A Semantic Approach to Recognizing Textual Entailment

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Abstract

Exhaustive extraction of semantic information from text is one of the formidable goals of state-of-the-art NLP systems. In this paper, we take a step closer to this objective. We combine the semantic information provided by different resources and extract new semantic knowledge to improve the performance of a recognizing textual entailment system.

1 Recognizing Textual Entailment

While communicating, humans use different expressions to convey the same meaning. Therefore, numerous NLP applications, such as, Question Answering, Information Extraction, or Summarization require computational models of language that recognize if two texts semantically overlap. Trying to capture the major inferences needed to understand equivalent semantic expressions, the PASCAL Network proposed the Recognizing Textual Entailment (RTE) challenge (Dagan et al., 2005). Given two text fragments, the task is to determine if the meaning of one text (the entailed hypothesis, $H$) can be inferred from the meaning of the other text (the entailing text, $T$).

Given the wide applicability of this task, there is an increased interest in creating systems which detect the semantic entailment between two texts. The systems that participated in the Pascal RTE challenge competition exploit various inference elements which, later, they combine within statistical models, scoring methods, or machine learning frameworks. Several systems (Bos and Markert, 2005; Herrera et al., 2005; Jijkoun and de Rijke, 2005; Kouylekov and Magnini, 2005; Newman et al., 2005) measured the word overlap between the two text strings. Using either statistical or WordNet’s relations, almost all systems considered lexical relationships that indicate entailment. The degree of similarity between the syntactic parse trees of the two texts was also used as a clue for entailment by several systems (Herrera et al., 2005; Kouylekov and Magnini, 2005; de Salvo Braz et al., 2005; Raina et al., 2005). Several groups used logic provers to show the entailment between $T$ and $H$ (Bayer et al., 2005; Bos and Markert, 2005; Fowler et al., 2005; Raina et al., 2005) and some of them made use of world knowledge axioms to increase the logic prover’s power of inference (Bayer et al., 2005; Bos and Markert, 2005; Fowler et al., 2005).

In this paper, we describe a novel technique which employs a set of semantic axioms in its attempt to exhaustively extract semantic knowledge from texts. In order to show the contribution that our semantic information extraction method brings, we append it as an additional module to an already existing system that participated in the RTE challenge. Our system (Fowler et al., 2005), first, transforms the text $T$ and the hypothesis $H$ into semantically enhanced logic forms, and, then, the integrated logic prover tries to prove or disprove the entailment using a set of world-knowledge axioms ($\text{die of blood loss} \rightarrow \text{bleed to death}$), linguistic rewriting rules which break down complex syntactic structures, like coordinating conjunctions, and WordNet-based lexical chains axioms ($\text{buy/VB/1} \rightarrow \text{pay/VB/1}$).
2 Approach

We believe that a logic-based semantic approach is highly appropriate for the RTE task\(^1\). Text \(T\) semantically entails \(H\) if its meaning logically implies the meaning of \(H\). Because the set of semantic relations encoded in a text represents its meaning, we need to identify all the semantic relations that hold between the constituents of \(T\) and, subsequently, between the constituents of \(H\) to understand the meaning of each text. It should be noted that state-of-the-art semantic parsers extract only some of the semantic relations encoded in a given text. To complete this information, we need semantic axioms that augment the extracted knowledge and, thus, provide a better coverage of the text's semantics. Once we gather this information, we state that text \(T\) entails hypothesis \(H\) if and only if we find similar relations between a concept from \(T\) and a semantically analogous concept from \(H\). By analogous concepts, we mean identical concepts, or words connected by a chain of SYNONYMY, HYPERNYMY or morphological derivation relations in WordNet.

Because the set of semantic elements identified by a semantic parser does not necessarily convey the complete meaning of a sentence, we shall use a set of semantic axioms to infer the missing pieces of information. By combining two semantic relations or by using the FrameNet’s frame elements identified in a given text, we derive new semantic information.

In order to show if \(T\) entails \(H\), we analyze their meanings. Our approach to semantic entailment involves the following stages:

1. We convert each text into logic form (Moldovan and Rus, 2001). This conversion includes part-of-speech tagging, parse tree generation, and name entity recognition.

2. Using our semantic parser, we identify some of the semantic relations encoded in the analyzed texts. We note that state-of-the-art semantic parsers cannot discover all the semantic relations conveyed implicitly or explicitly by the text. This problem compromises our system’s performance. To obtain the complete set of semantic relations that represents the meaning of the given texts, we introduce a new step in our algorithm.

3. We add semantic axioms to the already created set of world knowledge, NLP, and WordNet-based lexical chain (Moldovan and Novischi, 2002) axioms that assist the logic prover in its search for proofs. We developed semantic axioms that show how two semantic relations can be combined. This will allow the logic prover to combine, whenever possible, semantic instances in order to infer new semantic relationships. The instances of relations that participate in semantic combinations can be either provided by the text or annotated between WordNet synsets. We also exploit other sources of semantic information from the text. For example, the frames encoded in the text sentence provide information which complements the meaning given by the semantic relations. Our second type of axioms derive semantic relations between the frame elements of a given FrameNet frame.

We claim that the process of applying the semantic axioms, given the semantic relations detected by a semantic parser, will capture the complete semantic information expressed by a text fragment. In this paper, we show the usefulness of this procedure for the RTE task, but we are convinced that it can be used by any system which plans to extract the entire semantic information from a given text.

4. We load the COGEX logic prover (Moldovan et al., 2003) which operates by “reductio ad absurdum” with \(H\)’s negated form and \(T\)’s predicates. These clauses are weighted in the order in which they should be chosen to participate in the search. To ensure that \(H\) will be the last clause to participate, we assign it the largest value. The logic prover searches for new inferences that can be made using the smallest weight clauses. It also assigns a value to each inference based on the axiom it used to derive it. This process continues until the set of clauses is empty. If a refutation is found, the proof is complete. If a contradiction cannot be found, then the predicate arguments are relaxed and, if the argument relaxation fails, then predicates are dropped until a proof by refutation is found. Its score will be computed by deducting points for each argument relaxation and predicate removal. If this value falls below a threshold, then \(T\) does not entail \(H\). Otherwise, the \((T, H)\) pair is a true entailment.

We present a textual entailment example to show the steps of our approach. This proof will not

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\(^1\) After all, the entailment, inference, and equivalence terms originated from logic.
John and his son, George, emigrated with Mike, John’s uncle, to US in 1969.

Table 1: Entailment proof example. Table 2 lists the semantic relations and their abbreviations. Sections 3.2 and 4.1 will detail the semantics behind the axioms $T_{Axiom_1}$, $T_{Axiom_2}$, $T_{Axiom_3}, T_{Axiom_4}$, and $H_{Axiom_1}$.

| Frame | Axiom |
|-------|-------|
| $T_{Departing}$ | John and his son, George, emigrated with Mike, John’s uncle, to US in 1969. |
| $T_{Kinship}$ | John and his son, George, emigrated with Mike, John’s uncle, to US in 1969. |
| $T_{Axiom_1}$ | Kin(T, John, George) $ightarrow$ Kin(Mike, George) |
| $T_{Axiom_2}$ | Kin(Mike, George) $ightarrow$ Kin(John, George) |
| $T_{Axiom_3}$ | Kin(T, John, George) $ightarrow$ Kin(Mike, George) |
| $T_{Axiom_4}$ | Kin(T, Mike, George) $ightarrow$ Kin(T, John, George) |
| $H_{Arriving}$ | George and his relative, Mike, came to America. |
| $H_{Kinship}$ | [George, Ego_fe and his relative, Mike, Alter_fe, came to America. |
| $H_{Axiom_1}$ | Arriving,TArriving,F $ightarrow$ Loc(Theme_fe, Goal_fe) Loc(Mike, America) |
| $H_{Semantics}$ | Kin(George, Mike), Loc(George, America), Loc(Mike, America) |

Figure 1: $T_{Semantics}$ and $H_{Semantics}$. The solid arrows represent the relations identified by the semantic parser. The dotted arrows symbolize the lexical chains between concepts in $T$ and their analogous concepts in $H$ ($US_T$ and $America_H$ belong to the same WordNet synset). The dash arrows denote the relations inferred by combining two semantic relations. The long dash arrows indicate the relations between frame elements.

3 Semantic Calculus

3.1 Semantic relations

For this study, we adopt a revised version of the semantic relation set proposed by (Moldovan et al., 2004). Table 2 enumerates the semantic relations that we consider.

2See (Moldovan et al., 2004) for definitions and examples.
3.2 Combinations of two semantic relations

Our goal is to devise semantic axioms for combinations of two relations, $R_1$ and $R_2$, by observing the semantic connection between the $w_1$ and $w_3$ words for which there exists at least one other word, $w_2$, such that $R_1(w_1, w_2)$ and $R_2(w_2, w_3)$ hold true.\(^3\)

Harabagiu and Moldovan (1998) tackled the problem of semantic combinations, for the first time. Their set of relations included the WordNet1.5 annotations and 12 relationships derived from the WordNet glosses.\(^4\) In our research, unlike (Harabagiu and Moldovan, 1998), the semantic combinations use the relations identified in text with a rather minimal contribution from the WordNet relations.

Harabagiu and Moldovan (1998) also investigate the number of possible semantic combinations. Based on their properties, we can have up to eight combinations between any two semantic relations and their inverses, not counting the combinations between a semantic relation and itself.\(^5\) For instance, given an asymmetric relation and a symmetric one which share the same part-of-speech for their arguments, we can produce four combinations. $ISA \circ ANT$, $ISA^{-1} \circ ANT$, $ANT \circ ISA$, and $ANT \circ ISA^{-1}$ are the four possible distinct combinations between HYPERNYMY and ANTONYMY. “$\circ$” symbolizes the semantic composition between two relations compatible with respect to the part-of-speech of their arguments: for any two concepts, $w_1$ and $w_3$, $(R_i \circ R_j)(w_1, w_3)$ if and only if $\exists w_2$, a third concept, such that $R_i(w_1, w_2)$ and $R_j(w_2, w_3)$ hold. By $R^{-1}$,

$R(x, y)$ indicates that relation $R$ holds between $x$ and $y$.\(^6\) The equality holds only if the two composition terms exist.

While analyzing the combinations, we observed some regularities within the semantic composition process. For example, $R_1^{-1} \circ R_2^{-1} = (R_2 \circ R_1)^{-1}$ for any, not necessarily distinct, semantic relations $R_1$ and $R_2$.\(^6\) If one of the relations is symmetric ($R^{-1} = R$), the statement is still valid. Using $(R^{-1})^{-1} = R$ and the previous equality, we can reduce by half the number of semantic combinations that we have to compute for $R_1 \neq R_2$.

We plan to create a $40 \times 40$ matrix with all the possible combinations between any two semantic relations from the set we consider. Theoretically, we can have up to 27,556 semantic combinations, but only 25.79% of them are possible (for example, $MNR(r, v)$ and $SYN(n, n)$ cannot be combined). Many combinations are not semantically significant either because they are very rare, like, $KIN(n, n) \circ TMP(n, v)$, or because they do not result into one of the 40 relations, for instance, $PAH(a, n) \circ AGT(n, v)$.\(^8\) We identified two approaches to the problem mentioned above. The first tries to fill one matrix cell at a time in a consecutive manner. The second approach tries to solve the semantic combinations we come upon in text corpora. As a result, we analyzed the RTE development corpus and we devised rules for some of the $R_i \circ R_j$ combinations that we encountered. We validated these axioms by man-

\(^3\)Harabagiu and Moldovan (1998) also lists the exact number of possible combinations for several WordNet relations and part-of-speech classes.

\(^4\)This set includes the AGENT, OBJECT, INSTRUMENT, BENEFICIARY, PURPOSE, ATTRIBUTE, REASON, STATE, LOCATION, THEME, TIME, and MANNER relations.

\(^5\)Harabagiu and Moldovan (1998) also lists the exact number of possible combinations for several WordNet relations and part-of-speech classes.

\(^6\)The equality holds only if the two composition terms exist.

\(^7\)On average, each semantic relation has 2.075 pairs of arguments. For example, $SRC$ can connect two nouns ($US\text{ }investor$), or an adjective and a noun ($American\text{ }investor$) and, depending on its arguments, $SRC$ will participate in different combinations. Out of the 27,556 combinations, only 7,109 are syntactically possible.

\(^8\)n, v, a, and r stand for noun, verb, adjective, and adverb, respectively. As an example, $R(n, n)$ means that relation $R$ can connect two nouns.
Table 3: Examples of semantic combination axioms

4 FrameNet Can Help

The Berkeley FrameNet project\(^9\) (Baker et al., 1998) is a lexicon-building effort based on the theory of frame semantics which defines the meanings of lexical units with respect to larger conceptual structures, called frames. Individual lexical units point to specific frames and establish a binding pattern to specific elements within the frame. FrameNet describes the underlying frames for different lexical units and examines sentences related to the frames using the BNC corpus. The result is an XML database that contains a set of frames, a set of frame elements for each frame, and a set of frame annotated sentences.

4.1 Frame-based semantic axioms

With respect to a given target, the frame elements contribute to the understanding of the sentence. But they only link each argument to the target word (for example, THM\((theme, target)\) or AGT\((theme, target)\), LOC\((place, target)\), etc.). Often enough, we can find relations between the frame elements of a given frame. These new instances of semantic relations take as arguments the frame elements of a certain type. For example, given the DEPARTING frame, we can say that the origin of the theme is the source \((SRC(theme, source))\) and that the new location of the theme is the goal frame element \((LOC(theme, goal))\). Moreover, if the text specifies the cotheme frame element, then we can make similar statements about it \((SRC(cotheme, source)\) and \(LOC(cotheme, goal))\). These new relation instances increase the semantic information that can be derived from text.

So far, we manually inspected 54 frames and analyzed the relationships between their frame elements by examining their definitions and the annotated corpus provided with the FrameNet data. For each frame, we retained only the rules independent of the

\(^9\)http://framenet.icsi.berkeley.edu
frame’s lexical units. We identified 132 semantic axioms that hold in most cases\(^\text{10}\). We show some examples in Table 4.

### 4.2 Context importance

There are cases when the rules that we identified should not be applied. Let’s examine the sentence *John intends to leave the kitchen*. If we consider only the DEPARTING frame and its corresponding rules, without looking at the context, then our conclusions ($\neg$ LOC(*John, kitchen*) and SRC(*John, kitchen*)) will be false. This sentence states an intention of motion, not the actual action. Therefore, our semantic axioms apply only when the context they are in, allows it. To overcome this problem, we do not apply the axioms for target words found in planning contexts, contexts related to beliefs, intentions, desires, etc. As an alternative, we keep track of plans, intentions, desires, etc. and, if later on, we confirm them, then we apply the semantic axioms. Also, when we analyze a sentence, the frame whose rules we apply needs to be chosen carefully. For example, in the sentence [*A boat* *Agent* [*carrying*] *Target* [*would-be Moroccan illegal emigrants*] *Theme* [*from UK*] *Path* [*start*] *to Spain*] *Path_end sank in the Strait of Gibraltar on June 8*, the CARRYING frame’s axioms do not apply. The boat nor the emigrants reach Spain (the *path_end* of the motion) because the boat sank. Here, the rules given by *sink.v*’s frame should be given priority over the *carry.v*’s rules. We can generalize and conclude that, given a sentence that contains more than one target (therefore, maybe multiple frames), the dominant frame, the one whose rules should be applied, is the frame given by the predicative verb. In the previous sentence, the dominant frame is the one given by *sink.v* and its rules should be applied before the axioms of the CARRYING frame. It should be noted that some of the axioms semantically related to the CARRYING frame still apply (for example, SRC(*emigrants, UK*) or SRC(*boat, UK*)). Unlike LOC(*emigrants, Spain*), the previous relations do not conflict with the semantics given by *sink.v* and its location (*the Strait of Gibraltar*).

### 5 Experimental Results

#### 5.1 The RTE data

The benchmark corpus for the RTE task consists of seven subsets with a 50%-50% split between the positive entailment examples and the negative ones. Each subgroup corresponds to a different NLP application: Information Retrieval (IR), Comparable Documents (CD), Reading Comprehension (RC), Question Answering (QA), Information Extraction (IE), Machine Translation (MT), and Paraphrase Acquisition (PP). The RTE data set includes 1367 English \((T, H)\) pairs from the news domain (political, eco-

| CLOTHING\_PARTS\_F $\rightarrow$ PW(subpart, clothing) |
| CLOTHING\_PARTS\_F $\rightarrow$ PW(material, subpart) |
| Example: “Hello, Hank” they said from the depths of the [fur] Material [collars] Subpart, Target of [their] Wearer [coats] Clothing PW(fur, collar) and PW(collar, coat) |
| CLOTHING\_F $\rightarrow$ PAH(descriptor, garment) $\lor$ PAH(descriptor, material) |
| Example: She didn’t bring heels with her so she decided on [gold] Material [flip-flops] Garment, Target PAH(gold, leather) $\lor$ PAH(gold, flip — flop) |
| KINSHIP\_F $\rightarrow$ KIN(ego, alter) |
| Example: The new subsidiary is headed by [Rupert Soames] Alter, [son] Target [of the former British Ambassador to France and EC vice-president] Ego, |
| KIN(Rupert Soames, the former British Ambassador to France and EC vice-president) |
| GETTING\_F $\rightarrow$ POS(recipient, theme) |
| Example: In some cases, [the BGS libraries] Recipient had [obtained] Theme [copies of theses] Source [by purchase or gift] Source, and no loan records were available for such copies. |
| POS(the BGS libraries, copies of theses) and $\neg$ POS(author, copies of theses) |
| GETTING\_F $\rightarrow$ SRC(theme, source) (if the source is not a person) |
| Example: He also said that [Iran] Recipient [acquired] Theme [fighter-bomber aircraft] Source [from countries other than the USA and the Soviet Union] Source. |
| SRC(fighter-bomber aircraft, countries other than the USA and the Soviet Union) |

Table 4: Frames-related semantic rules
nomical, etc.). The development set consists of 567 examples and the test set contains the remaining 800 pairs.

### 5.2 Semantic axiom applicability

We measured the applicability of our set of semantic rules, by counting the number of times they extract new semantic information from text. Table 6 shows, in percentages, the coverage of the semantic axioms when applied to the texts $T$ and the hypotheses $H$. We also show the number of times the semantic rules solve a $(T, H)$ entailment without employing any other type of axioms.

| Semantic Axioms | True | False | Overall (True and False) |
|-----------------|------|-------|-------------------------|
| Test data (%)   |      |       |                         |
| applied to all $T$s | 15.75 | 11.75 | 13.75                   |
| applied to all $H$s | 2.00  | 3.74  | 2.87                    |
| both $T$s and $H$s | 8.87  | 7.75  | 8.31                    |
| solution for $(T, H)$ | 10.25 | 1.50  | 5.87                    |

| Development data (%) |      |       |                         |
| applied to all $T$s | 18.02 | 11.26 | 14.64                   |
| applied to all $H$s | 2.47  | 2.81  | 2.65                    |
| both $T$s and $H$s | 10.25 | 7.04  | 8.64                    |
| solution for $(T, H)$ | 12.36 | 1.76  | 7.05                    |

Table 6: Applicability on the RTE data

Clearly, because the texts $T$ convey much more information than $H$, they are the ones that benefit the most from our semantic axioms. The hypotheses $H$ are more straightforward and a semantic parser can extract all their semantic information. Also, the rules tend to solve more positive $(T, H)$ entailments. Because there are seven subsets corresponding to different NLP applications that make up the RTE data, we analyzed the contribution of our semantic axioms to each of the seven tasks. Table 5 shows the axioms’ impact on each type of data. The logic-based approach proves to be useful to tasks like Information Extraction, Reading Comprehension, or Comparable Documents, and it doesn’t seem to be the right choice for the more lexical-oriented applications like Paraphrase Acquisition, Machine Translation, and Information Retrieval.

### 5.3 RTE performance

To show the impact of our semantic axioms, we measured the contribution they bring to a system that participated in the RTE challenge. The ACC and F columns (Table 7) show the performance of the system before and after we added our semantic rules to the list of axioms needed by the logic prover.

| Task | Original | Enhanced |
|------|----------|----------|
|      | ACC      | F        | ACC      | F        |
| Test-IR | .478     | .472     | .5       | .505     |
| Test-CD | .78      | .736     | .847     | .819     |
| Test-RC | .514     | .558     | .6       | .636     |
| Test-QA | .485     | .481     | .523     | .537     |
| Test-IE | .483     | .603     | .575     | .687     |
| Test-MT | .542     | .444     | .567     | .49      |
| Test-PP | .45      | .585     | .44      | .576     |
| Test   | .551     | .561     | .604     | .621     |
| Development | .63 | .619 | .718 | .714 |

Table 7: The accuracy (ACC) and f-measure (F) performance values of our system

The results show that richer semantic connectivity between text concepts improve the performance of a semantic entailment system. The overall accuracy increases with around 5% on the test data and almost 8% on the development set. We obtained performance improvements for all application settings, except for the Paraphrase Acquisition task. For this application, we obtained the smallest axiom coverage (Table 5). The impact of the semantic axioms on each NLP application data set correlates with the
improvement that the addition of the rules brought to the system’s accuracy.

Our error analysis showed that the system did not take full advantage of our semantic axioms, because the semantic parser did not identify all the semantic relations needed as building blocks by the axioms. We noticed a significant decrease in the logic prover’s usage of world-knowledge axioms.

6 Conclusion

In this paper, we present a logic-based semantic approach for the recognizing textual entailment task. The system participating in the RTE competition used a set of world-knowledge, NLP, and lexical chain-based axioms and an in-house logic prover which received as input the logic forms of the two texts enhanced with semantic relation instances. Because the state-of-the-art semantic parsers cannot extract the complete semantic information encoded in text, the need for semantic calculus in NLP became evident. We introduce semantic axioms that either combine two semantic instances or label relations between the frame elements of a given frame. Preliminary statistical results show that incorporating semantic rules into the logic prover can double the semantic connectivity between the concepts of the analyzed text. Our process of identifying more semantic instances leads to a smaller dependency of the logic-based RTE system on world knowledge axioms, while improving its overall accuracy.

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