The Domain Restriction Hypothesis:
Relating Term Similarity and Semantic Consistency

Alfio Massimiliano Gliozzo
ITC-irst
Trento, Italy
gliozzo@itc.it

Marco Pennacchiotti
University of Rome Tor Vergata
Rome, Italy
pennacchiotti@info.uniroma2.it

Patrick Pantel
USC, Information Sciences Institute
Marina del Rey, CA
pantel@isi.edu

Abstract

In this paper, we empirically demonstrate what we call the domain restriction hypothesis, claiming that semantically related terms extracted from a corpus tend to be semantically coherent. We apply this hypothesis to define a post-processing module for the output of *Espresso*, a state of the art relation extraction system, showing that irrelevant and erroneous relations can be filtered out by our module, increasing the precision of the final output. Results are confirmed by both quantitative and qualitative analyses, showing that very high precision can be reached.

1 Introduction

Relation extraction is a fundamental step in many natural language processing applications such as learning ontologies from texts (Buitelaar et al., 2005) and Question Answering (Pasca and Harabagiu, 2001).

The most common approach for acquiring concepts, instances and relations is to harvest semantic knowledge from texts. These techniques have been largely explored and today they achieve reasonable accuracy. Harvested lexical resources, such as concept lists (Pantel and Lin, 2002), facts (Etzioni et al., 2002) and semantic relations (Pantel and Pennacchiotti, 2006) could be then successfully used in different frameworks and applications.

The state of the art technology for relation extraction primarily relies on pattern-based approaches (Snow et al., 2006). These techniques are based on the recognition of the typical patterns that express a particular relation in text (e.g. *"X such as Y"* usually expresses an *is-a* relation). Yet, text-based algorithms for relation extraction, in particular pattern-based algorithms, still suffer from a number of limitations due to complexities of natural language, some of which we describe below.

Irrelevant relations. These are valid relations that are not of interest in the domain at hand. For example, in a political domain, *"Condoleezza Rice is a football fan"* is not as relevant as *"Condoleezza Rice is the Secretary of State of the United States"*. Irrelevant relations are ubiquitous, and affect ontology reliability, if used to populate it, as the relation drives the wrong type of ontological knowledge.

Erroneous or false relations. These are particularly harmful, since they directly affect algorithm precision. A pattern-based relation extraction algorithm is particularly likely to extract erroneous relations if it uses *generic patterns*, which are defined in (Pantel and Pennacchiotti, 2006) as broad coverage, noisy patterns with high recall and low precision (e.g. *"X of Y"* for *part-of* relation). Harvesting algorithms either ignore generic patterns (Hearst, 1992) (affecting system recall) or use manually supervised filtering approaches (Girju et al., 2006) or use completely unsupervised Web-filtering methods (Pantel and Pennacchiotti, 2006). Yet, these methods still do not sufficiently mitigate the problem of erroneous relations.

Background knowledge. Another aspect that makes relation harvesting difficult is related to the

nature of semantic relations: relations among entities are mostly paradigmatic (de Saussure, 1922), and are usually established *in absentia* (i.e., they are not made explicit in text). According to Eco's position (Eco, 1979), the background knowledge (e.g. *"persons are humans"*) is often assumed by the writer, and thus is not explicitly mentioned in text. In some cases, such widely-known relations can be captured by distributional similarity techniques but not by pattern-based approaches.

Metaphorical language. Even when paradigmatic relations are explicitly expressed in texts, it can be very difficult to distinguish between facts and metaphoric usage (e.g. the expression *"My mind is a pearl"* occurs 17 times on the Web, but it is clear that *mind* is not a *pearl*, at least from an ontological perspective).

The considerations above outline some of the difficulties of taking a purely lexico-syntactic approach to relation extraction. Pragmatic issues (*background knowledge* and *metaphorical language*) and ontological issues (*irrelevant relation*) can not be solved at the syntactic level. Also, *erroneous relations* can always arise. These considerations lead us to the intuition that extraction can benefit from imposing some additional constraints.

In this paper, we integrate Espresso with a lexical distribution technique modeling semantic coherence through *semantic domains* (Magnini et al., 2002). These are defined as common discourse topics which demonstrate lexical coherence, such as ECONOMICS or POLITICS. We explore whether semantic domains can provide the needed additional constraints to mitigate the acceptance of erroneous relations. At the *lexical level*, semantic domains identify clusters of (domain) paradigmatically related terms. We believe that the main advantage of adopting semantic domains in relation extraction is that relations are established mainly among terms in the same Domain, while concepts belonging to different fields are mostly unrelated (Gliozzo, 2005), as described in Section 2. For example, in a chemistry domain, an *is-a* will tend to relate only terms of that domain (e.g., *nitrogen is-a element*), while out-of-domain relations are likely to be erroneous *e.g., driver is-a element*.

By integrating pattern-based and distributional ap-

proaches we aim to capture the two characteristic properties of semantic relations:

- *Syntagmatic properties*: if two terms X and Y are in a given relation, they tend to co-occur in texts, and are mostly connected by specific lexical-syntactic patterns (e.g., the patter "X is a Y" connects terms in *is-a* relations). This aspect is captured using a pattern-based approach.

- *Domain properties*: if a semantic relation among two terms X and Y holds, both X and Y should belong to the same semantic domain (i.e. they are *semantically coherent*), where semantic domains are sets of terms characterized by very similar distributional properties in a (possibly domain specific) corpus.

In Section 2, we develop the concept of semantic domain and an automatic acquisition procedure based on Latent Semantic Analysis (LSA) and we provide empirical evidence of the connection between relation extraction and domain modelling. Section 3 describes the Espresso system. Section 4 concerns our integration of semantic domains and Espresso. In Section 5, we evaluate the impact of our LSA domain restriction module on improving a state of the art relation extraction system. In Section 6 we draw some interesting research directions opened by our work.

2 Semantic Domains

Semantic domains are common areas of human discussion, which demonstrate lexical coherence, such as ECONOMICS, POLITICS, LAW, SCIENCE, (Magnini et al., 2002). At the *lexical level*, semantic domains identify clusters of (domain) related lexical-concepts, i.e. sets of highly paradigmatically related words also known as Semantic Fields.

In the literature, semantic domains have been inferred from corpora by adopting term clustering methodologies (Gliozzo, 2005), and have been used for several NLP tasks, such as Text Categorization and Ontology Learning (Gliozzo, 2006).

Semantic domains can be described by Domain Models (DMs) (Gliozzo, 2005). A DM is a com-

putational model for semantic domains, that represents domain information at the term level, by defining a set of term clusters. Each cluster represents a Semantic Domain, i.e. a set of terms that often co-occur in texts having similar topics. A DM is represented by a $k \times k'$ rectangular matrix $\mathbf{D}$, containing the domain relevance for each term with respect to each domain, as illustrated in Table 1.

	MEDICINE	COMPUTER_SCIENCE
HIV	1	0
AIDS	1	0
virus	0.5	0.5
laptop	0	1

Table 1: Example of a Domain Model

DMs can be acquired from texts in a completely unsupervised way by exploiting a lexical coherence assumption. To this end, term clustering algorithms can be used with each cluster representing a Semantic Domain. The degree of association among terms and clusters, estimated by the learning algorithm, provides a domain relevance function. For our experiments we adopted a clustering strategy based on LSA (Deerwester et al., 1990), following the methodology described in (Gliozzo, 2005). The input of the LSA process is a term-by-document matrix $\mathbf{T}$ reporting the term frequencies in the whole corpus for each term. The matrix is decomposed by means of a Singular Value Decomposition (SVD), identifying the principal components of $\mathbf{T}$. This operation is done off-line, and can be efficiently performed on large corpora. SVD decomposes $\mathbf{T}$ into three matrixes $\mathbf{T} \simeq \mathbf{V} \mathbf{\Sigma_{k'}} \mathbf{U}^T$ where $\mathbf{\Sigma_{k'}}$ is the diagonal $k \times k$ matrix containing the highest $k' \ll k$ eigenvalues of $\mathbf{T}$ on the diagonal, and all the remaining elements are 0. The parameter k' is the dimensionality of the domain and can be fixed in advance[1]. Under this setting we define the domain matrix $\mathbf{D_{LSA}}$[2] as

$$ \mathbf{D_{LSA}} = \mathbf{I^N} \mathbf{V} \sqrt{\mathbf{\Sigma_{k'}}} \qquad (1) $$

where $\mathbf{I^N}$ is a diagonal matrix such that $\mathbf{i^N_{i,i}} = \frac{1}{\sqrt{\langle \vec{w'_i}, \vec{w'_i} \rangle}}$ and $\vec{w'_i}$ is the ith row of the matrix $\mathbf{V} \sqrt{\mathbf{\Sigma_{k'}}}$.

---

[1]It is not clear how to choose the right dimensionality. In our experiments we used 100 dimensions.

[2]Details of this operation can be found in (Gliozzo, 2005).

Once a DM has been defined by the matrix $\mathbf{D}$, the Domain Space is a k' dimensional space, in which both texts and terms are associated to Domain Vectors (DVs), i.e. vectors representing their domain relevancies with respect to each domain. The DV $\vec{t'_i}$ for the term $t_i \in \mathcal{V}$ is the ith row of $\mathbf{D}$, where $\mathcal{V} = \{t_1, t_2, \ldots, t_k\}$ is the vocabulary of the corpus. The domain similarity $\phi_d(t_i, t_j)$ among terms is then estimated by the cosine among their corresponding DVs in the Domain Space, defined as follows:

$$ \phi_d(t_i, t_j) = \frac{\langle \vec{t_i}, \vec{t_j} \rangle}{\sqrt{\langle \vec{t_i}, \vec{t_i} \rangle \langle \vec{t_j}, \vec{t_j} \rangle}} \qquad (2) $$
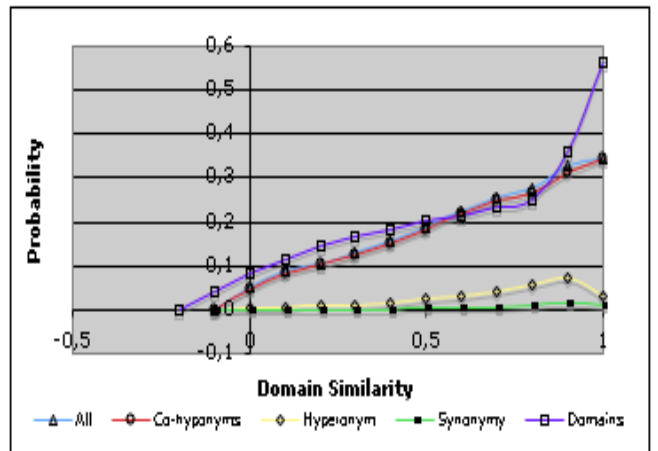

Figure 1: Probability of finding paradigmatic relations

The main advantage of adopting semantic domains for relation extraction is that they allow us to impose a domain restriction on the set of candidate pairs of related terms. In fact, semantic relations can be established mainly among terms in the same Semantic Domain, while concepts belonging to different fields are mostly unrelated.

To show the validity of the domain restriction we conducted a preliminary experiment, contrasting the probability for two words to be related in Word-Net (Magnini and Cavaglià, 2000) with their domain similarity, measured in the Domain Space induced from the British National Corpus. In particular, for each couple of words, we estimated the domain similarity, and we collected word pairs in sets characterized by different ranges of similarity (e.g. all the pairs between 0.8 and 0.9). Then we estimated the

probability of each couple of words in different sets to be linked by a semantic relation in WordNet, such as synonymy, hyperonymy, co-hyponymy and domain in WordNet Domains (Magnini et al., 2002). Results in Figure 1 show a monotonic crescent relation between these two quantities. In particular the probability for two words to be related tends to 0 when their similarity is negative (i.e., they are not domain related), supporting the basic hypothesis of this work. In Section 4 we will show that this property can be used to improve the overall performances of the relation extraction algorithm.

3 The pattern-based Espresso system

Espresso (Pantel and Pennacchiotti, 2006) is a corpus-based general purpose, broad, and accurate relation extraction algorithm requiring minimal supervision, whose core is based on the framework adopted in (Hearst, 1992). Espresso introduces two main innovations that guarantee high performance: (i) a principled measure for estimating the reliability of relational patterns and instances; (ii) an algorithm for exploiting *generic patterns*. Generic patterns are broad coverage noisy patterns (high recall and low precision), e.g. *"X of Y"* for the *part-of* relation. As underlined in the introduction, previous algorithms either required significant manual work to make use of generic patterns, or simply ignore them. Espresso exploits an unsupervised Web-based filtering method to detect generic patterns and to distinguish their correct and incorrect instances.

Given a specific relation (e.g. *is-a*) and a POS-tagged corpus, Espresso takes as input few seed instances (e.g. *nitrogen is-a element*) or seed surface patterns (e.g. *X/NN such/JJ as/IN Y/NN*). It then incrementally learns new patterns and instances by iterating on the following three phases, until a specific stop condition is met (i.e., new patterns are below a pre-defined threshold of reliability).

Pattern Induction. Given an input set of seed instances I, Espresso infers new patterns connecting as many instances as possible in the given corpus. To do so, Espresso uses a slight modification of the state of the art algorithm described in (Ravichandran and Hovy, 2002). For each instance in input, the sentences containing it are first retrieved and then generalized, by replacing term expressions with a terminological label using regular expressions on the POS-tags. This generalization allows to ease the problem of data sparseness in small corpora. Unfortunately, as patterns become more generic, they are more prone to low precision.

Pattern Ranking and Selection. Espresso ranks all extracted patterns using a *reliability measure* r_π and discards all but the top-k P patterns, where k is set to the number of patterns from the previous iteration plus one. r_π captures the intuition that a reliable pattern is one that is both highly precise and one that extracts many instances. r_π is formally defined as the average strength of association between a pattern p and each input instance i in I, weighted by the reliability r_ι of the instance i (described later):

$$r_\pi(p) = \frac{\sum_{i \in I} \left(\frac{pmi(i,p)}{max_{pmi}} * r_\iota(i) \right)}{|I|}$$

where $pmi(i, p)$ is the pointwise mutual information (pmi) between i and p (estimated with Maximum Likelihood Estimation), and max_{pmi} is the maximum pmi between all patterns and all instances.

Instance Extraction, Ranking, Selection. Espresso extracts from the corpus the set of instances I matching the patterns in P. In this phase generic patterns are detected, and their instances are filtered, using a technique described in detail in (Pantel and Pennacchiotti, 2006). Instances are then ranked using a reliability measure r_ι, similar to that adopted for patterns. A reliable instance should be highly associated with as many reliable patterns as possible:

$$r_\iota(i) = \frac{\sum_{p \in P} \left(\frac{pmi(i,p)}{max_{pmi}} * r_\pi(i) \right)}{|P|}$$

Finally, the best scoring instances are selected for the following iteration. If the number of extracted instances is too low (as often happens in small corpora) Espresso enters an expansion phase, in which instances are expanded by using web based and syntactic techniques.

The output Espresso is a list of instances $i = (X, Y) \in I$, ranked according to $r_\iota(i)$. This score accounts for the *syntagmatic* similarity between X and Y, i.e., how strong is the co-occurrence of X and Y in texts with a given pattern p.

A key role in the Espresso algorithm is played by the reliability measures. The accuracy of the whole extraction process is in fact highly sensitive to the ranking of patterns and instances because, at each iteration, only the best scoring entities are retained. For instance, if an erroneous instance is selected after the first iteration, it could in theory affect the following pattern extraction phase and cause drift in consequent iterations. This issue is critical for generic patterns (where precision is still a problem, even with Web-based filtering), and could sometimes also affect non-generic patterns.

It would be then useful to integrate Espresso with a technique able to retain only very precise instances, without compromising recall. As syntagmatic strategies are already in place, another strategy is needed. In the next Section, we show how this can be achieved using instance domain information.

4 Integrating syntagmatic and domain information

The strategy of integrating syntagmatic and domain information has demonstrated to be fruitful in many NLP tasks, such as Word Sense Disambiguation and open domain Ontology Learning (Gliozzo, 2006). According to the structural view (de Saussure, 1922), both aspects contribute to determine the linguistic value (i.e. the meaning) of words: the meaning of lexical constituents is determined by a complex network of semantic relations among words. This suggests that relation extraction can benefit from accounting for both syntagmatic and domain aspects at the same time.

To demonstrate the validity of this claim we can explore many different integration schemata. For example we can restrict the search space (i.e. the set of candidate instances) to the set of all those terms belonging to the same domain. Another possibility is to exploit a similarity metric for domain relatedness to re-rank the output instances I of Espresso, hoping that the top ranked ones will mostly be those which are correct. One advantage of this latter method-

ology is that it can be applied to the output of any relation extraction system without any modification to the system itself. In addition, this methodology can be evaluated by adopting standard Information Retrieval (IR) measures, such as mean average precision (see Section 5). Because of these advantages, we decided to adopt the re-ranking procedure.

The procedure is defined as follows: each instance extracted by Espresso is assigned a *Domain Similarity* score $\phi_d(X, Y)$ estimated in the domain space according to Equation 2; a higher score is then assigned to the instances that tend to co-occur in the same documents in the corpus. For example, the candidate instances *ethanol is-a nonaromatic_alcohol* has a higher score than *ethanol is-a something*, as *ethanol* and *alcohol* are both from the chemistry domain, while *something* is a generic term and is thus not associated to any domain.

Instances are then re-ranked according to $\phi_d(X, Y)$, which is used as the new index of reliability instead of the original reliability scores of Espresso. In Subsection 5.2 we will show that the re-ranking technique improves the original reliability scores of Espresso.

5 Evaluation

In this Section we evaluate the benefits of applying the domain information to relation extraction (ESP-LSA), by measuring the improvements of Espresso due to domain based re-ranking.

5.1 Experimental Settings

As a baseline system, we used the ESP- implementation of Espresso described in (Pantel and Pennacchiotti, 2006). ESP- is a fully functioning Espresso system, without the generic pattern filtering module (ESP+). We decided to use ESP- for two main reasons. First, the manual evaluation process would have been too time consuming, as ESP+ extracts thousands of relations. Also, the small scale experiment for EXP- allows us to better analyse and compare the results.

To perform the re-ranking operation, we acquired a Domain Model from the input corpus itself. To this aim we performed a SVD of the term by document matrix T describing the input corpus, indexing all the candidate terms recognized by Espresso.

As an evaluation benchmark, we adopted the same instance sets extracted by ESP- in the experiment described in (Pantel and Pennacchiotti, 2006). We used an input corpus of 313,590 words, a college chemistry textbook (Brown et al. 2003), pre-processed using the Alembic Workbench POS-tagger (Day et al. 1997). We considered the following relations: **is-a**, **part-of**, **reaction** (a relation of chemical reaction among chemical entities) and **production** (a process or chemical element/object producing a result). ESP- extracted 200 *is-a*, 111 *part-of*, 40 *reaction* and 196 *production* instances.

5.2 Quantitative Analysis

The experimental evaluation compared the accuracy of the ranked set of instances extracted by ESP- with the re-ranking produced on these instances by ESP-LSA. By analogy to IR, we are interested in extracting positive instances (i.e. semantically related words). Accordingly, we utilize the standard definitions of precision and recall typically used in IR . Table 2 reports the Mean Average Precision obtained by both ESP- and ESP-LSA on the extracted relations, showing the substantial improvements on all the relations due to domain based re-ranking.

	ESP-	ESP-LSA	
is-a	0.54	**0.75**	(+0.21)
part-of	0.65	**0.82**	(+0.17)
react	0.75	**0.82**	(+0.07)
produce	0.55	**0.62**	(+0.07)

Table 2: Mean Average Precision reported by ESP- and ESP-LSA

Figures 2, 3, 4 and 5 report the precision/recall curves obtained for each relation, estimated by measuring the precision / recall at each point of the ranked list. Results show that precision is very high especially for the top ranked relations extracted by ESP-LSA. Precision reaches the upper bound for the top ranked part of the **part-of** relation, while it is close to 0.9 for the *is-a* relation. In all cases, the precision reported by the ESP-LSA system surpass those of the ESP- system at all recall points.

5.3 Qualitative Analysis

Table 3 shows the best scoring instances for ESP- and ESP-LSA on the evaluated relations. Results
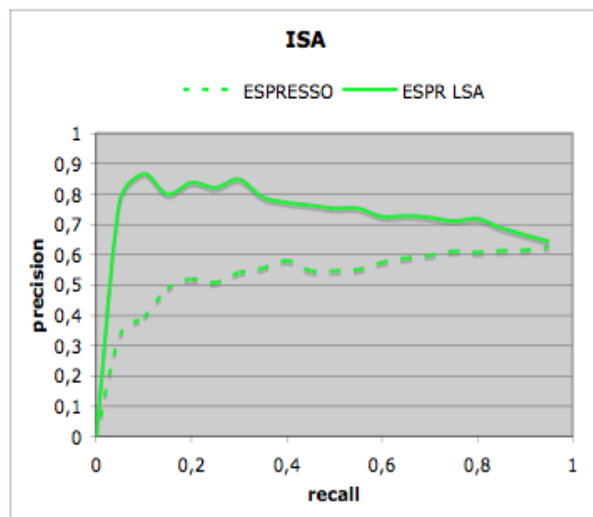

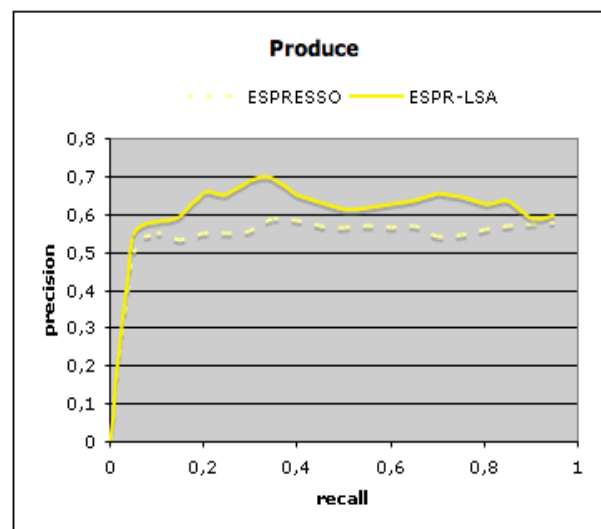Figure 2: Syntagmatic vs. Domain ranking for the **is-a** relation

Figure 3: Syntagmatic vs. Domain ranking for the **produce** relation

show that ESP-LSA tends to assign a much lower score to erroneous instances, as compared to the original Espresso reliability ranking. For example for the *part-of* relation, the ESP- ranks the erroneous instance *geometry part-of ion* in 23th position, while ESP-LSA re-ranks it in 92nd. In this case, a lower score is assigned because *geometry* is not particularly tied to the domain of chemistry. Also, ESP-LSA tends to penalize instances derived from parsing/tokenization errors:
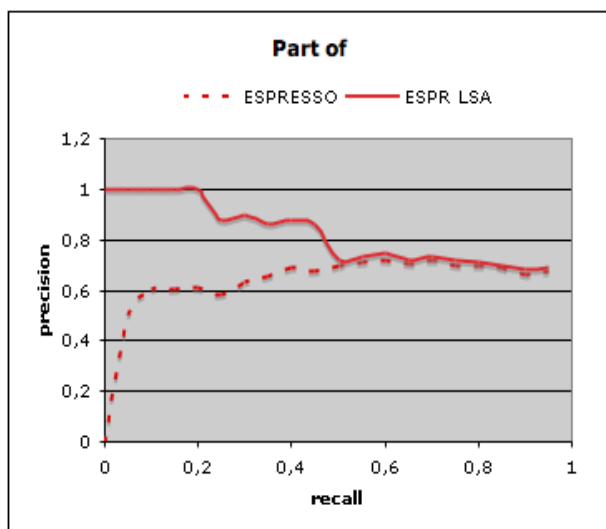
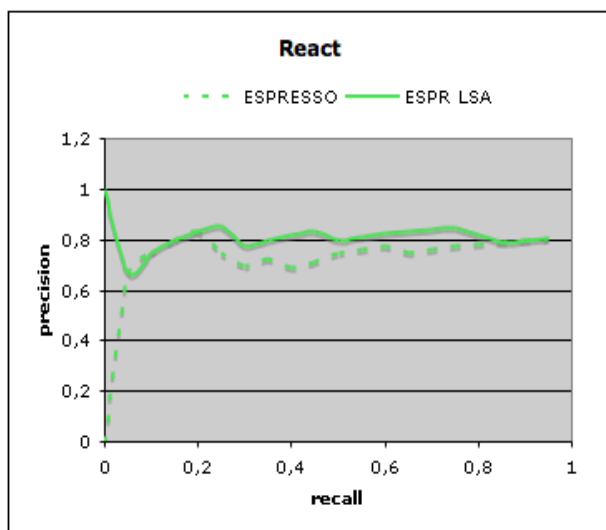Figure 4: Syntagmatic vs. Domain ranking for the **part-of** relation

Figure 5: Syntagmatic vs. Domain ranking for the **react** relation

]_binary_hydrogen_compounds_hydrogen react elements is 16th for ESP-, while in the last tenth of the ESP-LSA. In addition, *out-of-domain relations* are successfully interpreted by ESP-LSA. For example, the instance *sentences part-of exceptions* is a possibly correct relation, but unrelated to the domain, as an *exception* in chemistry has nothing to do with *sentences*. This instance lies at the bottom of the ESP-LSA ranking, while is in the middle of ESP- list. Also, low ranked and correct relations ex-

tracted by ESP- emerge with ESP-LSA. For example, *magnesium_metal react elemental_oxygen* lies at the end of ESP- rank, as there are not enough syntagmatic evidence (co-occurrences) that let the instance emerge. The domain analysis of ESP-LSA promotes this instance to the 2nd rank position. However, in few cases, the strategy adopted by ESP-LSA tends to promote erroneous instances (e.g. *high voltage produce voltage*). Yet, results show that these are isolated cases.

6 Conclusion and future work

In this paper, we propose the domain restriction hypothesis, claiming that semantically related terms extracted from a corpus tend to be semantically coherent. Applying this hypothesis, we presented a new method to improve the precision of pattern-based relation extraction algorithms, where the integration of domain information allows the system to filter out many irrelevant relations, erroneous candidate pairs and metaphorical language relational expressions, while capturing the assumed knowledge required to discover paradigmatic associations among terms. Experimental evidences supports this claim both qualitatively and quantitatively, opening a promising research direction, that we plan to explore much more in depth. In the future, we plan to compare LSA to other term similarity measures, to train the LSA model on large open domain corpora and to apply our technique to both generic and specific corpora in different domains. We want also to increase the level of integration of the LSA technique in the Espresso algorithm, by using LSA as an alternative reliability measure at each iteration. We will also explore the domain restriction property of semantic domains to develop open domain ontology learning systems, as proposed in (Gliozzo, 2006).

The *domain restriction hypothesis* has potential to greatly impact many applications where matching textual expressions is a primary component. It is our hope that by combining existing ranking strategies in applications such as information retrieval, question answering, information extraction and document classification, with knowledge of the coherence of the underlying text, one will see significant improvements in matching accuracy.

Relation	ESP-	ESP - LSA
X is-a Y	Aluminum ; metal nitride_ion ; strong_Br heat_flow ; calorimeter complete_ionic_equation ; spectator	F ; electronegative_atoms O ; electronegative_atoms NaCN ; cyanide_salt NaCN ; cyanide_salts
X part-of Y	elements ; compound composition ; substance blocks ; tripeptide elements ; sodium_chloride	amino_acid_building_blocks ; tripeptide acid_building_blocks ; tripeptide powdered_zinc_metal ; battery building_blocks ; tripeptide
X react Y	hydrazine ; water magnesium_metal ; hydrochloric_acid magnesium ; oxygen magnesium_metal ; acid	magnesium_metal ; elemental_oxygen nitrogen ; ammonia sodium_metal ; chloride carbon_dioxide ; methane
X produce Y	bromine ; bromide oxygen ; oxide common_fuels ; dioxide kidneys ; stones	high_voltage ; voltage reactions ; reactions dr_jekyll ; hyde yellow_pigments ; green_pigment

Table 3: Top scoring relations extracted by ESP- and ESP-LSA.

Acknowledgments

References

P. Buitelaar, P. Cimiano, and B. Magnini. 2005. *Ontology learning from texts: methods, evaluation and applications*. IOS Press.

F. de Saussure. 1922. *Cours de linguistique générale*. Payot, Paris.

S. Deerwester, S. Dumais, G. Furnas, T. Landauer, and R. Harshman. 1990. Indexing by latent semantic analysis. *Journal of the American Society of Information Science*.

U. Eco. 1979. *Lector in fabula*. Bompiani.

O. Etzioni, M.J. Cafarella, D. Downey, A.-M A.M. Popescu, T. Shaked, S. Soderland, D.S. Weld, and A. Yates. 2002. Unsupervised named-entity extraction from the web: An experimental study. *Artificial Intelligence*, 165(1):91–143.

R. Girju, A. Badulescu, and D. Moldovan. 2006. Learning semantic constraints for the automatic discovery of part-whole relations. In *Proceedings of HLT/NAACL-03*, pages 80–87, Edmonton, Canada, July.

A. Gliozzo. 2005. *Semantic Domains in Computational Linguistics*. Ph.D. thesis, University of Trento.

A. Gliozzo. 2006. The god model. In *Proceedings of EACL*.

M.A. Hearst. 1992. Automatic acquisition of hyponyms from large text corpora. In *Proceedings of the 14th International Conference on Computational Linguistics. Nantes, France*.

B. Magnini and G. Cavaglià. 2000. Integrating subject field codes into WordNet. In *Proceedings of LREC-2000*, pages 1413–1418, Athens, Greece, June.

B. Magnini, C. Strapparava, G. Pezzulo, and A. Gliozzo. 2002. The role of domain information in word sense disambiguation. *Natural Language Engineering*, 8(4):359–373.

P. Pantel and D. Lin. 2002. Discovering word senses from text. In *Proceedings of ACM Conference on Knowledge Discovery and Data Mining*, pages 613–619.

P. Pantel and M. Pennacchiotti. 2006. Espresso: Leveraging generic patterns for automatically harvesting semantic relations. In *ACL-COLING-06*, pages 113–120, Sydney, Australia.

M. Pasca and S. Harabagiu. 2001. The informative role of wordnet in open-domain question answering. In *Proceedings of NAACL-01 Workshop on WordNet and Other Lexical Resources*, pages 138–143, Pittsburgh, PA.

D. Ravichandran and E. Hovy. 2002. Learning surface text patterns for a question answering system. In *Proceedings of ACL-02*, pages 41–47, Philadelphia, PA.

R. Snow, D. Jurafsky, and A.Y. Ng. 2006. Semantic taxonomy induction from heterogenous evidence. In *Proceedings of the ACL/COLING-06*, pages 801–808, Sydney, Australia.