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On the semantics of noun compounds

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Abstract

This paper provides new insights on the semantic characteristics of two and three noun compounds. An analysis is performed using two sets of semantic classification categories: a list of 8 prepositional paraphrases previously proposed by Lauer [Designing statistical language learners: experiments on noun compounds, Ph.D. Thesis, Macquarie University, Australia] and a new set of 35 semantic relations introduced by us. We show the distribution of these semantic categories on a corpus of noun compounds and present several models for the bracketing and the semantic classification of noun compounds. The results are compared against state-of-the-art models reported in the literature.

1. Introduction

The semantic interpretation of noun compounds (NCs) deals with the detection and semantic classification of the relations between noun constituents. The problem is complex and has been studied intensively in linguistics, psycho-linguistics, philosophy, and computational linguistics for a long time. There are several reasons that make this task difficult. (a) NCs have implicit

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semantic relations; for example, "*spoon handle*" encodes a PART-WHOLE relation, (b) NCs' interpretation is knowledge intensive and can be idiosyncratic. For example to correctly interpret "*GM car*" one has to know that GM is a car-producing company. (c) There can be more than one semantic relation encapsulated in a pair of nouns. For example, "*Texas city*" can be tagged as a PART-WHOLE relation as well as a LOCATION relation. (d) The interpretation of NCs can be highly context-dependent. For example, "*apple juice seat*" can be defined as "seat with apple juice on the table in front of it" (cf. Downing, 1977).

Although researchers (Jespersen, 1954; Downing, 1977) argued that noun compounds encode an infinite set of semantic relations, many agree (Levi, 1978; Finin, 1980) there is a limited number of relations that occur with high frequency in noun compounds. However, the number and the level of abstraction of these frequently used semantic categories are not agreed upon. They can vary from a few prepositional paraphrases (Lauer, 1995) to hundreds and even thousands more specific semantic relations (Finin, 1980). The more abstract the categories, the more noun compounds are covered, but also the more room for variation as to which category a compound should be assigned. Lauer (Lauer, 1995), for example, considers eight prepositional paraphrases as semantic classification categories: *of*, *for*, *with*, *in*, *on*, *at*, *about*, and *from*. According to this classification, the noun compound "*bird sanctuary*", for instance, can be classified both as "*sanctuary* **of** *bird*" and "*sanctuary* **for** *bird*". The main problem with these abstract categories is that much of the meaning of individual compounds is lost, and sometimes there is no way to decide whether a form is derived from one category or another.

On the other hand, lists of very specific semantic relations are difficult to build as they usually contain a very large number of predicates, such as the list of all possible verbs that can link the noun constituents. Finin (1980), for example, uses semantic categories such as "**dissolved in**" to build interpretations of compounds like "*salt water*" and "*sugar water*". Although, there were several proposals of possible large sets of semantic relations, there has been no attempt to map one set to another, and more importantly, to define the most appropriate level of abstraction for the interpretation of compounds in general, or for a specific application in particular.

Due to the recursiveness of compounding (Selkirk, 1982), much of the semantics of two-word noun compounds applies to multi-word compounds. However, the interpretation problem becomes significantly more complicated for larger noun sequences, such as three noun compounds since both the modifier and the head nouns can form noun compounds generating *structural ambiguities*. This task is called *bracketing* or *attachment* and is the first step in interpreting multiword noun compounds. Choosing the most probable binary bracketing for a given noun sequence represents a difficult task as attachments are not syntactically, but semantically governed. Consider, for example, the following noun compounds: (1) ((*consumer confidence*) *survey*), (2) (*state* (*gasoline tax*)), and (3) (*car* (*radio equipment*)) or ((*car radio*) *equipment*). The noun compound (1) is left-bracketed, while the noun compound (2) is right-bracketed. There are also situations such as (3) in which both left- and right-branching solutions are possible. Sometimes, the disambiguation is provided only by the context.

The automatic interpretation of noun compounds is a difficult task for both unsupervised and supervised approaches. Currently, the best-performing NC interpretation methods in computational linguistics focus only on two-word noun compounds and rely either on rather ad-hoc, domain-specific, hand-coded semantic taxonomies, or on statistical models on large collections of unlabeled data. Recent results have shown that symbolic NC interpretation systems using

Machine Learning techniques coupled with a large lexical hierarchy perform with very good accuracy, but they are most of the time tailored to a specific domain (Rosario and Hearst, 2001).

The majority of corpus statistics approaches to noun compound interpretation collect statistics on the occurrence frequency of the noun constituents and use them in a probabilistic model (Resnik, 1993; Lauer, 1995; Lapata and Keller, 2004). The problem is that most noun compounds are rare and thus, statistics on such infrequent instances lead in general to unreliable estimates of probabilities. More recently, Lapata and Keller (2004) showed that simple unsupervised models applied to the noun compound interpretation task perform significantly better when the *n*-gram frequencies are obtained from the web (accuracy of 55.71% on Altavista), rather than from a large standard corpus. However, although the web-based solution might overcome the data sparseness problem, the probabilistic models are limited by the lack of linguistic information. Most of the time the probabilities are computed on lexical items with or without inflected forms. This simplistic approach introduces a number of ambiguities ranging from syntactic and structural, to semantic.

In this paper we describe various domain independent models that use supervised machine learning techniques and a set of linguistic features. The main feature of these models is the use of the word sense disambiguation information of the noun constituents extracted based on their surrounding context. We focus only on two and three noun compositional compounds, i.e., those whose meaning can be derived from the meaning of the constituent nouns (e.g., "*door knob*"), and tackle both the bracketing and the interpretation tasks. However, we check if the constructions are lexicalized (non-compositional), ie. the meaning is a matter of convention (e.g., "*soap opera*"), but only for statistical purposes. We present empirical observations on the distribution of a core set of semantic relations in noun compounds and provide a mapping between two sets of semantic classification categories. The noun compound interpretation system has been tested on a list of 8 general prepositional paraphrases (Lauer, 1995) and a list of 35 semantic relations (Moldovan and Girju, 2003). We also compare our results for bracketing and interpretation tasks against two baselines and against two state-of-the-art interpretation systems.

The paper is organized as follows. Section 2 presents the general approach for the interpretation of noun compounds and lists the semantic categories used along with observations regarding the distribution of these semantic categories in the corpus. Sections 3 and 4 present models and results for the interpretation of two, respectively, three noun compounds. Finally, some conclusions are offered in Section 5.

2. Approach

We approach the problem top-down, namely identify first the characteristics or feature vectors of noun compounds, then develop models for their semantic classification. This is in contrast to our prior approach (Girju et al., 2003) where we studied one semantic relation at a time, and learned constraints to identify only that relation. The distribution of noun compound semantic relations in a corpus is analyzed shedding some light on the resulting *semantic spaces*. We define a semantic space as the set of relations encoded by noun compounds. We aim at uncovering the general aspects that govern the semantics of noun compounds, and thus delineate the semantic

space within different sets of semantic classification categories. These feature vectors are then employed in various learning models.

2.1. Lists of semantic classification relations

In this paper we consider two sets of semantic classification categories for the interpretation of noun compounds. The first is Lauer's list of 8 prepositional paraphrases presented in Section 1 and the second is a list of 35 semantic relations identified by us after many iterations over a period of time (Moldovan and Girju, 2003). This list, presented in Table 3 along with examples, is general enough to cover a large majority of text semantics while keeping the semantic relations to a manageable number.

We selected these sets as they are of different size and contain semantic classification categories at different levels of abstraction. Lauer's list is more abstract and, thus capable of encoding a large number of noun compound instances found in a corpus, while our list contains finer grained semantic categories. We show below the coverage of these semantic lists on a fairly large corpus, how well they solve the interpretation problem, and the mapping from one list to another.

2.2. Corpus analysis

In order to devise an automatic method for the detection of semantic relations in noun compounds, we analyzed the semantic behavior of these constructions on a large, domain independent corpora of examples. Our intention is to answer questions like: (1) Given a set of semantic classification relations and a corpus of examples, what is the core subset frequently encoded by noun compounds? otherwise said, Is there a subset of preferred meanings? (2) What is their distribution on a large corpus?, (3) Are there semantic relations that are not allowed in noun compounds?, (4) How well can noun compounds be paraphrased with prepositional paraphrases, and, respectively, with more specific semantic relations?, and (5) How many NCs are lexicalized?

2.2.1. The data

For each type of noun compounds considered, a training corpus was assembled from two sources: Wall Street Journal (WSJ) articles from TREC-9,[1] and extended WordNet glosses (XWN 2.0) (www.xwn.hlt.utdallas.edu). We used XWN since all its glosses are syntactically parsed and words are semantically disambiguated which saved us a considerable amount of time. Table 1 shows the number of randomly selected sentences from each text collection and the corresponding number of instances of annotated pairs after the inter-annotator agreement. The annotation of each example consists of specifying its feature vector and the most appropriate interpretation based on: (1) the list of 35 semantic relations (35 SRs) (Table 3) and (2) the Lauer's list of 8 prepositional paraphrases (8 PPs) (cf. Lauer, 1995).

Since we wanted to compare our approach with two state-of-the-art unsupervised probabilistic models, we selected as test sets those randomly obtained by Lauer from Grolier Encyclopedia for

[1] TExt Retrieval Conference (TREC-9), Question Answering competition, 2000 (www.trec.nist.gov/).

Table 1
Number of sentences and training noun compound instances after agreement selected from each text collection considered

Collection	Two noun compounds		Three noun compounds
	WSJ	XWN	WSJ
Number of sentences	3217	5672	49,208
Number of annotated training instances after agreement	2606	1379	362

each type of noun compounds: 282 noun–noun pairs for two noun compounds, and 244 three noun instances for three noun compounds. However, the training and test sets for each noun compound type have different distributions. Thus, we further shuffled the training and test corpora and randomly split them again maintaining the same ratio. We call these training and test sets *unshuffled* and, respectively, *shuffled*.

2.2.2. Corpus annotation and inter-annotator agreement

Two Ph.D. students in Computational Semantics have annotated separately all the noun compounds in the training corpora. Sequences of two and three nouns were extracted from syntactically parsed sentences (Charniak's parser – Charniak, 2000) using Lauer's heuristic (Lauer, 1995) (for XWN we used the gold parse trees). The heuristic looks for consecutive nouns of size two and, respectively, three, that are neither preceded nor succeeded by a noun. In order to eliminate the wrong instances selected by the heuristic, the annotators were provided with the sentence in which the nouns occurred and were asked to manually check the noun compounds. The remaining NCs were tagged with their corresponding WordNet senses if found in WordNet (360 instances were not found in WordNet or the correct sense was missing) and semantic classification relations. Whenever the annotators found an example encoding a semantic relation and a prepositional paraphrase other than those provided or they didn't know what interpretation to give, they had to tag it as "OTHERS-SR" and, respectively, "OTHERS-PP". Besides the type of relation, the annotators were asked to provide information about the order of the modifier and the head nouns in a noun–noun pair if applicable. For instance, in "*honey bee*"-MAKE/PRODUCE the product *honey* is followed by the producer *bee*, while in "*GM car*"-MAKE/PRODUCE/r the order is reversed (r means reversed). On average, 34% of the noun–noun training examples and 24% of the three noun compound instances had at least a noun–noun pair in reverse order.

Most of the time, one instance was tagged with one semantic relation and, respectively, prepositional paraphrase, but there were also situations in which an example could belong to more than one relation in the same context. For example, "*Texas city*" was tagged as a PART-WHOLE/PLACE-AREA relation and as a LOCATION relation, and, respectively, as "*city of Texas*", "*city from Texas*", and "*city in Texas*". Overall, for noun–noun compounds 608 instances were tagged with more than one semantic relation and almost all paraphrasable instances were tagged with more than one prepositional paraphrase. Moreover, the annotators were asked to indicate if the instance was lexicalized or not. They found that 30% of the two noun compounds were lexicalized, from which 18% were proper names.

For three noun compounds, the annotators had the additional task of bracketing them in context and then adding the corresponding semantic classification relations to the bracketed noun–noun pairs. For example, "((*consumer confidence*)EXPERIENCER *survey*) TOPIC" is left-branching. We obtained a bracketing agreement of 87% which was computed as the number of pairs bracketed in the same way by both annotators, over the number of instances classified in the bracketing category considered, by at least one of the judges. For three noun compounds, 33.7% of the instances contained at least one WordNet noun–noun concept that led to an automatic bracketing. From these, 58% were right bracketed, while 68% of the non-WordNet compounds were left bracketed. For example, "((*stock market*) *boom*)" is automatically left bracketed since "*stock market*" is a WordNet concept.

For the two test corpora, we used Lauer's bracketing and prepositional paraphrase annotations. The annotators added the other annotations considered for the training corpora: they disambiguated the noun constituents in isolation (as Lauer provided no context) and tagged the noun–noun pairs with the 35 semantic relations.

The annotators' agreement was measured using Kappa statistics (Siegel and Castellan, 1988), one of the most frequently used measure of inter-annotator agreement for classification tasks: $K = \frac{Pr(A)-Pr(E)}{1-Pr(E)}$, where $Pr(A)$ is the proportion of times the annotators agree and $Pr(E)$ is the probability of agreement by chance. The K coefficient is 1 if there is a total agreement among the annotators, and 0 if there is no agreement other than that expected to occur by chance.

Table 2 shows the inter-annotator agreement on the unshuffled training corpora for each semantic interpretation category. We computed the K coefficient only for those instances tagged with one of the 35 semantic relations, respectively, 8 prepositional paraphrases. We also computed the number of pairs that were tagged with OTHERS by both annotators for each semantic interpretation relation, over the number of examples classified in that category by at least one of the judges. Due to time constraints, we were unable to annotate the set of three noun compounds with prepositional paraphrases.

In the training corpus, 6.9% of the instances tagged with prepositional paraphrases were included in OTHERS category. From these, 4.2% could be paraphrased with other prepositions than those considered by Lauer (e.g., "*bus service*" – "*service by bus*"), and 2.7% could not be paraphrased with prepositions (e.g., "*daisy flower*").

The K coefficient shows a fair to good level of agreement for the training data on the set of 35 relations, taking into consideration the task difficulty. As Table 2 shows, the level of agreement

Table 2
The inter-annotator agreement on the semantic annotation of the noun compounds in the unshuffled training corpora

	Kappa agreement (1–35)		OTHERS
	Two noun compounds	Three noun compounds	
8 PPs	0.80	NA	91%
35 SRs	0.58	0.69	76%

For the noun compound instances that encoded more than one semantic classification category, the agreement was done on one of the relations only. The agreement on the semantic relations for three noun compounds was computed on gold bracketing. "NA" means not available (due to time constraints, we were unable to annotate the set of three noun compounds with prepositional paraphrases).

for the prepositional paraphrases was much higher. All these can be explained by the instructions the annotators received prior to the annotation and by their expertise in lexical semantics.

On the test corpora, the annotation with the set of 35 semantic relations was also done by the two annotators. The disagreement instances were solved by a third judge.

Table 3
The distribution of semantic relations on the annotated unshuffled training corpora after agreement

No.	Semantic relations	N N		N N N			
		%	Example	Left bracket (%)		Right bracket (%)	
				n_1–n_2	n_2–n_3	n_1–n_3	n_2–n_3
1	POSSESSION	3.41	"*family estate*"	1.8	2.5	5.12	3.8
2	KINSHIP	0	–	0	0	0	0
3	ATTRIBUTE-HOLDER	8.48	"*quality sound*"	14.1	8.6	16.7	24.4
4	AGENT	4.88	"*crew investigation*"	7.4	21.5	12.8	15.4
5	TEMPORAL	0.93	"*night flight*"	0.6	0.6	14.1	5.1
6	DEPICTION-DEPICTED	0.04	"*image team*"	0	0	0	0
7	PART-WHOLE	16.98	"*girl mouth*"	7.4	9.8	11.5	2.6
8	IS-A (HYPERNYMY)	2.13	"*Dallas city*"	1.2	0	0	0
9	ENTAIL	0	–	0	0	0	0
10	CAUSE	0.04	"*malaria mosquito*"	0	0	0	0
11	MAKE/PRODUCE	3.68	"*shoe factory*"	4.3	8.6	0	1.3
12	INSTRUMENT	2.04	"*pump drainage*"	1.8	1.8	0	3.8
13	LOCATION/SPACE	8.14	"*Texas university*"	8.0	6.1	6.4	10.3
14	PURPOSE	11.96	"*migraine drug*"	3.1	4.3	0	14.1
15	SOURCE	1.75	"*olive oil*"	0	1.2	0	0
16	TOPIC	13.07	"*art museum*"	6.1	13.5	3.8	6.4
17	MANNER	0.17	"*style performance*"	2.5	0.6	1.3	0
18	MEANS	0.57	"*bus service*"	0	0	0	0
19	ACCOMPANIMENT	0	"*friends meeting*"	0	0.6	1.3	0
20	EXPERIENCER	0.37	"*disease victim*"	1.2	1.2	1.3	1.3
21	RECIPIENT	0.28	"*worker fatalities*"	6.7	3.1	3.8	0
22	FREQUENCY	0	–	0	0	0	0
23	INFLUENCE	0	–	0	0	0	0
24	ASSOCIATED WITH	0	–	0	0	0	0
25	MEASURE	1.44	"*session day*"	0.6	0.6	0	0
26	SYNONYMY	0	–	0	0	0	0
27	ANTONYMY	0	–	0	0	0	0
28	PROBABILITY	0	–	0	0	0	0
29	POSSIBILITY	0	–	0	0	0	0
30	CERTAINTY	0	–	0	0	0	0
31	THEME	10.99	"*car salesman*"	31.9	10.5	12.1	11.6
32	RESULT	1.64	"*combustion gas*"	1.2	4.9	2.6	0
33	STIMULUS	0	–	0	0	0	0
34	EXTENT	0	–	0	0	0	0
35	PREDICATE	0	–	0	0	0	0
OTHERS-SR		6.64	"*airmail stamp*"	3.7		7.1	
Total no. of examples		4504		328		156	

The semantic relations for which there was no example given were not encoded by the noun compounds.

2.3. Distribution of semantic relations over the training and test corpora

Although noun compounds are very productive allowing for a fairly large number of possible interpretations, Table 3 shows that a relatively small subset of the 35 semantic relations covers most of the semantic distribution of these constructions on a large open-domain

Table 4
Mapping between the two sets of semantic classification categories: 8 prepositional paraphrases (PPs) and 35 semantic relations (SRs)

SRs/PPs	of (%)	for (%)	in (%)	on (%)	at (%)	from (%)	with (%)	about (%)	OTHERS-PP (%)	Total
1	96.10	1.94	0	0	0	0	1.94	0	0	154
2	0	0	0	0	0	0	0	0	0	0
3	49.47	0.26	2.09	0.78	0	0	0.26	0	47.12	382
4	68.18	13.63	5.90	2.27	1.81	1.36	0	0	6.81	220
5	45.23	0	33.33	4.76	4.76	0	0	0	11.90	42
6	100	0	0	0	0	0	0	0	0	2
7	71.37	0.65	23.79	0.26	0.26	0.78	1.56	0	1.30	765
8	51.04	0	0	0	0	0	3.12	0	45.83	96
9	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	100	2
11	62.04	3.61	4.21	0	0	27.10	1.20	1.80	0	166
12	1.08	21.73	2.17	0	0	0	75	0	0	92
13	5.01	0.52	67.81	18.73	7.65	0	0.26	0	0	379
14	9.46	87.94	0.18	2.04	0	0	0.18	0.18	0	539
15	3.79	0	0	0	0	96.20	0	0	0	101
16	18.16	3.56	0.84	9.33	0	0	0.67	67.40	0	589
17	12.5	37.5	12.5	0	0	0	37.5	0	0	8
18	0	0	0	0	0	0	0	0	100	4
19	0	0	0	0	0	0	0	0	0	0
20	94.11	0	5.88	0	0	0	0	0	0	17
21	15.38	76.92	0	0	0	0	7.69	0	0	13
22	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0
25	41.53	4.61	0	0	0	0	0	0	53.84	65
26	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0
31	84.24	6.66	5.85	2.62	0	0	0.40	0.20	0	495
32	10.81	0	1.35	17.56	0	70.27	0	0	0	74
33	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0
Total	1869	616	524	175	38	182	103	402	296	4205

The mapping was obtained on the unshuffled training corpora.

corpus. For example, in the unshuffled two noun compound training corpora there were 21 relations found from the total of 35 relations considered. The most frequently occurring relations were PART-WHOLE, ATTRIBUTE-HOLDER, PURPOSE, LOCATION, TOPIC, and THEME. The semantic relations that did not occur in two noun compounds were KINSHIP, ENTAIL, ACCOMPANIMENT, FREQUENCY, ANTONYMY, PROBABILITY, POSSIBILITY, CERTAINTY, STIMULUS, EXTENT, and PREDICATE.

For three noun compounds, the most frequently occurring semantic relations were ATTRIBUTE-HOLDER, AGENT, TOPIC, and THEME (for left branching) and, respectively, ATTRIBUTE-HOLDER, AGENT, TEMPORAL, PART-WHOLE, LOCATION, PURPOSE, and THEME (for right branching).

Table 4 shows the mapping between the two sets of semantic classification categories for the unshuffled training corpora.

3. Models for the interpretation of two noun compounds

The task of noun compound interpretation consists of determining the semantic relations between the noun constituents. In this section we present two main types of learning models: unsupervised and supervised. For both types, the interpretation task is defined as a semantic classification problem. We use two different lists of semantic target categories: the list of 35 semantic relations and the list of 8 prepositional paraphrases and compare our results with those obtained on the same test set by Lauer (1995) and Lapata and Keller (2004). Note that Lauer and Lapata and Keller tested their model only on the list of 8 prepositional paraphrases.

3.1. Unsupervised probabilistic models

Lauer (1995) was the first to devise and test an unsupervised probabilistic model for noun compound interpretation on Grolier encyclopedia, an 8 million word corpus, based on a set of 8 prepositional paraphrases. His probabilistic model computes the probability of a preposition p given a noun–noun pair n_1–n_2 and finds the most likely prepositional paraphrase $p* = \arg\max_p P(p|n_1, n_2)$. However, as Lauer noticed, this model requires a very large training corpus to estimate these probabilities. More recently, Lapata and Keller (2004) replicated the model using the web as training corpus and showed that the best performance was obtained with the trigram model $f(n_1, p, n_2)$. In their approach, they used as count for a given trigram the number of pages returned by Altavista on the trigram corresponding queries. For example, for the test instance "*war stories*", the query was "*stories about war*".

3.2. Supervised models

The supervised learning models proposed here are centered around two fundamental notions in automatic text understanding: *word sense disambiguation* (WSD) and *lexical specialization* on the general-purpose semantic noun hierarchies offered by WordNet. Each noun in the noun compound is mapped into its corresponding WordNet 2.0 sense determined in context and then clas-

sified in its specific WordNet semantic category. The idea is that the meaning of compositional compounds can be successfully derived from the meaning of the noun constituents.

So far, we have identified and experimented with the following two features:

1. `Semantic class of head noun` specifies the WordNet sense (synset) of the head noun and implicitly points to all its hypernyms. The NC semantics is heavily influenced by the meaning of the noun constituents. For example: "*GM car*" is a MAKE/PRODUCE relation while "*family car*" is a POSSESSION relation. In case the noun has multiple inheritance, the first semantic class is chosen. For example, the hypernyms of "*car #1*" are: {*motor vehicle*}, {*self-propelled vehicle*}, {*wheeled vehicle*}, {*vehicle*}, {*conveyance*}, {*instrumentality*}, {*artifact*}, {*object*}, {*entity*}.
2. `Semantic class of modifier noun` specifies the top semantic class of the WordNet synset. For example "*morning meeting*" – TEMPORAL, while "*business meeting*" – a TOPIC relation.

We present here three supervised models: *semantic scattering* (SS) (Moldovan et al., 2004), *iterative semantic specialization* (ISS) (Girju et al., 2003), and *support vector machines* (SVM). The first two are briefly described below, the third being well known from the machine learning literature.

3.2.1. Semantic scattering

The SS model was designed and used by us to semantically classify genitive constructions and is applicable to noun compounds (Moldovan et al., 2004). Essentially, it consists of using a training data set to establish a boundary $G*$ on WordNet noun hierarchies such that each feature pair of noun–noun senses f_{ij} on this boundary maps uniquely into one of the 35 semantic relations, and any feature pair above the boundary maps into more than one semantic relation. Due to the specialization property on noun hierarchy, feature pairs below the boundary also map into only one semantic relation. For any new pair of noun–noun senses, the model finds the closest boundary pair, in semantic sense, using a procedure called semantic scattering.

3.2.2. Iterative semantic specialization

ISS is a multi-class extension of a binary classification technique initially devised for the PART-WHOLE semantic relation (Girju et al., 2003). The iterative semantic specialization method consists of a set of iterative procedures of specialization of the training examples on the WordNet IS-A hierarchy. Thus, after a set of necessary specialization iterations, the method produces specialized examples which through supervised machine learning are transformed into sets of semantic rules for the noun compound interpretation task.

Initially, the training corpus consists of examples that follow the format ⟨*noun1#sense*; *noun2#sense*; *target*⟩, where *target* belongs to the set of classification categories considered. From this initial set of examples an intermediate corpus is created by expanding each example with the corresponding WordNet top semantic classes for each noun constituent. At this point, the generalized training corpus contains two types of examples: unambiguous and ambiguous. The second situation occurs when the training corpus classifies the same noun–noun pair into more than one semantic category. For example, both relationships "*woman#1 apartment#1*"-POSSESSION and

"*woman#1 hand#1*" PART-WHOLE are mapped into the more general type ⟨*entity#1*, *entity#1*, POSSESSION/PART-WHOLE⟩. We recursively specialize these examples to eliminate the ambiguity. By specialization, the semantic class is replaced with the corresponding hyponym for that particular sense, i.e. the concept immediately below in the hierarchy. These steps are repeated until there are no more ambiguous examples. For the unambiguous examples in the generalized training corpus (those that are classified with a single semantic relation), constraints are determined using cross validation on C4.5.

3.2.3. Support vector machines

In order to achieve classification in n semantic classes, $n > 2$, we built a binary classifier for each pair of classes (a total of C_n^2 classifiers), and then used a voting procedure to establish the class of a new example. For the experiments with semantic relations, the simplest voting scheme has been chosen; each binary classifier has one vote which is assigned to the class it chooses when it is run. Then the class with the largest number of votes is considered to be the answer. The software used in these experiments is the package LIBSVM, (www.csie.ntu.edu.tw/~cjlin/libsvm/) which implements an SVM algorithm. We tested with the radial-based kernel and experimented with the features generated by the specialization procedure described in the previous supervised models.

3.3. Experimental results and observations

The supervised models were trained and tested on both Lauer's data (un-shuffled) and random data (shuffled) using the two different lists of semantic classification categories. The results obtained with each model on each test set (*unshuffled*, respectively, *shuffled)* are presented in Table 5 using the standard measure of *accuracy* (number of correctly labeled instances over the number of instances in the test set).

Table 5
The performance obtained by the supervised models on Lauer's test data (*unshuffled*) and, respectively, on the random test data (*shuffled*) for the interpretation task

List of classif. categ.	Supervised models (%)				Baseline#l (%) (no WSD, with specializ.)				Baseline#2 (%) (no WSD, no specializ.)			
	SS	ISS	SVM	SVM (+PP)	SS	ISS	SVM	SVM (+PP)	SS	ISS	SVM	SVM (+PP)
Unshuffled test data												
8 PPs	33.68	39.72	36.26	–	32.35	35.46	33.33	–	32.35	31.91	33.33	–
35 SRs	44.32	37.23	43.53	66.78	34.37	30.17	36.50	61.39	32.03	31.20	20.54	54.25
Shuffled test data												
8 PPs	55.38	50.71	58.07	–	52.74	45.74	54.09	–	48.14	49.29	43.41	–
35 SRs	58.70	43.26	63.91	83.93	50.08	29.08	54.20	77.88	42.56	36.87	27.04	72.59

Two sets of semantic classification categories were considered: 8 PPs (8 prepositional paraphrases), and 35 SRs (35 semantic relations). 'SVM (+PP)'' employs the same feature set as the SVM model plus the corresponding prepositional paraphrase.

We wanted to measure the impact of each basic notion employed in this research, *word sense disambiguation* and *WordNet* IS-A *lexical hierarchy specialization*, and defined two baseline measures. Baseline 1 does not take advantage of WSD (sense#1), but it differentiates between unambiguous and ambiguous training examples by specializing the ambiguous ones. In Baseline 2, the noun constituents are tagged with the default sense#1 (no WSD), and the ambiguous examples are not specialized.

The table shows that the supervised models give better results on the list of 35 semantic relations than on the 8 prepositional paraphrases (with the exception of the SS model) on both test sets. This observation is consistent with the initial idea that prepositional paraphrases are more abstract, and thus more ambiguous. Moreover, the comparison with Baseline#1 results shows that word sense disambiguation (WSD) does not represent a very important factor for the noun interpretation as prepositional paraphrases. However, for the classification with 35 semantic relations, the disablement of WSD (sense#1) generates an average drop in accuracy of 7.36% on the unshuffled test set, and, respectively, of 9.64% on the shuffled test data.

Compared with the WSD feature, the semantic specialization seems to be more important for the noun compound interpretation with prepositional paraphrases, especially for the SVM model on the shuffled test data. Baseline#2 shows an average drop in accuracy of 13.46% for Lauer's test set and, respectively, of 17.6% for the shuffled test set. The models most affected by the disablement of both the WSD and specialization features were SS and SVM on both test data sets.

3.4. Comparison with previous work

On the unshuffled test set, Lauer obtained an accuracy of 40% and Lapata and Keller 55.71%. For the shuffled test set, we replicated Lapata and Keller's experiments (Lapata and Keller, 2004) using Google[2] and obtained an accuracy of 46.09%. We formed inflected queries with the patterns they proposed and searched the web. After experimenting with various trigram instances $f(n_1, p, n_2)$, we had the following observations:

1. The order of the constituent nouns in the prepositional paraphrase is important. For example, "war story" (cf. Lapata and Keller, 2004) can be paraphrased as "story about war" and "story of the war", where the order of the nouns is reversed. However, there are situations in which the order of the nouns remains the same as the one in the noun compound (e.g., "*blood vessels*" as "*blood in vessels*" and "*vessels of blood*"). For example, 28.19% noun–noun paraphrasable pairs preserved the order in the corresponding prepositional paraphrases. Thus, we tried all plausible alternative queries to cover all possible orderings.
2. Many of the noun compound instances had two or more correct paraphrases. Like Lapata and Keller, in this experiment we considered only the paraphrase with the largest web count provided by the search engine.

[2] As Google limits the number of queries to 1000 per day per computer, we repeated the experiment using 10 computers for a number of days. Although Keller and Lapata used Altavista for the interpretation of two noun compounds, they showed that there is almost no difference between the correlations achieved using Google and Altavista counts.

Table 6
Experimental results with Lapata and Keller's web-based unsupervised interpretation model on different types of test sets

Test set	Ambiguity		Accuracy (%)
	Syntactic (POS)	Semantic (WSD)	
Set #1	No	No	34.69
Set #2	Yes	No	33.01
Set #3	No	Yes	50.82
Set #4	Yes	Yes	44.46

"No" means not ambiguous and "Yes" means ambiguous.

3. We manually checked the first five entries generated by Google for each most frequent prepositional paraphrase and noticed that about 38% of them were wrong due to syntactic (e.g., POS) and/or semantic ambiguities.

Since we wanted to measure the impact of syntactic and semantic ambiguities of noun compounds on the interpretation performance, we further tested the probabilistic web-based model on four distinct test sets selected from the Wall Street Journal text collection, each containing 200 noun–noun pairs encoding different types of ambiguity: in set#1 the noun constituents had only one part of speech and one WordNet sense; in set#2 the nouns had at least two possible parts of speech and were semantically unambiguous, in set#3 the nouns were ambiguous only semantically, and in set#4 they were ambiguous both syntactically and semantically. Table 6 shows that for unambiguous compounds (set#1), the model obtained an accuracy of 34.69%, while for more semantically ambiguous compounds it obtained an accuracy of about 50% (sets #3 and #4). This shows that for more semantically ambiguous noun–noun pairs, the web-based probabilistic model introduces a significant number of false positives.

4. Models for the interpretation of three noun compounds

The interpretation of three noun compounds consists of two inter-related phases: the bracketing and the automatic annotation with semantic categories. As the meaning of these recursive constructions is given by the two semantic relations they encode, first we have to determine the pair of nouns that encodes each relation in the construction. In this section we: present experimental results with unsupervised probabilistic and supervised models on bracketing and semantic annotation of three noun compounds. The results are drawn from two test sets: Lauer's 244 test data (*unshuffled*), and a randomly selected set of 244 noun compound instances (*shuffled*). For the semantic annotation we use the list of 35 semantic relations proposed in Section 2.

4.1. Unsupervised probabilistic models for the bracketing of three noun compounds

The task of noun compound bracketing is defined as follows: given a three-word noun compound $n_1\ n_2\ n_3$, if $(n_1\ n_2)$ is the most correct bracketing of the noun sequence, then the structure is $((n_1\ n_2)\ n_3)$, otherwise the correct structure is $(n_1\ (n_2\ n_3))$.

Most of the unsupervised probabilistic approaches to noun compound bracketing (Resnik, 1993; Lauer, 1995; Lapata and Keller, 2004) are based on two models: *adjacency* and *dependency* (cf. Lauer, 1995). The *adjacency model* compares frequencies of (n_1 n_2) to (n_2 n_3). The *dependency model* compares the probabilities of occurrence of (n_1 n_2) to (n_1 n_3), ignoring previous occurrences of (n_1 n_3). Lauer estimated the frequencies of each possible bracketing on Grolier encyclopedia based on a taxonomy or thesaurus. In Eqs. (1) and (2), for example, t_1, t_2, and t_3 represent thesaurus conceptual categories and w_i are noun members of these categories. The probability $P(t_1 \rightarrow t_2)$ denotes the modification of a noun in category t_2 by a noun in category t_1.

$$R_{\text{adj}} = \frac{\sum_{ti \in cats(w_i)} P(t_1 \rightarrow t_2)}{\sum_{ti \in cats(w_i)} P(t_2 \rightarrow t_3)}, \tag{1}$$

$$R_{\text{dep}} = \frac{\sum_{ti \in cats(w_i)} P(t_1 \rightarrow t_2) P(t_2 \rightarrow t_3)}{\sum_{ti \in cats(w_i)} P(t_1 \rightarrow t_3) P(t_2 \rightarrow t_3)}. \tag{2}$$

Like Lapata and Keller, we also experimented with both adjacency and dependency web-based models on the shuffled test set using lexical items rather than semantic categories.

4.2. Supervised model for the bracketing and semantic annotation of three noun compounds

An initial empirical investigation of the three noun compound corpus suggested that the noun constituents mapped most of the time to corresponding verb-argument structures. This observation indicated that a more complex feature vector should be considered. For the bracketing subtask, we experimented with a list of 15 linguistic features employed in the C5.0 decision tree model. For each of the three nouns in a compound, the following five features were computed based on the WordNet sense of each noun constituent determined in context:

1. `WordNet derivationally related form` specifies if that sense of the noun is related to a verb in WordNet. Example: "*coffee maker industry*", where the correct sense in this case *maker#3* is related to the verb *to make#6*.
2. `WordNet top semantic class of the noun`. Example: "*coffee maker industry*", where *maker#3* is a {*group, grouping*}#1.
3. `WordNet second top semantic class of noun`. Example: "*coffee maker industry*", where *maker#3* is a *social_group*#1.
4. `WordNet third top semantic class of noun`. Example: "*coffee maker industry*", where *maker#3* is *organizational#1*.
5. `Nominalization` indicates if the noun is a nominalization or not based on the NomLex dictionary of nominalizations (Macleod et al., 1998). We also consider nominalizations those nouns that could not be found in NomLex but are *events* or *actions* in WordNet. Example: "*coffee maker industry*", where *maker* is a nominalization.

For the semantic annotation subtask we used the same feature set, to which we added the bracketing information as a new feature. We experimented with four different target classes: (1) semantic relation SR#1 (the semantic relation between $n_1 n_2$ (if left branching) and, respectively,

between n_1n_3 (if right branching)); (2) semantic relation SR#2 (the semantic relation between n_2n_3 irrespective of branching); (3) semantic relation #2 with semantic relation #1 as feature, and (4) semantic relation #1 with semantic relation #2 as feature. Consider the following examples:

(4) ((*debt#2 reduction #1*)/THEME/*r exercise#3*)/PURPOSE,
(5) (*morning* #1 (*package #2 sort#4*)/THEME/*r*)/TEMPORAL

In (4) the semantic relations were added on a left-branching structure, and in (5) on a right-branching one. The tag "*r*" indicates that the nouns are in *reverse* order.

4.3. Experimental results and observations

For the bracketing task, we compared the results obtained with both the supervised and the unsupervised probabilistic models. For the semantic annotation task we used only the C5.0 decision tree model. All models were tested on each of the two test sets: Lauer's data set (unshuffled) and the shuffled set.

On the unshuffled test set, Lauer obtained an accuracy of 80.70% and Lapata and Keller (Lapata and Keller, 2004) an accuracy of 78.68% with the dependency model (77.86% with the adjacency model, respectively). For the shuffled test set, we replicated Lapata and Keller's bracketing experiments using again inflected queries on Google, and obtained an accuracy of 77.36% with the depen-

Table 7
The performance obtained by the supervised and unsupervised probabilistic models on the two test data sets for the interpretation task

Learning models		Semantic annotation task (sem. rels. cf. bracketing)		Bracketing task
		SR#1	SR#2	
		n_1n_2 (left), n_1n_3 (right)	n_2n_3 (left and right)	
Supervised	Unshuffled test data			
	C5.0	45.10%	37.10%	73.10%
	Baseline (no WSD)	36.21%	31.01%	72.80%
	C5.0 (+SR#1)	–	26.40%	–
	C5.0 (+SR#2)	34.30%	–	–
	Shuffled test data			
	C5.0	50.50%	50.60%	83.10%
	Baseline (no WSD)	42.08%	40.20%	74.40%
	C5.0 (+SR#1)	–	53%	–
	C5.0 (+SR#2)	54.08%	–	–
	Unshuffled test data			
Unsupervised probabilistic	Adjacency	–	–	77.86%
	Dependency	–	–	78.68%
	Shuffled test data			
Lapata & Keller's web-based model	Adjacency	–	–	73.45%
	Dependency	–	–	77.36%

"C5.0 (+SR#i)" means the supervised model applied to the basic feature set plus SR#i as feature.

dency model, and 73.45% with the adjacency model, respectively. The results obtained with each model on each test set are presented in Table 7 and are compared against a baseline (no WSD).

4.3.1. Comparison with previous work

According to our knowledge, all solutions proposed before to the automatic interpretation of three noun compounds focused only the bracketing problem. As mentioned previously, most of these approaches are probabilistic and are based on the assumption that the probability of occurrence of a pair of nouns is independent of the third noun, which most of the time is unrealistic and leads to errors.

Unlike previous work, we focus on a set of semantic features employed in a supervised machine learning model. Instead of considering noun compounds in isolation, our model brackets them in context through the use of the WSD feature.

5. Discussion

Our approach to noun compound interpretation is novel in several ways. The semantic interpretation problem is tackled for both two and three noun compounds. We provide empirical observations on the distribution of the meaning of noun compounds on fairly large corpora by performing various experiments with human judgments on two state-of-the-art semantic classification lists. A mapping between the two classification sets based on the noun compound distribution on the corpora is also provided. For both the bracketing and semantic annotation tasks, the paper presents experimental results with supervised learning models based on linguistic features and compares them against state-of-the-art probabilistic approaches and against the optimal performance obtained by two human annotators.

Our supervised models use an iterative semantic specialization method that allows us to go deeper into the semantic complexity of noun compounds. According to our knowledge, the system is the only domain independent noun compound interpretation tool that uses word sense disambiguation and WordNet IS-A specializations. One other symbolic system, SENS (Vanderwende, 1995) makes some use of IS-A generalizations, but considers only the first sense of the noun constituents in WordNet. The current state-of-the-art systems in automatic detection of semantic roles (Gildea and Jurafsky, 2002) that are probabilistic-based have also tried to use lexico-semantic hierarchies, such as WordNet, to generalize from noun lexical features. However, they also rely on the first sense listed for each noun occurring in the training data. Other approaches, such as Resnik's conceptual association algorithm (Resnik, 1996), attempt to automatically detect semantic roles based on semantic similarity measures applied to large lexical hierarchies, such as WordNet. However, not many of these attempts make use of lexico-semantic hierarchies for generalization, due to the unavailability of word sense disambiguation tools. For example, Brill and Resnik (1994) have used the conceptual association algorithm to solve the prepositional phrase attachment problem. However, the similarities computed on WordNet for various noun–noun or verb–noun pairs linked by a preposition were not sufficient for the attachment task, as the pairs were not linked hierarchically.

The system presented here makes use of an existing lexical resource, Word-Net, that contains general purpose information that can be successfully used in domain independent and general

purpose applications. Moreover, the system maps the disambiguated noun constituents into the WordNet noun hierarchies. The system is also unique in the sense that it uses a specialization procedure on the WordNet noun hierarchies in order to generate the best semantic constraints for the noun compound interpretation.

One main drawback of the approach is the use of supervised models that require a large annotated corpus. Another drawback is the heavy reliance on WordNet which has been criticized by some. As we have demonstrated, the impact of the WSD is considerable, however, the current state-of-the-art in WSD is not satisfactory yet.

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References

Brill, E., Resnik, P., 1994. A rule-based approach to PP attachment disambiguation. In: Proceedings of the International Conference on Computational Linguistics (COLING), Japan, pp. 1198–1204.

Charniak, E., 2000. A maximum-entropy-inspired parser. In: Proceedings of the North American Chapter of the Association for Computational Linguistics (NAACL), Seattle, WA, pp. 132–139.

Downing, P., 1977. On the creation and use of English compound nouns. Language 53 (4), 810–842.

Finin, T., 1980. The semantic interpretation of compound nominals. Ph.D. Dissertation, University of Illinois at Urbana-Champaign.

Gildea, D., Jurafsky, D., 2002. Automatic labeling of semantic roles. Computational Linguistics 28 (3), 245–288.

Girju, R., Badulescu, A., Moldovan, D., 2003. Learning semantic constraints for the automatic discovery of part-whole relations. In: Proceedings of HLT, Boston, pp. 80–87.

Jespersen, O., 1954. A modern English grammar on historical principles. In: G. Alien, Unwin Ltd. (Eds.), London, pp. 1909–1949.

Lapata, M., Keller, F., 2004. The Web as a baseline: evaluating the performance of unsupervised Web-based models for a range of NLP tasks. In: Proceedings of the Human Language Technology conference (HLT/NAACL), Boston, MA, pp. 121–128.

Lauer, M., 1995. Designing statistical language learners: experiments on noun compounds. Ph.D. Thesis, Macquarie University, Australia.

Levi, J., 1978. The Syntax and Semantics of Complex Nominals. Academic Press, New York.

Macleod, C., Grishman, R., Meyers, A., Barrett, L., Reeves, R., 1998. Nomlex: a lexicon of nominalizations. In: Proceedings of the 8th International Congress of the European Association for Lexicography, Liege, Belgium, pp. 187–193.

Moldovan, D., Girju, R., 2003. Knowledge discovery from text. In: The Tutorial Proceedings of the 41st Annual Meeting of the Association for Computational Linguistics (ACL), Sapporo, Japan.

Moldovan, D., Badulescu, A., Tatu, M., Antohe, D., Girju, R., 2004. Models for the semantic classification of nonnominalized noun phrases. In: Proceedings of the HLT Computational Lexical Semantics work shop, Boston, MA, pp. 60–67.

Resnik, P., 1993. Selection and information: a class-based approach to lexical relationships. Ph.D. Dissertation, Department of Computer and Information Science, University of Pennsylvania, MA, pp. 60–67.

Resnik, P., 1996. Selectional constraints: an information-theoretic model and its computational realization. Cognition (61), 127–159.

Rosario, B., Hearst, M., 2001. Classifying the semantic relations in noun compounds via a domain-specific lexical hierarchy. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP), Pittsburgh, PA, pp. 82–90.

Selkirk, E., 1982. The Syntax of Words. MIT Press, Cambridge.

Siegel, S., Castellan, N.J., 1988. Non Parametric Statistics for the Behavioral Science. McGraw-Hill, New York.

Vanderwende, L., 1995. The analysis of noun sequences using semantic information extracted from on-line dictionaries. Ph.D. Dissertation, Georgetown University.