REPRESENTING AND REASONING FOR EXPLICIT, IMPLICIT AND IMPLICATED TEXTUAL INFORMATION

Moldovan D. (moldovan@hlt.utdallas.edu)

Human Language Technology Research Institute

University of Texas at Dallas

Explicit, implicit and implicated text meaning

It is useful to distinguish between explicit and implicit information, and between implicit and implicated knowledge conveyed by natural language.

Explicit information is what the reader gathers only from the strict meaning of words. For instance, the explicit information conveyed by *The car is cheap* (S_1) is that a particular automobile is inexpensive.

Implicit information, also called **impliciture**, is built up from the explicit content of the utterance by conceptual strengthening or "enrichment", which yields what would have been made fully explicit if lexical extensions had been included in an utterance. In our example, one may complete the sentence saying that the car is cheap compared to other cars.

Implicated information, called **implicature**, is completely separated from what is said and goes beyond what is said. They are additional propositions external to what is said, heavily dependent on the context of the situation. The speaker of S_1 may want to make a derogatory remark about the driver of the car, or may praise its owner who is rather wealthy for driving an average car and not wasting unnecessary money on a vehicle. Similarly, *Mary has a boyfriend* implicates that Mary has exactly one boyfriend. However, many other implicatures are possible depending on the context; for example: one should not ask Mary out, Mary is not a lesbian, Mary is getting a divorce, or she will be getting a divorce.

Most implicated information is conveyed during conversations. For example, given the following exchange between two users of twitter.com:

A: *Dinner's ready! prawns, grouper in some sauce, vegetables, rice and shark's fin melon soup! Still waiting for lotus root soup this week!*
B: *Eeeeeee lotus root?*
A: *so what you having for dinner?*

several facts are stated *explicitly* (*the dinner is ready*, a list of dishes: *prawns, grouper with sauce, rice, soup* made of *shark's fin* and *melon*, *lotus root soup* for later in the week, A's question about what B will have for dinner). *Implicitly*, A's first utterance discloses the existence of a *meal* which includes all the dishes it explicitly mentions. B's *Eeeeeee* points to *disgust*, a feeling of dislike. Last but not least, the *implicatures* conveyed by each utterance complete its understanding tying together the explicit and implicit information it communicated: *A has prepared the ready dinner which includes the list of mentioned dishes*; *A is excited of having prepared this gourmet dinner*, *B dislikes lotus root and cannot believe that A would choose to eat it*; *A has a poor opinion of B's gastronomic knowledge*.

We note that text understanding ranges from extracting explicit information to more complex implicitures or entailments, all the way to implicatures that take into account contextual information. Thus, implicitures or implications are implicit in what is said, whereas implicatures are implied by what is said. Implicatures depend largely on context of the utterance, whereas implications depend less of context. Sentences imply certain things, but speakers implicate. Speaker utters a sentence and in fact implicate something else which can be true or false.

Hierarchical knowledge representation

In order to represent the information conveyed by natural language texts (explicit, implicit or implicated), we proposed a hierarchical knowledge representation, consisting as several layers (Figure 1). Each layer in the hierarchy builds upon the previous layer by bringing new information. The base is the *lexico-syntactic* layer, which reveals the text's syntactic parse trees. The *semantic* layer adds semantic relations between the concepts identified by the previous layer. Next, the identified *events* bring a new level of abstraction to the process of representing knowledge since events tend to dominate the meaning of text. Last, *relations between events* are established with the goal of determining the text coherence at the highest level.

In order to derive the explicit information conveyed by natural language, which is to be represented using the formalism described above and stored for later use by more advanced applications, a library of robust NLP tools are needed to extract lexical, syntactic and semantic information from natural language input. Our NLP pipeline includes a text tokenization module, a part-of-speech tagging system, a sentence boundary detection tool, a collocation identification module, a named entity recognizer, a chunk parser, a word sense disambiguation system[4], a full-syntactic parser [1], a nominal and pronominal coreference resolution module, a semantic parser [2],[9], and an event and event relation identification tool [3],[5].

Logical representation of knowledge

In order to facilitate the consumption of derived knowledge by a natural language reasoner, the hierarchical information must be converted into a *logical form*. For this purpose, a logical predicate is created for each textual concept that participates in a semantic relation. The name of each predicate derived from a concept is a concatenation of the lexeme's base form, its part of speech, and corresponding WordNet sense number. For questions, a special predicate is introduced to capture the target type, the answer type of the question. Furthermore, for each predicate associated with a named entity or event, a new predicate is added to the logical form of the text that describes this property. Last, but not least, logical predicates denoting the semantic relations and event relations identified during the NLU process are included to complete the logical representation of the derived knowledge.

Given these simple logical transformation of text rules, an accurate multi-layered first order logical form of the knowledge conveyed by *Gilda Flores's kidnapping occurred on January 13, 1990. A week before, he had fired the kidnappers* can be derived (Figure 1).

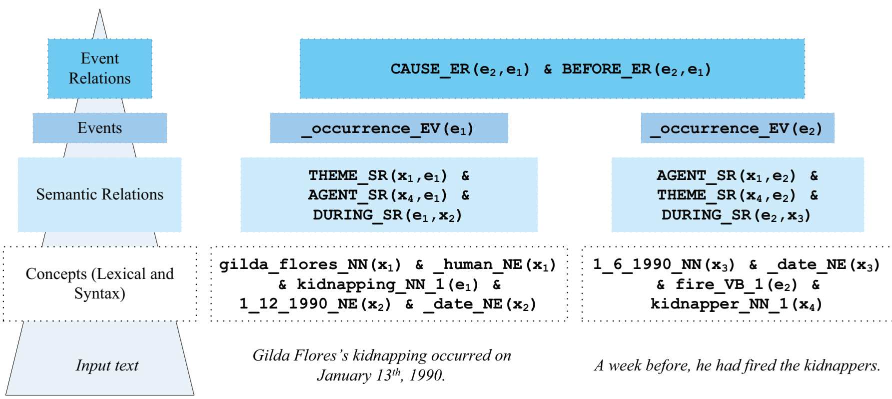


Figure 1. Hierarchical knowledge representation

More specifically, all concepts mentioned in the text constitute the bottom layer of the representation. Named entity classes (e. g., *Gilda Flores* = *human*) and normalized values of temporal expressions (e. g., *a week before January 13, 1990* = 01/06/1990) are captured within this layer of lexical information. The next level of knowledge is dedicated to semantic relations identified between the text's concepts (e. g., theme(*Gilda Flores*, *kidnapping*)). Co-referring concepts are also stored in this layer of representation (*he* = *Gilda Flores*). Events and their properties are identified and represented as the third layer of information (e. g., *kidnap*, theme(*Gilda Flores*), agent(*kidnappers*), during(*01/13/1990*)), with the final level of representation consisting of event-event relations (cause(*fire, kidnapping*), before(*fire, kidnapping*)). Finally, there is a causation relations, namely, firing (e_2) is the cause of kidnapping (e_1) and has preceded the kidnapping. The reason for kidnapping is the firing of employees and the two sentences can be summarized as a *revenge* action.

A model for representing knowledge

In order to represent the meaning of natural language, we define a model that captures not only the *explicit* information transmitted to the hearer, but also the *implicit* and *implicated* information conveyed by a speaker.

By characterizing a speaker S by his utterance ($S_U = \{u_1,..., u_m\}$, where u_i is a speaker utterance (what speaker says)) and his intentions ($S_I = \{i_1,..., i_k\}$, where i_i is a speaker intention conveyed by S_U) and the hearer H by his understanding of S_U (H_{TM} denotes the hearer understanding of the *explicit* text meaning; H_{TE} represents the hearer understanding of the *implicit* text meaning, i. e. entailments, and H_I symbolizes *implicatures* H made from S_U), the 7-tuple

$$\{\mathbf{S_U, S_I, H_{TM}, H_{TE}, H_I, C, K}\}$$

captures the *complete* meaning of an utterance. Our model's *C* component represents the context and *K* denotes the common sense knowledge needed by H to derive S's implicatures.

Noting that each of these components are hierarchical representations of explicit, implicit as well as implicated knowledge conveyed by a natural language text, the model establishes a standard of representation for natural language meaning.

An instantiation of this model for A's first utterance, part of the exchange shown above, *Dinner's ready! prawns, grouper in some sauce, vegetables, rice and shark's fin melon soup! Still waiting for lotus root soup this week!* is

S_U/H_{TM}: DINNER_NN_1(x_1) & READY_JJ_1(x_2) & VALUE_SR(x_2,x_1) & EXCLAMATORY_TYPE & PRAWN_NN_1(x_3) & GROUPER_NN_1(x_4) & SAUCE_NN_1(x_5) & PART_WHOLE_SR(x_4,x_5) & VEGETABLE_NN_1(x_6) & RICE_NN_1(x_7) & SHARK_NN_1(x_8) & FIN_NN_1(x_9) & PART_WHOLE_SR(x_9,x_8) & MELON_NN_1(x_{10}) & SOUP_NN_1(x_{11}) & PART_WHOLE_SR(x_{10},x_{11}) & PART_WHOLE_SR(x_9,x_{11}) & STILL_RB_1(x_{12}) & WAIT_VB_1(e_1) & _OCCURRENCE_EV(e_1) & MANNER_SR(x_{12},e_1) & LOTUS_NN_1(x_{13}) & ROOT_NN_1(x_{14}) & PART_WHOLE_SR(x_{14},x_{13}) & SOUP_NN_1(x_{15}) & PART_WHOLE_SR(x_{14},x_{15}) & THEME_SR(x_{15},e_1) & WEEK_NN_1(x_{16}) & _DATE_NE(x_{16}) & DURING_SR(e_1,x_{16})

H_{TE}: DISH_NN_1(x_{17}) & PART_WHOLE_SR(x_5,x_{17}) & MEAL_NN_1(x_{18}) & PART_WHOLE_SR(x_{17},x_{18}) & PART_WHOLE_SR(x_5,x_{18}) & DISH_NN_1(x_{19}) & ISA_SR(x_{11},x_{19}) & MEAL_NN_1(x_{20}) & PART_WHOLE_SR(x_{19},x_{20}) & PART_WHOLE_SR(x_{11},x_{20})

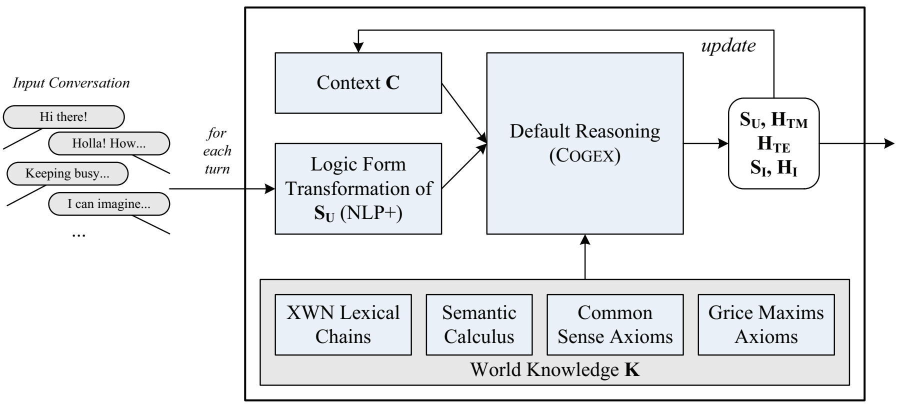
S_I/H_I: SHOW_VB_1(e_2) & _A_USER(x_{21}) & AGENT_SR(x_{21},e_2) & STRONG_JJ_1(x_{22}) & FEELING_NN_1(x_{23}) & VALUE_SR(x_{22},x_{23}) & THEME_SR(x_{23},e_2) & =(x_1,x_{18},x_{20}) & COOK_VB_1(e_3) & THEME_SR(x_{18},e_3) & AGENT_SR(x_{21},e_3)

C: ∅

Reasoning

The NLU methodologies mentioned above are the first step taken by automated systems to determine the *complete* meaning of a natural language text. They derive the *explicit* information conveyed by the text: the meaning of the words used by the speaker (given by the named entity recognizer or the word sense disambiguation modules) and their semantic connections (given by the coreference resolution module and the semantic parser). However, in order to go beyond what is being said, to derive the *implicit* and *implicated* information conveyed by the text, and, thus, to expand the understanding of explicit information, reasoning mechanisms that exploit the derived knowledge using various types of natural language axioms within an abductive reasoning framework must be implemented.

The natural language reasoner presented here processes the natural language of a conversation one turn at a time and derives the logical implications and implicatures communicated by each speaker utterance, updating the conversation's context after each individual analysis. Below, we show the architecture of the system, highlighting the roles and interactions of our model's components ($\{S_U, S_I, H_{TM}, H_{TE}, H_I, C, K\}$).



Cogex, a natural language reasoning engine

Cogex is a heavily modified version of the Otter theorem prover[1], which uses the Set of Support (SoS) strategy to prove by contradiction: a hypothesis is proved by showing that it is impossible for it to be false in the face of the provided evidence and background knowledge (BackgroundKnowledge, Evidence & ¬Hypothesis → ^).

Cogex has been successfully employed within a question answering engine to re-rank the final list of candidate answer passages based on the degree of entailment between each passage and the given question [16]. For the Recognizing Textual Entailment task, Cogex computes the extent to which a text snippet entails a hypothesis as a normalized score between 0 and 1 and compares this value to a threshold learned during training to determine whether the given hypothesis is entailed by the given text [6],[7],[8].

Within these settings, the initial usable list contains various natural language axioms, which can be used to infer new information (BackgroundKnowledge), while the logical clauses corresponding to the candidate passage/text snippet (Evidence)

1 http://www.cs.unm.edu/˜mccune/otter/

as well as the negated question/hypothesis (¬Hypothesis) are added to the SoS list. Given Otter's best-first clause selection mechanism, the heavily weighted question/hypothesis clauses are the last clauses to be processed by the system. Thus, when resolutions using these clauses are attempted, it is guaranteed that all other inferences ([BackgroundKnowledge & Evidence]+) have been made and are stored in the usable list.

For the task of deriving *implicit* and *implicated* information conveyed by natural language, Cogex exploits the first order logical representations of the meaning model components. It makes use of the S_U, C, and K components to derive the values of S_I , H_{TM}, H_{TE}, and H_I , which, in turn, will be used to update the context of future conversational turns (Figure 2). Given that our current assumptions include that the communication channel is noise-free, $H_{TM} = S_U$. Futhermore, $S_I = H_I$ since it is difficult to determine whether the speaker intended all the implicatures S_U conveyed at the time of S_U's analysis. These values are revised if future conversational turns cancel some of the implicatures derived during S_U's analysis.

When the analysis of a conversation begins, the context C is empty, the set of axioms described above form the knowledge component (K), and the semantic representation of the speaker utterance make up the model's S_U component. Furthermore, the first order clauses of the C and K model components form the usable list and the logical clauses of S_U serve as the initial SoS. As the reasoning process unfolds, all S_U predicates and the inferences they produce (entailments as well as implicatures) are moved to the usable list, where they become part of the context C of future conversational turns.

The reasoning process terminates when no more inferences can be made from S_U (i. e., SoS is empty). In this situation, the clauses inferred from a given utterance using non-default axioms and/or context clauses that were explicitly stated or entailed by previously analyzed utterances (i. e., previous S_U/H_{TM} and H_{TE} components) are marked as logical entailments, or *implicitures* (H_{TE}). All clauses inferred from default axioms as well as abductive rules and/or context clauses that were previously labeled as implicatures (i. e., previous S_I/H_I components) are marked as the *implicatures* conveyed by the current S_U (S_I,H_I). This is the most expected outcome of an analysis of a conversational turn.

However, if a refutation is found during the reasoning process, the clauses that caused the inconsistency may indicate that (1) the speaker made a false statement (the contradiction stems from S_U clauses alone), which carries certain Quality-flouting implicatures or (2) a previously identified implicature must be canceled (information from current S_U contradicts previous S_I/H_I), in which case, the implicature clauses are removed and the reasoning process is restarted.

Natural language axioms

The axioms used during the reasoning process capture the world knowledge people use to derive the information *implicitly* conveyed by natural language texts. Various types of axioms are needed to encode this vast pool of information.

eXtended WordNet lexical chain axioms

The lexical chain axioms link WordNet concept by exploiting the semantic relationships present in the eXtended WordNet (XWN)[2]. In addition to WordNet's semantic relations between synsets, this valuable semantic resource stores a highly semantic logical representation of WordNet's plain text glosses, a rich source of world knowledge made available to automated systems by our NLP tools. Using the structured representation of WordNet's glosses provided by XWN, new semantic links are identified between WordNet's synsets. Examples include:

PRAISE_VB_1(e_1) & AGENT_SR(x_1,e_2) & THEME_SR(x_2,e_1) → EXPRESS_VB_1(e_2) & ISA_SR(e_1,e_2) & APPROVAL_NN_1(x_3) & THEME_SR(x_3,e_2) & AGENT_SR(x_1,e_2) & THEME_SR(x_2,x_3) — WordNet gloss for *praise*: "express approval of"
PHONE_CALL_NN_1(x_1) → TELEPHONE_NN_1(x_2) & ISA_SR(x_1,x_2)

Semantic calculus axioms

We introduced the notion of Semantic Calculus to describe the various combinations of two semantic relations. The Semantic Calculus axioms describe the semantic relation R_0 that holds between two concepts c_1 and c_2 linked by two semantic relationships R_1 and R_2 (not necessarily distinct) that share a third concept c_3 as a common argument. More formally, $R_1(c_1,c_3)$ & $R_2(c_3,c_2) \rightarrow R_0(c_1,c_2)$ [12],[13].

We note that not any two semantic relations can be combined. Furthermore, the accuracy of each Semantic Calculus axiom was measured as the correctness with which it predicted the correct semantic relation that links two concepts also connected by the semantic relations that are combined (for each linguistic context where $R_1(c_1,c_3)$ and $R_2(c_3,c_2)$ hold, for any c_1, c_2, and c_3, consider if $R_0(c_1,c_2)$ also holds).

These axioms greatly increase the semantic connectivity between concepts. This is particularly important when no immediate semantic link can be found between two concepts of interest. Examples include:

ISA_SR(x_1,x_2) & ISA_SR(x_2,x_3) → ISA_SR(x_1,x_3)
ISA_SR(x_1,x_2) & LOCATION_SR(x_2,x_3) :→ LOCATION_SR(x_1,x_3)
QUANTITY_SR(x_1,x_2) & INSTRUMENT_SR(x_3,x_1) :→ QUANTITY_SR(x_1,x_3)

Common sense axioms

This type of axioms encodes the common sense knowledge required by an automated system to derive unstated implications. These axioms describe not only various

[2] http://xwn.hlt.utdallas.edu/index.html

properties of concepts, but also how the concepts interact in the world and how people speak about them. Most of the semantic rules belonging to this class are default axioms. They also have an abductive nature, implicating the best-guess outcomes. Fully automatic methods for deriving these semantic axioms are yet to be proposed. Examples of world knowledge axioms include:

TOPIC_SR(x_1,x_2) & PURPOSE_SR(e_1,x_2) & COMMUNICATE_VB_1(e_1) → TOPIC_SR(x_1,e_1) — this axiom states that *the topic of something used for communication becomes the topic of the communication*

EXPRESS_VB_1(e_1) & APPROVAL_NN_1(x_1) & THEME_SR(x_1,e_1) & PERSON_NN_1(x_2) & THEME_SR(x_2,x_1) & AGENT_SR(x_2,e_2) :→ THEME_SR(e_2,x_1) — this axiom states that *if expressing approval of person that is the agent of action, then express approval of action*

Furthermore, valuable world knowledge can be identified by exploring the semantic relations identified in textual documents. Unlike the semantic relations stored within machine readable dictionaries, such as WordNet, these relationships link concepts mentioned within a document's content that belong to all part-of-speech classes. These semantic relations are contextual, locally true, and may not seem useful for a reasoning engine that operates outside of their context. However, most of the concepts they connect are defined in WordNet's hierarchies and, thus, they can be abstracted to more general concepts. Using this process of generalization, we can axiomatically describe the selectional restrictions of certain concepts by noting regularities in the types of arguments that they pair with.

For instance, the axiom shown below can be derived based on the high frequency of agent semantic relations that link the verb *communicate* and various hyponyms of *person* — we include here all *_human* named entities, most of which are not included in WordNet:

COMMUNICATE_VB_1(e_1) :→ _HUMAN_NE(x_1) & AGENT_SR(x_1,e_1) — this axiom states that *people are usually the agents of communicating*

We note that these semantic rules are default axioms. Each is associated with a weight that is proportional with the frequency of the defining semantic relation within a large corpus.

Grice Maxims axioms

The implicit assumptions and default inferences that capture our intuitions about a normal interpretation of a communication have been analyzed and formalized by language philosophers as principles of rational human communication behavior. For instance, Grice's Cooperative Principle explains the link between utterances and what is understood from them. Grice's Maxims [14],[15], which are derived from this principle, can be leveraged by an automated system aiming to derive the *implicatures* conveyed by natural language utterances.

The set of macro-axioms encoding the essence of Grice's Maxims make use of the components of the model we defined above. Before being used by an automated system for the analysis of a particular utterance, each Gricean maxim axiom must be instantiated with the values of the various components of the existing conversational model. Examples include:

$\_\text{RELEVANCE}\_\mathtt{GM} \rightarrow (\text{PREDICATE}_I(x_j) \in \mathtt{LF}(S_U)\ \&\ \text{PREDICATE}_I(x_k) \in (C)\ :\rightarrow x_J = x_K)$ — this axiom states that *there must be at least one common predicate between the (enhanced) logical forms of* S_U (speaker utterance) *and* C (context) — given that the speaker's utterance must be relevant to the established common ground. In the case of floutings of the Relevance Maxim, this axiom can be used to *assume the unification of two identically named predicates from* S_U *and* C

$\_\text{QUALITY}\_\mathtt{GM}\ \&\ S_U(x_1)\ \&\ \_\text{QUESTION}(x_1) \rightarrow S(x_2)\ \&\ \text{BELIEVE}\_\mathtt{VB\_1}(e_1)\ \&\ \text{EXPERIENCER}\_\mathtt{SR}(x_2,e_1)\ \&\ H(x_3)\ \&\ \text{KNOW}\_\mathtt{VB\_1}(e_2)\ \&\ \text{EXPERIENCER}\_\mathtt{SR}(x_3,e_2)\ \&\ \text{THEME}\_\mathtt{SR}(e_2,e_1)\ \&\ \text{THEME}\_\mathtt{SR}(x_1,e_2)$ — this axiom states that for all speaker utterances that are questions, S (the speaker) *believes* H (the hearer) *knows the answer to his question*

$\_\text{MANNER}\_\mathtt{GM} \rightarrow ((\_\text{CAPITALIZED}\_\text{CHARS}(x_1)\ \&\ S_U(x_1))\ :\rightarrow (S(x_2)\ \&\ \text{EXCITED}\_\mathtt{JJ\_1}(x_3)\ \&\ \text{VALUE}\_\mathtt{SR}(x_3,x_2)))$ — this axiom states that *capitalized texts within the speaker's utterance indicate the excitement of the speaker*

$\_\text{QUANTITY}\_\mathtt{GM}\ \&\ S_U:(P(x_i) \rightarrow P(x_i)) \rightarrow \text{PREDICATE}_0(x_0) \in \mathtt{LF}(C)\ \&\ (\text{PROPERTY}\_\mathtt{SR}(x_0,x_i)\ |\ \text{VALUE}\_\mathtt{SR}(x_0,x_i))\ \&\ \_\text{ALWAYS}\_\mathtt{TMP}(x_0)\ \&\ -(\text{PREDICATE}_x(x_x) \rightarrow -(\text{PROPERTY}\_\mathtt{SR}(x_0,x_i)\ |\ \text{VALUE}\_\mathtt{SR}(x_0,x_i)))$ — this axiom states that *if the speaker's utterance is of the form "X is X", then one of X's (essential) properties that is relevant to the existing common ground always happens in X and nothing can change that*

References

1. *Elliot Glaysher and Dan Moldovan*. 2006. Speeding Up Full Syntactic Parsing by Leveraging Partial Parsing Decisions. In Proceedings of COLING/ACL 2006, Sydney, Australia, July 2006
2. *Adriana Badulescu and Munirathnam Srikanth*. 2007. LCC-SRN: LCC's SRN System for SemEval 2007 Task 4. In Proceedings of SemEval-2007, Prague, Czech Republic, June 23–24, 2007
3. *Congmin Min, Munirathnam Srikanth, and Abraham Fowler*. 2007. LCC-TE: A Hybrid Approach to Temporal Relation Identification in News Text. In Proceedings of SemEval-2007, Prague, Czech Republic, June 23–24, 2007
4. *Adrian Novischi, Muirathnam Srikanth, and Andrew Bennett*. 2007. LCC-WSD: System Description for English Coarse Grained All Words Task at SemEval 2007. In Proceedings of SemEval-2007, Prague, Czech Republic, June 23–24, 2007
5. *Marta Tatu and Munirathnam Srikanth*. 2008. Experiments with Reasoning for Temporal Relations between Events. In Proceedings of COLING 2008, Manchester, UK, 18–22 August, 2008

6. *Marta Tatu, Brandon Iles, John Slavick, Adrian Novischi and Dan Moldovan*. 2006. COGEX at the Second Recognizing Textual Entailment Challenge. In Proceedings of the Second PASCAL Challenges Workshop on Recognizing Textual Entailment. Venice, Italy, May 2006
7. *Marta Tatu and Dan Moldovan*. 2006. A Logic-based Semantic Approach to Recognizing Textual Entailment. In Proceedings of COLING/ACL 2006, Sydney, Australia, July 2006
8. *Marta Tatu and Dan Moldovan*. 2007. COGEX at RTE 3. In Proceedings of ACL-2007 Workshop on Textual Entailment and Paraphrasing. Prague, Czech Republic, June 2007
9. *Dan Moldovan and Eduardo Blanco*. 2012. Polaris: Lymba's Semantic Parser. In Proceedings of LREC 2012, Istanbul, Turkey, May 2012
10. *Dan Moldovan and Adriana Badulescu*. 2005. A Semantic Scattering Model for the Automatic Interpretation of Genitives. In Proceedings of HLT-EMNLP 2005, Vancouver, British Columbia, Canada, October, 2005
11. *Dan Moldovan and Vasile Rus*. 2001. Logic Form Transformation of WordNet and its Applicability to Question Answering. In Proceedings of ACL-2001, Toulouse, France, July 2001.
12. *Eduardo Blanco and Dan Moldovan*. 2011. Unsupervised Learning of Semantic Relation Composition. In Proceedings of ACL-HLT 2011, Portland, OR, USA.
13. *Eduardo Blanco and Dan Moldovan*. 2011. A Model for Composing Semantic Relations. In Proceedings of IWCS 2011, Oxford, UK.
14. *Grice H. P.* 1969. Utterer's Meaning and Intentions. In Philosophical Review 78: 147–177 [Reprinted in [15]]
15. *Grice H. P.* 1989. Studies in the Way of Words. Cambridge, MA: Harvard University Press
16. *Dan Moldovan, Marta Tatu, and Christine Clark*. 2010. Role of Semantics in Question Answering. In Semantic Computing, pages 373–419. John Wiley & Sons, Inc.