YAHOO!

The quantitative study of user behavior online

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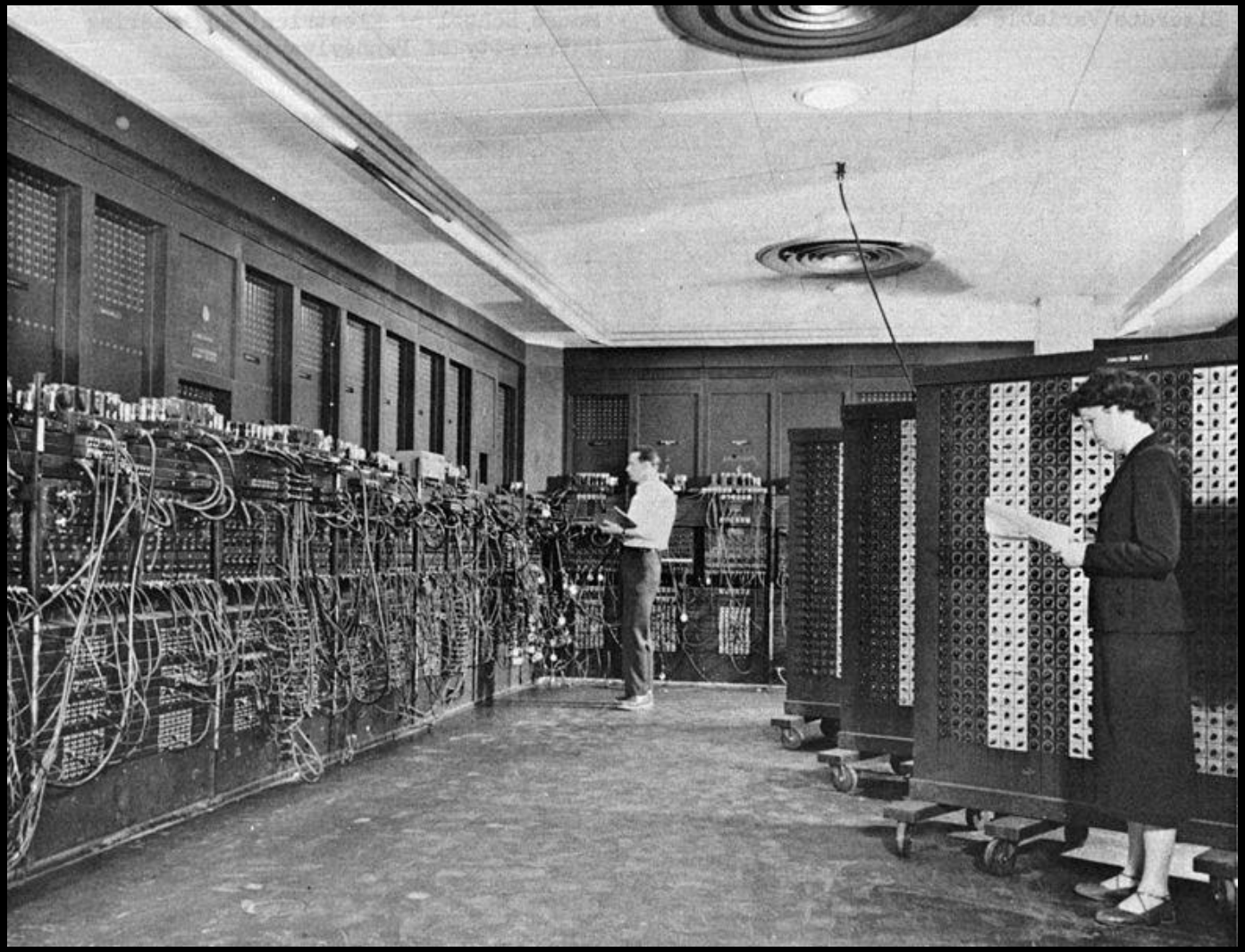
Over 50 years of computers



ENIAC: Less computing power than an iphone

Today – Yahoo! data center

Thousands of computers, each million times faster than ENIAC

Some trends

- Moore's Law: Computers double in speed every 18 months
  - Every 15 years, computers get 1000 times faster!!
- All information in the world about everything, is available everywhere, forever
  - The millions of computers at Google, Yahoo, Facebook, Amazon … are available to you all the time

The most important trend

- Most computer cycles are used
  - Not for computing …
  - … but for communications
  - Not by scientists or specialists
  - … but by ordinary consumers
- Ergo: the big question is not
  - What can be computed …
  - … but what users will do with computing

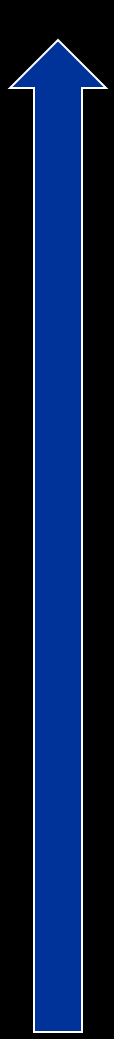
The scientific shift

- Computer scientists study computation
- Social scientists study people
- Now – we must study the combination!

In this lecture

- Some vignettes of such studies
- Why this is hard
  - But important
- The new opportunity: the Web
  - Biggest observatory of social behavior

Learning about users on the Web



- Lab/field studies
  - Eye-tracking, interviews
  - Pursue defined tasks
- Instrumented panels
  - Toolbars, clients
  - Log what users do on their own
- Click logs
  - Can experiment with interfaces
  - No clue why people click what they click

Grimes et al. 2007

- “the field study, the instrumented user panel, and the raw query log, provide complementary sources of data”
- “logs can only measure the how and the what, rather than the why. For example, if we have a sequence of queries, we only know the sequence of queries, but we have no evidence of why the user is typing in that particular sequence.”

Vignettes

General theme

- What questions can we answer by these methods?
- Quantitative sociology meets data mining

All behavior has social meaning
Alfred Adler

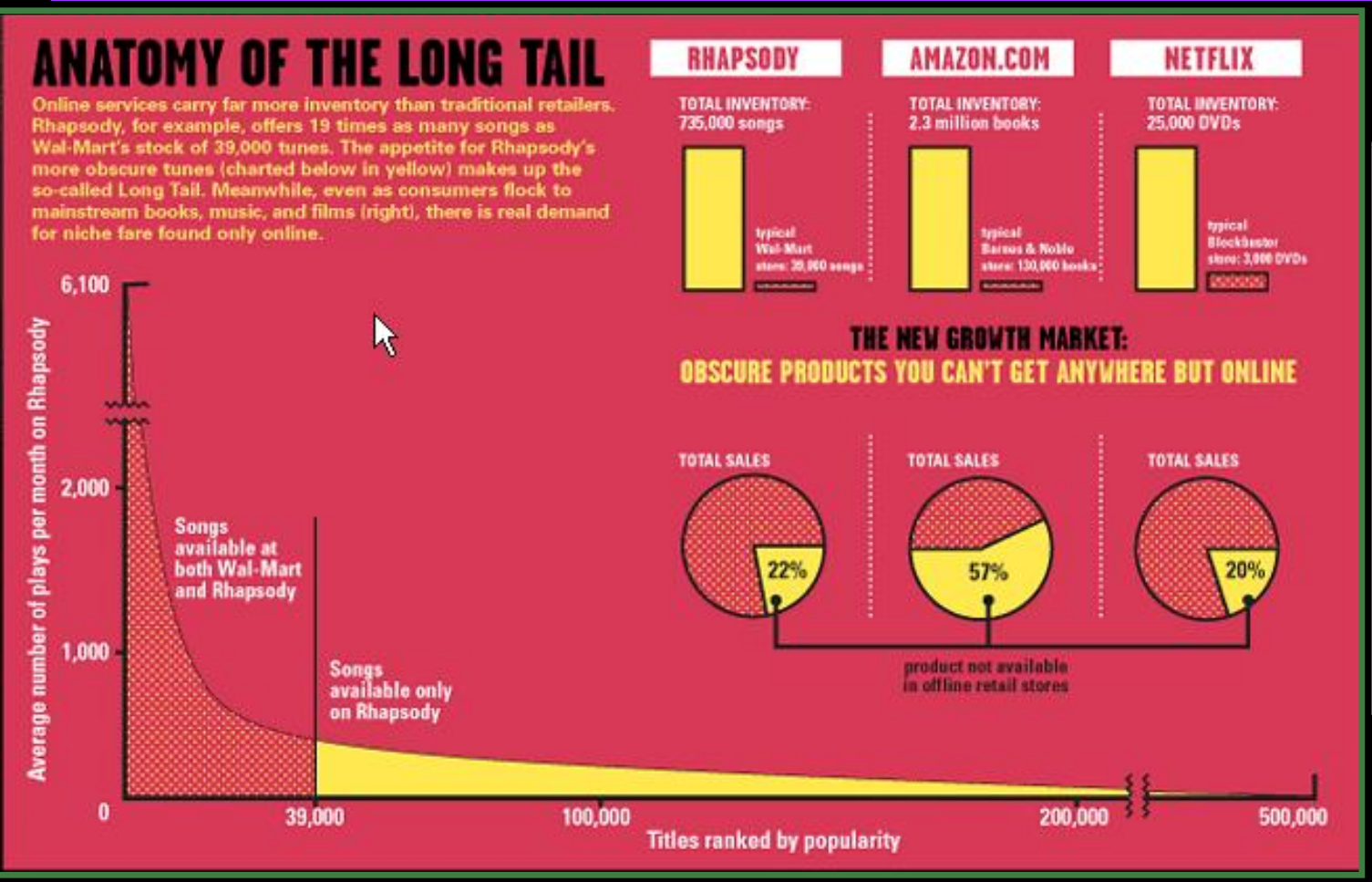
Long Tail, Heavy Tail?

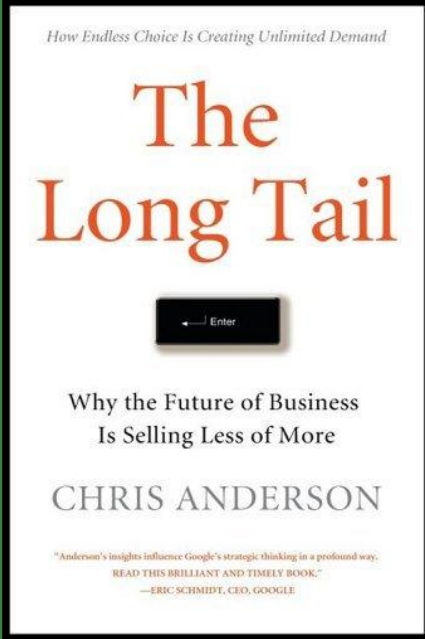
Observation:

Many products, each purchased very few times, together make up a large fraction of all purchases

Movies … Songs … Queries to a search engine ….

“The Long tail”

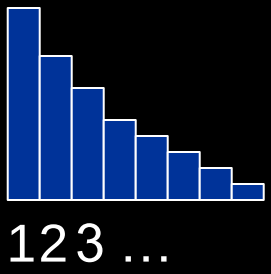




Chris Anderson, Wired, Oct 2004

Heavy tails

- Decreasing historgrams over numbers *[1,n]*
  - E.g., movie popularities

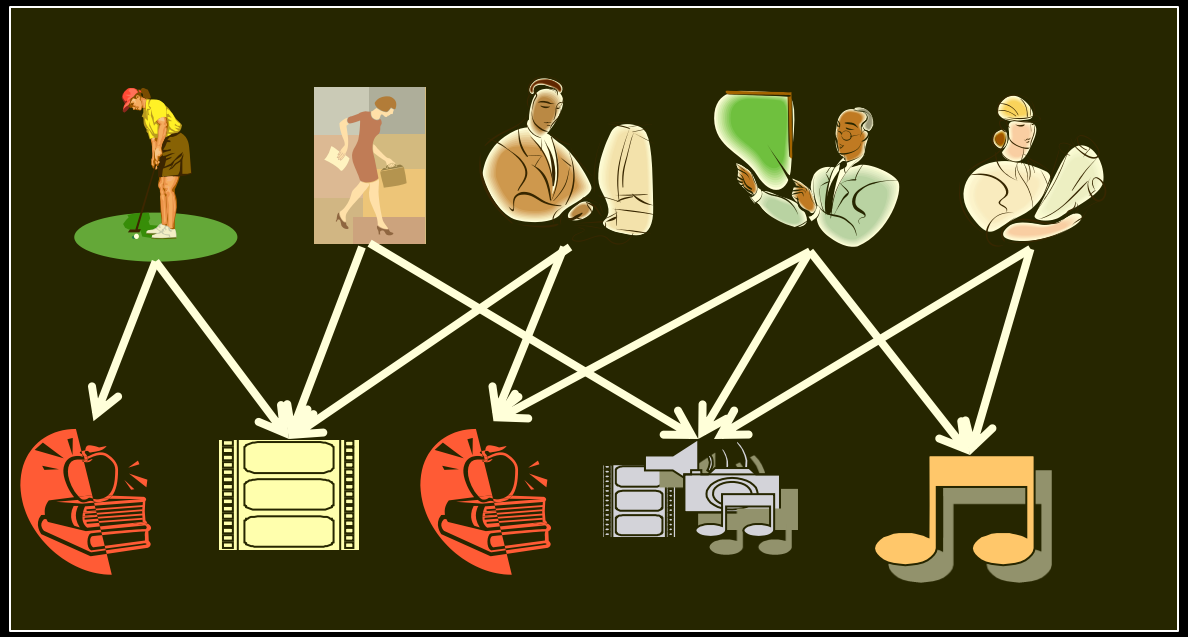


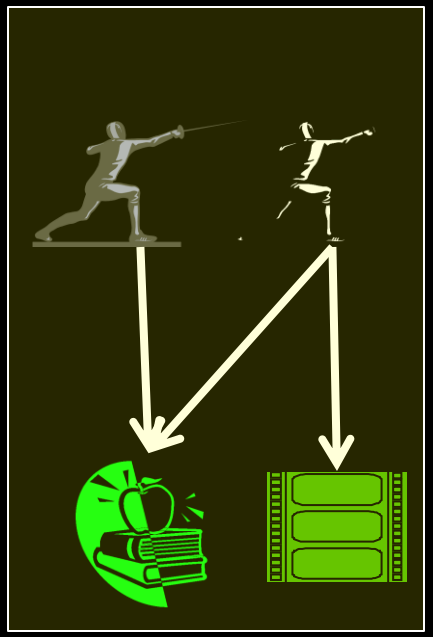
- For any fixed *k* (say, 10000), the fraction in all buckets >*k* is quite big
- Arise in observed statistics arising from human behavior
  - Number of friends, search queries, popular songs, books …

Heavy tail of user interests

- Many queries, each asked very few times, make up a large fraction of all queries
  - Movies watched, blogs read, words used …

One explanation





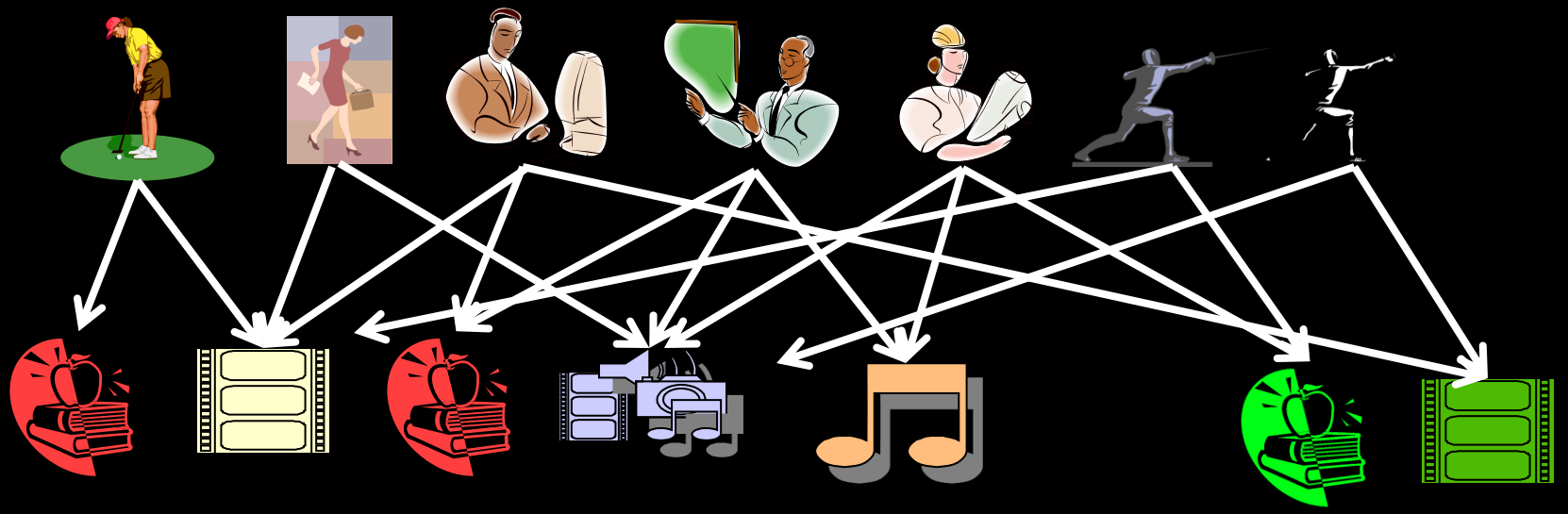
Normal people

Weirdos

Heavy tail of user interests

- Many queries, each asked very few times, make up a large fraction of all queries
  - Movies watched, blogs read, words used …

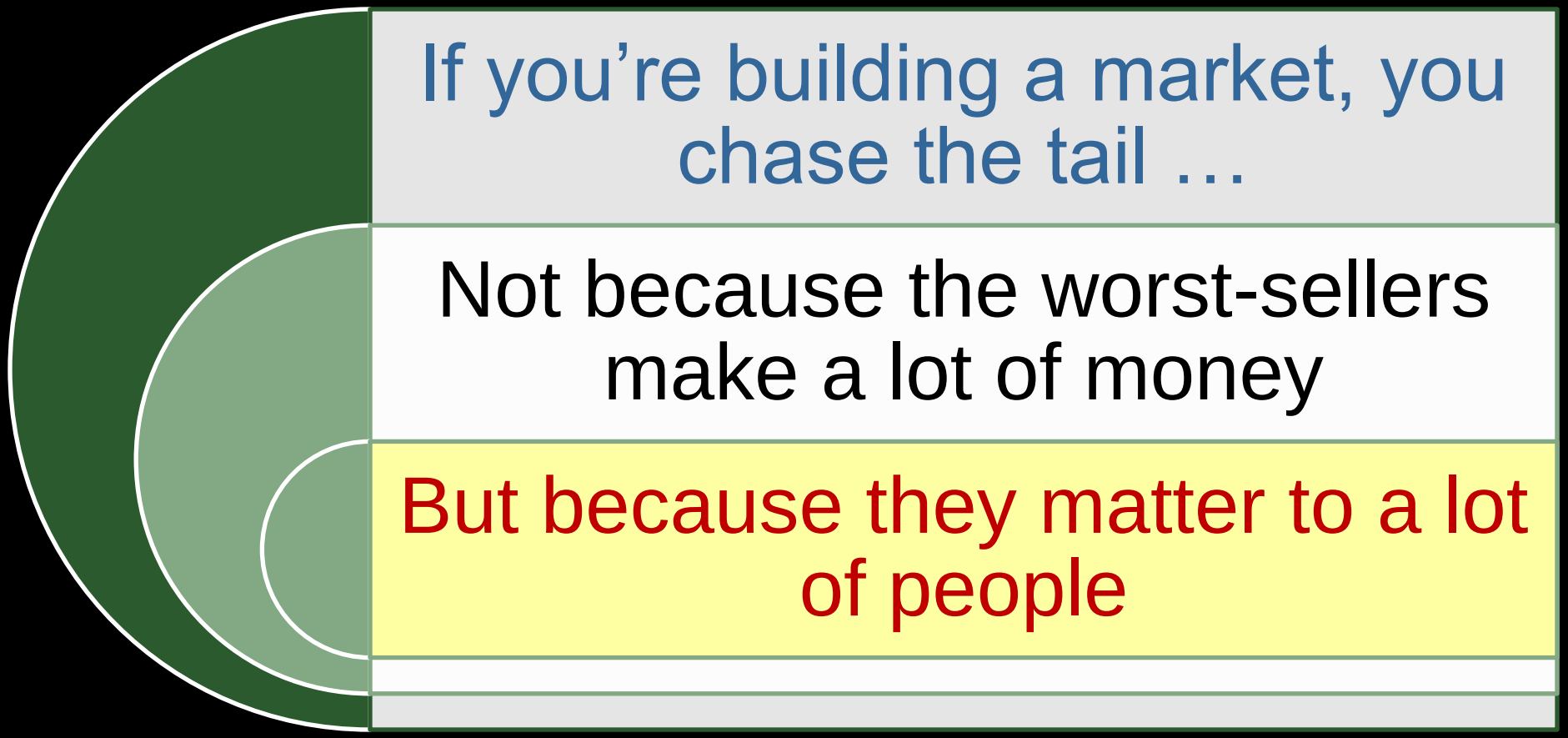
The reality



We are all partially weird!

Broder et al 2009

Why the heavy tail matters



The change for Computer Science

- Social phenomena repeatedly create such heavy tails
  - We can observe them on the Web at scale
  - Traditional analysis is inadequate
- We need a new style of analysis
  - New experimental tools
  - New mathematical tools

Social influence

Six degrees of separation ...

Social attention and influence

- In 1940's Paul Lazarsfeld :
  - "Who talks to whom about what, and with what effect?"
- Difficult to answer
  - Measuring "who talks to whom" hard at scale
  - Measure "who influences whom" even harder
- Web 2.0 brings the answer within reach
  - Fascinating implications for web companies, users … and for science

Is it a small world?

ORIGIN OF 6 DEGREES

- 1960's: Milgram and Travers "small world" experiment
- Subjects given letter for target individual
- Could only send to a friend
- Protocol generated 300 "letter chains" - 64 reached target
- Led to the famous "six degrees" phrase

6 DEGREES – WEB EDITION

- 2001-02: recreate w/email
- Milgram: one target, 300 chains
- Now: 18 targets around world, 24,163 chains, 61,168 hands, 166 countries
- 400 reached targets

Dodds *et al.* 2001

From Connections → Influence

Cultural Markets (songs …)

- "Hits" are many times more successful than average
  - Success seems obvious in retrospect, but hard to predict
- Can inequality and unpredictability be explained by social influence?
- Problem: Experiment would require 1,000s of participants
  - Each "market" requires hundreds of participants
  - Need to compare many markets

From Connections → Influence

- Experiment with subjects asked to rate new songs
- Control group: songs presented in random order
- Treatment group: songs presented in order of popularity for other users

Salganik et al. 2008, 2009

Influence in cultural markets

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

Influence and twitter

- Twitter is ideally suited to answer questions about influencers
  - Fully-observable network of individuals who explicitly opt-in to follow each other
  - Twitterers are expressly motivated to be influential
- Relatively easy to track diffusion
  - Popularity of URL shorteners means can track tweets over hops
- Objective is to predict influence as function of
  - # Followers, # Friends, # Reciprocated Ties
  - # Tweets, Time of joining
  - Past influence score

Watts et al. 2007 -

The Kardashian question

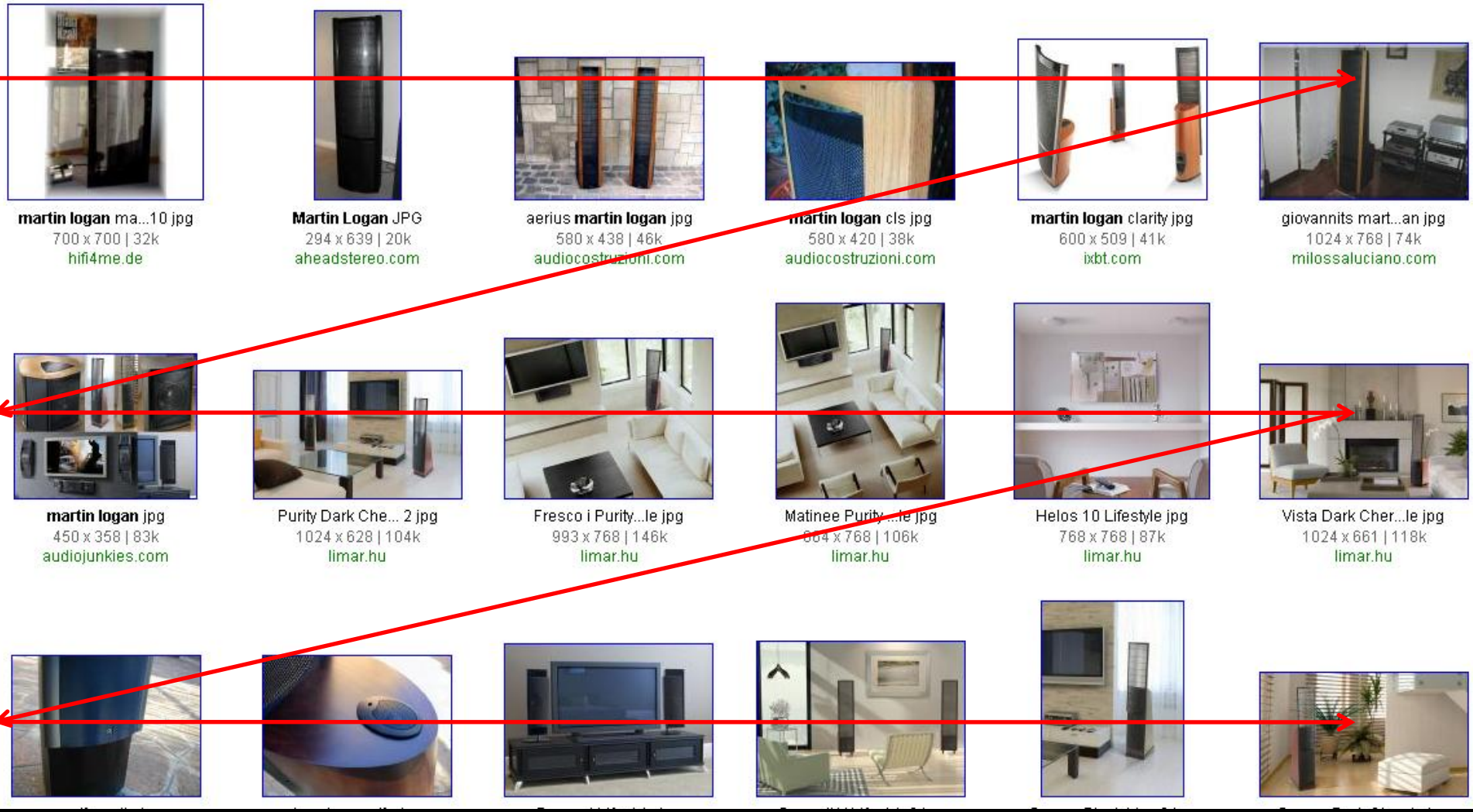
- Large cascades are rare, hence:
  - "Social epidemics" are extremely rare
  - Probably impossible to predict them or how they will start
  - Better to trigger many small cascades
- $10,000 per tweet isn't good value
- But "Ordinary Influencers" are promising
  - Only influence one other person on average
  - Average influence is close to zero (0.28)

Understanding the observations

- Can create model, prove theorems
- Can address “which influencers should we target?”
  - Can run experiments at scale
- But … no sociological understanding yet of why/how all this happens
  - No experimental loop

How users see search results

Image and product search



Ordered by decreasing score in row-major order

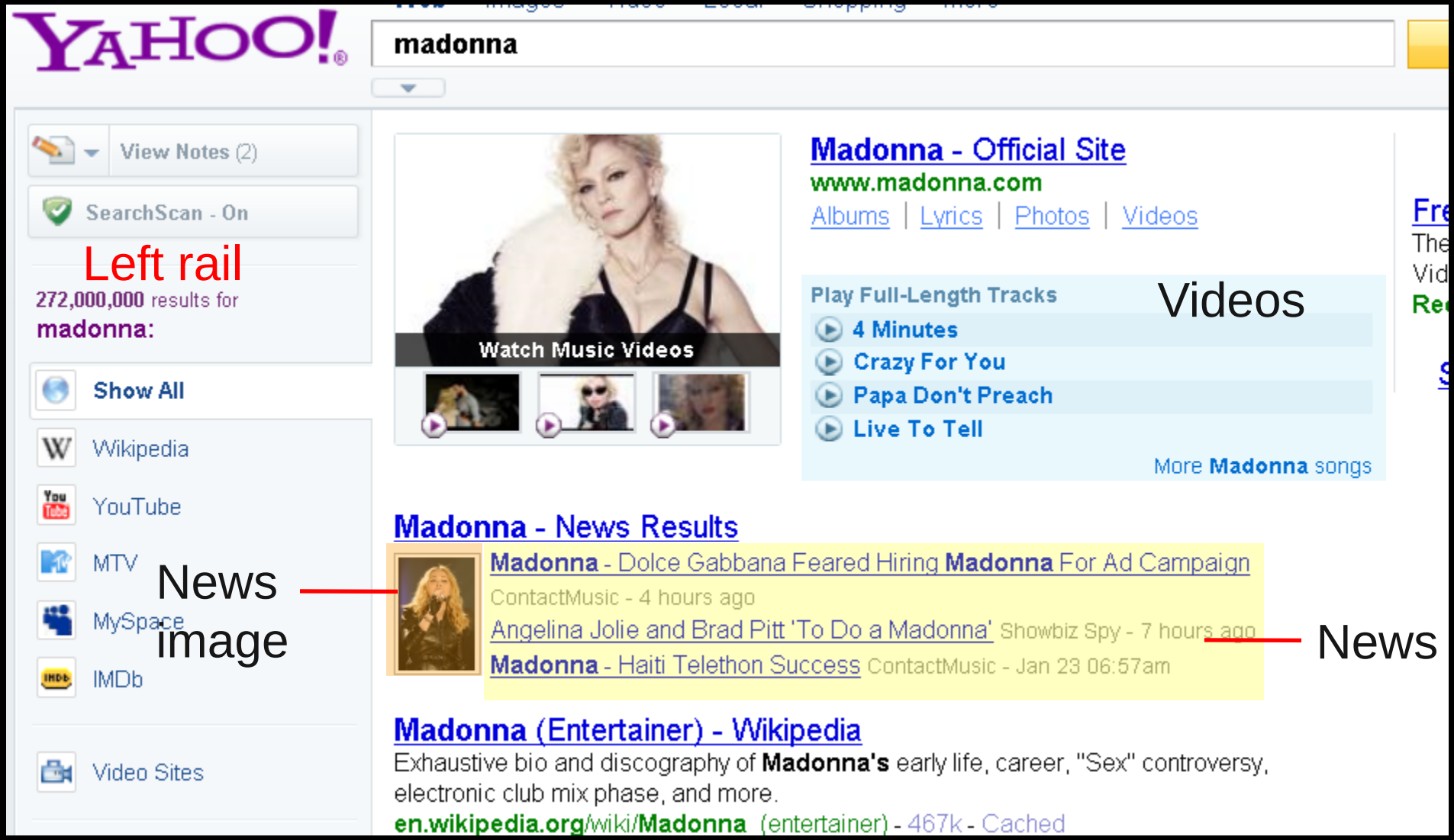
Users don’t see row-major

- Variety of evidence that users’ eye scans don’t go row-major
  - Eye tracking at search engines
- Visual cues not well understood
- Diversity

More general 2-d layout

- The problem goes beyond image/product results
  - Search engines doing general two-dimensional results presentation
  - Heterogeneous objects being laid out in the results page

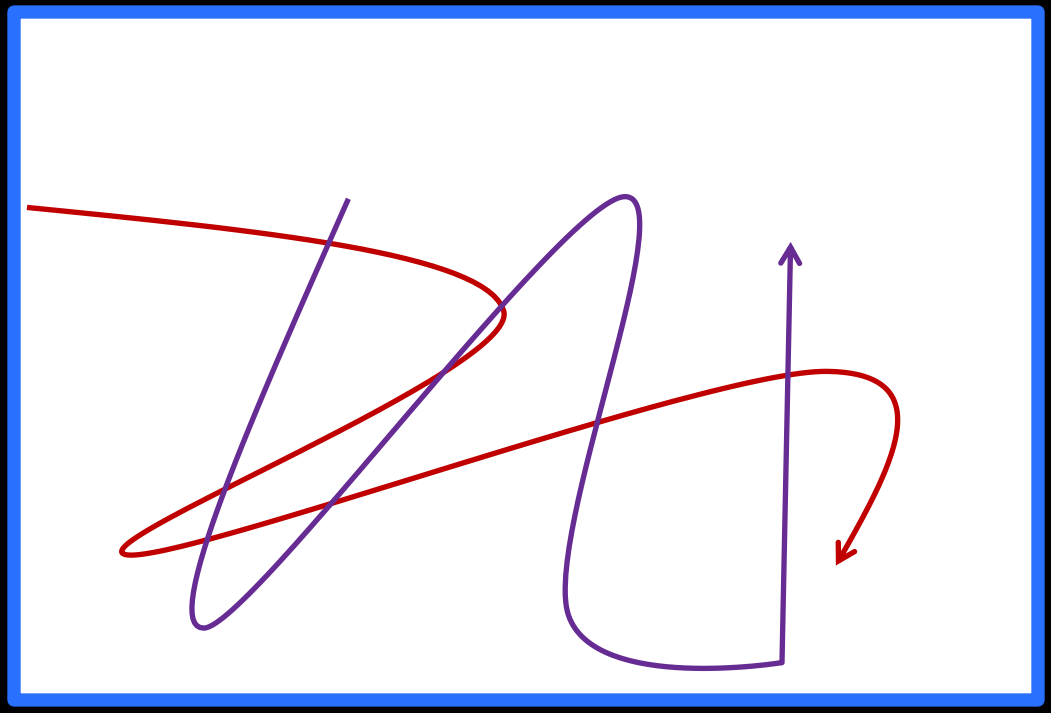
Richer use of 2-d real estate



How do we lay out all these links on the screen?

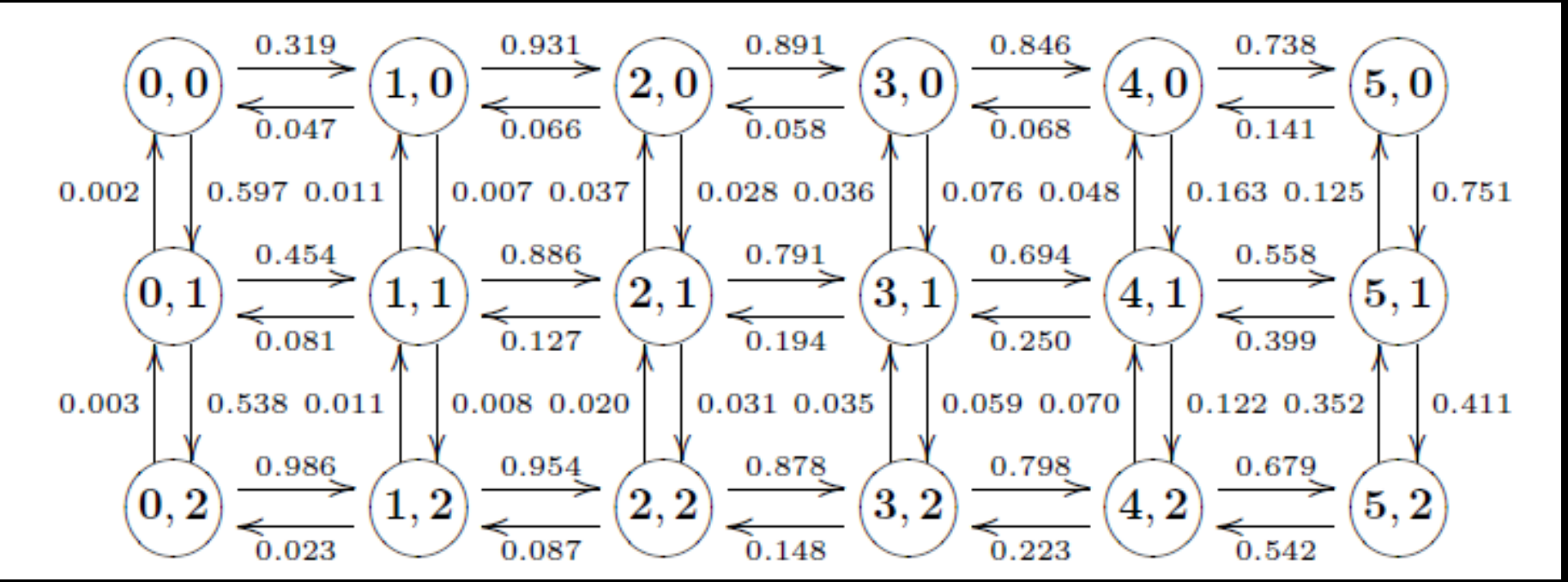
New approach +Chierichetti, Kumar

- Analyze click logs
  - Where do users click on the screen, and in what order



Analyze 100's of millions of users

Calculate a model of users

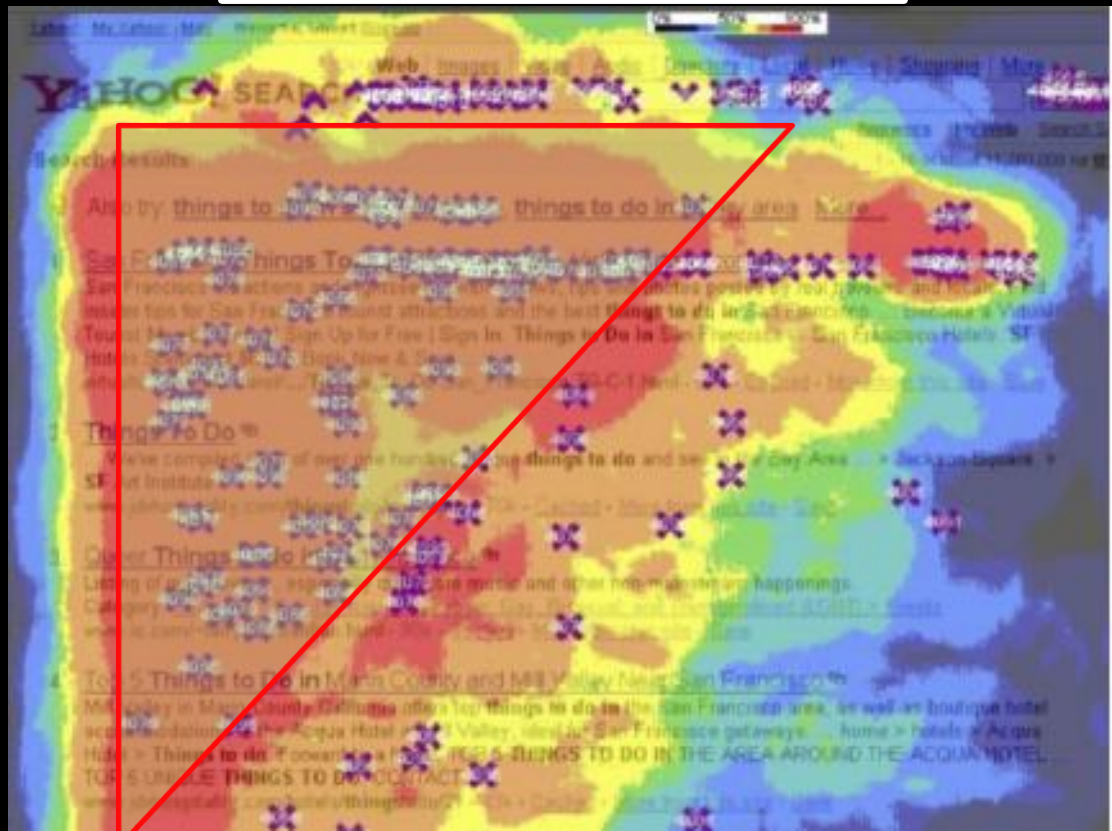


Model tells us where users' eyes go on the screen

What does this model tell us?

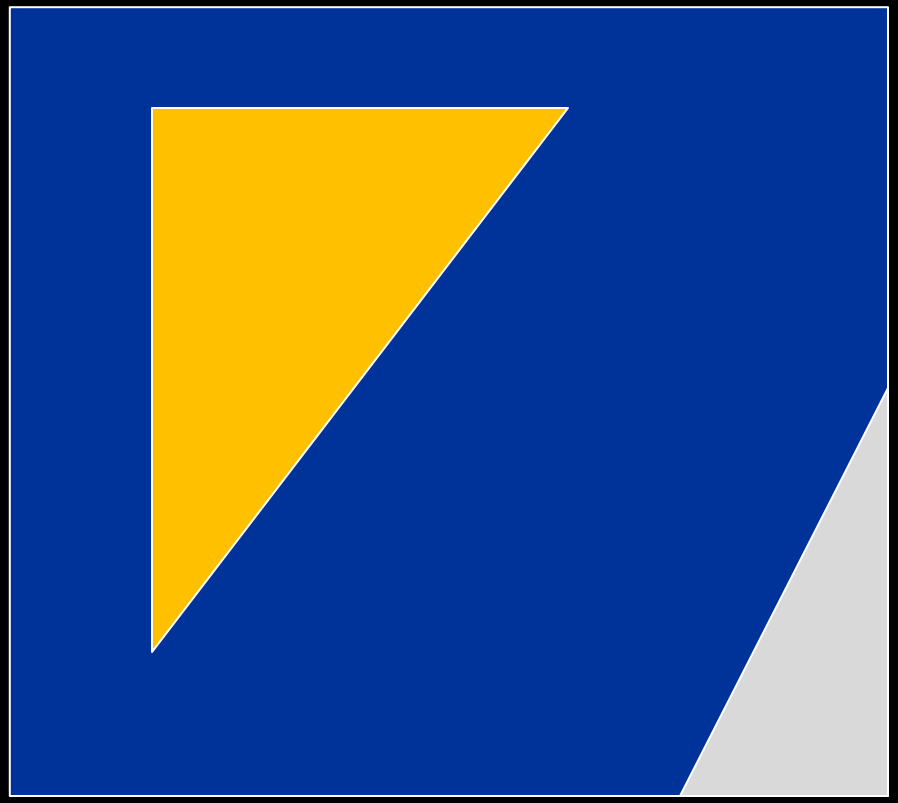
- Large scale validation of eye-tracking
  - First results page different from rest
  - *Golden* triangle

Eye tracking heat map

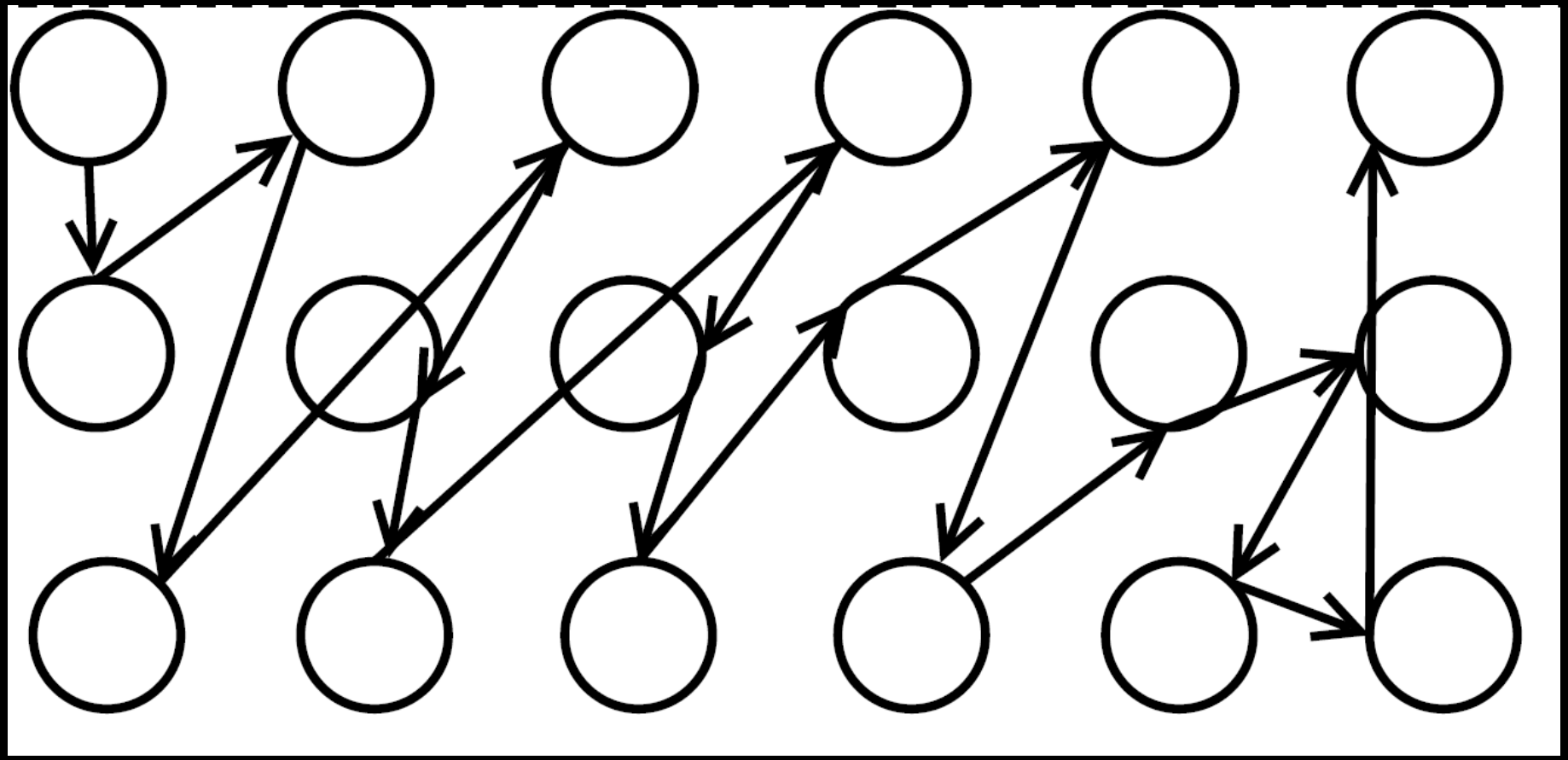


What's new

- Silver triangle
- Now can place images where users look



Where to put the images

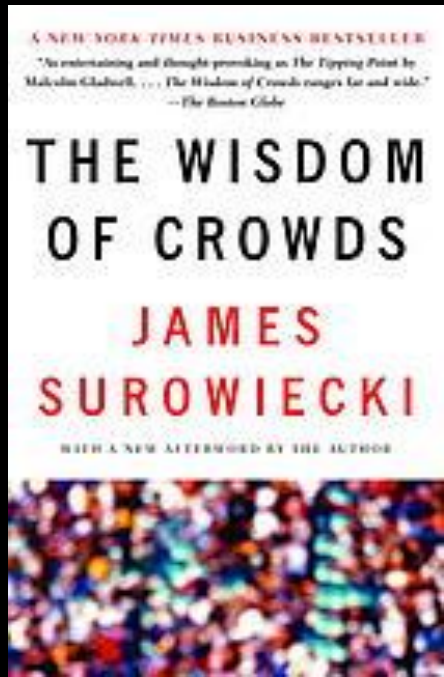


Prediction Markets

"The Wisdom of the Crowds"

Prediction markets

- Idea: a group of people can collectively make a prediction better than an expert
  - *The Wisdom of the Crowds*
- *E.g.,* employees in a project predict when the project will finish
  - Generally, a better prediction than the official project timeline!



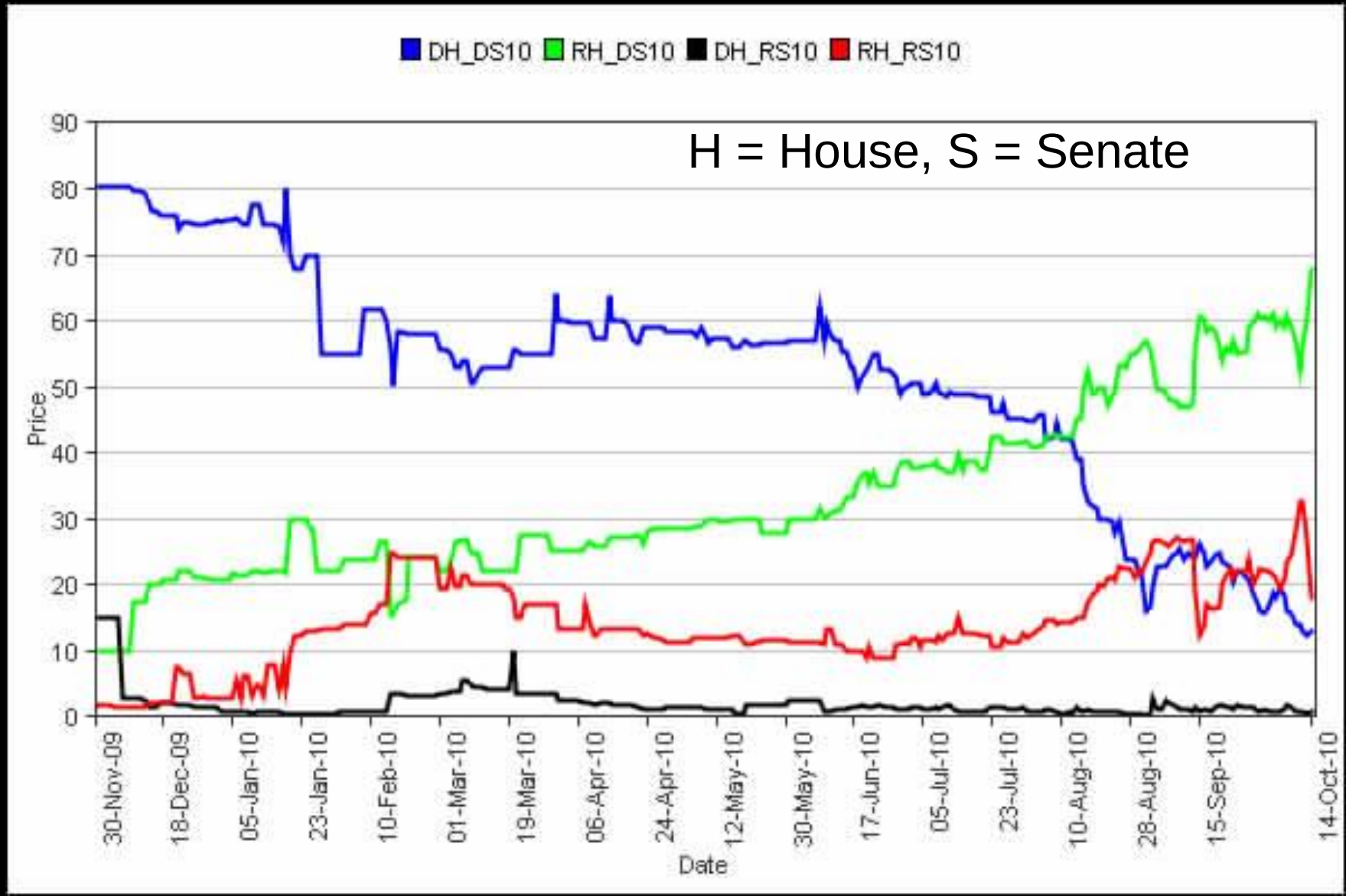
Prediction markets

- Markets where you buy/sell predictions
  - *E.g.,* “stock price” that the next AS Roma game will be a draw is 92 cents
  - Buy and sell stocks as crowd predicts
  - Over time, these prices are a good predictor of actual outcome
- Not an opinion poll!

Example: Iowa Electronic Markets

- Operated by the Business School at the University of Iowa
  - Used for academic studies
- Can buy/sell outcomes of US elections
- http://tippie.uiowa.edu/iem/index.cfm

IEM prices for 2010 US elections



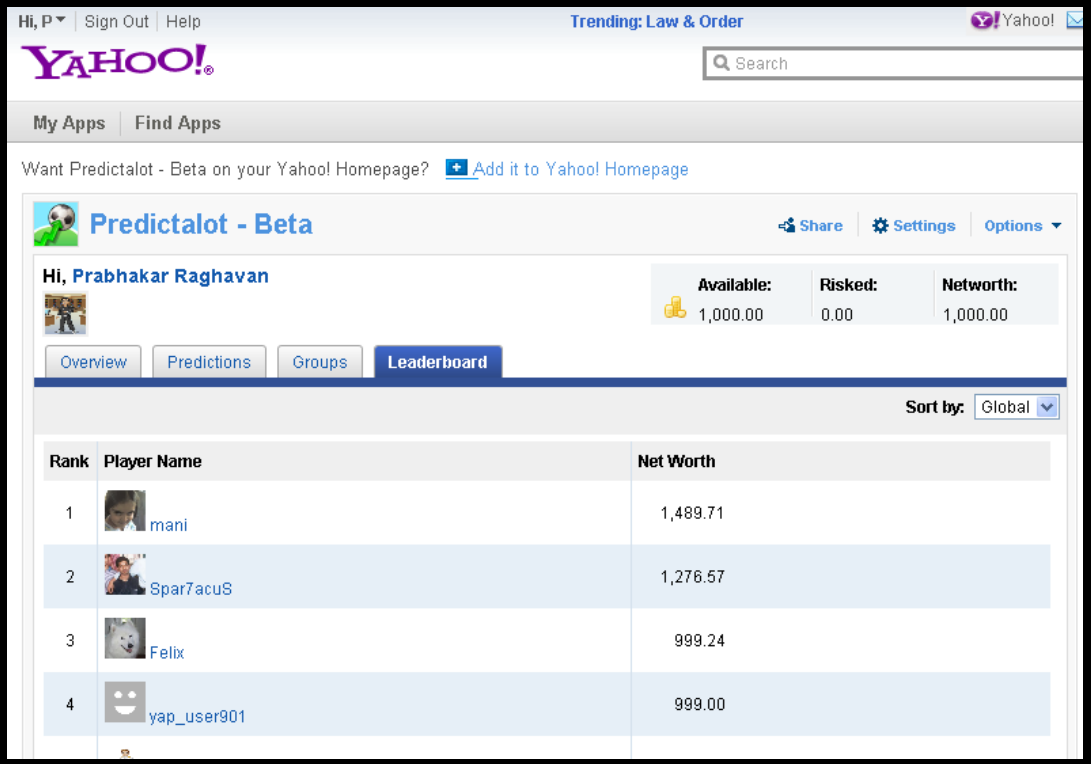
Are prediction markets truly powerful?

- Goel *et al.* 2010
  - Studied thousands of football games, music, …
- Prediction markets can be better than other techniques such as machine learning and polls
  - But the advantage is very slight
- Thus, the Wisdom of the Crowds may not be as powerful as believed!

Combinatorial prediction markets

Predictalot and variants

- **Can buy combinations: e.g., all four semi-final teams will be from Europe, etc.**
- **Predictions of various participants will interact**



Looking ahead …

What have we seen so far

- Many vignettes of human behavior
  - Studied at varying scales
- The Web affords us an observatory into social behavior

We have the Observatory

- What are some big questions?
  - Qualitative studies of user engagement
    - What do people want to do?
  - Quantifying user engagement
  - Inventing new genres of online experience
  - Optimizing user experiences
  - Whose happiness are we optimizing?
    - Social choice questions
    - Privacy

What are the academic challenges?

- Social scientists – study audiences at small scale, but deep understanding
- Computer scientists – large scale, but little understanding
- How can we combine these academic disciplines?

A new convergence

- Social sciences meet massive computing
  - Already happening in computational microeconomics

Grazie!

– http://labs.yahoo.com