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Exploring Citations for Conflict of Interest Detection in Peer Review System

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***Abstract*: Peer review in scientific communications plays an important role in the advancement of any given field of study. However, different sorts of conflict of interest (COI) situations between authors and reviewers can compromise the review decision. Current COI detection systems primarily rely on co-authors networks, inferred from publicly available bibliographic databases as an implicit measure of collaborative and social relationships between researchers. However, different citations relationships have also been claimed to be indicative of various social and cognitive relationships between authors. This can be useful to identify those hidden relationships that can not be handled by traditional systems. This paper is an effort in the direction where we investigate to find any pattern in citations that can predict existence or non-existence of social relationships. It also explores citations relationships as a potential indicator of different types of cognitive relationships between researchers.**

Keywords: peer review, conflict of interest, socio-cognitive, bias, cognitive distance, citations**.**

I. Introduction

The peer review of manuscripts in journals and conferences is considered as a basis for the advancement of any discipline. Despite the criticisms on peer review process such as: objectivity problem, breach in secrecy, conflict of interest and delays in review time [1], [2], it is widely accepted among scientific community because people seek some form of guarantee that the published manuscripts are trustworthy [2], [3]. There are also other methods of scholarly communications such as pre-prints, but in the absence of any quality assurance system, the quality of the work is primarily judged by readers themselves, which requires extra efforts from them [4].

Conflict of Interest (COI) in the context of peer review is a situation that can influence the decision of a reviewer. There are many types of COIs that can exist between any particular reviewer and author such as: same affiliation, collaborators, colleagues, friends, family member, financial relationships, personal beliefs and last but not least scientific COIs [5].

The COI detection problem is usually addressed manually on the basis of declarations from the reviewers or authors. The process of currently available automated COI detection systems depends on analyzing the social relationships of authors and reviewers. These social relationships are typically derived from the collaborative information of authors, which is explicitly available in the form of co-author, co-editor and co-affiliation relationships in publicly available bibliographic databases. For example, the system introduced by [6] uses the suffix of email addresses in addition to previous co-authorship relations inferred from DBLP (Digital Bibliography & Library Project) as a measure to determine potential COIs. Similarly, the authors in [7] integrated social networks of researchers from DBLP and FOAF (friend of a friend) documents by using ontologies to disambiguate authors, and developed an algorithm for the detection of possible COIs. But the problem with these automated approaches is that they consider only certain COI situations, such as co-authors and co-affiliations and ignore other types of COIs. Moreover, they are based on a limited portion of co-authors inferred from publicly available databases as all papers from a particular author are not necessarily indexed by these databases. Some social networking websites, e.g., LinkedIn.com, MySpace.com, Facebook.com can also provide implicit or explicit social information of people to detect COIs, but the integration and privacy concerns of these sites put a limitation to utilize this enriched opportunity [7]. The authors in [8], [9] introduced automated approaches that can be used to extract social networks of academic researchers by querying the web. These methods are not feasible for large number of entities pairs due to the costly processing of text for large number of web pages. Although the link analysis on a network of homepages is another possibility that can be utilized to predict the communities of people and the context of their relationships [10], but finding people homepages is challenging and it is not necessary that every person has a homepage and that it contains links to other people [11]. However, some bibliographic digital libraries such as CiteSeer [12] often present other attributes of a particular author that can be explored for COI detection. One of the most interesting components is the citation relationship.

In literature, different citations relationships have been claimed to be indicative of both social and cognitive relationships between researchers. This paper works in this direction and explores the potential of citations relationships to improve the existing COI detection approaches as an additional or alternative mean to identify possible social and cognitive biases in peer review system.

The rest of the paper is organized as follows: Section II provides a brief overview about the peer review system and its different types. In section III, we describe different types of COI situations that can exist between researchers and broadly classify them in two categorize, i.e. social and cognitive COIs. We also provide a brief summary about citations theory in section IV and describe earlier studies reporting citations relationships as an indicator of social and cognitive acquaintanceships. In section V, we describe our detailed experiments to predict the existence of social relationships from citations relationships. Similarly, in section VI, we discuss the potential of citations relationships as an indicator of cognitive distance between our selected authors and reviewers from WWW2006 conference. We further describe different contexts and sentiments that can be assigned to these cognitive relationships. We report our experiments to highlight the possibility of automated prediction of these context and sentiments. These contexts and sentiments in turn can help in spotlighting the possible severity of cognitive COIs between authors and reviewers.

II. The Peer Review System

The peer review in scholarly journals is in practice at least from 1752 [13]. In the peer review process, the experts and experienced researchers scrutinize the papers to be published by examining their quality [5]. Their objective reviews and comments establish standards in a particular field [5]. However, there are also various shortcomings in this process such as: objectivity, breach in secrecy, conflict of interest and delays in review time [1], [2]. In literature, various types of peer review models have been proposed to overcome these deficiencies. These models broadly vary from complete blind review to full open reviews [13]. A detailed discussion about these models can be found in an editorial by Kundzewicz and Koutsoyiannis [13]. According to the authors in [13], the most widely opted option among scholarly communities is half blind review. In this model the names of reviewers are kept anonymous [13]. The authors further pointed out that this model is prone to some problems that include: subjectivity, bias, abuse, frauds, and misconduct. The open peer review tries to overcome few shortcomings of half blind review, such as bias and abuse by declaring names of both authors and reviewers [13]. However, the reviewers in most of the cases hesitate to expose their identity due to various reasons, e.g., criticizing work of a person in power or a friend or colleague, to protect self-image where superficial reviews have been done due to time constraints or uninteresting topic [13], [14]. In a study, conducted by Dolan [15] for Aquatic Microbial Ecology journal, the author found that 54% of the reviewers prefer anonymity while only 8% were ready to expose their identity. Another peer review model consisting of complete blind or double blind review is believed to tackle bias and discrimination in peer review by hiding the names of both authors and reviewers from each other [13]. However, according to the authors in [13], this method is technically costly and contains many problems to operationalize, and the removal of name and affiliation of authors from the article cannot guarantee the anonymity of the authors. The authorship of a paper in some cases can be guessed by hidden information in terms of self-citations or sentences about previous publications, which cannot always be removed from the manuscript [13]. In some cases, the authors and reviewers are working on the same problem and know each other in advance. These scenarios can be exemplified by a real life experiment conducted for the British Medical Journal, where the reviewers were able to identify anonymous authors of manuscripts in 42% of the cases [16]. With the advent of World Wide Web, a new concept of interactive journals is emerging [4], [17]. The interactive journals employ two step procedure where in first step the submitted manuscript is discussed in an open forum by the community [4]. The article is revised by the author for improvements on the basis of recommendations from the community, and in the next step the article is submitted to the standard peer review system [4]. By engaging a large number of community members, this system can greatly reduce the reviewers' workload and can provide variety of different comments for author [4]. However, this system has the tendency to overwhelm author with too many superficial and redundant reviews [4]. Furthermore, the researchers sometimes are reluctant to engage with such pre-prints that have not yet evaluated [13].

III. Conflict of Interest in Peer Review System

In any peer review system, reviewers' identification has always remained a challenging task to review a manuscript. The editors and conferences organizers usually rely on their personal knowledge, literature search and professional networks to select appropriate reviewers for submissions [5]. The expertise of the reviewer in the relevant field is the most important selection criteria [5]. In literature, there are also various algorithms [18-20] for the automated discovery of reviewers. These algorithms usually involve matching reviewers' research interests and articles' material [21]. Recently, authors in [21] introduced a robust algorithm that utilizes the co-authors networks in references of a manuscript and proposes potential reviewers by assigning each of them a context-sensitive weight.

During the peer review process, the reviewers sometimes are presented by an awkward situation known as "conflict of interest" [5]. The Conflict of Interest (COI) can be broadly defined as *"a situation in which personal interests could compromise, or could have the appearance of compromising, the ability of an individual to carry out professional duties objectively"* [22]. The presence of COI between authors and reviewers in the context of peer review can influence the decision of a reviewer. In literature, many types of COIs between an author and a reviewer have been identified which can be broadly classified in two categories, i.e., Social and Cognitive. However, the boundary between these categories is blurred and not always neatly separable. The social COI situations impose some degree of acquaintanceship between authors and reviewers, such as same affiliation, collaborators, colleagues, friends, family members, financial relationships, employer and employee, people in power, and even disliked people [5]. The cognitive COI on other hand depends upon the cognitive contents of the reviewer. A strong personal, ethnic, religious belief of reviewer can really affect the evaluation of a manuscript [5]. Similarly, researchers in some cases promote their own field and give favor to work that conforms their hypothesis or theory, and may decline any competitive work.

IV. Citations Theory

Citations were first used as a unit of analysis in the field of bibliometrics and scientometrics to evaluate the performance of individuals, journals, departments, research laboratories and nations [23-28]. Although some researchers believe the applicability of citations counts as an implicit measure of intellectual and scientific impact, but there are several studies that doubt its use. This is due to the dependence of citations counts on various factors, such as time, field, journal, article type, language, and availability [28]. However, the main criticism on citations counts is due to its lack of capability to highlight the motivation of citers [28]. According to this camp of researchers, the use of citations counts as a measure of scientific impact is only applicable if the citing author has really used the cited document and citation is truly depicting its significance and quality [28], [29].

Authors often cite each other due to various reasons, such as related work, competitive work, extension of previous work, to name a few. One of the first works describing the citations motives was done by Garfield in 1962 [30]. The motive behind citations has always remained debatable between researchers. The citations between authors are usually considered to be representative of intellectual influence [31], [32]. However, the authors in [33], [34] found that the repetitive citations can also highlight various social acquaintanceships between authors. This might be due to the fact that researcher within a discipline or across disciplines usually work together to achieve specific tasks, one output of which is inter-citation [35]. In this context, the notion of “invisible college” is really important where scientists (even geographically distant) gather together to achieve specific tasks by using both formal and informal communications [36]. With the advent of new technologies and concepts, such as blogs, wikis, file sharing, instant messaging, emails, open access initiatives, these invisible colleges are really emerging. Cronin [37] further emphasized about the social dimension of citations motive as follows:

“there is a battery of social and psychological reasons for citing, which may have as much to do with, for instance, rhetorical gamesmanship (persuading the reader of one’s viewpoint through selective under- or over-citation) or strategic coat-tailing (citing friends, immediate colleagues or celebrity authors) as with the topical appropriateness or semantic suitability of the citations themselves”.

Half a century ago, Kessler [38] and Small [39] introduced bibliographic coupling and documents co-citation as a measure to group documents thematically. In [40], the authors introduced a new technique called authors co-citations to understand the intellectual structure of a discipline by grouping co-cited authors together, who work on similar themes as seen by citers. Recently, the authors in [41] studied author’s bibliographic coupling as a complementary approach of author’s co-citations to reveal the current internal structure of a discipline by grouping authors thematically. The authors’ co-citation studies have also been claimed to be representative of social relationships between pairs of authors [42], while authors' bibliographic coupling until now has only been studied from the perspective of cognitive distance [41].

In the context of COI detection, one can conclude from the discussion of this section that different citations relationships between authors have the capability to highlight the possibility of both cognitive and social biases in peer review system.

V. Citations as Predictor of Socio-Cognitive Relationships

The citations and social relationships of authors often overlap up to some extent usually due to socio-cognitive ties between authors [35]. This overlap can be depicted by a hypothetical Venn diagram as shown in Fig. 1. The socio-cognitive is a special term used by White [35] to describe the relationship between any two authors, where both authors have intellectual as well as some kind of social relationship with each other. The co-authors, colleagues, student/mentor and editors/contributo-rs are few examples of socio-cognitive ties.

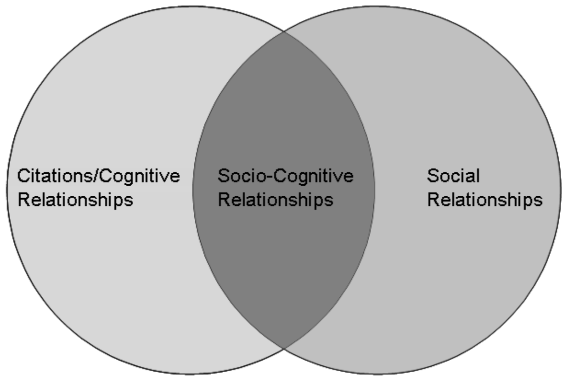

Figure 1. Structure of social, citations/cognitive and socio-cognitive relationships.

This section works in this direction and explores to discover any pattern in citations relationships that can act as a predictor to identify these socio-cognitive relationships. The current investigation is limited to two types of socio-cognitive relationships, i.e., co-authors and co-affiliation/collegial relationships. Moreover, it also investigates, which particular citation relationship or group of citations relationships can act as a good predictor for such socio-cognitive relationships. The results of this study in turn can help in improving existing COI detection approaches by exploiting citations as an additional or alternative means to determine socio-cognitive relationships between authors and reviewers. Some preliminary results gathered from this study have also been reported in our previous paper [43].

A. Design of the Study

1) Citations and Socio-Cognitive Measures

In this study, different citations measures have been used, i.e., co-cited, co-cites and cross-cites. These measures will be referred as basic citations measures in the rest of this study. The details about these measures are as follows:

-Co-Cited. The co-cited is the frequency that two authors have been cited together in literature, independent of the contents of the cited documents.

Table 1. List of randomly selected primary authors for experiments.

Sr. No.	Name	Co-Authors	Papers	Inward Citations	Outward Citations
1	Micha Sharir	64	188	1234	949
2	Marc Moonen	69	24	271	333
3	Wim H. Hesselink	24	37	46	48
4	Rainer Lienhart	35	35	126	83
5	Franz Baader	58	141	125	804
6	Peter Bro Miltersen	50	74	242	187
7	Minyue Fu	42	58	45	69
8	Panos Constantopoulos	32	116	272	543
9	Jian Shen	21	31	48	41
10	Prabhakar Raghavan	95	191	1721	542
11	Sanjoy Baruah	33	56	135	323
12	M. Tamer	44	102	265	282
13	Tapas Kanungo	42	61	167	184
14	Ljubomir Josifovski	16	17	43	63
15	Ellen W. Zegura	42	100	1053	407
16	Eyal Kushilevitz	44	120	718	823
17	Jennifer Seberry	67	160	310	268
18	Remzi H. Arpaci-dusseau	25	54	79	579
19	Ferenc A. Jolesz	24	63	223	136
20	B. R. Badrinath	49	93	1411	540

-Co-Cites. The co-cites is the number of times that two authors cite together one or more documents. It is similar to bibliographic coupling [38], but instead of documents, authors have been taken as a unit of analysis.

-Cross-Cites. The cross-cites as its name implies represents the asymmetric number of citations that any particular author has given to any other author. There are two kinds of cross-cites relations that have been used in this study, i.e., from “primary author” to “secondary author” and vice versa. The primary authors are those randomly selected authors for whom various citations and socio-cognitive relationships have been computed. The secondary authors represent those authors that have any citations relationships with primary authors. Further details about both primary and secondary authors can be found in the forth coming sub-sections.

Two kinds of socio-cognitive relationships have been considered in this study, i.e., co-authors and co-affiliation. The details about these relationships are as follows:

-Co-Affiliation. The co-affiliation relationship symbolizes whether any two authors have ever been associated with the same organization or institution.

-Co-Authors. The co-authors relationship is further categorized in two categories, i.e., direct co-authors and indirect co-authors. The direct co-authors relationship represents whether any two authors have ever published a paper together. The indirect co-authors relationship on other hand represents the existence of any common collaborator/co-author between two authors.

These socio-cognitive relationships will be used as ground truth for the classification experiments in sections V.A.3 and V.A.4.

2) *Selection of Datasets*

In order to determine citations and socio-cognitive relationships, a free publicly available bibliographic data about publications has been used from CiteSeer as the primary input for the experiments. CiteSeer contains approximately 700,000 papers from computer and information science disciplines. It contains both inward (cited) and outward (citing) citations information, but only for those papers that are indexed in CiteSeer. There were only 337,118 unique papers (approx. 48%) that have outward citations and 196,134 unique papers (approx. 28%) having inward citations. The CiteSeer also indexes the affiliations and location information of authors. We further noticed that several papers have duplicated copies in CiteSeer, for the same year. We removed these duplicate copies based on the corresponding authors' names information, resulting in approximately 550,000 papers. Similarly, we further normalized the papers references by removing the duplication of referenced papers for any citing paper. This resulted in only one reference “to” a paper “by” a particular paper. We performed this step because it is time consuming to ensure that the duplicated references were due to the data entry mistake or due to the multiple referenced sentences to a paper by the citing paper.

In order to conduct the experiments where most of the citations, coauthors and affiliation information are available, 20 random authors were selected based on the following criteria, i.e., the authors having minimum 10 papers, 10 co-authors, 10 inward citations, 10 outward citations and at least one affiliation information. These authors will be referred as primary authors in the rest of this study. As peer reviewers are usually experts in a given domain, it is expected that they can easily meet this criteria. The Table 1 shows these primary authors and their corresponding selection attributes.

3) *Citations and Socio-Cognitive Measures Calculation*

In the first step, the papers that belong to randomly selected authors were separated from CiteSeer. Next, all the authors having any citations relationship with primary authors were determined. These authors will be referred as secondary authors in the rest of this study. The frequency of citations relationships of primary authors with secondary authors, i.e., co-cited, co-cites, cross-cites from primary to secondary author (cross-cites$_{ptos}$) and cross-cites from secondary to primary authors (cross-cites$_{stop}$) were computed. The numbers of secondary authors having any citation relationship with primary authors are summarized in Table 2.

Table 2. Number of authors having any citations relationship with primary authors.

Co-Cited	Co-Cites	Cross-Cites$_{ptos}$	Cross-Cites$_{stop}$	Total unique secondary authors
53,570	124,163	4,880	8,282	158,728

In the next step, the secondary authors that also have any socio-cognitive (co-affiliation, direct co-authors, indirect co-authors) relationship with primary authors were determined. The affiliations information of primary and secondary authors was matched using Q-Gram [66] string distance measure with a threshold of 0.90, which was chosen empirically. In order to increase the accuracy of the affiliation names matching, stop words and keywords, such as “university”, “college”, “school”, “institute”, “department” were avoided in determining similarities. As CiteSeer indexes only limited papers, the additional co-authors information has been extracted from DBLP, which contains approximately 1,940,000 bibliographic records from computer science discipline. In order to retain only original articles, the titles that correspond to “proceedings”, “symposiums”, “home page” and “workshops” were removed from DBLP. Moreover, DBLP contains very little citations and affiliation information of authors, which are not included in the experiments. The number of secondary authors having both citations and socio-cognitive relationships are shown in Table 3.

Table 3. Number of authors having both citations and socio-cognitive relationships with primary authors.

Citations and direct co-authors	Citations and affiliation	Citations and indirect co-authors	Total unique authors
1,116	2,651	11,643	12,843

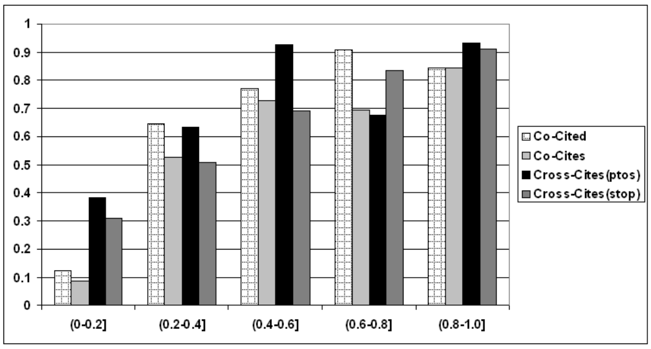

Figure. 2. Probability of socio-cognitive relationships. X-axis: normalized citations counts, Y-axis: probability.

From the various calculated citations and socio-cognitive measures, it was noticed that the probability of the existence of socio-cognitive relationship increases with the increase in the strength of citations relationships as shown in Fig. 2. The probability even approaches to more than 90 percent in the case of co-cited and cross-citations, which is quite encouraging for the development of a predictor based on citations relationships to highlight socio-cognitive relationships.

For the different citations measures that were computed from the corpus, decision tree (J-48) and Support Vector Machines (SVM) classifiers were trained and tested using WEKA [44] to predict the existence or non-existence of socio-cognitive relationships. The decision tree was chosen because of its strong capability to classify instances by branching at different values of the features. Similarly, SVM which is based on statistical learning theory has received considerable attention these days and has shown promising results in many classification problems [45]. In our experimentations, we used nonlinear SVM, which basically transforms the input features in a high dimensional space via kernel trick and creates a maximum-margin hyper-plane between them to differentiate the instances of different classes. We used Radial Basis Function (RBF) kernel for SVM and LIBSVM [46] library for SVM implementations which is also available as WEKA plug-in. The citations features belonging to each primary author were normalized ranging from 0 to 1 using the formula, i.e., $X_{new}=(X - X_{min})/(X_{max} - X_{min})$. There are also other normalization methods used in literature such as correlation, cosine similarity between two authors' citations relationships vectors. However, these approaches were adopted for limited number of authors' pairs and can be very costly in terms of computations for the current study. The target class or ground truth values in each classification experiment were given in the form of binaries, where class “yes” and class “no” represents the existence and non-existence of any socio-cognitive relationship respectively. In each classification experiment 10-fold cross validation were used in WEKA. The final classification results obtained were evaluated using Precision, Recall and F-Measure, where precision can be defined as the proportion of instances which truly belong to class x among all those instances that are classified as class x. Similarly, recall is the proportion of instances that are classified as class x, among all those instances that truly belong to class x. The F-Measure is simply a combined measure of precision and recall that can be calculated by the formula, i.e., (2*recall*precision)/(recall+ precision). The purpose of F-Measure is to obtain a single measure to characterize the overall performance of a classifier for a particular class.

It was observed that the distribution of classes “yes” and “no” in this classification experiment are extremely unbalanced. Only 8% of total citations relationships have instances for class “yes”. The input citations features are also observed to be sparse. The citations features are dense for approximately 10% of total overlapped socio-cognitive relationships. Due to the sparsity and lack of balanced dataset, it was decided to mainly focus in the training and testing of the classifiers for dense dataset where all citations features are available, and later focus on the unbalanced and sparse dataset.

The Table 4 summarizes the performance of decision tree and SVM classifiers for class “yes” and class “no”. It can be observed from the table that both classifiers performed adequately in terms of precision, recall and F-Measure for

Table 4. Precision, recall and F-Measure for class "yes" and class "no" using basic citations measures.

Decision Tree				Support Vector Machine			
Precision	Recall	F-Measure	Class	Precision	Recall	F-Measure	Class
0.79	0.92	0.85	yes	0.79	0.86	0.82	yes
0.49	0.22	0.31	no	0.38	0.27	0.31	no

Table 5. Precision, recall and F-Measure for class "yes" and class "no" using basic and temporal citations measures.

Decision Tree				Support Vector Machine			
Precision	Recall	F-Measure	Class	Precision	Recall	F-Measure	Class
0.80	0.92	0.86	yes	0.80	0.99	0.88	yes
0.54	0.27	0.36	no	0.86	0.24	0.38	no

Table 6. Precision, recall and F-Measure for class "yes" and class "no" using basic and unique papers measures.

Decision Tree				Support Vector Machine			
Precision	Recall	F-Measure	Class	Precision	Recall	F-Measure	Class
0.81	0.89	0.85	yes	0.80	0.98	0.88	yes
0.51	0.34	0.41	no	0.81	0.21	0.34	no

class "yes". However, the results of both classifiers are not satisfactory for class "no". It can be further noticed that the decision tree performed relatively better than SVM for both classes. The classifiers were also evaluated individually for direct co-authors and authors with similar affiliations, but none of them was found to be strong enough in terms of precision, recall and F-Measure. The results obtained for indirect co-authors were not too much different from the ones presented in Table 4. The possible reason for such results is due to the major proportion of indirect co-authors in collective socio-cognitive measures and substantial overlap with direct co-authors and authors with similar affiliations.

4) Extending Citations Features

After analyzing results from the experiments in previous section, it was decided to include more citations based measures. An interesting set of measures associated with citations relationships is temporal information. It is expected that academics inter-cite, co-cite or get co-cited with social acquaintances in relatively shorter period of time after publishing a paper. Similarly, the raw count of unique papers that interconnect two authors through any citations relationships may also provide useful information. It is expected that social acquaintances are usually interconnected through more than one paper via any citation relationship.

Based on these assumptions two extended sets of citations measures were defined that can be evaluated for classification in combination with basic citations measures.

The first group of measures is based on temporal information of citations. The details about these measures are as follows:

-Co-Cited Average Time. It is the average difference in the publication years of co-cited papers. However, it must be noted that if a particular paper A from one author is co-cited with more than one papers B_n of the other author. Then a paper B_i with minimum publication year will be selected for computing the difference with paper A. This measure was calculated for both primary authors and secondary authors resulting in two separate measures.

-Co-Cites Average Time. It is the average difference in the publication years of papers that co-cites together. If a particular paper A from one author co-cites with more than one papers B_n of the other author. Then a paper B_i with minimum publication year will be selected for computing the difference with paper A. This measure was calculated for both primary authors and secondary authors resulting in two different measures.

-Cross-Cite Average Time. It is the average of number of years when any author cites any paper of the other author for the first time. Similar to the basic citations relationships, this measure has been calculated from "primary author" to "secondary author" and vice versa, resulting in two separate measures.

The second group of measures is based on the unique papers that interconnect any two authors through any citation relationship. The details about these measures are as follows:

-Unique Papers Co-Cited. It is the number of unique papers of any author that has been co-cited with the papers of other author. This measure was calculated for both "primary authors" and "secondary authors" resulting in two different measures.

-Unique Papers Co-Cites. It is the number of unique papers of any author that co-cites with the papers of other author. This measure was also calculated for both "primary authors" and "secondary authors" resulting in two separate measures.

-Unique Papers Cross-Cites. It is the number of unique papers of any author that cites the papers of other author. This measure has also been calculated for both "primary authors" and "secondary authors". Similar to the basic citations relationships, this measure has been calculated from "primary author" to "secondary author" and vice versa resulting in four different measures.

The Tables 5 and 6 summarizes the performance of classifiers for both above mentioned groups in combination with basic citations measures. It can be observed from these tables that the performance of class "no" has significantly improved for SVM classifier. The classifier was able to identify instances of class "no" with more than 0.80 precision in both cases. However, the classifier was able to identify class "no" instances with 0.24 and 0.21 recall for temporal and unique papers based measures respectively.

Table 7. Precision, recall and F_Measure for class “yes” and class “no” using all citations measures.

Decision Tree				Support Vector Machine			
Precision	Recall	F-Measure	Class	Precision	Recall	F-Measure	Class
0.82	0.91	0.86	yes	0.80	0.98	0.88	yes
0.57	0.36	0.44	no	0.84	0.24	0.37	no

Similarly the results for class “yes” in each case have also increased in terms of recall (0.98-0.99) in the case of SVM. Furthermore, it can be observed that temporal information performed relatively better than unique papers based measures in terms of precision and recall for class “no”. The decision tree on other hand again did not perform adequately for class “no” in terms of precision, recall and F-measure. The classifiers were also evaluated by combining all basic and extended citations measures as shown in Table 7. However, it did not result in any significant improvement for both decision tree and SVM classifiers. The performance of classes even declined as compared to the results of temporal based citations measures in case of SVM classifier.

In summary, although our classifiers were not able to identify all the cases for class “no”, but they performed sufficiently for class “yes” and in terms of precision for class “no”. After obtaining some considerable classification results as observed in Tables 5 to 7 for SVM classifier. We decided to train and test the SVM classifier for our complete dataset (unbalanced and sparse) with all citations features (basic and extended). The results of the classifications are summarized in Table 8.

Table 8. Precision, recall and F-Measure for class “yes” and class “no” using all citations measures.

Support Vector Machine			
Precision	Recall	F-Measure	Class
0.79	0.05	0.09	yes
0.92	0.99	0.95	no

As it can be observed from the table that the classifier performed adequately for the instances of class “no” with 0.92 precision and 0.99 recall. This might be due to the extremely unbalanced class priors as mentioned earlier. Furthermore, it can be observed that the classifier was able to identify instances of class “yes” with only 0.05 recall, but with 0.79 precision.

Apart from our original hypothesis, we also used similar venues and journal titles information, text similarity of paper titles and abstracts (we used cosine vector model [47] for text similarity), location (city and country) in addition to citations information for our classification experiments, but the results did not provide any significant improvements. Similarly, we also conducted few experiments to classify the instances of direct co-authors and indirect co-authors from other instances based on their collaboration strengths as used in [7], but that also did not have very significant improvements.

From these experiments, it can be concluded that the possibility of using citations to automate the process of potential socio-cognitive relationship detection, one can only identify some proportion of possible cases with considerable precision. However, there are many other social relationships, such as friends, allies, regular correspondents, and sought advices that are not considered in this study might further improve the results.

VI. Citations as a Measure of Cognitive Distance

A. Selection of Dataset

As we discussed in section IV that different citations relationships can be indicative of both social and cognitive ties between authors. This section is an effort to explore the applicability of citations as a potential indicator of cognitive conflict of interest in peer review system. In order to demonstrate and analyze the effectiveness of using citations as a potential indicator of cognitive distance, we used the subset of authors and reviewers from the WWW2006 conference's performance track. We used the same CiteSeer database as mentioned in section V.A.2 to compute the frequency of different citations relationships, i.e., co-cited, co-cites and inter-citations for both authors and reviewers. To further understand the applicability of citations based cognitive distance measures, we also computed the co-authors network of reviewers up to two degree, i.e., direct co-authors and indirect co-authors (co-authors of direct co-authors) from CiteSeer and DBLP.

B. Weighting Citations Relationships for Cognitive Distance

Traditionally, in authors’ co-citations and bibliographic coupling, the strength of cognitive relationships has always been computed using the Pearson product-moment correlation coefficient between authors’ pairs. However, the authors in [48] highlighted the disadvantages of this approach by demonstrating the effects of adding zeros in raw co-citation counts matrix with both hypothetical and real life data. They found that the correlation coefficient value between a pair of authors may decreases with the inclusion of those authors in the matrix that do not have been co-cited with both authors. They recommended researchers to choose an appropriate association measure depending on the nature of the problem under investigation. Similarly, in the context of the COI detection, the association measures like correlation coefficient, Salton’s cosine [47] and Jaccard measure [49] between authors and reviewers may not be feasible. The reason behind this rational is that the similarity score of an author and reviewer might be low if both are even co-cited together frequently, but simultaneously co-cited with a complete or partial disjoint set of other authors or authors with small co-cited values. This can be explained with a simple hypothetical example in Table 9, where Ai represents an author and R1 represents a reviewer. The results of the different similarity measures between an author A1 and reviewer R1 can be summarized in Table 10, which is very low even with a high co-citation rate between A1 and R1.

Table 9. Hypothetical raw citation relationship matrix (5 authors and 1 reviewer in the sample).

	A1	A2	A3	A4	R1	A5
A1	-	2	0	2	55	12
R1	55	0	6	10	-	0

Table 10. Similarity counts.

Similarity Measure	Similarity Score
Pearson correlation	-0.55
Cosine Similarity	0.01
Jaccard Index	0.003

Based on the results in Table 10, it was decided to use standard normalization formula, i.e., $X_{new}=(X - X_{min})/(X_{max} - X_{min})$ to compute the cognitive distance between authors and reviewers. The adopted approach has the capability to assign an appropriate score to the cognitive distance between authors and reviewers in relation to other authors. This can be confirmed by the same hypothetical example in Table 9. The cognitive distance of A1 with R1 for this particular example is equal to 1 and vice-versa. Moreover, it was observed that the normalized similarity score from only reviewer's side might be sufficient. Because it is the reviewer who has to make the final decision and normalizing any type of citation relationship in this way can depict how close the author is working in domain of the reviewer in comparison with other authors.

The Table 11* summarizes the results of assigning normalized citations counts between our selected reviewers and authors of WWW2006 along with the type of the citations relationships. It can be noticed from this table that there are significant cases where reviewers and authors do not have any visible social relationships in terms of co-authors network, but have strong intellectual ties. For example in the case of "Alec Wolman" and "Balachander Krishnamurthy", the reviewer is citing at a significant rate to author, but apparently do not have any social tie. This may imply that the reviewer is already aware of the author's work and influenced with his research methods and materials.

Similarly, in the case of "Michael Rabinovich" and "Craig E. Wills", the author and reviewer appears to be working in a close research area due to high bibliographic coupling between them and substantial citations for reviewer's work from the author. Additionally, they have not collaborated with each other in terms of publications, but they are inter-connected with each other through a common collaborator. Another interesting case is about "Alec Wolman" and "Amin Vahdat" where the author and the reviewer have never published a paper together, but they are citing each other at a significant rate, implying that they know each others work in advance. Finally, the cases where cognitive distance is not very significant can be ignored.

Although Table 11 has highlighted various cases of cognitive distances between authors and reviewers, but an analysis of the citations context by an expert or an automated system can further elaborate the meanings associated with these citations relationships. This in turn can help in identifying the severity of the possible conflict of interest between authors and reviewers. The next section discusses in detail about the possible citations contexts and their abstract classes of sentiments that can be assigned to our identified citations relationships. It also reports about our experiments for the automated classification of these citations contexts. Finally, we discuss some results after assigning these citations contexts to our WWW2006 authors and reviewers who have significant frequency of citations relationships between each other as mentioned in Table 11.

*The Table 11 is available at the end of the article.

C. Existing Work for Citations Context Identification

In literature, there are number of studies that describe the reasons why an author has cited other author. One of the earliest works in this direction was done by Garfield [30]. Garfield in his paper [30], described fifteen reasons for citing, but it is said to be the foundation of various citations classifications schemes developed later [50]. The first formal classification of citations was done by Moravcsik and Murugesan [51], [61]. Their classification scheme contained four main categories with the possibility of more than one citations in each category [50]. This classification was done by using 702 citations used in 30 articles published from 1968 to 1972 in Physical Review [50]. Later, various authors [52-55] developed and modified existing classification schemes depending upon their research hypothesis [50]. Similar to defining the classification schemes for citations, much of the efforts have also been done in the automated classification of citations contexts. Garzone [56], Nanba and Okumura [57] defined rule based schemes to automatically classify the citations [50]. Although, their classifiers work satisfactory, but defining such parsing rules is difficult and requires an expert knowledge in linguistic domain [50]. Similarly, another rule based classification system was developed by Pham and Hofmann [58], which is similar to decision trees [50]. The advantage of their system is that it does not require any knowledge engineer, but relies on the knowledge of the domain expert in defining the rules for the nodes in the tree [50]. The authors showed that their system outperformed the methodology of Nanba and Okumura [50].

Teufel et al. [59] were the first to use machine learning techniques for the classification of citations as mentioned in [50]. They selected a subset of articles from a corpus of 360 conference articles for citations annotations by three annotators, according to the guidelines defined from another subset of articles. Despite the complexity and the number of citations categories, they found a significantly high inter-annotator agreement. They further identified number of features to be used by the IBk (k-nearest neighbor) algorithm for automated classification. These features include: 1762 cue phrases identified from 80 articles, two main agent types (author of current paper, and other people) modelled by 185 patterns, 20 manually acquired verb clusters, verb tense, modality, location of the citation sentence in the article, section and paragraph, 892 cue phrases extracted during annotations by annotators and self-citations. The training and testing for citations classification was performed on 2829 citations instances extracted from 116 separate articles and achieved substantially significant results. In another article by Teufel and Moens [60], the authors described a common sequence of sentences in the introduction of academic articles, i.e., general background. then specific related work in a neutral language, after that description of previous works' limitations to give motivation of the current article [61]. Angrosh et al. [61] used this rhetorical pattern to classify the citations sentences and even sentences adjacent to these citations with significantly high accuracy that appeared in the related work sections of 50 articles.

D. Citations Relationships Context Identification and Classification Experiments

In order to determine and demonstrate the automated classification of contexts associated with citations relationships between our WWW2006 authors and reviewers. We downloaded only those articles of reviewers and authors which are listed in our CiteSeer database, and has been utilized to determine cognitive distances in section VI.B. The total downloaded articles were 472. The downloaded files were first converted in to XML format. There were 57 papers that were scanned and could not be converted in XML. We then wrote small scripts to extract the citations sentences from these files using regular expressions. Our routines located the names of the cited authors in the references list and extracted the sentences containing those references. For bibliographic coupling scenario, we also matched the cited paper titles to extract only those references which have been cited by any two author and reviewer associated through bibliographic coupling. As a result, we found 137 unique inter-citations sentences, 1006 unique citations instances for bibliographic coupling, and 51 unique co-cited instances. The whole parsing process was challenging because of typo errors and in some cases the XML conversion was not in the form to be parsed. Similarly, there were few cases where cited author's name was mistakenly not mentioned in the references section. As we mentioned earlier in section V.A.2 that we removed the duplication of references and each paper now contains only one citation for a particular paper. But during the extraction process of citations sentences from downloaded papers, we found more citations sentences for the same reference in a paper, while they were counted as one in our CiteSeer database. However, for the computation of final results described in section VI.E, we normalized the count of the additionally found sentences to unit one.

1) Classification Schemes for Citations Relationships

For our experimentations, we used a modified version of the citations classification scheme of Teufel et al. [59]. One category, i.e., "strength" has been taken from [61]. We preferred this scheme because it is easy to operationalize without any explicit knowledge of the domain and can provide enough information for our COI application. For simplification, we decided to classify the citations only on the basis of context of the sentences that contain the citations. However, one can go further to locate pronouns and abbreviations of authors' names and theories in other sentences, which is technically not possible for all the cases [59]. Similarly, the context of the citation can be identified at a paragraph level or at an article level. The details of our adopted classification scheme are summarized in Table 12.

Table 12. Inter-citations classification scheme.

Class	Description
Similar	Author's work is similar to the cited work.
Supports/ Confirm	Author's work supports or confirm the cited work.
Strength	Author's work describes the strength of the cited work.
Weak	Author's work describes the shortcomings of the cited work.
Motivated/ Extends	Author's work is motivated by the cited work.
Contrast	Author's work is in contrast/comparison with the cited work.
Uses	Author's work uses/modifies/adapts the cited work.
Neutral	Cited work is described in a neutral way, or enough textual information is not available.

Unlike previous works, we treated co-citations as a separate classification problem from inter-citations. This is due to the fact that sometimes a sentence can contain more than one citation, and it is important to discover about the purpose of these citations and their inter-relationship with each other. For example, consider the sentence *"Emerging technologies such as PlanetLab [19] and ScriptRoute [22] may help enable these more detailed measurements"* [62]. In the case of inter-citations, the author of the article is describing the strength of the cited work, but on the other hand in case of co-citation, both cited works appears to be similar. Similarly, in this study, we considered only those citations as co-citations if they were present in a single sentence, unlike previous works that consider two citations as co-citations if they are present in two consecutive sentences. The co-citations can be classified similar to inter-citations. As we mentioned earlier, that we found only 51 co-citations sentences. We then decided to use the citations sentences from our inter-citations and bibliographic coupling corpus for defining co-citations context classification scheme and their automated classification experiments. In this collection, we found 233 unique instances of co-citations sentences. After a detailed analysis of this co-citations data, we used the scheme listed in Table 13.

Table 13. Co_citations classification scheme.

Class	Description
Similar	Co-Cited works are similar.
Uses	One work uses other work.
Motivated/ Extends	One work extends or motivated by other work.
Contrast	One work is in contrast with other.
Neutral	Enough textual information is not available.

Table 14. Percentage distribution of citations sentences among citations context classes.

Neutral	Uses	Contrast	Motivated/ Extends	Weak	Strength	Supports/ Confirm	Similar
68.48%	11.07%	1.33%	1.05%	6.2%	8.59%	1.33%	2.19%

Table 15. Additional generalized categories of terms.

Category	Examples	Description
Usage terms	uses, adopt, utilize	terms describing usage of anything.
Confirming terms	confirm, consistent with	terms confirming other work.
Example terms	example, like, such as	terms used to give a list of examples.
Similarity terms	similar, likewise	terms used to show similarity between two works.
Motivation terms	motivated, inspired by	terms used to show motivation.
Extension terms	extends, extension	terms describing extension of previous work.

2) Results of Classification Experiments

We manually annotated all the citations and co-citations according to the defined classification schemes. The distribution of citations sentences among the citations context classes is summarized in Table 14. In defining the features for automated classification experiment, we followed the set used by Angrosh et al. [61]. We extracted cue words and phrases from each sentence and grouped them in to generalize categories as described in [61]. These categories include background terms, subject of inquiry terms, outcome terms, strength terms, shortcoming terms, subjective pronouns, words of stress, alternate approach terms, result terms, and contrasting terms. However, after analyzing citations and depending upon our own classification scheme, we defined six more categories that are summarized in Table 15. We identified a total of 556 cue words. The distribution of these cue words in each generalized categories is listed in Table 16.

Table 16. Frequency of terms in each generalized terms categories.

Category	Number of cue words
Background terms	47
Alternative approach terms	5
Confirming terms	5
Contrasting terms	20
Example terms	25
Extension terms	6
Motivation terms	3
Outcome terms	33
Result terms	11
Shortcoming terms	26
Similarity terms	15
Subject of inquiry terms	232
Subjective pronouns terms	12
Strength terms	35
Usage terms	54
Words of stress terms	27

In our experiments, we used Hidden Naive Bayes (HNB) algorithm [63] for citations classification. We used the presence and absence (binary) of generalized categories as input features for the HNB classifier. We choose HNB because some input features were observed to be conditionally dependent on each other. The results of the classification for inter-citations sentences and sentences used in bibliographic coupling are listed in Table 17.

Table 17. Classification results of citations context for inter-citations.

Precision	Recall	F-Measure	Class
0.81	0.85	0.83	uses
0.75	0.64	0.69	contrast
0.83	0.87	0.85	similar
0.87	0.63	0.73	motivated/extends
0.87	0.63	0.73	supports/confirm
0.68	0.66	0.67	weak
0.77	0.73	0.75	strength
0.92	0.93	0.93	neutral

As it can be observed from Table 17 that by following a simple approach, we can achieve considerable results for citations' classification. None of the class has F-Measure below 0.65. The F-Measure in case of classes "uses", "similar" and "neutral" is above 0.80. The citations classes can further be grouped in a more abstract scheme of sentiments as mentioned in [59]. According to this scheme, the classes, i.e., similar, uses, motivated/extends, supports/confirm and strength can be grouped as positive class, while contrast and weak classes can be grouped as negative class. The classification results for the sentiments based generalization scheme is summarized in Table 18. Although, by grouping citations classes in sentiments the F-measure for the negative has reached 0.66, but it is quite significant for positive class, i.e., 0.85. The precision, recall and F-measure remained same for neutral class. As in conflict of interest situations both positive (e.g., similar or confirming work) and negative (e.g., competitive or criticizing work) sentiments are important. We can further combine these sentiments in another abstract scheme. More specifically, we can combine positive and negative sentiments as polarity class and can separate their sentences from neutral class. The experimental results of this classification are presented in Table 19. It can be observed from Table 19 that the classification accuracy in this case is quite significant for both classes, which is 0.85 for polarity class and 0.93 for neutral class.

Table 18. Classification results of generalized citations sentiments for inter-citations.

Precision	Recall	F-Measure	Class
0.85	0.86	0.85	positive
0.72	0.61	0.66	negative
0.92	0.93	0.93	neutral

Table 19. Classification results of abstract level citations polarity for inter-citations.

Precision	Recall	F-Measure	Class
0.86	0.84	0.85	polarity
0.93	0.94	0.93	neutral

In case of co-citations, the distribution of co-citation sentences among identified co-citations classes is summarized in Table 20. We found only one example of motivated/extends category, which we ignored for our classification experiments. However, it can be used for generalized scheme of sentiments.

Table 20. Percentage distribution of co-citations sentences among co-citations context classes.

Neutral	Similar	Uses	Contrast	Motivated/Extends
24.6%	63.2%	8.22%	3.46%	0.43%

For our co-citations classification experiment, we first transformed co-citations sentences in simplified versions. We replaced each citation by a reserve word. We found that citations occurring consecutively and separated by either ",", "and", "or", "or by", "and by", ", noun" or combinations of these can be considered as similar work. We considered these patterns and citations as a single unit and replaced them with a single reserve word. For example, the sentence *"Krishnamurthy and Arlitt [16] and Krishnamurthy and Wills [19] examine accesses to many Web sites"* [64] can be transformed in a simple sentence as "RESERVE_WORD examine accesses to many Web sites". We simplified sentences because it made the features extraction process easier (which will be explained later), and furthermore, we found that most of the simplified sentences with a single reserve word belong to the "similar" category (47.94% of total similar category) and few for neutral category (12.2% of total neutral category). We used this property as a binary feature for our classifier training and testing. We also used the same generalized cue words categories as mentioned earlier. However, for the co-citation classification experiment, we marked usage and contrasting terms as present if they exist in between of any two reserve words. This approach was adopted after reviewing the usage of these terms in the co-citations annotated as "uses" and "contrast". We further defined a binary feature on the basis of two coordinating conjunctions, i.e., "and", "or" present between two reserve words, and found it helpful in the co-citations classification experiments. We also identified 25 cue words and some patterns that can be helpful in separating neutral co-citations from other categories. Some examples of these cue words includes: "broad efforts", "variety of tasks", "several", "other domains", etc. The examples of some patterns include: "for RESERVE_WORD *any sequence of words* for RESERVE_WORD", "the RESERVE_WORD *any sequence of words* the RESERVE_WORD", "RESERVE_WORD on RESERVE_WORD", "within RESERVE_WORD", "via RESERVE_WORD", etc. We used these cue words and patterns as a single binary feature for co-citations classification experiment. The results of the classification experiment are outlined in Table 21. However, it must be noted that in a co-citation sentence, there can be more than two citations. In our experiments, we classified the relationship between only those co-citations in a sentence that have the features or patterns as mentioned earlier.

Table 21. Classification results of co-citations contexts.

Precision	Recall	F-Measure	Class
0.83	0.94	0.88	similar
0.78	0.88	0.82	contrast
0.75	0.63	0.69	uses
0.77	0.53	0.63	neutral

It can be observed from Table 21 that the F-Measure in case of "similar" and "contrast" classes is more than 0.80. The F-measure for "uses" class is 0.69 with the precision 0.75 and recall 0.63. In case of "neutral" class, although F-Measure is 0.63, but the precision is 0.77. This implies that we can identify some proportion of "neutral" class, but with considerable precision. Similar to inter-citations, the co-citations classes can also be grouped in abstract classes of sentiments. The classification results for sentiments classes are summarized in Table 22. It can be observed from Table 22 that the precision of neutral class in this case has reached 0.88. The F-measure for negative class in this case is 0.71 with 0.67 precision and 0.75 recall. The F-measure for positive class has reached 0.91 with 0.85 precision and 0.97 recall. Similarly, the classification results of the polarity and neutral class for co-citations are listed in Table 23. It can be observed from Table 23 that by combining the positive and negative sentiments classes under polarity class, the F-measure for neutral class has increased to 0.67 with 0.86 precision. The F-measure for polarity class in this case is 0.92 with 0.87 precision and 0.97 recall.

Table 22. Classification results of generalized co-citations sentiments.

Precision	Recall	F-Measure	Class
0.85	0.97	0.91	positive
0.67	0.75	0.71	negative
0.88	0.51	0.64	neutral

Table 23. Classification results of abstract level co-citations polarity.

Precision	Recall	F-Measure	Class
0.87	0.97	0.92	polarity
0.86	0.54	0.67	neutral

In above experiments, we talked about the annotation and automated classification of contexts and sentiments between two authors on the basis of inter-citations and co-citations. In case of bibliographic coupling, one can use the context classification similar to inter-citations, and can use this information to know the relationship between two authors. However, to determine sentiments for bibliographic coupling relationships, we can use the concept of "birds of a feather flock together". This concept has been widely investigated in the field of psychology. The researchers found the similarity of personality, physical appearance, race, values, demographics and even cognitive similarity as a major driving force for decision making [65]. As the citations can be classified as positive, negative, or neutral. Any two authors with similar sentiments for a third author can be grouped together and can be assigned positive sentiments for each other. The only exception to this scheme is for "uses" and "similar" classes. If for example, an author A has "uses" relationship with a third author C, and another author B has "similar" relationship with the same author C. The relationship or sentiment in this case is not clear between author A and author B. In this case they can be assigned neutral sentiments for each other. Similarly, any two authors with opposite sentiments for a particular author can be assigned negative sentiments for each other. However, if both or either one author has neutral sentiments then the neutral sentiments can be assigned between them. These rules are summarized in Table 24.

Table 24. Sentiments assignment scheme for bibliographic coupling.

Author's sentiment	Reviewer's sentiment	Bibliographic sentiment
positive	positive	positive
positive	negative	negative
negative	positive	negative
negative	negative	positive
neutral	negative/positive/ neutral	neutral
negative/positive/ neutral	neutral	neutral

E. Results after Assigning Contexts to Citations Relationships

After the detailed discussion about identification of contexts associated with citations relationships and the possibility of their automated classifications. We present the results after assigning these contexts and sentiments to our WWW2006 authors and reviewers. The Table 25* lists some sample results about the presence and absence of polarity between the authors and reviewers for their citations relationships. We ignored the normalized citations counts below 0.2 and considered them insignificant for further discussion. However, the journals' editors and conferences' managers can vary these thresholds depending upon the availability of reviewers. As we mentioned earlier that during citations extraction process, in some cases we found more citations sentences for the same reference in a paper, which were counted as one in CiteSeer.
In this scenario, we assigned each additional citation sentences a proper weight on the basis of the total citations listed in Cite Seer for that reference in a paper. For example, if we found two citations sentences for a reference. In this case, we can assign a weight of 0.5 to each citation sentence. The sum of these weights is similar to the count for this reference listed in CiteSeer. Such normalization was necessary as it can increase the final normalized citations counts or cognitive distance presented in Table 11 and reproduced in Table 25.

*The Table 25 is available at the end of the article.

The Table 25 also lists the proportion of normalized citations counts that we were able to extract from the PDF files in comparison to actual listed in CiteSeer. The extraction process, however, can be further enhanced to discover complete information about these citations relationships. It can be observed from Table 25 that the presence of polarity among most of the citations relationships is not at a very critical level. The only interesting case for further discussion is about "Alec Wolman", where reviewer is citing to authors with the possibility of some sentiments with reasonable normalized citations counts.

We can further elaborate the context associated with these polar relationships. In case of "Alec Wolman" and "Amin Vahdat" the reviewer is positively associated with author with 0.16 normalized citations count. These positive sentiments are due to 0.09 normalized citations counts for using the work of author and 0.06 for the similarity of work. In case of "Craig E. Wills", the reviewer "Alec Wolman" is negatively associated to author with 0.12 normalized citations counts. These negative sentiments are due to the identification of weakness in the work of author by reviewer. In the case of "Alec Wolman" and "Balachander Krishnamurthy", the reviewer is associated to author with 0.1 normalized counts for positive sentiments and 0.05 for negative sentiments. These positive and negative sentiments by the reviewer are due to the description of the strength and weakness of the cited work respectively.

VII. Conclusions and Future Work

In this paper, we discussed the problem of conflict of interest (COI) situations in peer review system for scholarly communications. In this context, we described different kinds of COIs that can exist between an author and a reviewer. We categorized these COIs in two broad categories, i.e., Social COIs and Cognitive COIs. We further identified current approaches that are primarily based on social network analysis of authors that are implicitly available in the form of co-authors networks in digital bibliographic databases. We also mentioned the limitations of extracting social networks from social networking websites, authors' homepages and querying the web. With a brief review of citations theory, we highlighted that different citations relationships can be an indicator of both social and cognitive relationships between researchers. This in turn can be helpful in improving existing COI detection approaches as an additional or alternative means to identify possible social and cognitive bias in peer review system. We investigated in this direction, and performed some experiments to predict the existence of social relationships from citations relationships. We found that a few proportion of social relationships can be predicted using citations relationships with considerable accuracy. Similarly, we performed an experiment on the authors and reviewers of the WWW2006 conference performance track, and described the potential of citations relationships as an indicator of cognitive distance between these authors and reviewers. We described different contexts and sentiments that can be assigned to these cognitive relationships. We conducted some experiments to highlight the possibility of automated prediction of these context and sentiments. These contexts and sentiments in turn can help in spotlighting the possible severity of cognitive COIs between authors and reviewers. Although, we did not find a very severe case of cognitive COI for our selected authors and reviewers, but we believe that such analysis might be helpful in other cases.

In future, we plan to apply our identified features to predict the social networks of larger set of other authors to further validate the results reported in this paper. It is expected that the inclusion of other social relationships such as: friends, allies, regular correspondents, sought advices might further improve the results. However, the collection of this information is not easy. Perhaps, we might need to contact the corresponding authors through emails. In case of cognitive COIs detection, we plan to acquire the COI declarations information from the administration of journals or conferences and tally this information with the cognitive COIs detected through our proposed approach to support our arguments more firmly.

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Table 11. Normalized citations relationships count between authors and reviewers of WWW2006 performance track.

cd: Co-Cited, cs: Co-Cites, co: Citations from reviewer, ci: Citations from author, dark gray cell: Direct co-authors, light gray cell: Indirect co-authors

Authors \ Reviewers	Martin F. Arlitt				Jeffrey S. Chase				Michael Rabinovich				Oliver Spatscheck				Maarten Van Steen				Alec Wolman			
	cd	cs	co	ci	cd	cs	co	ci	cd	cs	co	ci	cd	cs	co	ci	cd	cs	co	ci	cd	cs	co	ci
Balachander Krishnamurthy	0.18	0.08	0	0.2	0.01	0.01	0	0	0.45	0.26	0.45	0.16	0.04	0.006	0.2	0	0.01	0.02	0.02	0	0.06	0.24	0.37	0
Craig E. Wills	0.07	0.09	0	0.1	0.01	0.02	0	0	0.28	0.41	0.11	0.38	0.02	0.10	0	0	0.004	0.02	0.007	0	0.03	0.37	0.37	0
Tracy Kimbrel	0.01	0.03	0	0	0.05	0.09	0.14	0.02	0.02	0.002	0	0	0.004	0	0	0	0	0	0	0	0.01	0.003	0	0
Giovanni Pacifici	0	0	0	0	0	0	0	0	0.003	0.003	0	0	0.004	0	0	0	0	0	0	0	0	0	0	0
Mike Spreitzer	0.003	0	0	0	0.002	0.005	0.04	0	0.006	0.01	0	0	0	0	0	0	0.01	0	0.015	0	0	0	0	0
Patrick Reynolds	0	0.01	0	0.1	0	0.02	0	0.02	0	0.02	0	0	0	0	0	0	0	0.01	0	0	0.04	0.07	0.18	0
Amin Vahdat	0.09	0.11	0	0.3	0.10	0.61	0.43	0.30	0.08	0.33	0.04	0.04	0.07	0.19	0	0	0.04	0.12	0.02	0.02	0.13	0.56	0.31	0.25

Table 25. Polarity relationships between authors and reviewers of WWW2006 performance track. dark gray cell: Direct co-authors, light gray cell: Indirect co-authors

Authors / Reviewers	Sentiments	Martin F. Arlitt	Jeffrey S. Chase			Michael Rabinovich				Oliver Spatscheck	Alec Wolman		
		ci	cs	co	ci	cd	cs	co	ci	co	cs	co	ci
Balachander Krishnamurthy	Polarity	0				0.05	0.01	0.07		0.03	0.01	0.14	
	Neutral	0.2				0.01	0.08	0.29		0.08	0.1	0.23	
	Found/ Total	0.2/0.2				0.06/0.45	0.09/0.26	0.36/0.45		0.11/0.2	0.11/0.24	0.37/0.37	
Craig E. Wills	Polarity					0.02	0.01		0.04		0.02	0.12	
	Neutral					0.01	0.09		0.15		0.12	0.25	
	Found/ Total					0.03/0.28	0.10/0.41		0.19/0.38		0.14/0.37	0.37/0.37	
Amin Vahdat	Polarity	0.1	0.01	0.03	0.02		0.01				0.04	0.16	0.03
	Neutral	0	0.12	0.04	0.15		0.09				0.2	0.09	0.1
	Found/ Total	0.1/0.3	0.13/0.61	0.07/0.43	0.17/0.30		0.10/0.33				0.24/0.56	0.25/0.31	0.13/0.25