Integrating Multiple Knowledge Sources for Robust Semantic Parsing

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Abstract

This work explores a new robust approach for Semantic Parsing of unrestricted texts. Our approach considers Semantic Parsing as a Consistent Labelling Problem (CLP), allowing the integration of several knowledge types (syntactic and semantic) obtained from different sources (linguistic and statistic). The current implementation obtains 95% accuracy in model identification and 72% in case-role filling.

1 Introduction

A central issue in Semantic Parsing is the production of a case-role analysis in which the semantic roles –such as *agent* or *instrument*– played by each entity are identified (Brill & Mooney 97). This is a crucial task in any application which involves some level of Natural Language Understanding.

This paper presents a new approach to Semantic Parsing (SP). The aim of this research is to develop a robust (able to work on unrestricted text) and flexible (portable and extensible) approach to Semantic Parsing. We will try to do so by formalizing semantic parsing as an Consistent Labelling Problem (CLP), specially focusing on the interaction between syntax and semantics, as well as on verbs, as the head sentence components.

Mahesh (Mahesh 93) proposes a classification of Natural Language Understanding models in: *sequential*, *integrated* and *interactive* depending on the interaction between syntax and semantics. In *Sequential* models, each level receives the output of the previous one, and sends its output to the next. Thus, syntax is solved before any semantic analysis is carried out. On the other hand, in *Integrated* and *Interactive* models, syntactic and semantic processing are performed simultaneously and share a common knowledge representation.

Another relevant issue related to syntax and semantics interaction is the required level of syntax analysis. Chunk parsing (Abney 91) has been widely used in several fields (e.g. Information Extraction) as an alternative to deal with the lack of robustness presented by traditional full parsing approaches: close world assumption (full coverage grammar and lexicon), local errors produced by global parsing considerations (Grishman 95) and the selection of the best parse tree among a forest of possible candidates. Given that the verb is the central sentence component, there is no doubt that subcategorization information may not only improve parsing —e.g. taking into account probabilistic subcategorization on a statistical parser (Carroll *et al.* 98), but also provide the basic information to assemble those chunks in larger structures.

Following this brief introduction, sections 2, 3 and 4 present, respectively, the basic ideas of our system and its architecture, as well as the way in which the different sources of knowledge are integrated. Section 5 describes the experiments carried out and reports the results obtained. Finally, section 6 presents some conclusions and outlines further research lines.

2 PARDON approach

Our view of semantic parsing is based on compositional semantics and lexicalized models (i.e. the meaning of a sentence is the result of combining the meaning of its words and the possible combinations are determined by their models). Bearing that in mind, PARDON approach combines the *Interactive Model* and chunk parsing. Roughly speaking, PARDON combines semantic objects associated to chunks in order to build a case-role representation of the sentence. This combination is carried out using syntactic and semantic knowledge obtained from a linguistic approach (subcategorization frames) and complemented with a statistical model of lexical attraction.

For instance, starting from the chunks in the sentence "Este año en el congreso del partido se habló de las pensiones"[1] shown in Figure 1, we

[1] *Literal Translation: This year in the meeting of the political party one talked about the pensions*

Este año	en el congreso	del partido	se	habló	de las pensiones
head:año hdle: pos:NP num:sg gen:m sem:Time	head:congreso hdle:en pos:PP num:sg gen:m sem:Top	head:partido hdle:de pos:PP num:sg gen:m sem:Group Human	head:se hdle: pos:se num: per: sem:Top	head:hablar hdle:hablar pos:VP num:sg per:3 sem:Commun.	head:pensión hdle:de pos:PP num:pl per:3 sem:Top

Figure 1: Chunks for "Este año en el congreso del partido se habló de las pensiones"

Este año	model:impersonal event:habló se:se entity:de las pensiones	model:N_{de} head:en el congreso modif:del partido

Figure 2: Case-role structures obtained for the sentence in Figure 1

will obtain the case-role representation shown in Figure 2 by combining:

- The initial semantic objects associated to those chunks
- The impersonal model of the verb "hablar" (to talk) shown in Table 1
- The noun modifier model shown in Table 2

3 PARDON architecture

We propose a novel architecture where high level syntax and semantics decisions are fully integrated. There are two main steps in PARDON: The first step is the *Sentence Analyzer*, which performs PoS-tagging, chunking and semantic annotation. It also accesses the subcategorization (hand build) and lexical attraction (statistical) knowledge bases, to complete the sentence model with those kinds of knowledge.

The verbal subcategorization information is obtained from LEXPIR (Fernández & Martí 96; Fernández *et al.* 99; Morante *et al.* 98) developed inside the Pirapides[2] project. Table 1 shows the basic and impersonal models for the verb "hablar" (*to talk*). In this work we used 61 verbs belonging to the LEXPIR trajectory class, which includes the equivalent of Levin's movement and communication classes.

The second step is *Selection*, which solves the Consistent Labelling Problem to find out which is the most appropriate verbal model for the sentence and role filling for each chunk.

4 PARDON Formalization

We formalize PARDON approach by setting the case-role interpretation problem as a *Consistent Labelling Problem* (CLP), where the different kinds of knowledge are applied as weighted constraints.

A CLP basically consists of finding the most consistent label assignment for a set of variables, given a set of constraints. Once the sentence and its knowledge is represented in terms of a CLP, a relaxation labelling algorithm is used to obtain the most consistent interpretation. See (Padró 98) for details on the use of these algorithm for NLP tasks.

This formulation allows us to naturally integrate different kinds of knowledge coming from different sources (linguistic and statistic), which may be partial, partially incorrect or even inconsistent.

PARDON represents the meaning of a sentence in terms of relationships between semantic objects, using two variables for each semantic object: the *model* ($object_{\text{model}}$) and *role* ($object_{\text{role}}$) variables. For instance, the semantic object associated to a chunk headed by "hablar" (to talk) can use a *basic* model (someone talks about something with someone: [$hablar_{\text{model}} = basic$]) or an *impersonal* model (*one* talks about something [$hablar_{\text{model}} = impersonal$]).

The *role* variable represents the role that a semantic object plays inside the model of another semantic object. For instance, the semantic object "pensiones" (the pensions) can play the role

[2] Pirapides is centered on the study of the English, Spanish and Catalan verbal predicates, based on Levin (Levin 93) and Pustejovsky's (Pustejovsky 95) theories. LEXPIR models include information about the number of arguments, their syntactic realization, prepositions they can take, their semantic component and restrictions, their agreement with the verb and their optionality.

basic model for "hablar"					
Synt.	Prep.	Comp.	Seman.	Agree.	Opt.
NP	x	starter	Human	yes	yes
PP	de, sobre	entity	Top	no	yes
PP	con	destination	Top	no	yes

impersonal model for "hablar"					
Synt.	Prep.	Comp.	Seman.	Agree.	Opt.
SE	x	se	Top	no	no
PP	de, sobre	entity	Top	no	yes
PP	con	destination	Top	no	yes

Table 1: Models for the verb "hablar"

entity for both models of "hablar" (to talk) (e.g. [$pensiones_{\text{role}}$ = *(entity, basic, hablar)*])

To identify a role from a model label we need a triple *(role, model, semantic object)*. For instance, the role *starter* of the *basic* model for "hablar", represented as *(starter, basic, hablar)*.

Since a CLP always assigns a label to all the variables, two null labels have to be added: the label NONE for the model variables (semantic objects which does not have/use a model, usually leaf semantic objects with no sub-constituents) and the label TOP for the role variables (semantic objects not playing a role in the model of a higher constituent, usually the sentence head). Figure 3 shows the variables and labels associated to the semantic objects in Figure 1.

After formalizing Semantic Parsing as a Consistent Labelling Problem, a set of constraints stating valid/invalid assignations is required to find a possible solution. PARDON uses three kinds of constraints: The first group contains the constraints that encode the linguistic information obtained from verb subcategorization models. The second group are additional constraints added to force a tree-like structure for the solution. Finally, a third set of constraints encoding statistical information about word cooccurrences, was added in order to complement the subcategorization information available.

Constraints are noted as follows:

[A = x] $\approx^{w}$ [B = y] denotes a constraint stating a compatibility degree w when variable A has label x and variable B has label y. The compatibility degree w may be positive (stating compatibility) or negative (stating incompatibility).

4.1 Subcategorization Constraints

Two different kinds of subcategorization models have been used: one about verbal subcategorization and one about noun modifiers.

For each chunk labelled as VP, all possible subcategorization models for the verb heading the chunk are retrieved from LEXPIR. For PP and NP we use the simple nominal modifier model N_{de} presented in table 2.

Due to the richness of natural language we cannot expect to find, in a real sentence sample, the exact prototypical subcategorization patterns that have been modelled in LEXPIR. Thus, a measure of the "goodness" of the possible model instantiation is defined in a similar way to the tree-edit based pattern matching used in (Atserias *et al.* 99; Atserias *et al.* 00).

In order to ensure the global applicability (minimal disorder, agreement, maximum similarity between the role and semantic object and maximal number of roles) and the consistence of the model (a unique instantiation per role and the instantiation of compulsory roles) the following constraints are automatically instantiated from the models:

- **Role Uniqueness**: The same role can not be assigned to different chunks, e.g.:

  [$pension_{\text{role}}$ = *(entity, basic, hablar)*] $\approx^{-1}$ [$partido_{\text{role}}$ = *(entity, basic, hablar)*]

  This constraint penalizes the current weight of the assignment [$pension_{\text{role}}$ = *(entity, basic, hablar)*] according to the current weight of the assignment [$partido_{\text{role}}$ = *(entity, basic, hablar)*]. Thus, the higher the weight for the latter assignment is, the faster the weight of the former will decrease.

N_{de} model for nouns					
Synt.	Prep.	Comp.	Seman.	Agree.	Opt.
PP	de	modifier	Top	no	no

Table 2: Model for noun modifiers

- **Model Support**: A model assignment is compatible with its optional roles, e.g.:

  $[hablar_{\text{model}} = \text{basic}] \approx^{+1}$
  $[pension_{\text{role}} = (entity, basic, hablar)]$
- **Model Inconsistence**: A model assignment is incompatible with the inexistence of any of its compulsory roles, e.g.:

  $[hablar_{\text{model}} = \text{impersonal}] \approx^{-1}$
  $\neg\ [se_{\text{role}} = (se, impersonal, hablar)]$
- **Role Support**: A role assignment is compatible with the assignment of its model, e.g.:

  $[pension_{\text{role}} = (entity, basic, hablar)]$
  $\approx^{+sim(pension,(entity,basic,hablar))}$
  $[hablar_{\text{model}} = \text{basic}]$

  The weight for this constraint is defined as a function sim, which measures the similarity between two feature structures yielding a value normalized in $[-1, 1]$, inversely proportional to the number of relabelling operations needed to transform one feature structure into the other. Currently, only semantics, gender and number are considered.
- **Role Inconsistence**: A role assignment is incompatible with the *no existence* of the assignment of its own model, e.g.:

  $[pension_{\text{role}} = (entity, basic, hablar)] \approx^{-1}$
  $\neg\ [hablar_{\text{model}} = \text{basic}]$

Additionally, a special set of constraints has been introduced to deal with PP-attachment:

- **Local PP attachment**: A prepositional phrase tends to be attached to its nearest head. The weight assigned to each constraint will decrease along with the distance (in words) between the semantic objects involved, e.g.:

  $[pension_{\text{role}} = (entity, impersonal, hablar)]$
  $\approx^{-distance(pension,hablar)}$ [ ].

4.2 Structural Constraints

Some further constraints must be included to force the solution to have a tree-like structure. These constraints are not derived from the subcategorization models.

- **TOP Uniqueness**: Different assignments of the label TOP are incompatible, e.g.:

  $[partido_{\text{role}} = \text{TOP}] \approx^{-1} [hablar_{\text{role}} = \text{TOP}]$.
- **TOP Existence**: There is at least a TOP. Notice that there is no right side on the constraint as it is valid for any context, e.g.:

  $[hablar_{\text{role}} = \text{TOP}] \approx^{+1}$ [ ]
- **No Cycles**: Two assignments forming a direct cycle are incompatible[3], e.g.:

  $[pension_{\text{role}} = (modif, N_{de}, partido)] \approx^{-1}$
  $[partido_{\text{role}} = (modif, N_{de}, pension)]$
- **NONE Support**: The NONE model is compatible with the inexistence of any role assignment of the semantic object models, e.g.:

  $[congreso_{\text{model}} = \text{NONE}] \approx^{+1}$
  $\neg\ [pension_{\text{role}} = (modif, N_{de}, congreso)] \wedge$
  $\neg\ [partido_{\text{role}} = (modif, N_{de}, congreso)]$

  If these constraints were not included, the NONE model would never be selected, since there would always be some other model with a very small non-zero support.

4.3 Statistical Constraints

In a similar way to (Yuret 98) we define also a language model based on lexical attraction. In our case, we estimate the likelihood of a syntactic relation not between two words but between two semantic objects.

Our hypothesis is that the relations between two semantic objects can be determined taking into account two special elements of their associated chunks, the *handle* and the *head*. The *handle* of a chunk is usually the preposition which specifies the type of relation it has with another chunk, while the *head* of a chunk is supposed to capture the meaning of the chunk (Basili *et al.* 98). For instance, the chunk "de las pensiones" (*about the pensions*) has handle "de" (*about*) and *head* "pensión" (*pension*).

Since related words are expected to occur together more likely than unrelated words, the

[3] In this first prototype of PARDON indirect cycles are not taken into account

Variable Name	*Possible Labels*
$año_{\text{model}}$	group NONE
$año_{\text{role}}$	*(starter, basic, hablar)* TOP
$congreso_{\text{model}}$	group NONE
$congreso_{\text{role}}$	TOP
$partido_{\text{model}}$	group NONE
$partido_{\text{role}}$	*(entity, basic, hablar)* *(entity, impersonal, hablar)* *(modif, N_{de}, año)* *(modif, N_{de}, congreso)* *(modif, N_{de}, pension)* TOP
se_{model}	NONE
se_{role}	*(se, impersonal, hablar)* TOP
$hablar_{\text{model}}$	basic impersonal NONE
$hablar_{\text{role}}$	TOP
$pensión_{\text{model}}$	group NONE
$pensión_{\text{role}}$	*(entity, basic, hablar)* *(entity, impersonal, hablar)* *(modif, N_{de}, año)* *(modif, N_{de}, congreso)* *(modif, N_{de}, partido)* TOP

Figure 3: CLP associated to the objects in figure 1

lexical attraction (the likelihood of a syntactic relation) between two words can be estimated/modeled through coocurrence. Cooccurence data can also indicate negative relatedness, where the probability of cooccurence is less than by chance. Thus, we will measure lexical attraction between two sematic objects with the coocurrence of both heads and the cooccurrence of the head and the handle (which gives an implicit direction of the dependence).

Since the coocurrences were taken from the definitions of a Spanish dictionary, lemma coocurrences were used instead of word coocurrences in order to minimize the problems caused by unseen words (Dagan *et al.* 99). 175,333 head-handle coocurrences and 961,470 head-head cooccurences were obtained out of 40,591 different head-lemmas and 160 different handle-prepositions. The cooccurrences were used to compute Mutual Information for each lemma–preposition pair.

$$MI(head_i, handle_j) = log \frac{P(head_i \cap handle_j)}{P(head_i) \times P(handle_j)}$$

In the case of lemma-lemma pairs, sparseness is much higher. Thus, an indirect measure was applied, namely context vector cosine (also used in IR and WSD (Schtze, 1992)) in order to calculate the lexical attraction between heads:

$$cos(head_i, head_j) = \frac{\sum_k a_{ki} a_{kj}}{\sqrt{\sum_k a_{ki}^2 \sum_k a_{kj}^2}}$$

where a_{pq} is the cooccurrence frequency of lemma p and lemma q, and k ranges over all the lemmas cooccurring with any of both heads.

Thus, for any two semantic objects the following constraints are added:

- A_i-H_j constraint, which supports any assignment of a role from $object_j$ to $object_i$, e.g.:

  $[partido_{\text{role}} = (modif,\ N_{de},\ congreso)]$
  $\approx^{MI(congreso,de)}$ [ ]
- H_i-H_j constraint, which supports any assignment of a role from $object_i$ to $object_j$, or viceversa, e.g.:

  $[pensión_{\text{role}} = (entity,\ impersonal,\ hablar)]$
  $\approx^{cos(hablar,pension)}$ [ ]

H_i-H_j and A_i-H_j constraints can be used to identify adjuncts or relations for which we have no models. For instance, in the result obtained for the sentence shown in Figure 1, the sematic object "en el congreso" (*in the meeting*) will be identified as depending on the verb "hablar", even when its role can not be determined.

5 Experiments

170 real sentences were taken from a Spanish newspaper and were labelled by hand with the verbal models and the meaning components. The sentence average length is 8.1 words, ranging from 3 to 23. Only one-verb sentences were selected, since our knowledge base does not include models for subordination or coordination. However, our approach to semantic parsing has been designed to manage multiple models simultaneously competing for their arguments.

Each sentence in the corpus was tagged and parsed with a wide-coverage grammar of Spanish (Castellón *et al.* 98) to obtain a chunk parse tree. Spanish Wordnet (Atserias *et al.* 97) was used to semantically annotate the corpus with the 79 semantic labels defined in the preliminary version of the EuroWordnet Top Ontology (Rodríguez *et al.* 98).

In order to reduce the complexity of the relaxation process, the possible role labels (which indicate the roles an object can play in any of the models retrieved) are filtered considering the unary constraints about POS and prepositions, while constraints about semantics and agreement are taken as a measure of how similar (*sim*) is the semantic object and the role. Models which can not match compulsory roles are not considered.

For instance, the semantic object *año* (*year*) in the example sentence will be allowed to match the role *starter* of the impersonal model of the verb *hablar* even though its semantics is not Human, but the semantic object *congreso* will not be considered as a candidate to fill the *entity* role of *hablar*, since the preposition *en* in the semantic object does not match the model requirements for that role (preposition *de, sobre*).

All these filters produce the candidate labels shown in Figure 3, and are the input to PARDON *Selection* step.

5.1 Results

The results reported have been calculated using Message Understanding Conferences (MUC95) evaluation metrics applied to our particular case of verbal model identification and case-role filling.

Model identification metrics evaluate how well our system identifies the right model for a semantic object. Our corpus has 2.7 models per verbal semantic object as average ambiguity.

Since it is assumed that there is only one right model per chunk in each sentence, the answer can only be correct (COR) or incorrect (INC), thus, the used metrics are precision and recall. Table 3 shows the results obtained in the verbal model identification task: 95% precision and 91% recall.

COR	INC	PRE	REC
155	8	95%	91%

Table 3: Verbal Model identification results

Case-role filling consists in assigning each semantic object to the right role it plays in the models for other semantic objects. In this case, the casuistics is more complex, since in addition to the correct/incorrect distinctions, other cases must be considered, such as the roles that are (correctly/incorrectly) left unassigned (because they were optional, or there was no semantic object that fitted them, etc.). The MUC evaluation metrics establish the following cases:

- **Correct** (COR): Roles correctly assigned by the system.
- **Incorrect** (INC): Roles incorrectly assigned by the system.
- **Missing** (MIS): Roles unassigned by the system when they should have been assigned.
- **Spurious** (SPU): Roles assigned by the system when they should have been unassigned.

These cases lead to the definition of the following measures, where **Possible** (POS) are the roles that should be assigned (COR+INC+MIS) and **Actual** (ACT) are the roles actually assigned by the system under evaluation (COR+INC+SPU):

- **Undergeneration** $UND = 100 \times \frac{MIS}{POS}$
- **Overgeneration** $OVR = 100 \times \frac{SPU}{ACT}$
- **Substitution** $SUB = 100 \times \frac{INC}{COR+INC}$
- **Error** $ERR = 100 \times \frac{INC+SPU+MIS}{COR+INC+SPU+MIS}$
- **Precision** $PRE = 100 \times \frac{COR}{ACT}$
- **Recall** $REC = 100 \times \frac{COR}{POS}$

In addition, precision and recall may be combined in different F-measures ($P\&R$, $2P\&R$ and $P\&2R$). Table 4 shows the results in the case-role filling for verbal arguments.

COR	INC	MIS	SPU	POS	ACT
203	27	60	51	290	281

UND	OVR	SUB	ERR	PRE	REC
20%	18%	12%	40%	72%	70%

$P\&R$	$2P\&R$	$P\&2R$
71%	70%	72%

Table 4: Verbal case-role filling results

To our knowledge there is neither a similar general approach nor case-role filling experiments to which our results can be compared. In any case, our preliminary results (72% PRE - 70% REC) are very encouraging.

It is also remarkable that our system produces low values for UND, OVR and SUB measures, pointing that it properly uses the different kinds of knowledge, and that it does not take uninformed or gratuitous decisions.

Errors in the preprocessing steps caused most of miss-identified models (table 3, INC) The *missing* and *spurious* roles (table 4, MIS and SPU) were due either to the lack of semantic information or to the lack of a verbal model for adjuncts, which caused miss-identification of adjuncts as arguments, as in "(Juan) (esquía) (este fin) (de año)"[4], where the chunk "este fin de año" (*on New Year's Eve*) is wrongly identified to fill the *route* role even though its semantics is *Time*. This is due to the lack of a selectional restriction that forces the *route* to be a *Place*, and to the lack of a model that identifies the chunk as time adjunct.

6 Conclusions & Further Work

This paper has presented a new approach to Semantic Parsing for non domain-specific texts based on the *Interactive Model*. The robustness and flexibility of PARDON is achieved combining a chunk parsing approach with the framing of the semantic parsing problem in a CLP. The flexibility of our approach enables the integration of different types of knowledge (linguistically motivated subcategorization models plus statistical information obtained from corpora).

Currently, PARDON obtains a 95% precision on model identification and 72% precision on role filling. Although the experiments have been carried out on a limited corpus and lexicon, they have proven the feasibility of the method.

Further work should includes a more realistic evaluation of the system, using a larger corpus with sentences having multiple verbs. In this case, verbal models will compete in a sentence for their arguments. We also plan to include more statistical knowlege (measures/language models) and to extend the coverage and expressiveness of the subcategorization models. Furthermore, the output of the current system could also be used as feedback to improve the existing verbal models.

Exploration of linguistic and statistical models for the identification/distinction of verbal adjuncts should also be addressed, since it seems one of the main causes of the miss-identification of the verbal arguments.

[4] *John goes skying on New Year's Eve*

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