Attractiveness Based Conference Ranking

Chen Zhang
Dalian University of Technology
Dalian, China
chen.zhang07@outlook.com

Falih Febrinanto
Federation University Australia
Ballarat, Australia
falihgozifebrinanto@students.federation.edu.au

Mujie Liu
Ningbo Tech University
Ningbo, China
mjliu_jade@outlook.com

Xiangjie Kong*
Zhejiang University of Technology
Hangzhou, China
xjkong@acm.org

Dongyu Zhang
Dalian University of Technology
Dalian, China
zhangdongyu@dlut.edu.cn

Sardar M. N. Islam
Victoria University
Melbourne, Australia
Sardar.Islam@vu.edu.au

ABSTRACT

Conferences have a significant impact on the academic world. Academic conferences aim to exchange information about research results with others. The quality of the conference is highly considered because it involves the credibility of the research papers produced. Creating a ranking system is an effective way to measure conference quality and compare it with other venues. The existing conference ranking systems do not have a unified index or are still manually evaluated by humans, so there is a gap to create an academic conference evaluation system that is objective, comprehensive, and universal. To further improve the ranking system, we propose two new indicators in this work. In these two indicators, we quantify the attractiveness of conferences and combine them with the traditional three indicators to calculate the scores of 10 conferences in the field of data science through the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) model. The proposed new evaluation system can help authors understand conferences more comprehensively and screen conferences more sensibly.

CCS CONCEPTS

• **Information systems** → **Learning to rank**; • **Computing methodologies** → *Learning to rank*;

KEYWORDS

Conference Rankings, Citation Analysis, Entropy Method, Evaluation System

ACM Reference Format:
Chen Zhang, Falih Febrinanto, Mujie Liu, Xiangjie Kong, Dongyu Zhang, and Sardar M. N. Islam. 2022. Attractiveness Based Conference Ranking. In *The 37th ACM/SIGAPP Symposium on Applied Computing (SAC '22), April 25–29, 2022, Virtual Event,* . ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3477314.3507065

*Corresponding author

SAC '22, April 25–29, 2022, Virtual Event,

ACM ISBN 978-1-4503-8713-2/22/04…$15.00
https://doi.org/10.1145/3477314.3507065

1 INTRODUCTION

We have seen a growing trend in academic exchanges at home and abroad in the last two decades. There are many forms of academic exchange, of which academic conferences are an important one [2]. There are some differences between journals and conferences. Conferences pay more attention to straightforward communication with a page limit on published papers and a shorter publication cycle so that the authors will get an acceptance or rejection letter at a specific time. It is more helpful for researchers to display and discuss their findings promptly and keep pace with their research fields' frontiers and research trends. At the same time, these papers are open to the public so that scholars can share their ideas and work results with researchers from all over the world, which promotes the generation of more ideas.

There is a problem that the quality of academic conferences directly affects the academic exchange, and ultimately, affects the quality and efficiency of knowledge production and innovation. Li et al. [1] explore the impact of conference rankings on the publishing patterns of different countries. Their experimental results show that the ranking system constructed by a country itself can significantly affect the publishing behavior of its domestic researchers.

There are already some conference evaluation systems. For example, Computing Research & Education (CORE) Ranking are managed by the CORE Executive Committee and adjusted regularly. Moreover, The China Computer Federation also provides a list of recommended conferences, which is mainly reviewed and determined by experts. They divide them into three categories: *A*, *B*, and *C*. Aminer [4] also describes conferences through six dimensions. The focus and results of these rankings are quite different, but they provide some references for researchers when choosing conferences.

After analyzing the existing ranking methods mentioned above, we found that most of the metrics are still based on publication citations. To describe the conference in a more detailed way, we focused on the behavioral preferences of authors and quantified them. Previous studies have shown that the addition of new members helps to generate inspiration and promotes the team. This also applies to conferences. However, emerging conferences will inevitably impact some earlier conferences. Therefore, we should also consider the attractiveness of the conference to previous scholars.

The frequent participation of scholars in the conference reflects the mutual recognition between scholars and the conference, bringing in new authors.

Related Work. The entropy method has an important role in measuring value dispersion in decision-making. The implementation of the entropy weight method has been widely used to solve problems in the data analysis field. Shi et al. [3] used the entropy weight method to construct the coordinate transformation and compensation matrix of the radar spectrum. Zhao et al.[5] constructed the entropy weight network model to explore the evolution of music. With various applications that can be applied using the entropy method, in this work, we are confident in using the entropy method to calculate the weight coefficients in the conference ranking system so that our evaluation can be more objective.

Contributions. This paper proposes a new conference evaluation system to provide a new perspective for researchers to better understand conferences.

(1) Attractiveness quantification. We use freshness and loyalty to quantify the attractiveness of conferences. Based on these two metrics, researchers can understand the situation of each conference participant.
(2) Conference rankings. We consider five metrics to evaluate 10 conferences in the data science field. We mainly use the TOPSIS model to combine these metrics and obtain a comprehensive score and ranking of each conference.

Organization. The rest of this paper is organized as follows. Section 2 illustrates the details of our proposed model and the process of conference ranking. Section 3 introduces the information about dataset. Section 4 analyzes the results. Section 5 concludes the paper.

2 THE PROPOSED MODEL

To perform conference raking using our model, Firstly, we need to calculate the evaluation metrics of each conference. The evaluation metrics are based on several factors that directly affect the quality of the conference. Therefore, our next step will be to evaluate the results of the evaluation metrics of each conference using our proposed model.

2.1 Evaluation Metrics

The influence of the conference is affected by many factors. Our method mainly considers the citation of the conference itself and its attractiveness to the author, etc., using the three existing metrics: H5-index, H-index, self-citation rate. Meanwhile, we propose two new metrics: Freshness and Loyalty to describe the attractiveness of conferences. The following is a detailed description of these metrics.

H5-index[1] is proposed by Google to evaluate the influence of journals. It indicates that H papers have been cited more than H times in 5 years.

H-index used to measure the influence and productivity of researchers. If a researcher has N papers cited at least N times in all his papers, his H-index is N. Here, we calculate the average H-index of all authors participating in the conference.

[1]https://scholar.google.com/intl/en/scholar/metrics.html#metrics

Self-citation rate refers to the percentage of the number of times that the conference is cited and the total number of times that the conference is cited.

Freshness is a new metric that measures the percentage of new authors each year. For a conference, the constant addition of new authors brings more knowledge and inspiration to the conference and also reflects the expansion of the coverage of the conference.

Let $A = (a_1, a_2, ..., a_{|A|})$ denote the set of authors in year i, and $B = (b_1, b_2, ..., b_{|B|})$ denote the set of authors before year i, the calculation formula is:

$$FN(i) = \frac{|A| - |A \cap B|}{|A|} \tag{1}$$

where $|\cdot|$ represents the number of elements in the set.

Loyalty depends on the average number of times an author attends a conference at a certain time. If the author participates in the conference frequently, this may indicate that the conference venue has gained the authors' trust and their research direction is in line with the conference. A conference's high loyalty reflects how well researchers recognized it.

Let $M = (m_1, m_2, ..., m_{|M|})$ denote the set of authors between year Y_0 and Y_n, the elements in M are not repeated. The calculation formula can be expressed as:

$$LD = \frac{\Sigma_{k=Y_0}^{Y_n} t_k}{|M|} \tag{2}$$

Herein, Y_0 and Y_n indicate the start and end times, respectively. t_k refers to the number of authors attending the conference in year k. Note that duplicate authors are only recorded once in the same year.

2.2 Topsis Model

After calculating the five metrics for each conference, we need to comprehensively evaluate the conference based on the results. We use the TOPSIS model to calculate the score of each conference. It is a commonly used comprehensive evaluation method, which reflects the gap between evaluation programs. This method mainly includes the following steps:

2.2.1 Forward processing. The initial matrix is expressed as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{3}$$

Here, m is the number of evaluation metrics, and n is the number of objects to be evaluated.

Evaluation metrics can be divided into positive metrics and negative metrics. Among the five metrics, except self-citation rate, the others are all positive metrics. The calculation formula is shown in Equation (4).

$$x' = \frac{1}{x} \quad (x > 0) \tag{4}$$

2.2.2 Standardized processing . To eliminate the influence of different data index dimensions, it is necessary to standardize the matrix.

The calculation formula is:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{5}$$

The standardized matrix is denoted as:

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1m} \\ z_{21} & z_{22} & \cdots & z_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{nm} \end{bmatrix} \tag{6}$$

2.2.3 Determination of the best and worst solution.

$$\begin{aligned} Z^{+} &= (\max\{z_{11}, z_{21}, \cdots, z_{n1}\}, \cdots, \max\{z_{1m}, z_{2m}, \cdots, z_{nm}\}) \\ &= (Z_1^{+}, Z_2^{+}, \cdots, Z_m^{+}) \end{aligned} \tag{7}$$

$$\begin{aligned} Z^{-} &= (\min\{z_{11}, z_{21}, \cdots, z_{n1}\}, \cdots, \min\{z_{1m}, z_{2m}, \cdots, z_{nm}\}) \\ &= (Z_1^{-}, Z_2^{-}, \cdots, Z_m^{-}) \end{aligned} \tag{8}$$

Here, Z^{+} and Z^{-} represent the optimal solution and the worst solution, respectively. If a solution is closer to the ideal optimal solution or farther from the worst solution, we have reason to think that the solution is better.

2.2.4 Calculation of weight coefficient. We use the entropy method to determine the weights, which objectively assign weights based on the difference in the order of the information contained in each metric. The specific calculation is as follows:

- Standardized processing:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{9}$$

Where x_{ij} is an element in the original matrix in Equation (3).

- Calculation of entropy:

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln p_{ij}, \quad (j = 1, 2, \cdots, m) \tag{10}$$

Where k is related to the number of samples, usually, $k = 1/\ln n$. If $p_{ij} = 0$, $p_{ij} \ln p_{ij} = 0$.

- Calculation of coefficient:

$$w_j = \frac{1 - e_j}{\sum_{k=1}^{m} (1 - e_k)}, \quad (j = 1, 2, \cdots, m) \tag{11}$$

2.2.5 Calculation of score.

$$D_i^{+} = \sqrt{\sum_{j=1}^{m} w_j \left(Z_j^{+} - z_{ij}\right)^2} \tag{12}$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{m} w_j \left(Z_j^{-} - z_{ij}\right)^2} \tag{13}$$

Herein, Z_j^{+} and Z_j^{-} represent the optimal solution and the worst solution of attribute j, respectively. z_{ij} refers to the value of the attribute j of object i. D_i^{+} and D_i^{-} represent the distance between the i^{th} object and the optimal solution and the worst solution, respectively.

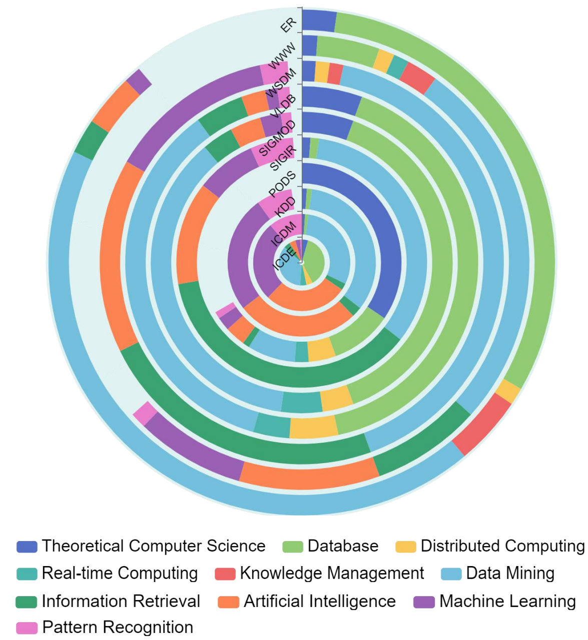

Figure 1: The distribution of research fields in 10 conferences.

The score of the $i^{th} (i = 1, 2, ..., n)$ evaluation object is represented as:

$$S_i = \frac{D_i^{-}}{D_i^{+} + D_i^{-}} \tag{14}$$

Here, $0 \le S_i \le 1$, the closer S_i is to 1, the better the evaluation object.

3 DATASET

The selection of data also has a specific impact on rankings, so we mainly consider two factors when obtaining data: research field and data coverage.

Research field: The citations in different research fields vary greatly and are not suitable for direct comparison. Therefore, we select 10 popular conferences in the field of data science for evaluation. They are the International Conference on Data Engineering (ICDE), International Conference on Data Mining (ICDM), ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD), ACM SIGMOD Conference on Principles of DB Systems (PODS), International Conference on Research and Development in Information Retrieval (SIGIR), ACM Conference on Management of Data (SIGMOD), International Conference on Very Large Data Bases (VLDB), International Conference on Web Search and Data Mining (WSDM), International World Wide Web Conference (WWW) and International Conference on Conceptual Modeling (ER).

Figure 1 shows the field distribution of these 10 conferences. We select 4 research fields of these conferences, which are relatively popular and composed of 10 fields for analysis. It can be seen that the research fields of these conferences are very similar.

Data coverage: Although there are many academic datasets, the metadata contained in different datasets are not the same. Some

Table 1: The results of conference ranking.

Name	H5-index	H-index	Loyalty	Freshness	Self-citation rate	Score	Rank
VLDB	38	10.446	1.551	0.654	0.007	0.891	1
KDD	53	10.219	1.462	0.601	0.022	0.317	2
WSDM	38	12.262	1.365	0.687	0.025	0.252	3
ICDM	24	8.925	1.326	0.766	0.024	0.234	4
WWW	51	9.864	1.384	0.660	0.040	0.214	5
ICDE	35	9.506	1.556	0.568	0.033	0.180	6
SIGMOD	44	9.521	1.654	0.555	0.071	0.159	7
SIGIR	37	9.564	1.651	0.517	0.065	0.130	8
PODS	16	18.006	1.921	0.482	0.050	0.106	9
ER	12	9.578	1.470	0.570	0.056	0.033	10

datasets have incomplete coverage of certain conferences or lack citation relationships, which may make the ranking results unfair. So we choose the Microsoft Academic Graph (MAG)[2] dataset, which is an open large-scale academic dataset that contains multiple disciplines. It consists of six types of entities, such as publications, authors, institutions, venues, research fields and events, and the relationships between these entities. Meanwhile, each type of entity is disambiguated with the same name and has a unique identifier.

We selected the data of these conferences in 2017 for research, and the basic information of 10 conferences is shown in Table 2.

Table 2: The basic information of 10 conferences.

Name	Paper	Author	Citation
ICDE	237	967	7,411
ICDM	404	1,445	7,500
KDD	248	1,067	22,274
PODS	36	114	1,828
SIGIR	284	1,033	9,942
SIGMOD	249	942	12,543
VLDB	57	191	7,282
WSDM	103	371	4,124
WWW	442	1,801	15,459
ER	60	193	768

4 RESULT AND ANALYSIS

The results of various metrics and rankings of each conference are shown in Table 1. As we can see, KDD has the highest H5-index value, which means that KDD may contain more influential papers in the past five years. The papers of ER are generally referred to by a small number of people. PODS has the highest H-index value, indicating that the conference has attracted more influential authors to participate. But its H5-index is not ideal, which may also be related to his less accepted papers. The average authors' H-index of the remaining conferences is not significantly different, indicating the quality of these conferences' authors is comparable. The loyalty of PODS is also relatively high, which shows that this conference is more attractive to authors. Compared with other conferences, its freshness is relatively low, but it is still close to half, and the distribution is even.

ICDM and WSDM both have high freshness. This may be because these two conferences appear relatively later than other conferences, so new authors are constantly participating. The self-citation rate of all conferences is relatively low, which is a very good phenomenon. The final score is obtained by combining the scores of the five dimensions and does not rank high because of a higher score in a certain dimension. It can be seen that VLDB scored much higher than other conferences, which may be because he scored well in all five metrics.

Through the above analysis, the conference ranking in this study enables scholars to understand the situation of each conference better and choose a more suitable conference for them to submit to. And if the ranking of a conference is quite different from the past few years, this is also an issue worthy of attention and research.

5 CONCLUSION

In this work, we propose two new metrics for conference evaluation and give a comprehensive ranking of 10 popular conferences. Although it enriches, the conference evaluation system still has limitations. Because the conference update speed is much faster than that of journals, the ranking will also change over time. In addition, the ranking of the conference is related to the conference itself and the selection of metrics. Further research, we need to study how to improve the accuracy of conference evaluation through regular updates and consideration of more metrics.

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