A Clustering-based Approach for Ranking Universities

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***Abstract*—In recent years, there has been an increasing interest among international organizations and academic communities in the evaluation and ranking of educational institutions. Such rankings are of great significance to various stakeholders, including students and their families, academic staff, funding agencies, and universities themselves. Ranking methodologies typically involve the use of diverse indicator categories, aimed at ensuring objectivity and reflecting the relative importance of each university. These categories may include, but are not limited to, research output and impact, teaching quality and learning environment, international diversity, and reputation in the employment market. Apart from conventional ranking methods, clustering-based techniques can also be used to group universities according to their common characteristics and to evaluate their performance within each cluster. In this paper, we seek to explore how universities from various regions can be clustered into distinct groups and ranked based on their unique features. For this purpose, we employ various clustering algorithms, each possessing distinct characteristics, and we present the similarities between them to obtain the most effective evaluation. We also analyze how university features can impact the evaluation and classification process into a cluster. We present some statistical results of university rankings and finally, we visualize the clustering process to facilitate a deeper understanding of the findings.**

***Index Terms*—University Rankings, Clustering, Quacquarelli Symonds**

I. Introduction

The selection of an excellent university is pivotal in securing a high-quality education, offering students a robust foundation of knowledge, skills, and credentials. Furthermore, it may lead to enhanced job opportunities with higher remuneration post-graduation as employers are more inclined to hire graduates from prestigious universities. Such institutions provide students with the opportunity to partake in pioneering research, acquire invaluable experience, and develop skill sets essential for their future endeavors.

The process of evaluating and ranking universities is a complex and multidimensional one, as it entails a variety of indicators that need to be carefully weighted and considered to ensure an objective and accurate evaluation. The ranking organizations, such as the Academic Ranking of World Universities (ARWU), Quacquarelli Symonds (QS), and Times Higher Education World University Rankings (THE), have developed sophisticated algorithms to evaluate universities based on various indicators, including academic reputation, faculty-student ratio, academic citations, and international diversity, etc. Each indicator is assigned a corresponding weight to reflect its relative importance in evaluating a university. According to [1], an examination of these indicators reveals the followings:

- The similarity of indicators among ranking lists is low, which means that organizations use mostly different indicators to evaluate universities.
- The weight that is used to signify the importance of an indicator, may be different among ranking lists.
- The research production and impact related indicators among ranking lists are similar.

University rankings serve not only to improve students' decisions but also to motivate universities to improve their performance in key areas such as research, teaching, and internationalization, which are vital to their stakeholders. Despite their notable advantages, university ranking methods also suffer from several limitations, including the following:

- **Subjectivity** - The selection of indicators and their corresponding weights can be based on arbitrary and controversial criteria, leading to rankings that are not representative of the universities' true capabilities and performance.
- **Narrow Focus** - The indicators used in ranking systems may not capture the full range of activities and outputs of universities, which can lead to a narrow and incomplete picture of their performance. For example, rankings that focus mainly on research productivity may not reflect the quality of teaching or the impact of universities on their local communities.
- **Incentive Distortion** - Ranking systems may create incentives for universities to prioritize certain activities over others, leading to the distortion of their missions and objectives.
- **Lack of Transparency** - The methodology and data sources used by ranking organizations are often not transparent, making it challenging for universities to identify and address areas of improvement. The lack of transparency can also lead to skepticism and mistrust of the rankings among the stakeholders.

The process of clustering universities based on specific

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characteristics or criteria may provide individuals with a more comprehensive understanding of the institutions' strengths and weaknesses, thereby enabling them to make more informed decisions about where to study or work. This approach may be preferred over simply ranking universities from best to worst for several reasons like:

- **A limitation of criteria** - Ranking methods typically use a limited set of criteria to evaluate the performance of each university, but some universities are performing very well in different areas of expertise, so clustering them can highlight their strengths.
- **Diverse needs** - Each individual has different priorities when choosing a university, such as, cost, location and academic courses.
- **Avoiding Stigma** - By ranking universities from best to worst, a hierarchy can be created that stigmatizes lower-ranked universities. This effect can be lessened and a more favorable and inclusive perspective of universities can be provided by clustering universities based on specific traits or areas of specialization.

The remaining of the article is organized as follows: In Section II we describe the relevant work, while Section III presents the dataset and the data pre-processing phase. Section IV presents the methodology and finally, Section V concludes the article.

II. Related Work

Clustering is a machine learning technique that belongs to the category of unsupervised learning and aims to group related objects together into distinct clusters.
There are several different types of clustering, each with its benefits and drawbacks. Some of the types of clustering are:

- **Hierarchical** - Employing this approach, clusters are arranged in a dendritic, tree-like configuration, wherein each smaller cluster constitutes a subset of a more extensive cluster. Two primary forms of hierarchical clustering exist: agglomerative [2] and divisive [3]. In the agglomerative clustering technique, each data point initiates within its individual cluster, ultimately culminating in the amalgamation of all clusters into a singular entity. Conversely, the divisive clustering method commences with all data points residing within a single cluster, which is then progressively partitioned into smaller clusters by the algorithm.
- **K-Means** - One of the most popular clustering techniques is known as K-means clustering [4]. The data must be divided into K clusters, where K is an adjustable parameter. The approach seeks to reduce the sum of the squared distances between each data point and the cluster center to which it has been assigned.
- **Fuzzy Clustering** - This method facilitates data points to possess multiple degrees of membership across numerous clusters. Fuzzy C-Means (FCM) clustering [5] represents the most prevalently employed fuzzy clustering algorithm within the field.
- **Density-Based** - Data points that are close to one another in a high-density area and are separated by areas of lower density are grouped using the density-based clustering technique. DBSCAN [6] is the most popular density-based clustering algorithm (Density-Based Spatial Clustering of Applications with Noise).
- **Model-Based** - This technique posits a blend of probability distributions as the source of the data points. The Gaussian Mixture Models (GMM) [7] algorithm is the most used model-based clustering approach.

Extensive research has been conducted in the realm of performance evaluation and ranking of academic institutions, encompassing universities, departments, and various academic domains.

A famous technique for ranking universities is the rank fusion [8]. Rank fusion, also known as meta-ranking, is a technique for combining the results of multiple university rankings to create a more comprehensive and reliable ranking. Rank fusion works by standardizing the different rankings and combining the results using a weighted average, where the weights reflect the importance of each ranking.

Compared to separate ranking algorithms or sources, rank fusion can offer a number of advantages. It facilitates a more steady and reliable rating and lessen the influence of outliers or inaccuracies in individual rankings. Also, it may take into account a broader range of factors or viewpoints and offer a more complete picture of the effectiveness or caliber of the ranking entities. Rank fusion should be used with caution, as the weights used to combine the rankings may be subjective or biased.

The rainbow ranking [9] is a famous ranking algorithm, that offers individual rankings for several facets of a university's success, including research, teaching, internationalization, and community participation, in contrast to typical university rankings that only offer a single overall score. Although rank fusion and rainbow ranking are related concepts, rainbow ranking is a specific method of rank fusion. For each factor, each university is given a ranking independently, and the results are added together to provide an overall rainbow ranking. The primary objective of the rainbow ranking system is to furnish a detailed and multifaceted evaluation of a university's performance, thereby facilitating the identification of potential areas for enhancement and targeted development.

The rainbow ranking's recognition of the diversity of universities and the many objectives and priorities they may have is one of its main benefits. For instance, a university that places a high priority on teaching might rank well in that category even if it falls short in other categories. As an alternative to conventional university rankings, the rainbow ranking has been adopted by various organizations and universities, and it has received recognition for its inclusivity and thoroughness. It has, however, also drawn criticism for being overly complicated and making it impossible to compare universities across multiple categories.

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For our study, we relied on [10], although [11] is pretty similar to our analysis. In [10], the researchers clustered universities from the National Taiwan University (NTU) ranking using the DBSCAN, EM [12] and K-Means algorithms, ending up to the conclusion that K-Means is the most appropriate one because its results are the closest to the NTU ranking. The clustering results they obtained through experimentation with 12 and 43 clusters resemble the rankings of the NTU.

In [11], the Quacquarelli Symonds (QS) dataset for the year 2022 was used for clustering and analysis. The author used six score indicators which we mention in section III and chose the Gaussian Mixture Model (GMM) as the main algorithm for clustering. The optimal number of clusters was chosen to be four using the Akaike's Information Criteria (AIC) [13] and Bayesian Information Criteria (BIC) [14]. In contrast to the ranking system currently used by QS, the results revealed a new classification system for universities.

Comparing our work to [10] and [11], we used the K-Means, GMM, Agglomerative and Fuzzy C-Means algorithms in order to provide a more diverse and nuanced perspective on the data, and to uncover different patterns and structures that may not be revealed by a single algorithm. In order to cluster the universities in a way that is more equal and fair, in addition to the six indicators that were used in [11], we also included three additional indicators from the dataset that are mentioned in section III. Finally, we used two techniques for normalizing the data that are also mentioned in section III.

III. Dataset and Data Pre-Processing

A. Dataset

For the purposes of this research, we acquired a dataset from the official website of the Quacquarelli Symonds (QS) for the year 2023. In the dataset, there are over 1400 universities from all over the world including universities from diverse locations of Europe, Asia and North America. We chose the specific dataset because of the different indicators that are used to evaluate the performance of a university, unlike other university rankings that use only bibliographic related indicators.

Totally, there are 27 columns in the dataset but according to the QS ranking, each university is ranked and assessed using only six columns/indicators named:

1) **Academic Reputation** (ar score) - Evaluates the teaching and research quality of the university.
2) **Employer Reputation** (er score) - Evaluates how competent, innovative, and effective students and graduates are for the employment market.
3) **Faculty/student ratio** (fsr score) - Evaluates how universities provide students with meaningful access to faculty staff.
4) **Citations per faculty** (cpf score) - Evaluates the total number of academic citations about the papers published the last five years.
5) **International student ratio** (isr score) - Evaluates the ability of a university to attract foreign students.
6) **International faculty ratio** (ifr score) - Evaluates the ability of a university to attract foreign faculty staff.

The above indicators, each in turn get a percentage of $40\%, 10\%, 20\%, 20\%, 5\%,$ and 5% of the total score.
In our analysis we include, in addition to the above, three more indicators named:

1) **Size** - The total number of full time degree-seeking students.
2) **Focus** - The broad subject areas of each university, e.g Arts, Humanities, Engineering and Technology, Natural Sciences etc.
3) **Age Band** - The age of each university.

The selection of the three supplementary indicators is premised on their ability to facilitate the categorization of universities according to their respective values. This enables the establishment of distinct and equitable rankings among the institutions, thus providing a more comprehensive evaluation of their performance across multiple dimensions.

Each of the three indicators captures a percentage of the total number of universities.

TABLE I: Size, Focus, Age Band

	Size	Students	Perc. (%)
XL	Extra Large	More than 30.000	23.8
L	Large	$\geq$ 12.000	46.6
M	Medium	$\geq$ 5.000	23.8
S	Small	Fewer than 5.000	5.8
	Focus	Faculty Area	
FC	Full comprehensive	5 faculty areas & medical school	41.6
CO	Comprehensive	5 faculty areas	32.5
FO	Focused	3 or 4 faculty areas	22.0
SP	Specialist	2 or fewer faculty areas	3.9
	Classification	Age	
5	Historic	100 years old and more	37.5
4	Mature	50-99 years old	34.4
3	Established	25-49 years old	20.4
2	Young	10-24 years old	6.7
1	New	Less than 10 years old	0.9

All the above indicators have been selected to be applicable to all universities regardless of geographical area.

B. Data Pre-Processing

After describing the indicators that were used for our analysis, some pre-processing of the data is a desirable prerequisite to clustering. First and foremost, we have to exclude the universities that have missing values on at least one of the above nine indicators, with the purpose of evaluating them equally. We convert the size and the focus indicators to a numerical value ranging from $0 - 100$, so as to examine how each indicator affects all the other indicators. Thus, we calculate a correlation matrix using the Pearson correlation

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coefficient [15]. The resulting correlation matrix for the nine indicators is provided in table II.

TABLE II: Correlation Matrix

	size	focus	age	ar	er	fsr	cpf	ifr	isr
size	1								
focus	0.45	1							
age	0.24	0.22	1						
ar	0.32	0.37	0.3	1					
er	0.19	0.23	0.21	0.84	1				
fsr	-0.2	0.09	0.12	0.38	0.35	1			
cpf	0.1	0.21	0.16	0.57	0.44	0.12	1		
ifr	-0.08	0.11	-0.03	0.4	0.35	0.17	0.45	1	
isr	-0.1	0.04	0.04	0.39	0.36	0.23	0.37	0.71	1

Upon scrutinizing the aforementioned table, several pertinent observations can be deduced, contributing to the formulation of meaningful conclusions in the context of the present research. The academic and employer reputation indicators have a relatively strong relation with most of the indicators and especially with one another. That implies that, as the academic reputation of a university increases, employers are more likely to hire students that graduated from that university. Also, there are some interesting things to note about the size, focus and the age band indicators. It seems that the three indicators do not have a strong relation with the other six indicators which means that, as the size, age, and the number of broad subject areas of a university increase, the other indicators do not get affected as much as we would expect. An exception can be made about the academic reputation, which has the highest relation with the three indicators, but overall, size, age and the broad subject areas do play a major role in the performance of a university.

Knowing which indicators are more important to our cluster analysis, we normalize the data. We used two techniques to normalize the data:

1) We multiplied each indicator by a custom weight that is chosen based on the importance of the indicator in evaluating a university and the initial weight values provided by QS. Then, we normalized their values to the scale $0 - 1$.
2) We excluded all the weights from the normalization in order to have a more balanced and fair clustering.

Each technique was used once per experimentation cycle. One experimentation cycle consists of clustering the data using N clusters and calculating the similarity measure of the clustering algorithms.

The similarity measure is calculated using the Rand Index (RI) [16] between every pair of algorithms. To compare the results of the clustering algorithms used in this study with the QS ranking list we employed the following steps:

1) We created, for each experimentation cycle, N clusters.
2) In each cluster, we assigned $\frac{\text{number of universities in QS rank list}}{N}$ universities according to the order they were ranked by the QS. The remaining universities were assigned in the last cluster.

The normalization algorithm we used is the MinMaxScaler which can be described by the following equation

$$x_{\text{scaled}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$

IV. Methodology

The clustering algorithms that were used for this analysis are the following:

1) **K-Means** - K-means can be a useful algorithm for university clustering in certain situations, particularly when simplicity, efficiency, and intuitive results are important.
2) **GMM** - Assuming the data can be described as a combination of Gaussian distributions, GMM can be a valuable technique for university clustering. It can offer adaptability, interpretability, and identification of universities with distant indicator values. It can also aid in improving comprehension and analysis of the performance of various university groups.
3) **Agglomerative** - Agglomerative clustering can be used when a hierarchy of clusters is needed, or when flexibility and interpretability are important. However, it may not be the best choice for all situations, particularly when the underlying data has complex relationships or non-linear distributions.
4) **Fuzzy C-Means** - Fuzzy C-Means is a useful algorithm for university clustering due to its ability to allow each university to belong to multiple clusters, with varying degrees of membership. Practically, for our case scenario, a university can be assigned to a specific cluster but it can also possess a high probability of being a member of a neighbouring cluster. Thus, it helps us to make a more nuanced analysis of the performance and characteristics of different groups of universities.

To find the optimal number of clusters using the nine indicators we used:

1) An EM algorithm implementation of the Weka [17] software tool (using the default values) that assigns a probability distribution to each instance which indicates the probability of it belonging to each of the clusters. EM can decide how many clusters to create by cross validation, or you may specify apriori how many clusters to generate [18].
2) The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) for a maximum of 30 clusters. The maximum number of clusters was chosen arbitrarily. Since AIC and BIC are both statistical measures used for model selection and

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comparison, we used the GMM algorithm for these measures.

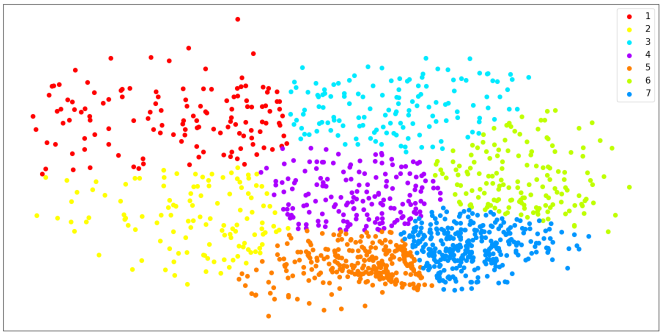
The EM algorithm gave us seven clusters. Using the AIC and BIC measures we came up with the graph that is shown in fig. 1. The number of clusters for the minimum value of BIC is seven which is identical to the results of the EM algorithm. The number of clusters for the minimum value of AIC is approximately 29 but we used 24, as the difference between the AIC value of 29 and 24 clusters is quite small.



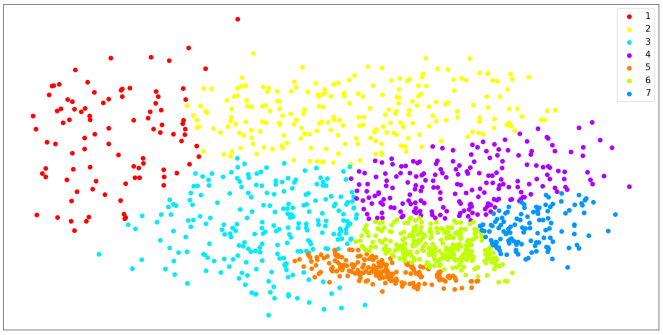
Fig. 1: AIC & BIC values for a maximum of 30 clusters and a minimum of two.

In order to visualize the clusters, we used the Multidimensional Scaling (MDS) algorithm [19] to reduce the initial dimensions of the data to two.
The clusters are *ordered* based on the mean value of each cluster. The mean value of a cluster is calculated by adding the indicator values of each university in that cluster divided by the total number of indicators used in our analysis. Then, by summing the means of each university and dividing by the size of the cluster we get the mean of the cluster. The top universities are therefore found in the red cluster, followed by the next best performing universities, which are found in the yellow and blue clusters, according to the results. The clustering results for seven clusters and nine indicators are shown in fig. 2. The sizes of each cluster for every algorithm are shown in table III.

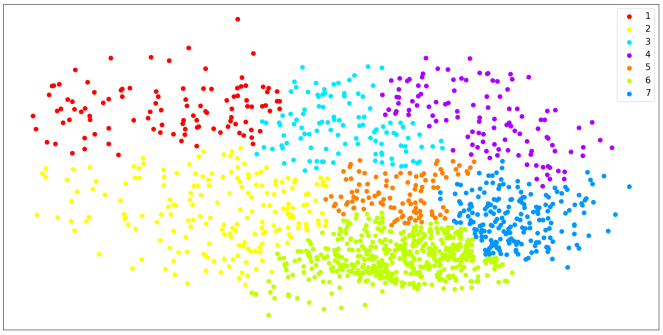
Visualizing the results of the clustering algorithms and calculating the Rand Index (see table IV), we can make a few observations. First of all, the cluster with the highest mean (red cluster), for every algorithm, has a very low density. That is to be expected given that universities in that cluster tend to have diverse values for their indicators, whereas universities in clusters with lower means tend to have similar values for these indicators. Thus, clusters with lower mean have higher density. Regarding the shape of the clusters, K-Means and Fuzzy C-Means are pretty similar despite the fact that their rand score isn't very high. Although Fuzzy C-Means assigns a



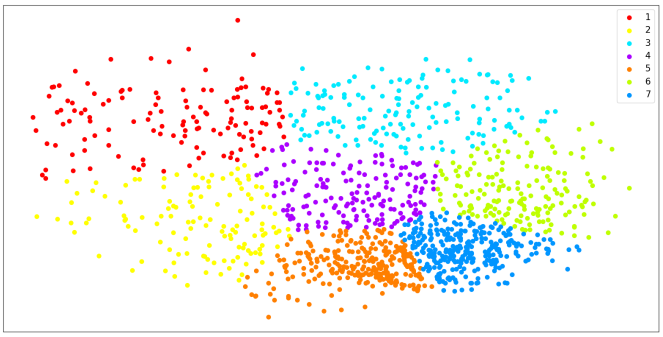
(a)



(b)



(c)



(d)

Fig. 2: Visualization for seven clusters. (a) K-Means (b) GMM (c) Agglomerative (d) Fuzzy C-Means

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TABLE III: Cluster sizes for seven clusters

	KM	GMM	Agg	Fuzzy
1	133	94	105	131
2	124	222	194	127
3	137	233	111	151
4	171	200	114	165
5	271	182	106	272
6	158	255	470	171
7	314	122	208	291

university to a cluster with a membership value, meaning that a university can belong to two different clusters with an equally high membership value, still, a university must be assigned to only one cluster. A clear distinction can be seen between K-Means and GMM clusters when looking at their shapes. GMM can handle clusters of different shapes, not only spherical ones.

TABLE IV: Rand Index for seven clusters

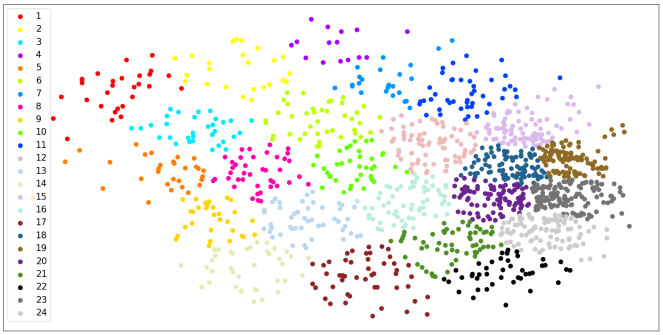
	KM	GMM	Agg	Fuzzy	QS
KM	1				
GMM	0.726408	1			
Agg	0.854153	0.739578	1		
Fuzzy	0.813539	0.726609	0.819637	1	
QS	0.777024	0.753249	0.782652	0.78123	1

The clustering results for 24 clusters and nine indicators are shown in fig. 3. According to table V, the Rand Index between every pair of algorithms has significantly increased and the results are now closer to the QS ranking. Considering that, we can conclude that as we increase the number of clusters, the similarity between every pair of algorithms and the initial QS ranking increases.

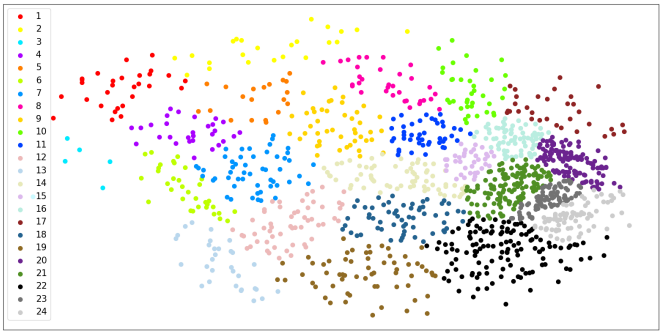
TABLE V: Rand Index for 24 clusters

	KM	GMM	Agg	Fuzzy	QS
KM	1				
GMM	0.879644	1			
Agg	0.940349	0.880343	1		
Fuzzy	0.896166	0.842625	0.885155	1	
QS	0.916113	0.872567	0.913869	0.866017	1

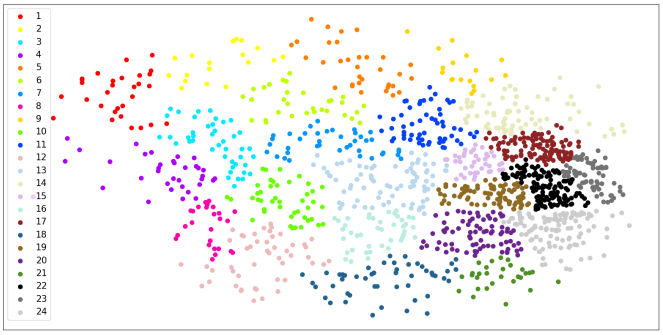
The clustering results for seven clusters and nine indicators multiplied by the weights are shown in fig. 4. The indicators and their corresponding weights are shown in table VII. The highest weight is assigned to the academic reputation indicator, as it is the indicator that affects the rest of them the most. Despite being used to facilitate in the categorization of universities, the size, age and focus indicators, have each received a weight of 0.1 due to the fact that they have a relatively low correlation to the other indicators. The initial weight values for the faculty and student ratio (fsr) and the citations per faculty (cpf) indicators were half of the academic reputation weight, so by assigning a weight of 0.125, we have



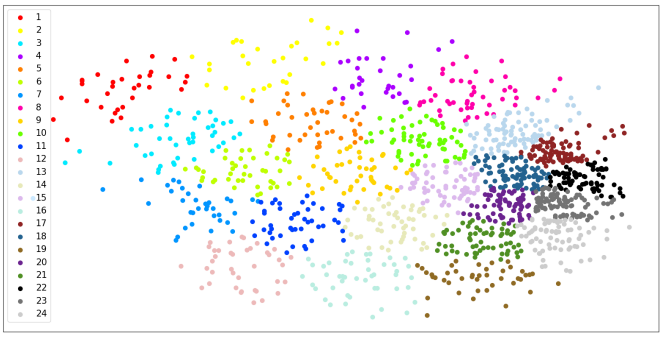
(a)



(b)



(c)



(d)

Fig. 3: Visualization for 24 clusters. (a) K-Means (b) GMM (c) Agglomerative (d) Fuzzy C-Means

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TABLE VI: Cluster sizes for 24 clusters

	KM	GMM	Agg	Fuzzy
1	29	29	30	32
2	24	23	18	29
3	32	6	43	43
4	15	29	35	31
5	30	20	33	41
6	41	34	31	42
7	24	52	40	36
8	41	33	26	48
9	30	45	18	44
10	38	37	44	60
11	45	44	57	45
12	71	55	49	39
13	47	31	77	79
14	38	65	67	52
15	81	37	40	59
16	60	72	42	46
17	48	32	111	86
18	90	60	49	83
19	107	62	80	42
20	87	121	77	67
21	59	127	29	61
22	44	129	132	74
23	129	84	69	92
24	98	81	111	77

kept the initial ratio constant. The international student and faculty ratio indicators have a small weight value so as not to be biased against universities that do not accept (or do not have the legal capacity to accept) foreign students/faculty. A distinguishable difference between this cluster analysis and the one with seven clusters and no weights, is the size of the first and last clusters. In this analysis, the first cluster for all algorithms has a smaller size compared to its counterpart with no weights. Accordingly, the size of the last cluster for the K-Means, GMM, and Agglomerative algorithms, with emphasis on GMM and agglomerative, is larger compared to the cluster size of the corresponding unweighted algorithms.

TABLE VII: Weights for nine indicators

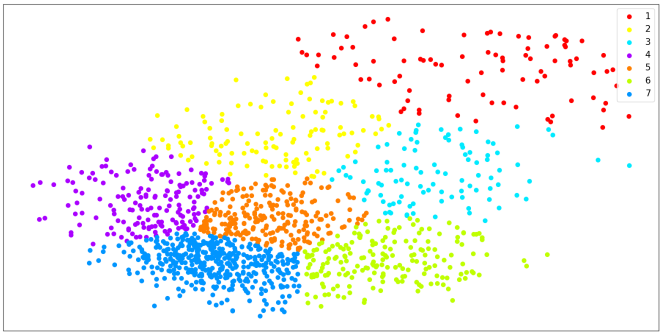
size	age	focus	ar	er	fsr	cpf	ifr	isr
0.1	0.1	0.1	0.25	0.1	0.125	0.125	0.05	0.05

TABLE VIII: Rand Index for seven clusters with weights

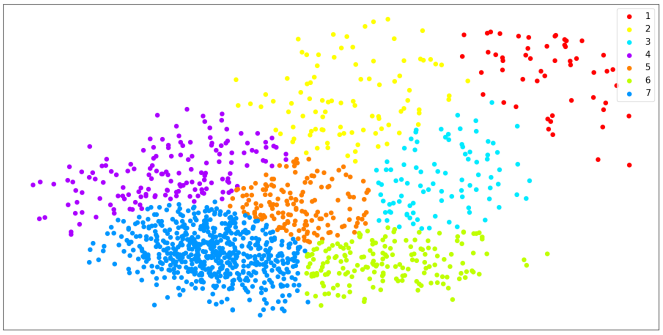
	KM	GMM	Agg	Fuzzy	QS
KM	1				
GMM	0.758163	1			
Agg	0.817264	0.722209	1		
Fuzzy	0.828477	0.729772	0.774022	1	
QS	0.789006	0.778478	0.750169	0.772918	1

V. Conclusion

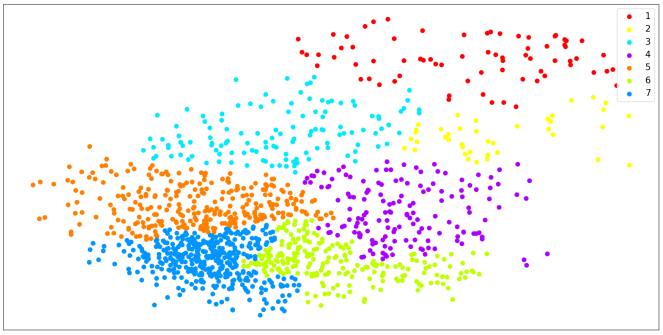
Based on the aforementioned analysis, it is evident that clustering methods can be applied in novel ways that expand beyond the traditional function of grouping institutions with similar characteristics. The outcomes have revealed an



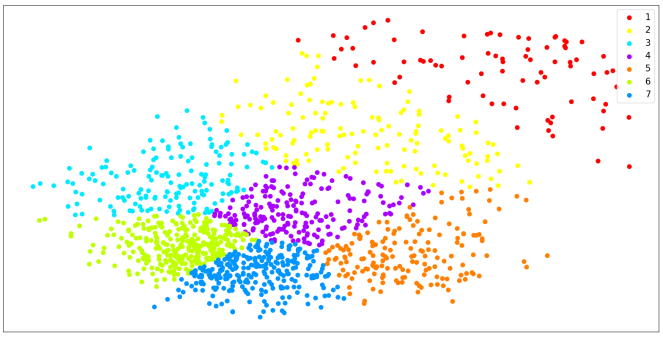
(a)



(b)



(c)



(d)

Fig. 4: Visualization for seven clusters with weights. (a) K-Means (b) GMM (c) Agglomerative (d) Fuzzy C-Means

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TABLE IX: Cluster sizes for seven clusters using indicators with weights

	KM	GMM	Agg	Fuzzy
1	89	53	72	79
2	116	94	40	133
3	99	93	124	158
4	165	156	156	196
5	227	153	291	170
6	193	177	226	302
7	419	582	399	270

innovative approach to ranking institutions by incorporating clustering methods and supplementary indicators from ranking organizations. This is achieved by ordering clusters based on the performance of institutions within them. Regarding the number of institutions within each cluster, the difference in size between the clusters that were formed using the custom weights, and those that did not, becomes apparent. Moreover, a comprehensive analysis of the features utilized in the clustering analysis has revealed the degree of correlation and importance of each feature in assessing an institution's performance. Finally, several clustering experiments have been performed to provide a diverse and nuanced perspective of the data, uncover interesting patterns and structures that may not be evident through a single method.

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