Odkrivanje skupin

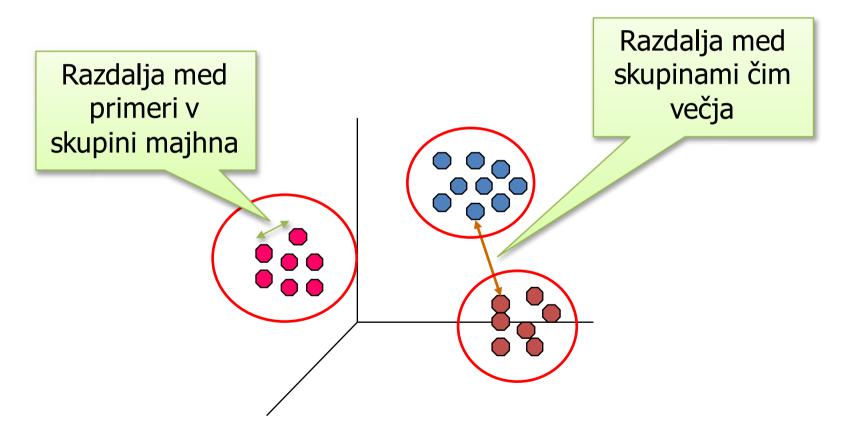
Tomaž Curk

metoda voditeljev (k-means) hierarhično razvrščanje (hierarchical clustering)

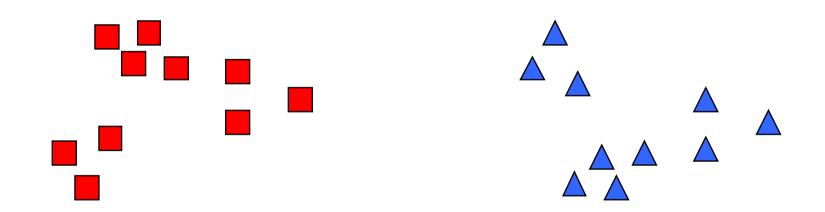
Tan, Steinbach & Kumar: Introduction to Data Mining http://www-users.cs.umn.edu/~kumar/dmbook/index.php

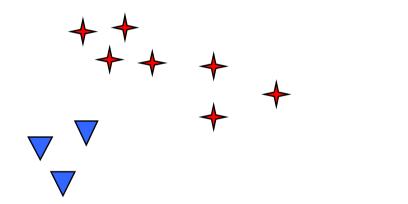
Odkrivanje skupin

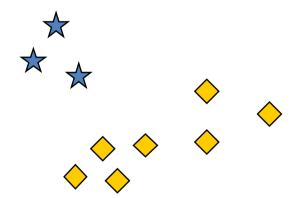
Poišči skupine primerov tako, da bo vsaka skupina vsebovala le podobne objekte.













Metode za razvrščanje v skupine

- Delitev primerov (Partitional clustering)
 - Primere delimo v neprekrivajoče skupine (clusters)
 - Primer: metoda voditeljev (k-means clustering)
- Hierarhično razvrščanje (Hierarchical clustering)
 - Odkrijemo hierarhijo skupin, kar prikažemo z hierarhičnim drevesom (dendrogramom)

Metoda k-voditeljev (k-means)

- Vsaka skupina ima svojega voditelja (centroid).
- Vsak primer pripišemo najbližjemu voditelju.
- Podati moramo K število voditeljev (skupin).
- Preprost algoritem.

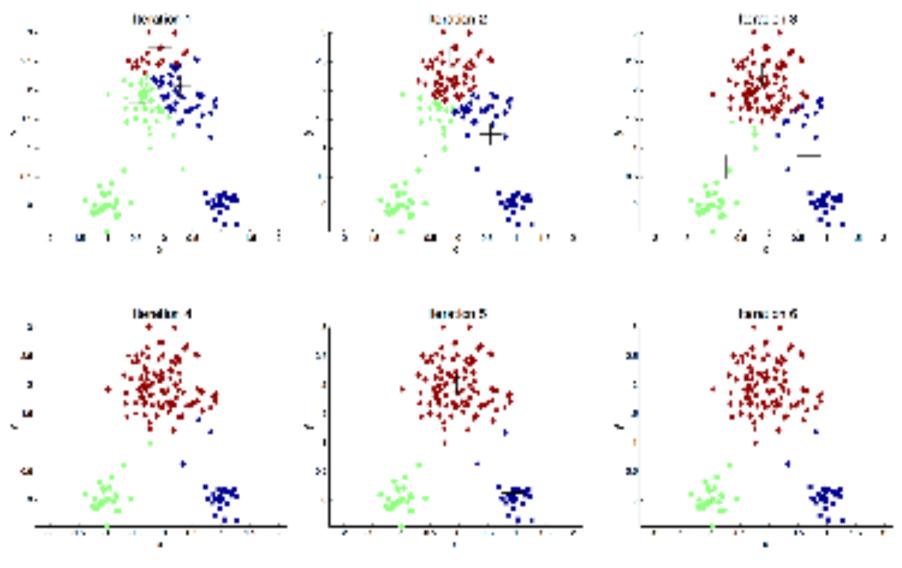
Algorithm 1 Basic K-means Algorithm.

- 1: Select K points as the initial centroids.
- 2: repeat.
- Form K clusters by assigning all points to the closest centroid.
- Recompute the centroid of each cluster.
- until The centroids don't change.

Metoda k-voditeljev (k-means)

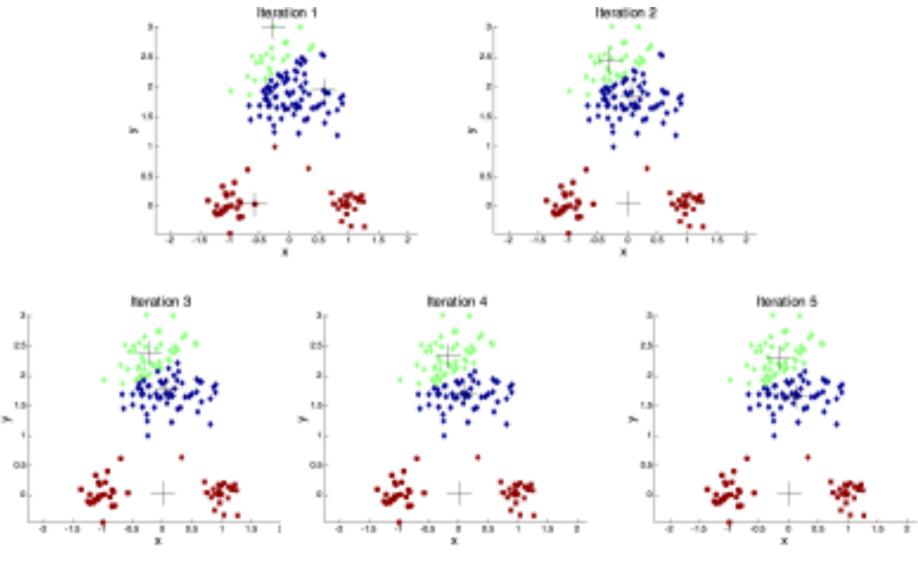
- Začetni voditelji izbrani naključno.
 - metoda je občutljiva na to izbiro
- Bližino merimo z Evklidsko razdaljo, kosinusno razdaljo, korelacijo, itd.
- Algoritem konvergira za zgornje mere.
 - Konvergira hitro, le v nekaj korakih.
 - Ustavitveni pogoj je navadno: "Until relatively few points change clusters"
- Potrebno predprocesiranje podatkov (normalizacija).

Metoda k-voditeljev (k-means)



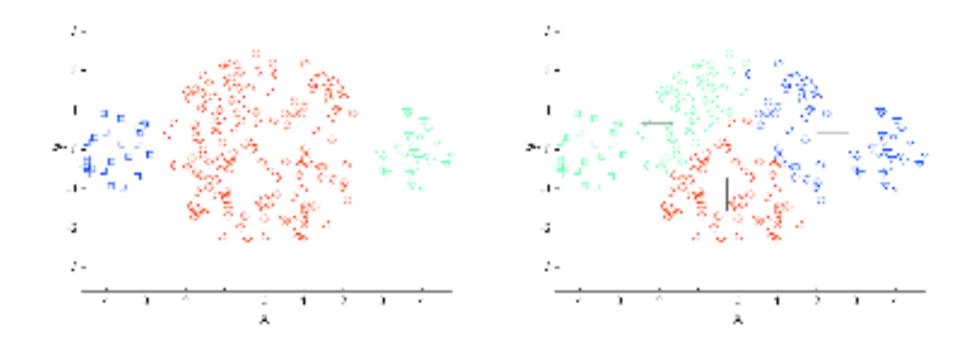
26.3.2015

Izbira začetnih voditeljev (centroidov)

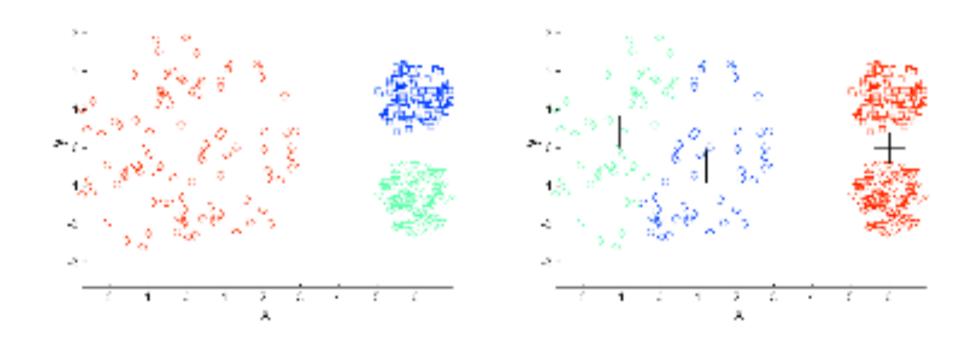


26.3.2015

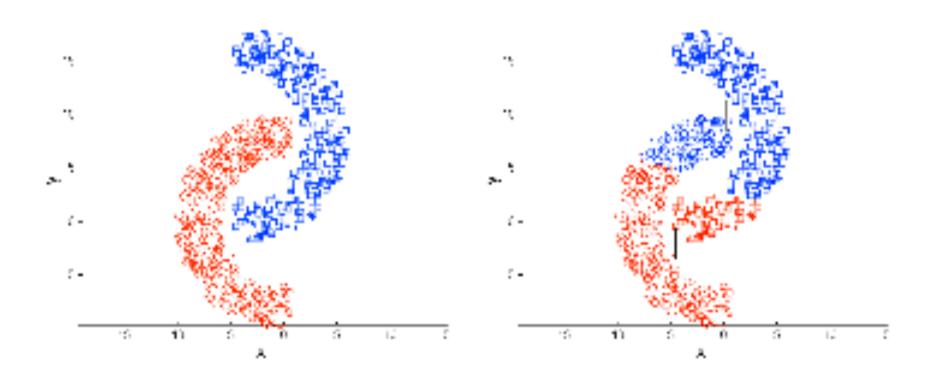
Omejitve: različne velikosti skupin



Omejitve: različne gostote skupin

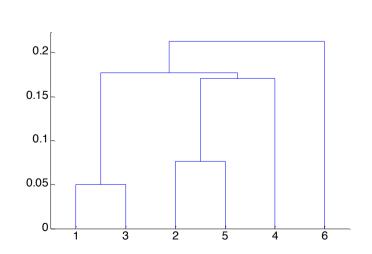


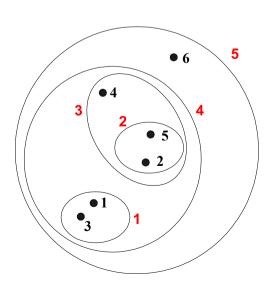
Omejitve: različne oblike



Hierarhično razvrščanje

- Rezultat je hierarhija skupin primerov.
- Prikažemo z dendrogramom
 - Iz drevesa je razvidno, kako so se združevale skupine.





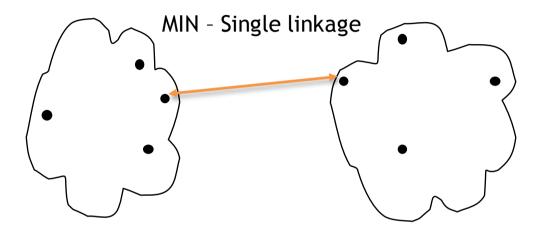
Prednosti

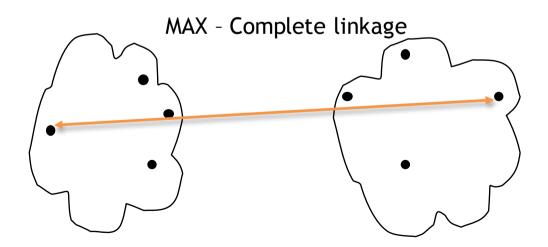
- Števila skupin ni potrebno podati.
 - Z "rezanjem" drevesa lahko pridobimo razbitje na poljubno število skupin.
- Skupine navadno sovpadajo s taksonomijami (razredom)
 - N.pr., rekonstrukcija filogenetskih dreves (zoo)

Razvrščanje v skupine na podlagi združevanja primerov (Agglomerative Clustering)

- 1. Izračunaj matriko podobnosti
- 2. Vsak primer svoja skupina
- 3. Repeat
 - Združi dve najbolj podobni skupini
 - Posodobi matriko podobnosti
- 4. Until ena skupina

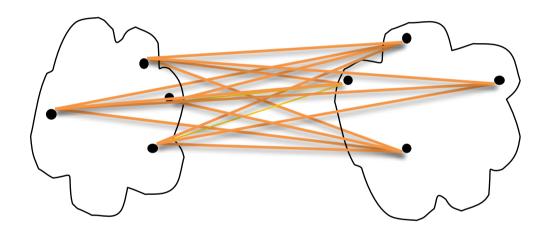
Podobnost med skupinami (Inter-Cluster Similarity)



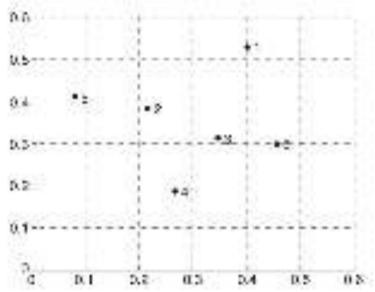


Podobnost med skupinami (Inter-Cluster Similarity)

Group average - average linkage



Primer hierarhičnega razvrščanja



Point.	z Courdinate	y Coordinate
pl	0.40	0.53
p2	0.22	0.38
р3	0.35	0.32
p4	0.26	0.19
p5	80.0	0.41
100	0.45	0.30

Figure 8.15. Set of 6 two-dimensional points.

Table 8.3. Try coordinates of 6 points.

	p1	p2	р3	р4	p5	_ p6
p1	0.00	0.24	0.22	0.37	0.34	0.23
p2	0.24	0.00	0.15	0.20	0.14	0.25
p3	0.22	0.15	0.00	0.15	0.28	0.11
p4	0.37	0.20	0.15	0.00	0.29	0.22
ρō	0.34	0.14	0.28	0.29	0.00	0.39
p6	0.23	0.25	0.11	0.22	0.39	0.00

Table 8.4. Euclidean distance matrix for 6 points.

Single linkage

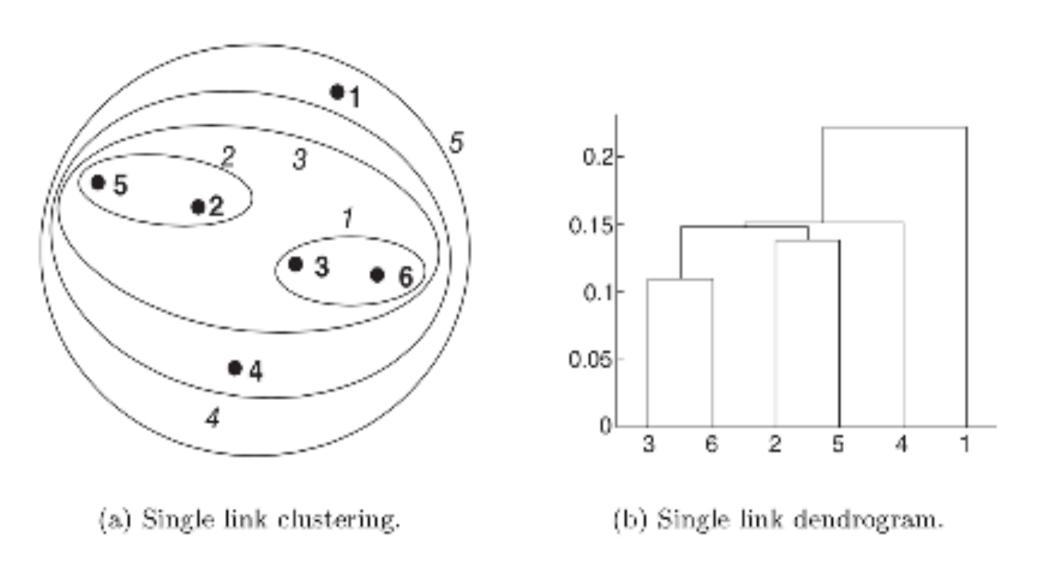


Figure 8.16. Single link clustering of the six points shown in Figure 8.15.

Complete linkage

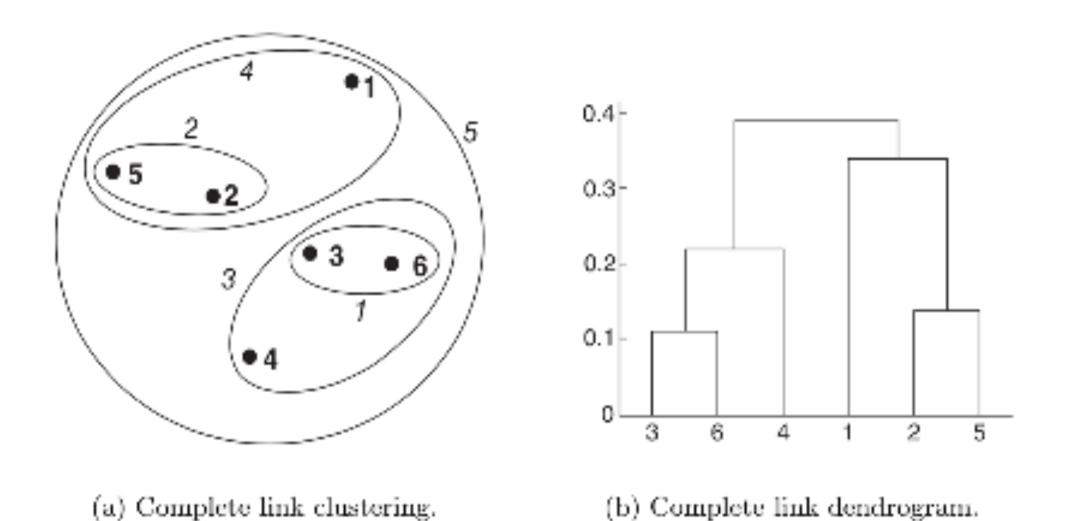
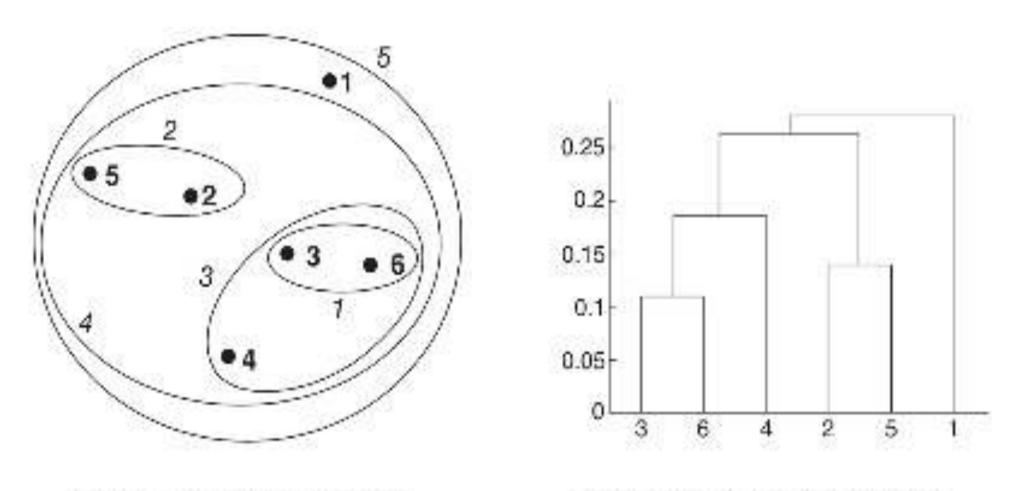


Figure 8.17. Complete link clustering of the six points shown in Figure 8.15.

Average linkage



(a) Group average clustering.

(b) Group average dendrogram.

Figure 8.18. Group average clustering of the six points shown in Figure 8.15.

Wardovo združevanje

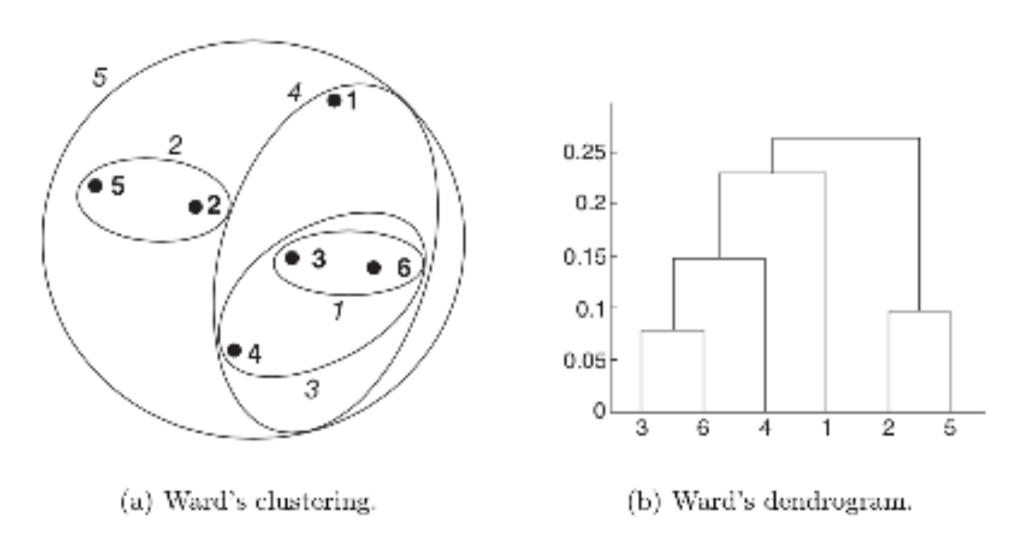


Figure 8.19. Ward's clustering of the six points shown in Figure 8.15.

Wardovo združevanje

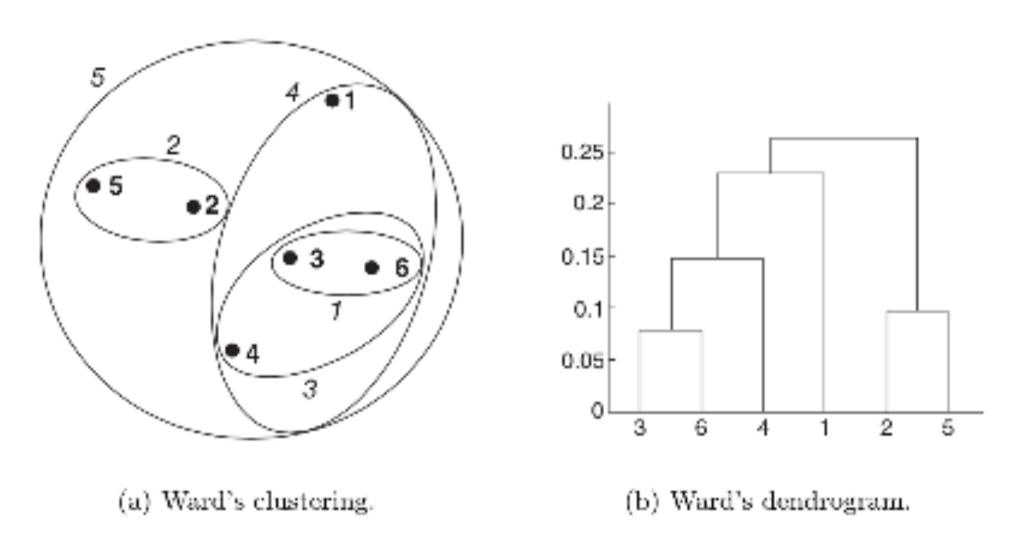


Figure 8.19. Ward's clustering of the six points shown in Figure 8.15.

Različne skupine

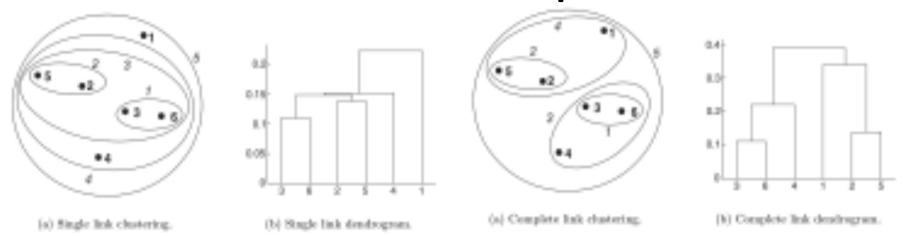


Figure 8.16. Single link dustering of the six points shows in Figure 8.15.

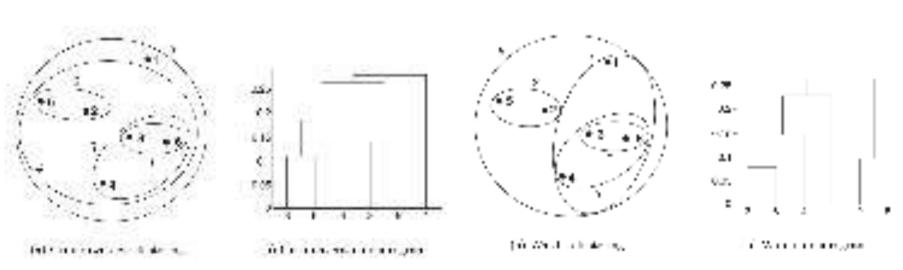


Figure 8 18. Both towards discovered to display show in Figure 9.1.

Agum & 18. Word's current of the skept vicishmenting a 6.16.

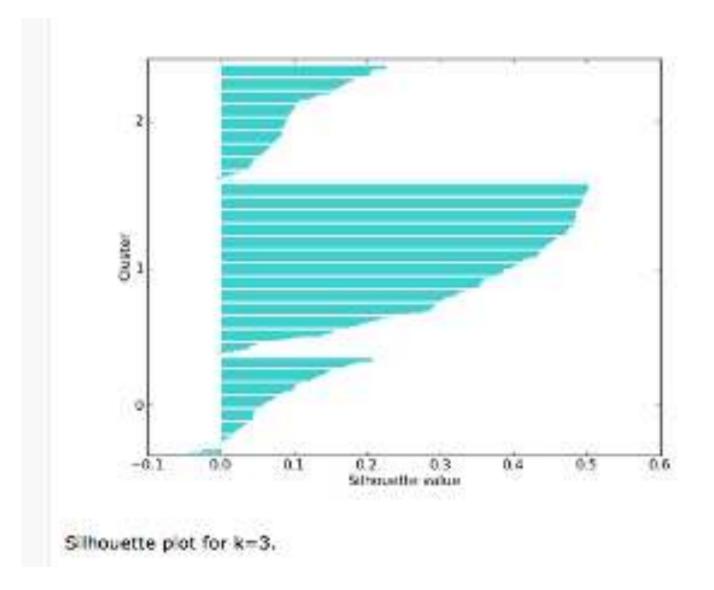
Figure 8.17. Complete link dustering of the six points shown in Figure 8.15.

Kvaliteta razbitja (Silhouette score)

http://orange.biolab.si/docs/latest/reference/rst/Orange.clustering.kmeans.html

```
The following code computes the elihouette score for k=1..7 and plots a siltuative plot for k=3 (kmans-willhouette.pv):
  import Drumpe
  woting = Oracoo data Table ("votice")
  # sable = Hosogo, data, fable/ "Irie")
  for k in cancet?, Sta-
      km = Orange_clustering.Rmeans.Clustering(voting, k, initialization=Orange.clustering.Rmeans.init.c
      score = Orange.clustering.kmeans.score milhoustbe(km)
      print k. score
 ks. - Orange clastering kseams Clustering (voting, 3, initialization-Orange clastering kseams init diver
 Orange clustering keessa plot silhouette(km, "keessa-silhouette.pag")
The analysis suggests that kin2 is preferred as it yields the maximal silbouette coefficient:
  6.0.353228492088
  7 D. 266357876964
```

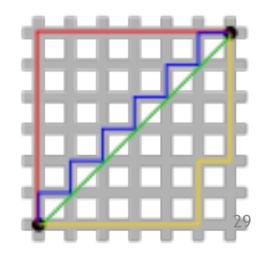
Silhouette



Primer

	sepal length	sepal width	petal length	petal width
1	4.9	2.4	3.3	1.0
2	6.7	3.0	5.0	1.7
3	5.5	2.4	3.7	1.0
4	6.2	2.9	4.3	1.3
5	6.8	3.0	5.5	2.1
6	6.9	3.1	5.4	2.1
7	6.2	3.4	5.4	2.3
8	5.9	3.0	5.1	1.8

- Single or complete linkage
- Manhattansko razdaljo $p_1 = (x_1, y_1), p_2 = (x_2, y_2), \text{ then } d_M = |x_1 x_2| + |y_1 y_2|.$
- Nariši dendrogram



Iris virginica petal leaves Iris versicolor sepal leaves http://statlab.uni-heidelberg.de/data/iris/

Skupine so seveda znane ...

	sepal length	sepal width	petal length	petal width	iris
1	4.9	2.4	3.3	1.0	Iris-versicolor
2	6.7	3.0	5.0	1.7	Iris-versicolor
3	5.5	2.4	3.7	1.0	Iris-versicolor
4	6.2	2.9	4.3	1.3	Iris-versicolor
5	6.8	3.0	5.5	2.1	Tris-virginica
6	6.9	3.1	5.4	2.1	Tris-virginica
7	6.2	3.4	5.4	2.3	Iris-virginica
8	5.9	3.0	5.1	1.8	Iris-virginica

Kakšno je ujemanje med odkritimi skupinami in dejanskim razredom?