Web Dynamics

Part 7 – Human Behaviour on the Web

7.1 Recommendation

7.2 Personalized Search

High-Level View of Recommendation

Input: Collected data on ***behavior of users***

- Items (books, dvds, cds,…) purchased
- Items (books, movies, hotels, …) rated
- Web sites browsed or bookmarked
- Searches and clicked search results
- Sequence of activities (browsing, searching, …)
- Mails, Documents read and written
- Profile in social networks (contacts)

$\Rightarrow$ build extensive ***user models***

High-Level View of Recommendation

Output: Items of ***potential interest*** to user

- Items (books, movies, hotels,…) to purchase/view/visit/…
- Web sites to visit
- Improved search results
- Potential query expansions/refinements
- People to meet in social networks

Three orthogonal approaches

User-centric approach („nearest neighbors"):

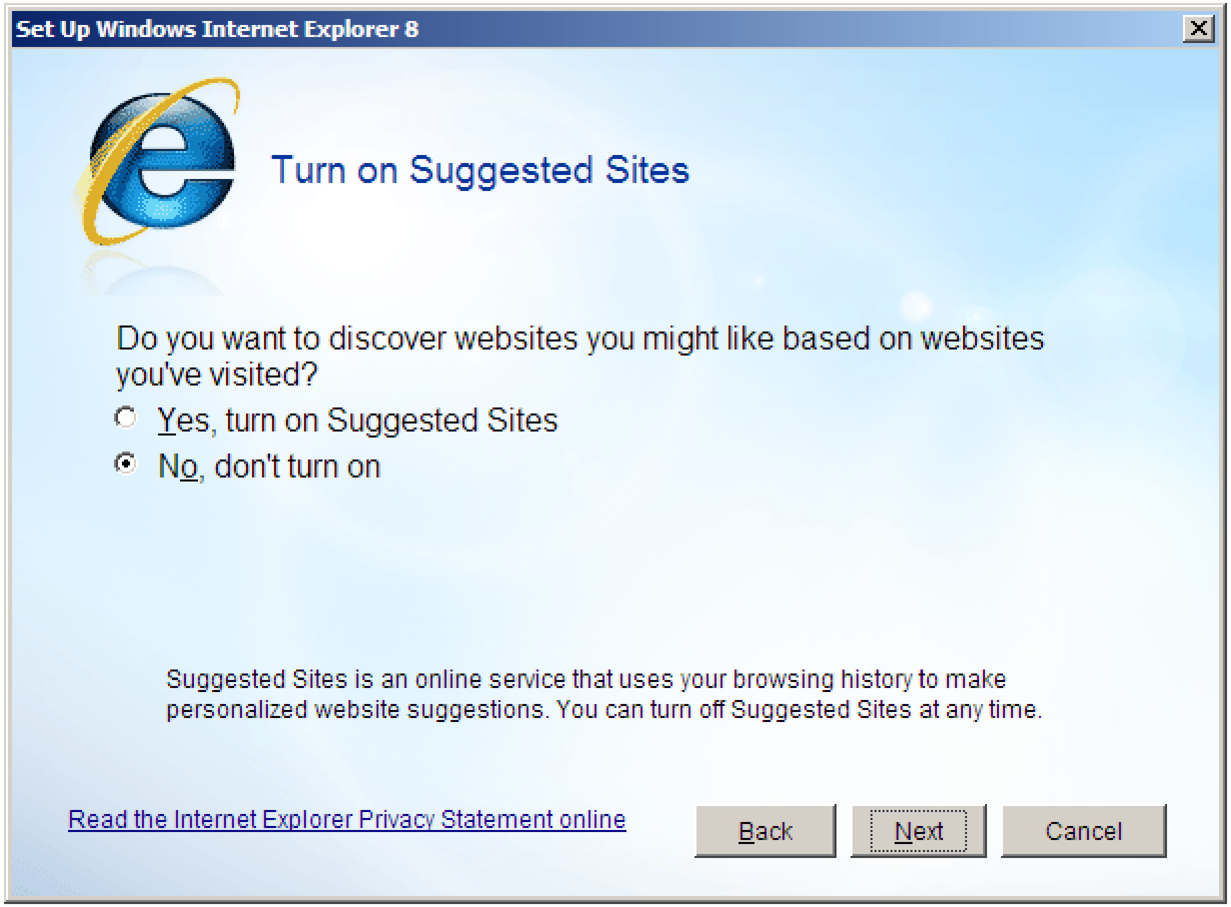
User A likes/buys/visits item X
(model of) user B similar to (model of) user A
→ user B may like item X as well

Item-centric approach:

User A likes/buys/visits item X
Item X similar to item Y
→ user A may like item Y as well

[***Static approach***: Many people buy X]

Example 1: Web site suggestion



Example 1: Web site suggestion

⇒ **item-centric approach, (seemingly) no user model used**

Example 2: Product Recommendations

Most Popular in Desktop Computers

[Apple iMac MB417LL/A 20...]
$1,194.00

[HP Pavilion A6700F Desktop PC]
~~$731.00~~ $429.79

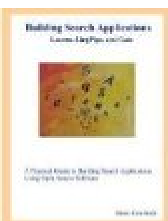
[Datenbanksysteme: Eine Einführung]
von Alfons Kemper (April 22, 2009)
Auf Lager.

Preis: EUR 39,80
[62 Angebote] ab EUR 39,80

Gehört mir   Kein Interesse   x|☆☆☆☆☆ Diesen Artikel bewerten
Diesen Artikel haben wir empfohlen, weil Sie **Übungsbuch Datenbanksysteme** gekauft haben.

Mehr zu entdecken

Sie haben sich angesehen:



[Building Search Applications: Lucene...] Taschenbuch von Manu Konchady
EUR 31,89

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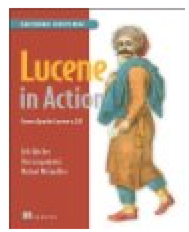

[Lucene in Action] Taschenbuch von Erik Hatcher, Otis...
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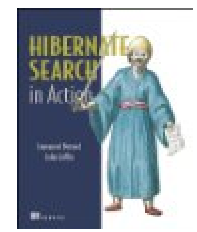
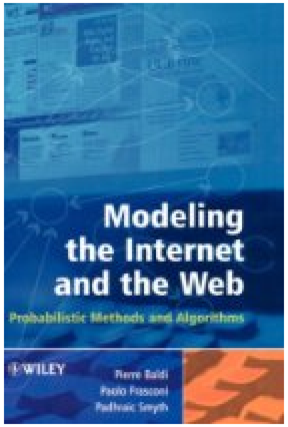


[Hibernate Search in Action] Tasche
Bernard...
EUR 33,95

› [Verwandte Artikel entdecken]

⇒ static and item-centric approach

Example 3: Book Recommendations



Modeling the Internet and the Web: Probabilistic Methods and Algo

by Pierre Baldi

Members	Reviews	Popularity	Ave
10	None	439,588	

▼ Book information

Modeling the Internet and the Web: Probabilistic Methods and Algorithms
by Pierre Baldi
Wiley (2003), Hardcover, 285 pages

LibraryThing recommendations

1. Web Metrics: Proven Methods for Measuring Web Site Success by Jim Sterne
2. Differentiated services for the Internet by Kalevi Kilkki
3. Internet Measurement: Infrastructure, Traffic and Applications by Mark Crovella
4. Designing Campus Networks by Terri Quinn-Andry
5. True Names: And the Opening of the Cyberspace Frontier by Vernor Vinge
6. Me++: The Cyborg Self and the Networked City by Wil
7. What Just Happened: A Chronicle from the Informatio Gleick
8. The Digital Sublime: Myth, Power, and Cyberspace by
9. 24 Hours in Cyberspace: Painting on the Walls of the Photographed on One Day by 150 of the World's Leac
10. Crypto Anarchy, Cyberstates, and Pirate Utopias by Pe

LibraryThing Recommendations

304 recommendations — page [1] | 2 | 3 | 4

1. **Machine Learning by Thomas Mitchell**
   169 copies. 1 reviews. Average rating 4.08.
   No thanks! | Why? (close why) Recommendation based on:
   Artificial Intelligence: A Modern Approach by Stuart J. Russell
   Data Mining: Practical Machine Learning Tools and Techniques, Second Edition (Morgan Kaufmann Series in Data Management by Ian H. Witten
   An Introduction to Support Vector Machines and Other Kernel-based Learning Methods by Nello Cristianini
   All of Statistics: A Concise Course in Statistical Inference (Springer Texts in Statistics) by Larry Wasserman

Towards user-centric recommendations

Assume n users U, m items I.

Model ***user-item relation*** as n x m – matrix V:

- $V=\{0,1\}^{nxm}$: binary ***purchase matrix***
- $V=[min,max]^{nxm}$: quantified ***preference matrix***

Both are very sparse!

(Librarything: 745,000 users, 40 mio books, less than 200 books for most users
$\Rightarrow$0,0005% non-zero entries)

„semantics“: v_{ij} seen as „vote“ of user i for item j

Recommendation Problem

Inputs:

- Set of votes of user u with items I_u
- Set of votes of other users

Goal: predict votes of u for items in $I \setminus I_u$
(to identify the items with highest votes)

$\Rightarrow$ yields scalability problem (|I| is large!)

Vote Prediction

Initial vote calibration (to remove bias):

$$v_i = \frac{1}{|I_i|} \sum_{j \in I_i} v_{ij} \qquad v_{ij}^{*} = v_{ij} - v_i$$

Predict vote of user u for item j as weighted average over the votes of all other users:

$$\hat{v}_{uj} = v_u + \frac{1}{C} \sum_{i=1}^{n} w_{ui} \cdot v_{ij}^{*} \qquad C = \sum_{i=1}^{n} |w_{ui}|$$

similarity of users a and i

Estimating User-User Similarity

- Correlation-Based similarity:

$$w_{ai} = \frac{1}{C_2} \sum_{j \in I_a \cap I_i} (v_{aj} - v_a)(v_{ij} - v_i)$$

$$C_2 = \left(\sum_{j \in I_a \cap I_i} (v_{aj} - v_a)^2 \sum_{j \in I_a \cap I_i} (v_{ij} - v_i)^2 \right)^{1/2}$$

Unreliable results if overlap between users is small

- Vector similarity (cosine):

$$w_{ai} = \sum_{j \in I} \frac{v_{aj}}{\sqrt{\sum_{k \in I_a} v_{ak}^2}} \frac{v_{ij}}{\sqrt{\sum_{k \in I_i} v_{ik}^2}}$$

Remaining problem: high dimensionality (number of users and items)

Reducing Dimensionality: SVD

Replace V by ***rank-k approximation*** of V using SVD:

$$V = A \times S \times B^T$$

A: **user-concept** similarity matrix (n×r)

S: diagonal matrix of **singular values** (with r nonzero entries, where r=rank(V)), corresponding to ***topics***

I: **concept-item** similarity (r×m)

Additionally ***restrict to k largest singular values*** to further reduce dimensionality

SVD Example

$$V = \begin{pmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \end{pmatrix}$$

$$= \underbrace{\begin{pmatrix} 0.707 & 0 & -0.544 & 0 & 0.707 \\ 0.5 & 0 & -0.707 & 0 & -0.5 \\ 0.5 & 0 & 0.707 & 0 & -0.5 \\ 0 & 0.788 & 0 & -0.615 & 0 \\ 0 & 0.615 & 0 & 0.788 & 0 \end{pmatrix}}_{A} \times \underbrace{\begin{pmatrix} 2.414 & 0 & 0 & 0 & 0 \\ 0 & 2.136 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0.662 & 0 \\ 0 & 0 & 0 & 0 & 0.414 \end{pmatrix}}_{S} \times \underbrace{\begin{pmatrix} 0.5 & 0.5 & 0.707 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.369 & 0.657 & 0.657 \\ -0.707 & 0.707 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -0.929 & 0.261 & 0.261 \\ 0.5 & 0.5 & -0.707 & 0 & 0 & 0 \end{pmatrix}}_{B^T}$$

SVD Example

$$V = \begin{pmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \end{pmatrix}$$

$$\approx \begin{pmatrix} 0.707 & 0 \\ 0.5 & 0 \\ 0.5 & 0 \\ 0 & 0.788 \\ 0 & 0.615 \end{pmatrix} \times \begin{pmatrix} 2.414 & 0 \\ 0 & 2.136 \end{pmatrix} \times \begin{pmatrix} 0.5 & 0.5 & 0.707 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.369 & 0.657 & 0.657 \end{pmatrix} = \begin{pmatrix} 0.854 & 0.854 & 1.207 & 0 & 0 & 0 \\ 0.604 & 0.604 & 0.854 & 0 & 0 & 0 \\ 0.604 & 0.604 & 0.854 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.621 & 1.106 & 1.106 \\ 0 & 0 & 0 & 0.485 & 0.864 & 0.864 \end{pmatrix}$$

A S B^T

Recommendations with SVD

- Predict votes on A, not on V
  $\Rightarrow$ compute estimate v'_{uj} for each topic j
- Extend the vote estimate from topics to items

$$v_{ui} = \sum_{j=1}^{k} \left(v'_{uj} \cdot S_{jj} \cdot B_{ji} \right)$$

New issue: Maintaining the SVD when data changes

SVD generates implicit clustering of items

Reducing Dimensionality: Clustering

- Reduce number of users by precomputing *K clusters of similar users*
- Represent each cluster P by its ***centroid*** c(P):

$$c(P)_i = \frac{1}{|P|} \sum_{u \in P} v_{ui}$$

- For prediction:
  - Assign user to one of the clusters
  - Compute „nearest neighbor“-prediction for clusters instead of users
- **Potential problem**: users may belong to multiple clusters

User-Centric is Expensive

- User actions are highly dynamic
  - difficult to precompute and maintain similarities
  - best recommendations based on items just bought
- One recommendation takes time $O(n+m)$:
  - needs to scan all users and their items
  - most users have $\leq C1$ items
  - few users ($\leq C2$) have $>C1$ items
  - cost bounded by $(n-C2) \cdot C1 + C2 \cdot m = O(n+m)$
  - n,m large
- Recommendations need to be computed in real time (≤200ms)

Item-centric Recommendations

Observation:

Relationships of items (i.e., correlation in purchases) a lot less dynamic than relationships of users

- information from yesterday still reasonably accurate today
- not recommending new items tolerable

Predict vote of user u for item j as weighted average over the votes of user u for other items:

$$\hat{v}_{uj} = v_u + \frac{1}{C}\sum_{i=1}^{m} w_{ji} \cdot v^*_{ui} \qquad C = \sum_{i=1}^{m} |w_{ui}|$$

similarity of items j and i

Requires only limited knowledge about the user

Estimating Item-Item Similarity

using correlation-based or cosine similarity
(similar to user-user similarity)

Example: cosine similarity

$$w_{ji} = \sum_{u \in U} \frac{v_{uj}}{\sqrt{\sum_{k \in U} v_{kj}^2}} \frac{v_{ui}}{\sqrt{\sum_{k \in U} v_{ki}^2}}$$

Computing similarities expensive ($O(m^2 n)$), but offline

Computing predictions is cheap ($O(m)$ if only constant number of items considered)

Using Search to Recommend

Assume we can identify ***features*** of items (genre, actors, director, keywords, …)

- Identify ***frequent/characteristic features*** for the user‘s items
- Submit ***search*** for those features and recommend the results

Problems:

- Does not scale well for many owned items
- Does not provide good recommendations

Probabilistic Models for Recommendation

Consider ***joint probability distribution*** for m-dimensional set of items (binary preferences):

$P[v_1 \ldots v_m]$: probability that random user has vote vector $(v_1,\ldots v_m)$

Predict unknown value v_{ui} as $P[v_i=1 | v_j=1 \text{ for } j \in I_u]$

Impossible to maintain explicitly (2^m parameters!)

$\Rightarrow$approximate through ***finite mixture***:

$$P[v_1 \ldots v_m] \approx \sum_{k=1}^{K} P[v_1 \ldots v_m \mid c=k] \cdot P[c=k]$$

assume independence within each component:

$$P[v_1 \ldots v_m \mid c=k] = \prod_{j=1}^{m} P[v_j \mid c=k]$$

Evaluating Recommender Systems

Goal:
Out of several recommendation algorithms, determine which gives best recommendations.

Required components of such a ***benchmark***:

- set of (user,item,rating) tuples for ***training*** (known to the algorithm in advance)
- set of (user,item,rating) tuples for ***testing*** (where the algorithm needs to predict *rating*)
  - Can be offline (part of the data) or live user experiment
- metrics for ***quantifying result quality***

Properties of Data Sets for Evaluation

- can be ***synthetic*** vs. ***real-life***
- features of the application domain
  - ***novelty*** vs. ***quality*** focus of recommendations
  - ***cost/benefit ratio*** of true/false positive/negatives
  - ***granularity*** of true user preferences (vs. ratings)
- inherent features of the data set (and ratings)
  - ***Implicit*** or ***explicit*** ratings
  - ***scale*** & ***dimensions*** of ratings
  - ***history*** of ratings (timestamps) and recommendations
- sample features
  - ***density*** of rating set (overall & for test users)
  - ***size*** of data set

Offline Evaluation vs. User Experiments

- ***Offline evaluation***: ***compare*** predicted votes to actual votes made by the user
  - low effort, can be done automatically
  - can be used to evaluate series of ratings (timestamps)
  - But: limited choice of predictions to evaluate
- ***Live user experiments***: ***ask*** user for opinion or ***observe*** user behavior
  - understand if and why people like (or dislike) recommendations, interfaces, systems

Evaluation metrics

Widely used: measure ***accuracy*** of predictions by measuring the ***error*** of prediction and actual rating

- mean absolute error (MAE)

$$|\overline{E}_{MAE}| = \frac{\sum_{i=1}^{N} |p_i - r_i|}{N}$$

p_i: prediction
r_i: recommendation
N: # recommendations

- Root mean square error (RMSE; emphasises large errors)

$$|\overline{E}_{RMSE}| = \sqrt{\frac{\sum_{i=1}^{N} (p_i - r_i)^2}{N}}$$

- precision/recall, rank accuracy metrics, …

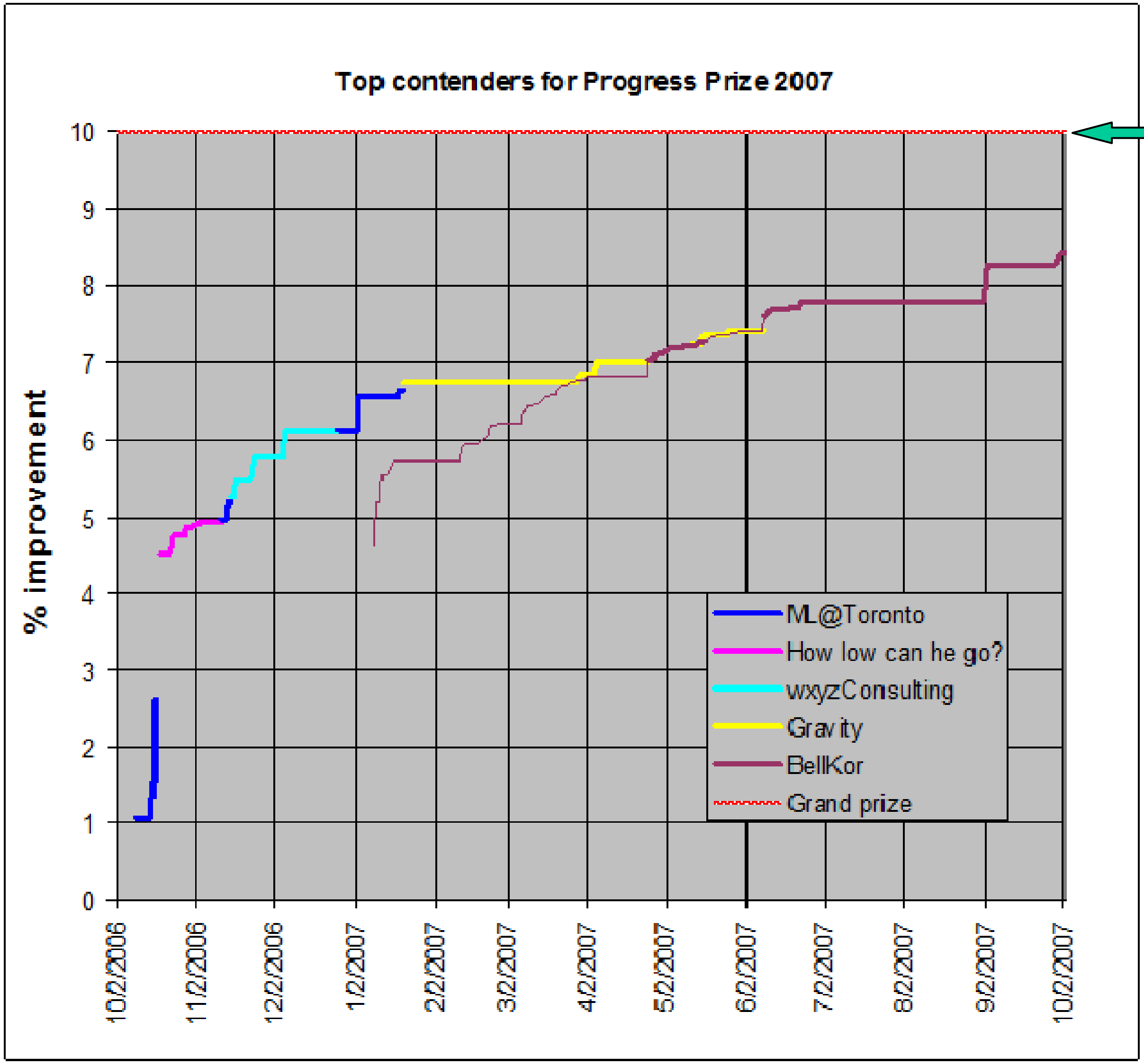
Additional Evaluation Dimensions

- ***Coverage***:
  - Recommendations for how many items
  - How many items are actually recommended
- ***Learning rate***:
  - How fast recommendation quality increases with increased amount of training date
- ***Novelty***:
  - Focus on items unknown to the user, but within its scope (e.g., new movie of favourite director)
- ***Serendepity***:
  - Surprising recommendations (e.g., new movie of new director that fits the user‘s taste)
- ***Confidence***

Benchmarks: Netflix Prize

- http://www.netflixprize.com
- set up by online movie portal
- provides (anonymized) training data (480,000 users, 18,000 movies, 10^6 ratings on a 1..5 scale)
- Goal: improve over portal's own recommender (RMSE: 0.9514)
- High reward to make the benchmark attractive: 1,000,000$ for the first 10% improvement in RMSE on test data (1.4 million user-movie pairs), 50,000$ intermediate progress award per year

Netflix: Result Improvements over Time



10% improvement reached just a few days ago

Web Dynamics

Part 7 – Human Behaviour on the Web

7.1 Recommendation

7.2 Personalized Search

Goal: Resolve inherent disambiguity of search

Example 1: Search for „IR“ may return

- Ingersoll-Rand Company
- Web pages in Arabic from Iran (*.ir)
- Infrared Light
- Information Retrieval

Example 2: Search for „Java“ should return

- Programming tools for a programmer
- Tutorials for a teacher
- FAQ lists for a novice user

global context of the user

Goal: Resolve inherent disambiguity of search

Example 3: Search for „restaurant“ should return

- places in Boston while planning for SIGIR 09
- places in Lyon while planning for VLDB 09
- places in Saarbrücken otherwise

Example 4: Search for „Saarbrücken“ should return

- Restaurants (when I‘ve been searching for them)
- Computer shops, dentists, hospitals, …

Search results may depend on current context (that is not constant and may change over time)

Dimensions of Personalized Search

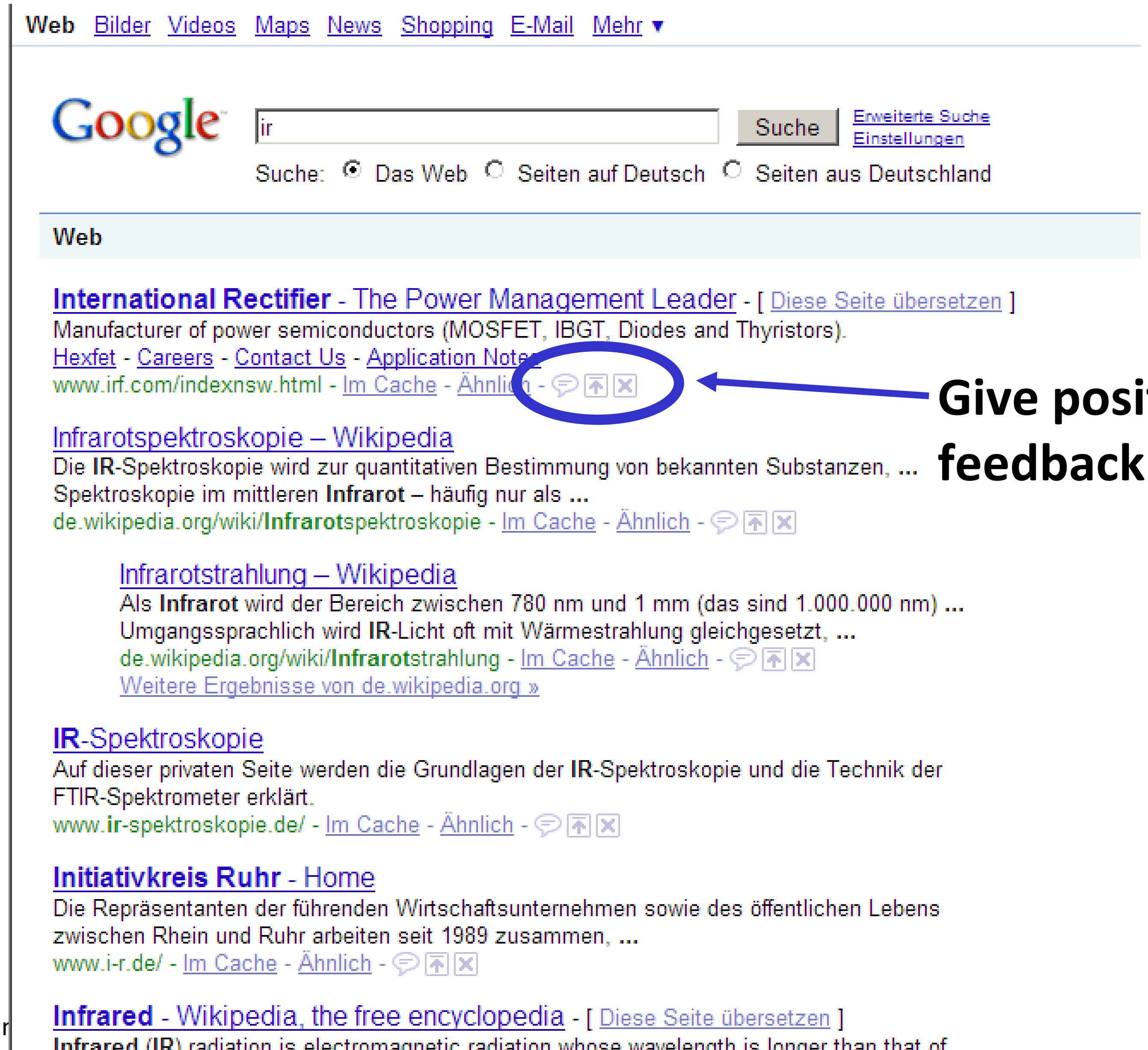
- Different ***kinds of user contexts***:
  - global: background of the user, long-term profile
  - session: set of queries following similar needs
  - query: use last query & actions

  each only for searches, for all browser actions, or for (more/all) actions
- Different ***places*** to collect & use context info:
  - server vs. local client
- Different ***actions*** to use context info:
  - modify query vs. rerank results

Simple Personalization: Relevance Feedback

- collect ***feedback from user*** for query results
  - explicit feedback (buttons in the interface)
  - implicit feedback (clicks of the user)
- generate ***improved query***
  - add new terms
  - drop some old terms
  - change weights of terms

Example: Simple Feedback on iGoogle



Give positive or negative feedback for results

Example: Simple Feedback on iGoogle

iGoogle: Collaborative Feedback

Alle Such-Wiki-Einträge

19 Einträge gespeichert für: **ir**

[IR Japan | 株式会社アイ・アールジャパン] - [Diese Seite übersetzen]
IR活動支援のパイオニア、アイ・アールジャパンは委任状争奪戦などの有事においてはプロキシーアドバイザー（PA）として、また、平時においては買収防衛策導入支援、 ...
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Infrarotstrahlung (**IR**-Strahlung) - auch als Wärmestrahlung bezeichnet - ist Teil der optischen Strahlung und damit Teil des elektromagnetischen Spektrums. **...**
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زوروا موقع اذاعة طهران العربية على الانترنت للاطلاع على آخر الاخبار والانباء والتقارير واهم عناوين الصحف العربية والايرانية واحداث العالم عبر الصور.
arabic.irib.**ir**/ - vor 3 Stunden gefunden - Im Cache - Ähnlich -
1 0 1 Kommentar

[Internal Revenue Service] - [Diese Seite übersetzen]
US government agency responsible for tax collection and tax law enforcement. Provides downloadable income tax forms, instructions, agency publications

Implicit Feedback from Clicks

General rules to collect implicit feedback:

- ***Clicked results*** are relevant for the query
  - unless the user left that page immediately
- ***Non-clicked*** results don‘t really help
  - User may immediately rate them as nonrelevant (from the snippet)
  - User may already know the result (which may be relevant or nonrelevant)
  - User may not have looked at the result (was satisfied by other results)

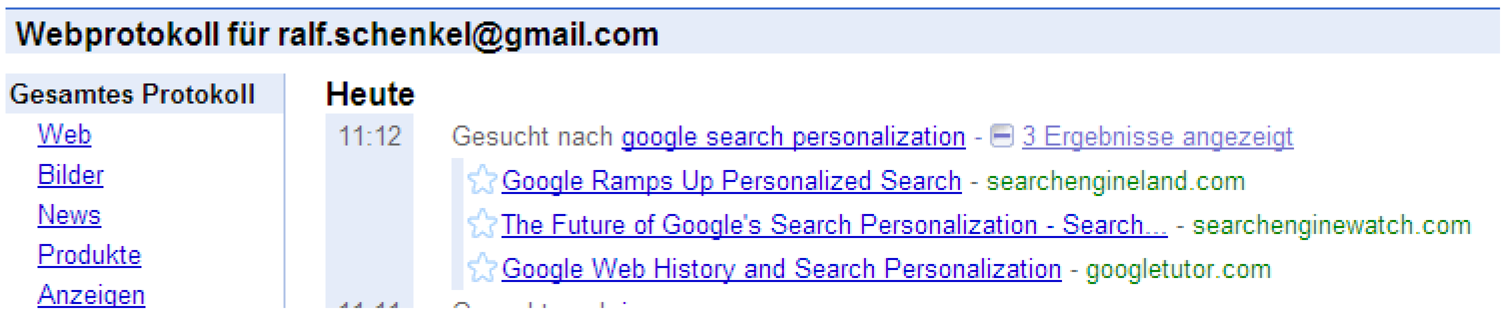
Advanced Implicit Feedback

Modify browser to collect ***behavior data***:

- dwelling time on a page
- scrolling
- mouse movements
- mouse clicks
- followed links

$\Rightarrow$ Yields better estimate of “relevance”

iGoogle: Logging Searches and Clicks



Standard RF: Rocchio's Method (1971)

- Goal: Find query that is close to relevant documents
- Compute ***Rocchio weights [1971]*** for each term (also used as weight in query):

$$w(t) = \alpha \cdot q(t) + \beta \frac{r_t}{R} - \gamma \frac{n_t}{N}$$

where

$q(t)$	weight of term t in the query
r_t	number of relevant results with term t
R	number of relevant results
n_t	number of nonrelevant results with term t
N	number of nonrelevant results

- Select n terms with highest weight to expand query

Simple Use of Feedback: Promoting

Idea: Push results with positive feedback up

- ***Locally*** for each user:
  - remember feedback for each user
  - promote results with feedback when query returns (approximately 30% of queries [Dou, WWW07])
- ***Globally*** for all users:
  - collect feedback for (frequent) queries
  - promote results with feedback from „most“ users
  - does not work well for ambigous queries

$\Rightarrow$ pure reranking approach

User Profiles

Goal: Construct ***summary*** of the user's interests

- from the pages she accessed
- from her documents, her mails, … (optional)

General approach:

- For each page p, consider term vector t(p)
- For set of browsed pages B, compute average term vector t(B):

$$t(B) = \frac{1}{|B|} \sum_{p \in B} t(p)$$

Persistent vs. Session Profile

Long-term interests of user may differ from interest in ***current search session***

$\Rightarrow$ maintain two profiles: persistent & session

- **Session profile**:
  - consider pages accessed in the current session only
  - Session boundaries by time or page coherence
- **Persistent profile**:
  - consider all pages ever visited by the user
  - lower weight for older pages (exponential decay)

Profile is mixture of session & persistent profiles

Personalization with User Profiles

Reranking of search result based on profile match:

- compute set of results R for query
- for each result p, measure ***similarity*** of p with profile vector (e.g., cosine)
- rank results in descending order of similarity

Improving Profiles by Collaborative Filtering

Problem:

User profile often sparse (based on few pages)

Approach:

Predict missing term weights analogously to user-centric recommendation

- Find similar users based on similarity of their profiles
- Compute predictions for term weights based on weighted average over neighborhood

Reranking Problem: Similar Results

Reranking cannot work when all results are similar (and nonrelevant to the query)

Example:

- Query: windows (as built into houses)
- Results: only about the operating system

Microsoft Corporation
Microsoft Virtualization: Download a free trial of **Windows** Server 2008 Hyper-V **...** Find a free trial, tools, and downloads that work with **Windows** Essential **...**
www.microsoft.com/ - Cached - Similar

Microsoft Download Center	Windows Vista
Windows XP	Windows 7
Microsoft Help and Support	Templates
Windows Update	Internet Explorer

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Microsoft **Windows**: software and services as unique as you are
With **Windows** on your mobile phone, PC, or the Web, you have access to a wide range of software, services, and devices to choose from.
Downloads - Windows XP - Windows 7 - Windows Vista
www.microsoft.com/**windows**/ - Cached - Similar

Microsoft **Windows** Update
Latest bug fixes for Microsoft **Windows**, including fixes for some possible DoS attacks.
windowsupdate.microsoft.com/ - Similar

Reranking diversified results

Exploit information about query sequences

Example:

windows → house windows → vinyl windows
→ windows xp → windows vista

Approach:

To get K results for reranking for query q,
submit top-$K/(k+1)$-queries for k most
frequent/diverse following queries of q in the log

Searches related to: **windows**

windows **azure**	**house** windows	windows **live**	windows **vista**
windows **xp**	windows **7**	**home** windows	windows **media player**

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