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BOARD # 256: IUSE: Analyzing Nestedness Variability for Bipartite Makerspace Tool-Tool Projection Models

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IUSE: Analyzing Nestedness Variability for Bipartite Makerspace Tool-Tool Projection Models

Introduction & Background

Academic engineering makerspaces give students a controlled environment to put their theoretical knowledge to practical use. As such, many universities are adding these spaces to their campuses and integrating them into their curricula [1]. Due to their rising popularity and perceived importance, it is important to further understand how best to create and manage these spaces. A number of universities have taken the initiative of tracking usage (number of users), however, this fails to detect any underlying patterns and trends [2]. Tracking usage patterns can identify the impact of intended and unintended policy consequences and support the design of new spaces/modification of existing ones to maximize effectiveness.

Analyzing human and machine interactions through network-based methods is a well-established practice further supported by the influx of data in the digital age. Modeling and analyzing data using network-based techniques can be found across various fields. Ecology uses Ecological Network Analysis (ENA) to model and analyze a range of complex species interactions in ecosystems, for example food webs model predator-prey interactions amongst species. Engineering studies using ENA have successfully translated the patterns found in ecological food webs to water distribution networks and power grids to increase their effectiveness and resilience [3, 4].

This NSF funded project has been successfully applying ENA methods to gain insight into makespace tool usage trends by modeling spaces as mutualistic, bipartite student-tool networks [5-10], inspired by the modeling and analysis of plant-pollinator type mutualistic networks found in nature. The user-tool makerspace networks document the mutually beneficial interaction (as opposed to a consumption-type interaction) of a student, or student group, using a tool in an interaction matrix. Graph and information theory-based metrics from ENA, such as nestedness [11-13], can then quantify usage patterns within the networks. Bipartite projection techniques are investigated here, allowing for further insight into how different individual nodes within the same set of actors are linked to one another [14, 15].

A user-tool makerspace network model has two possible projections: user-user and tool-tool. A tool-tool projection network creates links between tools when there are shared users in the user-tool network (i.e., student A using a 3D printer and a welder would connect the printer and welder in the tool-tool projection network model). The tool-tool projection model provides insights into non-obvious relationships between tools based on usage. These tool relationships can uncover hidden patterns and usage clusters that are not easily visible in previously studied user-tool network models or standard in person makerspace usage tracking. This study performs a preliminary exploration of the volatility of the ENA metric nestedness for tool-tool networks, with the goal of understanding the metric's response as tool-tool interactions are removed. This investigation supports future work into factors that influence the robustness of network metrics.

Methods

Data Collection

Makerspaces at two R1 institutions served as case studies. School A has a staff-managed space located in a central engineering building that is open to all engineering students but limited to course required use and select engineering competition teams. Additionally, there are strict PPE requirements for entering the space, regardless of what is being used, including safety goggles, closed toe shoes, ankle covering pants, and no jewelry. School B is a student volunteer managed space located inside the mechanical engineering building. As such, the space is used primarily by mechanical engineering students despite being open to all engineering students. Both personal and class-based projects are allowed. PPE requirements vary depending on the area of space being used, with the main area requiring none and the wood and metal workspaces needing closed toe shoes and safety goggles. Data was collected at both schools using end of semester surveys (see [10] for further details). The survey results from 3 spring semesters (2021-23) were utilized for this study (School A: $N_{students}$ = 121, 69, 70 and School B: $N_{students}$ = 84, 94, 80, respectively).

Network Creation

Survey responses were quantified in the form of bipartite interaction matrices (see [10] for more details). Using Equation 1, the user-tool interaction matrices [**B**] were projected as tool-tool matrices.

$$\mathbf{B}' = \mathbf{B} \cdot \mathbf{B}^T \tag{1}$$

This tool-tool network creation is further detailed in Figure 1. The projection (Figure 1-right) documents interactions between tools as a function of shared users, rather than direct interactions between users and tools in the user-tool matrix (Figure 1-left). The interaction or edge values in the tool-tool matrices are the number of shared users the paired tools have. Tools with no shared users have a b'_{ij} value of 0. The diagonal matrix elements for tool pairings involving the same tool (e.g., intersection of 3D printer and 3D printer), are defaulted to 0 to avoid inflation as these are not of interest.

$$\text{Users}\;\begin{array}{c|ccc|} & \multicolumn{3}{c}{\text{Tools}} \\ & \text{3D Printer} & \text{CNC Machine} & \text{Computer} \\ \text{Student 1} & 0 & 0 & 1 \\ \text{Student 2} & 0 & 0 & 1 \\ \text{Student 3} & 1 & 0 & 1 \\ \text{Student 4} & 1 & 0 & 1 \\ \text{Student 5} & 1 & 1 & 0 \\ \text{Student 6} & 0 & 1 & 0 \\ \text{Student 7} & 0 & 1 & 0 \end{array} \;\Longrightarrow\; \text{Tools}\;\begin{array}{c|ccc|} & \multicolumn{3}{c}{\text{Tools}} \\ & \text{3D Printer} & \text{CNC Machine} & \text{Computer} \\ \text{3D Printer} & 0 & 1 & 2 \\ \text{CNC Machine} & 1 & 0 & 0 \\ \text{Computer} & 2 & 0 & 0 \end{array}$$

$$\text{User-Tool Matrix Representation (B)} \qquad\qquad \text{Tool-Tool Matrix Representation (B')}$$

*Fig. 1: Projecting a 7x3 user-tool network model [**B**], with 7 users and 3 tools, into a 3x3 tool-tool network model [**B'**].*

Nestedness

Nestedness quantifies how hierarchical the interactions in a network are on a scale of zero to one. A value of 1 indicates a perfectly nested space where student 1 is connected to all tools, student 2 is connected to a subset of those, and student 3 a subset of those and so forth. A value of 0 indicates a completely random network with no hierarchical structure. Nestedness quantitatively supports our understanding of the dependencies of a space's tools. When examining the nestedness of a network, it's prudent to consider actor subsets known as generalists and specialists. In the context of a makerspace network, generalists are users who interact with a wide variety of tools, whereas specialists only interact with a smaller subset of those tools. In a nested network, the distinction between generalist and specialist are evident due to the clear hierarchical nature of the network.

A commonly used calculation for nestedness is Almeida-Neto's *Nestedness based on Overlapping and Decreasing Fill* (NODF) [16]. However, this method only works for binary networks. Because the tool-tool network model contains weights, a modified version of NODF by Almeida-Neto, known as *Weighted Nestedness based on Overlapping and Decreasing Fill* (WNODF), is used [17].

Sensitivity Analysis

Validation techniques help ensure that metrics used to analyze networks yield reliable and reproducible results. A sensitivity analysis was conducted to evaluate the robustness of nestedness for the tool-tool network model, giving insight into how changes in the network might affect the tool-tool structure [18]. A percentage (0-10%) of randomly selected links was removed and nestedness was recalculated at 1% removal intervals. The 10% threshold was experimentally decided to ensure that changes were visible, while still ensuring the network has structural integrity. The random removal and nestedness calculation were each iterated 10 times, with the result being the average of those 10 to minimize any random error. Sensitivity was then characterized at each removal step as the percent change in nestedness from the network's initial nestedness.

Results and Discussion

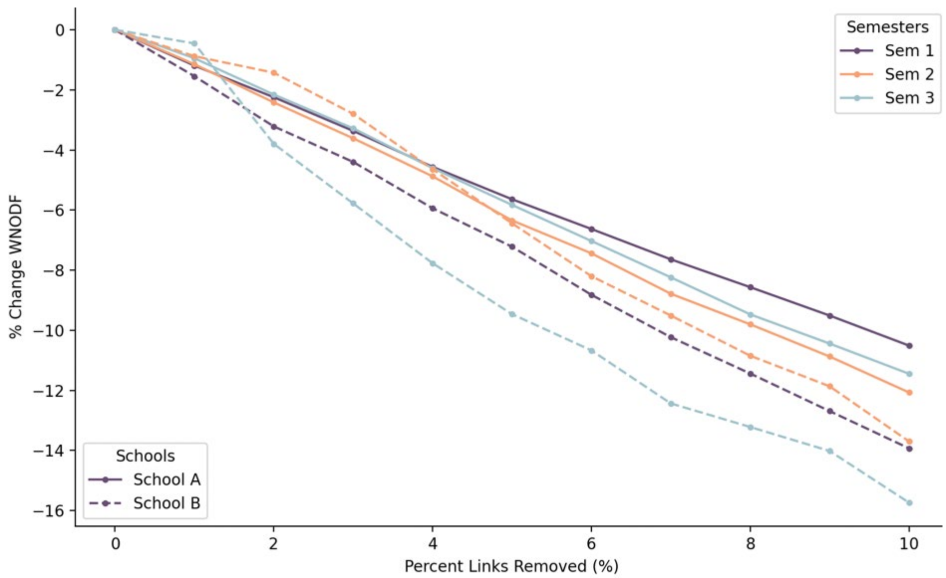

Fig. 2: Change in weighted nestedness (WNODF) across schools A and B during semesters 1 (2021), 2 (2022), and 3 (2023) as a function of the % of links removed.

Nestedness at both schools and across all three semesters decreased as edges were removed, as seen in Figure 2. This is expected because as edges are removed the hierarchical structure breaks down and a highly nested network requires a connectance, or links vs total possible links, of at least about 50% [19]. Notably, School B's nestedness is more strongly impacted by a loss of links than School A's across all semesters. This is interesting as, apart from the exception of Spring 2022, School B is more nested than School A. While School B's actual network each semester exhibits more of a specialist-generalist nested pattern, the steeper decline in nestedness may suggest a smaller proportion of specialists and thus fewer unique interactions (needed to create the nested structure). As such, any link removal will have a greater effect on School B's nestedness. Prior work suggested that the more structured and staff-managed approach of School A resulted in more tools requiring special training, while the freeform student-managed School B space had more students using more tools overall [19, 20]. The larger effect of link removal on the nestedness of School B also indicates that the nested structure that is there may be more fragile nested than School A. Quantitatively, the removal of tool-tool links from School B's network drops the connectance below the 50% threshold, resulting in a larger impact on nestedness.

As the makeup of the makerspaces in School A and School B are fundamentally different, it would be futile to draw concrete conclusions without first exploring other spaces similar to both schools A and B. This is because the changes in metrics/trends could be attributed to many differences, such as space usage purpose, ease of entry, school culture, etc. As such, further studies are required to substantiate the preliminary claims made in this paper.

Conclusions

Makerspaces can play a fundamental part in the formation of an engineer. It is thus prudent to develop tools and methodologies to understand usage patterns and gain insights into improving their design and operations. The analysis here combines previously used Ecological Network Analysis methods with newly applied bipartite projection techniques. Network projection offers makerspace researchers a fresh perspective on existing data by looking into intra-actor relationships through shared connections. The tool-tool projections focus on patterns created by shared usage – independent of individual users. Future work with this analysis has the potential to uncover hidden trends such as clusters of tools often used together, underutilized tools, or usage dependencies. This study validates the usage of bipartite projection techniques and nestedness analysis in tandem with sensitivity analysis to gain deeper insights into a makerspace network.

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