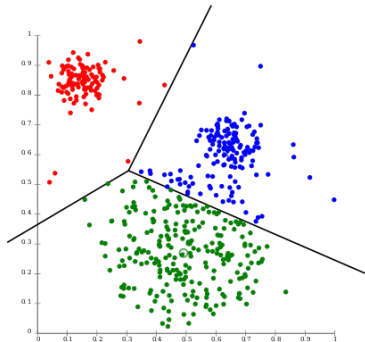
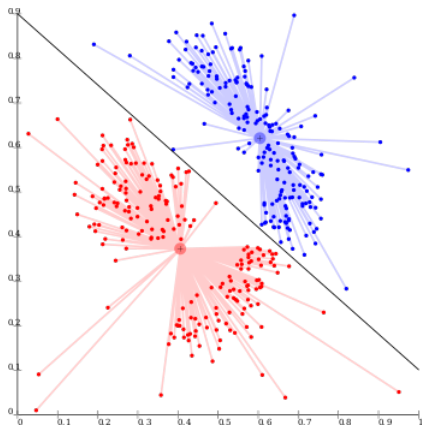


What are...clustering methods?

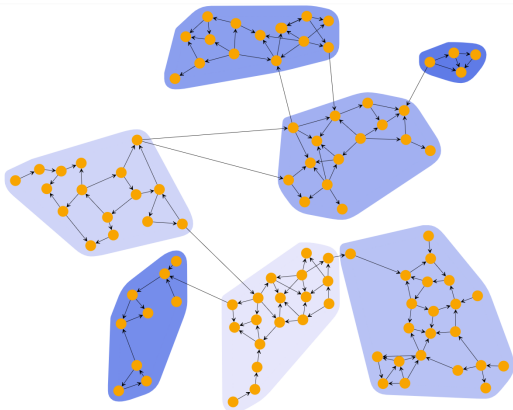
Or: Partitioning made easy

Analyzing data



- ▶ Given a large data set, one often wants to cluster it
- ▶ This means one wants to minimize the distance from (to be found) k centers
- ▶ There are good algorithms to do this in \mathbb{R}^m (not optimal, but good)

Clustering in graphs



-
- ▶ If the data is given as a graph, one can compute **eigenvectors**
 - ▶ Let u_1, \dots, u_m be the eigenvectors for the **smallest** Laplace eigenvalues
 - ▶ Assign **vertex x to $(u_i(x))_i$** and run an (\mathbb{R}^m, k) cluster algorithm

Back to cutting

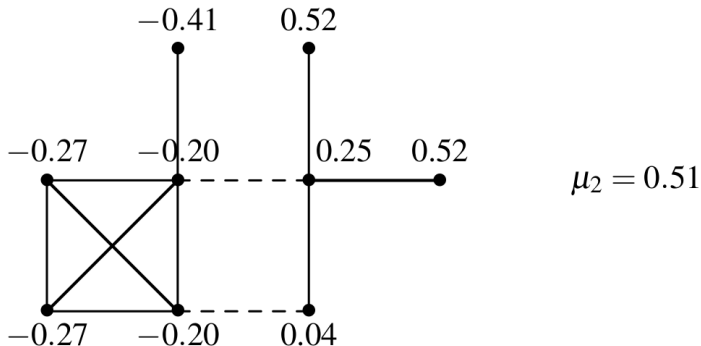


Fig. 3.2 Graph with 2nd Laplace eigenvector

- ▶ **Special case** The cheapest cut of the graph into two relatively large pieces
- ▶ Use $x \mapsto u(x)$ for the eigenvector for the second smallest Laplace eigenvalue
- ▶ Use clustering for $(\mathbb{R} = \mathbb{R}^1, k = 2)$

For completeness: A formal statement

For $G = (V, E)$ suppose $W \subset V$ is such that the induced subgraph on $V \setminus W$ is disconnected, then:

$$|W| \geq \mu_{-2}$$

- ▶ μ_{-2} = second smallest Laplace eigenvalue also called algebraic connectivity
- ▶ Induced subgraph = take all edges that make sense, e.g.:



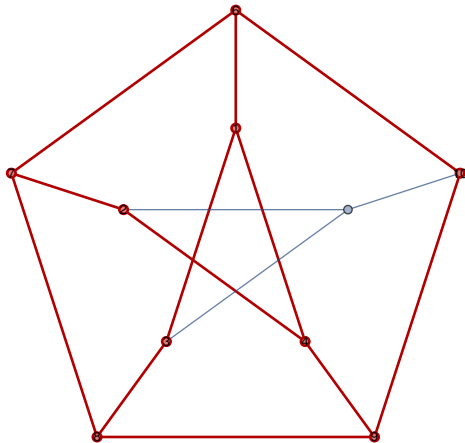
Subgraph (in red)



Induced Subgraph

- ▶ For the clustering algorithm I can only offer “it works well” – so take the above as a justification why one could expect it to work well

Algebraic connectivity



-
- ▶ The Petersen graph has $\mu_{-2} = 2$
 - ▶ Removing an arbitrary vertex will not disconnect the graph
 - ▶ The lower bound 2 is however not optimal (but we should not expect that anyway)

Thank you for your attention!

I hope that was of some help.