# Modeling Dynamic Web Polarization and Proximity Depolarization Processes by Compactness Measures

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### Abstract

In this paper, we deal with the possibility of simulating dynamic polarization and proximity depolarization processes in a software multi-agent community, modeling homophily and trust relationships usually present in human processes. Group polarization involves various disciplines, such as economics, social psychology, political science, sociology and many others, and it can be considered a critical process underlying relevant behaviors as, for instance, voting and conflictual intergroup relations in the society. Moreover, being a human social phenomenon, the polarization processes are subject to change over time or also effect overturning (i.e., depolarization). Our contribution consists of proposing a compactness-based model for equipping agents in order to simulate the complexity of such processes. We have simulated two case studies where polarization is ruled by compactness measures, combining similarity and trust with different percentages. We evaluated the results provided by compactness measures in order to verify the role of similarity and trust in the agent polarization processes.

### Keywords

Multiagent System, Compactness, Polarization, Similarity, Trust

## 1. Introduction

Human beings are intrinsically a social species characterized by complex and sophisticated social skills devoted to increase cooperation and well adapted group living. They originate from perceptual, cognitive, motivational and emotional processes [1, 2] and reflected in important acts of our everyday lives such as personal choices, market behaviors, political preferences, leadership, etc. [3]. However, such social processes are not stable over time.

Two main (but not exclusive) factors, deeply influencing the dynamics of formation and evolution of social relationships, can be identified in both homophily and trust [4, 5]. They play an important role in inducing us to interact with a potential counterpart tailoring our expectations to be engaged in reliable interactions, as well as in changing our disposition toward a partner over time, either strengthening or undermining it [6].

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More in detail, homophily relies on supposing the existence of affinities, usually represented by means a similarity measure, while trust (commonly intended as an interpersonal relationship, named reputation when considered at the community level) entails beliefs and attitudes about the degree to which other people are likely to be reliable, cooperative, or helpful with respect to specific situational contexts or in general terms [7]. However, providing a definition of trust is an elusive and hard task given that this construct is characterized by several measurable and unmeasurable dimensions (such as expertise, honesty, safety, dependability, etc.) and relies on the specific situational context in which the interactions take place. Therefore, because of its multi-faceted nature and context dependability, the term ”trust” (as well as the related term ”reputation”) is associated with several different meanings [8, 9, 10, 11]. In our perspective, we consider trust also as an individual predisposition based on subjective attitudes and perceptual abilities regarding the behavior of another person, group, device or virtual entity about the possibility of a defection or, conversely, the ability to meet our expectations [12, 13]. To this aim a large number of trust and reputation systems (and measures) have been proposed in the literature [14, 15, 16]. In particular, trust measures aim to provide the actors with information about the trustworthiness of their potential partners and the probability of having satisfactory social interactions [17]. Trust measures can rely on (*i*) direct information derived by a direct knowledge of the trustor about a trustee and/or (*ii*) indirect information considering ratings and/or opinions provided by others about a trustee [18]. Similarity and trust measures can be combined in a single measure, often named compactness [19].

Homophily and trust are implicated in a multitude of human processes, including dynamic polarization processes. The polarization processes - increased in number and relevance with the advent of Internet - involve various disciplines, such as economics, political science, sociology and many others [20, 21].

More specifically, a polarization process may bring individuals, or groups, to advocate more extreme attitude and behaviors than their initial inclinations, for example, in terms of voting, religious beliefs, political decision-making, racial prejudice, intergroup relations, etc. The relevance of polarization processes is also represented by the fact that they can be considered a critical process underlying conflicting intergroup relations in the society. Moreover, being a human social phenomenon, polarization processes are subject to change over time or also effect overturning (i.e., depolarization). Although nature and effects of these phenomena in real interactions have been widely investigated by social sciences, the impact of new technology on such processes requires further investigation.

The advent of Internet first, and social media later, impacted our society in a technological, social and economic way. Internet has given the opportunity to break down physical barriers such as *where*, *how* or *when* and has provided new opportunities for social interactions making easier commenting opinions and sharing multimedia contents. Moreover, such interactions are likely to involve humans as well as virtual (i.e. software) entities without necessarily foreshadowing a dystopian future.

We should also consider the bidirectionality of such processes: even if originated over the virtual dimension of Internet, they can easily reverse their effects on the real society and vice versa [22]. We can also observe an increasing number of dynamic polarization phenomena, typical over Internet, characterized from a sudden propagation/attenuation and, unfortunately, often by aggressiveness [23]. Therefore, it is important to investigate these phenomena even when they occur on the Internet, regardless the real or virtual (i.e. software) nature of both actors and interactions, i.e. human-to-human, human-to-machine or machine-to-machine.

In such a scenario, the study of polarization processes can take advantage from the exploitation of artificial intelligence techniques and from the agent technology, where an agent is a software entity autonomously and proactively operating on behalf of a human being, which delegates to the agent some particularly onerous or annoying tasks. An appropriate approach to simulate these processes consists of adopting agent and multi-agent software technologies which, thanks to the possibility of providing agents with social capabilities, allow a wide range of interactions of our interest to be reproduced with a high accuracy [24, 25]. To this end, software agents can be endowed with emotions, intentions, and beliefs in order to model cognitive aspects and personality traits for replicating the salient features of human behaviors such as benevolence, selfishness, honesty, and meanness even in virtual societies. Furthermore, it is possible to take into account the presence of other competing or cooperating partners in planning and implementing possible strategies to achieve agents' goals [26]. For such reasons, agent-based systems can be engaged to analyze complex forms of social relationships [27, 28], as cooperation [29, 30], self-coordination [31, 32], group formation [33, 34], as well as in very wide range of application contexts such as marketing and finance [35, 36], transportation systems [37, 38], manufacturing and process control [39, 40], IoT [41], etc.

Within the framework outlined above, this research aims to investigate the different behaviors patterns forged by similarity and trust measures, as well as their combination (named compactness measure), in modeling polarization processes. To this aim, we simulated two case studies, the former based on a dynamic Web scenario and the other one on a "proximity" scenario considering the ego-network of each simulated agent (see Section 2), as representative of polarization and depolarization processes. In both these case studies we assumed that the relationships among agents are qualitatively similar to those occurring in human societies.

In the two case studies we analyzed, the obtained experimental results confirmed a different modeling behavior of the three measures we tested and help us to better understand the implications linked to their use in terms of dynamic polarization and depolarization events in designing software agents environments. These results are potentially useful also in the domain of social science, to better understanding the dynamic of such processes in human communities.

It is important to highlight that in our study we have not considered the eventual presence of malicious agents, that is the possibility of agent behaviors trying to artificially direct polarization processes and, therefore, we do not deal with issues related to the identification of such particular agents.

The rest of the paper is organized as follows. Section 2 introduces the reference scenario, while in Section 3 the result of simulations are presented and discussed. Finally, some conclusions are drawn in Section 4.

## 2. The Reference Scenario

Our scenario deals with a set $W$ of $N$ agents simulating users active in a Web community. For the first case study, we consider also two agents $A$ and $B$ playing the role of leaders and performing, over time, two independent sequences of actions that may or may not meet the approval of the agents belonging to $W$, based on their inclinations, in order to simulate dynamic polarization processes. In the second case study, we exploited the individual agent ego-network to simulate depolarization processes.

In Section 2.1 we provide the description of the knowledge representation associated with the agents, while Section 2.2 deals with the leader's and agents' tasks and Section 2.3 give our measures of trust, similarity and compactness.

### 2.1. The Agents' Knowledge Representation

To characterize the interests and the preferences of each actor acting in our scenario, we associate a profile $p$ with each agent of $W$ and a profile $P$ with each leader (i.e., $A$ and $B$).

The agent profile stores three *properties* on which our model is based, namely *Inclination* ($I$), *Trust* ($T$) and *Ego-network* ($E$). We define the profile $p$ of an agent as a tuple $\langle I, T, E \rangle$, where the property $I$ is referred to the inclinations of the agent with respect to the categories considered in $W$. To this aim, we denote with $C$ the set of all the possible categories in $W$. Each element $c \in C$ is an identifier of a given category and $I$ is a mapping that, for each category $c \in C$, returns a real value ranging in $[0, \cdots, 1]$, where the values 0 and 1 identify the two extreme, opposite inclinations about a category. Categories play the role of ontological elements for all the agent community (like Facebook, where users can select categories of interest from a shared list), this gives us the opportunity of supposing a common, homogeneous semantic scenario. We also suppose that in a real scenario agents can perform the identification of the inclination automatically.

The property $T$ is a mapping associated with how much an agent trusts each other agent in $W$ and the two leaders. The mapping, $T$ returns a real value, ranging in $[0, \cdots, 1]$ representing the trust perceived by the trustor (i.e., an agent) with respect to the trustee (i.e., an agent or a leader), as detailed in Section 2.3. The property $E$ is referred to the relationship between an agent and other agents belonging to $W$. We can assume the relationships of an agent as its ego-network and define the trust that it perceives about the other agents belonging to its ego-network as the strength of their oriented relationships. Remember that, the trust has an asymmetric nature, see Section 2.3.

Finally, the profile $P$ of a leader only consists of its interests with respect to the common ontology.

### 2.2. The Agents' and Leaders' Tasks

According to the profiles and the properties defined above, the leader and the agents automatically perform the following basic tasks:

*Leader.* Over time, each leader performs a (different) sequence of actions (for example, publish a post or a comment). As a consequence the leader's profile will be updated to take into account the new activities.

*Agents.* Each agent will update its trust degree about a leader depending it on the last leader's action. The agent's trust degree about the leader will increase if the agent agrees with the leader's action, vice versa otherwise. Then, the new leader's profile and the corresponding agent trust will be exploited in computing a new *compactness measure* (see Section 2.3) that will define the agent as "polarized" or "not polarized" with respect to the leader. Moreover, based on their ego-network the agents can change their polarization status (i.e., depolarization) when in their ego-network is present another agent perceived as trustworthy (i.e., defined as closed to it or in its proximity) but polarized differently.

### 2.3. Trust, Similarity and Compactness

In the *Trust theory*, the level of satisfaction that any agent can directly express about the trustee is generally called *reliability* (i.e., direct trust) of the trustee $b$ as perceived by the trustor $a$. For example, in Online Social Networks (OSN) the satisfaction about someone is roughly obtained by clicking on buttons such as "I Like It/ I Do Not Like It" (e.g., on Facebook) or $+1/-1$ (e.g., YouTube). Differently, in our approach we represent the reliability of the trustee $b$ as perceived by the trustor $a$ with a real value denoted as $rel_{a\rightarrow b}$, ranging in the interval $[0, \cdots, 1]$, where 0 (resp., 1) is the lower (resp., higher) value of reliability. If the level of satisfaction of an agent is performed via the buttons "I Like It" and "I Do Not Like It" or similar, then the computation of $rel_{a\rightarrow b}$ can be expressed as the ratio between the positive and the total evaluations provided by that agent [42, 43]. Remember that the reliability is an asymmetric measure and this implies that $rel_{a\rightarrow b}$ is usually different from $rel_{b\rightarrow a}$ and, for such a reason, in our notation we have introduced the symbol $\rightarrow$ to specify the verse of the trust relationship. Moreover, the trust that the whole agent community perceives about the trustee $b$ is named *reputation* of $b$ (i.e., $rep_b$) or indirect trust. We can simply compute $rep_b$ as the average of all the reliability values $rel_{a\rightarrow b}$, for each member of the community with $a \neq b$.

Based on these two measures, each agent can compute a synthetic, global measure of the trust about each other agent of its community by integrating both the reputation of the trustee and the reliability from the trustor's personal viewpoint. Reputation and reliability are combined in the trust measure depending it on the importance the trustor gives to the reliability versus the reputation. More formally, we compute the *trust* of $a$ about $b$, denoted by $t_{a\rightarrow b}$ as:

$$t_{a\rightarrow b} = \alpha \cdot rel_{a\rightarrow b} + (1-\alpha) \cdot rep_b \tag{1}$$

where $\alpha$ is a real coefficient, ranging in $[0, \cdots, 1]$, representing how much relevant is for the trustor the reliability with respect to the reputation. In other words, when $\alpha = 0$ this means that the trustor does not give relevance to the reliability $rel_{a\rightarrow b}$ in computing $t_{a\rightarrow b}$ and vice versa when $\alpha = 1$. Note that $t$, $rel$ and $rep \in [0, \cdots, 1]$ and when $\alpha \neq 0$ also $t$ becomes an asymmetric measure due to the active presence of the reliability measure. More in general, when the direct knowledge of the trustor about the trustee is null then $\alpha$ can be set to 0 since the reliability measure will be null and, vice versa, when such a knowledge is sufficient for the trustor to directly esteem the trustee trustworthiness then $\alpha$ can be set to 1. In other words, the value of the parameter $\alpha$ can vary with the degree of direct knowledge of the trustor about the trustee.

The reliability an agent perceives about a leader is increased or decreased as a direct consequence of its actions, depending on the extent to which the agent agrees or not agrees with that action on the basis of its inclination (that we maintained unvaried along our experiments). Similarly, the reliability that an agent perceives about another agent is increased or decreased as a direct consequence of its satisfaction level for the last interaction carried out with the other agent. The reliability updating is performed by applying the following simple, common rule:

$$rel_{new} = \beta \cdot rel_{old} + (1 - \beta) \cdot \psi \tag{2}$$

where the parameter $\beta$, ranging in $[0, \cdots, 1]$, represents the relevance we desire assigning to the current values of the reliability with respect to the new contribution $\psi$ (belonging to $[0, \cdots, 1]$). This solution has been widely used in many trust-based approaches for multi-agent system, obtaining good results in terms of effectiveness (when the parameter $\beta$ is correctly set) [18, 44, 45].

The similarity measure $\sigma_{a,b}$ measures how much the profiles $a$ and $b$ are similar. The $\sigma_{a,b}$ measure is computed as the complement (with respect to 1) of the average difference between the inclination values of $a$ and $b$ for all the categories $c \in C$. More formally:

$$\sigma_{a,b} = 1 - \frac{\sum_{c \in C} |I_a(c) - I_b(c)|}{|C|} \tag{3}$$

The leaders' inclination measures are increased or decreased as a direct consequence of their actions, while the agents' inclinations currently are not updated. The updating is performed by applying the same approach adopted in Eq. 2 as:

$$I_{new} = \gamma \cdot I_{old} + (1 - \gamma) \cdot \vartheta \tag{4}$$

where the parameter $\gamma$, ranging in $[0 \cdots 1]$, represents the relevance we want to assign to the current values of the inclinations in a category with respect to the new contribution $\vartheta$.

Finally, the compactness measure referred to $a$ and $b$ includes both to their degree of similarity and trust associated with them. In particular, the compactness between $a$ and $b$, denoted by $\gamma_{a \to b}$, requires to consider both the similarity $\sigma_{a,b}$ and the trust $t_{a \to b}$. Similarly to trust, also the compactness $\gamma_{a \to b}$ is usually an asymmetric measure, i.e. $\gamma_{a \to b} \neq \gamma_{b \to a}$. Moreover, the computation of the compactness $\gamma_{a \to b}$ depends on how much importance is given to the similarity with respect to the trust. It is modeled by means of a real coefficient $\epsilon$, ranging in $[0 \cdots 1]$. Consequently, we define the compactness $\gamma_{a \to b}$ as:

$$\gamma_{a \to b} = \epsilon \cdot \sigma_{a,b} + (1 - \epsilon) \cdot t_{a \to b} \tag{5}$$

## 3. Evaluation

To examine the different behaviors of similarity, trust and compactness measures in modeling polarization processes, as introduced in Section 1, we simulated two case studies, by exploiting an in-house software platform and by assuming qualitatively human-like relationships between agents. In particular, we considered a dynamic scenario and a proximity scenario described and analyzed in detail in the following.

### 3.1. Dynamic Web Polarization Case Study

To simulate dynamic Web polarization processes, we considered a scenario formed by a set $W$ of 1000 agents, that played the same role of the "followers" or the "friends" in an Online Social Network (OSN), and two agents as leaders, named $A$ and $B$, that play a role analogue to that of the "influencers" in an OSN. A schema of the adopted architecture with agents and leaders (i.e., **A** and **B**) is represented in Figure 1.

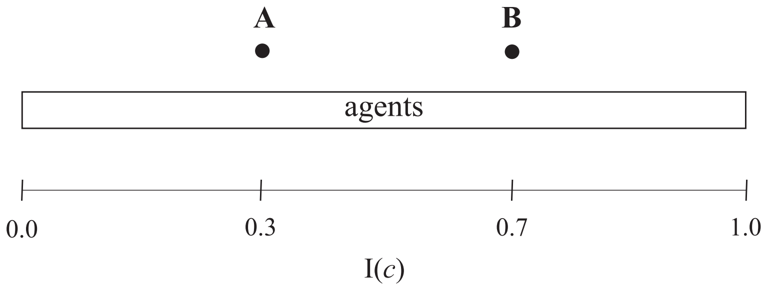


**Figure 1:** Dynamic Web polarization, schema of the adopted architecture with the agents and the leaders **A** and **B**.

Agents and leaders have been associated with individual profiles, compliant with the respective descriptions provided in Section 2.1. For sake of simplicity, we have considered a common ontology consisting of a single category $c$ and the inclination of each agent in that category has been randomly generated in a uniform manner in the real domain $[0, \cdots, 1]$ . Differently, we a priori set the inclination about $c$ of the two leaders, i.e. $A$ and $B$, to 0.3 and 0.7, respectively. Finally, the initial trust perceived by each agent about the leaders has been set to 0.5 that is a neutral value. Based on the agents' and leaders' inclinations about $c$, then the similarity measures between each agent and the two leaders have been updated in accordance with the leaders' actions.

In the case study outlined above, each leader performed a sequence of 1000 actions, always referred to $c$, within a context of leaders' "radicalization" (i.e., the inclination of $A$ moved towards 0 and that of $B$ towards 1). In order to study the ability of the considered measures to model dynamic Web polarization processes, the sets of actions has been exploited to study the system behavior in presence of radicalization processes implying continuous polarization updating.

In fact, after each action performed by a leader, then the leaders' inclination, together to the agent-leader similarities, trust and compactness measures have been updated as described in Section 2.3 by setting the parameters $\alpha = 1$ and $\beta = \gamma = 0.99$. To determine the polarization of an agent with respect to a leader, we assumed the agent as polarized with respect to that leader when its compactness measure is greater than 0.75 (that is a reasonable value for this case study). To deeply analyze the compactness behavior when the relevance of similarity vs trust measures varies, the parameter $\epsilon$ in Eq. 5, varied from 0 to 1 with step of 0.1. In such a way we obtained a family of results in terms of polarization as the parameter $\epsilon$ varied.

The results we obtained are synthetically shown in Figures 2 - 4, where in Figure 2 (i.e., Figure 3) is depicted how the maximum number of agents polarized on $A$ (i.e., $B$) changes as the actions of $A$ (resp., $B$) and the parameter $\epsilon$ varied.

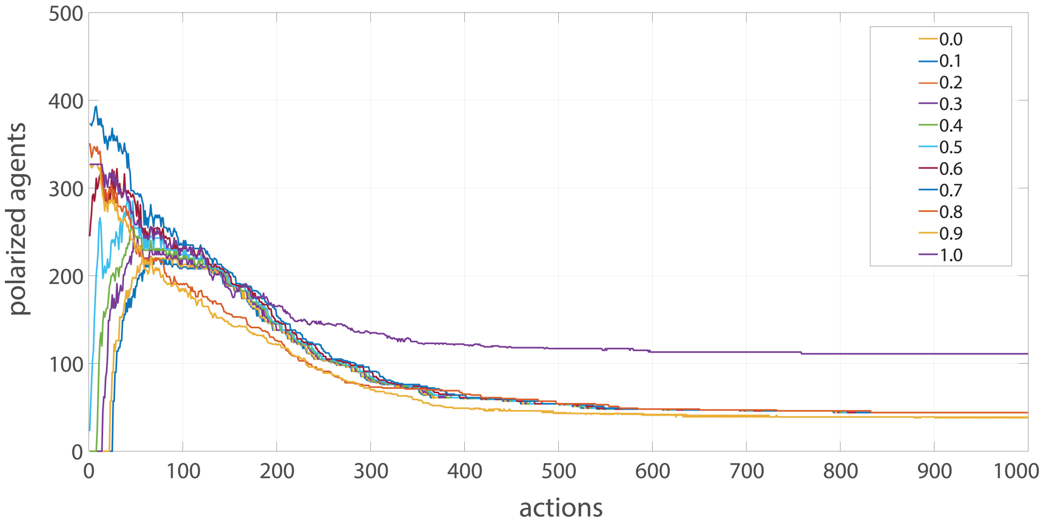


**Figure 2:** How the maximum number of agents polarized on $A$ changes as the actions of $A$ and the parameter $\epsilon$ varied.

Finally, in Figure 4 is represented how the inclinations of $A$ and $B$ leaders' actions move towards the two extremes.

It is worthy to note that computations exploiting compactness measure, similarity (i.e., for $\epsilon = 1$) or trust (i.e., for $\epsilon = 0$) only and their different combinations yielded different results in terms of capabilities to model dynamic Web polarization processes. Indeed, the analysis of the results shows as in the initial phase of the experiment the number of polarized agents varies as $\epsilon$ varies. However, independently from the value of $\epsilon$ the maximum number of polarized agents is always reached within the first 100-th interactions. Then, for all intermediate values of $\epsilon$, i.e., $\epsilon \neq 0$ and 1, corresponding to considering only the trust or the similarity measures in computing the compactness value, the number of polarized agents converges to a common value. Differently, with $\epsilon = 0$ or 1, i.e. calculating compactness only by using trust or similarity measures, the number of polarized agents will be the maximum or minimum, from the 200-th action. These results would indicate that on the long term trust is capable of inducing greater polarization in agents than the use of the similarity only or a combination of both.

These results differ from those obtained from the use of compactness in other contexts such as, for example, in a real-world scenario where the best results in group formation processes are obtained by combining measures of trust and similarity [19]. However, it should always be taken

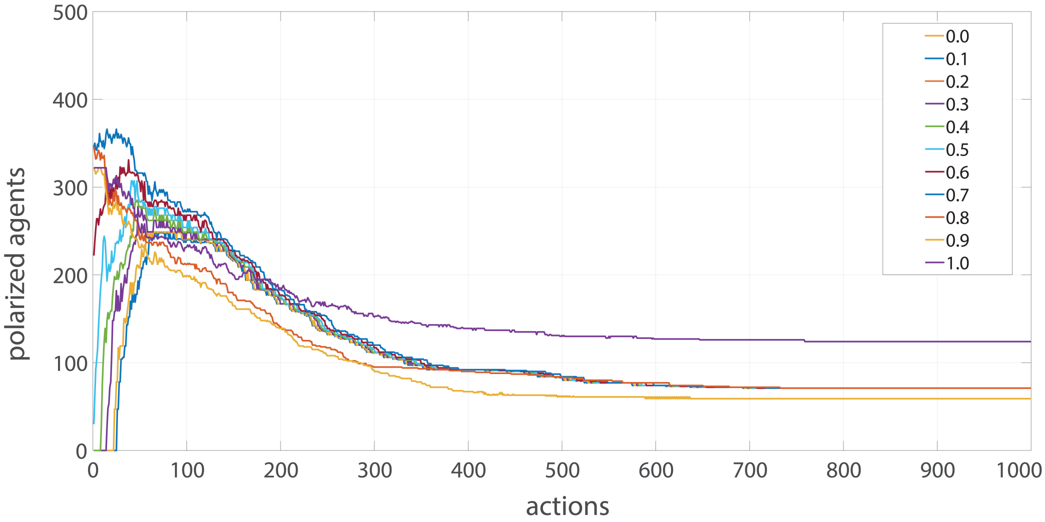


**Figure 3:** How the maximum number of agents polarized on $B$ changes as the actions of $B$ and the parameter $\epsilon$ varied.

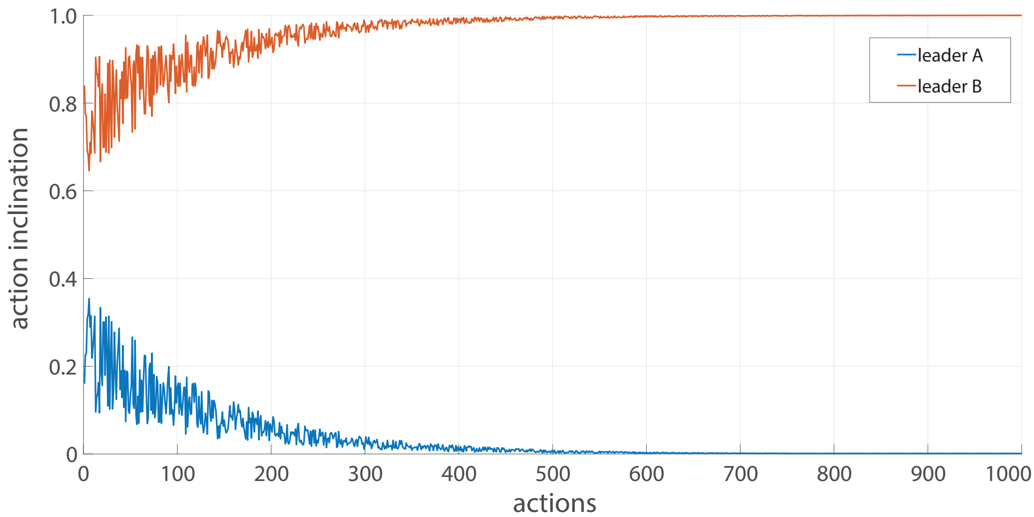


**Figure 4:** Inclinations of $A$ and $B$ leaders' actions.

into account that we simulated dynamic polarization processes and that the purpose of this experiment was exclusively to evaluate the role played by trust and similarity in modeling them. It should be also considered that to precisely model real polarization processes the parameter $\epsilon$ could be determined by using, for instance, machine learning techniques.

### 3.2. Proximity Depolarization Case Study

In the second case study we simulated a static proximity scenario considering the agents' ego-network for reproducing a depolarization activity. In such a scenario, we assumed each agent (i.e., trustor) provided with an ego-network consisting of 20 agents (i.e., trustees) randomly chosen in $W$. Profiles and agent polarization states of the trustor's ego-network agents have been inherited from the previous case study after the 50-th leaders' actions. The agent trust measures have been randomly generated in $[0.5, \cdots, 1]$, based on the consideration that usually an agent trusts the members of its ego-network. Similarly, to the first case study, the parameter $\epsilon$ in Eq. 5 varied from 0 to 1 with step of 0.1. Finally, the compactness measure threshold to change polarization has been always set to 0.75 to favor the comparison between the case studies.

Figure 5 displays the number of agents depolarized with respect to $A$ and $B$ as $\epsilon$ varies. Two aspects are evident from this case study, namely: *i*) the number of depolarized agents is generally low, in fact with $\epsilon = 0.1$ for the considered scenario it reaches less than 1.1% of the overall agent ego-network population (i.e., opportunity of agent proximity), and *ii*) as the relevance of the similarity measure is significantly lower than in the previous case study, high trust measures are required to activate the depolarization process.

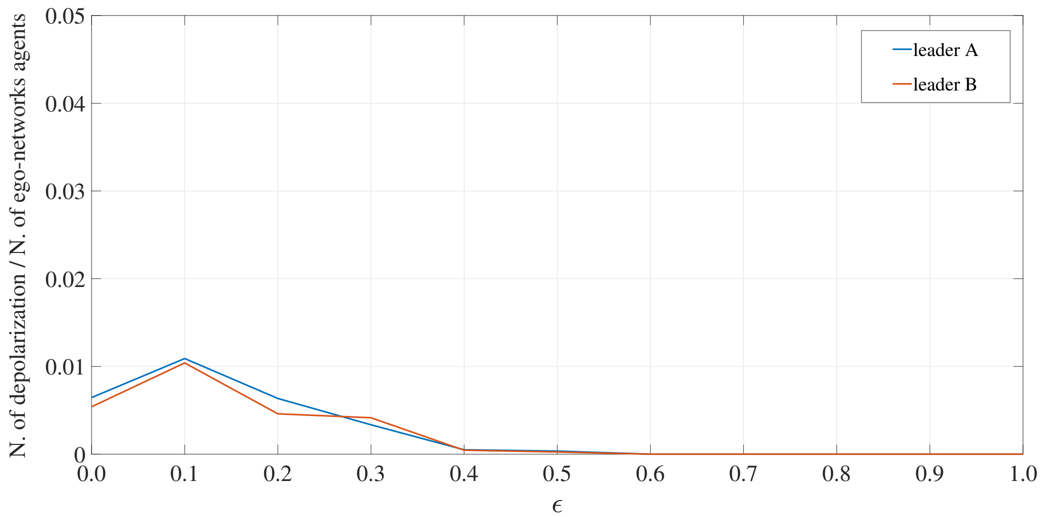


**Figure 5:** Number of agents depolarized from $A$ and $B$ when the parameter $alpha$ change.

According to the experimental findings presented and discussed here, in the case studies examined we appreciated different behaviors of the considered measures in modeling polarization processes. The implication of such results can help us in finding/testing new and more effective models for simulating dynamic polarization and proximity depolarization events in agent based environments.

## 4. Conclusion

An important issue in the organization of human societies, impacting in many crucial activities related to conflictual intergroup relationships, is the so-called *polarization*. In this context, we have analyzed the role of similarity and trust in polarization processes by simulating two case studies, i.e. dynamic Web polarization processes and proximity depolarization processes, in a software multi-agent community, modeling similarity and trust relationships usually present in human scenarios. The use of agents to simulate these processes is commonly adopted to support human beings in their activities and decisions, and provide them with possibility to observe a wide range of interactions of social interest. To this end, software agents can be endowed with emotions, intentions, beliefs, cognitive aspects and personality traits for replicating the salient features of human behaviors such as benevolence, selfishness, honesty, and meanness in real and virtual societies. Moreover, such agents model are likely to take into account the presence of other competing or cooperating agents in planning and implementing possible strategies to achieve their goals

We have considered that polarization processes are subject to change over time or also reversal: thus, our contribution is represented by the comparison of different way to model these processes in order to equip agents for simulating these relevant issues. We analyzed, similarity, trust measures and their combination in the compactness measure, with different percentages, and we evaluated the set of results provided by them with particular attention to the roles played by similarity and trust in the agent polarization. The obtained results contribute to clarify the impact of these measures in the polarization events. These findings could be useful in the domain of social science, to better understanding polarization dynamic in community of human beings.

In such a context, with the support of real data, our ongoing research will be devoted to investigate in which extent the effects evidenced in the multi-agent communities can also be found in social human communities.

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