

# Bypassing malware detectors with generative adversarial networks (GAN)

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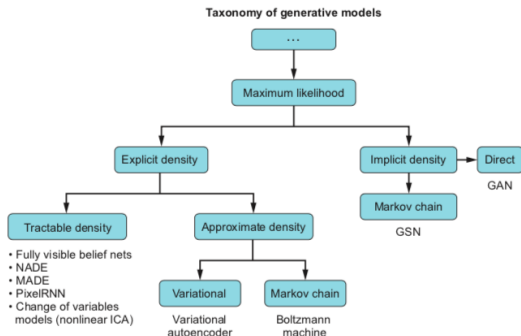
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- ▶ Adversarial Deep Learning
  1. Generative Modeling ,Distribution Approximation
  2. GAN
- ▶ Bypassing malware detectors MalGAN

# Distribution Approximation

- ▶ can we build a model to approximate a data distribution ?
- ▶ can we find  $p_{model}(x; \theta) \sim p_{data}(x)$
- ▶ Maximizing Likelihood-VAE(here we learn some prior)
- ▶ Generate samples directly -GAN

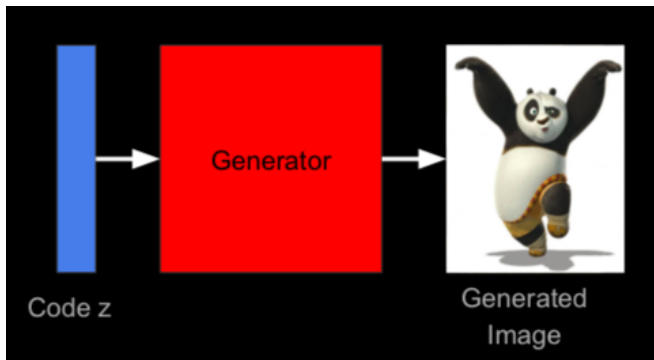


# Representation Learning

- ▶ generate new samples follows the same probabilistic distribution of a given a training dataset
- ▶ the generator has a prior  $p_{\theta}(z)$  and for maps each  $z$  to the observation space.

# Generative models

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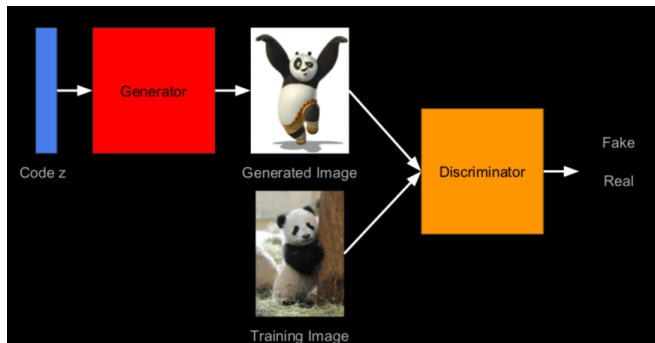


# Generative models: mathematic formulation

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

Annotations for the equation:

- Value of  $V(D, G)$
- Expectation  $\mathbb{E}_{x \sim p_{\text{data}}(x)}$
- prob. of  $D(\text{real})$
- prob. of  $D(\text{fake})$
- Minimize G (pointing to  $\min_G$ )
- Maximize D (pointing to  $\max_D$ )
- $x$  is sampled from real data
- $z$  is sampled from  $N(0, 1)$
- fake (pointing to  $D(G(z))$ )



# GAN

- ▶ Generative adversarial networks are composed of two parts: a generator and a discriminator.
- ▶ we generate from a latent space so that we map each  $z$  into the observation space that follow the distribution of the real data
- ▶ the generator is basically a neural network that we train in parallel of the discriminator.
- ▶ finding Nash equilibrium is challenging( $D_x$  and  $G_\theta$  needs to be good at the same time !)
- ▶ Very often we encounter a mode collapse, the latent space is mapped towards restricted space.
- ▶ when the two distribution are not disjoint it's hard to give a good measure of distance.


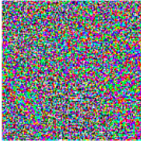

# Malware detection

- ▶ Detecting Malware is still a challenge for many information security professional.
- ▶ Information security professionals are doing their best to come up with novel techniques to detect malware and malicious software



# Direct gradient-based attacks

- ▶ perturbing the sample  $x$  in the direction that would most decrease the score.

	$+ .007 \times$		$=$	
$x$		$\text{sign}(\nabla_x J(\theta, x, y))$		$x + \epsilon \text{sign}(\nabla_x J(\theta, x, y))$
"panda"		"nematode"		"gibbon"
57.7% confidence		8.2% confidence		99.3 % confidence

# Learn this sophisticated sample

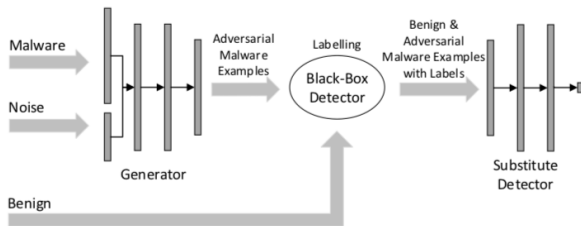


Figure 1: The architecture of MalGAN.

# API Feature

1. We construct an  $M$  binary dimensional vector where the each value is set to 1 if the corresponding API is called by the program.
2. Program that call the WriteFile API only,  $M = (1, 0, 0, 0..., 0)$ .
3. Last layer we use Sigmoid function and binarization

# Algorithm :

- ▶ While not converging do:
  1. Sample a minibatch of Malware  $M$
  2. Generate adversarial samples  $M'$  from the generator
  3. Sample a minibatch of Goodware  $B$
  4. Label  $M'$  and  $B$  using the detector
  5. Update the weight of the detector
  6. Update the generator weights

THANKS!