SEMINAR IN DATA SCIENCE AND INFORMATION TECHNOLOGY

ADVANCED LEARNING REPRESENTATIONS

LECTURE 1: OVERVIEW

WEEK 1-11

Instructor： Yang Li

SPRING 2023

LECTURE OUTLINE

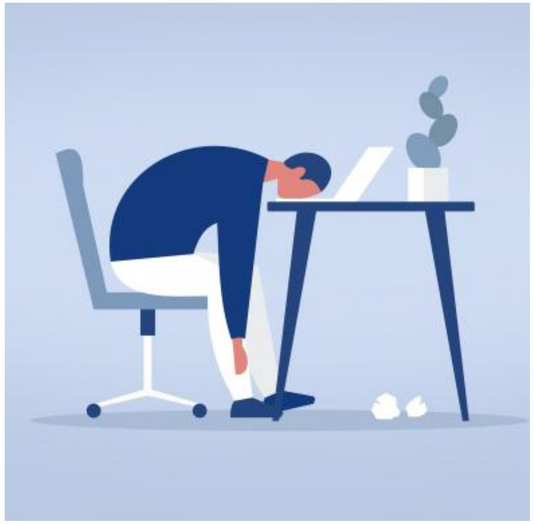
- About this class
- A preview of the topics we will cover
- Break
- Discussion on *Representation Learning: A New Perspective*

PURPOSE

- **What have we learned so far in Learning from Data:**
  - **Supervised Learning: discriminative & generative models, SVM, neural net**
  - **Unsupervised Learning: clustering & linear projection models (PCA/ICA/CCA)**
  - **Semi-Supervised Learning**
  - **Reinforcement Learning**

PURPOSE

- **What's next after Learning from Data?**



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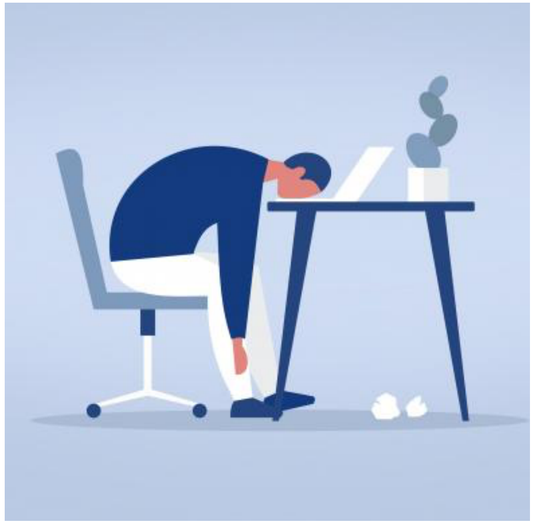
- **What's next after Learning from Data?**

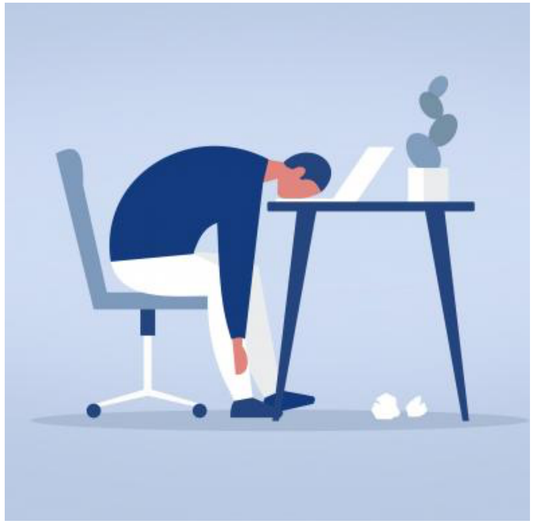


Given a new problem, how to find the best learning method?

PURPOSE

- **What's next after Learning from Data?**

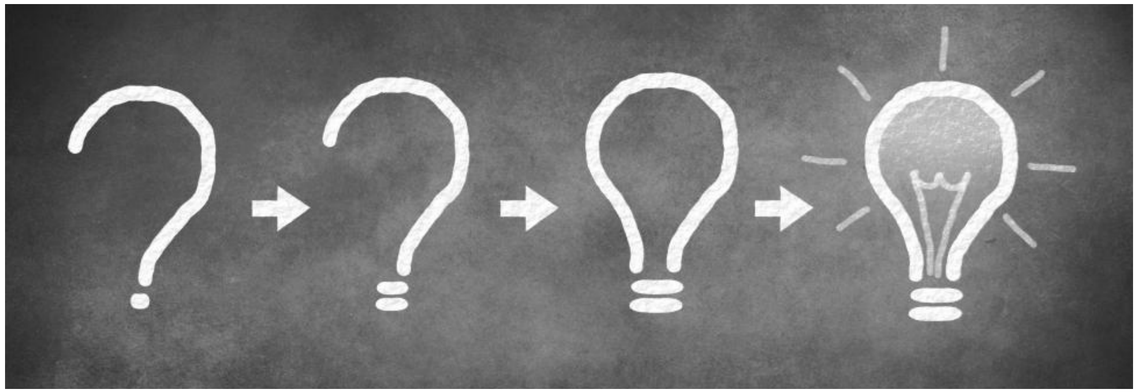
How to find "ideas" for machine learning research?



Given a new problem, how to find the best learning method?

PURPOSE

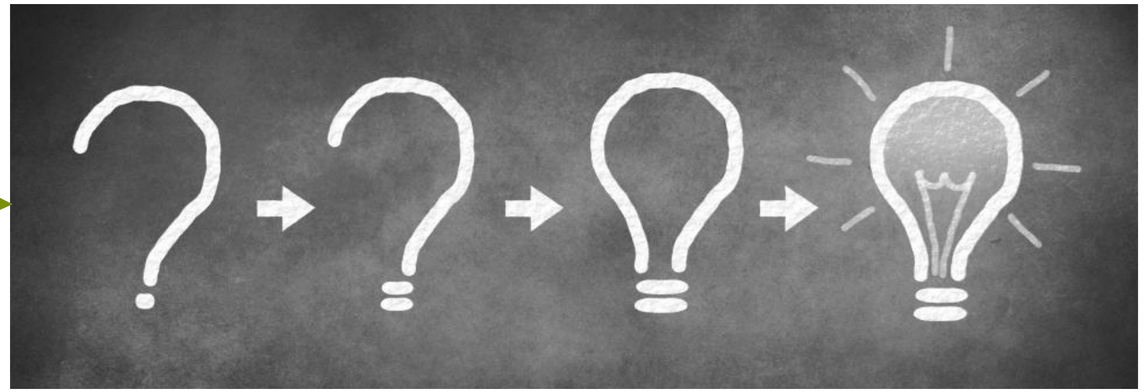
- **Learn from classic literatures**



PURPOSE

- **Learn from classic literatures**

Where did it draw inspiration from?

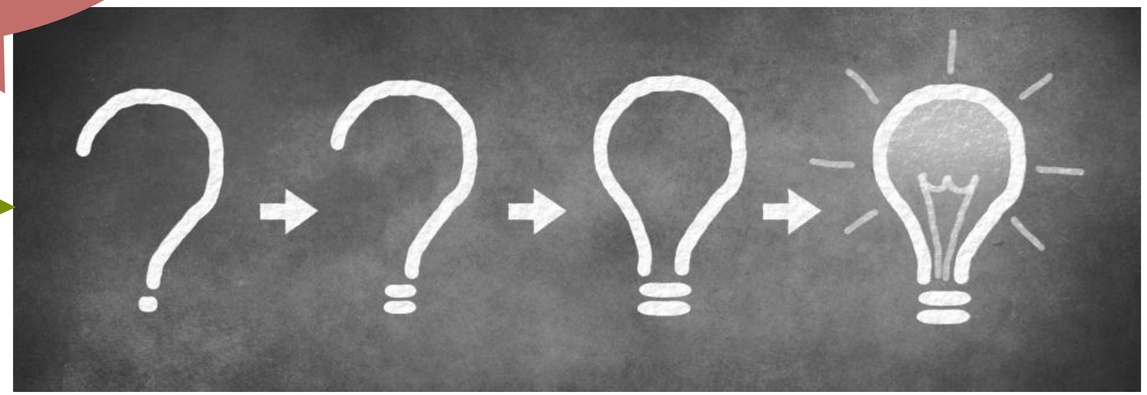


PURPOSE

- **Learn from classic literatures**

How was the problem formulated?

Where did it draw inspiration from?



PURPOSE

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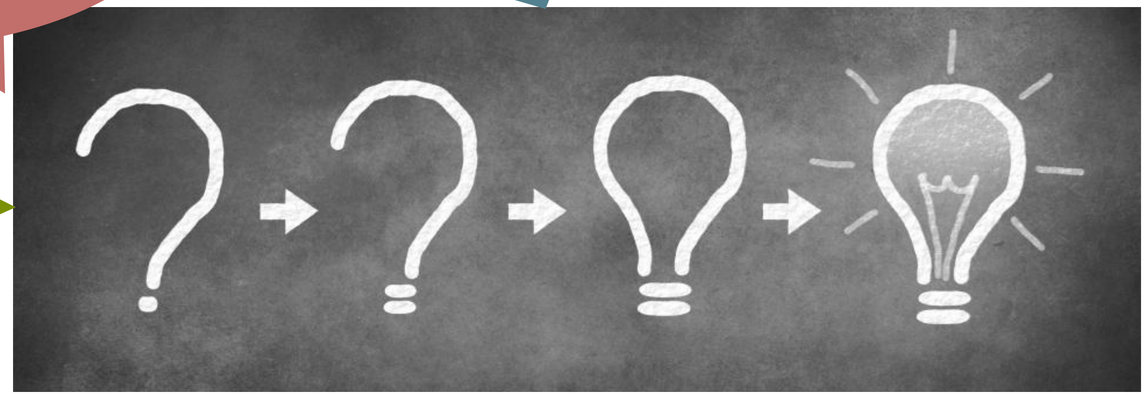

PURPOSE

- **Learn from classic literatures**

How was the method derived?

What priors or assumptions did it make?

How was the problem formulated?

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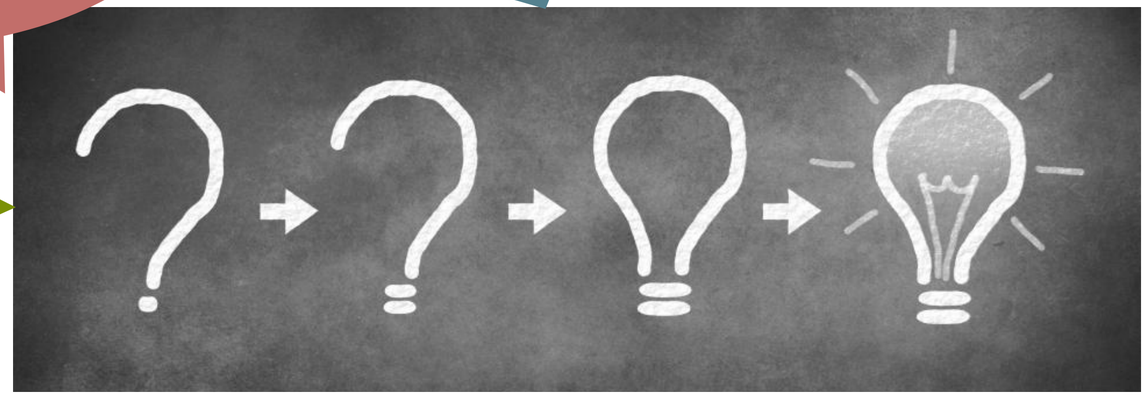

PURPOSE

- **Learn from classic literatures**

How was the problem formulated?

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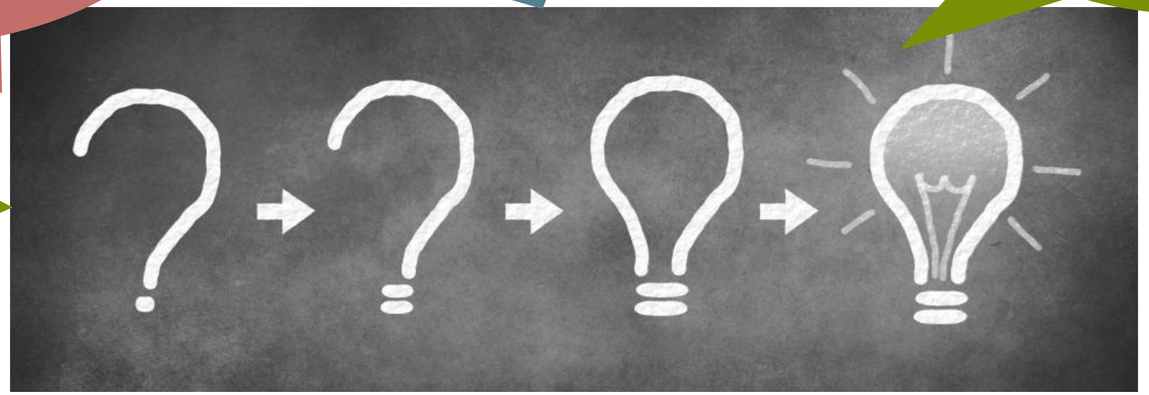
How was the method derived?

How did it contribute to the field?

Where did it draw inspiration from?



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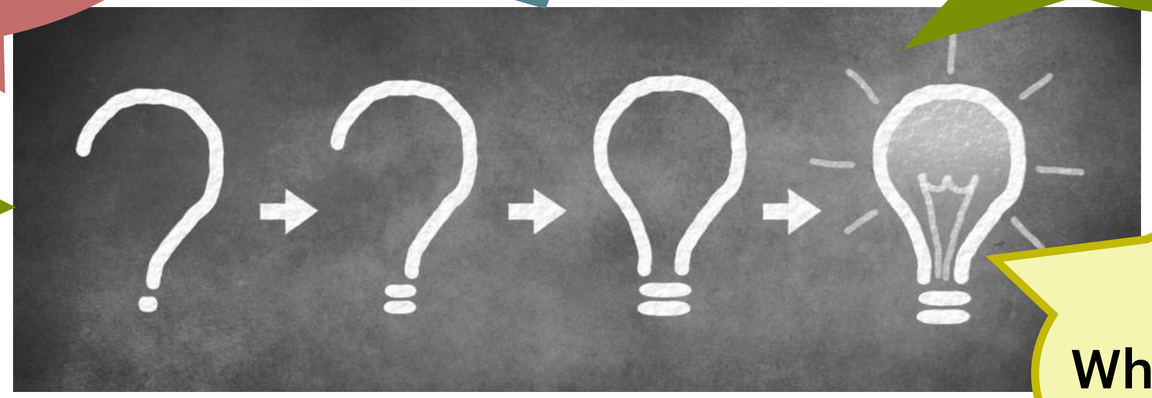
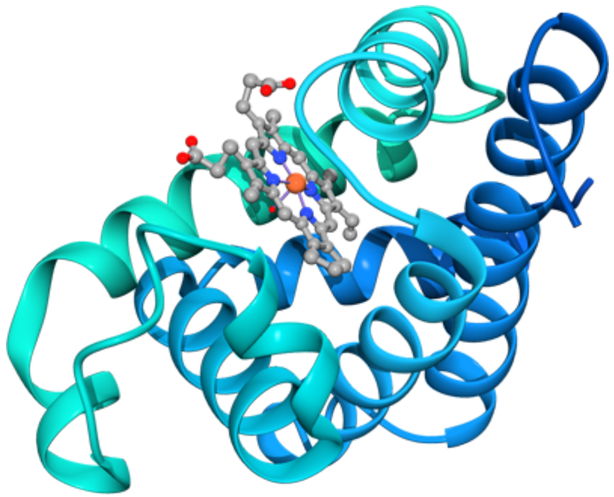
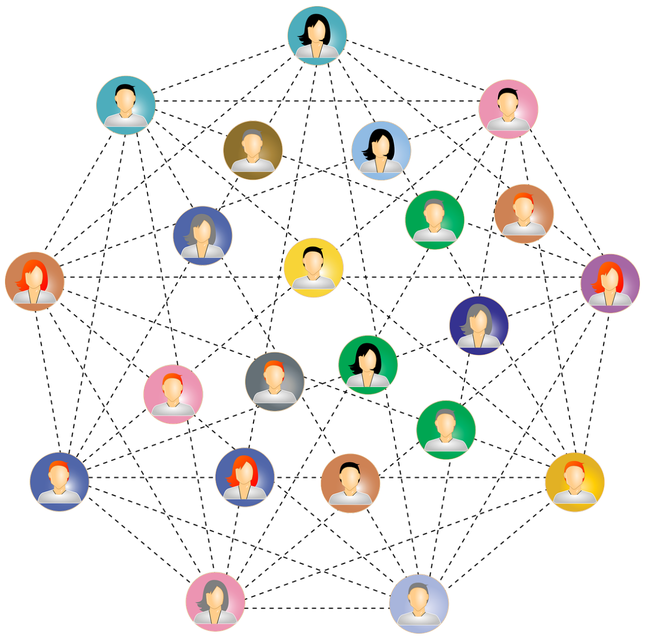


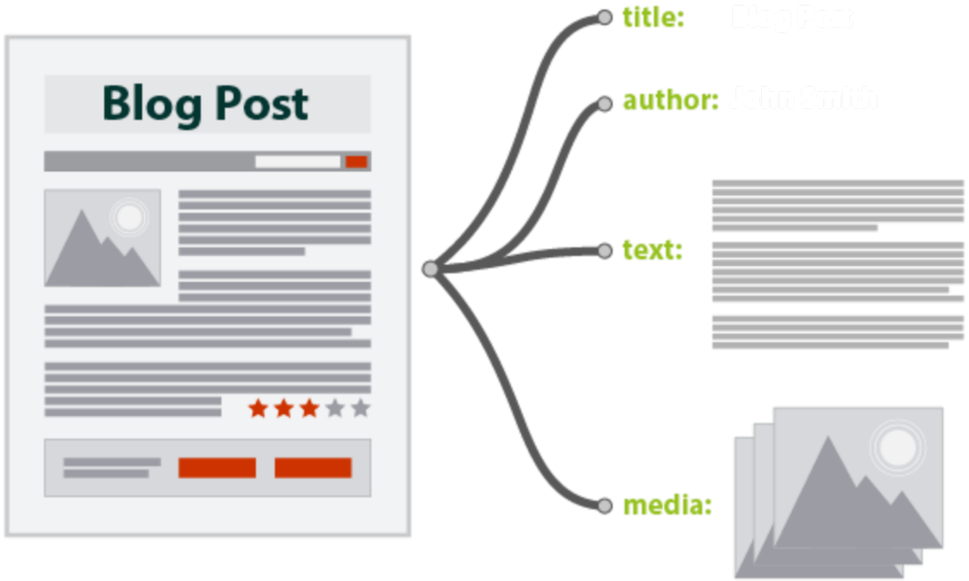
What can I learn from this work?

REPRESENTATION LEARNING

- **"Deep learning is about learning good representations"**



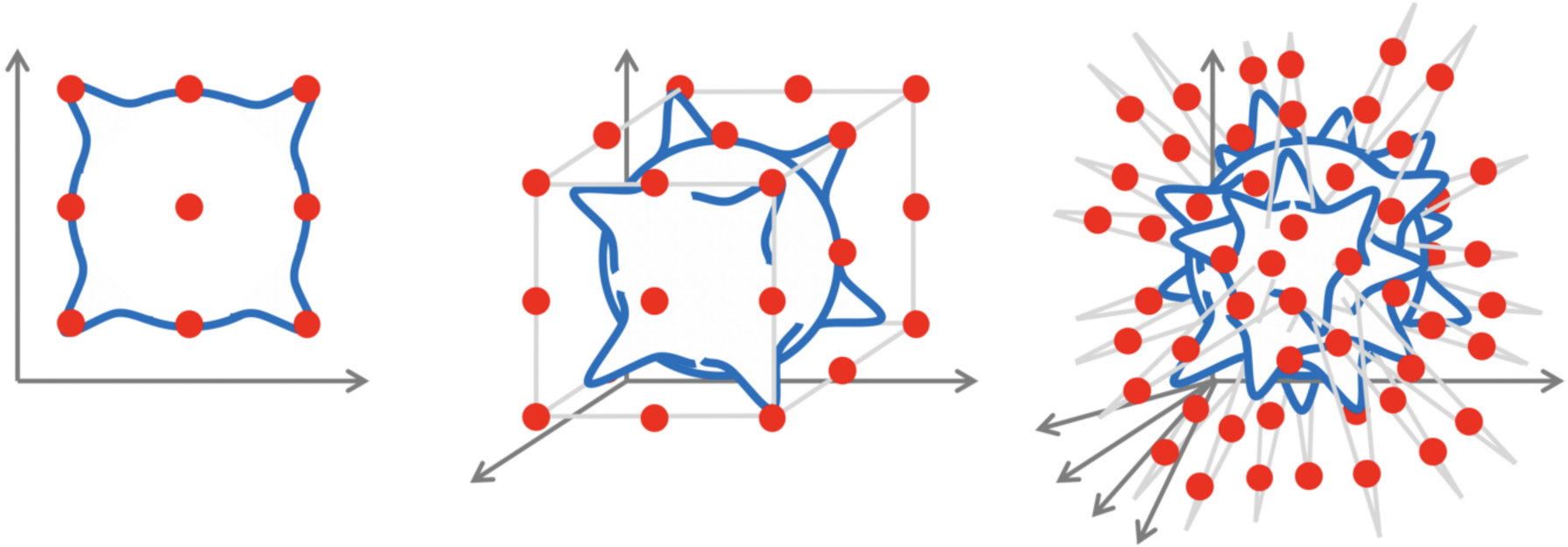




Examples of high dimensional, structured data

REPRESENTATION LEARNING

- **"Curse of dimensionality"**



Approximating a Lipschitz-continous function in R^d within error ε requires at least $\mathcal{O}(1/\varepsilon^d)$ samples

REPRESENTATION LEARNING

- This class focus on general paradigms for learning good representations
  - How to represent structured data in learning ? e.g. images, text, sequences, graphs
  - How to exploit the hidden structures and prior knowledge in data?

Learn from classic literature

SEMINAR FORMAT

- Read and discuss classic literature each week
  - Student will rotate to present the reading material
  - Form groups of 3-4 people for in-class discussion
- In-class programming exercises
- *Guest lecture

HOMEWORK

- Submit before each class
  - Write a 1-page reading summary
  - Answer pre-discussion questions

PRESENTATIONS & FINAL REPORT

- Each group needs to do at least one presentation
  - One of the required readings (Week 2-9)
  - A topic related to the required reading (Week 10 & 11)
- Group report:
  - A written report based on the topic your presented

GRADING

- **Homework: 60%**
- **Class participation: 20%**
- **Final presentation & report: 20%**

CLASS LOGISTICS

- **Join class WeChat group**
- **Class website**
- **Contact TA if you need to use the class GPU server**

http://yangli-feasibility.com/home/classes/dss2023spring/

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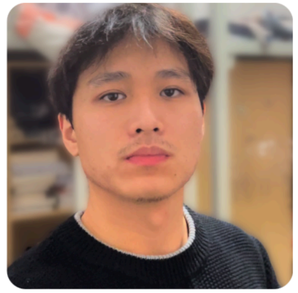

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TA
18342291462@163.com

Office hours

Name	Time	Location
Yang	Friday 2:00-4:00pm	Info Building 1108a
Tao	Monday 2:00-4:00pm	Info Building, 1111A
Guanlin	Monday 10:00-12:00am	Info Building, 702

You can also make appointments outside office hours.

LECTURE OUTLINE

- About this class
- A preview of the topics we will cover
- Break
- Discussion on *Representation Learning: A New Perspective*

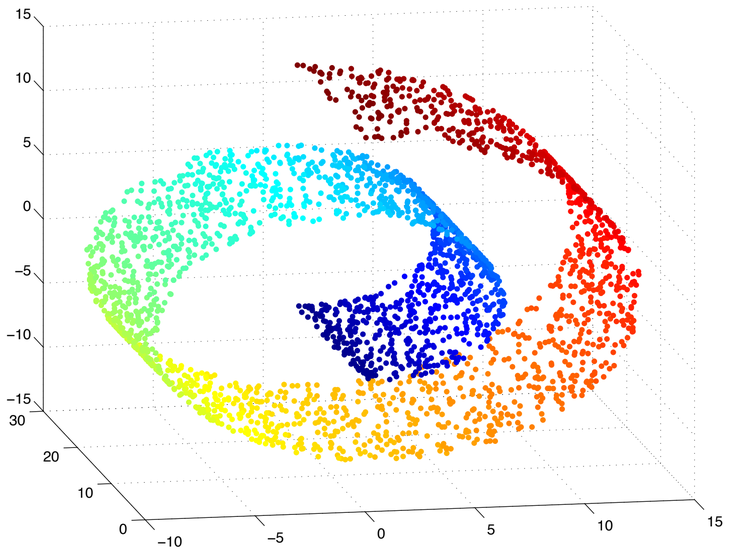
MAIN TOPICS

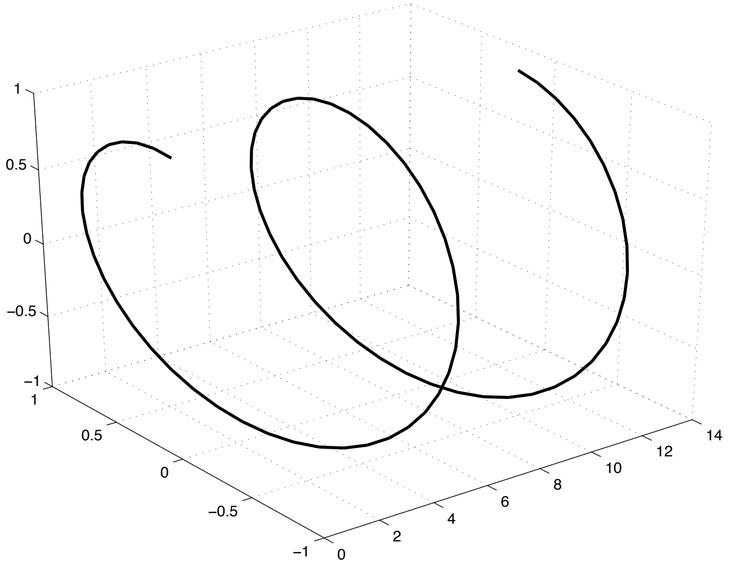
1. **Manifold learning**
2. **Generative modeling**
3. **Metric learning**
4. **Attention mechanism**
5. **Graph representation learning**

1. MANIFOLD LEARNING

- **Non-linear Dimension Reduction (NLDR): Recover meaningful low-dimensional structures hidden in high-dimensional data.**

- **Manifold Learning :Given *m* points $x^{(1)}, \ldots, x^{(m)}$ on a manifold M embedded in $\mathbb{R}^D$, find a set of points $y^{(1)}, \ldots, y^{(m)} \in \mathbb{R}^d, (d \ll D)$ such that $y^{(i)}$ represents $x^{(i)}$**

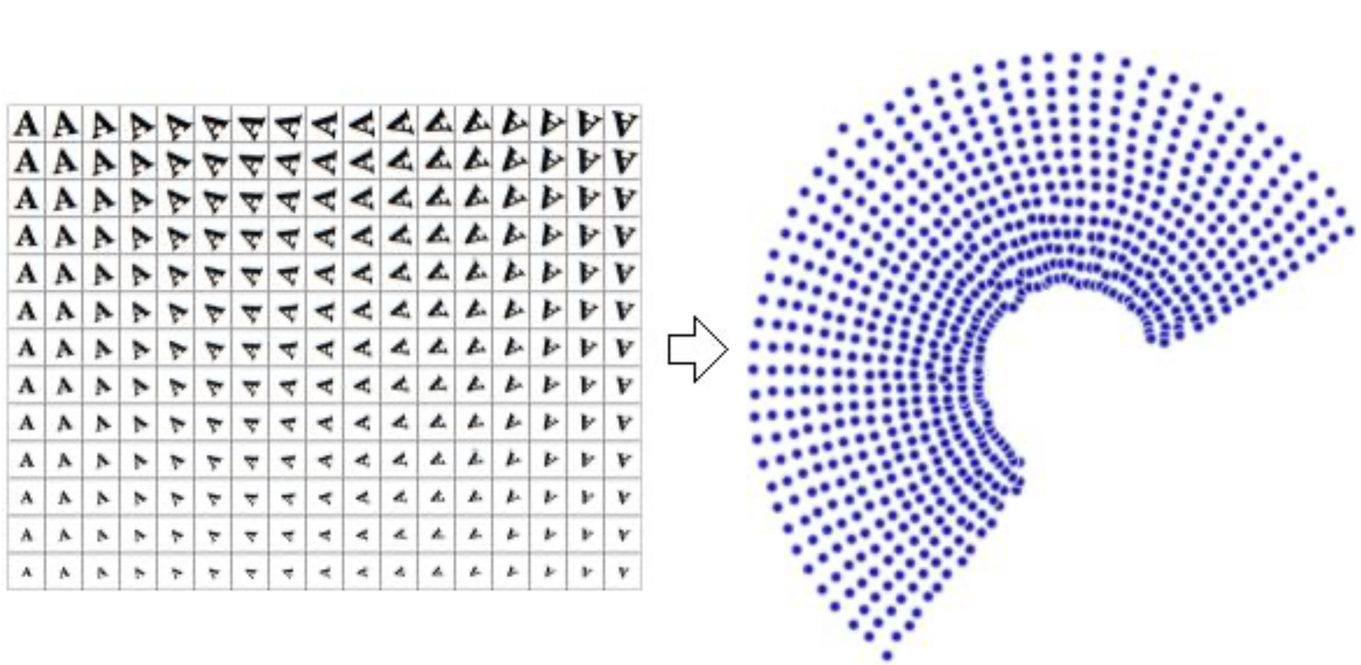


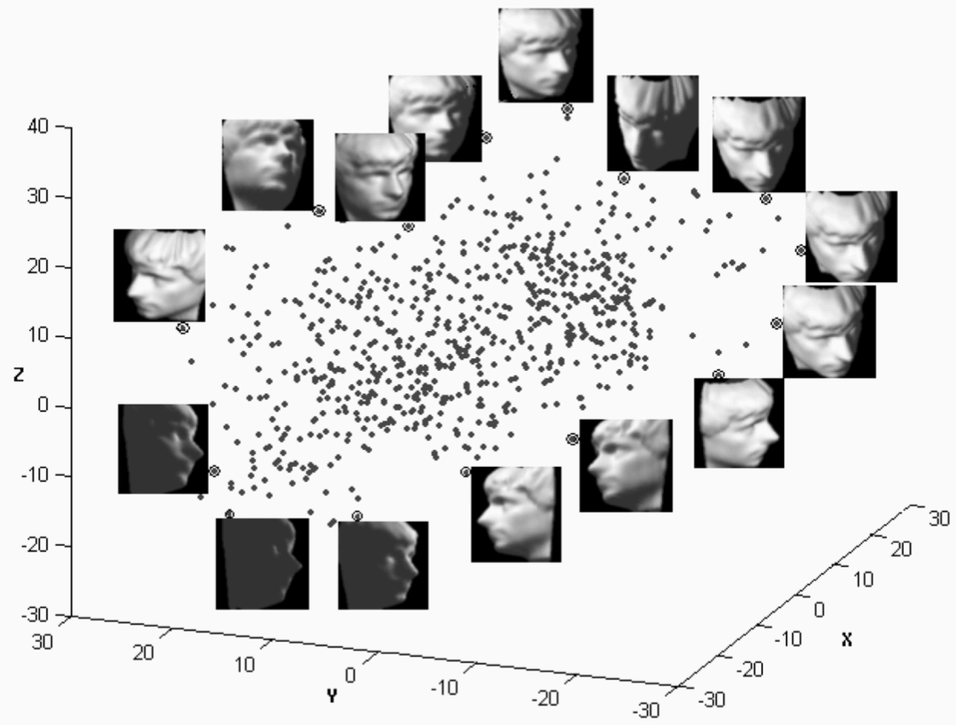


Manifold (informal): a latent space of a given dimension (degree of freedom)

1. MANIFOLD LEARNING

Examples of data manifold: *image dimension reduction*

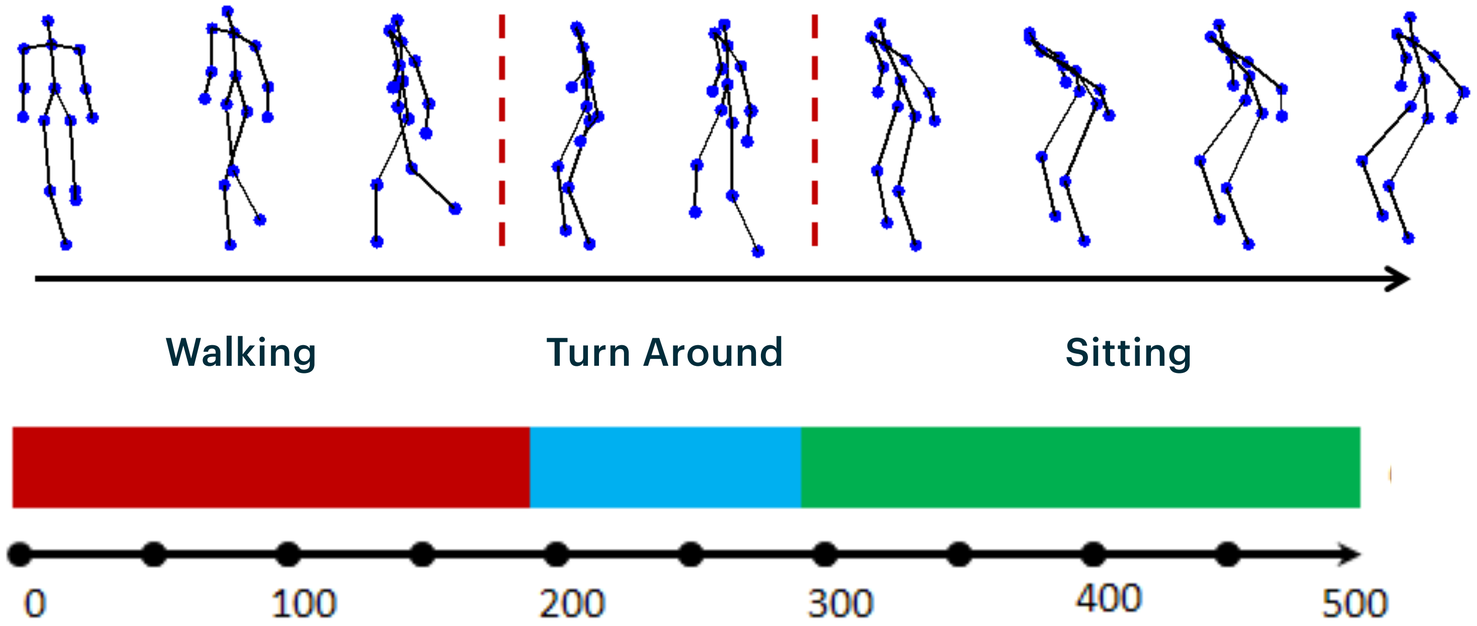


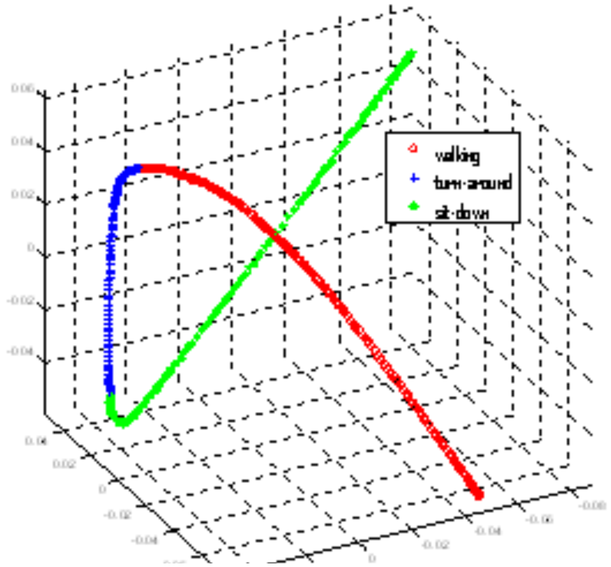


Tong Lin and Hongbin Zha, Riemannian Manifold Learning, IEEE TPAMI 2008

1. MANIFOLD LEARNING

Examples of data manifold: *segmenting a motion sequence*



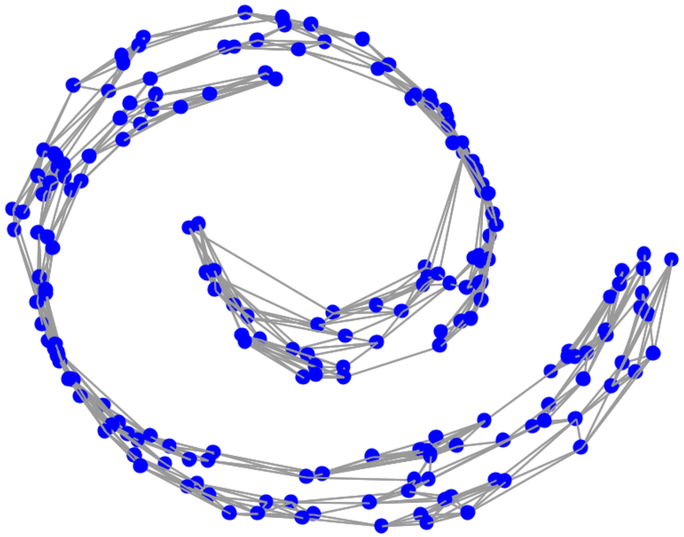


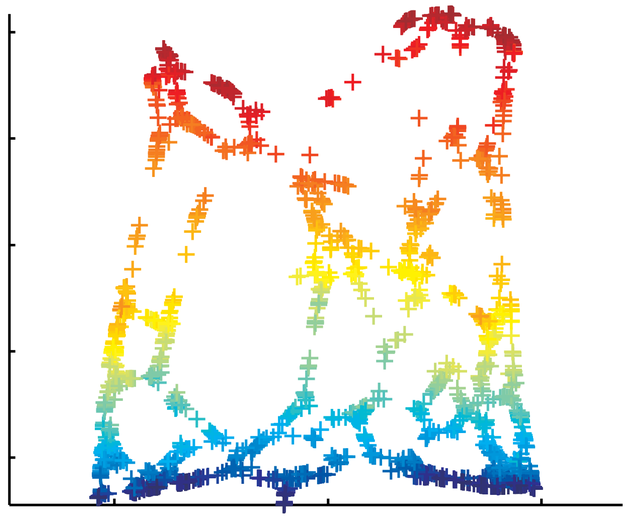
Skeleton joint features embedded in 3D

Dian Gong, Xuemei Zhao, Gérard Medioni, Robust Multiple Manifolds Structure Learning, ICML, 2012

1. MANIFOLD LEARNING

- **Graph-based Manifold Learning (e.g. Laplacian Eigenmaps)**
  - **Use a graph to encode neighborhood information**
  - **Find representation that preserves the local geometry of the data manifold**





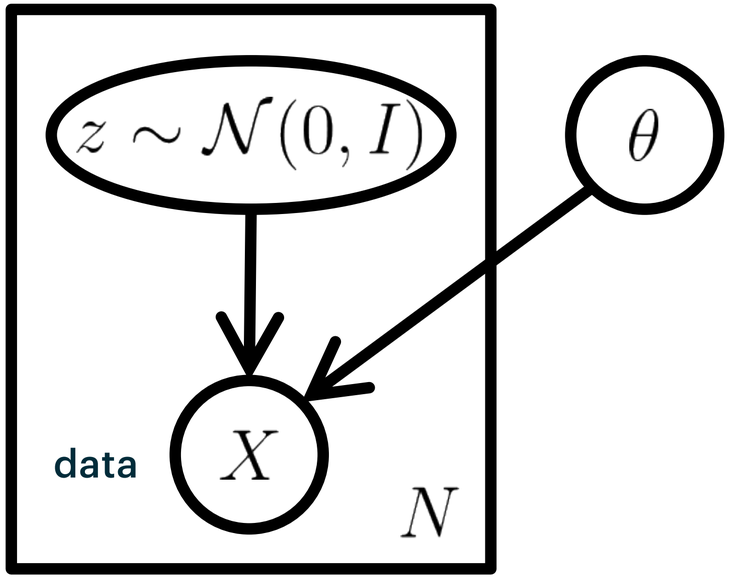
M. Belkin and P. Niyogi. Laplacian eigenmaps and spectral techniques for embedding and clustering. In *NIPS*, volume 14, pages 585--591, 2001.

2. GENERATIVE MODELS

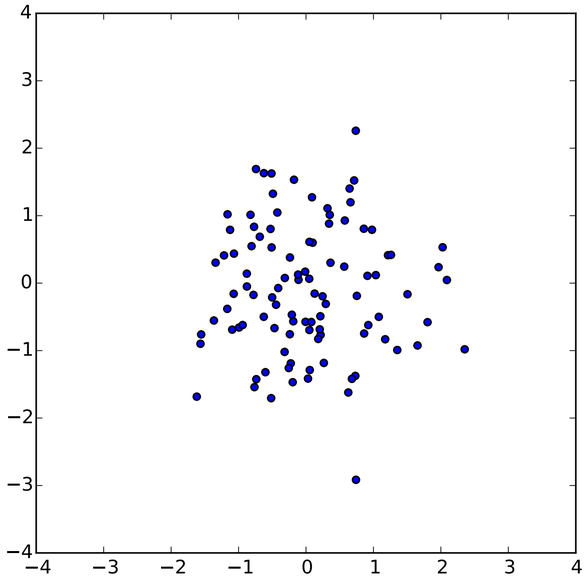
Variational Auto-Encoder (VAE)

A generative approach to non-linear dimension reduction

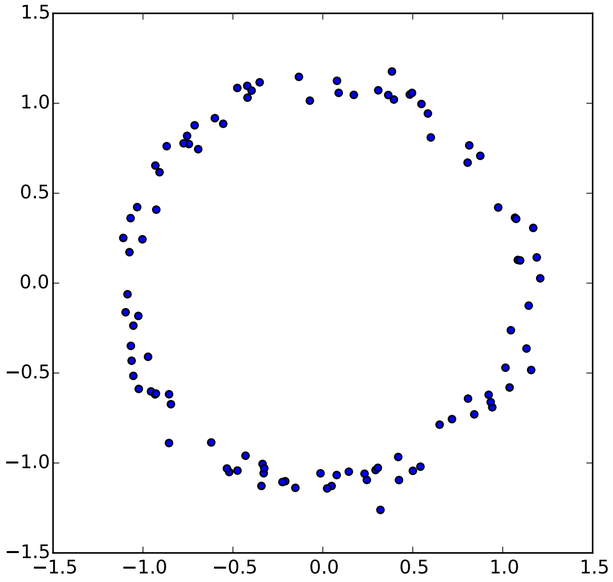
latent variable



$$P(X) = \int P(X|z;\theta)P(z)dz.$$



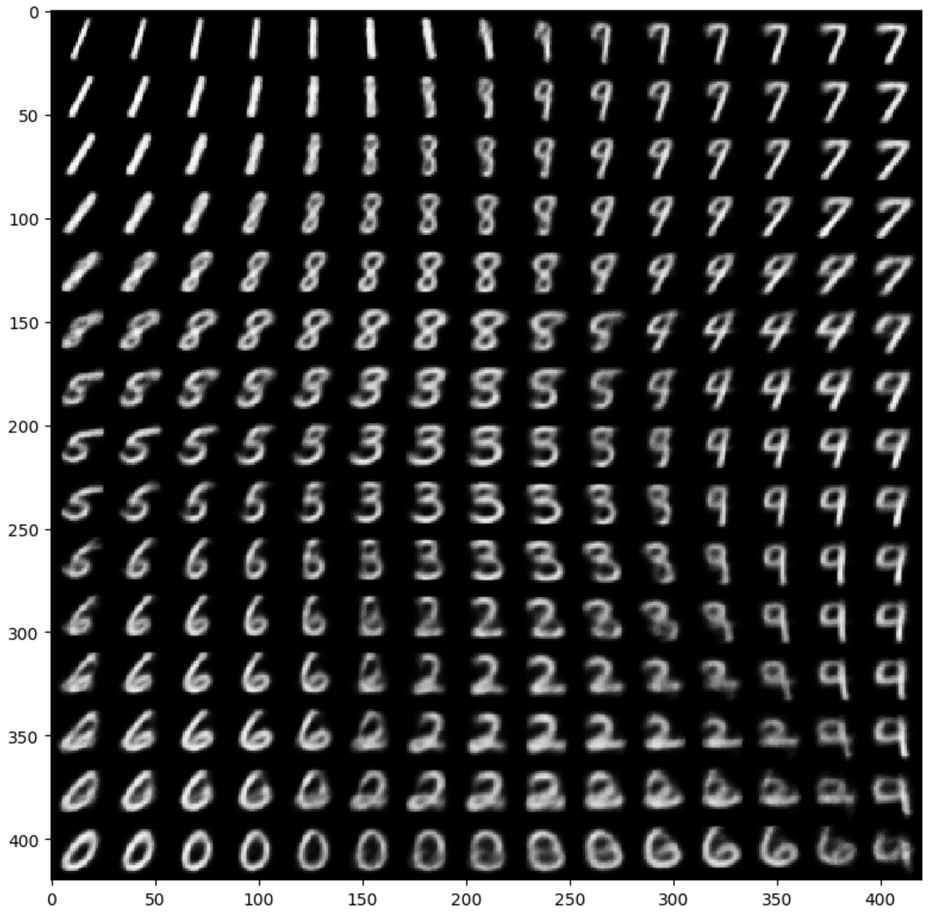
z



$x = z/10 + z/\|z\|$

2. GENERATIVE MODELS

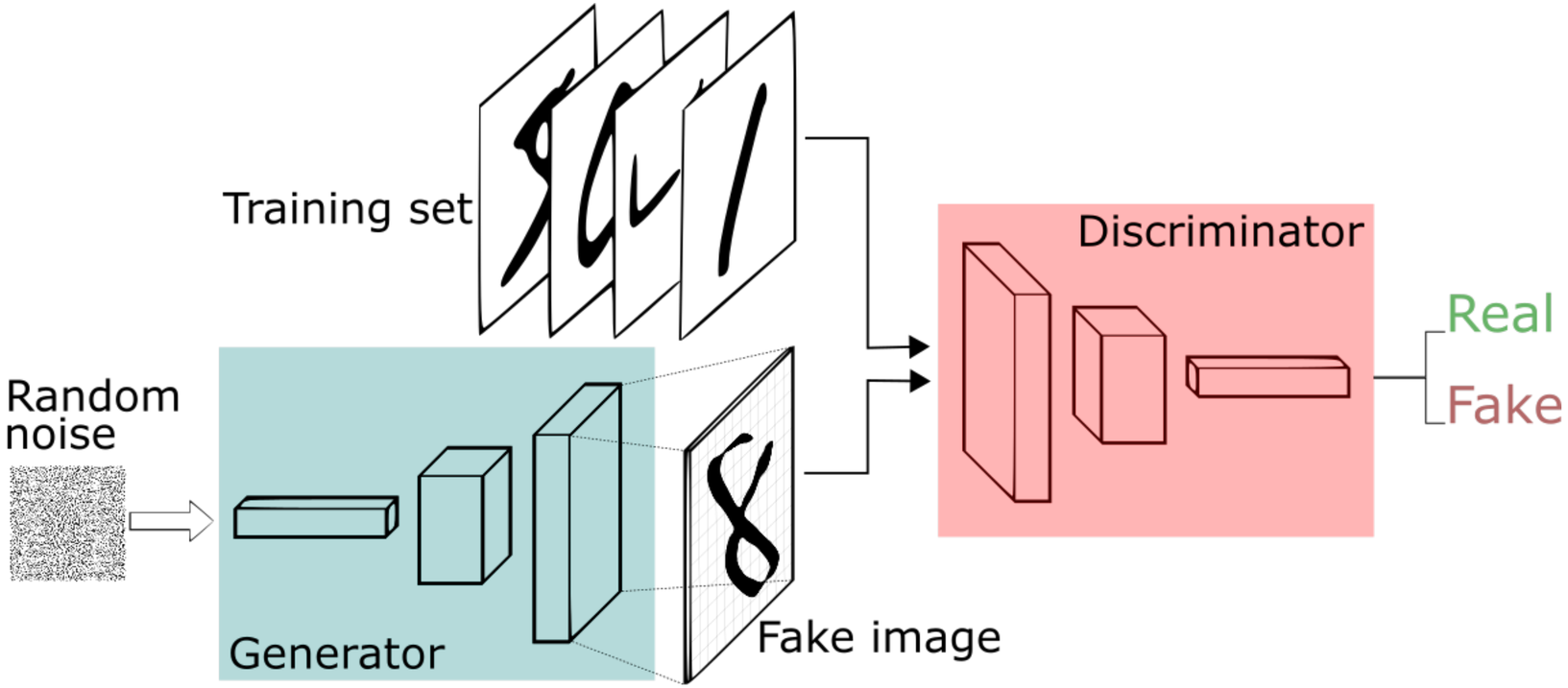
- Variational Auto-Encoder (VAE)
  - Has weak assumptions and small approximation error
  - Can be trained efficiently with backpropagation



MNIST Digits Generated by VAE visualized in 2D

2. GENERATIVE MODELS

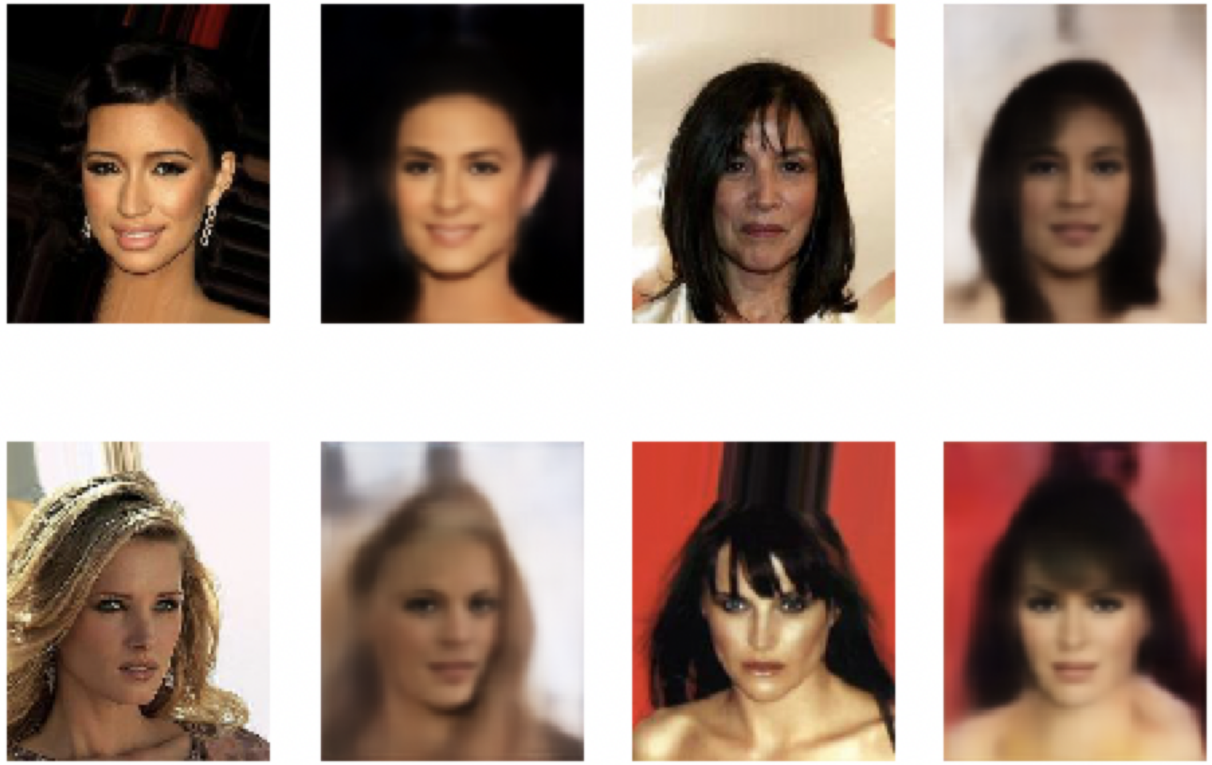
- **Generative models are difficult to approximate**
- **GAN: Generative modeling + Discriminative adversary**



2. GENERATIVE MODELS

GAN can generate more realistic images

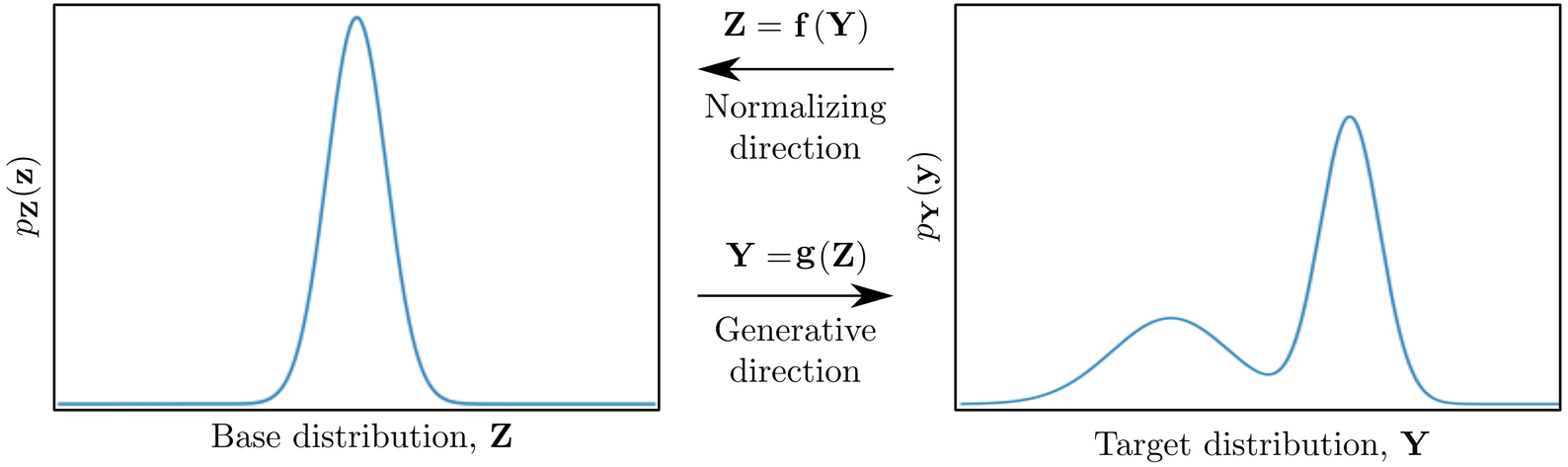
GAN (left) vs VAE (right)



GAN does not provide tractable estimation of density $P(x)$

2. GENERATIVE MODELS

- **Normalizing Flows： learning complex data distribution by transforming a simple density through an invertible map**
  - **allow both sampling and density evaluation.**
  - **Good for representing correlations in output structures**

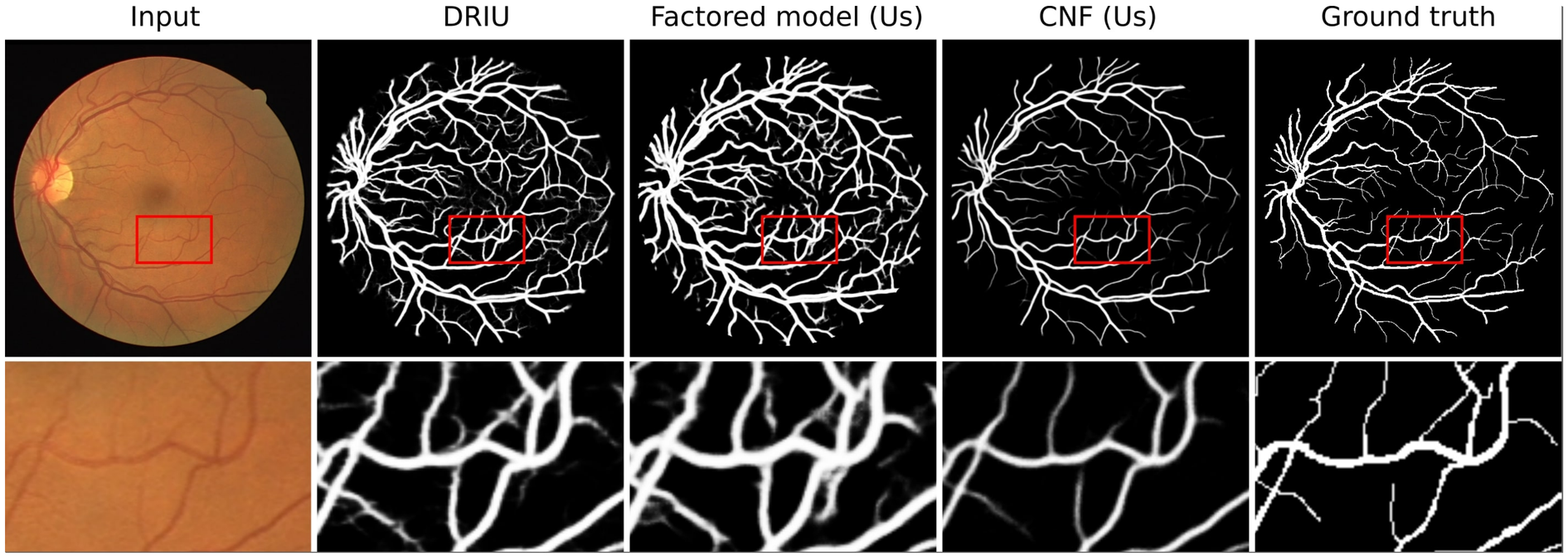


GAN (left) vs VAE (right)

Danilo Jimenez Rezende, Shakir Mohamed, Variational Inference with Normalizing Flows, 2015

2. GENERATIVE MODELS

Example of Conditional Normalizing Flows:

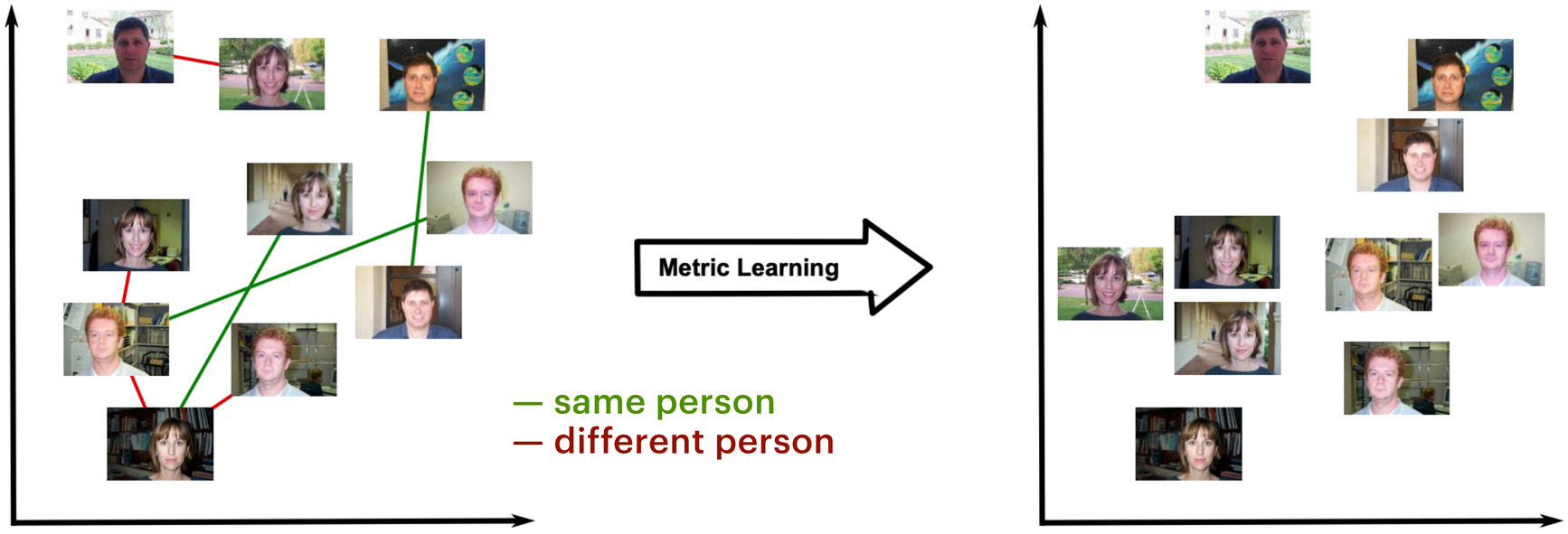


GAN (left) vs VAE (right)

Winkler, Christina, et al. "Learning likelihoods with conditional normalizing flows." arXiv preprint arXiv:1912.00042 (2019).

3. METRIC LEARNING

- **Learn the similarity metric between samples**
- **Useful for few-shot image classification, information retrieval etc**

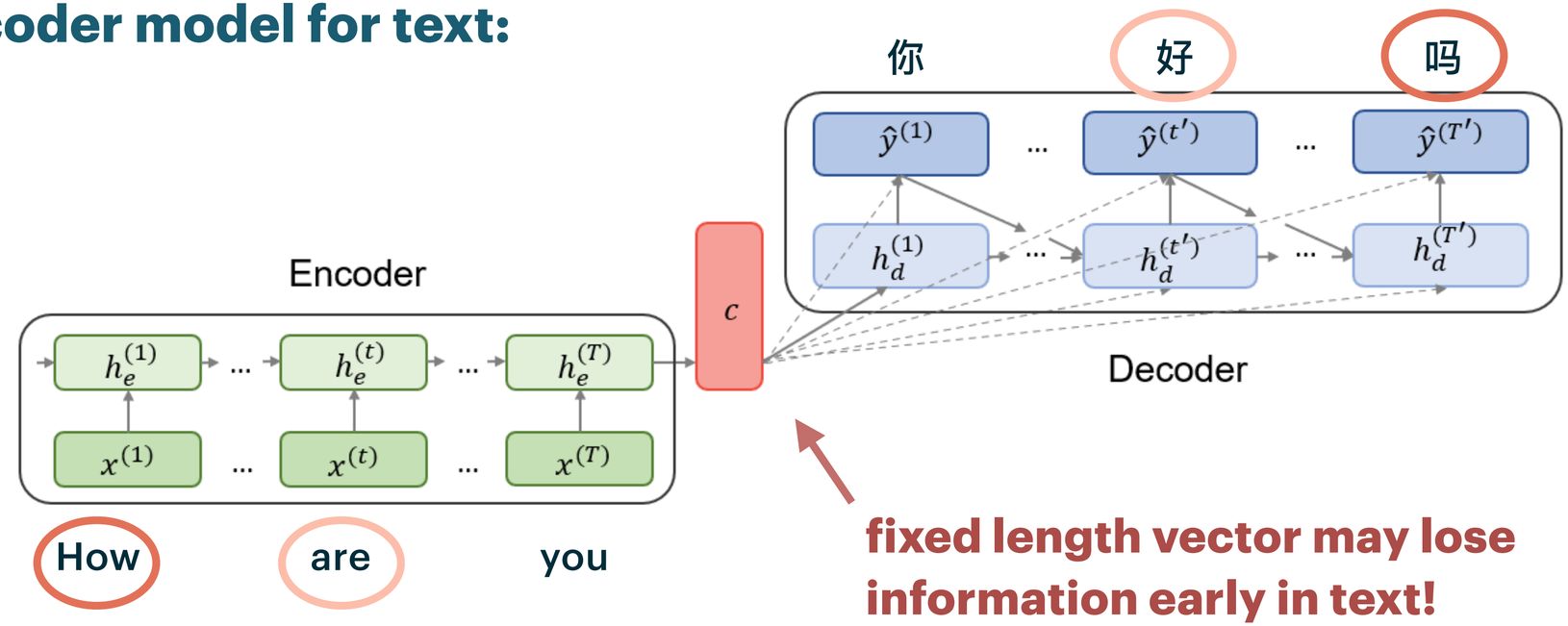


Pairwise constraints showing whether two pictures are the same person

Adapt the metric to the constraints

4. ATTENTION MECHANISM

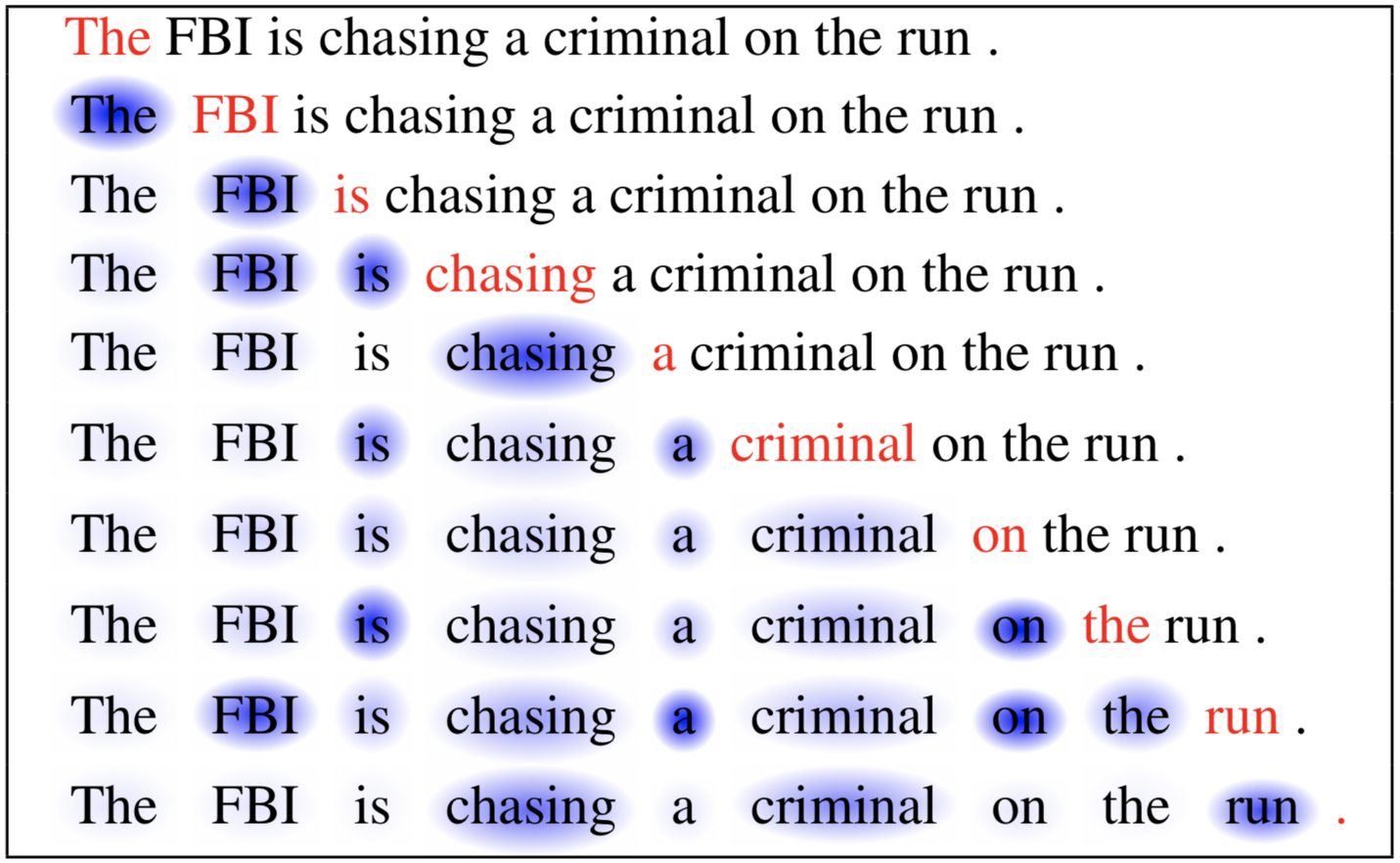
- **Sequence-to-Sequence Problem: map variable-length input sequences to variable-length output sequences (e.g. machine translation)**
- **Encoder-decoder model for text:**



fixed length vector may lose information early in text!

4. ATTENTION MECHANISM

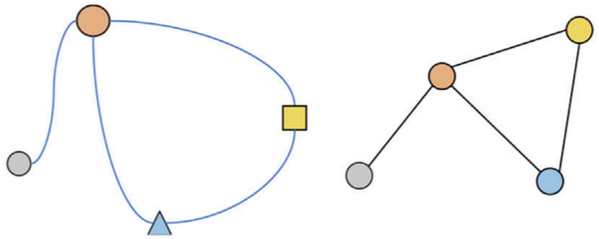
- **Attention enables decoder to "attend" to the whole input sentence.**
- **Self-Attention: A type of attention that relate to different positions of a sentence**



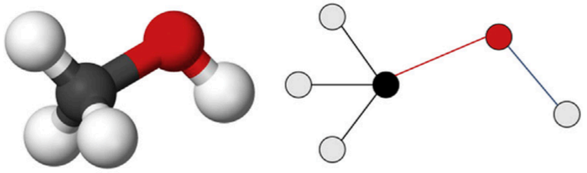
Vaswani, Ashish, et al. "Attention is all you need." *Advances in neural information processing systems* 30 (2017).

5. GRAPH REPRESENTATION LEARNING

- **Graph neural networks (GNNs): deep learning based methods that operate on graph domain**

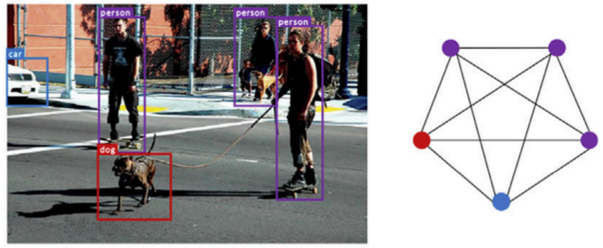


(a) Physics



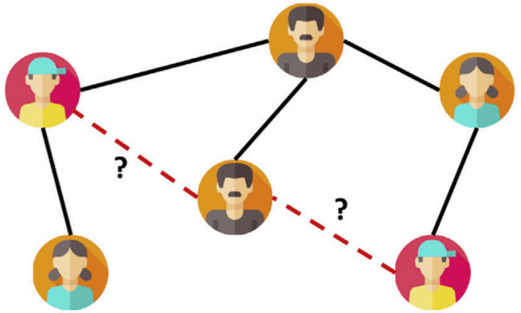
(b) Molecule

Useful for node classification, link prediction, clustering, etc



(c) Image

(d) Text



(e) Social Network

LECTURE OUTLINE

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DISCUSSION QUESTIONS

- **Discussion on *Representation Learning: A New Perspective***

NEXT CLASS

- **Reading Assignment：** ***Laplacian Eigenmaps for Dimensionality Reduction and Data Representation (Belkin & Niyogi, 2003)*** ***Section 5 is optional***

Recommended group size：3

Feel free to use other references

- **Homework （for non-presenters）**
  - **Reading summary**
  - **Pre-discussion questions**