

Drawing Actionable Insights from University Composite Rankings Using Explainable AI Counterfactuals: A Case Study

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ABSTRACT

University Rankings exert considerable influence in higher-education decision-making. Yet, rankings are largely unhelpful in conveying practical strategic insights to university administrators' intent on improving their college's rank.

This case study demonstrates how to use interpretable machine learning (IML) and explainable artificial intelligence (XAI) to appraise university rankings. These novel tools were originally developed to deconstruct obscure, black-box algorithms deployed to assist decision-making in fields such as financial credit-granting, hiring practices, and human resource administration, among many others.

The setting for this case study examines how academic administrators at the University of New Haven can draw actionable insights from a popular rankings platform using this methodology.

Explaining individual predictions opens up great opportunities for intervention and strategizing. The method is applicable to any extant rankings.

Keywords: College Rankings, Interpretable Machine Learning, Local Outlier Probability, Counterfactual, Local Outlier Factor

INTRODUCTION

The purpose of this study is to review the College Rankings environment impacting the University. The objective of this review is to draw an analysis leading to an outline, a roadmap, a strategy, or a set of next steps to take to improve the university's position in the rankings.

The task is challenging for a number of reasons. First, over the last few years there has been a veritable explosion in the proliferation of organizations publishing rankings. This expansion may be associated with the increased competitive intensity in the higher education market. Second, for their construction, rankings rely on any number of differing and often subjective, *ad-hoc* features. These may include subjectively weighted combinations of seemingly intuitive measures such as the 8-year graduation rate and the average net price paid. Additionally, they may include more contemporary metrics that have gained prominence, including social mobility and diversity and inclusion measures.

The variation in the construction across rankings is equally rich as to the conceptualization or focus. For instance, reputable organizations publish rankings that focus on various dimensions, including universities, countries, continents, institutional size, geographic regions, academic programs, emphases, public versus private status, amenities, and specific areas of focus (e.g. trade or vocational schools). There are presently rankings of colleges and universities, rankings of colleges or administrative units within colleges and universities, rankings of individual programs, all of the above combined across all type of regions both national and international.

Third, and compounding the matter, is the proliferation of advertising relying on softer, subjective metrics or surveys albeit served-up as rankings. The methodologies employed by ranking providers vary significantly, and the processes by which these rankings are generated often remain opaque. Many ranking producers maintain strict control over their methods and data, which poses a significant challenge to our objective of demystifying the "black box."

To accomplish the task, the team opted for an analytical method that produces actionable results. The analysts focused on the rankings published by the Washington Monthly. More specifically: the Washington Monthly College Guide: 2024 Best Bang for the Buck Rankings: Northeast (Washington Monthly, 2024). This particular survey was chosen for several reasons. First, the organization makes its data available – allowing for a close examination of its elements. Importantly, it is the only organization that published its data *and* includes the University of New Haven in the leaderboard. Second, it is contained to the Northeast, the region which encompasses the University of New Haven's footprint and where the University of New Haven strives to make its mark. Third, the elements of this particular rankings appear actionable. Put differently, it is built with features that college administrators can adjust.

METHODOLOGY

The methodology used for the analysis is drawn from the Explainable/Interpretable AI literature; the methodology is discussed in greater detail in Wachter, et al (Wachter, Mittelstadt, & Russell, 2018).

At its core – the methodology presumes to address questions that commonly emerge: why is the University of New Haven ranked 352th? What would happen if the Number of Pell graduates improve? Would the extant ranking change if the University's Net Price fell? Is the gap between Pell and non-Pell graduates important and by how much? This is known as a counterfactual, model-agnostic, local approach. The methodology is a general one, applicable to any rankings.

Data and Data Treatment

The Washington Monthly data titled 2024 Best Bang for the Buck Rankings: Northeast is available online as is the methodology used by its authors (Washington Monthly, 2024). It contains data for 376 colleges and universities in the Northeast consisting of eight variables or features, rankings for each variable, and the aggregated rank of each institution. Each of the attributes had an associated Rank; the ranks-variables was removed from the data set.

The resulting working dataset variables are listed below:

- Rank
- 8-Year Graduation Rate
- Predicted Graduation Rate Based on Percent of Pell Recipients Incoming SAT
- Pell non-Pell Graduation Rate Gap
- Number of Pell Graduates
- Actual vs Predicted Pell Enrollment
- Median Earnings 9-Yrs After Entering College
- Predicted Median Earnings 9-Yrs After Entering College
- Net Price of Attendance for Families with \$75,000 Income

Table 1 displays the top and bottom three institutions in the data and the associated variables. The column names have been shorted. There were two NA instances in the data set; Sterling University and the University of Maine-Machias reported NAs for the *Media Earnings 9 Yrs After Entering College* attribute. We replaced the NAs with the attribute median.

Rankings Reconstituted

The original rankings were reconstituted; in other words, all institutions were re-evaluated using a new ranking algorithm. The reconstituted rankings were recreated using unsupervised cluster analysis; specifically, the Local Outlier Factor and the Local Outlier Factor

Probability available via the R Programming Software packages “dbscan” and “DDOutlier”, respectively.

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), is a normalized version of the LOF. LoOp ranges from 0 to 1, and constitutes a direct measure of the likelihood of the particular point being dissimilar from each other. The 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.

RESULTS

Break Down Plots for the University of New Haven

Break Down (“BD”) plots offer a summary of the effects of explanatory variables on a model’s predictions. BD display graphically which variables contribute the most to the observed results. The plots present “attribute contributions;” put differently, they decompose the model’s prediction into contributions that can be attributed to different explanatory variables. Note that BD plots rely on a ceteris paribus assumption. In other words, breakdown plots capture the contribution of an explanatory variable to the model’s prediction by computing the shift in the expected value of Rank, while fixing the values of other variables.

In Figure 1, the row marked “intercept” presents the overall mean value (184) of predictions for the entire reconstituted rankings dataset. Consecutive rows present changes in the mean prediction induced by fixing the value of a particular attribute. Positive changes are indicated with green bars; negative differences are indicated with red bars.

The feature that influences the University of New Haven’s predicted rank the most is Net Price (with the value “\$30,220”). Median earnings – set at \$56,470 - accounts for another negative. All other features have smaller effects, with a few actually contributing positively.

Counterfactual

The analysis of counterfactuals returns the most similar observations to the University of New Haven from all the institutions in the data set whose prediction is in the desired outcome interval. The predicted rank of the University of New Haven is 143rd. Accordingly, we examined outcomes in the 135-140 positions. Only observations whose features values lie between the corresponding values in lower and upper are considered counterfactual candidates.

Table 3 shows the feature values of the counterfactual institutions as the difference to the University of New Haven. Positive values indicate an increase compared to the counterfactual. Negative values indicate a decrease. The parallel plot in Figure 2 connects the (scaled) feature values of each counterfactual and the University of New Haven in blue.

NEXT STEPS

The feature analysis set forth above in Figure 1 indicated that the most important attributes responsible for the University's position on the rankings are *Net Price* and the *Predicted Graduation Rate Based on Percent of Pell Recipients Incoming SAT*.

The gap analysis that emerges from the counterfactual exercise and visible above in Figure 2 indicates the differential that needs to be closed. Importantly, Table 3 reveals the difference between the actual feature values for the University of New Haven and those of each of the three counterfactuals.

Based on the information obtained here, any strategic plan aimed at improving the University of New Haven's position in the rankings should turn on addressing the imbalances between the university and the proffered counterfactual values.



APPENDIX

Table 1
2024 Best Bang for the Buck Rankings: Northeast

Inst	Rank	8 YR Grad Rate	Pred Grad Rate	Pell Grad Gap	Pell Grads	Act Pred Pell Enroll	9-Yr Med-Earns	Pred 9-Yr Med Earns	Net Price
MA Institute of Technology (MA)	1	0.96	1	-0.03	186	0.05	118345.5	94780.34	-1896.01
Charter Oak State College (CT)*	2	0.56	0.49	0.21	146.67	0.04	57397.5	44813.59	11147.62
Boricua College (NY)	3	0.79	0.56	0.04	193.33	0.31	31767.5	23842.33	13905.14

School of Visual Arts (NY)	73	0.74	0.78	-0.09	204.33	-0.07	41384	45497.23	47513.19
Dean College (MA)	74	0.44	0.54	-0.1	38.33	-0.08	32979.5	42667.33	29481.63
New England College (NH)	75	0.28	0.52	-0.11	111.67	0.03	34572.5	41312.36	27980.45
Berklee College of Music (MA)	76	0.64	0.62	-0.14	140.33	-0.06	29232.5	49102.47	43077.39

Note. Washington Monthly College Guide.

Table 2: Reconstituted Rankings
2024 Best Bang for the Buck Rankings: Northeast

Inst	8YR Grad Rate	Pred Grad Rate	Pell Grad Gap	Pell Grads	Act Pred Pell Enroll	9-Yr Med Earns	Pred 9-Yr Med Earns	Net Price	LoOP Rank
MA Institute of Technology (MA)	0.96	11	-0.03	186	0.05	118345.5	94780.34	-1896.01	1
Montserrat College of Art (MA)	0.58	0.67	-0.13	27.67	0.02	29364	34919.72	29733.97	2
Berklee College of Music (MA)	0.64	0.62	-0.14	140.33	-0.06	29232.5	49102.47	43077.39	3

Curry College (MA)	0.59	0.62	-0.14	176.67	-0.13	47129	52150.6	25146.17	373
DeSales University (PA)	0.6	0.65	-0.16	123.33	-0.07	53474	54653.43	23438.66	374
Alvernia University (PA)	0.61	0.59	-0.15	114.67	-0.09	47218	50684.88	25637.85	375
Long Island University (NY)	0.52	0.59	-0.13	698.33	-0.08	51724.5	54305.35	24320.18	376

Note. Wahington Monthly College Guide.

Figure 1

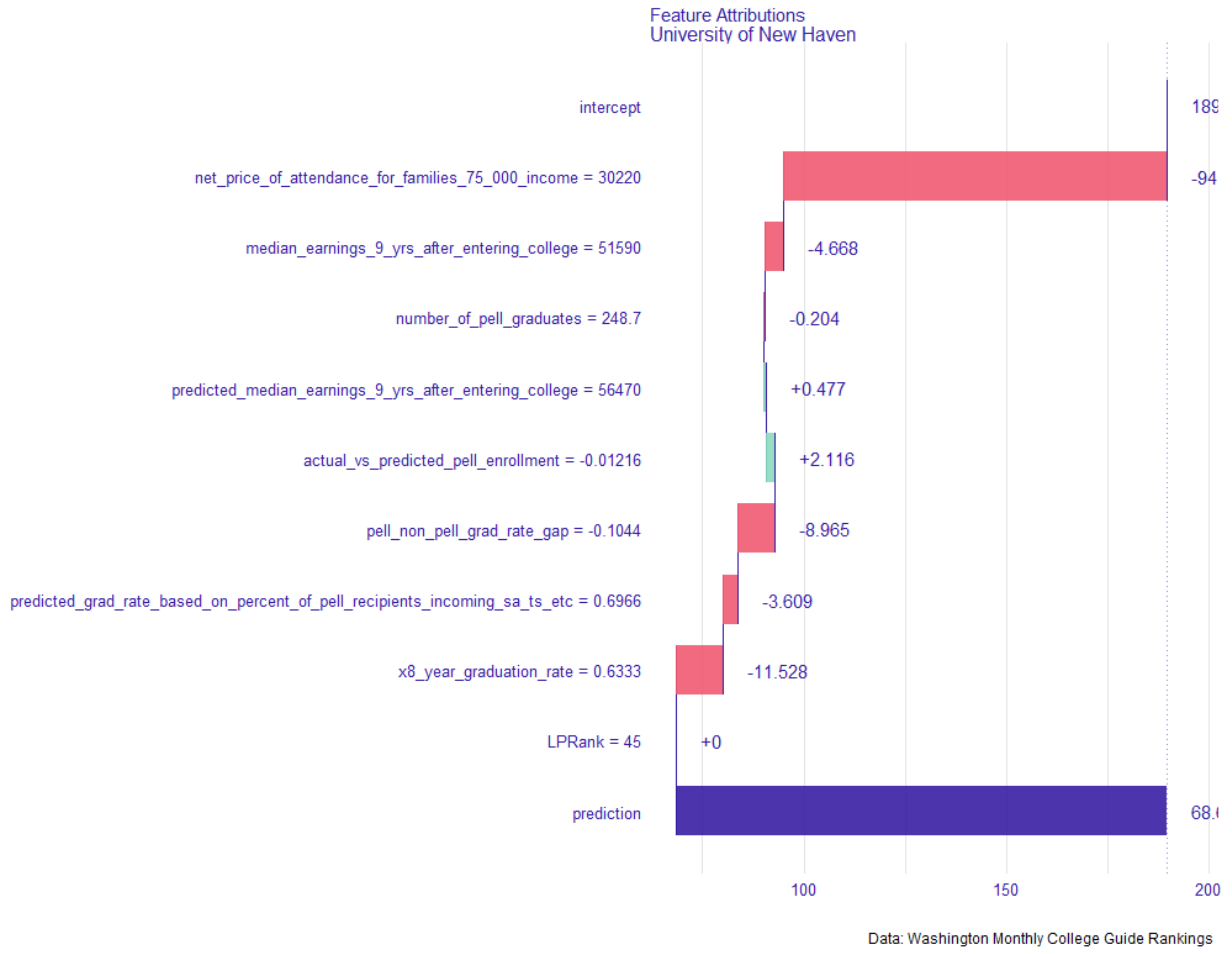


Figure 2

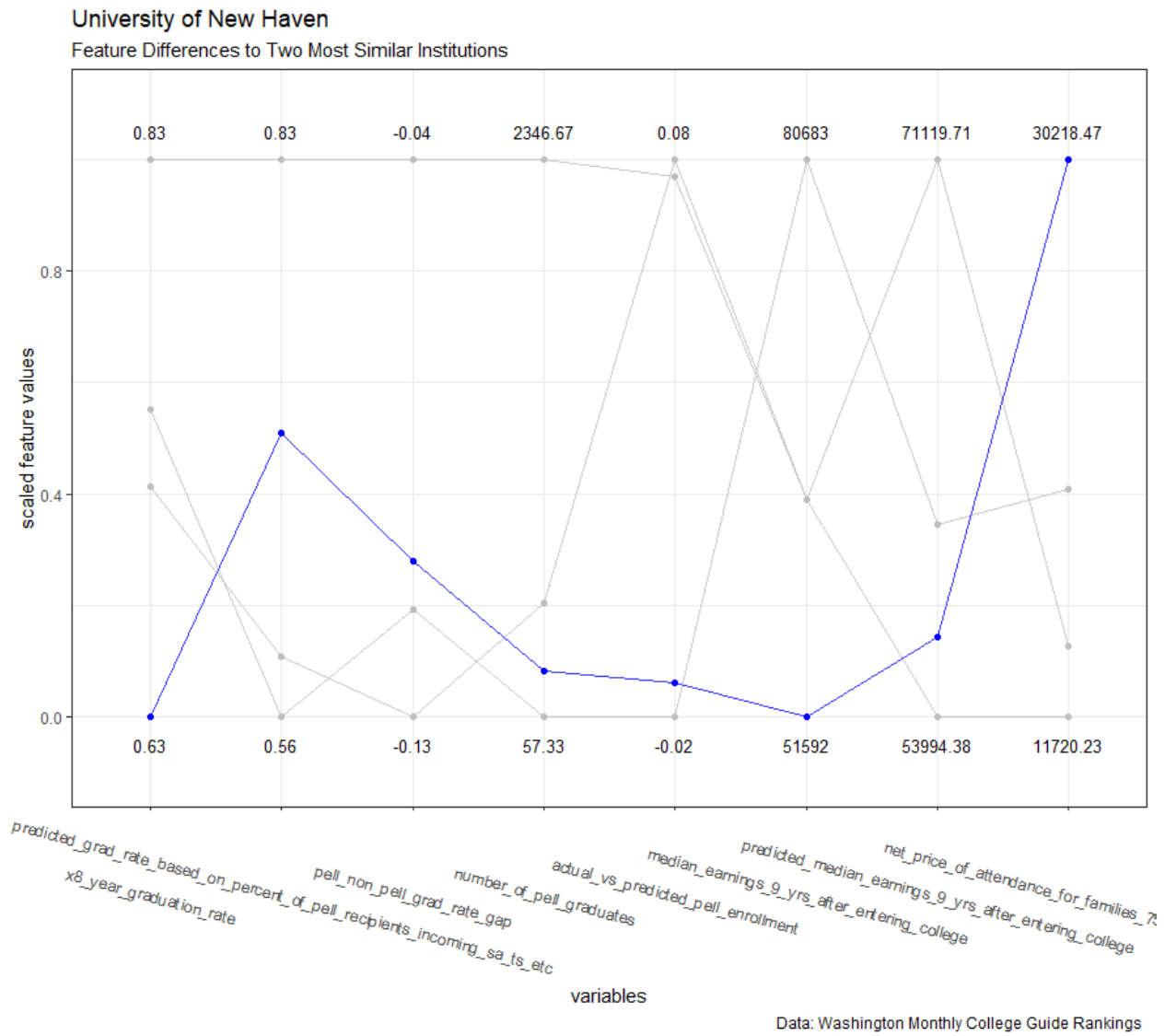


Table 3

Pred Grad Rate Pell Recipients	Pell non- Pell Grad Rate Gap	Net Price
-0.134	-0.00785	10956
-0.106	-0.02525	18498
0.129	0.06526	16152



References

- Alghushhairy, O., Alsini, R., Soule, T., & Ma, X. (2021). A Review of Local Outlier Factor Algorithms for Outlier. *Big Data and Cognitive Computing*, 1-24.
doi:<https://doi.org/10.3390/bdcc5010001>
- Breunig, M., Kriegel, H.-P., Ng, R. T., & Sander, J. (2000). LOF: Identifying Density-Based Local Outliers. *PROCEEDINGS OF THE 2000 ACM SIGMOD INTERNATIONAL CONFERENCE ON MANAGEMENT OF DATA*, 93-104.
doi:<https://doi.org/10.1145/342009.335388>
- Wachter, S., Mittelstadt, B., & Russell, C. (2018). Counterfactual Explanations Without Opening the Black Box: Automated Decisions and the GDPR. *Harvard Journal of Law & Technology*, 31, 841-854.
- Washington Monthly*. (2024). Retrieved October 4, 2024, from 2024 Best Bang for the Buck Rankings: Northeast: <https://washingtonmonthly.com/2024-college-guide/best-bang-for-the-buck-rankings-northeast/>

