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Co-Insights framework for collaborative decision support and tacit knowledge transfer

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ABSTRACT

Abundant software tools use visual analytics (VA) techniques to support various decisions with the aim of boosting better insights. Large organizations, however, lose efficiency in selecting the right tools to support the persons who apply the tools to various decision tasks. Consequently, the creation and sharing of insights are far from optimal, leading consistently to sub-optimal decisions. In this work, the Co-Insights framework is introduced with automated collaboration support features to enable effective creation and sharing of distributed insights. A collaboration network (*Co-Net*) is established to model the collaborative decision making process in an organization. Two important features of the Co-Insights framework are developed: *collaborative agent allocation analysis* (*CA3*) for task–participant matching; and a robust mechanism for the recommendation of selected VA tools, by *participant–tool matching*. Thus, by better matching of tasks and tools with participants, the creation and sharing of insights are improved in any collaborative team for better decision making, accompanied with the tacit knowledge transfer to sustain the entire organization. To validate the effectiveness of these two main features, two experiments built on the *Co-Net* model are performed to test the newly developed algorithms. It has been found that CA3 significantly improves the matching scores by up to 35%, compared with conventional task–participant matching methods. The neural network based participant–tool matching mechanism yields robust results with 4% mismatches for 10% noise levels, and with 16% mismatches for 30% noise levels. Real case applications and implications are described, and further plans to extend this new framework are also outlined based on the reported experiments and evaluations.

1. Introduction

To guide decisions and actions towards a desired goal, modern industrial enterprises demand the ability to collaboratively perceive complex interrelationships of presented facts in various, diverse datasets. Given that organizations are highly distributed and the global market forces them to be more customer-focused, responsive, available and sustainable, automated collaboration support systems have become essential (Anussornnitisarn, Nof, & Etzion, 2005). In such systems, implementation of information exchanges, as effective as they may be, is insufficient. Instead, the creation and sharing of *insights* are vital.

Insights often reveal the "how and why" underlying approaches to tasks or problems (Holste & Fields, 2010). Encouraging group activity stimulates better decisions based on a broader and stronger set of insights (Bennett, 1998). Insight-sharing not only provides a collective knowledge structure to improve the performance of the current collaboration but also facilitates tacit knowledge transfer to enhance learning and sustainability of the entire organization (Brown & Paul, 1991).

For effective decision making and knowledge transfer, particularly among geographically dispersed and/or functionally separated departments, the interfaces for insight sharing are essential. Research in visual analytics (VA) shows that many VA tools in decision support systems are efficient for humans to generate and to share insights in specific tasks (Ozsoy, 2011; Yi, Kang, Stasko, & Jacko, 2008). Organizations, however, still lose efficiency in selecting the right tools for the right experts to apply for different decision tasks, especially when the organizations and the supporting systems are of large scale. To tackle this problem, the following questions need to be answered: (1) How to boost insight sharing beyond VA among multiple decision makers who have diverse preferences? (2) Can automated techniques be used to facilitate this boost?

The current research focuses on (1) establishing a new framework of insight creation and sharing in collaborative decision support systems, (2) modeling the framework with multi-agent collaboration networks, and (3) improving the mechanisms for the management of VA tools to enhance collaborative decision making and tacit knowledge transfer.

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Abbreviations and Nomenclature

CCT	collaborative control theory
CI	collaborative intelligence
CA3	collaborative agent allocation analysis
CTR	collaborative telerobotics
ERP	enterprise resource planning
GrSA	greedy selection algorithm
HUB-CI	computing HUB with collaborative intelligence
MIMO	multiple input, multiple output
RSA	random selection algorithm
VA	visual analytics
WDN	water distribution network
A_i	individual participant in a given *Co-Net*
Co-Net	collaboration network
$C_{j,l}$	minimum number of participants required for a task profile
$\boldsymbol{D}(K_{j,l})$	vector of coefficients for the relative weights of expertise domains
$\boldsymbol{D}_{\min}(K_{j,l})$	vector of minimum years of experience required
$\boldsymbol{D}(\varepsilon_i)$	vector of years of experience of the ith participant
$E_{i,k}$	expertise of the ith participant in domain k
f_i	insights generated by the ith participant
g_s	neural network function for the sth VA tool
i	index of participants
IN_i	neural network inputs
$\widetilde{IN}_i$	neural network inputs with noise patterns
j	index of tasks
k	index of expertise domains
$K_{j,l}$	the list of required expertise for lth profile of jth task
l	index of task profiles
m	number of mismatches in participant–tool matching
n	noise level in dynamic participant and task profiles
$P_{j,l}$	the lth profile of jth task
$p_{i,j}$	probability of selection for ith participant to jth task
R_1	score function of task–participant matching
R_2	score function of participant–tool matching
R_{Total}	task–participant total matching score
s	index of visual analytics tools
S_i	maximum number of tasks the ith participant can selected to
V_s	sth visual analytics tool
w_i	weight (priority) for the ith participant
$w(K_{j,l})$	weights (priority) of a given the jth task and the lth profile
$x_{i,j}$	decision variable of selecting the ith participant to the jth task
$y_{i,s}$	the match preference of sth visual analytics tool for ith participant
z	overall Co-Insights generated to solve τ
α	set of activities for participants
ε_i	set of expertise for the ith participant
λ	set of resources that can be used in *Co-Net*
π	set of autonomous agents in *Co-Net*
σ	set of coordination mechanisms
τ	a decision problem

In the remainder of this article, Section 2 provides background in collaborative intelligence and e-collaboration. Detailed models and algorithms to solve the research problem are presented in Section 3. Two experiments are reported and analyzed in Section 4. The evaluations of the developed model and algorithms are discussed in Section 5, followed by Section 6 which concludes this article and indicates future directions.

2. Backgrounds

This section reviews the state-of-art technology of e-collaboration to support collaborative decision making and the gaps to be filled.

2.1. Dynamic teams and collaborative intelligence for e-collaboration

Modern production and service organizations are facing new challenges of complexity and scalability in responding to the demand for high quality and highly customized products. At the same time, they must maintain their lean and just-in-time operations cost-effective in a highly competitive environment. To respond to these challenges, traditional operations of people and systems are transformed by the emerging e-Work, which is defined as collaborative, computer-supported and communication-enabled operations in highly distributed organizations of humans/robots/autonomous systems (Nof, 2003; Nof, Morel, Monostori, Molina, & Filip, 2006). Through e-collaboration, namely cyber-supported collaboration, participants can perform a large range of activities, from basic information exchange to fully collaborative operations, to make various fast and smart decisions (Nof, 2007).

The flexibility of teams (e.g., temporary alliances, evolving virtual organizations) is essential in e-collaboration. First, it is obvious that different teams need to be formed to satisfy the various task requirements demanded. Moreover, to form team dynamically is critical for the sustainability of the entire organization. To support humans, schools of fish are applied as an example technique (Radakov, 1973). A regrouping of schools takes place as a rule after each task and disbanding. Hence, quite an intensive exchange of specimens goes on between and among schools; new schools with a new composition are formed each cycle. The fish passing from school to school bring with them their own reflexes (knowledge and expertise of how to defend against predators), adding to the “wealth” of other schools. For knowledge-intensive business, dynamic team formation for decision making provides an effective channel to retain and to transfer tacit knowledge (among human experts). The notion of team formation based on knowledge is under active research (Awal & Bharadwaj, 2014; Wi, Oh, Mun, & Jung, 2009). To further facilitate tacit knowledge transfer in an organization, this article defines an alternative construction of the team formation problem and provides an efficient solution.

As defined in previous research (Devadasan, Zhong, & Nof, 2013), the overall ability to achieve effective collaboration is defined as collaborative intelligence (CI). In collaborative decision making tasks, sharing data, information, and computing tools does not guarantee a successful collaboration. For example, information overload may drag the workflow (Nof, 2003). Special mechanisms and protocols are required to drive the increase of CI in an organization. HUB-CI has been developed as a CI augmentation for e-collaboration, which is aligned with the trend that decision support systems are moving towards cloud-based service-oriented computing environment (Seok & Nof, 2011). HUB-CI is based on *HUBzero*, a high performance computing middleware platform for scientific research collaboration and educational activities (Mclennan & Kennell, 2010). Collaborative Network Optimization is an example CI mechanism developed on HUB-CI (Devadasan et al., 2013). This mechanism finds the best e-service providers for knowledge-intensive tasks, and therefore improves the overall CI of the service network. The current work extends the notion of dynamic collaborator selection by addressing how decision making tools can be optimally allocated to the collaborators to facilitate effective e-collaboration.

2.2. Insight and tacit knowledge in e-collaboration

When making decisions for complex problems, humans apply *insights*. The definition of insight, however, is not commonly accepted in the research community: