ARTICLE IN PRESS
JID:IJA AID:8134 /FLA [m3G; v1.224; Prn:24/10/2017; 15:36] P.1 (1-16)
International Journal of Approximate Reasoning ••• (••••) •••–•••
Contents lists available at ScienceDirect
International Journal of Approximate Reasoning
www.elsevier.com/locate/ijar

Opinion diffusion and influence: A logical approach

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ARTICLE INFO

Article history:
Received 13 December 2016
Received in revised form 18 July 2017
Accepted 19 October 2017
Available online xxxx

Keywords:
???

ABSTRACT

This paper aims at modeling opinion diffusion among agents with a logical approach by assuming that opinions are propositional formulas. In a first part, we present a model in which an agent changes its opinion by merging the opinions of some influential agents, its influencers. More precisely, it merges these opinions, which may be contradictory, by taking into account an order of importance among its influencers. In a second part, we generalize this model so that influencers are ordered according to several orders of influence which depend on the topics of opinions.

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1. Introduction

Understanding the dynamics of opinion among agents is an important question which has recently received considerable attention in the community of autonomous agents and multi-agent systems [6,1,2,17,5,11,19,16]. This question depends on several parameters.

The first important parameter is the population of agents. This population may be unstructured, in such a case, agents interact randomly [13,6]. But generally, some relations exist between agents. The population of agents may be divided into communities modeling neighborhood relations between agents [12,1,5]. The population may also be structured via an influence relation which relates two agents, the opinion of one of these agents being influenced by the opinion of the other [17]. Graphs are widely used to model the structured population: nodes are agents and links are the relations between agents. Links are symmetrical or not, depending on the type of relations and they may also be labeled with probabilities [18].

The second parameter is the model of opinion. Here again, several options exist. Most of the works previously cited consider only one opinion and model it as a real number in $[0, 1]$. For instance, if the question is to evaluate the opinion of people about the fact that Canada will host the Winter Olympics in 2026, then an opinion which is close to 1 means that the agent is quite confident in Canada candidature or that according to this agent, the probability that Canada will host the Olympics is high. An opinion which is close to 0 means that the agent thinks that Canada candidature will be rejected or that according to this agent, the probability that Canada will host the Olympics is low. Some other works are based on formal logic and model opinions as propositional formulas or, more precisely, as the sets of their models. In [11], an opinion is a single interpretation, called a ballot. For instance, an agent whose opinion is $CAN \wedge acroski$, thinks that Canada will organize the Olympics in 2026 and that there will be acroski trials. Another agent whose opinion is $\neg CAN \wedge acroski$, thinks that 2026 Games will not be hosted by Canada but there will be acroski trials. More generally, [16] considers that an opinion is any propositional formula, thus modeled by a set of interpretations which is not necessarily a singleton. For

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https://doi.org/10.1016/j.ijar.2017.10.014
0888-613X/© 2017 Published by Elsevier Inc.

Please cite this article in press as: L. Cholvy, Opinion diffusion and influence: A logical approach, Int. J. Approx. Reason. (2017), https://doi.org/10.1016/j.ijar.2017.10.014

instance, an agent opinion is $(acroski \vee skijo\ddot{e}ring) \wedge CAN$ when it thinks that the 2026 Winter Olympics will be hosted by Canada and that there will be *acroski* trials or *skijoëring* trials.

The last parameter is the model of opinion dynamics. Many works in the field of opinion dynamics in multi-agent systems are based on a theory introduced in the field of Social Psychology called *Social Judgment Theory (SJT)*. The basic idea of *SJT* is that individual opinion changing is a judgmental process: if an agent considers that a presented opinion is close to its current opinion, then it is likely to shift in the direction of this opinion (*assimilation*); if it considers that the presented opinion is distant to its current opinion, then it is likely to shift away from this opinion (*contrast*); otherwise, the agent does not change its opinion (*non-commitment*). This general idea has led to different formal models [13,6,2] in which the thresholds agents use to characterize what are close and distant opinions are identical or not, universal or agent dependent. Some other works, like [17], are based on the theory of *motivated cognition*, defined in Cognitive Psychology, and which also says that agents are skeptical of another agent when their opinions diverge, but are more receptive to persuasion when their opinions better align. Some other works in the field of diffusion in multi-agent systems claim to be based on models provided by the Network Science community. For instance, [5] is based on the *SIR model* which says that the value of an agent's feature evolves according to the values of its neighbors feature values. For instance an agent is infected if one of its neighbor is. Or an agent may say that it believes something if its neighbors said that they also do.

Simulating opinion diffusion may be applied in many contexts. In particular, simulation of opinion diffusion is important to prepare Psychological Actions (PSYOPS) in the military context. These actions aim at changing the perception and the behavior of some people. They consist in elaborating and spreading out a message that must reach these individuals, directly or indirectly via their social networks [10,9].

In the present paper, we extend a work recently presented in [4].[1] We model opinions by any kind of propositional formulas. As a consequence, opinions may be in disjunctive form and thus be incomplete. We also assume that the population of agents is structured by a binary relation of influence which relates two agents when one influences the other. In a first part, we assume that any agent orders its influencers (i.e. agents which influence it) according to the strength of the influence relation. Then, any agent changes its opinion by merging the opinions of its influencers from the most influential one to the least. In a second part, we consider that agents order their influencers according to the topics of opinions. For instance, you may be more influenced by your friend $Paul$ than by your friend $Mary$ about *winter sport events* while being more influenced by $Mary$ than by $Paul$ about *literature*. In this case, any agent changes its opinion by merging the opinions of its influencers, topic by topic.

This paper is organized as follows. Section 2 presents the notion of Importance-Based Merging Operators and provides some original properties of these operators. Section 3 presents the notion of Influence-Based Opinion Diffusion Structures (IODS) to model opinion diffusion. Section 4 presents some properties of IODS. Section 5 extends IODS so that influencers may be ordered according to several orders of influence, depending on the topics of opinions. It also studies some of their properties. Finally, Section 6 presents some conclusions and discussions.

2. Importance-based merging operators

In this section, we aim at defining a merging operator which takes into account the relative importance of the formulas to be merged for building the result. For doing this, we adopt the same kind of approach introduced in [14]: we adopt a semantical approach and we characterize the models of the result from the models of the initial formulas; we also consider a special formula, called *integrity constraint*, which expresses some law of nature and which restricts the possible models.

We consider a finite propositional language L i.e. a finite set of propositional letters. A literals is a propositional letter or the negation of a propositional letter. By convention, an interpretation of L is represented by a set of literals so that a propositional letter is positive iff it is satisfied in the interpretation, negative iff it is not satisfied in the interpretation. If φ is a formula of L, $Mod(\varphi)$ denotes the set of models of φ i.e., the set of interpretations in which φ is true. A multi-set of formulas $\{\varphi_1, ..., \varphi_n\}$ equipped with a total order $\prec$ s.t. $\varphi_i \prec \varphi_{i+1}$ $(i = 1...n-1)$ is called *an ordered multi-set of formulas* and denoted $\varphi_1 \prec ... \prec \varphi_n$.

Given a consistent formula μ and an ordered multi-set of formulas $\varphi_1 \prec ... \prec \varphi_n$, an Importance-Based Merging Operator characterizes a formula $\Delta_\mu(\varphi_1 \prec ... \prec \varphi_n)$ whose models are selected among the models of μ by taking into account the relative importance of the formulas φ_i. More precisely, the operator selects the models of μ which first are the closest to the models of φ_1, then the closest to the models of φ_2 etc. For doing this, we assume a pseudo-distance d between interpretations of L. Notice that $\Delta_\mu(\varphi_1 \prec ... \prec \varphi_n)$ should be indexed by d but we write $\Delta_\mu(\varphi_1 \prec ... \prec \varphi_n)$ to simplify the notation. The formal definition of Δ is the following:

Definition 1 *(Importance-based merging operator).* An Importance-Based Merging Operator is a function Δ which associates a formula μ and a non-empty ordered multi-set of consistent formulas $\varphi_1 \prec ... \prec \varphi_n$ with a formula denoted $\Delta_\mu(\varphi_1 \prec ... \prec \varphi_n)$ so that: $Mod(\Delta_\mu(\varphi_1 \prec ... \prec \varphi_n)) = Min_{\leq_{d,\varphi_1 \prec ... \prec \varphi_n}} Mod(\mu)$ with:

[1] In this present paper, we prove many more properties on IODS and TIODS that we did in the previous paper. But the main difference between the two papers is that here, we changed the definition for TIODS so that *Unanimity Preservation* is now satisfied while it was not in the previous paper. It is also proved that TIODS extend IODS, which was not the case in the previous paper. Moreover, proofs are given in extension.

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