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ExpertHITS Algorithm for Expert Discovery and Interactions in Mixed Service Oriented Systems

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Abstract:

Web-based collaborations have become vital in today's business environments. They have paved the way for new type of collaborative system. As collaborative Web-based platforms develop into service oriented architectures (SOA), they promote mixed user enriched services. Due to the availability of various SOA frameworks, Web services emerged as the de facto technology to realize flexible compositions of services. Knowledge-intensive environments clearly demand for provisioning of human expertise along with sharing of computing resources or business data through software-based services. To address the challenges, an adaptive approach allowing humans to provide their expertise through services using SOA standards. Discovering the right actor in mixed service-oriented systems is challenging due to scale and temporary nature of collaborations. We present a novel approach addressing the need for flexible involvement of experts and knowledge workers in distributed collaborations. We argue that the automated inference of trust between members is a key factor for successful collaborations. Instead of following a security perspective on trust, we focus on dynamic trust in collaborative networks. We propose a context-sensitive trust-based algorithm called ExpertHITS inspired by the concept of hubs and authorities in Web-based environments. ExpertHITS takes trust-relations and link properties in social networks into account to estimate the reputation of users.

Keywords: Service oriented architecture, ExpertHITS algorithm, mixed service oriented systems.

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1. Introduction:

The existing platforms do not allow users to specify interaction platforms and if a web based system has to evolve into service-oriented architecture, then it should be able to promote composite and user-enriched services. Open service-oriented environments require a flexible yet reusable collaboration model because compositions comprise interactions between people and a number of software services [1]. A mixed service-oriented system composed of both human-provided and Software-Based Services was introduced to support such complex interaction scenarios. Mixed service-oriented system contains the following things.

1. *Service Avatar*. This concept is used to represent human capabilities as services on the Web.

2. *Personal Provisioning*. Personalized services can provide significant user benefits since they adapt their behavior to better support the user.

3. *Feedback-based Adaptation*. Feedback in all sciences is usually considered as a kind of a loop from an output of a certain action to its input.

The following figure 1 explains how Mixed service-oriented system can work.

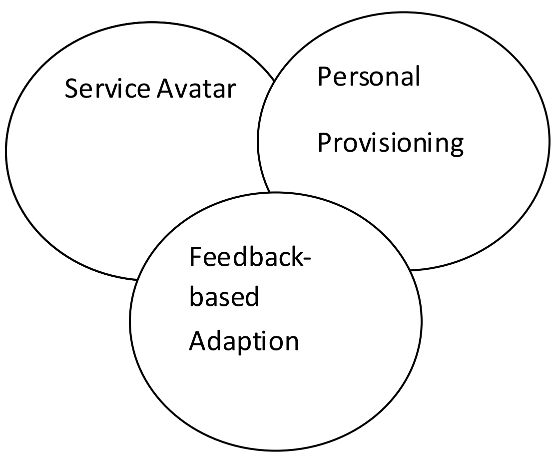

Figure 1.1 Components of mixed service-oriented system

2. Related Work:

The notion of service orientation is not only applicable to web services. Service orientation in human collaboration is becoming increasingly important. Major software vendors have been working on standards addressing the lack of human interaction support in service-oriented systems. WSHT [2] and Bpel4People [3] were released to address the emergent need for human interactions in business processes [4]. These standards specify languages to model human interactions, the lifecycle of human tasks, and generic role models. Role-based access models [5] are used to model responsibilities and potential

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task assignees in processes. While Bpel4People-based applications focus on top-down modeling of business processes, mixed service oriented systems [6] target flexible interactions and compositions of Human-Provided and software-based services. Open service-oriented systems are specifically relevant for future crowd sourcing applications [7]. While existing platforms (e.g., Amazon's Mechanical Turk [8]) only support simple interaction models (tasks are assigned to individuals), social network principles support more advanced techniques such as formation and adaptive coordination.

Task-based platforms on the web allow users to share their expertise [9]; or users offer their expertise by helping other users in forums or answer communities [10], [11]. By analyzing email conversations [24], the authors studied graph-based algorithms such as HITS [12] and PageRank [12] to estimate the expertise of users. In [13], an email analysis in enterprises, defining information flow metrics in the social interaction graph was presented. The work by [14] followed a graph-based approach and applied HITS as well as PageRank in online communities (i.e., a Java question and answer forum). While the above cited works attempted to model the importance of users based on interactions; they do not consider that interactions typically take place in different contexts. Approaches for calculating personalized PageRank scores [15] were introduced to enable topic sensitive search on the web. In contrast, we presented a model where expertise analysis is performed considering context information. We proposed an algorithm that can be computed online, while most other approaches demand for offline calculation due to computational complexity.

In this paper, we utilize Human-Provided Services (HPSs) enabling flexible interactions in service-oriented systems. We discuss the discovery and interactions in mixed service oriented systems comprising HPS and software based services (SBS). Experts offer their skills and capabilities as HPS that can be requested on demand. In this work, we present the following key contributions: 1) estimation of user reputation based on a context-sensitive algorithm. Our approach, called ExpertHITS, is based on the concept of hubs and authorities in web-based environments. 2) An approach for community reputation (the hub-expertise of users) influenced by trust relations. Dynamic link weights are based on trust and user rating influenced by the query context. ExpertHITS is calculated online, thus fully personalized based on the expert-requester's preferences (i.e., the demanded set of skills). 3) Implementation and evaluation of our approach demonstrating scalability and effectiveness of our proposed algorithm.

3. Expert Discovery System:

Expert Discovery System contains the following modules.

3.1 EexpertHITS Algortihm
3.2 Expert Hub Discovery
3.3 Expert HITS Model
3.4 Metric calculation

3.1 EexpertHITS Algortihm:

The basic approach is to use a metric to calculate the overlap of two sets A and B,

ISSN: 2320-1363

A straightforward way to define overlap similarity. An algorithm is presented for matching preferences through calculating overlap similarities of sets of properties. These preferences have impact on matching of skill properties on lower levels. As mentioned before, all nodes in the skill tree that do not have successor nodes are called leaf nodes. For simplicity, we do not consider unbalanced trees or complicated branching structures. An algorithm for matching elements which may have interaction data (RFS-based interactions) and user profiles holding skill information and also calculate hub and authority scores (shown in algorithm 1).

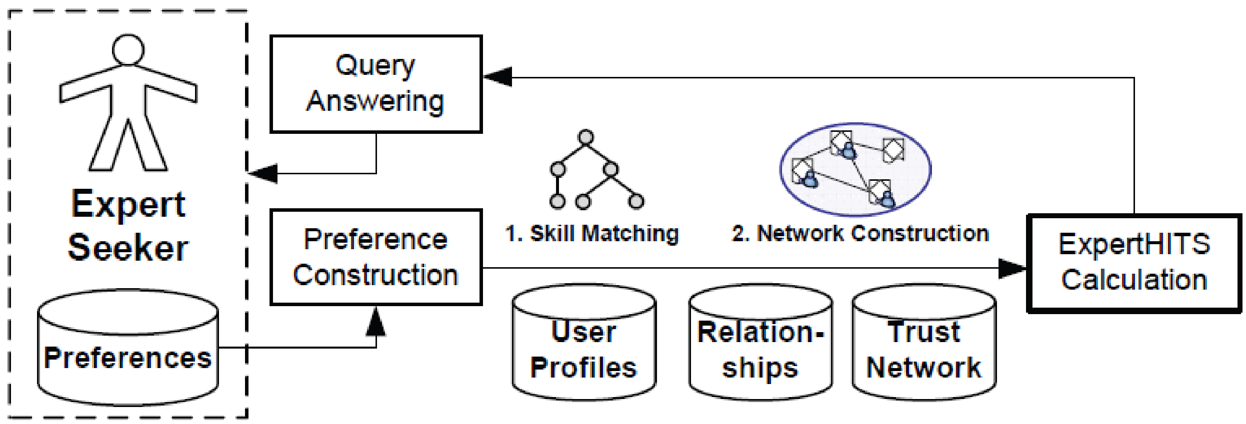


Figure 3.1.1 ExpertHITS Calculation steps

ExpertHITS Algorithm:

Input: Given a query context Q to discover expert hubs.

Output: Ranked elements

Algorithm:

Step 1: Find experts matching demanded set of skills.

Step 2: Start from the root node and match the query to the root node.

Step 3: Iterate through each level and calculate overlap similarity of property in query at current level i. If the node will be empty then go to next node.

Step 4: Calculate hub-expertise of expert given query context Q, For each expert calculate hub score. Hub score can be calculated as the rating through authorities based on delegation behavior.

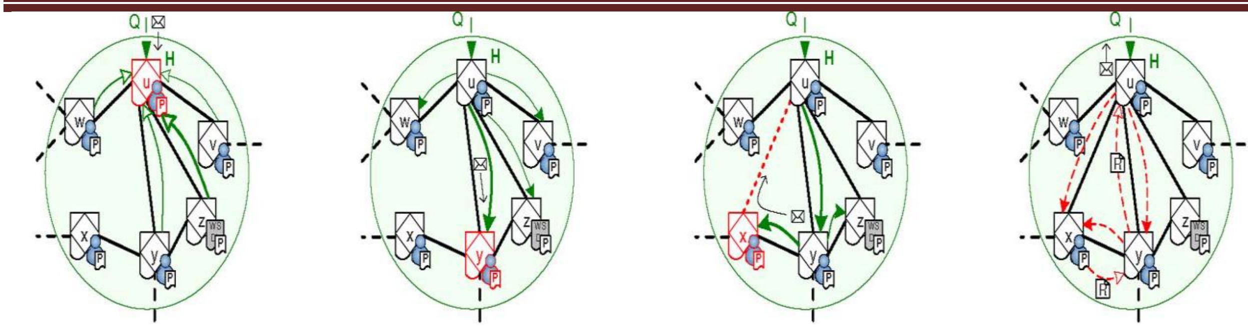
Step 5: For each expert calculate authority score. Authority score can be calculated as the rating through hubs based on reliability in processing delegated tasks.

Step 6: Ranked expert are listed

3.2 Expert Hub Discovery:

The basic Expert discovery model as shown in the given figure 3. The discovery and selection of expert hubs and authorities (Fig. 3a and 3b) followed by the definition of delegation patterns and ratings (Fig. 3c and 3d) is shown.

ISSN: 2320-1363



(a) Discovery of expert hub. (b) Trusted selection of authority. (c) Delegation of RFS. (d) RFS reply and rating.

Figure 3.2.1 ExpertHITS discovery model, advanced interaction patterns, and feedback ratings.

3.3 Expert HITS Model:

In this section, we discuss the formal model for our proposed expertise ranking algorithm consisting of two components. 1. Hub score of user u in query context Q and 2. Authority score of user v in the same query context Q.

3.4 Metric calculation:

Metrics support fast and reliable responses and neglect others such as costs. Calculate metrics in the scope of interactions (Request for support).For fast and reliable use metrics such as response time and success rate.

1. Response Time
2. Success Rate

Response Time is calculated as the duration between sending (or delegating) a request to a service and receiving the corresponding response. Success Rate is an RFS is considered successfully processed is the success rate.

4. Conclusion and Future Work:

Unlike traditional models found in process-centric environments, we proposed the combination of preplanned process steps *and* ad-hoc activities to solve emergent problems in distributed collaboration environments. Our approach is based on the Human-Provided Services concept enabling knowledge workers to offer their skills and expertise in service-oriented systems. Expert discovery is greatly influenced by (behavioral) trust and reputation mechanisms. We demonstrated a novel approach for estimating expert reputation based on link structure and trust relations. Trust information is periodically updated to capture dynamically changing interaction preferences and trust relations. We have shown that ExpertHITS can be computed in an online manner, thereby enabling full personalization at runtime. Existing approaches in personalized expertise mining algorithm typically perform offline interaction analysis. Our empirical evaluations have shown that ExpertHITS exhibits the desired properties; trust and rating weights influence hub- and authority scores. These properties ensure that our algorithm discovers experts which are well-connected to other experts.

Although we have focused on the application of ExpertHITS in human-centric

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and social collaborations, we believe that the underlying trust-based interaction model can be applied to coordination problems in distributed systems in general. In our future work, we will study *network effects* of two-sided markets in mixed service-oriented systems. Also, we plan to make the system available for public use.

References:

1. Schall, Daniel. "Human interactions in mixed systems-architecture, protocols, and algorithms." *Unpublished Ph. D. thesis, Vienna University of Technology* (2009).
2. A. Agrawal et al., "Web Services Human Task (WS-HumanTask), Version 1.0," 2007.
3. A. Agrawal et al., "WS-BPEL Extension for People (BPEL4People), Version 1.0," 2007.
4. F. Leymann, "Workflow-Based Coordination and Cooperation in a Service World," Proc. On the Move to Meaningful Internet Systems: CoopIS, DOA, GADA, and ODBASE, pp. 2-16, 2006.
5. D. Schall, H.-L. Truong, and S. Dustdar, "Unifying Human and Software Services in Web-Scale Collaborations," IEEE Internet Computing, vol. 12, no. 3, pp. 62-68, May/June 2008.
6. D. Schall, "Human Interactions in Mixed Systems—Architecture, Protocols, and Algorithms," PhD dissertation, Vienna Univ. of Technology, 2009.
7. D. Brabham, "Crowdsourcing as a Model for Problem Solving: An Introduction and Cases," Convergence, vol. 14, no. 1, pp. 75-90, 2008.
8. Amazon.com, "Amazon Mechanical Turk," http://www.mturk.com, 2010.
9. J. Yang, L. Adamic, and M. Ackerman, "Competing to Share Expertise: The Taskcn Knowledge Sharing Community," Proc.Int'l Conf. Weblogs and Social Media, 2008.
10. P. Jurczyk and E. Agichtein, "Discovering Authorities in Question Answer Communities by Using Link Analysis," Proc. 16th ACM Conf. Information and Knowledge Management (CIKM '07), pp. 919-922, 2007.
11. E. Agichtein, C. Castillo, D. Donato, A. Gionis, and G. Mishne, "Finding High-Quality Content in Social Media," Proc. Int'l Conf. Web Search and Web Data Mining (WSDM '08), pp. 183-194, 2008.
12. B. Dom, I. Eiron, A. Cozzi, and Y. Zhang, "Graph-Based Ranking Algorithms for E-Mail Expertise Analysis," Proc. Eighth ACM SIGMOD Workshop Research Issues in Data Mining and Knowledge Discovery (DMKD '03), pp. 42-48, 2003.
13. L. Page, S. Brin, R. Motwani, and T. Winograd, "The PageRank Citation Ranking: Bringing Order to the Web," technical report, Stanford Digital Library Technologies Project, 1998.
14. T. Karagiannis and M. Vojnovic, "Email Information Flow in Large-Scale Enterprises," technical report, Microsoft Research,2008.

ISSN: 2320-1363

15. J. Zhang, M.S. Ackerman, and L. Adamic, "Expertise Networks in Online Communities: Structure and Algorithms," Proc. 16th Int'l Conf. World Wide Web (WWW '07), pp. 221-230, 2007.
16. G. Jeh and J. Widom, "Scaling Personalized Web Search," Proc.12th Int'l Conf. World Wide Web (WWW '03), pp. 271-279, 2003.
17. Daniel Schall, Florian Skopik, and Schahram Dustdar "Expert Discovery and Interactions in Mixed Service-Oriented Systems" IEEE TRANSACTIONS ON SERVICES COMPUTING, VOL. 5, NO. 2, APR
18. IL-JUNE 2012,233.