COMPARING TREE KERNELS PERFORMANCES IN ARGUMENTATIVE EVIDENCE CLASSIFICATION

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ABSTRACT: The purpose of this study is to deploy a novel methodology for classifying argumentative support (or *evidence*) in arguments. The methodology shows that Tree Kernel can discriminate between different types of argumentative evidence with high scores, while keeping a good generalization. Moreover, the results of two different Tree Kernels are evaluated.

KEYWORDS: argument mining, argumentation, tree kernels, evidence detection.

1 Introduction, the Argument Mining pipeline

Argument Mining is relatively new field in the scientific community and several works have been written about this topic in the last few years (Cabrio & Villata, 2018, Lippi & Torroni, 2015). Broadly, its aim is to detect argumentative units from data and predict their relations. The achievement of this aim is not trivial and involves the resolution of multiple problems. In fact, Argument Mining can be seen as a a multifaceted problem and it is often considered as a pipeline. For example, Cabrio & Villata (Cabrio & Villata, 2018) described it as a pipeline composed of two steps, where the first step involves the identification of arguments and the second involves the prediction of argument relations. The first step includes both the classification *argumentative* vs *non-argumentative* and the identification of the arguments' components (claims, premises, etc.) along with their boundaries. The second step comprises predicting the nature of argument relations (e.g. *supports*, *attacks*) and the links between evidences and claims. The two steps are strictly dependent on the underlying argumentative model (e.g. the Waltonian claim/evidence dichotomy).

In this paper, a further step is considered, which involves fitting the achieved argumentative units into an Argument Schemes model, e.g. Walton's classification of Argument Schemes (Walton *et al.* , 2008). To achieve this aim, it is crucial to create classifiers capable of differentiating among different kinds of argumentative evidence (e.g. argument from Expert Opinion, argument from

Example). The proposed methodology is based on a Tree Kernel approach able to discriminate between different kinds of argumentative support.

2 Related Works

This work presents a method for classifying evidence typology within arguments using Tree Kernels (Moschitti, 2006), since being able to classify different kinds of support is crucial when dealing with Argument Schemes.

The advantage of Tree Kernels is the possibility to calculate similarities between different tree-structured data instead of engineering sophisticated features. Tree Kernels have already been used successfully in several NLP-related works. However, the application of Tree Kernel in the domain of Argument Mining has been relatively limited. One of the first implementations was presented by Rooney et Al. (Rooney *et al.* , 2012). Three years later, Lippi and Torroni suggested to exploit the ability of Tree Kernels of leveraging structural information to detect arguments (which can be considered the *first step* in the above-mentioned Argument Mining pipeline) (Lippi & Torroni, 2015).

This work is the continuation of a previous work (Liga, 2019) which aimed to classify argumentative support. A similar work (Liga & Palmirani, 2019) aimed to to classify argumentative opposition. Both these studies show that combining Tree Kernels and TFIDF vectorization can be a good strategy for this kind of classification. Particularly, the present approach tries to discriminate between two different kinds of evidence (or *premise*), comparing two different Tree Kernel functions.

3 Methodology

Following the method in Liga, 2019, two important Argument Mining datasets have been considered: the first (DS1) is taken from Al Khatib et al. (Al Khatib *et al.* , 2016) the second (DS2) from Aharoni et al. (Aharoni *et al.* , 2014). These two datasets have been built for different tasks but they share a very similar labelling system, which is the reason why the can be used jointly. More precisely, DS1 and DS2 classify argumentative texts depending on three common labels (i.e. Study/Statistics, Expert/Testimony, Anecdote). In particular, only the first two labels have been considered, with the aim of classifying evidences *from study* and *from expert*.

Two groups of classifiers were created using KeLP (Filice *et al.* , 2015), the first group was trained on DS1 while the second on DS2. For each classifier, a combination of a Linear Kernel and a Tree Kernel was employed, using a

GROUP 1	Performance on DS1					
	TFIDF + PTK			**TFIDF + SPTK**		
	P	R	F1	P	R	F1
Study	0.90	0.87	0.88	0.91	0.89	0.90
Expert	0.89	0.91	0.90	0.90	0.92	0.91
Average F1 (macro)	**0.89**			**0.91**		
	Performance on DS2					
Study	0.74	0.68	0.71	0.78	0.66	0.72
Expert	0.76	0.80	0.78	0.75	0.85	0.80
Average F1 (macro)	**0.75**			**0.76**		

GROUP 2	Performance on DS2					
	TFIDF + PTK			**TFIDF + SPTK**		
	P	R	F1	P	R	F1
Study	0.69	0.69	0.69	0.69	0.69	0.69
Expert	0.74	0.74	0.74	0.74	0.74	0.74
Average F1 (macro)	**0.72**			**0.72**		
	Performance on DS1					
Study	0.83	0.80	0.82	0.82	0.80	0.81
Expert	0.86	0.87	0.86	0.85	0.87	0.86
Average F1 (macro)	**0.84**			**0.84**		

Table 1. *Results of the two groups of classifiers (P=precision, R=recall, F1=F1 score)*

TFIDF vectorization and a GRCT (Grammatical Relation Centered Tree) representation. For the choice of the Tree Kernel function, two strategies have been attempted: the first deploys a Partial Tree Kernel (PTK, Moschitti, 2006), while the second deploys a Smoothed Partial Tree Kernel (SPTK, Croce *et al.* , 2011). To be sure that the classifiers were able to generalize, they were tested both on DS1 and on DS2 to detect whether sentences where an evidence from "Study/Statistics" or from "Testimony/Expert".

4 Results

As can be seen from Table 1, SPTKs outperform PTKs in group 1, while their performances in group 2 are mostly equal. Importantly, both Partial Tree Kernels and Smoothed Partial Tree Kernels keep a high degree of generalization, which is one of the main reasons why this methodology can be valuable for many classification problems in the Argumentation Mining pipeline.

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