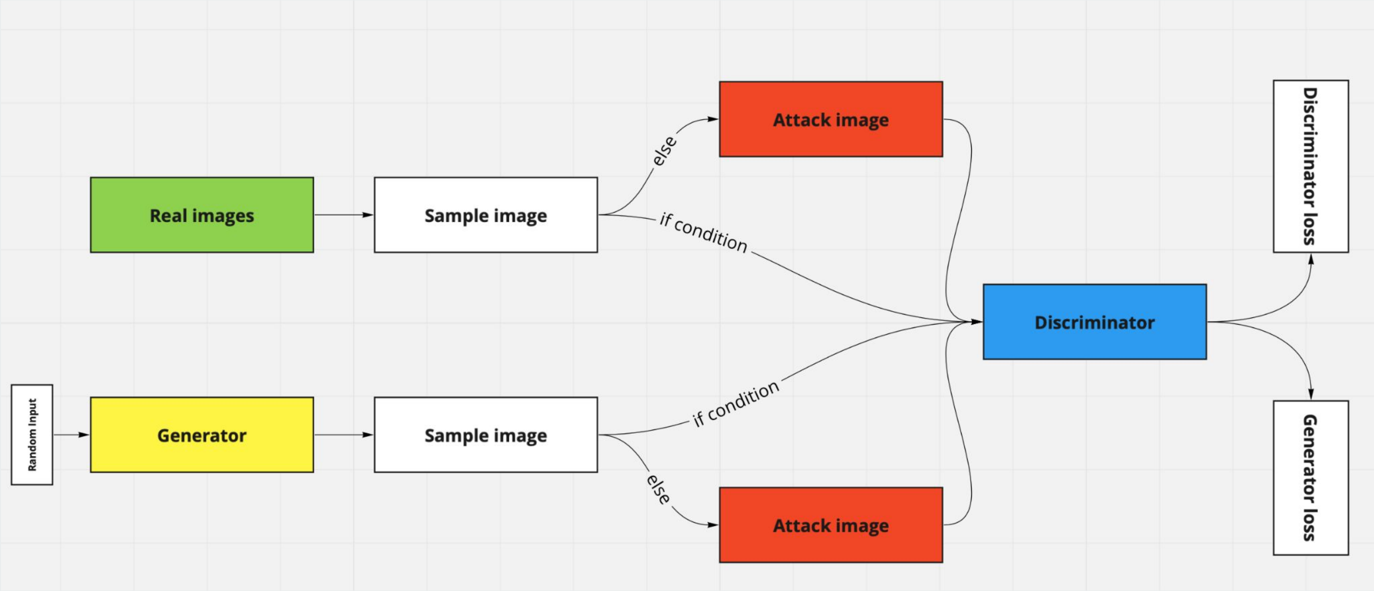
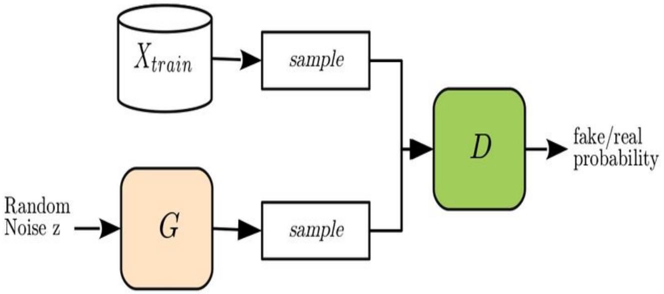
Training Generative Adversarial Networks with Adversarial Attacks



Coursework by Slava Pirogov, HSE AMI 2022
Supervised by Alanov Aibek, HSE visiting lecturer

Generative Adversarial Networks

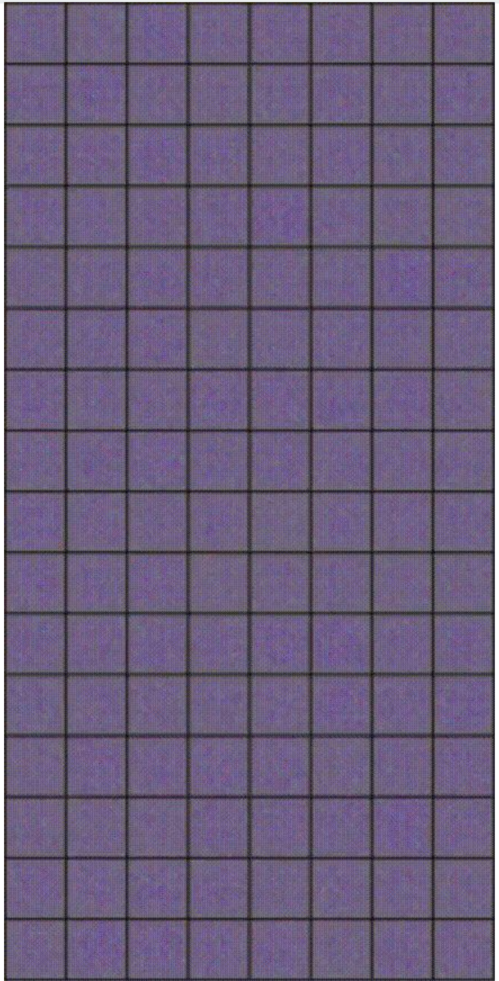
- Generative architecture, adversarial process
- Generator (G) and Discriminator (D)
- G aims to capture the distribution of the dataset
- D aims to estimate the probability that a sample came from the training data rather than G
- Minimax problem with value function V (G, D):



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

Relevance of the task

- Training with Adversarial Attacks can be applied to any GAN
- GANs are still popular (StyleGAN 2019, StyleGAN3 2021, more than 700 papers published in 2022 on arxiv with word GAN in the abstract)
- Vanishing Gradients (research)
- Only one article! (Rob-GAN: Generator, Discriminator, and Adversarial Attacker by Liu and Hsieh (2019))



Goal and tasks

- Goal: explore different ways of building GANs and compare them with GANs that have been trained using Adversarial Attacks (first of all in terms of quality)
- Tasks:
  - Realization of few Adversarial Attacks methods on multiple datasets
  - Realization of some popular GANs, calculation and comparison of key metrics on CIFAR-10 dataset
  - Development of GAN Adversarial training theory, and implementation of it with different GANs and hyperparameters.

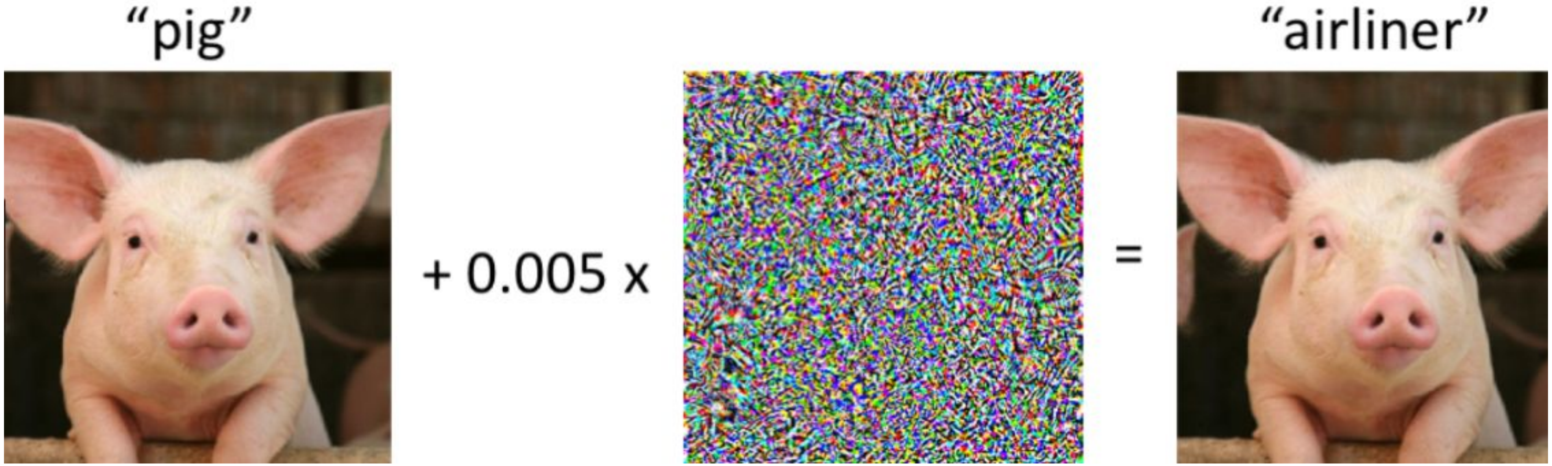
FGSM attack

J (θ, x, y) represents the loss of the network

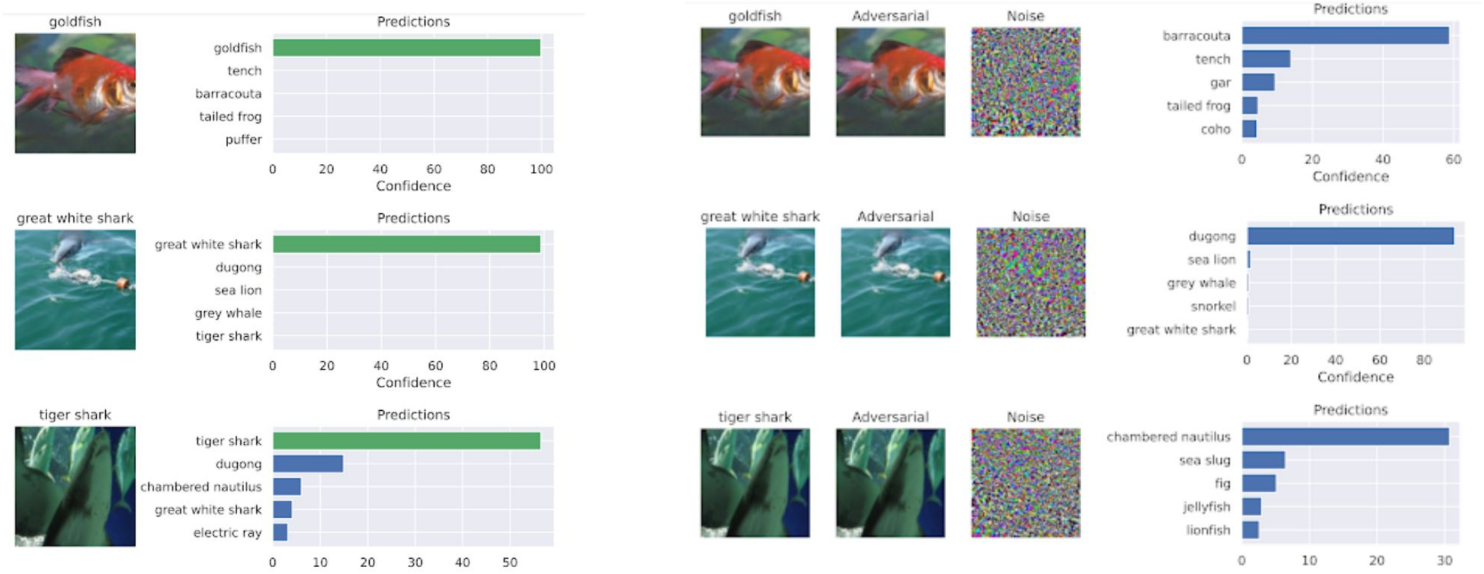
ε is the intensity of the noise

$\tilde{x}$ the final adversarial example

$$\tilde{x} = x + \epsilon \cdot \mathrm{sign}(\nabla_x J(\theta, x, y))$$



FGSM attack on ImageNet



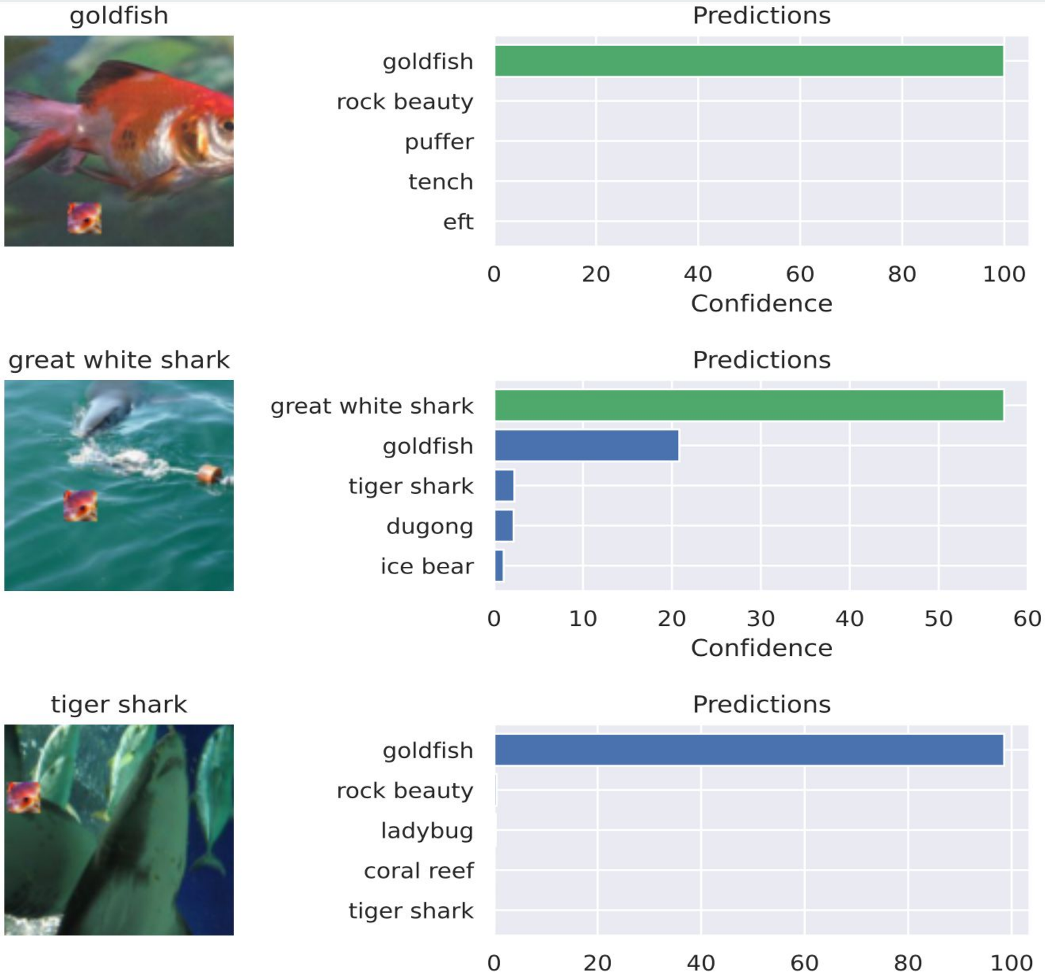
(a) dataset images

(b) FGSM images

Example of FGSM attacks on ImageNet

Adversarial Patches

Example of Adversarial Patches on ImageNet

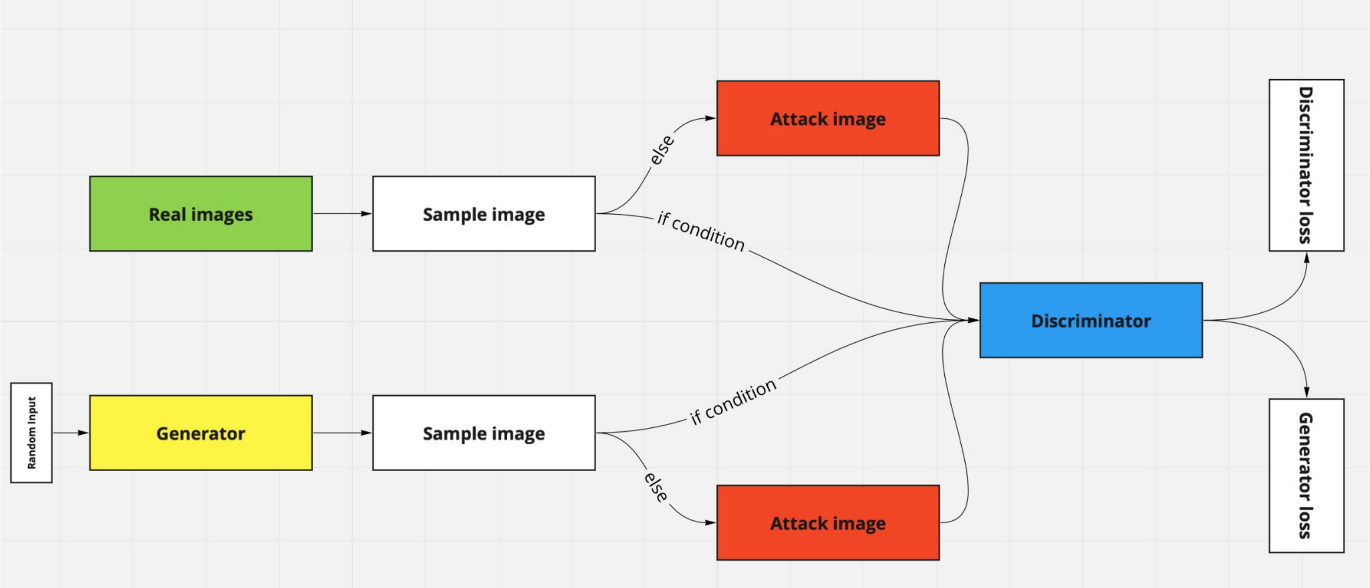


GANs

Model	Dataset	Inception Score ⇧	FID ⇩
our DCGAN	CIFAR10	6.40(0.06)	41.42
DCGAN	CIFAR10	6.26(0.06)	41.92
our WGAN-GP(CNN)	CIFAR10	7.71(0.11)	18.67
WGAN-GP(CNN)	CIFAR10	7.66(0.10)	19.83
our WGAN(CNN)	CIFAR10	6.00(0.08)	48.38
WGAN(CNN)	CIFAR10	6.62(0.09)	40.03
our SNGAN(CNN)	CIFAR10	7.76(0.13)	18.38
SNGAN(CNN)	CIFAR10	7.84(0.12)	17.81

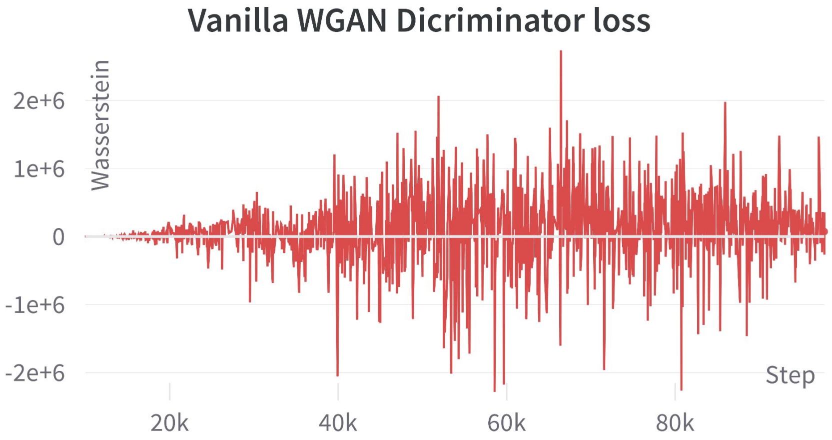
- DCGAN by Alec Radford (2015)
- SNGAN by Takeru Miyato (2018)
- WGAN by Martin Arjovsky (2017)
- WGAN-GP by Ishaan Gulrajanj (2017)

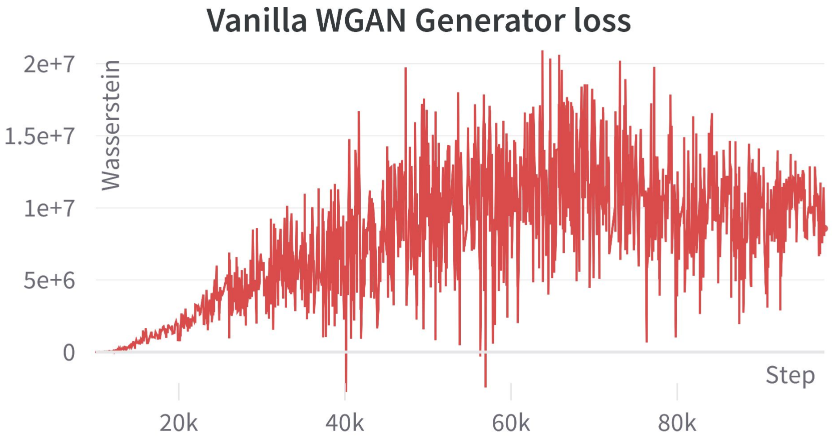
Theory of GAN Adversarial Training



- Start of attacks from 10% of epochs
- Chance to attack C
- ε in FGSM

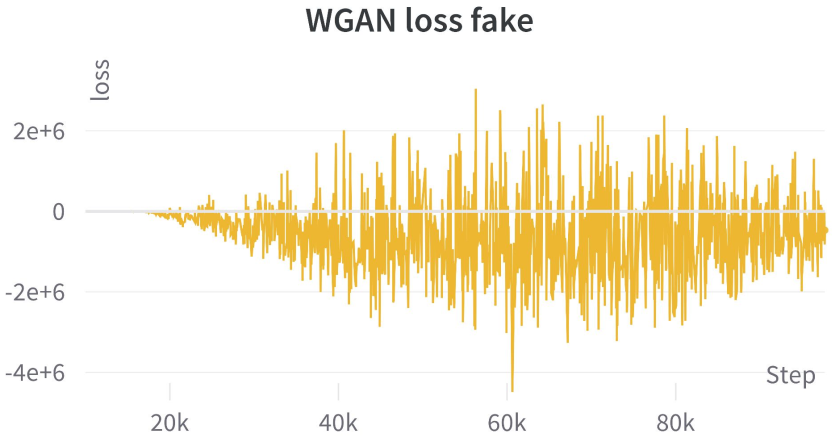
Theory of GAN Adversarial Training

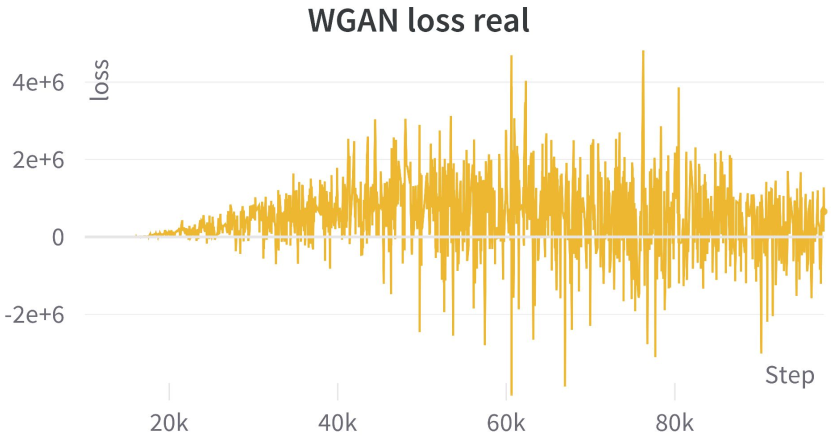




Monitor robustness and stability of the architecture

Theory of GAN Adversarial Training



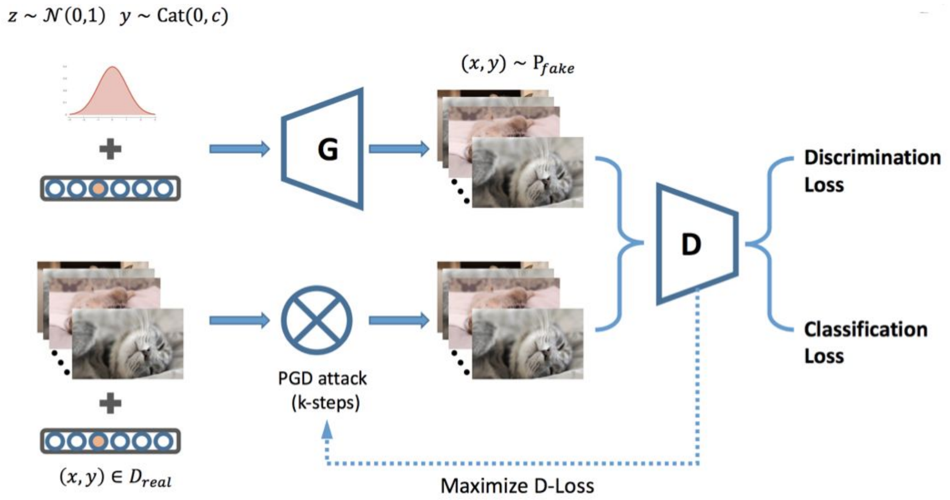


Split the Discriminator loss into real and fake parts

Related work

Rob-GAN: Generator, Discriminator, and Adversarial Attacker by Liu and Hsieh ([2019](#))

- Research about convergence speed of GAN training and the robustness of Discriminator
- Projected Gradient Descent attacks
- Auxiliary Classifier GAN
- Attack at every step



Experiments

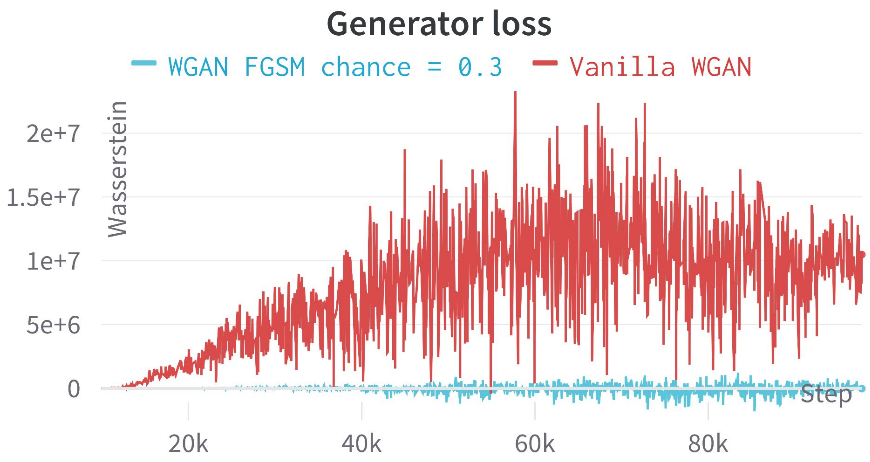
- CIFAR-10
- 1xV100 and 8xCPU
- Default ε = 0.02
- Left - real. Right - FGSM

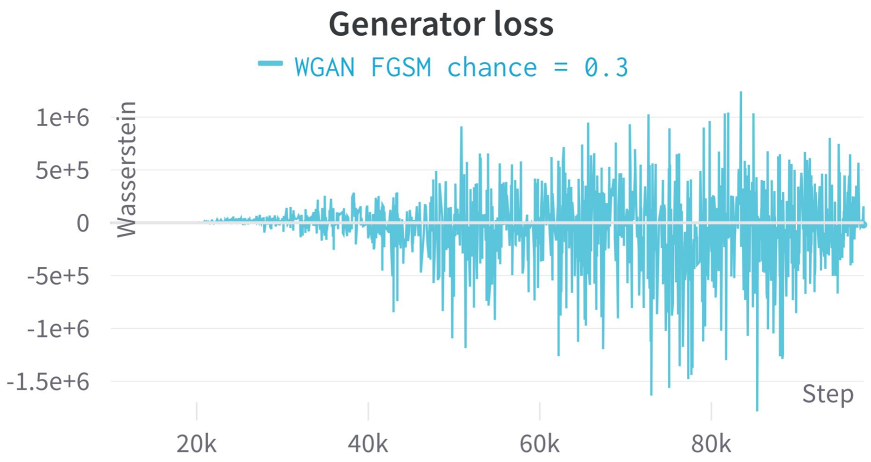
Experiments - WGAN

Model	FGSM chance	ϵ	Inception Score ⇧	FID ⇩	Time (min)
Baseline WGAN	–	–	6.00(0.09)	48.38	**502**
WGAN-FGSM	0.2	0.02	6.58(0.09)	35.21	538
WGAN-FGSM	0.3	0.02	6.53(0.06)	**33.60**	537
WGAN-FGSM	0.4	0.02	6.73(0.10)	35.56	595
WGAN-FGSM	0.3	0.01	**6.77(0.07)**	33.78	537

- IS improved by 10%
- FID improved by almost 30%
- Over 25 full experiments

Experiments - WGAN





Stabilizing of G loss

Red - vanilla version

Blue - FGSM version

Experiments - WGAN-GP

Model	FGSM chance	Inception Score	FID	Time (min)
Baseline WGAN-GP	–	**7.71(0.11)**	**18.67**	**613**
WGAN-FGSM	0.2	7.64(0.09)	19.97	645
WGAN-FGSM	0.4	3.35(0.03)	106.6	673
WGAN-FGSM	0.6	3.51(0.03)	112.57	693
WGAN-FGSM	0.8	4.19(0.07)	97.37	721

Several options for FGSM-attack on WGAN-GP

Only one explored

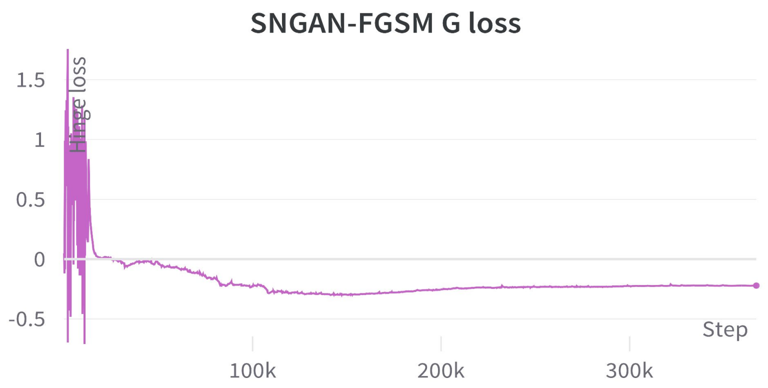
Experiments - DCGAN

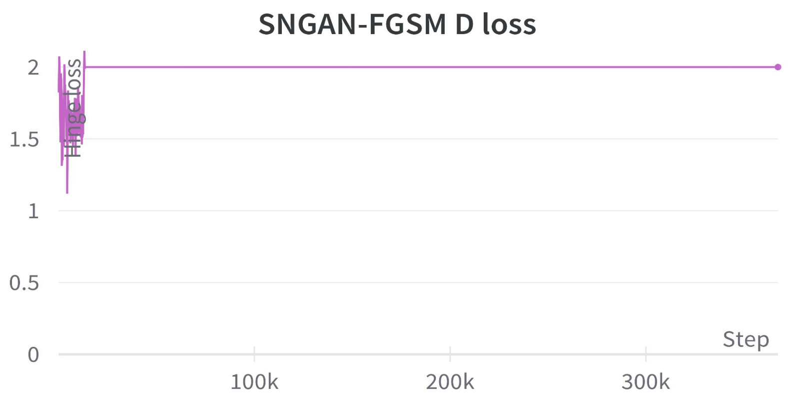
Model	FGSM chance	Inception Score ⇧	FID ⇩	Time (min)
Baseline DCGAN	–	6.40(0.06)	41.42	**590**
DCGAN-FGSM	0.2	**6.52(0.07)**	40.23	596
DCGAN-FGSM	0.4	6.15(0.09)	59.78	604
DCGAN-FGSM	0.6	6.34(0.04)	**39.10**	627
DCGAN-FGSM	0.8	5.97(0.05)	53.50	642

Metrics, loss behavior are similar

FGSM attacks don't necessarily improve weak GANs

Experiments - SNGAN





Many problems with the model at FGSM chance = 0.6, 0.8

Discriminator loss becomes constant

Decreasing start epoch of attack fix it

However, we learn different distribution

Experiments - SNGAN

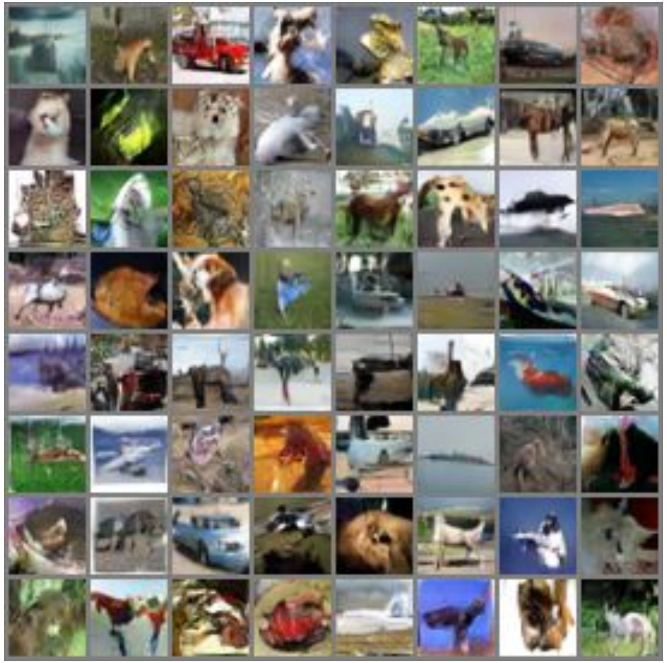
Model	FGSM chance	start FGSM	Inception Score ⇧	FID ⇩	Time (min)
Baseline SNGAN	–	–	**7.84(0.12)**	**17.81**	**503**
SNGAN-FGSM	0.2	10%	7.54(0.13)	19.20	750
SNGAN-FGSM	0.4	10%	7.36(0.03)	22.84	793
SNGAN-FGSM	0.6	5%	6.86(0.05)	28.34	580
SNGAN-FGSM	0.8	0%	6.64(0.08)	33.40	614

First model

Significant results were not achieved

Over 50 experiments were carried out

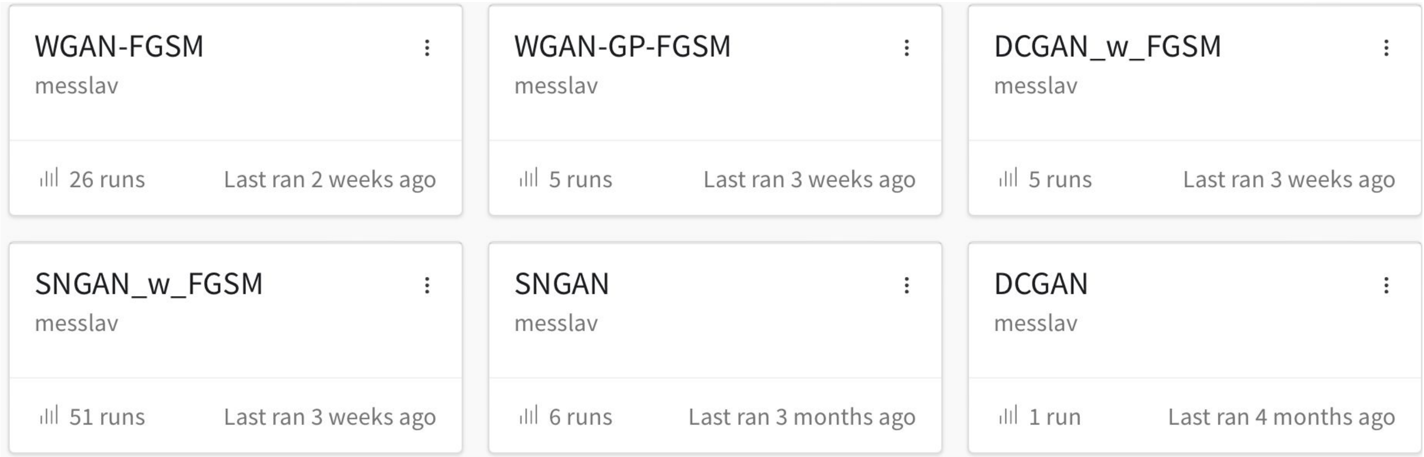
Experiments - SNGAN



Generated samples from SNGAN (left) and SNGAN-FGSM (right).
The same noise was in the input

Program Realization

- Github
- Python 3.7, PyTorch 1.10
- Almost 100 experiments, 30 days of computing resources



Results

- Implemented FGSM, Adversarial Patches attacks on ImageNet, MNIST, CIFAR-10 datasets
- Implemented DCGAN, SNGAN, WGAN, WGAN-GP with logging. Trained them on the CIFAR-10 dataset

★ Implemented GAN FGSM training with DCGAN, SNGAN, WGAN, WGAN-GP. Trained them on the CIFAR-10 dataset

★ Researched how FGSM attacks affects GAN losses and metrics

Acknowledgments

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