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Multivariate approach to imposing additional constraints on the Benefit-of-the-Doubt model: The case of QS World University Rankings by Subject

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Abstract

Composite indexes have become a valuable asset for stakeholders as they provide ranks of entities and information upon which decisions are made. However, certain questions about their development procedure have been raised recently, especially regarding the weighting process. To tackle the observed issue, in this paper we propose a new multivariate approach for defining weights. Namely, the model based on the Data Envelopment Analysis (DEA), the Benefit-of-the-Doubt (BoD) model, has been used with significant success in the process of composite index development. On the other hand, the Composite I-distance Indicator (CIDI) methodology stands out as an impartial method for assigning weights to indicators. By combining these two approaches, some of the limitations of the original BoD model could be overcome. As a result, new entity-specific weights which maximize the value of the composite index can be proposed. As a case study, we analysed the Quacquarelli Symonds (QS) World University Rankings by Subject in the field of statistics and operational research. The obtained results, which are based on the data-driven weights, can provide new insights into the nature of the observed ranking. The approach presented here might provoke further research on the topic of composite index weights and on the university rankings by subject.

Keywords: Benefit-of-Doubt model, Composite I-distance Indicator (CIDI), operational research, university rankings by subject.

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Introduction

In the last several years, a new trend in the university ranking appeared – ranking of universities by subject (Federkeil, 2015). The idea behind this type of ranking is that certain universities can be invisible on the overall global rankings while they perform remarkably in a specific academic field (IREG, 2015). In addition, another viewpoint in favour of rankings by subject is that international rankings provide information about some 500 universities while there are more than 19000 universities worldwide (Siwinski, 2015). Therefore, a need for rankings based on the university's performance in a particular scientific field emerged. Dobrota and Jeremic (in press) observed that a revolution in understanding the present and the future of university rankings has begun.

A need for rankings by subject appeared after the evidence shown that there are differences between citation patterns (Ziman, 2000). Namely, the scientific field to which the paper belongs to highly influences its later citation pattern (Bornmann & Marx, 2014). Therefore, when ranking universities using citation counts it is recommended to consider different citation behaviours (Zornic et al., 2015). This conclusion leads to the question of validity of university rankings that use total citation counts, which have not been normalized, across scientific fields.

Although specific rankings by subject aim to overcome some pitfalls of the overall university rankings, they have been criticized for several reasons. One of the main critiques is related to the reputation indicators, which are based on survey results (Rauhvargers, 2014). The validity of the conducted surveys can be questioned, as there have been universities, which are ranked on specific subject lists even though they do not offer courses, programmes or research in the observed topic (Rauhvargers, 2013). In addition, rankings, both subject specific and overall, have been criticized because of their subjective and often unelaborated weighting schemes (Jeremic et al., 2011; Dobrota et al., 2016). Finally, the main question is how to define field specific characteristics and chose the appropriate indicators, which will reflect the observed differences (Siwinski, 2015).

Nevertheless, many university ranking methodologies have turned towards rankings by subject. Just some of them are ARWU-Subject, THE Subject Ranking, QS World University Rankings by Subject, and URAP Filed Based Ranking. The number of fields each of them covers and the definition of scientific fields varies between the above-mentioned ranking methodologies. As the case study in our paper, we will put emphasis on the QS World University Rankings by Subject in the field of statistics and operational research.

The importance of the role of the statistical community has been widely recognized, particularly by the United Nations. They are aware that data scientists who are able to analyse a large amount of data to digestible, easily understandable, and useful information are crucial for the further development of the society (UN, 2014). Also, they note that quantitative goals, targets, and indicators are powerful tools for communication, but without statistically sound and reliable data and ranking methodologies, their quality and trustworthiness declines. Davenport and Patil (2012) in their article predicted that the shortage of data scientists would become a serious constraint in certain sectors, which might slow its development. Accordingly, future students should be given a clear and easy understandable ranking of universities, which have notable and recognizable results in the field statistics and operational research. Therefore, ranking lists of universities based on their expertise and achieved results in the field of statistics and operational research are needed.

Thus, in this paper, we present the Benefit-of-the-Doubt-CIDI model (BoD-CIDI) to analyse the QS World University Rankings in the field of statistics and operational research and propose entity specific weighting system. Namely, the Benefit-of-the-Doubt model has been employed with success in the composite index creation process to devise entity specific weights (Cherchye et al., 2007). However, the model has several shortcomings related to model constraints (Rogge, 2012). Therefore, we suggest the Composite I-distance Indicator Methodology (CIDI) (Jovanovic-Milenkovic et al., 2015; Dobrota et al., 2016), based on the I-distance method, to create data-driven weight constraints and overcome the main model obstacle: full freedom. Therefore, we propose a novel variation of the original BOD model, which employs CIDI weights as model constraints.

The following chapter sees a thorough literature view which introduces the QS World University Rankings in the field of statistics and operational research and the Composite I-distance Indicator Methodology (CIDI) which is crucial for the newly proposed BoD model. The data on which the research was conducted alongside the optimization problems and the BoD-CIDI model have been elaborated in detail in Section 3. The results are given in Section 4, while the conclusion is provided in the final chapter.

Literature review

Quacquarelli Symonds Ranking by Subject

Quacquarelli Symonds (QS) recognized the new direction in the development of university rankings. Therefore, it created World University Rankings by Subject. In 2015, the QS provided rankings in 36 individual subjects, which are based on four indicators: *Academic Reputation, Employer Reputation, Citations per Paper* and *H-index* (QS, 2015a). The first indicator, *Academic Reputation*, has been the core of any QS Ranking since its development. The aim of this indicator is to assess the reputation of an institution based on the opinion of related domestic and foreign academics who are considered experts in the specific field. *Employer Reputation*, similarly, assesses reputation, but this time from the employers' perspective. Finally, the last two indicators are bibliometric indicators drawn from the *Scopus* database. The *H-Index* is a metric that measures both productivity and citation impact of scholars. On the other hand, *Citations per Paper* deliver information on the impact of the institution's published work in the journals covered by *Scopus*. Together all four indicators aim at providing a comprehensive ranking of universities in the specific scientific field (QS, 2015a).

The four indicators are weighted differently depending on the subject (Intelligence Unit, 2015). The weighting employed in the QS ranking by Subject is adaptive weighting, meaning that the interdisciplinary differences have been acknowledged and that the indicators have been weighted accordingly. Namely, the importance of one indicator for the ranking process is not the same in the case of, for example, sciences and literature. Weights have been assigned by the pertinence of the indicator and the validity of the collected data (Intelligence Unit, 2015). The overall value of the ranking is calculated as the weighted sum of the four normalized indicators.

Out of the 36 published rankings by subject, this paper aims at analysing the ranking of universities by their achievements and reputation in the field of statistics and operational research. According to the official Intelligence Unit ranking overview (Intelligence Unit, 2015) 559 universities have been considered to enter the ranking on this subject, while only 200 universities have been eventually ranked. The actual values of indicators are provided for all 200 universities, while the overall result is published only for the first 50 ranked universities. Namely, the rest of the universities are ranked in groups of 50 and their overall results are not publicly available.

As mentioned before, QS University Ranking by Subject assigns adaptive weights to indicators based on the specific subject. The weights of input indicators in the field statistics and operational research are given in Table 1.

Table 1 Weights of QS Ranking by Subject indicators in the field of statistics and operational research

QS Ranking by Subject indicator	Weight
Academic Reputation	0.50
Employer Reputation	0.10
Citations per Paper	0.20
H-index	0.20

Source: QS, 2015a

Taking a closer look at the official weighting scheme, it can be concluded that indicators based on surveys, which tackle a highly subjective topic, have been assigned 60% of weight. On the other hand, bibliometric indicators, which are perceived as less biased and more objective (Marginson, 2014) have been underrepresented in this ranking methodology. Therefore, we propose two widely used methodologies to create a new data-driven weighting scheme. First, we suggest the CIDI methodology to obtain the initial data-driven weights (Dobrota et al., 2015) which could act as constraints in the Benefit-of-the-Doubt model which would select the most favourable weights to indicators to maximize the overall value of the composite index (Mizobuchi, 2014).

Composite I-distance indicator (CIDI) methodology

In the 1970's a need for a statistical method that could rank countries by the level of their socio-economic development using a large number of indicators appeared. One of the devised methods that stood out was the Ivanovic distance (I-distance) (Ivanovic, 1977). Since its development, the I-distance has been employed in many fields other than socio-economics (for example Jeremic et al., 2011; Maricic and Kostic-Stankovic, 2016) with great success.

The I-distance method belongs to the group of ranking methods whose overall values are based on the calculated distance from a referent entity. The referent entity can be a fictive or an observed entity from the analysed dataset, or it can be the minimal, maximum or average value of the observed variables. Herein we used the fictive minimal entity as the referent entity.

For a selected set of variables $X^T = (X_1, X_2, \ldots X_k)$ chosen to characterize the entities, the I-distance between the two entities $e_r = (x_{1r}, x_{2r}, \ldots x_{kr})$ and $e_s = (x_{1s}, x_{2s}, \ldots x_{ks})$ is defined as (Jeremic et al., 2011):

$$D^2(r,s) = \sum_{i=1}^{k} \frac{d_i^2(r,s)}{\sigma_i^2} \prod_{j=1}^{i-1} \left(1 - r_{ji.12\ldots j-1}^2\right), \tag{1}$$

where $d_i(r,s)$ is the distance between the values of a variable X_i for e_r and e_s, e.g. the discriminate effect would be:

$$d_i(r,s) = (x_{ir} - x_{is}) \qquad i = 1,\ldots,k, \tag{1a}$$

σ_i is the standard deviation of X_i, and $r_{ji.12...j-1}$ is the partial coefficient of the correlation between X_i and X_j, $(j < i)$ (Jeremic et al., 2011).

The I-distance has a special feature. Namely, the correlation coefficients between the variables and the obtained I-distance values show the level of importance of the variables for the ranking process. Therefore, they can be used to obtain weights and create a new composite index based on the I-distance results, which will be comparable to the results of the analysed index. The newly obtained composite index is called the Composite I-distance Indicator (CIDI) (Dobrota et al., 2016; Dobrota et al., 2015). The following formula is used to devise new weights based on the I-distance (Dobrota et al., 2016):

$$w_i = \frac{r_i}{\sum_{j=1}^{k} r_j}, \tag{2}$$

where r_i, $i = 1,...,k$ is the Pearson's correlation coefficient of the i-th input variable and the I-distance value. The sum of weights acquired using this approach is 1. The procedure of the CIDI methodology is the following. In the first step, the I-distance is employed on all variables and the value of the I-distance is obtained. Next, the correlation coefficients between each variable and the I-distance value are calculated. Then the new weights are obtained using (2). Finally, employing the new weights, which derive from the results of the I-distance, a new CIDI index is obtained whose results are comparable with the results of the scrutinized composite index. This is highly important as the values of I-distance represent distances and are thus, incomparable with the values of the composite index that is being analysed. The CIDI index allows comparison of the original values and the values based on the I-distance method.

So far CIDI has been employed with a lot of success to scrutinize composite indicators in various fields of science such as education (Maričić et al., 2016a; Dobrota et al., 2016), food security (Maricic et al., 2016b), and ICT development (Dobrota et al., 2015). Namely, the new weighting schemes led to the creation of a more stable metric according to the uncertainty and sensitivity analysis (Dobrota et al., 2016).

Methodology

Data

The dataset on which the analysis was performed contained all four QS Ranking by Subject indicator values for top 50 ranked universities in the subject of statistics and operational research for the year 2015. The data set is publicly available on the official website of the QS Rankings (QS, 2015b). As the indicators were already normalized and there was no missing data, the dataset was ready to perform the statistical analysis.

Statistical approach

The Benefit-of-the-Doubt (BoD) model was originally devised by Melyn and Moesen (1991), whereas it has its roots in the Data Envelopment Analysis (DEA) (Charnes et al., 1978). The basic idea behind the DEA is to calculate the maximum efficiency of decision making units (DMUs) based on the information on their inputs and outputs. On the other hand, the BoD model aims at maximizing the overall index value without prior information on the indicator weights. Therefore, we can say that the

BoD model is oriented only on the inputs. Nevertheless, there are conceptual similarities between DEA and BoD: first, between their goals and second, in the lack of available information on weights (Cherchye et al., 2007).

To overcome the issue of subjectively assigned weights, which has been recognized as a major stepping stone in the process of creation of composite indexes (Nardo et al., 2005), the BoD model assigns specific weights to each entity while maximizing the overall value of the index. Using the BoD model, all entities obtain the highest possible value of the composite index (Cherchye et al., 2007). The original BoD model is a linear programming problem (Rogge, 2012) which can be formulated for each entity $l = 1,...,n$:

$$\max \quad f_l(w) = \sum_{i=1}^{k} w_{i,l} y_{i,l}, \tag{3}$$

s.t

$$\sum_{i=1}^{k} w_{i,l} y_{i,l} \leq 1, \quad (i = 1,...,k) \tag{3a}$$

$$w_{i,l} \geq 0, \quad (i = 1,...,k) \tag{3b}$$

With $f_l(w)$ being the optimal value of the composite index for the observed entity *l*, $w_{i,l}$ the most favourable weighting scheme assigned to the entity *l*, and $y_{i,l}$ the value of the indicator *i* for the country *l*. The subscript *l* is associated with the number of observed entities, while the subscript *i* is associated with the number of framework indicators. After analysing the objective function attention should be placed on the model constraints. There are two constraints that the solution has to satisfy. The first one (3a) is the normalization constraint, and the second one (3b) is the non-negativity constraint. In case the indicator values are not normalized, the BoD model, using the constraint 3a normalizes them. It means that the overall values of the observed index are transformed to the interval [0, 1], where 0 is the minimum, and 1 is the maximum possible value of the index. Therefore, using the BoD model index creators need not normalize the data before calculation of the index, as the model already has that feature incorporated.

Although the BoD model has many benefits, there are some shortcomings. One of them is that the model, as presented, has the full freedom when assigning weights (Rogge, 2012). The full freedom is allowed by the constraint 3b, where the assigned weight can be zero. This means that the model can take into account only the value of one indicator whose values are the highest compared to others and assign zero weights to other indicators. Therefore, additional weight constraints are needed and recommended (Cherchye et al., 2007). Additionally, it should be observed that since the BoD model normalizes indicator values and thus overcomes the problem of choosing normalization method, the weights are expressed in indicator units. This means that the problem has been transferred from one place to another without being solved. Namely, the value of the composite index is not expressed in units, but the weights are. Accordingly, it is necessary to pay special attention when comparing the obtained weights. As a solution of the presented issue it is recommended or to normalize the indicator values prior to solving the model, or to impose additional weight constraints (Cherchye et al., 2007). Just to note, besides these constraints, there were specific constraints related to this case study.

Besides the original BoD model, another BoD model is of high importance for the conducted the research as it aims to overcome the shortcomings of the original model that are related to weights. Namely, Perišić (2015) presented an interesting variation of the original model:

$$\max \quad f_l(w) = \sum_{i=1}^{k} w_{i,l} y_{i,l}^{n}, \tag{4}$$

s.t

$$\sum_{i=1}^{k} w_{i,l} \leq 1, \quad (i = 1,...,k) \tag{4a}$$

$$0 \leq w_{i,l} \leq 1, \quad (i = 1,...,k) \tag{4b}$$

$f_l(w)$ is the objective function and represents the optimal value of the composite index of a specific entity. The aim is to maximize the $f_l(w)$, to maximize the value of the composite index. $w_{i,l}$ $(i = 1,...,k)$ is the most favorable weighting scheme that is assigned to the indicators of the observed entity *l*, while $y_{i,l}^{n}$ are the normalized values of indicators of entity *l*. Again, the subscript *l* is associated with the number of observed countries, while the subscript *i* is associated with the number of framework indicators. Constraints of this modified BoD model are significantly different from the constraints of the basic BoD model; this time, both restrictions are related to weights. The first constraint (4a) is that the sum of assigned weights must be 1, and the second (4b) is that the assigned weights must be found in the interval from 0 to 1. Key aspects of the modified model that we should emphasize are the usage of normalized data and that the sum of the weights must be 1. The consequence of the two constraints is that the final index value in the interval [0, 1], where 0 is the minimum and 1 the maximum possible value of the index.

The secondly presented BoD model tries to overcome several issues the original BoD model faces. First, the weights assigned by the modified model are not expressed in indicator units and therefore are comparable. The last end users, decision makers, policymakers, and the general public will understand the presented results more clearly. Secondly, the weights should be in the interval between 0 and 1 and their sum must be 1. The modified model tries to impose weights constraints and restricts the "full freedom" of the original model.

The modified BoD model is very important because its goal remains the same - maximizing the value of the composite index, but the interpretation of the obtained weights is simpler. However, it can be seen that the model still has the problem of full freedom. Although the weights are limited to the range from 0 to 1, the model can take into account only one or a few indicators while it assigns no weight to other indicators. In order to solve the perceived problem, we suggest combining the modified BoD model and the Composite I-distance indicator methodology (CIDI).

The weights obtained using I-distance can act as data-driven weight constraints as shown in Radojicic et al. (2015). Namely, they performed bootstrap I-distance to get weight restrictions for their DEA models. A similar approach can be made to the BoD model, which has roots in DEA to overcome the issue of full freedom. Therefore, after introducing both the CIDI methodology and the BoD models, a newly proposed model called Benefit-of-the-Doubt-CIDI (BoD-CIDI) model can be presented. The optimization problem can be formulated for each $l = 1,...,n$ as:

$$\max \quad f_l(w) = \sum_{i=1}^{k} w_{i,l} y_{i,l}^{n}, \tag{5}$$

s.t

$$\sum_{i=1}^{k} w_{i,l} = 1, \quad (i = 1,...,k) \tag{5a}$$

$$w_{i,l} \geq 0.75 \cdot w_{CIDIi}, \quad (i = 1,...,k) \tag{5b}$$

$$w_{i,l} \leq 1.25 \cdot w_{CIDIi}, \quad (i = 1,...,k) \tag{5c}$$

In the BoD-CIDI model, equation (5) is the objective function, which computes the composite index, and it is the same as the objective function in the original BoD model. Equation (5a) guarantees that the sum of weights assigned to the indicators of the observed entity will be 1. The equations (5b) and (5c) ensure that the new weights will be within the interval of ±25% of the weights suggested by the CIDI methodology. The chosen interval around the CIDI weights was used in order to ensure a wide enough interval to have proper robustness checks (Saisana and Saltelli, 2014). Using the suggested constraints, the proposed model guarantees that all indicators will be taken into account and that no indicator will be assigned zero weight. The BoD-CIDI model, therefore, overcomes the observed problem of the BoD model: full freedom. However, the model has its limitations. Namely, before solving it, the indicator values should be normalized to the range between 0 and 1. Accordingly, the question of the type of normalization arises. Herein we limit ourselves to the application of the proposed model on the already normalized data. Namely, we will not additionally examine the potential influence of the type of normalization on the obtained results. We concentrate ourselves to the impact of the new, entity specific weights.

Results

Our research saw the implementation of the newly devised BoD-CIDI model on the QS Rankings by Subject in the field of statistics and operational research. The aim was to maximize the value of the overall ranking score of each entity and to find entity specific weights.

The first step in our analysis was to apply the CIDI methodology to obtain the new data-driven weights. The CIDI weights and the upper and lower bounds of constraints of indicator weights for the BoD-CIDI model are presented in Table 2.

Table 2 CIDI weights along with the upper and lower bounds of constraints of indicator weights

Indicator	CIDI weight	Lower bound (0.75*CIDI weight)	Upper bound (1.25*CIDI weight)
Academic Reputation	0.217	0.163	0.271
Employer Reputation	0.258	0.194	0.323
Citations per Paper	0.289	0.216	0.361
H-index	0.237	0.177	0.295
Sum	1	0.75	1.25

Source: Authors

At first glance, the presented results show that the current weighting scheme could be enhanced and refined. The eye-catching difference is in the case of the indicator *Academic Reputation*. Namely, its weight has been reduced by almost 57%, from 0.5 to 0.217. Contrarily, the indicator *Employer Reputation* gained importance so it is now the second most important indicator for the ranking process after the *Citations per Paper*. The newly obtained weighting scheme has several benefits. Firstly, it reduces the overall importance of indicators, which are based on survey results. Secondly, it increases the importance of bibliometric indicators that rely on the data from the *Scopus* database. Finally, it creates a more balanced weighting scheme when it comes to the overall importance of reputation and research indicators.

The obtained CIDI weights acted as inputs to create the constraints of the BoD-CIDI model. Namely, the lower bound of the BoD-CIDI weight constraints is calculated as 75% of the weight assigned by the CIDI methodology. Similarly, the upper bound is obtained, whereas it is 25% above the weight assigned by the CIDI methodology. The upper and lower bounds of indicator weight constraints are presented in Table 2.

After calculating the upper and lower weight constraints, the BoD-CIDI model was utilized. This part of the research was done using Excel Solver. Namely, the model was conducted on each of the 50 observed universities to obtain university-specific weights. Those weights were later used to calculate the value of the BoD-CIDI index. Besides the BoD-CIDI index, we decided to present the CIDI index. Namely, the CIDI index is created as the weighted sum of indicators using CIDI weights. We believed it would be useful to compare all three rankings to explore in-depth the effects of the entity-specific weights. The BoD-CIDI index results along with the results of the QS index and CIDI index are presented in Table 3 for the top 15 universities by BoD-CIDI index.

Comparing the three rankings one can note that the top 3 universities have not changed. Harvard University, Stanford University, and University of California, Berkeley led the way regardless the weighting scheme employed. However, there are visible discrepancies moving down the ranks. For example, University of Toronto improved its rank for 11 positions and ranks 8th by the BoD-CIDI model. Namely, University of Toronto has high values of bibliometric indicators, while it is not that recognized by the surveyed academics. In addition, the University of Hong Kong advanced from 22nd to 15th place using the BoD-CIDI weights. The University of Hong Kong had high values of the most important indicator for the ranking process, *Citations per Paper*, while its *Academic Reputation* and *H-index* were a little bit lower. On the other hand, several universities significantly dropped ranks. University, which went out of the top 10, is the Georgia Institute of Technology. Using the proposed approach, it is 11th while it was ranked 4th by the official QS ranking. Namely, it has the highest value of the indicator *Academic Reputation*, while its citation counts are below expected.

However, it is also important to compare the results of the CIDI and BoD-CIDI index to analyse the consequences of assigning the indicators the most favourable weights in the defined weight range. Looking at the ranks presented in the Table 3, the results seem stable, and there are no major discrepancies. However, moving down the ranks, there are differences. Namely, the discrepancies are larger after the 39th rank and go up to 6 places. The observed result indicates that the favourable weighting has more effect on the rank of the entities, which have previously been ranked in the bottom of the list.

In addition, the correlation analysis between the three rankings has been performed. First, the Pearson's correlation coefficients were calculated. All of them are significant ($p<0.01$), whereas the largest correlation is between the CIDI index and BoD-CIDI index values ($r=0.996$), and the lowest is between the official QS index and BoD-CIDI index values ($r=0.890$). Additionally, the Spearman's correlation coefficients have been computed. The highest correlation is between the CIDI index and BoD-CIDI index ranks ($r_s=0.992$, $p<0.01$), while the lowest is between the official QS index and BoD-CIDI index ranks ($r_s=0.910$, $p<0.01$). The obtained results show all the correlations are high and that the rankings are similar.

Besides elaborating the overall BoD-CIDI values and ranks, the university-specific weights should be analysed. The assigned weights of the top and the bottom five universities are therefore presented in Table 4.

Table 3 Values and ranks of top 15 universities by the BoD-CIDI model, alongside with values and ranks of the official QS ranking and the CIDI ranking

University	BoD-CIDI values	BoD-CIDI rank	QS values	QS rank	CIDI values	CIDI rank
Harvard University	0.973	1	0.946	2	0.964	1
Stanford University	0.958	2	0.948	1	0.955	2
University of California, Berkeley	0.957	3	0.939	3	0.947	3
University of Cambridge	0.943	4	0.917	6	0.937	4
University of Oxford	0.923	5	0.896	9	0.914	6
Massachusetts Institute of Technology	0.923	6	0.914	7	0.919	5
University of Michigan	0.923	7	0.871	12	0.902	7
University of Toronto	0.913	8	0.833	19	0.895	10
Imperial College London	0.907	9	0.917	5	0.897	9
National University of Singapore	0.906	10	0.882	11	0.898	8
Georgia Institute of Technology	0.896	11	0.933	4	0.877	13
Princeton University	0.890	12	0.854	16	0.880	12
Swiss Federal Institute of Technology	0.889	13	0.900	8	0.883	11
University of California, Los Angeles	0.888	14	0.852	17	0.869	14
The University of Hong Kong	0.872	15	0.809	22	0.855	17

Source: Authors

Table 4 Assigned weights to top and bottom five universities using the BoD-CIDI model

University	Academic Reputation	Employer Reputation	Citations per Paper	H-Index	BoD-CIDI Rank
Harvard University	0.163*	0.323**	0.219	0.295**	1
Stanford University	0.163*	0.194*	0.348	0.295**	2
University of California, Berkeley	0.163*	0.194*	0.348	0.295**	3
University of Cambridge	0.163*	0.323**	0.219	0.295**	4
University of Oxford	0.163*	0.323**	0.337	0.177*	5
…	…	…	…	…	…
Shanghai Jiao Tong University	0.163*	0.299	0.361**	0.177*	46
The University of Warwick	0.268	0.194*	0.361**	0.177*	47
The Australian National University	0.163*	0.323**	0.337	0.177*	48
Tokyo Institute of Technology	0.271**	0.194*	0.358	0.177*	49
Eindhoven University of Technology	0.268	0.194*	0.361**	0.177*	50

Note: * The weight restriction attains the lower bound, ** The weight restriction attains the upper bound
Source: Authors

Firstly, Table 4 provides evidence that the proposed model can be solved without violating any constraints. The sum of weights is 1 and the assigned weights are in the pre-defined interval. In addition, the presented table gives insight on how the model assigns weights. Take the example of Harvard University whose indicator values were 0.918, 1, 0.936 and 1, respectively. The upper weight bound was assigned to indicators whose values were maximum, and not to the indicator that is the most important for the ranking process. Secondly, these results can be an additional source of information for the university administration. Namely, the new university specific weighting scheme can give a direction of further improvement of the university's performance in the field of statistics and operational research. Taking a look at the top five universities, we can observe that values of their *H-index* are high and that their *Academic reputation* could be improved. Analysing the bottom five universities, we can conclude that their publishing productivity and scientific impact could be enhanced, as indicator *H-Index* has been assigned the lower bound in all cases.

Besides presenting the top and bottom five weighting schemes, we carried out descriptive analysis of the obtained optimal weights (Table 5). Minimum and maximum assigned weights are in fact the upper and lower bounds of the BoD-CIDI model. This result again shows that it is possible to solve the proposed model without violating the imposed constraints. Taking a closer look on the average values of the assigned weights, we can conclude that they differ compared to CIDI weights. The largest positive deviation is in the case of the most important indicator for the ranking methodology, in the case of indicator *Citations per Paper*. The average value of the assigned weight is 0.327 compared to 0.289 proposed by the CIDI methodology. Mean values also indicate that the importance of indicators based on subjective opinion of academics and employers could be additionally reduced. The weights assigned to the indicator *Employer Reputation* showed the greatest degree of variation, 25.21%. On the other hand, the weights assigned to the indicator *Citations per Paper* proved to be more stable and consistent as its coefficient of variation is 15.29%.

Table 5 Descriptive analysis of the assigned weights and CIDI weights

	Minimum	Maximum	Mean	Std	CV (%)	CIDI weight
Academic Reputation	0.163	0.271	0.186	0.045	24.19	0.217
Employer Reputation	0.194	0.323	0.238	0.060	25.21	0.258
Citations per Paper	0.219	0.361	0.327	0.050	15.29	0.289
H-index	0.178	0.296	0.248	0.056	22.58	0.237

Source: Authors

Conclusions

Composite indexes proved to be a valuable asset for government representatives, decision makers, citizens, and other stakeholders as they can initiate discussion and debate leading to reform (Nardo et al., 2005). However, their construction methodology has been a major stepping stone in their way of being widely accepted by statisticians and related practitioners. Namely, the veil of subjectivity often covers the process of composite index creation, especially the process of assigning weights to index indicators.

This paper aims at introducing a new multivariate method for assigning flexible, data-driven weights to indicators, which make a composite index. The BoD-CIDI model presented herein is an extension of the BoD model, which aims to maximize the overall index value by assigning entity specific weights. The proposed model takes into account the results of the I-distance method as model constraints, surpassing the issue of full freedom of the BoD model (Rogge, 2012). The devised model was employed on the QS World University rankings in the field of statistics and operational research. The obtained results showed that the current weighting scheme could be altered and that the bibliometric indicators should be given more importance in the ranking process.

The results of the BoD-CIDI index are highly correlated with both original QS ranking and the CIDI ranking. However, rank discrepancies have been noticed, especially in the bottom of the ranking list. The rank changes between the QS and the CIDI ranks are the consequence of a less biased and more objective weighting scheme proposed by the I-distance method. On the other hand, the observed rank variations between the CIDI and the BoD-CIDI ranks are due to the assignment of the most favourable weighting scheme to a certain university.

The analysis of the BoD-CIDI weighting scheme can provide valuable information for policy and decision makers at the institutional level. In the presented case study, the results clearly show that the institutions at the bottom of the ranking have lower values of the *H-index* and *Employer Reputation*. Meaning these two aspects should be improved to advance in the ranking.

The presented paper has several benefits, which should be pointed out. First, it provides a new, data-driven weighting scheme using the CIDI methodology. Secondly, the BoD-CIDI model assigns entity specific weights, which maximize the composite index value. Thirdly, the proposed model overcomes the elaborated issue of full freedom of the original BoD model (Rogge, 2012) using an interval around the CIDI weights as weight constraints. However, the BoD-CIDI model has its limitations. Namely, the composite index values should be normalized before the model could be employed. One of the possible future directions of the study is to explore the influence of different normalization methods on the results of the BoD-CIDI model, along with the uncertainty and sensitivity analysis of both CIDI and BoD-CIDI indexes.

We believe that the proposed model for scrutinizing composite indices and devising new weighting schemes employed on the QS World University Ranking in the field of statistics and operational research can initiate further research on the index itself, on the weighing schemes of composite indices, and on future improvements of the BoD model.

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