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Automatic Exploration of Argument and Ideology in Political Texts

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The underlying argumentation of politically-opinionated texts tends to be informal and enthymematic, and commingled with non-argumentative text. It usually assumes an ideological framework of goals, values, and accepted facts and arguments. Our long-term goal is to create computational tools for exploring this kind of argumentation and ideology in large historical and contemporary corpora of political text. Overcoming the limitations of contemporary lexical methods will require incorporating lexical, syntactic, semantic, and discourse-pragmatic features into the analysis.

KEYWORDS: argumentation schemes, discourse parsing, framing, ideology, political argumentation, natural language processing, rhetorical structure theory, shibboleth, vocabulary

1. INTRODUCTION

Politically opinionated texts, whether written or spoken, are naturally occurring argumentation. They include oral speeches by members of a legislature and written opinion pieces in news publications. The goal of a politically opinionated text is to persuade the hearer or reader that a particular political position is correct, thereby changing or reinforcing the present beliefs of the hearer or reader. However, the underlying argumentation tends to be informal and enthymematic, and, especially

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in oral speeches, commingled with non-argumentative text. In particular, it tends to assume an ideological framework of goals, values, and accepted facts and arguments.

Converse (1964) defines an *ideology* as a system of beliefs that is "bound together by … constraint or functional interdependence" — that is, an individual's political beliefs are not chosen at random; rather, they fit together into a broader system. The most fundamental and enduring dimension of variation in ideology is *left versus right*, a divide that is pervasive in politics (Cochrane 2013, 2015). People of differing ideological positions will often *frame* matters differently in argumentation on any particular issue, where the *framing* of an issue is an ideological viewpoint or perspective on that issue: that is, a set of beliefs, assumptions, and pre-compiled arguments. Entman (1993, p. 52) describes framing as a matter of "selection and salience. To frame is to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described." For example, on the issue of how much immigration should be allowed into their country, one person might frame the argument as one of economic benefit or detriment, whereas a second person might frame it as one of the benefits or problems of multiculturalism, and a third might frame it as an imperative, or not, of social justice.

And this leads to the idea of computational methods that could look at a political discourse and identify the *ideological framework* that the speaker or writer is implicitly using — in practice, some kind of quantifiable semantic reflections of ideologically charged ideas or beliefs. The work that we will present below is directed towards this long-term goal, putting an emphasis on automatically finding the relations between clausal units and on finding the unspoken, and possibly ideological, premises in an enthymematic argument. This would include the creation of computational tools for finding and analyzing argumentation in large corpora of political texts, both historical and contemporary. For example, these tools might answer, or help us answer, questions such as *Find arguments that support the Antwerp debt-reduction plan*, *How do opponents of the Cabbage Abatement Act justify their positions?*, and *What ideological frameworks were used to argue against immigration in 1905?* We envision users of such a system to include political historians, journalists, and ordinary citizens. (In our own work, we are focusing on the digitized archives of the parliamentary proceedings of Canada, the U.K., and the Netherlands.)

Building a system such as this is an ambitious, long-term project for the research field. Its components include automatically discriminating the argumentative portions of the texts from the non-argumentative and metadiscursive portions. In the former, we want to then automatically find the structure of the arguments, distinguishing the premises from the conclusion, identifying the argumentation scheme, and, where possible, the unstated argumentative and ideological elements. Prior research with similar goals has taken approaches largely based on text-classification methods with primarily lexical features, achieving only modest success.

Automatically identifying implicit assumptions and conclusions remains a distant goal, but it is one that can be aided by simpler methods for the identification of ideological positions and background knowledge about particular ideologies, such as those to be discussed in the next two sections. If, in the course of automatic political argument analysis, a known ideological assumption can be fitted to the hypothesized argument, then confidence increases in both the identification of the argument and the identification of its underlying ideology.

2. THE ROLE OF VOCABULARY

In a political debate, or some other expression of a position on some specific topic, where exactly in the language that speakers and writers use does their ideology become apparent? We might expect that it's not in the words themselves, because the words relate to aspects of the topic of the debate regardless of which side the speaker[2] is on, and that it's only at higher levels — sentences and text — that the ideology becomes apparent. But in fact, what we find is that different ideological frameworks lead to different word usage even for the same topic.

So then perhaps we can identify the ideology of a speaker just from the vocabulary that they use in their argument — so-called *bags of words* with a weighted frequency count of each word spoken. And researchers in Natural Language Processing have tried to do exactly this. Overall, the results have been mixed. For example, Diermeier, Godbout, Yu, and Kaufmann (2007) tried to classify U.S. senators as ideologically liberal or conservative just by looking at the words they used. They found that this was easy to do for senators who were at the extremes of the ideological spectrum; but they couldn't do it for

[2] We will generally use the word *speaker* to subsume both speakers and writers. In the experiments described below in this section, the data is written transcripts of political speeches.

senators who were in the middle of the spectrum, for whom they obtained essentially chance accuracy. Nonetheless, when they looked at the vocabulary that discriminated the extreme senators, they found a few easy shibboleths: For example, if an extreme senator says the word *gay*, they're liberal, and if they say *homosexual* they're conservative. And that one word (if they use it at all) is sufficient to accurately classify them. But usually, it isn't that easy.

We followed up on Diermeier et al.'s work (Hirst et al., 2014) by looking at speeches in the European Parliament, where there is a multi-party spectrum of ideology that is much broader than in the U.S. Congress and in which a left–right ideological division is dominant (Hix et al., 2007). We took the English version of the proceedings of the European Parliament from 2000 to 2010, and asked whether we could classify each speaker, using only their vocabulary, as left-wing or right-wing, and *a fortiori* classify them by party membership. Figure 1 shows the ideological spectrum of the parties in the period that we studied. For ideology classification, to create a left–right split, we removed the ALDE in the centre, and grouped the other parties as either left-wing or right-wing. For the party-membership classification, we removed the small right-wing parties from the data and classified only members of the five largest parties. The classification algorithm that we used was a support-vector machine with 5-fold cross-validation.

⟵ Left –Centre– Right ⟶

European United Left / Nordic Green Left (GUE/NGL)	Progressive Alliance of Socialists and Democrats (PES)	The Greens / European Free Alliance (EFA)	Alliance of Liberals and Democrats (ALDE)	European People's Party (EPP)	Small right-wing groups (ECR, EDD, UEN, EFD, ITS)

Figure 1 – The ideological spectrum of parties in the European Parliament in 2000 to 2010.

We found that we could distinguish between speakers from left-wing parties and those from right-wing parties with an accuracy of 78.5%; this was 28 points above the baseline of just choosing the most frequent class, which was 50.5%. Further, we could distinguish which of the five major parties a speaker belonged to with an accuracy of 61.8%, which was 23 points above the most-frequent-class baseline. And again there were a few easy shibboleths: for example, the words *profits* and *militarization* indicate a speaker from the hard left, and the words *subsidiarity* and *competitiveness* indicate a speaker from the hard right.

However, there are serious limits to this approach. For example, we found that it utterly failed on speeches in the Canadian Parliament (Hirst et al., 2014). The method was able to distinguish the language of a governing party from that of an opposition party with very high accuracy — 84 to 97% depending on the exact conditions — but what the classifier had actually learned was the language of political attack and defence, with little or no expression of ideological positions at all. This finding reflects the adversarial nature of Canadian politics.

In addition to finding ideological positions across topics, vocabulary-based methods are also used for *stance detection*, the task of determining the speaker's position, pro or con, on a specific known issue. This is typified by the work of Anand et al. (2011) and Somasundaran and Wiebe (2010).

Now, a critic of all this work might say, with some justification, that it completely evades most of the problem. We don't want to know only what a speaker's ideology or position is; we also want to know *how* they argue for or justify that position. Yet all these methods do is use the speaker's vocabulary, without even any consideration of the order in which the words were uttered, let alone any thought about meaning or content or structure of the argumentation itself! Nonetheless, they demonstrate that textual analysis does not always need to use structure or meaning or deep semantic analysis to succeed in its aims. But surely we can do even better if, yes, we start using a more linguistically informed analysis and incorporating syntactic, semantic, and discourse-pragmatic features into the analysis, as we will now discuss.

3. SHALLOW LINGUISTIC ANALYSIS TO RECOGNIZE ARGUMENTATION SCHEMES[3]

Argumentation schemes are the templates or structures from which ordinary textual arguments are built — common forms of argument that are more usually presumptive and defeasible than deductive. Walton, Reed, and Macagno (2008) have catalogued 65 distinct schemes, and each scheme has an associated set of critical questions that challenge arguments in the scheme and their implicit premises. Many of these schemes are quite rare, so we concentrated on the five schemes that are

[3] This section is based on work that was first presented by Feng and Hirst (2011).

most frequent in the Araucaria database, a corpus of annotated arguments produced at the University of Dundee[4]:

- *Argument from example*, and *argument from cause to effect*, whose meanings are clear from their names.
- *Practical reasoning,* which is an argument that a certain pre-condition should be brought about in order to achieve a goal.
- *Argument from consequences,* which is an argument that something should be done because the consequences will be good, or should not be done because the consequences will be bad.
- *Argument from verbal classification*, which is a quasi-syllogistic — "quasi-" because it depends on defeasible classifications.

It should be understood that in this work we are *not* recognizing the presence in the text of the arguments themselves or their elements — their premises and conclusions. This is a task that has been studied, with some moderate success, by other researchers (e.g., Mochales and Moens, 2008, 2009a, 2009b; Stab and Gurevych, 2014; Nguyen and Litman, 2015), and we see argument-scheme recognition as being "downstream" in the analysis pipeline from this, assuming its eventual success.

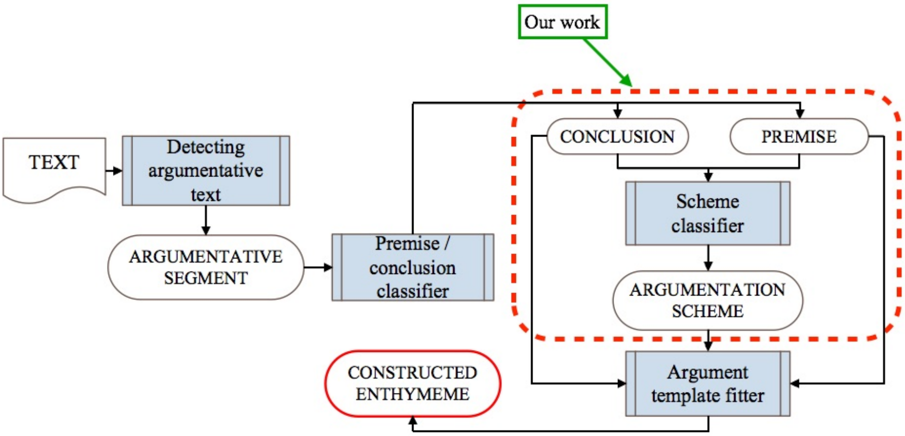

Figure 2 – The classification of argumentation schemes within an argument analysis system.

Hence, in a completed system (figure 2), prior processes would pick out argumentative segments of the input text, and try to identify the premises and conclusions in each. Given that, we then classify the

[4] http://araucaria.computing.dundee.ac.uk/doku.php

argumentation scheme that is being used, which, in turn, would be used by further processes to reconstruct the full enthymematic argument, and beyond that (not shown in the figure) to start to identify the ideological framing of the argument. Thus we are crucially assuming that current research on other aspects of argument analysis will be successful: detection and classification of the components, and determining whether an argument is linked or convergent — whether it requires a conjunction or merely a disjunction of its premises. We cast the problem as one of text classification.

Before any analysis of the text for argumentation, we first analyze it syntactically— specifically, a dependency analysis — using the Stanford parser (de Marneffe, MacCartney, and Manning, 2006)[5], which is a standard in the field. Then, to recognize argumentation schemes, we use a number of features that apply to all five schemes and some that are specific to each argumentation scheme. The features that apply to all schemes mostly concern the textual structure of the argument or whether it is a linked or convergent argument; the features are listed in table 1.

The location of the conclusion in the text.
The location of the first premise.
Whether the conclusion appears before the first premise.
The interval between the conclusion and the first premise.
The ratio of the length of the premise(s) to that of the conclusion.
The number of explicit premises in the argument.
Type of argumentation structure: linked or convergent.

Table 1 – Features used in classification for all five argumentation schemes.

The scheme-specific features are words and semantic patterns. For example, for argument from example, we look for the words *for example*, among others. For argument from cause to effect, we look for verbs that indicate cause, and we also use a number of textual patterns that indicate causal relationships (Gîrju, 2003); and analogously for practical reasoning. For argument from consequences, we look for propositions that are positive and negative, which we determine from the sentiment rating of the words in the *General Inquirer*, a computational lexicon (Stone, Dunphy, Smith, and Ogilvie, 1966)[6]. And

[5] http://nlp.stanford.edu/software/lex-parser.shtml

[6] http://www.wjh.harvard.edu/~inquirer

for argument from verbal classification, we look for textual similarities between the premises and the conclusions, and for appropriate dependency relations in both premises and conclusions: copulas, expletives, and negative modifiers. Details of these features are given by Feng and Hirst (2011).

Our classification algorithm was C4.5 (Quinlan, 1993), which builds a decision-tree for classification from a set of features, and we trained it on the Araucaria corpus of arguments from Dundee, introduced above, which is annotated with argumentation schemes. We created ten random pools of data in which baseline guessing was always 50%, and we then did 10-fold cross-validation on this data. We used two methods of evaluation: a one-versus-others classification in which we try to discriminate one scheme from all the others, and a pairwise classification for each of the ten possible pairings of the five schemes. Our evaluation metric was average accuracy.

The results for one-against-others classification are shown in table 2. We were able to distinguish argument from example and practical reasoning from all the others with accuracies above 90%. For argument from cause to effect, we achieved a more modest 70%, and accuracies were around 63% for the other two — which is still well above the baseline of 50%. The low accuracy for these last two schemes is probably due at least partly to the fact that they don't have the obvious cue phrases or patterns that the other three schemes have; and it is also perhaps because they were the schemes for which we had the least available training data. Table 3 shows the results for pairwise classification. For some pairs, we get near-perfect accuracy: practical reasoning versus argument from consequences and versus verbal classification; and practical reasoning versus argument from example and versus argument from cause to effect both achieve 93–94%. Many other pairs achieve accuracies around 86%. The result that stands out as poorest, at 64%, is between verbal classification and argument from consequences, which were also our two poorest categories for one-against-others classification.

Scheme	**Accuracy (%)**
Argument from example	90.6
Argument from cause to effect	70.4
Practical reasoning	90.8
Argument from consequences	62.9
Argument from verbal classification	63.2

Table 2 – Results of one-against-others argument scheme classification.

	Accuracy (%)			
	Example	**Cause**	**Reasoning**	**Consequences**
Cause	80.6			
Reasoning	93.1	94.2		
Consequences	86.9	86.7	97.2	
Classification	86.0	85.6	98.3	64.2

Table 3 – Results of pairwise argument scheme classification.

These results, then, can be the basis for future work to recover the missing premises of arguments. Some of these premises will be implied by the structure of the argumentation scheme itself, in conjunction with its critical questions. Others, we hope, will be found in a large set of what we are calling *"axioms"* of political argumentation and ideology, which we are presently working to derive from large corpora. Additional such "axioms" may be generated from the text itself, by textual entailment, implicature, or logical necessity. And some will come from searching more-general background knowledge, which is another present research area.

4. RECOGNIZING DISCOURSE STRUCTURE

Last, we briefly discuss the role of discourse parsing in the recognition of argumentation schemes — that is, determining the structure of an argumentative text in terms of *Rhetorical Structure Theory* (RST) (Mann & Thompson 1988). RST builds trees of relationships between the units of a discourse — the so-called *elementary discourse units* (EDUs), which are usually clauses or clause-like constituents of the text. There are 16 classes of relations possible between these units or between groups of units, which are listed in table 4. Some of the names, such as CAUSE and ENABLEMENT, already hint at the relationship between RST and argumentation. And in most of these relationships, a distinction is made in which one EDU is more prominent in the discourse than the other; the prominent unit is called the *nucleus* and the other is called the *satellite*.

ATTRIBUTION	CONDITION	EVALUATION	SUMMARY
BACKGROUND	CONTRAST	EXPLANATION	TEMPORAL
CAUSE	ELABORATION	JOINT	TOPIC-CHANGE
COMPARISON	ENABLEMENT	MANNER-MEANS	TOPIC-COMMENT

Table 4 – Classes of relationships in Rhetorical Structure Theory.

A number of the discourse relationships of Rhetorical Structure Theory (RST) have clear counterparts as argumentative relationships, and in the case of arguments, the RST structure of the text will mirror, at least to some extent, the structure of the argument; therefore, an RST analysis of a text will be an important component of the structural analysis of argumentation in a text. In one experiment using five common argumentation schemes, Cabrio, Tonelli, and Villata (2013) showed that an RST relation did indeed match the cognate argumentation scheme in about two-thirds of the cases where annotation was possible at all. Hence, RST relationships will be an important feature both in the analysis of arguments, and in recognizing argumentative text in the first place; and hence discourse parsing becomes part of this work. Discourse parsing is not a new topic, but recent work both by us (Feng and Hirst, 1012, 2014) and by others (Joty, Carenini, Ng, and Mehdad, 2013) has aimed to improve it substantially. This includes improving the initial segmentation into units, improving the parsing itself by using more linguistic knowledge and by building a smarter parser that works differently between sentences than within sentences. Feng and Hirst's parser also includes a post-editing adjustment process.

The results are generally increased accuracies in all aspects of the procedure compared to earlier work, and getting closer to human levels. Even though the role of some RST relations in the structure of argument is unclear or uncertain, we hypothesize that as features for classification, they will nonetheless have a positive effect on the structural analysis. RST structure, then, becomes another important feature for our recognition of arguments and argumentation schemes, and forms part of our current research.

5. CONCLUSION

Research in the automatic (or semi-automatic) analysis of political and opinionated text has begun to look more deeply at arguments, opinions, and ideologies. Shallow, word-based methods often suffice for simple analyses, but more-linguistically informed methods are necessary to get at the actual structure of arguments. This is a useful end in itself, but beyond that, we expect that this research will also become part of the general idea of semantic search, so that, with future developments, argumentation, opinion, and ideology can be used as facets in Web searches, or searches of large document collections; in automatically answering questions; and in automatically creating summaries and syntheses of large numbers of documents.

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