Investigating Algorithmic Decision-Making with Applications to Student Diversity at Illinois Tech

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Contents

Abstract

This study focuses on algorithmic decision-making and how structural inequalities can introduce inadvertent bias in an algorithm. There are a lot of efforts by universities in the United States to diversify the student body. Most of these efforts focus on outreach, but few focus on improving any internal processes first.

This study aimed to look for room for improvement to make internal processes more equitable so the rest of the efforts to diversify a student body would be more effective. Specifically, Illinois Tech admissions data was observed and patterns found were tested for statistical significance.

Overview

There is a straightforward reason for taking a look into improving internal processes first: budget. Across organizations, it is common to problem solve by increasing budgets. Naturally, spending more money on a problem will fix it, at least in the short term, or improve it. However, lasting change is brought about by more fundamental solutions that are also more efficient by saving the budget even in the short term. This project is built on the idea that before spending money on a problem, there needs to be a closer look inside an organization to see if anything can be fixed internally. By having this approach, an organization will be maximizing their time and resources because if there were any impediments, it would mean that the resources were not utilized to their maximum potential.

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Algorithms as Part of the Decision-Making Process

An algorithm is a set of instructions. Algorithmic decision-making is "the processing of input data to produce a score or a choice that is used to support decisions" [Cheng et al.].

The problem that comes with algorithmic decision-making is that sometimes it is perceived as fair if the steps are uniform across all input or accurate because a computer is producing the output, not a human. However, bias could enter an algorithm in several ways. One way of this happening has been documented in machine learning: if a model is trained on a data set that misrepresents the population, its outcome can be biased. Another way is when a formula is coded without a diverse population using it or underlying social inequalities.

An example of the inadvertent racial bias can be seen through an algorithm for a medical center that identified patients for an intensive care management program. After studying this algorithm, it was found and reported in [Strickland] that "black patients had to reach a higher threshold of illness before they were considered for enrollment." This study was conducted at one medical center, but several others also have similar screenings set in place. It was stated in [Strickland] that "According to industry estimates, these types of algorithms are making health decisions for 200 million people per year". This shows the importance of making sure algorithms are equitable and fair because their effects can be widespread.

The key takeaway from this study is that "if the outcome has built into it structural inequalities, the algorithm will still be biased." [Strickland]. When looking internally in an organization, one must consider if structural inequalities can influence the decision for every decision-making process. If so, that is an opportunity for the organization to improve.

A General Approach for Using Data to Look For Improvement

This section will discuss a data-driven approach an organization could take to identify room for improvement in any decision-making or screening processes.

1. Identify the target for improvement.

One can choose a broad topic, as future steps will specify the target even more. Some examples could be budgets, education, or diversity. For this report, diversity in a postsecondary institution will be selected as the target for improvement.

2. Identify what aspects are important for the target of improvement.

For diversity in postsecondary institutions, such aspects may include outreach, the application process, admissions, and retention. Then, pick one of these moving forward. For this report, admissions will be the selected aspect.

3. Find out the critical components of the selected aspect.

Some components may be an applicant's GPA, coursework, standardized exam scores, extracurricular activities, and the submitted admissions essays.

4. Explore the dataset.

Exploration involves observing patterns. One can do so by making lots of graphs of the variables present in the dataset. By observing patterns, one can identify how variables correlate with each other and how that may affect a decision-making process. The following examples are based on the Titanic dataset [3].

To see a single variable, one can do plots of their counts, such as the one below of the different classes of passengers [Waskom, 2021].

One can also graph two or more variables and see the relationships, such as the one below that graphs the counts of subgroups of classes and type of passenger [Waskom, 2021].

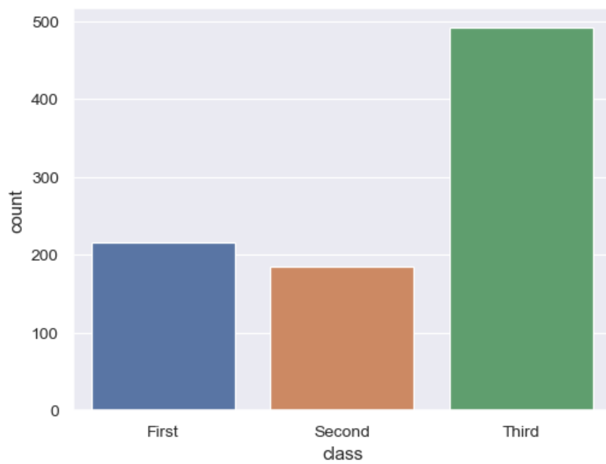

Figure 1: Example of a bar graph data visualization

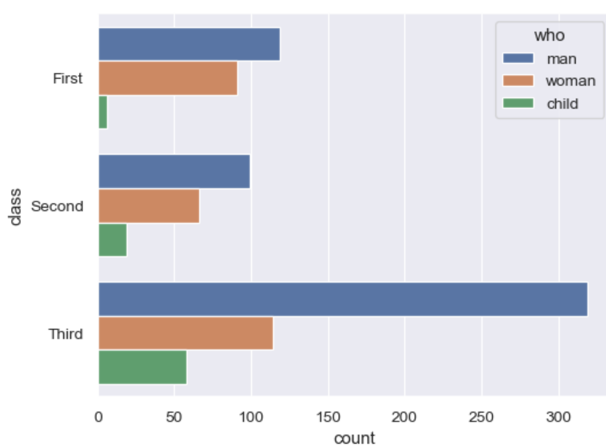

Figure 2: Example of a bar graph data visualization broken down by category

It is also helpful to look at tables of counts or proportions such as the one below that shows three variables, class, gender, and survival [Matthew Brett].

	survived	no	yes
class	**gender**		
1st	**child**	0.111111	0.888889
	female	0.031250	0.968750
	male	0.664634	0.335366
2nd	**child**	0.038462	0.961538
	female	0.125000	0.875000
	male	0.912752	0.087248
3rd	**child**	0.607843	0.392157
	female	0.512500	0.487500
	male	0.870801	0.129199

Figure 3: Example of a table of proportions broken down by multiple variables

A study of proportions can reveal underrepresentation within some populations in a dataset. Underrepresentation was observed during this project and was verified through the statistical significance of the differences. An example in the table above is that men were underrepresented in the survived category for first and second-class passengers.

5. Confirm That Observed Patterns Are Not Due to Random Chance.

There are different statistical methods available to determine if the patterns observed in the previous step are statistically significant.

- Test of independence of two or more categorical random variables
  - Example: Faculty salary and gender.
- Explore the correlation by computing correlation coefficients between two categorical or quantitative random variables and then testing if this correlation is significant.
  - Example: Standardized exam scores and GPA.
- Explore the linear relationship between a set of predictor variables and a response variable
  - Example: Sales versus money spent on advertising.

By confirming the significance of the patterns, one can find room for improvement in current algorithmic decision-making processes.

Diversifying the Student Body at Illinois Tech: A Closer Look at Admissions

> "We appreciate that our community comes from many backgrounds and many parts of the world. We embrace the contributions that differences offer, as diversity of thought and experience allows excellence to flourish."

This statement is an excerpt from Illinois Tech's Mission Statement [6]. In order to ensure the diversity of thought and experience, the student body also needs to be diverse. The Admissions Office at Illinois Tech is genuinely interested in the diversification of the student body. This can be seen through their initiative, The Chicago Difference, designed to support underrepresented youth in Chicago, and the DevUp Scholars Program that connects high school students from Chicago's South Side to STEM and entrepreneurship and prepares them to pursue STEM majors and careers. These are just some of the initiatives by Illinois Tech to increase diversity in the student body.

As mentioned at the beginning of the report, while it is crucial to spend money on improving issues, it is also essential to look into any algorithmic decision-making processes. The admissions decision is multi-faceted; from the outside, it is not possible - nor is it the goal of this project- to evaluate it in general. Rather, the goal is to look at various factors considered in the admissions decision and consider how they may interplay with diversity at Illinois Tech. This project focused on analyzing room for improvement in the admissions process through the lens of algorithmic decision-making.

Application of the Approach

Admissions Criteria

	Very Important	Important	Considered	Not Considered
Academic				
Rigor of secondary school record	X			
Class rank		X		
Academic GPA	X			
Standardized test scores	X			
Application Essay			X	
Recommendation(s)		X		
Nonacademic				
Interview			X	
Extracurricular activities			X	
Talent/ability			X	
Character/personal qualities			X	
First generation			X	
Alumni/ae relation			X	
Geographical residence				X
State residency				X
Religious affiliation/commitment				X
Racial/ethnic status				X
Volunteer work			X	
Work experience			X	
Level of applicant's interest			X	

Figure 4: Relative importance of each of the following academic and non-academic factors in first-time, first-year, degree-seeking (freshman) admission decisions 7.

As seen in the table above, academic factors such as rigor of secondary school record, academic GPA, and standardized test scores greatly influence admission decisions.

The admissions office provided the following data on applicants in the fall semesters over four years starting in 2018.

Variable Name	Description
Start Term and Year	The year and start term of an applicant; e.g. Fall 2019
Hispanic/Latino	Binary value that answers the question if an applicant is Hispanic or Latino
Ethnicity	All the ethnicities that an applicant identifies as separated by a semicolon
ACRK	A value ranging from 1 (highest) to 6 (lowest) that is predictive of the grade-point average that an applicant is expected to achieve after their first year of studies at Illinois Tech.
Admission Decision	Binary value for the admission decision of an applicant

Figure 5: Name and descriptions for variables in the dataset

ACRK

ACRK (Academic Rank) is a column that represents a value ranging from 1 (highest) to 6 (lowest) that is predictive of the grade-point average that a prospective student is expected to achieve after their first year of studies at Illinois Tech. For example, an admitted student who enrolls at Illinois Tech with an ACRK value of 1 is predicted to have a high GPA after their first year.

Although ACRK is not a factor listed in figure 4, it considers some of those factors in its calculation.

ACRK values are calculated by taking into account the following factors:

- High School Quality;
- Best Composite Standardized Exam Score;
  - Uses either the SAT (Scholastic Assessment Test) or the ACT (American College Test)
- High School GPA (Grade Point Average);
- High School Rank;
  - Does not exist at some schools, so the calculation considers that possibility
- Best Math Standardized Exam Score;
  - Uses the math component of either the SAT or ACT.

Analysis and Results

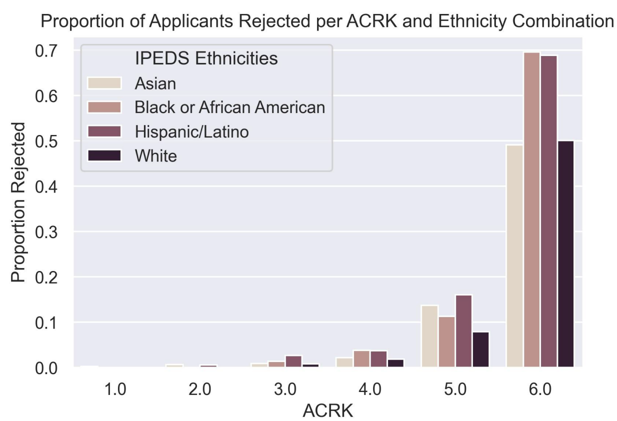

Figure 6: Graph of the proportion of applicants rejected per ACRK and ethnicity combination

Figure 6 provides a breakdown of the proportion of applicants rejected and ethnicity given an ACRK value. It can be observed that the proportion of rejected students broken down by ethnicity is not constant across ACRK values. However, the overall trend of higher rejection rates for ACRK 6 can be explained by noting that if a student applies to Illinois Tech and has very low credentials, they are automatically placed in ACRK 6. Therefore most students who are not admitted fall in the ACRK 6 group by design.

Figure 7 is a heatmap where darker colors indicate a higher proportion of students with a specified ACRK value earning a certain GPA after their first year. It can be observed that there is variation in GPA for each ACRK value, and more so in higher ACRK values, motivating the question: how accurately does ACRK predict student success?

Figures 8 and 10 show a correlation between ACRK and the GPA a student earns at the end of their first year, but the coefficient of determination, also known as R^2, is relatively low at 0.178, meaning that when taken alone, it is not a great predictor of student success. For example, students who had the highest ACRK value of 1 and still received relatively low GPAs between 3.5 and 2.5 compared to what they were expected to get, which is closer to 4.0. As well, the proportion rejected when ACRK is 6 is much higher than when

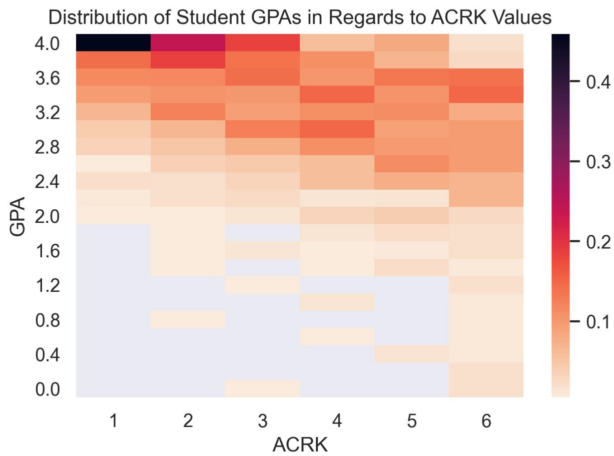

Figure 7: Heatmap of the distribution of student GPAs in regards to ACRK values

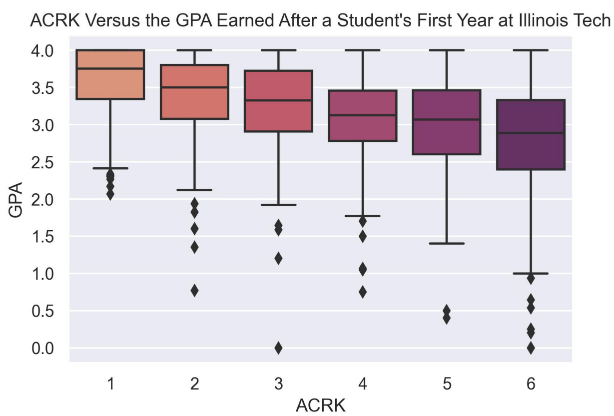

Figure 8: Boxplots of ACRK values and the GPA earned after a student's first year at Illinois Tech

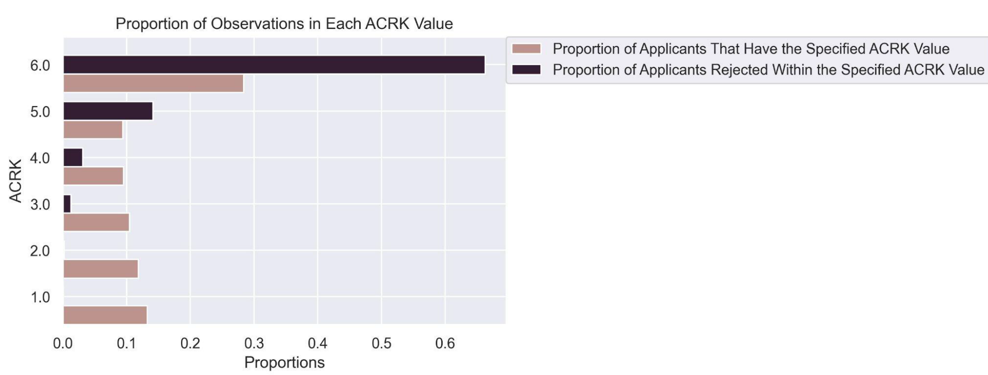

Figure 9: Proportion of Applicants in Each ACRK Value

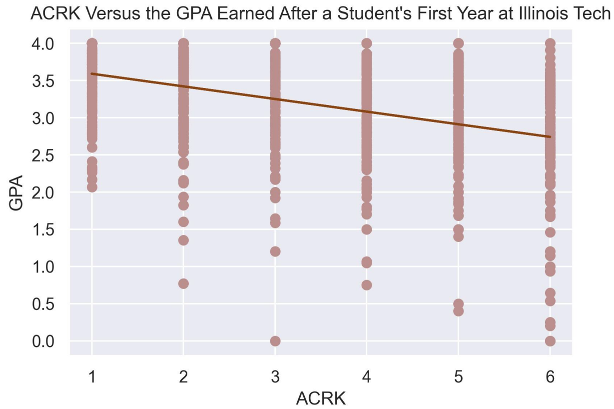

Figure 10: Scatterplot of ACRK values and the GPA earned after a student's first year at Illinois Tech with a line of best fit

ACRK is 5, as can be seen in Figure 9 even though the 25th percentile, 50th percentile, and 75th percentile marks are relatively close to each other for both boxplots. It should be noted that there is a higher variance of student performance when ACRK is 6, as indicated in figures 7, 8, and 10. On the other hand, many students with an ACRK value of 5 and 6 performed at or above a 3.0 GPA value.

Figure 10 is another visualization that shows the same result. It contains a line of best fit which has a relatively low coefficient of determination value of 0.178. This means that the ACRK value was accurate for 17.8% of students. A higher coefficient of determination would indicate that the ACRK value is a better predictor of a student's GPA after their first year at Illinois Tech.

The same visualizations were created for each ethnicity. All of them showed the same-that the coefficient of determination was relatively low between ACRK and the actual GPA a student earns at the end of their first year.

Although ACRK is not the sole criterion for admission, the statistical tests show that, when taken alone, it does not capture all of the variability in the data, and thus it offers some room for improvement. For example, the multiple linear regression model on which the ACRK is built could be retrained on new data that includes pandemic years, which may not include standardized test scores. Further, the ACRK values could be re-binned and re-tested for performance: are there better cutoff values that the regression can recommend so as to capture the high-performing ACRK 6 students into the ACRK 5 value? Finally, the ACRK value algorithm takes into account high school quality. High school quality is likely related to structural inequalities in the school systems. Does the coefficient of determination for ACRK increase when high school quality is removed as a factor and, in turn, does this affect student diversity?

Future Projects

Regarding diversity in a postsecondary institution, there can be projects that focus on one of the aspects laid out in step two of the general approach, identifying what aspects are important for the target of improvement. At this moment, focusing on outreach is the most critical project. That includes seeing what areas and demographics receive the most advertisements, admission counselor visits, and mail from Illinois Tech. After receiving that data, it can be analyzed whether there are underrepresented areas in communication from Illinois Tech and possibly create an alternative plan with costs.

The following is not a project but more of a question left unanswered. What is the correlation and coefficient of determination between standardized exam scores and a student's GPA after their first year at Illinois Tech? This is an important question to think about, especially as scores are not required for undergraduate applicants in all 2021, Spring 2022, and Fall 2022. After these semesters pass, will scores be required again?

There is an excellent opportunity to see if this factor should remain as data from years that required scores and data from COVID-19 years can be compared to find an answer to this question.

Closing Thought

A statement that I heard in a workshop and has stuck with me since is that "Diversity is not an outcome, it is a process." It is important to look beyond the numbers because once a benchmark is reached, we should not stop caring about it.

Supplementary Material

The technical details and technical conclusions of this study are not available for public release.

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