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Argument Mining Using Argumentation Scheme Structures

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Abstract. Argumentation schemes are patterns of human reasoning which have been detailed extensively in philosophy and psychology. In this paper we demonstrate that the structure of such schemes can provide rich information to the task of automatically identify complex argumentative structures in natural language text. By training a range of classifiers to identify the individual proposition types which occur in these schemes, it is possible not only to determine where a scheme is being used, but also the roles played by its component parts. Furthermore, this task can be performed on segmented natural language, with no prior knowledge of the text's argumentative structure.

Keywords. Argumentation Schemes, Argument Mining, Natural Language Processing

1. Introduction

The continuing growth in the volume of data which we produce has driven efforts to unlock the wealth of information this data contains. Automatic techniques such as Opinion Mining and Sentiment Analysis [12] allow us to determine the views expressed in a piece of textual data, for example, whether a product review is positive or negative. Existing techniques struggle, however, to identify more complex structural relationships between concepts. By identifying the argumentative structure and its associated premises and conclusions, we are able to tell not just *what* views are being expressed, but also *why* those particular views are held. In this paper, we use argumentation schemes [22], common patterns of human reasoning, to automatically determine instances where such a pattern is being used, as well as the roles played by its component parts.

1.1. Argumentation Schemes

Argumentation schemes capture structures of (typically presumptive) inference from a set of premises to a conclusion and represent stereotypical patterns of human reasoning. As such, argumentation schemes represent a historical descendant of the topics of Aristotle [1] and, much like Aristotle's topics, play a valuable role in both the construction and evaluation of arguments.

Several attempts have been made to identify and classify the most commonly used schematic structures [6,16,9,17,20,5,8,22]. Although these sets of schemes overlap in many places, the number of schemes identified and their granularity can be quite different. As such, most argument analyses tend to contain examples from only one scheme set, with the Walton set being the most commonly used. Several examples of Walton's argumentation schemes can be seen in Table 1.

Analogy (AN)

Premise [SimilarityOfCases]: Generally, case C1 is similar to case C2

Premise [Precedent]: A is true (false) in case C1

Conclusion: A is true (false) in case C2

CauseToEffect (CE)

Premise [Causal]: Generally, if A occurs, then B will (might) occur

Premise [Occurrence]: In this case, A occurs (might occur)

Conclusion: Therefore, in this case, B will (might) occur

PracticalReasoning (PR)

Premise [Goal]: I have a goal G

Premise [GoalPlan]: Carrying out this action A is a means to realise G

Conclusion: Therefore, I ought (practically speaking) to carry out this action A

VerbalClassification (VC)

Premise [ContainsProperty]: a has a property F

Premise [ClassificationProperty]: For all x, if x has a property F, then x can be classified as having a property G

Conclusion: a has property G

Table 1. Argumentation schemes

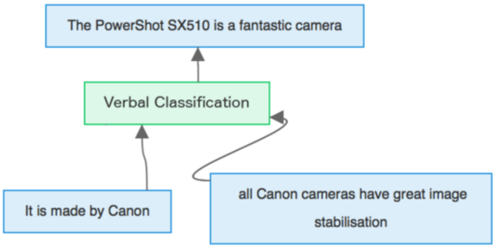
Understanding the argumentative structure being expressed in a piece of natural language text can help us gain a deeper understanding of what is being said compared to many existing techniques for extracting meaning. If we consider the product review shown below, then sentiment analysis techniques allow us to understand at a high level what views are being presented, for example, that this review is positive, but are unable to provide details on exactly why the reviewer likes the product.

> The PowerShot SX510 is a fantastic camera. It is made by Canon and all Canon cameras have great image stabilisation.

Looking at the argumentative structure contained within this review, we can see that the propositions "It is made by Canon" and "all Canon cameras have great image stabilisation" are working together to support the conclusion "The PowerShot SX510 is a fantastic camera". Furthermore, we can see that the link between the premises and conclusion is a form of Verbal Classification[1]. A graphical representation of the argument structure can be seen in Figure 1.

[1] In fact, the example here does not exactly conform to the Verbal Classification scheme. In a more thorough analysis, an enthymeme would be added showing that the premises actually support the fact that the camera has great image stabalisation and that this in turn is a feature of a fantastic camera.

Figure 1. Argument analysis of a product review, showing an example of the Verbal Classification scheme



The features of these common patterns of argument provide us with a way in which to both identify that an argument is being made and determine its structure. By using the specific nature of each component proposition in a scheme, we can identify where a particular scheme is being used and classify the propositions accordingly, thereby gaining a deeper understanding of the argumentative structure which a piece of text contains.

1.2. Argument Mining

Argument Mining[2] is the automatic identification and extraction of argument components and structure. One of the first attempts to automate this process was presented in [13,18], where a text is first split into sentences and then features of each sentence are used to classify them as “Argument” or “Non-Argument”. This approach was built upon in [14], where each argument sentence is additionally classified as either a premise or conclusion, a method referred to as “Argument proposition classification”. A Context-Free Grammar is then used to determine the internal structure of each individual argument.

The majority of the more recent developments in Argument Mining have followed a similar approach to this early work, applying a range of techniques to uncover the argumentative sections of a text, identifying premises and conclusions and attempting to link these together to determine the overall argument structure. This methodology has been applied to a range of domains including online user comments [15], social media [4] and essays [19], with the results obtained being generally encouraging. However, such attempts do not consider exactly how the discovered premises are working together to support the conclusion.

The concept of automatically identifying argumentation schemes was first discussed in [21] and [3]. Walton proposes a six-stage approach to identifying arguments and their schemes. The approach suggests first identifying the arguments within the text and then fitting these to a list of specific known schemes. A similar methodology was implemented by Feng & Hirst, who produced classifiers to assign pre-determined argument structures as one in a list of the most common argumentation schemes. Another possible approach is suggested in [2], where the connection between argumentation schemes and discourse relations is highlighted, however, this requires these discourse relations to be accurately identified before scheme instances can be determined.

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[2] Sometimes also referred to as Argumentation Mining

The main challenge faced by these approaches is the need for some prior analysis of the text to have taken place. By instead looking at the features of each component part of a scheme, we are able to overcome this requirement and identify parts of schemes in completely unanalysed text. Once these scheme components have been identified, we are able to group them together into specific scheme instances and thus obtain a complete understanding of the arguments being made.

2. Identifying Scheme Components

Being able to determine the argumentation scheme structure contained within a piece of text gives us a much deeper understanding of both what views are being expressed and why those views are held, as well as providing a route to the automatic reconstruction of certain types of enthymeme [7]. However, existing approaches to automatically identifying scheme instances have relied on the basic argumentative structure being previously identified.

By training a range of classifiers to identify the individual components of a scheme, we are able to identify not just the presence of a particular scheme, but also the roles which each of the premises play within a particular scheme instance. Furthermore, we are able to perform this based only on a list of the propositions contained within the text, requiring no previous analysis to have been performed. In Section 2.1 we look at using one-against-others classification to identify propositions of each type from a set of completely unstructured propositions. Being able to successfully perform this task for even one of the proposition types allows us to discover areas of the text where the corresponding scheme likely to be being used. This can be viewed as a first step in obtaining the argument structure following the extraction of propositions from natural text using a technique such as *Proposition Boundary Learning* [11], a specialised type of Elementary Discourse Unit identification.

In Section 2.2, we also consider the situation where some of the argumentative structure has already been determined. If we know that we have a set of premises supporting a conclusion and that a particular scheme is being used, then we wish to determine what role each premise is playing in the scheme. In order to achieve this, we implemented pairwise classifiers for each scheme type capable of classifying each premise into their respective role.

In order to accomplish these tasks, a range of classifiers for each proposition type was implemented using the *scikit-learn*[3] Python module for machine learning, with the features described in Table 2. Part Of Speech (POS) tagging was performed using the Python NLTK[4] POS-tagger and the frequencies of each tag added as individual features. The similarity feature was added to extend the information given by unigrams to include an indication of whether a proposition contains words similar to a pre-defined set of keywords. The keywords used for each type are shown in Table 3. Similarity scores were calculated using WordNet[5] to determine the maximum similarity between the synsets of the keywords and each word in the proposition. The maximum score for the words in the

[3]http://scikit-learn.org/stable/
[4]http://www.nltk.org/
[5]http://wordnet.princeton.edu/

proposition was then added as a feature value, indicating the semantic relatedness of the proposition to the keyword.

Feature	Description
Unigrams	Each word in the proposition
Bigrams	Each pair of successive words
Length	The number of words in the proposition
AvgWLength	The average length of words in the proposition
POS	The parts of speech contained in the proposition
Punctuation	The presence of certain punctuation characters, for example “ ” indicating a quote
Similarity	The maximum similarity of a word in the proposition to pre-defined words corresponding to each proposition type

Table 2. Features used for classification

Type	Keywords
AN Similar	similar, generally
AN Precedent	be (to be)
AN Conc	be (to be)
CE Causal	generally, occurs
CE Occurance	occurs
CE Conc	occurs
PR Goal	goal
PR GoalPlan	action
PR Conc	ought, perform
VC Property	be (to be)
VC Class	all, if
VC Conc	be (to be)

Table 3. Keywords used for each proposition type

Both of these tasks were carried out using annotated scheme data from AIFdb [10]. Although there are a number of argument analysis tools (such as Araucaria, Carneades, Rationale and OVA) which allow the analyst to identify the argumentation scheme related to a particular argumentative structure, the vast majority of analyses which are produced using these tools do not include this information. For example, less than 10% of the OVA analyses contained in AIFdb include any scheme structure. AIFdb contains the complete Araucaria corpus [18] used by previous argumentation scheme studies and, supplemented by analyses from other sources, offers the largest annotated dataset available.

The data available comes from a range of different domains, with analyses including details of schemes, and the types of scheme premises, from the Walton scheme set. Although there are over 500 examples of schemes identified in AIFdb, not all of these include complete annotation of the premise types.

Limiting the data to those schemes with at least twenty instances that are fully defined leaves us with four schemes to consider (the number of examples for each scheme type is shown in Table 4.)

Scheme	**Number of Examples**
Analogy (AN)	31
Cause To Effect (CE)	89
Practical Reasoning (PR)	68
Verbal Classification (VC)	38

Table 4. Number of example instances of each scheme type

2.1. One-against-others classification

For each of the scheme types previously discussed, the conclusions and each type of premise were classified using three different types of classifier (Multinomial Naïve Bayes, Support Vector Machines (SVMs) and Decision Trees) against a random selection of argument propositions from AIFdb.

Table 5 shows the precision, recall and F-score obtained using 10-fold cross validation for each proposition type with each classifier. For each proposition type, the F-Score of the best performing classifier is highlighted in bold.

As can be seen from the table, the Multinomial Naïve Bayes classifiers perform best in most cases, and even for those proposition types where one of the other methods perform better, the results are comparable. In particular, the results for SVMs are lower than those for the other types of classifier. This can be explained by the fact that our feature set is considerably larger than the sample, a situation in which SVMs generally perform less well.

Notably, the results for Analogy (Conclusion) and Cause To Effect (Occurrence) are quite weak in comparison to the other proposition types. In the case of Analogy, the conclusion often does not include details of the specific case being discussed, but instead refers to the general situation being discussed, for example "Invading Iraq has been a foolish action". Because of this, many of these conclusions take the form of very simple factual statements that are often hard to distinguish from other propositions. With Cause To Effect the Occurrence premise again suffers from a similar lack of complete specificity and details of the specific situation are often omitted.

The results for the remaining proposition types are more promising and, even for those schemes where the classification of one proposition type is less successful, the results for the other types are better. If we consider being able to correctly identify at least one proposition type, then our results give F-scores between 0.78 and 0.91 for locating an occurrence of the different scheme types. The results also show that in many cases it would be possible to not only determine that a scheme is being used, but to accurately classify all of its component propositions.

2.2. Pairwise Classification

For pairwise classification, we assume that identification of a specific argumentation scheme instance (along with its associated premises and conclusion) has previously been

Type	Naïve Bayes			SVM			Decision Tree		
	p	r	f1	p	r	f1	p	r	f1
AN Similar	0.58	1.00	**0.74**	0.60	0.43	0.50	0.56	0.71	0.63
AN Precedent	0.64	1.00	**0.78**	0.75	0.43	0.55	0.29	0.29	0.29
AN Conc	1.00	0.29	0.44	0.38	0.43	0.40	0.57	0.57	**0.57**
CE Causal	0.57	0.89	0.70	0.58	0.61	0.59	0.94	0.89	**0.91**
CE Occurance	0.50	0.72	**0.59**	0.40	0.22	0.29	0.38	0.33	0.35
CE Conc	0.73	0.89	**0.80**	0.54	0.78	0.64	0.57	0.72	0.63
PR Goal	0.65	0.79	**0.71**	0.55	0.86	0.67	0.59	0.71	0.65
PR GoalPlan	0.65	0.93	0.76	0.76	0.93	**0.84**	0.75	0.86	0.80
PR Conc	0.90	0.64	0.75	0.55	0.43	0.48	0.76	0.93	**0.84**
VC Property	0.88	0.88	**0.88**	1.00	0.50	0.67	0.75	0.75	0.75
VC Class	0.58	0.88	0.70	0.67	0.75	0.71	0.75	0.75	**0.75**
VC Conc	1.00	0.50	**0.67**	0.62	0.62	0.62	1.00	0.38	0.55

Table 5. Results of one vs others proposition classification using 10-fold cross validation (The highest f-score for each scheme component is highlighted in bold)

carried out, and look at classifying proposition types for each premise against the other premise proposition types. Being able to successfully perform this task would enable us to determine the full schematic structure of any argument previously analysed at the structural level, be it a manual analysis or one performed by another argument mining technique.

This task was firstly performed using the same approach as the one-vs-others classification, with a Naïve Bayes classifier created for each proposition type, but in this case using only the other premises from the same scheme to test against. The resulting probabilities for each premise type were then compared and assignment to each type was made. The precision, recall and F-score for these classifications can be seen in Table 6.

Type	p	r	f1
PR Goal/GoalPlan	1.00	0.79	0.88
CE Causal/Occurance	0.75	0.50	0.60
AN Similar/Precedent	1.00	0.43	0.60
VC Property/Class	0.75	0.75	0.75

Table 6. Results of pairwise premise classification

In order to take further advantage of the fact that each proposition is already known to belong to a certain scheme and that all of the other premises are also available, we also implemented comparative versions of some of the features. It can be seen from the scheme descriptions that the different premises in each scheme may often contain many of the same words. However, to differentiate between them we want to consider how the vocabulary used for each premise type differs. In order to help us understand this, unigrams were calculated using words appearing only in the proposition being considered and not in any of the other scheme instance's premises. Additionally, as each scheme we

Type	**p**	**r**	**f1**
PR Goal/GoalPlan	1.00	0.79	0.88
CE Causal/Occurance	**0.82**	0.50	**0.62**
AN Similar/Precedent	1.00	0.43	0.60
VC Property/Class	**0.78**	**0.88**	**0.82**

Table 7. Results of pairwise premise classification with additional comparative features

are considering has only two premise types, we were able to use the comparative length of the premises, giving an indication of whether one type of premise is generally longer or shorter than the other.

The results from adding these comparative features are shown in Table 7. The values highlighted in bold show where the addition of these features gave an improvement in the results (all of the other results remained unchanged.)

The difference caused by adding comparative features is particularly notable for the Verbal Classification scheme. This is suggested by the structure of this scheme as described in Table 1. Although the length of both premises may vary depending, for example, on the property that the scheme instance is discussing, the *ClassificationProperty* premise will very often be longer than the *ContainsProperty* premise.

In both sets of results, the performance when classifying the premises of Practical Reasoning schemes and Verbal Classification schemes is considerably greater than that for Analogy and Cause To Effect. It can be seen from the descriptions of these schemes that the premises for the latter pair have more in common than those for the former and as such it is unsurprising that these are harder to distinguish. These results provide a positive indication that being able to determine which of the premises in a pre-identified scheme instance are which, is at least feasible.

3. Identification of Scheme Instances

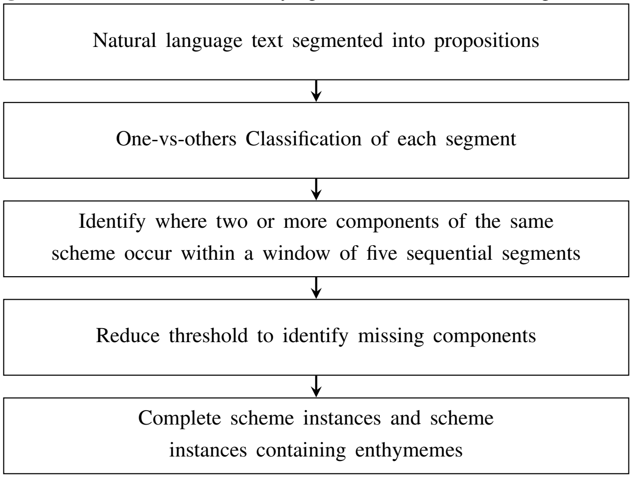
The one-against-others results suggest that it is feasible to classify propositions by type. Performing this classification on a piece of text would enable us to identify places where a particular scheme is being used. We now move on to look at how well these classifiers are able to identify not just individual occurrences of a proposition type but complete scheme instances. The ability to successfully perform this task would enable us to take a sample of natural language and understand a large amount of the argument structure it contains. In order to investigate this, we used the proposition corpus created for the Digging by Debating project[6]. This corpus contains over 1,000 sequential propositions extracted from three chapters of “THE ANIMAL MIND: A Text Book of Comparative Psychology” by Margaret Floy Washburn.

The aim of this experiment is not to identify the complete argumentative structure represented by the text, but to illustrate that, even considering the difference in language and methods of expression employed in a 19th century philosophy text, it is possible to use the classifiers that we have produced to extract complete scheme instances.

Our aim here is to identify complete occurrences of a particular scheme within a piece of natural language text. In order to accomplish this, we first perform one-vs-others

[6] `http://diggingbydebating.org/`

Figure 2. Process used for identifying scheme instances from segmented text



classification of each segment using the Multinomial Naïve Bayes classifiers discussed in Section 2.1. We then look at each group of five sequential segments, and identify places where two or more components of the same scheme type occur together. In cases where there is still a missing component, we reduce the threshold for the classifier corresponding to the missing piece. If reducing the threshold still does not offer a candidate for the missing scheme component, we assume that this is unstated enthymematic content in the argument. By performing these steps, we are able to take segmented text and identify either complete scheme instances, or partial scheme instances which have some enthymematic component. The process followed is illustrated in Figure 2.

The classification process identified 9 possible occurrences of Analogy, 14 of Cause To Effect, 18 of Practical Reasoning and 23 of Verbal Classification. The Animal Mind corpus is not annotated for scheme instances, however we can see that, although some instances may have been missed, many of those identified are a close match to the scheme descriptions. For example, the structure in Figure 3 was identified as an occurrence of Practical Reasoning. In this case, the proposition “Thorndike’s aim in this research was to place his animals (chicks, cats, and dogs) under the most rigidly controlled experimental conditions” was identified as a goal and “The cats and dogs, reduced by fasting to a state of ‘utter hunger,’ were placed in boxes, with food outside” as a plan for achieving that goal. Although these two propositions fit the scheme well, the suggested conclusion (“the process whereby they learned to work the various mechanisms which let them out was carefully observed”) does not follow the required pattern.

An example of an identified instance of Verbal Classification can be seen in Figure 4. Again, in this case, the premises fit the scheme quite well (*Classification Property*: “If it is argued that we have no direct, but only an inferential, knowledge of the processes in an animal’s mind, the argument is equally valid against human psychology” and *Contains Property*: “the psychologist has only an inferential knowledge of his neighbour’s mind”), but the conclusion does not follow.

A final example, this time showing an identified instance of Cause To Effect, is shown in Figure 5. Once more, the premises fit the scheme description, but the conclusion again does not follow. This difficulty in discovering the conclusions may be due to the

Figure 3. Automatically identified Practical Reasoning instance

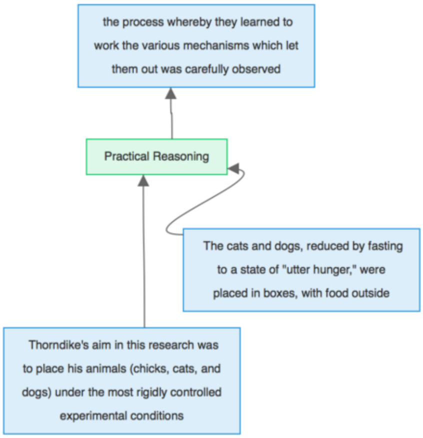
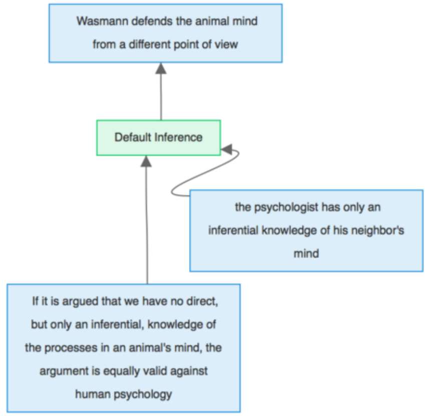
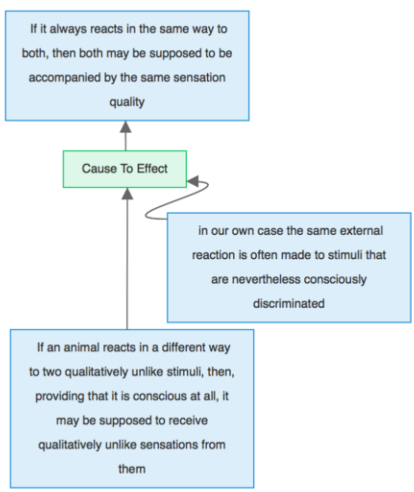


Figure 4. Automatically identified Verbal Classification instance



fact that generally conclusions are not as clearly stated and may be the general topic being discussed as opposed to a clearly expressed proposition located close to the supporting premises. This can be seen even in the example of Verbal Classification from section 1.1 and suggests that an amount of reconstruction may be necessary to fully identify all parts of a scheme.

Figure 5. Automatically identified Cause To Effect instance



Although these examples are not perfect identifications of scheme instances, it is clear that even with the limitations involved, we have come close to being able to identify at least where a scheme is occurring, and to correctly assign at least some of the propositions.

4. Conclusion

Whilst argumentation schemes have been detailed extensively in philosophy and psychology, perhaps due to the relative complexity of these structures, they have received little attention in argument mining. In [3], instances of particular schemes are classified from text which has previously been annotated for its argumentative structure, a process which could be considered as the second step in the six-stage approach to identifying arguments and their schemes suggested by [21].

Here, we have shown that by considering the features of the individual types of premise and conclusion that comprise a scheme, it is possible to reliably classify these scheme components. Despite the differing goals, our results are comparable results to those of Feng & Hirst, where the occurrence of a particular argumentation scheme was identified with accuracies of between 62.9% and 90.8%. Our results show that, on the same dataset, it is possible to identify individual scheme components with similar performance (F-scores between 0.78 and 0.91) can be achieved in identifying argumentation schemes in unanalysed text.

Furthermore, by searching for groupings of these proposition types, we have shown it is possible to determine not just that a particular scheme is being used, but to correctly assign assign propositions to their schematic roles. In future work accuracy of these techniques could be further improved by considering domain specific schemes, such as the Consumer Argumentation Scheme (CAS) [23] aimed specifically at product reviews.

Our results also compare favourably with those presented in [14] where sentences were classified as either premise (F-score, 0.68) or conclusion (F-score, 0.74). For each of the schemes we considered, we were able to classify conclusions with F-scores between 0.71 and 0.91, and premises with F-scores between 0.59 and 0.88. Although these values are not quite as high for all premise types, we are able to determine not only that something is a premise, but also what role it plays in the scheme, showing that scheme component identification offers valuable information that could play an instrumental role in determining the full argumentative structure, be it as a stand-alone method, a source of feature data for more complex classifiers or part of a larger ensemble approach.

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