Bipartite Network Analysis for Understanding Makerspace Tool Usage Patterns

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Abstract

Makerspaces continue to be a part of many university engineering programs. More work is needed to understand their impacts and how makerspaces should be implemented to maximize their impact for all students. Many of the available approaches to ascertain impact are highly effective but excessively time-intensive, especially for continuous monitoring of a space. This paper presents the use of bipartite network analysis of weighted and unweighted matrices of student tool usage to determine modularity as an easy-to-obtain metric to monitor space. To obtain the data needed, an end-of-the-semester survey asks students which tool they used in the space and how frequently. Data was collected in Spring 2021 and Spring 2022 as covid restrictions were being lifted, providing a data set where the modularity values should be changing. Prior work demonstrated unweighted modularity values as an effective tool for identifying changes in the health of a makerspace. Current work explores the inclusion of tool frequency use on the conclusion drawn from modularity analysis. Results show differing patterns of results between the weighted (includes frequency of use) and unweighted (only considers if a tool was used) modularity values. More work needs to explore the use of weighted bipartite network analysis and the benefits it may provide over the much simpler to obtain the unweighted analysis. Additional research is also needed on other methods to monitor the health of a makerspace and the benefits to all of its users.

Introduction & Background

More and more engineering schools around the world are implementing makerspaces into their facilities [1]. These spaces provide students an opportunity to apply their curricular knowledge to hands-on projects while fostering an environment of collaboration and creativity [2, 3]. Academic makerspaces typically feature a range of tools, varying in complexity, available to students. With the increase in popularity of these spaces, it is imperative to understand how these spaces are being used. Analyzing the interactions of students and tools provide valuable insights into the usage of makerspaces. Understanding usage trends will assist in ensuring that the space is able to be used to its full potential by all students. A further look into the insights unveiled through analysis of student and tool interactions can also contribute to minimizing any usage barriers students may face. Previous efforts using only surveys of students about their tool usage allowed researchers to analyze these interactions using network and graph theory showed insight into the effectiveness of the spaces [4, 5].

In following with prior work from the authors, this study utilizes mutualistic bipartite analysis originating from ecological studies of plant-pollinator networks. Utilizing bipartite network analysis allows researchers to quantify traits of a network that reflect different characteristics of it, such as modularity, nestedness, and connectance. These metrics reveal details of the intrinsic community structure of a network through single values. Having access to these metrics allows for there to be a common platform from which underlying network trends can be analyzed. Mutualistic bipartite networks contain two mutually interacting items, dubbed actors [6]. Bipartite network analysis is used over unipartite analysis when there are two distinct sets of entities interacting with one another and is highly effective at analyzing the interactions between the two [7].

In the context of makerspaces, the actors are students and tools. In keeping with the adaptation of ecological plant-pollinator network analysis methods to makerspace usage, students can be seen as corresponding to pollinators and tools as corresponding to plants. By modeling a makerspace as a bipartite network, researchers are able to identify the usage trends found within a space. The makerspace network can also be broken down into sub-networks characterized by demographic identifiers such as man or woman, as in this study [8]. Breaking down the network with respect to demographics can be a useful tool in determining any underlying inconsistencies in usage trends. Identifying trends within a makerspace through modularity analysis has been fruitful in the past [8, 9]. Modularity analysis equips researchers with the ability to identify and quantify the clustering within a space. These clusters, or modules, are often difficult to observe without such analysis techniques.

Beyond makerspaces, the approach of examining social environments as interaction networks and applying network analysis techniques have been highly effective. The rise of the internet has led to a wealth of data on user interaction. Online interaction data has been analyzed through social network analysis methods to categorize users of online shopping platforms, such as Amazon, into communities of shoppers with shared interests. These communities are then used to provide targeted recommendations based on what a user will most likely pursue [10]. Additionally, eco-industrial parks have been successfully modeled as unipartite networks to aid in the reduction of waste generation and increase effective resource utilization [11]. Furthermore, modularity analysis was applied by researchers in order to effectively identify communities within varying levels of schools and determine the differences in how negative relationships affect these communities as age increases [12]. Applying graph-based approaches to complex social environments allow these environments to be standardized and quantified, such that they are more interpretable to researchers.

Prior work applying modularity analysis to makerspaces converts the interaction data into a binary matrix, in tune with commonly used practice in bipartite network analysis [13, 14]. This technique is extremely valuable in identifying overarching trends within a network; however, a major limitation is that information from interaction frequency is lost [15]. Regardless of how much a tool has been interacted with by a student, it will be converted to a one, which means a high-usage tool for a specific student will have the same value in the matrix as a low-usage tool for the same student. In order to capture the frequency of usage, researchers have developed tools to analyze weighted bipartite networks [16]. These weighted analysis techniques ensure that intricacies in usage dictated by the amount a tool is used by a student is not lost. This study aims to expand on prior work and capture how further insights can be extracted from the usage data of a makerspace when performing modularity analysis on weighted networks as opposed to unweighted networks.

Methods

The focus of this study is School A, an R1 institution in the United States with a large engineering college. The makerspace utilized in this study is centrally located within the main engineering building. The space is open to all undergraduate engineering students. The space contains traditional tools found in makerspaces, such as 3D printers, electronic hardware tools, hand tools, mills, lathes, etc. There is also an open workspace area within the space to foster collaboration. The space is run by full-time staff, with assistance from part-time student workers. Personal projects are not officially allowed, so the space is exclusively used for curricular and capstone projects.

Data was collected using end-of-semester surveys [17-21]. Surveys were initially piloted and based on prior work, see [17-21] for more details. Participants for these surveys were recruited using flyers that were posted at the exit of the makerspace and distributed to classes known for high makerspace use. The surveys generally took around 20 minutes to complete, and participants received $20 as compensation. Students were asked which tools they used and how frequently they used them. The tools were split into categories of general tools and specific tools within the subsections as shown in Table 1. Additionally, the surveys collected background information such as student demographics, academic background, previous making experience, and whether they sought help or not. The results from this survey detailing self-reported usage serve as the input for network analysis.

Table 1: Tool categories and tools within each category included in the survey

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) Social Activities	Studied, Hung out, Met with a Group
(8) Got/Gave Help	Got Help From Makerspace Volunteer, Got Help From Someone Who Wasn't a makerspace volunteer, and Gave Help
(9) Soft Materials	Embroidery Machine, Sewing Machine, Vinyl/Paper Cutter, X-Acto Knife, Scissors, Glue Gun, Wire Cutters
(10) Paint Booth	Paint Booth
(11) CAD Station	CAD Station, Workbench, Whiteboards

Survey responses were converted to an interaction matrix as shown in Figure 1. This was done by first defining the two actors of the bipartite interaction matrix as students and tools. In the matrix, row labels represent student identifiers and column labels represent specific tool names. The network is populated by the number of interactions between students and tools. For example, if Student Y stated that they used Tool Z 9 times over the course of the semester, the matrix entry for Student Y x Tool Z would then be a 9. A binary interaction matrix was also created using the initial frequency-based matrix. In the binary matrix, a 1 denotes usage of a tool by a student, and a 0 denotes no use. The initial interaction matrix with usage frequency will be referred to as the weighted matrix, and the binary matrix will be referred to as the unweighted matrix.

Modularity values for the unweighted and weighted matrices were calculated using the bipartite package in R [22]. The Newman/Leading Eigenvector algorithm was used to generate modules and calculate the modularity value for the unweighted matrix using Eq. 1 [23]. In Eq. 1, d_j and k_i represent the number of interactions for each student and tool respectively, B_{ij} is the bipartite adjacency matrix, and E is the sum of all interactions within the matrix. The delta function δ equates to 1 when the nodes i and j are indexed to be within the same module, while it negates to 0 otherwise.

Eq. 1

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

Beckett's DIRTLPAwb+ algorithm modifies the Newman algorithm to allow for the input of weighted matrices and as such, is used to calculate modularity of the weighted data using Eq. 2 [16]. In Eq. 2, the weighted incidence matrix W_{ij} is inputted in place of the adjacency matrix, while E remains the sum of all interactions (albeit in this case weighted), and k_i and d_j remain the number of interactions for each student and tool.

Eq. 2

$$Q_b = \frac{1}{E}\sum_{ij}(W_{ij} - \frac{k_i d_j}{E})\delta(g_i, h_j)$$

For both algorithms, final modularity values range from zero to one, with a one representing a fully modular network, while a zero represents the opposite. A highly modular network indicates the presence of defined clusters within the network that have minimal interaction with other clusters, and this generally means students using fewer tools.

Results & Discussion

The modularity results from the network analysis provide insight into general trends in the makerspace (Figure 3) and provide a clearer picture of the general trend in the space as compared to evaluating the individual tool categories (Figure 2). Increases in modularity values indicate that students tend to use a smaller subset of tools. The modularity values from Spring 2021 to Spring 2022 decrease as expected, given that restrictions due to covid were being decreased over this time period providing easier access for the students. This same trend is observed when evaluating both the weighted and unweighted modularity values.

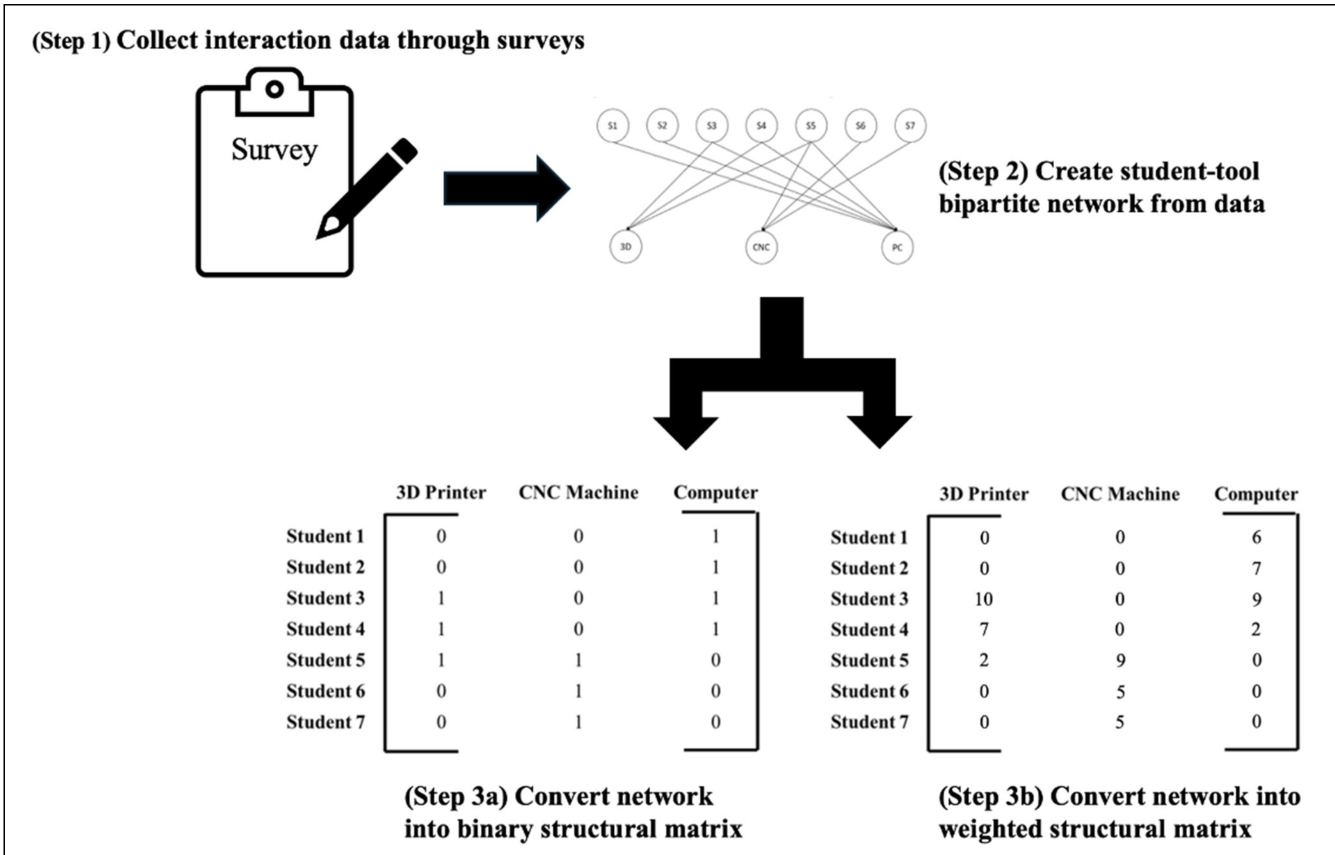

Figure 1: Student survey responses about their tool usage in the makerspace are converted to a bipartite network and then into a matrix for analysis.

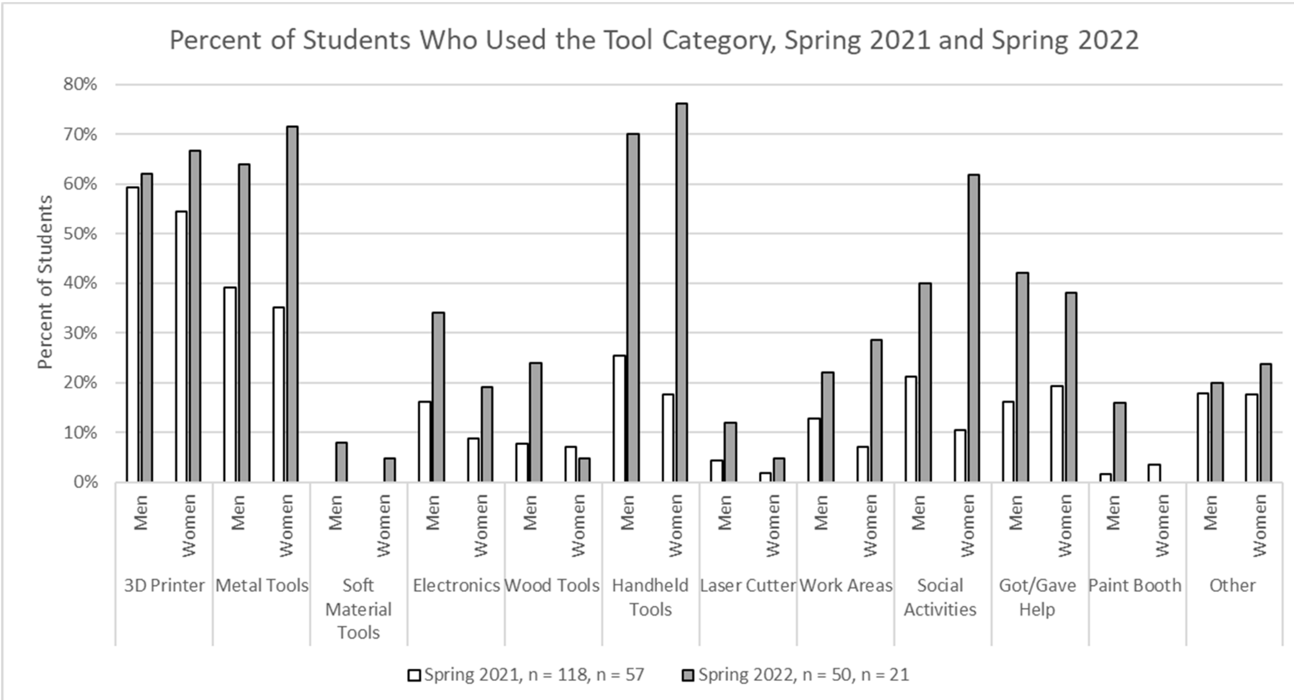

Figure 2: Percent of women and men that used a particular tool category.

In the case of covid restrictions on makerspaces, there was an expected increase in tool usage as the restrictions eased, providing a good opportunity to evaluate the potential of bipartite network modeling to provide insights into the changes within the spaces.

It was less clear if the weighted and unweighted networks would show a similar pattern of results. From Figure 4, it is clear that the weighted and unweighted modularity results would lead to different conclusions about what is occurring in the space. The unweighted modularity results show a consistent pattern of higher modularity for women, which indicates women likely use fewer of the tool groups. The weighted modularity results do not show a clear pattern between men and women, with women having lower modularity in Spring 2021 and greater in Spring 2022. These results indicate that while the unweighted data is much easier to collect since it only requires students to indicate which tools they are using, this may be insufficient to deeply understand tool usage patterns, especially as a function of different demographics or other important variables like major.

Changes in modularity of tool usage will not indicate the cause of a change, only that one has occurred. Further research methods would be needed to identify causes.

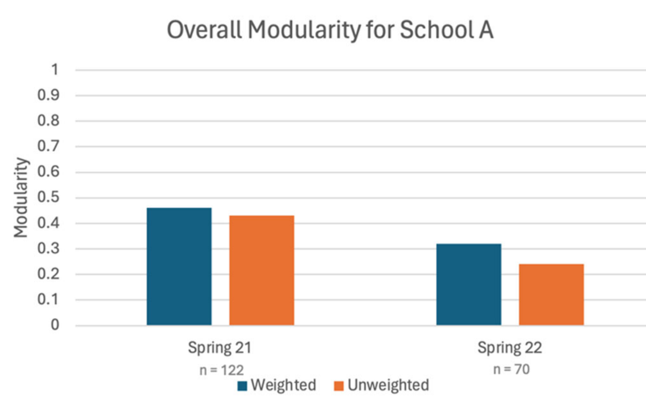

Figure 3: Moving from Spring 21 to Spring 22, as covid restrictions were reduced, modularity decreases indicating students are overall using a larger variety of tools.

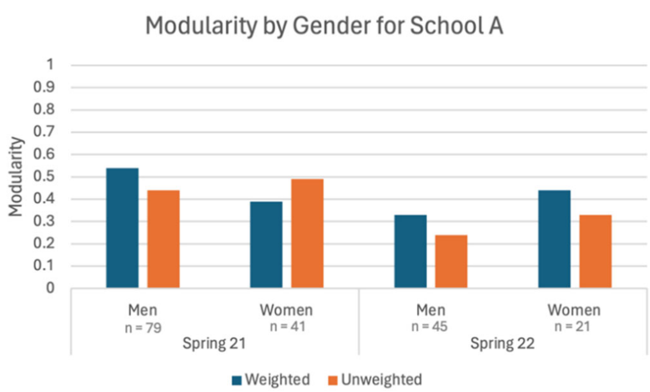

Figure 4: Comparison of the weighted and unweighted modularity results. For the unweighted modularity, women show higher modularity, whereas for the weighted results, there is not a clear pattern.

Conclusion

Low-overhead, easy-to-use methods for monitoring the health and impacts of a makerspace are needed. This paper investigates the use of weighted and unweighted bipartite network analysis to explore if simple end-of-the-semester surveys asking only if a tool was used (results in unweighted modularity) showed the same pattern of results as including the frequency of tool usage (weighted modularity). The weighted and unweighted modularity values for men and women showed a different pattern of results for Spring 2021 and Spring 2022, indicating more exploration of these two approaches is needed. It is possible that women and men use a similar variety of tools, but men tend to use them more frequently. This may or may not lead to significant differences in the benefits of the makerspace for the students. The data needed for the unweighted bipartite analysis requires students to only report if they use a tool or not and, thus, a much shorter survey. In contrast, the weighted bipartite analysis needs both the tools used and how frequently and, thus, a notably longer survey. More work needs to investigate different approaches within network analysis for monitoring makerspaces and into other low-overhead approaches for measuring the effectiveness and impact of makerspaces.

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