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PageRank (Google)



Sergey Brin

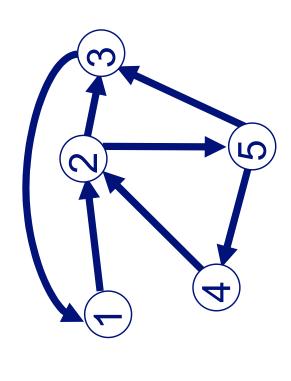
Larry Page

Search Engine. 7th Intl World Wide Web Conf. Anatomy of a Large-Scale Hypertextual Web Brin, Sergey and Lawrence Page (1998).

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PageRank: Problem

Given a directed graph, find its most interesting/central node

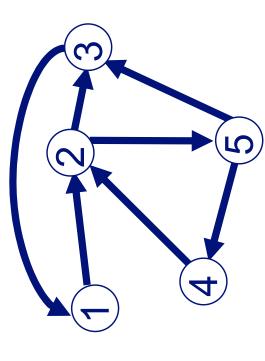


A node is important, if it is connected with important nodes (recursive, but OK!)

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PageRank: Solution

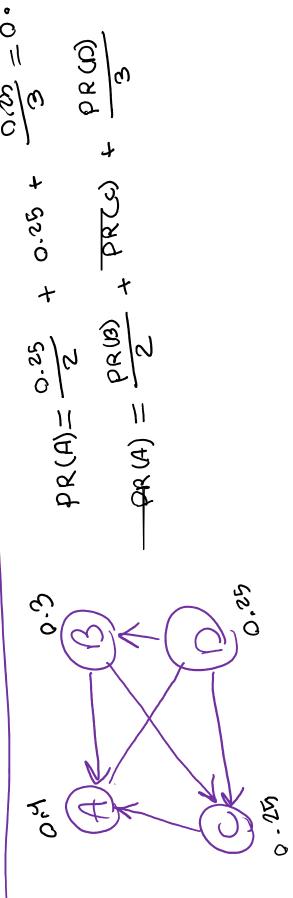
Given a directed graph, find its most interesting/central node Proposed solution: use random walk; most "popular" nodes are the ones with highest steady state probability (ssp)



with important nodes A node is important, (recursive, but OK!) if it is connected

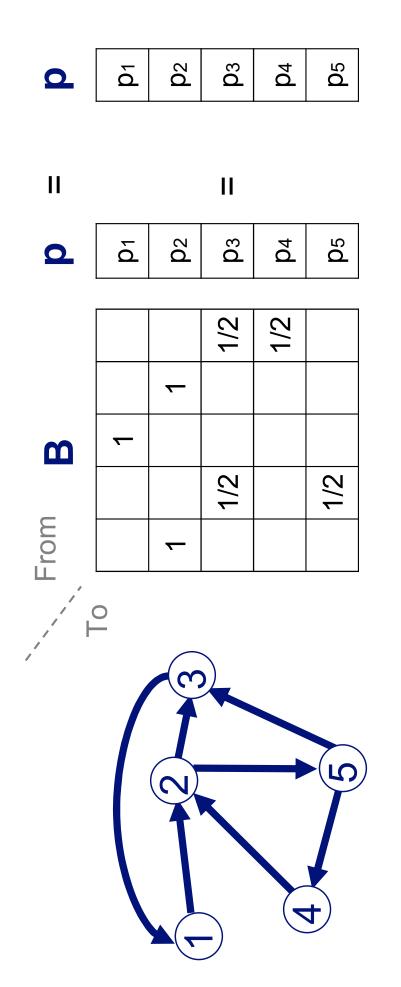
"state" = webpage

$$\frac{1}{4} = 0.05$$
 $\frac{1}{4} = 0.05$
 $\frac{1}{4} = 0.05$



(Simplified) PageRank

Let **B** be the transition matrix: transposed, column-normalized



How to compute SSP:

https://fenix.tecnico.ulisboa.pt/downloadFile/3779579688473/6.3.pdf

http://www.sosmath.com/matrix/markov/markov.html

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(Simplified) PageRank

3 p = 1 * p

Thus, **p** is the **eigenvector** that corresponds to the highest eigenvalue (=1, since the matrix is column-normalized)

Why does such a p exist?

p exists if B is nxn, nonnegative, irreducible [Perron-Frobenius theorem]

(Simplified) PageRank

- In short: imagine a person randomly moving along the edges/links
- A node's PageRank score is the steady-state probability (ssp) of finding the person at that node

Full version of algorithm:

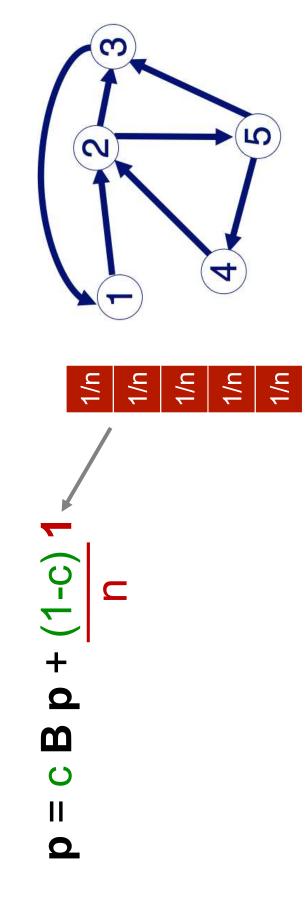
With occasional random jumps to any nodes

Why? To make the matrix irreducible.

Irreducible = from any state (node), there's non-zero probability to reach any other state (node)

Full Algorithm

With probability 1-c, fly-out to a random node Then, we have



How to compute PageRank for

huge matrix?

Use the power iteration method http://en.wikipedia.org/wiki/Power iteration

$$p = c B p + (1-c) 1$$

 \mathbf{m}

p1	p2	p3	p4	p5
		1/2	1/2	
	П			
		1/2		1/2

S

p3

p4

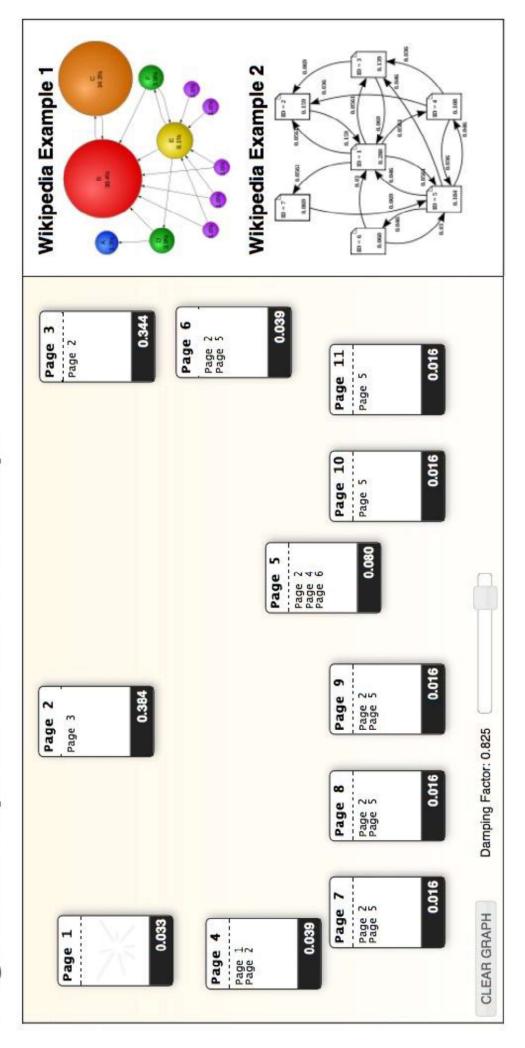
p5

p2

(1-c)

Can initialize this vector to any non-zero vector, e.g., all "1"s

PageRank Explained with Javascript



Also great for checking the correctness of your PageRank Implementation.

PageRank for graphs (generally)

You can run PageRank on any graphs

All you need are the graph edges!

Should be in your algorithm "toolbox"

Better than degree centrality

 Fast to compute for large graphs, runtime linear in the number of edges, O(E)

But can be "misled" (Google Bomb)

How?

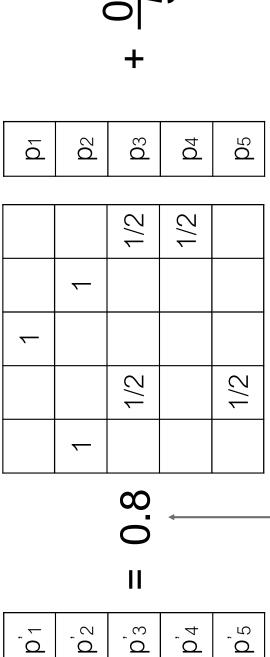
Personalized PageRank

Intuition: not all pages are equal, some more relevant to some people

Goal: rank pages in a way that those more relevant to you will be ranked higher How? Make just one small change to PageRank

a random node some preferred nodes With probability 1-c, fly-out to

$$p' = c B p + (1hc) 1$$



<u> </u>	~	~	~	<u></u>			
+ 0.2							

Default value for c

Can initialize this vector to any non-zero vector, e.g., all "1"s

Why Learn Personalized PageRank?

For recommendation

- If I like webpage A, what else do I like?
- If I bought product A, what other products would I also buy?

Visualizing and interacting with large graphs

Instead of visualizing every single nodes, visualize the most important ones

Very flexible — works on any graph

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Related "guilt-by-association" / diffusion techniques

- Personalized PageRank
- (= Random Walk with Restart)
- "Spreading activation" or "degree of interest" in Human-Computer Interaction (HCI)
- (powerful inference algorithm, for fraud detection, image segmentation, errorcorrecting codes, etc.) Belief Propagation

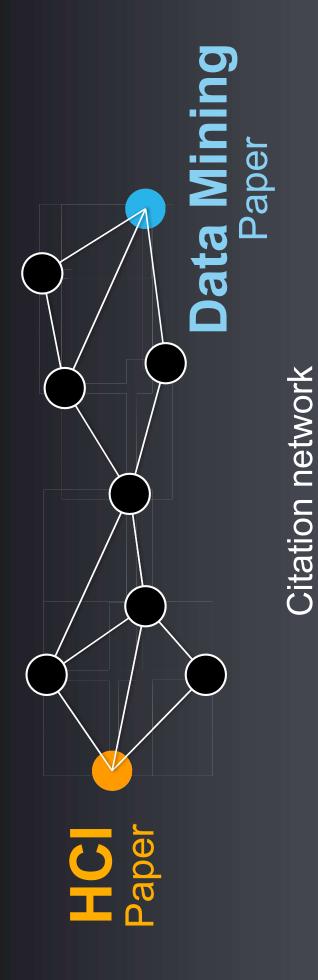
Why are these algorithms popular?

- Intuitive to interpret
- uses "network effect", homophily
- Easy to implement
- math is relatively simple (mainly matrixvector multiplication)
- Fast
- run time linear to #edges, or better
- Probabilistic meaning

Human-In-The-Loop Graph Mining

Learning + Visualization Machine CHI 2011 Apolo: Making Sense of Large Network Data by Combining Rich User Interaction and Machine Learning

Finding More Relevant Nodes

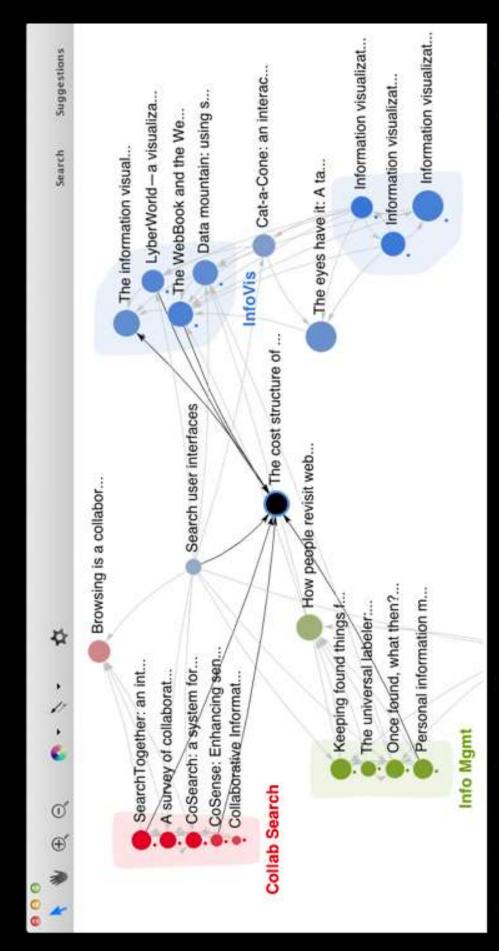


Apolo uses guilt-by-association

(Belief Propagation, similar to personalized PageRank)

Demo: Mapping the Sensemaking Literature

Nodes: 80k papers from Google Scholar (node size: #citation) **Edges**: 150k citations



The cost structure of sensemaking

Russell, D.M. and Stefik, M.J. and Pirolli, P. and Card, S.K.

245 citations 8 versions

ı



The cost structure of sen...

1997

The structure of the information...

Card, S.K. and Mackinlay, J.

The information visualizer, an inf... 1991

Card, S.K. and Robertson, G.G. and Macki...

Card, S.K. and Robertson, G.G. and York, W.

LyberWorld—a visualization user...

Hemmje, M. and Kunkel, C. and Willett, A.

The WebBook and the Web Forag...

2009

Card, S. and Mackinlay, JD and Shneiderm...

Information visualization

1995

An organic user interface for sear...

Mackinlay, J.D. and Rao, R. and Card, S.K.

1997

Moran, T.P. and Palen, L. and Harrison, S....

"I"ll get that off the audio": a cas...

PDF 1

Russell, D.M. and Stefik, M.J. and Pirolli, P. and Card, S.K.

8 versions

245 citations

The cost structure of sensemaking

Jigsaw: Supporting investigative... Stasko, J. and Görg, C. and Liu, Z.

2008

Investigating behavioral variabilit... 2007

White, R.W. and Drucker, S.M.

2007

Information foraging theory: Ada...

Pirolli, P.

2007

SearchTogether: an interface for c...

Morris, M.R. and Horvitz, E.

2007

Personal information management

Jones, W.P. and Teevan, J.

Using a landscape metaphor to re... 1993

Chalmers, M.

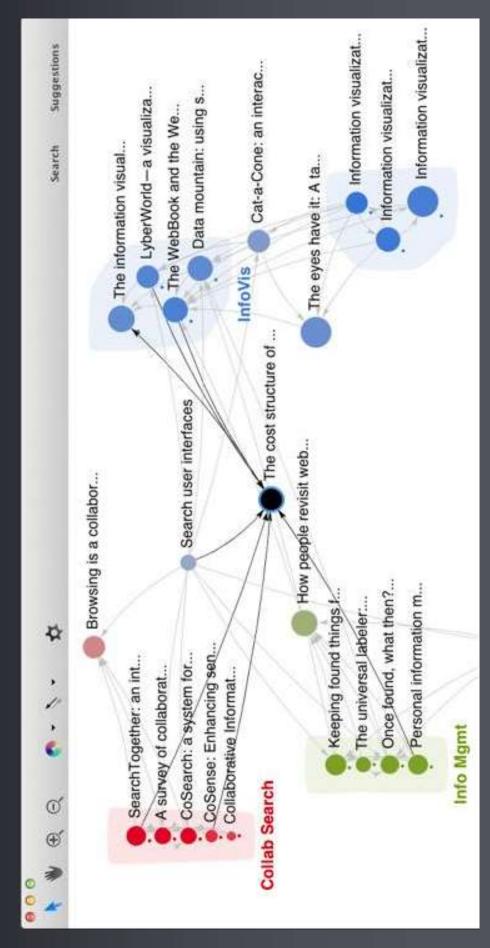
The cost-of-knowledge character... 1994
Card, S.K. and Pirolli, P. and Mackinlay, J.D. 54

Collaborative conceptual design:... 1996
Potts, C. and Catledge, L. 45

googlescholar.db

Key Ideas (Recap





Apolo's Contributions

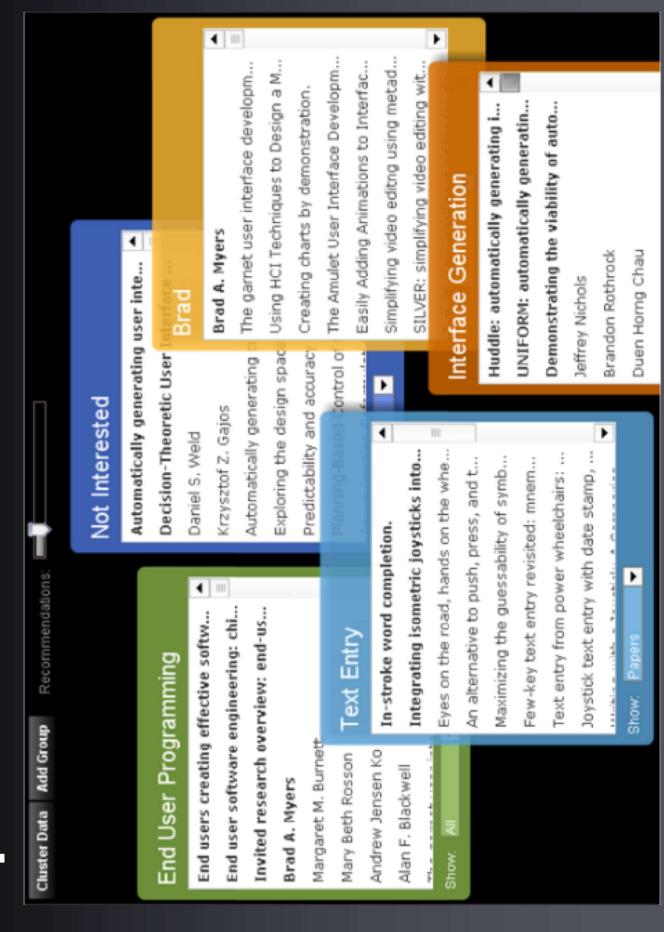
Human + Machine

partnership with the machine. It was like having a

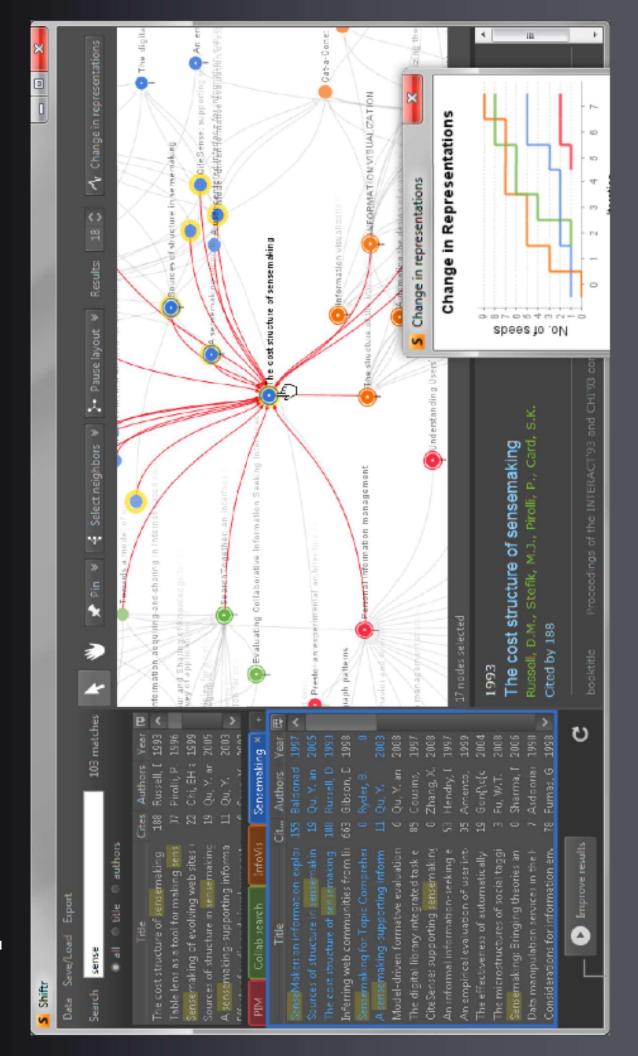
Apolo User

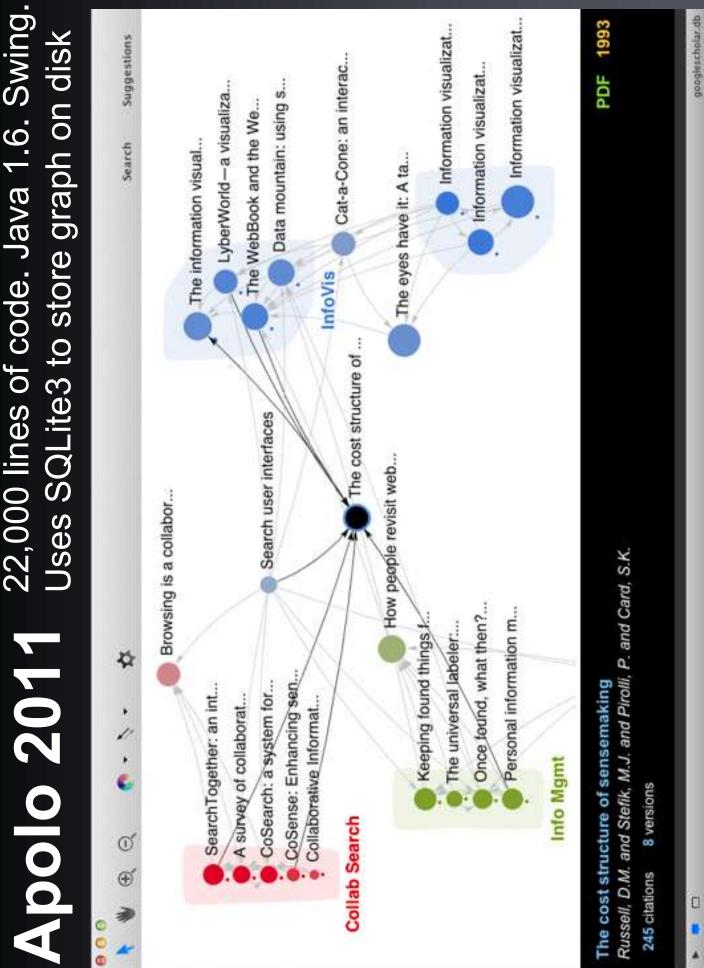
Personalized Landscape

Apolo 2009



Apolo 2010





User Study

Used citation network

Task: Find related papers for 2 sections in

a survey paper on user interface

Model-based generation of Ul

Rapid prototyping tools

Past, Present and Future of User Interface Software Tools

Brad Myers, Scott E. Hudson, and Randy Pausch

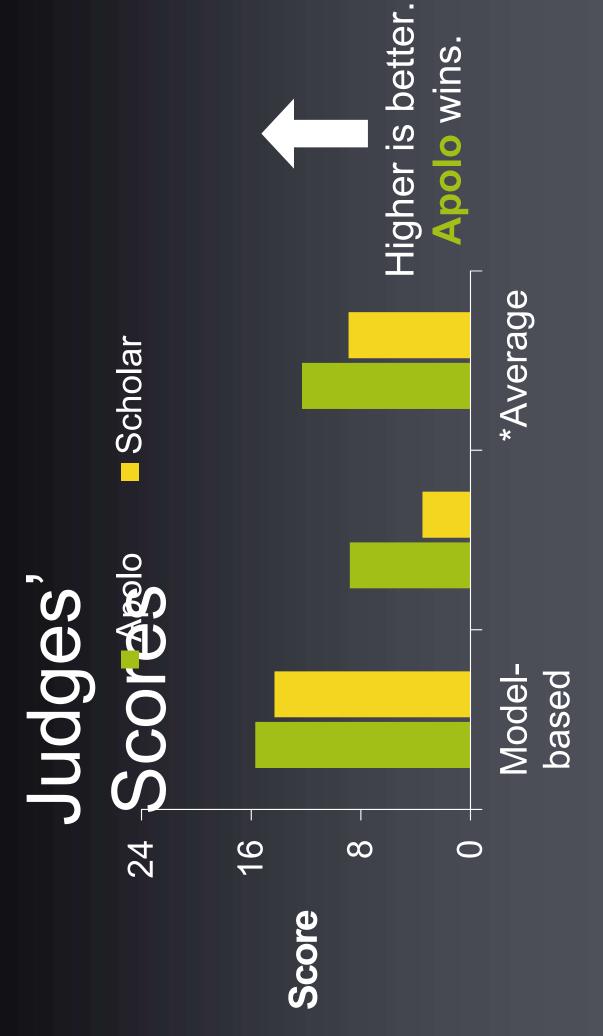
Human Computer Interaction Institute School of Computer Science Carnegie Mellon University



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Participants: **grad student** or **research staff**

Between subjects design



* Statistically significant, by two-tailed t test, p < 0.05

Practitioners' guide to building (interactive) applications

What kinds of **prototypes**?

Paper prototype, lo-fi prototype, high-fi prototype

Important to involve REAL users as early as possible

- Recruit your friends to try your tools
- Lab study (controlled, as in Apolo)
- Longitudinal study (usage over months)
- Deploy it and see the world's reaction!
- To learn more:
- CS 6750 Human-Computer Interaction
- CS 6455 User Interface Design and Evaluation

Practitioners' guide to building (interactive) applications

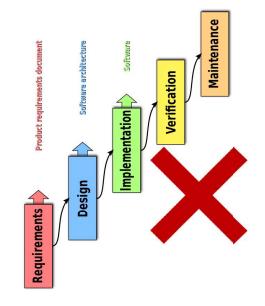
Think about scalability early

 Identify candidate scalable algorithms early on

Use iterative design approach, as in Apolo and industry

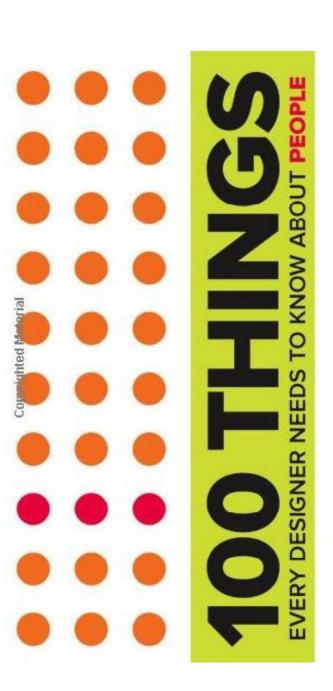
- Why? It's hard to get it right the first time
- Create prototype, evaluate, modify prototype, evaluate, ...
- important fixes early save you a lot Quick evaluation helps you identify of time overall

Waterfall model (software engineering)



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SUSAN M. WEINSCHENK, Ph.D.

