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 – 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	

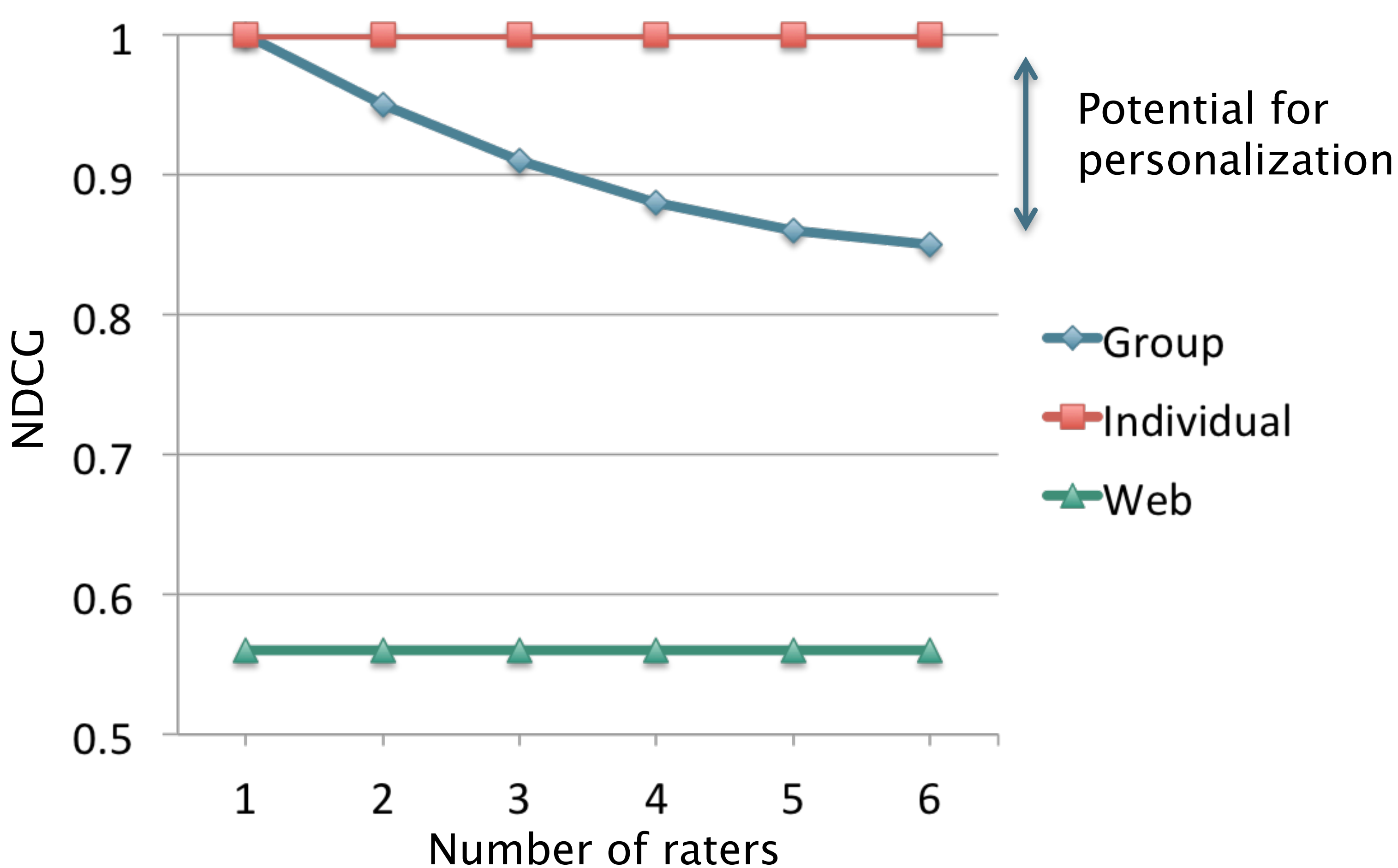
Average NDCG for raters: 0.97

Example: Potential for personalization

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	

Potential for personalization: 0.03

Potential for personalization graph



PERSONALIZING SEARCH

Personalizing search

[Pitkow et al. 2002]

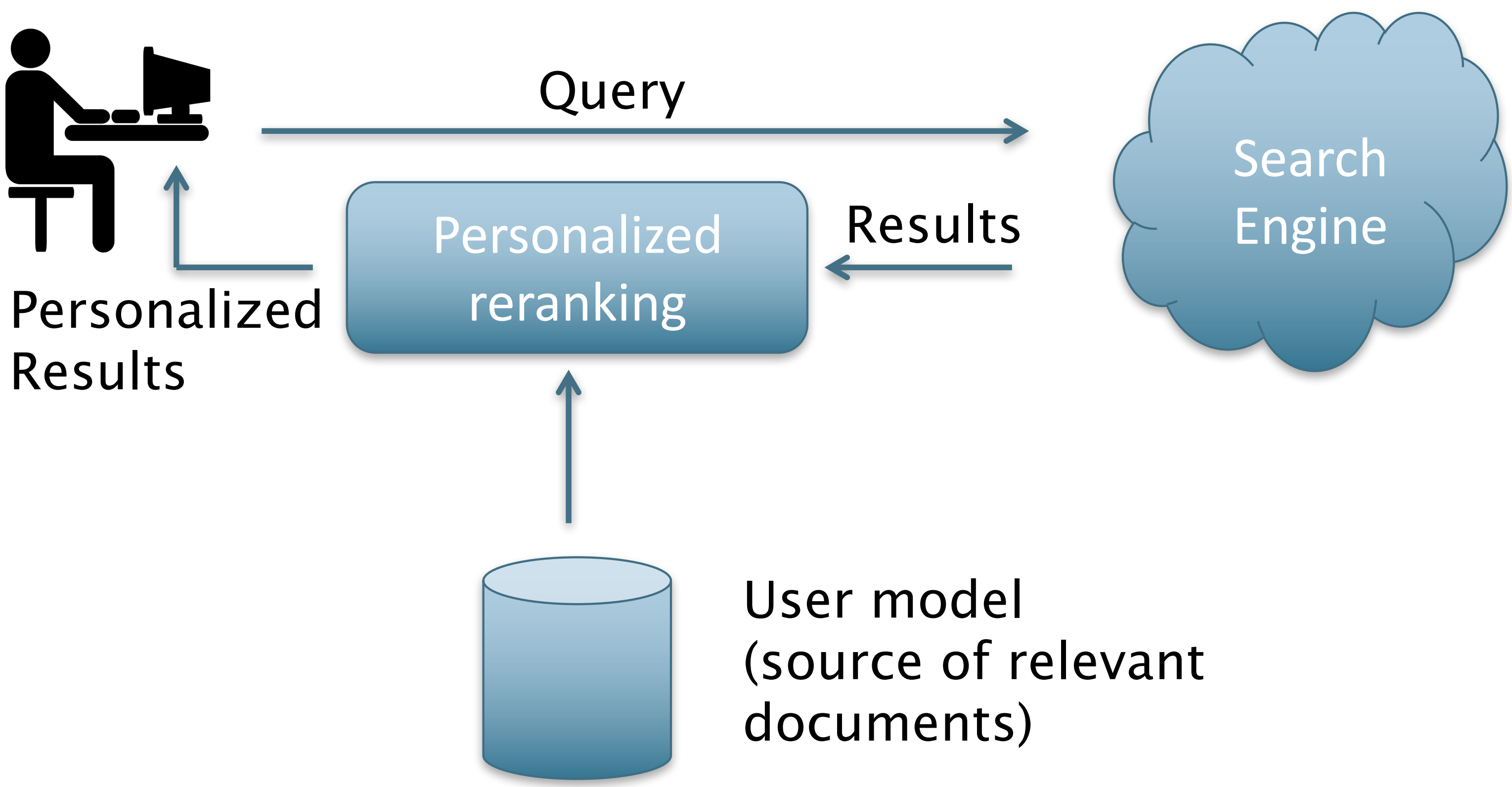
- Two general ways of personalizing search
  - Query expansion
    - Modify or augment user query
    - E.g., query term "IR" can be augmented with either "information retrieval" or "Ingersoll-Rand" depending on user interest
    - Ensures that there are enough personalized results
  - Reranking
    - 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:

$$c_i = \log \frac{p_i(1-r_i)}{r_i(1-p_i)}$$

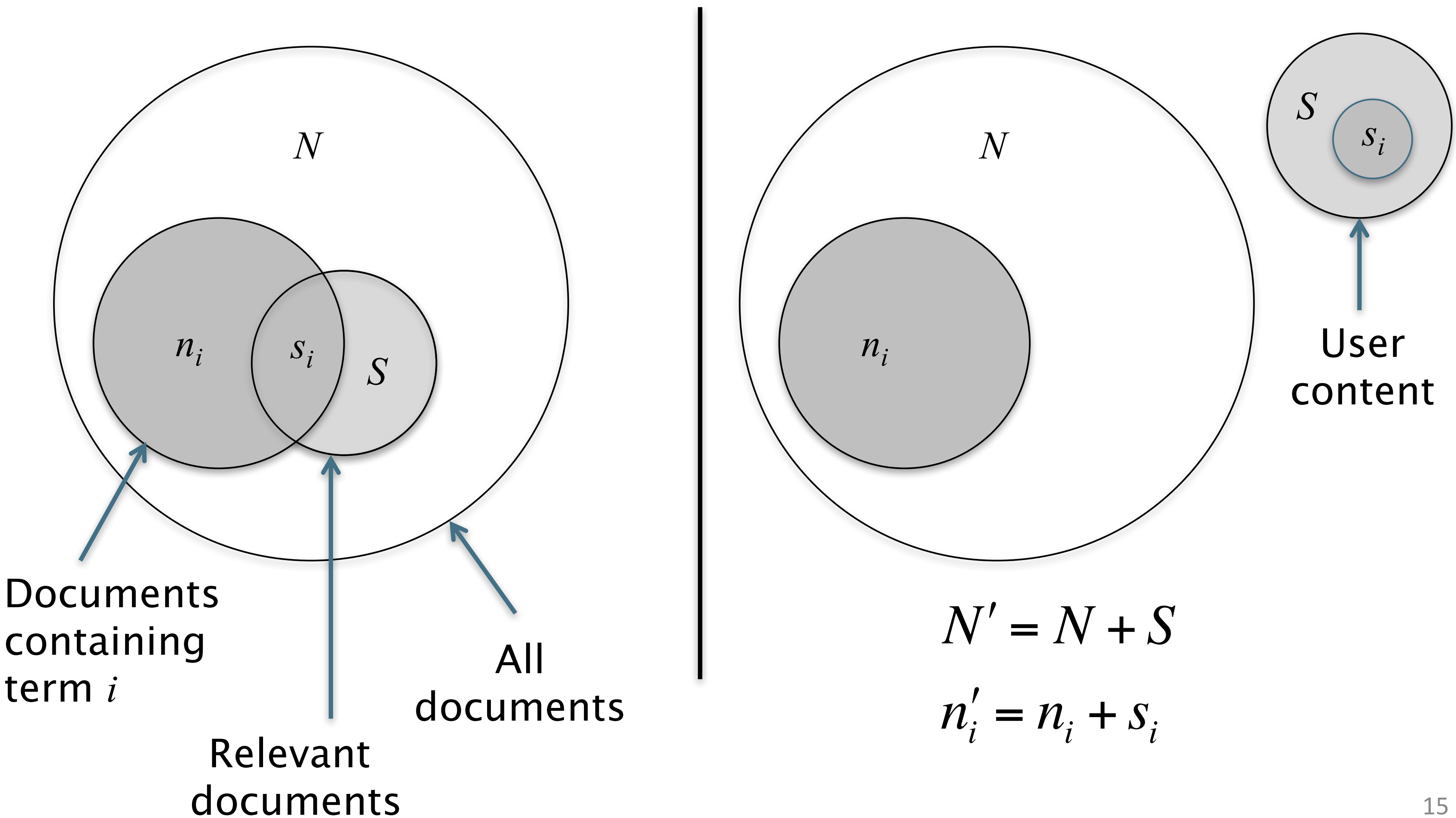
Documents	Relevant	Non-Relevant	Total
x_i=1	s_i	n_i-s_i	n_i
x_i=0	S-s_i	N-n_i-S+s_i	N-n_i
Total	S	N-S	N

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

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

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

Personalization as relevance feedback



$$N' = N + S$$

$$n_i' = n_i + s_i$$

Reranking

- BM25 scoring

$$\sum c_i \times tf_i$$

- Use updated weight c_i in BM25

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

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]

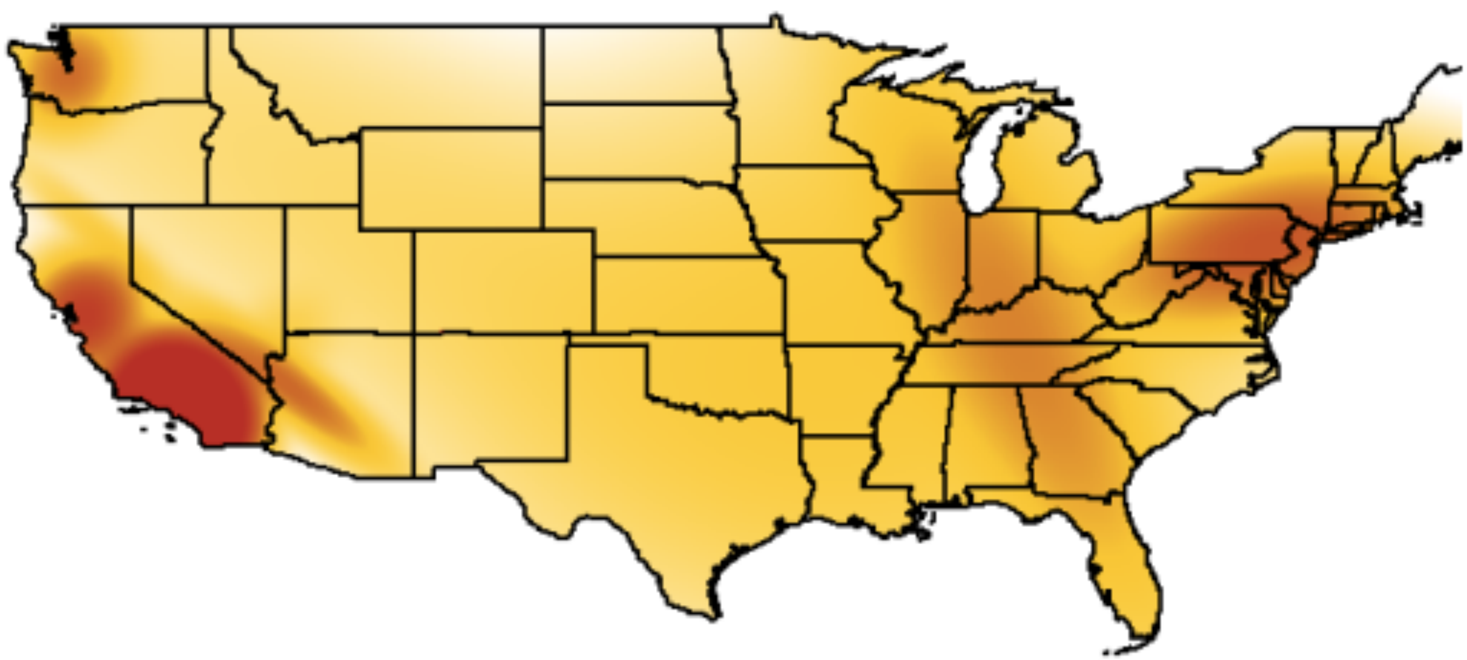
- *Usage statistics*, rather than locations mentioned in a document, best represent where it is relevant
  - I.e., if users in a location tend to click on that document, then it is relevant in that location

- 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

$$P(location = x \mid URL)$$



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

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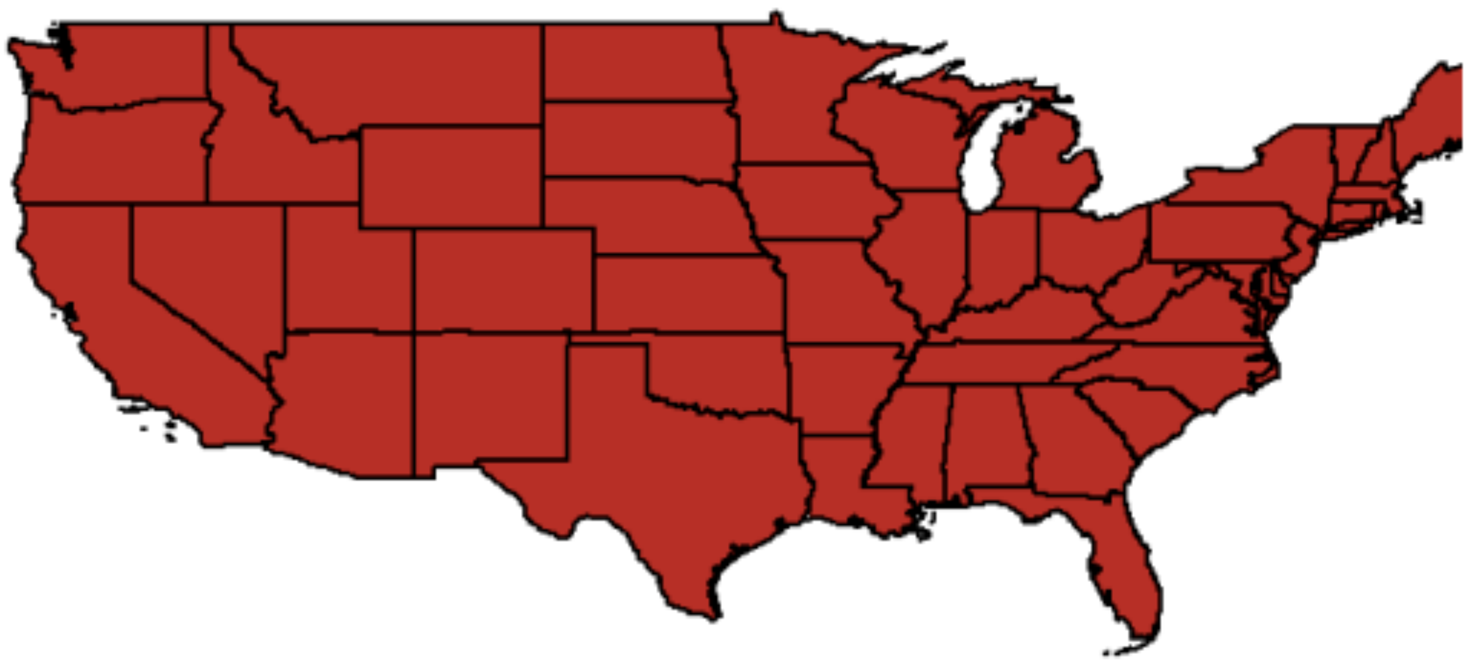


(d) Los Angeles Times: Crossword Puzzles and Games
http://games.latimes.com/

Learning the location interest model

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

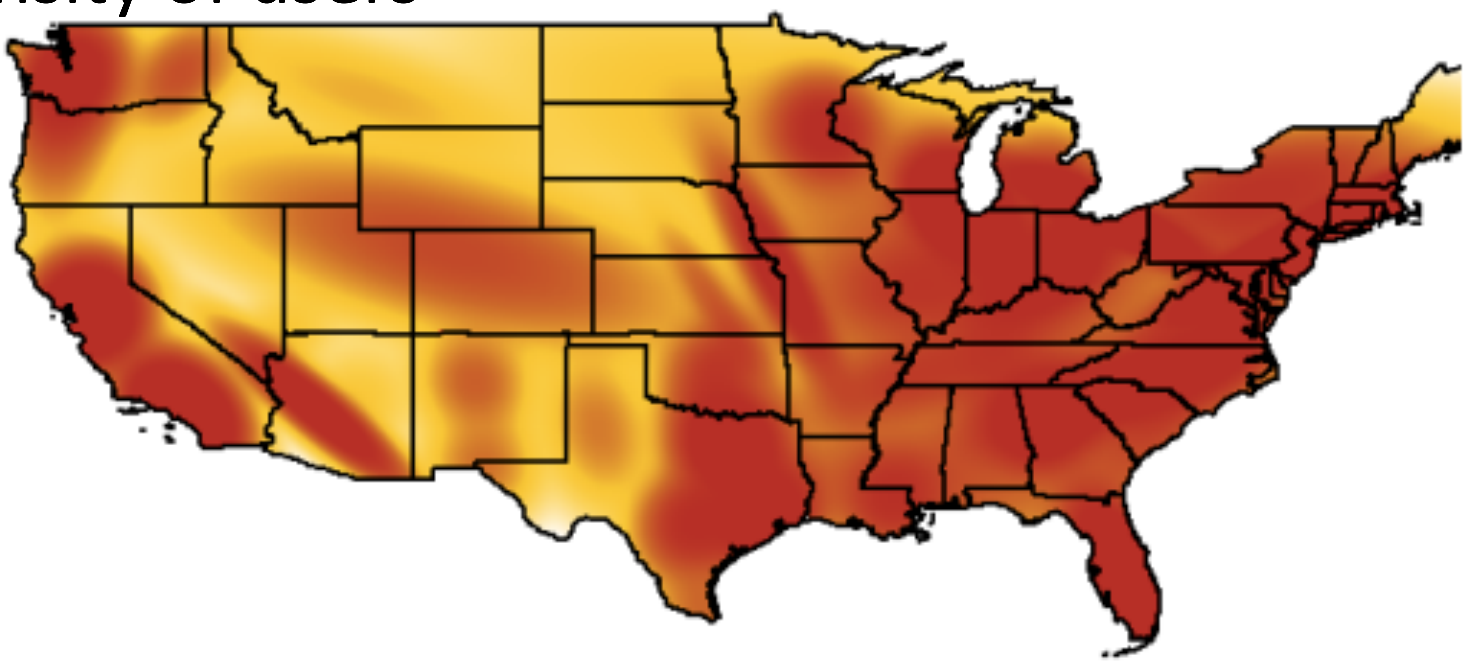
$$P(location = x \mid URL) = \sum_{i=1}^{n} w_i N(x; \mu_i, \Sigma_i)$$

$$= \sum_{i=1}^{n} \frac{w_i}{(2\pi)^2 \mid \Sigma_i \mid^{1/2}} e^{-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1} (x-\mu_i)}$$

- 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

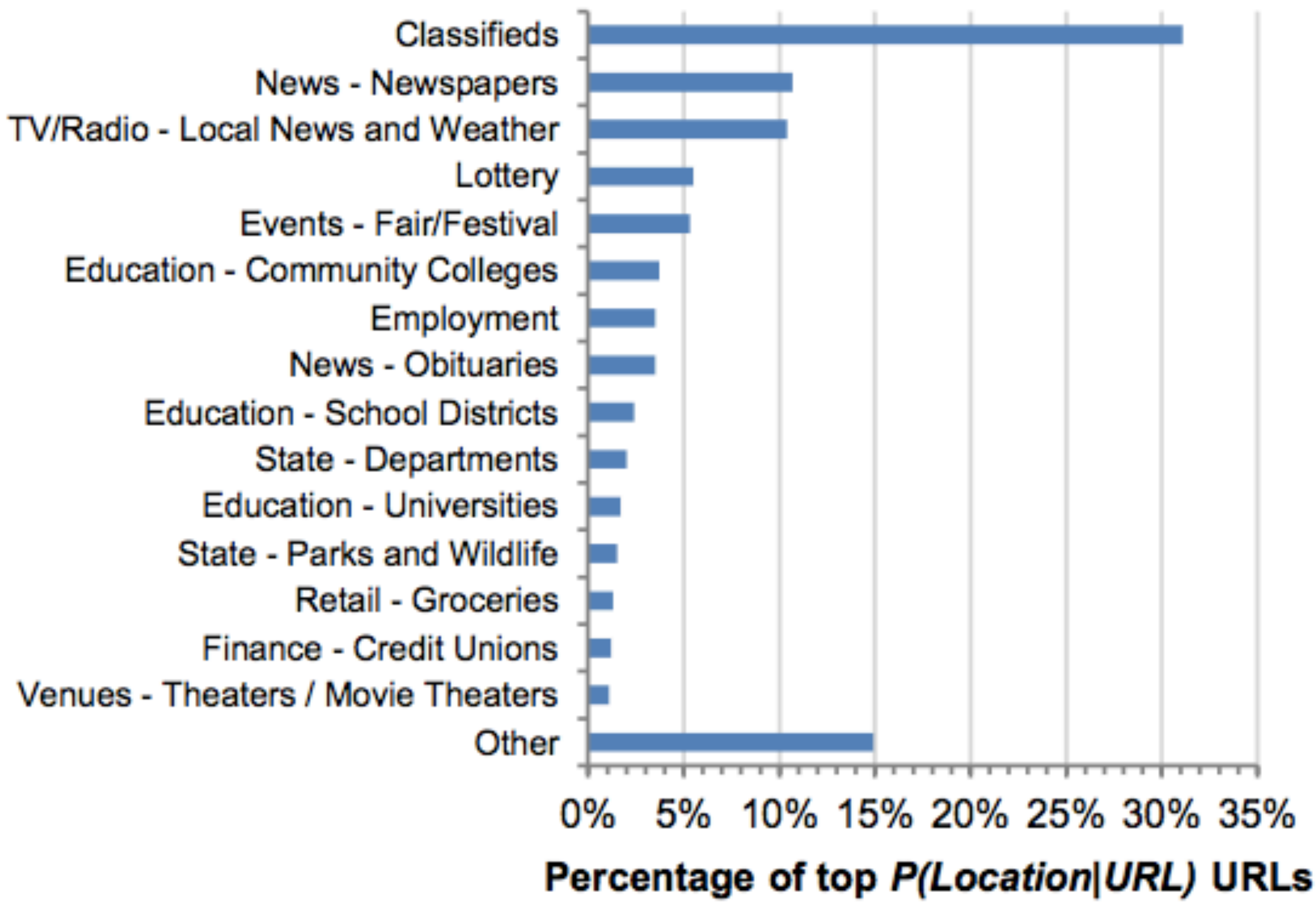
More location interest models

- 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*(user location | 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

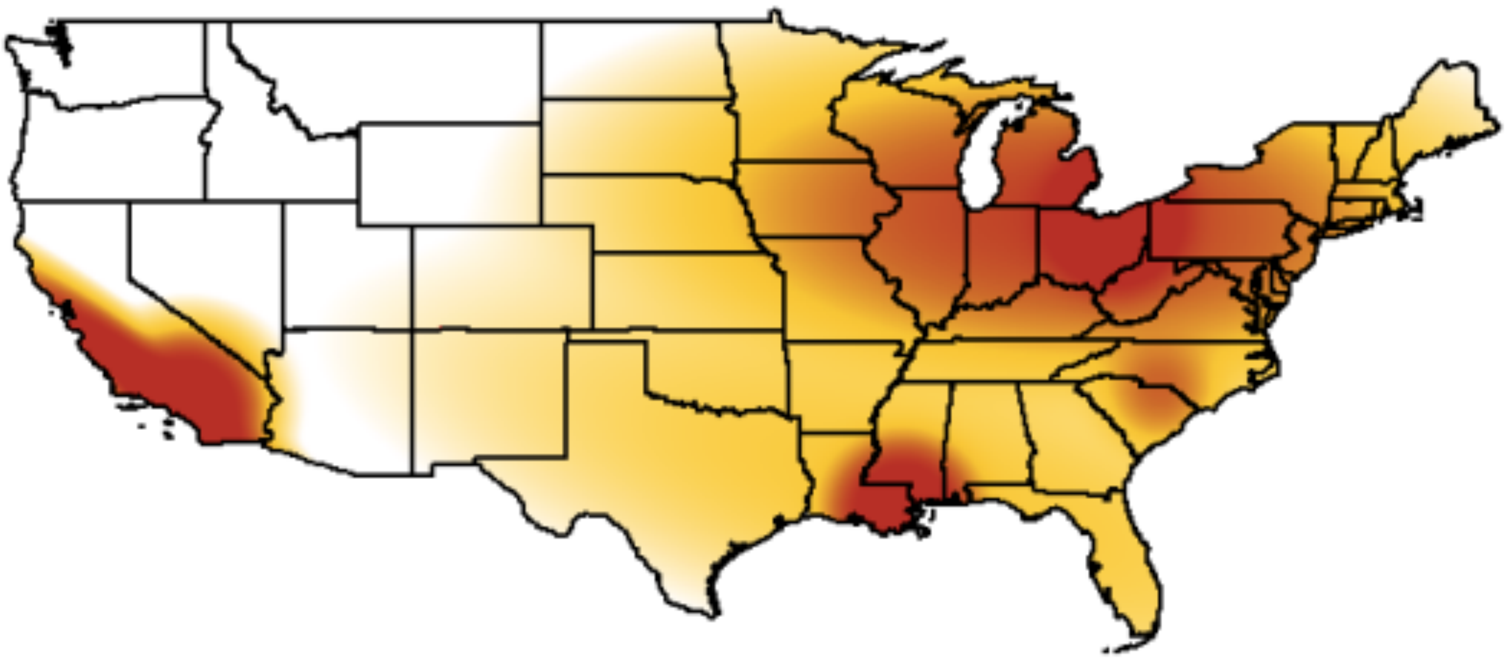
- Contextual features (user-dependent)
  - Feature: User’s location (naturally!)
  - Feature: Probability of the user’s location given the URL
    - Computed by evaluating URL’s location model at user location
    - Feature is high when user is at a location where URL is popular
    - Downside: large population centers tend to higher probabilities for all URLs
  - Feature: Use Bayes rule to compute *P*(URL | 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(URL | user location) turns out to be an important feature
  - KL divergence of the URL model from the background model also plays an important role

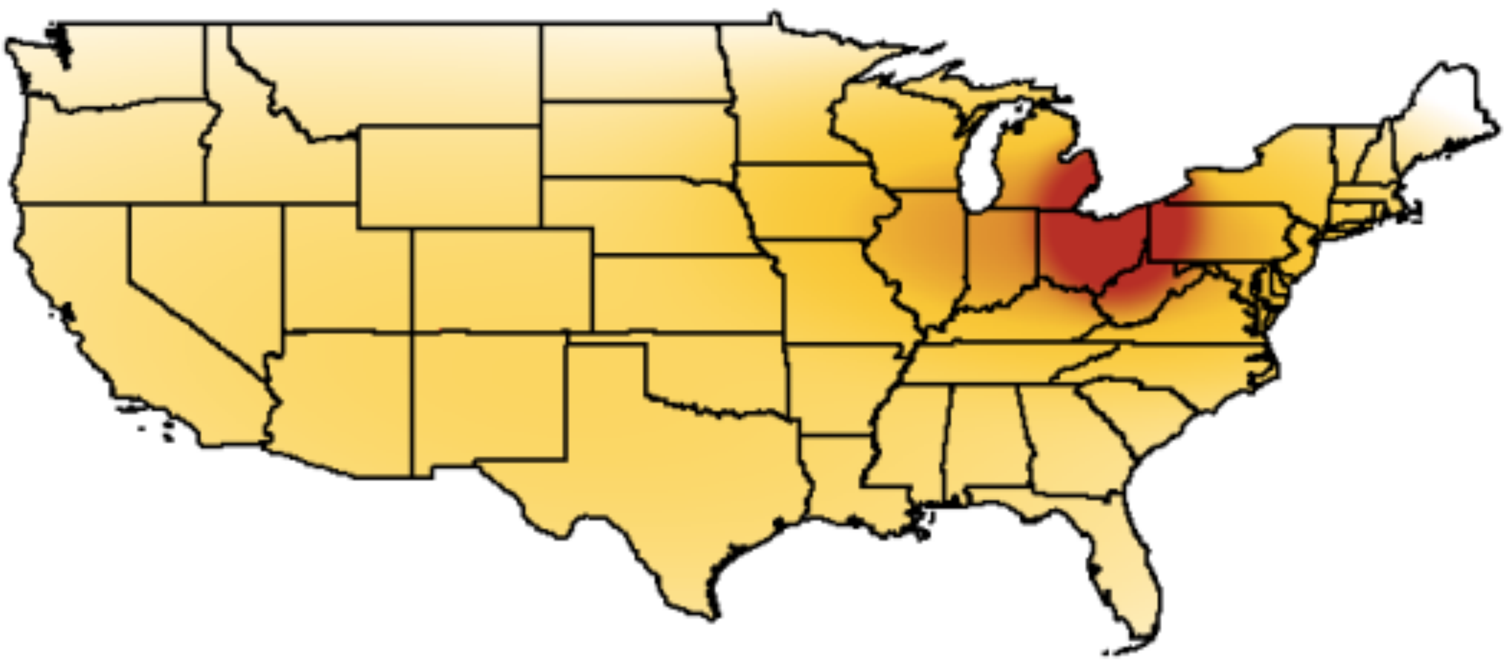
Query model for [rta bus schedule]

User in New Orleans



URL model for top original result

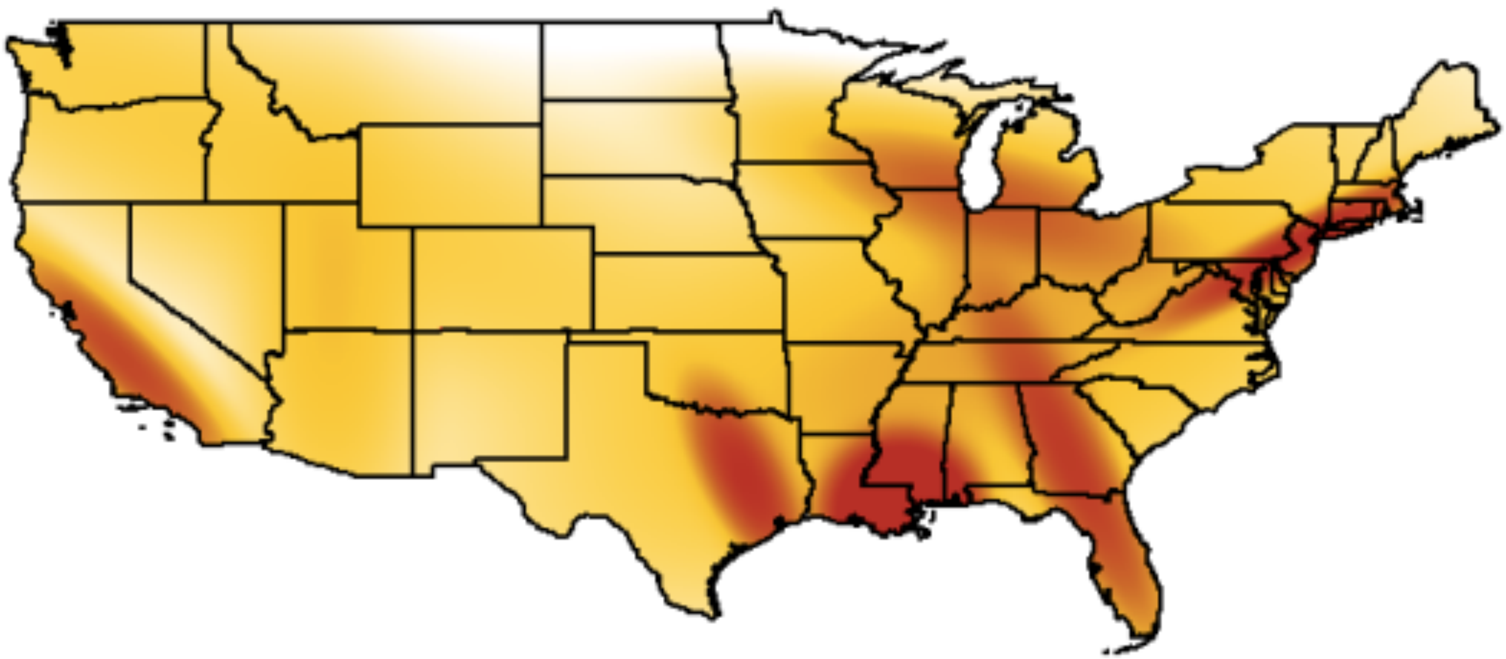
User in New Orleans



(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 x 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

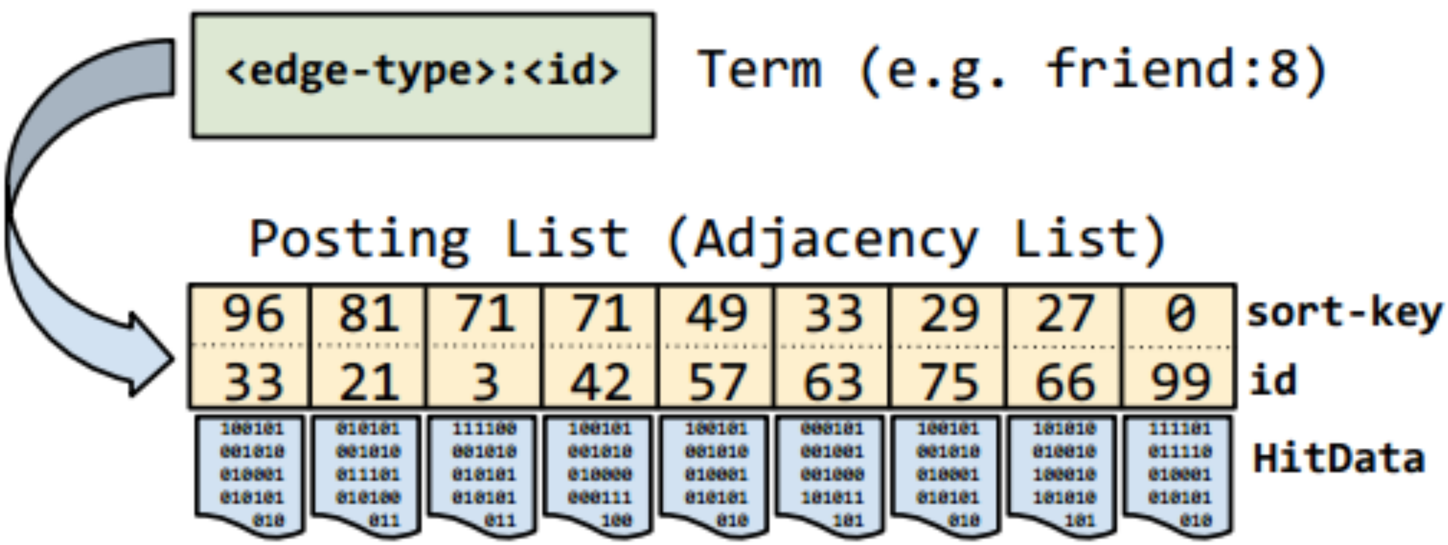
[Curtiss et al 2013]

- 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

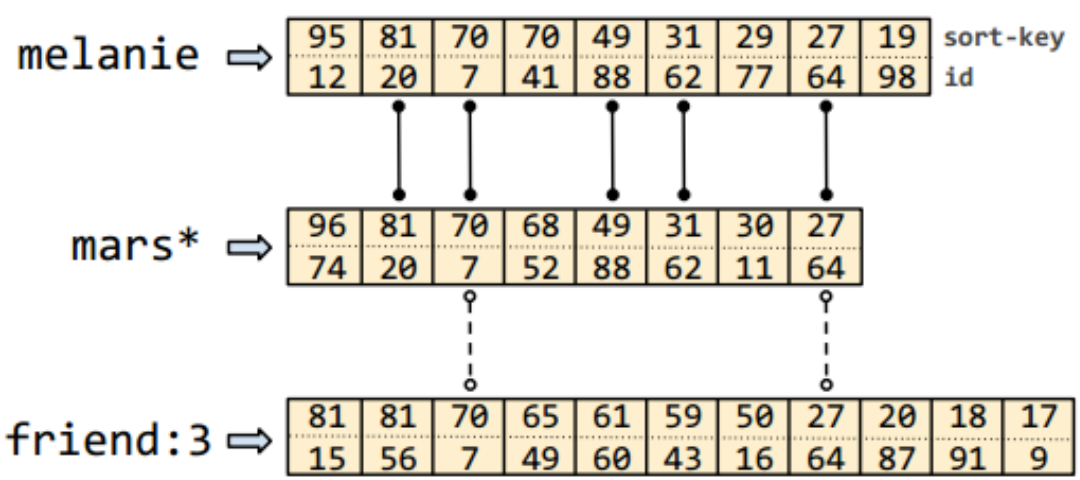
```
(and mel* friend:3)
```

  - 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 more than 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

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