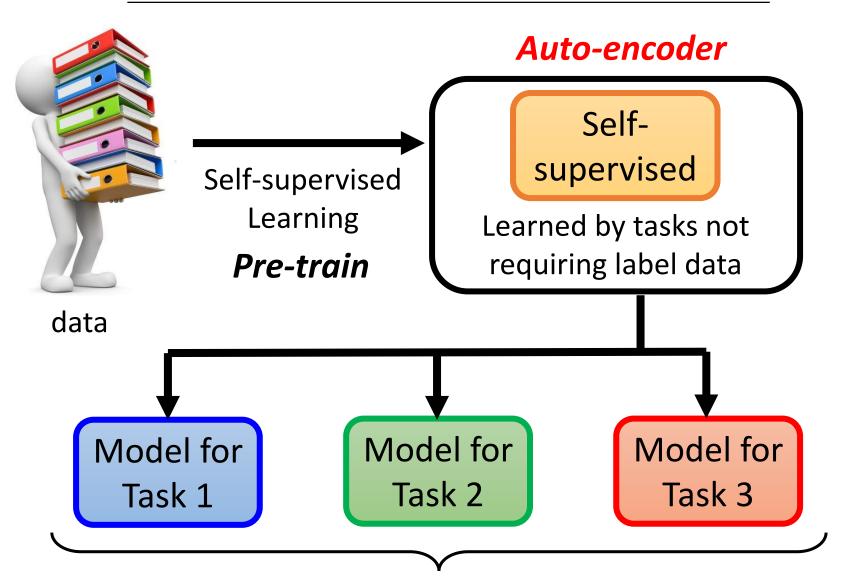
AUTO-ENCODER

Hung-yi Lee 李宏毅

Self-supervised Learning Framework



Downstream Tasks

Outline

Basic Idea of Auto-encoder

Feature Disentanglement

Discrete Latent Representation

More Applications

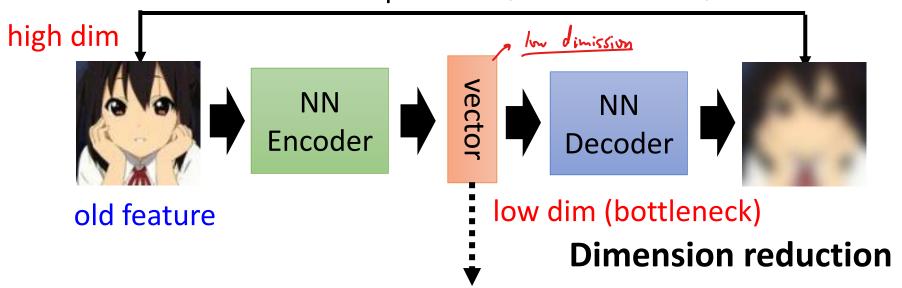
Auto-encoder

Unlabeled Images



Sounds familiar? We have seen the same idea in Cycle GAN. ©

As close as possible (reconstruction)



Embedding, Representation, Code New feature for downstream tasks

More Dimension Reduction

(not based on deep learning)



https://youtu.be/iwh5o_M4BNU

PCA



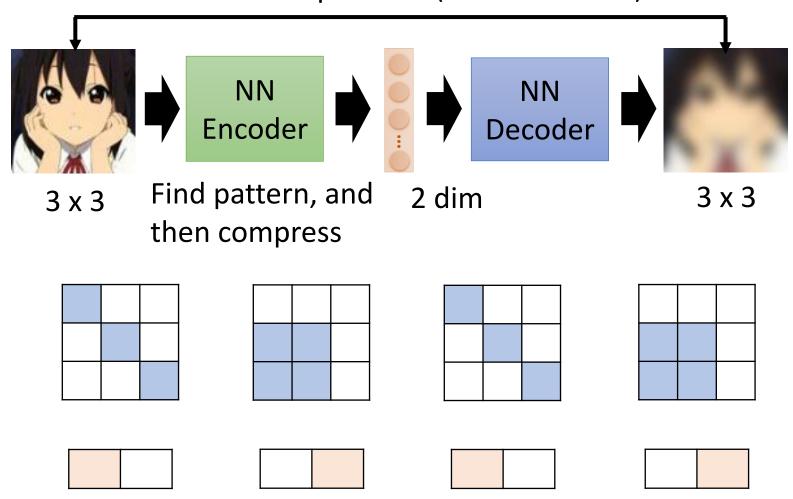
https://youtu.be/GBUEjkpoxXc

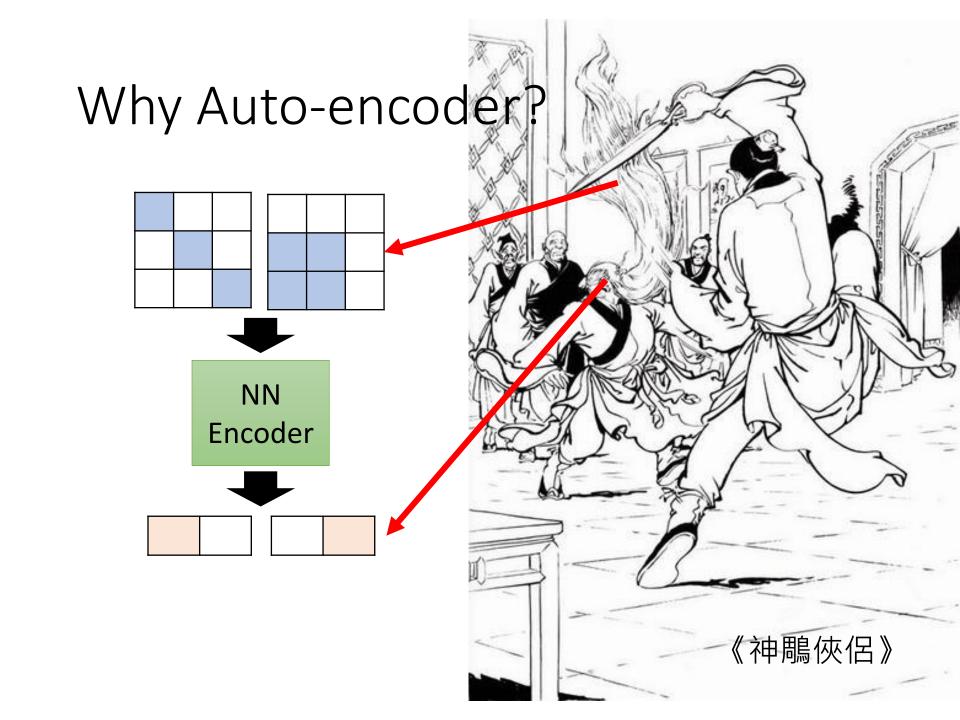
t-SNE

Why Auto-encoder? 《神鵰俠侶》

Why Auto-encoder?

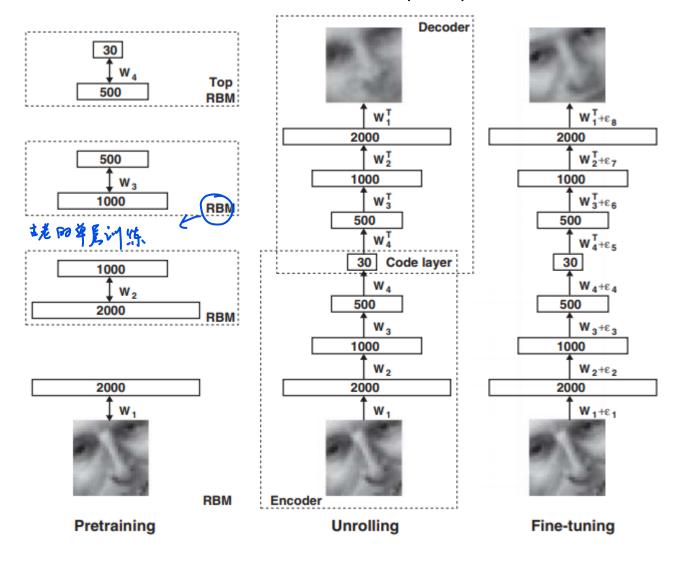
As close as possible (reconstruction)



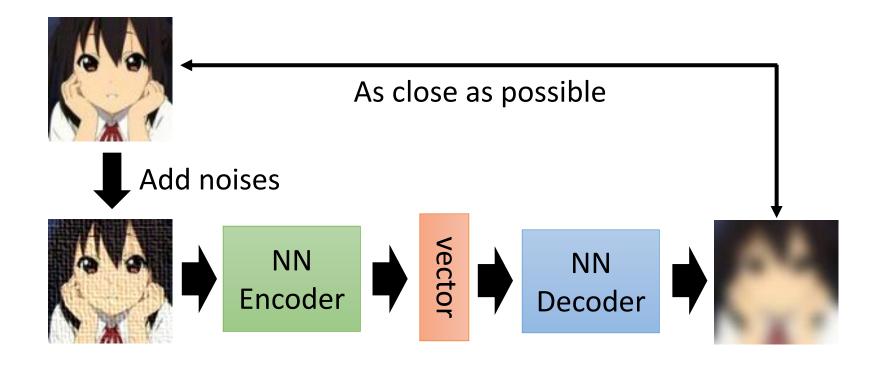


Auto-encoder is not a new idea

Hinton, Geoffrey E., and Ruslan R. Salakhutdinov. "Reducing the dimensionality of data with neural networks." *Science* 313.5786 (2006): 504-507



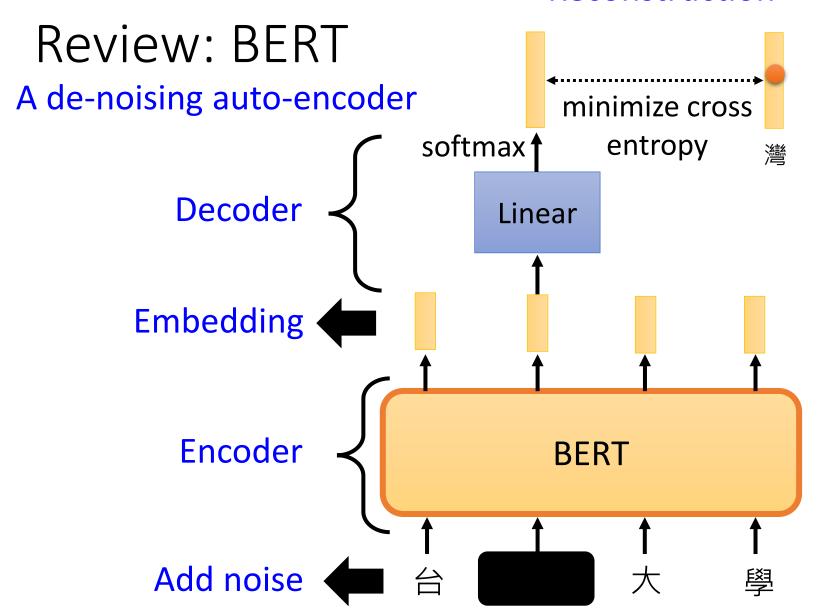
De-noising Auto-encoder



The idea sounds familiar? ©

Vincent, Pascal, et al. "Extracting and composing robust features with denoising autoencoders." *ICML*, 2008.

Reconstruction



Outline

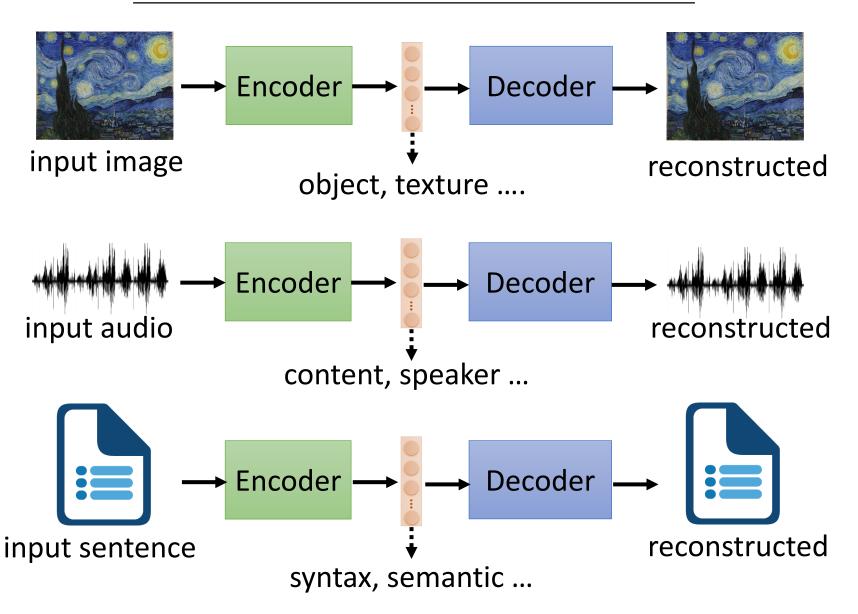
Basic Idea of Auto-encoder

Feature Disentanglement 🙏

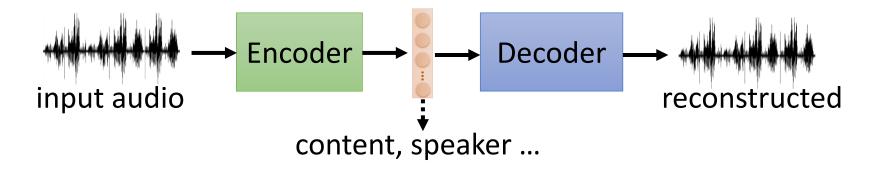
Discrete Latent Representation

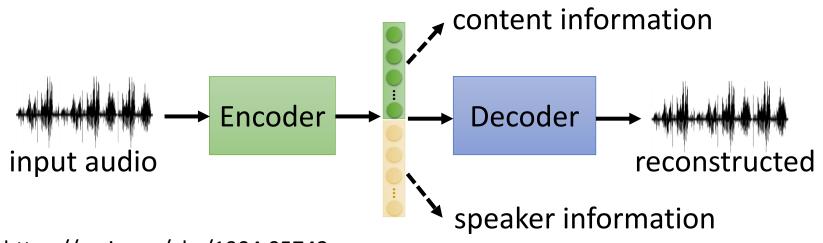
More Applications

Representation includes information of different aspects



Feature Disentangle



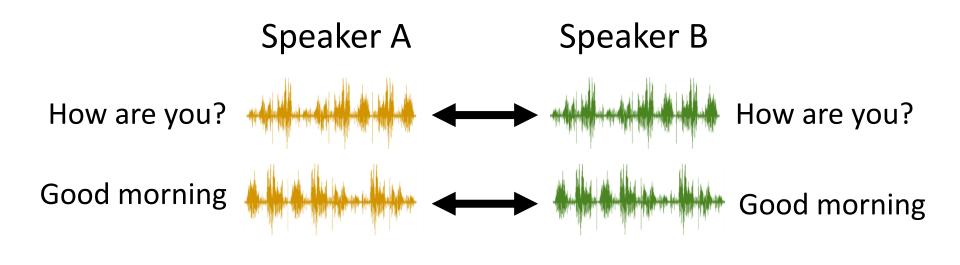


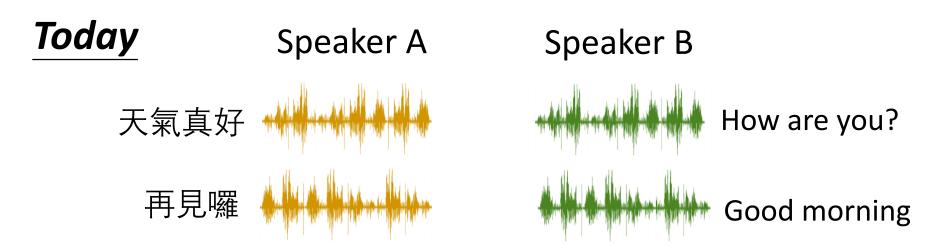
https://arxiv.org/abs/1904.05742 https://arxiv.org/abs/1804.02812 https://arxiv.org/abs/1905.05879



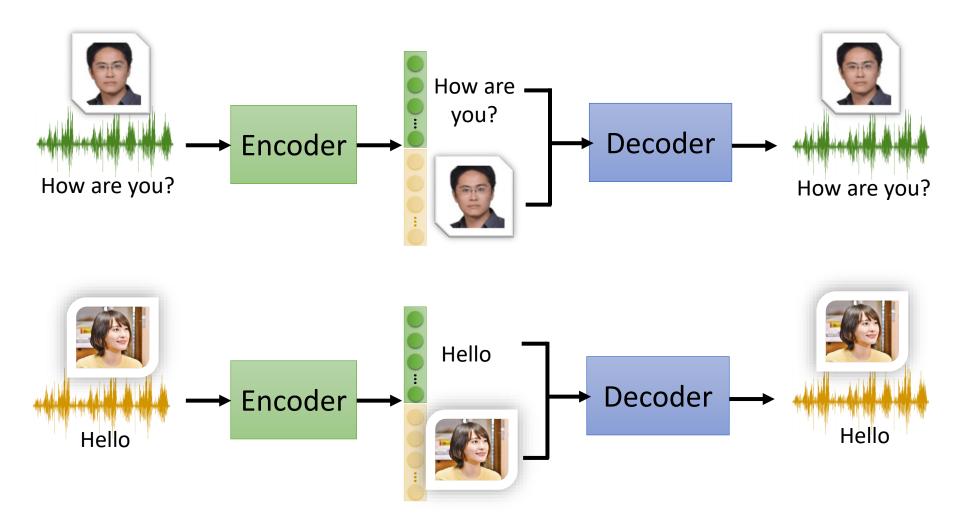
Application: Voice Conversion

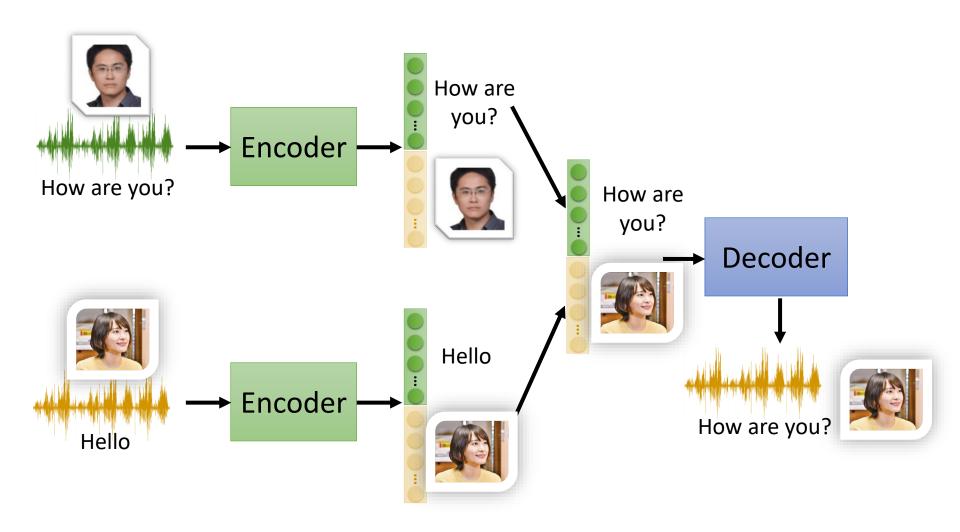
In the past

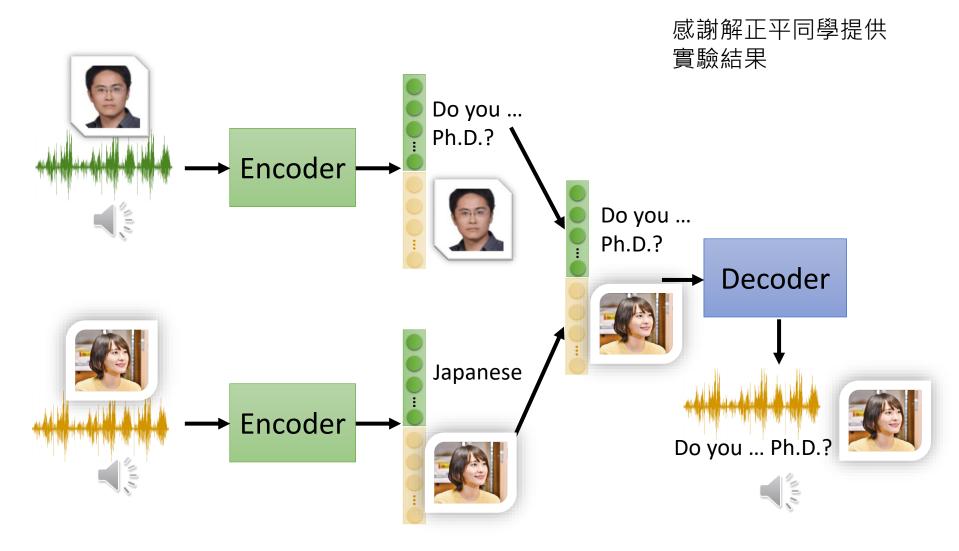


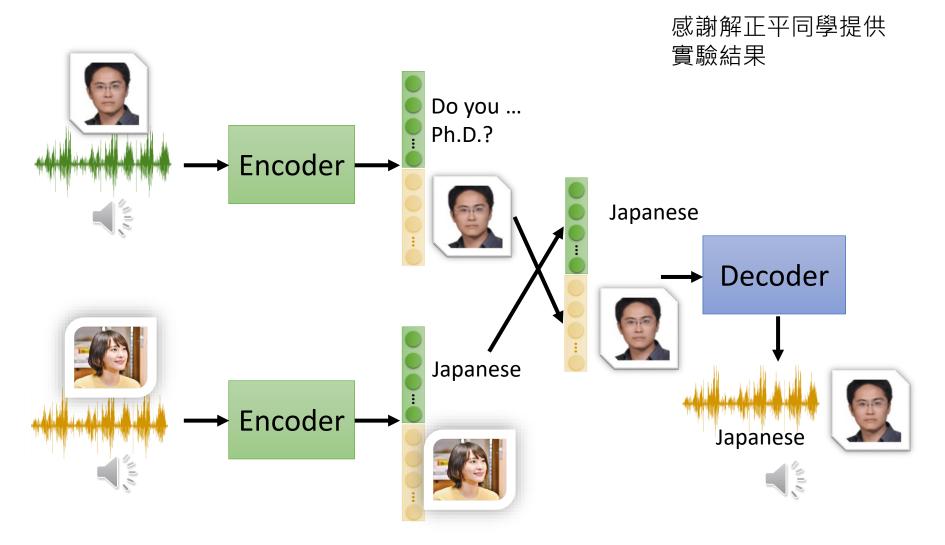


Speakers A and B are talking about completely different things.









Outline

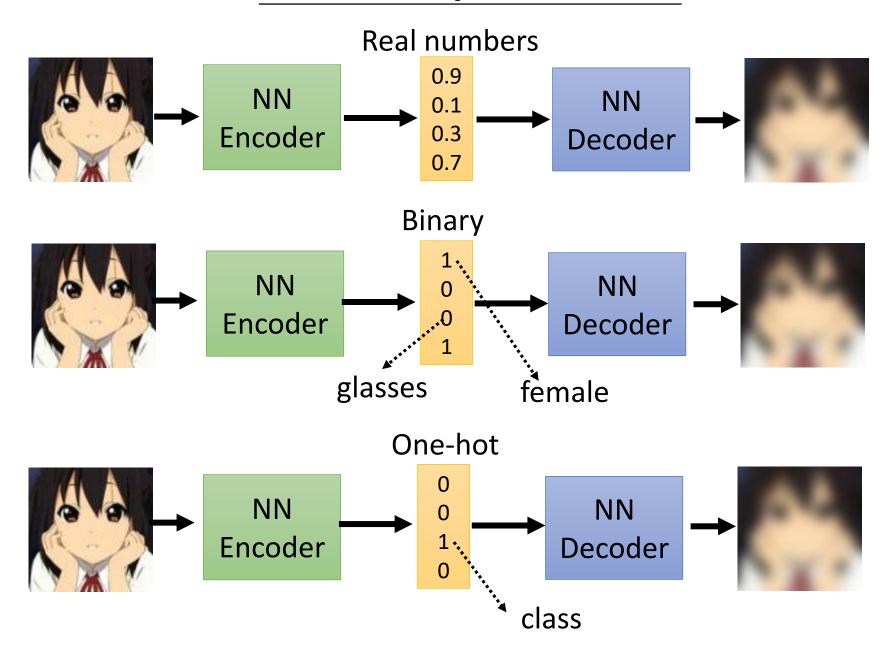
Basic Idea of Auto-encoder

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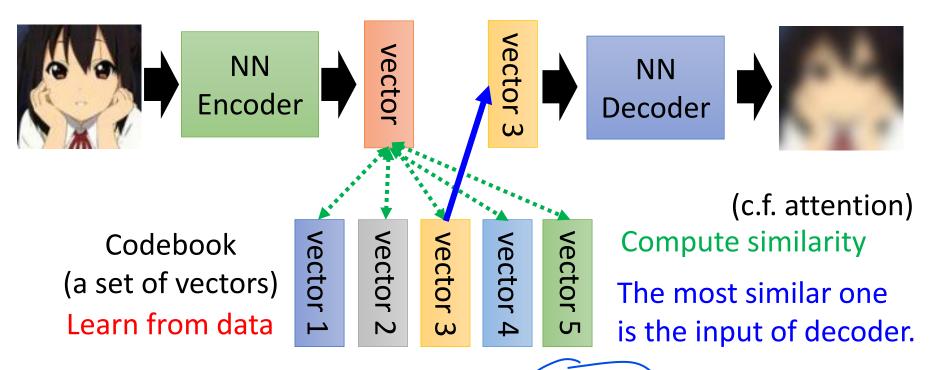
Discrete Representation



Discrete Representation

https://arxiv.org/abs/1711.00937

Vector Quantized Variational Auto-encoder (VQVAE)



For speech, the codebook represents phonetic information

https://arxiv.org/pdf/1901.08810.pdf

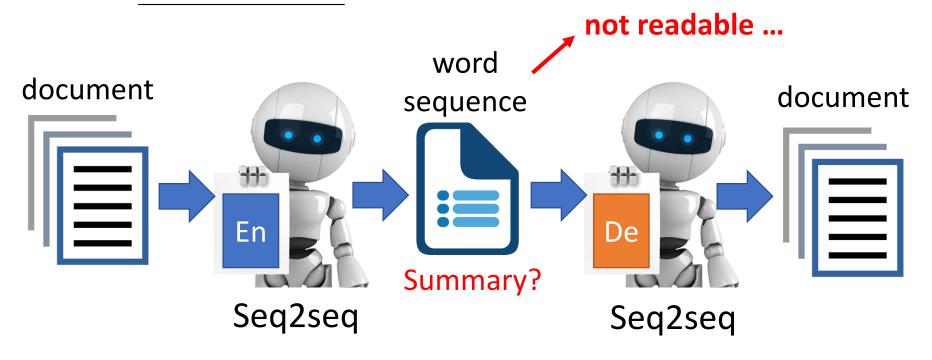
Text as Representation

Only need a lot of documents to train the model



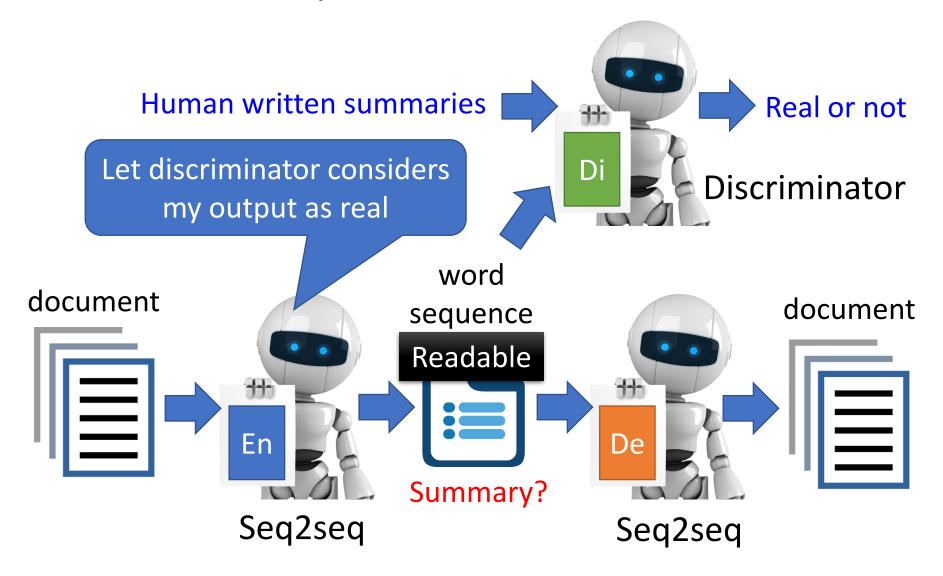
seq2seq2seq auto-encoder

Unsupervised Summarization



This is cycle GAN ©

Text as Representation



Text as Representation

• **Document**: 澳大利亞今天與13個國家簽署了反興奮劑雙邊協議, 旨在加強體育競賽之外的藥品檢查並共享研究成果

• Summary:

- Human: 澳大利亞與13國簽署反興奮劑協議
- Unsupervised: 澳大利亞加強體育競賽之外的藥品檢查
- **Document**:中華民國奧林匹克委員會今天接到一九九二年 冬季奧運會邀請函,由於主席張豐緒目前正在中南美洲進 行友好訪問,因此尚未決定是否派隊赴賽

Summary:

- Human:一九九二年冬季奧運會函邀我參加
- Unsupervised: 奧委會接獲冬季奧運會邀請函

Text as Representation

• **Document**:據此間媒體27日報道,印度尼西亞蘇門答臘島的兩個省近日來連降暴雨,洪水泛濫導致塌方,到26日為止至少已有60人喪生,100多人失蹤

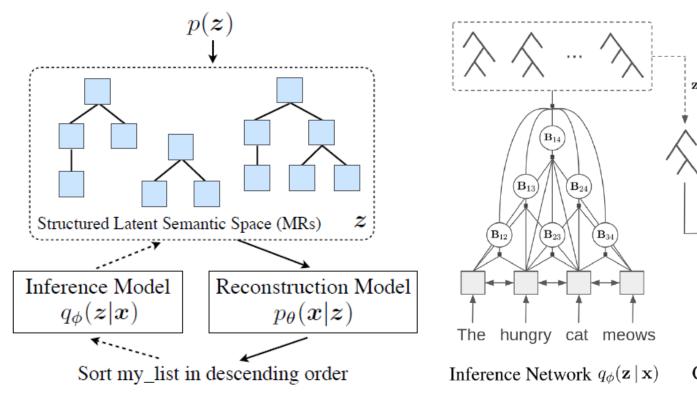
Summary:

- Human:印尼水災造成60人死亡
- Unsupervised:印尼門洪水泛濫導致塌雨
- **Document**:安徽省合肥市最近為領導幹部下基層做了新規 定:一律輕車簡從,不準搞迎來送往、不準搞層層陪同

Summary:

- Human:合肥規定領導幹部下基層活動從簡
- Unsupervised:合肥領導幹部下基層做搞迎來送往規定: 一律簡

Tree as Embedding



REDUCE The hungry cat Generative Model $p_{\theta}(\mathbf{x}, \mathbf{z})$

https://arxiv.org/abs/1806.07832

https://arxiv.org/abs/1904.03746

Outline

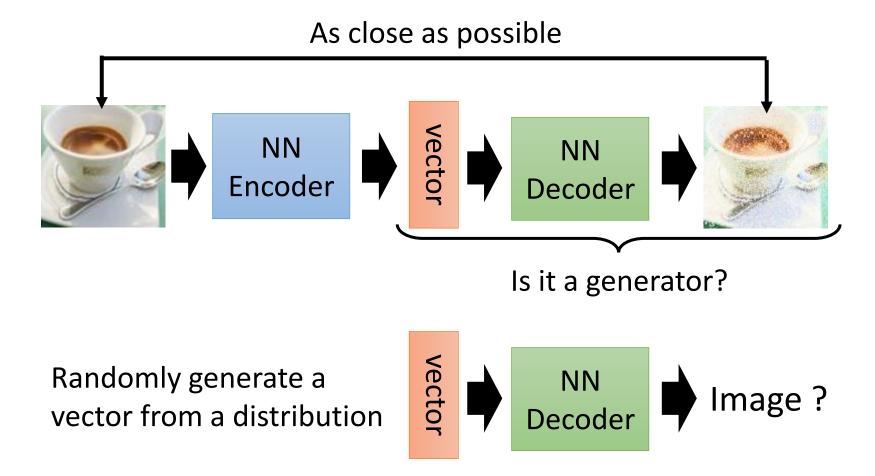
Basic Idea of Auto-encoder

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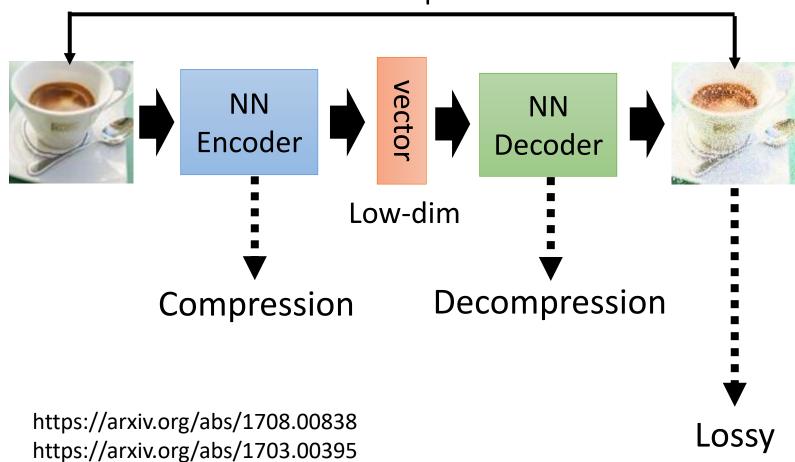
Generator



With some modification, we have variational auto-encoder (VAE).

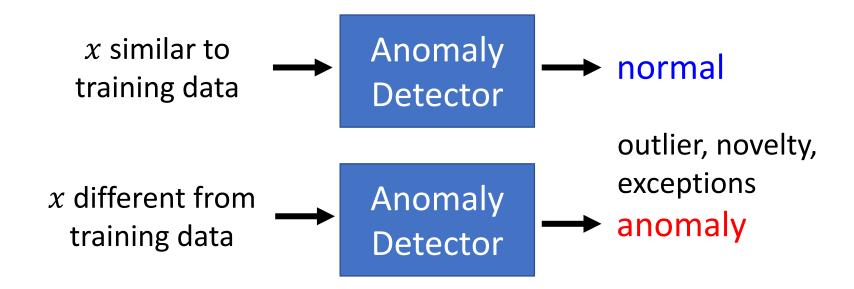
Compression

As close as possible



Anomaly Detection

- Given a set of training data $\{x^1, x^2, \dots, x^N\}$
- Detecting input x is similar to training data or not.



Anomaly Detection



Anomaly Detection We only have one class.

Binary Classification?
We only have one class.
Training auto-encoder

Fraud Detection

- Training data: credit card transactions, x: fraud or not
- Ref: https://www.kaggle.com/ntnu-testimon/paysim1/home
- Ref: https://www.kaggle.com/mlg-ulb/creditcardfraud/home

Network Intrusion Detection

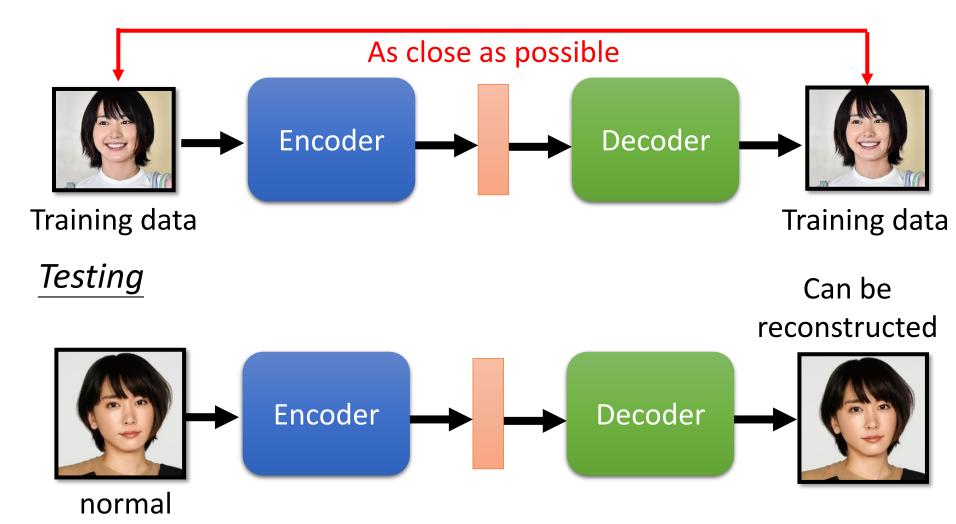
- Training data: connection, x: attack or not
- Ref: http://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html

Cancer Detection

- Training data: normal cells, x: cancer or not?
- Ref: https://www.kaggle.com/uciml/breast-cancer-wisconsin-data/home

Approach: Auto-encoder

<u>Training</u> Using **real human faces** to learn an <u>autoencoder</u>



Approach: Auto-encoder

Training Using **real human faces** to learn an **autoencoder** As close as possible Encoder Decoder Training data Training data Testing cannot be Large reconstruction loss → anomaly reconstructed Encoder Decoder

anomaly

More about Anomaly Detection

- Part 1: https://youtu.be/gDp2LXGnVLQ
- Part 2: https://youtu.be/cYrNjLxkoXs
- Part 3: https://youtu.be/ueDlm2FkCnw
- Part 4: https://youtu.be/XwkHOUPbc0Q
- Part 5: https://youtu.be/Fh1xFBktRLQ
- Part 6: https://youtu.be/LmFWzmn2rFY
- Part 7: https://youtu.be/6W8FqUGYyDo

Concluding Remarks

Basic Idea of Auto-encoder

Feature Disentanglement

Discrete Latent Representation

More Applications