

Design and Analysis of Large Scale Log Studies

A CHI 2011 course

v11

Susan Dumais, Robin Jeffries, Daniel M. Russell, Diane Tang, Jaime Teevan

CHI Tutorial, May, 2011

Introduction

Daniel M. Russell
Google

What Can We (HCI) Learn from Log Analysis?

- ▶ Logs are the traces of human behavior
 - ▶ ... seen through the lenses of whatever sensors we have
- ▶ Actual behaviors
 - ▶ As opposed to recalled behavior
 - ▶ As opposed to subjective impressions of behavior

Benefits

- ▶ Portrait of real behavior... warts & all
 - ▶ ... and therefore, a more complete, accurate picture of ALL behaviors, including the ones people don't want to talk about
- ▶ Large sample size / liberation from the tyranny of small N
 - ▶ Coverage (long tail) & Diversity
- ▶ Simple framework for comparative experiments
- ▶ Can see behaviors at a resolution / precision that was previously impossible
- ▶ → **Can inform more focused experiment design**

Drawbacks

- ▶ Not annotated
- ▶ Not controlled
- ▶ No demographics
- ▶ Doesn't tell us the *why*
- ▶ Privacy concerns
 - ▶ AOL / Netflix / Enron / Facebook public
 - ▶ Medical data / other kinds of personally identifiable data



00:32 ...now I know...
00:35 ... you get a lot of weird things..hold on...
00:38 “Are Filipinos ready for gay flicks?”
00:40 How does that have to do with what
I just....did...?
00:43 Ummm...
00:44 So that’s where you can get surprised...
you’re like, where is this... how does
this relate...umm...

What Are Logs for This Discussion?

- ▶ User behavior events over time
 - ▶ User activity primarily on web
 - ▶ Edit history
 - ▶ Clickstream
 - ▶ Queries
 - ▶ Annotation / Tagging
 - ▶ PageViews
 - ▶ ... all other instrumentable events (mousetracks, menu events....)
 - ▶ Web crawls (e.g., content changes)
 - ▶ E.g., programmatic changes of content

How to Generate Logs

- ▶ Use existing logged data
 - ▶ Explore sources in your community (e.g., proxy logs)
 - ▶ Work with a company (e.g., intern, visiting researcher)
 - ▶ Construct targeted questions
- ▶ Generate your own logs
 - ▶ Focuses on questions of unique interest to you
- ▶ Construct community resources
 - ▶ Shared software and tools
 - ▶ Client side logger (e.g., VIBE logger)
 - ▶ Shared data sets
 - ▶ Shared experimental platform to deploy experiments (and to attract visitors)
 - ▶ Other ideas?

Interesting Sources of Log Data

- ▶ Anyone who runs a Web services
- ▶ Proxy (or library) logs at your institution
- ▶ Publically available social resources
 - ▶ Wikipedia (content, edit history)
 - ▶ Twitter
 - ▶ Delicious, Flickr
 - ▶ Facebook public data?
- ▶ Others?
 - ▶ GPS
 - ▶ Virtual worlds
 - ▶ Cell call logs

Other Kinds of Large Data Sets

- ▶ Mechanical Turk (may / may not be truly log-like)
 - ▶ Other rater panels, particularly ones that generate behavioral logs
- ▶ Medical data sets
- ▶ Temporal records of many kinds...
 - ▶ *Example: logs from web servers for your web site*
 - ▶ *Example: an app that generates logs*
 - ▶ *a la the “instrumented Sketchup” application*
 - ▶ *Akers, et al., 2009*

Audience Discussion

- ▶ What kind of logs do you need to analyze?
- ▶ What kinds of logs does your work generate?
- ▶ Open Discussion

Overview

- ▶ Perspectives on log analysis
 - ▶ Understanding User Behavior (Teevan)
 - ▶ Design and Analysis of Experiments (Tang & Jeffries)
 - ▶ Discussion on appropriate log study design (all)

- ▶ Practical Considerations for log analysis
 - ▶ Collection & storage (Dumais)
 - ▶ Data Cleaning (Russell)
 - ▶ Discussion of log analysis & HCI community (all)



Section 1: Understanding User Behavior



Jaime Teevan & Susan Dumais
Microsoft Research

Kinds of User Data

User Studies

Controlled interpretation of behavior with detailed instrumentation



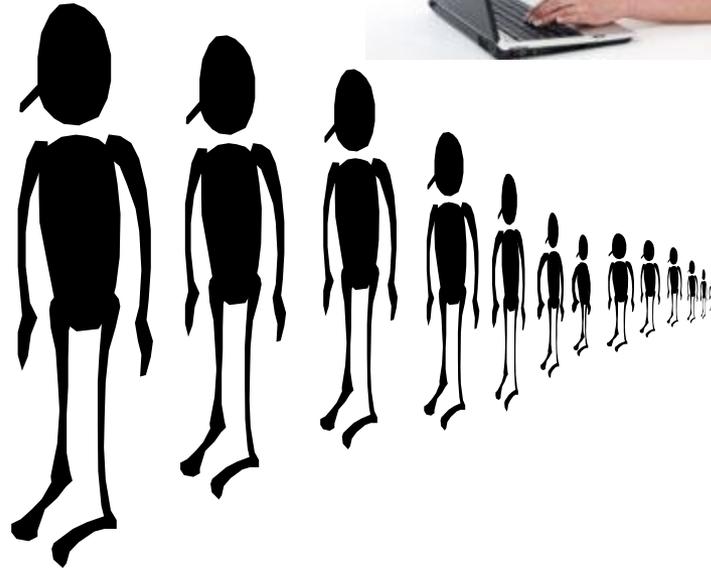
User Panels

In the wild, real-world tasks, probe for detail



Log Analysis

No explicit feedback but lots of implicit feedback



Kinds of User Data

	Observational
User Studies <i>Controlled interpretation of behavior with detailed instrumentation</i>	In-lab behavior observations
User Panels <i>In the wild, real-world tasks, probe for detail</i>	Ethnography, field studies, case reports
Log Analysis <i>No explicit feedback but lots of implicit feedback</i>	Behavioral log analysis

Goal: Build an abstract picture of behavior



Kinds of User Data

	Observational	Experimental
User Studies <i>Controlled interpretation of behavior with detailed instrumentation</i>	In-lab behavior observations	Controlled tasks, controlled systems, laboratory studies
User Panels <i>In the wild, real-world tasks, probe for detail</i>	Ethnography, field studies, case reports	Diary studies, critical incident surveys
Log Analysis <i>No explicit feedback but lots of implicit feedback</i>	Behavioral log analysis	A/B testing, interleaved results

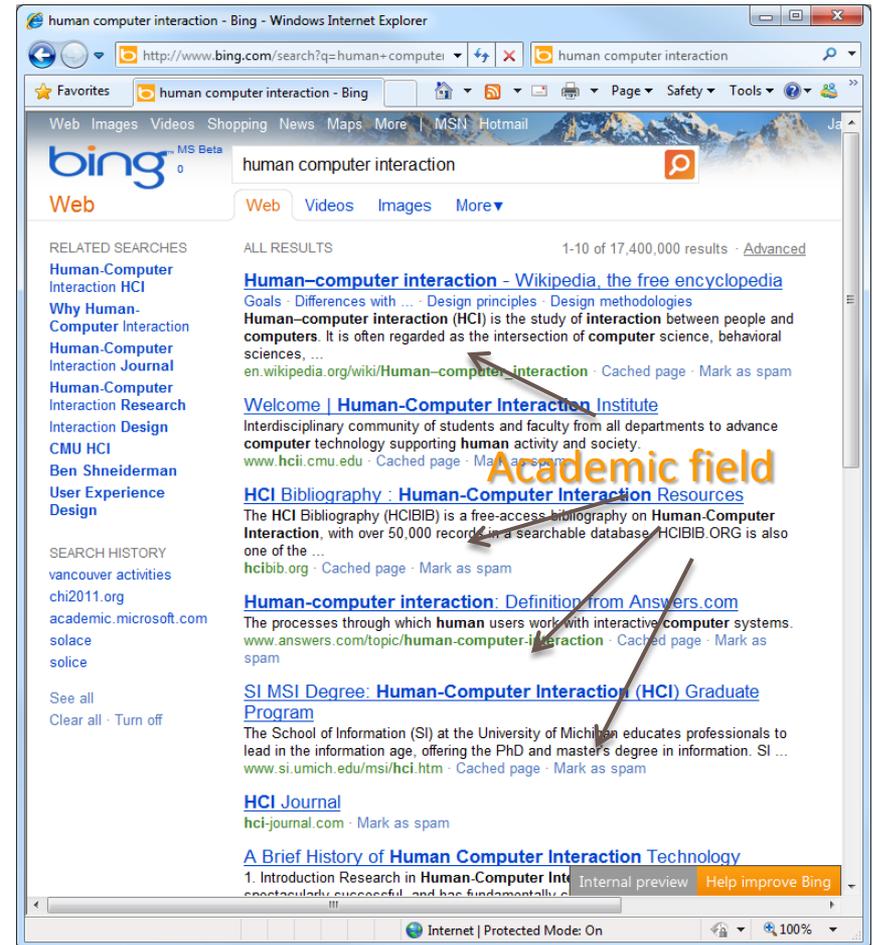
Goal: Build an abstract picture of behavior

Goal: Decide if one approach is better than another



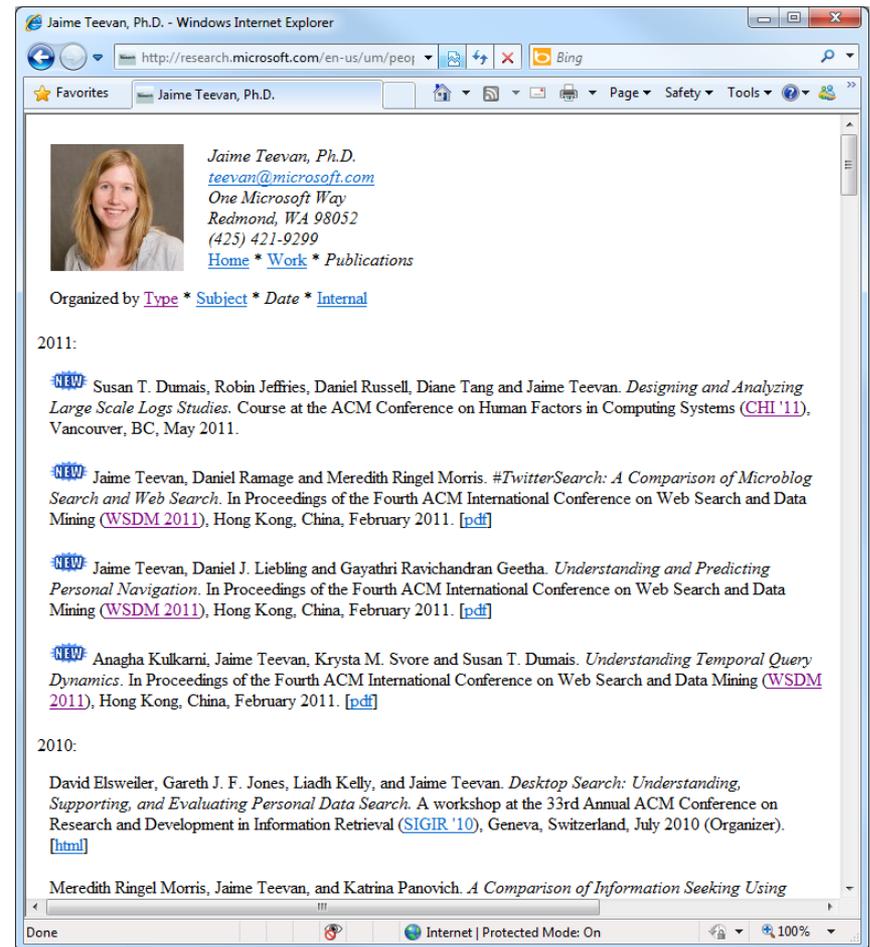
Web Service Logs

- ▶ Example sources
 - ▶ Search engine
 - ▶ Commercial site
- ▶ Types of information
 - ▶ Queries, clicks, edits
 - ▶ Results, ads, products
- ▶ Example analysis
 - ▶ Click entropy
 - ▶ Teevan, Dumais and Liebling. *To Personalize or Not to Personalize: Modeling Queries with Variation in User Intent*. SIGIR 2008



Web Browser Logs

- ▶ Example sources
 - ▶ Proxy
 - ▶ Logging tool
- ▶ Types of information
 - ▶ URL visits, paths followed
 - ▶ Content shown, settings
- ▶ Example analysis
 - ▶ Revisitation
 - ▶ Adar, Teevan and Dumais. *Large Scale Analysis of Web Revisitation Patterns*. CHI 2008



Web Browser Logs

▶ Example sources

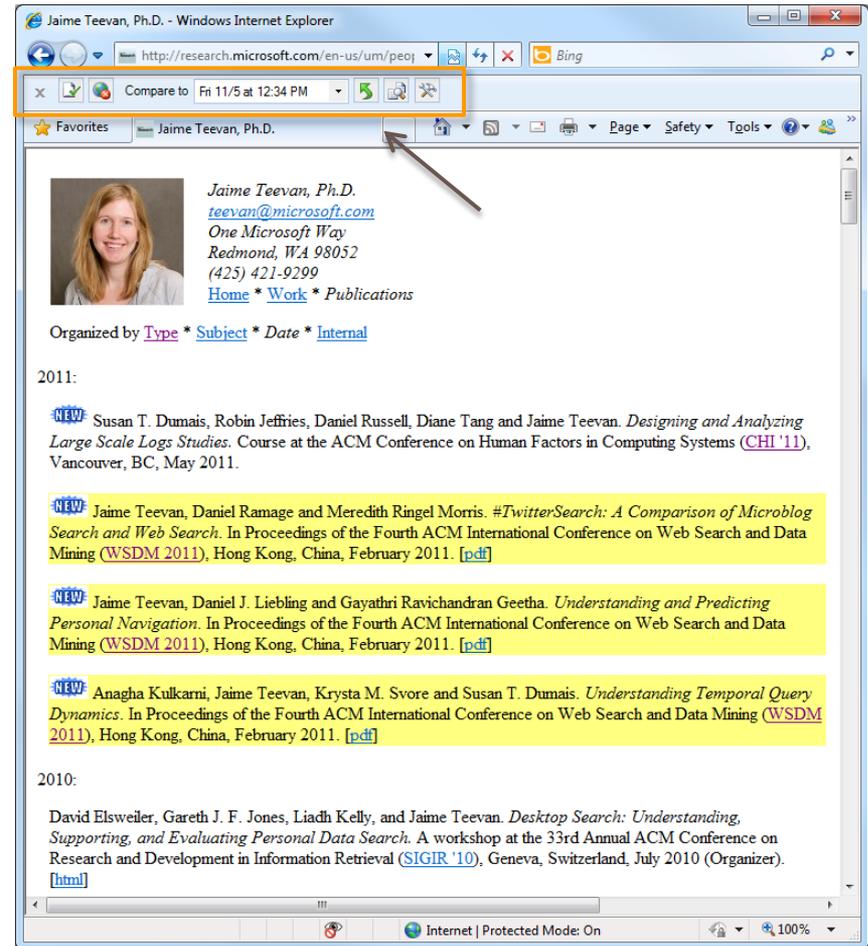
- ▶ Proxy
- ▶ Logging tool

▶ Types of information

- ▶ URL visits, paths followed
- ▶ Content shown, settings

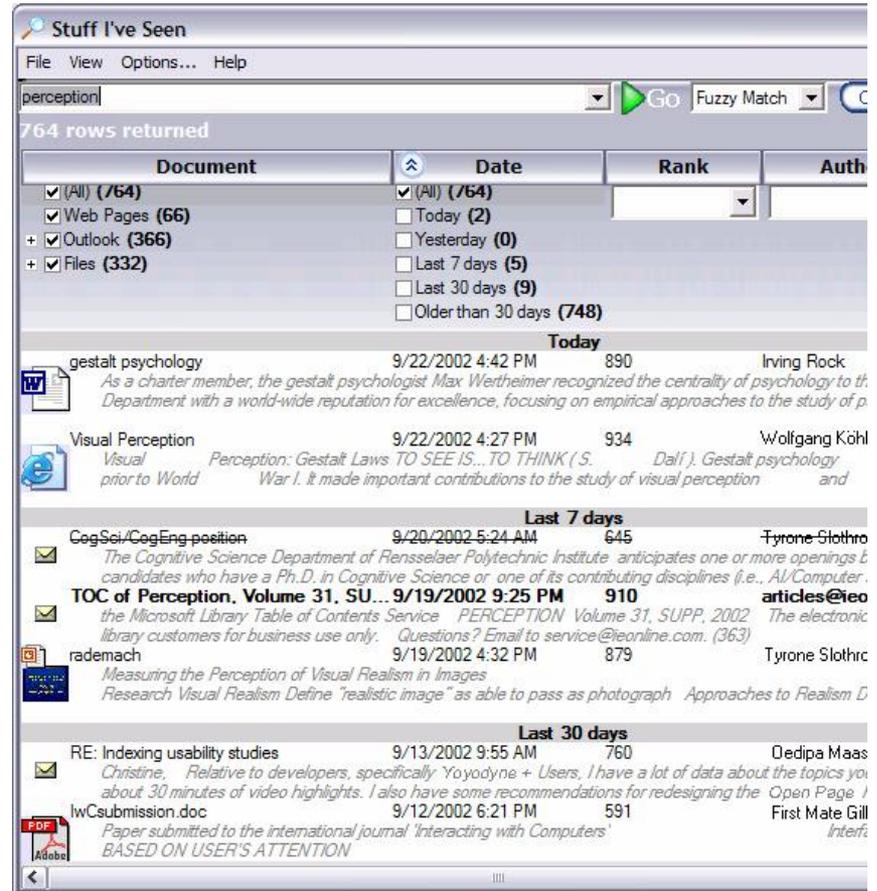
▶ Example analysis

- ▶ DiffIE
- ▶ Teevan, Dumais and Liebling. *A Longitudinal Study of How Highlighting Web Content Change Affects .. Interactions.* CHI 2010



Rich Client-Side Logs

- ▶ Example sources
 - ▶ Client application
 - ▶ Operating system
- ▶ Types of information
 - ▶ Web client interactions
 - ▶ Other client interactions
- ▶ Example analysis
 - ▶ Stuff I've Seen
 - ▶ Dumais et al. *Stuff I've Seen: A system for personal information retrieval and re-use*. SIGIR 2003



Logs Can Be Rich and Varied

Sources of log data

- ▶ **Web service**
 - ▶ Search engine
 - ▶ Commerce site
- ▶ **Web Browser**
 - ▶ Proxy
 - ▶ Toolbar
 - ▶ Browser plug-in
- ▶ **Client application**

Types of information logged

- ▶ **Interactions**
 - ▶ Queries, clicks
 - ▶ URL visits
 - ▶ System interactions
- ▶ **Context**
 - ▶ Results
 - ▶ Ads
 - ▶ Web pages shown

Using Log Data

- ▶ What can we learn from log analysis?
- ▶ What can't we learn from log analysis?
- ▶ How can we supplement the logs?

Using Log Data

- ▶ What can we learn from log analysis?
 - ▶ Now: About people's behavior
 - ▶ Later: Experiments
- ▶ What can't we learn from log analysis?
- ▶ How can we supplement the logs?

Generalizing About Behavior

Buttons clicks

Feature use

Structured answers

Information use

Information needs

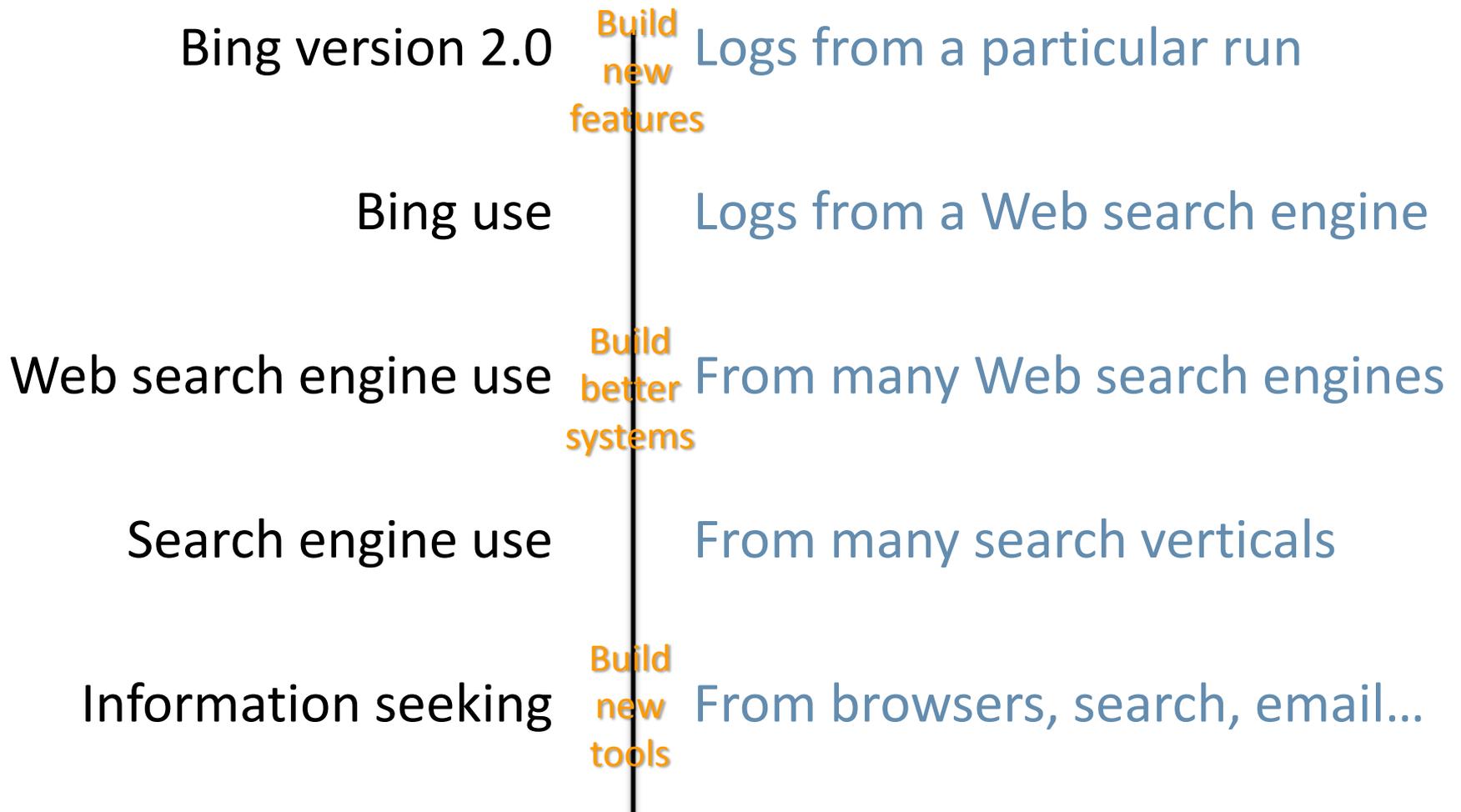
What people think

Human behavior

The collage includes several distinct UI components:

- Navigation icons: a home button, a back button, and a refresh button.
- A "Compare to" dropdown menu showing "Today at 9:36 AM".
- Contact form fields: "Main contact:" and "Alternate contact:" with input boxes and a red asterisk.
- A "Schedule" window showing a calendar for February 24, 2010, with a list of events.
- A "Friends" section showing "452 friends" and a "See All" link.
- A "What's happening?" section with a text input field, a "140" character count, and an "update" button.
- A "chi 2011" search bar with a magnifying glass icon and a dropdown arrow.
- A "What's on your mind?" text input field.
- An "Attach:" section with icons for image, video, calendar, and document, followed by a "Share" button.

Generalizing Across Systems



What We Can Learn from Query Logs

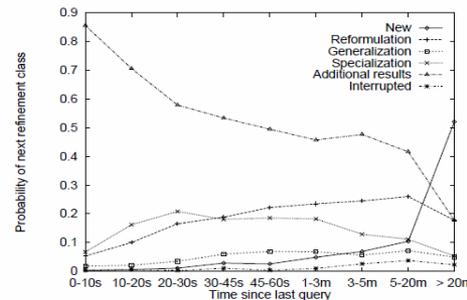
- ▶ Summary measures
 - ▶ Query frequency
 - ▶ Query length
- ▶ Analysis of query intent
 - ▶ Query types and topics
- ▶ Temporal features
 - ▶ Session length
 - ▶ Common re-formulations
- ▶ Click behavior
 - ▶ Relevant results for query
 - ▶ Queries that lead to clicks

Queries appear 3.97 times
[Silverstein et al. 1999]

2.35 terms
[Jansen et al. 1998]

Navigational,
Informational,
Transactional
[Broder 2002]

Sessions 2.20
queries long
[Silverstein et al. 1999]



[Lau and Horvitz, 1999]

	retrieval function		
	bxx	tfc	hand-tuned
avg. clickrank	6.26±1.14	6.18±1.33	6.04± 0.92

[Joachims 2002]

Query	Time	User
chi 2011	10:41am 2/18/10	142039
pan pacific hotel	10:44am 2/18/10	142039
fairmont waterfront hotel	10:56am 2/18/10	142039
chi 2011	11:21am 2/18/10	659327
restaurants vancouver	11:59am 2/18/10	318222
vancouver bc restaurants	12:01pm 2/18/10	318222
uist conference	12:17pm 2/18/10	318222
chi 2011	12:18pm 2/18/10	142039
daytrips in bc, canada	1:30pm 2/18/10	554320
uist 2011	1:30pm 2/18/10	659327
chi program	1:48pm 2/18/10	142039
chi2011.org	2:32pm 2/18/10	435451
mark ackerman	2:42pm 2/18/10	435451
fairmont waterfront hotel	4:56pm 2/18/10	142039
chi 2011	5:02pm 2/18/10	142039

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Query
typology

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Query
typology

Query behavior

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Query
typology

Query behavior

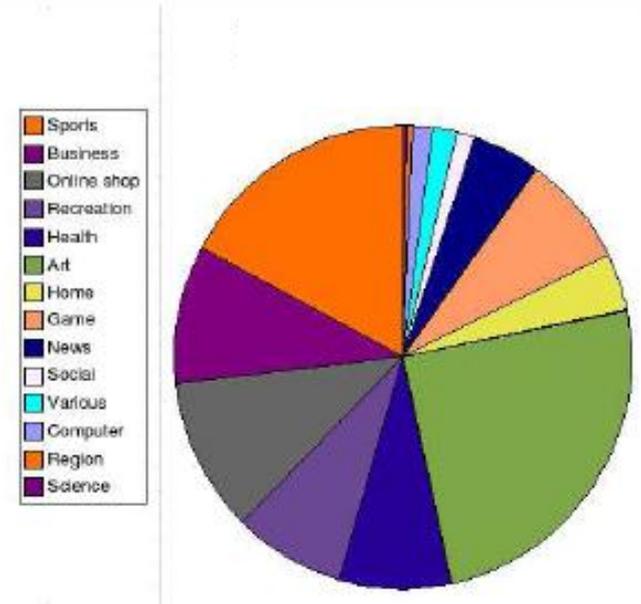
Long term trends

Uses of Analysis

- Ranking
 - E.g., precision
- System design
 - E.g., caching
- User interface
 - E.g., history
- Test set development
- Complementary research

Partitioning the Data

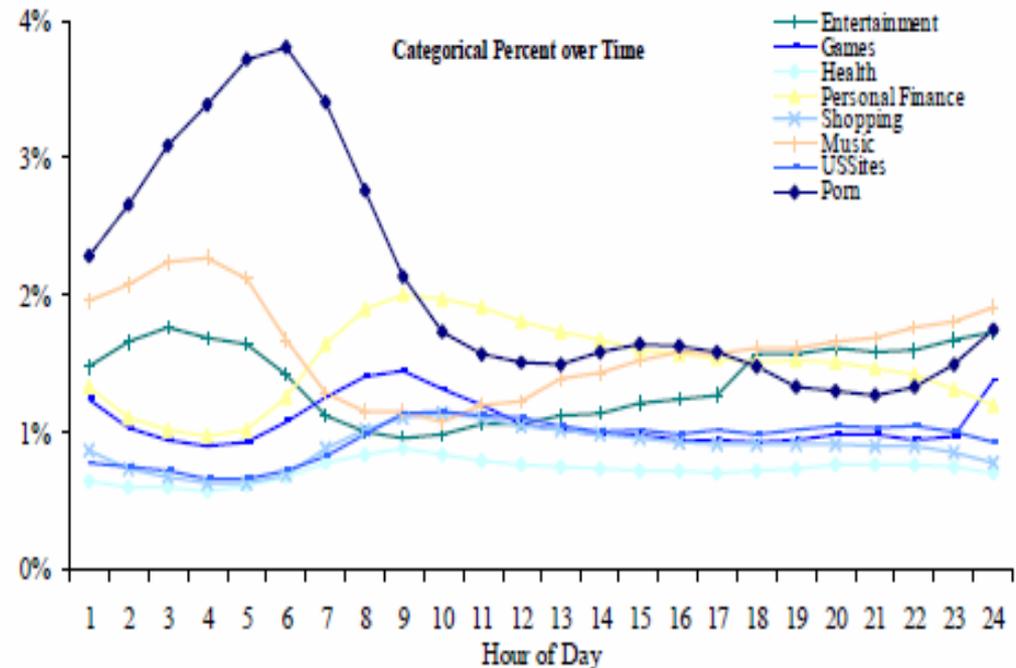
- ▶ Language
- ▶ Location
- ▶ Time
- ▶ User activity
- ▶ Individual
- ▶ Entry point
- ▶ Device
- ▶ System variant



[Baeza Yates et al. 2007]

Partition by Time

- ▶ Periodicities
- ▶ Spikes
- ▶ Real-time data
 - ▶ New behavior
 - ▶ Immediate feedback
- ▶ Individual
 - ▶ Within session
 - ▶ Across sessions



[Beitzel et al. 2004]

Partition by User

All queries: 13,060 queries (100%)	Overlapping Click Queries – 5072 queries (39%)				No Common Clicks 7988 (61%)
	Equal Click Queries – 3777 (29%)		Some Common Clicks 1295 (10%)		
	Single Identical Click 3737 (29%)	Multiple Identical Clicks 40 (< 1%)			
Equal Query Queries 4256 (33%)	Navigational Queries 3100 (24%)	36 (< 1%)	635 (5%)	485 (4%)	
Different Query 8804 (67%)	637 (5%)	4 (< 1%)	660 (5%)	7503 (57%)	

[Teevan et al. 2007]

- ▶ Temporary ID (e.g., cookie, IP address)
 - ▶ High coverage but high churn
 - ▶ Does not necessarily map directly to users
- ▶ User account
 - ▶ Only a subset of users

What Logs Cannot Tell Us

- ▶ People's intent
- ▶ People's success
- ▶ People's experience
- ▶ People's attention
- ▶ People's beliefs of what's happening
- ▶ Limited to existing interactions
- ▶ Behavior can mean many things



Example: Click Entropy

▶ Question: How ambiguous is a query?

▶ Approach: Look at variation in clicks.

[Teevan et al. 2008]

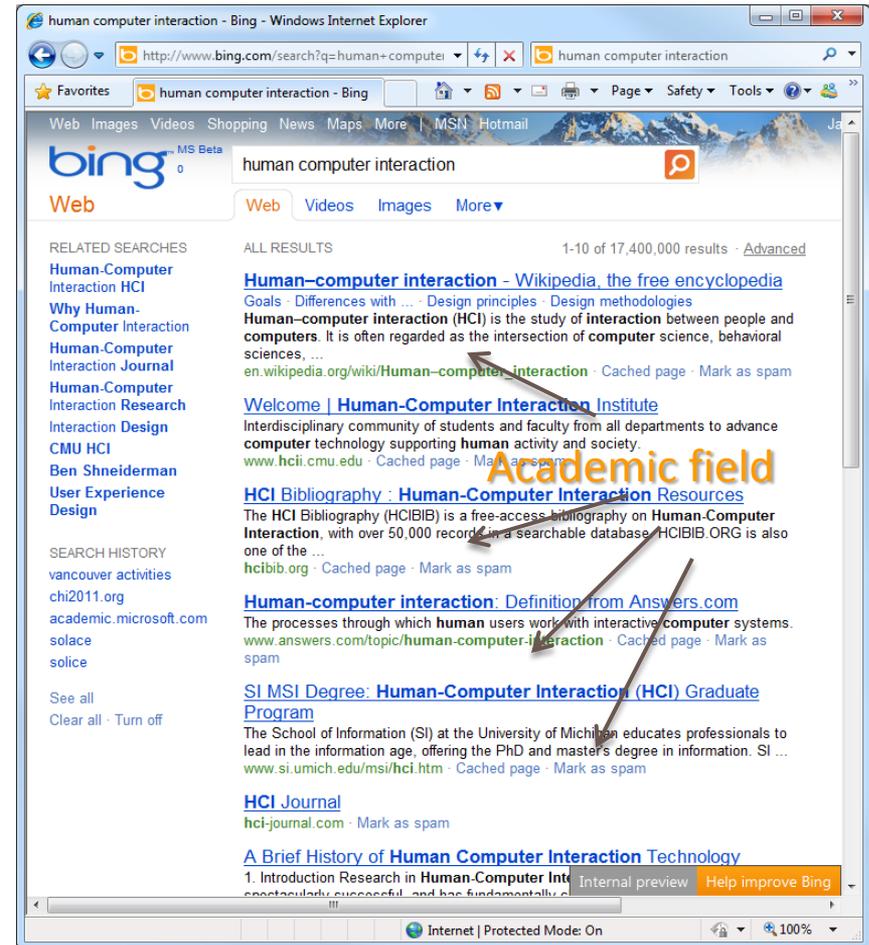
▶ Click entropy

▶ Low if no variation

human computer interaction

▶ High if lots of variation

hci



Which Has Lower Variation in Clicks?

▶ www.usajobs.gov v. federal government jobs

▶ find phone number v. [msn live search](https://www.msn.com)

▶ [singapore pools](http://singaporepools.com) v. singaporepools.com

Results change

Click entropy = 1.5

Result entropy = 5.7

Click entropy = 2.0

Result entropy = 10.7



Which Has Lower Variation in Clicks?

- ▶ `www.usajobs.gov` v. federal government jobs
- ▶ find phone number v. msn live search
- ▶ singapore pools v. singaporepools.com *Results change*
- ▶ tiffany v. tiffany's
- ▶ nytimes v. connecticut newspapers *Result quality varies*

Click entropy = 2.5

Click position = 2.6

Click entropy = 1.0

Click position = 1.6



Which Has Lower Variation in Clicks?

- ▶ www.usajobs.gov v. federal government jobs
- ▶ find phone number v. msn live search
- ▶ singapore pools v. singaporepools.com *Results change*
- ▶ tiffany v. tiffany's
- ▶ nytimes v. connecticut newspapers *Result quality varies*
- ▶ **campbells soup recipes** v. vegetable soup recipe
- ▶ **soccer rules** v. hockey equipment *Task affects # of clicks*

Click entropy = 1.7

Clicks/user = 1.1

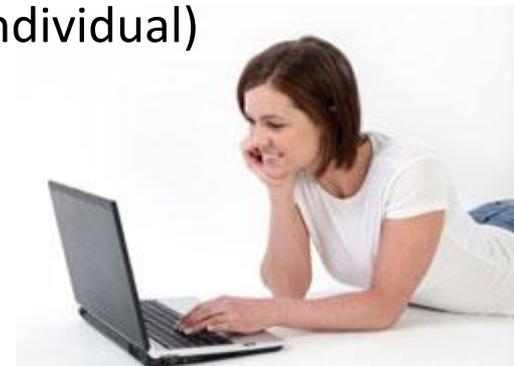
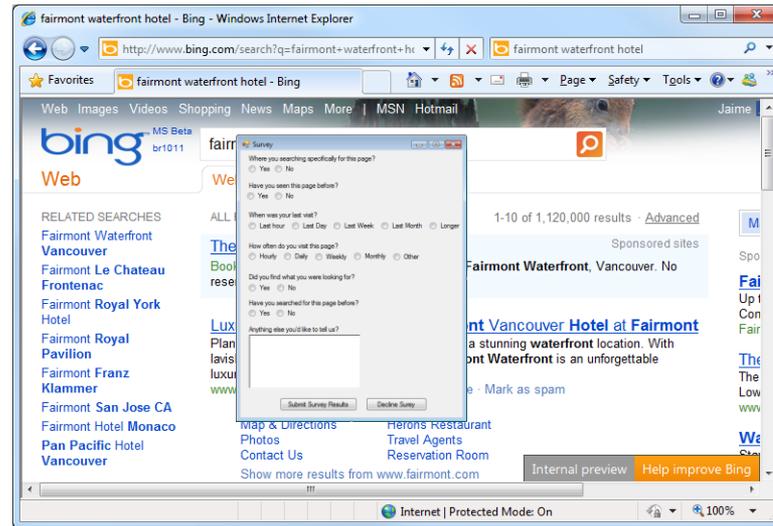
Click entropy = 2.2

Clicks/user = 2.1



Dealing with Log Limitations

- ▶ Look at data
- ▶ Clean data
- ▶ Supplement the data
 - ▶ Enhance log data
 - ▶ Collect associated information (e.g., what's shown)
 - ▶ Instrumented panels (critical incident, by individual)
 - ▶ Converging methods
 - ▶ Usability studies, eye tracking, surveys, field studies, diary studies



Example: Re-Finding Intent

- ▶ Large-scale log analysis of re-finding

[Tyler and Teevan 2010]

- ▶ *Do people know they are re-finding?*
- ▶ *Do they mean to re-find the result they do?*
- ▶ *Why are they returning to the result?*

- ▶ Small-scale critical incident user study

- ▶ Browser plug-in that logs queries and clicks
- ▶ Pop up survey on repeat clicks and 1/8 new clicks

- ▶ Insight into intent + Rich, real-world picture

- ▶ Re-finding often targeted towards a particular URL
- ▶ Not targeted when query changes or in same session

Summary: Understanding User Behavior

- ▶ Log data gives a rich picture of real world behavior
- ▶ There are many potential sources of log data
- ▶ Partition the data to view interesting slices
- ▶ Recognize what the data can and cannot tell you
- ▶ Supplement logs with complementary data



Section 2: Design and Analysis of Experiments



Robin Jeffries & Diane Tang

What Do We Mean by an Experiment?

- ▶ A change to the user experience, directly or indirectly
 - ▶ Have a hypothesis
 - ▶ Collect metrics to verify / nullify hypothesis
 - ▶ Measurability is key!
- ▶ Running on a live (web) app; data coming in from real users, doing their own tasks
- ▶ Multiple *arms*, each providing different experiences
 - ▶ At minimum, the new experience and the original *control*
 - ▶ Can be an entire space of parameters with multiple values for each parameter

Example Changes and Hypotheses

▶ Visible changes:

- ▶ Underlines: if I remove underlines, the page will be cleaner and easier to parse and users will find what they need faster
- ▶ Left Nav: by adding links to subpages, users will be able to better navigate the site
- ▶ Adding a new feature: the usage of this feature is better than what was previously shown in its place

▶ Less visible changes:

- ▶ Ranking: if I change the order of the (search) results, users will find what they are looking for faster (higher up on the page)

Why Do Experiments?

- ▶ To test your hypothesis
 - ▶ In reality (or ultimately): gather data to make an informed, data-driven decision
- ▶ Little changes can have big impacts. You won't know until you measure it.
- ▶ With big changes, who knows what will happen. Your intuition is not always correct
- ▶ **Law of unintended side effects:** what you wanted to impact gets better, but something else gets worse. You want to know that.

What Can We Learn from Experiments?

- ▶ How (standard) metrics change
- ▶ Whether/How often users interact with a new feature
- ▶ How users interact with a new feature
- ▶ Whether behavior changes over time. (learning/habituation)
 - ▶ But, remember, you are following a cookie, not a person

What Can't We Learn from Experiments?

- ▶ WHY: figuring out why people do things
 - ▶ Need more direct user input
- ▶ Tracking a user over time
 - ▶ Without special tracking software: only have a cookie
 - ▶ Cookie != user
- ▶ Measuring satisfaction / feelings directly
 - ▶ Only indirect measures (e.g., how often users return)
- ▶ Did users even notice the change?
- ▶ Did users tell their friends about feature x?
- ▶ Did users get a bad impression of the product?
- ▶ Did the users find the product enjoyable to use?
- ▶ Is the product lacking an important feature?
- ▶ Would something we didn't test have done better than what we did test?
- ▶ Is the user confused and why?

Section Outline

- ▶ Background
- ▶ Experiment design:
 - ▶ What am I testing & what am I measuring?
- ▶ Experiment sizing:
 - ▶ How many observations do I need?
- ▶ Running experiments:
 - ▶ What do I need to do?
- ▶ Analyzing experiments:
 - ▶ I've got numbers, what do they mean?

Basic Experiment Definitions

- ▶ Incoming request R has:
 - ▶ Cookie C
 - ▶ Attributes A:
 - ▶ Language, country, browser, etc.
- ▶ Experiment:
 - ▶ Diversion: is a request in the experiment?
 - ▶ Unit of diversion: cookie vs. request
 - ▶ May also depend on attributes
 - ▶ Triggering: which subset of diverted requests does an experiment actually change (impact)?
 - ▶ E.g., weather onebox vs. page chrome
 - ▶ Page chrome: triggering == diversion
 - ▶ Weather onebox: triggering << diversion
 - ▶ On triggered requests, experiment changes what is served to the user

Examples: Weather Onebox vs. Page Chrome

► **Weather for Mountain View, CA 94043** - [Add to iGoogle](#)

52°F | °C

Current: **Clear**

Wind: N at 3 mph

Humidity: 61%



62°F | 42°F



68°F | 45°F



70°F | 50°F



69°F | 49°F

Detailed forecast: [The Weather Channel](#) - [Weather Underground](#) - [AccuWeather](#)



Search

[Advanced Search](#)
[Preferences](#)

Web

Results **1 - 10** of about **155,000**

Experiment Design

- ▶ What decision do you want to make?
- ▶ 3 interlinked questions:
 - ▶ What do you want to test?
 - ▶ What is the space you will explore/what factors will you vary?
 - ▶ What hypotheses do you have about those changes?
 - ▶ What metrics will you use to test these hypotheses?
- ▶ How will you make your decision?
 - ▶ Every outcome should lead to a decision

Decisions, Goals, Underlying Assumptions

- ▶ **Ultimately: have a goal, make a decision**
 - ▶ Goal: improve the user experience
 - ▶ Assumption: if users find what they are looking for faster, then the user experience is improved
 - ▶ Decision: Will making the page less cluttered change how quickly users find what they want?
 - ▶ Goal: increase feature usage
 - ▶ Decision: Will changing the appearance of links on the page increase the click through to this feature?
 - ▶ Goal: increase time on site
 - ▶ Decision: Will adding dancing hamsters to the page lead visitors to spend more time on the site?

Changes: Design Space

- ▶ Which factors do you want to vary?
 - ▶ E.g., layout, positioning, features, colors, size, etc.
- ▶ Practical:
 - ▶ Are there options that are unacceptable?
 - ▶ E.g., Blue text on blue background
 - ▶ Full-factorial (all possible combinations) or not?
 - ▶ Analysis isn't easy for non-full factorial design
 - ▶ More arms in full factorial → increase in total work
 - ▶ Experiment size & number of arms can be an issue for full factorial
 - ▶ Confounds/nuisance factors
 - ▶ Not always possible to isolate: have a plan
 - ▶ Example: images coming from a separate server, which sometimes goes down, so image is not shown. Want to treat those requests differently than the requests that produce the intended results

Example: Video Inclusions

- ▶ Show a playable thumbnail of a video in web results for highly ranked video results
 - ▶ Explore different visual treatments for thumbnails **and** different levels of triggering the thumbnail
 - ▶ Treatments:
 1. Thumbnail on right and conservative triggering
 2. Thumbnail on right and aggressive triggering
 3. Thumbnail on left and conservative triggering
 4. Thumbnail on left and aggressive triggering
 5. Control (never show thumbnail; never trigger)
- **Note:** this is not a complete factorial experiment (should have 9 conditions)

Video Inclusions

News results for **superbowl commercials**



CBC.ca

Super Bowl Commercials: Super bowl ads. are they funny? - 19 hours ago
Super Bowl Commercials: Super bowl ads. We will update you on the Super Bowl 44 commercials here. I have been waiting since mid of 2009 to catch up NFL ...

[TV Shows Now! \(blog\)](#) - [19290 related articles](#) »

[Post Super Bowl: Ads, ads and more ads](#) -

[Reuters UK \(blog\)](#) - [1413 related articles](#) »

Super Bowl Commercials: Oprah, Dave and Jay Make it Easier to Take ... - [The Faster Times](#) - [3 related articles](#) »

Latest results for **superbowl commercials** - [Pause](#)

Super Bowl Ad – Oprah Winfrey, Jay Leno & David Letterman starrer ...

[Entertainment and Showbiz!](#) - 2 minutes ago

The **Super Bowl commercial** ads which were selling for US \$3.1 million per 30-seconds slot were another thing to look up to as giant companies unveiled their ...

[Errors of Enchantment](#) » **Super Bowl Commercial Hits Close to Home**

[Errors of Enchantment](#) - 2 minutes ago

I watched the **Super Bowl** last night and while the game was quite good, the **commercials** were pretty lame overall. However, one **commercial** by ...

[Watch all The Super Bowl Commercials in 2010 and Vote for the Best One](#)

Super Bowl Commercials [SuperBowl-Ads.com - News, Polls, History](#)

Super Bowl Commercials - Super Bowl Advertising - Watch all your favorite Super Bowl ads. [www.superbowl-ads.com/](#) - [Cached](#) - [Similar](#) - [🗨](#) [📄](#) [✕](#)

2010 Super Bowl Commercials – [NFL FanHouse](#)

Watch the 2010 **Super Bowl commercials** online. Every 2010 Super Bowl ad is here.

[superbowlads.fanhouse.com/](#) - [Cached](#) - [Similar](#) - [🗨](#) [📄](#) [✕](#)

Superbowl Commercials | 2010 Super Bowl Ads & Commercials

Hundreds of **superbowl commercials** shown from 1960 to 2010. Our Super Bowl ads are carefully selected from dozens of online services, so you don't have to go ...

[www.superbowl-commercials.org/](#) - [Cached](#) - [Similar](#) - [🗨](#) [📄](#) [✕](#)

Video results for **superbowl commercials**



Hyundai Super Bowl XLIV Advertising Brett ...

32 sec - 5 days ago

[www.youtube.com](#)



Hulu's Superbowl Commercial - 60sec

1 min 3 sec - Feb 1, 2009

[www.youtube.com](#)



Hypotheses

- ▶ Given the proposed changes, what effects do you expect to see?
 - ▶ More concrete than “it will be cool”
 - ▶ Will it impact *what* users do, *how often* they do it, *how long* it will take, their *satisfaction*?
- ▶ How will you measure these changes?
 - ▶ What vs. why
 - ▶ Hypotheses → metrics

Metrics

- ▶ Which metrics?
 - ▶ Often lots of metrics
 - ▶ What vs. why; need a suite of metrics to answer multiple questions
 - ▶ Some matter all the time: overall usage, whole page parsing, etc.
 - ▶ Some matter to your hypothesis:
 - “Increased feature usage”: click through rate, bounce rate, etc.
 - “Easier to parse”: time to first action
 - ▶ Metrics may “disagree”
 - ▶ Is TTR (time to result) faster, but success lower?
 - ▶ Is TTR faster, but users never come back?
 - ▶ Is TTR faster, but only for a subset of users (who overwhelm the metric)?
- ▶ How big of a change in the metrics matter?
 - ▶ Statistical vs. practical significance

Putting It Together: Experiments

- ▶ Given the decisions and space of possible changes:
 - ▶ Get set of possible arms
- ▶ For each arm, what are the hypotheses & metrics?
 - ▶ How different are the hypotheses?
 - ▶ Which hypotheses are measurable?
 - ▶ Do we need to run all possible arms to make the decision?
- ▶ Given this smaller set of arms, now come the practical issues:
 - ▶ How big do the arms need to be to get reasonable metrics?
Given that, how many arms can I actually run?
 - ▶ What else do I need to think about in order to actually run an experiment?

Experiment Sizing: Overview

▶ Metrics

- ▶ Power: How big a change do you want to detect? How many observations will you need in order to detect that change?

▶ Triggering

- ▶ How much of the incoming traffic is actually affected?

▶ Power + Triggering → How big your experiment is

- ▶ How many arms you can run concurrently?
- ▶ How big is each arm?
- ▶ What is the exposure risk (if this is a product)?

Power

- ▶ Power is the probability that when there really is a difference, you will statistically detect it
- ▶ Power depends on:
 - ▶ What you want to measure
 - ▶ Size of difference you want to be able to detect
 - ▶ Standard error of the measurement
 - ▶ Number of observations
- ▶ Power can (and should be) calculated before you run the experiment
 - ▶ Too many studies where it was discovered after the fact that there wasn't enough power to detect the effect of interest
 - ▶ There are standard formulas, e.g., en.wikipedia.org/wiki/Statistical_power

Power Example: Variability Matters

	Effect Size (% change you care about)	Standard Error	Observations Required
Metric A	1%	4.4	4,100,000
Metric B	1%	7.0	10,300,000

Power: Variance of Logs Data

- ▶ Logs data has high variance
 - ▶ Users vary widely: sophistication, language, strategy, etc.
 - ▶ Tasks vary widely
- ▶ Independence assumptions may not hold
 - ▶ Cookies vs. requests
 - ▶ Sequence of events from a cookie are correlated
 - If I clicked on a “show more” link before, I’m more likely to do it again
 - If I queried for a topic before, I’m more likely to query for that topic again
 - If I search a lot today, I’m more likely to search a lot tomorrow
 - ▶ Interacts with metrics (request-based metric vs. cookie-based metric)
 - ▶ Changes variance
- ▶ How to measure variance
 - ▶ Globally: A1 vs. A2 vs. ... experiments
 - ▶ Per-experiment: pre-periods and post-periods

Sizing and Triggering

- ▶ Triggering: what fraction of traffic actually shows the change?
- ▶ Power calculation: need X requests to detect change of $C\%$
- ▶ Triggering fraction: expt. affects Y (fraction) of requests
- ▶ Actual experiment size: X / Y
- ▶ Approach valid only if counterfactuals are logged in the control
 - ▶ Experiment: when does weather onebox show?
 - ▶ Control: when would weather onebox have shown? (counterfactual)
 - ▶ In some cases, you can't identify the counterfactual cases, and you have to calculate metrics on the full set of (diluted) data
- ▶ If no counterfactual, need to measure $(C * Y)\%$ change in metric on all traffic
 - ▶ The smaller Y is, the more dilution you have

Experiment Sizing: Example

Metric Standard Error	Trigger Rate	Effect Size on Affected Traffic	Needed Queries (Affected)	Queries Needed in Expt. (Counterfactuals Logged)	Effect Size if No Counterfactuals (Measured on All Traffic)	Queries Needed in Expt. (No Counterfactuals Logged)
5	1%	10%	52,500	5,250,000	0.1% (10% * 1%)	525,000,000
5	5%	10%	52,500	1,050,000	0.5% (10% * 5%)	21,000,000
5	20%	10%	52,500	262,500	2% (10% * 20%)	1,312,500
5	50%	10%	52,500	105,000	5% (10% * 50%)	210,000

Sizing: Other Design Choices

- ▶ How long will you need to run your experiment, given your sizing calculations?
 - ▶ How many arms do you have?
 - ▶ How much traffic can you devote to your experiment arms?
- ▶ Power vs. risk trade-offs
 - ▶ How many users are you willing to impact? (suppose it's a terrible user experience – how many users do you want to annoy?)
 - ▶ Risk of exposure (for potential new products)
 - ▶ Sequential vs. simultaneous arms
 - ▶ Sequential reduces risk, but introduces analysis issues such as seasonality and other timing issues (holidays, major weather event)
- ▶ How many days?
 - ▶ Shorter means faster, but units of weeks smooth out day of week effects

Within-subject vs. Between-subject

- ▶ **Within-subject:**
 - ▶ Has lower variance: need less traffic to get significant metrics
 - ▶ Two options:
 - ▶ Within-results: interleaved results (e.g., search results)
 - Within-results is inherently within subject
 - ▶ Within-subject: time slicing – show expt. and control at different times
 - ▶ Interleaved: very useful, but primarily for ranking changes
 - ▶ Same number of results, no UI changes
 - ▶ Time-slicing: within-user variance lower, but users may have different tasks, be on different OS/browsers, in different locations, etc.
- ▶ **Between-subject: More broadly useful, but higher variance, will need more traffic**

Running Experiments

- ▶ Selecting a population (diversion)
- ▶ Controls

Selecting a Population

- ▶ A population is a set of people
 - ▶ In particular location(s)
 - ▶ Using particular language(s)
 - ▶ During a particular time period
 - ▶ Doing specific activities of interest



- ▶ Important to consider how those choices might impact your results
 - ▶ Chinese users vs. US users during Golden Week
 - ▶ Sports related change during Super Bowl week in US vs. UK
 - ▶ Users in English speaking countries vs. users of English UI vs. users in US

Spain 2007

0
Jan 07 Feb 07 Mar 07 Apr 07 May 07 Jun 07 Jul 07 Aug 07 Sep

California 2007

Jan 07 Feb 07 Mar 07 Apr 07 May 07 Jun 07 Jul 07 Aug 07 Sep 07 Oct 07 Nov 07 Dec 07 Jan 08



Controls

- ▶ A control is the standard user experience that you are comparing a change to
- ▶ What is the right control?
 - ▶ Gold standard:
 - ▶ Equivalent sample from same population
 - ▶ Doing similar tasks
 - ▶ Using either:
 - The existing user experience
 - A baseline “minimal” “boring” user experience

How Controls Go Wrong

- ▶ Treatment is opt-in
- ▶ Treatment or control limited to subset (e.g., treatment only for English, control world-wide)
- ▶ Treatment and control at different times
- ▶ Control is all the data, treatment is limited to events that showed something novel (no counterfactual)
- ▶ Not logging counterfactuals at experiment time.
 - ▶ Often very hard to reverse-engineer later
 - ▶ Gives a true apples-to-apples comparison
 - ▶ But, not always possible (e.g., if what-to-display decisions are being made "on the fly")

Analyzing Experiments

- ▶ Sanity checking
- ▶ Metrics, confidence intervals, slicing
- ▶ Mix vs. metric shifts

Sanity Checking

Before looking at the metrics to draw conclusions, make sure that you believe the numbers!

- ▶ E.g., overall traffic
 - ▶ Very few changes impact overall traffic
 - ▶ Number of cookies, % of traffic
- ▶ Break data down along different dimensions / slicings
 - ▶ E.g., do you see different effects with different browsers? In different countries?
- ▶ Things that can screw things up
 - ▶ Bots visiting your site (did you mess with them?)
 - ▶ If you got mentioned in a blog, did that cause a traffic spike

Don't bother looking at other metrics unless sanity checks pass!

Managing Real World Challenges

▶ Data from all around the world

- ▶ E.g., collecting data for a given day (start/end times differ), collecting "daytime" data

▶ One-of-a-kind events

- ▶ Death of Michael Jackson/Anna Nicole Smith
- ▶ Problems with data collection server
- ▶ Data schema changes

▶ Multiple languages

- ▶ Practical issues in processing many orthographies
- ▶ E.g., dividing into words to compare query overlap
- ▶ Restricting language:
 - ▶ Language \neq country
 - ▶ Query language \neq UI language

When is a Metric Change Significant?

- ▶ Confidence interval (C.I.): interval around the treatment mean that contains the true value of the mean $x\%$ (typically 95%) of the time
- ▶ C.I.s that do not contain the control mean are statistically significant (statistically different from the control)
- ▶ This is an independent test for each metric
 - ▶ Thus, you will get 1 in 20 results (for 95% C.I.s) that are spurious -- you just don't know which ones
- ▶ C.I.s are not necessarily straightforward to compute.

How to Interpret Significant Metrics

- ▶ If you look at enough metrics, something will be significant by chance.
 - ▶ Confidence interval only tells you there is a 95% chance that this difference is real; not 100%
 - ▶ If only a few things significant, is chance the likely explanation?
 - ▶ Look for converging evidence (many metrics are correlated; do all the metrics correlated with this one move in the same direction?)
- ▶ If your parameters are continuous, you may be able to interpolate or extrapolate to other values (e.g., 1" submit button vs. 2"; how would 1.5" do?)
- ▶ You can miss significance because the true difference is tiny/zero or because you don't have enough power
 - ▶ If you did your sizing right, you have enough power to see all the differences of practical significance

More on Metrics

- ▶ Your experiment may have diverted on 10% of events, but only triggered on 20% of those events.
 - ▶ Which denominator are you using?
- ▶ It's obvious to look at the metrics that apply to your specific change, but what about the overall impact?
 - ▶ E.g., if your change slows things down, those who stay may have a great experience, but what about those who left?
- ▶ Slicing up the data
 - ▶ Country, language, browser, etc.
 - ▶ Great way to understand the effects better
 - ▶ Is most of the change coming from users of browser X; in country Y?
- ▶ Need to be careful re: mix vs. metric shifts (Simpson's paradox)

Simpson's Paradox: Simultaneous Mix and Metric Changes

Batting averages

	1995	1996	Combined
Derek Jeter	12/48 .250	183/582 .314	195/630 .310
David Justice	104/411 .253	45/140 .321	149/551 .270

Changes in mix (denominators) make combined metrics (ratios) inconsistent with yearly metrics

More on Simpson's Paradox

- ▶ Neither the individual data (the yearly metrics) or the combined data is inherently more correct
 - ▶ It depends, of course, on what your hypothesis is
- ▶ Once you have mix changes (changes to the denominators across subgroups), all metrics (changes to the ratios) are suspect
 - ▶ **Always** compare your denominators across samples
 - ▶ Maybe the point of the experiment was to produce a mix change
 - ▶ Can you restrict analysis to the data not impacted by the mix change (the subset that didn't change)?
 - ▶ Minimally, be up front about this in any writeup

Detailed Analysis → Big Picture

- ▶ Not all effects will point the same direction
 - ▶ Take a closer look at the items going in the "wrong" direction
 - ▶ Can you interpret them?
 - ▶ E.g., people are doing fewer next-pages because they are finding their answer on the first page
 - ▶ Could they be artifactual?
 - ▶ What if they are real?
 - ▶ What should be the impact on your conclusions? on your decision?
- ▶ Significance and impact are not the same thing
 - ▶ Couching things in terms of % change vs. absolute change helps
 - ▶ A substantial effect size depends on what you want to do with the data

Summary:

Critical Steps When Designing Experiments

- ▶ Determine your hypotheses
- ▶ Decide on which metrics
- ▶ Size your experiment
 - ▶ Take the triggering fraction into account
 - ▶ If at all possible, identify the counterfactual events in the control
- ▶ Sanity check your data
- ▶ Make sure you have enough power to not miss effects of interest; look for converging evidence to keep from acting on spuriously significant results
- ▶ Don't get bit by Simpson's Paradox

Discussion

All

Our story to this point...

▶ Perspectives on log analysis

▶ Understanding user behavior *Jamie*

- ▶ What you can / cannot learn from logs
- ▶ Observations vs. experiments
- ▶ Different kinds of logs

▶ How to design / analyze large logs *Robin & Diane*

- ▶ Selecting populations
- ▶ Statistical Power
- ▶ Treatments
- ▶ Controls
- ▶ Experimental error

Discussion

- ▶ How might you use logs analysis in your research?
- ▶ What other things might you use large data set analysis to learn?
 - ▶ Time-based data vs. non-time data
- ▶ Large vs. small data sets?

Section 3: Practical Considerations for Log Analysis

Susan Dumais and Daniel M. Russell

Overview

- ▶ **Data collection and storage** [Susan Dumais]
 - ▶ Logging the data
 - ▶ Storing the data
 - ▶ Using the data responsibly
- ▶ **Data analysis** [Daniel M. Russell]
 - ▶ How to clean the data
- ▶ **Discussion: Log analysis and the HCI community**



Section 3A: Data Collection, Storage and Use



Susan Dumais and Jaime Teevan
Microsoft Research

Overview

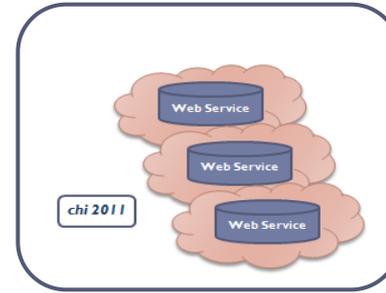
- ▶ Logging the data
- ▶ Storing the data
- ▶ Using the data responsibly
- ▶ Building large-scale systems out-of-scope

A Simple Example

- ▶ Logging search Queries and Clicked Results



A Simple Example (cont'd)



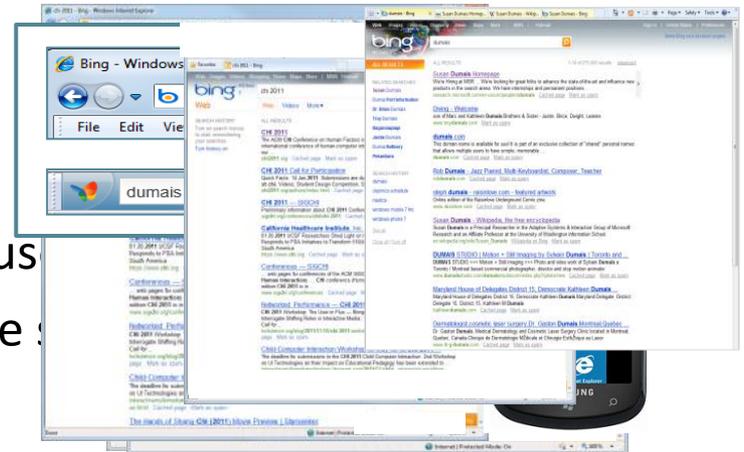
▶ Logging Queries

▶ Basic data: <query, userID, time>

▶ Which time? $time_{Client.send}$, $time_{Server.receive}$, $time_{Server.send}$, $time_{Client.receive}$

▶ Additional contextual data:

- ▶ Where did the query come from?
- ▶ What results were returned?
- ▶ What algorithm or presentation was used?
- ▶ Other metadata about the state of the system?



A Simple Example (cont'd)



▶ Logging Clicked Results (on the SERP)

▶ How can a Web service know which SERP links are clicked?

- ▶ Proxy re-direct
- ▶ Script (e.g., JavaScript)
 - Dom and cross-browser
- ▶ No download required; interaction

```

<script lang="text/javascript">
function changeImage(){ document.imgC.src="thank_you..gif "; }
function backImage(){ document.imgC.src="image.gif"; }
</script>
```

▶ What happened after the result was clicked?

- ▶ What happens beyond the SERP is difficult to capture
- ▶ Browser actions (back, open in new tab, etc.) are difficult to capture
- ▶ To better interpret user behavior, need richer client instrumentation

Browsers, Tabs and Time

► Interpreting what happens on the SERP

• Scenario 1:

- 7:12 SERP shown
- 7:13 click R1
<“back” to SERP>
- 7:14 click R5
<“back” to SERP>
- 7:15 click RS1
<“back” to SERP>
- 7:16 go to new search engine



• Scenario 2

- 7:12 SERP shown
- 7:13 click R1
<“open in new tab”>
- 7:14 click R5
<“open in new tab”>
- 7:15 click RS1
<“open in new tab”>
- 7:16 read R1
- 10:21 read R5
- 13:26 copies links to doc



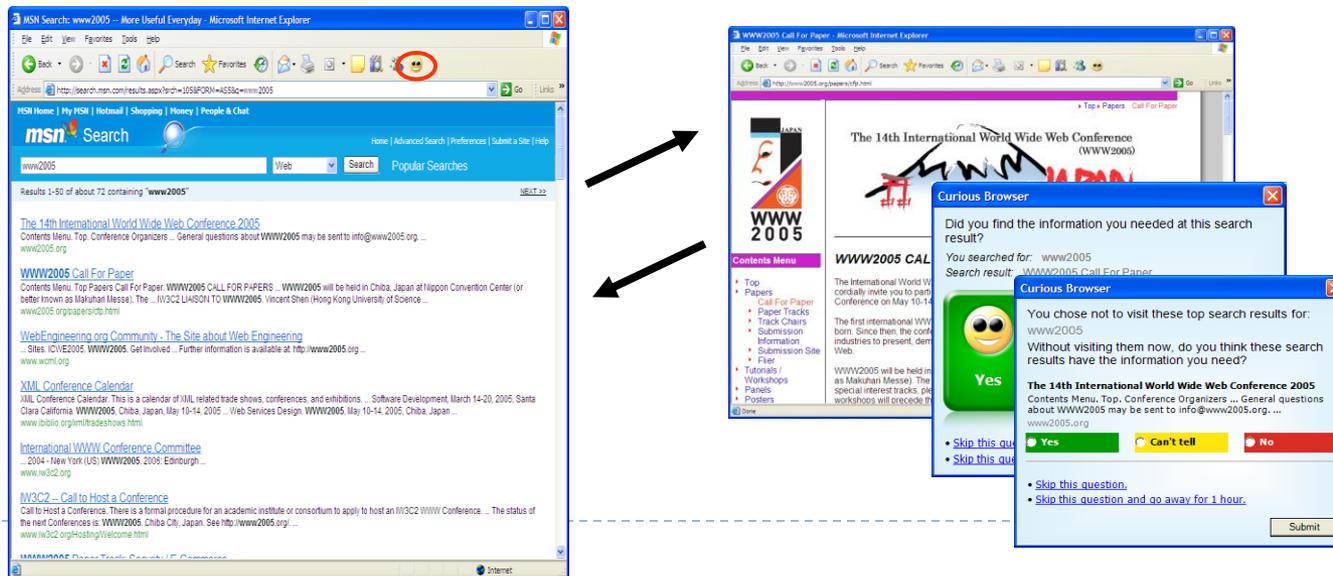
- Both look the same, if all you capture is clicks on result links
- Important to distinguish to interpret user behavior
 - Tabbed browsing accounted for 10.5% of clicks [Weinreich et al. 2006]
 - 81% of observed search sequences are ambiguous [Viermetz et al. 2006]

Richer Client Instrumentation

- ▶ **Toolbar (or other client code)**
 - ▶ Richer logging (e.g., browser events, mouse/keyboard events, screen capture, eye-tracking, etc.)
 - ▶ Several HCI studies of this type [e.g., Kellar et al., Cutrell et al.]
 - ▶ Importance of robust software, and data agreements
- ▶ **Instrumented panel**
 - ▶ A group of people who use client code regularly; may also involve subsequent follow-up interviews
 - ▶ Nice mix of *in situ* use (the what) and support for further probing (the why)
 - ▶ E.g., Curious Browser [Fox et al., next slide]
- ▶ **Data typically recorded on the client**
 - ▶ Still needs to get logged centrally on a server

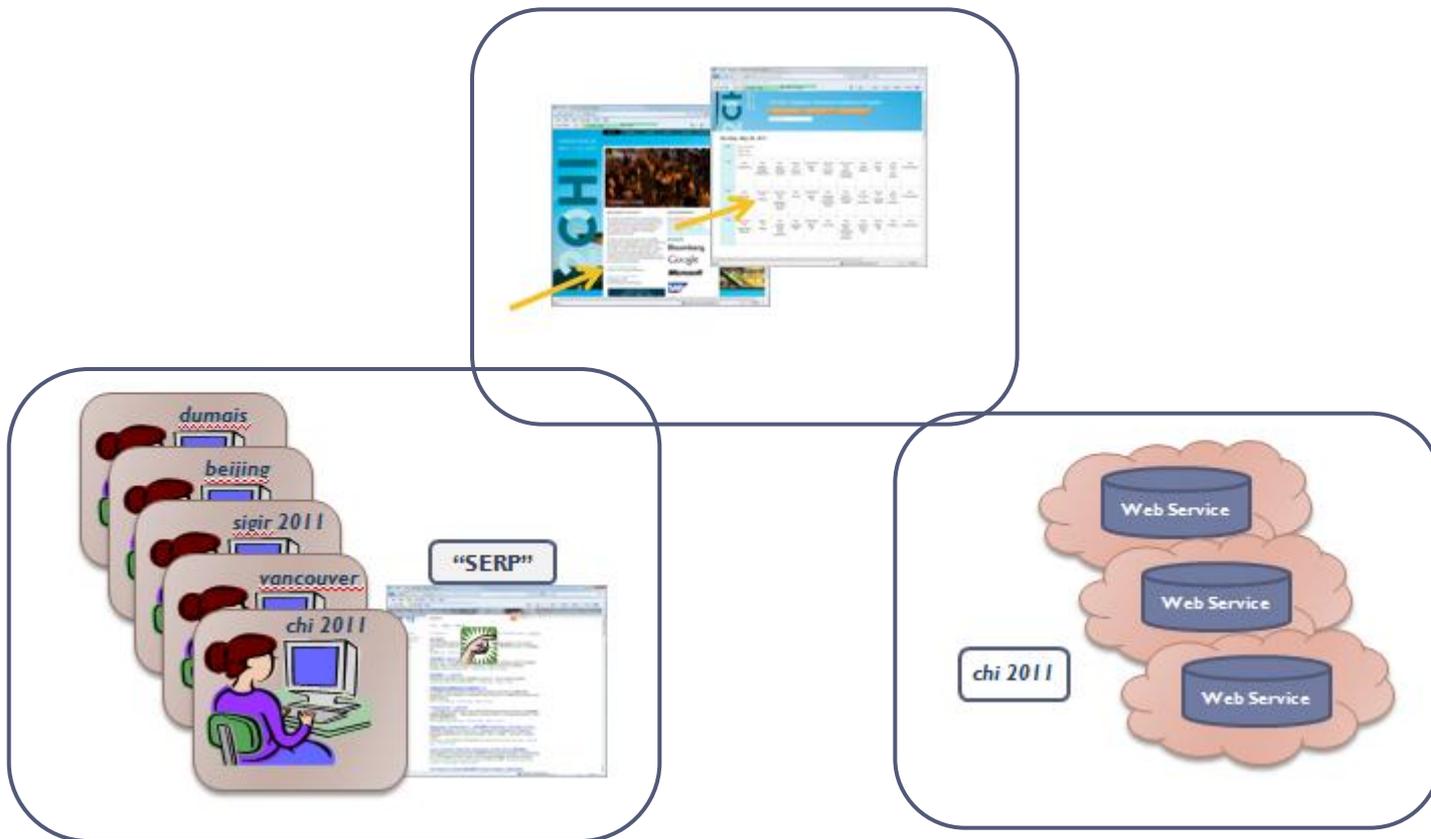
Example: Curious Browser [Fox et al. 2005]

- ▶ Browser plug-in to examine relationship between implicit and explicit behavior
 - ▶ Capture many implicit actions (e.g., click, click position, dwell time, scroll)
 - ▶ Probe for explicit user judgments of relevance of a page to the query
- ▶ Deployed to ~4k people in US and Japan
- ▶ Learned models to predict explicit judgments from implicit indicators
 - ▶ 45% accuracy w/ just click; 75% accuracy w/ click + dwell + session
- ▶ Used to identify important features; then apply model in open loop setting



A (Not-So-) Simple Example

- ▶ Logging: Queries, Clicked Results, and Beyond



Setting Up Server-side Logging

- ▶ What to log?
 - ▶ Log as much as possible
 - ▶ But ... make reasonable choices
 - ▶ Richly instrumented client experiments can provide some guidance
 - ▶ Pragmatics about amount of data, storage required will also guide
- ▶ What to do with the data?
 - ▶ The data is a large collection of events, often keyed w/ time
 - ▶ E.g., <time, userID, action, value, context>
 - ▶ Keep as much raw data as possible (and allowable)
 - ▶ Post-process data to put into a more usable form
 - ▶ Integrating across servers to organize the data by time, userID, etc.
 - ▶ Normalizing time, URLs, etc.
 - ▶ Richer data cleaning [see next section]

A Few More Important Practical Issues

- ▶ Time
- ▶ Scale
- ▶ Identifying “Users”
- ▶ Data Privacy and Security

Time (and Time Again)

▶ Time

- ▶ **Client time** is closer to the user, but can be wrong or reset
- ▶ **Server time** includes network latencies, but controllable
- ▶ In both cases, need to synchronize time across multiple machines

▶ Data integration

- ▶ Ensure that joins of data are all using the same basis (e.g., UTC vs. local time)
- ▶ Accurate timing data is critical for understanding the sequence of user activities, daily temporal patterns, etc.

Issues of Scale

▶ Data Collection

▶ Storage requirements

- ▶ E.g., 1k bytes/record x 10 records/query x 100 mil queries/day = 1000 Gb/day

▶ Network bandwidth

- ▶ Client to server; Data center to data center

▶ Data Analysis

▶ What are MapReduce, Hadoop, Pig all about?

▶ **MapReduce** – framework for processing huge datasets on compute clusters

- Key idea: partition problem into pieces which can be done in parallel
- Map: take input, and divide it into sub-problems which can be distributed
- Reduce: collect results, and combine them to get final answer

▶ **Hadoop** - open-source implementation of MapReduce

▶ **Pig** - execution engine on top of Hadoop

▶ Why would you want to use them?

▶ How can you use them?

How is a User Identified?

- ▶ **Http cookies, IP address, temporary ID**
 - ▶ Provides broad coverage and easy to use, but ...
 - ▶ Multiple people use same machine
 - ▶ Same person uses multiple machines (and browsers)
 - ▶ How many cookies did you use today?
 - ▶ Lots of churn in these IDs
 - ▶ Jupiter Res (39% delete cookies monthly); Comscore (2.5x inflation)
- ▶ **Login, or Download of client code (e.g., browser plug-in)**
 - ▶ Better correspondence to people, but ...
 - ▶ Requires sign-in or download
 - ▶ Results in a smaller and biased sample of people or data (who remember to login, decided to download, etc.)
- ▶ **Either way, loss of data**

Using the Data Responsibly

- ▶ What data is collected and how it can be used?
 - ▶ User agreements (terms of service)
 - ▶ Emerging industry standards and best practices
- ▶ Trade-offs
 - ▶ More data:
 - ▶ More intrusive and potential privacy concerns, but also more useful for understanding interaction and improving systems
 - ▶ Less data:
 - ▶ Less intrusive, but less useful
- ▶ Risk, benefit, and trust

Using the Data Responsibly (cont'd)

- ▶ **Control access to the data**
 - ▶ Internally: Access control; data retention policy
 - ▶ Externally: Risky (e.g., AOL, Netflix, Enron, Facebook public)
- ▶ **Protect user privacy**
 - ▶ Directly identifiable information
 - ▶ Social security, credit card, driver's license numbers
 - ▶ Indirectly identifiable information
 - ▶ Names, locations, phone numbers ... you're so vain (e.g., AOL)
 - ▶ Putting together multiple sources indirectly (e.g., Netflix, hospital records)
 - Linking public and private data
 - *k*-anonymity; Differential privacy; etc.

Example: AOL Search Dataset

- ▶ Indirectly identifiable information
 - ▶ Names, locations, phone numbers ... you're so vain
- ▶ AOL released data to academic community Aug 4, 2006
 - ▶ Anonymized query-click logs - 3 months; 650k users; 20mil searches
 - ▶ <AnonID, Query, QueryTime, ItemRank, ClickURL>

AnonID	Query	QueryTime	ItemRank	ClickURL
1234567	uist 2006	2006-04-04 18:18:18	1	http://www.acm.org/uist/uist2006/
1234567	uist 2006 deadline	2006-04-04 18:18:18	3	http://www.acm.org/uist/uist2006/
1234567	chi	2006-04-24 09:19:32		
1234567	chi 2006	2006-04-24 09:20:04	2	http://
1234567	chi program http://www.chi2006.org/docs/finalprogram2006.pdf	2006-04-24 09:25:50	2	
1234567	perlman montreal	2006-04-24 10:15:14	4	http://
1234567	uist 2006 notification	2006-05-20 13:13:13		

- ...
- ▶ Multiple queries for Jarrett Arnold (and other men)
 - ▶ NYT contacted all people in Lilburn with the last name Arnold
 - ▶ When contacted, Thelma Arnold acknowledged the search

A Face Is Exposed for AOL Searcher No. 4417749
By MICHAEL BARBARO and TOM ZELLER Jr.
 Published: August 9, 2006

Buried in a list of 20 million Web search queries collected by AOL and recently released on the Internet is user No. 4417749. The number was assigned by the company to protect the searcher's anonymity, but it was not much of a shield.

No. 4417749 conducted hundreds of searches over a three-month period on topics ranging from "numb fingers" to "60 single men" to "dog that urinates on everything."

And search by search, click by click, the identity of AOL user No. 4417749 became easier to discern. There are queries for "landscapers in Lilburn, Ga.," several people with the last name Arnold and "homes sold in shadow lake subdivision gwinnett county georgia."

It did not take much investigating to follow that data trail to Thelma Arnold, a 62-year-old widow who lives in Lilburn, Ga., frequently researches her friends' medical ailments and loves her three dogs. "Those are my searches,"



Eric S. Lipton for The New York Times
 Thelma Arnold's identity was betrayed by AOL records of her Web searches, like ones for her dog, Dudley, who clearly has a problem.

127 HOURS

SIGN IN TO E-MAIL THIS
 PRINT
 SINGLE PAGE
 REPRINTS

Example: Netflix Challenge

- ▶ Indirectly identifiable information
 - ▶ Putting together multiple sources indirectly
 - ▶ Linking public and private data; and k -anonymity
- ▶ Netflix Challenge announced Oct 2, 2006, \$1million prize
 - ▶ 100 million ratings, from 480k people, for 17k movies
 - ▶ <UserID, Rating, DateOfRating, Movie, MovieTitle>
 - ▶ Sept 21, 2009 – Grand Prize award to Belk

A Ratings

UserID	Rating	DateOfRating	Movie	MovieTitle
1:			[Movie 1 of 17770]	
12, 3,		2006-04-18	[CustomerID, Rating, Date]	
1234, 5,		2003-07-08	[CustomerID, Rating, Date]	
2468, 1,		2005-11-12	[CustomerID, Rating, Date]	
...				
				Movie_Titles
...				
10120,	1982,			"Bladerunner"
...				
17690,	2007,			"The Queen"

From Net
 "No, all cus
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 couldn't id
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 complete a
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 ratings tha

Bits
 Business • Innovation • Technology • Society
 September 21, 2009, 10:15 AM
Netflix Awards \$1 Million Prize and Starts a New Contest
 By STEVE LOHR



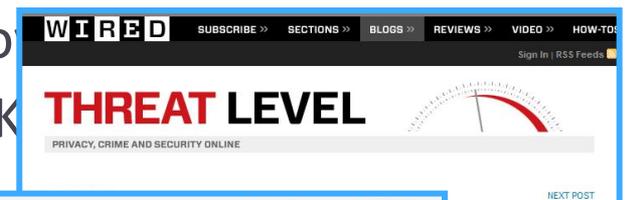
Netflix prize winners, from left: Yehuda Koren, Martin Chabbert, Martin Plotte, Michael Jahner, Andreas Toscher, Chris Volinsky and Robert Bell.

Update | 1:45 p.m. Adding details announced Monday about the extremely close finish to the contest.

Netflix, the movie rental company, has decided its million-dollar-prize competition was such a good investment that it is planning another one.

possible for her to be coaxed when it disclosed innocently anonymous information about nearly half-a-million customers as part of its \$1 million contest to improve its recommendation system.

zen
 s. This
 ple, you
 probably
 use **only a**
 n of our
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Using the Data Responsibly (cont'd)

- ▶ Control access to the data
 - ▶ Internally: Access control; data retention policy
 - ▶ Externally: Risky (e.g., AOL, Netflix, Enron, Facebook public)
- ▶ Protect user privacy
 - ▶ Directly identifiable information
 - ▶ Social security, credit card, driver's license numbers
 - ▶ Indirectly identifiable information
 - ▶ Names, locations, phone numbers ... you're so vain (e.g., AOL)
 - ▶ Putting together multiple sources indirectly (e.g., Netflix, hospital records)
 - Linking public and private data
 - *k*-anonymity; Differential privacy; etc.
- ▶ Transparency and user control
 - ▶ Publicly available privacy policy
 - ▶ Give users control to delete, opt-out, etc.

Summary

- ▶ Data collection and storage
 - ▶ Logging the data
 - ▶ At the server
 - ▶ On the results page
 - ▶ Richer client-side logging
 - ▶ Storing the data
 - ▶ Challenges of: time, scale, users
 - ▶ Using the data responsibly
 - ▶ Controlling access to data
 - ▶ Protecting privacy
 - ▶ Providing transparency and user control
- ▶ Data analysis [Daniel Russell]
 - ▶ Cleaning the data



Section 3B: Data cleaning for large logs



Daniel M. Russell

Why Clean Log Data?

- ▶ *The big false assumption:* Isn't log data intrinsically clean?
 - ▶ A: Nope.

Typical Log Format

210.116.18.93 - - [23/Jan/2005:13:37:12 -0800]

"**GET** /modules.php?name=News&file=friend&op=FriendSend&sid=8225 **HTTP/1.1**" **200 2705**
"http://www.olloo.mn/modules.php?name=News&file=article&catid=25&sid=8225" "**Mozilla/4.0**
(compatible; MSIE 6.0; **Windows NT 5.1; SV1**)" ...

– Client IP - 210.126.19.93

– Date - 23/Jan/2005

– Accessed time - 13:37:12

– Method - GET (to request page), POST, HEAD (send to server)

– Protocol - HTTP/1.1

– Status code - 200 (Success), 401,301,500 (error)

– Size of file - 2705

– Agent type - Mozilla/4.0

– Operating system - Windows NT

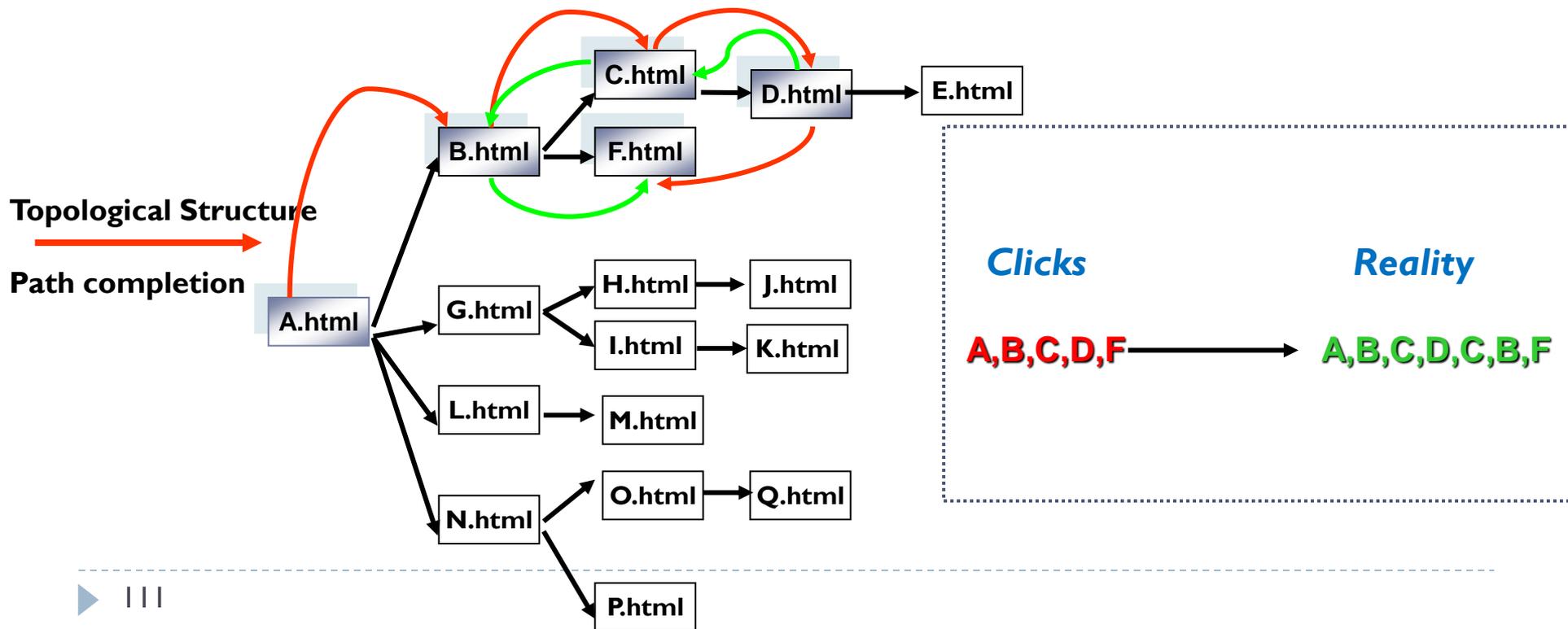
<http://www.olloo.mn/modules.php?name=News&file=article&catid=25&sid=8225> →

→ <http://www.olloo.mn/modules.php?name=News&file=friend&op=FriendSend&sid=8225>

What this really means... A visitor (210.126.19.93) viewing the news who sent it to friend.

Sources of Noise

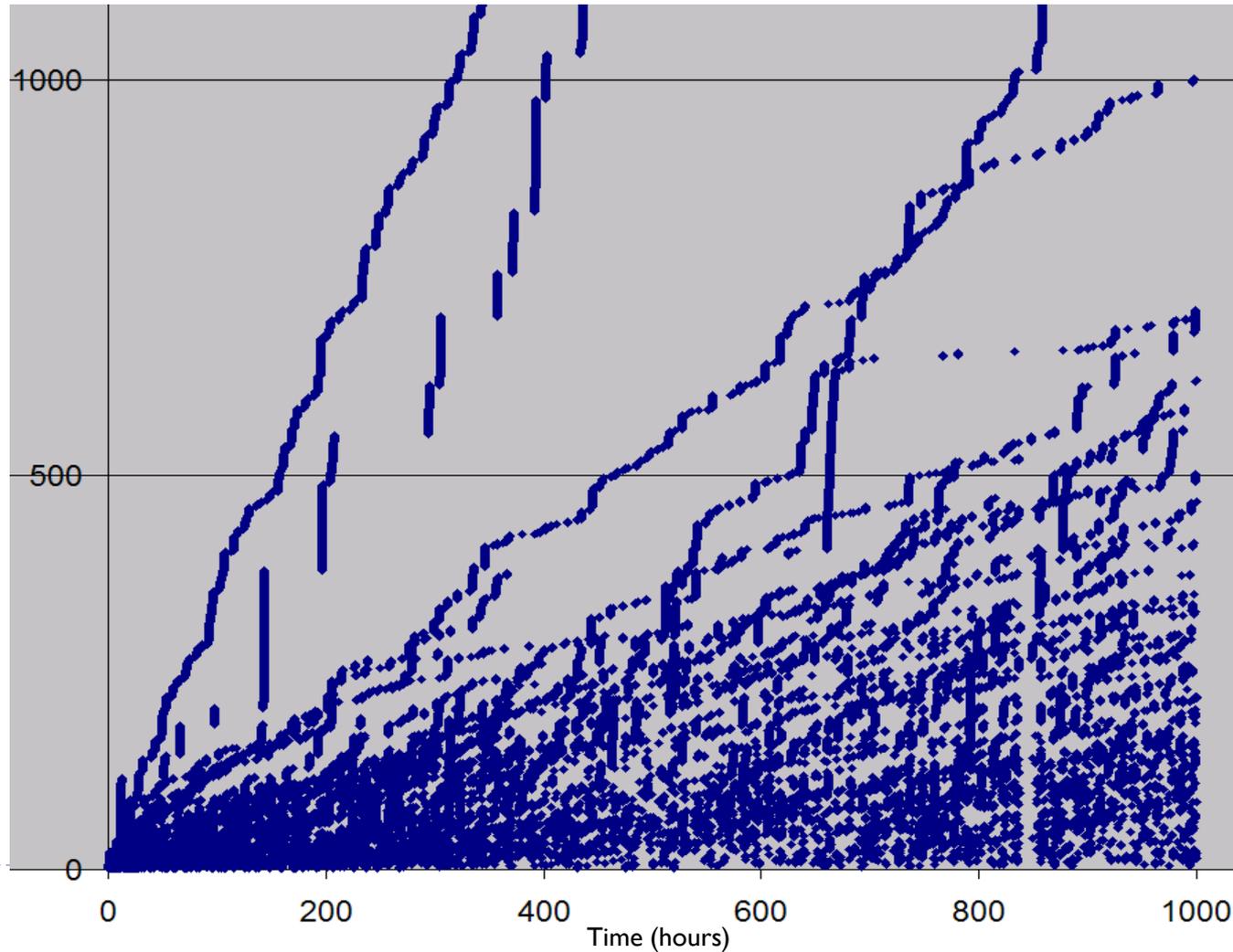
- ▶ Non-completion due to caching (back button)
- ▶ Also... tabs... invisible...
 - ▶ Also – new browser instances.



A Real Example

- ▶ A previously unknown gap in the data

Sum number of
clicks against
time



What We'll Skip...

- ▶ Often data cleaning includes
 - (a) Input / value validation
 - (b) Duplicate detection / removal
 - ▶ We'll assume you know how to do that
 - (c) Multiple clocks – syncing time across servers / clients

- ▶ But... note that valid data definitions often shift out from under you. (See schema change later)

When Might You NOT Need to Clean Data?

▶ Examples:

- ▶ When the data is going to be presented in ranks.
 - ▶ Example: counting most popular queries. Then outliers are either really obvious, or don't matter
- ▶ When you need to understand overall behavior for system purposes
 - ▶ Example: traffic modeling for queries—probably don't want to remove outliers because the system needs to accommodate them as well!

Before Cleaning Data

- ▶ Consider the point of cleaning the data
 - ▶ What analyses are you going to run over the data?
 - ▶ Will the data you're cleaning *damage* or *improve* the analysis?



So...what
DO I want to
learn from
this data?



How about
we remove
all the short
click
queries?



Importance of Data Expertise

- ▶ Data expertise is important for understanding the data, the problem and interpreting the results
 - ▶ *Often.. .background knowledge particular to the data or system:*
 - ▶ “That counter resets to 0 if the number of calls exceeds N”.
 - ▶ “The missing values are represented by 0, but the default amount is 0 too.”
- ▶ Insufficient DE is a common cause of poor data interpretation
- ▶ DE should be documented with the data metadata

Outliers

- ▶ Often indicative either of
 - ▶ Measurement error, or that the population has a heavy-tailed distribution.
 - ▶ Beware of distributions with highly non-normal distributions
 - ▶ Be cautious when using tool or intuitions that assume a normal distribution (or, when sub-tools or models make that assumption)
 - ▶ A frequent cause of outliers is a mixture of two distributions, which may be two distinct sub-populations

Outliers: Common Types from Search

- ▶ Quantity:

- ▶ 10K searches from the same cookie in one day
- ▶ Suspicious whole numbers: *exactly* 10,000 searches from single cookie

Outliers: Common Types from Search

▶ Quantity:

- ▶ 10K searches from the same cookie in one day
- ▶ Suspicious whole numbers:
exactly 10,000 searches from single cookie

Time of day	Query
12:02:01	[google]
13:02:01	[google]
14:02:01	[google]
15:02:01	[google]
16:02:01	[google]
17:02:01	[google]

▶ Repeated:

- ▶ The same search repeated over-frequently
- ▶ The same search repeated at the same time (10:01AM)
- ▶ The same search repeated at a repeating interval (every 1000 seconds)

Treatment of Outliers: Many Methods

- ▶ Remove outliers when you're looking for **average** user behaviors
 - ▶ *Methods:*
 - ▶ Error bounds, tolerance limits – control charts
 - ▶ Model based – regression depth, analysis of residuals
 - ▶ Kernel estimation
 - ▶ Distributional
 - ▶ Time Series outliers
 - ▶ Median and quantiles to measure / identify outliers

Sample reference:
*Exploratory Data Mining
and Data Quality*, Dasu
& Johnson (2004)

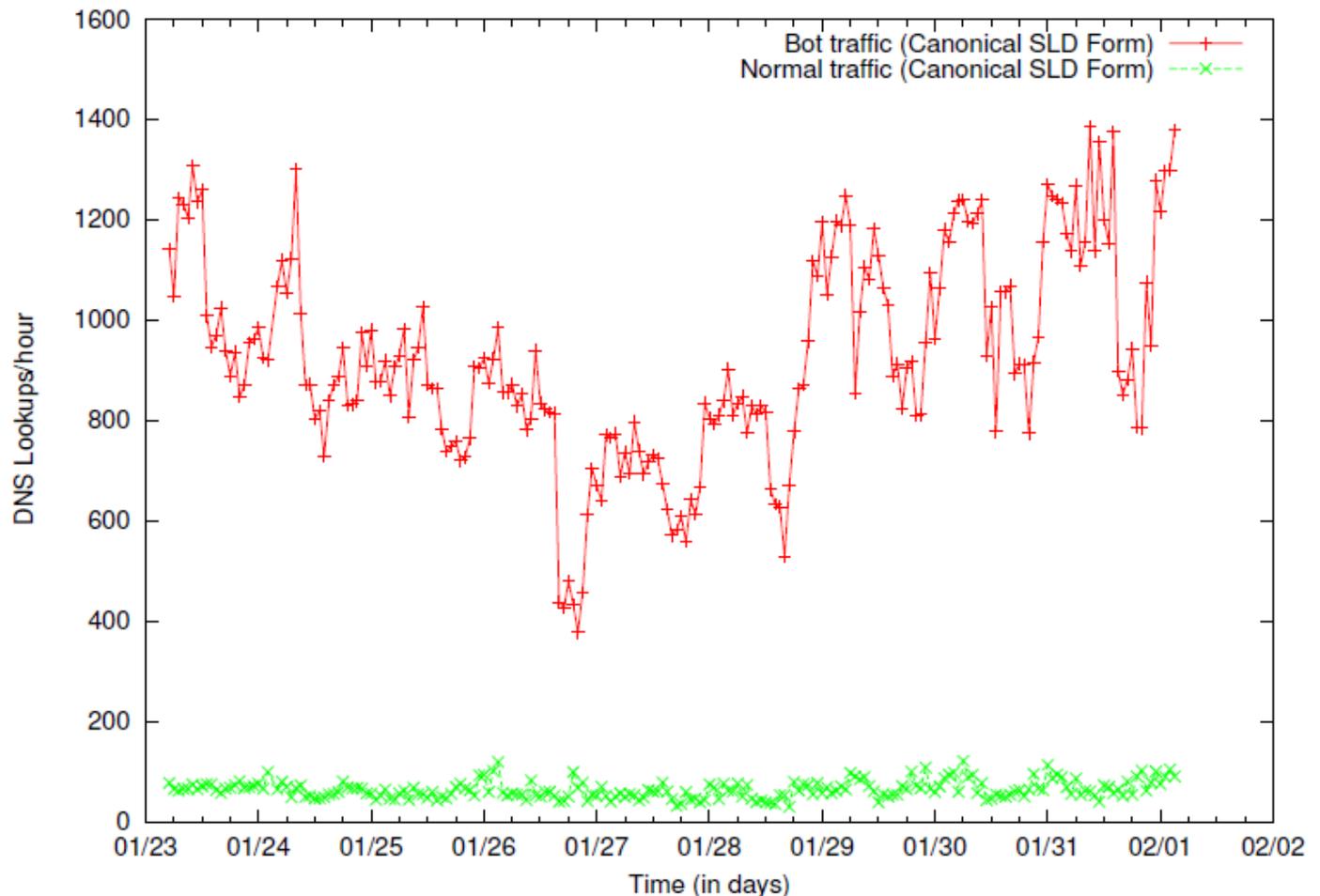
Identifying Bots & Spam

- ▶ Adversarial environment
- ▶ How to ID bots:
 - ▶ Queries too fast to be humanoid-plausible
 - ▶ High query volume for a single query
 - ▶ Queries too specialized (and repeated) to be real
 - ▶ Too many ad clicks by cookie



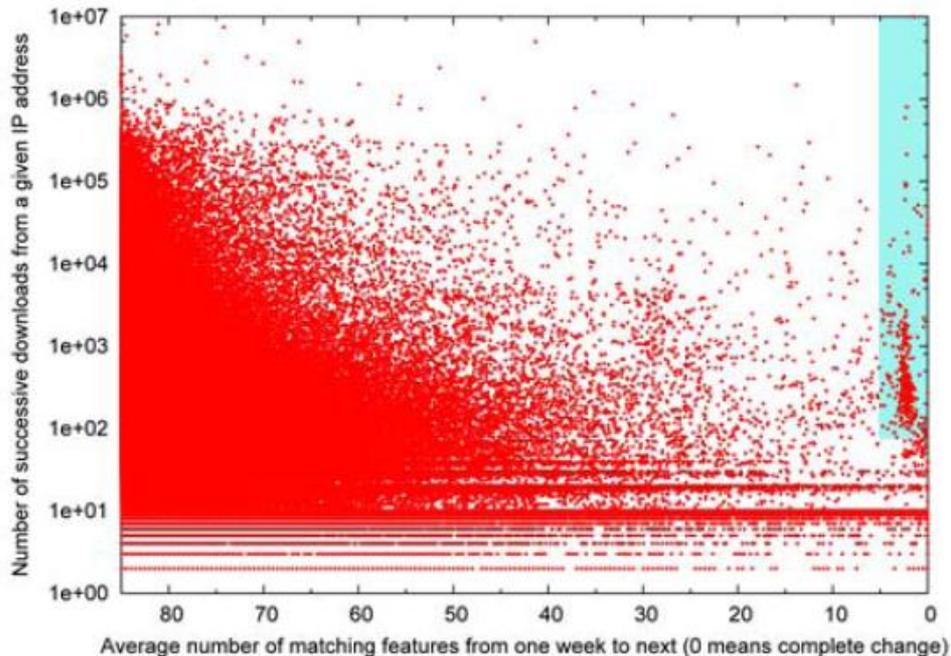
Bot Traffic Tends to Have Pathological Behaviors

- ▶ Such as abnormally high page-request or DNS lookup rates



How to ID Spam

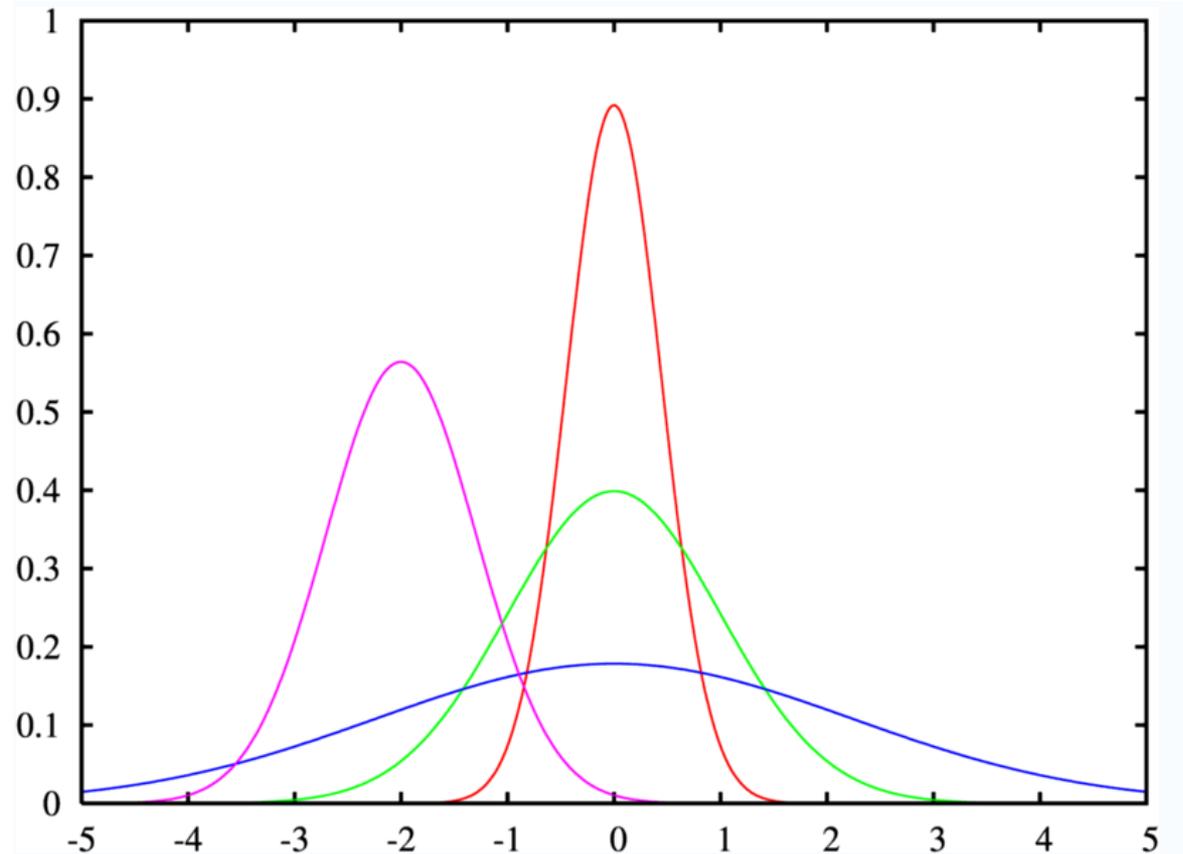
- ▶ Look for outliers along different kinds of features
 - ▶ Example: click rapidity, interclick time variability,



Spammy sites often change many of their features
(page titles, link anchor text, etc.) rapidly week to week

Bots / Spam Clicks Look Like Mixtures

- ▶ Although bots tend to be tightly packed and far from the large mass of data



Story About Spam...

- ▶ 98.3% of queries for [naomi watts] had no click
- ▶ Checking the referers of these queries led us to a cluster of LiveJournal users
- ▶ `img src="http://www.google.ru/search?q=naomi+watts..."`
- ▶ What??
- ▶ Comment spam by **greed114**. No friends, no entries. Apparently trying to boost Naomi Watts on IMDB, Google, and MySpace.



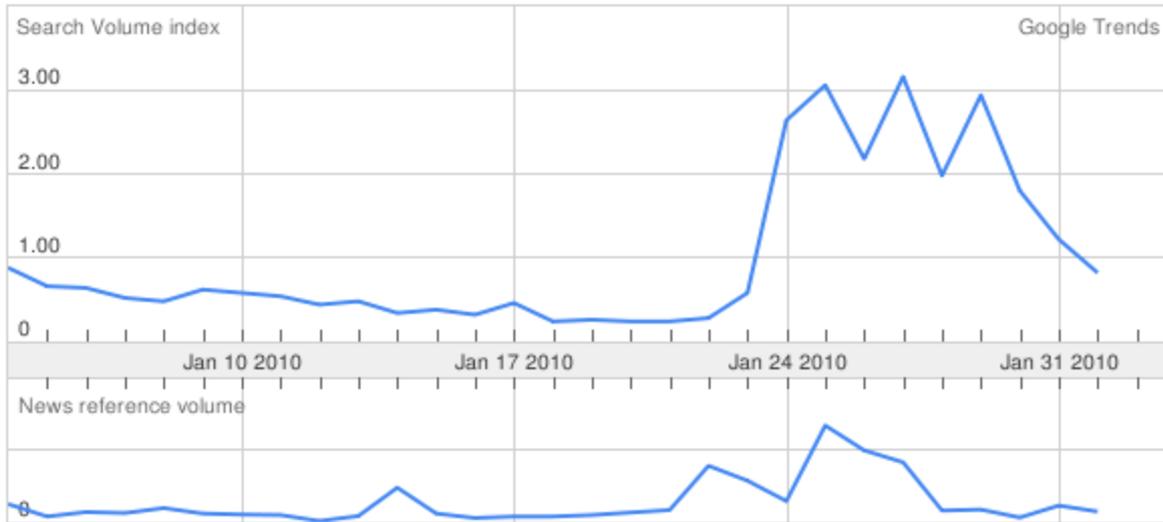
 [greed114](#)
2010-01-29 01:40 pm UTC ([link](#))

([Reply to this](#)) ([Parent](#))

Did it Work?

naomi watts

1.00



No news articles were found

Rank by

Regions

1. [Russian Federation](#) 
2. [Belarus](#) 
3. [Ukraine](#) 
4. [Latvia](#) 

Cities

1. Moscow, Russian Federation 
2. St Petersburg, Russian Federation 
3. Novosibirsk, Russian Federation 
4. Yekaterinburg, Russian Federation 

Cleaning Heuristics:

Be Sure to Account for Known Errors

- ▶ **Examples:**
 - ▶ Known data drops
 - ▶ e.g., when a server went down during data collection period – need to account for missing data
 - ▶ Known edge cases
 - ▶ e.g., when errors occur at boundaries, such as timing cutoffs for behaviors (when do you define a behavior such as a search session as “over”)

Simple Ways to Look for Outliers

- ▶ Simple queries are effective:

```
Select Field, count(*) as Cnt
from Table
Group by Field
Order by Cnt Desc
```

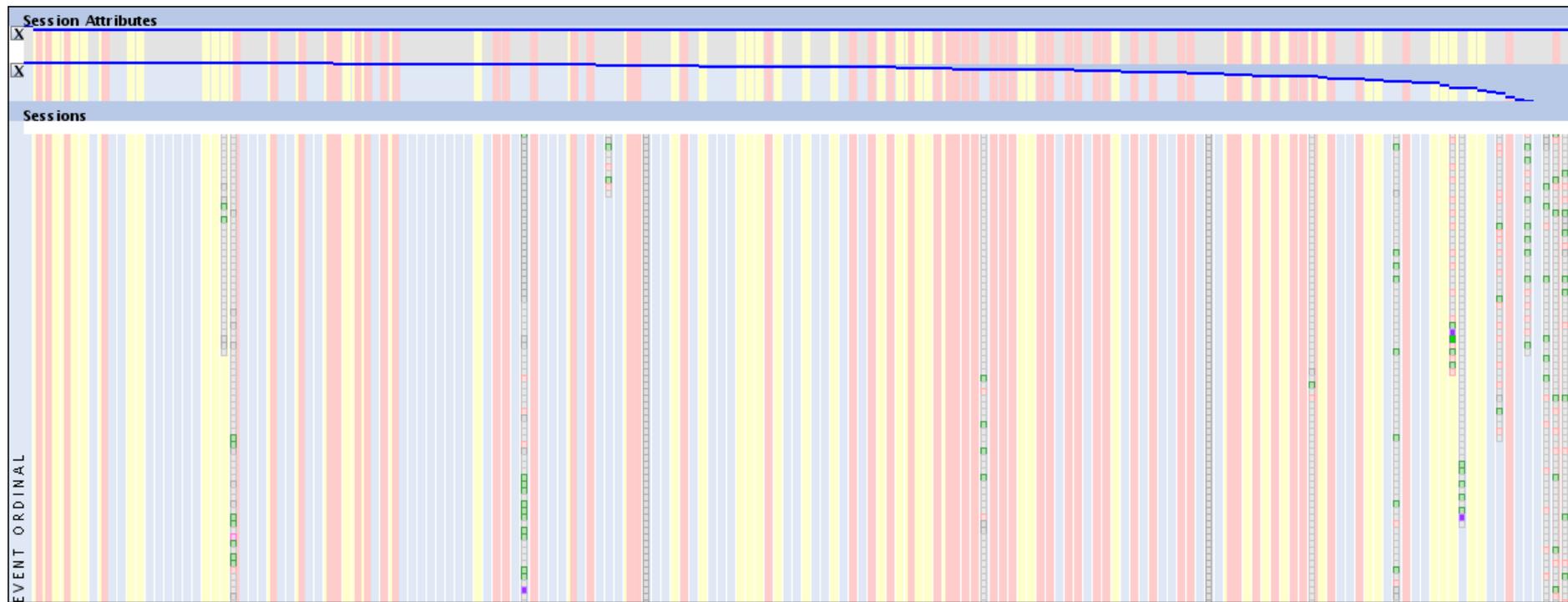
- ▶ Hidden NULL values at the head of the list, typos at the end of the list
- ▶ Visualize your data
 - ▶ Often can see data discrepancies that are difficult to note in statistics
 - ▶ LOOK at a subsample... **by hand**. (Be willing to spend the time)

But Ultimately...

- ▶ Nearly all data cleaning operations are special purpose, one-off kinds of operations

But Ultimately...

- ▶ Big hint: Visual representations of the data ROCK!
Why? Easy to spot all kinds of variations on the data quality that you might not anticipate *a priori*.



Careful About *Skew*, not Just Outliers

- ▶ For example, if an NBA-related query is coming from Wisconsin, search queries are biased by local preferences. Google Trends and Google Insights data shows pretty strong indications of this (look at the Cities entries in either product):
 - ▶ <http://www.google.com/trends?q=Milwaukee+bucks&ctab=0&geo=all&date=all&sort=0>
 - ▶ <http://www.google.com/trends?q=lakers&ctab=0&geo=all&date=all&sort=0>
 - ▶ <http://www.google.com/trends?q=celtics&ctab=0&geo=all&date=all&sort=0>
 - ▶ <http://www.google.com/trends?q=manchester+united&ctab=0&geo=all&date=all>
 - ▶ <http://www.google.com/trends?q=chelsea&ctab=0&geo=all&date=all&sort=0>
 - ▶ <http://www.google.com/insights/search/#q=lakers%2C%20celtics%2Cmilwaukee%20bucks&cmpt=q>
 - ▶ <http://www.google.com/insights/search/#q=arsenal%2Cmanchester%20united%2Cchelsea&cmpt=q>
- ▶ Using this data will generate some interesting correlations. For example, Ghana has a higher interest in Chelsea (because one of the Chelsea players is Ghanaian).
- ▶ Similarly for temporal variations (see Robin's query volume variation over the year)

Tip: Use commas to compare multiple search terms.

Searches [Websites](#)

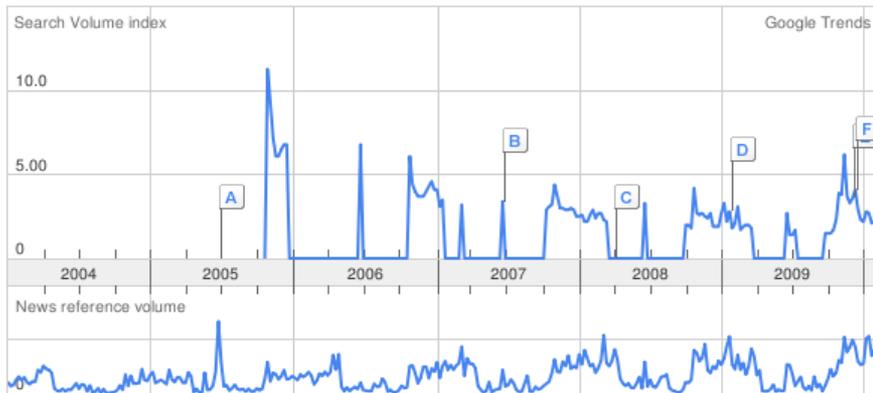
All regions

All years

Scale is based on the average worldwide traffic of **milwaukee bucks** in all years. [Learn more](#)

milwaukee bucks

1.00



- A** [Top pick visits Milwaukee Bucks, says he's glad draft is over](#)
Duluth News Tribune - Jun 29 2005
- B** [Milwaukee Bucks' image at stake after selecting Yi Jianlian at NBA draft](#)
CBC News - Jun 29 2007
- C** [New Jersey Nets \(32-47\) at Milwaukee Bucks \(26-53\), 8:30 pm](#)
TheNewsTribune.com - Apr 12 2008
- D** [Milwaukee Bucks Lose Michael Redd For The Rest Of The Season](#)
Bleacher Report - Jan 25 2009
- E** [Brandon Jennings scores 22 to lift Milwaukee Bucks over Toronto Raptors](#)
Appleton Post Crescent - Dec 10 2009
- F** [Kobe Bryant hits another game winner against the Milwaukee Bucks](#)
Examiner.com - Dec 17 2009

[More news results »](#)

Rank by [milwaukee bucks](#)

Regions	Cities	Languages
1. United States	1. Brookfield, WI, USA	1. English
2. Australia	2. Cedarburg, WI, USA	2. Turkish
3. Canada	3. New Berlin, WI, USA	3. Chinese
4. Spain	4. Waukesha, WI, USA	4. Spanish
5. China	5. Hawkins, WI, USA	5. French
6. United Kingdom	6. Milwaukee, WI, USA	6. German
	7. Fond Du Lac, WI, USA	
	8. Green Bay, WI, USA	
	9. Stevens Point, WI, USA	
	10. Appleton, WI, USA	

Pragmatics

- ▶ Keep track of what data cleaning you do!
 - ▶ Add lots of metadata to describe what operations you've run (It's too easy to do the work, then forget which cleaning operations you've already run.)
 - ▶ Example: data cleaning story from ClimateGate –only the cleaned data was available...
 - ▶ Add even more metadata so you can interpret this (clean) data in the future.
 - ▶ **Sad story:** I've lost lots of work because I couldn't remember what this dataset was, how it was extracted, or what it meant... as little as 2 weeks in the past!!

Pragmatics

- ▶ **BEWARE** of truncated data sets!
 - ▶ All too common: you think you're pulling data from Jan 1, 20?? – Dec 31, 20??, but you only get Jan 1 – Nov 17
- ▶ **BEWARE** of censored / preprocessed data!
 - ▶ Example: Has this data stream been cleaned-for-safe-search before you get it?
 - ▶ **Story:** Looking at queries that have a particular UI treatment. (Image universal triggering) We noticed the porn rate was phenomenally low. Why? Turns out that this UI treatment has a porn-filter BEFORE the UI treatment is applied, therefore, the data from the logs behavior was already implicitly run through a porn filter.

Pragmatics

- ▶ **BEWARE** of capped values
 - ▶ Does your measuring instrument go all the way to 11?
 - ▶ Real problem: time on task (for certain experiments) is measured only out to X seconds. All instances that are > X seconds are either recorded as X, or dropped. (Both are bad, but you need to know which data treatment your system follows.)
 - ▶ This seems especially true for very long user session behaviors, time-on-task measurements, click duration, etc.
 - ▶ Metadata should capture this
 - ▶ **Note:** big spikes in the data often indicate this kind of problem

Pragmatics

- ▶ **Do** sanity checks constantly
 - ▶ Don't underestimate their value.
 - ▶ Right number of files? Roughly the right size? Expected number of records?
 - ▶ Does this data trend look roughly like previous trends?
 - ▶ Check sampling frequency (Are you using downsampled logs, or do you have the complete set?)

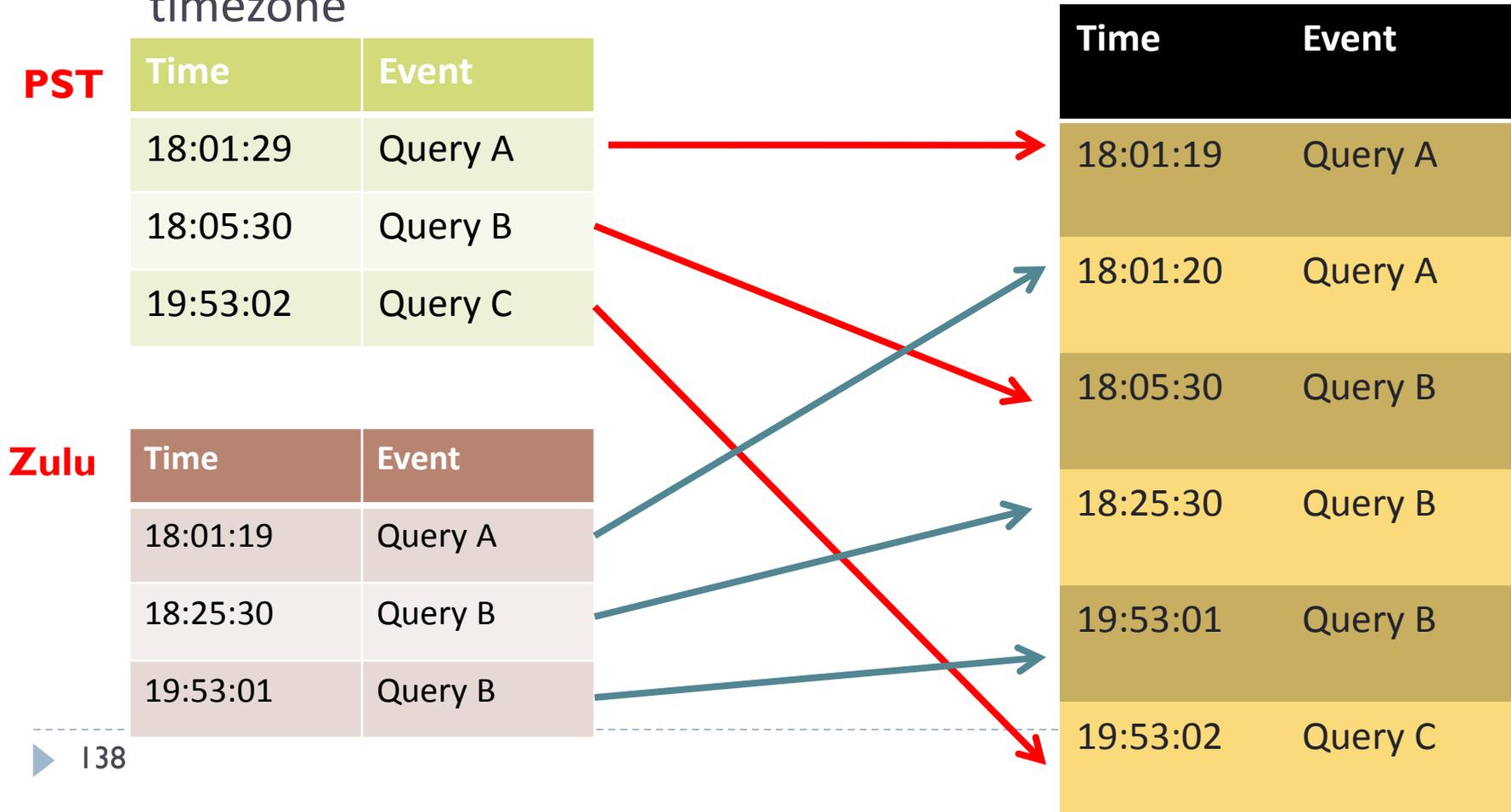
Pragmatics

- ▶ Metadata – describes your data, and what you’ve done to it over the course of time
 - ▶ Too many examples of data being extracted, and then becoming useless over time because you can’t figure out where it was extracted from, or what manipulations were done with it.
 - ▶ Example: dataset 1 (full logs from March 1, 2010 – April 1, 2010)
 - Despammed with Datacleaner.NoClickfarms and Datacleaner.NoBots
 - All long sessions removed
 - All non-EN interactions removed
 - All sessions of length 1 removed

And NOW, three months later, you find the file. It’s labeled “Data.txt”
Good luck.

Data Integration

- ▶ Be sure that joins of data are all using the same basis
 - ▶ E.g., time values that are measured consistently – UTC vs. local timezone



Often Can't Re-run Experiments

- ▶ **Too many basis factors have changed over time...**
 - ▶ The underlying web contents (and therefore index and all associated behaviors) have turned over
 - ▶ The cookies you based the first study on are all gone (or enough of them have changed/aged-out that within-cookies is no longer possible)
 - ▶ Logging system changes the kinds of behaviors that are logged
 - ▶ Underlying interpretations of key metrics might have changed (e.g., re-scaling the values—what once was a 5.0 is now a 3.5)
 - ▶ Policy changes may prevent certain kinds of data collection, retention or interpretation

Data Cleaning Summary

- ▶ **CAUTION:** Many, many potholes to fall into
- ▶ **Know** what the purpose of your data cleaning is for
- ▶ **Maintain** metadata
- ▶ **Beware** of domain expertise failure
- ▶ **Ensure** that the underlying data schema is what you think it is

Transition: This sets us up to consider how we can use logs analysis more generally in the HCI community...

Section 3C: Log Analysis and the HCI Community

All

Kinds of User Data

	Observational	Experimental
User Studies <i>Controlled interpretation of behavior with detailed instrumentation</i>	In-lab behavior observations	Controlled tasks, controlled systems, laboratory studies
User Groups <i>In the wild, real-world tasks, probe for detail</i>	Ethnography, field studies, case reports	Diary studies, critical incident surveys
Log Analysis <i>No explicit feedback but lots of implicit feedback</i>	Behavioral log analysis	A/B testing, interleaved results

Goal: Build an abstract picture of behavior

Goal: Decide if one approach is better than another

Discussion: Log Analysis and HCI

- ▶ Is log analysis relevant to HCI?
- ▶ How to present/review log analysis research
 - ▶ Observational
 - ▶ Experimental
- ▶ How to generate logs
- ▶ Sources of log data

Is Log Analysis Relevant to HCI?

- ▶ “Know thy user”
 - ▶ *In situ* large-scale log provide unique insights
 - ▶ Real behavior
- ▶ What kinds of things can we learn?
 - ▶ Patterns of behavior (e.g., info seeking goals)
 - ▶ Use of systems (e.g., how successful are people in using the current vs. new system)
 - ▶ Experimental comparison of alternatives

How to Present/Review Log Analysis

- ▶ **Examples of successful log analysis papers**
 - ▶ Several published logs analysis of observational type
 - ▶ But fewer published reports of the experimental type
- ▶ **Determining if conclusions are valid**
 - ▶ Significance unlikely to be a problem
 - ▶ Data cleanliness important
 - ▶ Only draw supported claims (careful with intent)

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