Structured argumentation modeling and extraction: Understanding the semantics of parliamentary content

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ABSTRACT

In information overload scenarios, the volume, structure and complexity of generated data represent a challenge that hinders the content comprehension. Aiming to overcome these dissuasive issues, the modeling and extraction of arguments in textual content has become a prominent topic in the information retrieval field. In this paper, we propose a new argumentation model, where different semantic components and their relationships are considered. Our proposal aims to enhance state of the art approaches, which limit their scope to identifying chunks of text as argumentative or not, leading to large amounts of texts left unanalyzed. The presented model, differently to domain-specific corpus methods, is designed to enable a generic, cross-lingual semantic annotation that promotes reusability. As a proof of concept, the model is exemplified in a case study for an e-government platform intended to annotate semantically, and provide information retrieval and filtering functionalities on content produced in the Spanish Parliament.

CCS CONCEPTS

• **Information systems** → **Information extraction**; **Information retrieval**; • **Computing methodologies** → **Discourse, dialogue and pragmatics**.

KEYWORDS

Argument Mining, Semantic Annotation, Parliamentary Content

1 INTRODUCTION

There is a vast and ever-increasing amount of multimedia material capturing debates, proposals and opinions. This issue, along with the unstructured nature of generated content, makes it difficult to organize, explore and retrieve relevant information.

An argument can be defined as a piece of text that provides proof or logic in support or against a particular subject. With the aim to assist in text interpretation, summarization and visualization, *Argumentation Mining* (AM) includes the tasks of identifying, extracting and evaluating claims, providing resources for decision making [15, 16]. Thus, AM itself presents a potential prospect of pursuing semantic annotations from public deliberations, serving as an instrument for assessing public opinion.

One of the limitations of previous research in AM is the fact that existing approaches have focused on the identification of claims and (non) argumentative text fragments. This leads to highly unbalanced annotated texts to classify and unravel, being most of the sentences left unanalyzed, as they are identified as non argumentative [3, 5,

8]. Besides, the principal trend in the AM research conducted so far is the development of corpus-driven approaches, which report features and insights derived from specific studies on particular texts [15, 16]. Hence, these works, which analyze and remark details and aspects of argumentative texts, are too specific and dependent on the analyzed corpora and addressed domains [5, 14, 19]. This results in non reproducible and non cross-lingual methods.

Aiming to overcome these limitations, in this paper, we propose a generic model that considers argument structures with different semantic components and relationships. To favor the understanding of the model, we present it by means of visual, explanatory diagrams. Hence, the claimed contributions of this position paper are:

- An extension of an argumentative model to empower its capabilities and overcome its limitations.
- A proposal of how to automatically extract structured arguments from texts, according to the proposed model.

To illustrate our proposal, we consider a case study on contents extracted from the Spanish Parliament; more specifically, from texts retrieved from TIPI Ciudadano, an online tool that tracks legislative behavior related to fighting injustice and discrimination. Conceived to address specific needs of citizens, journalists, social activists, and political leaders, TIPI crawles and parses textual content generated in the Spanish Congress of Deputies, and enables information retrieval and filtering functionalities on such content.

2 ARGUMENTATION MODELS

The general process of AM is tagging sentences or part of sentences according to (non) argumentative categories to later build a comprehensive, logical argumentation diagram. Existing approaches vary on a) their logical diagrams and thus the tags used to build them, and b) the techniques used to tag each "chunk of text"[15, 16]. Regarding the latter, Section 3.2.1 presents a quick overview. As for the former, two approaches can be considered as the most popular in the research literature. The first one is Toulmin's method [28], where six functional roles are proposed, namely claim, data, warrant, backing, qualifiers and rebuttal. This method, although widely used as a starting point to argument modeling, has a number of shortcomings identified by several researchers over the years [10, 21], advocating for a more serial structure and stating a redundancy of several of the defined roles. The second approach is RST (Rhetorical Structure Theory) [17], which arranges texts in regions, each of them with a central part (nucleus) that is essential to understanding the text, and a number of satellites that contain additional information. The nucleus and satellites are linked by 31 different relationships
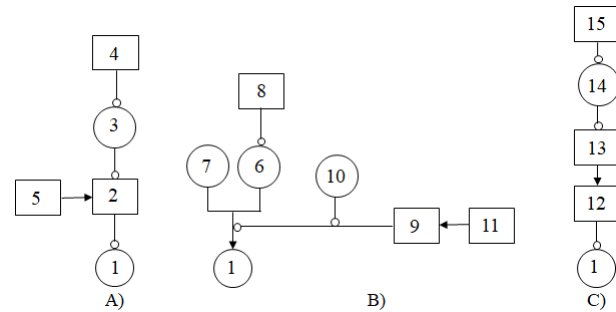
http://tipiciudadano.es

(e.g., circumstance, elaboration, and proof) that can be modified, distorted, inserted or subdivided according to the subject and the task at hand. RST argument analyses are usually depicted as trees, with a single top-level relationship that includes other relationships at a lower levels. Identified limitations of this method are the long-distance dependencies of different argumentation types [1, 23, 26], and the representation of rebuttal and counter-rebuttal arguments for which there are cases that cannot be captured by RST trees [23]. According to the reviewed literature [15, 16, 23], these two methods are not only the most popular but also the most adequate for AM. The survey by Peldszus and Stede [23] proposes a theoretical argumentation graph that models premises and conclusions connected by means of proponent-challenger relationships, and represents forms of rebutting/undercutting and attacks/counterattack both on the graph nodes and relations. The model is proved to be able to capture the relationships, structures and dependencies as Toulmin's and RST approaches. For this reason, we use it as a basis of our proposal. In their work, the authors assume that texts/sentences have already been classified as (non) arguments, and focus on a theoretical method for modeling text chunks with their argumentative roles, and the relations between chunks. Figure 1 illustrates the model behaviour given the following sentence examples: 1. This building needs to be demolished; 2. Even if it's meant to be a tourist destination; 3. Yet I've never seen any visitors in there!; 4. The building has 30 visitors per day; 5. Conserving would improve tourist income in X; 6. It is full of termites; 7. Infested buildings should be teared down. 8. Yet, no one ever did make a profound inspection of the infestation's extent; 9. It could be disinfected, though; 10. But according to reported news, it will be prohibitively costly; 11. In 2001 the mayor of X employed a successful cleaning of a termite infested public building; 12. On the other hand, a lot of people enjoyed the view from the top; 13. On holidays, the roof is normally packed with sunset parties; 14. Its too risky the roof might collapse and cause an accident!; 15. Protocol preventives measures are being executed so that this does not happen.

The approach understands an argument as a set of premises supporting a claim expressed in the text segments. In it:

- An argument can be either supported (those with an arrow-end) or attacked (those with a circle-end).
- An argument allows support and attack not only for statements (nodes) but also (recursively) for relations.
- The stance of each sentence (defined as the attitude towards a claim [12, 24, 29]) is represented by box nodes in the case of attacks of a challenger and by circle nodes in the case of supporters and counter-attacks of the proponent.
- Rebuttals can also be rebutted. Thus, building a branching tree of premises built along backing or rebutting premises (or relations) aiming to argument upon a claim.
- Arguments can have two different structures: i) linked, a unique end joining several premises (as in example B of Figure 1), and ii) standalone. In the latter, both arguments stand for themselves and each of them could be put forward without the other, i.e., arguments are independent from another in the sense that the supporting force of one argument would not be impaired if the supporting force of the other is undercut. For example, this is not the case of sentence 7, whose strength is linked to sentence 6.

Figure 1: Example of the theoretical argumentation model by Peldszus and Stede [23].

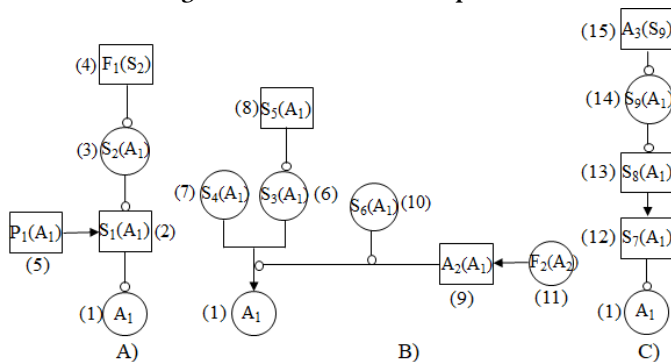- Serial relationships develop an argument already given, by supporting one of the argument premises.

We note that one of the limitations of this model is that it fully relies on properly pre-annotated texts that allow classifying each sentence as argumentative or non argumentative given a unique identified claim. In practice, however, several of the previously presented examples (particularly 4, 5, 6, 11, 13 and 15) would not have been analyzed as they would have been identified as non argumentative by state-of-the-art methods [5, 8, 14–16, 19, 22, 25], and thus are ignored in the subsequent AM steps. This is the case of the majority of implicit arguments or sentences that do not present an argument itself, but support with facts, statements or proposals other argumentative sentences. Another limitation of the approach is found in long serial arguments, where the opinion of the analyzed text, and thus its stance and box/square representation, should no longer refer to the original claim, but to an intermediate one. To overcome these two limitations, in the following we propose an extension of the model by including new component types and an argumentative function notation that allows grouping and substructure designs.

3 PROPOSAL: THE FAPS MODEL

3.1 Argument structure

As said before, AM approaches are mainly corpus-derived. Thus, following a top-down hierarchical classification, corpora are firstly annotated to distinguish between claims, neutral and argumentative fragments. Occasionally authors further tag domain-specific types of argument [5, 22]. This methodology leads to: i) highly unbalanced samples [3, 5, 14, 19, 22], where most of the sentences are left unprocessed as they are pre-classified as neutral, and thus limit the comprehensive, summarizing and visualizing capabilities of the devised approaches; and ii) domain- and corpus-dependent conclusions, which limits generalization and reproducibility.

We propose to overcome these limitations by designing a model that identifies further non-domain related argumenative categories, which being general characteristics of produced texts help redistributing the neutral and argumentative labels in 4 different semantic categories. Similarly to [5], these categories have been identified after manually reviewing hundreds of examples. Opposite to RST, which identifies 31 types of relationships between arguments making it difficult for the tagger/reader to interpret all the fine-grained subtleness of each definition, we keep the annotation to 4 types,

Figure 2: FAPS model example.

simplifying the problem yet empowering the classification by further outlining characteristics that are otherwise lost in previous models [23]. In our model, FAPS (**F**acts, **A**ctions, **P**redictions and **S**tatements), each text fragment is classified as either:

- Facts/warrants: something known to exist or have happened.
- Actions/proposals/objectives: proposing issues to be done or a curse of action.
- Predictions/assumptions: foretelling or declaring something in advance.
- Statements (that can either be positive or negative): stating or asserting something. This includes subjective judgments, such as opinions and beliefs.

This type of sentences can be used as an argument to support/rebut a claim or as a motivation to propose/present a claim. We believe that this refinement is needed to better comprehend arguments and facilitate their exploitation. Figure 2 exemplifies our proposal. The original sentence numbers are given close to each node, not as part of the model, but for comparison purposes with the original model in Figure 1. Based on the approach presented in Peldszus and Stede [23] –which as previously mentioned, outruns previous models (i.e., Toulmin's and RST)–, we propose to complement it by incorporating into our FAPS model enhanced summarization and visualization capabilities. In particular, instead of assuming a previously annotated text modeled as an argument and its stance towards a unique claim, we propose to further annotate each text with the above mentioned FAPS categories. This, as previously explained, overcomes the problem of highly unbalanced samples with unanalyzed texts, and allows identifying and analyzing stated sentences that would be ignored by previous two-fold (argumentative vs. non argumentative) classification approaches [5, 8, 14–16, 19, 22, 25]. In our model, instead of having numbers that refer to the positions of sentences within an argument, nodes have acronyms of their corresponding FAPS component categories and subindices indicating their ordering for that categories. As shown in Figure 2, the model includes groups and substructures through an argumentative function notation. This, as previously motivated, overcomes confusing serial arguments in the original model where both the sentence meaning and its corresponding stance refers to an intermediate sentence/argument and not to the original claim. This is the case of example C in Figure 2, where sentence 15 not only rebuts sentence 14 –which is captured by the original notation with a circle arrow end–, but also its negative

stance (represented as a box), which refers to that sentence and not the original sentence 1.

Our function notation allows describing this situation, whereas the model by Peldszus and Stede [23] fails to do so. In example B of Figure 2, the problem is even more acute: sentence 11 is a fact that strengthens statement 9; it does not indicate any stance towards the original claim. Given that, it supports sentence 9, which has a negative stance and would have been labeled as a negative stance and represented with a box shape, as in Figure 1. The sentence actually does not reflect any sentiment or opinion towards the original claim, and hence assumptions should not be done.

By implicitly highlighting FAPS categories in the text and visually restructuring it as in Figure 2, insights can be more easily observed. For instance: i) facts are more difficult to refute, and thus an argument being supported by numerous facts is more solid than those supported by mere statements; ii) facts rebutting an affirmation are more solid and serve to rule out the latter; iii) predictions are needed to ascertain or motivate what possible outcomes the argument at hand could have, meaning that actions proposed with predicted outcomes are typically more argumentative and solid; iv) arguments without proposals of actions to be taken are less solid than those proposing solutions or alternatives. This is frequently exemplified in politics where candidates expose empty proposals and endless arguments without presenting any solution.

To further exemplify our model, Table 1 presents FAPS categories of sentences extracted from the TIPI database introduced in Section 1. We note that in the considered domain, argument mining techniques have only been applied for thread analysis of online civic discussion in e-rulemaking [5, 8, 14, 19, 22, 25].

3.2 Argument extraction pipeline

To automate and generate the previously described model (exemplified in Figure 2), we propose to analyze the chunks of the text at sentence level, and extract 4-tuples (a, r, s, t) where a denotes the *text* being evaluated, r represents to whom it is connected, i.e., other *text* or null in the case of an initial claim, s is the stance towards the related *text* (positive/negative/neither), and t is the *text* component type according to the FAPS model. We note that AM approaches commonly follow the steps summarized next.

3.2.1 Argument detection. This step refers to the task of classifying a sentence as argumentative or non argumentative. In our case, it would consist in identifying FAPS categories. Traditional methods make use of annotated corpora in which they later run Machine Learning (ML) classification [16]. Previous works do not report a special difference in the performance of distinct ML approaches [16] (pointing at the *no free lunch theorem* [30]). Typical features used range from basic lexical properties, semantics, sentiment and subjectivity to metadata. In this context, prior classification to identify claims is often carried out. The need of a previously annotated corpus is an obvious limitation of reusability. In the literature, several approaches that follow similar steps and ML algorithms to adjust to and report the characteristics of their corpora and domains [5, 8, 14, 19, 22, 25]. By classifying examples from Table 1, we have identified a set of general rules that focus on semantics and lexical properties that could be trained, and are domain-independent and cross-lingual. For this reason, we propose to follow this approach.

3.2.2 Relations identification. This step aims to extract the relation of an argument either towards a known topic or towards an

Table 1: Examples from TIPI texts for each FAPS component.

Type	Example
Claims	"Enable by means of the appropriate legal form and transfer to the Autonomous Community of the Canary Islands the 8 million euros for well and desalinated water contemplated in the General State Budgets in force"; "IBI rebate in Lorca and infrastructure repair as a consequence of the seismic movements of May 11, 2011";
Facts	"Royal Legislative Decree 2/2004, of March 5, contemplates that municipalities apply a series of mandatory or optional bonuses in Articles 73.3 and 73.4 respectively"; "in Art. 73 Compulsory bonuses Point 3 refers to the compulsory bonus of 95% of rustic assets of agricultural cooperatives and community land exploitation"; "The Autonomous Community of the Canary Islands to lower the cost of desalination and the extraction of water from wells and galleries for agricultural irrigation in the Canary Islands authorized the transfer of the 8 million euros corresponding to the year 2018, on April of 2019"
Actions	"That the benefits of the hydroelectric jumps be used for the economic and social restitution of the territories affected by the hydroelectric installations and for other purposes of public utility or social interest of a general nature"; "We propose to make said property available to the community members at the necessary time and at the lowest possible cost."; "The program identifies three priority areas that require more actions aimed at protecting nature and strengthening ecological resilience: i) promoting low-carbon growth that uses resources efficiently..."
Predictions	"Said report predicts a rise in the mean sea level of between 50 cm and 1 m by the end of the century"; "A reduction in the activity of the tourist sector could be expected as a result of the degradation of the coast and the scarcity of water"; "It is to put them every year in the situation of applying or not a bonus and deciding in what percentage, which will create comparative grievances between different Municipal Corporations and also cause a situation of uncertainty"
Statements	"Practically all the investments made in hydroelectric exploitation respond to the investment-concession model"; "The same properties that make plastics so versatile in countless applications (durability and resistance to degradation) make these materials difficult or impossible for nature to assimilate"; "It does not make sense therefore that the necessary infrastructures for you to irrigate (the rafts), pay IBI"

argument previously expressed. This task can include micro and macro analysis. Micro analyses asses the consistency and completeness of the argument, whereas macro analyses (the most popular) express relations between arguments. Most of the designed methods [2, 4, 9, 13] classify relations between arguments as support/attack/neither by using annotated corpora in which they later run ML (with the limitations previously stated). This task is two fold: i) Identifying lexical dependencies between two *texts*; in our model, by linking two nodes. To automate this task, NLP tools such as the Stanford CoreNLP toolkit [18] may be used to extract entities and semantic dependencies. ii) Identifying semantic dependencies towards the *text* they are backing or refuting; in our modle, arrow or circle ends. Here we find two relation types: *causal*, which covers argumentative support, and *contrastive*, which covers rebuttal and counter-rebuttal arrangements. The PhD thesis by Knott [11] covers a comprehensive study of coherence relations, identifying several types of connectors (contrast, addition, example, etc.) and prefixed common useful expressions that identify topic presentation, sequence of ideas, opinions, possibility or comparisons. Thus, for the relation identification task, we propose to firstly analyze the lexical dependencies through the cited tools and continue analyzing the connectors (with the aid of part-of-speech tagging) through a set of rules. We note that there are two forms of connections: explicit and implicit. The former is characterized by the presence of certain syntactic constructions whereas the latter, where there is noticeable lack of these features, can be detected by previously acquired information and logical inferences. Noting that connector and word expressions are the main tools to establish different types of relationships between words and sentences and that, as stated before, the number of commonly used connectors in a language is relatively limited, and their employment in constructions is basically entailed, we believe this proposal could overcome the aforementioned limitations.

3.2.3 Stance detection. Relates to sentiment analysis and topic extraction [6, 12, 24, 29]. This task relates to evaluating the attitude towards a specific topic leveraging any kind of knowledge that may be gathered. The task to be performed is classifying each sentence into favor/against/neutral about a related topic, where the majority of related research [6, 12, 24] has focused on semi-supervised approaches and available small annotated datasets is adequate to mark larger unlabelled datasets, so that they can be

used to train ML models. Again, so far designed models suffer from reproducibility issues. For instance, those corpora and models devised in the same language that our case study (Spanish), even though they are popular and widely used [27], could not be reused for our purposes due to their specific nature (e.g., Stance and Gender Detection in Tweets on Catalan Independence). Hence, for this task traditional corpus based ML techniques would be followed.

3.2.4 Reliability-related tasks. A key step in AM is the study of the significance of the original claim, either in the form of assumptions or in the form of supported evidence and presented facts. While some of them are clearly supported by facts from reliable sources, others merely express feelings or baseless accusations instead of defending their assertions. This task falls out of the scope of this paper although we believe it is an interesting topic, specially related to the presented case study as it could lead to annotating the verisimilitude of speakers in the congress. We refer the reader to recent overviews of the topic [7, 20].

4 CONCLUSIONS

There are three key criteria to design AM models: i) The complexity level they are able to model, which is determined based on the number of components and relations each theory involves. In this aspect, many state-of-the-art models leave huge amounts of text unannotated due to their two-fold (argumentative or non argumentative) classification. ii) Their robustness. In this context, several state-of-the-art approaches loose comprehensive power when complexity and extension increase. iii) Their reproducibility in different domains. To overcome this, we have proposed a new AM model, FAPS, which enables a generic, cross-lingual semantic annotation that promotes reusability and robustness. To do so, new component argumentative types have been defined, by means of an argumentative function notation. Proposals on how to implement our model have been outlined following a small case study related to content generated in the Spanish Parliament.

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