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From Plant-Pollinator to Product-Customer: Bio-Inspired Network Modularity Analysis in Design for Market Systems

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Abstract

Bio-inspired design takes inspiration from nature to address challenges in human engineering, often delivering innovative and high-performing design solutions. Despite its significance, bio-inspired design is less applied in systems engineering contexts compared to the design of tangible artifacts. A recent study of student-tool bipartite network models of makerspaces found that bio-inspired network modularity (drawing inspiration from plant-pollinator networks) could facilitate the understanding of a makerspace's health and functioning. This work further explores the utility of bipartite network models and the associated modularity analysis by extending it to a study of product-customer relations. Focusing on the household vacuum cleaner market, we identify brand preferences among customer groups categorized by geo-location, age, and purchased vacuum cleaner type. A comparison between the modularity of plant-pollinator and product-customer networks reveals that the former exhibit greater modularity, an insight that sets the stage for using bio-inspired system design to inform the engineering design decisions for desired market performances. If successful, the approach could assist enterprises in understanding their target customers and formulating effective market strategies, such as targeted advertising to customer groups exhibiting limited interest in their products. This novel translation of bio-inspired modularity analysis underscores the viability of biomimetic design in complex socio-technical systems.

Keywords: Bio-inspired design; Network modularity analysis; Bipartite network; Plant-pollinator systems; Market systems

1. Background and Introduction

Bio-inspired design in the systems engineering (SE) context is an under-explored field but has significant potential to innovate SE approaches and discover new SE solutions and policies. In a recent study led by one of the authors, the viability of using a bio-inspired mutualistic network analysis to visualize and quantitatively understand interactions between entities in complex systems, i.e., student-tool interactions in an engineering makerspace, (Blair *et al.*, 2022, Brehm, Linsey, and Layton, 2020) has been explored. The model visualized tools and students as analogous to plants and pollinators. (Blair *et al.*, 2022) The resultant network modularity analysis was able to identify the roles of different tool groupings and potential tool hubs to inform meaningful design

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changes to facilitate space accessibility and track usage changes over time. Motivated by this work, this paper sets the stage for using a similar translation of bio-inspired bipartite models and a modularity analysis in designing and understanding market systems.

A market system consists of multiple stakeholders with complex relations and interconnections. Network modeling supports understanding of relationships between the system's entities and provides enterprises with leverage to improve their market position, including better targeted marketing and product attribute modifications. A vacuum cleaner market serves as our case study, where product attributes play a crucial role in influencing customers' consideration and purchase decisions. Demographics, such as age and location, can also influence a customer's preferences. In this bio-inspired study, products are visualized as analogous to plants and customers to pollinators using a bipartite network model to represent customers' considerations and purchases. The bipartite model supports the use of different aggregations within the vacuum cleaner market that enable the influence of preferences, demographics, and product attributes to be quantitatively clarified using a modularity analysis. The preliminary results here begin to draw comparisons between patterns found in mutualistic ecosystems and market systems and set the stage for using distinct system characteristics tied to ecosystem resilience to improve product-customer markets.

2. Research Method

2.1 Data Structure

Three ecological datasets of mutualistic networks (binary interaction matrices) were obtained from the Interaction Web Database hosted by the Department of Ecology at the University of São Paulo, Brazil. (IWDB, 2020) They were selected due to their comparable size of plant nodes to the product nodes in the market system of this study. The data includes plants (flowering plants, shrubs, and bromeliads) and pollinator species (hummingbirds, bees, and bats). The market dataset originated from our previous survey study (Xiao *et al*., 2022) and encompasses responses from 945 customers and data on 612 vacuum cleaner models. Customer demographics, the vacuum cleaners considered and purchased by customers, and the respective brands and categories of these products were all known attributes (customers in the study were limited to considering a maximum of seven products before selecting one to purchase).

2.2 *Bipartite Network Construction*

Bipartite network models consist of two sets of node types where only those connections occurring between the two node types are modeled. (Zhou *et al.*, 2007) Unweighted bipartite networks produce an adjacency matrix the size of $M \times N$, where M and N represent the sizes of two node sets. A matrix element equals one if a link exists between node i and node j, and zero otherwise. Two types of networks are compared here, plant-pollinator bipartite network models from ecology (Medan et al, 2002, Dupont, Hansen, and Olesen, 2007) and product-customer (vacuum) bipartite network models from market science. (Fu *et al.*, 2017) The plant-pollinator bipartite network model sets plants and pollinators as the two different node sets, with the adjacency matrix documenting an interaction a_{ij} as 1 when a visitation occurs, and 0 otherwise. The product-customer bipartite network model sets customers and the unique products considered or purchased by customers as the two different node sets. The adjacency matrix entries or links denote the consideration behaviors of customers, i.e., a_{ij} equals one when customer i considered product j. Customers and products were aggregated based on different criteria to investigate the impact of product attributes, with each aggregation producing a separate bipartite model. The adjacency matrices documenting the interactions are the inputs for the modularity analysis outlined in Section 2.3.

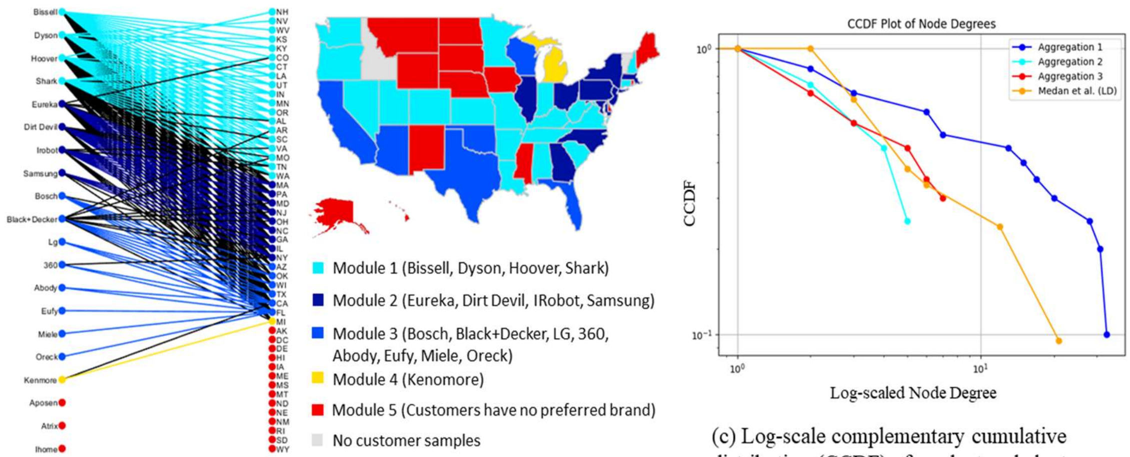
2.3 *Modularity*

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

A modularity analysis quantitatively captures architectural patterns in the way the two actor groups interact. Ecologists use modularity to study conservation priorities of hub species and taxonomical syndromes. (Olesen *et al.*, 2007) The Newman algorithm is used here to calculate modularity (*Q*), as defined in Eq. 1. (Newman, 2006) In the context of product-customer market systems, E represents the total number of product-customer connections as presented in the interaction matrix, denoted as B_{ij}. The variables k_i and d_j indicate the number of interactions each product or customer has with other entities in the network. Subsequently, a function assesses whether a specific product-customer pair (g_i, h_j) belongs to the same module. If they do, δ yields a value of 1, contributing to the overall network modularity, Q. If the two entities are not in the same module, δ results in 0. The Newman algorithm optimizes the assignment of modules for each interaction to maximize modularity.

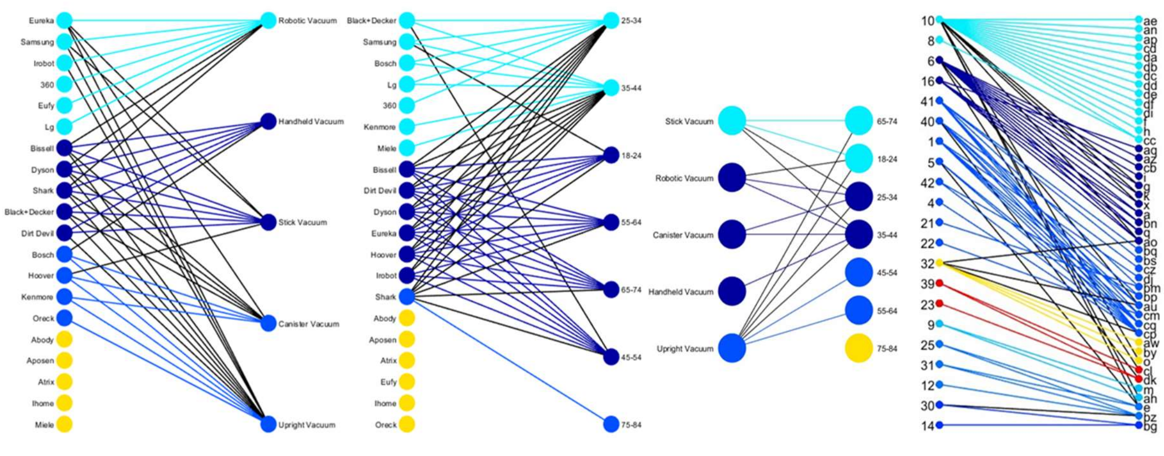
3. Results

Four aggregations of customers and products are considered. On the product side, the first three aggregations group products by brands, including only the top 20 most frequently considered brands by the 945 customers. The fourth aggregation groups product nodes by the vacuum cleaner types. On the customer side, *Aggregation 1* groups customers by geo-location, *Aggregation 2* by purchased vacuum cleaner type, and *Aggregation 3* and *4* by age. The bipartite network model captures only strong connections between product and customer groups, retaining only connections with interaction frequencies surpassing the median link weights post-aggregations. For example, in *Aggregation 3* (age groups), the median interaction frequency is 5 so connections are only drawn if the customers within that age group have considered the brand more than five times. *Aggregation 1*, *2*, and *4* have median values of 2, 8, and 48. This produces the bipartite network modularity results in Fig. 1 and 2.



(a) Aggregation 1 (b) Module assignments by geo-location (c) Log-scale complementary cumulative distribution (CCDF) of product and plant node degrees

Fig. 1 Brand-customer network and module assignments for customers aggregated by geo-locations (*Aggregation 1*). Nodes of the same color share a module and black lines indicate connections across modules



(a) Aggregation 2 (b) Aggregation 3 (c) Aggregation 4 (d) Medan et al. (LD)

Fig. 2 Brand-customer networks and module assignments for three types of customer groupings: (a) purchased product type, (b) age, (c) vacuum cleaner type-Age network, and (d) plant-pollinator network: numerical and alphabetical nodes refer to plants and pollinators, respectively

Figures 1 and 2 show four market network bipartite models (brands always shown on the left-hand side and customers on the right-hand side), alongside a plant-pollinator network from Medan *et al.* (LD), with module assignments indicated by color. Table 1 summarizes their network statistics and modularity results. The modules found by the brand-customer bipartite model in Fig. 1 reveal distinct customer preference based on geo-distributions for various brands (with 20 brands and customers in 49 states represented). Module 1 (Fig. 1a - light blue) encompasses four brands (Bissell, Dyson, Hoover, and Shark) and uncovers a concentration of customers in the central US region. Module 2 (Fig. 1a - dark blue) is also made up of four brands (Eureka, Dirt Devil, iRobot, and Samsung) and finds a predominant customer preference in the eastern US. Fig. 1b visualizes the same results in the form of a US map, facilitating the use of the modularity analysis approach to identify customer clusters. Fig. 1c considers the complementary cumulative distribution function (CCDF) for products in *Aggregation 1-3* and plants from Medan *et al.* (LD) to inspect their degree distributions. (Fornito, Zalesky, and Bullmore, 2016) The CCDF shape of the plant-pollinator network is visually most similar to that of *Aggregation 1*. Fig. 2a aggregates customers by the *type* of products they purchased versus the brands they considered. The modularity analysis reveals that customers who purchased robotic vacuum cleaners (Fig. 2a - light blue) tended to consider a wide variety of brands. The modularity analysis of the age group customer aggregation in Fig. 2b identifies a subset of brands considered only by customers between 25 and 44 (light blue). Young customers (aged 18-24, dark blue) also show a similar brand interest to customers between the ages of 45 and 74, possibly due to the influence of parents/adult caregivers over what could be the first vacuum cleaner that these young customers buy. These insights offer enterprises valuable strategic implications aiming to attract a wider or more specific customer base. Targeting advertising efforts in unconnected regions identified by the modularity analysis in Fig. 1 could attract new customers, for example.

Table 1 highlights the significantly higher modularity of the three ecological networks. Comparing the Medan *et al.* (LD) in Fig. 2d. to *Aggregation 1* in Fig. 1a, we notice that despite the comparable network sizes, number of modules, and CCDF shape, the plant-pollinator network has significantly fewer interactions occurring outside of modules (black interactions), resulting in a higher Q value (0.618 as compared to 0.191 for the vacuum market). Mutualistic plant-pollinator networks have been found to have higher modularity values and a better resilience when it comes to supporting highly specialized species (Landry, 2010), thus we see the potential for market networks to use a bipartite network model coupled with a modularity analysis to take advantage of similar architectures and resultant benefits. Additional work is needed to validate this approach, but this work sets the stage for that investigation.

Aggregation 4 (Fig. 2c) group products by vacuum cleaner type and customers by age, using a similar functional grouping technique used in these ecological models. The results show an increase in modularity as compared to other aggregations, suggesting that vacuum cleaner types may be a stronger characteristic of interest for different age groups (although it should be noted that the Q value of 0.227 for this aggregation is still very low and indicates a network that has a significant number of interactions that fall outside of modules). Future work may be able to automate aggregation selection to maximize Q and identify features or brands with specific customer markets. Market players may also be advised to exercise caution when aiming for higher modularity, as it can contribute to a specialized market and a reduction in market flexibility.

Table 1. Ecological and vacuum market bipartite network statistics and modularity calculation results

Dataset	# Plant node / product node	# Pollinator node / customer node	# Links	Q (Modularity)	# Modules
Ecological network					
Medan *et al.* (LD)[5]	21	45	83	0.618	7
Medan *et al.* (RB)[5]	23	72	125	0.574	11
Dupont *et al.*[6]	11	38	106	0.322	7
Market network					
Aggregation 1	20	49	211	0.191	5
Aggregation 2	20	5	43	0.120	4
Aggregation 3	20	7	43	0.180	4
Aggregation 4	5	7	16	0.227	4

4. Conclusion and Future Work

This paper presents preliminary work on the use of ecological bipartite network models and modularity analysis techniques for improving our understanding of different customer groups' preferences for products. Using household vacuum cleaners as a case study, various aggregated product-customer bipartite networks are created using customer survey data. The products are aggregated by brands and vacuum cleaner types, and customers are aggregated in three ways: geo-location (US states), purchased product type, and age. The visualizations of the modularized networks show some brand trends of customers from different modules. For example, it was found that customers who reside in the central US tend to prefer similar brands. These insights can give product companies a more in-depth understanding of their target audience and enable them to create more focused marketing strategies. Furthermore, a comparative analysis between the modularity of plant-pollinator networks and product-customer networks reveals a significantly greater modularity in the former. This suggests that none of the aggregations used here (or potentially none at all) find clear consideration-purchase patterns among the customer data. Finally, this study demonstrates the potential viability and utility of using biological systems to inform socio-technical system engineering and design. In our future work, we plan to apply this bio-inspired approach to a vehicle market to more carefully investigate the potential value of mimicking modularity levels found in these mutualistic ecosystems. Due to it being a larger commodity and having well-defined customer segmentations (sedan, SUV, etc.), we expect a stronger modular pattern to be found and the chance to test what a bio-inspired modularity means for a market system, especially when the market experiences disturbances. Those results will lead to the integration of modularity analysis results into engineering design, guiding the design of products that align with the preferences of a broader and targeted customer base.

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