

Location and Relevance

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Overview

- Mobile Local Search (MLS)
- Contextual Relevance in local mobile search
- MLS and LBS Issues
- Our Approach
- Early experiments and current efforts

Mobile Local Search (MLS)

- Key class of LBS applications
- Beyond classical Information Retrieval
- Also a broad metaphor for mobile local web use and activity
 - Ex: Search for Italian food, search for home repair services

Classical Information Retrieval

- Retrieve documents that fulfill a user query
 - Metric: Similarity, Relevance
 - Precision, recall
- $R(d/q) = \text{ThemeSimilarity}(T_d | T_q)$

R: Relevance

d: document, q: query

T_d : Document text

T_q : Query text

Text is sole proxy for Theme : Static

This is an oversimplification

Context in Information Retrieval

- “Environmental State” influencing search behavior
- $R(d/q) = f(\text{ThemeSimilarity}(T_d | T_q), \text{ContextSimilarity}(T_d | T_q))$

Contextual Relevance in local mobile search

- *Contextual Factors in local mobile relevance:*
 - Location: source, target
 - Environment, topography, topology
 - Search theme, sub-themes, relationships (semantic model)
 - History, cohort behavior
 - Results delivery medium
 - User profile
 - ...
 - Time-varying
 - Relevant results change while searcher is moving

Search Relevance: Classical vs. Local Mobile

- “coffee in glendale, ca” vs. “plumbers in glendale, ca” vs. “dentists in glendale, ca” vs. “lawyers in glendale, ca”
 - Product vs. service
 - “pizza” vs. “pizza delivery”
 - Semantic relationships
 - Coffee, tea
 - Pizza, beer, bowling
 - Role of distance
 - “thai food in Roswell, NM”
 - near empire state bldg vs new york city
 - Other aspects, e.g., socioeconomic
 - Restaurant in Lincoln Heights vs. Restaurant in Beverly Hills

MLS and LBS Issues

- *How does relevance in MLS differ from the classical version?*
- *What are appropriate ways of modeling relevance in MLS?*
- *What role does Location play in MLS relevance modeling?*

Possible model (linear):

- $R(d/q) = w \times \text{ThemeSimilarity}(T_d | T_q) + (1-w) \times \text{LocationSimilarity}(L_d | L_q)$

L_d : Document location context

L_q : Query location context

Our Approach

- Move beyond mashups and query parsing
- Address wide variety of mobile contexts corresponding to specific location context feature sets and specific query classes
 - have2P, have2Eat, local business search, iMatch, speak4It
- Use explicit location information of source and destination, along with knowledge derived from implicit context
 - Coffee shop 0.5 miles away vs. 0.3 miles away but across river
- Empirical studies of search results to develop adaptive relevance models
- Measuring the impact of
 - business category and density, area demographics, topological distance or travel time
 - ...
- Use machine learning techniques to tune models

Early experiments

- Very preliminary, not for publication yet
- Human relevance studies and Click log study of classic search application
- Linear regression model of relevance
- *Results Summary:*
 - Text Similarity is 3-8 times more predictive than location similarity
 - Significant residue or “unknown factor”

Linear regression modeling results

	Text (X1)	Location (X2)	Hit Norm (X3)	Residue (e)
Human	1.549	0.219	-0.190	0.07
Click Logs	0.06	0.02	N/A	0.349

$$R = X1*T + X2*L + X3*H + e$$

Human: ~8000 query-result pairs
Click Logs: order of 10M log entries

Current efforts

- Released some mobile apps
 - speak4It, have2P, have2Eat
- Gathering user behavior and relevance data
- Crowdsourced relevance testing
- Models other than linear

- Challenge:
 - Getting real-life usage data