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The influence of Semantic Roles in QA: A comparative analysis*

La influencia de los roles semanticos en BR: Un análisis comparativo

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Resumen: Los conjuntos de preguntas utilizados normalmente para evaluar los sistemas de búsqueda de respuestas (BR) están principalmente constituidos por preguntas cuyas respuestas son entidades nombradas (NE), por tanto, la mayoría de estos sistemas usan reconocedores de entidades para extraer las posibles respuestas. Últimamente, el etiquetado de roles semánticos y su contribución a la BR es un tema de especial interés. Sin embargo, los sistemas basados en NEs siempre funcionarán mejor que los basados en roles a la hora de extraer respuestas para preguntas cuya respuesta sea una NE. El objetivo de este artículo es evaluar ambos métodos para preguntas de lugar bajo las mismas condiciones, usando, no sólo preguntas basadas en nombres propios sino también basadas en nombres comunes. Para ello se presentan tres propuestas diferentes de un módulo de extracción de respuestas embebidas en un sistema de BR: una basada en entidades nombradas y dos basadas en roles semánticos. Los resultados obtenidos indican que mientras la propuesta de NE contesta mejor las preguntas basadas en nombres propios (+49, 57% MRR), las propuestas de roles obtienen los mejores resultados en las preguntas basadas en nombres comunes (+223, 48% MRR) siendo sus resultados de una precisión más alta para ambos tipos de preguntas.
Palabras clave: Roles Semánticos, Entidades Nombradas, Búsqueda de Respuestas

Abstract: Question sets normally used to evaluate QA systems are mainly based on questions whose answers are named entities, therefore most of these systems rely on NERs to extract possible answers. Nowadays, semantic role labeling and its contribution to question answering has recently become an interesting issue. Nevertheless, NE-based systems will always work better than SR-based ones extracting answers for questions with NE-based answers. The aim of this paper is to evaluate both of approaches for location questions under the same conditions and using not only NE-based questions but also common noun-based ones. In order to achieve this goal we present three different proposals of an answer extraction module embedded into a QA system: one based on named entities and two based on semantic roles. Results show that while NE-based approach performs better with NE-based questions (MRR +49.57%), SR-based approaches show the best results in common noun-based ones (MRR +223.48%) and obtain a higher precision in both types of questions.
Keywords: Semantic Roles, Named Entities, Question Answering

1 Introduction

Nowadays, question answering (QA) task represents one of the main lines of research of natural language processing (NLP). Its goal is the answering by computers to precise or arbitrary questions formulated by users in natural language (NL). Summarizing, the main objective of a QA system is determining "WHO did WHAT to WHOM, WHERE, WHEN, HOW and WHY?" (Hacioglu y Ward, 2003).

There exist conferences such as TREC[1]

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[1] http://trec.nist.gov/

and CLEF[2], whose aim is the evaluation of these systems requiring all participants to use same corpus to answer a concrete question set given by the organization. Question sets used to evaluate QA systems are mainly built with questions whose answer is a named entity (NE) (hereafter referred to as NE-based questions). Nevertheless, questions whose answer is composed of common nouns (hereafter referred as common noun-based questions) are not easy to find in these corpora.

Due to this fact, most QA systems have used named entity recognizers (NERs) to extract possible answers for a question (Pizzato y Moll-Aliod, 2005; Mollá, 2006). NERs identify entities and classify them into different categories. For each question, once the question type is recognized, NE-based QA systems extract NEs of this type as potential answers.

Recently, semantic role labeling (SRL) has received much attention, pointing question answering (QA) as one of the areas where the contribution of semantic roles (SR) will be more interesting (Gildea y Jurafsky, 2002). For each predicate in a sentence, semantic roles identify all constituents, determining their roles (agent, patient, instrument, etc.) and also their adjuncts (locative, temporal, manner, etc.). In this way, semantic roles represent 'WHO did WHAT to WHOM, WHERE, WHEN, HOW and WHY?" in a sentence (see figure 1), which indicates that its use in answer extraction could be very useful.

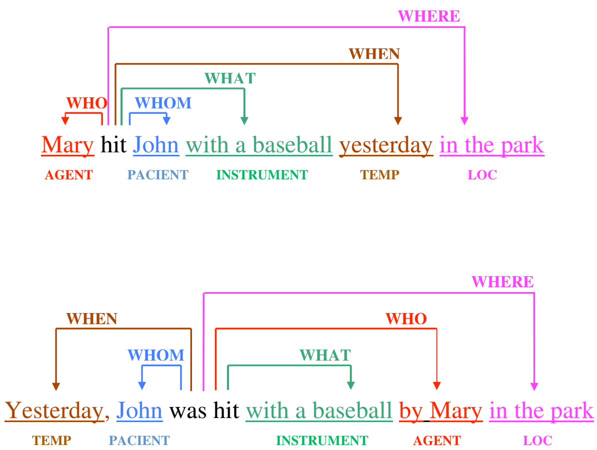

Figure 1: Application of semantic roles in QA

[2]http://www.clef-campaign.org/

There are some works using SR in answer extraction modules of QA systems (Ofoghi, Yearwood, y Ghosh, 2006; Kaisser, 2007; Lo y Lam, 2006; Shen et al., 2007) but all of them have been evaluated using NE-based questions.

In order to achieve our goal, we present a fair benchmark to evaluate both kinds of approaches using a balanced location question set containing both types of questions (common noun-based and NE-based). Moreover, we present three different proposals of answer extraction module embedded in a QA system. The answer extraction modules developed are: named entities-based, semantic roles-based using rules and semantic roles-based using patterns. In this manner, the influence of using semantic roles in QA systems will be analyzed and compared to a NE-based solution.

The paper is structured as follows: Section 2 introduces the background of SR field applied to QA systems, Section 3 describes our QA system and the three proposals for an answer extraction module: a) NEs b) SR using rules, and c) SR using patterns. Section 4 analyzes the evaluation of the results for the different approaches. Finally, some conclusions and orientations for future work are presented.

2 Background

Since the first automatic SRL system (Gildea y Jurafsky, 2002), the application of semantic roles to QA systems was presented as a proposal. One of the initial works using SR in QA was presented in (Narayanan y Harabagiu, 2004).

All QA systems have a very similar architecture, and as described in this field literature (Ferrández, 2003), this general architecture is summarized in the following modules:

- *Question analysis*: The main objective of this module is extracting all the useful information from the question (Pizzato y Moll-Aliod, 2005), such as type of question, type of answer, question focus and information related to the content of the question (keywords, syntactic and semantic information, question topic and so on).
- *Document retrieval*: This module uses information retrieval techniques in order to obtain a set of relevant documents and

thereby removing most of the documents in the collection from further processing.

- *Passage retrieval*: Only the relevant passages, or any other information unit such as documents or snippets, within the relevant documents are selected, using different natural language processing techniques.

- *Answer extraction*: In this module, the objective is determining which parts of the selected sentences are potential answers. Up to date, one of the simplest way to perform this task is returning the text of the sentence that is labeled as a named entity with the same type as the expected answer type. However, semantic role labeling and its contribution to question answering has recently become an interesting issue.

  Finally, all possible answers found are scored and re-ranked in order to determine the exact answer of the question.

Regarding the use of the semantic roles in the QA systems, systems can be divided into two main groups: a) systems using semantic roles to obtain extra information and complement other methods, and b) systems using semantic roles as a core method of a module in the QA architecture.

2.1 Roles as a complementary method

In this case, QA systems are based on NERs, and the use of semantic roles is only providing additional information in order to analyze the possible improvement in the results of the QA system (Sun et al., 2005; Lo y Lam, 2006; Shen et al., 2007; Melli et al., 2006). These types of approaches are only giving information about how semantic roles are able or not to complement a NER approach.

2.2 Roles as a core method

These approaches are using semantic roles to perform one module of the QA system. A brief summary of the main systems is presented in table 1.

As shown in the table, most of the systems are using a mapping between the semantic information of the question and the semantic information of candidate answers. The system of (Narayanan y Harabagiu, 2004) was the first proposal about using SR in QA systems and they were applied to determine

SYSTEM	QSET	USE	METHOD
Narayanan	ad-hoc	Type answer	Map. Q. Pattern Answer Pattern
Stenchikova	TREC Trivia	Answer Extrac.	Rules type Q. Answer role
Ofoghi	TREC	Answer Extrac.	Map. Q. Pattern Answer Pattern
Kaisser	TREC	Answer Extrac.	Map. Q. Pattern Answer Pattern
Moschitti	TREC	Q. Classif. A. Classif. A. Rerank.	Supervised Machine Learning
Fliedner	ad-hoc	Anwer Extrac.	Map. Q. *Frame* Answer *Frame*

Table 1: Summary of the use of semantic roles in QA systems

the type of the answer of complex questions. Their evaluation results over an ad-hoc set of 400 questions indicated a precision of 73,5% in which the type of the answer was properly detected. The work of (Ofoghi, Yearwood, y Ghosh, 2006) implemented a manual proof over a set of 15 questions in order to extract candidate answers to a question using semantic roles. The evaluation of this approach using TREC2004 question corpus showed an MRR of 38,89 %. Kaisser's system (Kaisser, 2007) is a very similar proposal to the explained before. This system was evaluated with a subset of TREC2002 question corpus and obtained a precision of 36,70%. Fliedner (Fliedner, 2007) proposes a representation of both question and passages containing a possible answer as FrameNet style structures. The answer is obtained by a mapping process between both structures. Results for open domain questions achieved a precision of 66% and a 33% in recall.

Besides, another system (Stenchikova, Hakkani-Tur, y Tur, 2006) is establishing a set of rules that relate some types of questions (who,when,where or what) with the role type for the expected answer. In this case, the evaluation of the system obtains an MRR of 30%.

Otherwise, Moschitti (Moschitti et al., 2007) proposes a supervised learning algorithm using information of semantic analysis tree composed of the sentence predicate and its arguments tagged with SR. Results obtained prove the usefulness of this information for classification (MRR 56.21%) and reclassification (MRR 81,12%) of answers, but not for the question classification.

One of the most important problems of all these systems is the extraction of the semantic roles of the question. This is due to the fact that the semantic role labeling tools have serious problems to annotate questions due to the fact that corpora used to train SRL tools do not contain many questions.

Once the different proposals have been analyzed, it seems obvious that the main contribution of SR to QA systems is in the answer extraction module. However, NE-based systems will always work better than SR-based ones extracting answers for questions with NE-based answers. Therefore, a balanced evaluation using not only NE-based questions but also common noun-based ones is proposed.

3 *Implementation: three answer extraction approaches in the same QA system*

To make a fair comparative analysis of the influence of SR and NE in QA systems, a QA system has been implemented, and three different extraction approaches have been embedded in it, being then evaluated separately in order to compare the results between them.

A simple QA system has been developed following the steps indicated in (Pizzato y Moll-Aliod, 2005). The information retrieval module uses snippets obtained from several Internet search engines and the answer extraction module has been modified in order to add the two SR approaches.

Since QA system behavior could be different depending of the type of SR, this work analyzes only location questions to minimize external influences. Same analysis could be done over other kind of questions by only defining appropriate rules or patterns for each answer extraction approach.

The first proposal is based on NEs to be able to compare its results to SR-based approaches. Second and third proposals are both based on SR. The second one uses semantic rules that establish relationships between the type of questions and SR and the third one uses semantic patterns built using the information of SR. Figure 2 shows an schema of the implemented system architecture.

3.1 NE-based answer extraction

This one is the simplest approach and the one used in the QA system described by Pizzato et al. Once question type is inferred by the system and the relevant snippets are collected as corpora to answer a question, all tagged NEs in corpora that match with question type are selected as potential answers. We used LingPipe[3] named-entity recognizer to identify location names.

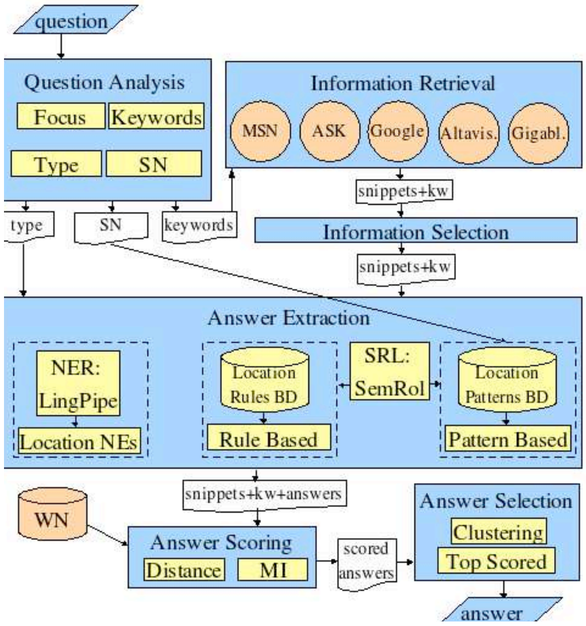

Figure 2: Architecture of the QA system with three different answer extraction modules

3.2 SR-based answer extraction using rules

For each different type of question, and its expected answer type, a different set of SR could be considered as a possible answer. It is possible to define a set of semantic rules that establishes relationships between the type of the question and a SR. A summary of these semantic relationships is shown in table 2 (Moreda, Navarro, y Palomar, 2007).

Using these rules, answer extraction module will select as possible answers all the arguments of the snippets returned by the information retrieval module that play the location role (AM-LOC). We used SemRol tool (Moreda y Palomar, 2006) to determine roles of sentence arguments.

[3]http://www.alias-i.com/lingpipe/

Question	Role	No Role
Where *In where* *In what + exp* *At what + exp*	Location	ProtoAgent Mode Temporal Cause ProtoPatient
When *In what + exp* *What + exp*	Temporal	ProtoAgent Mode Location Cause ProtoPatient
How	Mode Theme (if it is a diction verb)	ProtoAgent Location Temporal Cause Patient Beneficiary
Who	[Proto]Agent [Proto]Patient	Mode Temporal Location Theme beneficiary
What	Cause Theme	
Whose	Receiver Beneficiary Patient ProtoPatient	Agent Location Mode Temporal Theme Cause

Table 2: Set of semantic relationships

3.3 SR-based answer extraction using patterns

The motivation for the implementation of this third approach is that not all location arguments are represented by the specific location role (AM-LOC) and then, the previous approach is not considering all the possibilities.

For instance, the sentences in example 1 and example 2 that have an argument with the location role ("to the John's house" and "to the park", respectively) do not represent it with the AM-LOC role. Otherwise, in one case, the location role is represented by the A2 role (example 1), and in the other, by the A4 role (example 2).

(1) $[_{A0}$ Mary] is going $[_{A2}$ to the John's house].

(2) $[_{A0}$ Mary] is going $[_{A4}$ to the park].

Such as (Moreda, Navarro, y Palomar, 2007) showed, in PropBank, the location could be represented by the A2, A3, A4 or AM-LOC semantic roles.

Therefore, the answer extraction module based on rules is not able to detect all the possibilities. A first idea could be considering the AM-LOC when appears, and the other roles when not. This is possible because when the A2, A3 or A4 roles represent location, no other argument can have the location role. The problem is determining which of the roles, A2, A3 or A4, represent the location role if they appear in the same sentence.

To solve this problem, and considering the work presented in (Yousefi y Kosseim, 2006) about an answer extraction module based on patterns using named entities, the automatic construction of a set of semantic patterns based on semantic roles is proposed. This set of semantic patterns will cover most of the possibilities in which semantic roles represent location. This process consists of four stages:

1. Snippet retrieval. For each pair question-answer, the set of terms which a relevant document should contain, is defined. Then, a query using these terms is submitted to the Web and the snippets retrieved containing some of the terms are selected.
   (a) The set of relevant terms is composed of 1) the noun phrases of the question, and 2) all the possible combinations of sub-phrases of the answer.
   (b) The search engines used to submit the terms to the Web are MSN[4], AskJeeves[5], Google[6], Altavista[7] y Gigablast[8].
   (c) The first 100 snippets retrieved for each search engine containing the terms of the question and at least, one of the terms of the answer, in the same sentence, are selected.
2. Semantic Filtering of snippets. Sentences of snippets containing synonyms, hyperonyms or hyponyms of the question verb, are selected. This semantic information is obtained from WordNet (Miller et al., 1990).
3. Generating the answer pattern. Finally, the selected sentences are generalized in semantic patterns using information about semantic roles.

[4]http://es.msn.com/ (March 2008)
[5]http://es.ask.com/ (March 2008)
[6]http://www.google.es/ (March 2008)
[7]http://es.altavista.com/ (March 2008)
[8]http://beta.gigablast.com/ (March 2008)

(a) Each sentence is annotated with semantic roles using the SemRol tool(Moreda y Palomar, 2006) in order to identify location arguments (AM-LOC, A2, A3 or A4 semantic roles).

(b) The argument corresponding to some of the sub-phrases of the answer are replaced by its semantic role tag.

(c) Arguments corresponding to the noun phrases of the question are replaced by $< QARG_n >$ tags, where n is the phrase counter.

(d) Other arguments of the sentence are replaced by $< ARG_n >$ tags, where n is the argument counter. The rest of data is discarded.

4. Pattern clustering. Regardless the position of the tags, if two patterns have the same tags but different verbs, a single pattern is obtained containing the set of tags and a list of those verbs.

Once the described process is done, the answer extraction module operates in the following way: when a new location question is formulated, one or more patterns (one for each location semantic role AM-LOC, A2, A3, A4 in the sentence) for the returned snippets of this question are obtained and they are matched with the set of patterns in our database. If there is a coincidence, the text corresponding to the semantic role tag in the pattern is retrieved as an answer. To perform this, sentences of snippets are annotated with semantic roles, using the SemRol tool(Moreda y Palomar, 2006) and generalized in patterns.

4 Comparative evaluation and results analysis

4.1 Evaluation Environment

A set of 100 location questions has been used for testing. First 50 questions are based on NEs representing a subset of TREC1999 and TREC2000 factoid location questions and answers. Examples of these questions are:

What is the largest city in Germany? Berlin
Where is the actress, Marion Davies, buried? Hollywood Memorial Park

Last 50 questions are based on location common nouns and have been made by our team. Examples of these questions are:

Where is pancreas located? abdomen
Where are sheets put on? bed

Before carrying out the test, a Patterns database (DB) for SR pattern-based answer extraction module has to be built, as explained above. It has been built using a set of 200 questions, composed of a subset of TREC2003, TREC2006 and OpenTrivia.com factoid location questions and answers.

As explained in section 3, our system uses internet search engines results as corpus to answer the questions. We judged answers to be correct if they represent or contain the correct answer. The measures used to evaluate the system are Precision (*questions answered correctly/total questions answered*), Recall (*questions answered correctly/total questions*), F1 (*(2*Precision*Recall)/(Precision+Recall)*) and MRR (*Mean Reciprocal Rank measure used in TREC*).

4.2 Results Analysis

The QA system has been executed for the three implemented answer extraction modules. Neither manual review of sub-processes outputs nor post-execution adjustments have been made to automatic processes of the presented system.

Table 3 shows the results obtained in the evaluation for the three approaches emphasizing best MRR marks.

Approach		**Answer type**	
Name	**%**	**NE**	**common**
N. Entities	Pre	87.50	15.62
	Rec	84.00	10.00
	F1	85.70	12.19
	MRR	**87.25**	12.52
SR Rules	Pre	91.54	75.00
	Rec	52.00	30.00
	F1	66.32	42.85
	MRR	52.25	30.33
SR Patt.	Pre	93.54	95.23
	Rec	58.00	40.00
	F1	71.60	56.33
	MRR	58.33	**40.50**

Table 3: Evaluation Results for implemented approaches

Results clearly confirm that while NE-based approach works better for NE-based questions (MRR +66.98% over SR rules and +49.57% over SR patterns), SR-based approaches clearly surpass it for common noun-based questions (MRR +142.25% for rules and +223.48% for patterns).

On one hand, SR approaches results are more stable between the two different question types, showing an average 55.29% MRR on NE-based questions and a 35.41% average MRR for common noun-based ones. The difference obtained could be produced by the high availability of information for typical NE-based questions on the Internet and the information spareness for some common noun-based questions. Furthermore, the precision achieved by SR-approaches, specially patterns-based one, is higher than the one for NE-based approach. This is due to the fact that SR only tag as possible answers arguments representing a location role in a sentence whereas NEs select every location entity which increases the recall but sacrifices the precision.

On the other hand, NE-based approach, being the best approach for NE-based questions (87.25% MRR), has a drastic slump in common noun-based ones (12.52% MRR). Therefore, NE-based approaches have an important limitation on detecting non-entity based answers. Only NE-based questions can be answered due to selecting only named entities as possible answers. In fact, common noun-based questions answered correctly by the presented NE approach should not be answered because answers retrieved are no location NEs. We have analyzed the reason for this fact and we have concluded that it is produced due to a NER error in both detection and classification processes.

SRLs identify roles of arguments in sentences alleviating the handicap of detecting only entities. In this manner, as indicated by several studies, SR could be favorably used in QA task and, as proved by these results, specially in common noun-based questions.

Comparing the two presented SR approaches we can observe that patterns-based approach improves rules-based in recall because of the inclusion of A2, A3 and A4 roles as possible answers for some patterns and considering synonym, hyperonyms or hyponyms verbs in Patterns DB building process. Patterns obtained the highest precision as well, because while other approaches extract all locations as possible answers, it only considers location roles whose pattern represent one of the contained in Patterns DB. That way, patterns-based approach does a kind of semantic filtering of sentences, resulting in a more precise extraction of answers.

5 Conclusions and Further work

The aim of this paper is to analyze the influence of using semantic roles in question answering systems by comparing results obtained for both NE and common noun-based questions by different methods of answer extraction. To reach this goal a simple QA system has been implemented and three proposals of a QA answer extraction module have been embedded on it. The first proposal is based on named entities while the second and the third are based on semantic roles.

All proposals have been evaluated under the same conditions using a balanced location question set consisting in 50 questions based on NEs (TREC subset) and 50 questions based on common nouns.

Results from the evaluation show that while NE-based approach answers better NE-based questions (MRR +49.57% over SR patterns), SR-based approaches show the best results in common noun-based ones (MRR +223.48% for patterns) obtaining a higher precision in both types of questions.

Analyzing the obtained results we can conclude that using of SR in QA task, concretely in the answer extraction module, can be very worthy, specially in common noun based questions.

As further work some possible improvements have been proposed:

- Implementing the same system for other languages such as Spanish or Catalan in order to study if semantic roles affects in the same manner.
- Extending the QA system and SR-based extraction modules to other type of questions such as Person, Organization or Time-Date.
- Improving the QA system by implementing an Answer Clustering module based on semantic information of WordNet.

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