

# NON-LINEAR DIMENSION REDUCTION

## ISOMAP

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## ① Introduction

## ② Algorithm

## ③ Examples

## ④ Summary

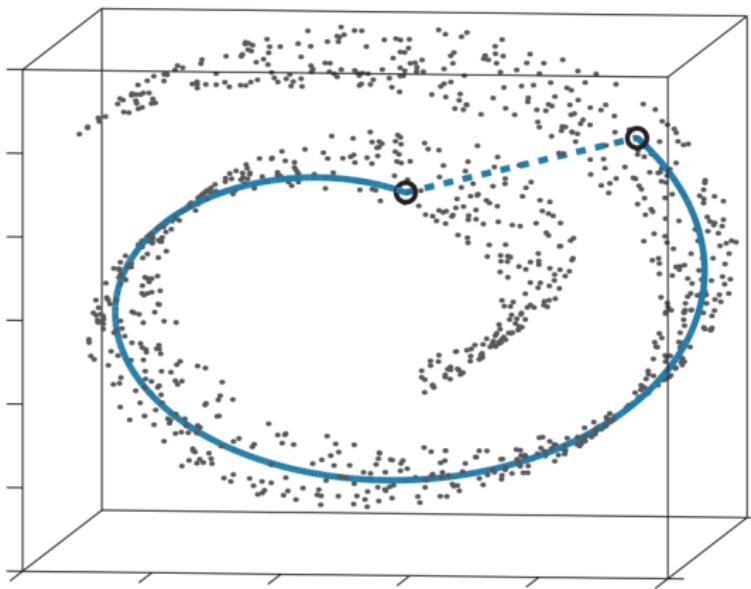
## ① Introduction

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## ④ Summary

# Geodesic distance



# ISOMAP idea

- Approximate pairwise geodesic distances in a manifold.
- Apply MDS on the distance matrix to find a 2-dim embedding that preserves geodesic distances.

## 1 Introduction

## 2 Algorithm

Construct neighborhood graph

Compute graph distances

MDS with graph distances

## 3 Examples

## 4 Summary

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Compute graph distances

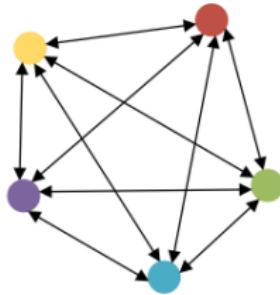
MDS with graph distances

## 3 Examples

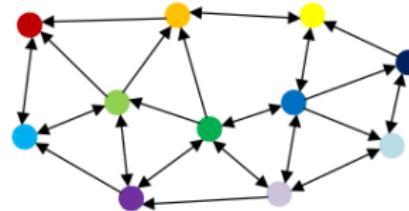
## 4 Summary

## Construct neighborhood graph

Create graph  $G$  of  $\{x_i\}$  by either using a K-NN rule or  $\epsilon$ -rule where each edge  $e = (x_i, x_j)$  is weighted by the Euclidean distance between the two points.



(a) local complete graph



(b) global KNN graph

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# Compute Graph Distances

There are two ways to compute the shortest path of two nodes

- Floyd's Algorithm: Can find the shortest path between all of the pairs
- Dijkstra's Algorithm: Better for sparse graph

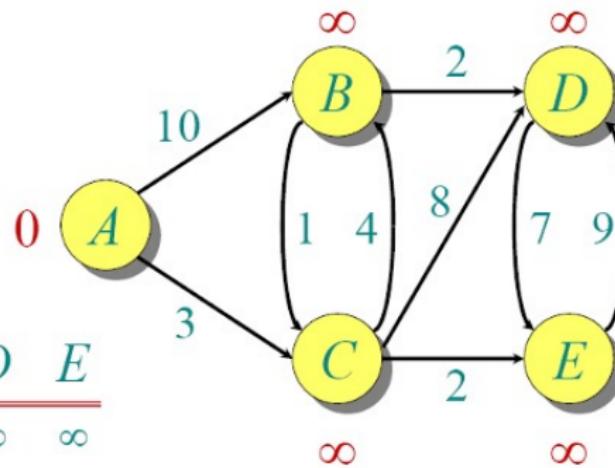
# Dijkstra Algorithm

- Dijkstra Algorithm is a greedy algorithm for solving the single source shortest path problem
- Method
  1. It divided sets of vertex into two sets  $S$  and  $V \setminus S$  where  $S$  contains the  $i$  nearest neighbors that have been find in first  $i$ th steps
  2.  $L(\omega) = \min\{L(\omega), L(u) + c(u, \omega)\}$  where  $u \in S, \omega \in V \setminus S$

# Dijkstra Algorithm Example

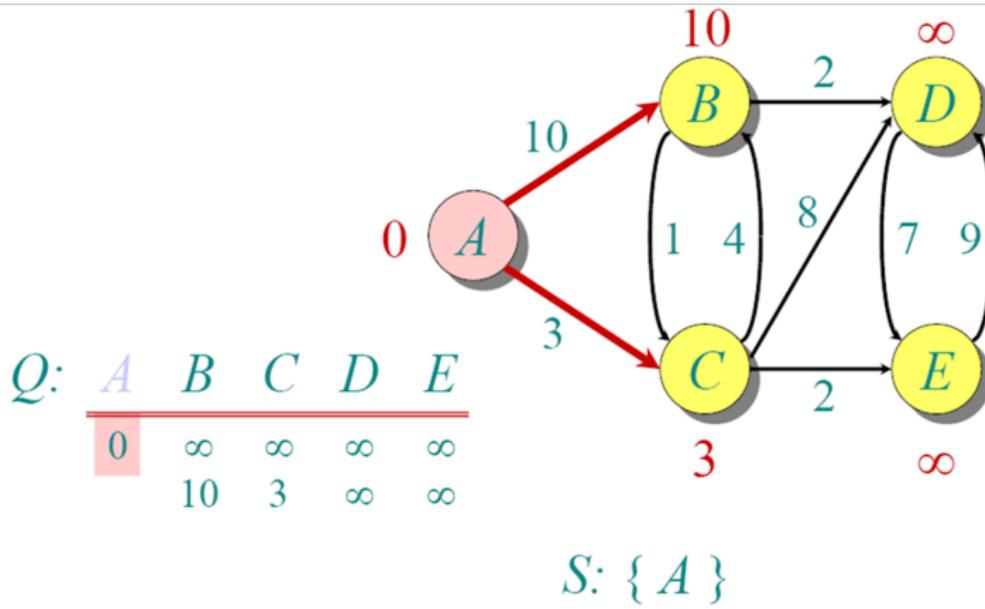
**Initialize:**

$$Q: \frac{A \quad B \quad C \quad D \quad E}{0 \quad \infty \quad \infty \quad \infty \quad \infty}$$

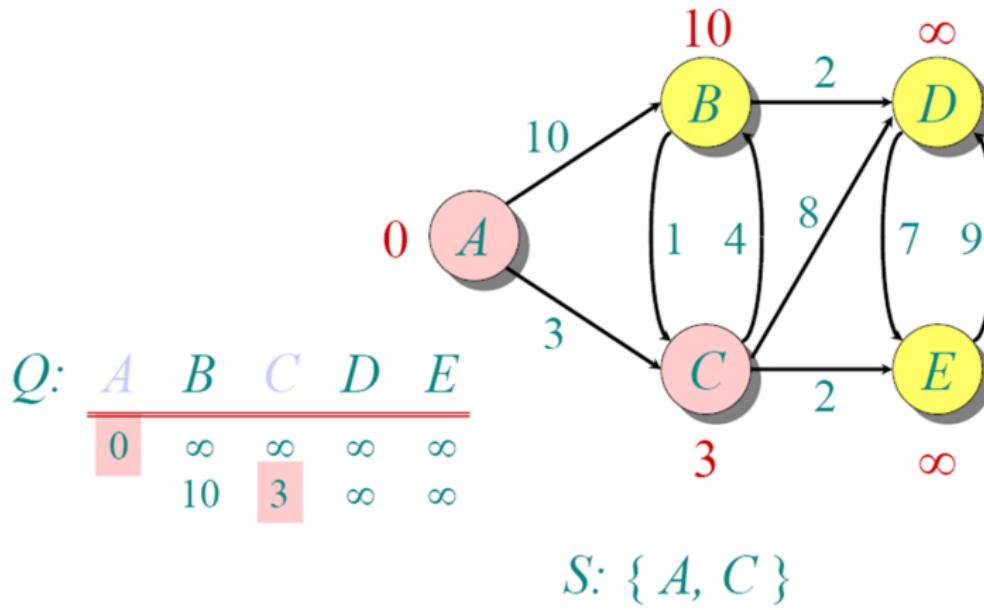


$$S: \{\}$$

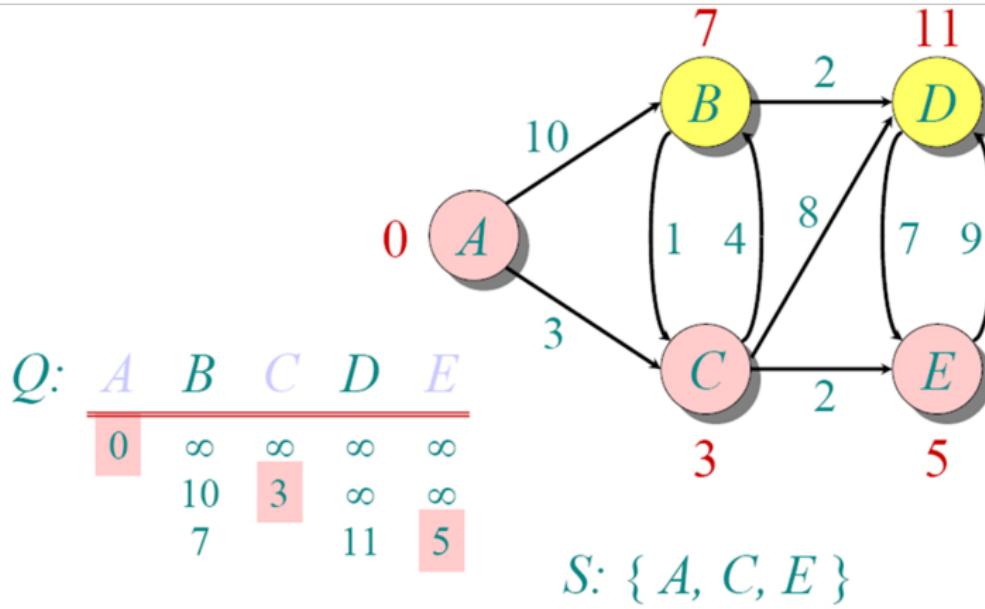
# Dijkstra Algorithm Example



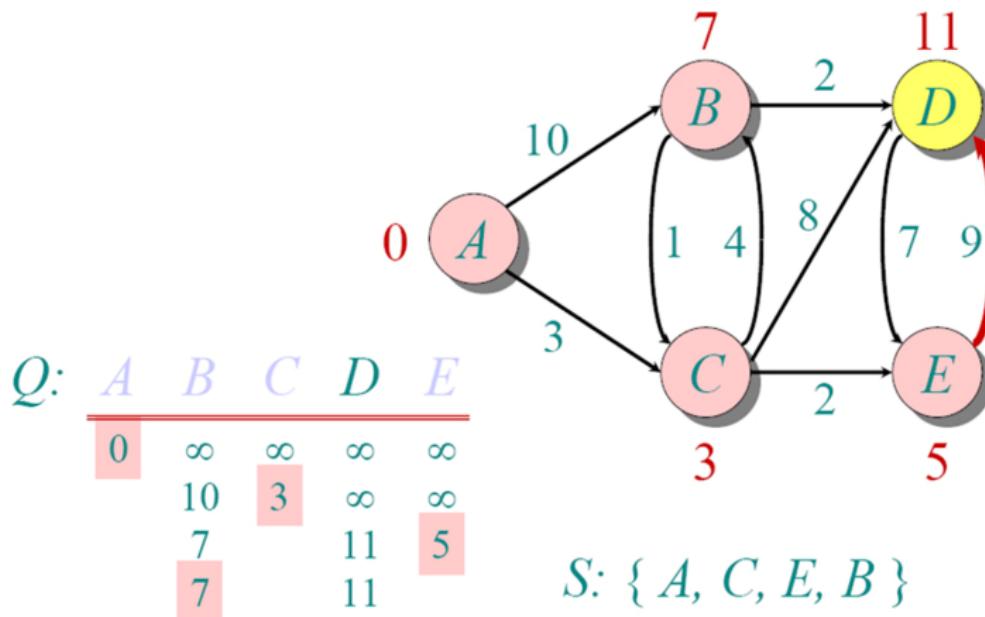
# Dijkstra Algorithm Example



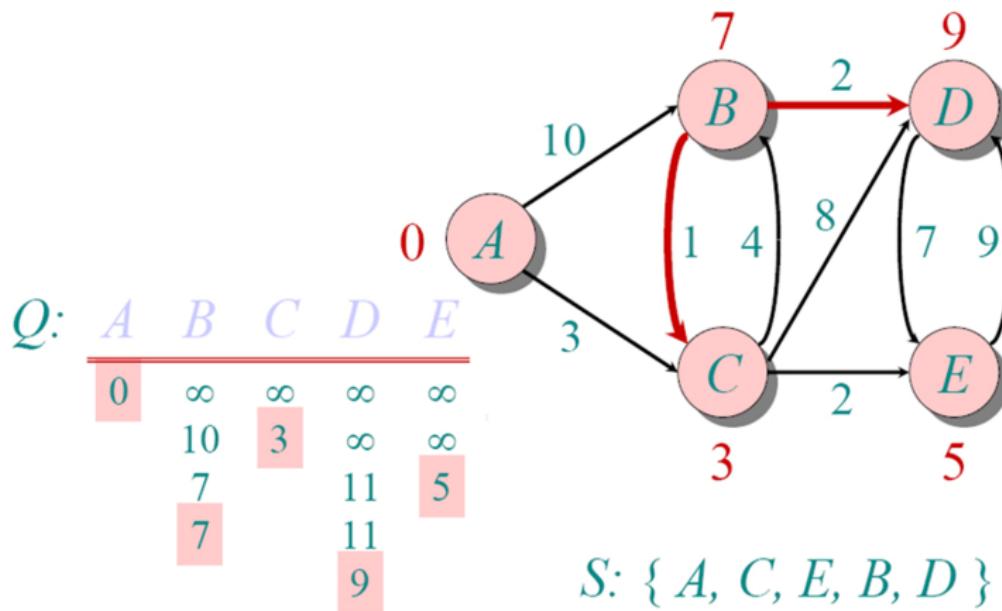
# Dijkstra Algorithm Example



# Dijkstra Algorithm Example



# Dijkstra Algorithm Example



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Construct neighborhood graph

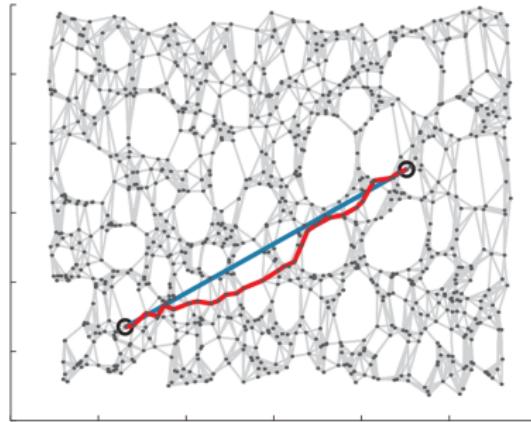
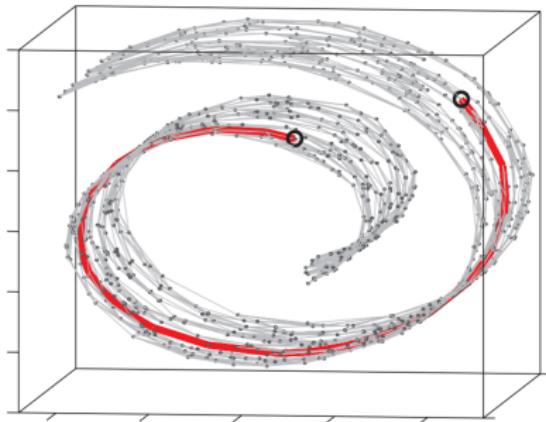
Compute graph distances

MDS with graph distances

## 3 Examples

## 4 Summary

# MDS with Graph Distance



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Swiss Roll Example

Real Data Example

## 4 Summary

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## 3 Examples

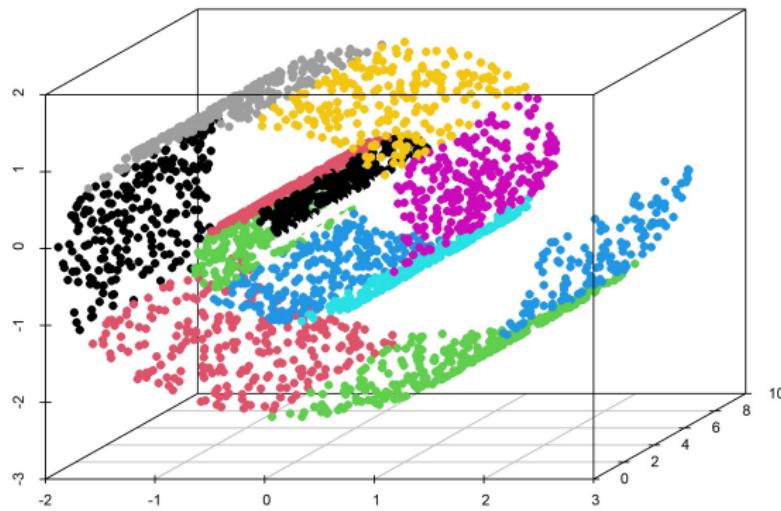
Swiss Roll Example

Real Data Example

## 4 Summary

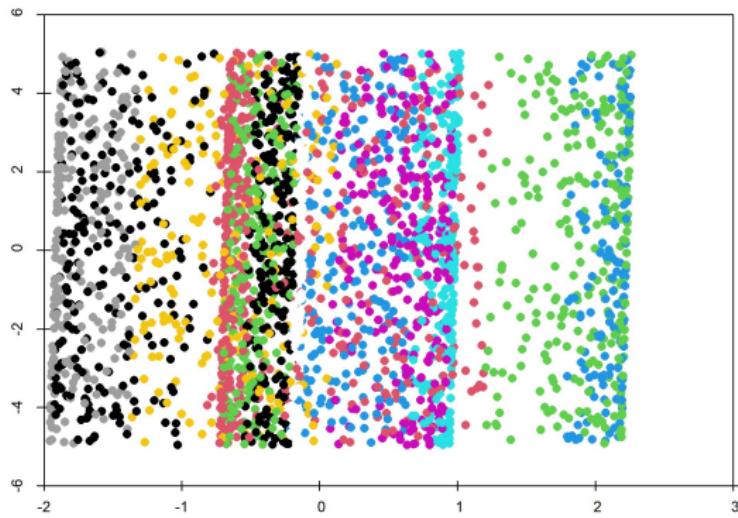
# Swiss Roll

$$(X_i, Y_i) \stackrel{iid}{\sim} U((0, 4\pi) \times (0, 4\pi)) \rightarrow \left( \frac{X_i}{5} \cos(X_i), \frac{X_i}{5} \sin(X_i), Y_i \right)$$



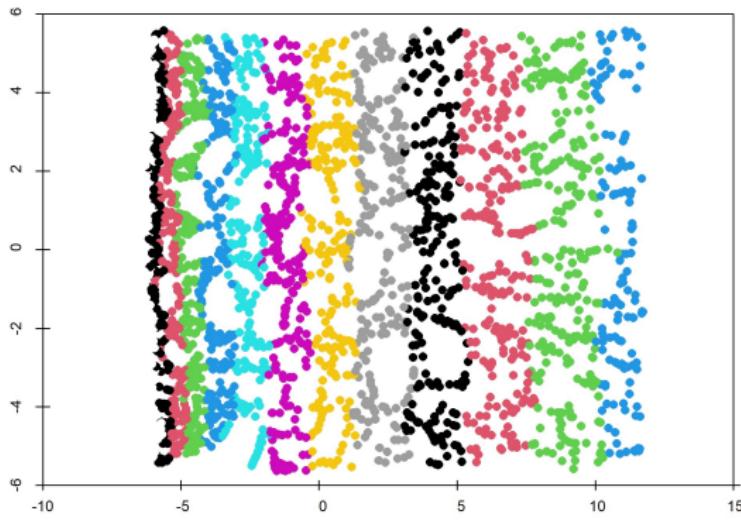
# MDS dimension reduction

```
D = dist(data, method = "euclidean")
mds = cmdscale(D, k=2, eig=T)
```



# Isomap dimension reduction

```
library(vegan)  
iso = isomap(D, ndim = 2, k = 5)
```



# Euclidean / Graph Distance Matrix

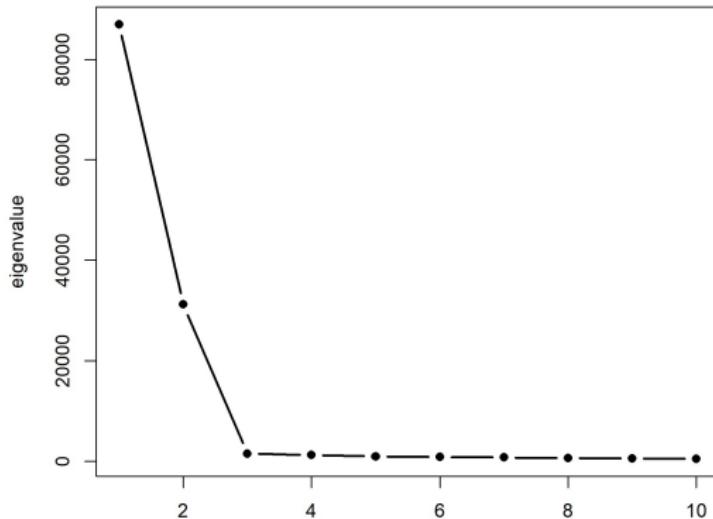
```
round(as.matrix(D) [1:6,1:6],2)
```

	1	2	3	4	5	6
1	0.00	7.80	7.21	3.82	3.11	5.87
2	7.80	0.00	1.02	4.05	10.29	2.66
3	7.21	1.02	0.00	3.47	9.60	2.75
4	3.82	4.05	3.47	0.00	6.52	2.45
5	3.11	10.29	9.60	6.52	0.00	8.70
6	5.87	2.66	2.75	2.45	8.70	0.00

```
graph.dist = isomapdist(D, k = 5)
round(as.matrix(graph.dist) [1:6,1:6],2)
```

	1	2	3	4	5	6
1	0.00	8.95	8.65	4.58	7.68	14.56
2	8.95	0.00	1.43	4.60	12.82	11.53
3	8.65	1.43	0.00	4.30	11.61	10.77
4	4.58	4.60	4.30	0.00	8.78	11.98
5	7.68	12.82	11.61	8.78	0.00	10.31
6	14.56	11.53	10.77	11.98	10.31	0.00

# Scree Plot



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Real Data Example

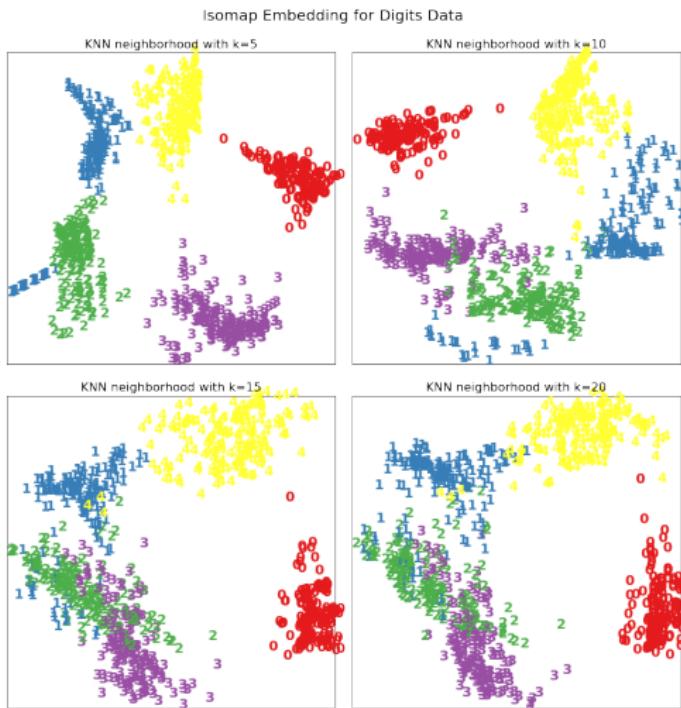
## 4 Summary

# Handwritten Digits

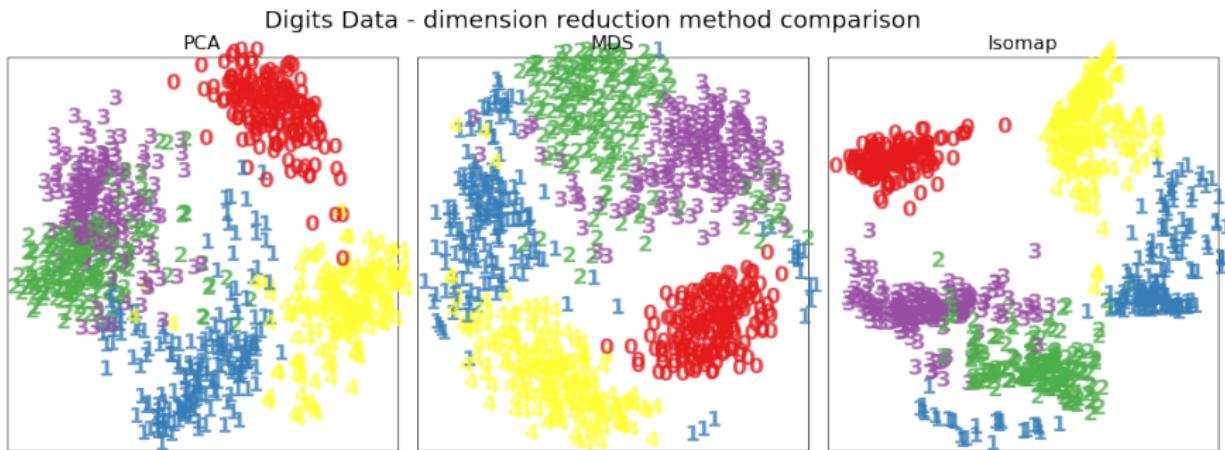
A selection from the 64-dimensional digits dataset



# Comparison of different number of neighbors



# Comparison with different Dimension Reduction Method



Compared to PCA and MDS, Isomap has done a good job in reducing dimensions from 64 to 2.

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# Conclusion

- Use graph distance to approximate geodesic distance.
- Apply MDS on the graph distance matrix.
- Deficiency : time consuming (Landmark ISOMAP)

# Questions

- How to obtain the graph distance matrix? (see 25/36)
- What is the difference between standard MDS and ISOMAP?  
(see 5/36)

# Reference

- Izenman, A. J. Modern multivariate statistical techniques. Regression, classification and manifold learning. (2008).
- J.B. Tenenbaum, V. de Silva and J. C. Langford. A global geometric framework for nonlinear dimensionality reduction. Science, vol. 290, pp. 2319—2323, 2000.

# Reference

- TD 1 - Dimensionality Reduction : <https://reurl.cc/M0NVR4>
- Scikit-Learn Manifold learning on handwritten digits :  
<https://scikit-learn.org/>
- Dijkstra's Algorithm by Laksman Veeravagu and Luis Barrera  
: <https://reurl.cc/j1G201>

*Thank You*