Generative Models: Distributional Mixtures

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Introduction to Machine Learning

CSCI-335

4/1/2026

You’re actually done learning machine learning – there’s nothing more for me to teach you - and we’ll just be assigning all of you perfect grades (since our logistic regression model told us to)! Yayyy!

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April
Fool's!

Generation vs. Discrimination

Generative Models

- Represent both the data and the labels
- Often, makes use of conditional independence and priors
- Examples
  - Naïve Bayes classifier
  - Bayesian network
  - Single/Dual-wing harmonium
  - Variational autoencoder
- Models of data may apply to future prediction problems

Discriminative Models

- Learn to directly predict the labels from the data
- Often, assume a simple boundary (e.g., linear)
- Examples
  - Logistic regression
  - SVM, perceptron, discriminants
  - Decision tree / An ensemble
  - MLP
- Often easier to predict a label from the data than to model the data

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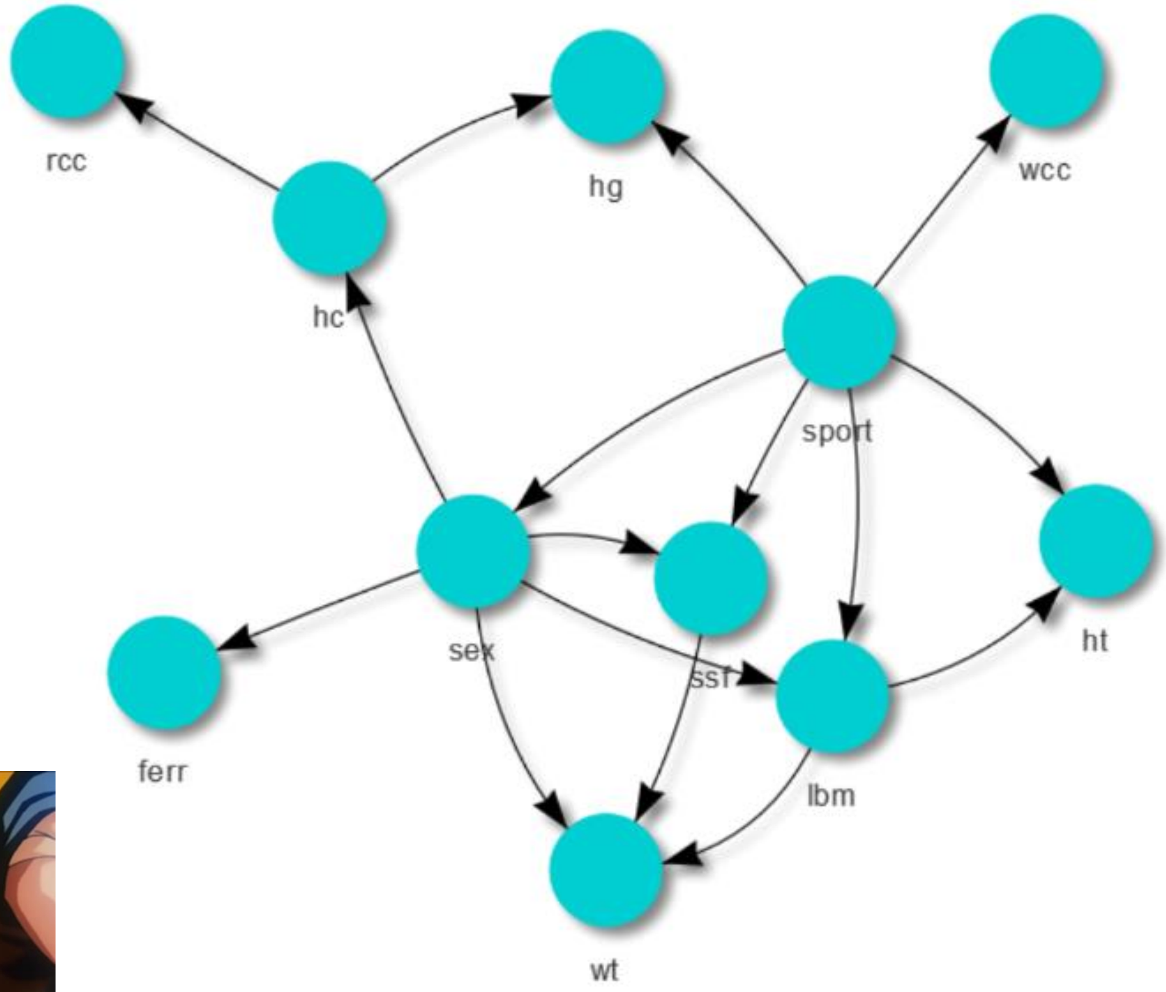
What would be beyond Naïve Bayes?
Answer: Bayesian Networks

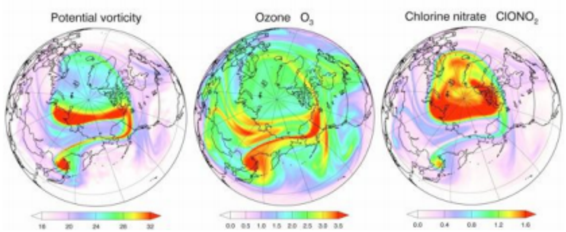


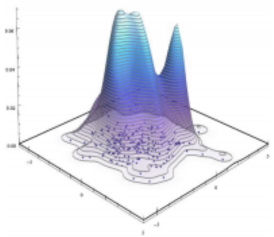
What is a Generative Model?

A model that allows us to learn a simulator of data	Models that allow for (conditional) density estimation	Approaches for unsupervised learning of data

Characteristics are:

- **Probabilistic** models of data that allow for uncertainty to be captured.
- **Data distribution p(x)** is targeted.
- **High-dimensiona**l outputs.





Beyond Classification

Move beyond associating inputs to outputs

Understand and imagine how the world evolves

Recognise objects in the world and their factors of variation

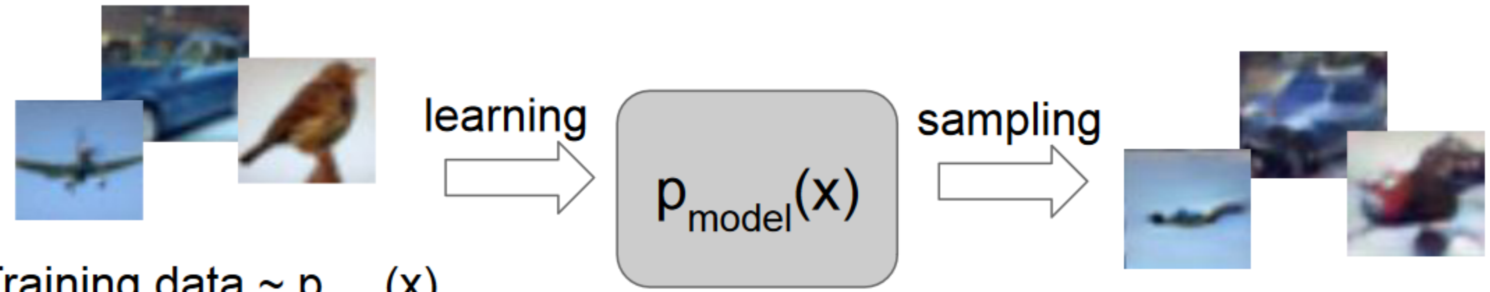
Detect surprising events in the world

Establish concepts as useful for reasoning and decision making

Anticipate and generate rich plans for the future

Generative Modeling

Given training data, generate new samples from same distribution



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

Objectives:

1. Learn $p_{model}(x)$ that approximates $p_{data}(x)$
2. **Sampling new x from $p_{model}(x)$**

Generative Modeling

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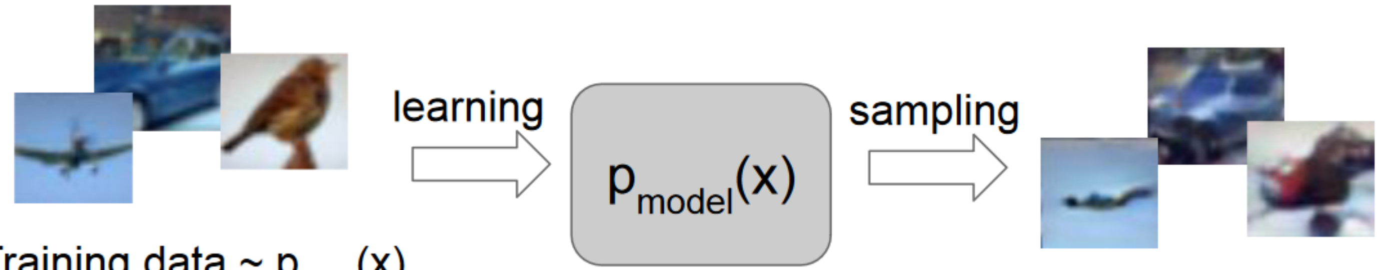


Training data ~ $p_{data}(x)$

Formulate as density estimation problems:

- **Explicit density estimation**: explicitly define and solve for $p_{model}(x)$
- **Implicit density estimation**: learn model that can sample from $p_{model}(x)$ **without explicitly defining it.**

Why Generative Modeling?



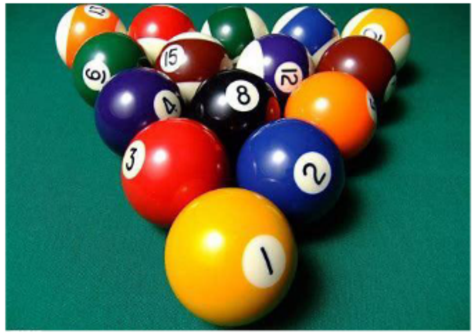
- Realistic samples for artwork, super-resolution, colorization, etc.
- Learn useful features for downstream tasks such as classification.
- Getting insights from high-dimensional data (physics, medical imaging, etc.)
- Modeling physical world for simulation and planning (robotics and reinforcement learning applications)
- Many more ...

- Generate data (e.g., image) in computer

Ball(color=yellow, position=(50, 100),...)
Ball(color=red, position=(30, 75),...)
Ball(color=blue, position=(30, 125),...)
...
...

Computer Graphics (CG)

Computer Vision (CV)
(Inverse CG!)



"description"

"observation"

- **Statistical Generative Models** are **data-driven** methods

Computer Graphics

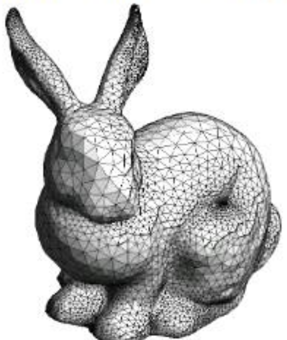
Statistical Generative Models

Prior Knowledge

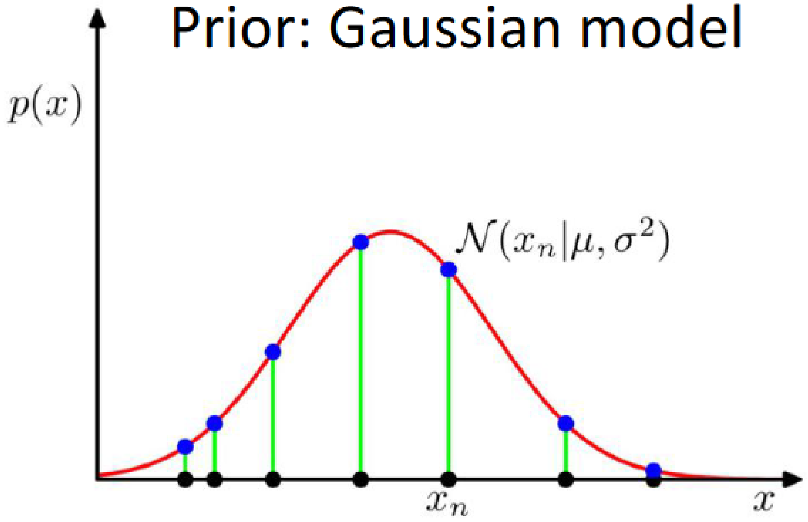
Data

Material, Physical Modeling, Lighting ....

Hard to scale up!



- **Statistical/Deep Generative Models**



- Given data samples
- Learn the probability distribution $p(x)$

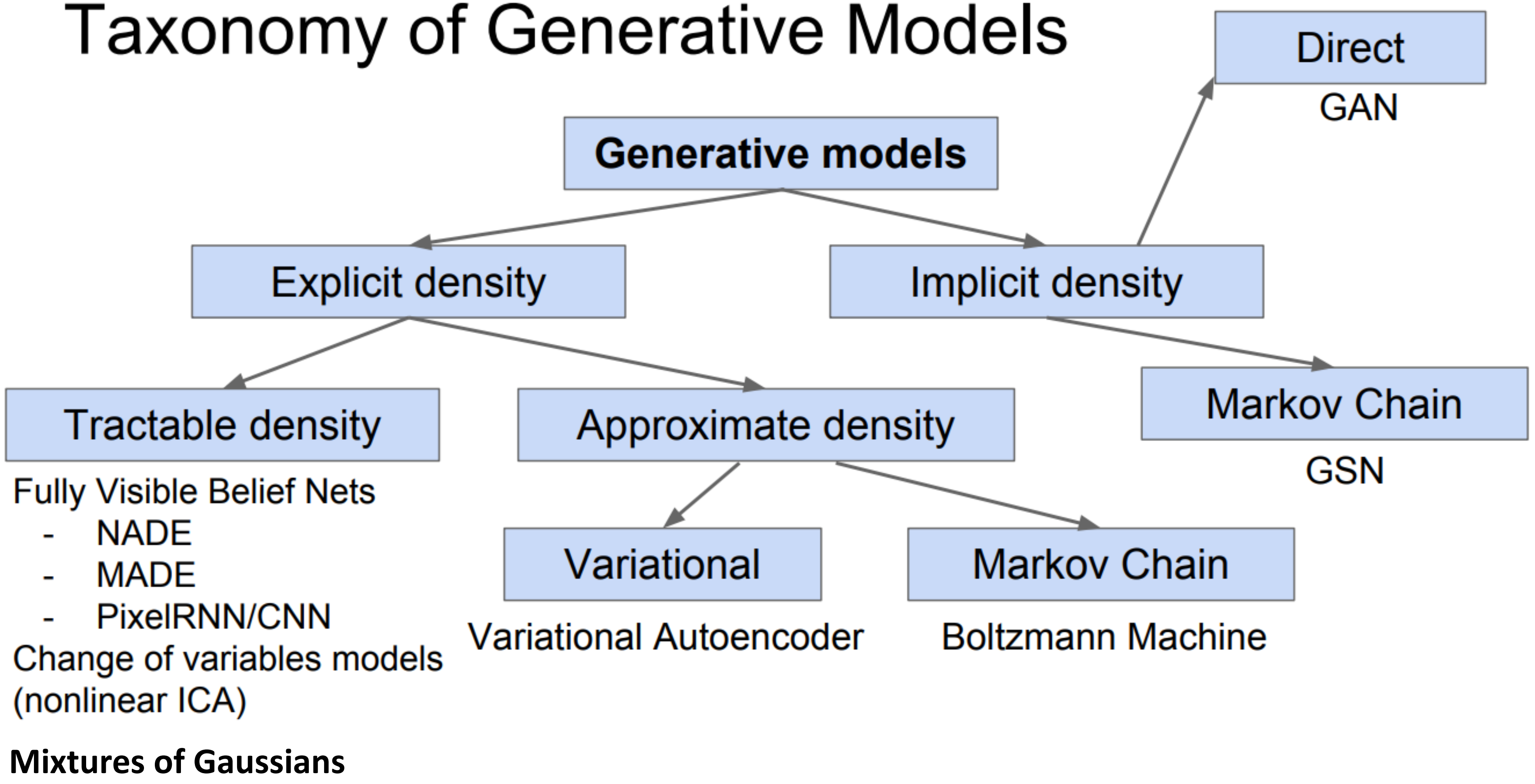
So that

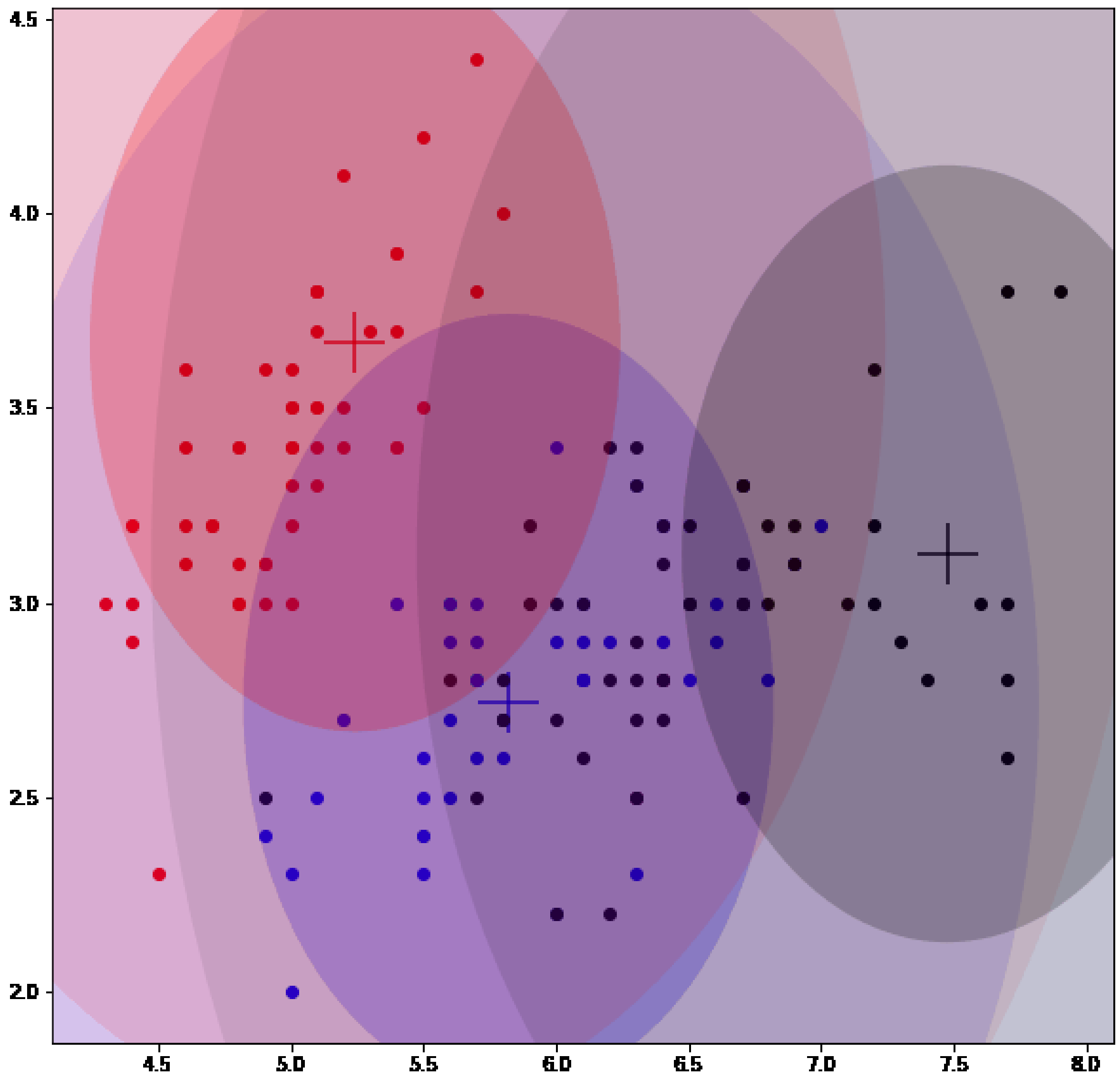
- It is generative because new data samples can be sampled from $p(x)$

$$x_{new} \sim p_x$$

The data distribution can be high-dimensional, like images

Taxonomy of Generative Models





Unsupervised Generative Modeling!

Let Us Build the Explicit-Density, Mixture-of-Gaussians (MoG)

White board time! Crafting a mixture of Gaussians model

Next time! We will build the optimization pillar for the GMM!

QUESTIONS?