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Insights into University Composite Rankings from Explainable AI Counterfactuals

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Abstract

University rankings exert considerable influence in higher-education decision-making. Yet, as an artifact of their construction, rankings are largely unhelpful in conveying practical strategic insights to university administrators' intent on improving their college's rank. Machine learning tools such as interpretable machine learning (IML) and explainable artificial intelligence (XAI), taking aim at piercing obscure, black-box algorithms have gained a lot of interest recently. However, there appear to be few deployments of their use in appraising University rankings. In this work, using as representative dataset the QS Rankings of USA MBA programs, we show how counterfactual XAI can support proactive responses by educational stakeholders to rankings outcomes. Explaining individual predictions opens great opportunities for intervention and strategizing. The method is applicable to any extant rankings.

Keywords: college rankings, local outlier factors; unsupervised classification; IML, XAI, counterfactual

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"Who comes out on top in any ranking system is really about who is doing the ranking."

Malcolm Gladwell (2011)

1. Introduction

Most individuals have difficulty accurately appraising the individual qualities and ultimate value of educational institutions. Like auto mechanics, and gastroenterologists, universities peddle a product whose value is difficult to determine before consuming it and even then, it may not be entirely clear. This asymmetry of information and a persistent inability to evaluate the product's utility is what characterizes "credence goods (Dulleck & Kerschbamer, 2006)." In credence goods markets the promise of delivering on what is promised must be taken on faith in the producer.

Choosing a college is a difficult task partly because of the considerable variation among universities and colleges in quality, amenities, programs, expense, location, among other features. But the most important criteria for picking where to go to school may be an unobservable one. It is difficult to ascertain the incremental value of a college's contribution to an individual's human capital. A student will be unable to know with any meaningful confidence, before attending, how much a particular college will contribute to his or her human capital and earnings capacity. Indeed, it is very difficult even after graduation to establish how much of a person's lifetime accomplishments are attributable to the college they attended (Carnevale, Cheah, & Van Der Werf, 2019) (Ponton, 2024).

This informational asymmetry between universities and prospective students characterizing credence goods markets can create externalities – unintended costs. In a highly competitive markets such as the higher education market, sellers may be less than candid, be prone to bluster and puffery, and may even tread the fraudulent in publicizing its achievements and features, its promises (Li, Horta, & Jung, 2022) (Lee, 2009) (Thaddeus, 2022).

The possibility of unchecked marketing hyperbole and credence goods invites a role for third-party evaluators such as the US News & World Reports College Rankings and other rankings platforms. University rankings exist as a supplement in aid of prospective consumers of university services. Rankings can impart independent, trustworthy information to prospective customers.

The task of aggregating disparate information into an individualized metric is, for the most part, useful to prospective students and consumers. However, rankings are largely inscrutable and unhelpful to the colleges and universities themselves (Gnolek, Falciano, & Kuncl, 2014) (Rybinski & Wodecki, 2022). The issue lies with their "secret sauce:" the conceptualizing and construction of composite rankings.

The scores ascribed to colleges, and listed in a rankings platform are an arbitrary weighted ranking of ranks. Put differently, attributes are selected, measured, ranked, and the ranks then combined (often with weighting) to produce a final ranking. There may be subordinate rankings. Ordinarily the weighting is arbitrary; the weightings of the subordinate rankings may also be arbitrary; the weightings of the subordinate rankings may also be different. Note also that the rankings disguise the size of the value differences between the ranks. The point is that all this dizzying algebraic kneading – the exact method sometimes guarded as closely-held information - makes the final rankings arbitrary. This entanglement undoubtedly masks any number of data artifacts, including the relationships between individual features. In sum, drawing actionable insights from college rankings is difficult. College rankings share this handicap with many machine learning models that mask the process adopted (Rodriguez, Ozkul, & Marks, 2019).

Rankings' opacity renders them unhelpful in conveying practical strategic insights. Rankings publishers provide little to no explanation as to what drives the rankings. No explanation is provided on how each variable impact an individual university's position in the proffered ranking, and what each university is doing – or not doing – right or wrong, and how could it be done differently. Rankings' inability to offer colleges any finer guidance or explanation beyond the constituent score variables can be especially frustrating for academic decision makers. Intentionally or not, the implicit assumption set forth by college rankings publishers is that universities and colleges should repair all the attributes set forth. Rankings proffer no model structure, predictor importance, underlying relationships, predictor complexity, or covariates with the outcomes.

If we consider, for example, the case of a particular university unfairly relegated to the academic minor leagues by an extant rankings purveyor, the reasons for the afflicted university's specific position are of interest to the university. The aggrieved college would want to review the soundness of the outcome, the validity of the process. An explanation revealing only the constituent variable metrics for the rank achieved, can be insufficient to understand how to change the outcome.

Some relief and assistance has reached academic strategists at the heels of the explosion of solutions and applications in interpretable machine learning (IML) and explainable artificial intelligence (XAI) (Gnolek, Falciano, & Kuncl, 2014) (Rybinski & Wodecki, 2022) (Nagy & Molontay, 2024). These tools were recently introduced to assist with piercing the black-box nature characterizing the more complex algorithms. Among them are counterfactual methods (Guidotti, 2024).

Counterfactual explanations suggest what should be different in the input instance to change the outcome of a black-box ranking system (Wachter et al. 2017). Counterfactuals can answer why a specific rank and more importantly, what changes in the features would lead to a different outcome (Molnar 2020). Counterfactual are used across a range of real applications such as leasing requests, college dropout prediction (Zhang, Dong, Lv, Lin, & Bai, 2022) (Nagy & Molontay, 2024), health-care triage (Salimiparsa, 2023), job applications (Barbosa de Oliveira, Goethals, Brughmans, & Martens, 2023), university admission (Waters & Miikkulainen, 2014), credit scoring (McGrath, et al., 2018) (Dastile, Celik, & Vandierendonck, 2022), etc.

In this study, we show how counterfactual methods drawn from explainable artificial intelligence methodologies can support proactive responses by educational stakeholders to Rankings outcomes. Specifically, we use the algorithm NICE from the R package *counterfactuals*; the algorithm searches for counterfactuals by iteratively replacing feature values of the college of interest with the corresponding value of its most similar institutions (Brughmans, Leyman, & Martens, 2021).

We illustrate the argument, method, and its use with data the 2024 QS Rankings of MBA programs. Our work stands as a proof-of-concept; its applicability extends to any ranking platform beyond those focused on US MBA programs.

We do so as follows: in the next section we provide a succinct review of existing work on counterfactuals as a particularly useful piece from the XAI toolbox; the volume of the latter topic is sizable – and we cannot presume to be exhaustive in our review. In the third section we set forth our methodology. A fourth section contains our results. The method is illustrated using the lowest-ranked college in the QS survey as a hypothetical, fictitious example. The last and fifth section provides concluding comments including limitations of the approach discussed here.

2. Background and Related Work

The ratcheting-up of the already intense competitive pressures impacting the higher education market has fostered a proliferation of ranking platforms. These platforms vary across universities, countries, continents, size, regions, programs, emphasis, public or private, amenities, and focus, *inter alia*. Scholars seeking to understand, grade, predict, and qualify these platforms have followed closely (Estrada-Real & Cantu-Ortiz, A data analytics approach for university competitiveness: the QS world, 2022) (Gadd, Holmes, & Shearer, 2021). Aiding researchers in this probe have been conventional tools as well as more recent, advanced tools, such as explainable and interpretable AI approaches (Guidotti, 2024).

Interpretable machine learning methods were introduced to explain the performance and outcome of black-box machine learning models. An especially useful method in this toolbox and an excellent one for the task of explaining single predictions of a model are counterfactual explanations. Counterfactuals work by determining the smallest change to the reported feature values of an institution that would change the model's prediction of that institution's rank.

By contrast, methods such as Local Interpretable Model-agnostic Explanations (LIME) and Shapley Values explain an institution's position in the rankings leaderboard by determining how much each feature contributed to the proffered rank (Lundberg & Lee, 2017) (Ribeiro, Singh, & Guestrin). Counterfactual explanations differ from feature attributions since they generate data points with a different, desired prediction instead of attributing a prediction to the features.

Counterfactual methods can be either model-agnostic or model-specific. A method is considered model-agnostic if it applies to any algorithm. In turn, model-agnostic methods can be global or specific. Global explanations reflect the average behavior of the model whereas local ones are more concerned with individual predictions (Molnar, 2022). Given that our interest is in explaining a particular outcome in university rankings platforms we limit our focus to model-specific approaches as in Wachter et al (Wachter, Mittelstadt, & Russell, 2018).

3. Methodology

University rankings are an instance of what are known as composite rating scales. These scales are based on the idea that an underlying or latent measure can be gauged by aggregating a weighted series of individual quantitative and qualitative features. Every organization that publishes college rankings relies on its own set of guidelines, preferences, and ranking methodology. There is no a priori applicable methodology and thus no standard controlling the construction of the various published rankings.

3.1 Local Outlier Probabilities

The Local Outlier Factor (LOF) algorithm is an unsupervised detection approach to identifying outliers in a dataset (Breunig, Kriegel, Ng, & Sander, 2000). It does this by computing the local density surrounding a given data point and compares it to the density around other data points. It considers outliers samples that have a substantially lower density than their neighbors. One of the appealing properties of LOF is that it can work with mixed variables, numeric and categorical columns.

The LOF algorithm requires the specification of k-nearest neighbors of a data point as a nuisance parameter. It then calculates the distance between the data point and each of its k nearest neighbors. In turn, the local outlier probability, which ranges from 0 to 1, constitutes a direct measure of the likelihood of the point being an outlier. The higher the outlier probability the more likely the data point is to be an outlier. By contrast, a low outlier factor indicates that a data point is more likely to be non-outlier data point. The algorithm is ideal for identifying points that are significantly different from their neighbors such as fraud detection or identifying financial frailty. The heterogeneity of the attributes involved in the college selection process also constitutes a good example. In our work we rely on the approach set forth in Alghushhairy, et. al. (Alghushhairy, Alsini, Soule, & Ma, 2021).

$$LoOP(p) = \max\left(0, er\,f\left(\frac{PLOF(p)}{\lambda * \sqrt{2}}\right)\right) \tag{1}$$

where, p is the point being evaluated, $er\,f$ is the error function, *PLOF(p)* is the Probabilistic Local Outlier Factor of point p and λ is a parameter controlling the sensitivity of the methods (often called “extent”). The PLOF is calculated as in Equation (2):

$$PLOF(p) = \frac{LRD(p)}{\overline{LRD}(N_k(p))} - 1 \qquad (2)$$

Where $LRD(p)$ is the Local Reachability Density of point p and $\overline{LRD}(N_k(p))$ is the average LRD of the k-nearest neighbors of p.

3.2 Data and Data Treatment

We use the 2024 QS Global MBA rankings for the United States to illustrate our approach (Estrada-Real & Cantu-Ortiz, A data analytics approach for university competitiveness: the QS world, 2022) (Note 1). QS makes its data publicly available. QS's rankings for the 25 Global MBA Ranking: US version, consist of five features. These are (1) Employability, (2) Entrepreneurship & Alumni Outcomes, (3) Return on Investment, (4) Thought Leadership, and (5) Diversity. Each feature is subsequently weighted to yield an overall score with a value between 1 and100. The institutions are then listed in descending order, the one with the highest score occupying the first position in the ranking. Table 1 lists the top four colleges in the QS Rankings as well as the Bottom four.

Table 1. 2025 QS Global MBA Rankings: US

Institution	Employ	Entrep Alumni Outcomes	Return on Invest	Thought Leader	Diversity
Stanford Graduate School of Business	97.6	100	90.9	95.2	68.9
Penn (Wharton)	98.6	83.9	95	95.9	78.3
Harvard Business School	96.4	96.9	90.4	96.5	72.9
MIT (Sloan)	98.6	88.4	90.5	99.1	70.5
	...	...	...	...	...
University of South Florida (Muma)	26.2	34.5	26.6	48.7	57.3
University of Tennessee, Knoxville – Haslam College of Business	27	27.2	60.5	30	38.8
William & Mary (Mason)	39.3	42.8	29.2	43.9	49.8
Worcester Polytechnic Institute (Foisie)	34.3	29.1	35.5	37.9	48.9

Note. Top and Bottom 4.

The QS Rankings do not avoid ties and often assign a range rather than a specific rank. For instance, Babson College and Texas A&M are ranked 27 in 2024; Lehigh University is ranked 51-60 in 2024.

Accordingly, to remove both the arbitrariness of the weightings and the inability to provide necessary refinements, we re-ranked the data using unsupervised cluster analysis; specifically, the Local Outlier Factor. The Local Outlier Factor (LOF) algorithm is an unsupervised detection approach to identifying outliers in a dataset (Breunig, Kriegel, Ng, & Sander, 2000). In turn, the local outlier probability (LoOP), which ranges from 0 to 1, constitutes a direct measure of the likelihood of the point being dissimilar from each other.

The LoF algorithm is ideal for identifying similarities among institutions and ranking them accordingly. The measure of LoOP is multiplied by 100; it is then used to create a ranking variable. Table 2 contains the data set displaying the first and last three institutions of the dataset listed according to the reconstituted rankings, labelled LoOP Ranks.

Table 2. 2025 QS Global MBA Reconstituted Rankings: US

Institution	**Employ**	**Entrep Alumni Outcomes**	**Return on Investment**	**Thought Leadership**	**Diversity**
Emory (Goizueta)	60.2	43.7	93.4	55.1	52.6
UC San Diego (Rady)	35.1	45.7	59.8	53	48.6
Tampa (Sykes)	35.5	46.4	72	39.2	62.9
Michigan (Ross)	83.6	70.3	98	79.8	67.3
	...	...	...	...	...
University of Massachusetts (Dartmouth)	26.3	27.5	51	21.1	44.5
Brigham Young (Marriott)	29.5	48	78.5	48.3	28.8
University at Albany	26.8	27.5	27.1	38.2	27.3
Howard University	38.9	34.3	86.5	31.4	34.3

Note. Top and bottom 4.

To illustrate via a fictitious case study, we select the lowest ranked institution in our ranking and find the three "counterfactual institutions" most like it. The predictor obtained from an SVM regression of the reconstituted rankings on the QS attributes. The predicted reconstituted rank from the algorithm for the university is 94.2.

Table 3. Attribute Values for Sampled Institution

Institution	Employability Score	Entrep	ROI	Thought Leadership	Diversity
122	38.9	34.3	86.5	31.4	34.3

We choose to examine counterfactuals in the desired outcome interval of 80 to 85.

4. Results

The feature analysis in Figure 1 displays the attributes responsible for the university's rank in order of importance. These attributes identify the relative contributions of the rankings elements associated with the university chosen for the case study.

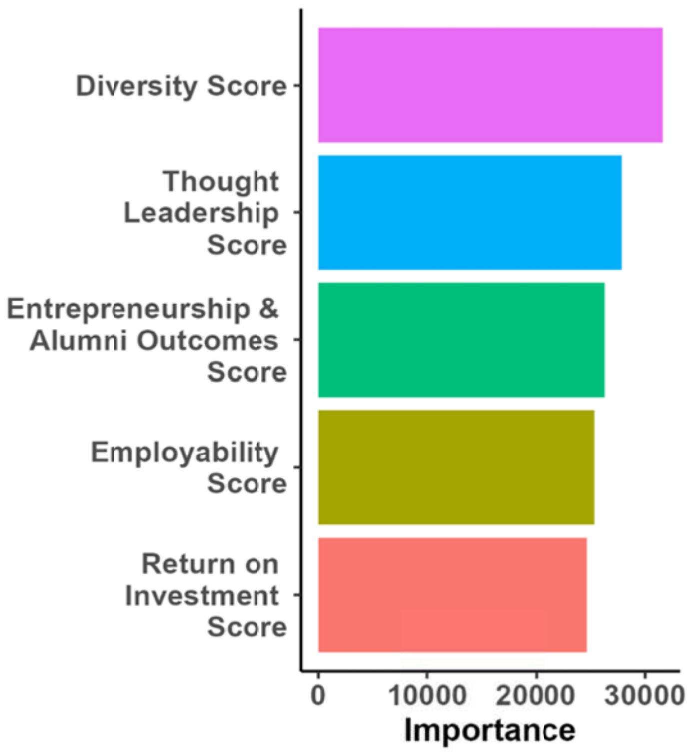

Figure 1. Most Important Attributes. 2024 QS MBA Rankings USA

The gap analysis from the counterfactual exercise is visible in Figure 2. The darker line reflects the position of the university and indicates the difference between the university and the three identified counterfactuals. To improve from its current last-place rank, Figure 2 shows the differentials, or gaps, that need to be closed or reduced between the lowest ranked institution used here as a prototypical example, and the counterfactuals.

These results should inform any actionable strategy intended to improve the rankings position of the institution. Note that the university's diversity score leaves significant room for improvement. The university's employability efforts could similarly benefit from some attention.

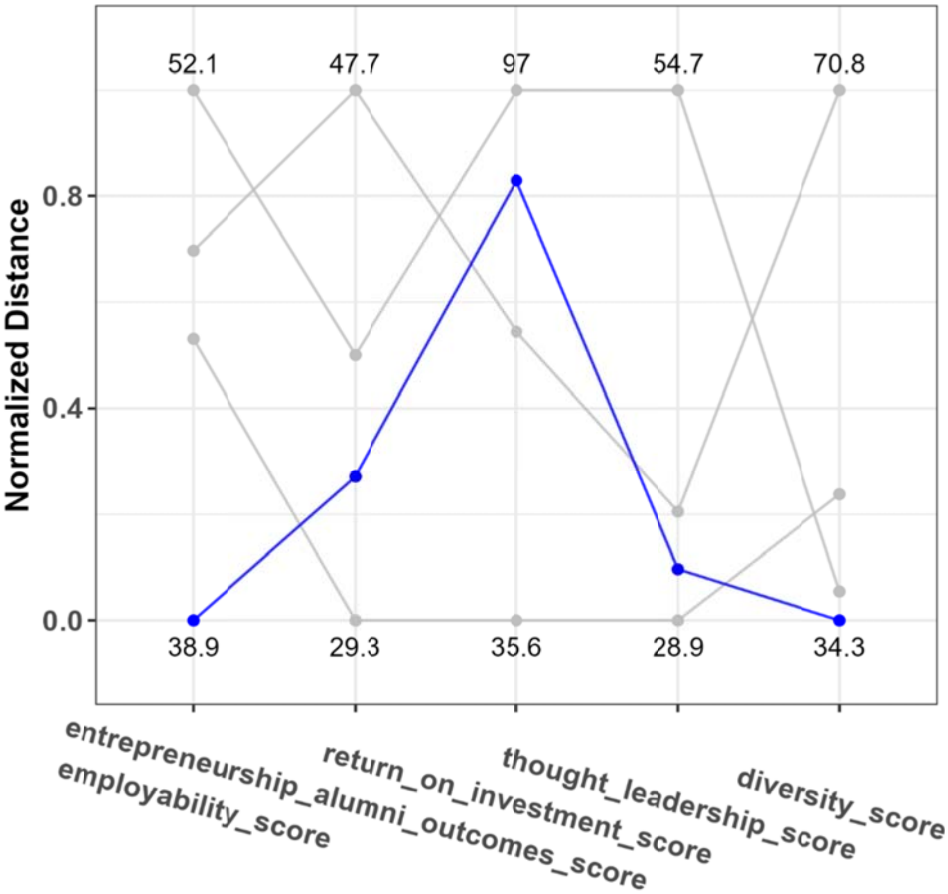

Figure 2. Gap Analysis

5. Concluding Comments

Advances in machine learning have led to the creation of powerful tools that have altered the way we analyze complex problems, such as scrutinizing college rankings. Rankings, especially composite rankings rely on elaborate, complex, and often closely held methods in their construction, which contribute to their inherent opacity.

We describe and articulate the use of XAI counterfactuals to extract insights and actionable information. To illustrate its insights, we explained the approach using the well-regarded QS rankings of US MBA programs and applied the method to a hypothetical institution. To this end, we selected the lowest ranked institution in the data set as the stand-in. The approach identified actionable attributes in the sense that it allows a clear roadmap for university administrators intent on improving their QS rankings position.

It should be clear that any analysis, insights or any derived strategic implications are limited by the extent and nature of the features constituting the scrutinized rankings. For example, the ranking platform used here is limited to five QS-specified features of US MBA programs. Thus, the method here is limited in its ability to circumvent any built-in biases or conceptual shortcomings of any of the ranking platforms used.

However, these two limitations of the proposed methodology suggest the following. First, it suggests a particular approach to harvesting actionable information. Prospective users of this approach need not base their analysis on only one ranking. To the extent that applying the method here returns different salient variables from different rankings, a college could craft an action plan resulting from a bespoke cost-benefit analysis of the various variables obtained from the analysis of two or more rankings platforms.

Second, in their construction, whether in the variables chosen, their assigned weightings, or both, rankings have changed and adapted over the years to accommodate changes in social and professional preferences. For example, today's appeal for diversity and inclusion measures were absent from the earlier versions of the most established college rankings. To the extent the rankings platform adapted their methodology over time, the method proposed here would naturally return different recommendations when applied to prior, earlier versions of rankings. This information could provide deeper insights for administrators looking to develop long-term strategies.

Notes

Note 1: Source: https://www.topuniversities.com/mba-rankings/united-states/2024, visited September 19, 2024; 2025 data is also available as a Kaggle dataset; https://www.kaggle.com/datasets/darrylljk/worlds-best-universities-qs-rankings-2025/data, visited October 4, 2024.

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