ArgMine: A Framework for Argumentation Mining

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Abstract. The aim of argumentation mining is the automatic detection and identification of the argumentative structure contained within a piece of natural language text. In this paper we present the ArgMine Framework: an alignment of tools and processes that facilitate and partially automate argumentation mining research. We also report on a preliminary exploitation of the framework, where we address argumentative zoning, a sub-task of argumentation mining, whose aim is to automatically select the zones of the text that contain argumentative content. The target corpus used to train the supervised machine learning algorithms was manually annotated and is composed of Portuguese news articles, to which argumentation mining does not seem to have been applied before. Given the dataset used in our experiments and from the critical analysis of the obtained results, we conclude that lexical and syntactic-based features are not enough to successfully address argumentation zoning.

1 Introduction

Argumentation is the process whereby arguments are constructed, presented and evaluated. An argument (e.g. *"All men are mortal and Socrates is a man. Therefore, Socrates is mortal."*) is composed by a set of propositions, where some of them (the premises) are pieces of evidence offered in support of a conclusion. The conclusion is a proposition that has truth-value (which is either true or false), put forward by somebody as true on the basis of the premises. The ability to engage in the process of argumentation is essential for the human beings. Humans use argumentation to communicate and defend their justifiable positions (or opinions), to understand new problems and to perform scientific reasoning. We can find arguments almost everywhere: scientific texts, legal texts and court decisions, biomedical texts, patents, reviews, debates, dialogs, news, and so on.

The aim of *argumentation mining*, a sub-domain of text mining, is the automatic detection and identification of the argumentative structure contained within a piece of natural language text. As input, this process receives a piece of natural language text. We aim to detect all the arguments presented in the text,

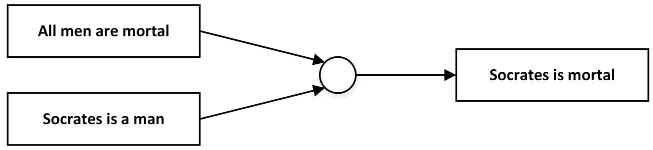

Fig. 1. Argument Diagram

the relations between them and the internal structure of each individual argument. In the end, we want to output the corresponding *argument diagram*: the visual representation of the arguments contained in the text. An argument diagram is a graph structure, where each node corresponds to a proposition (premise or conclusion) and arrows indicate relations of support or conflict between premises and conclusions, as shown in Figure 1. The full task of argumentation mining can be decomposed in several subtasks, as described in [11], namely: segmentation, identification of argumentative discourse units, argumentative discourse units classification, relation identification and relation type classification. In this paper, we address the problem of *segmentation*.

2 Background and Related Work

The current state-of-the-art in argumentation does not afford a universally accepted theory nor a theory that could be applied to every domain. Currently, there is a variety of approaches that differ considerably in conceptualization, scope and degree of theoretical refinement [2, 1, 15, 3, 16].

Our formalism to define the internal structure of an argument is based on [16], and determines that each elementary unit of an argument can be classified between premise and conclusion. To represent the relations between elementary units, we consider convergent and linked arguments, as introduced in [3].

Current approaches to automatically analyze argumentative content in text usually follow the supervised machine learning paradigm. One of the first works devoted to the identification of arguments in text was *Argumentative Zoning* [14], whose aim is the segmentation of a discourse into discourse segments or zones, each playing a specific rhetoric role in the text. Teufel et al. presented an algorithm which, on the basis of the annotated scientific articles, classifies the content into a fixed set of seven rhetorical categories.

The aim of argumentation mining is different from argumentative zoning. In the former, we are not only interested in classifying each text segment by their argumentative function, but we also aim to automatically identify the argumentative relations between each argumentative component, leading to the detection of full argument diagrams. One of the first and most influential attempts to apply machine learning techniques to the task of argumentation mining is presented in [9] and is based in text from legal domain. Palau et al. segmented the text into clauses and represented each clause by a set of linguistic features such as unigrams, bigrams, adverbs, legal keywords and word couples. The work is divided into three subtasks. In the first subtask, detection of argumentative clauses, they reported a F1 score of 74% using Maximum Entropy classifier. In the second subtask, classification of argumentative clauses into premises and conclusions, they reported a F1 score of 68% using a Support Vector Machine. In the third subtask, detection of the argumentative structure, they used a Context Free Grammar to recognize the argumentation structure with an accuracy of 60%.

As the field of argumentation mining continues its growth, an increasing number of contributions and different methods have been explored by the community in the last years [7, 13, 12, 5].

3 ArgMine Framework

The ArgMine Framework aims to integrate the creation of an annotated corpus with arguments and the semi-automated process of selection and experimentation of different models and relevant features in different steps of the argumentation mining process. Our target corpus are news written in Portuguese, namely opinion articles. We use *CitiusTagger* [4] to perform both PoS tagging and Named Entity Classification in the Portuguese language. To apply machine learning algorithms we use *Scikit-learn* [10].

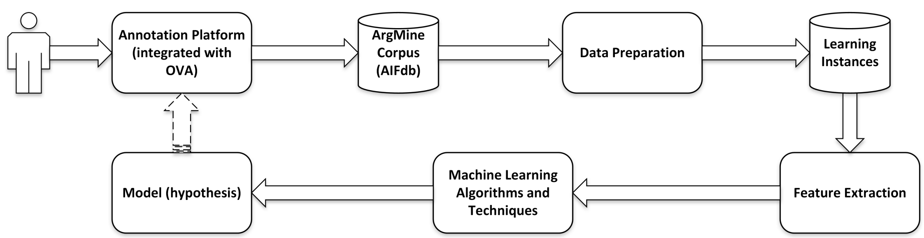

Fig. 2. ArgMine Framework

The ArgMine Framework is composed of a set of components depicted in Figure 2. The *Annotation Platform* allows users to annotate arguments and save these annotations in *AIFdb* [8] database. In the *Data Preparation* process, these annotations are transformed into *Learning Instances*, which will be the input of the learning process. Then, in the *Feature Extraction* step, we select the set of features that best represent the data. In the *Machine Learning Algorithms and Techniques* component, a set of models and feature analysis techniques are applied to determine the model and the subset of variables that performs better in the argumentation mining task. Finally, the predictive capabilities of our model are applied to suggest, in unannotated texts, potential arguments to users in the *Annotation Platform*.

3.1 Annotation Platform

Supervised machine learning algorithms need a set of labeled data (corpus) in order to build a model that learns how to map inputs to the desired outputs. As previously described, for the task of argumentation mining, the inputs are texts written in Portuguese and the outputs are argument diagrams corresponding to the structure of the arguments contained within the text. To the best of our knowledge, no such corpus exists. Thus, we have created an online and publicly available platform[4] where annotators can access news texts written in Portuguese and, in an intuitive way, identify and annotate the arguments presented in the text in the form of argument diagrams. The annotation platform is integrated with two external tools, namely *OVA* [6] and *AIFdb* [8]. *OVA* is a browser-based tool with a drag-and-drop interface that allows to manually build argument diagrams from text and save the resulting annotation in the standard *Argument Interchange Format (AIF)*. *AIFdb* is a database that allows the storage and retrieval of *AIF* compliant argument structures. The annotations obtained with this annotation platform are being collected in the *ArgMine Corpus*[5], the corpus used for the experiments presented in Section 3.2. The corpus contains, at the time of this writing, a total of 360 instances (147 argumentative sentences and 213 non argumentative sentences), extracted from 50 documents.

3.2 Argumentation Zoning

In the first approach to argumentation mining from text we did a relaxation of the original problem and we addressed the task of argumentation zoning, which aims to determine the zones of the text that have argumentative content. We make the simplifying assumption that the elementary unit of analysis is a sentence. Then, we trained classifiers that learned how to classify each sentence as argumentative or not argumentative (binary classification problem). Each sentence is represented with a set of features at the lexical and syntactic level:

- N-Gram: contiguous sequence of 1 to 3 tokens from a given sentence;
- Word couples: all possible combinations of word pairs within a sentence. The idea behind this feature is to retrieve pairs of words that capture argumentative reasoning, appearing not necessarily adjacent to each other (e.g. "Concluo [...] porque [...]", "Se [...] então [...]");
- Argumentative keywords: set of clue words directly indicating the structure of the argument (e.g. "logo", "porque", "portanto", amongst others). The presence of these words should be strong indicators of argumentative content;
- Text statistics: (*i*) Absolute Position: current sentence absolute position in relation to the document where the sentence was extracted; (*ii*) Average Word Length; (*iii*) Punctuation Marks; (*iv*) Sentence Length: number of words in current sentence;
- Adverbs: can signal argumentative content;
- Modal Auxiliary: words indicating the level of necessity, which are usually found in some type of arguments (e.g. "poder", "dever", "ter", amongst others).

[4] `https://web.fe.up.pt/~ei11124/argmine/`
[5] `http://www.arg.dundee.ac.uk/aif-corpora/ArgMine`

The best results were obtained using a Support Vector Machine classifier with a linear kernel and using the following set of features: word couples, argumentative keywords, average word length, absolute position, modal auxiliary and adverbs. The results in Table 1 were obtained using five-fold cross-validation.

	precision	recall	f1-score	support
no argument	0.70	0.68	0.69	213
argument	0.56	0.59	0.57	147
avg / total	0.64	0.64	0.64	360

Table 1. Argumentation Zoning Scores

We obtained better overall results in the detection of non argumentative sentences (0.69), as compared to the results obtained in the detection of argumentative sentences (0.57), which we associate with the higher number of non argumentative sentences. Unlike what could be expected, the presence of lexical clues does not seem to be as relevant as we initially thought for the detection of argumentative sentences. Some of the lexical clues, that are typically associated with explicit argumentative content, are often found also in non-argumentative sentences, transforming this intuitive set of features into an irrelevant set of features for the classifiers. Conversely, argumentative sentences do not necessarily contain such clues. For instance, in the sentences *"(...) Desde então, tudo piorou. O fluxo de migrantes agravou o peso do euroceptismo nos governos. (...)"* there is no lexical clue indicating the presence of the argument and an interpretation of the content at a contextual level is necessary to identify the argument.

Our results can be explained in two dimensions. On one hand, a detailed analysis of the features deemed as relevant by the classifier clearly indicate that our corpus is too small. Moreover, given the aforementioned lack of relevance of lexical clues, we conclude that lexical and syntactic-based approaches are not enough to address this complex task of identifying argumentative sentences, as the example above clearly shows.

4 Conclusions and Future Work

In this paper we described the ArgMine Framework. In our preliminary approach to argumentation mining, we addressed argumentation zoning exploring simple features, mainly lexical and syntactical level features. The critical analysis of the experimental results presented in this paper demonstrate the difficulty of the task. In future work, we expect to improve these results using a more sophisticated set of features (for instance, semantic level features). We would also like to experiment sequential models in addition to the classification models explored in this paper. Also, in future work, we expect to use the framework to address more subtasks of the entire Argumentation Mining process.

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