Knowledge and Information Systems (2019) 60:1397–1426
https://doi.org/10.1007/s10115-018-1267-x

REGULAR PAPER

Coupled intrinsic and extrinsic human language resource-based query expansion

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Received: 30 November 2016 / Revised: 4 July 2018 / Accepted: 17 August 2018 /
Published online: 10 September 2018

Abstract

Poor information retrieval performance has often been attributed to the query-document vocabulary mismatch problem which is defined as the difficulty for human users to formulate precise natural language queries that are in line with the vocabulary of the documents deemed relevant to a specific search goal. To alleviate this problem, query expansion processes are applied in order to spawn and integrate additional terms to an initial query. This requires accurate identification of main query concepts to ensure the intended search goal is duly emphasized and relevant expansion concepts are extracted and included in the enriched query. Natural language queries have intrinsic linguistic properties such as parts-of-speech labels and grammatical relations which can be utilized in determining the intended search goal. Additionally, extrinsic language-based resources such as ontologies are needed to suggest expansion concepts semantically coherent with the query content. We present here a query expansion framework which capitalizes on both linguistic characteristics of user queries and ontology resources for query constituent encoding, expansion concept extraction and concept weighting. A thorough empirical evaluation on real-world datasets validates our approach against unigram language model, relevance model and a sequential dependence-based technique.

Keywords Query expansion · Human language processing · Concept-based query segmentation · Ontology processing · Concept weighting

1 Introduction

Several query expansion efforts have emerged over the years in order to improve retrieval performance. Retrieval performance is often impeded by the query-document vocabulary mismatch problem which remains prominent due to the varying styles of writing by users as

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well as the semantic ambiguity that is present in natural language. In the context of search engines, query expansion involves evaluating a user's input (what words were typed into the search query area, and sometimes other types of data) and expanding the search query to match additional documents. The query expansion process requires the comprehension of the intended human search goal through: (1) subsequent identification of key concepts prior to generating additional concepts enriching the query and (2) assessing the importance of the original and added concepts through robust weighting schemes.

As far as the first issue is concerned, current research for key concept identification tasks (e.g. [20] incorporates a combination of syntactical analysis and statistical mining. Nouns are assumed to be of significance [8], whilst more often all non-stop words query terms are assumed to be representative of query content [53], in the same fashion as unigram models in early information retrieval efforts. Several other works on key concept extraction in documents [17] and queries [5, 25] also emphasize on noun phrases and key concepts that are established through the examination of frequency of occurrence of terms in documents, n-grams, query logs, etc. It is, however, inherent that query elements possess two different functionalities that are disregarded: concepts either characterize the content according to the search goal or are used to connect query elements. It is therefore important to consider that query constituents can take on several roles which if recognized and taken into account appropriately would render a more accurate understanding of the intended search goal.

Additionally, the nature of natural language dictates that there are intrinsic relationships between adjacent and non-adjacent concepts that highlight semantic notions pertaining to a search goal. Earlier works mostly fail to fully capitalize on these relationships between query terms which if considered appropriately would improve retrieval performance. One might argue that both adjacent and non-adjacent dependencies can be taken into account through full dependence modelling. This will however prove costly, in especially long queries, as multiple concept pairs will be derived, from which possibly a large number would not be very meaningful. Query expansion based on these pairs would generate unrelated concepts which in turn cause digression from the original search goal. We hypothesize that both adjacent and non-adjacent association among query concepts can be effectively capitalized from syntactical dependencies within queries. This then translates into meaningful query concept pairing for expansion.

Furthermore, rather than using statistical techniques for generating additional query concepts, the use of language-based resources such as ontologies allow spawning then integrating in the original query expansion concepts that are semantically consistent with its content.

A crucial element in query expansion is the process of weighting the original and expansion concepts to adequately reflect the search goal of a query. Thus far, state-of-the-art methods have placed most emphasis on the frequency of concepts within a document corpus either through simplistic term and document frequency computation (such as in [50] or through supervised learning mechanisms with multiple features but are also centred on the frequency of the concept within a variety of sources such as n-grams and query logs [37]. The drawback of such models is that key concepts are established based on the statistical occurrence of a concept which is not necessarily reflective of the search goal of a query. Instead, we believe concepts should be given due emphasis based on the conceptual role they play in representing the information need. There are several efforts that attempt to model query constituent weights using genetic algorithms [22, 49, 54]. However, these efforts do not consider the role of the concepts within a query.

We present a query expansion framework that consists of three components: (1) a linguistically motivated scheme for recognizing and encoding significant query constituents that characterize the intent of a query [48]; (2) a module for the generation of potential expansion terms based on an extrinsic lexical resource (ontology) that capitalizes on grammatically linked base pairs of query concepts; and (3) a robust weighting scheme reconciling original and expansion concepts that is reflective of the role types of query constituents in representing an information need. After analysing the state-of-the-art solutions in Sect. 2, we provide a detailed analysis of the framework components in Sect. 3 and present their algorithmic instantiation in Sect. 4. We present the evaluation of our framework on large-scale real-world datasets in Sect. 5.

2 Analysis of language resource-based query expansion frameworks

In Fig. 1, the general process flow of a language resource-based query expansion framework is illustrated [46]. Through the example processing of an original query ("*how to repair a car*"), we illustrate the three major query handling steps involved: (1) linguistic processing, (2) sense disambiguation and (3) lexical-semantic term pooling.

With regards to linguistic processing, most related works subject queries to minimal linguistic analysis where they are stemmed and stop words removed prior to the process of expansion. There are several efforts that recognize the importance of identifying phrases that occur in a query instead of treating all terms in a query independently [26, 38, 40]. They rely on an ontology to perform syntactical analysis in order to identify proper names and dictionary phrases, but it is not clear whether they cover all crucial non-compositional phrases such as phrasal verbs, idioms, collocations and acronyms. Also, they do not utilize syntactical dependencies to identify simple and complex phrases that are not found in the dictionary but instead devise a simple grammar that relies on the existence of noun phrases and content words (i.e. non-stop words).

Among the approaches for conducting word sense disambiguation, most authors handle only nouns and fail to consider verb senses in their approach. This may not be wise as verb senses could bring further improvement in understanding the intended meaning of the query. Liu et al. [27] perform word sense disambiguation in short queries, choosing the

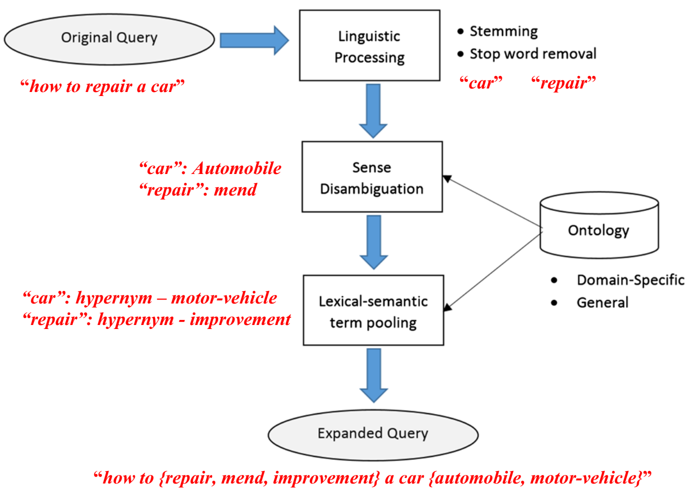


Fig. 1 Organization of language resource-based query expansion frameworks

right sense for a word in its occurring context. Noun phrases of the query are determined and compared against synonyms and hyponyms from WordNet to identify word senses. If it is not possible to determine the word sense in this manner, then a guess is made based on the associated frequency of use (i.e. the number of times a sense is tagged) available in WordNet. The approach of utilizing the "*first sense heuristic*" (i.e. choosing the first or predominant sense of a word) is reiterated by [33] as a method that is used by most state-of-the-art systems as a back-off method when text-based disambiguation is unsuccessful. Broadly speaking, sense disambiguation methods are far from perfect resulting in multiple research works that attempt to improve the accuracy of disambiguation through improved measures of relatedness (e.g. [36, 39]) and via information extracted from external sources (e.g. [35]).

As far as term pooling is concerned, based on the derived sense of the query concepts, lexical and semantically related expansion concepts are extracted from an ontology. Query expansion frameworks have often relied on lexical resources (i.e. dictionaries and thesauri) for the purpose of suggesting semantically related terms and sense disambiguation. Often, these resources are ontologies, either domain-specific or general. Query expansion using domain-specific ontologies is more suitable for static document collections. For Web collections, the ontologies would have to be frequently updated because the collections on the web are more dynamic in nature. Terminologies in domain-specific ontologies are less ambiguous; therefore, queries for narrower search tasks can be expanded with a higher chance of accuracy. General ontologies would be suitable for broad queries [6]. In previous research efforts involving external knowledge sources, [10, 19, 26, 34, 53], utilize general ontologies; [1, 7, 45, 51], use domain-specific ontologies whilst [52] evaluate their framework with both general and domain-specific ontologies. Query structures and varying query lengths [47] were not differentiated during the process of expansion in these efforts. However, retrieval performance in long queries may be improved through the approach of [45]. In the latter, an ontology is used to identify semantic *dimensions* of medical queries rather than extract related terms and a document is considered relevant if it contains one or more dimensions of the query. Unfortunately, identification of dimensions of a query is not straightforward in general queries as the terms utilized in such queries and those found in general ontologies are highly ambiguous. For non-domain-specific queries, this approach of identifying dimensions could be likened to the identification of main query concepts. Main query concepts can be identified in long queries, especially, allowing documents that contain one or more of the main concepts to be deemed as relevant. [1, 7, 10, 26, 53] use only one source of potential expansion terms, that is, the external knowledge base. [52] utilize the ontologies published in the ONKI Ontology Service. All works include lexically related terms; [10] use synonyms whilst [53] and [26] additionally utilize hyponyms. [7] make use of both synonyms and hypernyms. Hypernyms and meronyms are also integrated in Voorhees' model whilst [26] consider compound terms as well. [1] use common ontological relations and ontological relations specific to the Gene domain-specific ontology in their expansion process. The produced mix of concepts may not work well when terms which are of contrasting relations to a query topic (e.g. generalization and specialization) are utilized together causing the range of related documents to be less precise. Koopman et al. [21] models the entities and relationship types based on domain-specific ontologies and attempts to infer relevance through a graph inference model. The proposed model works to improve recall and precision for domain-specific queries, it is unable to perform well for concepts which are more generic in nature. To conclude, the current approaches do not handle non-compositional phrases and rely on simple syntactical analysis which focuses only on noun phrases in order to identify the key concepts in a query.

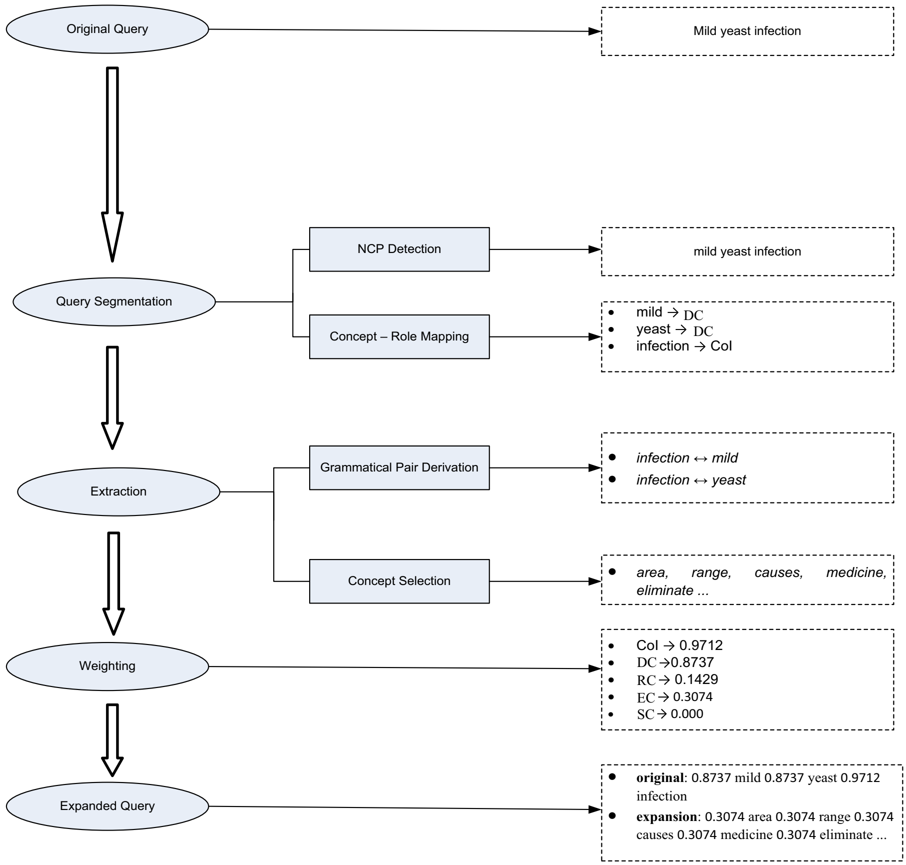


Fig. 2 General organization and processing flow of a query

They also do not sufficiently address the process of lexical-semantic term pooling where the relationships between terms are not considered prior to term pooling. The extracted terms are also not given adaptive weight to accurately reflect the role of the original and expansion terms.

3 Description of framework components

An enhanced query expansion framework is proposed to address the unresolved issues highlighted in Sect. 2. Figure 2 shows the stages of processing a query within the proposed query expansion framework and reflects the intermediate output of each phase for a sample query "mild yeast infection".

The framework consists of three phases, namely query segmentation, extraction and weighting. The query segmentation phase consists of the non-compositional phrase (NCP) detection and concept-role (CR) mapping processes. The NCP detection process serves to identify and preserve NCPs in their full form so as to accurately capture the original intent. The CR mapping phase aims to derive relationships between query terms and assign a role type to each term based on its functionality. The extraction phase focuses on the elicitation of lexical-semantic related terms from external knowledge sources given a base term pair. Lastly, the weighting phase handles the generation of term weights for each original and expansion term in an effort to fairly place emphasis on terms that truly reflect the original search goal. Each phase is described in greater detail in Sects. 3.1–3.3.

3.1 Query segmentation

3.1.1 Non-compositional phrase detection

Queries are typically made up of compositional and non-compositional phrases (NCPs). NCPs have to be isolated in order to preserve the desired intent of the user query. Among the various types of NCPs that exist within the English language, phrasal verbs, idioms, collocations, proper names and acronyms/abbreviations are of particular interest as they contribute directly towards a search goal.

3.1.2 Concept-role mapping

A query consists of constituents that play the role of either content or function words. Content words (e.g. nouns, verbs, adjectives and adverbs) refer to actions, objects and ideas in the everyday world. Function words (e.g. determiners, auxiliary pronouns, conjunctions and prepositions), on the other hand, express grammatical features like mood and definiteness, and pronouns reference or facilitate grammatical processes like rearrangement, compounding and embedding. Typically, nouns represent the subject of a sentence through names of persons, places, things and ideas whilst verbs are actions which are representative of a predicate. Other constituents such as determiners and adjectives modify nouns, whilst adverbs generally alter verbs. Similarly, prepositions take on a modifying role, acting as adjectives/adverbs, by describing a relationship between words. Conjunctions, on the other hand, connect parts of a sentence or specifically the content words. However, this crude distinction of content and function words based on parts of speech renders all nouns, verbs, adjectives and adverbs as key concepts. Closer scrutiny of queries reveals that content words (e.g. nouns and adjectives) sometimes serve as modifiers and complements which complete the meaning of a query, thus may not necessarily be key concepts. To illustrate, we refer to the example query "*coping with overcrowded prisons*". The parts of speech are identified where "*coping*" is a verb, "*with*" a preposition, "*overcrowded*" an adjective and "prisons", a noun. The content words in this case would be "*coping*", "*overcrowded*" and "*prisons*" whilst "*with*" takes the role of a function word. However, it would be more precise to say that "*prisons*" is the key concept of this query; "*overcrowded*", an adjectival modifier, describes the state of the prisons, whilst the word "*with*" connects both words to reflect the act of dealing with prison conditions. The existence of modifiers and complements indicates that there is a need to further specify the role of the various parts of speech to more accurately capture the intent of a given query for more effective query expansion. It is our postulation that query constituents may be categorized into four types of concepts (which we refer to as *role type* from this point on) that characterize the role of the constituents within a query: (i) concepts-of-interest (*CoIs*) are the key concepts in a query indicative of user intent; (ii) descriptive concepts (*DCs*) describe the key concepts in further detail; (iii) relational concepts (*RCs*) provide the link between query concepts; (iv) structural concepts (*SCs*) are stop words that help form the structure of a query.

A simplistic approach of role type categorization based only on parts of speech would result in the mislabelling of role type. Both adjacent and non-adjacent pairs of concepts should be considered in the concept-role mapping process. Thus, typed dependencies are used to discover links between individual query constituents [11] and consist of three main grammatical relation groupings: auxiliary, argument and modifier. The auxiliary dependencies consist of relations between words which are connected by stop words (e.g. conjunctions). The argument dependencies draw attention to subjects, objects and complements within a sentence. The modifier dependencies highlight several parts of speech-based modifiers (e.g. adjectival and noun compound) which describe and complete the meaning of other constituents in a sentence.

The concept-role mapping process entails two consecutive steps: (1) extraction of grammatical relations between query constituents and determination of *head* (i.e. word upon which everything in a phrase is centred) and *dependent* (i.e. every other word that is associated to the *head*)"; (2) assignment of concept roles depending on the functionality of the constituents linked by the grammatical relations.

All main grammatical relations (55 relations) defined in the Stanford Typed Dependency Scheme [32] are considered in this framework inclusive of auxiliaries, arguments and modifiers, as well as several sub-relations that further specify the main relations. The defined grammatical relations are used to infer the appropriate role-type assignment for query concepts in three categories (e.g. arguments, modifiers and auxiliaries) as shown in Table 1a, b, c.

In some cases, two issues, namely untagged and ambiguous concept-role mapping, may occur depending on the parse output of queries. Query concepts are untagged when the most generic grammatical relation, i.e. undefined (*undef*), is highlighted due to the inability to produce a more precise relation between a pair of terms. A statistical approach making use of the frequency of a concept to determine untagged concept role types is proposed. The frequency of terms can be obtained from Google as it provides the frequency of terms across all indexed documents on the Web. This is in line with most existing approaches of identifying key concepts where the assumption is that frequently occurring concepts are key concepts.

Thus, three rules are derived to handle untagged concepts:

1. if a term is tagged in one of the highlighted grammatical relations, its corresponding role is selected;
2. the term that occurs more frequently is the *CoI,* and the other is a *DC* unless a role has been previously assigned according to the first rule;
3. if both terms are equally frequent, both terms are tagged as *CoIs* unless a role has been previously assigned according to the first rule.

We consider an application of these rules given the example query "*United States control of insider trading*" in Table 2. A parser derives three relations among the query terms, i.e. noun compound modifier (*nn*), undefined (*undef*) and preposition (*prep_of*). The relationship between the terms "*United States*" and "*control*" is undefined (i.e. *undef*). According to the first rule, the term "*control*" is assigned the role-type *DC* from its occurrence in the relation *prep_of*. The term "*United States*" is originally tagged as *U*, which signifies that an appropriate role type was not found. However, upon examination of its frequency in accordance with the second rule, the term "*United States*" is tagged with the role-type *DC*.

Ambiguous concept-role mapping occurs due to the nature of natural language queries in which adjacent and non-adjacent terms can be syntactically or semantically associated. This means that a term can be linked to one or more terms within a query, playing a different

Table 1 Grammatical relations for CR mapping

Grammatical relations	Description	Concept roles	
		Head	Dependent
(a) *Arguments*			
Coordination	Relation between an element of a conjunct and the coordinating conjunction word of the conjunct	CoI	RC
Adjectival complement	Adjectival phrase which functions as the complement	DC	CoI
Clausal complement	Dependent clause with an internal subject which functions like an object of the verb or adjective	DC	CoI
Open clausal complement	Clausal complement without its own subject, whose reference is determined by an external subject	DC	CoI
Complementizer	Word introducing a clausal complement (subordinating conjunction “that” or “whether”)	CoI	RC
Direct object	Noun phrase which is the (accusative) object of the verb in a VP	DC	CoI
Indirect object	Noun phrase which is the (dative) object of the verb in a VP	DC	CoI
Object of a preposition	Head of an NP following the preposition or the adverbs	RC	CoI
Marker	Word introducing an adverbial clausal complement	CoI	RC
Relative	Head word of the WH-phrase introducing a relative clause	CoI	RC
Nominal subject	NP being the syntactic subject of a clause	DC	CoI
Passive nominal subject	NP which is the syntactic subject of a passive clause	DC	CoI
Clausal subject	Clausal syntactic subject of a clause, i.e. the subject is itself a clause	DC	CoI
Clausal passive subject	Clausal syntactic subject of a passive clause	DC	CoI
Expletive	Captures an existential “there”	RC	RC
Prepositional complement	Used when the complement of a preposition is a clause, prepositional phrase or adverbial phrase	RC	RC
Reconjunct	Relation between the head of an NP and a word that appears at the beginning\bracketing a conjunction	CoI	RC
(b) *Modifiers*			
Noun compound modifier	Any noun that serves to modify the head noun	CoI	DC
Adjectival modifier	Any adjectival phrase that serves to modify the meaning of an NP	CoI	DC

Table 1 continued

Grammatical relations	Description	Concept roles	
		Head	Dependent
Prepositional modifier	Any prepositional phrase that serves to modify the meaning of a verb, adjective, noun or another preposition	DC	CoI
Abbreviation modifier	Parenthesized NP that serves to abbreviate an NP	CoI	CoI
Appositional modifier	NP immediately to the right of an initial NP that serves to define or modify it	CoI	CoI
Adverbial clause modifier	Clause modifying a verb (temporal clause, consequence, conditional clause, etc.)	DC	CoI
Purpose clause modifier	Clause headed by “(in order) to” specifying a purpose	DC	CoI
Numeric modifier	Any number phrase that serves to modify the meaning of a noun	CoI	DC
Element of compound number	Part of a number phrase or currency amount	CoI	DC
Possession modifier	Holds between the head of an NP and its possessive determiner or a genitive’s complement	CoI	CoI
Phrasal verb particle	Identifies a phrasal verb, and holds between the verb and its particle	DC	CoI
Parataxis	Relation between the main verb of a clause and other sentential elements, such as a sentential parenthetical, or a clause after a “:” or a “;”	CoI	RC
Punctuation	Used for any piece of punctuation in a clause, if punctuation is being retained in the typed dependencies	CoI	SC
Referent	A referent of the head of an NP is the relative word introducing the relative clause modifying the NP	CoI	RC
Controlling subject	Relation between the head of an open clausal complement and the external subject of that clause	DC	CoI
(c) *Auxiliaries*			
Auxiliary	Non-main verb of a clause, e.g. modal auxiliary, “be” and “have” in a composed tense	CoI	RC
Passive auxiliary	Non-main verb of a clause which contains the passive information	CoI	SC
Copula	Relation between the complement of a copular verb and the copular verb	CoI	RC
Agent	Complement of a passive verb introduced by the preposition “by” and does the action	RC	CoI
Attributive	Complement of a copular verb such as “to be”, “to seem”, “to appear”	RC	RC

Table 1 continued

Grammatical relations	Description	Concept roles	
		Head	Dependent
Conjunction	Relation between 2 elements connected by a coordinating conjunction	CoI	CoI
Determiner	Relation between the head of an NP and its determiner	CoI	SC
Predeterminer	Relation between the head of an NP and a word that precedes and modifies the meaning of the NP determiner	CoI	RC

Table 2 Handling untagged query terms

Relation	Head	Role type	Dependent	Role type
nn	trading	CoI	insider	DC
undef	United_States	U	control	U
prep	control	DC	trading	CoI
prep	of	RC	–	–

role in each partnership. To address this, the role-type tag of the more significant role type is kept. When the contradiction is caused by either preposition or conjunction relation, the role-type tag of any other relation is retained. This is explained by the fact that these relations serve to concatenate terms and as such are assumed to be less significant than other relations. If the contradiction is between the preposition and conjunction relations, the role from the preposition relation is kept because prepositions connect terms that modify one another, whilst conjunctions simply connect two terms. Thus, three rules are derived to handle ambiguous roles:

1. the role-type tag of the more significant role is retained with *CoI* being the most significant role, followed by *DC*, *RC* and lastly *SC*.
2. if the contradiction is caused by conflicting relations, the role-type tag from the relation that has higher priority is retained, where all other relations are prioritized over the preposition and conjunction relations.
3. if the contradiction is between a preposition and a conjunction relation, the role-type tag from the preposition relation is retained where the preposition relation has higher priority than the conjunction relation.

The retention of the more significant role in the second case is illustrated for the query "*Iranian support for Lebanese hostage takers*" processed in Table 3. A parser derives two relations among the query concepts, i.e. adjectival modifier (*amod*) and prepositional modifier (*prep_for*). A contradiction in the role assignment is highlighted with the concept "*support*". The role derived from the relation *amod* (i.e. *CoI*) is then retained rather than the *DC* role type suggested when considering the *prep_for* relation.

To illustrate the process of concept-role mapping, we again refer to the query, "*mild yeast infection*". The linguistic parser returns that "*mild*" is an adjective and "yeast" a noun that both modify the noun "*infection"*. Referring to the set of concept-role assignments, we map each query term to its role, i.e. "*mild*" is a *DC*, "*yeast*" is also a *DC* and "*infection*" a *CoI*.

Table 3 Handling ambiguous concept-role mapping

Relations	Head	Role type	Dependent	Role type
amod	support	CoI	Iranian	DC
amod	hostage_takers	CoI	Lebanese	DC
prep_for	support	DC	hostage_takers	CoI
prep_for	for	SC	–	–

3.2 Extraction

3.2.1 Selection of base terms

Identification of candidate expansion terms for the external language resource-based processing approach of query expansion revolves around determining the pool of related lexical-semantic terms of individual terms in a query. At this point, a question arises as to which terms within a query are of particular importance in the process of expansion. Each term within a query plays a certain role which either exhibits content or function. Thus, blind expansion on terms that do not represent the main content of the query would cause deterioration of retrieval performance. The functionality of each term within a query had been represented using four role types through the concept-role mapping process defined in Sect. 3.1.2. Query terms which reflect the main goal of the query are annotated with the *CoI* and *DC* role types. *CoIs* represent the key concepts in a query, whilst terms labelled with the *DC* role type further specify the main search goal.

Thus, for the purpose of extracting lexical-semantic related terms, only the *CoI* and *DC* role types are used as *base terms*. Query terms which provide links between terms (i.e. the *RC* role type) as well as stop words which form the structure of the query (i.e. the *SC* role type) are not considered in the term pooling process. The constraint imposed on the terms to be selected as base terms is due to the nature of terms labelled based on the basic role types. *CoIs* and *DCs* are open-class words which represent content such as nouns, verbs (transitive and intransitive) and adjectives. The open-class words category is represented in the form of ontologies consisting of hierarchical, equivalence and associative relations among the terms. This would mean that *CoI*s and *DC*s, which represent the main search goal, are easily expandable through the traversal of ontologies. The set of term associations defined within the ontology model the multiple terms that form the topic of interest in a related document. On the other hand, *RC*s and *SC*s belong to the closed-class words category which consists of stop words such as determiners, conjunctions and prepositions. Modals (e.g. can, will and may), auxiliary verbs (e.g. be, have and do) as well as adverbs are also labelled as *RC*s or *SC*s. These groups of function words are not accepted as base terms as they do not possess semantic associations with other terms and are not representative of the search goal. The terms "*coping", "overcrowded"* and *"prisons"* are, respectively, annotated as *DC*, *DC* and *CoI,* whilst the preposition "*with*" is labelled as an *RC* in the example query "*coping with overcrowded prisons*". Hence, although the query consists of four terms, only three of them are adopted as base terms for the term pooling process.

3.2.2 Disambiguation of word senses for accurate term pooling

The identified base terms are central to the lexical-semantic term pooling process. They indeed are the only query terms which are expanded as they are the only components of the

Table 4 Possible related terms for the polysemous term *"Java"*

Term	Meaning	Related terms
Java	An Indonesian island	land, dry land
Java	A caffeinated beverage	beverage, drink, food, nutrient
Java	A programming language	object-oriented, artificial language

query which represent the search goals. However, each base term is prone to polysemy, a likely occurrence in natural language. This presents a problem in the term pooling process because polysemous terms have multiple meanings with variations found in and across the different parts of speech and as such leading to a different set of candidate expansion terms. For example, the polysemous term "*Java*" has three distinct sets of related terms in accordance with its intended meaning in a given context (cf. Table 4). If the wrong meaning of the term is assumed in the term pooling process, the expansion process would have caused a serious query drift. Therefore, all base terms should be disambiguated prior to extracting candidate expansion terms.

The word sense disambiguation (WSD) process consists of two essential steps: i) the determination of all the different senses for every word relevant to a term and ii) methods to assign the appropriate sense to a given term within a particular context.

The disambiguation technique applied for the lexical-semantic related term pooling process is the knowledge-based WSD for two main reasons. Firstly, this choice is based on the observation that when there are larger amounts of structure knowledge, WSD performance improves [12]. Secondly, although some may argue that knowledge sources such as ontologies are plagued by the data sparseness issue, there is a significant body of work aimed at the expansion of knowledge sources (e.g. [28–30]. The *all-words* disambiguation approach is most suited here as the base terms are usually open-class words, and each query typically contains multiple *CoI*/*DC* labelled base terms. The semantic distance between query terms must be computed in order to annotate a term with its correct sense within a given query context. In line with the chosen mode of knowledge-based WSD, similarity measures which are based on lexical resources are considered in this work. The relatedness measures available for knowledge-based disambiguation are commonly achieved through the representation of ontologies as a graph followed by the computation of relatedness from a path between two terms. On the other hand, the *gloss-based* disambiguation method quantifies the number of common words or phrases identified as overlaps between term definitions. Whilst both approaches have been applied on two prominent knowledge sources, WordNet and Wikipedia, a more significant amount of research has been focused on WordNet. Although Wikipedia is gaining prominence due to its ability to provide larger coverage, WordNet remains the preferred knowledge source for disambiguation [16]. The motivation behind this choice is the manual crafting of the WordNet ontology which lends greatly to the assurance of correctness in the annotation [23] and organization of explicit taxonomic relationships required in the term pooling process described next.

3.2.3 Term pooling

A document discussing a particular topic is likely to contain terms which are lexically or semantically related. Classical lexical-semantic relations are term relationships which are hierarchical, equivalent or associative as shown in Fig. 3.

Equivalence is recognized between terms which have similar meaning, whilst associative relationships link related-to/associated terms of a particular topic. Hierarchical term rela-

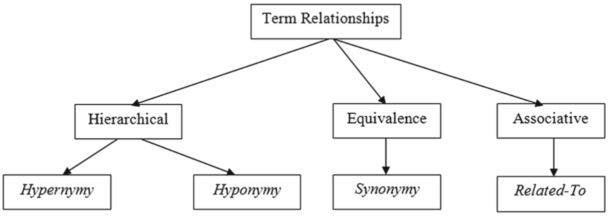


Fig. 3 Organization of lexical-semantic term relationships

tionships denote broader-to-narrower term relationships organized within multiple levels of superordination and subordination. The generic hierarchical relationship is the *is-a* link which connects a class and its members. Among the multiple existing lexical-semantic term relationships, the synonymy, hypernymy, hyponymy and *related-to* associations are considered in the term pooling process.

The sense disambiguated base terms are expanded through the extraction of lexical-semantic related terms. Since each term relationship denotes varying associations with one another, they cause redirection of the search goal in a very distinct manner. For example, the expansion of a term (e.g. "car") with its hypernym (e.g. "automobile") broadens the search, whilst the inclusion of its hyponym (e.g. "Ford") focuses the search results to a narrower scope. The further the hierarchy is traversed up or down, the further the results are specialized or generalized. Combining the terms from these varying relations would be conflicting. As such, the candidate expansion terms are pooled separately to avoid mixed redirection of the search goal. Since related terms are extracted for all base terms for each query, multiple occurrences of identical expansion candidate terms are bound to occur which are duly filtered.

All levels in a hierarchy of each relation are traversed during the extraction process, and the corresponding synonyms of each hypernym, hyponym and coordinate terms (which represent *related-to* associations between terms) are also retrieved from the WordNet ontology for optimal coverage. The semantic relatedness between the original queries and the related terms is then computed based on the Adapted Lesk [42] which is a gloss-based semantic relatedness measure. In cases where the accurate sense of a candidate expansion term cannot be determined, the most frequent sense of the term is assumed based on the first sense heuristics. In order to estimate the global relatedness of a candidate term to the entire query, the average relatedness is computed between each candidate expansion term and all original terms. However, the number of optimal terms to be included in the expanded query is empirically determined.

3.3 Concept weighting

The usefulness of a term within a query is not always determined solely by its functionality. Rather, retrieval performance is greatly enhanced by the inclusion of crucial terms where the common theme among the global pool of terms significantly impacts the query retrieval effectiveness. Intuitively it may be assumed that *CoIs* and *DCs* are more important than *RCs* and *SCs*, this assumption may not always hold true depending on the collective theme of the query terms. Thus, a technique that can randomly vary the term weights to optimize performance of a query is formalized through the use of a genetic algorithm (GA) formulation. GA is utilized to estimate the weights for each role type given a query for which the mean average precision (MAP) of retrieval is optimized. At this point, a fifth role type is introduced to characterize generated expansion concepts (*EC*). The GA optimization consists of the following: (1) initialization of the population of chromosomes and elements encoding potential solutions that consist of five genes representing each role type; (2) implementation of a fitness function for evaluating each potential solution where the performance measure is based on the maximum MAP; (3) selection of the fittest individual of the current population (i.e. corresponding to the maximum MAP) which is used for reproduction. The parameters and optimal rates utilized in the GA implementation are determined through a tuning phase by varying the parameters on a training set of 50 queries until a steady state of optimized retrieval performance is achieved. Role-type weights are generated for 4 out of 5 role types identified, i.e. *CoI*, *DC*, *RC* and *EC*, with a boundary condition set to restrict weights within a 0–1 weight range. The *SC* role type is enforced with a null weight in order to eliminate emphasis on common terms. The global role-type weights are generated at each iteration and used on each query. Population is evolved for an optimal number of iterations as a terminating condition. Random perturbations to the population of chromosomes are inflicted through the process of mutation and crossover. Concept scores for the example query "*mild yeast infection*" are given in Fig. 2.

4 Algorithmic instantiation

4.1 Query segmentation

The algorithm below summarizes the implementation of the query segmentation module:

```
Input: Q ← The set of web queries
for all q in Q do
  ArrayList Concepts=breakQueriesIntoConcepts()
  String[] NCPList = getNCPList()
  if q is in NCPList
    Format query to highlight NCPs
  ArrayList RCP = getRelation&ConceptPairs()
  for all rcp in RCP do
    Assign role-type tag to each concept pair
    for all c in Concepts do
      ArrayList RTCP=getRelation&TaggedConceptPairs()
      for all rtcp in RTCP do
        String[] ConceptTag = getConceptTags()
        for all ct in ConceptTag do
          if ct is "untagged"
            Resolve according to 2 cases
              Case 1: Frequency Dependence
              Case 2: Inheritance Dependence
          if ct is "ambiguous"
            Resolve based on Ranked Relations
        end for
      end for
    end for
  end for
end for
```

As far as NCP detection is concerned, the queries are compared against the *NCPList,* a knowledge base of NCPs which was built by compiling all such phrases from multiple sources such as ontologies (e.g. WordNet) and standard lists found on the Web. If a query is in *NCPList,* it has to be appropriately formatted to ensure accurate parse trees are generated from the parser. In the case of the linguistic parser, the components of the NCPs are joined with the "underscore" to represent the phrase as one unit. Proper names are capitalized and front slashes (/) substituted with the word "or". Hyphenated and bracketed words are retained, whilst double quotes are dropped and replaced by underscores to encase the terms. Acronyms are resolved into their full form.

For the concept-role mapping process, the fifty-five grammatical relations listed in Table 1 are considered inclusive of auxiliaries, arguments, modifiers and complements, extracted by the NLP parser. These grammatical relations capture semantic associations among adjacent and non-adjacent query constituents and are used to determine role types of the query terms. Each query concept pair in the parse output, *RCP,* is tagged based on the set of predefined role-type assignment that considers its functionality and detailed in Sect. 4.1. All concepts of a query are examined to determine whether there exist untagged or ambiguous concept-role mappings. As detailed in Sect. 3.1.2, untagged query concepts occur when the most generic grammatical relation (the *dependent* relation) is formed due to an inability to define a more precise relation within the relational hierarchy. A statistical approach capitalizing on the frequency of a concept is used to determine untagged concept role types. The *Frequency Dependence* Case in handling untagged concepts in the *ConceptTag* structure is based on the two rules provided in Sect. 3.1.2: (1) the concept that occurs more frequently is the *CoI,* and the other is a *DC*; (2) if both concepts are equally frequent, both concepts are tagged as *CoIs*. Lastly, an *Inheritance Dependence* rule is used based on the fact that if a concept is tagged in one of the defined relations, the untagged concept inherits the concept role. As also described in Sect. 3.1.2, ambiguous concept-role mapping occurs due to the nature of natural language queries in which adjacent and non-adjacent concepts may be syntactically or semantically associated. A *Ranked Relations* rule is defined to handle ambiguous concepts in the *ConceptTag* structure where the tag of the more significant role is retained according to the rules presented in Sect. 3.1.2.

4.2 Expansion concept extraction:

The lexical-semantic term pooling process is summarized in the algorithm below:

```
Input: Q ← The set of Web queries
for all q in Q do
    for all query terms in query do
        Determine correct sense of term through the disambiguation process
        Select base terms that are annotated as either CoIs or DCs
    end for
for all significant base terms (p) in query (q) do
    for each selected lexical-semantic relation(r)
        if r is synonymy
            Extract all synonyms
        if r is hypernymy
            Extract all hypernyms and their corresponding synonyms
        if r is hyponymy
            Extract all hyponyms and their corresponding synonyms
        if r is related-To
            Extract all related-To terms and their corresponding synonyms
    end for
    for each selected lexical-semantic relation pool (p_r)
        Identify multiple occurrences of identical terms, retain a single entry
        Compute semantic distance between each candidate term and all initial query terms
        Sort all candidate terms in descending order of semantic relatedness
    end for
end for
```

Sense disambiguation is performed to determine the correct meaning of a given term within the context of a query. For this purpose, a knowledge-based WSD technique is employed where overlaps within the definitions of two query terms are quantified via the Adapted Lesk semantic relatedness measure [3]. The set of base terms which will be used in the expansion term extraction process is then established based on the role type of the query terms. Among all role types, only terms which are annotated as *CoIs* and *DCs* are tagged as base terms. Candidate expansion terms are extracted into separate global pools consisting of extracted related terms from the four lexical-semantic term relationships (i.e. synonymy, hypernymy, hyponymy and *related-to*). All levels of the WordNet ontology are traversed to extract all relevant terms for each base term of a given query. The corresponding synonyms of each hypernym, hyponym and coordinate term are also included in the four global pools created. Each pool is then filtered to remove redundant candidate expansion terms generated for a single query. The semantic relatedness is computed to assess the global relatedness of a candidate expansion term to all original query terms, and final pool of candidate terms is sorted in descending order.

4.3 Concept weighting

The algorithm below describes the implementation of the concept weighting module:

```
Input: Q ← The set of Web queries
for all q in Q do
  InitializationOfGAParameters();
  String [ ] roleWeights = getGeneratedWeights()
  while (iterationNum != maxNumIterations) do
    Build input file for retrieval with generated weights
    tempMAP = getMAPfromToolkitOutputFile();
    if (tempMAP > maxMAP)
      Replace maxAP value with new MAP value
end for
```

Role-type scores are predicted and optimized through the use of a GA and begins with the *InitializationOfGAParameters* method. The GA implementation for maximization of MAP includes the mutation and crossover genetic operators which are set at a rate of 10 and 1000, respectively. Role-type weights are generated for 4 out of 5 role types identified (i.e. *CoI*, *DC*, *RC* and *EC*) with a boundary condition set to restrict weights within the [0,1] interval. The *SC* role type is enforced with a weight of 0 to eliminate emphasis on general concepts as described earlier. A population of 200 chromosomes representing the role-type weights is evolved over 100 iterations and serves as a termination condition. The mutation and crossover reproduction genetic operators are empirically set at a rate of 10 and 1000, respectively, for maximum performance. The set of *role*W*eights* generated are used in building the required input for the retrieval process via the Lemur Toolkit. Upon completion of the retrieval, *tempMAP* is assigned the MAP value of the query obtained from the toolkit output file. If at any iteration the *tempMAP* value exceeds that of the *maxMAP* established in earlier iterations, the *maxMAP* value is updated with the new higher *MAP* value. The fitness value is used as a basis in the fitness proportionate selection method where a roulette-wheel selection technique is employed for choosing the chromosomes with high fitness value for reproduction and propagation to subsequent evolutions. The fitness value of each chromosome is boosted based on the overall MAP generated with the highest boost given to the highest MAP (above 0.5) across all iterations. The fitness value is also used to determine the appropriate number of iterations as the termination condition to limit the execution time. Upon determining the termination condition, the GA runs are executed for all queries.

5 Evaluation

In this section, we introduce the test collections, detail the language-based processing experimental setup, introduce the compared frameworks and then present the retrieval results. We conclude the section with a discussion of the obtained results.

5.1 Test collections

The framework is tested on the Text REtrieval Conference (TREC) ad hoc test collections: Tipster Disc 1&2 consisting of documents from the Wall Street Journal (WSJ), Associated Press (AP), Federal Register (FR), Department of Energy (DOE) and Computer Select as well as GOV2 (.gov sites). These test collections were created as part of a text research project evaluation test bed by the National Institute of Standards and Technology (NIST). The collections used in this experiment range in size between 74,520 documents to 25,114,919

Table 5 Summary of TREC collections & topics

Dataset	# Docs	Topics	TREC
WSJ90_92	74,520	51–100	1
AP88-90	242,918	51–100	1
SJM1991	90,257	51–100	1
WSJ87_92	173,252	151–200	3
AP88_89	164,597	151–200	3
Disc 4&5	489,164	401–450	8
GOV2	25,114,919	751–800	Terabyte 2005

<top>

<num> Number: 151

<title> Topic: Coping with overcrowded prisons

<desc> Description:

The document will provide information on jail and prison overcrowding and how inmates are forced to cope with those conditions; or it will reveal plans to relieve the overcrowded condition.

<narr> Narrative:

A relevant document will describe scenes of overcrowding that have become all too common in jails and prisons around the country. The document will identify how inmates are forced to cope with those overcrowded conditions, and/or what the Correctional System is doing, or planning to do, to alleviate the crowded condition.

</top>

Fig. 4 Sample TREC topic "*coping with overcrowded prisons*"

documents (Table 5). For the purpose of evaluation, the datasets were sorted according to size and grouped as small (up to 100,000 documents), medium (above 100,000 documents and below 250,000 documents) and large (above 250,000 documents). This organization of dataset sizes was determined based on the average size of Tipster datasets (approximately 205,785 documents) and the largest dataset (i.e. GOV2) used in this publication. The TREC ad hoc test topics consist of title and description fields which represent information needs (cf. Fig. 4). In this study, the *title* field of the TREC 1, 3, 8 and Terabyte 2005 evaluation suites of the ad hoc retrieval test topics are examined. These query sets were chosen for their varying lengths and applicability to differing collection sizes. Each of these TREC evaluation suites consists of 50 topics (cf. Table 5).

Each topic has an associated set of binary judgments to indicate whether a document is relevant or irrelevant. These relevance judgments are used to assess the performance of the framework based on the number of relevant documents which are successfully retrieved.

5.2 Extrinsic language-based processing setup

Grammatical relations are identified between query terms using the Stanford Parser (v1.6.8) and the role types assigned as explained in Sect. 3.1. Incorporating lexical-semantic relations within the final expanded query requires several steps as defined in Sect. 3.2. Query terms that should be expanded are chosen on the basis of their functionality where terms annotated with the role types *CoI* or *DC* were selected as base terms to be expanded. The WordNet ontology is adopted as the knowledge source for external knowledge-based processing as it provides an organized database of lexical-semantic relations and it is also recognized as the preferred knowledge source for the WSD process [55]. WordNet consists of groups of terms arranged within synsets (bound by the lexical relation, synonym). Each synset is then linked to the corresponding semantically related synsets forming four separate hierarchies for each open-class part of speech noun, verb, adjective and adverb.

Disambiguation of polysemous terms was handled by the *WordNet::SenseRelate::AllWords (SR-AW)* tool. SR-AW determines the accurate sense of a given base term by considering a measure of relatedness between terms within a predetermined context window size. [41] showed that the performance of the Adapted Lesk [3] was superior to other relatedness measures based on an ontological hierarchy. The Adapted Lesk method was also selected as it crosses parts-of-speech boundaries in the computation of relatedness as differing parts of speech are common among query terms. Therefore, this semantic relatedness measure was used for disambiguation within a default context window of size 3. The tool accepts three types of input: raw, tagged (Penn Treebank tags which are automatically reduced to the four basic parts of speech, i.e. noun, verb, adjective and adverb) and the wnTagged (only the four basic POS as assigned by WordNet). The set of queries previously tagged with their parts of speech by the Stanford NLP parser is fed to SR-AW via its Tagged input option to maintain consistency of the linguistic processes within the framework. Terms which are labelled with the suffixes #ND (i.e. term does not exist in WordNet), #NR (i.e. term is not related to surrounding terms), #o (i.e. closed-class terms), #IT (i.e. invalid tag), #MW (i.e. missing term) are ignored during the disambiguation process. The most significant impact to the disambiguation process is caused by the #ND and #NR suffixes which were predominantly found in the WSD results. Very often these suffixes are tagged to compound words, nouns and adjectives which are typically base terms used for expansion. A large number of such occurrences would cause the accuracy of the disambiguation process to be significantly reduced.

The #ND tag occurs under several conditions such as: (1) unrecognized NCPs and missing terms, (2) inaccurate stemming and (3) misclassified stop words. Unrecognized NCPs include not only missing NCPs due to the sparseness of NCPs within WordNet but also user-formed compound terms (e.g. US-USSR). It is beyond the scope of this paper to compensate for the sparseness of the ontology. The inaccurately stemmed terms issue was resolved with manual intervention to correct the root term to match the stem found within WordNet. Misclassified stop words are also sometimes tagged as #ND, and this was handled by modifying the list of closed-class words recognized by the SR-AW to include all possible stop words. Since the number of remaining #ND tags after the issues were fixed was only about two to nine #ND tagged terms in each set of 50 queries, these terms were left unexpanded.

In the case of #NR tagged terms, terms could not be disambiguated due to a lack of relatedness to their surrounding terms. Varying the disambiguation window sizes showed that window size 2 resulted in a much larger number of #NR tags. There is no change in the number of #NR tags when utilizing windows sized 4 and 5. Here, the first sense of the term was assumed to be the correct sense. Through the extraction process defined in Sects. 3.2 and 4.2, four global pools of lexical-semantic related terms are created for synonyms, hypernyms, hyponyms and coordinate terms. Breadth and depth of the WordNet ontology hierarchy are traversed to extract all relevant terms for each base term of a given query. The global relatedness of a candidate expansion term was then determined through a computation of average relatedness between each candidate expansion term and all base terms of a query in each pool using the Adapted Lesk semantic relatedness measure. This resulted in a ranked set of candidate expansion terms for each lexical-semantic related term pool. Morphological variants of terms were identified by stemming all candidate terms according to Porter's Stemming Algorithm [44].

The optimal number of expansion terms to be included is determined based on the findings of [18]. An exploratory study to determine optimal thesauri-based query expansion processing methods in automatic and interactive environments was carried out with real users and real queries. The author reports the number of expansion terms selected by users for each lexical-semantic relation, similar to those considered in this paper, ranges between 0.8 and 6.5 terms.

5.3 Retrieval evaluation

To assess the performance of the proposed framework, it should experimentally be compared against recent research efforts in the field. However, the inconsistencies in the empirical setups of state-of-the-art frameworks prevent a fair comparison. It is acknowledged that the accepted de-facto standard for comparison is the unigram language model (LM) [43] and relevance model (RM) [24]. An analysis of state-of-the-art works by [9] highlights large differences of baseline MAP results reported even on identical test sets. Accordingly, although the test collections are similar as far as queries processed and document set size are concerned, the produced baseline results are often different. The performance of the proposed technique cannot therefore be assessed by comparison against the absolute MAPs achieved in existing research. Therefore, in line with the practice of state-of-the-art research work, we examine the performance of our Language Resource-Based Query Expansion (LRBQE) framework by comparing against LM and RM. LRBQE is itself declined into four experimental variants: LRBQE_Syn, LRBQE_Hyper, LRBQE_Hypo and LRBQE_CT, corresponding to the coupled application of the intrinsic linguistic techniques with the spawning and integration of ontology-produced synonyms, hypernyms, hyponyms and coordinate terms, respectively. The LM implementation produces the baseline results of the original queries without any modification. The RM performance itself translates the baseline performance of the state-of-the-art pseudo relevance feedback technique which considers the top n frequently occurring terms obtained from the top k documents returned for an initial query. A comparison is also made with a dependence-based query expansion (DQE) technique where base pairs are formed based on the notion of term dependencies [20], specifically sequential dependence where dependence is assumed to exist between adjacent query terms [2]. The expanded query consists of original and expansion concepts weighted via GA.

As far as the evaluation metric is concerned, MAP is considered for analysing the effectiveness of the compared frameworks similar to current research. MAP is the mean of the average precision scores for each query within the examined query pool. The paired *t*-test with 95% confidence level ($p < 0.05$) is performed to determine the statistical significance of differences in performance of the compared frameworks.

Table 6 Performance of LRBQE_Syn in retrieval tasks

Query No.	Dataset	LM	RM	DQE	LRBQE_Syn
51–100	WSJ90-92	0.1874	0.2011	0.2178	$0.2299^{\alpha\beta\gamma}$
	AP88-90	0.1979	0.2482	0.2314	$0.2558^{\alpha\beta\gamma}$
	SJM1991	0.1463	0.1658	0.1741	$0.1915^{\alpha\beta\gamma}$
151–200	WSJ87-92	0.2352	0.2874	0.2873	$0.3357^{\alpha\beta\gamma}$
	AP88-89	0.2575	0.3252	0.3063	$0.3558^{\alpha\beta\gamma}$
401–450	Disc 4-5	0.1926	0.2149	0.2124	$0.2281^{\alpha\beta\gamma}$
751–800	GOV2	0.2944	0.3063	0.3221	$0.34^{\alpha\beta\gamma}$

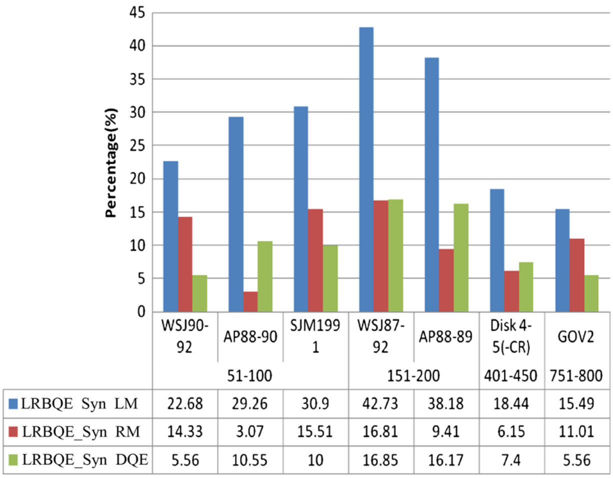


Fig. 5 Relative performance of the LRBQE_Syn variant

5.4 Results

5.4.1 Effect of using synonyms as expansion terms

The results of incorporating synonyms in the final expanded query are shown in Table 6. Statistically significant improvements in MAP over the baseline LM, RM and DQE are indicated by the symbols α, β and γ, respectively. Relative improvements in MAP are indicated in Fig. 5.

The inclusion of synonyms in the final expanded query results in increased retrieval performance across all datasets over baselines, LM and RM. The observable relative improvements range between 3.1 and 16.8% over LM, whilst a larger range of improvements were observed between 15.5 and 43% over RM.

Statistical significance is observed across all variations and datasets. These statistically significant improvements in retrieval performance are expected in line with the hypothesis that one of the leading causes of poor retrieval is the mismatch in the vocabulary chosen where varying terms are used to represent a single need. Also, expansion using synonyms results in relative improvements in MAP ranging from 5.56 to 16.85% across all datasets when

Table 7 Performance of LRBQE_Hyper in retrieval tasks

Query No.	Dataset	LM	RM	DQE	LRBQE_Hyper
51–100	WSJ90-92	0.1874	0.2011	0.2178	$0.2184^{\alpha\beta}$
	AP88-90	0.1979	0.2482	0.2314	$0.255^{\alpha\beta\gamma}$
	SJM1991	0.1463	0.1658	0.1741	$0.1853^{\alpha\beta\gamma}$
151–200	WSJ87-92	0.2352	0.2874	0.2873	$0.3404^{\alpha\beta\gamma}$
	AP88-89	0.2575	0.3252	0.3063	$0.331^{\alpha\beta\gamma}$
401–450	Disc 4-5	0.1926	0.2149	0.2124	$0.222^{\alpha\beta\gamma}$
751–800	GOV2	0.2944	0.3063	0.3221	$0.3304^{\alpha\beta\gamma}$

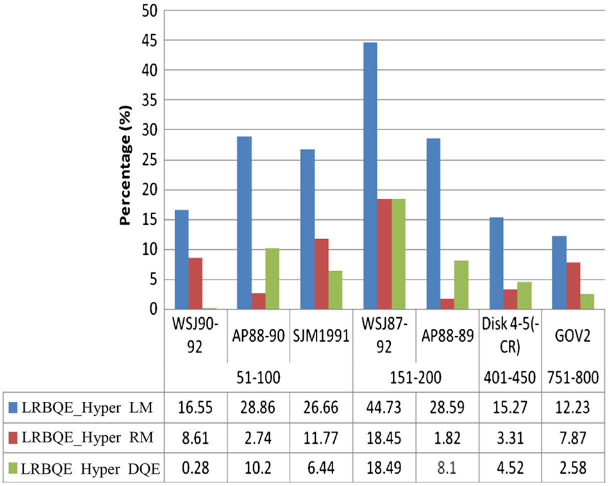


Fig. 6 Relative performance of the LRBQE_Hyper variant

compared with the performance of DQE. The improvements reported for all experimental variations are statistically significant.

5.4.2 Effect of using hypernyms as expansion terms

Retrieval performance achieved through the inclusion of hypernyms in the final expanded query is shown in Table 7.

Statistically significant improvements in MAP over LM, RM and DQE are indicated by the symbols α, β and γ. The relative improvements in MAP are indicated in Fig. 6. The expansion of queries using hypernyms resulted in increased retrieval performance across all datasets over baselines, LM and RM.

The increase in MAP ranges between 12.2 and 44.7% over LM, whilst the range of improvements observed over RM was between 1.8 and 18.5%. These improvements in retrieval performance were all statistically significant across all variations and datasets. The LRBQE_Hyper variant also shows relative improvements across all experimental variations when compared to the DQE model where the improvements on six of the seven experimental variations are statistically significant. This reaffirms the method of hypernym selection

Table 8 Performance of LRBQE_Hypo in retrieval tasks

Query No.	Dataset	LM	RM	DQE	LRBQE_Hypo
51–100	WSJ90-92	0.1874	0.2011	0.2178	$0.2164^{\alpha\beta}$
	AP88-90	0.1979	0.2482	0.2314	0.2322^{α}
	SJM1991	0.1463	0.1658	0.1741	$0.1778^{\alpha\beta\gamma}$
151–200	WSJ87-92	0.2352	0.2874	0.2873	$0.328^{\alpha\beta\gamma}$
	AP88-89	0.2575	0.3252	0.3063	$0.3125^{\alpha\gamma}$
401–450	Disc 4-5	0.1926	0.2149	0.2124	$0.215^{\alpha\gamma}$
751–800	GOV2	0.2944	0.3063	0.3221	$0.3145^{\alpha\beta}$

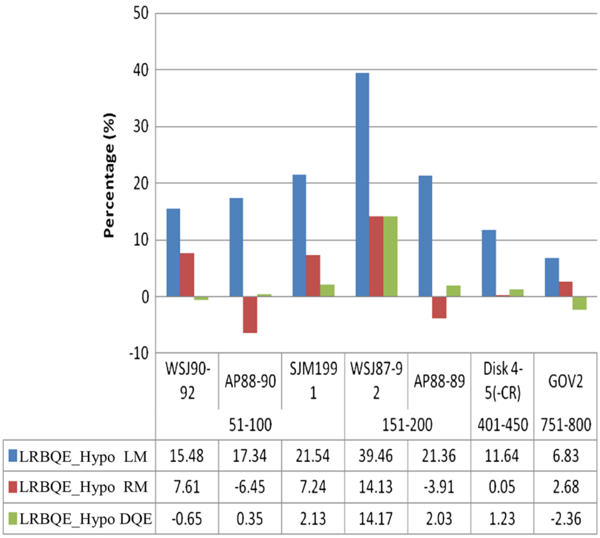


Fig. 7 Relative performance of the LRBQE_Hypo variant

used where the final expanded query is formulated with expansion terms that have the Top 5 highest global relation to all original query terms.

5.4.3 Effect of using hyponyms as expansion terms

Retrieval performance achieved through the inclusion of hyponyms in the final expanded query is shown in Table 8.

Statistically significant improvements in MAP over LM, RM and DQE are indicated by the symbols α, β and γ. The relative improvements in MAP are indicated in Fig. 7.

The use of hyponyms within the final expanded queries revealed a mixed outcome in terms of the achieved MAP. Overall, improvement in retrieval performance is observed over LM between 6.8 and 39.4%, whilst changes in MAP over RM are both positive and negative. Deterioration in retrieval performance compared to RM is seen in two cases: datasets AP88-90 and AP88-89, whilst all other cases show improvement in retrieval performance averaging at 6.3%. When compared against DQE, relative improvements in retrieval performance average at 4% with four of the experiments being statistically significant. Also, deterioration in retrieval performance is observed on two datasets: WSJ90_92 and GOV2. The

Table 9 Performance of LRBQE_CT in retrieval tasks

Query No	Dataset	LM	RM	DQE	LRBQE_CT
51–100	WSJ90-92	0.1874	0.2011	0.2178	$0.2171^{\alpha\beta}$
	AP88-90	0.1979	0.2482	0.2314	$0.2346^{\alpha\gamma}$
	SJM1991	0.1463	0.1658	0.1741	$0.1751^{\alpha\beta}$
151–200	WSJ87-92	0.2352	0.2874	0.2873	$0.3327^{\alpha\beta\gamma}$
	AP88-89	0.2575	0.3252	0.3063	$0.3097^{\alpha\gamma}$
401–450	Disc 4-5	0.1926	0.2149	0.2124	0.2145^{α}
751–800	GOV2	0.2944	0.3063	0.3221	$0.329^{\alpha\beta\gamma}$

modest improvement in retrieval performance and in some cases deterioration is attributed to the fact that query terms may possess more than one hyponym. The problem with having multiple hyponyms is related to the meaning of hyponym-type terms. Given that there may be several base terms used in the extraction process for a single query, there may also be multiple hyponyms for each query term. This issue cannot be easily resolved when dealing with automated query expansion as it is not possible to predict which of the many hyponyms may be of interest to a user. Improvement in retrieval performance may be observed in cases where the number of hyponyms related to a given base term is limited.

5.4.4 Effect of using coordinate terms as expansion terms

Retrieval performance achieved through the inclusion of coordinate terms in the final expanded query is shown in Table 9.

Statistically significant improvements in retrieval over LM, RM and DQE are indicated by the symbols α, β and γ, respectively, and relative improvements in MAP are indicated in Fig. 8. The inclusion of coordinate terms in the expansion process has resulted in some improvements as well as deterioration in retrieval performance across the datasets. Significant

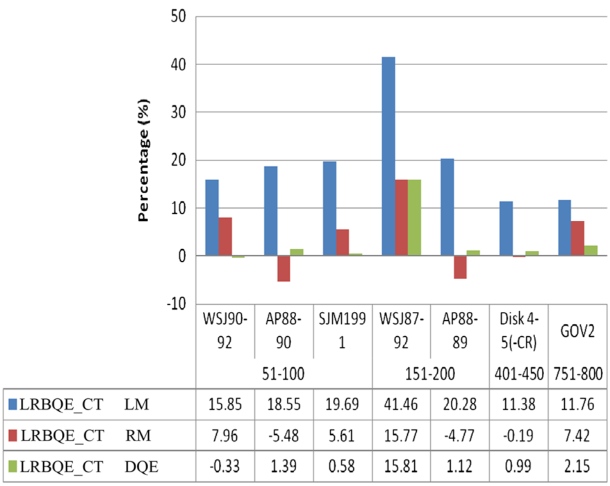


Fig. 8 Relative performance of the LRBQE_CT variant

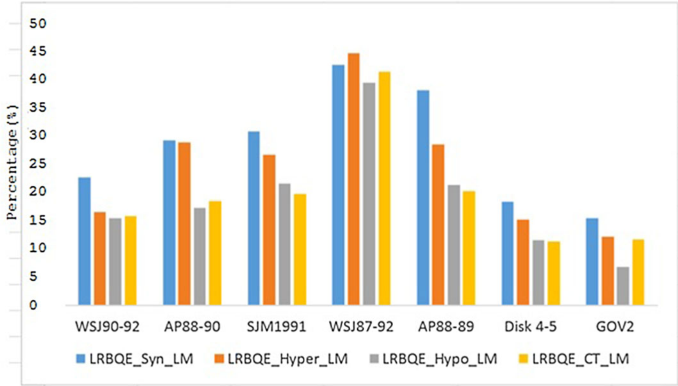


Fig. 9 Performance of lexical-semantic QE variations over LM

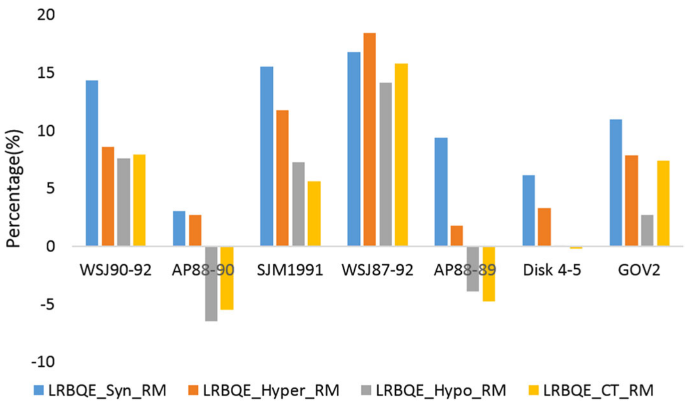


Fig. 10 Performance of lexical-semantic QE variations over RM

improvements are observed over LM within the range of 11.4–41.5%. Even though some improvements are observed on certain datasets, three tests showed deterioration over RM. When comparing with DQE, statistically significant improvements are only observed on four datasets with significant relative improvements averaging at 5%. Similarly to the impact of including hyponyms in the expanded queries, the use of coordinate terms results in the retrieval of irrelevant documents. The pool of terms considered in this form of expansion allows representing different aspects of a particular topic. This proves to be a difficult problem to resolve due to the inability to determine a user's possible preference in reformulation for an automated query expansion process. It may be possible to infer possible directions of reformulation by coupling the expansion process with personalization techniques examining users' search behaviour.

5.5 Discussion

Figures 9, 10 and 11 show the performance improvement of the 4 lexical-semantic QE variations (i.e. synonym, hypernym, hyponym and coordinate terms) over baseline systems LM, RM and DQE.

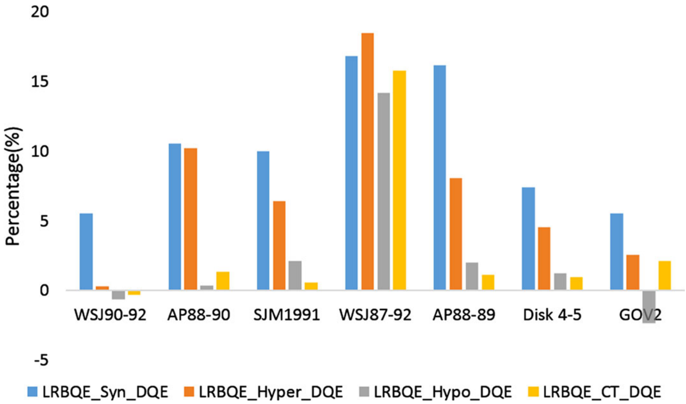
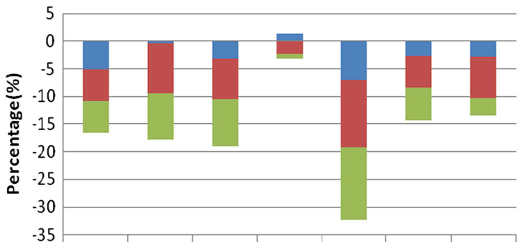


Fig. 11 Performance of lexical-semantic QE variations over DQE



	WSJ90-92	AP88-90	SJM1991	WSJ87-92	AP88-89	Disk 4-5	GOV2
		51-100		151-200		401-450	751-800
CoordTerms_Syn	-5.6	-8.3	-8.6	-0.9	-13	-6	-3.2
Hypo_Syn	-5.9	-9.2	-7.2	-2.3	-12.2	-5.7	-7.5
Hyper_Syn	-5	-0.3	-3.2	1.4	-7	-2.7	-2.8

Fig. 12 Relative performance of language resource-based expansion compared to LRBQE_Syn

It is observed that the addition of lexical-semantic relations independently has shown significant improvements over the LM and RM frameworks, especially for expansion with synonyms and hypernyms, answering one of the research issues on the usefulness of incorporating indirectly related terms in an expanded query. The improvements in MAP observed also validate the issue related to the use of lexical ontologies as a source of expansion terms. The LRBQE_Syn and LRBQE_Hyper empirical variants returned the largest range of increase over the baselines with most improvements being statistically significant. In the case of hyponyms (LRBQE_Hypo) and coordinate terms (LRBQE_CT), both increase and decrease in MAP were observed on specific datasets with the latter displaying more performance deterioration.

Since expansion using synonyms (LRBQE_Syn) is the most generic form of lexical-semantic relation-based expansion where the search goal is not altered by the process of expansion, the highest MAP is obtained in comparison with the expansion with hypernyms, hyponyms and coordinate terms. The three other variations deteriorate compared to LRBQE_Syn (cf. Fig. 12). The LRBQE_Hyper variant shows an insignificant 1.4% increase on the WSJ87_92 dataset, and a range of 0.3–7% decrease in MAP; LRBQE_Hypo shows negative change in MAP ranging between − 2.3 and − 12.2%; LRBQE_CT shows 0.9–13% drop in MAP, across all datasets.

Among the four best performing research frameworks highlighted by [9], only [26] is an extrinsic knowledge-based processing technique. Despite having used the same Disc 4&5 data collection as in our experiments, the exact query set examined was not clearly specified thus causing it to be not directly comparable. In the work of [8] previously discussed, a link model is proposed that considers three semantic relations, namely synonymy, hypernymy and hyponymy. The equivalent dataset found in [8] is the examination of topics 51-100 on the WSJ90_92, AP88_90 and SJM1991 datasets. In their work, relative improvements in MAP over the baseline LM model are reported between 5 and 11%. In the work of [13] relative improvements of about 16% are seen over baseline RM. Comparatively, the four LRBQE methods proposed in this paper show a larger increment in retrieval performance ranging between 17 and 30%. The large difference in retrieval performance is attributed to the fact that in the work of [8], the link model combines the contradicting hypernymy and hyponymy relations.

Regarding the drawbacks of using ontologies for query expansion, a noticeable limitation of WordNet is the limited coverage of concepts and phrases within the ontology. Query expansion via other external sources such as Wikipedia and search logs is of particular interest to fill the gaps of the WordNet ontology, if not replace it. This paper hypothesizes that extrinsic language resource-based query expansion would benefit most in the case where multiple sources are utilized in the concept generation process. This is because ontologies such as WordNet provide semantically related expansion concepts, whilst other corpus-based external sources rely on concept proximity to determine concept relatedness. This ensures that both direct and indirect links to a document are captured in the process of query expansion.

6 Conclusion

In this paper, we proposed a query expansion framework making use of intrinsic linguistic analysis to highlight the role of query concepts. Additionally, the use of an extrinsic knowledge-based resource made it possible to spawn concepts semantically coherent with the query content. In line with our postulation that grammatical pairing of query concepts, assessing the semantic relatedness of expansion concepts to the original query constituents and role-type-based weighting are essential in query expansion, we have demonstrated improvements in retrieval performance with our proposed approach. Even though the expansion term spawning strategy can produce "noisy" concepts, experimentally the gain in terms of mean average precision with respect to the compared techniques is significant, especially in the variants considering the inclusion of synonyms and hypernyms. In our future work, we will further investigate gains in retrieval performance by studying cognitive patterns for expansion and eventually coupling statistical and extrinsic language-based resources to ensure only closely related concepts are included in the enriched query. Also, an application in multimedia web retrieval [14] will be proposed enriching the works of [4, 15 and 31].

References

1. Alejandra Segura N, Salvador-Sanchez, Garcia-Barriocanal E, Prieto M (2011) An empirical analysis of ontology-based query expansion for learning resource searches using MERLOT and the Gene ontology. Knowl Base Syst 24(1):119–133
2. Balaneshin-Kordan S, Kotov A (2017) Embedding-based query expansion for weighted sequential dependence retrieval model. In: Proceedings of ACM SIGIR, pp 1213–1216

3. Banerjee S (2002) An adapted Lesk algorithm for word sense disambiguation using WordNet. In: Computational linguistics and intelligent text, pp 136–145
4. Belkhatir M (2011) A three-level architecture for bridging the image semantic gap. Multimed Syst 17(2):135–148
5. Bendersky M, Croft WB (2008) Discovering key concepts in verbose queries. In: Proceedings of ACM SIGIR, pp 491–498
6. Bhogal J, MacFarlane A, Smith P (2007) A review of ontology based query expansion. Inf Process Manag 43(4):866–886
7. Bhogal J, MacFarlane A (2013) Ontology based query expansion with a probabilistic retrieval model. In: Proceedings of 6th information retrieval facility conference (IRFC 2013)
8. Cao G, et al (2005) Integrating word relationships into language models. In: Proceedings of ACM SIGIR, pp 298–305
9. Carpineto C, Romano G (2012) A survey of automatic query expansion in information retrieval. ACM Comput Surv 44(1):1–50
10. Chauhan R, Goudar R, Rathore R, Singh P, Rao S (2012) Ontology based automatic query expansion for semantic information retrieval in sports domain. In: Eco-friendly computing and communication systems. ICECCS 2012. Communications in computer and information science, vol 305, pp 422–433
11. Covington MA (2001) A fundamental algorithm for dependency parsing. In: Proceedings of the annual ACM southeast conference, pp 95–102
12. Cuadros M, Rigau G (2006) Quality assessment of large scale knowledge resources. In: Proceedings of the conference on empirical methods in natural language processing, pp 534–541
13. Dipasree P, Mitra M, Datta K (2014) Improving query expansion using WordNet. J Assoc Inf Sci Technol 65(12):2469–2478
14. Fauzi F, Belkhatir M (2014) Image understanding and the web: a state-of-the-art review. J Intell Inf Syst 43(2):271–306
15. Fauzi F, Belkhatir M (2013) Multifaceted conceptual image indexing on the world wide web. Inf Process Manag 49(2):420–440
16. Fogarolli A (2011) Wikipedia as a source of ontological knowledge: state of the art and application. Intell Netw Collab Syst Appl 329:1–26
17. Frank E, et al (1999). Domain-specific keyphrase extraction. In: Proceedings of IJCAI, pp 668–673
18. Greenberg J (2001) Optimal query expansion processing methods with semantically encoded structured thesauri terminology. J Am Soc Inf Sci 52:487–498
19. Hollink L, Schreiber G, Wielinga B (2007) Patterns of semantic relations to improve image content search. J Web Semant 5(3):195–203
20. Huston S, Croft BW (2014) A comparison of retrieval models using term dependencies. In: Proceeding of ACM CIKM, pp 111–120
21. Koopman B, Zuccon G, Bruza P, Sitbon L, Lawley M (2016) Information retrieval as semantic inference: a Graph Inference model applied to medical search. Inf Retr J 19(1–2):6–37
22. Kraft DH, Petry FE, Buckles BP, Sadasivan T (1995) Applying genetic algorithms to information retrieval systems via relevance feedback. In: Fuzziness in database management systems, pp 330–344
23. Kuroda K, Bond F (2010) Why Wikipedia needs to make friends with WordNet. In: Proceeding of the 5th international conference on the global Wordnet Association, pp 9–16
24. Lavrenko V, Croft BW (2001) Relevance-based language models. In: Proceeding of ACM SIGIR, pp 120–127
25. Lioma C, Ounis I (2008) A syntactically-based query reformulation technique for information retrieval. Inf Process Manag 44(1):143–162
26. Liu S, Liu F, Yu C, Morgan S (2004) An effective approach to document retrieval via utilizing WordNet and recognizing phrases. In: Proceeding of ACM SIGIR, pp 266–272
27. Liu S, Yu C, Meng W (2005) Word sense disambiguation in queries. In: Proceeding of ACM CIKM, pp 525–532
28. Maree M, Belkhatir M (2011) A coupled Statistical/Semantic framework for merging heterogeneous domain-specific ontologies. In: Proceeding of international conference on tools with artificial intelligence, pp 159–166
29. Maree M, Belkhatir M (2013) Coupling semantic and statistical techniques for dynamically enriching web ontologies. J Intell Inf Syst 40(3):455–478
30. Maree M, Belkhatir M (2015) Addressing semantic heterogeneity through multiple knowledge base assisted merging of domain-specific ontologies. Knowl Base Syst 73:199–211
31. Maree M, Belkhatir M, Fauzi F, Sabha M (2016) Multiple ontology-based indexing of multimedia documents on the world wide web. In: Intelligent decision technologies 2016: proceedings of the 8th KES international conference on intelligent decision technologies (KES-IDT 2016) – Part II, pp 51–62

32. Marneffe MC, Manning CD (2008) Stanford typed dependencies manual. Technical report. Stanford University, Stanford
33. McCarthy D, Carroll J (2003) Disambiguating nouns, verbs, and adjectives using automatically acquired selectional preferences. Comput Linguist 29(4):639–654
34. Mestrovic A, Calì A (2016) An ontology-based approach to information retrieval. In: Int. KEYSTONE conference 2016, pp 150–156
35. Mihalcea R (2007) Using Wikipedia for automatic word sense disambiguation. In: Proceeding of HLT-NAACL, pp 196–203
36. Navigli R, Velardi P (2002) An analysis of ontology-based query expansion strategies. In: Proceeding of the international workshop on adaptive text extraction and mining, pp 42–49
37. Paik JH, Oard DW (2014) A fixed-point method for weighting terms in verbose informational queries. In: Proceeding of CIKM, pp 131–140
38. Park JH, Croft BW, Smith DA (2011) A quasi-synchronous dependence model for information retrieval. In: Proceeding of CIKM, pp 17–26
39. Patwardhan S, Banerjee S, Pedersen T (2007) UMND1: Unsupervised word sense disambiguation using contextual semantic relatedness. In: SemEval@ACL 2007, pp 390–393
40. Pinter Y, Reichart R, Szpektor I (2016) Syntactic parsing of web queries with question intent. In: Proceeding of HLT-NAACL, pp 670–680
41. Pedersen T, Kolhatkar V (2009) WordNet :: SenseRelate :: AllWords—A broad coverage word sense tagger that maximizes semantic relatedness. In: Proceeding of annual conference of the North American Chapter of ACL, pp 17–20
42. Pedersen T, Patwardhan S, Michelizzi J (2004) WordNet:: Similarity: measuring the relatedness of concepts. In: Proceeding of HLT-NAACL, pp 38–41
43. Ponte JM, Croft BW (1998) A language modeling approach to information retrieval. In: Proceeding of ACM SIGIR, pp 275–281
44. Porter M F (1980) An algorithm for suffix stripping. Program 14(3):130–137
45. Radhouani S, Lim JH, Chevallet JP, Falquet G (2006) Combining textual and visual ontologies to solve medical multimodal queries. In: Proceeding of IEEE ICME, pp 1853–1856
46. Selvaretnam B, Belkhatir M (2012) Human language technology and query expansion: issues, state-of-the-art and perspectives. J Intell Inf Syst 38(3):709–740
47. Selvaretnam B, Belkhatir M, Messom C (2013) A coupled linguistics/statistical technique for query structure classification and its application to Query Expansion. In: Proceeding of FSKD, pp 1105–1109
48. Selvaretnam B, Belkhatir M (2016) A linguistically driven framework for query expansion via grammatical constituent highlighting and role-based concept weighting. Inf Process Manage 52(2):174–192
49. Simon P, Sathya S (2009) Genetic algorithm for information retrieval. In: Proceeding of international conference on intelligent agent & multi-agent systems
50. Song R, et al (2008) Viewing term proximity from a different perspective. In: Proceeding of ECIR, pp 346–357
51. Tudhope D, Alani H, Jones C (2001) Augmenting thesaurus relationships: possibilities for retrieval. J Digit Inf 1:8
52. Tuominen J, Kauppinen T, Viljanen K, Hyvönen E (2009) Ontology-based query expansion widget for information retrieval. In: Proceeding of 5th workshop on scripting and development for the Semantic Web
53. Voorhees EM (1994) Query expansion using lexical-semantic relations. In: Proceeding of ACM SIGIR, pp 61–69
54. Yang J, Korfhage R, Rasmussen E (1992) Query improvement in information retrieval using genetic algorithms–a report on the experiments of the TREC project. In: Proceeding of TREC-1, pp 31–58
55. Zhang Z, Gentile AL, Ciravegna F (2011) Harnessing different knowledge sources to measure semantic relatedness under a uniform model. In: Proceeding of EMNLP, pp 991–1002

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