RECSM Summer School: Social Media and Big Data Research

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Course website:

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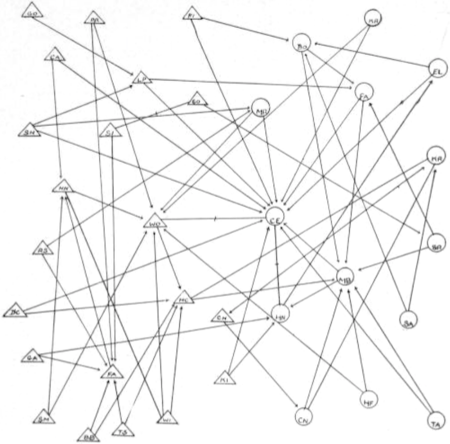
Discovery in Large-Scale Social Media Data

Human behaviour is characterized by connections to others

Digital technologies have led to an explosion in the availability of networked data

EVOLUTION OF GROUPS



CLASS STRUCTURE, 1ST GRADE

21 boys and 14 girls. *Unchosen*, 18, GO, PR, CA, SH, FI, RS, DC, GA, SM, BB, TS, WI, KI, TA, HF, SA, SR, KR; *Pairs*, 3, EI-GO, WO-CE, CE-HN; *Stars*, 5, CE, WO, HC, FA, MB; *Chains*, 0; *Triangles*, 0; *Inter-sexual Attractions*, 22.

Moreno, “Who Shall Survive?” (1934)

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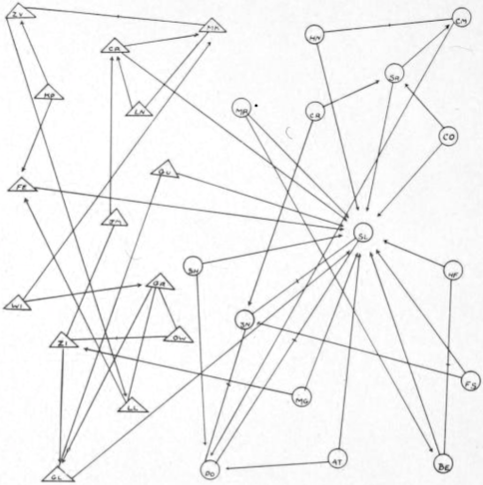
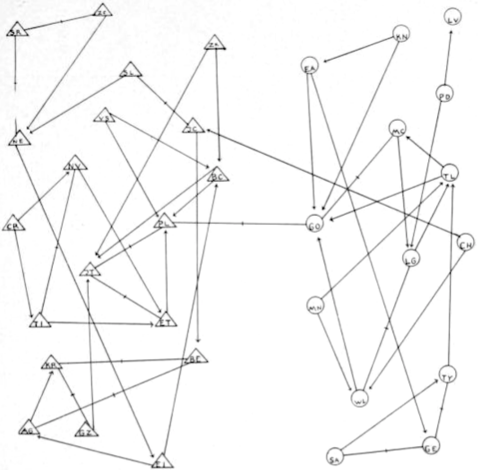


CLASS STRUCTURE, 2ND GRADE

14 boys and 14 girls. *Unchosen*, 9, WI, KP, MG, AT, FS, CN, CR, MR, SH; *Pairs*, 11, ZV-MK, MK-LN, OW-ZI, GR-LL, ZI-JM, HN-CM, SL-JN, JN-PO, PO-SL, HF-BE, GL-GU; *Stars*, 2, SL, PO; *Chains*, 0; *Triangles*, 1, SL-JN-PO; *Inter-sexual Attractions*, 5.

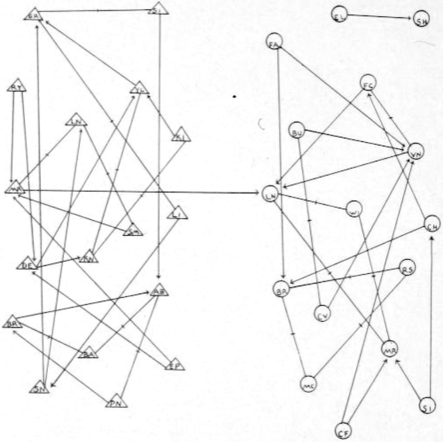
Moreno, “Who Shall Survive?” (1934)



CLASS STRUCTURE, 3RD GRADE

19 boys and 14 girls. *Unchosen,* **7**, VS, CR, CH, MN, PO, KN, ZK; *Pairs,* 14, SR-ZC, SR-NE, SL-JC, NV-TI, PL-JT, JT-ET, KR-BE, BE-AG, RR-GZ, PL-GO, GO-MC, WL-LG, SA-GE, GE-TY; *Stars,* **3**, GO, PL, JT; *Chains,* 1, ET-JT-PL-GO-MC; *Triangles,* **0**; *Inter-sexual Attractions,* **3**.

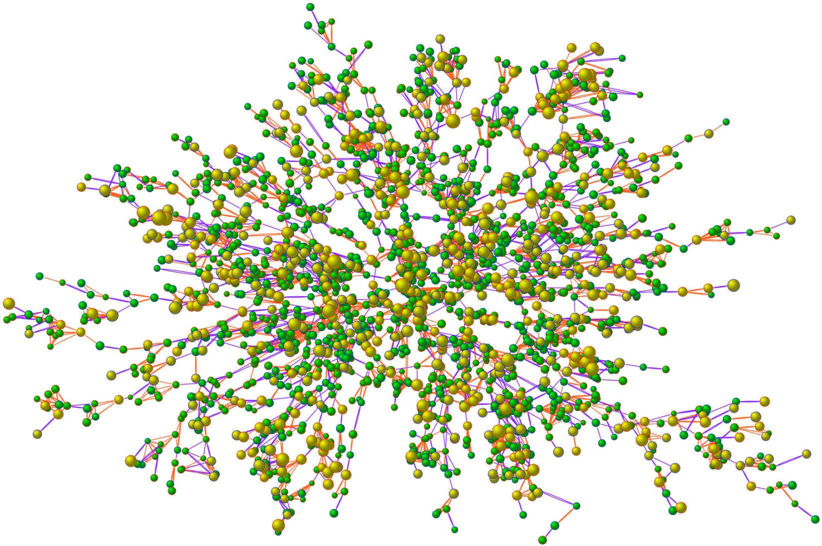
Moreno, "Who Shall Survive?" (1934)



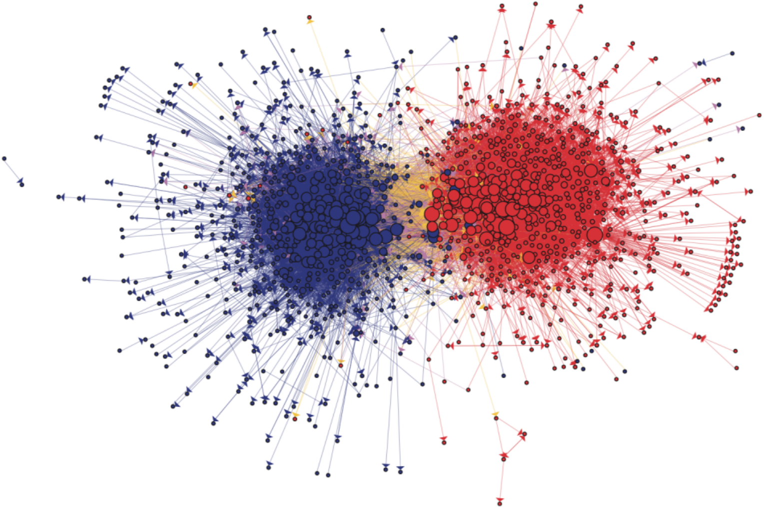
CLASS STRUCTURE, 4TH GRADE

17 boys and 16 girls. *Unchosen,* 6, EP, RY, EL, FA, SI, CF; *Pairs,* 17, GR-SI, GR-LI, MR-LN, LN-SM, YL-KN, AB-BA, BA-BR, KI-KN, AB-PN, FC-VN, BU-CV, LN-WI, LN-MR, BR-MC, BR-RS, WI-MR, MC-RS; *Stars,* 2, LN, VN; *Chains,* 0; *Triangles,* 2, BR-RS-MC; LN-WI-MR; *Inter-sexual Attractions,* 1.

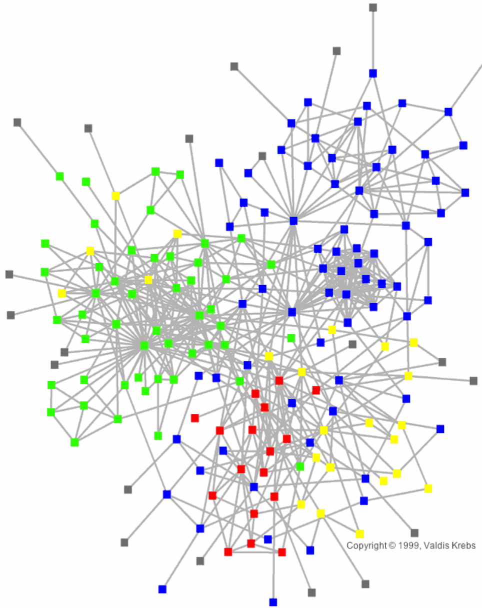
Moreno, “Who Shall Survive?” (1934)



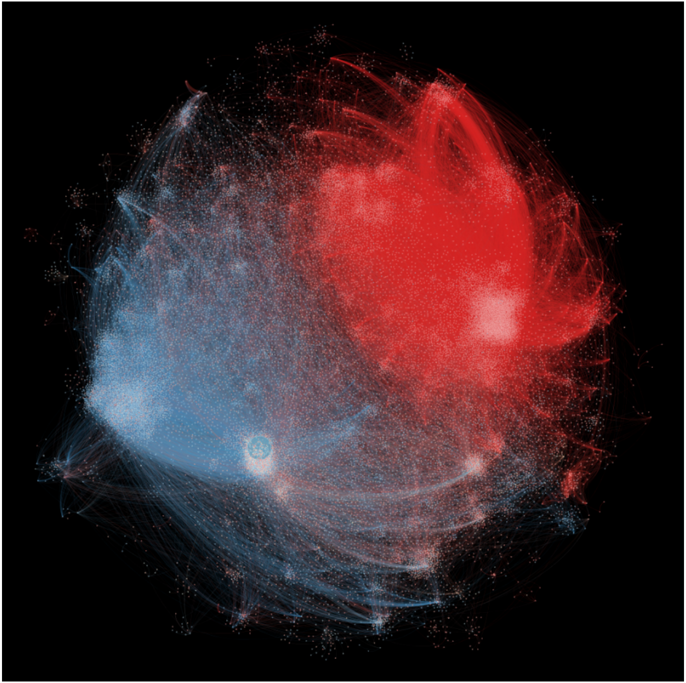
Christakis & Fowler, NEJM, 2007



Adamic & Glance, 2004, IWLD



Email network of a company



Barbera et al, 2015, Psychological Science

(Quick) introduction to social network analysis

What we will cover:

- Familiarity with **language of social network analysis**

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  - **Structure**: how to discover communities in a network?

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  - **Structure**: how to discover communities in a network?
- Characteristics of networks that emerge in **digital environments**, such as social media sites

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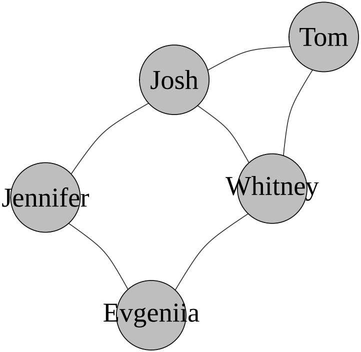
  i.e. a set of actors and their relationships

Basic concepts

Network Visualization



Adjacency Matrix

	P	J	E	W	T
P	0	1	1	0	0
J	1	0	0	1	1
E	1	0	0	1	0
W	0	1	1	0	1
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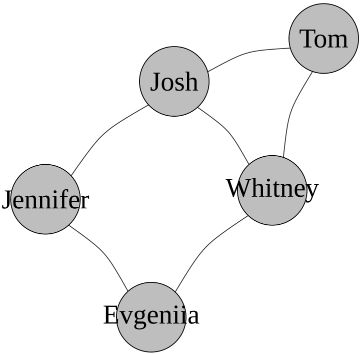

Edgelist

	Node1	Node2
1	Paul	Josh
2	Paul	Evgeniia
3	Josh	Whitney
4	Josh	Tom
5	Whitney	Tom
6	Evgeniia	Whitney

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- Facebook: friends / friendship connections
- Reddit: subreddits / users in common

Social network analysis: key dimensions of analysis

Node centrality

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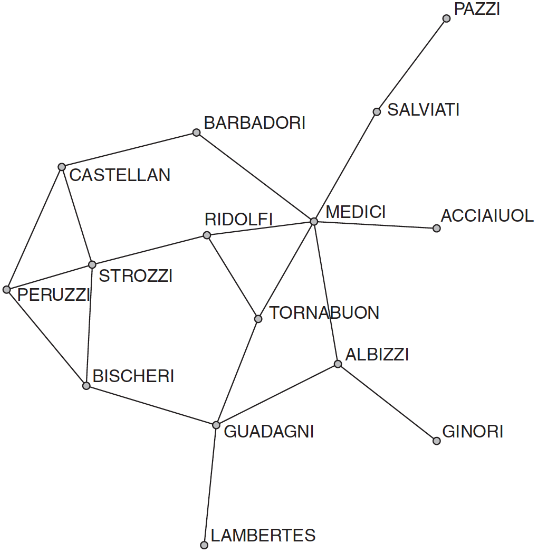
- **Eigenvector centrality and coreness**: centrality measured as being connected to other central neighbors

Florentine family marriages in the 15th century

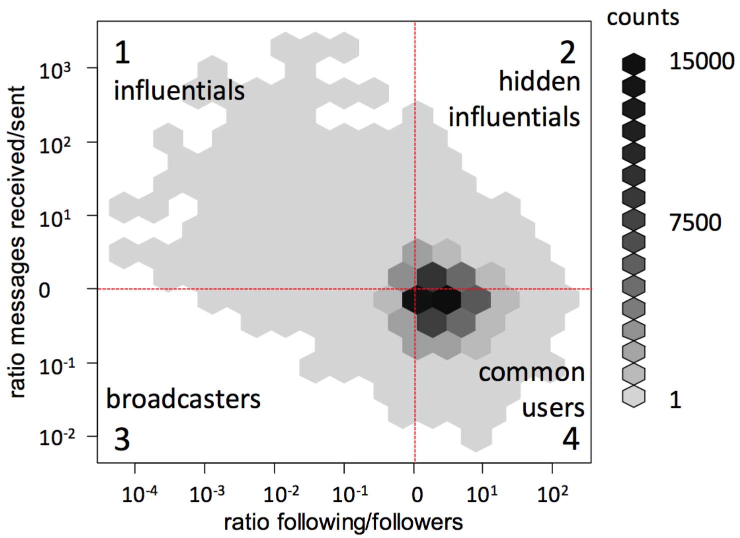


Source: Padgett (1993) and Sinclair (2016)

Occupy Wall Street Twitter networks

Source: Lotan (2011)

Protest networks on Twitter



Source: González-Bailón et al (2013)

Occupy Wall Street Twitter networks

Information Brokers

RT @GlobalRevLive: #TocandoaBankia live spanishrevolution.tv #mayo2013 fb.me/2Q6jOlkUs #ows #stopdeshuacios #spanishrevolution
Expand

N=8,082

N=51,212

N=74,007

Source: González-Bailón and Wang (2016)

Discovery in large-scale networks

How to understand the structure of large-scale networks?

- Latent communities or clusters

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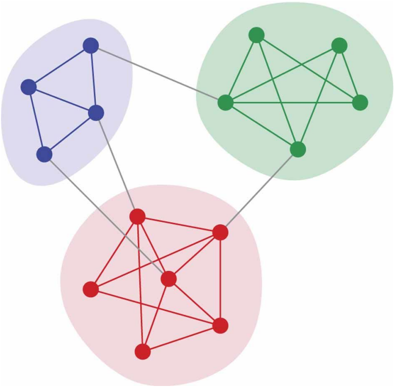
  - Also hierarchy: core-periphery detection

Community detection

Community structure:

- Network nodes often cluster into tightly-knit groups with a high density of within-group edges and a lower density of between-group edges
- **Modularity score**: measures clustering of nodes compared to random network of same size
- Many different community detection algorithms based on different assumptions



Source: Newman (2012)

Network hierarchy

- **Intuition**

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  - Large-scale networks have hierarchical properties

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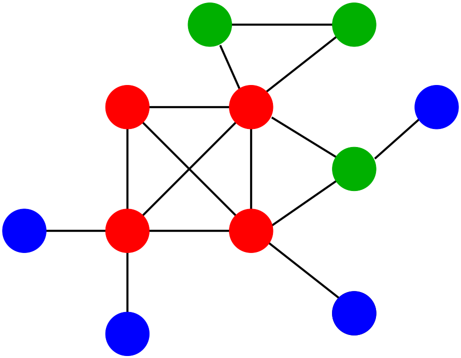
  - Many applications; scales well to large networks.

k-core decomposition



Source: Alvarez-Hamelin et al, 2005

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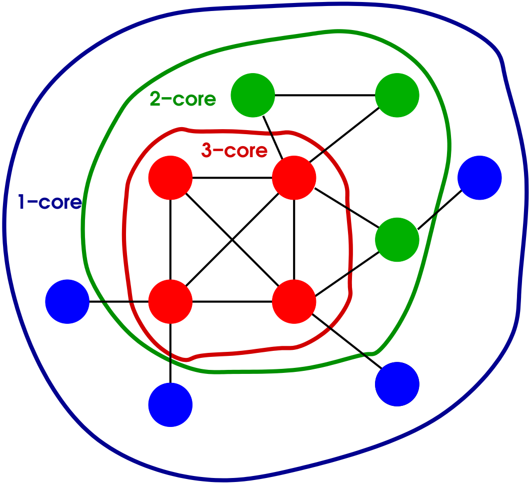

Source: Alvarez-Hamelin et al, 2005

k-core decomposition of #OccupyGezi network