

# Recommendation on Academic Networks using Direction Aware Citation Analysis

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## ABSTRACT

The literature search has always been an important part of an academic research. It greatly helps to improve the quality of the research process and output, and increase the efficiency of the researchers in terms of their novel contribution to science. As the number of published papers increases every year, a manual search becomes more exhaustive even with the help of today's search engines since they are not specialized for this task. In academics, two relevant papers do not always have to share keywords, cite one another, or even be in the same field. Although a well-known paper is usually an easy prey in such a hunt, relevant papers using a different terminology, especially recent ones, are not obvious to the eye.

In this work, we propose paper recommendation algorithms by using the citation information among papers. The proposed algorithms are *direction aware* in the sense that they can be tuned to find either recent or traditional papers. The algorithms require a set of papers as input and recommend a set of related ones. If the user wants to give negative or positive feedback on the suggested paper set, the recommendation is refined. The search process can be easily guided in that sense by relevance feedback. We show that this slight guidance helps the user to reach a desired paper in a more efficient way. We adapt our models and algorithms also for the venue and reviewer recommendation tasks. Accuracy of the models and algorithms is thoroughly evaluated by comparison with multiple baselines and algorithms from the literature in terms of several objectives specific to citation, venue, and reviewer recommendation tasks. All of these algorithms are implemented within a publicly available web-service framework which currently uses the data from DBLP<sup>1</sup> and CiteSeer<sup>2</sup> to construct the proposed citation graph.

## Categories and Subject Descriptors

H.3.3 [Information Storage Systems]: Information Search and Retrieval; H.3.3 [Information Storage Systems]: Online Information Services

## General Terms

Algorithms, Experimentation

<sup>1</sup><http://dblp.uni-trier.de>

<sup>2</sup><http://citeseer.ist.psu.edu/>

## Keywords

Literature search, graph, random walks, paper recommendation, web service

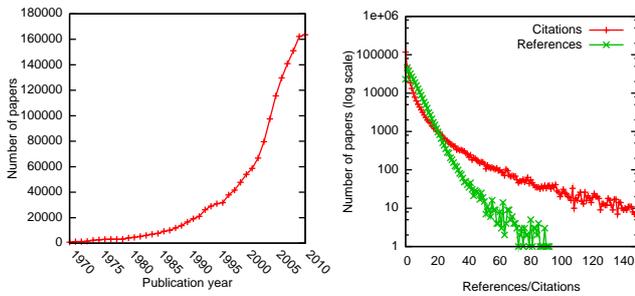
## 1. INTRODUCTION

The academic community has published millions of research papers to date and the number of new papers has been increasing with time. For example, based on DBLP, computer scientists published 3 times more papers in 2010 than in 2000 (see Figure 1-left). With more than one hundred thousand new papers each year, performing a complete literature search became a herculean task. A paper cites in average 20 other papers (see Figure 1-right), which means that there might be more than a thousand papers that cite or are cited by any paper a researcher write. Researchers typically rely on manual methods to discover new research such as keyword-based search on search engines, reading proceedings of conferences, browsing publication list of known experts or checking the reference list of paper they are interested. These techniques are time-consuming and only allow to reach a limited set of documents in a reasonable time. Developing tools that help researchers find unknown and relevant papers will certainly increase the productivity of the scientific community.

Some of the existing approaches and tools for the literature search cannot compete with the size of today's literature. Keyword-based approaches suffer from the confusion induced by different names of identical concepts in different fields. (For instance, *partially ordered set* or *poset* are also often called *directed acyclic graph* or *DAG*). Hence, a researcher may not be able to find the right paper even she is suggested to scan a long list of papers by a keyword-based approach. Conversely, two different concepts may have the same name in different fields (for instance, *hybrid* is commonly used to specify software hybridization, hardware hybridization or algorithmic hybridization) and such homonyms may drastically increase the number of suggested but unrelated papers. Some publishers and digital libraries automatically suggest papers to authors; however, their suggestions are usually based on the publication history of the researcher which may not match with her current interests.

To achieve this goal, we built a publicly available web service called *theadvisor*<sup>3</sup>. It takes a bibliography file containing a set of papers, i.e., *seeds*, as an input to initiate the search. The user can specify that she is interested in classical papers or in recent papers. Then, the service returns

<sup>3</sup><http://theadvisor.osu.edu/>



**Figure 1: Number of new papers published each year based on DBLP (left), and number of papers with given citation and reference count (right).**

a set of suggested papers ordered with respect to a ranking function. The user can guide the search or *prune* the list of suggested papers with a positive or negative feedback by declaring a subset *relevant* or *irrelevant*. In this case, the service completely refines the set and shows the new results back to the researcher. In addition to papers, the service also suggests researchers or experts, and conferences or journals of interest. We believe that it will be a valuable asset of a researcher while performing several tasks, such as:

- searching the literature in any topic she is interested,
- finding recent or traditional papers related to a problem,
- improving the reference list of a manuscript being written,
- finding conferences and journals for attendance, subscription, or paper submission,
- finding a set of researchers in a field of interest to follow their work,
- finding a list of potential reviewers, which is required by certain journals in the submission process.

The service uses the bibliographical information while suggesting relevant papers, venues, and people to the researcher. For each paper, it uses the authorship and venue information in addition to the list of papers it cites. The service works on a modified version of the *citation graph* which is constructed by using this information. In other words, the service recommends papers, experts, and venues using citation analysis. We do not take the textual data into account because our aim is finding all conceptually related and high quality documents even they use a different terminology. It has been shown that text-based similarity is not sufficient for this task and that most of the relevant informations are contained within the citation graph [24]. Besides, it is plausible that there is already a correlation between citation similarities and text similarities of the papers [21].

Our aim in this work is to evaluate the existing algorithms and to explain the new algorithms that power our service. We distinguish two types of algorithms in the literature. Some algorithms (such as Cocitation [23], Cocoupling [9] and CCIDF [11]) only use direct citations and references of the seed papers. Other methods (such as PaperRank [5] and Katz [24]) perform a deep search of the citation graph by traversing all its edges; they are often said to be eigenvector based. However, none of these methods allow explicitly to search the paper space looking for either old or recent papers.

In this work, we present the class of *direction aware* algorithms. They feature a parameter which allows to give more importance to either the citation of papers or their references. This parameter makes the citation suggestion process easily tunable for finding either recent or traditional relevant papers. In particular we extend two eigenvector based methods into direction aware algorithms, namely DARWR and DAKATZ.

This paper presents an evaluation of the existing and proposed algorithms for citation recommendation under the light of link prediction and citation patterns. We also investigate the potential of the positive and negative feedback mechanism our service exposes. Finally we show that citation recommendation can be used to recommend venues and reviewers better than methods commonly used by researchers.

The paper is organized as follows: In Section 2, we briefly present a survey for related work. The problems and the methods are formally presented in Section 3. The accuracy of the methods is experimentally analyzed in Section 4. Section 5 discusses about future work and concludes the paper.

## 2. RELATED WORK

Citation analysis has been successfully used for various tasks including expert finding [1], academic evaluation of researchers, conferences, journals and papers [3, 7], context-aware citation recommendation [6], and impact prediction [22].

There are various citation analysis-based paper recommendation methods depending on a pairwise similarity measure between two papers. Bibliographic coupling, which is one of the earliest works, considers papers having similar citations as related [9]. Another early work, the Cocitation method, considers papers which are cited by the same papers as related [23]. A similar cites/cited approach by using collaboration filtering is proposed by McNee et al. [18]. Another method, common citation  $\times$  inverse document frequency (CCIDF) also considers only common citations, but by weighting them with respect to their inverse frequencies [11].

More recent works define different measures such as Katz which is proposed by Liben-Nowell and Kleinberg for a study on the link prediction problem on social networks [15] and used later for information retrieval purposes including citation recommendation by Strohman et al. [24]. For two papers in the citation network, the Katz measure counts the number of paths by favoring the shorter ones. Lu et al. stated that both bibliographic coupling and Cocitation methods are only suitable for special cases due to their very local nature [16]. They proposed a method which computes the similarity of two papers by using a vector based representation of their neighborhoods in the citation network and compared the method with CCIDF. Liang et al. argued that most of the methods stated above considers only direct references and citations alone [14]. Even Katz and the vector based method of [16] consider the links in the citation network as simple links. Instead, Liang et al. added a weight attribute to each link and proposed the method Global Relation Strength which computes the similarity of two papers by using a Katz-like approach.

Many works use random walk with restarts (RWR) for citation analysis [5, 17, 13, 10]. RWR is a well known and efficient technique used for different tasks including comput-

ing the relevance of two vertices in a graph [19]. It is very similar to the well known PageRank algorithm which is used by Both Li and Willett [13] (ArticleRank) and Ma et al. [17] to evaluate the importance of the academic papers. Gori and Pucci [5] proposed an algorithm PaperRank for RWR-based paper recommendation which can also be seen as a Personalized PageRank computation [8] on the citation graph. Lao and Cohen [10] also used RWR for paper recommendation in citation networks and proposed a learnable proximity measure for weighting the edges by using machine learning techniques.

As far as we know, none of these works study the recent/traditional paper recommendation problem. The closest work is Claper [25] which is an automatic system that measure how much a paper is classical, allowing to rank a list of paper to highlight the most classical ones.

### 3. PROBLEMS AND METHODS

Let  $G = (V, E)$  be the *citation graph*, with  $n$  papers  $V = \{v_1, \dots, v_n\}$ . In  $G$ , each directed edge  $e = (v_i, v_j) \in E$  represents a *citation* from  $v_i$  to  $v_j$ . For the rest of the paper, we use the phrases “*references of v*” and “*citations to v*” as to describe the graph around vertex  $v$  (see Figure 2). We use  $deg^-(v)$  and  $deg^+(v)$  to denote the number of references of and citations to  $v$ , respectively.

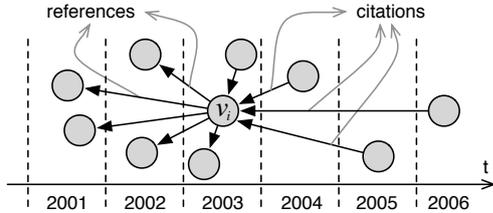


Figure 2: Citation graph around a paper  $v_i$  with references and citing papers.

In this work, we consider three query types:

- **Paper recommendation (PR):** Given a set of  $m$  seed papers  $\mathcal{M} = \{p_1, \dots, p_m\}$  and a parameter  $k$  s.t.  $\mathcal{M} \subset V$ , return top- $k$  papers which are relevant to the ones in  $\mathcal{M}$ .
- **Venue recommendation (VR):** Given a set of  $m$  seed papers  $\mathcal{M} = \{p_1, \dots, p_m\}$  and a parameter  $k$ , return top- $k$  venues related to the papers in  $\mathcal{M}$ .
- **Expert recommendation (ER):** Given a set of  $m$  seed papers  $\mathcal{M} = \{p_1, \dots, p_m\}$  and parameter  $k$ , return top- $k$  experts studying on topics related to the papers in  $\mathcal{M}$ .

These query definitions are generic. They can be used for various academic tasks by the researchers. In this paper, we target the manuscript preparation and submission process since all of queries above are useful in this process: executing a PR query is a very efficient way of finding overlooked citations in a manuscript with the cited papers as the input  $\mathcal{M}$ . VR queries are useful while deciding the conference or journal for submission. And ER queries are useful while submitting a manuscript to some journals which require a set of names of potential reviewers.

## 3.1 Citation recommendation

### 3.1.1 Random walk with restart

PAPER-RANK is based on random walks in the citation graph  $G$ . The current structure of  $G$  is not suitable for finding recent and relevant papers since such papers have only a few incoming edges. Moreover, since the graph is acyclic, all random walks will end up on old papers. To alleviate this, given a PR query with inputs  $\mathcal{M}$  and  $k$ , PAPER-RANK constructs a directed graph  $G' = (V', E')$  by slightly modifying the citation graph  $G$  as follows:

- A source node  $s$  is added to the vertex set:

$$V' = V \cup \{s\}$$

- Back-reference edges ( $E_b$ ), the edges from  $s$  to seed papers ( $E_f$ ), and restart edges from  $V$  to  $s$  ( $E_r$ ) are added to the graph:

$$E_b = \{(y, x) : (x, y) \in E\}$$

$$E_f = \{(s, v) : v \in \mathcal{M}\}$$

$$E_r = \{(v, s) : v \in V\}$$

$$E' = E \cup E_b \cup E_f \cup E_r$$

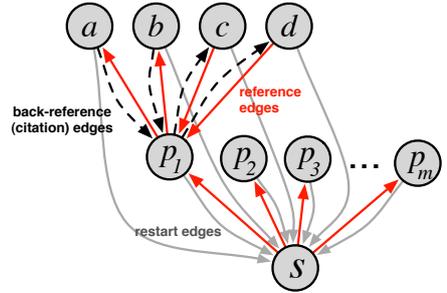


Figure 3: Citation graph with source node  $s$  and seed set  $\mathcal{M} = \{p_1, \dots, p_m\}$ . The papers  $a$  and  $b$  are cited by  $p_1$ , where  $c$  and  $d$  cites  $p_1$ . Note that there is a corresponding back-reference edge for every reference.

The new directed graph  $G'$  has *reference* (red), *back-reference* (dashed), and *restart* (gray) edges (see Figure 3). In this model, the random walks are directed towards both references and citations of the papers. In addition, the restarts from the source vertex  $s$  will be distributed to only the seed papers in  $\mathcal{M}$ . Hence, random jumps to any paper in the literature are prevented. We assume that a random walk ends in  $v$  continues with a neighbor with a damping factor  $d \in (0, 1]$ . And with probability  $(1 - d)$ , it restarts and goes to the source  $s$ . Let  $R_{t-1}(v)$  be the probability of a random walk ends at vertex  $v \neq s$  at iteration  $t - 1$ . Let  $C_t(v)$  be the contribution of  $v$  to one of its neighbors at iteration  $t$ . In each iteration,  $d$  of  $R_{t-1}(v)$  is distributed among its references and citations equally. Hence,

$$C_t(v) = d \frac{R_{t-1}(v)}{deg^+(v) + deg^-(v)}. \quad (1)$$

Initially, a probability score of 1 is given to the source node, meaning that a researcher expands the bibliography

starting with the paper itself:

$$R_0(x) = \begin{cases} 1, & \text{if } x = s \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where  $R_0$  is the probability at  $t = 0$ . The PAPERANK algorithm computes the probability of a vertex  $u$  at iteration  $t$  as

$$R_t(u) = \begin{cases} (1-d) \sum_{v \in V} R_{t-1}(v), & \text{if } u = s \\ \sum_{(u,v) \in E} C_t(v) + \frac{R_{t-1}(s)}{|\mathcal{M}|}, & \text{if } u \in \mathcal{M} \\ \sum_{(u,v) \in E} C_t(v), & \text{otherwise.} \end{cases} \quad (3)$$

The PAPERANK algorithm converges when the probability of the papers are stable, i.e., when the process is in a *steady state*. Let

$$\Delta_t = (R_t(u_1) - R_{t-1}(u_1), \dots, R_t(u_n) - R_{t-1}(u_n))$$

be the difference vector. We say that the process is in the steady state when the L2 norm of  $\|\Delta_t\|$  is smaller than given value  $\epsilon$ . That is,

$$\|\Delta_t\| = \sqrt{\sum_{u \in V} (R_t(u) - R_{t-1}(u))^2} < \epsilon.$$

For a given set of initial papers  $\mathcal{M}$ , and parameters  $d$  and  $\epsilon$ , suppose the algorithm converges.

**DEFINITION 1.** *The relevance score of a paper  $u$  with respect to the seed papers is equal to the steady state probability  $R(u)$ .*

We choose the top- $k$  non-seed papers with the highest relevance scores as the initial recommended paper set  $\mathcal{R}_{paper}$ .

**THEOREM 1.** *The PAPERANK algorithm converges to a steady state in a finite number iterations. Furthermore, there is only one steady state distribution and hence, the relevance scores are unique.*

**PROOF.** Consider the subgraph  $H = (V_H, E_H) \subseteq G'$  induced by the source  $s$  and all vertices reachable from the source. That is,  $V_H = \{u \in V' : R_t(u) > 0\}$  and  $E_H = (V_H \times V_H) \cap E'$ . For each  $u \in V_H \setminus \{s\}$  there is a directed edge  $(u, s)$  and a directed path  $s \rightarrow u$ . Hence, each vertex pair in  $V_H$  is connected to each other and  $H$  is strongly connected. Thus, the transition matrix of the corresponding Markov chain is irreducible. Hence, the steady state exists and is unique.  $\square$

### 3.1.2 Direction aware random walk with restart

A random walk with restart is a good way to find relevance scores of the papers. However, the PAPERANK algorithm treats the citations and references in the same way. This may not lead the researcher to recent and relevant papers if she is more interested with those. Old and well cited papers have an advantage with respect to the relevance scores since they usually have more edges in  $G'$ . Hence  $G'$  tends to have more and shorter paths from the seed papers to old papers. We define a *direction awareness* parameter  $\lambda \in [0, 1]$  to obtain more recent results in the top- $k$  documents. We then define two types of contributions of each paper  $v$  to a neighbor paper in iteration  $t$ :

$$C_t^+(v) = d\lambda \frac{R_{t-1}(v)}{\text{deg}^+(v)}, \quad (4)$$

$$C_t^-(v) = d(1-\lambda) \frac{R_{t-1}(v)}{\text{deg}^-(v)}, \quad (5)$$

where  $C_t^-(v)$  is the contribution of  $v$  to a paper in its reference list and  $C_t^+(v)$  is the contribution of  $v$  to a paper which cites  $v$ . Hence, for a non-seed, non-source paper  $u$ ,

$$R_t(u) = \sum_{(v,u) \in E_b} C_t^+(v) + \sum_{(v,u) \in E} C_t^-(v). \quad (6)$$

For a seed node  $u$ , the  $R_t(u)$  is computed similarly except that each seed node has an additional  $\frac{R_{t-1}(s)}{|\mathcal{M}|}$  in the equation.  $R_t(s)$  is computed in the same way as (3). With this modification, the parameter  $\lambda$  can be used to give more importance either to traditional papers with  $\lambda \in [0, 0.5]$  or recent papers with  $\lambda \in [0.5, 1]$ . We call this algorithm *direction aware random walk with restart* (DARWR).

Note that DARWR (6) has the *probability leak* problem when a paper has no references or citations. If this is the case some part of its score will be lost at each iteration. For such papers, we distribute the whole score from the previous iteration towards only its references or citations.

### 3.1.3 Katz and direction awareness

The direction awareness can be also adapted to other similarity measures such as the graph-based Katz distance measure [15] which was used before for the citation recommendation purposes [24]. With Katz measure, the similarity score between two papers  $u, v \in V$  is computed as

$$\text{Katz}(u, v) = \sum_{i=1}^L \beta^i |\text{paths}_{u,v}^i|,$$

where  $\beta \in [0, 1]$  is the decay parameter,  $L$  is an integer parameter, and  $|\text{paths}_{u,v}^i|$  is the number of paths with length  $i$  between  $u$  and  $v$  in the graph with paper and back-reference edges  $G'' = (V, E \cup E_b)$ . Notice that the path does not need to be elementary, i.e., the path  $uvw$  is a valid path of length 3. Therefore the Katz measure might not converge for all values of  $\beta$  when  $L = \infty$ .  $\beta$  needs to be chosen smaller than the larger eigenvalue of the adjacency matrix of  $G''$ . And in practice  $L$  is set to a fixed value (in our experiment  $L = 10$ ). In our context with multiple seed papers, the relevance of a paper  $v$  is set to  $R(v) = \sum_{u \in \mathcal{M}} \text{Katz}(u, v)$ .

We extend the Katz distance by using direction awareness to weight the contributions to references and citations differently with the  $\lambda$  parameter as in DARWR:

$$\text{DaKatz}(u, v) = \sum_{i=1}^L \left[ \lambda \beta^i |\text{Rpaths}_{u,v}^i| + (1-\lambda) \beta^i |\text{Cpaths}_{u,v}^i| \right],$$

where  $|\text{Rpaths}_{u,v}^i|$  (respectively,  $|\text{Cpaths}_{u,v}^i|$ ) is the number of paths in which the last edge in the path is a reference edge of  $E$  (respectively, a citation edge of  $E_b$ ).

## 3.2 Venue and Reviewer recommendation

Given a VR query with inputs  $\mathcal{M}$  and  $k$ , we execute the paper recommendation process and obtain the relevance scores of all papers in the database. The relevance score of each venue  $\nu$  is computed as the sum of relevance scores of all papers published in that venue, i.e.,

$$R(\nu) = \sum_{u \text{ is published in } \nu} R(u).$$

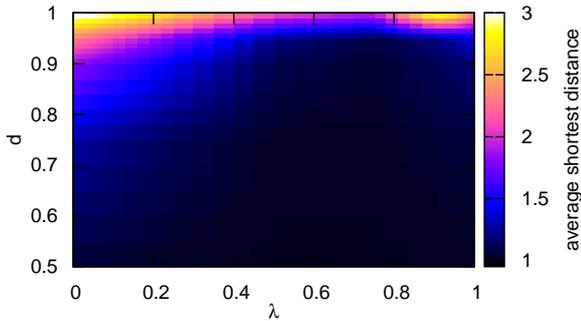


Figure 4: Average shortest distance of top-10 recommendations by DaRWR from seed papers based on the parameters  $d$  and  $\lambda$ .

We then choose the top- $k$  venues with the highest relevance scores as the suggestion set  $\mathcal{R}_{venue}$ .

Similarly, given an ER query with inputs  $\mathcal{M}$  and  $k$ , we execute the paper recommendation process and obtain the relevance scores of all papers in the database. The relevance score of each expert  $\alpha$  is computed as the sum of relevance scores of all papers written by  $\alpha$ , i.e.,

$$R(\alpha) = \sum_{u \text{ is written by } \alpha} R(u).$$

We then choose the top- $k$  researchers with the highest relevance scores as the suggestion set  $\mathcal{R}_{expert}$ .

## 4. EXPERIMENTS

We carefully evaluate the accuracy of the proposed direction aware algorithms by comparing them with existing baselines and algorithms. Here, we give the details and results of these experiments.

### 4.1 Dataset collection

The retrieval of bibliographic information and citation graph generation is a difficult task since academic papers are generally copyrighted and they are accessible through publishers' digital libraries. The usage of such data is usually not explicitly granted, therefore, we limited our study to data with license compatible with data mining.

We retrieved informations about 1.75M (as of Dec 2011) computer science articles from DBLP [12]. This data is well-formatted, author names are disambiguated; however, it does not contain any reference information. On the other hand, CiteSeer contains reference information but most of its data are automatically generated [4] and are often erroneous. We mapped each document in CiteSeer to at most one document in DBLP by using the title information (using an inverted index on title words and Levenshtein distance) and by their years. When two documents in CiteSeer map to the same document in DBLP, their citation information are merged. From the 1,748,199 documents references in DBLP, only 295,317 are properly associated with a reference in CiteSeer written by 1,028,288 authors. The graph has 1,601,067 citation edges. Notice that a mapping between CiteSeer data and DBLP data has been computed before using canopy clustering with three times higher coverage [20]. Although we could not match a that much of the data, we believe the data are enough to derive meaningful conclusions.

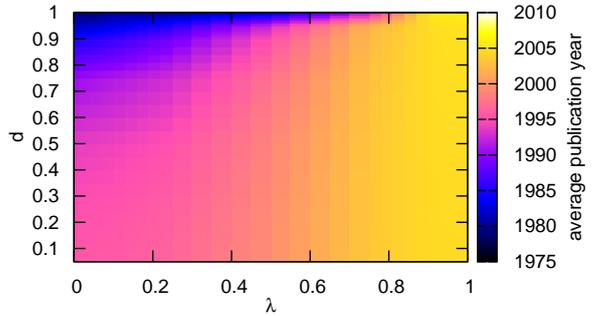


Figure 5: Average publication years of top-10 recommendations by DaRWR based on the parameters  $d$  and  $\lambda$ .

## 4.2 Citation recommendation experiments

### 4.2.1 Parameter tests

Before performing a comparison of the different methods presented in the paper, we study the impact of the damping factor  $d$  and the direction awareness parameter  $\lambda$  on the recommendations given by the DaRWR algorithm. In particular, we want to verify that changing these parameters allows the user to obtain suggestions that are farther away from the seed papers  $\mathcal{M}$  and to obtain suggestions that are either recent or more traditional. To verify these effects, a source paper published between 2005 and 2010 is randomly selected and the paper's references are used as the seed papers. We use the top-10 results as the set of suggestions. The test is repeated 500 times.

Figure 4 shows the impacts of parameters  $d$  and  $\lambda$  as a heatmap on the average shortest distance in the citation graph between the recommended papers  $\mathcal{R}_{paper}$  and the seed papers  $\mathcal{M}$ . When  $d$  increases, the probability that the random research jumps back to the source node  $s$  is reduced. Therefore, the distant vertices are visited with more probability between two successive restarts, resulting in papers away from  $\mathcal{M}$  being more likely to be in  $\mathcal{R}_{paper}$ . Figure 4 shows that  $\lambda$  makes little difference in the average distance to the seed papers. However, setting a higher value of  $d$  should allow to find relevant papers whose relation to the seeds are not obvious.

Figure 5 shows the impacts of parameter  $d$  and  $\lambda$  on the average year of the recommended papers in  $\mathcal{R}_{paper}$  as a heatmap. Increasing the damping factor leads to earlier papers since they tend to accumulate more citations. But for a given  $\lambda$ , varying the damping factor do not allow to reach a large diversity of time frames. The direction awareness parameter  $\lambda$  can be adjusted to reach papers from different years with a range from late 1980's to 2010 for almost all values of  $d$ . In our online service, the parameter  $\lambda$  can be set to a value of user's preference. It allows the user to obtain recent papers by setting  $\lambda$  close to 1 or finding older papers by setting  $\lambda$  close to 0.

Overall, first-level papers are often returned for  $d < 0.8$ ; yet many papers at distance 2 and more appear. Also, it is possible to choose between traditional papers (by setting  $\lambda < 0.4$ ) or recent papers (by setting  $\lambda > 0.8$ ) thanks to the direction awareness parameter.

### 4.2.2 Experimental settings

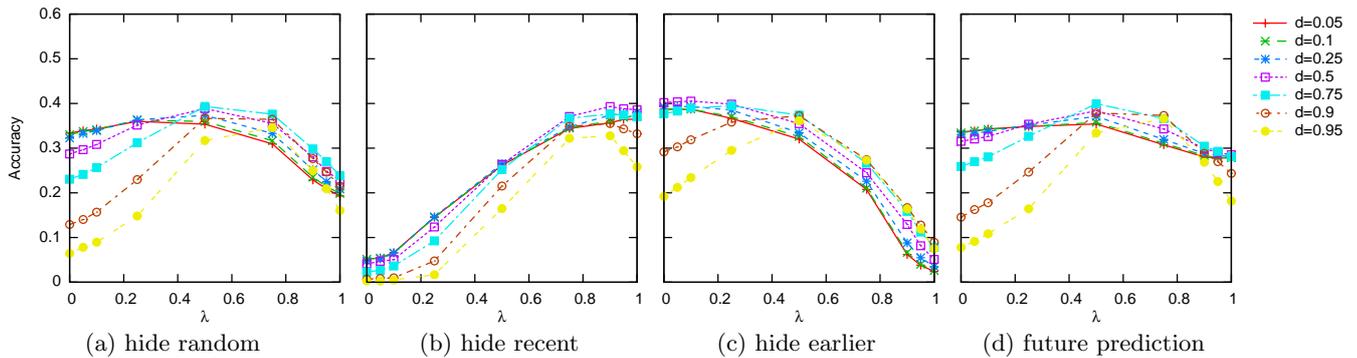


Figure 7: Accuracy of DaRWR method with different  $\lambda$  and  $d$  parameters on different experiments.

Table 6: Parameters used in the experiments.

Method	Random	Recent	Earlier	Future
Katz $_{\beta}$	$\beta = 0.0005$			
DAKATZ	$\beta = 0.005$ $\lambda = 0.25$	$\beta = 0.0005$ $\lambda = 0.75$	$\beta = 0.0005$ $\lambda = 0$	$\beta = 0.005$ $\lambda = 0.25$
PAPER RANK	$d = 0.5$	$d = 0.9$	$d = 0.9$	$d = 0.75$
DARWR	$\lambda = 0.5$ $d = 0.75$	$\lambda = 0.9$ $d = 0.5$	$\lambda = 0.1$ $d = 0.5$	$\lambda = 0.5$ $d = 0.75$

We test the quality of the recommended citations by different methods in four different scenarios.

**Hide random** scenario represents the typical use-case where a researcher is writing a paper and trying to find some more references. To simulate that, a source paper  $s$  with enough references ( $deg^+(s) \geq 20$ ) is randomly selected from the papers published between 2005 and 2010. Then we remove  $s$  and all the papers published after  $s$  from the graph (i.e.,  $G_s = (V_s, E_s)$  where  $V_s \subset V \setminus \{s\}$  and  $\forall v \in V_s, year[v] \leq year[s]$ ), simulating the time when  $s$  was being written. Out of  $deg^+(s)$ , 10% of the references are randomly put in the hidden set  $H$ , and the rest is used as the seed papers (i.e.,  $\mathcal{M} = \{v \notin H : (s, v) \in E\}$ ). We compute the citation recommendations on  $\mathcal{M}$  and report the average accuracy of finding hidden papers within the top  $deg^+(s)$  recommendations for 500 independent queries.

**Hide recent** scenario represents another typical use-case where the author might be well aware of the literature of her field but might have missed some recent developments. It differs from **hide random** while hiding the references. Here, the references that are put in  $H$  are not chosen randomly. They are the most recent references. Again, the average accuracy of finding hidden papers within the top  $deg^+(s)$  recommendations is reported for each source  $s$ .

In the **hide earlier** scenario, the author is interested in finding some key papers related to the field. This scenario is exactly the opposite of **hide recent**, i.e., the hidden papers are the oldest publications. The average accuracy of finding those hidden traditional papers within the top  $deg^+(s)$  recommendations is reported for each source  $s$ .

**Future prediction** scenario investigates the accuracy of a recommendation system while providing a link between two papers which are not known to be related yet. It verifies if the algorithm can predict which paper will be cited by a given paper. For this test, the source paper  $s$  is selected

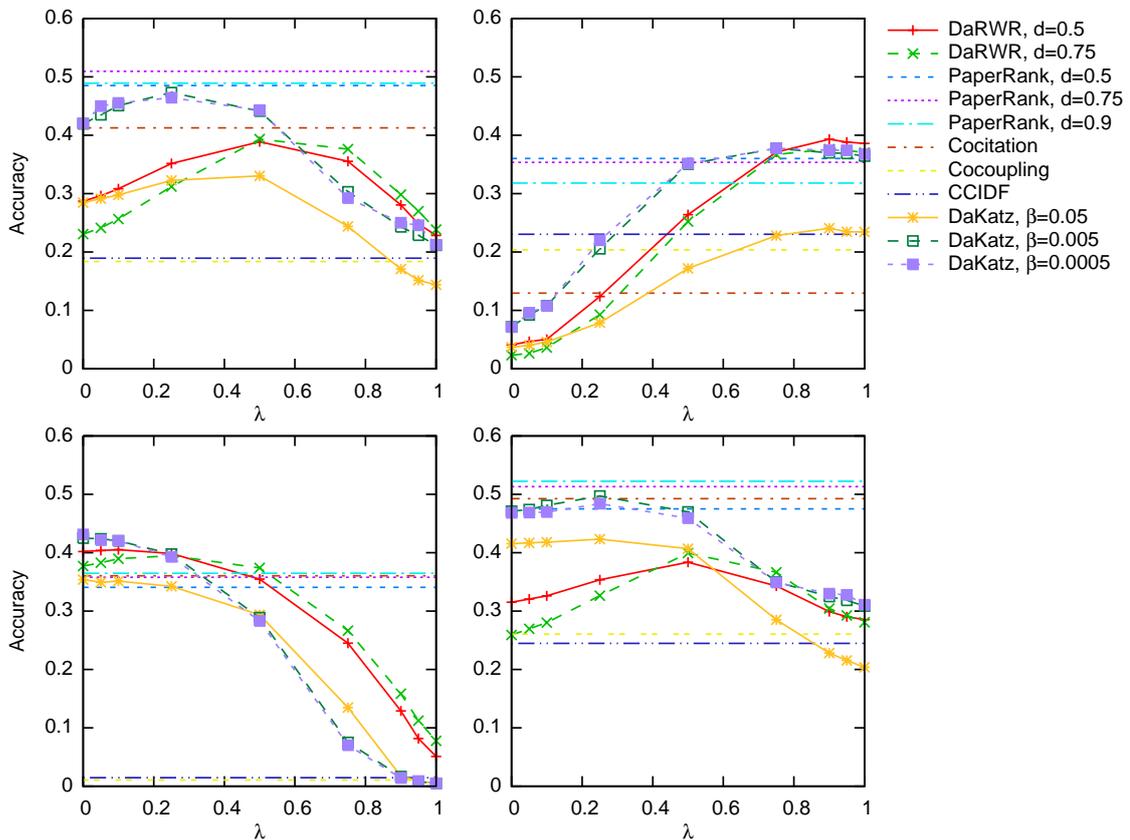
similarly. However, the graph selected for the recommendation include paper  $s$  but exclude all subsequent papers (i.e.,  $G_s = (V_s, E_s)$  with  $v \in V_s \iff year[v] \leq year[s]$ ). And all the references of the  $s$  are used as the seeds to obtain a top-10 recommendations. The accuracy of the algorithm is estimated by counting how many of the documents that appear in the top-10 is later co-cited with the source paper.

The methods we proposed are compared on the three scenarios against widely-used citation based approaches: bibliographic coupling [9], Cocitation [23], CCIDF [11], PAPER RANK [5] and the original Katz distance [15]. The algorithms and the parameters that lead to the best accuracy in different experiments are summarized in Table 6.

### 4.2.3 Results

Figure 7 presents the accuracy obtained by the DARWR for different combinations of the parameters  $d$  and  $\lambda$  on the four scenarios. The results show that extreme values of the parameter are typically not the one that obtain the highest accuracy. On the hide random experiment, DARWR performs best with  $d = 0.75$  and  $\lambda = 0.5$ . A similar combination set ( $d = 0.75, \lambda = 0.9$ ) obtains a high accuracy on the hide recent experiment. However it is best processed with parameters  $d = 0.5$  and  $\lambda = 0.9$ . As expected, the hide earlier experiment is best solved using a low value of the direction awareness parameter ( $d = 0.5, \lambda = 0.1$ ). The future prediction experiment is best solved by the  $d = 0.75, \lambda = 0.5$  parameter set. Still using  $d = 0.5$  leads to solutions of reasonable accuracy. It is interesting to notice that the hide random and future prediction experiments show similar pattern while the hide recent and hide earlier experiments show opposite patterns. This experiment tells us that it is enough to set  $\lambda$  as tunable for the service since tuning  $d$  has little impact once it is set to a reasonable value. Most likely, setting  $d$  as tunable will add only more complexity and no significant improvement in the accuracy.

Figure 8 presents a comparison of all the methods on the same scenarios. Many algorithms are represented as horizontal lines since they are not direction aware. The first remark is that Cocoupling and CCIDF perform poorly on all four scenarios. Cocitation performs the worse in the hide recent scenario and performs reasonably good but not the best in the other three scenarios. These methods which only consider counting and weighting of distance 2 edges at most from the seeds are out-performed by the eigenvector based methods which take whole graph into account.



**Figure 8: Accuracy of the algorithms on (top left) hide random, (top right) hide recent, (bottom left) hide earlier, and (bottom right) future prediction experiments based on  $\lambda$  and other parameters. Note that the accuracy of Katz is equal to DaKatz at  $\lambda = 0.5$ .**

Notice that PAPER-RANK performs well overall but for different values of the damping parameter  $d$ . The performance of DAKATZ is significantly varying with the parameter set but it is important to notice that the variations with the direction awareness parameter are similar to the one observed on DARWR. The results of KATZ are not explicitly presented but can be read on DAKATZ when  $\lambda = 0.5$ . Notice that DAKATZ is always a better method than KATZ. PAPER-RANK achieves the best results when the query is generic (on the hide random and future prediction scenarios); however direction aware methods lead to higher accuracy when the query is specific.

The previous experiments show that the method we proposed return results of higher accuracy. However, these results do not allow us to understand whether the methods return similar results or different results. Table 9 presents the intersection matrix of the different methods on four scenarios. Each method’s parameters are set to optimize the accuracy. The diagonal of the matrix shows the actual accuracy of the methods. Other values show the percentage of the intersection of two corresponding methods. For instance, one can read that on the hide random scenario, PAPER-RANK has an accuracy of 51.30% while CCIDF has an accuracy of 20.12%. The intersection between the results of CCIDF and PAPER-RANK has an accuracy of 17.23% indicating that most of the relevant results returned by CCIDF were also results by PAPER-RANK in that scenario. In the hide recent and hide random scenarios, the proposed method clearly dom-

inate the solution space. The other methods do not add many new relevant suggestions.

The case of the future prediction scenario is different. The intersection between the different methods often highlight that a significant portion of the returned suggestion differ between the algorithms. For instance, the intersection between DARWR and Cocoupling scores an accuracy of 5.68% which is 5 times smaller than the accuracy of Cocoupling (25.22%) and 7.5 times smaller than the accuracy of DARWR (39.08%).

#### 4.2.4 Citation patterns

For a better understanding of the difference between the accuracy obtain by different methods, we did a study on the properties of the suggestions returned by the methods and compare them to the properties of the actual references within the papers. We argue that highly relevant suggested papers should have similar patterns to the actual references.

One feature to measure the citation patterns is the *clustering coefficient* [26]. The clustering coefficient  $C_v$  of paper  $v$  is computed as:

$$C_v = \frac{|\{(i, j) \in E \mid i, j \in N_v \cup \{v\}\}|}{|N_v| \times (|N_v| + 1)},$$

where  $N_v$  is the set of neighbor papers of  $v$  which either cite  $v$  or are cited by  $v$ . Intuitively, the clustering coefficient indicates how close of being a clique a vertex and its neighbors are.

**Table 9: Intersection matrix of the results for (i) hide random, (ii) hide recent, (iii) hide earlier, and (iv) future prediction experiments.**

(i)	DARWR	P.R.	DAKATZ	Katz $_{\beta}$	Cocit	Cocoup	CCIDF	(ii)	DARWR	P.R.	DAKATZ	Katz $_{\beta}$	Cocit	Cocoup	CCIDF
DARWR	<b>40.62</b>	38.96	36.75	33.81	30.02	13.48	14.46	DARWR	<b>40.57</b>	33.51	31.68	31.13	7.86	16.78	19.92
P.R.		<b>51.31</b>	43.59	40.31	35.18	16.20	17.23	P.R.		<b>37.41</b>	30.89	31.37	9.67	17.19	20.18
DAKATZ			<b>48.72</b>	39.63	35.99	15.57	15.31	DAKATZ			<b>38.18</b>	35.72	8.48	19.28	21.19
Katz $_{\beta}$				<b>44.87</b>	31.10	17.17	16.89	Katz $_{\beta}$				<b>37.18</b>	9.35	19.07	21.06
Cocit					<b>42.57</b>	11.53	11.00	Cocit					<b>13.87</b>	6.28	5.96
Cocoup						<b>19.47</b>	15.04	Cocoup						<b>22.03</b>	18.08
CCIDF							<b>20.13</b>	CCIDF							<b>25.23</b>
(iii)	DARWR	P.R.	DAKATZ	Katz $_{\beta}$	Cocit	Cocoup	CCIDF	(iv)	DARWR	P.R.	DAKATZ	Katz $_{\beta}$	Cocit	Cocoup	CCIDF
DARWR	<b>60.72</b>	51.21	56.92	41.28	46.61	1.97	2.35	DARWR	<b>39.08</b>	28.75	24.59	20.82	18.91	5.68	6.31
P.R.		<b>55.17</b>	52.73	40.39	45.94	1.88	2.29	P.R.		<b>51.48</b>	32.55	30.87	24.50	9.56	10.57
DAKATZ			<b>65.11</b>	42.69	50.67	2.21	2.44	DAKATZ			<b>49.37</b>	26.50	30.66	6.34	5.21
Katz $_{\beta}$				<b>43.04</b>	39.53	2.10	2.35	Katz $_{\beta}$				<b>45.15</b>	17.41	13.99	12.30
Cocit					<b>53.02</b>	1.95	2.09	Cocit					<b>48.65</b>	3.41	2.48
Cocoup						<b>2.48</b>	1.18	Cocoup						<b>25.22</b>	14.78
CCIDF							<b>2.81</b>	CCIDF							<b>24.27</b>

The other metric we consider is the PageRank [2] of a vertex which can be calculated by putting all vertices in  $\mathcal{M}$  during the PAPERANK algorithm.

Figure 10 presents the cumulative density function of the clustering coefficient and of the PageRank of the documents suggested by each algorithm and of the hidden papers in the three hidden scenarios. The first observation is that on all charts the Cocitation algorithm is an outlier. Also, CCIDF and Cocoupling are almost indistinguishable on all charts. Interestingly, the clustering coefficient of the hidden papers in the hide earlier scenario are lower than in the hide random scenario and the clustering coefficient of the hidden paper in the hidden recent scenario are the highest. The trend is reverse with PageRank. Older papers have more time to become famous so their PageRank is higher. And since they have more citations, it is less likely that their neighbors are close to form a clique. This highlights that papers published in different years have different profiles, bolstering our claim that one should not use the very same algorithm and parameters to look for them.

For the hide random scenario, PAPERANK suggests papers of clustering coefficient very similar to the hidden paper, while DARWR, KATZ, and DAKATZ show a different but parallel trace. The PageRank distribution of the algorithm shows a similar picture, except KATZ is close the hidden paper and PAPERANK, DARWR, and DAKATZ are farther away.

In the hide recent scenario, most algorithms have a similar trace for both the clustering coefficient and PageRank. PAPERANK and KATZ are significantly different than their direction aware variants and the trace of the hidden paper. Recall that PAPERANK and KATZ are also less accurate than their direction aware variants on the hide recent scenario. Having a similar trace is an important property but it is not enough to reach a high accuracy. Indeed, Cocoupling and CCIDF show a trace similar to the that of hidden papers in that scenario but with less accuracy.

In the hide earlier scenario, the direction aware algorithm have patterns similar to the hidden paper for both metric explaining the high accuracy they reach. PAPERANK has a PageRank pattern similar to the hidden paper but a different clustering coefficient pattern and it does not reach the high accuracy level the direction aware algorithms ob-

tain. KATZ’s pattern is similar to that of the hidden paper neither in clustering coefficient nor on PageRank and it is the one with the lowest accuracy among all the eigenvector based methods.

This analysis shows that direction aware algorithms have overall similar citation patterns. CCIDF and cocoupling have typically similar citation patterns. The difference in accuracy of the eigenvector based methods can be explained by the similarity in citation patterns between the papers one is looking for and what is generated by the method. The direction aware methods are more flexible and can be tuned to match the property of the query leading to higher accuracy. The reasons of success or failure of the non-eigenvector based methods (Cocitation, Cocoupling, and CCIDF) seem to be unrelated to the citation pattern metrics we considered.

### 4.3 Relevance feedback experiments

Relevance feedback is an important part of the recommendation system since users may give positive and negative feedbacks on the results in order to reach to desired papers or topics. In this test, 500 source papers are randomly selected, and for each source paper  $s$  the graph is pruned by removing the papers published after  $s$ . Then, a target paper  $u$  is selected from the pruned graph, such that it is the most relevant paper at distance 5 from  $u$ . Assuming that a user can only display 10 results at a time, we measure the number of pages that the user has to go through until she reaches  $t$ . We compare the feedback mechanism with the following idealized user behavior:

**No feedback:** There is no feedback mechanism; therefore, user should keep looking the next page until she finds the target paper.

**Only positive feedback:** Results are labeled as relevant and added to  $\mathcal{M}$  in the next step or should not be displayed again.

**Only negative feedback:** Results are labeled as irrelevant to be removed from the graph or should not be displayed again.

**Both positive and negative:** Results are labeled as either relevant to be added to  $\mathcal{M}$  or irrelevant to be removed from the graph.

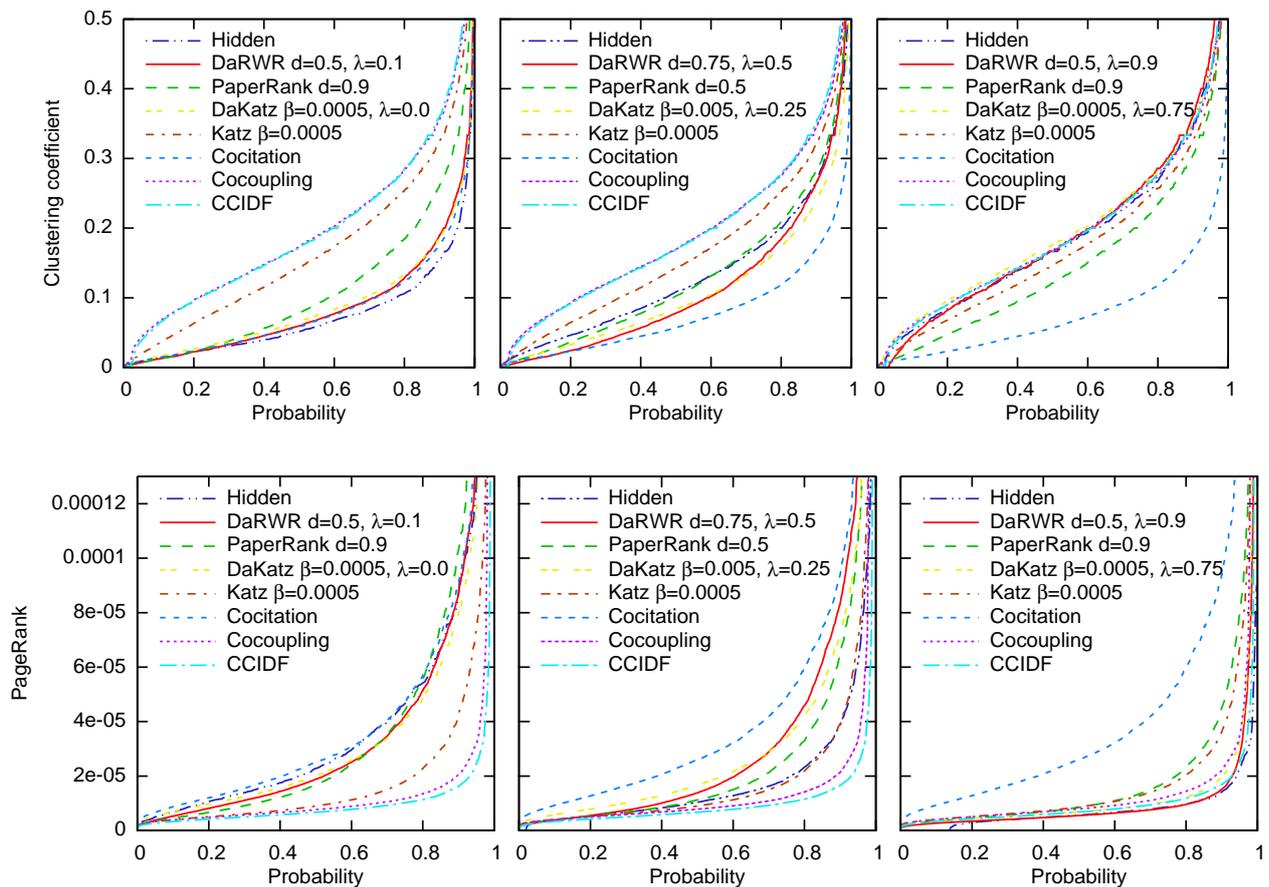


Figure 10: Clustering coefficient (top) and Pagerank (bottom) of the suggested citations for the hide earlier (left), hide random (center), and hide recent (right) experiments.

Detailed results for that experiment are omitted. Using negative feedback only reduces the number of pages one has to go through by 82.29% in average and using positive feedback allows to reduce the number of pages by 97.15% in average. Using both negative and positive feedback reduces the number of pages by 97.20% in average. This result shows that using the feedback mechanism allows to significantly speedup the process of searching for specific references.

#### 4.4 Venue and reviewer recommendation experiments

The venue recommendation methods is tested on the assumption that a paper is published in a venue where it is relevant. The following protocol relies on this assumption. A source paper is randomly selected and is removed from the graph as long as all subsequent papers. The objective is to find the venue of the source paper in  $\mathcal{R}_{venue}$  containing  $k = 10$  venues. We compare the performance of our methods against a method commonly employed by researcher, which consist in considering the top-10 most occurring venues of the paper of interest; e.g., the  $\mathcal{M}$  set. We call this algorithm **Baseline 1**. Another algorithm, **Baseline 2**, considers the venues of the paper at distance 2 of the source paper: it returns the top-10 most occurring venues in  $\mathcal{M}$  and the references and citation of these documents.

The reviewer recommendation experiment is based on the assumption that “the authors are the best reviewers for the

Table 11: Average accuracy of venue recommendation (VR) and reviewer recommendation (RR) experiments.

	VR	RR	
	Accuracy@10	Any@25	All@25
DARWR	63.2	76.4	48.19
PAPER RANK	60.6	74.4	45.85
DAKATZ	58.4	64.4	35.17
Baseline 1	56.0	73.0	48.38
Baseline 2	60.0	72.6	44.04

paper” (ignoring the obvious *conflict-of-interest*, and by best reviewers referring to people that have the enough knowledge on this candidate paper). The experiment is conducted similarly to the venue recommendation experiment. A source paper is selected and is removed from the graph as long as all subsequent papers. For a list  $\mathcal{R}_{expert}$  which contains  $k = 25$  experts, we distinguish whether none of the authors of the source paper is found, if any author is found or if all the authors are found. Both baselines are defined in the same way as in the venue recommendation experiment.

Table 11 presents the average accuracy of these methods when run on 500 random (uniform) source papers. For

venue recommendation, the three proposed methods perform better than Baseline 1 and DARWR perform better than Baseline 2. The differences are marginal (less than 10%) but statistically significant. For reviewer recommendation, DARWR performs the best. Interestingly Baseline 2 performs worse than Baseline 1 in both experiments.

## 5. CONCLUSION AND FUTURE WORK

In this paper, we present direction aware algorithms for citation recommendation. A direction aware model allows to tune the search for finding more recent or more traditional documents. We developed two algorithms based on the direction aware model, namely DAKATZ and DARWR. We also suggest to use the classical random walk with restart (PAPERANK) for academic recommendation. Experimentally, we confirmed that the parameters can be easily set to browse the academic web of knowledge. In our experiments, the direction aware algorithm we propose outperforms the existing algorithms for citation recommendation which are based only on the citation graph in experiments that focus on finding either traditional or recent papers. We implemented the algorithms in our webservice which allows any researcher to upload a bibliography file and obtain suggestions. This service is freely available and easy to use. Coupled with our efficient algorithms, we believe that our service will become a tool of major interest for researchers.

As future work, we want to improve our service both in theory and practice. We are planning to test weighting schemes on edges to have a better distribution of probability to papers with high quality. In practice, we will improve the amount and the quality of the bibliographic data by using existing techniques such as canopy clustering and by obtaining data from more public academic databases. We are also planning to conduct an intensive user study to obtain a real-world evaluation of the system.

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