

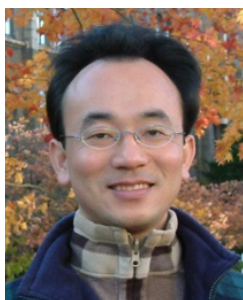
Big Data Mining 巨量資料探勘

分群分析 (Cluster Analysis)

1052DM05

MI4 (M2244) (3069)

Thu, 8, 9 (15:10-17:00) (B130)



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2017-03-16



課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
1	2017/02/16	巨量資料探勘課程介紹 (Course Orientation for Big Data Mining)
2	2017/02/23	巨量資料基礎：MapReduce典範、Hadoop與Spark生態系統 (Fundamental Big Data: MapReduce Paradigm, Hadoop and Spark Ecosystem)
3	2017/03/02	關連分析 (Association Analysis)
4	2017/03/09	分類與預測 (Classification and Prediction)
5	2017/03/16	分群分析 (Cluster Analysis)
6	2017/03/23	個案分析與實作一 (SAS EM 分群分析)： Case Study 1 (Cluster Analysis – K-Means using SAS EM)
7	2017/03/30	個案分析與實作二 (SAS EM 關連分析)： Case Study 2 (Association Analysis using SAS EM)

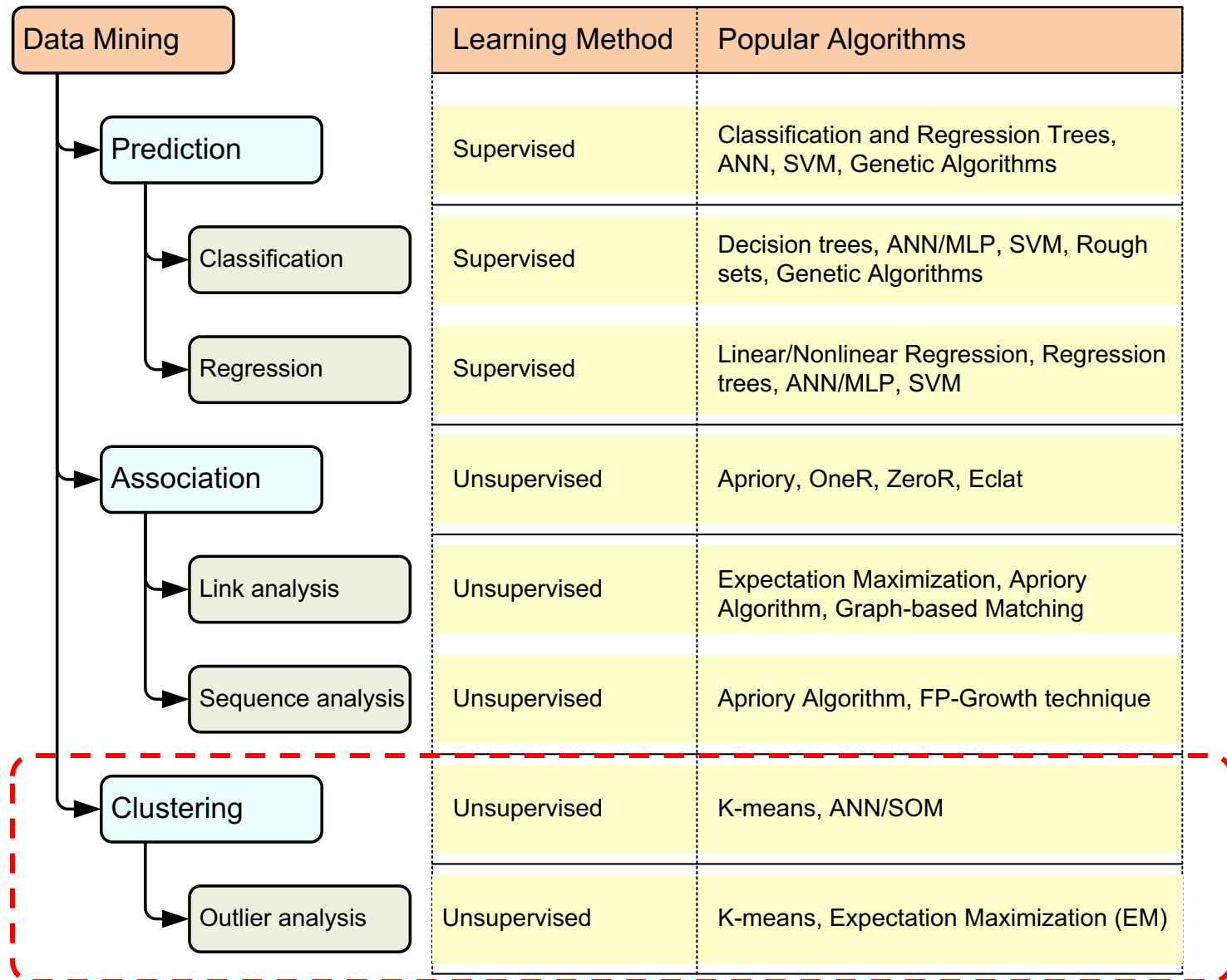
課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
8	2017/04/06	教學行政觀摩日 (Off-campus study)
9	2017/04/13	期中報告 (Midterm Project Presentation)
10	2017/04/20	期中考試週 (Midterm Exam)
11	2017/04/27	個案分析與實作三 (SAS EM 決策樹、模型評估) : Case Study 3 (Decision Tree, Model Evaluation using SAS EM)
12	2017/05/04	個案分析與實作四 (SAS EM 迴歸分析、類神經網路) : Case Study 4 (Regression Analysis, Artificial Neural Network using SAS EM)
13	2017/05/11	Google TensorFlow 深度學習 (Deep Learning with Google TensorFlow)
14	2017/05/18	期末報告 (Final Project Presentation)
15	2017/05/25	畢業班考試 (Final Exam)

Outline

- Cluster Analysis
- *K-Means Clustering*

A Taxonomy for Data Mining Tasks



Example of Cluster Analysis

Point	P	P(x,y)
p01	a	(3, 4)
p02	b	(3, 6)
p03	c	(3, 8)
p04	d	(4, 5)
p05	e	(4, 7)
p06	f	(5, 1)
p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

K-Means Clustering

Point	P	P(x,y)	m1 distance	m2 distance	Cluster
p01	a	(3, 4)	1.95	3.78	Cluster1
p02	b	(3, 6)	0.69	4.51	Cluster1
p03	c	(3, 8)	2.27	5.86	Cluster1
p04	d	(4, 5)	0.89	3.13	Cluster1
p05	e	(4, 7)	1.22	4.45	Cluster1
p06	f	(5, 1)	5.01	3.05	Cluster2
p07	g	(5, 5)	1.57	2.30	Cluster1
p08	h	(7, 3)	4.37	0.56	Cluster2
p09	i	(7, 5)	3.43	1.52	Cluster2
p10	j	(8, 5)	4.41	1.95	Cluster2

m1 (3.67, 5.83)

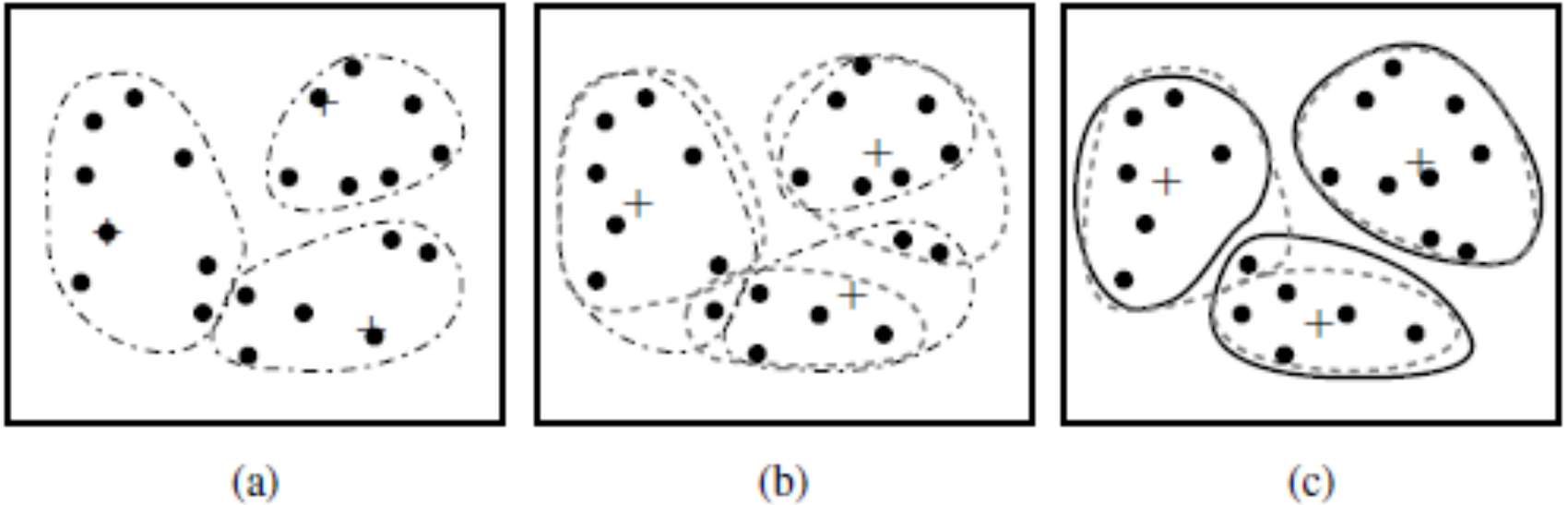
m2 (6.75, 3.50)

Cluster Analysis

Cluster Analysis

- Used for automatic identification of **natural groupings** of things
- Part of the machine-learning family
- Employ **unsupervised learning**
- Learns the clusters of things from past data, then assigns new instances
- There is not an output variable
- Also known as **segmentation**

Cluster Analysis

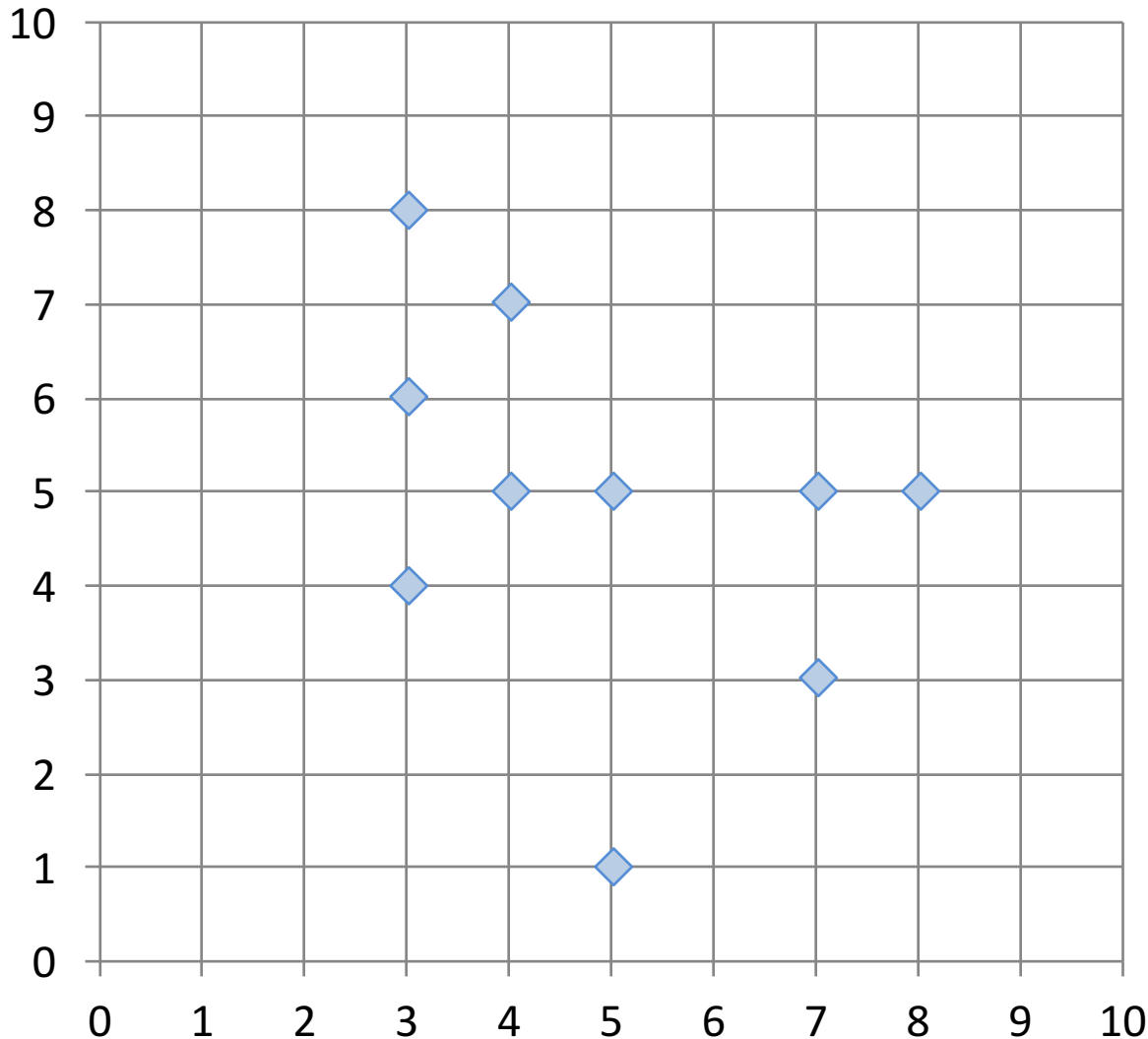


Clustering of a set of objects based on the *k-means method*.
(The mean of each cluster is marked by a “+”.)

Cluster Analysis

- Clustering results may be used to
 - Identify natural **groupings of customers**
 - Identify rules for assigning new cases to classes for targeting/diagnostic purposes
 - Provide characterization, definition, labeling of populations
 - Decrease the size and complexity of problems for other data mining methods
 - Identify **outliers** in a specific domain (e.g., rare-event detection)

Example of Cluster Analysis



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p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

Cluster Analysis for Data Mining

- Analysis methods
 - **Statistical methods**
(including both hierarchical and nonhierarchical),
such as *k-means*, *k-modes*, and so on
 - **Neural networks**
(adaptive resonance theory [**ART**],
self-organizing map [**SOM**])
 - **Fuzzy logic** (e.g., fuzzy c-means algorithm)
 - **Genetic algorithms**
- Divisive versus Agglomerative methods

Cluster Analysis for Data Mining

- **How many clusters?**
 - There is not a “truly optimal” way to calculate it
 - Heuristics are often used
 1. Look at the sparseness of clusters
 2. **Number of clusters = $(n/2)^{1/2}$** (n: no of data points)
 3. Use Akaike information criterion (AIC)
 4. Use Bayesian information criterion (BIC)
- Most cluster analysis methods involve the use of a **distance measure** to calculate the closeness between pairs of items
 - **Euclidian** versus **Manhattan** (rectilinear) **distance**

***k*-Means Clustering Algorithm**

- k : pre-determined number of clusters
- Algorithm (**Step 0**: determine value of k)

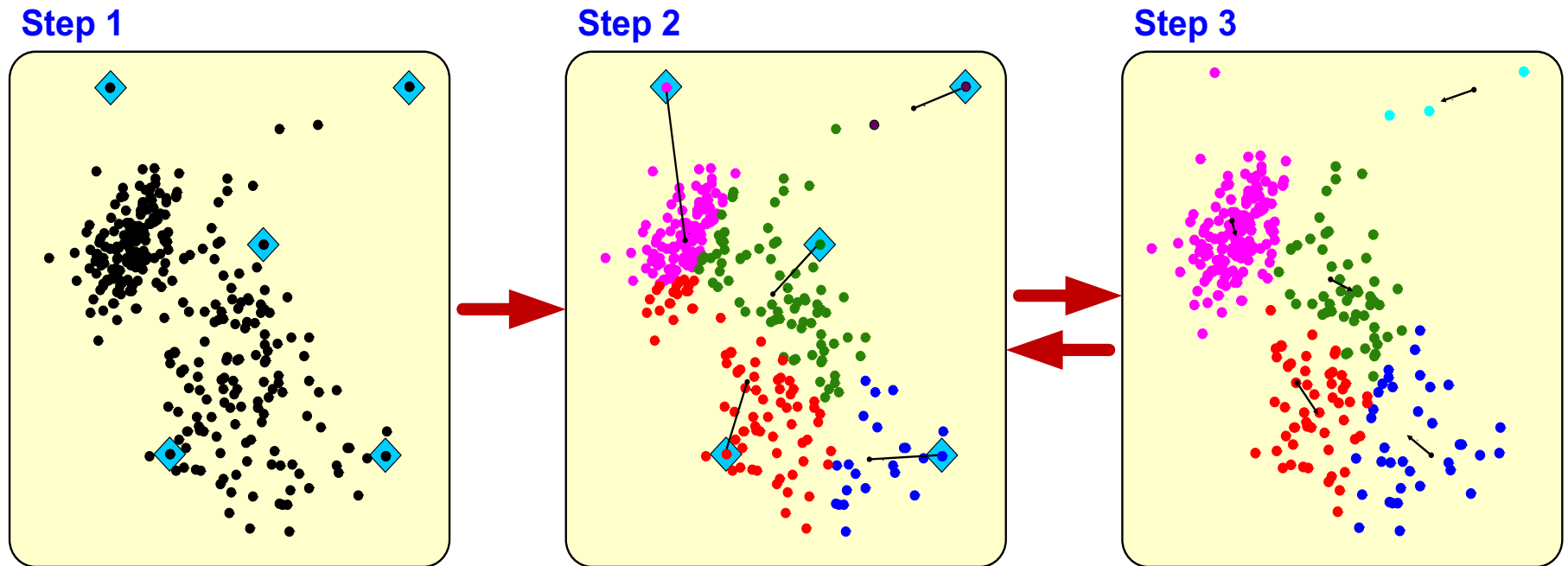
Step 1: Randomly generate k random points as initial cluster centers

Step 2: Assign each point to the nearest cluster center

Step 3: Re-compute the new cluster centers

Repetition step: Repeat steps 2 and 3 until some convergence criterion is met (usually that the assignment of points to clusters becomes stable)

Cluster Analysis for Data Mining - *k*-Means Clustering Algorithm



Similarity

Distance

Similarity and Dissimilarity Between Objects

- Distances are normally used to measure the similarity or dissimilarity between two data objects
- Some popular ones include: *Minkowski distance*:

$$d(i, j) = \sqrt[q]{(|x_{i1} - x_{j1}|^q + |x_{i2} - x_{j2}|^q + \dots + |x_{ip} - x_{jp}|^q)}$$

where $i = (x_{i1}, x_{i2}, \dots, x_{ip})$ and $j = (x_{j1}, x_{j2}, \dots, x_{jp})$ are two p -dimensional data objects, and q is a positive integer

- If $q = 1$, d is **Manhattan distance**

$$d(i, j) = |x_{i1} - x_{j1}| + |x_{i2} - x_{j2}| + \dots + |x_{ip} - x_{jp}|$$

Similarity and Dissimilarity Between Objects (Cont.)

- If $q = 2$, d is **Euclidean distance**:

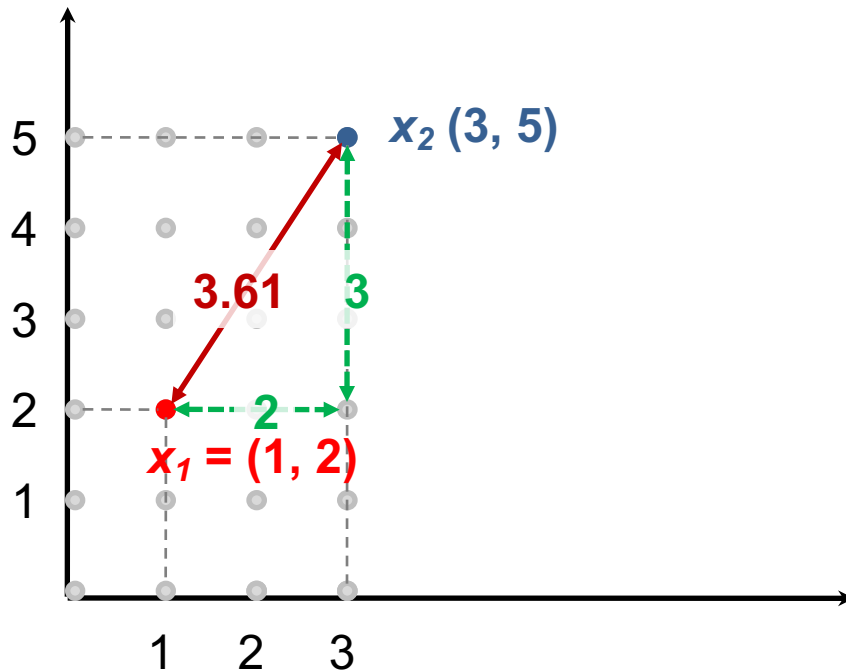
$$d(i,j) = \sqrt{(|x_{i_1} - x_{j_1}|^2 + |x_{i_2} - x_{j_2}|^2 + \dots + |x_{i_p} - x_{j_p}|^2)}$$

– Properties

- $d(i,j) \geq 0$
 - $d(i,i) = 0$
 - $d(i,j) = d(j,i)$
 - $d(i,j) \leq d(i,k) + d(k,j)$
- Also, one can use weighted distance, parametric Pearson product moment correlation, or other dissimilarity measures

Euclidean distance vs Manhattan distance

- Distance of two point $x_1 = (1, 2)$ and $x_2 (3, 5)$



Euclidean distance:

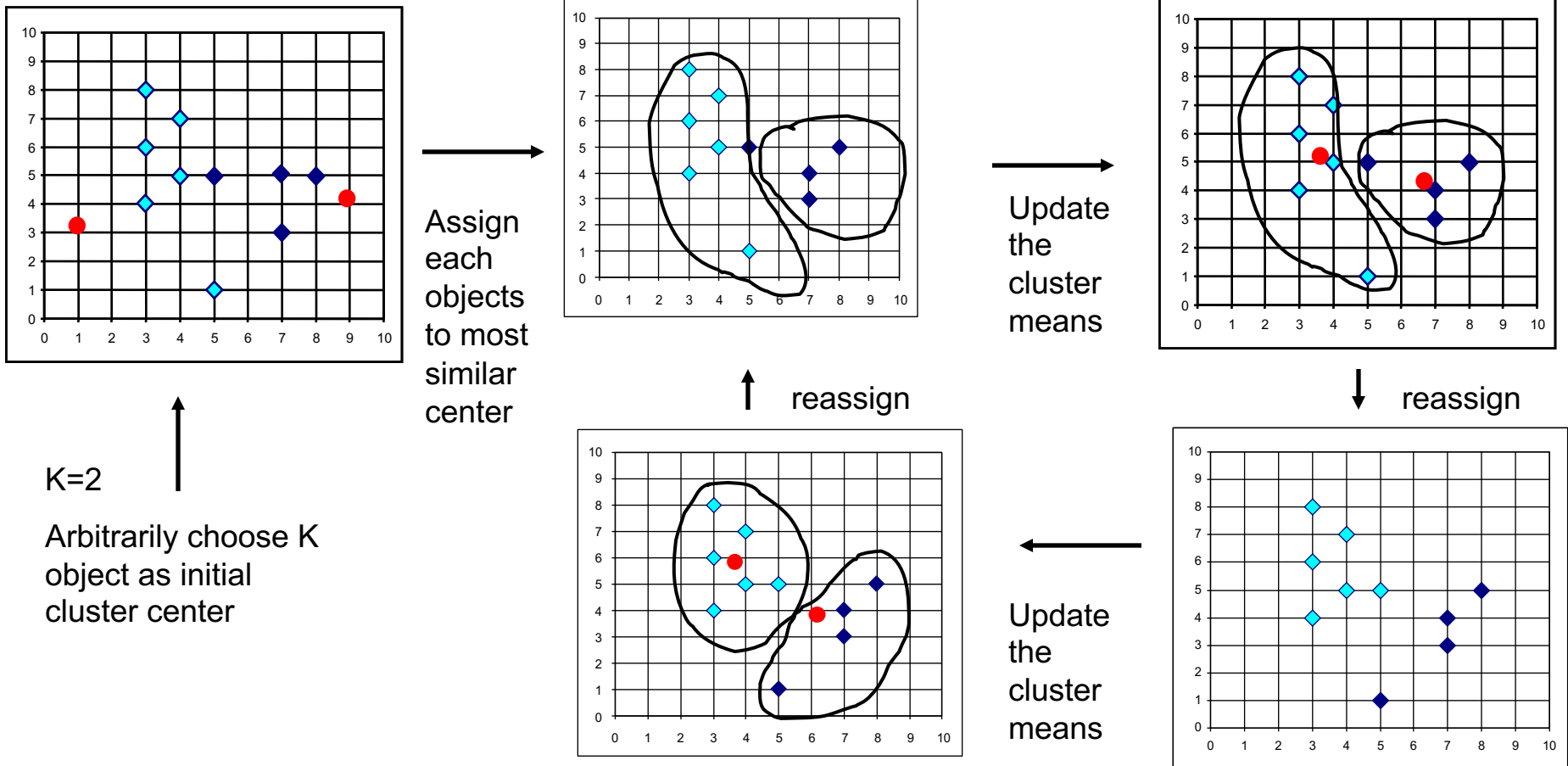
$$\begin{aligned} &= ((3-1)^2 + (5-2)^2)^{1/2} \\ &= (2^2 + 3^2)^{1/2} \\ &= (4 + 9)^{1/2} \\ &= (13)^{1/2} \\ &= 3.61 \end{aligned}$$

Manhattan distance:

$$\begin{aligned} &= (3-1) + (5-2) \\ &= 2 + 3 \\ &= 5 \end{aligned}$$

The *K-Means* Clustering Method

- Example



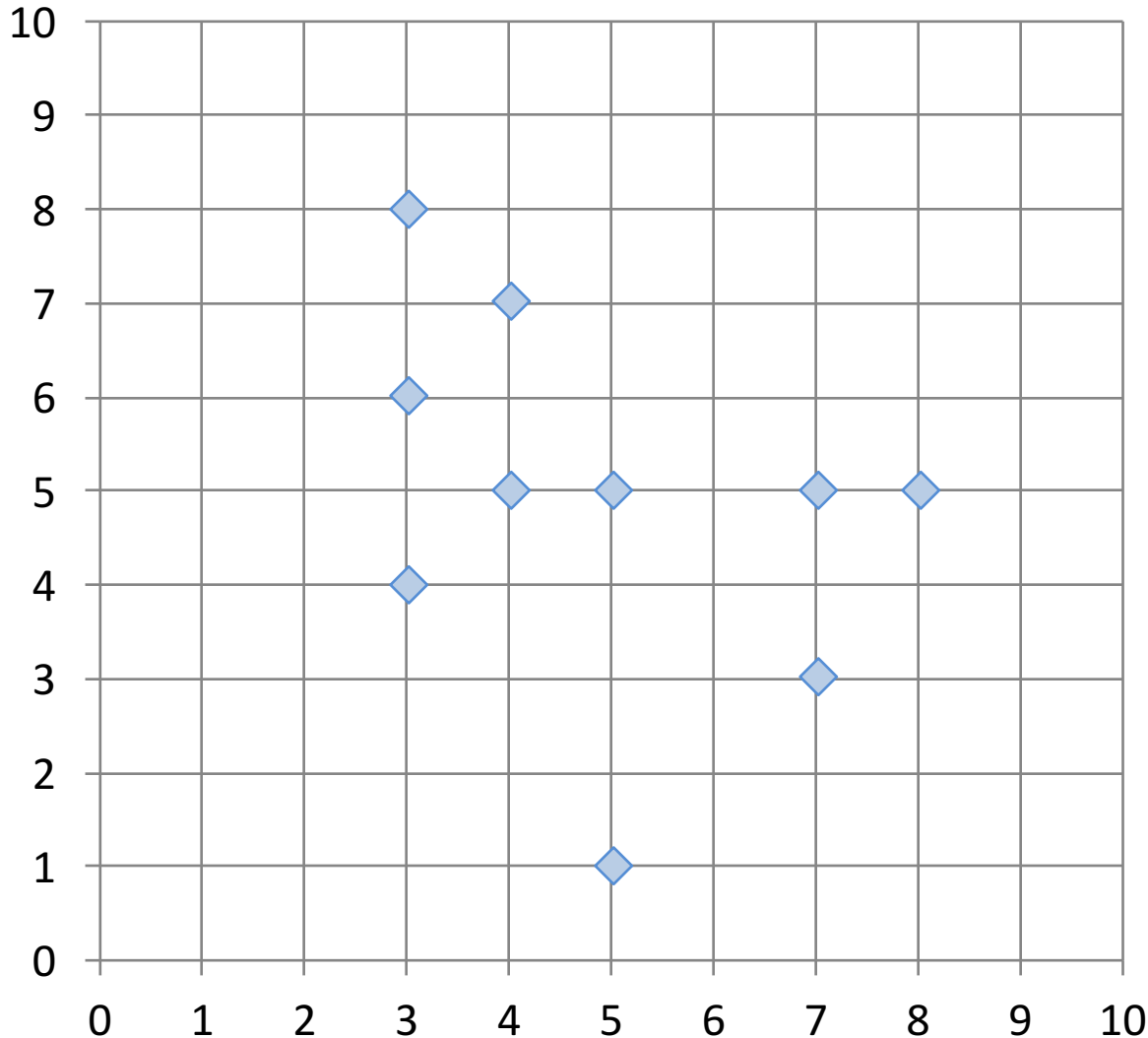
K-Means Clustering

Example of Cluster Analysis

Point	P	P(x,y)
p01	a	(3, 4)
p02	b	(3, 6)
p03	c	(3, 8)
p04	d	(4, 5)
p05	e	(4, 7)
p06	f	(5, 1)
p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

K-Means Clustering

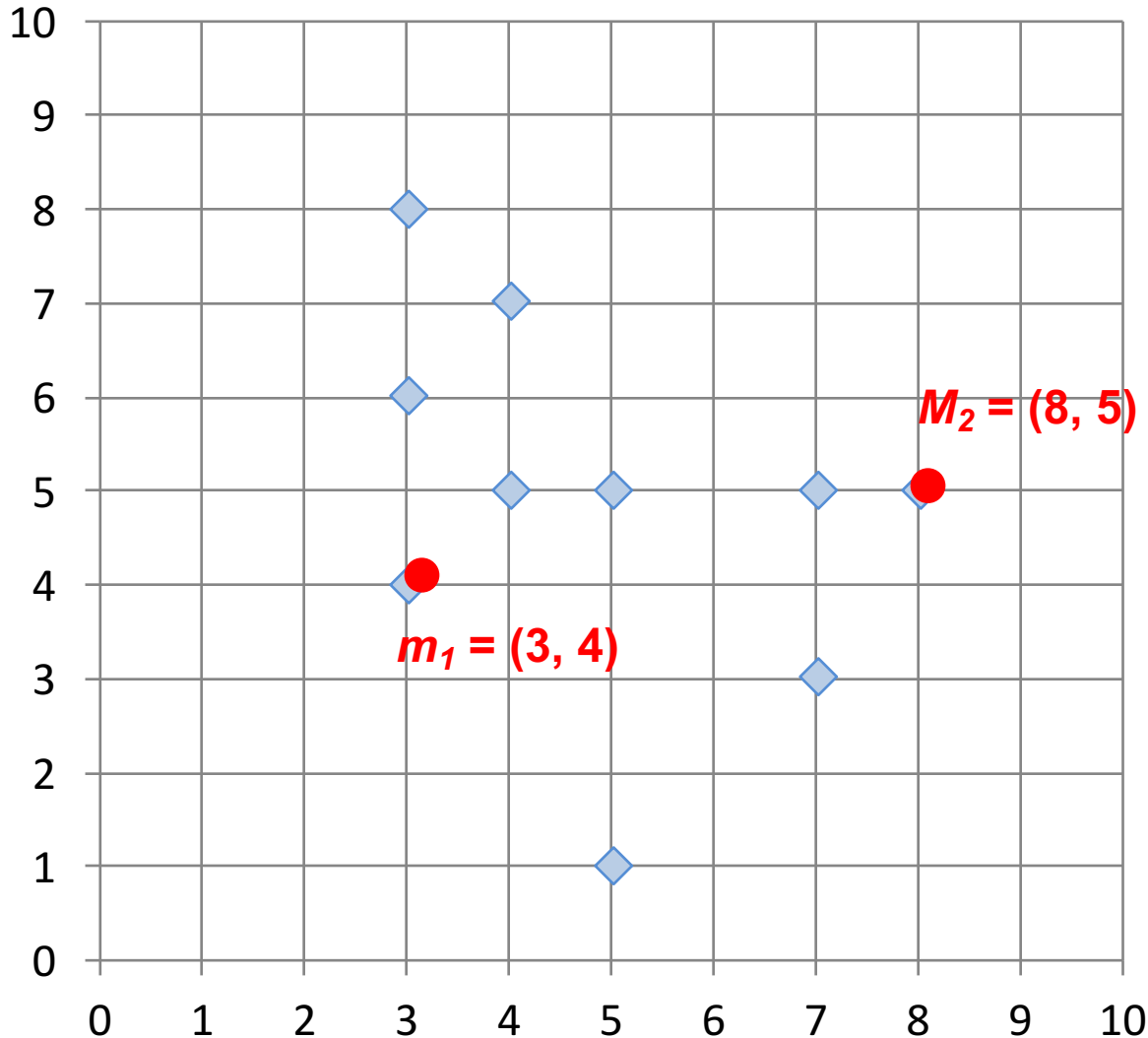
Step by Step



Point	P	P(x,y)
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p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

K-Means Clustering

Step 1: K=2, Arbitrarily choose K object as initial cluster center

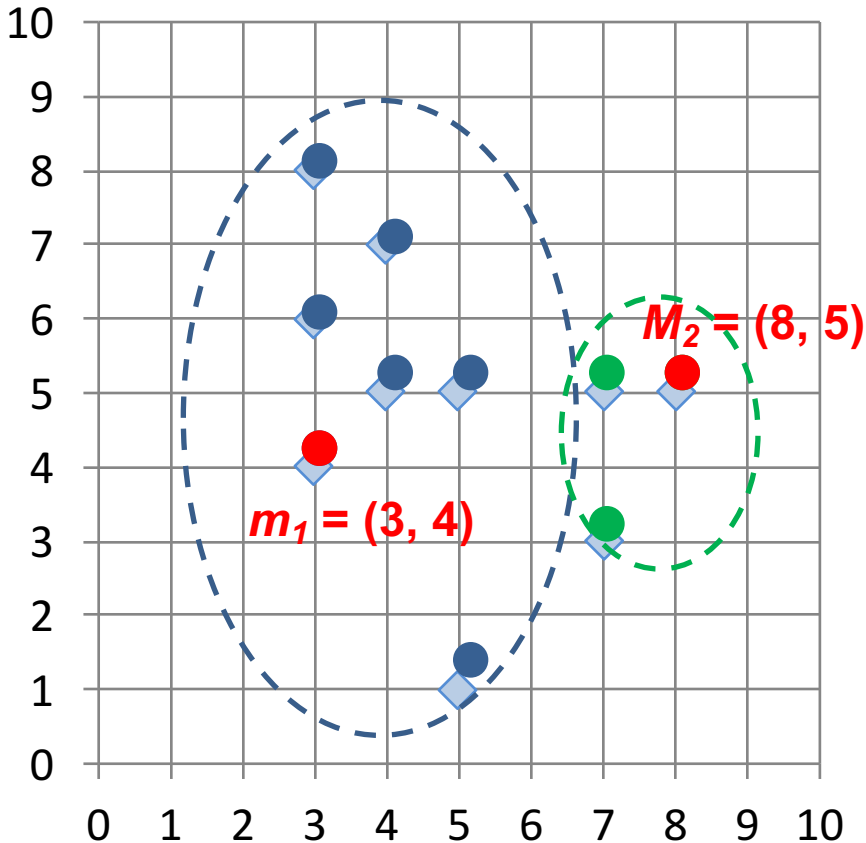


Point	P	P(x,y)
p01	a	(3, 4)
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p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

Initial m_1 (3, 4)
Initial m_2 (8, 5)

Step 2: Compute seed points as the centroids of the clusters of the current partition

Step 3: Assign each objects to most similar center



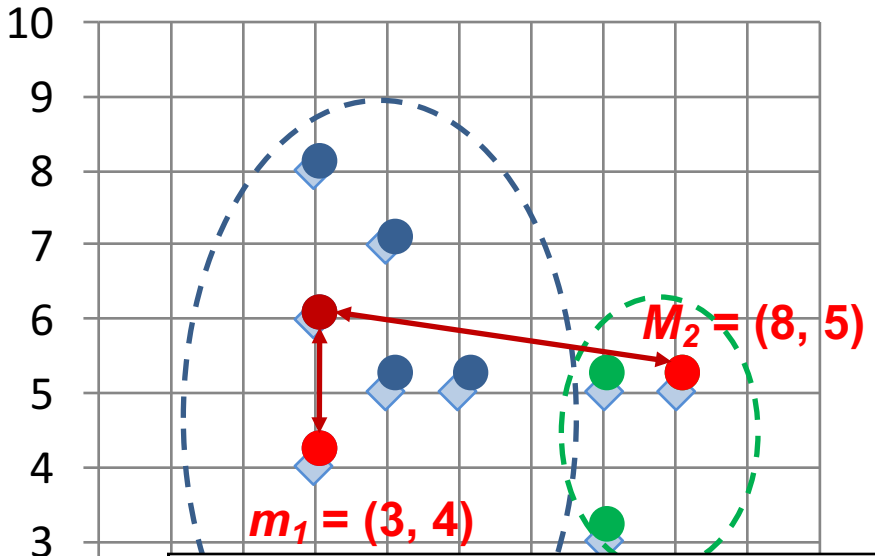
Point	P	P(x,y)	m1 distance	m2 distance	Cluster
p01	a	(3, 4)	0.00	5.10	Cluster1
p02	b	(3, 6)	2.00	5.10	Cluster1
p03	c	(3, 8)	4.00	5.83	Cluster1
p04	d	(4, 5)	1.41	4.00	Cluster1
p05	e	(4, 7)	3.16	4.47	Cluster1
p06	f	(5, 1)	3.61	5.00	Cluster1
p07	g	(5, 5)	2.24	3.00	Cluster1
p08	h	(7, 3)	4.12	2.24	Cluster2
p09	i	(7, 5)	4.12	1.00	Cluster2
p10	j	(8, 5)	5.10	0.00	Cluster2

Initial m1 (3, 4)
Initial m2 (8, 5)

K-Means Clustering

Step 2: Compute seed points as the centroids of the clusters of the current partition

Step 3: Assign each objects to most similar center



Point	P	P(x,y)	m1 distance	m2 distance	Cluster
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p03	c	(3, 8)	4.00	5.83	Cluster1
p04	d	(4, 5)	1.41	4.00	Cluster1

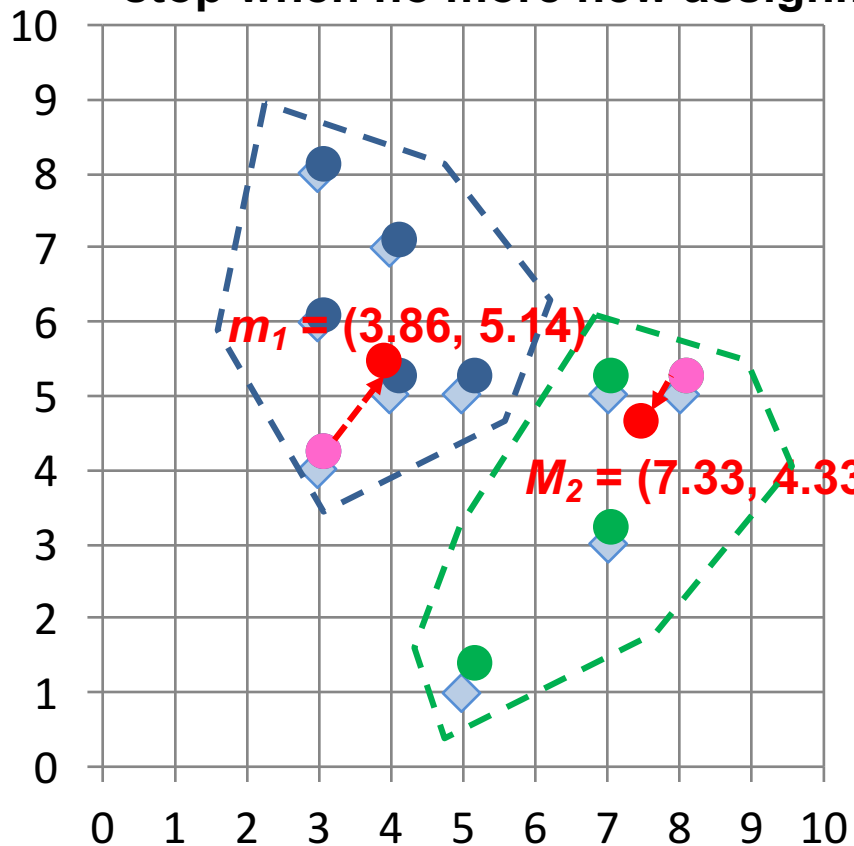
K-1

Euclidean distance
 $b(3,6) \leftrightarrow m1(3,4)$
 $= ((3-3)^2 + (4-6)^2)^{1/2}$
 $= (0^2 + (-2)^2)^{1/2}$
 $= (0 + 4)^{1/2}$
 $= (4)^{1/2}$
 $= 2.00$

Euclidean distance
 $b(3,6) \leftrightarrow m2(8,5)$
 $= ((8-3)^2 + (5-6)^2)^{1/2}$
 $= (5^2 + (-1)^2)^{1/2}$
 $= (25 + 1)^{1/2}$
 $= (26)^{1/2}$
 $= 5.10$

Initial m1 (3, 4)
 Initial m2 (8, 5)

**Step 4: Update the cluster means,
Repeat Step 2, 3,
stop when no more new assignment**



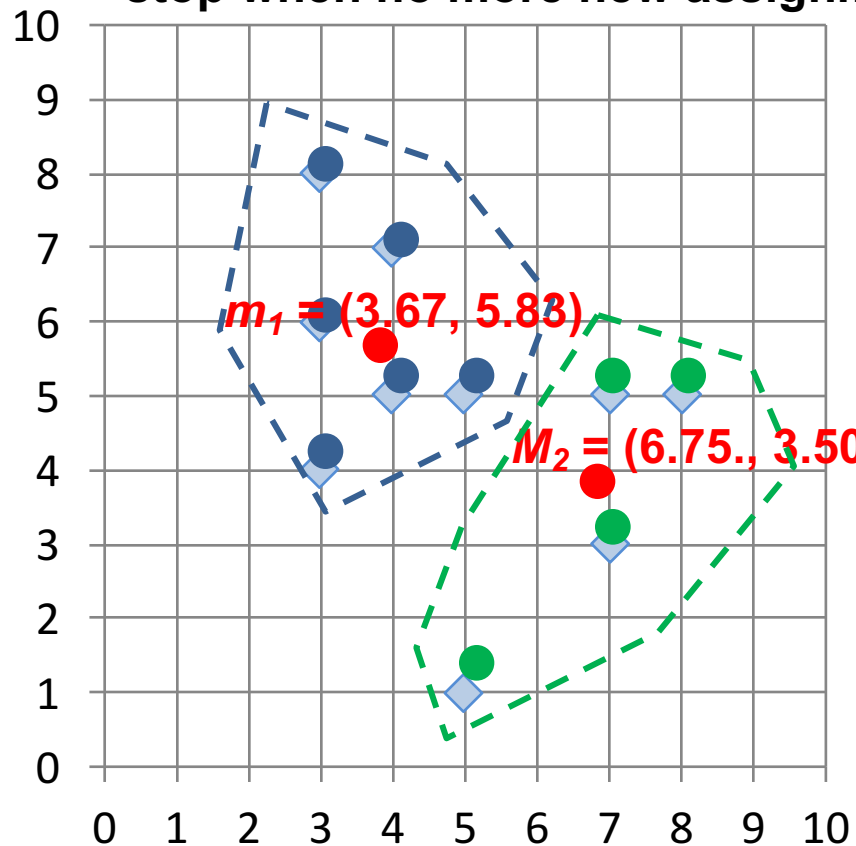
Point	P	P(x,y)	m1 distance	m2 distance	Cluster
p01	a	(3, 4)	1.43	4.34	Cluster1
p02	b	(3, 6)	1.22	4.64	Cluster1
p03	c	(3, 8)	2.99	5.68	Cluster1
p04	d	(4, 5)	0.20	3.40	Cluster1
p05	e	(4, 7)	1.87	4.27	Cluster1
p06	f	(5, 1)	4.29	4.06	Cluster2
p07	g	(5, 5)	1.15	2.42	Cluster1
p08	h	(7, 3)	3.80	1.37	Cluster2
p09	i	(7, 5)	3.14	0.75	Cluster2
p10	j	(8, 5)	4.14	0.95	Cluster2

m1 (3.86, 5.14)

m2 (7.33, 4.33)

K-Means Clustering

**Step 4: Update the cluster means,
Repeat Step 2, 3,
stop when no more new assignment**



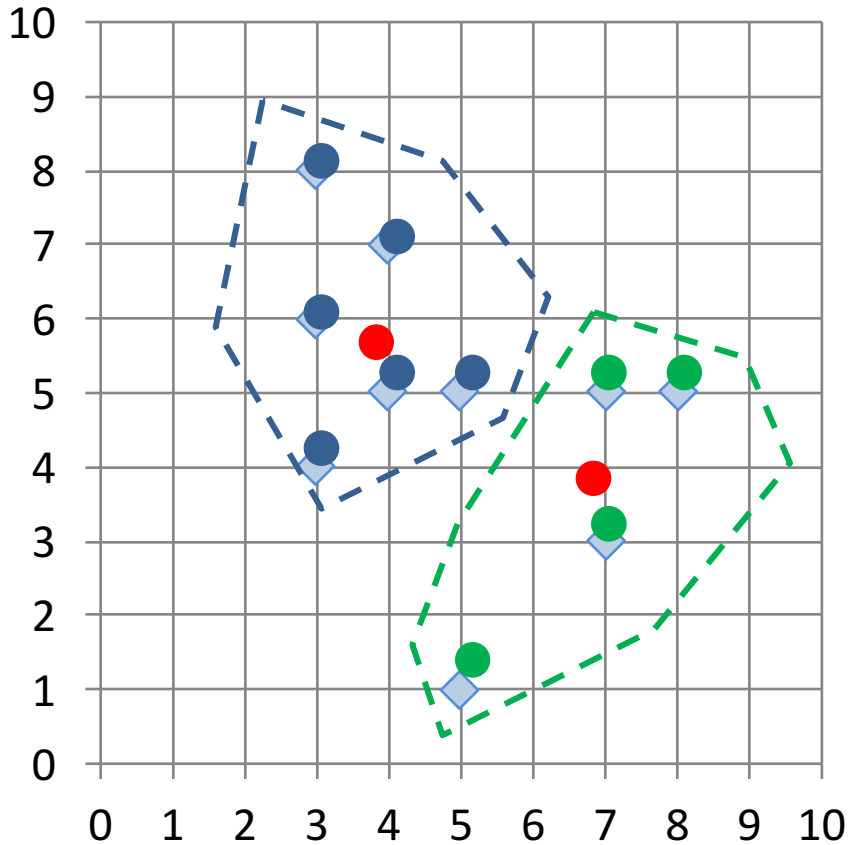
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p05	e	(4, 7)	1.22	4.45	Cluster1
p06	f	(5, 1)	5.01	3.05	Cluster2
p07	g	(5, 5)	1.57	2.30	Cluster1
p08	h	(7, 3)	4.37	0.56	Cluster2
p09	i	(7, 5)	3.43	1.52	Cluster2
p10	j	(8, 5)	4.41	1.95	Cluster2

m1 (3.67, 5.83)

m2 (6.75, 3.50)

***K-Means* Clustering**

stop when no more new assignment



Point	P	P(x,y)	m1 distance	m2 distance	Cluster
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p10	j	(8, 5)	4.41	1.95	Cluster2

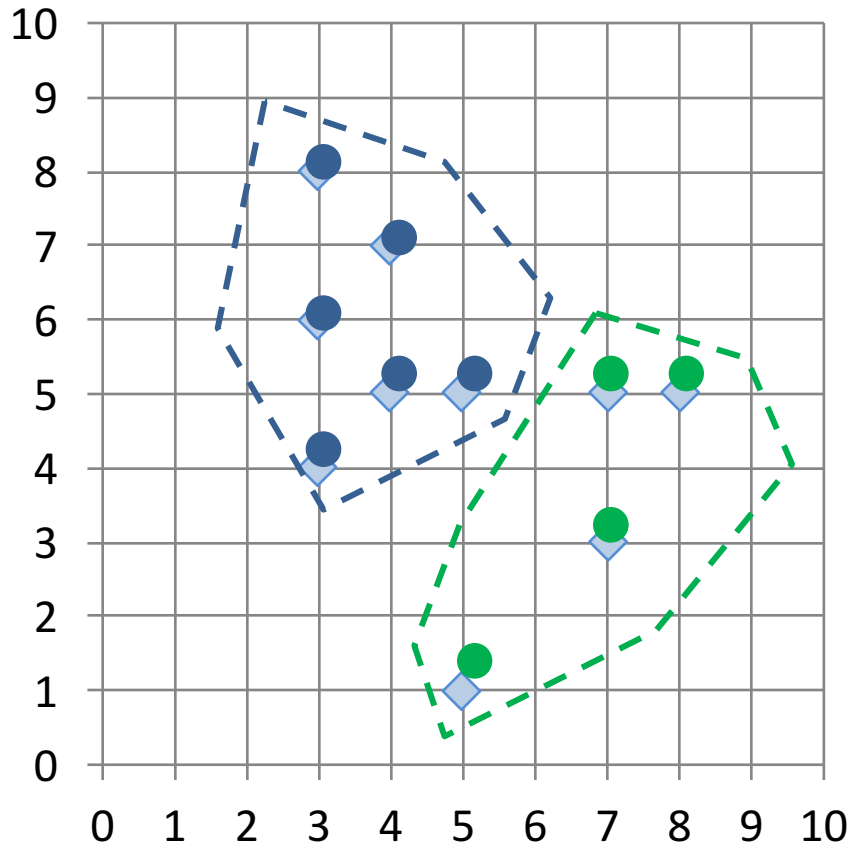
m1 (3.67, 5.83)

m2 (6.75, 3.50)

K-Means Clustering

K-Means Clustering ($K=2$, two clusters)

stop when no more new assignment



Point	P	P(x,y)	m1 distance	m2 distance	Cluster
p01	a	(3, 4)	1.95	3.78	Cluster1
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K-Means Clustering

m1 (3.67, 5.83)

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K-Means Clustering

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p10	j	(8, 5)	4.41	1.95	Cluster2

m1 (3.67, 5.83)

m2 (6.75, 3.50)

Summary

- Cluster Analysis
- *K-Means Clustering*

References

- Jiawei Han and Micheline Kamber, Data Mining: Concepts and Techniques, Second Edition, Elsevier, 2006.
- Jiawei Han, Micheline Kamber and Jian Pei, Data Mining: Concepts and Techniques, Third Edition, Morgan Kaufmann 2011.
- Efraim Turban, Ramesh Sharda, Dursun Delen, Decision Support and Business Intelligence Systems, Ninth Edition, Pearson, 2011.