Demystifying the Carnegie Classifications

A Sensitivity Analysis

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Introduction: What are the Carnegie Classifications?

- The Carnegie Classifications group like institutions on research characteristics
- Three groups of **276** Doctoral-Granting Universities: R1, R2, R3
- **Not Rankings!** These are designed for classification of institutions

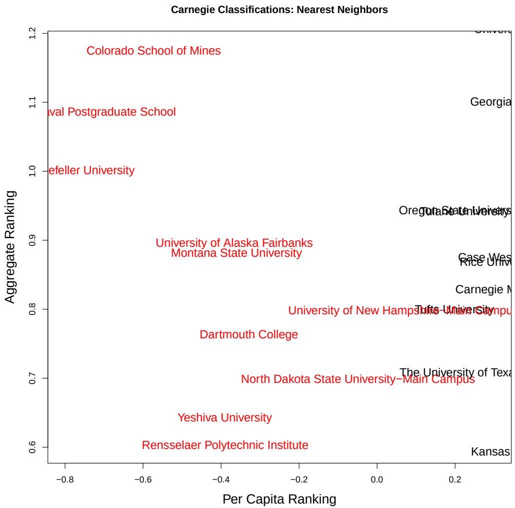
Figure 1: Montana State (R-2), Stanford (R-1), Boise State(R-3):

Montana State University: The 2015 Update

- Montana State had been classified as R-1: "Very High (Highest) Research Activity" in 2005 and 2010
- In 2015, Montana State moved to R-2: "Higher Research Activity"
- We can examine universities near Montana State to get an idea of our peer group

So what do Montana State's peers look like?

Montana State's Peer Group



How are the Classifications Calculated: Two Indices

The classifications are based on two weighted averages of ranked institutional output:

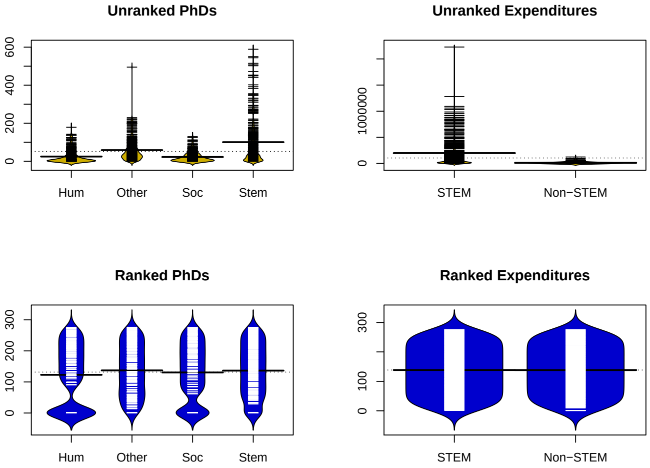
Aggregate Index:

- STEM PhD
- Social Sciences PhD
- Humanities PhD
- Other PhD
- STEM expenditures
- Non-STEM expenditures
- Research Staff

Per Capita Index: *(Divided by Faculty Size)*

- STEM Expenditures
- Non-STEM Expenditures
- Research Staff

Raw Data vs Ranks



Calculating Indices

- Rank each institution on each variable
- Perform two Principal Components Analyses on the correlation matrix of both ranked datasets
- Plot the first PC score from the aggregate index vs the first PC score from the per-capita index
- Loadings:

	Hum	Other	Soc	STEM	Staff	S. Exp	N.S. Exp
Aggregate	0.43	0.27	0.42	0.4	0.4	0.38	0.33
Per Cap	-	-	-	-	0.64	0.64	0.42

Principal Components Analysis

Goal: To reduce a p-dimensional set of variables into k components via eigenvalue decomposition. PCA can be done on covariance or correlation matrix.

Given p variables $x_1, x_2, ...x_p$, we generate via an eigenvalue decomposition of correlation matrix of $\mathbf{X}$ a set of p new variables $y_1, y_2, ..., y_p$. The y's are ordered so that y_1 explains the most variation in the underlying x's, and y_p the least. These are called the **Principal Components**.

Scores: Each observation's value on the new scale. These are functions (weighted averages) of the original variables.
Loadings: The loadings give the formula used to calculate the scores from the original covariates. These are the **weights** that we examined before.

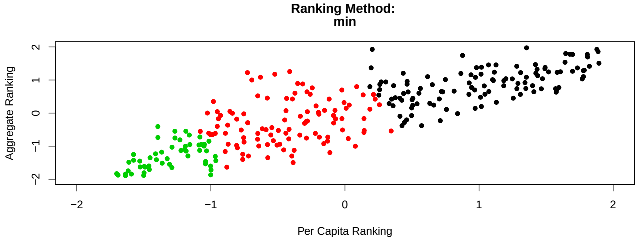
By using only the first k PCs, we do dimension reduction.
The Carnegie Classifications use only the first score from each PCA run.

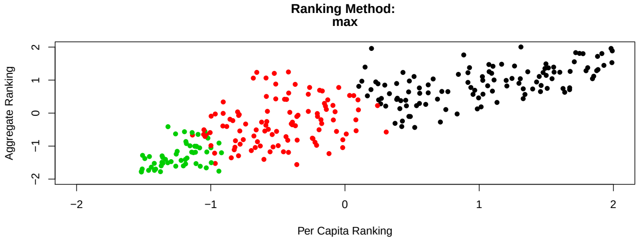
Dealing with Ties

Since most of the variables used are counts, many schools will be tied, especially for the aggregate index. But there are several ways to handle tied ranks:

- **Average** (R's default): If the first 3 schools are tied, each would get rank 1.5. Tie-breaking leads to gain by about half.
- **Minimum**: If the first 3 schools are tied, each would get rank 1 (smallest to largest). Tie-breaking leads to gain by the number of institutions that are tied.
- *The loadings from the minimum closely matched the Carnegie Classifiaction loadings.*
- **Maximum**: If the first 3 schools are tied, each would get rank 3 (largest to smallest). Tie-breaking leads to no gain.

Methods for Ties: Minimum Method Used



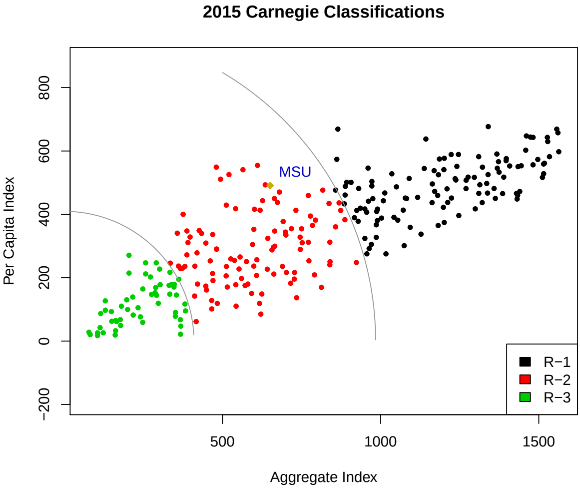


Where were lines drawn between groups?

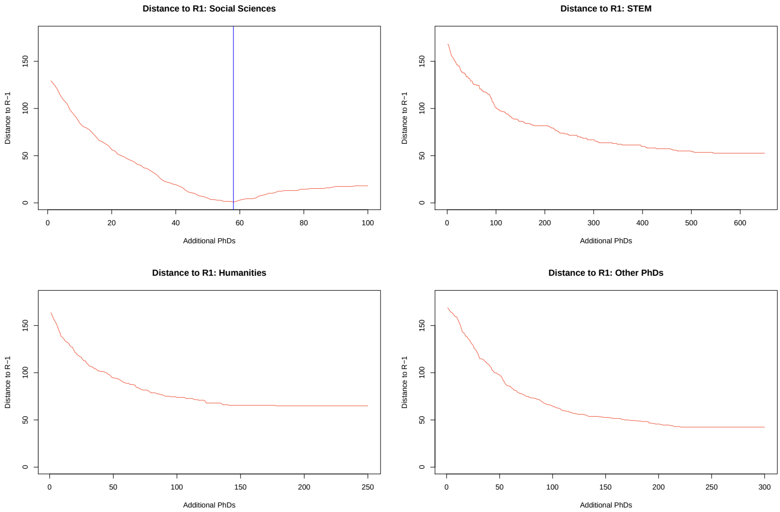
The Carnegie Classifications are based on three groups. However, the data do not form 3 distinct clusters.

- In 2010, lines were hand drawn (Borden 2017)
- In 2015, scores were un-standardized and circles with radii 984.007 and 409.461
- The choices of radii were still arbitrary

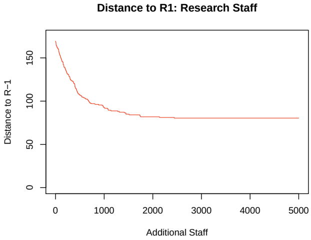
The Carnegie Classifications:

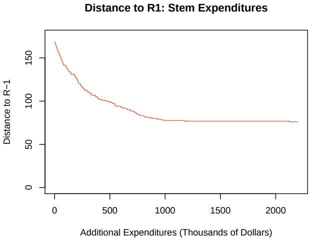


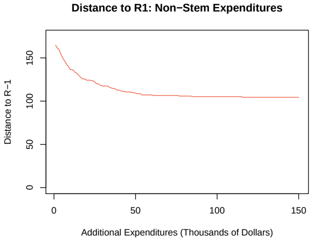
Single Metric Changes: Aggregate Index



Single Metric Changes: Per Capita Index







Multi-Dimensional Movement

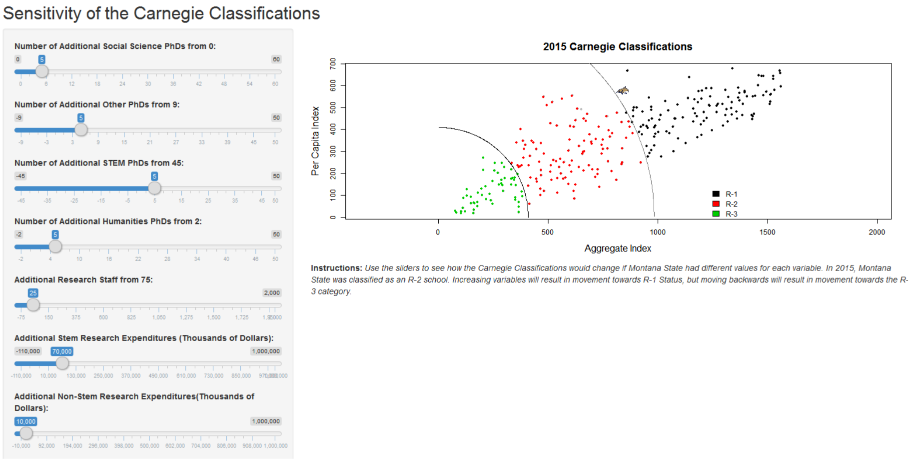


Figure 2: Increase PhDs by 5, research staff by 25, STEM Expenditures by $70 million and Non-STEM Expenditures by $10 million:

Multi-Dimensional Movement

It is clear that to move up, Montana State needs to focus on increasing on **multiple** dimensions. Focusing on the more sensitive metrics (Social Science PhDs) is important, but gains on all metrics together move things more quickly.

- Aggregate variables only move us to the right or left
- Per-Capita Variables move us up or down
- The way that we report/classify research staff could impact classifications

Can you get to R1? *Come to my poster presentation Friday 9:30-12:30 in the SUB Ballrooms or snap a photo of the QR code to see where MSU would be with multidimensional movement!*

Conclusions

The Carnegie Classifications are **subjective** measurements of some institutional characteristics, not a measurement of institutional quality!

- Maintaining high per-capita metrics is helpful, but we need to produce more PhDs as well
- While we are closer to R-1 than R-3, maintaining out status should be our first goal
- It may be easier to lose ground (towards R-3) than to get closer to R-1
- Breaking ties can lead to big gains: Just a single Social Sciences PhD would help MSU move from rank 1 to rank 61!

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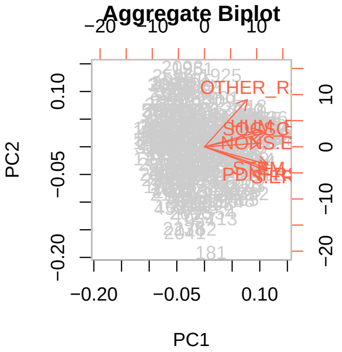
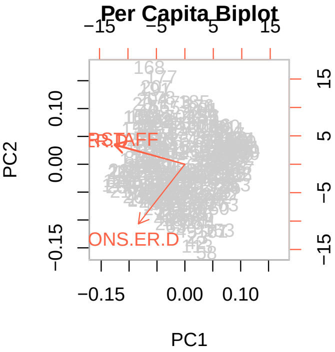
Supplemental Slide: Biplots





Supplemental Slides: Some Things to Think About

Some of the decisions made by the researchers creating the Carnegie Classifications are worth discussion:

- Using only the **first** PC to create the index. The Aggregate index explains 70% of the variation in the original aggregate variables, the Per-Capita index explains 71% (Borden 2016).
- However, the second PC score explains an additional 25% more variation for the per capita index and 12 percent more for the aggregate index. Should they have included those?
- Finally, is PCA the best way to work with these data? Only 3 variables are used to create the per-capita index and only 7 for the aggregate - dimension reduction is usually more of interest with **big** sets of covariates.
- Raw vs. Ranked vs. PC Scores of two groups of variables