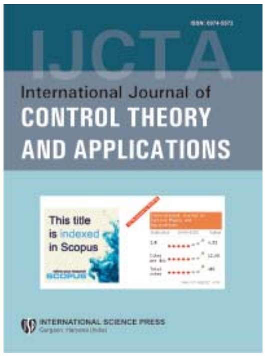

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Recognition of Textual Entailment using Composition of Semantic Relation

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Abstract: The Recognition of textual entailment is a generic approach to find whether a given two sentence infer the same meaning. There are various approaches for recognition of textual entailment but in this article we have chosen semantic based approach because it gives higher level of understanding when compared to the syntactic approaches or other approaches. Among various Semantic approaches extracting Semantic role label use the semantic parser to detect relations in the form of verb argument structure. But the semantic parser finds only the basic relation. The observation that combining elementary semantic relations yields more relations is introduced in CSR algorithm[2]. In This work we have applied the CSR algorithm for recognizing the textual entailment and the accuracy is enhanced by pre-processing the T-H pair for Co-Reference resolution. The obtained relation is extended to RTE-4 challenge with the capability of Sense Disambiguation

Keywords: *Textual entailment,Semantic Parser,Co-Reference Resolution,Semantic Based Approach*

1. INTRODUCTION

The fundamental phenomenon of any a natural language is variability in its semantic meaning i.e. similar meaning can be expressed by two different texts. Natural Language processing applications like Question Answering, Summarization, Information Retrieval systems etc. often requires a framework to capture major semantic inferences in order to deal with the challenges created by this phenomenon. The below Example taken from RTE-3 challenge explains such scenario.

For example: Text: The purchase of Houston-based LexCorp by BMI for $2Bn prompted widespread sell-offs by traders as they sought to minimize exposure. LexCorp had been an employee-owned concern since 2008

Hypothesis: BMI acquired an American company.

2. RELATED WORK

Several systems have been attempted for Recognition of Textual entailment since 2005. Each system has its own advantages and limitations. In a Machine Learning approach [4] the system considers Lexical, semantic and syntactic Features. For each text fragment and hypothesis, a pre-processing is performed, including stemming, part-of-speech tagging, named entity recognition and anaphora resolution. For feature extraction, lexical, syntactic and semantic features are selected. Additionally, named entity relations are taken a s specific features to identify explicit entailed relations; the features are given to the classification algorithm and the two ways entailment labeling is done. The system was only able to perform binary classification (SVM), it was unable to further classify for other challenges. In a logical Inference based system [5] deep semantic analysis and shallow deep word overlap is done. To check whether an entailment holds or not, the system use two kinds of automated reasoning tools: Vampire, a theorem prover and Paradox, a model builder. Textual entailment can also be seen as graph matching problem. In this approach [3], the systems convert the hypothesis H and text T into graphs. There are various ways, syntactic or semantic, to convert a natural language sentence to graph. After getting the text and hypothesis graph, it's about finding subsumption of sub-graphs. The system applies some graph matching techniques to determine the matching score between the two graphs. If the score attains a certain threshold, entailment is labeled as valid.

In a Semantic based approach [7], the system used WordNet to calculate the semantic similarity between a T (text) and an H (hypothesis) Word Sense Disambiguation is carried by the Lesk algorithm based on WordNet definitions (glosses) must be performed. Then a semantic similarity matrix between words in T and H is defined. A function Fsim is applied to T and H. Where the Function Fsim could be one of the following nine functions such as Resnik, Lin, Jico, Pise, PA, Lech, HIST, AD, Sim.

3. TEXTUAL ENATILMENT

3.1. Definition

Textual Entailment can be defined as the phenomenon of inferring a text from another. The entailment relation holds when the truth of one text fragment follows from the truth of the other. Conventionally, the entailing fragment is called as text and entailed one is called as hypothesis. [1]

Definition 1: The classical definition is a text T entails hypothesis H if human reading H will infer that H is most likely true. [1]

The two-way RTE task requires that systems label each entailment pair as either Entailed or Not Entailed – i.e. either T entails H, or T does not entail H. The three-way RTE task introduces the concept of contradiction. The three-way RTE task requires that systems label each entailment pair as Entailed, Contradicted, or Unknown.

Definition 2. The Hypothesis H of an entailment pair contradicts the Text T if a human reader would say that the relations/events described by H are highly unlikely to be true given the relations/events described by T. [1]

For Example:

Text: A black race car starts up in front of a crowd of people.

Hypothesis: A man is driving down a lonely road

3.2. The RTE Challenge

Table 1
RTE Challenges

RTE Challenges	*Description Of the challenge*		
	Year	*Length of the Sentence*	*Entailment output*
RTE-1	2005	Shorter sentence	True/False

RTE Challenges	*Description Of the challenge*		
	Year	*Length of the Sentence*	*Entailment output*
RTE-2	2006	Shorter Sentence	True/False
RTE-3	2007	Longer text were given as t-h pairs	True/False
RTE-4	2008	Same length as RTE-3 sentence	True/ false/ Contradiction/ Unknown
RTE-5	2009	Document Level Search	T in n-documents entailed with H
RTE-6	2010	The Entailment task was applied for Summarization & Knowledge Base Population Scenario	
RTE-7	2011	Text up to paragraph for Summarization, Knowledge Base Population Scenario	
RTE-8	2012	Longer Sentence	correct/partially correct/ contradictory/ irrelevant/ not in the domain

4. BACKGROUND

4.1. Semantic Role Labelling

The primary task of semantic role labeling (SRL) is to indicate exactly what semantic relations hold among a predicate and its associated verb in that sentence. Semantic Representation of a text is a key approach for understanding text and reasoning. They are the formal way of expressing a text. The text when given as the input to the Semantic parser gives all the basic relation in a text.

John painted his truck : The above sentence will give the following semantic relation as Agent (John, painted), theme (truck, painted), Possession (Truck, john). Typical roles that are labeled in SRL are such as Agent, Patient, and Location for the entities participating in an event, and Temporal and Manner for the characterization of other aspects of the event or participant relations. This type of role labeling thus yields a first level semantic representation of the text that indicates the basic event properties and relations among relevant entities that are expressed in the sentence. In this article we have taken 26 relations similar to the work of [2]. The relation are described in the table

4.2. Composition of Semantic Relation

The goal of CSR algorithm is to apply inference axioms over already identified relations in a text to obtain the unrevealed relations. Unlike other approaches it does not consider the lexical or syntactic information, it works on previously extracted relation [2].The necessary condition for combining two relations R1(x, y) and R2(y, z) is that they are required to have a common argument y. This is achieved using the domain range compatibility. Given a semantic relation R, DOMAIN(R) and RANGE(R) are defined as the first and second argument respectively.

5. SYSTEM OVERVIEW

The T-H pair is downloaded from RTE Dataset. The T and H sentences are pre-processed for Co-Reference resolution. The pre-processed sentences are separately given to the Semantic parser. The output of the semantic parser is the basic relations. The basic relation of the Text alone is given as the input to the CSR algorithm because of the semantic complexity in text is more compared to Hypothesis in T-H pair .The output of algorithm is then compared with the relation-set of the Hypothesis and based on the comparison the T-H pair is classified as Entailed/Not Entailed/Unknown/Contradiction. The architecture of the proposed system is shown in the Figure

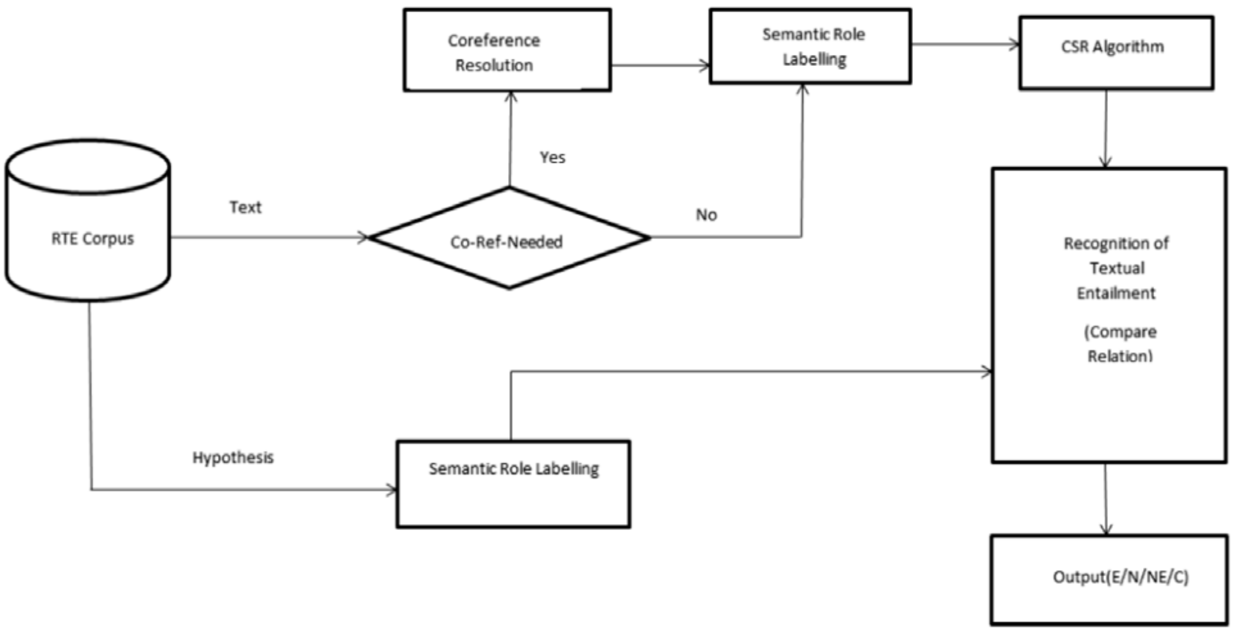

Figure 1: Architecture Diagram

5.1. Corpus

The two dataset used for the approach is RTE-3 dataset and the RTE-4 dataset. The RTE-3 dataset is readily available in NLTK corpus. In the gold standard test sets, each pair is labeled according to whether or not the text 'entails' the hypothesis; the entailment value is mapped to an integer 1 (True) or 0 (False). The RTE-4 dataset are available in Semeval-2014 task. The task contains 10,000 English sentence pairs, each annotated as Entailment, Unknown and Contradiction

5.2. Co-Reference Resolution

In linguistics, co-reference occurs when two or more expressions in a text refer to the same person or thing; they have the same referent,

Example:

Bill said he would come : The proper noun Bill and the pronoun he refer to the same person, namely to Bill. Co-Reference is the main concept underlying binding phenomena in the field of syntax. If this step is not performed, then there would be an ambiguity during semantic role labeling and while comparing the text and the hypothesis relation set. Hence this task is done as the pre-processing step when two expressions are co-referential, the one is usually a full form (the antecedent) and the other is an abbreviated form (the anaphor).

Our system used the Stanford NLP tool for Co-Reference resolution. The output of this step is again a sentence with the anaphor replaced by the antecedent.

5.3. Semantic Role Labelling

The output of the sentence is given to the Semantic Parser. We have used the SENNA which performs semantic role labeling along with many NLP pipeline tasks. The SENNA has achieved state of art performance of 75.49%. The tool takes the sentence as the input and gives the basic semantic roles. The output of the module is explained with the following example

Example:

TEXT (T): Belknap married and lost his first two wives, Cora Leroy and Carrie Tomlinson, and married Mrs. John Bower, his second wife's sister.

T1 AGT (Belknap, married)

T2 THM (wives, married)

T3 QNT (first two, wives)

T4 ISA (Carrie Tomlinson, wives)

HYPOTHESIS (H): Belknap was married to Carrie Tomlinson.

H1: AGT (Belknap, was married)

H2: THM (Carrie Tomlinson, was married)

5.4. CSR Algorithm

The algorithm takes the semantic roles from the semantic parser for example the algorithm takes all the four relation T1, T2, T3, T4 as the input. Among the four relation it finds only the T2 and T4 has domain and range compatibility. The algorithm loops over all the possibilities for the relation and results a new relation T5 THM (Carrie Tomlinson, married)

5.5. Comparison of T-H Relations

An important task before comparing the relation is understanding the common sense knowledge among the complicated phrase in the arguments of semantic role like *car owner* and the *person owning the car* is the same. Similarly system should understand that phrases like *stick* and *wood* are same. These similarities are crucial because these phrases inside roles form the foundation for deciding whether or not sentence entails.

These similarities are identified based on the score value obtained from Cosine Similarity and WordNet. If the relation in the Hypothesis matches with Text relation then the arguments in the relation are compared using above two measures and a score is given, Based on the score the final output such as whether Entailment, Not Entailment, Unknown or contradiction is given.

6. RESULT AND ANALYSIS

The existing system [2] has evaluated their approach with 60 RTE-3 pairs among which 23% of sentence was solvable using basic semantic parser and when CSR was added 35% was solvable. The rest 65 % were not solvable because of the lack of co-reference resolution and disability to resolve sense disambiguation. The results obtained by our approach are tabulated below:

Table 2
Result Analysis

Output	CSR(Existing Approach)			CO-Reference + CSR+ Sense Disambiguation		
	Prec	Recall	F-Measure	Prec	Recall	F-Measure
Entailment	62.4	63.5	58.3	72.9	75.8	74.3
Not-Entailed	61.4	62.1	55.6	71.1	70.65	71.90
Contradiction	67.6	62.6	59.3	69.2	70.5	70.1
Unknown	43.2	40.2	42.4	50.3	52.3	55.8

7. CONCLUSION

Natural Language processing applications requires an approach to identify the major semantic inferences in order to deal with various challenges. Textual entailment plays a major role in identifying these inferences. Hence a semantic based approach using the CSR algorithm was designed to recognize the textual entailment. But the CSR algorithm fails to finds all the possible semantic relation of the sentence. Therefore to increase the accuracy and the working of the algorithm, the co-reference resolution has been added as the pre-processing step and the system has also acquired the capability of sense disambiguation using wordnet and cosine similarity.

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