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An Argumentation Scheme-Based Framework for Automatic Reconstruction of Natural Language Enthymemes

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Abstract. An important open challenge in the area of computational argumentation is the automatic reconstruction of natural language enthymemes. Such argumentative figures are commonly used in natural language human discourse to improve the naturalness and efficiency of speech. They also represent a major challenge when developing computational argumentation systems that need to work with natural language data, since enthymemes bring irregularity to the representations proposed in classical models of argumentation. In this paper, we propose a new framework based on the theory of argumentation schemes aimed at automatically reconstructing natural language enthymemes. The proposed framework consists of a two-module pipeline: (i) scheme classification, and (ii) enthymeme reconstruction. We validate the proposed framework by comparing its performance to a baseline pipeline that does not take the argumentation scheme theory into account. We evaluate the framework by analysing the validity of the complete reconstructed arguments, establishing a new set of baselines that can be used as reference for future work in this direction.

Keywords. Argument Mining, Enthymeme Reconstruction, Argumentation Schemes

1. Introduction

Argumentation theorists have studied and proposed different approaches for modelling and understanding human argumentation. Some of the most influential and accepted models of argument include the one proposed by Toulmin [1, 2] in which an argument is divided into six main components (i.e., claim, grounds, warrant, qualifier, rebuttal, and backing). Differently, the Rogerian model [3, 4] can be perceived as a rhetoric strategy of argument proposed based on the inclusion of concepts coming from human psychology. Including the dialogue as an intrinsic part of argumentation, the pragma-dialectic model of argumentation proposed by Van Eemeren [5] provides ten basic rules of critical discussion that, if broken, an argument becomes fallacious. In a similar direction, but focusing more on the structure of the argument, Walton et al. proposed the concept of argumentation schemes [6] which provide a semi-formal structural definition for more than sixty stereotyped patterns of argumentative reasoning and inference. Furthermore, these schemes come together with a set of critical questions, which are defined specifically to

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challenge the validity of a given argumentation scheme, and failing to give a satisfactory answer to one or multiple of them can be an indicator of a fallacious argument.

Natural language argumentation, however, is sometimes flexible and unpredictable, making it difficult to model it according to one of the previously mentioned models of argument. A good and common example of such flexibility is the use of enthymemes in human argumentative speeches. An enthymeme consists, basically, on the omission of part of an argument's structure in order to make human communication more direct and natural [7]. For example, by removing a premise which can be easily inferred from the context, or leaving a claim implicit in the discourse. This natural aspect of human argumentation has a direct effect in the area of computational argumentation, by making it much harder to propose robust computational models of argument that can work with natural language argument data.

In this paper, we propose, implement, and validate for the first time a framework based on the argumentation scheme theory that allows to automatically reconstruct natural language enthymemes into complete arguments. For that purpose, we use a recently published corpus of natural language argumentation schemes large enough to experiment and train deep learning algorithms, something that was not possible before [8]. Our framework consists of two main modules, the Scheme Classification and the Enthymeme Reconstruction. This way, for a given enthymeme (i.e., a natural language argumentative proposition), we firstly identify to which argumentation scheme it belongs to by modelling the inference rule represented in its natural language, and then we reconstruct the complete argument by pairing the enthymemes available in our dataset. Our contribution therefore leverages the theoretical concepts of argumentation schemes and reasoning structures to make the reconstruction of natural language enthymemes easier for state-of-the-art NLP algorithms. A potential application of the proposed framework would be to complete partial arguments by retrieving their missing premises from a premise database, or by generating them using a Large Language Model and linking them to the arguments with our system.

2. Related Work

Originally defined by Aristotle [9], an enthymeme is categorised as an argumentative structure in which some of its components (e.g., premises) have been intentionally omitted. From then to the present date, this concept has been widely studied from different perspectives such as linguistics and philosophy [10, 11]. In this direction, enthymemes have also been integrated into formal dialogue models [12], given that argument structures become more diffuse when considering natural language dialogue (i.e., informal) argumentation. In fact, argumentative dialogue is where enthymemes play an important role, and where they deserve further attention [13]. As it is discussed in [14], the argumentation scheme model provides the foundations necessary to represent and reconstruct enthymemes into complete natural language arguments. From a linguistic viewpoint, enthymeme reconstruction represents a way of recovering implicit information existing in the natural language argumentative dialogues and discourses, allowing to go deeper into the natural language analysis of dialogue argumentation [15]. As pointed out in [16], it is also important to note that enthymemes can be used as a communicative resource, thus losing some important discourse information related for example to the communicative strategy, when reconstructing them.

Given the research done in argumentation theory, and the observed impact of enthymemes in discourse, computational argumentation researchers have also paid attention to this phenomenon. In that area of research, enthymemes have been investigated from two main different perspectives: formal argumentation including abstract and structured models of arguments, and informal argumentation investigating the automatic analysis of natural language argumentation.

The main focus of enthymeme research in formal argumentation has been on complementing formal models of argumentation (e.g., abstract argumentation frameworks [17]) with enthymemes, reformulating some of the logics/semantics of argumentation [18]. In this approach, the inclusion of enthymemes has been researched in more depth when it comes to argumentative dialogues [19]. In [20], the authors proposed a formalisation for the exchange of enthymemes in argumentative dialogues. A different type of dialogue is considered in [21], where the authors explore a formal approach to include enthymemes into an inquiry dialogue system. Finally, the addition of the enthymeme concept into multi-agent dialogues also proved to be useful, specifically in the reconstruction of arguments and agent belief modelling [22].

From an informal argumentation NLP-based perspective, automatic reconstruction of enthymemes is one of the less investigated aspects, possibly because of the lack of large-enough suitable corpora, and the high complexity of automatising a process that involves modelling of natural language and its underlying reasoning and inference mechanisms. Most of the work in the analysis of enthymemes in natural language argumentation has been focused on enthymeme detection [23]. Some of these works have addressed the detection of enthymemes with the use of machine learning algorithms [24], and deep learning architectures [25]. Recent work also explored the use of generative approaches for enthymeme reconstruction [26], and a complete pipeline for enthymeme detection and reconstruction for learner arguments [27]. Despite the recently increased interest from the NLP community, we can observe a slight disconnection from argumentation theory concepts (e.g., Walton's argumentation schemes) which could be helpful to assist the implemented systems in the enthymeme reconstruction task from a computational perspective.

3. Framework

3.1. Background

Computational argumentation studies the computational modelling and automation of human argumentative reasoning. This modelling is studied from different perspectives including the analysis, the evaluation, or the generation of arguments from a computational viewpoint [28]. With the latest advances in state-of-the-art NLP, the area of computational argumentation has experienced a shift from being mostly based on formal argumentation research [17, 29, 30] to becoming an even more multidisciplinary area of research allowing for informal argumentation research focused on the analysis and modelling of natural language argumentation [31, 32, 33]. Unfortunately, this opening also brought some drawbacks, like the partial disconnection from fundamental concepts belonging to argumentation theory. This disconnection is caused, in part, by the outstanding performance of NLP algorithms when modelling natural language without the need to manually define any features from the text [34]. This disconnection, however, does not happen in real-world data, where concepts from argumentation theory are present in natural language argumentation [35]. NLP algorithms such as Large Language Models excel at modelling and generating natural language but are limited at reasoning tasks, thus benefiting from bringing together concepts and approaches from both areas [36, 37]. Enthymemes are common in natural language human argumentation, and widely studied in argumentation theory, but they tend to be overlooked in argument mining research. This makes more difficult the application of theory-grounded models of human argumentation in the process of analysing natural language argumentation computationally.

Premises in an argument are intended to provide support for the conclusion, and the inference mechanism by which that support is given can be described and classified with an argumentation scheme. There is a number of different interpretations of argumentation schemes. In this work, we theoretically ground our proposed framework on Walton's theoretical definition of argumentation schemes, described in [6]. An example of one such scheme is the *Argument from Expert Opinion*:

> Major premise: <*E*> *is an expert in domain* <*S*> *containing proposition* <*A*>.
> Minor premise: <*E*> *asserts that proposition* <*A*> *(in domain* <*S*>*) is true.*
> Conclusion: <*A*> *may plausibly be taken to be true.*

It is worth mentioning that under Walton's model, different schemes can have different structural representations with variations in the number of premises and their role within the argument. Considering these structured representations of arguments, we can define an enthymeme as a subset of the complete scheme, in which some of the premises have been omitted. The framework presented in this paper partly relies on the grouping of argument premises by their argumentation scheme. The main objective of the proposed framework is, therefore, to reconstruct the complete structure of the natural language argumentation scheme by analysing the previously segmented natural language premises (i.e., the enthymemes).

3.2. The Scheme-based Framework for Enthymeme Reconstruction

The scheme-based framework consists of multiple modules connected together in a pipeline. Each of the modules creates an output that the next one processes. Our proposed framework consists of two main modules: Scheme Classification (SC), and Enthymeme Reconstruction (ER). The second module further consists of two components, the first of which creates all possible premise pairs, while the second one identifies the correct pairs. For visualisation of the complete pipeline, see Figure 1.

The SC module has the task of classifying premises by argumentation scheme. The input data is a collection of premises that have been previously segmented and extracted from natural language texts, and the module assigns one of 20 possible labels to each premise. There is one label for each of Walton's argumentation schemes present in the dataset. The result of this module are 20 non-overlapping sets of premises.

The ER module aims to create valid pairs of premises that belong together in an argument. The module processes each of the 20 outputs of the previous module independently. Using a Premise Pairing-up component, it first creates all possible pairs of the premises, not taking into account whether they belong together or not. Each pair of premises is a possible argument. The premise pairs are then evaluated by an Argument

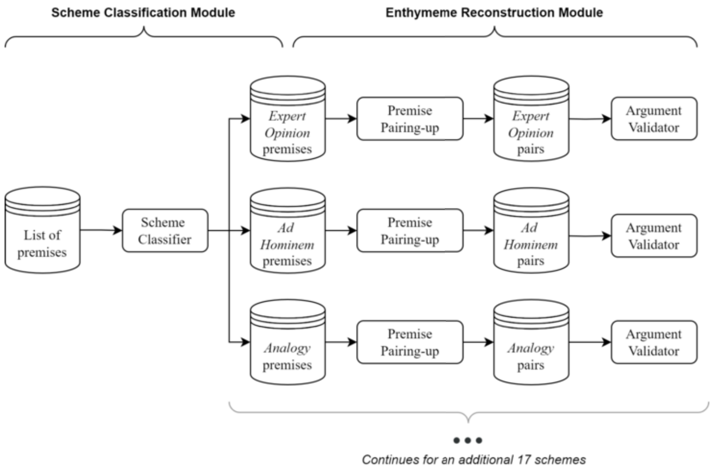


Figure 1. The Scheme-based Framework.

Validator (AV) component, which must identify which pairs actually belong together in a single argument. The two-component process is repeated for each argumentation scheme. In total, the ER module outputs 20 sets of premise pairs (i.e., reconstructed arguments), where each pair is accompanied by a binary label indicating whether it's a valid pair or not. With this proposed framework, we leverage the theory of argumentation schemes as a pre-processing step that helps us to structure the extracted argumentative propositions (i.e., premises) and match them between potential groups created according to 20 different patterns of argumentative inference.

Aiming to find a more simplified but effective version of the scheme-based enthymeme reconstruction framework, we also consider a variation of the previously described framework with a structural simplification on the ER module. Instead of using a bespoke AV component for each scheme, all premise pairs are evaluated by a single, universal AV, requiring less computational resources. This simplified version of the pipeline is visualised in Figure 2.

4. Data

The availability of structured argumentation data is severely lacking. The golden standard is to train human annotators, which carries self-evident issues of scaling and cost. The small quantity of data containing argumentation scheme annotations is best evidenced with some examples: [38] presents a dataset of 345 arguments, [39] annotates 505 arguments from a political debate, and [40] examines relations on 400 online comments. Of special concern is the fact that the different annotation efforts frequently use different argumentation schemes and therefore cannot be combined, as concluded in [41]. Since none of the individual datasets are large enough, and cannot be combined, we concluded that human-annotated data is not feasible for a systematic validation of our proposed framework.

To bridge the gap between the required and available quantity of data, we opted to use a corpus of synthetically generated arguments validated by expert human annotators,

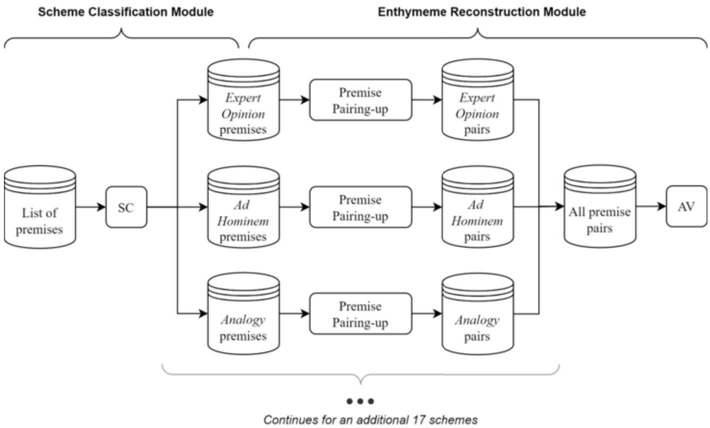


Figure 2. The simplified scheme-based framework.

namely the English section of the NLAS-multi corpus [8]. The NLAS corpus used in this paper contains a total of 3,888 arguments over a broad domain of 100 topics. Each argument carries a property specifying its argumentation scheme per Walton's theory of argumentation schemes. Note that the dataset features 20 schemes from a total of more than 60 argumentation schemes identified in the literature. This selection was based on how commonly they are used in argumentation. Table 1 shows a per-scheme breakdown of arguments and the premises they contain. In the rest of the paper, we refer to schemes by their abbreviations introduced in the aforementioned table.

The use of synthetic arguments has several advantages: it is plentiful, covers a variety of topics and domains, and most importantly consistent. The predictability of such complete natural language argumentation schemes, however, means that although the arguments were validated by humans and they follow the intended argumentation scheme, the NLAS corpus may have a limited applicability in real-world human argumentation contexts where enthymemes are used instead of complete structured arguments. With this paper, it is our objective to address this difference partially bridging the gap between synthetic and real-world argumentation by automatically addressing the challenging task of enthymeme reconstruction from individual premises.

5. Experimental Validation

5.1. Experimental Setup

The scheme-based framework largely relies on the use of fine-tuned large language models. It features a total of 21 models - one for Scheme Classification, and one model per each scheme to validate the final reconstructed argument as part of the Enthymeme Reconstruction module. The base of all the models is a distilled version of BERT [42], selected as a good balance between performance and computational requirements. The hyperparameters were kept consistent during the 10-epoch long training runs, with a learning rate of 1e-5, weight decay of 0.01 and batch size 12. Deterministic algorithms are used in processing the dataset and some interim components. In all of the frameworks,

Table 1. Counts of English-language arguments and their premises in the extended NLAS-multi dataset

Scheme	Abbreviation	Arguments	Premises
position to know	AFPK	200	597
expert opinion	AFEO	200	597
direct ad hominem	AFAH	200	397
inconsistent commitment	AFIC	189	564
popular practice	AFPP	194	577
popular opinion	AFPO	198	590
analogy	AFAN	199	594
precedent	AFPR	198	579
example	AFEX	197	393
established rule	AFER	195	582
cause to effect	AFCE	189	591
verbal classification	AFVC	198	591
slippery slope	AFSS	175	693
sign	AFSI	200	597
ignorance	AFIG	193	576
threat	AFTH	185	737
waste	AFWS	186	547
sunk costs	AFSC	192	570
witness testimony	AFWT	200	797
best explanation	AFBE	200	797
total count		3,888	11,966

including the baseline, we do not consider the conclusions because they don't have any internal argumentative structure, and in most cases they can be directly inferred from the sentiment, with sentiment analysis being a widely studied topic [43]. The code for the experiment is publicly available on the first author's GitHub repository[2].

The SC module faces a 20-class classification problem. The BERT-based model was fine-tuned on 3,110 arguments. The number of premises in each argument varied depending on the argument scheme, with most arguments consisting of two to three premises. In the end, we had a total of 9,584 premises for training following an 80-10-10 proportion for training, development, and testing.

The first part of ER module, the Premise Pairing-up component, is entirely deterministic. It creates all possible combinations of the premises, ignoring any repetitions. The term *combinations* here is consistent with its mathematical definition

$$_nC_r = \frac{n!}{r!(n-r)!}$$

where r always carries the value of 2, and n is the number of premises to create pairs from. It is important to note that, even though this component only creates pairs, it doesn't mean that ER is limited to two-premise arguments. Once correct premise pairs have been identified, it would be trivial to form complete arguments with more than two premises by combining premise pairs that have one shared premise.

Finally, each argumentation scheme has its corresponding Argument Validator model, for a total of 20 models. Since the Premise Pairing-up component would already organise premises into pairs, the classification problem that Argument Validator needs

[2] github.com/zvonimir-delas/COMMA24-Enthymeme-Reconstruction

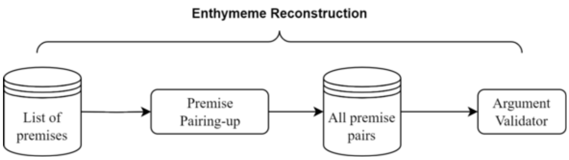


Figure 3. The baseline pipeline.

to tackle is a binary one, assigning a positive or a negative label to each pair depending if the premise pair belongs to the same argument or not. Given the massive class imbalance between positive and negative samples that we would have if considering all 3,888 premises included in NLAS, we only considered half of the NLAS dataset to generate negative pairs of premises. With this adjustment, a total of 10,094 positive pairs and 551,393 negative pairs were used for the fine-tuning the models for argument validation.

As previously visualised in Figure 2, we also considered a simplified variation of the scheme-based framework. This simplified version of the framework has an identical implementation up to the Argument Validator model. Instead of using one AV model per each argumentation scheme, making a total of 20 models, the segmented premise pairs are combined together, and fed into a universal Argument Validation model. The AV model has the same binary-labelling task as its scheme-specific equivalents, but its training corpus was created by combining all of the scheme-specific premise pairs into a single dataset, rather than having 20 different scheme-specific datasets for fine-tuning.

5.2. Baseline

To create a comparable baseline that allows us to highlight the benefits of combining the theory of argumentation schemes with NLP algorithms and techniques, we assemble a pipeline implementing a straightforward approach to the automatic reconstruction of enthymemes, with no prior involvement of the Scheme Classification module. Instead of first grouping premises by argumentation scheme, our baseline pipeline opts to create all possible combinations of premise pairs. The Premise Pairing-up component operates in an identical manner as in the scheme-based framework, except that its input premises are not grouped by scheme. There is a single Argument Validator model, trained in the same manner as in the simplified variation of the scheme-based framework. The baseline pipeline architecture is visualised in Figure 3.

5.3. Results

We find that both the full and the simplified scheme-based framework significantly outperform the baseline pipeline. The Scheme Classification module achieved a macro-F1 score of 0.93, with a breakdown shown in Figure 4. Following the execution of the Premise Pairing-up component on the classified premises, Argument Validation models achieved an averaged macro F1-score of 0.77. It is also important to note that two of the argumentation schemes (AFAH, AFEX) present in the dataset contain only one premise, and as such were not considered for evaluation in the ER module. The AV component of the simplified scheme-based framework performed very similarly, with a macro F1-score of 0.78. The baseline, however, lagged behind significantly with a macro F1-score of 0.51. A breakdown of the results is shown in Table 2.

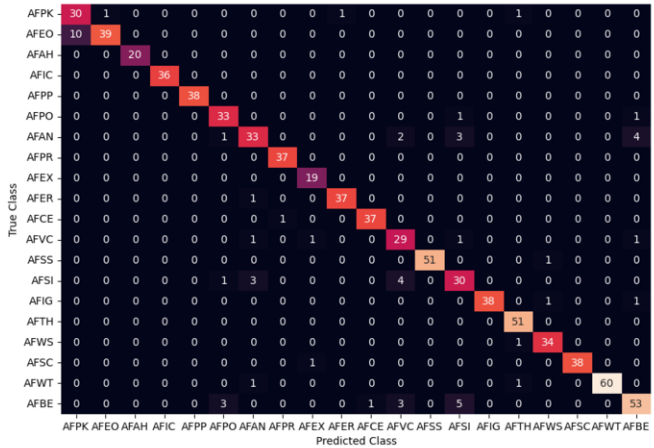


Figure 4. Scheme Classification module confusion matrix.

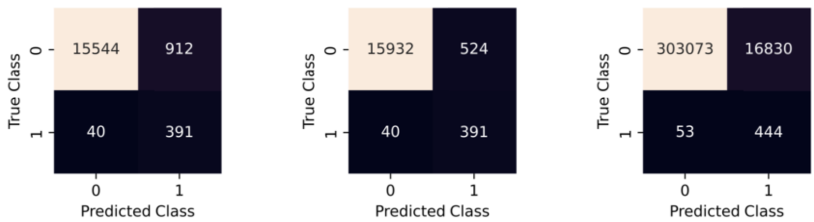
Table 2. Results of the three different approaches for Enthymeme Reconstruction (macro-averaged).

	Precision	Recall	F1-score
Baseline	0.51	0.92	0.51
Scheme-based Framework	0.72	0.93	0.77
Simplified Scheme-based Framework	0.71	0.93	0.78

Our first conclusion is that including the theory of argumentation schemes into the process of reconstructing enthymemes can help significantly. Second, that in the ER module, a universal AV model is enough, meaning that the existing inference relationship between premises can be learnt without needing to consider different argumentation schemes independently. The results can also be observed, and explained from the perspective of count of premise pairs fed into the ER module. The full and simplified scheme-based framework's SC module generated an aggregated 16,887 possible arguments. The baseline, because it could not segment premises by scheme, has many more negative pairs, resulting in a total of 320,400 arguments. The confusion matrices in Figure 5 show that false positive results were the most erroneous, and with many more negative examples to classify, the baseline's false positives overshadowed its good performance on true positives. We can therefore deduce than any efforts to reduce the number of negative examples, one of which is the scheme classification module presented in this paper, would help with the overall performance.

6. Conclusion

In this paper we propose a novel computational framework for the reconstruction of natural language enthymemes. Our framework, in addition to its deep learning implementation, is heavily based on Walton's theory of argumentation schemes and the definition of enthymeme in this context. By bringing together concepts from argumentation theory and NLP, it has been possible to achieve a significant improvement of 27% with respect to macro F1-score compared to our NLP baseline. This improvement can be mainly at-



(a) Scheme-based framework (aggregated). (b) Simplified scheme-based framework. (c) Baseline.

Figure 5. Enthymeme Reconstruction module confusion matrices.

tributed to the fact that the SC module allows for a better informed management of the premises, first reducing the number of inferences to be drawn between pairs of premises and second, minimising the chances of false positives among our reconstructed arguments.

This paper represents an important step forward in the implementation and development of automatic enthymeme reconstruction systems by providing promising results on this task from a theoretical-practical perspective, leaving the door open for further research in this direction, extending previous purely NLP-oriented approaches. It remains, however, future work to to explore the performance of our proposed framework in natural language dialogues, and see how the synthetic data used for training can be leveraged in real-world argumentative scenarios.

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