Learning User Reformulation Behavior for Query Auto-Completion

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Query Auto-Completion (QAC)

- A common feature in modern search engines
  - Help users formulate queries while typing in the search boxes
- Given a user-typed prefix, N ranked completions are shown

Why Query Auto Completion?

- Typing queries costs too much
  - Users can save their keystrokes
- Further benefits
  - Spelling errors, query expansion, speed, ...

The goal of QAC

Rank the user's intended query in a high position
with as few keystrokes as possible

Context-Aware Approaches

- Context captures user's search intents.
  - submitted queries
  - click-through information

$$\underbrace{q_1 \rightarrow q_2 \rightarrow \cdots \rightarrow \cdot q_{T-1}}_{context} \rightarrow q_T$$

- Previous work statistically models query dependencies and similarity.

Query Session

- query dependencies [He2009]
- query similarity [Bar-Yossef2011]
- personal history [Shokouhi2013]

Click-through Data

- relevant queries [Mei2009]
- query clusters [Liao2011]
- click behavior [Ozertem2012]

However, a user may have some behavior in the context.

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Example Completions

$$\underbrace{\textit{“stomach sounds”} \rightarrow \textit{“irritable bowel syndrome”}}_{\textit{Context}} \rightarrow \underbrace{\textit{“cramps stomach”}}_{\textit{Intended Query}}$$

Completions from Conventional Approaches

- *“colon cancer symptoms”* (query similarity/dependencies)
  - from a context-aware QAC approach [Bar-Yossef *et al.*, 2011]
- *“celiac disease”* (query dependencies)
  - from a context-aware QS approach [He *et al.*, 2009]
- *“colon cancer”* (query clusters)
  - from a cluster-based context-aware QS approach [Liao *et al.*, 2011]

How users reformulate their queries in search sessions?

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User Reformulation Behavior

- Studied as query reformulation strategies [Huang *et al.*, 2009].

Semantic Relations [Akahani *et al.*, 2002] – Difficult to Analyze

- *specialization*: narrow the search constraints, e.g., *computer* $\rightarrow$ *mac*
- *generalization*: relax the search constraints, e.g., *lion* $\rightarrow$ *animal*

Syntactic Relations [Rieh *et al.*, 2006] – Simple to Analyze

- Syntactic and explicit changes between queries
  - Such as adding terms, removing terms, acronym expansion.
- Clear definitions of reformulation types [Jansen *et al.*, 2009]
- Personalization [Jiang *et al.*, 2011]

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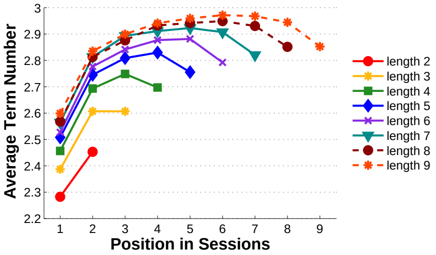
Number of Terms in Queries

The number of terms will change while adding or removing terms.

- Queries in longer sessions tend to contain more terms.
- The first reformulation increases more than other steps.
- Increase along sessions, and drop near the end of sessions.



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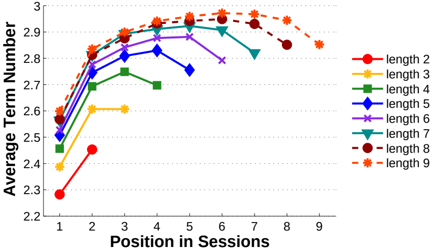

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From Syntactic Relations to Semantic Relations

Semantic Relations

- Specialization: narrow the search constraints
  - More terms are required to describe the intents (constraints).
- Generalization: relax the search constraints
  - Terms (constraints) can be removed.

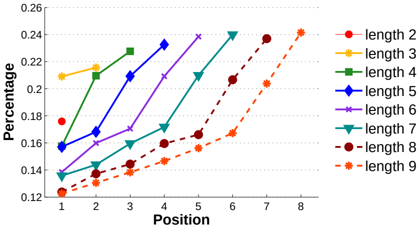
- 2,283 consecutive query pairs from 1,136 sessions are sampled and labeled.
- The syntactic analysis can help us learn semantic relations.

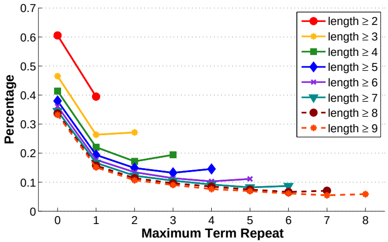
Relation	% in Log	Average Position	Median Position	Change of Term Number	% in Relation	Example
Specialization	27.7%	2.9951	2	Increase	**84.2%**	camera → digital camera
				Decrease	3.7%	perennial plants → stonecrop
				Equal	12.1%	guest book for party → anniversary party guest book
Generalization	12.2%	3.3122	3	Increase	4.0%	airport parking newark → airport parking new york
				Decrease	**82.5%**	great lakes auto → great lakes
				Equal	13.5%	honda blue book → car blue book

Repeated Terms

A usual behavior is to use the repeated terms in previous queries.

"stomach sounds" → *"irritable bowel syndrome"* → *"cramps stomach"*





- Users tend to reuse the terms in the nearest queries.
- Longer sessions are more likely to utilize previously used terms.

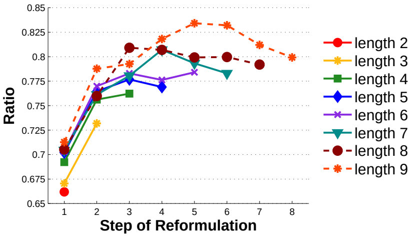
Click Behavior and Repeated Terms

Satisfaction Assumption

The satisfaction (click behavior) might effect a user choose repeated terms.

- 36.06%/**50.54%** of clicking/**no-click** users used repeated terms.
  - If a query is without click, its terms would be reused probably later.

- Difference in the first step of reformulation is the largest.
- The first step is more dependent to click behavior than others.



Summary of User Behavior Analysis

Summary

- The number of terms in queries
  - Trends of syntactic and semantic relations along sessions
- Repeated terms
  - How users utilize terms in the context
- Click behavior and repeated terms
  - How the satisfaction (click behavior) effect users' behavior

Learning user reformulation behavior is helpful for predicting queries!

Query Auto-Completion with Reformulation

Problem Definition

- A session is a sequence of queries $\langle q_1, q_2, \cdots, q_T \rangle$
  - Each query q_i is issued in time t_i, and has c_i clicks.
  - Treat $\langle q_1, q_2, \cdots, q_{T-1} \rangle$ as the context and q_T as the intended query.
- Given the context, the prefix and a candidate set $Q_T = \{q'_j\}$
- The goal is to rank queries in Q_T and let q_T in a high position.

Our Approach

- A supervised framework with *LambdaMART* learning-to-rank model.
- Various reformulation-based features in three categories
  - Term-level, Query-level and Session-level features
  - Attempt to capture how the user changes queries along the session.

Term-level Features

Measure the effectiveness of terms in queries

- Reformulation Types [Akahani *et al.*, 2002]
  - Add terms, Remove terms or Keep terms
  - Encoded as several categorical features
- Term-set Operation
  - Treat a query as a set of terms
  - Union, Intersection, Complacent of context and the query term-sets
  - Estimate how much information conveyed by information need
- Terms contained in both context and the candidate
  - Repeated terms are expected

Query-level Features

Measure relations between context and queries in query-level

- Query Similarity
  - Similar syntactic structures under the same information need
  - term-based cosine similarity and Levenshtein distance are adopted
- Query Length
  - Trend of term numbers
  - Number of terms may not alter rapidly
- Query Frequency
  - Statistical information provided by search logs
  - Relevant frequency to the last query in the context

Session-level Features

Measure how users reformulate queries along whole sessions

- Position Number
  - The stage of the session
  - Reformulation strategies may change over different positions
- Click-through Information
  - Click information is related to term-usage
  - Number of clicks and term set with clicks
- Time Duration (dwell time)
  - Duration of time users stay on the search results
  - Indirectly represent the users' satisfaction

Summary of Reformulation-based Features

Summary

- Term-level features
  - modeled for term effectiveness
  - reformulation types, term-set operation and repeated terms
- Query-level features
  - modeled for query-session relationship
  - query similarity, query length and query frequency
- Session-level features
  - modeled for behavior along whole session
  - position number, click-through information and time duration

Reformulation-based features describe users' behavior in different levels.

Experimental Settings (1/2)

- A commercial search engine log from 1 May, 2013 to 7 May, 2013.
  - Results are consistent and reproducible in public MSN and AOL log.

Data Pre-processing

- 30-minute threshold as the session boundary
- 4-day data for training, the remaining 3-day for testing
- Drop queries appear less than 10 times
- The prefix is the first character of q_T.
- The top-10 frequent queries are the candidate queries.
- Drop sessions with no answers in the candidate set.

Experimental Settings (2/2)

Testing Datasets

- Divide whole testing sessions into four datasets
  - Whole Testing Set (all sessions)
  - Short Sessions (sessions with 2 queries)
  - Medium Sessions (sessions with 3 to 4 queries)
  - Long Sessions (sessions with 5 or more queries)
- Evaluate performance on sessions with different lengths

Evaluation Metrics

- Mean Reciprocal Rank (MRR)
- Success Rate at top-k completions (SR@k)
  - The average percentage of the answers can be found in top-k completions.

- Fine-tune our *LambdaMART* ranking model with parameters of 1,000 decision tress across all experiments.

Four Competitive Baseline Models

- Most Popular Completion (MPC)
  - *Maximum Likelihood Estimation* (MLE) approach
  - Rank candidates by their frequencies
  - The **naïve QAC** baseline approach
- Hybrid Completion (Hyb.C) [Bar-Yossef *et al.*, 2011]
  - **Context-sensitive query completion** method.
  - Consider both context information and the popularity
- Query-based VMM (QVMM) [He *et al.*, 2009]
  - **Context-aware query suggestion** method
  - Learn the probability of query transition along sessions with VMM models
- Concept-based VMM (CACB) [Liao *et al.*, 2011]
  - **Concept-based** context-aware **query suggestion** method
  - Cluster queries into several concepts
  - Learn the concept transition along sessions with VMM models

Overall Performance

Dataset	Measure	MPC	Hyb.C	QVMM	CACB	Our Approach
Whole Testing Set	MRR	0.6415	0.6604 (+2.95%)	0.7137 (+11.25%)	0.7112 (+10.86%)	**0.7433 (+15.87%)**
	SR@1	0.4756	0.5017 (+5.50%)	0.5658 (+18.97%)	0.5593 (+17.61%)	**0.6095 (+28.16%)**
	SR@2	0.6410	0.6625 (+3.36%)	0.7349 (+14.66%)	0.7363 (+14.88%)	**0.7672 (+19.70%)**
	SR@3	0.7623	0.7729 (+1.39%)	0.8293 (+8.79%)	0.8305 (+ 8.94%)	**0.8474 (+11.16%)**
Short Sessions (2 Queries)	MRR	0.6338	0.6335 (−0.04%)	0.7125 (+12.43%)	0.7074 (+11.62%)	**0.7224 (+13.98%)**
	SR@1	0.4654	0.4633 (−0.45%)	0.5636 (+21.10%)	0.5519 (+18.59%)	**0.5794 (+24.49%)**
	SR@2	0.6283	0.6310 (+0.43%)	0.7329 (+16.64%)	0.7348 (+16.95%)	**0.7450 (+18.58%)**
	SR@3	0.7575	0.7567 (−0.10%)	0.8291 (+9.46%)	0.8298 (+9.54%)	**0.8320 (+9.84%)**
Medium Sessions (3 to 4 Queries)	MRR	0.6513	0.6906 (+6.04%)	0.7161 (+9.95%)	0.7160 (+9.93%)	**0.7654 (+17.50%)**
	SR@1	0.4889	0.5443 (+11.33%)	0.5707 (+16.74%)	0.5695 (+16.49%)	**0.6420 (+31.32%)**
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- Hyb.C method is similar to MPC in short sessions.
  - Short sessions have less context.

Overall Performance

- Hyb.C method performs better in longer sessions.
  - Longer sessions have more context.

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QVMM outperforms Hyb.C by modeling query transitions.

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CACB has no improvement against QVMM because of sparseness.

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Whole Testing Set	MRR	0.6415	0.6604 (+2.95%)	0.7137 (+11.25%)	0.7112 (+10.86%)	**0.7433 (+15.87%)**
	SR@1	0.4756	0.5017 (+5.50%)	0.5658 (+18.97%)	0.5593 (+17.61%)	**0.6095 (+28.16%)**
	SR@2	0.6410	0.6625 (+3.36%)	0.7349 (+14.66%)	0.7363 (+14.88%)	**0.7672 (+19.70%)**
	SR@3	0.7623	0.7729 (+1.39%)	0.8293 (+8.79%)	0.8305 (+ 8.94%)	**0.8474 (+11.16%)**
Short Sessions (2 Queries)	MRR	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	SR@1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	SR@2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	SR@3	0.7575	0.7567 (−0.10%)	0.8291 (+9.46%)	0.8298 (+9.54%)	**0.8320 (+9.84%)**
Medium Sessions (3 to 4 Queries)	MRR	0.6513	0.6906 (+6.04%)	0.7161 (+9.95%)	0.7160 (+9.93%)	**0.7654 (+17.50%)**
	SR@1	0.4889	0.5443 (+11.33%)	0.5707 (+16.74%)	0.5695 (+16.49%)	**0.6420 (+31.32%)**
	SR@2	0.6552	0.6991 (+6.70%)	0.7369 (+12.47%)	0.7368 (+12.44%)	**0.7892 (+20.45%)**
	SR@3	0.7692	0.7928 (+3.06%)	0.8294 (+7.83%)	0.8305 (+7.98%)	**0.8626 (+12.15%)**
Long Sessions (5 or more Queries)	MRR	0.6522	0.7076 (+8.49%)	0.7130 (+9.32%)	0.7162 (+9.82%)	**0.7842 (+20.24%)**
	SR@1	0.4885	0.5707 (+16.83%)	0.5631 (+15.27%)	0.5676 (+16.20%)	**0.6656 (+36.27%)**
	SR@2	0.6632	0.7149 (+7.79%)	0.7394 (+11.49%)	0.7422 (+11.91%)	**0.8139 (+22.72%)**
	SR@3	0.7674	0.7974 (+3.91%)	0.8300 (+8.16%)	0.8335 (+8.61%)	**0.8798 (+14.65%)**

Our approach significantly outperforms all baselines.

Overall Performance

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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	**0.7672 (+19.70%)**
	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	**0.8474 (+11.16%)**
Short Sessions (2 Queries)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	**0.7224 (+13.98%)**
	SR@1	0.4654	0.4633 (−0.45%)	0.5636 (+21.10%)	0.5519 (+18.59%)	**0.5794 (+24.49%)**
	SR@2	0.6283	0.6310 (+0.43%)	0.7329 (+16.64%)	0.7348 (+16.95%)	**0.7450 (+18.58%)**
	SR@3	0.7575	0.7567 (−0.10%)	0.8291 (+9.46%)	0.8298 (+9.54%)	**0.8320 (+9.84%)**
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- Performs better in longer sessions
  - Longer sessions are easier to model behavior

Summary of Overall Performance

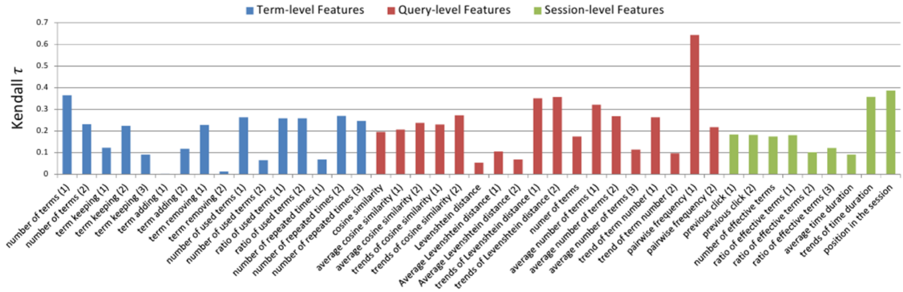
For baseline approaches

- Hyb.C method is similar to MPC in short sessions (less context)
- Hyb.C method performs better in longer sessions (more context)
- QVMM outperforms Hyb.C by modeling query transitions
- CACB has no improvement against QVMM because of sparseness

For our approach

- Significantly outperforms all of baseline approaches
- Performs better in longer sessions (easier to model behavior)

Feature Effectiveness Analysis



- The query-frequency is the most significant feature (conventional approaches)
- Query length is useful (the analysis of term numbers)
- Most of term-level features are helpful (modeling complex reformulation behavior)
- The position in the session is highly related (reformulation stage)
- Clicks (satisfaction) and time duration are also effective.

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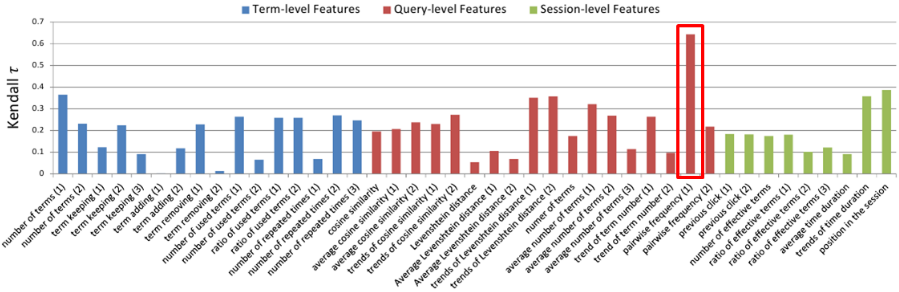

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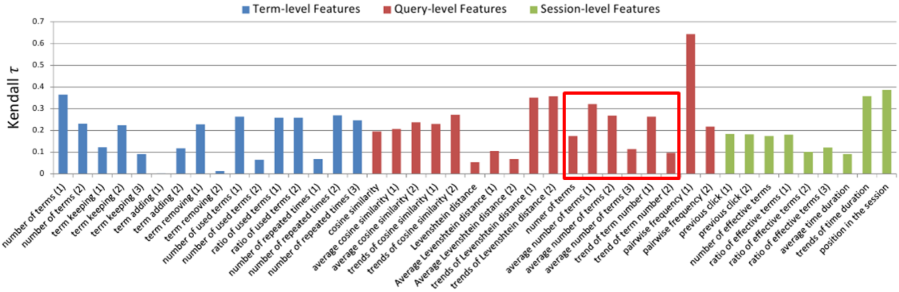

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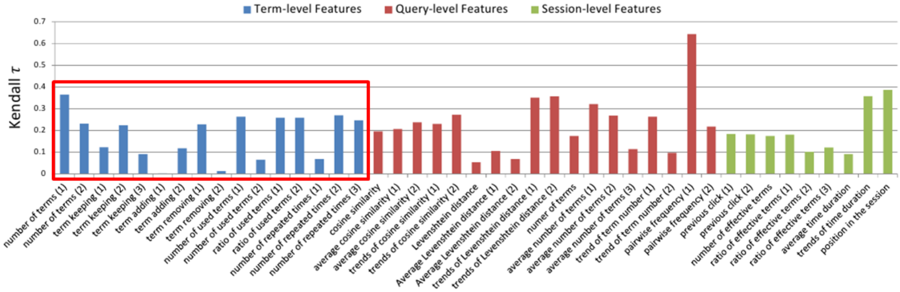

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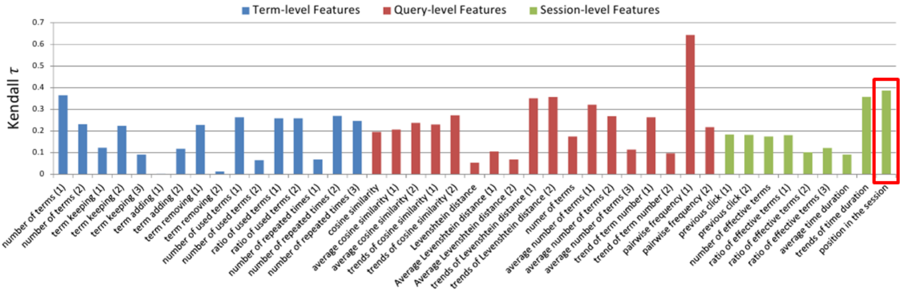

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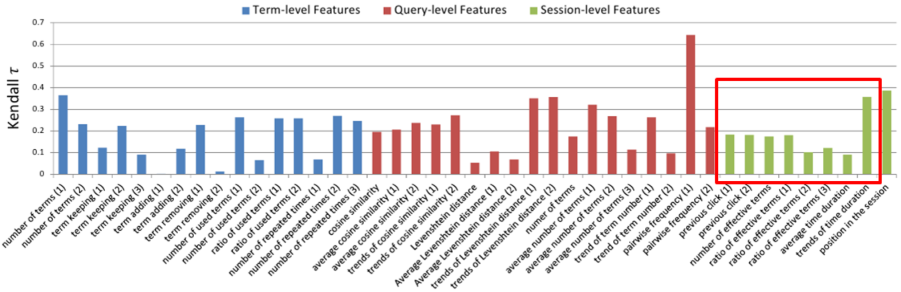

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Application: Query Suggestion

- Query suggestion is an application of our approach.
- Queries in high positions may be also relevant.
- The adjacency frequency $P(q_T|q_{T-1})$ is the naïve baseline.
- Experimental settings
  - Sample 100 sessions from testing data and apply 3 approaches
  - Manually labeling top 15 queries and evaluate with NDCG

NDCG	Adj. Freq.	QVMM	Our Approach
@5	0.5817	**0.6036 (+3.76%)**	0.5973 (+2.68%)
@10	0.5941	0.6152 (+3.55%)	**0.6175 (+3.94%)**
@15	0.6949	0.7090 (+2.03%)	**0.7127 (+2.56%)**

Conclusions

- Extensive analysis shows reformulation behavior is helpful for QAC
- Propose a supervised approach for query auto-completion
- Our approach requires less data for training
- Our approach considers different user behavior for reformulation
- All of three-type features are useful and important.
- Our approach actually helps users save their keystrokes.

Thank you for listening! Questions?

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