Towards a Conceptual Model for Trustworthy Skills Profiles in Online Social Networks*

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Abstract For many users online profiles displaying other people's skills are increasingly important, e. g., when contracting freelancers or finding candidates for a job opening. However, current profiles found in information systems offer either unstructured free text that is hard to handle efficiently or simplistic rating schemes that do not convey meaningful information. In addition, it is unclear how trustworthy the information on the profile is. In this paper, we propose a novel approach to online skills profiles based on users' confirmations and the SkillRank credibility ranking and describe its prototype implementation. As spadework, we set forth six basic requirements for online skill evaluations which should generally be reflected in corresponding IS design.

1 Introduction

In the light of the growing dissemination of online social networks, the significance of online profiles is increasing for a wide variety of domains. Both in leisure networks, such as Facebook or the German StudiVZ, and in business networks, such as Plaxo, LinkedIn or XING, profile pages are a pivotal means for judging a person. Particularly in the context of serious business contacts, it can be of monetary value to know how trustworthy the information on a profile page is, e. g., if a headhunter needs to assess whether the person in question truly fits a specific job description or whether it is just pretense.

Having been engaged massively in social activities on the Internet since the rise of the web 2.0 phenomenon [9, 13], people have become interested in not only con-

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templating other people's virtual profiles but also deducing their real-world skills from these profiles or recommending them to possible employers. One crucial aspect of a meaningful skills profile is the rating of individual skills. Only by means of a rating mechanism – however simple or elaborate – it is possible to provide a differentiated skills profile that also (at least rudimentarily) reflects strengths and weaknesses of the person in question.

Traditionally, an important offline "system" for evaluation and rating of various entities, such as products and people, has always been and still is word of mouth, i. e., gossip [7, 5]. All social networks nowadays provide functionality for communication and interaction in various ways [3] and most also feature functions for evaluating objects, profiles, or real-world skills.

The advantages of online – in contrast to offline – evaluations are scalability and formalization [1, 8]. Scalability in this context means that estimates can be gathered from and communicated to a multitude of parties, independent of time and place [17]. Users can access a huge number of evaluations provided by other users in an easy and cost-efficient manner [5]. According to [6], especially the fast diffusion of up-to-date information is a major advantage. In addition, evaluations become more comprehensible through unification of gathering, aggregation and presentation and hence their acceptance increases [18]. The formalization of the results also offers new possibilities for automated processing, e. g., enhanced search, structured comparisons or job matching.

However, the evaluation or rating functionality provided is still very limited and mostly constrained to direct rating schemes (cf. [21]). In online business networks, such as XING, Viadeo or LinkedIn, users can advertise their alleged hard and soft skills on their profile pages using free text, enforcing neither structure nor truthfulness and significantly reducing the utility of these claims. On the other hand, there are many formalized rating algorithms on the Internet, but only a few allow rating user skills. For instance, web pages such as RateMDs.com for the rating of medical services or RateMyTeacher.com for the rating of high school employees allow a simple assessment of professional skills. Generally, these mechanisms are simplistic and their results not very meaningful [21].

Acknowledging that people will always want to present themselves in a favorable light, especially when it comes to the job market [10], we strive for a mechanism that allows for positive profiles – leaving out a person's negative aspects. On the other hand, we already argued that reliable profiles are desirable. So the approach needs to include a mechanism which prevents false statements to appear in the profiles while reinforcing true claims. Coincidentally, the evaluation of people has to be much more meticulous than that of innate objects because the results may have severe negative effects on that person's life. Measuring skills and assessing people in general is, however, a complex endeavor whose validity is highly dependent on a sound theoretical approach [19]. Considering these aspects, it follows that providing IS developers with a set of guidelines for integrating assessment functionality into their IS based on a solid theoretical foundation is a favorable goal.

In that light, our contributions are these: We first state six basic requirements for online skill evaluations and, consequently, propose a novel approach for the unsupervised creation of skills profiles in a social network that addresses these requirements. The approach provides a structured presentation of a user's skills. The credibility of the claims is provided by the users' confirmation in their personal networks and manifested as a ranking based on the SkillRank algorithm described as well. Finally, we describe a reference implementation that was developed in cooperation with a large European social network.

The remainder of this paper is organized as follows: After a short theoretical background in Section 2, we set forth the requirements for online skills evaluation in Section 3. Addressing them, we present the new approach in Section 4. After that, we sketch the prototype implementation in Section 5. Section 6 exhibits some limitations of our approach as well as a brief roadmap for future work. Section 7 concludes the paper.

2 Theoretical Background on Skill Evaluations on the Internet

The basic idea of online evaluation systems is to let users evaluate entities by means of web applications and hence to collect, aggregate, and distribute estimates [17]. The aggregated estimates about an entity, a person, or his or her skills can be used to derive a score, e. g., a trust or reputation score, which can then be communicated to other parties. The scores can assist these parties in deciding whether or not to transact with certain other parties in the future [12].

The use of online evaluation systems requires an adequate design of the underlying mechanisms. According to [4], one of the main decisions refers to the gathering of information. Operators of such systems must determine which users are allowed to rate which entities. Especially, the evaluator's capability of evaluating an entity and his relationship to the evaluated entity needs to be considered. Furthermore, deliberate manipulations by single users must be avoided [8].

In a state-of-the-art study of 102 rating mechanisms [21], it is concluded that evaluation mechanisms are kept very simple in general. Various entities such as people, skills, products or services are evaluated by simple ratings, mostly based on scales. In few cases there are relative evaluations (evaluation of characteristics of one entity compared to those of another one). However, according to [21] there is hardly any suitable mechanism for competency evaluation on the Internet.

The increasing relevance and spread of rating systems forms a new distinct research field. In this context, socio-technical systems as used in the web 2.0 context may offer new opportunities [20]. According to [16], there is an increasing need to do research on the forms, effects and validity of rating systems. Nevertheless, the recent analysis [21] did not identify any mechanisms that explicitly address the possibilities of evaluating or presenting competencies with the help of social graphs and hence of relationships between various users on the Internet. Thus, with our approach we contribute to the body of knowledge regarding the design of trustworthy online skills profiles in social networks.

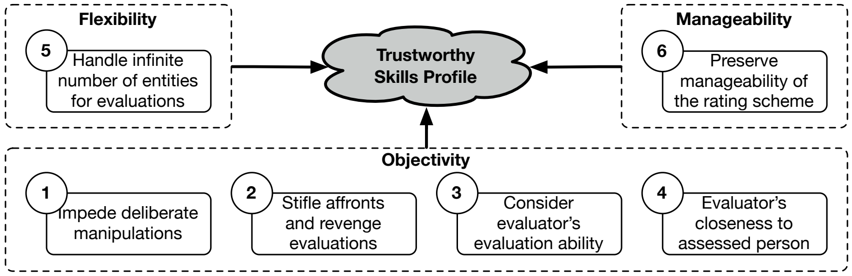


Fig. 1 Requirements for online skills profiles.

Motivated by [2], we have investigated the similarities of website link structures and social structures and have started our research with a closer look at the PageRank algorithm [15]. In essence, SkillRank is an adaptation of PageRank to the context considered here.

3 Six Requirements For Online Skills Evaluation

In order to formalize the discussion on "reliable profiles" up to this point, we now deduce six requirements that can be used to judge whether the approach in question indeed allows reliable profiles that convey substantial information about a person while being apt for large-scale social networks. These requirements are mainly derived from the literature. A schematic overview of them is shown in Figure 1. Together, requirements ① through ④ ensure that the approach delivers reliable, i. e., "objective", results suitable for serious business networks. Note that these requirements – specifically ① and ② – generally rule out direct rating schemes. ⑤ and ⑥ ensure that the approach is feasible even in larger social networks where there is no moderator that can watch over the generated evaluations.

On a sidenote, in order for the user to accept and use the application, he or she must always remain in full control of what appears on the profile. As this is an implicit requirement for any profile page on the Internet, we do not state it explicitly as part of our requirements for skills evaluation.

① **Impede Deliberate Manipulations** As the skills profiles are aimed to be used in sensitive areas such as the job market, the evaluation mechanism needs to impede deliberate manipulations (cf. [8]). This is quite easy to see: Positive evaluations of one's own skills may help in applying for a new job, establishing trust in e-commerce transactions, etc. Hence, it is most likely that some people will try to deliberately manipulate their own or a third party's skill evaluations in a palliating or decrying way. For example, they may only ask friends for their very positive evaluations or a group of students may arrange that they collectively give a bad rating to a teacher. This problem may even be extended to groups of people cartelizing in order assign very good ratings within the group and bad ratings to outsiders. An online evaluation must ensure that such fraudulent behavior is prevented as best as possible.

② **Stifle Affronts and Revenge Evaluations** Many events internal or external to the social network, such as a personal quarrel, may cause people to feel annoyed with one another. In such situations, it is very likely that *revenge evaluations* appear on the platform, i. e., users giving deliberately and unjustly bad ratings, as observed by [18]. This is especially true for direct rating schemes. Apart from the rating, a revenge evaluation may contain insulting comments that appear on the user's profile (cf. [18]). Thus, an online evaluation must ensure that no offending content is published on the users profile without the user's consent. In addition, the revenge ratings should not or at least not significantly influence the evaluation score. Note that any regular direct rating scheme as used on the web today cannot completely fulfill this requirement without relying on moderators (cf. ⑥).

③ **Consider Evaluator's Evaluation Ability** Only people with suitable know-how will be able to properly evaluate other people's skills, e. g., a person who is not able to speak English will not be able to properly judge another person's proficiency in that language. However, he might be able to judge whether someone is speaking English at all (without being able to note mistakes or bad articulation). An online evaluation needs to consider this in order to produce more reliable ratings (cf. [21]).

④ **Consider Evaluator's Closeness to Assessed Person** The closeness of two people has an influence on their mutual evaluations [4]. On the one hand, close relationships between evaluator and evaluated person may help in precisely assessing skills. On the other hand, however, close relations may lead to unjustified evaluations in order to win favor or because of inclination or dislike towards that person. While it is certainly not decidable without detailed data whether and in which way the relationship between two people influences the evaluation, an online evaluation should strive to consider this aspect, although the only feasible option may be to exclude it deliberately.

⑤ **Handle an infinite number of entities for evaluations** It is generally impossible to identify a common set of suitable skills (especially hard skills) for all users beforehand. Furthermore, each person has different skills. Hence, online skill evaluation needs a high degree of individual skill selection freedom. In consequence, evaluation results for individuals may hardly be comparable. For example, one person may be interested in dancing in general and asks for evaluations on his dancing skills. Another one may be interested in Latin dancing only. An online evaluation must be able to handle an infinite number of skills or provide, if possible at all, an exhaustive taxonomy of skills a priori.

⑥ **Preserve manageability of the rating scheme** In popular social networks, the number of participants quickly reaches a level where the social network provider does not have the resources to supervise the rating process and check for fraud or offensive behavior. Thus, the evaluation approach must provide reliable results independently of a moderator that intervenes and filters out offensive comments or evaluations. This is a hard requirement for any online evaluation that addresses a generally unbounded number of participants and is not confined to clearly limited, very small groups.

4 Conceptual Model

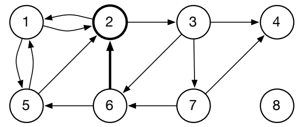
In order to meet the requirements from Section 3, we propose a new approach that relies on *confirmations* rather than direct ratings. Using confirmations, the task of evaluating is basically delegated to the user himself. Each user is able to create a skills profile that he or she finds representative for his or her competencies and that contains only those aspects he or she wants to publish. The alleged skills are then substantiated by *experiences* that the user provides together with specific experience levels. The experiences represent verifiable facts about the user employing or showing the skill at a particular proficiency level. By giving a short textual description, the user can convey the situation in his words. For example, a programmer may want to advertise his Java expertise that he has gained (among other occasions) from a recent programming project. For that, he creates a skill "Java SE programming" and provides an experience describing his programming project. Associated with the experience, he specifies the experience level "expert" because the project involved a lot of very tricky Java programming. Colleagues or teammates that have witnessed the particular skill demonstration can then *confirm* the experience. The confirmation includes a direct reference to the name and the profile page of the confirming user to allow easy verification of his reputation. A textual note can be attached to the confirmation, e. g., describing the evaluator's confidence about the confirmed experience and its level; the confirmed level, however, cannot be modified.

Given the skills profile, a user's actual skill level can be derived from the confirmed rated experiences by calculating a weighted average over the confirmed experience levels. By implication, the user is not able to set a definite skill level himself but has to "suggest" a skill level for each experience. If other people find this suggestion appropriate, they can confirm it. The confirmation is backed by their names and reputations. Without loss of generality, we constrain our considerations in this paper to the three experience levels "<u>nov</u>ice", "<u>adv</u>anced" and "<u>exp</u>ert" with associated weights $w_{\text{nov}} = 1$, $w_{\text{adv}} = 2$ and $w_{\text{exp}} = 3$. This simplified view can easily be extended to allow for a more detailed assessment in a straightforward manner.

Let $C = C_{\text{nov}} \cup C_{\text{adv}} \cup C_{\text{exp}}$ be the sets of confirmed experiences at the respective experience levels. A user's actual skill level l is then defined as

$$l = \frac{w_{\text{nov}} \cdot |C_{\text{nov}}| + w_{\text{adv}} \cdot |C_{\text{adv}}| + w_{\text{exp}} \cdot |C_{\text{exp}}|}{|C|}.$$

For w_i as defined above, this results in an average skill level $1 \leq l \leq 3$ for each skill which can be interpreted as follows. If $l = 1$, the user is an absolute novice. A level $l = 2$ indicates an advanced user, and $l = 3$ states that the user is an expert. Interme-



$\pi(1) = 0.21562$ $\pi(5) = 0.17069$
$\pi(2) = 0.25177$ $\pi(6) = 0.11224$
$\pi(3) = 0.13456$ $\pi(7) = 0.05756$
$\pi(4) = 0.05756$ $\pi(8) = 0.00000$

Fig. 2 Sample skill graph with SkillRank values for $\alpha = 0.95$.

diate values are likely to occur: For example, the aforementioned Java programmer may have a level of $l = 2.4$ for his "Java SE programming" skill indicating him as an advanced user with some expert knowledge, almost half way to being an expert.

While this approach produces a rating for the user's skill level with an implicit credibility provided by the confirming users, the credibility is still not obvious. In order to make the credibility of the claim explicit, we adopt a Markov chain approach as proposed in [2], which has also been adopted in a similar manner for Google's PageRank algorithm [15] that measures the importance of web pages. For the web, the intuitive idea of importance can be formulated as a recursive conjecture: *An important web page is one that is linked to by other important web pages* [14]. Despite having been extended and tweaked in various ways, the PageRank still remains a very robust measure for page importance.

Returning to skills profiles, we can formulate a similar conjecture for our skill evaluation mechanism: *A person's claim to possess a certain skill at a specific level is credible if other people who are credible for the same skill confirm it.*

This conjecture leads eventually to a directed graph $G = (V,E)$ for each skill whose nodes $v_i \in V$ represent the users having that skill. The edges $(v_i, v_j) \in E$ of the graph represent user i's confirmation of some piece of user j's experience. We refer to the resulting graph as the *skill graph* for a specific skill. Accordingly, the algorithm to calculate the credibility ranking is called SkillRank, in analogy to the PageRank.

The example in Figure 2 shows a very small skill graph with eight users. Supposing node 2 represents the Java progammer, the edge (v_6, v_2) in the graph indicates that user 6 has confirmed some part of user 2's Java experience. The most credible users for this skill are user 2 and 1, user 2 having the highest credibility rank of $\pi(2) \approx 0.25177$. Note that the $\pi(2)$ is not the same as the user's skill level.

In order to ensure the existence of a unique solution to the fixed-point problem, we need to make three adjustments to the graph – or rather the corresponding transition matrix – somewhat similar to Google's adjustments as described in [14]. The first adjustment is that all dangling nodes are treated as though they were connected to all nodes in the graph. This is necessary to eliminate "rank sinks", i. e., nodes that would accumulate an unjustifiably high credibility rank [14]. Figuratively speaking, the accumulating credibility flow is skimmed and re-inserted into the calculation in the fairest manner possible.

The second adjustment is to apply a dampening factor $0 \ll \alpha \leq 1$ so that the cycles in the graph are broken up and the convergence to a unique solution is ensured. The dampening factor introduces a small random element into the calculation so that a portion of $(1-\alpha)$ of the intermediate results in each iteration are distributed over all nodes in the graph. In context of the SkillRank, it is desirable to have $\alpha = 1$

Table 1 Fulfillment of the requirements by the new skills profiles approach.

Req.	Fulfillment by the proposed approach
①	Deliberate manipulations by a single user are inherently impossible because of the confirmations approach. Multiple users cartelizing to upvalue their profiles are addressed by the SkillRank which ought to report low credibility for such claims.
②	Revenge evaluations are impeded by the confirmations approach because a malicious user cannot take any action except intentionally *not* confirming an experience he or she knows to be true. Offending remarks are filtered out by the profile owner because he or she has to acknowledge every received confirmation before it is published.
③	Due to scarce information provided by the OSo API, this requirement has not yet been addressed by the prototype described in Section 5. In general, however, the approach can take into account that two users have similar background (e. g., worked in the industry or for the same company) or that they have been reliably confirmed for the skill in question.
④	Due to insufficient information in the social graph of our partner from practice (which represents the typical information a social network provider has), the only clue we can use to decide on the evaluator's closeness to the evaluated user is whether they are direct contacts in the social network. If they are, it is supposed that they can evaluate one another fairly accurately, otherwise, they may not confirm each other's experiences.
⑤	The approach allows the user to enter any free text he deems appropriate for a skill descriptor. This allows for highest flexibility at the price of having synonyms or spelling variants in the database. As R6 generally does not allow a moderator to build an ontology or curate these variants, we suggest an auto-suggest mechanism that suggests the most popular spelling variant to the user when such a situation is detected.
⑥	Apart from the typical systems administration, occasional user support and routine checks on the application, there is no specific need for human intervention in our approach. Still, it is recommended to have dedicated staff who can set examples of good profiles, answer questions or spot unforeseen problems in the system.

because that would take only the structure of the skill graph into account for the calculation of the credibility ranking. However, the dampening factor also serves the purpose of ensuring that the Markov chain is primitive, which is a necessary precondition for a quick convergence to a well-defined fixed-point solution. The web graph can be considered primitive for all practical purposes [14]. In case of skill graphs, however, there are quite often loops that inhibit primitivity. Also, a choice of $\alpha \approx 1$ usually increases the number of iterations as well as the sensitivity of the solution to small changes in the graph [14]. So the problem is trading off respecting the exact graph structure against fast and guaranteed convergence to the solution as well as a "correct" solution against a "stable" solution. For the skill graphs we have tested so far, a compromise of $0.95 \leq \alpha < 1$ seems to deliver sufficiently good rankings in all cases. This has to be verified by formalized experiments, though.

The third adjustment addresses isolated nodes in the skill graph. These occur when a user's claim to have a skill does not have any confirmations, yet. Obviously, such a node is not connected to the remainder of the graph, a fact that cannot happen for the web graph as it is built strictly by following hyperlinks. For a skill graph, all users having a skill are taken into consideration, including unconfirmed claims. The resulting disconnected nodes, however, cannot be included in the SkillRank computation and are assigned a SkillRank value of 0. This is quite intuitive as the claim obviously cannot be confirmed within the social network and, thus, is not credible. In the example from Figure 2, user 8 is such an isolated node.

In combination, the confirmations mechanism and the SkillRank algorithm provide a novel approach to online skill profiles that addresses the requirements set forth in Section 3, which is made evident in Table 1. Based on these results, a prototype implementation of the approach is sketched in the next Section.

5 Implementation of the Conceptual Model

In order to test the theoretical concepts discussed above, a skills profile prototype has been implemented based on OpenSocial, Ruby on Rails and Java. OpenSocial (OSo) is an API that allows social network websites to incorporate portable programs, so-called *gadgets*. We chose OSo for the skills profile gadget mainly because of the potential portability that theoretically allows the application to be "plugged into" any OSo-enabled social network. Ruby on Rails and Java are used in the back-end server for the more complex calculations.

An OSo gadget is defined by an XML file that usually contains or references JavaScript programs and HTML/CSS contents. The gadget is usually provided as an `<iframe>` by the OSo container, for which we use the reference implementation *Apache Shindig*. As the social network, we use the bare-bones social network *Partuza* that serves exactly the purpose of experimenting with OSo gadgets in a social network.[2] As the web server, we chose the Apache HTTP Server. This part of the system architecture is required for all OSo gadgets and does not need to be modified when programming new gadgets. The corresponding elements in Figure 3 are shown in light gray shading, generated web pages (the "GUI") are shown in white.

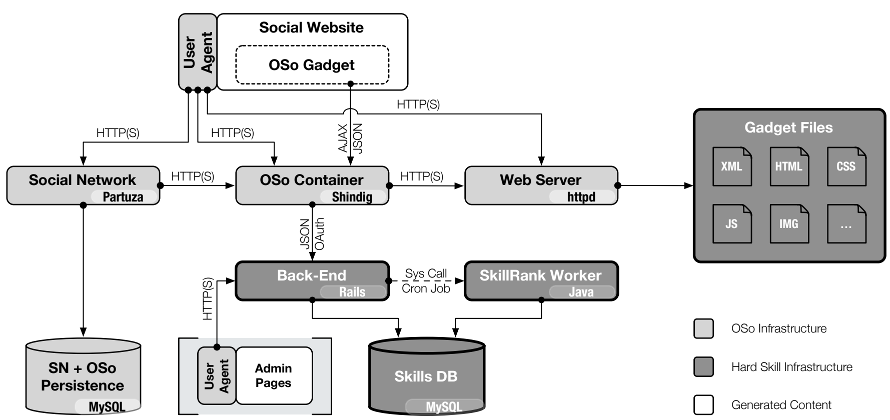


Fig. 3 Architecture of the reference implementation within a large European social network.

[2] For the final release, Partuza was replaced by the social network software of our research partner.

The front-end is supported by a back-end server based on Ruby on Rails that takes care of data storage and the more complex parts of the application logic (cf. Figure 3 for an architectural overview). Requests to the back-end are proxied by the OSo container and secured using OAuth. The Rails back-end also starts the Skill-Rank calculation whenever necessary. The SkillRank implementation is a multi-threaded Java program built on the Colt high-performance computing library. It uses the iterative algorithm from [11] to calculate the SkillRank values for all users and skills in an efficient manner. Even large skill graphs can be calculated in a matter of seconds.[3] The parts provided specifically for the skills profile gadget are shown in dark gray shading in Figure 3.

The gadget allows a user to create an individual skills profile which is displayed as a table or *Skill Cloud*, i. e., similar to a tag cloud (see screenshots[4] in Figure 4). The size of the skill in the Skill Cloud represents the user's level of expertise for that skill while the intensity of the color indicates how credible the entry is according to the SkillRank calculation. The Skill Cloud is an important tool to get a quick overview of a person's skills profile. The list view presents another perspective on the user's skills including additional information like the date of the last confirmation and the option to publish or hide a skill.

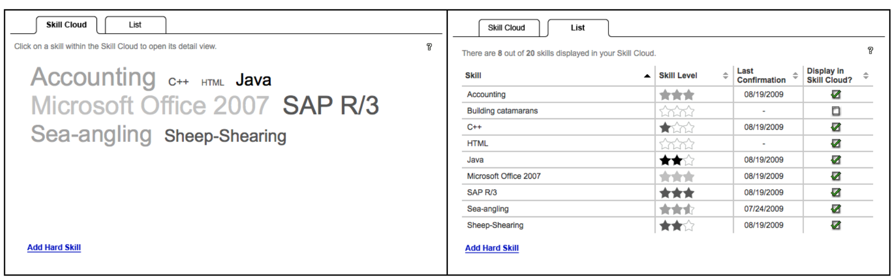


Fig. 4 Screenshots of a sample Skill Cloud (left) and the corresponding list view (right).

6 Limitations and Future Work

The proposed approach has been adequately grounded on ample theory. First informal tests by a small group of users have been very positive and promising. A larger test phase in a large real-live social network will be conducted during the following months.

[3] A reasonably sized skill graph of 10,000 users with around 200,000 confirmations is computed in slightly more than one second on an average quad-core PC.

[4] These "screenshots" have been defaced at the request of our research partner from practice, yet the fundamental concepts are unchanged.

While the confirmations approach held up very well in the first tests, the SkillRank needs more investigation. A viable way to render it more intuitive might be to use “credibility brackets” where an unknown person U is enclosed between two known persons A and B, such that $A \prec U \prec B$ (where “$\prec$” means “is less credible than”). This allows the viewer a better judgment of U’s absolute credibility because he can compare it with two instinctively familiar credibility scores.

A second limitation of the SkillRank is that credibility does not apply to the skill level, but only to the skill as such. Currently, careful planning a skills profile can lead to a situation where both the average skill level as well as the credibility is lifted to an unduely high figure. This situation is hard to replicate even in small groups, but additional experiments have to show how much influence users can have on their credibility result.

The choice of OpenSocial also imposes technical limitations. While the implementation has proven viable, the application has outgrown the typical size of an OSo gadget. Many parts of the algorithm access the base data in an intensity for which the OSo API is not designed. Moreover, some important features require data not provided by the OSo API which forced us to extend it in some places.

The gadget has been deployed for general use at our research partner from practice so that we are able to collect real-world data which will be invaluable for future evaluation of the approach. Apart from evaluating the approach in its current state, we also would like to extend our research into other directions, including the following:

- What additional information can be incorporated into the credibility calculation to make it more robust?
- How can we take into account the aging of old experiences and the different “half-life periods” for various skills?
- How good is the user acceptance for the prototype application?

7 Conclusion

In this paper, we have presented a novel approach to online skills profiles based on user confirmations and the SkillRank credibility ranking. The approach allows a completely unsupervised presentation of rated skills in a social network, including a statement about the user’s alleged proficiency in a skill as well as the credibility for that claim. We have motivated it based on the deficiencies of existing rating schemes and have presented a thorough description of the conceptual model, arguing about its plausibility. In addition, a prototype implementation was presented and current limitations as well as future research were outlined. Due to space limitations we have concentrated on describing the core of the approach and masked out related issues such as the automatic identification of identical skills, additional incentives for the users to use the gadgets etc. In conclusion, we have set forth that our approach is conceptually sound and works from a theoretical point of view. Preliminary user responses confirm this claim. As next steps in our research, we are going to gather more comprehensive empirical data and overcome existing limitations in the approach.

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