Divergence of an Observed User Profile and a Simulated Real State of User due to Social Communication

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Abstract. In this paper, we extend our previous modular model of a social collective with hierarchical knowledge structure, and we propose an additional step in tuning information retrieval systems after dataset experiments and before testing them with real users. For this purpose, we add a simulation of the group of users as a social collective model and run the information retrieval system on it. Here, we take first steps in that direction, by focusing on a subsystem of a recommender system and simulating what type of social collective it is most effective with. We present details on the social collective model and the information retrieval subsystem model, as well as how to put them together in one simulation. We run several experiments and present some initial findings. In our opinion, this overall approach could be used to greatly enhance further tests with real users.

Keywords: Collective intelligence · Recommender system · Group modeling · Multi-agent simulation

1 Introduction

Information retrieval is one of the most known and most researched areas of computer science. One of the typical problems considered in the area is recommendation, i.e. providing a user with items that may be potentially relevant to him at a given moment. Interestingly, even without the modern focus on taking into account social networks, it was determined that no universal solutions are applicable [18]. With the social graph, the situation becomes more complex, as external influences come in real time from many directions, and the context is harder to determine. *Computational collective intelligence* is one of several approaches that formalize the very broad and multidisciplinary research area of collective intelligence, also known as the wisdom of the crowds. One of the research directions in this area is modelling groups of intelligent agents working towards a common purpose or simply exchanging knowledge related to some specific unsolved problem. A complete model of such a group could be used to show the process of knowledge diffusion or opinion formation in a social network,

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connecting these two research areas. There is no significant overlap between information retrieval and computational collective intelligence.

In this paper, we extend the previous modular model of the social collective with a new variant of the knowledge structure – a hierarchical one based on a predefined thesaurus. This structure is identical to the one we have previously used in research in the information retrieval area, which was motivated by the idea to use them together. Information retrieval systems are usually tested with historical data, but sometimes require also live user input. In the second case, such tests are very time consuming and require a long preparation time. A series of simulations that pretune some parameters of the system would help with the quality of this preparation. This is the place where having a good model of the user group, instead of just a single user, is helpful. While the idea may appear similar to adversarial learning, it is very distinct, as only one model is tuned against the other.

With such a motivation, the final aim is to have a good model of a social group that also participates in the information retrieval activity (e.g., uses a recommender system) and then adapt the IR system to offer the best recommendations to the users in the modeled group. After that, less work would be needed when working with the real world group. As an initial step of this research, we start with adapting only parts of the information retrieval system. Additionally, we set up the group model to be similar to the one used in IR in terms of the knowledge structure used and then set up the parameters of the model to better fit the information retrieval one. While this would not be done in the final system, it serves as a demonstration if such an approach is even viable.

This paper is organized as follows: in Section 2 we describe the research works that are relevant to both the social collective model and the collaborative filtering model that are used in this paper; Section 3 contains details on both models, with the first being in the Facebook-based variant, and the second in the modified median variant; in Section 4 we describe the setup of both models in a simulation environment and the results of those simulations; finally in Section 5 we give some concluding remarks and present our intended further work in combining both research areas.

2 Related Works

One part of our research in this paper is based on a combination of work done in the areas of social influence (in sociology) and collective intelligence (in computer science). It has been observed that in real-world groups there are various levels of influence in a collective depending on individual and group factors, e.g., subjective norms, group norms, or social identity [4]. As a result, individuals may have different resistance to changes in their internal knowledge (internalization or induction), from no resistance at all to full resistance to any inputs [7]. Different aspects may further modify this, for example known competence of the speaker or the previous knowledge level of the person listening [17]. As an interesting example, the less a person knows, the more they can learn – but also

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the less they are willing to learn. The collective intelligence was best introduced in Surowiecki's popular book in 2004 [20] and, among other elements, describes the necessary postulates for wise crowds. Some of the works following this are based on consensus theory [15], where the informal descriptions of Surowiecki are formalized into mathematical postulates. Still, the entire area of research is not applicable in many cases and has come under criticism recently due to being unable to represent real world groups [19]. This problem is addressed by our research combining the mathematical aspect of collective intelligence with real-world based social influence theory, making it more closely resemble real world groups.

Representations of groups in a similar manner are also often done from the point of view of social network research. What we developed in our research and use in this paper may be understood as an influence maximization model in these terms. These are usually understood as a type of predictive models, i.e., they are created with the aim of predicting the network behavior when a new node is added to the network. This may be based on the probability of a person sending a message to other group members [16] or observing how the content of the messages in the group changes over time [1]. Alternatively, in threshold-based approaches, the authors may consider the number of messages concerning a given topic before the receiver is influenced by them [3]. The final group of social network models to consider are explanatory influence models where classifying a person to a specific subgroup (e.g., active or passive members) helps to determine which of them have the most influence on the entire group [2].

The other part of our research in this paper combines more classical information retrieval systems with collective intelligence. The general idea we use as a basis are recommender systems, which have been described as being able to record user actions and use them to refine further results [9]. While the initial approach to those is nowadays limited to very formulaic systems, the modern approaches are based on analysis of the communities they are applied to [10]. Even in those, the user query remains the main tool of the user and the main source of information for the algorithms. The consistent problem is that it may still not reflect real user needs, or even the same query may have a different meaning for different users. One of the classic approaches [14] is using different knowledge structures to represent user profiles (models) and then personalizing the results, but these days an effect similar to overfitting leads to the problem of echochambers [8]. In case of a new user, the profile is still to be built. Instead of making no recommendations at that time, a type of default profile may be instead given to the user temporarily [6]. This profile is then adapted using different models towards real user knowledge [21].

3 Group Models

The overall idea we study in this paper is that there are two models of a group working concurrently. The first model is a collective with members communicating and sharing opinions, and the second is as an additional system that models

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each user and builds a centroid for the whole group. The centroid is then used for other purposes, e.g., content recommendation, cold-start problem avoidance, anomaly detection, etc. We created a model of the first part and applied it as input to the modeling system operating on the basis of a different representation of the group. Both parts were implemented and run simultaneously in a simulation environment with their end results compared (see Section 4).

3.1 Model of the Social Collective

The model of the communicating group is based on our previous research on modeling a social collective as an agent system [12]. We constructed those models to intentionally resemble online social networks. The general model of the social collective allows for flexibility in certain parts, which in the case of this paper is used to model the Facebook social network. The three main components are the knowledge structure used, the types of communication used, and the methods of knowledge internalization.

In this paper, we use the hierarchical structure of agent knowledge as a novel variant. This approach was originally used in the second model and we use it in this one to remove any unnecessary difference between them. The hierarchical structure of knowledge assumes that there exists exactly one graph representing the relations between all individual knowledge statements. The internal representation of this knowledge for each agent is always a subgraph of this representation. In implementation terms, all agents always have the full representation of the knowledge graph, but if the associated weight is 0, then the agent does not *know* this statement. As the graph structure is common between agents, the hierarchical structure of individual knowledge statements is stored in a vector format, with a weight associated with each. This weight is interpreted as a numerical representation of either the sentiment towards the issue (a higher value represents a more positive sentiment) or the agents certainty that the knowledge statement is true. The knowledge and sentiment of each agent a about each issue k_i is represented by a set of pairs $k_i = \{< k_i^a, w_i^a >\}$ (in implementation: only a set of weights in range $[0, W]$). Any message an agent sends is a single pair $\{< k_i^a, w_i^a >\}$, which is sufficient for the receiver due to the common structure.

The model of communication based on Facebook social network may be described in general terms as four main modes of communication: a private chat between users, a public post, public comment under a post or another comment, or a public reinforcement of a post or comment. Other methods of communication are derivative of those. In the presented model, all of those are allowed. An agent may use any of them with a probability of P_i^c. As even public messages are initially only displayed to that persons *friends*, in the model, each agent has a limited list of agents that he can communicate with (a list of vertices that connect it to other agents – nodes in the social graph). Specifically, the communication modes are:

– Each time communication may occur, an agent may randomly select to send a message containing one statement from the the hierarchical knowledge

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structure to one or more agents it is connected to, selected at random (with the possibility of any one agent being selected multiple times). This represents posts on Facebook *wall*, where people may skip a message or read it several times.
- Each time communication may occur, an agent may randomly select to send a message, that is a copy of any previous message it received, to one or more agents it is connected with, selected at random (with the possibility of any one agent being selected multiple times). 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.
- Each time communication may occur, an agent may randomly select to send a message, that is a copy of any previous message it received, but with the weight modified to the agents own opinion on the statement, to one or more agents it is connected with, selected at random (with the possibility of any one agent being selected multiple times). 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.
- Each time communication may occur, an agent may also randomly select to send a message containing one statement from the the hierarchical knowledge structure to exactly one agent it is connected to, selected at random, but concurrently the other agent will send back the message containing the same knowledge statement, but with its own associated weight. Processing the messages is done after the bidirectional communication occurs, so agents are only informed of the others opinion prior to communication and not already influenced by it. This type of communication represents discussions via the chat option between two different people.

In reaction to incoming communication, agents in this model internalize the incoming knowledge by changing their own. This is done by applying specific knowledge integration algorithms that we have based on various research in different areas of literature, from psychology to purely mathematical models. A message may be internalized immediately, or it may be stored in the agent's memory until several messages on the same topic are accumulated. Algorithmically speaking, the input is one or more pair $k_i = \{< k_i^a, w_i^a >\}$ and the agent's initial knowledge state, while the output is the agent's final knowledge state. In this paper, we do not use all integration algorithms (which we call integration strategies in our research), but only those most similar to the other model used:

- Substitute – the idea for this integration algorithm is derived from the sociological concept of *no resistance to induction*. An agent (person) internalizes all incoming opinions or knowledge. The strategy works by immediately changing the weight of the knowledge statement given in any incoming message from its own weight to the weight provided in the incoming message.
- Extend – is a modification of the *Substitute* strategy, in which the changes are only applied to previously neutral (unknown to the agent) knowledge statements. If the agent already has any knowledge (opinion) on some topic, then it remains as is.

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- Immediate consensus (Merge) – the idea for this integration algorithm is derived from the mathematical principles of consensus theory. It is severely limited, as it only applies to one incoming message (instead of several, like the following four strategies). Following the concepts of consensus theory, the approach to determining the new numerical value from two different weights assigned to knowledge statements, is the average of those values. For neutral knowledge (unknown to the agent), that means that the weight is halved from the incoming message.
- Delayed voting (Majority) – the four algorithms named *delayed* are also based on consensus theory. The basis of all the algorithms is accumulating several messages concerning one knowledge statement, before integration is conducted and the internal value of the weight associated with the knowledge statement is changed. In case of *delayed voting*, determining a new knowledge state is done by selecting the most common one among the gathered messages.
- Delayed weighted average consensus – as previously, a message buffer is used. To calculate the new state of knowledge that the agent will have on the given topic, in this strategy, the *average* of received (and own) knowledge or opinions is calculated. This means that the algorithm looks for a centroid that has the smallest sum of squared distances to all other elements.
- Delayed nonweighted median consensus – as previously, a message buffer is used. In this integration strategy, all gathered knowledge states are sorted according to a predefined ordering and the middle state is selected. For an even number of opinions, one of the middle states is selected at random.
- Delayed weighted median consensus – as previously, a message buffer is used. The algorithm is similar to the previous one, but messages with higher weights are copied multiple times in the sorted list, corresponding to their weights (normalized for a maximum of ten repetitions for the maximum allowed weight).

In some of our research [13] we have also considered agents forgetting knowledge (here: the weight is changed to 0: neutral/unknown), but this aspect is not considered in the current paper.

3.2 Model of the Collaborative Filtering Group

The second model was based on the research in the area of collaborative recommendation that was presented in [11]. It was created as a means to limit the *cold start problem*, i.e. new users in the system being presented with bad or no recommendations. The proposed solution was to find other users similar to the new one (based on short initial searches or other information, e.g. demographic), then determine a centroid representative of this group. Such centroid would be used as the initial representation of the new user, until sufficient proper information about him has been gathered. In effect, the centroid of the group represents its average opinion as gathered in the user profiles, and should be very close to the average of real opinions as represented in real user preferences. The paper

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[11] specifically distinguishes what is the real user preference and how the system represents him as a user profile, but uses the same knowledge structure and agent representation for both. Here, we use the same knowledge structure, but for the user preferences agents are represented as in Section 3.1, and for the user profile, as in [11].

The idea of the user profile as a hierarchical structure is based on a common thesaurus and weights reflecting the frequencies of particular terms in user queries. This is based on the well-known assumption that when the user is interested in a term, he includes this term in his queries and the more interested he is, the more often the term is contained in a query. The hierarchical thesaurus allows determining relationships between terms and better grouping users due to the possible generalization of their interests. Based on the assumption that only one term from each path between a leaf and root (excluding the root itself) may occur in a query, such profile is further limited by the following constrains:

– Total Frequency Minimum (K1) – as each user query contains at least one term, the sum of the frequencies of queried terms in the tree (i.e. weights) should be no smaller than 1. This comes from normalization when queries consist only of one term.
– Path Frequency Maximum (K2) – as each element on a path in the thesaurus may occur only once in each query, the sum of weights on a single path should be no larger than 1.
– Total Frequency Maximum (K3) – as user queries consist of a limited number of terms, the total sum of weights in the tree should not be larger than some constant b (e.g. [5] states that typical user query has at most 3 terms, therefore both in this paper and in [11] we assumed $b = 3$).

We build a centroid by gathering observations of user activity, then calculating the frequencies and storing them as weights of appropriate nodes in the hierarchical structure.

Based on the given assumptions on the user profile, there are several postulates formulated which a satisfactory centroid should satisfy:

– Reliability (Re) – this postulate requires the centroid profile to satisfy K1, K2, and K3 constraints on the profile. Otherwise, the profile is not valid.
– 1-Optimality (O1) – this postulate requires that the result of the integration should minimize the sum of distances to all profiles in the group (according to some metric). In practical terms, it is the median of the weights of each node in the hierarchical structure.
– 2-Optimality (O2) – this postulate requires that the result of the integration should minimize the sum of squared distances to all profiles in the group (according to some metric). In practical terms, it is the average of the weights of each node in the hierarchical structure.
– Conflict Solving (CS) – a conflict occurs in a constructed centroid when the difference between the weights of terms that have the same parent is greater than some assumed threshold. This postulate requires that all conflicts are

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solved. This is done by increasing the preference of the parent and reducing the preference of the elements in conflict, in the following way:

$$\Big(w_{t_i}(v_x) < (\psi - \frac{\gamma}{2})\Big) \wedge \Big(w_{t_j}(v_x) > (\psi + \frac{\gamma}{2})\Big) \wedge$$
$$\wedge \Big(w_{t_i}(v_y) < (\psi - \frac{\gamma}{2})\Big) \wedge \Big(w_{t_j}(v_y) > (\psi + \frac{\gamma}{2})\Big) \rightarrow$$
$$\rightarrow \Big(w_{t_{cs}}(v_x) = 0\Big) \wedge \Big(w_{t_{cs}}(v_y) = 0\Big) \wedge \Big(w_{t_{cs}}(v_p) > max(w_{t_i}(v_p), w_{t_j}(v_p))\Big)$$

where where v_x and v_y are nodes in conflict, with a common parent v_p; the initial weights come from trees t_i and t_j, and the integrated tree is t_{cs}.

Unfortunately, it is mathematically impossible for a centroid to satisfy all four postulates in any nontrivial situation. For all combinations, we always require at least Reliability and one other postulate to be satisfied.

In this paper, for the purpose of building the integrated centroid, we apply one of algorithms from [11]: the Closest Tree Algorithm (CTA). The algorithm has two main phases. In the first, we determine the median of weights for each node, which makes it satisfy some of the conditions laid down for the desired centroids. The second phase is focused on another condition and optimizes the weight values towards it, in effect transferring some value of the weights towards the root of the tree. The effect on the conditions is that at the end two are satisfied (Re and CS) and one is almost satisfied (O1). The complexity of this algorithm is between $O(|V| \cdot N)$ and $O(|V| \cdot |V| \cdot N)$ (no conflict and only conflicts, respectively, to solve in the second phase). The full details of the algorithm can be found in [11].

3.3 Combining the Models

In this paper, we create a system where both models work concurrently, with some flow of information between them, as shown in Fig. 1. The social collective simulates a group of real users, while the function of the collaborative filtering model is identical as in the full information retrieval system (i.e. building centroids that are a good representative of a group of users).

Initially, both models start with the same set of agents (with randomly generated knowledge, see Section 4). The social collective model treats them as members of the collective, while the CF model interprets them as initial profiles of users. Thus, at initialization, both user preference (real needs of users) and user profile (a representation of the user in CF model) are identical. In a real world system, this would only be the case for users with no initial interest, therefore of limited applicability (e.g., elearning platforms). The collaborative filtering model immediately builds an initial centroid out of those profiles.

Following the initialization, the social collective model works through its iterations, with agents communicating and exchanging knowledge. Meanwhile, the CF model observes nonprivate communication (here: all but *chat* messages) and updates user profiles. Periodically, it also updates the representative centroid.

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At some chosen point, the concurrent run of both models ends. We calculate the mean knowledge of all agents in the collaborative model and then compare it with the last centroid calculated by the collaborative filtering model. Thus, we observe how both models diverge over time from the initial identical start. Following this, we could determine if the social collective approach is viable as a tool for pretuning information retrieval systems for further tests with real users.

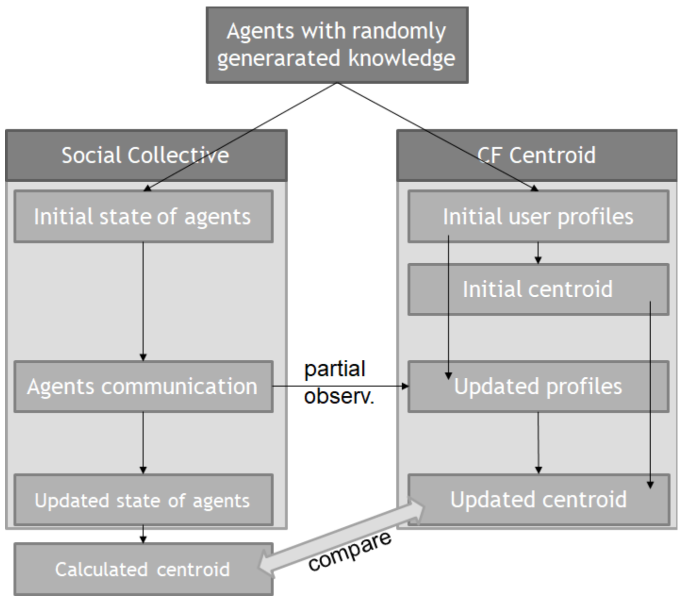

Fig. 1. Schema of experimental system with the flow of information between both models.

4 Evaluation of the Model

In our previous research, we were using different measures to evaluate each of the models. Collaborative filtering model was initially developed as a part of a larger information retrieval system, and as such, traditional measures could be used to measure its influence on the overall system, e.g., precision, recall, and f-measure. Additionally, in [11] this specific part of the overall system was evaluated using a criterion defined as BQC (Basic Quality Criterion), which states that if the profiles of each group member are in some neighbourhood of size ϵ, then the centroid solution would also be inside. Similarly, for the social collective model, we formulated a measure of drift based on the sociological literature, to calculate the average change of all opinions (weights associated with knowledge) in the group overtime. Following, the criterion for a good collective was that it had

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a small drift when there was no outside influence, and a larger one with such influence exerted. Unfortunately, neither of those can be applied directly for measuring the divergence of both models.

Instead, the divergence of the collective models was instead evaluated in a series of runs in a simulation environment. We have implemented both models and run them concurrently, as described in detail in the previous section. The collective model of the the social collective was simulating a group of real social network (Facebook) users, and the collaborative recommendation model was used to build to create a centroid profile of the group. The initial knowledge structures were identical, and after the end of the simulation run, we compared the calculated median of agents in the social collective (real group centroid) with the centroid as calculated by the collaborative recommendation part.

The parameters of the social collective model have been set up as follows:

- Number of possible knowledge statements: 128,
- Initial number of statements for each agent (with nonzero wights) : 16,
- Range of allowed weights : [0,1],
- Weight distribution : uniform in the entire range,
- Maximum number of agents in *friend* relation : 10,
- 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,
- Probability of diffeent type of communication : depending on experimental series.

The parameters of the collaborative filtering model have been set up as follows:

- Parameter for K3 postulate $b = 3$;
- Parameter for Conflict Solving criterion $\epsilon = 5$
- Parameter for Conflict Solving Ciretion $\psi = 0.3$

The simulation was run for 1000 agents for 1000 iterations (time moments, during which interaction between agents is possible). We have run the simulation for every applicable integration strategy (as described in Section 3) and for varying probabilities of using different communication modes, repeating each permutation 100 times, and averaging the results. Some of the visually clearest of the aggregated results have been shown in Fig. 2 and Fig. 3, which present the difference between both models in the most generic term in the hierarchical structure and in the most specific one, respectively.

General results of the experiments show that there is a difference of ca. 0.02 – 0.05 between the social collective and collaborative filtering models after the simulation run (within the range $[0, 1]$). The CF model follows the social collective model quite closely, but it is never exact and the difference is statistically significant.

When agents use integration strategies that are based on gathering more outside information, instead of changing the previous knowledge state immediately,

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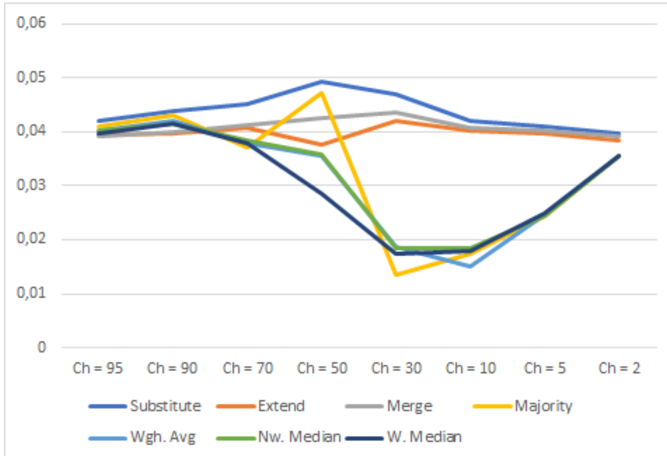

Fig. 2. Divergence between two models after the simulation. Difference measured by opinion weight for all simulated variants of the social collective model with different probabilities of observed and unobserved user behavior (*Ch* value represents probability of agent using unobserved communication). Figure presents divergence for the issue at the root of the tree.

the parameters of the communication in the model start having an influence on how good is the CF model. Generally, the more communication may be observed, the closer the CF model is to the social collective one. This is an expected result in any system of the type. However, after some threshold, the model is overfitted and does not react in time to changes in the agent. In our observations, it happened mostly with more than ca. 90% of all messages were observed (i.e., less than 10% were of the private chat type). Barring some strategy-specific cases, we have observed that the CF model is the closest when it can observe 70-90% of interactions between users (i.e., chat messages consist of no more than 10-30% of them). This can be seen to happen for every node in the tree, as seen in the root in Fig. 2, and in the leafs in Fig. 3.

We also performed statistical tests if the difference between the typical situation and the one with *optimized* number of observable interaction in terms of the aggregated value is statistically significant and we have done so for the data resulting in all presented averages. The p-values were smaller than 10^{-15}, therefore we could abandon the null hypothesis that the data is from the same distribution.

5 Conclusions

As stated in the introduction, this paper represents only the initial stages of the overall idea to have a good model of a social group that also participates in the information retrieval activity (e.g., uses a recommender system) and then adapt

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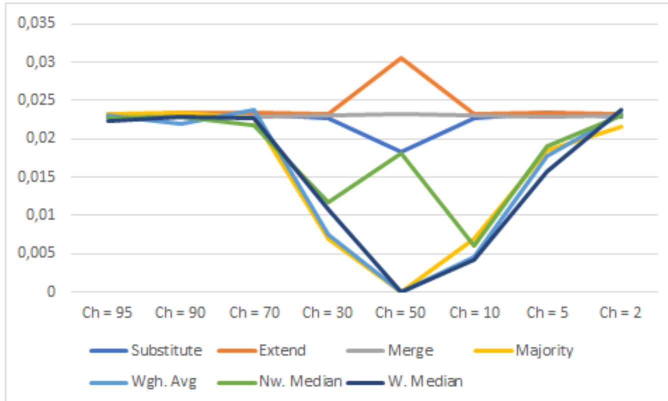

Fig. 3. Divergence between two models after the simulation. Difference measured by opinion weight for all simulated variants of the social collective model with different probabilities of observed and unobserved user behavior (*Ch* value represents probability of agent using unobserved communication). Figure presents divergence for the issue in a leaf of the tree.

the IR system to offer the best recommendations to the users in the modeled group. This would create a situation where less work is needed when working with the real world group. This paper shows that the models are not identical, but may be modified to be more similar, so the approach is viable.

The experiments performed in this paper were opposite to the final idea, i.e., we modified the parameters of the social collective to observe how the information retrieval model diverges from it. We have chosen such an approach, as it was possible to use two existing models that were already proved to be good in their own specific areas, and change only the social collective model by using a different knowledge structure in its modular construction, so that we could use both of them in the experiments. Any future research we plan will start from building a model of the group that best represents the one occuring in the application area and tune it, then create a fitting model for the recommender system, conduct finetuning of the second in the simulations, and finally, start the experiments with the group of real users. This will be a direct follow-up study after this paper, which will allow to estimate the possible profit from using this approach.

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