Towards Finding Non-obvious Papers: An Analysis of Citation Recommender Systems

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Abstract As science advances, the academic community has published millions of research papers. Researchers devote time and effort to search relevant manuscripts when writing a paper or simply to keep up with current research. In this paper, we consider the problem of citation recommendation by extending a set of known-to-be-relevant references. Our analysis shows the degrees of cited papers in the subgraph induced by the citations of a paper, called projection graph, follow a power law distribution. Existing popular methods are only good at finding the long tail papers, the ones that are highly connected to others. In other words, the majority of cited papers are loosely connected in the projection graph but they are not going to be found by existing methods. To address this problem, we propose to combine author, venue and keyword information to interpret the citation behavior behind those loosely connected papers. Results show that different methods are finding cited papers with widely different properties. We suggest multiple recommended lists by different algorithms could satisfy various users for a real citation recommendation system. Moreover, we also explore the fast local approximation for combined methods in order to improve the efficiency.

Keywords Citation recommendation · Graph analysis · Academic graph · Local approximation · Projection Graph

1 Introduction

Scientists around the world have published tens of millions of research papers, and the number of new papers has been increasing with time. For example, according to DBLP [21], computer scientists published 3 times more papers in 2010 than in 2000. At the same time, literature search became an essential task performed daily by thousands of researchers around the world. Finding relevant research works from the gigantic number of published articles has become a nontrivial problem.

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Currently, many researchers rely on manual methods, such as keyword search via Google Scholar\(^1\) or Mendeley\(^2\) to discover new research works. However, keyword based searches might not be satisfying for two reasons: firstly, the vocabulary gap between the query and the relevant document might result in poor performance; secondly, a simple string of keywords might not be enough to convey the information needs of researchers. There are many instances where such a keyword query is either too broad, returning many articles that are loosely relevant to what the researcher actually need, or too narrow, filtering many potentially relevant articles out or returning nothing at all [5].

To alleviate the above mentioned problems, many research works proposed citation recommendation algorithms which use a manuscript instead of a set of keywords as query [29, 9, 10, 24, 11]. For example, context-aware citation recommendation is designed to recommend relevant papers for placeholders in the query manuscript based on local contexts [9, 10]. Manuscript based citation recommendation is great to help with the writing process. However, we are interested here in helping the research process which usually comes long before manuscripts are fleshed out. Researchers have devoted efforts on citation recommendation based on a set of seed papers [25, 3] 3 [8, 3, 20]. Most approaches rely on the citation graph to recommend relevant papers, such as collaborative filtering [25] and random walk framework [5]. The different approaches to recommending academic papers have been extensively surveyed by [11].

We consider in this paper the problem of extending a set of known references, which is helpful in recommender system and academic search engine, such as theAdvisor [19]. We show that classic methods (namely, PaperRank and Collaborative Filtering) perform reasonably well, but have an inherent bias. Because they base their decision on citation patterns, they tend to only find papers that have many links to the known references, a set of papers that are obvious. Unfortunately, less than half of the references of a paper are connected to more than two other references. This causes the algorithms to ignore lightly connected papers despite being half of the references in practice.

We propose to use metadata information, such as authorship and textual information, to identify the non-obvious connections between papers. Besides meta path based methods, we design two types of algorithms. One type only uses metadata: logAVK directly scores candidate papers based on the similarity of their metadata to the query papers. And one extends PaperRank with some metadata; C+X extends PaperRank by adding author, venue or keyword nodes in the graphs to enable random walk paths between papers with similar metadata. Moreover, various keywords extraction strategies for C+K are investigated.

Our experiments show that the methods that extend PaperRank can improve the quality of the recommendation. Also logAVK provides a different perspective on the queries, despite it does not score as well in various quality metrics as other algorithms. For a practical citation recommendation system, the efficiency of underlying recommendation algorithm is also important. Therefore, we propose local C+X methods which is 15x faster while they are as effective as original C+X methods.

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\(^1\) https://scholar.google.com/
\(^2\) https://www.mendeley.com/
A preliminary version of this work was published in [13]. We extend in this paper with following major extensions:

- We conduct additional experiments on 7 different meta path-based approaches.
- We investigate the impact of various keywords extraction strategies on C+K;
- We explore the fast local approximation methods for C+X in order to improve the efficiency.

The paper is organized as follows: we introduce related work in Sec. 2. In Sec. 3, we define the citation recommendation problem and present existing methods. Based on the analysis of Sec. 4, we propose to use metadata to enhance the performance on loosely connected papers in Sec. 5. Sec. 7 argues the use of the different algorithms in a practical system. Finally, Sec. 8 discusses the usefulness in real systems.

2 Related Work

Many works addressed citation recommendation.

Seed papers based citation recommendation. Given a "basket" of citations, McNee et al. [25] explore the use of Collaborative Filtering (CF) to recommend papers that would be suitable additional references for a target research paper. They create a ratings matrix where citing papers correspond to users and citations correspond to items. The experiments show CF could generate high quality recommendations. As a follow-up, Torres et al. [33] describe and test different techniques for combining Collaborative Filtering and Content-Based Filtering. A user study shows many of CF-CBF hybrid recommender algorithms can generate research paper recommendations that users were happy to receive. However, offline experiments show those hybrid algorithms did not perform well. In their opinion, the sequential nature of these hybrid algorithms: the second module is only able to make recommendations seeded by the results of the first module. To address this problem, Ekstrand et al. [4] propose to fuse the two steps by running a CF and a CBF recommender in parallel and blending the resulting ranked lists. The first items on the combined recommendation list are those items which appeared on both lists, ordered by the sum of their ranks. Surprisingly, Collaborative Filtering outperforms all hybrid algorithms in their experiments.

Gori et al. [8] devised a random walk based method, to recommend papers according to a small set of user selected relevant articles. Küçüktan et al. designed a personalized paper recommendation service, called theAdvisor [20, 19], which allows a user to specify her search toward recent developments or traditional papers using a direction-aware random walk with restart algorithm [17]. The recommended papers returned by theAdvisor are diversified by parameterized relaxed local maxima [15]. Küçüktan et al. proposed sparse matrix ordering and partitioning techniques to accelerate citation such recommendation algorithms [16].

Caragea et al. [3] addressed the problem of citation recommendation using singular value decomposition on the adjacency matrix associated with the citation graph to construct a latent semantic space: a lower-dimensional space where correlated papers can be easily identified. Their experiments on Citeseer show

http://theadvisor.osu.edu/
this approach achieves significant success compared with Collaborative Filtering methods. Wang et al. [34] proposes to include textual information to build an topic model of the papers and adds an additional latent variable to distinguish between the focus of a paper and the context of the paper.

A typical related paper search scenario is that a user starts with a seed of one or more papers, by reading the available text and searching related cited references. Sofia is a system that automates this recursive process [7].

The approach proposed by [5] returns a set of relevant articles by optimizing a function based on a fine-grained notion of influence between documents; and also claim that, for paper recommendation, defining a query as a small set of known-to-be-relevant papers is better than a string of keywords.

Manuscript based citation recommendation. Stohman et al. [29] examined the effectiveness of various text-based and citation-based features on citation recommendation, they find that neither text-based nor citation-based features performed very well in isolation, while text similarity alone achieves a surprisingly poor performance at this task. He et al. [9] considered the problem of recommending citations for placeholder in query manuscripts and a proposed non-parametric probabilistic model to measure the relevance between a citation context and a candidate citation. To reduce the burden on users, [10] proposed different models for automatically finding citation contexts in an unlabeled query manuscript.

Recently, citation recommendation from heterogeneous network mining perspective has attracted more attention. Besides papers, metadata such as authors or keywords are also considered as entities in the graph schema. Two entities can be connected via different paths, called meta-paths, which usually carry different semantic meanings. Many work build discriminative models for citation prediction and recommendation based on meta-paths [35, 23, 22, 26].

The vocabulary used in the citation context and in the content of papers are usually quite different. To address this problem, some works propose to use translation model, which can bridge the gap between two heterogeneous languages [24, 11]. Based on previous work [9, 10, 11], Huang et al. built a citation recommendation system called RefSeer [12] which perform both topic-based global recommendations and citation-context-based local recommendations.

Based on the hypothesis that an author’s published works constitute a clean signal of the latent interests of a researcher, [30] examined the effect of modeling a researcher’s past works in recommending papers. Specifically, they first construct a user profile based on her/his recent works, then rank candidate papers according to the content similarity between the candidate and the user profile. Furthermore, in order to achieve a better representation of candidate paper, [31] exploit potential citation papers through the use of collaborative filtering.

http://refseer.ist.psu.edu/
Table 1: Data Statistics

| Attribute             | Number  |
|-----------------------|---------|
| Papers                | 2,035,246 |
| Citations             | 12,439,090 |
| Papers with text      | 374,999  |
| Keywords              | 195,989  |
| P-K Edges             | 14,779,751 |

| Attribute             | Number  |
|-----------------------|---------|
| Authors               | 1,208,641 |
| P-A Edges             | 5,977,884 |
| Venues                | 9,777   |
| P-V Edges             | 2,035,246 |

3 Citation Recommendation

3.1 Data Preparation

To obtain a clean and comprehensive academic data set, we match Microsoft Academic Graph, CiteSeerX and DBLP datasets for their complementary advantages and derive a corpus of Computer Science papers. On one hand, Microsoft Academic Graph contains abundant information from various disciplines but it is fairly noisy: some important attributes are missing or wrong. In contrast, the records in DBLP are much more reliable although it does not contain citation information. So we first merge MAG and DBLP records through DOI and titles to get an academic citation graph (within the scope of Computer Science) with rather clean metadata.

On the other hand, CiteSeerX dataset indexes 2 million papers and provides full-texts in PDF format which neither MAG or DBLP contains. We merge CiteSeerX and DBLP records through titles and refine the result with other metadata, like published year. This data set gives us for each paper the name of the authors, the venue of publication, the title of the paper, full text (for about a fifth of the papers), and citation information. We derived keywords using KP-Miner for those with full text and using non-stop words from titles for others. High level statistics of this dataset is given in Table 1.

3.2 Problem Statement

Let $G = (V, E)$ be the citation graph, with $n$ papers $V = \{v_1, \ldots, v_n\}$. In $G$, each edge $e \in E$ represents a citation relationship between two papers. We use $Ref(v)$ and $Cit(v)$ to denote the reference set of and citation set to $v$, respectively. And $Adj(v)$ is used to denote the union of $Ref(v)$ and $Cit(v)$.

In this paper, we focus on citation recommendation problem assuming that researchers already know a set of relevant papers. Therefore, the task can be formalized as:

Citation Recommendation. Given a set of seed papers $S$, return a list of papers ranked by relevance to the ones in $S$. 

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5 https://www.microsoft.com/en-us/research/project/microsoft-academic-graph/
6 http://citeseerx.ist.psu.edu/
7 http://dblp.uni-trier.de/xml/
3.3 Algorithms

**CoCitation** [2] The number of cocitations is often used to measure the relevance between two papers. In the citation recommendation scenario, cocitation ranks a candidate paper according to the sum of the times it was cocited with papers in the seed set.

\[
R(x) = \sum_{s \in S} \sum_{v \text{ for } s, x \in \text{Cit}(v)} 1
\]

**CoCoupling** [2] CoCoupling is a complementary metric of cocitation. It counts the number of times that two papers cite a same paper. Here, we use cocoupling to measure the relevance between the candidate paper and seed papers according to the following formula:

\[
R(x) = \sum_{s \in S} \sum_{v \text{ for } s, x \in \text{Ref}(v)} 1
\]

**PaperRank** [8] (PR) PaperRank is a biased random walk proposed to recommend papers based on citation graph. In particular, the restarts from any paper will be distributed to only the seed papers. PR assumes a random walker in paper \(v\) continues to a neighbor with a damping factor \(d\), and with probability \((1 - d)\) it restarts at one of the seed papers in \(S\). The edges are followed proportionally to the weight of that edge \(w_{ji}\) which is often set to 1, but can be set to the number of time \(i\) is referenced by \(j\).

\[
R(v_i) = (1 - d) \frac{1}{S} + d \sum_{v_j \in \text{Adj}(v_i)} \frac{w_{ji}}{\sum_{v_k \in \text{Adj}(v_j)} w_{jk}} R(v_j)
\]

**Collaborative Filtering** [25] (CF) has been proven to be an effective idea for most recommendation problems. For citation recommendation, a ratings matrix is built using the adjacent matrix of citation graph, where citing papers correspond to users and citations correspond to items. A pseudo target paper that cites all seed papers is added to the matrix. CF computes the \(k\) neighborhoods that are top \(k\) similar papers to the target paper. Then each citation in neighbors is summed up with the count weighted by the similarity score.

4 A First Evaluation

In order to simulate the typical use case where a researcher is writing a paper and tries to find some more references, we design the random-hide experiment. First of all, a query paper \(q\) with 20 to 200 references and published between 2005 to 2010 is randomly (uniformly) selected from the dataset. We then remove the query paper \(q\) and all papers published after \(q\) from the citation graph to simulate the time when the query paper was being written. Instead of using hide-one strategy [25, 33], we randomly hide 10% of the references as hidden set. This set of hidden paper is used as ground truth to recommend. The remaining (18 and 180 depending on \(q\)) papers are used as the set of seed papers.

Finally, to evaluate the effectiveness of recommendation algorithm, we use \(\text{recall}_k\), the ratio of hidden papers appearing in top \(k\) of the recommended list.
Table 2: Global Performance

| Method      | Recall@10   | Recall@20   | Recall@50   |
|-------------|-------------|-------------|-------------|
| PaperRank   | 0.234413    | 0.326096    | 0.471510    |
| CF          | 0.191736    | 0.266961    | 0.391736    |
| CoCitation  | 0.192626    | 0.267617    | 0.392197    |
| CoCoupling  | 0.055778    | 0.088216    | 0.146737    |

Table 2 shows the results of popular methods on average recall for 2,500 independent randomly selected queries. We call these scores global performance, as we will analyze the common features of the hidden papers found by those methods to reveal the bias behind the algorithms.

To analyze the performance of the algorithms, we investigate the local structure of the citation graph. The citation projection graph of a paper $p$ is the graph induced by the papers cited by $p$ [27]. For a query paper, it is the graph where the vertex set is composed of the seed papers and the hidden papers, and the edge set is composed of the citations between these vertices. The citation projection graph focuses on the cited papers and the relationships among them; it is known to help understanding the local pattern in the citation graph [27].

We investigated the relations between various properties of the projection graph and whether hidden papers were found or not. We identified that the degree of the hidden papers in the projection graph, we call proj-degree, is a good indicator of whether the hidden paper will be discovered or not. We computed the average recall@10 scores on hidden papers grouped by proj-degree and reported these numbers in Figure 2. Popular graph based methods are quite good at finding hidden papers that are highly connected in the citation projection graph. But these methods achieve poor performance on loosely connected ones. Unfortunately, over 50% of the hidden papers have a proj-degree of 2 or less. The distribution of proj-degree is shown in Figure 3.
5 Finding Loosely Connected Papers

5.1 Are these papers random citation?

The analysis of the last section shows that popular methods are good at finding papers that are highly connected in citation projection graph. But they perform poorly on papers that are not well connected in the citation projection graph.
despite they are the majority. Therefore, we focus our analysis on loosely connected papers.

The key question is why do authors cite these papers? According to [27], some papers create random reference across various fields. This might sound reasonable to explain the fact that these references are loosely connected in the citation projection graph. However, as Figure 3 shows, about 50% of cited papers have one or no link to others. Therefore, we believe they must share some common patterns or features with others cited papers that are not apparent in the citation graph. We expect other features such as authors, venue, or keywords, convey helpful information.

A preliminary analysis of the metadata of loosely connected papers shows that about 46% of the papers connected to two of the seeds or less share at least one common author with at least one of the seed papers. 60% of the loosely connected papers appeared in the venue of one of the seed paper. And 95% of the loosely connected paper shared at least one keyword with one of the seed paper. This indicates that the citations are not random citations; but authors chose to cite them for reasons that are not clearly explained by the citation graph.

5.2 Algorithms using Metadata

Based on above analysis, we explore different approaches that use metadata for citation recommendation. We firstly define a group of paper ranking schemes based on meta path in the bibliographic network. Then we propose two random walk based methods to examine the ability of metadata for identifying loosely connected papers. One is based on the metadata themselves, and we combine the metadata and citation graph in the other one.

5.2.1 MetaPath

Recently, similarity search among the same type of entities in heterogeneous networks has attracted more attention. Intuitively, two entities are similar if they are linked by many paths in the network. However, most existing similarity measures are defined for homogeneous networks. Therefore, meta path-based similarity is proposed [32].

A meta path is a path defined on the heterogeneous network schema, and is denoted in the form of $O_1 \rightarrow R_1 \rightarrow O_2 \rightarrow R_2 \rightarrow \ldots \rightarrow R_l \rightarrow O_{l+1}$, which defines a composite relation $R$ between type $O_1$ and $O_{l+1}$.

In a heterogeneous network, two entities can be connected via different meta paths. For example, in bibliographic network, two authors can be connected via "author-paper-author" path, "author-paper-venue-paper-author" path, and so on. Different meta paths usually carry different semantic meanings.

For citation recommendation problem, we are looking for papers that are relevant to the seed papers. To measure the relevance between a pair of papers, 5 basic meta paths are defined:

- **Paper – Author – Paper (PAP):** Two papers may be relevant if they share a common author.
- **Paper – Venue – Paper (PVP):** Two papers may be relevant if they are published in the same venue.
Fig. 4: Meta path examples: Paper-Author-Paper

- **Paper - Keyword - Paper (PKP)**: Two papers may be relevant if they share a keyword.
- **Paper → Paper ← Paper (PCiP)**: Two papers may be relevant if they share a citation.
- **Paper ← Paper → Paper (PCoP)**: Two papers may be relevant if they are cited by the same paper.

Given a paper-to-paper meta path, several similarity measures can be defined according to the path instances between them following the meta path. A straightforward measure will be:

**PathCount Measure**: Given a meta path \( P \) and a pair of papers \( x \) and \( y \), the similarity between them is defined as:

\[
PathCount(x, y, P) = |\{ p_{x\rightarrow y} : p_{x\rightarrow y} \in P \}|
\]

Essentially, PathCount is the number of path instances \( p \) between \( x \) and \( y \). This kind of similarity always favors entities with large degrees. Therefore, Sun et al. [32] propose a new meta path-based similarity measure, called PathSim, which tries to capture the subtlety of peer similarity:

**PathSim Measure**: Given a symmetric meta path \( P \), the similarity between two entities of the same type \( x \) and \( y \) is:

\[
PathSim(x, y, P) = \frac{2 \times |\{ p_{x\rightarrow y} : p_{x\rightarrow y} \in P \}|}{|\{ p_{x\rightarrow x} : p_{x\rightarrow x} \in P \}| + |\{ p_{y\rightarrow y} : p_{y\rightarrow y} \in P \}|}
\]

where \( p_{x\rightarrow y} \) is a path instance between \( x \) and \( y \), \( p_{x\rightarrow x} \) is that between \( x \) and \( x \), and \( p_{y\rightarrow y} \) is that between \( y \) and \( y \).

The intuition behind PathSim is that two similar peer entities should not only be strongly connected, but also share comparable visibility, where the visibility is defined as the number of path instances between themselves.

Figure 4 shows two examples induced from the bibliographic network. In \( G_1 \), both \( P_1 \) and \( P_2 \) are written by the same two authors, while in \( G_2 \), \( P_1 \) also shares
two common authors with $P_2$ but $P_1$ and $P_2$ have 3 and 4 authors in total respectively. The $PathCount(P_1, P_2, PAP)$ scores between $P_1$ and $P_2$ in $G_1$ and $G_2$ are the same since there are 2 PAP paths for both examples. However, the $PathSim(P_1, P_2, PAP)$ scores are different: for $G_1$, $PathSim(P_1, P_2, PAP) = \frac{2 \times 2}{2 + 2} = 1$ and for $G_2$, $PathSim(P_1, P_2, PAP) = \frac{2 \times 2}{3 + 3} = 0.57$.

Based on above similarity measures, the relevance between a candidate paper $x$ and seed papers can be denoted as:

$$Score(x, Seed, P) = \sum_{s \in Seeds} \frac{Score(x, y, P)}{|\{s : s \in Seeds\}|}$$

where $Score$ function is either $PathCount$ or $PathSim$.

Now we have 5 different paper-to-paper meta paths and 2 meta path-based measures. Theoretically, there will be $5 \times 2 = 10$ ways to rank the candidate papers. In particular, $PathCount_{PC_iP}$ is essentially the CoCoupling method and the same for $PathCount_{PCoP}$ and the CoCitation method. Besides, as a paper-to-venue is always a one-to-one pair, $PathCount_{PV P}$ and $PathCSim_{PV P}$ will be the same thing. Therefore, we have 7 meta path based ranking methods, namely: $PathCount_{PAP}$, $PathCount_{PKP}$ and $PathSim_{PAP}$, $PathSim_{PV P}$, $PathSim_{PKP}$, $PathSim_{PCiP}$ and $PathSim_{PCoP}$.

### 5.2.2 LOGAVK

In order to compute the similarity between one paper to a set of other papers, we build attribute graphs for author, venue and keyword respectively. Let us take author as example, we first define an undirected weighted graph of authors where an edge represents the number of papers two authors have written together. Then we normalize the adjacent matrix of this graph as $M^{AA}$, where $A$ is the set of authors. Once the graph is constructed, we can measure the similarity between a candidate author and the authors of seed papers by random walk as follows:

$$R^A = \begin{cases} \alpha M^{AA} R^A + (1 - \alpha) \frac{1}{|S|} & \text{For authors of seed papers} \\ \alpha M^{AA} R^A & \text{otherwise} \end{cases}$$

The keyword graph $M^{KK}$ and venue graph $M^{VV}$ are constructed and the similarity score $R^K$ and $R^V$ are computed in the same way. LogAVK recommends the loosely connected papers according to the summation of the similarity scores of authors, venue and keywords with corresponding seed papers.

$$Score_{LogAVK} = \log R^A + \log R^V + \log R^K$$

### 5.2.3 Combining Citation graph and Metadata

Aiming to combine the citation information and metadata information, we build bipartite graphs with two kinds of nodes: papers and metadata. A random walk algorithm passes information back and forth between the papers and the metadata. Taking the paper-author graph as an example, the vector of paper scores is denoted by $R^P$ and the vector of author scores is denoted by $R^A$. The scores of authors is computed by:
Table 3: Global Performance

| Method       | Recall@10 | Recall@20 | Recall@50 |
|--------------|-----------|-----------|-----------|
| PaperRank    | 0.234413  | 0.329996  | 0.415109  |
| CF           | 0.230617  | 0.318206  | 0.463204  |
| C+A          | 0.230531  | 0.323125  | 0.461898  |
| C+K          | 0.231086  | 0.315485  | 0.461507  |
| LogAVK       | 0.053934  | 0.084901  | 0.129175  |
| PathCount,PAP| 0.053291  | 0.079318  | 0.125647  |
| PathCount,PKP| 0.031268  | 0.050866  | 0.085056  |
| PathSim,PAP  | 0.053734  | 0.079897  | 0.125602  |
| PathSim,PVP  | 0.003057  | 0.005231  | 0.010377  |
| PathSim,PKP  | 0.031662  | 0.051366  | 0.098917  |
| PathSim,PCiP | 0.061189  | 0.095165  | 0.158142  |
| PathSim,PCoP | 0.192168  | 0.269849  | 0.396291  |

\[ R^A = M^AP R^P \]

which means an author score is collected from the papers she published. Some of the paper scores are transferred between papers within the citation graph:

\[ R^P_1 = M^{PP} R^P \]

And a paper also collects scores from its authors:

\[ R^P_2 = M^{PA} R^A \]

A paper in the seed set \( S \) also receives scores by random jumping from others.

\[ R^P_3 = \frac{1}{S} \]

The final score of a paper is the weighted sum of above parts.

\[
R^P_A = \begin{cases} 
\alpha R^P_1 + \beta R^P_2 + (1 - \alpha - \beta) R^P_3 & \text{for seed papers} \\
\alpha R^P_1 + \beta R^P_2 & \text{otherwise}
\end{cases}
\]

where \( \alpha \) (\( \beta \), resp.) is the fraction of the rank following a citation edge (an author edge, resp.). In the experiments, we set \( \alpha = .65, \beta = .2 \).

We will refer to any method that combines the citation information and a metadata in this manner as C+X. In particular, C+A will denote combining citation and authorship; C+K will denote combining citation and keyword; and C+V will denote combining citation and venue.

5.3 Evaluation

General performance. We evaluate the general effectiveness of the recommendation algorithms using recall@\( k \); the ratio of hidden papers appearing in top \( k \) of the recommended list. Table 3 shows the results of popular methods and the methods on average recall for 2,500 independent queries.
Table 4: Performance by proj-degree: Recall@10

| Method       | δ = 0 | δ = 1 | δ = 2 | δ = 3 | δ = 4 | δ = 5 |
|--------------|-------|-------|-------|-------|-------|-------|
| Cocitation   | 0.10465 | 0.20760 | 0.46879 | 0.73410 | 0.88774 | 0.95030 |
| Cocoupling   | 0.01723 | 0.03577 | 0.11962 | 0.25298 | 0.46489 | 0.64429 |
| Co. Filtering| 0.09914 | 0.20051 | 0.47150 | 0.73821 | 0.89120 | 0.94630 |
| PaperRank    | 0.12172 | 0.20284 | 0.50463 | 0.76831 | 0.91358 | 0.96979 |
| C+A          | 0.11193 | 0.20719 | 0.51515 | 0.76490 | 0.91319 | 0.97147 |
| C+V          | 0.11544 | 0.18023 | 0.49938 | 0.76661 | 0.92168 | 0.97147 |
| C+K          | 0.14160 | 0.17829 | 0.50260 | 0.76008 | 0.91242 | 0.97147 |
| logAVK       | 0.02394 | 0.10287 | 0.30427 | 0.55820 | 0.80671 | 0.91778 |
| PathSim,PCoP | 0.10488 | 0.20875 | 0.47083 | 0.73461 | 0.88218 | 0.94630 |

The results show that the C+X methods do not perform quite as well as PaperRank; while the performance of logAVK is lower than that of PaperRank by a factor of about 4.

It seems methods that merely rely on metadata are not working well for citation recommendation task. Nevertheless, we can still conclude some interesting findings from those methods: Author path and keyword path are more useful than venue path; Pathsim tends to be a better meta path measure comparing with PathCount. In the following sections, we keep the best performed meta path, PathSim,PCoP, for further study.

Performance by proj-degree. In order to evaluate the ability to recommend papers with a particular degree in the citation projection graphs, we design the second experiment. We define recall@k for δ = ∆ as the ratio of hidden papers with proj-degree d to seeds papers appearing in top k of the recommended list, where only the papers with proj-degree ∆ to seeds papers are considered as candidates. The results are shown in Table 4.

For particular values of proj-degree, the combined methods (C+X) outperform current methods. One can easily see that most methods perform well on high proj-degrees. Indeed, there are few vertices that are very connected with the seed papers. So any reasonable algorithm will find most of them. It is on lower proj-degrees (0, 1, and 2) that the algorithms start finding less than 50% of the hidden papers.

Figure 5 shows the evolution of the recall when the number of returned papers varies for three definitions of low proj-degree (δ = 0, δ ≤ 1, δ ≤ 2). The performance of the algorithms for δ ≤ 1 and δ ≤ 2 are similar: all graph based methods perform about the same (except cocoupling). logAVK performs significantly worse. For completely disconnect papers (δ = 0), the graph based algorithms exhibit more difference. And in particular, C+K performs better than all other tested algorithms, besting PaperRank by .02. This indicates that metadata help finding loosely connected paper.

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8 We call it property proj-degree for simplicity. Indeed the method would need to know which are the hidden paper to do the filtering on proj-degree. We mean degree to the seed, which differs from the real proj-degree by the number of connections to the unknown hidden.
6 How the quality of metadata affects the performance

As we can see in above section, metadata can help us to find some relevant results from a different perspective on the data. However, it is difficult to guarantee the accuracy of metadata since they are automatically extracted from multi-source data in most cases.

In our experiments, authors and venues are rather clean because they are extracted from DBLP, which is a well-maintained high-quality database, and matched with Microsoft Academic Graph Metadata. Therefore, we focus on keywords in this section. In specific, we discuss different keywords extraction strategies and conduct a empirical study to show their affects on the performance.

Keywords are the words that provide a brief and precise description for a document. Even though there are so much work on automatic keyword extraction problem, state-of-the-art methods can not get satisfying performance, which means this problem is till far from being solved. Most popular methods rely on part-of-speech tags, which is very expensive for large corpus. Here we use KP-Miner [6], which is fast and proven to be effective for keywords extraction task from scientific documents [15].
Table 5: Different keyword extraction strategies

| Method               | Recall@10 | Recall@20 | Recall@50 |
|----------------------|-----------|-----------|-----------|
| KP-Miner+Titles      | 0.231308  | 0.315485  | 0.461507  |
| KP-Miner+Propagation | 0.214116  | 0.295392  | 0.429822  |
| Titles               | 0.231203  | 0.314752  | 0.460039  |

However, all existing methods are designed for extracting keywords from text-abundant documents. In our case, only 374,999 of 2,035,246 papers contain full text information, while the rest of them just have titles. And our target is to derive keywords for each paper. So we propose the following three strategies and show their performance on citation recommendation task.

- **KP-Miner+Titles** This is the default strategy we used in above experiments. In specific, we derive keywords using KP-Miner for those with full text and using non-stop words from titles for others.
- **KP-Miner+Propagation** We derive keywords using KP-Miner for those with full text and propagate the derived keywords on citation graph through label propagation algorithm.
- **Titles** We derive keywords using non-stop words from titles for all papers.

Table 5 shows the global performance of C+K with different strategies on the citation recommendation task. In particular, **KP-Miner+Propagation** is slightly worse than **KP-Miner+Titles**, the main reason is that propagating keyword information on citation graph will mislabel some papers. Surprisingly, the strategy that derives keywords from titles for all papers is as good as **KP-Miner+Titles**. To keep consistency, we still use **KP-Miner+Titles** strategy for C+K in the rest of this paper.

7 On the usefulness of different algorithms

7.1 Difference between methods

Looking at recall numbers gives a single perspective on the usefulness of the methods. Recall numbers tell us how the algorithms perform on some particular task. While informative to pick a single “best” algorithm, a user wants to explore a dataset and see it through different lenses.

Table 6 allows us to understand how similar the sets recommended by the algorithms are for loosely connected papers. The diagonal shows the number of hidden papers that were found in the top-10 by a particular algorithm, while an off diagonal entries shows the number of paper found by the algorithm of the row and that were not found by the algorithm on the column. For instance, Cocitation recommended correctly 408 papers but only 393 of those were not correctly identified by CoCoupling.

This table allows us to understand that PaperRank, C+A, C+K, and C+V essentially identify the same papers. Indeed each set is composed of about 400 papers, but the difference between these sets is smaller than 100 papers and often smaller than 50 papers. Similarly, Cocitation and Collaborative Filtering both find about 400 papers, but only about 40 of these papers are actually different.
Table 6: Differences between the top-10 sets ($\delta \leq 2$)

|                | CoCt | CoCoup | CF | PR  | C+A  | C+V  | C+K  | logAVK | PathSim_PCoP |
|----------------|------|--------|----|-----|------|------|------|--------|--------------|
| CoCt           | 408  | 393    | 45 | 245 | 284  | 289  | 293  | 389    | 10           |
| CoCoup         | 62   | 77     | 50 | 57  | 64   | 66   | 65   | 75     | 62           |
| CF             | 33   | 379    | 296| 229 | 268  | 274  | 278  | 278    | 35           |
| PR             | 253  | 396    | 249| 416 | 83   | 79   | 84   | 396    | 254          |
| C+A            | 259  | 370    | 255| 50  | 383  | 58   | 62   | 362    | 260          |
| C+V            | 252  | 361    | 250| 35  | 47   | 372  | 17   | 356    | 256          |
| C+K            | 256  | 359    | 253| 50  | 16   | 371  | 356  | 256    |              |
| logAVK         | 94   | 111    | 95 | 93  | 92   | 97   | 96   | 113    | 94           |
| PathSim_PCoP   | 13   | 396    | 50 | 249 | 288  | 292  | 296  | 392    | 411          |

The similarity between these sets is explained by Figure 6 that shows a scatter plot of the ranks of hidden papers in the different algorithms. Besides Cocitation and PathSim_PCoP, Collaborative Filtering and Cocitation are also highly correlated in terms of the rank of hidden papers. This is not particularly surprising provided Collaborative Filtering and Cocitation are using the same principles with a different weighting function. In other words, Collaborative Filtering and Cocitation are essentially redundant algorithms.

The relations of C+X with PaperRank are somewhat different. There are definitely a strong correlations between these methods, but some papers see a large difference in ranks between the two methods. For instance, two hidden papers were ranked around 1-millionth by PaperRank but was ranked top-10 by C+A. Note also that only few hidden paper see their rank being significantly degraded by the addition of an other features (few papers are in the top left corner). This indicates that the algorithms are mostly redundant, but they are using different richer features. As such a better way of using these features could certainly be designed.

Figure 7 shows the correlation of ranks between the remaining algorithms. C+A, C+V, C+K, Cocitation and PathSim_PCoP are not included because of their high correlation with either PaperRank or CF.

The rank comparison of Collaborative Filtering and Cocoupling reveals an interesting structure. Notice that there are some hidden papers with highly correlated with ranks over $10^5$. Digging manually in the data show that these hidden papers are not cocited with a seed paper nor are they cociting a common paper with a seed paper. Obviously these papers can not be found by either method. This phenomena explains the denser region of that scatter plots with rank over $10^5$ for Collaborative Filtering and CoCoupling.

Collaborative Filtering and PaperRank show some correlation on the papers of rank less than $10^4$, though the papers that are not cocited with a seed paper are essentially randomly ordered by Collaborative Filtering.

Cocoupling does not appear to be an interesting algorithm in our test. Indeed, Cocoupling mostly worsens the rank of hidden papers compared to PaperRank (the hidden papers are mostly located in the upper left region).

The logAVK method does not correlate with any other method, nor does it seem to mostly worsen the performance of the paper nor improve them compared to another method. logAVK does provide a completely different perspective on the data than the other algorithms. This is not particularly surprising since it is the only method that does not consider the citation information.
7.2 Peeking into the Future

The current way of estimating the quality of a paper relies on identifying the papers that were hidden from the list of references of a particular paper. That experiment assumes that the author of each paper is a data point in the ground truth. But authors are imperfect and may not have known some papers. Rather than using a single paper to evaluate the quality of a recommendation, we suggest to use all the future publications.
To quantify the relevance of a recommendation, we define three metrics to explore different aspects of the problem.

**Relevance-r** For each pair of papers \(<i,j>\), where \(i\) is a recommended paper and \(j\) is a seed paper, we define co-cited probability as:

\[
PrCo(i,j) = \frac{|C_{i,j}|}{|C_i|}
\]

where \(C_{i,j}\) denotes papers citing both \(i\) and \(j\) in the future and \(C_i\) denotes papers citing \(i\) in the future. Then, the relevance of a recommended paper to the seed papers is:

\[
Relevance(i) = \frac{\sum_{j \in S} PrCo(i,j)}{|S|}
\]

Now we can evaluate the quality of a citation recommendation algorithm by the average relevance for top K results:

\[
Relevance@K = \frac{\sum_{i \in topK} Relevance(i)}{K}
\]

**Relevance-rb** The relevance-r between a recommended paper and seed papers could be biased by a few frequently co-cited pairs. To address this problem, we propose a binary version of co-cited probability that just consider about whether there is a paper citing both \(i\) and \(j\) in the future.

\[
PrCo(i,j) = \begin{cases} 
1 & \exists C_{i,j} \text{ in the future} \\
0 & \text{otherwise}
\end{cases}
\]
Relevance-rbd Note that we are actually interested not only in making good recommendation, but also in making links between papers that were not previously seen as relevant. This version of Relevance only considers the cocitation of a seed-recommended pairs that were not previously cocited.

\[ PrCo(i,j) = \begin{cases} 
1 & \exists C_{i,j} \text{ in the future and not in the past} \\
0 & \text{otherwise} 
\end{cases} \]

We computed the three relevance metrics on the same instances of the problem we run before. We report the results of that experiment in Figure 8.

Not surprisingly, the relevance decreases when the number of returned papers increases. But the relevance does not decrease as fast as one could expect. For instance on \( \delta = 0 \), the relevance-r of algorithm C+V decreases from .013 to .011 when \( k \) goes from 10 to 50. It means that 1.3% of the future citation to the top-10 papers recommended by C+V were in papers that also cited a seed paper; while the relevance-r of top-50 was 1.1%. In other words, the 50th paper recommended by C+V is not much more irrelevant than the 10th.

Not surprisingly, current cocitations is a good predictor of future cocitation: The Collaborative Filtering, PathSim_PCoP and Cocitation algorithm perform usually best on the relevance-r and relevance-rb metrics. Though when looking at relevance-rbd that removes the citations that were already known in the present, Collaborative Filtering, PathSim_PCoP and Cocitation no longer are the better algorithms. PaperRank is the algorithm that find the most relevant relations that were not known before.

It is also interesting to see that over 20% of the recommended-seed pairs for PaperRank will be cited in the future and half of these pairs were not known at the time. This suggests that the algorithms we test are actually much more helpful in practice than simple recall tests suggest. The logAVK method also performs interestingly. About 6% of the recommended-seed pairs will be cited in the future (at top-10) and most of them have not been cited before (5% at top-10).

| Metric          | top-10  | top-20  | top-30  | top-40  | top-50  |
|-----------------|---------|---------|---------|---------|---------|
| Relevance_r     | 0.28693 | 0.20592 | 0.17024 | 0.14897 | 0.13433 |
| Relevance_rb    | 0.88069 | 0.70267 | 0.59016 | 0.52056 | 0.47333 |
| Relevance_rbd   | 0.77802 | 0.60551 | 0.50517 | 0.44379 | 0.40249 |

Table 7: Upper bound for \( \delta = 0 \)

| Metric          | top-10  | top-20  | top-30  | top-40  | top-50  |
|-----------------|---------|---------|---------|---------|---------|
| Relevance_r     | 0.36808 | 0.27218 | 0.22593 | 0.19759 | 0.17800 |
| Relevance_rb    | 0.99830 | 0.97588 | 0.87942 | 0.78706 | 0.71720 |
| Relevance_rbd   | 0.86858 | 0.76866 | 0.67437 | 0.60042 | 0.54578 |

Table 8: Upper bound for \( \delta \leq 4 \)

We computed upper bounds on the relevance metrics to quantify how good the different algorithms are. Indeed, we can use the knowledge of the future to easily
compute for each query the relevance of each paper and greedily pick the $k$ papers of highest relevance. We report the upper bound on best relevance for $\delta = 0$ in Table 7 and for $\delta \leq 4$ in Table 8. The upper bounds are much higher than the relevance of the algorithms: a factor of 10 on relevance-r, 4 on relevance-rb, and 5 on relevance-rbd. This indicates that there is a significant room for improvement in our paper recommendation tasks: there are better set of papers that will be cocited with the seed papers than the methods are recommending.
7.3 Implications for a practical system?

We evaluated many algorithms, namely PaperRank, Collaborative Filtering, Cocitation, Cocoupling, C+A, C+V, C+K, PathSim_PCoP and LogAVK. The evaluation was performed across different tests, metrics, and by looking at different slices of the solution space. We present here a summary of the discussion with a focus on selecting algorithms for inclusion in a practical system.

Cocitation, PathSim_PCoP and Collaborative Filtering are variations of the same algorithm and their performance are hard to distinguish. (See correlation in Figure 6 and the difference in recommendation in Table 6). There is no point in including both algorithms in a system: we will pick Collaborative Filtering.

Cocoupling is often one of the worst algorithm and is essentially worse than PaperRank. (See correlation plot in Figure 7). As such, we do not believe it makes sense to include Cocoupling if any variants of PaperRank were to be included.

The C+V, C+A, C+K algorithms are somewhat correlated to PaperRank but they exhibit improvement for many cases (see Figure 6). C+K has the highest recall on the $\delta = 0$ study case (see Figure 5), and C+A and C+K showed the highest relevance-$r$ in the $\delta \leq 4$ case (see Figure 8). We believe one of these methods should be included in practice, but more work in integrating metadata in the recommendation is necessary.

The logAVK algorithm provides a much lower recall than the other algorithm (See correlation plot in Figure 5 for example). However, we believe it could be of some interest to discover loosely connected papers. Indeed, it returns papers that are very different from the other methods (See Table 5) while having a relevance that is within a factor of 2 or 3 of the other algorithms (see Figure 8 for $\delta = 0$). We believe that LogAVK could provide a view of the problem that is complementary to the one provided by the citation based methods.

7.4 Fast C+X Recommendation

For a practical citation recommendation system, the efficiency of underlying recommendation algorithm is also important. The running time of random walk based methods typically depends on the size of input graph and thus tends to be more expensive. While some other method like collaborative filtering essentially computes the weighted co-citation relationships and thus does not need to take the global graph into account. Previous work has shown that LocRank, which is a local version of PaperRank, is as effective as PaperRank while being much faster than PaperRank and CF. Here we will explore the local methods for C+X.

We define a local induced subgraph of a query $q$: $G_q = (V_q, E_q)$, where $V_q$ contains all nodes in $S$ and any node which is a neighbor of at least one seed paper:

$$V_q = S \cup S_n$$

where $S_n$ denotes

$$S_n = \bigcup_{s \in S} \{v : v \in Adj(s)\}$$

$E_q$ remains all citation relationships between nodes in $V_q$. In other words, $G_q$ is the subgraph induced by the distance 1 neighborhood of the seed papers. Then,
Table 9: Performance for fast recommendation

| Method  | Sec/query | Recall@10   | Recall@20   | Recall@50   |
|---------|-----------|-------------|-------------|-------------|
| C+A     | 3.52      | 0.230617    | 0.323125    | 0.461898    |
| C+V     | 3.59      | 0.230531    | 0.323125    | 0.461898    |
| C+K     | 3.91      | 0.231308    | 0.315485    | 0.461507    |
| C+A_Local| 0.24      | 0.229565    | 0.308260    | 0.448141    |
| C+V_Local| 0.22      | 0.215549    | 0.296508    | 0.436924    |
| C+K_Local| 0.25      | 0.221331    | 0.303953    | 0.446463    |

Fig. 9: Runtime on 100 instance queries

we extend $G_q$ to a heterogeneous graph $G_q$ by adding metadata information of $V_q$, local C+X computes a random walk on $G_q$.

In our experiments, all codes are written in C++ and the graphs are represented in Compressed Row Storage format for compact storage. The codes are compiled with g++ 4.8.2 with option -O3. The codes are run on 1 core of an Intel(R) Xeon CPU E-5-2623 @ 3.00GHz processor.

As we can see from the Table 9, the column Sec/query shows the average runtime per query for each method. In general, local C+X is 15x faster than original methods. It is not surprising because the runtime of local methods only depends on the size of local induced graph, while original ones are global ranking methods; Moreover, a local induced graph tends to have a smaller diameter, which means local C+X can reach the convergence within less iterations. In Figure 9, we take C+A as example and show the runtime for 100 randomly sampled independent queries. Note that since we remove the query paper q and all papers published after q from the citation graph to simulate the time when the query paper was being written, the size of the global graph is different for queries with different publication date.

Besides the much better efficiency of local C+X methods, the quality of recommendation is still competitive comparing with original methods. Essentially, local methods are tradeoffs between the upper bound of recall and the efficiency. It turns out that they have equivalent abilities to find hidden papers as global methods,
which demonstrates that many findable hidden papers are actually neighbors of seed papers.

8 Conclusion

This manuscript investigates the problem of recommending a set of papers to extend a query composed of a set of known paper. This problem is common in academic recommender systems and academic search engines. The two most common citation recommendation algorithms, PaperRank and Collaborative Filtering, do not uniformly discover relevant papers; they mostly find a set of papers that are highly connected to the query by citations. Unfortunately, real-world citation patterns are not as obvious to find since about 50% cocited papers do not have a direct connection. The key to improving the quality of an academic recommender system lies in identifying those loosely connected, yet relevant, papers. While we consider the problem of identifying highly connected papers essentially solved by the existing methods.

We provided two ways of discovering citations that use the metadata of the papers rather than their citation patterns, LogAVK that only uses the metadata and the C+X algorithm which combine the citation pattern and the metadata. The C+K and C+A algorithms are promising in retrieving papers that are loosely connected to the query. Despite logAVK is about 3 times less relevant than PaperRank, it identifies papers that are known to be important and which are likely to be unknown to the user and the community.

Using a single test/metric to qualify algorithms provides an incomplete picture of how good an algorithm is. We believe that the proposed relevance metrics provide additional insights in the quality and desirability of algorithms.

Future works will focus on building new models for integrating metadata inside a random walk framework to connect better similar papers that are not connected by citations. Currently existing methods require to return a large number of papers to achieve desired recall. Therefore, there is a need in presenting a set of paper to a user in a structured non-list format so that the user can easily navigate the recommendation and identify the papers that appear more relevant.

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