

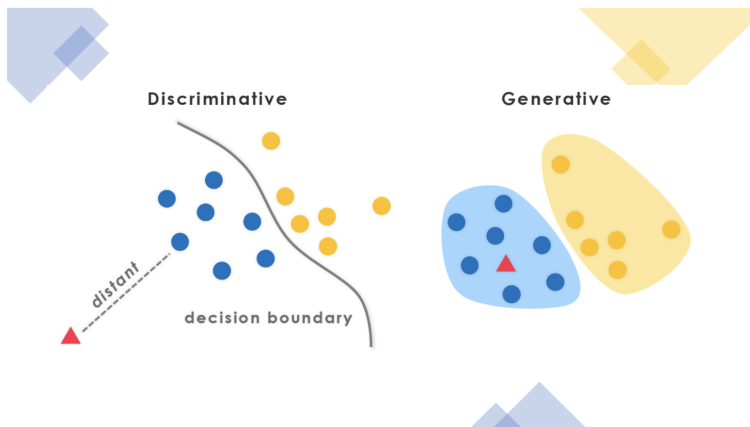
Generative Adversarial Networks

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Generative Modeling



1

¹Image Taken from <https://www.kdnuggets.com/2020/05/microsoft-research-three-efforts-advance-deep-generative-models.html>

Generative Modeling

- ▶ Can you generate a sample from Normal Distribution? ²
- ▶ Can you generate an MNIST image?

²[https:](https://bjlkeng.github.io/posts/sampling-from-a-normal-distribution/)

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Lecture Outline: Paper References

- ▶ Paper 1: Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems. 2014. ³
- ▶ Paper 2: Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." ⁴

³<https://proceedings.neurips.cc/paper/2014/file/5ca3e9b122f61f8f06494c97b1afccf3-Paper.pdf>

⁴<https://arxiv.org/pdf/1511.06434.pdf>

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Advantages of VAEs (over GANs)

- ▶ VAEs have a probabilistic formulation as a result of maximizing a lower bound on the log-likelihood.
- ▶ Usually easier to train and get working.
- ▶ Relatively easy to implement and robust to hyperparameter choices.
- ▶ Tractable likelihood.
- ▶ Has an explicit inference network allowing us to do reconstruction. ⁵

⁵https://www.reddit.com/r/MachineLearning/comments/4r3pjy/variational_autoencoders_vae_vs_generative/

Advantages of GANs (over VAEs)

- ▶ GANs have much higher visual fidelity in generated samples.
- ▶ GANs are better at generating visual features (adversarial loss is better than mean-squared loss).

Adversarial Approach vs. Adversarial Examples

The approach of GANs is called adversarial since the two networks have antagonistic objectives.

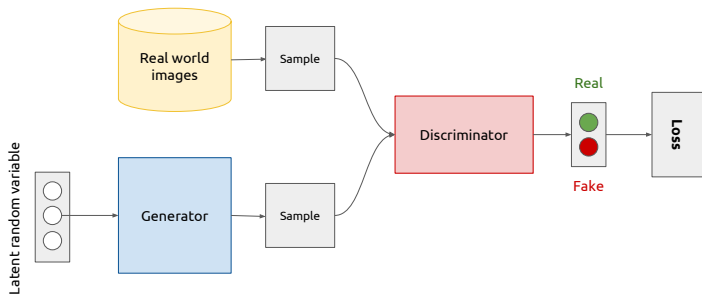
This is not to be confused with adversarial examples in machine learning.

See these two papers for more details:

<https://arxiv.org/pdf/1412.6572.pdf>

<https://arxiv.org/pdf/1312.6199.pdf>

Generative adversarial networks (conceptual)



More Formally

- ▶ The **generator**

$$\mathbf{G} : \mathbb{R}^D \rightarrow X \quad (1)$$

is trained so that it gets a random input and produces a sample following the data distribution as output (ideally).

- ▶ The **discriminator**

$$\mathbf{D} : X \rightarrow [0, 1] \quad (2)$$

gets a sample as input and predicts if it is real or fake.

More Practically

- ▶ Training a standard GAN is difficult and often results in two undesirable behaviors
 1. Oscillations without convergence. Contrary to standard loss minimization, we have no guarantee that the loss will actually decrease.
 2. The **mode collapse** problem, when the generator models very well a small sub-population, concentrating on a few modes.
- ▶ Additionally, performance is hard to assess and often boils down to heuristic observations.

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Deep Convolutional Generative Adversarial Networks (DCGANs)

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- ▶ GANs known to be unstable to train, often resulting in generators that produce "nonsensical outputs".
- ▶ Extensive model exploration to identify a family of architectures that result in **stable** training across a range of datasets and allowed for training higher resolution and deeper models.

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- ▶ Use ReLU activation in the generator for all layers except for the output, which uses Tanh.
- ▶ Use LeakyReLU activation in the discriminator for all layers.

GANs Awesome Applications

<https://github.com/nashory/gans-awesome-applications>

GANs Useful Applications

<https://arxiv.org/pdf/2202.00419.pdf>