Tsai, Wan-Ling

蔡宛玲

25歲

國立陽明交通大學 應用數學系

數學建模與科學計算碩士班

About me

學歷

Sep 2022 – July 2024
GPA: 4.20/4.30

國立陽明交通大學
應用數學系 數學建模與科學計算碩士班

Sep 2018 – June 2022
GPA: 3.21/4.30

國立陽明交通大學
應用數學系

工作經驗

> 聯發科技股份有限公司機器學習 實習生

> 應數系必修課 助教(微積分、線性代數、計算數學)

> 國高中家庭教師、高中補習班數學教師、理科輔導老師

課外表現

會長、副會長 – TWSIAM NYCU

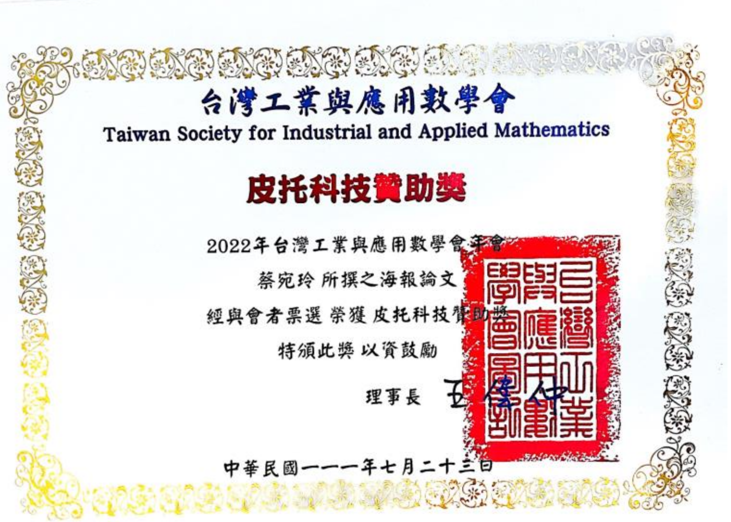
隊長 – 陽明交大應數系女子排球隊

副召 – 三系聯合迎新宿營

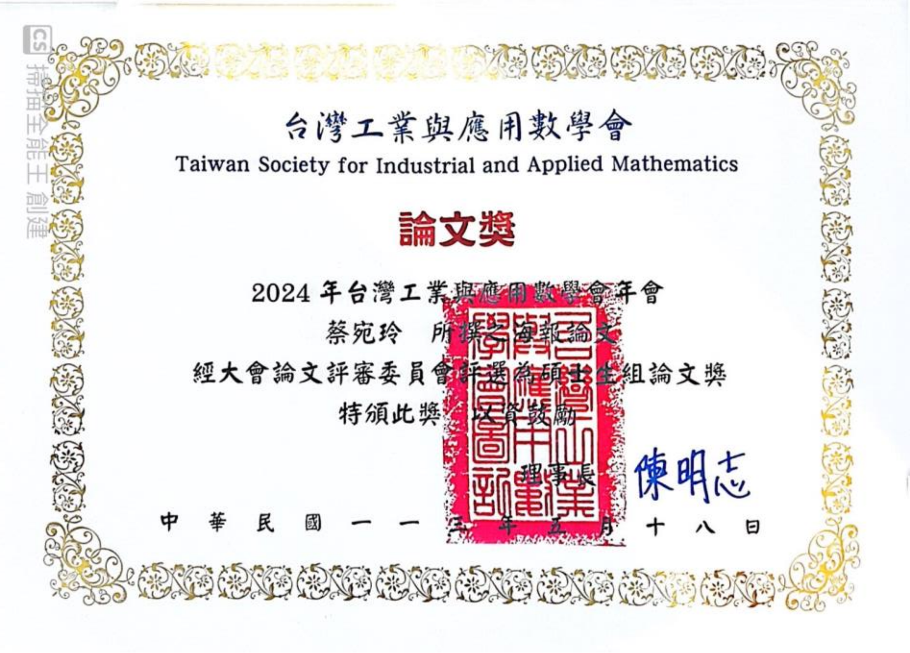
組員 – 系學會活動組、學術組

Honor

- 交通大學 應用數學系 期末專題海報展 專題研究優秀論文獎
- TWSIAM 2024 工業應用數學年會 海報論文 研究生組論文獎(第一名)、人氣獎
- TWSIAM 2022 工業應用數學年會 海報論文 大學生組皮托科技贊助獎(第一名)、人氣獎


台灣工業與應用數學會
Taiwan Society for Industrial and Applied Mathematics
皮托科技贊助獎
2022年台灣工業與應用數學會年會
蔡宛玲 所撰之海報論文
經與會者票選 榮獲 皮托科技贊助獎
特頒此獎 以資鼓勵
理事長
中華民國一一一年七月二十三日


獎 狀
蔡宛玲 同學參加本系 110 學年
第二學期專題研究成果發表會
表現優異特頒此狀 以資鼓勵
國立陽明交通大學
應用數學系系主任
中華民國 111 年 6 月 8 日



台灣工業與應用數學會
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論文獎
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經大會論文評審委員會評選為碩士生組論文獎
特頒此獎 以資鼓勵
理事長 陳明志
中華民國一一三年五月十八日

Intern

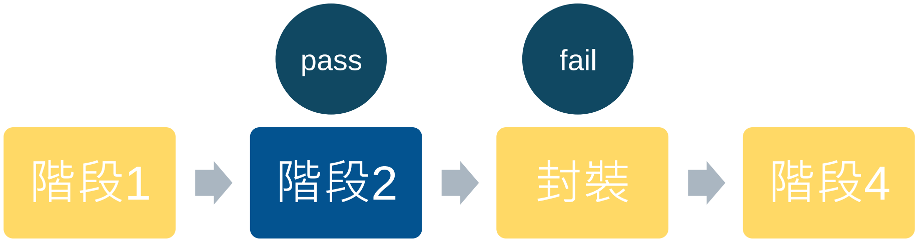
🖵 Python, Git, Parallel, Linear Algebra, scikit-learn, etc.

1

Weak IC Prediction (PJ1)

目的: 預測Weak IC，減少封裝成本

- Anomaly detection
- Model ensemble
- Single-perspective → Multi-perspectives

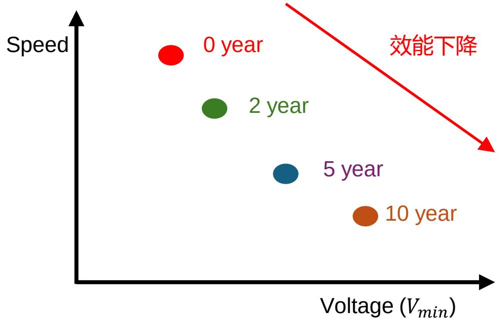


2

Modem Aging (PJ2)

目的(User Team): 預測出廠晶片在未來老化後所需的最小電壓
目的(Project Team): 資料量少，尋找資料特性

- Anomaly detection – 沿用PJ1開發的模型 (Model ensemble)
- Data mining, extract insights
  > 將資料根據隱含的anomaly pattern分成三個等級



(示意圖)

Intern

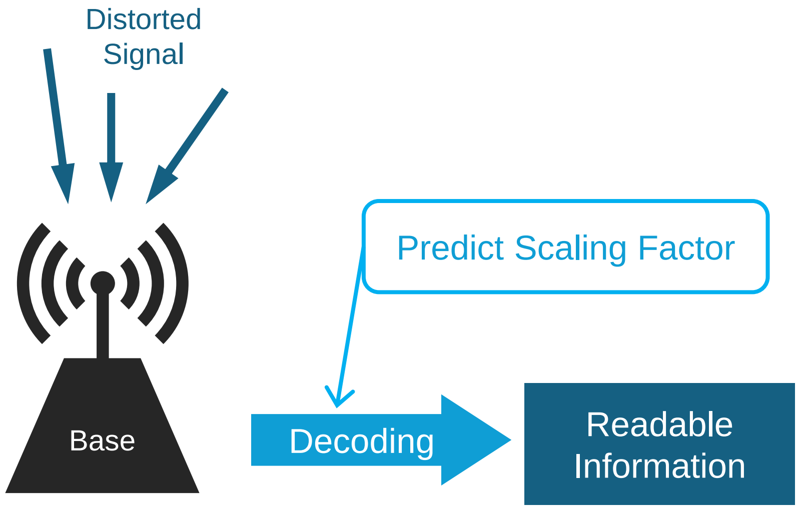
- Python, Parallel, Decision tree, etc.

3

AI-LLR (PJ3)

目的: 預測解碼係數(Scaling Factor)，減少人工試錯

- Data mining, extract insights.
  > 發現資料有特定的偏好、規律
- Reveal the data bias.
- Model compression
  1. Quantization
  2. Pruning the decision tree
     > Reducing 20% cycles

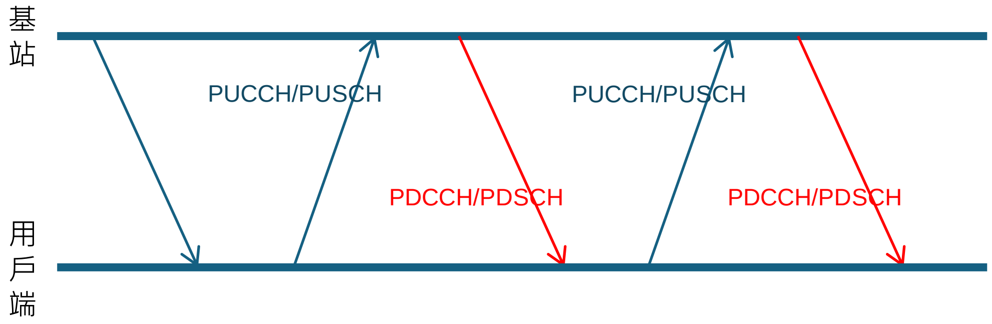


4

Traffic-Pattern Prediction (PJ4)

目的: 預測不同訊號應使用何種通道解碼，節省電量

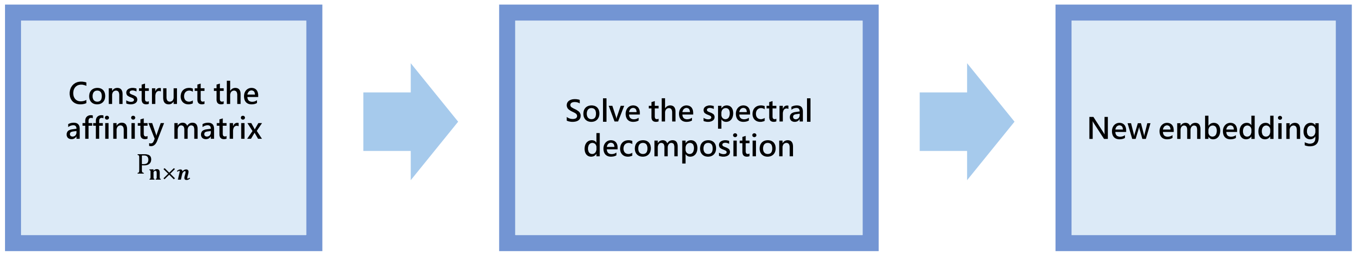
- Data preprocessing and data mining
- Online Model



Manifold Learning – Diffusion Maps & Roseland

Code: tsaiwanling/Manifold_Learning (github.com)

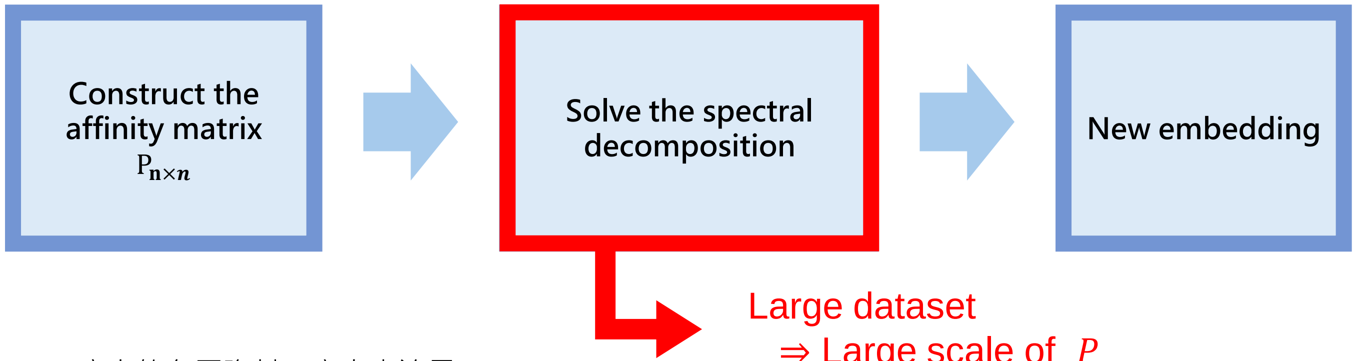
- Nonlinear dimensionality reduction tool
- Unsupervised learning



Manifold Learning – Diffusion Maps & Roseland

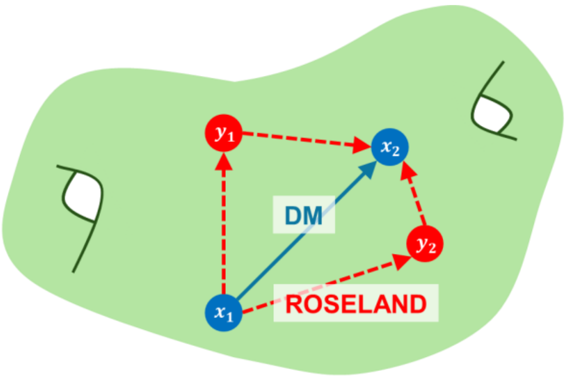
Code: [tsaiwanling/Manifold_Learning (github.com)]

- Nonlinear dimensionality reduction tool
- Unsupervised learning
- Disadvantage:
  - cannot work on large dataset
  - Solution: ***Roseland***



Large dataset
⇒ Large scale of P
⇒ computationally expensive

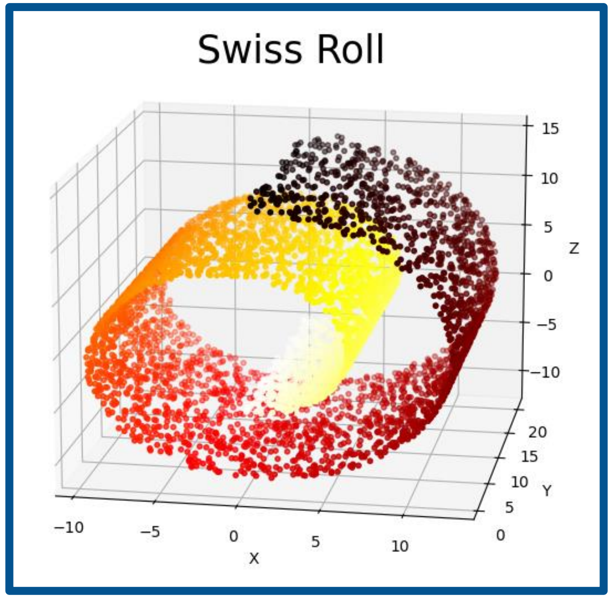
Ex. 病人的血壓資料、龐大車流量

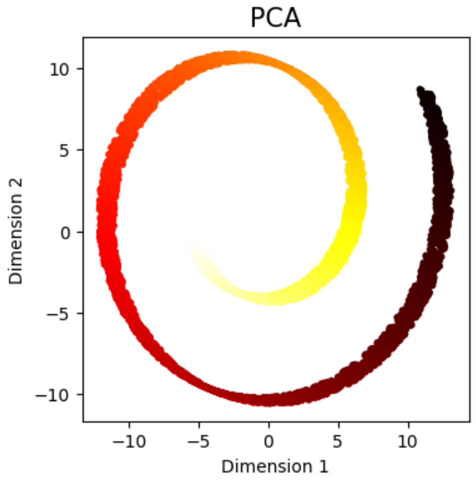


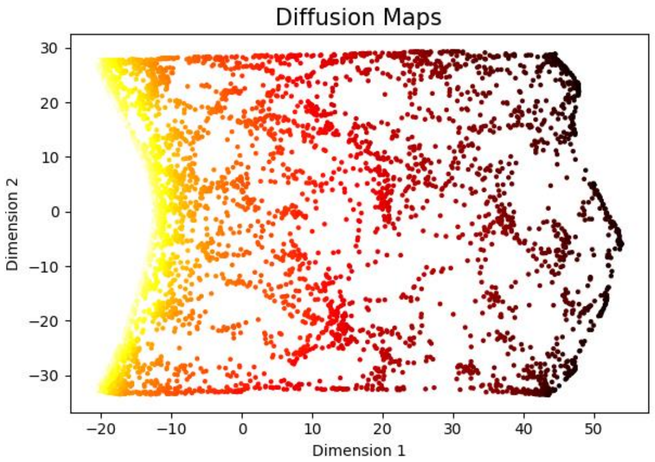
The most important difference is the way of constructing affinity matrix $\widehat{\boldsymbol{W}}$.

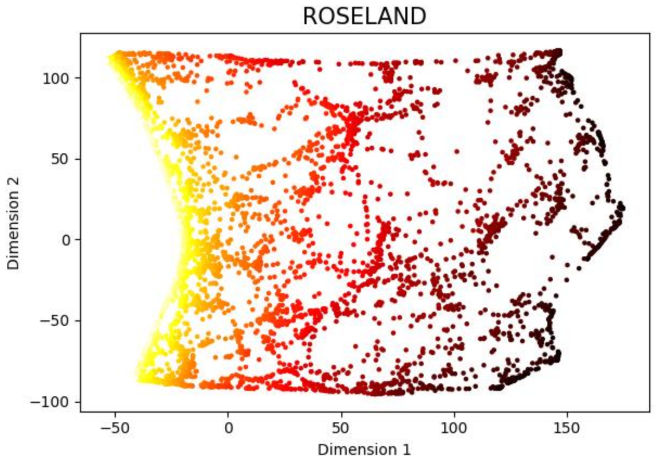
- DM: measure the diffuse between two points directly $\widehat{W} = P_{n\times n}$
- Roseland: measure the similarity between two points $\widehat{W} = P^{(r)}_{n\times m} {P^{(r)}}^{T}_{n\times m}$

Diffusion Maps – Application









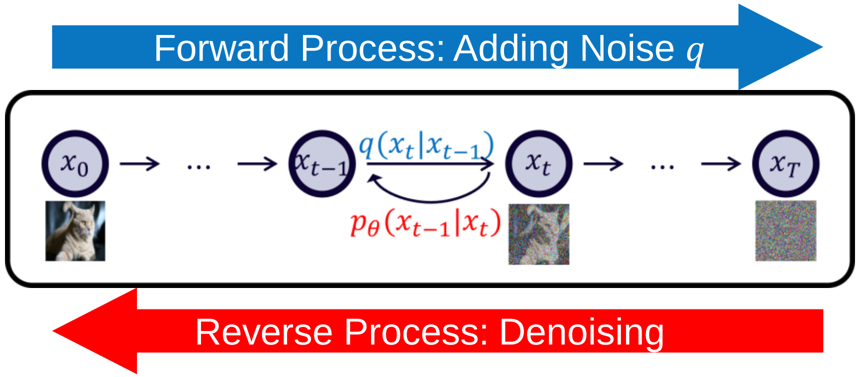
1. Model Evaluation
   - In-depth analysis of Generative AI (碩士論文)
2. Interpretation of experimental results
   - LDA apply on MNIST dataset
3. Structure of Dataset
   - Categorical dataset (2D data)
   - Imbalanced data
   - Time series data

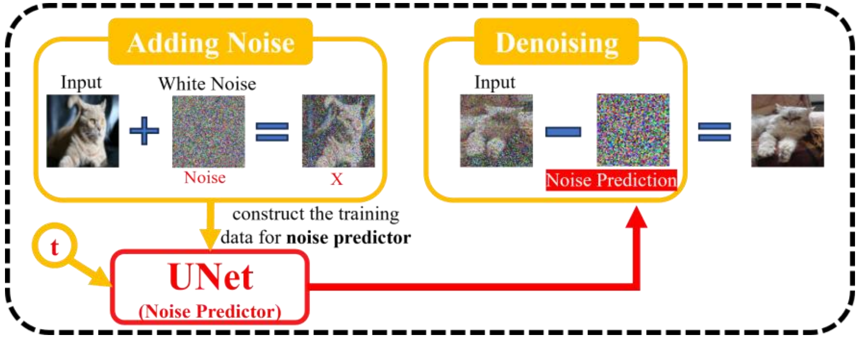
	Diffusion Maps	Roseland
Spent time	21.1s	9.9s

碩士論文: In-depth analysis of Generative AI

Project: tsaiwanling/DDPM: Denoising Diffusion Probabilistic Models (github.com)

- Python, Pytorch, plotly, etc.

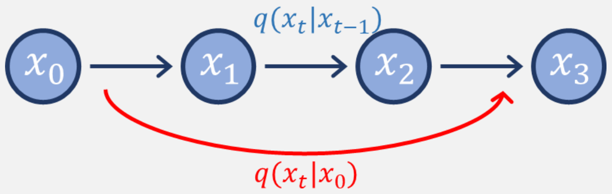




Acceleration

- **One-Step Forward** [DDPM]

$$q(x_t|x_0) = \mathcal{N}\left(\sqrt{\overline{\alpha}_t}x_0, (1 - \overline{\alpha}_t)I\right)$$

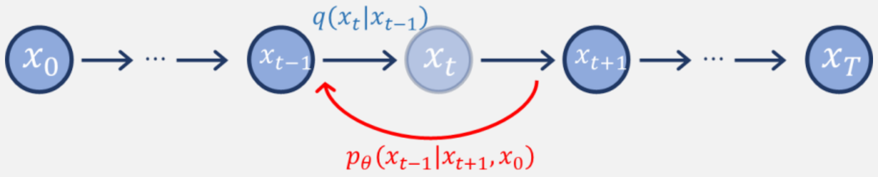


- **non-Markovian Reverse** [DDIM]

$$p_\theta(x_{t-1}|x_t, x_0) = \mathcal{N}(Ax_t + b, \sigma_t^2 I)$$

$$A = \sqrt{\frac{1 - \overline{\alpha}_{t-1} - \sigma_t^2}{1 - \overline{\alpha}_t}}$$

$$b = \sqrt{\overline{\alpha}_{t-1}}x_0 - A\sqrt{\overline{\alpha}_t}x_0$$



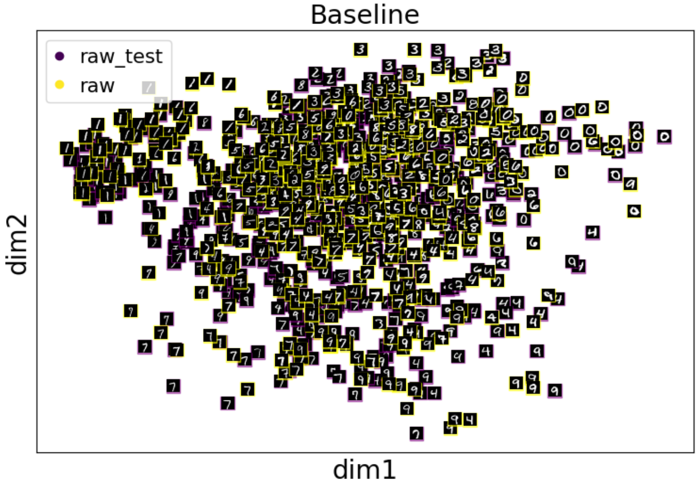
Model Evaluation by data structure

碩士論文: In-depth analysis of Generative AI

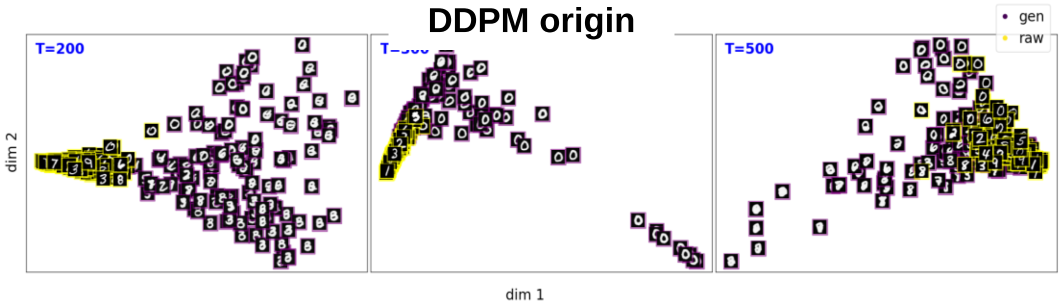
Generating data

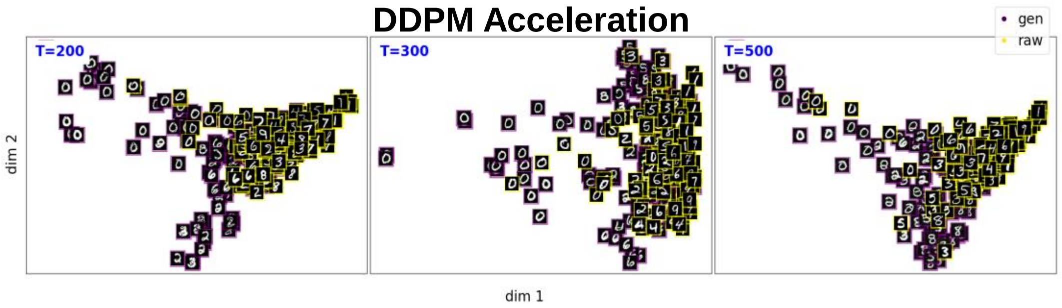
DDPM origin | **DDPM Acceleration**

Apply ROSELAND on the generating data and raw data



Speed up the evaluation time
⇒ 360s → 2s

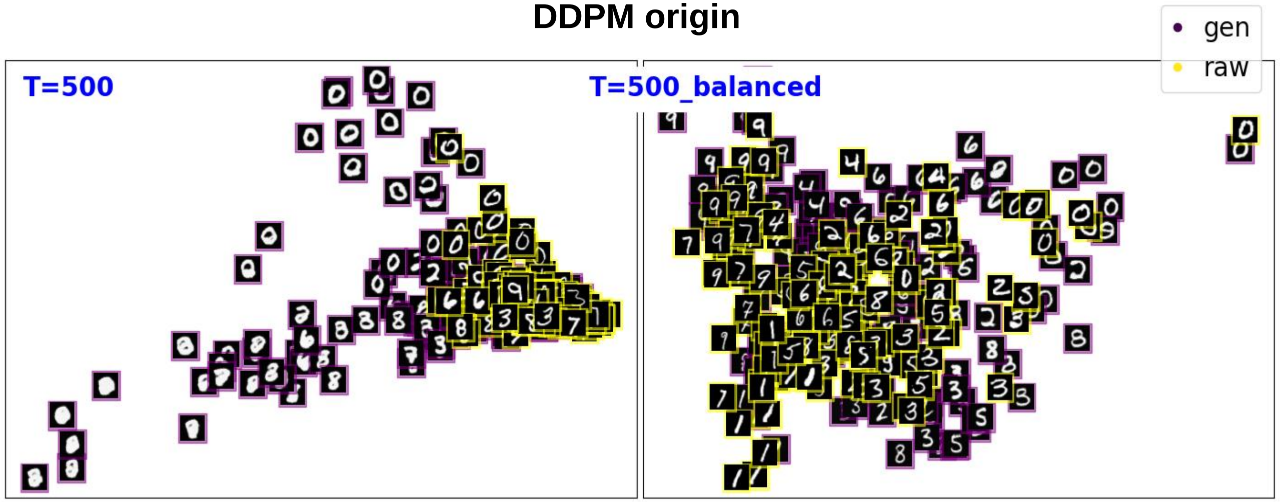




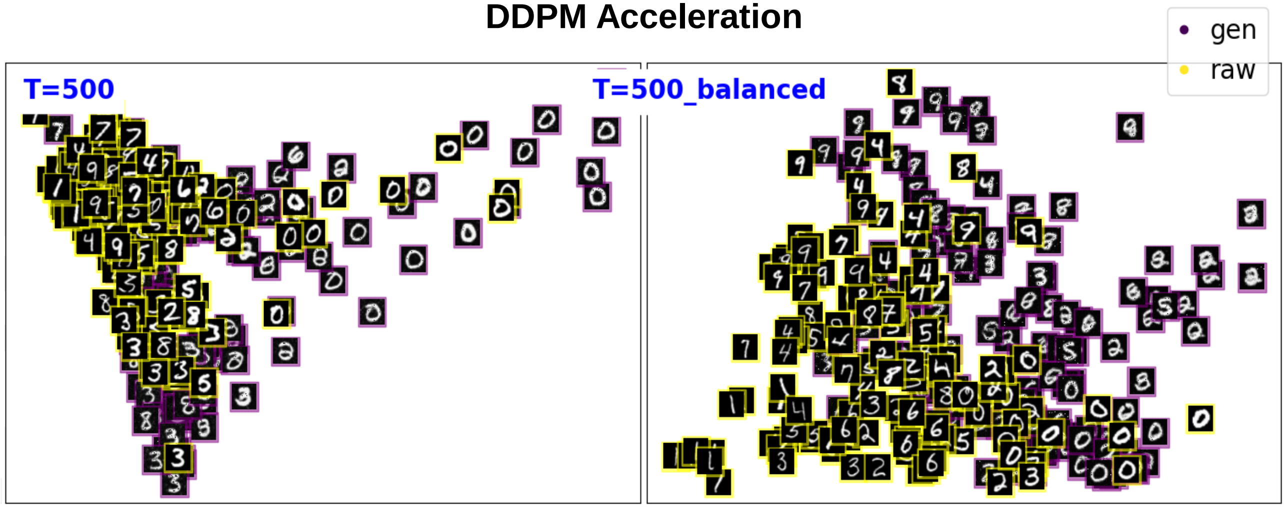
Example – re-balanced train data

	Origin	Balanced
0	30	15
1	30	50
2	30	30
3	30	30
4	30	30
5	30	30
6	30	30
7	30	50
8	30	20
9	30	50

DDPM origin



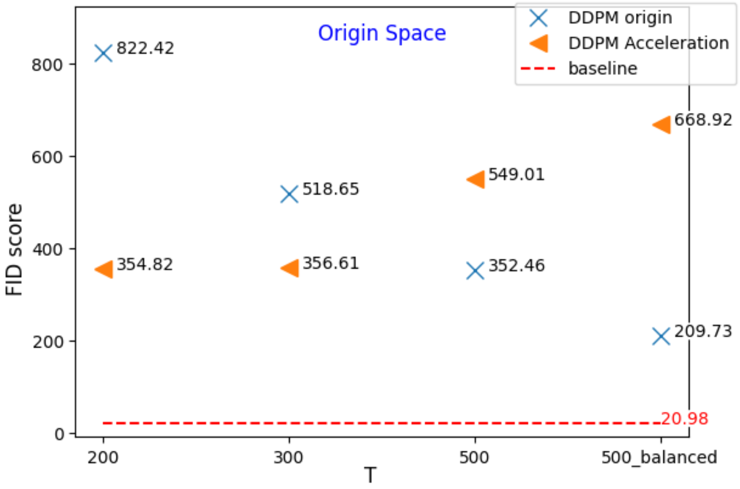
DDPM Acceleration

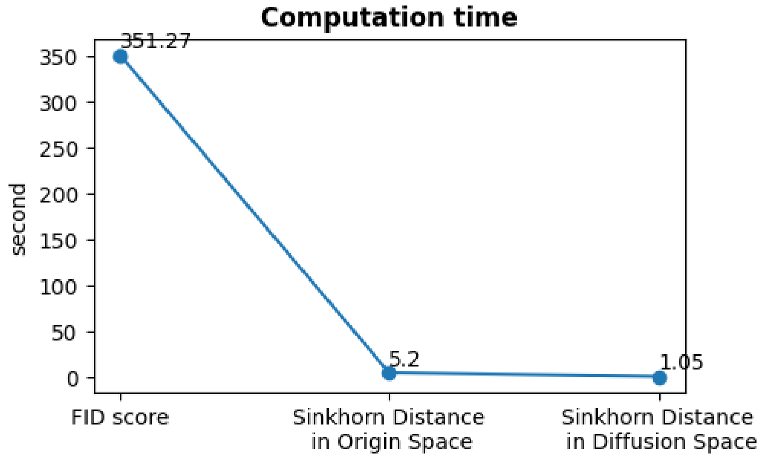


Evaluation: FID score & Sinkhorn distance

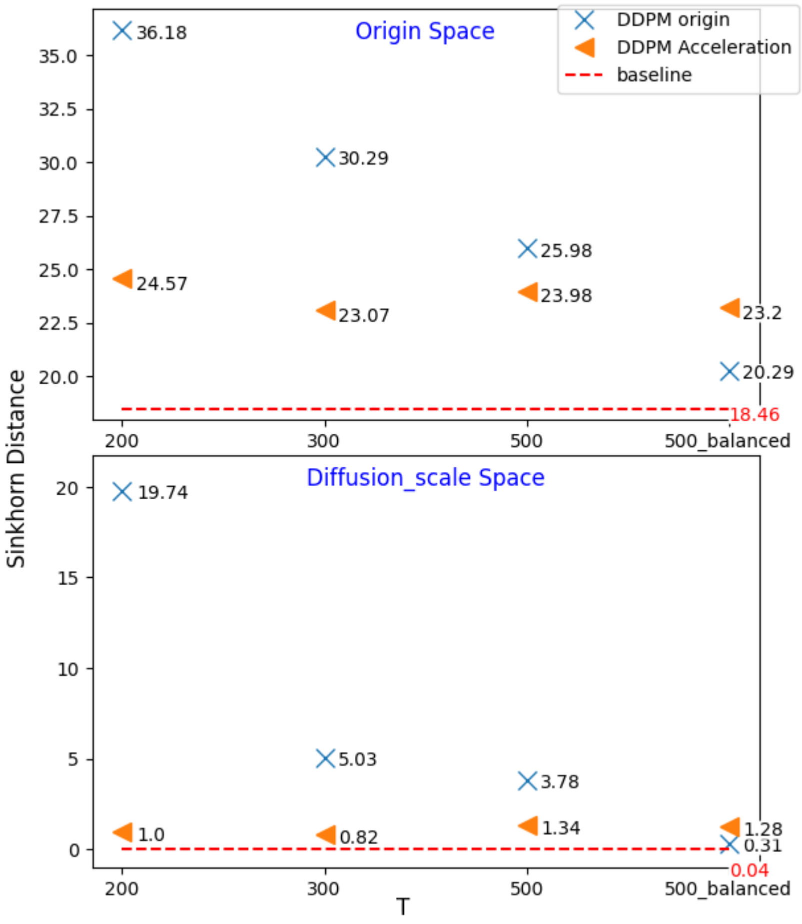
- Origin space: image dimension 32×32
- Diffusion space: reduction dimension 6×1

FID score





Sinkhorn Distance



Interpretation of experimental results

- Project: Why is Linear Discriminant Analysis (LDA) inappropriate for the MNIST dataset?

*Appendix ：*LDA

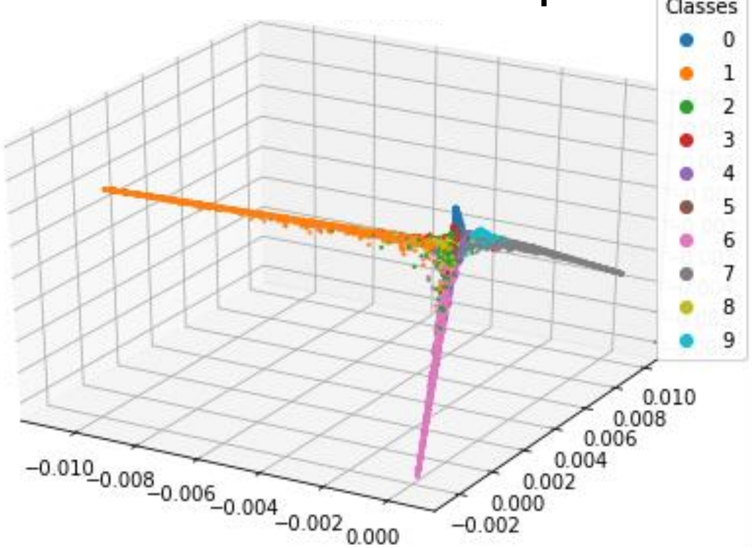
- Accuracy：87.3%

0	1	2	3	4
95.92%	96.56%	79.07%	87.43%	90.43%
5	**6**	**7**	**8**	**9**
82.4%	89.46%	84.05%	81.11%	85.33%

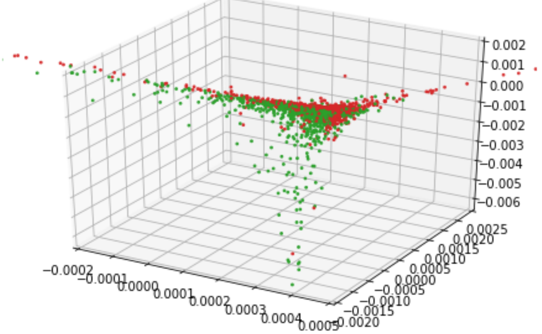
- Confusion matrix：

	0	1	2	3	4	5	6	7	8	9
0	940	0	15	5	0	8	12	2	7	9
1	0	1096	32	5	12	8	8	30	27	7
2	1	4	816	25	6	4	11	15	8	1
3	4	3	34	883	0	44	0	9	27	13
4	2	2	21	4	888	12	25	22	20	63
5	13	2	5	25	4	735	29	2	53	6
6	9	3	37	3	7	15	857	0	10	0
7	1	0	9	16	2	10	0	864	6	37
8	9	25	57	29	10	38	16	4	790	12
9	1	0	6	15	53	18	0	80	26	861

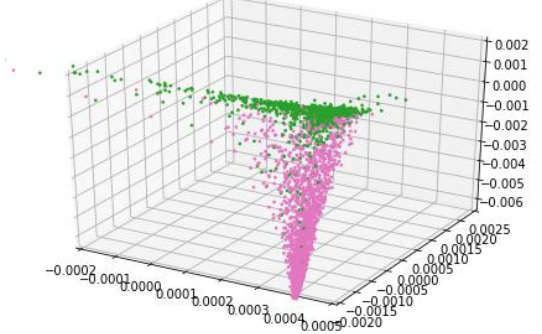
MNIST dataset in diffusion space



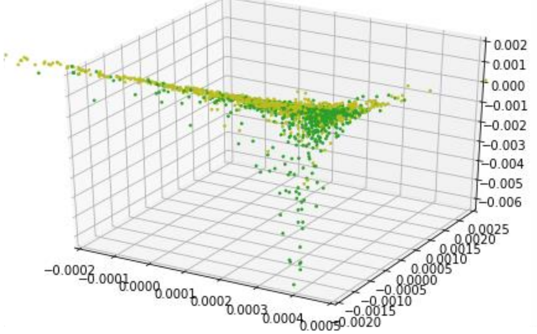
digit [2, 3]



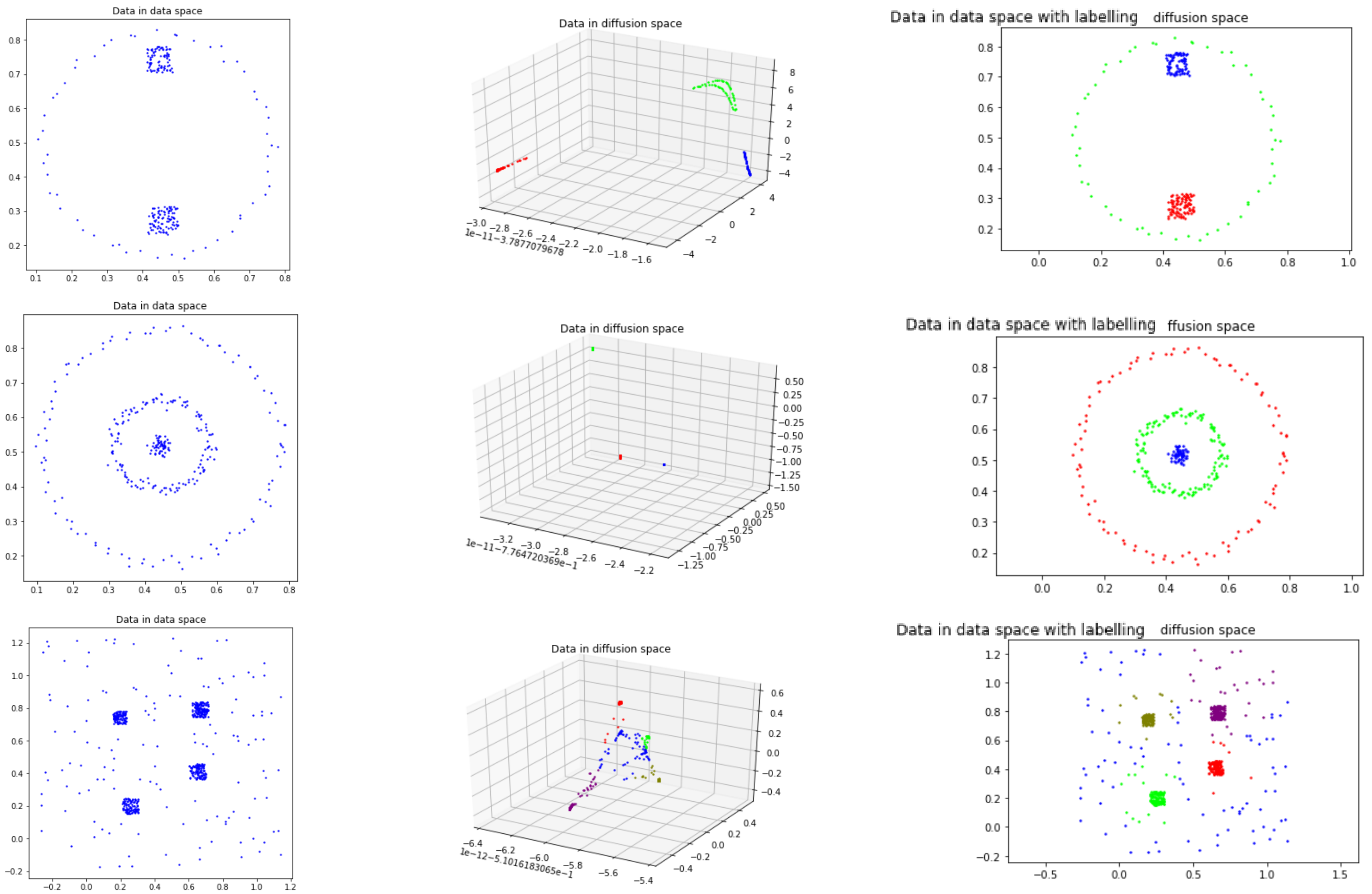
digit [2, 6]



digit [2, 8]



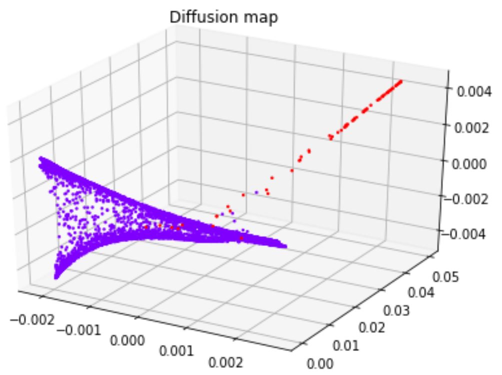
Dataset – Categorical data

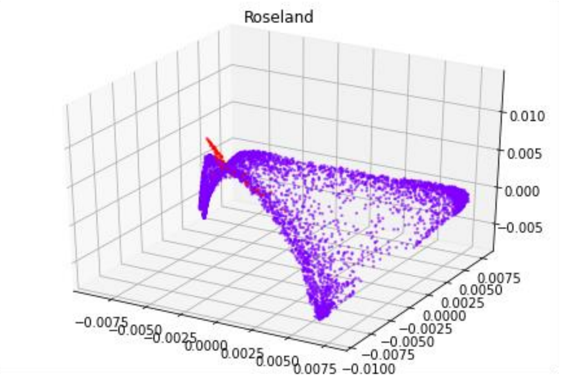


Dataset – Imbalanced data

Satimage-2

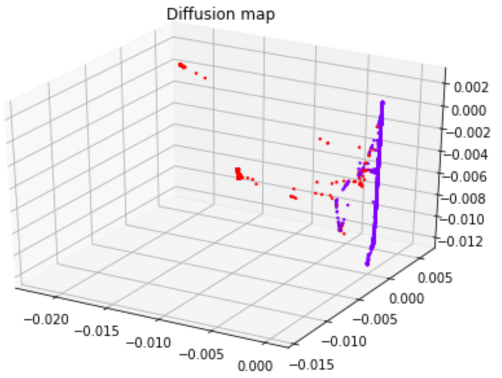
- 5803 samples, 36-dim
- Outliers : 1.2% (red points)
- Spent time
  - ➢ Diffusion maps: 50.6s
  - ➢ Roseland: 0.7s

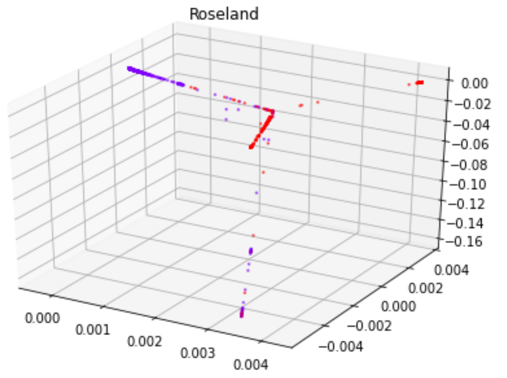




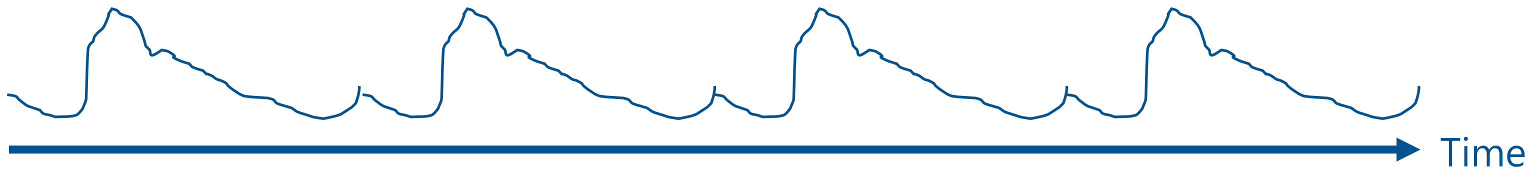
Shuttle

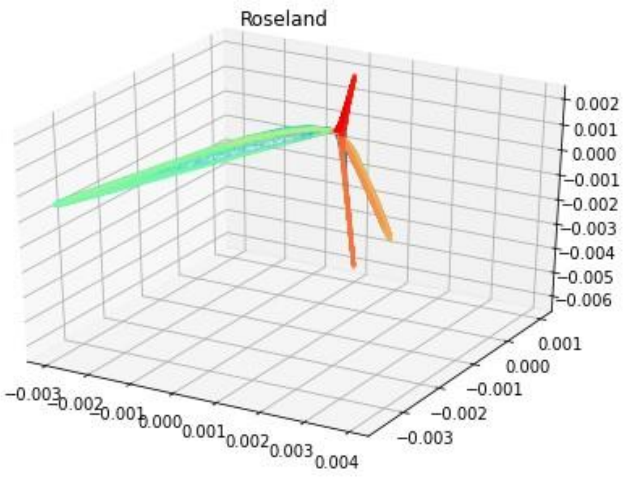
- 10000 samples, 9-dim
- Outliers : 7.12% (red points)
- Spent time
  - ➢ Diffusion maps: 386s
  - ➢ Roseland: 9.6s



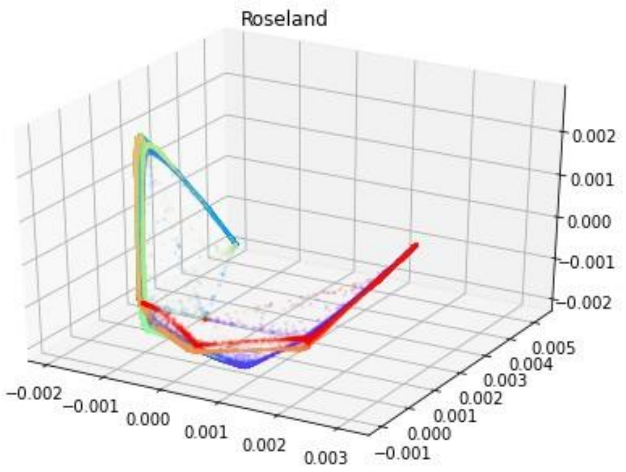


Dataset – Time series data

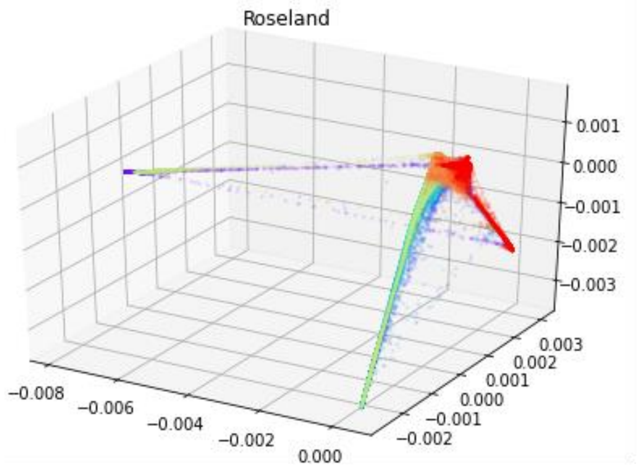




- Data size = 113460
- Landmark size = 188
- Data features : 601



- Data size = 120725
- Landmark size = 194
- Data features : 177



- Data size = 121814
- Landmark size = 194
- Data features : 177

Appendix: Linear Discriminant Analysis

1. Minimize within-class scatter

2. Maximize between-class scatter

Here, we use the scatter matrix(散佈矩陣) to estimate the scatter of the data.