International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Comparative Analysis of Different Argumentation Frameworks

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Submitted: 05/02/2024 **Revised**: 13/03/2024 **Accepted**: 19/03/2024

Abstract- Argumentation Mining is considered a much harder task than generic information extraction or event mining because argumentation structures can be nested recursively. That is, a complete argumentation structure (claim and premises) might function as the premise of some more general claim, and so on. Recognizing the relationships among components of an argument also requires real-world knowledge, including knowing when one thing is a subtype of another. Both use NLP methods to map unstructured text onto graph-like structures or databases. The resulting information is easier to analyze for a variety of tasks, such as learning about social or political views, advising people about how to weigh the evidence for or against some choice, or helping companies to market products or perform quality assurance. Most of these tasks use hand-built templates that have been specified to fit a particular task or observed style of communication.

Keywords: *Natural Language Processing, Argumentation Mining, Structured and Unstructured Data sets, Artificial Intelligence, Computational Argumentation.*

1. Introduction

With the emergence of the research area of argumentation mining, several methodologies have been developed to address this challenging, multi-faceted task. Due to the complexity of the problem, which embraces many different concepts at the intersection of artificial intelligence, computational linguistics, and knowledge representation, all the proposed approaches have to deal with a variety of intertwined sub-tasks. AM is becoming one of the core study and research areas in the field of cognitive sciences, where some studies have indicated that the functioning of the human brain itself is argumentative. The two main approaches in computational argumentation are called abstract argumentation, and structured argumentation. The former is rooted in Dung's work, and it considers each argument as an atomic entity without internal structure. It thus provides a very powerful framework to model and analyze "attack" relations between arguments, or sets of them, which may or may not be justified according to some semantics. The latter proposes an internal structure for each argument, described in terms of some knowledge representation formalism. Structured argumentation models are those typically employed in AM, as defining the structure of an argument is crucial when the goal is to extract portions of arguments from natural language.

According to P.M Dung, one of the pioneers in argument computation and most of the recent studies on abstract argumentation are based on Dung Framework," The natural human reasoning is argumentative itself". One of the other most promising fields of AM is taking out inferences from legal texts, where the judgments given by court run into several hundred or thousands of pages, and inference has to be drawn from the judgment, in where human intervention may take a lot of effort and time, however, with AM this process is simplified.

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2. Overview of the Research

Besides, more or less abstract computational argumentation models and theories now seem more than ever to the "real world" and the community seems eager to contribute to the creation of significant domains where very expressive models and efficient algorithms developed in recent years can be tested and applied. Another reason for its rapid expansion is that AM poses a scientifically engaging challenge, especially from a machine learning (ML) perspective. Indeed, AM is a difficult NLP task that merges many different components, such as information extraction, knowledge representation, and discourse analysis. This is also creating new opportunities in the computational argumentation community. Advanced statistical and sub-symbolic reasoning methods have never been so tightly conjugated with a discipline, whose roots are in symbolic AI.

Most often, we see AM as a source of new opportunities for the formal argumentation community, drawing a bridge between formal models and theories and argumentative reasoning as it emerges from everyday life. In this field, different models have been developed during the past years which can be categorized mainly into three different categories Monological Models, Dialogical, and Monological Models. Monological Models assume a tentative proof of a given argument and then apply a set of rules to its internal structure. These models try to establish a link between the different components of the arguments and how the conclusion relates to the given premises or a set of premises. Their main focus is on the relationships that can exist between the different components of the argument in a monological structure. Dialogical Models have stressed the existing relationships between the arguments, which at times are considered abstract entities and discarding their internal structure. These types of models emphasize the argument structure similar to a dialogical framework. Dialogical and Monological models consider the macro (external) and micro (internal) structure of the arguments. Some of the models do not follow both of these two approaches. These models are called rhetorical models which follow the rhetorical structure of arguments (schemas or rhetorical patterns). In these models, the aim is to take into account the way of using the arguments for persuasion.

All the argument mining frameworks proposed so far can be described as multi-stage pipeline systems, whose input is a natural, free text document, and whose output is a markup document, where arguments (or parts of arguments) are annotated. Each stage addresses a sub-task of the whole argumentation mining problem, by employing one or more machine learning and natural language processing methodologies and techniques.

Traditional machine learning algorithms, tend to be more readily explainable while being relatively less powerful in terms of predictive performance. Other advanced algorithms, such as deep learning models, remain much harder to explain while being more powerful in complex systems. Table 1 instead highlights the similarities between AM sub-tasks and problems typical of machine learning and natural language processing (NLP).

Argumentation Mining	**Machine Learning and Natural Language Processing**
Argumentative sentence detection	Sentence classification Hedge cue detection Sentiment analysis Question classification Subjectivity prediction
Argument component boundary detection	Sequence labeling Named entity recognition Text segmentation
Argument structure prediction	Link prediction Discourse relation classification Semantic textual similarity

Table 1: Differentiation between Argumentation Mining & Machine Learning and Natural Language processing tasks.

3. Results and Findings

Research work carried out focused on the study of accuracy rates generated by several algorithms i.e. Support Vector Machine, Linear Regression, Naive Bayes, Decision Tree, Random Forest, Recurrent Neural Network, Conditional Random Fields, and Textual Entailment Suites.

After analyzing programmatically using Python programming Language, we found the results as follows: Accuracy rate of 0.606, 0.979, 0.973, 0.860, 0.965, 0.940 and 0.897 for Support Vector Machine (SVM), Linear Regression (LR), Naive Bayes (NB), Decision Tree (DT), Random Forest (RF), Recurrent Neural Network (RNN), Conditional Random Fields (CRF) and Textual Entailment Suites (TES) respectively. On taking the average we found the average value of accuracy on the structured data set to be 0.889.Figure 1 shows the accuracy of different Models on different data sets,

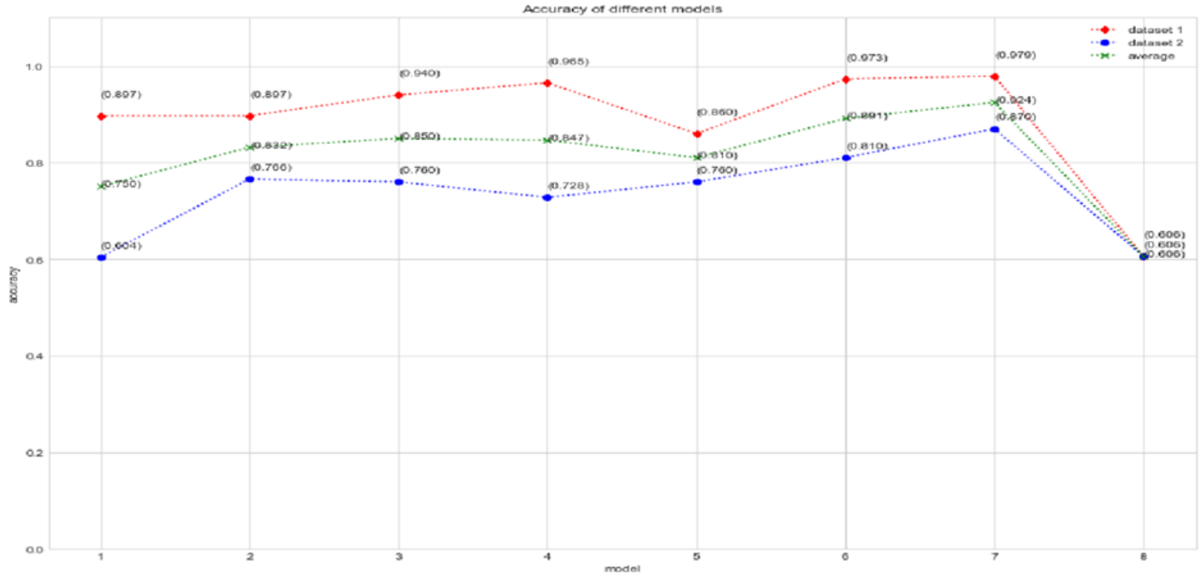

Fig 1: Accuracy of different Models on different data sets.

Following is the comparison Table 2 of the different approaches we discuss already the accuracy rates for each algorithm vary significantly when because input data is structured (average value of accuracy = 0.889) or unstructured (average value of accuracy = 0.753). Through this, we concluded that in the system of argumentation mining as a whole, we can increase the structural arrangement or in other words reduce the chaotic (unused) components of the data entered or fed to the AM system in its initial phase, we would be able to control the result or accuracy to a large extent in our favor.

Algorithms Used	Data Set		Average Accuracy Rates (Structures + Unstructured)
	Structured	Un-Structured	
Support Vector Machine	0.897	0.604	0.750
Parsing algorithms	0.897	0.766	0.831
Logistic Regression	0.940	0.760	0.850
Naive Bayes	0.965	0.728	0.846
Decision Tree	0.860	0.760	0.810
Random Forest	0.973	0.810	0.891
Recurrent Neural Network	0.979	0.604	0.924
Conditional Random Fields	0.606	0.870	0.606
Textual Entailment Suites	0.889	0.606	0.821
Average Accuracy Rates	0.897	0.753	0.750

Table 2: Comparative Average Accuracy Rates on Structured and Un-Structured Data Set by: Support Vector Machine, Linear Regression, Naive Bayes, Decision Tree, Random Forest, Recurrent Neural Network, Conditional Random Fields and Textual Entailment Suites.

4. Conclusion

Today, computational mathematics has made easier the sophisticated processing of data. In the digital world, all functioning of computer science is primarily computational mathematics only. In this paper, we propose to resolve the problem of unstructured data through computational mathematics. The worldwide data when put together as a single entity is quite dynamic and constantly expanding. The proposed system consists of approximately 10% structured data in a specific format and likewise, 90% of unstructured data is still not formatted, which is the focal problem in our consideration. A format here has been regarded as a pure form or preliminary stipulation of this system. Reducing complexity will have an inverse effect on unstructured data mining, analysis, response, and management processes. Further, this methodology may be adopted by academia as well as related industries. This upon implementation might be a game changer in the field of data mining, storage, usability, and all the related activities on Big Data. We argue that current approaches too often rely on methodologies that demand a great deal of effort in the development of powerful but highly domain-dependent features, and are thus difficult to generalize. Moreover, we believe that a major obstacle to progress in AM is the lack of a standardized methodology for annotating relevant corpora.

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