

# Clustering methods: Part 7

# Outlier removal

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# Outlier detection methods

## Distance-based methods

- Knorr & Ng

## Density-based methods

- KDIST:  $K^{\text{th}}$  nearest distance
- MeanDIST: Mean distance

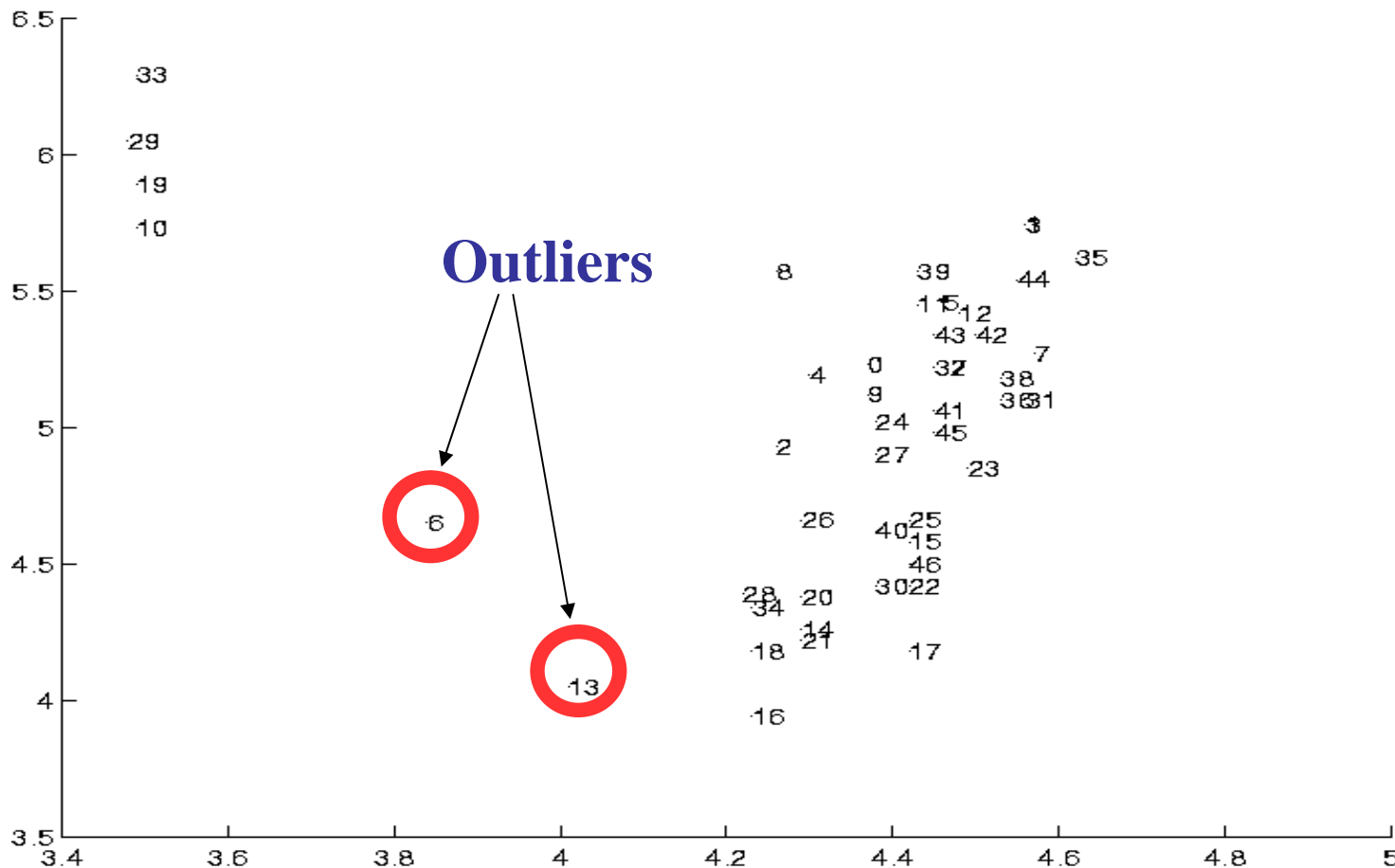
## Graph-based methods

- MkNN: Mutual K-nearest neighbor
- ODIN: Indegree of nodes in k-NN graph

# What is outlier?

**One definition:** Outlier is an observation that deviates from other observations so much that it is expected to be generated by a different mechanism.

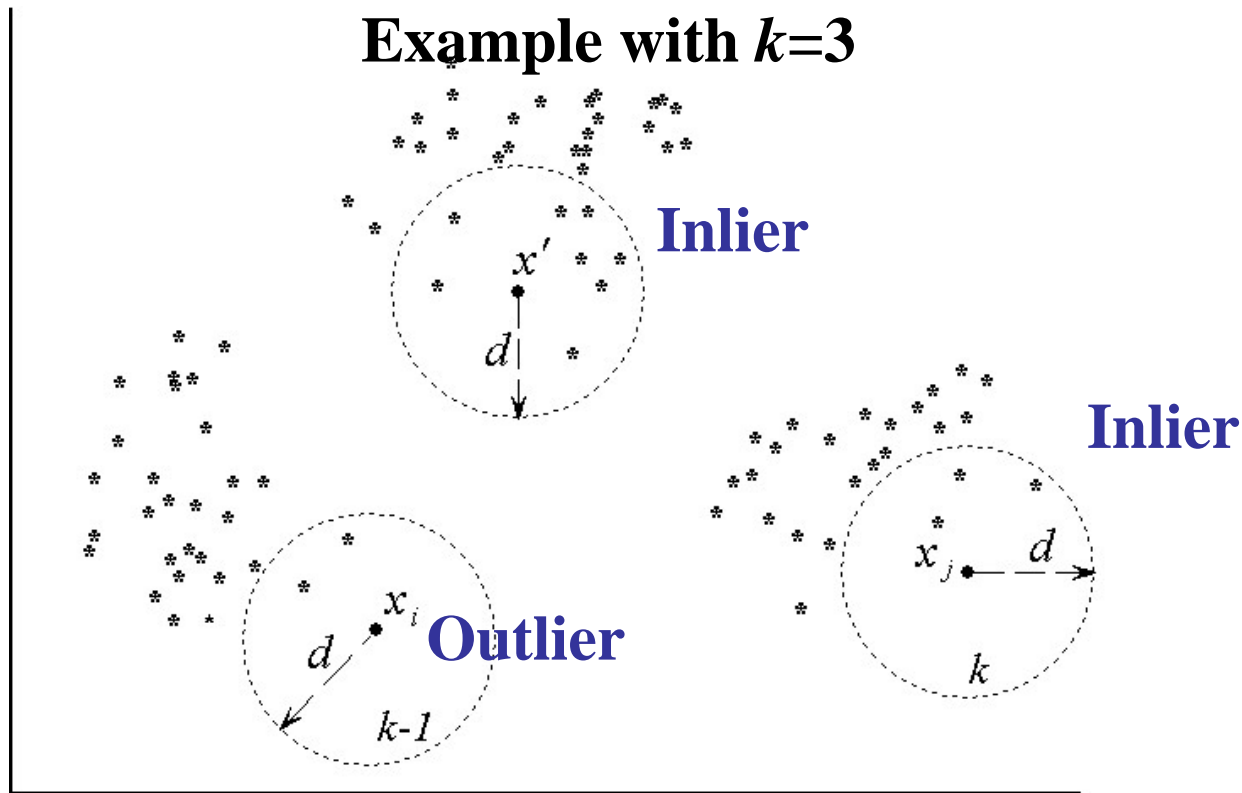
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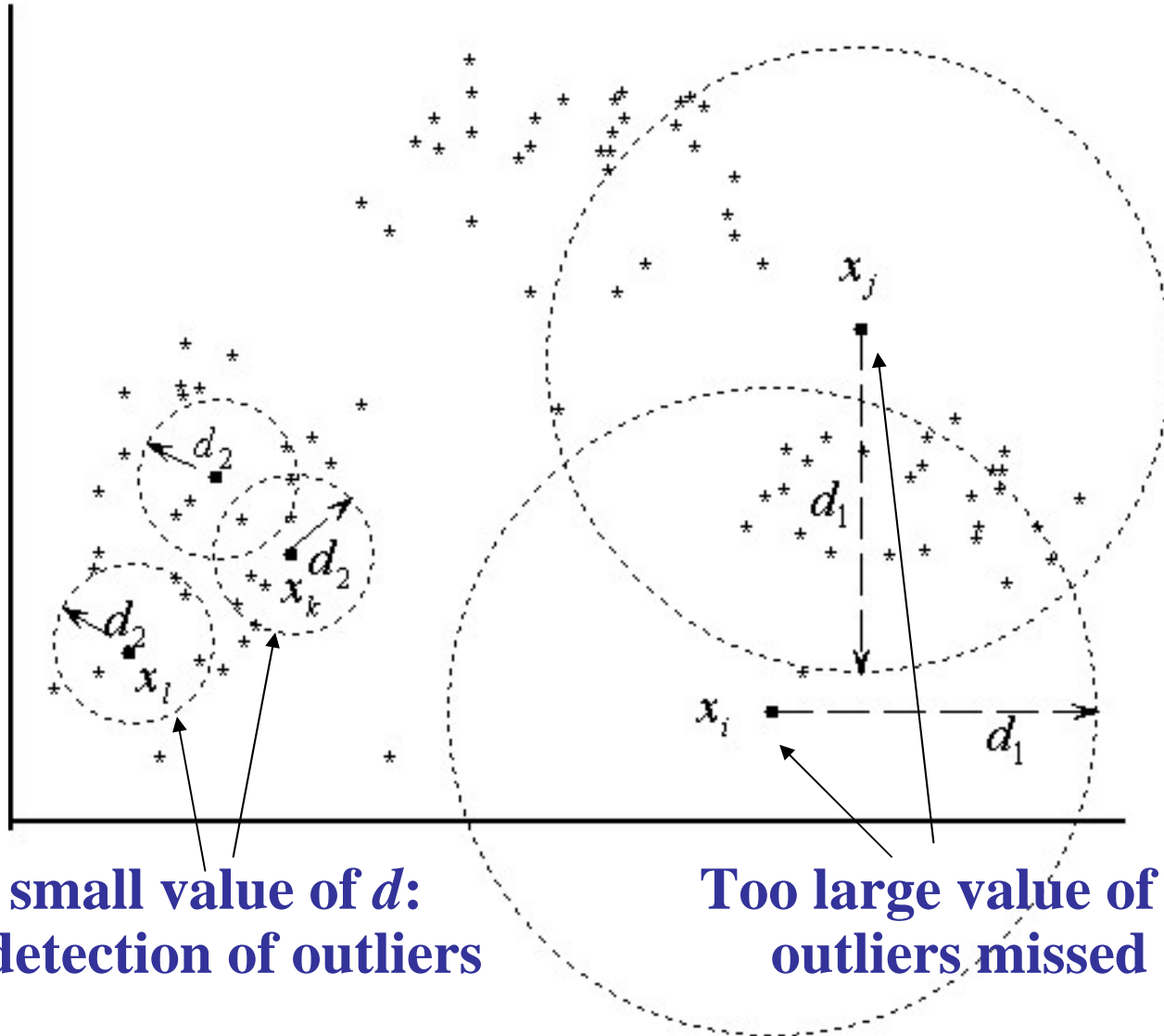
# Distance-based method

[Knorr and Ng , CASCR 1997]

**Definition:** Data point  $x$  is an outlier if at most  $k$  points are within the distance  $d$  from  $x$ .



# Selection of distance threshold



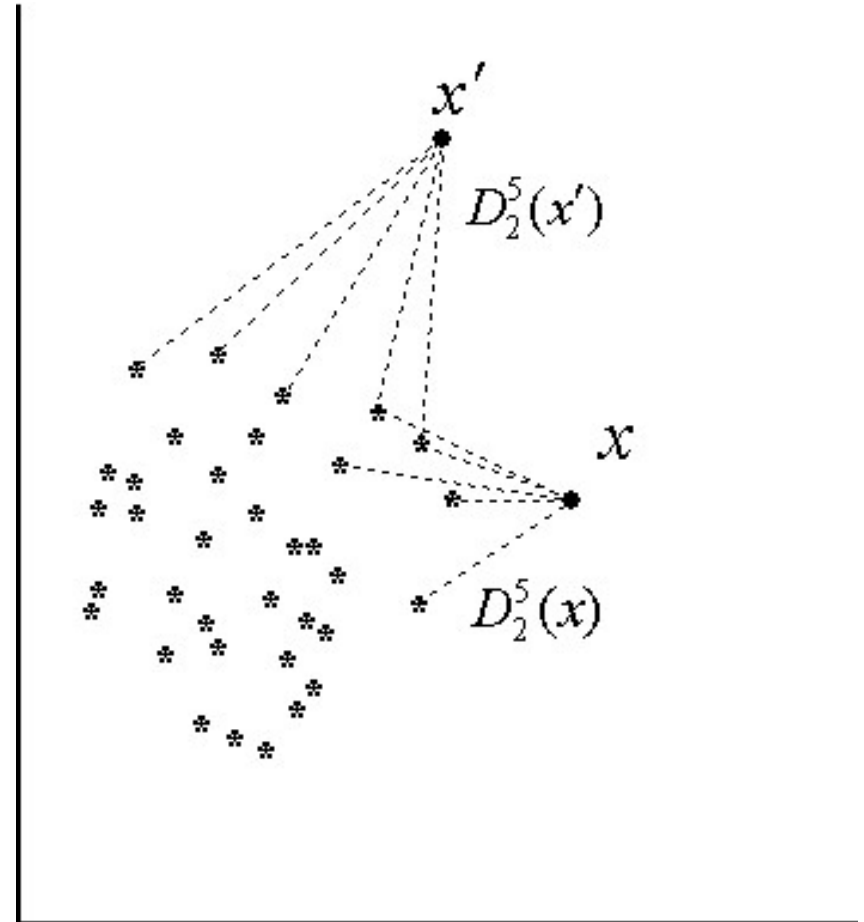
Too small value of  $d$ :  
false detection of outliers

Too large value of  $d$ :  
outliers missed

# Density-based method: KDIST

[Ramaswamy *et al.*, ACIM SIGMOD 2000]

- Define *KDIST* as distance to the  $k^{\text{th}}$  nearest point.
- Points are sorted by their *KDIST* distance. The last  $n$  points in the list are classified as outliers.



# Density-based: MeanDist

[Hautamäki *et al.*, ICPR 2004]

MeanDIST = the mean of  $k$  nearest distances.

User parameters: Cutting point  $k$ , and local threshold  $t$ :

$$T = \max(L_i - L_{i-1}) \cdot t$$

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## Algorithm 2 MeanDIST

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Compute  $T$  using Eq. 1 with  $t$

Calculate kNN graph of  $S$

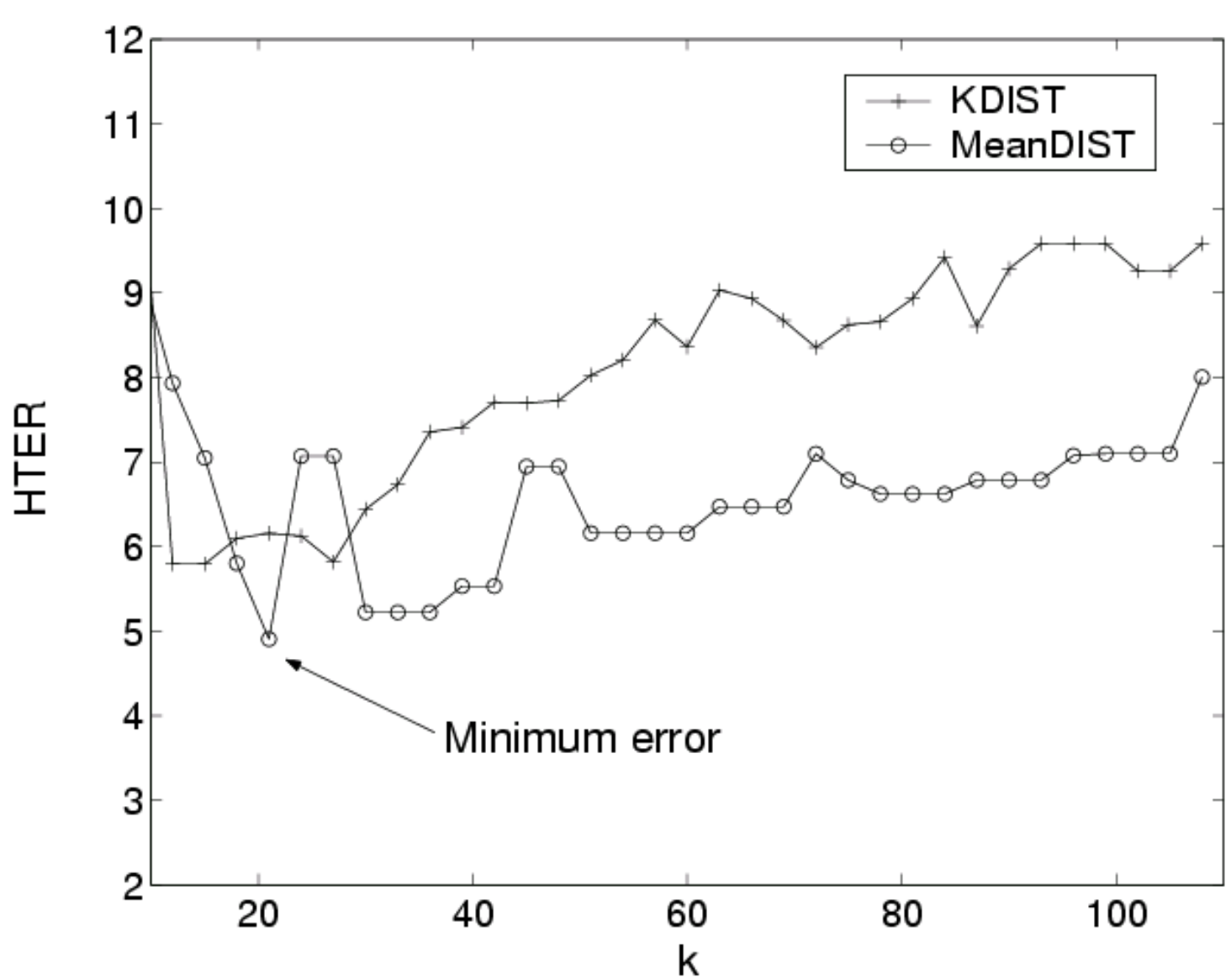
$L \leftarrow$  Sort vectors in ascending order by kNN density

Find smallest  $i$  for which  $L_i - L_{i-1} \geq T$

Mark  $L_i, \dots, L_{|S|}$  as outliers

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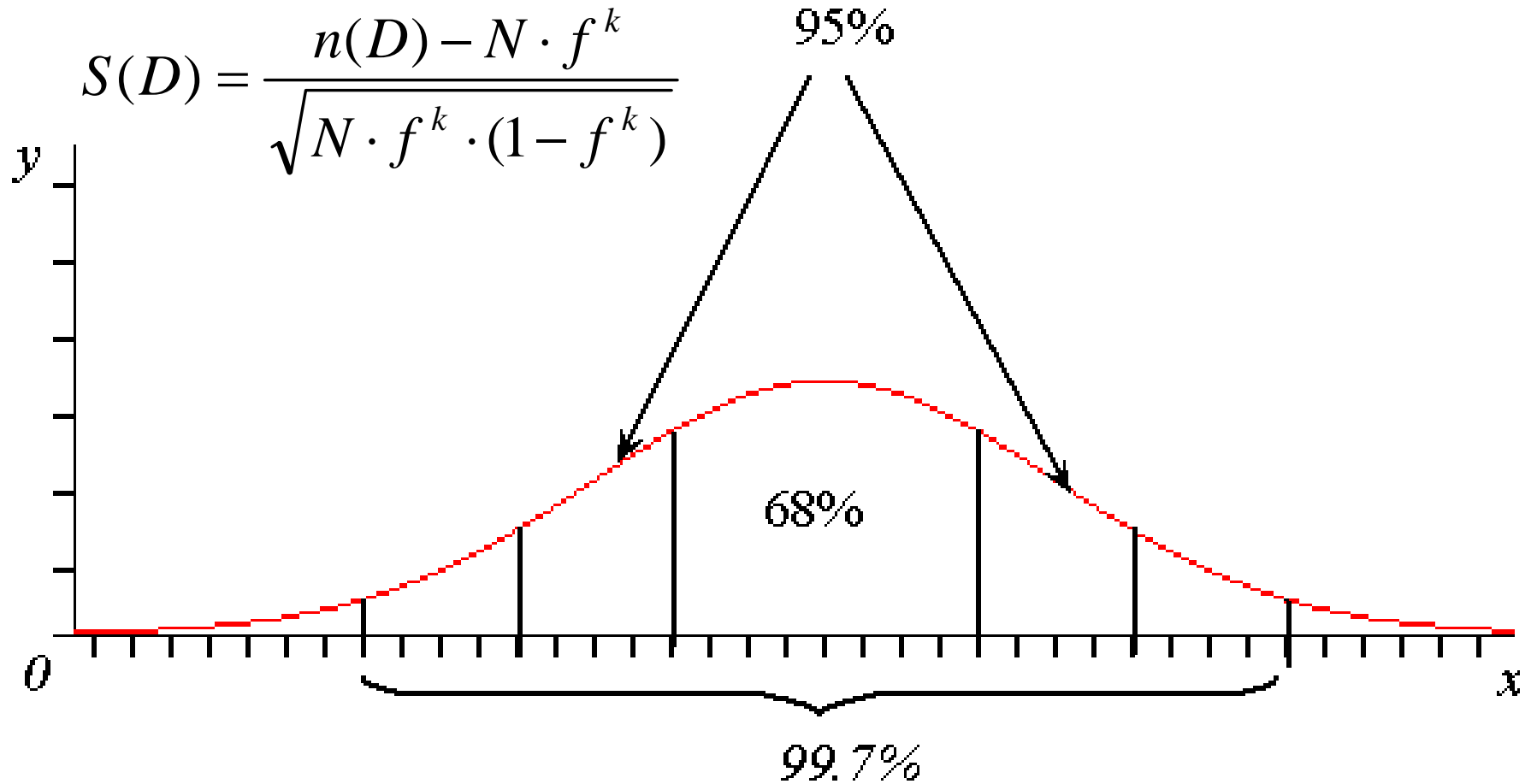
# Comparison of KDIST and MeanDIST



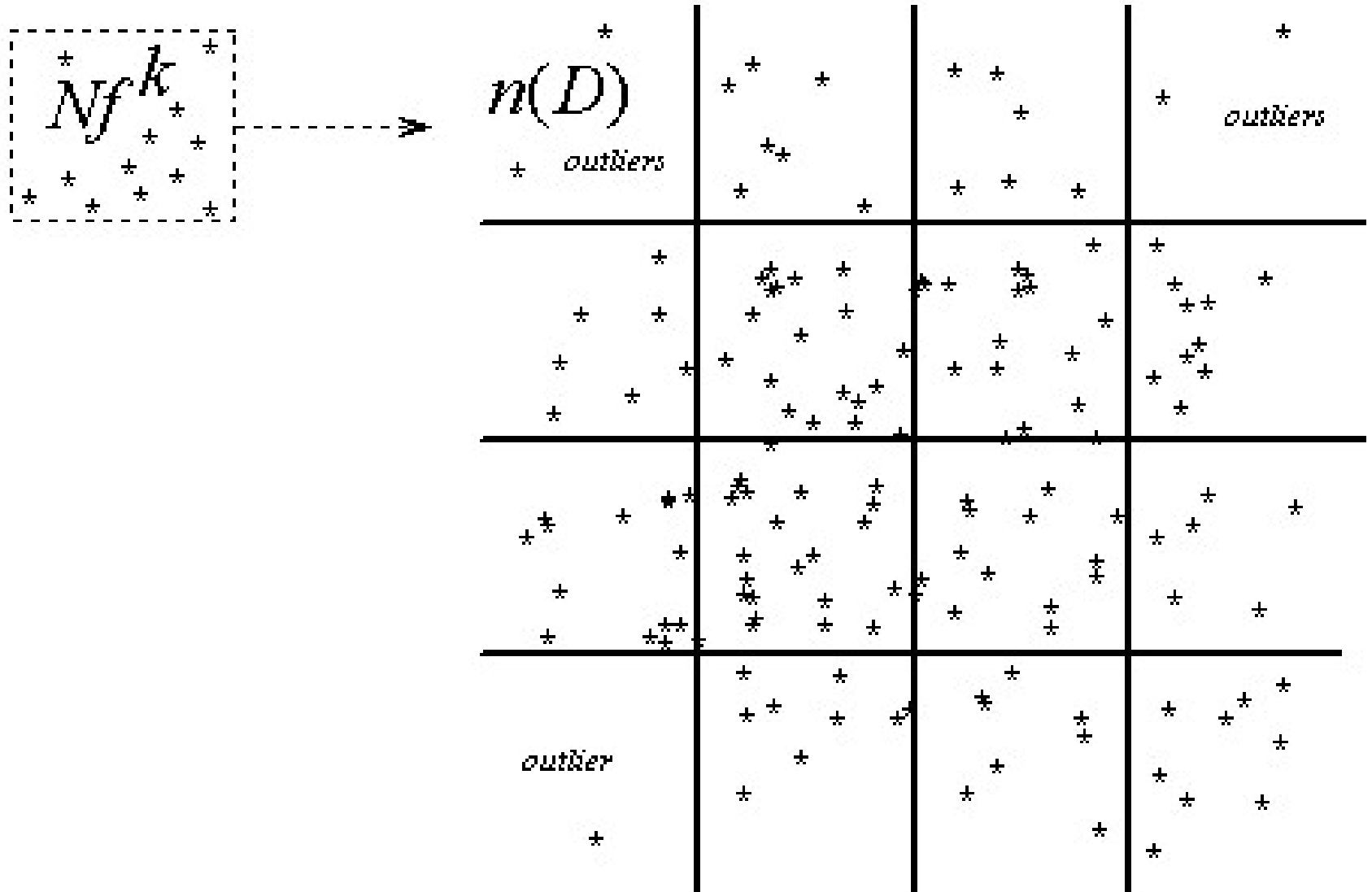


# Distribution-based method

[Aggarwal and Yu, ACM SIGMOD, 2001]



# Detection of sparse cells



# Mutual $k$ -nearest neighbor

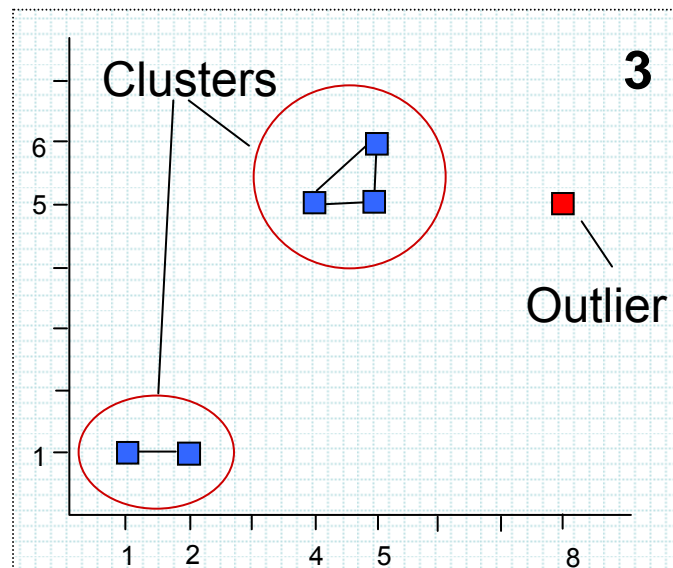
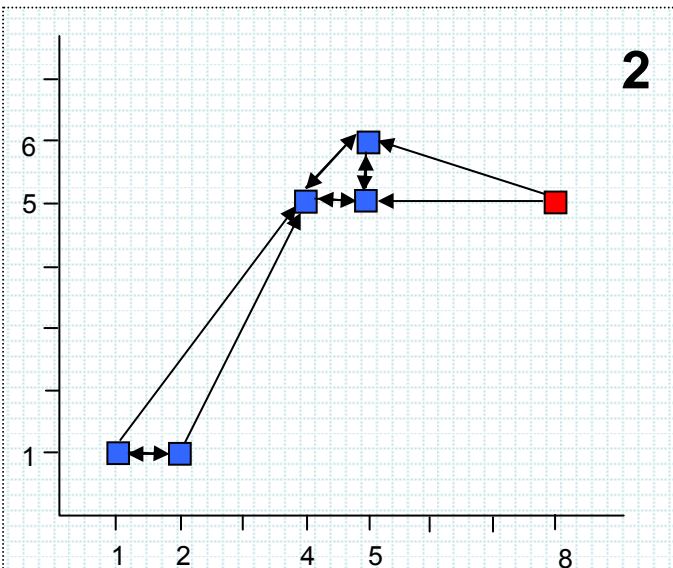
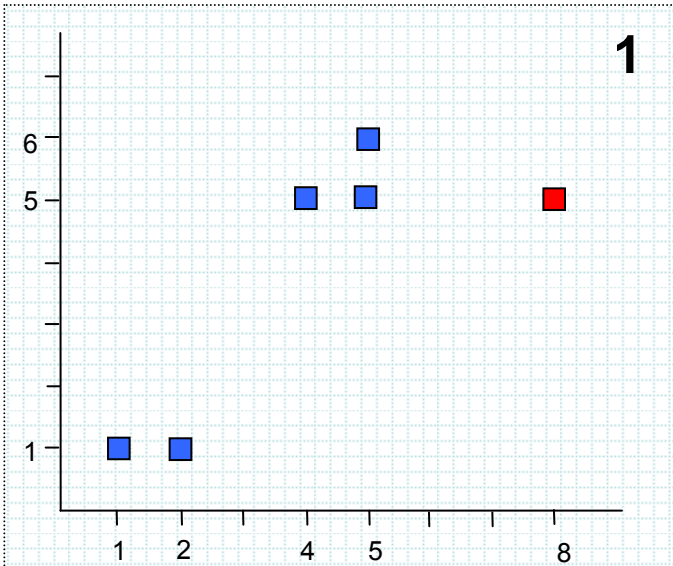
[Brito et al., *Statistics & Probability Letters*, 1997]

- Generate directed  $k$ -NN graph.
- Create undirected graph:
  1. Points  $a$  and  $b$  are *mutual neighbors* if both links  $a \rightarrow b$  and  $b \rightarrow a$  exist.
  2. Change all mutual links  $a \leftrightarrow b$  to undirected link  $a - b$ .
  3. Remove the rest.
- Connected components are clusters.
- Isolated points as outliers.

# Mutual $k$ -NN example

$$k = 2$$

1. Given a data with one outlier.
2. For each point find two nearest neighbours and create directed 2-NN graph.
3. For each pair of points, create link if both  $a \rightarrow b$  and  $b \rightarrow a$  exist.



# ODIN: Outlier detection using indegree

[Hautamäki et al., ICPR 2004]

**Definition:** Given kNN graph, classify data point  $x$  as an outlier its indegree  $\leq T$ .

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## Algorithm 1 ODIN

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$T$  is indegree threshold

Calculate kNN graph of  $S$

**for**  $i = 1$  to  $|S|$  **do**

**if** indegree of  $v_i \leq T$  **then**

        Mark  $v_i$  as outlier

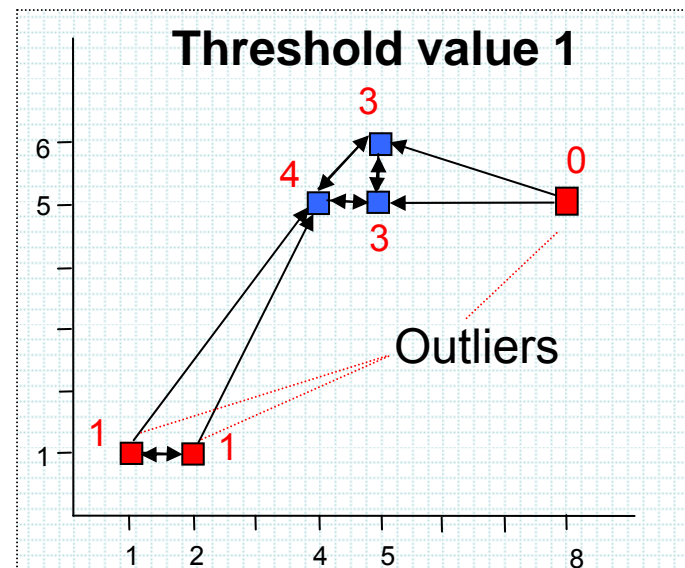
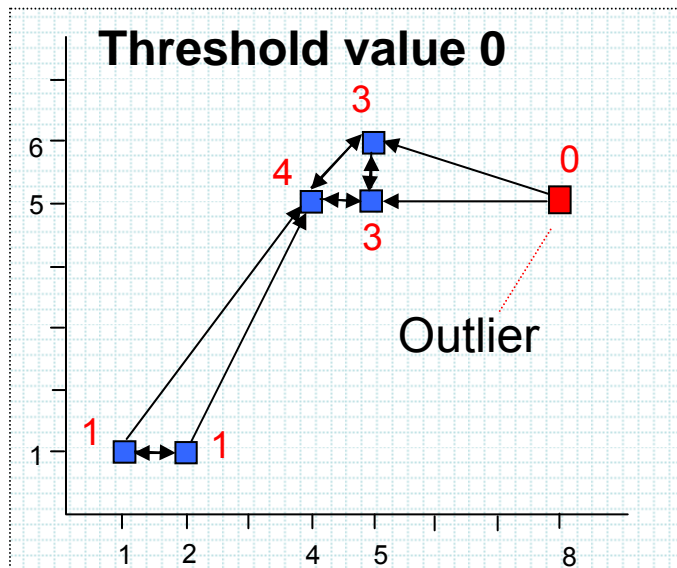
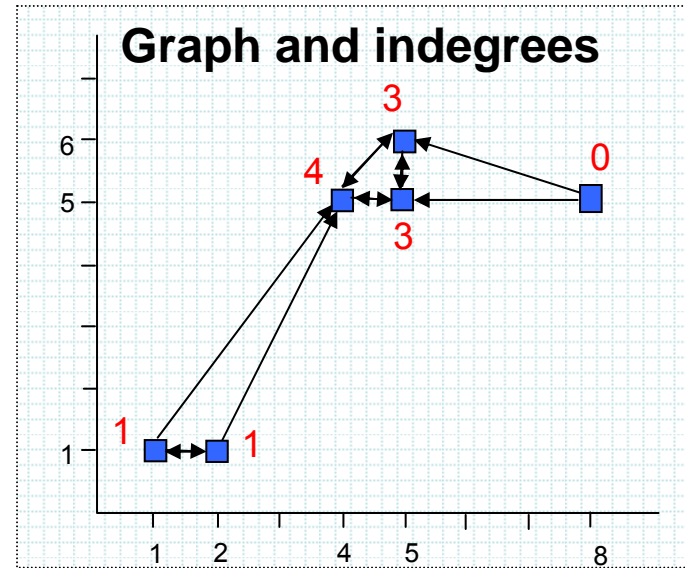
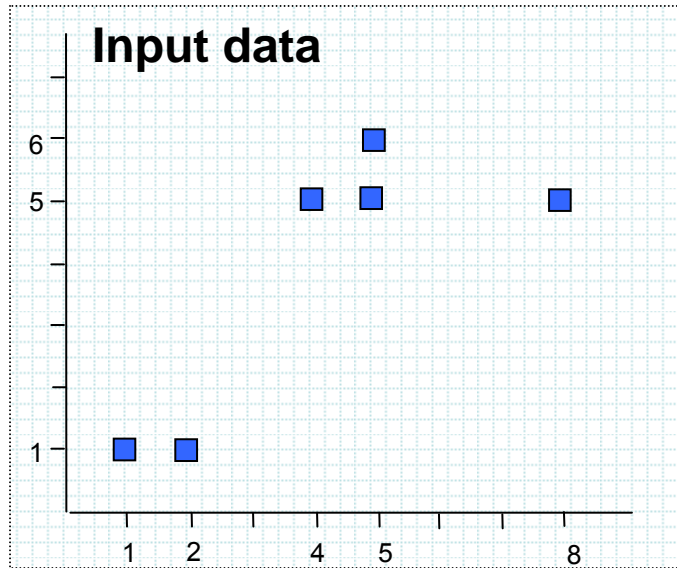
**end if**

**end for**

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# Example of ODIN

$k = 2$

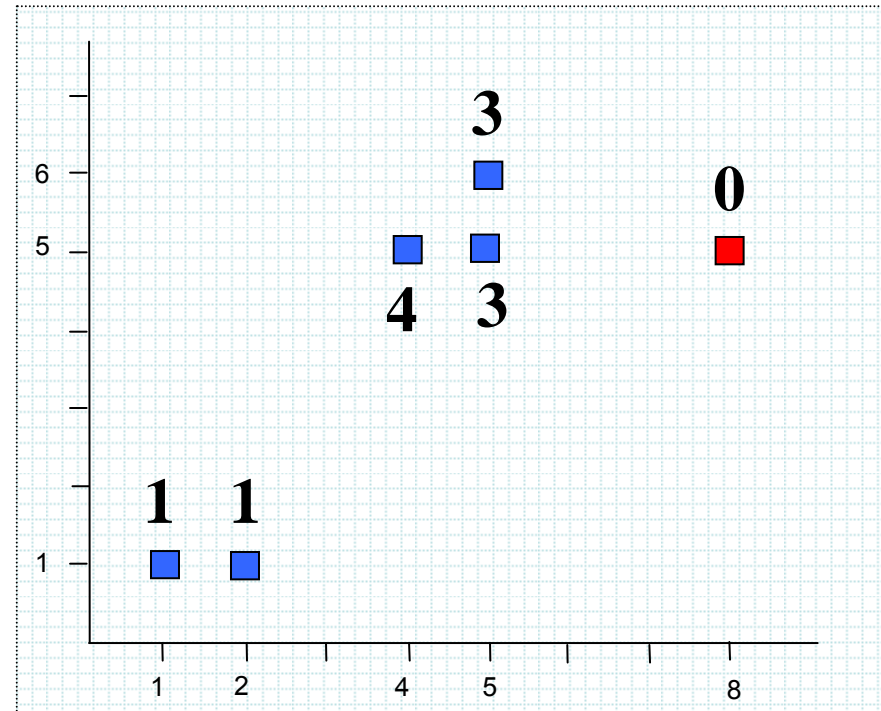


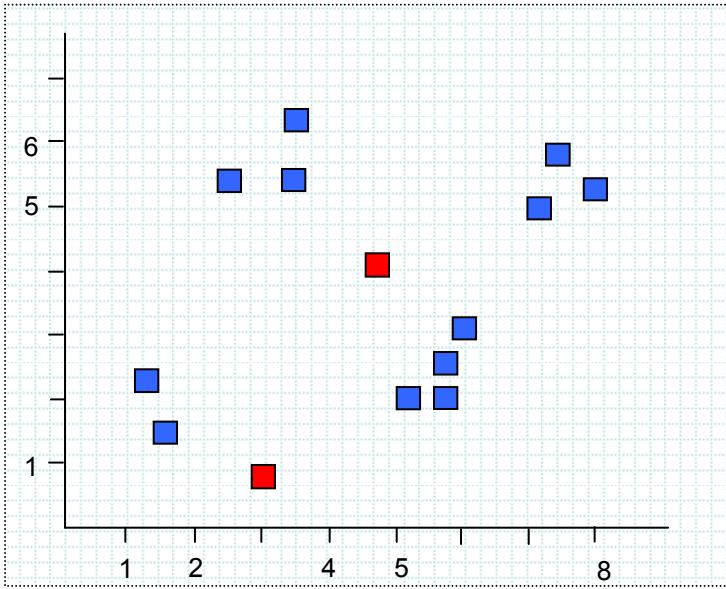
# Example of FA and FR

$k = 2$

$T$	False Acceptance	False Rejection
0	0/1	0/5
1	0/1	2/5
2	0/1	2/5
3	0/1	4/5
4	0/1	5/5
5	0/1	5/5
6	0/1	5/5

Detected as outlier with different threshold values ( $T$ )







# Experiments

## Measures

- False acceptance (FA):
  - Number of outliers that are not detected.
- False rejection (FR):
  - Number of good points wrongly classified as outlier.
- Half total error rate:
  - $HTER = (FR+FA) / 2$

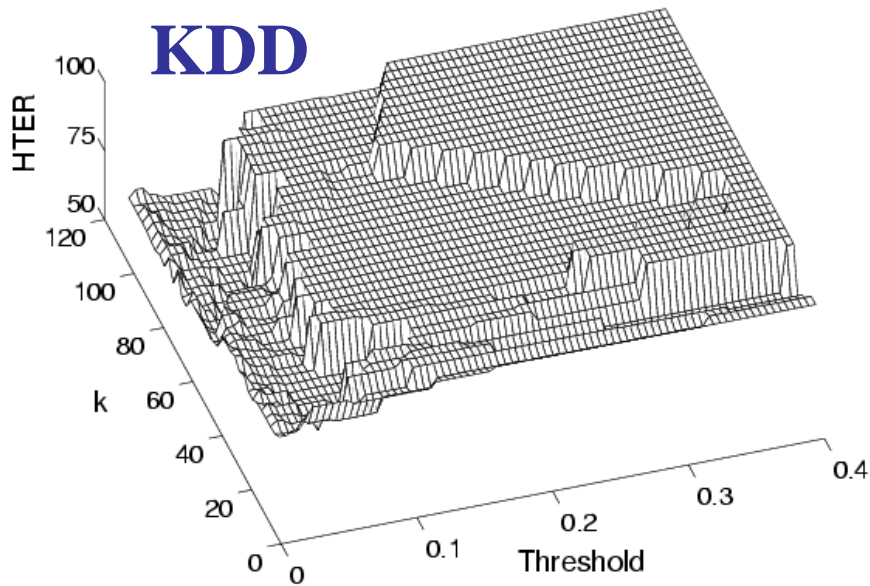
# Comparison of graph-based methods

Name	$N$	$d$	Outliers
HR [12]	47	2	2
KDD [9]	60318	3	486
NHL1 [8]	681	3	2
NHL2 [8]	731	3	1
synthetic	5165	2	165

Method	synthetic	KDD	HR	NHL1	NHL2
MkNN [1]	50.0 (13)	77.0 (1)	25.0 (5)	25.0 (29)	44.4 (28)
ODIN	9.0 (190,26)	49.6 (1,2)	<b>0.0</b> (7, 1)	<b>0.0</b> (87, 9)	<b>0.0</b> (36, 2)
MeanDIST	<b>4.9</b> (21, 0.05)	49.6 (232, 0.19)	30.0 (1, 0.15)	16.7 (20, 0.05)	43.8 (1, 0.57)
KDIST [11]	5.7 (12, 0.06)	<b>48.6</b> (72, 0.40)	30.0 (1, 0.15)	30.0 (1, 0.02)	41.7 (7, 0.75)

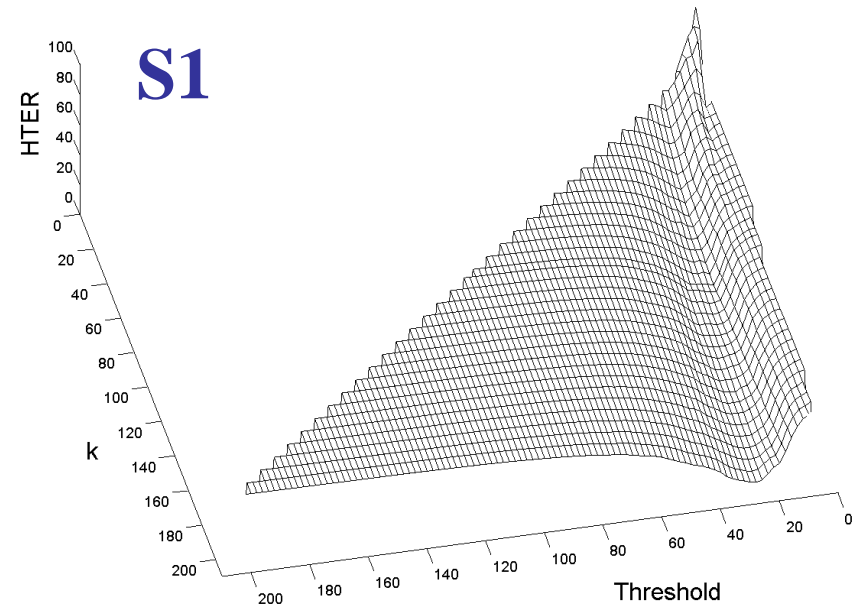
# Difficulty of parameter setup

**MeanDIST:**



Value of  $k$  is not important as long as threshold below 0.1.

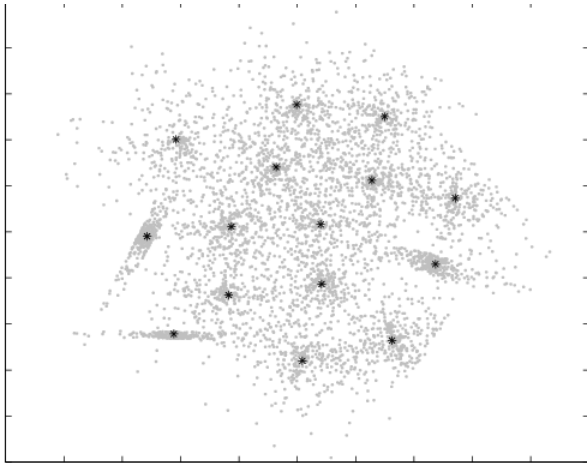
**ODIN:**



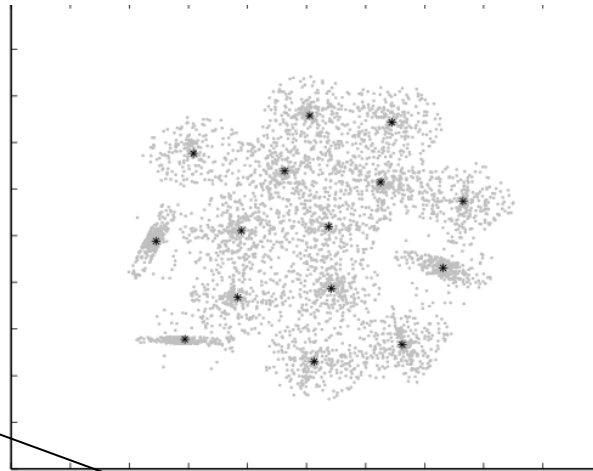
A clear valley in error surface between 20-50.

# Improved k-means using outlier removal

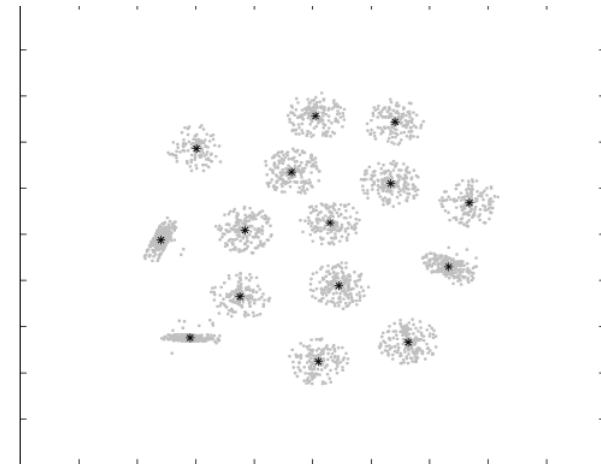
Original



After 40 iterations



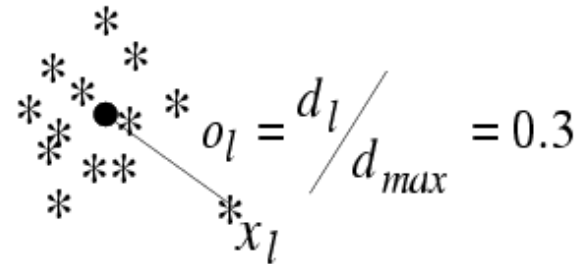
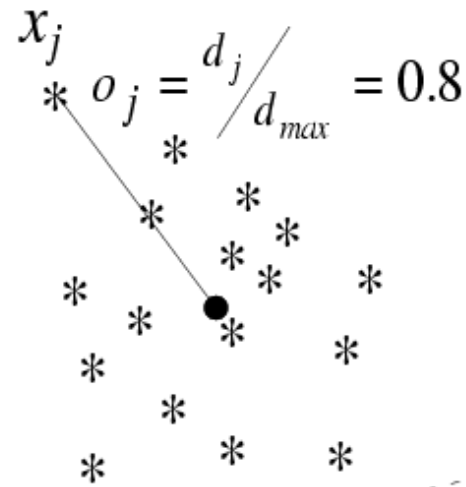
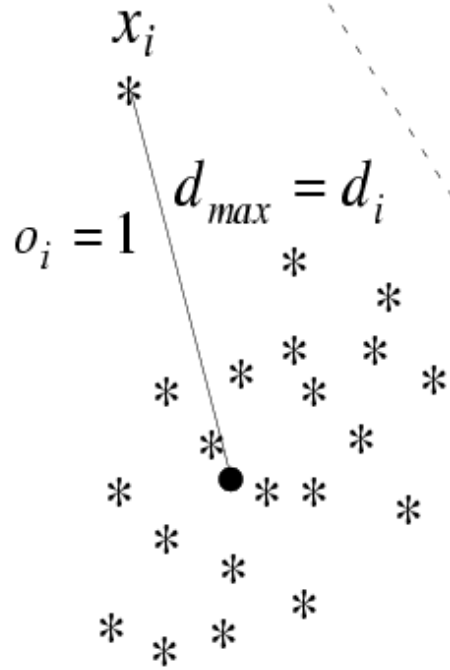
After 70 iterations



At each step, remove most diverging data objects and construct new clustering.

# Example of removal factor

$$o_i = \frac{\|x_i - c_{p_i}\|}{d_{max}}$$



# CERES algorithm

[Hautamäki et al., SCIA 2005]

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**Algorithm 1** CERES( $I, T$ )

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$C \leftarrow$  Initialize codebook

**for**  $j \leftarrow 1, \dots, I$  **do**

$d_{\max} \leftarrow \max_i \{ \|\vec{x}_i - \vec{c}_{p_i}\| \}$

**for**  $i \leftarrow 1, \dots, N$  **do**

$o_i = \|\vec{x}_i - \vec{c}_{p_i}\| / d_{\max}$

**if**  $o_i > T$  **then**

$X \leftarrow X \setminus \{\vec{x}_i\}$

**end if**

**end for**

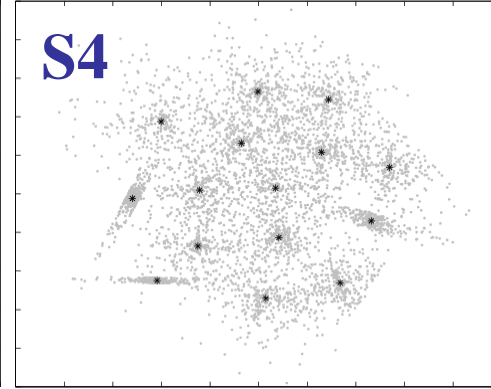
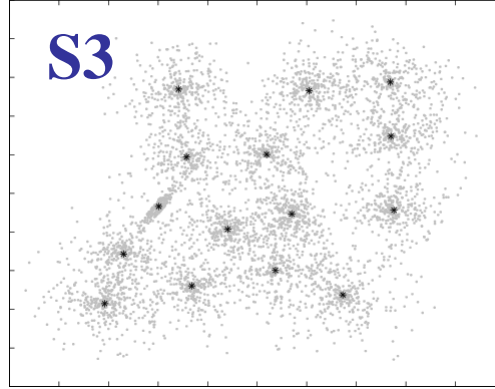
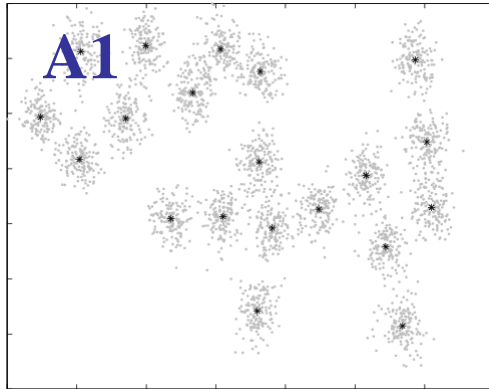
$(C, P) \leftarrow$  K-means( $X, C$ )

**end for**

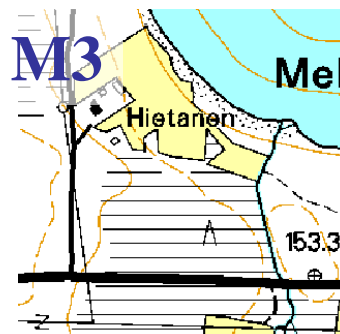
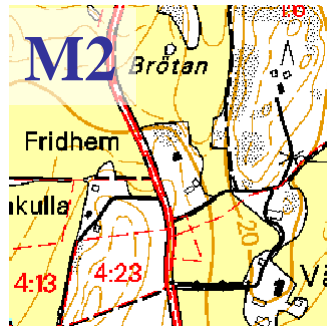
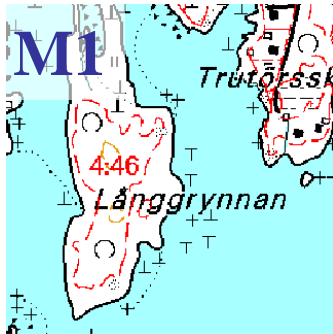
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# Experiments

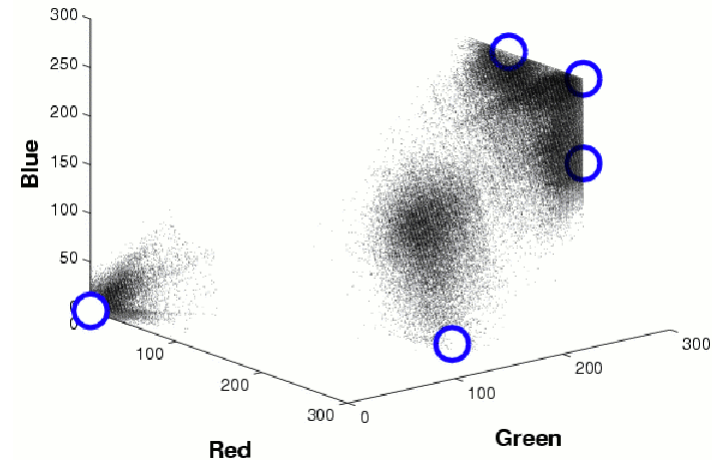
## Artificial data sets



## Image data sets



## Plot of M2



# Comparison

Algorithm	A1	S3	S4	M1	M2	M3
K-means	60	5719	7100	47	32	26
EM	525	3586	3507	46	49	35
CERES	56	3329	2813	45	13	23



# Literature

1. D.M. Hawkins, *Identification of Outliers*, Chapman and Hall, London, 1980.
2. W. Jin, A.K.H. Tung, J. Han, "Finding top-n local outliers in large database", In *Proc. 7th ACM SIGKDD Int. Conf. on Knowledge Discovery and Data Mining*, pp. 293-298, 2001.
3. E.M. Knorr, R.T. Ng, "Algorithms for mining distance-based outliers in large datasets", In *Proc. 24th Int. Conf. Very Large Data Bases*, pp. 392-403, New York, USA, 1998.
4. M.R. Brito, E.L. Chavez, A.J. Quiroz, J.E. Yukich, "Connectivity of the mutual k-nearest-neighbor graph in clustering and outlier detection", *Statistics & Probability Letters*, 35 (1), 33-42, 1997.

# Literature

5. C.C. Aggarwal and P.S. Yu, "Outlier detection for high dimensional data", *Proc. Int. Conf. on Management of data ACM SIGMOD*, pp. 37-46, Santa Barbara, California, United States, 2001.
6. V. Hautamäki, S. Cherednichenko, I. Kärkkäinen, T. Kinnunen and P. Fränti, Improving K-Means by Outlier Removal, In *Proc. 14th Scand. Conf. on Image Analysis (SCIA'2005)*, 978-987, Joensuu, Finland, June, 2005.
7. V. Hautamäki, I. Kärkkäinen and P. Fränti, "Outlier Detection Using k-Nearest Neighbour Graph", In *Proc. 17th Int. Conf. on Pattern Recognition (ICPR'2004)*, 430-433, Cambridge, UK, August, 2004.