Expertise Ranking in Human Interaction Networks based on PageRank with Contextual Skill and Activity Measures

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We introduce a link intensity-based ranking model for recommending relevant users in human interaction networks. In open, dynamic collaboration environments enabled by Service-oriented Architecture (SOA), it is ever more important to determine the expertise and skills of users in an automated manner. Additionally, a ranking model for humans must consider metrics such as availability, activity level, and expected informedness of users. We present *DSARank* for estimating the relative importance of users based on the concept of eigenvector centrality in collaboration networks. We test the applicability of our ranking model by using datasets obtained from real human interaction networks including email conversations and cellular phone communications. The results show that DSARank is better suited for recommending users in collaboration networks than traditional degree-based methods. Furthermore, we show applications of DSARank in emerging Service-oriented environments. We present ranking and recommendation in a system where humans can provide services based on their expertise.

Categories and Subject Descriptors: H.1.2 [**User/Machine Systems**]: Human information processing; H.4.m [**Information Systems Applications**]: Miscellaneous; K.4.2 [**Computers and Society**]: Employment—*human provided services*

General Terms: Algorithms, Experimentation

Additional Key Words and Phrases: Service-oriented systems, human interactions, context-aware link analysis, expert finding

1. INTRODUCTION

The collaboration landscape has changed dramatically over the last few years by allowing users to shape the Web and availability of information. While in the past collaborations were bounded to, for example, intra-organizational collaborations using a companies specific platform, and also limited to messaging tools such as email, it is nowadays possible to utilize the knowledge of many people participating in interactions on the Web. The shift toward the Web 2.0 allows people to write blogs about their activities, share knowledge in forums, write Wiki pages, and utilize social-services to stay in touch with other people. Recently, task-based platforms

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such as Amazon's Mechanical Turk[1] enable businesses to access the manpower of thousands of people on demand by posting human-task requests on Amazon's site.

Thus, in this open, dynamic collaboration environment, where a very large number of people collaborate and interact using various tools, it is ever more important to determine the *importance* and *expertise/skill level* of a user. Somebody seeking help/advice on a specific problem or businesses issuing task requests using, for example, above mentioned platforms need to be able to find the right person who can assist with offering his/her expertise. Recent work in expert finding, e.g., [Becerra-Fernandez 2006] and [Aleman-Meza et al. 2007], has been addressing search for persons with the right skill level by using ontologies and by combining divers semantic information from user/skill profiles. Since Web-scale collaborations involving many users not only demand for scalable algorithms and ranking solutions, but in many cases it is also desirable to consider the global properties of a human interaction network in order to determine the importance of users. Algorithms and models designed for ranking Web documents in the Web graph such as Google's PageRank or HITS (Hyperlink-Induced Topic Search) have been applied in online communities (e.g., Java discussion forums) [Zhang et al. 2007].

In this paper we propose link analysis techniques, which we derive from the popular PageRank model. Essentially, the PageRank model regards a node in a network (e.g., a Web document) as important if the node has many inbound links from other (important) nodes. We believe that this model is a good starting point to determine the importance of a user in a human interaction network.

1.1 Motivating Example

To support dynamic collaborations, we developed a framework, which we call Human-Provided Services (HPSs), enabling humans to "participate" in service-oriented collaborations (see [Schall et al. 2008]). Such services act as proxies for interactions with real humans. We envision collaboration scenarios where people define services based on their skills/expertise. Other people (the expert seeker) can interact with experts through HPSs, without needing to know who the best available expert is.

HPS not only supports human interactions, but also interactions with software processes. Figure 1 illustrates a simple example of a *human activity* in a process. For example, such processes can be defined in BPEL (Business Process Execution Language) [Andrews et al. 2003] comprising both human activities as well as activities enacted by executing Web services. BPEL4People is a language specifying how to model human interactions in business processes [Amend et al. 2007].

Regardless of the interaction scenario, human-to-human interactions or human activities in a process, the expert seekers must be able to find the right person based on skills and expertise. We hypothesize that link-analysis of human interactions is suited for determining the expertise of users.

1.2 Problem Formulation

The expertise and thus importance of users continuously change over time depending on performed tasks, interactions with other users because users gain know-how

[1] `http://www.mturk.com/mturk/welcome`

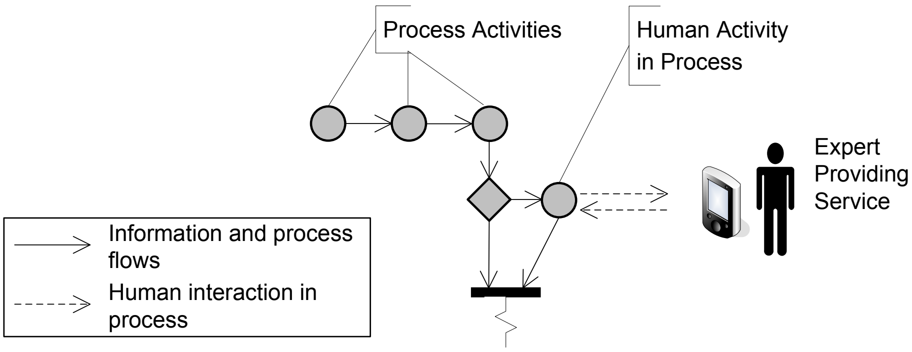


Fig. 1. Example use case of Human-Provided Services: a process comprises multiple activities enacted by Web services. In some cases the process may require human input which is modeled as a *human activity*. Human-provided Services (i.e., experts) allow the process to retrieve the needed input to continue its execution.

by collaborating with other experts, and based on the information users receive from other people. Also, the ranking model must consider a user's *interest* in a certain area. For example, a scientist may have done research in a certain field, however, the scientist might change his/her principle research domain over time and therefore no longer be the right expert to contact, if the interest and activity level of that person in a field are not considered.

However, we believe that ranking and recommendation models should not rely on profiles and skill information, which need to be (manually) maintained by users. In addition, it is unlikely that a single ontology is sufficient to express skills and expertise of collaborations in various domains. Research has shown (e.g., [Golder and Huberman 2006]) that *tagging* models are well accepted by a broad number of users to categorize information. Therefore, tags provide a) input for deriving users' skills and interests and b) the "contextual cues" of activities and interactions. The challenge is to devise a ranking model accounting for these properties.

1.3 Contributions

In this paper we propose link analysis methods to determine the importance of users in human interaction networks. Specifically, we adopt and significantly extend the PageRank model [Page et al. 1998] for human interaction analysis. The benefit of such a model is that the global properties of an interaction graph are taken into account when establishing the importance of users, i.e., a variant of eigenvector centrality. We provide empirical results by evaluating our ranking model using real interaction networks — human interaction graphs based on email and phone conversations. We devise a new model that captures interaction dynamics, thereby ensuring that ranking scores are distributed based on the activity level of individuals. In addition, we propose link-analysis in subgraph partitions of the human interaction network to obtain context-sensitive rankings.

We structure this paper in a bottom-up manner because existing literature in using the PageRank model for link-analysis in human interactions is still very sparse. We discuss related work in Section2. In Section 4, we present human interaction networks and properties thereof, which we use to study different ranking models. We review the PageRank model in Section 5 and apply PageRank in a human interaction graph. In Section 6 we propose refinements of the ranking model and present *DSARank*, which is a ranking model targeted at human interaction networks. We discuss context-aware ranking in Section 7 along with additional subgraph metrics. In Section 8, we present experiments based on human interactions captured in a mobile phone network as well as email-based interactions in a corporate environment. Finally, we conclude the paper in Section 9.

2. RELATED WORK

The focus of our research is to determine expertise-level of users in Web-based collaborations. In the context of the Internet, Becerra-Fernandez [2006] described a system and ontologies expressing skills of experts. Furthermore, Aleman-Meza et al. [2007] proposed the combination of divers semantic information to derive skill profiles and expertise of users. However, these works did not discuss how to obtain information regarding users' expertise in an automated manner. Models and algorithms to determine the expertise of users are important in future service-oriented environments. The notion of service-orientation is not only applicable to Web services. Service-orientation in human collaboration is becoming increasingly important. For example, task-based platforms allow users to share their expertise [Yang et al. 2008], users offer their expertise in helping other users in forums. By analyzing email conversations, Dom et al. [2003] studied graph-based algorithms such as HITS [Kleinberg 1999] and PageRank [Page et al. 1998] to estimate the expertise of users. Shetty and Adibi [2005] follow a graph-entropy model to measure the importance of users. [Karagiannis and Vojnovic 2008] present an email analysis in enterprises, defining information flow metrics in the social interaction graph. Zhang et al. [2007] follow a graph-based approach and apply HITS as well as PageRank in online communities (i.e., a Java question and answer forum), naming their approach *ExpertiseRank*. More precisely, the Java form and discussion threads act as "proxies" to capture underlying human interactions. We cite some results in the following: (i) The authors found that structural information in human interactions can be used for determining expertise of users. (ii) Structural characteristics matter when using social network-based algorithms. (iii) Algorithms such as PageRank did nearly as well as human raters.

Analysis of social networks has a long history of research in social sciences. However, most studies usually focus on the structural characteristics of such networks. In a similar manner, *ExpertiseRank* is mainly based on structural characteristics of the human interaction network. While the above cited works attempt to model the importance of users based on interactions and information flow, they ignore the fact that interactions may take place in different *contexts*. In contrast, we propose a model where expertise analysis is performed in context-dependent subgraph partitions. Rodrigues et al. [2006] as well as Tang et al. [2007] studied subgraph extraction and visualization in co-author networks using the DBLP computer science bibliography.

Beyond structural analysis of interaction networks, Barabási [2005] introduced models to capture the dynamics in human communications. Onnela et al. [2007]

introduced metrics to measure the dynamics in human communications in cellphone networks. Human dynamics must be considered in ranking models which attempt to recommend the right expert.

The PageRank Model

We provide a brief overview of PageRank and related literature because our ranking model relies on the probabilistic formulation of the "Random Surfer Model". PageRank [Page et al. 1998] [Brin and Page 1998] is an eigenvector centrality-based model for ranking documents on the Web. The basic idea is that the importance of a Web page v depends on the citation links pointing to v. Recently, much research has been done to better understand the theoretical foundations of the PageRank model, e.g., Bianchini et al. [2005] and Brinkmeier [2006]. See the work of Berkhin [2005] for a state of the art review in this area.

Personalized PageRank: In PageRank, the "Random Surfer" follows the outlinks of a Web page with probability α, usually a value between 0.8 - 0.9 according to Page et al. [1998], or with probability $(1-\alpha)$ "jumping" to a randomly selected Web page. Richardson and Domingos [2002] introduced the *Intelligent Surfer Model*, arguing that users do not select Web pages at random. Haveliwala [2002] proposed a topic-sensitive ranking model by computing personalized PageRank vectors over different categories of Web pages. Topic-sensitive ranking scores can be aggregated into a composite score at query time. White and Smyth [2003] define a variant of this model called PageRank with priors. Beyond topic-sensitivity, Jeh and Widom [2003] show that personalized PageRank vectors can be decomposed to compute personalizations for individual Web pages. Recently, Fogaras et al. [2005] and Chakrabarti [2007] proposed Monte Carlo methods to compute fingerprints of personalization vectors. Personalization in PageRank-based link analysis is an important tool because the importance of nodes in a graph (e.g., humans as part of the interaction network) can be customized based on context information. However, to our best knowledge there is no existing work in the area of personalized PageRank in human interaction analysis.

3. PRELIMINARIES

Let us start with the definition of some basic concepts. The interaction graph is defined as $\mathcal{G} = (V, E)$, $V = \{v_1, v_2, \ldots, v_n\}$ the set of vertices and $E = \{e_1, e_2, \ldots, e_n\}$ the set of directed edges between vertices. Given an instance of $\mathcal{G}$, we create a row-oriented adjacency matrix of that interaction graph

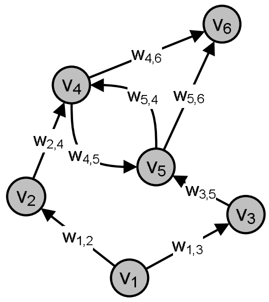
$$A_{i,j} = \begin{cases} 1 & \text{, if } i \text{ is connected to } j \\ 0 & \text{, otherwise} \end{cases} \tag{1}$$

Typically, an edge has a weight, which can be calculated by, for example, counting the number of interactions. Suppose that W is a weighted adjacency matrix whose weights are positive entries $w_{i,j} \geq 0$ satisfying

—$w_{i,j} > 0$, if a directed edge connects i to j

—$w_{i,j} = 0$, if there is no edge between i and j

In Figure 2 we show a) an example interaction graph and b) the corresponding weighted adjacency matrix W.



$$W = \begin{bmatrix} 0 & w_{1,2} & w_{1,3} & 0 & 0 & 0 \\ 0 & 0 & 0 & w_{2,4} & 0 & 0 \\ 0 & 0 & 0 & 0 & w_{3,5} & 0 \\ 0 & 0 & 0 & 0 & w_{4,5} & w_{4,6} \\ 0 & 0 & 0 & w_{5,4} & 0 & w_{5,6} \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 2. Directed interaction graph (left) and matrix representation (right).

Notation

In the following, we will present graph-based ranking models that are inspired by PageRank concepts. While our approach is not limited to interactions based on human collaboration networks — for example, our ranking model can be used to analyze interactions in service networks — we focus mainly on human-based interactions. In this case, $\mathcal{G}$ is composed of vertices occupied by the set $\mathcal{U} = \{u_1, u_2, \ldots, u_n\}$ of users. Throughout this work, we depict a weighted edge as the interaction link ℓ. Depending on the context of the discussion, we define whether $\ell(u)$ is an out- or incoming interaction link. Furthermore, by following the PageRank model, we create a transpose matrix (that is, a column-oriented matrix) based on the row-oriented description of W. Let us define the column-stochastic transition matrix I

$$I_{j,i} = \text{probability of transitioning from node } i \text{ to node } j. \tag{2}$$

Column-stochastic means that the sum of all column elements equals 1. Table I gives an overview of operators and descriptions of basic metrics in interaction graphs. An edge $e \in E$ points from v to u, if $e \in \texttt{outlinks}(v) \cap \texttt{inlinks}(u)$. In other words, ℓ denotes an interaction link between users, which may comprise many interactions that are aggregated into a single link.

Operator	Description
`inlinks`(u)	Denotes the set of u's inbound interaction links. For example, $v \in \texttt{inlinks}(u)$ has *initiated* an interaction towards u. The set cardinality $\lvert\texttt{inlinks}(u)\rvert$ is given as `indegree`(u).
`outlinks`(u)	All interactions initiated by u towards other users are denoted by the set `outlinks`(u) and similarly, `outdegree`(u) is the number of links in the set.

Table I. Basic graph metrics and operators.

4. HUMAN INTERACTION NETWORKS

We study link-based ranking models using two types of interaction networks. On the one hand, we experiment with different ranking algorithms based on an interaction network, which we establish based on cell phone communications between users in a mobile phone network. The cardinality in human interactions is one-to-one because the used dataset does not comprise conference calls among users. Analyzing human interactions in mobile phone networks is well suited for our ranking approach as we can measure characteristics such as *intensities* of interactions between two users considering underlying properties such as the duration of calls. We use the "Reality Mining" dataset[2], which was made available by the MIT Media Lab, see [Eagle and Pentland 2006]. Figure 3 shows an example graph captured in April 2005. The dataset comprises communication, proximity, and location information captured at MIT for the academic year 2004-2005.

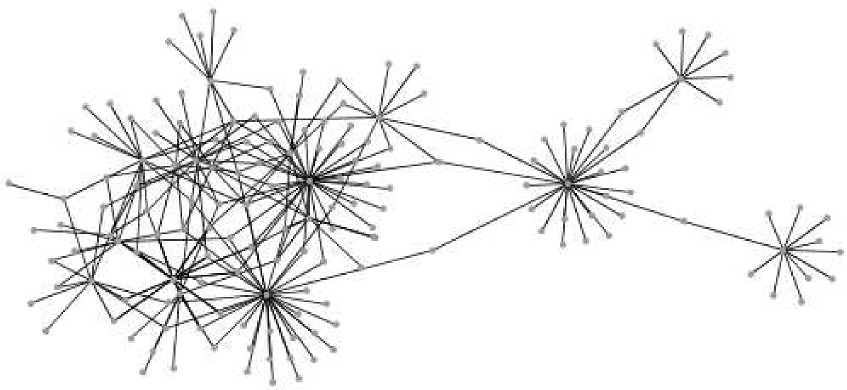


Fig. 3. Example interaction graph of point-to-point human communications in mobile phone network.

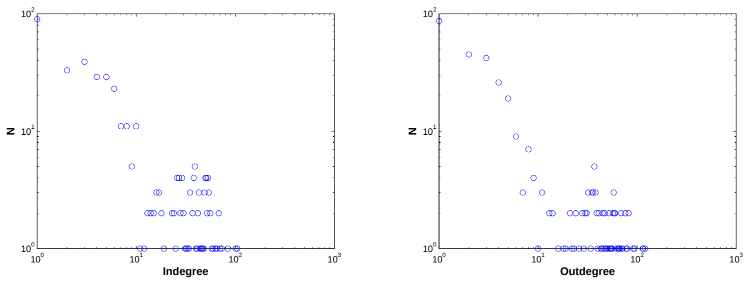


Fig. 4. Degree distributions of human communications in cellular network: (a) indegree and (b) outdegree distribution of telephone calls in mobile phone network. Vertical axis **N** (counterclockwise rotation) shows the cumulative number of users.

[2]`http://reality.media.mit.edu/`

The public database image comprises both *participants* of the study and *non-participants*. Non-participants are users who did not have any logging software installed on their cell phones, but whose interactions were captured as incoming/outgoing calls on participants' devices. We perform filtering and select users if their degree of incoming links is greater than 1 (if a user interacts with at least two different users). The clustering coefficient is a measure to determine whether a graph is a small-world network [Watts and Strogatz 1998]. The coefficient indicates whether the graph, or a neighborhood of the graph, is well connected or not. The shown network exhibits a low clustering coefficient of 0.2 due to peripheral users, which are not well connected. Partial observations of interactions limited to the small set of participants explains the low clustering coefficient in Figure 3. The structure in terms of in- and outdegree distributions is shown in Figure 4.

The second dataset is an email interaction network. Email messages exchanged between people serve as input to establish the interaction graph. Each interaction is a directed link between sender and receiver of a message. The cardinality of email-based interactions is naturally one-to-many as multiple recipients can be specified.

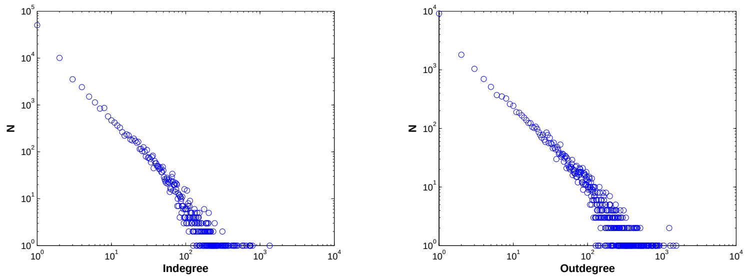


Fig. 5. (a) Indegree and (b) outdegree of human interactions in email conversations. Vertical axis **N** (counterclockwise rotation) shows the cumulative number of users.

Figure 5 shows in/outdegree distributions of an email interaction graph. Both distributions have a power low tail as it can be observed in many structures and dynamics on the Web, for example, the structure in human task networks [2008], the Web graph [2006], or the dynamics in human interactions [2005]. Figure 5 describes the Enron email interaction network[3].

5. LINK ANALYSIS USING PAGERANK

We propose to determine the importance of users by using link analysis techniques. Let us first review the PageRank model and an iterative algorithm to compute PageRank scores. Then, we discuss the application of PageRank in human interaction networks.

[3] `http://bailando.sims.berkeley.edu/enron_email.html`

5.1 PageRank Primer

Using PageRank, u's importance is influenced by nodes $v \in \texttt{inlinks}(u)$ that are in some manner linked to u. For example, in the Web graph, a link is a hyperlink between Web pages, whereas in social networks a link might represent a connection in the network. As an example, the *knows* property in a FOAF[4] profile can be used to create links between people.

The idea of PageRank is best explained in its original context. A user browsing the Web (the "Random Surfer") navigates through a set of Web pages by selecting one of the links on a given page. In other words, the random surfer follows a link with probability α, usually a value between 0.8 - 0.9 according to [1998], or with probability $(1-\alpha)$ teleports to a randomly selected Web page. PageRank in directed graphs is defined as follows:

$$PR(u) = \alpha \sum_{v \in \texttt{inlinks}(u)} \frac{PR(v)}{\texttt{outdegree}(v)} + (1-\alpha)p(u) \tag{3}$$

Symbol	**Meaning**
α	The predefined PageRank damping factor (usually a value between 0.8 and 0.9).
$\vec{PR}$	The PageRank vector for parameter α.
$\vec{p}$	The teleportation distribution vector called *personalization vector*.

Table II. PageRank and related symbols.

Algorithm 1 Iterative method to compute PageRank scores in interaction graphs.

input: A human interaction graph.
input: Convergence criteria: error ϵ smaller than desired precision.
output: Ranking scores available in vector $\vec{PR}$.
for each user $u \in \mathcal{U}$ **do**
    $PR(u) = (1-\alpha)p(u)$
end for
while not converged **do**
    for each user $u \in \mathcal{U}$ **do**
        for each user $v \in \texttt{inlinks}(u)$ **do**
            $w \leftarrow getEdgeWeight(v, u)$
            $PR(u) \leftarrow wPR(v)$
        end for
        $PR(u) \leftarrow \alpha PR(u) + (1-\alpha)p(u)$
    end for
end while

[4] `http://xmlns.com/foaf/spec/`

The vector $\vec{PR}$ can be calculated using an iterative algorithm, for example, the Jacobi iteration as demonstrated in Algorithm 1. A simple measure to test whether the algorithm has converged — $\vec{PR}^{(k)}$ holding the importance scores obtained in iteration k — is to look at the error ϵ so that

$$max||\vec{PR}^{(k)} - \vec{PR}^{(k-1)}|| \leq \epsilon$$

However, in practice, a fixed number of iterations is used and measures such as Kendall's τ (a rank correlation coefficient, e.g., see [Berkhin 2005]) to determine whether the ranking scores obtained in iteration k and $(k-1)$ will change the position of u within $\vec{PR}$.

5.2 PageRank in Human Interaction Networks

There are different views on how we can recast PageRank for expertise analysis in human interaction networks:

(1) The first view is closely related to the random surfer model. Discussion forums, for example, are popular platforms when users require help or advise. Typically, the user — or *expert seeker* — creates a description of the problem by posting a question in the forum. Other users reply to the question with either a) a description of a potential solution of the given problem or b) a reference to an existing solution description (e.g., recommending existing postings in the same or some other forum). Hence, the expert seeker decides to navigate through the set of postings or may choose a random posting until he finds a helpful solution or aborts his endeavor. Indeed, the very idea of PageRank is to use citation links as sources for reputation.

(2) On the other hand, we can interpret each link between people as a channel to propagate information in a network [2006]. The strength of a link limits the flow of information between v and u. For example, v may notify one of its neighbors u about some news or forward information to a randomly chosen person.

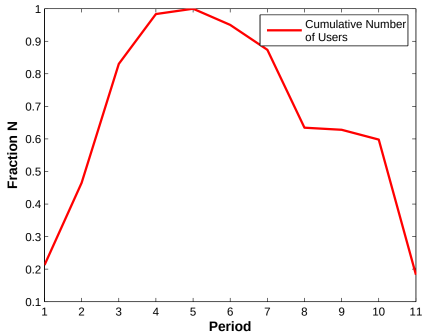
We hypothesize that PageRank is a suitable model for user-importance ranking. To test this proposal, we calculate PageRank vectors $\vec{PR}_{\Delta t}$ of all users in a time window Δt. Before doing so, we also provide the characteristics of the mobile phone dataset over time, starting with Figure 6 (a) showing the fraction of users active in a given month (period 2004 - 2005). Each link in the interaction graph is established based on phone calls. The ranking results, given the model in Equation 3, are obtained using Algorithm 1 using the following parameters

—Uniform teleportation distribution: $p(u) = 1$

—Degree based link weights: $w_{v,u} = 1/outdegree(v)$

In Figure 6 (b) we show the difference between the set of users in two consecutive months as the Jaccard index, which is often used to measure the distance of two sets. It is defined as $\texttt{jaccard}(U_1, U_2) = |U_1 \backslash U_2|/|U_1 \cup U_2|$. The Jaccard index is a useful (set) metric because a high index indicates that many changes happened in the network; in terms of joining or leaving users. In such cases, we expect $\vec{PR}_{t_1}$

and $\vec{PR}_{t_2}$ to be less correlated. (The index of the interaction network is shown in Figure 6 (b)). In the same figure, we show the correlation coefficient of PageRank vectors in two consecutive months. We calculate the Pearson correlation coefficient, which is defined within the interval $[-1, 1]$, and perform a simple mapping of the interval $[0, 1]$ so we can show both coefficients on the same scale. We see in Figure 6 (b) that the vectors $\vec{PR}_{t_1}$ and $\vec{PR}_{t_2}$ are highly correlated.



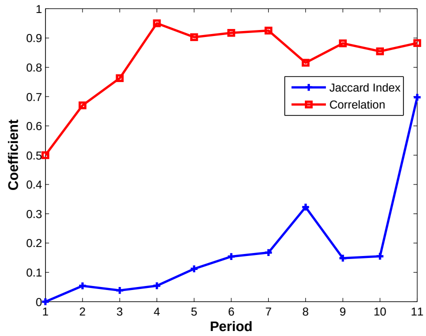


Fig. 6. (a) The cumulative number of users over time in mobile phone network. (b) Jaccard distance index of network and correlation of PageRank scores over the entire period 2004 - 2005 using a 1 month time-window to update ranking scores. We index each month starting 2004-07 as period 1 and ending at 2005-05 denoted as period 11.

In period 8 (February 2005) we see a spike in the interaction network's Jaccard index, resulting in lower correlation of ranking scores. As mentioned before, this is an expected observation since many joining or leaving users introduce a new collaboration (interaction) setting. For example, "important" people joining the observable network. Overall, the PageRank model — applied to human interaction networks — captures well the importance of users since ranking scores are in general highly correlated in a relatively stable interaction network.

6. TOWARDS DSARANK

PageRank has been hugely popular in ranking Web pages on the Internet. To date, the company Google provides one of the most successful search engines. Over the past years intense research has been done to better understand the PageRank model and optimizations in computing the rank of Web pages in a large graph of billions of pages. Berkhin [2005], for example, provided a comprehensive survey on PageRank.

However, while we believe that PageRank fits also well to determine the *importance* of users in human interaction networks, our goal of ranking users is motivated by a concrete application scenario (that is, HPS). Specifically, our aim is to devise a ranking model that is able to recommend users who can perform tasks or, more generally, participants in collaborations. In human interaction networks, we must consider the workload of users in terms of the set of incoming tasks or requests, and also the *intensity* and importance of interactions. Therefore, the goal of our work is different when compared to social network analysis, which attempts to understand the structure of human interaction networks and the role of human actors. For example, in social network analysis, one objective is to determine the *prestige* of users. In this work, however, importance of a user also means to find the most relevant user or expert who can assist in solving a problem.

While in the Web graph hyperlinks usually represent a binary choice, page u is connected to page v, if there is a hyperlink between them, in human interaction networks we can measure the importance of links by considering the intensity of interactions. Also, additional metadata associated with links such as *tags* help us to determine the context of an interaction. We argue that a ranking model with the objective of finding collaborators based on expertise must account for the network *dynamics* in interactions. Hence, we propose a model that regards those users who actively contribute to interactions in a specific collaboration network as important peers. Our model has the following ingredients:

—**Collaboration dynamics.** We extend the PageRank model by introducing various human-centered metrics to account for the dynamics in human collaboration networks. Such metrics include *availability* and *activity level* of a user. Our model attempts to balance between the importance and the activity level (*interaction intensity*) of users.

—**Skill, activity, and action aware recommendations.** Here we go a step further and propose additional parameters for personalized ranking. Interactions in collaborations are always performed in a certain context — that is, in the scope of a certain activity. Recall from previous discussions, we have established the following concepts:
  - —An *activity* describes in which kind of work users are engaged. To give examples, a scientist may declare his/her field of research as activities such as "graph algorithms" or "Web service discovery".
  - —*Actions* are usually performed in the scope of certain activities, for example, creating documents or research papers in a certain research domain.
  - —In this work, the notion of human *skills* is equivalent to expertise of a user and can be declared by the user as activities. However, the actual skill level is obtained based on observations of actions (e.g., interaction logs) serving as evidence.

    As an example, the expertise (skill level) of a scientist in a given field depends on the output in form of published paper — actions in a given research activity.

In the remainder of this work, we refer to our approach — accounting for the above mentioned properties — as *DSARank*. DSARank stands for *Dynamic Skill- and Activity-aware* PageRank. Before introducing DSARank, we define a set of human-centered metrics capturing the dynamic nature of human collaboration.

6.1 Intensity Metrics

In this section we define availability and intensity metrics to measure dynamics in human interaction networks. We introduce these metrics in the context of point-to-point human communications (e.g., phone conversations), but we can apply similar metrics to measure dynamics in, for example, messaging-based interactions.

Definition 6.1 *Availability.* Let us define a user's availability[5] as the entire duration user u interacts with other users, i.e., $\{v|v \in \mathcal{U}, v \in A(u)\}$, $A(u)$ defining the set of those users adjacent to u. We define t_{call} as the duration of a specific phone call. Here, $call \in (u, v)$ is commutative (a call can be an incoming or outgoing call). Given the captured telephone logs, we calculate u's estimated availability as

$$\texttt{availability}(u) = \sum_{v \in A(u)} \sum_{call \in (u,v)} t_{call}(u, v) \tag{4}$$

Definition 6.2 *Link Intensity.* Let us define the intensity of an interaction link ℓ as

$$i(\ell) = \left[\prod_{call \in \ell} t_{call} \right]^{1/|\ell|} + \kappa \tag{5}$$

The single link intensity is the geometric mean of $|\ell|$ calls plus a small smoothing factor κ defined as

$$\frac{\text{Number of missed calls}}{\text{Total number of calls} \in \ell \text{ with } t_{call} > 0} \tag{6}$$

In general, the geometric mean is used when values in a set of numbers influence each other. For example, when growth rate or relative change in a series of numbers is analyzed. In other words, the single link intensity is the *average product* of a set of calls between people to exchange information. Every information flow between people, perhaps gossip or work-related news, depends on a set of calls that mutually influence each other. (At the moment, we do not consider the context of interactions.)

Definition 6.3 *Interaction Intensity.* For a specific user, we define interaction intensity as follows

$$i(\ell; u) = i(\ell) * |\ell| \left[\sum_{\ell \in \texttt{links}(u)} i(\ell) \right]^{-1} \tag{7}$$

The set $\texttt{links}(u)$ contains directed interaction links. For out intensities i_{out}, we demand links to be outgoing links, and similarly for in intensities i_{in}, links must be incoming links.

Definition 6.4 *Interaction Intensity Level.* Based on the definition of $i(\ell)$ and $i(\ell; u)$ we define the interaction intensity level IIL as

$$IIL(u) = \left[\beta^2 \left(\sum_{\ell \in \texttt{outlinks}(u)} i_{out}(\ell; u) \right)^2 + (2 - \beta)^2 \left(\sum_{\ell \in \texttt{inlinks}(u)} i_{in}(\ell; u) \right)^2 \right]^{(1/2)} \tag{8}$$

[5]Availability is defined based on already captured interactions.

The factor $\beta \in [0, 2]$ allows IIL to be biased towards i_{in} or i_{out}, where 1 means no bias, i.e., equal importance for in-/out intensities. Biasing IIL is only valid for *all* users.

Definition 6.5 *IIL Imbalance.* We define the imbalance $imb(IIL) \in [-1, 1]$ as

$$imb(IIL) = \begin{cases} \dfrac{\displaystyle\sum_{\ell \in \mathtt{inlinks}(u)} i_{in}(\ell; u) - \sum_{\ell \in \mathtt{outlinks}(u)} i_{out}(\ell; u)}{\displaystyle\sum_{\ell \in \mathtt{links}(u)} i(\ell; u)} & \text{, if } \displaystyle\sum_{\ell \in \mathtt{links}(u)} i(\ell; u) > 0 \\ \infty & \text{, otherwise} \end{cases} \tag{9}$$

Specifically in messaging-oriented communications, $imb(IIL)$ is a useful measure to determine extreme values:

—*Passive* involvement of users in interactions such as observers yields $imb(IIL) = 1$

—*Active* involvement, but in the extreme case, all interactions could be outgoing and none of the interactions is replied by the other users (no incoming interactions), thus $imb(IIL) = -1$

6.2 Intensity-based DSARank

In this section we introduce DSARank, a model to capture the dynamic nature of collaborations. More precisely, in the DSARank model we assume that expert seekers interact with *well-informed* users depending on the intensity of interactions (that is, IIL-dependent) and also with users that are typically highly available. DSARank is better suited to recommend users (experts) in human collaboration. Our model does not only rely on the structure of the network, for example $\mathtt{indegree}(u)$ and $\mathtt{outdegree}(u)$ of a particular user u, but also captures the dynamics in collaborations. Also, it is important to consider the *context* of interactions. Context allows us to refine rankings of users based on skill information and expected expertise level of users. DSARank has the following important properties:

Non-uniform personalization vectors. Previously, we used $p(u) = 1$. However, a user does not randomly establish interactions (or collaborations) with other users. In particular, the expert seeker chooses to request an opinion or input from users who are potentially those people influencing or controlling the flow of information.

User preferences. Typically, there is a trade-off between various personalization metrics. For example, interaction metrics include availability and interaction intensity. We should be able to favor one metric over the other. We can then decide which of those metrics should mainly influence rankings, for example, of the set of users recommended for collaboration.

As mentioned earlier, I is a column-stochastic matrix. Thus, the sum of outgoing edge weights of a particular node v must be equal to 1. The sum of weights is given as

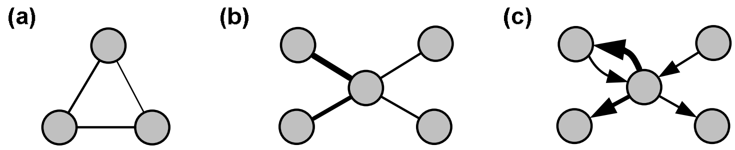


Fig. 7. Schematic illustration intensity metrics: (a) depicts a subgraph in the network (triangle), (b) undirected, weighted links of nodes in the network, and (c) directed links between nodes.

Here we give some background related to our intensity-based approach. *Motifs* are "small" subgraphs that appear a number of times in complex networks. These simple building blocks Milo et al. [2002] can be found in biological, technological, and sociological networks Milo et al. [2004] and can be of very different sizes and connectivities. For example, the authors in Adamic et al. [2008; Yang et al. [2008] analyzed motifs in online communities (question/answer forums).

Onnela et al. [2005] proposed motif detection in weighted complex networks considering motif intensity and coherence. Figure 7 (a) shows a simple subgraph (triangle) and its paths. Each link in the path may have different weights. In Onnela et al. [2005], motif intensities were studied to detect the *strength of interactions*. Furthermore, in Onnela et al. [2007], the authors studied the homogeneity of weights in subgraphs, which they defined as *subgraph coherence*. To study coherence of *weights*, the ratio of the geometric to the arithmetic mean can be defined. We also use the geometric mean to calculate the strength of interactions. As mentioned in Onnela et al. [2005], it is important to consider the coupling between network structure and interaction strength. However, in our work, even an *attempt* to interact with some other actor in the network (e.g., a user attempted but failed to contact another users) is appended as smoothing factor κ to the link intensity $i(\ell)$. This is done because certain communication means (e.g., the physical network) are unreliable in terms of establishing the communication channel between actors. We calculate the strength of interactions as undirected links, Figure 7 (b), and calculate the *homogeneity of interaction strengths* (see interaction intensity $i(\ell; u)$). For example, to calculate if the strength of a specific link is much higher, or lower, than the average strength. In particular, we use the ratio of $i(\ell)$ — the strength of a specific link — an the arithmetic mean of the strength of all links $\ell \in \texttt{links}(u)$. Finally, we create the directed, weighted graph Figure 7 (c).

Symbol	**Meaning**
m	A metric or measured value in human interaction networks. For example, a metric depicts availability or intensity of interaction links. Metrics can be obtained by observing the interaction in a specific context, or the (whole) interaction network in general. The set $M_R = \{m_1, m_2, \ldots, m_n\}$ defines the various interaction-based ranking metrics.
w_m	Denotes the weight of a metric. For example, one may define preferences for different metrics. If weights are not explicitly specified, we regard each metric to be equally important and use the following definition of weights: $W_{M_R} = \{w \mid w_m = 1/\lvert M_R \rvert, \forall m \in M_R\}$. Also, the sum of metric weights must be equal to 1.

Table III. Metrics and weights in interaction networks.

$$ws_v = \sum_{z \in \texttt{outlinks}(v)} w_{v,z} \tag{10}$$

Next, we define the formula for the basic DSARank

$$DSA(u) = \alpha \sum_{v \in \texttt{inlinks}(u)} \left(\frac{w_{v,u}}{ws_v}\right) DSA(v) + (1-\alpha) \sum_{w_m \in W_{M_R}} w_m p_m(u) \tag{11}$$

with $||\vec{p}|| = 1$

Remark 6.6 *Normalization.* The personalization vector $\vec{p}$ has to represent a valid probability distribution (i.e., $||\vec{p}|| = 1$). Therefore, we need to normalize availability and IIL. Let $p_1(u)$ denote the personalization for availability and $p_2(u)$ for IIL:

$$p_1(u) = \frac{\texttt{availability}(u)}{\sum_{v \in \mathcal{U}} \texttt{availability}(v)} \qquad p_2(u) = \frac{IIL(u)}{\sum_{v \in \mathcal{U}} IIL(v)} \tag{12}$$

In the following, we go a step further and introduce personalization not only based on availability and IIL, but also additional skill-metrics to rank users based on *interaction contexts.*

7. CONTEXT-AWARE DSARANK

The next step is to introduce our approach to determine the most relevant user (expert) based on interaction contexts. In Figure 8, we show the three essential steps: (1) capturing activity-/action information, and metadata associated with interactions, (2) perform ranking in subgraph partitions, and (3) aggregation of rankings based on the expert seeker's preferences.

Interactions between two users may have different scopes. Therefore, we determine a user's expertise by considering context because interactions take place at different levels of importance (i.e., the weight of a link) and intensities. However, there might be a "coupling" between contexts because a link may convey information relevant for multiple context topics.

—**Step 1.** Capturing interactions in human collaboration networks and associated metadata including tags and activity information, which can be provided by users, to define the *interaction context.* As discussed in Sec. 6.1, we derive metrics to calculate the dynamics and user involvement given the entire flow of interactions in the network.

—**Step 2.** Perform ranking based on the interaction context by decomposing the interaction network into subgraphs. Decomposing the network can be performed using applied tags, user profiles, or content analysis of messages (e.g., emails, forums, discussion groups, etc.). The subnetworks (i.e., graphs) serve as input to calculate `Context Dependent Rankings`. This step is computed offline.

—**Step 3.** The expert seeker formulates a query, for example, specifying a set of skills or keywords, which is evaluated by a `Query Processing` module. The next step is to utilize the precomputed rankings to perform `Aggregation` of ranking

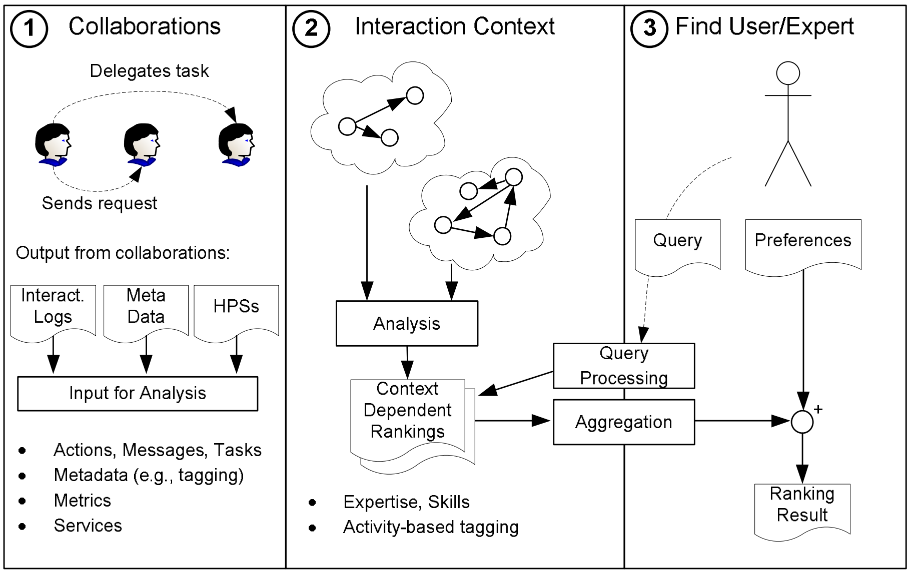


Fig. 8. Schematic illustration of context-aware DSARank.

scores of those users matching the query. This is done by taking the expert seeker's `Preferences` into account.

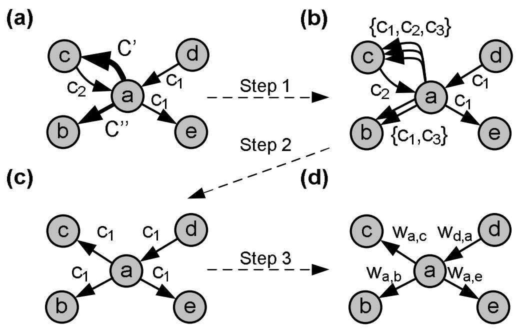
7.1 Interaction Context

We discuss context in a general setting and define *context tags* as any information that can be used to determine the interaction context.

Definition 7.1 *Interaction Context*. We define the context $C = \{c_1, c_2, \ldots, c_n\}$ of an interaction as the set of context tags. An interaction takes place in a certain context $C' \subseteq C$, if a link ℓ is annotated with $c \in C'$. The context between $u, v \in \mathcal{U}$ is determined by the scope of a link $\ell(C')$. For users in a particular context c, we can create a subgraph g based on subset of links $\{\ell(c)\}$. The set of users $U(c) \subseteq \mathcal{U}$ interact in a context c.

As an example for context tags, users tag email messages if these messages are related to a certain project or activity. We assume that different types of context tags are applied to interaction links with a certain frequency c_f. To account for misplaced or missing tags, we perform additive smoothing which is a simple but effective method to calculate probabilities of tags. Usually a smoothing factor γ ranging from $0 < \gamma < 1$ is used. The smoothened tag occurrence probability is $P(c_f; \gamma) = (c_f + \gamma)/(\sum_{c \in C'} c_f + \gamma)$, where C' denotes all context tags used in a link ℓ between u and v.

In Figure 9 we show (a) an example interaction graph with tagged links, (b) the graph with decomposed links based on tags, (c) the context-dependent subgraph (for example c_1), and (d) the weighted subgraph. Also, we show the weighted transpose matrix W^T of the subgraph. As shown in Figure 9 (a) and (b), each interaction link ℓ is tagged with a certain frequency c_f. We interpret context tags



$$W^T = \begin{bmatrix} 0 & 0 & 0 & w_{d,a} & 0 \\ w_{a,b} & 0 & 0 & 0 & 0 \\ w_{a,c} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ w_{a,e} & 0 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 9. Example of tagged graph and corresponding (weighted) subgraph.

applied to interaction links as follows: User v interacts with user u in different contexts C'. However, some tags appear with higher frequency than other tags. Thus, we assume that v regards some interactions with u as important in a specific context — the relevance of a link in a context c is proportional to the tag's frequency. Therefore, we use smoothened tag frequencies as weights to depict the relevance of an interaction link ℓ for c. For example, the chance of receiving an item of information or that u will be contacted in a specific context c. Given the set of context dependent links $\{\ell c\} \in g$, we estimate the expertise of users interacting in c as

$$SE(u; c) = \sum_{v \in \texttt{inlinks}(u)} \left(\frac{w_{v,u}}{ws_v} \right) SE(v; c) \tag{13}$$

Compared to $PR(u)$, $SE(u)$ is computed in a similar manner; however, in $SE(u)$ we do not use personalization vectors (i.e., $\vec{p}$) because $SE(u)$ will be used in a context-dependent subgraph g, which is already itself a personalization. Notice, depending on the interaction network, $SE(u)$ can also be interpreted as the *expected informedness* of a user.

Definition 7.2 *Context-Sensitive IIL*. Previously, we discussed IIL without considering interaction context. However, for many collaboration and ranking scenarios, it is important to find users that are highly involved in specific projects, activities — the context in general — because a user's expertise and expected informedness or not equal for all contexts in which the user is participating. For a given context c, we calculate $IIL(u; c)$ based on the set of context dependent links $\{\ell(c)\}$ in g.

7.2 Context-Sensitive DSARank

As mentioned before, $SE(u)$ is the context-dependent skill- and expertise level of a user. We could use $SE(u)$ as a weighted preference in the ranking process by including $SE(u)$ when computing DSARank as defined in Equation 11. However, this is an impractical solution because we cannot precompute the vector $\vec{DSA}$ for every possible combination of demanded skills (i.e., depending on the expert seekers preferences). On the other hand, we must consider the *context* of interactions to recommend the right expert. The following equality helps to solve this problem:

Theorem 7.3 Linearity. *[Haveliwala 2002][Jeh and Widom 2003] For any personalization vectors $\vec{p}_1, \vec{p}_2$ and weights w_1, w_2 with $w_1 + w_2 = 1$, the following equality holds:*

$$\vec{PR}(w_1\vec{p}_1 + w_2\vec{p}_2) = w_1\vec{PR}(\vec{p}_1) + w_2\vec{PR}(\vec{p}_2) \tag{14}$$

The above equality states that personalized PageRank vectors $\vec{PR}(\sum_{w_m \in W_{M_R}} \vec{p_m})$ can be composed as the weighted sum of PageRank vectors. Thus, we can restate the definition of DSARank, w_c depicting the weight for a particular context c, as

$$DSA(u;C') = \sum_{c \in C'} w_c DSA \left[\sum_{w_m \in W_{M_R}} w_m p_m(u) \right] \tag{15}$$

It is clear that not all users participate in context C'. For a specific context c, we set

$$p(u) \equiv \begin{cases} p_m(u) & \text{, if } u \in U(c) \\ 0 & \text{, otherwise} \end{cases} \tag{16}$$

8. RANKING EXPERIMENTS

First, we establish a set of ranking metrics to test the effectiveness of DSARank compared to PageRank. We provide graph visualizations of ranking results using the intensity-based DSARank as well as the context-aware DSARank, followed by discussions of results based on ranking statistics.

8.1 Evaluation Metrics and Comparison of Ranking Algorithms

—**Kendall's** τ: We use the definition of Kendall's τ by [2005]. Consider the pairs of vertices v, w. The pair is *concordant* if two rankings agree on the order, *disconcordant* if both rankings disagree on the order, *exact-tie* if the exact ranking does not order the pair, and *approximate-tie* if the approximate ranking does not order the pair. Denote the number of these pairs by $c, d, e,$ and a, respectively. Given the total number of pairs as $m = \frac{n(n-1)}{2}, n = |\mathcal{U}|$, then Kendall's $\tau \in [-1, 1]$ is defined as:

$$\tau = \frac{c - d}{\sqrt{(m-e)(m-a)}} \tag{17}$$

Kendall's τ helps us to understand whether two algorithms are rank-similar. In other words, if τ equals 1, there are no cases where the pair v, w is ranked in a different order.

—**Relative Ranking Change** (RRC) [2008]: Suppose a user u is ranked at position d by $DSARank$ and at position p by $PageRank$, then u's $RRC \in [-1, 1]$ is given as:

$$RRC(u) = \frac{d - p}{d + p} \tag{18}$$

If $RRC(u) < 0$, then u is in the set RRC_p of those users *promoted* by $DSARank$, otherwise *demoted* RRC_d. We calculate the percentage of promoted users as:

$$PP = \frac{|\sum_{u \in RRC_p} RRC(u)|}{|\sum_{u \in RRC_p \cup RRC_d} RRC(u)|} \tag{19}$$

—**Top-k Set Metrics**: We define the overlap similarity $OSim(T_{k1}, T_{k2})$ of the top-k sets T_k ranked by $DSARank$ and $PageRank$ as $OSim(T_{k1}, T_{k2}) = \frac{T_{k1} \cap T_{k2}}{k}$ [Haveliwala 2002].

For a small teleportation probability $(1 - \alpha)$, ranking results are robust in terms of τ. Low α (e.g., $\alpha < 0.45$) results in frequent teleportation swamping the resulting ranked network. For all experiments, we use a damping factor of $\alpha = 0.85$.

8.2 Effect of Interaction Intensities

Here we compare DSARank and PageRank results using i_{in}, i_{out}, and IIL metrics given the structure and dynamics of the interaction network. We make no assumptions about the nature of underlying interactions, position of people, or the context of a conversation (private or business-related). We entirely focus on the effect of interaction intensities on ranking results. In Figure 10, we see the visualization of ranked nodes in a network.

Remark 8.1 *Applied Filtering.* We perform filtering of users to select those users with `indegree` greater than 1; that is, if a user interacts with at least two different users. In addition, we remove duplicated call information, for example, multiple call records between two users that have the same time interval.

The properties of the resulting rankings are that the importance of users is not only influenced by the degree of incoming links but also the intensities of interactions with other (important) users. Interestingly, we find that users having high IIL with important nodes, but low indegrees, still fill top positions in the ranking results. We use equal metrics weights for IIL and `availability`. Figure 10 shows the resulting visualization.

In the following we show two tables: Table IV contains $\vec{DSA}$ and $\vec{PR}$ scores and rankings of users based on selected conversations in the mobile phone network. In particular, we select only those calls in *2004-08*. Users are sorted by decreasing DSARank score. Table V is created in a similar manner; however, users are sorted based on PageRank scores. Also, in both tables i_{out} and i_{in} intensities are percentage values and the metric `availability` is abbreviated as AV.

Discussion Table IV. The first observation in Table IV is that high-IIL with important users increases the position of users dramatically. For example, although the user 187 (in Fig. 10, 187 is displayed as the second-largest node located next to the most important user — largest node in the network) is ranked as "unimportant" by the unbiased PageRank (only at position 90 in $\vec{PR}$); user 187 is promoted to the top-10 list due to very high-IIL with a user, whose PageRank is already very high. This is the desired behavior in our ranking model because we expect close collaborators of important users to be important as well; regardless of `indegree`.

Additionally, we see in Table IV two users with $imb(IIL) = 1$ moving up to the top-10 ranked users. Given that the dataset contains partial observations of

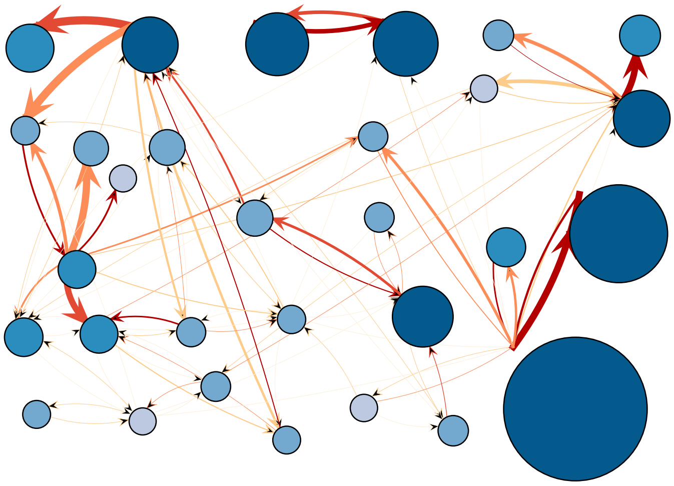


Fig. 10. (Color online) Top-30 ranked users by DSARank based on selected communications. Users are depicted as nodes in the graph where the size of each circle is proportional to the user's importance (a cut-off is applied to limit the maximum size of a node). Edges are colored based on edge-strengths proportional to interaction intensities (normalized). Personalization is performed by using dynamic properties of the human interaction network. High IIL yields high importance because IIL is a metric for the users' contribution to the information flow. Acting with high intensity (locally) matters for global importance.

ID	$score_{\vec{DSA}}$	$rank_{\vec{DSA}}$	$score_{\vec{PR}}$	$rank_{\vec{PR}}$	i_{out}	i_{in}	IIL	AV
43	0.110183	1	0.030705	6	2.74	0.58	0.027978	0.077728
187	0.071380	2	0.004090	90	6.60	8.85	0.110395	0.052550
39	0.050639	3	0.028502	8	1.11	0.62	0.012730	0.032829
313	0.049208	4	0.004369	74	13.21	4.72	0.140244	0.021839
21	0.047523	5	0.029582	13	1.26	0.78	0.014839	0.018402
29	0.043959	6	0.031956	11	5.29	0.72	0.053370	0.090770
83	0.043492	7	0.042618	1	2.71	0.57	0.027711	0.101583
49	0.035641	8	0.003925	100	0.00	10.76	0.107589	0.045642
95	0.027682	9	0.003708	105	0.00	8.57	0.085738	0.048684
50	0.025403	10	0.004090	93	4.38	3.14	0.053894	0.004553

Table IV. Top-10 list of users based on DSARank.

interactions, it is likely that only a fraction of both users' interactions have been captured. However, as in real collaboration scenarios, it is unlikely that we can capture all interactions of users at all times. We can verify in Figure 10 that ID 49 (located in top-left corner having a single high-weighted, `inlink` from a high-ranked user) and ID 95 (located in top-right corner and similarly connected with a single high-ranked user) are not well connected with the rest of the network, but have i_{in} links from very important users.

Discussion Table V. We show in Table V the same collaboration network sorted by $\vec{PR}$ scores. For example, we see that the user with ID 8 was demoted

ID	$score_{\vec{PR}}$	$rank_{\vec{PR}}$	$score_{D\vec{S}A}$	$rank_{D\vec{S}A}$	i_{out}	i_{in}	IIL	AV
83	0.042618	1	0.043492	7	2.71	0.57	0.027711	0.101583
85	0.037551	2	0.008548	25	0.40	0.08	0.004114	0.009620
8	0.033555	3	0.003750	48	0.08	0.08	0.001195	0.005848
57	0.032718	4	0.020943	15	0.35	0.19	0.004004	0.019368
29	0.031956	5	0.043959	6	5.29	0.72	0.053370	0.090770
43	0.030705	6	0.110183	1	2.74	0.58	0.027978	0.077728
21	0.029582	7	0.047523	5	1.26	0.78	0.014839	0.018402
39	0.028502	8	0.050639	3	1.11	0.62	0.012730	0.032829
20	0.024837	9	0.023832	12	0.71	1.10	0.013113	0.038612
18	0.021950	10	0.009347	24	0.26	0.21	0.003324	0.014028

Table V. Top-10 list of users based on PageRank.

substantially because IIL is very low compared to other top ranked users.

8.2.1 *Summary of First Observations.* To conclude our discussion on these first observations, DSARank accounting for IIL and `availability` metrics is better suited to recommend users. In our ranking model two facts help to discover important users. On the one hand i_{in} intensities with high-ranked users promote the importance of individuals. For example, in collaborations these users receive much information from knowledgeable people — even if the link-degree of those nodes (users) is low.

On the other hand, high-`indegree` nodes with low IIL are demoted by DSARank. A possible interpretation of this behavior is, for example: if ranking scores are updated within relatively short time frames, say every week or second week, we may discover that individuals are perhaps overloaded in terms of the amount of tasks or requests users have to work on. Thus, users may not interact with high IIL because of their workload that has accumulated over time. Thus, DSARank can prevent individuals from being overloaded by considering the IIL of users. If low IIL is preferred in the ranking model, we could simple use the inverse value of IIL. One might argue that users with few inbound links from a single source, potentially with i_{in}-skewed IIL characteristic like in the interactions of the nodes with ID 49 and 95 (see Figure 10); should not be able to improve their importance rankings substantially. We could additionally penalize these cases by varying the IIL parameter β.

In the following we discuss Kendall's τ and ranking changes in the mobile phone network using a 1 month time window to update rankings. We index each month from 1 - 11 by starting at *2004-07*, depicted as period 1, until *2005-05*, depicted as period 11.

8.2.2 *Kendall's τ.* Table VI shows the comparison of DSARank and the unbiased PageRank with $p(u) = 1$ and `outdegree`-based edge weights; and also PageRank in the weighted network using intensity-based weights.

The first comparison (`unbiased`) shows that there is no strong disagreement between $D\vec{S}A$ and $\vec{PR}$. Otherwise, we would violate our initial assumption that PageRank applied to human interaction analysis is suitable to determine the importance of users. A stronger agreement in rankings is achieved by using i_{out} intensity based link weights (comparison `weighted`).

Period	1	2	3	4	5	6	7	8	9	10	11
τ (unbiased)	0.35	0.34	0.51	0.54	0.48	0.51	0.44	0.43	0.33	0.26	0.36
τ (weighted)	0.63	0.61	0.82	0.87	0.82	0.81	0.74	0.70	0.65	0.68	0.51

Table VI. Comparison DSARank and PageRank showing Kendall's τ in different periods.

8.2.3 *Relative Ranking Change.* The next step in our evaluation is to determine for which users we observe ranking changes. We measure whether users get *promoted* or *demoted* given the users' `availability` and IIL. We calculate the range for both metrics as $max(\texttt{availability}) - min(\texttt{availability})$ and $max(IIL) - min(IIL)$, respectively. For both metrics, we segment the range linearly into a number of buckets. Then, we calculate RRC and PP for each bucket to show how many users given `availability` and IIL were promoted; that is

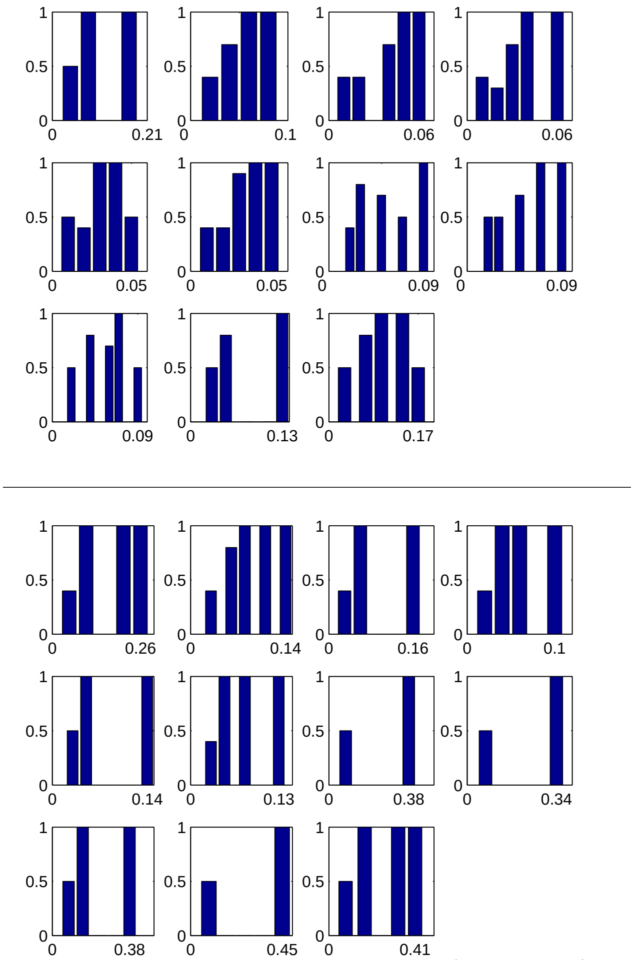


Fig. 11. RRC and PP measured for `availability` (top figures) and IIL (bottom figures) delimited by horizontal line.

$RRC < 0$. We compare the relative ranking change by using DSARank and the unbiased PageRank. Over the entire period (period 1 - 11) we observer that on average the number of promoted users PP equals 0.46 for both metrics. In other words, given the total number of users in a certain period, on average a fraction of 0.46% were promoted and 0.54% demoted.

In Figure 11, we show two sets of figures delimited by the horizontal line: the top set shows RRC for `availability` and the bottom set of figures RRC for IIL. Each set has 11 sub-figures, which depict the ranking changes for each metric in periods ranging from for 1 to 11. Given a set of figures (for a specific metric), we show ranking changes for period 1 in the top-left sub-figure, continue with the second sub-figure in the same row to denote period 2 and continue in this manner (left to right and top to bottom) until period 11. Typically, 5 buckets are shown at the horizontal axis. However, empty buckets are not shown.

Discussion `availability`. In most cases we see regularities in promoting users with increasing availabilities. A 10% rule applies: 90% of the users in RRC_p are in the first bucket (lower availability segment), while the remaining 10% are distributed across the other buckets. Interaction intensities have a strong impact on link-weights and thus PP in general. If both metrics are equally weighted; intensities dominate promotion of users, which we confirm in the IIL-related sub-figures.

Discussion IIL. A similar distribution rule of users across buckets applies. All users having high IIL were promoted but never demoted. Also, we see an upper threshold of $PP = 0.5$ in the lower IIL segment (e.g., first bucket). Users with low IIL are more likely demoted than promoted.

8.2.4 *Overlap Similarities.* In Table VII, we show $OSim$ in various top-k sets of obtained rankings. $OSim$ of DSARank and the unbiased PageRank are denoted as *nobias*.

$\vec{DSA}, \vec{PR}$	$k = 10$ (nobias)	$k = 10$ (weighted)	$k = 30$ (nobias)	$k = 30$ (weighted)	$k = 50$ (nobias)	$k = 50$ (weighted)
avg	0.38	0.65	0.55	0.81	0.67	0.85
σ	0.08	0.13	0.06	0.05	0.11	0.05

Table VII. $OSim$ DSARank versus PageRank: avg is the average overlap similarity (period 1 - 11) and σ the standard deviation of overlap similarities.

Table VII confirms our initial assumption of not having strong disagreements between DSARank and the unbiased PageRank. On average, we see an overlap of $OSim = 0.3$ in the top-10 segment compared to the unbiased PageRank.

8.2.5 *Summary.* To summarize our evaluation on the role of intensity and availability metrics: `availability` is coupled with IIL and not always dominant in the upper availability segments. For IIL, we see clear regularities. Users with high-IIL are always promoted and, on the contrary, low-IIL more likely demotes users' importance. This behavior covers the requirements of real-life collaboration environments: availability itself does not guarantee promotion of users because individuals need to be active players and involved in interactions and collaborations.

8.3 Experiments in Labeled Interaction Graph

In this section we specifically focus on the proposal of ranking users in context-based interactions. For this purpose, we use the Enron email dataset[6].

8.3.1 *Tagged Message Corpus.* A subset of messages of the entire message corpus were labeled by UC Berkeley's Natural Language Processing group. These tags were applied to about 1700 messages. The tagged message corpus serves well to test our context-based ranking approach. Different categories of tags were applied to interaction links comprised of messages between people with the focus on business-related emails. 13 categories or *contexts* are available (Table VIII).

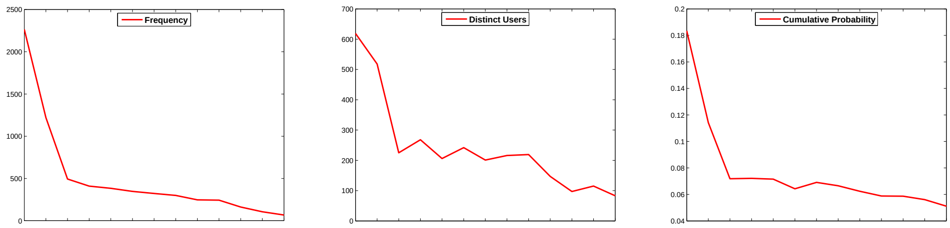


Fig. 12. Tag-statistics in email interactions: left figure shows the frequency of tags given as the total number of occurrences; middle figure depicts the distinct number of users participating in an interaction context (i.e., if one of the user's interaction links contains the tag); right figure shows the cumulative smoothened probability of tags.

Table VIII. Primary categories in labeled interaction graph. The index establishes the correspondence to the tag-statistics in Fig. 12 (horizontal axis).

ID	Index	Description
3.1	2	Regulations and regulators (includes price caps)
3.2	5	Internal projects – progress and strategy
3.3	3	Company image – current
3.4	6	Company image – changing / influencing
3.5	10	Political influence / contributions / contacts
3.6	1	California energy crisis / California politics
3.7	7	Internal company policy
3.8	9	Internal company operations
3.9	11	Alliances / partnerships
3.10	4	Legal advice
3.11	13	Talking points
3.12	8	Meeting minutes
3.13	12	Trip reports

[6]Enron email: `http://bailando.sims.berkeley.edu/enron_email.html`

8.3.2 *Applied Expansion and Filtering.* We expand the subset of labeled messages by searching the entire email-message corpus for related messages. For example, given a labeled message, we search for messages which are most likely related to the labeled message; for example, in `reply-to` or `forwarded` messages. Thereby, we expand the existing labeled message corpus by adding 5248 related messages. However, some messages are simply "broadcast" messages (e.g., announcements or periodic auto-generated messages from a person), which we filter out because these messages might distort ranking results. In addition, sender and recipient of messages must be real people (e.g., we filter messages from — and to — distribution lists) because we are interested in link-based importance rankings of people.

8.3.3 *Ranking Parameters.* In all experiments presented in this section, we set the IIL parameter β to 1.2; therefore assigning a bias to out-intensities. In our previous experiments, we did not use an imb threshold (imb denoting the imbalance of interactions).

Here we use a filter of $-0.9 < imb(IIL) < 0.9$. If $imb(IIL)$ of a user is not within this range, we "downgrade" the user's $IIL(u; c)$ to 0. This is motivated by the following reason: phone calls are synchronous, thereby guaranteeing an information flow between users. Whereas email links between users might be irrelevant if IIL is strongly imbalanced. For example, a user who is active in a given context, but never receives a reply ($\texttt{indegree}(u) = 0$ as well as $imb(IIL) = -1$). In addition, we will focus on the impact of IIL and SE, which we equally weight, without parameterizing DSARank with `availability`.

8.3.4 *Context Coupling and Subgraph Intensities.* For context-dependent IIL, we calculate the interaction intensity of all users in g as subgraph intensity using the following definition:

$$i(g) = \frac{1}{|U(c)||C|} \sum_{c \in C} \sum_{u \in U(c)} IIL(u; c) \tag{20}$$

Figure 13 shows whether different interaction contexts have many shared (i.e., overlapping) links. In other words, interaction links may contain tags that belong to different contexts. Therefore, we speak of an overlapping link $\ell(C')$ between c_1 and c_2, if $\{c_1, c_2\} \subseteq C'$.

Table IX. Intensities $i(g)$ for different subgraphs ($10^3 \times i(g)$). Top-row denoting ID of context and bottom-row $i(g)$.

3.9	3.6	3.2	3.10	3.1	3.3	3.4	3.7	3.8	3.12	3.5	3.11	3.13
7.43	6.03	5.98	4.54	4.42	4.04	3.96	3.10	3.06	2.83	2.12	1.81	1.06

We connect two categories if links are annotated with the same context tags. The node size and coloring scheme is based on subgraph intensities as depicted in Table IX. The context (category) 3.9 constitutes the subgraph with the highest intensity, whereas 3.6 has the highest degree of shared links.

8.3.5 *Filtering Algorithm.* In the following experiments, the visualization of ranking results and interactions between users are filtered using the following algorithm:

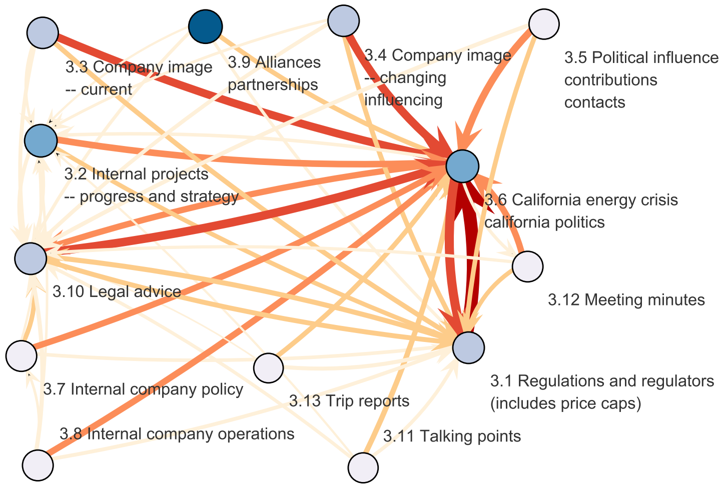


Fig. 13. (Color online) Visualization of shared links between different contexts.

(1) We create two sets T_{k1} and T_{k2} of top-k ranked users.

(2) If $\texttt{rank}(u) \leq k1$, we add u to T_{k1}, otherwise to T_{k2} if $\texttt{rank}(u) \leq k2$.

(3) We remove all users $u \in g$ which are not in $T_{k1} \cup T_{k2}$.

(4) For each user in T_{k2} we demand a minimum degree $\texttt{min}_{k=1}$ of connectedness to T_{k1} users. We remove $u \in T_{k2}$, if u is not connected to at least $\texttt{min}_{k=1}$ users.

(5) For each user in T_{k1}, we test whether $u \in T_{k1}$ is connected to at least $\texttt{min}_{k=1\cup 2}$ users in $T_{k1} \cup T_{k2}$.

By using the above algorithm, we ensure that all users in the visualized graph are connected to a minimum number of top-ranked users.

8.3.6 *Applying DSARank in Context-Dependent Interactions.* As a first example, we select the subgraph for 3.6 (i.e., the specific interaction context) and rank all users.

Table X. Top-10 ranked users by DSARank. Selected subgraph corresponds to category 3.6. Users are sorted by decreasing DSARank score.

ID	$score_{D\vec{S}A}$	$rank_{D\vec{S}A}$	$score_{\vec{PR}}$	$rank_{\vec{PR}}$	IIL	imb
37	0.109475	1	0.004121	21	7.31	-0.81
8	0.102375	2	0.020758	1	5.13	0.11
90	0.043071	3	0.008326	9	1.1	0.08
253	0.029936	4	0.001733	170	2.07	-0.85
347	0.020443	5	0.001665	282	1.39	-0.87
92	0.016677	6	0.003912	23	0.39	0.82
152	0.016375	7	0.013148	2	1.16	1.0
47	0.014248	8	0.003593	27	0.66	0.41
29	0.014195	9	0.005415	16	1.14	1.0
14	0.014084	10	0.010911	4	2.27	1.0

The detailed results are provided in Table X[7]. Figure 14 shows the visualization of interactions of top-ranked users (according to the filtering algorithm).

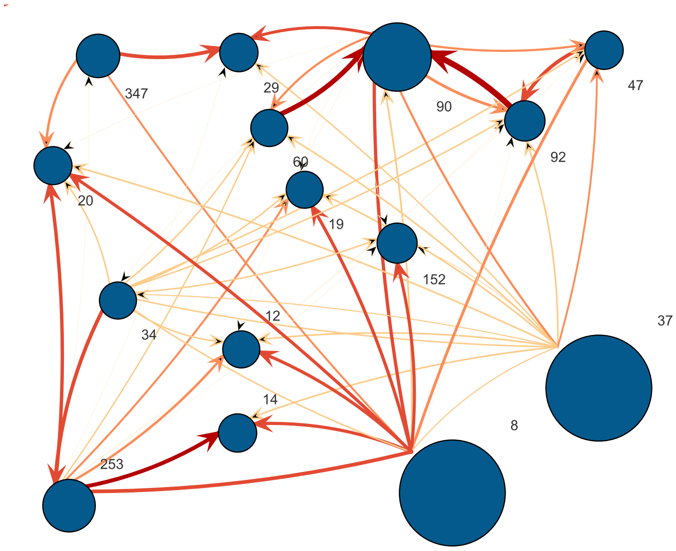


Fig. 14. (Color online) Example of context-aware DSARank: we select context 3.6 (California energy crisis / politics) and perform ranking. The subgraph g comprises 11839 messages, 1852 links, and 469 users. We use two metrics, IIL with bias $\beta = 1.2$ and calculate SE within g. Both metrics are weighted with 0.5.

.

We set $\mathtt{min}_{k=1} = 2$, $\mathtt{min}_{k=1\cup 2} = 2$, $|T_{k1}| = 5$, and $|T_{k2}| = 15$. With these parameters we have a reasonable number of interactions and users in our graph visualization. In Figure 14, we see similar characteristics in terms of importance rankings as we observed previously in rankings based on mobile phone calls. Not only many incoming interactions with important users matter, intensity in a given context dependent subgraph g plays a keyrole. It is well possible that users get promoted (in some cases substantially) because they interact with important users in a given context with high intensity. Thus, DSARank provides accurate results as users are not ranked in a single context.

8.3.7 *Kendall's τ.* In the next step we compare Kendall's τ of DSARank when compared to PageRank. In particular, we rank in different subgraphs and combine results using the formula for the context-aware DSARank (see Equation 15) to create composite DSARank scores. Each context-dependent result vector $w_{c1} * D\vec{S}A(c_1)$ and $w_{c2} * D\vec{S}A(c_2)$ is combined with $w_{c1} = w_{c2}$.

[7]For validation, we provide the identities as well as descriptions of specialism (where available) at this location `http://www.infosys.tuwien.ac.at/staff/dschall/email/`. Using DSARank in category 3.6, one can verify that the top-ranked user was indeed the key person in the given context.

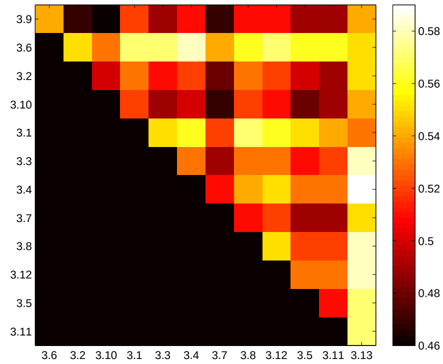


Fig. 15. Kendall's τ for composite contexts corresponding to entries in Table XI.

Table XI. Kendall's τ for comparison of PageRank and DSARank in composite contexts.

	3.6	3.2	3.10	3.1	3.3	3.4	3.7	3.8	3.12	3.5	3.11	3.13
3.9	0.54	0.47	0.46	0.52	0.49	0.51	0.47	0.51	0.51	0.49	0.49	0.54
3.6		0.55	0.53	0.57	0.57	0.58	0.54	0.56	0.57	0.56	0.56	0.55
3.2			0.5	0.53	0.51	0.52	0.48	0.53	0.52	0.5	0.49	0.55
3.10				0.52	0.49	0.5	0.47	0.52	0.51	0.48	0.49	0.54
3.1					0.55	0.56	0.52	0.57	0.56	0.55	0.54	0.53
3.3						0.53	0.49	0.53	0.53	0.51	0.52	0.58
3.4							0.51	0.54	0.55	0.53	0.53	0.59
3.7								0.51	0.52	0.49	0.49	0.55
3.8									0.55	0.52	0.52	0.58
3.12										0.53	0.53	0.58
3.5											0.51	0.57
3.11												0.57

To create PageRank scores, we use the entire interaction graph $\mathcal{G}$ to create the vector $\vec{PR}$. Kendall's τ for different combinations of contexts is shown in Table XI. We created Fig. 15 based on the data in Table XI; making it easier to see whether there is a strong disagreement in terms of τ in different contexts.

Discussion Table XI. Contexts with many shared links (for example 3.1 and 3.6 as depicted in Figure 13) yield stronger agreements between DSARank and PageRank. Intuitively, 3.6 and 3.1 become more dominant when combined with other contexts. It is therefore less likely that the order of rankings change. On the other hand, if a context, for example 3.13 has few shared links with other contexts; and also low subgraph intensity (3.13 has the lowest subgraph intensity), then we observe also stronger agreements in rankings. This can be explained as the limited impact of low intensity contexts on changing the position of users within ranking results.

8.3.8 *Overlap Similarities.* Here we compare DSARank and PageRank in terms of overlap similarities. Table XII contains the results for $OSim_{k=10}$ and Table XIII the results for $OSim_{k=30}$. In Figure 16 we show the visualizations of the results in both tables. By comparing the top-10 segment of ranked users (Figure 16 left), we see higher overlap similarities between high-intensity contexts, for example, the context pairs (3.9, 3.6), (3.9, 3.2). Low intensity contexts such as 3.13 combined with, for example (3.13, 3.9), yields also high similarities. The top-30 segment (Figure 16 right) shows stronger similarities in 3.1 as well as 3.6 — both contexts have many shared links with other contexts.

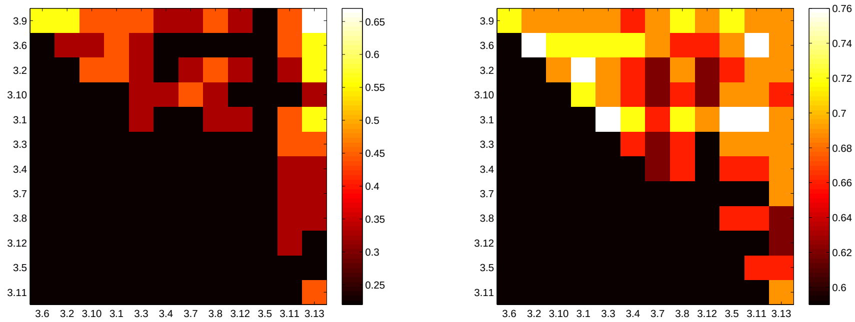


Fig. 16. Overlap similarities for composite contexts: left figure shows $OSim_{k=10}$ and right figure $OSim_{k=30}$.

Table XII. $OSim_{k=10}$ for composite contexts.

	3.6	3.2	3.10	3.1	3.3	3.4	3.7	3.8	3.12	3.5	3.11	3.13
3.9	0.56	0.56	0.44	0.44	0.44	0.33	0.33	0.44	0.33	0.22	0.44	0.67
3.6		0.33	0.33	0.44	0.33	0.22	0.22	0.22	0.22	0.22	0.44	0.56
3.2			0.44	0.44	0.33	0.22	0.33	0.44	0.33	0.22	0.33	0.56
3.10				0.22	0.33	0.33	0.44	0.33	0.22	0.22	0.22	0.33
3.1					0.33	0.22	0.22	0.33	0.33	0.22	0.44	0.56
3.3						0.22	0.22	0.22	0.22	0.22	0.44	0.44
3.4							0.22	0.22	0.22	0.22	0.33	0.33
3.7								0.22	0.22	0.22	0.33	0.33
3.8									0.22	0.22	0.33	0.33
3.12										0.22	0.33	0.22
3.5											0.22	0.22
3.11												0.44

8.3.9 *Skill and Expertise Rank in Subgraphs.* We implemented the algorithm to compute SE as a variant of the iterative PageRank algorithm (Jaccobi iteration introduced in Algorithm 1). However, SE is not personalized by adding teleport vectors $\vec{p}$. In other words, we do not add $(1-\alpha)\vec{p}$ in each iteration. In addition, we perform a *fixed number* of iterations to compute SE for each subgraph g to keep computational complexity low. In our experiments, we perform 6 iterations in each subgraph. When comparing the ranking results of SE and the unbiased PageRank, we observed that even though $\vec{p}$ was not used in the computation, both vectors $\vec{SE}$ and $\vec{PR}$ were rank-similar with Kendall's τ approximately equal to 1.

Table XIII. $OSim_{k=30}$ for composite contexts.

	3.6	3.2	3.10	3.1	3.3	3.4	3.7	3.8	3.12	3.5	3.11	3.13
3.9	0.72	0.69	0.69	0.69	0.69	0.66	0.69	0.72	0.69	0.72	0.69	0.69
3.6		0.76	0.72	0.72	0.72	0.72	0.69	0.66	0.66	0.69	0.76	0.69
3.2			0.69	0.76	0.69	0.66	0.62	0.69	0.62	0.66	0.69	0.69
3.10				0.72	0.69	0.66	0.62	0.66	0.62	0.69	0.69	0.66
3.1					0.76	0.72	0.66	0.72	0.69	0.76	0.76	0.69
3.3						0.66	0.62	0.66	0.59	0.69	0.69	0.69
3.4							0.62	0.66	0.59	0.66	0.66	0.69
3.7								0.59	0.59	0.59	0.59	0.69
3.8									0.59	0.66	0.66	0.62
3.12										0.59	0.59	0.62
3.5											0.66	0.66
3.11												0.69

9. CONCLUSION

We presented DSARank, a ranking model for estimating the expertise and importance of users in human interaction networks. DSARank is better suited for recommending relevant people in collaborations than existing models relying mainly on the degree of interaction links between users. Our experiments confirm that interaction intensities in a given context play a key role. When compared with PageRank, in some cases we see dramatic changes in rankings of users having high interaction intensities with other important users. This reflects real collaboration domains where interaction links cannot be treated as equally important. DSARank can be customized for different contexts, allowing expert seekers to specify the demanded set of skills. Thus, DSARank is flexible and can be applied in different interaction and collaboration domains. Our future work includes scalability analysis of DSARank in interaction networks with a larger number of users. In addition, we would like to combine information from different sources of interaction traces. For example, how the rankings of users are influenced by considering sources such as messaging tools, phone conversations, task-based platforms, etc. This poses a challenge in data correlation and provenance management.

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