



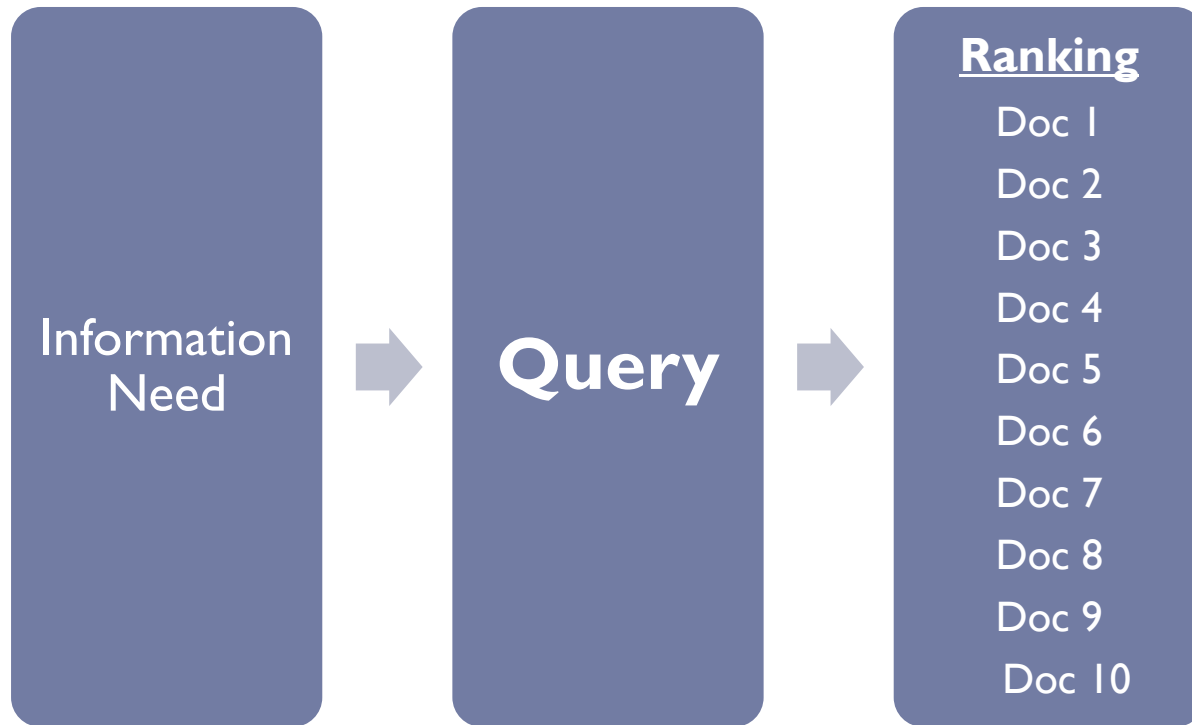
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Discovering Key Concepts in Verbose Queries

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Outline

- ▶ Why long queries?
- ▶ Key concepts in long queries
- ▶ Key concepts identification
- ▶ Putting it all together: Retrieval with weighted structured queries



Ad hoc Information Retrieval

- ▶ Performance is measured based on
 - ▶ Explicit Relevance Judgments
 - ▶ e.g., ***mean average precision***
 - ▶ Implicit User Feedback
 - ▶ e.g., ***click patterns***

Introducing the problem

- ▶ Most research in ad hoc IR is focused on keyword queries
 - ▶ Sufficient for expressing simple information needs
 - ▶ Common in many domains, including web search
- ▶ In some domains long queries are more natural, as they can express more complex information needs
 - ▶ Q&A
 - ▶ Text reuse
 - ▶ Academic and enterprise search
 - ▶ Search-in-Context



What is a long query?

- ▶ Natural Language Queries
 - ▶ *ways in which the Federal Reserve conducts monetary policy*
 - ▶ *picture of Zephyr mythical figure that depicts wind blowing*
- ▶ Questions in Q&A archives
 - ▶ *What should I bring when traveling to Bolivia?*
- ▶ Queries with multiple keywords/noun phrases
 - ▶ *Jefferson Medical Center, Philadelphia, PA*
- ▶ “Copy-Paste” Queries
 - ▶ *required installation file could not be found SKU112.CAB*

Do Long Queries Work?

For people, yes; for search engines, no

- ▶ Unpredictable results with current web search engines
 - ▶ Sparser click-data
 - ▶ Often suffer from term mismatch
- ▶ TREC description queries don't work as well as title queries
 - ▶ More details follow
- ▶ Searching Q&A archives is not very effective

(Xue and Croft, 2008)

Long Queries on the Web



Live Search

how to avoid morning traffic in seattle



Web 1-10 of 1,090,000 results · [Advanced](#)

See also: [Images](#), [Video](#), [News](#), [Maps](#), [More](#) ▼

[How to Avoid Morning Traffic to airport \(Houston, West: travel, safe ...](#)

I will be leaving Houston on a Friday **morning** during rush hour from Sam Houston Toll/Westpark Toll Westchase and I will be traveling to the airport (IA ...

www.city-data.com/forum/houston/390189-how-avoid-morning-traffic-airport.html · [Cached page](#)



Live Search

"morning traffic" + seattle



Web 1-10 of 15,100 results · [Advanced](#)

See also: [Images](#), [Video](#), [News](#), [Maps](#), [More](#) ▼

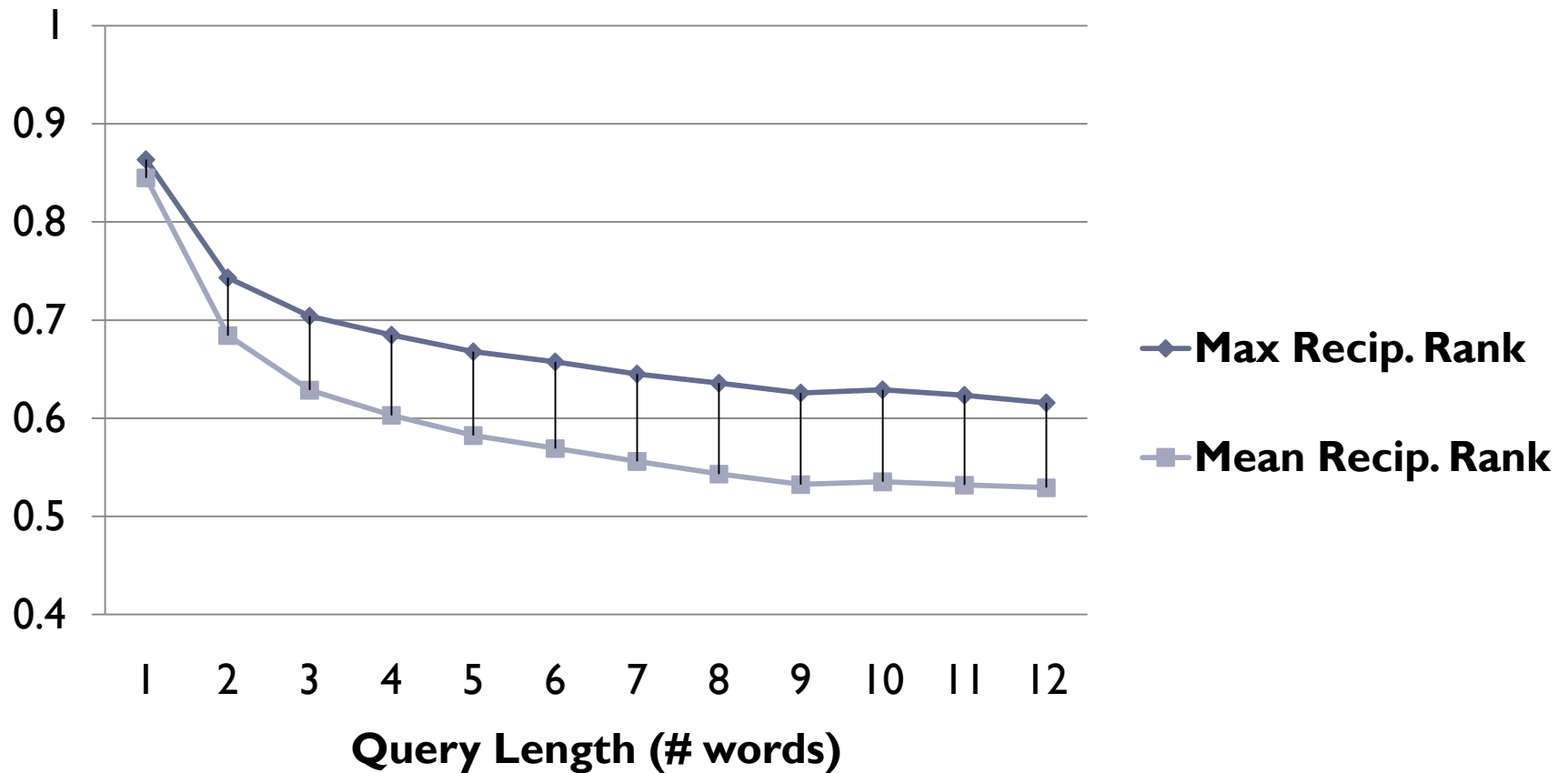
[Bus fire causes morning traffic jam | KOMO News - Seattle ...](#)

SEATTLE -- A Metro Access bus that caught fire Thursday morning on Interstate 5 burned to the frame and caused a large traffic backup. The bus caught fire just before 8 a.m. in the ...

www.komonews.com/news/9899567.html · [Cached page](#)



Long Queries on the Web – Click Patterns



Based on 15M query sample from a Live Search log

<title> *Spanish Civil War Support*

<desc> *Provide information on all kinds of material international support provided to either side in the Spanish Civil War*

(TREC Topic 829)

Long Queries on TREC

Text Retrieval Conference

“encourages research in information retrieval and related applications by providing a large test collection, uniform scoring procedures, and a forum for organizations interested in comparing their results”

<http://trec.nist.gov/>

Long Queries on TREC – Avg. Precision

	ROBUST04		W10g		GOV2	
	MAP	w/q	MAP	w/q	MAP	w/q
<title>	25.3	2.7	19.3	4.2	29.7	3.1
<desc>	24.5	8.3	18.6	6.4	25.3	6.1

Mean Average Precision vs. Words Per Query

Past Work On Long Queries in TREC

- ▶ **(Allan et al., 1997; Callan et al., 1995)**
 - ▶ Improving performance of long TREC queries
- ▶ **(Murdock & Croft, 2005; Balasubramanian et. al. 2007)**
 - ▶ Sentence Retrieval
- ▶ **(Kumaran & Allan, 2006; Kumaran & Allan 2008)**
 - ▶ Interactive reduction/expansion of long queries



Hypothesis

Identification of the key query concepts will have a (significant) positive impact on the retrieval performance for verbose queries



Hypothesis Motivated

- ▶ Verbose queries tend to mix key (**Spanish Civil War**) and complementary (*material international support*) concepts
- ▶ Current retrieval techniques tend to treat these equally
- ▶ Potentially, this results in a loss of focus on the main query topic(s)

Concept Identification – *The Ideal*

- ▶ **Everything is a potential concept**

(Bentivogli & Pianta, 2003)

- ▶ Single words: *dog, cat*
- ▶ Phrasal verbs: *catch up, come on*
- ▶ Idioms: *break a leg, spend time*
- ▶ Open compounds: *science fiction*
- ▶ Named entities: *Spanish Civil War, Steve Jobs*
- ▶ Free word combinations: *long queries*

Noun Phrases as Concepts

- ▶ In this work, we approximate concept identification by noun-phrase extraction
- ▶ Reasonable approximation for the task at hand: nouns usually serve as query topics
- ▶ Works well in practice
- ▶ Used in a previous work involving key phrases extraction
 - ▶ *Allan et al. (1997) – Core concepts in TREC queries*
 - ▶ *Hulth (2003) – Keywords in scientific abstracts*
 - ▶ *Yih et. al (2006) – Keywords for web advertisement*



***Provide information on all kinds of
material international support
provided to either side in the Spanish
Civil War***



Concept Extraction

***[information, kinds,
material international support,
side, Spanish Civil War]***

Concept Weighting Principle [1]

- ▶ Not all concepts are equally important for the query
- ▶ Weigh concept \mathbf{c}_i by $p(\mathbf{c}_i | \mathbf{q})$
 - ▶ how well concept \mathbf{c}_i represents query \mathbf{q} .

*Provide information on all kinds
of material international
support provided to either side
in the Spanish Civil War*



Weighted Concepts

*information
kinds*

*material international support
side*

Spanish Civil War

Concept Weighting Principle [2]

- ▶ Either
 - ▶ Estimate $p(c_i | q)$ directly from the query
- ▶ Or
 - ▶ Leverage non-query specific information to estimate $p(c_i | q)$
- ▶ We choose the second option
 - ▶ Queries do not provide enough context
 - ▶ This is what we humans do

Concept Weighting Principle [3]

Assumption A

Each concept \mathbf{c}_i can be assigned to one of the mutually exclusive classes

- ▶ **KC** (*key concepts class*)
- ▶ **NKC** (*non-key concepts class*)

Assumption B

A global function $h_k(\mathbf{c}_i)$ indicates the confidence that concept \mathbf{c}_i belongs to class **KC**

Concept Weighting Principle [4]

- ▶ Following the assumptions, weigh each query concept

$$\hat{p}(c_i | q) = \frac{h_k(c_i)}{\sum_{c_i \in q} h_k(c_i)}$$

- ▶ That is, we ***rank query concepts***
- ▶ **Concepts which have the highest confidence in membership in class KC are regarded as the best query representatives**

Estimating $h_k(\mathbf{c}_i)$

- ▶ As $h_k(\mathbf{c}_i)$ is query-independent, we can
 - a) Take an unsupervised approach to estimate it
 - ▶ e.g., use concept **IDF**
 - b) Try to learn it using a set of given concepts and features
- ▶ What kind of features?
 - ▶ As $h_k(\mathbf{c}_i)$ is query-independent, we can use any concept related features

Query-Based Features

- I. ***is_cap(c_i)*** Is concept capitalized in the query?
 - ▶ ***If TREC queries were not capitalized, we could resort to corpus-based capitalization***

Collection-Based Features [1]

2. **$cf(c_i)$** Concept frequency in the collection

3. **$idf(c_i)$** Concept IDF in the collection

$$idf(c_i) = \log_2 \frac{N}{df(c_i)}$$

- ▶ **N** – number of documents in the collection
- ▶ **$df(c_i)$** – number of documents in the collection containing c_i

Collection-Based Features [3]

4. $ridf(c_i)$ Concept residual IDF in the collection

- ▶ *Deviation of an actual IDF from Poisson model prediction*

(Church & Gale, 1995)

$$ridf(c_i) = idf(c_i) - \log_2 \frac{1}{1 - e^{\theta_i}}$$

- ▶ θ_i – average number of occurrences of concept c_i per document

Collection-Based Features [4]

5. $wig(c_i)$ Concept Weighted Information Gain

- ▶ *Information gain from a state where only average document is retrieved*

(Zhou & Croft, 2007)

$$wig(c_i) = \frac{\frac{1}{|T|} \sum_{d \in T} \log p(c_i|d) - \log p(c_i|C)}{-\log p(c_i|C)}$$

- ▶ T – a set of top 50 documents retrieved from a collection in response to concept c_i

Collection-Independent Features

6. **$g_cf(c_i)$** Concept frequency in *Google n-grams*.
 - ▶ Estimates concept frequency in a large web collection

7. **$l_qp(c_i)$** Number of times a concept was used as a part of a web search query
 - ▶ Extracted from an excerpt of *MSN* search log

8. **$l_qe(c_i)$** Number of times a concept was used as an exact query
 - ▶ Extracted from an excerpt of *MSN* search log

Collections

Collection	# Docs	# Topics
ROBUST04	528,155	250
W10g	1,692,096	100
GOV2	25,205,179	150



Concept Classification: The Task

- ▶ **Task: identifying key concepts**
- ▶ Simplifying assumption: a single key concept per query
- ▶ Train an ***AdaBoost.M1*** classifier on a set of labelled concept instances: $\mathbf{x}_i \in \{KC, NKC\}$
- ▶ Rank concepts for each query in the test-set according to their confidence in membership in class ***KC***

Concept Classification: Results

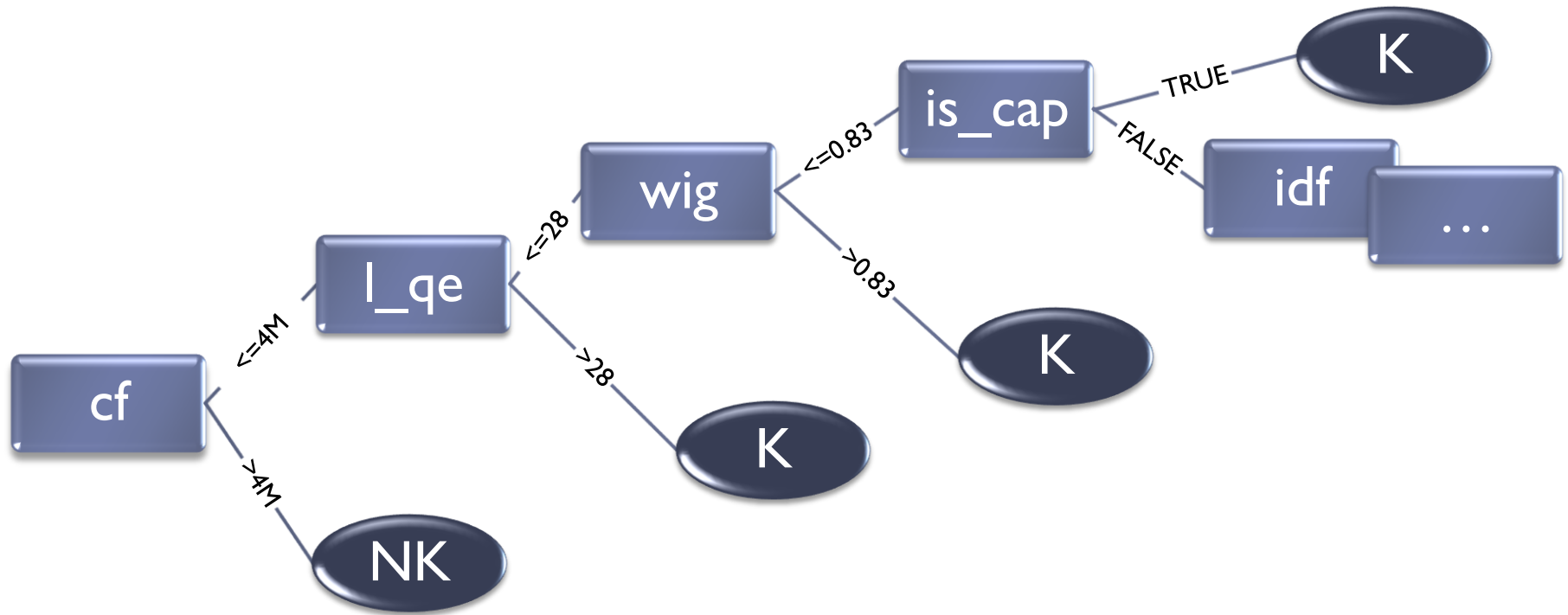
	AdaBoost		idf(c_i)	
	Accuracy	MRR	Accuracy	MRR
ROBUST04	<u>76.4</u>	<u>84.5</u>	56.4	74.2
W10g	<u>81.0</u>	<u>85.3</u>	66.0	78.6
GOV2	<u>84.0</u>	<u>88.9</u>	74.7	85.7

Accuracy and MRR results:

3-fold cross-validation with **AdaBoost.M1** vs. **IDF**



What Makes a Key Concept?



Example:

A high-weight decision tree for key concept classification for GOV2

What About Retrieval?

- ▶ **Does identifying key concepts help at all?**
- ▶ **Does the concept weighting help?**

Concept Weighting for Ranking

- ▶ Having estimated $p(\mathbf{c}_i | \mathbf{q})$ we may use a linear combination of query and all weighted concepts for ranking

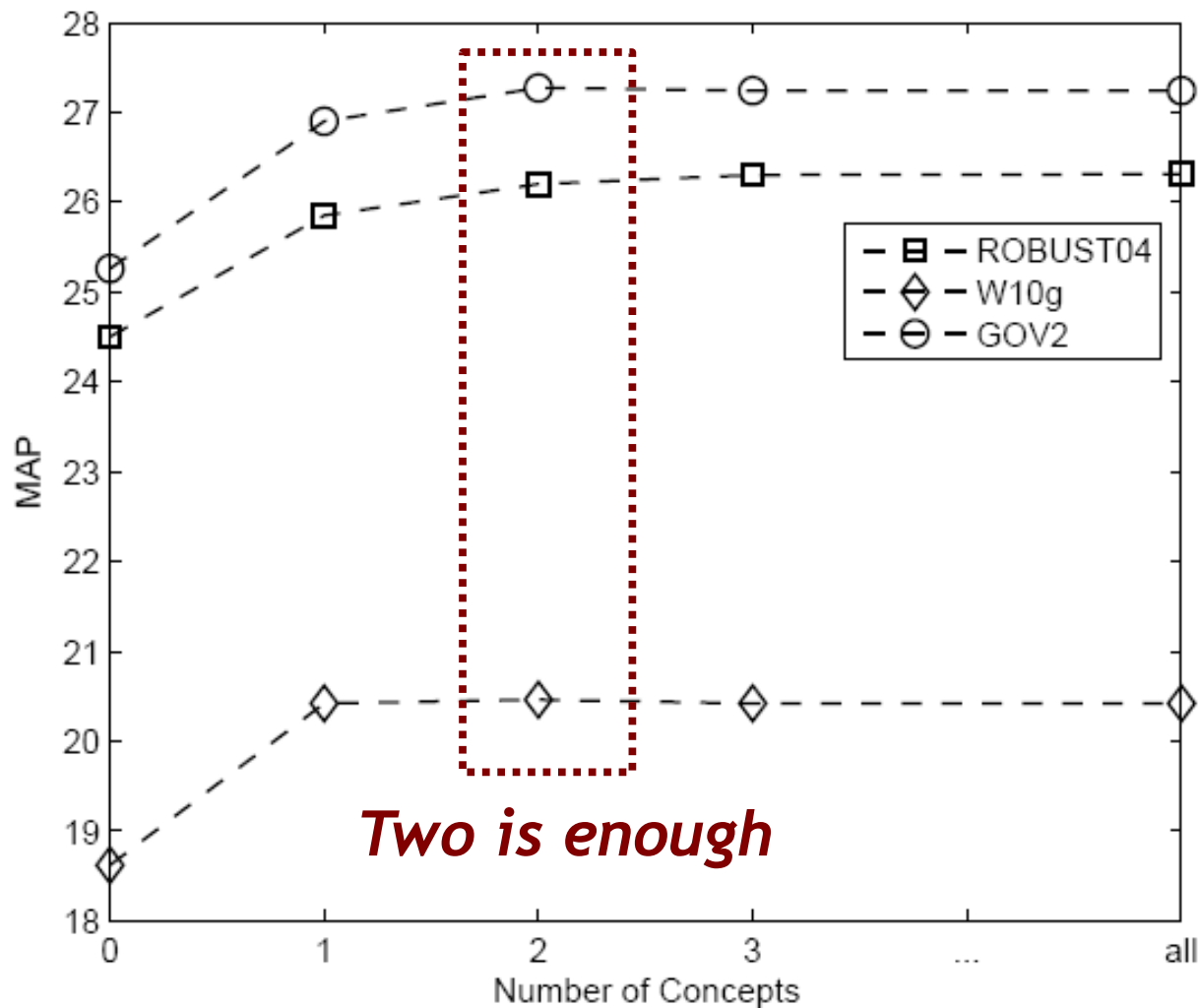
Concept Weight

$$\text{rank}(d) \propto \lambda \log p(q | d) + (1 - \lambda) \sum_{c_i \in q} \log p(c_i | d) p(c_i | q)$$

Query Score

Concept Score

How Many Concepts?



- ▶ Simple bag-of-words query

- ▶ **#combine** (*spanish civil war*)

- ▶ Phrase Operators

- ▶ **#l** (*spanish civil war*)

- ▶ **#uw8** (*spanish civil war*)

- ▶ Weights

- ▶ **#weight** (*0.8 #combine*(*spanish civil war*)

- 0.1 #l*(*spanish civil war*)

- 0.1 #uw8*(*spanish civil war*))

Indri Query Language: Crash Course

Indri – Open Source search engine

“The Indri query language... allows complex phrase matching, synonyms, weighted expressions, Boolean filtering, numeric fields, and the extensive use of document structure...”

<http://www.lemurproject.org/>

<title> and <desc> - #COMBINE query

```
#combine( Spanish Civil War support )
```

```
#combine( information kinds material international support provided side Spanish Civil War )
```



<desc> - Sequential Dependence Model

(Metzler & Croft, 2005)

```
#weight(  
  0.85 #combine( information kinds material international support provided side Spanish Civil War )  
  0.10 #combine( #1(information kinds) #1(kinds material) #1(material international)  
                 #1(international support) #1(support provided) #1(provided side)  
                 #1(side Spanish) #1(Spanish Civil) #1(Civil War) )  
  0.05 #combine( #uw8(information kinds) #uw8(kinds material) #uw8(material international)  
                 #uw8(international support) #uw8(support provided) #uw8(provided side)  
                 #uw8(side Spanish) #uw8(Spanish Civil) #uw8(Civil War) ))
```

<desc> - Key Concepts Expanded

```
#weight(  
  0.8 #combine( information kinds material international support  
           provided side Spanish Civil War )  
  0.2 #weight( 0.99994 #combine ( Spanish Civil War )  
           0.00006 #combine ( material international support )))
```

Retrieval Results [1]

	ROBUST04	W10g	GOV2
	<i>MAP</i>	<i>MAP</i>	<i>MAP</i>
<title>	25.28	19.31	<u>29.67</u> _d
<desc>	24.50	18.62	25.27 ^t
SeqDep<desc>	25.69 _d	19.28	27.53 ^t _d
KeyConcept[2]<desc>	<u>26.20</u> _d	<u>20.46</u> ^t _d	27.27 ^t _d

***Comparison of methods performance
(Mean Average Precision)***

Retrieval Results [2]

	ROBUST04	W10g	GOV2
	<i>MAP</i>	<i>MAP</i>	<i>MAP</i>
<title>	25.28	19.31	<u>29.67</u> _d
<desc>	24.50	18.62	25.27 ^t
SeqDep<desc>	25.69 _d	19.28	27.53 ^t _d
KeyConcept[2]<desc>	<u>26.20</u> _d	<u>20.46</u> ^t _d	27.27 ^t _d

► Query expansion by key concepts

- a) always outperforms the original description queries
- b) comparable performance to **SeqDep** model
- c) more efficient than **SeqDep** model



Future (and Present) Work

- ▶ Finding text reuse on the web
 - ▶ Did I see this story somewhere else?
(Bendersky & Croft, To appear in WSDM 2009)
- ▶ “Learning to Rank” is an active field in IR
 - ▶ Can we reweight query terms based on available relevance judgments?
(Lease et al., To appear in ECIR 2009)
- ▶ Investigating long queries in web search logs
 - ▶ Insight into how and why people formulate long queries
 - ▶ Possibly leverage the insights into other domains

