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Towards a Framework for Evaluating Scientific Efficiency of World-Class Universities

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***Abstract*—**Evaluating the efficiency of decision making units has been frequently elaborated on in numerous publications. In this paper, the theoretical framework for a novel method of Distance Based Analysis (DBA) is presented. In addition, the method is performed on a sample of the ARWU's top 54 Universities of the United States; the findings of which clearly demonstrate that the best ranked Universities are far from also being the most efficient.

***Keywords*—**Evaluating Efficiency, Distance Based Analysis, Ranking of Universities, ARWU.

I. Introduction

IN order to evaluate and project the "greatness" of a phenomenon, as well as to create interrelationships between complex systems, many different variables may be used while each may still provide only a partial perspective of the phenomena observed. The basic question and formulation of the problem is as to whether it is possible to form one global, satisfactory index by combining these variables together. If the variables are scale, then only a single order of classification shall be able to create a rank of the entities and thus their interrelationships. Therein, if factor F is the scale and if its value is calculated through a set of variables X, it is then possible to determine the rank list of P entities as compared to F [1]. However, numerous obstacles towards achieving such a global index also exist. The statistical representation of one phenomenon's greatness lies in many different measurement units; consequently, it is not possible to create an index that will represent the variables entirely. It is essential here to also note that the index created will need to integrate as much information from the input variables as possible, even if the subsequent loss of information is an absolute necessity. Thus, in the data set of the entities observed, one global index of greatness may be presented as the relative relationship of that entity to others [1].

Furthermore, some variables/indicators possess larger amounts of information on the greatness of the phenomena observed, while others are not significant; i.e., not all variables possess enough importance for the raking process itself. The question raised therefore is how exactly to select preferable variables and how to establish weighting factors for each selected, all of which must be done in order to avoid certain variables from gaining too much in importance. Additionally, one must be extra careful when taking into account the variability of an indicator. Finally, the difference between two entities, as far as one variable is concerned, is more important if the variability of that indicator is smaller.

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It is also crucial to note that variables are not independent of one another since the information that one variable provides for the ranking process is partially integrated into other variables. Bearing this in mind, the Ivanovic I-distance method has been created to avoid such information redundancy, as it is based on different variables, yet which are still necessary for the ranking process itself [1]. Having this been made clear, a further description of the I-distance method follows: Let $X = x_1, x_2, ..., x_k$ be those variables/indicators that are observed. Additionally, let $P = p_1, p_2, ..., p_n$ be the data set of entities that are to be evaluated for their "greatness" and to be compared. Therein, any two entities of P_r and P_s are to be defined and their values for each of the X variables/indicators compared. If all differences are equal to zero, there is then no possibility that any difference between these two actually exists. This observation is able to be changed if additional variables are introduced into the ranking process. If in a particular situation no additional information is available, it is to be claimed that for $\forall i\ (i\in\{1,2,...,k\}\Rightarrow x_{ir} = x_{is})$, and the entities P_r and P_s are to be of the same "greatness". Otherwise, if only one of these differences is not zero, these entities cannot be claimed to be of the same "greatness".

The difference $d_i(r,s) = x_{ir} - x_{is}$, is defined as the discrimination effect of the variable X_i in the ordered entities $\langle P_r,P_s\rangle$. The discrimination effect of the variable set X in the ordered entities $\langle P_r,P_s\rangle$ is the vector $d_x(r,s) = \langle d_1(r,s),...,d_k(r,s)\rangle$, while the matrix

$$d_x(P)=\begin{bmatrix} 0 & d_x(1,2) & \cdots & d_x(1,n) \\ -d_x(1,2) & 0 & \cdots & d_x(2,n) \\ \vdots & \vdots & 0 & \vdots \\ -d_x(1,n) & -d_x(2,n) & \cdots & 0 \end{bmatrix}$$

represents the discrimination effect of X in P.

The large number of variables/indicators makes the process of ranking very difficult. Indeed, for each selected indicator that is compared to the appropriate values of the two entities of P_r and P_s, a situation may occur in which one entity is larger than the other (as observed from one indicator), yet smaller when compared according to another variable/indicator [1]. The nature of this problem does not allow one to create a single global index that will absolutely represent the "greatness" of the phenomena being ranked. However, only that which is appropriate shall be able to determine the relative position of one entity when compared to others from the dataset P. Thusly, the term of the distance between the two entities as compared to their greatness is defined.

This distance itself must integrate many conditions. Therein, let $D(r,s)$ be the distance between the entities P_r and P_s. If each entity is to be represented as a dot in topological space and, in order for the space to be metric, the following conditions must be met:

- ***Non-negativity*** - the distance is not a negative real number

$$D(r,s) \geq 0 \text{ and } D(r,r) = 0.$$

- ***Commutability*** - the distance between P_r and P_s is equal to the distance between P_s and P_r,

$$D(r,s)=D(s,r).$$

- ***Triangular*** - for any of the three entities, P_s, P_r and P_q, the following claim is true

$$D(r,s) + D(s,q) \geq D(r,q).$$

- ***Homogeneity*** - the distance between the two entities is a homogenous function of the selected variables' differences; thus, $D(r,s) = 0$ only when all differences equal zero.
- ***Growth*** – the distance is of no declining function of all the differences.
- ***Variability*** – the differences of $d_i\ (r,s),\ i \in \{i,...,k\}$ are weighted for their influence in creating distance $D(r,s)$ as related to the standard deviation of the appropriate variables of $X_i,\ i \in \{1,...,k\};$ thusly, the differences $d_i\ (r,s)$ will appear in the form:

$$\frac{|\,d_i\,(r,s)|}{\sigma_i} \text{ or } \frac{d_i^2(r,s)}{\sigma_i^2}.$$

- ***Annulling Information Duplicity*** – the distance $D(r,s)$ needs to be created in a manner where any excess information is avoided and only a pure amount of information is introduced into the distance's calculation.
- ***Asymmetry*** - as not all variables have a similar impact on the ranking process, it is necessary to provide a list's rank according to the amount of information provided for the ranking. The distance is to be created in such a manner where the decline in importance of one indicator will subsequently cause a decline in its own respective area of creating the I-distance.
- ***Independence*** - if all variables are mutually independent, then no redundancy of information should occur; in order to do so, the formula for the distance needs to be in the form

$$\mathrm{D(r,s)} = \sum_{i=1}^{k} \frac{|\,d_i\,(r,s)|}{\sigma_i} \text{ or } \mathrm{D^2(r,s)} = \sum_{i=1}^{k} \frac{|\,d_i^2(r,s)|}{\sigma_i^2}$$

- ***Linear Dependence*** – if any linear dependency does exist between all variables, then the formula for calculating their distance is

$$D(r,s) = \frac{|d_1(r,s)|}{\sigma_1} \quad \text{or} \quad D^2(r,s) = \frac{{d_1}^2(r,s)}{{\sigma_1}^2}.$$

- ***Independent Groups*** - if one group of the m variables is to be independent from the group with the remaining $k\text{-}m$ variables, the following relation must be true

$$D_k(r,s) = D_m(r,s) + D_{k-m}(r,s).$$

If this is met, the distance between the entities of P_r and P_s must be able to be calculated independently: first on the basis of the m variables, then on the basis of the remaining $k\text{-}m$ variables. The distance based on all k variables is to equal the sum of the two previously calculated distances.

- ***Independence from the Origin*** – it is possible to create the two fictive entities of P_+ and P_-, whose respected values of the variables X_i^+ and X_i^- are subjectively chosen, but only if each phenomenon and every single chosen indicator/variable stands as

$$X_i^- \leq X_{ir} \leq X_i^+ \quad i \in \{1, \dots, k\}$$

- ***Technical*** - based on the k variables, the distance of $D_k\ (r,s)$ between P_r and P_s is calculated. If one additional variable is added, it is desirable that the new distance of $D_{k+1}(r,s)$ equal the sum that had been previously calculated, and that the additional value reflect the influence of the new variable X_{k+1}; essentially

$$D_{k+1} = D_k + E_{k+1},$$

where E_{k+1} is the additional value reflecting the new variable. For calculating the value of D_{k+1}, it is sufficient to calculate only E_{k+1}, after which the already calculated value of D_k.is added

Concerning k variables, let these be chosen according to the importance of the information order in the ranking phenomenon process, $X = \langle X_1, \dots, X_k \rangle$. Let $P = \{P_1, \dots, P_n\}$ be the observed dataset of entities [1]. The following table is to be used in this selection:

TABLE I
DATA SET OF CONCERN

variables / entities	X_1	X_2	...	X_k
P_1	x_{11}	x_{21}	...	x_{k1}
P_2	x_{12}	x_{22}	...	x_{k2}
...	...	...	...	...
P_n	x_{1n}	x_{2n}	...	x_{kn}

The calculation of the statistical parameter variable X_i requires information on the weighting coefficient of the basic elements for x_{ij}. With reference to different variables, weighting coefficients need not be the same. If f_i^r defines the relative coefficient of the weighting for x_{ir}, the following table is to be used:

TABLE II
MATRIX OF RELATIVE IMPORTANCE

X / P	X_1	X_2	...	X_k
P_1	f_1^1	f_2^1	...	f_k^1
P_2	f_1^2	f_2^2	...	f_k^2
...	...	...	...	...
P_n	f_1^n	f_2^n	...	f_k^n

When identical values are to be found in more than one column, the mean and variance of variable X_i is to be

$$\bar{x}_i = \sum_{r=1}^{n} f_i^r x_{ir} \qquad i \in \{1, \dots, k\};$$

$$\sigma_i^2 = \sum_{r=1}^{n} f_i^r x_{ir}^2 - \bar{x}_i^2 \qquad i \in \{1, \dots, k\}.$$

The calculation of the covariance w_{ij} requires the two-dimensional weighting coefficients f_{ij}^r, as well as comparing the variables X_i and X_j. Nonetheless, there is further information available concerning two-dimensional distributions $[f_{ij}^r]$; therefore, their approximate values are to be used instead

$$\left(f_{ij}^r\right)^* = \frac{\sqrt{f_i^r f_j^r}}{F_{ij}}; F_{ij} = F_{ji} = \sum_{r=1}^{n} \sqrt{f_i^r f_j^r}\ ; i \in \{1, \dots, k\};$$
$$j \in \{1, \dots, k\}.$$

The appropriate approximate value of the covariance is to be

$$w_{ij} = \frac{1}{F_{ij}} \sum_{r=1}^{n} \sqrt{f_i^r f_j^r} \left(x_{ir} - \bar{x}_i\right)\left(x_{jr} - \bar{x}_j\right)$$

and the correlation coefficient

$$r_{ij} = \frac{w_{ij}}{\sigma_i \sigma_j};\ i \in \{1, \dots, k\}; j \in \{1, \dots, k\} \quad [1]$$

Through the elements of the correlation matrix $\boldsymbol{R} = \lfloor \boldsymbol{r_{ij}} \rfloor$, the coefficient of partial correlation can be calculated from

$$r_{ji.t} = \frac{r_{ij} - r_{jt} r_{it}}{\sqrt{\left(1 - r_{jt}^2\right)\left(1 - r_{it}^2\right)}}\ ; i > j;\ \{j, i\} \in \{1, \dots, k\};\ t \notin \{j, i\}.$$

The iterative approach offers the opportunity to calculate the following coefficient of partial correlation

$$r_{ji.12\dots j-1} = \frac{r_{ji.12\dots j-2} - r_{j-1,i.12\dots j-2}\, r_{j-1,j.12\dots j-2}}{\sqrt{\left(1 - r_{j-1,i.12\dots j-2}^2\right)\left(1 - r_{j-1,j.12\dots j-2}^2\right)}}$$

Accordingly, the matrix of the partial correlations is defined as

$$R = \begin{bmatrix} 1 & r_{12} & r_{13} & \cdots & r_{1k} \\ r_{12} & 1 & r_{23.1} & \cdots & r_{2k.1} \\ r_{13} & r_{23.1} & 1 & \cdots & r_{3k.12} \\ \vdots & \vdots & \vdots & 1 & \vdots \\ r_{1k} & r_{2k.1} & \cdots & \cdots & 1 \end{bmatrix}.$$

According to the type of data and the distances calculated for individual variables, three types of the I-distance may be subsequently calculated: *(I) basic I-distance, (II) square I-distance, and (III) structural I-distance.*

II. THE FOUNDATIONS OF DISTANCE BASED ANALYSIS

Quite frequently, the ranking of specific marks is done in such a way that it can seriously affect the process of taking exams, entering competitions, UN participation, medicine selection, and many other areas [2]. I-distance is a metric distance in an *n*-dimensional space. It was originally proposed and defined by B. Ivanovic, and has appeared in various publications since 1963 [1]. Ivanovic originally devised this method to rank countries according to their level of development on the basis of several indicators; many socio-economic development indicators had been considered and the problem was how to use all of them in order to calculate a single synthetic indicator which would thereafter represent the rank [3].

For a selected set of variables $X^T = (X_1, X_2 \dots, X_k)$ chosen to characterize the entities [2], the I-distance between the two entities $\beta_r = (x_{1r}, x_{2r}, \dots, x_{kr})$ and $\beta_{1i} = (x_{1i}, x_{2i}, \dots, x_{ki})$ is defined as

$$\mathrm{D}\,(\mathrm{r,s}) = \sum_{i=1}^{k} \frac{|\,\mathrm{d_i}\,(\mathrm{r,s})|}{\sigma_i} \prod_{f=1}^{i-1} \left(1 - r_{fi12\dots f-1}\right)$$

where $d_i\,(r,s)$ is the distance between the values of variable $X_i$for e_r and , β_xe.g. the discriminate effect,

$$d_i\,(r,s) = x_{ir} - x_{ix}, i \in \{1, \dots, k\}$$

σ_i the standard deviation of X_i, and $r_{ji.12\dots j-1}$ is a coefficient of the partial correlation between X_i and X_j, (j < i), [4].

The construction of the I-distance is iterative; it is calculated through the following steps:

- Calculate the value of the discriminate effect of the variable X_1 (the most significant variable, that which provides the largest amount of information on the phenomena that are to be ranked)

- Add the value of the discriminate effect of X_2 which is not covered by X_1
- Add the value of the discriminate effect of X_3 which is not covered by X_1 and X_2.
- Repeat the procedure for all variables [5].

In order to rank the entities, it is necessary to have one entity fixed as a referent in the observing set using the I-distance methodology [4]. The entity with the minimal value for each indicator or a fictive minimal, maximal, or average value entity may all be utilized as the referent entity, since the ranking of the entities in the set is based on the calculated distance from the referent entity [6]. In that, the I-distance method shall be applied to several Input indicators as to calculate their $\mathrm{I-distance}_{input}$ values. The same approach shall be applied to Output indicators and the $\mathrm{I-distance}_{output}$ values will be calculated for these as well. The obtained values will be brought to a 0-1 level by implementing an L∞ norm. The efficiency of the DMU will be calculated as the $\mathrm{DBA=I-distance}_{output} / \mathrm{I-distance}_{input}$. Any DMU with an efficiency ratio of at least 1 (DBA≥1) is to be considered as efficient [4].

III. Case Study: An Efficiency Assessment of the Scientific Output of US Universities

As a possible example of the utilization of the proposed method, the efficiency of US Universities has been selected and the results elaborated upon.

The issue of ranking higher education institutions (HEI) has drawn much attention as of late [7]. Many different stakeholders, especially students, use rankings as an indicator of a university's reputation and performance [2]. The most cited ranking list is likely the Academic Ranking of World Universities (ARWU) which has been the focus of researchers since its creation in 2003 [8]. The Shanghai (ARWU) ranking is based on six different criteria and aims to measure academic performance. Within each category, the best performing university is given a score of 100 and then becomes the benchmark against which the scores of all other universities are therein measured [9]. Universities are then ranked according to the overall score they obtain, which is simply a weighted average of their individual category scores [9]. Within these six categories, ''HiCi'' and ''PUB'' reflect researcher output: ''HiCi'' is the number of highly cited researchers, while ''PUB'' is the number of articles indexed in the Science Citation Index Expanded and the Social Science Citation Index [10].

Yet, almost immediately after the release of its first ranking, the ARWU attracted a great deal of criticism concerning arbitrary chosen weighting factors, favoring Nature & Science journals or generally comments that ARWU ranking mainly reflects the size of a university [11], [12]. One of the potential weaknesses frequently elaborated [13], [5] is absence of scientific quality indicators such as high quality papers (as those ranked in the first quartile ~ 25% ~ in their categories) etc. Thus, the latest release of the SCImago Institutions Rankings (SIR) quickly emerged as a potential alternative to the ARWU. The SIR approach integrates one quantitative (size of the publication output of an institution) and various qualitative variables [14] such as International Collaboration (IC), Normalized Impact (NI), High Quality Publications (Q1), Specialization Index (SI), Excellence Rate (ER), Scientific Lead (Lead) and Excellence with Leadership (EwL). This methodology was additionally upgraded with CWTS team which created Leiden Ranking. However, despite all the similarities between SCImago and CWTS Leiden methodologies (both of them are based on bibliometric data, both rankings focus on the research performance of institutions), there are also a number of substantial differences between the SIR and the Leiden Ranking [14]. The SIR ranking is based on the Scopus database, while the Leiden Ranking uses Thomson Reuters WoS. In addition, in Leiden ranking the journals which are not published in English or authors are concentrated in one or a few countries (the journal does not have a strong international scope) and the journals with a small number of references to other journals in the Web of Science database are being excluded from the analysis [14]. In addition, the Leiden Ranking by default reports size-independent indicators (average statistics per publication, such as a university's average number of citations per publication). The advantage of size-independent indicators is that they enable comparisons between smaller and larger universities. Precisely this is the reason why wanted to re-evaluate ARWU ranking, since it is hugely influenced by size of university. Although ARWU rankings do provide the world's best University rankings, they also fail to display their efficiency. This is particularly interesting since larger and better financed Universities tend to obtain a greater number of researchers and postgraduates students. This exact disproportion of researchers implies that more powerful Universities have a greater probability of achieving better scientific output. In this respect, it is essential to provide more insight into University research efficiency, which is hereafter explored through application of the statistical Distance Based Analysis method.

In order to evaluate the researcher efficiency of a particular university, the following Input indicators are here used: (I1) Financial endowment, (I2) Academic staff, and (I3) Postgraduate students. On the other hand, researcher output is evaluated by the official ARWU score for the variables (O1) HiCi and (O2) PUB (highly-cited authors and the number of publications in SCIe & SSCI journals). The sample presented in this paper here consists of 54 US Universities which are placed at Top 100 in the official ARWU ranking. These institutions have been specifically chosen as US universities have consistent data concerning Input data; for instance, financial endowment. The results achieved by means of the DBA method are shown in Table III.

As can be seen from Table III, the California Institute of Technology tops the DBA method list. When the DBA ranking is compared to the official ARWU ranking, great inconsistencies can be found. The DBA efficiency score emphasizes universities that perform far better than can be expected from their Input indicators. In order to further elaborate on this matter, a Data Envelopment Analysis (DEA) has been performed on the same dataset. The DEA rankings are also presented in Table III. The universities' ranks achieved by the DEA method are quite similar to the DBA method, the subsequent correlation is significant with r_s=0.788, p<0.01. The same conclusion applies when comparing the official ARWU to DEA rankings, r_s=0.431, p<0.01. A particularly interesting fact is that the DBA method has a far greater correlation with the official ARWU ranking than does the traditional efficiency DEA method, with r_s=0.654, p<0.01.

IV. Conclusion

In this paper, the aim has been to evaluate the scientific output of leading US universities by applying an Ivanovic-Jeremic Distance Based Analysis. With a growing worldwide interest in university rankings, the academic world is becoming ever more concerned about the assessment of higher education [15]. These rankings are very often used as a marketing tool for universities to show their educational or research excellence. This is precisely the reason as to why it is exceptionally important to provide rankings that are as accurate as possible. Moreover, in addition to the ranking of higher education institutions, the efficiency of their academic staff is an issue of equal concern [16]-[18]. As a remedy to this matter, the use of the statistical DBA method has here been proposed. The results from Table III suggest that the DBA ranking is quite similar to the official ARWU list. However, it is essential to emphasize that the DBA method better correlates with the official ARWU list than does the traditional efficiency DEA method.

There are several contributions which must be here singled out. First of all, by utilizing the approach presented in this work, it is possible to evaluate the efficiency of profit or non-profit oriented organizations. Moreover, not only is a ranking provided, but a difference between entities as well. A large number of variables can be included in the analysis performed, generating one aggregated quantitative indicator. In addition to the above mentioned contributions, it should be noted that the DBA has provided information as to which input variables are crucial in determining an individual entity's performance. Thus, each DMU can re-evaluate its performance and strive to improve its ranking by further developing its own most significant indicators. Finally, a completely new model for evaluating the efficiency of any organizational unit has also been presented in this paper, which has many advantages, but its primary one is its ability to implement a large number of variables that are of various units of measure. Therein, this model is able to contribute significantly to the field of efficiency measurement. Currently, the majority of research papers employ DEA and SFA as efficiency measurement methods. However, DBA possesses numerous advantages over these two, as it does not place any weighting factor on its variables (DEA) or is based on dissimilar assumptions about the distribution of the inefficiency term u (SFA).

TABLE III
Results of the DBA Method, the DBA Efficiency Value and Rank, ARWU, and DEA Ranking

University	DBA Efficiency	DBA Rank	ARWU Rank	DEA Rank
California Institute of Technology	3.957	1	5	3
University of California, San Francisco	2.723	2	17	9
University of California, San Diego	2.680	3	12	2
University of California, Santa Barbara	2.250	4	24	7
University of Colorado at Boulder	1.518	5	25	15
University of California, Irvine	1.484	6	33	6
University of California, Berkeley	1.382	7	2	4
Rockefeller University	1.343	8	26	1
Massachusetts Institute of Technology (MIT)	1.305	9	4	11
Stanford University	1.049	10	3	10
Brown University	1.031	11	41	16
University of Wisconsin - Madison	0.935	12	15	22
University of California, Los Angel.	0.931	13	11	5
Princeton University	0.920	14	6	12
Cornell University	0.891	15	10	30
University of Rochester	0.857	16	47	18
Harvard University	0.789	17	1	14
University of Pennsylvania	0.788	18	13	20
Duke University	0.752	19	27	26
University of Washington	0.736	20	14	17
University of California, Davis	0.724	21	32	29
University of Illinois at Urbana-Champaign	0.705	22	19	36
University of Chicago	0.705	23	8	32
Northwestern University	0.615	24	21	40
Carnegie Mellon University	0.614	25	39	19
Yale University	0.612	26	9	21
University of Michigan - Ann Arbor	0.611	27	18	13
Washington University in St. Louis	0.605	28	22	33
University of Maryland, College Park	0.599	29	28	41
University of Pittsburgh	0.594	30	38	34
Texas A&M University – College Station	0.583	31	51	24
Columbia University	0.582	32	7	28
University of North Carolina at Chapel Hill	0.573	33	30	43
University of Virginia	0.549	34	52	25
The Johns Hopkins University	0.539	35	16	45
The University of Texas Southwestern Medical Center at Dallas	0.533	36	35	23
University of Minnesota, Twin Cities	0.503	37	20	35
Rutgers, The State University of New Jersey - New Brunswick	0.483	38	37	39
Vanderbilt University	0.483	39	36	37
The Ohio State University - Columbus	0.465	40	40	50
University of Arizona	0.463	41	45	27
Michigan State University	0.456	42	49	48
Pennsylvania State University - University Park	0.430	43	31	51
The University of Texas at Austin	0.383	44	29	47
University of Florida	0.376	45	42	49
University of Utah	0.354	46	48	38
University of Southern California	0.312	47	34	53
Purdue University - West Lafayette	0.302	48	43	44
New York University	0.287	49	23	54
Boston University	0.283	50	44	52

Indiana University Bloomington	0.206	51	50	46
Case Western Reserve University	0.206	52	53	31
Arizona State University - Tempe	0.184	53	46	42
Rice University	0.140	54	54	8

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