Human Navigation in Networks

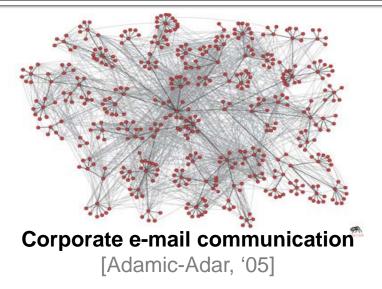
Jure Leskovec
Stanford University



Transformation



Online friendships
[Ugander-Karrer-Backstrom-Marlow, '11]



Social Transformation of Computing

- Technological networks intertwined with social
- Profound transformation in:
 - How knowledge is produced and shared
 - How people interact and communicate
 - The scope of CS as a discipline

Two Issues: One

- Two issues for foundations of computing
 - (1) How do we design in this space?
 Combine social models with core ideas from computing
 - Complex networks: design, analysis, models
 - Algorithmic game theory: designing with incentives
 - Social media: reputation, recommendation, contagion



Two Issues: Two

- Two issues for foundations of computing
 - (2) Science advanced when the invisible becomes visible.
 - Can we recognize fundamental patterns of human behavior from raw digital traces?
 - Can new computational models address long-standing social-science questions?



Invisible Becomes Visible

- We are surrounded by linked objects
 - Social networks:
 - Friendships/informal contacts among people
 - Collaboration in companies, organizations, ...
 - Information networks:
 - Content creation, markets
 - People seeking information
- Traditionally networks were hard to obtain

Invisible Becomes Visible

Now: Large on-line systems

- Social networks:
 - On-line communities: Facebook, Twitter, ...
 - E-mail, blogging, electronic markets
- Information networks:
 - Hypertext, Wikipedia, Web

What have we learned about these networks?

Social & Information Networks

We know a lot about the structure

Network Property	Social Networks (MSN [Leskovec, Horvitz '08])	Information Networks (Web [Broder et al. '00])
Connectivity: Well connected	Giant component of 99.9% nodes	Giant component of 90% nodes
Degrees: Heavy-tailed	Log-normal	Power-law
Diameter: Small	6-degrees of separation	~20
Model	Small-world	Bow-tie Core 40%

Social & Information Networks

- We know much less about processes!
- What process is common to both?
- Navigation!
 - How people find their way through social networks?
 - How people find information on the Web, Wikipedia?



Navigating Information Nets

Browsing the Web



Literature search

introduction. Cambridge University Press.

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Teevan, J.; Alvarado The perfect search of behavior in directed West, R., and Leskov networks. In WWW- 121 C Tavers, J. & Milgram, S. (1967) Psychol. Today 1, 61–67.

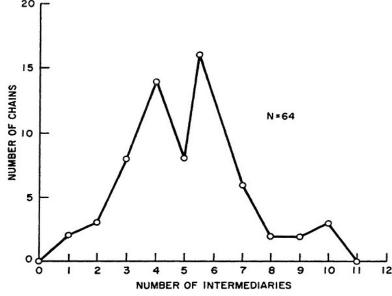
West R : Pineau I : and Precup D 2009 Wikispeedia: An online
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Consulting an encyclopedia



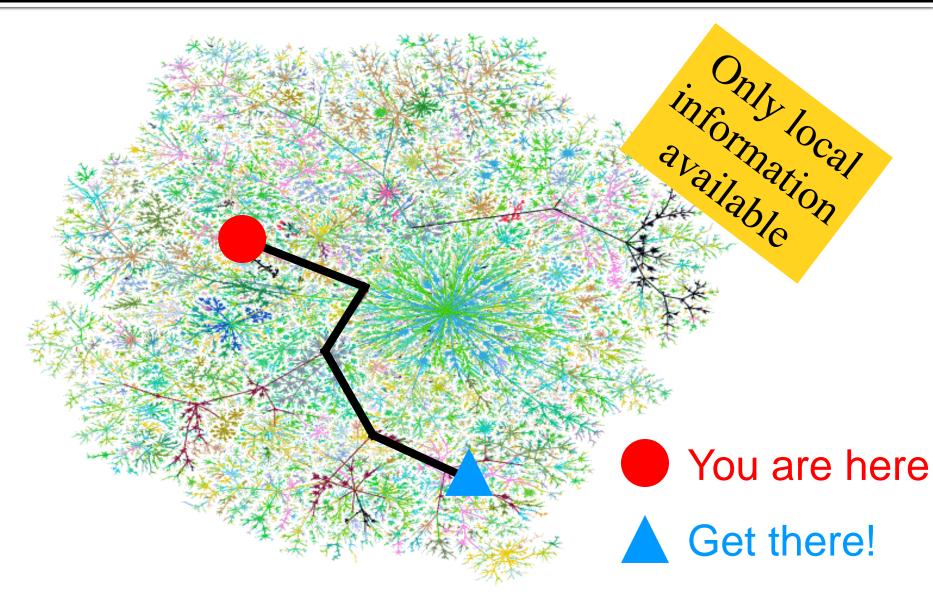
Navigating Social Networks

- Milgram's small-world experiment ['67]
 - People forward letters via friends to far-away targets they don't know
 - Six steps on avg. → Six degrees of separation



Milgram experiment (Travers-Milgram '70)

Navigation: Abstraction

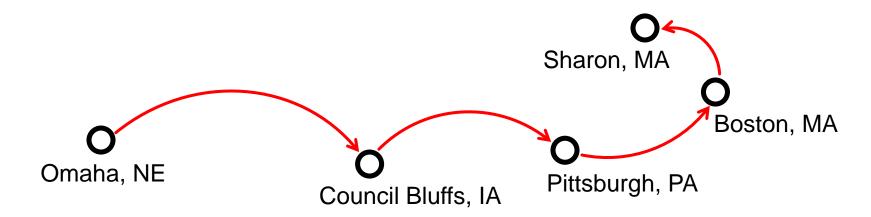


Plan for the Talk

- Study navigation in social as well as information networks
 - What is common? What differs?
 - What are the design implications for computing applications and systems?
- Common theme:

Use large-scale online data to as a 'telescope' into these processes

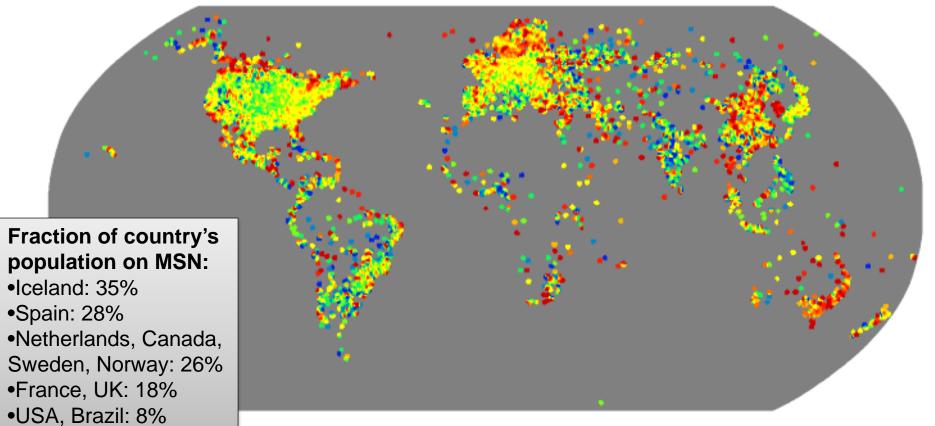
Navigating Social Networks



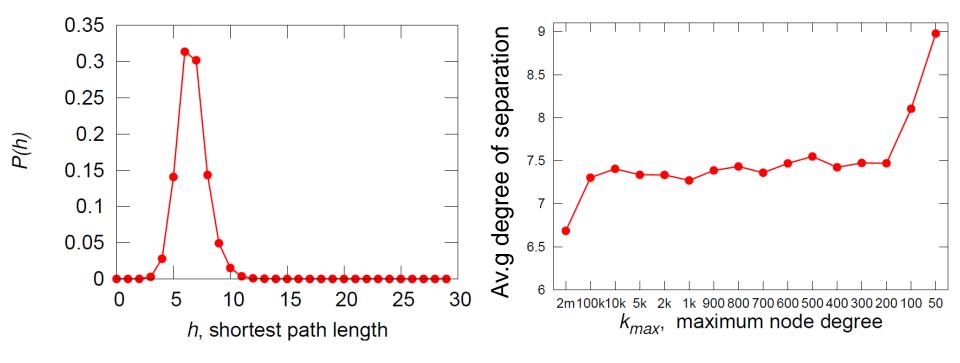
- Why should strangers be able to find short chains of acquaintances linking them together?
 - Models for decentralized routing in social networks [Kleinberg '00, Watts-Dodds-Newman '02, ...]

The MSN Network

- The MSN Messenger network:
 - 180 million people, 1.3 billion edges



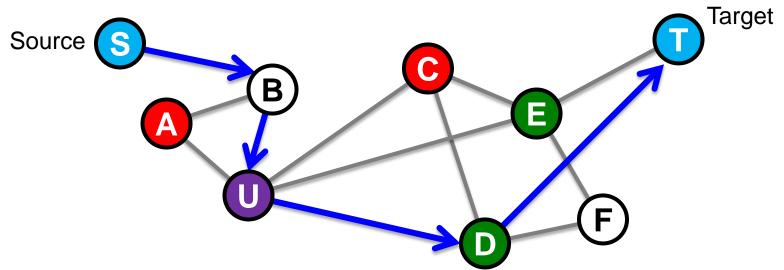
6-Degrees of Messaging



- Avg. degree of separation = 6.6, mode=6
- Long paths (>30) exist in the network
- Network is robust to removal of hubs

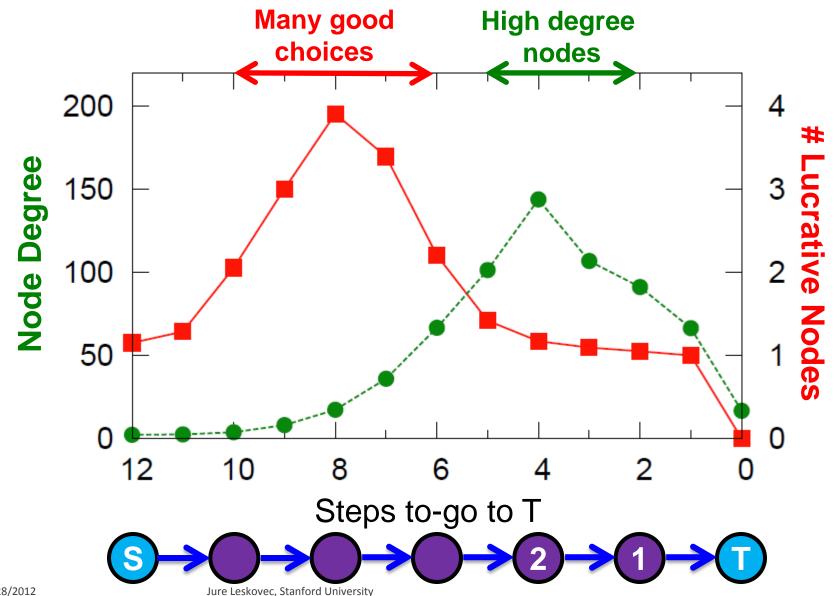
Navigating the MSN Network

- What are characteristics of short paths?
- How hard is it to find them?
- Strategy: S-T shortest-paths
 - Pick random S-T, run Dijkstra, examine the paths

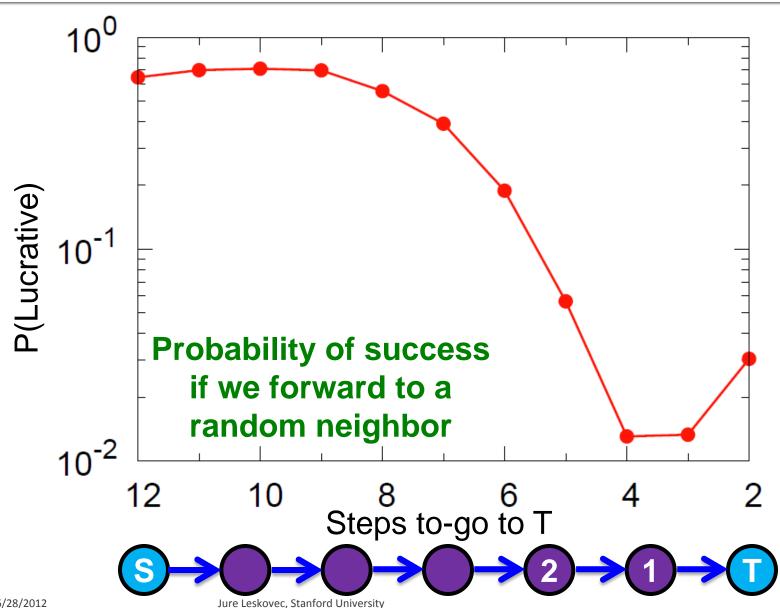


Def: Node is lucrative, if it leads "closer" to T

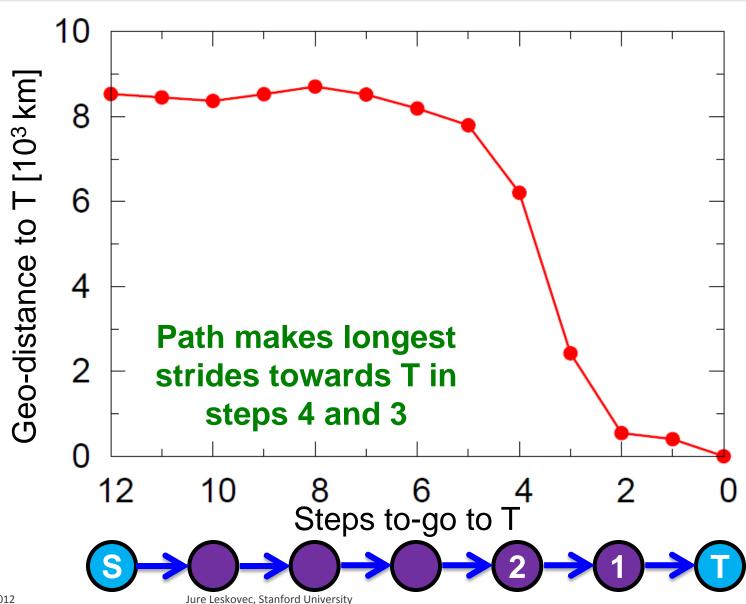
Anatomy of Short Paths



Finding a Lucrative Node



Does geography help?



Navigational Heuristics

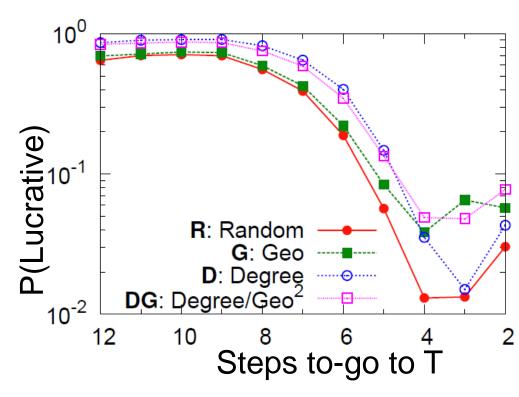
- How good are heuristics at navigation?
- Heuristics: Jump to a node X chosen:

R: Random

• **G**: min geo(X, T)

 \blacksquare D: max deg(X)

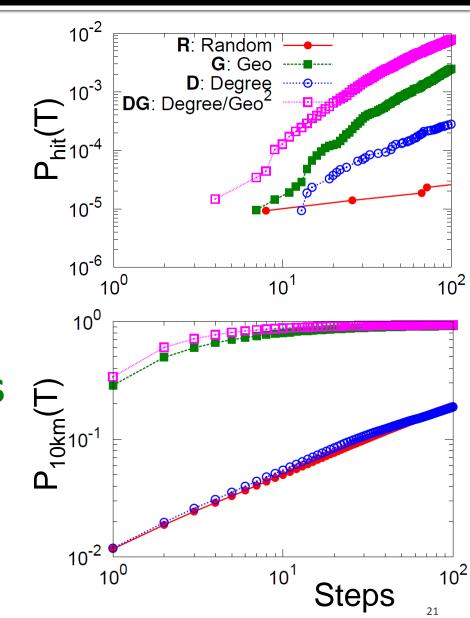
DG: $\min \frac{geo(X,T)}{\deg^2(X)}$



Hitting vs. Getting Close

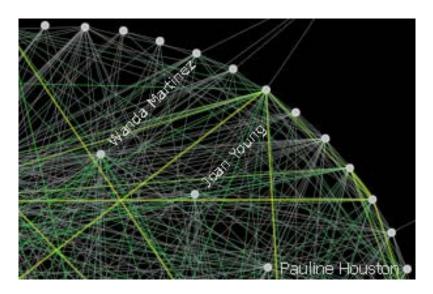
Bottom line:

- P(hit T in $\leq 10 \text{ steps}) = 0.001$
- P(get in 10km of T in \leq 10 steps) = 1
- Geography provides an important cue but fails in local neighborhoods



Information Networks

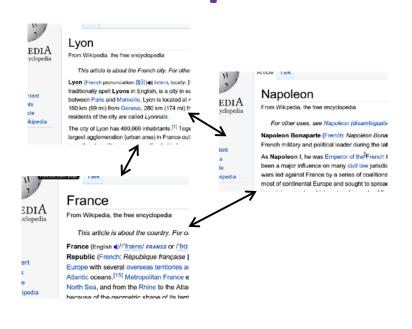
- How do these translate to navigation in information networks?
 - Web-browsing
 - Encyclopedia navigation



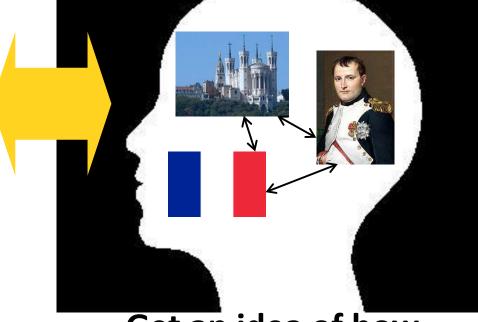


Navigating Information Nets

Large-scale study of navigation in Wikipedia

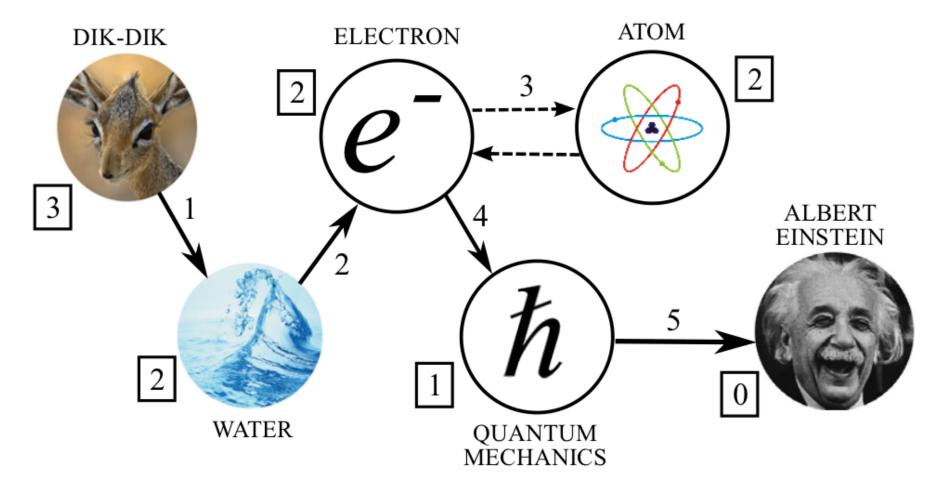


Understand how humans navigate Wikipedia



Get an idea of how people connect concepts

Navigating Wikipedia



Goal-directed navigation of Wikipedia

Optimal solution: (DIK-DIK, WATER, GERMANY, EINSTEIN)

Wikispeedia



6/28/2012

Wikispeedia: Statistics

- Graph: "Wikipedia Selection for schools"
 - 4,000 articles, 120,000 links
 - Shortest paths between all pairs: median 3, mean 3.2, max 9

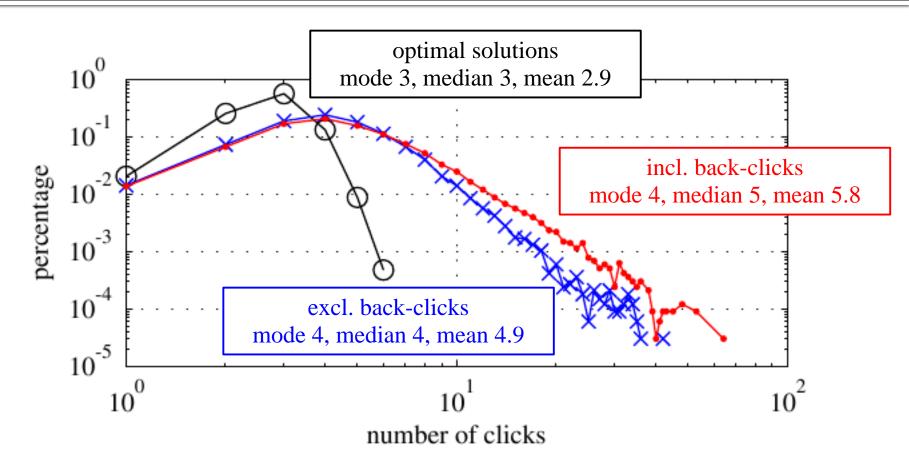
Wikispeedia

- 30,000 games since Aug 2009
- 9,400 distinct IP addresses
- Important:

We know the target!

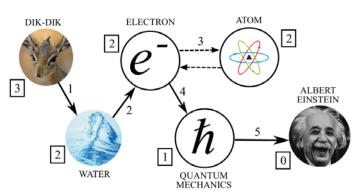


How good are humans?



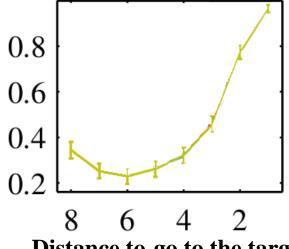
- Larger variance in human than opt. paths
- Overall, humans not much worse than opt.

Anatomy of Wayfinding

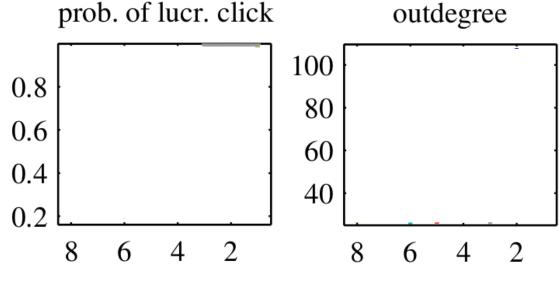


Only missions of SPL 3

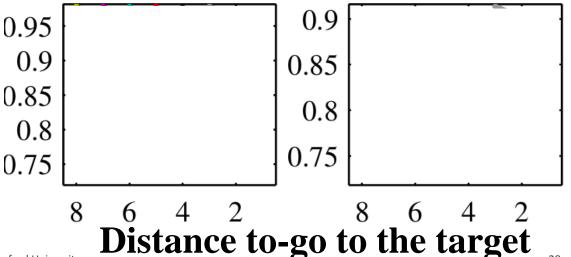
prob. of lucr. click



Distance to-go to the target

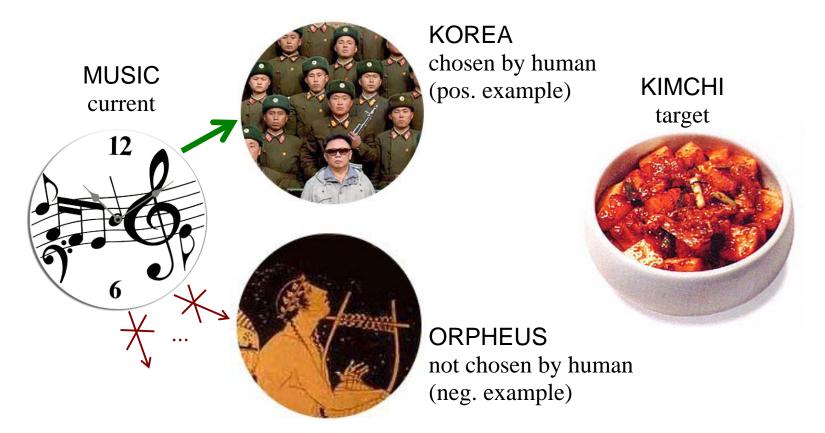


TF-IDF dist. to target TF-IDF dist. to next



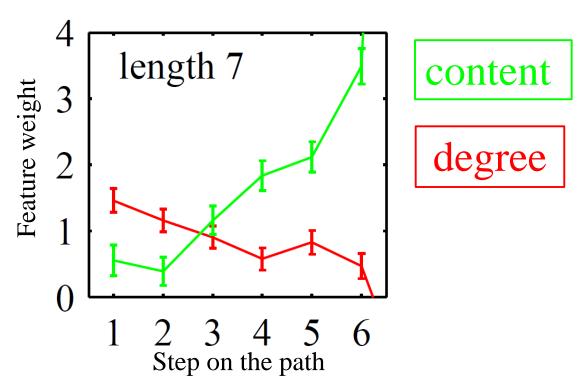
Content vs. the Network

- For each path position:
 - Logistic regression to predict human choice



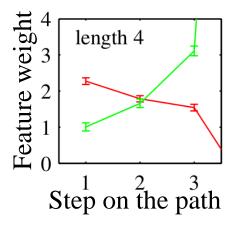
Content vs. the Network

- For each path position:
 - Logistic regression to predict human choice
 - Inspect weights for content similarity & degree



Content vs. the Network

- For each path position:
 - Logistic regression to predict human choice
 - Inspect weights for content similarity & degree



content degree

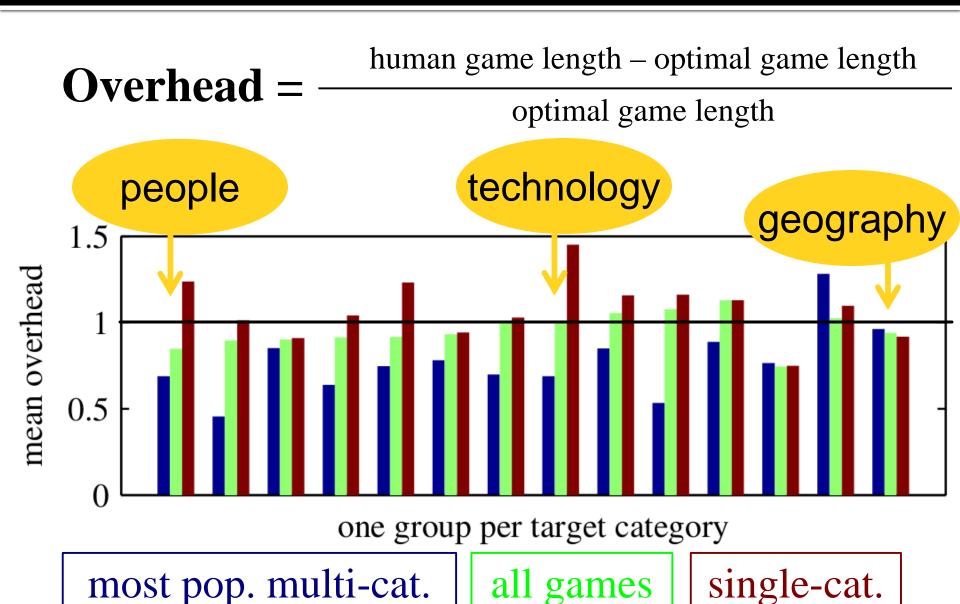
6/28/2012

Endgame Strategies

Path:

- $... \rightarrow$ Water \rightarrow Germany \rightarrow Albert Einstein
- Endgame strategy:
 - Map last 3 articles to categories:
 - Science → Geography → People
- Few popular endgame strategies
 - (Target category)³ typically most popular
- Among non-target categories,
 Geography most popular

Endgame Efficiency



13

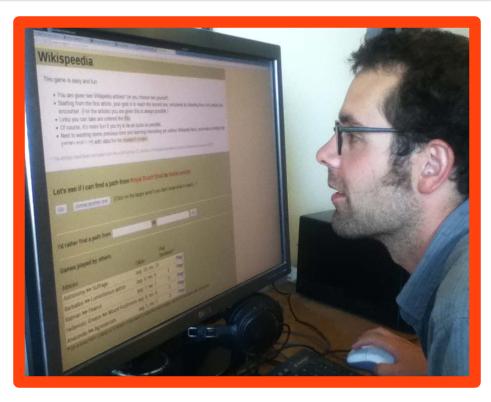
Machine vs. Human



Can we build machines that navigate better than humans?

Machine vs. Human

```
🗓 *WikispeediaAgent.java 🏻
       public Result play(String start, String goal)
           while (!stack.empty()) {
               // take node from stack:
               s = stack.pop();
               // remember when we've visited the curr
               nodeSequence.add(s);
               nodeSet.add(s):
               // we found what we're looking for, so
               // from the predecessor record:
               if (s.equals(goal)) {
                    return new Result(nodeSequence, pre
                            lucrativeClicks, goalDistHi
               // find the successors that haven't bee
               // Set<String> succ = Sets.diff(index.d
               Set<String> succ = Sets.diff(index.gets
               // no unvisited successors; this means
```



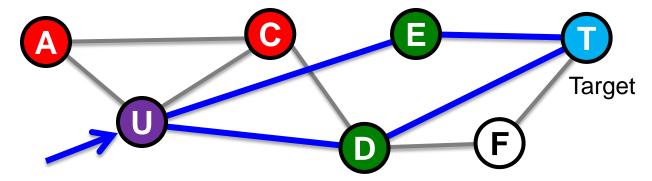
No common sense, only low-level knowledge such as word counts

Common sense and high-level background knowledge

Who is better?

Decentralized Agents

An agent aims to navigate to target T



 Agent is currently at node U and navigates to neighbor W s.t.

$$W = \arg \max_{U \to W} V(W|U,T)$$

- Ideally: V(E|U,T) > V(C|U,T)
- What is the value function?

Machine Agents

- (1) Human
- (2) Similarity based (TXT):
 - V(W|U,T) = tf-idf(W,T)
 - Go to W that is textually most similar to T
- (3) Machine learning agents (ML):
 - Use human/shortest paths to learn the value function
 - Support Vector Machines
 - Reinforcement Learning

Machine Learning Agents

- Features for the machine learning agents
 Inspired by analysis of human behavior
 - sim(next, target)

(TF-IDF cosine)

- sim(current, next)
- deg(next)
- taxdist(next, target)

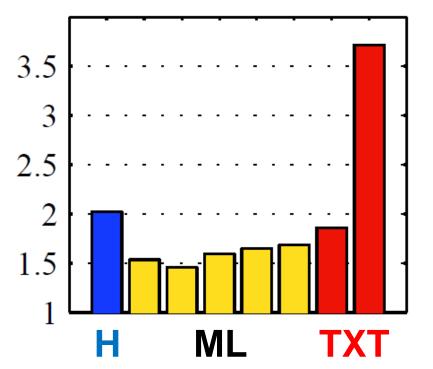
(taxonomical distance)

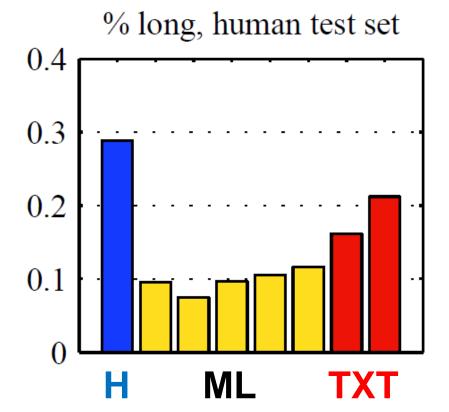
linkcos(next, target)

(cosine similarity in outgoing hyperlinks)

Results

overhead factor, human test set





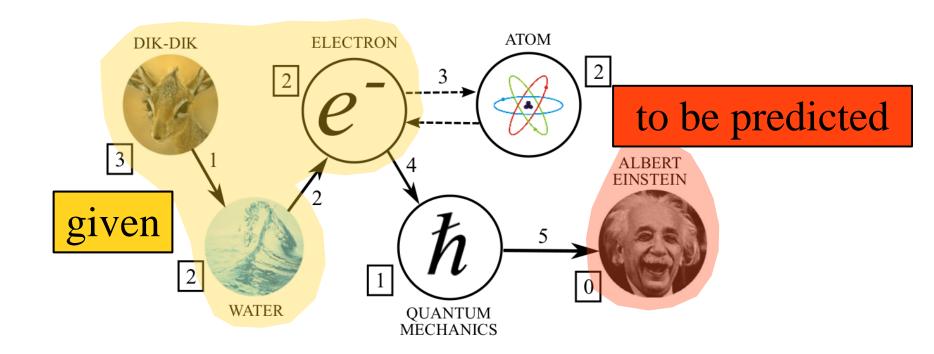
- Machine beats human!
- But, machines can get terribly lost
- Humans are sloppy (83% they miss a direct link)

Application: Target Prediction



Can we predict where the user is going?

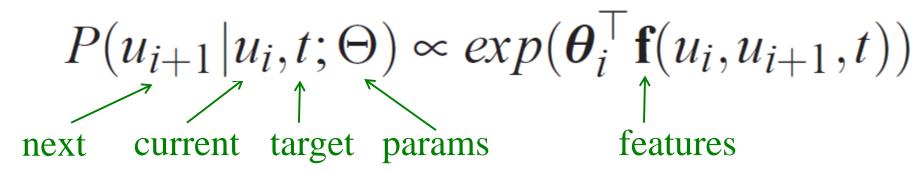
Application: Target Prediction



- Task: Given first few clicks
- Predict the target player is trying to reach

Model of Navigation

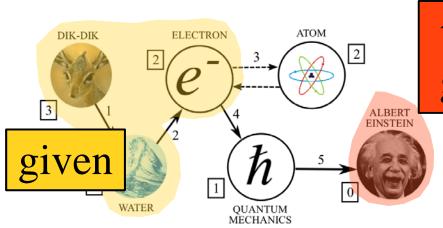
Markov model of human navigation



Predict the most likely target

$$\underset{t}{\operatorname{arg\,max}} P(q|t;\Theta) = \underset{t}{\operatorname{arg\,max}} P(u_1) \prod_{i=1}^{k-1} P(u_{i+1}|u_i,t;\Theta)$$
 given path prefix

Target Prediction: Training



to be predicted & given for training

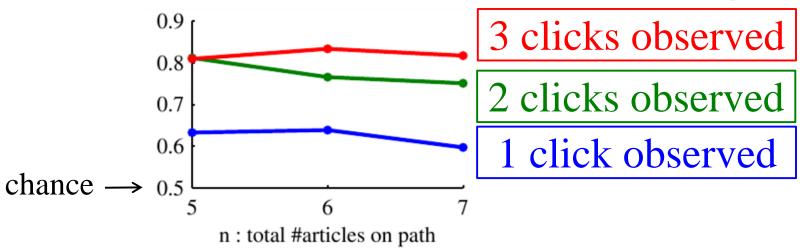
Fit ⊕ in learning-to-rank setup [Weston et al. '10]

initial Θ final Θ Kimchi Gopher training Football Albert Einstein Orpheus

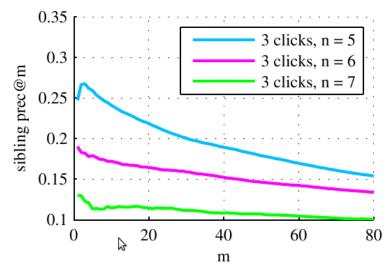
Albert Einstein

Target Prediction: the Model

Given choice of 2, choose true target



 Rank articles such that true target gets high rank



Conclusion: Navigation

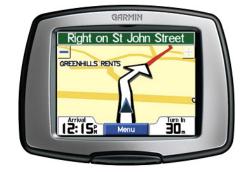
- Humans manage to find their ways in large networks, despite having only local information
- How do they do it?
- Analyze large-scale data from the MSN network and Wikispeedia game
- Answer: They leverage expectations about network connectivity, based on background knowledge

Reflections: Navigation

- Computational ideas play 2 crucial roles
 - Designing systems in this new space
 - Modeling the social processes
- Designing systems: Search engines
 - User click-trails for web search ranking [Bilenko-White, '08]
 - Web revisitation patterns for crawling [Adar et al. '08]

Reflections: Navigation

- Designing systems: Navigational tools Is user lost? Where is she trying to go?
 - User facing tools and browsers:
 ScentTrails [Olston-Chi, '03]
 - Creating navigable networks
 - Navigable maps, ontologies
 [Helic-Strohmaier et al., '11]
 - Social browsing



Enter chat here

Final Reflections

- Models: How we search for information
 - Information scent [Chi et al., '01]
 - Information foraging [Pirolli, '99]



- Targeted search vs. Casual browsing
- Can all this help us understand ourselves and each other any better?





