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# Building social-aware software applications for the interactive learning age

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# Building social-aware software applications for the interactive learning age

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There have been a number of frameworks and models developed to support different aspects of interactive learning. Some were developed to deal with course design through the application of authoring tools, whereas others such as conversational, advisory, and ontology-based systems were used in virtual classrooms to improve and support collaborative activities. Although these methodologies have brought new processes and practices to interactive learning systems, current applications have not fully capitalized on the rising power of social computing to discover and explore the wealth of social-based information derived from the communities of practice that are formed. This article presents a comprehensive social computing framework for web-based learning environments that aims at representing a systematic means of acquiring, sharing, and using relationships effectively within an interactive learning environment so that participants can use them to create opportunities to work cooperatively in learning communities with other students. The proposed framework integrates several aspects of those relations into a decision-making criteria engine that is based on social networks and reputation systems. A description of the proposed methodology and its implementation are presented along with an example application. This research is expected to assist participants of online learning classrooms to make decisions that facilitate the exploration and discovery of co-learners while promoting increased awareness of the virtual classroom structure and information exposure given by their social presence.

**Keywords:** social computing; interactive learning; reputation systems; social network

## Introduction

The proliferation of existing and emerging web technologies and resources such as Wikis, Folksonomies, tagging, ontologies, YouTube, Facebook, MySpace, social networks, online chat rooms, instant messaging, and blogs (to name a few) has changed the breadth, depth, and opportunities for the learning experience. The classic educational scenario where participants (teacher, tutors, students, etc.) meet face-to-face is becoming steadily more integrated into virtual central spaces that are easily accessible via web interfaces. In this context, the educational systems shaped by technologies and practices cited above are numerous.

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For instance, in terms of ontology, Stojanovic, Staab, and Studer (2001) first explained how semantic web technologies based on ontologies could improve different aspects of the management of e-Learning resources, followed by Jonassen (2006), who discussed the ontology-based ways that knowledge is organized and represented in curricula, learning environments, and information and knowledge management systems in the educational context. Further, Albano, Gaeta, and salerno (2006) presented three ontology-based models to achieve the purpose of representing the knowledge that is objective of learning (i.e. Knowledge Model), the context where the educative process is realized (i.e., Learner Model), and the learning preferences and demands of the student that the process addressed (i.e., Didactic Model). The system that was implemented thereafter created a sequence of learning activities associated to each model's elementary metadata concept to extract personalized learning paths, which are specific to characteristics of a particular student. Tane, Schmitz, and Stumme (2004) presented a methodology and implementation of an ontology-based 'Courseware Watchdog', which supports the user in finding and organizing distributed courseware resources by offering a common framework for the retrieval and organization of courseware material. Heiwy (2006) addressed the problem of building new resources for curricula by reusing existing resources and by assembling resource components and defined reusable resource components were defined and stored in a Learning Object Repository described by standard meta-data or ontology of domain used as selection criteria (Lytras & Garcia, 2008; Lytras & Ordóñez de Pablos, 2007).

Another advance towards educational software applications is the applications based on Intelligent Educational Systems. The main characteristic of those systems is the ability to adapt presentation of the educational content to the needs of specific users, which need large amounts of educational content (Prentzas & Hatzilygeroudis, 2002). In this respect, Brusilovsky, Knapp, and Gamper (2006) developed an adaptive vocabulary acquisition system based on a language content authoring component that allows teachers to develop the educational content by themselves. This is to increase the chances that the content will performs its functions more successfully, once professional design teams are more prone to deliver core-authored material.

In recent years, social computing has received considerable attention in North America and worldwide as well. The proliferation of online social networking services, in which millions of members publicly articulate mutual 'friendship' relations, has given rise to many forms of online sociality. These tendencies to form online social groups or live in an online community have also powered the rise of social computing upon fundamentals such as computer-mediated communication tools, reputation systems and social network analyses, and specify frameworks to integrate that these three aspects have been successfully proposed (Capuruço & Capretz, 2008). In fact, social presence and interaction play a critical role in all forms of formal education, including those delivered at a distance. According to Rourke, Anderson, Archer, and Garrison (1999), the ability of learners to project themselves socially and affectively into a community of inquiry (i.e. virtual classroom) that is formed has a pivotal role in not only setting the education climate but also in supporting discourse and creating the educational experience.

However, incorporating social presence into interactive learning environments complicates and renders traditional methodologies as insufficient to deal with the distinct formulation involved. This is because the existing education software methodologies and models have vastly dealt with approaches to build stronger learning content and to foster student–content interaction, but they still have some drawbacks that may hinder the student–student orchestration to support learning processes that are formed from the social presence that the interactive education experience provides.

In addition, the very many current interactive learning applications provide participants very little to none opportunities to build upon the social spaces, casual interactions, and meaningful exchanges that occur within their own classroom. This often leads to reduced interactivity and productivity as they are not aware of all available expertise and resources that could greatly contribute to their own learning endeavour, and most importantly, how to reach those optimally. A new methodology is needed, which the present research is attempting to overcome.

The proposed framework represents a systematic means of acquiring, sharing, and using relationships effectively within an interactive learning environment so that participants can use them to create opportunities to work cooperatively in learning communities with other students. It integrates several aspects of those relations into a decision criteria based on social networks and reputation systems. The framework developments and its implementation on a prototype application are outlined and a numerical example is presented to demonstrate the applicability of the proposed model. The output of the model is a set of strategies to search and guide participants reciprocally throughout the interactive learning environment. Future work to incorporate other components is then outlined.

## Components of a social-aware interactive learning application

The main components of a social-aware interactive learning application that incorporates all of the above are as follows (Figure 1):

- Detailed Models (online interaction tools, social network, and reputation-dependent perceptions of qualities, attributes, and interaction experiences)
- Constraints (social context, social relation, social reputation, user-defined constraints such as interaction relation intensity, priority, etc.)
- Decision Support Module (user interface, community database, interaction relation assessment, reputable search, visualization)

### *Framework models*

At the core of a successful social-aware interactive learning application are proper models for promoting classroom interaction, and for capturing relationship patterns of the individuals so that those associations can be used to form social communities and to estimate the several patterned interactions.

#### *Interaction model*

People form online communities by using a combination of one-to-one (e.g. instant messages, e-mails, chat rooms), one-to-many (e.g. web pages and blogging), and many-to-many (e.g. wikis) communication modes (Shirky, 2003). These modes are also used within virtual classrooms to create, publish, exchange, share, and

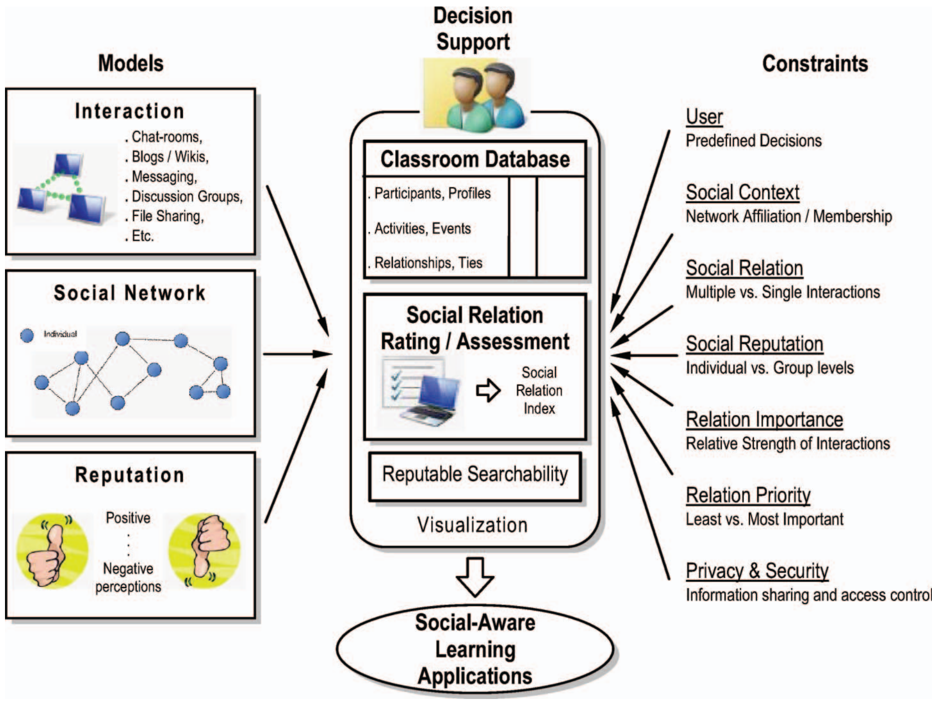


Figure 1. Components of a social-aware interactive learning application.

cooperate on learning resources. In this model, these tools are the entry-point by which personal networks are formed within the virtual classroom environment, as participants collaborate and communicate ones to another.

### *Social network model*

On the basis of the theoretical constructs of sociology and mathematical foundations of graph theory, social network analysis models offer a unique methodology for visualizing and investigating social structures and relations (Lytras, Rafaeli, Downes, Naeve, & Ordóñez de Pablos, 2007; Wasserman & Faust, 1994). As a component of the proposed framework, the social network model represents the logical structure that embodies the patterns of the relationships between classmates at several scales and the possible statements that can be drawn from those by using social network analyses-based techniques.

In this research, a combination of Laumann, Marsden, and Prensky's (1989) three generic approaches to decide on the set(s) of objects that lie within a social network and Scott's (1991) definition of the principal types of data to be considered to fulfil those approaches was employed. As such, this model uses two types of data as its building blocks: attribute- and relational-based data. Yet according to Scott (1991), *Attribute data* relates to the attitudes, opinions and behaviours of objects – in this case, the learners – combined with their basic characteristics to define formal membership criteria. These data sets are regarded as the properties, qualities or characteristics that belong to them as individuals or groups. *Relational data*, on the other hand, are the contacts, ties, and connections, the group attachments and meetings, which relate one participant to another and so cannot be reduced to their properties only; these relations connect pairs of learners into the larger relational system.

The two basic types of data are translated into the classroom participants' profile and their connections features. Although a set of socio-demographic characteristics such as age, gender, education, etc. is the most natural dataset candidate to be organized as attribute data, an assortment of opinions representing expressions of the experience when dealing with particular classmates can be also structured as attribute data. The collection of relations connecting pairs of individuals such as *'friend of whom', 'has studied with', 'has messaged who'*, etc. emerges as specific community-generated content that can be mapped as relational data.



### *Reputation model*

Reputation and trust are the bedrock of community ongoing interaction and cooperation, and are a vital source of social information and control (Kollock & Smith, 1996; Ordóñez de Pablos, 2004a–c, 2005). There are a number of reputation system models developed to capture trustworthy in the online interaction process.

Gupta, Judge, and Ammar (2003) have examined peer-to-peer applications including KaZaA[1] and a trust model is proposed where different parameters such as the average query-response message size, the ration of Mbytes uploaded, and the amount of content-shared are used for computing a reputation score associated with peers. On the other hand, Dellarocas and Resnic (2003) is an example of research on reputation systems that are largely used only for online trading communities, such as e-Bay.[2] The reliability of participants in such environments is measured by calculating a score associated with one or more of a user's participation level (e.g., number of successful transactions), availability of physical identities (e.g. valid email), and feedback about interactions with each other.

In this article, the reputation model is designed to take into account both individual and group perceptions of trust for the person with whom others are linked. The perception of trust in this model can be divided into four parts: (i) the category the reputation information belongs to, (ii) the amount of reputation (i.e. rating) assign to a particular category, (iii) the feedback type used to collect those judgments, and finally (iv) the relative importance (i.e. weight) among the categories.

These perceptions of trust are aggregated into a numerical value, which synthesizes the impressions of interaction quality and trust that not only a person has about another, but also perceptions the community (i.e., classroom) as a whole has about an individual.

The parameters shown in Table 1 allow the calculation of an individual-based Social Reputation Score (Equation (1)) for each online classmate. The score can be determined as a weighted sum of the reputation ratings of each of

$$\mathrm{SRS}_{\mathrm{individual}} = \frac{\sum (\text{Task rating} \times \text{Importance})}{\sum \text{Importance}} \tag{1}$$

the categories, considering the respective category importance (weights) one to another, and dividing them by the sum of the weights. This score represents the total informed judgment on the trustworthiness of participants based on the technical proficiency and performance derived from typical classroom tasks.

The parameters shown in Table 2 allow the calculation of a group-based Social Reputation Score (Equation (2)) for the connection existing between each pair of classmates. The score can be determined as a weighted sum of the relation ratings of each of the relation types, considering the respective relation importance (weights) to

Table 1. Task-based reputation types.

| Seq. | Task-based category | Rating | Rules | Feedback type | Weight |
|---|---|---|---|---|---|
| 1. | Participation in class | 1 to 5 | Number of messages posted in online discussions | Implicit | 100 |
| 2. | Class attendance | | Number of logins to the application | Implicit | 25 |
| 3. | Completion of tasks | | Carrying out tasks as agreed to the sessions (delivery on time, etc.) | Implicit | 25 |
| 4. | Coursework evaluation | | The grade assigned to exams, essays, quizzes, etc. | Implicit | 75 |
| 5. | Tutoring services | | Number of bookmarks shared with others | Implicit | 25 |
| 6. | Participation in groups | | Number of different affiliations in discussion groups | Implicit | 50 |
| 7. | Role model for others | | Number of accessed bookmarks and recommendations | Implicit | 25 |
| 8. | Sharing private information | | Member has a visible profile and has allowed to be partially or totally found by other participants | Implicit | 50 |

Table 2. Relation-based reputation types.

| Seq. | Relation type | Rating | Rules | Feedback type | Weight |
|---|---|---|---|---|---|
| 1. | Friendship | 1. Unknown<br>2. Have heard of, but not met<br>3. Have heard of, and met<br>4. Familiar<br>5. Very Familiar with | Levels of notion specific to interpersonal relationships | Explicit | 75 |
| 2. | Teamwork player? | 1. Not a team player<br>2. Not so good to work with<br>3. Neutral<br>4. Good to work with<br>5. Excellent to work with | Level of participation in group work activities | Explicit | 50 |
| 3. | Overall likeability | 1. Terrible to be with<br>2. Dislike being with<br>3. Neutral<br>4. Like being with<br>5. Love being with | The ability to produce positive experiences to others | Explicit | 25 |

each other, and dividing the summation result by the sum of the weights. This score represents the total intuitive

$$\mathrm{SRS}_{\mathrm{group}} = \frac{\sum(\text{Relation rating} \times \text{ Intensity})}{\sum \text{Intensities}} \qquad (2)$$

judgment on the trustworthiness of participants based on their paired interaction.

The weights shown on both Tables 1 and 2 are for illustration only; the community members can customize them to reflect their unique discerning knowledge about what category matters the most.

### *Framework constraints*

As illustrated in Figure 1, several practical constraints should be taken into consideration for implementing social-aware applications. These constraints can be categorized as follows: *social context*, a specific and common relation environment among pair of people in which social interactions happen; *social relations*, the different types of interactions among pair of people; *social reputation*, the measure of judgments and perceptions about the character, stability, reliability, behaviour, performance, etc. of people who interact in a given community; *relation importance*, the measure of the relative strength, influence or 'bond energy' among interactions; *relation priority*, the measure of importance of the relationship among pair of people; *user*, the ability of a community member to enforce his or her decision on the decided one; *privacy and security*, the governing policies that allow disclosure of personal information and access privileges to those.

These are important aspects to be considered in the design of a general social computing system applied to e-learning environments because they allow great flexibility in defining the decision criteria that is used by the decision support module, which is explained next.

### *Framework decision support*

The decision support module integrates the three essential models and the constraints to arrive at a social-aware application that is capable of taking advantage of the social data it stores. The decision support component comprises of a reputable search optimization model linked to the portfolio (database) of classrooms and to a social relation assessment model that applies all the previous models to all framework's components.

#### *Classroom database*

The underlined physical structure of the community that supports the virtual classroom's social network model is a familiar database schema based on node-link representation, where nodes represent members of the classroom and links denote the articulated 'social relationships' (e.g. interaction, ties) between them. Each node and link has attributes associated that allow users to calculate and store reputation information. Each link is associated with a particular social context, and a pair of nodes may have one or more links, thus representing different social contexts of interactions.

On the basis of both profile and connection attributes, a relational database management system was designed and two main tables – nodes and links, respectively – were implemented to store, in real-time, the network objects and the associations between objects. This network model is the working data repository that becomes available for further processing by the decision support engine.

### *Social relation assessment*

A social relation rating system had to be developed to perform the condition assessment of the social reputations and social relations in the network. As shown in Tables 1 and 2, the condition rating used in this article varies according to the reputation category and relation type.

The ratings that are calculated for each of the reputation categories are always scaled from 1 to 5. This is to account for the high variability expected in the counts for each category prior to aggregation through Equations (1) and (2). This scale also assumes that social reputations and relations are valued as from the worst to the best, respectively. Condition ratings are used to describe the existing condition of trust and opinions among individuals in the social network. It is considered as the most important phase on which subsequent decisions are based.

The Social score calculation mechanism also works as a function of the type of user feedback required: when the network is capable of obtaining complete and accurate information about the transactions they mediate (e.g. number of logins per member), without explicit input from the participants, this is aggregated and stored automatically. On the other hand, in order to record the state of the several relations, explicit input from the rest of the community members is needed. Generally, this is achieved by employing some sort of online voting system.

### *Reputable searchability*

Having defined the present condition of a social network with the online interaction model and reputation model, the proposed framework uses a Path-based optimization model (Dijkstra, 1959) to determine optimum priority list of members and their social relations conditions. *Reputable Searchability* is a newly coined term to define the class of social computing search engines that are capable of showing a target member based on a desired level of individual- and/or group-based reputation. *Reputable Searchability* is very important to consider because a member of a community is not defined by its ethnographic attributes only; rather, he/she is characterized by a combination of those with his or her social ties (Simmel, 1902). The reputable search engine also optimally 'guides' the searcher to its desired destination, functioning as the means or medium for showing all linkages between two or more people. As such, the procedure searches for the path with lowest cost between a community member and every other member with respect to user-defined constraints.

To develop a sound reputable search mechanism, a Social Relation Index as a combination of group- and individual-based perceptions was constructed to account for the social distance between a pair of members, as per Equation (3).

The Social Relation Index (SRI) is calculated as the weighted sum of the individual (i.e. Task-based Social Reputation Score) and group (i.e. Relation-based Social Reputation Score) scores, considering the relative importance between these two levels (i.e. weight), and dividing the result by the sum of the weights. This index represents the total 'Social Distance' between a pair of members, which is the basis for the cost structure that was implemented, so that the path-related algorithm can use it to function as expected.

Implementing a graph search algorithm in the framework involves four main steps: (1) eliciting community

$$\mathrm{SRI} = \frac{(\mathrm{SRS}_{\mathrm{individual}} \times \mathrm{Weight}) + (\mathrm{SRS}_{\mathrm{group}} \times \mathrm{Weight}_{\mathrm{g}})}{\sum \mathrm{Weights}_{\mathrm{i,g}}} \tag{3}$$

members and their connections for a given social context; (2) setting the source and destination participants; (3) deciding on the evaluation criteria, higher or lower SRIs; and (4) applying the relaxation principle to generate short paths.

After defining the cost structure, the constraints considered in the algorithm are as follows:

(1) choose a Social Context – This will filter out members and/or connections;
(2) choose one or more Social Relations, assigning corresponding weights: this will affect the calculation of the Social Score at the individual level;
(3) Choose 'Group' or 'Individual' reputation: this will affect not only the calculation of the Social Score at the group level, but it will also affect the calculation of the whole Social Index by including/excluding either or both levels;
(4) Specify whether to use lower or higher scores: this will affect the selection of target members by the algorithm.

To evaluate a possible solution (list of members), the reputable search algorithm identifies, analyses and builds the cost structure by using the desired constraints and social context for a particular population of participants. Once the target population of that community has been created, the *Social Distance* is calculated for each social interaction for all of their members. Then, beginning from the source member (node), paths from one member to another whose total cost is the least among all such paths is calculated until the target node is reached.

Because the searching algorithm always looks for the least cost, the calculation procedure had to be adapted to account for highest costs as well; that is, finding paths with highest reputability, interactivity, etc.

### *Visualization*

The visualization model (Figure 2) includes representation and presentation features suggested by Carpendale and Montagnese (2001). The model also supports a range of basic exploratory search features by such methods such as panning, scrolling, zooming, etc. providing visualization of the rich profile and connection data characteristics as of traditional 'Sociograms' (Freeman, 2000).

Interaction with the visualization is conducted primarily with the mouse. Clicking a node causes the corresponding profile to display in the proper dialog box. Likewise, clicking a link causes the corresponding connection to display in another proper dialog box. The dialog boxes are not modal, meaning that the user

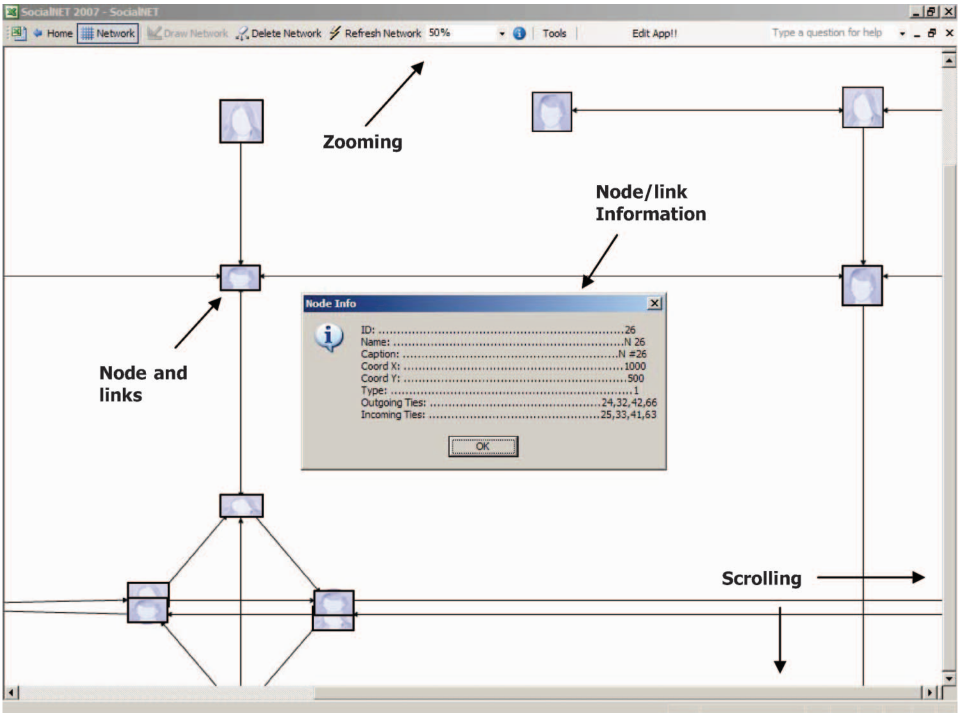


Figure 2. Prototype's user interface.

can zoom-in/out, pan, and/or scroll horizontally and/or vertically while displaying them; this gives a great amount of flexibility to locate a specific member of interest in the network while keeping the application's decision support tools handy. Dragging a node allows the user to reposition items, subject to the constraints of the user-interface.

By using a specific interface (not shown), a 'find member' query can be conducted over all the available profile attribute values, so that in turn a unique member is returned; this functionality is constraint by the sharing private information variable. The find query uses a sort of backing 'trie' data structure (Black, 2006), which maintains a prefix-tree of the text in the attribute values for all currently visualized profiles: as members and their connections enter or leave the visualization by replying to a user's invitation to be part of his/her social personal network, they are appropriately added or removed from the 'trie' data structure, and the underlined social database as well.

## Prototype and example

The proposed social models and reputable searchability exploration engine were implemented on a commercial spreadsheet program. In this study, Microsoft Excel software is selected for the implementation of the proposed model because of its ease of use and powerful programming features.

Using the Visual Basic language of Microsoft Excel, various procedures were coded to form a complete Social-Aware application. These developments involved a substantial effort in coding the several components and providing a user interface. The data of a social network of people are input into the system (a small random classroom social network of 35 members and 74 connections among them is used for demonstration purposes). Information about each member and the interactions between a pair of members included profile and relations data with ratings. For each member, inputs are: name, age, education, task-based reputation scores, information sharing, member since for each connection between a pair of members, the inputs are: from member, to member, social context, friendship, teamwork, and likeability. Other inputs that represent the model variables are the unique identifiers (ID) associated with every object within the network. The search and exploration engine will use these internally along with the scores to calculate the social distance for each object.

Once the social network data are available, any logged user to the system can start the exploration and discovery of members by the means of the 'Reputable Search' engine form (Figure 3). In this form, the user can define several search criteria constraints. For example, defining the target and destination members (i.e. from member no. 1 to member no. 35), whether or not higher or lower rewarding relations are of interest (i.e. 'Least' social cost), whether or not the overall Social Relation Index will be compromised of both or either one of the available reputation levels (i.e., individual and group), the set of social relations of interest (i.e., cognitive and affective), and the relative strength (i.e., weights) associated with each reputation element (i.e., 'Intensity' tab). These inputs are fixed during the optimization; however, the user can change these values and re-optimize to examine the sensitivity of the results to different weights, for example.

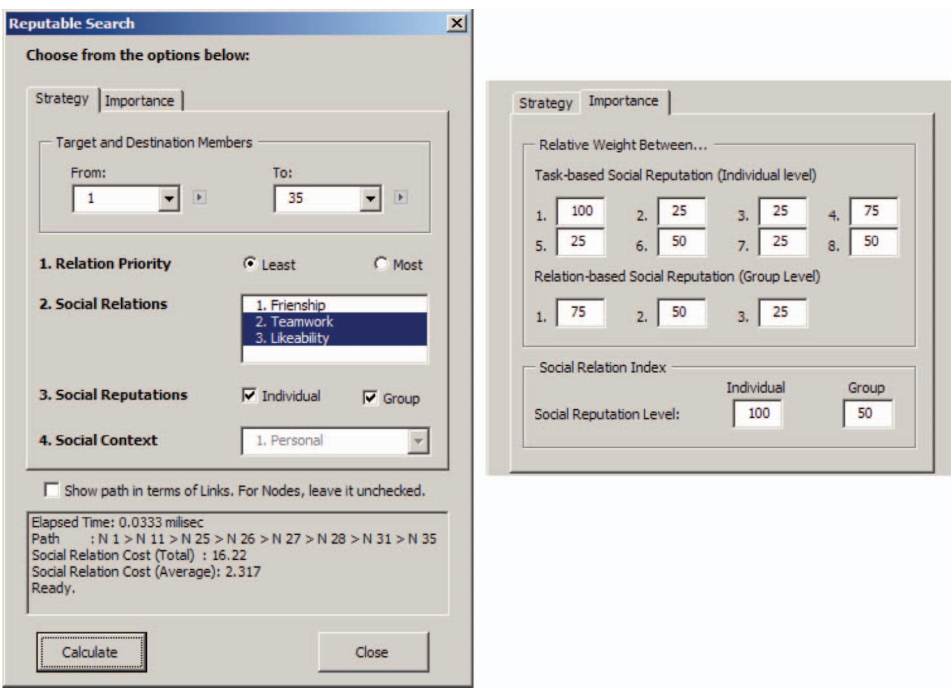


Figure 3. User-defined reputable searchability strategy.

After defining the different parameters in the search strategy form, the user is ready to ask the model to find the members who correspond to the custom search criteria. This involves interactively calculating the social distance for each member and their connections to other members – based on the weighted reputation scores – until the destination member is found. The result panel at the bottom of the form shows the typical search results: the overall processing time (i.e. 0.033 milliseconds), the list of members who met the search criteria (i.e. N1 > N11 > N25 > N26 > N27 > N28 >N31 > N35), and the total and average calculated social relation cost 16.21 and 2.31, respectively. Optionally, the list of connections could be shown instead of the list of members. The average relation cost is calculated as being the total relation cost divided by the number of connections between the displayed members list.



## Discussion and future work

The framework model presented in this article has been demonstrated to work effectively on the example application. Further experimentation was conducted on different combinations of personal networks with different properties, and the model proved to consistently produce the expected results. In addition to its expandable data structure, some of the flexible features of the proposed framework that make it an efficient model for building social-aware learning software applications include:

- combination of three research venues (online social interaction, social network, and reputation systems) into a single methodology;
- reputable searchability exploration and search engine with optimization feature that respects desirable social distance;
- incorporate Social Relation Index as indicator to assess the social relation condition of the network;
- consider two levels of reputation: group and individual;
- consider variable types of relationships;
- consider variable categories of social context, one at a time; and,
- framework constructed upon separate modules, which are large research areas by themselves that are outside the scope of this article; however, this modular feature creates a proliferation of possibilities that can be rearranged, replaced, combined, or interchanged easily.

Being a preliminary research in the integration of social-aware features into interactive learning applications, the present model has a number of areas in which it can be improved (currently being pursued by the authors), including:

- consider embedding the framework directly into the web-based learning system architecture for improved interaction and overall functionality;
- extend the model to include other types of advanced visualization techniques. These techniques could help users to both explore and play with their network in more interactive ways, for instance: performing visual analyzes and more powerful filtering by engaging in social narratives while exploring community structures by expanding the network to quite large depths and visualizing different network map representations;

- consider more performing algorithms to try to speed up the reputable search process, such as the ones that apply heuristics techniques;
- extend the model to include more virtual classroom-related social contexts, and to consider them all together;
- extend the model to include other types of relationships. The calculation of the reputation score should be related to the conditions of the most relevant types of relationships among people to closer capture the experiences as they happen in real-life.
- Consider developing a desirable average condition for the reputation, so that reputable searches for each individual in the network are performed in respect to this threshold.

## Conclusion

In this article, literature related to online interaction tools, social network analyses, and reputation systems has been reviewed and a model is presented to integrate these three aspects into a unified social-aware interactive learning application framework. The proposed framework incorporates a reputable search engine based on path-related algorithms to calculate the social relations conditions for participants of an online learning community and optimally generate a list of members between any target and destination learners. The developed model is flexible and allows for several customizations for more effective searches. The model was implemented on a spreadsheet program to utilize its familiar interface and powerful functions. Programming scripts were written to facilitate user inputs of social networks' data, and activate the search procedure. An example application was then presented to demonstrate the practicality and powerful capabilities of the application prototype.

## Notes

1. www.kazaa.com
2. www.ebay.com

## Notes on contributors

Renato A.C. Capuruço is a doctorate student with special interest in recent advances in the field of social networks, recommender and reputation systems. Prior to joining the University of Western Ontario, he worked as a research assistant and teaching assistant for the Faculty of Engineering at the University of Waterloo where he received his Master of Applied Science degree. A former Natural Sciences and Engineering Research Council of Canada's scholarship awardee, he has also gained advanced research experience in industry while publishing in top tier peer-reviewed journals and presenting the results of his findings in conferences nationwide. Other research interests include soft computing and intelligent systems design, theory, tools and applications.

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