Tamkang University
淡江大學

Tamkang University

# Big Data Mining
# 巨量資料探勘

# 分群分析
# (Cluster Analysis)

1062DM05
MI4 (M2244) (2995)
Wed, 9, 10 (16:10-18:00) (B206)


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2018-04-11

# 課程大綱 (Syllabus)

| 週次 (Week) | 日期 (Date) | 內容(Subject/Topics) |
|---|---|---|
| 1 | 2018/02/28 | 和平紀念日(放假一天) (Peace Memorial Day) (Day off) |
| 2 | 2018/03/07 | 巨量資料探勘課程介紹 (Course Orientation for Big Data Mining) |
| 3 | 2018/03/14 | 大數據、AI人工智慧與深度學習 (Big Data, Artificial Intelligence and Deep Learning) |
| 4 | 2018/03/21 | 關連分析 (Association Analysis) |
| 5 | 2018/03/28 | 分類與預測 (Classification and Prediction) |
| 6 | 2018/04/04 | 兒童節(放假一天)(Children's Day) (Day off) |
| 7 | 2018/04/11 | 分群分析 (Cluster Analysis) |
| 8 | 2018/04/18 | 個案分析與實作一 (SAS EM 分群分析)：Case Study 1 (Cluster Analysis - K-Means using SAS EM) |

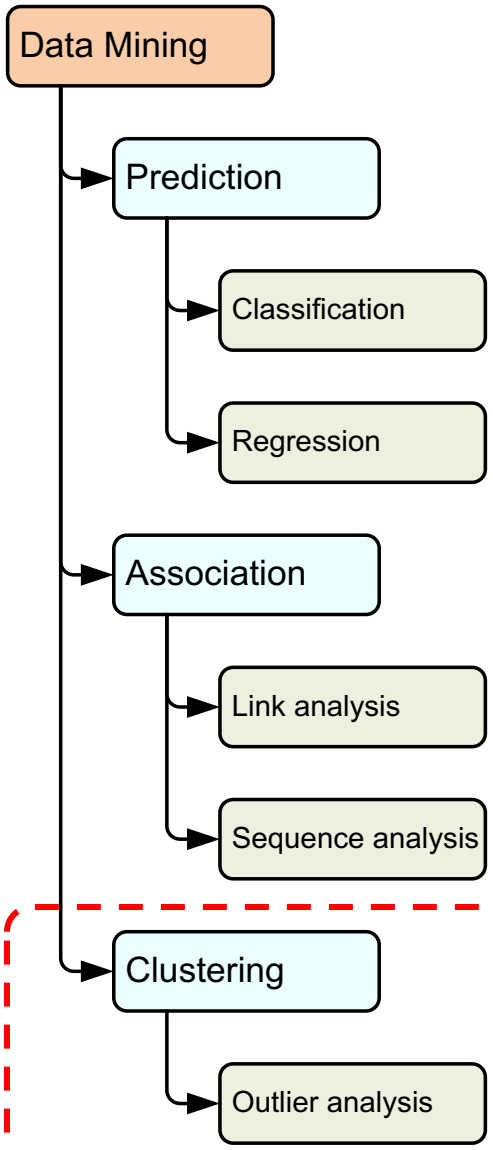
# 課程大綱 (Syllabus)

| 週次 (Week) | 日期 (Date) | 內容 (Subject/Topics) |
|---|---|---|
| 9 | 2018/04/25 | 期中報告 (Midterm Project Presentation) |
| 10 | 2018/05/02 | 期中考試週 |
| 11 | 2018/05/09 | 個案分析與實作二 (SAS EM 關連分析)：<br>Case Study 2 (Association Analysis using SAS EM) |
| 12 | 2018/05/16 | 個案分析與實作三 (SAS EM 決策樹、模型評估)：<br>Case Study 3 (Decision Tree, Model Evaluation using SAS EM) |
| 13 | 2018/05/23 | 個案分析與實作四 (SAS EM 迴歸分析、類神經網路)：<br>Case Study 4 (Regression Analysis,<br>Artificial Neural Network using SAS EM) |
| 14 | 2018/05/30 | 期末報告 (Final Project Presentation) |
| 15 | 2018/06/06 | 畢業考試週 |

# Outline

- Cluster Analysis
- *K-Means* Clustering

# A Taxonomy for Data Mining Tasks




| Learning Method | Popular Algorithms |
|---|---|
| Supervised | Classification and Regression Trees, ANN, SVM, Genetic Algorithms |
| Supervised | Decision trees, ANN/MLP, SVM, Rough sets, Genetic Algorithms |
| Supervised | Linear/Nonlinear Regression, Regression trees, ANN/MLP, SVM |
| Unsupervised | Apriory, OneR, ZeroR, Eclat |
| Unsupervised | Expectation Maximization, Apriory Algorithm, Graph-based Matching |
| Unsupervised | Apriory Algorithm, FP-Growth technique |
| Unsupervised | K-means, ANN/SOM |
| Unsupervised | K-means, Expectation Maximization (EM) |

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

# 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 |

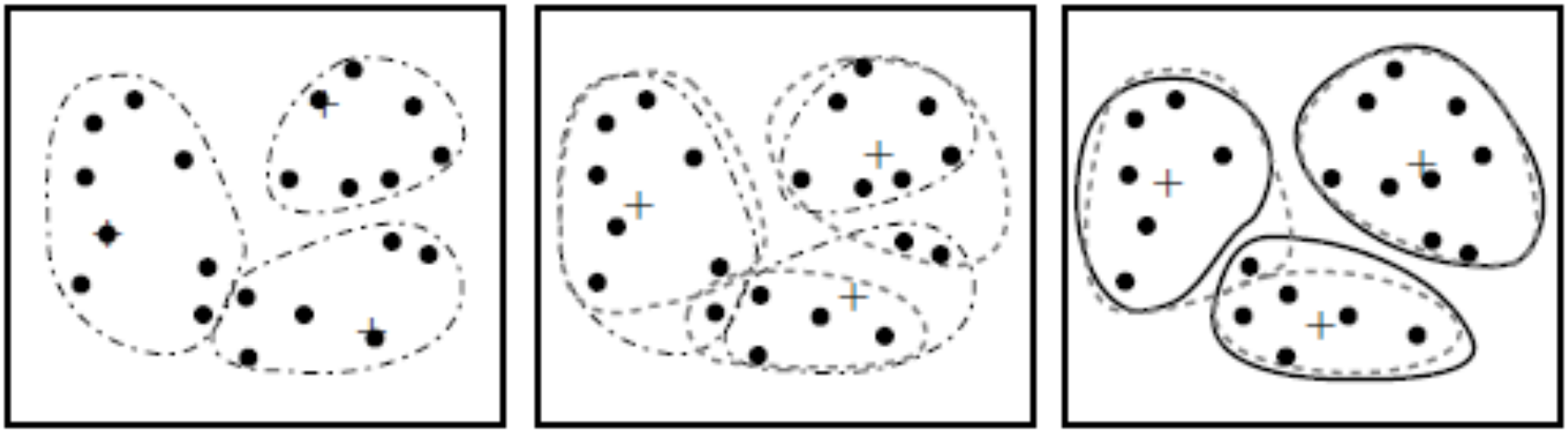
| | |
|---|---|
| m1 | (3.67, 5.83) |
| m2 | (6.75, 3.50) |

# 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



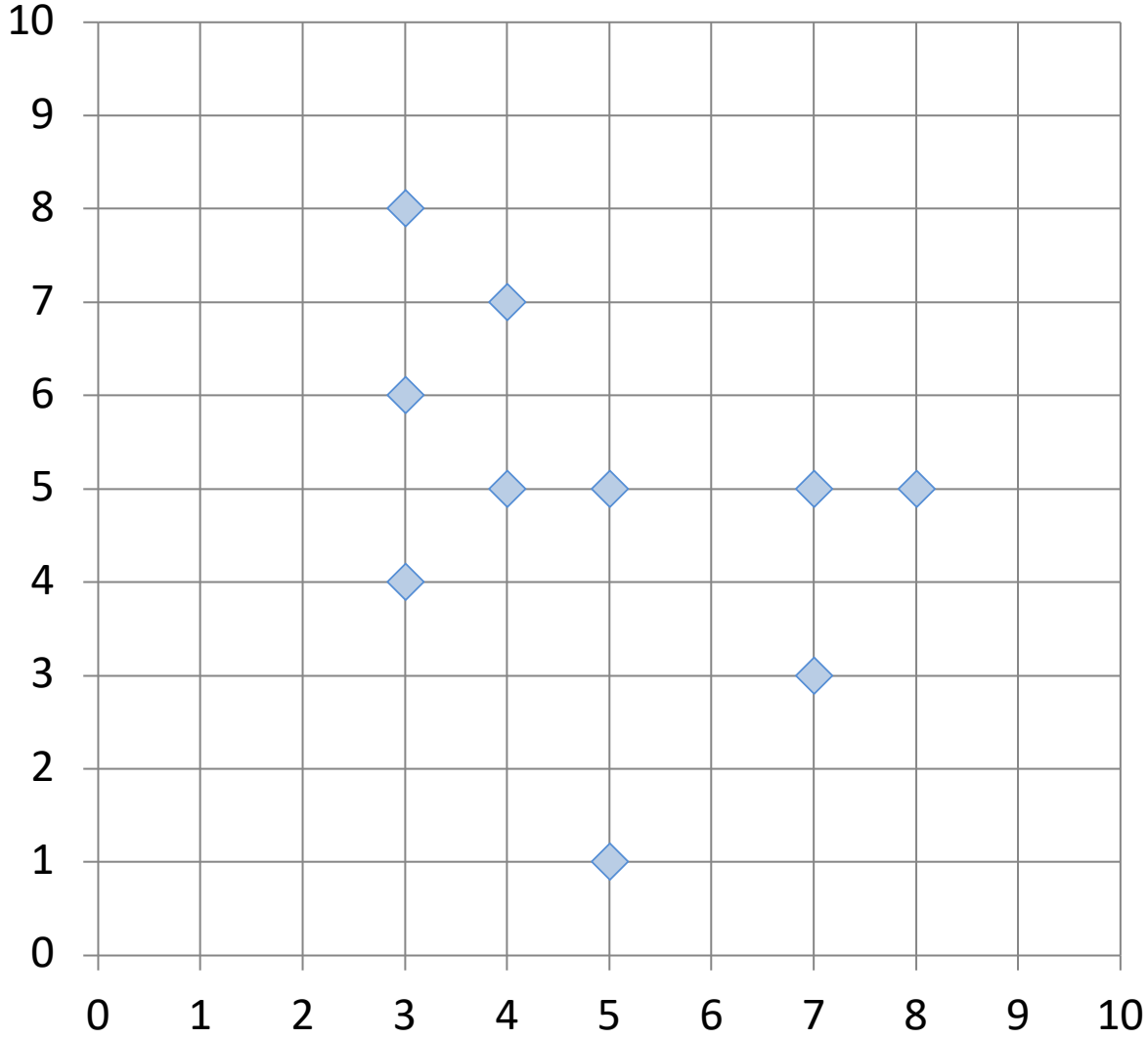

Clustering of a set of objects based on the *k-means method.*
*(The mean of each cluster is* marked by a "+".)

Source: Han & Kamber (2006)

# 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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| 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) |

# 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*)

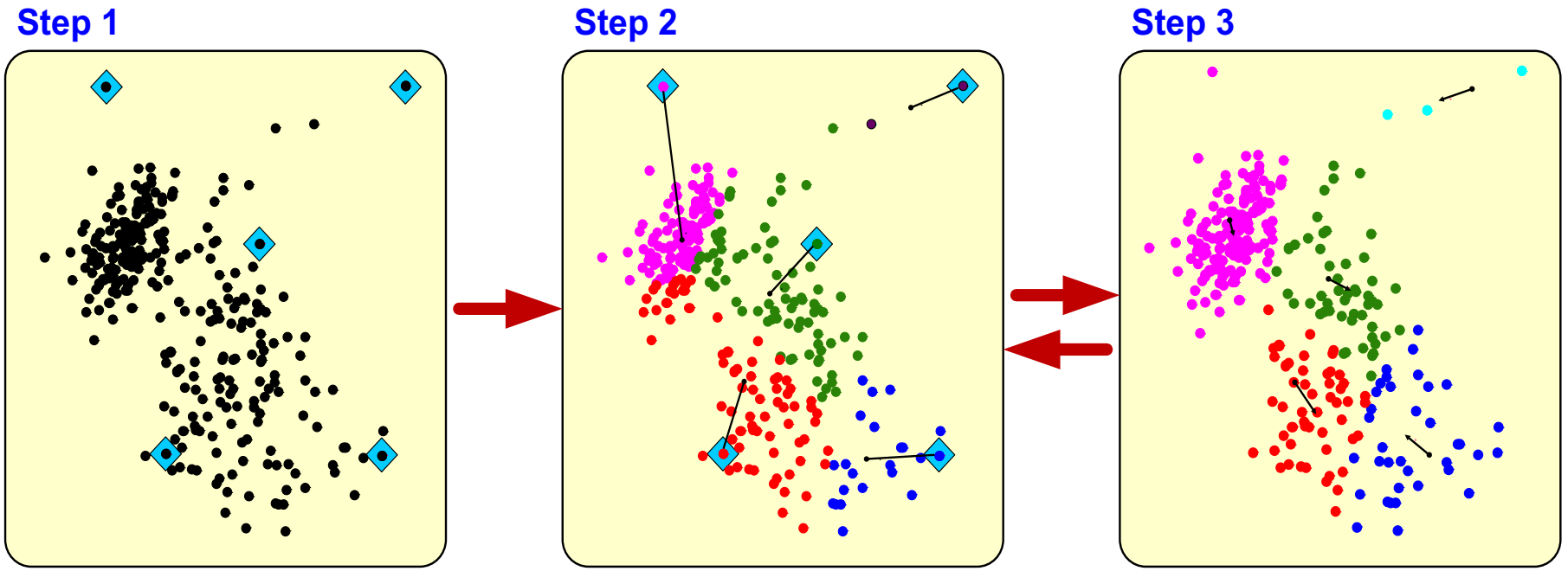
Step 1: Randomly generate *k* random points as initial cluster centers

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




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*:

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

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

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

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

Source: Han & Kamber (2006)

# Similarity and Dissimilarity Between Objects (Cont.)

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

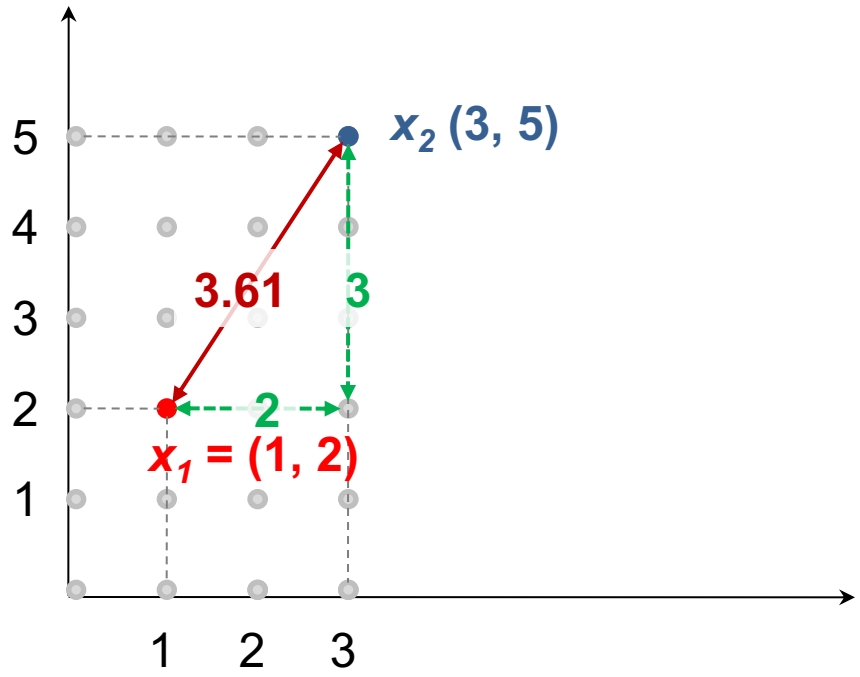
$$d(i,j)=\sqrt{(|x_{i_1}-x_{j_1}|^2+|x_{i_2}-x_{j_2}|^2+...+|x_{i_p}-x_{j_p}|^2)}$$

  - 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:

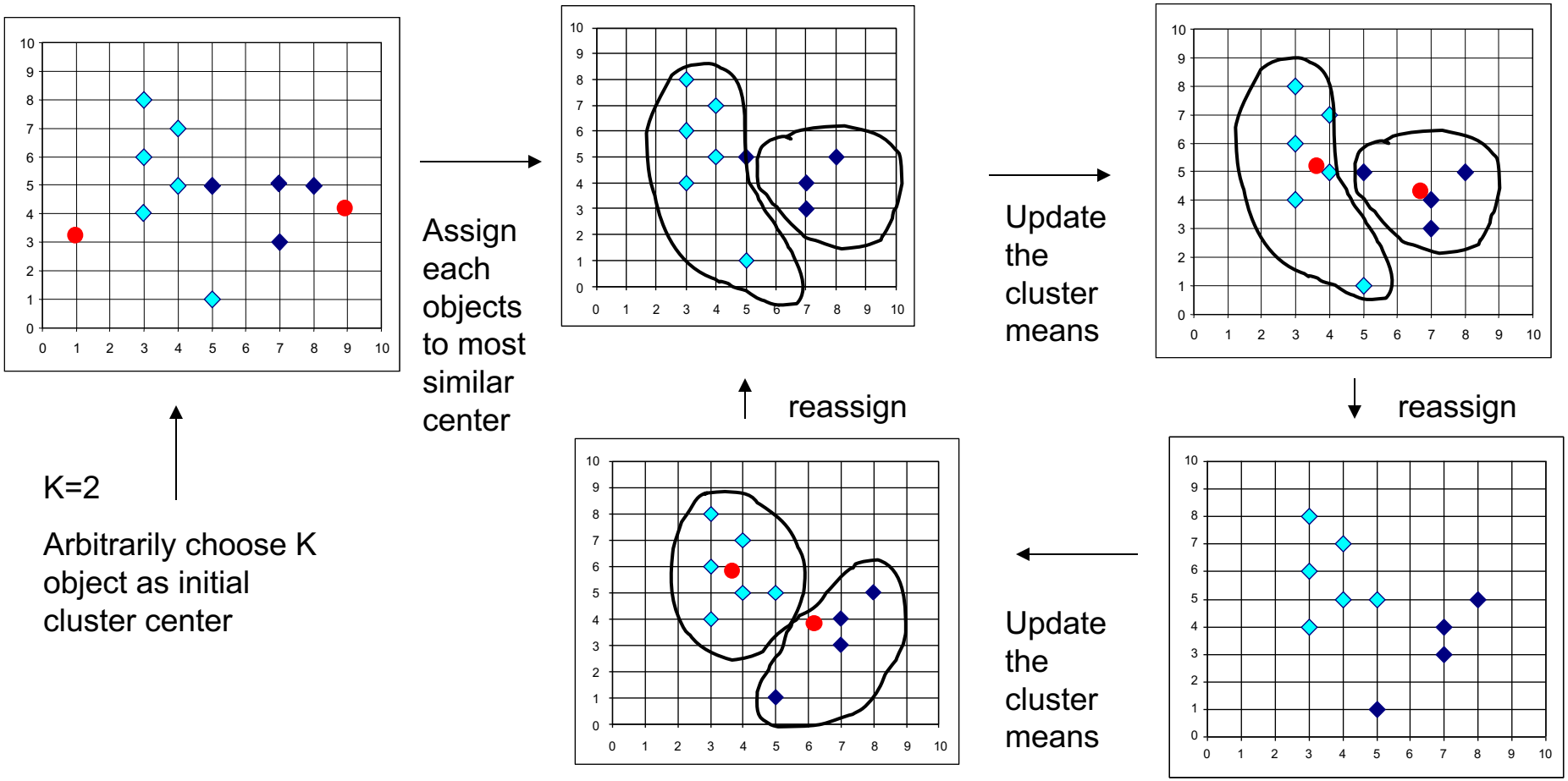
$= (3-1) + (5-2)$

$= 2 + 3$

$= 5$

# The *K-Means* Clustering Method

- Example




Source: Han & Kamber (2006)

# *K-Means* Clustering

# Example of Cluster Analysis

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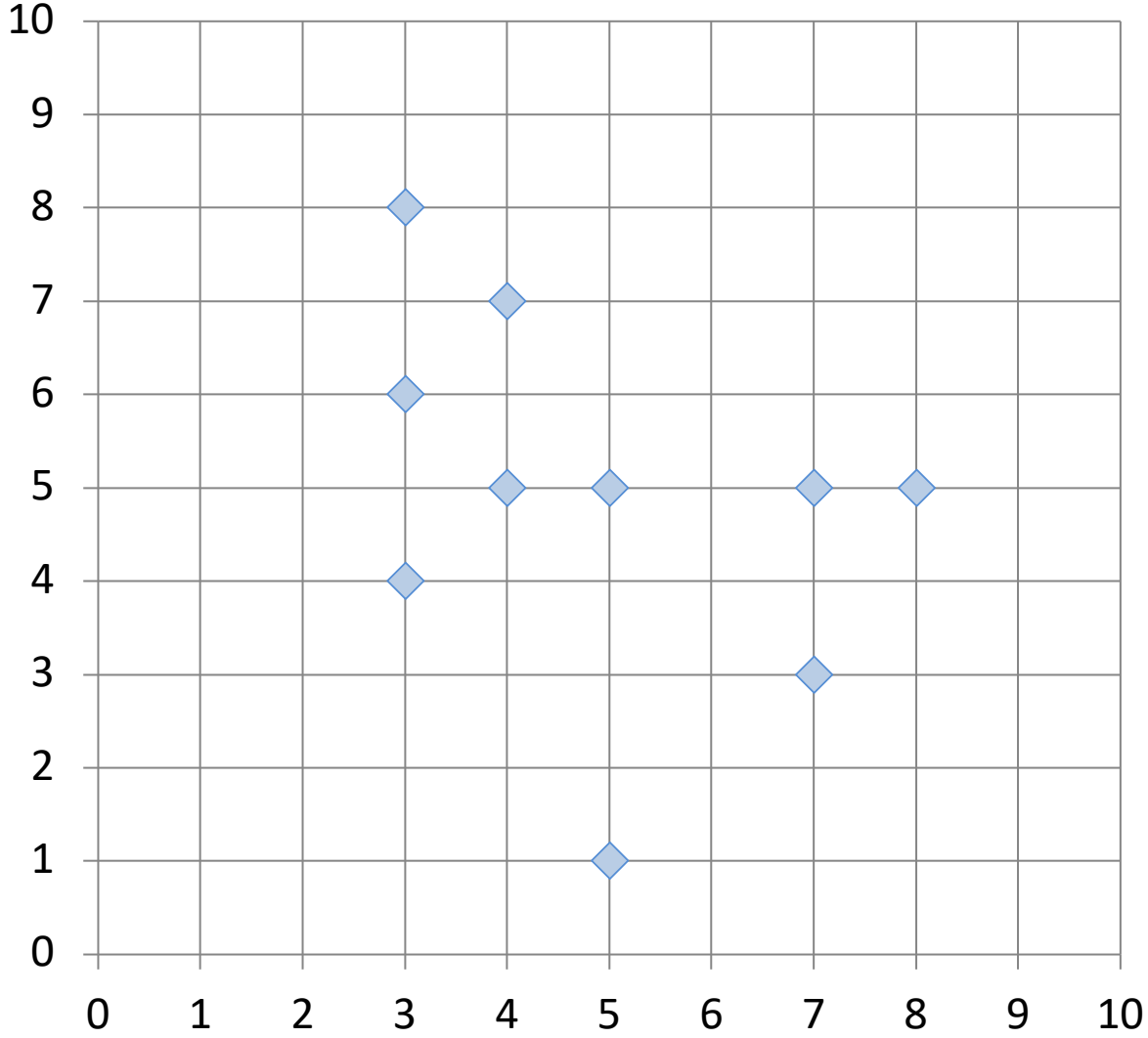
| p02 | b | (3, 6) |
| p03 | c | (3, 8) |
| p04 | d | (4, 5) |
| p05 | e | (4, 7) |
| p06 | f | (5, 1) |
| p07 | g | (5, 5) |
| p08 | h | (7, 3) |
| p09 | i | (7, 5) |
| p10 | j | (8, 5) |

# *K-Means* Clustering

## Step by Step

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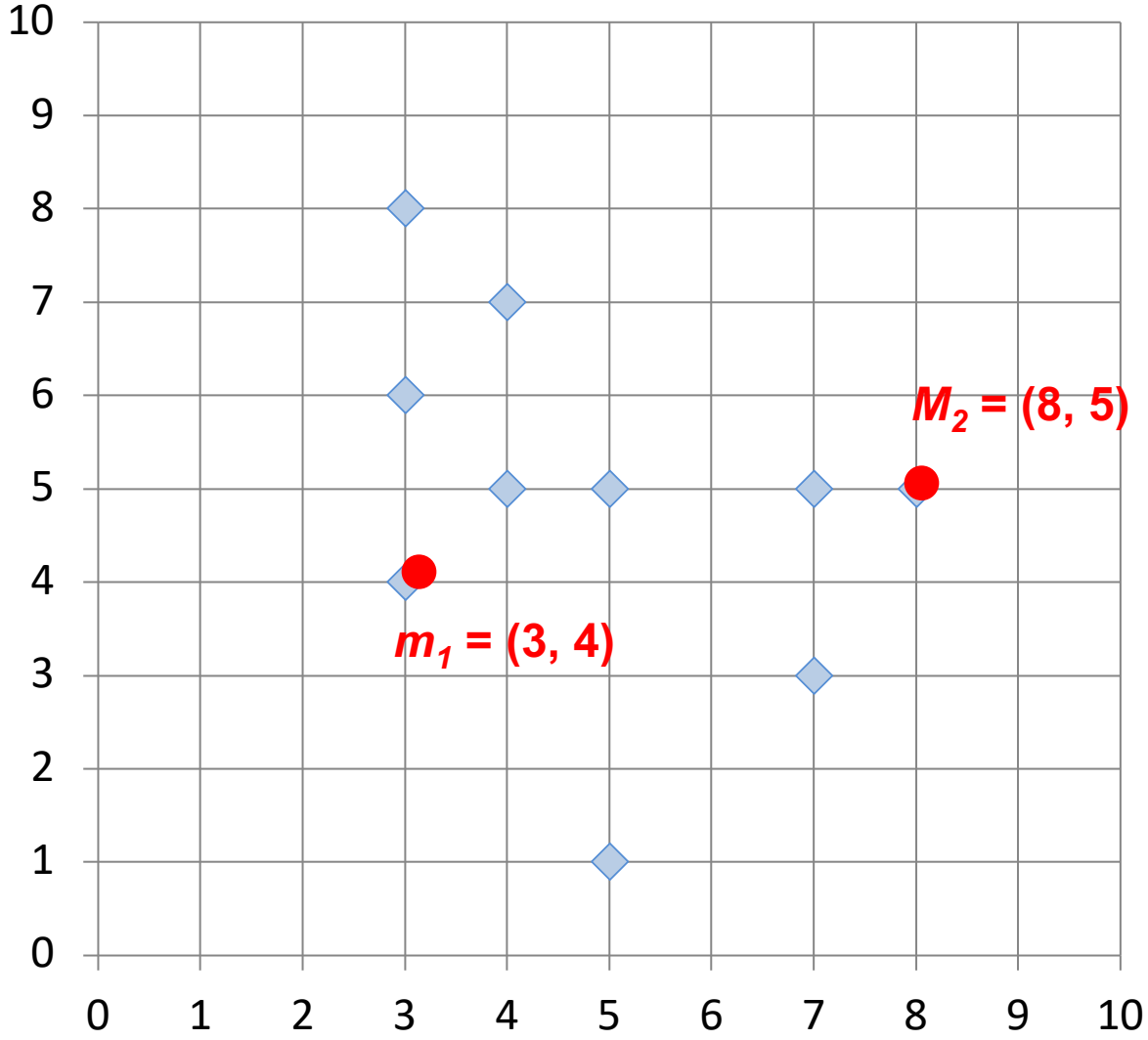
| p08 | h | (7, 3) |
| p09 | i | (7, 5) |
| p10 | j | (8, 5) |

# *K-Means* Clustering

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




| Point | P | P(x,y) |
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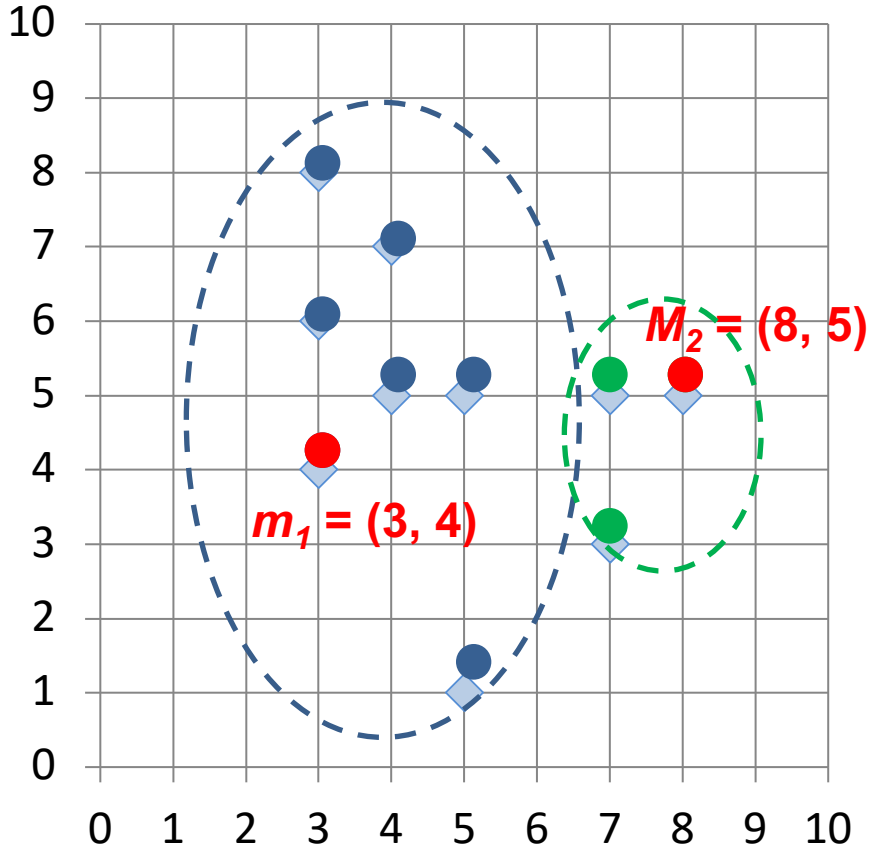
| p07 | g | (5, 5) |
| p08 | h | (7, 3) |
| p09 | i | (7, 5) |
| p10 | j | (8, 5) |
| | | |
| Initial | m1 | (3, 4) |
| Initial | m2 | (8, 5) |

**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 |

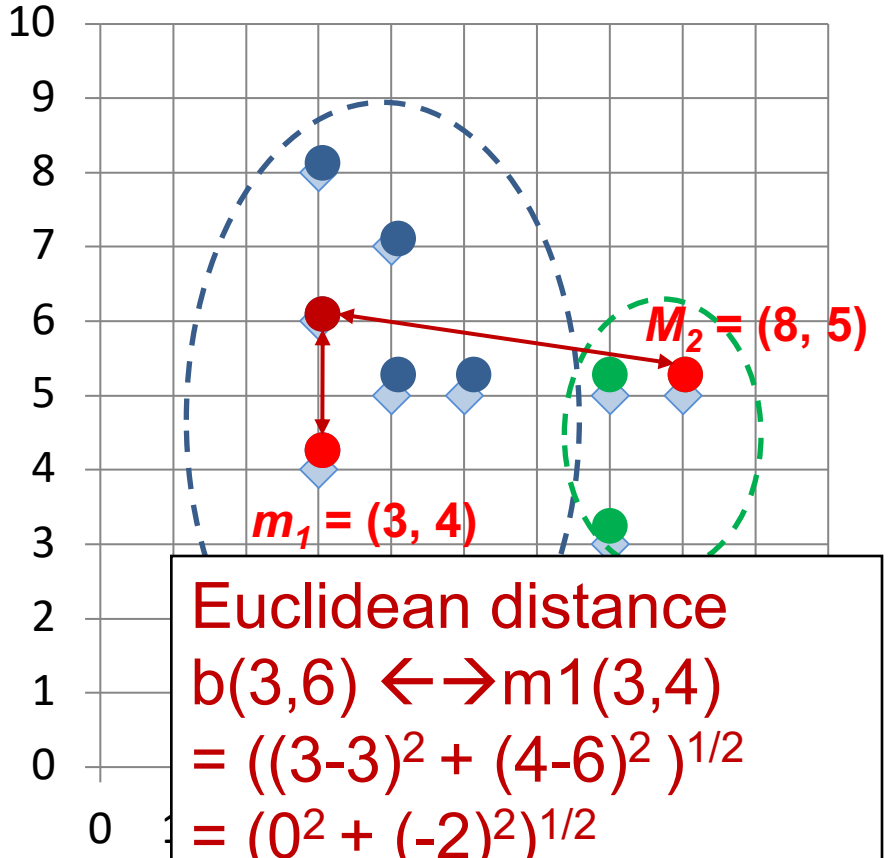
# *K-Means* Clustering

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 |
|---|---|---|---|---|---|
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| 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 | | | | | ster1 |
| p06 | | | | | ster1 |
| p07 | | | | | ster1 |
| p08 | | | | | ster2 |
| p09 | | | | | ster2 |
| p10 | | | | | ster2 |

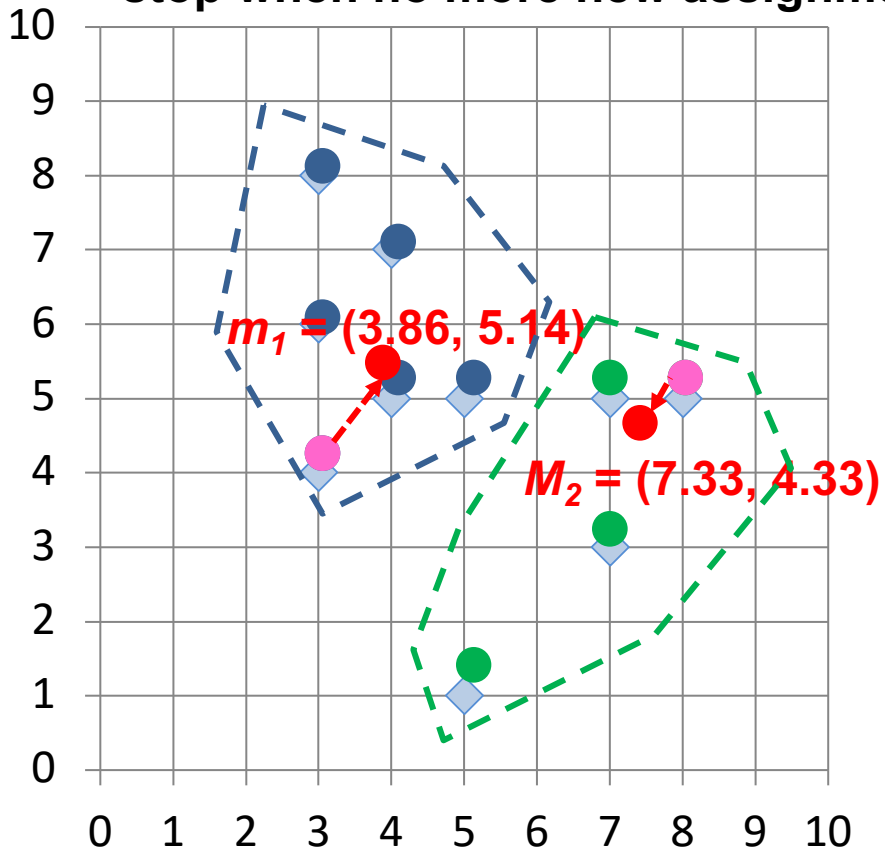
Euclidean distance
b(3,6) ←→m1(3,4)
$= ((3-3)^2 + (4-6)^2)^{1/2}$
$= (0^2 + (-2)^2)^{1/2}$
$= (0 + 4)^{1/2}$
$= (4)^{1/2}$
$= 2.00$

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

Initial m1 (3, 4)

Initial m2 (8, 5)

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



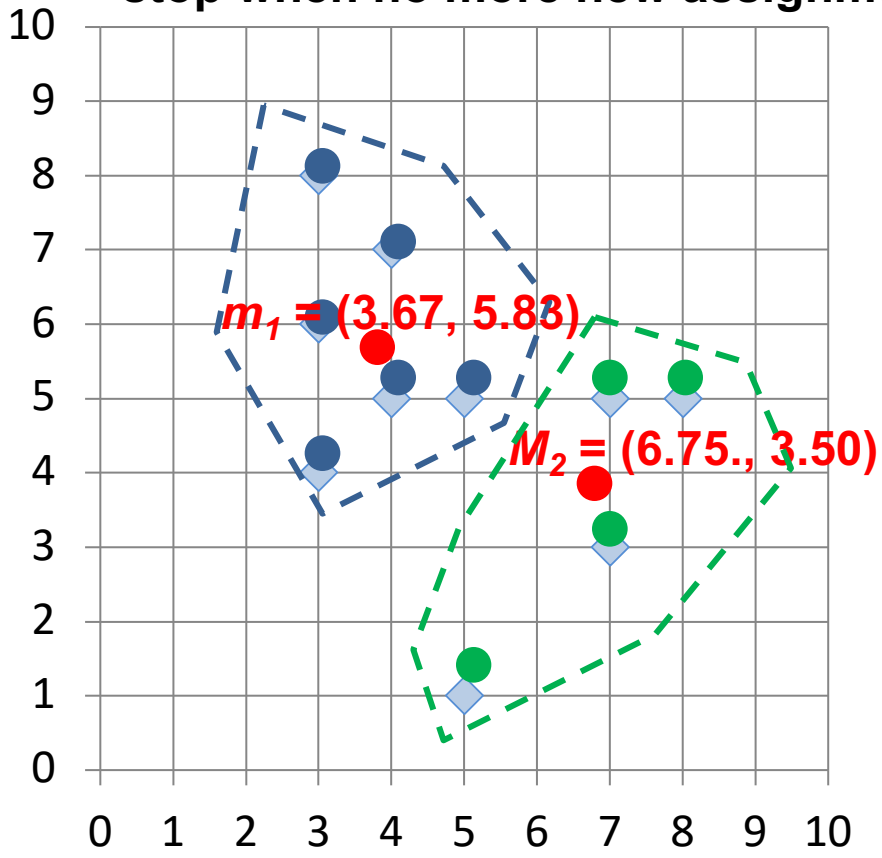

| Point | P | P(x,y) | m1 distance | m2 distance | Cluster |
|---|---|---|---|---|---|
| p01 | a | (3, 4) | 1.43 | 4.34 | Cluster1 |
| p02 | b | (3, 6) | 1.22 | 4.64 | Cluster1 |
| p03 | c | (3, 8) | 2.99 | 5.68 | Cluster1 |
| p04 | d | (4, 5) | 0.20 | 3.40 | Cluster1 |
| p05 | e | (4, 7) | 1.87 | 4.27 | 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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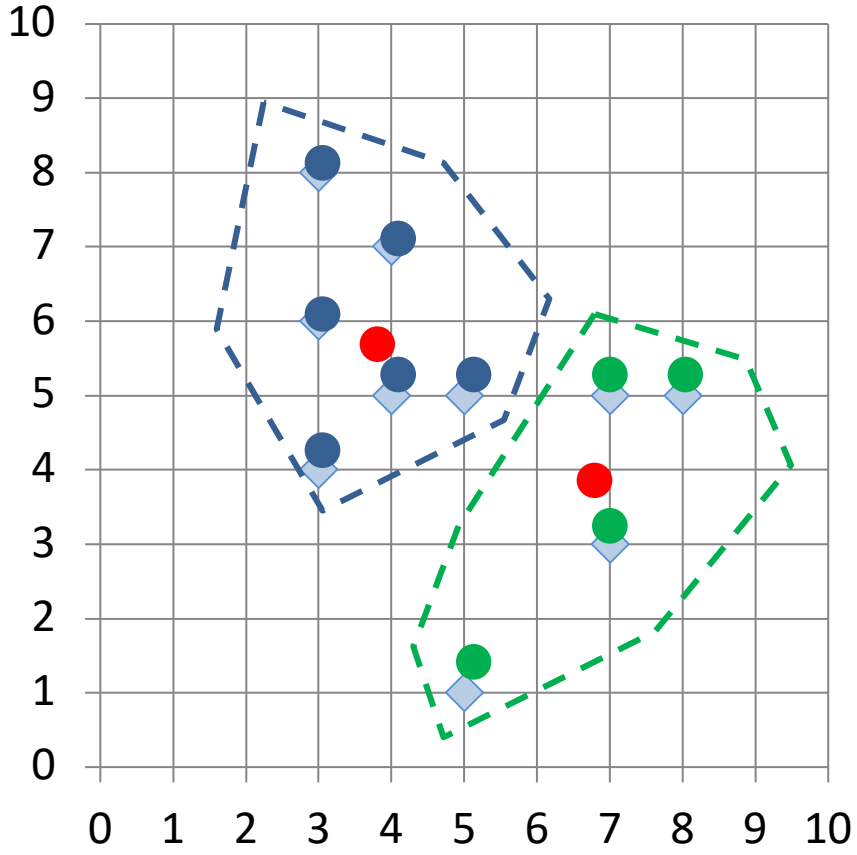
| p02 | b | (3, 6) | 0.69 | 4.51 | Cluster1 |
| p03 | c | (3, 8) | 2.27 | 5.86 | Cluster1 |
| p04 | d | (4, 5) | 0.89 | 3.13 | Cluster1 |
| p05 | e | (4, 7) | 1.22 | 4.45 | Cluster1 |
| p06 | f | (5, 1) | 5.01 | 3.05 | Cluster2 |
| p07 | g | (5, 5) | 1.57 | 2.30 | Cluster1 |
| p08 | h | (7, 3) | 4.37 | 0.56 | Cluster2 |
| p09 | i | (7, 5) | 3.43 | 1.52 | Cluster2 |
| p10 | j | (8, 5) | 4.41 | 1.95 | Cluster2 |

# *K-Means* Clustering

m1 (3.67, 5.83)

m2 (6.75, 3.50)

**stop when no more new assignment**

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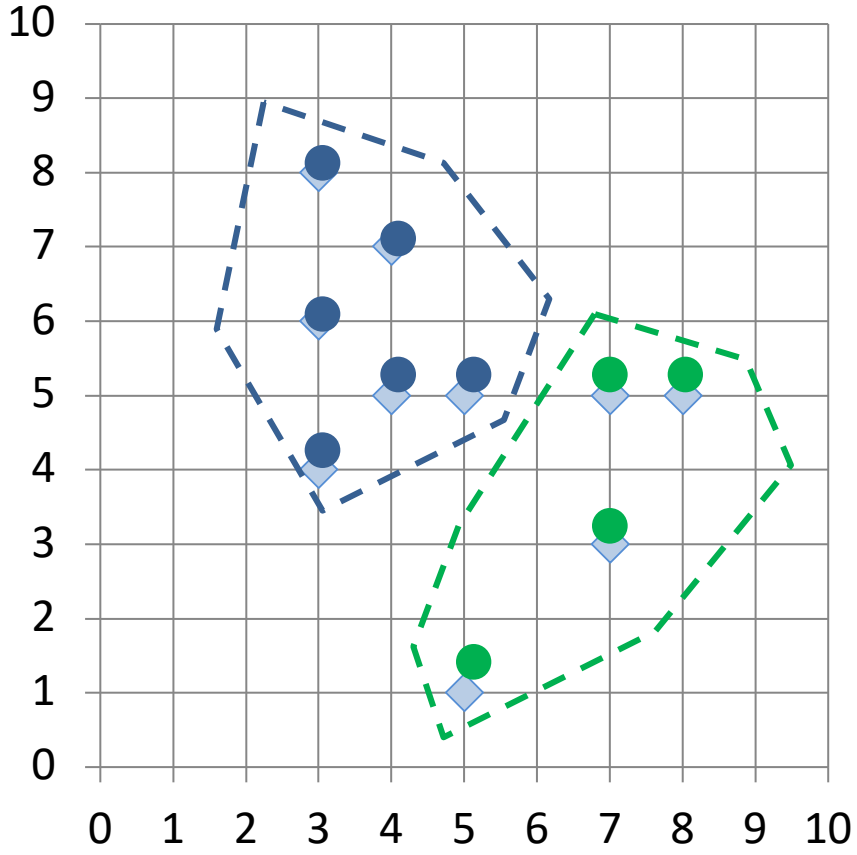
# *K-Means* Clustering

m1 (3.67, 5.83)

m2 (6.75, 3.50)

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

**stop when no more new assignment**

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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

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| p10 | j | (8, 5) | 4.41 | 1.95 | Cluster2 |

| | |
|---|---|
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| 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.