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Development of Reviewer Assignment Method with Latent Dirichlet Allocation and Link Prediction to Avoid Conflict of Interest

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Abstract

The number of published academic papers has been increasing rapidly from year to year. However, this increase in publications must be linear by an emphasis on quality. In order to ensure that academic papers meet the required standard of quality, the process of peer review is necessary. The main goal of reviewer assignment is to find the appropriate reviewer who can conduct a review based on their field of research. However, there are potential obstacles when there is a conflict of interest in the process. This study aims to develop a method for assigning reviewers that overcomes such obstacles. Our approach involves combining the Latent Dirichlet allocation (LDA), classification, and link prediction methods. LDA is used to find topics from the research data of prospective reviewers, to ensure that the assigned reviewers are well-suited to the submitted paper. This data used as training data for classification using Random Forest. Finally, link prediction implemented to make reviewer recommendations. We evaluated and compared our proposed method with previous research that used Cosine similarity for the last step in recommendation, using Mean Average Precision (MAP). Our proposed method achieved a MAP value of 0.87, which was an improvement compared to the previous approach. These results suggest that our approach has the potential to improve the effectiveness of academic peer review.

Keywords: *reviewer; conflict of interest (CoI); DBLP dataset; latent dirichlet allocation (LDA); random forest; link prediction*

1. Introduction

The number of academic documents, including scientific publications, is increasing rapidly year over year. According to [1], there were more than 75 million publications recorded by 2019. Meanwhile, [2] recorded that there have been additional publications in the field of computer science, totaling over 500,000 by 2021. Bibliometric analysis predict this data will continue to grow at a rate of 4.1%, doubling every 11 years [3].

The significance of research in domains such as data privacy and its influence on society, organizations, and nations cannot be overstated. Given the potential dangers associated with such research, funding for it is often provided by sponsors, government departments, and other organizations. To ensure that the research produced is of high quality and meets the desired standards, the peer review process plays a crucial role in the research community. This process evaluates the content and writing quality of research papers to ensure that they meet the established standards before being published.

Normally, peer reviews are conducted by academic reviewers and professional experts. However, it is important to note that these reviewers may have limitations in terms of their experience, scientific fields, and perspective. The process of selecting reviewers is not straightforward and random selection may not yield optimal results. It is therefore important to ensure a match between the papers to be published and the candidate reviewers in several aspects, such as areas of expertise and potential conflict of interest (CoI).

A good match between the areas of expertise of the reviewers and the papers being reviewed can enhance the efficiency of the review process. One approach to achieve this match is through the use of topic modeling, a method for uncovering implicit meanings in a document [4]. By identifying reviewers with similar areas of expertise (based on their previous research), a common ground can be established in terms of scientific similarity

However, having similar research fields does not ensure that the reviews will be of high quality. Bias can sometimes occur in the review process, one example being conflicts of interest. Conflicts of interest occur

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between two main actors, namely the principal and the agent. In the academic field, this relationship can occur between students and instructors, journal editors and other journal editors, and reviewers and researchers [5], [6]. Even when reviewers are experts in the same field, biases can still influence their judgment and make it subjective. Some factors that can cause conflicts of interest include shared institutional or organizational affiliations and previous collaboration on research projects [7].

Several researchers have studied the issue of reviewer assignment in the peer review process. One approach, as described in research by [8], offers a large multi-tiered case study model to engage a wider segment of the scientific community to support decision making on science issues. In doing so it is divided into 2 levels where level 1 has 5 panels, and the second level has 2 panels. And invite reviewers to register according to each panel's choice. With this model, we can find out whether there are reviewers in the research review who don't want to be involved, the diversity of panels can be managed properly.

Another approach, as described in research by [9], which resolves the CoI problem with link prediction (neo4j graph database), and link open data for reviewer recommendations in the academic field. Both of them are doing the same research data extraction from paper headers, in the case of link prediction they store article data in graph form. Then from the research title, latent dirichlet allocation (LDA) is used to choose from 10 suitable authors to be used as reviewers with Link prediction algorithm. If the value is equal to 0 then the reviewer is suitable. Then further research, conduct CoI management with linked open data. This will be done using LDA topic modeling to find reviewers who do not have CoI. And can also recommend authors who have CoI so that the two results will be reduced and produce authors with appropriate fields without CoI.

And the last is [10] which proposed a two-pronged approach that processes topics and conflicts of interest using the LDA and Cosine Similarity methods. This research using dataset provided by aminer which provide list of publication data. LDA used to make cluster topic in order to filter the expertise of reviewer. Cosine similarity then performed to calculate similarity between reviewer name and their organization.

This research proposes a method for finding the best reviewers by combining the LDA method for identifying appropriate topics and graph representations to prevent conflicts of interest from author relationships. The LDA results are used as ground truth, which are then used to determine the topic of new data and combined with graph mapping. Graph used to detect the predicted edge that occur in author relationship, which is have an impact to increase CoI. Finally, link prediction is performed on the graph results to determine and exclude potential reviewer candidates as evaluators of a publication.

2. Research Methods

The proposed method must undergo several steps in order to be executed, including processing the dataset, preprocessing, performing topic modeling, and link prediction. Figure 1 shows the general process of methodology.

2.1. Dataset

The dataset employed in this research was obtained from the DBLP website [11]. DBLP is a collection of research in the field of computer science proposed by [12] that has been accumulate since 2009 and it contains more than 4 million studies and 45 million relations in the latest version. However, it should be noted that this dataset only contains research data and does not possess any ground truth.

The dataset then divided into two samples, Sample 1 and Sample 2. Sample 1 contains more than 2000 research titles and used as ground truth for classification later, and processed using the LDA method. Sample 2 is the original dataset in XML format, which will used to generate graphs. This dataset is limited to publication list conducted by Informatics Engineering lecturers from ITS.

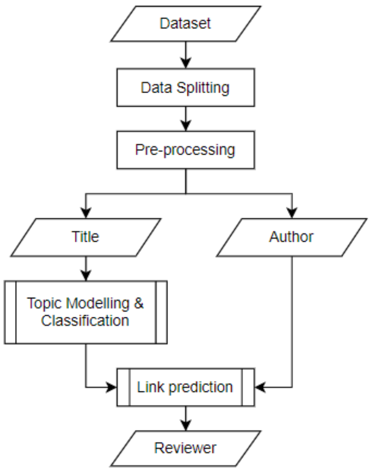

Figure 1. Research Methodology

2.2. Pre-processing

The preprocessing used in this study is the standard preprocessing in natural language processing. This stage includes the following processes: converting words to lowercase to avoid ASCII errors, removing stop words that are not relevant to the computation process, removing punctuation marks, performing lemmatization to convert words to their basic forms, and tokenizing sentences to separate them into individual words. This stage is the process of data improvement as a step to facilitate the computation of the dataset content in topic modeling and classification.

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The pre-processing stage is performed on all the dataset samples specifically those with the title attribute.

2.3. Topic Modeling & Classification

This section describes a proposed step in the research, which involves performing topic modeling on a set of research title data in the dataset. The sample 1 dataset is used for this stage. LDA is employed for topic modeling. The process for topic modeling and classification is illustrated in Figure 2.

LDA, as described by [13], utilizes text data as input to uncover hidden topics within a document and determine which lines of text have stronger associations with specific topics. Topic Modeling does not require a labelling process in documents [14]. In general, the steps in LDA involve determining the number of topics for document clusters, assigning probabilities for each topic and word, performing topic mapping on each word in each document, calculating the probability of each word being included in each topic for each document, and repeating this process until all words in the document have been allocated to a topic [15]. LDA equation is written as Formula 1.

$$P(W,Z,\theta|\alpha,\beta) = P(\theta|\alpha)\prod_{t=1}^{N} P(Z_n|\theta)P(W_n|Z_n,\beta) \quad (1)$$

W_n is the n^{th} word in the document, Z_n is topic for the n^{th} word in the document. Θ is distribution of topics in the document, φ is word distribution in the topic, α is topic distribution parameters in the document and β is word distribution parameters in the topic.

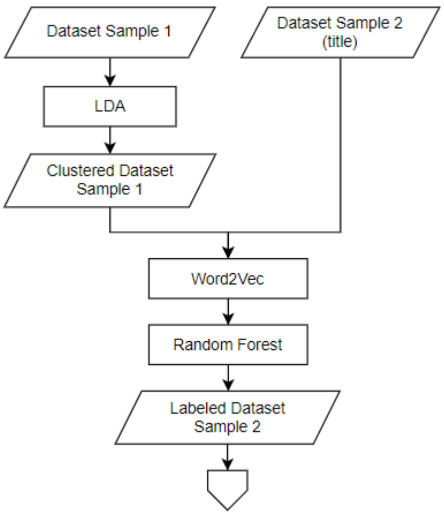

Figure 2. Topic Modeling & Classification

The outcome of LDA is to create topic clusters in the sample 1 dataset. The research title data then labeled according to the discovered clusters. These labeled research titles will used as ground truth for classification process of the sample 2. The classification method is supervise and requires ground truth as part of the training process.

The next step is to perform the classification process. The classification conducted on the Sample 2 dataset, which includes the author's name and title. However, only the research title is used in this stage. The list of research titles then transformed into a vector representation using the word2vec. Word2Vec is a method proposed by Mikolov [16], which have an advantages that its vector representation is able to capture the syntax and meaning of words in a language [17]. Word2Vec is a deep learning-based technique used for natural language processing and word embeddings. It is used to represent words as vectors in a high-dimensional space, where similar words are closer to each other in that space. Word2Vec has shown to be effective in a wide range of applications, including language modeling, sentiment analysis, and text classification [18]. Afterwards, the Random Forest classifier is used to classified topic from dataset sample 2. Random Forest is a method that combines multiple decision trees, where each tree depends on the value of a random variable. This method works by creating multiple decision trees and taking a majority vote to determine the final decision can be seen in Figure 3. It is also considered as one of the superior methods for text classification [19].

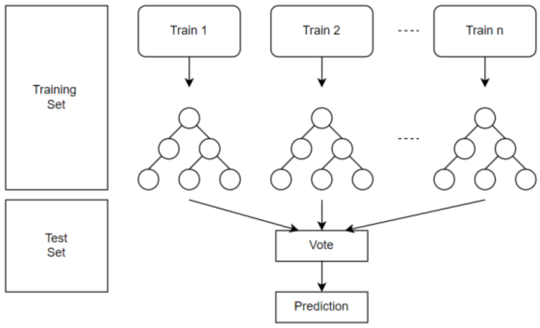

Figure 3. How random forest works

2.4. Link Prediction

Link prediction is also one of our proposed method in this research. Link prediction is an approach that has the function to discover the existence of a relationship that occurs between one node and another node in an existing network [20]. Figure 4 explains how link prediction in this research work.

At this stage, the initial step is to construct a graph from the sample 2 dataset, which captures the relationships between authors. The authors represented as nodes, and the relationships as edges. If an author is part of a research with more than one author, an edge or relationship will generated, creating a complete graph. Once a complete graph formed, the author data is calculate through a combination process with two pairs. This is because every author in the same publication will have a co-authorship relationship. The combination can be done using formula 2.

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$$Combination = \frac{n!}{(k!*(n-k)!)} \quad (2)$$

Where n is the number of authors in the study, and k is the desired number of co-authorship pairs (2 in this case).

The next process is filter. There are several steps, first is selecting authors who are in the same field. Second selecting the author who has the most publications related to the topic in the test data.

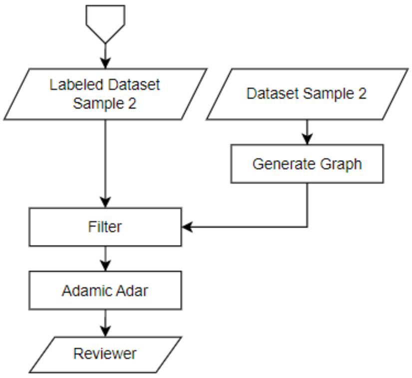

Figure 4. Link prediction

After going through the filtering process, the final reviewer candidates will be select again through the Adamic Adar Coefficient (AAC). Conceptually, the more relationships an author has, the lower the score they will receive with this method. Therefore, neighbors of a pair of nodes with fewer neighbors will contribute more than nodes with many neighbors [21]. And in graph data processing, AAC has the best accuracy compared to others [22]. AAC can be calculate using formula 3.

$$AAC = \sum_{z \in s\, \Gamma_{(x)} \cap \Gamma_{(y)}} 1/\log|\Gamma_z| \quad (3)$$

Where x is node x, y is node y, z is the common neighbor from x and y, and Γ is degree from each node (number of neighbor).

2.4. Evaluation

To show the reliability of our research, the results of the proposed method will compared with our previous research. Evaluation carried out using the Mean Average Precision (MAP). MAP is a method that suitable in ranking-based recommendation systems [23]. The method is suitable because the data used in this research also produces a list of recommended reviewer names. The precision In MAP means the number of relevant items divided by the number of items recommended.

The precision mentioned earlier is the calculation of each single value in a list of recommended items. To calculate the recommendation results on 1 publication, then the Average Precision (AP) is calculated. AP is calculated using Formula 4.

$$AP@N = \frac{1}{m} \sum_{k=1}^{N} P(k).rel(k) \quad (4)$$

Where AP is average precision, N is the number of author recommended by our method, and m is number of author that relevant to the ground truth.

To evaluate the overall recommendation results (all test sets) MAP is utilized. MAP is the average of all from Formula 4 divided by the number of test data. MAP calculation can be done using Formula 5.

$$MAP@N = \frac{1}{|U|} \sum_{u=1}^{N} |U|(AP@N)_u \quad (5)$$

Where MAP is mean average precision, and |U| is the number of item.In determining precision, a label or ground truth is necessary. As the dataset does not provide it, author itself as an expert will assess the recommendation results.

3. Result and Discussion

3.1. Result of data splitting

The DBLP dataset divided into sample 1 and sample 2. Sample 1 dataset contains only research title data presented in Table 1. The number of research titles in this is 2000. Sample 1 processed in LDA so that this data has a topic number as a label. Sample 2 is the DBLP dataset in XML format, which collects research data based on research titles, followed by author attributes and others. Figure 5 are examples of sample 2.

Table 1. Example of dataset sample 1

ID	Title
1091	Preliminary Design Of a Network Protocol Learning Tool Based On The Comprehension Of High School Students: Design By An Empirical Study Using a Simple Mind Map
1388	Further Results On Independence In Direct-Product Graphs
1674	a Methodology For The Physically Accurate Visualization Of Roman Polychrome Statuary
1688	Comparison Of Garch, Neural Network And Support Vector Machine In Financial Time Series Prediction
5411	Comparing GNG3D And Quadric Error Metrics Methods To Simplify 3D Meshes

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    <author orcid="0000-0002-3390-0756" pid="02/8408">Tohari Ahmad</author>
    <author pid="319/5319">Alek Nur Fatman</author>
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    <author orcid="0000-0002-3390-0756" pid="02/8408">Tohari Ahmad</author>
    <title>Hybrid model for bot group activity detection using similarity and correlation approac
    <pages>4219-4232</pages>
    <year>2022</year>
    <volume>34</volume>
    <journal>J. King Saud Univ. Comput. Inf. Sci.</journal>
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    <url>db/journals/jksucis/jksucis34.html#HostiadiA22</url>
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```


Figure 5. Example of dataset sample 2

3.2. Result of text pre-processing

The pre-processing step only applied to the datasets that contain the research title attribute. This is because the title taken to both LDA and classifier for further process. The data converted to lowercase, removed stop words and punctuation, lemmatization, and tokenization to transform sentences into a per-word format. Table 2 shows the research title before and after undergoing pre-processing.

Table 2. Result of pre-processing research title

Title	Pre-processed Title
Preliminary Design Of a Network Protocol Learning Tool Based On The Comprehension Of High School Students: Design By An Empirical Study Using a Simple Mind Map	[preliminary, design, network, protocol, learning, tool, based, comprehension, high, school, students, design, empirical, study using, simple, mind, map]
Further Results On Independence In Direct-Product Graphs	[further, results, independence, direct, product, graph]
a Methodology For The Physically Accurate Visualization Of Roman Polychrome Statuary	[methodology, physically, accurate, visualization, roman, polychrome, statuary]
Comparison Of Garch, Neural Network And Support Vector Machine In Financial Time Series Prediction	[comparison, garch, neural, network, support, vector, machine, financial, time, series, prediction]
Comparing GNG3D And Quadric Error Metrics Methods To Simplify 3D Meshes	[comparing, gngd, quadric, error, metrics, methods, simplify, meshes]

3.3. Result of Topic Modeling

The number of topics selected in this research is 5. It was determined that too many topics would result in decreased accuracy, while using only two or binary topics would lead to less accurate topic classification. The results of the LDA topic modeling are presented in Table 3.

In Table 3, in each topic produced by LDA, there are the most relevant words for each topic and the percentage that indicates the degree of importance of the word. If in the research title a word is found in 2 topics, then the topic of the research title will be taken according to the highest percentage count. The Figure 6 shows how the topic mapping on the research title works and Table 4 shows the topic distribution through dataset sample 1.

Table 3/ Topic generated by LDA

Topic	Words
0	0.087*"use" + 0.056*"image" + 0.032*"speech" + 0.030*"multi" + 0.030*"method" + 0.022*"cluster" + 0.022*"support" + 0.021*"structure" + 0.021*"algorithm" + 0.018*"optimization"
1	0.149*"model" + 0.104*"systems" + 0.067*"design" + 0.036*"parallel" + 0.030*"time" + 0.029*"simulation" + 0.028*"use" + 0.023*"control" + 0.020*"improve" + 0.019*"system"
2	0.080*"approach" + 0.048*"study" + 0.041*"time" + 0.041*"service" + 0.038*"web" + 0.035*"software" + 0.035*"learn" + 0.034*"applications" + 0.030*"towards" + 0.028*"development"
3	0.118*"network" + 0.054*"management" + 0.040*"process" + 0.037*"system" + 0.033*"mobile" + 0.032*"knowledge" + 0.031*"algorithms" + 0.028*"graph" + 0.024*"information" + 0.020*"sensor"
4	0.083*"data" + 0.059*"analysis" + 0.043*"system" + 0.042*"use" + 0.039*"information" + 0.034*"detection" + 0.031*"performance" + 0.028*"application" + 0.026*"object" + 0.024*"program"

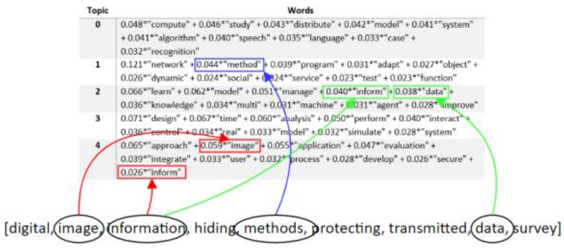

Figure 6. How LDA mapping the title

Table 4. Topic distribution

Topic				
0	1	2	3	4
550	350	375	340	385

Classification in this research aims to provide labels / classes to data test, which is sample 2. Meanwhile, sample 1 is used as the ground truth. The example results of the classification using random forest can be seen in Table 5.

Table 5. Classification result of dataset sample 2

ID	Title	Topic
1091	Preliminary Design Of a Network Protocol Learning Tool Based On The Comprehension Of High School Students: Design By An Empirical Study Using a Simple Mind Map	2
1388	Further Results On Independence In Direct-Product Graphs	4
1674	a Methodology For The Physically Accurate Visualization Of Roman Polychrome Statuary	2
1688	Comparison Of Garch, Neural Network And Support Vector Machine In Financial Time Series Prediction	2
5411	Comparing GNG3D And Quadric Error Metrics Methods To Simplify 3D Meshes	0

3.4. Result of Link Prediction

After conducting topic classification on the sample 2, the data transformed into a graph representation. As depicted in Figure 5, each data record in the dataset consists of one research title and several authors. The edges between authors in a given research title are created using Formula 2, connecting each author with one another in a non-redundant manner, forming a complete graph of co-authorship for each research title. Figure 7 provides a small illustration of a complete graph derived from 5 research title.

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Then, a graph encompassing all research titles is constructed by assigning a default weight of 1 on each author relationship or edge. Upon generation of this graph, redundant edges identified by increasing the weight value and represented by different lines. Figure 8 illustrates the full relationship from the graph derived from the sample 2. The final step in determining reviewer recommendations for a publication is filter and AAC process. The recommendations are determined based on several factors that are extracted from the dataset, including the match between publication and area od expertise of the candidate reviewer, the potential for a relationship to exist between the authors, and the consideration of the frequency of relationships between authors and candidate reviewers.

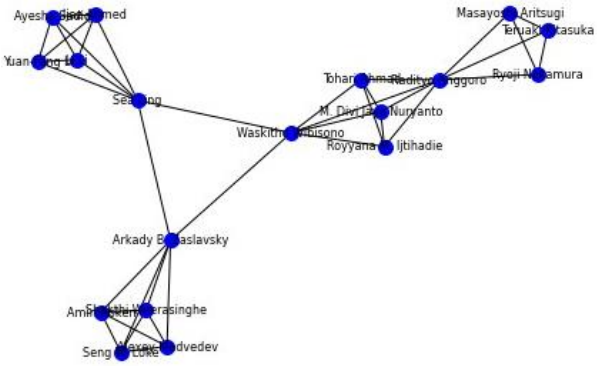

Figure 7. Example of complete graph from 5 publication

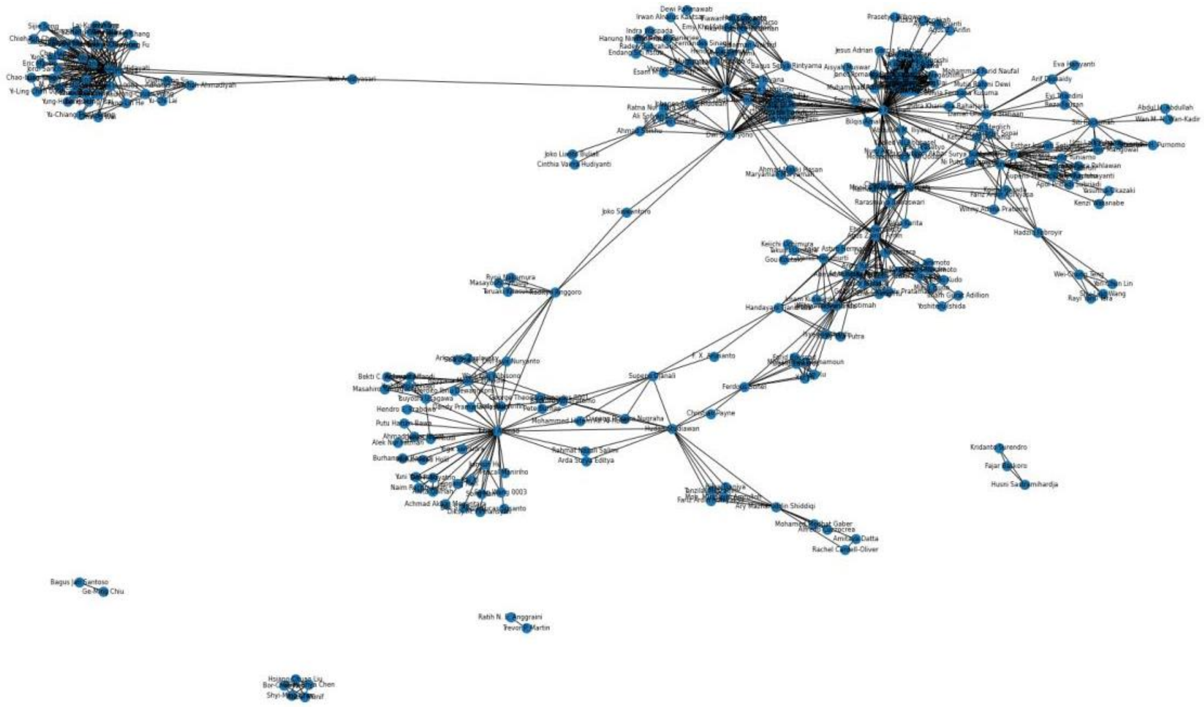

Figure 8. Graph from dataset sample 2

Determining the field of study of a candidate reviewer is obtained from the existing sample 2 in the graph as shown in Figure 7 and 8. Each publication is grouped based on the candidate reviewer with the data on the most frequently worked topics and the number of times those topics were worked on. Table 6 shows the determination of the field of study (topic) of the reviewer candidate from sample 2.

Table 6. Example of 5 reviewer candidate field of study (topic)

Author/Reviewer Candidate	Topic	Publication frequency
Tohari Ahmad	0	9
Waskitho Wibisono	0	1
Riyanarto Sarno	1	4
Riyanarto Sarno	2	3
Chastine Fatichah	2	5

Table 6 shows that candidate reviewer can have expertise in multiple topic. The data then ranked to sort candidate reviewers based on their research topics and the number of publications they have wrote. The final filter applies the AAC formula 3 to determine the likelihood of relationships after considering the closeness of the node (author) in the graph. The results of these recommendations are ranked to avoid CoI among the recommended reviewers.

If there is a new publication (data test) that need to be reviewed like Table 7, then the candidate reviewer for those data test can be seen in Table 8. Data test was obtained from the 13th ICTS conference held by ITS.

Table 7. Example of data test

No.	Title	Authors
1	Comparative Analysis of Hands-Free Mouse Controlling Based on Face Tracking	Salsabiil Hasanah, Aulia Teaku Nururrahmah, Darlis Herumurti
2	Classification Gas Measurement of Human Axillary Odor Using Electronic Nose	Shoffi Izza Sabilla, Malikhah Malikhah, Riyanarto Sarno
3	Bilingual Question Answering System Using Bidirectional Encoder Representations from Transformers Best Matching Method	Dini Adni Navastara, Ihdiannaja Ihdiannaja, Agus Zainal Arifin
4	Sensor Placement Strategy to Localize Leaks in Water Distribution Networks with Fluctuating Minimum Night Flow	Ary Mazharuddin Shiddiqi, Ervin Nurhayati, Agus Budi Raharjo,
5	Ensemble Methods Classifier Comparison for Anomaly Based Intrusion Detection System on CIDDS-002 Dataset	Ainurrochman, Raditia Wahyuwidayat , Ary Mazharuddin Shiddiqi
6	Detection of Covid-19 from Chest CT Images Using Deep Transfer Learning	Akhmad Irsyad, Handayani Tjandrasa
7	Evaluating The Preliminary Models to Identify Fake News on COVID-19 Tweets	Ayu Mutiara Sari, Nurul Fajrin Ariyani, Adhatus Solichah Ahmadiyah
8	A Novel Approach on Conducting Reviewer Recommendations Based on Conflict of Interest	Adi Setyo Nugroho, Aizul Faiz Iswafaza, Ratih Nur Esti Anggraini, Riyanarto Sarno
9	Website, AR, VR: Comparison for Learning Motivation	Mikhael Ming Khosasih, Darlis Herumurti
10	Variance Threshold as Early Screening to Boruta Feature Selection for Intrusion DS	Muhammad Al Fatih Abil Fida, Tohari Ahmad, M. Ntahobari

Table 8. Recommended candidate reviewer

Paper	Candidate Reviewer
Paper 1	Chastine Fatichah, Riyanarto Sarno, Tohari Ahmad
Paper 2	Tohari Ahmad, Daniel Oranova S, Kai Lung Hua
Paper 3	Chastine Fatichah, Tohari Ahmad, Shintami Chusnul Hidayati
Paper 4	Chastine Fatichah, Riyanarto Sarno, Tohari Ahmad
Paper 5	Riyanarto Sarno, Nanik Suciati, Diana Purwitasari
Paper 6	Wen Huang Cheng, Nanik Suciati, Agus Zainal Arifin
Paper 7	Martin Leonard Tangel, Fangyan Dong, Kaoru Hirota
Paper 8	Shintami Chusnul Hidayati, Wen Huang Cheng, Hudan Studiawan
Paper 9	Wen Huang Cheng, Hudan Studiawan, Mauridhi Hery Purnomo
Paper 10	Nanik Suciati, Diana Purwitasari, Mauridhi Hery Purnomo

3.5. Evaluation

To evaluate the implementation of our proposed method, we compared it with the previous research discussed in Section 2.4, which served as the primary reference for updating the method in this paper. While both the previous method and the proposed method yield similar outcomes, the focus is limited to a single publication data that includes one title and multiple authors. Moreover, the reviewer recommendation results tend to remain stagnant, as they do not take into account the number of prominent candidate reviewers for a specific research topic. This leads to some candidate reviewers being recommended multiple times for new test publication data.

In the proposed method, the results of the reviewer recommendation are more dynamic as they adapt to new test publication data. The assignment of candidate reviewers is based on both the research topic and the candidate reviewer's publication record, ensuring a more balanced workload distribution among the reviewers. This approach prevents the situation where one reviewer is assigned to review all test data related to a particular topic, promoting fairness and diversity in the review process.

Additionally, the reliability of the proposed method can be calculated using formula 5. Before calculating the mean, each list of candidate reviewers needs to be evaluated by experts using formula 4. Formula 4 calculates the accuracy of the recommended list of reviewers, providing a measure of the reliability of the proposed method. By incorporating this evaluation step, we can assess the quality and effectiveness of the reviewer recommendation process more accurately.

The comparison of the mean average precision (MAP) between the previous method and our proposed method is presented in Table 9. This allows us to quantitatively assess the performance improvement achieved by the proposed method. By analyzing the MAP scores, we can determine the extent to which the proposed method outperforms the previous method in terms of reviewer recommendation accuracy and overall system reliability.

Table 9. MAP evaluation

Method	MAP Value
Proposed	0,87
Nugroho (2021)	0,32

In summary, our proposed method offers several advancements over the previous method. It introduces a dynamic reviewer recommendation process that adapts to new test publication data, ensures a balanced workload distribution among reviewers, and improves the reliability of the recommendation results. By incorporating expert evaluation and calculating the MAP, we can quantitatively measure the effectiveness and performance of the proposed method. The comparison presented in Table 9 further highlights the

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superiority of our method in achieving more accurate and reliable reviewer recommendations.

4. Conclusion

This research successfully combines the LDA method and link prediction. Topic modeling is done using the LDA method which mapping probability on all title data resulting in a dataset that has topic clusters and continues with the classification process. While the link prediction method for determining candidate reviewers is done using the AAC method which analyzes the probability of co-authorship that causes the potential CoI.

Reviewers are select based on several considerations. The first is the relevance of the research field obtained from the topic modeling process. The second is the size of the candidate reviewer's contribution to a particular topic. In this case, it will be chose based on the author with the greatest contribution. And last is the co-authorship analysis obtained from the AAC value to determine the recommended candidate reviewer.

In measuring the success of the method, the MAP matrix is used. The value of the comparison matrix compared to previous research also shows a good enough number of 0.87 because of the ranking mechanism and weighted consideration.

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