AI 518: Deep Generative Models

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Syllabus

- Fully observed likelihood-based models
  - Autoregressive
  - Flow-based models
- Latent variable models
  - Variational learning
  - Inference amortization
  - Variational autoencoder
- Implicit generative models
  - Two sample tests, embeddings, F-divergences
  - Generative Adversarial Networks
- Learn about algorithms, theory & applications

Prerequisites

- Basic knowledge about machine learning from at least one of AI 501, 502, 503, 519, or 705.
- Basic knowledge of linear algebra, probabilities, and calculus:
  - Linear independence, Basis, Subspace, Singular Value Decomposition
  - Gradients, gradient-descent optimization, backpropagation
  - Random variables, independence, conditional independence
  - Bayes rule, chain rule, change of variables formulas
- Proficiency in some programming language, preferably Python, required.

Logistics

- Class webpage: https://blackboard.unist.ac.kr/
- Suggested Textbooks:
  - *Deep Generative Modeling* by Jakub M. Tomczak. Online version available free from our library.
  - *Deep Learning* by Ian Goodfellow, Yoshua Bengio, Aaron Courville. Online version available free here.
  - Probabilistic Machine Learning: Advanced Topics by Kevin Murphy. Online version available free here.
- Teaching Assistants: Pumjun Kim, Sanghun Shin, Wooseok Song, Kyeongkook Seo

Logistics – Grading policies

- Grading Policy
  - Five homeworks (40%): mix of conceptual and programming based questions
  - Midterm (20%)
  - Course Project (40%)
    - Proposal (1 page): 5%
    - Progress Report (3 pages): 5%
    - Presentation: 20%
    - Final Report: 10%

Homework (tentative plan)

- **HW1:** Autoregressive Models
- **HW2:** Flow Models
- **HW3:** Latent Variable Models
- **HW4:** Implicit Models / GANs
- **HW5:** Diffusion Models

Homework Policy

- **Collaboration:** Students may discuss assignments. However, each student must code up and write up their solutions independently.
- **Report:** After finishing each homework, you must submit a full report.
- **Late assignments:** Recognizing that students may face unusual circumstances and require some flexibility in the course of the semester, each student will have **a total of 7 free late (calendar) days** to use as s/he sees fit, but **no more than 4 late days can be used on any single assignment**. Late days are counted at the granularity of days: e.g., 3 hours late is one late day.

Midterm

- **Date:** 4/15 (during lecture slot), mark your date.
- **Topics:** everything covered through (and including) 4/10
- **Rationale:** opportunity to force yourself to fully internalize key derivations and concepts

Final Projects

- Course projects will be done in groups of up to three students
- Write a review paper about generative models in suggested (TBD) research area.

Final Projects – Timeline

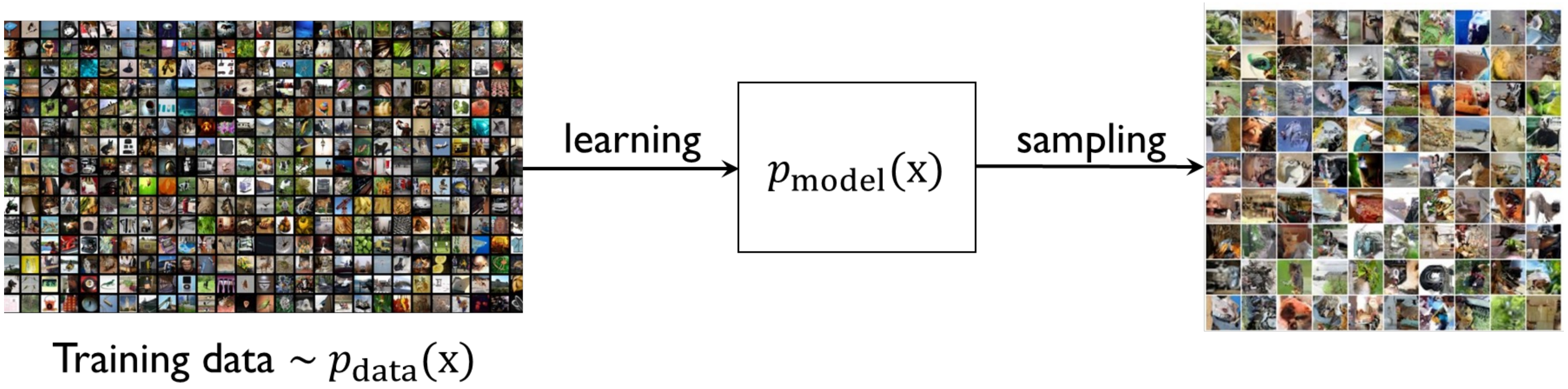
- **Project Proposals Due:** One page description of project + goals for milestone.
  -- Submission through google doc shared with instructors, so we can give feedback/suggestions most easily.
- **Three-Page Milestone Due:** This is to make sure you are indeed making progress on the project and an opportunity to get feedback on your progress thus far, as well as on any revisions you might want to propose to your project goals. Expectation is that you report on some initial experimental findings (or if you are doing something purely theoretical, some initial progress on that front).
  -- Submission through google doc shared with instructors, so we can give feedback/suggestions most easily.
- **Project Presentations:** (same as lecture slot)
- **Eight-Page Final Project Reports Due:** Use this template (Copy it to your project)

Summary

Week	Date	Contents
01	2/26, 2/28	Course logistics & Overview
02	3/4, 3/6	Graphical model and inference
03	3/11, 3/13	Autogressive Models | **HW1 out**
04	3/18, 3/20	Normalizing Flow Models
05	3/25, 3/27	Variational Autoencoder | **HW2 out**
06	4/1, 4/3	Energy-Based Model
07	4/8, 4/10	Generative Adversarial Networks | **Proposal: 1p w/ goals for milestone**
08	4/15, 4/17	Midterm exam period
09	4/22, 4/24	Generative Adversarial Networks | **HW4 out**
10	4/29, 5/1	Diffusion Models
11	5/6, 5/8	Diffusion Models | **HW5 out**
12	5/13, 5/15	Evaluation of Generative Models | **Milestone check up: 3p**
13	5/20, 5/22	Applications & Advanced topics
14	5/27, 5/29	Applications & Advanced topics
15	6/3, 6/5	Guest Lectures
16	6/10, 6/12	Final presentation | **Final project reports**

What is Generative Model?

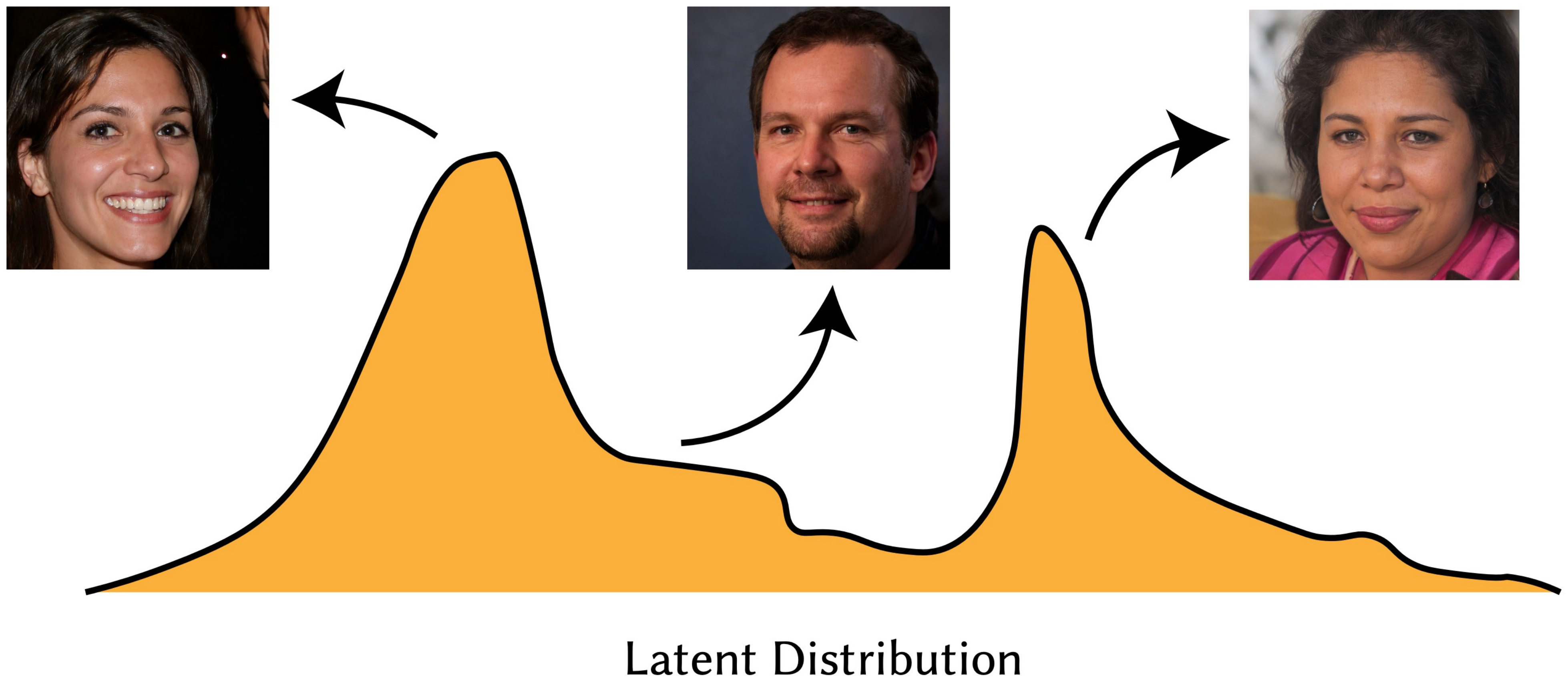
- Given train set, generate new samples from same distribution.



- Objectives:

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

What is Generative Model?



[image courtesy: CVPR tutorial]

Why Generative Model?

- Discriminative vs. generative

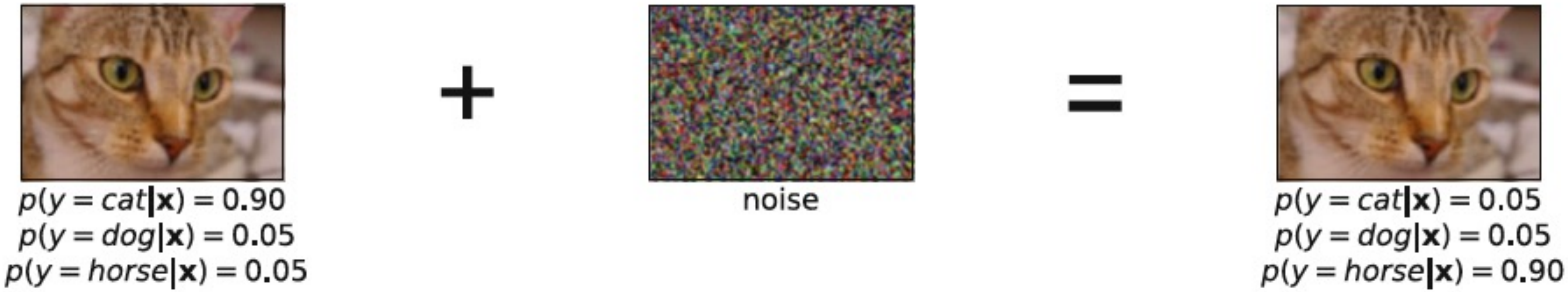


Fig. 1.1 An example of adding noise to an almost perfectly classified image that results in a shift of predicted label

Why Generative Model?

- Discriminative vs. generative

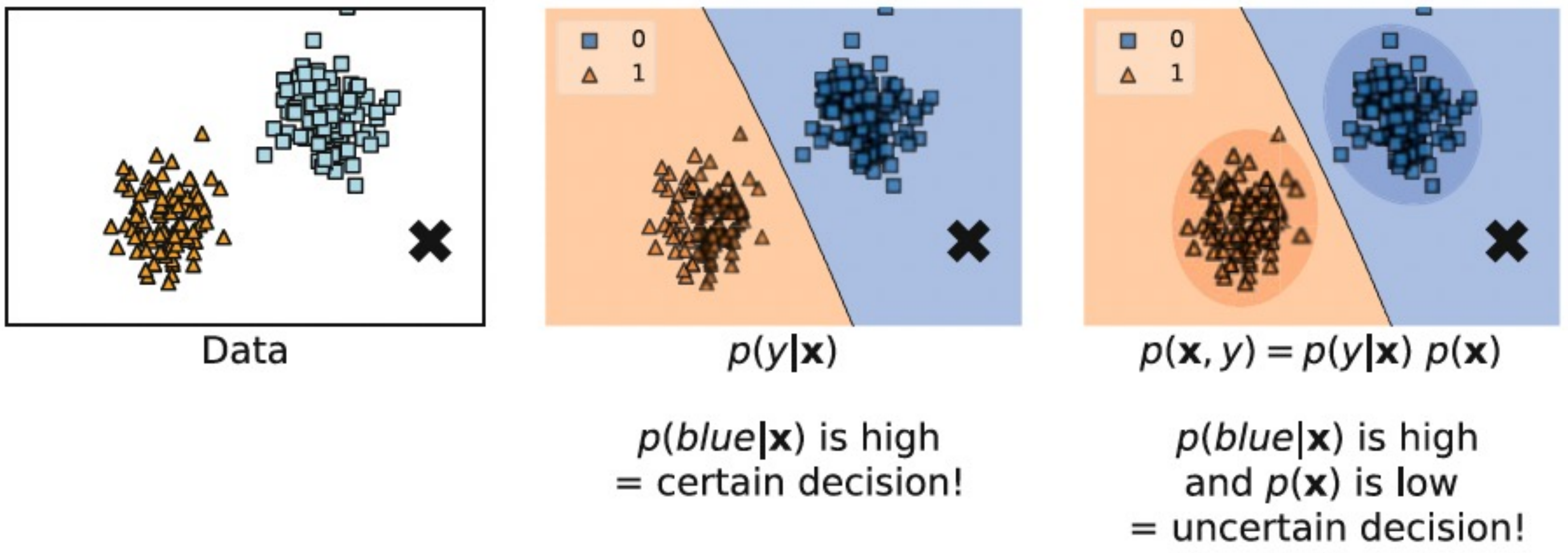


Fig. 1.2 And example of data (*left*) and two approaches to decision making: (*middle*) a discriminative approach and (*right*) a generative approach

Applications



- 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).
- Modeling physical world for simulation and planning (robotics and reinforcement learning approaches).
- Many more …

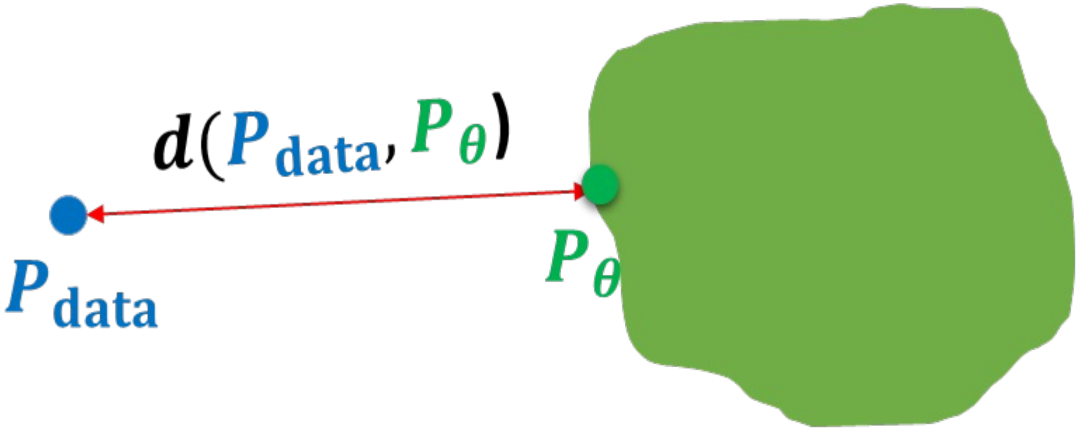
[slide courtesy: Stanford, CS231]

Roadmap and Key Challenges

Representation & Learning

$\mathbf{x}_i \sim P_{\text{data}}$

$i = 1, 2, \ldots, n$



$\theta \in M$

Model family

Roadmap and Key Challenges

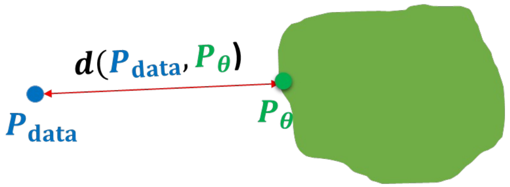
Inference

- **Density estimation:** Given a datapoint **x**x, what is the probability assigned by the model, i.e., $p_\theta(x)$?
- **Sampling:** How can we *generate* novel data from the model distribution, i.e., $x_{\text{new}} \sim p_\theta(x)$?
- **Unsupervised representation learning:** How can we learn meaningful feature representations for a datapoint x?

Summary

- **Representation**: how do we model the joint distribution of many random variables?
  - Need compact representation
- **Learning**: what is the right way to compare probability distributions?

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



$\theta \in M$

Model family

- **Inference**: how do we invert the generation process (e.g., vision as inverse graphics)?
  - Unsupervised learning: recover high-level descriptions (features) from raw data

Questions?