



Tutorial Business Analytics

Tutorial 9: Ensemble Methods and Clustering

Decision Sciences & Systems (DSS)

Department of Informatics

TU München





Tutorial 9 Business Analytics: Clustering and Ensemble Methods

Today's Agenda

2. Clustering

2.1 Theory: Difference Between

Classification and Clustering (Tutorial Video)

2.2 Theory: Partitional Clustering: K-Means

Practise: Exercise 9.1

2.3 Theory Probabilistic Clustering: **EM Algorithm**

Practise: Exercise 9.2

1. Ensemble Methods (Tutorial Video)

1.1 Theory: What are **Ensemble**Methods?

1.2 Theory: Bagging

1.3 Theory: **Boosting**

1.4 Theory: Stacking

Homework

- Exercise 9.3
- Exercise 9.4
- Exercise 9.5





2.2 Partitional Clustering: K-Means – A centroid-based technique

Idea: 2-step method to partition the instances into k clusters, $C_1 \dots C_k$, with high intra-cluster similarity and high inter-cluster dissimilarity.

Method:

- [init] Initially choose k random centers or randomly pick k instances as initial centers
- [repeat]
 - Step 1: Assign instances to the closest cluster
 - Step 2: Update cluster center
- [until no change]

Step 1: How to Identify the Closest Cluster?

Distance function: Euclidean distance

$$d(p,c) = \sqrt{(x(p) - x(c))^2 + (y(p) - y(c))^2}$$

Step 2: How to Update Cluster Centre

Calculate centroid:

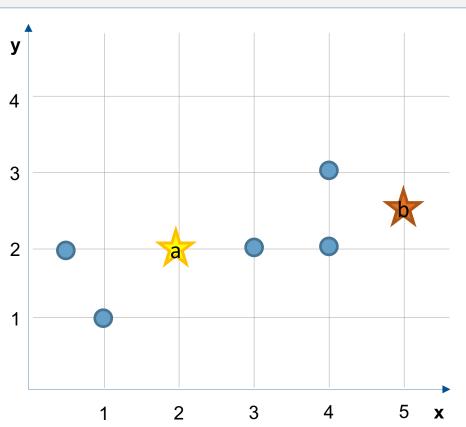
$$x'(c_i) = \frac{\sum_{p \in C_i} x(p)}{|c_i|} \text{ and } y'(c_i) = \frac{\sum_{p \in C_i} y(p)}{|c_i|}$$





2.2 Partitional Clustering: K-Means – Example

Group the data into two clusters applying the k-Means algorithm and the Euclidean distance function



Dataset		
p _i	X	У
1	4	3
2	0.5	2
3	3	2
4	4	2
5	1	1

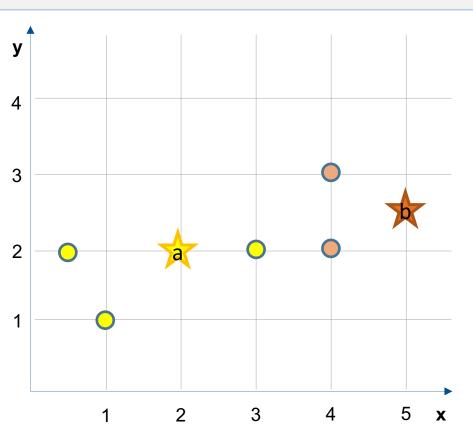
Centroids		
X	У	
2	2	
5.0	2.5	
	x 2	

[©] Chair of Decision Sciences and Systems, Technical University of Munich

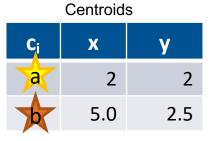




Step 1: (Re)assign instances to the closest cluster



Dataset		
p _i	Х	У
1	4	3
2	0.5	2
3	3	2
4	4	2
5	1	1

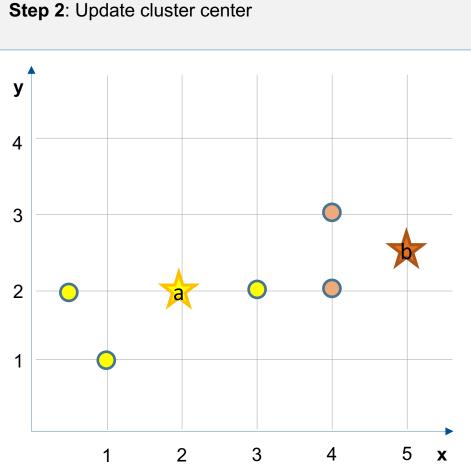


[©] Chair of Decision Sciences and Systems, Technical University of Munich

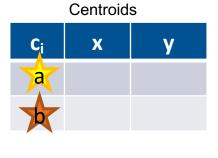




E.Z. Fartitional Clastering. R Wearis - Example



p _i	Datas	у
1	4	3
2	0.5	2
3	3	2
4	4	2
5	1	1



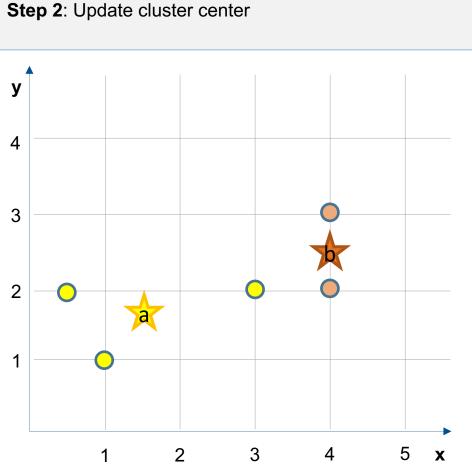
[©] Chair of Decision Sciences and Systems, Technical University of Munich





2.2 Partitional Clustering: K-Means – Example

2.2 i artitional clustering. K-Wearis Example



p _i	Х	у
1	4	3
2	0.5	2
3	3	2
4	4	2
5	1	1

Datacat

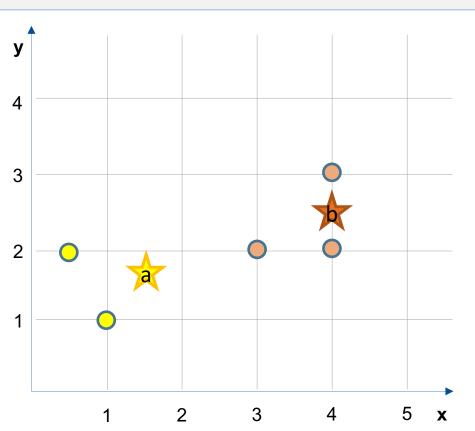
Centrolas		
C _i	x	У
a	1.5	1.67
b	4	2.5

[©] Chair of Decision Sciences and Systems, Technical University of Munich





Step 1: (Re)assign instances to the closest cluster



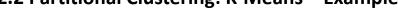
p _i	х	У
1	4	3
2	0.5	2
3	3	2
4	4	2
5	1	1

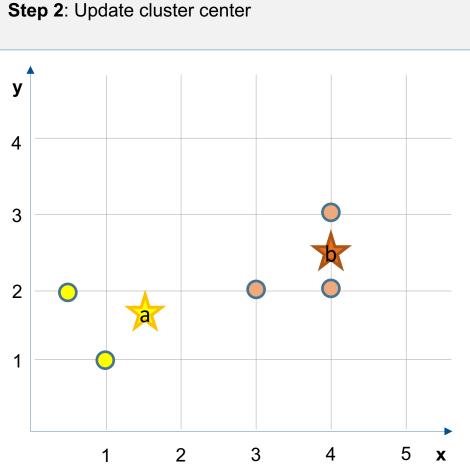
Centroids		
C _i	х	У
a	1.5	1.67
b	4	2.5

[©] Chair of Decision Sciences and Systems, Technical University of Munich

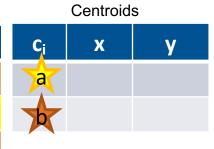








Dataset		
p _i	X	у
1	4	3
2	0.5	2
3	3	2
4	4	2
5	1	1

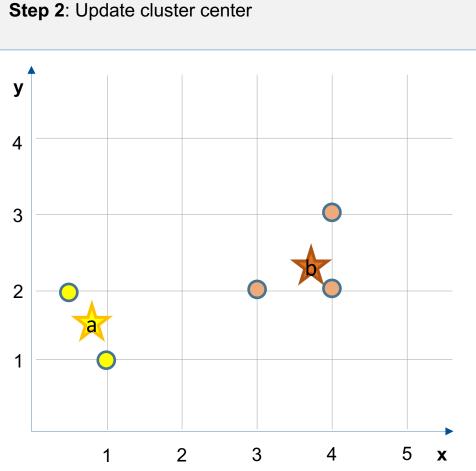


[©] Chair of Decision Sciences and Systems, Technical University of Munich





2.2 i artitional clustering. K-Means Example



Dataset		
p _i	x	у
1	4	3
2	0.5	2
3	3	2
4	4	2
5	1	1

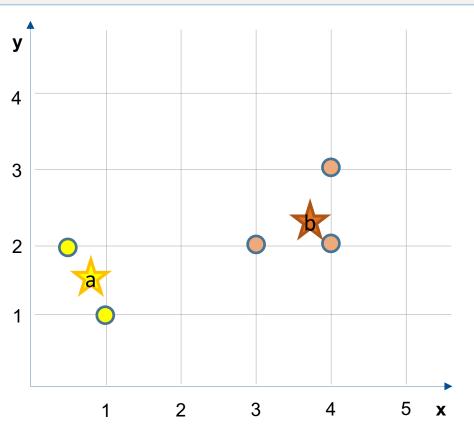
Centroids		
c _i	х	у
a	0.75	1.5
b	3.67	2.33

[©] Chair of Decision Sciences and Systems, Technical University of Munich





Step 1: (Re)assign instances to the closest cluster – No Reassignment: Algorithm terminates



p _i	х	у
1	4	3
2	0.5	2
3	3	2
4	4	2
5	1	1

Centroids		
C _i	X	у
a	0.75	1.5
b	3.67	2.33

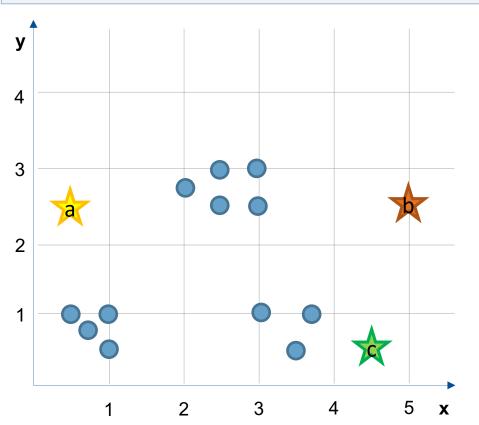
[©] Chair of Decision Sciences and Systems, Technical University of Munich





2.2 Partitional Clustering: K-Means – Exercise 9.1

Group the data into three clusters applying the k-Means algorithm and the Euclidean distance function



Dataset		
p _i	X	У
1	2.5	3
2	3	3
3	2	2.75
4	2.5	2.5
5	3	2.5
6	0.5	1
7	1	1
8	3	1
9	3.75	1
10	0.75	0.75
11	1	0.5
12	3.5	0.5

Dataset

C _i	Х	У
a	0.5	2.5
b	5.0	2.5
C	4.5	0.5

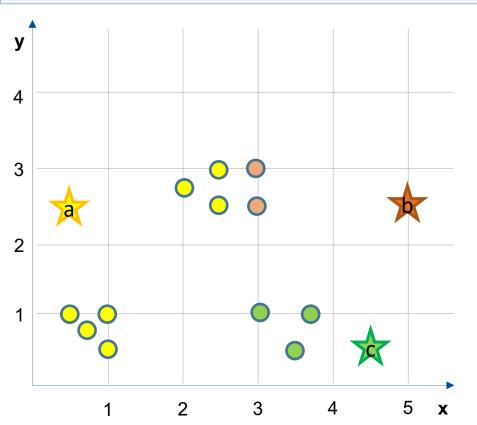
[©] Chair of Decision Sciences and Systems, Technical University of Munich





2.2 Partitional Clustering: K-Means – Exercise 9.1

Solution Step 1: (Re)assign instances to the closest cluster



p _i	х	У
1	2.5	3
2	3	3
3	2	2.75
4	2.5	2.5
5	3	2.5
6	0.5	1
7	1	1
8	3	1
9	3.75	1
10	0.75	0.75
11	1	0.5
12	3.5	0.5

Dataset

C _i	X	у
a	0.5	2.5
b	5.0	2.5
C	4.5	0.5

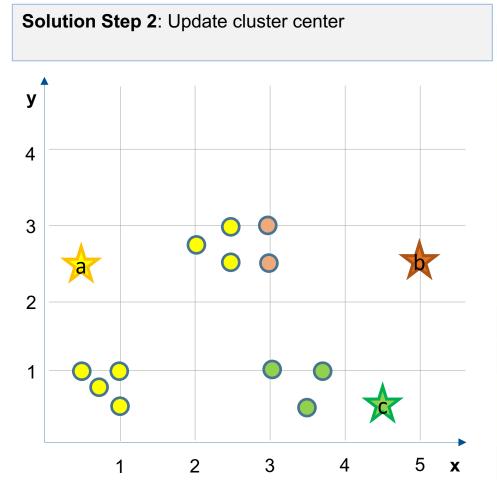
Centroids

[©] Chair of Decision Sciences and Systems, Technical University of Munich





2.2 Partitional Clustering: K-Means – Exercise 9.1



p _i	х	У
1	2.5	3
2	3	3
3	2	2.75
4	2.5	2.5
5	3	2.5
6	0.5	1
7	1	1
8	3	1
9	3.75	1
10	0.75	0.75
11	1	0.5
12	3.5	0.5

Dataset

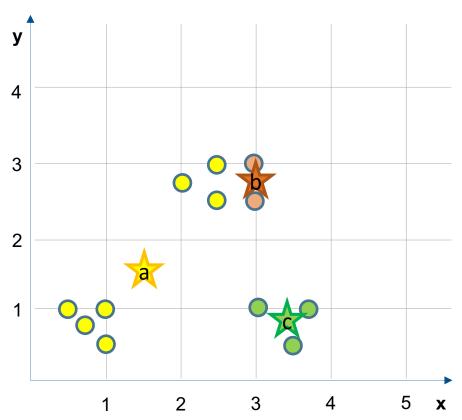
Centroids		
c _i	х	у
a		
b		
C		





2.2 Partitional Clustering: K-Means – Exercise 9.1

Solution Step 2: Update cluster center



Dataset		
p _i	x	у
1	2.5	3
2	3	3
3	2	2.75
4	2.5	2.5
5	3	2.5
6	0.5	1
7	1	1
8	3	1
9	3.75	1
10	0.75	0.75
11	1	0.5
12	3.5	0.5

Datacat

c _i	X	У
a	1.46	1.64
b	3.00	2.75
TOT	3.42	0.83

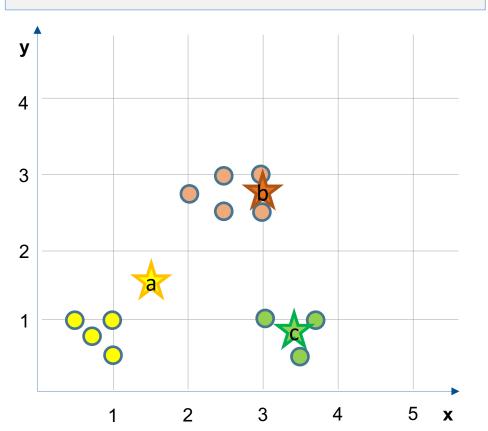
Centroids





2.2 Partitional Clustering: K-Means – Exercise 9.1

Solution Step 1: (Re)assign instances to the closest cluster



Dalasel		
p _i	x	У
1	2.5	3
2	3	3
3	2	2.75
4	2.5	2.5
5	3	2.5
6	0.5	1
7	1	1
8	3	1
9	3.75	1
10	0.75	0.75
11	1	0.5
12	3.5	0.5

Dataset

a	1.46	1.64
b	3.00	2.75
C	3.42	0.83

Centroids c_i

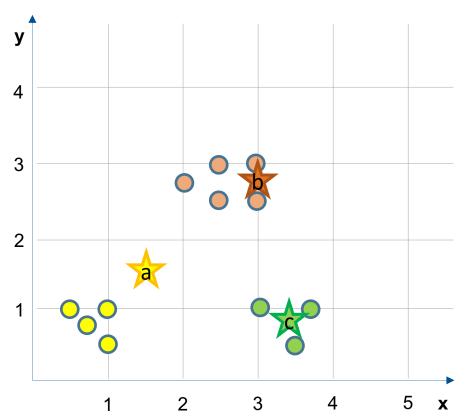
X





2.2 Partitional Clustering: K-Means – Exercise 9.1

Solution Step 2: Update cluster center



Dataset		
p _i	X	У
1	2.5	3
2	3	3
3	2	2.75
4	2.5	2.5
5	3	2.5
6	0.5	1
7	1	1
8	3	1
9	3.75	1
10	0.75	0.75
11	1	0.5
12	3.5	0.5

Datacat

Centroids c _i				
C _i	X	у		
a				
b				
C				

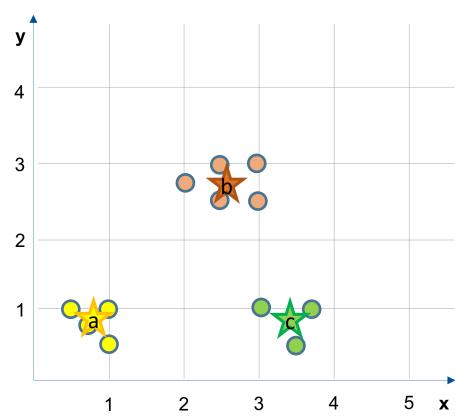
[©] Chair of Decision Sciences and Systems, Technical University of Munich





2.2 Partitional Clustering: K-Means – Exercise 9.1

Solution Step 2: Update cluster center



Dataset				
p _i	x	у		
1	2.5	3		
2	3	3		
3	2	2.75		
4	2.5	2.5		
5	3	2.5		
6	0.5	1		
7	1	1		
8	3	1		
9	3.75	1		
10	0.75	0.75		
11	1	0.5		
12	3.5	0.5		

Dataset

c _i	х	у		
a	0.81	0.81		
b	2.60	2.75		
TO	3.42	0.83		

Centroids c

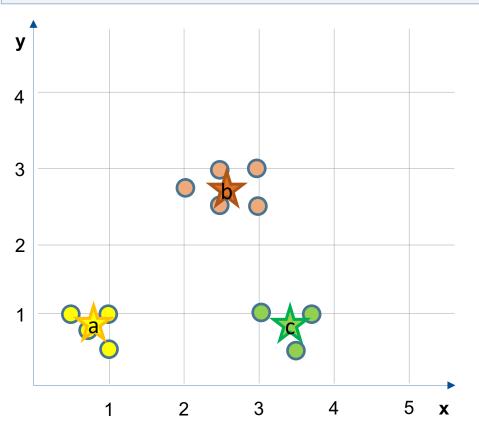
© Chair of Decision Sciences and Systems, Technical University of Munich





2.2 Partitional Clustering: K-Means – Exercise 9.1

Solution Step 1: (Re)assign instances to the closest cluster – No Reassignment: Algorithm terminates



Dalasel				
p _i	x	У		
1	2.5	3		
2	3	3		
3	2	2.75		
4	2.5	2.5		
5	3	2.5		
6	0.5	1		
7	1	1		
8	3	1		
9	3.75	1		
10	0.75	0.75		
11	1	0.5		
12	3.5	0.5		

Dataset

Centrolas c _i				
Cį	х	у		
a	0.81	0.81		
b	2.60	2.75		
TOT	3.42	0.83		

Centroids c.





2.3 Probabilistic Clustering: Expectation-Maximization (EM) – Fuzzy Clustering

Why Fuzzy Clustering?

So far: Each object p in our data set can be assigned to one of clusters only

However: Sometimes, a fuzzy or flexible cluster assignment is realistic

Idea: 2-step method to calculate cluster assignment probabilities (1) & estimate distr. parameters (2) Method:

- [init] Start with guesses for cluster centers and define k
- [repeat]
 - Expectation step: calculate likelihoods for instance p belonging to distribution (=cluster) A
 - Maximization step: optimize the distribution parameters based on the instance likelihoods
- [until convergence/no changes]

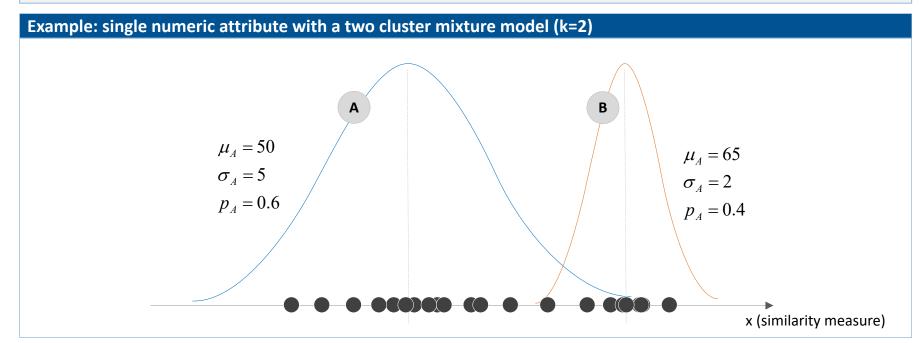




2.3 Probabilistic Clustering: Expectation-Maximization (EM) – Fuzzy Clustering

- Model the various clusters as probability distributions
- Identifying the best distribution for one cluster: Maximum Likelihood estimates
- Maximum-Likelihood estimates for the Standard Normal Distribution are

$$\mu = \bar{x}$$
 and $s^2 = \frac{\sum (x_i - \bar{x})^2}{n}$



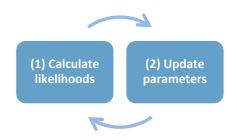




2.3 Probabilistic Clustering: Expectation-Maximization (EM) – Fuzzy Clustering

Initialization

- Assume equal probabilities p_i for each distribution/cluster
 Initial guess for parameters
- μ = define one instance as the cluster mean
- σ = set standard deviation of each distribution to 1



(1) Expectation Step (given k = A and B)

$$f(x, \mu_A, \sigma_A) = \frac{1}{\sigma_A \cdot \sqrt{2\pi}} \cdot e^{-\frac{(x - \mu_A)^2}{2 \cdot \sigma_A^2}}$$
$$\Pr[x] = f(x, \mu_A, \sigma_A) \cdot p_A + f(x, \mu_B, \sigma_B) \cdot p_B$$

Given instance x, the probability it belongs to cluster A is:

$$\Pr[A|x] = \frac{f(x, \mu_A, \sigma_A) \cdot p_A}{\Pr[x]}$$

Pr[A|x] serves as the weight w_i in the maximization step.

(2) Maximization Step

Optimize distribution/cluster parameters based on the instance weights w_i (= the likelihoods):

$$\mu_{A} = \frac{w_{1}x_{1+} w_{2}x_{2} + \dots + w_{n}x_{n}}{w_{1} + w_{2} + \dots + w_{n}}$$

$$\sigma_{A} = \sqrt{\frac{w_{1}(x_{1} - \mu_{A})^{2} + \dots + w_{n}(x_{n} - \mu_{A})^{2}}{w_{1} + w_{2} + \dots + w_{n}}}$$

$$p_{A} = \frac{\sum w_{A}}{\sum w_{A} + \sum w_{B}}; \quad p_{B} = 1 - p_{A}$$

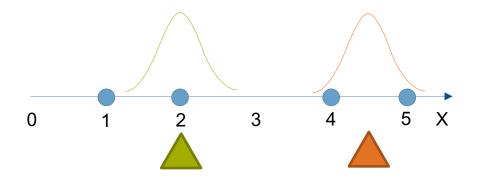




2.3 Probabilistic Clustering: Expectation-Maximization – Example

Given k=2, perform EM algorithm with the following instances

Instance	1	2	3	4
Value	1	2	4	5



Initialisation

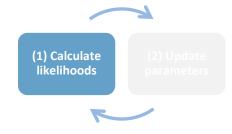
μ_{A}	2
σ_{A}	1.00
p _A	50%
μ_{B}	4.5
σ_{B}	1.00
p _B	50%
	σ _A





2.3 Probabilistic Clustering: Expectation-Maximization – Example

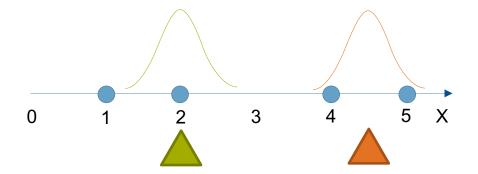
phase 1, step 1: Calculate cluster probabilities



Instance	1	2	3	4
Value	1	2	4	5



μ_{A}	2
σ_{A}	1.00





1.00
50%
4.5
1.00
50%

	1	2	3	4
Pr[A x]	99.64%	95.79%	13.30%	1.24%
Pr[B x]	0.36%	4.21%	86.70%	98.76%

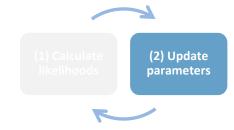
[©] Chair of Decision Sciences and Systems, **Technical University of Munich**



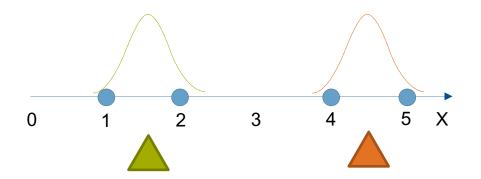


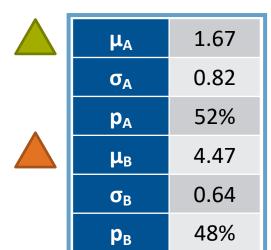
2.3 Probabilistic Clustering: Expectation-Maximization – Example

phase 1, step 2: Update distribution parameters



Instance	1	2	3	4
Value	1	2	4	5





	1	2	3	4
Pr[A x]	99.64%	95.79%	13.30%	1.24%
Pr[B x]	0.36%	4.21%	86.70%	98.76%

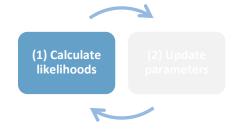
[©] Chair of Decision Sciences and Systems, Technical University of Munich



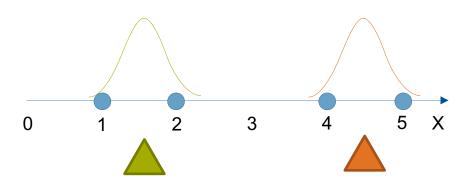


2.3 Probabilistic Clustering: Expectation-Maximization – Example

phase 2, step 1: Calculate cluster probabilities



Instance	1	2	3	4
Value	1	2	4	5





μ_{A}	1.67
σ_{A}	0.82
p _A	52%
μ_{B}	4.47
σ_{B}	0.64
p _B	48%

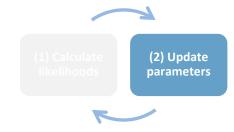
	1	2	3	4
Pr[A x]	100.00%	99.93%	1.95%	0.03%
Pr[B x]	0.00%	0.07%	98.05%	99.97%



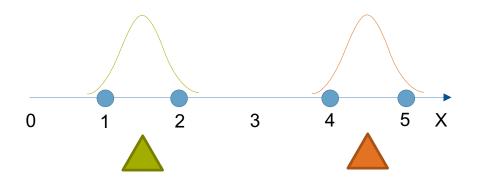


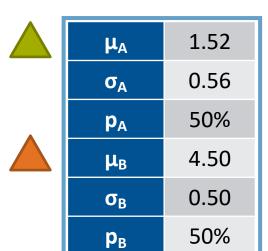
2.3 Probabilistic Clustering: Expectation-Maximization – Example

phase 2, step 2: Update distribution parameters



Instance	1	2	3	4
Value	1	2	4	5





	1	2	3	4
Pr[A x]	100.00%	99.93%	1.95%	0.03%
Pr[B x]	0.00%	0.07%	98.05%	99.97%

[©] Chair of Decision Sciences and Systems, Technical University of Munich

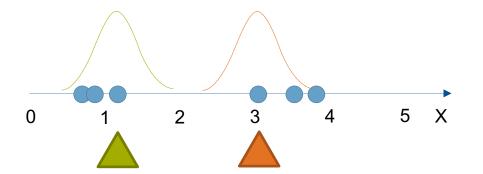




2.3 Probabilistic Clustering: Expectation-Maximization – Exercise 9.2

Given k=2, perform EM algorithm with the following instances

Instance	1	2	3	4	5	6
Value	0.76	0.86	1.12	3.05	3.51	3.75



$\begin{array}{c|cccc} & \mu_A & 1.12 \\ & \sigma_A & 1.00 \\ & p_A & 50\% \\ & \mu_B & 3.05 \\ & \sigma_B & 1.00 \\ \end{array}$

 p_B

Initialisation

50%

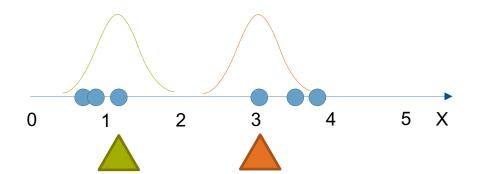


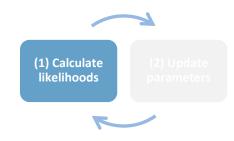


2.3 Probabilistic Clustering: Expectation-Maximization – Exercise 9.2

Solution phase 1, step 1: Calculate cluster probabilities

Instance	1	2	3	4	5	6
Value	0.76	0.86	1.12	3.05	3.51	3.75





μ_{A}	1.12
σ_{A}	1.00
p _A	50%
μ_{B}	3.05
σ_{B}	1.00
p _B	50%

	1	2	3	4	5	6
Pr[A x]	92.81%	91.41%	86.56%	13.44%	6.01%	3.87%
Pr[B x]	7.19%	8.59%	13.44%	86.56%	93.99%	96.13%

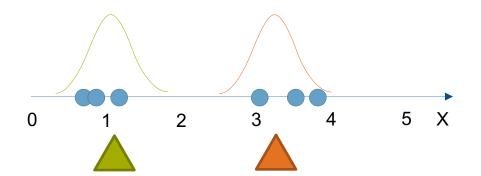


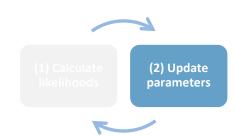


2.3 Probabilistic Clustering: Expectation-Maximization – Exercise 9.2

Solution phase 1, step 2: Update distribution parameters

Instance	1	2	3	4	5	6
Value	0.76	0.86	1.12	3.05	3.51	3.75





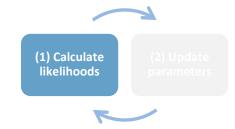
μ_{A}	1.10
σ_{A}	0.66
PΑ	49%
$\mu_{ extsf{B}}$	3.21
$\sigma_{\scriptscriptstyle B}$	0.78
p _B	51%

	1	2	3	4	5	6
Pr[A x]	92.81%	91.41%	86.56%	13.44%	6.01%	3.87%
Pr[B x]	7.19%	8.59%	13.44%	86.56%	93.99%	96.13%





2.3 Probabilistic Clustering: Expectation-Maximization – Exercise 9.2



Solution	phase 2, step	1: Calculate	cluster probabilities
----------	---------------	--------------	-----------------------

Instance	1	2	3	4	5	6
Value	0.76	0.86	1.12	3.05	3.51	3.75



μ_{A}	1.10
σ_{A}	0.66



٦.	49%
JA	43/0

	П
	r



σ_{B}	0.78

p _B	51%
----------------	-----

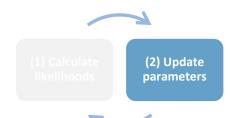
_						
0	1	2	3	4	5	X

	1	2	3	4	5	6
Pr[A x]	99.25%	98.97%	97.55%	1.49%	0.16%	0.05%
Pr[B x]	0.75%	1.03%	2.45%	98.51%	99.84%	99.95%





2.3 Probabilistic Clustering: Expectation-Maximization – Exercise 9.2



Solution phase 2, step 2: Update distribution parameters

Instance	1	2	3	4	5	6
Value	0.76	0.86	1.12	3.05	3.51	3.75



μ_{A}	0.92
g.	0.22





μ_{B}	3.40

σ_{B}	0.4

p _B	51%
----------------	-----

^		2	3	1	5	Χ
U	1	2	3	4	5	^

	1	2	3	4	5	6
Pr[A x]	99.25%	98.97%	97.55%	1.49%	0.16%	0.05%
Pr[B x]	0.75%	1.03%	2.45%	98.51%	99.84%	99.95%