sciendo

Shedding Light on the Doing Business Index: a Machine Learning Approach

Milica Maričić, Milica Bulajić, Zoran Radojičić, Veljko Jeremić
University of Belgrade, Faculty of Organizational Sciences, Department of Operational Research and Statistics, Belgrade, Serbia

Abstract

Background: The World Bank (WB) acknowledged the importance of business regulatory environment and therefore created a metric which ranks 190 countries based on their level of business regulation for domestic firms measured by the Doing Business Index (DBI). **Objectives:** The question which attracted our attention is whether all the observed entities should be given the same weighting scheme. **Methods/Approach:** The approach we propose as an answer is two-fold. First, we cluster the countries covered by the DBI. In the next step, we apply the statistical multivariate Composite I-distance Indicator (CIDI) methodology to determine new, data-driven weights for each of the retained clusters. **Results:** The obtained results show that there is a difference between the weighting schemes proposed by the CIDI methodology. **Conclusions:** One can argue that one weighting scheme does not fit all the observed countries, meaning that additional analyses on the DBI are suggested to explore its stability and its weighting scheme.

Keywords: CIDI methodology, Doing Business Index, international business, machine learning algorithms
JEL classification: C43, C38, F23, M16
Paper type: Research article

Received: Apr 20, 2018
Accepted: Nov 12, 2018

Citation: Maričić, M., Bulajić, M., Radojičić, Z., Jeremić, V. (2019), "Shedding Light on the Doing Business Index: a Machine Learning Approach", Business Systems Research, Vol. 10, No. 2, pp. 73-84.
DOI: 10.2478/bsrj-2019-019

Introduction

owth (Adams, 2009; Basu and Guariglia, 2007). Namely, they are believed to alleviate poverty (Gohou and Soumaré, 2012), drive the employment of women (Neumayer and de Soysa, 2011), and play a significant role in the development of emerging markets (Konings, 2001). Accordingly, the goal of governments is to attract as much FDI as possible to boost the national economy (Büthe and Milner, 2008). One of the ways to attract the FDI is to reform business regulation and ease doing business.

As the level of ease of starting and doing business is an essential factor for institutional investors to decide where to invest, it slowly but surely, became a topic on which countries, regions or even cities could be ranked (Brunetti et al., 1997; Davis et al., 2012). One of the means of ranking, which has seen extensive development and application, in particular in the public sector, is the use of composite indices (Bird et al., 2005). First such ranking of countries based on their economic openness to business dates from the 1990s. Namely, the ranking proposed Cavusgil (1997) ranks emerging markets using seven dimensions. The World Bank followed the trend and in 2003 created a complex and sophisticated composite index, the Doing Business Index (DBI) which aims at ranking countries based on their level of business regulation for domestic firms (World Bank, 2017).

Our research hypothesis is that one weighting scheme does not fit all entities when the composite index ranks a large number of entities. The hypothesis of the research is starting to attract attention within the scientific community (Maricic et al., 2017). Our proposed approach is to firstly divide entities into groups and secondly, to rank and weight them accordingly within each group. The goal of this research is to employ machine-learning algorithm and statistical methodologies on the indicators which make a specific composite index to scrutinise its structure and weighting scheme. Namely, this research attempts to cluster entities using the official data and non-hierarchical cluster method, the K-means algorithm and determine new weighting schemes per retained cluster using the statistical multivariate Composite I-distance Indicator (CIDI) methodology (Dobrota et al., 2016). We believe our approach could provide insights on whether or not it is reasonable to rank a large number of countries and apply a single weighting scheme. Therefore, the contribution of the research is twofold: it will provide results of clustering analysis, and second, it will provide novel data-driven weighting schemes per retained cluster.

Having the entire scope of the research in mind, as the case study in our paper, we will put emphasis on the Doing Business Index (DBI) developed by the World Bank. The next section sees a brief literature review on composite indices, and weighting methodologies applied. The following one sees the overview of the Doing Business Index methodology. The research methodology on the clustering approach and the weighting procedure follow in Section 4. The results are given in Section 5, while the discussion and the concluding remarks follow.

Literature review

Composite indicators or composite indices are usually defined as the aggregate value of individual variables which are chosen with the goal to capture dimensions of a multidimensional phenomenon such as countries' competitiveness (Nardo et al., 2005; Paruolo et al., 2013). Although composite indices can initiate public debate, draw attention of the wider public, and serve as valuable source of information for governmental decision-makers (Saisana et al., 2011), experts from various fields pointed out that their results should be taken with caution due to their methodologies (Cherchye et al., 2007; Despotis, 2005; Jovanovic et al., 2012). Special attention was given to their weighting schemes (for example, Amado et al., 2016; Cherchye et al., 2008; Dobrota et al., 2016). Namely, it is believed that the weighting process is usually covered with the veil of subjectivity (Maricic, Bulajic, et al., 2016).

The methodological step we aim to explore in this paper is the weighting procedure. Namely, the process of devising the weighting scheme is usually cited as the stepping stone (Becker et al., 2017; Soh, 2014; Zhou et al., 2010). There are three major groups of weighting methodologies: data-driven, normative, and hybrid (Decancq and Lugo, 2013). Data-driven methodologies such as Principal Component Analysis (PCA), Ivanovic distance (I-distance), Data envelopment analysis (DEA), and Benefit-of-Doubt (BoD) assign weights based on statistical and optimization methods and completely exclude expert opinion (Nardo et al., 2005). Contrarily, normative methodologies are completely based on expert opinion. Some of such methodologies are Analytic Hierarchy Process (AHP) and budget allocation (Singh et al., 2007). Hybrid methodologies aim to find a balance between data-driven and normative (Maricic et al., 2015). Booysen (2002) observes that no group of weighting methodologies is beyond critique. Nevertheless, data-driven weighting methodologies are believed to be more reliable as they are less prone to subjective opinion (Jeremic et al., 2011; Nardo et al., 2005).

A recently developed data-driven methodology that attracted our attention is the Composite I-distance Indicator (CIDI) proposed by Dobrota et al. (2016). As the CIDI methodology is applied in this paper, here, we will put emphasis on its previous applications, while the theoretical overview of the methodology is given in Section Research methodology. So far CIDI has been applied with a lot of success for analysis of official weighting schemes, in the process of creation of the novel composite index, and for determining weights in optimization problems.

When it comes to the application of CIDI for the analysis of official weighting schemes, Dobrota et al. (2016) showed that the weighting scheme of the QS university ranking could be altered using the CIDI. Namely, their results proved to be more stable and less susceptible to rank change. On the other hand, Maricic et al. (2015) proposed a hybrid weighting scheme for the ICT Development Index (IDI). On the indicator level, they applied CIDI to obtain new pillar values. In the following step, they applied equal weights, as suggested by the official methodology. Their results were more stable than the official ones when the uncertainty of the weighting scheme is observed.

Determining weights is an important step in the process of composite index creation (Munda, 2008). Therefore, some experts believe that the weighting scheme should be completely unbiased and data-driven (Dobrota et al., 2015; Huang, 2012; Soh, 2014). Accordingly, CIDI was used to assign weights of a novel composite index. Maricic, Zornic & Jeremic (2016) proposed a university ranking based on the level of cooperation between universities and the industry. To determine the weighting scheme of the University-Industry Research Connections Index (UIRC Index), they used CIDI methodology with a lot of success.

Besides determining data-driven weighting schemes for currently devised composite indices or for determining weighting schemes of novel composite indices, the CIDI is being used to constraint optimization models. For example, Radojicic et al. (2015) used bootstrap CIDI weights to constrain DEA models. On the other hand, Maricic et al. (2016) used a ±25% interval around CIDI weights to additionally constrain BoD model.

The presented literature review shows the importance of the weighting scheme for the process of composite index creation. It also points out that there are multiple approaches to tackle the issue. The CIDI methodology drew our attention as it is data-driven and has been applied with success in various occasions. Our idea is to use CIDI, but not to alter a specific ranking methodology, whereas to examine whether one weighting scheme fits all the observed entities, which are ranked. Namely, the question, which arises, is whether one weighting scheme fits 50 and 500 entities? A recently conducted in-depth analysis of the ARWU and Alternative ARWU rankings which rank 500 entities (universities) showed that there are significant differences between groups of 100 universities and that the length of the ranked universities should be taken into account when creating a composite index (Maricic et al., 2017). Therefore, herein, we aim to expand the current literature on the topic.

Doing Business Index (DBI)

The Doing Business Index (DBI) is a multidimensional measurement of the aspects of business regulation, which affect domestic small and medium-size firms. It is developed by the World Bank who acknowledged the importance of ease of doing business for the economic development of countries. In this paper, we scrutinised the Doing Business Index 2018. The index aims to rank and compare 190 countries worldwide using 41 indicators divided into ten topics, which are listed in Table 1. The index topics are formed of indicators. However, in our analysis, we did not take into account the indicator values, as the publicly available indicator data is not normalized.

Table 1
DBI Topics, their Codes, and Assigned Weights

DBI topic	Code	Weight
Starting a business	T1	10%
Dealing with construction permits	T2	10%
Getting electricity	T3	10%
Registering property	T4	10%
Getting credit	T5	10%
Protecting minority investors	T6	10%
Paying taxes	T7	10%
Trading across borders	T8	10%
Enforcing contracts	T9	10%
Resolving insolvency	T10	10%

Source: (World Bank, 2017)

The first topic, *Starting a business,* is intended to measure the number of procedures, time, cost, and minimum paid-in capital to start a limited liability company. Dealing with construction permits measures the number of procedures, time, and cost to complete all formalities to build a warehouse and the quality control and safety mechanisms in the construction permitting system. Next topic, *Getting electricity*, quantifies procedures, time, and cost to get connected to the electrical grid, the reliability of the electricity supply and the transparency of tariffs. Registering property is related to procedures, time, and cost to transfer a property and the quality of the land administration system — the following topic, *Getting credit* measures movable collateral laws and credit information systems. Next, *Protecting minority investors* deals with minority shareholders' rights in related-party transactions and corporate governance. Payments, time, and total tax and contribution rate for a firm to comply with all tax regulations as well as post-filing processes are measured by the topic of Paying taxes. Time and cost to export the product of comparative advantage and import auto parts are quantified in the topic *Trading across borders*. Next, *Enforcing contracts*, measures how commercial disputes are resolved and how the quality of judicial processes is attained. The final topic deals with time, cost, outcome, and recovery rate for commercial insolvency and the strength of the legal framework for insolvency (World Bank, 2017).

The data collection process is based on a detailed reading of domestic laws and regulations as well as administrative requirements. The process itself is guided and overlooked by World Bank experts. A signal that the data collected for the DBI is precise and of interest is the fact that there are 17 different data projects or indexes that use Doing Business Index data as one of their data sources (World Bank, 2017). Nevertheless, Arruñada (2007) argues that the procedure of indicator and topic data collection could be altered to represent the actual policies better.

After the data has been collected and normalised, it is weighted and summed to make the DBI. As can be seen from Table 1, the World Bank suggests equal weighting. The current methodology of the DBI has been evaluated in several studies. Namely, the Independent Evaluation Group (2008) positively evaluated the index methodology. Also, Djankov et al. (2002) showed that the chosen set of indicators, which make the DBI, comply with the theoretical basis of foreign investment. Contrarily, Hoyland, Moene, and Willumsen (2008) showed that the indicators do not capture the underlying business environment due to their weak discriminating power. The ambiguous results indicate that the DBI could be scrutinised more thoroughly.

Herein we place our attention on the weighting scheme of the DBI and the rationale to weight indicators the same when ranking a large number of entities. The question we raise is whether one weighting scheme and equal weighting scheme fits all 190 observed countries. To provide an answer, we propose two widely used methodologies. First, we suggest clustering the observed countries using the K-means algorithm (Hartigan and Wong, 1979), followed by the application of the CIDI methodology to each of the retained clusters to obtain the data-driven weighting scheme (Dobrota et al., 2015).

Research methodology

K-means

The K-means algorithm has proved to be very useful in producing good clustering results for many practical applications (Celebi et al., 2013). K-means clustering algorithm aims to partition the observed entities into K clusters in which each observation belongs to the cluster with the nearest mean, serving as the centre of the cluster. The objective function is to minimise the sum of squares between the entities and the cluster centre.

The K-means algorithm requires three user-specified parameters: number of clusters K, cluster initialisation, and distance metric. One of the specific drawbacks of the algorithm is that the number of clusters should be pre-defined (Škrabuľáková et al., 2016) and that there is no single answer to how to choose K. While no unique mathematical criterion exists, a number of heuristics and indexes have been devised (Tibshirani et al., 2001). To overcome the drawback of the K-means algorithm and to determine the number of clusters we consulted the recently developed R package "NbClust". Namely, the package can calculate 30 indexes for the choice of the best number of clusters (Charrad et al., 2014). Performance of iterative clustering algorithms such as K-means, which converges to numerous local minima, highly depends on initial cluster centres. Nevertheless, most commonly initial cluster centres are selected randomly. When it comes to distance metric used, there are several options possible: Euclidean, Manhatten, Mahalanobis, Itakura–Saito, Bregman distances, and others (Jain, 2010). In the presented case study, we used the Euclidean distance.

Composite I-distance Indicator (CIDI) methodology

The Composite I-distance methodology (CIDI) is a recently-developed multivariate methodology for creating composite indexes based on the results of the I-distance method devised by Ivanovic (1977) (Dobrota et al., 2016). The I-distance method gained popularity as it overcomes the issues of normalisation, determination of the weighting scheme, and aggregation (Jeremic et al., 2011; 2013; Maricic, Bulajic, et al., 2016). Nevertheless, the result of the I-distance method is the distance of an observed entity from a fictive entity what makes it difficult to compare with other currently devised metrics. In addition, there was a growing need to take into account the issues of sensitivity and uncertainty and to compare the data-driven weights and the official weights. Therefore, the CIDI methodology, which overcomes the observed issues, was devised. It creates a comparable composite index, using the weights, which derive from the I-distance method. Therefore, before conducting the CIDI methodology, the I-distance method must be applied.

Pearson's correlation coefficient is used to measure the importance of each variable for the ranking process (Jeremic et al., 2011). Namely, Pearson's correlation coefficient accounts for the proportion of the variability between the two variables. Therefore, it can identify which variables contribute the most to the overall I-distance value. Accordingly, to establish the novel CIDI weighting scheme, it is necessary to acquire information about the importance of each variable for the ranking process. Therefore, it is necessary to determine the Pearson's correlation coefficients between the variables and the obtained I-distance value. The new weights are formed by dividing the Pearson's correlation coefficient by the sum of correlation coefficients. The formula is:

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

where r_i, (i=1,...,k) is Pearson's correlation coefficient between the i-th input variable and the I-distance value. The sum of weights obtained using CIDI is 1 (Dobrota et al., 2016). The new weighting scheme is unbiased as it derives from the collected data and because no expert opinion has been included in the weighting process. The final step in the CIDI methodology is to obtain the new composite index. Usually, the value of the novel index is obtained as the weighted sum of the chosen indicators. Of course, different aggregation methods can be used, such as the weighted geometric mean.

Results

The dataset on which the analysis was performed contained all ten-topic values for all 190 countries for the year 2018. The data is publicly available in the official Doing Business Report (World Bank, 2017). As the dataset was already normalised, the first step in our analysis was to apply the clustering method, the K-means algorithm.

For our case study (190 entities, K-means algorithm, Euclidean distance), the "NbClust" package was able to obtain the results of 23 indexes out of 30. The number of clusters suggested by the highest number of indexes was retained. In our case, ten indices proposed to retain two clusters. Next, the descriptive statistics of the two retained clusters are presented in Table 2. The first column indicates the size of the clusters. We can observe that the clusters are of similar size, 94 and 96 countries. Some of the countries, which make cluster 1, are Australia, Belgium, Canada, Germany, Japan, Russia, Spain, and the USA. On the other side, some of the countries, which make cluster 2, are Brazil, Honduras, Nigeria, Cambodia, and Pakistan. As the clusters are large, the list of countries, which make each cluster, will not be listed. Nevertheless, the full list is available on demand. The column average (Avg) is the mean value of a topic per cluster and at the same time represents the cluster centre. The first cluster can be identified as a cluster of countries which perform well according to the DBI topics and whose laws aim to facilitate and stimulate doing business. On the other hand, it can be observed that Cluster 2 can be characterised as the cluster of countries which have visibly lower average values, especially of topic T5 (Getting credit). Therefore, we can conclude that in countries which make Cluster 2 there are certain difficulties in starting and doing business.

In addition, the analysis of minimum values of topics per cluster shows those countries, which have lower values of topics (values of 0), are clustered in Cluster 2. What can also be observed from Table 2 is that the standard deviation (StD) of topics per cluster is high and that the range of topics values in Cluster 2 is also high. This could lead to the conclusion that although the countries have been grouped into two clusters, the structure of the clusters is not that coherent.

Table 2
Basic Descriptive Statistics of the Retained Clusters

C1	Size	Avg	Min	Max	StD	C2	Size	Avg	Min	Max	StD
T1	94	89.47	65.91	99.96	5.81	T1	96	76.36	25.00	93.65	13.27
T2	94	71.52	38.80	86.79	9.06	T2	96	57.75	0.00	78.07	17.28
T3	94	78.95	44.19	99.92	12.08	T3	96	53.27	0.00	90.63	19.78
T4	94	72.69	44.64	94.47	12.64	T4	96	49.96	0.00	81.19	15.37
T5	94	66.33	15.00	100	16.50	T5	96	35.63	0.00	90.00	20.10
T6	94	61.96	26.67	85.00	11.15	T6	96	43.07	0.00	75.00	12.54
T7	94	78.34	39.66	99.44	10.78	T7	96	58.89	0.00	92.48	16.27
T8	94	83.35	44.31	100.00	14.09	T8	96	56.01	0.00	97.48	21.17
T9	94	62.88	34.29	84.15	10.41	T9	96	48.24	6.13	68.11	11.89
T10	94	60.75	0.00	93.44	18.27	T10	96	28.07	0.00	69.79	17.73

Source: Authors' work
Note: C1 and C2 indicate Clusters 1 and 2

To additionally inspect the clustering structure group means were compared using t-test as used by Russell et al. (2017) to compare means of clusters of countries. The results are presented in Table 3. As it can be observed, there is a statistically significant difference in group means for all ten topics. This could signal that the two-retained clusters differ and that they are well separated. The absolute mean difference varies from 13.11 (T1) to 32.68 (T10). The high absolute mean difference can also be acknowledged for T5 (30.7) and T8 (27.34).

Table 3
Results of the Cluster Means Comparison Using t-test

Topics	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
t*	8.85**	6.90**	10.83**	11.12**	11.50**	10.97**	9.73**	15.50**	9.04**	12.51**
Abs mean diff*	13.11	13.77	25.68	22.73	30.7	18.89	19.45	27.34	14.64	32.68

Source: Authors' work
Note: * t – the value of t-statistics, Abs mean diff – Absolute mean difference between cluster means; ** – $p<0.01$

The next step in the analysis was the application of the CIDI methodology on the retained clusters. The results given in Table 4 provide interesting insights.

It is evident that the weighting schemes differ. When it comes to Cluster 1, the weights vary from 2.6% to 12.5%, while in Cluster 2 they vary from 5.7% to 13.2%. In Cluster 1, the most important topics for the ranking process are topics T9 and T1, Enforcing contracts and Starting a business. On the other side, in Cluster 2, the ranking order is entirely different. The most important topics for the ranking process are topics T3 and T6, Getting electricity, and Protecting minority investors.

Table 4
CIDI Weighting Schemes per Two Retained Clusters

Cluster 1		Cluster 2	
Topic	Weight	Topic	Weight
T9	12.5%	**T3**	13.2%
T1	12.1%	**T6**	11.7%
T2	11.6%	**T2**	10.9%
T10	11.1%	**T1**	10.9%
T7	11.1%	**T7**	10.9%
T4	10.8%	**T4**	9.9%
T6	10.7%	**T8**	9.9%
T3	9.0%	**T9**	9.6%
T8	8.4%	**T5**	7.3%
T5	2.6%	**T10**	5.7%

Source: Authors' work

It is also of interest to observe the difference in the importance of topics between the two ranking schemes. For example, indicator T6 is the 7th most important indicator for the ranking procedure in Cluster 1 with the weight of 10.7%, while in Cluster 2 the same indicator is the 2nd most important indicator with the weight of 11.7%. The importance of indicator T10, Resolving insolvency, also visibly differs. In Cluster 1, it was given 11.1% weight and 4th importance, while in Cluster 2, the same indicator is least important with only 5.7% weight. Comparing the two ranking schemes, there are similarities: the importance of topics T2, T7, and T4. Namely, in both weighting schemes, they are the 3rd, 5th, and the 6th most important topics for the ranking procedure.

What should also be inspected is the comparison of the newly obtained weighting scheme and the official weighting scheme proposed by the World Bank. Taking a closer look of Cluster 1, several topics were assigned weights above the official 10%. Nevertheless, the observed weights were not significantly higher than the official threshold. However, the weight of indicator T5 attracts attention, as its weight decreased for 7.4 weight points, from 10% to 2.6%. In Cluster 2, there are also topics whose weights are above the official 10%. Again, they were not significantly higher than the official threshold. In this cluster, the weight of indicator T10 is visibly below the official weight; it is just 5.7%. The presented comparison provides evidence that one weighting scheme does not fit all observed countries and that the equal weighting scheme could be additionally scrutinised.

Discussion and conclusion

In this research, we aimed to inspect whether one weighting scheme can be used to create a composite index, which ranks a large number of entities. The conducted analysis was twofold: first, we clustered the entities using the K-means algorithm, and second, we proposed a novel, data-driven indicator weights for each of the retained clusters using CIDI methodology.

The analysis of the obtained CIDI weighting schemes per cluster provides valuable information for policy and decision makers. In the presented case study, the results show that there is a difference in the weighting schemes and in the importance of topics for the ranking procedure between the two clusters. Meaning that a single weighting scheme might not be an adequate solution. Using the herein proposed weighting schemes, the decision makers can be sure that the difference in the topic's values and differences between the observed countries have been taken into account when assigning weights.

The presented research has several benefits, which should be pointed out. First, it provides insights on how can 190 countries ranked by Doing Business Index be clustered. Secondly, it provides a new, data-driven weighting scheme for each cluster using the CIDI methodology. Thirdly, is signalises that the current weighting scheme and the list of countries ranked could be modified and scrutinised more thoroughly. The scientific contribution of the paper is that composite index creators should take into account the number of entities they plan to rank as there is evidence that one weighting scheme might not fit them all.

The conducted research has limitations, which should also be taken into account. Namely, the clustering approach and the data-driven weighting methods have been chosen based on expert knowledge of the authors. Other clustering approaches would have suggested different clustering structures and therefore, different weighting schemes within clusters. In addition, different data-driven weighting methods would suggest different weighting schemes. The presented experimental setting showed there is a difference between weighting schemes of the two clusters. However, we cannot guarantee that other experimental setting would show the same. In addition, in the presented case study, we scrutinised a composite index, which ranks a very large number of countries. Maybe there would not have been differences if the composite index ranked less than 100 entities.

Further directions of the study could be twofold. One direction of the study would be towards reducing the number of observed topics, which make the DBI. For example, post-hoc I-distance could be implemented (Savic et al., 2016). The second direction would be towards implementing hierarchical clustering methods (Miyamoto, 2012) or more advanced clustering methods, such as biclustering (Kasim et al., 2016) as the clustering results indicate that the currently suggested clustering scheme could be modified.

We believe that the proposed approach for the analysis of composite indices and devising new weighting schemes could initiate further research on the topic of weighting schemes within composite indices.

References

1. Adams, S. (2009), "Foreign Direct investment, domestic investment, and economic growth in Sub-Saharan Africa", Journal of Policy Modeling, Vol. 31, No. 6, pp. 939-949.
2. Amado, C. A. F., São José, J. M. S., Santos, S. P. (2016), "Measuring active ageing: A Data Envelopment Analysis approach", European Journal of Operational Research, Vol. 255, No. 1, pp. 207-223.
3. Arruñada, B. (2007), "Pitfalls to avoid when measuring institutions: Is Doing Business damaging business?", Journal of Comparative Economics, Vol. 35, No. 4, pp. 729-747.
4. Basu, P., Guariglia, A. (2007), "Foreign Direct Investment, inequality, and growth", Journal of Macroeconomics, Vol. 29, No. 4, pp. 824-839.
5. Becker, W., Saisana, M., Paruolo, P., Vandecasteele, I. (2017), "Weights and importance in composite indicators: Closing the gap", Ecological Indicators, Vol. 80, pp. 12-22.
6. Bird, S. M., Sir David, C., Farewell, V. T., Harvey, G., Tim, H., Peter C. S. (2005), "Performance indicators: good, bad, and ugly", Journal of the Royal Statistical Society: Series A (Statistics in Society), Vol. 168, No. 1, pp. 1-27.
7. Booysen, F. (2002), "An overview and evaluation of composite indices of development", Social Indicators Research, Vol. 59, No. 2, pp. 115-151.
8. Brunetti, A., Kisunko, G., Weder, B. (1997), Institutional Obstacles to Doing Business: Region-by-Region Results from a Worldwide Survey of the Private Sector, World Bank Publications.
9. Büthe, T., Milner, H. V. (2008), "The Politics of Foreign Direct Investment into Developing Countries: Increasing FDI through International Trade Agreements?", American Journal of Political Science, Vol. 52, No. 4, pp. 741-762.

10. Cavusgil, S. T. (1997), "Measuring the potential of emerging markets: An indexing approach", Business Horizons, Vol. 40, No. 1, pp. 87-91.
11. Celebi, M. E., Kingravi, H. A., Vela, P. A. (2013), "A comparative study of efficient initialization methods for the k-means clustering algorithm", Expert Systems with Applications, Vol. 40, No. 1, pp. 200-210.
12. Charrad, M., Ghazzali, N., Boiteau, V., Niknafs, A. (2014), "NbClust: An R Package for Determining the Relevant Number of Clusters in a Data Set", Journal of Statistical Software, Vol. 61, No. 6.
13. Cherchye, L., Moesen, W., Rogge, N., Van Puyenbroeck, T. (2007), "An introduction to 'benefit of the doubt' composite indicators", Social Indicators Research, Vol. 82, No. 1, pp. 111-145.
14. Cherchye, L., Moesen, W., Rogge, N., Van Puyenbroeck, T., Saisana, M., Saltelli, A., Liska, R., Tarantola, S. (2008), "Creating composite indicators with DEA and robustness analysis: the case of the Technology Achievement Index", Journal of the Operational Research Society, Vol. 59, No. 2, pp. 239-251.
15. Davis, K. E., Kingsbury, B., Merry, S. E. (2012), "Indicators as a Technology of Global Governance", Law & Society Review, Vol. 46, No. 1, pp. 71-104.
16. Decancq, K., Lugo, M. A. (2013), "Weights in Multidimensional Indices of Wellbeing: An Overview", Econometric Reviews, Vol. 32, No. 1, pp. 7-34.
17. Despotis, D. K. (2005), "A reassessment of the human development index via data envelopment analysis", Journal of the Operational Research Society, Vol. 56, No. 8, pp. 969-980.
18. Djankov, S., La Porta, R., Lopez-de-Silanes, F., Shleifer, A. (2002), "The Regulation of Entry", The Quarterly Journal of Economics, Vol. 117, No. 1, pp. 1-37.
19. Dobrota, M., Bulajic, M., Bornmann, L., Jeremic, V. (2016), "A new approach to the QS university ranking using the composite I-distance indicator: Uncertainty and sensitivity analyses", Journal of the Association for Information Science and Technology, Vol. 67, No. 1, pp. 200-211.
20. Dobrota, M., Martic, M., Bulajic, M., Jeremic, V. (2015), "Two-phased composite I-distance indicator approach for evaluation of countries' information development", Telecommunications Policy, Vol. 39, No. 5, pp. 406-420.
21. Gohou, G., Soumaré, I. (2012), "Does Foreign Direct Investment Reduce Poverty in Africa and are There Regional Differences?", World Development, Vol. 40, No. 1, pp. 75-95.
22. Hartigan, J. A., Wong, M. A. (1979), "Algorithm AS 136: A K-Means Clustering Algorithm", Applied Statistics, Vol. 28, No. 1, pp. 100-108.
23. Hoyland, B., Moene, K., Willumsen, K. (2008), Be Careful When Doing Business, Report to the Norwegian Ministry of Foreign Affairs.
24. Huang, M.-H. (2012), "Opening the black box of QS World University Rankings", Research Evaluation, Vol. 21, No. 1, pp. 71-78.
25. Independent Evaluation Group (2008), Doing Business: An Independent Evaluation. Taking the Measure of the World Bank-IFC Doing Business Indicators, World Bank, Washington, DC.
26. Ivanovic, B. (1977), Teorija Klasifikacije, Institut za ekonomiku industrije, Beograd.
27. Jain, A. K. (2010), "Data clustering: 50 years beyond K-means", Pattern Recognition Letters, Vol. 31, No. 8, pp. 651-666.
28. Jeremic, V., Bulajic, M., Martic, M., Radojicic, Z. (2011), "A fresh approach to evaluating the academic ranking of world universities", Scientometrics, Vol. 87, No. 3, pp. 587-596.
29. Jeremic, V., Jovanovic Milenkovic, M., Radojicic, Z., Martic, M. (2013), "Excellence with Leadership: the crown indicator of Scimago Institutions Rankings Iber report", El Profesional de La Información, Vol. 22, No. 5, pp. 474-480.
30. Jovanovic, M., Jeremic, V., Savic, G., Bulajic, M., Martic, M. (2012), "How does the normalization of data affect the ARWU ranking?", Scientometrics, Vol. 93, No. 2, pp. 319-327.
31. Kasim, A., Shkedy, Z., Kaiser, S., Hochreiter, S., Talloen, W. (2016), Applied Biclustering Methods for Big and High-Dimensional Data Using R, Chapman and Hall.

32. Konings, J. (2001), "The effects of foreign direct investment on domestic firms Evidence from firm-level panel data in emerging economies", The Economics of Transition, Vol. 9, No. 3, pp. 619-633.
33. Maricic, M., Bulajic, M., Martic, M., Dobrota, M. (2015), "Measuring the ict development: the fusion of biased and objective approach", Naval Academy Scientific Bulletin, Vol. 18, No. 2, pp. 326-334.
34. Maricic, M., Bulajic, M., Radojicic, Z., Jeremic, V. (2016), "Multivariate approach to imposing additional constraints on the Benefit-of-the-Doubt model: The case of QS World University Rankings by Subject", Croatian Review of Economic, Business and Social Statistics, Vol. 2, No. 1, pp. 1-14.
35. Maricic, M., Zornic, N., Jeremic, V. (2016), "Ranking European Universities Based on Their Level of Collaboration with the Industry: The Univesity-Industry Research Connections Index", in proceedings of the International Conference on Education and New Learning Technologies, IATED, pp. 6095-6105.
36. Maricic, M., Zornic, N., Pilcevic, I., Dacic-Pilcevic, A. (2017), "ARWU vs. Alternative ARWU Ranking: What are the Consequences for Lower Ranked Universities?", Management: Journal of Sustainable Business and Management Solutions in Emerging Economies, Vol. 22, No. 1, pp. 1-14.
37. Miyamoto, S. (2012), "An Overview of Hierarchical and Non-hierarchical Algorithms of Clustering for Semi-supervised Classification", in Torra V., Narukawa Y., López B., V. M. (Eds.), Modeling Decisions for Artificial Intelligence, Springer Berlin Heidelberg, pp. 1-10.
38. Munda, G. (2008), Social Multi-Criteria Evaluation for a Sustainable Economy, Springer Berlin Heidelberg, Berlin, Heidelberg.
39. Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., Giovannini, E. (2005), Handbook on Constructing Composite Indicators, OECD Statistics Working Papers.
40. Neumayer, E., De Soysa, I. (2011), "Globalization and the Empowerment of Women: An Analysis of Spatial Dependence via Trade and Foreign Direct Investment", World Development, Vol. 39, No. 7, pp. 1065-1075.
41. Paruolo, P., Saisana, M., Saltelli, A. (2013), "Ratings and rankings: voodoo or science?", Journal of the Royal Statistical Society: Series A (Statistics in Society), Vol. 176, No. 3, pp. 609-634.
42. Radojicic, M., Savic, G., Radovanovic, S., Jeremic, V. (2015), "A novel bootstrap dba-dea approach in evaluating efficiency of banks", Naval Academy Scientific Bulletin, Vol. 18, No. 2, pp. 375-384.
43. Russell, L. B., Bhanot, G., Kim, S.-Y., Sinha, A. (2017), "Using Cluster Analysis to Group Countries for Cost-Effectiveness Analysis: An Application to Sub-Saharan Africa", Medical Decision Making, Vol. 38, No. 2, pp. 139-149.
44. Saisana, M., D'Hombres, B., Saltelli, A. (2011), "Rickety numbers: Volatility of university rankings and policy implications", Research Policy, Vol. 40, No. 1, pp. 165-177.
45. Savic, D., Jeremic, V., Petrovic, N. (2016), "Rebuilding the Pillars of Sustainable Society Index: A Multivariate Post Hoc I-Distance Approach", Problemy Ekorozwoju - Problems of Sustainable Development, Vol. 12, No. 1, pp. 125-134.
46. Singh, R. K., Murty, H. R., Gupta, S. K., Dikshit, A. K. (2007), "Development of composite sustainability performance index for steel industry", Ecological Indicators, Vol. 7, No. 3, pp. 565-588.
47. Škrabuľáková, E. F., Ivanova, M., Michaeli, E. (2016), "Usage of clustering methods in mathematics, geoinformatics and related fields of university study", in proceedings of 17th International Carpathian Control Conference (ICCC), IEEE, pp. 723-728.
48. Soh, K. (2014), "Nominal versus attained weights in Universitas 21 Ranking", Studies in Higher Education, Vol. 39, No. 6, pp. 944-951.
49. Tibshirani, R., Walther, G., Hastie, T. (2001), "Estimating the number of clusters in a data set via the gap statistic", Journal of the Royal Statistical Society: Series B (Statistical Methodology), Vol. 63, No. 2, pp. 411-423.
50. World Bank (2017), Doing Business 2018: Reforming to Create Jobs, Washington, D.C, available at:

http://www.doingbusiness.org/~/media/WBG/DoingBusiness/Documents/Annual-Reports/English/DB2018-Full-Report.pdf (06 November 2018).
51. Zhou, P., Ang, B. W., Zhou, D. Q. (2010), "Weighting and aggregation in composite indicator construction: A multiplicative optimization approach", Social Indicators Research, Vol. 96, No. 1, pp. 169-181.

About the authors

Milica Maričić, MsC is a Teaching associate at the Faculty of Organizational Sciences, University of Belgrade, Department of Operational Research and Statistics. After graduation in 2014 at the Faculty of Organizational Sciences, she got her MSc at the same faculty, where she specialized in business analytics and statistics. Currently, she is on her Ph.D. studies at the Faculty of Organizational Sciences, where she is studying Quantitative management with a special interest in computational and applied statistics. The author can be contacted at **milica.maricic@fon.bg.ac.rs.**

Milica Bulajić, Ph.D. graduated from Faculty of Mathematics, the University of Belgrade in 1981. She received her Ph.D. in 2002 at the Faculty of Organizational Sciences where she works since 2003 as a full professor for the scientific field of computational statistics. She is engaged in probability theory, statistics, econometric methods, data analysis, and other subjects of the Department of Operations Research and Statistics. She is a member of the Statistical Society of Serbia. She speaks English, Italian, and French. The author can be contacted at **bulajic.milica@fon.bg.ac.rs**.

Zoran Radojičić is a full professor at the Faculty of Organizational Sciences in Belgrade. He teaches several subjects in the field of statistics at the University of Belgrade and the University of Novi Sad. Head of the Laboratory of Statistics on the basic faculty and member of the Department of Operations Research and Statistics. The author can be contacted at **radojicic.zoran@fon.bg.ac.rs**.

Veljko Jeremić is an assistant professor at the Department of Operational Research and Statistics at the Faculty of Organizational Science, University of Belgrade. He finished his Ph.D. thesis in the field of computational statistics. He has published over 60 scientific papers with an emphasis on ISI indexed journals. He is a co-author of one university textbook. He has acted as a reviewer for many ISI indexed journals such as Jasist, Scientometrics, and Journal of applied statistics. The author can be contacted at **jeremic.veljko@fon.bg.ac.rs**.