Strategical Argumentative Agent for Human Persuasion

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Abstract. Automated agents should be able to persuade people in the same way people persuade each other - via dialogs. Today, automated persuasion modeling and research use unnatural assumptions regarding persuasive interaction, which creates doubt regarding their applicability for real-world deployment with people. In this work we present a novel methodology for persuading people through argumentative dialogs. Our methodology combines theoretical argumentation modeling, machine learning and Markovian optimization techniques that together result in an innovative agent named SPA. Two extensive field experiments, with more than 100 human subjects, show that SPA is able to persuade people significantly more often than a baseline agent and no worse than people are able to persuade each other.

1 Introduction

Persuasion is designed to influence others by modifying their beliefs or actions. People often engage in persuasive interactions through dialog in which parties who hold (partially) conflicting points of view can exchange arguments. Automated agents should be able to persuade people in the same manner; namely, by presenting arguments during a dialog.

Persuasive technologies offer various techniques for an automated agent (the *persuader*) to convince a human (the *persuadee*) to change how she thinks or what she does [17]. Some of these techniques use argumentative dialogs as their persuasion mechanism. However, strategical aspects of argumentative persuasive dialogs are still under-developed (see [51] for a review). Argumentation Theory has recently investigated the challenge of finding optimal persuasion strategies in dialogs [26, 24]. In particular, the proposed approaches do not assume that the opponent will play optimally, which is a common assumption in game theoretical analysis of persuasion dialogs [20, 40], and do not assume perfect knowledge of the persuadees' characteristics. The proposed methods have yet to be investigated with people, mainly due to their assumed strict protocols for the dialog which make their implementation with people very challenging.

In this paper we present a novel methodology for designing automated agents for human persuasion through argumentative dialogs without assuming a predefined protocol. Our methodology is based on a newly designed argumentation framework called the *Weighted Bipolar Argumentation Framework (WBAF)* which we introduce in this paper and for which we suggest a semantic. The framework and semantic are aimed at modeling the initial beliefs held by a reasoner (in our case, the persuadee) as well as the fuzzy nature in which arguments and opinions within the framework affect each other. Unlike classic semantics which label each argument in the framework as justified or not, our suggested semantic allows each argument to carry a continuous value representing its justification level within the framework. Then, we formally define the persuasion task given the assumption that the *persuadee* acts stochastically. The persuasion task's goal is to maximize the probability that the persuadee will take the desired action or change her views on a given matter by presenting arguments. We reduce the persuasion task to a Partially Observable Markov Decision Process (POMDP) [28] and approximate its solution using the prediction of the persuadee's argumentation framework and argumentative behavior. This prediction is done using Machine Learning (ML) techniques based on collected human argumentative data. Using the obtained policy, which approximates the optimal policy for the corresponding POMDP, our agent presents arguments to its human interlocutor during a dialog.

In two field experiments, with a total of more than 100 human subjects[3], we show that our agent, which we named SPA, was able to persuade subjects to change their opinions and take a desired action significantly more often than when interacting with a baseline agent and no worse than when subjects attempted to persuade each other. To the best of our knowledge, this is the first work within the context of strategical argumentation to consider the optimization of persuasive dialogs with people.

The remainder of the paper is organized as follows. In Section 2 we survey related work. In Section 3 we present the theoretical argumentation framework used in this work and suggest a semantic for it. In Section 4 we formally define the persuasion task and in Section 5 we describe our methodology and solution using a novel arguments provision agent (named SPA). In Sections 6 and 7 we evaluate our methodology in two real-world domains. Finally, in Section 8 we provide a summary and list future directions for this line of study.

2 Related Work and Background

Theoretical modeling and strategical studies of agents' behavior in persuasion interactions, within both argumentation theory and multi-agent systems, have presented logics, protocols and policies which enable agents to engage each other in a meaningful manner [52, 30, 36, 31, 7, 37, 13, 19]. In this realm, studies rely on the assumption that the engaging agents adhere to strict protocols and logics or that the agents are given unrealistic prior knowledge on their opponent's knowledge and beliefs [51]. Furthermore, strategic persuasion is inherently NP-complete [21].

The literature on the optimization of persuasive strategies in argumentative dialogs can be divided into 2 broad approaches:

1. *Game Theory* – in which the agent assumes that its counter-part maximizes expected utility acts optimally.
2. *Heuristic-Based* – in which the agent uses a strategy following some rule-of-thumb notion.

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[3] All experiments were authorized by the corresponding IRB.

In the Game Theory approach, theoretically founded methods and guarantees are provided for computing optimal argumentative strategies (e.g., [40]). However, it has been shown that people often do not adhere to the optimal, monolithic strategies that can be derived analytically in the argumentative context [41, 42, 43]. Therefore, this work is suited to the Heuristic-Based approach.

In the Heuristic-Based approach, the persuadee is neither assumed to be strategical nor is she assumed to act optimally. Several heuristics for persuasive dialog policies have been proposed in the literature, for example, the heuristic of selecting arguments supporting the agent's most important values is proposed in [5], revealing as little information as possible [34] or presenting arguments which have a high success rate from past experiences [53]. As observed in [23], a history of previous dialogues can be used to predict the arguments that the persuadee might put forward. Naturally, this prediction (sometimes called persuadee or opponent modeling) is a key component in designing persuasive arguments; a recent example is presented in [29]. In this realm, the persuadee is usually assumed to act *stochastically*, an assumption we also make in this work. However, the persuader is not assumed to have perfect knowledge of the persuadee's characteristics. To address this shortcoming, we propose a methodology for predicting people's argumentative choices during a dialog using Machine Learning (ML) techniques. Rosenfeld and Kraus [43] have recently showed that ML can be extremely useful in predicting human argumentative behavior in human discussions. We use the authors' suggested methodology in this work such that given a certain state of the dialog, the persuader can estimate the persuadee's next argument using ML.

Hadoux et al. [24] have suggested a variation of a Markovian model to optimize persuasive behavior in dialogs. As in previously suggested modelings, the authors impose restrictive assumptions on the persuader's and persuadee's behavior which are relaxed in this work. Hunter [26] also presented a probabilistic modeling of the persuasive dialog using *asymmetrical* dialog procedure, in which only the persuader can posit arguments. In this work, we assume a symmetric dialog in which both parties can posit arguments. Neither of the works mentioned above, like most other works in the field, have been evaluated with people. This fact raises concerns regarding the applicability of the suggested and well thought out theoretical modelings when accounting for human argumentative behavior. Thus far, very little investigation has been done regarding how well the proposed Argumentation Theory modelings apply to humans. As far as we know, only a handful of papers address the topic [3, 38, 18, 12, 43]. These papers do not account for persuasive argumentative interactions.

The Natural Language Processing (NLP) community has also addressed the issue of automatic persuasion in various settings. For example, by generating personalized smoking cessation letters [39], ranking textual arguments by their persuasiveness [22] and the analysis of the persuasiveness of arguments in online forum discussions [49]. The proposed methods focus on linguistic features rather than strategical human-agent interaction, and therefore complement the proposed notions of this paper. Note that the development of automated argumentation-based agents, such as the one presented in this study, necessitates the assumption that natural language statements can be automatically mapped into arguments. Despite recent advancements in NLP and Information Retrieval (IR) and their studied connections to argumentation [1, 32, 9, 33, 48, 8], this assumption is not completely satisfied by existing automated tools. Hence, throughout this work we use a human expert annotator whom we hired as a research assistant. We hope that this work will inspire other researchers in NLP and IR to tackle the problem of automatically mapping natural language statements into arguments as well as other open problems of great importance in argumentation-based systems.

3 Theoretical Modeling

In order to perform reasoning in a persuasive context, an argumentation framework needs to be defined (see [6, 10] for recent reviews). In its most basic form, an argumentation framework consists of a set of arguments A and an attack relation R over $A \times A$ (see [14]). In our previous investigations of human argumentative behavior [42, 41, 43] we noticed that people often use supportive arguments rather than attacking ones, which necessitates the addition of the support relation as suggested in [11]. Furthermore, we noticed that people associate different belief levels in arguments, as suggested in [50, 4], and different strength levels with interactions between arguments, as suggested in [15].

Therefore, throughout this work we use the newly proposed *Weighted Bipolar Argumentation Framework* (WBAF) which integrates the basic notions from the Bipolar Argumentation Framework [11], the Weighted Argumentation Framework [15], the Quantitative Argumentation Debate (QuAD) Framework [4] and the Trust Argumentation Framework [50].

Definition 1. *Let V be a completely ordered set with a minimum element (V_{min}) and a maximum element (V_{max}). A Weighted Bipolar Argumentation Framework (WBAF) $< A, R, S, W, B, \omega >$ consists of a finite set A called arguments[4], two binary relations over A called attack (R) and support (S), an interaction weighing function $W : R \cup S \to V$ and an argument belief function $B : A \to V$. $\omega \in A$ is a designated argument which represents the discussed issue.*

We will refer to the WBAF as the "argumentation framework" from this point forward.

In Definition 1, we assume 2 types of possible interactions between arguments: attack and support. That is, if argument $a \in A$ relates to an argument $b \in A$, then aRb or aSb holds, respective of the relation type. It is argued that the use of both support and attack relations in argumentation frameworks is essential to representing realistic knowledge (see [2] for a survey). We also allow relations to carry different weights. The weighing function $W : R \cup S \to V$ returns a value for each pair of arguments belonging to the attack or support relations representing the degree to which one argument attacks or supports the other. Based on preliminary experiments, we assume that while the attack and support relations are not disputable in our modeling, each agent may have a different W function. We also incorporate a belief function $B : A \to V$ in our model. The belief function represents the belief that a reasoner has in each argument on its own, regardless of other arguments. Again, beliefs are personal and different agents may have different beliefs. ω denotes the argument of interest. Specifically, a reasoner seeks to evaluate ω in the context of the argumentation framework.

Example 1. *The following is a **part** of an argumentation framework on the topic "You should have a Computer Science Master's Degree" as collected in Section 6.1.*
A consists of the following arguments: ω ="You should have a Computer Science Master's Degree", a = "A Master's Degree helps in getting well-paying jobs.", b ="Experience is more important than education. Therefore, a master's degree will not help in getting better jobs." and c ="Conducting academic research is challenging

[4] In this work, represented as short textual statements.

and interesting". R is defined to be $\{< b, a >\}$ as argument b attacks argument a. S is defined to be $\{< a, \omega >, < c, \omega >\}$ as both a and c directly support ω. W and B could be defined differently by each reasoner. For example, W can be defined as $W(< b, a >) = 0.5, W(< a, \omega >) = W(< c, \omega >) = 0.2$, indicating that the reasoner who uses this argumentation framework believes that b's attack on a is stronger than a's support of ω and c's support of ω. B can be defined as $B(a) = 0.1$, $B(\omega) = 0.5$, $B(b) = B(c) = 0.7$, indicating that the belief of the reasoner in a (not taking into account any other arguments) is lower than she has in b. See Figure 1 for an illustration.

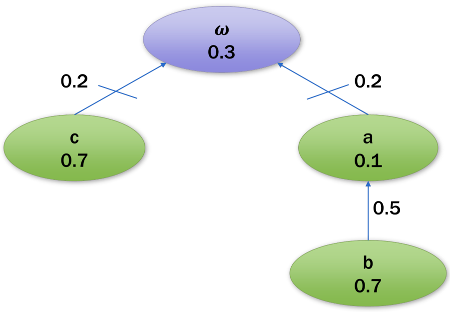

Figure 1. An example of a WBAF, as specified in Example 1. Nodes represent the arguments, arrows indicate attacks and arrows with diagonal lines indicate support. The numbers within the nodes represent the belief function and the numbers next to the edges represent the weighing function.

In our framework we assume that a reasoner uses an evaluation function $v : A \to V$ which assigns a real value to each argument while contemplating the argumentation framework. Note that v is different from the belief function B as the belief function captures the belief a reasoner has in an argument on its own, regardless of other arguments in the argumentation framework. The evaluation function v can be defined in various ways capturing different underpinning principles. In any suggested evaluation function one needs to address 3 issues:

1. **Propagation** - how does the valuation of argument a influence argument b given the weight of the relation between a and b?
2. **Summation** - how do attacking (supporting) arguments accrue?
3. **Consolidation** - how are the attacking arguments and supporting arguments incorporated?

These three issues are addressed in Definition 2, which is an extension of the gradual valuation in Bipolar Argumentation Frameworks [11] to gradual belief valuation in WBAFs.

Definition 2. *Let $WBAF =< A, R, S, W, B, \omega >$ where W and B are defined over V, and let V^* be the set of all finite length tuples of values in V. Let $h : V \times V \to V$ be a **propagation function**, evaluating the quality of attack/support which one argument has on another; let $f_{att} : V^* \to F_{att}$ (resp. $f_{sup} : V^* \to F_{sup}$) be the **summation function**, evaluating the quality of a set of attacking (resp. supporting) arguments; and let $g : F_{att} \times F_{sup} \times V \to V$ be the **consolidation function** which combines the impact of the attacking arguments with the quality of the supporting arguments and the initial belief in the argument.*

*Consider $a \in A$ with arguments $b_1, \ldots, b_n$ as attacking arguments ($b_i R a$) and $c_1, \ldots, c_m$ as supporting arguments ($c_i S a$). A **gradual belief valuation function** on AF is $v : A \to V$ such that $v(a) = g(f_{sup}(h(v(b_1), w(b_1, a)), \ldots, h(v(b_n), w(b_n, a)))$, $f_{att}(h(v(c_1), w(c_1, a)), \ldots, h(v(c_m), w(c_m, a)))$, $B(a))$.*

An instantiation of a gradual belief valuation function is considered *legitimate* if it satisfies the following axioms (for convenience, in the following f indicates both f_{att} and f_{sup}):

1. $h(x, y)$ must be non-decreasing in both x and y.
2. $x_i > x_i' \to f(x_1, \ldots, x_i, \ldots, x_n) > f(x_1, \ldots, x_i', \ldots, x_n)$
3. $f(x_1, \ldots, x_n) > f(x_1, \ldots, x_n, x_{n+1})$
4. $f() = \alpha \leq f(x_1, \ldots, x_n) \leq \beta$[5].
5. $g(x, y, z)$ must be non-decreasing in x and z and non-increasing in y.

The above axioms capture basic principles that should be followed by any legitimate gradual belief valuation function. Axiom 1 assures that the propagating value from one argument to another depends on the source argument's justification level and the interaction weight in a non-negative manner. Axioms 2, 3 and 4 assure that the summation function increases in the number and quality of the relevant arguments, yet the value is bounded. Axiom 5 assures that the consolidation function does not decrease in the summed strength of the supporting arguments and does not increase in the summed strength of the attacking arguments. Furthermore, it assures that the function does not decrease in the belief level of the argument.

Definition 2 gives rise to a family of valuation functions. Given an argument of interest, the value returned by the valuation function represents the reasoner's ability to support that argument and defend it against potential attacks. The higher the strength level, the easier it is to support and defend the argument, and the harder it is to attack it. In this study we use the following instantiation:

$$h = min, V = [-1, 1], F_{sup} = F_{att} = [0, \infty],$$
$$f_{sup}(x_1, \ldots, x_n) = f_{att}(x_1, \ldots, x_n) = \sum_{i=0}^{n} \frac{x_i + 1}{2}$$
$$\text{and } g(x, y, z) = max\{\tfrac{1}{1+y} - \tfrac{1}{1+x}, z\}.$$

The above instantiation is inspired by the ArgTrust application [50], which uses a propagation function of min, and extends the gradual valuation function definition in [11] to incorporate belief and propagation. The motivation for this choice is twofold: first, the selection of min as a propagation function induces an upper bound on the affect one argument has on the other. The selection of the summation and consolidation functions is a natural extension of [11] and they provide desirable properties such as the ones described above as axioms. An example for the use of the above gradual belief valuation function is presented in Example 2.

Proposition. *The suggested instantiation is a gradual belief valuation function.*

Example 2. *Using Example 1's argumentation framework, our proposed gradual belief valuation function will provide the following: $v(\omega) = 0.53$, $v(a) = -0.43$, $v(b) = 0.7$ and $v(c) = 0.7$. If we were to remove a and b from the argumentation framework, $v(\omega)$ would decrease to 0.37. Similarly, if we remove c from the argumentation framework, $v(\omega)$ would decrease to 0.3 (its belief level).*

[5] α (β) is the minimal (maximal) value of F_{sup} (resp. F_{att})

We assume that the higher $v(\omega)$ is within a reasoner's argumentation framework, the more positive the reasoner's attitude will be towards the topic of interest (ω). Therefore, in a persuasive setting, it is the persuader's task to try and maximize the persuadee's valuation $v(\omega)$. We discuss this task next in Section 4.

4 Persuasive Dialog Optimization

A persuasive dialog is a finite sequence of arguments $< a_1, a_2, \dots, a_n >$ where arguments at odd indices are presented by the persuader and arguments at even indices are presented by the persuadee. A dialog is terminated when the persuader uses the "terminate" argument, which is only available to him.

We denoted D as the set of all finite length dialogs. At every even index of the dialog, the persuader observes the current state of the dialog $d \in D$ and posits an argument a according to a persuasive policy π. That is, π maps each possible even length dialog to an argument that the persuader should posit.

A persuasive agent seeks to execute an *optimal* persuasive dialog policy, π^*. Namely, π^* maximizes the expected value of $v(\omega)$ in the persuadee's argumentation framework by following it until the dialog terminates.

We consider an environment in which the persuader is *Omniscient*, namely, it is aware of all arguments affecting ω, the designated argument which represents the discussed issue. On the other hand, we assume that the persuadee may only be aware of a subset of the arguments of which the persuader is aware. This asymmetrical situation is common when the persuader is an expert in the discussed issue and the persuadee is not. Namely, an extensive WBAF which contains all possible arguments affecting ω is maintained by the persuader. However, each persuadee holds a different WBAF that may differ from the one held by the persuader. Consequently, the persuader seeks to estimate the persuadee's WBAF and strives to influence it. The persuader can influence the persuadee's evaluation of ω (denoted as $v(\omega)$) under the persuadee's argumentation framework by introducing new arguments of which the persuadee was unaware. Once presented with an argument of which the persuadee was unaware, we assume that the argument is added to the persuadee's argumentation framework and $v(\omega)$ is updated accordingly. In our environment, the persuadee's argumentation framework is not assumed to be known to the persuader prior to or during the dialog. However, we do assume that the persuader can obtain a probability distribution χ of the possible persuadee's argumentation frameworks, possibly from past interactions. However, due to the infinite number of possible argumentation frameworks (recall that the WBAF's B and W functions may return continuous numbers), constructing and using χ is not straightforward. Note that the persuader can only be certain that arguments that have actually been presented in the dialog are in the persuadee's argumentation framework.

We assume the persuadee's choice of arguments depends heavily on her argumentation framework. Namely, after an argument is presented by the persuadee, the persuader may change its estimations of the persuadee's argumentation framework as the persuadee's arguments act as "signals" to her argumentation framework. Namely, when the persuadee posits argument a, the persuader learns that a is part of the persuadee's argumentation framework. Then the persuader can speculate *why* the persuadee chose to posit that argument. For example, a reasonable explanation may be that the persuadee thinks that a is well supported in her argumentation framework. A more practical way to look at this phenomenon, which we use later in this paper, is that the persuader speculates which argumentation frameworks are likely to result in the persuadee presenting argument a given the current state of the dialog.

Given any non-terminated dialog d, an optimal persuasive dialog policy π^* satisfies the following equation:

$$\pi^*(d) = argmax_a \, \mathbb{E}_{\pi^*}[v(\omega)|da] \qquad (1)$$

where $\mathbb{E}_{\pi^*}$ denotes the expected value given that the agent consistently follows policy π^* until the dialog terminates.

Note that calculating π^* is infeasible due to the infinite number of possible argumentation frameworks and the exponential number of possible dialogs. Therefore, a persuader can only approximate the optimal persuasive dialog policy. We address both issues next in the design of our agent, SPA, in Section 5.

5 Strategical POMDP Agent (SPA)

In order to approximate the optimal solution for the dialog optimization problem (Section 4), we show a reduction of this problem to a Partially Observable Markov Decision Process (POMDP) [28]. As discussed in Section 4, we do not assume that the persuadee's argumentation framework is known to the persuader prior to or during the dialog. In other words, the persuadee's **state**, i.e., her argumentation framework, is only partially observable to the persuader. Nevertheless, the persuader does see the dialog that takes places, which we will refer to as the **observation**, and can use it to derive insights regarding the persuadee's state. As the dialog progresses more arguments are presented, which change the persuader's observation and possibly the persuadee's state if new arguments are added to her argumentation framework. The persuader posits arguments, i.e., takes **actions**, in order to influence the persuadee's argumentation framework. That is, following an action by the persuader a change in the system occurs according to some **transition function** which we will soon discuss. The persuadee also presents arguments in the dialog. However, the persuadee cannot posit arguments of which she is unaware (i.e., they are not in her argumentation framework), therefore the persuadee's arguments only change the observation and thereby, as discussed in Section 4, play an important role in estimating the persuadee's state. Naturally, the persuader seeks to maximize the expected value of $v(\omega)$ in the persuadee's argumentation framework by following the optimal persuasion policy. At the same time, the persuader wishes to avoid prolonging the dialog, as long dialogs may bother or annoy the persuadee. To that end, the persuader may use a **discounting factor** to favor short dialogs.

We model the persuasive dialog optimization problem as a Partially Observable Markov Decision Process (POMDP).

Definition 3. *A Partially Observable Markov Decision Process is a tuple* $< \mathcal{S}, \mathcal{A}, \mathcal{T}, D, \mathcal{R}, \Phi, \gamma >$ *where:*

- $\mathcal{S}$ *is the set of all possible argumentation frameworks.* $s \in \mathcal{S}$ *is a persuadee's argumentation framework.*
- $\mathcal{A}$ *is the set of all arguments that may affect the evaluation of* ω *and the argument "terminate".* $a \in \mathcal{A}$ *is an argument that the persuader can posit, i.e.,* a *is in the persuader's argumentation framework. Recall that we assume that the persuader is Omniscient, and thus aware of all arguments affecting* ω *(see Section 4).*
- $\mathcal{T}$ *represents the state transition dynamics, where* $\mathcal{T} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \mapsto \{0, 1\}$. $\mathcal{T}(s, a, s')$ *is an indicator function specifying whether a transition from* s *to* s' *using* a *is valid. Formally,*
  $\mathcal{T}(s,a,s') = \begin{cases} 1 & \textit{if } s' = s \oplus a \\ 0 & \textit{otherwise} \end{cases}$

where $s \oplus a$ is the resulting framework from adding argument a to s.

- *D is the set of all possible finite length dialogs. In our setting, D is also the set of all possible observations.*
- *$\mathcal{R} : \mathcal{S} \times D \mapsto V$ is the reward function for arriving at state s with dialog d. We define*
$$\mathcal{R}(s,d) = \begin{cases} 0 & \textit{if } d \textit{ is non-terminated} \\ v(\omega) & \textit{otherwise} \end{cases}$$
- *Φ is the conditional probability $\Phi(d \mid s', a)$. We will discuss Φ later in this section.*
- *γ is the discounting factor, representing the likelihood for the persuadee to be bothered or annoyed by a prolonged dialog.*

SPA approximates the optimal solution for the above POMDP using Monte-Carlo Planning, an algorithm known as POMCP [46]. POMCP is a general purpose algorithm for approximating an optimal policy in large POMDPs. The POMCP algorithm uses a Monte-Carlo search tree to evaluate each argument that the persuader can posit (at odd levels of the tree) given the state of the dialog (a node in the tree). The search tree is rooted in the empty dialog.

The deployment of the POMCP algorithm does not necessitate the explicit definition of Φ. Instead, POMCP requires 3 components:

1. $\mathcal{I}$, a black-box simulator for sampling $s \in \mathcal{S}$ according to each state's initial probability χ (discussed in Section 4).
2. $\mathcal{G}(s,d,a)$, a generative model of the POMDP. This simulator returns a sample of a successor state (s'), dialog (d') and reward (r) given (s,d,a), denoted $(s',d',r) \sim \mathcal{G}(s,d,a)$.
3. $\pi_{rollout}$, a policy that is deployed once leaving the scope of the search tree.

SPA approximates $\mathcal{I}$ using Algorithm 1. In words, SPA is given an annotated corpus C of dialogs between humans (without any agent intervention) on a given topic ω. SPA assumes that the use of an argument a in C is an indicator of its likelihood to appear in the persuadees' argumentation frameworks. Therefore, Algorithm 1 samples an argument subset A' out of all arguments available in C according to each argument's Maximum Likelihood Estimation (MLE) [45]. R and S are defined according to a manual annotation of the relation between each pair of arguments in C. More details regarding the annotation process are provided in [42]. For the definition of B and W SPA is given two answer sets of questionnaires answered by human participants, denoted Q_1 and Q_2. In Q_1, human participants rate the persuasiveness of each argument in C on its own, namely, while disregarding all other arguments they may be aware of. We model each subject's answers in Q_1 as the subject's B function in the corresponding argumentation framework. In Q_2, the same participants whose answers were recorded in Q_1 rate the degree to which arguments affect others. That is, participants are presented with pairs of arguments from C for which a relation was annotated in the first place. Participants rate the degree to which the first argument affects the second one. We model each subject's answers in Q_2 as the subject's W function in the corresponding argumentation framework. In order to sample B and W, and thus complete the definition of the sampled argumentation framework, SPA uses the well-established Kernel Density Estimation (KDE) sampling method [47]: First, SPA samples a participant at random from the participant list and retrieves her answers in both Q_1 and Q_2. Then, SPA uses a Gaussian KDE method to smooth out the contribution of each of the subject's answers (in Q_1 and Q_2) over a local neighborhood of possible answers, resulting in a probability distribution centered around the subject's actual answers. Then, SPA samples the probability distribution and uses the sample as B and W. This process makes it possible to sample an infinite variety of B and W, while using a finite set of points as "anchors" for the sampling process.

Algorithm 1 Simulating $\mathcal{I}$

Require: Dialog corpus C, answers sets Q_1, Q_2.
```
A ← getArguments(C)
A′ ← {ω}                         ▷ Create a set with the designated argument
for all a ∈ A do
    MLE(a) ← (#a appearances in C)/|C|
    Add a to A′ with probability MLE(a)
S, R ← manually annotated relations among argument in A′
id ← uniformly sample a participant id.
B ← KDE(Q_1(id))
W ← KDE(Q_2(id))
return < A′, R, S, W, B, ω >
```

SPA approximates $(s',d',r) \sim \mathcal{G}(s,d,a)$ using Algorithm 2. In words, similar to the input of Algorithm 1, SPA is given (the same) annotated corpus C of dialogs between humans (without any agent intervention) on a given topic ω. If $a =$ "terminate" then $s' = s$, $d' = da$ (denoting the concatenation of a to the end of dialog d), and $r = v_s(\omega)$ (the evaluation of ω in the argumentation framework s). Recall that once the persuader posits "terminate", the dialog ends. Otherwise, the dialog continues with an argument by the persuadee. To simulate the persuadee's answer, a Machine Learning algorithm, $P(a'|d)$, is trained *offline* using C to predict the likelihood of each argument being presented next, given dialog d. Algorithm 2 returns $s' = s \oplus a$, denoting the addition of argument a to s and $d' = dab$ where b is an argument sampled according to $P(b|da)$. The reward can be defined as $r = -c_a$ where c_a is the cost of positing argument a. We define $r = 0$ for all arguments as we assume there is no direct cost for positing arguments. In our modeling, the cost of prolonging the dialog is captured by γ (the discounting factor).

Algorithm 2 Simulating $\mathcal{G}(s,d,a)$

Require: Dialog corpus C.
```
P ← predModel(C)                 ▷ Constructed once.
if a="terminate" then
    return < s, da, v_s(ω) >
Add a to s.
b ∼ P(da) s.t b ∈ s.
return < s, dab, 0 >
```

As for the rollout policy $\pi_{rollout}$, SPA uses a simple policy where an argument a is selected at random at odd indices of the dialog and the predication model $P(a|d)$ (see Algorithm 2) is used at even indices to simulate the persuadee's responses.

Training SPA

In order to train SPA, we need to construct a prediction model P for estimating the likelihood that an argument b will be presented next, given dialog d. To that end, SPA uses the ML methodology suggested in [42]. The method uses a standard decision tree learning algorithm that returns a probability model estimating the probability of each possible argument being presented next. P is used in the definition of $\mathcal{G}(s,d,a)$ – the generative process of the POMDP (see Definition 3).

During its training, the POMCP algorithm maintains a search tree which keeps changing and expanding as long as the algorithm is running. Many POMDP-based applications that implement the POMCP Algorithm, especially in game playing [25], train the POMCP algorithm offline against itself. Namely, two instances of the POMCP algorithm are implemented and are trained simultaneously. The first POMCP learns to play against the second POMCP, which in turn learns to play against the first. This methodology cannot be implemented in the scope of this work as we assume that the persuadee is not strategical and hence cannot be represented as a POMCP instance. However, the prediction model P does capture the non-strategic behavior of the persuadee, hence it is used in the definition of $\mathcal{G}(\cdot)$. Note that during actual deployment SPA uses the persuadee's actual arguments instead of simulated arguments provided by sampling P.

6 Evaluation in Attitude Change

First we evaluate SPA in an attitude change task. In an attitude change task the agent's goal is to increase positive attitude and decrease negative attitude towards a given topic. The topic we chose to focus on was the *"You should have a Computer Science Master's Degree"*, where the persuader's goal is to change senior computer science students' attitude towards the enrollment to a master's program. The topic is of great interest to senior students and hence was selected.

6.1 Data Collection

Phase 1 - We recruited 56 senior bachelors students studying Computer Science – 37 males and 19 females with an average age of 28. First, each student was asked to rate a series of five statements using an online questionnaire. The statements were regarding the students' personal academic experience, such as "I would volunteer during my studies if I would get credit for it". The statement of interest to us was "I plan to enroll in a Master's degree program". For each statement, students provided a rating on the following Likert scale; 1-Strongly Agree, 2-Agree, 3-Neutral, 4-Disagree and 5-Strongly Disagree.

Students were represented in the system using a special identification number that was given to them prior to the experiment by our research assistant. We made sure that the students were aware that the identifier could not be traced back to their identity in order to avoid possible influences on the students' behavior. Students were divided into 3 groups according to their answers to the question of interest: Positive, Neutral and Negative.

A week afterwards, we matched the students such that each student was coupled with a student from outside her group. The coupling was carried out manually by our research assistant who asked the subjects for their preferred time slots and matched every couple accordingly. The students were asked to converse about the topic *"You should have a Computer Science Master's Degree"* for a minimum of 5 minutes, and to try and convince their interlocutor to adopt their point of view. Dialogs ranged in length from 5 arguments to 11 (mean 7). Each dialog ended when one of the deliberants chose to exit the chat environment. All dialogs were manually annotated for arguments and the relation between those arguments by a human expert using the annotation methodology used in [42], resulting in an annotated dialog corpus C.[6] Immediately after the chat, students were again asked for their rating of the statement "I plan to enroll in a Master's degree program" using the same scale.

In our previous study [42], we showed that people do not adhere to the reasoning rules proposed by the argumentation theory in real-world deliberations. It turns out that this result extends to persuasive interactions as well. For example, only 67% of the students participating in this phase of the data collection used a *conflict free* argument set in their dialog. Namely, 33% of the students used at least two arguments a and b such that a attacks b or vice versa during their dialog.

Phase 2 - We recruited an additional 107 senior bachelors students studying Computer Science – 68 males and 39 females with an average age of 27. Students were asked to answer two online questionnaires, a week apart. In the first one, students were asked to rate the persuasiveness of each of the 16 arguments in C on its own on a scale of 0 to 1, where 0 is "The argument is not persuasive at all" and 1 is "The argument is very persuasive". In the second one, students were asked to rate the degree to which one argument effects another over pairs of arguments. The scale that was used was again of 0 to 1, where 0 stands for "No effect" and 1 is "Very strong effect".

In C, 16 distinct arguments were detected (8 pro and 8 con). First, a prediction model P was trained using the methodology discussed in Section 5. For comparison, we also considered using a *Bigram model* [27]. In Bigram, the model calculates the probability $P(a_2|a_1)$ for every pair of arguments a_1, a_2. That is, the probability that a_2 follows a_1. These probabilities are estimated using a Maximum Likelihood Estimator with smoothing on the dialogs from C. Both models were evaluated in a one-left-out fashion where each dialog was taken out of C one at a time, both models were trained over the remaining dialogs and were evaluated in relation to the left-out dialog. The perplexity measurement of P was significantly lower than that of Bigram ($p < 0.05$), which makes it preferable.

6.2 Experimental Setting

For the evaluation of SPA we recruited 30 senior bachelors students studying Computer Science, 20 males and 10 females with an average age of 28. Students were first asked to rate two statements using an online questionnaire. The statements were: 1) "I plan to enroll in a Master's degree program", and 2) "A Master's degree will help me in the future". For each statement, students provided a rating on the same Likert scale as used in Section 6.1, namely 1-Strongly Agree, 2-Agree, 3-Neutral, 4-Disagree and 5-Strongly Disagree.

The agent's goal is to persuade students to change their opinion and rate the 1^{st} statement higher. That is, to encourage them to enroll in a master's degree program. If a student has already planned to enroll in a master's degree program prior to the experiment (i.e, she ranked the 1^{st} statement as "Strongly Agree", which was the case for 2 students), then the agent seeks to persuade the student to rate the 2^{nd} statement higher. Note that none of the students provided the highest rating for the 2^{nd} statement prior to the dialog.

We use a between-subjects experimental design with 3 conditions:

1. **SPA**. SPA was trained for 72 hours in which more than 22,700 sessions were simulated. For the evaluation of SPA, we replaced the use of the prediction model P with the persuadee's actual arguments. Recall that P was used to simulate the persuadee's response in the offline training of the POMCP (Section 5). For the evaluation we use the student's actual arguments as presented in the dialog.
2. **Baseline**. The Baseline agent uses the relevance heuristic suggested in [42] and presents a random argument that has not yet

[6] A second expert human annotator was also asked to annotate the dialogs in order to ensure the quality of the annotation. In 10% of the cases, a disagreement between the two annotators was recorded, making the annotation relatively reliable.

been presented in the dialog and directly relates to the last argument presented in the dialog. Of course, the agent only suggests arguments that positively relate to ω, that is, support it indirectly. If no such argument exists, the agent suggests an argument which directly supports argument ω and does not relate to the last argument presented in the dialog. If all directly supporting arguments of ω were already presented, the agent finishes the dialog.[7]

3. **Human**. Recall that during the data collection of human dialogs (with no agent intervention, see Section 6.1) the students' rating changes were recorded. We use the 56 subjects' answers as an additional benchmark in the analysis.

Subjects were pseudo-randomly assigned to each of the first 2 conditions (the 3^{rd} condition is described as part of the data collection in Section 6.1), such that each of the two subjects who rated the 1^{st} statement in the questionnaire as "Strongly Agree" was assigned to a different agent (SPA or Baseline).

A week after answering the questionnaire, each student was asked to engage in a chat with her agent. Note that students were not told that they would interact with an automated agent. On the other hand, they were not told that they would interact with another human either. This was done to avoid biasing the results.

As discussed earlier in this paper, the automatic extraction of arguments from texts is not in the scope of this work. Therefore, the identification of the arguments used by the students was done using a *Wizard of Oz* methodology, where during the chat a human expert[8] mapped each of the persuadee's sentences into an argument extracted from C (see Section 6.1). In case no argument in C fits the presented statement, a designated "NULL" argument was selected. This was rarely used. The possibility of adapting the agent's framework online will be addressed in future work. In order to bolster the natural flow of the dialog, the Wizard of Oz was also in charge of framing the agent's argument using discourse markers. Namely, the wizard was not allowed to alter the content of the argument but could add discourse markers such as "However", "Moreover", etc.

At the end of the dialog, subjects were asked to answer the online questionnaire once again.

6.3 Results

Out of the 15 students who were equipped with SPA, 4 students (26.6%) changed their rating by one category. Three subjects changed from Positive to Very Positive and one from Neutral to Very Positive. Only a single student (6.6%) from the 15 students who were equipped with the Baseline agent changed her rating (from Negative to Neutral). Out of the 56 students who were asked to persuade each other in Section 6.1, 15 (26.7%) changed their opinion by at least 1 category. Out of these 15 students, 4 (7.4%) changed their opinion by 2 categories. This result is slightly better than the results obtained by SPA, yet the difference is not statistically significant. Nevertheless, the Baseline agent was significantly outperformed by the other examined conditions using Fisher's exact test ($p < 0.05$).

[7] We chose to compare our method with another method that has already been tested with human subjects. Unfortunately, existing proposals in persuasive argumentation were not tested with people thus far. We hope to inspire other researchers in the field to test their proposed methods with human subjects.

[8] In order to prevent the expert from being biased toward one of the agents, the expert was not involved in any other part of the research, in particular in building the agents.

7 Evaluation in Behavior Change

We also evaluate SPA in a behavior change task. In a behavior change task the agent's goal is to persuade its interlocutor to choose a desired action that does not fit with the interlocutor's initial choice. A prominent example of such a behavior change task is persuading people to make healthier life styles choices [17]. The practical decision we chose to focus on was *"Would you rather receive a piece of chocolate cake or an energy bar as a free snack?"*, where the persuader's goal is to change its interlocutor's choice given her initial one. Therefore, two persuasive policies were learned, one that is aimed at persuading people to choose the piece of chocolate cake, and one to persuade people to choose the energy bar. Unlike attitude change (Section 6), in behavior change evaluation we wish to make the decision-making concrete and practical in order to assert that the change had taken place. Therefore, subjects were awarded with their chosen snack at the end of the experiment (see Section 7.2).

SPA assumes that a higher $v(\omega)$ value suggests a higher probability that an alternative will be chosen by the persuadee. Therefore, the agent seeks to maximize the probability that the persuadee will take the desired action by maximizing its $v(\omega)$ value.

7.1 Data Collection

Phase 1 - We recruited 28 subjects – 18 males and 20 females, with an average age of 33. Instead of rating a series of questions on a Likert scale, as done in Section 6.2, in this experiment we asked subjects to answer only a single question with a binary answer - *"Would you rather receive a piece of chocolate cake or an energy bar as a free snack?"*. Students were divided into 2 groups according to their answers.

A week afterwards, we again matched the subjects such that each subject was coupled with a subject from outside her group. The coupling was carried out manually by our research assistant who asked the subjects for their preferred time slots and matched every couple accordingly. The subjects were asked to discuss the topic *"Would you rather receive a piece of chocolate cake or an energy bar as a free snack?"* for a minimum of 5 minutes, and try and convince their interlocutor to adopt their point of view. Dialogs ranged in length from 4 arguments to 11 (mean 7). Each dialog ended when one of the participants chose to exit the chat environment. Immediately after the chat, subjects were again asked to answer the binary question *"Would you rather receive a piece of chocolate cake or an energy bar as a free snack?"*. All dialogs were manually annotated for arguments and the relation between those arguments by a human expert using the annotation methodology used in [42], resulting in an annotated dialog corpus C.

Similar to the analysis presented in Section 6.1, only 79% of the subjects participating in this phase of the data collection used a *conflict free* argument set in their dialog. Namely, 21% of the students used at least two arguments a and b such that a attacks b or vice versa during their dialog.

Phase 2 - We recruited 40 additional subjects – 24 males and 16 females, with an average age of 30. Subjects were asked to answer two online questionnaires. In the first one, subjects were asked to rate the persuasiveness of each of the 26 arguments extracted from the dialogs collected in Phase 1 (denoted C) on its own on a scale of 0 to 1, where 0 is "The argument is not persuasive at all" and 1 is "The argument is very persuasive". In the second questionnaire, subjects were asked to rate the degree to which one argument effects another over pairs of arguments. The scale that was used was 0 to 1, where 0 stands for "No effect" and 1 is "Very strong effect".

In C, 26 distinct arguments were detected (13 in favor of a piece of chocolate cake and 13 against). A prediction model P was trained to estimate the likelihood that an argument b will be presented next given dialog d. Similar to the analysis in Section 6.1, the perplexity measurement of P was again significantly lower than that of a Bigram prediction method ($p < 0.05$), which makes it preferable.

7.2 Experimental Setting

For the evaluation of SPA we recruited 30 subjects - 15 males and 15 females, with an average age of 29. Subjects were first asked to answer the question *"Would you rather receive a piece of chocolate cake or an energy bar as a free snack?"*. Out of the 30 subjects, 16 preferred to have a piece of chocolate cake and 14 preferred to have an energy bar.

We used a between-subjects experimental design with 3 conditions, the same conditions used in Section 6. Namely: SPA, Baselines and Human.

Subjects were pseudo-randomly assigned to each of the 2 agents (SPA and Baseline), such that each agent was assigned 15 subjects, 8 of which prefer to have a piece of chocolate cake and 7 who prefer to have an energy bar. At the end of the dialog, subjects were again asked to choose between a piece of chocolate cake and an energy bar. Subjects were awarded with their snack of choice in return for their participation in the experiment.

7.3 Results

Out of the 15 students who were equipped with SPA, 3 students (20%) changed their decision – 2 from a piece of cake to an energy bar and 1 from an energy bar to a piece of chocolate cake. Only a single subject (6.6%) from the 15 subjects who were equipped with the Baseline agent changed her decision (from a piece of cake to an energy bar). Out of the 28 subjects who were asked to persuade each other in Section 7.1, only 3 subjects (10.7%) changed their decisions following the chat. This result is worse than the results obtained by SPA, yet the difference is not statistically significant.

8 Conclusions and Future Work

In this paper we presented and evaluated a novel methodology for human persuasion through argumentative dialogs. To that end, we proposed a new argumentation framework called Weighted Bipolar Argumentation Framework (WBAF) and suggested a gradual belief valuation method for allowing reasoning within that framework. Our methodology, combining the WBAF argumentative modeling, machine learning on human generated dialogs and argumentative data, and Markovian optimization techniques enabled our automated agent, SPA, to persuade people in 2 distinct environments. In both an attitude change environment and a behavior change environment, SPA was able to perform on a human-like level and significantly better than a baseline agent.

This study is part of our ongoing effort to investigate the connections and challenges between Argumentation Theory and people [42, 41, 43]. We hope that the encouraging results shown in this work (and in previous ones) will inspire other researchers in the field to investigate other argumentation-based methods in human experiments. We believe that bridging the gap between formal argumentation and human argumentation is essential for making argumentation practical for a wider range of applications.

We plan to continue this line of work by investigating other human argumentative interactions such as negotiations [35, 16, 44]. In negotiations, both parties try to maximize some personal utility in the face of partially conflicting interests, while striving to reach an agreement.

We will be pleased to share the constructed corpora for future research.

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