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Pro-Metrics

ORIGINAL ARTICLE

Neural longitudinal mapping of multidimensional performance profiles of Latin American universities

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ABSTRACT

Objective. To introduce an artificial intelligence method and to use it to analyze the evolution of the multidimensional performance profiles of the most prominent Latin American universities, according to the Times Higher Education Latin America University Rankings.

Design/Methodology/Approach. To multidimensionally characterize universities' performance profiles, we use the rankings' sub-scores indicators, which quantify five dimensions of academic endeavor assessed by this ranking. Our method uses an artificial neural network to compare and visually analyze the evolution of performance profiles automatically.

Results/Discussion. The neurocomputational procedure allowed us to discover all the characteristic performance profiles of the 50 best-ranked universities (20 institutional profiles in 2019) and to visualize, in a knowledge map, the universities' groups sharing similar profiles. Furthermore, the profile's evolution of this group of universities was analyzed, and visually displayed in a sequence of knowledge maps covering the four-year period 2016-2019. In general, these universities showed a remarkable improvement in teaching, research, and citation scores from 2016 to 2019. The profile diversity of the best-ranked universities and the predominance and homogenization process of Brazilian universities' profiles are noteworthy.

Conclusions. Performance profile characterization using multiple indicators is a matter of interest in diverse domains. However, visualization or comparison of multidimensional performance profiles is not easy for the human mind. Even more challenging is the visual analysis of multidimensional performance profiles evolution. The neuro-longitudinal technique introduced is useful for analyzing and visualizing the evolution of multidimensional performance profiles.

Originality/Value. The approach and techniques introduced in the paper have an important degree of generality and can be used to analyze other rankings or multidimensional data.

Keywords: multidimensional temporal data visualization; self-organizing maps; THE Latin American university ranking; neural longitudinal mapping; SOM neural network; university performance profile.

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1. INTRODUCTION

1.1. Multidimensional performance profiles evolution

Progress in developing bibliometric indicators has favored the quantitative characterization of academic performance profiles of institutions, countries, or researchers. Each indicator quantitatively estimates performance in a particular dimension of academic accomplishment, and, from a holistic perspective, a set of several indicators produces a multidimensional characterization of an academic performance profile.

However, dealing with multidimensional profiles is not : we have to face the human mind's limitations in imagining and comparing objects in abstract spaces of more than three dimensions. To make sense of a multidimensional profile of any unit of analysis, it must be considered in the relative perspective of an appropriate set of 'peers'. For instance, a university's multidimensional performance profile must be assessed in the context of other universities' performance profiles.

Two fundamental challenges arise when carrying out multidimensional profile performance assessment of an analysis unit (e.g university). Firstly, we need to develop techniques that are helpful in carrying out profile comparisons: it is desirable to have visual representations that allow us to identify particular profiles in their peers' context. Assuming that a set of academic entities is given and their profiles have been appropriately compared, the second challenge is to develop techniques to picture their evolution during some specified time interval.

Diverse efforts have been directed to analyze multidimensional profiles and to face these two problems. For instance, some authors have developed techniques and software tools for the comparison and clustering of multidimensional profiles by means of 2D projections: Van Eck & Waltman (2007, 2010) developed the software system VOS-Viewer, supporting multidimensional scaling based on distance-based maps, built from co-occurrence matrices. More recently, Villaseñor-García *et al.* (2017) developed a neural network-based methodology implemented in the software system LabSOM to automatically compare and visualize universities' multidimensional performance profiles. Other authors have resorted to spider charts to visualize the profile evolution of an individual academic entity (Glänzel, 2000; García *et al.,* 2012).

Here, we develop an analysis and visualization technique based on a machine learning algorithm capable of dealing with the complexity of multidimensional data. With it, we compare Latin American universities' multidimensional performance profiles and provide visualizations which facilitate knowledge discovery. The analysis is based on the *Times Higher Education Latin America Ranking's* data (THE-LA, 2019). This technique allowed us to graphically represent current states and Latin American universities' performance profile evolution during 2016-2019.

1.2. University rankings

In the last decades, diverse university rankings have increased. They serve students to choose universities, governments to define policy, and universities authorities to assess academic performance (Hazelkorn, 2015). Rankings' producerRankings' producers have devised a variety of criteria and mathematical formulations have devised a variety of criteria and mathematical formulation producers to calculate academic performance indicators or compounded indexes to rank, with just one number, universities' academic performance. These approaches have widely accepted, and simple, one-dimensional rankings are very common in other social activities like sports. But this is a naive one-dimensional approach to simplifying, which has a more complex nature.

Most influential rankings use a weight-and-sum methodology to calculate the Overall index used to rank universities (e.g. Academic Ranking of World Universities (ARWU), Quasquarelli Symonds (QS), and The Times Higher Education Ranking (THE). These compounded indexes produce an ordered list starting with 'the best university' according to the ranking. The oversimplified perspective is welcomed by those not aware of the variety of goals and complexity of universities' academic activity and overlooks the diversity of universities' performance profiles (Wende & Don, 2009). We do not expect a physician to measure our health with just one number but by analyzing a complex set of physiological indicators. Similarly, universities' assessments must be approached from a multidimensional perspective.

Generally, rankingoverall scores are based on their calculation in terms of lower level indicators (sub-scores) and assessing various academic activities and endeavors. For instance, The Times Higher Education Ranking (THE) considers five sub-score indicators. However, the general public and news media overlook these indicators and tend to pay attention exclusively to the information provided by the overall score (Soh, 2017b). This implies a waste of worthy information, but it is understandable since comparing universities, characterized by multiple indicators, is not an easy task but represents a major challenge.

Following this line of thought, there are rankings that avoid using a composite 1-D indicator and emphasize the importance of a multidimensional perspective in comparing universities (e.g., U-Multirank, 2021; Leiden Ranking, 2021). In general, there has been a reiterative call to multidimensionality in the assessment of universities. Still, the lack of computational and visualization tools for multidimensional data has limited the advancement on this matter.

Some rankings provide charting tools for the users interested in going beyond the Overall. . Still, it proves difficult to carry outStandard charts (spider, bar, and line charts) are useful resources for analyzing individual universities. Still, they prove difficult to carry out in more complex group studies. A popular charting tool is scatter plots which provide linear 2D projection, and permit the examination of the data from different projected perspectives, e.g., Leiden's Chart View (Leiden Ranking, 2021). Nevertheless, these visualizations have limitations in terms of search patterns in multi-dimensional data (Moed, 2017) and are not suited to perform temporal analysis with a multidimensional perspective.

Besides the issues described above, rankings' realm has been previously analyzed with other objectives and perspectives. However, to the extent of our knowledge, rankings have not been analyzed using the novel visualization approach we are introducing in this paper. Some authors studied socio-political and economic implications (Marginson & Van der Wende, 2007; Hazelkorn, 2015; Peters, 2019) or described and benchmarked university performance and rankings (Çakır *et al.,* 2015; Millot, 2015; Tsvetkova & Lomer, 2019), and others have criticized ranking methodologies (Fauzi *et al.,* 2020; Williams and De Rassenfosse, 2016; Soh, 2017a; Kim, 2018; Luque-Martínez & Faraoni, 2020).

2. DATA

Our analysis is based on Times Higher Education Latin America University Rankings (THE-LA) data. This ranking must be differentiated from the more general Times Higher Education World University Rankings (THE-WUR). THE-LA has adjusted its methodology to account for regional peculiarities. Therefore, we find that the order of relations among some universities might change if we compare them with the global ranking. Still, this difference does not affect the purposes of the present investigation.

The first edition of THE-LA ranking was launched in 2016, and our study covers the versions published from 2016 to 2019. It assesses universities' performance by measuring five-dimension indicators of academic activity (sub-scores): Teaching, Research, Citations, International Outlook, and Industry Income. We use these five sub-score indicators, without weights, to characterize the performance profile of each university. No scaling or normalization was needed, because all the indicators have the same range of variation: from zero to one hundred. The five-dimensional indicators and one-dimensional rank (overall) are publicly available on the web page of THE-LA ranking.

3. METHODS

The self-organizing map (SOM) algorithm is a neural network technique (Kohonen, 2013) that has proved to be useful in diverse data science applications, particularly in science mapping studies to visualize multidimensional data (White, Lin, & Mccain, 1998; Sotolongo-Aguilar *et al.* 2001 & 2002, Polanco, 2001; Guzmán *et al.* 2014; Moya-Anegón *et al.* 2006; Skupin *et al.* 2013; Villaseñor, *et al.* 2017; Arencibia, *et al.* 2016; Ruíz-Coronel *et al.* 2020).

Despite the many applications of SOM neural networks (SOM-NN) in diverse knowledge domains, they have not been used yet to carry out a longitudinal analysis. This is because of some difficulties that preclude using SOM algorithms for temporal analysis, but the methodology introduced here overcomes these technical difficulties. It is applied to tackle two main tasks:

(1) Classification. The multidimensional performance profiles compare the 50 best-ranked Latin American universities, plus the identification of those groups of universities that share the most similar profiles.
(2) Profile dynamics. The evolution analysis during 2016-2019, of the various multidimensional performance profiles identified by the neural network for this group of universities.

3.1. SOM neural network

The SOM neural network uses an unsupervised training method to discover data set structure. It has two layers of neurons: an input layer with as many neurons as the number of indicators used to characterize the performance profiles and an output layer, which is a hexagonal grid of neurons in a 2D space. Every neuron is associated with a weight vector that belongs in the input data space (Kohonen, 2013).

During the training phase, all the profile data (vectors in a multidimensional space) are sequentially presented to the input layer, triggering an adaptive process by which the output layer neurons compete to determine the winning neuron to which the vector data will be assigned. Each iteration adjusts the weight vectors associated with neurons to resemble the data they won. Once the training process ends, all the input data (universities' profiles) are distributed in the output layer so that neurons close in this neural plane grid will receive similar data.

The output layer hexagonal grid of neurons is colored to create visual sceneries or knowledge maps. In this paper, we use visual sceneries called cluster maps and Component *maps*. The software tool we employ uses Vesanto's methodology (Vesanto, Alhoniemi, 2000) to create a cluster map, which applies an agglomerative hierarchical clustering algorithm over the output layer's weights and assigns the same color to the neuron's hexagons belonging to the same cluster. To interpret the implicit knowledge in the Clusters map, we display five Component maps corresponding to each of the five indicators we use to define the universities' performance profiles: Teaching, Research, Citations, International Outlook and Industry Income. Accordingly, in this paper, we will refer to them as Dimension maps. Dimension maps are colored according to a chromatic scale, assigning red to those map's zones where the highest indicator values appear, green to the lowest, and yellow to intermediate indicator values.

3.2. Classification

As pointed out in the introduction, to make sense of the multidimensional profile of any unit of analysis, it must be considered from the relative perspective of an appropriate set of 'peers'. Mathematically, the performance profile of each university is represented as a point in a multidimensional space. In this space, groups of universities with similar profiles form cluster points. Each cluster (class) is interpreted here as a qualitative profile. The SOM neural network can identify this cluster structure in the data set and generate a 2D Cluster map to display it. This solves the problem of identifying and comparing profiles in a multidimensional space. The SOM neural network positions each profile in this Clusters map, considering their peers' context, enabling us to visually assess each profile relatively to the others.

3.3. Profile dynamics

Once the universities' qualitative profiles have been identified, it is natural to investigate the profile dynamics: What universities have changed their profiles, and what type of changes they have experienced? How do these profile changes compare with those of other universities?

To answer these questions, we resorted to the classical Garfield's longitudinal mapping idea (Garfield, 1994). Garfield analyzed data evolution, creating a sequence of maps that constitute time slices of the state of things in different moments. Here, we develop a way of doing so using a SOM-NN. To the best of our knowledge, this has not been done previously. It is the case that a straightforward application of the SOM algorithm to longitudinal mapping does not give positive results: if we execute the training algorithm separately for each year's data, map's orientation changes, precluding visual comparisons, and results interpretation. This problem arises due to the inherent stochasticity of the neural network learning algorithm. Maps orientation usually changes, even when we run the algorithm with the same data. However, here we demonstrate that a neuro longitudinal mapping sequence can be obtained with satisfactory results through a simple technical procedure that does not require changes of the SOM-NN's training algorithm but an appropriate selection of hyperparameters and initial synaptic weights.

During the training process of the SOM, two main phases are conceptualized: a global ordering phase to identify the gross data patterns and a refinement phase to explore data structure at a higher level of detail. The crucial observation that led us to the development of our procedure is that universities' profiles do not change drastically from year to year, nor do the gross distribution of the fifty universities' profiles substantially change. Consequently, from the second year of the maps sequence on, we can use the weights that resulted from the previous year's training. These weights are convenient because they were previously adapted to the data's global structure; therefore, the training for the next longitudinal map will only be used to identify small profile changes.

However, the execution of a standard training with weights from the previous year is not enough. Good results are not obtained because the neural network training will mess up the structure provided by the chosen initial weights. To fix this, we have to find a way to go directly to the refinement training phase, skipping the global ordering phase. We have found that this can be achieved by choosing small values for the learning factor and the neighborhood size in the hexagonal grid, simulating an advanced stage of the training process in this way.

In summary, the procedure follows: for the first year, execute a full training, starting with the weights randomly. For the other three years, choose the initial weights of the ones resulting from the previous year's training and then skip the global ordering phase to execute only the refinement phase of training.

We tested the procedure with the batch and online version of the training algorithm (Kohonen, 2013), getting positive results. The maps presented in this work were obtained using an online algorithm.

The hyperparameters of the online algorithm are the number of training epochs (presentation of the full data set), the initial value of the neighborhood function's size (sigma), and the initial value of the learning factor (alpha). We use a rectangular neural grid with 10 x 20 hexagons.

The software tool we use (LabSOM) linearly decreases sigma and alpha as the number of epochs increases. Sigma is decreased from the initial value to 1 and alfa from the initial value to 0.02. Table 2 shows the hyperparameters used in this paper to generate the longitudinal map sequence for 2016-2017-2018- 2019.

	2016: Full training	**2017, 2018, 2019: Refinement training phase**
Initial weights	Random	Previous year's trained weights
Initial sigma	7.5 (one half of grid's average size: ½ * (10+20)/2)	1.875 (one eighth of grid's average size: ⅛ * (10+20)/2)
Initial alfa	0.9	0.1
Training epochs	1000	200

Table 1. Hyperparameters used to create the neuro longitudinal mapping for the years 2016-2017-2018- 2019.

3.4. Software Tool

Thehe neural net was trained with LabSOM, a free software tool developed at the Nonlinear Dynamics Laboratory from the Faculty of Sciences, National Autonomous University of Mexico (Jiménez-Andrade *et al.* 2019).

4. RESULTS AND DISCUSSION

The organization of this section is as follows:

1. Firstly, we analyze the evolution of the Latin American countries' participation in both Times Higher Education World University

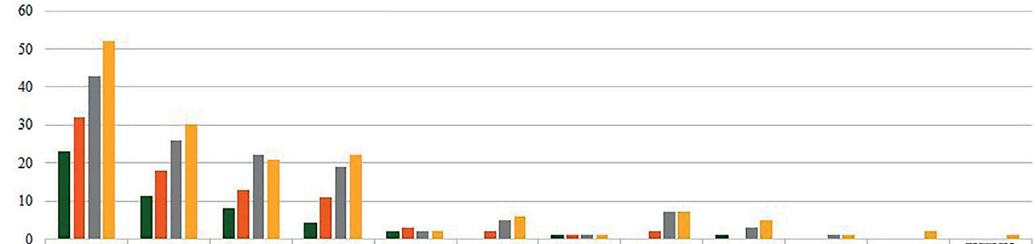
Rankings (THE-WUR) and Times Higher Education Latin America University Rankings (THE-LA). This is done to contextualize the performance of Latin American universities in the worldwide context.
2. Next, we introduce neurocomputational techniques to:
   i) Compare the top 50 universities' profiles, identify all qualitative profiles of this university set, and display them in a clusters map which exhibits those universities sharing similar profiles in the year 2019;
   ii) analyze the profiles' evolution from 2016 to 2019 utilizing a longitudinal neuro-mapping.

4.1. Rankings evolution

From 2016 to 2019, the presence of Latin American universities in the Times Higher Education World University Rankings (THE-WUR) has tripled, going from 28 in 2016 to 87 in 2019, representing only seven percent of the 1,258 universities included in the 2019 THE-WUR ranking.

A position in the interval 251-300 of THE-WUR ranking is the best achieved by a Latin American University since 2016, and the University of São Paulo has occupied it. Due to criteria differences, there are discrepancies in order ranks among THE-LA and THE-WUR. For example, the Pontifical Catholic University of Chile occupies the first place of THE-LA 2019 ranking, while the University of São Paulo is the best ranked of all Latin American universities in THE-WUR 2019.

The THE-LA ranking tripled its size from 2016 to 2019 (Fig. 2 & 3): it started in 2016 with 50 universities from 7 countries ending in 2019 with 150 universities from 12 countries; the major growth was from continental universities. Note in Figure 3 the 12 countries that have universities in the top 50 places of the rank and the relevance of public universities. Another observation is that Caribbean countries remain underrepresented in this ranking.



	BRAZIL	CHILE	MEXICO	COLOMBIA	VENEZUELA	ECUADOR	COSTA RICA	ARGENTINA	PERU	JAMAICA	CUBA	PUERTO RICO
2016	23	11	8	4	2	0	1	0	1	0	0	0
2017	32	18	13	11	3	2	1	2	0	0	0	0
2018	43	26	22	19	2	5	1	7	3	1	0	0
2019	52	30	21	22	2	6	1	7	5	1	2	1

Figure 1. Evolution of the number of Latin American universities participating in *THE-LA* ranking, 2016-2019.

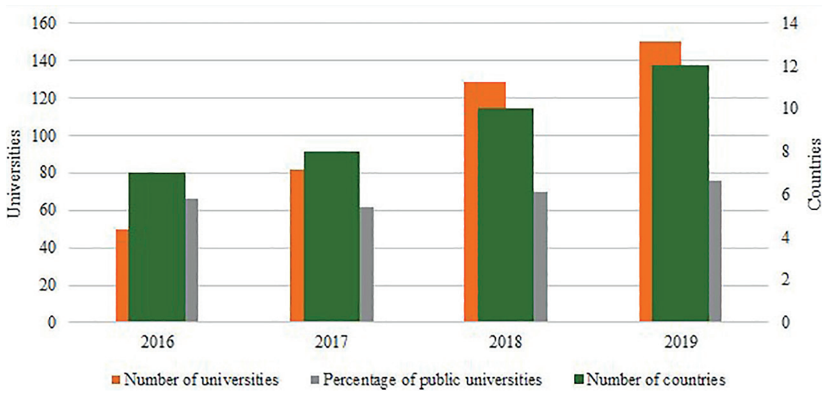


Figure 2. Evolution of participant countries and universities in *THE-LA* Ranking, 2016-2019. Percentage of public universities is read on the left scale.

4.2. Top fifty Latin American universities

For the profile analysis we consider the universities that have been ranked in the first 50 places of THE-LA at least once during the period 2016-2019. Since the set of universities ranked in the first fifty places varies from year to year, there are variations in the 50 universities groups: some of the lower-ranked universities may go out, leaving a place for others to get into the group. Therefore, the number of universities that have been in the top 50 from 2016-2019 adds up to 80 (Table S1).

The leading countries in this ranking are Brazil, Chile, Mexico, and Colombia, which have outstanding scores compared to the rest of Latin American countries. However, the supremacy of Brazil in this group is unquestionable since the first regional ranking edition in 2016 (Figure 2 & Table 2). During the period 2016-2019, forty-six percent of the top fifty places were occupied by Brazilian universities. One notable absence in this leader group is Argentina, despite its higher education system size similar to Chile, Mexico, and Colombia and its comparable Scopus' scientific production per one thousand inhabitants (Albornoz & Barrere, 2019). Nonetheless, almost half of its participant universities are in the top 50 in 2019 (3 of 7 universities) and 5 of 7 in 2018.

Among the leading countries, Colombia increased its presence the most in THE-LA, going from 4 universities in 2016 to 22 in 2019 (Figure 2). However, only 4 ranked in the top 50 (Table 2). Chile and Mexico almost tripled their participation in THE-LA, but both countries lost positions in the top fifty: Chile lost three positions from 2016, and Mexico lost 4. Meanwhile, Brazil doubled its participation in the THE-LA ranking, keeping its half-share of the top fifty, with 2017 as the only exception.

Country	2016	2017	2018	2019	Total 2016-19
Brazil	23	18	24	25	31
Chile	11	16	9	8	16
Mexico	8	6	4	4	10
Colombia	4	5	4	4	7
Venezuela	2	3	1	0	3
Ecuador	0	1	0	0	1
Costa Rica	1	1	0	1	1
Argentina	0	1	5	3	6
Peru	1	0	2	2	2
Jamaica	0	0	1	1	1
Cuba	0	0	0	1	1
Puerto Rico	0	0	0	1	1
TOTAL	**50**	**51**	**50**	**50**	**80**

Table 2. Distribution by country and year of the number of universities in the top fifty THE-Latin American ranks.

4.3. Neurocomputational comparison of multidimensional institutional performance profiles

The analysis is automatically performed by a SOM neural network of 200 neurons, and its results are displayed in a set of six maps (Figure 5). One of these maps is the 'clusters map', a cartography whose colored regions (clusters) represent universities' groups sharing similar profiles. Accompanying the clusters map, five 'dimension maps' are also displayed in Figure 5. Each of these dimension maps is a heat map replica of the clusters map, associated with one of the dimension indicators, and constitutes a visual tool for interpreting the clusters maps. The dimensions indicators' values range from zero to 100, and the five maps use a chromatic scale ranging from green to red. Red represents the highest value of the indicator for this set of universities, yellow the mean value of the scale (50), and green is the lowest one.

Universities belonging to the same cluster, will have similar performance profiles but will not necessarily be close in rank since the similarity measure has not been weighted- among other reasons. For example, if we look in the clusters map of Figure 5 for the universities 24 USACH.CL (University of Santiago de Chile) and 48 UH.CU (University of Havana), we see that they occupy very different places in the rank (24th and 48th), but both belong to cluster C13. This cluster is coloured green in the Citations map, meaning these universities have low values of the citations indicator. To completely understand what it means for a university to belong to this cluster, we look at the colors of this cluster in the other dimension maps (Teaching, Research, and International Outlook were colored orange, meaning these two universities have above-average values in these indicators).

The absence of green color in the Teaching and Research dimensions' maps, contrasts with the rest where the green areas (low values in the indicators) are more extended. So, most universities in the top 50 perform well in these two dimensions. On the other hand, the extended presence of green color in the other dimensions maps reveals more differences among these universities in the other three indicators.

Dimensions maps are also useful for visually discovering the five indicators' correlation degree. In Figure 5, we clearly see the coloration similarity between the Teaching dimension's map and the Research dimension's map. Meaning that, for the universities of this sample, there is a high degree of correlation among those. Analyzing the coloration patterns of the dimensions' maps we also see that the rest of the indicators are not very correlated and that the zone where cluster C1 lies are privileged. It is the hottest region of the map - where the red color is predominant. The best ranked university UC.CL (Pontifical Catholic University of Chile) lies in this cluster. This university lies in the map's lower right region, with four little clusters (C1, C3, C8, C20) outstanding for its high Industry Income. We also see that 5 ITESM.MX shares a cluster with the first-ranked university (UC.CL), so they have very similar profiles. Observe that 2 USP.BR is better ranked than 5 ITESM.MX, but its profile is farther away from UC.CL's.

For this set of 50 universities and the 2019 data, the SOM identified 20 institutional profiles (20 clusters in Figure 5). Some profile types are shared by several universities (e.g., C2 contains three universities and C15 contains 7), but there are four universities with singular profiles: 4 PUC-RIO.BR (Pontifical Catholic University of Rio de Janeiro), 20 PUCP.PE (Pontifical Catholic University of Peru), 45 UDEC.CL (University of Concepción) and 18 UAM.MX (Metropolitan Autonomous University of Mexico). Notice that these profiles are not quantitative outliers due to out-of-range indicators but because of their peculiar profiles. Most clusters have universities from two or more countries (eleven clusters: C1, C5, C6, C8, C10, C13, C14, C16, C17, C18, C19). But five clusters (C2, C4, C7, C9, and C15) contain most Brazilian universities (18 of the 25 Brazilian Universities).

Notably, all Brazilian profiles (except 41 UFABC.BR) are concentrated in the lower half of the cluster map (below the diagonal that descends from left to right) and most non-Brazilian universities lie above. So, Brazilian universities' profiles are relatively homogeneous, characterized by high scores in Teaching and Research dimensions, but not so high in Citations, Industry Income and International Outlook. Four PUC-RIO.BR, three UNICAMP.BR and two USP.BR, leaders of the Brazilian group, are exceptions, having high values in these last three indicators.

After 25 Brazilian universities, eight Chilean universities constitute the second largest group in the top fifty of the rank, with two of them ranked in the top 10. Contrasting with Brazilian profiles, there is a group of five Chilean universities situated on the map's right side; three of them differentiate the most from the Brazilian profiles on the map's upper right side.

There are also two groups of non-Brazilian universities under the diagonal (9 UNIANDES.CO, 7 UCHILE.CL, 1 UC.CL, 5 ITESM.MX) and (50 IPN.MX, 36 UDEA.CO). The first group, with very good scores in all indicators, ranks in the top 10 and shares with 4 PUC-RIO.BR a triangular zone in the lower right corner of the map. The second group, surrounded by Brazilian Universities in the map's lower left corner, has high Teaching and Research values but low Citations and International Outlook scores.

Interestingly, best Citations scores were not obtained by the best-ranked universities or leading countries, but by universities from countries with less participation in the top fifty group (Jamaica, Costa Rica, Puerto Rico and Colombia). It calls for our attention that the presence of universities 37 UCR.CR and 49

UPR.PR is outstanding in the highest citation region despite having the lowest scores in Research. Another four universities, 25 UPCH.PE, 27 AUSTRAL.AR, 28 PUJ.CO and 32 UWI.JM also scored very high in Citations, but they scored better in Research than 37 UCR.CR and 49 UPR.PR, which explains why they hold better positions in the ranking.

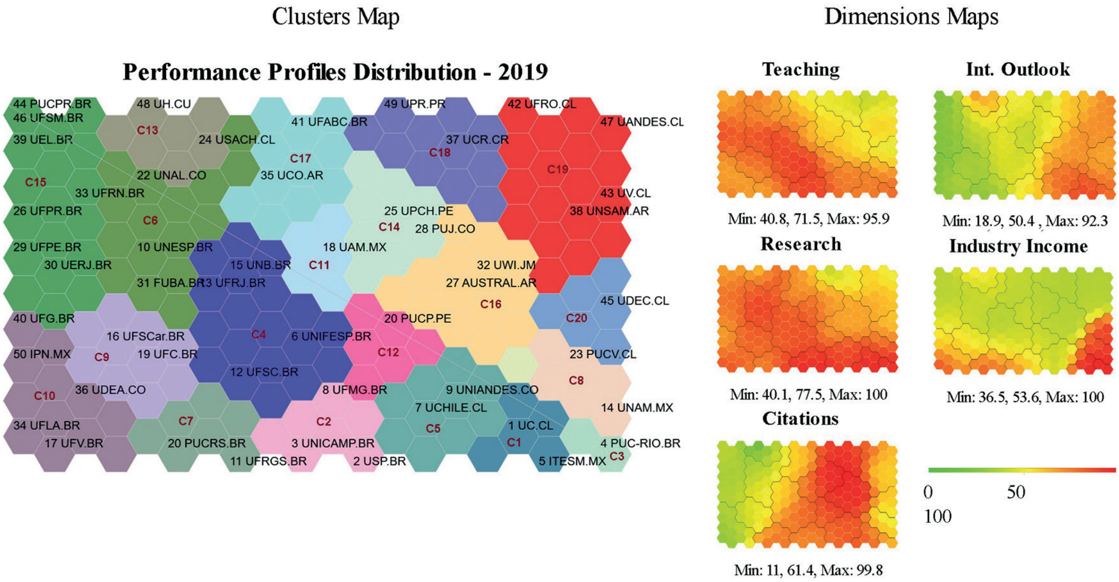


Figure 3. Multidimensional performance profiles in the first 50 universities of the *THE-LA* 2019 ranking. Each cluster is numbered with a label, *Cn,* where *n* is the cluster's number. The farther away two clusters are on the map, the more different their profiles will be. In the Clusters map, the acronyms for the universities' names are mapped together with their ranking number and the country's acronym (see acronyms in Table S2, supplementary material). Clusters/profile characteristics are visually encrypted in the heat maps associated with the five dimensions of academic activity: *Teaching, Research, Citations, International Outlook and Industry Income.* For example, the institutional profile of the universities *49 UPR.PR* and *37 UCR.CR* (cluster C18) is characterized by low values in *Industry Income,* high values in *Citations,* and average values in *Teaching, Research,* and *International Outlook.* We have added the minimum, average, and maximum values found in the data to each dimension map.

4.4. Neural longitudinal mapping (2016-2019)

In the previous section, we carried out a detailed analysis of the performance profiles of the more prominent Latin American universities in2019. It is also of interest to know what kind of changes this set of universities have been through. For this, in this section, we analyze the evolution from 2016 to 2019 of these universities' performance profiles by means of a neuro-longitudinal mapping, as reported in Figure 6.

It is convenient to observe changes in this neuro-longitudinal map sequence at three different levels of analysis: macro, meso, and micro. At the macro level, we observe color variations in regions of the heat maps corresponding to each one of the five considered indicators; at the meso level, we look for changes in the cluster structure; and at the micro level, we observe displacements of individual universities in the clusters map.

4.4.1. Macro level analysis

The most general level of analysis, e, macro level, is carried out by observing: 1) displacements of green and red zones in the sequence of heat maps; 2) evolutive trends of some university groups (e.g., Brazil's or Chile's universities).

As we go from one year to the next, the progressive dominance of the red color reveals a general improvement trend of the top fifty universities from 2016 to 2019. In particular, these fifty universities had a remarkable improvement in Teaching and Research scores, reaching 2019 without green color in the dimensions maps corresponding to these two indicators. In the Citations dimension, we also observe some improvements towards 2018 and 2019. Still, there have been no major changes in the International Outlook and Industry Income indicators during the four years of the analysis.

In the previous section, we observed that almost half of the top 50 Latin American universities are Brazilian, and most occupy the lower half of the clusters map of Figure 5. n the longitudinal map of Figure 6, we see how most Brazilian universities descended on the map to finish in 2019 below the diagonal. In particular, these universities developed profiles with very good performance in Research and Teaching but rather low International Outlook scores.

In contrast, in 2016, most Chile's universities concentrated on the upper right corner of the map. In 2017, in which Chile had its greatest participation in this rank, 14 of the 16 universities had performance profiles above the diagonal. Two exceptions were UC.CL and UCHILE.CL (ranked 3 and 4, respectively) which remained below or close to the diagonal during the four years of the study. So, in general, Chilean universities have profiles that are complementary with respect to Brazilian universities: they do not exhibit strength in teaching and research productivity, nor in industry income, but they have outstanding citation scores. Other countries have a smaller representation in this rank; we can not do this kind of analysis for them.

These results raise some questions. Are there factors that could explain the profile homogeneity of some countries? Could it be explained in terms of ideology or national policies? These are interesting questions but are beyond the scope of this study.

4.4.2. Meso level analysis

At this level, we focus on the cluster dynamics (cluster unions or divisions in Figure 6) and the migration of universities from one cluster to another. Cluster splitting may be interpreted as profile differentiation, while cluster unions as profile homogenization.

For instance, the cluster integrated by PUC-RIO.BR and ITESM.MX in 2016, is characterized by high values of Industry Income and above average (orange) values on the other four dimensions. In the following year (2017) UNAM.MX changed the profile, migrating to this cluster. In 2018, UDEC.CL also adopted this profile, but finally, in 2019, the cluster split itself, and PUC-RIO kept the original profile, meanwhile ITESM.MX, UNAM.MX and UDEC.CL incorporated themselves into other clusters. ITESM.MX's improvements in Research and Citations led it to join the best-ranked university in cluster C1, while UNAM.MX had a slight diminution in the Research and Citation indicators, which caused its integration to cluster C8 with PUCV.CL. We will comment more about UDEC.CL evolution in what follows.

Another instance of this behavior is found in cluster C5. In 2019, its profile was shared by UCHILE.CL and UNIANDES.CO, but during the years 2016 and 2017, this profile (cluster) was shared by UC.CL and UCHILE.CL. The next year, 2018, both universities differentiated their profiles, splitting the cluster. At that time, Colombian university, UNIANDES.CO, migrated from an adjacent cluster to join UCHILE.CL. In 2019, these two universities confirmed their performance profile similarity remaining in cluster C5.

In general, the profiles show considerable variability through the four years of analysis. Still, exceptionally, some profiles do not change every year, such as the two clusters that contain the four best-ranked universities. Notice that the cluster of USP.BR and UNICAMP.BR remained unchanged in the maps for the first three years of analysis and the cluster of UC.CL and UCHILE.CL did not suffer change in the maps of the first two years.

4.4.3. Micro level analysis

To analyze the evolution of particular universities, we observe their displacement on the cluster map. This type of analysis constitutes what we call micro-level dynamics.

The movement of a university to a new cluster implies a performance profile change. Still, small displacements within a cluster are not considered a profile change here. Most of the changes imply a movement from one cluster to an adjacent one in the maps (e.g., PUCRS.BR and UNIANDES.CO from 2018 to 2019). However, some universities go beyond, moving to a different zone, e.g., Mexican universities UAM.MX and IPN.MX.

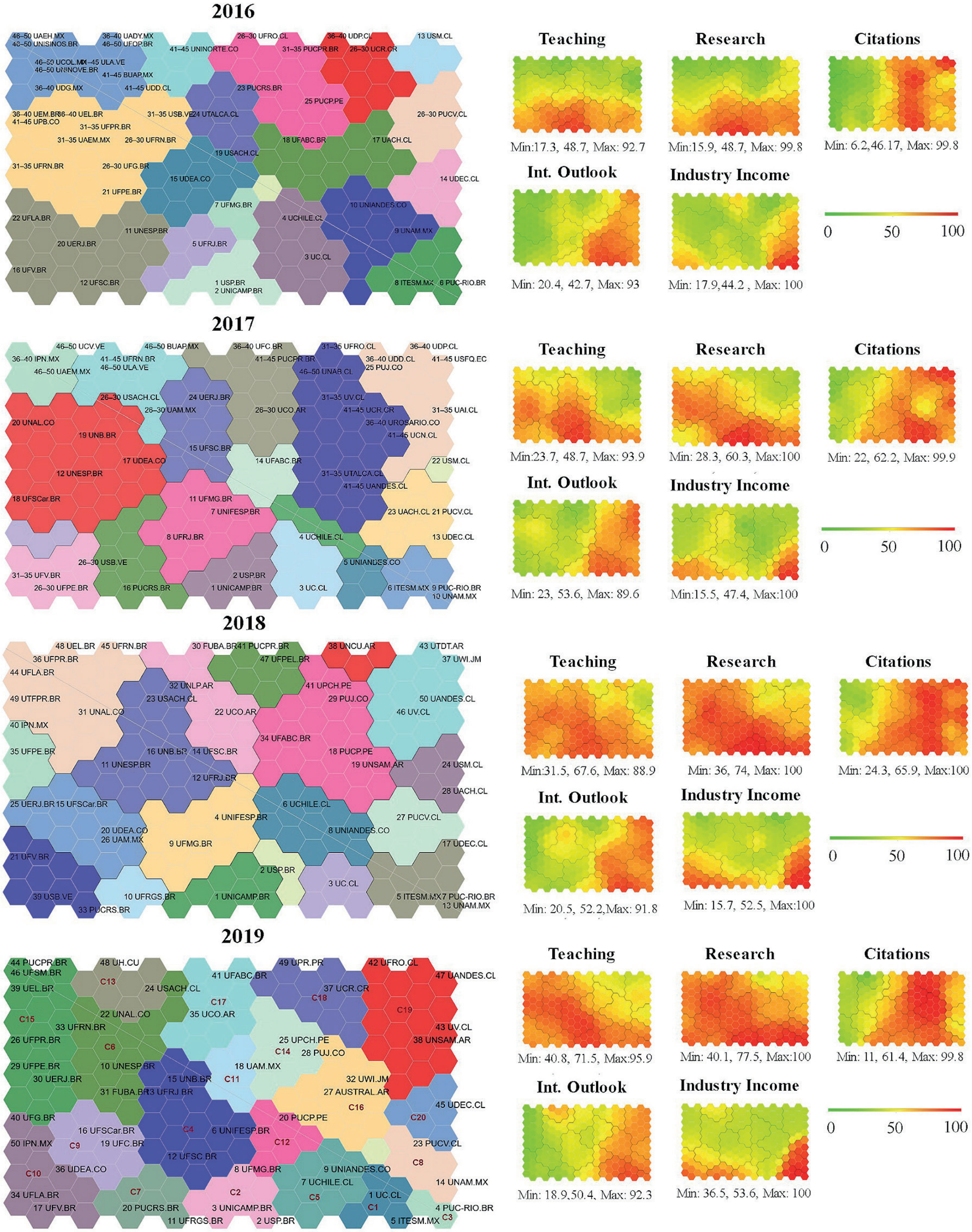


Figure 4. Longitudinal mapping by SOM. Evolution of the 50 Latin American universities' performance profiles from 2016 to 2019. On how to characterize the profiles, see Figure 5's footnote.

In section 4.4, we identified some universities that did not share in 2019 their profile with any other university, and we called them singular profiles (UDEC.CL, PUC-RIO.BR, UAM.MX). By looking for these universities in the map sequence, we observe that they shared their profile with other universities in previous years, confirming the transitory character of being a singular profile. Other cases are present in maps from previous years (UFRJ.BRA in 2016, USM.CL in 2017, and UC.CL in 2018).

As a closing example of this type of analysis, we consider the University of Costa Rica, UCR.CR, one of the best scores in Citations in 2019. This university caught our attention because 2018, it left the group of the best 50 universities in the ranking, but in 2019 it jumped to 37th place, improving in almost all dimensions. In 2016, it got the 26-30 interval position with a profile characterized by low values in Industry Income (green), below-average values in Teaching and Research (light green), and average values in Int. Outlook (yellow) and above average in Citations (light orange). The following year, it stayed in the same map's zone, and its cluster went from having two to eight members. Its profile did not change much. It had small improvements in International Outlook and Industry Income, but fell to the 41-45 interval position. This means that the decline in rank from 2016 to 2017 was not because of a worsening performance profile, but rather because the profile of other universities improved. In the last year under review, this university returned to the same map zone, achieving high values in Citations and average values in Teaching and Research.

5. CONCLUSIONS

It is reasonable to claim that universities' comparisons and assessments must be carried out considering multiple measures rather than a single weighted overall ranking. Therefore, going beyond table leagues and considering multidimensional performance profiles is a desirable but challenging objective.

A table league provides a one-dimensional order in which each university is linearly framed in the context of other universities, and dealing with this order relation represents an easy task for the human mind. However, comparisons of profiles characterized by more than three indicators force us to imagine clouds of points in an abstract Euclidean space: in the present case, we are using the five subscore indicators considered in THE Latin American ranking (THE-LA), so we would have to figure out the universities' profiles relative positions, in a 5-D space, where we do not have geometrical intuition.

Here, we have introduced a novel neuro-longitudinal technique that is a useful tool for analyzing and visualizing the evolution of multidimensional performance profiles. The application of this approach allowed us to compare and picture the profile evolution, during 2016-2019, of the most prominent Latin American universities, according to the THE-LA Ranking.

This neurocomputational procedure allowed us to automatically discover a variety of qualitative performance profiles of the best-ranked universities (20 institutional profiles in 2019) and to visualize, in a sequence of knowledge maps, the evolution of these universities' groups sharing similar profiles. In these maps, we can observe general trends, the predominance of some profiles, or the evolution of profiles of particular universities. In general, these universities showed a remarkable improvement in teaching, research, and citation scores from 2016 to 2019. The profiles' diversity of the best-ranked universities, and the predominance and homogenization process of Brazilian universities' profiles are noteworthy.

The relative profile stability of top-ranked universities raises the question of whether this is a more general regularity that could be observed in other rankings. A recent study on rankings dynamics observed an important degree of stability at the top of the ranking list (Iñiguez *et al.,* 2022). The maps sequence reveals evolution at different levels of analysis: at the macro level, color variations in the associated heat maps allow us to draw conclusions about the dynamics of the whole set of fifty universities; at meso level, cluster splitting may be interpreted as profile differentiation and cluster merging as profile homogenization; finally, the micro level analysis reveals profile changes of individual universities. The maps produced by the neural net encode a good deal of information and are a useful tool for ranking's users for diverse purposes. Besides the results referred to so far, they also allow us to identify visually:

1. The most abundant profiles in a region or a country
2. The profiles of the best-ranked universities of the region or a country

3. The better-ranked universities with a given profile
4. The universities with peculiar profiles
5. The profiles of the universities of a given country
6. The countries in which there are well-ranked universities with a given profile

It is worth mentioning that the approach and techniques introduced here have an important degree of generality and could be used to analyze other rankings or other country regions. Furthermore, beyond the education realm, this neural longitudinal mapping technique could also be applied to analyze multidimensional data evolution in different contexts of human activity (e.g., social, economic, political, etc.).

Conflict of interest

The author declares that there is no conflict of interest.

Statement of data consent

The data generated during the development of this study has been included in the manuscript.

Contribution statement

Conceptualization, Methodology, Investigation, Formal Analysis, Writing – review & editing: José Luis Jiménez-Andrade.

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APPENDIX

Table A1. Universities' full names and acronyms.

Full Name	Acronym	Full Name	Acronym
Adolfo Ibáñez University	UAI.CL	National University of San Martín	UNSAM.AR
Andrés Bello University (UNAB)	UNAB.CL	Nove de Julho University	UNINOVE.BR
Austral University	AUSTRAL.AR	Pontifical Bolivarian University (UPB) - Medellín	UPB.CO
Austral University of Chile	UACH.CL	Pontifical Catholic University of Chile	UC.CL
Autonomous University of Hidalgo State (UAEH)	UAEH.MX	Pontifical Catholic University of Paraná	PUCPR.BR
Autonomous University of Puebla	BUAP.MX	Pontifical Catholic University of Peru	PUCP.PE
Autonomous University of Yucatán	UADY.MX	Pontifical Catholic University of Rio Grande do Sul (PUCRS)	PUCRS.BR
Autonomous University of the State of Mexico	UAEM.MX	Pontifical Catholic University of Rio de Janeiro (PUC-Rio)	PUC-RIO.BR
Catholic University of the North	UCN.CL	Pontifical Catholic University of Valparaíso	PUCV.CL
Del Rosario University	UROSARIO.CO	Pontifical Javeriana University	PUJ.CO
Diego Portales University	UDP.CL	Rio de Janeiro State University (UERJ)	UERJ.BR
Federal University of ABC (UFABC)	UFABC.BR	Simón Bolívar University	USB.VE
Federal University of Bahia	FUBA.BR	State University of Maringá	UEM.BR
Federal University of Ceará (UFC)	UFC.BR	São Paulo State University (UNESP)	UNESP.BR
Federal University of Goiás	UFG.BR	The University of the West Indies	UWI.JM
Federal University of Lavras	UFLA.BR	Torcuato Di Tella University	UTDT.AR
Federal University of Minas Gerais	UFMG.BR	Unisinos University	UNISINOS.BR
Federal University of Ouro Preto	UFOP.BR	Universidad Central de Venezuela	UCV.VE
Federal University of Paraná (UFPR)	UFPR.BR	Universidad Peruana Cayetano Heredia	UPCH.PE
Federal University of Pelotas	UFPEL.BR	University of Antioquia	UDEA.CO
Federal University of Pernambuco	UFPE.BR	University of Brasília	UNB.BR
Federal University of Rio Grande do Norte (UFRN)	UFRN.BR	University of Campinas	UNICAMP.BR

Full Name	Acronym	Full Name	Acronym
Federal University of Rio Grande do Sul	UFRGS.BR	University of Chile	UCHILE.CL
Federal University of Rio de Janeiro	UFRJ.BR	University of Colima	UCOL.MX
Federal University of Santa Catarina	UFSC.BR	University of Concepción	UDEC.CL
Federal University of Santa Maria	UFSM.BR	University of Costa Rica	UCR.CR
Federal University of São Carlos	UFSCar.BR	University of Desarrollo	UDD.CL
Federal University of São Paulo (UNIFESP)	UNIFESP.BR	University of Guadalajara	UDG.MX
Federal University of Technology - Paraná	UTFPR.BR	University of Havana	UH.CU
Federal University of Viçosa	UFV.BR	University of La Frontera	UFRO.CL
Federico Santa María Technical University	USM.CL	University of Puerto Rico	UPR.PR
Fluminense Federal University	UFRN.BR	University of San Francisco, Quito	USFQ.EC
Londrina State University	UEL.BR	University of Santiago, Chile (USACH)	USACH.CL
Metropolitan Autonomous University	UAM.MX	University of São Paulo	USP.BR
Monterrey Institute of Technology and Higher Education	ITESM.MX	University of Talca	UTALCA.CL
National Autonomous University of Mexico	UNAM.MX	University of Valparaíso	UV.CL
National Polytechnic University (IPN)	IPN.MX	University of the Andes, Chile	UANDES.CL
National University of Colombia	UNAL.CO	University of the Andes, Colombia	UNIANDES.CO
National University of Cuyo	UNCU.AR	University of the Andes, Venezuela	ULA.VE
National University of Córdoba	UCO.AR	University of the North, Colombia	UNINORTE.CO
National University of La Plata	UNLP.AR	University of the Sinos Valley	UNISINOS.BR