

Introduction to **Information Retrieval**

CS276

Information Retrieval and Web Search

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Personalization

Ambiguity

- Unlikely that a short query can unambiguously describe a user's information need
- For example, the query [chi] can mean
 - Calamos Convertible Opportunities & Income Fund quote
 - The city of Chicago
 - Balancing one's natural energy (or ch'i)
 - Computer-human interactions

Personalization

- Ambiguity means that a single ranking is unlikely to be optimal for all users
- Personalized ranking is the only way to bridge the gap
- Personalization can use
 - Long term behavior to identify user interests, e.g., a long term interest in user interface research
 - Short term session to identify current task, e.g., checking on a series of stock tickers
 - User location, e.g., MTA in New York vs Baltimore
 - Social network
 - ...

Potential for Personalization

[Teevan, Dumais, Horvitz 2010]

- How much can personalization improve ranking?
How can we measure this?
- Ask raters to explicitly rate a set of queries
 - But rather than asking them to guess what a user's information need might be ...
 - ... ask which results *they would personally consider relevant*
 - Use self-generated and pre-generated queries

Computing potential for personalization

- For each query q
 - Compute average rating for each result
 - Let R_q be the optimal ranking according to the average rating
 - Compute the NDCG value of ranking R_q for the ratings of each rater i
 - Let Avg_q be the average of the NDCG values for each rater
- Let Avg be the average Avg_q over all queries
- Potential for personalization is $(1 - \text{Avg})$

Example: NDCG values for a query

Result	Rater A	Rater B	Average rating
D1	1	0	0.5
D2	1	1	1
D3	0	1	0.5
D4	0	0	0
D5	0	0	0
D6	1	0	0.5
D7	1	2	1.5
D8	0	0	0
D9	0	0	0
D10	0	0	0
NDCG	0.88	0.65	

Average NDCG for raters: 0.77

Example: NDCG values for optimal ranking for average ratings

Result	Rater A	Rater B	Average rating
D7	1	2	1.5
D2	1	1	1
D1	1	0	0.5
D3	0	1	0.5
D6	1	0	0.5
D4	0	0	0
D5	0	0	0
D8	0	0	0
D9	0	0	0
D10	0	0	0
NDCG	0.98	0.96	

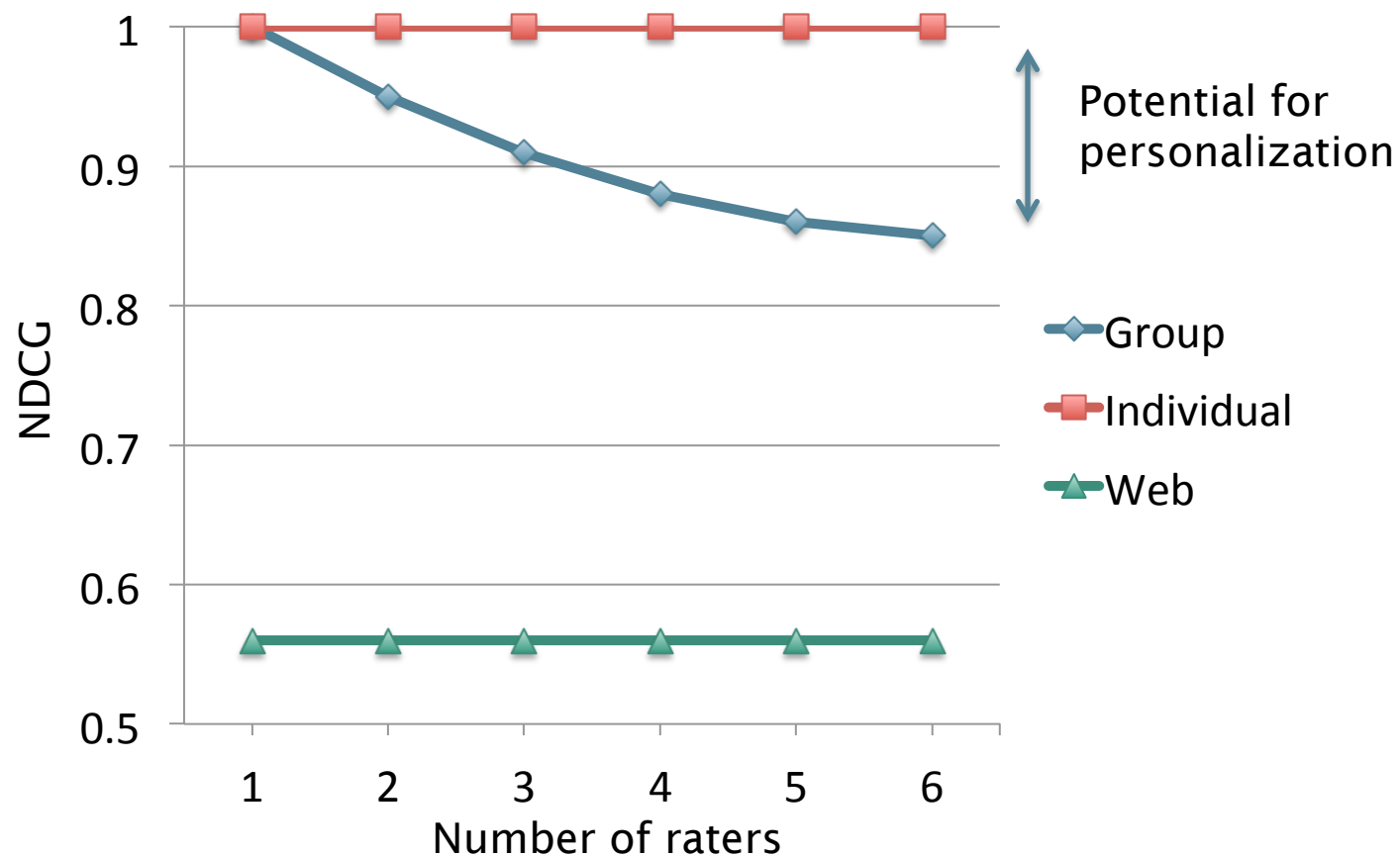
Average NDCG for raters: 0.97

Example: Potential for personalization

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D5	0	0	0
D8	0	0	0
D9	0	0	0
D10	0	0	0
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Potential for personalization: 0.03

Potential for personalization graph



PERSONALIZING SEARCH

Personalizing search

[Pitkow et al. 2002]

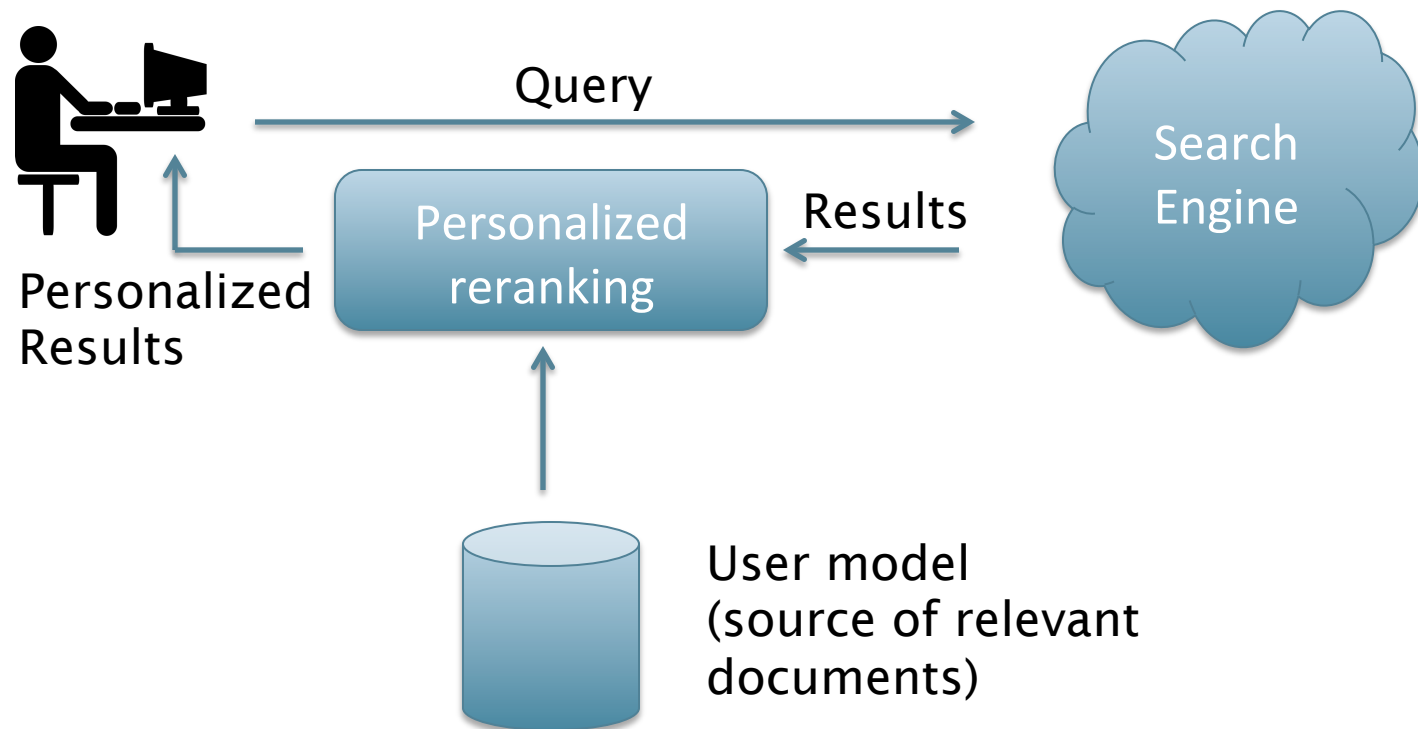
- Two general ways of personalizing search
 - Query expansion
 - Modify or augment user query
 - E.g., query term “IR” can be augmented with either “information retrieval” or “Ingersoll-Rand” depending on user interest
 - Ensures that there are enough personalized results
 - Reranking
 - Issue the same query and fetch the same results ...
 - ... but rerank the results based on a user profile
 - Allows both personalized and globally relevant results

User interests

- Explicitly provided by the user
 - Sometimes useful, particularly for new users
 - ... but generally doesn't work well
- Inferred from user behavior and content
 - Previously issued search queries
 - Previously visited Web pages
 - Personal documents
 - Emails
- Ensuring privacy and user control is very important

Relevance feedback perspective

[Teevan, Dumais, Horvitz 2005]



Binary Independence Model

- Estimating RSV coefficients in theory
- For each term i look at this table of document counts:

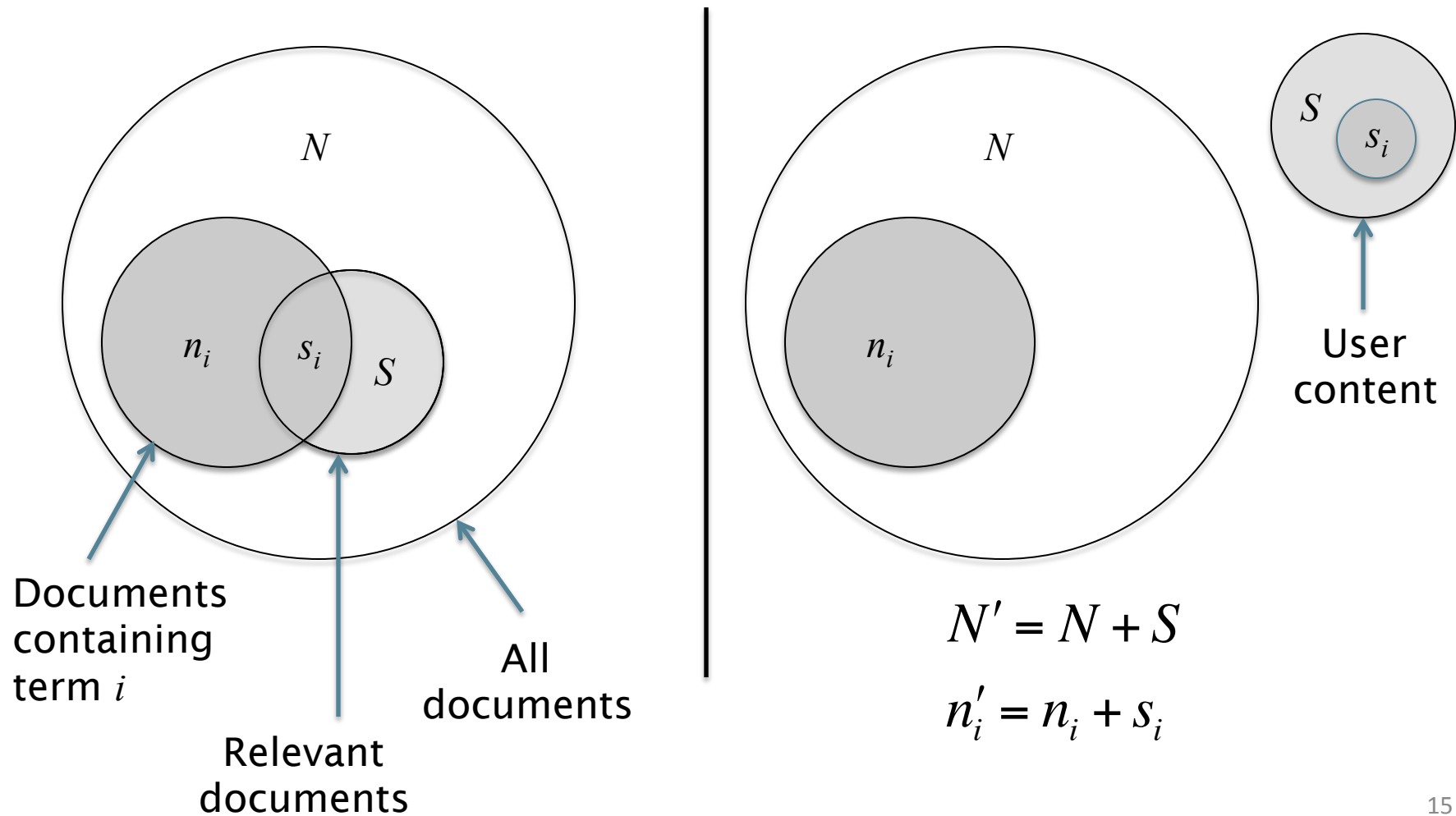
Documents	Relevant	Non-Relevant	Total
$x_i=1$	s_i	$n_i - s_i$	n_i
$x_i=0$	$S - s_i$	$N - n_i - S + s_i$	$N - n_i$
Total	S	$N - S$	N

- Estimates: $p_i \approx \frac{s_i}{S}$ $r_i \approx \frac{(n_i - s_i)}{(N - S)}$

$$c_i \approx K(N, n_i, S, s_i) = \log \frac{s_i / (S - s_i)}{(n_i - s_i) / (N - n_i - S + s_i)}$$

For now, assume no zero terms. See later lecture.

Personalization as relevance feedback



Reranking

- BM25 scoring

$$\sum c_i \times tf_i$$

- Use updated weight c_i in BM25

$$c_i = \log \frac{(s_i + 0.5)(N - n_i + 0.5)}{(n_i + 0.5)(S - s_i + 0.5)}$$

where we have used

$$N' = N + S$$

$$n'_i = n_i + s_i$$

Corpus representation

- Estimating N and n_i
- Many possibilities
 - N : All documents, query relevant documents, result set
 - n_i : Full text, only titles and snippets
- Practical strategy
 - Approximate corpus statistics from result set
 - ... and just the title and snippets
 - Empirically seems to work the best!

User representation

- Estimating S and s_i
- Estimated from a local search index containing
 - Web pages the user has viewed
 - Email messages that were viewed or sent
 - Calendar items
 - Documents stored on the client machine
- Best performance when
 - S is the number of local documents matching the query
 - s_i is the number that also contains term i

Document and query representation

- Document represented by the title and snippets
- Query is expanded to contain words near query terms (in titles and snippets)
 - For the query [cancer] add underlined terms

The American **Cancer** Society is dedicated to eliminating **cancer** as a major health problem by preventing **cancer**, saving lives, and diminishing suffering through ...

- This combination of corpus, user, document, and query representations seem to work well

LOCATION

User location

- User location is one of the most important features for personalization
 - Country
 - Query [football] in the US vs the UK
 - State/Metro/City
 - Queries like [zoo], [craigslist], [giants]
 - Fine-grained location
 - Queries like [pizza], [restaurants], [coffee shops]

Challenges

- Not all queries are location sensitive
 - [facebook] is not asking for the closest Facebook office
 - [seaworld] is not necessarily asking for the closest SeaWorld
- Different parts of a site may be more or less location sensitive
 - NYTimes home page vs NYTimes Local section
- Addresses on a page don't always tell us how location sensitive the page is
 - Stanford home page has address, but not location sensitive

Key idea

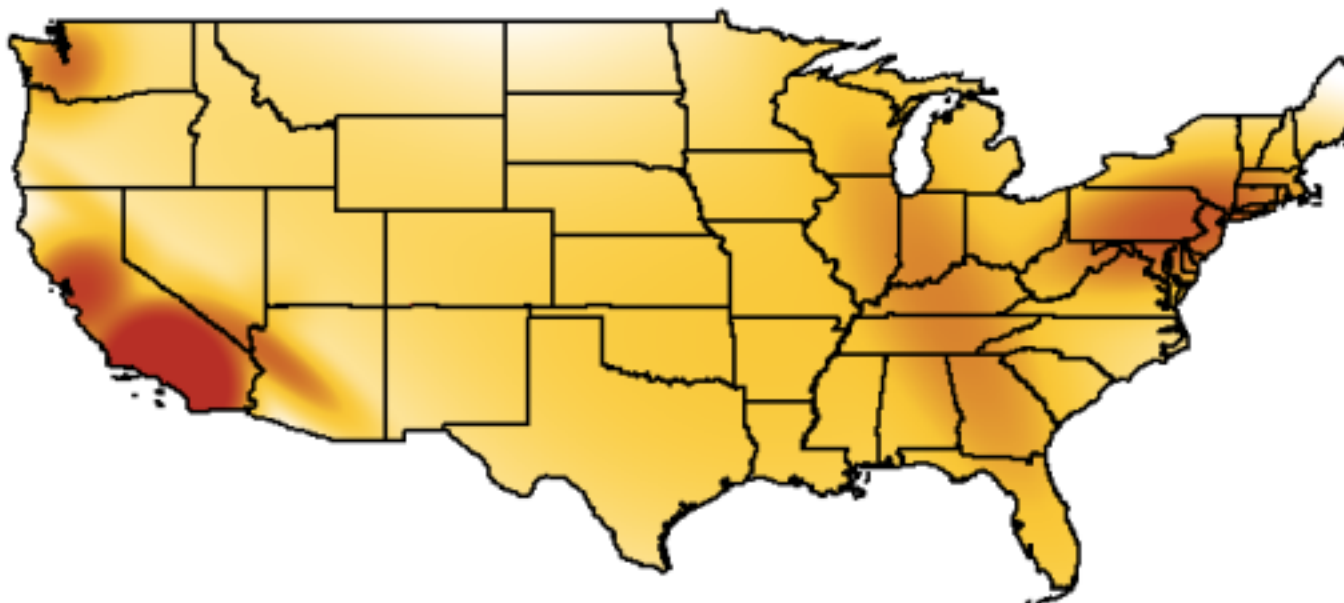
[Bennett et al. 2011]

- *Usage statistics*, rather than locations mentioned in a document, best represent where it is relevant
 - I.e., if users in a location tend to click on that document, then it is relevant in that location
- User location data is acquired from anonymized logs (with user consent, e.g., from a widely distributed browser extension)
 - User IP addresses are resolved into geographic location information

Location interest model

- Use the logs data to estimate the probability of the location of the user given they viewed this URL

$$P(location = x | URL)$$

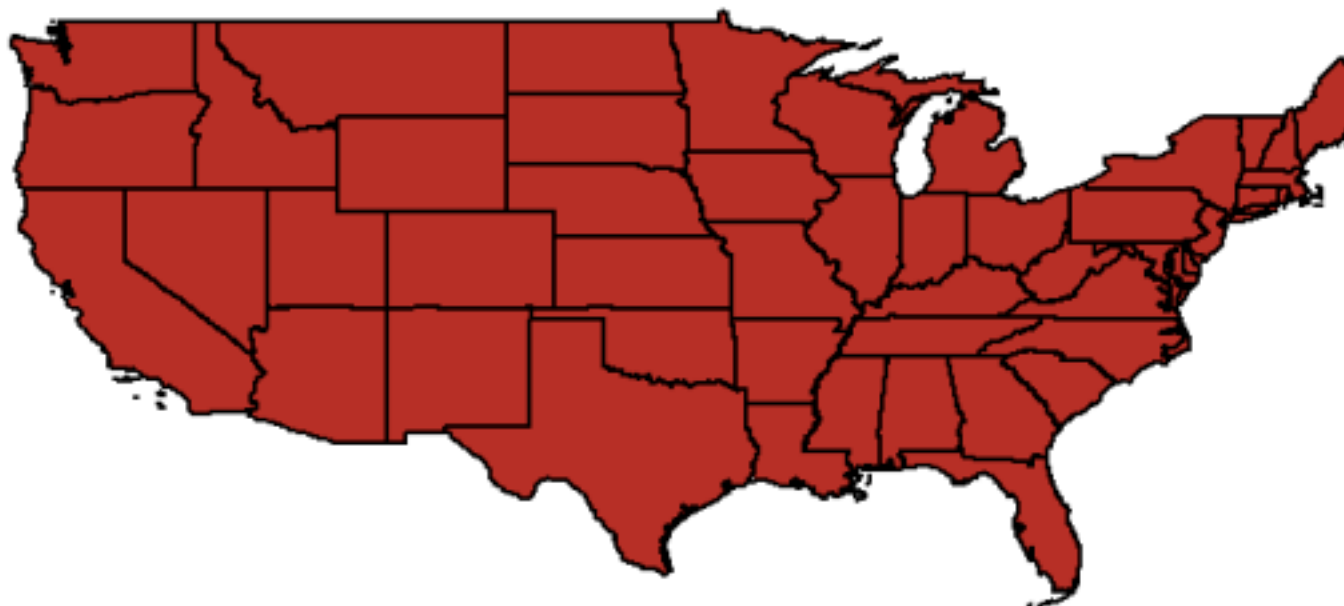


(c) Los Angeles Times: Reviews and Recommendations
<http://findlocal.latimes.com/>

Location interest model

- Use the logs data to estimate the probability of the location of the user given they viewed this URL

$$P(location = x | URL)$$



(d) Los Angeles Times: Crossword Puzzles and Games
<http://games.latimes.com/>

Learning the location interest model

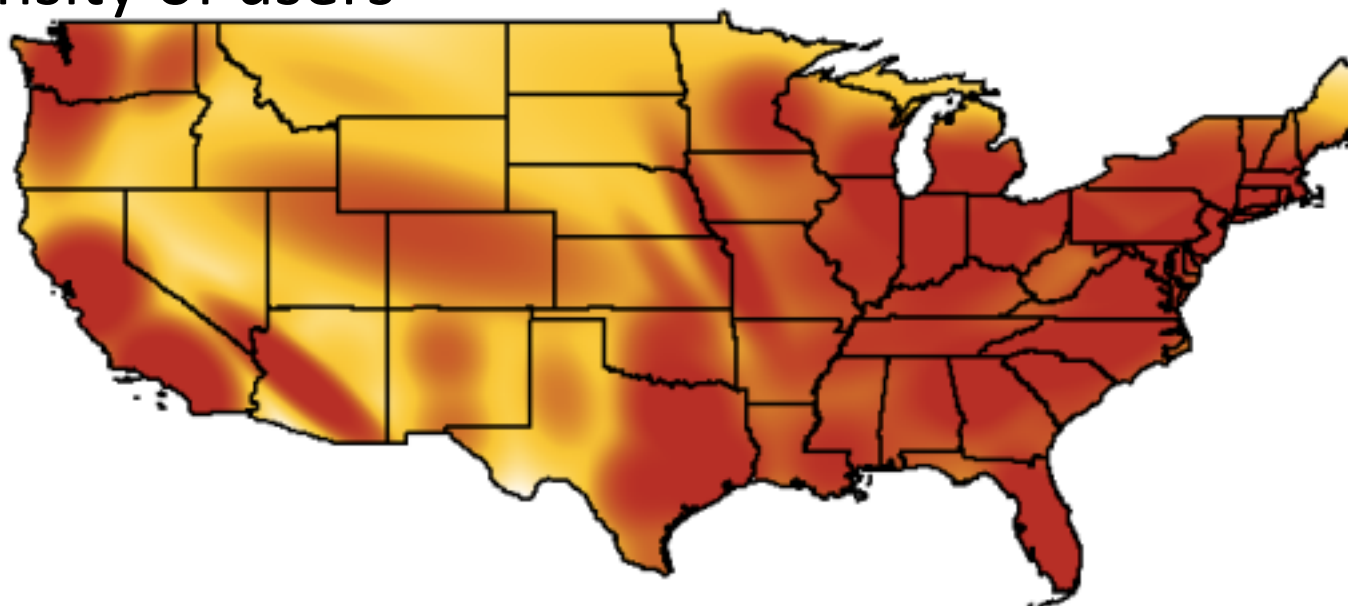
- For compactness, represent location interest model as a mixture of 5-25 2-d Gaussians (x is [lat, long])

$$\begin{aligned} P(\text{location} = x | URL) &= \sum_{i=1}^n w_i N(x; \mu_i, \Sigma_i) \\ &= \sum_{i=1}^n \frac{w_i}{(2\pi)^2 |\Sigma_i|^{1/2}} e^{-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1} (x-\mu_i)} \end{aligned}$$

- Learn Gaussian mixture model using EM
 - Expectation step: Estimate probability that each point belongs to each Gaussian
 - Maximization step: Estimate most likely mean, covariance, weight

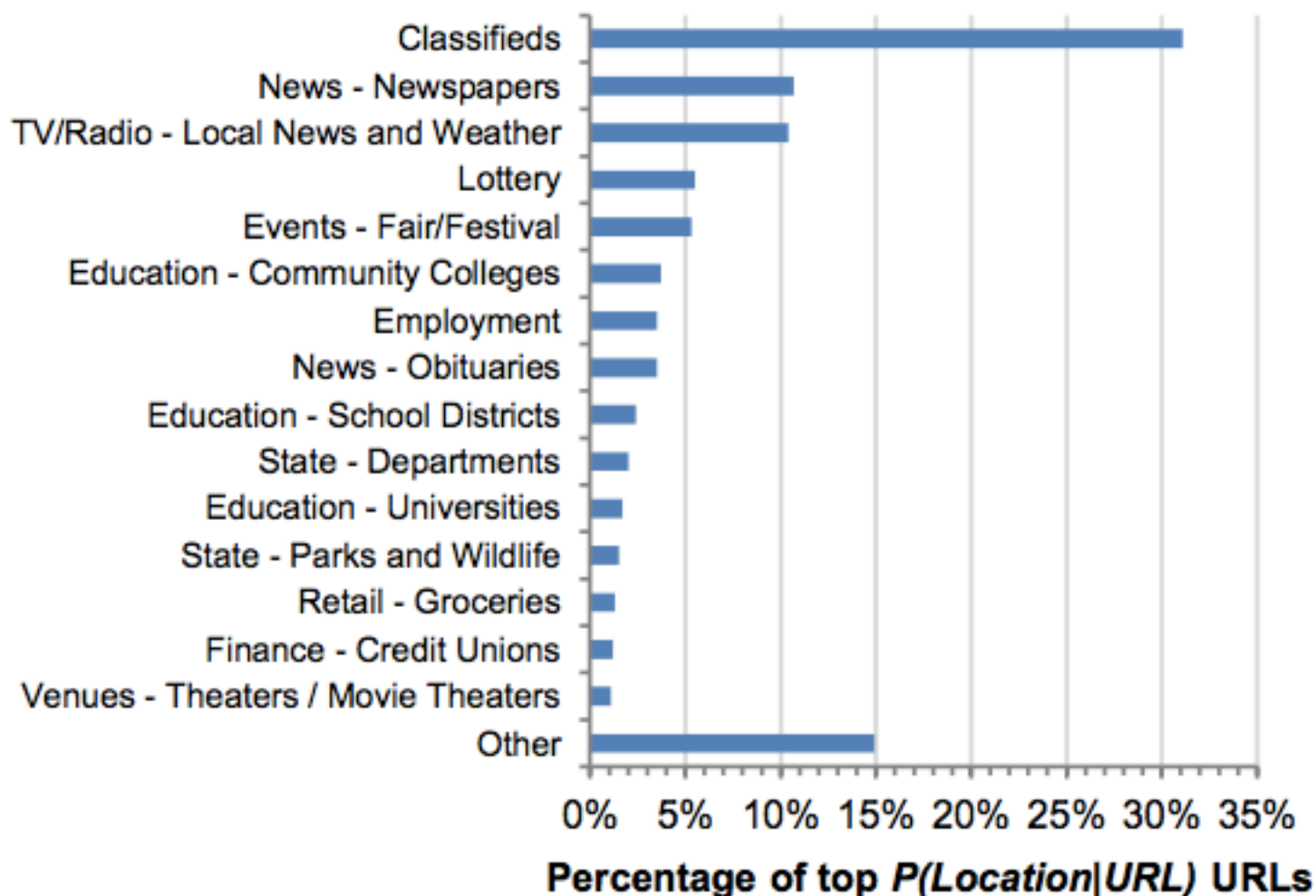
More location interest models

- Learn a location-interest model for queries
 - Using location of users who issued the query
- Learn a background model showing the overall density of users



(e) Background Model

Topics in URLs with high $P(\text{user location} \mid \text{URL})$



Location sensitive features

- Non-contextual features (user-independent)
 - Is the query location sensitive? What about the URLs?
 - Feature: Entropy of the location distribution
 - Low entropy means distribution is peaked and location is important
 - Feature: KL-divergence between location model and background model
 - High KL-divergence suggests that it is location sensitive
 - Feature: KL-divergence between query and URL models
 - Low KL-divergence suggests URL is more likely to be relevant to users issuing the query

More location sensitive features

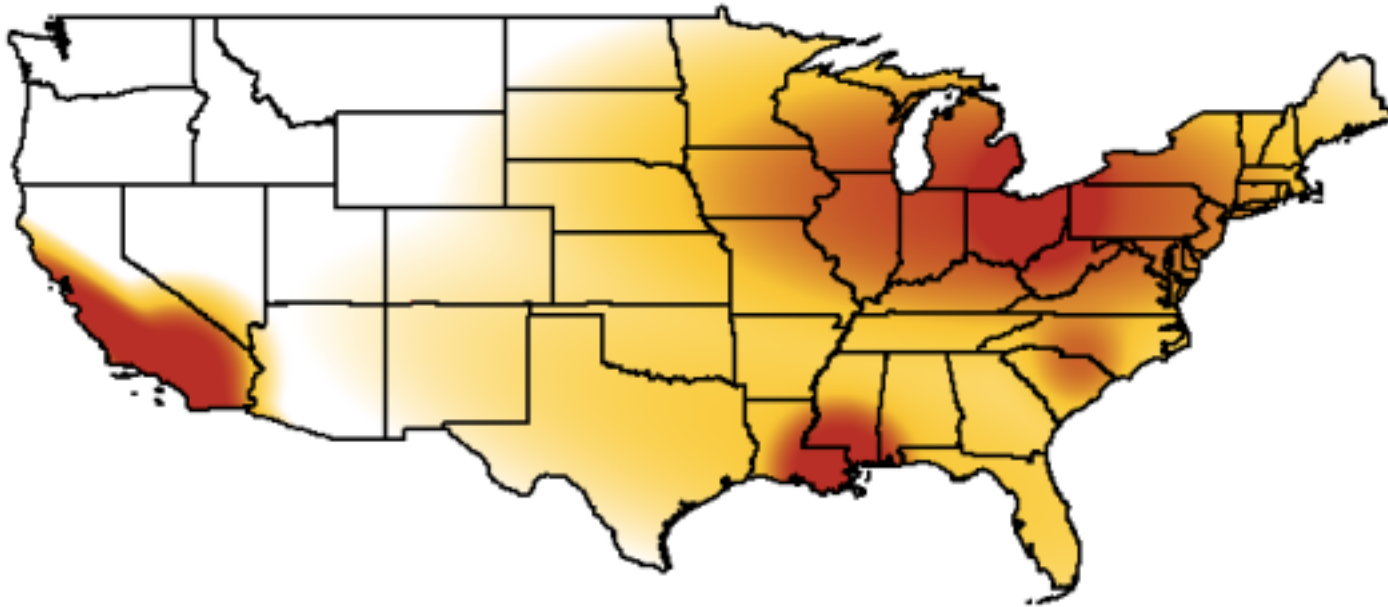
- Contextual features (user-dependent)
 - Feature: User's location (naturally!)
 - Feature: Probability of the user's location given the URL
 - Computed by evaluating URL's location model at user location
 - Feature is high when user is at a location where URL is popular
 - Downside: large population centers tend to higher probabilities for all URLs
 - Feature: Use Bayes rule to compute $P(\text{URL} \mid \text{user location})$
 - Feature: Also create a normalized version of the above feature by normalizing with the background model
 - Features: Versions of the above with query instead of URL

Learning to rank

- Add location features (in addition to standard features) for machine learned ranking
 - Training data derived from logs
 - $P(\text{URL} \mid \text{user location})$ turns out to be an important feature
 - KL divergence of the URL model from the background model also plays an important role

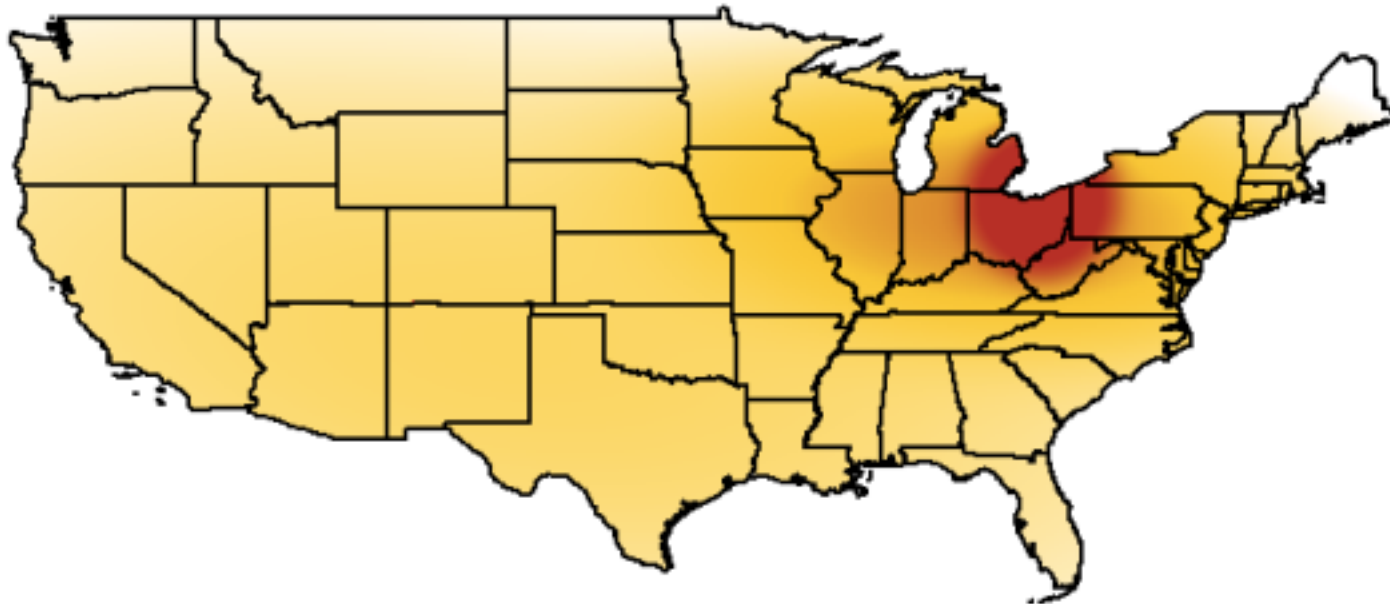
Query model for [rta bus schedule]

User in New Orleans



URL model for top original result

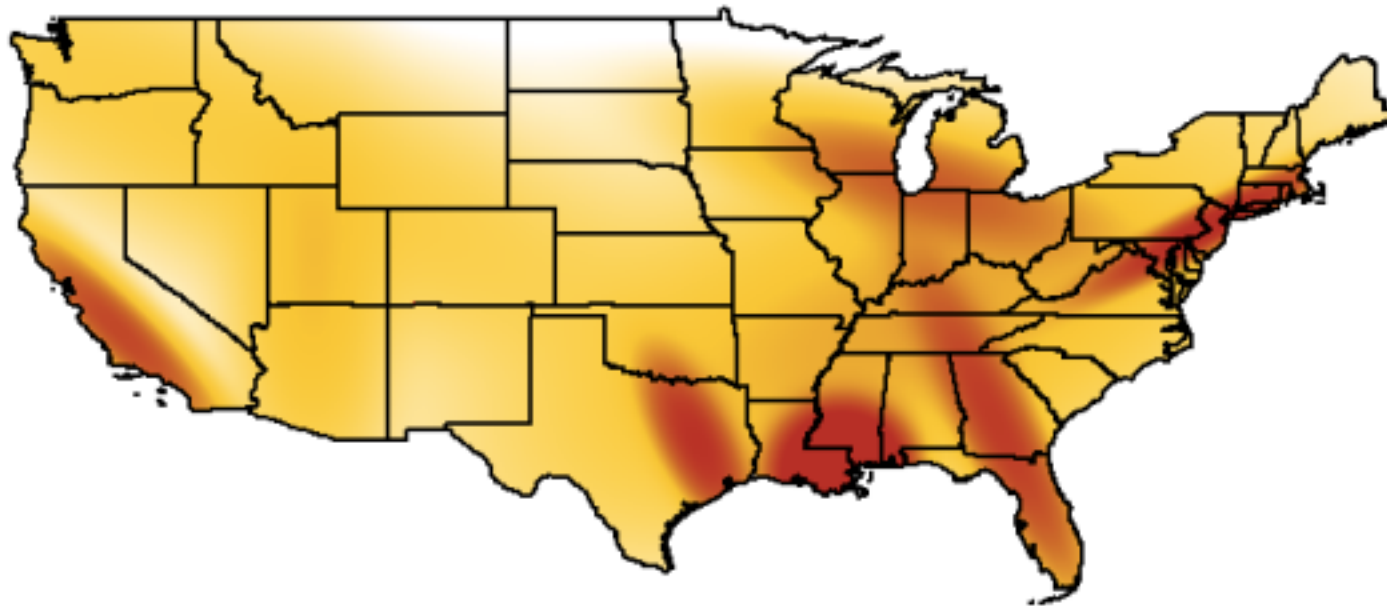
User in New Orleans



(a) <http://www.riderta.com/maps-schedules.asp>

URL model for promoted URL

User in New Orleans



(b) <http://www.norta.com/>

PERSONALIZED PAGERANK

Pagerank review

- Let \mathbf{A} be the stochastic matrix corresponding to the Web graph G over n nodes
 - No teleportation links (but assume no deadends in G)
 - If node i has o_i outlinks, and there is an edge from node i to node j , then $\mathbf{A}_{ij} = 1/o_i$
- Let \mathbf{p} be the teleportation probabilities
 - $(n \times 1)$ column vector with each entry being $1/n$
- Pagerank vector \mathbf{r} is defined by the following

$$\mathbf{r} = (1 - \alpha)\mathbf{A}\mathbf{r} + \alpha\mathbf{p}$$

Personalized pagerank

[Haveliwala 2003] [Jeh and Widom 2003]

- In the basic pagerank computation, teleportation probability vector \mathbf{p} is uniform over all pages
- But if the user has preferences on which pages to teleport to, that preference can be represented in \mathbf{p}
 - \mathbf{p} could be uniform over user's bookmarks
 - Or it could be non-zero on just pages on topics of interest to the user
- Pagerank would be personalized to user's interests
- But computing personalized pagerank is expensive

Linearity theorem

- For any preference vectors \mathbf{u}_1 and \mathbf{u}_2 , if \mathbf{v}_1 and \mathbf{v}_2 are the corresponding personalized pagerank vectors, then for any non-negative constants a_1 and a_2 such that $a_1 + a_2 = 1$, we have

$$a_1 \mathbf{v}_1 + a_2 \mathbf{v}_2 = (1 - \alpha) \mathbf{A}(a_1 \mathbf{v}_1 + a_2 \mathbf{v}_2) + \alpha(a_1 \mathbf{u}_1 + a_2 \mathbf{u}_2)$$

- Proof

$$\begin{aligned} a_1 \mathbf{v}_1 + a_2 \mathbf{v}_2 &= a_1((1 - \alpha) \mathbf{A} \mathbf{v}_1 + \alpha \mathbf{u}_1) + a_2((1 - \alpha) \mathbf{A} \mathbf{v}_2 + \alpha \mathbf{u}_2) \\ &= a_1(1 - \alpha) \mathbf{A} \mathbf{v}_1 + a_1 \alpha \mathbf{u}_1 + a_2(1 - \alpha) \mathbf{A} \mathbf{v}_2 + a_2 \alpha \mathbf{u}_2 \\ &= (1 - \alpha) \mathbf{A}(a_1 \mathbf{v}_1 + a_2 \mathbf{v}_2) + \alpha(a_1 \mathbf{u}_1 + a_2 \mathbf{u}_2) \end{aligned}$$

Topic-sensitive pagerank

- Compute personalized pagerank vector per topic
 - 16 top-level topics from the Open Directory Project
 - Each ODP topic has a set of pages (hand-)classified into that topic
 - Preference vector for the topic is uniform over pages in that topic, and 0 elsewhere
- Note: [Jeh and Widom 2003] provide a more general treatment

Query-time processing

- Construct a distribution over topics for the query
 - User profile can provide a distribution over topics
 - Query can be classified into the different topics
 - Any other context information can be used to inform topic distributions
- Use the topic preferences to compute a weighted linear combination of topic pagerank vectors to use in place of pagerank

SOCIAL NETWORKS

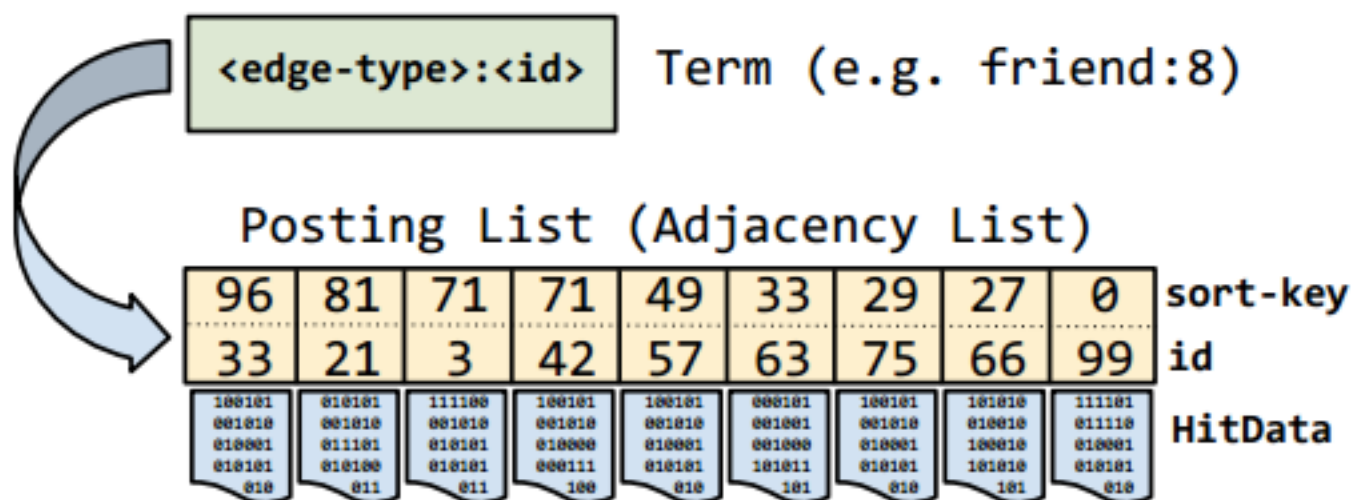
Unicorn

[Curtiss et al 2013]

- Primary backend for Facebook Graph Search
- Facebook social graph
 - Nodes represent people and things (entities)
 - Each entity has a unique 64-bit **id**
 - Edges represent relationships between nodes
 - There are many thousands of edge-types
 - Examples: `friend`, `likes`, `likers`, ...

Data model

- Billions of nodes, but graph is sparse
 - Represent graph using adjacency list
 - Postings sorted by `sort-key` (importance) and then `id`
 - Index sharded by `result-id`



Basic set operations

- Query language includes basic set operations
 - and, or, difference
 - Friends of either Jon Jones (id 5) and Lea Lin (id 6)
`(or(friend:5 friend:6))`
 - Female friends of Jon Jones who are not friend of Lea Lin
`(difference (and friend:5 gender:1)
friend:6)`

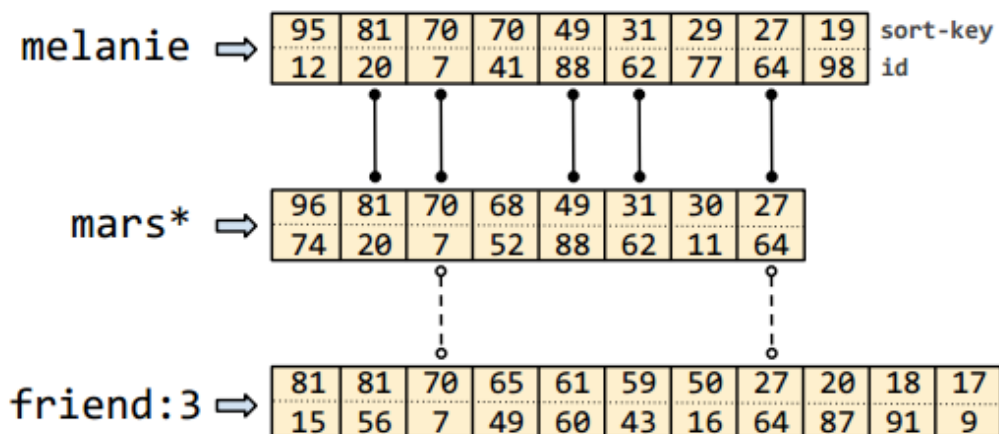
Typeahead

- Find users by typing first few characters of their name
- Index servers contain postings lists for every name prefix up to a predefined character limit
 - Simple typeahead implementation would simply return ids in the corresponding postings lists
- Simple solution doesn't ensure social relevance
- Alternate solution: Use a conjunctive query
`(and mel* friend:3)`
 - Misses people who are not friends
 - Issuing two queries is expensive

WeakAnd operator

- Provides a mechanism for some fraction of results to possess a trait without requiring trait for all results
- WeakAnd allows missing terms from some results
 - These optional terms can have an optional count or weight
 - Once the optional count is met, the term is required

(weak-and (term friend:3 :optional-hits 2) (term melanie) (term mars*))



Graph Search

- Graph Search results are often one edge away from source nodes
 - Example: Pages liked by friends of Melanie who like Emacs
- Unicorn provides additional operators to support Graph Search
 - Apply
`(apply likes: (and friend:7 likers:42))`
 - Extract
 - Extract and return (denormalized) ids stored in HitData

References

- [J. Teevan, S. Dumais, E. Horvitz. Potential for personalization. 2010](#)
- [J. Pitkow et al. Personalized search. 2002](#)
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- [M. Curtiss et al. Unicorn: A system for searching the social graph. 2013](#)