Community detection

Leonid E. Zhukov

School of Data Analysis and Artificial Intelligence Department of Computer Science National Research University Higher School of Economics

Network Science



IATIONAL RESEARCI UNIVERSITY

Overlapping communities Olique percolation method

Multi-level optimization
 Fast community unfolding



Community detection

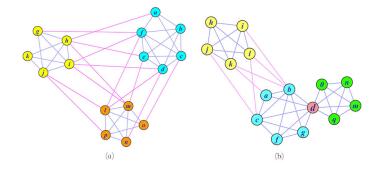
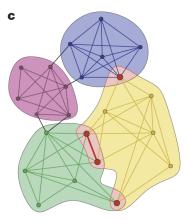
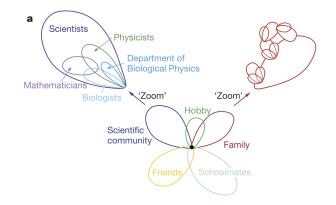


image from W. Liu , 2014

Overlapping communities

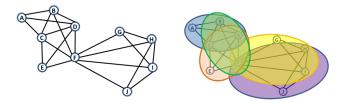


Overlapping communities



k-clique community

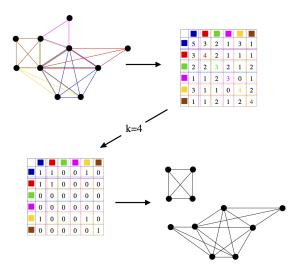
- *k*-clique is a clique (complete subgraph) with *k* nodes
- *k*-clique community a union of all *k*-cliques that can be reached from each other through a series of adjacent *k*-cliques
- two k-cliques are said to be adjacent if they share k 1 nodes.



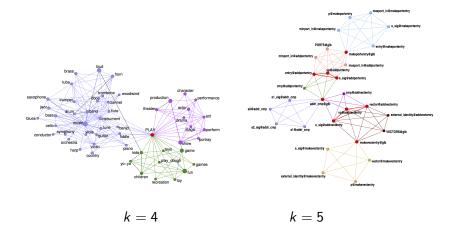
Adjacent 4-cliques

- Find all maximal cliques
- Create clique overlap matrix
- Threshold matrix at value k-1
- Communities = connected components

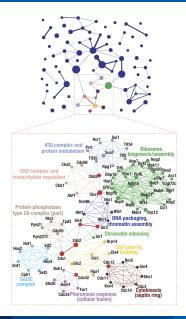
k-clique percolation



k-clique percolation



k-clique percolation

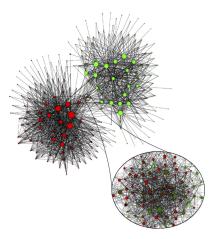


Leonid E. Zhukov (HSE)

Lecture 10

Fast community unfolding

Multi-resolution scalable method



$\underset{V. Blondel et.al., 2008}{\text{2 mln mobile phone network}}$

Leonid E. Zhukov (HSE)

"The Louvain method"

- Heuristic method for greedy modularity optimization
- Find partitions with high modularity
- Multi-level (multi-resolution) hierarchical scheme
- Scalable

Modularity:

$$Q = \frac{1}{2m} \sum_{i,j} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta(c_i, c_j)$$

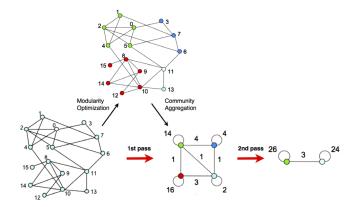
V. Blondel et.al., 2008

Algorithm

- Assign every node to its own community
- Phase I
 - For every node evaluate modularity gain from removing node from its community and placing it in the community of its neighbor
 - Place node in the community maximizing modularity gain
 - repeat until no more improvement (local max of modularity)
- Phase II
 - Nodes from communities merged into "super nodes"
 - Weight on the links added up
- Repeat until no more changes (max modularity)

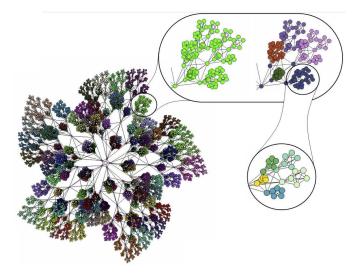
V. Blondel et.al., 2008

Fast community unfolding



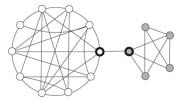
V. Blondel et.al., 2008

Fast community unfolding



V. Blondel et.al., 2008

Communities and random walks



 Random walks on a graph tend to get trapped into densely connected parts corresponding to communities.

- Consider random walk on graph
- At each time step walk moves to NN uniformly at random $P_{ij} = \frac{A_{ij}}{d(i)}$, $P = D^{-1}A$, $D_{ii} = diag(d(i))$
- P_{ij}^t probability to get from *i* to *j* in *t* steps, $t \ll t_{mixing}$
- Assumptions: for two *i* and *j* in the same community P_{ii}^t is high
- if *i* and *j* are in the same community, then $\forall k, P_{ik}^t \approx P_{ik}^t$
- Distance between nodes:

$$r_{ij}(t) = \sqrt{\sum_{k=1}^{n} \frac{(P_{ik}^{t} - P_{jk}^{t})^{2}}{d(k)}} = ||D^{-1/2}P_{i}^{t} - D^{-1/2}P_{j}^{t}||$$

Computing node distance r_{ij}

- Direct (exact) computation: $P_{ij}^t = (P^t)_{ij}$ or $P_i^t = P^t p_i^0$, $p_i^0(k) = \delta_{ik}$
- Approximate computation (simulation):
 - Compute K random walks of length t starting form node i
 - Approximate $P_{ik}^t \approx \frac{N_{ik}}{K}$, number of walks end up on k

Distance between communities:

$$P_{Cj}^{t} = \frac{1}{|C|} \sum_{i \in C} P_{ij}^{t}$$
$$r_{C_{1}C_{2}}(t) = \sqrt{\sum_{k=1}^{n} \frac{(P_{C_{1}k}^{t} - P_{C_{2}k}^{t})^{2}}{d(k)}} = ||D^{-1/2}P_{C_{1}}^{t} - D^{-1/2}P_{C_{2}}^{t}||$$

1

Algorithm (hierarchical clustering)

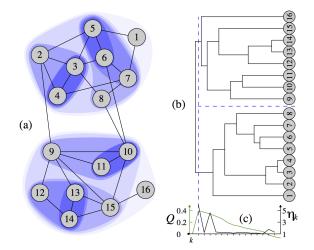
- Assign each vertex to its own community $S_1 = \{\{v\}, v \in V\}$
- Compute distance between all adjacent communities r_{CiCi}
- Choose two "closest" communities that minimizes (Ward's methods):

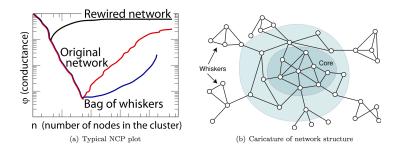
$$\Delta\sigma(C_1, C_2) = \frac{1}{n} \left(\sum_{i \in C_3} r_{iC_3}^2 - \sum_{i \in C_1} r_{iC_1}^2 - \sum_{i \in C_2} r_{iC_2}^2 \right)$$

and merge them $S_{k+1} = (S_k \setminus \{C_1, C_2\}) \cup C_3$, $C_3 = C_1 \cup C_2$

update distance between communities

After n-1 steps finish with one community $S_n = \{V\}$





Best conductance of a vertex set S of size k:

$$\Phi(k) = \min_{S \in V, |S|=k} \phi(S), \quad \phi(S) = \frac{cut(S, V \setminus S)}{\min(vol(S), vol(S \setminus V))}$$

where $vol(S) = \sum_{i \in S} k_i$ - sum of all node degrees in the set

J. Leskovec, K. Lang, 2010

Leonid E. Zhukov (HSE)

Community detection algorithms

Author	Ref.	Label	Order
Eckmann & Moses	(Eckmann and Moses, 2002)	EM	$O(m\langle k^2 \rangle)$
Zhou & Lipowsky	(Zhou and Lipowsky, 2004)	ZL	$O(n^3)$
Latapy & Pons	(Latapy and Pons, 2005)	LP	$O(n^3)$
Clauset et al.	(Clauset et al., 2004)	NF	$O(n \log^2 n)$
Newman & Girvan	(Newman and Girvan, 2004)	NG	$O(nm^2)$
Girvan & Newman	(Girvan and Newman, 2002)	GN	$O(n^2m)$
Guimerà et al.	(Guimerà and Amaral, 2005; Guimerà et al., 2004)	SA	parameter dependent
Duch & Arenas	(Duch and Arenas, 2005)	DA	$O(n^2 \log n)$
Fortunato et al.	(Fortunato et al., 2004)	FLM	$O(m^3n)$
Radicchi et al.	(Radicchi et al., 2004)	RCCLP	$O(m^4/n^2)$
Donetti & Muñoz	(Donetti and Muñoz, 2004, 2005)	DM/DMN	$O(n^3)$
Bagrow & Bollt	(Bagrow and Bollt, 2005)	BB	$O(n^3)$
Capocci et al.	(Capocci et al., 2005)	CSCC	$O(n^2)$
Wu & Huberman	(Wu and Huberman, 2004)	WH	O(n+m)
Palla et al.	(Palla et al., 2005)	PK	$O(\exp(n))$
Reichardt & Bornholdt	(Reichardt and Bornholdt, 2004)	RB	parameter dependent

Author	Ref.	Label	Order
Girvan & Newman	(Girvan and Newman, 2002; Newman and Girvan, 2004)	GN	$O(nm^2)$
Clauset et al.	(Clauset et al., 2004)	Clauset et al.	$O(n \log^2 n)$
Blondel et al.	(Blondel et al., 2008)	Blondel et al.	O(m)
Guimerà et al.	(Guimerà and Amaral, 2005; Guimerà et al., 2004)	Sim. Ann.	parameter dependent
Radicchi et al.	(Radicchi et al., 2004)	Radicchi et al.	$O(m^4/n^2)$
Palla et al.	(Palla et al., 2005)	Cfinder	$O(\exp(n))$
Van Dongen	(Dongen, 2000a)	MCL	$O(nk^2), k < n$ parameter
Rosvall & Bergstrom	(Rosvall and Bergstrom, 2007)	Infomod	parameter dependent
Rosvall & Bergstrom	(Rosvall and Bergstrom, 2008)	Infomap	O(m)
Donetti & Muñoz	(Donetti and Muñoz, 2004, 2005)	DM	$O(n^3)$
Newman & Leicht	(Newman and Leicht, 2007)	EM	parameter dependent
Ronhovde & Nussinov	(Ronhovde and Nussinov, 2009)	RN	$O(m^{\beta} \log n), \beta \sim 1.3$

Fortunato, 2010

References

- G. Palla, I. Derenyi, I. Farkas, T. Vicsek, Uncovering the overlapping community structure of complex networks in nature and society, Nature 435 (2005) 814?818.
- P. Pons and M. Latapy, Computing communities in large networks using random walks, Journal of Graph Algorithms and Applications, 10 (2006), 191-218.
- V.D. Blondel, J.-L. Guillaume, R. Lambiotte, E. Lefebvre, Fast unfolding of communities in large networks, J. Stat. Mech. P10008 (2008).
- J. Leskovec, K.J. Lang, A. Dasgupta, and M.W. Mahoney. Statistical properties of community structure in large social and information networks. In WWW 08: Procs. of the 17th Int. Conf. on World Wide Web, pages 695-704, 2008.

- M.A Porter, J-P Onella, P.J. Mucha. Communities in Networks, Notices of the American Mathematical Society, Vol. 56, No. 9, 2009
- S. E. Schaeffer. Graph clustering. Computer Science Review, 1(1), pp 27-64, 2007.
- S. Fortunato. Community detection in graphs, Physics Reports, Vol. 486, Iss. 3-5, pp 75-174, 2010

Summary

Lectures 1-10

- Network characteristics:
 - Power law node degree distribution
 - Small diameter
 - High clustering coefficient (transitivity)
- Network models:
 - Random graphs
 - Preferential attachement
 - Small world
- Centrality measures:
 - Degree centrality
 - Closeness centrality
 - Betweenness centrality
- Link analysis:
 - Page rank
 - HITS

Summary

Lectures 1-10

- Structural equivalence
 - Vertex equivalence
 - Vertex similarity
- Assortative mixing
 - Assortative and disassortative networks
 - Mixing by node degree
 - Modularity
- Network structures:
 - Cliques
 - k-cores
- Network communities:
 - Graph partitioning
 - Overlapping communities
 - Heuristic methods
 - Random walk based methods