Introduction of Unsupervised Learning
Part II

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Reference

❑ 강의 슬라이드 및 실습코드는 아래의 링크에서 받으실 수 있습니다

- http://www.smartdesignlab.org/dl_aischool_2021.html
- Contributors: 김성신, 유소영, 이성희, 김은지

❑ 강의 소스

- Andrew Ng의 ML Class (www.holehouse.org/mlclass/)
- Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n: Convolutional Neural Networks for Visual Recognition, Stanford (http://cs231n.stanford.edu/)
- Stefano Ermon & Aditya Grover, CS 236: Deep Generative Models , Stanford (https://deepgenerativemodels.github.io/)
- 모두를 위한 딥러닝 (https://hunkim.github.io/ml/)
- 모두를 위한 딥러닝 시즌 2 (https://deeplearningzerotoall.github.io/season2/lec_tensorflow.html)
- 이활석, Autoencoders (https://www.slideshare.net/NaverEngineering/ss-96581209)
- 최윤제, 1시간만에 GAN(Generative Adversarial Network) 완전 정복하기 (https://www.slideshare.net/NaverEngineering/1-gangenerative-adversarial-network?qid=c53ce33f-6643-4437-8e93-88776c9cebb1&v=&b=&from_search=5)
- 김성범, [핵심 머신러닝] Principal Component Analysis (PCA, 주성분 분석) (https://youtu.be/FhQm2Tc8Kic)

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- **Ch1: Introduction to Unsupervised Learning Part I** → Probability & Maximum Likelihood
- **Ch2: Introduction to Unsupervised Learning Part II** → Generative Model & Dimensionality Reduction
- **Ch3: Principal Component Analysis (PCA)** → Machine Learning Model
- **Ch4: Autoencoder & Anomaly Detection**
  + 실습
- **Ch5: Variational AutoEncoder (VAE)**
  + 실습
- **Ch6: Generative Adversarial Network (GAN)**
  + 실습

→ Deep Learning Models

- **Ch7: Application: Mechanical Design + AI** → CAD/CAM/CAE/Design Optimization + AI

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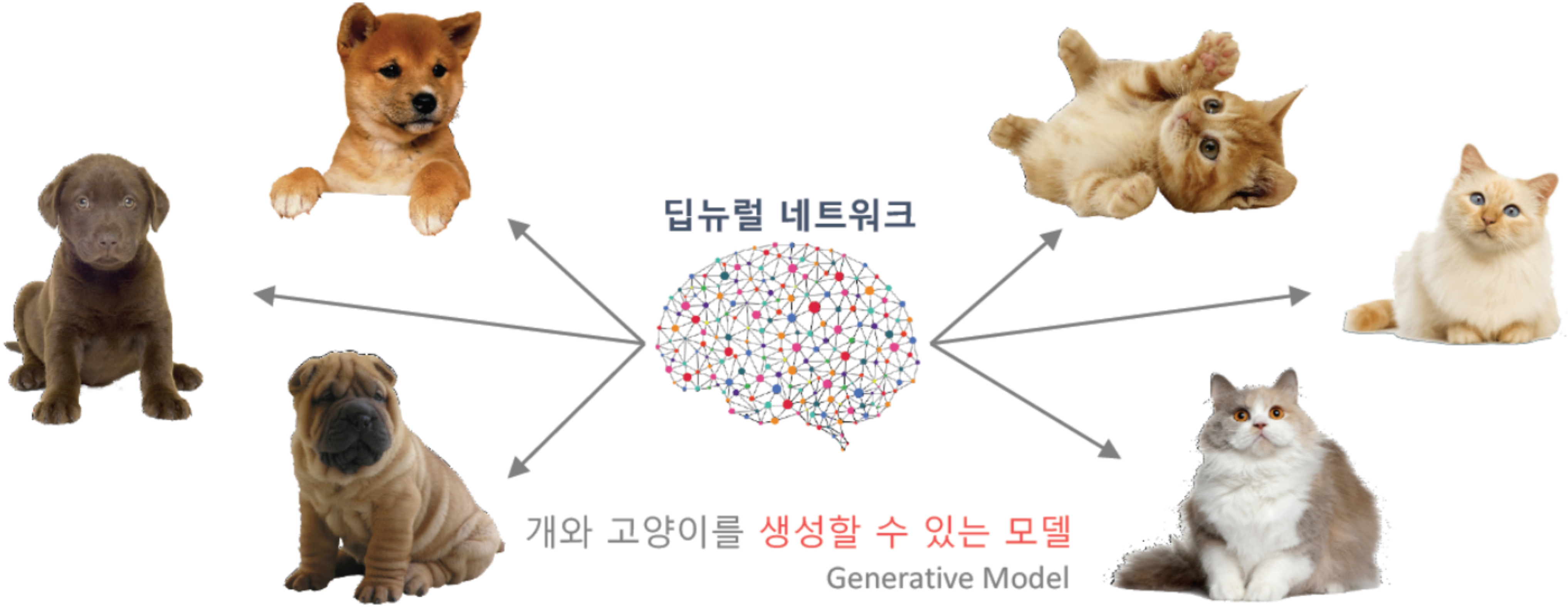
Generative Models



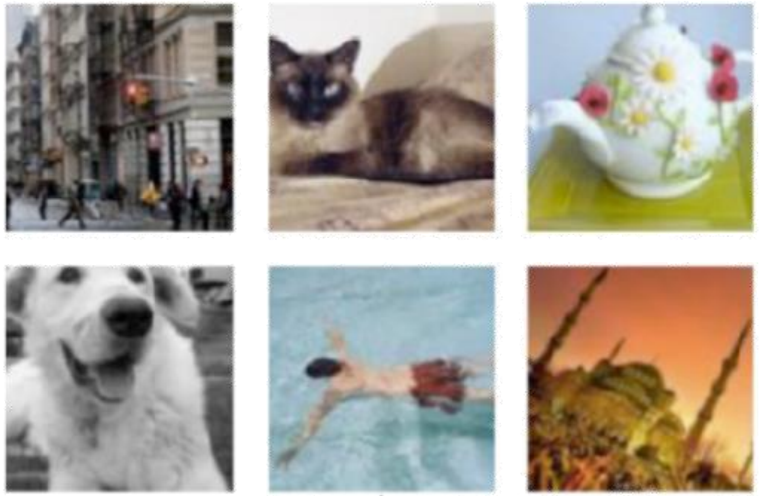
분류 모델 보다는 개와 고양이를 제대로 **이해하고 있다**

"What I cannot create, I do not understand." - Richard Feynman

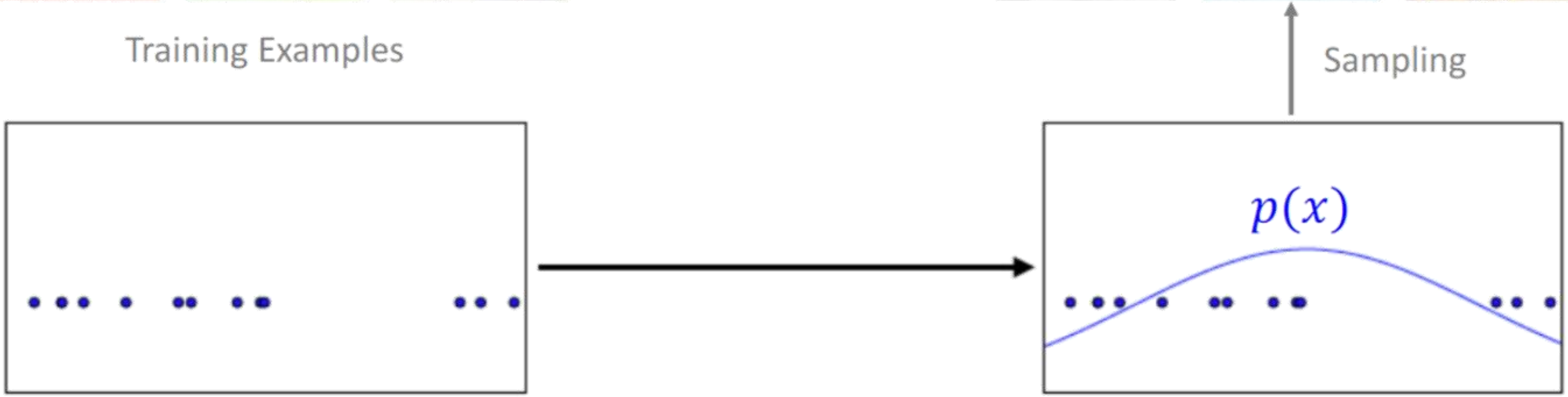
Generative Models

Density Estimation

Training Examples



Sampling

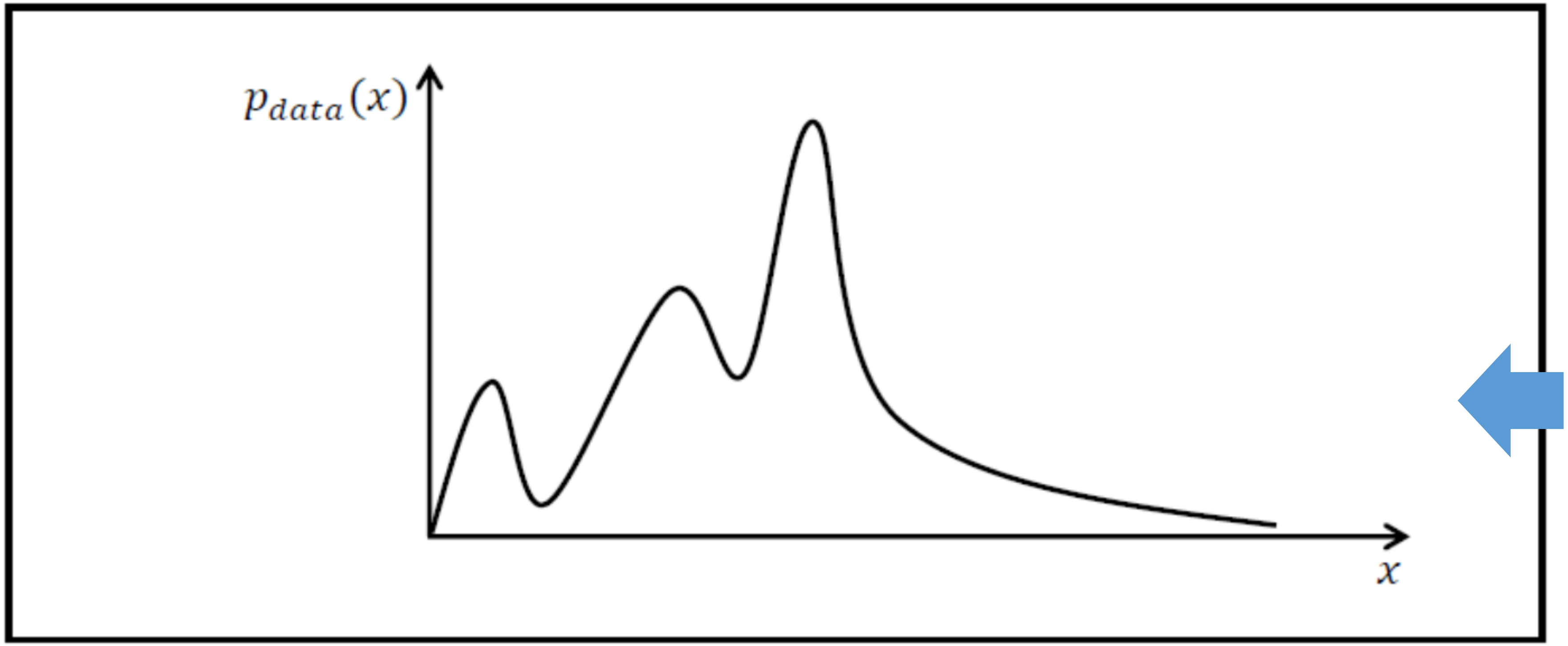


Maximum Likelihood

Generative Models

Probability density function (pdf)

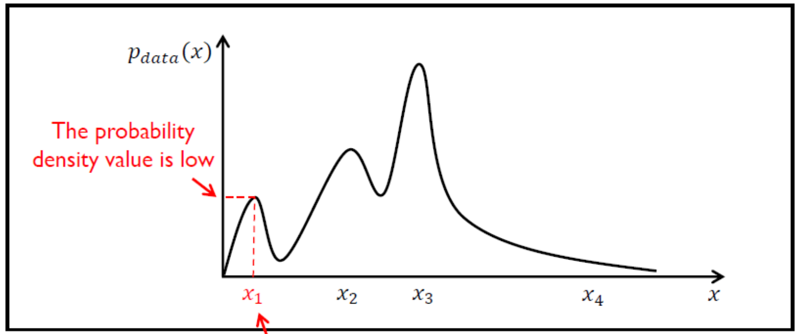
There is a $p_{data}(x)$ that represents the distribution of actual images.



x is actual images in the training data, and it can be represented as a (for example) 64x64x3 dimensional vector.

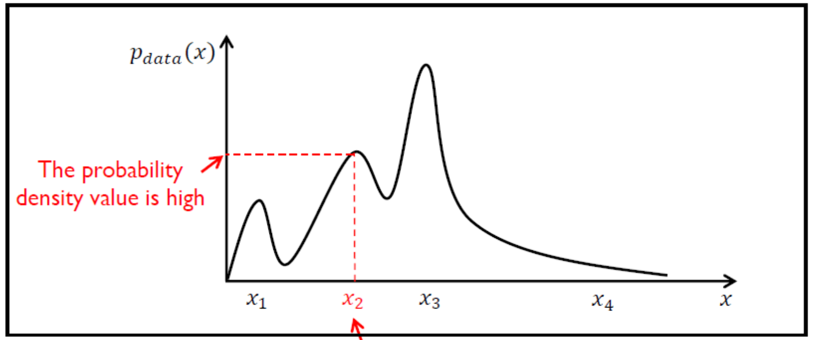
Generative Models

Men with glasses



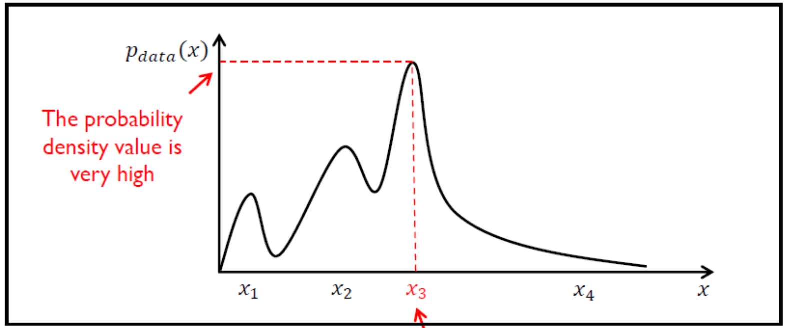
x_1 is a 64x64x3 high dimensional vector representing a man with glasses.

Women with black hair



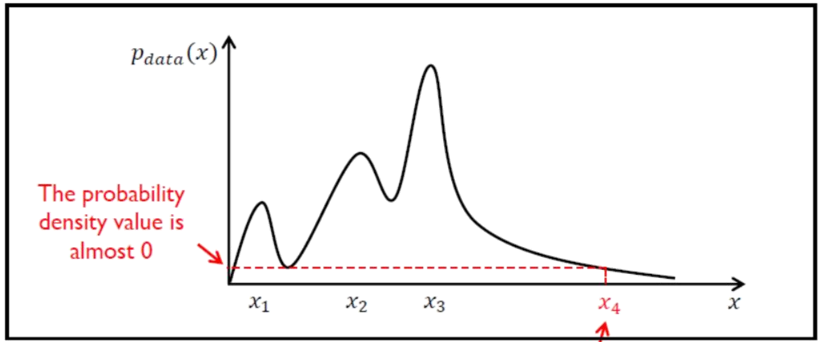
x_2 is a 64x64x3 high dimensional vector representing a woman with black hair.

Women with blonde hair



x_3 is a 64x64x3 high dimensional vector representing a woman with blonde hair.

Strange images



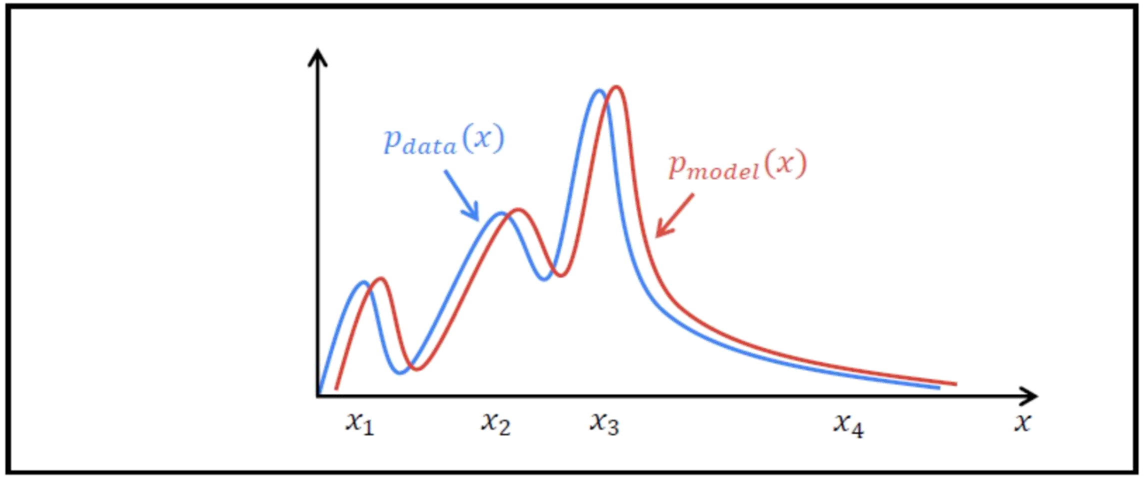
x_4 is an 64x64x3 high dimensional vector representing very strange images.

Generative Models

Distribution of images generated by the model

The goal of the generative model is to find a $p_{model}(x)$ that approximates $p_{data}(x)$ well.

Distribution of actual images



Then, generate new samples from $p_{model}(x)$

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

Generative Models

Taxonomy of Generative Models

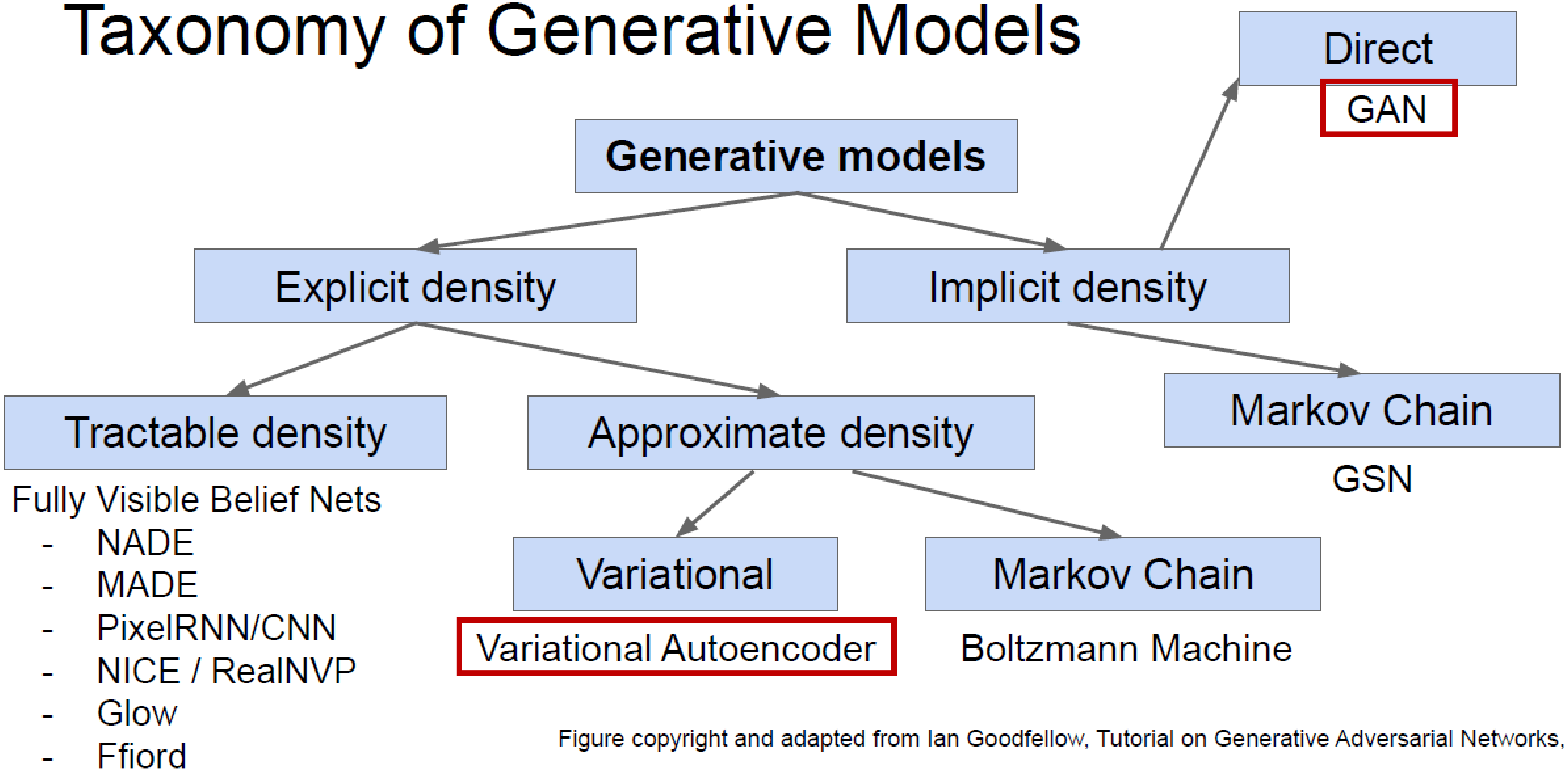


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

Generative Models

Why Generative Models?

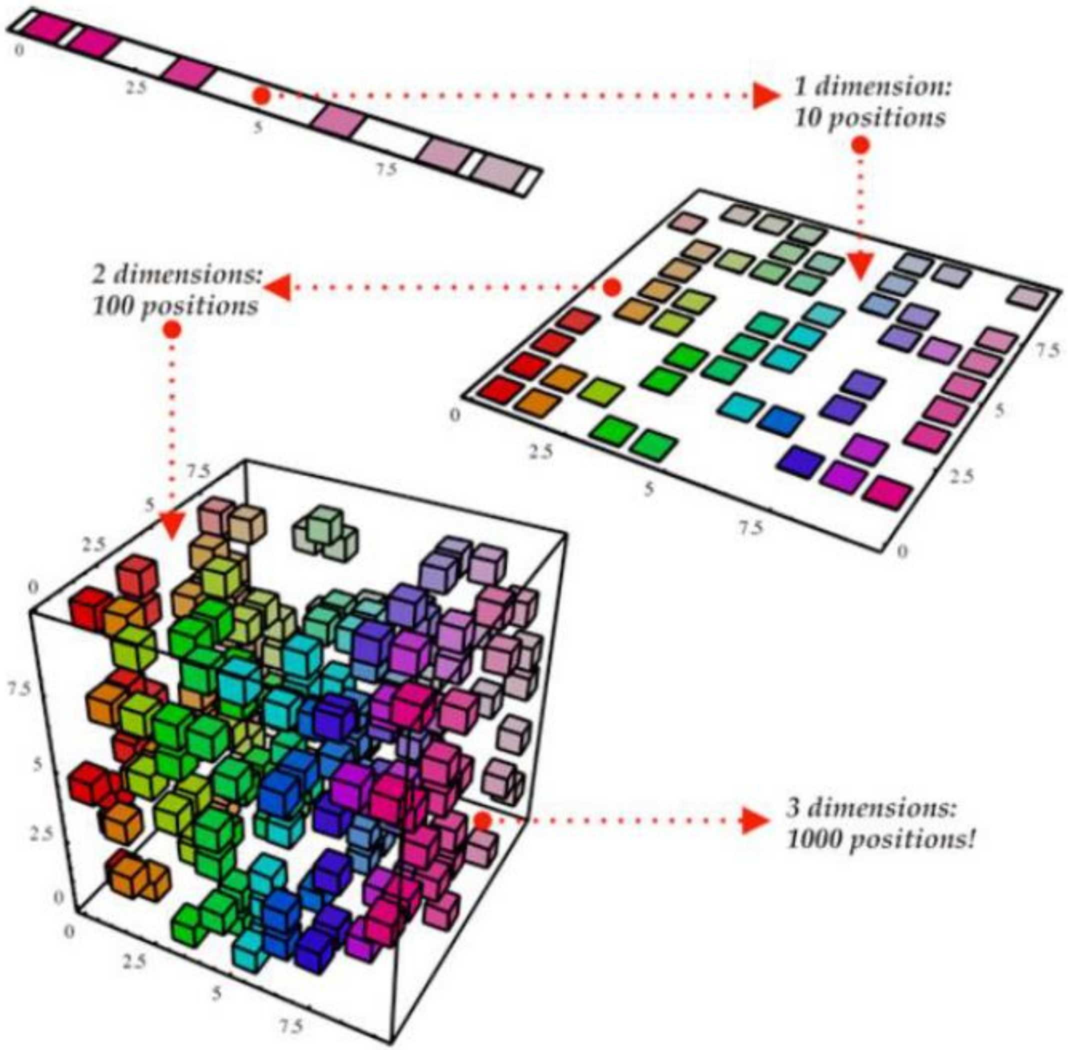
- Realistic samples for artwork, super-resolution, colorization, etc.

- 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 ➔ *Dimensionality Reduction (Manifold Learning)*

Curse of dimensionality

데이터의 차원이 증가 할수록 해당 공간의 크기(부피)가 기하급수적으로 증가하기 때문에 동일한 개수의 데이터의 밀도는 차원이 증가할수록 급속도로 희박해진다.

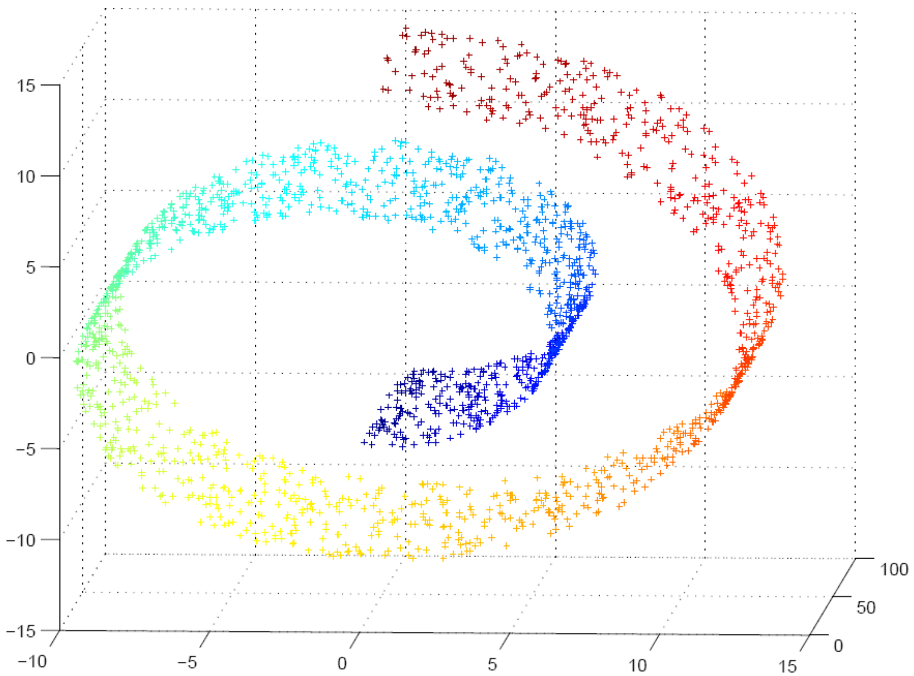
따라서, 차원이 증가할수록 데이터의 분포분석 또는 모델추정에 필요한 샘플데이터의 개수가 기하급수적으로 증가하게된다.



Manifold Hypothesis (assumption)

- 고차원의 데이터의 밀도는 낮지만, 이들의 집합을 포함하는 저차원의 매니폴드가있다.

- 이 저차원의 매니폴드를 벗어나는 순간 급격히 밀도는 낮아진다.



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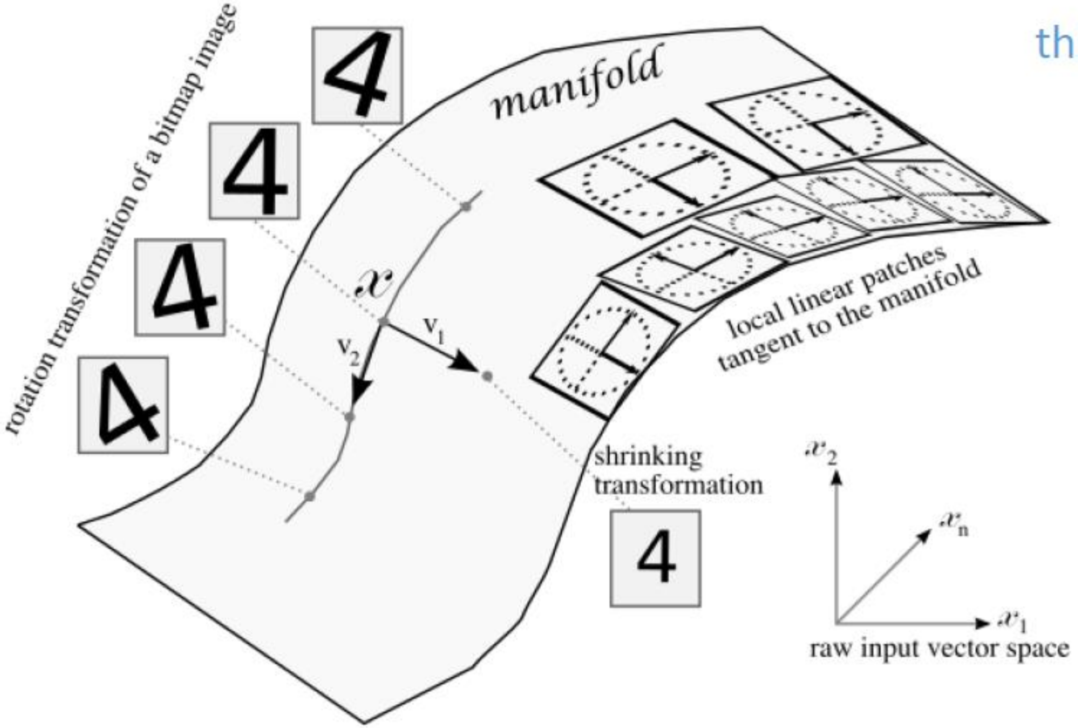
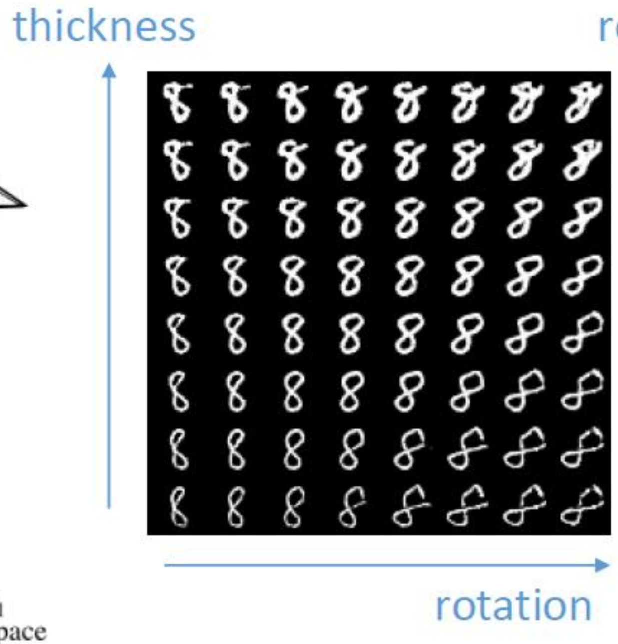
Dimensionality Reduction

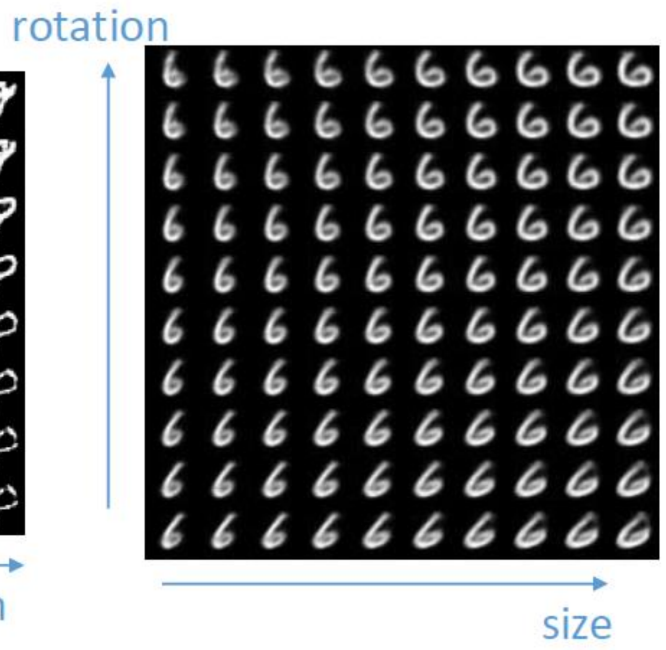
Discovering most important features

매니폴드 학습결과 평가를 위해 매니폴드좌표들이 조금씩 변할때 원데이터도 유의미하게 조금씩 변함을 보인다.





From InfoGAN

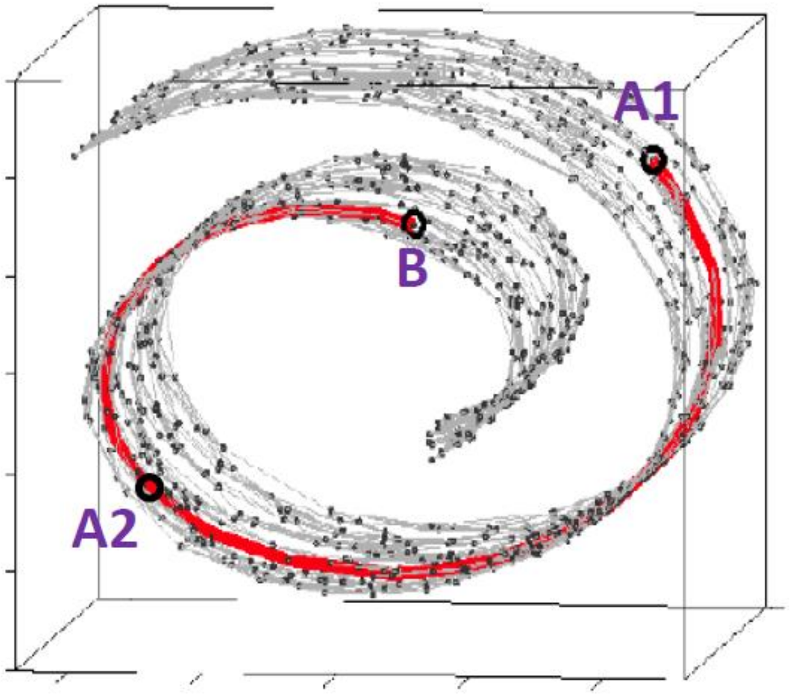


From VAE

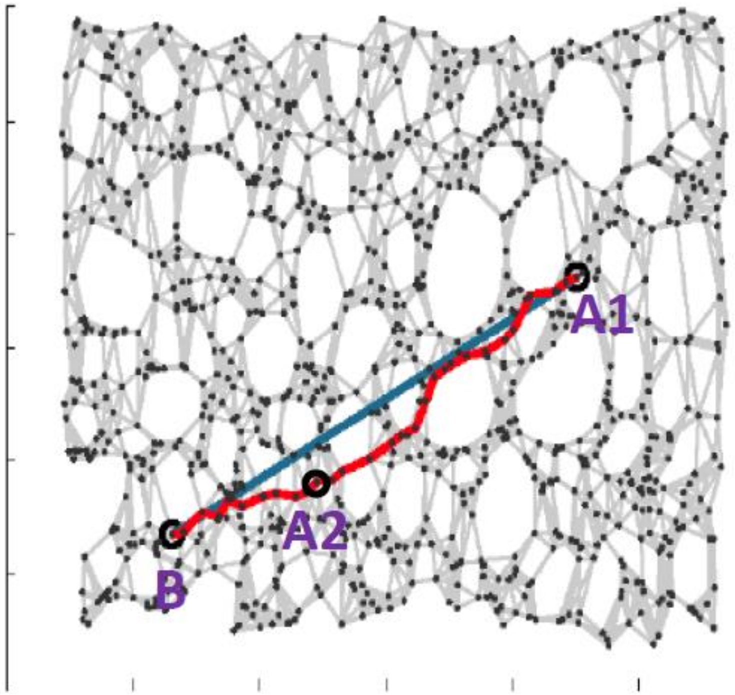
Dimensionality Reduction

Reasonable distance metric

- 의미적으로가깝다고생각되는고차원공간에서의두샘플들간의거리는먼경우가많다.
- 고차원공간에서가까운두샘플들은의미적으로는굉장히다를수있다.
- 차원의저주로인해고차원에서의유의미한거리측정방식을찾기어렵다.



Distance in high dimension

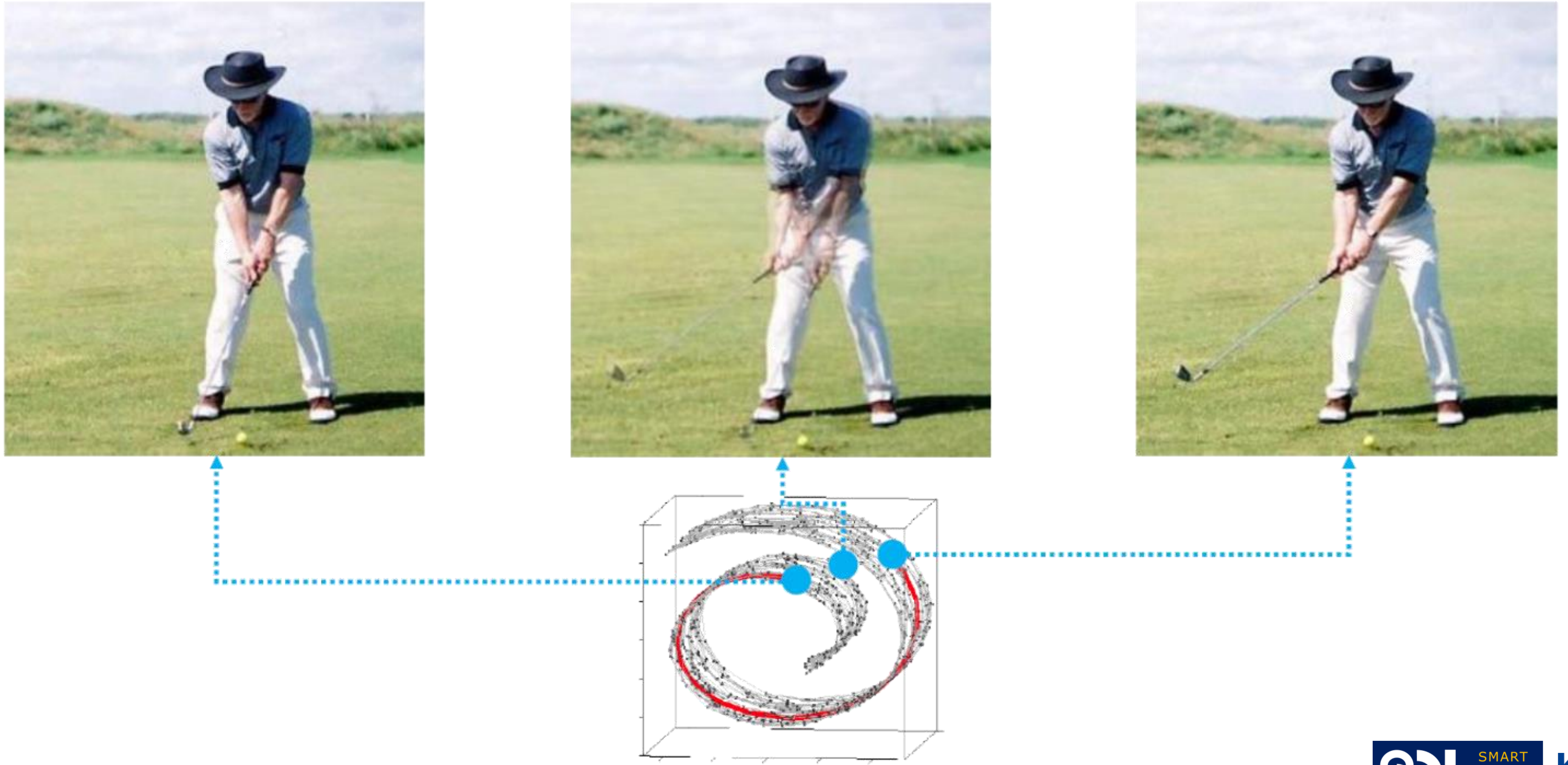


Distance in manifold

중요한 특징들을 찾았다면 이 특징을 공유하는 샘플들도 찾을수 있어야 한다.

Reasonable distance metric

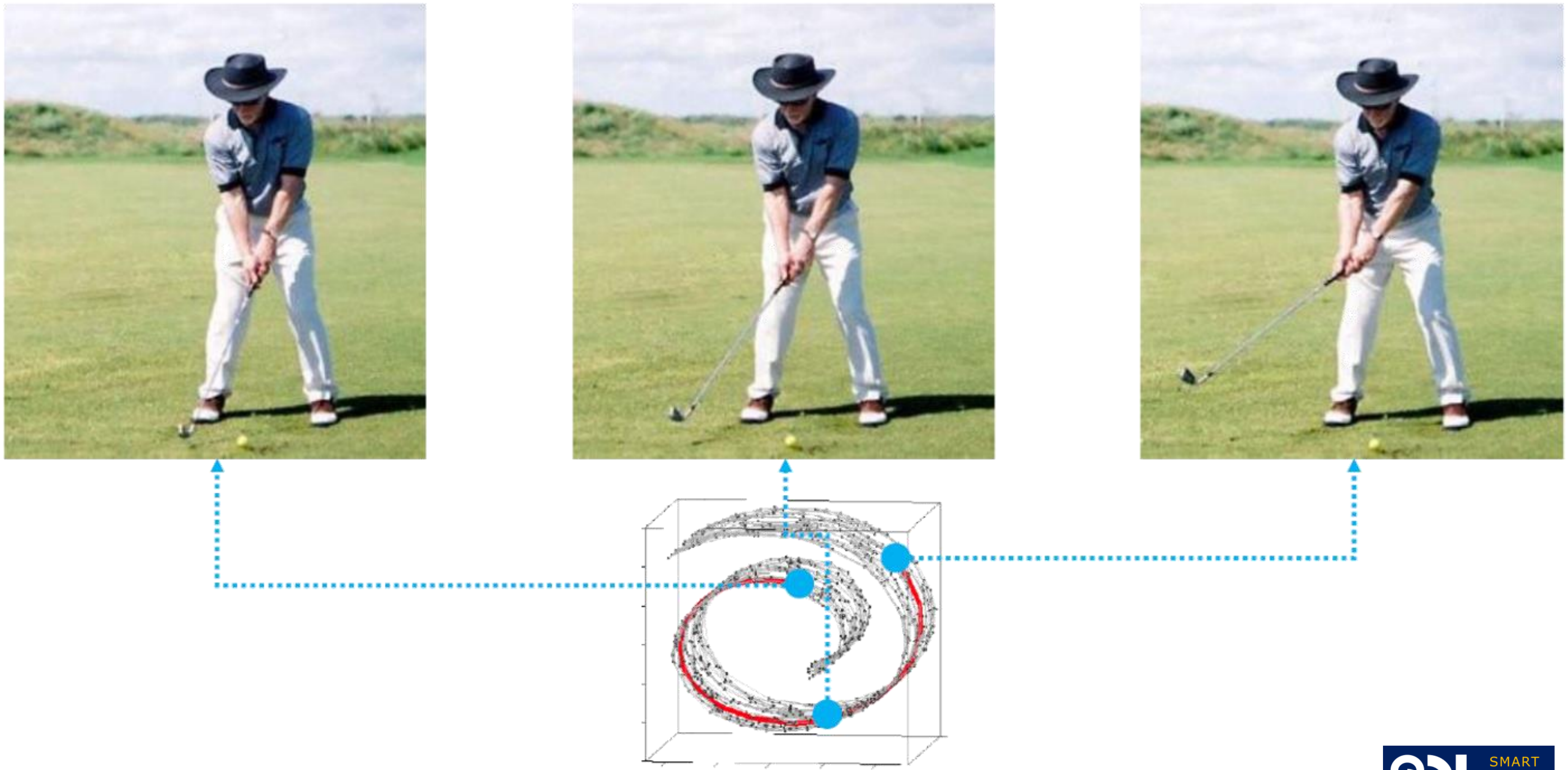
Interpolation in high dimension



Dimensionality Reduction

Reasonable distance metric

Interpolation in manifold

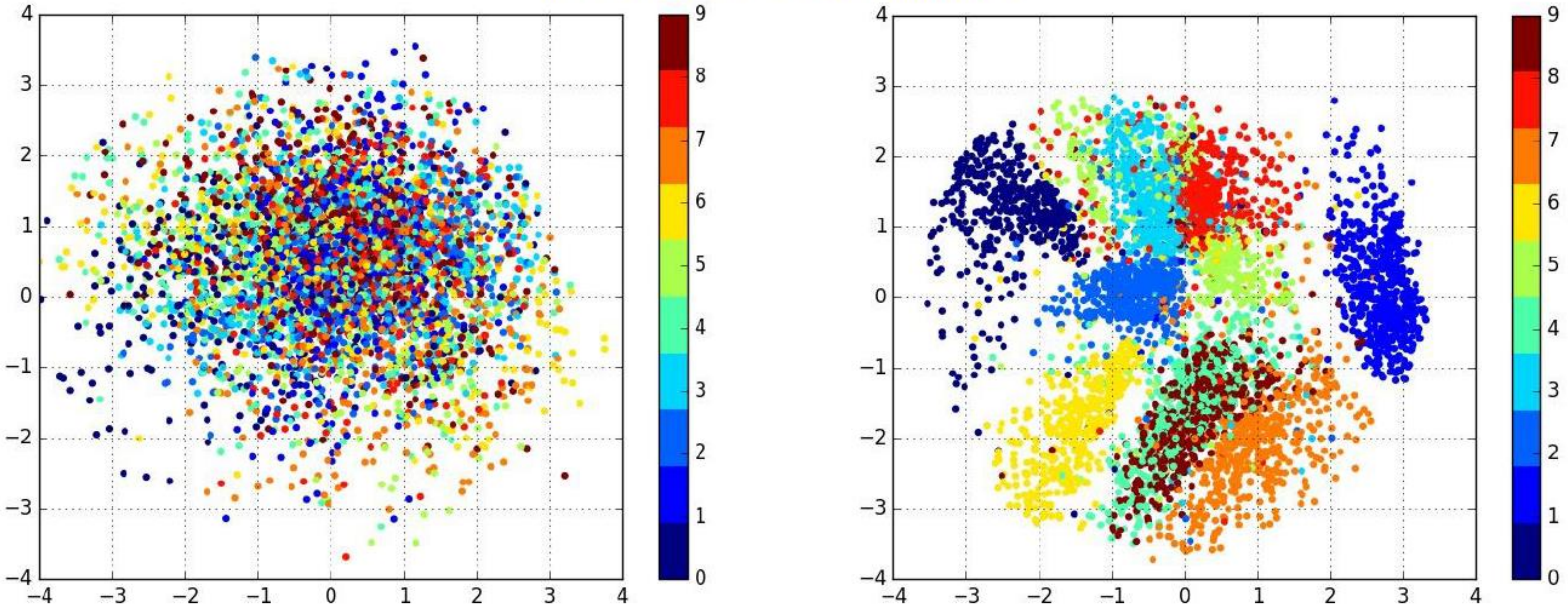


Dimensionality Reduction

Needs disentagling the underlying explanatory factors

- In general, learned manifold is entangled, i.e. encoded in a data space in a complicated manner.
- When a manifold is disentangled, it would be more interpretable and easier to apply to tasks

MNIST Data → 2D manifold



Entangled manifold

Disentangled manifold

What Questions Do You Have?

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