Semi Cognitive approach to RTE 6 - Using FrameNet for Semantic Clustering

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Abstract

We present a new system, for recognizing textual entailment, known as Sangyan[1], which tackles the inherently complex syntactic and semantic ambiguities involved in RTE Task by making use of multiple techniques of text processing. Sangyan employs Syntactic Dependency Tree Match for recognizing syntactic similarity with the aid of an anaphora resolution system, an in-house developed NER system etc. Since syntactic matching techniques cannot map the semantically same but syntactically different constructs, Sangyan utilizes certain heuristics that attempt to bring the different dependency tags together under the umbrella of equivalent semantics. To handle semantic variability, instead of a typical rule based approach, Sangyan uses "FrameNet Frames" and Shalmanesar semantic parser for 'Semantic Clustering' of words into groups. To improve coverage, we've added many new frames over and above the ones provided by the FrameNet after considerable experimentation over the past RTE data and the RTE6 Development Sets.

1. Introduction

The recognition of textual entailment, i.e. deducing whether the information present in hypothesis passage can be inferred from the information present in text passage, leads to interesting scenarios which can be classified in many ways on the basis of different criteria. One interesting criterion is the cause of ambiguity involved. The inherent ambiguity in natural language can be caused by either syntactic or semantic variability.

From this perspective, it's safe to say that any system that targets RTE will have to take care of the presence of both semantic and syntactic variability in the Text-Hypothesis pairs. If a system takes care of only syntactic variability (most of the shallow lexical match based systems), then it is quite likely to hit the boundary soon, after which constructive improvisations will be very difficult.

On the other hand, only semantic analysis is not only difficult, but also infeasible, since shallow syntactic match resolve many cases with minimal processing while semantic modeling and analysis requires more complex methods which can be very expensive computationally. Thus, many systems have undertaken a hybrid approach or processing in multiple phases, trying to establish a balance in this interesting equation with syntactic and semantic analysis as the two critical parameters.

However, most of such approaches with multiple phases will lead to systems with non-deterministic performance. These systems suffer from a very subtle problem: Right results because of wrong reasons. And here, subtle changes in the test data, even if it retains the basic pattern, may lead to drastic changes in the performance of the system. Moreover, adding knowledge resources such as WordNet (Fellbaum 1998), VerbOcean (Chklovski and Pantel 2004), and DIRT (Lin and Pantel 2001) etc. will not have a significant impact on performance of the system unless the model used is appropriate to utilize the resources to their full potential.

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[1] Sangyan is a Sanskrit word, which means 'Cognition'.

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On the other hand, rule based approaches are used to tackle semantic variability, wherein rules added for handling specific instances can extract semantic information to aid entailment process. However, this approach suffers from serious drawbacks such as limited applicability of rules and lack of sufficiency and coverage.

Our system, Sangyan, is yet another attempt at finding the balance in order to overall improve the entailment deduction. We attempt to target the above problems with small but significant steps, maintaining the determinism of the output at each stage of improvisation.

In the following section, “System Architecture”, a brief overall architecture overview is followed by detailed description of each module of the system. Section 2.1 highlights the preprocessing stage. Section 2.2 elaborates on the two-phased ‘Syntactic Module’ which uses the Stanford dependency tree (Manning et al. 2008) to exploit the syntactic similarity between the t-h pair to establish entailment. The syntactic module also discusses the Generically Applicable Heuristics derived from Dependencies (GAH), which attempts to bring the different dependency tags together under the umbrella of equivalent semantics.

Sangyan utilizes the FrameNet (Fillmore et al. 2004) resource to represent semantics of text. Frames are a powerful means of representation since they provide a single platform through which we can represent the meanings for events, objects, or ideas. Often, same event, being described by two sentences, is difficult to map due to subtle syntactic/semantic variation such as noun-verb alteration. Such problems can be successfully resolved using the frames which model the event semantics irrespective of the syntactic structure, as illustrated in details in section 2.3, “Semantic Module”.

Section 3, “Results and Evaluations” presents the results at RTE 6 with many illustrative examples. And in the end, in Section 4, “Conclusions and Future Works”, we’ve discussed both strengths and improvement areas of the techniques incorporated in Sangyan.

2. System Architecture

The architecture of system Sangyan, presented in Figure 1, works on the view that entailment can be asserted by establishing either syntactic or semantic similarity between the text and hypothesis. Thus, the system follows a two phased approach that analyzes the t-h pair at both the syntactic and semantic level in different phases and then gives the entailment result. The system architecture can be broadly categorized into the Preprocessing Module, Syntactic Module and Semantic Module.

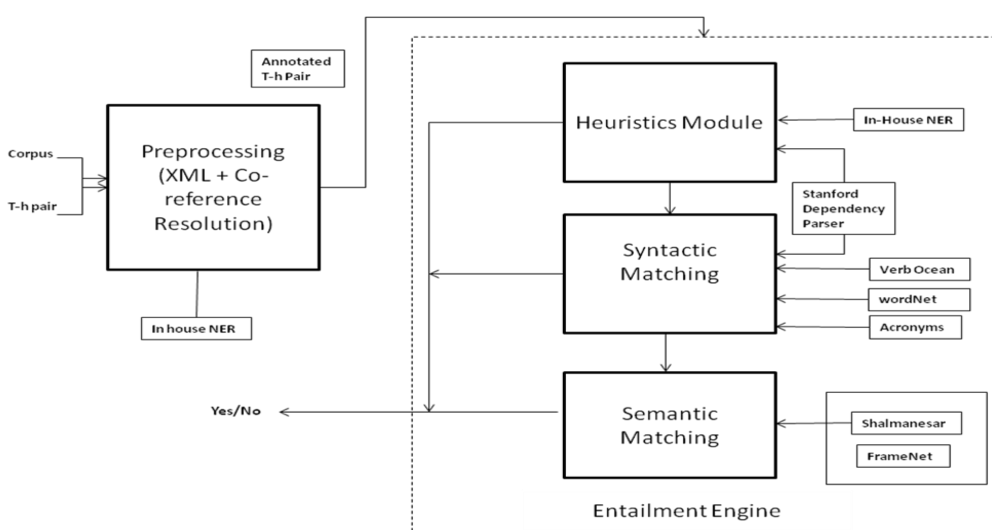

Figure 1: System Architecture

2.1 Pre-processing

The Preprocessing module is composed of sub-modules common in text processing systems, i.e. a tokenizer, NE recognition module, a POS tagger (Stanford Parser is used for POS tagging); and then the Stanford dependency parser. Sangyan utilizes an in-house NER system that not only annotates the words with the basic information such as location, human, gender, organization etc but also annotates the words with more complex and useful information such as container relationships like “New York belongs to US”. It also extracts information related to designation like Irish Prime Minister will contain the information that the word is a designation type, belonging to the container Ireland. Such annotations facilitate the process of entailment.

The open source co-reference resolution system Lingpipe (Alias-i 2008) is integrated into Sangyan to resolve all the anaphoric references present in the entire document to which the TH pair belongs to. While, our system uses this anaphora resolution as the document analysis to extract some information from the text, we believe that a more extensive document analysis could aid the entailment process much more.

Our entailment engine also employs Tree Tagger (Schmid 1994) as a lemmatizer to facilitate the matching of different forms of the same word. Tree Tagger produces accurate lemmas of the words, thus reducing the error at the processing level.

2.2 Syntactic Module

One way to deduce entailment between two sentence fragments is to determine whether the similar words in both the sentences play similar *syntactic role*, since entities playing same syntactic role will have similar semantics.

Illustration I: Tom killed John.
Illustration II: John was killed by Tom.
Illustration III: John killed Tom.

In both Illustrations I and II, Tom is the agent of the sentence and John the object. Hence, entailment can be deduced by exploiting syntactic similarity between the two sentences. Although, in Illustration-III, the lexical overlap with Illustration I and II is high but the entities play different roles (John is the agent and Tom is the object), hence entailment cannot be established.

To determine syntactic similarity between text-hypothesis pair, Sangyan includes two sub-modules: Heuristics Module and Dependency Tree Match Module. These syntactic modules take the dependency trees of both the text and hypothesis as input. Preserving and utilizing the annotations of the NER and co-reference resolution at the lexical level, we also we make use of resources such as WordNet and Verb Ocean while matching the different entities.

2.2.1 Dependency Tree Match Module

The ‘Syntactic roles’ (as explained above) can be derived from a dependency tree or constituent parse tree. We extract these roles from Stanford dependencies (generated from Stanford dependency parser). The dependency tree overlap measures the syntactic similarity between the t-h pairs. This match gives equal importance to all the relations and does not give weightage to relations that contribute more to the meaning.

Illustration IV:
Hypothesis: The Irish Republican Army is a Catholic paramilitary group.
Text I: Answering questions in parliament, Ahern told MPs that the meetings with Adams, whose party is the political wing of the IRA, Northern Ireland's main Catholic paramilitary group, had merely been to maintain dialogue.

Text II: The United States, he said, welcomed statements made this week by British Prime Minister Tony Blair and Irish Prime Minister Bertie Ahern that the key to moving forward was for the Irish Republican Army (IRA), Northern Ireland's main Catholic paramilitary group, to end all violence unequivocally.

This illustration highlights the fact that the dependency tree match with high probability deduces entailment between the pairs but a closer look reveals that the high match is contributed by less significant relations like amod and det, that are generally quantifiers that capture local relationship between words. More important relations like nsubj that contain information essential for meaning inference, are not matched as this meaning deducing information in both T1 and T2 are not present as nsubj but as appos. Hence, though the system was able to deduce the entailment correctly but as shown is Illustration V, the method is extremely brittle and the performance is unreliable.

Illustration V:
Hypothesis: A beautiful blue-eyed girl is dancing graciously in a big dirty playground.
Text: A beautiful blue-eyed girl is running quickly in a big dirty playground.

In this illustration, the action performed in the t-h pair is different but due to high match of less significant relations, true entailment is given. Such a high match fails to capture the important relations and hence gives a result that is highly susceptible to error. Thus, it highlights the importance of intelligent match rather than high match.

To address the above issue of to some extent, we have used a Heuristic module, which is elaborated in the next section.

2.2.2 Heuristics Module

Our heuristics extract and represent various conceptual/semantic relationships present in a sentence. This sub-module works on the syntactic dependency tree and extracts and maps the different syntactic structure.

As can be seen in Illustration IV, both text and hypothesis represents the same information present in different syntactic structures i.e. the hypothesis information is present in the text but is playing a different syntactic role. As discussed, matching such cases using dependency trees may not always give us the desired result.

To overcome such problems, we have devised certain heuristics known as GAH rules (Generically Applicable Heuristics derived from Dependencies) that extracts the inherent meaning of the sentence from dependency relationships and converts them into "*meaning based relationships*". Meaning based relations such as existential relation (is-a) converts dependency relations of the sentences into semantic relations.

For example: "Tom is an author" and "The author, Tom …" essentially mean the same thing 'Tom "is-a" author'. The following table expresses the number of ways in which the same existential relation "is-a" is expressed using different syntactic structures. Table 1 uses Illustration IV to represent these meaning based relationships.

T-H pairs (RTE-6 Development Set)	**Meaning**	**Syntactic Role**
Hypothesis : The Irish Republican Army is a **Catholic paramilitary group**	Irish Republican Army "is-a" Catholic paramilitary group	nsubj(group, Army)
Text I: Answering questions in parliament, Ahern told MPs that the meetings with Adams, whose party is the political wing of the **IRA, Northern Ireland's main Catholic paramilitary group,** had merely been to maintain dialogue.	IRA "is-a" Northern Ireland's main Catholic paramilitary group	appos(IRA, group)

Text II: The United States, he said, welcomed statements made this week by British Prime Minister Tony Blair and Irish Prime Minister Bertie Ahern that the key to moving forward was for **the Irish Republican Army (IRA), Northern Ireland's main Catholic paramilitary group**, to end all violence unequivocally.	Irish Republican Army "is-a" Northern Ireland's main Catholic paramilitary group	appos(Army, group)

Table 1

T-H pairs (RTE-6 Development Set)	**Meaning**	**Syntactic Role**
Hypothesis: Gerry Adams is the **leader of Sinn Fein.**	Gerry Adams "is-a" leader of Sinn Fein	nsubj(leader, Adams)
Text I: London and Dublin are awaiting for an Irish Republican Army response to a call from **Gerry Adams, leader of the group's Sinn Fein political wing,** for an end to violence.	Gerry Adams "is-a" leader of the group's Sinn Fein political wing	appos(Adams, leader)
Text II: Irish Prime Minister Bertie Ahern admitted on Tuesday that he had held a series of private one-on-one meetings on the Northern Ireland peace process with **Sinn Fein leader Gerry Adams,** but denied they had been secret in any way.	Gerry Adams "is-a" leader of Sinn Fein	nn(Adams, leader)

Table 2

In the heuristics module, we try to extract the inherent meaning and model them in a generic representation which is independent of any dependency tag (based on the syntactic role played). Following is the set of few heuristics rules used for the transformation of sentence.

Transformation Rules[2] :

appos (X,Y)	X " is-a " Y
nsubj (X,Y)	Y " is-a " X
amod (X,Y)	X " quantifier of " Y
nn(X,Y)	Y " of " X
poss(X,Y)	X "belongs to" Y
abbrev(X,Y)	X " is-a " Y

Table 3

[2] These transformations are not simply derived from the syntactic dependencies, but they are extracted using extensive set of rules and world knowledge. For Example, depending on the rule applicable syntactic dependency tag nn(x,y) may be transformed into a number of 'meaning based relationships'

The heuristic module models not only the ‘Global meaning relationship’ that captures the semantics of the sentence, but also local relationships. These local relationships are derived using the transformation rules and the additional information obtained from the NER system.

Illustration VI[3]:
Text (T3): Irish Prime Minister Bertie Ahern admitted on Tuesday that he had held a series of private one-on-one meetings on the Northern Ireland peace process with Sinn Fein leader Gerry Adams, but denied they had been secret in any way.

The heuristic extracts relation global relations such as:
nn(Bertie_Ahern[4], Irish_Prime_Minister)→ Bertie Ahern ‘is a’ Prime Minister;
nn(Gerry_Adams, leader) → leader ‘of’ Sinn Fein

And local relations such as:
Irish Prime Minister ‘belongs to’ Ireland
Bertie Ahern ‘has-designation’ Prime Minister ‘of-Location’ Ireland

Hence, such a generic system will be able to entail the following hypothesis for T3:
H1: Bertie Ahern is Irish Prime Minister.
H2: Bertie Ahern is the Prime Minister of Ireland.
H3: Gerry Adam is a leader.

This module attempts at matching which gives less probabilistic results by inferring the meaning instead of predicting it which is the case in shallow syntactic techniques. Though the coverage of this module is small as of now, it is a significant step towards deterministic syntactic match and we plan to extend it to contain more generically applicable heuristics, thus giving more robust results with increased coverage.

2.3 Semantic Module

The Semantic module forms the second of the two phased approach taken by our system. If the syntactic module is not able to deduce entailment[5], it is assumed that syntactic variability does not exist and thereafter the Semantic Module is invoked to try and establish semantic relatedness between the TH pair. This module uses FrameNet along with the Shalmanesar Semantic Parser to extract semantic information and deduce entailment based on that information.

Frames are the basic semantic units for representing concepts. They are usually single-word nouns or verbs but a number of phrasal frames also exist e.g. ‘Withdraw_from_participation’. Each frame can be evoked by a number of different words or phrases. And depending on the context, a particular word may evoke different frames. Thus, each term is placed in context, allowing a user to distinguish between for example "bureau" the office and "bureau" the furniture. Frames essentially allow us to cluster words in separate semantic groups representing a particular concept. This implies that a word can belong to multiple groups depending upon the role it plays in the context.

Illustration VII (From RTE 1 Development Set):
Text: Satomi Mitarai died of blood loss.
Hypothesis: Satomi Mitarai bled to death.

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[3] Refer to Table 2 for more details

[4] Our system’s NER module concatenates multi-word Named Entities. For Example, Bertie Ahern will be interpreted as Bertie_Ahern.

[5] If the syntactic module deduces true entailment, TH pair is not further processed by semantic module

In this illustration, the frame of both “died” and “death” is “Death” giving a complete frame match, thus enabling the system to give the correct entailment result.

While resources like WordNet and VerbOcean, deal with meanings of individual words, but are unable to establish their semantic associations with other words and concepts. Using FrameNet instead, our system tries to interpret the meaning in context of the sentence and assign appropriate frames to reflect the meaning of the sentence. The meaning of each word is expressed in terms of the frame it belongs to. Thereby, an abstract representation is created for the meaning which can thereafter be used to match the meaning of two sentences.

Shalmanesar (Erk and Pado 2006) is a freely available semantic parser for shallow semantic parsing based on machine learning techniques and it is pre-trained on the FrameNet corpus. Shalmanesar provides a complete system which performs preprocessing with Collins parser and TreeTagger and then performs frame and role assignment.

In this module, we have used the frame overlap between the text and hypothesis as an indication of the semantic overlap between them. Since both text and hypothesis are represented in terms of their respected frames; a high frame overlap indicates similarity in the meaning of text and hypothesis. However, in order to further substantiate the results obtained by the frame overlap, we combine the frame match with the lexical overlap of important entities (nouns, verbs etc.) between the text and hypothesis. The FLMatch (Frame-Lexical Match) Score is computed as follows:

*FLMatch Score = (2 * FrameMatch * LexicalMatch) / (FrameMatch + LexicalMatch)*

This effectively means that the Semantic Match would be high only when there is high lexical overlap as well as meaning correlation between the text and hypothesis, thus giving us a much more reliable criterion for entailment judgment.

Illustration VIII:
Text: The Patriot Act, passed by Congress a few weeks after the Sept. 11, 2001, terror attacks, gave federal law enforcement officials broader powers of surveillance and prosecution against suspected terrorists, their financiers and their sympathizers.
Hypothesis: Congress passed the Patriot Act after September 11, 2001.

In this illustration, the frame “Giving” matches in both text and hypothesis and there is a high lexical overlap between the text and hypothesis. Therefore, the system correctly gives the positive entailment result.

In our analysis, we observed that certain frames were equivalent in effect. We identified some such frames and added the functionality to equate them during the match process. This helps in widening the match criterion of the frame match.

Although FrameNet is a useful resource, a major shortcoming is the lack of coverage provided by the FrameNet resource. Although FrameNet contains more than 6500 fully annotated lexical units and associated frames, but the coverage provided by this resource may still not be sufficient for many real world scenarios such as RTE-6. Also, it takes expert human supervision for the addition of new frames, which is a time consuming task. We’ve used FrameNet to cluster words for meaning inference, and therefore it wasn’t required to concentrate on utilizing the Frame Elements[6]. Thus, for improving the coverage we increased the number of frames by just adding the frame information along with the example sentence, ignoring the frame elements which made the process much quicker.

6 Each frame comes with its own set of semantic roles called frame elements. These are the participants and propositions in the abstract situation described(Burchardt et al. 2009)

Illustration IX:
Text: Her interpreter, Allan Enwiyah, 32, was shot dead and his body abandoned nearby by the kidnappers, while her driver got away.
Hypothesis: Jill Carroll’s driver escaped.

In this illustration, the frame of “escape” is “Departing” and that of “get away” is “Evading”. However, the meaning of escape and get away are same in the context of an accident. Thus, after the addition of the frame “Evading” to both the Lu(s) (Lexical unit), we are able to get the required frame information and thus are able to give the correct entailment result.

3. **Results and Evaluations**

We intended to develop a system that aimed at achieving both deterministic behavior and decent accuracy that could be deployed in real world settings. Following are the results of the system on the development and test sets of RTE-6. Due to the high execution time of the system, we could only submit one run to the TAC 2010 RTE track. Following are the results:

RTE 6 Main Task					
Development Set			**Test Set**		
Precision	Recall	F-Measure	Precision	Recall	F-Measure
30.64	33.00	31.78	21.66	46.03	29.46

Table 4

One of the major reasons for the system's low F-measure is the low precision of our system. This is partly due to the probabilistic nature of the syntactic module of our system, which causes the system to give many false positives. This is highlighted in the Illustration X.

Illustration X:
Text: The White House on Monday carefully distanced itself from Vice President Dick Cheney’s delayed notification about his accidental shooting of a hunting companion.
Hypothesis: Harry M. Whittington is Vice President Dick Cheney’s hunting companion.

Some of the other reasons for the low precision are the lack of coverage of the FrameNet resource and the low accuracy for the frame assignment. The low accuracy of the frame assignment can be attributed to a number of reasons such as failure of Collin parser to parse some t-h pairs and frame not being available in the training data and thus is unavailable to the classifier.

Illustration XI:
Text: Merck announced a global withdrawal Thursday of Vioxx, a blockbuster arthritis drug, after a study showed it increased the risk of strokes and heart attacks.
Hypothesis: Merck pulled Vioxx off the market on September 30, 2004.

This pair could have been entailed correctly by our system as the semantic module would have detected the frame ‘Withdraw_from_participation’ for both words “pull off” and “withdraw”. But due to the failure of the Collin's parser, the system could not detect the entailment.

In some cases it has also been seen that Shalmanesar recognized incorrect frames leading to correct entailment judgment but because of wrong reason.

Illustration XII:
Text: Harry Whittington, 78, was peppered with shotgun pellets after Cheney turned to shoot quail that had just been flushed out of the brush, Cheney spokeswoman Lea Anne McBride confirmed Sunday.
Hypothesis: Harry M. Whittington was shot by Vice President Dick Cheney.

In this case, Shalmanesar incorrectly assigned the frame "Behind the Scene" to the word "shot" which stems from a different sense of the same word in the context of "movie making". Despite this incorrect frame, the system gives correct result as it incorrectly tags the frame in both text and hypothesis. Though the reason for giving true entailment is not correct, but unlike other shallow syntactic techniques, this 'right result because of wrong reason' would not lead to high level of non-determinism. That is because, the chances of high Lexical Match, along with high Frame match[7] is very thin because of wrong reason. This particular case just suffers from absence of the correct sense of word (which is gun-shot) which can be improved by attempting to add all the senses of the word to the corpus.

Ablation Results for RTE Main Task			
Resource Ablated	**Precision**	**Recall**	**F-Measure**
Shalmanesar Semantic Parsers	30.04	32.49	31.22
WordNet	22.96	42.65	29.85
Verb Ocean	21.54	46.24	29.39

Table 5

The results of the system when key resources were ablated from the system are given in Table []. The results indicate that the semantic module substantially increases the system's tendency to give true results. This on one hand increases the recall of the system due to true positives but on the other hand, is also responsible for large number of false positive leading to low precision of the system. Due to this, the F-measure of the system does not vary much when the Shalmanesar parser was ablated from the system. The semantic module developed suffers from the problem of coverage for the RTE task. The numbers of frames generated per text and hypothesis does not sufficiently reflect the complete meaning of the sentence.

Illustration XIII:
Text: London and Dublin are awaiting for an Irish Republican Army response to a call from Gerry Adams, leader of the group's Sinn Fein political wing, for an end to violence.
Hypothesis: The Irish Republican Army is a Catholic paramilitary group.

In the illustration above, only the frame 'Aggregate' is matched; this does not effectively reflect the overall meaning of the sentence. Due to the high frame overlap the system incorrectly deduces entailment. The problem is further aggravated by lexical match added to the module. Illustration XIV elaborates on the same.

Illustration XIV:
Text: Vice President Dick Cheney accidentally sprayed a companion with birdshot while hunting quail on a private Texas ranch, injuring the man in the face, neck and chest, the vice president's office confirmed yesterday after a

[7] As discussed in section 2.3, we calculate a score that gives importance to both Lexical and Frame Match

Texas newspaper reported the incident.
Hypothesis: Harry M. Whittington is Vice President Dick Cheney's hunting companion.

In this illustration, despite the low frame match, the true entailment is deduced due to the high lexical overlap. Being shallow syntactic, lexical overlap proves to be a weak replacement for the frame elements in many cases.

4. Conclusions and Future Works

We've just started to scrape the surface of this powerful technology of semantic clustering of words and it has proved to be very promising giving decent results in RTE 6. On the other hand, thorough analysis of the output has strengthened our belief that a balance between increasing correctness of entailment deduction and deterministic output can be achieved with a hybrid system containing modules for syntactic/semantic processing, which accomplish the assigned tasks in well defined phases.

We took special care while designing our heuristics, so that our system does not suffer from typical problems of case specific rules based systems with low applicability which soon reaches the stage of "rule bloat". Sangyan uses heuristics which are more generic in nature, and thus have a greater spectrum which improves applicability while keeping the number of rules minimal. Further analysis will help us add more such heuristics, with constant consideration of generic applicability.

FrameNet is a powerful resource and its contribution in our system has helped us to induce the first patch of subtle "cognition" to Sangyan. However, till now we have only used it for the semantic clustering and we are excited about the immense possibilities with "role recognition" and "role assignment". These roles are local to the frame which is different from usual semantic role labeling. While this difference seems more promising in RTE, it also makes the modeling for optimum utilization more challenging. We plan to integrate this promising aspect of "Frame Elements" in Sangyan for improving its cognition. These roles or frame elements will be much superior alternative to the current Lexical Match parameter in the FLMatch Score.

On the other hand, while FrameNet and Shalmanesar combination seemed to have worked fine for this time, we plan to investigate Detour (Burchardt et al. 2005). Moreover, the Collins parser (Bikel 2004) that we've used with FrameNet, does seem to have some limitations and we want to test Minipar to see if it would be good replacement for Collins parser, or perhaps some combination of the two would be better.

Our current matching mechanism for semantic clusters which we form using FrameNet is not utilizing the meta-relations (Inheritance, Precedes etc) which would further improve the matching. We also plan to further improvise our in house 'Frame Enhancer' in order to broaden the coverage of the semantic module of our system.

As a final note, we plan to perform thorough Document Analysis in future, which we believe would have had significant impact of the performance of the system in RTE 6.

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