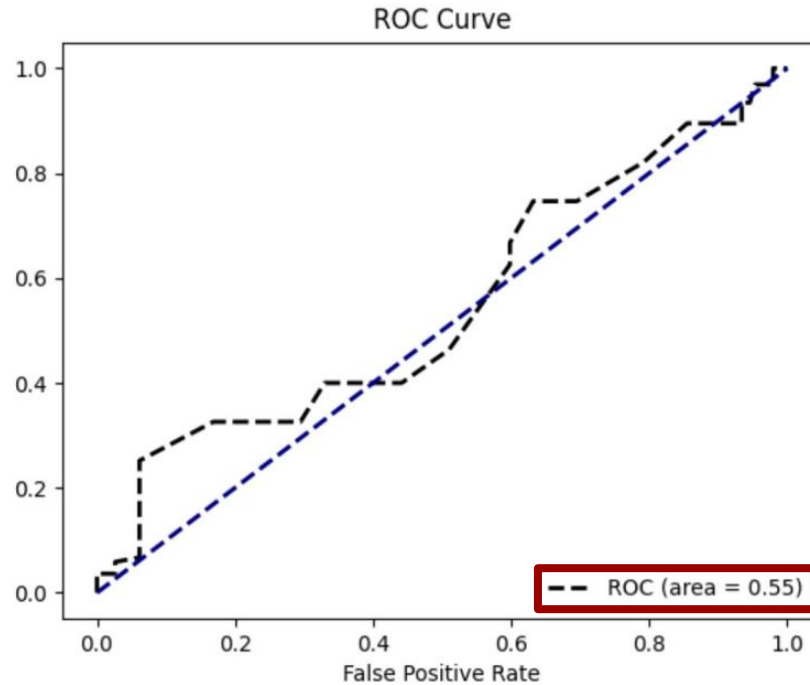
ATTACKS	Acc with TFHM	Acc without TFHM
Naive Bayes	0.593	0.911
Decision Tree	0.612	0.936
SVM	0.569	0.895
DeepCorr	0.749	0.951

DEFENSE MODEL COMPARISON

Model Name	DeepCorr	Full-Connection Networks	TFHM
Accuracy	0.951	0.843	0.749

Yuan S. Research on the generation technology of encrypted traffic based on generative adversarial nets. [D]. Hubei China : Hubei University, 2020.

Generative Adversarial Networks (GAN) Results



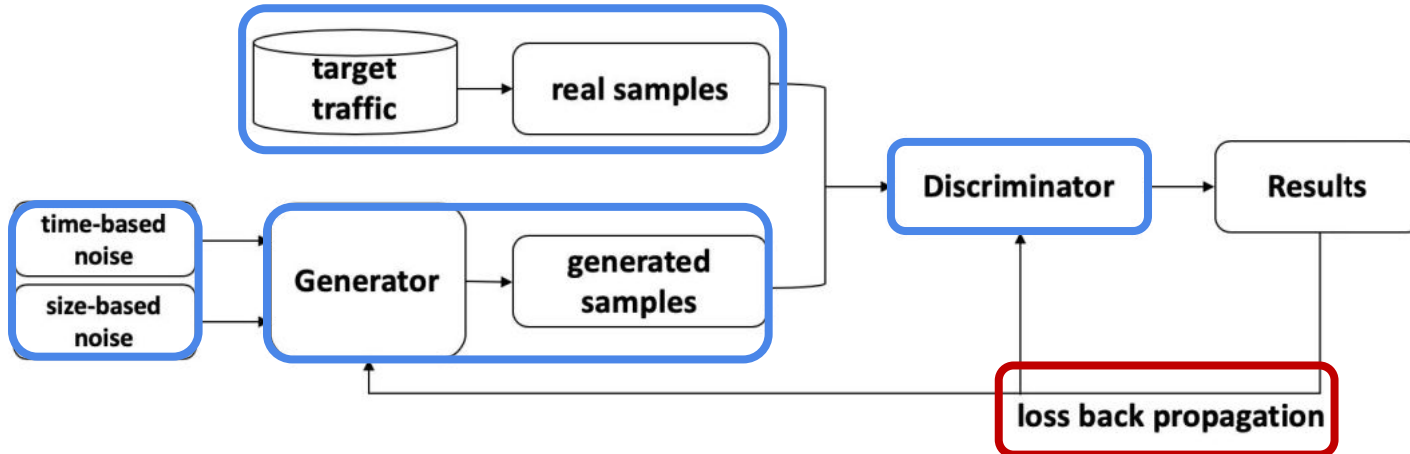
Generative Adversarial Networks (GAN)

Problems

Limitations

- Limited features contribute to attackers
- Discriminator optimization
- Hybrid models

Generative Adversarial Networks Framework



Generative Adversarial Networks (GAN)

Possibilities

- Deep-learning-based unsupervised framework
- Generated data similar to real data
 - Full datasets
 - Balance existing datasets

Generative Adversarial Networks (GAN)

Problems

- Difficult to train
- Unfeasible for real-time or near-real-time applications
- New threats probably require new models
- Does not tackle the threats identification problem

Problems regarding the Project



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