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An Inference Mechanism for Question Answering*

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ABSTRACT

This work describes an inference mechanism applied to AliQAn Question Answering System for Spanish in open domain. AliQAn is based fundamentally on the use of syntactic patterns to identify the possible answers. An inference mechanism is applied to the questions set of economic type. In this way, our system improves the accuracy of this question type from 33% to 57%.

Keywords: Natural Language Processing, Question Answering for Spanish, Inference Mechanism, Logic Proof.

1. INTRODUCTION

Natural Language Processing (NLP) is an essential part of the Artificial Intelligence by means of which computational mechanisms are investigated and formulated. These mechanisms allow the development of systems capable of understanding the knowledge expressed in texts of a given language.

In the last years, the investigation on the NLP has been focused on the development of resources that provide multiple levels of syntactic and semantic analysis. These resources are applied to different applications like systems of machine translation, information retrieval (IR), question answering (QA), recognition of entities, classification and filtrate of documents, generation of summaries, etc.

This work is focused in QA. These QA systems follow the IR systems in that we need a concrete answer to a given question. The objective of the classic IR systems is to return an ordered list of documents in function of their relevance on the question carried out by the user. On the other hand, the objective of the QA systems is a lot more ambitious than the one of improving the precision of the returned results; these systems try to recover the text fragment that contains the information required by the user, and not the complete document. However, the current state of the QA systems is still in its beginnings. The level of knowledge required for the understanding of the documents is every time bigger and this makes the difference in the precision of the current QA systems.

The investigating activity starts from the implementation of the question answering system AliQAn [25, 5] of open domain for the Spanish language. AliQAn has participated in the competitions of the monolingual $CLEF^1$ 2005, getting an accuracy of 33%. In 2006,

AliQAn also has participated in the same task, not only for the Spanish language but also in the English language, that is to say questions in English and texts in Spanish.

If the QA systems presented in competitions, such as the CLEF, are characterized according to the level of NLP resources used, those that reach up to a syntactic level or at the most up to a superficial semantic level (by means of the use of synonymy, hyperonymy among other similar relationships) do not overcome certain range of precision (50% of effectiveness approximately). The systems that greatly overcome this value it is due to the utilization of more complex techniques by means of the use of knowledge sources. This investigation seeks to begin a work of great scope: to develop a robust tool capable of reasoning automatically in open domain for the Spanish language that will be able to be integrated into different applications of NLP like QA, Entailment or Information Extraction among others.

The ability to reason in the QA systems appeared at the late 70's in restricted domain. Recently, the systems that gradually integrate inference components have still not evolved as those of restricted domain [2].

In spite of the fact that the available resources for the Spanish language are very scarce, it has been demonstrated that the improvement of this technique can help significantly in the effectiveness of systems such as the QA systems.

In section 2, a classification of the systems that use reasoning is presented. Section 3 presents our proposal. Finally in the last two sections the results of the tests elaborated in the section 4 are discussed and future works to extend the method presented in this paper are shown.

2. BACKGROUND

In the last years, the results of the $TREC^2$, CLEF or $NTCIR^3$ campaigns have demonstrated the need of methods with more grade of semantic knowledge. However, although valuable techniques have arisen there are still many problems left to solve.

Hence, it is indispensable to have a unified knowledge representation that provides a hierarchical codification of the semantic, relational and structural properties of a given text and to with an inference mechanism that can be used on such representation.

3 NII Test Collection for IR Systems (NTCIR)

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¹ Cross-Language Evaluation Forum (CLEF)

http://www.clef-campaign.org/ (visited on January 30, 2007). ² Text REtrieval Conference (TREC)

http://trec.nist.gov/ (visited on January 30, 2007).

http://research.nii.ac.jp/ntcir/ (visited on January 30, 2007).

The generally accepted background for the study of the reasoning applied to different "intelligent systems" is the approach based on knowledge. The idea is to store the knowledge in some representation language. The sentences expressed with this language are stored in a "Knowledge Base" (KB). Finally, a reasoning mechanism is used to determine what can be inferred from the sentences in the KB. Different representation systems (set of logic rules, probabilistic networks, etc.) are associated with mechanisms of reasoning, each one with their own merits and application range [16, 21]. Given a knowledge base for example, the reasoning can be abstracted as a deduction task: to determine if a sentence is logically implied by the KB.

Classification

The knowledge representations of general purpose along with their corresponding inference algorithms of general purpose do not solve the key topic of what to represent and how to derive an abstract representation efficiently considering, besides, the complexity of the problem. Within this background we can distinguish the techniques or methods based on knowledge and probabilistic (the last one will not be treated in this paper because we are focused on the study of KB techniques). The methods based on knowledge generally use as underlying representation language the Logic Forms (LF) of which we can find in literature a fan of variants.

To be able to carry out a system classification it will be made according to the tasks involved in the knowledge process:

- **Knowledge Representation (KR):** The KR is the language to represent the knowledge. The following examples can be KR of general purpose: FOL⁴, probabilistic or hybrid.
- **Procedure to obtain this representation:** It is the mechanism by means of which the KR in the language previously mentioned is achieved.
- **Inference Mechanism:** It is an effective mechanism to be used as a way of deduction to decide if a question is deductible starting from a KB described in the presentation language chosen.

Knowledge Representation

A reasoning system should select an appropriate symbolic structure to be able to represent the knowledge and a mechanism of appropriate reasoning to be able to assimilate new information and to respond to questions. As a first introduction in the classification we can see that

the representation can be based on models or based on LF.
Model-based Representation: [12, 11, 13] the

- KB is represented as a models set of the world instead of describing it as a LF set. Another proposal is the one presented for [4] in which the semantics of stable models defined for [7] is used to grant semantics to the logic programs with negation.
- **LF-based Representation:** Logic Forms is representation level of the meaning independent of the context. There are diverse representation forms [8, 18, 26, 20, 22]. We can consider that the empirical content of the LF theory has two aspects: one concerns the syntax and the relation of this with the form of the sentences; the other

one concerns the role of the LF in the explanation of the general notion of meaning. The LF theories and the model-theoretical semantics are very similar in some aspects. Both are related to the structural meaning, going away from the meaning of the word and from the pragmatics, and both propose a logic language that represents the structural meaning of the sentences. In this way, it could be said that in the two theories the LF is a sub-theory discreet of the meaning theory. The model-theoretical semantics go even further when affirming that the LF, more than an established theoretical interpretation of this, is a discreet sub-theory of the meaning theory.

Process to obtain the chosen representation

The process to obtain the chosen representation is a study topic itself. Although the task of choosing an appropriate representation is important, the way in which we arrive to it is even more important. It is hard to classify the systems at this point since each one of them is very particular and we would need to detail the mechanism of each one of them in a particular way. The sets that we can identify are the following systems:

- Systems based on relationships of dependences [3, 9, 10, 14]
- Systems based on syntactic analysis [19, 17, 18, 8]
- Systems based on mixed analysis [23, 24, 1]

Inference Mechanisms

To infer is to conclude or to decide starting from something well-known or assumed. In turn, to reason is to think coherent and logically, establish inferences or conclusions starting from well-known or assumed facts.

The reasoning process, therefore, involves the realization of inferences, starting from well-known facts. To carry out inferences means to derive new facts starting from a facts set known as true.

Among the inference systems we can mention:

- *Direct inference systems:* They apply a reasoning mechanism "forward": starting from well-known results (the axioms and the premises in the case of reasoning proof) they apply inference rules successively until arriving to the formula to prove. Examples: axiomatic systems or Hilbert systems, natural deduction, secuent calculation.
- *Indirect or by refutation inference systems:* They apply an indirect reasoning mechanism based on the reduction to absurdity technique: to demonstrate that a formula is valid it starts from its negation and inferences are carried out until arriving to a contradiction. Examples: resolution method, semantic tableaux.

Unfortunately, the NLP uses big quantities of text that can be transformed in knowledge. Classical Logic is adapted to work in certain concrete domains, but it is insufficient to model the reasoning of this knowledge type correctly.

Hence, other logics have been developed, denominated generically Non-Classical Logics, which are built based on Classical Logic but with more expressive power and with multiple practical applications:

• Logics that incorporate applicable operators on formulas (belief, possibility, necessity or

⁴ First Order Logic.

temporary operators, ...): modal logics, temporary logics.

 Logics that allow to work with incomplete, uncertain or imprecise information: multivalued logics, probabilistic logics, fuzzy logics, nonmonotonous logics.

3. OUR PROPOSAL

As it was previously mentioned, the systems that use NLP resources up to a syntactic level do not overcome a certain precision range. A new generation of systems has begun and they go a step further than these types of systems. The new tendency in the QA systems tends to incorporate more semantics in the process of texts comprehension by means of the use of more complex techniques using external knowledge sources.

In our approach, we propose a new reasoning system to incorporate to the QA system in order to improve the obtained results.

Next, the chosen representation, the LF translating process, the corrections made starting from the input of the process and, later on, the inference system will be detailed.

Logic Representation

To choose an appropriate representation it is necessary to have in mind the utility we are going to make of it, the used resources, the chosen language and future extensions among other things.

Systems that use LF for the Spanish language do not exist and, therefore, feasible resources to be used to help to the inference process do not exist. It is well-known that the English language is a language in which most resources are available. Keeping in mind this, it has been decided to choose for a representation that is easy to adapt to the resulting representation of the translation to Spanish of some of these resources. This representation is the one used by the ExtendedWordNet⁵ (XWN).

Process of transformation in the chosen representation

Figure 1 shows the architecture of the translation process of the syntactic analyzer output to LF and their later input to the inference process.

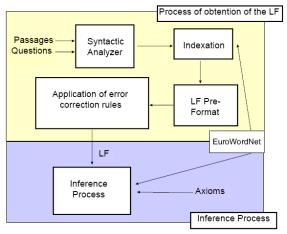


Figure 1: Architecture of the reasoning system.

To transform a paragraph in their logic representation, we start from the output of the partial syntactic analyzer

SUPAR [6]. Figure 2 shows the output of SUPAR for a question.

After this, both the question and the passages are indexed. In the indexation process, a disambiguation process is carried out [25, 5].

· What country invaded Irak in 1990? ¿A qué país invadió Irak en 1990? <@000,1,Frase maco castellano> <@CCC> ¿ Fia ¿ NOSTEM Ă SPS00 a NOSTEM qué PT0CS000 qué NOSTEM <@SNS,,sustAdj,,> <@NSN> país NCMS000 país NOSTEM < @/NSN ><@/SNS,,sustAdj,,> <@VBC> invadió VMIS3S0 invadir NOSTEM <@/VBC> <@SNS,,sustAdj,,> <@NSN> Irak NP00000 Irak NOSTEM <@/NSN> <@SPS> en SPS00 en NOSTEM <@SNS,sp,pron,fechaHora,> 1990 W [??:??/??/1990:??.??] NOSTEM <@/SNS,sp,pron,fechaHora,> <@/SPS> <@/SNS,,sustAdj,,> ? Fit ? NOSTEM <@/CCC> <@/OOO,1,Frase maco castellano>

Figure 2: Example of output of SUPAR.

The world population will increase a 50 percent during the next 35 years, mainly in the developing countries, reaching the figure of 8.500 million people, which will create more difficulties, according to the World Bank.
La población mundial aumentará un 50 por ciento en los próximos 35 años, sobre todo en los países en desarrollo, alcanzando la cifra de 8.500 millones de personas, lo que creará más dificultades, según el Banco Mundial.

3|1|C|X;F;F;Fg;#

|O;la;La;NP00000;01547674 01353399 00550797 00366547 01563290 11288204 07485702 12408908 01232923 04513542*poblacion;población; NCFS000;00509473 04699283 10100482 12668165 12384195*mundial;mundial;AQ0CS0;#I#I#

|V;aumentar;aumentará;VMIF3S0;00136946 01937583 00754271 02308524,00436817 01227164 01470863 00169989 00153292,00606271 01937583 00754271 02308524,01204939 00136946 01937583 00754271 02308524,01540637 02175245 02007386 02308524,01753713 00866031 01278826,01937583 00754271 02308524,02143984 01705360 00136946 01937583 00754271 02308524,02205361 02520193 00827403

|S;uno;un;DI0MS0;#*50/100;50_por_ciento;Zp;# !(en;en±el;los;DA0MP0;#*proximo;próximos;AQ0MP0; #*35;35;Z;#*año;años;NCMP000;05642123 01536186 06022468 04513542,11162972 01536186 06022468 04513542,13991652 01536186 06022468 04513542±#±#)!#

⁵ http://xwn.hlt.utdallas.edu/ (visited on January 30, 2007)

Figure 3: Example of output of an indexed passage.

Figure 3 shows a fragment of an indexed passage. We obtain a hierarchy of the text divided in sentences and at the same time divided in clauses.

AliQAn stores the syntactic blocks obtained from the result of the indexation. These blocks can be of different types: Objects (O), Subjects (S), Verb (V), Complements (C), Relative (R) and Loose Words (X).

Starting from the output of the indexation process, a preformat of the LF will be obtained. The transformation process does not consider all the element types. Some of them are irrelevant or can interfere in a correct functioning of system. Another reason for which only some types are taken into account is the future extension of the process to other languages such as English. In this extension the translation process is usually difficult since there are not substantial translation resources for big volume of words.

The logical representation is given by the synset of the word, this way we reduce the work of considering the synonymy relationship of EuroWordNet⁶ (EWN) since it is implicit. The lemma is the first parameter and the rest of the parameters depend on the label.

If the nouns are in EWN, the second parameter represents the first two characters of the PoS tagger label, which identify the category and the type of each one, and the last parameter we have the variable that will be used to relate the predicates between them. If the nouns were not in EWN, the predicate name is given by the lemma unified to the characters corresponding to the type; the parameters in this case will consist in the last parameter of the previous case corresponding to the variable.

The case of the verbs is similar to nouns with the difference that two more parameters are added. The second parameter corresponds to the event that represents, the following parameter ties the subject and the third argument represents the object that it modifies.

The adjectives will have the same variable as a parameter corresponding to the variable of the noun that it modifies. In the same way, the adverbs will have the variable of event that has the verb which is modifying.

Since the syntactic analyzer is partial, certain errors are produced, which are necessary to identify and correct. Since the correction process is carried out in Prolog, the recognition before mentioned is done to form a predicate called **flooo**. This structure is of the form:

flooo(OOO, [CCC, Type, [[type, Predicate1, Predicate2, ...], ...]], [CCC, Type, [[type, Predicate1, Predicate2,...],...]]).

An example of the analysis and transformation to this structure is given by Figure 4. Next, reduction and correction rules are applied to use some heuristics for to correct these errors. An example of this error type is given in Figure 5 when the conjunction case y (and) is in the beginning of a clause. In this case an error takes place since it is not making the correct connection between the coordinated elements. Thus, when in the first clause we find the relative pronoun *que* (that) and the second clause begins with coordinated conjunction y (and), then it will be a new clause with the union of both clauses and the parameters of the conjunction will bind to the events of the verb of the first clause and with the following verb of the clause where we found the element y (in the example are *e1* and *e2*).

 The 37 year old Zimbabwean player was stopped on Tuesday in the course of a wide El jugador zimbabuo de 37 años, fue detenido el martes en el transcurso de un amplio
Flooo(3, [[1,c,[[0,s03209158(jugador1,nc,x33), zimbabuo1_aq(x33)], [c, de_(x35,x36), numero_Z(`37´,x36), s05642123(anyo1, nc, x36)], [v, s(ser1, vs, x37), detener1_vm(e1, x38, x39)], [s, fecha_w(`martes,S0,S1,S2,S3,S4´,x39), en_(x39,x40), transcurso1_nc(x40), de_(x40,x41), amplio1_aq(x41), [rr, 2]], [r,4]

Figure 4: Example of output of the flooo structure.

[/	′,1,C,
	[O s03791797(grupo1,nc,x141)]
	[X <i>que</i> 1_pr(x143)el1_p0(x144)]
	[V mostrar1_vm(e1,x145,x146)
	complacer1_vm(e1 ,x146,x147)]]
[7	7,2,C,
	[X y 1_cc(x147,x148)]
	[O sorprendido1_aq(x148) por_(x148,x149)
	s01850955(acogida1,nc,x149) recibido1_aq(x149)]
	[V s(haber1,va,x150) convivir1_vm(e2,x151,x152)]
	O s(este1,dd,x152)s03973112(dia1,nc,x152)
	con (x152,x153)
	s02225991(familia1,nc,x153)
	s01569280(japones1,aq,x153)]
	1
1	-

Figure 5: Example of an error produced by the parser.

Inference process

The inference process is the resolution. The resolution strategy chosen is the one of the support set for being complete and sound, using multiresolution. There are diverse reasoners such as Otter, Vampire among others. In this work we use the first reasoner mentioned.

In a formal theory we find a well formed formula set, a subset of these that are the axioms and an inferences rules set. Well formed formulas set of our proposal are the LF described previously. The inference process uses axioms. Some of them generated automatically and others are created manually. Next, we will exemplify some classes of used axioms, in particular the axioms that will be used in the Figure 6 will be shown:

- Axioms automatically generated by the relationships of EWN: for example, synonymy, hyperonymy, hyponymy, etc.
- Linguistic Axioms: These types of axioms are manually generated.
 - The axioms that relate number with quantities, for example this would be useful for the identification of the type of answer expected: $\forall X, X_1$ (*numero_zm*(*X*, *X*₁) \rightarrow *cantidad*(*X*₁)) (see Figure 6 |23|.)
 - If a verb has as subject a name or a noun phrase so this are related by means of a preposition **de** (of): $\forall X, X_1$ (*interpol1_np*(X) & & *disponerde1_vm*(E, X, X_1) &

⁶ http://wordnet.princeton.edu/ (visited on January 30, 2007)

 $s02607133(presupuesto1, nc, X_1) \rightarrow de_(X_1, X))$ (see Figure 6 [18].)

- Axioms of Union: In this case, if a verb is followed by a preposition and the word forming by the join between the verb and the preposition is included in EWN, this union is used. Let us consider the following line of the Figure 6: [11]. interpol1_np (x98) &
 - |12|. disponer1 vm (e1, x98, x99) &
 - |13|. de_(x99, x100) &
 - |14|. s02607133 (budget1, nc, x100) &
 - |15|. de_(x100, x101) &
 - |16|. numero_Zm (2800000_dolar, x101)

In this case the verb **disponer** (to dispose) is followed by the preposition **de** (of). Carrying out multiword recognition, we determine that the term **disponerde** (disposeof) is contained in EWN. In this way, we can replace the LFs [12]. and [13]. in a single LF and whose union variables will be combined in such way that the resulting LF will be: *disponerde_vm(e1, x98, x100*) through the following axiom: $\forall X, X_1, X_2$ (*interpol1_np(X1) & disponerde_vm(E, X1, X2)* & s02607133(presupuesto1, nc, X2) \rightarrow s02607133(presupuesto1, nc, X2) & de(X2,X1) & interpol1_np(X1)) (see Figure 6 [17].)

Next, an example (Figure 6) where AliQAn responds of wrong form to a question and our proposal finds the correct passage in which the answer is contained is shown. Let us consider the following question:

What is the Interpol's budget? (¿Cuál es el presupuesto de la INTERPOL?)

The LF of this question is given by:

cantidad(X2) & s02607133(presupuesto1, nc, X2) & de (X2,X3) & interpol1_np(X3).

1 cantidad(X2) -s02607133(presupuesto1, nc,
$X2$)-de (X2,X3)-interpol1_np(X3).
2. s06880763(narcotrafico1,nc,x88).
[3]. representar1_vm(e1,x90,x91).
4. actualmente1 rg(e91).
[5]. numero_Zm(40000000000_dolar,x92).
$ 6 $. de_(x92,x93).
[7]. s02348211(beneficio1,nc,x93).
8 . al (x93,x94).
9. s05642123(anyo1,nc,x94).
$ 10 $. mientras_que1 cs(x95).
111. interpol1_np(x98).
[12]. disponer1_vm(e1,x98,x99).
13 . de_(x99,x100).
14. s02607133(presupuesto1,nc,x100).
15 . de_(x100,x101).
[16]. numero_Zm(28000000_dolar,x101).
17 disponer1_vm(E, X, X1) -de(X1, X2)
disponerde1_vm(E, X, X2).
18 interpol1_np(X) -disponerde1_vm(E, X, X1) -
s02607133(presupuesto1, nc, X1) de (X1,X).
21 -s02607133(presupuesto1,nc,X) -de(X,X1) -
numero_ $Zm(C,X1)$ numero_ $Zm(C,X)$.
$ 23 $ numero_Zm(X,X1) cantidad(X1).
24 . disponerde1_vm(E,98,100)(12,13,17)
25 . de_(100,98)(11,14,18,24)
[26]. numero_Zm(2800000_dolar,x100)
(14,15,16,21)

27 . cantidad(x100)(23,26))
28 . 🗆(1,14,11,25,27)	

Figure 6: Example of proof for the question: What is the Interpol's budget?

All the terms of the question are derived in their positive form through of the lines |24| to |28|. Thus, the line |28|and the hyperresolution of all the derived terms with the negated question from line |1| of the proof indicate that a proof by contradiction has been succeeded. The success of this proof boosts the candidate answer to the first position. Thus, the system returns the candidate answer, which is correct in this case.

4. EVALUATION

In this section, the results obtained by means of the use of the proposal described previously will be detailed, which demonstrate that the strategy followed improves the precision of AliQAn system. Before showing the results carried out, a series of aspects are detailed, such as the set of facts used and the measure of evaluation necessaries to obtain conclusions of the results.

The evaluation carried out on the AliQAn system [25] and the application of the inference module have been carried out using the questions set proposed by the CLEF 2006 classified for AliQAn as economical, and the documents collection of the EFE agency (1994 and 1995) provided by CLEF for the same year.

Each solution returned by the system can be classified among the following categories:

- **Correct**: the answer returned by the system is exact and does not contain elements or extra components.
- Wrong: two situations may occur:
 - Answers returned by the system do not respond to the formulated question.
 - Questions have not been answered although a solution in the documents exists.
- **Inexact**: the answer returned by the system is correct but:
 - It includes some extra element or component.
 - It lacks some element with regard to what should be the correct solution.
- **Unsupported**: They are correct solutions discovered at random, that is to say, the system responds one correct solution that has been extracted from documents of which the answer cannot be inferred.

To be able to carry out an evaluation of the system precision, a measure that values the general system results in each one of the experiments carried out is needed.

This task is performed using the measure proposed in CLEF 2003 [15]. Equation (1) shows the Mean Reciprocal Rank (MRR) where only the correct answers are graded:

$$MRR = \frac{\left(\sum_{i=1}^{Q} \frac{1}{far(i)}\right)}{Q} \tag{1}$$

where Q is the total number of questions and far(i) indicates the position of the first correct answer. For questions in which answers cannot be found, the value of l/far(i) will be 0.

The evaluation of AliQAn system is only carried out for the monolingual task in Spanish. It has only been kept in mind the evaluation of questions of economic type. In the future the evaluation will be extended to other questions type using new linguistic resources incorporated as knowledge in the inference process. Table 1 shows the increase in the accuracy of the economic type questions of AliQAn system by means of the incorporation of inferences techniques

Test Set	MRR AliQAn(%)	AliQAn with Reasoning
Economic type	33	58 (+75%)
of questions (CLEF 2006)		

 Table 1: Results of applying our inference proposal on
 AliQAn.

As can be observed in Table 1, an improvement of 75% in MRR has been achieved with our approach using the new inference techniques. We can conclude that the adding of semantic information by means of our proposal inference mechanism has significantly improved the selection of the passages that can contain the correct answer and, consequently, a benefice in the ranking of correct answers.

5. CONCLUSIONS

It can be affirmed that the incorporation of inference mechanisms in QA systems is crucial for the increase in the precision of these systems.

Although there is still work to do of them really effective or so that they are able to evolve as those in restricted domains. For it, a detailed study and careful of NLP resources is necessary, among others, to develop a robust tool capable of reasoning automatically in open domains. In this paper a classification that characterizes the existent systems has been created, the reasoning mechanisms have been presented, although diverse more elaborated techniques that will be studied later as subsequent steps in this task got left out. These techniques are the application of non-monotonous reasoning theories, restriction satisfaction, among others. Furthermore, a robust

mechanism of application of rules has been developed by means of which is sought to solve some types of problems that introduce the previous phases. These improvements help to increase the quality of information incorporated to the inference system. Along with this, it has been provided whit transformation techniques starting from the available resources used in the AliQAn system.

An inference tool has been developed for the Spanish language, language in which this type of tools have still not been developed and from which few resources capable of being used by an inference method exist.

Finally, the representation in LF by itself can be seen as a change in the representation of the output of a syntactic analyzer and that does not assist any improvement in the precision of the QA systems, just the proportionate knowledge whether explicitly or implicitly does it. The application of the rules improves the quality of the output of the previous phases just as PoS tagger and syntactic analyzer and the incorporation of a minimum quantity of external knowledge has contributed to an increase in the precision which results proportional to the quantity of external knowledge incorporated in 75%.

It is important to highlight that this study area is new and the creation of resources is necessary for the Spanish language, strengthening our language in this investigation field.

6. FUTURE WORKS

As it has been commented previously, the fan of available techniques that can facilitate the creation of a robust and effective reasoning system is big. Hence, a meticulous study of the techniques used by the existent systems and also of the techniques feasible to be used but that still have not is necessary.

A task that is not easy will be the study and elaboration of tools to be used as a knowledge resource. These tools can be a result of the tools translation available in other language, of the use of ontologies starting from corpus, among other means. As it has been demonstrated in the systems that are already using inference in their systems, the acquisition of such resources is crucial in the improvement of the precision of the QA systems precision. The Spanish language, unlike the English language, for example, is very free in the generation of valid sentences. This produces that an idea is expressed in a bigger number of correct forms. This fact works negatively in the automatization of a QA system for Spanish. However, it is possible to compensate this characteristic, among other things by means of the incorporation of more axioms that represent valid external knowledge to be used in the inference mechanism and therefore be able to achieve independence from the text representation.

7. REFERENCES

[1] S. Abreu. Isco: To practical language for heterogeneous information system construction. In Proceedings of INAP'01. 2001.

[2] F. Benamara, M. Moens, and P. Saint-Dizier. Knowledge and reasoning for answering questions. In Workshop associated with IJCAI05. 2005.

[3] G. Bouma, J. Mur, G. goes Noord, L. goes der Plas, and J. Tiedemann. Question ansering for dutch using dependency relations. In Workshop of Cross-Language Evaluation Forum (CLEF). 2005.

[4] O. Elkhatib, E. Pontelli, and T. Cao Is. Asp-prolog: To system for reasoning about answer Sep programs in prolog. In proceedings 10th International Workshop on Non-Monotonic Reasoning (NMR 2004). 2004.

[5] S. Ferrández, S. Roger, A. Ferrández, A. Aguilar, and P. López-Moreno. To new proposal of word sense disambiguation for nouns on to question answering system. Advances in Natural Language Processing. Research in Computing Science. ISSN: 1665-9899. 7th International Conference, CICling, 18:83-92. 2006.

[6] A. Ferrández. Aproximación computacional al tratamiento de la anáfora pronominal y de tipo adjetivo. PhD thesis, University of Alicante. 1998.

[7] M. Gelfond and V. Lifschitz. The Stable Model Semantics for Logic Programs. In International Symposium on Logic Programming, 1070-1080. 1988.

[8] S. Harabagiu, M. A. Pasca, and S. J. Maiorano. Experiments with textual open-domain question answering. In Proceedings of the COLING-2000. Association for Computational Linguistics. Morgan Kaufmann. 2000.

[9] V. Jijkoun, J. Mur, and M. of Rijke. Information extraction in question answering: Improving recall through syntactic patterns. In Colling 2004, 1284-1290. 2003.

[10] B. Katz and J. Lin. Selectively using relations to improve precision in question answering. In Proceedings of the workshop Natural on Language Processing for Question Answering (EACL 2003), 43-50. 2003.

[11] H. Kautz, M. Kearns, and B. Selman. Horn approximations of empirical dates. Artificial Intelligence, 74:129-145. 1995.

[12] R. Khardon and D. Roth. Reasoning with models. Artificial Intelligence, 87:187-213. 1996.

[13] R. Khardon and D. Roth. Defaults and Relevance in Model Based Reasoning. Artificial Intelligence. 1997.

[14] Kenneth C. Litkowski. Use of metadata for question answering and novelty tasks. In E. M. Voorhees and L. P. Buckland, editors, Proceeding of the eleventh Text Retrieval Conference (TREC 2003), 161–170. 2004.

[15] B. Magnini, S. Romagnoli, A. Vallin, J. Herrera, A. Peñas, V. Peinado, F. Verdejo, and M. Rijke. The Multiple Language Question Answering Track at CLEF 2003. Comparative Evaluation of Multilingual Information Access Systems: 4th Workshop of the Cross-Language Evaluation Forum, CLEF, Trondheim, Norway, 21-22, 2003, Revised Selected Papers.Lecture Notes in Computer Science. 2003.

[16] J. McCarthy and P. Hayes. Some philosophical problems from the standpoint of artificial intelligence. In B. meltzer and D. Michie, editors, 4. 1969.

[17] D. Moldovan, S. Harabagiu, R. Girju, P. Morarescu, F. Lacatusu, A.Novischi, A. Badulescu, and O. Bolohan. Lcc tools for question answering. In Voorhees and Buckland, editors, Proceedings of the 11th Text REtrieval Conference (TREC-2002), NIST, Gaithersburg. 2002.

[18] D. Moldovan, S. Harabagiu, C. Clark, and S.

Maiorano. Cogex: A logic prover for question answering.

In HLT-NAACL, 87-93. 2003.

[19] D. Moldovan and V. Rus. Logic form transformation of wordnet and its applicability to question answering. In ACL, 394–401. 2001.

[20] D. Molla and M. Gardiner. Answerfinder: question answering by combining lexical, syntactic and semantic information. In Australiasian Language Technology Workshop (ALTW). 2004.

[21] J. Pearl. Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference. In Workshop of Cross-Language Evaluation Forum (CLEF). 1988.

[22] J. Prager, J. Chu-Carroll, and K. Czuba. Question answering using constraint satisfaction: Qa-by-dossierwith-contraints. In ACL, 574–581. 2004.

[23] C. Prolo, P. Quaresma, I. Rodrigues, P. Salgueiro, and R. Vieira. A question-answering system for portuguese. In Knowledge and Reasoning for Answering Questions. Workshop associated with IJCAI05, 45–48. 2005.

[24] P. Quaresma and I. Rodrigues. A logic programming based approach to the qa@clef05 track. In Cross Language Evaluation Forum: Working Notes for the CLEF 2005 Workshop). 2005.

[25] S. Roger, S. Ferrández, A. Ferrández, J. Peral, F. Llopis, A. Aguilar, and D. Tomás. AliQAn, Spanish QA System at CLEF-2005. InWorkshop of Cross-Language Evaluation Forum (CLEF). 2005.

[26] V. Rus. Logic Forms for WordNet Glosses. PhD thesis, School of Engineering Southern Methodist University. 2002.