Towards an Argumentative Dialogue System

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ABSTRACT

In this work we propose a scheme for an Argumentative Dialogue System that allows a user to discuss a certain topic with a virtual agent using natural language. Starting from an agent vs agent case, we address the optimization of the agent strategy by formulating the problem as a Stochastic Game and show that this formalism generally allows the inclusion of additional strategical moves that are not based on the content of the argument. In a second step we propose our approach for the Natural Language Understanding of arguments by combining recent results of argumentation mining with a keyword-based mapping.

CCS CONCEPTS

• **Computing methodologies** → *Natural language processing*; *Discourse, dialogue and pragmatics*; *Machine learning approaches*; *Stochastic games*;

KEYWORDS

Argumentation, Natural Language Understanding, Stochastic games

1 INTRODUCTION

Resolving different viewpoints of virtual agents can be addressed as a dialogical task in which arguments are exchanged. Thereby it is possible for each side to persuade the opponents by establishing a convincing argumentation structure. An Argumentative Dialogue System is a system that allows an agent to carry out argumentative tasks such as persuasion or negotiation against a human. Despite the strong theoretical grounding [8], implementations of these kind of systems are rather scarce since they have to overcome different obstacles (see [13] for a detailed discussion).

Following the classification of dialogues presented in [9] we consider a persuasion scenario and discuss approaches to tackle two important issues, namely the Natural Language Understanding (NLU) of arguments and the development of a flexible agent strategy. Whereas in recent work the first issue is bypassed by using human annotators to map utterances to argumentative concepts [10] or by presenting a variety of possible answers to the user [6, 12], the second problem is addressed in various ways. Examples are by use of heuristics [12], decision trees [5], a formulation as planning problem [2] or machine learning [4, 10]. However, most of the work done in this direction is focused on the argumentative structure, i.e. which argument to present when, whereas a discussion between humans yields additional strategical aspects. An example is the *challenge move* discussed in the framework of Prakken [7] that allows to question the validity of an argument. For the considered persuasive scenario we summarize these actions as dodge moves since they do not present an additional argument component and sometimes aim for a distraction from the underlying argumentation structure.

We will focus on a debating-like setup in which each player aims for establishing his own argumentative structure and tries to demolish the one of the opponent. To this end, each side is allowed on-turn to either introduce an additional argument component or to perform a dodge move. Thereby, each move has to be directly related to a previous (but not necessarily the last) one. We assume that both sides have full knowledge of the underlying argument structure. By first employing the formalism of Stochastic Games in an agent vs agent scenario, we aim for an optimized agent policy the user can debate with. The problem of NLU of arguments is addressed by combining recent results from the field of argumentation mining [11] with a keyword mapping and established methods from NLU.

The reminder of this paper is as follows: In Section 2 we discuss the optimization of the agent policy while Section 3 covers our approach for the NLU of arguments in our system. In Section 4 we conclude by summarizing the presented ideas.

2 ARGUMENTATIVE DIALOGUE AS STOCHASTIC GAME

Previous work showed that the problem of optimizing an agent strategy can be formulated as (partially observable) Markov Decision Process (POMDP) [4, 10] and thus be addressed by Reinforcement Learning (RL). However, as this approach optimizes only the strategy of one agent, it requires either pre-defined rules for the respective opponent or a training corpus to learn from. Moreover, the so developed strategy directly depends on the rules or the available data, respectively.

We propose an approach based on Stochastic Games that extend the MDP formalism by enabling each involved agent to adapt its strategy to previous actions of others. Thereby, no prior knowledge about the agents behavior or data is required as all strategies can be developed by use of RL. Moreover, the existence of a Nash Equilibrium in Stochastic Games can be guaranteed [1]. It should be mentioned that scenarios with opposite agent goals (which is the case we consider) is a special case of a Stochastic Game and referred to as zero sum game.

To apply this formalism to our system, an additional extension of the frameworks proposed in previous work is required since they did not include dodge moves. The formalism of MDP (and therefore of Stochastic Games as well) requires the definition of states in which the actual stand of the debate is expressed. Argument components and their relations are usually represented as a tree or (directed) graph as depicted in Figure 1. If dodge moves are not included, all possible moves can be tied to argument components and states can thus be expressed as sub-graphs. Since we want to rely on this representation, we plan to include each dodge move as a content-free component into the subgraph. We stress that these additional components are not part of the underlying argumentation structure and only affect the states.

A second issue is the dimensionality of the associated state space. It is known from previous work [4] that this space rapidly increases with the number of argument components. As we aim for the inclusion of dodge moves as well as a reasonable amount of argumentation components, the number of states in our case will be comparatively large. Therefore, the choice of a proper learning algorithm seems to be crucial for a successful optimization of the agent strategies. A selection of methods that were employed in the field of dialogue systems can be found in [1, 3] and serve as a starting point for our case.

3 NATURAL LANGUAGE UNDERSTANDING OF ARGUMENTS

The difficulty in NLU of arguments lies in its dependence on the content of the utterance. Given that the complete argument (i.e. all argument components) can be represented as a graph or tree, it requires a mapping of the utterance to a specific node in this representation as depicted in Figure 1. Since each node represents an argument component that is associated with a certain content, it is inevitable to include contextual information into this mapping.

Our approach to this problem consists of two steps. First, we plan to employ techniques presented in recent work on argumentation mining that allow for a detection of argument components and their relations (*support* or *attack*) to others, e.g. in written essays [11]. Although this classification is not content dependent, it will decrease the set of candidates in question if applied to our scenario. The remaining options will be distinguished in a second step where we plan to search the utterance for keywords previously assigned to each argument component. The one with the best match is then picked as final mapping.

It should be mentioned that the reviewed scenario includes an additional task regarding the dodge moves. Whereas the distinction of different dodge moves and a general argumentative move is comparable to the NLU in existing systems and will be addressed by established methods, dodge moves may (depending on the type) require further processing in view of their relations to other components. For example in the case of a *challenge move*, the component that is challenged has

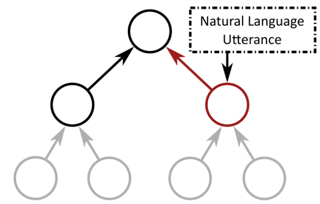

Figure 1: Sketch of the graph representation of arguments and the mapping of a user utterance to a specific component in it. The subgraph depicted by black elements indicate the actual state, the red component (node and edge) indicates the argument component the recent user utterance is mapped to and gray elements indicate additional components the system is aware of. Nodes represent a certain content, edges a relation (e.g. *support* or *attack*) which is not specified herein for the sake of readability.

to be determined. In some formal frameworks the relation itself is given by its type (e.g. [8]), thus allowing to leave out the first of the above discussed steps. In such case, only a detection of the aim (the component it is related to) is required and we will focus on suchlike frameworks in the scope of this work. To determine the aim, the key words assigned to each component will again be employed.

In the case of completely free speech argumentation it is possible that one utterance contains more then one argumentative component or that the component the user refers to is split in more than one turn. To circumvent this problem, we consider a restricted scenario in which the user is allowed to only bring up one argumentative component at a time. Although this approach also restricts the language of the user and requires knowledge about the underlying argumentation structure, we consider it an important and reasonable step towards natural language argumentation.

4 CONCLUSIONS

The purpose of this work is to present and discuss our plan for an Argumentative Dialogue System including natural language. We proposed an approach for optimizing the agent policy by employing the formalism of Stochastic Games. In addition we discussed the inclusion of dodge moves into this framework and proposed a scheme for the NLU of arguments that combines a keyword based approach with recent results from argumentation mining.

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