Leveraging Hybrid Citation Context for Impact Summarization

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Abstract. Impact summarization aims to highlight the influential aspects of a cited paper by selecting a few representative citation sentences into the summary. Most existing work considers only the citation sentence information while the hybrid citation context associated with each citation sentence has been ignored. This paper proposes a context-aware approach. In the approach, different kinds of relationships among papers and authors are leveraged to jointly infer the impact of hybrid citation context, which is further integrated in a sentence language smoothing model to measure citation sentence relationships more effectively. The experimental results show that the proposed approach can achieve significantly better results than several baselines.

Keywords: impact summarization, hybrid citation context, bibliographic network relationships.

1 Introduction

With the rapid evolution of scientific research, the volume of literature keeps on expanding fast. However, the explosive growth of the publications makes it rather difficult to identify the influential aspects of papers quickly and effectively.

The abstract part of a scientific paper may help researchers quickly understand the main content of the paper, but it only presents what the authors think to be the important contribution but not necessarily the actual impact of the paper. Actually, the impact of a paper should be judged by the consent of research community instead of the author himself. Moreover, the impact of a paper may dynamically change due to the progress of research. For example, a paper published before may be no longer the state of the art, but the research problem it addressed or the method it proposed will still attract peer attention.

Therefore, we argue that only the abstract part representing the author's point of view is not enough, and how other papers cite and describe the target paper needs to

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be comprehensively investigated to generate an impact summary, which can not only help researchers digest the results of research better, but also facilitate other literature mining applications such as research trend prediction, and survey generation, etc.

Actually, given a scientific paper, different citation sentences often focus on different aspects of that paper and all the citation sentences will provide a rich information source to summarize its impact [1]. Although some research has been done based on citation sentences, to the best of our knowledge, simultaneous consideration of the impact from hybrid citation context associated with each citation sentence has not been investigated. Therefore, we propose a novel approach by incorporating the impact of hybrid citation context into the summarization process. In the proposed approach, three kinds of relationships among papers and authors are first leveraged to jointly infer the impact of hybrid citation context. Next, the hybrid citation context and its impact are integrated in a sentence language smoothing model to measure citation sentence relationships more effectively. Lastly, a unified graph ranking algorithm is adopted to evaluate the significance of each citation sentence by taking advantage of the relationships between citation sentences.

The remainder of this paper is organized as follows. Section 2 reviews related work. The proposed approach is presented in Section 3. We then report the experimental results in Section 4. Finally, we present our conclusion and future work in Section 5.

2 Related Work

Automatic creation of scientific summaries has been studied for many years [2-4], but most previous work considers only the local features of the scientific paper, while other contextual information has been mostly ignored.

Recently, researchers have begun to make use of contextual information to aid news and webpage summarization [5-10]. Likewise, in order to summarize a paper, differentiating and utilizing citations from context have received increasing interests. Nakov et al. used sentences surrounding citations to create training and testing data for scientific paper summarization [11]. Nanba and Okumura classified different citation sentences into three categories and explored how to use them to aid survey generation [12]. Schwartz and Hearst utilized the citation sentences to summarize the key concepts and entities in bioscience texts [13]. Teufel et al. adopted rhetorical status analysis to reveal the scientific attribution of a paper, in which each citation sentence is labeled as one of Own, Other, Background, Textual, Aim, Basis, and Contrast [14]. Kan et al. used annotated bibliographies to cover certain summarization aspects [15]. Elkiss et al. performed a large-scale study on the PubMed repository and confirmed the importance of citation sentences in understanding what a paper contributes [16]. They also concluded that the citation sentences contain more focused information that generally does not appear in the abstract part of a paper.

Recently, Mei and Zhai proposed a language model based approach to impact summarization [17]. Qazvinian and Radev presented two different methods for the task [18] [19]. One utilized all the citation sentences of a paper to construct a similarity graph first, and then applied network analysis technique to cluster graph nodes and produce an impact summary. Another method first extracted a number of key phrases from the citation sentences, and then used these phrases to build the impact summary. How to produce more readable summaries based on citation sentences have also been investigated in [20]

As far as we know, none of the previous studies has investigated the impact from hybrid citation context (i.e., the combination of citation paper context and citation author context), and has used the citation context in the same way as we did. In this study, we propose a context-aware approach to simultaneously consider the impact from hybrid citation context and what is more, we further incorporate the hybrid citation context and its impact into a sentence language smoothing model to measure the citation sentence relationships beyond sentence level.

3 Impact Summarization Based on Hybrid Citation Context

Our approach incorporates hybrid citation context into the impact summarization, which consists of three steps: inferring the impact of hybrid citation context, estimation of citation sentence language model, and impact summary generation.

3.1 Inferring the Impact of Hybrid Citation Context

In the study, the sentence containing an explicit reference to the target paper and describing the work being cited is called a citation sentence. All the other citing papers and citing authors associated with the citation sentences are called hybrid citation context. The citation sentences occurring in the papers with higher topical relevance will contribute more than those in less important papers. The citation sentences written by the authors with better authority expertise will contribute more than those written by less professional authors. Therefore, to summarize the impact of a particular paper, the impact of hybrid citation context (i.e., the topical relevance of citing papers and the authority expertise of citing authors) should be inferred first.

Our approach operates over a bibliographic network G. $G=(V, E)=(V_P \cup V_A, E_P \cup E_A \cup E_{PA})$. G connects three subgraphs G_P, G_A, and G_{PA}. $G_P=(V_P, E_P)$ is a directed graph representing the citation relationships between papers. $V_P=\{p_i \mid p_i \in V_P\}$ denotes a collection of $|V_P|$ papers and E_P is the set of citation links between them. $G_A=(V_A, E_A)$ is an undirected graph representing the co-authorship relationships between authors. $V_A=\{a_i \mid a_i \in V_A\}$ is the set of authors with size $|V_A|$, and E_A is the set of co-authorship links between them. $G_{PA}=(V_P \cup V_A, E_{PA})$ is a bipartite graph that ties G_P and G_A and represents authorship associations between papers and authors.

Let $R_P(p_i)$ and $R_A(a_i)$ denote the topical relevance of paper p_i and the authority expertise of author a_i respectively. A query q can be constructed by extracting the title and keywords from the target paper, and then the initial scores $R_P^0(p_i)$ can be calculated by $R_P^0(p_i) = p(q \mid \theta_{p_i}) = \prod_{t \in q} p(t \mid \theta_{p_i})^{n(t,q)}$. Where $p(t \mid \theta_{p_i})$ is the maximum likelihood estimation of the term t in the paper p_i, and n(t, q) is the number of times that term t occurs in query q. Since an author a_i can be represented by the set of papers authored by a_i, the initial score $R_A^0(a_i)$ for author a_i can be calculated similarly.

Inspired by [22] and based on the assumption that similar papers will have similar relevance for a given query, we refine the topical relevance of citing papers by making use of the paper citation graph G_P and the initial topical relevance of papers.

Firstly, the adjacency matrix $W_P \in \Re^{|V_P| \times |V_P|}$ for the graph G_P is constructed. If a paper p_i cites another paper p_j ($i \neq j$), then we set the corresponding element $w_{p_{ij}}$ in W_P as 1, otherwise set it as 0. Then W_P is further normalized as a random walk transition matrix S_P by $S_P = \frac{D_P^{-1/2} W_P D_P^{-1/2} + D_P^{-1/2} W_P^T D_P^{-1/2}}{2}$. Where D_P is the diagonal matrix with (i,i)-element equal to the sum of the i-th row of W_P.

Next, inspired by [21], a regularization framework is developed by regularizing the smoothness of relevance over the graph and the cost function associated with it is defined as follows:

$$\Omega_P = \frac{1}{2}\sum_{i,j=1}^{|V_P|} s_{p_{ij}} \left\| \frac{R_P(p_i)}{\sqrt{d_{P_{ii}}}} - \frac{R_P(p_j)}{\sqrt{d_{P_{jj}}}} \right\|^2 + \frac{1}{2}\sum_{i=1}^{|V_P|} \left\| R_P(p_i) - R_P^0(p_i) \right\|^2 \tag{1}$$

Where the first tem defines the global consistency of the refined relevance over the graph, while the second term defines the constraint to fit the initial relevance. By minimizing Ω_P, the topical relevance of papers can be refined.

Similarly, based on the assumption that if two authors co-authored many papers related to a given query, then their authority expertise in the queried field will be similar, we can refine the authority expertise of citing authors by making use of the author co-authorship graph G_A and the initial authority expertise of authors.

Firstly, the adjacency matrix $W_A \in \Re^{|V_A| \times |V_A|}$ for the graph G_A is constructed. If an author a_i coauthored with another author a_j ($i \neq j$), then we set the corresponding element $w_{a_{ij}}$ in W_A as the number of papers that they collaborated, otherwise set it as 0. Then W_A is further normalized by $S_A = D_A^{-1/2} W_A D_A^{-1/2}$. Where D_A is the diagonal matrix with (i,i)-element equal to the sum of the i-th row of W_A.

Next, a regularization framework is developed by regularizing the smoothness of expertise over the graph and the cost function associated with it is defined as follows [21]. By minimizing Ω_A, the authority expertise of authors can be refined.

$$\Omega_A = \frac{1}{2}\sum_{i,j=1}^{|V_A|} s_{a_{ij}} \left\| \frac{R_A(a_i)}{\sqrt{d_{A_{ii}}}} - \frac{R_A(a_j)}{\sqrt{d_{A_{jj}}}} \right\|^2 + \frac{1}{2}\sum_{i=1}^{|V_A|} \left\| R_A(a_i) - R_A^0(a_i) \right\|^2 \tag{2}$$

In addition to Ω_P and Ω_A, another cost function Ω_{PA} is also presented based on the graph G_{PA} by considering the authorship relations between papers and authors.

$$\Omega_{PA} = \frac{1}{2}\sum_{i=1}^{|V_P|}\sum_{j=1}^{|V_A|} s_{pa_{ij}} \left\| \frac{R_P(p_i)}{\sqrt{d_{P_{ii}}}} - \frac{R_A(a_j)}{\sqrt{d_{A_{jj}}}} \right\|^2 + \frac{1}{2}\sum_{j=1}^{|V_A|}\sum_{i=1}^{|V_P|} s_{ap_{ji}} \left\| \frac{R_A(a_j)}{\sqrt{d_{A_{jj}}}} - \frac{R_P(p_i)}{\sqrt{d_{P_{ii}}}} \right\|^2 \tag{3}$$

The intuition behind Ω_{PA} is that the authority expertise of an author is consistent with that of the relevant papers he published.

To define the cost function Ω_{PA}, the adjacency matrix $W_{PA} \in \Re^{|V_P| \times |V_A|}$ for the graph G_{PA} is constructed. If a paper p_i is written by an author a_j, then we set the corresponding element $w_{pa_{ij}}$ in W_{PA} as 1, otherwise set it as 0. Then W_{PA} is further normalized as S_{PA} such as the sum of each row of the matrix equal to one.

Next, a hybrid cost function Ω that combines Ω_P, Ω_A, and Ω_{PA} is developed in a unified regularization framework.

$$\Omega = \frac{1}{2}(\Omega_P + \Omega_A) + \frac{1}{2}\Omega_{PA} \tag{4}$$

We can minimize the hybrid cost function Ω using the standard conjugate gradient method, and a closed-form optimal solution can be derived. However, for a large-scale dataset, an iterative–form computation strategy would be more effective. So in the study, we calculate the optimal solutions R_P^* and R_A^* by adopting the equivalent iterative computation strategy, which details are omitted due to space limit, and you can find it in [21].

Finally, the converged solutions R_P^* and R_A^* correspond to the topical relevance of citing papers and the authority expertise of citing authors respectively.

3.2 Estimation of Citation Sentence Language Model

After inferring the impact of hybrid citation context, the next step is to make use of the contextual information to evaluate the relationships between citation sentences.

From the language model perspective, it can be assumed that a citation sentence s is generated from a sentence language model θ_s and Dirichlet prior smoothing [23] is often adopted to estimate θ_s as follows.

$$p(w \mid \theta_s) = \frac{c(w,s) + \mu_s * p(w \mid B)}{|s| + \mu_s} \tag{5}$$

Where |s| is the length of s, c(w, s) is the count of term w in s, p(w|B) is usually estimated by $\frac{c(w,B)}{\sum_{w' \in W} c(w',B)}$. Here B is the whole background paper set and μ_s is the sentence smoothing parameter which is set as 1000 as in [17].

In this study, we propose a citation sentence language smoothing model inspired by [6] to estimate $p(w \mid \theta_s)$ by using hybrid citation context as background, which can be defined as follows.

$$p(w \mid \theta_s) = \alpha * p(w \mid s) + \beta * R_P(p_s) * p(w \mid p_s) + \gamma * \sum_i R_A(a_{i_s}) * p(w \mid a_{i_s}) \tag{6}$$

Where α, β, and γ belong to [0, 1] and $\alpha+\beta+\gamma=1$. p_s is the citing paper that citation sentence s belongs to and $\mathrm{R_P}(p_s)$ denotes the topical relevance of paper p_s. a_{i_s} is the i-th citing author of the citing paper p_s. $\mathrm{R_A}(a_{i_s})$ denotes the authority expertise of author a_{i_s}. $p(w \mid a_{i_s})$ is estimated by the papers authored by a_{i_s}.

Based on the estimated citation sentence language model, the distance $Dis_{AvgKL}(s_i, s_j)$ between two citation sentences s_i and s_j can be measured by the average KL divergence as follows.

$$Dis_{AvgKL}(s_i, s_j) = \frac{Dis_{KL}(s_j \parallel s_i) + Dis_{KL}(s_i \parallel s_j)}{2} \tag{7}$$

$$Dis_{KL}(s_j \parallel s_i) = \sum_{w \in W} p(w \mid \theta_{s_j}) \log \frac{p(w \mid \theta_{s_j})}{p(w \mid \theta_{s_i})} \tag{8}$$

$$Dis_{KL}(s_i \parallel s_j) = \sum_{w \in W} p(w \mid \theta_{s_i}) \log \frac{p(w \mid \theta_{s_i})}{p(w \mid \theta_{s_j})} \tag{9}$$

Where W is the set of terms in our vocabulary and w is a term in W. And the similarity $\mathrm{Sim}(s_i, s_j)$ between two citation sentences s_i and s_j can then be inferred by the following formula.

$$\mathrm{Sim}(s_i, s_j) = \frac{1}{1 + e^{Dis_{AvgKL}(s_i, s_j)}} \tag{10}$$

3.3 Impact Summary Generation

In this step, all the citation sentences are to be evaluated by the significance and a few sentences with highest significant scores will be selected into the impact summary.

In most of the methods for impact summarization, all citation sentences are treated uniformly. However, different citation sentences from different citation contexts should be treated differently, since the citation sentences from a more important context should receive higher significant score. Therefore, it is more reasonable to assign unequal weights to different citation sentences in accordance with the impact of different citation contexts which they belong to.

Given a set of citation sentences S for a target paper, let $G_S=(V_S, E_S)$ be an undirected graph to reflect the relationships between citation sentences in S. Here V_S is the set of citation sentences. E_S is the set of edges and each edge $e_{s_{ij}}$ is associated with the similarity $\mathrm{Sim}(s_i, s_j)$ between sentences s_i and s_j ($i \neq j$), which is calculated by formula 10. Two sentences are connected if their similarity is larger than 0 and we let $\mathrm{Sim}(s_i, s_i)=0$ to avoid self transition. We use the affinity matrix $\mathrm{M_S}$ to describe G_S. Then $\mathrm{M_S}$ is normalized to $\widetilde{\mathrm{M_S}}$ by making the sum of each row equal to 1.

Based on $\widetilde{M}_S$, the significant score $\text{SigScore}(s_i)$ for citation sentence s_i can be deduced from those sentences linked with it, which can be formulated in a recursive form as follows:

$$\text{SigScore}(s_i)=\delta * \sum_{all\ j \neq i} \text{SigScore}(s_j) * \widetilde{M}_{S_{ji}} + \frac{1-\delta}{|V_S|} \tag{11}$$

Where δ is the damping factor usually set to 0.85, as in the PageRank algorithm. For implementation, the initial significant scores of all citation sentences are set to 1. Usually the convergence of the iteration algorithm is achieved when the difference between the scores computed at two successive iterations for any citation sentences fall below a given threshold (0.0001 in this study).

After evaluating the significance of each citation sentence, we select a few representative sentences with highest significant scores to generate the impact summary.

Recall that in the proposed approach, we incorporate diverse relationships on G_P, G_A, and G_{PA} into a unified regularization framework to infer the impact of hybrid citation context, and then rank citation sentences on G_S by leveraging both the impact of hybrid citation context and the relationships between citation sentences, which can be intuitively represented by Figure 1.

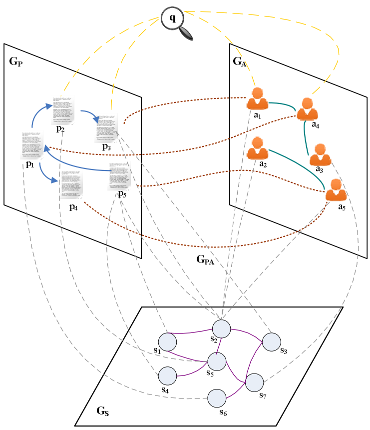

Fig. 1. The intuitive representation of the proposed approach

4 Experiments and Evaluation

4.1 Data Collection

We evaluate the proposed approach on the dataset[1], which contains 25 highly cited papers from computational linguistics domain. Each paper has a set of manually

[1] http://www-personal.umich.edu/~vahed/resources/single.tar.gz

selected terms representing the most important impacts of that paper and shared by multiple evaluators who has read all the citation sentences of that paper.

Considering that hybrid citation context may improve the performance of impact summarization, we extend the dataset by adding a number of papers with similar topic and related authors from the ACL Anthology Network[2], which is a large collection of more than 18,000 papers from computational linguistics domain. Table 1 shows general statistics about the extended dataset.

Table 1. The general statistics about the extended dataset

Papers	7921
Authors	1475
Citation links between papers	38542
Co-authorship links between authors	14176
Authorship links between papers and authors	13951

We deem that a good impact summary should cover more important impacts of the target paper. If an impact fact occurs in more citation sentences, it should be regarded as more important and be assigned higher weight. Under the condition, the citation sentence including more impact facts with higher weight will become a good candidate for impact summary. Accordingly, we construct a reference summary for each of the 25 highly cited papers by making use of the manually selected impact terms. We pick citation sentences that cover new and highly weighted impact terms into the reference summary until the defined summary length is reached. By this way, we expect a good system generated summary to be closer to the reference summary.

4.2 Evaluation Metrics

In the study, the ROUGE toolkit [24] is adopted, which was officially adopted by DUC for automatic summarization evaluation. ROUGE metrics measure a summary's content quality by counting overlapping units such as n-gram, word sequences, and word pairs between the automatically generated summary and the reference summary. The higher the ROUGE scores, the similar the two summaries are.

A few recall-oriented ROUGE metrics have been employed including ROUGE-1, ROUGE-2, and ROUGE-SU4, etc. Among the different ROUGE scores, ROUGE-1 has been shown to agree with human judgment most [24]. Therefore, we only report ROUGE-1 in the following experiments since other metrics gives very similar results.

4.3 Experimental Results

We compared our proposed approach with several baselines as follows. All the approaches for comparison are required to extract a few representative citation sentences into the impact summary for each of the 25 highly cited papers. The main difference

[2] http://clair.eecs.umich.edu/aan_site2/index.php

between our approach and other baselines is that we leverage the hybrid citation context associated with each citation sentence while other baselines do not.

Random: In this baseline, the sentences are selected randomly from the set of citation sentences and added to the impact summary.

OTS [25]**:** It integrates shallow NLP techniques with statistical word frequency analysis to rank and select citation sentences.

LexRank [26]**:** It runs on the set of citation sentences by first constructing a citation sentence affinity graph, and then extracting a few informative citation sentences based on eigenvector centrality.

C-LexRank [18]**:** This is another state-of-the-art impact summarizer in which the citation sentences are firstly clustered, and then the sentences within each cluster are ranked via LexRank algorithm.

We show the evaluation results of different methods in Tables 2, and the highest ROUGE-1 scores are shown in bold type.

Table 2. The evaluation results of different methods

Method	ROUGE-1
Our Approach	**0.39507**
C-LexRank	0.37837
LexRank	0.36021
OTS	0.34404
Random	0.32966

In the experiments, the best result of our approach is achieved when the weight adjusting parameters in the formula 6 are set as follows: α =0.4, β =0.3, and γ =0.3. These parameters give different weights to the citation sentence, the citation paper context, and the citation author context respectively.

Seen from Table 2, our proposed approach using the hybrid citation context achieves the best performance compared to that of the baseline approaches (i.e. C-LexRank, LexRank, OTS, and Random), which demonstrates that both citation paper context and citation author context are critical for improving the performance of impact summarization.

C-LexRank and LexRank perform better than those of OTS and Random. This is mainly because both C-LexRank and LexRank make use of the inter-relationships between citation sentences to rank them globally, while OTS only depends on the local features.

C-LexRank outperforms LexRank in our experiments, which indicates the use of appropriate cluster-level information is an improvement over the use of citation sentences alone.

Note that all these baselines generate the impact summary based only on the citation sentences or sentence clusters, regardless of the impact from hybrid citation context. Our proposed approach shows significantly better performance on ROUGE scores, and the result difference between our approach and other baselines is significant at the 95%

statistical confidence level. These observations again demonstrate the effectiveness of our approach by exploiting hybrid citation context to aid impact summarization.

In the following, we will explore the effect of different parameters in our approach. The key parameters we want to investigated are α, β, and γ.

Figure 2 to 4 demonstrate the influence of these parameters in the proposed approach when we tune a parameter from 0 to 1 with the step length 0.1 and vary the other two for the best performance to achieve.

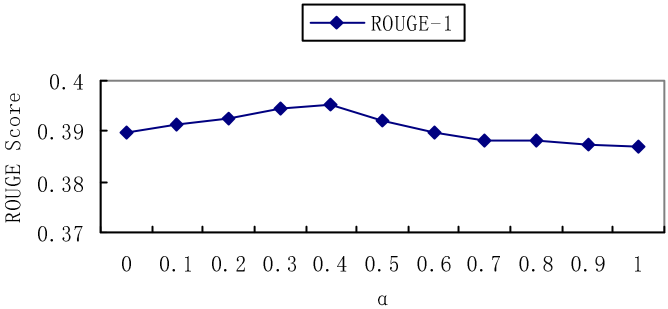

Fig. 2. ROUGE-1 score of the proposed approach vs. α

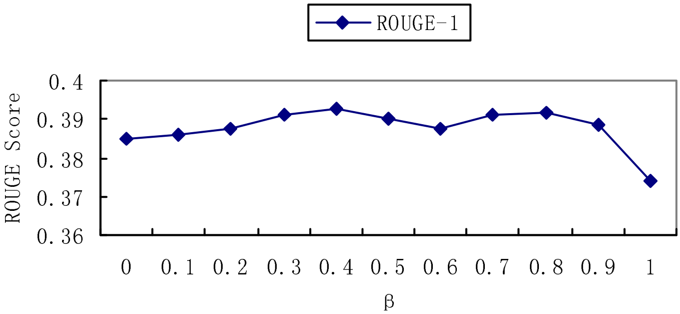

Fig. 3. ROUGE-1 score of the proposed approach vs. β

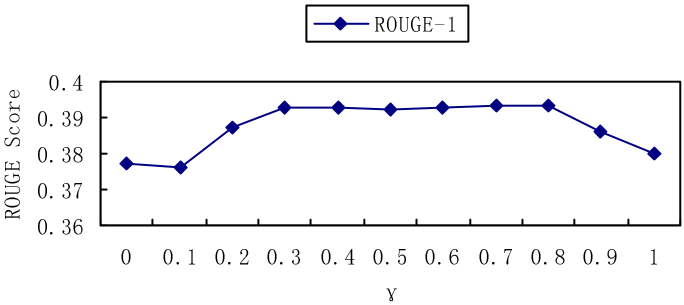

Fig. 4. ROUGE-1 score of the proposed approach vs. γ

From Figure 2 to 4, it can be found that the citation sentence information controlled by the parameter α is relatively stable and have little impact on the performance. Both citation paper context and citation author context can help improve the performance, but excessive dependence on any one of them will impair the performance to a certain extent.

5 Conclusion and Future Work

This paper proposes a context-aware approach to impact summarization. In the proposed approach, different kinds of relationships among papers and authors are leveraged to jointly infer the impact of hybrid citation context, which is further integrated in a sentence language smoothing model to measure citation sentence relationships more effectively.

In future work, it would be interesting to investigate the performance of the proposed approach on larger bibliographic datasets such as DBLP, ArnetMiner, etc. Besides, we will explore machine learning based methods to determine the parameters of our approach in an adaptive way.

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