A new framework for ABMs based on argumentative reasoning ⋆

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Abstract. We present an argumentative approach to agent-based modeling where agents are socially embedded and exchange information by means of simulated dialogues. We argue that this approach can be beneficial in social simulations, allowing for a better representation of agent reasoning, that is also accessible to the non computer science savvy, thus filling a gap between scholars that use BDI frameworks and scholars who do not in social sciences.

Keywords: Agent based social simulation, behavioral models, abstract argumentation, social networks, opinion dynamics.

1 Introduction

ABMs within the social sciences can be classified into two streams of research: (*a*) a first stream that uses mathematical approaches; (*b*) a second stream that uses formal logics and BDI frameworks.

Analytical, generative and computational sociologists advocate ABMs to model social interactions with a finer-grained realism and to explore micro-macro links [20]. As a result, there are many proposals for ABMs of social phenomena, such as human hierarchies [26], trust evolution [19], cooperation [4], cultural differentiation [5] and collective behaviors [17]. All these models belong to the first stream and share at least two common features: (*a*) a network representation [27] to mimic social embeddedness; (*b*) a preference for mathematical, game theoretical or evolutionary computing techniques. In all these models, agents do, in fact, interact socially within a large population, but very little explicit reasoning is done. The second stream is focused on how social agents should reason, and it encompasses models of trust [11], cognitive representations[12] and norms evolution and evaluation [2]. These models usually rely on formal logics[1] and BDI frameworks [24] to represent agent opinions, tasks and decision-making capabilities. What emerges from this duality is that ABM in social sciences always

⋆ This paper is an extended version of the short paper accepted by AAMAS 2013 [14]

1 The relevance of logic in social simulations is an open issue, with both detractors and supporters [10].

assume agent's reasoning capabilities (in the sense of information processing), but rarely this feature is explicitly modeled. Agents are pushed or pulled, with some degree of resistance, but such a representation of influence has already been challenged [22]. We hypothesize that BDI frameworks have not encountered a wide diffusion among social scientists because most BDI architectures are complex to use by non-computer-scientists. It is no coincidence that cognitive, AI and computer scientists use this approach instead of social scientists. On the other hand, cognitive and computer scientists do not implement agents that interact socially to any significant extent in simulations.

This paper aims at evaluating a new framework for agent-based modeling, which may be appealing for both streams of research in social simulation: it explicitly models agents reasoning capabilities *and* it can be applied to socially embedded and interacting agents. The approach we propose is built on well established theories from social, cognitive, and computer science: the "strength of weak ties" by Granovetter [18], the "argumentative nature of reasoning" by Mercier & Sperber [21] and "computational abstract argumentation" by Dung [9]. Computational abstract argumentation is a reasoning approach that formalizes arguments and their relations by means of networks, where arguments are nodes and attacks between arguments are directed links between such nodes. We believe that this formalization, while it offers a logical and computational machinery for agent reasoning, it is nevertheless friendly to social scientists, who are already familiar with network concepts. There is already a plea for the use of logic-related approaches in ABM [25], but we are not aware of any previous ABM that uses argumentation to investigate social phenomena. Our approach represents a framework in the sense that it leaves the modeler many degrees of freedom: different embedding structures can be accommodated, as well as different trust models and different ways of processing information. The only pivotal point is the representation of information and reasoning with abstract argumentation.

The paper proceeds as follows: in the next section, we discuss the concept of embeddedness [18] that will be used to connect our agents in a relational context; we then present a brief formalization of how agent reasoning and interacting capabilities unfold; we present an implementation of this idea by means of an ABM, along with its scheduling and discuss some experimental results; finally, we conclude and present some ideas for future work.

2 Weak ties and social agents

In social simulations, embeddedness is almost always represented with (more or less explicit) network structures. Embeddedness could be something abstract, i.e. represented with relational networks, or spatial, i.e. represented with Von Neuman or Moore neighborhoods. In any case, these different kinds of embeddedness may all be explicitly represented by network topologies.

The basic idea of this social trait comes from Granovetter's hypothesis, which states that our acquaintances are less likely to be connected with each other than our close friends [18]. This tendency leads to social networks organized as densely knit clumps of small structures linked to other similar structures by bridges between them. Granovetter called this type of bridges "weak ties", and demonstrated their importance in permitting the flow of resources, particularly information, between otherwise unconnected clusters [17]. Embeddedness and bridges express a network topology which exhibits small-world features [28].

Building on Granovetter's "strength of weak ties" theory [18], sociological research on "small world" networks suggests that in a social network the presence of bridges promotes cultural diffusion, homogeneity and integration, but only under the assumption that relations hold a positive value [13]. This last concern is a trademark of the social simulation stream which uses a non-reasoning approach to agent modeling. We will show that our model does not need such a specification.

Following the experimental design by Flache & Macy [13], we use a "caveman graph" to represent a situation where clusters are maximally dense. We use this topology as a starting point to confront our results with a renown model in literature. We then allow for two kind of structural settings:

- a first one where each "cave", i.e. each cluster of the graph, is disconnected from the others, thus agents can interact within their own cluster only;
- a second one where a random number of bridges is added between caves, thus agents can interact occasionally with members of different caves. Even if our mechanism does not guarantee that all the caves become connected, on average the resulting networks exhibit small-world network characteristics.

Such a network structure is imposed exogenously to agents and kept static once generated. Random bridges play the role of weak links. By connecting previously unconnected densely knit caves, they play the role that acquaintances play in real life, and thus bridges are supposed to carry all the information beyond that available in a single cave. However, we do not impose a positive or negative value to links. Instead, links only represent the possibility of communication between any two pair of agents. The bit of information transmitted may have a positive or negative value, depending on the content exchanged: something that reinforces agent opinions or that radically changes them.

We call the stream of information exchanged between two agent a "simulated dialogue". The dialogue mechanism represents the micro-level assumption that governs our model and builds on Mercier & Sperber's work.

3 Agent reasoning and interaction

According to Mercier & Sperber's argumentative theory of reasoning [21], the function of human reasoning is argumentative and its emergence is best understood within the framework of the evolution of human communication. Reasoning developed as a "tool" to convince others by means of arguments exchanged in dialogues. We report a brief summary of a communication process according to Mercier & Sperber:

1. Every time an addressee receives a new bit of information, she checks if it fits what she already believes. If this is the case, nothing happens, otherwise, if the new information uncovers some incoherence, she has to react to avoid cognitive dissonance;
2. She faces two alternatives: (a) either to reject the new information because she does not trust the source enough, to start a revision of her own opinions. In that case, the addressee can reply with an argument that attacks the new information; (b) or to accept the new information because she trusts the source enough, to start a coherence checking and allow for a fine-grained process of opinion revision;
3. The source can react as well to the addressee's reaction: if the addressee decides to refuse the new information, the source can produce arguments to inject trust in the addressee, like exhibiting a social status which demonstrates competences on the subject matter. Otherwise, the source can produce arguments to persuade the addressee that the new information is logical and coherent, or to rebut the addressee's reply.
4. Both addressee and source may have to revise their own opinions while involved in such a turn-taking interaction, until: (a) addressee (or source) revises her own opinions; (b) they decide to stop arguing because they do not trust each other.

Such a turn-taking interaction between communicants is called a "dialogue". As said before, our agents argue through *simulated* dialogues. Before discussing how such a simulated role-taking process unfolds, we introduce how agents represent their knowledge by means of abstract argumentation. In computational abstract argumentation, as defined by Dung [9], an "Argumentation Framework" (AF) is defined as a pair $\langle \mathcal{A}, \mathcal{R} \rangle$, where $\mathcal{A}$ is a set of atomic arguments and $\mathcal{R}$ is a binary *attacks* relation over arguments, $\mathcal{R} \subseteq \mathcal{A} \times \mathcal{A}$, with $\alpha \to \beta \in \mathcal{R}$ interpreted as "argument α attacks argument β." In other words, an AF is a network of arguments, where links represent attack relations between arguments. Consider this simple exchange between two discussants, D_1 and D_2:

- D_1: My government cannot negotiate with your government because your government doesnt even recognize my government (a).
- D_2: Your government doesn't recognize my government either (b).
- D_1: But your government is a terrorist government (c).

Abstract argumentation formalizes these positions through a network representation, as shown in Figure 1. Once the network has been generated, abstract argumentation analyzes it by means of *semantics* [6], i.e. set of rules used to identify "coherent" subsets of arguments. Semantics may range from very credulous to very skeptical ones. Each coherent set of arguments, according to the correspondent semantics, is called an "extension" of $\mathcal{A}$. Some well-known semantics defined by Dung are the *admissible* and the *complete* semantics. To illustrate the rules imposed by these semantics, let us consider a set S of arguments, $S \subseteq \mathcal{A}$:

- S is *conflict-free* if $\forall \alpha, \beta \in S, \alpha \to \beta \notin \mathcal{R}$;

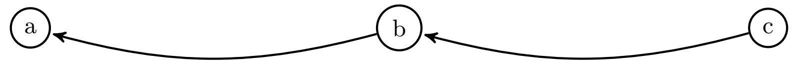


Fig. 1. Sample argumentation framework from Dung [9]

– an argument $\alpha \in S$ is *acceptable* w.r.t S if $\forall \beta \in \mathcal{A}$ s.t. $\beta \rightarrow \alpha \in \mathcal{R}$, $\exists \gamma \in S$ s.t. $\gamma \rightarrow \beta \in \mathcal{R}$;
– S is an *admissible* extension if S is conflict-free and all its arguments are acceptable w.r.t. S;
– S is a *complete* extension if S is admissible and $\forall \alpha \in \mathcal{A} \setminus S$, $\exists \beta \in S$ s.t. $\beta \rightarrow \alpha \in \mathcal{R}$.

In the words of Dung, abstract argumentation formalizes the idea that, in a debate, the one who has the last word laughs best. Consider again the very simple AF in Figure 1 and a credulous semantic like the complete semantic, which states that a valid extension is the one which includes all the arguments that it defends. It is easy to see that $\{a, c\}$ is a complete extension. a is attacked by b, but since c attacks b and does not receive any attack, c defends a, i.e. a is reinstated.

Our agents use a simulated dialogue process, introduced in [15], to exchange similar attacks between their AFs. A simulated dialogue $\mathcal{D}$ starts with an "invitation to discuss" from A (communicator) to B (addressee), by picking a random argument σ in her own extension. If B evaluates σ as coherent with her own AF, the dialog stops: A and B already "agree". On the contrary, if σ is not included in any of B's extensions, B faces an alternative: if she *trusts* A, she will revise her own opinions (i.e., by adding the new information to her AF and by updating her extensions); if instead B does not trust A, she will rebut α against σ and wait for a reaction from A. The exchange between A and B continues until one of the agents changes her mind (agreement is thus reached), or if both agents leave the dialogue because neither is persuaded.

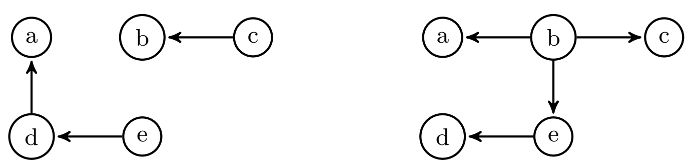
For the sake of generality, we left several choice points open. Mainly, we do not commit to any specific argumentation semantics and we do not commit to any specific opinion revision mechanism. We also assume that agents rely on a trust model. Arguably, a realistic model of trust would to take into account the *authoritativeness*, *rank* and *social status* of the interlocutor [26]. To date, our dialogue model is orthogonal to trust, we define trust thresholds statically but different trust models can be accommodated in the future. Furthermore, in our model information is either accepted or rejected. Argumentative frameworks can handle situations in which human beings partially accept information by means of weighted argumentative frameworks [7] where a certain level of inconsistency between arguments is tolerated. Such argumentation semantics are called conflict-tolerant, whereby arguments in the same extension may attack each other [3]. Again, for the sake of simplicity, we use conflict-free semantics.

4 ABM and arguments: NetArg

We used NetLogo [29] to develop NetArg[2] [14,16]: a model for simulating discussions between argumentative agents, along with a software module (a NetLogo add-on) that performes the computational argumentation analysis.

The model comprises a number of agents (100 in our experiments) distributed in 20 distinct caves. Every agent reasons from the same set of arguments, and she selects, with a fixed probability, one set of attack relations among the two ones available at the beginning, as shown the AFs in Figure 2, derived from a real debate in an online discussion forum about renewable energies[3]. We tested the model with different AFs, with random attacks and up to 10 arguments, as well as AFs taken from empirical contexts and we found results to be stable.

At each time step, each agent is asked to start a dialogue with one of her neighbors extracted at random (see Algorithm 1), who could be restricted to the same cave or not, depending on the presence of bridges. The random extraction assures that the probability to "argue" with members of the same cave is higher than with out-cave neighbors, according to the fact that bridges (weak ties) are less activated than strong ties.



(a) AF1 (b) AF2

Fig. 2. The two argumentative frameworks distributed among the agents.

The agent selected to start a dialogue picks one random argument in her extensions (i.e., an argument she believes in) and addresses the previously selected neighbor. The opponent replies, by following the dialogue procedure briefly sketched in the previous section.

In all our experiments, we opted for the complete semantics, which agents refer to when computing their extensions. At the beginning, each agent believes either $\{a, c, e\}$ or (b, d), the two possible extensions that a complete semantic returns from the AFs used. It is evident from the two plots in Figure 3 that, after some steps, agents adopt new opinions by means of dialogues: in (**a**) only two bars are present at time 0, each of which represents one of the two extensions available at the beginning (the distribution probability is set to 0.5 so they are equally distributed); in (**b**) more bars are present at time 50, i.e. more extensions

[2] The model can be downloaded from here: `http://lia.deis.unibo.it/~pt/Software/NetARG-ESSA2013.zip`

[3] `http://www.energeticambiente.it`

Algorithm 1 Simulate an iteration of the model.

Require: $N_I > 0$ {N_I is the number of iterations}
Require: $N_A > 0$ {N_A is the number of agents}
  for $I = 1 \rightarrow N_I$ **do**
    for $A = 1 \rightarrow N_A$ **do**
      select a random agent B within A's neighbors
      initiate dialog with B
    end for
    record statistics
  end for

are now available, because agents, by exchanging and accepting attacks, alter their own arguments network and thus new extensions are possible.

This opinion revision process gives raise also to a polarization effect at the population level. By polarization we mean that a population divides into a small number of factions with high internal consensus and strong disagreement between them. A perfectly polarized population contains two opposing factions whose members agree on everything with each other and fully disagree on everything with the out-group.

Using a modified version of the measure used by Flache & Macy [13], we measure the level of polarization P at time t as the variance of the distribution of the AF distances $d_{ij,t}$:

$$P_t = \frac{1}{N(N-1))} \sum_{i \neq j}^{i=N,j=N} (d_{ij,t} - \gamma_t)^2$$

where:

- N represents the number of agents in the population;
- $d_{ij,t}$ represents the AF distance between agents i and j at time t, i.e., the fact that agent i has an argument in her extension ($\bigcup_{\mathcal{E}}^{i}$) while the other does not, averaged across all available arguments ($|\mathcal{A}|$):

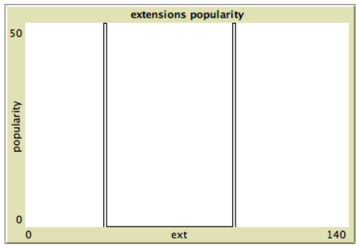
$$d_{ij} = \frac{|\bigcup_{\mathcal{E}}^{i} \setminus \bigcup_{\mathcal{E}}^{j} \cup \bigcup_{\mathcal{E}}^{j} \setminus \bigcup_{\mathcal{E}}^{i}|}{|\mathcal{A}|};$$

- γ_t represents the average distance value at time t.

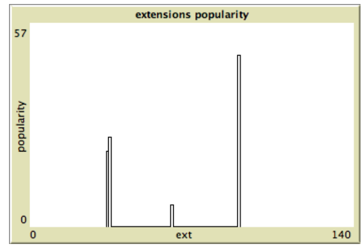
In the next section, we present and discuss the results of three experiments made with NetArg.

5 Experimental results

We present here the results of three different experiments that make use of the AFs in Figure 2. Each parameters combination has been ran 30 times and plots



(a) NetArg model at time 0, with bridges allowed in the caveman graph.

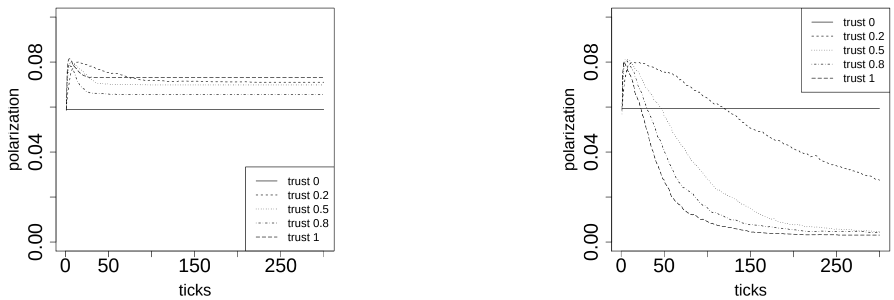


(b) New opinions emerge from interaction in dialogues at time 50.

Fig. 3. The distribution of extensions, at the population level, at time 0 and at time 50. In (b) it is evident the presence of newly formed extensions, not present at setup.

display averaged values for each combination. The first experiment that we discuss aims at testing if the model can reproduce Granovetter's theory about weak ties: does the presence of bridges lower polarization even with our argumentative agents? We set the AFs distribution fixed at 0.5 and allowed trust to take values: 0, 0.2, 0.5, 0.8 and 1. Results are shown in Figure 4. Dialogues enhance polarization because they give raise to new opinions sets, thus increasing opinion distance among the agents. With no bridges connecting caves (**a**), each cave quickly stabilizes at a local minimum. However, different caves will end up in different local minima, which results in a high polarization overall. Trust is able to lower the curve, but only until 0.8, because at 1 every agent changes her mind continuously so that polarization is even enhanced. In a sense, agents with total trust are "gullible" agents ready to believe anything. The instability arises if *all* agents are gullible, because there is no stable opinion. On the contrary, when bridges are present (**b**) polarization levels are lowered considerably. This time, caves can receive information from other caves, and this "small-world" topology lets the population exit from local minima. Increasing trust is more effective in this case, and values as low as 0.5 are able to lower polarization nearly to 0. We then control for different combinations of the two AF among the population, along with different level of trust. We can conclude that the model fits the predictions of Granovetter's theory: (1) the presence of bridges between caves fosters agreement and consensus, increasing the number of "like-minded" agents and (2) since only caves with bridges to other caves can receive new information, only connected caves learn new relations between arguments and change their minds.

In the second experiment we want to test if "majority wins", or if one AF is more "invasive" that the other, controlling for different distribution of the AFs among the agents. We distributed AF_1 among agents with different probabilities (0.2, 0.4, 0.6 and 0.8), controlling for different level of trust (0.2, 0.5 and 0.8). We replicated the experiment with and without bridges. Results are shown in Figure 5. In (*a*) no bridge is allowed, neither AF_1 (in white) nor AF_2 (in black) lose



(a) Polarization without bridges

(b) Polarization with bridges

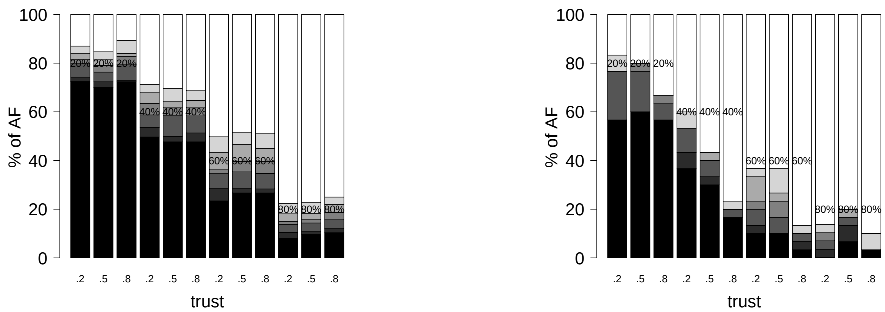
Fig. 4. Average polarization levels (over 100 runs) without bridges, and with bridges. AFs distribution is 0.5. Different levels of trust are shown.

their positions (see the percentage for the initial distribution) to a significant extent. In (b) bridges are allowed, and the jump toward blacks is quite evident: no matter what the initial distribution is, even when AF_1 starts from 20% of the population, it still increase its audience if trust is high. AF_1 results much more aggressive toward AF_2 if bridges are present. A number of other new extensions arise, even if they are a strict minority. AF_2 contains more attacks, nevertheless is not able to win the population nor to defend itself from AF_1. More investigation toward AFs properties involved in ABM is needed in order to better understand this process.

In the third experiment, we check for AF resilience. Since AF_1 appears to be more aggressive, we label agents with AF_1 "innovators" and we explore if it is possible for a relatively small amount of innovators to convince the population to believe their extension, i.e. $\{a, c, e\}$. We can see in Figure 6 that AF_1 has a chance of winning over the whole population even if a low number of innovators is allowed (8% of total population). It is worthwhile noticing that, if bridges are not allowed, the proportion of agents who know $\{a, c, e\}$ at the end of the simulation is more or less equal to the beginning, and the level of trust does not influence agents much. When bridges are permitted, $\{a, c, e\}$ has a much higher probability to spread and, interestingly, results are much sharper: if $\{a, c, e\}$ reaches a tipping point, it wins the whole population, i.e., all agents change their minds and believe $\{a, c, e\}$, otherwise $\{a, c, e\}$ gets forgotten also by innovators. We conclude that bridges not only permit the diffusion of new ideas, but are the real key for innovations to happen, provided they succeed to overcome the threshold.

6 Conclusions

Using a network representation at different levels (social embedding and information), we have built a simple framework for social agents where reasoning



(a) Final diffusion of AFs without bridges.

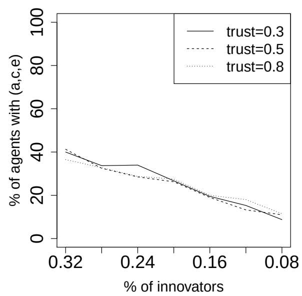
(b) Final diffusion of AFs with bridges.

Fig. 5. Diffusion of AFs. The percentages on the bars indicate the initial distribution when only two AFs (the black and the white) where present.

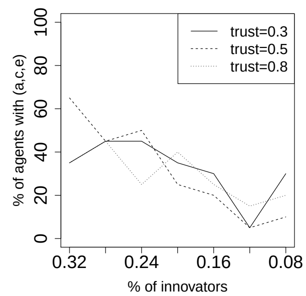
is explicitly represented. We used abstract argumentation and argumentative theory of reasoning to build agents that exchange information through simulated dialogues. We demonstrated that our approach is, in principle, sufficient to reproduce two macro-behavior embedded in Granovetter's theory, i.e., the tendency to inclusion of weak ties and a competitive advantage for non-isolated caves. We showed that some argumentative frameworks are stronger than others and thus can, in principle, spread more efficiently when large audiences come into play. Finally, we also found that a small amount of "argumentative innovators" can successfully spread their opinions among a population, even at very low threshold.

As future work, we plan to further investigate patterns, strengths and weaknesses of AFs from a social science perspective (e.g., to understand which argumentation semantics better model human behavior, and if/why some opinions are stronger than others in a social debate). To accomplish this task, we will analyze real-world debates, like sustainable energy and political discussions within the e-Policy project.

There is a large literature on revising beliefs in artificial intelligence and knowledge representation. In particular, work by Alchourrón et al. [1] was influential in defining a number of basic postulates (known as *AGM postulates* in the literature) that a belief revision operator should respect, in order for that operator to be considered rational. Cayrol et al. [8] propose a framework for revising an abstract AF along these lines. However, considering our application, which is modeling possible outcomes of human debates, respecting the AGM postulates may not be a necessary requirement after all. We plan however to investigate the application of these and other methods, and evaluate which one performs best in simulating opinion diffusion in social networks.



(a) Diffusion without bridges



(b) Diffusion with bridges

Fig. 6. The diffusion of a new argument among caves. On the x-axis, the initial percentage of innovators. On the y-axis, the percentage of agents that believes $\{a, c, e\}$ after the simulation.

To the best of our knowledge, our proposal is original in the social sciences, where argumentation has never been used for social simulation. It represents also a way for qualitative approaches to fit ABM formal requirements: for instance, discourse analysis results can be formalized as AF and fed into a simulator. Our approach envisages possible new grounds for cross-fertilization between the social and computer sciences, whereby surveys could be devised to retrieve arguments rather than numeric variables, possibly with the aid of argument extraction tools [23], and ABMs could be calibrated with empirically grounded AFs, to study the spreading of information, ideas and innovations with a finer-grained realism.

References

1. Alchourrón, C.E., Gärdenfors, P., Makinson, D.: On the logic of theory change: Partial meet functions for contraction and revision. J. Symb. Logic 50, 510–530 (1985)
2. Andrighetto, G., Villatoro, D., Conte, R.: Norm internalization in artificial societies. AI Communications 23, 325–333 (2010)
3. Arieli, O.: Conflict-tolerant semantics for argumentation frameworks. In: Proc. 13th JELIA. LNCS, vol. 7519, pp. 28–40. Springer (2012)
4. Axelrod, R.M.: The complexity of cooperation: agent-based models of competition and collaboration. Princeton University Press, Princeton, N.J. (1997)
5. Axelrod, R.M.: The dissemination of culture: A model with local convergence and global polarization. J Conflict Resolut. 41(2), 203–226 (1997)
6. Baroni, P., Giacomin, M.: Semantics of abstract argument systems. In: Argumentation in Artificial Intelligence. Springer (2009)
7. Bistarelli, S., Santini, F.: A common computational framework for semiring-based argumentation systems. In: ECAI 2010 - 19th European Conference on Artificial Intelligence. pp. 131–136. Lisbon, Portugal (August 2010)

8. Cayrol, C., de Saint-Cyr, F.D., Lagasquie-Schiex, M.C.: Revision of an argumentation system. In: Brewka, G., Lang, J. (eds.) Principles of Knowledge Representation and Reasoning: Proc. 11th Int Conf, KR 2008. pp. 124–134. AAAI Press, Sydney, Australia (September 16-19 2008)
9. Dung, P.M.: On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games. Artif. Intell. 77(2), 321 – 357 (1995)
10. Edmonds, B.: How formal logic can fail to be useful for modelling or designing mas. Online resource, `http://cfpm.org/logic-in-abss/papers/Edmonds.html`
11. Falcone, R., Castelfranchi, C.: Trust and relational capital. Journal of Computational and Mathematical Organization 17(2), 179–195 (2011)
12. Falcone, R., Pezzulo, G., Castelfranchi, C., Calvi, G.: Contract nets for evaluating agent trustworthiness. Lecture Notes in Computer Science 3577, 43–58 (2005)
13. Flache, A., Macy, M.W.: Small worlds and cultural polarization. J. Math. Sociol. 35(1-3), 146–176 (2011)
14. Gabbriellini, S., Torroni, P.: Arguments in social networks. In: Proceedings of the Twelfth International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2013). IFAAMAS (2013)
15. Gabbriellini, S., Torroni, P.: Ms dialogues: Persuading and getting persuaded. a model of social network debates that reconciles arguments and trust. In: Proc. 10th ArgMAS (2013)
16. Gabbriellini, S., Torroni, P.: NetArg: An agent-based social simulator with argumentative agents (demonstration). In: Proc. 12th AAMAS (2013)
17. Granovetter, M.: Threshold models of collective behavior. Am. J. Sociol. 83(6), 1420–1443 (1978)
18. Granovetter, M.: The strength of weak ties: a network theory revisited. Sociological Theory 1, 201–233 (1983)
19. Macy, M., Skvoretz, J.: The evolution of trust and cooperation between strangers: a computational model. Am. Sociol. Rev. 63, 638–660 (1998)
20. Manzo, G.: Variables, mechanisms and simulations: can the three methods be syntesized. Revue Française de Sociologie 48(5), 35–71 (2007)
21. Mercier, H., Sperber, D.: Why do humans reason? arguments for an argumentative theory. Behavioral and Brain Sciences 34(02), 57–74 (2011)
22. Palloni, A.: Theories and models of diffusion in sociology. Working Paper 11, Center for Demography and Ecology (1998)
23. Pallotta, V., Delmonte, R.: Automatic argumentative analysis for interaction mining. Argument & Computation 2(2-3), 77–106 (2011)
24. Rao, A., Georgeff, M.: Modeling rational agents within a BDI-architecture. In: Readings in Agents. Morgan Kaufmann (1998)
25. Reich, W.: Reasoning about other agents: a plea for logic-based methods. JASSS 7(4) (2004)
26. Skvoretz, J., Fararo, T.: Status and participation in task groups: A dynamic network model. Am. J. Sociol. 101(5), 1366–1414 (1996)
27. Wasserman, S., Faust, K.: Social network analysis: methods and applications. CUP, Cambridge (1999)
28. Watts, D.J., Strogatz, S.H.: Collective dynamics of small-world networks. Nature 393, 440–442 (1998)
29. Wilensky, U.: Netlogo (1999), cCL and Computer-Based Modeling, Northwestern University. Evanston, IL.