Argumentation Based Multi-Agent Framework with Natural Language Features

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Abstract. This paper presents our approach to build an argumentation-based multi-agent framework, where agents can engage in debates with other agents and also with humans in natural language (English). The structure of the agent society and the architecture of the agents are described, with focus on the natural language processing module. We chose statistical methods for extracting arguments from text. We present our results in argumentation mining, comparing them with results from similar research works.

Key words: multi-agent systems, argumentation, natural language processing, statistical learning, artificial intelligence

1 Introduction

During the last decade Argumentation has been gaining importance within Artificial Intelligence especially in multi agent systems. Argumentation based dialogues have proved to be a general approach to agent communication in which the agents exchange not only statements of what they believe and what they want but also the reasons why. There is some research made in the field and several abstract argumentation frameworks were proposed like [3], [11].

A nice overview on argumentation tasks and concepts was given by Douglas Walton in his research reports, especially in the first chapter of [12]. He distinguishes four challenges undertaken by argumentation: identification of arguments which means finding the premises and conclusion of arguments in a text and fitting that argument in an argumentation scheme; analysis which involves the identification of implicit premises or conclusion of arguments (such an argument is called an enthymeme); evaluation where the strength of an argument must be determined using a general criteria; invention which means constructing new arguments that can be used to prove some conclusion.

The general approach or methodology of argumentation can be described as distinctively different from the traditional approach based on deductive logic. The traditional approach concentrated on a single inference, where the premises and conclusion are designated in advance, and applied formal models like propositional calculus and quantification theory determine whether the conclusion conclusively follows from the premises. This approach is often called monological. In contrast, the argumentation approach is called dialogical (or dialectical) in that it looks at two sides of an argument, the pro and the contra. According to this approach, the method of evaluation is to examine how the strongest arguments for and against a particular proposition at issue interact with each other, and in particular how each argument is subject to probing critical questioning that reveals doubts about it. By this dialog process of pitting the one argument against the other, the weaknesses in each argument are revealed, and it is shown which of the two arguments is the stronger.

Our goal is to build an argumentation based framework for multi-agent interaction. Agents will use a public communication protocol to exchange arguments but will also use natural language to engage into dialogues with humans. Several other multi-agent argumentation frameworks were proposed for resolution of conflicts amongst desires and norms [8], practical reasoning [2], ontology mapping [16] or information exchange in prediction markets [9]. As it will be shown, in our system agents can have different topic ontologies, providing a more general framework for argumentation which is not restricted to a given subject.

For the natural language processing module our approach uses statistical methods for extracting the argumentative clauses, separate arguments in text and integrating sentences into argumentation schemes.

Some relevant work in this area has been done by R.M. Palau and M-F Moens in [10]. In the paper they analyze the main research questions when dealing with argumentation mining and the different methods they have studied and developed in order to successfully confront the challenges of argumentation mining in legal texts.

A more structured approach is taken by Safia ABBAS , Hajime SAWAMURA in [1]. The environment uses different mining techniques to manage a highly structured arguments repository.

We use AraucariaDB corpus to train our classifiers and to compare our results to those obtained by Palau and Moens. AraucariaDB is an online database of marked up arguments maintained at the University of Dundee. The argument markup language (AML) [13] defines a set of tags that indicate delimitation of argument components, tags that indicate support relationships between those components, and tags that indicate the extent of instances of argumentation schemes.

2 Society Overview

In this section we present the structure of the agent society and the argumentation framework used in interaction between agents. First our argumentation framework consists of a number of intelligent agents capable of exchanging arguments using the AIF[4]. These agents can understand human language and are able to extract arguments from text in English. In addition to the AIF at least one topic ontology is needed in the framework to provide the ground knowledge accepted by all agents in the system. Note that the society is not constrained to use a specific ontology as a whole, but rather each agent needs at least one ontology. This allows agents to play different roles in the society analogous to the roles humans play in our society. For example an agent may have several ontologies describing legal concepts, while other agent may only know about animals. In this approach ontologies shared by all agents represent a limited form common sense knowledge. As we will see in section[3] the framework can be augmented with additional capabilities to retrieve data from external sources and insert it into AIF.

Humans can also take part in a debate using English language. A human can debate on a given topic with one or more agents. As shown in section[3] each agent has it's own behavior and different agents may accept different arguments as valid based on their knowledge and various behavior parameters. In a debate each agent maintains an own view of the argumentation and will try at best to attack and defend arguments based on it's own position in the debate. If an agent can't determine the acceptability of an argument he may ask other agents. This is a two step process involving a query to the Facilitator which returns a list of agents discussing on a given topic. In the next step a query is sent to all agents that might know about this argument. If an agent knows the accessibility value of the property of the argument than an additional query can be made for an argumentation schema. This process may continue in a manner similar to a backward-chaining proof. Note that this process involves agents that share at least one ontology, other than AIF. Because of this agents may form interest groups in the society and interactions only occur within these groups.

3 Agent Architecture

In this section we present the architecture of the agent. Each agent can understand natural language and interact with humans and other agents. The NLP module is used to create a schema of argumentation from the text. This schema is used by the reasoning module to determine the argumentation plan and the admissibility of arguments using Dung acceptability[5]. Each agent has also an associated behavior that is essentially a set of parameters that control the algorithms used in the reasoning module. Finally each agent has a communication module used to interact with other agents as described in section[2]. Although the use of an ontology has many advantages over other sources of information, such a database or a knowledge base the AIF does not enforce the structure of

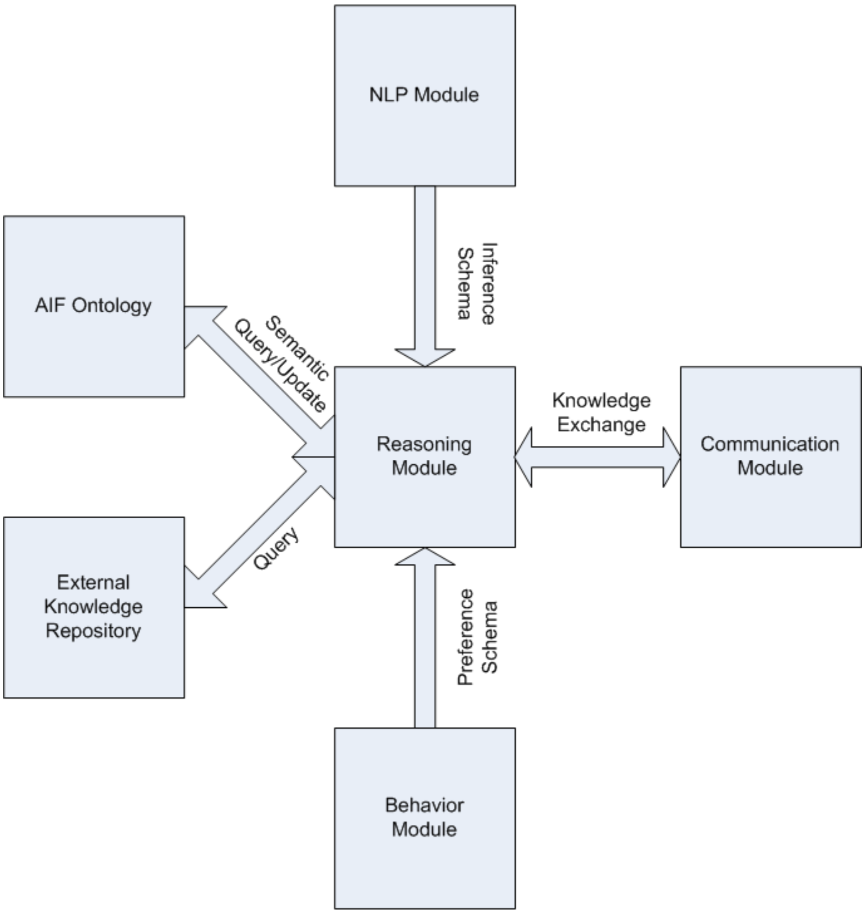

Fig. 1. Top Level Agent Architecture

the domain knowledge used by agents. Because of this any agent can be augmented with capabilities for extracting knowledge. This can be used to support the admissibility of arguments. In this section we present the architecture of the agent. At the top level we have build an autonomous intelligent agent that has it's own behavior module and reasoning capabilities. Moreover each agent can understand natural language and interact with humans and other agents.

4 NLP Module Description

The NLP (Natural Language Processing) module is an important component of the overall agent architecture. Its role gains significant attention in the scenario where a human counterpart is engaged in a debate with one or several agents. In such a setting, the human counterpart will communicate with the agent system using the English language. An individual engaged in a debate will enter text that defines his current standpoint in the entire argumentation process. The purpose of the NLP module then becomes that of parsing this text and of producing an internal representation of the current argument intended by the user. The output of the module will consist in an inference scheme which will be used by the main reasoning module of each agent to update its current beliefs and behavior (the way in which it will possibly try to being a counter-argument).

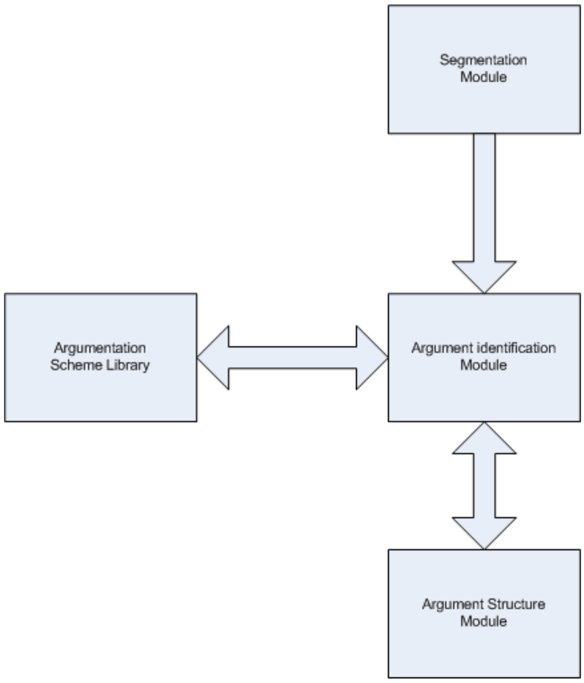

Fig. 2. Representation of the submodules contained in the NLP component

Figure 2 shows the general architecture of the NLP module. A description of each module will be given next.

Argument Identification Module The Argument Identification Module classifies all sentences into argumentative and non-argumentative utterances. This module's essential role is to determine which parts of the text are also parts of argument structures. This module will use a classifier in order to extract argumentative sentences from the input text.

Our approach takes two possible implementation options into consideration: a naive Bayes classifier and a maximum-entropy method. Regardless of the classifier used, the following list gives a short overview of the features we intend to use in order to discriminate between argumentative and non-argumentative clauses.

– Punctuation: The sequence of punctuation marks present in the sentence is used as a feature (e.g. “:.”). When a punctuation mark occurs more than once in a row, it is considered the same pattern (e.g. two or more successive commas both result in “,+”).
– Modal auxiliary: Indicates if a modal auxiliary is present using a POS tagger.
– Verbs: Detected with a POS tagger. Only the main verbs (excluding “to be”, “to do” and “to have”) are considered.
– Adverbs: Detected with a part-of-speech (POS) tagger (e.g. QTag 1).
– Key words: Keywords refer to several words or word sequences obtained from a list of terms indicative for argumentation. Examples from the list are “but”, “consequently”, and “because of”.

The module will produce an output consisting of a set of sentences deemed as being argumentative. This set will be given as input to the segmentation module described next.

Segmentation Module The Argumentation Identification Module uses this module to partition different argumentative sentences (units) into their corresponding arguments, that is, to determine the limits of each individual argument.

In order to achieve this we opt to calculate the semantic distance between the different argumentative units, and group sentences in one argument if they discuss content that is semantically related. As in the work of Palau and Moens[10], we assume that the relatedness of two sentences is a function of the relatedness of their words.

Given this assumption we take the semantic relatedness of words to be given by their semantic distances in a lexico-semantic resource such as WordNet. We consider the use of three potential word similarity measures. They are all based on the information content of the least common subsumer (LCS) of concepts A and B. Information content is a measure of the specificity of a concept, and the LCS of concepts A and B is the most specific concept that is an ancestor of both A and B. These measures include res (Resnik, 1995)[15], lin (Lin, 1998)[7], and jcn (Jiang and Conrath, 1997)[6]. The lin and jcn measures augment the information content of the LCS with the sum of the information content of concepts A and B themselves. The lin measure scales the information content of the LCS by this sum, while jcn takes the difference of this sum and the information content of the LCS. The default source for information content for concepts is the sense-tagged corpus SemCor.

Using these measures we can compute an overall semantic relatedness of the argumentation units. By means of a hierarchical clustering algorithm that will use the distances given by the above mentioned methods we can then segment sentences into their corresponding arguments (clusters), thus finding the intended argument limits. The hierarchical clustering algorithm computes a dendrogram (a tree like structure) of its given elements. Using an empirically computed threshold, we will cut the tree at the given depth, thus finding the appropriate sentence clusters.

Argumentation Scheme Library The Argumentation Scheme Library contains abstract forms of argument that capture patterns of reasoning. Each argumentation scheme describes the relations between internal parts (the premises and the conclusion) of a complex argument and, also, the set of critical questions that may attack that argument. Chris Reed and Douglas Walton[14], in their research report "Towards a Formal and Implemented Model of Argumentation Schemes in Agent Communication" describe the conventional techniques to handle the structure of argumentation schemes in such way that agents may use them in reasoning and also that communication structures can be built around those schemes.

Example of Argumentation Scheme - Argument from Position To Know:

- Major Premise: Source a is in a position to know about things in a certain subject domain S containing proposition A.
- Minor Premise: a asserts that A (in Domain S) is true (false).
- Conclusion: A is true (false).

This type of argument is defeasible by questioning. Matching the argument from position to know are three critical questions:

- CQ1: Is a in a position to know whether A is true (false)?
- CQ2: Is a an honest (trustworthy, reliable) source?
- CQ3: Did a assert that A is true (false)?

Our Argumentation Scheme Library will be trained from Araucaria DB, which contains several real instantiations of argumentation schemes. The representation used is Argument Markup Language, based upon the industry standard XML.

Argument Structure Module The Argument Identification Module and Segmentation Module were used to distinguish between argumentative and non-argumentative sentences and to group argumentative sentences together into their corresponding argument.

The purpose of this module thus becomes to determine the internal structure of an argument, i.e. the organization of its clauses into conclusions and supporting premises.

We will consider two possible approaches for this task.

The first relies again on work done by Palau and Moens[10] in Argumentation Mining: The Detection, Classification and Structuring of Arguments in Text and considers the partition of an argument's units into premises or conclusions.

For each argument, certain features will be determined. The list can comprise features such as:

- Tense of Main Verb: Tense of the verb from the main clause of the sentence; having as nominal values "Present", "Past" or "No Verb".
- History: The most probable argumentative category of previous and next sentence.
- Rhetorical Patterns: Type of rhetorical pattern occurring on current, previous and next sentences (e.g. "however,")

– Argumentative Patterns: Type of argumentative pattern occurring in sentence

A SVM (Support Vector Machine) based algorithm that uses these features will then be used to classify the sentences of an argument into either premises or conclusions.

The second approach is an extension of the first one. Rather than just distinguishing between premise and conclusion, this approach tries to map the argument's structure onto one or several argumentation schemes.

The definition and format of these schemes is provided by the Argumentation Scheme Library module.

Making use of more extended features, that will also include the ones listed above, our SVM based algorithm will this time be trained to distinguish between different argumentation schemes.

5 Results and Future Work

The role of the segmentation module is that to partition different argumentative sentences (units) into their corresponding arguments, that is, to determine the limits of each individual argument.

As presented in the description of the NLP module capabilities, we opt to calculate the semantic distance between the different argumentative units, and group sentences in one argument if they discuss content that is semantically related.

The module receives a list of argumentative sentences as its input. It then uses a word tokenizer to split the sentences into lists of words. Stopwords such as "the", "in", "with" etc. are removed before going to the next step.

We assume the semantic relatedness of words to be given by their semantic distances in a lexico-semantic resource such as WordNet. We use the lin similarity measure to compute the relatedness of two synsets. As each word in a sentence can have several senses, one would first have to go through a word sense disambiguation process to determine the most probable meaning. As this process is time-consuming, the current approach employs the use of the most common sense, as defined by WordNet, for each word we encounter.

Using the lin similarity we compute a word similarity matrix between every pair of words, one from each sentence.

To compute the estimated similarity between two sentences we then use the following method. Given two sentences A and B, for each word from sentence A we compute the most similar word from sentence B, as given by the previously computed matrix.

$$b^* = arg \max_b Sim(a, b)$$

In a similar manner, for each word in sentence B we compute the most similar word from sentence A.

$$a^* = arg \max_a Sim(a, b)$$

Afterwards the similarity between sentences A and B is given by

$$(\sum a^* + \sum b^*)/(2 * (\mid A \mid + \mid B \mid)$$

The above process yields a sentence similarity matrix. This matrix is used as an input to a hierarchical clustering algorithm. We take an empirically determined cutoff distance of 0.875 to cut the resulting cluster dendrogram at the corresponding depth. This results in a list of sentence clusters, each of which contains the components of an individual argument.

Case study

Here is a simple example. The initial text:

"It is well established that if any statement is made on the floor of the House by a Member or Minister which another Member believes to be untrue, incomplete or incorrect, it does not constitute a breach of privilege. In order to constitute a breach of privilege or contempt of the House, it has to be proved that the statement was not only wrong or misleading but it was made deliberately to mislead the House. A breach of privilege can arise only when the Member or the Minister makes a false statement or an incorrect statement willfully, deliberately and knowingly. On a perusal of the comments of the Ministers in the matter, I am satisfied that there has been no misleading of the House by them as alleged by the Member. I have accordingly disallowed the notice of question of privilege. Copies of the comments of the Ministers have already been made available to Dr. Raghuvansh Prasad Singh."

The determined word lists:

L1: [‘It’, ‘well’, ’established’, ’statement’, ’made’, ’floor’, ’House’, ’Member’, ’Minister’,u’another’, ‘Member’, ’believes’, ’untrue’, ’incomplete’, ’incorrect’, ’constitute’, ’breach’, ‘privilege’]
L2: [’In’, ’order’, ’constitute’, ’breach’, ’privilege’, ’contempt’, ’House’, ’proved’, ’statement’, ’wrong’, ’misleading’, ’made’, ’deliberately’, ’mislead’, ’House’]
L3: [’A’, ’breach’, ’privilege’, ’arise’, ’Member’, ’Minister’, ’makes’, ’false’, ’statement’, ’incorrect’, ’statement’, ’wilfully’, ’deliberately’, ’knowingly’]
L4: [’On’, ’perusal’, ’comments’, ’Ministers’, ’matter’, ’I’, ’satisfied’, ’misleading’, ’House’, ’alleged’, ’Member’]
L5: [’I’, ’accordingly’, ’disallowed’, ’notice’, ’question’, ’privilege’]
L6: [’Copies’, ’comments’, ’Ministers’, ’already’, ’made’, ’available’, ’Dr’, ’Raghuvansh’, ’Prasad’, ’Singh’]

The (simmetric) sentence similarity matrix:

	1	*2*	*3*	*4*	*5*	*6*
1	1.00	0.24	0.24	0.19	0.10	0.13
2	0.24	1.00	0.21	0.19	0.14	0.10
3	0.24	0.21	1.00	0.16	0.13	0.11
4	0.19	0.19	0.16	1.00	0.13	0.12
5	0.10	0.14	0.13	0.13	1.00	0.06
6	0.13	0.10	0.11	0.12	0.06	1.00

The resulting sentence clustering (only the indexes of the sentences are show):

$$[[5], [4, 3, 1, 0, 2]]$$

We can see that sentences 1-5 belong to one argument and sentence 6, which is actually non-argumentative, this being only an illustrative example, belongs to a separate cluster.

The current method yields some promising results, but there is still room for improvement, especially in the process of determining word similarities, where we hope to be able to implement a more advanced measurement solution. In particular, the Lin measure can only compute the similarity between words which have the same part of speech (noun, verb etc). The lesk or gloss-vector measures, which we will try to implement in future developments can cross these boundaries and are not limited by is-a relations.

Future work The next step we have to take towards completing the argumentation mining module of the agents consists of extracting argumentation schemes from natural text. Our approach will use a SVM classifier trained on AraucariaDB corpus with features like the position of sentence in the text, the tense of main verb, the most probable argumentative category of previous and next sentences or argumentative patterns to split argumentative propositions into premises and conclusions. Those sentences will then be integrated into higher level structures using the schemes define by Walton in [17].

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