Temporal Dynamics and Information Retrieval

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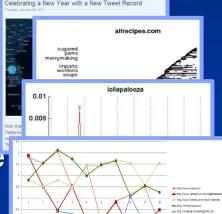
In collaboration with:

Eric Horvitz, Jaime Teevan, Eytan Adar, Jon Elsas, Dan Liebling, Richard Hughes, Krysta Svore, Kira Radinsky

Change is Everywhere in IR

Change is everywhere in digital information systems

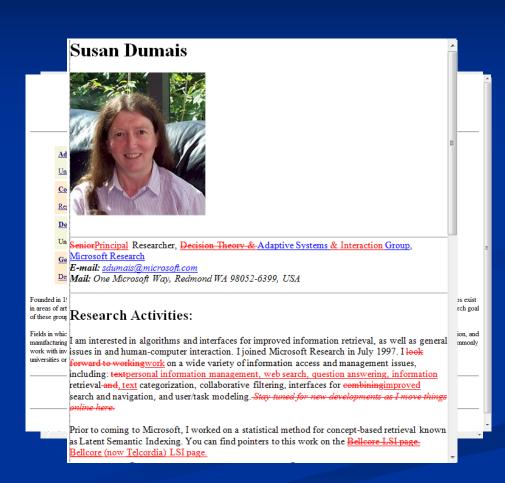
- New documents appear all the time
- Document content changes over time
- Queries and query volume change over time
- What's relevant to a query changes over time
 - E.g., *U.S. Open 2012* (in May vs. Sept)
- User interaction changes over time
 - E.g., anchor text, "likes", query-click streams, social networks, etc.
- Relations between entities change over time
 - E.g., President of the US is <> [in 2008 vs. 2004 vs. 2000]
- Change is pervasive in digital information systems ... yet, most retrieval systems ignore it!



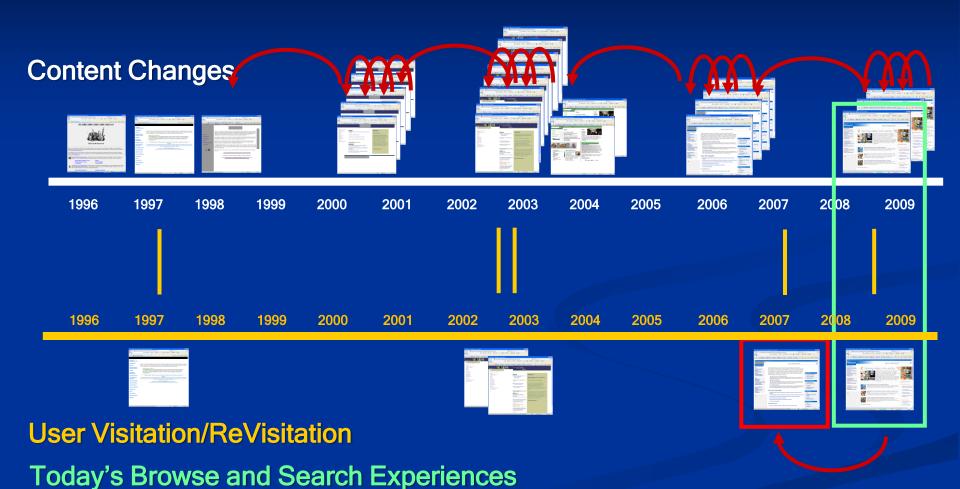
Digital Dynamics Easy to Capture

Easy to capture

But ... few tools support dynamics



Web Dynamics



Stanford InfoSeminar 3/9/12

Overview

- Change on the Web
 - Content changes over time
 - <u>User interaction</u> varies over time (queries, re-visitation, anchor text, query-click stream, "likes")
 - Tools for understanding Web change (e.g., Diff-IE)
- Improving Web retrieval using dynamics
 - Query trends over time
 - Retrieval models that leverage dynamics
 - Task evolution over time

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Characterizing Web Change



- Large-scale Web crawls, over time
 - Revisited pages
 - 55,000 pages crawled hourly for 18+ months
 - Unique users, visits/user, time between visits
 - Pages returned by a search engine (for ~100k queries)
 - 6 million pages crawled every two days for 6 months

Measuring Web Page Change

- Summary metrics
 - Number of changes
 - Amount of change
 - Time between changes
- Change curves
 - Fixed starting point
 - Measure similarity over different time intervals
- Within-page changes

Measuring Web Page Change

- Summary metrics
 - Number of changes

- 33% of Web pages change
- 66% of <u>visited</u> Web pages change
 - 63% of these change every hr.

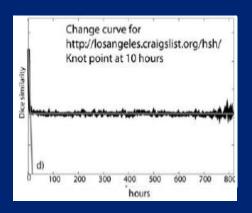
- Amount of change
- Time between changes

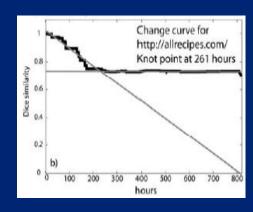
- Avg. Dice coeff. = 0.80
- Avg. time bet. change = 123 hrs.
- edu and .gov pages change infrequently, and not by much
- .com pages change at an intermediate rate, but by a lot
- popular pages change more frequently, but not by much

Measuring Web Page Change

- Summary metrics
 - Number of changes
 - Amount of change
 - Time between changes
- Change curves
 - Fixed starting point
 - Measure similarity over different time intervals







Measuring Within-Page Change

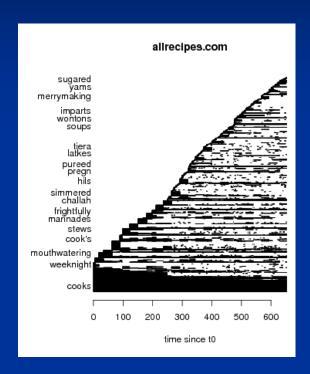
- Term-level changes
 - Divergence from norm
 - cookbooks
 - salads
 - cheese
 - ingredient
 - bbq
 - **...**
 - "Staying power" in page

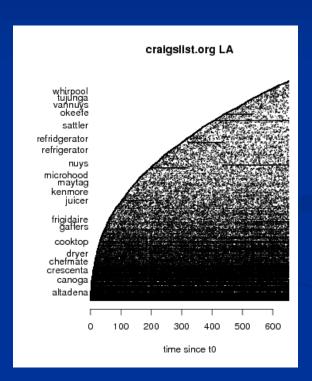


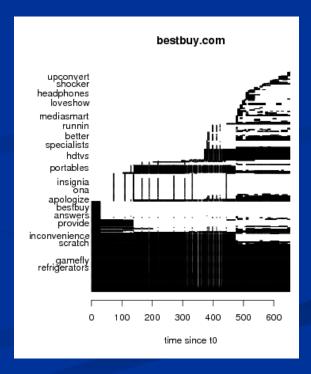
Sep. Oct. Nov. Dec.

Time

Example Term Longevity Graphs







Revisitation on the Web

- Revisitation patterns
 - Log analyses
 - Toolbar logs for revisitation
 - Query logs for re-finding
 - User survey to understand intent in revisitations



User Visitation/ReVisitation

What was the last Web page you visited? Why did you visit (re-visit) the page?

Measuring Revisitation

- Summary metrics
 - Unique visitors
 - Visits/user
 - Time between visits
- Revisitation curves
 - Histogram of revisit intervals
 - Normalized





Four Revisitation Patterns

- Fast
 - Hub-and-spoke
 - Navigation within site
- Hybrid
 - High quality fast pages
- Medium
 - Popular homepages
 - Mail and Web applications
- Slow
 - Entry pages, bank pages
 - Accessed via search engine



Relationships Between Change and Revisitation



- Interested in change
 - Monitor
- Effect change
 - Transact
- Change unimportant
 - Re-find old
 - Change can interfere with re-finding

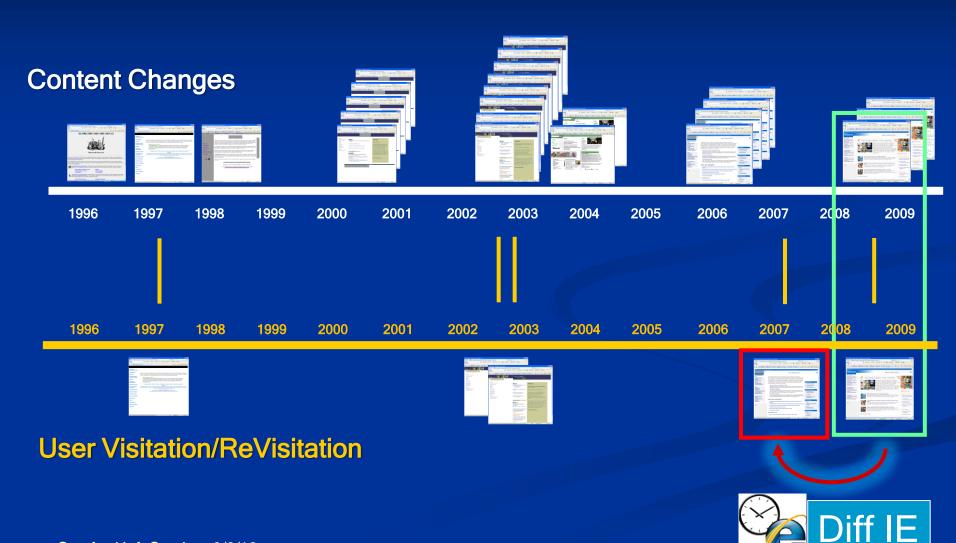
[Teevan et al., SIGIR 2007] [Tyler et al., WSDM 2010] [Teevan et al., WSDM 2011]

Revisitation and Search (Re-finding)

- 60-80% of the Web page visits are re-revisits
- 33%-43% of queries are re-finding
 - Repeat query (33%)
 - Q: microsoft research
 - Click same or different URLs
 - Repeat click (39%)
 - http://research.microsoft.com/
 - Q: *microsoft research; msr*
 - Big opportunity (43%)
 - 24% "navigational revisits"

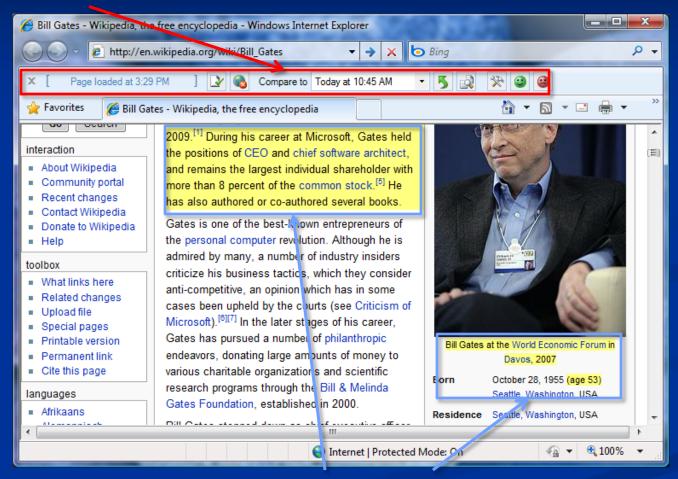
			\ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \
		Repeat Click	New Click
Repeat Query	33%	29%	4%
New Query	67%		

Building Support for Web Dynamics



Diff-IE

Diff-IE toolbar



Changes to page since your last visit

Interesting Features of Diff-IE



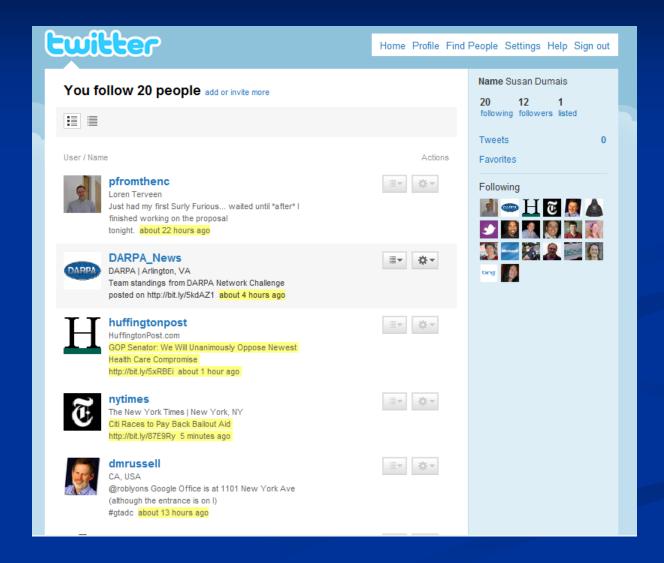
Try it: http://research.microsoft.com/en-us/projects/diffie/default.aspx

Examples of Diff-IE in Action

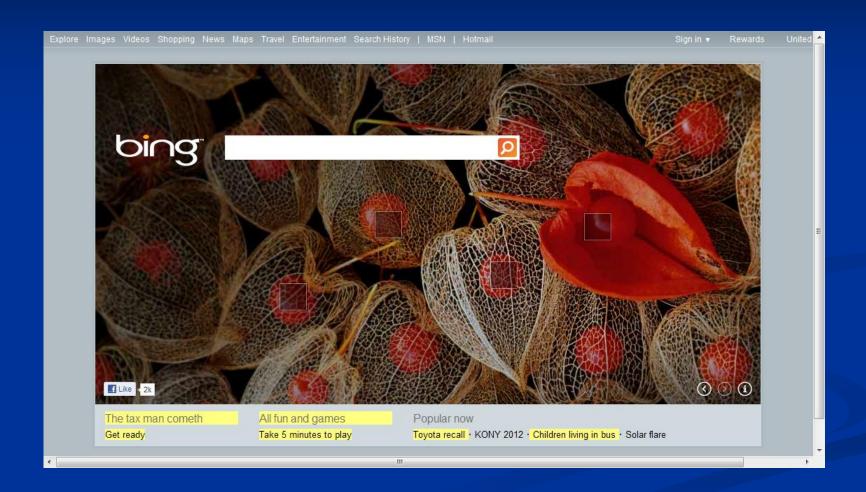
Expected New Content



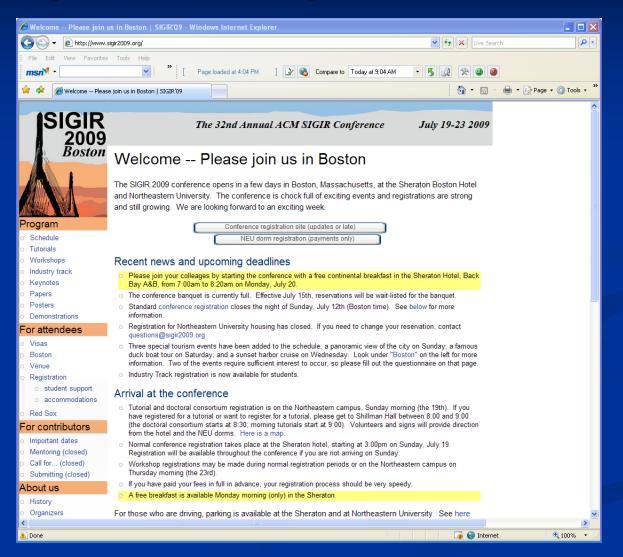
Monitor



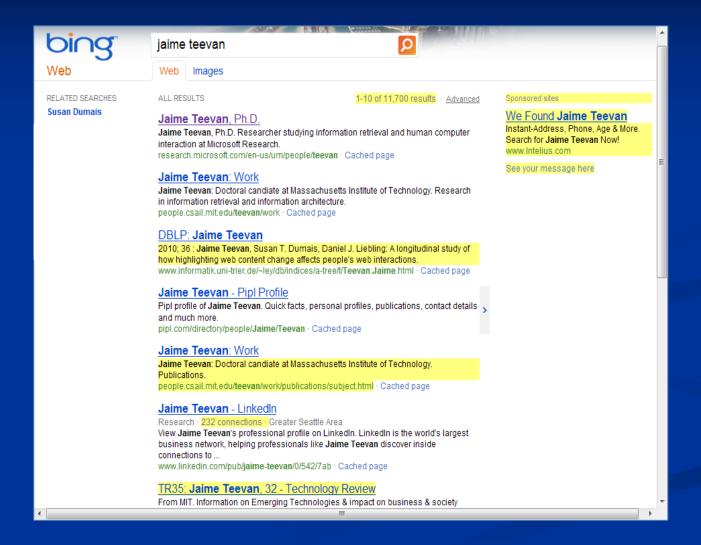
Serendipitous Encounters



Unexpected Important Content



Understand Page Dynamics



Expected



Expected
New Content



Monitor



Unexpected Important Content



Attend to Activity



Serendipitous Encounter



Unexpected Unimportant Content

Unexpected



Edit



Understand Page Dynamics

Studying Diff-IE

- Internal study of Diff-IE
- Logging
 - URLs visited



- Amount of change when revsited
- Feedback buttons





- Survey
 - Prior to installation
 - After a month of use
- Experience interview





Experience Longitudina

In situ

People Revisit More

- Perception of revisitation remains constant
 - How often do you revisit?
 - How often are revisits to view new content?



- Actual revisitation increases
 - First week: 39.4% of visits are revisits
 - Last week: 45.0% of visits are revisits
- Why are people revisiting more with DIFF-IE?

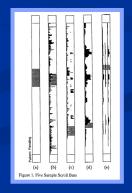
Revisited Pages Change More

- Perception of change increases
 - What proportion of pages change regularly?
- How often do you notice unexpected change?
- Amount of change seen increases
 - First week: 21.5% revisits changed, by 6.2%
- 51+%
- Last week: 32.4% revisits changed, by 9.5%
- Diff-IE is driving visits to changed pages
 - It supports people in understanding change

Other Examples of Dynamics and User Experience

- Content changes
 - Diff-IE (Teevan et al., 2008)
 - Zoetrope (Adar et al., 2008)
 - Diffamation (Chevalier et al., 2010)
 - Temporal summaries and snippets ...
- Interaction changes
 - Explicit annotations, ratings, "likes", etc.
 - Implicit interest via interaction patterns
 - Edit wear and read wear (Hill et al., 1992)





Overview

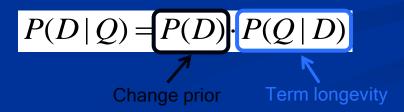
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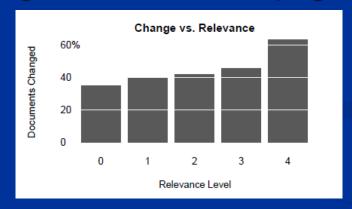
Temporal Retrieval Models 1 (content-based)

- Current retrieval algorithms look only at a single snapshot of a page
- But, Web page content changes over time
- Can we can leverage this to improved retrieval?
 - Pages have different rates of change
 - Different priors (using change rate vs. link structure)
 - Terms have different longevity (staying power)
 - Some are always on the page; some transient
 - Language modeling approach to ranking



Relevance and Page Change

- Page change is related to relevance
 - Human relevance judgments
 - 5-point scale Perfect/Excellent/Good/Fair/Bad
 - Rate of Change -- 60% Perfect pages; 30% Bad pages

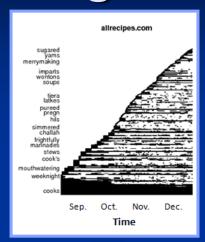


- Use change rate as a document prior (vs. priors based on link structure like Page Rank)
 - Shingle prints to measure change

$$P(D | Q) = P(D) \cdot P(Q | D)$$
Change prior

Relevance and Term Change

- Terms patterns vary over time
- Represent a document as a mixture of terms with different "staying power"
 - Long, Medium, Short



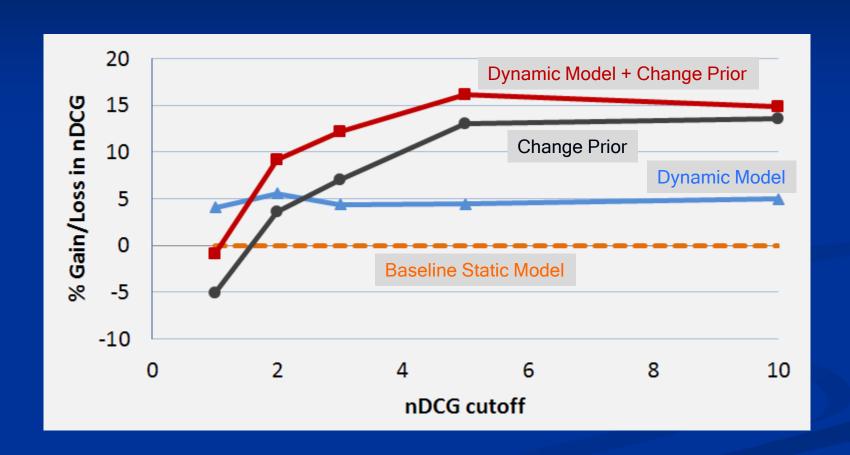
$$P(Q \mid D) = \lambda_L P(Q \mid D_L) + \lambda_M P(Q \mid D_M) + \lambda_S P(Q \mid D_S)$$

$$P(D | Q) = P(D) \cdot P(Q | D)$$
Term longevity

Evaluation: Queries & Documents

- 18K Queries, 2.5M Judged Documents
 - 5-level relevance judgment (Perfect ... Bad)
- 2.5M Documents crawled weekly for 10 wks
- Navigational queries
 - 2k queries identified with a "Perfect" judgment
 - Assume these relevance judgments are consistent over time
- Measure changes in nDCG

Experimental Results



Temporal Retrieval Models 2 (behavior-based)

- Initial evaluation
 - Navigational queries; assume relevance is "static" over time
- But, relevance often changes over time
 - E.g., Super Bowl -- in 2012 vs. in 2011
 - E.g., *US Open 2012 --* in May (golf) vs. in Sept (tennis)
 - E.g., *March madness 2012 --* before/during/after event
 - Before event: Schedule and tickets, e.g., stubhub
 - During event: Real-time scores, e.g., espn, cbssports
 - After event: General sites, e.g., wikipedia, ncaa

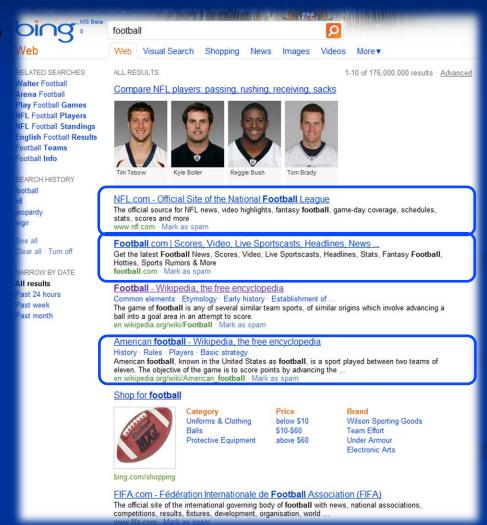
Current evaluation

 Collect explicit and implicit relevance judgments, query frequency, interaction data, and page content <u>over time</u>

Relevance over Time

Query: football [season Sep - Jan]

 Need to model time of query, pages and events



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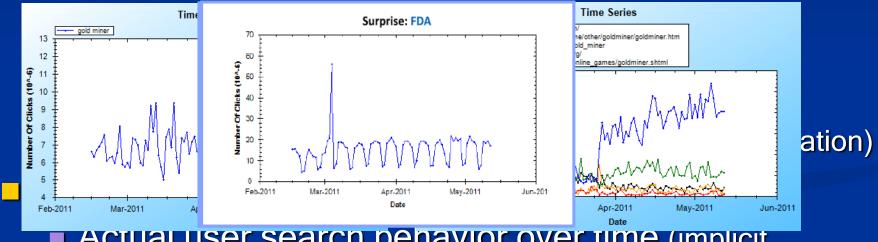
Relevance over Time

- Query: sigir
- Why is old content ranked higher?
 - User interaction data more prevalent for older documents
 - E.g., query-clicks, anchor text, etc.
- Need to weight user behavior signals appropriately



Experimental Setup

- Data
 - Queries and clicked URLs, over 4 months



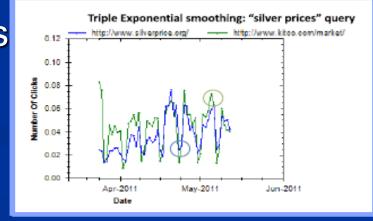
- Actual user search behavior over time (implicit measure)
- Model temporal dynamics of behavior
- Use model to improved ranking

Time Series Modeling

- Model search behavior as time series
 - Assume that the series of behavioral observations $Y_1 ... Y_n$ is generated sequentially based on some underlying structure (e.g., a sequence of *state vectors*)
- Linear State Space Model (SSM)
 - Let X_t be a state vector at moment of time t, then a semilinear state space model is defined by:

$$Y_t = w(\theta)X_t + \epsilon_t$$
 (observation eqn.)
 $X_t = F(\theta)X_{t-1} + G(\theta)\epsilon_t$ (state transition eqn.)

- Model state with Holt-Winters
 - Smoothing
 - Trend (+Level)
 - Periodic/Seasonal



Experimental Details

- Train: Learn time series models
- Predict: Future query and click behavior
- Ranking models
 - Predicted clicks as the <u>only</u> feature for ranking
 - Temporal features (+other features) as input to learned ranker
- Three types of features
 - No user behavior (i.e., just content)
 - Historical average of user behavior
 - Uniform, Linear, Power
 - Temporal models of user behavior
 - Smoothing, +Trend, +Trend+Periodicity
- Measure: Correlation (predicted vs. actual) rankings

Experimental Results

Predicted clicks as the only feature

Query Type	Baselines			
Query Type	Average	Linear weight	Power weight	
General	0.91	0.92	0.93	
Tail	0.18	0.21	0.22	
Periodic	0.91	0.92	0.93	
Dynamic	0.28	0.35	0.38	
Alternating	0.80	0.82	0.84	
Temp Reform	0.95	0.95	0.95	

Table 2: Pearson correlation on ordering of our temporal models compared to baseline models. Statistically significant differences based on a paired t-test (p < .05) are shown in bold.

Ranker trained with temporal features

	Query Type	No User Behavior	Baseline Models		
Ш	Query Type	Base Features	Base Features	Base Features	Base Features
Ш			+Average	+Linear weight	+Power weight
Ш					
Ш					
Ιİ	General	0.47	0.97	0.98	0.98
Ш	Tail	0.31	0.20	0.07	0.02
Ш	Periodic	0.78	0.87	0.91	0.91
Ш	Dynamic	-0.08	0.30	0.30	0.39
	Alternating	0.23	0.64	0.90	0.74
Ш	Temp Reform	0.19	0.73	0.97	0.96

Table 4: Pearson Correlation on ranking using Base features without user behavior, with stat using our temporal models. Statistically significant differences based on a paired t-test when operforming algorithm (p < .05) are shown in bold.

Best-performing queries

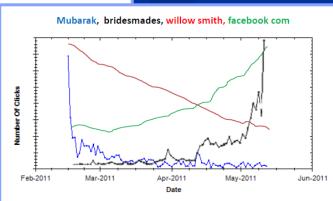
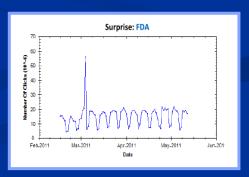


Figure 6: Dominant query shapes for queries where temporal model yielded better rankings than baseline rankers.

Temporal IR Summary

- Goal: Improve Web retrieval by modeling temporal dynamics
- Content-based models
 - Rate of page change
 - Detailed term-level changes
- Behavior-based models
 - Query frequency over time
 - Click patterns over time
- Ongoing work
 - Combine content and behavior features
 - Surprise detection
 - Snippet generation





Other Examples of Dynamics and Information Systems

- Temporal retrieval models
 - Radinski et al. (submitted); Elsas & Dumais (2010); Liu & Croft (2004); Efron (2010); Aji et al. (2010)
- Document dynamics, for crawling and indexing
 - Adar et al. (2009); Cho & Garcia-Molina (2000); Fetterly et al. (2003)
- Query dynamics
 - Kulkarni et al. (2011); Jones & Diaz (2004); Diaz (2009); Kotov et al. (2010)
- Extraction of temporal entities within documents
- Protocol extension for retrieving versions over time
 - E.g., Memento (Van de Sompel et al., 2010)

Summary

Temporal IR:

Leverages change for improved IR

Web content changes: page-level, term-level











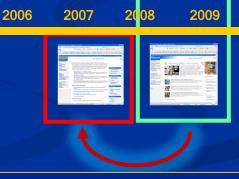
Relating revisitation and change allows us to

- Identify pages for which change is important
- Identify interesting components within a page





People revisit and re-find Web content



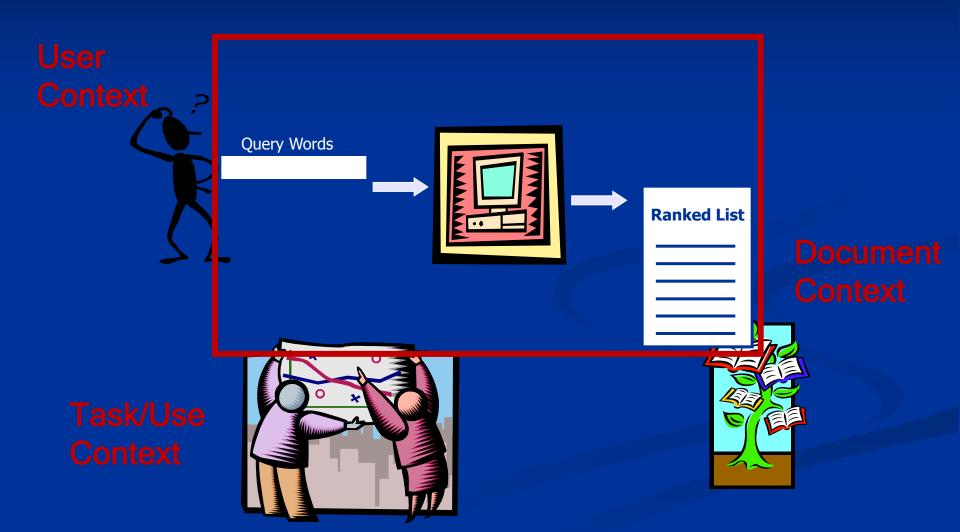
Diff-IE: Supports (and influences) interaction and understanding

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Challenges and Opportunities

- Temporal dynamics are pervasive in information systems
- Influence many aspect of information systems
 - Systems: protocols, crawling, indexing, caching
 - Document representations: meta-data generation, information extraction, sufficient statistics at page and term-level
 - Retrieval models: term weights, document priors, etc.
 - User experience and evaluation
- Better supporting temporal dynamics of information
 - Requires digital preservation and temporal metadata extraction
 - Enables richer understanding of the evolution (and prediction) of key ideas, relations, and trends over time
- Time is one important example of <u>context</u> for IR
 - Others include: location, individuals, tasks ...

Think Ouseidreth Résearch) Boxes



Thank You!

Questions/Comments ...

More info, http://research.microsoft.com/~sdumais

Diff-IE ... try it!



http://research.microsoft.com/en-us/projects/diffie/default.aspx