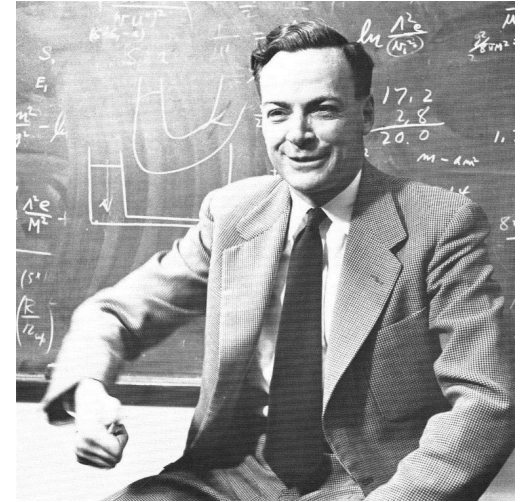


Deep Generative Models

University of Victoria - PHYS-555

What I cannot create,
I do not understand.



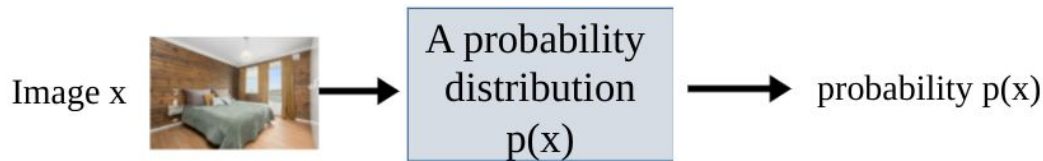
Richard Feynman: “*What I cannot create, I do not understand*”

Generative modeling: “*What I understand, I can **create***”

Statistical Generative Models

A statistical generative model is a **probability distribution** $p(\mathbf{x})$

- **Data:** samples (e.g., images of cats, spectra, particle tracks,...)
- **Prior knowledge:** parametric form (e.g., Gaussian?), loss function (e.g., maximum likelihood?), optimization algorithm, etc.



It is generative because **sampling from $p(\mathbf{x})$ generates new images**



Supervised

Data: (\mathbf{x}, y)

features

labels

Learn mapping $\mathbf{x} \rightarrow y$: $p(y|\mathbf{x})$

Unsupervised

Data: \mathbf{x}

no labels

Learn hidden structure: $p(\mathbf{x})$

Generative Model

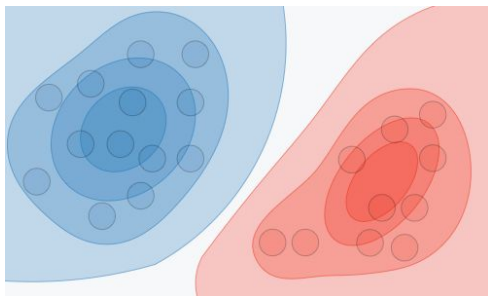
A generative model is a probabilistic model $\mathbf{x} \sim p(\mathbf{x}; \theta)$ that can be used to simulate new data that is as close to the true and unknown data distribution $p(\mathbf{x})$ but for which we have real samples.

Go beyond estimating $p(y|\mathbf{x})$ such as in discriminative models:

- Understand and imagine how the world evolves
- Recognize objects in the world and their factors of variations
- Establish concepts for reasoning and decision making

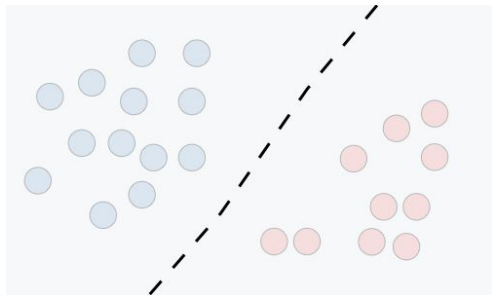
Generative vs. Discriminative

- Generative learns joint probability distribution: $p(\mathbf{x}, y)$



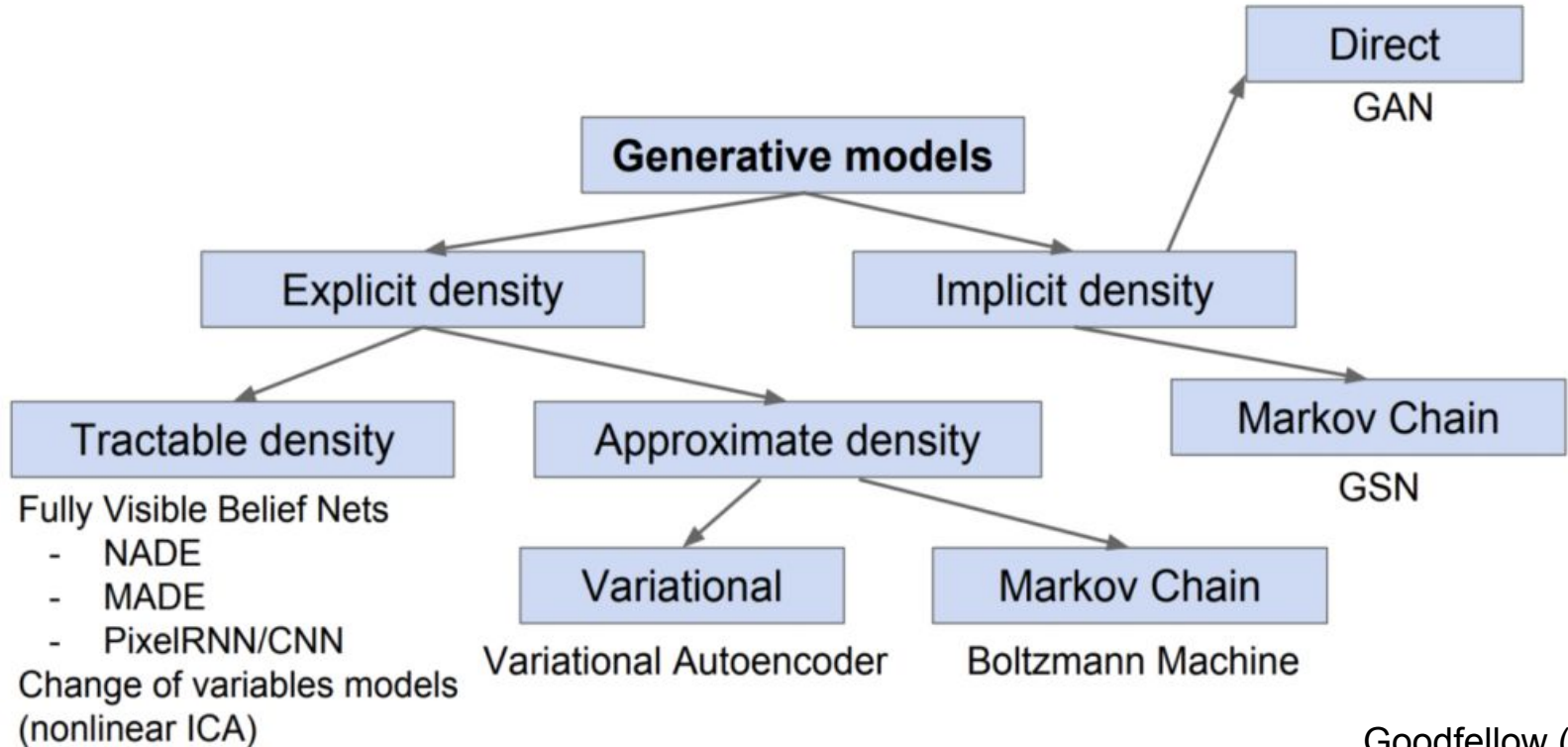
$$\frac{\text{Probability}}{\sum \text{ samples}}$$

- Discriminative learns conditional probability distribution $p(y|\mathbf{x})$



$$\frac{\text{Probability}}{\text{subsamples}}$$

Generative Models Taxonomy



Why caring about Generative Models in Physics?

- Classic use

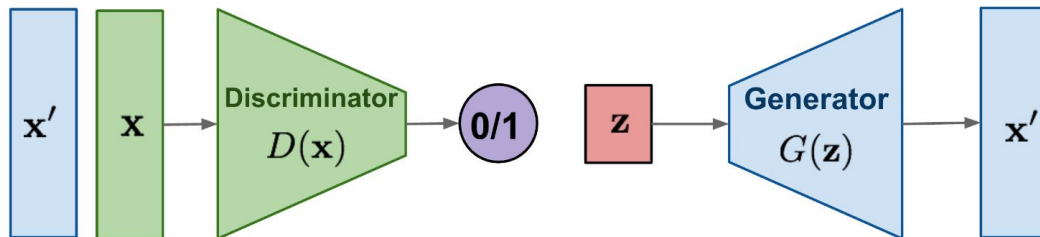
- With maximum likelihood, we can obtain physical parameters for a hand designed $p(\mathbf{x};\theta)$
- We can learn a joint distribution with labels $p(\mathbf{x},\mathbf{y};\theta)$ and transform to $p(\mathbf{y}|\mathbf{x};\theta)$

- Modern use

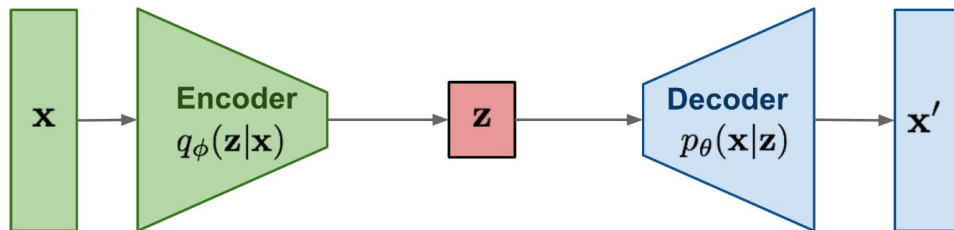
- Fast generation of computationally expensive tasks in complex, nonlinear physics
aka emulator of simulators, surrogate modelling
- Interpolation between high dimensional distribution samples

In deep learning, 4 types of generative models are currently dominating

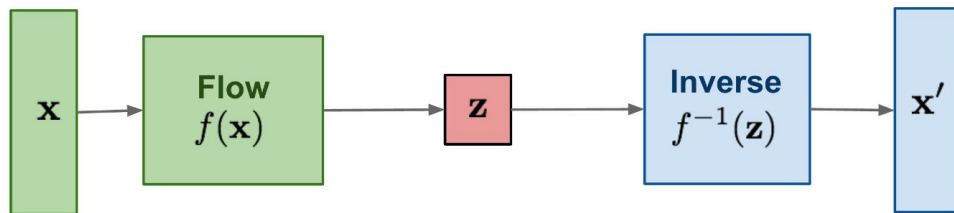
GAN: Adversarial training



VAE: maximize variational lower bound



Flow-based models:
Invertible transform of distributions



Diffusion models:
Gradually add Gaussian noise and then reverse

