Reverse-Engineering Conference Rankings: What Does it Take to Make a Reputable Conference?

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Abstract

In recent years, several national and community-driven conference rankings have been compiled. These rankings are often taken as indicators of reputation and used for a variety of purposes, such as evaluating the performance of academic institutions and individual scientists, or selecting target conferences for paper submissions. Current rankings are based on a combination of objective criteria and subjective opinions that are collated and reviewed through largely manual processes. In this setting, the aim of this paper is to shed light into the following question: to what extent existing conference rankings reflect objective criteria, specifically submission and acceptance statistics and bibliometric indicators? The paper specifically considers two conference rankings in the field of Computer Science: an Australian national ranking and an informal community-built ranking. It is found that, while in the former ranking acceptance rate is the dominant criterion, in the latter one, both acceptance rate and bibliometric indicators are equally important determinants of rank. It is also found that in both rankings, top-tier conferences can be identified with relatively high accuracy through acceptance rates and bibliometric indicators. On the other hand, acceptance rates and bibliometric indicators fail to discriminate between

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mid-tier and bottom-tier conferences.

Keywords: conference ranking, bibliometrics, conference acceptance rate, reputation, objective criteria

1. Introduction

In terms of publication practices, a distinguishing feature of the field of Computer Science, relative to the bulk of other research disciplines, is that peer-reviewed conferences play a role almost as equally important as that of established journals [1]. Indeed, conferences often have lower acceptance rates and higher citations-per-paper than comparable journals [1]. One of the reasons that has been advanced to explain this phenomenon is the need for shorter dissemination cycles given the rapid evolution of the field.

The practice of conference publication in Computer Science, combined with the rather large number of conferences, has engendered a need for conference rankings that can serve as a proxy for quality in the context of researcher or research group evaluations. One of the most systematic attempts at building a conference ranking for Computer Science was initiated by the Computing Research and Education Association of Australasia (CORE)[1]. Their initial 2005 draft ranking, manually established by a committee, classified 1500 computer science conferences into 4 tiers (A+, A, B, C) and a separate tier for local conferences (L)[2]. The tiers in this ranking were defined in terms of acceptance rate – lower acceptance rates being associated with higher tiers, but without fixing any numeric thresholds – and composition of Program Committees (PCs) – PCs with representatives from top-universities being associated to higher tiers. This initial ranking was opened for comments, allowing researchers to submit requests to add new conferences or to amend the ranking of existing conferences, taking into account the definitions of the tiers. Requests for amendments were reviewed by a committee. After multiple iterations, the CORE ranking

[1] `http://www.core.edu.au/`

[2] Subsequently, tiers A+ and A were merged and tier L was removed.

became part of the broader ERA Ranking managed by the Australian Research Council[3]. Another conference ranking, namely Perfil-CC[4] has been established within the Brazilian Computer Science community through an open voting procedure based on a fixed set of conferences, without a committee-driven review of the results of the voting. Finally, a third conference ranking[5] – which we call the "X-Rank" – has been compiled by a small group of researchers without reference to any specific criteria and without any formalized process.

Generally speaking, conference rankings are constructed based on a mixture of objective criteria and subjective opinions. This raises the following questions: (i) to what extent existing (Computer Science) conference rankings are driven by objective criteria? and (ii) which specific objective criteria drive these rankings and what is their relative weight. In order to address these questions, this paper applies machine learning techniques to "reverse-engineer" computer science conference rankings in order to identify the features and rules that determine the rank of a given conference.

Previous work by Silva Martins et al. [2, 3] have found that machine learning models based on citation counts and submission/acceptance metrics can be used to predict the rank of conferences in the Perfil-CC ranking with an accuracy of up to 68% (measured in terms of F-score). In this paper, we extend this previous study to cover the two other conference rankings referenced above. Our results confirm those of Silva Martins et al. [2, 3], particularly their observation that acceptance rates are better predictors of conference ranking than citation metrics, and that the constructed models are more accurate at distinguishing between top-tier conferences and lower-tier conferences than they are at distinguishing between mid-tier and low-tier conferences. Furthermore, our study finds that models with higher accuracy can be obtained in the context of the ERA ranking (compared to the Perfil-CC ranking) while models with lower accuracy are obtained in the case of the more informal X-Rank. These findings

[3]http://www.arc.gov.au/era/era_2010.htm
[4]http://www.latin.dcc.ufmg.br/perfilccranking/
[5]http://www3.ntu.edu.sg/home/assourav/crank.htm

suggest that objective criteria play a more important role in rankings that are driven by formalized criteria and processes.

The rest of the paper is structured as follows. Section 2 describes the data collection method and the characteristics of the collected data. Next, Section 3 presents the methods used to construct the machine learning models and summarizes the experimental results. Section 4 discusses threats to validity. Finally, Section 5 reviews related work while Section 6 draws conclusions.

2. Data Collection

In this section we briefly describe the data collected to train the machine learning models, and the characteristics of these data.

For conferences rankings we used the following data sources:

1. **Rank X**: `http://www3.ntu.edu.sg/home/assourav/crank.htm` (mirrored with some modifications by `http://dsl.serc.iisc.ernet.in/publications/CS_ConfRank.htm`)—a list of Computer Science conferences containing (at the time of retrieval in October 2010) 527 entries for conferences giving their acronymes, names, rankings and subdiscipline of Computer Science;
2. **Perfil-CC**: `http://www.latin.dcc.ufmg.br/perfilccranking/`—ranking of Computer Science conferences compiled to assess the production quality of the top Brazilian Computer Science graduate programs [4]. The conferences are ranked into three tiers (from top tier to the bottom tier): A tier, B tier, and C tier based on the voting procedure where Brazilian Computer Science researchers that hold an individual grant from The Brazilian National Research Council and faculty members of all Computer Science graduate programs in the country were invited to participate;
3. **ERA 2010**: `http://www.arc.gov.au/era/era_2010.htm`—ERA 2010 ranking of conferences and journals compiled by the Australian Research Council. The list of Computer Science conferences are ranked into three

tiers (from top tier to the bottom tier): A tier, B tier, and C tier. These lists are the result of a consultation across all Computer Science department in Australia. Basically, researchers propose that a conference be classified as A, B or C, and these proposals are sent to a committee which has to approve the tier of a conference (based on majority consensus). So in a way ranking is based on a voting procedure. More details on ERA ranking has been presented by Vanclay [5] together with some criticism with respect to its journal rankings.

While the first ranking can be seen as a sort of *ad hoc* community-driven ranking with no published evaluation criteria, the two last ones present national rankings with well-documented ranking guidelines and revision procedures. In fact, there is a large intersection [3] between the CORE (which is antecedent of ERA 2010) and the Perfil-CC conference lists, the main exceptions being regional and local conferences (e.g., Asian-pacific conferences) which are included in the CORE list. It is important to note that Perfil-CC is a younger ranking compared to ERA 2010 and therefore is based on less formal procedure. This claim is based on the assumption that the longer ranking procedures are applied more exceptions are handled and added to the ranking process.

For acceptance rates and other features data from the following sources were extracted in October 2010:

- `http://wwwhome.cs.utwente.nl/~apers/rates.html`—database conferences statistics from Peter Aper's Stats Page;
- `http://www.cs.wisc.edu/~markhill/AcceptanceRates_and_PCs.xls`—architecture conference statistics for conferences such as ISCA, Micro, HPCA, ASPLOS by Prichard, Scopel, Hill, Sohi, and Wood;
- `http://people.engr.ncsu.edu/txie/seconferences.htm`—software engineering conference statistics by Tao Xie;
- `http://www.cs.ucsb.edu/~almeroth/conf/stats/`—networking conference statistics by Kevin C. Almeroth;

- `http://web.cs.wpi.edu/~gogo/hive/AcceptanceRates/`—statistics for conferences in graphics/interaction/vision by Rob Lindeman;
- `http://faculty.cs.tamu.edu/guofei/sec_conf_stat.htm`—computer security conference statistics by Guofei Gu;

Finally, for retrieving bibliometric data, such as the number of papers published at a conference and the overall number of citations to conference papers, we used Microsoft Academic Search (`http://academic.research.microsoft.com/`). We retrieved data for 2511 Computer Science conferences.

Data distribution on conference acceptance rates with respect to the listed sources is summarized in Figure 1 while data distribution with respect to the past years is depicted in Figure 2. In both figures all instances of data records for conferences are counted even if there is some redundancy due to listing of the same conference in multiple sources. In Figure 1 the number of data records is counted as the overall number of acceptance rates for all conferences for all years for which we have data. The major data source is the Web page of Tao Xie and Kevin C. Almeroth. In Figure 2 similarly the number of acceptance rate entries per particular year are displayed. One can see that the data is mainly about the period of 1995–2010.

After taking the arithmetic average of all acceptance rates for all years per conference we compiled 6 datasets from three main datasets—one with conference acceptance rates, one with bibliometric indices and one with both acceptance rates and bibliometric indices. These three base datasets were matched with ERA 2010 ranking and Rank X resulting in 6 datasets. Since some conferences had either no acceptance rate information, no bibliometric data or no ranking available, we had to prune these from the final datasets. Aggregated data distribution with respect to rankings and features are summarized in Table 1 and Table 2.

We also analyzed correlation between the ERA 2010 and Rank X[7]. Table 3

[7] Multiple versions of this ranking are circulating in the Web while its real origin and the

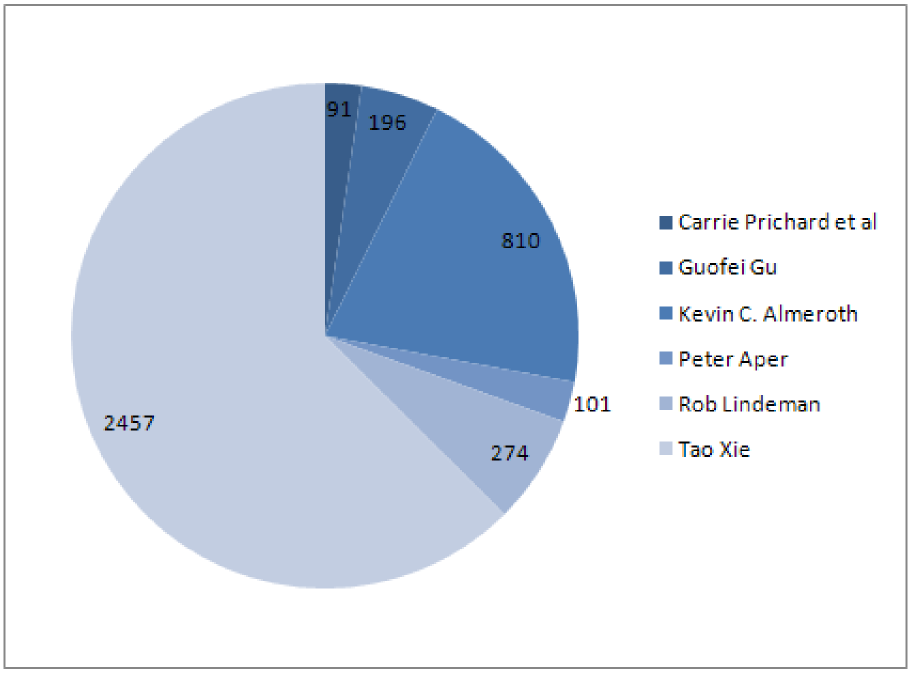


Figure 1: Data distribution with respect to sources.

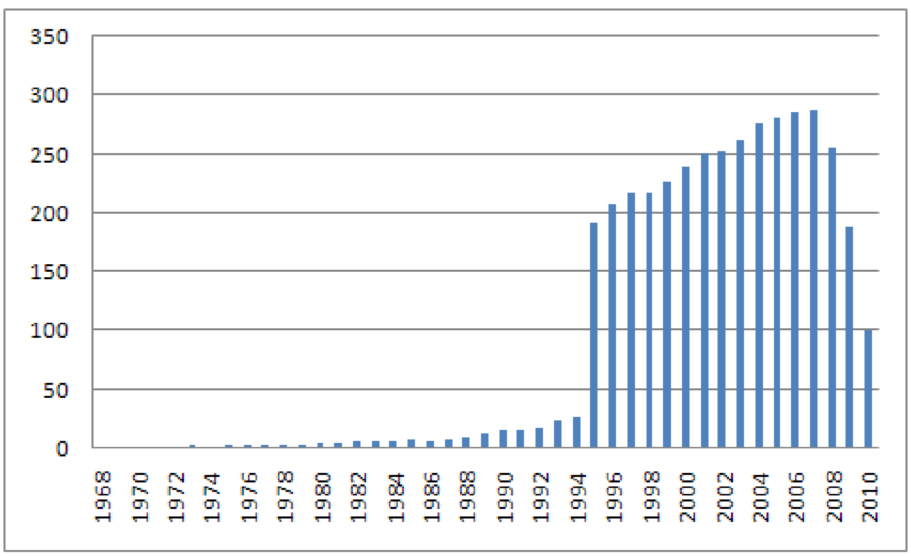


Figure 2: Data distribution with respect to past years.

Table 1: Dataset size and distribution with respect to ranking classes with and without acceptance rates (AR).

Class	Rank X	ERA 2010	Rank X + AR	ERA 2010 + AR
A	65	137	31	58
B	113	117	36	19
C	150	66	9	6
D[6]	199	0	17	0
Total	527	320	93	83

Table 2: Dataset size and distribution with respect to features.

Dataset size	ERA 2010	Rank X
Acceptance rates	83	93
Bibliometrics	262	353
Combined	82	91

summarizes the correlation between these 2 rankings. Although the correlation between these 2 rankings is statistically average (Pearson correlation of 0.555) in general, for some research fields, such as Databases, there is larger correlation. Generally ERA 2010 ranks conferences higher than Rank X, which is more conservative from that perspective. Thus we can clearly state that although the selected rankings agree on ranks of some conferences, in general there is no strong relation between them.

In Figure 3 there is a pivot table with average citation per paper for each ERA 2010 evaluation ranking (A,B,C) and subdiscipline of Computer Science based on Microsoft Academic Search data. The figure shows that generally it is true that proceedings of highly-rated conferences include higher citation per article, except in some subdisciplines such as Data Mining and Human-Computer Interaction, Multimedia, Natural Language & Speech and Networks & Communications. It is interesting to note that according to Shi et al [6] Information

ranking methodology is unknown.

Table 3: Correlation between Rank X and ERA 2010 conference rankings.

Area	**Correlation**
Whole data	0.555
Databases	0.857
Artificial Intelligence and Related Subjects	0.648
Hardware and Architecture	0.509
Applications and Media	0.575
System Technology	0.667
Programming Languages and Software Engineering	0.461
Algorithms and Theory	0.450
Biomedical	0.535
Miscellaneous	0.109

Retrieval, Data Mining and Computer Graphics are the subdisciplines[8], which cite in proportionally larger extent than other Computer Science subdisciplines to papers outside their subdiscipline. This might indicate that higher citation per paper can be useful metric for conference ranking in subdisciplines which minor information diffusion to other subdisciplines of Computer Science.

3. Experimental Setup and Results

For measuring in which extent objective criteria are reflected in conference rankings we reverse-engineered the selected rankings by using machine learning methods with a set of available objective measures as features. From that perspective weighted average f-measure, used for measuring performance of learned classifiers in machine learning, is the objective measure we chose to identify in which extent certain features are reflected in rankings. F-measure is the harmonic mean of precision and recall and captures both measures in a compact manner. Since we wanted to extract human-interpretable models from the selected set of features we used decision tree learning methods. We experimented with several decision tree learning algorithms by using the following combinations of features by using the 6 datasets we compiled:

[8]Note that a slightly different taxonomy for conference categorization into subdisciplines is used than in Microsoft Academic Search.

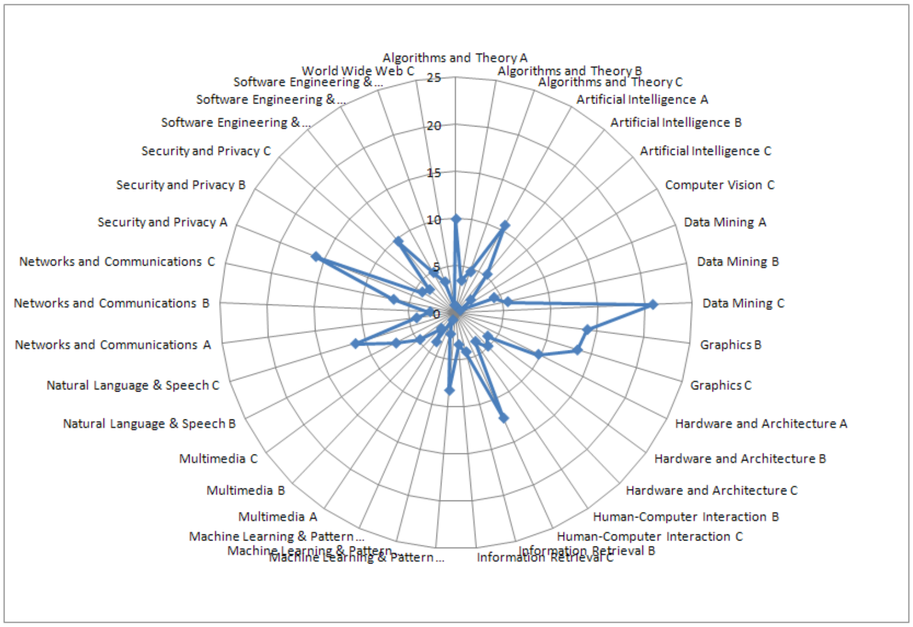


Figure 3: Average citation per paper with respect to conference rankings in different subdisciplines.

- conference statistics (average number of submissions over time, average number of accepted paper over time, average acceptance rate over time, rankings (both ERA 2010 and Rank X));
- bibliometric indicators (the overall number of articles, citations and citation per article) + conference ranking only (both ERA 2010 and Rank X);
- conference statistics together with bibliometric indicators (both ERA 2010 and Rank X).

We extracted classification rules with the main decision tree learning methods including ZeroR, IB1, J48, LADTree, BFTree, NaiveBayes, NaiveBayesMultinominal, NaiveBayesUpdateable, OneR, RandomForest, and RandomTree. The best-performing algorithms with respect to weighted average f-measure are summarized in Table 4. Generally the best learning method was

RandomTree.

Table 4: Summary of learning methods with best performance.

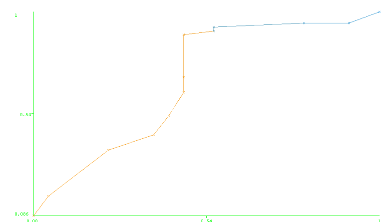
Learning method	**ERA 2010**	**Rank X**
Acceptance rates	RandomTree	RandomTree
Bibliometrics	J48	RandomTree
Combined	RandomTree	RandomTree

Weighted average f-measure of learned classifiers with respect to rankings and feature vectors for the learning methods summarized in Table 4 are summarized in Table 5. The experimental results presented in Table 5 confirm that acceptance rate is generally the major objective criteria for identifying a conference ranks in Computer Science. Learned classifier for ranking a conference by using its acceptance rate only provides f-measure of 0.72 in case of ERA 2010 and 0.48 in case of Rank X. This is contrasts with significantly lower f-measure of 0.48 for both Rank X and ERA 2010 in case of bibliometric indicators. Although acceptance rate of a conference is the best predictor of its rank, some increase in f-measure can be achieved by using acceptance rate and bibliometric indicators together. More specifically, f-measure of 0.75 and 0.55 can be achieved respectively for ERA 2010 and Rank X. These numbers clearly show strong reflection of bibliometric indicators and acceptance rates in conference rankings.

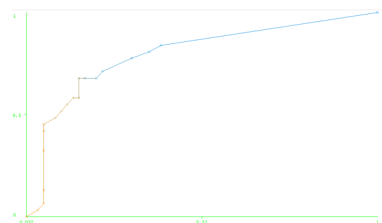
Table 5: Evaluation summary of f-measure of learned classifiers.

Weighted average f-measure	**ERA 2010**	**Rank X**
Acceptance rates	0,72	0,48
Bibliometrics	0,56	0,48
Combined	0,75	0,55

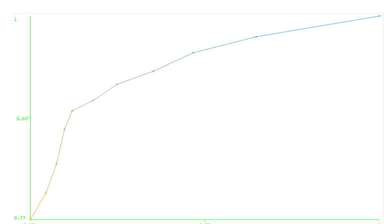
In subfigures (a), (b), (c), (d), (e) and (f) of Figure 4 ROC (Receiver Operating Characteristic) curves for top-tier conference classification are presented for the 6 datasets we used in experiments. ROC provides techniques for visualizing classifier performance, and evaluating classifier learning algorithms. In figures x-axis and y-axis denote correspondingly false positive rate and true positive rate. As can be seen from the figures the true positive rate outperforms significantly false positive rate for all datasets, which means that the learned classifiers are relatively good in predicting the top-tier conferences.



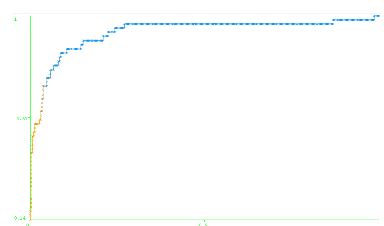
(a) ROC curve for acceptance rate with respect to ERA 2010.



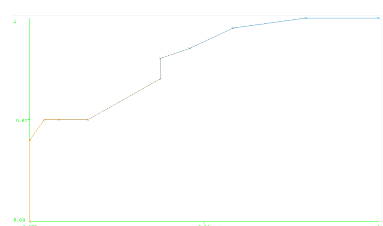
(b) ROC curve for acceptance rate with respect to Rank X.



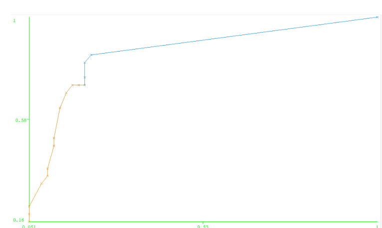
(c) ROC curve for bibliometric indicators with respect to ERA 2010.



(d) ROC curve for bibliometric indicators with respect to Rank X.



(e) ROC curve for combined acceptance rate and bibliometric indicators with respect to ERA 2010.



(f) ROC curve for combined acceptance rate and bibliometric indicators with respect to Rank X.

Figure 4: ROC curves of top-tier conference classifiers with respect to the 6 datasets.

Classifications of particular conferences according to both X-Rank and ERA 2010 are visualised in Figure 5, Figure 6 and Figure 7. In these figures the following color codes are used—red presents rank D/unranked, green denotes to conference being ranked as of rank C, yellow reflects rank B and finally blue shows that a conference is ranked A (a top-tier conference). One can see from the figures that rank A conferences are clearly separated from lower-ranked conferences, while finer separation between other conferences is not possible while using a classification function based on bibliometric indicators and conference statistics.

The graph in Figure 5 visualizes conference rankings from citations per article versus average conference acceptance rate perspective. The following classification rules, which we learned from the data for classifying rank A conferences, can be visually perceived here:

- *Average conference acceptance ratio* < 0.23;
- *Average conference acceptance ratio* $< 0.25 \wedge$ *Citations per article* ≥ 0.76.

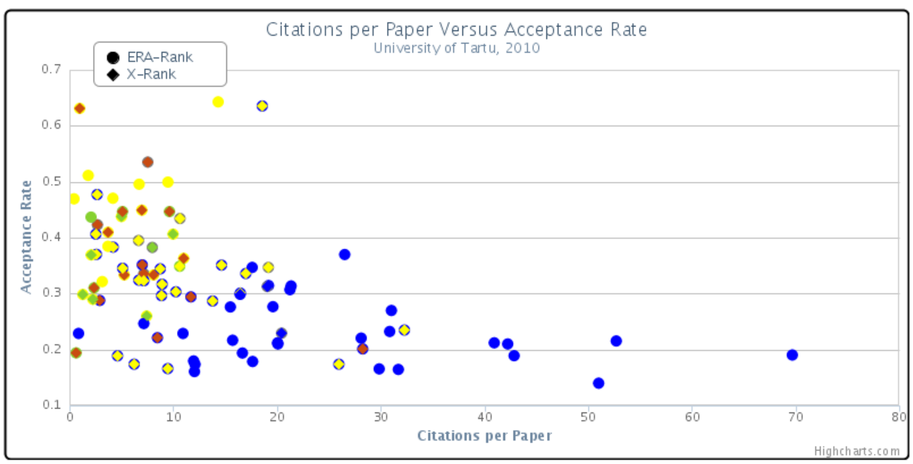


Figure 5: Citation per paper vs acceptance rate.

The graph in Figure 6 visualizes conference rankings from overall number of citations to articles of a conference versus average conference acceptance rate (throughout past years) perspective. The following classification rules, which we learned for visualizing rank A conferences, are visualized here:

- *Number of citations* ≥ 5814;

- *Number of citations* $\geq$ 8338 $\wedge$ *Average conference acceptance ratio* $<$ 0.32.

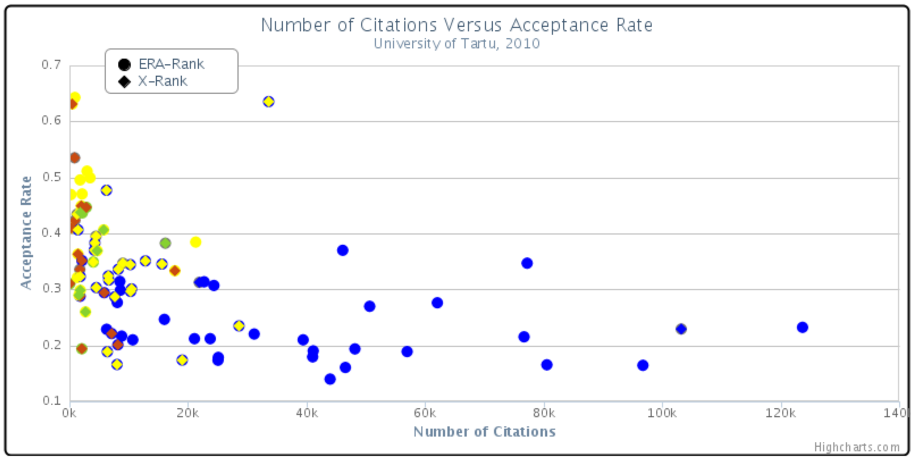


Figure 6: Number of citation vs acceptance rate.

The graph in Figure 7 visualizes conference rankings from the overall number of citations for conference articles versus citations per paper perspective. The following classification rules, which we learned for classification of rank A conferences, are visualized here:

- *Number of citations* $\geq$ 33710 $\wedge$ *Citations per article* $\geq$ 10.23;
- *Number of citations* $>$ 4088 $\wedge$ *Citations per article* $>$ 10.68;
- *Number of citations* $>$ 5869 $\wedge$ *Citations per article* $>$ 10.23.

For rank B we learned that the following rules applies:

- *Number of citations* $\geq$ 5890 $\wedge$ *Citations per article* $<$ 10.23.

Additionally the following correlations can be indirectly explained with Figure 7:

- *Number of citations* $\geq$ 5814.5 $\wedge$ *Number of articles* $<$ 3161;
- *Number of citations* $>$ 5760 $\wedge$ *Number of articles* $\leq$ 5048.

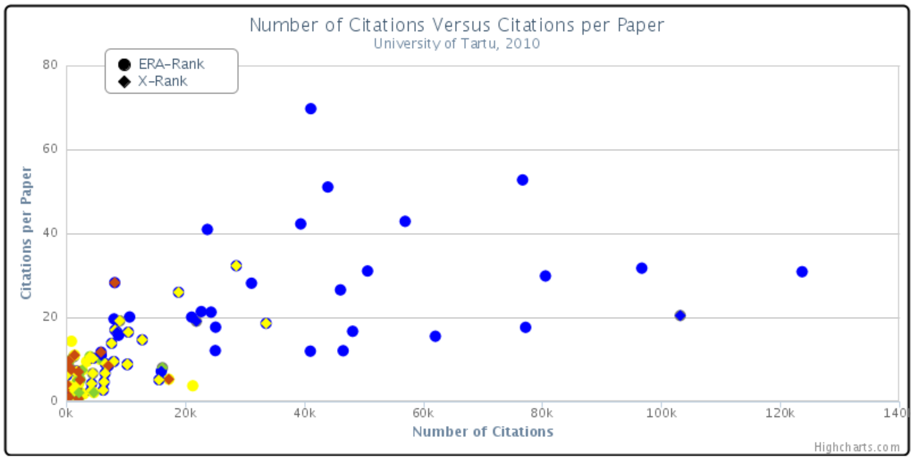


Figure 7: Number of citations vs citations per paper.

These findings presented in this paper confirm that while in national rankings the acceptance rate is the dominant feature, in community-driven rankings both acceptance rate and bibliometric indicators are equally important in deciding the reputation of a conference. It also turns out that only top-tier conferences can be identified though bibliometric indicators and acceptance rates.

4. Threats to Validity

The distribution of data, which we used for machine learning, is unbalanced with respect to classes to be learned. However, Batista et al [7] provide empirical evidence that class imbalance does not systematically hinder the performance of learning systems. Moreover, the problem seems to be related to learning with too few minority class examples in the presence of other factors, such as class overlapping.

In our study we summarized the publication and citation data over all years and used average acceptance rate of conferences. Since we completely ignored the temporal aspects of conferences, there is a risk that we also ignored some aspects of the current trends in the publication process. However, this is the situation with reputation as well—if you are going to use a single number for measuring reputation, then this is usually an aggregation of certain features over time. However, the latter has been accepted in the studies of trust and reputation.

Given that in different subdisciplines of Computer Science the publication patterns vary, the predictive power of bibliographic indicators and acceptance rates may depend also on the domain of the conference venue. For instance, papers in larger domains attract more citations because of intra-community references [8]. This aspect definitely needs further studies.

Finally, one may argue that by using the ERA 2010 ranking we reverse-engineered this particular ranking. However, in fact it turns out that, although the learned classification rules have significantly different f-measure between ERA 2010 and Rank X, there is some consensus of both classifiers on automatically classifying top-tier conferences.

5. Related Work

The most common approach to assess research consists in using bibliometric indicators that range from very simple citation counts to sophisticated indexes like the h-index [9] or the g-index [10]. Although these indicators have been widely used in latter years, there are also voices arguing about its potential problems. For example, some authors argue that H-index favors publishing in bigger scientific domains over smaller ones [11, 8]. Laloe and Mosseri[11] suggest that in order to maximize metrics such as H-index and G-index, the authors should focus to more mainstream research topics with respect to more revolutionary work, which have impact in long-term perspective.

The results of Shi et al [8] show that crossing-community, or bridging citation patterns are high risk and high reward since such patterns are characteristic for both low and high impact papers. The same authors conclude that citation networks of recently published paper are trending toward more bridging and interdisciplinary forms. In the case of conferences it implies that more interdisciplinary conferences should have higher potential for high impact.

One of the early steps in automated evaluation of scientific venues was the work of Garfield [12] who proposed a measure for ranking journals and called it the ImpactFactor. The initial version was an approximation of the average number of citations within a year given to the set of articles in a journal published during the two preceding years.

Based on this early work, a variety of impact factors have been proposed prominently exploiting the number of citations per articles. The latter approached led to measuring the popularity of the articles but not the prestige. The latter is usually measured by scores similar to PageRank [13], which was adopted to the citation network in order to rank scientific publication [14, 15].

Liu et al [16] extended the reach of PageRank from pure citation networks to co-authorship networks while ranking scientists. Zhou et al [17] confirmed through empirical findings that the ImpactFactor finds the popularity while PageRank score shows the reputation.

Sidiropoulos and Manolopoulos [18] presented one of the first approaches to automated ranking of collections of articles, including conference proceedings. The ranking was based on analyzing citation networks. The main shortage of this paper is that the rankings were not validated with respect to rankings constructed by manually by a set of experts in the field.

Jensen et al [19] have identified that bibliometric indicators predict promotions of researchers better than random assignment the best predictor for promotion being H-index [9] followed by the number of published papers. The study was performed on analyzing promotions of about 600 CNRS scientists. Our results confirm that the same principles apply to conferences as well though better predictor is the acceptance rate. Hamermesh and Pfann [20] identified that the number of published papers has generally small impact for reputation though it implies that a scholar is able to change jobs, and it also raises salaries.

We agree with the criticism of Adler et al [21] in the context of evaluating researchers' performance and impact of publications and venues based on bibliometric indicators, such as h-index, is that their meaning is not well understood though the intuition is clear. Thus any automatically computed ranking, which is based on a simplified model without any empirical validation, should be used with care, especially when we aim at quantifying intangible properties such as reputation with the help of quantifiable features. More specifically, some articles are highly cited for reasons other than high quality and some research groups are not reputable despite of the volume of publications or their citations.

Moed and Visser [22] analyzed rank correlation between peer ratings and bibliometric indicators of research groups. It was found that the bibliometric indicator showing the highest rank correlation with the quality peer ratings of the Netherlands academic Computer Science groups, is the number of articles in the Expanded WoS database. The authors propose that this can be interpreted also as evidence that the extent to which groups published in refereed international journals and in important conference proceedings (ACM, LNCS, IEEE) has been an important criterion of research quality for the Review Committee.

Zhuang et al [23] identified and evaluated a set of heuristics to automatically discriminate between top-tier and lower-tier conferences based on characteristics of the Program Committees (PC). Among other things, they found that top-tier conferences are characterized by larger PCs, more prolific PC members (in terms of number of publications) and greater closeness between PC members in the co-authorship graph. However, their study has limited applicability given that it is based on collection of 20 top-tier conferences (ranked by the conference impact factor) and 18 low-tier conferences identified manually by the authors. This contrasts with the hundreds of entries found in the conference rankings studied in this paper.

6. Conclusion

In this paper we presented our results on "reverse-engineering perceived reputation of conferences with the aim to reveal to what extent existing conference rankings reflect objective criteria, specifically submission and acceptance statistics and bibliometric indicators. We used conference rankings as a metric for their perceived reputation and used machine learning to figure out the rules, which would enable identifying conference rankings in terms of their bibliometric indicators and acceptance rates. It turns out that acceptance rate of a conference is generally the best predictor of its reputation for top-tier conferences. However, combination of acceptance rates and bibliometric indicators, more specifically the number of citations to articles in conference proceedings and citations per article count, gives even better results for identifying top-tier conferences both in community-driven and a national ranking.

We also found empirical evidence that acceptance rates and bibliometric indicators are good features in identifying top-tier conferences from the rest, whereas there is a little help of these features in distinguishing middle-tier and bottom-tier conferences from each-other. This might indicate that other, intangible features or subjective opinions, are those, which explain rankings of conferences, which are not top-tier. Another explanation for this finding could be that perceived reputation of conferences divides conferences into top-tier and other conferences.

A recent study of the major database conferences and journals shows that many of the citations reach back at least five years [24]. Thus citation statistics takes time to accumulate and we probably have to target this aspect in our future studies as well. As one of the future works we would like to run the experiments with wider array of features such as conference location, season etc. Our current intuition tells that in such a way a better classifier for distinguishing middle-tier and bottom-tier conferences. Additionally we would like to learn more about the dynamics of conferences to predict the perceived reputation of conferences in their beginning.

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References

[1] A. Goodrum, K. W. McCain, S. Lawrence, C. L. Giles, Scholarly publishing in the internet age: a citation analysis of computer science literature, Inf. Process. Manage. 37 (5) (2001) 661–675.

[2] W. S. Martins, M. A. Gonçalves, A. H. F. Laender, G. L. Pappa, Learning to assess the quality of scientific conferences: a case study in computer science, in: Proceedings of the Joint International Conference on Digital Libraries (JCDL), Austin, TX, USA, June 2009, ACM, 2009, pp. 193–202.

[3] W. Silva Martins, M. A. Gonçalves, A. H. F. Laender, N. Ziviani, Assessing the quality of scientific conferences based on bibliographic citations, Scientometrics 83 (1) (2010) 133–155.

[4] A. H. F. Laender, C. J. P. de Lucena, J. C. Maldonado, E. de Souza e Silva, N. Ziviani, Assessing the research and education quality of the top brazilian computer science graduate programs, SIGCSE Bull. 40 (2008) 135–145. doi:http://doi.acm.org/10.1145/1383602.1383654.
URL http://doi.acm.org/10.1145/1383602.1383654

[5] J. K. Vanclay, An evaluation of the australian research council's journal ranking, Journal of Informetrics 5 (2) (2011) 265–274. doi:DOI: 10.1016/j.joi.2010.12.001.

[6] X. Shi, B. Tseng, L. Adamic, Information diffusion in computer science citation networks, in: Proceedings of the International Conference on Weblogs and Social Media (ICWSM 2009), 2009.

[7] G. E. Batista, R. C. Prati, M. C. Monard, A study of the behavior of several methods for balancing machine learning training data, ACM SIGKDD Explorations Newsletter 6 (1) (2004) 20–29.

[8] X. Shi, J. Leskovec, D. A. McFarland, Citing for high impact, in: Proceedings of the 10th Annual Joint Conference on Digital Libraries, ACM, 2010, pp. 49–58.

[9] J. E. Hirsch, An index to quantify an individual's scientific research output, Proceedings of the National Academy of Sciences 102 (46) (2005) 16569–16572.

[10] L. Egghe, Theory and practice of the g-index, Scientometrics 69 (1) (2006) 131–152.

[11] F. Laloë, R. Mosseri, Bibliometric evaluation of individual researchers: not even right... not even wrong!, Europhysics News 40 (5) (2009) 26–29.

[12] E. Garfield, Citation analysis as a tool in journal evaluation, American Association for the Advancement of Science, 1972.

[13] L. Page, S. Brin, R. Motwani, T. Winograd, The PageRank citation ranking: bringing order to the web, Tech. rep., Stanford Digital Library Technologies Project (1998).

[14] N. Ma, J. Guan, Y. Zhao, Bringing PageRank to the citation analysis, Information Processing & Management 44 (2) (2008) 800–810.

[15] P. Chen, H. Xie, S. Maslov, S. Redner, Finding scientific gems with Google's PageRank algorithm, Journal of Informetrics 1 (1) (2007) 8–15.

[16] X. Liu, J. Bollen, M. L. Nelson, H. Van de Sompel, Co-authorship networks in the digital library research community, Information Processing & Management 41 (6) (2005) 1462–1480.

[17] D. Zhou, S. A. Orshanskiy, H. Zha, C. L. Giles, Co-ranking authors and documents in a heterogeneous network, in: Seventh IEEE International Conference on Data Mining, ICDM 2007, IEEE, 2008, pp. 739–744.

[18] A. Sidiropoulos, Y. Manolopoulos, A new perspective to automatically rank scientific conferences using digital libraries, Information Processing & Management 41 (2) (2005) 289–312.

[19] P. Jensen, J. B. Rouquier, Y. Croissant, Testing bibliometric indicators by their prediction of scientists promotions, Scientometrics 78 (3) (2009) 467–479.

[20] D. S. Hamermesh, G. A. Pfann, Markets for reputation: evidence on quality and quantity in academe, SSRN eLibrary.
URL http://ssrn.com/paper=1533208

[21] R. Adler, J. Ewing, P. Taylor, Citation statistics, Tech. rep., Joint IMU/ICIAM/IMS Committee on Quantitative Assessment of Research (2008).
URL http://www.mathunion.org/fileadmin/IMU/Report/CitationStatistics.pdf

[22] H. F. Moed, M. S. Visser, Developing bibliometric indicators of research performance in computer science: An exploratory study, Tech. Rep. CWTS Report 2007-01, Centre for Science and Technology Studies (CWTS), Leiden University, the Netherlands (2007).
URL http://www.cwts.nl/pdf/NWO_Inf_Final_Report_V_210207.pdf

[23] Z. Zhuang, E. Elmacioglu, D. Lee, C. L. Giles, Measuring conference quality by mining program committee characteristics, in: Proceedings of the 7th ACM/IEEE-CS Joint Conference on Digital Libraries, ACM, 2007, pp. 225–234.

[24] E. Rahm, A. Thor, Citation analysis of database publications, ACM Sigmod Record 34 (4) (2005) 48–53.