Generative Adversarial Networks

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Lecture Outline

- Paper 1: Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems. 2014.
- Paper 2: Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." arXiv preprint arXiv:1511.06434. 2015.
- Paper 3: Arjovsky, Martin, Soumith Chintala, and Leon Bottou. "Wasserstein generative adversarial networks." International Conference on Machine Learning. 2017.

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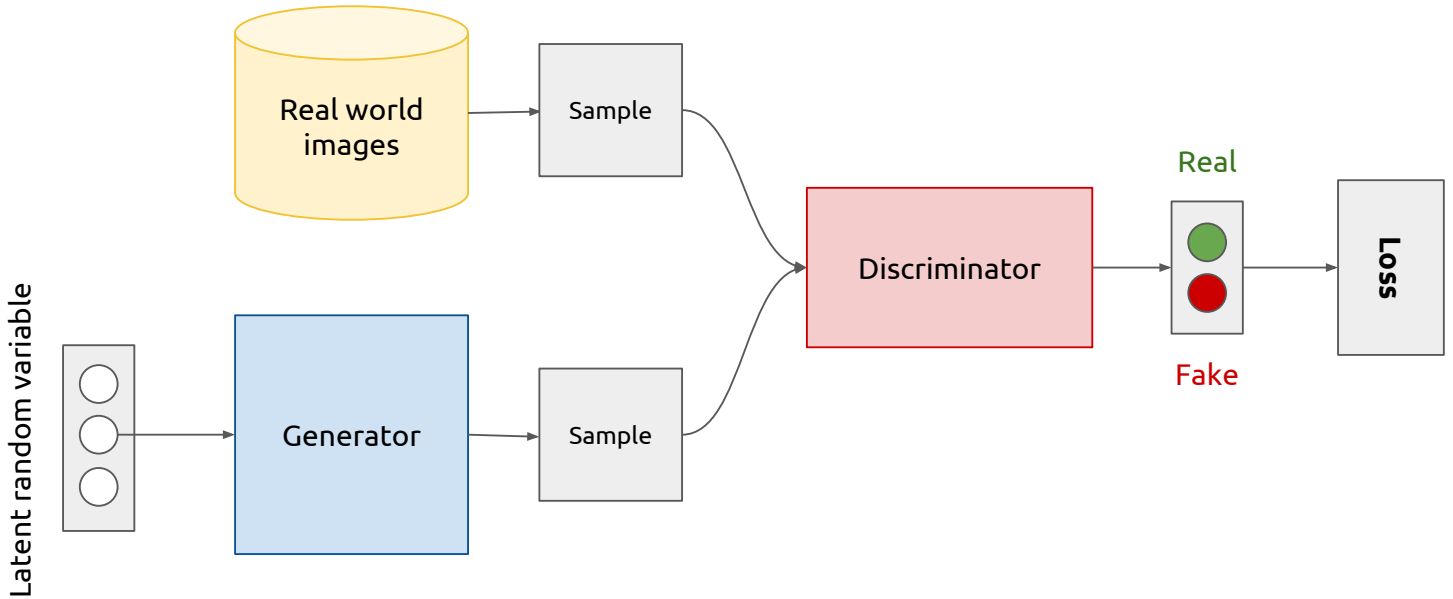
Adversarial Approach vs. Adversarial Examples

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)



[1]

[1] Credit: Xavier Giro-i-Nieto

More Formally

- The **generator**

$$\mathbf{G} : \mathbb{R}^D \rightarrow X \tag{1}$$

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

- The **discriminator**

$$\mathbf{D} : X \rightarrow [0, 1] \tag{2}$$

  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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- 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 LeakyReLU activation in the discriminator for all layers.