Self-introduction Presentation

Looking for a research assistant job

Liu Peng 刘鹏

Hebei University of Technology (211)
Computer Science and Technology

August 1, 2023

1. Overview of myself in HEBUT
2. Learn AI knowledge
3. Bachelor thesis

Overview

- Hebei University of Technology (211)
- B.Eng. in Computer Science and Technology, GPA 3.8/4
- August 2019 -June 2023
- Outstanding graduates of HEBUT (10%)
- Changed major to computer science and technology (Only two members)
- Give up the opportunity to study in a graduate school without examination

Achievements

- Outstanding graduate of HEBUT, 2023
- Innovation training program for college students, AI +Fiance, Leader, Province-level, 2023
- Entrepreneurship training program for college students, Software, Leader, Province-level, 2022
- First-class scholarship of Hebei University of Technology x 2, 2020, 2021
- Merit student of Hebei University of Technology x 2, 2020, 2021

Vision and research interests

Vsion: Let real AI come true, and use AI to make social good.
Research Intersets: Foundation models, Generative AI and Multimodal (CV, NLP, etc.)

1. Overview of myself in HEBUT
2. Learn AI knowledge
3. Bachelor thesis

Have read

- *Deep Learning* (Ian Goodfellow, Yoshua Bengio and Aaron Courville)
- *Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow* (Aurelien Geron)
- 机器学习 (周志华)
- 统计学习方法 (李航)
- 百面机器学习 (诸葛越主编，葫芦娃著)
- Parts of *Deep Learning with Python* (François Chollet)
- Parts of *Deep Learning with PyTorch* (Eli Stevens, Luca Antiga, and Thomas Viehmann)
- Parts of *Generative Deep Learning* (David Foster)

Current Reading

- *Pattern Recognition and Machine Learning* (Christopher Bishop)
- *Natural Language Processing: A Machine Learning Perspective* (Yue Zhang and Zhiyang Teng)

Books


第2版
Scikit-Learn, Keras和TensorFlow 的机器学习实用指南（影印版）
Aurélien Géron 著
东南大学出版社
O'REILLY
第2版
Scikit-Learn, Keras和TensorFlow 的机器学习实用指南（影印版）
Aurélien Géron 著
东南大学出版社
DEEP LEARNING
Ian Goodfellow, Yoshua Bengio, and Aaron Courville
机器学习
周志华 著
清华大学出版社
机器学习公式详解
谢文睿 秦州 编著
人民邮电出版社
统计学习方法（第2版）
李航 著
清华大学出版社
百面机器学习
算法工程师带你去面试
人民邮电出版社
生成式深度学习（影印版）
David Foster 著
东南大学出版社
PATTERN RECOGNITION AND MACHINE LEARNING
CHRISTOPHER M. BISHOP
6445
ZHANG • TENG
NATURAL LANGUAGE PROCESSING

Online courses

- *CS 231N Deep Learning for Computer Vision* (Stanford) (Have watched 2017 Version, to continue several new lectures of 2023 Version)
- *CS 224N Natural Language Processing with Deep Learning* (Stanford) (2023 Version 8/19)
- *6.S191 Introduction to Deep Learning* (MIT) (2023 Version 7/10)
- *Natural Language Processing - A Machine Learning Perspective*(Westlake University) (2023 Version 7/16)

Geneartive Models Research and Chinese Painting Generation
生成模型研究与中国画生成

1. Geneartive Models Research
2. Chinese Painting Generation

Generative Models Research - Background

- ChatGPT、AIGC
- Richard Feynman–What I cannot create, I do not understand
- Litte systematical materials about generative models

Generative Models Research - What I do

- Classify main generative models.
- A lot of formulation derivations for generative models.
- Necessary knowledge in appendix, math, machine learning, physics, etc.
- Many materials, papers, blogs, courses, etc.

Generative Models Research - Classify main generative models

Classification Method + Main Generative Models = My Classfication for generative models

- Classification Method (NIPS 2016 Tutorial, Ian Goodfellow)
- Main Generative Models (CVPR 2022 Diffusion Tutorial)

Generative Models Research - Classify main generative models

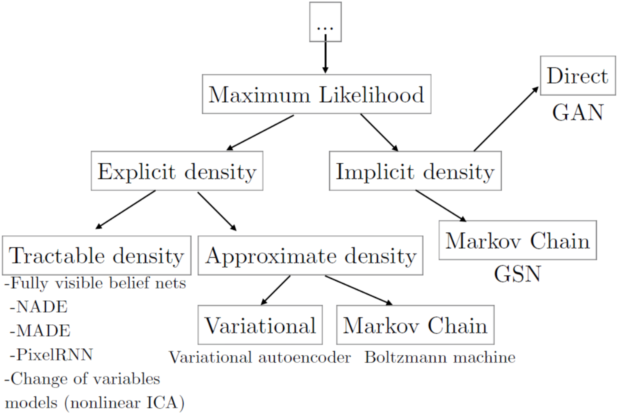

Fig. 2: NIPS 2016 Tutorial: Generative Adversarial Networks, Ian Goodfellow

Generative Models Research - Classify main generative models

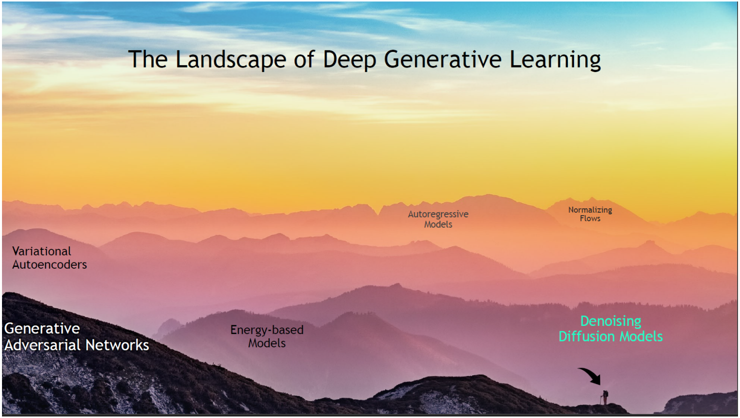

Fig. 3: CVPR 2022 Tutorial: Denoising Diffusion-based Generative Modeling: Foundations and Applications, Karsten Kreis, Ruiqi Gao, Arash Vahdat

Generative Models Research - Classify main generative models

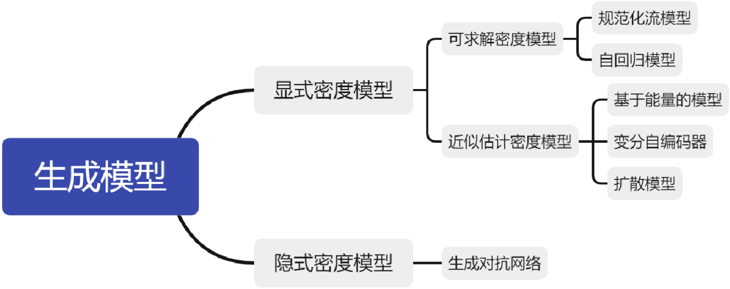

Fig. 4: Generative models classification in my bachelor thesis

Generative Models Research - Formulation derivations example

证据下界可以扩展为：

$$\log p(\boldsymbol{x}) = \log \int p(\boldsymbol{x}, \boldsymbol{z}_{1:T}) d\, z \qquad \text{（根据式A.49）} \tag{2.44}$$

$$= \log \int p(\boldsymbol{x}, \boldsymbol{z}_{1:T}) \frac{q_\phi(\boldsymbol{z}_{1:T} \mid \boldsymbol{x})}{q_\phi(\boldsymbol{z}_{1:T} \mid \boldsymbol{x})} d\, z \tag{2.45}$$

$$= \log \int \frac{p(\boldsymbol{x}, \boldsymbol{z}_{1:T}) q_\phi(\boldsymbol{z}_{1:T} \mid \boldsymbol{x})}{q_\phi(\boldsymbol{z}_{1:T} \mid \boldsymbol{x})} d\, z \tag{2.46}$$

$$= \log \int q_\phi(\boldsymbol{z}_{1:T} \mid \boldsymbol{x}) \frac{p(\boldsymbol{x}, \boldsymbol{z}_{1:T})}{q_\phi(\boldsymbol{z}_{1:T} \mid \boldsymbol{x})} d\, z \tag{2.47}$$

$$= \log \mathbb{E}_{q_\phi(\boldsymbol{z}_{1:T} \mid \boldsymbol{x})} \left[\frac{p(\boldsymbol{x}, \boldsymbol{z}_{1:T})}{q_\phi(\boldsymbol{z}_{1:T} \mid \boldsymbol{x})} \right] \qquad \text{（根据期望定义式A.21）} \tag{2.48}$$

15

Fig. 5: VAE ELBO formulation derivations

Generative Models Research - Appendix knowledge example

对式A.37关于参数$\boldsymbol{\theta}$ 求偏导，即：

$$
\begin{aligned}
\frac{\partial E(\boldsymbol{x};\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} &= \frac{\partial \log Z(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} - \frac{1}{K}\sum_{i=1}^{K}\frac{\partial \log f(x_i;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} && \text{(A.38)}\\
&= \frac{\partial \log Z(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} - \mathbb{E}_{p_{data}}\left[\frac{\partial \log f(x;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right] && \text{(A.39)}\\
&= \frac{1}{Z(\boldsymbol{\theta})}\frac{\partial Z(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} - \mathbb{E}_{p_{data}}\left[\frac{\partial \log f(x;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right] && \text{(A.40)}\\
&= \frac{1}{Z(\boldsymbol{\theta})}\frac{\partial \int f(x;\boldsymbol{\theta})\,dx}{\partial \boldsymbol{\theta}} - \mathbb{E}_{p_{data}}\left[\frac{\partial \log f(x;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right] && \text{(A.41)}\\
&= \frac{1}{Z(\boldsymbol{\theta})}\int \frac{\partial f(x;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\,dx - \mathbb{E}_{p_{data}}\left[\frac{\partial \log f(x;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right] && \text{(A.42)}\\
&= \frac{1}{Z(\boldsymbol{\theta})}\int f(x;\boldsymbol{\theta})\frac{\partial \log f(x;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\,dx - \mathbb{E}_{p_{data}}\left[\frac{\partial \log f(x;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right] && \text{(A.43)}\\
&= \int p(x;\boldsymbol{\theta})\frac{\partial \log f(x;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\,dx - \mathbb{E}_{p_{data}}\left[\frac{\partial \log f(x;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right] && \text{(A.44)}\\
&= \mathbb{E}_{p(x;\theta)}\left[\frac{\partial \log f(x;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right] - \mathbb{E}_{p_{data}}\left[\frac{\partial \log f(x;\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right] && \text{(A.45)}
\end{aligned}
$$

Fig. 6: Appendix knowledge about contrastive divergence

Chinese Painting Generation - What I do

- Train diffusion model to generate Chinese paintings

Chinese Painting Generation - Diffusion model

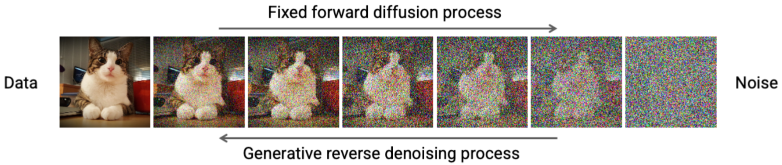

Fig. 7: Diffusion model

Chinese Painting Generation - Dataset

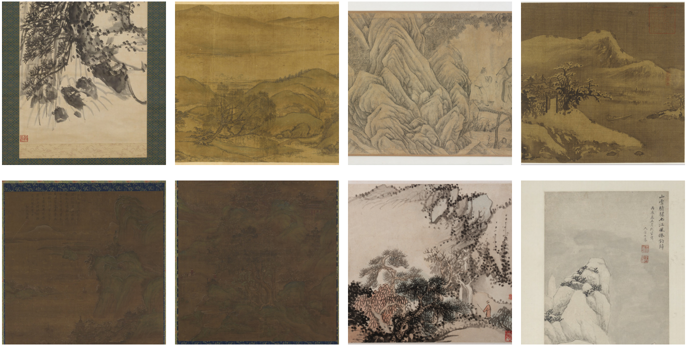

Fig. 8: Dataset-complete

Chinese Painting Generation - Dataset

Fig. 9: Dataset-light

Chinese Painting Generation - Dataset

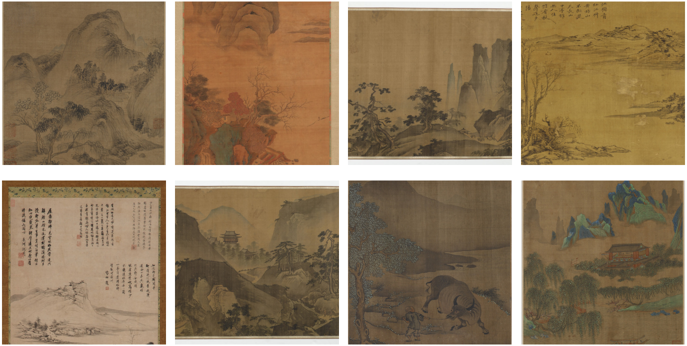

Fig. 10: Dataset-Dark

Chinese Painting Generation - Experiment 1 Dataset-complete

- Dataset-complete
- A100- 80GB GPU
- Batch size of 128
- Train 15 hours

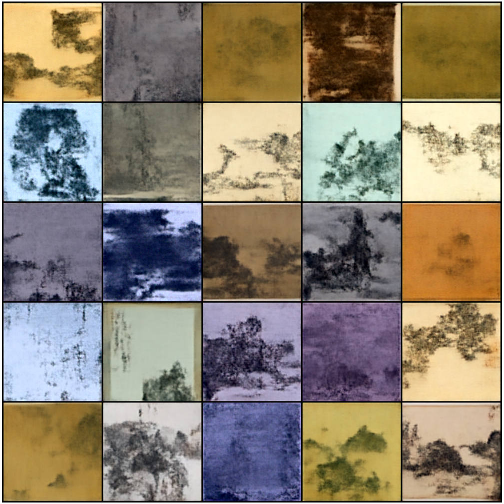

Fig. 11: Experiment 1 Samples

Chinese Painting Generation - Experiment 2 Dataset-light large batch

- Dataset-light
- A100- 40GB GPU
- Batch size of 64
- Train 48 hours

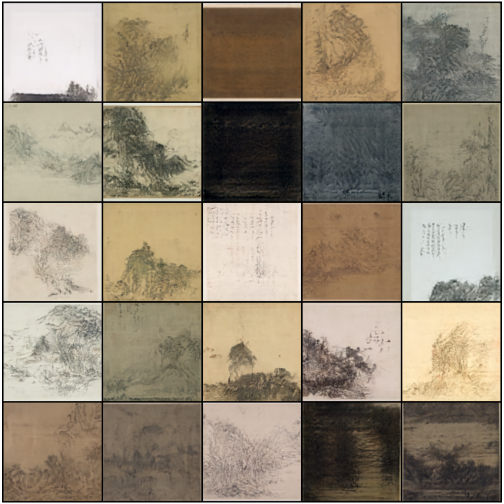

Fig. 12: Experiment 2 Samples

Chinese Painting Generation - Experiment 3 Dataset-light small batch

- Dataset-light
- 3090- 24GB GPU
- Batch size of 32
- Train 48 hours

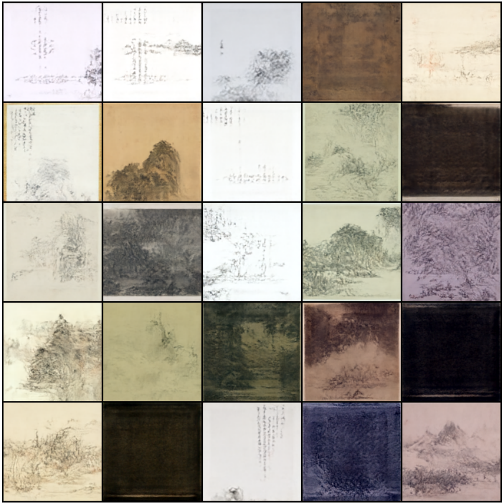

Fig. 13: Experiment 3 Samples

Chinese Painting Generation - Experiment 4 Dataset-dark

- Dataset-dark
- A100- 40GB GPU
- Batch size of 64
- Train 36 hours

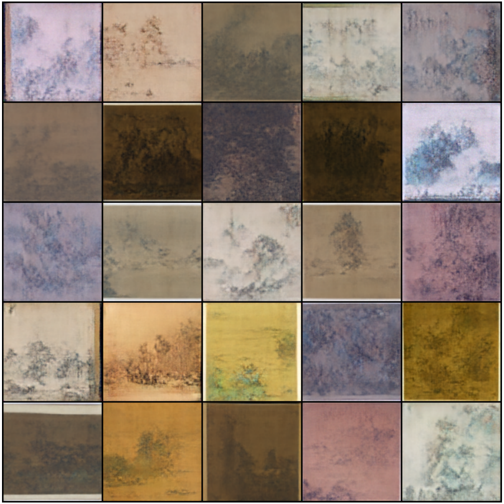

Fig. 14: Experiment 4 Samples

Bachelor Thesis - Conclusion and Prospect

1. Conclusion
   - Classification for Generative models
   - Train different model for different styles of Chinese paintings
   - Larger batch size, higher quality
2. Prospect
   - Expect a book about generative models
   - Expect to apply generative models to other traditional culture

Let AI benefits mankind