Representation Learning on Networks

Algorithms, Theory, and Applications

Jie Tang
Tsinghua University

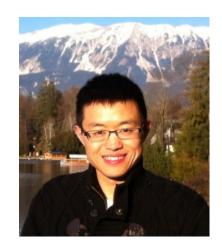
TSING WILL THE WAR THE

Yuxiao Dong Microsoft Research, Redmond



A bit about Jie...

- Jie Tang, Professor, Associate Chair of Dept. of Computer Science of Tsinghua University. Interests include social network, data mining, machine learning, knowledge graph.
- I have been visiting scholar at Cornell U. (working with John Hopcroft, Jon Kleinberg), UIUC (working with Jiawei Han), CUHK (with Jeffrey Yu), and HKUST (with Qiong Luo).



- I was awarded with the NSFC for Distinguished Young Scholars, NSFC for Excellent Young Scholars, CCF Young Scientist Award, Newton Advanced Fellowships Award, IBM Innovation Faculty Award, and KDD Service Award.
- Have published more than 200 paper on international conf/journals, including KDD (24), IJCAI/AAAI (24), WWW (8), NIPS/ICML, ACM/IEEE Trans. (27)
- #Citation: 12,466 and h-index: 58
- Have a notable system, AMiner.org for academic researcher network analysis.
 The system has attracted 10 million users from 220 countries/regions.
- HP: http://keg.cs.tsinghua.edu.cn/jietang/

A bit about Yuxiao...

- Yuxiao Dong, Senior Applied Scientist at Microsoft Research, Redmond. I received his Ph.D. from University of Notre Dame and has been a visiting scholar at Tsinghua University, U.S. Army Research Lab, and AMiner.org.
- My research focuses on data mining, network science, and computational social science, with an emphasis on applying computational models to addressing problems in large-scale networked systems, such as the Microsoft Academic Graph (MAG), mobile communication, and online social media.
- My work has been mainly published in KDD and interdisciplinary journals, winning four best paper awards/nominations as well as the 2017 ACM SIGKDD Doctoral Dissertation Award Honorable Mention.
- Homepage: https://ericdongyx.github.io/



JAN 2018

DIGITAL AROUND THE WORLD IN 2018

KEY STATISTICAL INDICATORS FOR THE WORLD'S INTERNET, MOBILE, AND SOCIAL MEDIA USERS

TOTAL POPULATION



7.593
BILLION

URBANISATION:

55%

INTERNET USERS



4.021
BILLION

PENETRATION:

53%

ACTIVE SOCIAL MEDIA USERS



3.196
BILLION

PENETRATION:

42%

UNIQUE MOBILE USERS



5.135
BILLION

PENETRATION:

68%

ACTIVE MOBILE SOCIAL USERS



2.958
BILLION

PENETRATION:

39%

Physical life coupled with digital world

facebook.

• FB: **1.47B DAU** & 2.23B MAU

Instagram: 1B MAU

• 2.5 trillion minutes/month

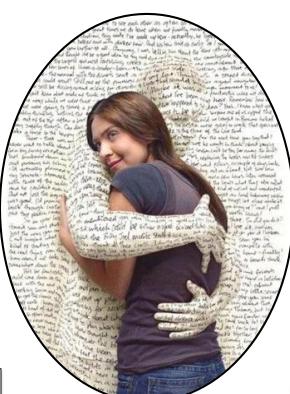


• 330 million MAU

Peak: 143K tweets/s



- 100M Prime users
- \$2B on Prime Day







WeChat: 1.04B MAU

QQ: 865 million MAU



- 350M MAU
- influencing our daily life



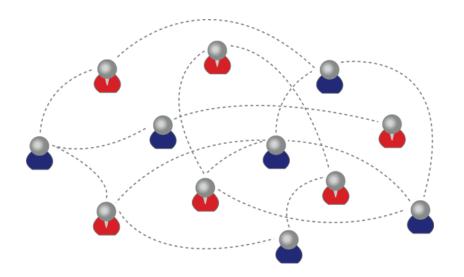
- Alipay: 300M DAU & 777M Trans
- \$200B on 11/11/2018 Single's Day

The era of (digitally) connected world

— the world is more **closely** connected than you might think.

A social network is a graph made up of :

- a set of **individuals**, called "nodes", and
- tied by one or more interdependency, such as friendship, called "edges".

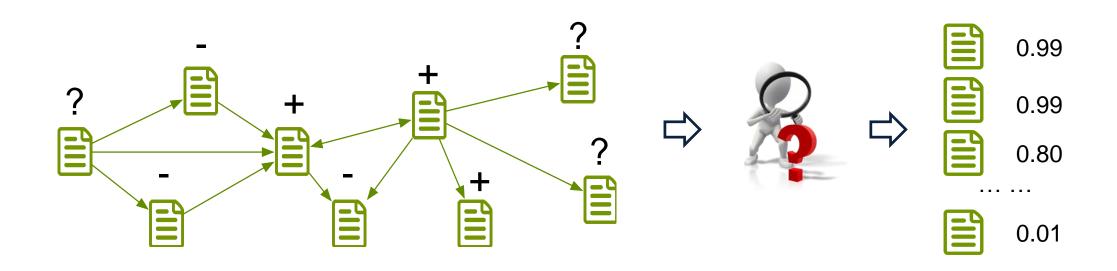


- So, that is Social Network?
- To understand it, we need to trace back…

30 years before...

Web 1.0 = Information Space

- Google's PageRank
- Kleinberg's HITS

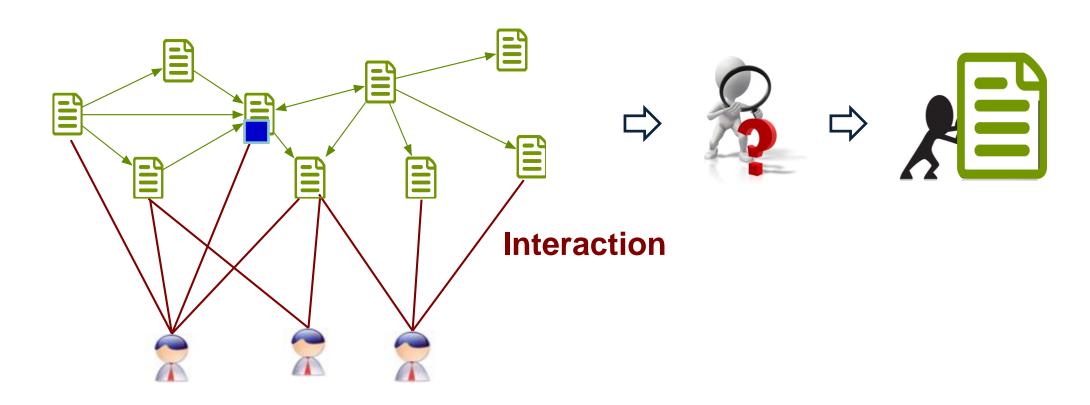


- 1. L. Page, S. Brin, R. Motwani, & T. Winograd. (1999). The pagerank citation ranking: bringing order to the web. Stanford University.
- 2. J. M. Kleinberg. Authoritative sources in a hyperlinked environment. Journal of the ACM (JACM) 46.5 (1999): 604-632.

20 years before...

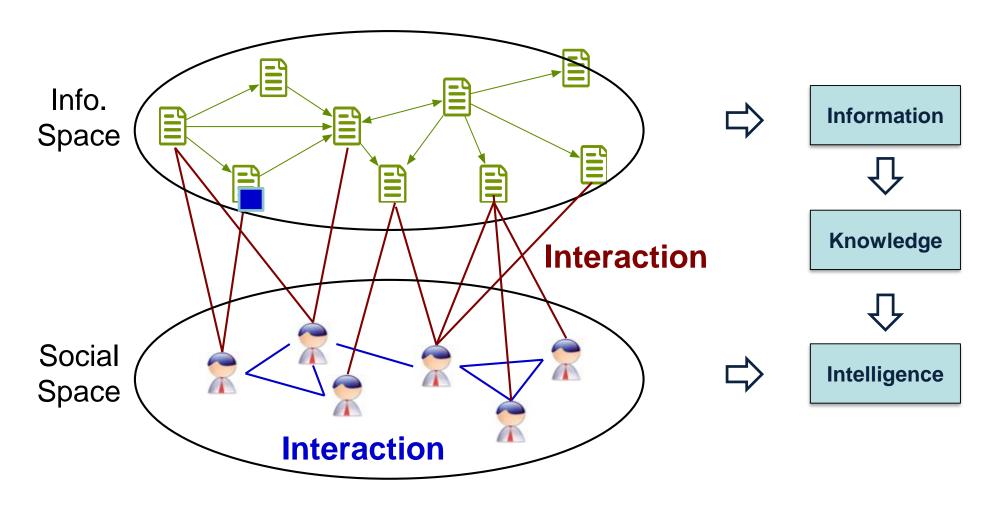
Web 2.0 = Info Space + Users

- Personalized recommendation
- Collaborative Filtering



10 years before...

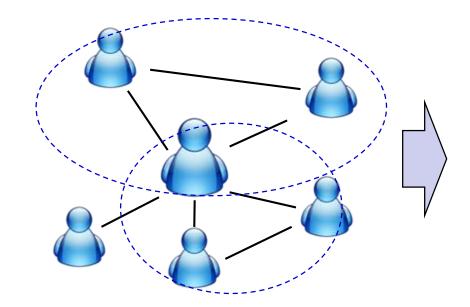
Web 3.0 = Social Web = Info. Space + Social Space



- 1. J. Scott. (1991, 2000, 2012). Social network analysis: A handbook.
- 2. D. Easley and J. Kleinberg. Networks, crowds, and markets: Reasoning about a highly connected world. Cambridge University Press, 2010.

Recent 5 years...

Web 4.0: Learning for the Web

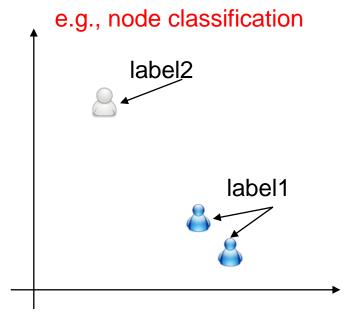


d-dimensional vector, *d*<<|*V*|



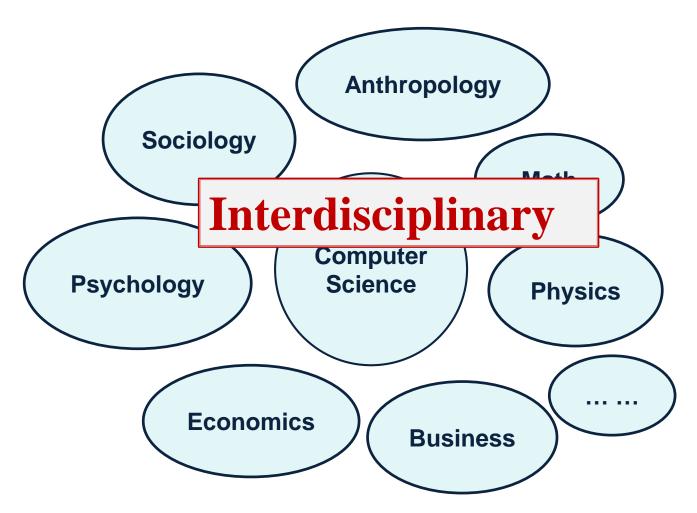
0.8 0.2 0.3 ... 0.0 0.0

Users with the same label are located in the *d*-dimensional space closer than those with different labels



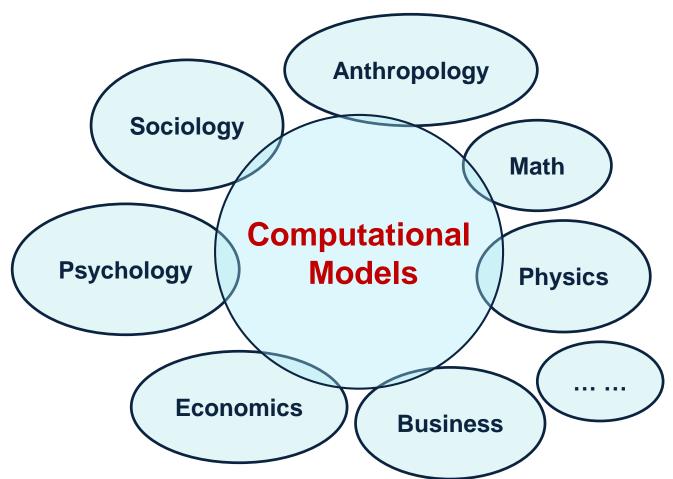
1. B. Perozzi, R. Al-Rfou, and S. Skiena. 2014. Deepwalk: Online learning of social representations. *KDD*, 701–710.

Social & Information Network Analysis

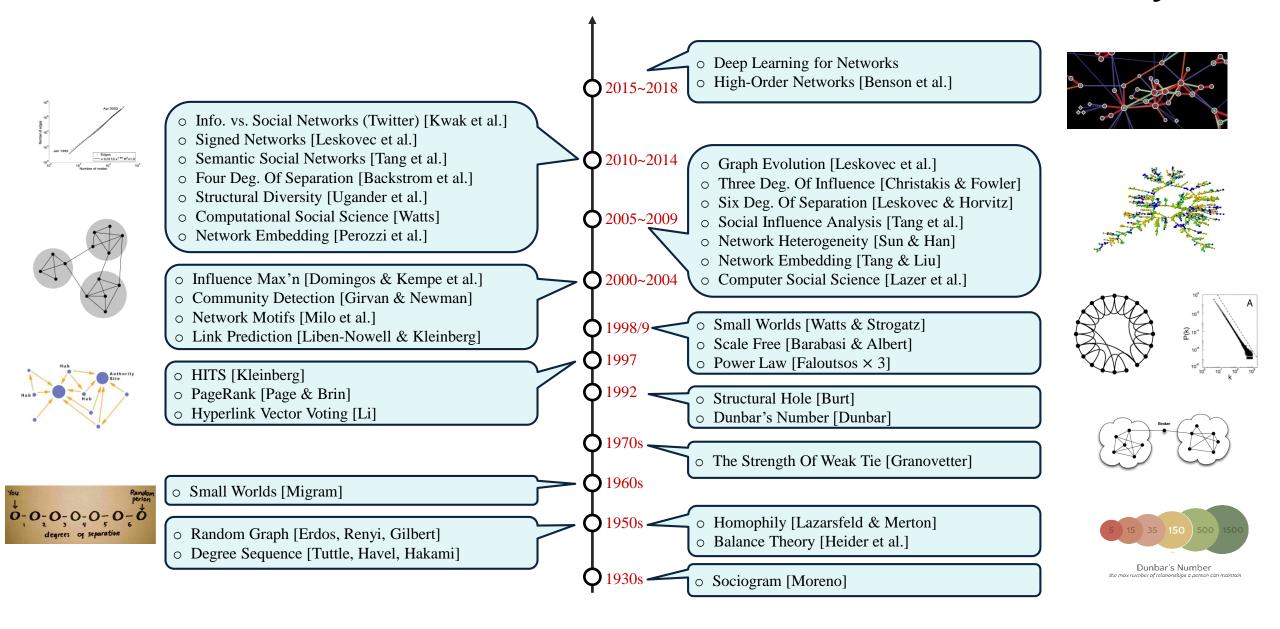


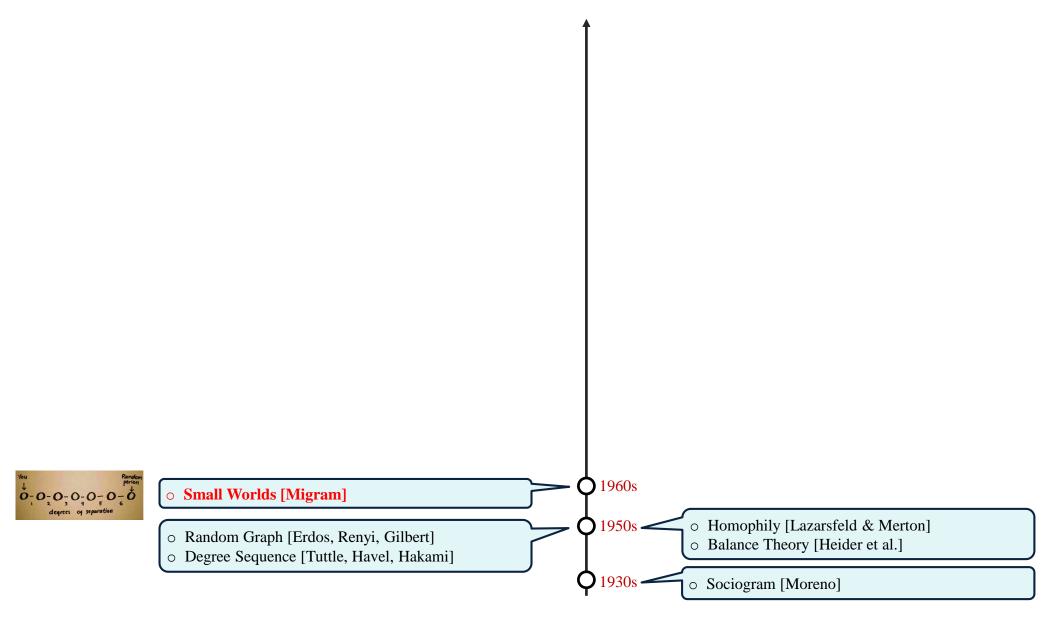
"A field is emerging that leverages the capacity to collect and analyze **data at a** scale that may reveal patterns of individual and group behaviors."

Computational Models for Social & Information Network Analysis



"A field is emerging that leverages the capacity to collect and analyze **data at a** scale that may reveal patterns of individual and group behaviors."

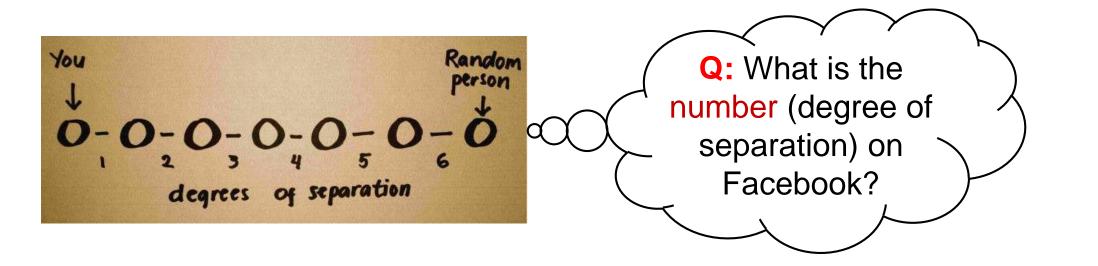




1967: Six Degrees of Separation

- "Given two individuals selected randomly from the population, what is the probability that the minimum number of intermediaries required to link them is 0, 1, 2, ..., k?"
- Milgram "selected 296 volunteers and to distribute a mail to a stockholder living in Boston."
- "The average number of intermediaries in the mailing chains was 5.2."

3.5 in 2016!

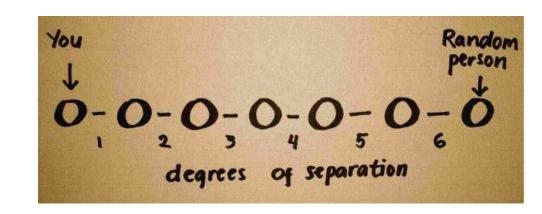


1. Stanley Milgram. The small world problem. Psychology Today, 2(1):60–67, 1967. Cited by 8500+ (as of Aug 2018)

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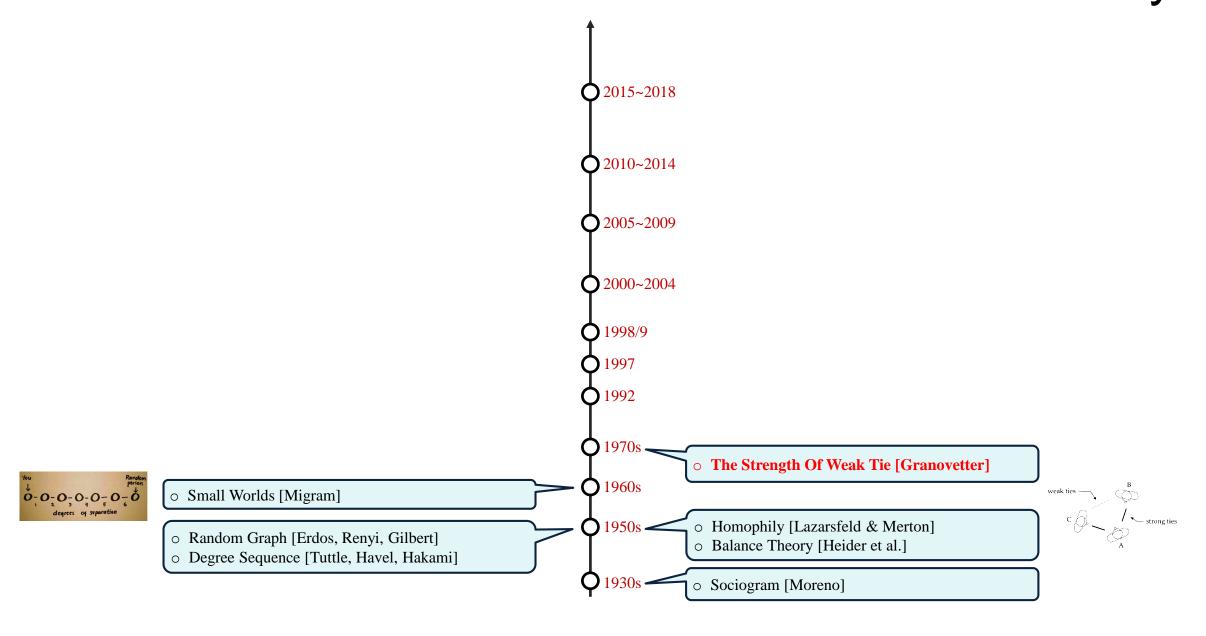
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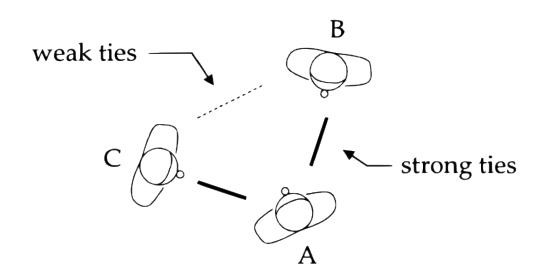
Mark Zuckerberg3.17 degrees of separation

1. Stanley Milgram. The small world problem. Psychology Today, 2(1):60–67, 1967. Cited by 8500+ (as of Aug 2018)

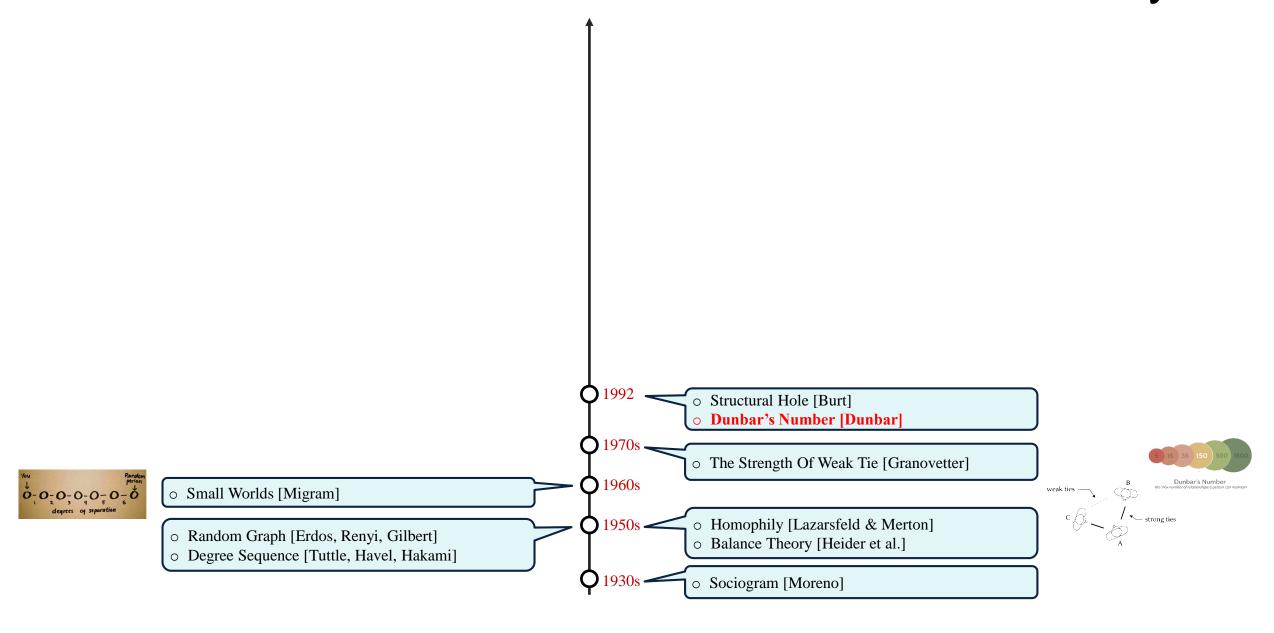


1973: Weak Tie

- The **weak tie hypothesis** argues, if A is linked to both B and C, then there is a greater-than-chance probability that B and C are linked to each other.
- Essentially form "A friend's friend is also my friend"
- Another important hypothesis based on weak tie is that information diffusion through weak ties rather than srong ties.

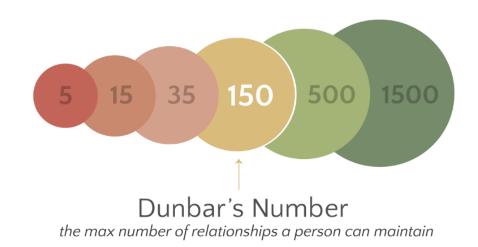


1. Granovetter, Mark S. The strength of weak ties. *American journal of sociology* 78.6 (1973): 1360-1380. Cited by 49000+ (as of Aug 2018)

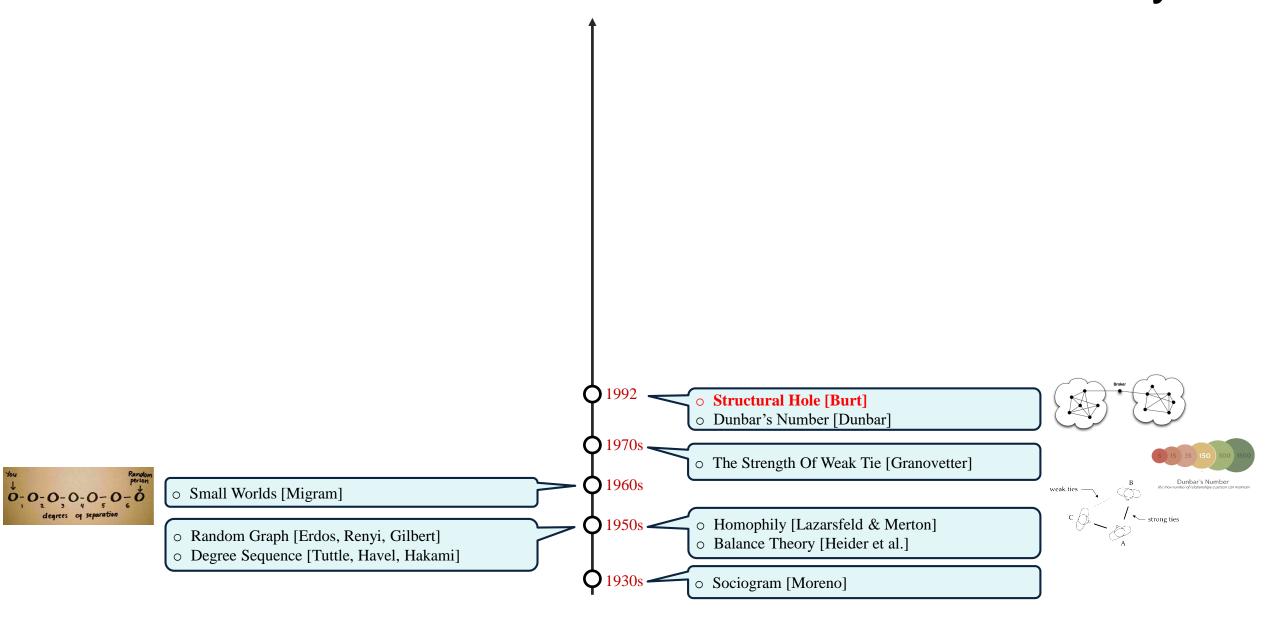


1992: Dunbar's Number

- "Dunbar's number is a suggested cognitive limit to the number of people with whom one can maintain stable social relationships."
- Dunbar "proposed that humans can only comfortably maintain **150** stable relationships."

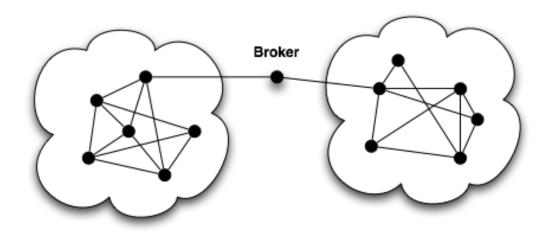


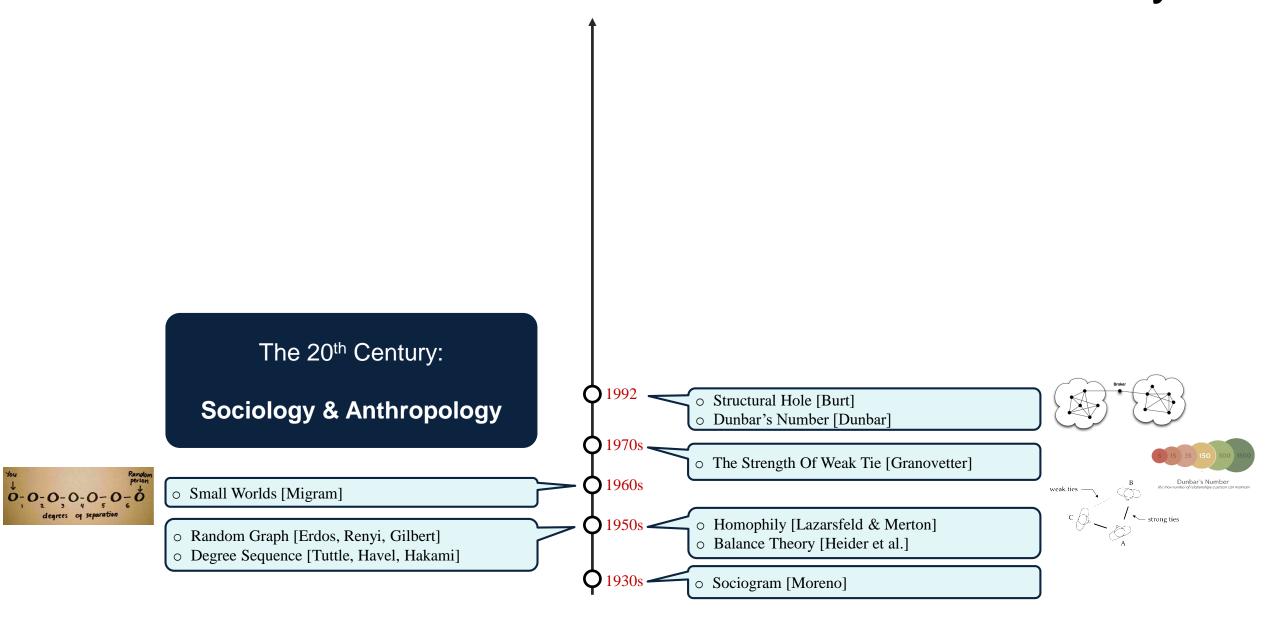
1. Robin I. M. Dunbar. Neocortex size as a constraint on group size in primates. *Journal of Human Evolution* 22 (6): 469–493. Cited by 2000+ (as of Aug 2018)

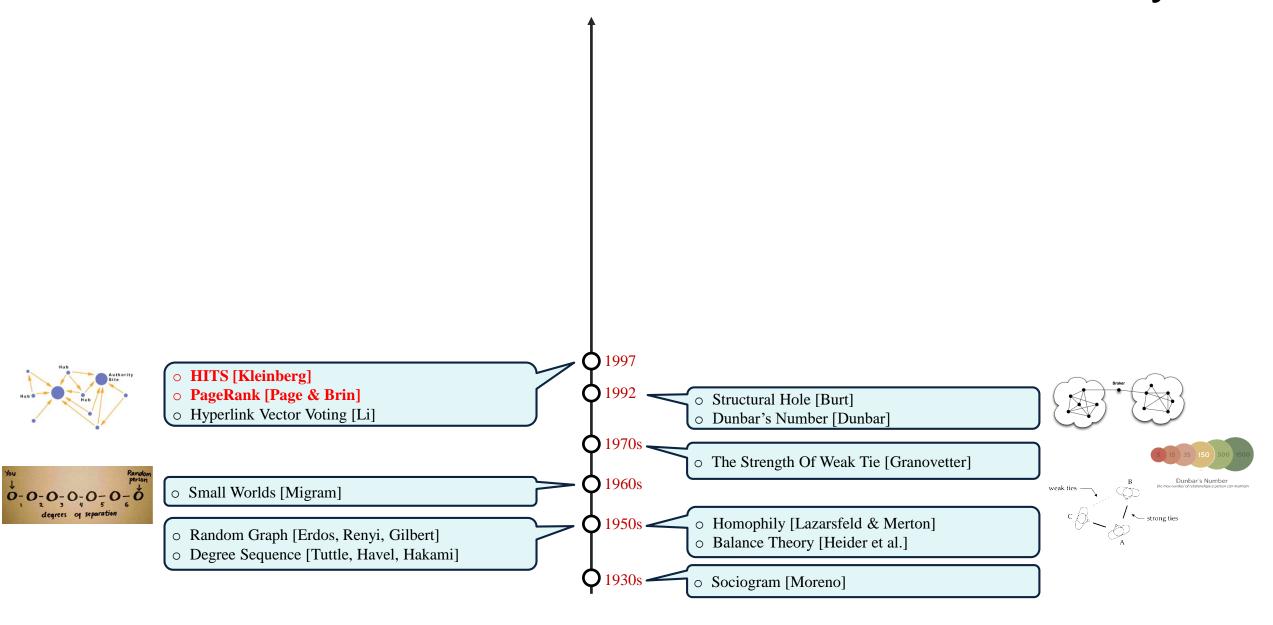


1992/5: Structural Holes

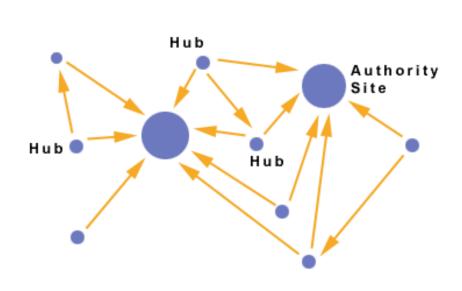
- "The position of a bridge between distinct groups allows him or her to transfer valuable information from one group to another."
- "The individual can combine all the ideas he or she receives from different sources and come up with the most innovative idea among all."





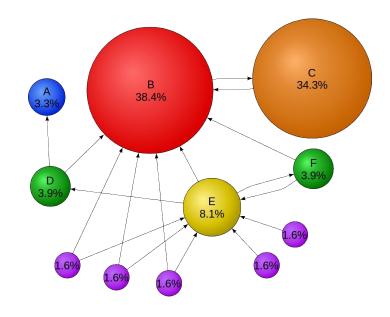


1997-1998: HITS and PageRank



$$\operatorname{auth}(p) = \sum_{i=1}^n \operatorname{hub}(i)$$

$$\operatorname{hub}(p) = \sum_{i=1}^n \operatorname{auth}(i)$$



$$PR(u) = \sum_{v \in B_u} rac{PR(v)}{L(v)}$$

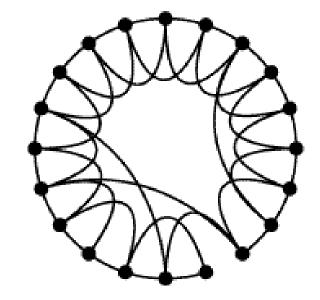
- 1. Jon M. Kleinberg. Authoritative sources in a hyperlinked environment. In ACM SODA, 1998. Also at IBM Research Report RJ 10076, May 1997. Cited by 12000+ (as of Aug 2018)
- 2. Sergey Brin, Lawrence Page. The anatomy of a large-scale hypertextual Web search engine. In WWW'07, Pages 107-117,1998. Cited by 17000+ (as of Aug 2018)

1998: Small World—Watts-Strogatz (WS) model

Comparing with the ER random graph model, WS model is a random graph generation model with Small-World properties.

Small-World Properties:

- 1. short average path lengths
- 2. high clustering coefficients



For each edge, rewire it with a probability

1999: Scale Free—Barabási-Albert (BA) model

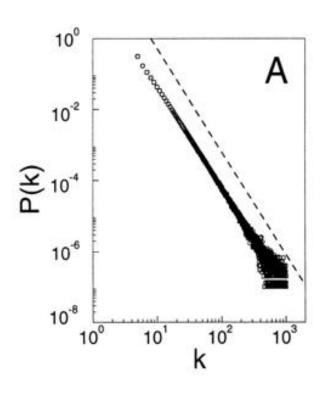
BA model is a random graph generation model using a preferential attachment mechanism: new nodes connect an existing node with the following probability:

$$p_i = rac{k_i}{\sum_j k_j}$$

- "A scale-free network is a network whose degree distribution follows a power law."
- The fraction P(k) of nodes having k connections to other nodes:

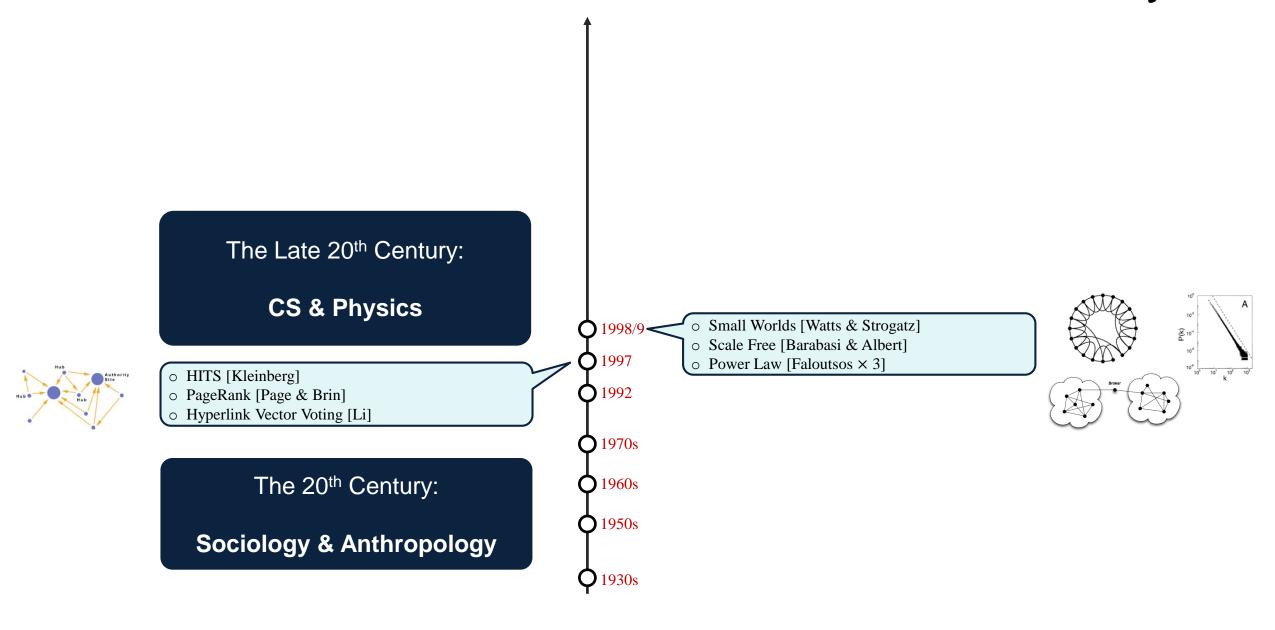
$$P(k) \sim k^{-\gamma}$$

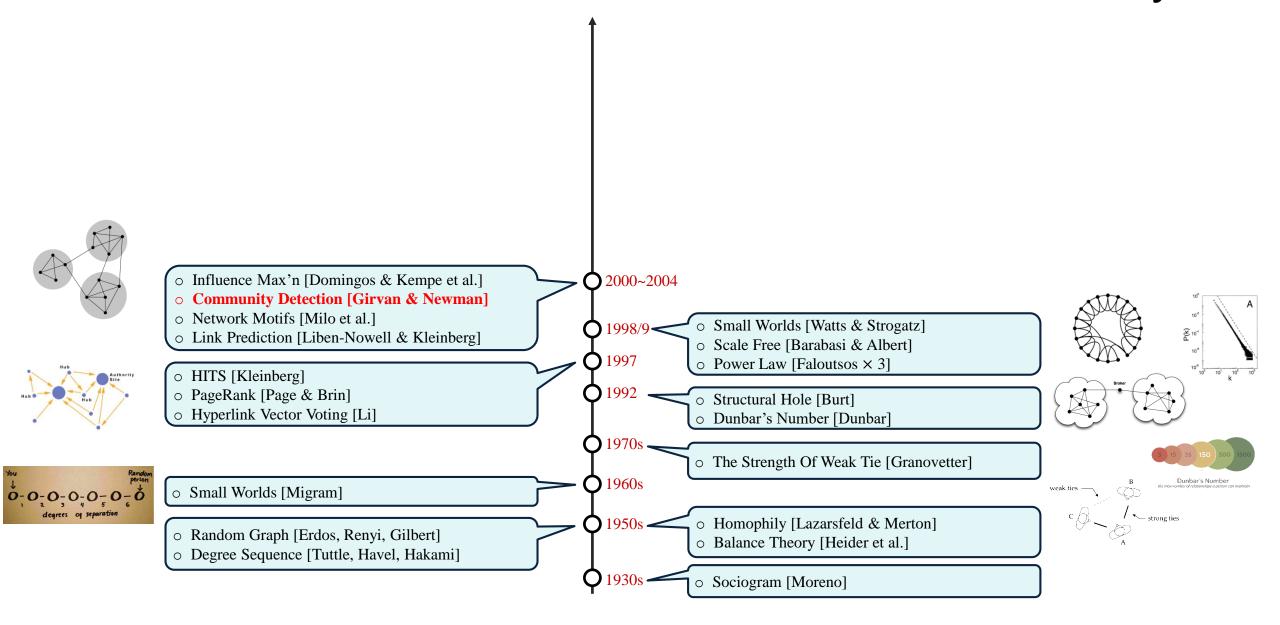
where γ is a parameter whose value is typically in the range $2 < \gamma < 3$



^{1.} Albert-László Barabási, Réka Albert. Emergence of scaling in random networks, Science, 286:509–512, 1999. Cited by 31000+ (as of Aug 2018)

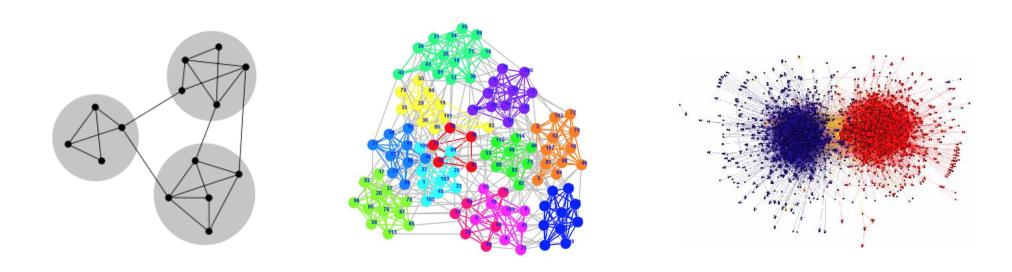
^{2.} Michalis Faloutsos, Petros Faloutsos, Christos Faloutsos. On power-law relationships of the internet topology. In ACM SIGCOMM 1999. Cited by 6400+ (as of Aug 2018)





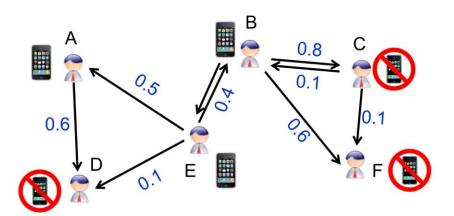
2002: Community Detection

• "The property of community structure, in which network nodes are joined together in tightly knit groups, between which there are only looser connections."



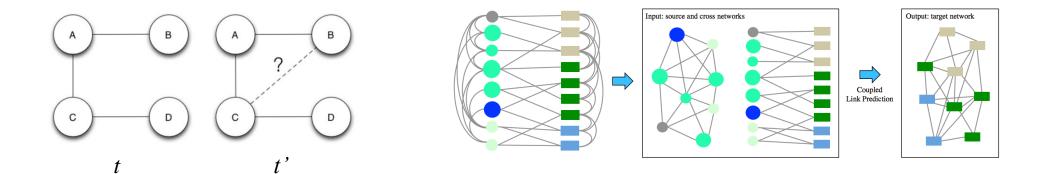
2003: Influence Maximization

• Minimize marketing cost and more generally to maximize profit, e.g., to get a small number of influential users to adopt a new product, and subsequently trigger a large cascade of further adoptions.

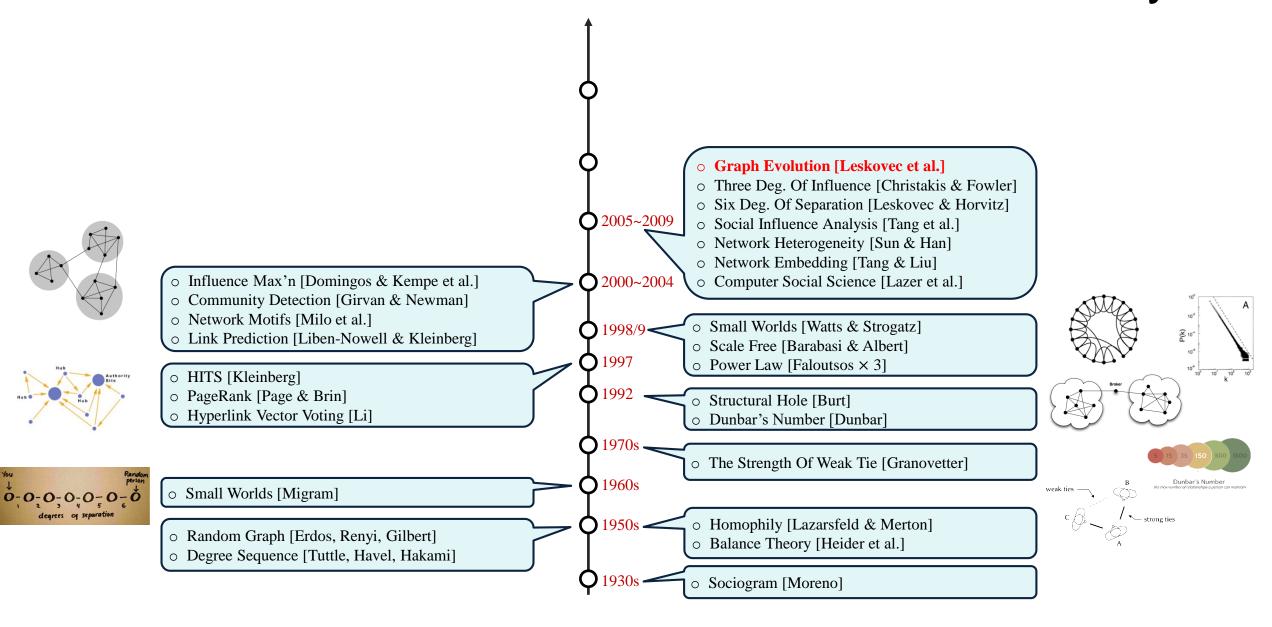


2003: Link Prediction

• "Given a snapshot of a social network at time t, we seek to accurately predict the edges that will be added to the network during the interval from time t to a given future time t'."

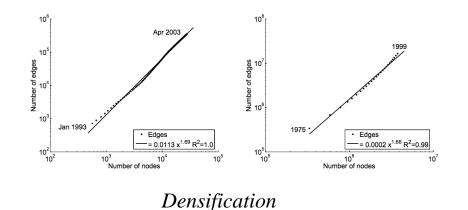


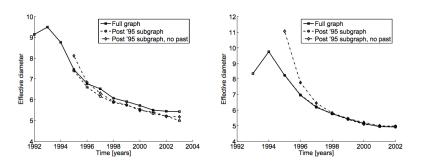
1. D. Liben-Nowell, J. Kleinberg. The Link Prediction Problem for Social Networks. In ACM CIKM, 2003. Cited by 3900+ (as of Aug 2018)



2005: Network Evolution

- "Most of graphs densify over time, with the number of edges growing superlinearly in the number of nodes."
- "The average distance between nodes often shrinks over time."





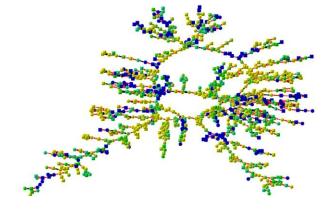
Shrinking Diameters

1. J. Leskovec, J. Kleinberg, C. Faloutsos. Graphs over Time: Densification Laws, Shrinking Diameters and Possible Explanations. In KDD, 2005. **Best Research Paper Award & Test of Time Award**. Cited by 2000+ (as of Aug 2018)

2007: Diffusion and Influence

"If the husband became obese, the likelihood that his wife would become obese increased by 37%."

—by tracking 10,000+ people for 32 years

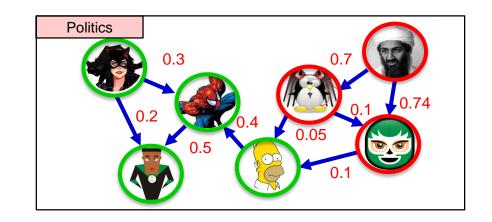


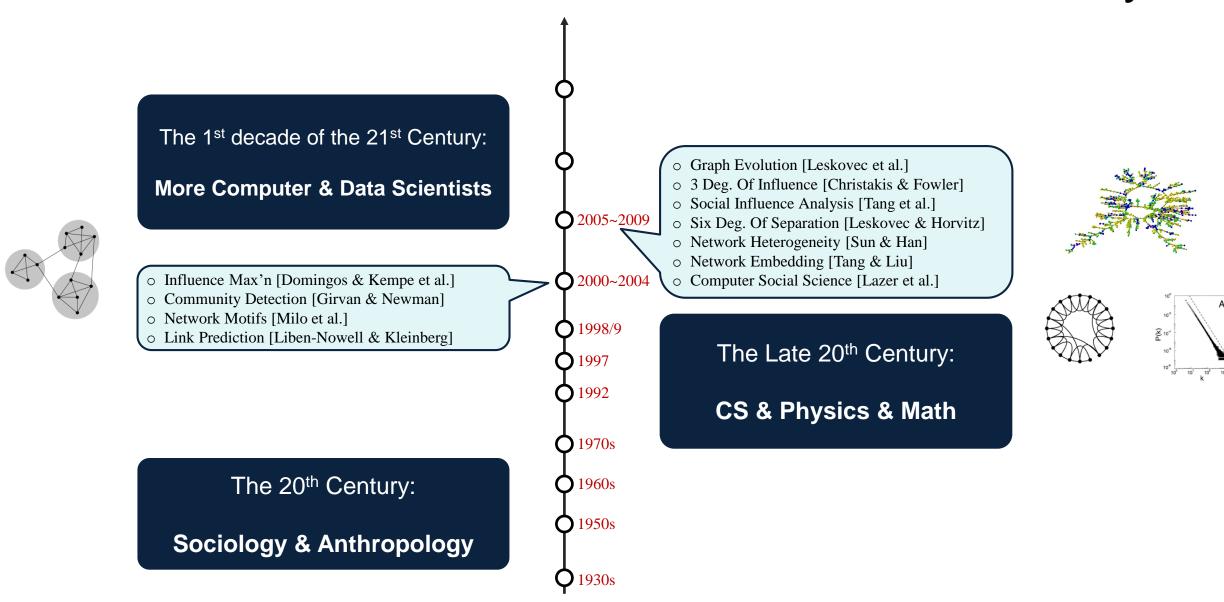
1. Nicholas Christakis, James Fowler. The Spread of Obesity in a Large Social Network Over 32 Years. The New England Journal of Medicine 357 (4): 370–379, 2007. Cited by 4600+ (as of May 2016)

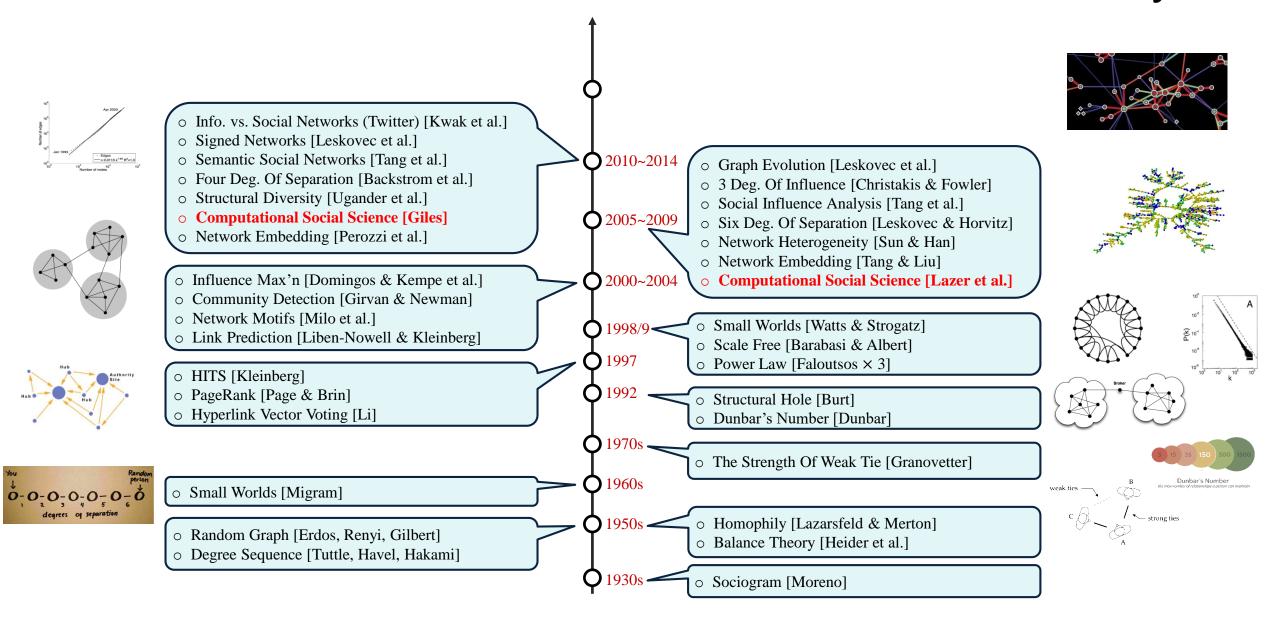
2009: Social Influence Analysis

- "Social influence is a prevalent, complex and subtle force that governs the dynamics of all social networks."
- How to quantify the *social influences* from different topics?

—Topical Affinity Propagation (TAP)



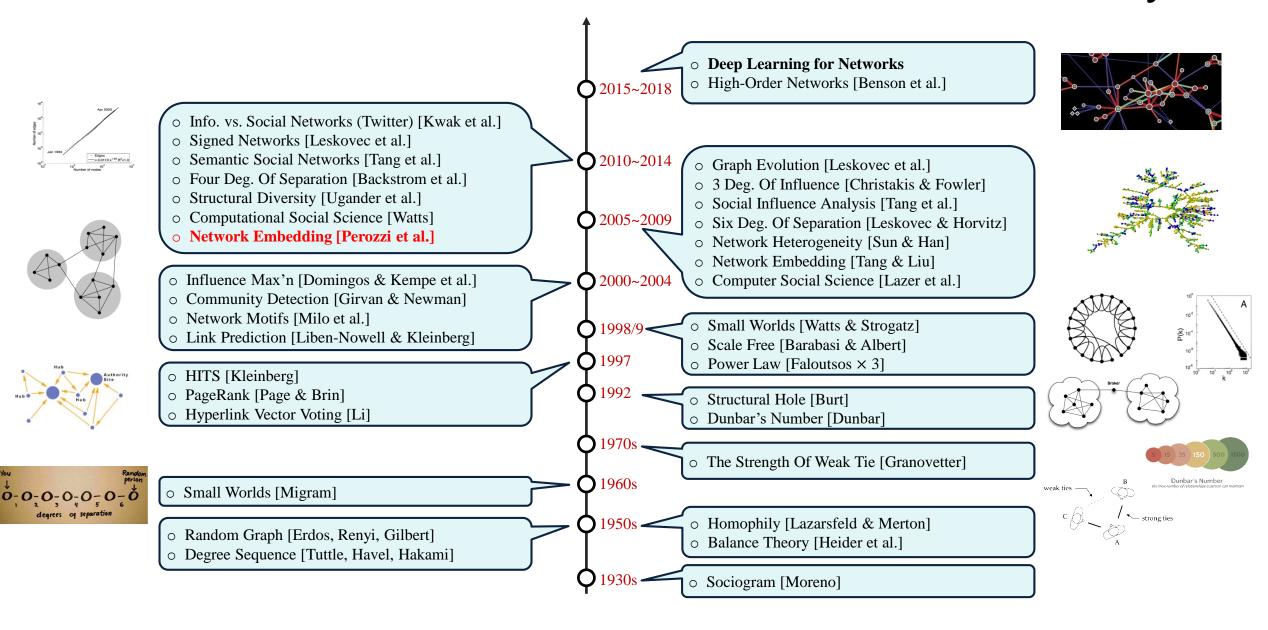




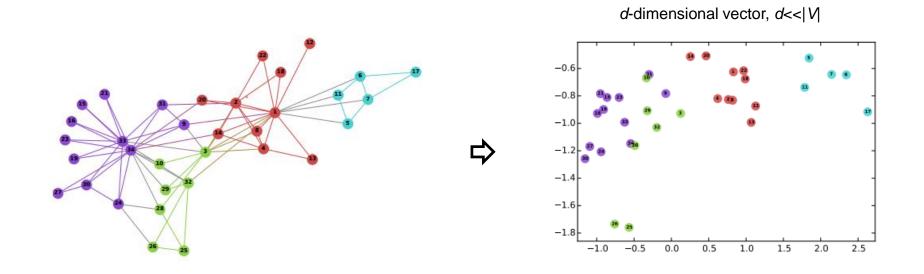
"A field is emerging that leverages the capacity to collect and analyze **data at** a scale that may reveal patterns of individual and group behaviors."

—David Lazer, Alex Pentland, Lada Adamic, Sinan Aral, Albert-Laszlo Barabasi, et al. from Sociology, Computer Science, Physics, Business, Government, etc. at Harvard, MIT, Northeastern, Northwestern, Columbia, Cornell, etc.

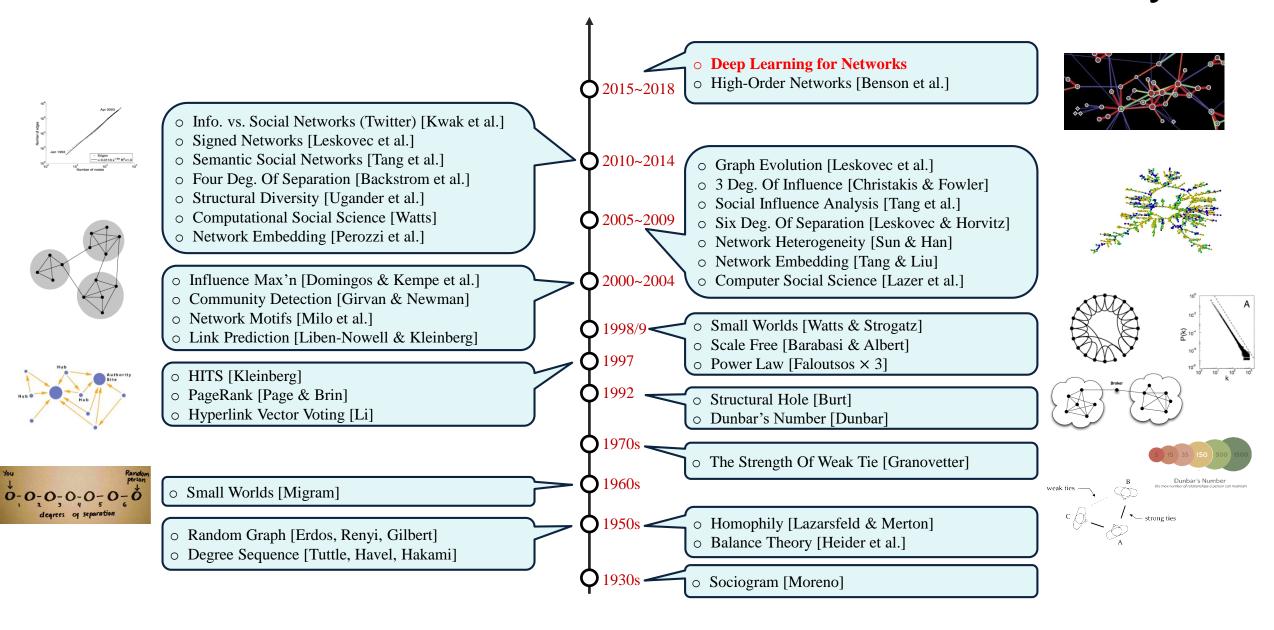
- 1. David Lazer et al. Computational Social Science. Science 2009.
- 2. James Giles. Computational Social Science: Making the Links. Nature 2012.



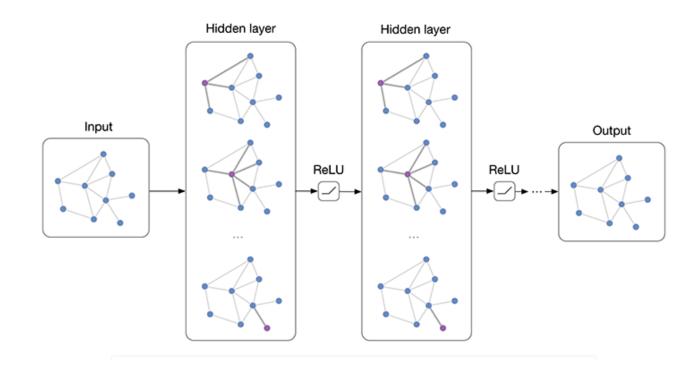
Network Representation Learning



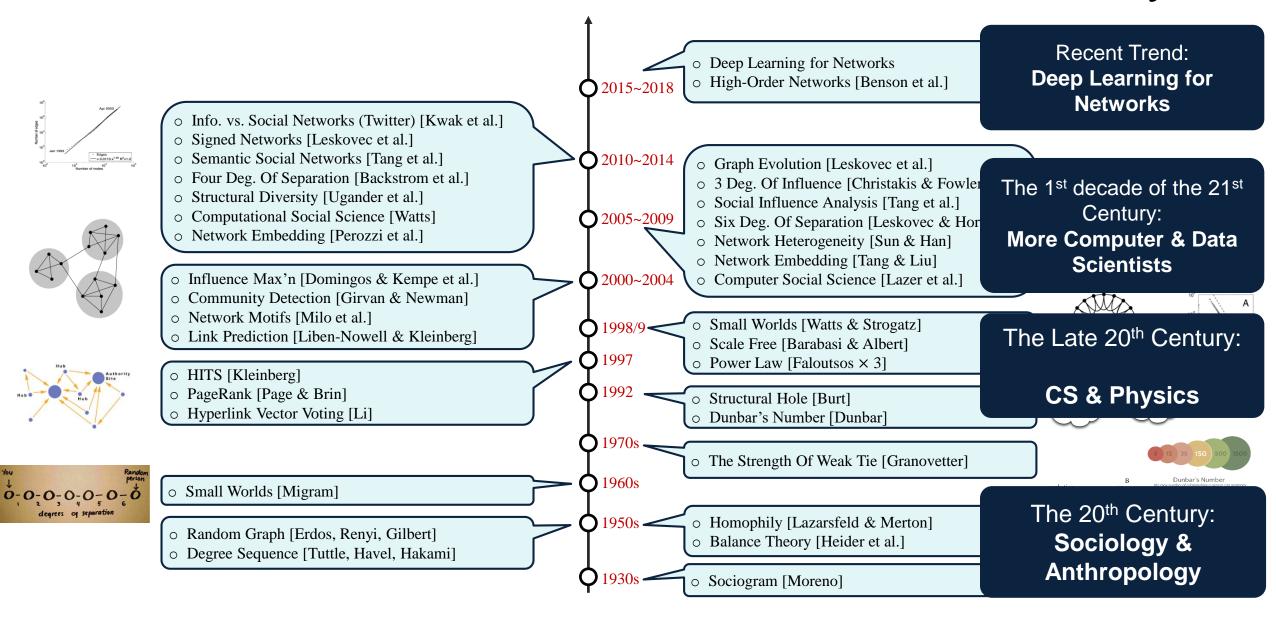
- 1. Lei Tang and Huan Liu. Relational learning via latent social dimensions. In KDD 2009.
- 2. Bryan Perozzi, Rami Al-Rfou, and Steven Skiena. DeepWalk: Online learning of social representations. In KDD 2014. The most cited paper in KDD'14. (as of Aug 2018)



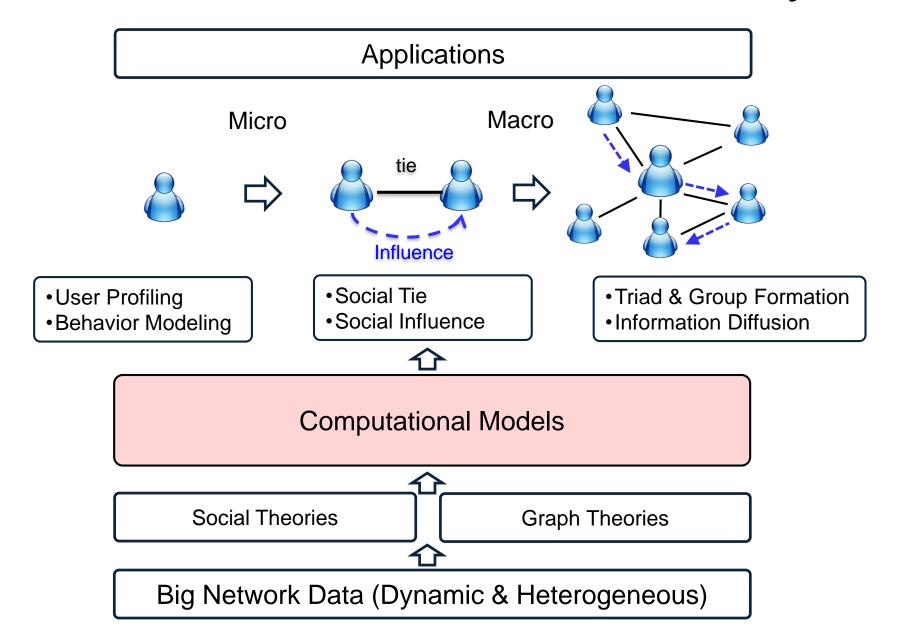
Deep networks for networks



- 1. Kipf & Welling, Semi-Supervised Classification with Graph Convolutional Networks. In ICLR 2017.
- 2. Petar Velickovic, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Y Bengio. Graph Attention Networks. In ICLR 2018.



Social & Information Network Analysis



Representation Learning on Networks

The first part:

- Conventional network analysis
 - Node classification
 - Social tie & link prediction
- Network embeddings
 - Embedding models
 - Theoretical understanding
 - Large-scale embedding

The second part:

- Graph neural networks
 - Graph convolution
 - Graph GAN
 - Dynamic Representation
 - Heterogeneous Representation
- Large-scale applications
 - Knowledge graph linking
 - Recommendation in E-commerce
 - Online-to-offline recommendations
 - Social influence in gaming

Applications in this talk











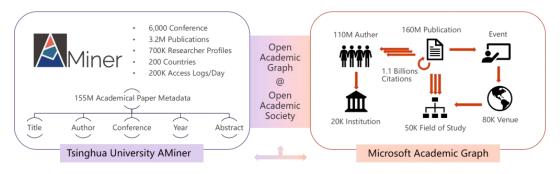






OAG: Open Academic Graph

https://www.openacademic.ai/oag/



Data set	#Pairs/Venues	Date	
Linking relations	29,841	2018.12	
AMiner venues	69,397	2018.07	
MAG venues	52,678	2018.11	

Table 1: statistics of OAG venue data

Data set	#Pairs/Papers	Date	
Linking relations	91,137,597	2018.12	
AMiner papers	172,209,563	2019.01	
MAG papers	208,915,369	2018.11	

Table 2: statistics of OAG paper data

Data set	#Pairs/Authors	Date	
Linking relations	1,717,680	2019.01	
AMiner authors	113,171,945	2018.07	
MAG authors	253,144,301	2018.11	

Open Academic Graph

Open Academic Graph (OAG) is a large knowledge graph unifying two billion-scale academic graphs: Microsoft Academic Graph (MAG) and AMiner. In mid 2017, we published OAG v1, which contains 166,192,182 papers from MAG and 154,771,162 papers from AMiner (see below) and generated 64,639,608 linking (matching) relations between the two graphs. This time, in OAG v2, author, venue and newer publication data and the corresponding matchings are available.

Overview of OAG v2

The statistics of OAG v2 is listed as the three tables below. The two large graphs are both evolving and we take MAG November 2018 snapshot and AMiner July 2018 or January 2019 snapshot for this version.

1. Zhang, et al. OAG: Toward Linking Large-scale Heterogeneous Entity Graphs. In KDD'19.

Datasets for Social Network Analysis

Datasets for Social Network Analysis

https://www.aminer.cn/data-sna

SN	Name	Node	Edge	Behavior/Content	Description			
	Microblogging networks							
1	Twitter-Dynamic-Net	90908 users	443,399 time varying following relationships	99,696,204 tweets associated with 156,487 users	Dynamic twitter following network and tweets.			
2	Twitter-Dynamic-Action	7514 users	304,275 time varying following relationships	730,568 tweets	Tweeting actions of users on a specific topic "Haiti Earthquake"			
3	Twitter-Competitor	87,603 Twitter users		1,033,750 tweets covers 1393 companies	Twitter content related to companies			
4	Twitter-Net-Tweet	41.7 million users	1.47 billion social relations	4,252 trending topics, 106 million tweets	The entire Twitter site in 2010			
5	Weibo-Net-Tweet	1,776,950	308,489,739	300,000 original microblogs and 23,755,810 retweets	Sina weibo users, relationships, and their tweets and retweets.			
	Patent data set from Patentminer.org							
6	Patent	2,334,093 inventors	11,504,051 coauthor relationships	4,179,629 patents and 584,380 companies	Co-patent and patent citation network			
	Other online social networks							
7	Slashdot-large	93139 users	577025 friend/foe relationships	35065 news and 3505736 comments	Slashdot friend and foe network and news comment data			
8	Slashdot-small	13,182 users	309,14 friends, 5,424 foes		Slashdot friend and foe network			
9	Epinions-1	25,148 users	74,060 trust relationships, 31,001 distrust relationships		Epinioins trust/distrust network			
10	Epinions-2	22,166 users	355,813 links between users	296,277 items, 27 categories, 922,267 ratings	Epinions trust/distruct network and user rating item data			
11	Enron	151 users	133 manager-subordinate relationships, 132 colleague relationships		Email communication network			
12	Flickr-large	2,037,538 users	219,098,660 friend relationships	655,917 groups, 1,262,978 images, 1,4913,164 user comments	Flick friend network and image comments			
13	Flickr-medium	215,495 users	9,114,557 relationships		Flick friend network			

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 - Influence & behavior modeling
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 - Embedding models
 - Theoretical understanding
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 - Social influence in gaming

Thank you!

Collaborators: John Hopcroft, Jon Kleinberg, Chenhao Tan (Cornell)

Jiawei Han (UIUC), Philip Yu (UIC)

Jian Pei (SFU), Hanghang Tong (ASU)

Tiancheng Lou (Google&Baidu), Jimeng Sun (GIT)

Wei Chen, Ming Zhou, Long Jiang, Chi Wang, Kuansan Wang (Microsoft)

Hongxia, Jingren Zhou, Chang Zhou (Alibaba)

Jiezhong Qiu, Jie Zhang, Fanjin Zhang, Qibin Chen, Yukuo Cen, et al. (THU)

Jie Tang, KEG, Tsinghua U, **Download all data & Codes**,

http://keg.cs.tsinghua.edu.cn/jietang

http://arnetminer.org/data

http://arnetminer.org/data-sna