Deep Generative Models

Introduction

Hamid Beigy

Sharif University of Technology

February 7, 2025

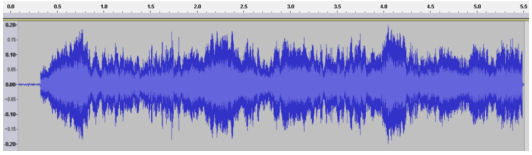
Table of contents

Introduction

How do you understand complex and unstructured inputs?

Computer vision

Computational speech



Natural language processing

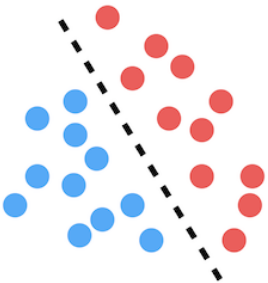
Robotics

Credit: Aditya Grover

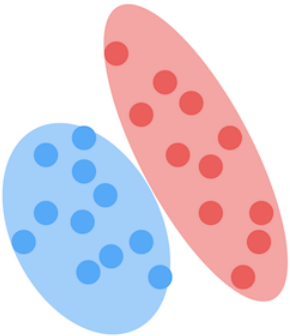
Generative and Discriminative Models

1. **Discriminative modeling** estimates the conditional distribution $p(\mathbf{y} \mid \mathbf{x})$.
2. **Generative modeling** estimates the joint distribution $p(\mathbf{x}, \mathbf{y})$.

Discriminative modeling



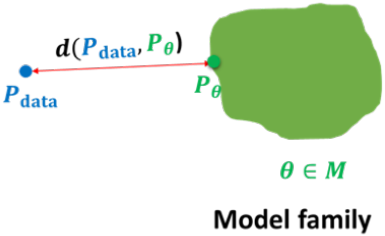
Generative modeling



3. Without assuming $\mathbf{y}$, generative models learn $p(\mathbf{x})$ from given data.
4. $p(\mathbf{x})$ enables us to generate new data similar to the training dataset.

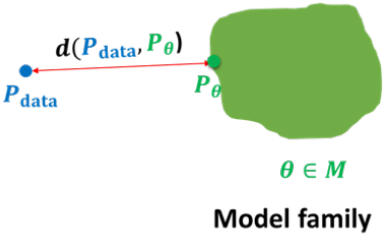
1. **A Generative model** (GM) is a probability distribution $p(\mathbf{x})$.
   - A statistical GM is a trainable probabilistic model, $p_\theta(\mathbf{x})$.
   - A deep GM is a statistical generative model parametrized by a neural network.
2. A generative model needs
   - Data ($\mathbf{x}$): Complex, unstructured samples such as images, speech, molecules, text, etc.
   - Prior knowledge: parametric form (e.g., Gaussian, mixture, softmax), loss function (e.g., maximum likelihood, divergence), optimization algorithm, etc.

$\mathbf{x}_i \sim P_{\text{data}}$
$i = 1, 2, \ldots, n$



Credit: Aditya Grover

Key Questions



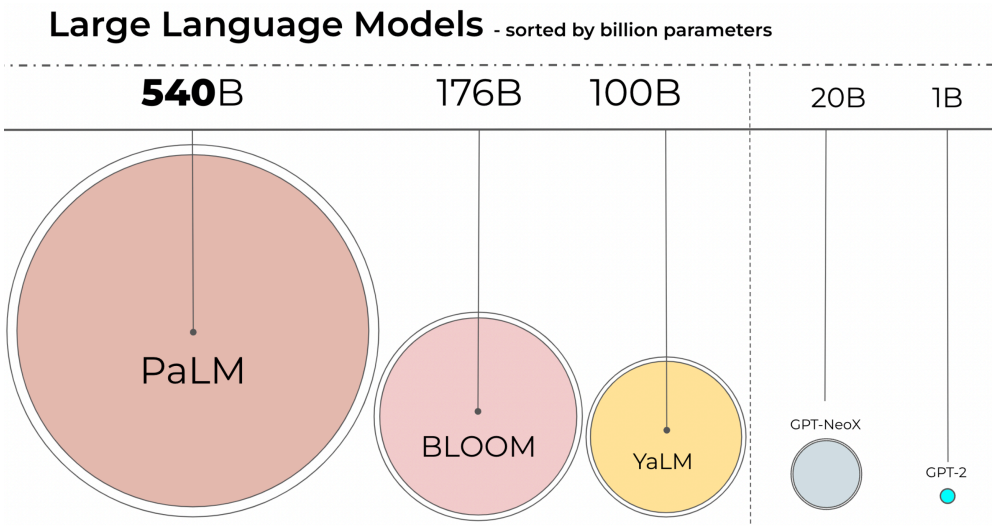
1. **A Representation:** how do we parameterize the joint distribution of many random variables?
2. **A Learning:** what is the right way to compare probability distributions?
3. **A Inference:** how do we invert (or encode) the generation process?

Credit: Aditya Grover

Deep Generative Models

Progress in Deep Generative Models

Credit: Ian Goodfellow, 2019


Large Language Models - sorted by billion parameters
540B
176B
100B
20B
1B
PaLM
BLOOM
YaLM
GPT-NeoX
GPT-2

Sample Applications of Generative Models

Image generation

Text prompt: an armchair in the shape of an avocado ...

Language Generation

Text prompt: to get an A+ in deep generative modes, students should have to

Completion

To get an A+ in deep generative models, students have to be willing to work with problems that are a whole lot more interesting than, say, the ones that most students work on in class. If you're a great student, the question above can be avoided and you'll be able to do great work, but if you're not, you will need to go beyond the basics before getting good.

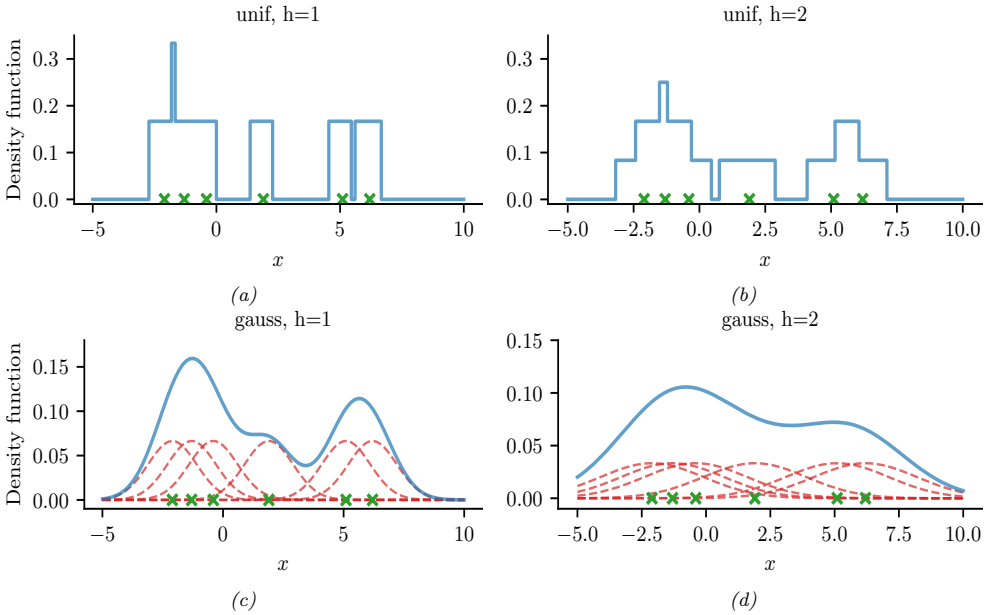
Now to be clear, this advice is not just for the deep-learning crowd; it is good advice for any student who is taking his or her first course in machine learning.

The key point is that if you have a deep, deep brain of a computer scientist, that's just as important to you.

Credit: Aditya Grover

Applications of Deep Generative Models

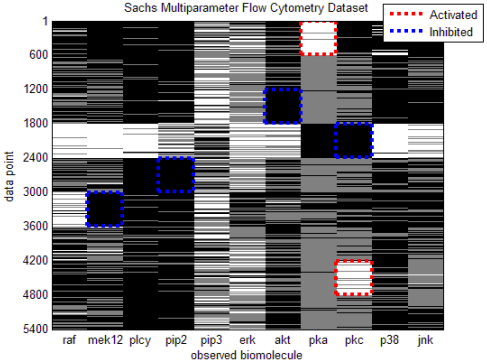
Generating Data

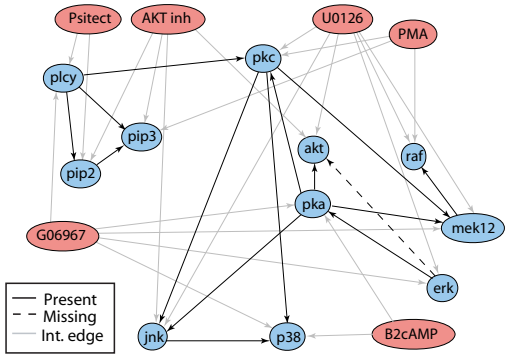

unif, h=1
Density function
0.0
0.1
0.2
0.3
−5
0
5
10
x
(a)
unif, h=2
0.0
0.1
0.2
0.3
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
x
(b)
gauss, h=1
Density function
0.00
0.05
0.10
0.15
−5
0
5
10
x
(c)
gauss, h=2
0.00
0.05
0.10
0.15
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
x
(d)

Imputation (Filling in missing values)

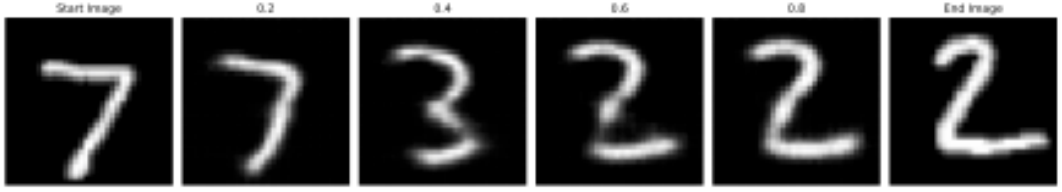
	Variables			Missing values replaced by means		
Data sample	A	B	C	A	B	C
1	6	6	NA	2	6	**7.5**
2	NA	6	0	**9**	6	0
3	NA	6	NA	**9**	6	**7.5**
4	10	10	10	10	10	10
5	10	10	10	10	10	10
6	10	10	10	10	10	10
Average	***9***	***8***	***7.5***	*9*	*8*	*7.5*

Structure Discovery

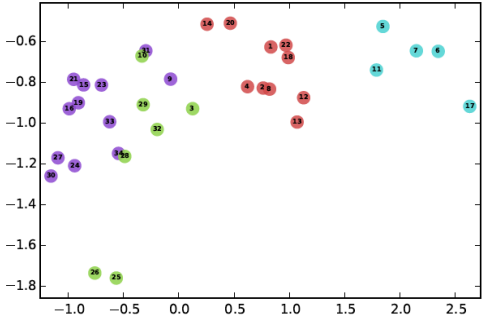




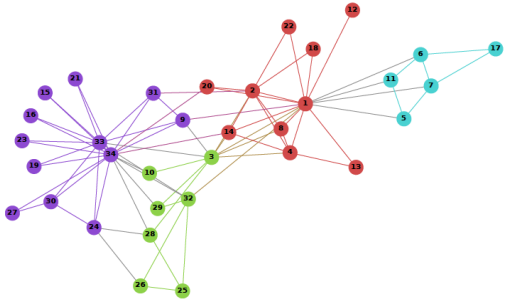
Latent Space Arithmetic



Input pattern



Representation



Course Information

Course Information

1. Course name : **Deep Generative Model**
2. Instructor : Hamid Beigy Email : beigy@sharif.edu
3. Class : CE 201
4. Virtual class link: https://vc.sharif.edu/beigy
5. Course Website: http://sharif.edu/~beigy/14032-40957.html
6. Lectures: Sat-Mon (10:30-12:00)
7. Teaching Assistant : Parham Mohammadi Email: parhammohammadi7804@gmail.com
8. Similar Courses:
   - CMU
   - Aalto
   - Cornell
   - Stanford
   - UCLA

Course overview

Course overview

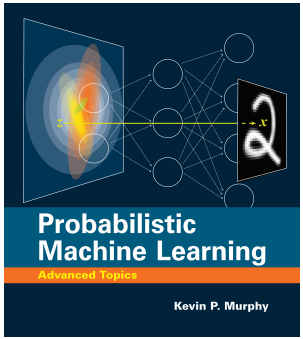
1. Introduction
2. Structured density estimation and Sampling
3. Representation learning and evaluation
4. Generative adversarial network
5. Flow-based models
6. Variational auto-encoder
7. Autoregressive models
8. Energy-based models
9. Score-based models
10. Diffusion models
11. Hybrid models
12. Multi-modal generative models
13. Evaluation of generative models
14. Differential privacy
15. Causal representation learning and Causal generative models

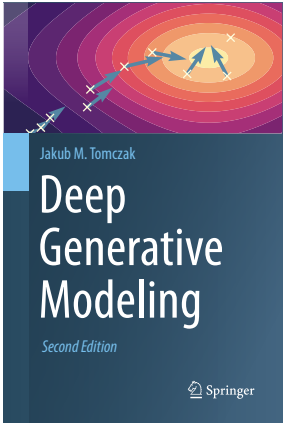
Course evaluation

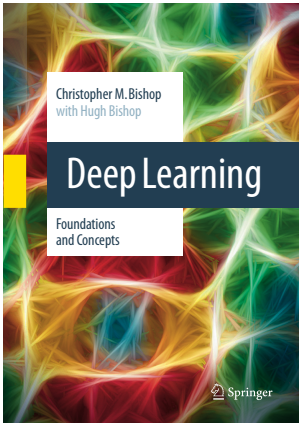
- Evaluation:

Mid-term exam	20%	**1404-01-30**
Final exam	25%	
Homeworks	35%	
Quiz	15%	
Paper	10%	**Hard deadline for paper selection: 1403-01-30**
Class activity	5%	

Main references







- Bishop, Christopher M. and Hugh Bishop (2024). *Deep Learning: Foundations and Concepts*. Second edition. Springer.
- Murphy, Kevin P. (2023). *Probabilistic Machine Learning: Advanced Topics*. The MIT Press.
- Tomczak, Jakub M. (2024). *Deep Generative Modeling*. Springer.

Several research papers will be used as references in the class.

References

Reading

1. Chapter 20 of Probabilistic Machine Learning: Advanced Topics (Murphy 2023).
2. Chapter 1 of Deep Generative Modeling (Tomczak 2024).

References

- Bishop, Christopher M. and Hugh Bishop (2024). *Deep Learning: Foundations and Concepts*. Second edition. Springer.
- Murphy, Kevin P. (2023). *Probabilistic Machine Learning: Advanced Topics*. The MIT Press.
- Tomczak, Jakub M. (2024). *Deep Generative Modeling*. Springer.

Questions?