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A new influence based network for opinion propagation in social network based scenarios

Raquel Ureña[a,*], Francisco Chiclana[a,b], Enrique Herrera-Viedma[b]

[a] *Institute of Artificial Intelligence (IAI),School of Computer Science and Informatics, De Montfort University, Leicester, UK*
[b] *Department of Computer Science and A.I, University of Granada, Granada, Spain*

Abstract

Thanks to the expansive development of the Internet based technologies the on-line communities in which millions of users interact in real time is living and apogee. Leverage these networks as tools to carry out massive decision making processes such as the ones involved in e-democracy and e-health communities constitutes not only an extraordinary opportunity but an important research challenge. In this context issues such us influence propagation, agents interaction, and malicious users identification and isolation are key to provide successful solutions to this challenge. In this contribution we aim to address these issues by presenting a new opinion propagation network in which the influence that each agent exert with respect to their neighbours is assessed by means of a combination of the following three aspects: (i)agents' self-confidence, (ii)inter-agents opinions similarity, (iii) the quality of the information provided by each agent, that is, the lack of contradiction also called as consistency. The proposed network allows to allocate more influence to those agents providing higher quality information and to isolate those who may present a malicious behaviour.

Keywords: Group decision making; Influence; Opinion dynamics; Information propagation; e-democracy; Social networks

1. Introduction

Social networks can be regarded as large group of users or agents interacting between each others [25]. Leverage social networks as tools to carry out multi-person decision making is becoming the more and more popular. For example, with the objective of involving the population in global decision making, in politics there are new trends denominated e-democracy, e-Governance and public deliberation [20, 16, 22, 34], a practical example is *the European*

* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000.
* Corresponding author.
E-mail address: raquel.urena@dmu.ac.uk

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citizens' initiative [5], an european commission initiative to motivate EU citizens to take part in the development of EU policies. Obviously, in this type of communities the members are very heterogeneous presenting different backgrounds, confindence and participation rates, [2, 9, 38]. Therefore, in this scenarios, achieving a consensus solution, that is, a solution accepted by the widely majority of the participants become a challenging task. A recent survey on consensus approaches in social networks [8] remarks the necessity to find out procedures to identify and clasify the agents between influencers and followers and provide selective recommendations according to their profile.

Several initiatives have been presented with this regard, such us the ones based in trust in [36] that presents consensus approaches in which the recommendations are provided to the agents by means of a trust network or the one in [21] that deals with heterogeneous agents by adjusting the level of feedback depending on a pre-given value of agents importance. In the majority of this approaches trust information or experts importance is given for granted. However in real world scenarios this information is hard to get in a time/memory effective manner, consequently it is interesting to infer the agents influence directly from their opinions. An alternative to the existing approaches consists on assessing the influence as a measure of centrality in the network, that is the agents that have a more prominent position are the ones exercising a major influence [29] or based on the agent's self-confidence [33, 32]. The drawbacks of these approaches are how to asses the influence in sparse networks, or when there is not an existing network, as is the case in some e-democracy or large scale decision making scenarios, where the users interact between each other for the first time. In this contribution we present a new network in which the agents' influence is estimated based on the following three aspect: (i) The quality of the information provided, (ii)the agent's self confidence, (iii) the agent's proximity between each other.

To do so this contribution is organized in the following way: In section 2 the main mathematical frameworks are described. The proposed influence based social network for opinion propagation is presented in Section 3. Section 4 points out some preliminary simulation results. Finally in Section 5 we expose the conclusions giving the future research challenges that this contribution introduces.

2. Background

In this section the basis of Group decision making and opinion dynamics are described in order to ensure the reader's understanding of our proposal.

2.1. Opinion dynamics networks

Influence networks may be regarded as "social cognition structures assembled by individuals who are dealing with a common issue" [17, 10, 11].

Definition 1. Social influence network

$$W = [w_{ij}],\ w_{ij} \in [0,1] \forall i, j,\ \sum_j w_{ij} = 1\ \forall i \tag{1}$$

Each edge of this network correspond to a value of the matrix W representing the influence and weight accorded by agent i to agent j.

In the literature there exists two fundamental models for opinion dynamics, The DeGroot model [6] and its generalization, the FJ Model. [10, 11]. The first one proposes that the agents opinions evolve as a weighted combination of the opinions of the agents in its vicinity whereas the FJ Model, also takes into consideration the evolution of an agent with respect to its own opinions. The mathematical formulation of this model is as follows:

$$y(t+1) = \delta W y(t) - (l_n - \delta) y(0), t = 0, 1, 2, \cdots \tag{2}$$

where I_n is a positive diagonal matrix that models the agents own individuals opinions

Other particular cases of the FJ Model are the bounded confidence models. These models, propose that each agent solely communicates with the agents who hold similar opinions. Considering this similarity as a confidence level between agents. Therefore in these models, the similarity between agents as well as their initial opinions determine the opinion neighbourhood in which the expert is likely to interact at every instant. The two main approaches are the Hegselmann-Krause model [12], and the Deffuant-Weisbuch model [35].

2.2. Group decision making

A particular case of use of an opinion dynamic network is what is known as a multi agent decision making process. In this case, the agents express their opinions toward each of the alternatives in the set (X), and a resulting global preference value is obtained. In order to reach a solution accepted by the majority of the members, a negotiation between the agents is carried out. In order to express the preferences a widely adopted way is by means of pairwise comparison [19]. One of the most widely used way of expressing pairwise comparison based opinions is preference relations that allows to indicate three different preference states namely: preference of one alternative to the other, indifference between them or impossibility of expressing them [1] .

Definition 2 (Preference Relation). *A preference relation P on a set X is a binary relation $\mu_P : X \times X \to D$, where D is the domain of representation of preference degrees provided by the decision maker.*

According to the previous definition, a preference relation P might be represented as a matrix $P = (p_{ij})$ of dimension $\#X$, in which $p_{ij} = \mu_P(x_i, x_j)$ constitutes the degree of preference of alternative x_i over x_j. These values can be numeric or linguistic [37].

2.3. Consistency

Consistency of fuzzy preference relations may be regarded as the ”transitivity in the pairwise comparison among any three alternatives. For example, if alternative x_i is preferred to alternative x_j ($x_i \succ x_j$) and x_j is preferred to x_k ($x_j \succ x_k$) then alternative x_i might be preferred to x_k ($x_i \succ x_k$). This is normally known as as *weak stochastic transitivity*” [4]. Obviously, consistency is q good indicator of the coherence of the opinions provided. [23]. Among the variou consistency properties [4, 14, 30], in this contribution we focus on Tanino's Multiplicative transitivity.

Definition 3 (Multiplicative transitivity [26]). *A fuzzy preference relation $R = (r_{ij})$ on a finite set of alternatives X is multiplicative transitive if and only if*

$$r_{ij} \cdot r_{jk} \cdot r_{ki} = r_{ik} \cdot r_{kj} \cdot r_{ji} \;\; \forall i, k, j \in \{1, 2, \ldots n\} \tag{3}$$

The preference value between a pair of alternatives (x_i, x_j) with $(i < j)$ can be estimated, using another different intermediate alternative x_k $(k \neq i, j)$ by means of the multiplicative consistency property (3) as follows:

$$mr_{ij}^{k} = \frac{r_{ik} \cdot r_{kj} \cdot r_{ji}}{r_{jk} \cdot r_{ki}} \tag{4}$$

Definition 4 (Multiplicative Consistency,[3]). *A fuzzy preference relation $R = (r_{ij})$ is multiplicative consistent if and only if $R = MR$.*

The degree of similarity existing between the values r_{ij} and mr_{ij} has been proposed in [13] as a measure of the level of consistency existing on a given fuzzy preference relation:

Definition 5 (Consistency index on the fuzzy preference relation).

$$C_T = \frac{\sum_{i=1;\ i\neq j; j>i}^{n} 1 - d(r_{ij}, mr_{ij})}{n(n-1)} \tag{5}$$

Where $d(r_{ij}, mr_{ij})$ is the distance between the values r_{ij} and mr_{ij}.

3. Proposed Influence network

In a social network, when agents are exposed to others opinions their own opinions evolve. In particular, it has been witnessed that those agents who present higher level of self confidence with their answers are the ones leading the group, whereas those more insecure are mores susceptible to change their mind following others advices [28, 39].However self-confidence cannot be used as the only indicator of influence, otherwise that will lead to serious biased or even abusive use, since malicious users could arrange themselves to set the highest self-confidence levels in order to become the most influential [29].

3.1. Agent's influence

The agent's influence in the network is assesed, in this contribution by means of the Agent's Knowledge Influence, KI. This KI is obtained by taking into consideration both the expert's degree of confidence and the consistency of his/her opinions, in the following way:

Definition 6. *Expert Knowledge Influence*

$$KI^h = T(C_T^h, C_F^h) \tag{6}$$

where T, is a T-norm operator that can be mathematically formulated as follows:

$$T(a,b) = \begin{cases} 0 & \text{if } a = b = 0 \\ \frac{ab}{a+b-ab} & \text{otherwise} \end{cases} \tag{7}$$

Note that this operator T tends to penalize the low values. Thus, in order to get a high KI Score and expert must have both high values of confidence and consistency.

3.2. Agents classification

Taking into consideration the KI the proposed framework classifies the agents in three different profiles that will be leveraged to stablish the inter-agents communication in the network as follows

Given a set of n agents $H = 1, 2 \cdots, n$ and an agent $h \in H$ having a KI score KI^h and given a Minimum KI Threshold $KI_{THmin} \in \{0, 1\}$ and a superior KI threshold $KI_{THsup} \in \{0, 1\}$, the agents are classified as follows:

- **Definition 7.** ***HCC Experts, Influencers*** *An expert h is considered as a HCC expert if and only if*

$$KI^h > KI_{THsup}$$

  Note that this type of agents present both high levels of consistency and confidence, and so they can be considered as influencers. In the proposed network they only provide advise to the other but they will not receive any recommendation, in order to boost the consensus. An special case are the outliers , that is HCC experst whose opinions are far from the others. In this particular case they will be disconnected from the network.
- **Definition 8.** ***MCC agents***
  An agent h is considered as a MCC expert if and only if

$$KI_{THmin} \leq KI^h \leq KI_{THsup}$$

  This is the type of profile that represents the majority of the users in the system. In this case the agents have medium levels of consistency and confidence.
- **Definition 9.** ***LCC agents*** *An agent h is considered as a LCC agent if and only if*

$$KI^h < KI_{THmin}$$

  Notice that, given the mathematical structure of the T-norm operator, the agents in this category encompasses three different types of sub-profiles: (i)Low consistency and low confidence agents. (ii) high consistency and low confidence agents. (iii) Low consistency and high confidence agents. In the proposed network the agents with this profile receive feedback HCC and MCC neighbours in their vicinities but they are not allowed to provide any advice.

3.3. Influence based network

In this subsection a new influence network is proposed taking into consideration to build this network the KI and the similarity between the agents' opinions. The proposed network is based on the idea that in a social network the agents that are close will interact [18, 24, 29]. In the proposed network each agent is regarded as a node of a directed graph, and a combination of both KI and similarity is used to calculate the value of the edges.

Definition 10. *The adjacency matrix $M = (m_{kl})_{HxH}$ of the graph $G = (N, M)$. The value of each edge, m_{kl} is calculated as the Similarity between the preferences for the expert k with a matrix of preferences P^k and the expert l with preferences P^l.*

$$m_{kl} = \begin{cases} S^{kl} & if\, S^{kl} > \alpha_{sim} \wedge (Profile_l = HCC \vee Profile_l = MCC)) \\ 0 & if\, S^{kl} < \alpha_{sim} \vee Profile_l = HCC \vee Profile_l = LCC) \end{cases} \tag{8}$$

Where $k, l \in [1, H] \wedge l > k$ and α_{sim} is a minimum similarity threshold, so if the similarity between two agents is less than the threshold these two agents will not be connected. This measure allows to automatically isolate the agents that even though they present profile HCC their opinions far from the other ones for different reasons including those with malicious intentions.

The similarity between agents is calculated by mean of the Jaccard Distance [15].

The way the agents communicate in the proposed network is summarized in figure 1. As explained in the previous section, eac agent receives the combination of the opinions of the HCC and MCC agents in its vicinity. This opinion fusion is carried out using eacg agent's KI as a weighting factor.

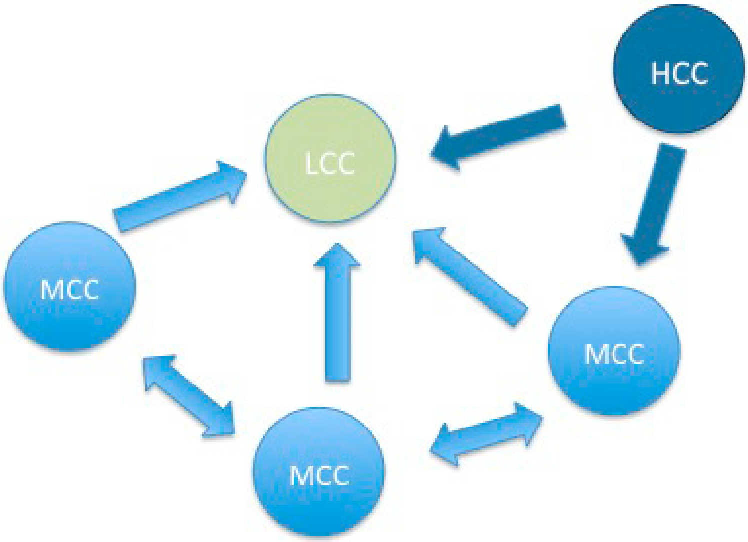

Fig. 1. Feedback spreading scheme.

4. Simulation results

With the objective of testing and validating the proposed network a simulation framework has been set up in R [27, 31]. The dataset containing the agents preferences is generated synthetically with the following characteristics

- The probability of fully consistent expert in this data set follows a binomial distribution set by the parameter $probConsistent$.
- The probability of an expert accepting the recommendation from the network follows a binomial distribution set by the parameter p.

In the following the evolution of the network topology through the different iterations is analysed. In order to generate space-effective and easy to understand graphics the simulations are carried out with N= 25 agents. The parameter setting for this simulation is indicated in table 1. Note that for all the experiments the Monte Carlo simulation is conducted 1000 times [7, 29].

In Table 2 we can observe how the network topology evolves within the iterations. In order to easily recognize the agents' profile, the node's colour represents the profile in the following way: deep blue, light blue and light green correspond to HCC, MCC and LCC agents respectively. Furthermore the nodes' size is proportional to the agent's KI. As we can observe the generated network presents the following properties: (i)The small-world effect, the majority of the pairs of nodes are connected by a short path through the network. (ii)The degree distribution follows a power law. These are properties a real world social networks [24, 7]. With regards to the connectivity in the network we can verify that the HCC agents obtain high-in degree, and so they present high influence in their neighbours. Conversely, the LCC agents get a high out-degree but a null in-degree, thus they get deeply exposed to their neighbours' opinions without having any influence in them.

Table 1. Parameter setting for the experimental simulation

Parameter	Value
Number of agents	$N = 25$
Number of Alternatives	$A = 3$
Probability of fully consistent expert	$probConsistent = 0.3$
Adoption probability	$p = 0.7$
KI minimum Threshold	$KD_{THmin} = 0.3$
KI superior Threshold	$KD_{THsup} = 0.8$
Similarity Threshold	$\alpha_{sim} = 0.6$

Regarding to the evolution of the agents influence, we can observe how the LCC agents that are connected to the network increase their influence with the iterations (note how expert 15 evolves from LCC to HCC). The contrary occurs with the agents that get disconnected for example agent 4 get isolated in iteration 1 and after it does not register any evolution. Note that this is the desired behaviour with regard to potential malicious agents.

5. Conclusion and future work

In this contribution a new influence based network has been presented. In the proposed network, the influence that each agent exert with respect to their neighbours is assessed by means of a combination of the following three aspects: (i)agents' self-confidence, (ii)inter-agents opinions similarity, (iii) the lack of contradiction in the information provided also called as consistency. With the objective of avoiding malicious behaviours both consistency and self confidence are combined in an unique influence value using the T-norm operator, that only allocates a high value to the influence when both of them presents a high value. Taking into consideration this measure the agents are classified in three different profile. In this way central position in the network is allocated to those agents having a higher influence as well as limiting the influence of those agents that tagged as malicious. It has been proved by extensive simulations that this type of network evolves to a stable state with their interactions. As future work we plan to analyse the role of this network to reach consensus or agreement between the agents. Moreover, it will be interesting to carry out a simultaneous analysis in which both the proposed network and an already existing network coexist to analyse how to combine aspects such us friendship, number of likes between users to asses the influence in a decision making environment.

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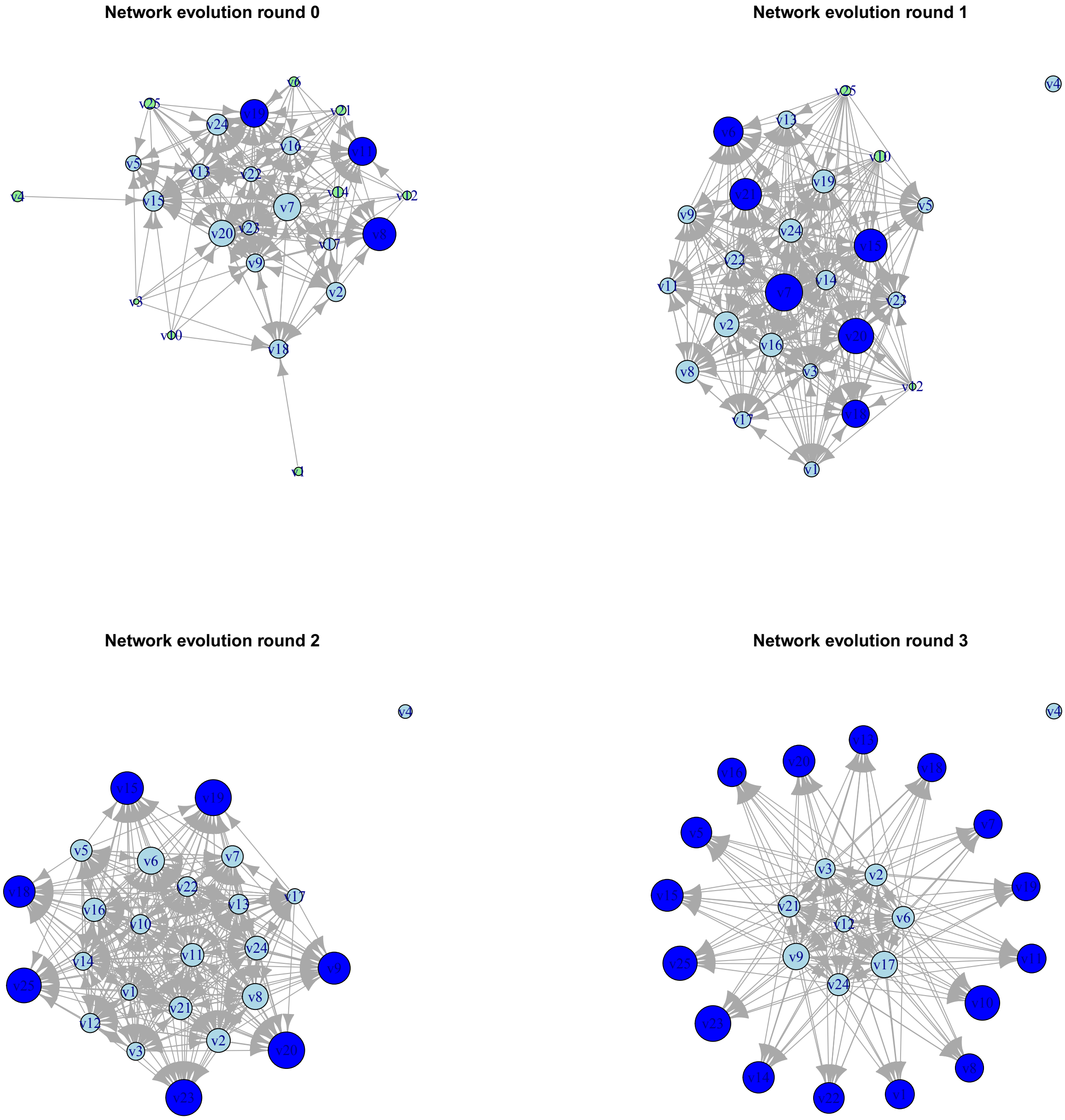

Table 2. Evolution of the similarity based network.

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