Makerspace Network Analysis for Identifying Student Demographic Usage

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Samuel Blair[1], Garrett Hairston[2], Henry Banks[3], Julie Linsey[4] , and Astrid Layton[5]
[1]Samuel Blair; Dept. of Mechanical Eng., Texas A&M University; samuelblair4@tamu.edu
[2]Garrett Hairston; Dept. of Mechanical Eng. Texas A&M University; garretthairston@tamu.edu
[3]Henry Banks; Dept. of Mechanical Eng., Georgia Institute of Technology; hbanks6@gatech.edu
[4]Dr. Julie Linsey; Dept. of Mechanical Eng., Georgia Institute of Technology; jlinsey3@gatech.edu
[5]Dr. Astrid Layton; Dept. of Mechanical Eng., Texas A&M University; alayton@tamu.edu

Introduction & Background

Makerspaces are increasingly becoming a critical part of engineering programs worldwide [1]. Makerspaces provide unparalleled hands-on experiences for students. Understanding the interactions that occur in these spaces is critical to improving the engineering education. Understanding interactions in these spaces, especially student interactions with *tools*, is important in ensuring that all students find the entire space accessible. Visualizing students and tools in a makerspace as interacting groups using a directional graph and network analysis has had previous success [2, 3]. This work follows that, drawing inspiration from ecology's study of plant-pollinator bipartite networks. Here we visualize tools as analogous to plants and students to pollinators [4, 5]. Modularity analysis is primarily used by ecologists to identify co-dependent groups of plants and pollinators to map interactions and understand intricate dependencies between the two groups [5]. Prior work has shown that translating ecosystem characteristics to human networks can improve their sustainability [6, 7] and resilience [8, 9]. Co-dependencies found here between tools and student groups suggest that future work could use modularity analysis to improve the makerspace experience of all students but especially those who are underrepresented.

Visualizing such a space as a network is a commonly found approach in social network analysis, where "actors" interact with "events" and create an interaction network that can be explored [10]. NASA for example used this approach to determine innovation networks for their space app challenge, allowing them to identify "catalyst" and barriers to innovation that could aid or impede the challenge [11]. The approach has not yet been applied to engineering makerspaces outside of the authors' preliminary investigations [3, 2]. A network model of makerspaces here is used to better understand co-dependencies between different student groups and tools.

Several studies have focused on barriers to entry and how the makeups of different spaces impact their usage. Expanding on that work, here we use a quantitative network analysis method, called a modularity analysis, to evaluate how different groups of students (major, race, and gender) interact with tools. One university is used as case study for the approach. The results provide insight as to how demographics affect a student's makerspace interactions.

Methodology

School A serves as the case study for this approach, an R1 university with a large engineering college in the United States. The makerspace serves all the engineering disciplines and is centrally located for engineering students on campus. The makerspace is equipped with a conventional array of tooling, including 3D printers, metal tools, wood tools, electronics tools, craft tools, work areas, hand tools, etc. The makerspace is managed by full-time staff and employs student workers. Participants for the study here were recruited via flyers placed throughout the makerspace and with emails and course website announcements distributed to students in classes known for their high makerspace use.

Data was collected with an end of semester survey distributed to all students who completed makerspace training. The survey requested information regarding student demographics, past making experiences, academic information, and tool usage data. The surveys were distributed at the end of the semester, taking students roughly 20 minutes. Students were compensated $20 for their completed survey. The survey supplied self-reported tool usage data is the primary input for the network analysis. This includes information such as the tools students used, for what purposes, and the order used. The tools are grouped into general categories as seen in Table 1. The student demographic data and tool use responses are transferred to an interaction network like the one found in Fig. *1*. The interaction network includes a one for when a student interacted with a tool and a zero when the student did not interact with a tool.

The individual students in the matrix of Fig. 1c were then condensed into demographic groups. For example, if students 1 and 3 in the sample network makerspace in Fig. 1 were both Hispanic students, their interactions were averaged for the tools they used. The analysis here uses a 10% usage as a cutoff for average interactions, meaning: if 10% of the Hispanic students had shared interactions then the Hispanic student group would have an interaction value of one for that tool. If it was less than 10%, it would receive a value of zero. This cutoff ensures that one student with one interaction doesn't skew the interactions for the entire student group.

Table 1: Tool selection included in survey with the sub tools that are encompassed by each category.

Tool Category	Specific Tools Included
(1) 3D Printing	Ultimaker 3D Printer, Formlabs Form 2 Printer, Stratasys 3D Printer, 3D Scanner Arm
(2) Metal Tools	Angle Grinder, Band Saw, CNC Metal Mill, Manual Mill, Manual Lathe, Drill Press, Belt Sander, Polishing Wheel, Table Vice
(3) Laser Cutter	Laser Cutter
(4) Wood Tools	Band Saw, Belt Sander, Circular Saw, Miter, Jigsaw, Drill Press, CNC Wood Router, Router, Planer, Table Saw, Hammers, Measuring Tape, Hand Saw, Dremel
(5) Handheld Tools	Pliers, Vice Grips, Clamps, Screw Drivers, Hand Drills, Chisels, Tin Snips
(6) Electronic Tools	Circuit Board Plotter, Multimeter, Power, Supply, Soldering Station, Oscilloscope, Logic Analyzer
(7) Studied	Studied, Hung Out, Met with a Group
(8) Got Help	Got Help from Makerspace Volunteer, Got Help from Someone Who Wasn't a Makerspace Volunteer, Gave Help
(9) Crafting	Embroidery Machine, Sewing Machine, Vinyl/Paper Cutter, X-Acto Knife, Scissors, Glue Gun, Wire Cutters
(10) CAD Station	Cad Station, Workbench, Whiteboards
(11) Paint Booth	Paint Booth

$$Q = \frac{1}{E} \sum_{ij} \left(B_{ij} - \frac{k_i d_j}{E} \right) \delta(g_i, h_j) \qquad (1)$$

Matrices for each demographic grouping were put through the Newman algorithm (Eq. 1) modularity analysis to find tool usage modules [2]. In Eq. 1, E represents the total number of tool-student connections present in the bipartite adjacency matrix for the makerspace, Bij. The variables ki and dj provide the number of interactions each tool or student, respectively, has with other actors in the network. Finally, the tool and student module indices (gi and hj) are checked by function δ to determine whether any given pair of tool and student actors is assigned to the same module. If so, δ produces a value of 1, contributing to the overall Q of the network. If the two actors do not belong to the same module, δ becomes a 0, negating the effect of their relationship. The Newman/Leading Eigenvector method was used for the optimization in the modularity analysis, as the method generates a reproducible set of module assignments given consistent inputs [12]. Modules here are clusters of student-tool interactions that have minimal interactions outside their cluster. Module assignments for each interaction are found such that modularity is always maximized. Modules are added by repeating this process within each module, creating a new module subdivision only if it increases the modularity of the entire network [13]. Finally, optimal assignments are determined when no additional subdivisions exist that would result in an increase in modularity.

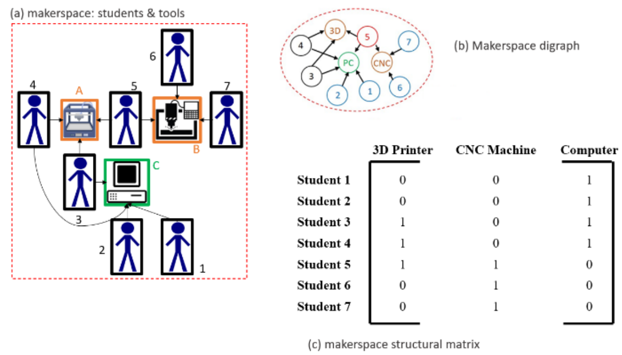

Fig. 1: Sample Network Creation. a) Hypothetical makerspace network with students interacting with tools. b) graphic representation of the network space. c) final interaction network.

Results & Discussion

Table 2A: School A 2021 Tool Group Usage by Gender

	Gender		
	Men	**Women**	**Prefer not to say**
n	117	56	13
3D Printers	59%	54%	69%
Metal Tools	39%	34%	23%
Laser Cutter	4%	2%	0%
Wood Tools	8%	7%	15%
Handheld tools	26%	18%	31%
Electronics tools	16%	9%	15%
Vinyl/paper cutter	0%	0%	8%
Foam Cutter	0%	0%	0%
Sewing Machine	0%	0%	8%
Cad station	13%	7%	15%
Studied	21%	11%	15%
Got help	16%	20%	8%
Paint Booth	2%	4%	0%
Other	18%	18%	15%

Table 2B: School A 2021 Tool Group Usage by Race/Ethnicity (W=White, A=Asian, B=Black, NA=Native American, H=Hispanic, and P=Prefer not to say)

	Race					
	W	**A**	**B**	**NA**	**H**	**P**
n	119	34	3	4	39	11
3D Printers	61%	53%	33%	75%	51%	45%
Metal Tools	38%	38%	67%	25%	31%	27%
Laser Cutter	3%	9%	0%	25%	5%	0%
Wood Tools	9%	6%	0%	25%	8%	9%
Handheld tools	25%	21%	33%	0%	26%	45%
Electronics tools	14%	12%	0%	25%	18%	18%
Vinyl/paper cutter	1%	0%	0%	0%	0%	0%
Foam Cutter	0%	0%	0%	0%	0%	0%
Sewing Machine	0%	0%	0%	0%	0%	0%
Cad station	13%	15%	0%	0%	5%	9%
Studied	18%	18%	67%	25%	21%	18%
Got help	16%	29%	0%	0%	10%	9%
Paint Booth	3%	3%	0%	0%	0%	0%
Other	18%	15%	0%	25%	28%	27%

Table 2C: School A 2021 Tool Group Usage by Major (M=Mechanical, A=Aerospace, I=Industrial, B=Biomedical, E=Electrical, C=Computer, Na=No answer)

	Major						
	M	A	I	B	E	C	Na
n	90	8	23	9	17	5	34
3D Printers	67%	25%	61%	89%	35%	20%	50%
Metal Tools	49%	13%	61%	0%	0%	20%	24%
Laser Cutter	4%	13%	0%	0%	0%	0%	3%
Wood Tools	10%	13%	0%	0%	6%	0%	12%
Handheld tools	27%	25%	13%	11%	35%	20%	21%
Electronics tools	4%	0%	0%	11%	71%	40%	21%
Vinyl/paper cutter	0%	0%	0%	0%	0%	20%	0%
Foam Cutter	0%	0%	0%	0%	0%	0%	0%
Sewing Machine	0%	0%	0%	0%	0%	0%	3%
Cad station	13%	0%	9%	11%	12%	20%	9%
Studied	17%	25%	4%	0%	35%	60%	18%
Got help	17%	0%	17%	0%	24%	40%	18%
Paint Booth	2%	13%	0%	0%	0%	0%	3%
Other	13%	38%	13%	0%	18%	20%	32%

Tables 2A-2C includes all the tool usage statistics for the various student demographic categories and tool groupings used to consolidate both portions of the interaction network. Instances where less than 10% of students within a demographic subset had an interaction with one of the tool groupings are highlighted in red. These are the student-tool pairings that did *not* meet the established usage threshold to constitute the presence of a link between the student group and the tool. A matrix like the one in Fig. 1c, depicting the bipartite network, is then Table 2 with the red cells replaced with a zero and the green cells with a one.

The usage values in Tables 2A to 2C reveal the tool groups that were used most and least consistently across the three categories of demographics. 3D-printers, for instance, shows consistent use by all student subgroups (greater than 10% of each demographic). Conversely, usage for the vinyl/paper cutter only crossed the 10% threshold for a single student demographic (at 20% which was only for 1 out of 5 total students), computer engineering majors. The demographics of the students using 3D-printers and the vinyl/paper cutter clearly show that the 3D-Printer is a general use tool, and the cutter is a specialized tool in this makerspace. As such, we expect the modularity analysis of the network to assign very different functional roles to each of them.

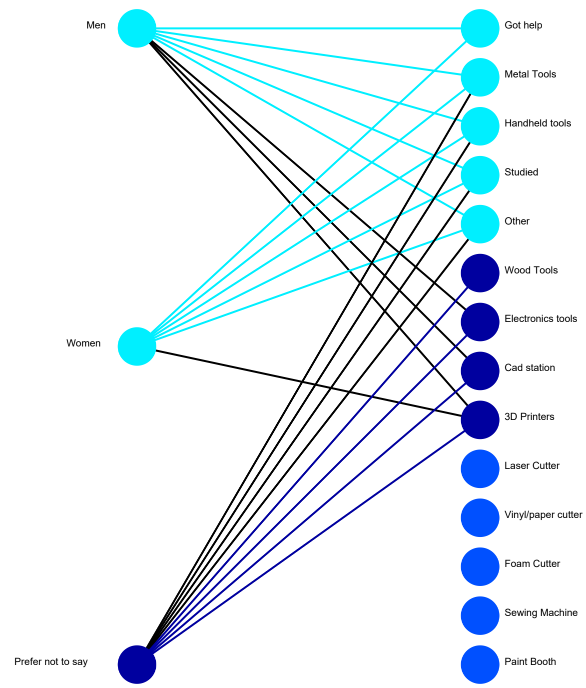

Fig. 2A: School A bipartite makerspace network and module assignments for various student demographic groupings: A) Gender B) Race C) Major. A connection between a student demographic group and a tool grouping indicates that at least 10% of that demographic interacted with that tool grouping.

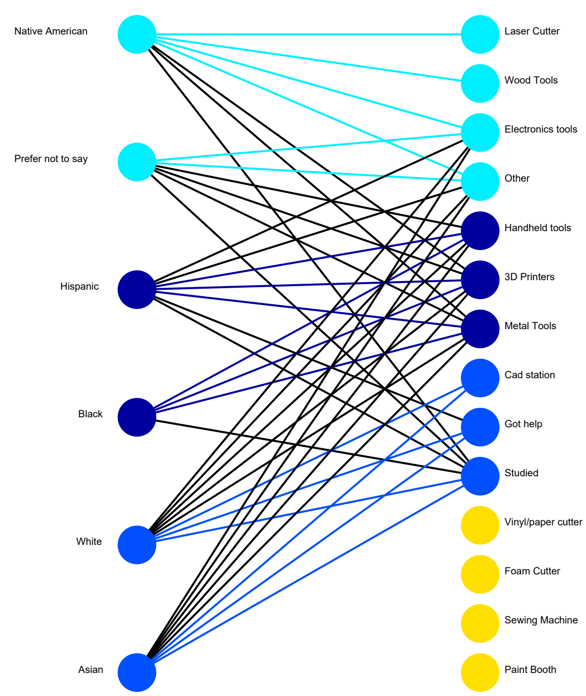

Fig. 3B: School A bipartite makerspace network and module assignments for various student demographic groupings: A) Gender B) Race C) Major. A connection between a student demographic group and a tool grouping indicates that at least 10% of that demographic interacted with that tool grouping.

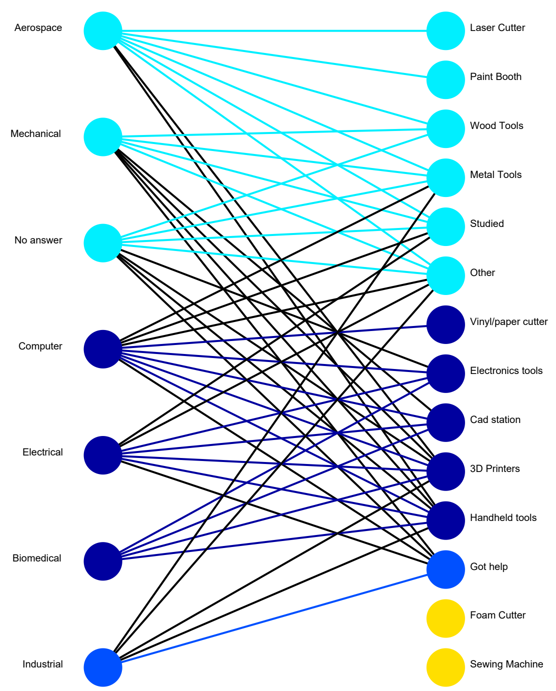

Fig. 4C: School A bipartite makerspace network and module assignments for various student demographic groupings: A) Gender B) Race C) Major. A connection between a student demographic group and a tool grouping indicates that at least 10% of that demographic interacted with that tool grouping.

Fig. 2A-C show the three resulting networks (based on student gender, student race, and student major). Actors (student groups and tools) of the same color share a module and black lines represent connections between modules. Of the three demographics groupings, the major-based network (Fig. 2C) is the easiest to analyze. On the student side, the modules can be viewed as three general categories: the first module consisting of mechanics-based majors (aerospace and mechanical engineering), the second module consisting of electronics/devices-based majors (computer, electrical, and biomedical engineering), and the third module serving as something of a hybrid between the first two (only containing industrial engineering). The way the tools are slotted into these three modules offers some expected findings, wood and metal tools sharing a module with the mechanics-based majors, for example, and some unexpected findings. One such unexpected finding is the placement of the handheld tools, a category generally associated with high usages from aerospace and mechanical engineering majors, in the electronics-based majors' module. Further knowledge of School A's makerspace would help suggest that this module assignment is a result of the handheld tool checkout desk being located much closer to the electronic work benches than to the wood or metal tool workshops.

A final point of interest from this demographic-based modularity analysis is the Q values (Eq. 1) for each network. As discussed, Q is a measure of how modular a network is. While it is difficult to establish performance expectations based on Q, there is some value in the comparison between the difference networks. Conceptually, certain demographic categorizations make more sense to display high modularity values. A bipartite network based on student major, for example, could be expected to contain the presence of a modular structure, with majors grouped with the tools related to their respective specializations. Gender and race, however, would ideally display far lower degrees of network modularity. For these sorts of demographics, high values of modularity might suggest the existence of some inequity regarding how different students feel comfortable using the space. This discussion is supported by Table 2, where the major-based network displays the highest Q value (it is worth noting that the module assignments for these networks were generated to optimize Q) of the three demographics.

Table 2: Modularity (Q, Eq. 1) of School A makerspace networks by demographic categorization.

Demographic Categorization	Q (Modularity)
Gender	0.099
Race	0.126
Major	0.160

Q can also be used as the basis for an objective function to design a makerspace from scratch using a computational model, but implementation would likely differ for different demographics. For demographics like gender and race, being highly modular might be a negative as you would want to see the same usage patterns regardless of the gender/race. Larger sample sizes are needed for underrepresented STEM groups however to make stronger conclusions. The results shown here however do suggest that special events specifically targeting tools that are causing modularity in specific student subsets could be used in future work to minimize overall modularity. Future work will investigate this further, to determine if makerspace design can be informed by minimizing modular characteristics. Prior work has found increasing modularity to correlate with increasing resilience of both human and biological networks, but this trend is highly dependent on the network type [14, 15]. Water distribution systems (WDSs) are one example of an exception to this correlation, as highly modular WDSs are more likely to leave entire communities disconnected as a result of a system disturbance [14]. Because of this variety in the effect of modularity on system performance, more research would need to be done to establish the nature of the relationship between modularity and makerspaces, specifically with students consolidated by major. Ultimately, the desired effect of makerspace design on modularity (Q) will likely depend on administrative preferences, i.e., whether it is more desirable for a makerspace to display more homogeneous usage across all majors or whether it is preferable that certain modules of tools and students are able to continue functioning despite a disturbance within a different module.

Conclusion

The work discussed represents the first time that demographic-based modularity analysis has been conducted on university makerspaces. While largely dependent on the survey data used to make the bipartite networks, the results for School A serve as an example of how this technique could offer a novel means of viewing these makerspaces. At the broadest level, this approach provides insight into the ways in which different subsets of students use the space, both in terms of raw usage statistics and in terms of the module assignments for both student and tool groupings.

Identifying the Q values (a representative measure of how modular the structure of a given network is) for each network can also help to establish a baseline from which meaningful design changes could be made. For the race and gender-based networks, successful makerspace design would see a decrease in Q, indicating that these two demographics do not influence how students are interacting with the makerspace. When looking at the network from a major perspective, the desired change on Q is less apparent, and more work will need to be done to see whether increasing the modularity in these networks does help with system resilience (maintaining high levels of makerspace operation despite failures of certain tools), as has been observed in some biological and manmade networks, or if higher modularity represents an undesirable separation in the space between different majors and the tools they tend to use.

Future work to expand on this research will first use the module assignments to determine the functional roles of student and tool groupings. This will help identify the degree to which types of actors within the makerspaces are responsible for connecting other actors, both within and between modules. Furthermore, the implementation of actual design changes in operational makerspaces and a repeating of the analysis done here will allow for a better understanding of how makerspaces might be changed to affect their performance, and how the changes would manifest themselves through the lens of modularity.

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