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Artificial Intelligence Related Publication Analysis Based on Citation Counting

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ABSTRACT Artificial intelligence is one of the most popular technologies in recently years. Journals and conferences are widely viewed as major tools to track the development of technologies. Citation counting analysis is one of the most acknowledged metrics in spite of its controversial drawbacks. To the best of our knowledge, most methods based on citation counting do not taken into account the citation weight in different years. In this paper, we focused on citation counting and designed a scheme to calculate both the citation weight and weighting of the cited credits of different publications, which are used to verify the efficiency of the proposed scheme. We also evaluated the popularity of publications by calculating their popularity scores. Unlike other ranking regulations, our proposed measure was able to compare journals and conferences simultaneously. In addition, we extracted ranking results to calculate the pairwise similarity via a generalized measure, which provided a more objective insight into the differences between publications. Several interesting observations were found from the experimental results with real data.

INDEX TERMS Artificial intelligence, citation counting, recommendation lists.

I. INTRODUCTION

Artificial Intelligence has been widely studied in various fields, such as scientific discovery, economic construction and social life, and has received a large amount of attention from academics and industries. Numerous valuable research results have been published in different related journals and conferences. Therefore, journal and conference papers have become foundational for tracking the development of various technologies. A hybrid collection of artificial intelligence topics can be accessed through the website.[1] However, this collection focuses on topics, and a large amount of references were contributed before 2010. In addition, there is a lack of relation between these papers and the discussed quality of the corresponding published journals or conferences.

In many research fields, the quality of journal publications is considered to be better than that of conference publications. However, this is not always true in the fields of computer science [1]. Usually, conference papers in a number of computer science fields have a higher status than those in other disciplines [2]. In computer science, because of the short audit cycle, conferences are updated faster and are used to more easily share knowledge, which is in line with the characteristics of the computer discipline. A conference is a timely and appropriate way to share research results with other researchers [3], [4]. The majority of computer scientists pay more attention to conferences, and some of them even believe that it is somewhat superfluous to publish papers in journals [2].

To better understand the characteristics of both journal and conference papers, researchers have conducted

[1]https://liinwww.ira.uka.de/bibliography/Ai/index.html

further research from various perspectives. The representative work includes citation networks [5], [6], credit allocation of co-authors [7], [8], advisor-adviser relationship between authors [9]–[11], and rankings of authors [12]–[14]. Citation counting is a foundational method for these works in spite of its controversial drawbacks [15]–[17]. Qian *et al.* [18] found that the citation count was related to the type of publication, category of publication of the China Computer Federation (CCF),[2] annual average number of papers published by the publication, number of authors and maximum h-index of all authors of a paper. Yan and Ding [19], and Ding and Cronin [20] found that the weight of a citation is affected by the prestige of the citing papers. Luo *et al.* [21] leveraged the affiliations of the citing papers to determine the prestige of citing papers [21]. Thelwall [22] and [23], Thelwall and Wilson [24] used the lognormal distribution, power law and hooked power law to analyze the distribution of citation counts, and they found that it was impossible to logically or empirically prove that any given statistical distribution fits citation counts perfectly [25]. To the best of our knowledge, these studies did not take into account the citation weights of different years. According to commonsense background knowledge, the differing importance of citation counting in different years cannot be ignored. For example, suppose that there are two papers, p_1 and p_2, from the same journal J_i and that both of them were cited 100 times. p_1 was published in 2000 and p_2 was published in 2010. It is reasonable to believe that p_2 is more important or popular than p_1. In other words, p_2 has a higher citation weight than p_1.

In this paper, we constructed our data sets based on the CCF's recommendation list for AI and related scholarly data, including data from the Digital Bibliography and Library Project (DBLP)[3] and Google Scholar.[4] The abbreviations and full names of the journals and conferences are provided in section VI. Pairwise similarities were calculated for a number of public ranking lists of journals and conferences in computer sciences, including the Scimago Journal & Country Rank,[5] Guide2Research,[6] Chinese Academy of Sciences's (CAS's) ranking, and Journal Citation Reports' (JCR') ranking. We investigated the relationship between citation counting of papers and the frequency of citation counting, from which we found that citation counting obeys a skewed distribution. We found that the geometric mean was a better option for the skewed data set, while the arithmetic mean might cause undesirable results [26], [27]. Based on the information distribution, we designed a scheme to calculate the citation weight of each journal and conference in different years from 2007 to 2016 and the weighting cited credits of every journal and conference to classify these publications and verify the efficiency of the designed scheme. Finally, we used other ranking results and a generated measure, AIRmm [28], to evaluate the similarity between each ranking result.

This paper is organized as follows. Section II introduces the data set, including the data source and some of the operations on the data set. Section III introduces the schemes to calculate the citation weights and weighting of the cited credits. In addition, the methods for creating the ranking result matrices and calculating the similarity between each ranking result matrix are introduced. Section IV analyzes the differences between journals and conferences. Furthermore, the efficiency of the designed scheme is verified, and the popularity of these publications is analyzed. Finally, the top 10 most popular journals and conferences are extracted, and the similarity between each ranking result is calculated. Section V concludes our work.

II. DATA

The CCF was established in 1956 and is one of the largest national academic organizations in China. In 2015, the CCF released a catalogue that included ten subfields of important international journals and conferences in the field of computer science (1. Computer Architecture/ High Performance Computing/ Storage Systems, 2. Computer Networks, 3. Network and Information Security, 4. Software Engineering/ System Software/ Programming Languages, 5. Database/ Data Mining/ Content Retrieval, 6. Scientific Theory, 7. Computer Graphics and Multimedia, 8. Artificial Intelligence, 9. Human-Computer Interaction and Pervasive Computing, and 10. Cross/ Emerging/ Synthesis). Furthermore, the journals and conferences were divided into three different categories: A, B, and C, according to their reputation. Category A is for the top international journals and conferences. Category B includes some famous journals and conferences that have significant international academic influence. Category C refers to some important and universally accepted journals and conferences in international academic circles. Papers from the CCF's recommendation list are referred to as full papers or regular papers, and all of the other forms of conference papers (Short paper/Poster/Demo paper/Technical brief/Summary) are not included.[7] It is important to note that this catalogue is a recommendation list that the CCF considers worthy of publishing by researchers in the field of computer science. In this paper, we took the eighth subfield, Artificial Intelligence (AI), as the guideline for constructing the dataset to study AI related publications.

We first extracted the papers' titles from the links, which were given by the CCF's recommendation list for AI. According to our research, we found that not all the links provided enough data to suit our needs, including the Journal of Automated Reasoning,[8] Journal of Speech, Language, and Hearing Research,[9] among others. Therefore, we were only able to obtain data from the links that contain published papers

[2] http://history.ccf.org.cn/sites/ccf/paiming.jsp.
[3] http://dblp.uni-trier.de/
[4] https://gfsoso.99lb.net/scholar.html
[5] http://www.scimagojr.com/journalrank.php
[6] http://www.guide2research.com/journals/
[7] http://history.ccf.org.cn/sites/ccf/paiming.jsp
[8] http://dblp.uni-trier.de/db/conf/par/
[9] http://jslhr.pubs.asha.org/

TABLE 1. The number of journals and conferences of different CCF categories (the numbers of journals/conferences with available data in our work).

	Category A (useful links)	Category B (useful links)	Category C (useful links)
Journal	4(4)	21(15)	37(23)
Conference	7(7)	12(12)	20(17)

from 2007 to 2016 or portions of these ten years. Table 1 shows the number of useful links and problem links. Furthermore, journals and conferences were removed from the dataset if the annual number of their published papers was less than 30 because these types of journals and conferences may be greatly influenced by some highly cited papers. Table 2 provides the detailed information of these problem links and the removed publications. From 2007 to 2016, categories A, B and C of conferences (abbreviated as CA, CB, CC) published 27332, 24473, and 42796 papers, respectively. Categories A, B, C of journals (abbreviated as JA, JB, JC) published 4952, 13775, and 41749 papers, respectively. Using these paper titles, we extracted the citation counts of each paper via Google scholar (until Nov. 20 2017). We hypothesized that all of the papers that we extracted from CCF's recommendation list were able to be found in Google Scholar. When entering a paper title as a query criterion in Google Scholar, we set the query results to be sorted by relevance. Therefore, we selected the citation count of the first query result as the paper's real citation count.

TABLE 2. The removed journals/conferences from the CCF categories because of unavailability for their data.

No.	Name of publication	Category of the publication
1	Journal of Automated Reasoning	JB
2	Journal of Speech, Language, and Hearing Research	JB
3	Evolutionary Computation	JB
4	Journal of Automated Reasoning	JB
5	IEEE Transactions on Audio, Speech, and Language Processing	JB
6	International Journal of Uncertainty, Fuzziness and KBS	JC
7	International Conference on Inductive Logic Programming	JC
8	IET Computer Vision	JC
9	Machine Translation	JC
10	IEEE Transactions on Computational Intelligence and AI in Games	JC
11	IET Signal Processing	JC
12	Journal of Experimental and Theoretical Artificial Intelligence	JC
13	Computational Intelligence	JC
14	International Journal of Computational Intelligence and Applications	JC
15	Natural Language Engineering	JC
16	International Journal on Document Analysis and Recognition	JC
17	Connection Science	JC
18	Web Intelligence and Agent Systems	JC
19	Neural Computing & Applications	JC
20	Asian Conf. on Machine Learning	CC
21	The Annual Conference of the North American Chapter of the Association for Computational Linguistics	CC
22	International Conference on Algorithmic Learning Theory	CC

III. METHOD

In this section, we introduce the schemes to calculate the citation weights, weighted citation credits, popularity score of each publication, and similarity between ranking result pairs.

A. CHARACTERISTIC OF THE CITATION COUNTING DISTRIBUTION

For citation counting of these papers, we first investigated the relationship between the citation counting and frequency of citation counting to analyze the distribution characteristics of the citation counts. The results are shown as Fig. 1 and Fig. 2. From these figures, we observe that the citation counts of all journals and conferences roughly obey Zipf's law [29], which indicates that the data set is skewed. This information is significant in that the geometric mean may be a better scheme to reduce the efforts of some high value data rather than the arithmetic mean [26], [27] when calculating the mean of citation counts.

Moreover, the citation count distributions of journals and conferences are different between each category, and there are some differences between journals and conferences in the same category. We drew figures to describe the relationship between the citation counts and the frequency of citation counts of journals and conferences. To make the figure easier to visualize, we used the logarithm of the values of the citation counts (we added 1 to the base of the citation count to avoid null values) and frequency of the citation counts. When comparing the citation counts between different categories of journals or conferences, all of the citation counts of categories A, B and C are drawn in the same figure. When comparing the citation counts of the same category between journals and conferences, we draw the citation counts of the same category in the same figure.

B. DESIGN AND VERIFICATION OF THE SCHEME

It is reasonable to believe that the significance of the citation counts in various years should be different. Motivated by the characteristic of the citation count distribution, we calculated the citation weights by considering the time factor, as shown in the following Eq. (1),

$$C_P^{(W)} = \frac{1}{N_P} \sum_{i=1}^{n} \frac{\log(C_i + 1)}{\Delta t} \tag{1}$$

In Eq. (1), $C_P^{(W)}$ is the citation weight of publication P. Δt is the time span of a paper from the published year to 2017. N_P is the number of papers in publication P. C_i is the citation count of paper i. In this equation, we use $\log(C_i+1)$ instead of $\log C_i$ because some papers may not have been cited during these years. If we use $\log C_i$ directly, it will cause an error, while $\log(C_i + 1)$ can avoid errors.

With the citation weight calculation scheme, we use Eq. (2) to calculate the citation weights of every journal and

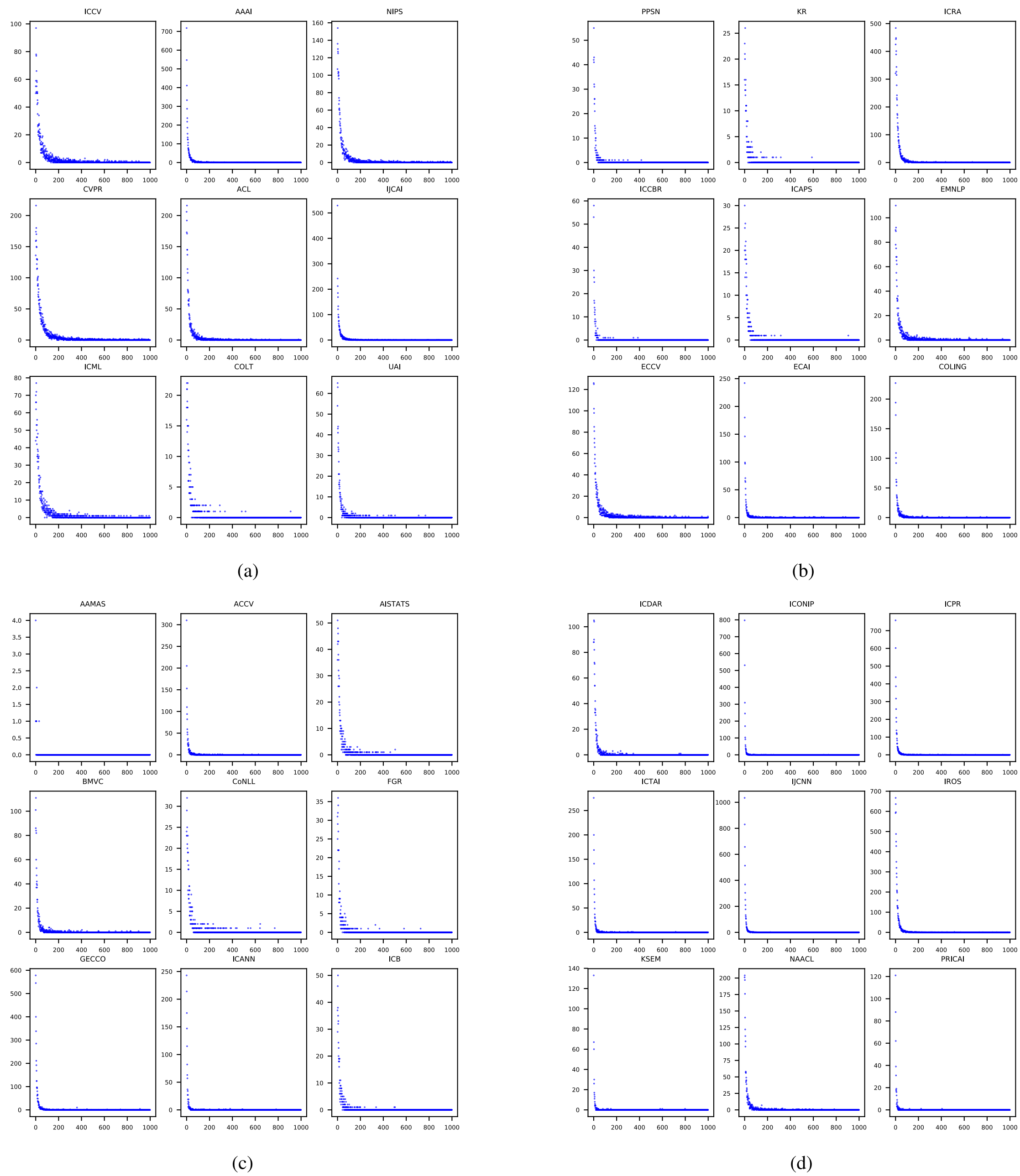


FIGURE 1. The distribution of different conferences, which roughly obey to the Zipf's law. (a) The distribution of different conferences i. (b) The distribution of different conferences ii. (c) The distribution of different conferences iii. (d) The distribution of different conferences iv.

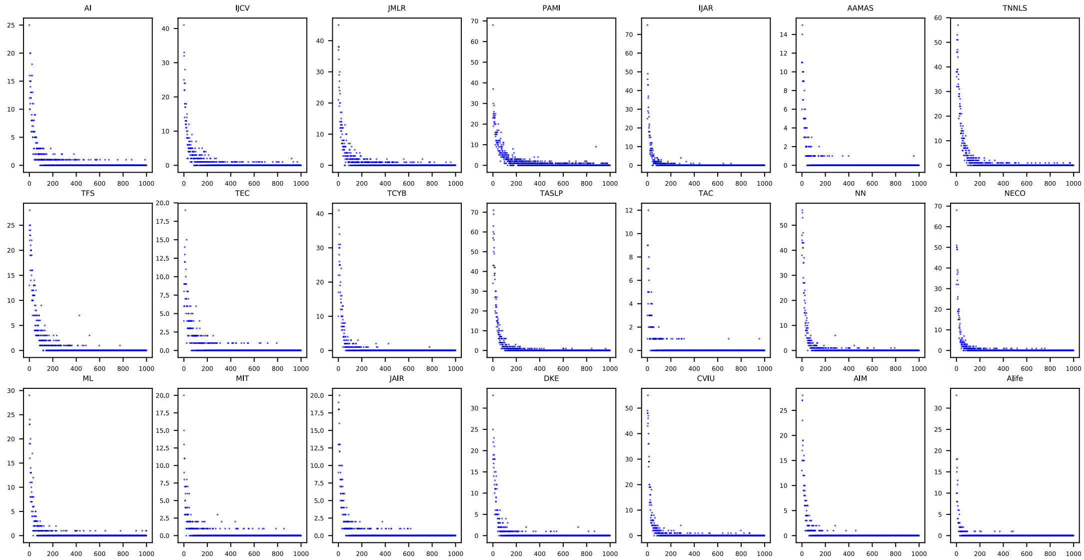
conference in the different categories from 2007 to 2016.

$$C_{P_y}^{(W)} = \sum_{i=1}^{n} \frac{\log(C_i + 1)}{(2017 - y_i)N_{cj}^{(P_y)}} \tag{2}$$

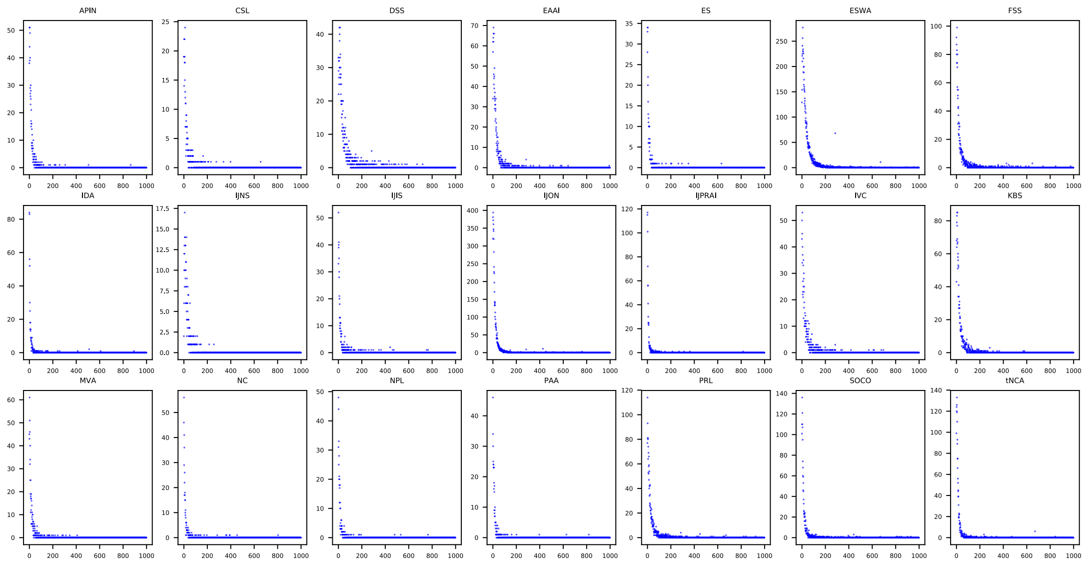
In Eq. (2), $C_{P_y}^{(W)}$ is the citation weight of publication P. y_i is the published year of paper i. $N_{cj}^{(P_y)}$ is the number of journals or conferences in the category to which the publication P belongs in year y.

The weighted cited credits of each journal and conference can thus be calculated though Eq. (3) based on the citation weights of the different categories from 2007 to 2016. With these weighted cited credits, we can classify the journals and conferences and compare the classified result with the CCF's recommendation list to verify whether the proposed scheme is efficient. We hypothesized that if the classified accuracy was high enough, our measure would be able to describe the citation counts.

$$W_P^{(C)} = \frac{1}{N_P} \sum_{i=1}^{N_P} \log(C_w^{(P_y)} C_i + 1) \tag{3}$$



(a)



(b)

FIGURE 2. The distribution of different journals, which roughly obey to the Zipf's law. (a) The distribution of different journals i. (b) The distribution of different journals ii.

In Eq. (3), $W_P^{(C)}$ is the weighted citation counting of publication P. N_P is the number of papers of publication P. $C_w^{(P_y)}$ is the citation weight of publication P in year y.

Inspired by the different distribution characteristics between the various categories of journals and conferences, we calculated the mean citation weight of various categories of journals and conferences using Eq. (4) to measure the differences between them.

$$C_c^{(W)} = \sum_{i=1}^{n} \frac{\log(C_i + 1)}{(2017 - y_i)N_{cj}^{(P_y)}} \tag{4}$$

In Eq. (4), $C_c^{(W)}$ is the citation weight of category c.

Finally, we used Eq. (5) to calculate the popularity score of the journals and conferences.

$$S_P = \frac{1}{N_P \sum_{y=2007}^{2017} N_y^{(P)}} \sum_{i=1}^{n} \log(C_i + 1) \tag{5}$$

In Eq. (5), the S_P is the popularity score of publication P. The $\sum_{y=2007}^{2017} N_y^{(P)}$ is the number of years for which publication P has data.

C. CREATION OF THE RANKING RESULT MATRIX

There are many journal and conference ranking regulations with various ranking results. To better compare these different ranking results, we first arrange the journals and conferences

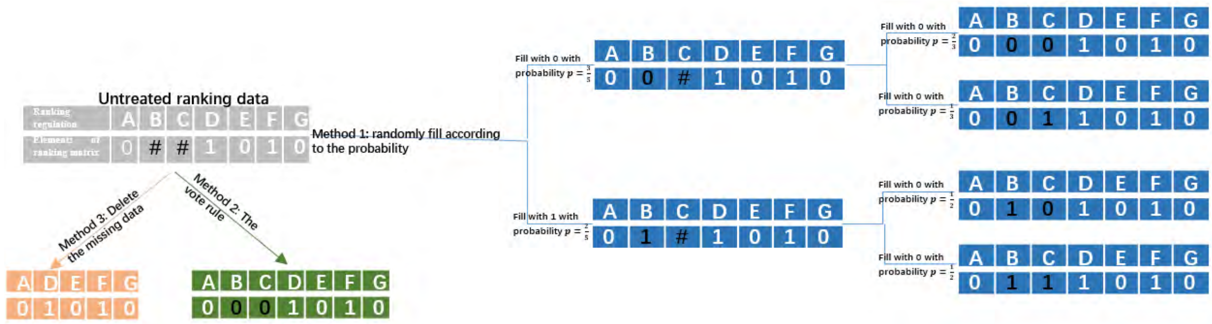


FIGURE 3. The detail processing of the missing data.

in a fixed order and then calculate the ranking matrices of these journals and conferences in this arrangement.

Values of 0 and 1 are used to fill the ranking result matrices according to Eq. (6). If a publication ranked higher than the other one, we set it to 1 in the corresponding position of the matrix. If the publication ranked lower than the other one, it is set to 0. For example, if journal i is ranked higher than j in the CORE ranking result, we set $M_{ij}^{(P)} = 1$ and $M_{ji}^{(P)} = 0$. From the characteristics of the matrix generation process, we know that the diagonal symmetry elemental values of the ranking result matrix have the same meaning. In other words, we obtain all of the information from the upper triangular elements of the ranking result matrix, and the upper triangular elements are used to perform calculations on these ranking result matrices.

$$\mathbf{M}_{ij}^{(P)} = \begin{cases} 1, & if\ \mathbf{V}_i < \mathbf{V}_j \\ 0, & if\ \mathbf{V}_i > \mathbf{V}_j \end{cases} \tag{6}$$

However, some journals and conferences are not listed in the different ranking lists. For example, the Parallel Problem Solving from Nature (PPSN) does not appear in Aminer's and Tsinghua University's ranking results. Machine Translation (MT) does not appear in Guider2Research's, JCR's or CAS's ranking lists. When facing this situation, we used three methods to address these missing data, and the detailed processing of these methods is shown in Fig. 3. From Fig. 3, we observe that for a journal or conference, there are seven ranking results: A, B, C, D, E, F, and G. However, B and C are missing some ranking data, so we assigned them as '#'. Method 1 is a dynamic process in which missing data are filled according to a set probability at random. We do not consider missing data to have a fixed value since they can be either 0 or 1. The result is randomly generated, but it has strong relevance with the probability. Therefore, the result will adjust the generated probability after each fill operation. Method 2 is based on the vote rule. We find that if a journal or a conference is not listed in a ranking result, it does not mean that it is not listed in the other ranking results. For example, PPSN does not appear in Aminer's and Tsinghua University's ranking lists, but it appears in CORE's, Guider2Research's, and other ranking results. Therefore, we use the vote rule to decide the value of the missing data. The results will be beneficial for ranking rules that have more of the same ranking results. Method 3 deletes missing data directly since the missing data are only a small part of the original data set. The missing data will not have a great influence on the overall results, even if some data are deleted. In this situation, we only considered the journals and conferences that appeared in both the CCF's recommendation list and the other ranking results. As a result, this method can reflect the actual situation of different ranking results more accurately. In addition, we integrated the multiple ranking results into a consensus ranking matrix using Eq. (7). The consensus ranking matrix $M_{ij}^{(Q)}$ stands for the mixed matrix of the integration of multiple ranking results.

$$\mathbf{M}_{ij}^{(Q)} = \begin{cases} 1, & if\ \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{P=1}^{n} \mathbf{M}_{ij}^{(P)} > \frac{n}{2} \\ 0, & if\ \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{P=1}^{n} \mathbf{M}_{ij}^{(P)} < \frac{n}{2} \end{cases} \tag{7}$$

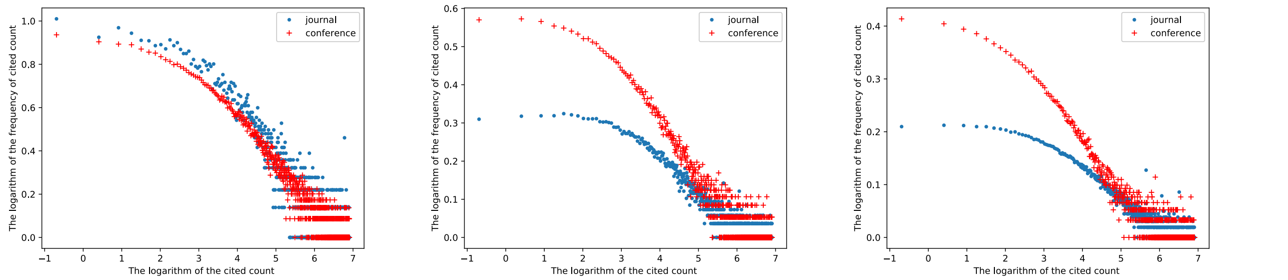
D. COMPUTATION OF THE SIMILARITY BETWEEN TWO CONSENSUS RANKING MATRICES

In this section, we used a generated measure, AIRmm [28], to evaluate the similarity between two consensus ranking matrices acquired from Eq. (7). The AIRmm is based on the Adjusted Rand Index (ARI) [30], and the AIRmm is an efficient way to calculate the similarity of two matrices. For two $N \times N$ matrices $\mathbf{A}$ and $\mathbf{B}$, $\mathbf{A}$ and $\mathbf{B}$ are the upper triangular matrices and the elements are 0 or 1. In this paper, we calculated the similarity between $\mathbf{A}$ and $\mathbf{B}$ by replacing them with matrices $\mathbf{M}_{ij}^{(P)}$ and $\mathbf{M}_{ij}^{(Q)}$.

We used the following Eqs. (8) and (9) to calculate the similarity of each matrix.

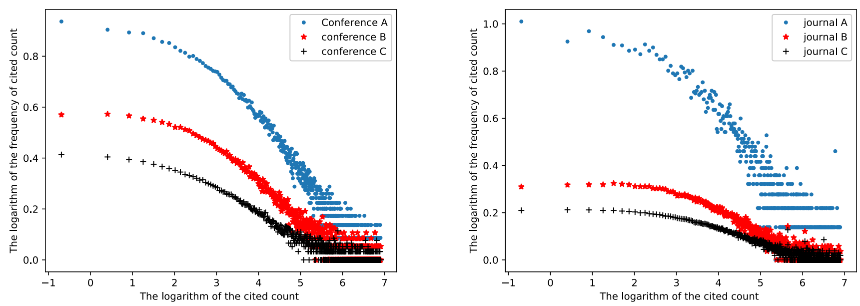
$$r_0 = \sum_{i \neq j} \frac{\mathbf{A}_{ij} B_{ij}}{2}, \quad r_1 = \sum_{i \neq j} \frac{\mathbf{A}_{ij}}{2}$$
$$r_2 = \sum_{i \neq j} \frac{\mathbf{B}_{ij}}{2}, \quad r_3 = \frac{2 r_1 r_2}{N(N-1)} \tag{8}$$

$$ARImm(\boldsymbol{A}, \boldsymbol{B}) = \frac{r_0 - r_3}{0.5(r_1 + r_2) - r_3} \tag{9}$$



(a) (b) (c)

FIGURE 4. The compare results of journals and conferences in different categories. (a) The compare results of journals and conferences in category A. (b) The compare results of journals and conferences in category B. (c) The compare results of journals and conferences in category C.



(a) (b)

FIGURE 5. The compare result on different categories of journals and conferences. (a) The compare result on different categories of conferences. (b) The compare result on different categories of journals.

IV. EXPERIMENTS AND RESULTS

In this section, we compare the differences between the journals and conferences in the AI field and verified whether the scheme that was designed above is efficient. Then, we calculate the weighted cited credit of each publication and compare the results with the CCF's recommendation list by ranking these weighted cited credits in descending order. Next, we simultaneously compare these journals and conferences used two measures and extract the top 10 most popular journals and conferences. Finally, we calculate and analyze the similarities between each ranking regulation.

A. COMPARISON OF THE DIFFERENCE BETWEEN JOURNALS AND CONFERENCES

According to the above introduction, we drew the figures to represent the differences between various categories in journals and conferences, which are shown in Fig. 4. From these figures, we found an interesting phenomenon: journals always have more highly cited papers than conferences in category A in the AI field. In regard to categories B and C, however, the opposite was found. This result is influenced by the characteristics of the AI discipline. AI technologies have greatly developed over the past few years, and conferences are a good way to share achievements, which has attracted many scholars. Meanwhile, top-level journals have a special status and meaning in the academic field, and some researchers still try to publish in them.

The differences in the same category between journals and conferences are shown in Fig. 5. From Fig. 5; we observe that papers published in journals of category A always have more high citation counts and are cited more frequently than those of categories B and C. Papers published in journals in category B always have more high-citation counts and are cited more frequently than those of category C. Moreover, the same results are found for conference papers.

B. CALCULATION OF THE CITATION WEIGHTS

According to Eq. (2), we can calculate the citation weights of journals and conferences in different categories from 2007 to 2016. Table 3 shows the results, from which we observe that the citation weight progressively increased from 2007 to 2016 in each category of journals and conferences, which is in line with the commonsense background knowledge. Furthermore, it is interesting that the journals in category A have a higher citation weight than conferences in every year from 2007 to 2016. However, in regard to category B and category C, the opposite was found. This finding indicates that the top-level journals may sometimes have a greater influence than top-level conferences in the AI field, but this may not be valid for middle tier journals and conferences. Therefore, we should adjust our attitude to journals and conferences because journals are not always more influential than conferences in the AI field.

TABLE 3. The citation weights of different categories form 2007 to 2016.

Year	CA	CB	CC	JA	JB	JC
2007	0.048577	0.024346	0.01134	0.107392	0.020359	0.009217
2008	0.05381	0.027186	0.011679	0.114216	0.021454	0.0101
2009	0.063041	0.030176	0.013864	0.110533	0.023453	0.011662
2010	0.065752	0.033317	0.015215	0.143072	0.026136	0.012621
2011	0.072736	0.035988	0.017878	0.160123	0.029433	0.014252
2012	0.08851	0.042197	0.019412	0.19168	0.034156	0.015907
2013	0.097816	0.04911	0.023535	0.21903	0.040481	0.018788
2014	0.129094	0.058329	0.025266	0.277394	0.051094	0.023457
2015	0.166964	0.076685	0.035262	0.349503	0.067267	0.030817
2016	0.237939	0.117023	0.041674	0.589454	0.107668	0.050333

TABLE 4. The classified result of journals based on the weighting cited credits (Journals in category A, B, and C are colored in Black, Red, and Blue respectively.)

Journal names	Weighting Cited Credits	Journal Names	Weighting Cited Credits
PAMI	25.06161	FSS	0.615608
IJCV	17.20961	ESWA	0.611271
JMLR	16.74412	KBS	0.549629
AI	10.69291	IVC	0.500528
TAC	7.704913	PRL	0.481689
TEC	2.729982	IJON	0.462886
TCYB	2.27854	EAAI	0.454257
TFS	2.071009	IJNS	0.443719
MIT	1.917817	CSL	0.441404
ML	1.834322	tNCA	0.439211
TNNLS	1.627044	AIM	0.430891
GAIR	1.486329	IJIS	0.3515
CVIU	1.416319	MVA	0.346894
DSS	1.256618	SOCO	0.329669
NN	1.256091	APIN	0.296922
AAMAS	1.200236	Alife	0.288867
TASLP	1.175606	NC	0.267679
NECO	1.113726	NPL	0.256463
DKE	1.027105	PAA	0.229417
IJAR	0.828864	IDA	0.15168
ES	0.695836	IJPRAI	0.139678

C. VERIFICATION OF THE EFFICIENCY OF THE SCHEME

We used the citation weights of different categories from 2007 to 2016 to calculate the weighted cited credits of each journal and conference with Eq. (3). Table 4 and Table 5 show the results, which are sorted in descending order of the weighted cited credits. From the tables, we conclude that the weighted cited credits are able to effectively classify the journals and conferences. When comparing the classified results to the CCF's recommendation list for AI, only one journal, Decision Support Systems (DSS), and five conferences, ACL, IJCAI, ICRA, COLING and ICAPS, were misclassified. The classified accuracy is approximately 92.3%, which is better than that of the other ranking regulations. For example, the classified accuracy of JCR's ranking regulation of journals is 60.0%, while it is 58.5% for CAS and 57.5% for the ranking regulation of guide2research. This results provided a necessary foundation for determining the efficiency of the designed equation. However, do not propose a new scheme to classify or rank journals and conferences, but we will perform a related analysis based on the data.

D. ANALYSIS THE CITATION WEIGHT OF JOURNALS AND CONFERENCES

From the above results, we observed that there were some differences between journals and conferences in different categories. We used Eq. (4) to calculate and analyze the differences between journals and conferences according to the citation weight. Table 6 presents the results. From Table 6, we found that journals had a higher citation weight compared with conferences in category A, while conferences had higher citation weights than journals in categories B and C. This result is similar to the conclusion regarding the differences between journals and conferences in different categories.

TABLE 5. The classified result of conferences based on the weighting cited credits (Journals in category A, B, and C are colored in Black, Red, and Blue respectively.)

Conference Names	Weighting Cited Credits	Conference Names	Weighting Cited Credits
AAAI	9.468487	ICRA	1.415434
CVPR	8.237687	GECCO	1.33068
NIPS	7.786655	CoNLL	1.159143
ICML	7.189199	COLING	1.146787
ICCV	6.963641	ICAPS	1.131825
COLT	6.239731	NAACL	0.892241
ECAI	5.071069	PRICAI	0.836311
ICCBR	4.615985	IJCNN	0.572815
ACL	4.544895	FGR	0.555367
IJCAI	4.219535	ICONIP	0.528971
ECCV	3.113666	ACCV	0.487702
UAI	2.351147	ICTAI	0.439433
EMNLP	2.285713	ICPR	0.43363
PPSN	1.957082	IROS	0.432175
AAMAS	1.82121	ICB	0.369775
KR	1.797278	ICANN	0.337366
BMVC	1.688653	ICDAR	0.316033
AISTATS	1.449643	KSEM	0.295758

TABLE 6. The citation weights of different categories of journals and conferences (the bigger citation counting is bold marked).

	Category A	Category B	Category C
journals	**0.2403**	0.0433	0.0188
conferences	0.1038	**0.05019**	**0.0221**

E. SIMULTANEOUS COMPARISON OF THE CONFERENCES AND JOURNALS

Unlike other ranking regulations that can only compare journals or conferences (such as the JCR, CAS, Aminer, etc.), the measure proposed in this paper can evaluate journals and conferences at the same time in two ways. One way based on the weighted citation credits, which can be used to compare the rankings of journals and conferences. The other way based on the popularity score, which is used to compare the popularity of journals and conferences. Table 7 shows the results of the weighted citation credits. We find that the top-level journals rank higher than conferences, while at the other level, the conferences dominate the ranking results. The top-level and middle-level conferences are usually ranked higher than the middle-level and bottom-level journals.

Using Eq. (5), we can calculate the popularity score of journals and conferences. Table 8 shows the compared results of journals and conferences based on the popularity score. From these results, we found that the popularity score of IJCV (0.883117) was close to those of the CVPR (0.89408) and ECCV (0.90335). In fact, IJCV is a top-level journal

TABLE 7. The mixture compared result of journals and conferences based on the weighting citation credits (Journals are marked as the gray background).

No.	Name	Weigting citation credit	No.	Name	Weigting citation credit
1	PAMI	25.06161	40	ICAPS	1.13182
2	IJCV	17.20961	41	NECO	1.113726
3	JMLR	16.74412	42	DKE	1.027105
4	AI	10.69291	43	NAACL	0.89224
5	AAAI	9.46849	44	PRICAI	0.83631
6	CVPR	8.23769	45	IJAR	0.828864
7	NIPS	7.78666	46	ES	0.695836
8	TAC	7.704913	47	FSS	0.615608
9	ICML	7.18920	48	ESWA	0.611271
10	ICCV	6.96364	49	IJCNN	0.57281
11	COLT	6.23973	50	FGR	0.55537
12	ECAI	5.07107	51	KBS	0.549629
13	ICCBR	4.61598	52	ICONIP	0.52897
14	ACL	4.54489	53	IVC	0.500528
15	IJCAI	4.21954	54	ACCV	0.48770
16	ECCV	3.11367	55	PRL	0.481689
17	TEC	2.729982	56	IJON	0.462886
18	UAI	2.35115	57	EAAI	0.454257
19	JAR	2.321722	58	IJNS	0.443719
20	EMNLP	2.28571	59	CSL	0.441404
21	TCYB	2.27854	60	ICTAI	0.43943
22	TFS	2.071009	61	tNCA	0.439211
23	PPSN	1.95708	62	ICPR	0.43363
24	MIT	1.917817	63	IROS	0.43217
25	ML	1.834322	64	AIM	0.430891
26	AAMAS	1.82121	65	ICB	0.36978
27	KR	1.79728	66	IJIS	0.3515
28	BMVC	1.68865	67	MVA	0.346894
29	TNNLS	1.627044	68	ICANN	0.33737
30	AISTATS	1.44964	69	SOCO	0.329669
31	CVIU	1.416319	70	ICDAR	0.31603
32	ICRA	1.41543	71	APIN	0.296922
33	GECCO	1.33068	72	KSEM	0.29576
34	DSS	1.256618	73	Alife	0.288867
35	NN	1.256091	74	NC	0.267679
36	AAMAS	1.200236	75	NPL	0.256463
37	TASLP	1.175606	76	PAA	0.229417
38	CoNLL	1.15914	77	IDA	0.15168
39	COLING	1.14679	78	IJPRAI	0.139678

published by Springer, which is famous in the field of computer vision. ECCV and CVPR are two of the most famous conferences in the field of computer vision around the world. Therefore, they have similar scores. Compared with the top journals, the rankings of conferences are relatively inferior, and it is interesting to find that the TEC and TFS are ranked higher than some top conferences and journals, which indicates that the TEC and TFS may have been more popular over these ten years. However, it does not mean that the TEC and TFS are more prestigious than other journals and conferences.

F. EXTRACTION OF THE TOP 10 MOST POPULAR JOURNALS AND CONFERENCES

According to Table 8, we can extract the top 10 most popular journals and conferences, and the results are shown in Table 9. From Table 9, we find that approximately 90% of the top 10 most popular journals and conferences belong to categories A and B. This result indicates that some highly influential journals and conferences are more popular than lower level publications. However, it is interesting that there is a journal in category C, Decision Support Systems (DSS), and a conference in category C, Artificial Intelligence and Statistics (AISTATS), that appear in the top 10 most popular publications, which means that this journal and conference were more popular than some top journals and conferences over these ten years, but it does not mean that they have more prestige than other publications.

TABLE 8. The mixture compared result of journals and conferences based on the popularity score (Journals are marked as the gray background).

No.	Name	Popularity score	No.	Name	Popularity score
1	TCYB	1.434977	40	DKE	0.630105
2	TAC	1.049888	41	NECO	0.619561
3	PAMI	1.003286	42	IVC	0.617992
4	TEC	0.932566	43	ICB	0.61765
5	ECCV	0.90335	44	tNCA	0.617425
6	CVPR	0.89408	45	ICRA	0.60819
7	IJCV	0.883117	46	IJAR	0.604663
8	TFS	0.868223	47	BMVC	0.60452
9	ICML	0.85394	48	AAAI	0.59989
10	JMLR	0.846705	49	APIN	0.59911
11	TNNLS	0.835288	50	SOCO	0.59819
12	AI	0.832594	51	UAI	0.59496
13	DSS	0.800265	52	FGR	0.57842
14	NIPS	0.78738	53	IJIS	0.571979
15	COLT	0.77832	54	MVA	0.561925
16	ESWA	0.764848	55	ECAI	0.55319
17	KR	0.75740	56	COLING	0.53133
18	KBS	0.753958	57	NPL	0.52911
19	MIT	0.750356	58	Alife	0.528481
20	AISTATS	0.74877	59	PAA	0.514644
21	IJNS	0.741136	60	PPSN	0.50994
22	TASLP	0.723363	61	ES	0.505822
23	NN	0.723294	62	AAMAS	0.50193
24	AAMAS	0.722832	63	IROS	0.49171
25	ML	0.722343	64	NC	0.489746
26	EMNLP	0.71728	65	IJCAI	0.48408
27	ICCV	0.71606	66	ICCBR	0.44409
28	JAR	0.709891	67	ICDAR	0.44156
29	EAAI	0.690014	68	GECCO	0.43116
30	CVIU	0.680588	69	ICPR	0.39272
31	AIM	0.678523	70	IDA	0.378998
32	ACL	0.67226	71	ACCV	0.37823
33	NAACL	0.66776	72	IJPRAI	0.376664
34	PRL	0.666794	73	IJCNN	0.35791
35	IJON	0.666725	74	PRICAI	0.34638
36	CSL	0.660002	75	ICTAI	0.33566
37	FSS	0.653416	76	ICANN	0.30214
38	CoNLL	0.63513	77	KSEM	0.28650
39	ICAPS	0.63466	78	ICONIP	0.24784

TABLE 9. The top 10 popular journals and conferences (Journals in category A, B, and C are colored in Black, Red, and Blue respectively.)

Journal names	Popularity score	Conference names	Popularity score
TCYB	1.43498	ECCV	0.90335
TAC	1.04989	CVPR	0.89408
PAMI	1.00329	ICML	0.85394
TEC	0.93257	NIPS	0.78738
IJCV	0.88312	COLT	0.77832
TFS	0.86822	KR	0.75740
JMLR	0.84670	AISTATS	0.74877
TNNLS	0.83529	EMNLP	0.71728
AI	0.83259	ICCV	0.71606
DSS	0.80026	ACL	0.67226

G. EVALUATION OF THE SIMILARITY BETWEEN RANKING RESULTS

According to the ranking result matrix of each ranking regulation, we can calculate the similarity between them using Eq. (9). Table 10 to Table 15 show the results of the similarity. We found that the results calculated by method-1 and method-2 cannot reflect the real information of these ranking

TABLE 10. The similarity between each journal ranking results via method-1.

Journals	arrCORE	arrGUIDE	arrSJR	arrACS	arrJCR	arrCCF	arrThisPaper	mixArrAll
arrCORE	1.00000	0.28028	0.28824	0.34217	0.35253	**0.29914**	0.28279	0.46759
arrGUIDE	0.28028	1.00000	0.01755	-0.07205	-0.11431	**0.17000**	0.34861	0.04165
arrSJR	0.28824	0.01755	1.00000	0.84288	0.81725	0.04465	0.49362	0.79922
arrACS	0.34217	-0.07205	0.84288	1.00000	0.91829	0.11221	0.49529	0.84532
arrJCR	0.35253	-0.11431	0.81725	0.91829	1.00000	0.12147	0.46165	0.83089
arrCCF	0.29914	0.17000	0.04465	0.11221	0.12147	1.00000	0.05915	0.20525
arrThisPaper	0.28279	0.34861	0.49362	0.49529	0.46165	0.05915	1.00000	0.56121
mixArrAll	0.46759	0.04165	0.79922	0.84532	0.83089	0.20525	0.56121	1.00000

TABLE 11. The similarity between each conference ranking results via method-1.

Conferences	arrCORE	arrGUIDE	arrGII	arrTsinghua	arrAminer	arrCCF	arrThisPaper	mixArrAll
arrCORE	1.00000	0.51335	0.09200	0.24556	0.41860	**0.64021**	0.60195	0.77509
arrGUIDE	0.51335	1.00000	0.05998	0.15712	0.22107	**0.57831**	0.61361	0.66963
arrGII	0.09200	0.05998	1.00000	0.24809	0.31216	0.16997	0.09523	0.23346
arrTsinghua	0.24556	0.15712	0.24809	1.00000	0.49178	0.03209	0.18698	0.31034
arrAminer	0.41860	0.22107	0.31216	0.49178	1.00000	0.32819	0.32400	0.57322
arrCCF	0.64021	0.57831	0.16997	0.03209	0.32819	1.00000	0.79684	0.60187
arrThisPaper	0.60195	0.61361	0.09523	0.18698	0.32400	0.79684	1.00000	0.65440
mixArrAll	0.77509	0.66963	0.23346	0.31034	0.57322	0.60187	0.65440	1.00000

TABLE 12. The similarity between each conference ranking results via method-2.

Conferences	arrCORE	arrGUIDE	arrGII	arrTsinghua	arrAminer	arrCCF	arrThisPaper	mixArrAll
arrCORE	1.00000	0.51374	0.12769	0.26302	0.46623	**0.64616**	0.61829	0.80017
arrGUIDE	0.51374	1.00000	0.08815	0.16755	0.23818	**0.58566**	0.62785	0.66820
arrGII	0.12769	0.08815	1.00000	0.26504	0.33023	0.16997	0.09523	0.26308
arrTsinghua	0.26302	0.16755	0.26504	1.00000	0.48058	0.04789	0.18856	0.31823
arrAminer	0.46623	0.23818	0.33023	0.48058	1.00000	0.35320	0.33183	0.59885
arrCCF	0.64616	0.58566	0.16997	0.04789	0.35320	1.00000	0.79684	0.62135
arrThisPaper	0.61829	0.62785	0.09523	0.18856	0.33183	0.79684	1.00000	0.66389
mixArrAll	0.80017	0.66820	0.26308	0.31823	0.59885	0.62135	0.66389	1.00000

TABLE 13. The similarity between each journal ranking results via method-2.

Journals	arrCORE	arrGUIDE	arrSJR	arrACS	arrJCR	arrCCF	arrThisPaper	mixArrAll
arrCORE	1.00000	0.27041	0.34258	0.40319	0.41272	**0.29232**	0.34396	0.52012
arrGUIDE	0.27041	1.00000	0.03384	-0.02407	-0.07020	**0.18673**	0.35639	0.09207
arrSJR	0.34258	0.03384	1.00000	0.83220	0.82179	0.04465	0.49362	0.79971
arrACS	0.40319	-0.02407	0.83220	1.00000	0.93670	0.14277	0.50142	0.85779
arrJCR	0.41272	-0.07020	0.82179	0.93670	1.00000	0.13862	0.47892	0.83863
arrCCF	0.29232	0.18673	0.04465	0.14277	0.13862	1.00000	0.05915	0.22413
arrThisPaper	0.34396	0.35639	0.49362	0.50142	0.47892	0.05915	1.00000	0.57701
mixArrAll	0.52012	0.09207	0.79971	0.85779	0.83863	0.22413	0.57701	1.00000

TABLE 14. The similarity between each conference ranking results via method-3.

Conferences	arrCORE	arrGUIDE	arrGII	arrTsinghua	arrAminer	arrCCF	arrThisPaper	mixArrAll
arrCORE	1.00000	0.65308	0.81196	0.77021	0.65793	**0.77140**	0.43573	0.82382
arrGUIDE	0.65308	1.00000	0.77788	0.75094	0.78261	**0.76609**	0.39371	0.82425
arrGII	0.81196	0.77788	1.00000	0.79910	0.71942	0.80455	0.42653	0.85230
arrTsinghua	0.77021	0.75094	0.79910	1.00000	0.75928	**0.98714**	0.46985	0.92662
arrAminer	0.65793	0.78261	0.71942	0.75928	1.00000	0.77428	0.39282	0.80460
arrCCF	0.77140	0.76609	0.80455	0.98714	0.77428	1.00000	0.48083	0.93984
arrThisPaper	0.43573	0.39371	0.42653	0.46985	0.39282	0.48083	1.00000	0.50422
mixArrAll	0.82382	0.82425	0.85230	0.92662	0.80460	0.93984	0.50422	1.00000

TABLE 15. The similarity between each journal ranking results via method-3.

Journals	arrCORE	arrGUIDE	arrSJR	arrACS	arrJCR	arrCCF	arrThisPaper	mixArrAll
arrCORE	1.00000	0.60239	0.68592	0.63679	0.61005	**0.83786**	0.45430	0.69785
arrGUIDE	0.60239	1.00000	0.83089	0.93975	0.98076	**0.66099**	0.34644	0.91214
arrSJR	0.68592	0.83089	1.00000	0.85273	0.84239	0.73312	0.37164	0.91671
arrACS	0.63679	0.93975	0.85273	1.00000	0.93614	**0.68807**	0.36847	0.92830
arrJCR	0.61005	0.98076	0.84239	0.93614	1.00000	**0.66793**	0.35211	0.91598
arrCCF	0.83786	0.66099	0.73312	0.68807	0.66793	1.00000	0.51633	0.74649
arrThisPaper	0.45430	0.34644	0.37164	0.36847	0.35211	0.51633	1.00000	0.41196
mixArrAll	0.69785	0.91214	0.91671	0.92830	0.91598	0.74649	0.41196	1.00000

results. For example, if we used method-1 to address the missing data, the same ranking regulation might cause large differences in the ranking results' similarity between journals and conferences. The journal ranking results' similarity between guide2research's and CCF's recommendation lists is 0.17, while the conference ranking results similarity between them is approximately 0.578. When method-2 is used to address the missing data, the journal ranking results' similarity between guide2research's and CCF's recommendation lists is 0.187, while the conference ranking results' similarity between them is approximately 0.586. The ranking results' similarity between CORE's and CCF's recommendation lists reaches the same conclusion. However, when we delete the missing data, the ranking results' similarity between journals and conferences are only slightly different from each other. The journal ranking results' similarity between guide2research's and CCF's recommendation lists is approximately 0.661, while the conference ranking results' similarity between them is approximately 0.766. Therefore, we believe that method-3 is more effective for addressing the missing data.

Furthermore, the ranking results' similarity between the integration of multiple ranking results and other ranking results is close, which indicates that the integrated results can reflect the information of most ranking regulations. Integrating the multiple ranking results is an ensemble learning idea that makes use of all of the information of these ranking results. Therefore, integration of the multiple ranking results can reflect the characteristics of most ranking results and has a higher similarity with these ranking results. Table 14 shows that the similarity of the conference ranking results of Tsinghua University are the closest to the CCF's recommendation list, and the value of the similarity is approximately 0.987.

V. CONCLUSION

In this paper, we studied the differences between journals and conferences in the AI field based on the CCF's recommendation list. We found that publications in journals have higher citation counts than those in conferences in category A, while the opposite observation is found in categories B and C. This is one of the main characteristics of the AI field, which is very different from other disciplines. Moreover, the publications in category A have higher citation counts than those in category B, and those in category B have higher citation counts than those category C, which is consistent for both journals and conferences.

Using the designed scheme, we found that the citation weight was different between categories and published years. For each level of journals and conferences, the citation weights progressively increased from 2007 to 2016. The experiments on real data illustrated the efficiency of our proposed scheme. We acquired a high accuracy of 92.3% when we classified the journals and conferences based on the weighted citation credits and compared them with the CCF's recommendation list of AI, which suggests the importance for our scheme to take into account of the citation weight according to the difference of the published years.

We extracted the top 10 journals and conferences over the last ten years. The results show that 90% of the top 10 most popular journals and conferences belong to categories A and B, but it was interesting to find only one journal (Decision Support Systems, DSS) and one conference (Artificial Intelligence and Statistics, AISTATS)

TABLE 16. The abbreviations and the full names of journals.

No.	Abbreviated names	Full names
1	AI	Artificial Intelligence
2	TPAMI	IEEE Trans on Pattern Analysis and Machine Intelligence
3	IJCV	International Journal of Computer Vision
4	JMLR	Journal of Machine Learning Research
5	TAP	ACM Transactions on Applied Perception
6	TSLP	ACM Transactions on Speech and Language Processing
7	COLING	Computational Linguistics
8	CVIU	Computer Vision and Image Understanding
9	DKE	Data and Knowledge Engineering
10	EC	Evolutionary Computation
11	TAC	IEEE Transactions on Affective Computing
12	TASLP	IEEE Transactions on Audio, Speech, and Language Processing
13	TCYB	IEEE Transactions on Cybernetics
14	TEC	IEEE Transactions on Evolutionary Computation
15	TFS	IEEE Transactions on Fuzzy Systems
16	TNNLS	IEEE Transactions on Neural Networks and learning systems
17	IJAR	International Journal of Approximate Reasoning
18	JAIR	Journal of AI Research
19	JAR	Journal of Automated Reasoning
20	JSLHR	Journal of Speech, Language, and Hearing Research
21	ML	Machine Learning
22	NECO	Neural Computation
23	NN	Neural Networks
24	PR	Pattern Recognition
25	AAMAS	Autonomous Agents and Multi-Agent Systems
26	TALIP	ACM Transactions on Asian Language Information Processing
27	APIN	Applied Intelligence
28	AIM	Artificial Intelligence in Medicine
29	Alife	Artificial Life
30	CI	Computational Intelligence
31	CSL	Computer Speech and Language
32	Connection	Connection Science
33	DSS	Decision Support Systems
34	EAAI	Engineering Applications of Artificial Intelligence
35	ES	Expert Systems
36	ESWA	Expert Systems with Applications
37	FSS	Fuzzy Sets and Systems
38	T-CIAIG	IEEE Transactions on Computational Intelligence and AI in Games
39	IET-CVI	IET Computer Vision
40	IET-SPR	IET Signal Processing
41	IVC	Image and Vision Computing
42	IDA	Intelligent Data Analysis
43	IJCIA	International Journal of Computational Intelligence and Applications
43	IJDAR	International Journal on Document Analysis and Recognition
43	IJIS	International Journal of Intelligent Systems
43	IJNS	International Journal of Neural Systems
43	IJPRAI	International Journal of Pattern Recognition and Artificial Intelligence
43	IJUFK	International Journal of Uncertainty, Fuzziness and KBS
43	JETAI	Journal of Experimental and Theoretical Artificial Intelligence
43	KBS	Knowledge-Based Systems
43	MT	Machine Translation
43	MVA	Machine Vision and Applications
43	NC	Natural Computing
43	NLE	Natural Language Engineering
43	NCA	Neural Computing & Applications
43	NPL	Neural Processing Letters
43	IJON	Neurocomputing
43	PAA	Pattern Analysis and Applications
43	PRL	Pattern Recognition Letters
43	SOCO	Soft Computing
43	WIAS	Web Intelligence and Agent Systems

TABLE 17. The abbreviations and the full names of conferences.

No.	Abbreviated names	Full names
1	AAAI	AAAI Conference on Artificial Intelligence
2	CVPR	IEEE Conference on Computer Vision and Pattern Recognition
3	ICCV	International Conference on Computer Vision
4	ICML	International Conference on Machine Learning
5	IJCAI	International Joint Conference on Artificial Intelligence
6	NIPS	Annual Conference on Neural Information Processing Systems
7	ACL	Annual Meeting of the Association for Computational Linguistics
8	COLT	Annual Conference on Computational Learning Theory
9	EMNLP	Conference on Empirical Methods in Natural Language Processing
10	ECAI	European Conference on Artificial Intelligence
11	ECCV	European Conference on Computer Vision
12	ICRA	IEEE International Conference on Robotics and Automation
13	ICAPS	International Conference on Automated Planning and Scheduling
14	ICCBR	International Conference on Case-Based Reasoning
15	COLING	International Conference on Computational Linguistics
16	KR	International Conference on Principles of Knowledge Representation and Reasoning
17	UAI	International Conference on Uncertainty in Artificial Intelligence
18	AAMAS	International Joint Conference on Autonomous Agents and Multi-agent Systems
19	PPSN	Parallel Problem Solving from Nature
20	ACCV	Asian Conference on Computer Vision
21	CoNLL	Conference on Natural Language Learning
22	GECCO	Genetic and Evolutionary Computation Conference
23	ICTAI	IEEE International Conference on Tools with Artificial Intelligence
24	ALT	International Conference on Algorithmic Learning Theory
25	ICANN	International Conference on Artificial Neural Networks
26	FGR	International Conference on Automatic Face and Gesture Recognition
27	ICDAR	International Conference on Document Analysis and Recognition
28	ILP	International Conference on Inductive Logic Programming
29	KSEM	International conference on Knowledge Science,Engineering and Management
30	ICONIP	International Conference on Neural Information Processing
31	ICPR	International Conference on Pattern Recognition
32	ICB	International Joint Conference on Biometrics
33	IJCNN	International Joint Conference on Neural Networks
34	PRICAI	Pacific Rim International Conference on Artificial Intelligence
35	NAACL	The Annual Conference of the North American Chapter of the Association for Computational Linguistics
36	BMVC	British Machine Vision Conference
37	IROS	IEEE/RSJ International Conference on Intelligent Robots and Systems
38	AISTATS	Artificial Intelligence and Statistics
39	ACML	Asian Conf. on Machine Learning

that belong to category C, which may suggest their large potential.

Moreover, other related works propose ranking regulations for journals or conferences separately. However, our proposed scheme is able compare journals and conferences simultaneously. Thus, our scheme is more general and can be used for more different cases.

VI. FUTURE WORK

In this paper, we designed a scheme to describe the citation counts of journal and conference papers. In the future, we will use page ranking algorithms to rank journals and conferences, such as the PageRank Algorithm, Hyperlink-Induced Topic Search (HITS) Algorithm, and so on, by adjusting their citation count weights. The citation relationship between publications and the connection relationship to web pages are both directed graphs. The two are similar, although somewhat different. It is theoretically feasible to apply page ranking algorithms to journal rankings.

ACKNOWLEDGMENT

Availability: The data sets and exemplar Python (Version: 2.7.11) source codes used in the paper are available at Github: https://github.com/wisebenYang/CitationAnalysis.

APPENDIX

The abbreviations and the full names of these journals and conferences are shown in Table 16 and Table 17.

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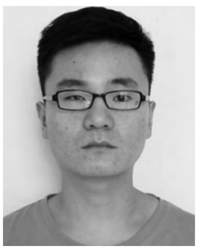

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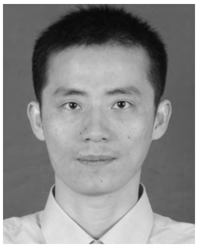

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