University of Pannonia

Thesis Summary

Beyond Tradition: A New Approach to Constructing University Leagues

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Introduction and Research Questions

Since the first appearance of American universities' rankings in 1983 by the U.S. News and World Report, and the first world university ranking by Shanghai Jiao Tong University, several university rankings are published yearly.

University rankings are heavily criticized from several angles (see, for example, Liu and Cheng, 2005; Daraio and Bonaccorsi, 2017; Soh, 2017; Moed, 2017; Safón and Docampo, 2020; Chirikov, 2022. The author grouped the problems into three main categories. One common point of the criticisms is that rankings can not be considered "fair" because they compare entities with highly different input-output structures, sizes, and funding (Lawrence and Green, 1980; Bengoetxea and Buela-Casal, 2013; Daraio and Bonaccorsi, 2017). To address this, the author proposes that only similar institutions (or countries' Higher Education Systems) should be compared to achieve a fairer ranking.

The author considers a ranking "fair" if the compared entities are similar in some nature following the work of Lawrence and Green (1980), Bengoetxea and Buela-Casal (2013), and Daraio and Bonaccorsi (2017). A key aspect of fairness is that not all entities can be compared using the same indicators. Some entities excel in certain indicators, while others perform below average.

The term "league" in this work is borrowed from English football and signifies a group of teams engaged in competitive sports, participating in contests against one another. "Group of teams" in this case are Higher Education Institutions competing for students, resources, funds, and talents, not just on their national field, but on an international level as well to achieve higher and better rankings.

In this work, leagues are specified by an unsupervised bi-clustering method. "Unsupervised" means that the data set does not have a labeled training data set. In other words, there are no examples of the input-output pairs (e.g. an entity belonging to a given league) to learn from. The algorithm has to explore the patterns without guidance and reveal the subgroups within the data (Alashwal et al., 2019).

Leagues are defined simultaneously by a set of indicators and a set of countries/universities. The top-, mid-, and lower-performing leagues are specified based on a given threshold. The proposed set of leagues allows overlapping both on indicators and on universities. The overlaps show university management which indicators should improve the position of their institution in the ranking or permit entering a higher league. League membership has a double message for students. The member universities are similar with respect to a number of indicators. Membership in a particular league indicates a set of similar universities to students, i.e., they have comparable conditions and similar strengths and weaknesses.

Research questions:

RQ1: **Are universities comparable "fairly" based on an arbitrarily pre-defined set of ranking indicators?**

RQ2: **Is it possible to create homogeneous groups that contain entities (countries or institutions) that has above-average, below-average, and similar performance?**

RQ3: **Is it possible to determine a distinct set of indicators that specifies the entities' (countries or institutions) potential for development, leading them towards an above-average performing group?**

RQ4: **Are there any indicators that clearly identify entities (countries or institutions) belonging to the above-average performing group?**

Related Studies and Research Proposals

The higher-education-related rankings suffer from numerous "deadly sins" as Soh (2017) calls them. Following the work of Daraio and Bonaccorsi (2017), the author grouped these issues into the following three main categories:

- Data and indicator-related problems;
- Methodology-related issues;
- Impact and implication of university rankings.

One problem is derived from the fact that global university rankings do not consider the different disciplinary/field compositions of institutions. Most universities are internally diverse, with different missions and staff compositions (Liu and Cheng, 2005; Charon and Wauters, 2007; Bengoetxea and Buela-Casal, 2013), which makes the institutional-level comparison problematic (Daraio and Bonaccorsi, 2017; Bengoetxea and Buela-Casal, 2013). In recent years, subject rankings have appeared next to global rankings - see, for example, the QS World University Rankings by Subject or the THE World University Ranking by Subject.

A common approach for rankers is only to consider the extreme top data quantiles, such as Nobel prize winners, papers in Nature and Science, or highly cited researchers (HiCi). This approach leads to not measuring quality but HEIs capability to attract top scientists (Bonaccorsi and Daraio, 2008).

World university rankings are biased towards a small group of institutions. They favor old research-intensive universities with long ranking histories that use English language (Dill and Soo, 2005; Charon and Wauters, 2007; Bengoetxea and Buela-Casal, 2013; Boyadjieva, 2017). They claim that they create a "world" ranking. However, Moed (2017) shows that ARWU is biased towards North America, THE towards Anglo-Saxon countries, and Leiden towards emerging Asian nations. And as Bengoetxea and Buela-Casal (2013) points out, only 2-3% of HEIs are listed; smaller, lesser-known, more diverse institutions are left out.

The ranking organization arbitrarily chooses the indicators and weights used in rankings. The weight values can greatly impact the outcome, and this fact often remains unnoticed (Becker et al., 2017). Furthermore, the chosen weights lack any theoretical foundation, and users assume that weights are maintained as specified (Dill and Soo, 2005; Lukman et al., 2010; Soh, 2011; Soh, 2014). Soh (2011) uses the example of the 2010 ARWU ranking. The original ARWU ranking's methodology states that "Staff winning Nobel Prizes and Field Medals" worth twice as much (20% of overall score) than "Alumni winning Nobel Prizes and Field Medals" (10% of overall score). Regression analysis' standardized coefficients (beta-weights) show that Staff's contribution to the overall score is about 24 times than Alumni's. Both Soh (2011) and Soh (2014) conclude that assigned (nominal) weights and actual (attained) weights differ, thus leading users to misinterpret the ranking results.

Last but not least, one main problem with university rankings is the heterogeneity of institutions which is also the scope of this work. Several authors argue that entities should not be compared if they have differences in size, funding, and budgets (Dill and Soo, 2005; Guarino et al., 2005; Charon and Wauters, 2007; Marginson and van der Wende, 2007; Saisana et al., 2011; Bengoetxea and Buela-Casal, 2013; Daraio and Bonaccorsi, 2017). For example, in 2021, Harvard University's annual budget was approximately \$5.2 billion, whereas Hungary's annual budget for tertiary education was approximately \$2.9 billion in 2021 (Eurostat, 2021). Rankings compare institutions such as Harvard with significantly smaller HEIs. Török and Konka (2020) further observes that while comparing Hungarian universities to Serbian or Austrian counterparts may be relevant, such comparisons lose significance when comparison is extended to institutions in the United Kingdom or Ethiopia.

Moreover, in 2006, the 16 Berlin Principles on Ranking of Higher Education Institutions stated that rankings must specify the linguistic, cultural, and economic contexts of the institutions (IREG, 2006) so users can better understand and interpret the results.

Daraio and Bonaccorsi (2017) also defines the principles of "fair" comparison. First of all, the compared entities should have similar input structures. Secondly, the trade-off between outputs should be explicitly recognized. Thirdly, a higher ranking should be associated with higher performance. Lawrence and Green (1980, p. 3) also notes that ”if comparisons must be made, they should be made between similar types of institutions”.

In addition to arbitrary classification, clustering methods are used to separate clusters (see, e.g., (Rad et al., 2011; Ibáñez et al., 2013)). Ibáñez et al. (2013) clustered public universities in the area of computer sciences into four groups based on their productivity, visibility, quality, prestige, and internalization. However, clustering alone cannot be used to specify regional or other rankings because, beforehand or in parallel, clustering indicators should be selected for ranking similar universities or countries (Poole et al., 2017).

Bi-clustering methods are relatively new, almost entirely unknown, and unused in the social sciences. The author demonstrates the capabilities of these methods in clustering and ranking Higher Education Systems (countries) and Higher Education institutions. One can find meaningful but far-from-evident leagues of both countries and indicators using well-chosen elements of the family of bi-clustering methods. The selected indicators shed light on HEIs’ and countries’ strengths, weaknesses, and positions in the rankings. Last but not least, the proposal opens a new direction of multivariate analysis free of subjective or ad-hock weights and does not require indicator selection over non-comparable indicators.

A fair comparison of HEIs can be performed within leagues. In the present paper, the author creates three leagues within HESs and HEIs, which are denoted as A, B, and C and have simple characteristics to make the methods and results as transparent as possible while still being able to make nontrivial observations.

League A: Upper league,

League B: Middle league,

League C: Lower league.

Bi-clustering is a data mining technique that enables the simultaneous clustering of the rows and columns of a matrix. The term was first introduced by Mirkin (1998) to name a technique that was introduced many years previously, in 1972, by J. A. Hartigan (1972). This clustering method was not generalized until 2000 when Cheng and Church (2000) proposed a bi-clustering algorithm based on the variance and applied it to biological gene expression data. Many bi-clustering algorithms have been developed for bioinformatics; see an excellent review in Pontes et al. (2015). Until recently, these methods were rarely used in other fields of science.

A *bicluster* refers to a subset of rows that display similar behavior across a subset of columns, and vice versa (Madeira and Oliveira, 2004).

There are different types of bi-clusters (Madeira and Oliveira, 2004):

BIC1 Bi-clusters with constant values (in rows and/or columns) (see Table 2.1(a));

BIC2 Bi-clusters with similar values (on rows and/or columns) (see Table 2.1(b)).

The BIC1-type bi-clustering algorithms re-order the rows and columns of the matrix in an attempt to bring similar rows and columns as close together as possible at the same time and then to find bi-clusters with similar (constant) values (see, e.g., Table 2.1(a)). In contrast, BIC2-type algorithms seek bi-clusters with similar values in rows and columns. Similarity can be measured in many ways; the simplest way is by analyzing the variance between groups using the co-variance between rows and

TABLE 2.1: Cell Selection Results. (X,O: selected cells; ■: upper/ ❏: lower than a specified threshold)

[Bi-clusters with constant values]

Countries/Institutions	Indicators 1	2	3	4	5	6	7	8	9	10
1	X		X			X		X		
2										
3	X		X			X		X		
4	X		X			X		X		
5										
6										
7										
8										
9										
10										
11	X		X			X		X		
12	X		X			X		X		
13	X		X			X		X		

[Bi-clusters with similar values]

Countries/Institutions	Indicators 1	2	3	4	5	6	7	8	9	10
1	O	O	O		O		O			O
2	O	O	O		O		O			O
3	O	O	O		O		O			O
4	O	O	O		O		O			O
5										
6										
7										
8										
9										
10										
11	O	O	O		O		O			O
12	O	O	O		O		O			O
13										

columns. In Cheng and Church (2000)'s theorem, a bi-cluster is defined as *a subset of rows and columns with almost the same score*. The score is the measure of the similarity of the rows and columns. Typical clustering algorithms are based on global similarities of rows or columns of the expression (or feature) matrix.

This paper first demonstrates the method on a relatively small number of objects, namely, the U21 countries' HESs, then performs the analysis on a larger data set of institutions to show that well-selected bi-clustering methods can identify leagues (countries/institutions and indicators simultaneously). For simplicity, the paper identifies only three leagues: upper league A, middle league B, and lower league C. For that purpose, two bi-clustering methods are used.

The first one is the **i**terative **B**inary **Bi**-clustering of **G**enes (iBBiG) (Gestraud et al., 2014) method.

This algorithm is a BIC1-type method that produces bi-clusters, where the cells exceed the threshold (i.e., median) (see Table 2.1(a)). The procedure starts with the normalization of the indicators, as defined in (**??**).

iBBiG does not require all unique cells within a bi-cluster to be above or below a threshold (i.e., the median). However, the medians for the selected cells must be above/below both the row/column median and the medians of the excluded rows and columns.

The next step in iBBiG involves determining a threshold based on the median of the matrix. A new binary matrix is then created, where cells with values above the threshold are assigned a value of one, while all other cells are assigned a value of zero. The key step of iBBiG is thus to find the cells that form similar rows and columns.

As a result, we obtain the upper league A. The binary reversed data and the same procedure yield the lower league C. The iBBiG method can produce more than one bi-cluster (i.e., leagues), which can overlap if the above procedures are applied with different thresholds.

Let the author note here that when using different thresholds to develop several alternative clusters, a quality test is needed to evaluate the results. For simplicity, the author does not apply multiple thresholds; instead, to identify the middle league, another bi-clustering method, namely, **Bi**-**c**lustering **A**nalysis and **R**esults **E**xploration (BicARE), is used. Through implementation of the BicARE technique, we are able to produce a bi-cluster that effectively defines a middle league of nations/institutions that intersect with both (A) and (C), thereby yielding a more comprehensive comprehension of their respective accomplishments. The position of the countries with respect of the created leagues is depicted in Fig. 3.2)

BicARE is a BIC2-type method, where the similarity measure is the correlation (see Table 2.1(b)). BicARE (Gestraud et al., 2014) is the improved and enhanced version of the **FL**exible **O**verlapped bi**C**lustering (FLOC) algorithm proposed by Yang et al. (2003). This method is based on the notion of residue, which is a measure of the similarity of the elements in a bi-cluster (see Yang et al., 2005 for a definition of the residue). The smaller the residue is, the more similar the elements of the bi-cluster are. Similarly to the interpretation of the upper and lower leagues, when interpreting the middle league (see the cells of Table 2.1(b) that are marked by 'O'), the BicARE method specifies a group (submatrix) of countries/institutions and indicators whose values are similar (their variances are as small as possible) for both countries and indicators.

To obtain a preliminary picture of the possible bi-clusters and to later compare these potential bi-clusters with the obtained bi-clusters, a visualization method, i.e., a seriation method can be used. Seriation is an exploratory combinatorial data analysis technique for reordering objects into a sequence (Liiv, 2010). Typically, finding an optimal seriated matrix is also an NP-hard problem (similar to finding bi-clusters). Therefore, heuristic methods are usually applied. In this study, the hierarchical cluster-based matrix seriation (Hahsler et al., 2008) is used.

The analysis consists of 5 steps, both in case of countries and institutions:

Step 1: Replacing missing values;

Step 2: Normalization;

Step 3: Data binarization and reversal of binary entries;

Step 4: 100 iterations of bi-clustering and selection of bi-clusters with the largest significant score values; and

Step 5: Calculation of partial rankings for the significant bi-clusters.

As a result, the following three bi-clustering can be defined:

- League A (the bests): iBBiG on normalized basic data (X)
- League B (the midfield): BicARE on basic data (X)
- League C (the laggards): iBBiG on the reverse (1-X) of normalized basic data (X)

Overlaps can also be found between these leagues for the indicators and countries/institutions.

In the last step (Step 5), partial rankings were calculated and compared to the corresponding part of the U21 and RUR rankings. When calculating partial rankings for countries and institutions in the specified bi-cluster(s), the original weights of U21's and RUR's indicators were used, and the total scores for the countries/institutions were calculated using the selected indicators in the given bi-cluster.

Research Proposals

P1: To make a fair comparison of universities, it is important to ensure that the entities being compared are similar in nature. This means that not all entities can be evaluated using the same set of indicators.

P2: The clustering method of bi-clustering can be used to create university leagues that simultaneously select the countries/universities and the set of indicators.

P2.1: The iterative Binary Bi-clustering of Genes (iBBiG) method can be used to determine the above-average performing group of entities (countries or institutions) and their common set of indicators, and the below-average performing group and their shared set of indicators.

P2.2: The Bi-clustering Analysis and Results Exploration (BicARE) can be used to determine those entities (countries and institutions) that have the same performance regarding the set of indicators selected by the method.

Results and Research Theses

The analyses were performed first on the U21 ranking of countries, and then on the data of the RUR World University Ranking.

The U21 rankings of countries by their Higher Education Systems (HESs) (Williams et al., 2012; Williams et al., 2013; Williams et al., 2014; Williams et al., 2015; Williams et al., 2016; Williams et al., 2017; Williams and Leahy, 2020) are developed at the University of Melbourne. In what follows, the paper presents the evaluation of the U21 rankings and their indicators in details. The U21 rankings cover 9 years (2012-2020) and 50 countries. The rankings for a given year are published in May of that year. Forty-eight countries were examined in 2012, and Saudi Arabia and Serbia were added in 2013. The overall U21 rank scores are calculated from 4 groups based on resources (R), environment (E), connectivity (C), and output (O). Each (sub)indicator is a weighted average of multiple variables.

The overall scores U21 ranking are available for each year, but the (sub)indicators are available only for the years 2012-2014. For the appropriate application of bi-clustering, only the (sub)indicators must be considered. Since (sub)indicators of the U21 rankings are not available from 2015, the year 2014 was selected. The ranking agency published its last country ranking in 2020 (**williams2020**). The author also run the analyses on this dataset and compared the results to the results of 2014.

The data of RUR (World University Ranking 2020[1]) on 828 institutions were selected for analysis because the weights of reputation surveys in RUR are less than those in THE. Bowman and Bastedo (2010) showed that anchoring effects have an influence on reputational assessments. More precisely, being ranked highly in a ranking increases reputation, not the other way around. This means that reputation surveys are biased towards

[1] https://roundranking.com/ranking/indicator_ranking.html#academic-staff-per-students_SO-2020

TABLE 3.1: List of Indicators (Williams et al., 2014)

w	Abbr.		Variables
5.0%	**Resources** 20%	R1	Government exp. on tertiary education institutions as a % of GDP
5.0%		R2	Total exp. on tertiary education institutions as a % of GDP
5.0%		R3	Annual exp. per student (full-time equivalent) by tertiary education institutions in USD, PPP
2.5%		R4	Exp. in tertiary education institutions for R&D as a % of GDP
2.5%		R5	Exp. in tertiary education institutions for R&D per head of population at USD, PPP
2.0%	**Environ-** ment 20%	E1	% of female students in tertiary education
2.0%		E2	% of female academic staff in tertiary institutions
2.0%		E3	A rating of data quality.
14.0%		E4	Qualitative measure of the policy environment.
4.0%	Connectivity 20%	C1	% of international students in tertiary education
4.0%		C2	% of articles that are co-authored with international collaborators (coverage is all institutions that publish at least 100 papers).
2.0%		C3	Webometrics web transparency measure: sum of values from 4,200 universities divided by the country's population.
2.0%		C4	Webometrics visibility index (external links that university web domains receive from third parties). Sum of data for 10,000 tertiary institutions divided by the country;s population.
4.0%		C5	Responses to question "Knowledge transfer is highly developed between companies and universities", which was asked of business executives in the annual survey by IMD World Development Centre, Switzerland
4.0%		C6	% of university research publications that are co-authored with industry researchers
13.3%	Output 40%	O1	Total number of journal articles that are produced by higher education institutions
3.3%		O2	Total number of articles that are produced by higher education institutions per capita
3.3%		O3	Average impact of articles, as measured by citations in 2014 of articles that were published in previous years using the Karolinska Institute normalized impact factor.
3.3%		O4	Depth of world-class universities in a country. This is calculated as an average of the institutions' score of a country that is listed in the top 500 of the Shanghai ranking, divided by the country's population
3.3%		O5	Excellence of a nation's best universities, which is calculated by summing the Shanghai Jiao Tong scores for the nation's three best universities
3.3%		O6	Enrollment in tertiary education as a % of the eligible population, which is defined as the 5-year age group after secondary education
3.3%		O7	% of the population aged 25-64 with a tertiary qualification
3.3%		O8	Number of researchers (full-time equivalent) in the nation per population
3.3%		O9	Unemployment rates among tertiary-educated aged 25-64 years compared with unemployment rates for those with only upper-secondary or post-secondary non-tertiary education

Notes: *w*: weights, exp.: expenditure, PPP: purchasing power price elite universities, and because of this, the author chose not to use THE (as surveys count higher in their rankings than in the RUR).

Table 3.2 shows the construction of RUR. Only the 20 basic indicators were employed; the four aggregated subindicators and the overall scores were ignored.

It is important to note that, unlike classical clustering, bi-clusters can overlap, depending on the method applied. Moving forward, the author will highlight scenarios where belonging to a single cluster or multiple clusters holds particular significance. In both cases, it is essential to consider both the country and indicator positions simultaneously.

After seriation, two bigger homogeneous blocks can be identified based on Figure 3.1. The block of the darker cells on the top left corner of Figure 3.1 indicates the top league, while the bigger lighter block, which indicates the remaining (lower) league, can be discovered at the bottom of the figure. The dendrogram of two-way clustering also shows that regarding rows and columns two main blocks can be specified. Even though the heat map of the normalized data suggests two bi-clusters, only the bi-clustering algorithm, and F-tests will help to determine the significant bi-clusters.

The iBBiG algorithm on normalized data specifies League A because the cell values from the bi-cluster are significantly higher than those of the excluded data. The iBBiG algorithm on the reversed data identifies League C.

When selecting League(s) A and C, it is important to also specify League(s) B in a similar manner. To determine the middle league, a unique concept of similarity is utilized. The author aims to identify a middle league where the differences between countries and indicators are minimal. This is achieved using the BicARE method, which generates bi-clusters that meet these criteria. Then, one can identify a significant bi-cluster by conducting an F-test to compare variances for both countries and indicators between included and excluded cells.

			Leagues		
			A	B	C
		No. of institutions at a threshold of 0.50:	398		430
		0.75:	174	280	192
		0.90:	78		81
		No. of indicators at a threshold of 0.50:	17		17
		0.75:	11	10	15
		0.90:	3		15
INDICATORS					
Teaching	T1	Academic staff / students			
(T)	T2	Academic staff / bachelor degrees awarded			
8-8%	T3	Doctoral Degrees awarded / academic staff	X		X
40%	T4	Doctoral degrees awarded / bachelor degrees awarded	X		X
	T5	World teaching reputation	X	X	X
Research	R1	Citations / academic and research staff	X	X	X
(R)	R2	Doctoral degrees awarded / admitted PhD	X		X
8-8%	R3	Normalized citation impact	X	X	X
40%	R4	Papers / academic and research staff	X	X	X
	R5	World research reputation	X	X	X
International diversity	I1	Share of international academic staff	X	X	X
(I)	I2	Share of international students	X		X
2-2%	I3	Share of international co-authored papers	X		X
10%	I4	Reputation outside region	X	X	X
	I5	International level	X	X	X
Financial sustainability	F1	Institutional income / academic staff	X	X	X
(F)	F2	Institutional income / students	X		X
2-2%	F3	Papers / research income			
10%	F4	Research income / academic and research staff	X	X	X
	F5	Research income / institutional income	X		X

Notations of the results of the different thresholds applied in the iBBiG method for determine league A and C:

- X: threshold = 0.5
- threshold = 0.5 and 0.75
- threshold = 0.5, 0.75 and 0.9

TABLE 3.2: The leagues formed on RUR 2020

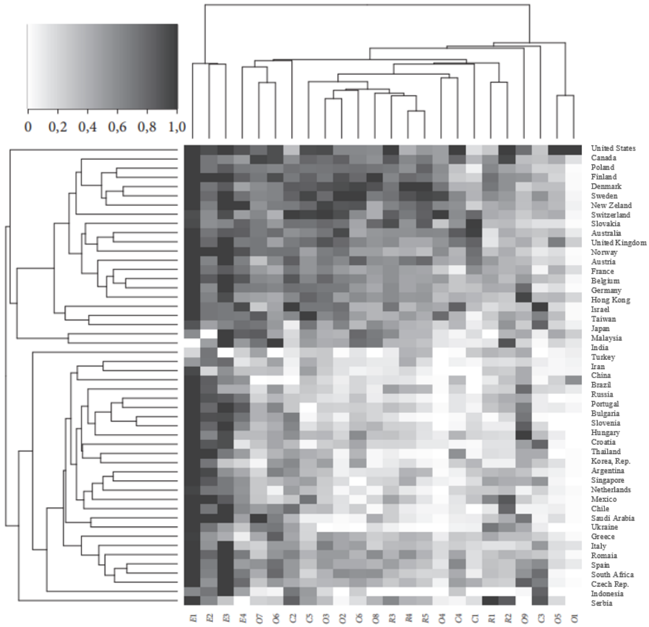

FIGURE 3.1: Heat Map of the Normalized and Seriated Matrix

Since a country can have several high and low values simultaneously, it can be a member of more than one league. Similarly, if an indicator has a high relative variance, its high-value cells can be included in League A, and lower-value cells can be included in League C (see the overlaps of columns of cells that are labeled X or O in Table 2.1). Therefore, the results of bi-clusters can specify overlaps (see Fig. 3.2). An in-depth analysis can highlight which countries are separated, and the analysis of the overlaps can provide a detailed picture of the countries and indicators.

As mentioned at the beginning of this section, bi-clusters might (or might not) have overlaps (see Fig. 3.2), which is worth analyzing case by case.

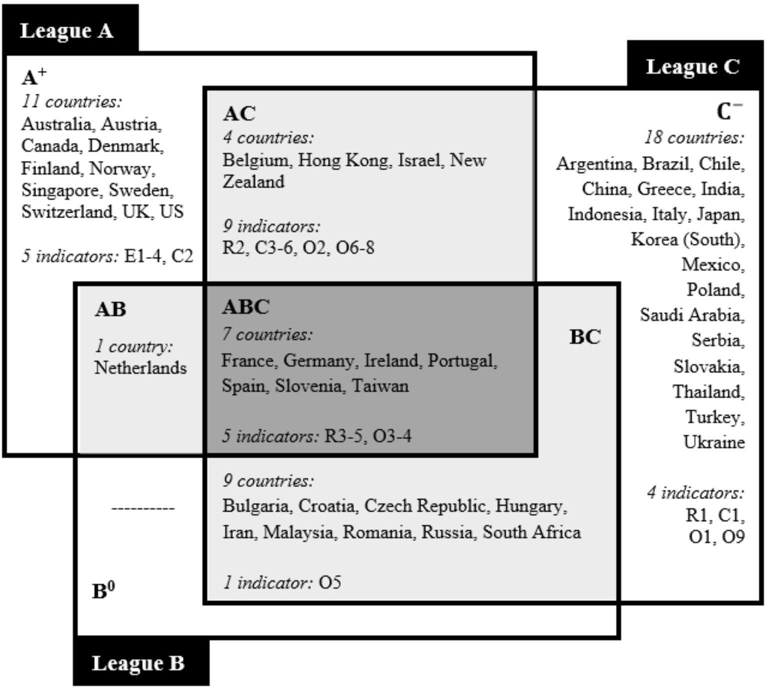

FIGURE 3.2: Leagues specified by bi-clustering algorithms - results

League A: League A contains 23/50 countries and 19/24 indicators. The remaining variables are journal articles (O1), the score of the nation's best three universities by Shanghai (O5), unemployment rates (O9), government expenditure (R1), and international students (C1). These are the indicators for which countries of League A do not perform equally well. The absence of indicator O1 in League A is not surprising because, among all the indicators, this one has the highest relative standard deviation.

League C: League C includes most of the countries (38) and those 19 indicators which were not in League A^+. This means there are more less-well-performing countries (38 in League C) than well-performing ones (23 in League A). Nevertheless, the number of indicators in League A and League C are equal (19), and 14 of them are common. In addition to these 14 common indicators, the countries of League A perform well in the environmental indicators (E1-4) and in the articles with international collaborators (C2). The countries of League C usually perform worse in government expenditure (R1), international students (C1), journal articles (O1), the nation's best three universities by the Shanghai ranking (O5) and unemployment rate (O9).

League B: League B includes 17 countries and 6 indicators from the resources (R3-5) and output O3-5) categories. The 17 countries of League B are from the middle and lower segments 14-49) of the original U21 ranking, except the Netherlands (which can be found in the 7th place of the original U21 ranking). This result shows that League A is better separated from the midfield league than League C. The applied method (BicARE) assigned those countries and indicators to this league, which became more similar after bi-clustering. Environmental indicators belong to A^+ because of their higher means and lower variances. The absence of connectivity indicators could be caused by their large variance.

An important aspect to consider is whether the results obtained are consistent over time. To examine this, the author conducted further analyses on the 2020 dataset of U21 (U21:2020), to compare the changes observed with those in the year 2014 (U21:2014). It is worth noting that 2020 was the final year when the organization responsible for U21 published its country ranking.

In the U21:2020 ranking the number of countries is the same as in the U21:2014 ranking. However, between the 2014-2020 period, several changes were made in the indicators and their weights. New indicators were introduced, for example, E5 which comes from the responses to a survey: „How well does the educational system in your country meet the needs of a competitive economy?" (see more details in Williams and Leahy, 2020).

The bi-clustering method was run on the U21:2020 dataset, searching for League A, League B, and League C. Figure 3.3 juxtaposes the outcomes of the 2014 and 2020 datasets through a Sankey chart. The left side illustrates the 2014 standings, while the right side shows the composition of leagues in 2020. Each side displays the count of countries within each league. The ribbons in the chart signify the transition of countries between leagues, and their width is proportional to the number of countries involved, as indicated by the numerical values on the ribbons.

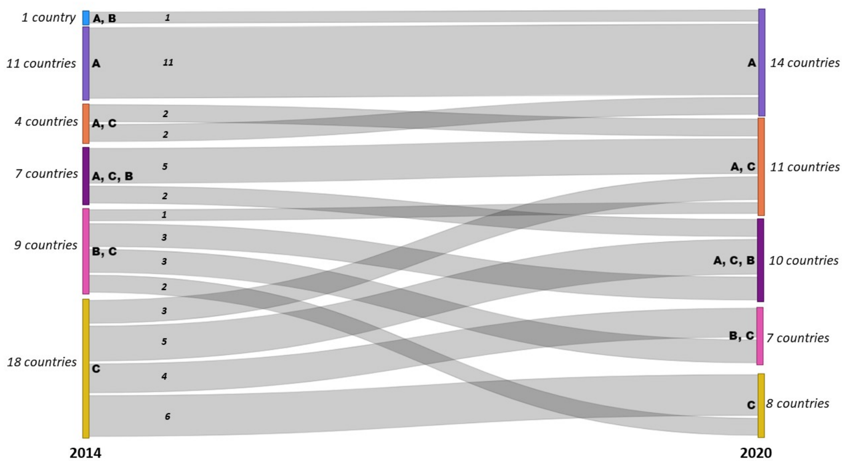

FIGURE 3.3: Comparison of the Results of the Leagues of U21:2014 to U21:2020

A notable contrast in the outcomes of the two years lies in the increased representation of countries in League A^+ in 2020, coupled with a decrease in the count of countries in League C^-. Specifically, the Netherlands, Belgium, and New Zealand successfully climbed up to League A^+ by 2020. In 2014, the Netherlands stood as the sole representative in League AB, while the remaining two countries were situated at the intersection of League A and League C (League AC). The other 11 countries that comprised League A in 2014 maintained their position within the same league in 2020.

Out of the 18 countries initially placed in League C^- in 2014, only six nations - Brazil, China, India, Korea, Slovakia, and Turkey - remained in the same league by 2020. This implies their lack of success in advancing across multiple metrics, including governmental expenditure on tertiary education institutions as a share of GDP (R1), the percentage of international students (C1), the number of journal articles (O1), and unemployment rates (O9).

In the case of the results of the RUR, Table 3.2 summarizes the results as follows: the number of universities and the indicators classified into each league (A, B, C) using different thresholds (0.5, 0.75, 0.9). The higher the threshold, the fewer the universities and indicators entering the leagues. Table 3.2 also indicates the specific indicators included in each league.

At a threshold of 0.5, the indicators marked with 'light gray background X' were classified into leagues A and C. The threshold does not affect the indicators in league B, denoted by X.

Out of the 20 variables, i) both leagues A and C included the same 17 indicators, ii) and 10 of them are in league B, too. Finding i) is interesting in two respects. On the one hand, the best institutions are the best in the same indicators as those in which the lagging universities are the worst.

The 10 indicators in finding ii) are the ones with the lowest variance in the universities included in league B; however, they are decisive in the fact that their high (low) value is required to league A (C) - in addition to

7 other indicators. These 10 variables played a role in the development of all three leagues:

- an interesting finding is that all three reputation surveys were included here:
  - T5 World teaching reputation
  - R5 World research reputation
  - I4 Reputation outside region
- R1 Citations per academic and research staff
- R3 Normalized citation impact
- R4 Papers per academic and research staff
- I1 Share of international academic staff
- I5 International level
- F1 Institutional income per academic staff
- F4 Research income per academic and research staff

To RUR's ***League A*** (at the 0.5 threshold), the algorithm assigned 398 institutions. In this League, we can find the Anglo-Saxon countries' most prestigious universities, like Cambridge, Imperial College London, Oxford, and Harvard. These institutions exhibit high scores in all the 17 indicators selected by the method. They have an average score of 0.7 (out of 1.0) on the Teaching (T) indicators with a high score of "World teaching reputation" (T5). They perform well in the Research (R) category as well, and have a high score of the "World research reputation" (R5).

In League A, Hungary is represented by two institutions: the Central European University and Semmelweis University. In the partial ranking, which includes only the indicators and universities selected by the bi-clustering method, the Central European University secures the 176th place, while Semmelweis is positioned at 322nd. The University of Cambridge (UK) claims the top spot, followed by Imperial College London (UK) in second place, and Caltech (USA) in third.

Compared to Harvard, Central European University (CEU) has a similar score of the number of PhDs awarded compared to the bachelor degrees awarded (T4), and also in the "Institutional income/students" (F2). CEU has lower scores on the reputation indicators (T5, R5, I4) but shows a higher scores for the proportion of international academic staff (I1), international students (I2), and international co-authored papers (I3). These results suggest that while CEU may have lower scores in reputation indicators compared to Harvard, it excels in internationalization aspects earning its position in League A.

In RUR's ***League C*** (at the threshold of 0.5) there are 430 institutions. Russia is represented by the largest number of universities, accumulating 17% of the institutions. It is followed by China and Iraq with 37 universities. Hungary has three institutions in League C: the Eotvos Lorand University, the University of Szeged, and the University of Debrecen. Eotvos Lorand University secures an impressive 43rd place, positioning it in the upper-middle range of the partial ranking. The University of Szeged holds the 121st place, and the University of Debrecen is at the 154th place. Gwangju Institute of Science and Technology (Republic of Korea) holds the 1st place, Ason University (UK) has the 2nd, and Istanbul Technical University (Turkey) has the 3rd spot.

These institutions show lower average scores for the 17 indicators. They have an average score of 0.26 (out of 1.0) for the "World teaching reputation" (T5), a similar value of the "World research reputation" (R5), and 0.3 for the "Reputation outside the region" (I4).

The ***League B*** of RUR has 280 institutions and 10 indicators. More than 20% of the institutions are from the USA, but notably, Russia also has 40 universities listed in this League. Only one Hungarian university can be found here: the University of Szeged.

California Institute of Technology (USA), Stanford University (USA), Harvard (USA), and Princeton (USA) hold the first four places in this League, and the University of Szeged secures the 75th position. Due to the method, the variances of these institutions and indicators are minimal.

To refine the results, leagues A and C were also generated to higher thresholds by the iBBiG method. This modifies columns A and C in Table 3.2. League B is not affected by changing the threshold, as it is determined differently (by the BicARE method). At a threshold of 0.75/0.9, the indicators marked with medium/dark gray background X remained in leagues A, and C.

The following focuses only on League A, which contains the best. At the threshold of 0.5, the high value of 17 indicators ensured the classification of an institution in the A-League, at the threshold of 0.75, 11 of them, and at the threshold of 0.9 only 3. The latter means that if we collect universities in a league with 0-1 normalized data above 0.9, only three indicators will determine the best institutions. These are the three international reputation surveys based on the annual data of the Academic Reputation Survey of Clarivate Analytics (which was implemented by Ipsos Media CT):

- T5 World teaching reputation
- R5 World research reputation
- I4 Reputation outside region: both teaching and research are taken into account, but only respondents' opinions matter who live outside the university region. The regions considered are as follows: Asia, Europe, North America, Oceania, and South America.

In order to see the changes in the results, the bi-clustering methods were also performed on the latest available rankings of RUR. The author ran the analyses on both the ranking of 2022 (RUR:2022) and the ranking of 2023 (RUR:2023) datasets. The RUR:2022 ranking still uses the same indicators as in RUR:2020. On the other hand, in 2023, RUR decided to change its three major survey-based reputation indicators to be more objective in their rankings. They "firmly believe that this data is far more valuable and will enable the evaluation of universities' reputation and their influence on society in a more balanced manner" RUR (2023).

The bi-clustering methods were run at different thresholds for the RUR:2022 ranking as well. The RUR:2020 results showed the dominance of the three reputation indicators at the 0.9 threshold, indicating that to become a world-class institution, the high value of these three indicators is required.

The outcome of the RUR:2022 further emphasized the dominance of the reputation surveys. At the 0.9 threshold of League A, four indicators remained. These included the three reputation survey indicators (T5, R5, I4), underscoring the sustained influence of reputation-related metrics. Additionally, a financial metric measuring institutional income per student (F2) found a place among the influential indicators in this league.

Since the RUR:2020 and RUR:2022 bi-clustering results showed the dominance of the reputation-based indicators, the author was curious whether the new three indicators that were introduced to replace them would dominate again or not.

The "World teaching reputation" (T5) was changed to "Online visibility" which measures the university's prominence and the frequency with which users access its resources via the Google search engine (RUR 2023). The "World research reputation" (R5) was changed to "Social media visibility" which assesses the university's level of engagement with its audience across key social media platforms like Facebook, Twitter, Instagram, LinkedIn, or YouTube. The "Reputation outside region" (I4) was changed to "New media impact" representing the average number of subscribers to a university's social media resources.

The bi-clustering results of RUR:2023 for League A showed that these three new indicators remained again in the top league at the threshold of 0.9. This result underscores not just the robustness of the bi-clustering method, but also the importance of these indicators. Even though the measurements were changed to a "more object" method, the bi-clustering, and also the correlation analysis confirm that to become a world-class institution, it is a must to maintain a high level of media visibility. Studies showed that social media has a significant impact on students' decisions when selecting an institution (Constantinides and Stagno, 2012; Gautam and Bahl, 2020). As Generation Z, known for its high reliance on social media (Mude and Undale, 2023), shapes perceptions about institutional reputation based on content observed on platforms such as Facebook, Instagram, YouTube, and others, the significance of media visibility in the academic landscape becomes increasingly evident.

As the outcome of the dissertation, four theses were defined:

Thesis 1. The proposed method can simultaneously find homogenous Leagues, containing the maximum possible number of indicators and entities (countries or institutions). The proposed method is capable of identifying three primary types of Leagues.

Thesis 1. 1. The Top League (A) includes the maximum number of indicators and entities (countries or institutions) that exhibit performance above a predefined threshold in terms of the selected indicators determined by the method. The Lower League (C), in contrast, contains entities that demonstrate performance below a specific threshold with respect to the method-selected indicators.

Thesis 1. 2. The Middle League (B) includes the highest possible number of entities (countries or institutions) that have the same performance level in terms of the indicators selected by the method.

Thesis 2. The proposed method is capable of defining overlaps of the Leagues. These intersections contain entities and indicators that are part of multiple Leagues, indicating the strength of these entities across multiple academic domains.

Thesis 3. The overlap results assist in establishing a developmental trajectory for entities. As these entities demonstrate strength across various academic domains, focusing on refining appropriate indicators can promote them into higher Leagues.

Thesis 4. The partial rankings made on the different Leagues can be considered fair as the entities in the Leagues are similar in nature.

Conclusion

When comparing countries or universities, the first and most fundamental question is which subjects can be compared and which indicators can be used in the comparison. In this regard, the author believes that the bi-clustering method can play an important role in ranking and benchmarking. Although interpreting bi-clustering is more challenging than explaining the results of traditional clustering, analyzing overlaps and separations provides an opportunity to understand why top countries or institutions are separated from others and why some of the entities belong to more than one league.

The proposed bi-clustering methods can identify common indicators that can be used for global rankings or benchmarks. Even if there is no common indicator, bi-clusters can be specified to define regional or partial rankings. This approach ensures that entities are evaluated based on comparable indicators rather than arbitrarily determined ones from a selected region. By analyzing the results of bi-clustering, one can gain a detailed understanding of countries belonging to the same league or those that are separated. This analysis can help to identify the strengths and weaknesses of a given HES. Additionally, one may uncover a point of necessary intervention (refer to Figure 4.1).

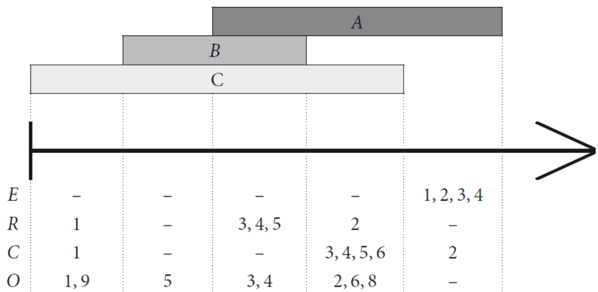

FIGURE 4.1: Development opportunities among leagues

The implications of using the bi-clustering method for ranking and benchmarking countries or universities are significant and offer valuable insights for scholars in the field of higher education and global rankings. The adoption of bi-clustering allows for a more nuanced and sophisticated approach to understanding the factors that contribute to the success or differentiation of institutions.

The results of bi-clustering offer benefits not only to scholars but also to students. Rather than relying on pre-selected indicators that rank all entities uniformly, students can use bi-clustering to compare institutions within the same League. This allows them to identify a group of universities that share their preferred fields of study or research areas and allows for a fair comparison of the institutions.

Bi-clustering and university Leagues offer unique advantages that go beyond traditional ranking methods, providing decision-makers with valuable insights and tools to improve their decision-making processes. The method allows decision-makers to identify the subjects and indicators that can be meaningfully compared across countries or universities. This ensures a more accurate and relevant evaluation of entities, as it focuses on comparable factors rather than arbitrary criteria.

Publications

Most of the introduced methodologies and figures are previously appeared in the scientific articles listed below:

1. Zsolt T. Kosztyán, Zsuzsanna Banász, Vivien V. Csányi, and András Telcs (2019). "Rankings or Leagues or rankings on Leagues? - Ranking in fair reference groups". In: *Tertiary Education and Management* 25.4, pp. 289–310. DOI: 10.1007/s11233-019-09028-x. URL: https://link.springer.com/article/10.1007/s11233-019-09028-x

2. Zsolt T. Kosztyán, Zsuzsanna Banász, Vivien V. Csányi, and András Telcs (2019). "Felsőoktatási ligák, parciális rangsorok képzése biklaszterezési eljárásokkal". In: *Közgazdasági Szemle* 9, pp. 905–931. DOI: 10.18414/KSZ.2019.9.905. URL: https://ideas.repec.org/a/ksa/szemle/1861.html

3. Zsuzsanna Banász, Zsolt T. Kosztyán, Vivien V. Csányi, and András Telcs (2022). "University Leagues alongside Rankings". In: *Quality & Quantity* 57.1, pp. 721–736. DOI: 10.1007/s11135-022-01374-0. URL: https://link.springer.com/article/10.1007/s11135-022-01374-0

4. Zsolt T. Kosztyán, Zsuzsanna Banász, Vivien V. Csányi, László Gadár, and András Telcs (2020). "Egyetemi rangsorok tudománymetriai és statisztikai megalapozással". In: *Statisztikai Szemle* 98.8, pp. 930–957. DOI: 10.20311/stat2020.8.hu0930. URL: https://www.ksh.hu/statszemle_archive/all/2020/2020_08/2020_08_930.pdf

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