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Short communication

Measuring contextual partner importance in scientific collaboration networks

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ABSTRACT

Scientific collaboration commonly takes place in a global and competitive environment. Coalitions and consortia are formed among universities, companies and research institutes to apply for research grants and to perform joint projects. In such a competitive environment, individual institutes may be strategic partners or competitors. Measures to determine partner importance have practical applications such as comparison and rating of competitors, reputation evaluation or performance evaluation of companies and institutes. Many network-centric metrics exist to measure the important of individuals or companies in social and collaborative networks. Here we present a novel context-based metric to measure the importance of partners in scientific collaboration networks. Well-established graph models such as the notion of hubs and authorities provide the basis for this work and are systematically extended to a flexible, context-aware network importance measure.

1. Introduction

Scientific collaboration in an international environment takes place among partners such as organizations, universities or research institutes to jointly perform projects. The main motivation for organizations and individual research groups to collaborate is to enable knowledge and resource sharing to effectively perform research projects. Scientific collaboration can be defined as *interaction taking place within a social context among two or more scientists that facilitates the sharing of meaning and completion of tasks with respect to a mutually shared, superordinate goal* (Sonnenwald & Cronin, 2007). Formation of coalitions and consortia is influenced by partner reputation (Fu, Hauert, Nowak, & Wang, 2008), institutional constraints, and mechanism of self-organization (Wagner & Leydesdorff, 2005). Scientific collaboration can be analyzed at the level of researchers through co-authorship and citation networks (Ding, 2011; Guns, Liu, & Mahbuba, 2011; Newman, 2004) or at the level of organizations or research institutions (Lavrac et al., 2007). Scientific collaboration and endorsement can be analyzed according to three different methods (Milojević, 2010): (i) qualitative methods such as using a questionnaire-based approach, (ii) bibliometric methods including publication and citation counting or co-citation analysis, and (iii) complex network methods including network centrality metrics such as PageRank (Page, Brin, Motwani, & Winograd, 1998) or Hyperlink Induced Topic Search (HITS) (Kleinberg, 1999).

Here we focus on the analysis of scientific collaboration at the organizational or institutional level. We apply complex network methods to automate the analysis of 'network importance' in scientific collaboration. Complex network methods need to be enhanced to consider contextual information and the 'sociability' of individual collaboration partners. Sociability in this work is characterized as the tendency of a company or institution to perform multiple projects with the same partner. We propose a model for importance that is based on well-established techniques such as the notion of hubs and

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authorities (Kleinberg, 1999) and PageRank (Page et al., 1998). PageRank can be personalized (Page et al., 1998) to estimate node importance with regards to certain topics (Haveliwala, 2002; Haveliwala, Kamvar, & Jeh, 2003; Jeh & Widom, 2003). After the seminal work of Page et al. (1998) and the far-reaching work of Haveliwala (2002), related research addressed, for example, efficient computation of personalized PageRank (Chakrabarti, 2007; Fogaras, Csalogany, Racz, & Sarlos, 2005) and a generalization of personalized PageRank for bipartite graphs (Deng, Lyu, & King, 2009). Our previous work addressed PageRank personalization techniques for expertise ranking in a social network context (Schall, 2012a, 2012b). Here we propose a unified HITS/PageRank model that is able to measure network importance at the individual as well as the organizational or institutional level with respect to a certain context.

The proposed model is tested with data from the ICT research projects having received grants under the EU's Seventh Framework Programme (FP7) (Munisteri, 2012). The data covers a period from 2007 to 2011. Research projects have multiple partners and an organization can be the partner of multiple projects. In this work, participation of a partner in a research project is understood as a carrier of authority and corresponds to *partner importance*.

2. Partner importance model

2.1. Hubs and authorities

Here we provide a description of the basic approach and model. A project is regarded as important if the partners contributing to it are also regarded as important (e.g., knowledgeable and reputable). In turn, the importance of a partner is based on it's involvement in important projects. This is a recursive definition of importance and can be modeled by using the intuitive notion of hubs and authorities as proposed by Kleinberg (1999). Assume the set of projects V_R with $r \in V_R$ and the set of organizations V_U with $u \in V_U$:

$$A(u) = \sum_{(r,u) \in E} H(r) \qquad H(r) = \sum_{(r,u) \in E} A(u) \tag{1}$$

The set E depicts the project involvement relations $(r, u) \in E$ of an organization u in project r. In the model, an organization u obtains an authority score depicted by $A(u)$ and a project r obtains a hub score denoted by $H(r)$. The drawback of this model is the 'stability' of rankings. A ranking algorithm is stable if the algorithm returns similar results upon small disturbances. We follow the *randomized HITS* approach as proposed in (Ng, Zheng, & Jordan, 2001) and expand the equations as follows:

$$A(u) = (1-\lambda_a)p(u) + \lambda_a \sum_{(r,u) \in E} H(r) \qquad H(r) = (1-\lambda_h)p(r) + \lambda_h \sum_{(r,u) \in E} A(u) \tag{2}$$

The adjusted model is a natural way of designing a random-walk based algorithm following the HITS model. The randomized HITS approach is, like PageRank, stable to small perturbations (Ng et al., 2001). The symbols $p(u)$ and $p(r)$ depict personalization vectors that may be assigned uniformly for each node such that $p(u) = \frac{1}{|V_U|}$ and $p(r) = \frac{1}{|V_R|}$. Non-uniform personalization vectors result in personalized rankings. The parameters λ_a and λ_h with $0 \leq \lambda \leq 1$ allow for balancing between authority/hub weights and personalization weights. A typical value for λ is 0.85 (Page et al., 1998). Assigning lower values to λ means that higher importance is given to the personalization weights; thereby reducing the '*network effect*' of the ranking algorithm.

2.2. Contextual partner importance

The idea of our contextual partner importance ranking approach is to compute ranking scores with respect to certain *areas of expertise*. The demanded areas of expertise are passed via the keyword based query $Q = \{q_1, q_2, \ldots, q_n\}$ to the ranking algorithm. Each query keyword q_n corresponds to a desired area of expertise. A query returns a ranked list of organisations based on the demanded set of expertise areas. Let us define the query sensitive authority score $A(u\,; Q)$ and the query sensitive hub score $H(r\,; Q)$ as follows:

$$A(u; Q) = (1-\lambda_a)p(u; Q) + \lambda_a \sum_{(r,u) \in E} w_{ru} H(r; Q) \tag{3}$$

$$H(r; Q) = (1-\lambda_h)p(r; Q) + \lambda_h \sum_{(r,v) \in E} w_{rv} A(v; Q) \tag{4}$$

The weights w_{ru} and w_{rv} respectively are edge weights based on the organizations' project involvement. To compute authority scores using a single equation we substitute $H(r\,; Q)$ in Eq. (3) by Eq. (4) and have:

$$A(u; Q) = (1-\lambda_a)p(u; Q) + \lambda_a(1-\lambda_h) \sum_{(r,u) \in E} w_{ru} p(r; Q) + \lambda_a \lambda_h \sum_{(r,u) \in E} \sum_{(r,v) \in E} w_{ru} w_{rv} A(v; Q) \tag{5}$$

Based on Eq. (5), let us define the personalization vector $p'(u\,;Q)$ as follows:

$$p'(u;Q) = \frac{1-\lambda_a}{1-\lambda_h} p(u;Q) + \lambda_a \sum_{(r,u)\in E} w_{ru} p(r;Q) \tag{6}$$

If $\lambda_a = \lambda_h$, Eq. (6) can be simplified to:

$$p'(u;Q) = p(u;Q) + \lambda \sum_{(r,u)\in E} w_{ru} p(r;Q) \tag{7}$$

In the following step we rewrite Eq. (5) by using the personalization vector $p'(u\,;Q)$ as defined in Eq. (7).

$$A(u;Q) = (1-\lambda) p'(u;Q) + \lambda^2 \sum_{(r,u)\in E} \sum_{(r,v)\in E} w_{ru} w_{rv} A(v;Q) \tag{8}$$

Eq. (8) has a PageRank-like structure. An important tool for personalization based on the PageRank model is the *linearity theorem* as introduced in Haveliwala (2002). For any personalization vectors p_1, p_2 and weights w_1, w_2 with $w_1 + w_2 = 1$, the following equality holds:

$$\mathrm{PPV}(w_1 p_1 + w_2 p_2) = w_1 \mathrm{PPV}(p_1) + w_2\, \mathrm{PPV}(p_2) \tag{9}$$

The linearity theorem states that personalized PageRank vectors *PPV* can be composed as the weighted sum of PageRank vectors. Eq. (10) shows how to derive the weighted sum of personalized authority ranking scores using Eq. (8). The goal is to obtain a structure as depicted by the right part of Eq. (9).

$$\begin{aligned} A(u;Q) &= (1-\lambda) p'(u;Q) + \lambda^2 \sum_{(r,u)\in E} \sum_{(r,v)\in E} w_{ru} w_{rv} A(v;Q) \\ &= (1-\lambda) \sum_{q\in Q} w_q p'(u;q) + \lambda^2 \sum_{(r,u)\in E} \sum_{(r,v)\in E} \sum_{q\in Q} w_{ru} w_{rv} w_q A(v;q) \\ &= \sum_{q\in Q} w_q (1-\lambda) p'(u;q) + \sum_{q\in Q} w_q \lambda^2 \sum_{(r,u)\in E} \sum_{(r,v)\in E} w_{ru} w_{rv} A(v;q) \\ &= \sum_{q\in Q} w_q [(1-\lambda) p'(u;q) + \lambda^2 \sum_{(r,u)\in E} \sum_{(r,v)\in E} w_{ru} w_{rv} A(v;q)] \\ &= \sum_{q\in Q} w_q [A(u;q)] \end{aligned} \tag{10}$$

The weight w_q is associated with a particular keyword q with $w_q = 1/|Q|$ for uniform weights and $\sum_q w_q = 1$. The proposed model brings the following important benefits:

- Ranking scores for individual expertise areas can be precomputed and saved in a database (offline computation). For large networks, the computation of ranking scores may take a long time depending on available hardware and resources.
- Once a concrete expert query is formulated, the saved (precomputed) ranking scores can be retrieved and aggregated to a composite score (online calculation).

2.3. Personalization metrics

Here we define various metrics to calculate weights and personalization vectors. In our model, the personalization vector for projects $p(r)$ is assigned as $p(r) = \mathrm{funding}(r)/\sum_{r'\in V_R} \mathrm{funding}(r')$ where funding(r) depicts the monetary funding received by project r. For simplicity, we do not consider Q for the project-based personalization vector. The edge weight w_{ru} is based on the funding received by partner u in project r and is calculated as $w_{ru} = \mathrm{funding}(r, u)/\sum_{v\in adj(r)} \mathrm{funding}(r, v)$ where $adj(r)$ depicts the set of nodes adjacent to r (i.e., the set of partners involved in project r). Next we discuss the computation of the organization specific personalization vector. Assume α is an expertise area and $p(u\,;\alpha)$ is the corresponding personalization vector. Notice, at query time α is matched against q to compute $A(u\,;q)$ as described previously.

The vector $p(u\,;\alpha)$ is composed of two components: *context weight* with respect to α and a weight to measure the *sociability* of a given organization. To measure the context weight, we create keyword-based organization profiles obtained through the project descriptions they are involved in. Each profile keyword is associated with a frequency depending on the keyword's appearance in projects descriptions. An expertise area α can be composed of a single or multiple keywords. The context weight is given as $c-weight(u;\alpha) = \sum_{kw\in\alpha} f(kw, u)/\sum_{v\in O(\alpha)} \sum_{kw\in\alpha} f(kw, v)$. For brevity, let $O(\alpha) = match(V_U\,;\alpha)$ be the set of organizations matching the expertise area α. The variable kw depicts a keyword, $f(kw, u)$ the keyword frequency of the given keyword kw of the organization u. The second part of the organization specific personalization vector is *sociability*. The derive sociability based on the idea of the h-index (Hirsch, 2005). Recall, h-index is based on the idea that a scientist has index h if h of his/her papers have at least h citations each. In a similar spirit, an organization has sociability s if s of its projects have

Table 1
Exemplary data to illustrate calculation of personalization weights.

Project	Partner	Funding	Expertise area
Project A	Org1	100	services
Project A	Org2	200	services
Project B	Org2	200	internet
Project B	Org3	100	internet
Project C	Org1	300	services
Project C	Org2	100	services
Project C	Org3	50	services

been performed s-times with the same partner. The vector $p(u\,;\alpha)$ is given as $p(u;\alpha) = w_1 c - weight(u;\alpha)/max(c - weight) + w_2 sociability(u)/max(sociability)$ with $w_1 + w_2 = 1$. The function max yields the numerically largest value of c-weight and sociability respectively.

2.3.1. Illustrative example

Here we give an example of how the personalization metrics are calculated and assigned. Let us suppose a collaboration scenario as depicted in Table 1 (see also Fig. 1).

Table 1 lists three projects and three organizations. Each organization participates in projects and receives funding. Each project is also associated with a particular expertise area. In our simple case, each project's expertise area is identified by a simple string. The total amount of funding received by Project A is 300, Project B 300 and Project C 450. The total funding is 1050 calculated as the sum of each project's funding.

Based on the project involvement in Table 1 the graph as depicted in Fig. 1 can be constructed. A project is depicted by a circle and a partner by a rectangle (because they are different types of nodes). Projects are surrounded by dashed circles based on the expertise area.

- *Edge weights.* The weight of an edge from a project to a partner is based on the funding the partner receives. For example, the weight w_{A1} of the edge pointing from Project A to Org1 is calculated as $w_{A1} = 100/300 = 0.33$ (see also right hand side of Fig. 1).
- *Project personalization vector.* As explained before, the project specific personalization vector is given as $p(r) = \text{funding}(r)/\sum_{r' \in V_R} \text{funding}(r')$ (i.e. the project funding divided by the total funding available). In our case, the personalization weights are given as: Project A has $p(A) = 300/1050 = 0.29$, Project B has $p(B) = 300/1050 = 0.29$, and Project C has $p(C) = 450/1050 = 0.43$.
- *Context weight.* As a next step the organization profiles based on the project involvement can be constructed. This is done by counting the frequency of the organizations' involvement in a specific expertise area. Table 2 lists the organization expertise area profiles. As an example, Org1 was involved in a services related project and thus the weight is calculated as $2/(2+2+1) = 0.4$.

  Recall that $c - weight$ is divided by $max(c - weight)$ so the resulting context weights for both 'service' and 'internet' and shown in Table 3.

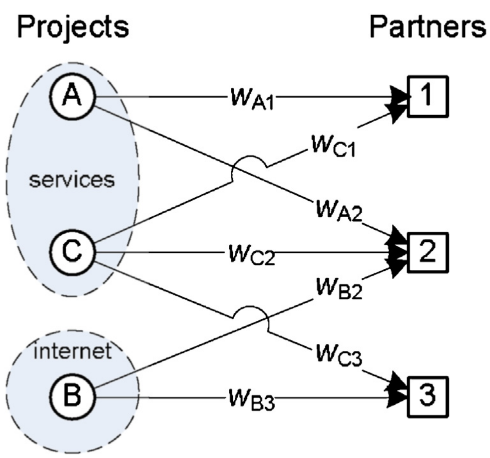

Fig. 1. Example project/partner graph and edge weights between projects and partners.

Table 2
Organization expertise area profiles.

Partner	Expertise area	Weight
Org1	Services	0.40
Org2	Services	0.40
Org2	Internet	0.50
Org3	Internet	0.50
Org3	Services	0.20

Table 3
c – Weights for combined expertise areas ‘service’ and ‘internet’.

	Org1	Org2	Org3
Aggregated weight	0.40	0.90	0.70
c – Weight	0.44	1.00	0.78

Table 4
Partner specific personalization weights.

Partner	Personalization weights
Org1	$0.5 \times 0.44 + 0.5 \times 0.50 = 0.47$
Org2	$0.5 \times 1.00 + 0.5 \times 1.00 = 1.00$
Org3	$0.5 \times 0.78 + 0.5 \times 0.50 = 0.64$

- *Sociability*. Sociability is based on the idea of the h-index and in our example is given: Org1 with 1, Org2 with 2 and Org3 with 1. Recall also that sociability is divided by *max*(sociability) and thus the final sociability results are Org1 with 0.5, Org2 with 1, and Org3 with 0.5.
- *Partner personalization vector*. By combining *c – weights* and sociability with equal weights we have the following final personalization scores with respect to ‘service’ and ‘internet’ in Table 4:

Note that the personalization weights are not the final ranking scores. These weights are used to assign the personalization vectors for each partner. The ranking model as previously defined in Eqs. (8) and (10) calculates partner importance scores by using the project and partner specific personalization vectors (the bias towards a specific network node).

3. Results and discussion

In this section we present results based on the data as described in (Munisteri, 2012). To date, the FP7 ICT program has allocated funding to 1469 projects for a total Union funding of 4,979,301,152 Euro. This results in 14,781 participations by 4718 distinct legal entities.

The top 20 ranking results are depicted by Table 5. The first column depicts the rank, the second column the organizations’ name, the third column the number of the organizations’ projects as indegree, the forth column the context weight based

Table 5
Ranking results using query keywords ‘services’ and ‘internet’.

Rank	Organization	Indegree	*c – Weight*	Sociability	r-Change (funding)	r-Change (HITS)
1	TELEFONICA INVESTIGACION Y DESARROLLO SA	76.0	0.0320	2	−4	−9
2	FRAUNHOFER-GESELLSCHAFT	272.0	0.0284	2	1	1
3	SAP AG	68.0	0.0286	2	0	−11
4	INSTITUTE FOR BROADBAND TECHNOLOGY	31.0	0.0119	4	−59	−50
5	ATOS ORIGIN SOCIEDAD ANONIMA ESPANOLA	62.0	0.0185	3	−19	−19
6	FRANCE TELECOM SA	46.0	0.0154	3	−40	−9
7	UNIVERSITY OF SURREY	47.0	0.0151	3	−7	−12
8	TELECOM ITALIA S.p.A	31.0	0.0153	3	−73	−25
9	DEUTSCHES ZENTRUM FUER LUFT/RAUMFAHRT	37.0	0.0066	4	−19	−56
10	UNIVERSITY OF ATHENS	31.0	0.0047	4	−72	−47
11	UNIVERSITY OF ESSEX	18.0	0.0040	4	−147	−83
12	INTERUNIV. MICRO-ELECTRONICA CENTRUM	90.0	0.0032	4	8	6
13	NOKIA SIEMENS NETWORKS	12.0	0.0037	4	−227	−133
14	CONSIGLIO NAZIONALE DELLE RICERCHE	96.0	0.0111	3	5	6
15	INRIA	94.0	0.0190	2	4	11
16	UNIVERSITAET STUTTGART	39.0	0.0111	3	−25	−28
17	ALCATEL-LUCENT BELL LABS FRANCE	21.0	0.0107	3	−90	−50
18	TECHNISCHE UNIVERSITAET DRESDEN	43.0	0.0098	3	−17	−48
19	UNIVERSIDAD POLITECNICA DE MADRID	65.0	0.0178	2	−13	−1
20	ALCATEL-LUCENT DEUTSCHLAND AG	25.0	0.0091	3	−36	−36

on the query keywords 'services' and 'internet' (to illustrate the impact of personalization), the fifth column the sociability, the sixth column the ranking change when organizations are ranked based on the funding they received, and finally the ranking change when organizations are ranked by the standard HITS model (cf. Eq. (1)). The columns r-change are calculated as the rank of a given organization based on the presented contextual partner importance approach minus the rank from traditional ranking models. These models include a funding based rank (organizations are ordered by the total amount of funding they receive – see also Munisteri, 2012) and the standard HITS model. This allows us to compare the impact of personalization.

$$\text{r-change} = \begin{cases} \text{negative sign} & \text{if } u \text{ is ranked higher by } A(u;Q) \text{ than by the funding based rank or HITS} \\ \text{positive sign} & \text{if } u \text{ is ranked lower by } A(u;Q) \text{ than by the funding based rank or HITS} \\ 0 & \text{otherwise} \end{cases}$$

The proposed contextual partner importance approach delivers better results with regards to the specified query context $Q = \{\text{'services'}, \text{'internet'}\}$ when compared with a funding based ranking. This is evident by looking at the principle expertise of the top-ranked organizations. All top-ranked organizations have a context weight c-weight greater than 0. This means that all organizations have performed some projects related to the specific expertise areas depicted by Q. Sociability has changed the rank of the organizations at positions between 9 and 13. Sociability mostly improved the rank with regards to Q (the organization at 12 was ranked at a lower position).

With respect to the standard HITS model, the proposed partner importance model also resulted in significant changes in the ranking positions of partners. All positions within the top-20 ranking results have been reordered (with r-change $\neq 0$). The query context Q (and thus personalization) has significant impact on partner ranks. Indeed, this is the desired behavior because not only 'global' network importance is significant for partner selection but also expertise with regards to specific expertise areas. The partners in Table 5 are all experienced in the context 'services' and 'internet' (c-weight greater than 0). Thus, the model is able to capture the notion of contextual partner importance.

4. Conclusions

The proposed model provides a valuable tool for context-based partner importance ranking. The model is flexible and can be parameterized by various metrics. The presented results demonstrate the applicability of the ranking model in a real science collaboration network consisting of numerous partners performing joint projects in the EU FP7 ICT context. The next steps in this research include the detailed analysis of different parameters and personalization metrics. Different queries need to be formulated and the results need to be compared in a systematic manner. We also plan to compare the results with other well-established academic rankings (e.g., the 'Shanghai Ranking'). Another aspect of future work will be the application of online team formation algorithms (Anagnostopoulos, Becchetti, Castillo, Gionis, & Leonardi, 2012) to scientific collaboration networks to suggest competitive alliances and consortia.

References

Anagnostopoulos, A., Becchetti, L., Castillo, C., Gionis, A., & Leonardi, S. (2012). Online team formation in social networks. In *Proceedings of the 21st international conference on World Wide Web (WWW'12)* ACM, New York, NY, USA, (pp. 839–848).

Chakrabarti, S. (2007). Dynamic personalized pagerank in entity-relation graphs. In *Proceedings of the 16th international conference on World Wide Web (WWW'07)* ACM, New York, NY, USA, (pp. 571–580). http://dx.doi.org/10.1145/1242572.1242650

Deng, H., Lyu, M. R., & King, I. (2009). A generalized co-hits algorithm and its application to bipartite graphs. In *Proceedings of the 15th ACM SIGKDD international conference on knowledge discovery and data mining (KDD'09)* ACM, New York, NY, USA, (pp. 239–248). http://dx.doi.org/10.1145/1557019.1557051

Ding, Y. (2011). Scientific collaboration and endorsement: Network analysis of coauthorship and citation networks. *Journal of Informetrics*, *5*(1), 187–203.

Fogaras, D., Csalogany, K., Racz, B., & Sarlos, T. (2005). Towards scaling fully personalized pagerank: Algorithms, lower bounds, and experiments. *Internet Mathematics*, *2*(3), 333–358.

Fu, F., Hauert, C., Nowak, M. A., & Wang, L. (2008 August). Reputation-based partner choice promotes cooperation in social networks. *Physical Review E*, *78*, 026117.

Guns, R., Liu, Y., & Mahbuba, D. (2011). Q-measures and betweenness centrality in a collaboration network: A case study of the field of informetrics. *Scientometrics*, *87*(1), 133–147. http://dx.doi.org/10.1007/s11192-010-0332-3

Haveliwala, T., Kamvar, S., & Jeh, G. (2003). *An analytical comparison of approaches to personalizing pagerank*. Tech. rep., Stanford University.

Haveliwala, T. H. (2002). Topic-sensitive pagerank. In *Proceedings of the 11th international conference on World Wide Web (WWW'02)* ACM, New York, NY, USA, (pp. 517–526). http://dx.doi.org/10.1145/511446.511513

Hirsch, J. E. (2005). An index to quantify an individual's scientific research output. *Proceedings of the National Academy of Sciences of the United States of America*, *102*(46), 16569–16572.

Jeh, G., & Widom, J. (2003). Scaling personalized web search. In *Proceedings of the 12th international conference on World Wide Web (WWW'03)* ACM, New York, NY, USA, (pp. 271–279). http://dx.doi.org/10.1145/775152.775191

Kleinberg, J. (1999). Authoritative sources in a hyperlinked environment. *Journal of the ACM*, *46*, 668–677.

Lavrac, N., Ljubic, P., Urbancic, T., Papa, G., Jermol, M., & Bollhalter, S. (2007 May). Trust modeling for networked organizations using reputation and collaboration estimates. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, *37*(3), 429–439.

Milojević, S. (2010 July). Modes of collaboration in modern science: Beyond power laws and preferential attachment. *Journal of the American Society for Information Science and Technology*, *61*(7), 1410–1423.

Munisteri, F. (2012 February). *ICT statistical report for annual monitoring 2011*. http://ec.europa.eu/digital-agenda/sites/digital-agenda/files/stream_2012_0.pdf

Newman, M. E. J. (2004). Coauthorship networks and patterns of scientific collaboration. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(Suppl. 1), 5200–5205.

Ng, A. Y., Zheng, A. X., & Jordan, M. I. (2001). Stable algorithms for link analysis. In *Proceedings of the 24th annual international ACM SIGIR conference on research and development in information retrieval (SIGIR'01)* ACM, New York, NY, USA, (pp. 258–266).

Page, L., Brin, S., Motwani, R., & Winograd, T. (1998). *The pagerank citation ranking: Bringing order to the web*. Tech. rep., Stanford University.

Schall, D. (2012a]). Expertise ranking using activity and contextual link measures. *Data and Knowledge Engineering*, *71*(1), 92–113.

Schall, D. (2012b]). *Service oriented crowdsourcing: Architecture, protocols and algorithms*. *Springer Briefs in Computer Science* New York, NY, USA: Springer.

Sonnenwald, D. H., & Cronin, B. (2007). Anonymous, scientific collaboration: A synthesis of challenges and strategies. In *Proceedings of the annual review of information science and technology, vol. 4th, Information Today* (pp. 2–37).

Wagner, C. S., & Leydesdorff, L. (2005). Network structure, self-organization, and the growth of international collaboration in science. *Research Policy*, *34*(10), 1608–1618.