School of Information
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The Social Hyperlink

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LADA ADAMIC

CURRENT

PAST

ALWAYS

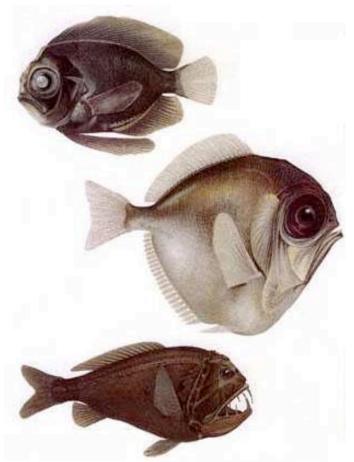
ME

YOU

THEM

WORK PLAY

ladamic@umich.edu



THEM

TJ Stacy Eytan Orkut Rajan Ryan Wendy Sergio Amy Josh Annie Martin Jen Amnon Julie



Becky



0

Hi, I'm Julie!

I'm studying...

I like ...

My friends are...

My favorite links:

TIN ORING OF THE SECOND OF THE

Hey, I'm Becky.

I study...

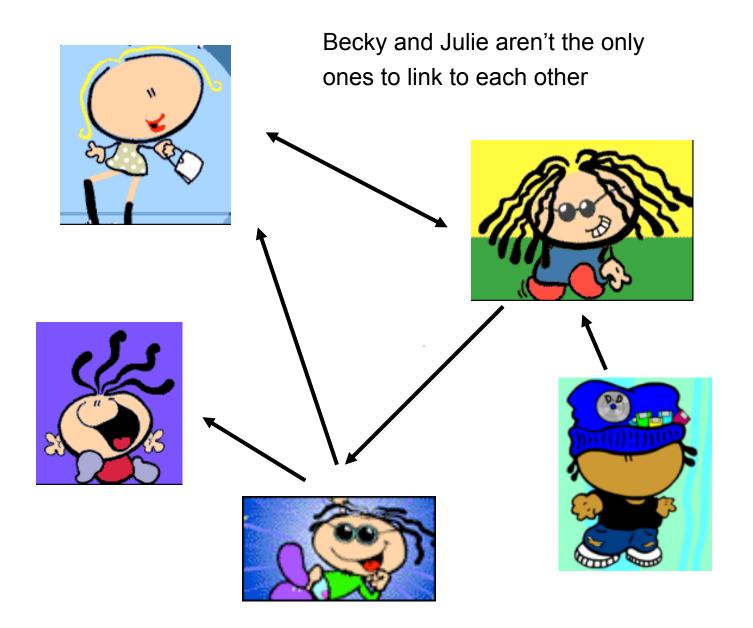
I live in ...

My favorite books

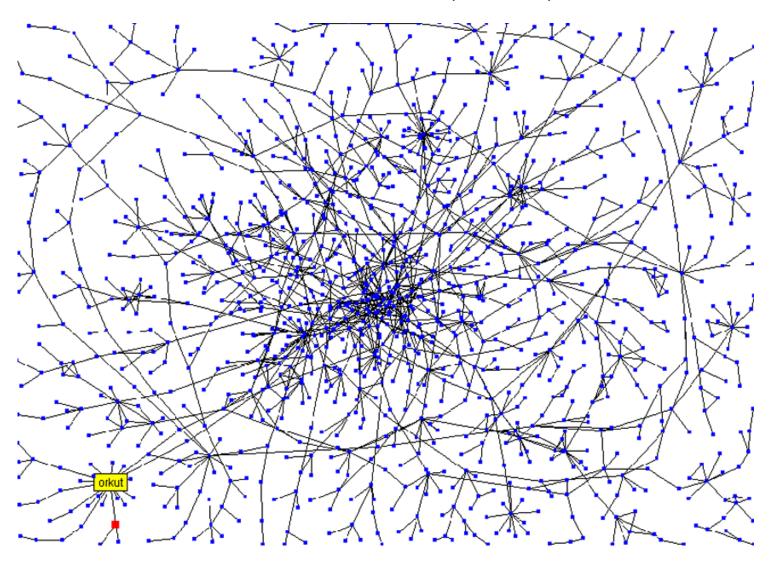
are...

Here are some

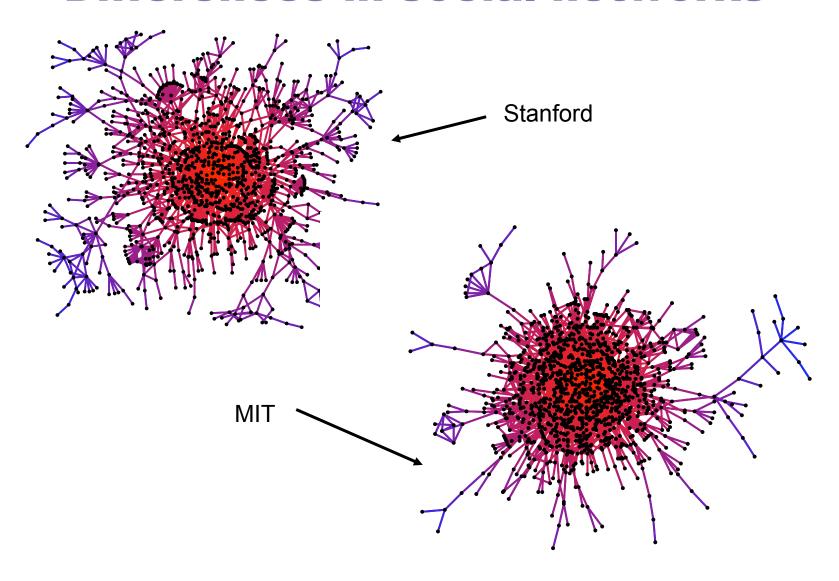
photos...



Stanford Social Web (ca. 1999)



Differences in social networks



Link prediction reveals why individuals associate

MIT Top Things	Stanford Top Things
Union Chicana (student group)	NTUA (National Technical University of Athens)
Phi Beta Epsilon (fraternity)	Project Aiyme (mentoring Asian American 8th graders)
Bhangra (traditional dance, practiced within a club at MIT)	pearl tea (popular drink among members of a sorority)
neurosci (appears to be the journal Neuroscience)	clarpic (section of marching band)
Phi Sigma Kappa (fraternity)	KDPhi (Sorority)
PBE (fraternity)	technology systems (computer networking services)
Chi Phi (fraternity)	UCAA (Undergraduate Asian American Association)
Alpha Chi Omega (sorority)	infectious diseases (research interest)
Stuyvesant High School	viruses (research interest)
Russian House (living group)	home church (Religious phrase)



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	Clu5N	ZUKS			define you	irself
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	profile	buddy list	bı	uddy groups	settings	_
ory sys	ur Buddy List forms the stem will construct you xus. add buddy	ne backbone of the ur social network -	Club Nexu - a require	us system. From yo d step to enjoy an	ur list of frienc y usage of Clu	ds, the ib
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Use	e Buddy Finder for ea over 21,400 Stanford	ısy one-click adding students and facu	g to your b ilty!	uddy list. Find frien	ds from a data	abase
Use	e Buddy Finder for ea	sy one-click adding students and facu	ilty! seard	uddy list. Find frien ch by: st name		abase
Use	e Buddy Finder for ea over 21,400 Stanford buddy finder value:	sy one-click adding students and facu	ilty! seard	ch by:	name	abase t by <u>last</u>
Use	e Buddy Finder for ea over 21,400 Stanford buddy finder value:	sy one-click adding students and facu	ilty! seard	ch by:	name	
Use	e Buddy Finder for ea over 21,400 Stanford buddy finder value: find buddy list	students and facu	searc • fir usernam	ch by: st name Olast r eemail	name sort	t by <u>last</u>
Use of d	e Buddy Finder for ea over 21,400 Stanford buddy finder value: find buddy list na	students and facu	seard • fir usernam drago	ch by: st name Clast r e email drago@stanford	name sort .edu	t by <u>last</u> <u>edit</u>
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Use of a	e Buddy Finder for ea over 21,400 Stanford buddy finder value: find buddy list na Dragomir Anguelov Jian Silverstein Orkut Buyukkokten Sergio Marti	me	seard fir usernam drago jians orkut	ch by: st name C last r e email drago@stanford liu@psych.stanf orkut@stanford.	name sort .edu ord.edu edu t.edu du	edit edit edit edit edit edit

Major and personality

personality (% of total)	major
free time: learning (17%)	Physics (46%), Philosophy (37%), Math (31%), EE (26%), CS (24%)
free time: reading (26%)	English (55%)
free time: staying at home (8%)	History (24%)
free time: doing anything exciting (52%)	undecided/undeclared (62%)
you: weird (12%)	Physics (34%), Math (28%), EE (18%)
you: intelligent (32%)	Philosophy (59%), CS (42%)
you: successful (4%)	CS (7%)
you: attractive (16%)	Political Science (29%), International Relations (25%)
you: lovable (12%)	Political Science (24%)
you: kind (25%)	Public Policy (45%)
you: funny (25%)	Philosophy (6%)
you: creative (22%)	Product Design (62%), English (42%)
you: sexy (8%)	English (18%), EE (2%)

Nexus Karma

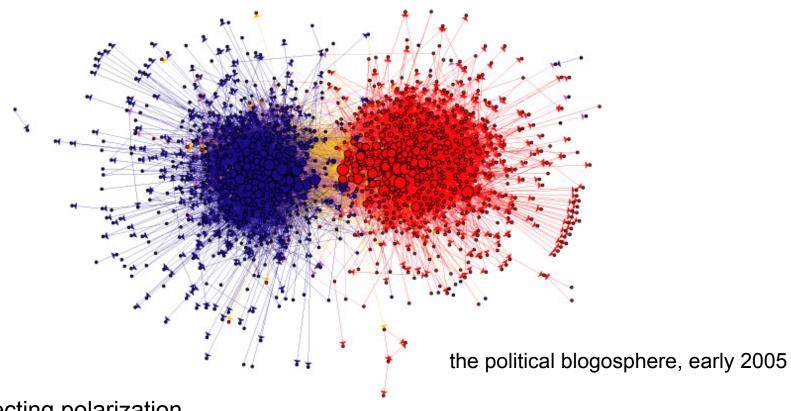
	trusty (3.22)	nice (3.37)	cool (3.13)	sexy (2.83)
responsible	3.36		→ 3.02	2.67
sexy	3.10	3.23		3.03
attractive	3.09	3.25		2.93
kind	3.34	3.46		
friendly		3.44		
weird				2.67
funny		→ 3.31		

Rank how 'trusty', 'nice', 'cool', and 'sexy' your buddies are on a scale of 1 to 4

Interests and association ratios

	high association	low association
book	gay & lesbian, professional & technical, computers, teen, sex, sports	history, fiction & literature, outdoor & nature
movie genres	gay & lesbian, performing arts, religion, erotic & softcore, sports	drama, mystery, documentary, comedy
music genres	gospel, jungle, bluegrass/rural, heavy metal, trance	pop, classical, rock
land sport	lacrosse, field hockey, wrestling, cricket	tennis, martial arts, bicycling, racquetball
water sport	synchronized swimming, diving, crew	swimming, fishing windsurfing
social	raving, ballroom dancing, Latin dancing	partying, camping

Can we understand community dynamics?

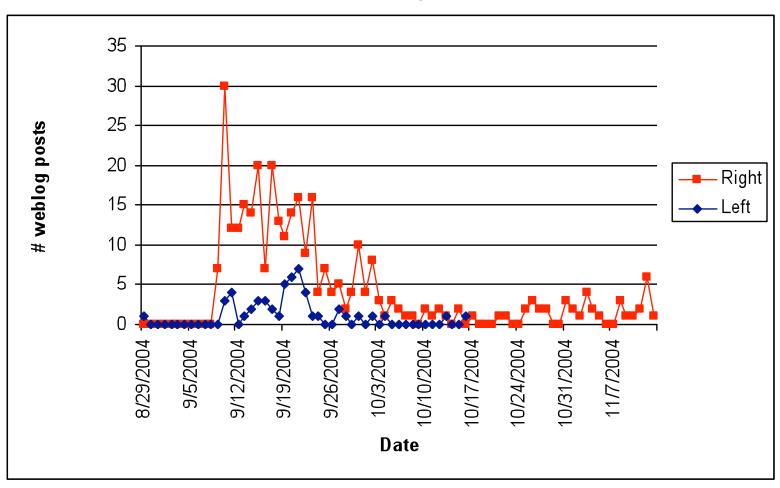


- detecting polarization
- analyzing discourse

Adamic & Glance, LinkKDD 2005

Liberals and conservatives differ in the topics they discuss

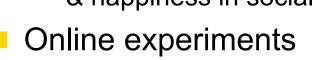
Discussion of "forged documents"



the social influence hyperlink

Survey data:

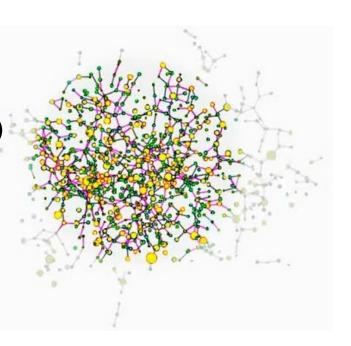
- Studies of innovation adoption
- hybrid corn (Ryan and Gross, 1943)
- prescription drugs (Coleman et al. 1957)
- Christakis and Fowler (spread of obesity & happiness in social networks) 2008



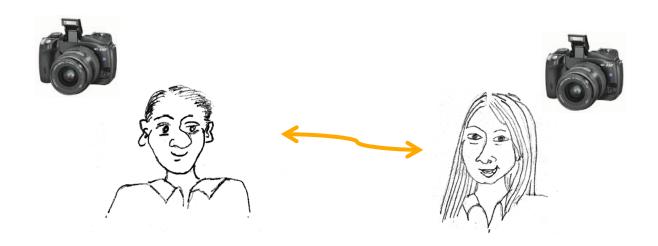
Salganik et al. 2006 (music)



- Lerman (spread of FlickR photos & Digg stories) 2007
- Backstrom et al. (joining LiveJournal groups & CS conferences) 2006



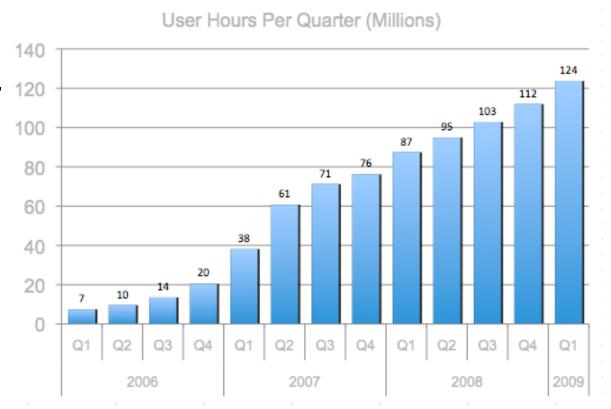
social networks: influence or correlation?



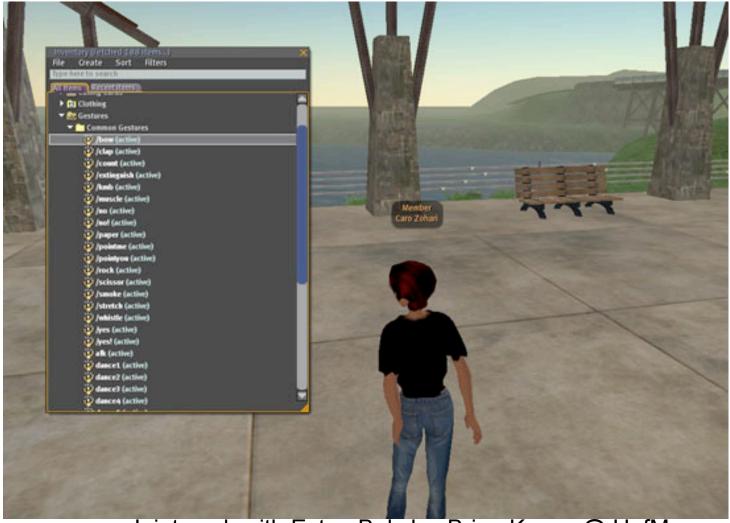


Why study second life?

- digital traces!
- content is usercreated
- content is shared and traded



gestures in second life

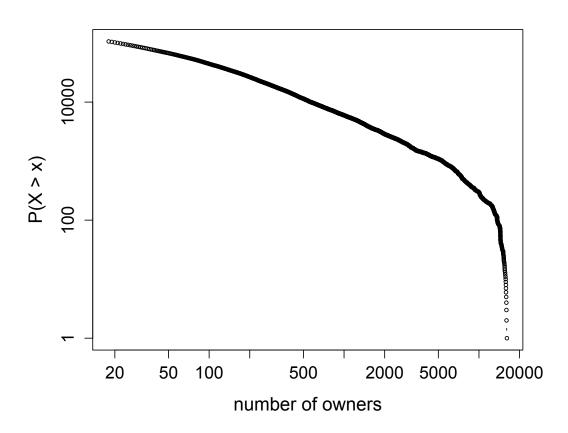


Joint work with Eytan Bakshy, Brian Karrer @ UofM accepted at EC (Electronic Commerce Conference) '09

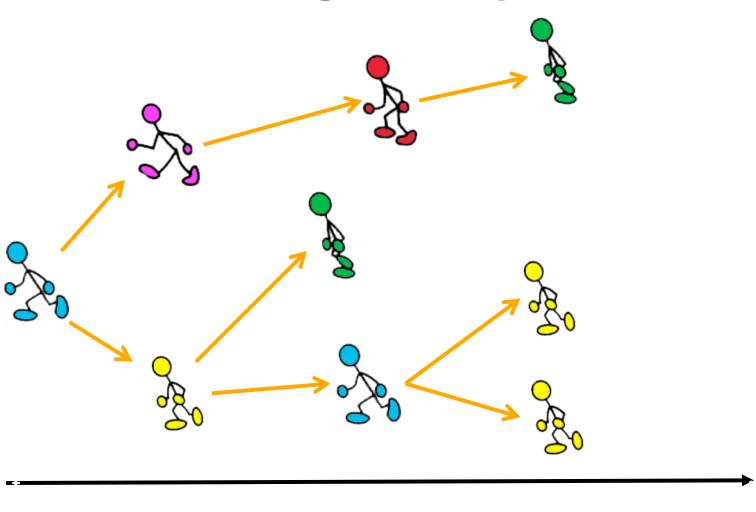


how does on discover content in the long tail?

(heavy tail: there are > 5 million different gestures)



How do gestures spread?



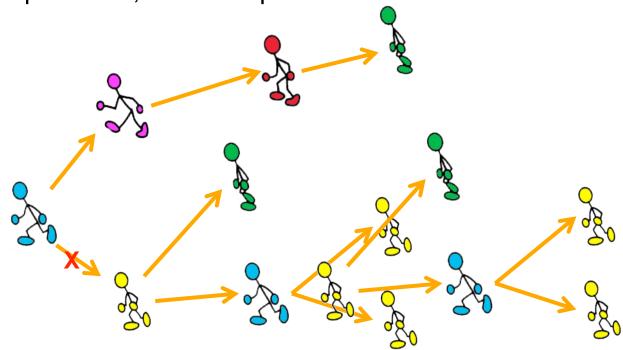
time

Dataset

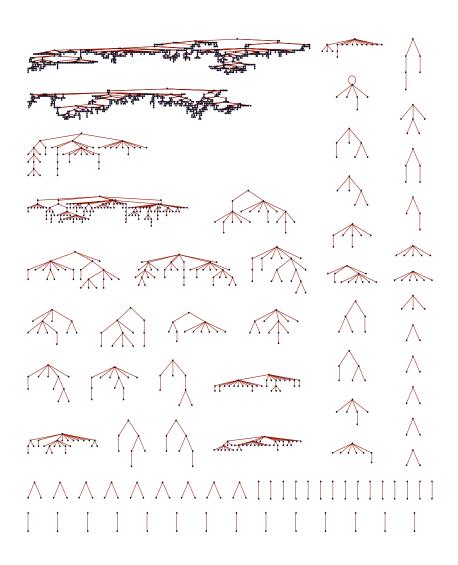
- gesture transfers 9/2008-1/2009
- 100,229 users who exchanged at least 1 object
- 106,499 assets with at least 16 unique owners & not distributed by Linden Lab

missing links

- 12.6 million asset transfers
- 3.4 million (23%) have accurate previous owner info
 - per asset, ~ 43% of previous owner info available

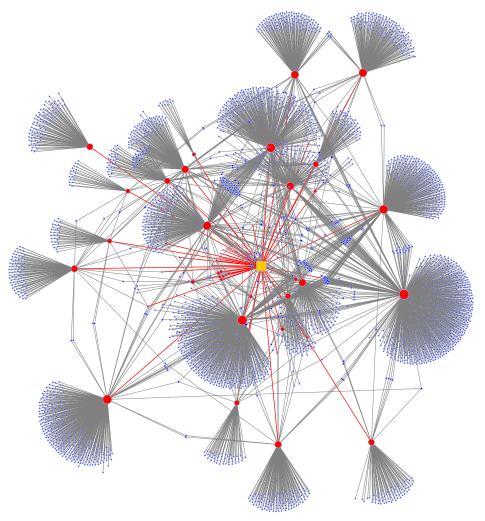


spread of an aerosmith gesture



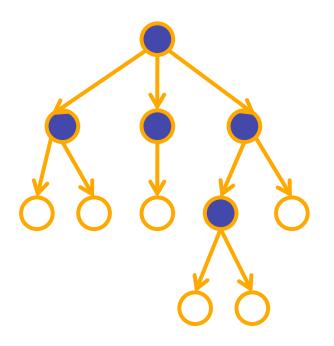
the role of the social network

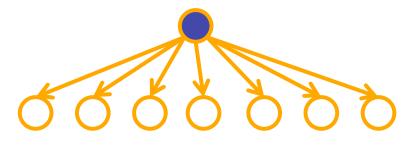
- weekly snapshots
- direct influence:
 - 48% of transfers occur between friends
- indirect influence:
 - of the remainder 38% occur after at least one friend has adopted



spread through the social network: boost or brake?

cascades spreading through the social network are deeper (higher percentage of non-leaf nodes) (ρ = 0.42)



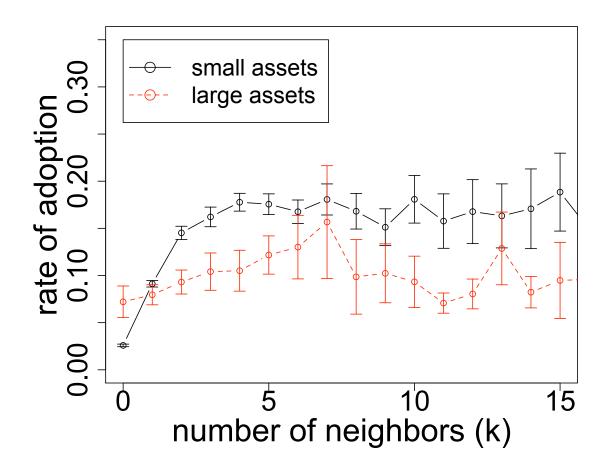


spread through the social network associated with limited reach

- observe adoptions over first 30 days of assets' existence
- predict adoptions over next 60

	model 1	model 2
log (initial adoptions)	0.508	0.476
% direct or indirect social		-0.897
R^2	0.164	0.196

new assets and eventual adopters



-> small difference in λ_0 accounts for large difference in asset size

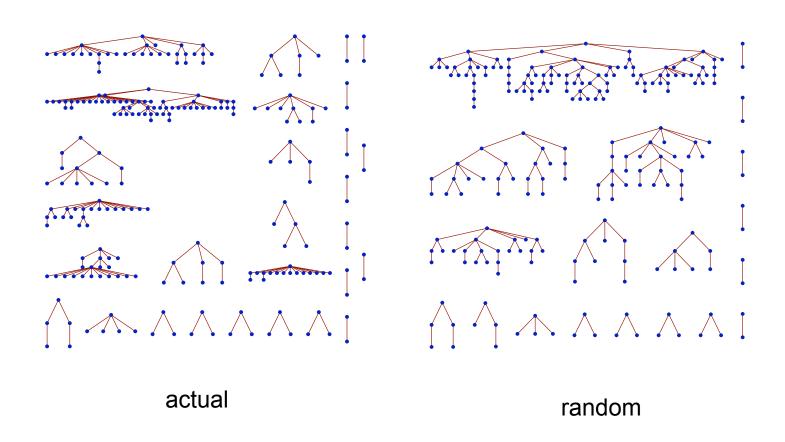
influencers (connectors?)

- heavy tailed distribution in number of times each user shares an asset
- users who have more friends share assets more often (ρ = 0.15)





actual vs. random cascade



early adopters (mavens?)

- characterize ~800 users who have >=20 assets, but were among the first 5% to adopt each one
- compare to laggards (among the last 50% in adopting all their gestures)

what early adopters are not particularly

early in joining Second Life (only 2 months older than

laggards)

gregarious (8 friends fewer on average out of ~ a mean of 60)

early adopters are not influencers...

- lower γ (ρ = -0.015, p < 0.001)
- number of transfers the user makes ($\rho = -0.02$, $p < 10^{-7}$)
 - Malcom Gladwell distinguished mavens from connectors in the 'Tipping Point'



The social influence hyperlink: wrap up

- social network influences adoption
- niche items get a bigger boost
- some individuals more influential than others
- but early adopters not necessarily connectors

The knowledge exchange hyperlink







WikiAnswers The Q&A Community **Developer Forums**

Sun Forums















Knowledge iN



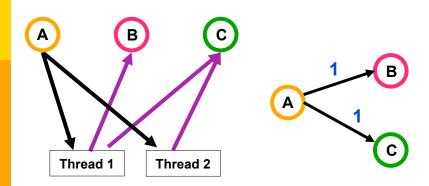
Related work

- Analysis of online communities
 - NetScan (Smith, Fisher, et al. at Microsoft)
 - Motivations of online participation (Lakhani & Hippel, Kraut)
- Expertise sharing studies
 - Expertise recommenders
 - ContactFinder (Krulwich et al.), Answer Garden (Ackerman)
 - Small Blue (Lin)
 - Automatic evaluation of expertise levels
 - Using different text resources (Kautz, et al, and a lot of others)
 - Using email networks (Campbell et al.)

Related work: Q&A sites

- Harper et al. how can one obtain good answers?
 - Harper et al. CHI 2008: paying for (Google) Answers lead to higher answer quality than not (Yahoo! Answers), but inconsistent with Chen et al...
 - Harper et al. CHI 2009: automatically identify question types, predict answer quality
- Agichtein et al.: Identifying good answers, facts, experts (CIKM2007, WSDM 2008, WWW 2008, SIGIR 2008, WWW2009..)
 - use text & link analysis, clicks, and community ratings

Constructing a community expertise network



Thread 1: Large Data, binary search or

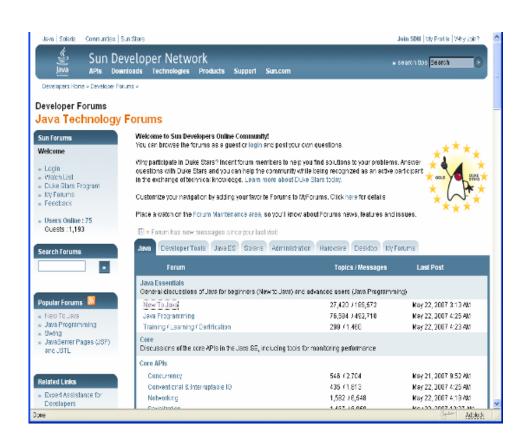
hashtable? user A

Re: Large... user B

Re: Large... user C

Thread 2: Binary file with ASCII data user A

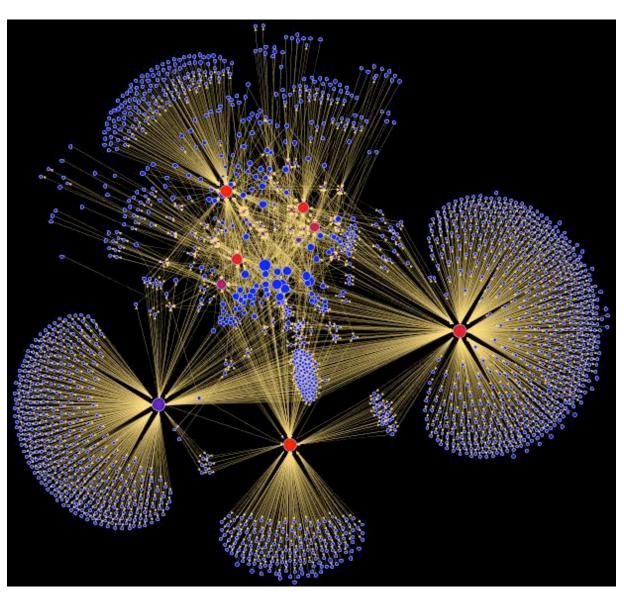
Re: File with... user C



Java Forum

Zhang, Ackerman, Adamic WWW'07

fragment of the Java Forum

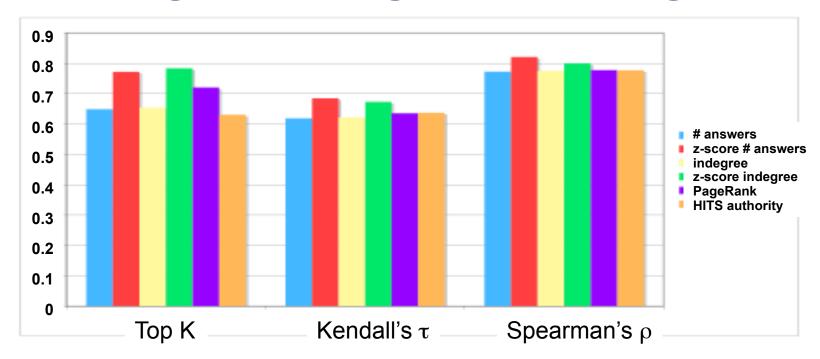


Relating network structure to Java expertise

- Human-rated expertise levels
 - 2 raters
 - 135 JavaForum users with >= 10 posts
 - inter-rater agreement (τ = 0.74, ρ = 0.83)
 - for evaluation of algorithms, omit users where raters disagreed by more than 1 level (τ = 0.80, ρ = 0.83)

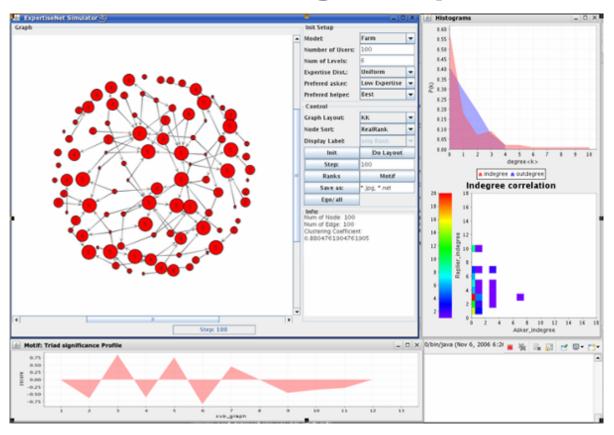
L	Category	Description
5	Top Java expert	Knows the core Java theory and related advanced topics deeply.
4	Java professional	Can answer all or most of Java concept questions. Also knows one or some sub topics very well,
3	Java user	Knows advanced Java concepts. Can program relatively well.
2	Java learner	Knows basic concepts and can program, but is not good at advanced topics of Java.
1	Newbie	Just starting to learn java.

Algorithm Rankings vs. Human Ratings



simple local measures do as well (and better) than measures incorporating the wider network topology

Modeling community structure to explain algorithm performance

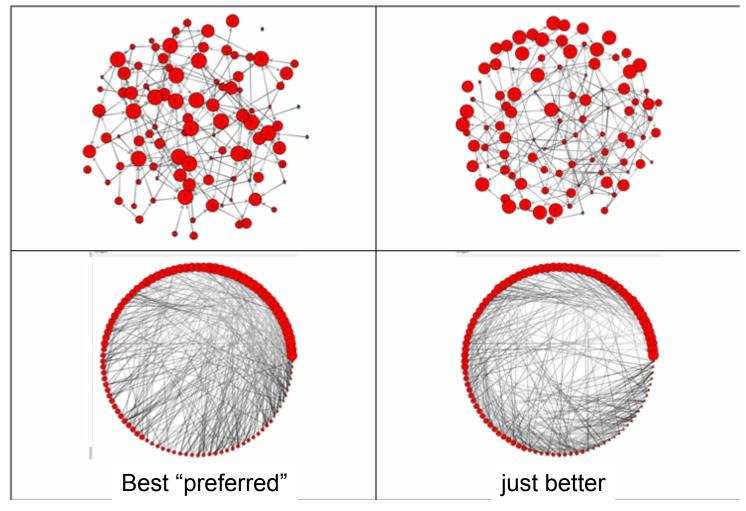


ExpertiseNet Simulator

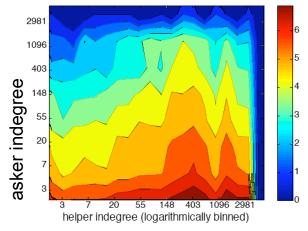
Control Parameters:

- Distribution of expertise
- Who asks questions most often?
- Who answers questions most often?
 - best expert most likely
- someone a bit more expert

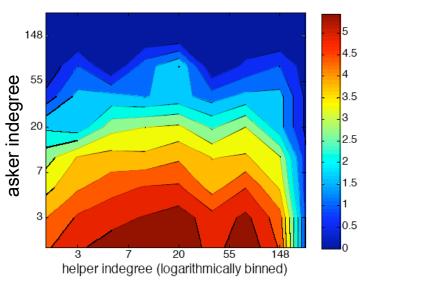
Visualization

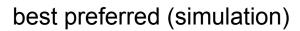


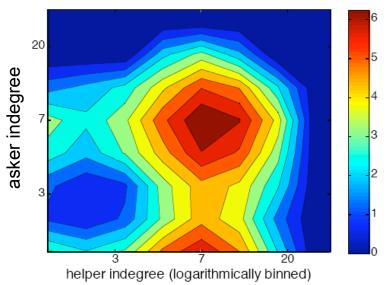
Degree correlation profiles



Java Forum Network

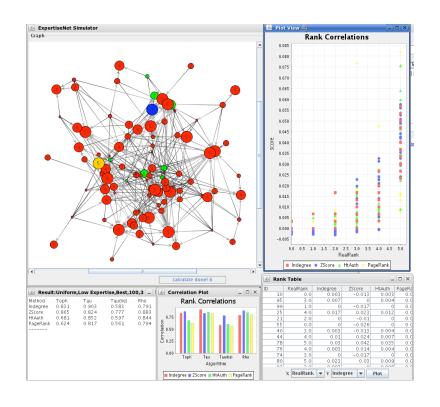


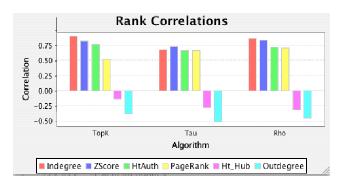




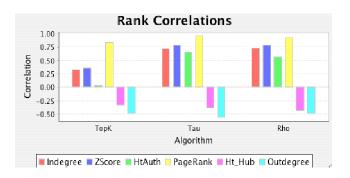
just better (simulation)

It can tell us when to use which algorithms



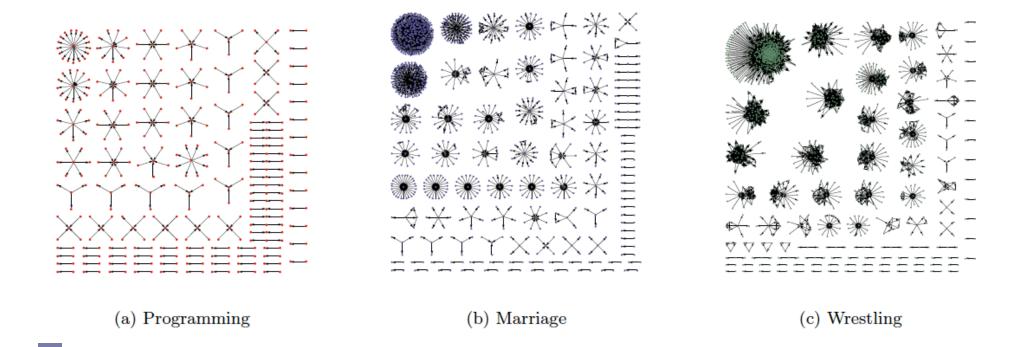


Preferred Helper: 'best available'



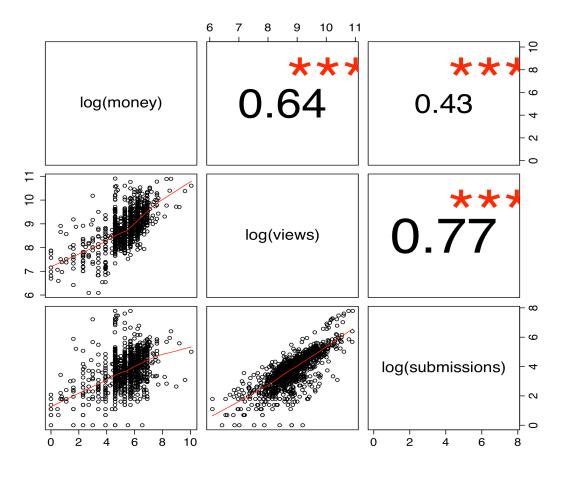
Preferred Helper: 'just better'

Knowledge sharing across topics: Y! Answers



Adamic, Zhang, Bakshy, Ackerman WWW'08

Does money matter?

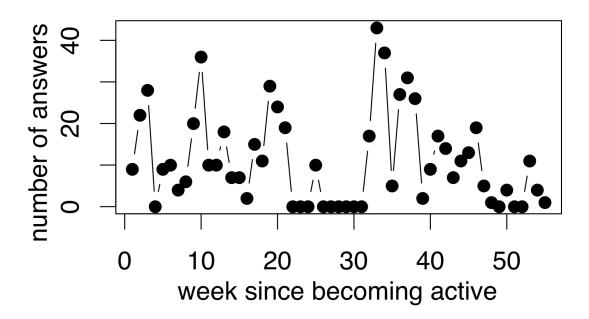




best answers are financially rewarded

Is there a stable core of participants?

- even the most active users have intermittent activity
- intermittency negatively correlated with quality



Why?

- What motivates users to answer hundreds to thousands of questions?
- From interviews of Naver (Korean Q&A site) participants
 - Altruism
 - Learning
 - Hobby
 - Business
 - Points

what to answer?

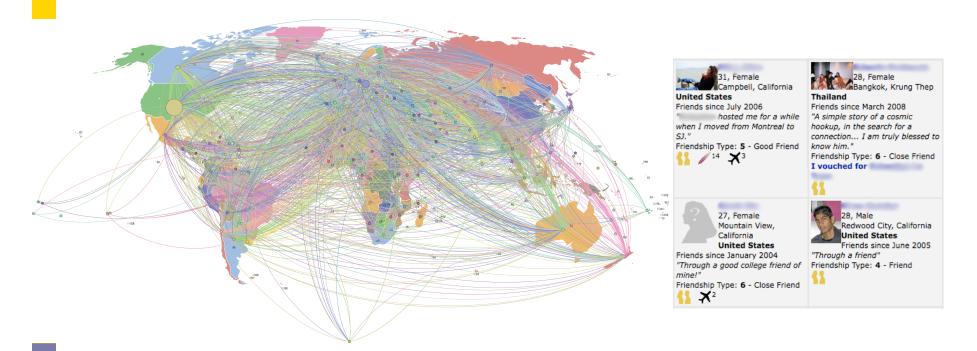
- filling in the blanks: users select unanswered questions
- correcting others: last answer picked as best most often



The knowledge sharing hyperlink

- hyperlinks in Q&A reflect information exchange between individuals
- they are keys to identifying expertise and experts

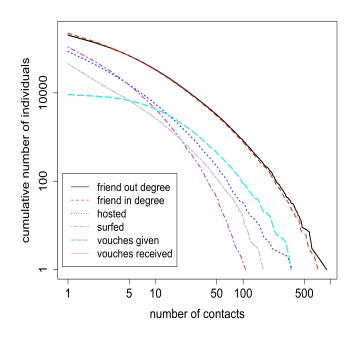
the trust hyperlink: whose couch would you sleep on?

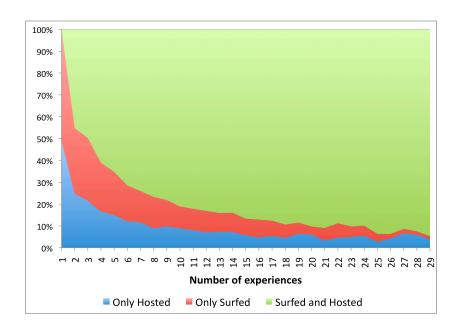


Lauterbach et al., 'Surfing a web of trust, Reputation and Reciprocity on CouchSurfing.com', SIN 2009

the web of trust

600,000 users, 156,000 surfed or hosted

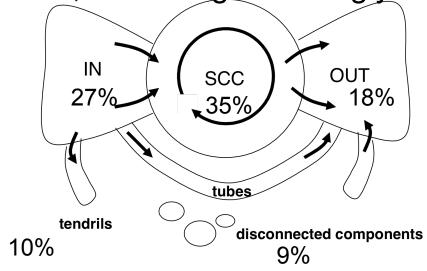




reciprocity and the web of trust

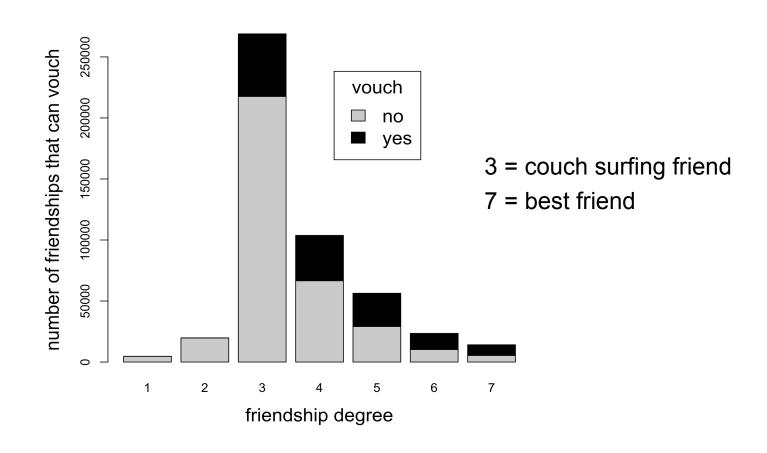
- direct reciprocity: 12-18%
- generalized reciprocity

■ 55,000 in largest strongly connected component





Can you trust web-based social hyperlinks?



Conclusion

- Social hyperlinks permeate the web
- Contribute to understanding of social phenomena
 - homophily
 - information diffusion
 - social influence
 - knowledge exchange
 - trust & reciprocity
 - more info: http://www-personal.umich.edu/~ladamic