Improving Query Expansion by Automatic Query Disambiguation in Intelligent Information Retrieval

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Abstract: We study in this paper the impact of Word Sense Disambiguation (WSD) on Query Expansion (QE) for monolingual intelligent information retrieval. The proposed approaches for WSD and QE are based on corpus analysis using co-occurrence graphs modelled by possibilistic networks. Indeed, our model for relevance judgment uses possibility theory to take advantages of a double measure (possibility and necessity). Our experiments are performed using the standard ROMANSEVAL test collection for the WSD task and the CLEF-2003 benchmark for the QE process in French monolingual Information Retrieval (IR) evaluation. The results show the positive impact of WSD on QE based on the recall/precision standard metrics.

1 INTRODUCTION

Users of information retrieval (IR) systems choose generally short queries to express their needs. The submitted request is matched with the indexes of documents, according to a specified matching model and search results are returned sorted by descendant order of the computed relevance scores. These results may contain noise (irrelevant documents) due to the shortness of query.

One possible solution which can enhance results consists in expanding the context of the query, thus satisfying the user. Query expansion (QE) consists in enriching the user's query by adding new terms to better express his need (Elayeb et al., 2011; Carpineto and Romano, 2012). Another solution arises when one or more terms in query have more than one sense (ambiguous). If we expand the query using wrong sense information, search results would be probably irrelevant to the user (Krovetz, 1997; Paskalis and Khodra, 2011).

Then it is necessary to identify, in a second step, the exact sense of ambiguous words, what is called word sense disambiguation (WSD). It is defined as the ability to identify the meaning of words in context using one or more sources of knowledge to associate the most appropriate senses with ambiguous terms (Navigli, 2009).

WSD is an important field of natural language processing (NLP). However, WSD is also used in information retrieval and proved its impact to improve the search process (Liu et al., 2005; Zhong and Ng, 2012).

Many studies about query expansion and WSD were conducted (Chifu and Ionescu, 2012). We present in this work a comparative study of the contribution of WSD to IR and its impact on query expansion based on possibilistic networks. The presented results focus on queries issued from the CLEF-2003 corpus and containing ambiguous words from the ROMANSEVAL benchmark for WSD in French language.

In this paper, we propose, assess and compare a new possibilistic query expansion approach using word sense disambiguation on a graph of co-occurrence. As a background of our work, we

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present in Section 2 some related works. The proposed possibilistic approach is detailed in Section 3 and a set of experimentations, results and interpretations is made in Section 4.

2 RELATED WORK

We present in this section some useful IR concepts and related works from the literature.

Query Expansion (QE) is one of the strategies implemented in IR systems to improve their performance and better satisfy users. (Carpineto and Romano, 2012) classify QE into two main techniques: interactive query expansion (IQE), which relies on user guidance, and automatic query expansion (AQE). In both cases, QE can be achieved by various techniques such as exploitation of external linguistic resources (thesauri, dictionaries, etc.), corpus analysis and relevance feedback techniques (Manning et al., 2008).

QE approaches based on relevance feedback can be classified into three main categories (Manning et al., 2008). The first approach is “user relevance feedback” which includes user judgment of the returned results. The second one is “indirect relevance feedback” (called often implicit relevance feedback) using indirect sources of evidence such as number of hits on web page’s links. The last approach is “pseudo relevance feedback” (also known as blind relevance feedback). In this method, the IRS uses the top *k* retrieved documents which are the most relevant to expand the initial query. Thus, a set of candidate terms from these documents is added using often variants of Rocchio algorithm (Rocchio, 1971).

Although relevance feedback may reduce noise in IR results, all these techniques do not provide direct way to exactly identify the meaning of the query terms, thus needing other approaches for query disambiguation.

Word sense disambiguation (WSD) is a commonly known task in natural language processing (NLP) problems and IR (Banerjee and Pedersen, 2002). According to (Navigli, 2009), WSD heavily relies on knowledge sources which are classified into two groups: structured resources (such as thesauri, electronic dictionaries, etc.) and unstructured resources (such as corpora documents).

Pinto and Pérez-sanjulián (2008) studied the impact of applying WSD on automatic QE using WordNet as external linguistic resource for both WSD and QE. Experiments were conducted using short and long queries from the TREC-8 text collection. Results proved that QE applied on both short and long queries is not able to improve retrieval performance without identifying the correct meaning of ambiguous word from the set of extracted synonyms from WordNet (Miller et al., 1990). The search performance was better for short queries.

Paskalis and Khodra (2011) analyzed many scenarios on IR process by using QE, WSD, stemming and a relevance feedback technique. WSD was applied using an extended implementation of Lesk algorithm (Banerjee and Pedersen, 2002; Banerjee and Pedersen, 2003). For the QE task, they used two components: a co-occurrence based thesaurus built automatically from the documents collection and pseudo relevance feedback by assuming a set of top documents as relevant and injecting representative terms in the original query (Manning et al., 2008).

Elayeb et al. (2011) and Ben Khiroun et al. (2012) proposed respectively QE and WSD approaches based on possibilistic networks. However, they did not apply their WSD algorithm on query disambiguation. They also used dictionaries as lexical resources. To the best of our knowledge, no research about using co-occurrence graphs for both WSD and QE tasks were conducted in the French language. Besides, the possibilistic approach has not been tested for query disambiguation. Thus, we need to experiment possibilistic networks for enhancing IR results, by studying many combinations of scenarios of WSD, QE and relevance feedback.

Based on this survey, we propose a study of a combined approach for WSD and QE tasks, using on possibilistic networks and applied on an extracted co-occurrence graph.

3 A POSSIBILISTIC APPROACH FOR COMBINED WSD & SQE

Our approach combines automatic QE, WSD and pseudo relevance feedback. For the first two tasks, we need to compute the similarity between queries’ terms (in the case of expansion) or between terms and senses (in the case of disambiguation). In this paper, we opted for co-occurrence graphs extracted from corpora to model contextual and similarity links. Nevertheless, our implementation of similarity calculus is generic enough to be used with other types of graphs (e.g. dictionary graphs in (Elayeb et al., 2011)).

3.1 Graph-based Knowledge Representation

Our approach is based on possibilistic networks for WSD and QE. In fact, we consider, for building the co-occurrence graph, that two nodes are related if they exist in the same sentence. The edges are bi-oriented and weighted by the normalized co-occurrence frequency of the related terms. On the other hand, ambiguous words are related with their appropriate senses in the dictionary.
We consider the different components as follow:

- T: the set of terms in the corpus.
- S: the set of senses in the dictionary.
- A node t_i is related to a node t_j if t_i and t_j co-occur in the same sentence; where $\{t_i, t_j \in T\}$.
- A node t_i is related to a node s_j if t_i is an ambiguous term and s_j represents a sense of t_i; where $\{t_i \in T\}$ and $\{s_j \in S\}$.

3.2 Graph-based Possibilistic Similarity

To compute terms similarity in both QE and WSD tasks, we based our approach on the possibilistic theory introduced by (Zadeh, 1978) and developed by several authors (Dubois and Prade, 2011; Dubois and Prade, 2012). We adapted the possibilistic model architecture of (Elayeb et al., 2011) to be applied on co-occurrence graphs. We define the Degree of Possibilistic Relevance (*DPR*) for each co-occurrence graph' node n_j given a query Q = (t_1, t_2, …, t_T) by:

$$\mathrm{DPR}(n_j) = \Pi(n_j \mid Q) + N(n_j \mid Q) \quad (1)$$

Where $\Pi(n_j|Q)$ and $N(n_j|Q)$ represent respectively the possibility and necessity measures (Elayeb et al., 2009). The former allows to reject the non-relevant nodes (those who are not close to the context of the query and may not be used to expand or disambiguate it). The latter is used to reinforce the relevance of the most important nodes. The two measures are computed as follows:

$$\begin{aligned}\Pi(n_j \mid Q) &= \Pi(t_1 \mid n_j) * \ldots * \Pi(t_T \mid n_j)\\ &= \mathrm{nft}_{1j} * \ldots * \mathrm{nft}_{Tj}\end{aligned} \quad (2)$$

$$N(n_j \mid Q) = 1 - [(1 - \phi n_{1j}) * \ldots * (1 - \phi n_{Tj})] \quad (3)$$

Where nft_{ij} represents the normalized frequency of query terms in the co-occurrence graph:

$$\mathrm{nft}_{ij} = \frac{\mathrm{tf}_{ij}}{\max_k(\mathrm{tf}_{kj})} \quad (4)$$

In this formula tf_{ij} is the weight of the edge relating the nodes t_i and n_j (i.e. the number of times the two nodes co-occur).
And:

$$\phi n_{ij} = \mathrm{Log}_{10}\left(\frac{\mathrm{nCN}}{\mathrm{nN}_i}\right) * \mathrm{nft}_{ij} \quad (5)$$

Where:

- nCN = total number of nodes in the co-occurrence graph related to the query terms;
- nN_i = number of nodes related to the term t_i.

Using the *Log* function (such as in TF-IDF) allows to compute the discriminative power of the query terms. Thus, we select the graph nodes which are closest to the most discriminative items of the contextual information represented in the query.

3.3 Query Treatment Process

The process in Figure 1 presents the different resources used in the WSD task, QE and pseudo relevance feedback.

Starting from an initial query, the QE module is executed to generate an expanded query. In the case of ambiguous terms, the WSD module is used before applying QE. Thus, the best sense node having the greater possibilistic score is selected and the terms existing in its definition are used for expanding the original query.

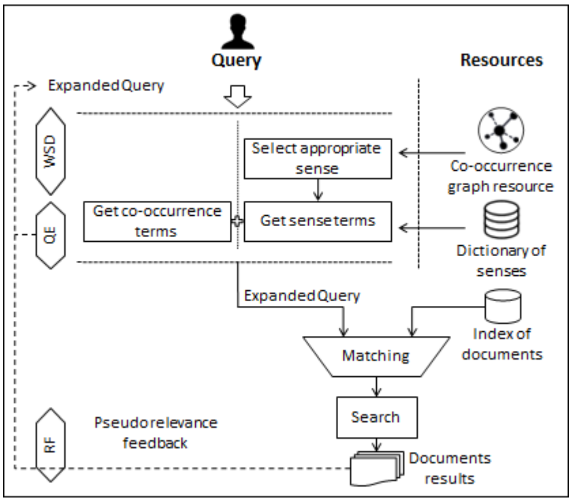

Figure 1: Query expansion using WSD process.

For both QE and WSD processes, the co-occurrence graph is used to achieve possibilistic calculus. The expanded query is matched with documents to achieve results.

A pseudo relevance feedback is applied at the end of the process by extracting the most significant terms from the top first returned documents.The whole process may be iterated.

In order to perform pseudo relevance feedback based on the document collection, we used the Bo1 (Bose-Einstein 1) pseudo relevance feedback method implemented in the Terrier information retrieval platform (Ounis et al., 2005). The default settings are specified as follows: the number of terms to expand a query is set to 10 and the number of top-ranked documents from which these terms are extracted is limited to 3 documents.

3.4 Illustrative Example

We consider in this example an excerpt of an ambiguous query:

```
Les règles d'orthographe et de
ponctuation pour la langue allemande
ont été considérablement simplifiées
```

Which may be translated as follows:

```
The rules of spelling and
punctuation for the German language
has been considerably simplified
```

The query is tokenized and lemmatized ignoring stop words (like pronouns, articles, etc.) as follow:

```
règle (rule), orthographe
(spelling), ponctuation
(punctuation), langue (language),
allemand (German), considérable
(considerable), simple (simple)
```

The output query contains the ambiguous word "simple" (simple). So the WSD is executed and the sense having the best possibilistic score from ROMANSEVAL dictionary is selected (in this example we consider the sense AII1):

```
[…]
AI2  Qui n'est formé que […]
AI3  Qui suffit à soi seul […]
AII1 Qui est facile à comprendre […]
```

Translated as:

```
[…]
AI2  Which is formed only by[…]
AI3  Sufficient to itself alone […]
AII1 That is easy to understand […]
```

The corresponding terms in the definition are injected in query:

```
règle (rule), orthographe
(spelling), ponctuation
(punctuation), langue (language),
allemand (German), considérable
(considerable), simple (simple),
facile (easy), comprendre
(understand)
```

Afterwards, the disambiguated query is processed to be expanded by the QE module.

4 EXPERIMENTAL RESULTS

In order to study the impact of WSD on QE in French language, we used two test collections to experiment our approach: CLEF-2003 and ROMANSEVAL.

In all our experiments, we focused only on queries from CLEF-2003 test collection which contains ambiguous terms included in ROMANSEVAL test collection. The two test collections are presented in the following sub-sections.

4.1 CLEF-2003 Test Collection

We used series of standard tests from the Cross-Language Evaluation Forum (CLEF). It provides necessary tools for the evaluation of information retrieval systems on large corpora including a set of documents, a set of queries and the list of relevant documents for each query.

Each query is represented in the XML format by a title containing its terms, a description and a detailed narrative text. The CLEF-2003 collection for French language is composed of Le Monde94, ATS94, and ATS95 sub-collections forming 57 test queries and more than 300 MB of data (Braschler and Peters, 2004).

4.2 ROMANSEVAL Test Collection

For the WSD task, we used the ROMANSEVAL standard test collection which provides the necessary resources for WSD including a set of documents and a list of test sentences containing ambiguous words.

A set of 60 ambiguous words distributed on three grammatical categories (20 nouns, 20 adjectives, 20 verbs) were annotated by 6 members in accordance with the senses. Each word occurrence may have one or several labels of sense or none (Segond, 2000).

4.3 Experimental Setup

The query sub-set used for experiments is composed of 15 queries containing ambiguous words from the ROMANSEVAL test collection.

In the first step, we studied in sub-section 4.4 the impact of QE, as a separated process, on the IR performance. Then, WSD is experimented apart in sub-section 4.5 to evaluate the disambiguating process. The impact of WSD on QE is experimented in sub-section 4.6.

We used the Terrier experimental platform for IR to evaluate our system (Ounis et al., 2006). Two common IR measures where used: (6) The precision measured by the ratio of relevant documents retrieved to the number of documents retrieved and (7) The recall presenting the ratio of relevant documents retrieved to the number of relevant documents in the collection.

$$\text{Precision} = \frac{\#(\text{relevant retrieved documents})}{\#(\text{retrieved documents})} \quad (6)$$

$$\text{Recall} = \frac{\#(\text{relevant retrieved documents})}{\#(\text{relevant documents in the collection})} \quad (7)$$

In this paper our experiments are limited to the using of the Okapi (BM25) matching model already available in Terrier platform. But, we plan in the future to experiment our approach via the possibilistic matching model proposed by (Elayeb et al., 2009) in order to compare results to those obtained via Okapi. In fact, our goal is to approve that our approach is generic as it is independent of the used matching model.

4.4 Evaluating QE Approach

We compare in Table 1 different QE scenarios based on co-occurrence possibilistic graph (CooQE) built from the ROMANSEVAL Test Collection.

Ogilvie et al. (2009) studied the number of expansion terms to use in automatic QE through eight IR systems. The results show that the number of expansion terms that optimizes mean average precision varies widely across systems and topic sets. For many topics, ten or fewer expansion terms provided the best average precision according to the experiments of (Ogilvie et al., 2009).This assumption is studied for the French language as follows.

The number of expansion terms in Table 1 was varied from *N div 4* terms to *N* terms where *N* represents the number of terms in the original query.

These numbers for expansion terms are chosen by considering that the narrative part of test queries is long (more than 10 terms). Applying QE on such long queries as detailed by (Pinto and Pérez-sanjulián, 2008) may produce noisy and non-interpretable results. Thus, we fixed the quarter of query terms as minimum scenario to have significant expansion results.

The last two columns of table 1 present the MAP measure, which is the mean of the average precision scores for each query and the exact precision (R-Precision), which is the precision at rank *R*; where *R* is the total number of relevant documents (Manning et al., 2008). Baseline results, applied on reference initial queries without QE, are also presented in Table1.

Table 1: Query expansion results.

Method	Number of terms for QE	MAP	R-precision
baseline	-	0.5487	0.5174
CooQE	N	0.4180	0.4043
	N div 2	0.4700	0.4633
	N div 4	0.5083	0.4742

The experimented results show a decrease in IR performance when applying the QE process proportionally to the number of expansion terms in both MAP and R-precision measures.

According to the Recall-Precision curve presented in Figure 2, the results for the three QE scenarios are not satisfying in comparison with the default baseline results.

However, we can affirm that QE (mainly for *N div 4* scenario) is better than the baseline at high recall levels (initially better at retrieving the relevant documents).

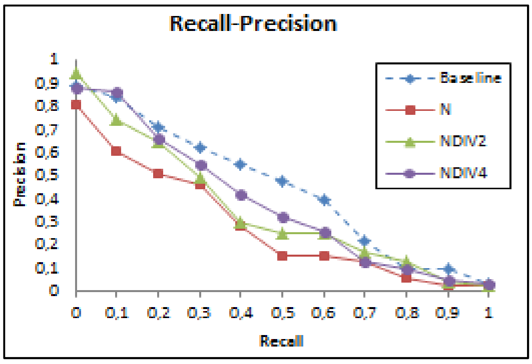

Figure 2: Recall-Precision curve for QE.

These results are affected by the ambiguity of the queries and the difficulty of distinguishing the right sense for the ambiguous terms. In fact, the longer the query is the worst IR performance results are.

4.5 Evaluating the Possibilistic WSD Approach

In this section, we experiment the efficiency of WSD using the possibilistic approach described in Section 3. We consider only the sense having the best *DPR* score according to the possibilistic co-occurrence graph-based calculus.

Afterwards, we performed expert-based evaluation for the relevance of the selected sense according to the original query and tagged it by three degrees of relevance: 1 (relevant), 0 (partially relevant) or -1 (not relevant).

After applying WSD on the 15 sub-test ambiguous queries, we identified 5 relevant senses and 4 senses as not relevant (cf. Table2).

Table 2: Evaluating WSD approach.

#Relevant senses	#Partially relevant senses	#Not relevant senses
5	6	4

This evaluation was conducted manually for the lack of ambiguous contexts' tagging of ROMANSEVAL words according to CLEF-2003 collection's queries.

4.6 Combining WSD and QE Approaches

The final set of experimentations consists in applying WSD on queries before expanding terms. This task may help in selecting the best sense for ambiguous words before applying a QE process aiming to reduce noise.

Therefore, the terms composing the selected sense are injected in the query and a QE process is then applied (*WSD_QE* test).

We also applied the pseudo relevance feedback technique in our experiments at the end of disambiguation and expansion chain (*WSD_QE_RF* test).

For all the expanded queries in Figure 3 (adding N terms), Figure 4 (adding N div 2 terms) and Figure 5 (adding N div 4 terms), the WSD applied alone after possibilistic QE has a minor enhancement in comparison with the results of QE without WSD. Nevertheless, the two experiments results (i.e. *WSD_QE* and *QE*) are above the reference baseline.

However, when combining pseudo relevance feedback with QE and WSD, we observe better IR performance especially for a limited number of expansion terms (cf. Figure 4 and Figure 5).

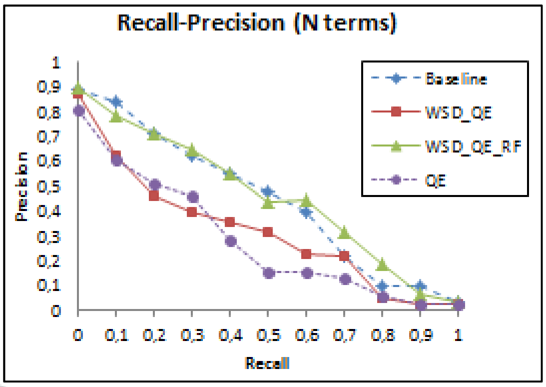

Figure 3: Recall-Precision curve by adding N terms for each ambiguous query with and without WSD.

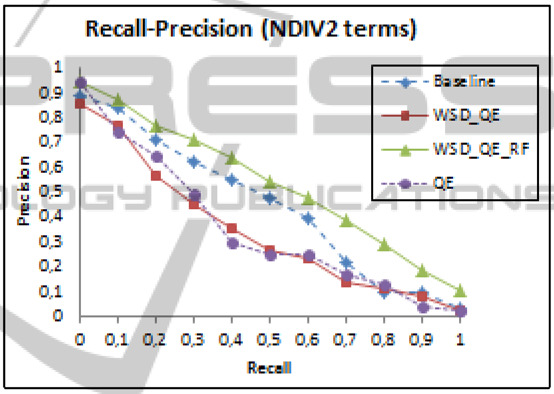

Figure 4: Recall-Precision curve by adding N div 2 terms for each ambiguous query with and without WSD.

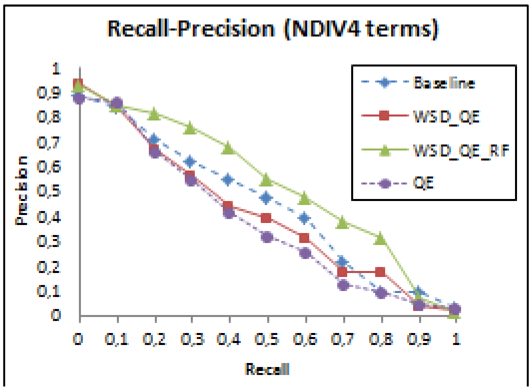

Figure 5: Recall-Precision curve by adding N div 4 terms for each ambiguous query with and without WSD.

According to the three scenarios, we can confirm the positive performance impact of WSD on QE mainly for the initial recall levels (<10%). Combining relevance feedback with WSD and QE contributed also in the enhancement of IR performance.

The same positive impact of relevance feedback was observed by (Paskalis and Khodra, 2011). We also join the works interpretations of (Pinto and Pérez-sanjulián, 2008) who studied the IR performance according to short and long queries which may generate noise while applying QE.

5 CONCLUSIONS

In this work, we present a possibilistic approach to study the impact of Word Sense Disambiguation (WSD) on Query Expansion (QE). The approach was applied for the French language to verify many query treatment scenarios, but it is also applicable to other languages. As a first step, we prepared a co-occurrence graph from the documents' collection. Then, this resource was used in the selection of candidate sense/terms for both WSD and QE. Final results confirmed that WSD is necessary in the IR process overcome the ambiguity problem.

Furthermore, Pseudo Relevance Feedback plays an important role in the combined WSD and QE approach proposed in this paper. However, the retrieval performance is decreased when using many expansion terms. This fact is interpreted by the noise effect issued from the co-occurrence graph resource.

As future perspectives of the current work, we propose to compare the use of document knowledge extraction (as presented in the current work by co-occurrence graph presentation) to other external resources such as dictionaries. We aim to study also the effectiveness of possibilistic networks in query disambiguation compared to other probabilistic approaches such as the circuit-based calculus (Elayeb et al., 2011). Finally, the graph-based query treatment algorithms were implemented in a generic manner which may be applied with other languages such as English, Spanish and Arabic.

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