11-642:
Search Engines

Search Log Analysis

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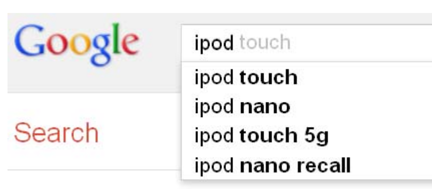
Lecture Outline

- **Query suggestions**
- **Query intents**
- **Click models**
- **Within-session learning**



Search Trails

A search trail is a single information seeking session

– One person, a series of queries, all within a short timespan
– Maybe the first query didn't find what the person wanted
– Maybe the sequence corresponds to query reformulations

Example	**Counterexample (?)**
ipod	ipod video discount
ipod nano	ipod video rebate
ipod nano recall	ipod video repair
ipod nano recall 2011	refurbished ipod video

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Query Suggestions

Popular destinations for <u>frequent</u> queries can be looked up
… however, most queries are not frequent

- 57% of queries (20% of all searches) are unique
  97% of queries (66% of all searches) occur less than 10 times
  – *White, et al., 2007; 2008*

We cover two types of query suggestion approaches

- **Pseudo documents**
  – Works well for many (most?) queries
- **Co-occurrence statistics**
  – Works well for reasonably frequent queries

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Query Suggestions #1: Pseudo Documents

Obtain <query$_i$, query$_{last}$> pairs from logs

- <"ipod", "ipod nano recall 2011">
- <"ipod nano", "ipod nano recall 2011">
- : : : :
- <"ipod repair", "ipod nano recall 2011">

Assume the last query in a session is successful

- Other success criteria is covered later in the course

Each query$_{last}$ is a candidate query suggestion

Query logs

: : : :
-- Session start --
ipod
ipod nano
ipod nano recall
ipod nano recall 2011
-- Session end –
: : : :
-- Session start --
ipod repair
ipod nano recall 2011
-- Session end –
: : : :

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Query Suggestions #1: Pseudo Documents

Create a "pseudo document" for each candidate query suggestion

- The title is the query suggestion (query$_{last}$)
- The contents are the queries that preceded query$_{last}$ in the query log

Given a new query, rank the suggestion candidates

- Apply your favorite retrieval model to the pseudo document corpus

Pseudo documents are a very general technique

- Used to rank all kinds of things besides queries

Pseudo document for a suggestion

<TITLE>
ipod nano recall 2011
</TITLE>
<BODY>
ipod, ipod nano,
ipod shuffle,
music players,
small ipod, ipod,
ipod micro, nanno,
buy ipod, …
</BODY>

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Query Suggestions #2: Co-occurrence Statistics

Select queries that contain the user query q as a substring

- **Set_1:** 100 most frequent queries with q as a substring
- **Set_2:** 100 most frequent queries that followed q in a search session
- All queries in Set_1 and Set_2 are potential query suggestions q_s

$$Score(q_s) = \frac{Count(q_s) + \lambda_1}{N_1 + \lambda_1} \times \frac{Count_{follows}(q, q_s) + \lambda_2}{N_2 + \lambda_2}$$

q_s is frequent **q_s frequently follows q**

Jamie's understanding of N_1 and N_2 (the papers are vague)

- N_1: Sum of Count(q_s) for all candidates
- N_2: Sum of Count(q_s, q) for all candidates

(White, et al., 2007; 2008)

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Query Suggestions #2: Co-occurrence Statistics

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q_s is frequent **q_s frequently follows q**

This baseline method does as well as two experimental methods

(White, et al., 2007; 2008)

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Query Suggestions: Summary

Three methods for generating 'related query' suggestions

- Pseudo documents
  - Almost any query
- Co-occurrence #1
  - Mid-frequency queries
- Co-occurrence #2
  - Common queries

Lecture Outline

- Query suggestions
- **Query intents**
- Click models
- Within-session learning

Many Queries Have Multiple Intents

We have discussed the different intents behind some queries

- **jaguar:** A car, an animal, an operating system, …
- **flash:** Software, a superhero, part of a camera, …
- **mercury**: An element, a planet, a god, a car, …
- **michael jordan:** An athlete, a professor, a businessman, …
- **ai:** Artificial intelligence, Americal Idol, art institute, …

Query suggestions are one possible source of query intents

- Can they be inferred in other ways?

(Radlinski, et al., 2010)

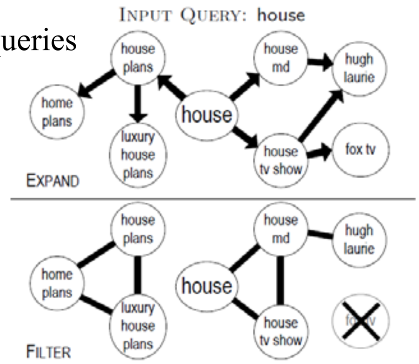
Identifying the Most Common Intent for a Query

For a query q

- Identify q's neighborhood **("expand step")**
  - Identify the 10 most common reformulations q' of q
  - Identify the 10 most common reformulations q'' of each q'
- Reduce the neighborhood to the most related queries **("filter")**
- **Cluster** the queries to find intent groups
- **Estimate the popularity** of each query and intent group
- The **name** of an intent group is its most popular query

(Radlinski, et al., 2010)

Identifying the Most Common Intent for a Query



Expand: Identify possibly-related queries

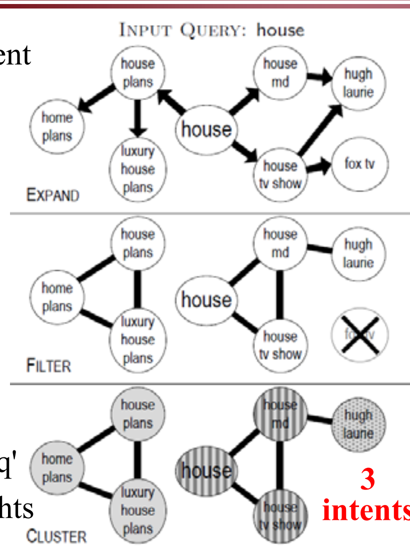
- (q, q') for at least 2 users
- $q'_{time} - q_{time} < 10$ min
- (q, q') must occur $\geq \delta$ times
  - Filters out frequent q' (e.g., hotmail)

Filter: Improve precision

- Connect (q, q') if often clicked for same d
  - Removes many q'
  - May add some new q'
- Remove components with < 2 members

(Radlinski, et al., 2010)

Identifying the Most Common Intent for a Query



Cluster: Find groups with same intent

- E.g., use your favorite algorithm
- Similarity metric: Random walk

Estimate popularity

- Random walk for two iterations

$$w_q = 1$$

$$w_{q'} = \frac{w^q \cdot count(q \to q')}{\sum_{r \in R(q)} count(q \to r)}$$

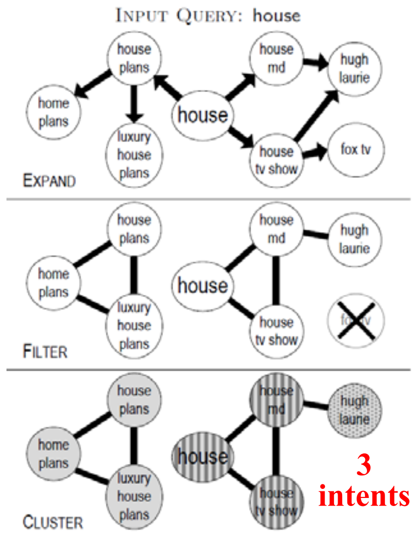
- R(q): the set of all related queries q'
- Cluster score: Sum of query weights

(Radlinski, et al., 2010)

Identifying the Most Common Intent for a Query

Name the intent group

- Use its highest-scoring query



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(Radlinski, et al., 2010)

Identifying the Most Common Intents for a Query

juvenile delinquency

• juvenile delinquency	($w_c = 1.16$)	w_c: estimated relative popularity of each intent cluster
• causes of juvenile delinquency	($w_c = 0.50$)	
• delinquency prevention	($w_c = 0.25$)	
• definition of juvenile delinquency	($w_c = 0.20$)	
• articles on juvenile delinquency	($w_c = 0.18$)	
• reasons for juvenile delinquency	($w_c = 0.15$)	

Intents created by TREC analysts

- What are the rates of juvenile crime in various jurisdictions, what is the nature of the offenses, how are they punished, and what measures are taken for prevention?

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(Radlinski, et al., 2010)

Identifying the Most Common Intents for a Query

physical therapists

• physical therapist	(w_c = 1.22)	w_c: estimated relative popularity of each intent cluster
• physical therapists salary	(w_c = 0.80)	
• how to become a physical therapist	(w_c = 0.21)	
• physical therapy schools in california	(w_c = 0.15)	
• physical therapist school of california	(w_c = 0.11)	
• physical therapist assistance programs	(w_c = 0.11)	

Intents created by TREC analysts

- How can I obtain information about training, licensing, and skills needed for physical therapists?

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(Radlinski, et al., 2010)

Identifying the Most Common Intents for a Query

wireless communications

• wireless communications	(w_c = 1.07)	w_c: estimated relative popularity of each intent cluster
• what is wireless comm.	(w_c = 0.56)	
• wireless comm. systems	(w_c = 0.19)	
• history wireless technology	(w_c = 0.13)	
• wireless cell phone companies	(w_c = 0.13)	
• wireless broadband providers	(w_c = 0.10)	

Intents created by TREC analysts

- Information on existing and planned uses, research/technology, regulations and legislative interest.

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(Radlinski, et al., 2010)

Identifying the Most Common Intents for a Query

Key ideas

- Reformulation patterns + click information can be combined to identify common intents for ambiguous queries
- An ambiguous query may have several common intents
  - Not a surprise ☺
  - An intent is expressed by a group of queries with the same goal
- Popular intents may differ from what well-informed people expect

Lecture Outline

- Query suggestions
- Query intents
- **Click models**
- Within-session learning

Click Models

Typical search behavior

- A person issues a query q
- A **s**earch **e**ngine **r**esult **p**age (SERP) is returned
- The person examines the SERP
  - – Maybe the person clicks on one or more links
- The person stops interacting with the SERP
  - – Perhaps issues a new query
  - – Perhaps moves on to a new task

(Chuklin, et al., 2016)

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Click Models

Click models represent user search behavior as a sequence of observed and hidden events

- E: An item on the SERP is **e**xamined
  - – May depend on the document's rank (position)
- A: User is **a**ttracted by the item's representation
  - – May depend on the snippet quality
  - – May depend on the document's relevance to the query
- C: An item is **c**licked
- S: The information need is **s**atisfied

(Chuklin, et al., 2016)

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Click Models

Click models define dependencies among events

- E.g., p(E | rank=r): Probability of examining page at rank r
- E.g., p(C | E): Probability that an examined page is clicked

Learn model parameters from a search log

(Chuklin, et al., 2016)

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Random Click Model (RCM)

Random Click Model

- Assume each document (url) u is equally likely to be clicked

  $p(C_u) = \rho$ Probability of clicking document (url) u
- Learn ρ from data

Maximum likelihood estimate of ρ

$$\rho = \frac{1}{\sum_{s \in S} |s|} \sum_{s \in S} \sum_{u \in s} c_u^s$$

S: Search sessions

c_u^s: Document (url) u was clicked in session s

The RCM is not very accurate

(Chuklin, et al., 2016)

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Click-Through Rate (CTR) Models: RCTR

Rank-Based CTR (RCTR)

- The click likelihood depends upon the rank *r*

  p (C_r) = ρ_r Probability of clicking document at rank *r*
- Learn ρ_r for each rank *r*

Maximum likelihood estimate of ρ_r

$$\rho_r = \frac{1}{|S|} \sum_{s \in S} c_r^s$$

S: Search sessions

c_r^s: Document at rank r was clicked in session *s*

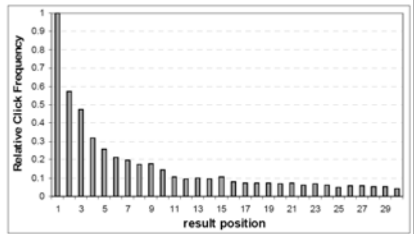

Figure 3.1: Relative click frequency for top 30 result positions over 3,500 queries and 120,000 searches.

(Agichtein, et al, 2006)
(Chuklin, et al., 2016)

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Click-Through Rate (CTR) Models: DCTR

Document-Based CTR (DCTR)

- Estimate a click-through rate for every query-document pair

  p (C_u) = ρ_{uq} Probability of clicking document *u* for *q*
- Learn ρ_{uq} for each query-document pair

Maximum likelihood estimate of ρ_{uq}

$$\rho_{uq} = \frac{1}{|S_{uq}|} \sum_{s \in S_{uq}} c_u^s$$

S_{uq}: Sessions for query q that contain document u

c_u^s: Document u was clicked in session *s*

DCTR is prone to overfitting

- Little or no data for many document-query pairs

(Chuklin, et al., 2016)

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Attractiveness

Some models incorporate the document attractiveness

- Usually attractiveness is a measure of snippet quality
- Usually $p(A_u)$ is independent of rank r

  $p(A_u) = \alpha_{uq}$ Probability that document u is considered attractive

(Chuklin, et al., 2016)

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Position-Based Model (PBM)

Position-Based Model (PBM)

- Click probability depends on examination and attractiveness

  $p(C_u) = p(E_u) \cdot p(A_u)$

  $p(E_u) = \gamma_{r_u}$ Document at rank r_u is examined

  $p(A_u) = \alpha_{uq}$ Document u is attractive for query q

Model parameters can be estimated using EM

$$\alpha_{uq} \quad \alpha_{uq}^{(t+1)} = \frac{1}{|\mathcal{S}_{uq}|} \sum_{s \in \mathcal{S}_{uq}} \left(c_u^{(s)} + \left(1 - c_u^{(s)}\right) \frac{\left(1-\gamma_r^{(t)}\right)\alpha_{uq}^{(t)}}{1-\gamma_r^{(t)}\alpha_{uq}^{(t)}} \right),$$

where $\mathcal{S}_{uq} = \{s_q : u \in s_q\}$

$$\gamma_r \quad \gamma_r^{(t+1)} = \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} \left(c_u^{(s)} + \left(1 - c_u^{(s)}\right) \frac{\left(1-\alpha_{uq}^{(t)}\right)\gamma_r^{(t)}}{1-\gamma_r^{(t)}\alpha_{uq}^{(t)}} \right)$$

(Chuklin, et al., 2016)

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Cascade Model (CM)

Assume that the user examines the SERP from top to bottom until they find a relevant document

• $p(C_r) \leftrightarrow p(E_r) \cdot p(A_r)$	Clicked ↔ Examined & Attractive
• $p(E_r) = 1$	First rank is always examined
• $p(A_r) = \alpha_{r_u q}$	Attractiveness depends on rank & query
• $p(E_r \mid \neg E_{r-1}) = 0$	Sequential examination
• $p(E_r \mid E_{r-1}, \neg C_{r-1}) = 1$	Keep examining until click
• $p(E_r \mid C_{r-1}) = 0$	Stop examining after a click

Can only describe sequential examination with a single click

- Less general that the position-based model (PBR)

(Chuklin, et al., 2016)

Cascade Model (CM)

Maximum likelihood estimate for CM

$$\alpha_{uq} = \frac{1}{|S_{uq}|} \sum_{s \in S_{uq}} c_u^s$$

S_{uq}: Sessions for query q that contain document u

Each session *s* is truncated at its first click

c_u^s: Document u was clicked in session *s*

Click Models

There are many click models ...

- E.g., consider time spent examining a SERP item
  - – Time between click and subsequent click
- E.g., consider scrolling behavior
- E.g., consider eye movement behavior
- …

None seem dominant at this point

- DCTR is popular because ρ_{uq} can be treated as an (overfitted) relevance score for training LeToR
- Time-Aware Click Model (TACM) claims to correlate well with human assessors

(Chuklin, et al., 2016)

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Click Models

How accurate are different models?

- WSCD 2012 dataset (Yandex), 1 million sessions

Model	Log-likelihood	Perplexity	Cond. perplexity	Time (sec)
RCM	−0.3727	1.5325	1.5325	**2.37**
RCTR	−0.3017	1.3730	1.3730	2.45
DCTR	−0.3082	1.3713	1.3713	9.39
PBM	−0.2757	1.3323	1.3323	77.95
CM	$-\infty$	1.3675	$+\infty$	12.17

The Position-Based Model (PBM) is best of this group

- On this dataset, the best models are about 10% better than PBM

(Chuklin, et al., 2016)

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Click Models

Click models have several uses

- Improve understanding of user behavior
  - – E.g., model what SERP characteristics affect user behavior
- Guide development of better evaluation metrics
  - – E.g., something more realistic than NDCG
- Measure deviation of observed behavior from 'typical' behavior
  - – E.g., people click on this document much more than expected
- Generate realistic artificial data
  - – E.g., for testing software
  - – E.g., infer relevance from clicks
- Very important in web-based advertising

(Chuklin, et al., 2016)

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Click Models

Click models can be used to generate artificial clicks

Input: Click model M, document ranking s

Output: Vector of simulated clicks $c_1 \ldots c_r$

Algorithm:

for rank = 1 to $|s|$

compute $p(C_r=1|C_1=c_1, \ldots, C_{r-1}=c_{r-1})$ given M and $c_1 \ldots c_{r-1}$

convert $p(C_r=1|C_1=c_1, \ldots)$ to $\{0, 1\}$ using a Bernoulli function

(Chuklin, et al., 2016)

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Click Models

Click models can be used to generate artificial relevance judgments

- Any individual click is a noisy signal
- Use a click model such as DCTR to learn ρ_{uq} for each query-document pair *uq*
- Measure NDCG@k using ρ_{uq} as the relevance label

Lecture Outline

- Query suggestions
- Query intents
- Click models
- **Within-session learning**

Within-Session Learning

People gain domain knowledge as they search

- Through exposure to and interaction with new information
- Is it useful for the search engine to support this learning?
  - Should the search engine select information differently?

During the last several years, this has gained increasing attention

- We examine one line of work from Microsoft Research (MSR)

Two types of informational information needs were studied

- Acquisition of procedural knowledge ("how to do something")
- Acquisition of declarative knowledge ("knowing about a topic")

(Eickhoff et al., 2014)

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Within-Session Learning

Identify procedural search sessions in a query log

- Select queries that are last in a session that ends at eHow.com
- Rank query n-grams by pointwise KL-divergence between the eHow query log and a general query log

$$\text{score}(t) = p_{\text{eHowLog}}(t) \log \frac{p_{\text{eHowLog}}(t)}{p_{\text{generalLog}}(t)}$$

t: A query n-gram (e.g., 'fix wifi')

- Select the top 10 n-grams (*indicator terms*)
- Select sessions that contain an indicator term (*procedural sessions*)
- Discard navigational sessions (proprietary classifier)

Repeat for declarative search sessions using Wikipedia.org

(Eickhoff et al., 2014)

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Within-Session Learning

Indicator terms

Rank	Procedural	Declarative
1	to	what
2	how	what is
3	how to	who
4	how do	list of
5	to make	syndrome
6	how to make	biography
7	how do I	what is a
8	computer	about
9	can you	is the
10	change	history of

A query in a session needed to contain one of these terms

- General terms … but sessions also ended at eHow or Wikipedia

(Eickhoff et al., 2014)

Within-Session Learning

Example queries

Procedural		
#	Query	Clicked URL
1	Weak wireless signal	-
2	How to expand wifi range	http://www.repeaterstore.com/.../fg24008.php
3	Wifi repeater how to	-
4	Wifi repeater tutorial	http://forum.ubnt.com/showthread.php?t=13735
5	How to boost wifi signal	http://www.ehow.com/...boost-wifi-signal.html

Declarative		
#	Query	Clicked URL
1	What do sponges look like	a-z-animals.com/animals/sponge/
2	What do sponges feed on	tolweb.org/treehouses/?treehouse$_i d = 3431$
3	Sponges as pets	http://www.buzzle.com/articles/sponge-facts.html
4	How do sponges reproduce	http://answers.yahoo.com/...127140016AANRe91
5	Where do sponges live	http://en.wikipedia.org/wiki/Sponge

Manual inspection indicates 87% accuracy

(Eickhoff et al., 2014)

Within-Session Learning

Metrics previously used to describe user expertise and behavior

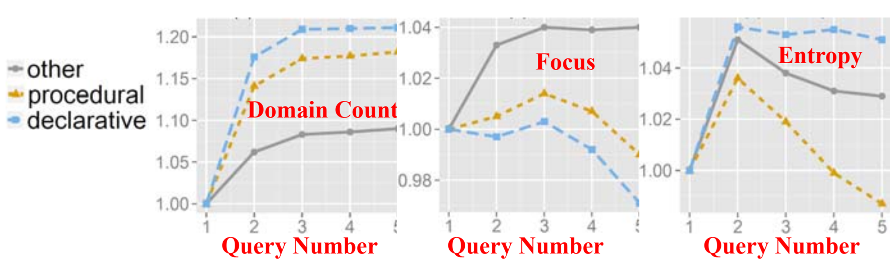
- **Domain count:** Number of unique domains in the SERPs
- **Focus:** % of SERP entries in the dominant category
- **Entropy:** Entropy of the SERPs topic distribution
  – Low entropy → search results cover few topics
- **Branchiness:** How often a person's browsing branches
- **Display time:** Average reading time
  – Experts typically have lower averages
- **Query complexity:** Reading difficulty of query terms

SERP: Search Engine Result Page

(Eickhoff et al., 2014)

Within-Session Learning

Results for sessions of length 5 (similar results for other lengths)

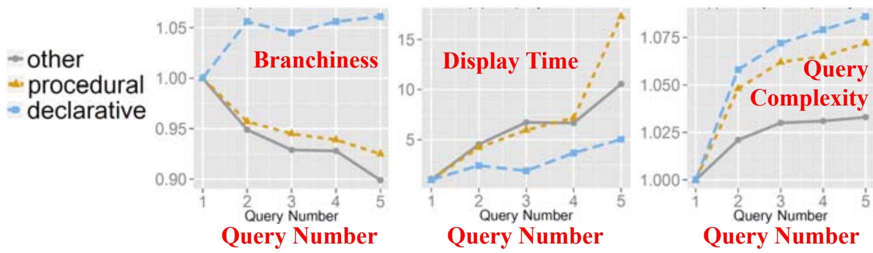


- Broader exploration for procedural and declarative searches
  – Procedural exploration becomes exploration within a topic

(Eickhoff et al., 2014)

Within-Session Learning

Results for sessions of length 5 (similar results for other lengths)



- Declarative searchers explore more paths
- Procedural searchers read more as they zero in on their topic
- Knowledge acquisition queries are more complex than others

(Eickhoff et al., 2014)

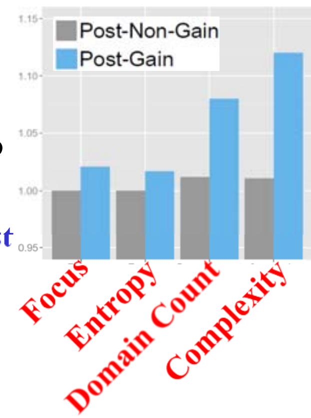
Within-Session Learning

Does expertise acquired in one session persist in later sessions?

- Compare people that gained expertise to people that did not
- Gains for focus and entropy don't persist
- Gains for domain count and complexity do

It's not clear why some gains do not persist

- An open research problem



(Eickhoff et al., 2014)

Within-Session Learning

What is the source of vocabulary in subsequent queries?

	Snippet	Short page visits	Long page visits ($t \geq 30$ sec)	None
D_{other}	0.27	0.13	0.41	0.52
D_{proc}	0.23	0.12	0.44	0.49
D_{decl}	0.26	0.10	0.45	0.49

Recall of subsequent query terms from different sources

Long page visits have almost 4× the influence of short page visits

- Perhaps query suggestions should be generated (mostly? only?) from queries that produce long page visits?

(Eickhoff et al., 2014)

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Within-Session Learning

Can pages that support knowledge acquisition be identified?

Methodology

- Train a classifier to predict which pages will be followed immediately by an increase in query complexity and domain count

Features

- Text length, sentence length, term length
- Coverage of query terms in title, distribution of query terms
- Part of speech (POS) distribution
- Page complexity, page complexity vs. query complexity
  – Reading difficulty metrics

(Eickhoff et al., 2014)

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Within-Session Learning

Classifiers: Support Vector Machines (SVM)

Accuracy: F_1=0.76

The best pages had a vocabulary that was a little more complex than the user's observed vocabulary

- Consistent with what is known about other forms of learning

(Eickhoff et al., 2014)

Within-Session Learning

Key ideas

- Mining search logs to identify very specific query types
  - Far beyond "informational, navigational, transactional"
- A sophisticated approach to measuring success
  - Measuring an increase in knowledge vs. measuring clicks
- Rediscovery of ideas known to learning scientists
  - The search engine should help you become smarter
- Advanced work done with familiar tools
  - Search logs, KL divergence, typical features, classification

Microsoft has studied these topics for several years

Lecture Outline

- **Query suggestions**
- **Query intents**
- **Click models**
- **Within-session learning**

For More Information

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