

# 機器學習於材料資訊的應用

## Machine Learning on Material Informatics

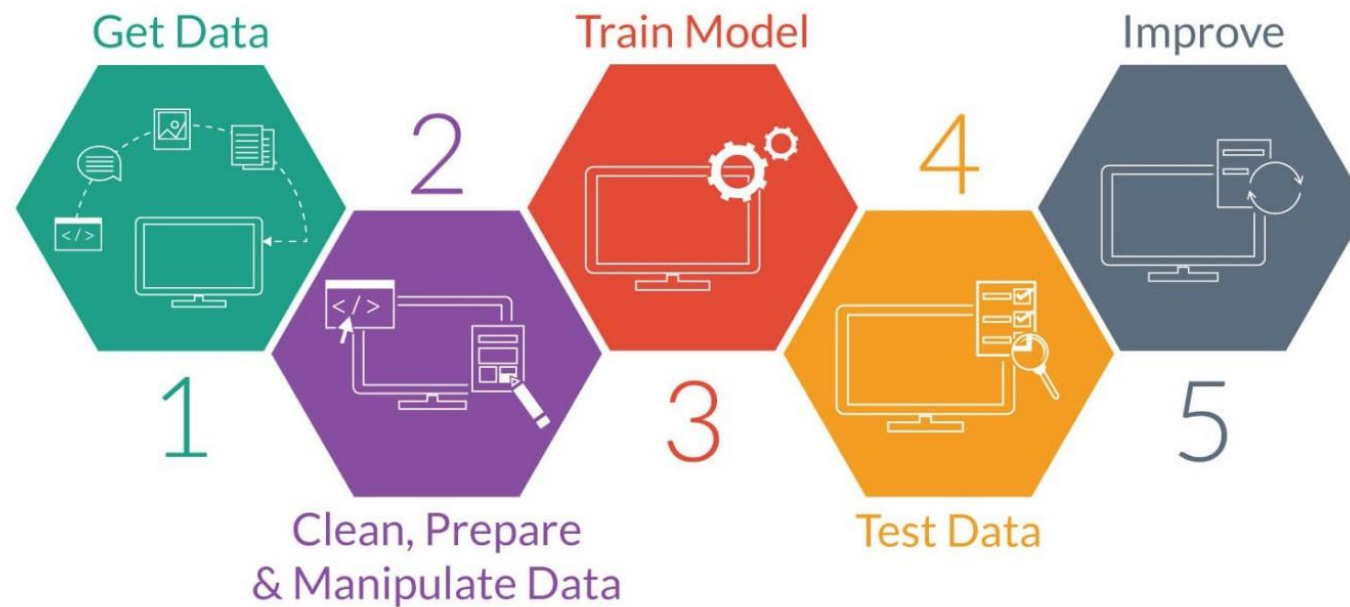
---

陳南佑(NAN-YOW CHEN)

[nanyow@narlabs.org.tw](mailto:nanyow@narlabs.org.tw)

楊安正(AN-CHENG YANG)

[acyang@narlabs.org.tw](mailto:acyang@narlabs.org.tw)



使用軟體產生資料

檔案處理

建立網路

用測試資料  
檢驗演算法

調整萃取特徵  
方法

特徵萃取

分群演算法

LAMMPS



ASE

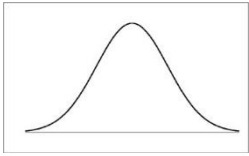
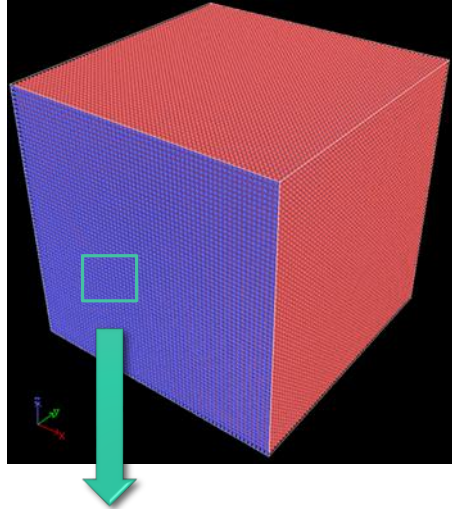
# 檔案處理&特徵萃取

---

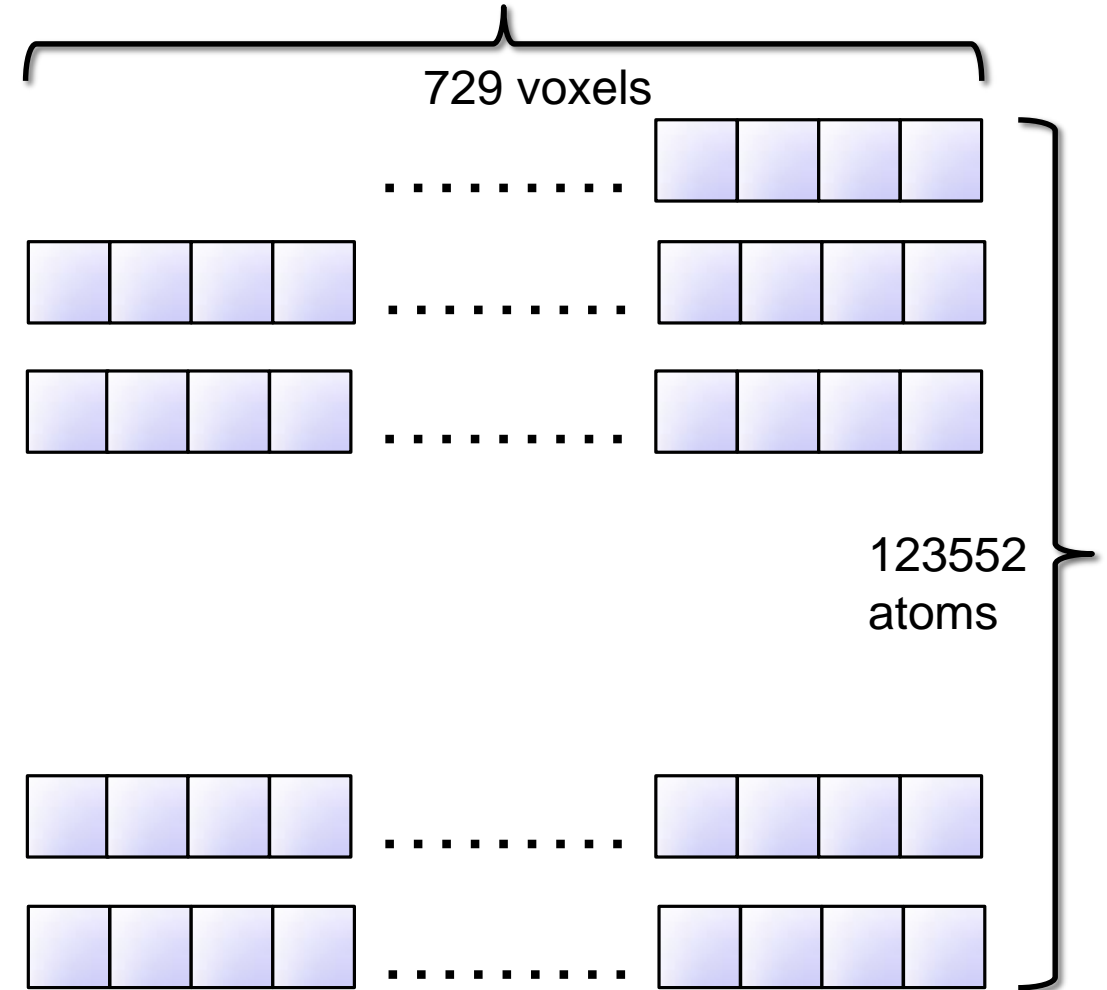
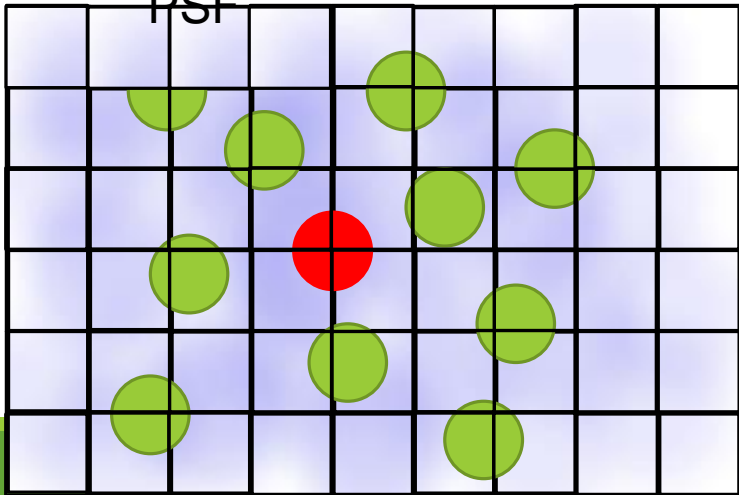
- LAMMPS可以輸出dumpfile(cfg) , xyz , trajectory file(dcd) , 自己打造Parser的話不用特別考慮。
  - dumpfile(cfg):在模擬過程中標準輸出檔案，ascii檔，人可以直接讀和編輯。(MDANALISIS不能讀，需要用ovito轉成data檔)
  - xyz:輸出另一種檔案形式，ascii檔，人可以直接讀和編輯。(MDANALISIS可以讀，但是缺了mass info。)
  - trajectory file:輸出另一種檔案形式，binary檔，人不能直接解讀。(MDANALISIS可以讀，ovito讀不了。)
- 特徵萃取:結構分類問題是局部的，考慮一個原子的特徵，需要從與周遭原子的關係下手。
  - Voxelize local region (This class)
  - Local environment
  - Nearest neighbor

# Feature of local environment

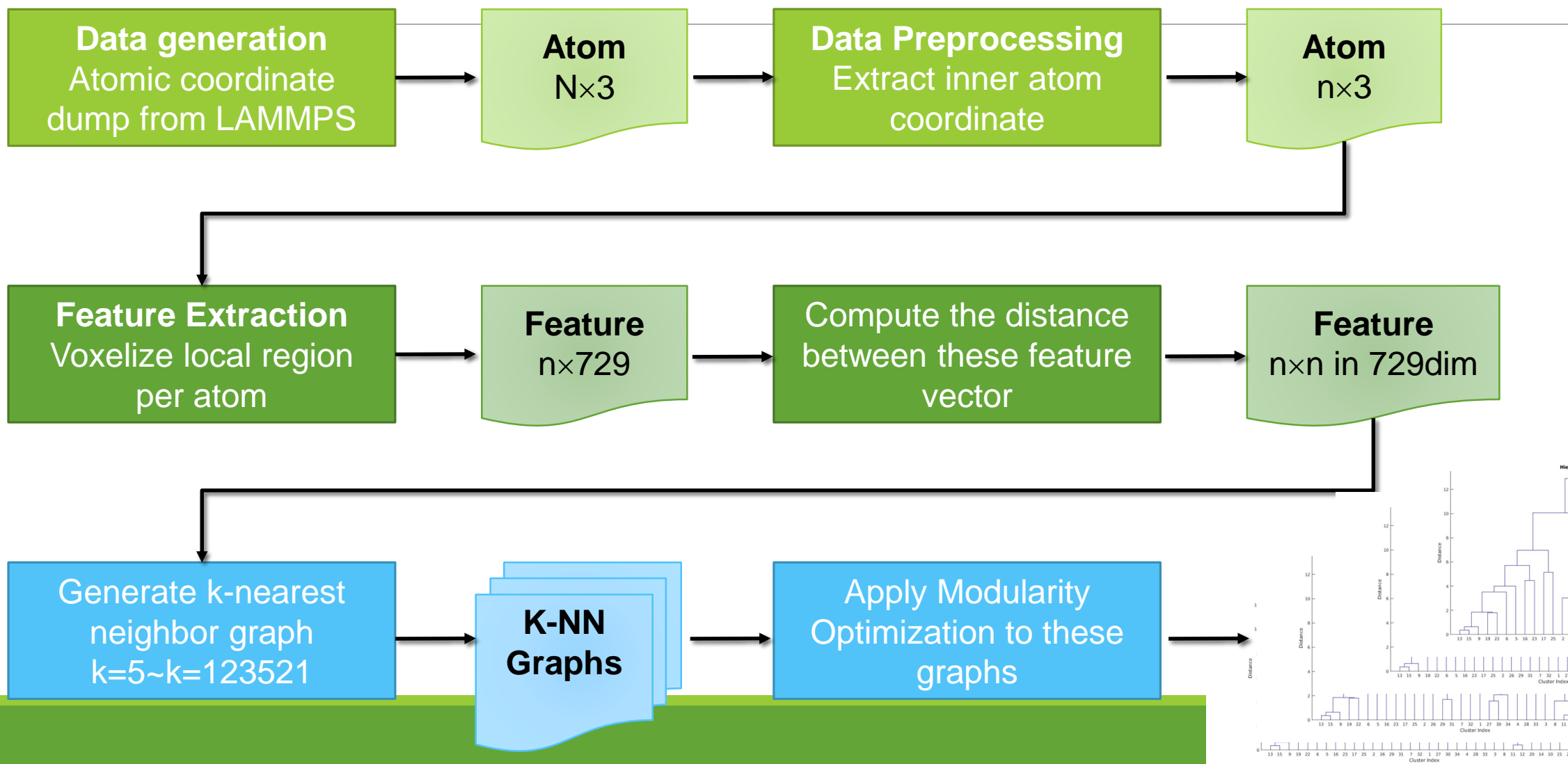
>python feature\_engineering.py



Apply  
PSF



# Flowchart



# More on descriptors

---

- Atom-centered Symmetry Functions (ACSF)
- Smooth Overlap of Atomic Positions (SOAP)
- Gaussian descriptor
- Behler type Symmetry function(目前最多人採用)
- ...

# 分群演算法

---

- ❑ 原子結構的分類，避免直接從原子座標(卡式座標系統)進行分類，反而是從原子的其他座標系統去挑選特徵(座標系統的基底)，來描述原子的local environment。
- ❑ 有了原子的local environment，便可以在這些座標系統進行原子的分類，scikit-learning已提供多種現成的分群演算法可以使用。
  - K-means
  - Affinity Propagation
  - Hierarchical clustering
  - DBSCAN
- ❑ 雖然已經有多種分群演算法可以直接使用，但無可避免的是這些方法都還是需要人來挑選演算法參數，容易淪為先射箭再畫靶。
- ❑ 所以我們嘗試導入網路分析(network analysis)中的Modularity方法來進行微結構分類，最大的不同在於Modularity是非監督式學習，不需要人工決定分群的參數，比起其他方法要來的客觀。

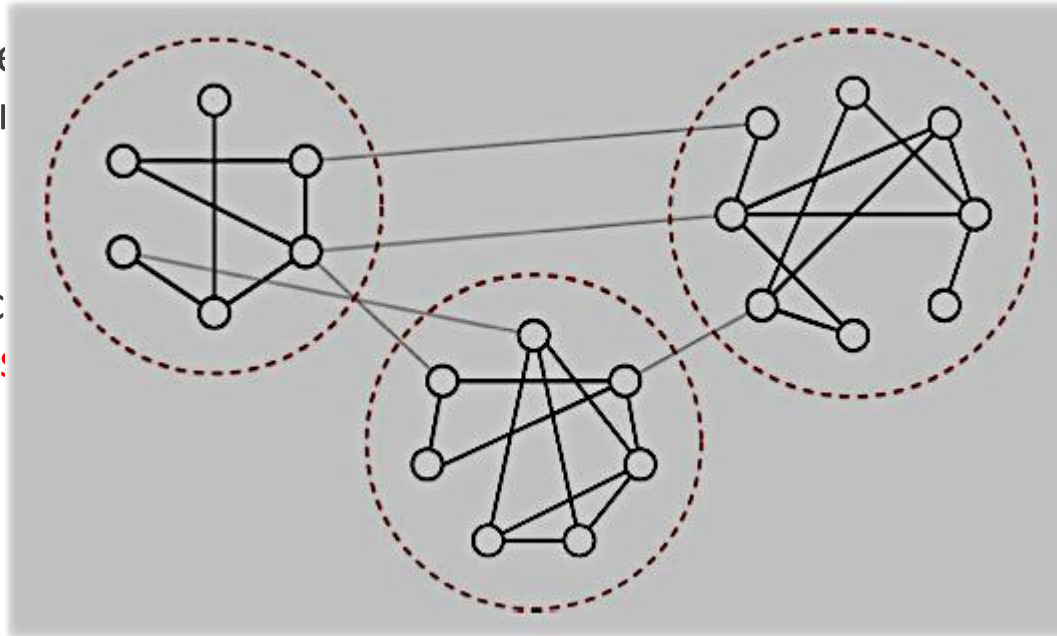
# Modularity of networks

---

□ Definition of a module: loosely linked island of densely connected nodes.

□ Partitioning a network into modules  
and are as different as possible

□ In order to describe a network  
we also need a similarity measure



are similar to each other

ne a **similarity measure** and



# Modularity of networks

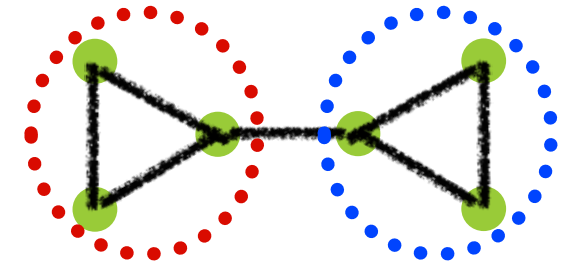
□ Definition of modularity:

$$Q = \sum_{s=1}^{N_M} \left[ \frac{l_s}{L} - \left( \frac{d_s}{2L} \right)^2 \right]$$

where

- $N_M$ : number of modules in the network
- $l_s$ : number of intra-modular links in module  $s$
- $d_s$ : sum of the degrees of the nodes in module  $s$
- $L$ : total number of links in the network

- $Q = 0.357$



$$N_M = 2$$

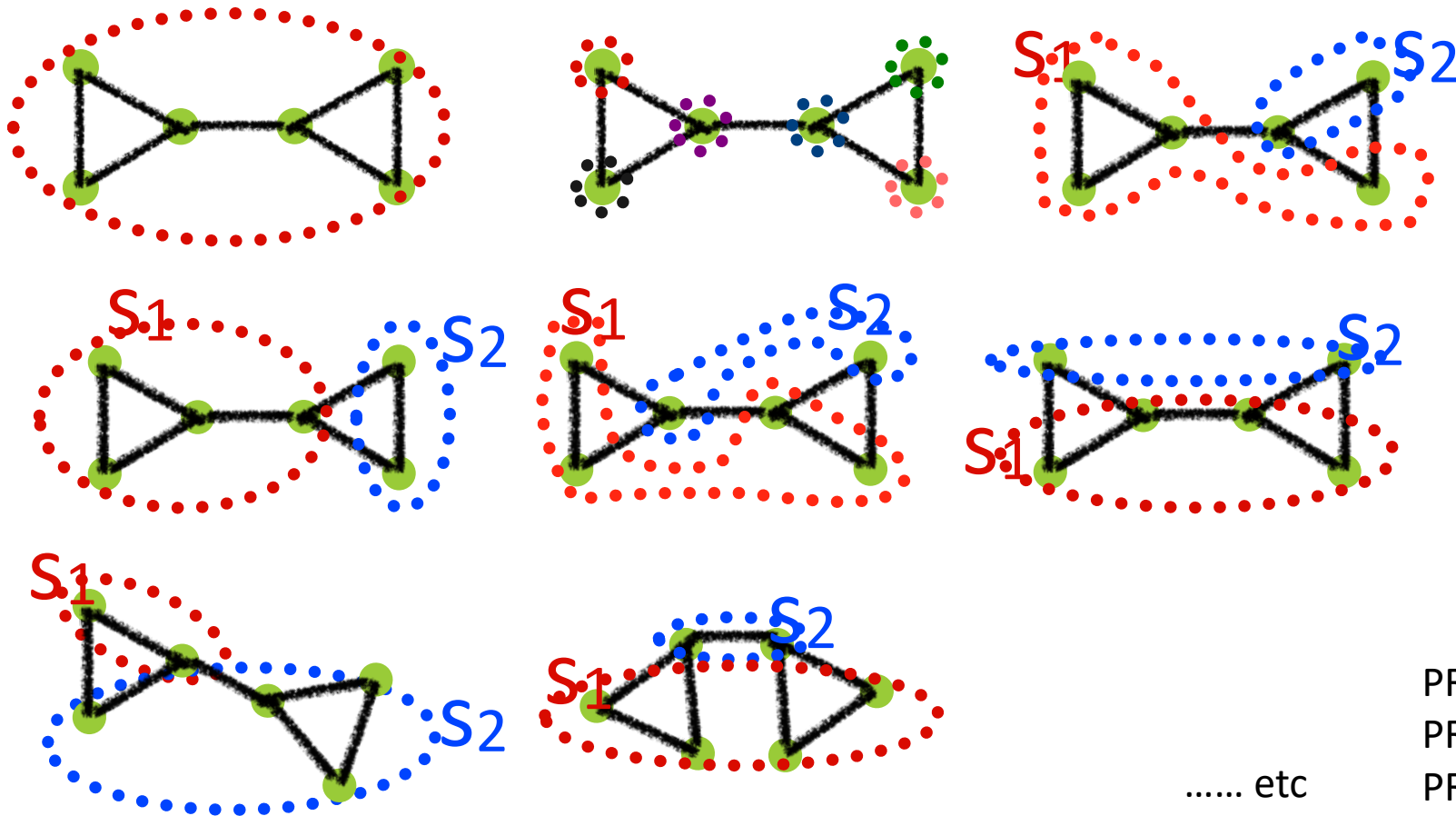
$$l_1 = 3, l_2 = 3$$

$$d_1 = 7, d_2 = 7$$

$$L = 7$$

Roger Guimerà, et al.: Nature **433**, 895 (2005)

# Modularity of networks



..... etc

PRE 68, 026121 (2003)  
PRE 69, 026113 (2004)  
PRE 70, 025101 (2004)

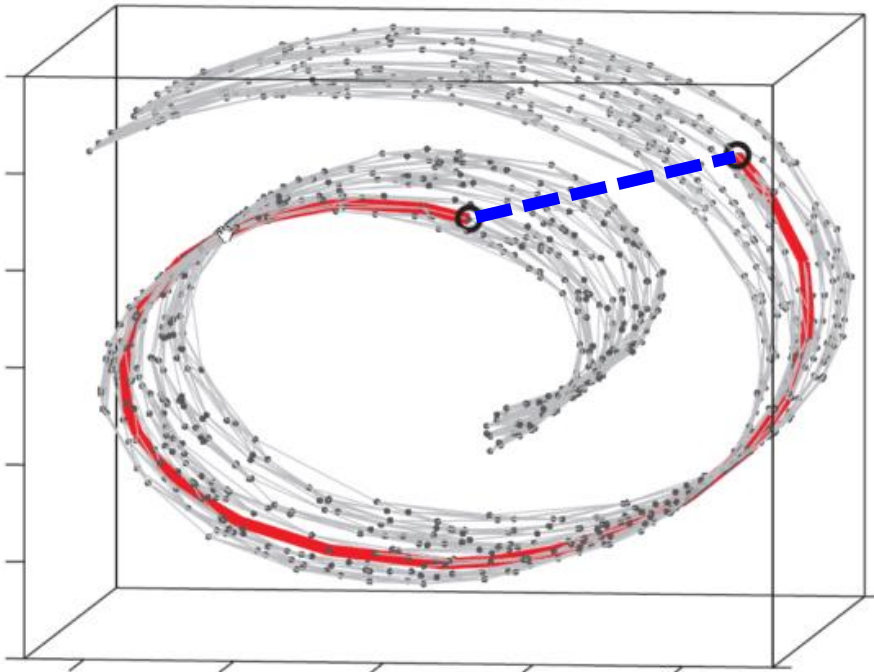
# 建立網路

---

- **Modularity**是基於網路分析的方法，所以比起其他分群演算法，需要多一個建立資料點的網路關係。
- 網路式建立於資料點的空間，不是原本問題的卡式座標。
- 距離的定義有許多種，歐式距離、曼哈頓距離、Dijkstra distances ...
- 網路連通的定義也要選擇。

# Isomap

- Isomap is an extension of multi dimensional scaling (MDS), where pairwise euclidean distances between data points are replaced by **geodesic distance** on a high-dimensional manifold which is constructed by these data points.



For two arbitrary points (circled) on a nonlinear manifold, their Euclidean distance in the high dimensional input space (**length of blue dashed line**) may not accurately reflect their intrinsic similarity.

The **red solid line** is the geodesic distance (*i.e.* Dijkstra's distance) and the **blue dashed line** is the euclidean distance between two points, respectively.

Joshua B. Tenenbaum, et al.: Science **290**, 2319 (2000).

# Dijkstra's algorithm

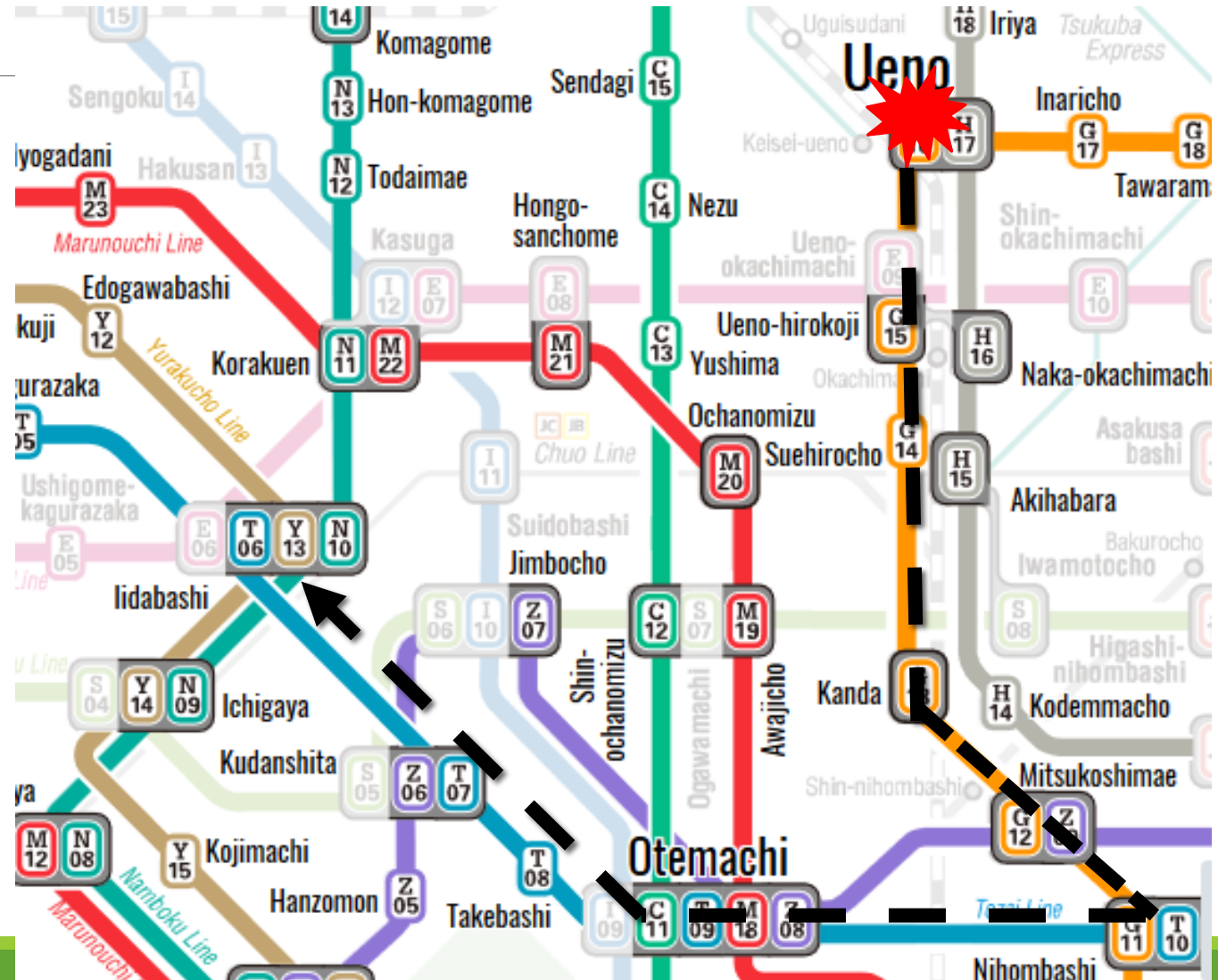
□ Dijkstra's algorithm is an algorithm for finding the shortest paths between nodes in a graph, which may represent, for example, road networks. It was conceived by computer scientist Edsger W. Dijkstra in 1956.

Ex. Ueno and Iidabashi

□ Euclidean distances : 3.2km

□ Dijkstra distances :  $3.4 + 3.7 = 7.1$ km

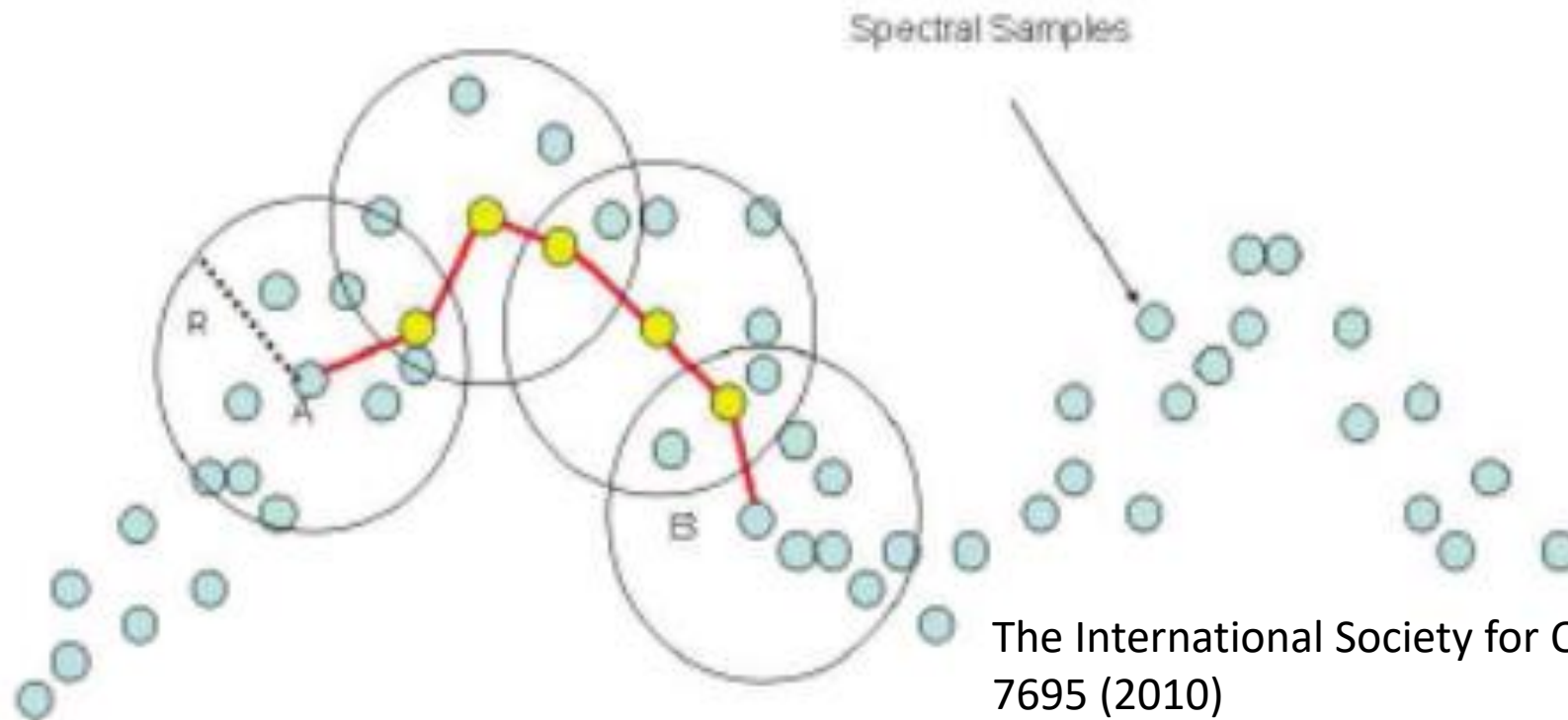
(Ueno → Nihonbashi → Iidabashi)



# Construct Networks

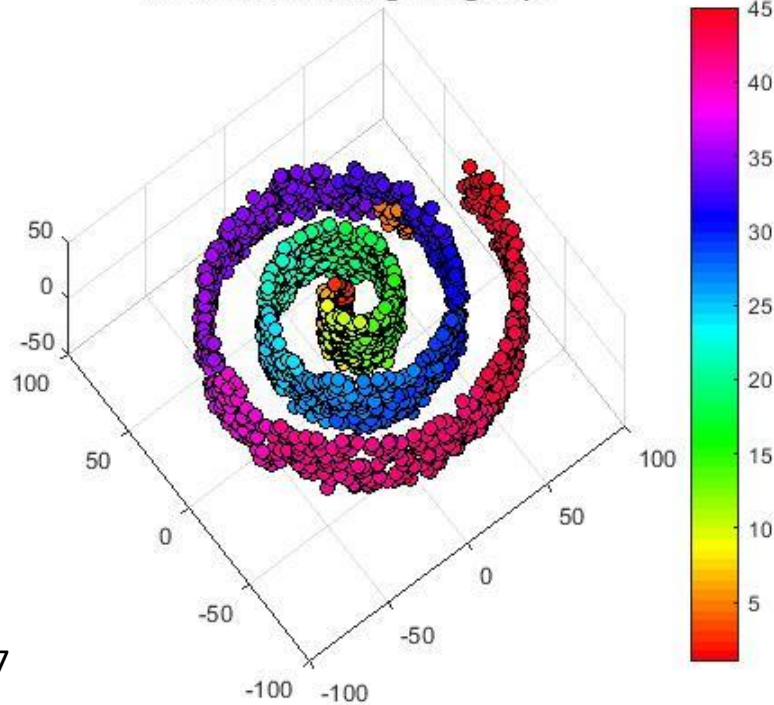
## □ Steps:

- Build graph with  $k$ -neighbors or  $\epsilon$ -ball.
- Weight graph with euclidean distance.
- Compute pairwise geodesic distances by Dijkstra's algorithm.



# Testing case - swiss roll manifold

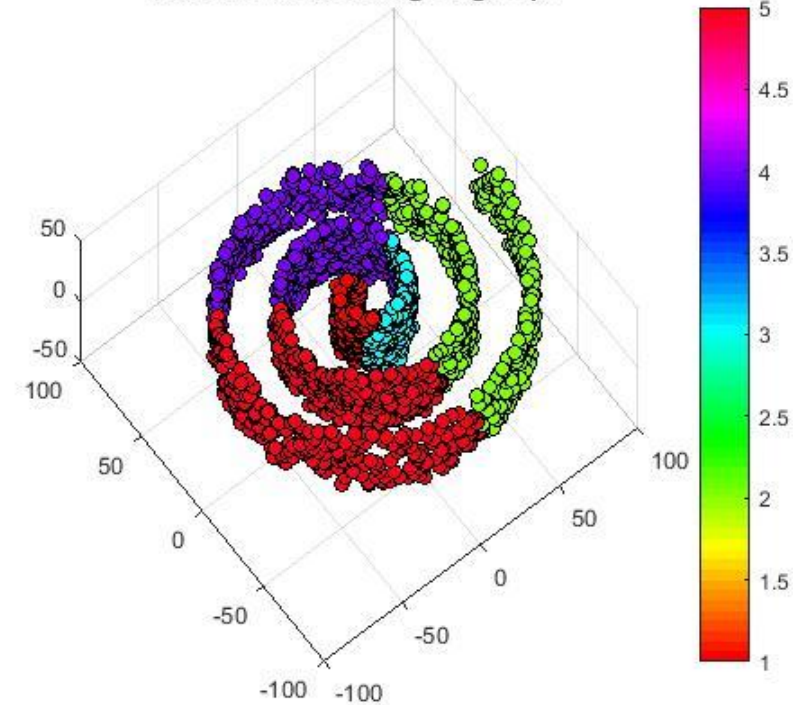
Geodesic Clustering : 45 groups



Nodes = 2000  
Edges = 6036  
Ave. Degree = 6.036  
Modularity Q = 0.937

(5-neighbors)

Euclidean Clustering : 5 groups



Nodes = 2000  
Edges = 1999000  
Ave. Degree = 1999  
Modularity Q = 0.187

(1999-neighbors)