Demystifying the Carnegie Classifications: A Sensitivity Analysis

Paul Harmon

Adviser: Dr. Mark Greenwood

Montana State University

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Abstract

The Carnegie Classifications of research activity are used to compare like institutions in higher education. In 2015, the newest update of the Carnegie Classifications were released, with Montana State University moving from the top-tier category of "Highest Research Activity" to second highest tier, "Higher Research Activity." The classification system is based on two separate indices calculated using Principal Component Analysis (PCA). The first index is based on a set of aggregate covariates and the other on a set of per-capita metrics.

This analysis re-creates the calculation of the classifications and examines how sensitive they are to changes in the underlying characteristics of a given institution, focusing on Montana State University. Care should be taken when interpreting the results of this analysis; a static analysis of a dynamic process can illuminate the most sensitive aspects of the classifications but cannot forecast the way that other institutions will grow with respect to Montana State University. That being said, this analysis informs how difficult it would be to move from the R2 status to R1 in the future, but more importantly, it further illuminates the reasons for why Montana State was placed in the "Higher Research Activity" classification in 2015. Additionally, alternative methods for classification of the unviersities are discussed.

1 Introduction

The Carnegie Classifications of Institutions of Higher Education (CCIHE) are released every 5 years. They are intended to be used for institutions to identify other schools which are similar in size, research production, and research spending so that meaningful comparisons can be made between institutions. They are unfortunately often mistaken as a ranking system; however, the classifications of each institution are not meant to identify schools as being better or worse than institutions in other classifications. Nevertheless, the classifications of doctoral-granting institutions (R1,R2, and R3) imply an ordinal ranking, and thus administrators at various schools have interpreted them as such.

In 2014, the Center for Postsecondary Research at the Indiana University School of Education took over the formulation of the classifications from the Carngie Foundation for the Advancement of Teaching. When the 2015 updates were released, Montana State University - among a cohort of several institutions - moved from the "Very High Research Activity" to the "Moderately High Research Activity" category. Institutions are scored on both an aggregate index of research productivity, which considers doctorates awarded along with expenditures and research staff, as well as a per-capita index of research activity.

This analysis seeks to recreate the classifications produced by the researchers at Indiana University. Further, I analyzed the sensitivity of the classifications to minor perturbations in the underlying indices used to calculate each school's score. This allowed me to determine which variables most strongly affect the score for a given institution, specifically focusing on Montana State. I also created an interactive web application that demonstrates where Montana State would end up relative to the other institutions in the dataset if it experienced these slight marginal changes. Administrators at Montana State University (and other institutions like it) have made obtaining R1 status an institutional goal; this sensitivity analysis shows that the path from the current classification to the higher one would be at least somewhat arduous.

2 Methods and Data

2.1 The Data

The data used here were obtained from both the Montana State University Office of Planning and Analysis but are available more generally from the Carnegie Classifications website. In either case, the data contain information pertaining to many levels of institutions; only those that grant doctoral degrees are of interest. The data are therefore processed in order to remove the non-doctoral granting institutions. The data that are reported come from a variety of sources, including the Integrated Postsecondary Education Data System (IPEDS), the CCIHE, and the National Science Foundation (NSF).

In the final dataset, 335 institutions granted doctoral degrees during the period of interest. However, some of the smaller institutions do not report expenditures for STEM-related fields. Therefore, I removed 59 institutions from the dataset, all of which were classified as "high research activity." Doing so leaves a count of 276 schools on which the classifications were calculated.

2.2 Principal Components Analysis

The Carnegie Classifications are built using a methodology known as Principal Components Analysis (PCA). The main goal of PCA is to do dimension reduction, meaning that this methodology is used to take a large set of variables and reduce it down to a more manageable number of covariates.

Consider a set of p predictors $x_1, x_2, ...x_p$. Methods for dimension reduction such as Principal Components Analysis seek to reduce the number of p covariates by creating a new set of covariates $y_1, y_2, ...y_q$ via an eigenvalue decomposition of either the correlation matrix or covariance matrix of the X's. These y variables are then interpreted as linear combinations of the x's; further, they are ordered so that the first new variable, y_1, accounts for the most variation in the original x covariates (Everitt and Hothorn 2011). Note that we have not yet achieved dimension reduction; PCA by itself returns the same number of re-parameterized covariates as what we started with. However, since the new covariates contain information about the variation in the old covariates, it is possible to use only a subset of the first few y

variables without losing much information about the variation in the x's. In this way, often the first two or three y's are used to describe the entire set of q x's.

2.3 Calculating Scores and Loadings

Principal components analysis returns two key pieces of information: the **scores** and the **loadings**. In the more general case of factor analysis, of which PCA is just a single method, the scores are sometimes referred to as factors. The scores are the aforementioned y values.

The first principal component, y_1 can be represented as follows for the $x_1, \ldots, x_q$ original covariates: $y_1 = a_{11}x_1 + a_{12}x_{12} + \ldots + a_{1q}x_q$

The scores can be thought of as an "index" for a more complicated underlying process; each score is just a weighted average of the original x variables. In the Carnegie Classifications, the researchers explicitly define the scores used in the analysis as a "per-capita index" and an "aggregate index."

The loadings are the coefficients by which each original covariates must be multiplied obtain the original data. These are standardized by dividing by the square root of the eigenvalues themselves. The scores can be interpreted as weighted averages of the original covariates; the loadings are the weights on which those averages are calculated.

PCA can be done on either the correlation matrix or the covariance matrix(Everitt and Hothorn 2011). In the Carnegie Classifications, the correlation matrices were used. In R, calculation of the Principal Components Analysis can be done using the function `prcomp` (R Core Team, 2017).

2.4 Dimension Reduction: How Many Scores Should Be Used

The question of how many scores should be used has no definitive answer; it is often left up to the researcher to define the optimal degree of dimension reduction. Certainly, the number of scores used should be less than the original number of covariates; otherwise, the researcher might as well work with the original data.

In the Carnegie Classifications, the researchers used only the first score for each index created. This allowed for researchers to directly plot two independently-calculated indices against each other; however, using only a single score for the index means that they explained less variance in the original covariates. Indeed, in the 2015 update, the aggregate index score only explained 70 percent of the variation in the original data and the per-capita index explained only 71 percent (Borden 2017).

2.5 Regression and Classification

Principal Components Analysis is a powerful tool for dimension reduction; it can be used both in a classification setting and a regression setting. For classification, using the singular value decomposition to create a subset of k principal components scores allows for comparison on a reduced set of covariates. In regression, the linear predictor can be rewritten as $y = \mathbf{X}\beta + \epsilon = \mathbf{F}\theta + \epsilon$ where $\mathbf{F}$ is called the Factor Matrix; it contains only the set of k scores (West 2003). Singular Value Regression, or Principal Components Regression, is useful for some regression problems. This analysis focuses mainly on the classification aspect of PCA; however, it is worth noting that the methods used here could be utilized in a regression setting for prediction. As pointed out by Everitt and Hothorn, PCA is "overwhelmingly an exploratory technique"(Everitt and Hothorn 63) and in the case of the Carnegie Classifications, it is used primarily to describe graphically the differences between institutions rather than to predict them.

3 Recreating The Carnegie Classifications

3.1 The 2015 Update

The classifications are calculated from two different indices, one on the aggregate counts for each institution, and the other on a per-capita basis. The classifications themselves do not count the per-capita measures based on student populations at each school; rather, they focus on the size of the faculty at each institution in terms of a raw headcount of tenurable and non-tenurable faculty.

In general, institutions with relatively large values in one index are likely to be relatively large in the other index. In 2010 the linear Pearson correlation between the two indices was a strong positive 0.83 and in 2015, it was 0.84. The two indices are calculated in the following way:

1. Each variable is ranked from smallest to largest. Ties are all assigned the minimum rank.
2. Two Principal Components Analyses are fit on the correlation matrix of the ranked data.
3. An Aggregate and Per-Capita Index are calculated from the first Principal Component of each PCA.
4. The indices are rescaled and new Aggregate Index is plotted against the new Per-Capita Index to create Figure 1.
5. Arcs are drawn with arbitrary radii to define breakpoints between categories.

3.2 Why Rank the Data?

There is no mathematical reason that the indices could not be based on the raw counts of PhDs, research staff, and expenditures. However, due to economies of scale, large schools tend to produce research and spend money at significantly higher rates than smaller schools. Counts of PhDs awarded, expenditures, and research staff/faculty sizes are therefore severely positively skewed. For instance, Johns Hopkins University spent over 2 billion dollars on STEM expenditures in 2015 compared to a relatively paltry 104 million dollars for Montana State University, which was above the 50th percentile. Ranking the data prior to classification increases

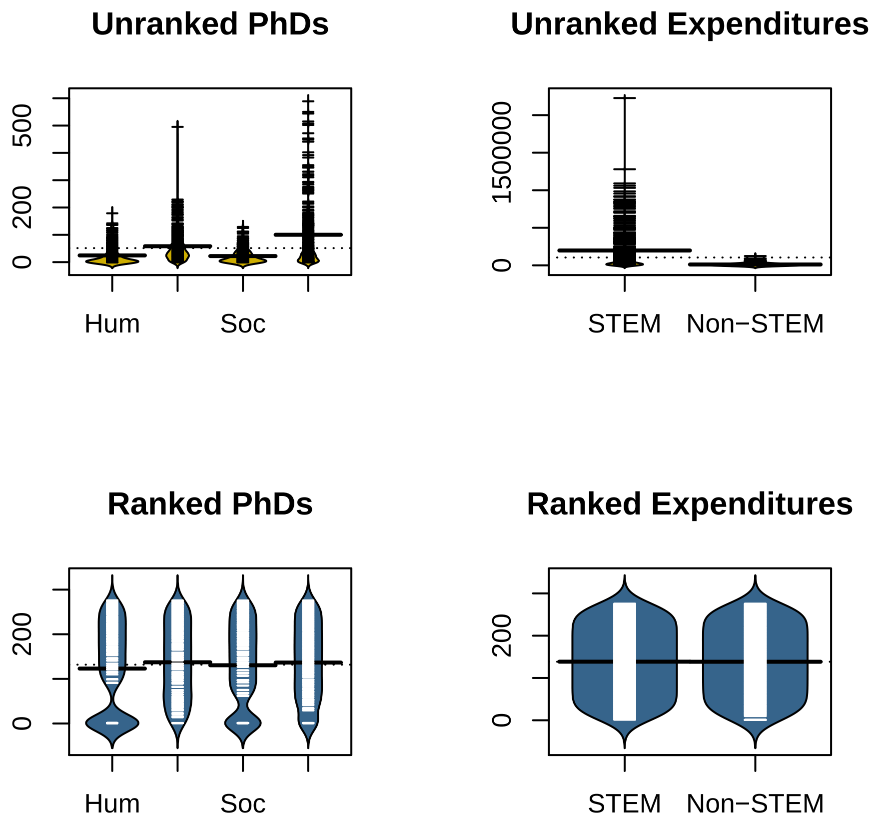


Figure 1: Distributions of ranked and raw data. The raw data are highly positively skewed, but the ranking the data decreases the disparities between larger and smaller schools.

separation between institutions at the low end and decreases separation between institutions with large variable values. Figure 1 shows beanplots (Kampstra 2008) that display the distributions of both the ranked and raw data. The narrow lines refer to each institution's value in the dataset; the wide lines refer to the mean values for each variable. For some of the PhD counts, the distributions of ranked counts appear bimodal because there were many schools that did not offer PhDs in that category in 2015.

3.3 Aggregate Index

The Carnegie Classifications are based on a plot of two indices, the aggregate index and the per-capita index. The x-variable in the Carnegie Classifications is the aggregate index. It includes PhD degrees awarded in one of four categories: humanities, professional fields, social sciences, and STEM fields. However, it also includes the research staff, STEM expenditures, and non-STEM expenditures that are also used in the per-capita calculation.
The formula for the aggregate index is given below for the ith institution:

$$\text{AggregateIndex}_i = .37HumD_i^* + .27STEMD_i^* + .39SocSciD_i^* + .27OtherD_i^* + .40STEMExp_i^* + .38NonSTEM_i^* + .33ResStaff_i^* \quad (1)$$

3.4 Per Capita Index

The per-capita index is the y-variable used in the Carnegie Classifications. It considers only three variables: non-faculty research staff, STEM expenditures, and non-STEM research expenditures divided by the size of the faculty at the given institution. The weights on each variable are calculated from the loadings generated by the per-capita PCA.

The formula for the per-capita index is given below for the ith institution:

$$PerCapitaIndex_i = \frac{.64ResStaff_i^* + .64STEMExp_i^* + .42NonSTEMExp_i^*}{FacultySize_i^*} \quad (2)$$

3.5 Combining the Indices

After calculating the individual per-capita and aggregate indices, the two are combined with a single plot. The per-capita index is plotted along the y-axis and the aggregate index is plotted along the x-axis, as previously noted. The Carnegie Classifications are then based on the natural clustering that occurs in the data; in some years the three groups of institutions are fairly well-separated into three clusters and in other years they are not.

In 2015, no distinct clusters were formed; further, there were no obvious spaces of separation that would define the two borders between the three groups. The classifications were found by dividing the per-capita index roughly into three groups and finding the areas of greatest separation between points in that region (Borden 2017). In the 2010 update, the lines that divided groups were hand drawn; however, in 2010 the lines were drawn by calculating circles with uniform radius from the origin. Using circles allows for institutions with outlying scores in a single index (especially the per-capita index) to be more likely to end up in the highest classification.

3.6 Method For Ties

In replicating the classification done by the Carnegie Institute, a handful of decisions must be made. The most important choice comes in the ranking step. When ranking institutions that are tied, there are several methods for calculating rank that have important consequences for an analysis, especially where an institution can move up or down in rank in subsequent years. In the statistical software package R (R Core Team 2017), the default setting of the rank function is to take the average of the ranks (Becker et. al. 1988). For instance, if the first five institutions have the same value for STEM Expenditures, each institution would receive a rank value of 2.5. Alternative methods include taking the first, last, minimum, or maximum of the ranks. The first and last methods result in taking a permutation of each of the potential ranks with first involving increasing values and last involving decreasing values. The minimum rank method refers to the more commonly known ranking method used in sports; in the previous example, each of the five institutions would be ranked 1st. Similarly, the maximum rank gives the largest rank to all of the observations; in the previous example, each institution would be ranked fifth.

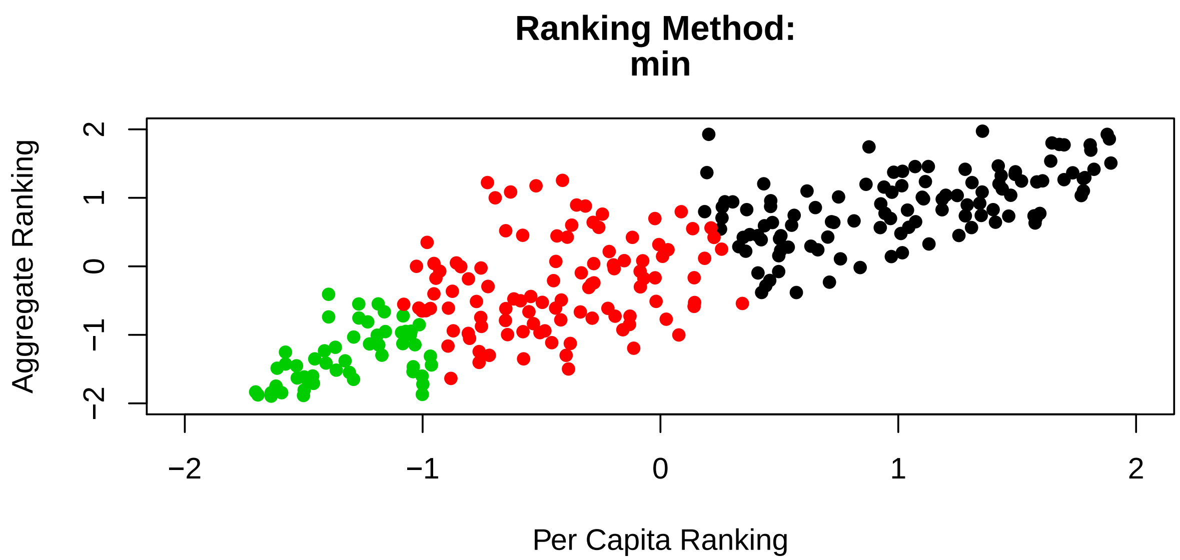
The literature on the Carnegie Classifications does not specify exactly the method that the institute used for tied ranks, but comparing each method to the final results indicates a clear picture. Table 1 is a table of standardized loadings for each method along with the loadings generated from the actual classifications. The standardized loadings did not exactly match for any method (largely due to rounding and software differences), but the minimum method had the closest results. The loadings for the average method did not match closely at all.

Aggregate Rankings							
Ties Method	HUM	OTHER	SOSC	STEM	STAFF	STEM exp	NS exp
Average	0.83	0.618	0.881	0.916	0.907	0.899	0.792
First	0.822	0.615	0.882	0.918	0.908	0.899	0.788
Last	0.824	0.62	0.876	0.913	0.907	0.899	0.795
Min	0.818	0.616	0.873	0.914	0.902	0.899	0.792
Max	0.837	0.619	0.886	0.917	0.912	0.899	0.792
Actual	0.82	0.617	0.874	0.915	0.902	0.9	0.79
Per Capita Rankings							
Average	-	-	-	-	0.93	0.932	0.615
First	-	-	-	-	0.93	0.933	0.61
Last	-	-	-	-	0.929	0.932	0.615
Min	-	-	-	-	0.928	0.93	0.616
Max	-	-	-	-	0.93	0.934	0.615
Actual	-	-	-	-	0.928	0.931	0.614

Table 1: Standardized Loadings: The standardized loadings generated with the minimum method for ties had the most exact matches and the closest overall matches to the actual Carnegie Classifications. The small differences may be due to software or rounding differences.

The loadings give some evidence that the minimum method was used to deal with ties in the rankings; however, the plots of the indices generated by each of the methods confirm that the minimum ranking was used. Other methods generate plots where institutions are misclassified; further, the separation for the minimum ranking is better than for any of the other methods. For institutions that endeavor to improve their classification - or for institutions that seek to avoid dropping into the lower category - this is of particular importance. Breaking ties with one additional PhD in a category can lead to much larger changes in the ranked data if many institutions are tied, compared to other methods of handling ties.

For Montana State, this implies that Social Science PhDs are important. Montana State University is tied with 61 institutions that have 0 social science doctorates. Under the average ranking method, each of those institutions would be ranked as the average rank; however, using the minimum rank, an institution with a single social science PhD would improve its position by 61 points. To be clear, the use of the minimum rank method for dealing with ties indicates that Montana State could gain substantial ground simply by going from having 0 Social Science PhDs to a single one in the next iteration of the classifications Moreover, increasing the number of STEM PhDs is unlikely to have the same impact as increasing Social Science PhDs because Montana State is tied with fewer institutions for STEM PhDs.



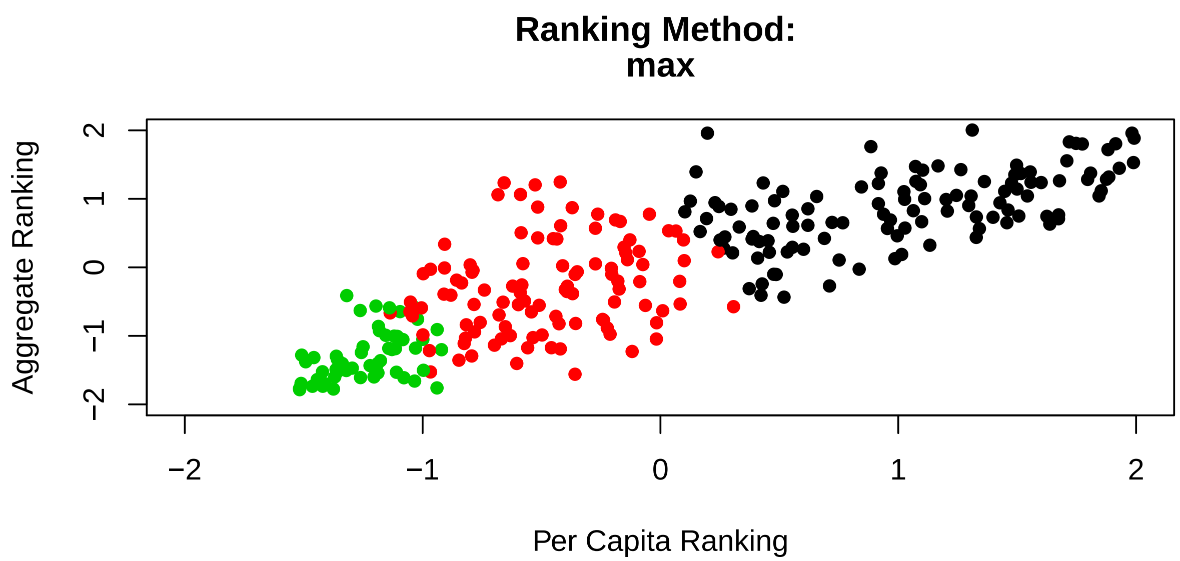


Figure 2: Classifications with different methods for ties. The overlapped colors in the maximum plot and well-separated groups in the minimum plot indicate that the researchers used the minimum method.

4 Exploring the 2015 Classifications

4.1 Similar Institutions

Recall that the purpose for which the classifications are designed is not to rank school quality but instead allow institutional researchers to make meaningful comparisons between schools with similar research qualities. Examining the classifications allows for administrators and other decision makers at Montana State to identify a cohort of similar institutions. By examining the plot of nearest neighbors to Montana State, it is possible to determine a list of like institutions. Figure 3 shows the plot of the most similar institutions to Montana State.

It is evident that University of Alaska-Fairbanks is the institution that most closely resembles Montana State. Interestingly enough, when comparing the raw numbers, they do not look all that similar; Montana State is clearly more productive in producing doctorates in every category save for Social Sciences. Further, while Alaska-Fairbanks spends more money on STEM expenditures, Montana State spends more on non-STEM and has a larger research staff cohort. The key similarities lie not in the raw data but the averaged rankings. Table 2 gives the actual values of each variable for the two schools.

Institutional researchers and administrators ought to use this cohort of nearest neighbor schools to make meaningful comparisons. From a research perspective, for instance, Carnegie Mellon University, Oregon State University, and Rice University are more similar to Montana State in terms of research characteristics than they are to the large-scale R1 schools such as Stanford, Johns Hopkins or the University of Washington. The cohort of similar institutions, along with their scaled distance from Montana State, is given in Table 3.

NAME	FACULTY	HUM	OTHER	SOSC	STEM	STAFF	STEM Exp	NS Exp
Montana State	456	2	9	0	45	75	104646	8702
Alaska Fairbanks	374	1	5	4	34	50	152352	3417

Table 2: Comparison of Montana State to University of Alaska Fairbanks. Although not similar across all values on the raw data, both universities have similar scores on the Carnegie indices.

4.2 Montana State compared to R1 Institutions

In 2010, Montana State was classified as an R1 institution. The reason for this is not entirely clear; however, Montana State had a high per-capita index value and continued to

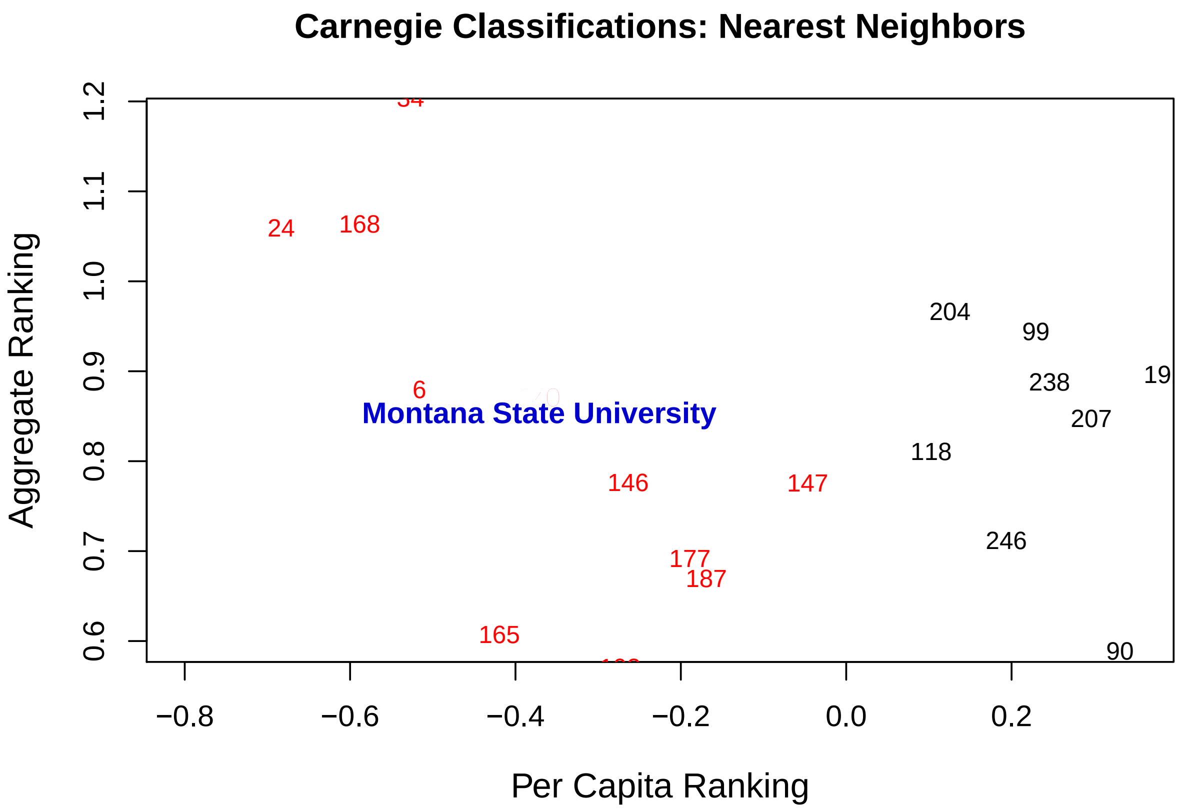


Figure 3: Nearest Neighbor institutions to Montana State University.

ID Number	Name	Scaled Euclidean Distance from MSU
6	University of Alaska Fairbanks	0.02
146	Dartmouth College	0.12
177	Yeshiva University	0.24
165	Rensselaer Polytechnic Institute	0.28
34	Colorado School of Mines	0.36
187	North Dakota State University-Main Campus	0.36
24	Naval Postgraduate School	0.39
168	Rockefeller University	0.42
147	University of New Hampshire-Main Campus	0.44
118	Tufts University	0.56
204	Oregon State University	0.58
246	The University of Texas at Dallas	0.66
99	Tulane University of Louisiana	0.67
238	Rice University	0.67
207	Carnegie Mellon University	0.74

Table 3: Comparison of Montana State to nearest neighbors. Montana State's cohort of similar schools includes an impressive cohort of institutions, both R1 and R2.

have this in 2015; the per-capita score for Montana State was above the 75th percentile.

Of all doctoral-granting institutions, Montana State's research expenditures on STEM-related fields were above the median value, as were its non-STEM expenditures. That, combined with the above-median research staff size, may explain why the Montana State scored highly on the per-capita scale. However, output in terms of PhD degrees awarded is less than the 50th percentile for all degree types awarded, even STEM doctorates. A naive examination of any single variable makes it appear that Montana State would be reasonably well-classified in the R1 group. As seen in Table **??**, outside of Social Science PhDs, MSU produces PhDs, spends research money, and hires research staff at a rate that would be relatively similar to many of the smaller R1 schools.

	HUM	OTHER	SOSC	STEM	Staff	STEM	NonSTEM
Montana State University	2.00	9.00	0.00	45.00	75.00	104646.00	8702.00
Mean R1	51.00	87.00	44.00	202.00	604.00	411742.00	21672.00
Median R1	45.00	76.00	37.00	152.00	387.00	319818.00	14914.00
Min R1	0.00	0.00	1.00	27.00	32.00	5719.00	725.00

caption Comparison of Montana State to R1 schools. MSU looks like it could fit in on any single metric, but would be near the bottom when considering all variables.

Many R2 schools have instituted policy goals geared towards moving from the "lesser" R2 category to the R1 category. Indeed, both the University of Idaho (McClintick 2016) and the University of Montana (University of Montana 2017) are making R1 a policy goal. But is this a reasonable goal for Montana State? Does Montana State compare favorably with R1 schools on the metrics used to calculate the Carnegie Classifications?

However, comparing MSU on individual metrics to R1 schools is misleading since the Carnegie Classifications are based on weighted averages of these covariates, not the individual variables themselves. A more fair comparison would be to look at Montana State across all metrics vs. R1 schools on all metrics. This can be achieved with a Parallel Coordinate Plot, as is given in Figure 4. The nearest R1 schools, Oregon State and Tufts Universities, are both shown as well. The difference between the majority of R1 schools and Montana State is striking; MSU produces fewer PhDs across the board and spends less money on research than nearly all of the schools in the top tier category. Even if Montana State were classified in the R1 group, it would be near the minimum in all categories. In 2015, Montana State lagged behind most of the R1 institutions in expenditures, staff sizes, and doctorates awarded. While Montana State had more Other, Humanities, and STEM doctorates awarded than the smallest R1 institutions, it lagged behind the mean and median R1 values by a large margin. Moreover, expenditures and research staff sizes were much smaller than the average R1 schools, even if they were slightly larger than the smallest R1 school.

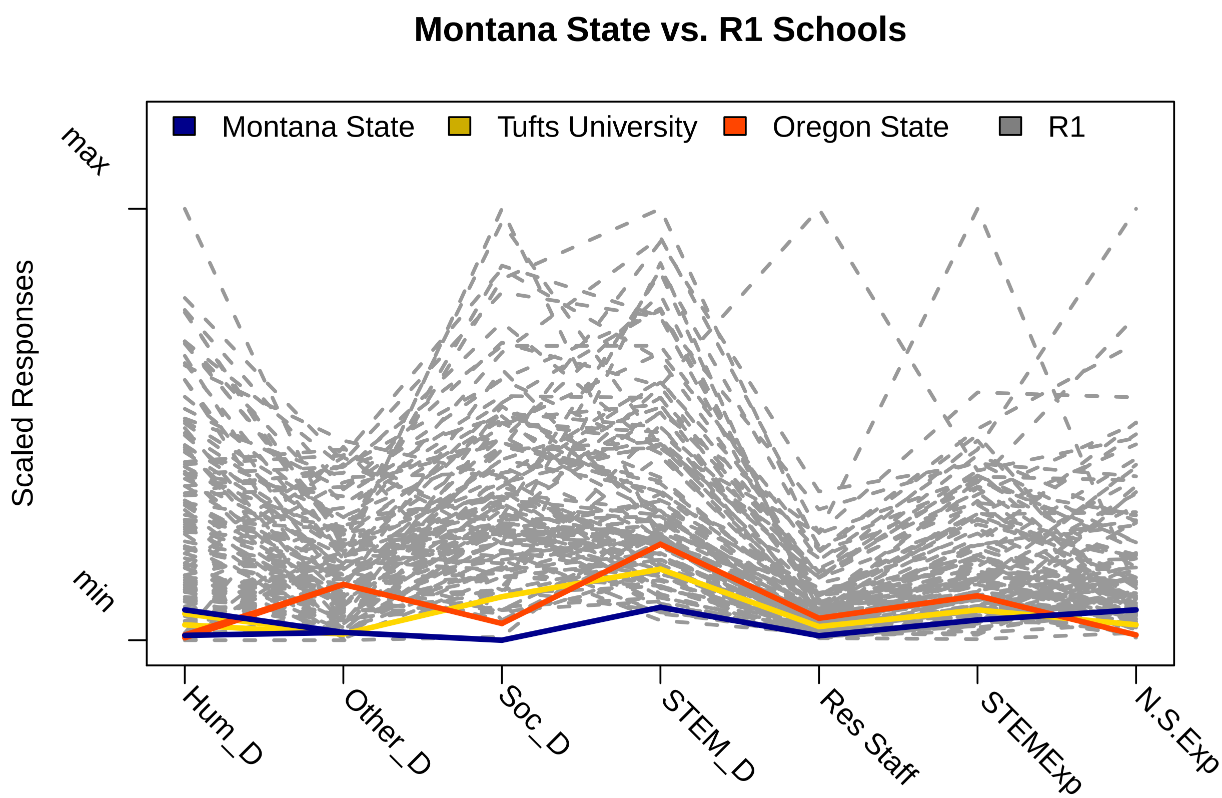


Figure 4: The above plot shows Montana State vs. the R1 Institutions on all of the variables used in the classifications. Montana State would be near the bottom on all variables.

5 Sensitivity of the Rankings

5.1 Single Variable Movement: Aggregate Index

One important question to examine is not only whether it is possible to attain the R1 status, but what might be the best way to get there? Certainly, there are many different ways to move up in classifications; in general, increases on both indices could be achieved by increasing any one of the variables that underlie the classifications. Could Montana State (or any institution, for that matter) focus solely on a single metric to move up to R1 status?

Recall that the aggregate scale is just a weighted average of four counts of Doctoral degrees awarded, STEM and Non-STEM Expenditures, and a headcount of research staff. The PhD counts only impact the aggregate index whereas the latter three covariates also factor into the per-capita index. If Montana State were to focus solely on adding a single type of doctoral degree, could the institution move up from R2 to R1?

The plots in Figure 5 indicate the distance to the boundary associated with marginal increases in each covariate. Starting with additional doctoral degrees in the Social Sciences, it is clear that a small gain from 0 to even a single PhD is associated with a jump towards the R1 boundary. Since Montana State University had no social science PhDs awarded in 2015, they were tied with 61 other institutions that did not grant any degrees. Moving up to a single PhD allows breaks that tie and gives Montana State a jump in 60 rank-units. Adding additional PhDs in the social sciences moves Montana State into and out of more ties, moving the institution closer to the boundary. After 58 Social Science Doctorates awarded, Montana State would hit the boundary and move across the classification border. At 130, the institution would cease to move as it would have attained the highest rank; however, at that point it would already have reached the R1 status. While it is possible to move across the border based solely on Social Science PhDs, it is neither efficient nor feasible to add 58 Social Science PhDs when none were awarded prior to 2015.

For the other doctorate types, it is not possible to move up to R1 status simply by increasing numbers of a single degree type. For STEM PhDs, Montana State already finds itself nearly halfway through the rankings - in 2015 it ranked 125th highest of the 276 ranks. Even if Montana State were to add 545 doctorates (in order to pass University of California-Berkley to attain top rank), it would still be roughly 60 units away from R1 status, ceteris paribus. Of course, even considering adding 545 additional PhDs is absurd. Humanities and Other doctorates experience the same problem; even though marginal gains in either degree type can yield differing increases in each rank, increasing either degree without changing anything else does not yield enough of a gain to move the institution across the R1 border.

This makes sense. The aggregate index is just a weighted average of seven different metrics. If one is changed, the effect it has may make a difference on the index itself; however, that effect is likely to be dampened by the other six un-changed covariates. The reason that Social Science PhDs can take Montana State all the way across the border is because the institution was at the lowest end-point already; on the other metrics, Montana State simply cannot grow enough to get over the border.

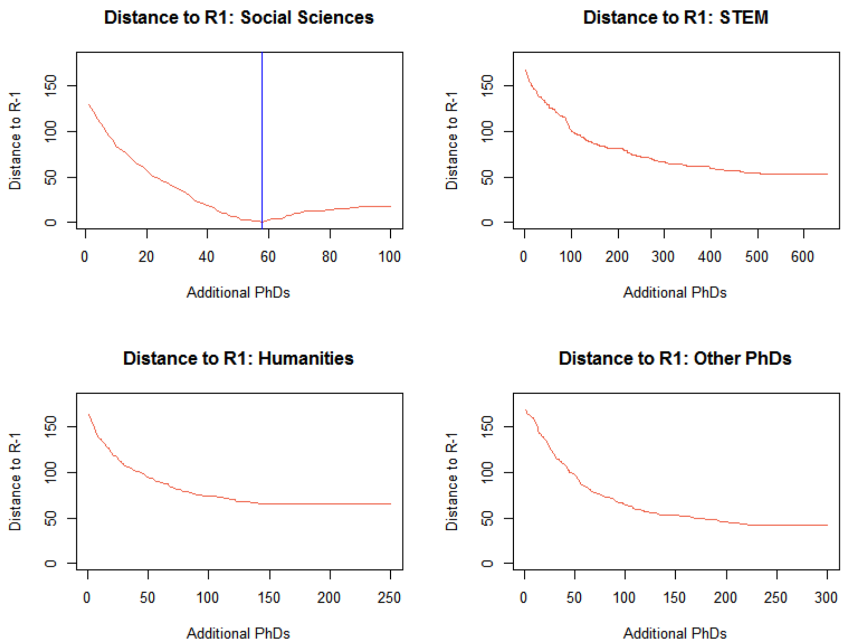


Figure 5: Single Variable Movement: Increasing counts of a single type of PhD lead to movement to the right on the plot. However, only a 58 PhD increase in Social Sciences would get Montana State across the R1 border.

5.2 Single Variable Movement: Both Indices

If increasing awarded doctoral degrees is not enough to move the institution to R1, could the variables that count for both indices work? Indeed, increasing PhDs awarded only moves a given institution to the right or left since those covariates only influence the aggregate index;

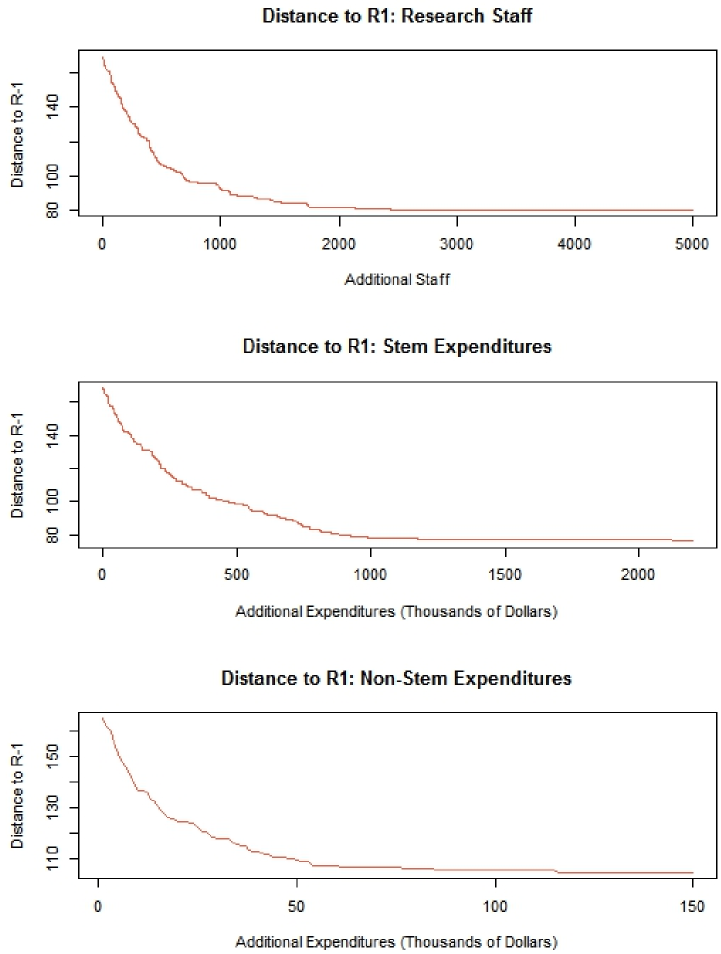


Figure 6
Single Variable Movement: Changes in expenditures and research staff lead to movement in all directions since they are used in both indices. However, increases in any single variable do not lead to large enough movement to get across the R1 threshold.

however, the STEM Expenditures, Non-STEM Expenditures, and Research Staff variables affect both the per-capita and aggregate indices. Thus, increases in either of those three covariates could lead to a given institution moving both up and to the right. It would seem reasonable, then, that changes in any of the variables used in both indices could be enough to move Montana State across the R1 border.

Reasonable though the theory may sound, the plots in Figure 6 indicate that neither STEM expenditures, non-STEM expenditures, nor additional research staff can, in and of themselves, move Montana State into the R1 status. Montana State had 75 research staff in 2015; to move up to the top rank the institution would need to add 7223 additional researchers (to break a tie with Harvard, with 7297). Disregarding the absurdity of adding that many researchers, such an increase would still leave Montana State more than 80 units away from R1, a distance that could be obtained by adding fewer than 20 Social Science doctorates. Moreover, increasing STEM and non-STEM expenditures even by billions of dollars would only lead to modest decreases in the distance from the R1 boundary.

It is worth noting that some single metric changes are more reasonable than others. For instance, while it may be reasonable to consider adding an additional STEM PhD without resulting in changes in the other covariates. However, large increases in STEM expenditures would likely result in more research staff being hired and possibly more PhDs being produced. The above plots only consider movement on single variables without regard to the consequences of those movements. Ultimately, the narrative that this analysis informs is that in order to move up in the classifications from R2 to R1, decision makers must focus on a multi-dimensional approach. While increases in a single covariate will help move the university up towards the boundary, changes in multiple variables simultaneously will prove much more effective.

5.3 Shiny App: Simultaneous Movements

Movement on multiple dimensions is hard to analyze for several reasons. First, there are eight variables to consider, all of which could increase or decrease in the next update. There are countless combinations of changes in each variable that could hypothetically occur. I created an interactive web application using the R package Shiny (Winston 2016) that allows for interactive modeling of changes in the classifications. The application is intended to be used by institutional researchers, administrators, and other stakeholders at Montana State for simulating the classifications under any of those circumstances.

The application can be found at the following URL: https://paulharmon.shinyapps.io/Carnegie2/. The end user can adjust Montana State's of PhDs, expenditures, or research staff by moving the slide bars. The application then re-ranks the institutions, re-calculates the two PCAs, and plots the new classifications. Small perturbations may change where Montana State is located in the plot, but they do not necessarily change the structure of the classifications; however, large changes in the values for Montana State can actually slightly change the locations of other schools in the ranked PCA, even though their values are held constant for all variables. This highlights an important feature of the Carnegie Classifications: changes in one school can

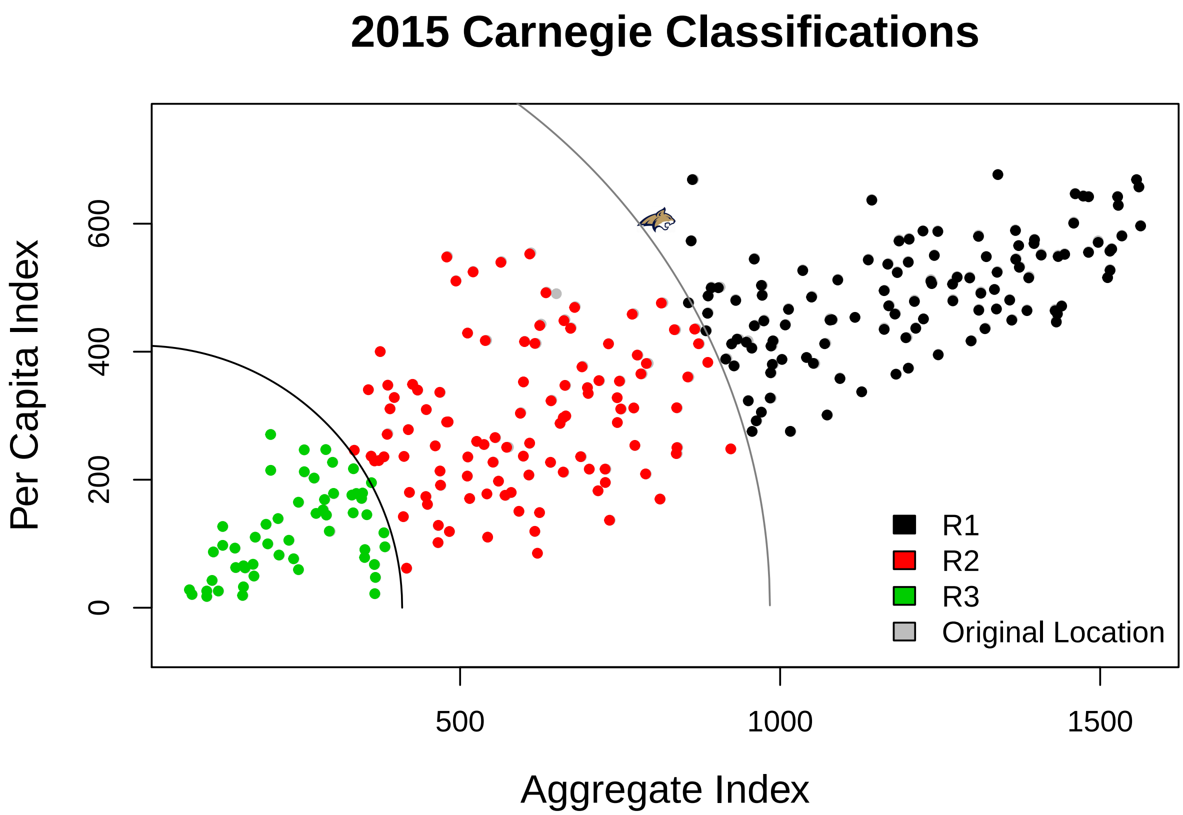


Figure 7: Large increases to STEM PhDs and expenditures could get Montana State across the R1 threshold, given small gains in non-STEM fields.

actually impact the position of other schools.

The following plots illustrate a handful of changes that could be made. Figure 7 illustrates a STEM-heavy change:

- Increase non-STEM PhD counts by 1
- Increase STEM PhDs by 15
- Double STEM expenditures (Increase by $104,646)
- Increase non-STEM expenditures by 5 million dollars
- Increase research staff by 75

Another possible change that could be considered would be to focus solely on non-STEM degrees, as seen in Figure **??**. Investing in humanities, social sciences, and other non-STEM fields may not be efficient for Montana State given the relative lack of non-STEM infrastructure, but could be considered. Given the dynamics of Montana State, I include small gains to the STEM fields as well. The below scenario involves the following changes:

- 10 additional PhDs in all non-STEM categories
- 5 additional STEM PhDs
- Increase research staff by 25
- Increase STEM expenditures by 3 million dollars
- Increase non-STEM expenditures by 10 million dollars

Note that this change indicates another key element of the Carnegie Classifications. Well-rounded institutions generally have larger values on both indices than do institutions that specialize only in STEM or non-STEM fields. Compared to the STEM-heavy path, this path seems less arduous; however, there are only a few non-STEM doctoral programs offered at Montana State.

Reducing tenured/tenurable faculty could also help move Montana State towards the boundary; however, it would not be a particularly good long-term solution. The below plot shows where Montana State would be with a reduced tenurable teaching faculty but additional researchers. Reducing faculty may be a way to move towards R1, but it is likely not the best way to do it. The following scenario illustrated in Figure **??** considers a 25% reduction in the size of the tenurable/tenured faculty at Montana State along with modest increases in expenditures, PhDs, and a re-allocation of research faculty.

- Increase non-STEM PhDs by 1
- Increase STEM PhDs by 5
- Increase nontenurable research staff by 100
- Increase STEM expenditures by 10 million dollars
- Increase non-STEM expenditures by 5 million dollars

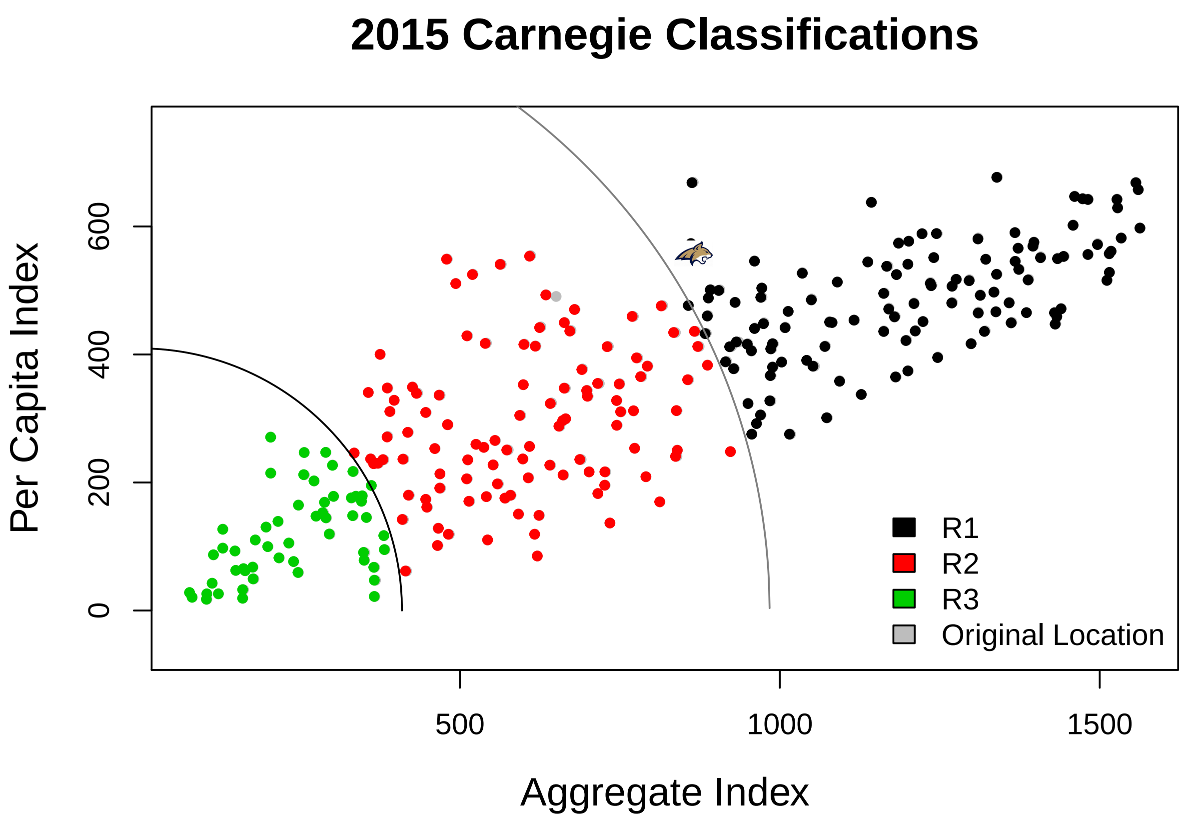


Figure 8: Increases in non-STEM fields could get Montana State across the border, but the university may not have the infrastructure to support large non-STEM growth.

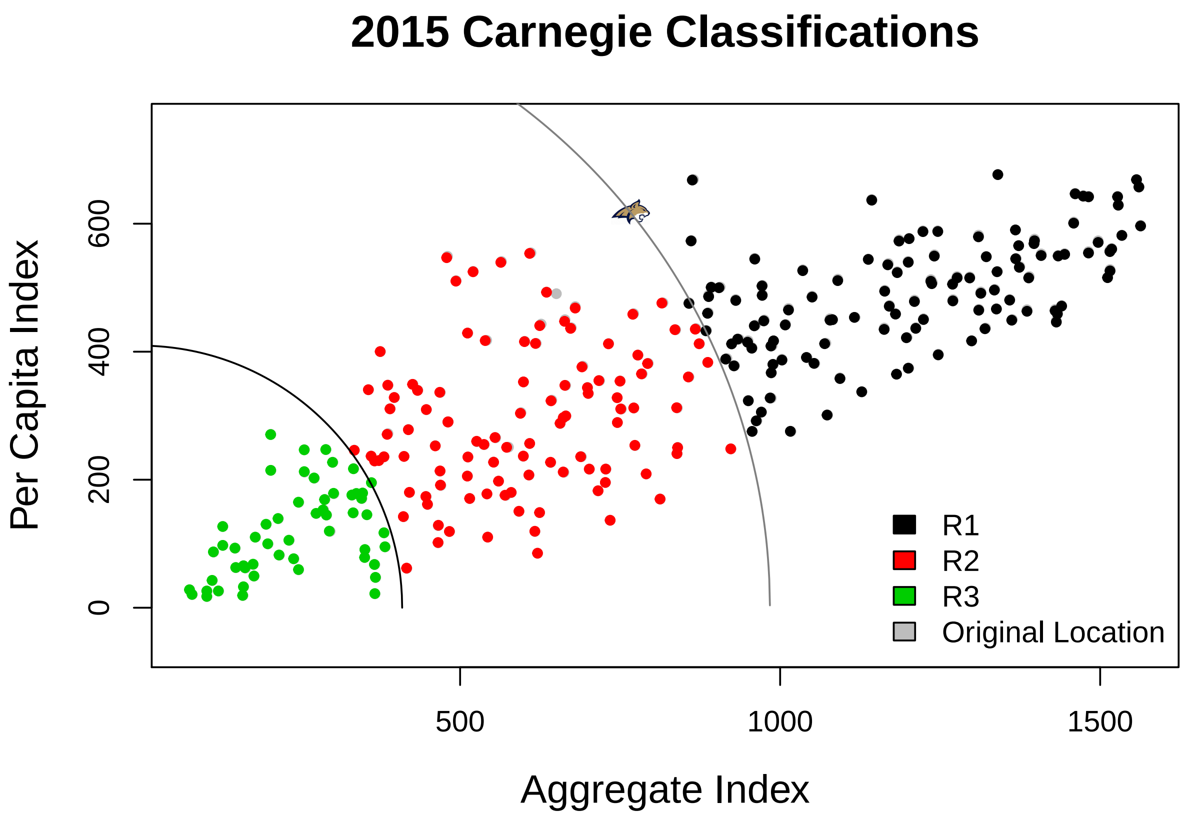
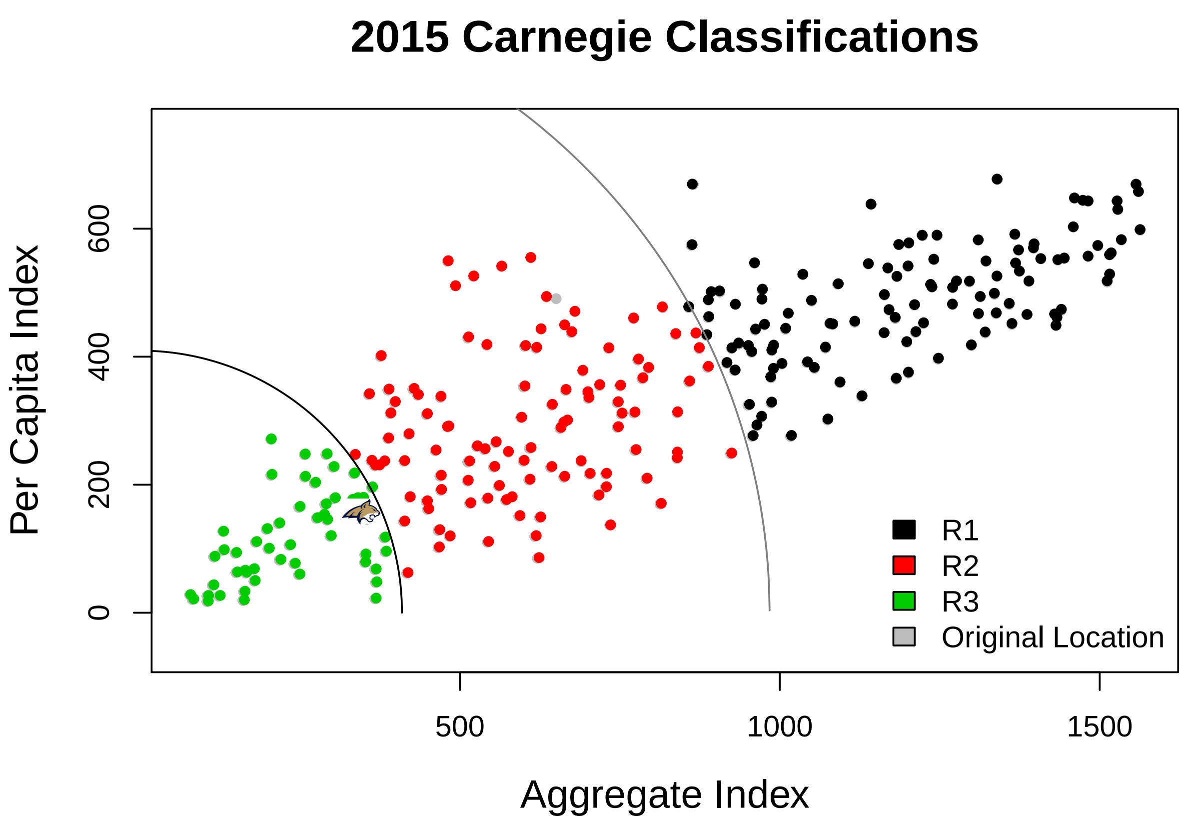


Figure 9: Reduction in faculty size by 25 percent, along with modest gains in other variables, could get Montana State across the border. However, long-term efficacy of cutting faculty is questionable at best.

- **Reduce** tenured/tenurable faculty size by 25%

While moving to R1 is the policy goal envisioned by administrators, the specter of moving towards R3 is always a possibility. The following scenario includes small reductions in the number of PhDs produced and research staff combined with wholesale cuts on research expenditures:

- Reduce all PhDs by 1
- Reduce non-tenured research staff by 25
- Reduce STEM expenditures entirely by 104 million dollars
- Reduce non-STEM expenditures by 8 million dollars



The Carnegie Classifications App can be used to model these as well as many other hypothetical scenarios. As a tool for making decisions, it could be used as a starting point for doing economic Cost-Benefit Analysis. Decision-makers could plot out a potential change and then assess the accounting and economic costs of that change in order to determine the lowest-cost methods for potential movements towards R1. Care should be taken when considering these changes; although it may be more mathematically efficient to change one variable, it may not be economically efficient. For instance, adding 10 social science PhDs would likely cost the university more than adding 10 STEM PhDs. Finally, while moving towards R1 classification may not be a bad idea, it is worth remembering that moving towards R3 is just as feasible given the right negative circumstances.

6 Analyzing the Classifications

6.1 Model-Based Clustering

One of the most subjective aspects of the Carnegie Classifications is where the delineations between groups are drawn. Rather than hand-drawing lines and basing the three groups off of those arbitrary delineations, it might be worthwhile to let the data speak for themselves. This can be achieved via model-based clustering on the two indices. I tried several different clustering options:

- Model-Based Clustering with data-driven clusters
- Model-Based Clustering with 3 clusters
- K-Means Clustering with 3 clusters

6.1.1 MBC with Data-Driven Clusters

The model-based method of clustering does not require prior specification of the number of clusters; it can generate either the best solution given a pre-specified number of clusters or it can generate the best solution for any number of clusters. I allowed the data to speak for themselves and let the algorithm pick the optimal number of clusters. The model-based clustering algorithm chose 4 clusters, which are shown in 10. This solution places most of the smaller R3 instituions in a distinct category; it clusters the large R1 and most of the R2 schools together into a single group. Whlie most of the R1 instituitons would not drop be classified with the R2 schools, this algorithm breaks up the R1 group and classifies the largest few institutions seperately. Even more fascinatingly, the schools with the largest scores on the Per-Capita ranking appear to get classified with their similar institutions on the Aggregate Index, even if they are outlying in the y-direction.

6.1.2 MBC with 3 Clusters

Since the Carnegie Classifications have only three classifications, I tried fitting a model-based clustering solution with only 3 groups. Fixing the number of clusters has an interesting effect on the groups; Montana State would be an R3 school by this manner of delineation. It

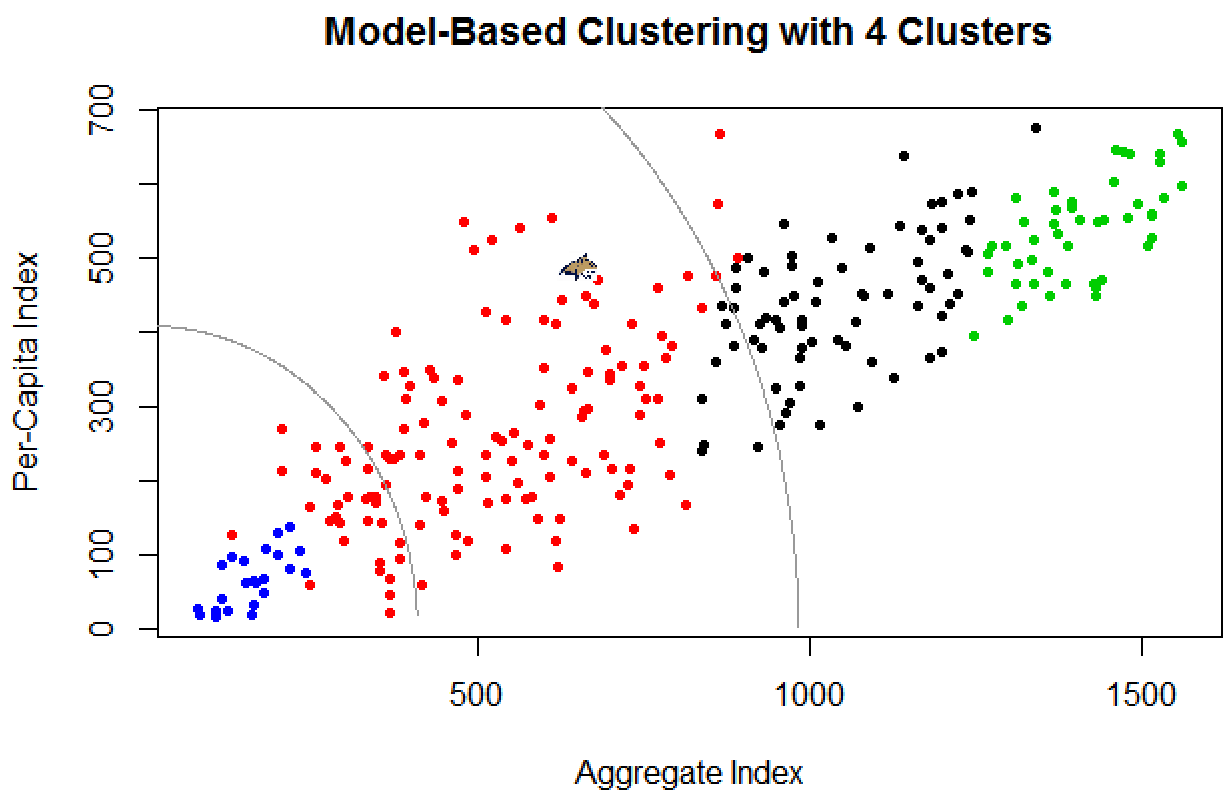


Figure 10: The model-based cluster solution is given below with the optimal number of clusters.

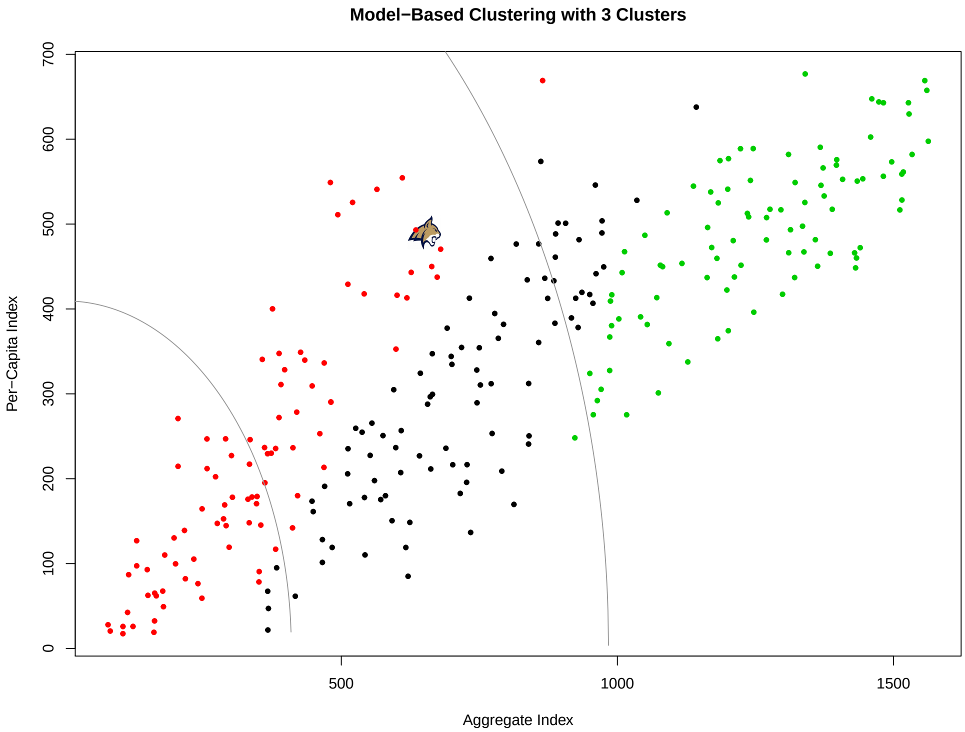


Figure 11: The model-based cluster solution is given below with the optimal number of clusters.

does some non-sensical things in terms of classification as well; this classifies Massachussets Institute of Technology as an R3 school. The 3-cluster model-based solution is given in Figure 11.

K Means K-means clustering differs from model-based clustering in several ways. First, by specifying 3 medoids, the K-means algorithm starts with 3 guesses at cluster medoids. Then, the algorithm iteratively moves the centers of each cluster in order to minimize within-cluster variance (Friedman, Hastie and Tibshirani 2009). The K-Means solution is given in the figure below. Compared to the model-based clustering options, the K-means solution most resembles the groups given in the Carnegie Classifications; however, it differs fairly significantly. THe K-means solution increases the number of R3 institutions from 54 to 101; moreover, the number of R1 institutions is reduced to 79 from 115. Montana State would remain classified in the R2 category; moreover, it would be farther away from the R1 group than in the Carnegie Classifications in their current form. This K-means solution is whown in Figure 12.

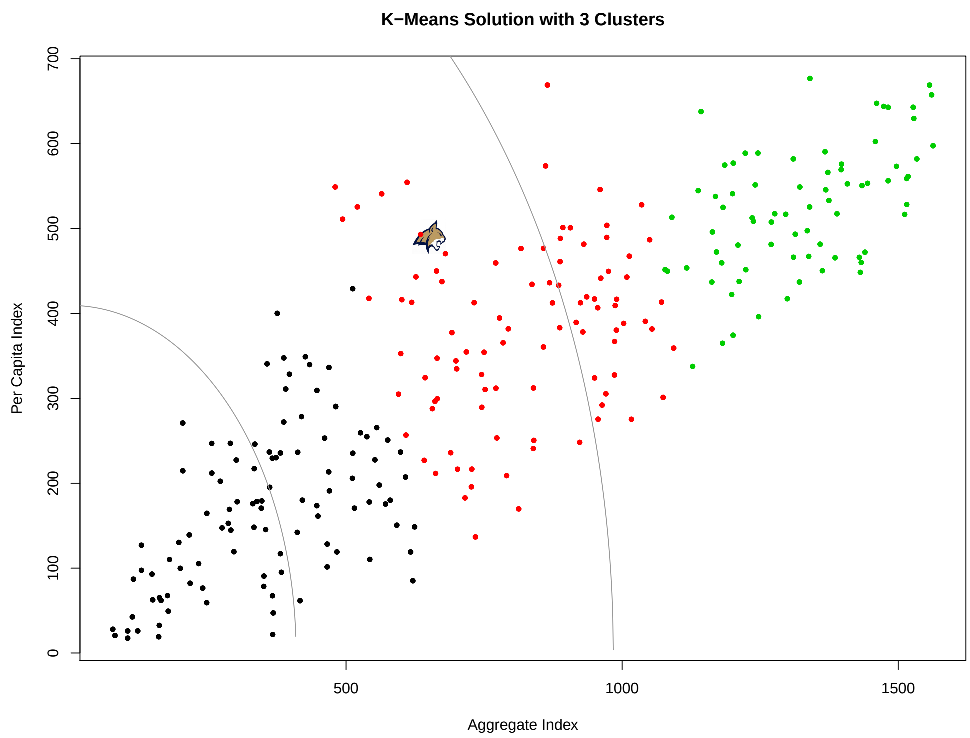


Figure 12: K-Means solution with 3 clusters. This looks more like the Carnegie Classifications; however it is more restrictive in terms of classifying schools as R1.

7 Discussion

7.1 Montana State as an R2 Institution

Montana State University had previously been classified in the highest tier of "Very High Research Activity" in the 2010 Carnegie Classification update. However, it may not have been well-classified. Most R1 schools produce more doctoral degrees of each type than Montana State; moreover, the typical R1 institutions spend more money on research expenditures in STEM and non-STEM fields than did Montana State. It is worth recalling that the Carnegie Classifications are not intended to measure quality of educational experience; rather, they are used to identify similar institutions to a given school. In this case, Montana State's research output, size, and expenditures are more similar to North Dakota State University than to, for instance, the University of Michigan; the Carnegie Classifications reflect this.

7.2 Moving Up: How Hard Would It Be?

There is no single way to move from R2 to R1, nor is there a single way to move down to the R3 category. Both are possible for Montana State to achieve under the right set of circumstances. While breaking ties can help lead to large movements in the variables, this is likely more important for the Aggregate Index because the PhD counts are more likely to be tied. Montana State could improve from rank 1 to rank 61 in the Social Sciences PhD variable by adding just a single doctorate in the social sciences; this may actually occur with the addition of a Psychology PhD program in 2015.

Although Montana State is close to the R1 category, getting across the border would necessitate fairly significant gains in PhDs produced across all four categories and research staff size as well as large increases in STEM and non-STEM expenditures. The research staff and PhD counts are likely feasible; Montana State's growing infrastructure and faculty allow for increases in those variables that ought to be enough to at least move MSU towards the border. However, without nearly doubling non-STEM expenditures and adding STEM expenditures in the tens of millions of dollars, changes in the underlying variables simply are not enough to get MSU to R1.

7.3 Snapshots vs. Averages

The data are collected via a snapshot over the course of a year. To ensure that the data used are properly vetted, often data from the IPEDS several years prior to the update are used -i.e. in the 2020 update, the 2018 IPEDS is likely to be used. While expenditures and research staff may stay relatively constant over a period of a few years, counts of PhDs may be relatively variable. Given that uncertain nature of doctoral programs, it is difficult to predict exactly how many PhD students may graduate in a given year (at least compared to undergraduates or master's students). Year-to-year variation in the number of PhDs produced may drive some variability in the classifications. An interesting analysis - one that would require a great deal more data are available in the Carnegie Classifications update - would be to examine a five-year average of all the variables at each institution and compare them to the snapshot-driven analysis performed by the Indiana University Center on Postsecondary Research.

7.4 Limitations of Static Analysis

This analysis considers changes at Montana State, holding the values at other institutions constant. Certainly, the assumption that other institutions will stay static over the next five years is unrealistic; however, we cannot predict with a high degree of certainty how other institutions will change before the next update.This analysis should be treated in a manner similar to that of a linear regression problem with multiple covariates; in such a situation, parameters are estimated under the assumption that the others are held constant. In this instance, the same methodology can be applied. These small perturbations are made under the assumption that the data for other institutions are held constant.

One way for policy makers at Montana State to attempt to circumvent this problem would be to think less about the borders between the groups themselves and rather focus on moving to a point in the center of the R1 designation. The delineations between each group are the least predictable and most likely to change aspect of the classifications. Instead of trying to determine the most efficient way to get to the border, I would suggest that policy makers make getting to a central position in the R1 cluster a goal.

7.5 Final Thoughts

The Carnegie Classifications are useful for institutional research; however, they have little utility as a metric of institutional quality. R1 schools are not intended to be thought of as better than R2 schools; however, some campus administrators, faculty, and media have used them in this way. The delineations between each group are highly subjective; moreover, the nature of the dimension reduction used to create both indices leaves room for some debate. For instance, the Carnegie Classifications would contain more information about the underlying covariates if more than a single Principal Component were used in each index. Finally, the nature of the self-reported snapshot data used in this analysis leads to the possibility of miscalculation due to either clerical errors, different definitions of variables at different schools, or other problems. The data, though mostly vetted, may not be entirely consistent across institutions. Given all this, the Carnegie Classifications should be taken with a grain of salt. They are useful tools for identifying similar institutions; however, prioritizing one status over another is not an appropriate policy goal for any institution of higher education, especially Montana State University.

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