An Intelligent Social Collective with Facebook-based Communication

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Abstract. This paper describes the model of an intelligent social collective based on the Facebook social network. It consists of three main elements: social agents with a specified knowledge structure, a list of communication modes describing how agents send outbound messages, and a list of integration strategies describing how agents react to incoming messages. The model is described in detail, with examples given for important subalgorithms. The model is then analyzed in comparison to epidemic SI models in knowledge diffusion tasks and tested in a simulated environment. The tests show that it behaves according to the expectations for real world groups.

Keywords: Collective intelligence · Group modeling · Multi-agent simulation · Knowledge diffusion · Collective model

1 Introduction

Computational Collective Intelligence is a current research area that tackles multiple problems of modern computing. One of those is modelling groups of intelligent agents that work towards some common purpose or exchange knowledge to solve specific problems. Such intelligent collectives are a method used in the area to work with problems of group dynamics, knowledge diffusion, opinion formation, or problems from other research areas, e.g., influence maximization in social network research. A properly constructed model of an intelligent collective should be usable to work with at least one of those tasks.

In our previous research, we first focused on asynchronous communication between agents, but as more and more parameters were added to the developing model of an intelligent social collective, it became similar to how communication works in the Twitter social network [10]. In this paper, we translate the same model to represent the Facebook social network, in most part by changing the modes of communication between agents to reflect it. We also improve the formal description of the intelligent social collective, which allows us to perform an analytical evaluation of some aspects of the model, instead of only using simulations.

This paper is organized as follows: in Section 2 we describe the research works that were key to creating the proposed social collective model and some

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models that describe the problem from the point of view of other research areas; Section 3 contains details of the Facebook-based model, with some examples of its functioning; in Section 4 we present a short analysis of some properties of the model and describe simulation experiments testing the model; finally in Section 5 we give some concluding remarks and present our intended further work on intelligence social collectives.

2 Related Works

In order to develop the presented model of social collective, we applied theoretical approaches from multiple varying fields of research, mostly focused on sociology and collective intelligence research.

The research in the area of social influence is the main motivation for using multiple possible modes of communication and multiple possible responses to communication in the model. The focus of the area is describing how people are influenced by others in social settings. Following some classical research in the area, [5] discusses different levels of influence in a collective depending on individual and group factors, e.g. subjective norms, group norms, or social identity. Other works discuss compliance with and internalization of group rules to better fit the group [8]. Both approaches allow different levels of response to outside information, from no resistance to full resistance. A divergent area of research called social proof takes additional elements into account, including the competence or the amount of knowledge of the receiver – the less they know, the more likely they are to learn [14].

A parallel area in the field of computer science are influence maximization models in social network research. They are often built as a type of predictive models, that is, they are created with the aim of predicting the network behavior when a new node is added to the network. Approaches bearing the most similarity to ours would be those focusing on calculating the probability of a person sending outgoing messages [12] and those observing changes in the distribution of discussed topics in the network [1]. There is also a subgroup of linear threshold models, where the most similarity to our model can be found in [4]. In that paper, the authors consider a threshold number of received messages before a person acknowledges incoming information. There are also explanatory influence models, where the aim is to determine the node or community with the most influence on others in the existing network. In this group, the ones most similar to our research work with classifying agent behavior to specific groups, e.g., active, subject leader [3].

As stated, our research was also influenced by different aspects of collective intelligence research, especially in its computational aspects. There is some criticism about its applicability to realistic groups [15], but we consider the typical approaches from the position of a single agent. This allows us to assume that the messages received by an agent fit the Surowiecki postulates [16], which cannot be said about the whole group. Instead of focusing on the whole group, we derive the collective behavior from changes occurring in such single agents. The spe-

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cific methods we use are mostly derived from consensus theory [11], that states several requirements for algorithms, but in practical terms often requires only to calculate the centroid of a group as a median or average.

3 Model of the Social Collective

Following our previous research, where we introduced a social collective based on the Twitter social network [10], the model of the Facebook-based collective proposed in this paper comprises of three main parts: the individual social agents, the methods they use to initiate communication and the methods they use to integrate any received knowledge or opinions.

Each social agent $a_i \in A$ has some internal knowledge or opinion k_i, at least one associated communication mode Mo_i^a that he uses, and at least one Integration Strategy S_j^a that he uses on received messages. Additionally, the agent may follow some context-based rules (e.g., in context A they use integration strategy Mo_i^1, and in context B they use integration strategy Mo_i^2).

The knowledge of agents is represented in the form of "vector of statements" with associated weights (sentiment represented as numerical values): $k_i = \{< k_i^a, w_i^a >\}$. The use of simple statements (e.g. "light bulbs require electricity") is based on the observation that social network messages often cover only a single issue, but are augmented with multiple emotional descriptors. In turn, the messages that are generated for such representation of knowledge consist of single pairs from the internal knowledge base of an agent, selected at random with probability proportional to the associated weight (more precisely to the absolute value of the weight). For simplicity of implementation, we consider only positive and negative weights (generic positive and negative sentiment) in range $[-W, W]$.

There are multiple allowed approaches to communication in the model. While in our previous Twitter-based model, only asynchronous communication was possible, in Facebook-based model we also allow a specific type of synchronous and symmetric communication (simulating real-time chat). Each communication mode has a probability P_i^c of using this mode, which sums up to 1 for all modes. The communication modes allowed in this model are based on the Facebook social network and there are multiple possible levels of relation and communication between agents (user accounts): synchronous bi-directional chat, asynchronous posting, liking and replying to wall messages, and derived approaches defaulting to the previous (e.g. interest groups). Following, each social agent in the model has a list of *friends* (bi-directional relation) and we define four communication modes:

- At any moment an agent may send a message consisting of part of their knowledge (opinion) to any one or more agents from their list of *friends*. The receivers are selected at random, with possibility of the same agent being selected multiple times. This represents posts on Facebook *wall*, where people may skip a message or read it several times.

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- Each agent may also, instead of initiating communication on some new topic, make a public agreement with a previous message from some other agent. In effect, the agent copies a previously received message, then uses the same approach to determine a new list of receivers, and sends the same message again. This represents people using the *Like* function of some Facebook wall posts. Again, people may see the *Like* many times, or not see it at all. There is an additional parameter determining the additional probability of not using this mode.
- Similarly to the previous option, the agent may make an own statement based on the message that they received. In this case, the agent also uses a previously received message as a template, but instead of copying it, they instead create a message with their own knowledge (opinion) on the same topic. Then they determine the list of receivers, using the same approach as in the two previous communication modes, and send the message. This represents people commenting on posts on Facebook *wall* (including commenting on other comments). Again, people may see the comment many times, or not see it at all. There is an additional parameter determining the additional probability of not using this mode.
- Each agent may also initiate a bi-directional communication with any single agent from his list of *friends*. In this case, the agent selects the part of their knowledge and sends it as a message to the selected agent and the selected agent sends back a message containing their state of knowledge (opinion) of the same topic. As processing incoming messages occurs independently of sending them, the returning message may either already consider the message from the first agent, or be the original knowledge of the second agent. This type of communication represents discussions via chat option between two different people.

The reaction of a social agent to incoming messages is one of the integration strategies S_j, which are knowledge integration algorithms we have based on various research in the areas of sociology and collective intelligence. It is also possible for incoming messages to be aggregated and the integration to be done at a later time. The input of the algorithms are the incoming message (messages) and agents own knowledge on the specific topic (two or more pairs $< k_i^a, w_i^a >$, where $\forall_{j1 \neq j2} k_{j1}^a = k_{j2}^a$), and the output is the new knowledge of the agent (a single such pair). In the model, we use the following possible integration strategies, but more can be introduced as needed:

- Substitution – this integration strategy is based on sociological works in the area of social influence (mainly [8]) and follows the concept of *no resistance to induction*. This can be understood as a person accepting any outside knowledge and immediately adding it to their internal knowledge base (colloquially: *is very naive*). This basic integration strategy uses the same approach: upon receiving any incoming knowledge (opinion), the agent immediately adds it to his own knowledge base and, if necessary, substitutes his previous knowledge on the topic with the newly received one.
  Example 1:

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- agent previous knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >\}$
- new message : $\{< C, -1 >\}$
- agent new knowledge : $\{< A, 3 >, < B, -2 >, < C, -1 >\}$

Example 2:

- agent previous knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >\}$
- new message : $\{< D, -1 >\}$
- agent new knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >, < D, -1 >\}$

– Discard – following the same sources, the opposite reaction is called *full resistance to induction*. In such situation, a person does not internalize any received knowledge. As an integration strategy, this means no change to the internal knowledge base and is only used for some specific experiments.
Example:

- agent previous knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >\}$
- new message : $\{< C, -1 >\}$
- agent new knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >\}$

– Delayed voting – this integration strategy is based on research in the area of collective intelligence, specifically consensus theory [11]. It requires buffering several (T_i^{dv}, consensus theory favors odd numbers) messages on the same knowledge statement before the integration occurs (this includes own knowledge on the topic, if it exists). The new knowledge-weight pair is selected based on plurality vote on the weight. In case of ties, a random pair is selected among the winners.
Example 1:

- agent previous knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >\}$
- full buffer for $T_i^{dv} = 7 : \{< C, -1 >, < C, -1 >, < C, 2 >, < C, 2 >, < C, 2 >, < C, 7 >\}$
- agent new knowledge : $\{< A, 3 >, < B, -2 >, < C, 2 >\}$

Example 2:

- agent previous knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >\}$
- full buffer for $T_i^{dv} = 7 : \{< D, -1 >, < D, -1 >, < D, -1 >, < D, 2 >, < D, 2 >, < D, 2 >, < D, 7 >\}$
- agent new knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >, < D, -1 >\}$

– Delayed weighted average consensus – this integration strategy is based on similar research as the previous one, and it also requires a buffer of messages. The integration is done by determining the average weight of the pairs used in calculation.
Example 1:

- agent previous knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >\}$
- full buffer for $T_i^{dv} = 7 : \{< C, -1 >, < C, -1 >, < C, 2 >, < C, 2 >, < C, 2 >, < C, 7 >\}$
- agent new knowledge : $\{< A, 3 >, < B, -2 >, < C, 2.6 >\}$

Example 2:

- agent previous knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >\}$
- full buffer for $T_i^{dv} = 7 : \{< D, -1 >, < D, -1 >, < D, -1 >, < D, 2 >, < D, 2 >, < D, 2 >, < D, 7 >\}$
- agent new knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >, < D, 1.4 >\}$

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– Polarization – this integration strategy is based on a different approach to social influence called Social Judgment Theory [2]. It is based on the notion that a person hearing an opinion opposed to theirs, will further distance themselves from it, while when hearing a similar opinion, they will take it into account to increase the similarity. In the strategy, we calculate the distance to weights in incoming messages ($\delta(w_1, w_2) = |w_1 - w_2|$), if it smaller than the threshold D_0 then the weight associated with agents internal knowledge changes towards it by $\delta(w_1, w_2) \cdot d_1$, otherwise it changes to increase the distance by $\delta(w_1, w_2) \cdot d_2$. Our initial assumption based on sociological literature study was that $d_1 > d_2$ and our experiments have shown that it is close to $d_1 = 10 \cdot d_2$. If the knowledge is previously unknown to the agent, the strategy defaults to *Substitution*.
  Example 1:
  - agent previous knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >\}$
  - parameters $D_0 = 5, d_1 = 0.5, d_2 = 0.05$
  - new message : $\{< C, -1 >\}$
  - agent new knowledge : $\{< A, 3 >, < B, -2 >, < C, 7.4 >\}$

  Example 2:
  - agent previous knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >\}$
  - parameters $D_0 = 5, d_1 = 0.5, d_2 = 0.05$
  - new message : $\{< C, 3 >\}$
  - agent new knowledge : $\{< A, 3 >, < B, -2 >, < C, 5 >\}$

  Example 3:
  - agent previous knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >\}$
  - parameters $D_0 = 5, d_1 = 0.5, d_2 = 0.05$
  - new message : $\{< D, -1 >\}$
  - agent new knowledge : $\{< A, 3 >, < B, -2 >, < C, 7 >, < D, -1 >\}$

4 Evaluation of the Model

4.1 General Properties

Assuming that the network is the *small world* type (at most L connection in the graph between any two nodes) and agents do not change their internal knowledge, time to communicate the statement $k_1^{a'}$ from agent a_1 to a random agent in a network (a_L) is:

$$T(a_1, a_L) = \tau \Pi_{i \in \{1,\ldots,L-1\}} \left(\frac{w_i^{a'}}{\sum_a w_i^a} \cdot \frac{r_i}{card(R_i)} \right) \tag{1}$$

where τ is the base delay between subsequent communications, r_i is the (expected value of) number of other agents that receive each message and $card(R_i)$ is the total number of agents that can be communicated with (ie. in the agents *friend* list). Similar equations would also hold for other types of networks, with a more complex estimation of the number of required intermediate steps. In a more practical situation, where other statements are also communicated and lead to

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changes in internal knowledge, the equation needs to be modified by making the weights a function of time.

Based on the above, we can estimate how the proposed social collective behaves in terms of an epidemic SI model of a social network [13]. This type of model divides the group into those Susceptible and Infected ($S(t)$ and $I(t)$, respectively, with $S(t) + I(t) = N$ as the entire group) and it can be described in terms of equations determining the increase of the number of Infected over time. Assuming that we have one person with some knowledge $I(0) = 1$, the time until it is spread to the entire collective depends on the time required to spread to the furthest member, and using the equation from [13] for change of the number of Infected:

$$\frac{d(\frac{I(t)}{N})}{dt} = \lambda \frac{I(t)}{N}(1 - \frac{I(t)}{N}) \tag{2}$$

The parameter λ that describes the network can be calculated using Eq. 1 as follows:

$$\lambda = \frac{N-1}{\tau \Pi_{i \in \{1,\ldots,L-1\}}(\frac{w_i^{a'}}{\sum_a w_i^a} \cdot \frac{r_i}{card(R_i)})} \cdot \frac{1}{\frac{1}{N}(1 - \frac{1}{N})} \tag{3}$$

The proposed model is not inherently of the SI class, so Equation 3 describes only the spread of the knowledge statement throughout the network, not the weight of it (ie. if it is positive or negative statement).

On the other hand, the proposed model does not conform to some proposals of general collective intelligence in real-world groups, as described in [6, 9], in large part because of the lack of deeper intelligence present in any individual agent. The former paper defines a measure of collective intelligence based on specific abilities of the group: generating tasks, choosing tasks, executing tasks, remembering tasks, and sensing tasks. The proposed model can be slightly expanded to allow choosing or remembering tasks by changing the knowledge representation and adding memory (forgetting parts of knowledge), but other abilities would require a complete rebuild of the model towards a more objective-oriented one. The latter paper describes real-world collectives where members exchange information on multiple topics. The authors have observed a specific type of peak of interest (increase of communication frequency) on some topics and described it in mathematical terms. The main parameters of such dynamics are growth by imitation, self-inhibiting saturation, and competition with other topics. While our proposed model contains elements of both growth and competition, the frequency of communication on each topic does not tend to peak in the same manner. It would be possible to modify the model to introduce an element of saturation, but without a thorough rebuilding of the whole model, it would lead to limiting its applicability in knowledge diffusion.

4.2 Simulation of Social Collectives

To further evaluate the proposed model, we implemented it in the simulation environment we have been using in our previous research [10], which uses discrete

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time moments (iterations) during which the agents may communicate. The simulation setups a group of agents with uniformly random distribution of knowledge and opinions and lets them interact for some time. Meanwhile we can observe how the knowledge (opinion) of selected agents or the whole group changes. We can also add agents with atypical knowledge or atypical behaviour.

For the purposes of testing and comparing the models, we have adapted the notion of *drift* from sociological research [7] and defined it as follows:

Definition 1. k_i-drift is the absolute value of the average change of weights describing the knowledge statement k_i in the whole collective over one iteration.

Definition 2. Collective Drift is the average of k_i-drifts about every knowledge statement k_i possible in the Closed World interpretation.

Definition 3. ϵ, τ-stability. A collective is ϵ, τ-stable, if the average weights describing knowledge of its members change over time τ by no more than ϵ.

Definition 4. Stable collective. A collective is called stable if it is drift is no larger than 0.1. Otherwise, it is called unstable.

Following the sociological research, a proper group with initially uniform distribution of opinions (here: weights describing knowledge statements) should be stable, but any introduced heterogeneity should make it unstable. Therefore, in the experiments we conduct a large-scale simulation of a collective of agents over a long period of time and compare the initial and final knowledge (weights) to calculate the Collective Drift.

The overall model has multiple parameters that we have initially determined in our previous research and further tuned for purposes of the Facebook model. Additionally, some specific parameters were adjusted for different experimental runs (and are provided in their descriptions). The common parameters are:

- Number of agents in simulation : 1000,
- Number of possible knowledge statements: 100,
- Initial number of statements for each agent : 20,
- Range of allowed weights : [-10,10],
- Weight distribution : uniform in the entire range,
- Number of agents in *friend* relation : 10,
- Length of simulation τ : 1000 (discrete time moments),
- Probability of starting communication by an agent in each time moment : 0.2,
- Maximum number of receivers for a message : 5,
- Size of message buffer for delayed strategies T^{dv} : 11,
- Polarization threshold D_0 : 5,
- Polarization weights $d_1 = 10 \cdot d_2$: 0.5.

The general aim of the simulations was to determine the model parameters, where a homogeneous collective is stable, but introducing even one agent using Discard strategy makes it unstable. We have conducted multiple runs and compiled the results of the most interesting and realistic configurations (averaged over multiple simulation runs for each combination of parameters) in Table 1.

The gathered results show that Substitution, Delayed voting and Delayed weighted average consensus for all realistic and most overall combinations of

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tuned parameters behave as expected from a real group, that is, they are stable when homogeneous and unstable when an outside disturbance (Discard agent) is introduced. Polarization is a different class of integration strategies as it leads to the gradual evolution of two opposed subgroups for every issue. Introducing an outside interference leads to faster (and larger) distancing between the groups. Otherwise, it behaves like any polarizing group [2].

Table 1. Collective opinion on a single knowledge statement for different integration strategies, results averaged over several simulation runs. Selected interesting configurations only. The value of *Collective Drift*, which is calculated as average change of opinion over time. Homogeneous and heterogeneous (one Discard agent) collectives for different configurations of the experimental environment. Probabilities given for modes: bi-directional messages / wall posts / wall likes / comments, as well as probability of not responding to post / comment.

Configuration (prob.)	Sub	D.vote	D.avg	Pol	D.+Sub	D+D.vote	D+D.avg	D+Pol
0.1/0.4/0.3/0.2 , 0.2/0.5	0.17	0.07	0.08	0.93	2.55	1.12	0.89	4.12
0.3/0.3/0.3/0.1 , 0.2/0.5	0.75	0.07	0.1	1.27	3.01	1.11	1.2	4.89
0.5/0.2/0.2/0.1 , 0.2/0.5	0.6	0.1	0.08	2.14	2.97	1.32	1.33	5.4
0.5/0.2/0.2/0.1 , 0.0/0.0	0.33	0.11	0.08	1.89	2.63	1.25	1.57	4.66
0.5/0.2/0.2/0.1 , 0.5/0.5	0.47	0.05	0.09	1.74	2.73	0.97	1.64	4.39
0.5/0.2/0.2/0.1 , 0.7/0.7	0.59	0.11	0.12	1.61	2.89	1.22	1.66	4.17
0.5/0.2/0.2/0.1 , 0.9/0.9	0.71	0.08	0.07	1.67	3.15	1.18	1.89	4.26
0.1/0.1/0.7/0.1 , 0.7/0.5	0.28	0.04	0.03	0.99	2.49	1.01	0.97	4.23

To better present the results, we have also organized them by increasing the probability of using specific communication modes (with other modes having equal probability), as shown in Fig. 1. Here one may observe that the changing probabilities of communication modes do not have a significant influence on the drift values, but in several cases such influence can be found. Polarization integration strategy is slightly influenced by the increasing probability of bi-directional chat communication, less influenced by the probabilities of post or like communication modes, and not influenced by the comment type of communication. Substitution integration strategy is also slightly influenced by bi-directional chat, post and like communication and not by comment communication mode. The remaining integration strategies are not influenced by these probabilities in a statistically significant way.

The parameters of the communication modes, that are based on the notion of *"skipping post/comment"* in the Facebook social network, do not change the behavior of the strategies, but rather lower the drift by extending the effects of communication in time.

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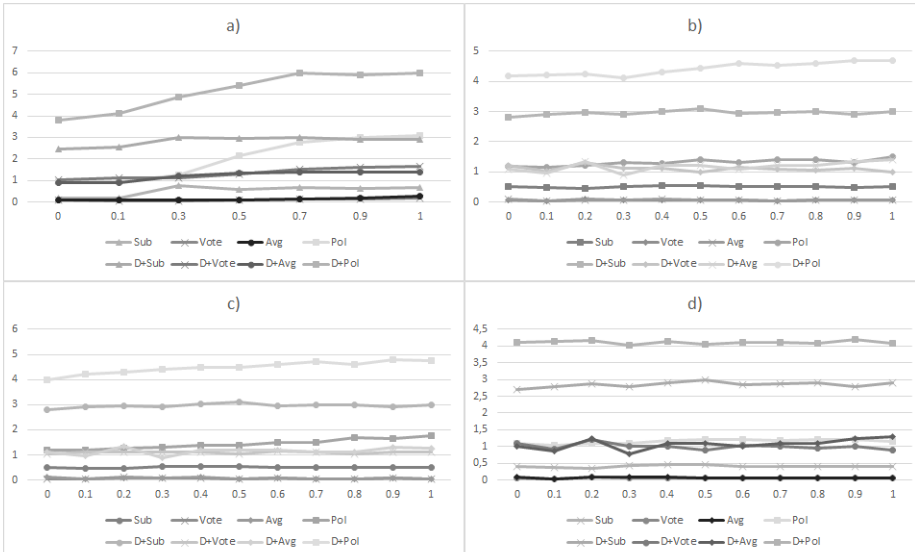

Fig. 1. Drift of specific homogeneous (Sub = Substitution, D.vote = Delayed voting, D.avg = Delayed weighted average consensus, Pol = Polarization) and heterogeneous (D.+ = one Discard agent added to homogeneous group) collectives. Graphs represent varying probabilities of using specific communication modes (a) bi-directional chat b) posting c) likes d) comments) with other modes having equal probability.

5 Conclusions

This paper details a model of an intelligent social collective with communication based on Facebook social network. It operates on a simple structure of knowledge and uses multiple methods for internalization of knowledge by agents. We have evaluated the model in terms of drift – a measure proposed by us in some previous papers, as well as by translating it to a standard epidemic model.

In some of our other papers, we have developed more integration strategies that can easily be applied to this model. We have also used the notion of agents forgetting part of their knowledge and it is also possible to use this method for Facebook-based model. Both those enhancements do not provide a novel research point, so were not included in this paper.

We find that the largest step required for the completion of our model is the further development of the use of more complex knowledge structures, e.g., ontologies. Such a structure may better reflect the internal organization of knowledge in real people, but it requires the development of advanced knowledge integration algorithms that could later be translated into functional integration strategies.

While the group of models we develop in our overall research works well for tasks related to computational collective intelligence, it can be also applied to social network research. There is however a difficulty in obtaining sufficient

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knowledge about the social network to receive any substantial gains from the social collective model. The main problem are the integration strategies, which are internal processes occurring when social network users internalize knowledge. We can only approximate them based on how their expressed knowledge changes. To gain this knowledge for a fully comprehensive test of the model, we would need to conduct an experiment on a working social network with explicit questionnaires given after each new message is read. In fact we are taking preliminary steps to prepare such experiment, with input from researchers in the sociology area.

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