

Information Retrieval with Verbose Queries

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Contents

Preface	2
1 Introduction	5
1.1 Null Queries	5
1.2 Verbose Queries are Frequent	6
1.3 Search Engine Performance for Verbose Queries	7
1.4 Datasets	8
1.5 Metrics	9
1.6 Organization of the Survey	10
1.7 Summary	12
2 Properties of Verbose Queries	14
2.1 Performance for Verbose Queries	15
2.2 Categories of Verbose Queries	17
2.3 Query Log Traffic Representation	18
2.4 Other Properties	19
2.5 Summary	20
3 Query Reduction to a Single Sub-Query	22
3.1 Introduction	22
3.2 Will Query Reduction help?	24
3.3 Candidates for Sub-queries	25

3.4	Features to Extract a Single Sub-query	27
3.5	Methods to Combine the Features for Query Reduction	36
3.6	Efficiency Aspect of Query Reduction Methods	43
3.7	Ask for User Input to Guide Query Reduction	44
3.8	Summary	45
4	Query Reduction by Choosing Multiple Sub-Queries	46
4.1	Introduction	46
4.2	Sub-query Distributions using CRF-perf	47
4.3	Sub-query Distributions using ListNet	50
4.4	Reformulation Trees Method	50
4.5	Summary	53
5	Weighting Query Words and Query Concepts	55
5.1	Introduction	55
5.2	A Fixed-Point Method	57
5.3	Word Necessity Prediction using Regression	58
5.4	Regression Rank	59
5.5	Sequential Dependence (SD) Model using Markov Random Fields	60
5.6	Integrating Regression Rank with Markov Random Fields (MRFs)	62
5.7	Quasi-synchronous Dependency (QSD) Language Model	63
5.8	Weighted Sequential Dependence (WSD) Model	64
5.9	Parameterized Query Expansion (PQE) Model	66
5.10	Multiple Source Formulation (MSF)	69
5.11	Query Hypergraphs	70
5.12	Summary	73
6	Query Expansion by Including Related Concepts	75
6.1	Introduction	75
6.2	When Could Query Expansion Help?	76
6.3	Adding a Category Label to Queries	78
6.4	Parameterized Latent Concept Expansion	79
6.5	Expansion using User-supplied Reference Documents	79
6.6	Selective Interactive Reduction and Expansion	82

6.7	Summary	82
7	Query Reformulation for Verbose Queries	84
7.1	Introduction	84
7.2	Reformulation using Translation-based Language Model . .	85
7.3	Reformulation using Random Walks	87
7.4	Reformulation using Query Logs	91
7.5	Reformulation using Anchor Text	93
7.6	Summary	94
8	Query Segmentation for Verbose Queries	95
8.1	Introduction	95
8.2	Statistical Methods	96
8.3	Supervised Methods	97
8.4	Generative Methods	98
8.5	NLP-based Methods	100
8.6	Summary	101
9	Sources and Treatment of Verbose Queries	103
9.1	Finding Images for Books	103
9.2	Finding Related Videos	105
9.3	Question Answering	107
9.4	Searching for Medical Information	108
9.5	Fact Verification	109
9.6	Natural Language Interface for Databases	111
9.7	E-Commerce	111
9.8	Search Queries from Children	112
9.9	Music Search	113
9.10	Queries from User Selected Text	114
9.11	Summary	116
10	Summary and Research Directions	117
10.1	Towards a Unified Verbose Query Processing Framework .	118
10.2	Multi-modal Verbose Query Processing	119
10.3	Search Personalization	120
10.4	Natural Language Query Understanding	120

Acknowledgements	122
Appendices	123
A Basic Information Retrieval Concepts	124
A.1 Language Modeling	124
A.2 Query Likelihood Model	125
A.3 Pseudo-Relevance Feedback	125
A.4 Divergence from Randomness Framework	126
A.5 Singular Value Decomposition	126
A.6 Metrics	127
B Graphical Models: MRFs and CRFs	130
B.1 Markov Random Fields (MRFs)	130
B.2 Conditional Random Fields (CRFs)	131
C Dependency Parsing	133
References	135
Index	145

Abstract

Recently, the focus of many novel search applications has shifted from short keyword queries to verbose natural language queries. Examples include question answering systems and dialogue systems, voice search on mobile devices and entity search engines like Facebook's Graph Search or Google's Knowledge Graph. However the performance of text-book information retrieval techniques for such verbose queries is not as good as that for their shorter counterparts. Thus, effective handling of verbose queries has become a critical factor for adoption of information retrieval techniques in this new breed of search applications.

Over the past decade, the information retrieval community has deeply explored the problem of transforming natural language verbose queries using operations like reduction, weighting, expansion, reformulation and segmentation into more effective structural representations. However, thus far, there was not a coherent and organized survey on this topic. In this survey, we aim to put together various research pieces of the puzzle, provide a comprehensive and structured overview of various proposed methods, and also list various application scenarios where effective verbose query processing can make a significant difference.

Preface

Information retrieval with verbose natural language queries has gained a lot of interest in recent years both from the research community and the industry. Search with verbose queries is one of the key challenges for many of the current most advanced search platforms, including question answering systems (Watson or Wolfram Alpha), mobile personal assistants (Siri, Cortana and Google Now), and entity-based search engines (Facebook Graph Search or Knowledge Graph). Therefore, we believe that this survey is very timely and should be interesting to readers from both academia as well as industry.

Scope of the Survey

We cover an exhaustive list of techniques to handle verbose queries. Intuitively verbose queries are long. Also empirical observations show that often times long queries are verbose in nature. We use the terms “verbose” queries and “long” queries interchangeably in this survey.

In order to stay focused, following is a list of related topics that we do not cover as part of this survey.

- Automatic Speech Recognition (ASR)
- Processing null queries other than verbose queries

- Methods (e.g., [Yang et al., 2009] and [Tsagkias et al., 2011]) and applications (e.g., [Yih et al., 2006]) which consider documents as queries
- Query processing tasks for short queries which do not need any non-trivial modification to be applicable to long queries
- Community-based question-answering systems

Development of the Survey

Many tutorials and surveys dedicated to general query handling or query log analysis have been conducted by researchers in information retrieval and web mining. However, all of them focus on short queries; none of these have explicitly focused on long verbose queries. This survey is based on a full-day tutorial offered by the authors at the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2015). The slides for the tutorial can be obtained from http://research.microsoft.com/pubs/241895/gupta15_verbose.pptx.

This survey is entirely based on previously published research and publicly available datasets, rather than the internal practices of the respective employers of the authors. As such, it should prove useful for both practitioners and academic researchers interested in reproducing the reported results.

Audience

Researchers in the field of information retrieval will benefit the most, as this survey will give them an exhaustive overview of the research in the direction of handling verbose web queries. We believe that the survey will give the newcomers a complete picture of the current work, introduce important research topics in this field, and inspire them to learn more. Practitioners and people from the industry will clearly benefit from the discussions both from the methods perspective, as well as from the point of view of applications where such mechanisms are starting to be applied.

After reading the survey, the audience will be able to appreciate and understand the following.

- What are the interesting properties of complex natural language verbose queries
- Challenges in effective information retrieval with verbose queries
- State-of-the-art techniques for verbose query transformations that yield better expected search performance
- State-of-the-art ranking methods for verbose queries, including supervised learning-to-rank methods
- What user/industry segments can be affected by better retrieval with verbose queries and what are the possible applications

Writing Style

We have tried to make the survey as self-contained as possible. However, for some sections, we have deliberately adopted a reference paper writing style, to enable a holistic overview of the research field. In such cases, we discuss those pieces of work from a more general and abstract standpoint, and advise the readers to go through the referenced papers for details. We provide a basic introduction to preliminary information retrieval concepts, graphical models and dependency parsing in the Appendices.

1

Introduction

Web search has matured significantly in the past two decades. Beyond the ten blue links, search engines display a large amount of heterogeneous information including direct factual answers, task panes, image answers, news answers, video answers, social results, related searches, etc. Broadly, queries to a search engine can be divided into two parts: head and tail. Head queries are the highly popular queries while the tail queries occur with a low frequency in the query log. Although the head queries are handled very elegantly by the popular search engines, there is a large room for improvement when handling the tail queries, a part of which return no results.

1.1 Null Queries

Null queries are queries for which the search engine returns zero results. This could be because of the following reasons.

- Query verbosity
- Mismatch between the searcher and the publisher vocabulary

- Unavailability of relevant documents (temporally, or general rarity)
- Inability of the naïve users to formulate appropriate queries

In this survey, we focus on the verbosity aspect of such “null” or difficult to handle queries. We use the terms “verbose” queries and “long” queries interchangeably. This work focuses on verbose queries as well as on long queries which may or may not be verbose.

1.2 Verbose Queries are Frequent

As shown in Figure 2.1, the percentage of the total query traffic follows a power law distribution with respect to the query length [Arampatzis and Kamps, 2008, Bailey et al., 2010], i.e., for a query Q ,

$$p(|Q|) = C|Q|^{-s}, \text{ for } |Q| \geq k_0 \quad (1.1)$$

where $|Q|$ is the query length in words, C is a normalizing constant, s is the slope, k_0 is the lower bound from which the power law holds.

We consider queries with five or more words as verbose or long queries. In 2006, Yahoo! claimed that 17% of the queries contained five or more words.¹ Figure 2.1 shows that $\sim 15\%$ queries contain five or more words.

Popular usage of speech-based personal assistants like Cortana, Siri, and Google Now attract an even higher percentage of verbose queries. Crestani and Du [2006] and Yi and Maghoul [2011] analyzed the properties of written versus spoken queries which were manually generated by participants to satisfy TREC topic information needs. They found that while written queries had an average length of 9.54 and 7.48 words with and without stop words respectively, spoken queries had an average length of 23.07 and 14.33 words respectively. Voice queries were considerably longer than the typed mobile queries.

While most of the verbose queries are explicitly asked by the users, some of them are implicit. Users ask verbose queries explicitly in a large

¹<http://www.zdnet.com/blog/micro-markets/yahoo-searches-more-sophisticated-and-specific/27>

number of scenarios. Advanced users searching for an exhaustive list of relevant documents in medical literature or patent documents often use verbose comprehensive queries. Naïve users like children or the elderly are not trained to ask short queries to search engines and hence end up using full sentence queries. Community-based question answering platforms also attract long queries. Sometimes users end up using long queries implicitly. Long queries could be an outcome of cut-and-paste behavior. For example, a user just found some text on some topic (say a news headline) and fires it as a query to find related news articles. Similarly, to find a relevant image for a paragraph in a textbook, one may fire the entire paragraph as a query to the search engine. We discuss both the implicit and explicit examples of verbose queries in more details in §9.

1.3 Search Engine Performance for Verbose Queries

Past research in information retrieval found that long queries increase the retrieval performance. However, for web search queries, many researchers have observed that search engines perform poorly on verbose queries. The reasons for poor performance are as follows.

- High degree of query specificity. To satisfy their specific (or narrow) needs, users put additional non-redundant information in verbose queries. But since there are not many web-pages to satisfy such highly specific information needs, it is difficult for search engines to surface the right results.
- Term redundancy or extraneous terms (lot of noise). Often times, verbose queries contain a lot of noise, such as extraneous terms that users believe are important to conveying their information needs, but in fact are confusing to automatic systems.
- Rarity of verbose queries. Most search engines optimize for highly popular (or head) queries. Since verbose queries are rare, search engine algorithms are not tweaked to always perform well for them.

- Lack of sufficient natural language parsing. Longer queries can be answered more effectively if the semantics can be understood using natural language understanding techniques. However, search engines currently do not perform such deep parsing because (a) they are optimized for short queries for which deep natural language parsing is not required, and (b) such deep parsing has performance implications.
- Difficulty in distinguishing between the key and complementary concepts. A verbose query can have multiple concepts. The performance can be improved if the results that contain key concepts are shown at the top. However, identifying key concepts from a verbose query is challenging.

Hence, a large number of efforts have been made to understand such long queries in a more effective manner.

1.4 Datasets

Most of the papers in this area have used the TREC datasets for evaluating their approaches. ROBUST04, W10g, GOV2, ClueWeb-09-Cat-B, TREC123, and CERC are the most popular TREC² datasets. ROBUST04 is a Newswire collection, while W10g, GOV2 and ClueWeb-09-Cat-B are web collections. TREC123 is a collection of documents from TREC disks 1 and 2. CERC is the CSIRO Enterprise Research Collection (CERC), a crawl of *.csiro.au (public) web sites conducted in March 2007 and used in the 2007 edition of the TREC Enterprise track. Table 1.1 gives a summary of the dataset statistics. Each of these datasets contain relevance judgments for multiple topics (or queries). The judgments are for multiple documents and are binary or graded (e.g., non-relevant, relevant, highly relevant). TREC topics illustrate the difference between a keyword query and a description query. A TREC topic consists of several parts, each of which corresponds to a certain aspect of the topic. In the example at Figure 1.1, we consider the title (denoted \langle title \rangle) as a keyword query on the topic, and the de-

²<http://trec.nist.gov>

Collection	Content	#Docs	Topics
Robust04	Newswire	528155	250
W10g	Web	1692096	100
GOV2	Web	25205179	150
ClueWeb-09-Cat-B	Web	50220423	150
TREC123	TREC disks 1 and 2	742611	150
CERC	Enterprise Documents from *.csiro.au	370715	50

Table 1.1: Statistics for TREC Datasets

scription of the topic (denoted $\langle \text{desc} \rangle$) as a natural language description of the information request. In general, the description field is intended to model what a searcher might first say to someone who will actually help them with their search. The verbose description is therefore often used as the verbose query. Another popular similar dataset is the NTCIR-4/5 English-English ad-hoc IR tasks dataset with an average length of 14 query words for description queries.

Some of the recent papers have also used real web query logs [Balasubramanian et al., 2010, Parikh et al., 2013, Yang et al., 2014]. A few researchers have also used document paragraphs or passages as verbose queries [Agrawal et al., 2011, Lee and Croft, 2012, Gupta, 2015].

1.5 Metrics

A variety of standard information retrieval metrics have been used to evaluate the methods for verbose query processing. Most of the researchers that use TREC datasets evaluate their methods using Mean Average Precision (MAP), Mean Reciprocal Rank (MRR), and Precision@K measures against the relevance judgments. Researchers using query logs also use Normalized Discounted Cumulative Gain (NDCG) with respect to the original long query as a metric. We provide a short description of these metrics in §A.6.

```
<num> Number 829
<title> Spanish Civil War support
<desc> Provide information on all kinds of material
international support provided to either side in the
Spanish Civil War.
```

Figure 1.1: An Example of \langle title \rangle and \langle desc \rangle Parts of a TREC Topic

1.6 Organization of the Survey

In this survey we present an organized summary of efforts towards improved information retrieval for verbose queries. We begin with a study of the specific properties of verbose queries (§2) which makes them especially challenging in information retrieval applications. Next, we discuss six main ways of handling long queries – query reduction to a single sub-query, query reduction to multiple sub-queries, query weighting, query expansion, query reformulation, and query segmentation in §3 to §8. Table 1.2 shows examples of each of the techniques.

Long verbose queries can be reduced to a single sub-query which could be, for example, the most important noun phrase in the query (§3). Or the long query could be processed to extract multiple short queries (§4). Rather than reducing queries by dropping terms from long queries, each term could be assigned a weight proportional to its importance (§5). Another way to handle long queries is to add concept words to the original query to make the intent clearer (§6). If the words used in the long queries are very specific, they could be completely reformulated to a new query which could potentially match a larger number of documents (§7). Finally, a verbose query can contain multiple pieces of the user information need. Such a query could be segmented and then each such segment can be reduced, weighted, expanded or reformulated to get desired results (§8). For each of these techniques, we group together related methods and present comparisons of these methods. We put together various domains in which verbose queries are frequent, and also discuss how various verbose query processing techniques have been used to handle them (§9). We conclude this survey with a brief

Technique	Original Query	Modified Query
Query Reduction to a Single Sub-query (§3)	ideas for breakfast menu for a morning staff meeting	breakfast meeting menu ideas
Query Reduction to a Multiple sub-queries (§4)	identify any efforts proposed or undertaken by world governments to seek reduction of iraq's foreign debt	reductions iraq's foreign debt, iraq's foreign debt
Query Weighting (§5)	civil war battle reenactments	civil:0.0889, war:0.2795, battle:0.1310, reenactments:0.5006
Query Expansion (§6)	staining a new deck	staining a new deck Shopping/Home and Garden/Home Improvement
Query Reformulation (§7)	how far is it from Boston to Seattle	distance from Boston to Seattle
Query Segmentation (§8)	new ac adapter and battery charger for hp pavilion notebook	new, ac adapter, and, battery charger, for, hp pavilion notebook

Table 1.2: Examples of Various Techniques for Handling Verbose Queries

Notation	Meaning
$Q = \{q_1, q_2, \dots, q_n\}$	Original verbose query
P^Q	Power set of Q
P	A sub-query of Q
C	Collection
$ C $	Number of words in C
N	Number of documents in C
$m(P, M)$	Target measure of effectiveness of ranking function M for query P
$tf(q_i)$	Term frequency of q_i in C .
$tf_d(q_i)$	Term frequency of q_i in document or document collection d .
$df(q_i)$	Document frequency of q_i in C .
$T_M(Q)$	Top M relevant documents for query Q .

Table 1.3: Table of Notations

overview of future research directions (§10). Table 1.3 presents a list of frequent notations that we use in this survey.

1.7 Summary

Query verbosity is one of the main reasons for zero results returned by search engines. Verbose queries occur in multiple domains and are increasing with increase in usage of speech-based personal assistants. Currently, search engines perform poorly for such long verbose queries. Hence, a large number of efforts have been made to understand such long queries in a more effective manner. In this survey we present an organized summary of efforts towards improved information retrieval for verbose queries.

Suggested Further Reading: [Arampatzis and Kamps, 2008]: Query length analysis and distribution fitting for multiple datasets; [Crestani and Du, 2006]: Comparison between written and spoken queries in terms of length, duration, part-of-speech, aptitude to describe rele-

1.7. *Summary*

13

vant documents, and retrieval effectiveness; <http://trec.nist.gov/>:
Details of the various TREC datasets.

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Index

- 5w1h Question Reformulation Patterns, 91
- Affinity Algorithm, 105
- Aggregated Labeled Query Trails, 78
- Average Precision, 128
- Binary Dependencies, 31
- c-commanding, 32, 63, 134
- Cancer Queries, 108
- Centrality, 57
- CERC, 8
- Chi Square Statistic, 34
- Children Queries, 112
- Clarity, 90
- Click Graph, 88
- Clique, 60
- ClueWeb-09-Cat-B, 8
- Comity Algorithm, 105
- Conditional Distribution, 131
- Conditional Random Fields, 131
- Coordinate Ascent, 68, 70, 72
- Core Term Identification, 37
- CRF, 118, 131
- CRF-perf, 47, 48
- Cumulative Gain, 127
- Dependencies, 56, 133
- Dependency Parsing, 63, 133
- DFR, 126
- Difference Prediction, 42
- Dirichlet Prior Method, 16
- Discounted Cumulative Gain, 127
- Divergence from Randomness Framework, 126
- DM+SubQL, 49
- E-Commerce, 111
- Endogenous Features, 66
- Exogenous Features, 66
- Fact Verification, 109
- Fixed-Point Method, 57
- Full Dependence Model, 60
- Full Independence Model, 60
- Global Hyperedge, 71
- GOV2, 8
- Head Queries, 5
- Hidden Markov Models, 131
- Higher Order Term Dependencies, 70
- HMM, 131
- Hyperedges, 70
- Hypergraphs, 70
- Ideal DCG, 128
- Ideal Discounted Cumulative Gain, 128
- Independent Prediction, 42
- Info, 76
- Info_Bo2, 76
- Information Need Specificity, 19
- Interactive Query Expansion, 44, 82
- Interactive Query Reduction, 44, 82
- Joint Query Annotation, 100
- KC, 39
- Key Concept Discovery, 39
- LambdaMerge, 88
- Language Modeling, 124
- LCE, 68
- ListNet, 47, 50

- Local Hyperedges, 71
- Log Likelihood Ratio, 35
- Loopy Belief Propagation, 132

- MAP, 9, 128
- Markov Random Field, 130
- Maximum Entropy Markov Models, 131
- Mean Average Precision, 128
- Mean Reciprocal Rank, 129
- MeMM, 131
- MLE, 56
- MRF, 60, 130
- MRR, 9, 129
- MSF, 69
- Multi-modal Verbose Query Processing, 119
- Multi-word Expression, 96
- Multiple Source Formulation, 69
- Music Search, 113
- Mutual Information, 29, 34, 96

- N-Gram Language Model, 125
- NaLIX, 111
- NDCG, 9, 127
- NLP, 120
- Normalized Discounted Cumulative Gain, 127
- NTCIR, 9
- Null Queries, 5

- ODP, 78
- Open Directory Project, 78

- Pachinko Allocation Model, 110
- PAM, 110
- Parameterized Latent Concept Expansion, 79
- Parameterized Query Expansion Model, 66
- Parse Tree, 64
- PhRank, 40
- POS Blocks, 26
- Potential Function, 60
- Power Law, 6
- PQE, 66, 79
- Precision@K, 9, 127
- Pseudo-Relevance Feedback, 56, 125

- QL+SubQL, 49
- QSD, 63
- QSegment, 96, 112
- Quasi-sync. Dependency Lang. Model, 63
- Quasi-synchronous Dependencies, 32
- Quasi-synchronous Model, 133
- Query Clarity, 35
- Query Drift, 36
- Query Expansion, 75
- Query Hypergraphs, 70, 118
- Query Likelihood Model, 125
- Query Reduction, 22, 46
- Query Reformulation, 84
- Query Scope, 35
- Query Segmentation, 95

- Query Specificity, 7
- Query Transformations, 118
- Query Weighting, 55
- Question Answering, 107

- Rank SVM, 50
- RAPP, 90
- Rareness, 59
- Reformulation Trees, 47, 50
- Regression Rank, 59
- Repetition Factor, 18
- Replaceability, 59
- Residual IDF, 28
- Rewrite Rank, 90
- RM, 68
- ROBUST04, 8

- SCQ Score, 28
- SD, 60
- Search Personalization, 120
- Searchonyms, 58
- Sequential Dependence Model, 60
- Sim. Collection/Query-based Score, 28
- Simplified Clarity Score, 28
- Singular Value Decomposition, 126
- SRank, 50
- Stop Structure, 40
- Sub-query Candidates, 25
- Sub-query Distributions, 47
- SubDM, 49
- SubQL, 48
- SVD, 58, 126
- Synchronous Grammars, 133
- Synonymy, 58
- Syntactic Configurations, 63

- Tail Queries, 5
- Term Redundancy, 7
- Term-Query Graph, 88
- Topic Centrality, 58
- Translation-based Language Model, 85
- TransLM+QL, 87
- TREC, 8
- TREC123, 8

- Unigram Language Model, 124
- User Modeling, 120

- Verbose Queries, 2, 6
- Voice Queries, 6

- W10g, 8
- Weighted Information Gain, 35
- Weighted Sequential Dependence Model, 64
- Word Necessity, 58
- WSD, 64

- XQuery, 111