Geography and Friendship

Joint work with:
David Liben-Nowell: Carleton College
Ravi Kumar, Jasmine Novak, Prabhakar Raghavan:
Yahoo! Research
Daniel Gruhl: IBM
Ramanathan Guha: Google

Work performed at IBM, Verity, Yahoo!, Carleton

Some social networks in Yahoo!

- MyWeb 2.0
  - Friendship network
- Instant messenger
  - Buddy list
- Flickr
  - Photo sharing and tagging
- Yahoo!
  - Topically focused communities

What can be studied?

- Structural analysis
- Understanding social phenomena
- Information propagation and diffusion
- Prediction (buzz, information, social)
- Modeling

A study of blogs

- Joint work with:
  - Dan Gruhl (IBM)
  - R. Guha (Google)
  - Ravi Kumar (Yahoo!)
  - David Liben-Nowell (Carleton)
  - Jasmine Novak (Yahoo!)
  - Prabhakar Raghavan (Yahoo!)

- WWW May 2003; CACM Dec 2004; PNAS Aug 2005; KDD Aug 2005; WIP

Etymology

From the OED new ed. (draft entry, Mar 2003) …

blog *intr.* To write or maintain a weblog. Also: to read or browse through weblogs, esp. habitually.

web¢log *n.* **2.** A frequently updated web site consisting of personal observations, excerpts from other sources, etc., typically run by a single person, and usually with hyperlinks to other sites; an online journal or diary.

blog¢space *n.* The collection of weblogs; = blogosphere, blogsphere, blogistan, …

Blogs 101

- Characteristics
  - Pages with reverse chronological sequences of dated entries
  - Usually contain a persistent sidebar containing profile (and other blogs read by the author – “blogroll”)
  - Usually maintained and published by one of the common variants of public-domain blog software
- From Slashdot, 1999

  “… a new, personal, and determinedly non-hostile evolution of the electric community. They are also the freshest example of how people use the Net to make their own, radically different new media”

Look and feel

- Quirky
- Highly personal
- Consumed by a small number of regular repeat visitors
- Often updated multiple times each day
- Highly interwoven into a network of small but active micro-communities
- Eg: LiveJournal, Blogger, …

The blog era

- Blogs began in 1996, but exploded in popularity in 1999
  - Proliferation of authoring tools
- Newsweek 2002 estimates ~500K
- Annual Blogathon for charity
  - Bloggers update their Blogs every 30m for 24h
  - Sponsors pay …
- Impact of blogs
  - “Miserable failure”, “French military victories”

Livejournal blogspace

- Livejournal.com: popular blog site
- 1.3M bloggers (Feb 2004)
- 3.9M bloggers (Oct 2005)
- Each blogger has a profile
  - Name, age, …
  - Geographic information (city, state, zip, …)
  - Friends and friend of
  - Interests/communities

Eg, LiveJournal user "bill"

User: bill (3215)

Name: bill

Website: Girvan Attractions on the Net

Location: Girvan, United Kingdom

Birthdate: 1954-04-12

E-mail: b.caddis@btinternet.com

Friends: **3:** ajose, webfran, zaxwrit

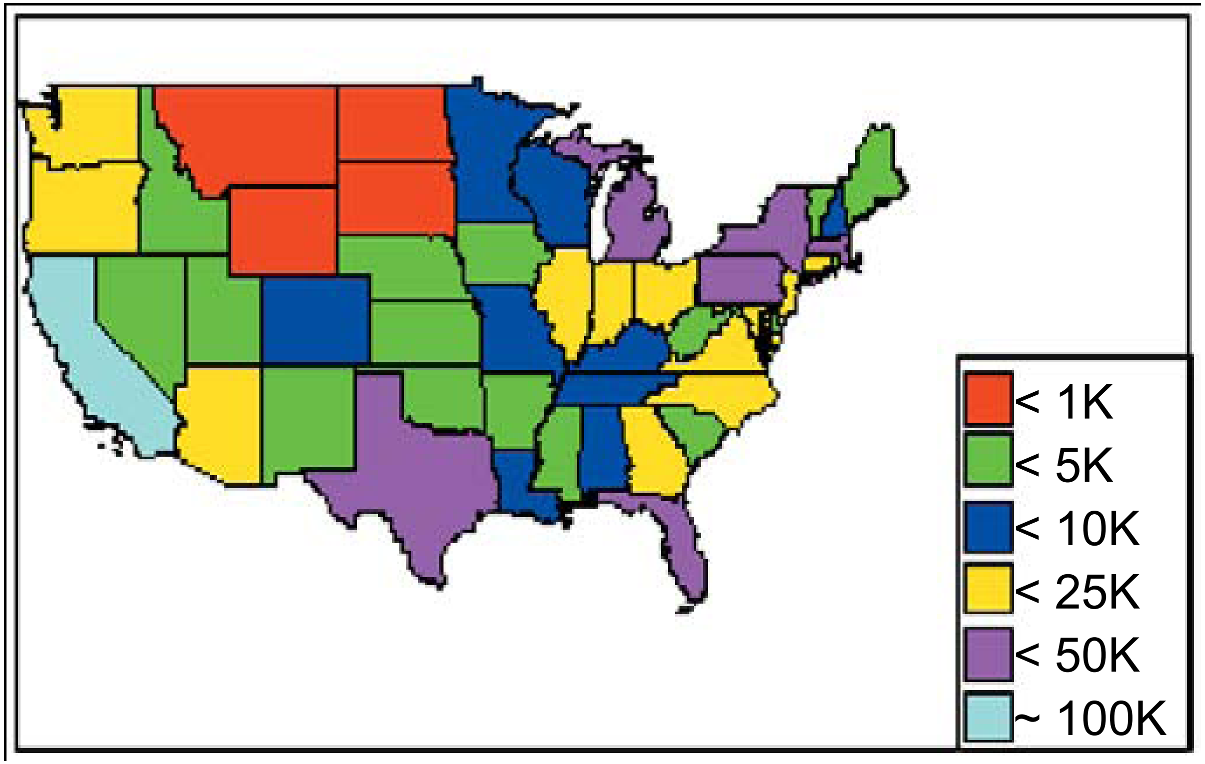
Friend of: **36:** aqdale, ajose, b4_darkness, boris_the_blade, dkm977, epitaph87, farthead, flatland83, gabbymoe, ghettofabublous, glenda, glitzysgurl, goooooooooooogle, gothgrouch, gruntbill, hammerman, insanephycopath, jakup, jazzzman, laxprincess, louwleadvocals, mandaj8705, marksantos, mini_skeeby, protogonoi, reallyrandom06, sammeh, shortstac, sweetsugar829, sys_developer, thebluesbros, uglyo, uno_bitch, webfran, wikitmel, xo_krista_ox

Member of: **1:** paidmembers

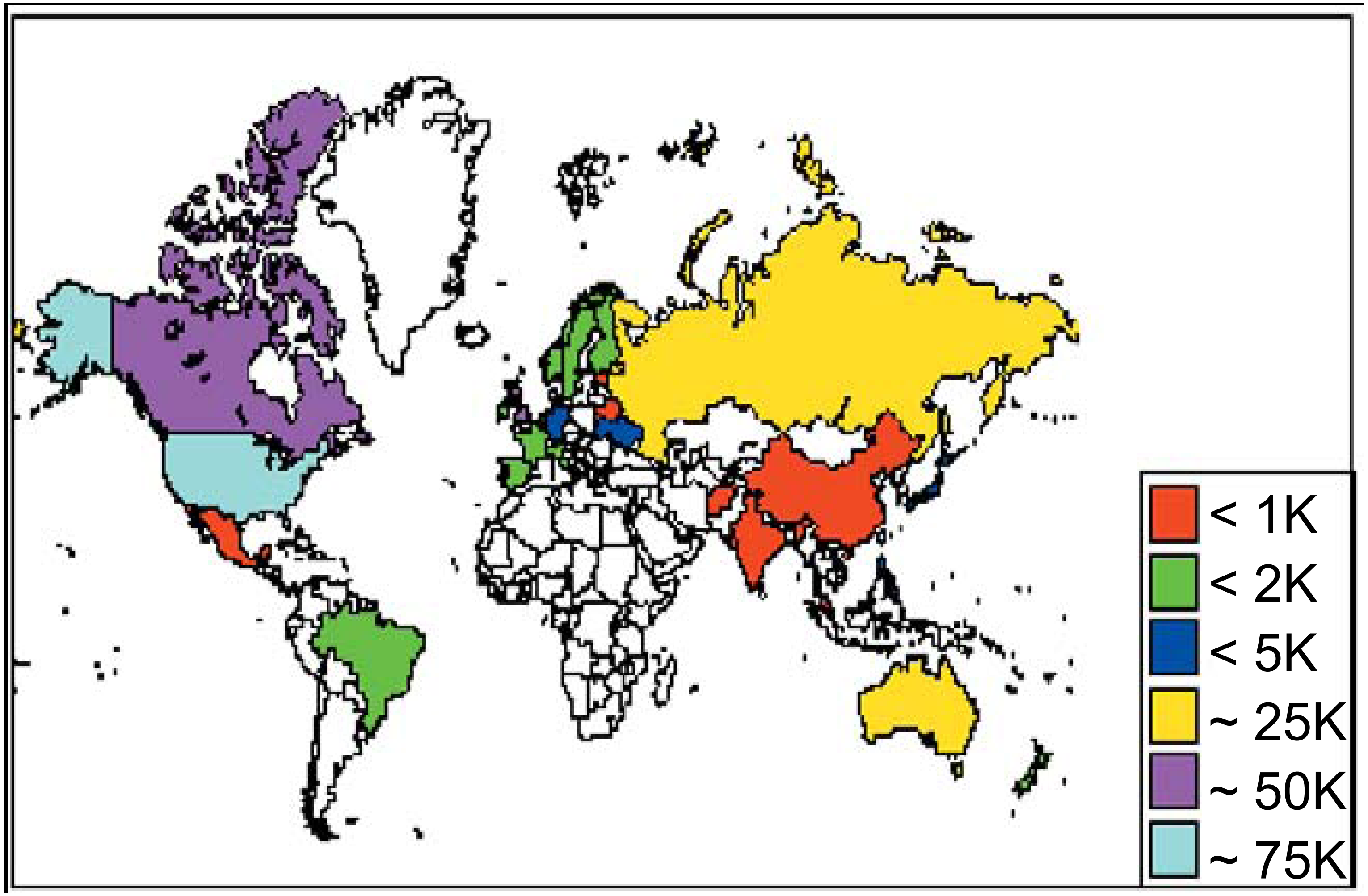
Account type: Early Adopter

(more details...)

LJ bloggers in US



LJ bloggers world-wide

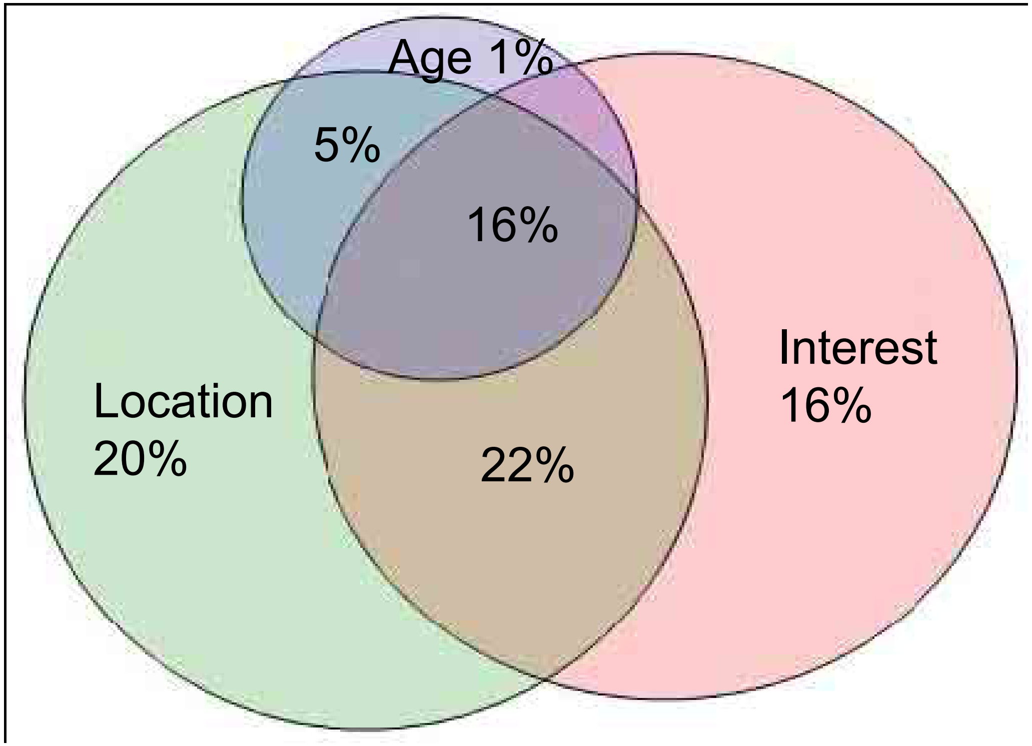


Who are they?

Age	%	Representative interests
1 to 3	0.5	treats, catnips, daddy, mommy, purring, mice, playing, napping, scratching, milk
13 to 15	3.5	webdesigning, Jeremy Sumpter, Chris Wilson, Emma Watson, T. V., Tom Felton, FUSE, Adam Carson, Guyz, Pac Sun, mall, going online
16 to 18	25.2	198{6,7,8}, class of 200{4,5}, dream street, drama club, band trips, 16, Brave New Girl, drum major, talkin on the phone, highschool, JROTC
19 to 21	32.8	198{3,5}, class of 2003, dorm life, frat parties, college life, my tattoo, pre-med
22 to 24	18.7	198{1,2}, Dumbledore's army, Midori sours, Long island iced tea, Liquid Television, bar hopping, disco house, Sam Adams, fraternity, He-Man, She-Ra
25 to 27	8.4	1979, Catherine Wheel, dive bars, grad school, preacher, Garth Ennis, good beer, public radio
28 to 30	4.4	Hal Hartley, geocaching, Camarilla, Amtgard, Tivo, Concrete Blonde, motherhood, SQL, TRON
31 to 33	2.4	my kids, parenting, my daughter, my wife, Bloom County, Doctor Who, geocaching, the prisoner, good eats, herbalism
34 to 36	1.5	Cross Stitch, Thelema, Tivo, parenting, cubs, role-playing games, bicycling, shamanism, Burning Man
37 to 45	1.6	SCA, Babylon 5, pagan, gardening, Star Trek, Hogwarts, Macintosh, Kate Bush, Zen, tarot
46 to 57	0.5	science fiction, wine, walking, travel, cooking, politics, history, poetry, jazz, writing, reading, hiking
> 57	0.2	death, cheese, photography, cats, poetry

Friendship graph

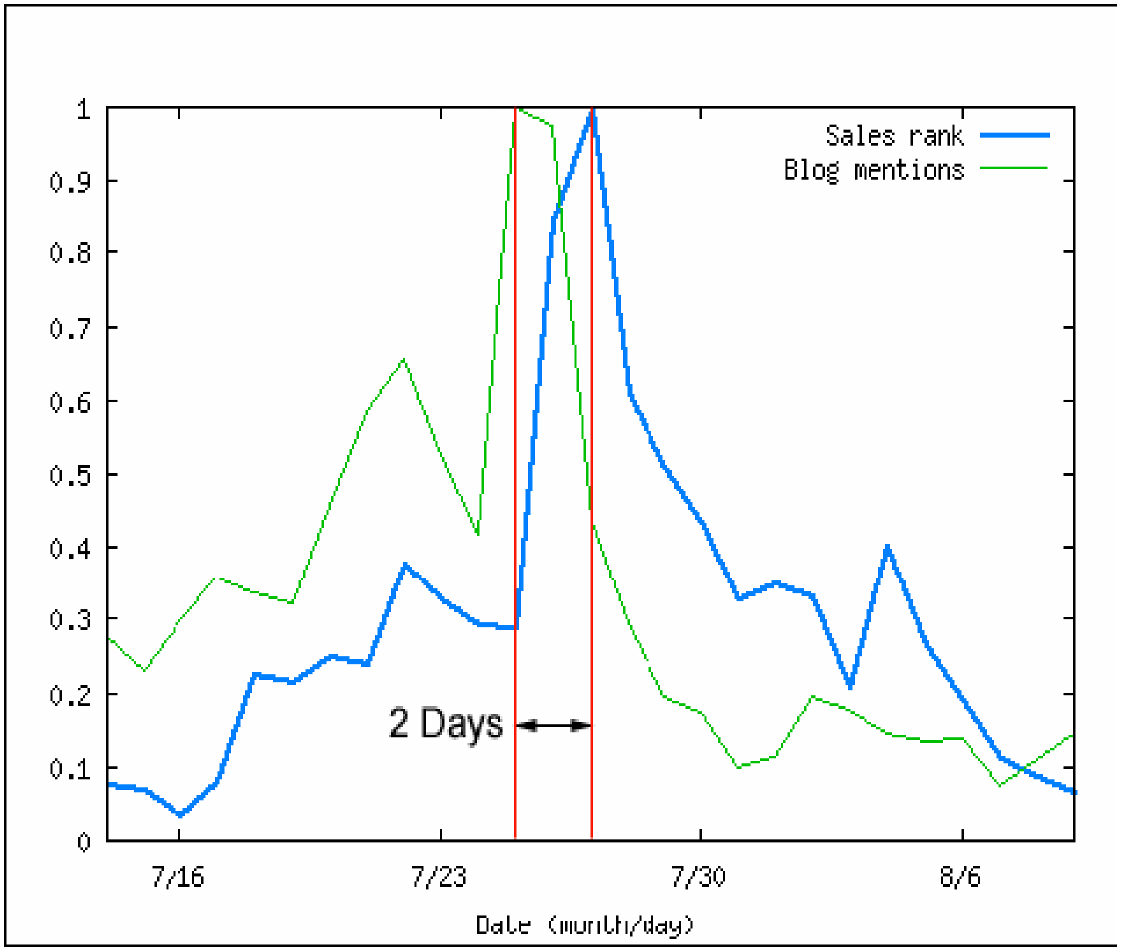
- Directed
- 80% mutual
- Average degree ~ 14
- Power law degrees
- Clustering coeff. ~ 0.2
- Most friendships explained by age, location, interest



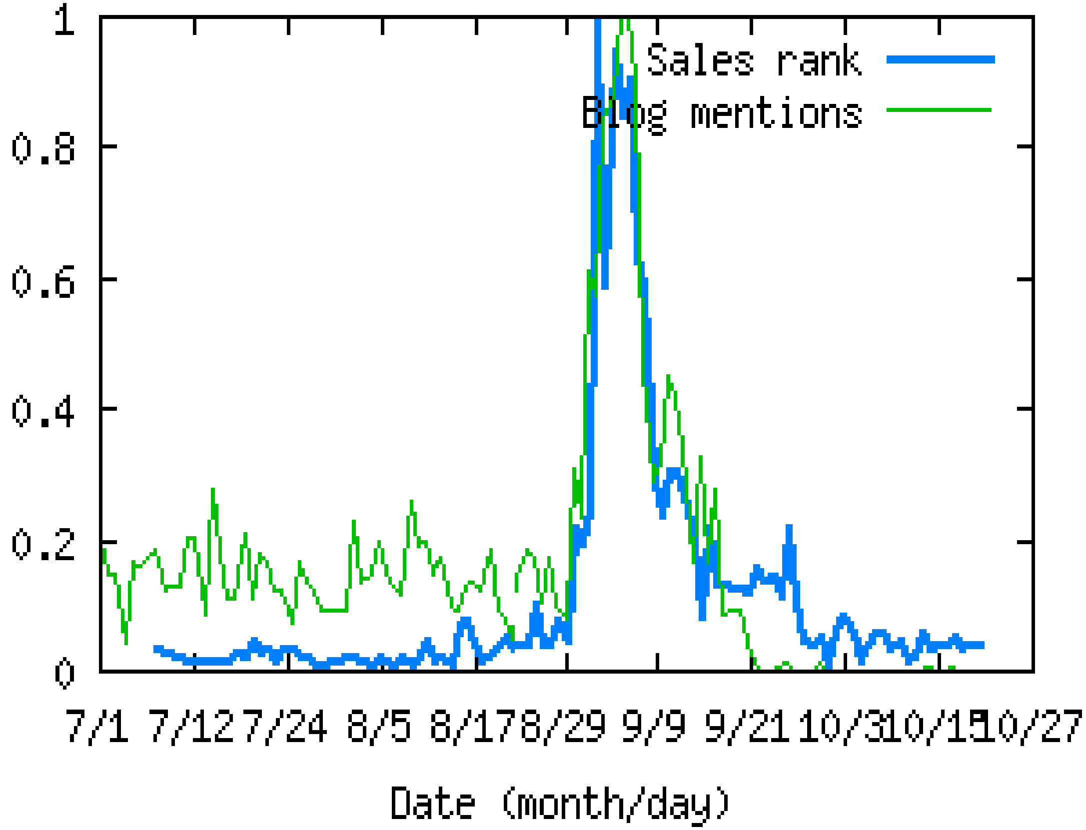
Blogs as trend indicators

- Can blogs be used to predict trends?
- Data
  - Amazon sales rank of some books
  - Blog chatter in an index
- Questions
  - How well do they correlate?
  - Can sales rank be predicted using blogs automatically?

The Lance Armstrong Performance Program

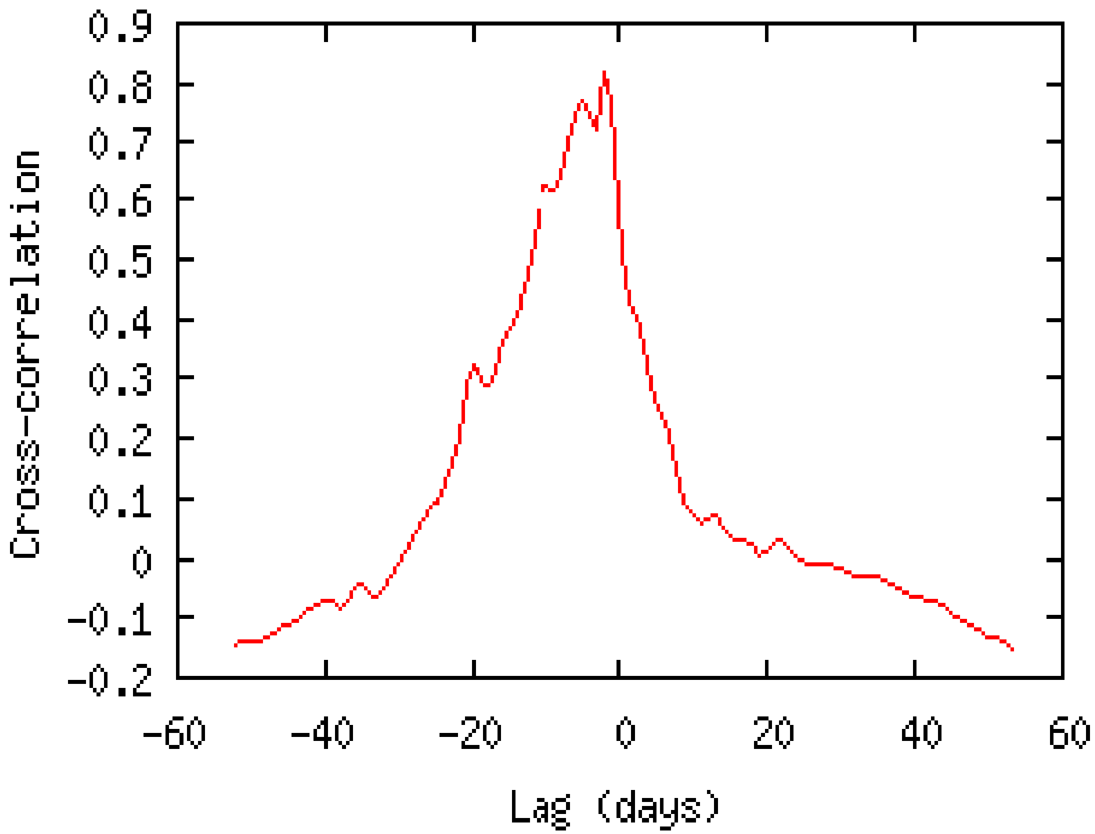


Vanity Fair



1
0.8
0.6
0.4
0.2
0
Sales rank
Blog mentions
7/1
7/12
7/24
8/5
8/17
8/29
9/9
9/21
10/3
10/15
10/27
Date (month/day)

Cross-correlation for Lance Armstrong



Simple inferences

- How to formulate queries automatically
  - Depends on the object (book, CD, DVD, …)
  - Simple heuristics work well
- Predicting sales motion is hard
- Predicting spikes appears relatively easier
- More to be done …

Another question:

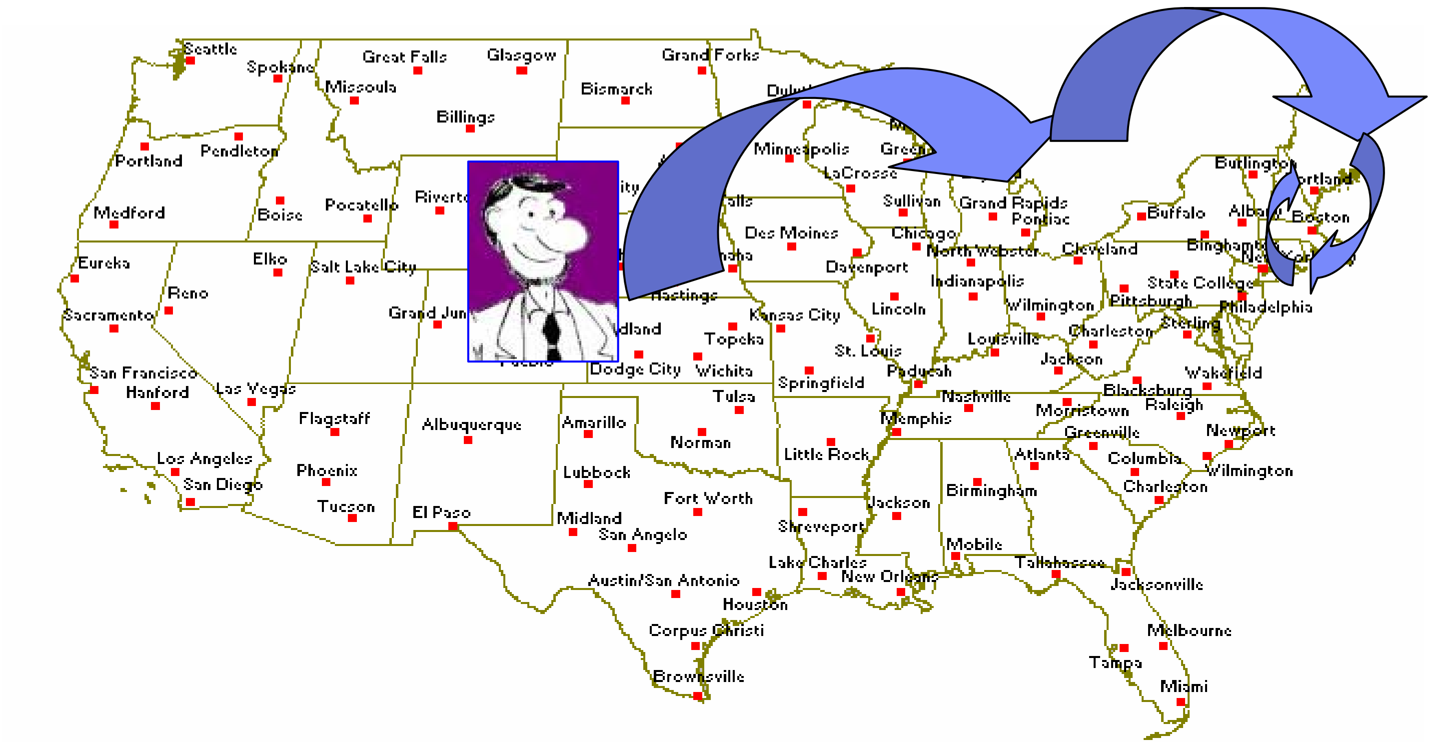
- How does friendship depend on geographic distance?

Dataset

- 1.3M LiveJournal bloggers, as of February 2004
- 500K list a home town in the United States
- Home towns mapped to lat/long
- Granularity of locations: roughly cities
- Extracted self-reported “friends” of each blogger: 4M friendships
- 80% of friendships are reciprocal
- ¾ of network form giant strongly-connected component
- Clustering coefficient: 0.2
- Lognormal degree distribution
- Each blogger has a profile
  - Name, age, …
  - Geographic information (city, state, zip, …)
  - Friends and friend of
  - Interests/communities

Message forwarding

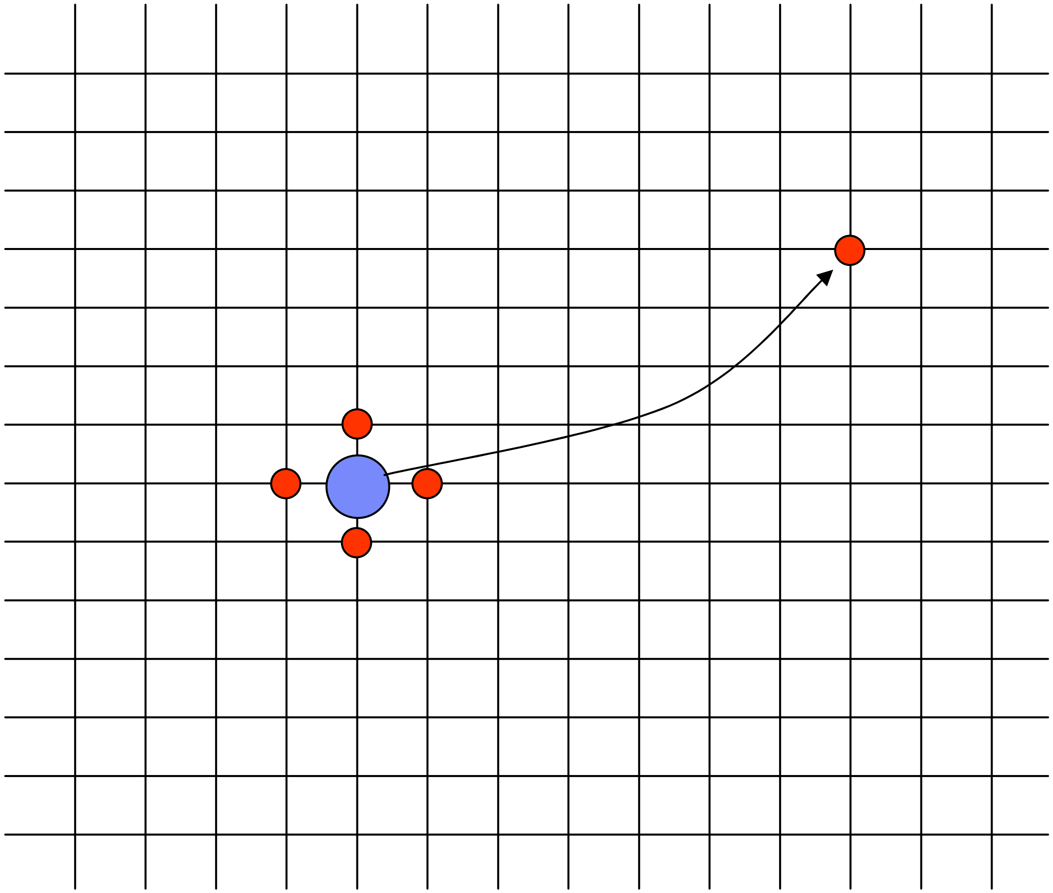
- Stanley Milgram: short paths in social networks, small worlds, and “Six degrees of separation”, 1967.



What's surprising about Milgram?

- Surprising fact number one (observed by Milgram): network contains short paths
- Surprising fact number two (observed much later by Kleinberg): a purely local algorithm allows discovery of these short paths

Models to explain greedy routing



- Each grid point is a person
- Each person "knows" the four neighbors
- Each person also knows one other person

[Kleinberg 2000]

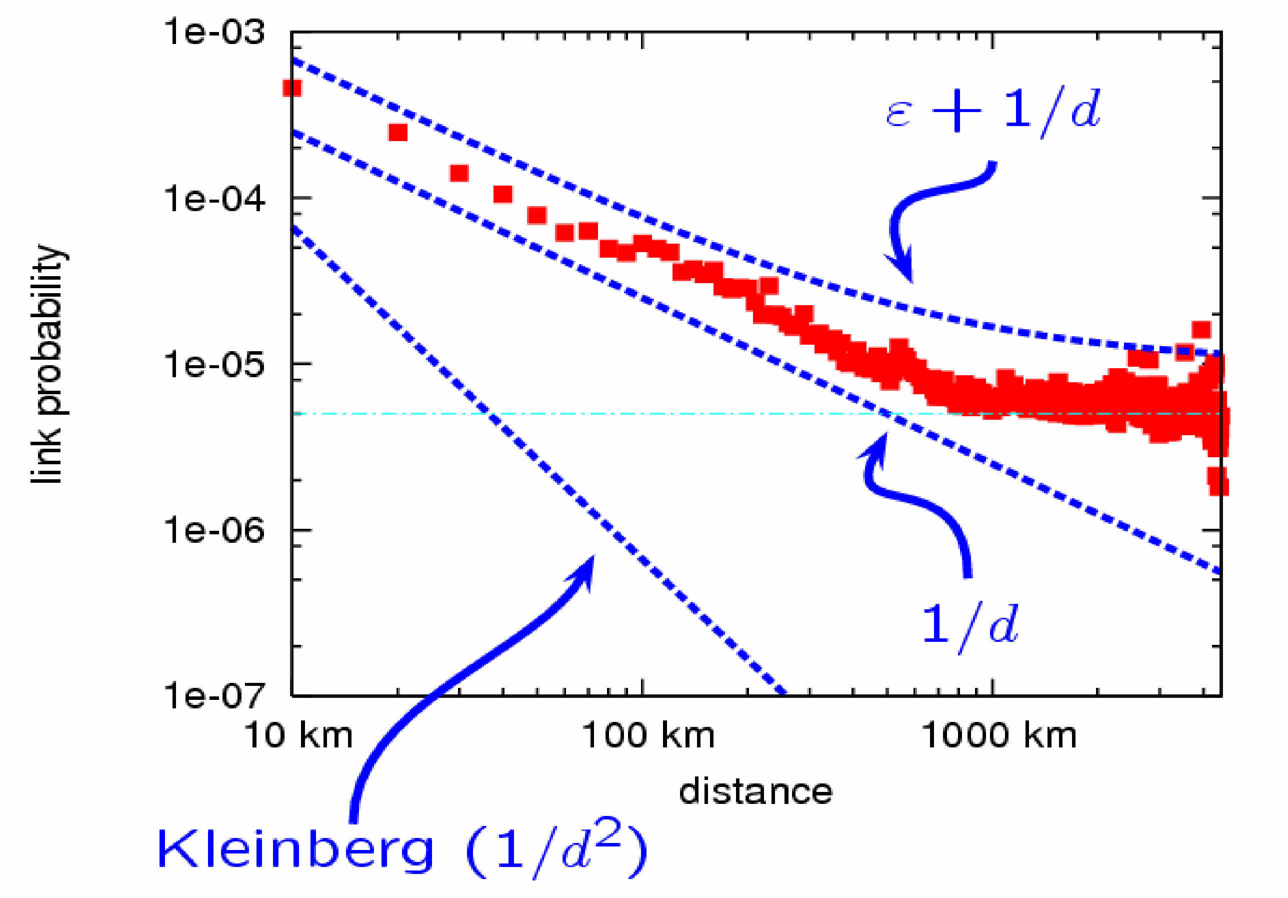
How should the "long-range" neighbor be chosen

- For a candidate neighbor x at distance d away,
  Pr[*x* is the long-range neighbor] ~ $1/d^k$
- If k=2:
  - Network contains short paths for every pair (polylog(n))
  - Short paths can be discovered by local greedy routing
- If k != 2:
  - Networks does not contain short paths (poly(n))
- Exponential gap between k=2 and k!=2

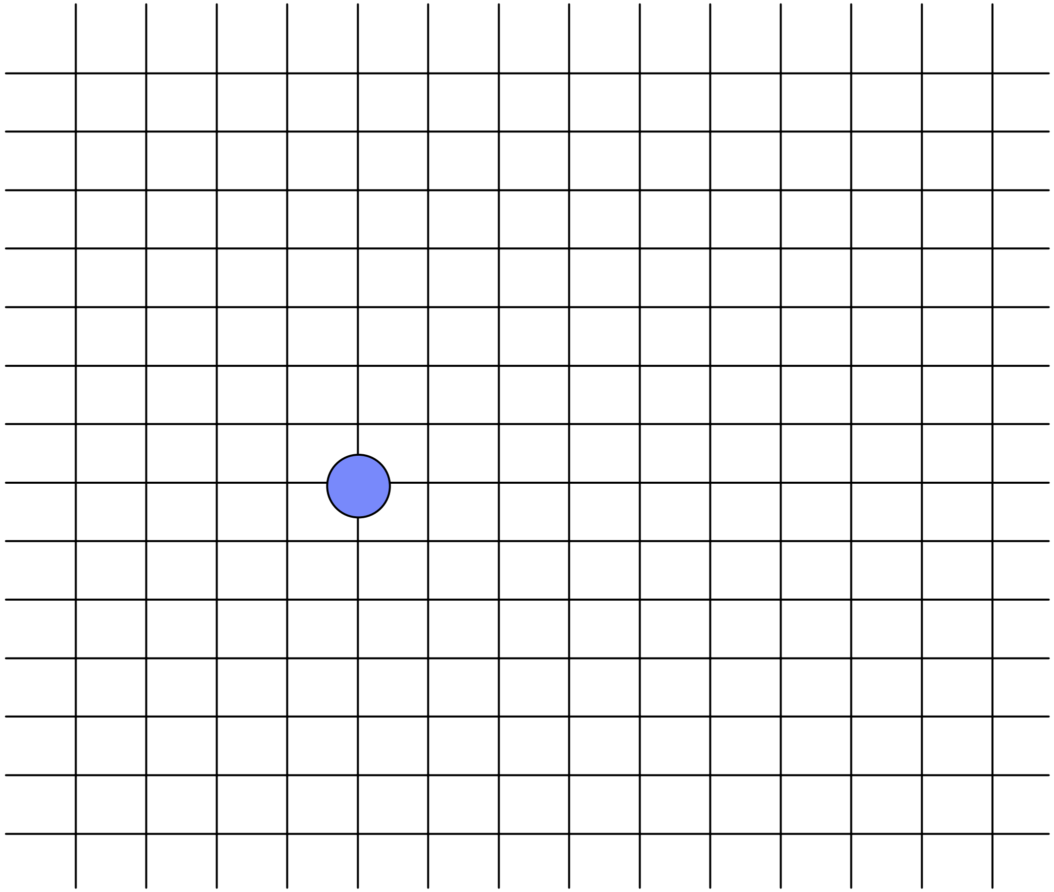
Simulating geographic greedy routing on LiveJournal data

- Can simulate geographic greedy routing on the LiveJournal network
- Results show short paths between most pairs – similar to Milgram's experiment
- So relationship between friendship and distance should follow $1/d^2$

Results

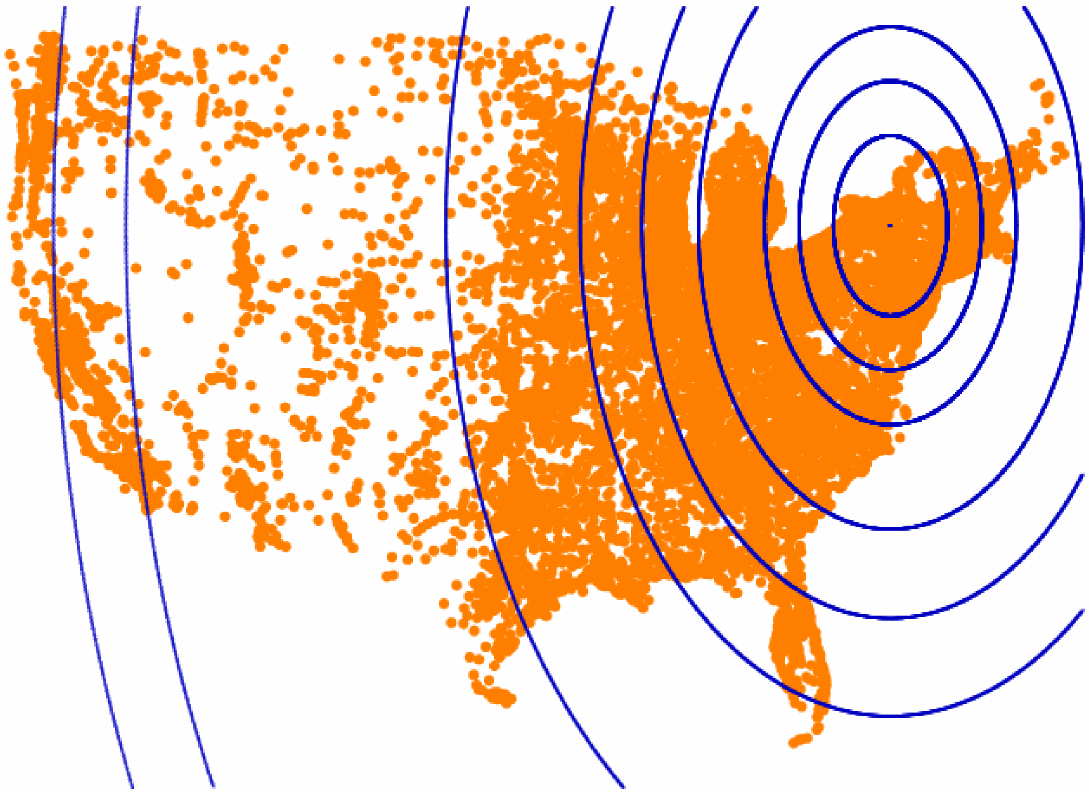

1e-03
1e-04
1e-05
1e-06
1e-07
link probability
10 km
100 km
1000 km
distance
$\varepsilon + 1/d$
$1/d$
Kleinberg $(1/d^2)$

What's happening?



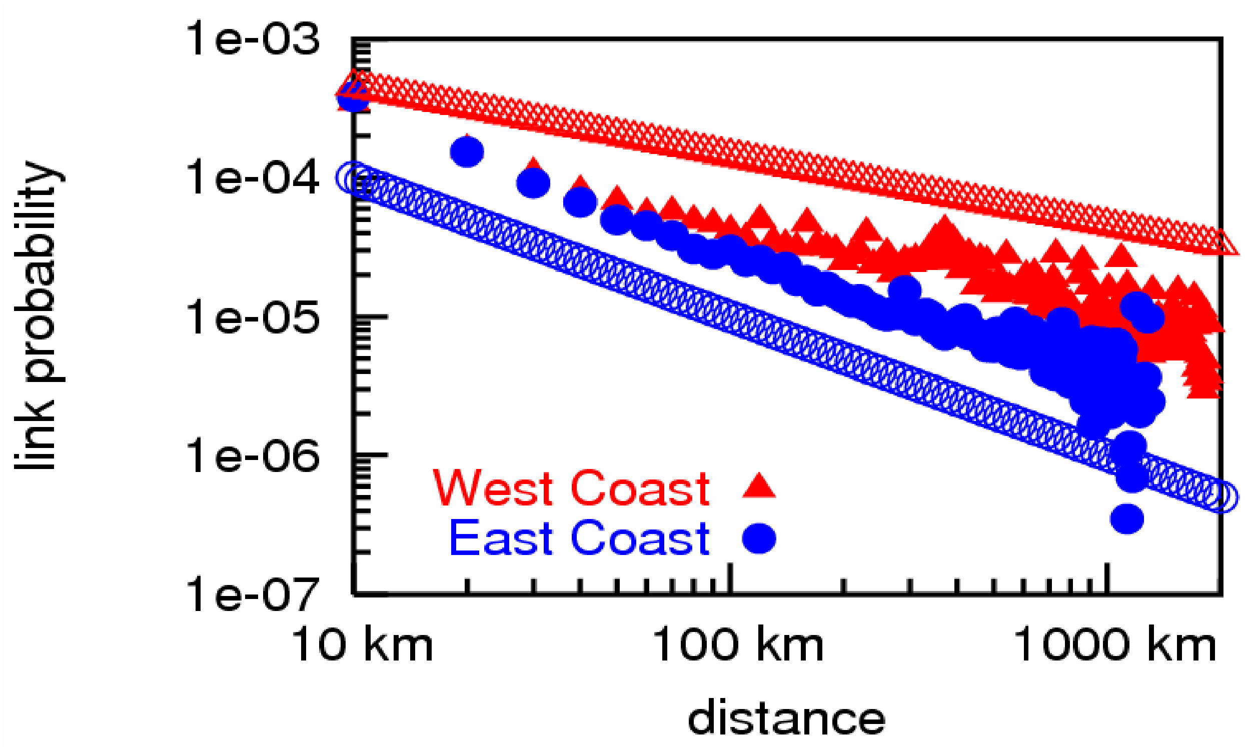
- Assumption: one person per grid point
- Reality: highly varying number of people per grid point

Population density



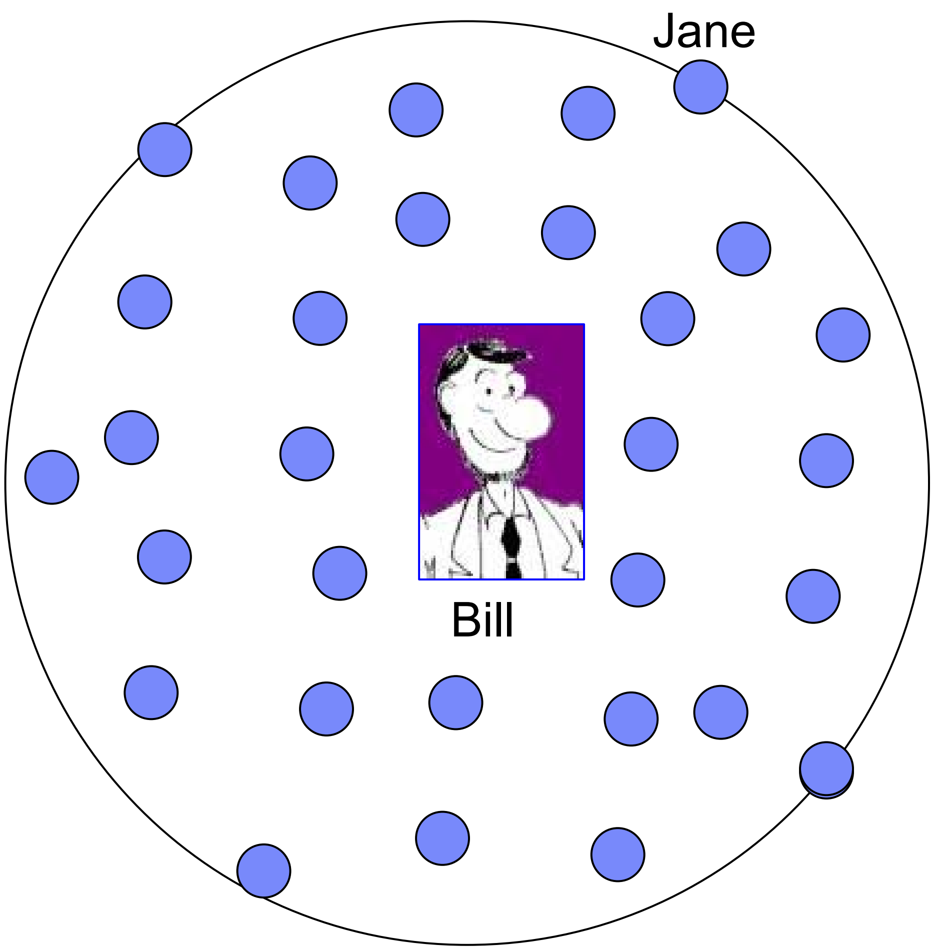
- Dot for every inhabited location
- Each circle represents 50,000 bloggers
- Centered on Ithaca, NY

Does population density (or other factors) impact the relationship between friendship and geography?



Our solution

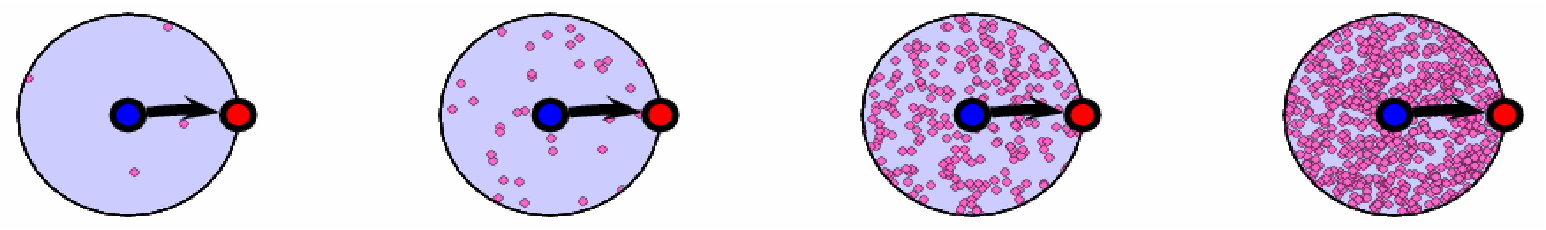
- Why use distance to determine friendship probabilities?
  - –Two people who live a mile apart in Beijing will never meet
  - –Two people who live a mile apart in Iowa will be close acquaintances
- What's the difference?
  - –Within Manhattan, there are thousands of people living within a mile
  - –Within Iowa, there are very few
- Probability of friendship should depend on the size of the candidate population



Pr[friendship] ~ 1 / (# of closer people)

Properties of Rank-based friendship

- Population density determines relationship between distance and friendship



- For uniform density, rank-based friendship is equivalent to Kleinberg – same theorems hold
- For non-uniform density, a similar theorem can be shown…

Theorem

- For any *n*-person population network, for arbitrary source *s*, and uniformly-chosen target *t*, the expected length of a geographic greedy routing path from s to the location of t is $O(\log^3 n)$
- Compared to Kleinberg:
  - Lose: expectation rather than with high probability
  - Lose: another log factor
  - Gain: arbitrary population distributions

Generalization 1: General metric spaces

- Motivation: “distance” between people may represent complex phenomena: shared interests, similar backgrounds, personality similarity, etc. Would like to allow as general a distance function as possible.
- Model:
  - Local edges: pick a shortest path graph in the metric space, include all “local” neighbors that are on a shortest path
  - Long-range edges: rank-based friendship
- Input: an n-person social network whose underlying metric space has doubling dimension alpha, aspect ratio AR, and long-range degree d
- Theorem: For arbitrary source person s and uniformly chosen target person t, the expected length of a path from s to the location of t is $O(\log(n) \log^2(AR)\ 2^{alpha}/d)$.

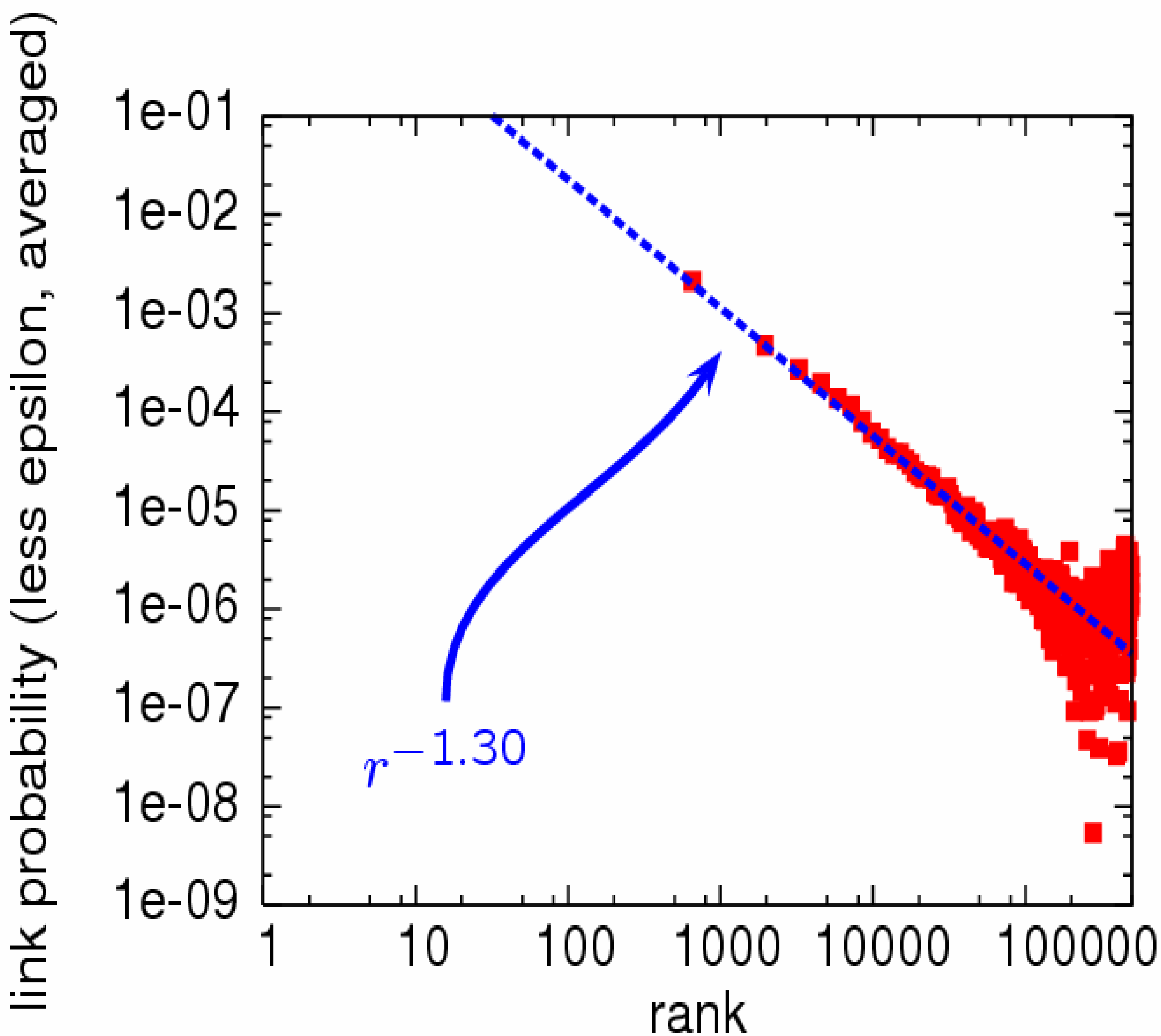
Generalization 2: Recursive networks

- Motivation: send a message to Manhattan, then route within the sub-network to the correct building, then to the correct room
- Model: As in a standard population network, but each point contains either a singleton person or a recursive sub-network
- Input: a recursive population network of depth O(poly(n))
- Theorem: For arbitrary source person s and uniformly chosen destination person t, the expected path length from s to t is O(T x min{log(n), depth}) where T is the expected path length of a non-recursive network

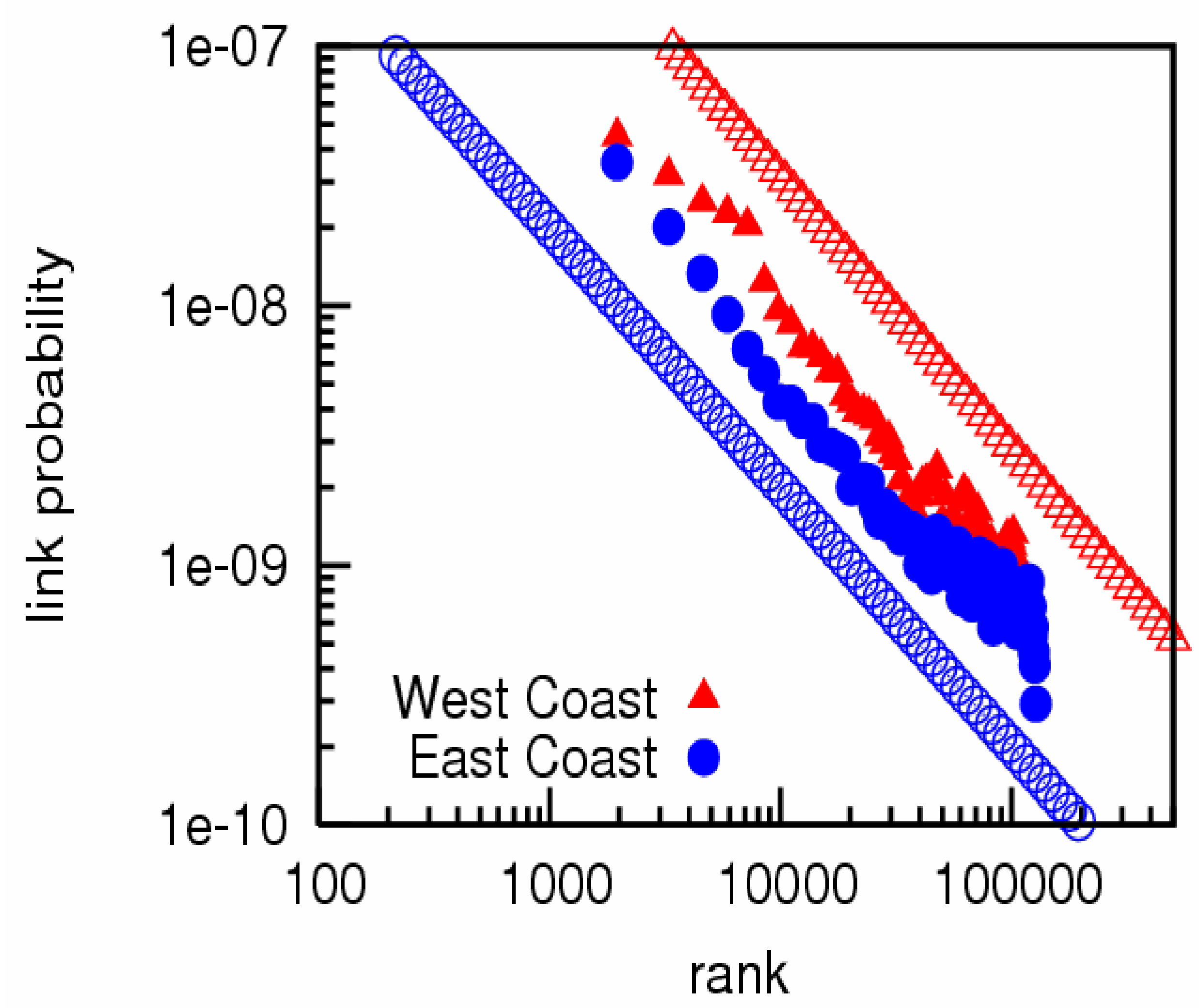
Generalization 3: Trees with no local edges

- Motivation: many models for social networks have been proposed for trees, without strong routing results
- Input: binary tree of depth $\log^k(n)$
- Model:
  - Each person has $\log^{k+1}(n)$ long-range links by rank-based friendship
  - Local links: none
- Theorem: With arbitrary probability, for arbitrary source person s and uniformly chosen destination person t, the expected path length from s to the location of t is $O(\log^k(n))$

Friendship versus rank

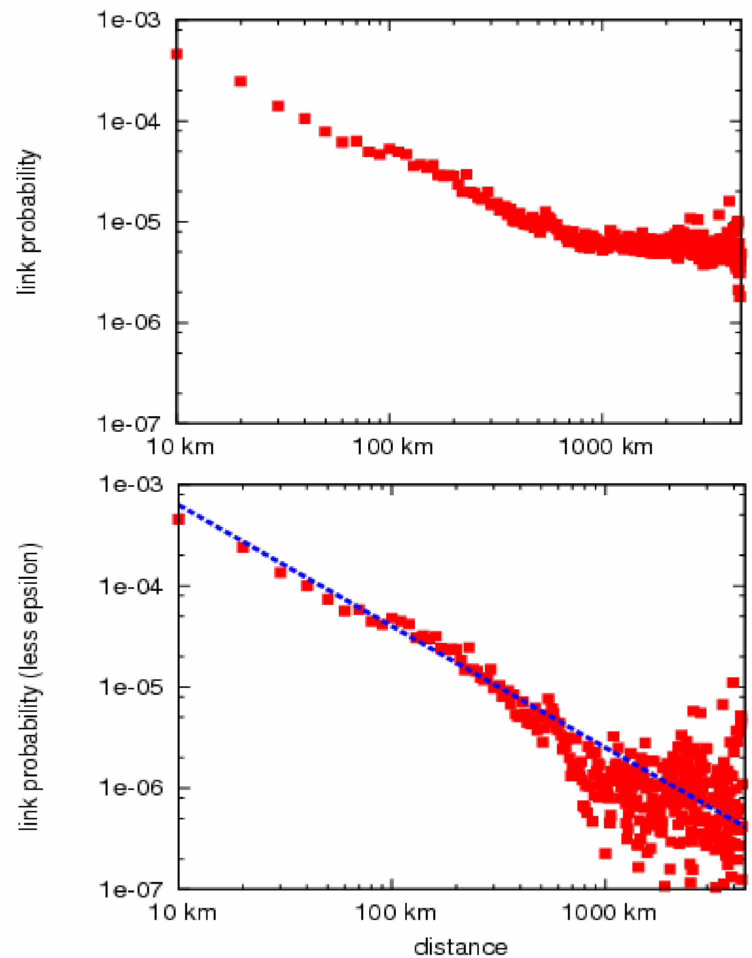


East versus West Coast revisited



How much does geography explain?

- Graph of distance versus friendship probability
- Good estimator of friendship: function of distance *plus* constant
- Constant term represents geographically-independent reasons for friendship
- Back-solving, we find that 2.5/8 friends are non-geographic
- Could shared interests explain these friendships?



Switching gears: Visualization of Social Networks using Connection Subgraphs

Joint work with:
Christos Faloutsos, CMU
Kevin McCurley, Google

Work performed at IBM Almaden Research Center

Appeared at KDD 2004

Outline

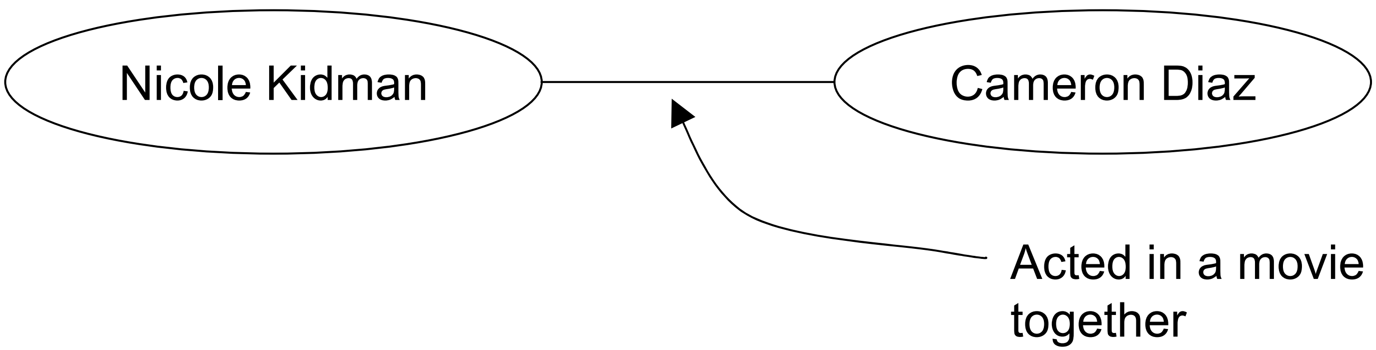
- Introduction / Motivation
- Survey
- Proposed Method
- Algorithms
- Experiments
- Conclusions

Informal Problem Statement

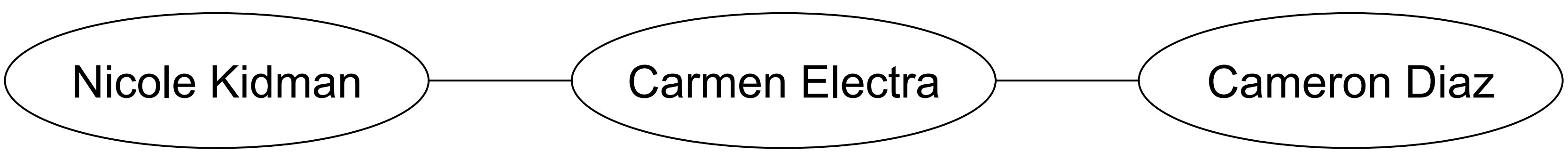
- Given a large social network and two distinguished vertices s and t, show the “relationship” between s and t in the network
- Example: show the relationship between “Nicole Kidman” and “Cameron Diaz”

Standard Approaches

- Standard approach number 1: show an edge if one exists:

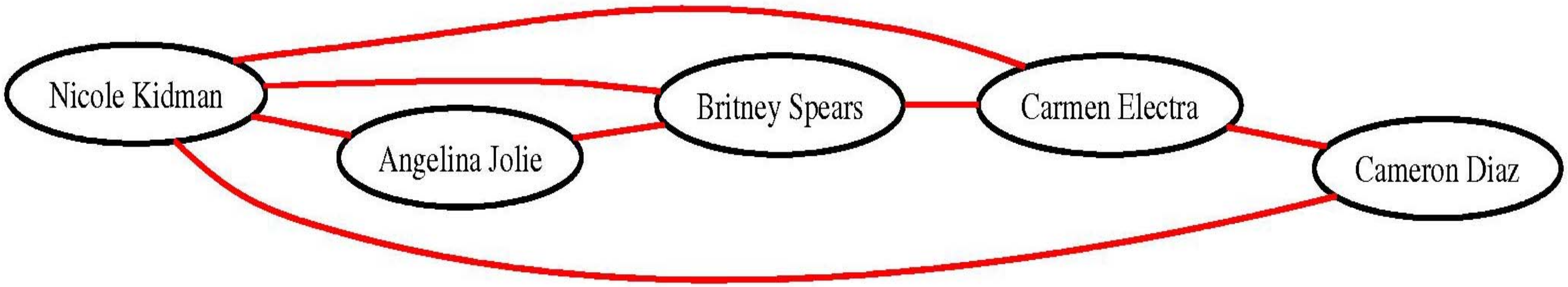


- Standard approach number 2: if no edge exists, show a path:

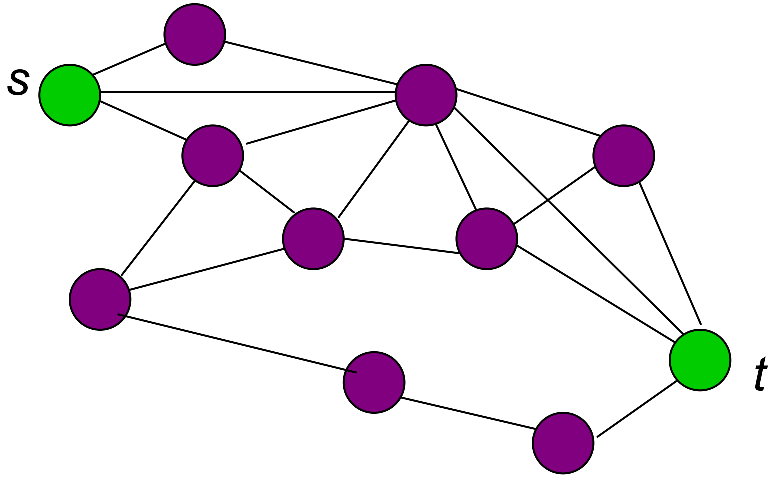


Proposed Approach

- Show a small subgraph that may capture exponentially many paths concisely:

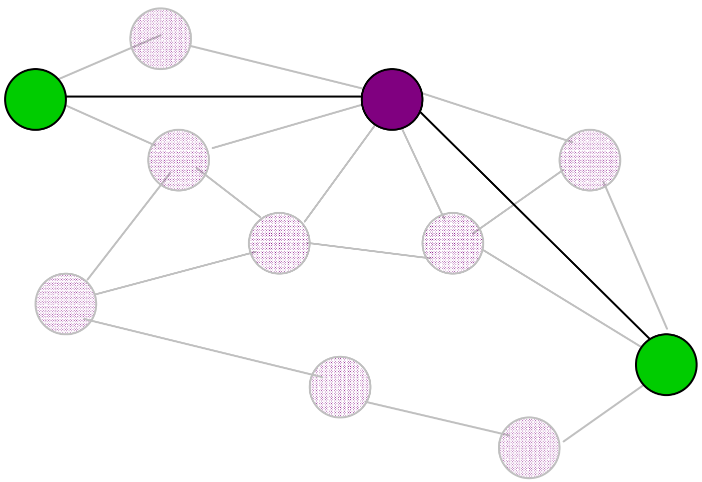


How big a subgraph?

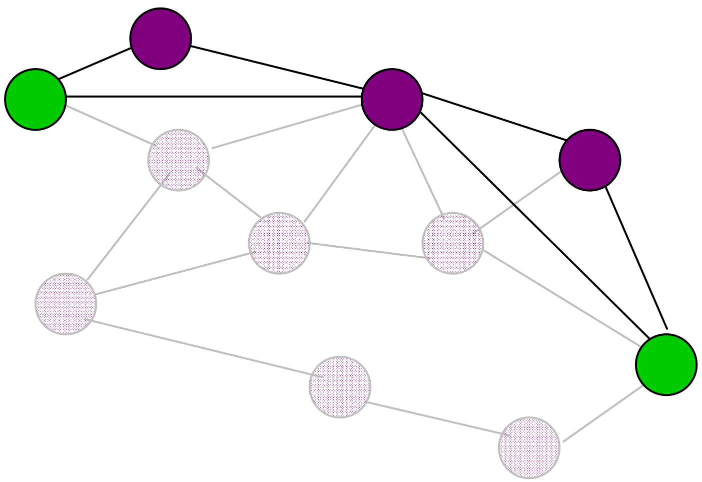


Given a graph with *initial* and *final* vertices *s* and *t*, and a budget *B*, return a *B*-node subgraph that best connects *s* and *t*.

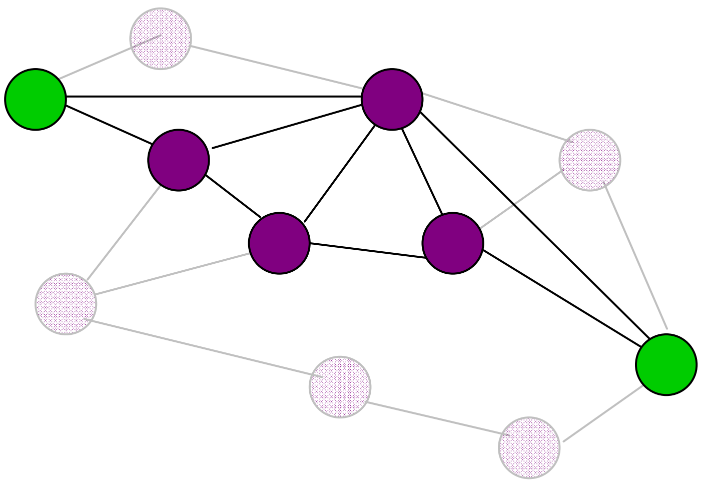
Budget: 3 nodes



Budget: 5 nodes

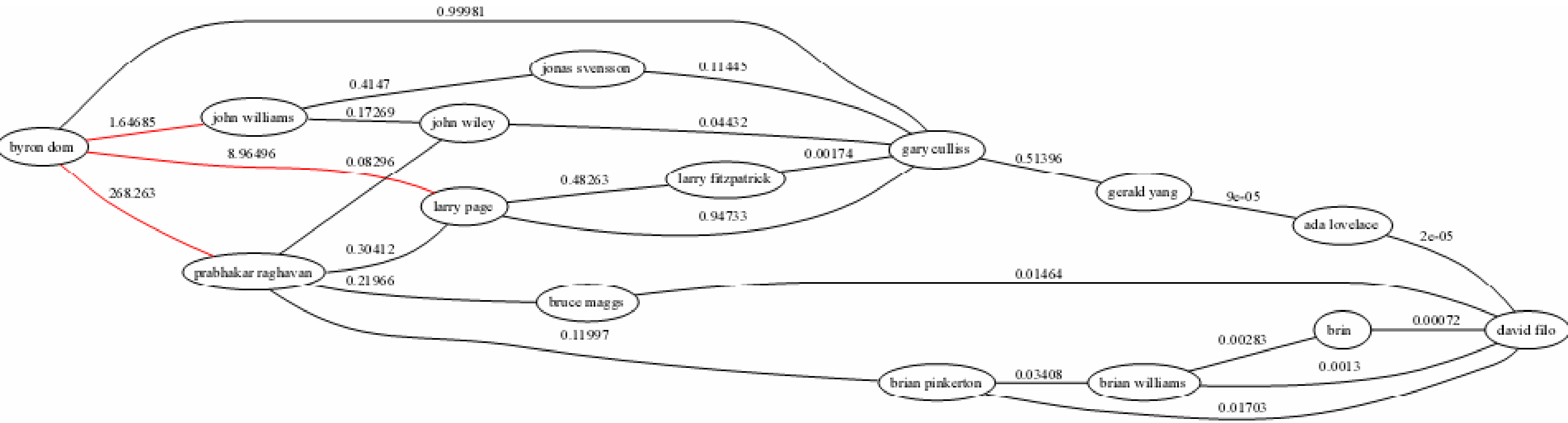


Budget: 6 nodes

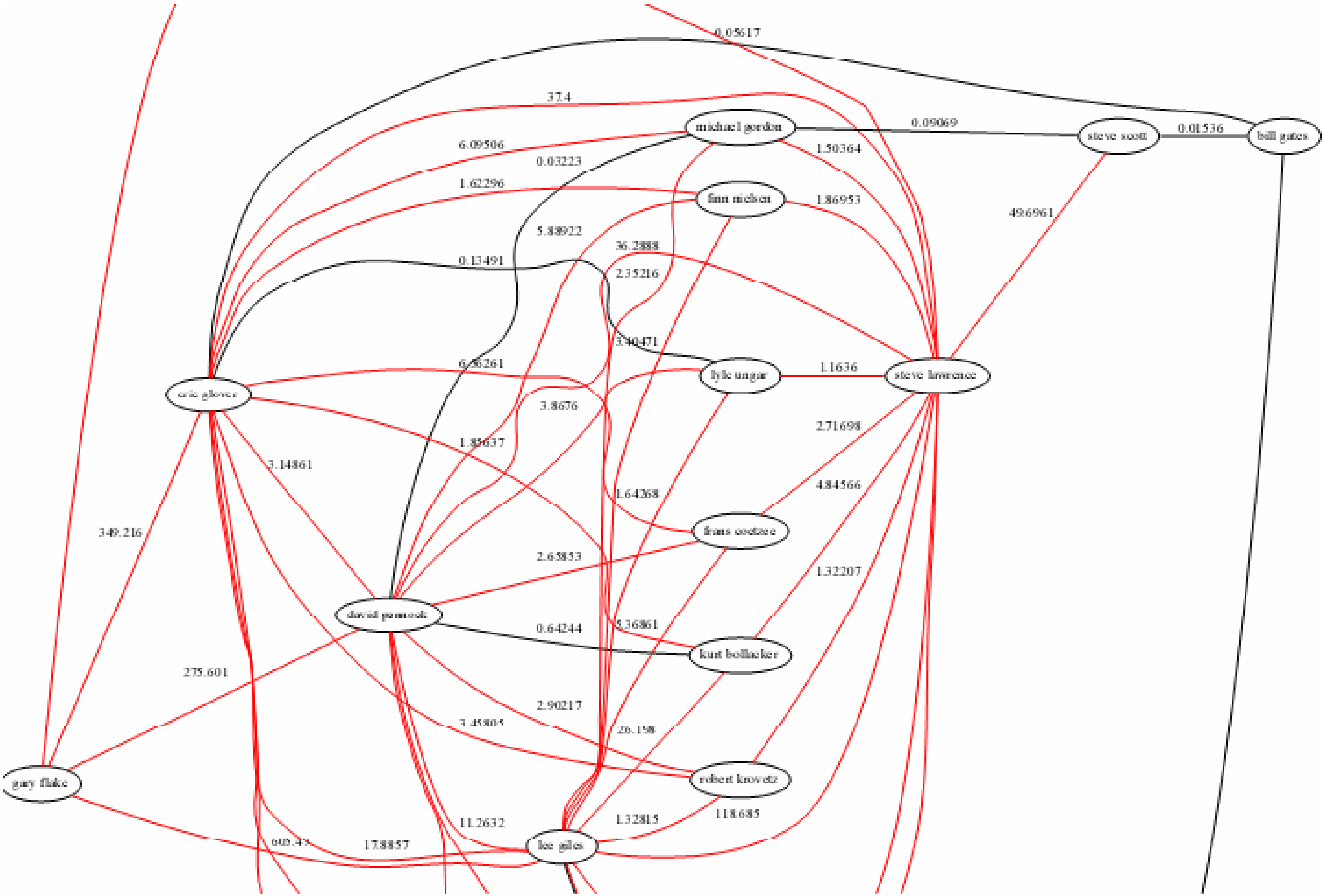


A larger example: Jan Pedersen to Andrew Tomkins

An example: Byron Dom to David Filo

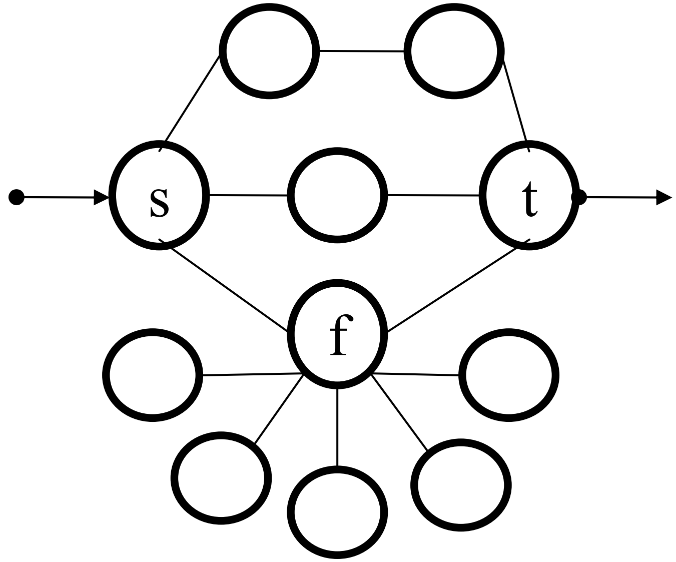


Fragment of Gary Flake to Bill Gates



Problem definition

- Given a graph, and two nodes *s* and *t*, and a 'budget' *b* of nodes
- Find the best *b* nodes that capture the relationship between *s* and *t*



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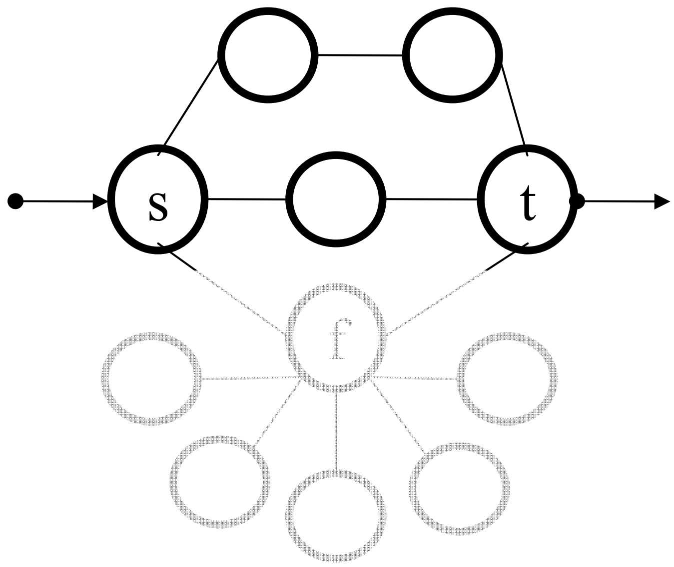

Problem definition

- Part 1: How to quantify the goodness?
- Part 2: How to pick ‘best few’ nodes?
- Part 3: Scalability: large graphs (10**7 nodes)

Survey

- Graph Partitioning
  - [Karypis+Kumar]; [Newman+];
  - etc
- Communities
  - [Flake+]; [Kumar, Kleinberg+]
- External distances [Palmer+]

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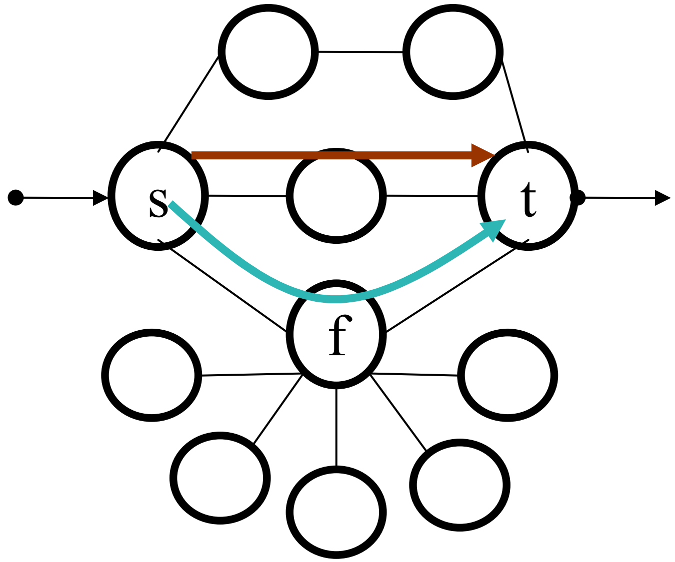
Proposed method for selecting a subgraph

- part 1: measuring quality of a path:
  - electrical current / random walks
- part 2: selecting a subgraph
  - dynamic programming
- part 3: scalability
  - heuristics

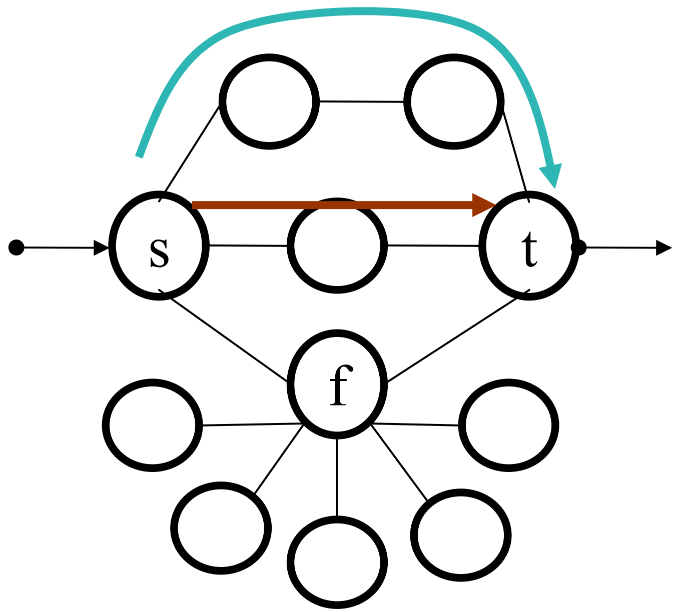
Path quality, part 1

- Why not shortest path?



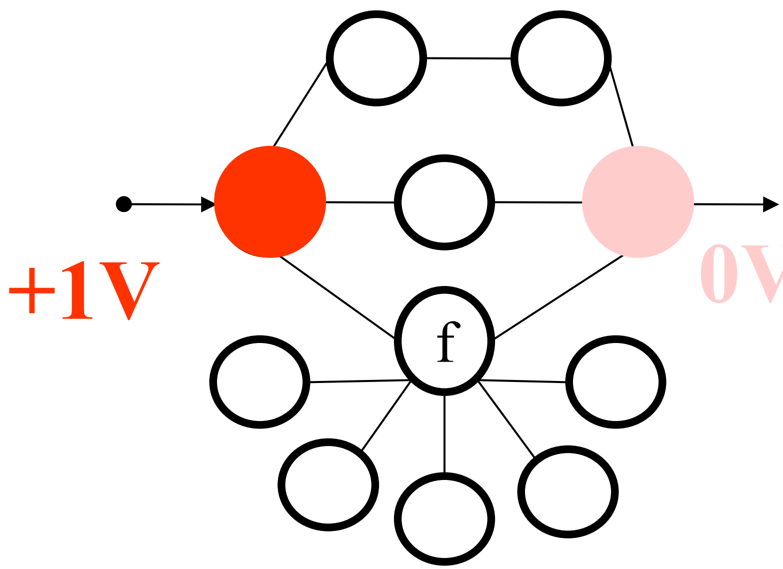
Path quality, part 2

- Why not shortest path?
- Why not net. flow?



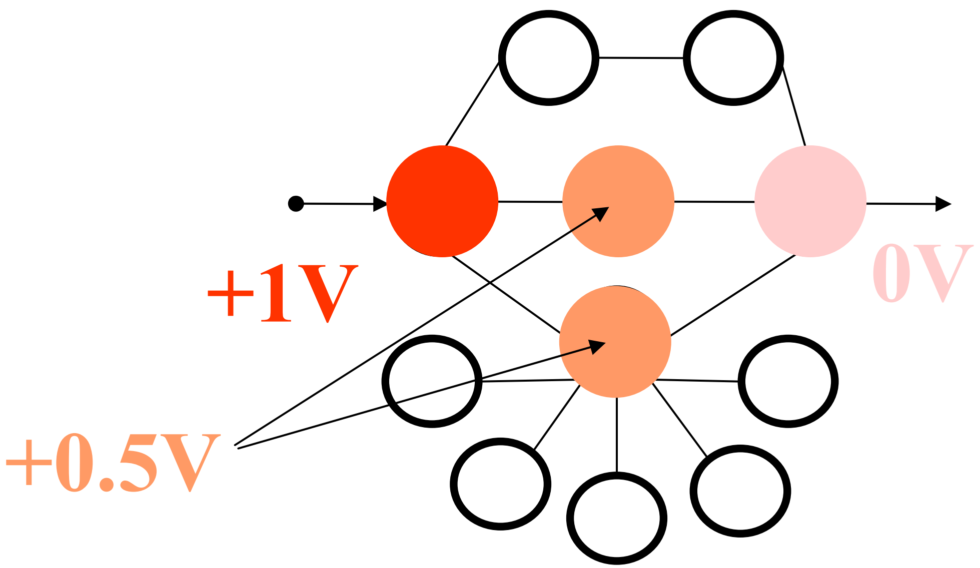
Path quality, part 3

- Why not shortest path?
- Why not net. flow?
- Why not plain ‘voltages’?



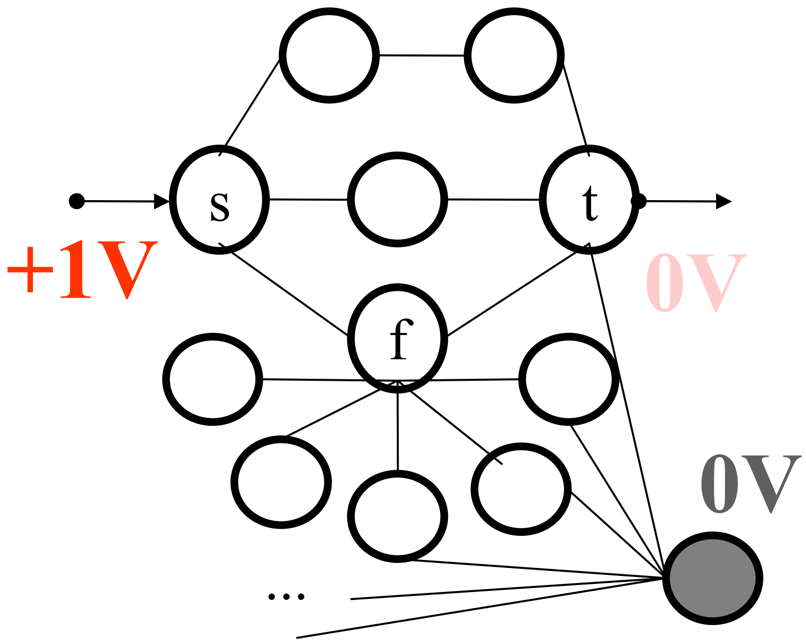
Path quality, part 4

- Why not shortest path?
- Why not net. flow?
- Why not plain ‘voltages’?



Proposed path quality measure

- Proposed method: voltages **with** universal sink:
  - ~ ‘tax collector’
- goodness of a path:
- its electric current(*)!



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Electricity – Algorithm

- Voltages/Amperages can be computed easily (O(*E*))
- without universal sink:

  $v(i) = \Sigma um_j\ [v(j) * C(i,j) / C(i,*)\ ]$

  i != source, sink

  v(source)=1; v(sink)=0

Electricity – Algorithm

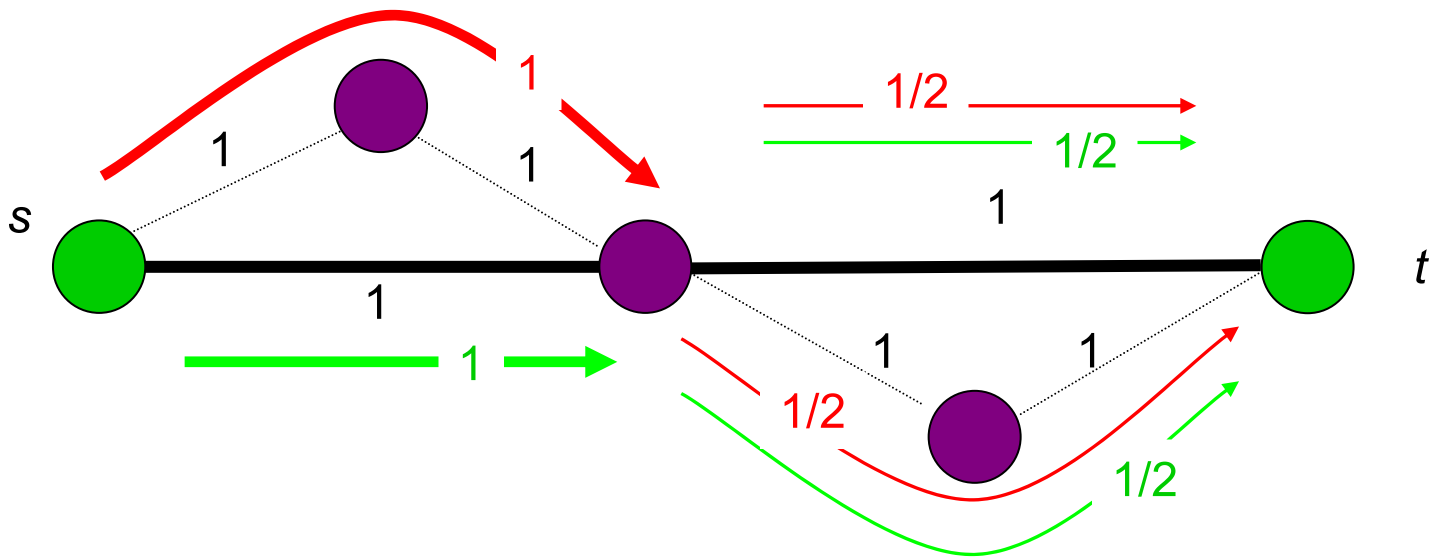
With universal sink:

$v(i) = \mathbf{1/(1+a)}\ \Sigma um_j\ [v(j) * C(i,j) / C(i,*)\ ]$

(~ insensitive to a (=1))

Part 2: From paths to subgraphs

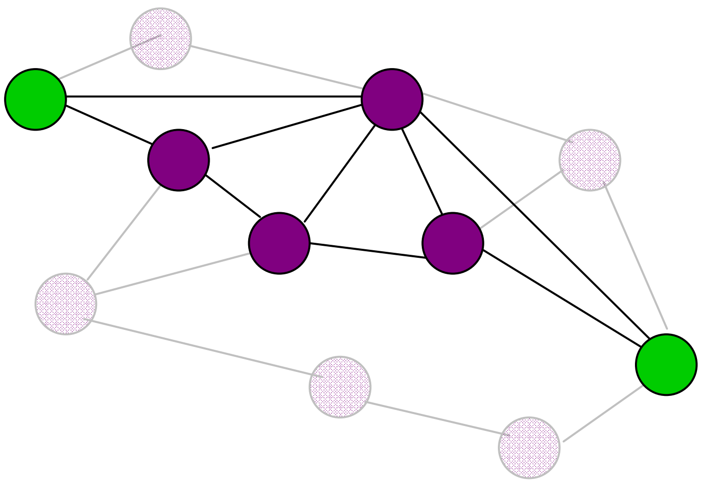
- Using Part 1, compute an s-t flow on the entire graph
- Find a subgraph that "captures" much of this flow



- Given the flow above, how good is the specified path?
- "Delivered current": how many electrons travel from s to t along that path

Delivered current of a subgraph

- All units of flow (ie, electrons) that travel from s to t via edges in the subgraph:



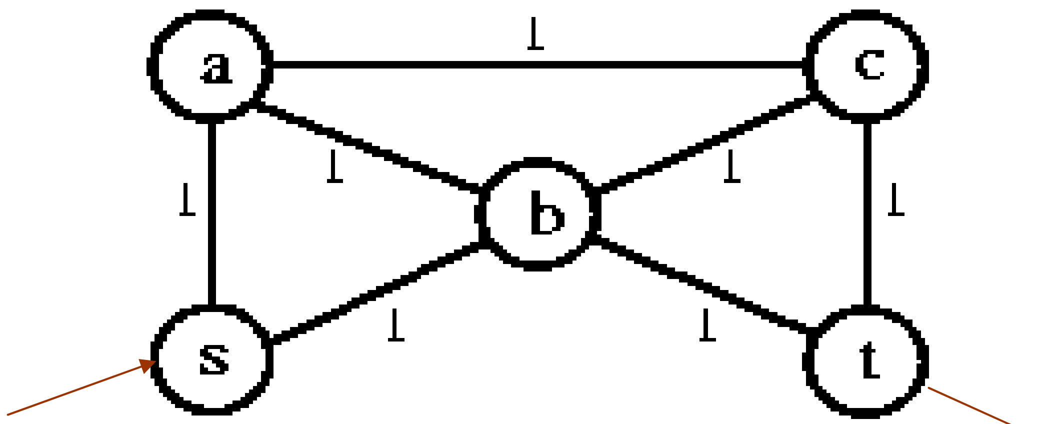
Algorithm for selecting subgraph

- Combinatorial problem: find a B-node subgraph to optimize delivered current – hard to solve exactly or provide approximation algorithms
- Dynamic program to compute:
  - Path which maximizes delivered current per node
- Recursive greedy application

Part 2: DisplayGen

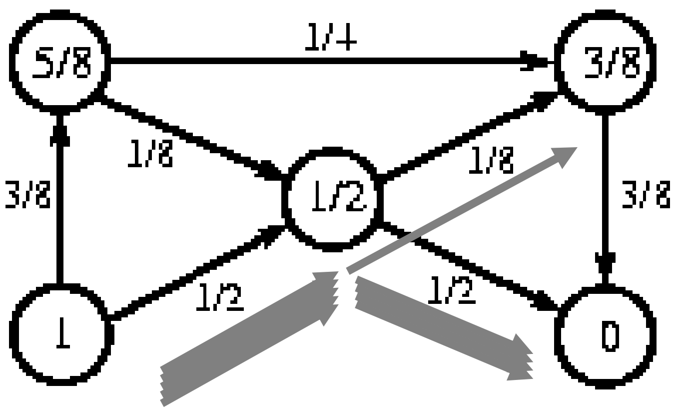
Given the voltages and currents

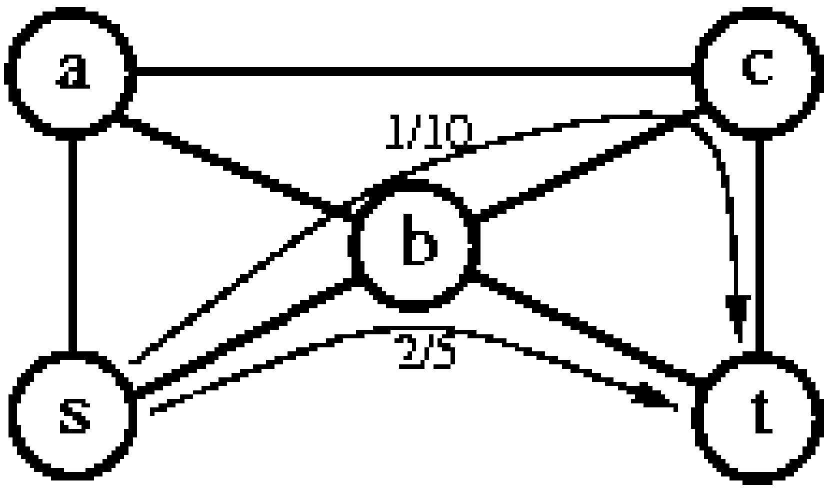
- Which *b* nodes to keep?



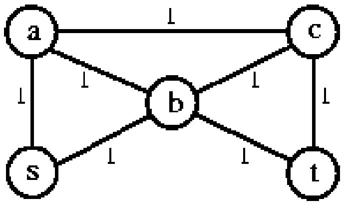
Part 2: DisplayGen

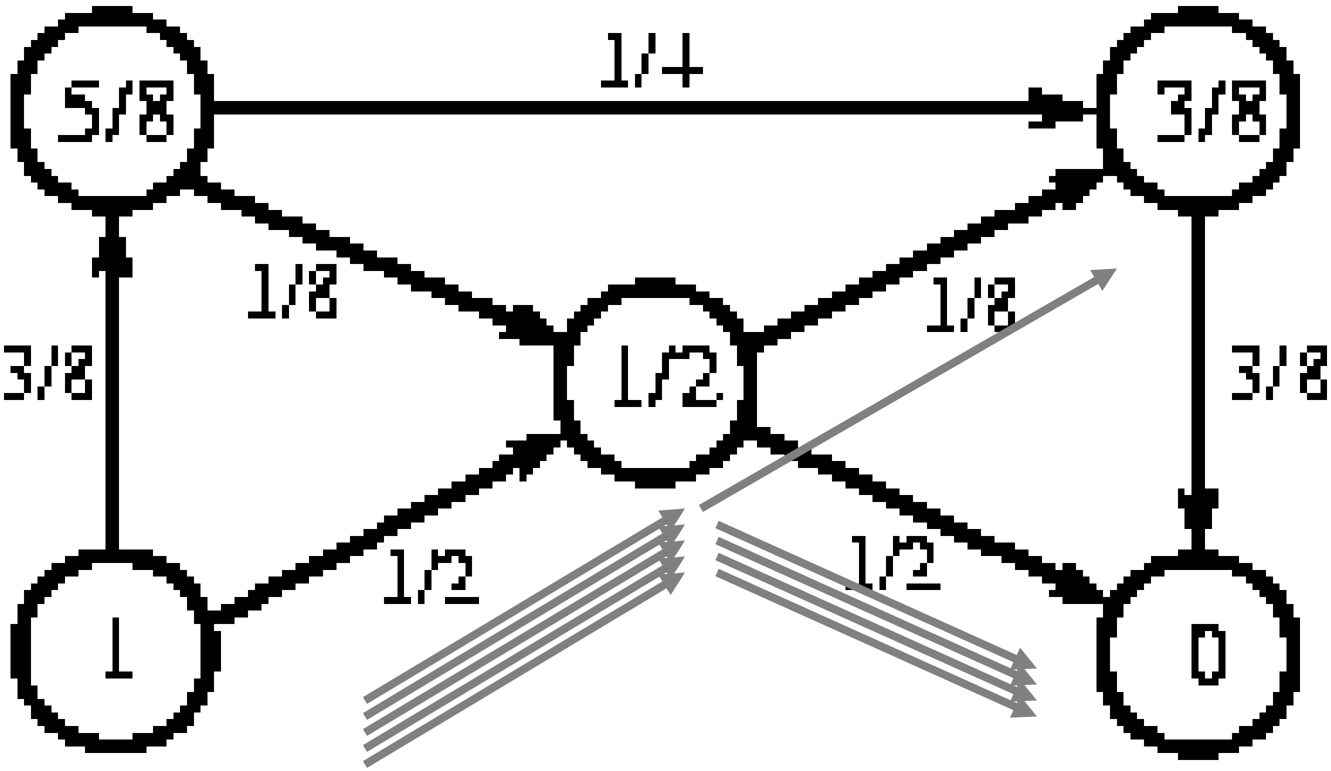
- ‘delivered current’ of a path:
  - ~ ‘how many electrons’ choose this path





Part 2: DisplayGen





Part 2: DisplayGen

- find path to maximize marginal delivered current per node
  - Dynamic programming
- Incrementally, add paths to solution

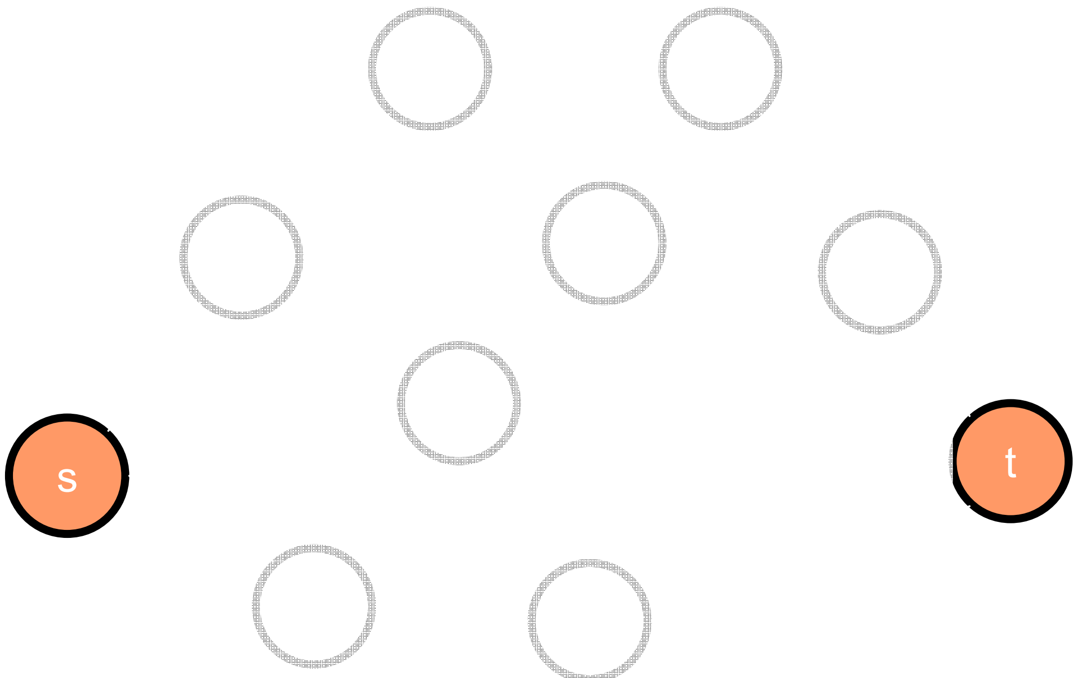
Part 3: Scalability

Begin with enormous out-of-core graph
Slowly expand from s and t to find a candidate subgraph for algorithm:

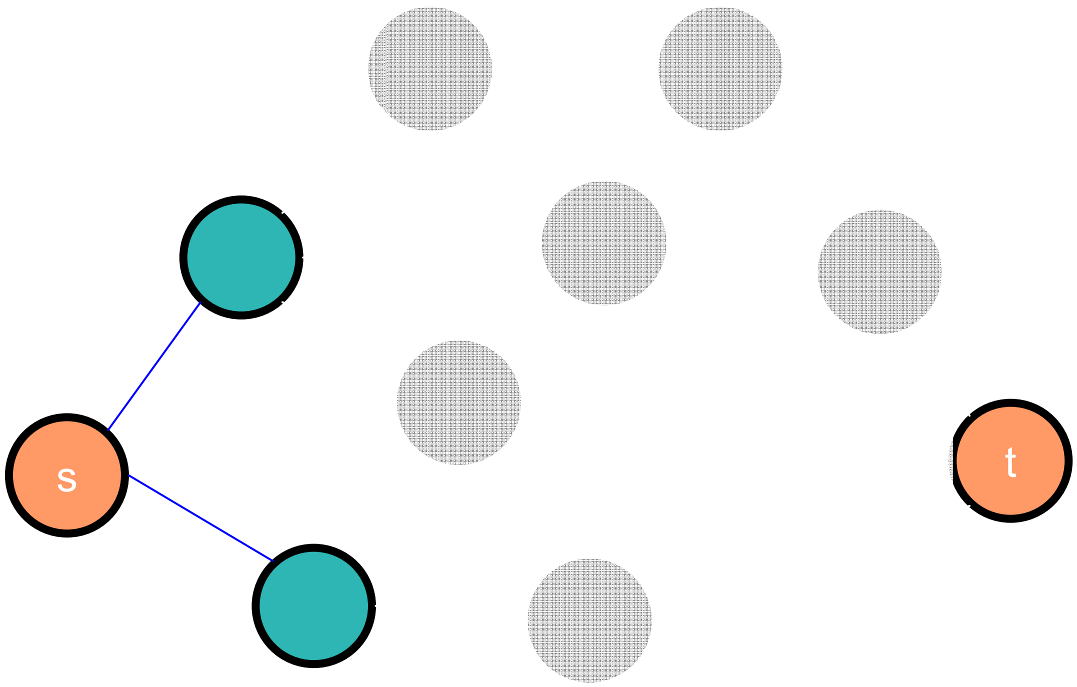
Begin with nodes s and t in expansion pool
Until (*stoppingCriterion*)
  Use *pickHeuristic()* to pick a node *n* from expansion pool
  Add n to candidate subgraph
  Add neighbors of n to expansion pool
Apply electrical flow and dynamic program to candidate subgraph

Part 3: Scalability

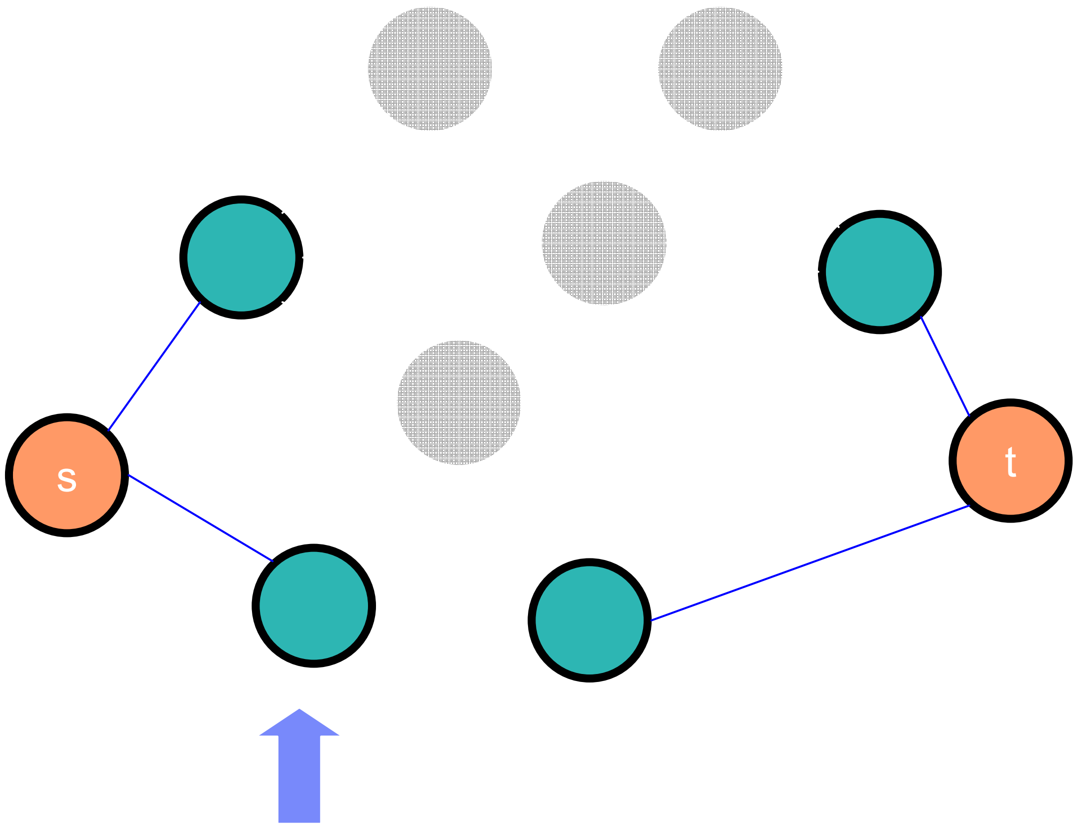
- By successive, careful expansions



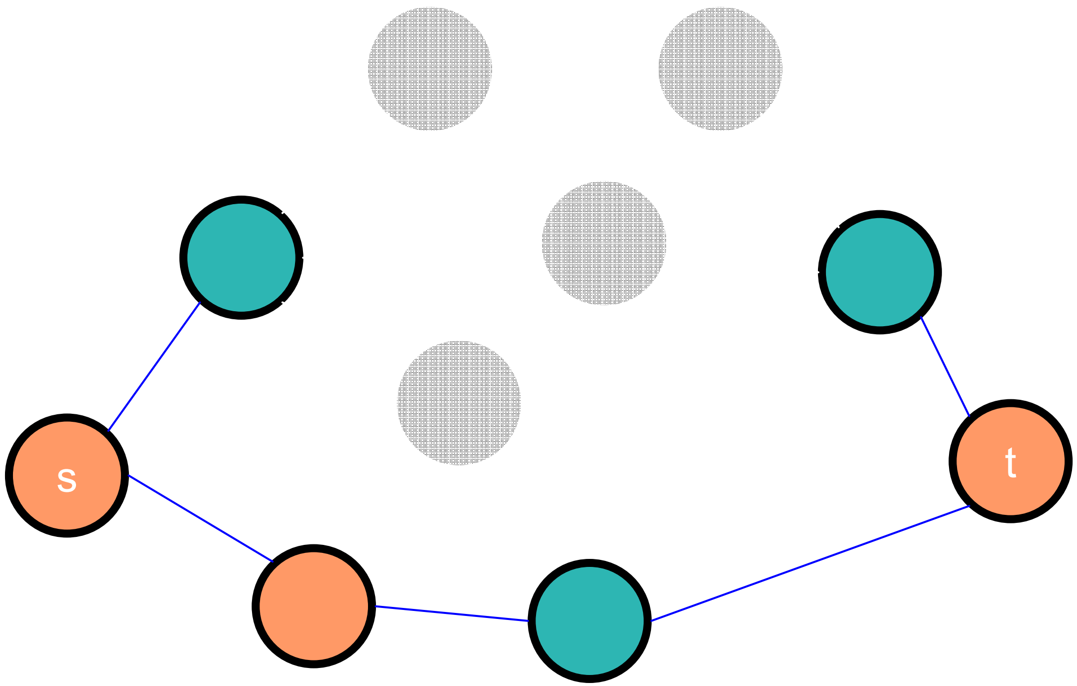
Part 3: Scalability



Part 3: Scalability



Part 3: Scalability



Pseudo-code

```
Until (stoppingCriterion)
    use pickHeuristic() to pick a node n
  expand node n
```

Pseudo-code

pickHeuristic() favors

- Nearby nodes with
  - Strong connections to source or sink
  - Small degree

Outline

- Introduction / Motivation
- Survey
- Proposed Method
- Algorithms
- Experiments
- Conclusions

Experiments

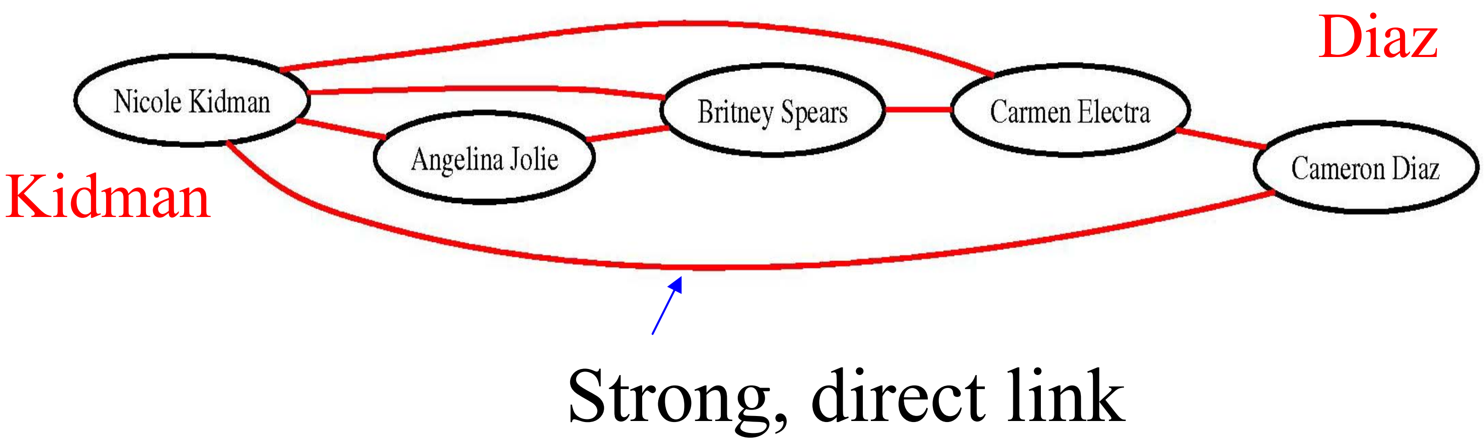
- on large real graph
  - ~15M nodes, ~100M edges, weighted
  - ‘who co-appears with whom’ (from 500M web pages)
- Q1: Quality of ‘voltage’ approach?
- Q2: Speed/accuracy trade-off?

Q1: Quality

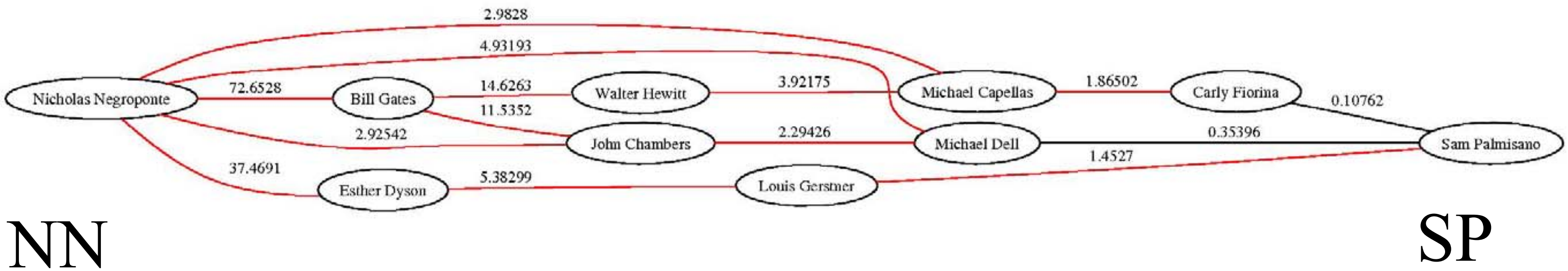
- Actors (A); Computer-Scientists (CS)
- Kidman-Diaz (A-A)
- Negreponte-Palmisano (CS-CS)
- Turing-Stone (CS-A)

(A-A) Kidman-Diaz

- What are the best paths between ‘Kidman’ and ‘Diaz’?

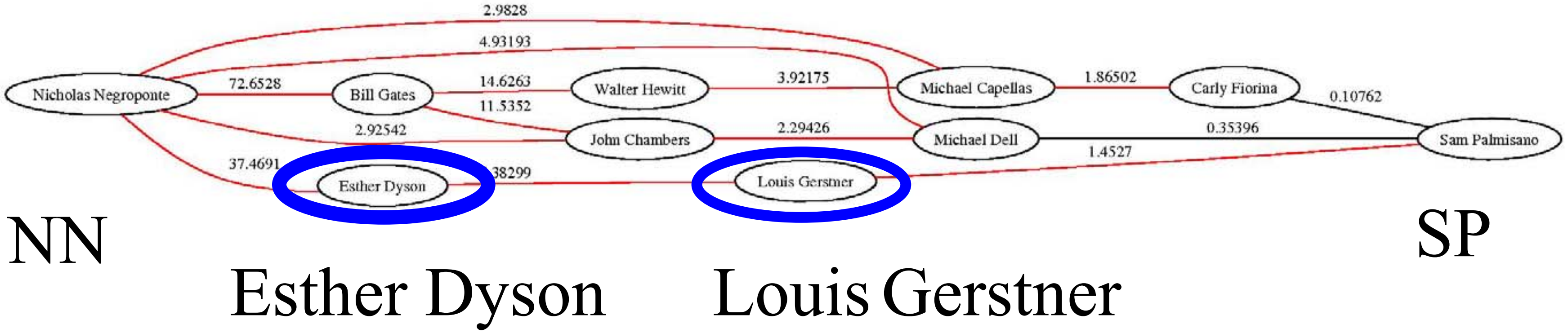


CS-CS: Negreponte - Palmisano

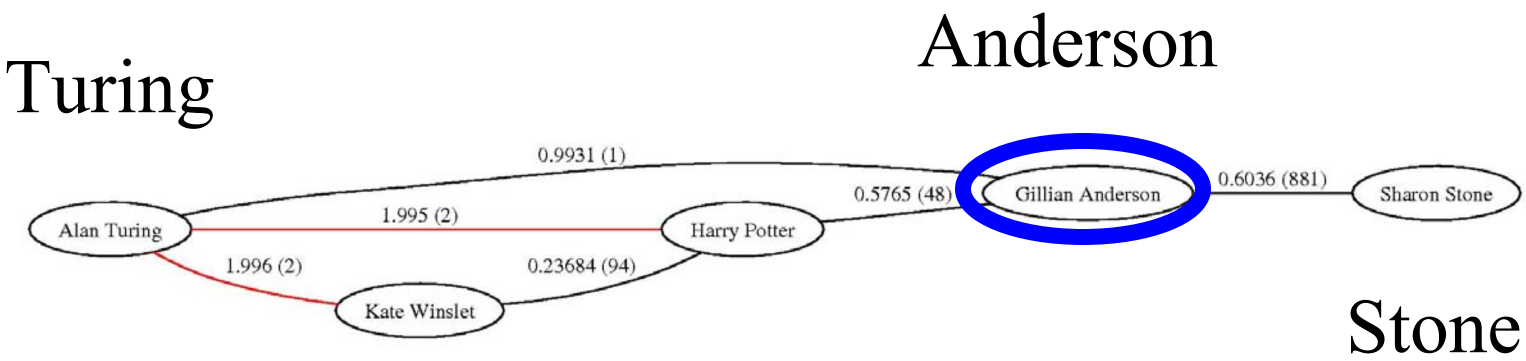


• Mainly: CEOs of major Computer companies (Dell, Gates, Fiorina, ++)

CS-CS: Negreponte - Palmisano



CS-A: Turing - Stone

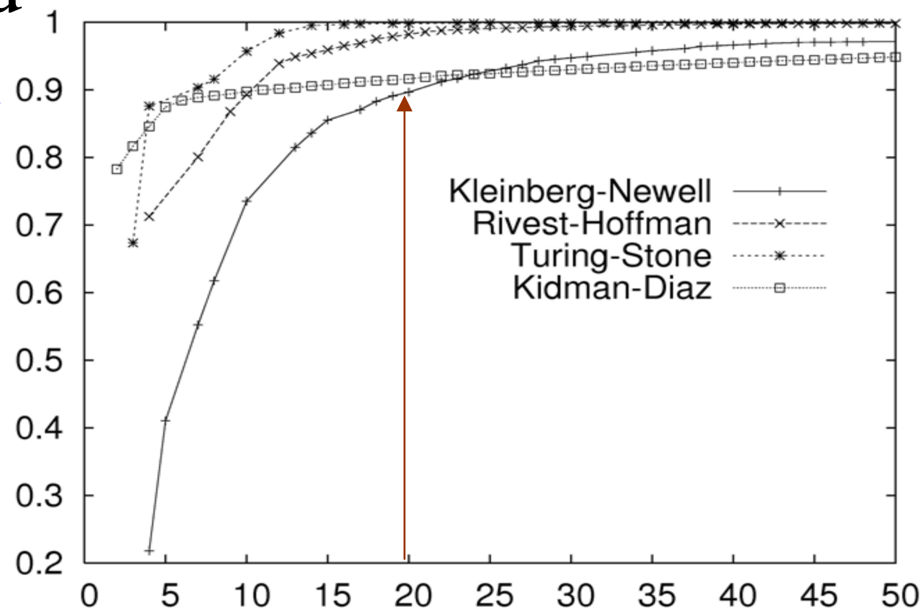


Outline

- Introduction / Motivation
- ...
- Experiments
  - Q1: quality
  - Q2: speed/accuracy trade-off
- Conclusions

Speed/Accuracy Trade-off

delivered current



Kleinberg-Newell
Rivest-Hoffman
Turing-Stone
Kidman-Diaz

number of nodes kept (‘b’)

Speed/accuracy trade-off

- 80/20-like rule:
- the first few nodes/paths contribute the vast majority of ‘delivered current’
- Thus: CandidateGen makes sense

Conclusions

- Defined the problem
- Part 1: Electricity-based method to measure quality
- Part 2: Dynamic programming to spot best paths (‘DisplayGen’)
- Part 3: Scalability with good accuracy (‘CandidateGen’)
- Operational system

Conclusions

- Friendship and Distance are strongly related
- Modeling friendship as a function of distance is problematic
- Rank is a better measure of friendship than distance
- Some friendships form with no geographic correlation (2.5/8)

More Information

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