



Using the Web to Do Social Science

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What makes Social Science “Social”?

- Social phenomena arise when individuals interact to produce collective entities that have their own attributes, rules etc.
 - Families, firms, markets, associations, societies, cultures
- Yet historically social scientists have tended to study either individual or aggregate behavior, but not both at the same time
 - “microeconomics” vs. “macroeconomics”
 - psychology vs. sociology
- Difficulty is that “micro” → “macro” transition depends on **networks** of information / influence
 - Result is “emergent” behavior:
 - Systemic risk in financial systems, changes in cultural norms, collapse of political regimes



The Web and Social Science

- Two big reasons for lack of progress
 - Networks hard to measure, especially at scale, over time
 - Can't do “macro” experiments (i.e. on large groups)
- Very hard to do science when you can't measure anything or test theories with experiments
- Recent technological advances may lift these historical constraints
 - Email, IM, Social Networking Sites, Online communities, Phone, SMS, Twitter, etc. are generating mountains of **observational network and behavioral** data
 - Also possible to do **human subjects experiments** on a previously unimaginable scale
- These changes are bigger than the WWW proper, but I'll use the term “Web” loosely to mean the whole gamut.



Outline For Rest of Talk

- Will describe four projects dating back to 2001, right up until the present
- All four motivated by a general interest in social networks and relevance to other questions of social science
 - Each captures a different aspect of problem
 - Each has also taught us something about using the web to do social science
- Looking forward, can speculate about what might be possible



1. Small World Experiment

- 1960's: Stanley Milgram and Jeffrey Travers designed first “small world” experiment
 - A single “target” in Boston
 - 300 initial “senders” in Boston and Omaha
 - Each sender asked to forward a packet to a friend who was “closer” to the target
 - The friends got the same instructions
- Protocol generated 300 “letter chains” of which 64 reached the target.
- Found that typical chain length was 6
- Led to the famous “six degrees” phrase

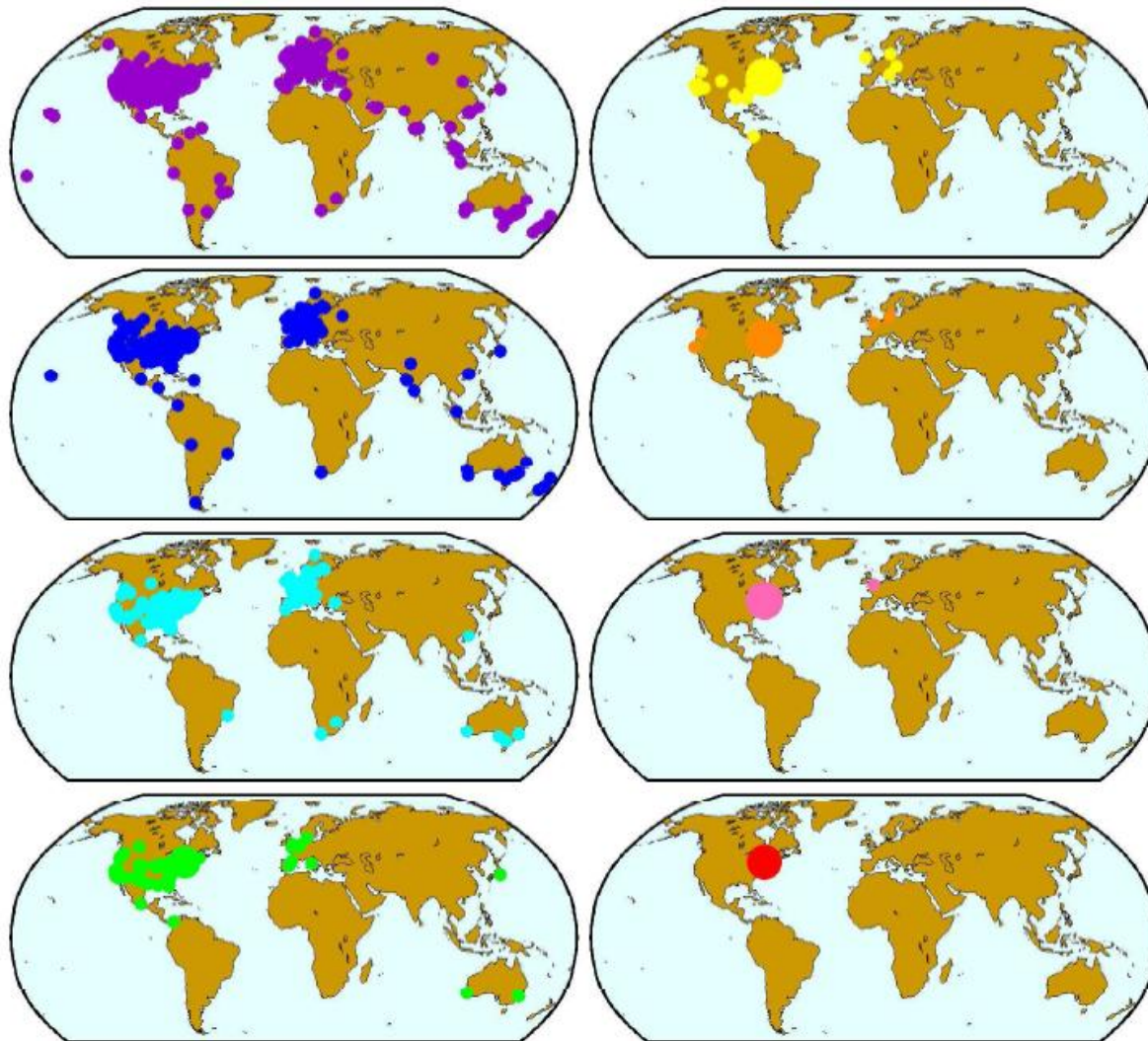


The Small World Web

- 2001-2002: decided to recreate Travers and Milgram's experiment
 - But using email/web server instead of physical packets
- Whereas Milgram had
 - one target (Boston)
 - 300 chains (Boston and Omaha)
 - 64 reached target
- We used
 - 18 Targets around world
 - A university professor in upstate New York
 - A policeman in Perth, Australia
 - An librarian in Paris
 - A veterinarian in Norway, etc...
 - 24,163 chains passing through 61,168 hands in 166 countries
 - Roughly 400 reached targets



Chain Progression For One Target





The “Bored At Work” Network

- Results mostly confirmed Milgram’s findings
 - 6 degrees is surprisingly accurate (median is 7)
 - Dodds et al (Science, 2003); Goel et al (WWW, 2009)
- But we also learned something else:
 - **We managed to run an experiment with over 60,000 participants, on a global scale, at virtually zero cost**
 - BAWN: Millions of people ready to do social science
- What to do next?
 - Small-world experiment not really a “lab” experiment
 - Could we create a “virtual lab” on a web scale?



2. Social Influence and Cultural Markets

- In markets for books, music, etc., suspect
 - Individuals influence each other's choices
 - Social influence leads to inequality and unpredictability
- Wanted to conduct lab experiment in which
 - Can run same process many times under identical conditions, exploring multiple “histories”
 - Can carefully control who is exposed to what
- Problem was that each “history” is a whole distribution of popularity over some set of objects
- Even in a modest experiment, just one history would require at least hundreds of people
 - Entire experiment would require many thousands
 - Far too many to fit in a physical lab
 - What about the web?



The Virtual Lab on The Web

Music Lab - Mozilla Firefox

File Edit View Go Bookmarks Tools Help

http://musiclab.columbia.edu/

MUSIC LAB

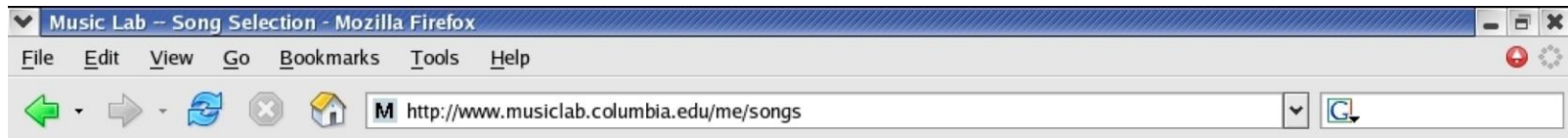
COLUMBIA UNIVERSITY

CLICK HERE TO START

FREE MUSIC DOWNLOADS



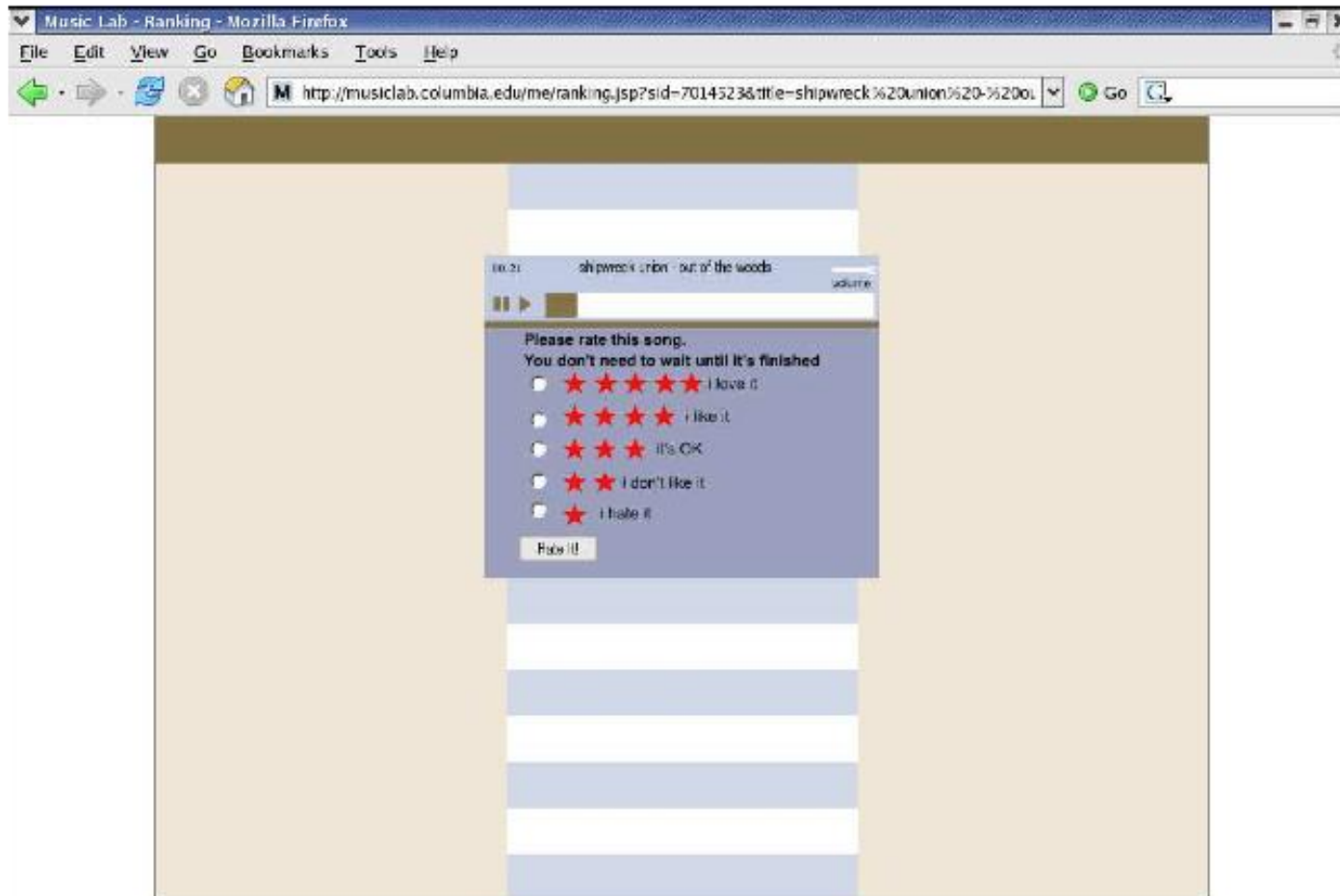
Music Lab: 48 Unknown Bands



	# of down loads	[Help] [Log off]	# of down loads	# of down loads	
HARTSFIELD: "enough is enough"	20	GO MOREDAI: "it does what its told"	12	UNDO: "while the world passes"	24
DEEP ENOUGH TO DIE: "for the sky"	17	PARKER THEORY: "she said"	47	UP FOR NOTHING: "in sight of"	13
THE THRIFT SYNDICATE: "2003 a tragedy"	20	MISS OCTOBER: "pink aggression"	27	SILVERFOX: "gnaw"	17
THE BROKEN PROMISE: "the end in friend"	19	POST BREAK TRAGEDY: "florence"	14	STRANGER: "one drop"	10
THIS NEW DAWN: "the belief above the answer"	12	FORTHFADING: "fear"	24	FAR FROM KNOWN: "route 9"	18
NOONER AT NINE: "walk away"	6	THE CALEFACTION: "trapped in an orange peel"	20	STUNT MONKEY: "inside out"	46
MORAL HAZARD: "waste of my life"	8	52METRO: "lockdown"	17	DANTE: "lifes mystery"	14
NOT FOR SCHOLARS: "as seasons change"	27	SIMPLY WAITING: "went with the count"	16	FADING THROUGH: "wish me luck"	10
SECRETARY: "keep your eyes on the ballistics"	5	STAR CLIMBER: "tell me"	38	UNKNOWN CITIZENS: "falling over"	34
ART OF KANLY: "seductive intro, melodic breakdown"	10	THE FASTLANE: "til death do us part (i dont)"	31	BY NOVEMBER: "if i could take you"	20
HYDRAULIC SANDWICH: "separation anxiety"	20	A BLINDING SILENCE: "miseris and miracles"	17	DRAWN IN THE SKY: "tap the ride"	12
EMBER SKY: "this upcoming winter"	25	SUM RANA: "the bolshevik boogie"	15	SELSIUS: "stars of the city"	22
SALUTE THE DAWN: "i am emor"	13	CAPE RENEWAL: "baseball warlock v1"	12	SIBRIAN: "eye patch"	14
RYAN ESSMAKER: "detour_(be still)"	14	UP FALLS DOWN: "a brighter burning star"	11	EVAN GOLD: "robert downey jr"	10
BEERBONG: "father to son"	12	SUMMERSWASTED: "a plan behind destruction"	17	BENEFIT OF A DOUBT: "run away"	38
HALL OF FAME: "best mistakes"	19	SILENT FILM: "all i have to say"	61	SHIPWRECK UNION: "out of the woods"	16

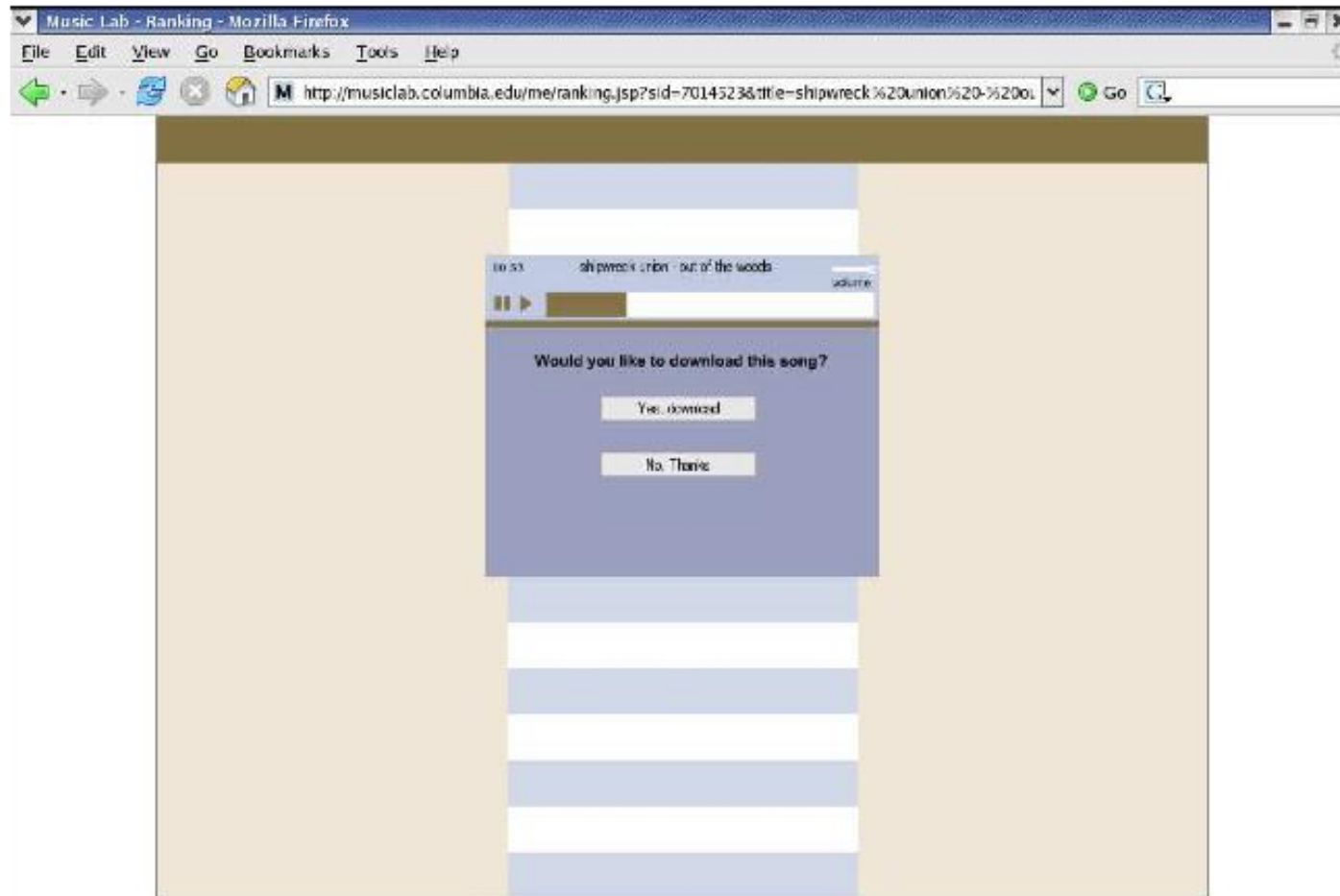


Subjects can listen to songs (via streaming) and rate them...





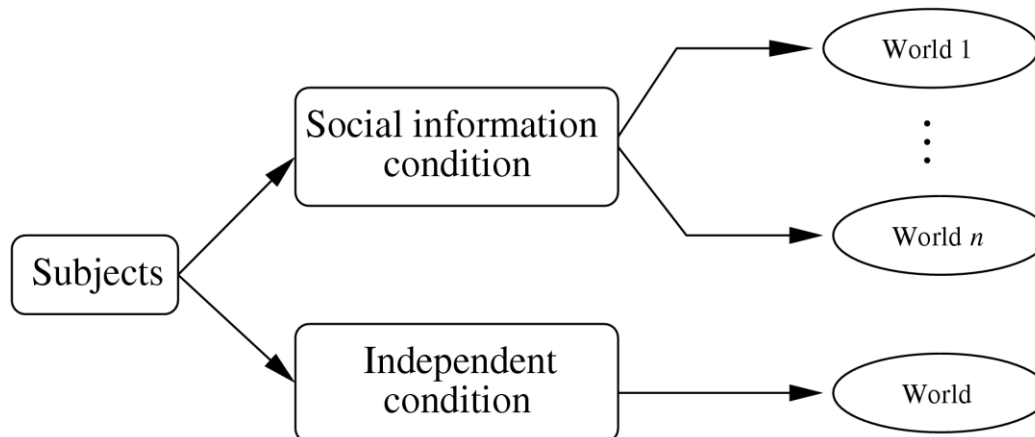
At which point they can also elect to download song





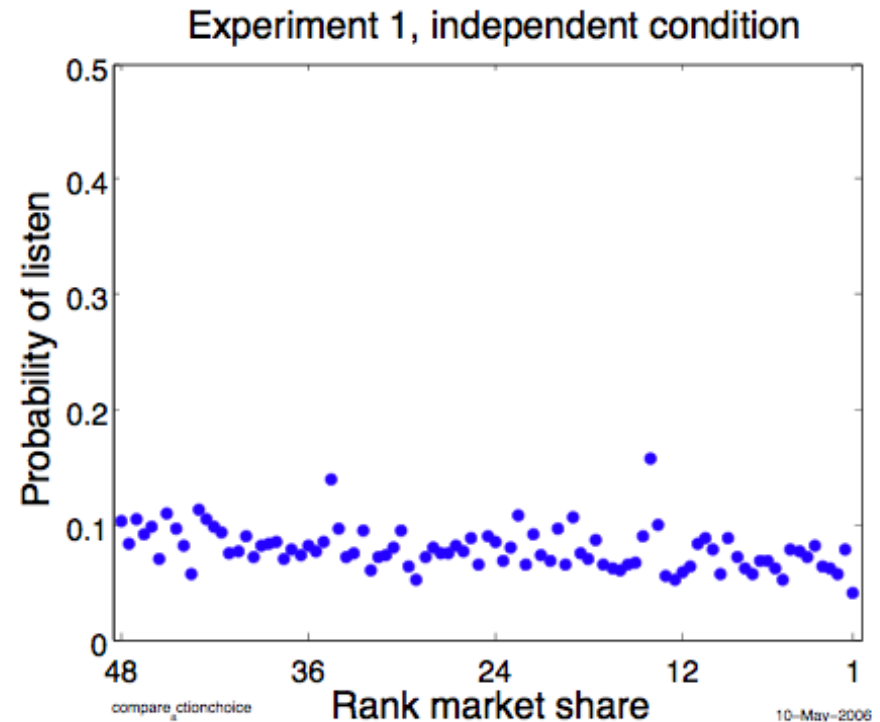
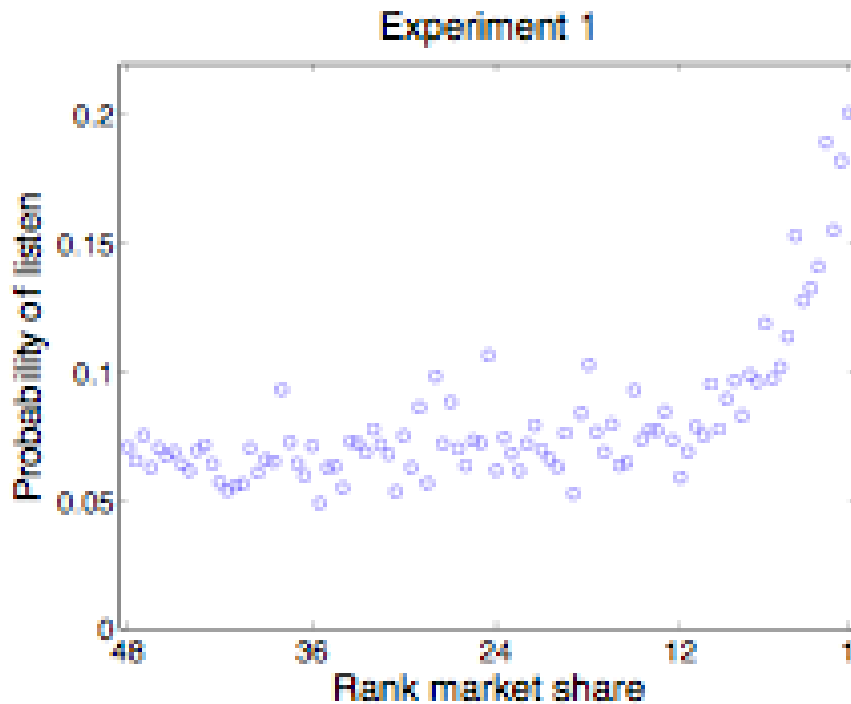
Experimental Design

- As subjects arrive, they are allocated randomly into one of two conditions
 - Independent
 - Just see the names of bands, and songs
 - Social Influence
 - In addition see number of previous downloads
 - Weak signal, can choose to ignore it
 - In addition, social influence condition is broken into eight (8) “worlds”
 - Arriving subjects in each world can see downloads of previous participants in that world only





Social Influence at Micro Level:



$$m_i = d_i / \sum_{k=1}^S d_k$$

m_i = market share for song i
 d_i = downloads of song i



Properties at Macro Level

1. Inequality of Success

- Measure with Gini Coefficient (G)
 - Expected difference in market share m_i between two randomly chosen songs, normalized to the range $[0,1]$
 - $G = 0$ (all objects have equal market share)
 - $G = 1$ (one object has entire market)

2. Unpredictability of Success

- Quantity (U) defined as average difference in market share of songs across R realizations of the world
- Also normalized between $[0,1]$
- Result is measure of “inherent unpredictability”
 - i.e. if you know market share in one world, how much could you predict about another?



Four experiments (N = 27,267)

Influence	Population 1	Population 2
Weak	Experiment 1 (N = 7,149)	
Strong	Experiment 2 (N = 7,192)	Experiment 3 (N = 2,930)
Deception		Experiment 4 (N = 9,996)



Music Lab Results

- Individuals are influenced by their observations of the choices of others
 - The stronger the social signal, the more they are influenced
- Collective decisions are also influenced
 - The popular songs are more popular (and unpopular songs are less popular)
 - However, which particular songs become the popular ones becomes harder to predict
- The paradox of social influence is that
 - Individuals have more information on which to base choices
 - But the collective choice (i.e. what becomes popular) reveals less and less about individual preferences
 - Salganik Dodds, and Watts (*Science* 2006)
- Manipulating social influence not so easy
 - Can create self-fulfilling prophecies at level of individual songs, but not for entire market
 - Salganik and Watts (*SPQ*, 2008)



3. Networks and Diffusion

- Small World Experiment explored structure of global social networks and Music Lab explored social influence
 - But influence in real life diffuses through networks
- In recent years, attention has focused on so-called “**influencers**,” who exert disproportionate influence over others
 - Oprah Winfrey and Books
 - Sarah Jessica Parker and Shoes
 - Jeff Jarvis and Dell Customer Service
- Marketers love this idea:
 - Find the influencers and they will do all the work!
- Problem is: influencers generally identified after the fact, when to be useful marketers need to identify them ex-ante
 - No evidence that they can do this consistently



Influencers on Twitter

- Twitter is ideally suited to study influencers
 - Fully-observable network of “who listens to whom”
 - URL shorteners enable us to track diffusion of unique pieces of information
 - Millions of diffusion “events”
- Bakshy et al (*WSDM*, 2011)
- 1B public twitter posts between 9/15/09-11/15/09
- 90M posts containing bit.ly URL's from 1.6M users
 - We'll focus on this subset
- Crawled 56M Twitter users, 1.7B edges



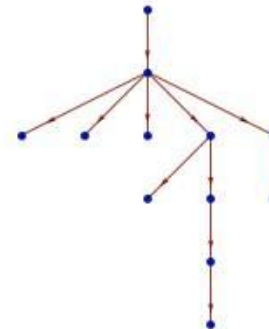
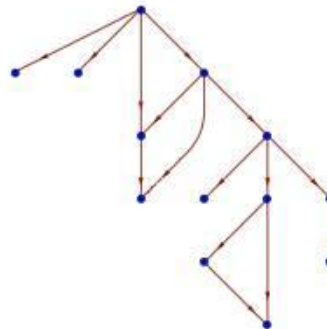
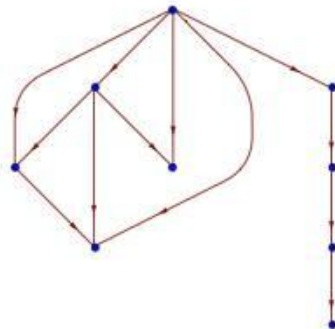
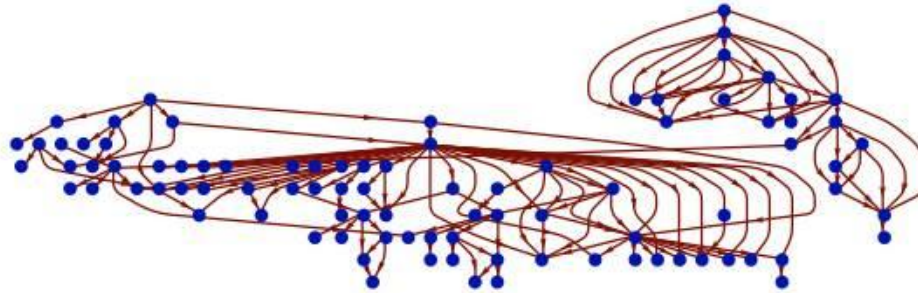
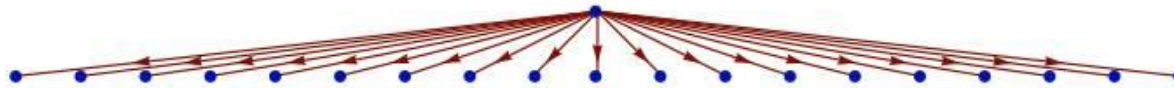


Computing Influence on Twitter

- An individual “seed” user tweets a URL (here we consider only bit.ly)
- For every follower who subsequently posts same URL (whether explicit “retweet” or not), seed accrues 1 pt
- Repeat for followers-of-followers, etc. to obtain total influence score for that “cascade”
- Average individual influence score over all cascades
 - Highly conservative measure of influence, as it requires not only seeing but acting on a tweet
 - Click-through would be good, but not available to us

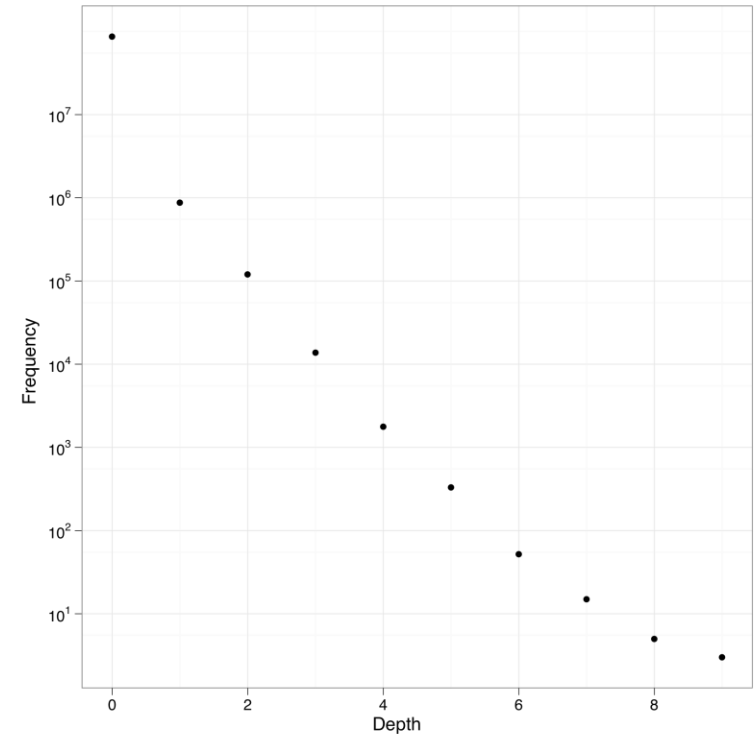
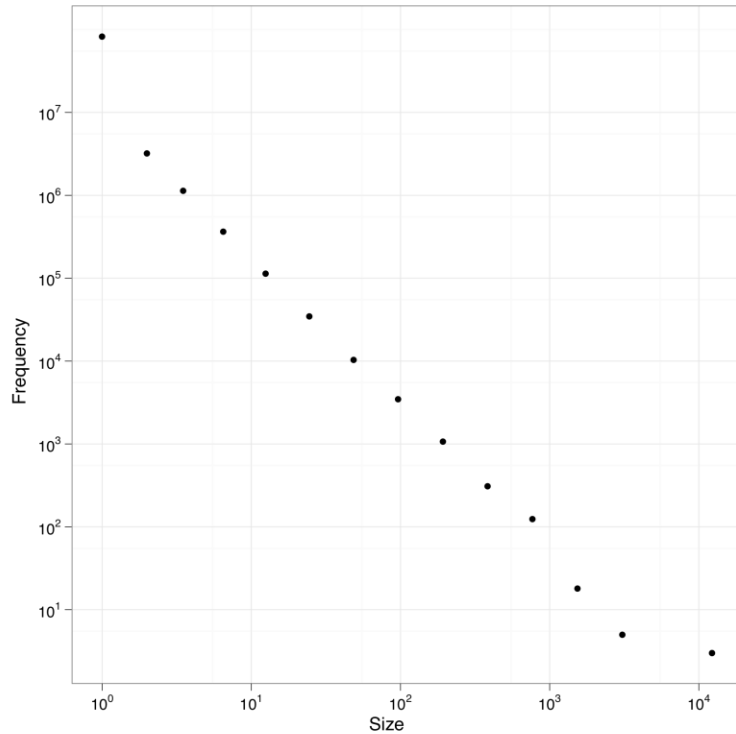


Cascades on Twitter





Cascade Distribution Highly Skewed



- Almost all cascades are small and shallow
 - Average size = 1.14; Median size = 1
- A tiny fraction reach thousands and propagate up to 8 hops



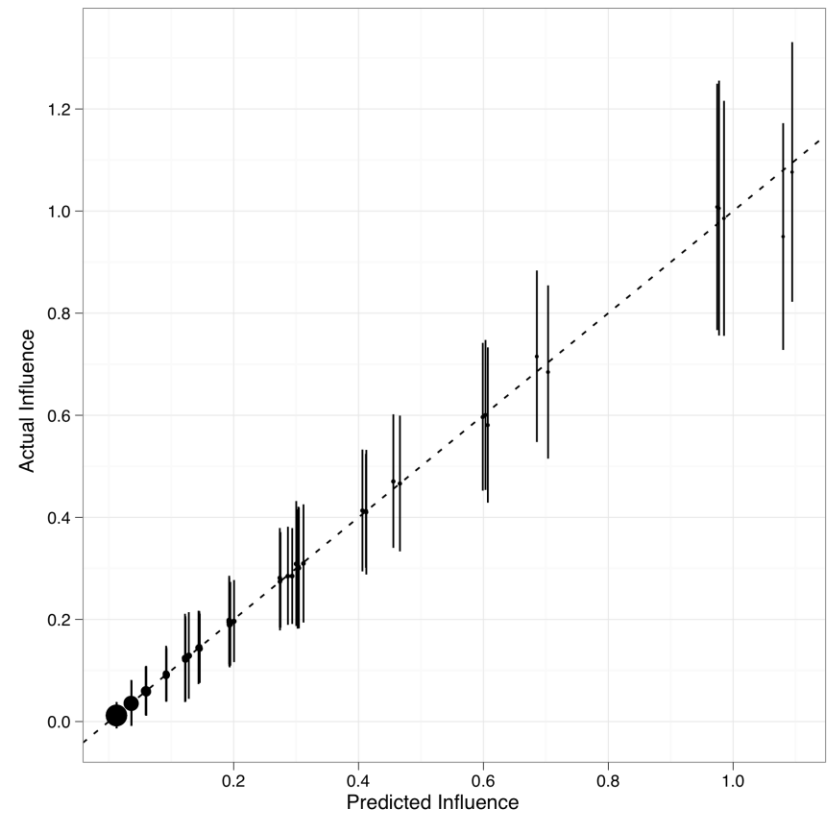
Predicting Influence

- Objective is to predict log (influence score) for future cascades as function of
 - Log # Followers, log # Friends, log # Reciprocated Ties
 - log # Tweets, Time of joining
 - Log (past influence score)
- Fit data using regression tree
 - Recursively partitions feature space
 - Piecewise constant function fit to mean of training data in each partition
 - Nonlinear, non-parametric
 - Better calibrated than ordinary linear regression
 - Use five-fold cross-validation
 - For each fold, estimate model on training data, then evaluate on test data
 - Every user gets included in one test set



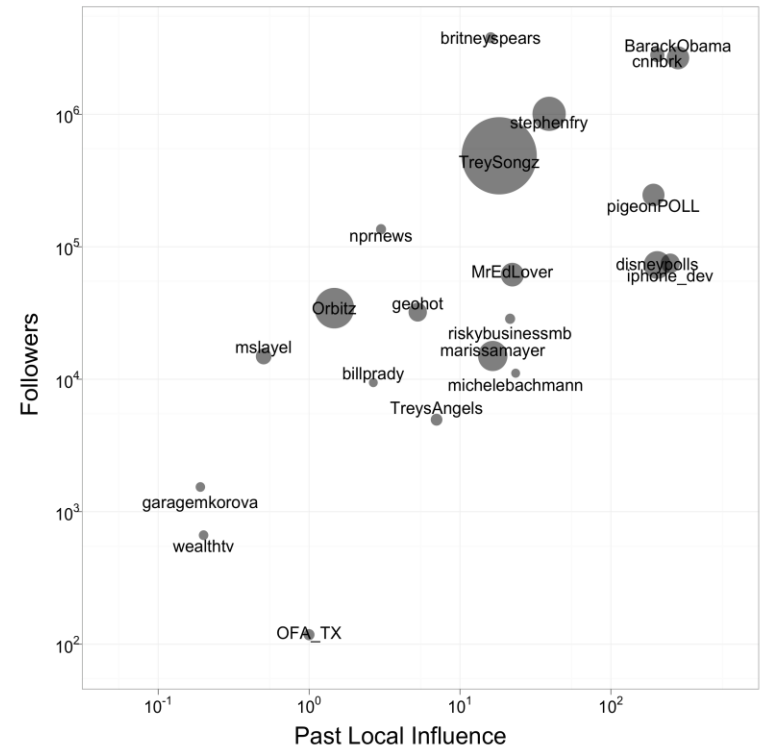
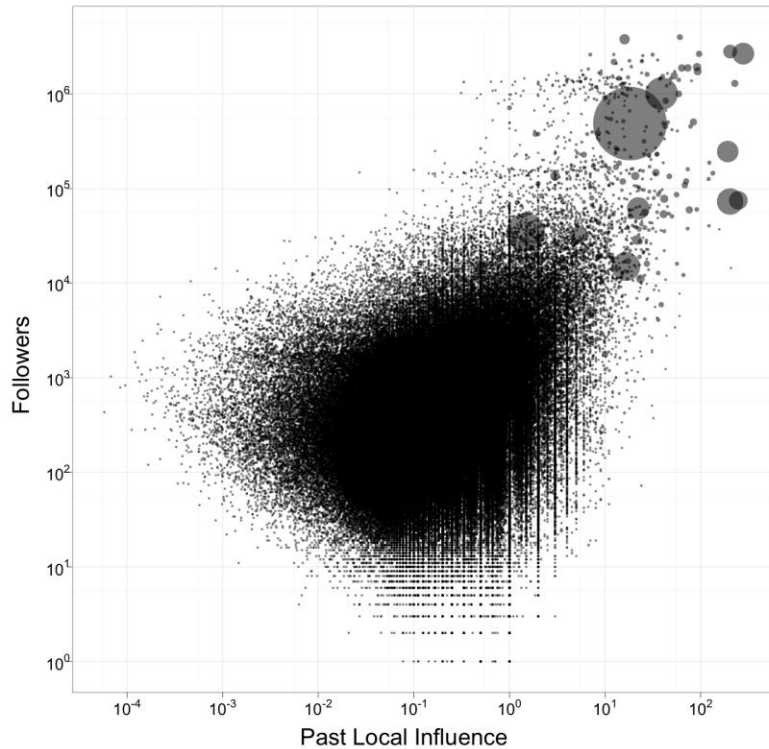
Results

- Only two features matter
 - Past local influence
 - # Followers
- Surprisingly, neither # tweets nor # following matter
- Model is well calibrated
 - average predicted close to average actual within partitions
- But fit is poor ($R^2 = 0.34$)
 - Reflects individual scatter
- Also surprisingly, content doesn't help





Who are the Influencers?



Circles represent individual seeds (sized by influence)



Necessary but not sufficient

- Seeds of large cascades share certain features (e.g., high degree, past influence)
- However, many small cascades share those features, making “success” hard to predict at individual level
- Common problem for rare events
 - School shootings, Plane crashes, etc.
 - Tempting to infer causality from “events,” but causality disappears once non-events accounted for
- Lesson for marketers:
 - Individual level predictions are unreliable, even given “perfect” information
- Fortunately, can target *many* seeds, thereby harnessing average effects



Should Kim Kardashian Be Paid \$10,000 per Tweet?

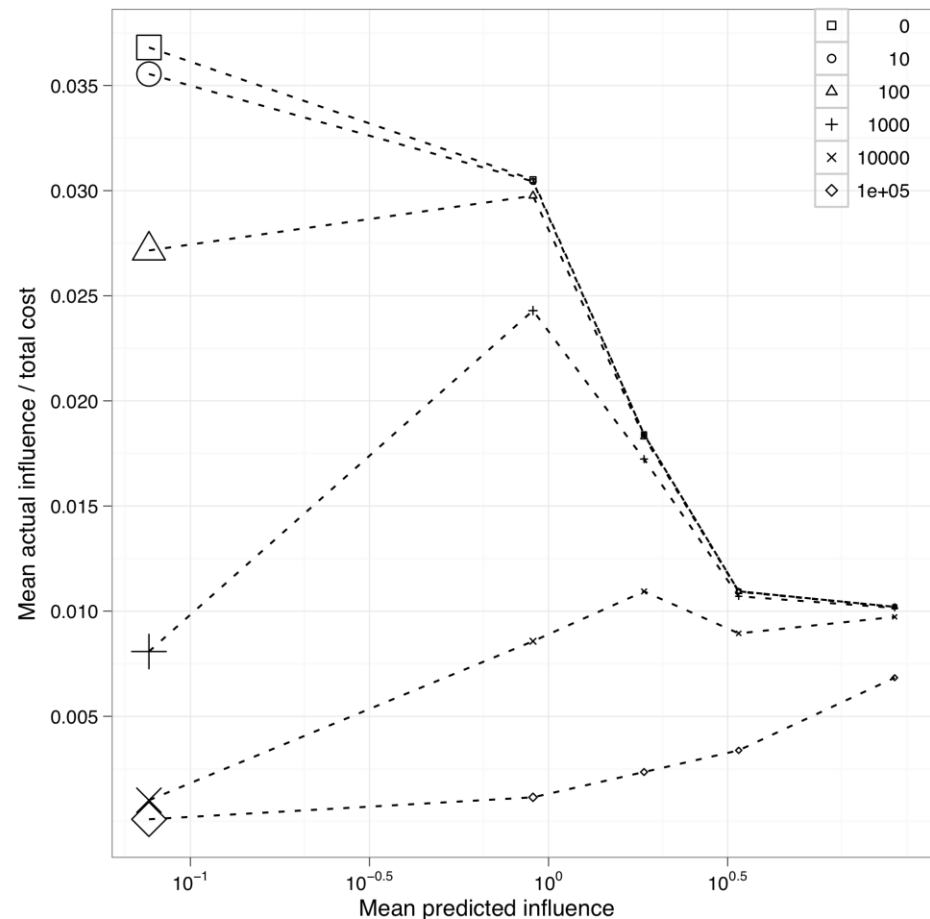
- On average, some types of influencers are more influential than others
 - Many of them are highly visible celebrities, etc. with millions of followers
 - But these individuals may also be very expensive (i.e. Kim Kardashian)
- Assume the following cost function
 - $c_i = c_a + f_i * c_f$, where c_a = acquisition cost; c_f = per-follower cost
 - Also $c_a = a * c_f$, where a expresses cost of acquiring individual users relative to sponsoring individual tweets
- Should you target:
 - A small # of highly influential seeds?
 - A large # of ordinary seeds with few followers?
 - Somewhere in between?



“Ordinary Influencers” Dominate

- Assume $c_f = \$0.01$
 - Equivalent to paying \$10K per tweet for user with 1M followers
- When $c_a = \$1,000$, ($a = 100,000$) highly influential users are most cost effective
- But for lower ratios, most efficient choice can be individuals who influence at most one other

Influence per Follower





4. Networked Experiments

- Twitter study included both networks and influence
 - But not an actual experiment; so no causal statements possible
- Would like to study impact of network structure in an experimental setting, akin to Music Lab
 - Kearns et al have studied “networked games” in specially equipped labs
 - Graph coloring, consensus, exchange, etc.
 - In all cases, network structure important
 - Can these experiments also be run on the Web?
- Unlike Small World Experiment and Music Lab, subjects must play synchronously
 - Easy to solve in a lab, but not on the web



Cooperation on Networks

- Question of why presumptively selfish people cooperate one of the most studied in all of social science
 - Dates back to Hobbes.
 - Elinor Ostrom: 2009 Nobel in Economics
- A standard model of problem is “linear public goods” game (also common pool resource, voluntary contribution mechanism)
 - On each of N “rounds”, each member of a group given an endowment
 - Members choose how much of their endowment to contribute
 - Contributions multiplied by some constant (hence “linear”)
 - Then redistributed equally to all members
- Situation poses a dilemma
 - Everyone better off if everyone contributes than if nobody does
 - Individuals better off if everyone else contributes and they don't



Public Goods Games

- Public Goods games have been studied extensively in experiments (Fehr/Gächter)
 - Contributions start out high and end low
 - Players will pay to punish non-contributors
 - Punishment increases contributions
- But all these experiments are for “groups” in which everyone plays everyone (N=4)
 - How do these results depend on network structure?

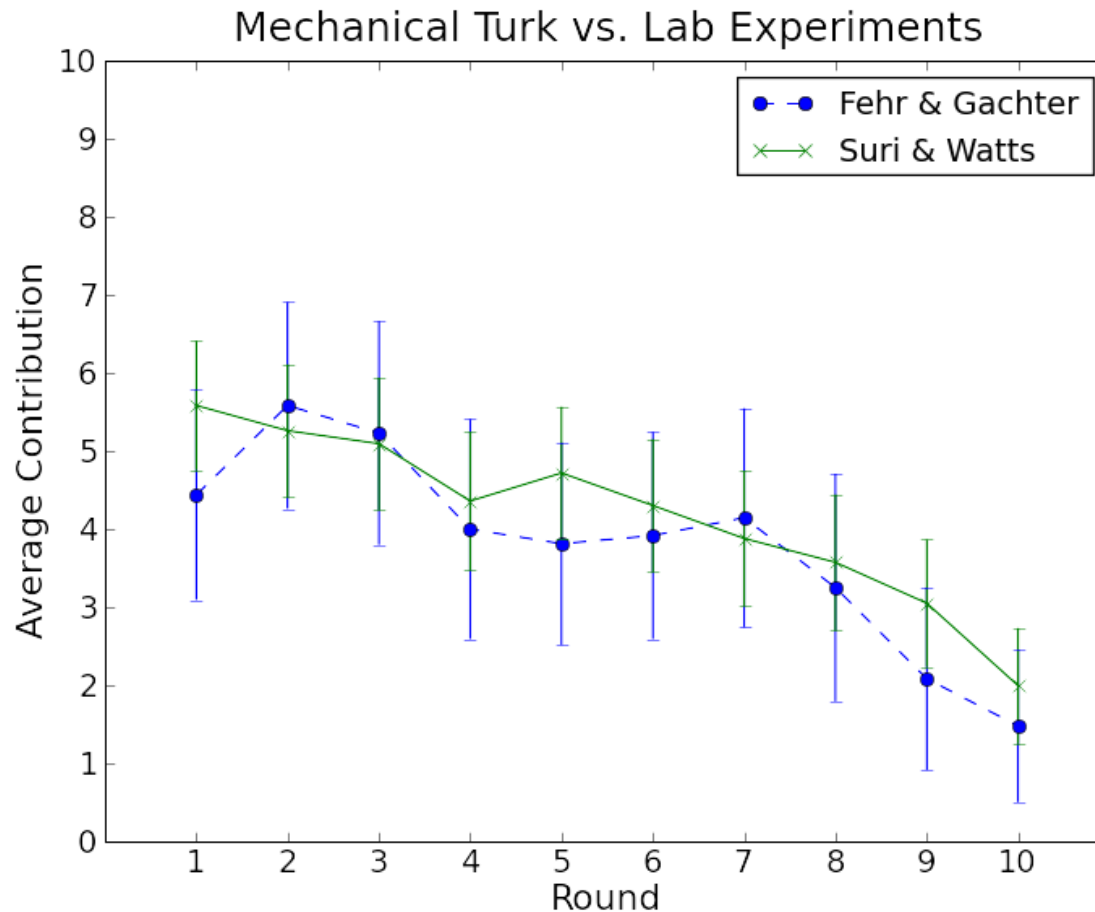


Amazon's Mechanical Turk

- AMT originally designed for “crowd sourcing”
 - “Requestors” post “HITS” (human intelligence tasks)
 - “Turkers” accept HITS for piece rates
- Increasingly used by behavioral scientists as a virtual lab for conducting human subjects experiments
 - Mason and Suri (2010) recently written a handbook for running experiments on AMT
- Solving the synchronous play problem:
 - In series of preliminary games, recruited a panel of ~ 100 players
 - Notified them in advance of games
 - Scheduled up to four sessions per day
 - Games of 24 players fill up in ~ 2 mins
- Also used preliminary experiments to calibrate AMT

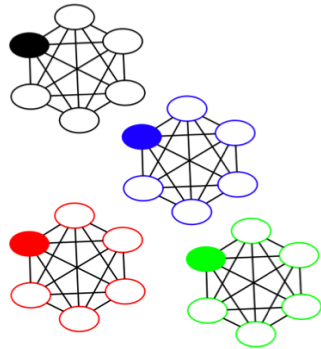


Comparison with Physical Lab Results (F&G, AER, 2000)

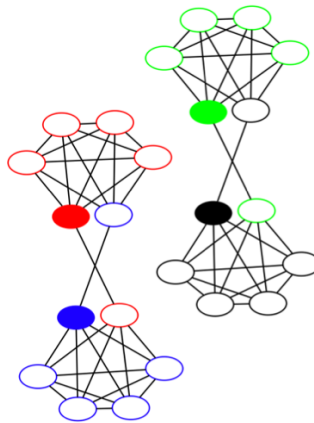




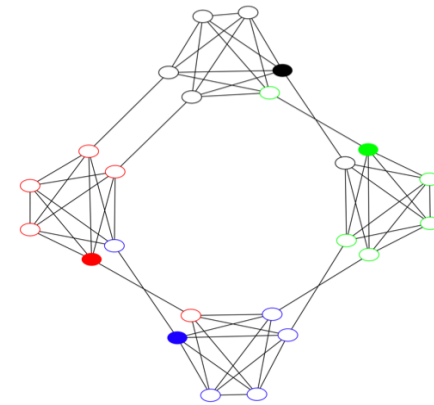
Networks ($N = 24$, $k = 6$)



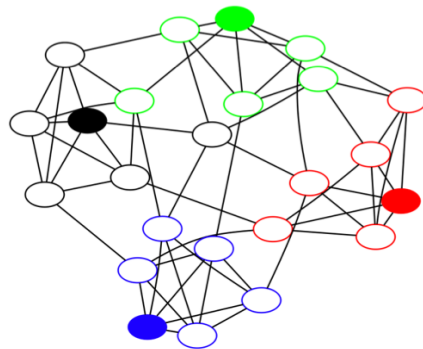
(A) Cliques



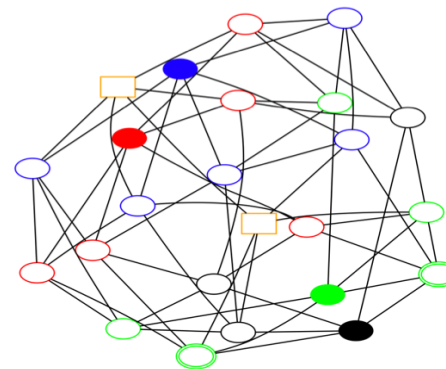
(B) Paired Cliques



(C) Cycle



(D) Small World



(E) Random Regular

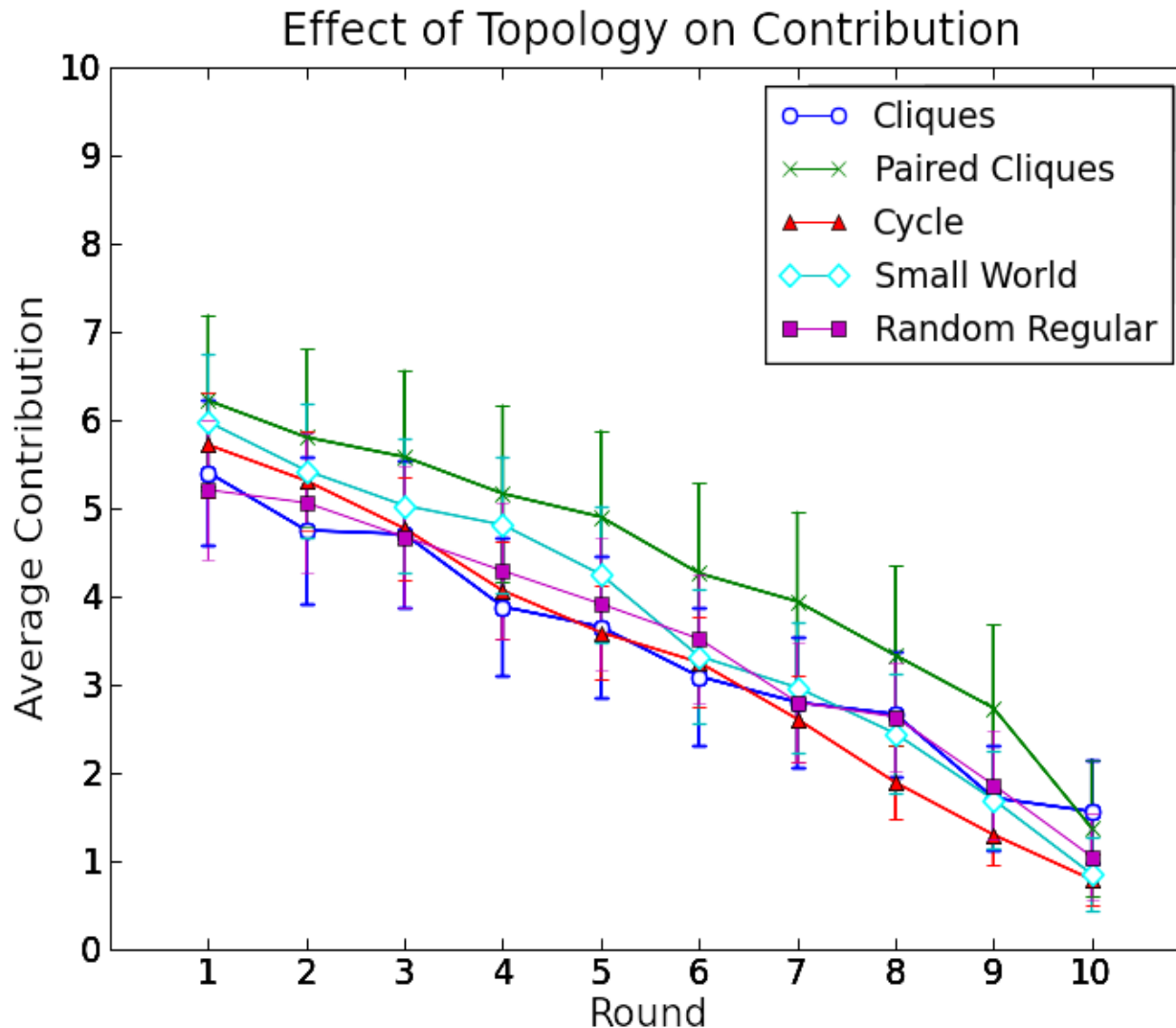


Network Stats

	Cliques	Paired Cliques	Cycle	Small World	Random Regular
Clustering Coefficient (C)	1.00	0.80	0.60	0.41	0.09
Average Path Length (L)	1.00	1.81	2.54	2.23	2.01
Diameter (D)	∞	∞	5	4	3
ROI	1.04	1.09	1.38	0.80	1.00



Surprisingly (to us) Networks Don't Seem to Affect Aggregate Contributions





When Do Networks Matter?

- Hypothesized importance of networks comes from intuition that cooperation is conditional
 - “I’ll cooperate if at least X of my neighbors do”
 - Works better when cooperators interact preferentially
 - Cooperation should be contagious
- By introducing fully-contributing agents in various configurations, we found that
 - Players do cooperate conditionally, but overall bias towards swamps everything
 - No evidence of positive contagion
- Raises interesting theoretical question of when networks matter and when they don’t
 - Contrast with coordination / anti-coordination games



Advantages of the AMT Lab

- Overall, we have now run 113 experiments with $N=24$ players
 - Up to 20 experiments per week
- Cost of roughly \$1 per player per game
 - An order of magnitude cheaper than physical lab
- Greater speed and lower cost allows us to speed up hypothesis-testing cycle
- Also allows us try more variations
 - Different information conditions (friends of friends etc.)
 - Nonlinear production function, rewiring, etc.
 - Larger N , more topologies



Where have we come in 8 years?

- Small-World experiment large (global) scale network experiment, but no control
- Music Lab medium scale, and no network, but better control
- Twitter, large-scale network with diffusion, but not experimental
- Public Goods games are genuine controlled, web-based, networked games, but scale is still small
 - Main constraint is the size of our panel (now about 100).



Where are we going now?

- Build “virtual labs” on the web for running all manner of macro economic and sociological experiments
 - Hope to construct large standing panel
- Run field experiments, akin to bucket testing of ads / search results
 - David Reiley at Yahoo! has already done some experiments with brand advertising
- Ultimately, combine study of real world networks (e.g. Mail/IM) with experimental science



Computational Social Science?

- The web promises to dramatically improve
 - Our ability to measure individual level behavior and interactions on a massive scale in real time
 - Our ability to run “macro sociological” lab experiments and field experiments
- There is a long way to go to from existing studies to the “big” questions of social science
 - Systemic risk, economic development, terrorism
- Nevertheless, technological innovations have revolutionized science in the past (Telescope, Microscope)
- Could Web/Internet revolutionize social science?
 - Will at least provide lots of interesting problems for computer scientists!



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