Argumentation Mining: Where are we now, where do we want to be and how do we get there?

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ABSTRACT

This paper gives a short overview of the state-of-the-art and goals of argumentation mining and it provides ideas for further research. Its content is based on two invited lectures on argumentation mining respectively at the FIRE 2013 conference at the India International Center in New Delhi, India and a lecture given as SICSA distinguished visitor at the University of Dundee, UK in the summer of 2014.

Categories and Subject Descriptors

I.2.7 [**Artificial Intelligence**]: Natural Language Processing—*Text Analysis*

Keywords

State-of-the-Art Survey, Structured Learning, Text Entailment

1. INTRODUCTION

Argumentation mining is currently in the center of attention of the text mining research community. In human discourse - whether written or spoken - argumentation always plays an important role. Arguing means that you claim that something is true and you try to persuade your audience that your claim is true by providing evidence to support your claim. Argumentation is probably as old as mankind, as in our communication humans try to convince or inform other people of certain findings and use arguments for this matter.

Argumentation is defined as the act or process of forming reasons and of drawing conclusions and applying them to a case in discussion (Merriam-Webster). This will be the definition if argumentation that we will use in this paper. The act or process of giving reasons for or against something, which is often referred to as the act or process of presenting arguments, forms an important part of argumentation. The arguments together with the conclusion or claim form a complete argumentation. So, the main components of argumentation include: 1) The point of view also called claim or conclusion, that is, something humans are arguing in favour of or against or more formally the proposition, put forward by somebody as true; 2) The evidence humans are using to argue with to support the claim, called the argument(s) or premises; and 3) Possibly a statement called warrant that links the initial claim to the argument(s) and which ensures that the audience understands how the argument(s) function. However, argumentation structures are often more complex. Argumentation may involve chains of reasoning, where a claim and its premises are used as a premise for deriving a more general claim, forming a recursive tree structure. Arguments and claims can form other complicated graph structures or argumentation schemes, which are well studied in the argumentation literature.

Argumentation mining can be defined as the detection of the argumentative discourse structure in text or speech and the recognition or functional classification of the components of the argumentation. Argumentation mining is part of the broader field that recognizes rhetorical discourse structures in text, where rhetoric is the art of discourse that aims to improve the capabilities of writers and speakers to inform, persuade or motivate particular audiences in specific situations ([10], p. 1). Argumentation has been studied by philosophers throughout the history. From Ancient Greece to the late 19th century argumentation was a central part of Western education. Public speakers and writers were trained to persuade audiences with their arguments. Until the 1950s the approach of argumentation was based on rhetoric and logic, and argumentation was a common part of university education. Highlights are the logical treatises of Aristotle (4th century BC) bundled by his followers in the Organon, the seminal work on argumentation of George Pierce Baker [4], the work of Chaïm Perelman and Lucie Olbrechts-Tyteca [25], who describe techniques of argumentation used by people to obtain the approval of others for their opinions, and the work of Stephen Toulmin [33] who explains how argumentation occurs in the natural process of an everyday argument.

We find argumentation in a variety of written and spoken discourse types including legal texts and court decisions, descriptions of medical cases, scientific texts, patents, reviews, online forums, user generated content, debates, interactions, dialogues, and many others.

Given the overload of information we use digital tools that assist in searching and mining this information. Because argumentation is so popular in human discourse we want to build tools that help users to quickly find arguments that sustain a certain claim or conclusion without having to read tons of information. Argumentation mining refines search and information retrieval tasks or provides the end user with instructive visualizations and summaries of an argumentative structure [27].

2. STATE-OF-THE-ART OF ARGUMENTATION MINING

Argumentation mining is a young discipline with the earliest work dating from 2007 that focused on mining argumentation from legal cases [20]. Already at the end of the 1990s progress was made with regard to argumentative zoning, which regards the classification of segments in a discourse into different types of information. Recently we see a large interest in mining argumentation found in user generated content, i.e., online user comments and discussions.

2.1 Argumentative zoning

Argumentative zoning regards the segmentation of a discourse into discourse segments or zones that each play a specific rhetoric role in a text [31, 32]. For instance, in a scientific article one can identify the sections that cover the general scientific background, the sections that contain the aims of the paper, sections that discuss contrasting and comparing statements with work of others, and statements about the current organization of the paper, among others. Other work on argumentative zoning regards the identification of the components of a criminal court decision including the names of the parties (e.g., name of the victim(s), name of the accused, the alleged offences, the opinion of the court, its grounds and legal foundations, the verdict and the conclusion) [21]. Argumentative zoning is seen as a classification task: a rule based or statistical classifier is trained respectively based on manual inspection or annotation of training examples. Typical features used in the classification are signaling word patterns, layout features, and syntactic features such as part-of-speech tags.

2.2 Argumentation mining of legal cases

Legal cases or court decisions contain the decisions of judges and supporting arguments of these decisions. Recognizing the argumentation of judges is very valuable in finding precedent cases and in precedent reasoning [3, 7]. Legal professionals have a large interest in using arguments and conclusions from older legal cases. They search for a type of reasoning that they can follow in their current case, e.g., acceptance or rejection of a claim, hence their large interest in automated argumentation mining from the texts of the decisions.

Argumentation mining adds an additional dimension to argumentative zoning. Not only the discourse is segmented and the segments are classified by their argumentative function, also the argumentative relationships between the segments are recognized by the machine, leading to the detection of full argumentative structures and the classification of their components.

As mentioned above the first works on argumentation mining in legal cases was published in 2007 [20] and 2012 [23]. In

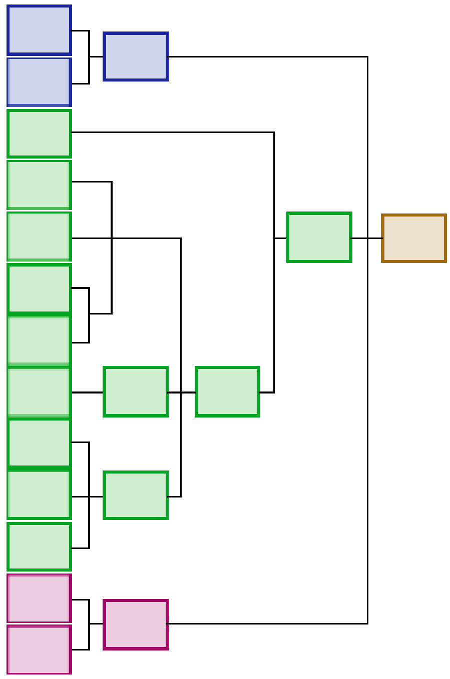

Figure 1: An example argumentation structure of a legal case of the ECHR.

this work argumentation is seen as a process whereby arguments are constructed, exchanged and evaluated in the light of their interactions with other arguments and claims, where argumentation is represented as a recursive tree structure (Figure 1). The court decisions used in this research were decisions of the European Court of Human Rights (ECHR)[1].

In a first approach the argumentative text is parsed based on a context free grammar that is manually constructed, where the terminal symbols are composed of typical rhetorical markers that signal the rhetorical relationships between segments, and keywords that are representative for the function of the segment in the argumentative structure.

In a second approach clauses in the texts are described by linguistic features such as unigrams, bigrams, adverbs, legal keywords, and word couples over adjacent clauses. A cascade of classifiers is trained to identify whether the clause is part of a premise, conclusion or of no argumentation. First a maximum entropy classifier is trained to detect whether the clause is part of the argumentation and then a support vector machine is learned for distinguishing premises from conclusions. The recognition of clauses that act as premises or conclusions in the decisions has yielded a F1 measure of respectively 74% and 68% when using the cascade of classifiers, and respectively 67% and 64% when using the context free grammar. The use of a context free grammar allowed recognizing the tree-shaped argumentation structure with an accuracy of 60%. No structured machine learning methods were tried in this work to recover the tree structure (see below).

[1]HUDOC database found at http://hudoc.echr.coe.int/

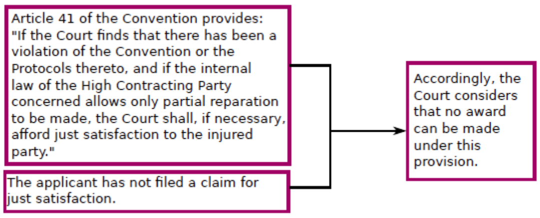

Figure 2: An example sub-argument of the argumentation structure shown in Figure 1 which itself is composed of two premises (left) and a conclusion (right).

2.3 Argumentation mining of online user generated content

Another recent argumentation mining task regards the support for online user comments. This task is complementary to opinion mining as it provides arguments that explain why online users are positive or negative about a certain situation, product or person. Online user comments contain argumentation with appropriate or missing justifications. [24] classify comments into the classes "UnVerifiable", "Verifiable", "Verifiable Non-Experiential", "Verifiable Experiential" or none of these. The authors use typical linguistic and discourse features such as n-grams, part-of-speech tags, presence in core clause or sub-clause, sentiment clue, speech event anchors, imperative expression count, emotion expression count, tense count and person count. They obtain results in terms of F1 measure close to 70% macro-averaged over the results of the above classes. Also [6] process argumentation in online discussions, and more specifically they identify properties of comment-argument pairs that were manually segmented. They label the pairs with the following labels: "explicitly attacks the argument", "implicitly attacks the argument", "no use of the argument", "implicitly supports the argument", and "explicitly supports the argument" and obtain a F1 score that ranges between 70% and 80% by using a set of interesting features such as entailment features, semantic text similarity features and stance alignment features where the stance or polarity is known a priori. The entailment features are obtained from pretrained entailment decision algorithms (which among others use linguistic resources such as WordNet [13] and VerbOcean [9]). The authors use a multiclass support vector machine for classification.

3. GOAL OF ARGUMENTATION MINING

The output of argumentation mining is mostly used in information retrieval and more specifically precedent search, in case based reasoning in which arguments from an older case are used to solve the current case, and in information visualization. All these applications require that the structure of the argumentation and its composing elements are recognized by the machine. We want to connect premises with the right conclusion (Figure 2) and possibly detect the full reasoning structure, so that the argumentation can be used in similar cases, or the argumentation can be visualized for easy and quick understanding of the discourse. So far this has not been realized in state-of-the-art research except for one attempt where the argumentation grammar was manually built [23].

4. PERSPECTIVES FOR ADVANCED ARGUMENTATION MINING

The above goal opens many perspectives for more advanced processing of argumentative discourse. Several novel text processing methods seem appropriate to pursue in future research. We will go deeper into 1) Structured machine learning for the joint recognition of a claim and its composing arguments; and 2) Using textual entailment and event causality to improve the recognition of relations between argumentation components.

4.1 Structured machine learning

Argumentation forms a structure composed of a claim and its arguments (Figure 2). Such structure can be nested: A more general claim can be supported by arguments that each in turn forms an argumentative structure on its own composed of a claim and its arguments. Such a recursive argumentation structure is often found in legal cases (Figure 1). The machine learning and natural language processing communities have developed promising structured learning approaches, for instance, by segmenting and jointly classifying the syntactic [34] or semantic components of sentences [18]. Such methods could also be applied for processing more complex argumentation structures such as the ones defined by Stephen Toulmin [33], or the many different argumentation schemes discussed in the works of Douglas Walton [35], Henri Prakken [26], Thomas Gordon [14], Trevor Bench-Capon [5], Adam Wyner [36] and Jodi Schneider [29].

Joint or global machine learning models learn collectively a full structure composed of labels and their relationships. In case of the recognition of argumentation in text, the model would jointly recognize premises and the corresponding conclusion, or even more interestingly recognize a full argumentation tree (e.g., in the ECHR decisions). One of the most seminal papers in this respect is [34]. The technique is different from the local learning of independent classifiers that separately learn a model for each component or relationship. However, the most simple joint learning model trains independent classifiers and after their application optimizes the results based on constraint combination rules often coded as linear integer programs [28]. More advanced models train one classification model for the global structure whose output is a graph of labels with the relationships between the labels tagged [34]. Although not yet applied for the recognition of argumentation structures or other discourse structures, the technique recently received attention for the recognition of complex semantics in text where the labels and their relations take the form of an ontological structure [18]. Such a model allows that the text to which the classification model is applied is presented to the machine as different types of input components: single words, phrases, sentences, paragraphs, etc. depending on the type of text snippet to which a label will be assigned. Each input component is assigned a set of features: lexical, syntactic, discourse distance, or others. Feature functions link an input component with a possible label (notion of feature templates). The main objective discriminant function is a linear function in terms of the combined feature representation associated with each candidate input component and an output label according to the template specifications. The learning model optimizes the weights of the feature function given the training examples that are manually labeled. A popular discriminative training approach is to minimize the convex upper bound of the loss function over the N training data. Given that there are an enormous amount of negative examples (in the form of labeled nodes in the graph structure and their labeled relations) that correspond to one positive example, structured learning approaches have focused on finding a suitable cutting plane algorithm that allows learning only from the negative examples that mostly violate the positive training example. In [18] this approach is used to train a classifier for spatial relation recognition where jointly a model that recognizes the relation and the function of the entities involved in the relation (i.e., trajector and landmark of the spatial relation) and the relation's attributes are learned. In this work the structured learning model is implemented as a support vector machine, structured perceptron and averaged structured perceptron. The most violated negative examples are found by inference over a set of constraint rules that are spatial relation specific with a linear integer programming solver. Also probabilistic graphical models [17] can be used for training structured learners. As discussed above, considering the interdependencies and structural constraints over the output space easily leads to intractable training and prediction situations. When training with the most violated negative examples is not sufficient to handle the computational complexity (e.g., when models for complex graphical structures need to be learned) the current literature proposes models for decomposition, communicative inference, and message passing that reduce the computational complexity of training the model and identifying the best output structure [30].

Although not yet empirically tested, we believe that the approach of structured or global learning is very valuable for recognizing argumentation structures in text and for recognizing discourse structure in general. As seen above structured machine learning explicitly models the interdependencies between output labels, and background or domain knowledge can be imposed using constraint optimization techniques (such as linear integer programming) during prediction and training. More specifically, the constraints used can be domain-specific or task-specific (e.g., that a premise cannot function as a claim in the same argumentative relation) and can be integrated to identify the most violated negative examples during training and to decode the best structure during prediction.

Up until now such models have never been used for argumentation mining, but recent work on recognizing the structure of scientific documents [16] follows this line of thinking.

4.2 Textual entailment and event causality

Another important issue in argumentation mining is the correct identification of the relationships between text segments (e.g., the relationship of being a premise for a certain conclusion) and defining appropriate features that indicate this relationship. Discourse relationships are often signaled by typical keywords (e.g., ”in conclusion”, ”however”, ”accordingly”), but often this is not the case. Humans who understand the meaning of the text can infer whether a claim is a plausible conclusion given a set of premises, or whether an argument forms a valid rebuttal. This means that humans have background or domain knowledge that an argumentation mining tool should acquire to accomplish this task. In the legal field such background knowledge is often gained over years during the training of the legal professionals. So the question is how can the machine acquire this knowledge? Building such a knowledge base manually, especially when the knowledge is very specific and detailed, seems a daunting task, so the question becomes how can the machine acquire this knowledge automatically?

In this respect current work on textual entailment [8] and event causality [12] might give valuable solutions for relationship recognition between argumentation components.

Textual entailment in natural language processing [2] is seen as a directional relation between text fragments. Textual entailment methods recognize, generate, or extract pairs of natural language expressions, such that a human who reads (and trusts) the first element of a pair would most likely infer that the other element is also true. This a broad definition and in argumentation mining the relationships to be found are more constrained than in general textual entailment research. Nevertheless the comprehensive overviews of methods used for textual entailment described by [2] and [11] are certainly worth studying in the frame of argumentation mining. We think that especially the entailment approaches that use vector space models of semantics and that employ machine learning methods have value in an argumentation mining context. It might also be interesting to link research of textual entailment to the logic based approaches that have been extensively studied when reasoning with arguments.

Related to textual entailment is event causality. Recognizing event causality is an important part of text understanding. We humans are very good in inferring causal relations in a discourse (e.g., recognizing that the arrest of a murderer by the police is the consequence of a murder), but for a machine, which lacks the world knowledge that humans use in this process, this is not so obvious. Again, the text might explicitly mention a causal relation between two events mentioned (e.g., the use of the word ”because”), but often such cues are missing. To acquire knowledge on event causality automatically, current work focuses on methods developed in distributional semantics, such as co-occurrence counts of events collected automatically from an unlabeled corpus, to measure and predict the existence of causality relations between event pairs [12] resulting in resources such as VerbOcean [9]. Finally, it needs to be investigated whether word patterns could be translated into latent variable concepts, which would support current interest in the use of factors in argumentation [1]

5. EVALUATION AND DATA SETS

As argumentation mining up till now has focused on the recognition of individual argumentation components or on the classification of the properties of given arguments, evaluation was restricted to measuring recall, precision and F1 of the recognized labels of nodes (text segments) and their relations. When in the future more complex argumentation structures will be recognized, there is certainly room to investigate adequate evaluation measures that combine the performance of the individual recognitions with the recognition of the global structure and possibly its composing substructures.

Finally, it seems useful to mention available corpora that have been used in past research. Apart from corpora mentioned in the references of this paper or mentioned in the papers of the First Workshop on Argumentation Mining (ArgMining 2014) during the Annual Conference of the Association for Computational Linguistics in 2014[2], famous argumentation corpora include the Araucaria corpus (constructed by Chris Reed at the University of Dundee in 2003) now extended to the AIFdb corpus [19], the ECHR corpus containing 25 legal cases annotated by legal experts [22], and the NoDE corpus that contains natural language arguments in online debates[3]. There are also plans to build an argumentation corpus composed of biomedical publications in the genetics domain [15].

6. CONCLUSIONS

Argumentation mining is a novel and promising research field. It has the potential of further developing many advanced computational linguistics and machine learning methods such as joint learning of an argumentation structure integrating expert knowledge and known interdependencies between the structural components in the argumentation. Argumentation mining research opens possibilities to study advanced features for natural language and discourse understanding and could advance the field of information retrieval by its novel visualization paradigms and novel precedent case search. Argumentation mining has numerous interesting applications. Especially we foresee a large impact of argumentation mining in the frame of sentiment analysis and opinion mining, as it enriches a recognized opinion with arguments that support the opinion.

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8. REFERENCES

[1] Latifa Al-Abdulkarim, Katie Atkinson, and Trevor J. M. Bench-Capon. Support for factor-based argumentation. In *Computational Models of Argument - Proceedings of COMMA 2014, Atholl Palace Hotel, Scottish Highlands, UK, September 9-12, 2014*, pages 447–448, 2014.

[2] Ion Androutsopoulos and Prodromos Malakasiotis. A survey of paraphrasing and textual entailment methods. *Journal of Artificial Intelligence Research*, 38(1):135–187, May 2010.

[3] Kevin D. Ashley. *Modeling Legal Arguments: Reasoning with Cases and Hypotheticals*. MIT Press, Cambridge, MA, USA, 1991.

[4] George Pierce Baker. *Principles of Argumentation.* 1895.

[5] Trevor J. M. Bench-Capon and Paul E. Dunne. Argumentation in artificial intelligence. *Artificial Intelligence*, 171(10-15):619–641, 2007.

[2]http://www.uncg.edu/cmp/ArgMining2014/
[3]http://www-sop.inria.fr/NoDE/

[6] Filip Boltužić and Jan Šnajder. Back up your stance: Recognizing arguments in online discussions. In *Proceedings of the First Workshop on Argumentation Mining*, pages 49–58, Baltimore, Maryland, June 2014. Association for Computational Linguistics.

[7] L. Karl Branting. A reduction-graph model of ratio decidendi. In *Proceedings of the 4th International Conference on Artificial Intelligence and Law*, ICAIL '93, pages 40–49, New York, NY, USA, 1993. ACM.

[8] Elena Cabrio and Serena Villata. Combining textual entailment and argumentation theory for supporting online debates interactions. In *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics, Proceedings of the Conference, July 8-14, 2012, Jeju Island, Korea - Volume 2: Short Papers*, pages 208–212, 2012.

[9] Timothy Chklovski and Patrick Pantel. VerbOcean: Mining the web for fine-grained semantic verb relations. In Dekang Lin and Dekai Wu, editors, *Proceedings of EMNLP 2004*, pages 33–40, Barcelona, Spain, July 2004. Association for Computational Linguistics.

[10] Edward P.J. Corbett. *Classical Rhetoric for the Modern Student.* Oxford University Press, 1971.

[11] Ido Dagan, Dan Roth, Mark Sammons, and Fabio Massimo Zanzotto. *Recognizing Textual Entailment: Models and Applications*. Synthesis Lectures on Human Language Technologies. Morgan & Claypool Publishers, 2013.

[12] Quang Xuan Do, Yee Seng Chan, and Dan Roth. Minimally supervised event causality identification. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, EMNLP '11, pages 294–303, Stroudsburg, PA, USA, 2011. ACL.

[13] Christiane Fellbaum. WordNet and wordnets. In Keith Brown, editor, *Encyclopedia of Language and Linguistics*, pages 665–670, Oxford, 2005. Elsevier.

[14] Thomas F. Gordon. *Foundations of Argumentation Technology: Summary of Habilitation Thesis.* Technical University of Berlin, 2009.

[15] Nancy Green. Towards creation of a corpus for argumentation mining the biomedical genetics research literature. In *Proceedings of the First Workshop on Argumentation Mining*, pages 11–18, Baltimore, Maryland, June 2014. ACL.

[16] Yufan Guo, Roi Reichart, and Anna Korhonen. Improved information structure analysis of scientific documents through discourse and lexical constraints. In *Proceedings of the Human Language Technologies: Conference of the North American Chapter of the Association of Computational Linguistics, Proceedings, June 9-14, 2013, Westin Peachtree Plaza Hotel, Atlanta, Georgia, USA*, pages 928–937, 2013.

[17] D. Koller and N. Friedman. *Probabilistic Graphical Models: Principles and Techniques.* MIT Press, 2009.

[18] Parisa Kordjamshidi and Marie-Francine Moens. Global machine learning for spatial ontology population. *Journal of Web Semantics*, Special Issue on Semantic Search:1–29, 2014.

[19] John Lawrence and Chris Reed. AIFdb corpora. In *Computational Models of Argument: Proceedings of COMMA 2014, Atholl Palace Hotel, Scottish*

Highlands, UK, September 9-12, 2014, pages 465–466, 2014.

[20] Marie-Francine Moens, Erik Boiy, Raquel Mochales Palau, and Chris Reed. Automatic detection of arguments in legal texts. In *Proceedings of the Eleventh International Conference on Artificial Intelligence and Law, Proceedings of the Conference, June 4-8, 2007, Stanford Law School, Stanford, California, USA*, pages 225–230, 2007.

[21] Marie-Francine Moens and Caroline Uyttendaele. Automatic text structuring and categorization as a first step in summarizing legal cases. *Information Processing and Management*, 33(6):727–737, 1997.

[22] Raquel Mochales Palau and Aagje Ieven. Creating an argumentation corpus: do theories apply to real arguments? A case study on the legal argumentation of the ECHR. In *Proceedings of the 12th International Conference on Artificial Intelligence and Law, Proceedings of the Conference, June 8-12, 2009, Barcelona, Spain*, pages 21–30, 2009.

[23] Raquel Mochales Palau and Marie-Francine Moens. Argumentation mining. *Artificial Intelligence and Law*, 19(1):1–22, 2011.

[24] Joonsuk Park and Claire Cardie. Identifying appropriate support for propositions in online user comments. In *Proceedings of the First Workshop on Argumentation Mining*, pages 29–38, Baltimore, Maryland, June 2014. Association for Computational Linguistics.

[25] Chaïm Perelman and Lucie Olbrechts-Tyteca. *Traité de l'argumentation: la nouvelle rhétorique*. Paris: Presses Universitaires de France, 1958.

[26] Henry Prakken. *Logical Tools for Modelling Legal Argument. A Study of Defeasible Reasoning in Law.* Kluwer Law and Philosophy Library, 1997.

[27] Chris Reed and Glenn Rowe. Araucaria: Software for argument analysis, diagramming and representation. *International Journal on Artificial Intelligence Tools*, 13(4):983, 2004.

[28] Dan Roth and Wen-tau Yih. Integer linear programming inference for conditional random fields. In *Proceedings of the 22nd International Conference on Machine Learning*, ICML '05, pages 736–743, New York, NY, USA, 2005. ACM.

[29] Jodi Schneider. Automated argumentation mining to the rescue? Envisioning argumentation and decision-making support for debates in open online collaboration communities. In *Proceedings of the First Workshop on Argumentation Mining*, pages 59–63, Baltimore, Maryland, June 2014. ACL.

[30] David Sontag, Amir Globerson, and Tommi Jaakkola. Introduction to dual decomposition for inference. In Suvrit Sra, Sebastian Nowozin, and Stephen J. Wright, editors, *Optimization for Machine Learning.* MIT Press, 2011.

[31] Simone Teufel, Jean Carletta, and Marc Moens. An annotation scheme for discourse-level argumentation in research articles. In *Proceedings of EACL 1999, 9th Conference of the European Chapter of the Association for Computational Linguistics, June 8-12, 1999, University of Bergen, Bergen, Norway*, pages 110–117, 1999.

[32] Simone Teufel and Marc Moens. Summarizing scientific articles: Experiments with relevance and rhetorical status. *Computational Linguistics*, 28(4):409–445, 2002.

[33] Stephen Toulmin. *The Uses of Argument.* Cambridge University Press, 1958.

[34] Ioannis Tsochantaridis, Thorsten Joachims, Thomas Hofmann, and Yasemin Altun. Large margin methods for structured and interdependent output variables. *Journal of Machine Learning Research*, 6:1453–1484, December 2005.

[35] Douglas Walton. *Argumentation Schemes for Presumptive Reasoning.* Lawrence Erlbaum Associates, 1996.

[36] Adam Wyner and Trevor Bench-Capon. Argument schemes for legal case-based reasoning. In *Proceedings of the 2007 Conference on Legal Knowledge and Information Systems: JURIX 2007: The Twentieth Annual Conference*, pages 139–149, Amsterdam, The Netherlands, The Netherlands, 2007. IOS Press.