



It's Y!ou—Content Optimization at Yahoo!

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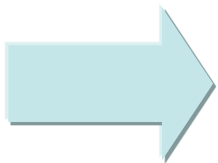
The Message

- The Web will be increasingly personalized, but “personalization” will mostly happen within the context of
 - Content optimization
 - Semantic interpretation of web content and user intent
 - Socialization of the web



Content Optimization

- Content
 - Portal content, Search, Social
- Optimization objective
 - Engagement, revenue, retention, `voice`
- Signals:
 - Content features
 - Topic/entity
 - Popularity
 - Links, referrals, clicks, CTRs
 - User features
 - Content consumption, social, explicit





Personalization

- Why?
 - Engagement, revenue, retention, `voice`
- Why not?
 - Discovery, privacy, search bias
- Who?
 - User profiles
- How?
 - Algorithms, infrastructure



User Interest Modeling

- User—Topic (entities, categories) affinity
 - From logs (clicks, views, purchases, etc.)
- Latent Factor models
 - Topic affinities based on activity of user and “similar” users
- Search history
 - Online and offline
- Responses to recommendations
 - Current session history
- Explicit user declaration
 - When and what should we ask users?

raghu ramakrishnan - Yahoo! Search Results - Mozilla Firefox

File Edit View History Bookmarks Yahoo! Tools Help del.icio.us

http://search.yahoo.com/search?p=raghu+ramakrishnan&ei=UTF-8&fr=moz2

Yahoo! Maps My UW-Madison Gmail AMEN-RA Horns07 UFFP FBG Wire FBG board FBG FBG FBOutsiders MSN.com Find Your Home Value...

Y! raghu ramakrishnan Search Web Flickr My Web Answers del.icio.us Finance

Start Stumbling... or Sign-in

How the Packers ran on the Vikings - T... raghu ramakrishnan - Yahoo! Se... VLD BE Private Docs -- Home page

Yahoo! Mail Welcome, scyllawi Sign Out

Web Images Video Local Shopping more

raghu ramakrishnan Search Options

1-10 of 289,000 for raghu ramakrishnan (About) - 0.30 sec

Also try: data mining, raghu ramakrishnan research fellow, yahoo! research, More...

Yahool!s: Report bad results or ads. Bucket test: None

- Raghu Ramakrishnan's Home Page**
Raghu Ramakrishnan. Professor of Computer Sciences. Research Interests. Database systems. ... Raghu Ramakrishnan got his B.Tech. ...
pages.cs.wisc.edu/~raghu - 11k - [Cached](#)
- Database Management Systems (Third Edition)**
www.cs.wisc.edu/~dbbook - 5k - [Cached](#)
- DBLP: Raghu Ramakrishnan**
AnHai Doan, Philip Bohannon, **Raghu Ramakrishnan**, Xiaoyong Chai, Pedro DeRose, ... Vinod Yegneswaran, Paul Barford, **Raghu Ramakrishnan**: Toward a Query Language for ...
www.sigmod.org/dblp/db/indices/a-tree/r/Ramakrishnan:Raghu.html - 134k - [Cached](#)
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... Purple Patch on the Web **Raghu Ramakrishnan**, Chief Scientist for Audience, Yahoo! ... over Evolving Text Jun Yang (Duke University), **Raghu Ramakrishnan** (Yahoo! ...
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- Raghu Ramakrishnan - Wikipedia, the free encyclopedia**
Raghu Ramakrishnan. From Wikipedia, the free ... **Raghu Ramakrishnan** is a renowned researcher in the areas of database and information management.

Done

start Inbox - Microsoft Out... 4 Reminders raghu ramakrishnan - ... CommunitySystemsGr... Microsoft PowerPoint ...



- “Just look at our homepage, for example. Since we began pairing our **content optimization technology** with editorial expertise, we’ve seen **click-through rates in the Today module more than double**. And we’re making additional improvements to this technology that will make the user experience ever more personally relevant.”
- **Carol Bartz, Analyst Call, January 27, 2010**

CONTENT OPTIMIZATION FOR PORTALS



Team from Y! Research



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Nitin
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Joe Zachariah



Scott Roy



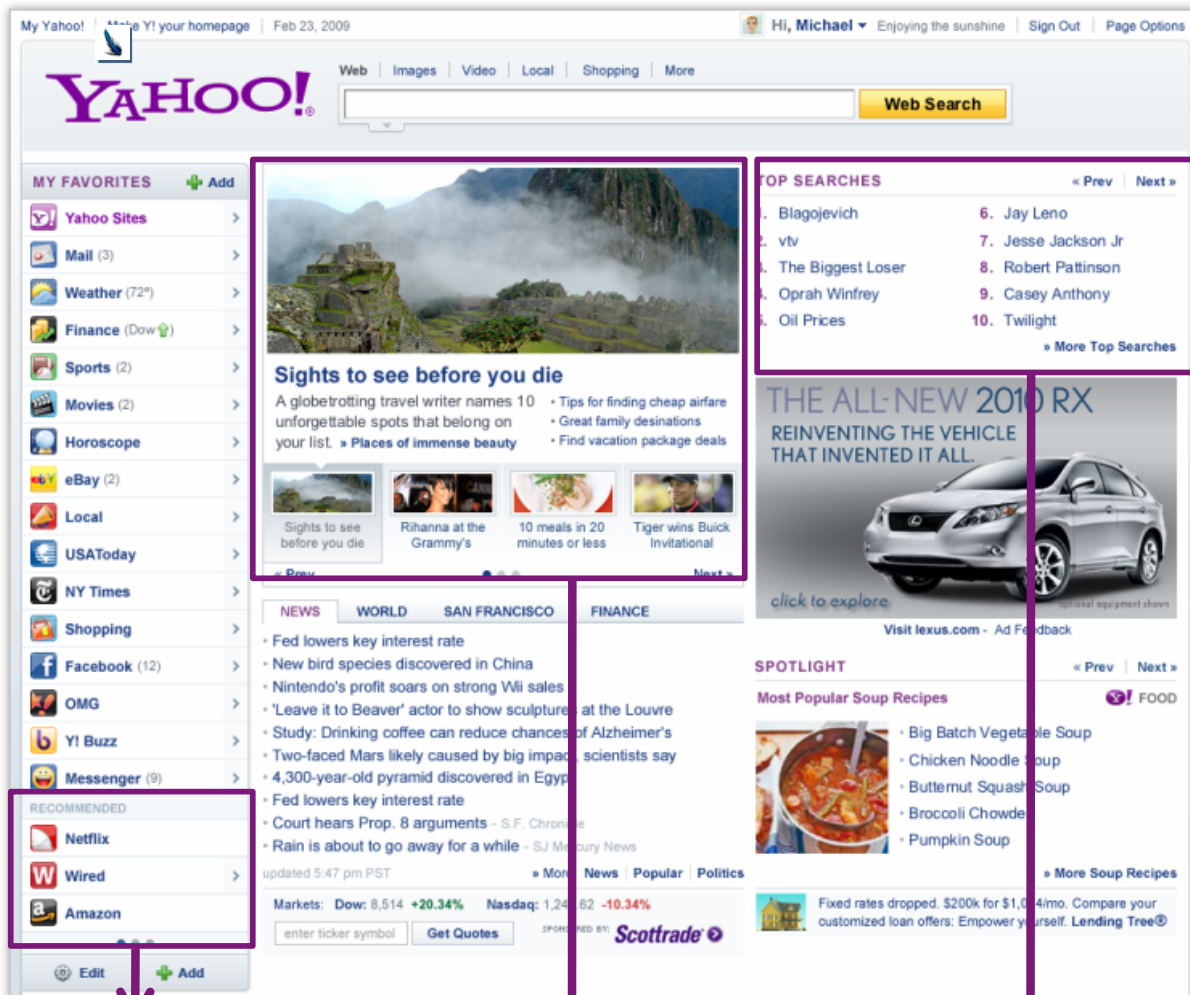
Kenneth Fox



Todd Beaupre



Content Optimization



Recommended links

+79% clicks

vs. randomly selected

News Interests

+200% clicks

vs. one size fits all

Top Searches

+43% clicks

vs. editor selected

Key Features

Package Ranker (CORE)

Ranks packages by expected CTR based on data collected every 5 minutes

Dashboard (CORE)

Provides real-time insights into performance by package, segment, and property

Mix Management (Property)

Ensures editorial voice is maintained and user gets a variety of content

Package rotation (Property)

Tracks which stories a user has seen and rotates them after user has seen them for a certain period of time

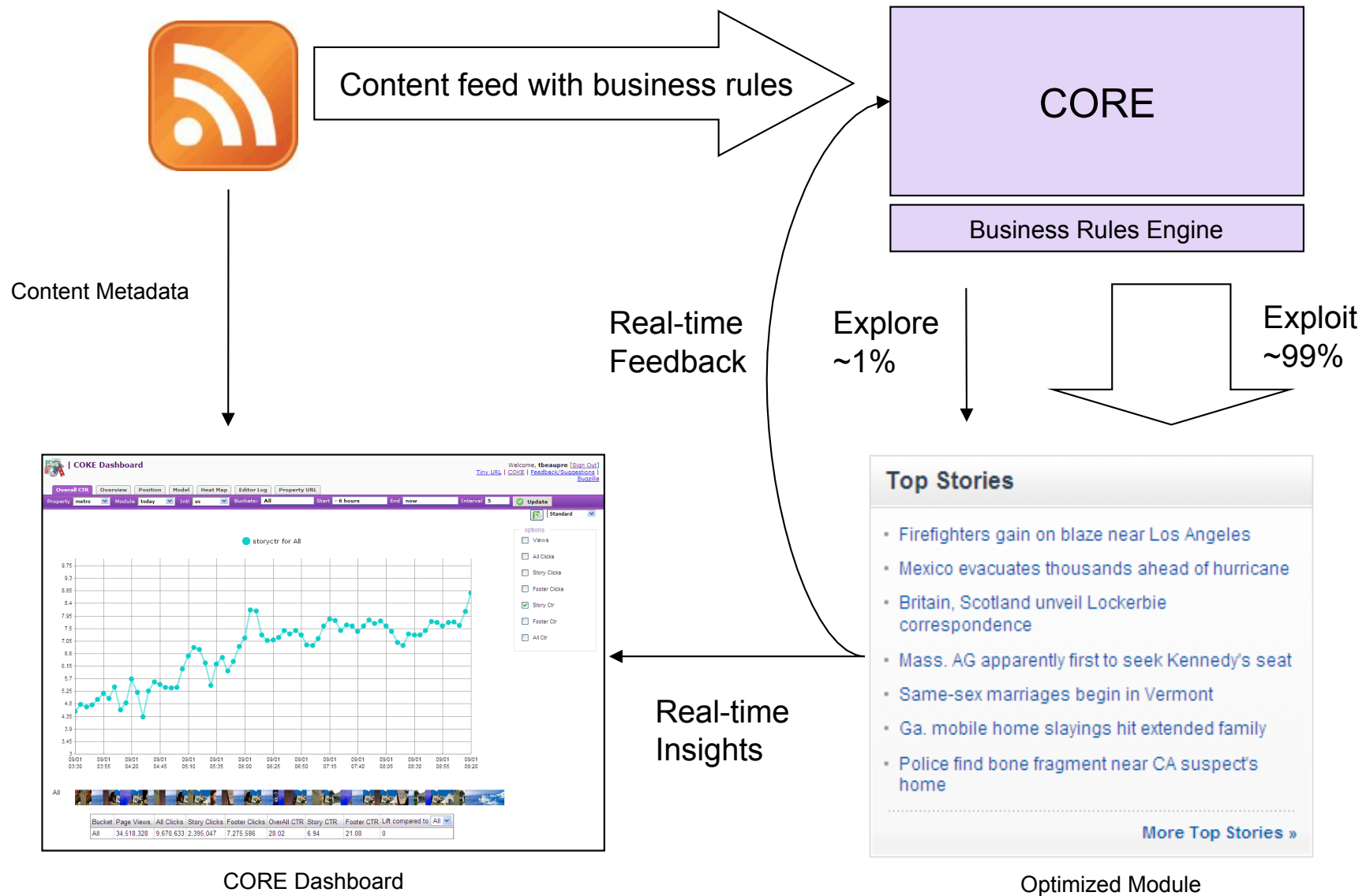
Key Performance Indicators

Lifts in quantitative metrics

Editorial Voice Preserved



CORE Data Flow





Recommender Approaches



Estimate Most Popular (EMP)

“What’s most engaging overall?”



Behavioral Affinities

“People who did X, did Y”



Attribute Similarities

“Related items with similar metadata”



Social Recommendations

“What are my trusted connections into?”



Business Optimization

“What generates most business value?”



Personalized Recommendations

“What’s most relevant to me based on my interests, attributes and relationships?”



CORE Modeling Overview

Offline Modeling

- Exploratory data analysis
- Regression, feature selection, collaborative filtering (factorization)
- Seed online models & explore/exploit methods at good initial points
- Reduce the set of candidate items

Online Learning

- Online regression models, time-series models
- Model the temporal dynamics
- Provide fast learning for per-item models

Explore/Exploit

- Multi-armed bandits
- Find the best way of collecting real-time user feedback (for new items)

Large amount of
historical data
(user event streams)

Near real-time user feedback



Ranking in CORE

- Pure feature based (did not work well):
 - Article: URL, keywords, categories
 - Build offline models to predict CTR when article shown to users
 - Models considered
 - Logistic Regression with feature selection
 - Decision Trees, Feature segments through clustering
- Track CTR per article in user segments through online models
 - **This worked well; the approach we took eventually**



Explore/Exploit

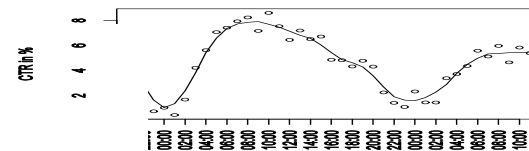
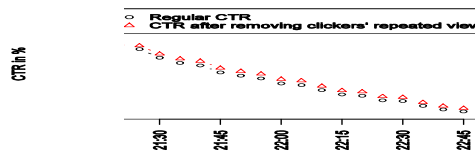
- What is the best strategy for new articles?
 - If we show it and it's bad: lose clicks
 - If we delay and it's good: lose clicks
- Solution: Show it while we don't have much data if it looks promising
 - Classical **multi-armed bandit** type problem
 - Our setup is different than the ones studied in the literature; new ML problem

(Online Models for Content Optimization, NIPS 2008: D. Agarwal, B. Chen, P. Elango, N. Motgi, S. Park, R. Ramakrishnan, S. Roy, J. Zachariah)



Challenges in Our Setting

- Dynamic item pools
- Article CTRs decay over time
- Time-of-day /day-of-week effects





Some Other Complications

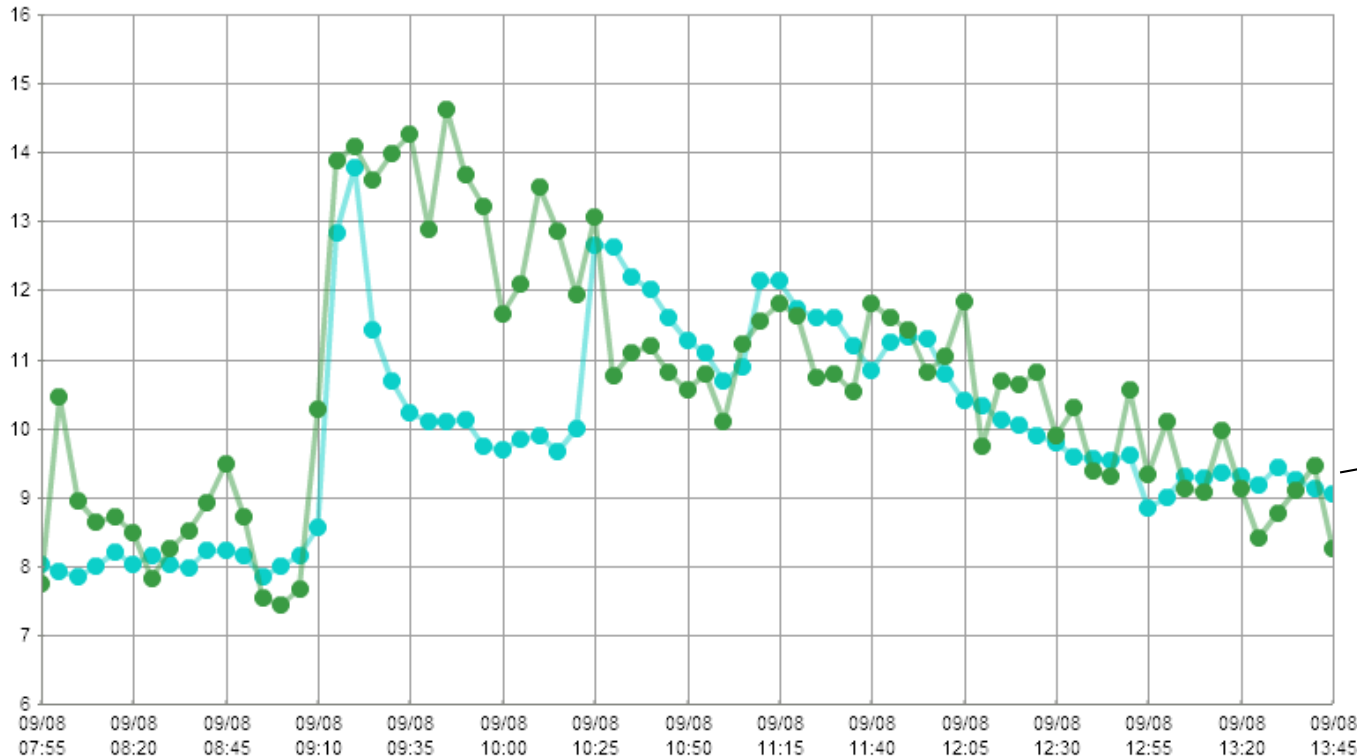
- We run multiple experiments (possibly correlated) simultaneously; effective sample size calculation a challenge
- Serving Bias: Incorrect to learn from data for serving scheme A and apply to serving scheme B
 - Need unbiased quality score
 - Bias sources: positional effects, time effect, set of articles shown together
- Incorporating feature-based techniques
 - e.g., logistic regression; tree-based (hierarchical bandit)



CORE Dashboard: Overall CTR

Compare performance of models and historical benchmarks

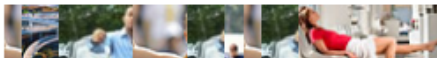
● storyctr for All ● storyctr for c21



Compare buckets and models over time

See which content was promoted most across time

c21



All



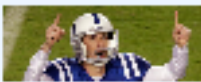




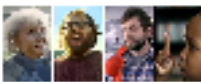





Compare bucket metrics

Bucket	Page Views	All Clicks	Story Clicks	Footer Clicks	OverAll CTR	Story CTR	Footer CTR	Lift compared to	All
All	43,005,783	13,061,688	4,286,407	8,775,281	30.37	9.97	20.4	0	
c21	281,821	84,853	29,777	55,076	30.11	10.57	19.54	6.02	



CORE Dashboard: Segment Heat Map

Package	male	female	OMG	BUAuto	BUEnt	BU Fin	Health	BUSport+	NBA	BUTrav	ALL
	408,260 18,440 0.0452 8.477	390,404 14,449 0.037 -11.113	270,039 16,940 0.0627 50.661	121,080 7,389 0.061 46.564	270,038 16,940 0.0627 50.661	325,873 20,012 0.0614 47.488	195,796 12,763 0.0652 56.553	350,152 21,454 0.0613 47.152	132,916 9,457 0.0712 70.879	123,388 7,896 0.064 53.691	923,611 38,457 0.0416 0
	1 8,067 852 0.1056 153.654	1 7,657 674 0.068 111.405	1 5,125 720 0.1405 237.406	1 2,382 286 0.1201 188.362	1 5,125 720 0.1405 237.406	1 6,415 858 0.1337 221.221	1 3,769 532 0.1412 239	1 6,750 917 0.1369 226.272	1 2,585 385 0.1489 257.696	1 2,490 330 0.1325 218.294	1 18,137 1,738 0.0958 130.143
	5 9,968 644 0.0646 55.164	3 12,847 777 0.0605 45.256	2 8,569 885 0.1033 148.043	4 3,529 326 0.0924 121.86	2 8,569 885 0.1033 148.043	3 9,744 922 0.0946 127.252	3 6,067 643 0.106 154.537	2 10,187 1,004 0.0986 136.702	5 3,820 420 0.1059 164.058	2 4,037 433 0.1073 157.558	4 25,744 1,595 0.062 48.798
	2 3,326 249 0.0749 79.8	5 3,954 212 0.0536 28.769	5 2,521 231 0.0916 120.066	2 1,004 102 0.1016 143.995	5 2,521 231 0.0916 120.066	5 3,016 276 0.0915 119.782	5 1,860 186 0.1 140.167	3 3,291 310 0.0942 126.229	3 1,141 136 0.1192 186.264	3 1,039 100 0.0962 131.152	3 8,500 541 0.0636 52.859
	11 2,562 133 0.0519 24.677	13 2,004 81 0.0404 -2.926	3 1,250 122 0.0976 134.403	6 629 51 0.0811 94.73	3 1,250 122 0.0976 134.403	4 1,608 151 0.0939 125.53	2 919 103 0.1121 169.175	4 1,669 154 0.0923 121.604	4 655 74 0.113 171.334	4 591 55 0.0931 123.506	10 5,342 252 0.0472 13.295
	3 2,881 206 0.0715 71.727	2 3,242 230 0.0709 70.384	4 2,071 196 0.0946 127.295	3 949 95 0.1001 140.42	4 2,071 196 0.0946 127.295	2 2,614 254 0.0972 133.368	4 1,605 165 0.1028 146.901	5 2,740 239 0.0872 109.489	10 1,036 94 0.0907 117.912	9 958 78 0.0814 95.543	2 7,043 493 0.07 68.114
	6 10,785 649 0.0602 44.523	4 12,768 742 0.0591 39.571	7 8,580 694 0.0809 94.261	7 3,511 283 0.0806 93.584	7 8,580 694 0.0809 94.261	6 9,725 795 0.0817 96.332	6 6,138 550 0.0896 115.204	6 10,670 866 0.0812 94.925	11 3,669 321 0.0875 110.122	5 3,785 339 0.0896 115.104	5 27,331 1,641 0.06 44.2
	10 22,202 1,212 0.0546 31.106	7 23,328 1,200 0.0514 23.543	6 15,593 1,289 0.0827 98.535	5 6,552 533 0.0813 95.374	6 15,593 1,289 0.0827 98.535	7 17,652 1,376 0.078 87.214	8 10,797 915 0.0847 103.532	7 19,050 1,522 0.0799 91.882	9 6,639 604 0.091 118.498	7 6,435 552 0.0858 106.018	6 52,978 2,786 0.0526 26.299
	22 26,685 1,160 0.0435 4.401	10 35,405 1,530 0.0432 3.786	8 19,832 1,572 0.0793 90.371	9 7,844 552 0.0704 69.011	8 19,832 1,572 0.0793 90.371	8 21,743 1,641 0.0755 81.26	7 13,721 1,167 0.0851 104.267	8 22,168 1,743 0.0786 88.836	8 8,249 788 0.0955 129.424	8 8,327 689 0.0827 98.721	18 74,559 3,167 0.0425 2.014
	4 7,745 518 0.0669 60.628	26 7,202 185 0.0257 -38.308	13 4,898 322 0.0657 57.889	15 2,308 148 0.0641 54.007	13 4,898 322 0.0657 57.889	11 6,051 423 0.0699 67.891	19 3,652 235 0.0643 54.544	9 6,436 506 0.0786 88.82	2 2,552 308 0.1202 188.726	12 2,359 189 0.0716 72.057	7 17,235 834 0.0484 16.217
	7 7,699 460 0.0597 43.495	29 7,201 169 0.0235 -43.635	11 4,809 340 0.0707 69.8	10 2,269 158 0.0696 67.239	11 4,809 340 0.0707 69.8	9 6,004 433 0.0721 73.205	14 3,544 243 0.0696 64.674	10 6,247 475 0.076 82.615	6 2,482 257 0.1035 148.682	11 2,329 167 0.0717 72.211	12 17,169 783 0.0456 9.529
	12 7,688 393 0.0511 22.77	9 7,229 336 0.0465 11.628	9 4,785 363 0.0759 82.196	17 2,280 139 0.061 46.418	9 4,785 363 0.0759 82.196	12 6,037 403 0.0668 60.324	13 3,501 245 0.07 68.069	11 6,319 430 0.068 63.431	15 2,397 182 0.0759 82.355	15 2,312 152 0.0657 57.895	8 17,275 833 0.0482 15.809



Examples

- **ACQUISITION:** A “Star Trek” package was #3 with 18-20 demo, #2 with 21-24 demo, but #9 overall. We can acquire younger audiences with targeted content like this.

		325,214	116,525	14,71	97,003	199,032	218,869	220,622	234,47	207,2	259,018	246,445	211,542
		8	5,513	5,895	47	487	676	1,047	1,557	1,525	2,651	1,903	482
		397	189	5	13	40	77	33	75	159	34	38	13
		0.072	0.0321	0.1064	0.0267	0.0592	0.0735	0.0533	0.0491	0.06	0.0441	0.0362	0.027
		109,205	-9,629	200,197	-24,573	66,973	107,528	90,425	38,688	69,247	24,559	2,124	-23,892
		5,819	5,895	53	549	751	1,099	1,534	1,450	2,715	1,953	1,059	502

- **ENGAGEMENT:** “Kobe’s astonishing shot” was #25 with women, but #5 with men. We can better engage men (or sports fans) by showing more like this, women by showing less.

	5	8,754	486	0.0555	33,528	25	8,485	191	0.0225	-45,859	X	65	4	0.0515	48,01	8	703	27	0.0384	-7,625	9	1,244	55	0.0442	6,337	7	1,781	87	0.0488	17,489	17	2,565	92	0.0359	-13,767	11	2,345	101	0.0431	3,547	17	4,002	149	0.0372	-10,453	19	2,607	94	0.0361	-13,278	19	1,361	51	0.0375	-9,873
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- **REACH:** A package about a hair-pulling soccer player was just plain interesting to everyone (#1-3). We can maintain reach by programming content for the mass audience.

	1	8,415	800	0.0951	128,654	2	8,292	583	0.0703	69,103	X	54	2	0.037	-10,92	1	680	47	0.0591	66,239	1	1,267	97	0.0766	84,135	3	1,702	127	0.0745	79,468	2	2,511	204	0.0812	95,401	2	2,253	163	0.0723	74,008	2	3,863	345	0.0893	114,802	2	2,530	221	0.0874	110,095	2	1,342	137	0.1021	145,534
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Degrees of Personalization



Most Popular

Most engaging overall based on objective metrics



Most Popular + Per User History

Engaging overall, and aware of what I've already seen



Light Personalization

More relevant to me based on my age, gender and property usage



Deep Personalization

Most relevant to me based on my deep interests and relationships



Voice and
Business Rules



Real-time
Dashboard








Business
Optimization



Matching Users to Content

We learn how user attributes correlate with engagement for each item

	Default	Male	Female	18-24	25-34	Heavy Sports
	7.1	-0.4	+0.4	+0.3	+0.1	-0.5
	6.8	+1.0	-1.0	+0.2	+0.3	+2.1
	6.5	-0.6	+0.6	+0.5	+0.3	-0.8
	6.2	0	0	-0.7	-0.5	-0.3
	5.9	-1.1	+1.1	-0.5	-0.2	-0.2



We compute rankings for each user based on his/her attributes



Collaborative Filtering

Movies

users	5			2		
		1		5		
	5		5	4		
				1		

Explicit ratings

User features

e.g. ?sports, ?music,

users	1	0				
		1		.8		
	0		1	1		
				.5		

Feature values

Q: Can we use additional feature information to better predict explicit ratings?

Feature information maybe incomplete, uncertain



Content Recommendation

Articles on Yahoo front pg

users

1			0		
	1		0		
			1		
1		1	1		
			0		

Implicit click information

Articles on Yahoo news

	1		0	0	
	1		0	0	
				0	
1		1	1		
			0	0	

Implicit click information

Users in two contexts are different but some are common

Articles in the two contexts maybe different with no overlap

Q: Can we make click prediction better in both contexts?



Problem Setup

- User x item matrices in n different contexts

Context 1						Context 2						Context 3					
5			5			0			1			0	1		1		
			2				1		0						0		
	1	5	4					1	0				1	0			
5			1						0			0			1		
						0			1								

- Items
 - Item-ids, feature values
- Response/ratings
 - Explicit/implicit ratings, feature values
- Matrices could be incomplete/complete



Localized Matrix Factorization (LMF)

- Assume a joint distribution on user factors across contexts

- E.g. $k = 2$:
$$\begin{matrix} \mathbf{z}_{i1} \\ \mathbf{z}_{i2} \end{matrix} \sim \text{iid} \text{ MVN} \left(\begin{matrix} \mathbf{0} \\ \mathbf{0} \end{matrix}, \begin{matrix} \sigma_{z,1}^2 I & \Sigma_{12} \\ \Sigma'_{12} & \sigma_{z,2}^2 I \end{matrix} \right)$$

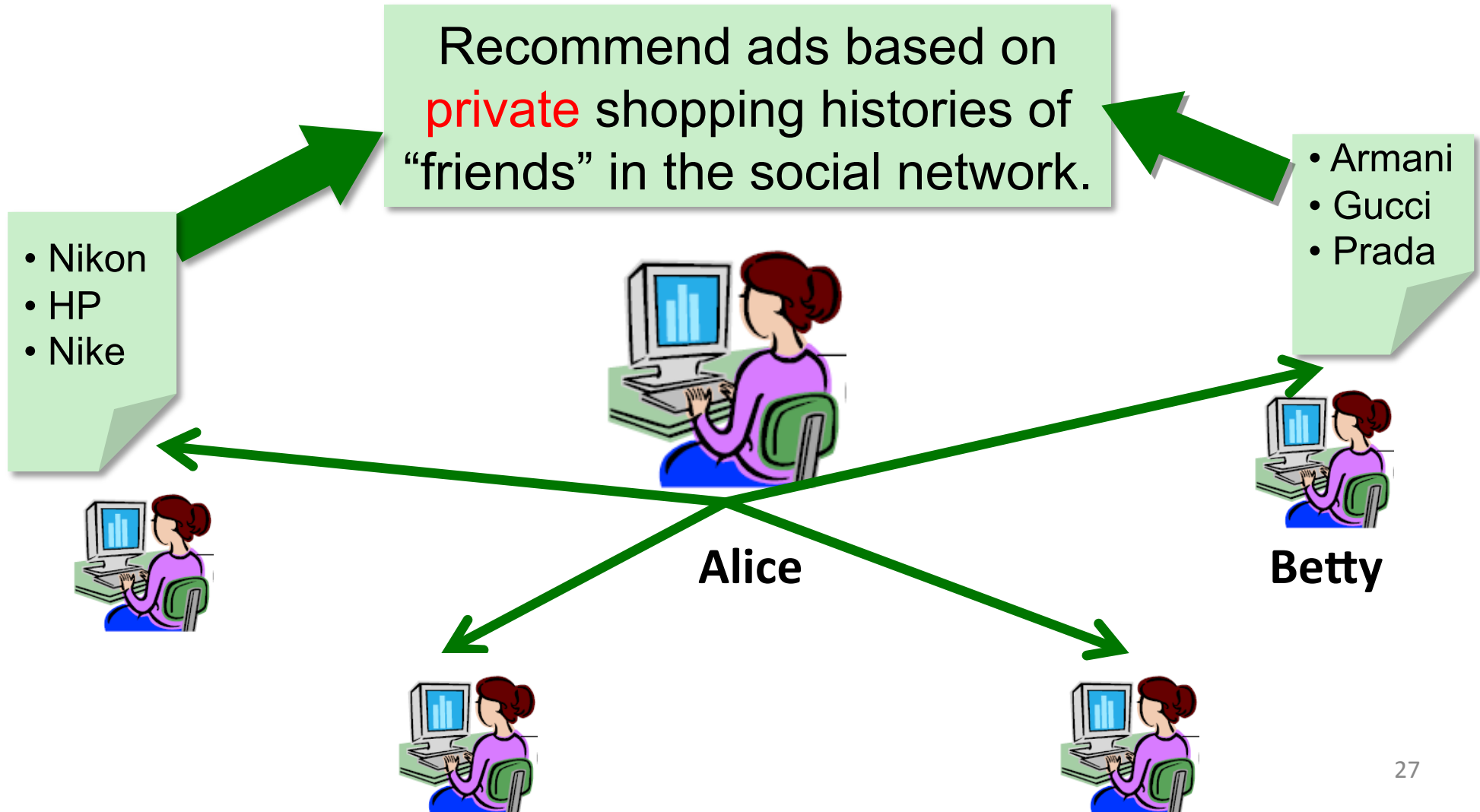
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Factor covariance

- Estimate factor covariance from data and borrow information across contexts through conditionals
 - Amount of information borrowed depends on covariance
 - Measurement error taken care of through joint modeling



Social Advertising

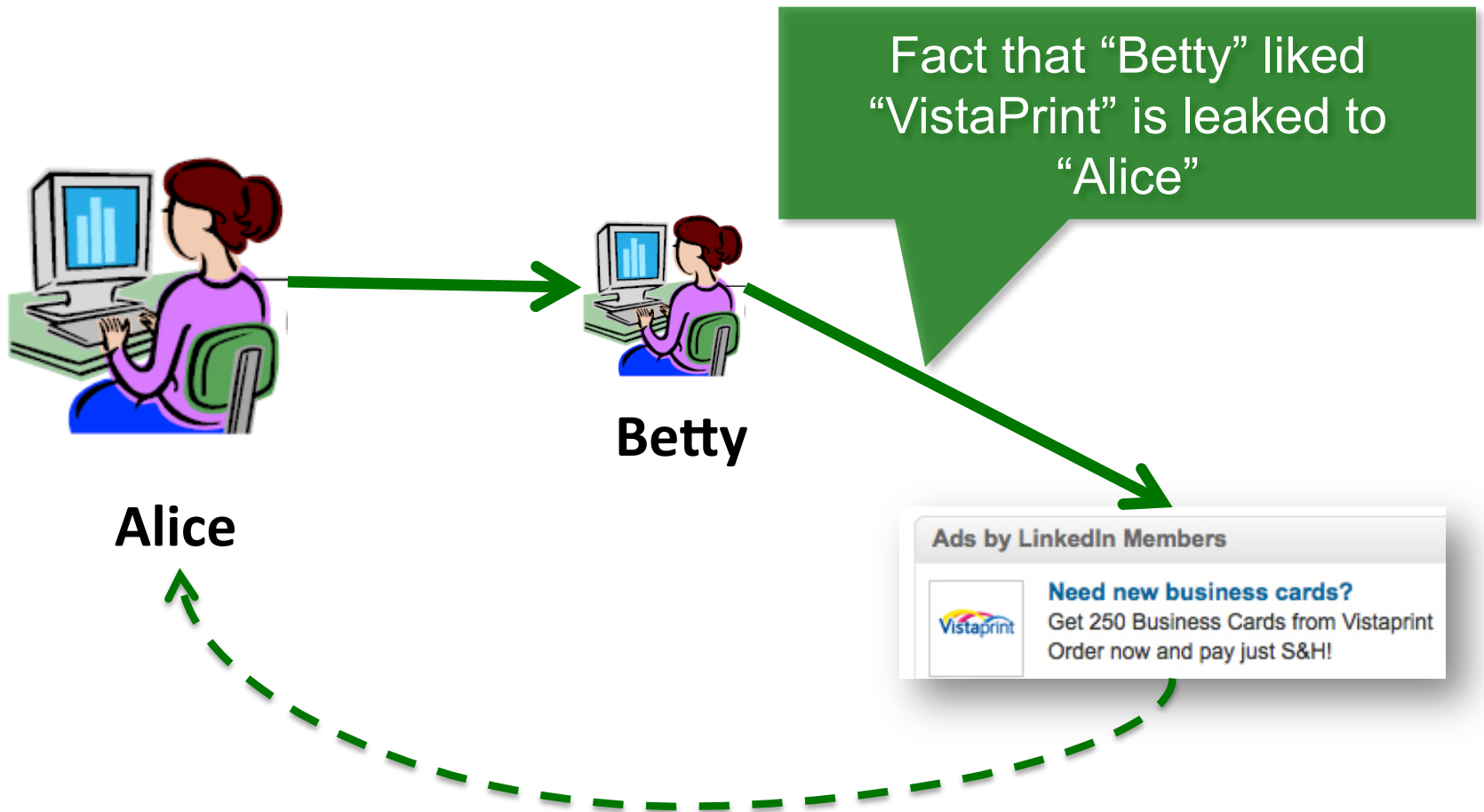


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Privacy in Social Advertising

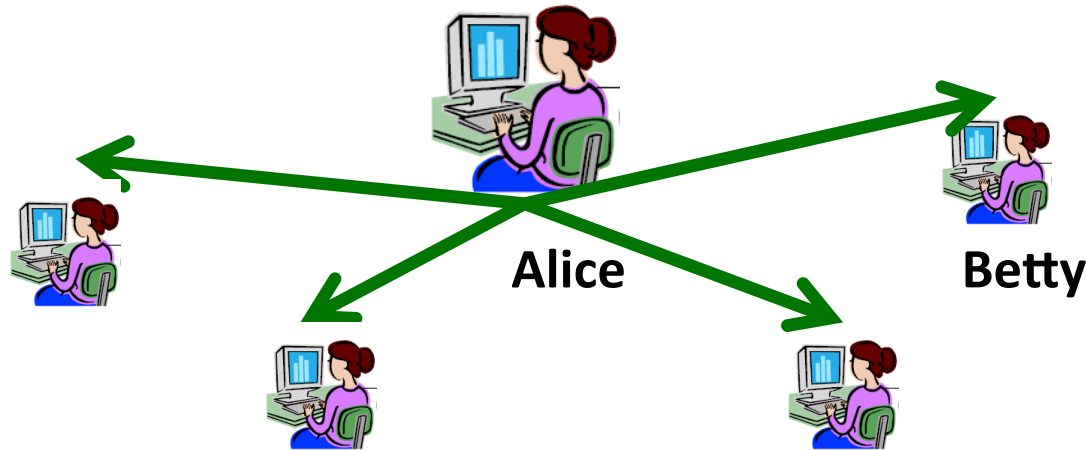
Items (products/people) liked by Alice's friends are better recommendations for Alice





Privacy in Social Advertising

Alice is recommended 'X'



Can we provide *accurate* recommendations to
Alice
while ensuring that
Alice *cannot* deduce that Betty likes 'X' ?



Takeaway ...

- “For majority of the nodes in the network, recommendations must either be inaccurate or violate differential privacy!”
 - Maybe this is a “bad idea”
 - Or, Maybe **differential privacy is too strong a privacy definition to shoot for.**



System Challenges

- Highly dynamic system characteristics:
 - Short article lifetimes, pool constantly changing, user population is dynamic, CTRs non-stationary
 - Quick adaptation is key to success
- Scalability:
 - 1000's of page views/sec; data collection, model training, article scoring done under tight latency constraints



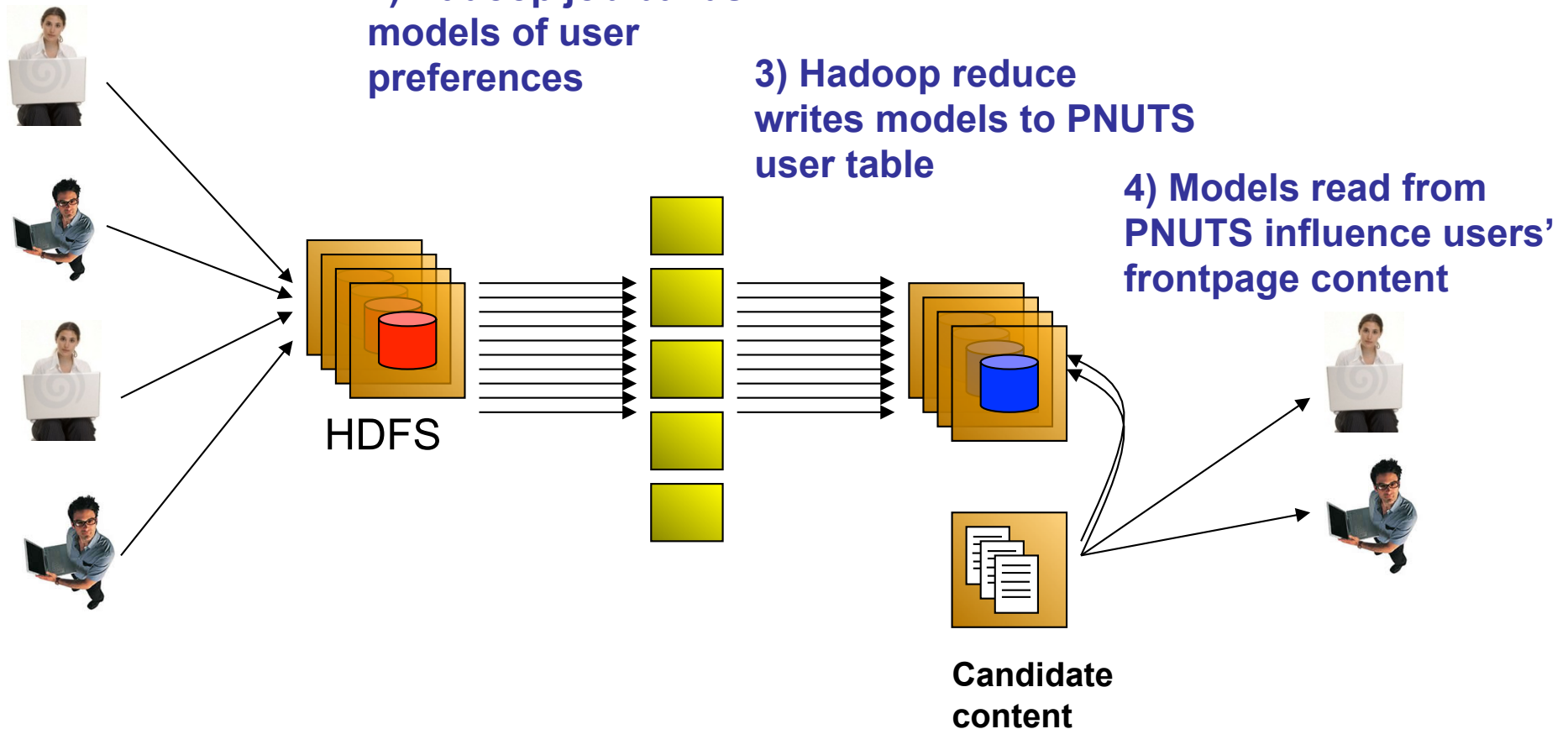
Data Management in CORE

1) User click history logs
stored in HDFS

2) Hadoop job builds
models of user
preferences

3) Hadoop reduce
writes models to PNUTS
user table

4) Models read from
PNUTS influence users'
frontpage content





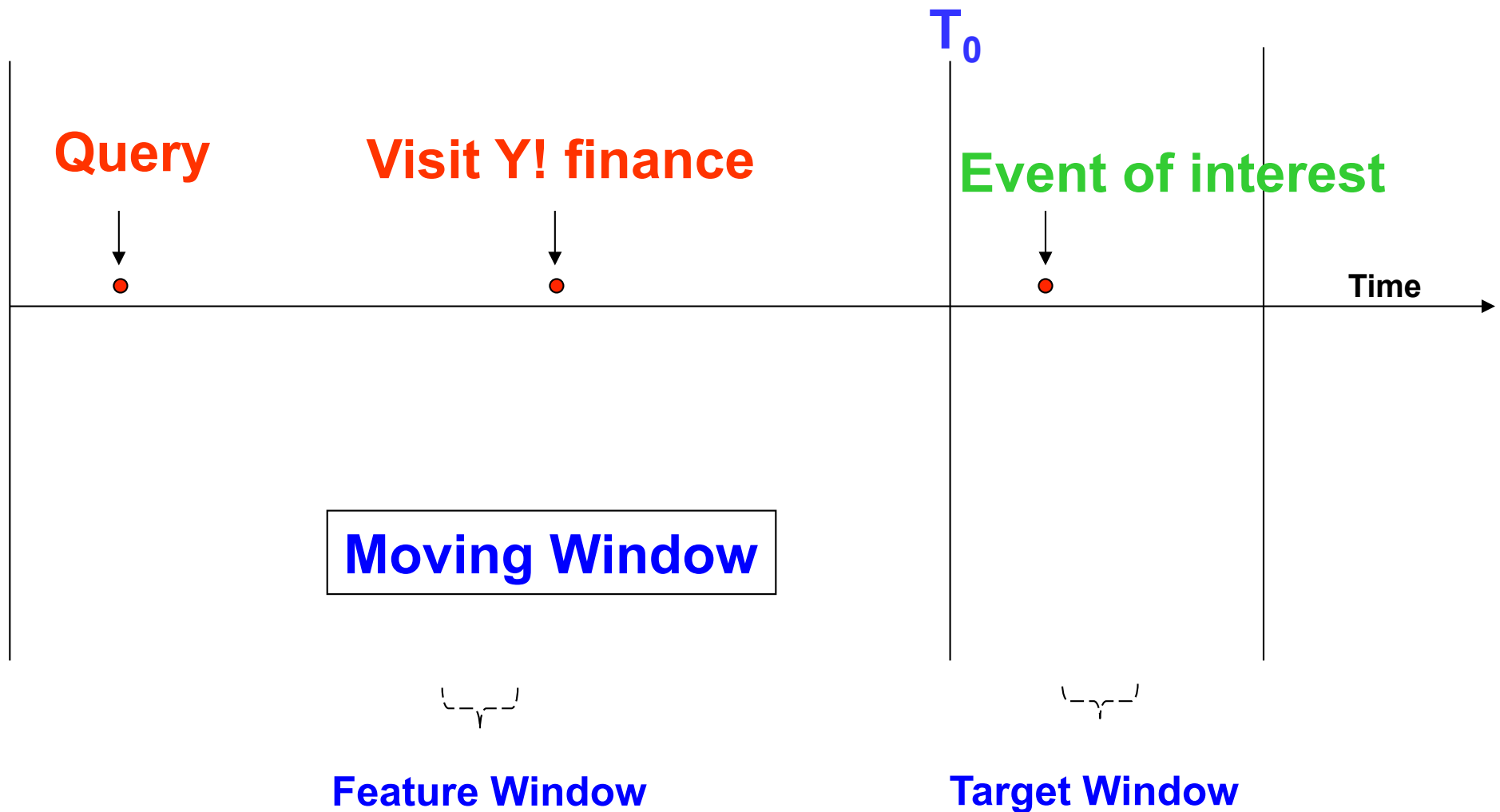
User Activity Modeling

- Large dimensionality vector describing possible user activities
- But a typical user has a sparse activity vector

Attribute	Possible Values	Typical values per user
Pages	~ MM	10 – 100
Queries	~ 100s of MM	Few
Ads	~ 100s of thousands	10s



Feature and Target Windows





User Modeling Pipeline

Component	Data Processed	Time
Data Acquisition	~ 1 Tb per time period	2 – 3 hours
Feature and Target Generation	~ 1 Tb * Size of feature window	4 - 6 hours
Model Training	~ 50 - 100 Gb	1 – 2 hours for 100's of models
Scoring	~ 500 Gb	1 hour

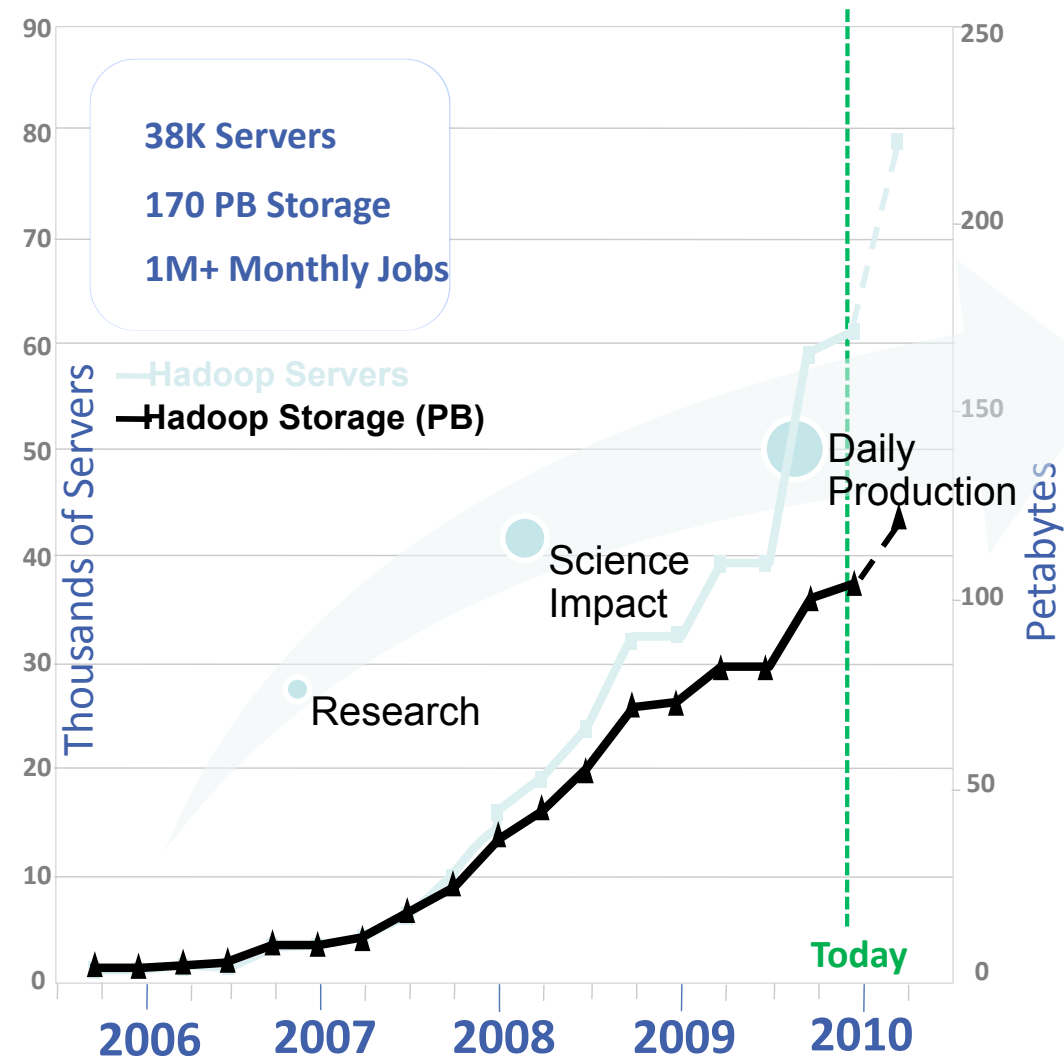


Hadoop: Stability at Scale

Hadoop powers the Yahoo! Network: must be rock-solid

We fix bugs before you see them

- We run very large clusters
- We have a large QA effort
- We run a huge variety of workloads
- Recent spinoff (HortonWorks)





Related Work

- Amazon, Netflix, Y! Music, etc.:
 - Collaborative filtering with large content pool (see KDD Cup, 2011)
 - Achieve lift by eliminating bad articles
 - We have a small number of high quality articles
- Search, Advertising
 - Matching problem with large content pool
 - Match through feature based models



Summary of Approach

- Offline models to initialize online models
- Online models to track performance
- Explore/exploit to converge fast
- Study user visit patterns and behavior; program content accordingly

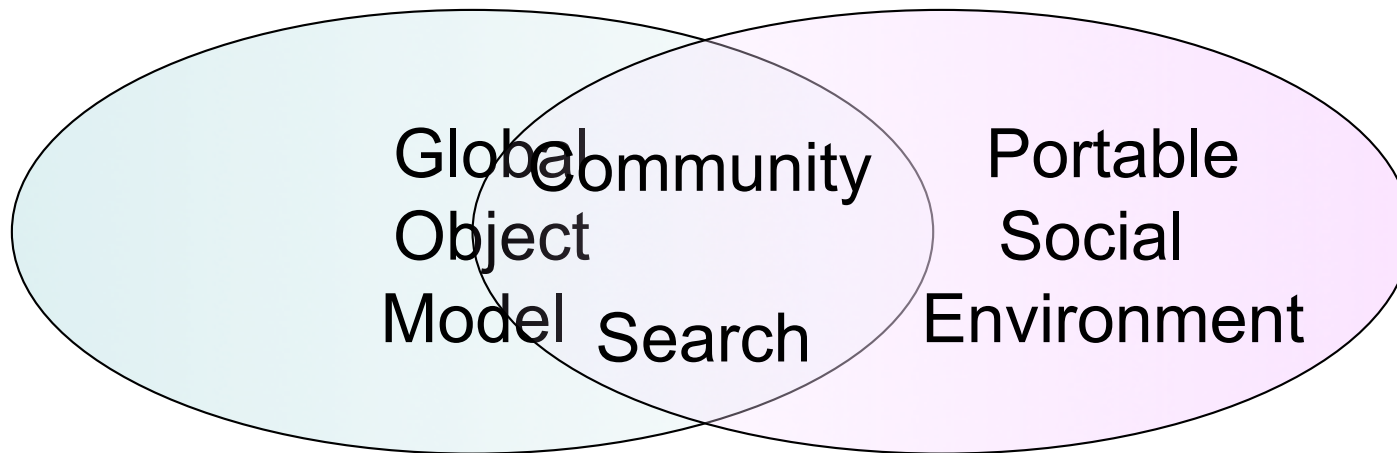


The Social Web

Social networks and online communities will result in personalized experiences in a number of ways



PeopleWeb: Site-Centric \Rightarrow People-Centric



- **Common web-wide id for objects (incl. users)**
- As users move across sites, their personas and social networks will be carried along
- **Increased semantics on the web through community activity (another path to the goals of the Semantic Web)**

(Towards a PeopleWeb, Ramakrishnan & Tomkins, IEEE Computer, August 2007)



The Power of Social Media

- Flickr – community phenomenon
- Millions of users share and tag each others' photographs (why???)
- The wisdom of the crowds can be used to search
- The principle is not new – anchor text used in “standard” search

Tags / jaguar / clusters

jaguar

SEARCH

(Or, try an [advanced search](#).)



[car](#), [cars](#), [auto](#), [etype](#), [automobile](#), [classic](#),
[vintage](#), [autoshow](#), [red](#), [show](#)

➔ [See more in this cluster...](#)



[zoo](#), [animal](#), [cat](#), [animals](#), [bigcat](#), [seattle](#),
[woodlandparkzoo](#), [sleep](#), [edinburgh](#), [caged](#)

➔ [See more in this cluster...](#)



[guitar](#), [fender](#)

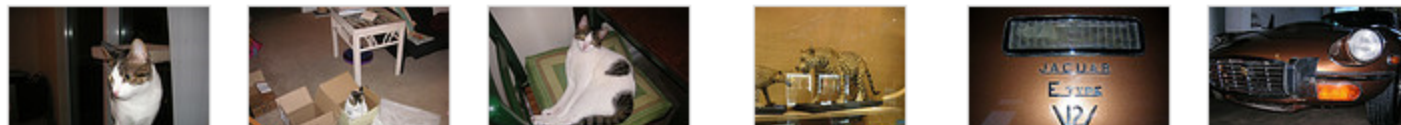
➔ [See more in this cluster...](#)



[aircraft](#), [raf](#)

➔ [See more in this cluster...](#)

These are the *most recent* photos tagged with jaguar. [See more...](#)



Web Search Results for *Lisa*

YAHOO! SEARCH Lisa Search the Web My Web (beta)

My Web BETA My Search History OFF | On Search Services Adv

Search Results Results 1 - 10 of about 129,000,000 for Lisa -

Also try: [lisa lynnnette clark](#), [lisa loeb](#), [lisa raye](#), [mona lisa](#) More...

News Results for **Lisa**

[Lisa Lynn Sargeson \(Olsen\) Marsolek](#) - Independent Record - 4 minutes ago
[UCLA's Lisa Willis Named Women's Basketball Pac-10 Player of the Week](#) ←
By LISA MEYER TRIGG Editor - Banner Graphic - Nov 23 11:37 AM
[Yahoo! Shortcut](#) - [About](#)

My Web Results for **Lisa** (41)

1. [The Localization Industry Standards](#) ← 41 results from My Web!
Remember me. Quick Links. Welcome to LISA. Becoming a global enterprise is one of the most important challenges that your organization will ever face. There is no one right way to do it, but you should not have to reinvent the wheel. ... LISA is the leading international forum for organizations doing business globally ...
Category: [Software > Translation](#)
RSS: [View as XML](#) - [Add to My Yahoo!](#)
[www.lisa.org](#) - [More from this site](#) - [Save](#) - [Block](#)

2. [Laser Interferometer Space Antenna](#) ←
The Laser Interferometer Space Antenna is a mission that will detect and study gravitational wave sources involving massive black holes and galactic binaries. ... Download new LISA PDF file) LISA is a joint mission between the European Space Agency and NASA (Structure and Evolution ...
[lisa.jpl.nasa.gov](#) - 19k - [Cached](#) - [More from this site](#) - [Save](#) - [Block](#)

3. [ESA Science & Technology: LISA](#) ←
... THE MISSION: LISA is an ESA-NASA mission involving three spacecraft flying approximately 5 million kilometres apart in ... Letter of Intent to Participate in LISA data processing study ...
[sci.esa.int/science-e/www/area/index.cfm?fareaid=27](#) - 31k - [Cached](#) - [More from this site](#) - [Save](#) - [Block](#)

4. [a modern girl](#) ←

Latest news results for "Lisa". Mostly about people because Lisa is a popular name

41 results from My Web!

Web search results are very diversified, covering pages about organizations, projects, people, events, etc.

“Social” Search Results for *Lisa*

YAHOO! SEARCH






My Web 2.0 BETA [Home](#) [Invite Contacts](#) [Add Page](#) [Tools](#)

[Pages](#) [Tags](#) [Contacts](#) [History](#) [Blog](#) [FAQ](#) [Discuss](#) [Preferences](#)

Search Results Results 1 - 10 of 41 for **Lisa** shared by your contacts and their contacts.

Related tags: [lisa](#), [2005](#), [usenix](#), [blog](#) [More...](#)

My Community's Results (41)

1. [SAGEwire | LISA 2005 Blog](#) 
system administrator n.a system administrator is one who, as a primary job function, manages computer and network systems on behalf of another, such as an employer or client. LISA 2005 Blog. David N.
Saved by: [Zhichen Xu](#)  and 1 other 10:05 AM PST - [Details](#)
Tags: [blog](#), [lisa](#), [usenix](#)
<http://sagewire.sage.org/article.pl?sid=05/08/16/0237249> - [Save](#)
2. [The LISA '05 Conference Blog](#) 
Behind the Scenes at the Largest System Administration Conference in the World. November 2005 (here's another burning-hot news nugget that will be posted on the official conference site within a few days)
Saved by: [Jianchang \(JC\) Mao](#)  10:09 AM PST - [Details](#)
Note: **Official Lisa conference blog. A lot of good stuff behind the scene**
Tags: [2005](#), [blog](#), [lisa](#), [usenix](#)
<http://blog.lisaconference.org/> - [Save](#)
3. [19th Large Installation System Administration Conference ...](#) 
Administrators of all specialties and levels of expertise meet at LISA to exchange ideas, sharpen old skills, learn new techniques, debate current issues, and meet colleagues and friends.
Saved by: [Jianchang \(JC\) Mao](#)  on November 26, 2005 - [Details](#)
Note: **Qi is giving a keynote speech. Excellent system conferece. Dates: Dec 4-9, 2005**
Tags: [conference](#), [lisa](#), [systems](#)
<http://www.usenix.org/events/lisa05> - [Save](#)

Excellent set of search results from my community because a couple of people in my community are interested in Usenix Lisa-related topics



Yahoo! My Web 2.0

My Web 2.0 Home Page

YAHOO! SEARCH
My Web 2.0 BETA

My Web (beta)

Search the Web

Search buttons.
My Web search
includes search for
both My Stuff and
community stuff

Sun. 11/13/05 2:10pm PST

Now Serving 319,070 pages and 84,650 tags

Personal
knowledge

My Web: [308 Saved Pages](#) [add] | [171 Tags](#) | [Search History](#) [OFF - On]

Community
knowledge

My Community's Web: [4,935 Saved Pages](#) | [3,879 Tags](#) | [53 Contacts](#) [invite]

[Recent Pages](#) | [Popular Pages](#)

» [Scoble Pulls Anti-Google Post InsideGoogle](#) » part of the Blog News Channel

Note: scoble pulls post

Shared by: [Tim](#) 😊 Tags: [scoble google](#) 19 minutes ago - [Details](#) - [Save](#)

Community vitality
• Statistics
• Recent pages
• Popular pages

Public
knowledge

Everyone's Web: [319,070 Saved Pages](#) | [84,650 Tags](#)

[Recent Pages](#) | [Popular Pages](#)

[Tips for Working Securely from Hotspots](#)

Shared by: [hermosa1001](#) Tags: [security](#), [wireless](#) 14 minutes ago - [Details](#) - [Save](#)

Public vitality
• Statistics
• Recent pages
• Popular pages

(Courtesy: Raymie Stata)



Save / Tag Pages You Like

You can save / tag pages you like into My Web from toolbar / bookmarklet / save buttons

You can pick tags from the suggested tags based on collaborative tagging technology

Type-ahead based on the tags you have used

You can specify a sharing mode

You can save a cache copy of the page content

Enter your note for personal recall and sharing purpose

Save To My Web

YAHOO! SEARCH Welcome [Sign out, My Account]

My Web [View My Saved Pages](#)

Save this page to My Web:

URL <http://blog.lisaconference.org/>

Title The LISA ~05 Conference Blog

Add Note Great place to get updated info about Lisa'05

Suggested: 2005 blog lisa unix

Tags 2005, lisa, bl
* Separate multiple tags with commas

Access: ☐ Me ☒ My Community ☐ Everyone

☒ Store a copy of this page.

Save Cancel

(Courtesy: Raymie Stata)



My Web Overlays

Search Results Results 1 - 10 of about 279,000,000 for We

News Results for Web 2.0
[Zoovy, Inc.'s New Web 2.0/AJAX Based Software Boosts Ecommerce Sales](#) - RedNova - Apr 04 4:44 PM
[Web 2.0 Journal: Intel Focuses on World PC Markets](#) - Linux World - Apr 03 6:55 AM
[The State of Web 2.0: The Future of Web Software](#) - Slashdot - Apr 03 8:53 AM
[Yahoo! Shortcut - About](#)

My Web Results for Web 2.0 (1,205) **Subscriptions Results for web 2 0 (2)**

- Web 2.0 Conference 2006**
Speakers, schedule, and other info for the annual Web 2.0 Conference on innovation in the Internet economy.
Category: [Internet > Conferences and Events](#)
Saved by [Matt](#) and 74 others - [Details](#)
Note: Home page of the annual Web 2.0 conferences. The conferences feature presentations by innovators in Internet technology and scholarship.
[www.web2con.com](#) - 38k - [Cached](#) - [More from this site](#) - [Save](#)
- Web 2.0 Conference**
... Web 2.0 Coverage IT Conversations presents audio archives of the Web 2.0 Conference held October 5-7 2004 ... told attendees at the Web 2.0 conference in San Francisco that the ...
Saved by 5 people
[www.web2con.com/web2con/coverage.csp](#) - 81k - [Cached](#) - [More from this site](#) - [Save](#)
- UserDriven: Web 2.0 Conference blog roundup**
Web 2.0 Conference blog roundup. Here are pointers to some of the best of the blog coverage of the Web 2.0 Conference (The official press coverage page is here)
Saved by 3 people
[www.userdriven.com/2004/10/web_20_conferen.html](#) - 16k - [Cached](#) - [More from this site](#) - [Save](#)
- Wikipedia: Web 2.0**
... Web 2.0 generally refers to a second generation of services available on the World Wide Web that lets ... contrast to the first generation, Web 2.0 gives users an experience closer ...
Quick Links: [Introduction](#) - [Market Drivers of Web 2.0](#) - [New web-based communities](#)
Saved by [Jeremy Zawodny](#) and 71 others - [Details](#)
Note: good description of web 2.0 ideas
[en.wikipedia.org/wiki/Web_2.0](#) - 50k - [Cached](#) - [More from this site](#) - [Save](#)

Joining My Web data into
Web Search results

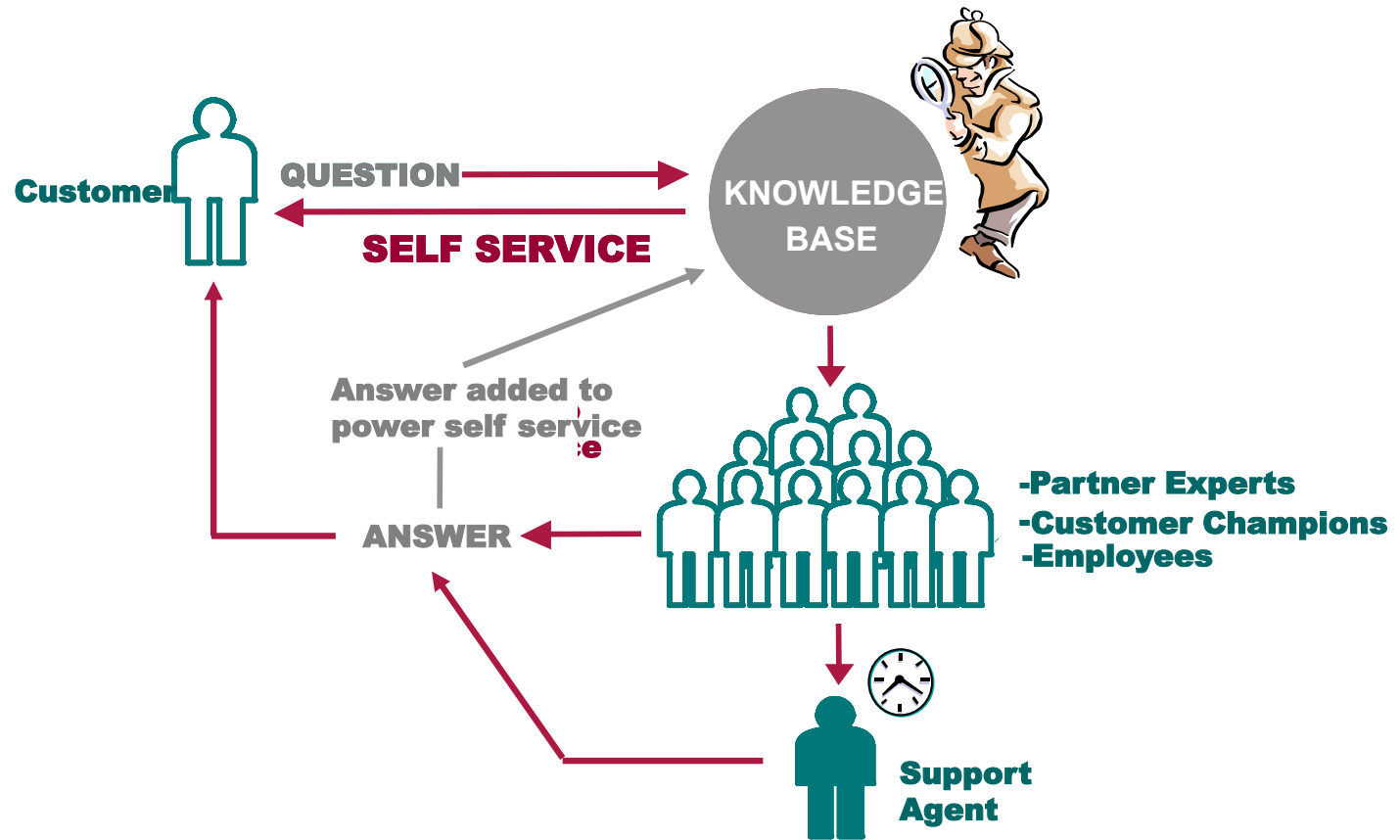




“In newsgroups, conversations disappear and you have to ask the same question over and over again. The thing that makes the real difference is the ability for customers to collaborate and have information be persistent. That’s how we found QUIQ. It’s exactly the philosophy we’re looking for.”

“Tech support people can’t keep up with generating content and are not experts on how to effectively utilize the product ... Mass Collaboration is the next step in Customer Service.”

– Steve Young, VP of Customer Care, Compaq





What is a Relevant Group? (7 M Y! groups)

- A group whose content is relevant to the query keywords.
- A group to which many of my buddies belong.
- A group where many of my buddies post messages.
- A group with some of my preferred characteristics: traffic, membership.

Social Search

- Explicitly open up search
 - Enable communities, sites and consumers to explicitly re-define search results (e.g., SearchMonkey, Boss)
 - Right unit for a “search result”? Can we “stitch together” more informative abstracts from multiple sources?
 - Creation of specialized ranking engines for different tasks, or different user communities
- Implicitly leverage socially engaged users and their interactions
 - Learning from shared community interactions, and leveraging community interactions to create and refine content
- Expanding search results to include sources of information
 - E.g., Experts, sub-communities of shared interest, particular search engines (in a world with many, this is valuable!)

Reputation, Quality, Trust, Privacy



Challenges in Social Search

- How do we use annotations for better search?
- How do we cope with spam?
- Ratings? Reputation? Trust?
- What are the incentive mechanisms?



Web Images Video Local Shopping News More

eggplant parmigiana baltimore

Search

Options

Start typing to see suggestions.

Explore related concepts:

Pizza mushrooms
veal tomato sauce
Chicken Little Italy
Italian Restaurant Crab Cake

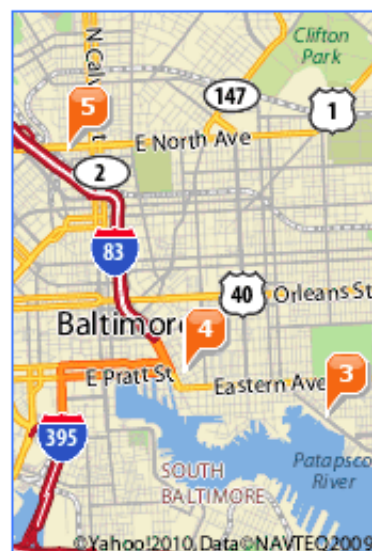
Settings

Eggplant Parmigiana Restaurants near Baltimore, MD

Neighborhood

All (36) Canton (2) Charles North (1) Downtown (1)
Abell (1) Central Bal... (4) Chinguapin... (1) Federal Hill (1)

- Ciao Bella - Baltimore** ★★★★★ (11)
local.yahoo.com
(410) 685-7733 - 236 S High St, Baltimore, MD
Menu: eggplant parmigiana
[4 Reviews](#) | [Overview](#) | [2 Photos](#) | [Directions](#)
- Amicci's** ★★★★★ (20)
amiccis.com
(410) 528-1096 - 231 S High St, Baltimore, MD
Menu: eggplant parmigiana
[14 Reviews](#) | [Overview](#) | [23 Photos](#) | [Directions](#)
- Pasticcio** ★★★★★ (8)
local.yahoo.com
(410) 522-7700 - 2400 Boston St, Baltimore, MD
Menu: eggplant parmigiana
[5 Reviews](#) | [Overview](#) | [3 Photos](#) | [Directions](#)
- Caesar's Den** ★★★★★ (7)
caesarsden.com
(410) 547-0820 - 223 S High St, Baltimore, MD
Menu: eggplant parmigiana
[4 Reviews](#) | [Overview](#) | [11 Photos](#) | [Directions](#)



Search Pad

SearchScan - On

30,300 results for
eggplant parmigiana

Show All

Los Angeles Times

Local Business Sites

YAHOO!

julia roberts

Search

Options

julia roberts twins
julia roberts movies
lyle julia roberts
julia roberts babies
julia roberts henry daniel moder

Explore related concepts:

actor
Episodes
Pretty Woman
Best movies

julia roberts photos
Julia Roberts News
julia roberts biography
Julia Fiona Roberts

Search Pad

SearchScan - On

40,500,000 results for
julia roberts

Related People



Scarlett Johansson



Emma Roberts



Hilary Swank



Lindsay Lohan



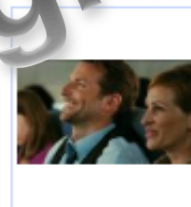
Tom Hanks



Halle Berry

Julia Roberts - Image Results

News & Photos



[more Julia Roberts photos...](#)

Latest News:

[Hindus concerned about Julia Roberts' 'Eat, Pray, Love'](#) - New Kerala - 6 hours ago

[Trailer For 'Eat Pray Love' Starring Julia Roberts](#) - KPBS San Diego - Mar 19 03:18pm

[Link Party: Julia Roberts' New Movie Will Teach You How to Live](#) - El Online - Mar 18 05:48pm

[more Julia Roberts news...](#)

Julia Roberts - Wikipedia

[Early life](#) | [Career](#) | [Influence](#) | [Personal life](#)

Julia Fiona Roberts is an American actress. She is known for starring in the romantic comedy *Pretty Woman* opposite Richard Gere, which grossed \$463 million worldwide. After receiving...

en.wikipedia.org/wiki/Julia_Roberts - 122k - [Cached](#)

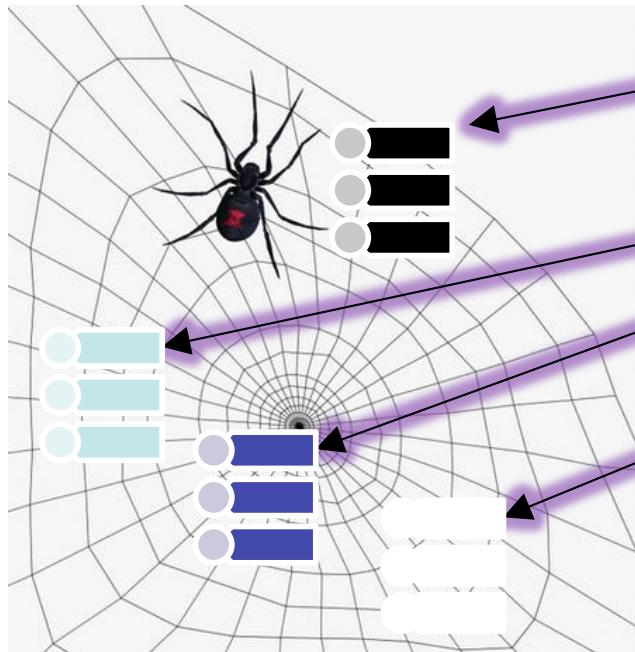




Web of Concepts

rich, aggregated data

concept



Aggregated KB

madonna

mumbai
restaurant

san jose

• • •

INDEX

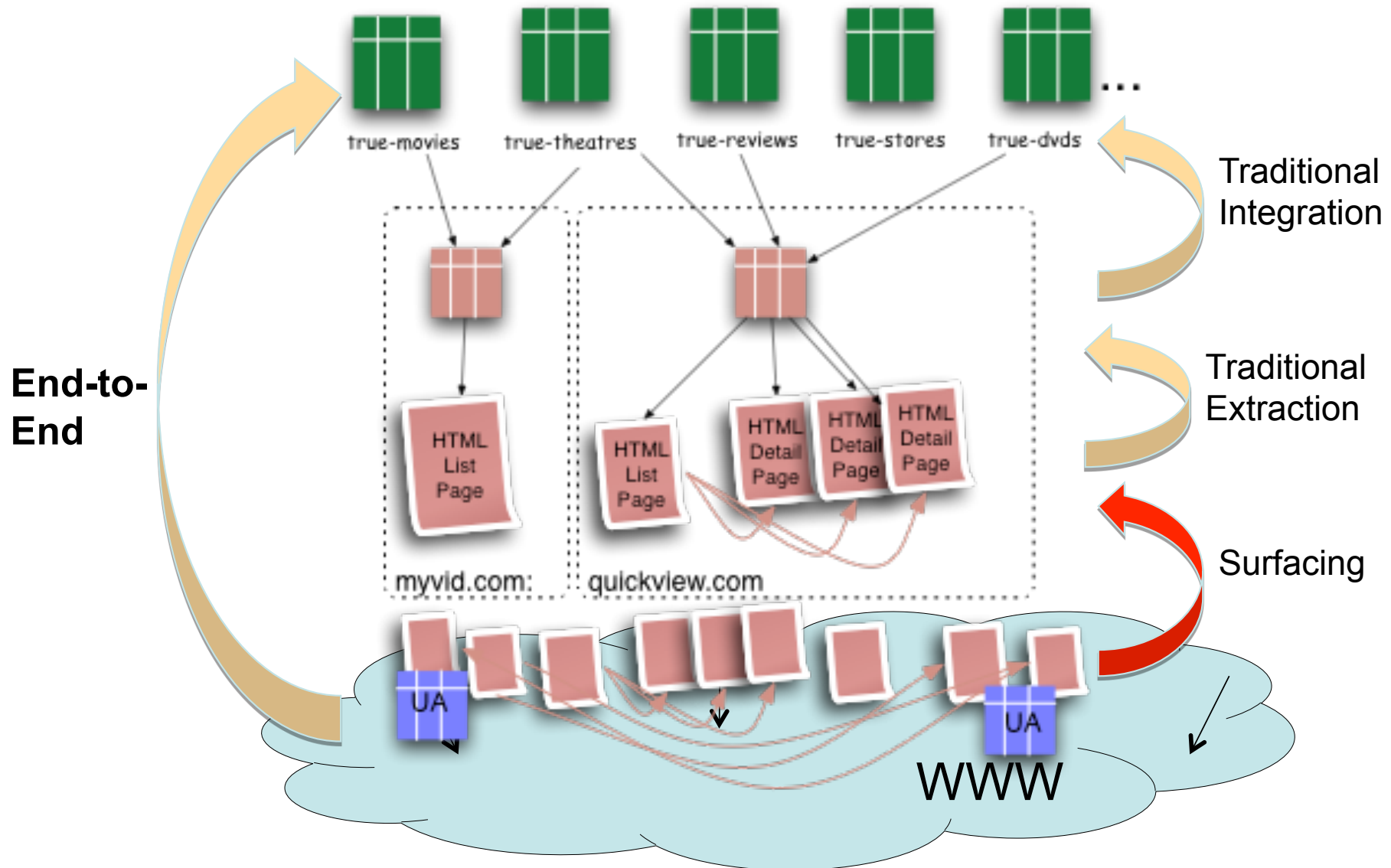


SERP

The “index” is keyed by concept instance, and organizes all relevant information (data describing the concept instance and its relationship to other instances), wherever it is drawn from, in semantically meaningful ways



Web IE: Surfacing, Extraction, Integration





Summary

- The Web will be increasingly personalized, but “personalization” will mostly happen within the context of
 - Content optimization
 - Semantic interpretation of web content and user intent
 - Socialization of the web