An Multi Agent System for Argumentation
Research Report

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Abstract. **Key words:** natural language processing, machine learning, argumentation, statistical learning, multi agent system

1 Introduction

1.1 History of Argumentation Theory

Argumentation has its roots in Ancient Greece, where the art of rhetoric developed first. Aristotle defines the rhetorician as someone who is always able to see what is persuasive. Correspondingly, rhetoric is defined as the ability to see what is possibly persuasive in every given case. Argumentation theorists have searched for the requirements that make an argument correct, by some appropriate standard of proof, by examining the errors of reasoning we make when we try to use arguments. These errors have been called fallacies. Until the 1950s, the approach of argumentation was based on rhetoric and logic.

In 1895, George Pierce Baker writes "The Principles of Argumentation" giving the following definition: "Argumentation is the art of producing in the mind of someone else a belief in the ideas which the speaker or writer wishes the hearer or reader to accept". In the United States debating and argumentation became an important subject on universities and colleges. In the 1960s and 1970s Perelman and Toulmin were the two of the most influential writers on argumentation. Perelman tried to find a description of techniques of argumentation used by people to obtain the approval of others for their opinions. Perelman called this 'new rhetoric. Toulmin developed his theory (starting in 1950s) in order to explain how argumentation occurs in the natural process of an everyday argument. He called his theory 'The uses of Argument'.

Hamblin took, as well, a radical approach to argumentation. Considering the fact that deductive logic did not seem to be enough, Hamblin proposed a new concept for describing arguments: he considered it not just as an arbitrarily designated set of propositions, but as a move one party makes in a dialog to offer premises that may be acceptable to another party who doubts the conclusion of the argument. Hamblin and Perelman's work announced a new field of study: informal logic. Nowadays, research in informal logic increasingly incorporates the approaches to argumentation found in cognate disciplines and fields like Speech Communication, Rhetoric, Linguistics, Artificial Intelligence, Cognitive Psychology and Computational Modeling. Looked at from this perspective, informal logic as a discipline is an integral part of a much broader multi-disciplinary attempt to develop an "argumentation theory" that can account for informal reasoning.

1.2 Argumentation in Computer Science

With regards to computer science, the study of argumentation is crucial in many artificial intelligence and natural language research problems.

For example, in the field of Multi Agent Systems (MAS) reasoning agents need to communicate with each other and apply argumentation-based reasoning mechanisms to resolve the conflicts arising from their different views of goals, beliefs, and actions. Another example are question answering systems, which deal with finding the correct response to questions like "Why was this decision taken?" and therefore integrate the analysis of argumentation as a crucial part of identifying the answer to the questions as well as the pros and cons that make up the answer.

The field of computer-supported collaborative learning (CSCL) has, in particular, been interested in argumentation and how students can benefit from it[1]. So-called "collaborative argumentation" is viewed as a key way in which students can learn critical thinking, elaboration, and reasoning. Therefore, it is a crucial point to understand the characteristics and models of argumentation.

Some relevant work in this area has been done by R.M. Palau and M-F Moens in[2][3]. In these papers 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 different approach is taken by Safia ABBAS and Hajime SAWAMURA in[4]. Their environment uses different mining techniques to manage a highly structured arguments repository.

This area of natural language processing also lacks corpora resources. In our knowledge there are only two corpora used extensively in argumentation research, the *Araucaria*[5][13] developed by Chris Reed and Glenn Glove in the Argumentation Research Group at University of Dundee and *HUDOC* developed by the European Court of Human Rights[6]. Below is a summary of the structure of these two corpus:

Table 1. Structure of arguments in ECHR and Araucaria

Characteristics	ECHR	Araucaria
Number of documents	47	641
Number of arguments	257	641
Number of words	92190	76970
Number of sentences	2571	3798

Overall, the task of argument extraction from free text is a new and difficult research area, one that will hopefully see a lot of activity in the near future, because the results that can be obtained will be of great use in many related fields of natural language processing.

2 Argumentation Concepts Overview

A nice overview on argumentation tasks and concepts was given by Douglas Walton in his research reports[7]. The next sections are inspired by his work.

2.1 Main problems

There are four tasks undertaken by argumentation:

Identification 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

2.2 Argument definition

An argument is a set of statements (propositions), made up of three parts, a conclusion, a set of premises and inference from the premises to the conclusion. An argument can be supported by other arguments, or it can be attacked by other arguments, and by raising critical questions about it.

The definition of 'argument' relied on so far could be called a minimal inferential definition, and the method of argument diagramming shown so far fits this minimal definition. The boxes represent propositions and the arrows represent inferences from some propositions to others.

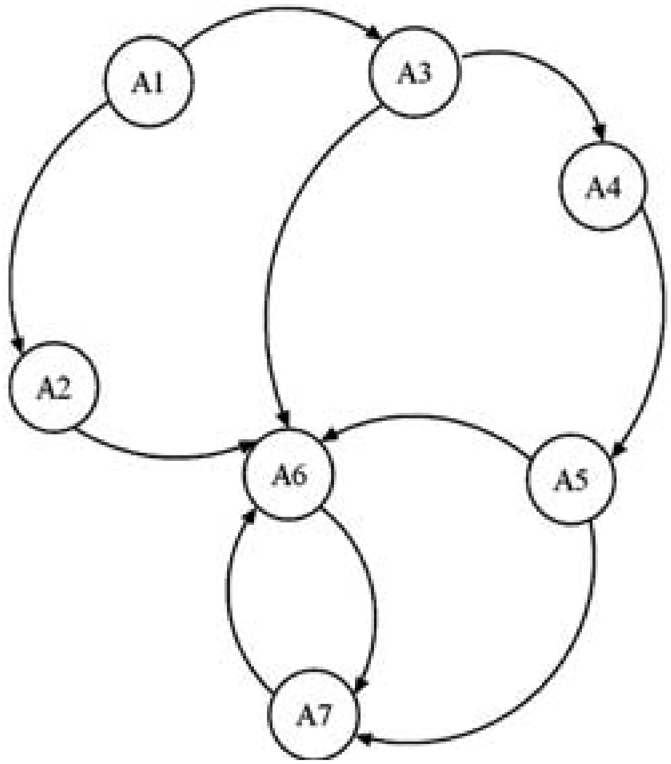
The general approach or methodology of argumentation can be described as distinctively different from the traditional approach based on deductive logic. The traditional approach concentrated on a single inference, where the premises and conclusion are designated in advance, and applied formal models like propositional calculus and quantification theory determine whether the conclusion conclusively follows from the premises. This approach is often called mono-logical.

In contrast, the argumentation approach is called dialogical (or dialectical) in that it looks at two sides of an argument, the pro and the contrary. 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.

2.3 Argument Attack and Refutation

There are several ways to attack an argument and the easiest way is to ask an appropriate critical question that raises doubt about the acceptability of the argument. When this happens, the argument temporarily defaults until the proponent can respond appropriately to the critical question. Another way to attack an argument is to question one of the premises. A third way to attack an argument is to put forward counter-argument that opposes the original argument, meaning that the conclusion of the opposing argument is the opposite (negation) of the conclusion of the original argument.

A simple way to represent a sequence of argumentation is using a directed graph:



2.4 Argumentation Schemes

Some of the most common schemes are: argument from witness testimony, argument from expert opinion, argument from popular opinion, argument from example, argument from analogy, practical reasoning (from goal to action), argument from verbal classification, argument from sign, argument from sunk costs, argument from appearance, argument from ignorance, argument from cause to effect, abductive reasoning, argument from consequences, argument from alternatives, argument from pity, argument from commitment, ad hominem argument,argument from bias, slippery slope argument, and argument from precedent. Each scheme has a set of critical questions matching the scheme and such a set represents standard ways of critically probing into an argument to find aspects of it that are open criticism.

2.5 Types of dialog

There are six types of dialogs:

Persuasion generated by a **Conflict of Opinions** in which each party tries to **Persuade Other Party** in order to **Resolve or Clarify Issue**

Inquiry generated by the **Need to Have Proof** in which each party tries to **Find and Verify Evidence** in order to **Prove (Disprove) the Hypothesis**

Negotiation generated by a **Conflict of Interests** in which each party tries to **Get What He Most Wants** in order to reach a **Reasonable Settlement Both Can Live With**

Information-Seeking catalyze by the **Need of Information** in which each party **Acquires or Gives Information** in order to **Exchange Information**

Deliberation generated by a **Deliberation Dilemma or Practical Choice** that is needed in which the participants try to **Co-ordinate Goals and Actions** in order to **Decide on Best Available Course of Action**

Eristic generated by a **Personal Conflict** in which each party tries to **Verbally Hit Out at Opponent** in order to **Reveal Deeper Basis of Conflict**.

On our project we will focus on inquiry dialogs.

2.6 Argumentation in Multi Agent Systems

Argumentation systems is a domain with large applications in industry, especially in e-commerce transactions, asset market and e-negotiation. 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[9][10].

We have designed a system that supports domain based argumentation. Each agent participating in a conversation has a knowledge base supported by one or more ontologies specific to a domain. This allows specialization of agents in a society.

3 Agent 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[14]. 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[4] 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[4] 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.

4 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[15]. 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[3]. 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

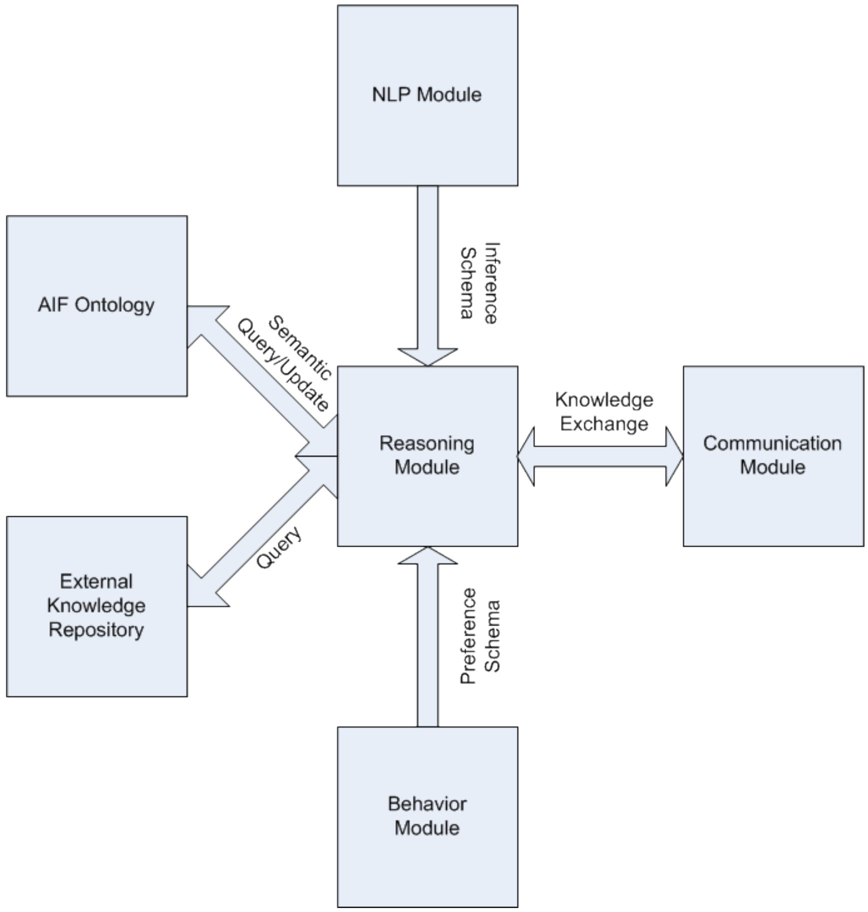


Fig. 1. Top Level Agent Architecture

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.

4.1 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). The next section will provide a detailed description of this module as well as the results obtained.

5 NLP Aspects Overview

As stated in the introduction section the goal of project becomes that of identifying the arguments and the relations that exist between them in a given text. As such, the task of this module can be modeled as a classification problem.

As presented previously, there exist a number of models for both the intrinsic structure of a model, as well as for the relations that can hold between them. The above sections gave a classification of the different types of dialog and argumentation schemes. What is interesting to notice is that each type of dialog supports some argumentation schemes better than others. Thus, having chosen one specific type of dialog, the most relevant argumentation schemes pertaining to that dialog model will be chosen as structure guidelines for our arguments. In addition, a Toulmin (S. E. Toulmin. *The Uses of Argument*) based alternative representation of an argument will be considered.

5.1 Main problems

Having laid out this model, we are faced with the following challenges of Argumentation Mining:

Detect all the arguments in a free text (classification problem)
Determine argument limits (segmentation problem)
Determine arguments type (complex)
Detect argumentation structure (complex)

The Corpus that will be used to for solving the above problems is the one provided by *Arauacaria* (*http://www.arg.dundee.ac.uk/projects/araucariadb/search.php*), which, albeit being not very large, has the advantage of giving annotated argument examples.

In the work by R.M. Palau and M-F Moens[2] some solutions to this problems are proposed, some of which we consider to be very useful for our project. For the problem of argument detection statistical classifiers are employed. In particular, good results can be obtained by using the *maximum entropy model* and *multinomial naive Bayes* classifier which learns a model of the joint probability of an element x and its label y, $p(x, y)$, and makes its predictions by using Bayes rule to calculate p(y|x) and then selects the most likely label y.

For the problem of determining argument limits (grouping of argumentative statements into their corresponding argument) we consider computing the semantic distance between different argumentative units (sentences) and group sentences in one argument if they discuss content that is semantically related. Like in the work of Palau and Moens, we assume that the relatedness of two sentences is a function of the relatedness of their words. We want to employ an ontology based semantic relatedness measure, where the relatedness of words depends on their semantic distances in a lexico-semantic resource such as WordNet.

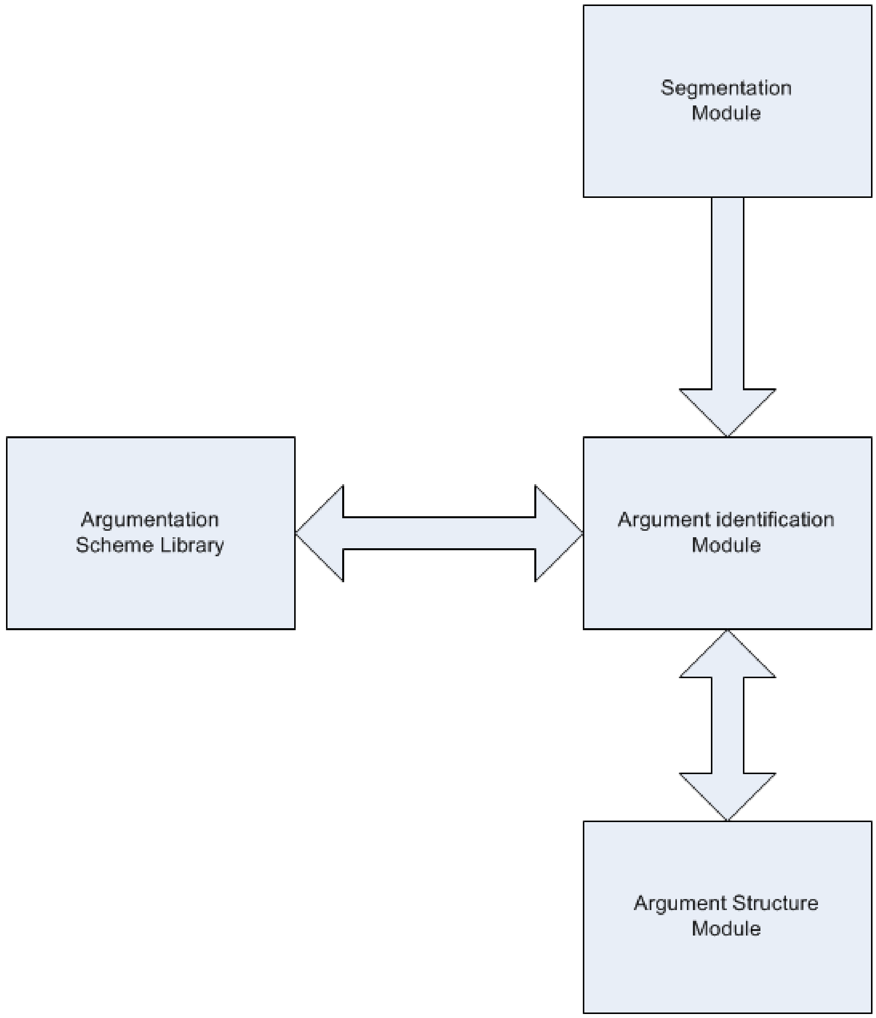
In the determination of argument types, we also consider the use of statistical classifiers. The problem here is that while a classification of argumentative statements into premises and conclusions is possible (as shown by Palau and Moens by use of a SVM), the task of determining a specific scheme for an argument is much more challenging. In particular, we have to rely on some domain ontology in order to be able to find semantic features that will allow us to classify the arguments as belonging to a certain scheme.

Extensive use of other NLP tools such as POS taggers will also be made in order to enrich the possible set of features used for classification.

Lastly, the problem of determining the argumentation structure, that is, of relations existing between the arguments, will have to take all the results obtained by the previous steps into consideration. The employed algorithm will make the assumption that the discourse follows the rules of the chosen dialog type and that arguments used within it belong to the appropriate argumentation schemes.

6 Natural Language Module architecture

This section gives a general overview of the most important modules of our application. We will give a graphical representation of the main modules and of the relation between them. Afterwards, we will give a more detailed description of each module, highlighting the approaches and algorithms considered for their implementation.



6.1 Argumentation Identification Module

The Segmentation 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 part of arguments.

The main assumption used by this module is that various arguments are made up from smaller units called elementary units. An elementary unit represents a span of text that can't be further divided from an argumentation point of view. We use sentences as elementary units because naturally people structure their ideas in sentences. There are some cases in which only a part of a sentence is part of an argument and the rest of the sentence has no argumentative function. In this case we will include the entire sentence in the argumentation analysis.

We have used two classifiers from the Natural Language Toolkit(NLTK) library: the naive Bayesian classifier and the maximum entropy classifier. For both classifiers we have used the same set of features:

Adverbs Detected with a part-of-speech (POS) tagger from NLTK.
Verbs Detected with a POS tagger. Only the main verbs (excluding "to be", "to do" and "to have") are considered.
Modal auxiliary Indicates if a modal auxiliary is present using a POS tagger.
Text statistics Sentence length, average word length and number of punctuation marks.
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 ",+").
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".

In building these features we have used the Punkt Word Tokenizer and the Punkt Sentence Tokenizer from NLTK. This splits the text into sentences quite well but it's not one hundred percent accurate. In addition to this Araucaria is annotated by humans and in several cases the assumption we made on the argument delimitation is violated. Because of this we use an algorithm that matches intervals of sentences from training examples with those obtained from parsing.

From the above mentioned features only the presence of key words specific to argumentation is computationally expensive using a classical approach. Instead of comparing each word with every word in a list we have used the Aho-Corasick algorithm that has a running time linear in the size of the text plus the total number of matches.

6.2 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, 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.

Measures of relatedness are more general in that they can be made across part of speech boundaries, and they are not limited to considering is-a relations.

Several measures of relatedness which are based on the WordNet database can be used.

- The hso (Hirst and St-Onge, 1998) measures classifies relations in WordNet as having direction, and then establishes the relatedness between two concepts A and B by finding a path that is neither too long nor that changes direction too often.
- The lesk (Banerjee and Pedersen, 2003) and vector measures incorporate information from WordNet glosses. The lesk measure finds overlaps between the glosses of concepts A and B, as well as concepts that are directly linked to A and B.
- The vector measure (Patwardhan, 2003) creates a co-occurrence matrix for each word used in the WordNet glosses from a given corpus, and then represents each gloss/concept with a vector that is the average of these co-occurrence vectors.

WordNet provides modules that implement these measures and that offer a specific API for their usage.

Using these measures we can compute an overall semantic relatedness of the argumentation units. By means of a 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.

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.

6.3 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, in their research report "Towards a Formal and Implemented Model of Argumentation Schemes in Agent Communication"[11] 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.

An example of Argumentation Scheme is 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. For representation Argument Markup Language(AML) is used, which in turn is based upon the industry standard XML.

The scheme library contains some abstract schema from the Walton schema set[11]. These are used in turn for mapping the actual discourse and creating schema instantiations. Thus an argumentation is represented as the relation between arguments as elementary units and the type of relation is given by a schema. In[11] each schema has an unique name and we have used the same names as they describe the schema.

6.4 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 and to group arguments into argumentation structures by instantiating schemas from the Schema Library.

This relies again on work done by Palau and Moens in [2] and [3] 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.

In addition to 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.

For this task we tried a SVM based on various features and a HMM based on the number of arguments and identification of main subject and relevant noun phrases.

7 NLP Module Results

We have trained the NLP module on Araucaria corpus. This is an mixed corpus and albeit small it provides a good measure of argumentation in various domains. This section outlines some of the results obtained with this module.

7.1 Argument Identification Module

The Araucaria corpus, consisting of approximately one thousand AML files was split in half for training and testing of both classifiers. At sentence level the Punkt module has an accuracy around 90% and the reader may refer to [12] for details about the algorithm used by this tokenizer.

For the problem of classification of sentences as argumentative or non-argumentative both the naive Bayesian and the maximum entropy gave approximately the same results. Overall the maximum entropy is slightly better with an average difference in accuracy of 2%. We obtained around 78% accuracy with a recall around 85%. In their work [2] Palau and Moens obtained a better accuracy using HUDOC corpus.

As we can see in figure 2 there is a good performance overall but there are cases in which the accuracy is as low as 20%. This can be explained by the structure of Araucaria. Because it is an argumentation corpora the number of argumentative sentences is much larger than the number of non-argumentative ones. There are AML files that do not fall into this general pattern and the classifiers gives poor results for this instances.

In figure 3 the F1 score is shown for a session of testing of the maximum entropy classifier. This shows an overall good performance of the classifier.

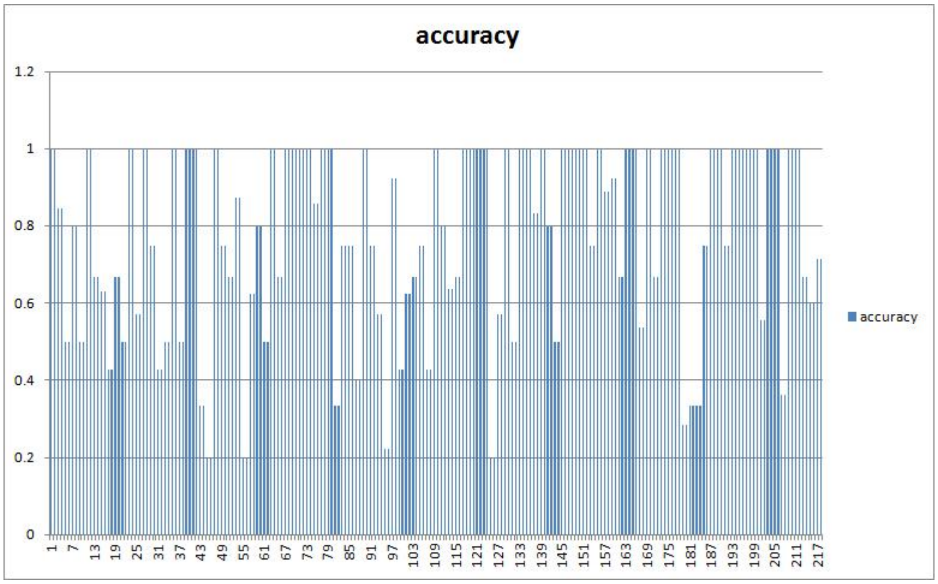


Fig. 2. Accuracy for Naive Bayesian Classifier

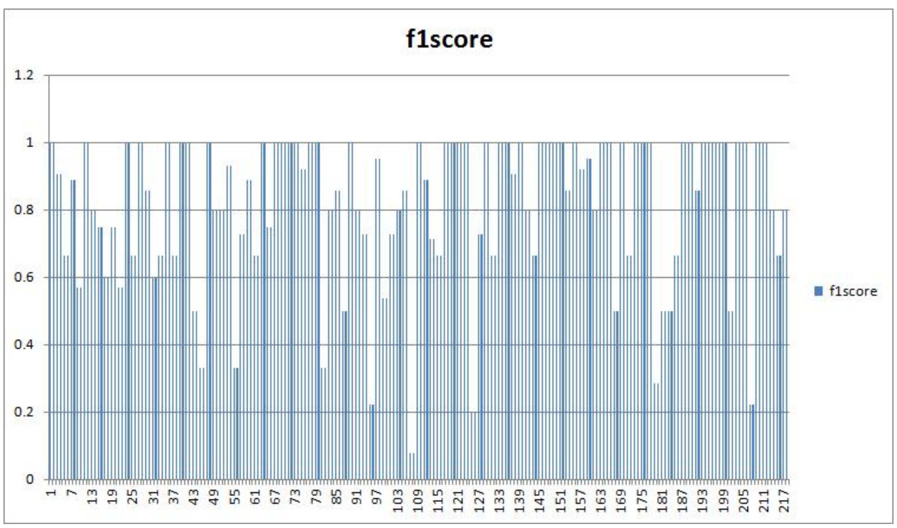


Fig. 3. F1 score for the maximum entropy classifier

As shown in figure 4 the maximum entropy classifier has a good recall and because we want argumentative sentences this is a good measure of performance. Even if some of the non-argumentative sentences are classified as argumentative they will be part of some argument in the segmentation phase and won't alter the result.

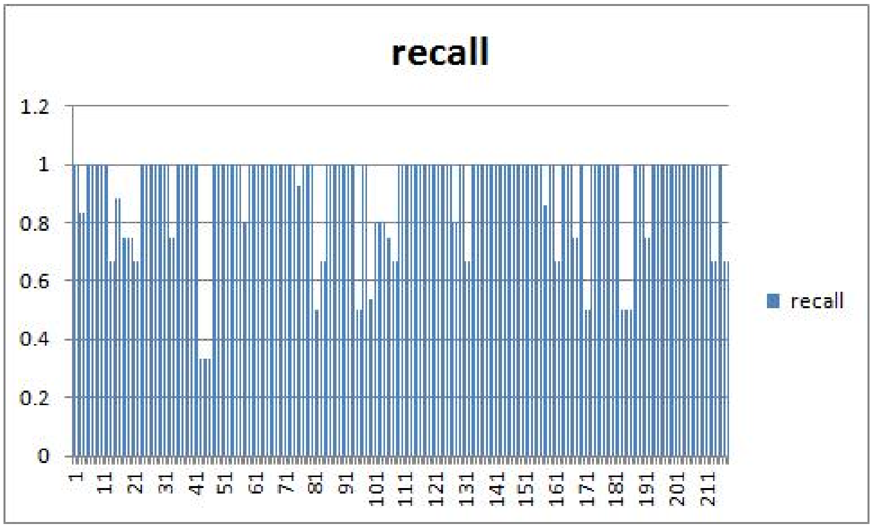


Fig. 4. Plot of the recall for the maximum entropy classifier

As shown above the classification of sentences in argumentative and non-argumentative is a feasible problem and we have obtained good results on Araucaria corpus. However in a multi agent argumentation system usually the arguments exchanged with humans tend to have a better structure, imposed by the form of communication. This argumentation is based on dialog and we humans tend to give one argument at time or at most a small argumentation structure to support an argument and then wait for a reply.

From the point of view of classification this is very different from texts, in which an entire argumentation is given in the text in addition to non-argumentative spans of text that may interleave with it. Because of this we have tested the argument identification module on several dialog based argumentation texts produced by us and our colleagues in the Natural Language Processing course. Although the number of tests is relatively small we have noticed a slight increase in accuracy that proves the system is suited usage in a dialog based multi agent system.

7.2 Segmentation Module

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.

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', '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 (symmetric) 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.

7.3 Argument Structure Module

For the task of classification of sentences in premises and conclusions we have used cross validation with 7 bins to obtain a good measure of the performance of this module. Our SVM based algorithm uses the list of argumentative sentences partitioned in arguments as well as the list of non-argumentative sentences as history feature. We have obtained around 67% accuracy for the SVM classifier.

An example of the output of this classifier is shown below:

[(To scientific naturalist this suggestion is "creationist" and therefore unacceptable in principle, because it inv
, [(In that case there could be real prophets-persons with a genuine knowledge of God who are neither frauds nor dreamers.', 0.0), (Such persons could conceivably be dangerous rivals for the scientists as cultural authorities.', 1.0)], [(Suppose that a skeptic argues that evidence for biological creation by natural selection is obviously lacking, and that in the circumstances we ought to give serious consideration to the possibility that the development of life required some input from a pre-existing, purposeful creator.', 1.0), (What is worse, it suggests the possibility that this creator may have communicated in some way with humans.', 1.0)]]

For determining the argumentation structure the results obtained so far are below average. The HMM proved a better choice but there is still a lot of space for improvements.

References

1. Karsten Stegmann, Armin Weinberger and Frank Fischer: Facilitating argumentative knowledge construction with computer-supported collaboration scripts. International Journal of Computer-Supported Collaborative Learning, Vol. 2, No. 4, Springer New York
2. Raquel Mochales Palau and Marie-Francine Moens: Argumentation Mining: The Detection, Classification and Structuring of Arguments in Text. International Conference on Artificial Intelligence and Law, 2009.
3. Raquel Mochales Palau and Marie-Francine Moens :Study on the Structure of Argumentation in Case Law.Proceeding of the 2008 conference on Legal Knowledge and Information Systems, 2008.
4. Safia ABBAS, Hajime SAWAMURA: ALES: An Innovative Argument Learning Environment, Proceedings of the 17th International Conference on Computers in Education, 2009.
5. Chris Reed, Raquel Mochales Palau, Glenn Rowe and Marie-Francine Moens: Language Resources for Studying Argument.The International Conference on Language Resources and Evaluation, 2008.
6. Raquel Mochales Palau and Aagje Ieven: Creating an argumentation corpus: do theories apply to real arguments?Proceedings of the 12th International Conference on Artificial Intelligence and Law, 2009.
7. Glenn Rowe, Fabrizio Macagno, Chris Reed and Douglas Walton: Araucaria as a Tool for Diagramming Arguments in Teaching and Studying Philosophy, 2009.
8. Douglas Walton: Argumentation Theory: A Very Short Introduction. Argumentation in Artificial Intelligence, Springer US, 2009.
9. Amgoud L., Maudet N. and Parsons S.: Modeling dialogues using argumentation. Proceedings. Fourth International Conference on Multi Agent Systems, 2000.
10. Parsons S., Sierra C. and Jennings N.:Agents that reason and negotiate by arguing.Journal of Logic and Computation, 1998
11. Chris Reed and Doug Walton: Towards a Formal and Implemented Model of Argumentation Schemes in Agent Communication. Lecture Notes in Computer Science, Springer Berlin / Heidelberg, 2005
12. Kiss Tibor and Strunk Jan: Unsupervised Multilingual Sentence Boundary Detection.Computational Linguistics 32: 485-525,2006.
13. C. Reed and G. Rowe: Araucaria: Software for argument analysis, diagramming and representation.International Journal of AI Tools, 14(3-4):961980, 2004.
14. Carlos Chesnevar, Jarred McGinnis, Sanjay Modgil, Iyad Rahwan, Chris Reed, Guillermo Simari, Matthew South, Gerard Vreeswijk and Steven Willmott: Towards an Argument Interchange Format.The Knowledge Engineering Review, pages 1-25, 2007.
15. Phan Minh Dung: ON THE ACCEPTABILITY OF ARGUMENTS AND ITS FUNDAMENTAL ROLE IN NONMONOTONIC REASONING, LOGIC PROGRAMMING AND N-PERSONS GAMES, Asian Institute of Technology.