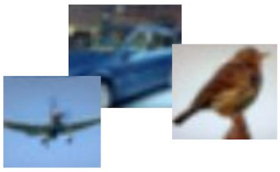
Generative Models

Given training data, generate new samples from same distribution



Training data ~ $p_{data}(x)$

Generated samples ~ $p_{model}(x)$

Want to learn $p_{model}(x)$ similar to $p_{data}(x)$

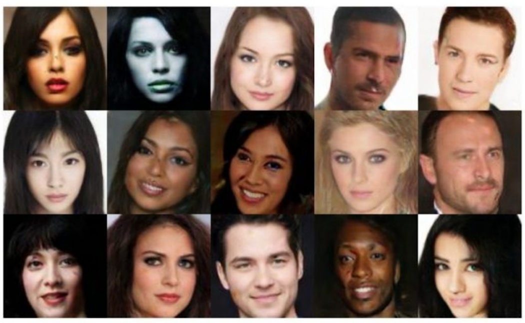
Addresses density estimation, a core problem in unsupervised learning

Several flavors:

- Explicit density estimation: explicitly define and solve for $p_{model}(x)$
- Implicit density estimation: learn model that can sample from $p_{model}(x)$ w/o explicitly defining it

Why Generative Models?

- Realistic samples for artwork, super-resolution, colorization, etc.



- Generative models of time-series data can be used for simulation and planning (reinforcement learning applications!)
- Training generative models can also enable inference of latent representations that can be useful as general features

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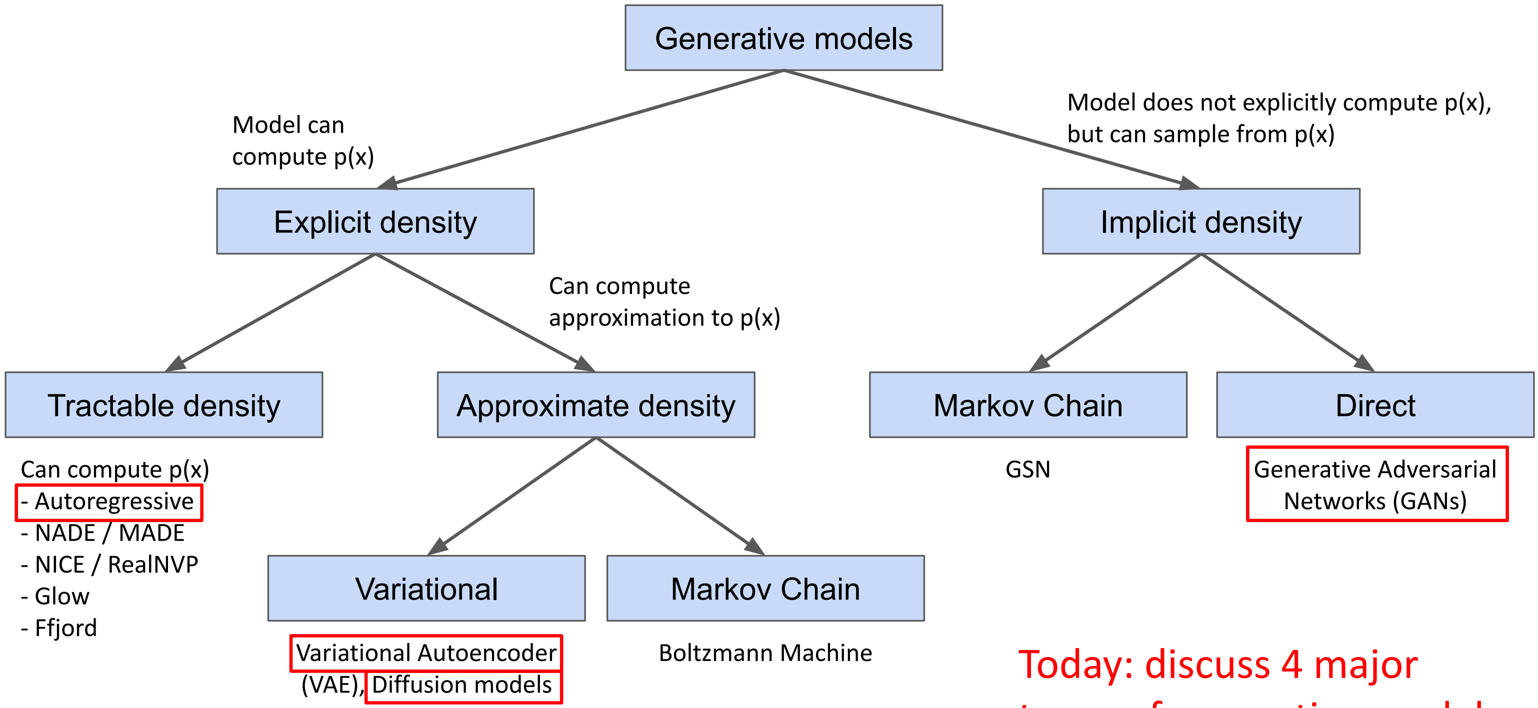
Taxonomy of Generative Models

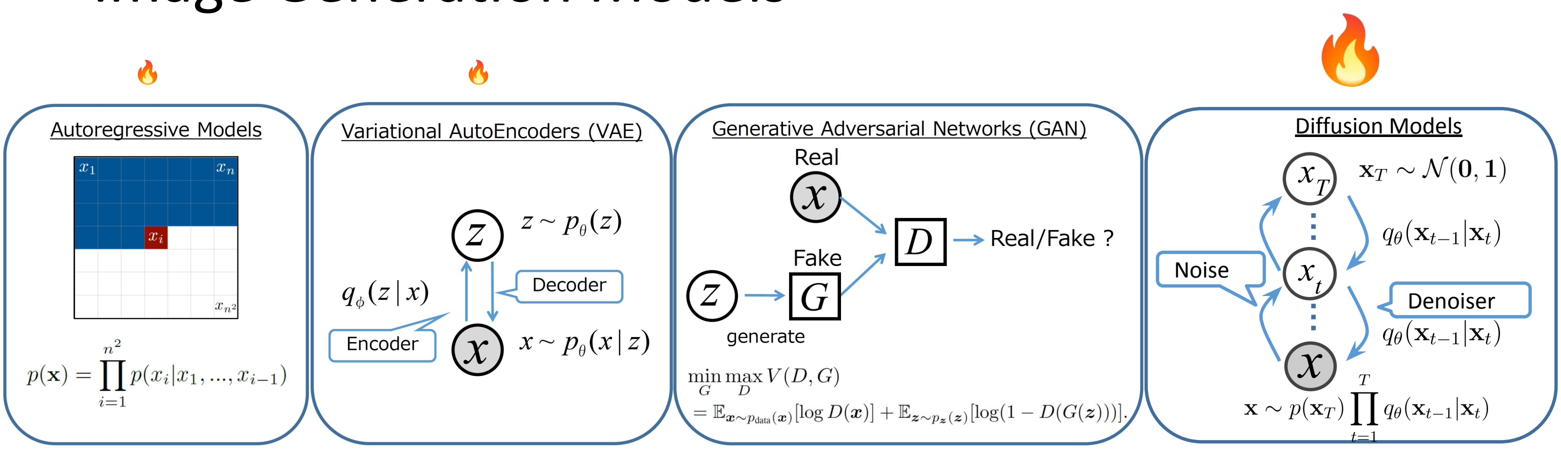


Today: discuss 4 major types of generative models

Slide credit: Justin Johnson

Image Generation Models

Current research interest in image generation:



	Autoregressive Models	VAE	GAN	Diffusion Models
Pros	simple and stable training process Currently gives the best log likelihood Tractable likelihood	Efficient inference with approximate latent variables	Generate sharp image No need for any Markov Chain or approx networks during sampling	Simple and stable training process Best samples!
Cons	Relatively inefficient during sampling	Generated samples tend to be blurry	Difficult to optimize due to unstable training dynamics	Relatively inefficient during sampling