Tamkang University
淡江大學

Big Data Mining
巨量資料探勘

分群分析
(Cluster Analysis)

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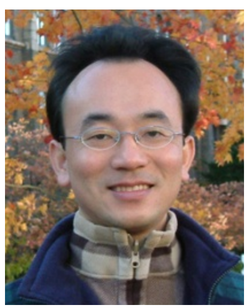

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2020-03-17

Tamkang
University

課程大綱 (Syllabus)

週次 (Week) 日期 (Date) 內容(Subject/Topics)

1 2020/03/03 巨量資料探勘課程介紹
(Course Orientation for Big Data Mining)

2 2020/03/10 AI人工智慧與大數據分析
(Artificial Intelligence and Big Data Analytics)

3 2020/03/17 分群分析 (Cluster Analysis)

4 2020/03/24 個案分析與實作一 (SAS EM 分群分析)：
Case Study 1 (Cluster Analysis - K-Means using SAS EM)

5 2020/03/31 關連分析 (Association Analysis)

6 2020/04/07 個案分析與實作二 (SAS EM 關連分析)：
Case Study 2 (Association Analysis using SAS EM)

7 2020/04/14 分類與預測 (Classification and Prediction)

8 2020/04/21 期中報告 (Midterm Project Presentation)

課程大綱 (Syllabus)

週次 (Week) 日期 (Date) 內容(Subject/Topics)

9 2020/04/28 期中考試週

10 2020/05/05 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)

11 2020/05/12 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)

12 2020/05/19 機器學習與深度學習
(Machine Learning and Deep Learning)

13 2020/05/26 期末報告 (Final Project Presentation)

14 2020/06/02 畢業考試週

15 2020/06/09 教師彈性補充教學

Outline

- Cluster Analysis
- *K-Means* Clustering

Data Mining Tasks & Methods

Data Mining Tasks & Methods	Data Mining Algorithms	Learning Type
Prediction		
Classification	Decision Trees, Neural Networks, Support Vector Machines, kNN, Naïve Bayes, GA	Supervised
Regression	Linear/Nonlinear Regression, ANN, Regression Trees, SVM, kNN, GA	Supervised
Time series	Autoregressive Methods, Averaging Methods, Exponential Smoothing, ARIMA	Supervised
Association		
Market-basket	Apriori, OneR, ZeroR, Eclat, GA	Unsupervised
Link analysis	Expectation Maximization, Apriori Algorithm, Graph-Based Matching	Unsupervised
Sequence analysis	Apriori Algorithm, FP-Growth, Graph-Based Matching	Unsupervised
Segmentation		
Clustering	*k*-means, Expectation Maximization (EM)	Unsupervised
Outlier analysis	*k*-means, Expectation Maximization (EM)	Unsupervised

Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

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
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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)

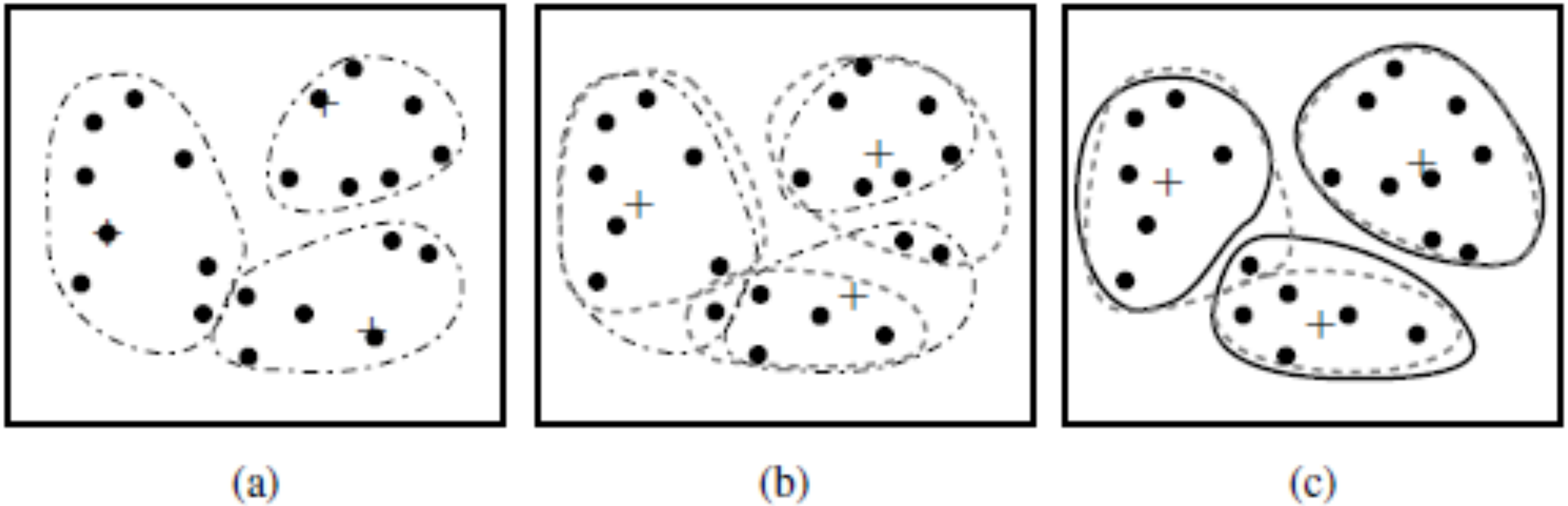
Cluster Analysis

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

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

Cluster Analysis



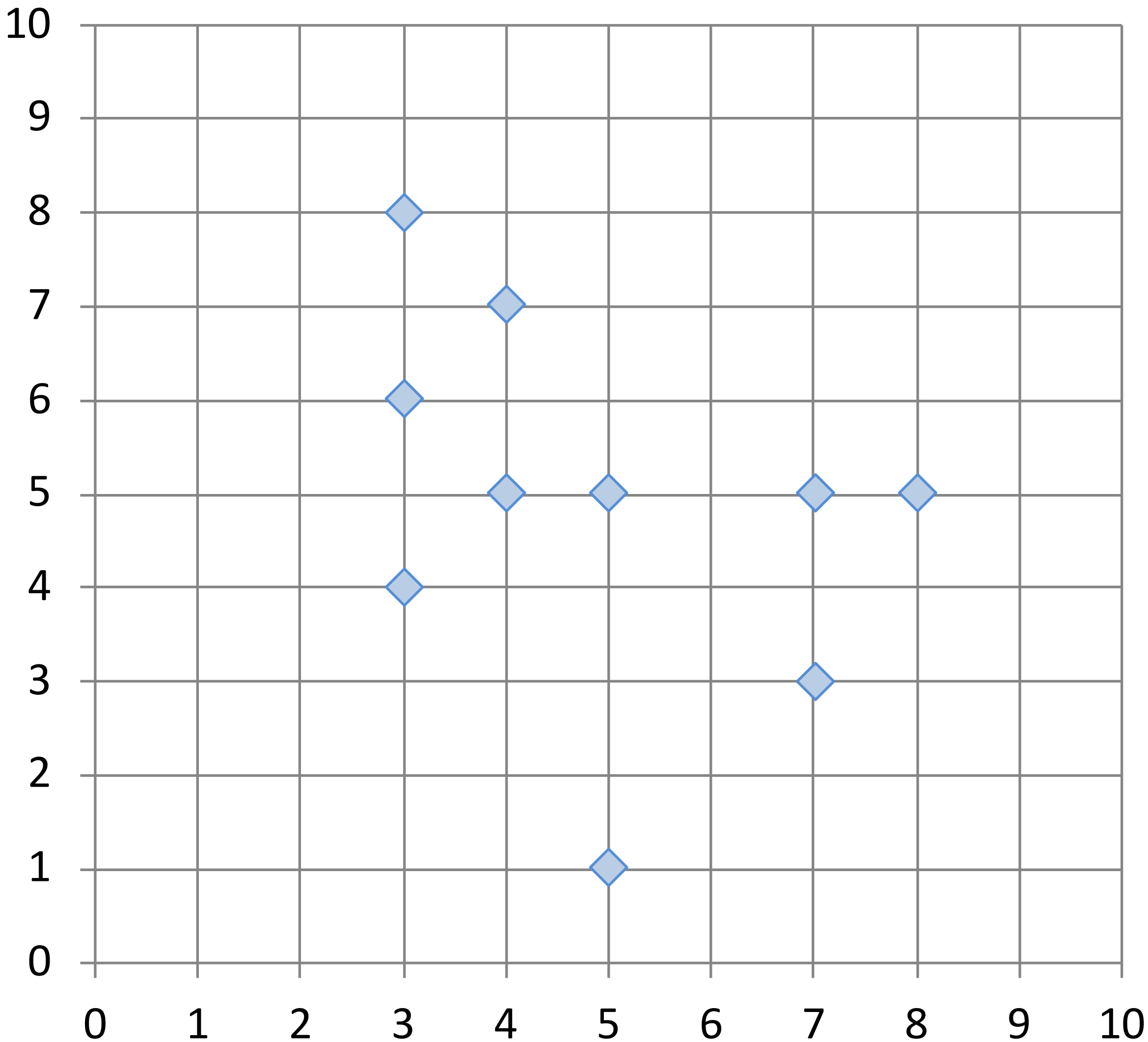
Clustering of a set of objects based on the *k-means method.*
(The mean of each cluster is marked by a "+".)

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)

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

Example of Cluster Analysis



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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

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

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

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

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

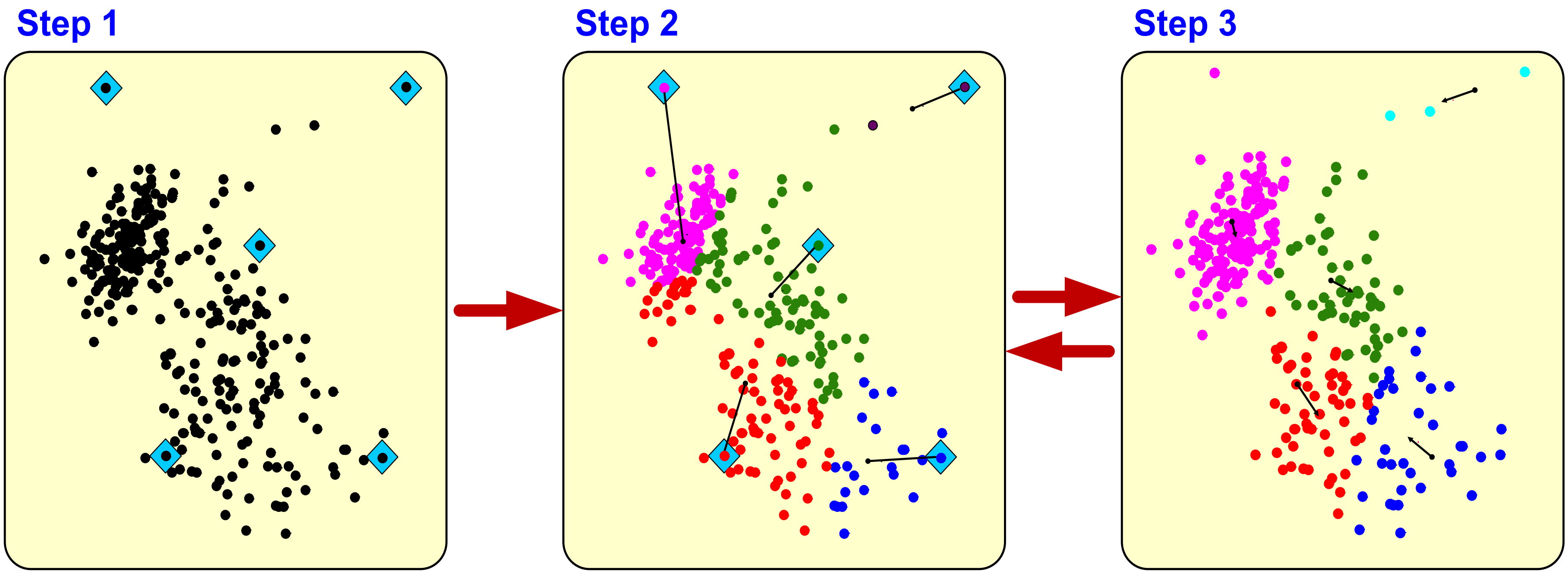
Step 2: Assign each point to the nearest cluster center

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)

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

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



Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

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*:

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

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

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

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

Similarity and Dissimilarity Between Objects (Cont.)

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

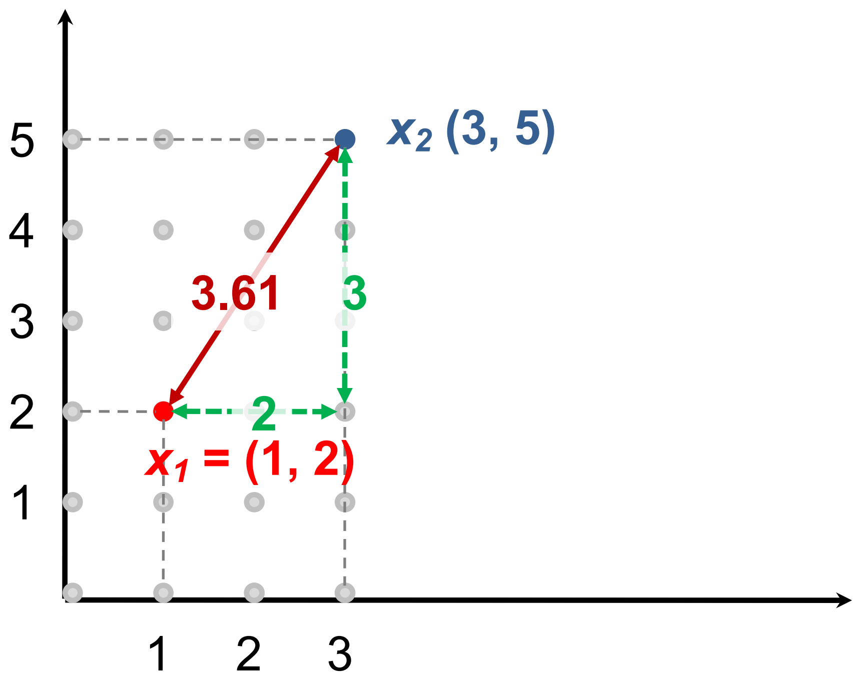
$$d(i,j) = \sqrt{(|x_{i_1} - x_{j_1}|^2 + |x_{i_2} - x_{j_2}|^2 + \ldots + |x_{i_p} - x_{j_p}|^2)}$$

  - 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 disimilarity measures

Source: Han & Kamber (2006)

Euclidean distance vs Manhattan distance

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

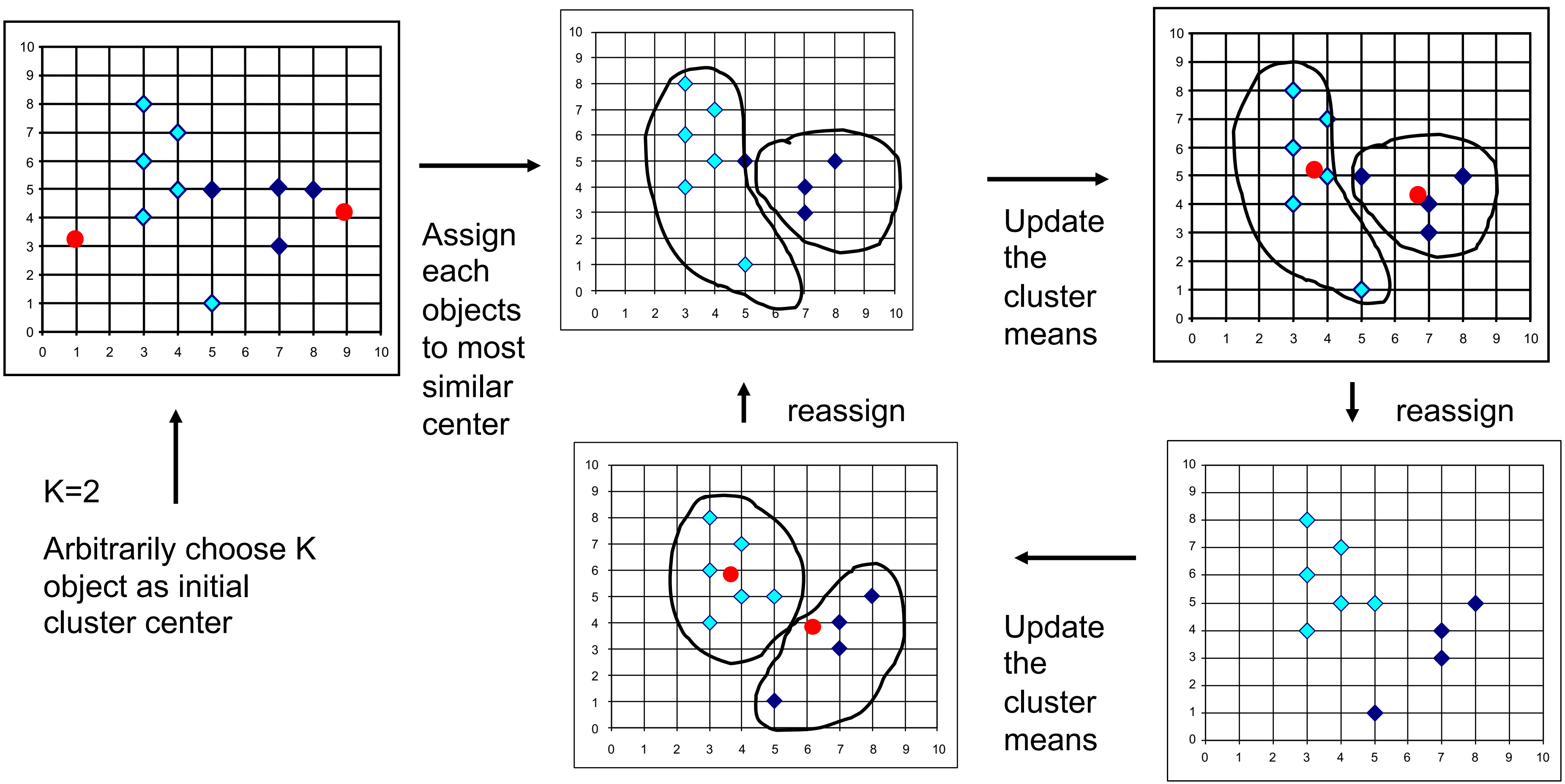


Euclidean distance:
$= ((3-1)^2 + (5-2)^2)^{1/2}$
$= (2^2 + 3^2)^{1/2}$
$= (4 + 9)^{1/2}$
$= (13)^{1/2}$
$= 3.61$

Manhattan distance:
$= (3-1) + (5-2)$
$= 2 + 3$
$= 5$

The *K-Means* Clustering Method

- Example



Source: Han & Kamber (2006)

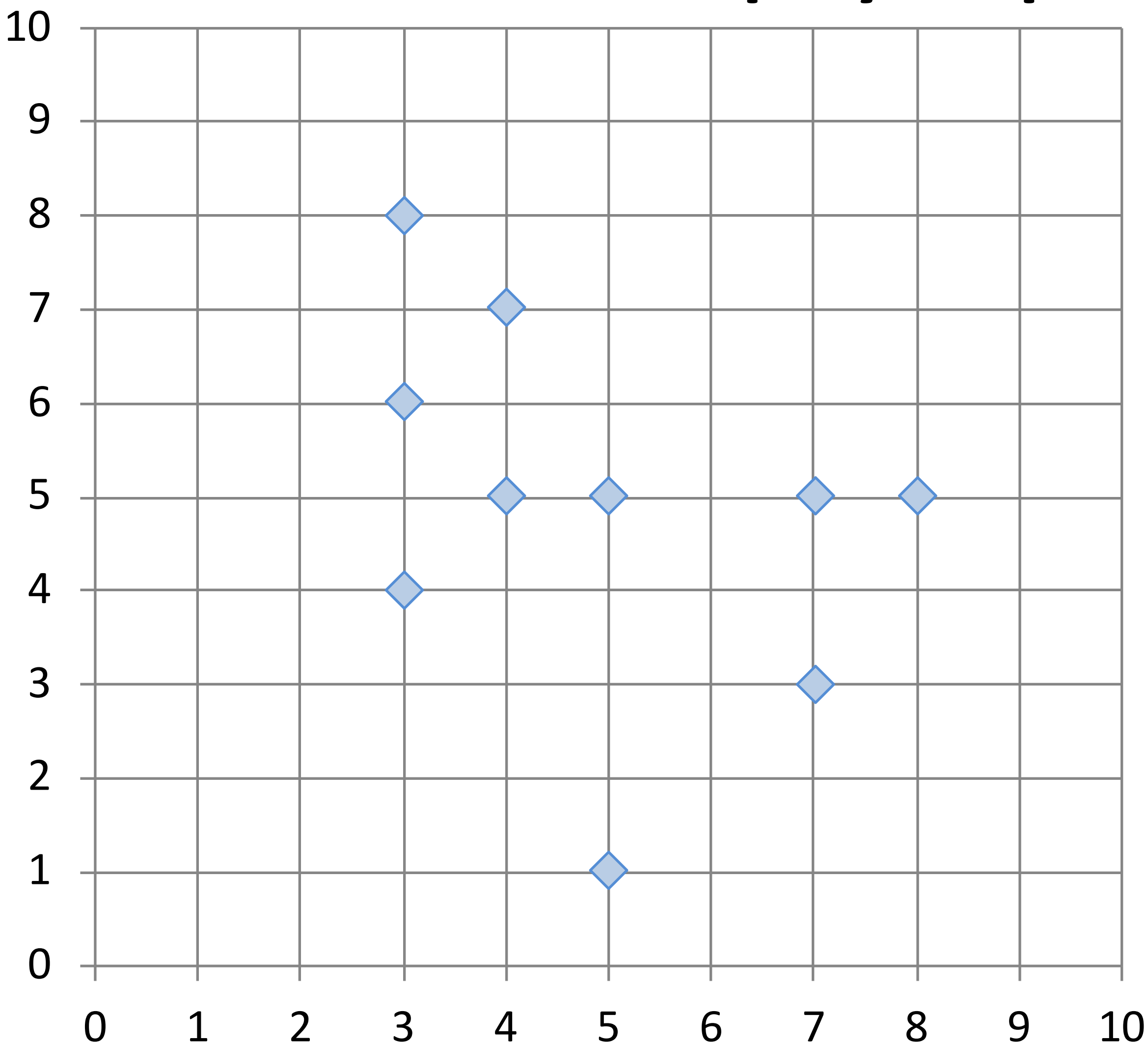
K-Means Clustering

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



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p03	c	(3, 8)
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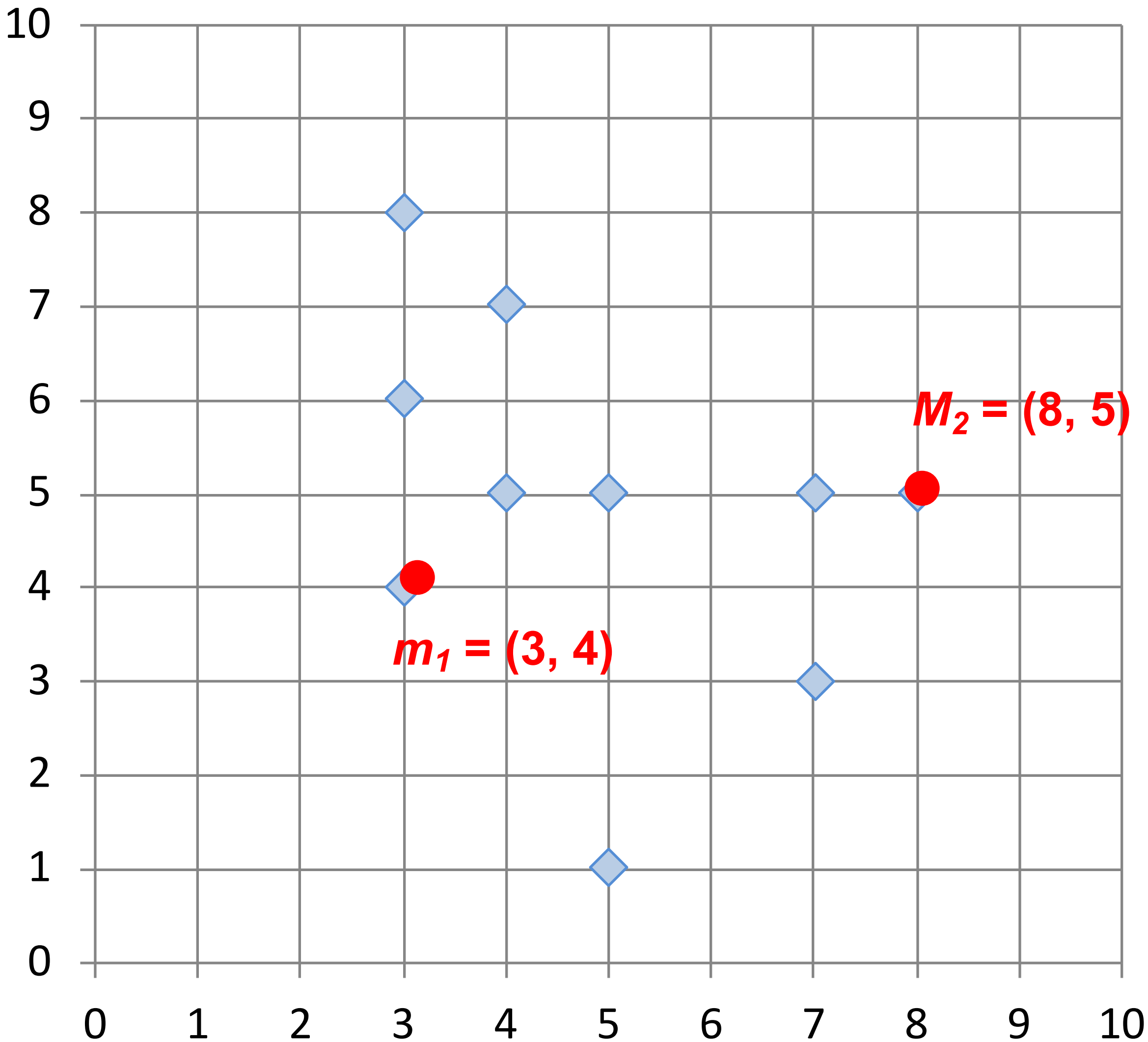
p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

K-Means Clustering

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



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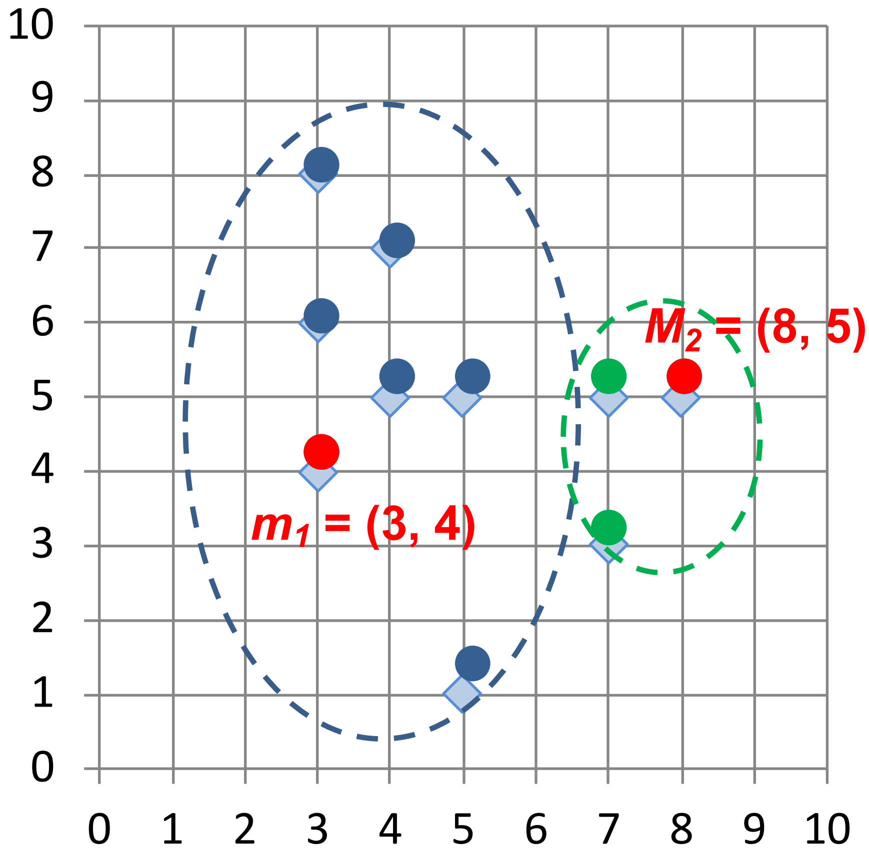
p05	e	(4, 7)
p06	f	(5, 1)
p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)
Initial	m1	(3, 4)
Initial	m2	(8, 5)

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

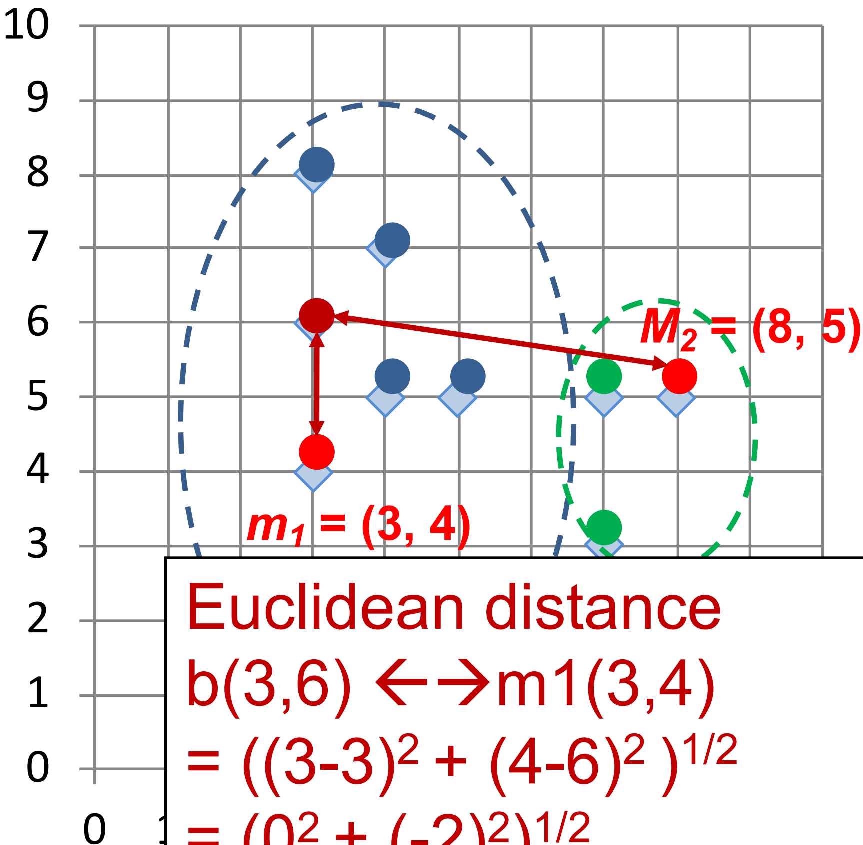
Initial m1 (3, 4)

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



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p04	d	(4, 5)	1.41	4.00	Cluster1
p05					ster1
p06					ster1
p07					ster1
p08					ster2
p09					ster2
p10					ster2

Initial m1 (3, 4)

Initial m2 (8, 5)

Euclidean distance

b(3,6) ←→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) ←→m2(8,5)

$= ((8-3)^2 + (5-6)^2)^{1/2}$

$= (5^2 + (-1)^2)^{1/2}$

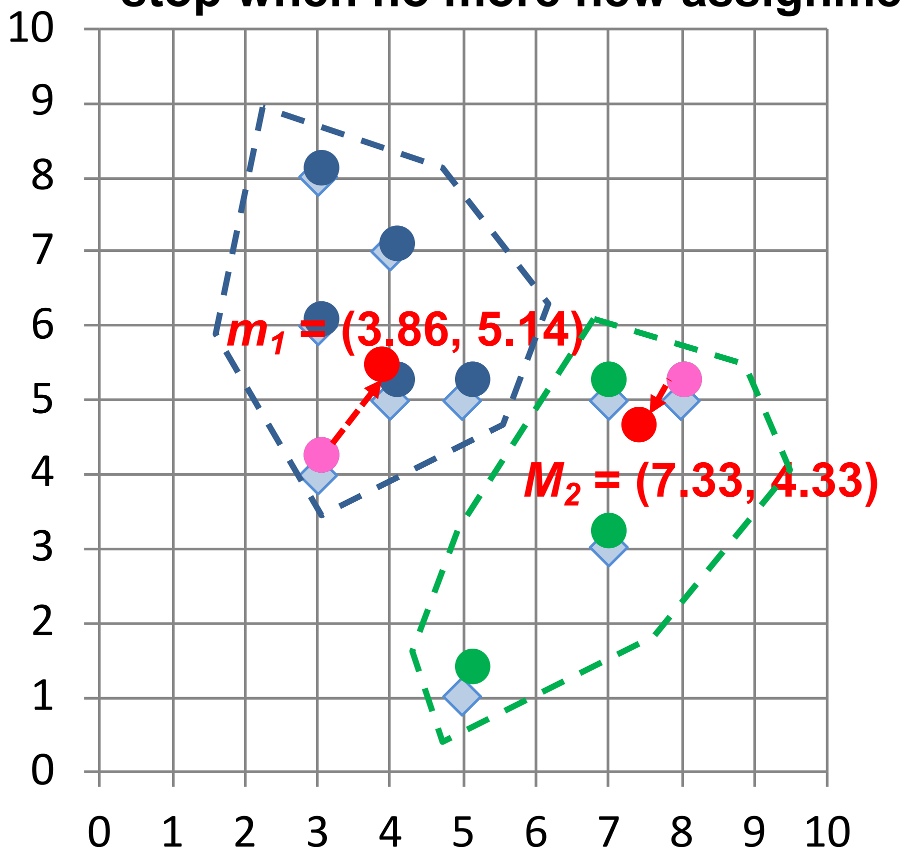
$= (25 + 1)^{1/2}$

$= (26)^{1/2}$

$= 5.10$

K-M

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



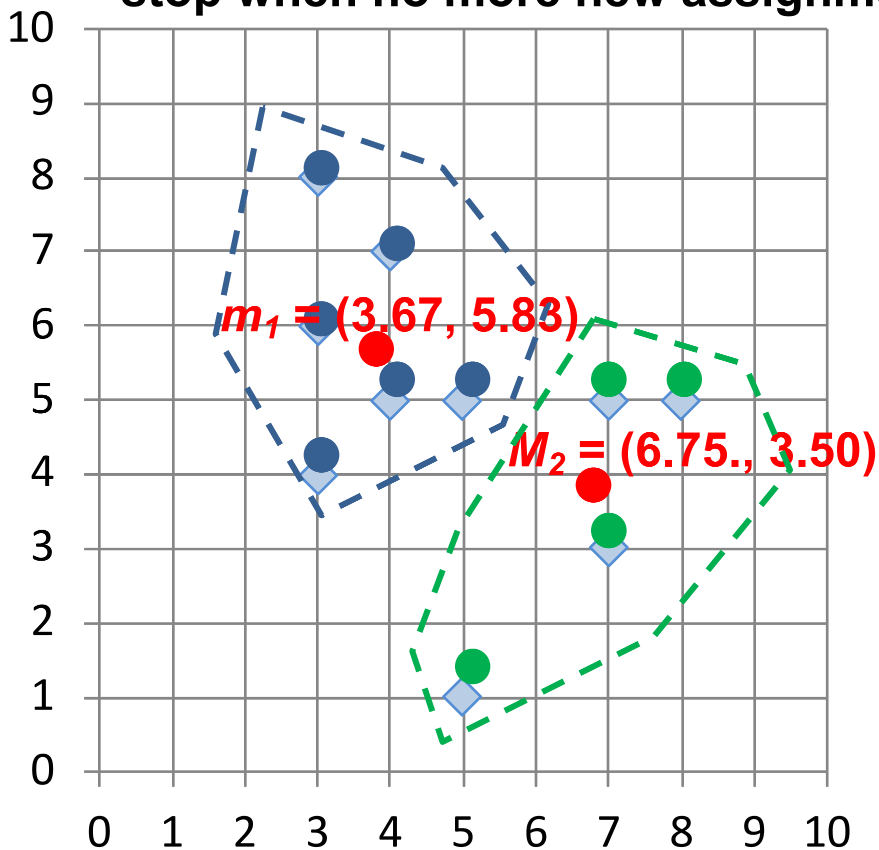
Point	P	P(x,y)	m1 distance	m2 distance	Cluster
p01	a	(3, 4)	1.43	4.34	Cluster1
p02	b	(3, 6)	1.22	4.64	Cluster1
p03	c	(3, 8)	2.99	5.68	Cluster1
p04	d	(4, 5)	0.20	3.40	Cluster1
p05	e	(4, 7)	1.87	4.27	Cluster1
p06	f	(5, 1)	4.29	4.06	Cluster2
p07	g	(5, 5)	1.15	2.42	Cluster1
p08	h	(7, 3)	3.80	1.37	Cluster2
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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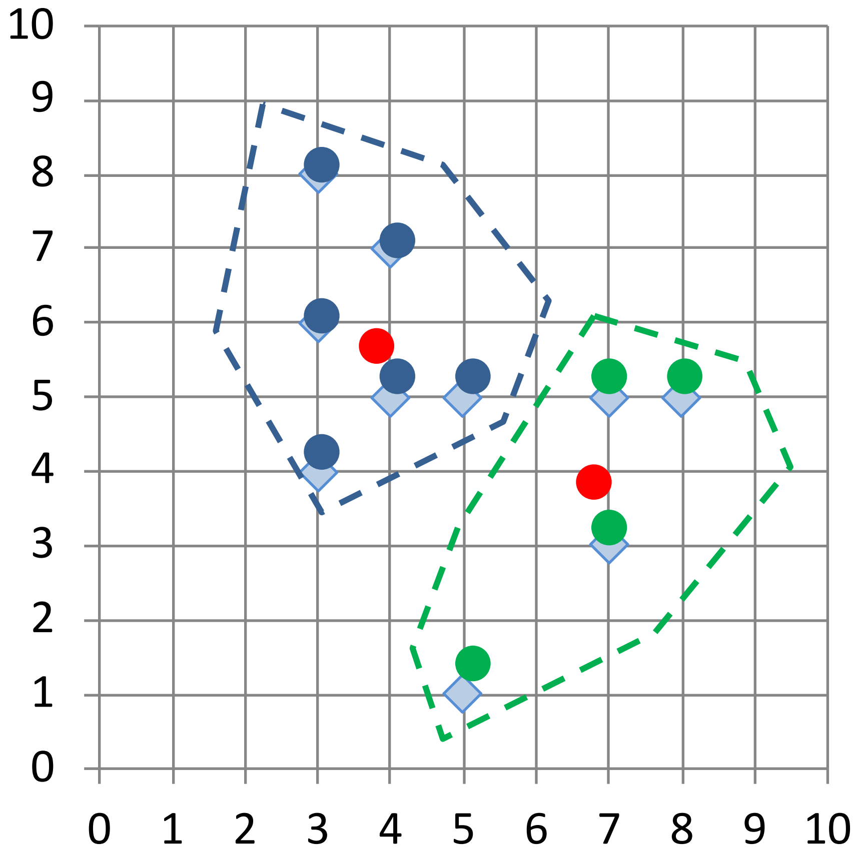
p09	i	(7, 5)	3.43	1.52	Cluster2
p10	j	(8, 5)	4.41	1.95	Cluster2

m1 (3.67, 5.83)

m2 (6.75, 3.50)

K-Means Clustering

stop when no more new assignment



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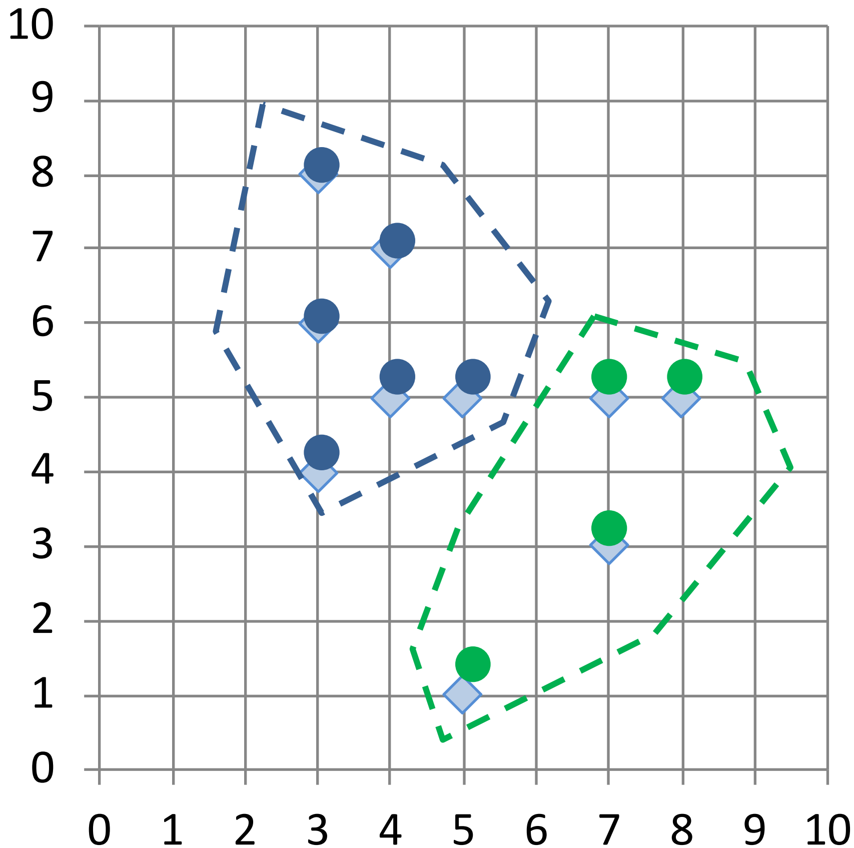
m1 (3.67, 5.83)

m2 (6.75, 3.50)

K-Means Clustering

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

stop when no more new assignment



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K-Means Clustering

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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.