Project Name : Social Network Analysis

Research Paper

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Table of contents

Social Network Analysis

Executive Summary

Leveraging datasets by analyzing its Social network structure, I explored and interpreted the depth of engagement across Arizona State University's units and their partnered community organizations. The goals were to 1) Understand quantitative characteristics from the dataset and apply them to construct network structures. 2) Use those structures to explore effective communication patterns and interpret the depth of engagement across strong partners. 3) To monitor the level of engagement and visualize in the form of macro-level patterns across years.

Greater numbers of higher education institutions are integrating comprehensive community engagement as part of their strategy to achieve their mission and vision. Collaboratory gathers information that enables institutions to define and assess their own engagement strategies.Collaboratory is a software product specifically for higher-education institutions to standardize their data collection for community engagement activities. Collecting this information on community involvement enables organizations to communicate more clearly with those who matter most to them—whether they are donors, partners, or regular people—and to synthesize engagement activity data into key metrics. But going a step further, this data also provides a rich repository of information about work that is happening between various stakeholder groups - universities and schools, businesses, nonprofits, and the government sector.

Quantitative attributes have been determined and applied for network model construction using the information gathered from Collaboratory administrators, community engagement specialists, and institutional research team members. The quantitative attributes are formatted, transformed and analyzed to reveal generic network patterns. Among 1463 ASU partners, the constructed network structure revealed 145 highly engaged connections. The findings serve as a foundation for further qualitative evaluation of the 145 highly engaged partnerships.

Gathering Analytical data

To fulfill its mission and vision, Arizona State University has included community participation in its strategy. ASU uses Collaboratory as a platform to gather data that assist in articulating and evaluating its engagement activities. In the context of this paper, activity is any endeavor in which a community partner and an ASU unit collaborate on a mutually beneficial project.Activities are the Collaboratory's unit of analysis, consisting of numerous qualitative and quantitative data fields that represent information on who, what, where, when, and why the work is being done. They vary in size, scope, and type. For example, long-term academic research engagement with an organization or one-time community engagement associated with either public service or community organization.

By gathering information on community engagement activity, ASU may compile it into important factors that will help them better communicate their message to the people that matter most to them, whether they be funders, partners, or regular people. This promotes a culture of creativity, better active member participation in activities, and identifies effective communication patterns.Additionally, it offers a range of details regarding collaboration across different stakeholder groups, including ASU, corporations, nonprofit organizations, and the public sector. The acquired information is extensively used for analytical purposes to further the community engagement field.The research's outputs and outcomes assist emerging scholar-practitioners who are engaged to use this data to enhance the field of community engagement.

Social Network Analysis

The dataset of community engagement data provided by Collaboratory acts as an input source to identify ASU's partnership and network establishment across the years. The purpose of this study was to explore different ways of presenting or visualizing the network partners at ASU from Collaboratory dataset.

Network visualization adds a visual aspect to network monitoring and analysis by providing a graphical representation of network components, network metrics, and data flows. Network maps, graphs, charts, and matrices are some of the subcategories of network visualization, of which graphs have been chosen for this research.

Social network analysis (SNA) is the process of investigating social structures using networks and graph theory characterizing networked structures in terms of nodes (ASU Units and Community Partners) and the ties, edges, or links (relationships, interactions, or engagement) that connect them. Examples of social structures commonly visualized through social network analysis include social media networks, business networks, knowledge networks, social networks, and collaboration graphs through Sociograms. Sociograms are the graphs in which nodes are represented as spheres and ties are represented as lines.

This overall construction of relational network structure of ASU with their partners begins with a large dataset of community partnerships from which the depth of the engagement that an ASU unit and community partner have in various activities has been visualized in the form of graphs termed as sociograms by using python for data processing and R for visualizing . This enables ASU's Data analysts to comprehend the network's current state and to track growth and development as members and connections emerge and vanish.

Building the Model

Using the Collaboratory dataset, this research explores and analyzes the breadth of community-university collaborations. There were 487 distinct ASU Community Partners in the dataset at the time of this investigation (September 2022), forming 1463 networks throughout 136 unique ASU Units.

Data evaluation using a computer algorithm is referred to as data modeling. In our instance, we constructed a model where we let the computer read all of the partnerships in the data set and then apply logic to determine the depth of the engagement among the partners and ASU .The attributes that are commonly considered for this logic creation are

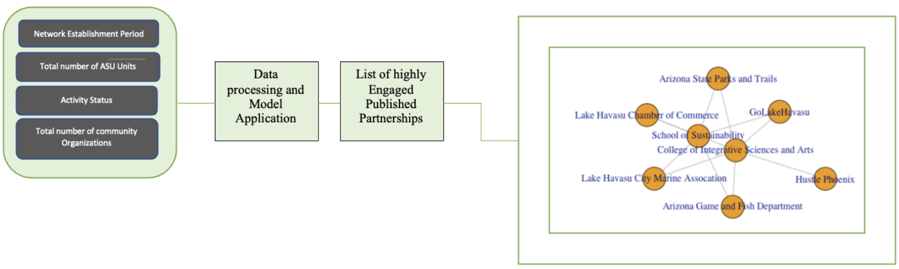
- Start date for a specific partner.
- The total number of ASU units associated with a partner.
- Publishing status of the activities.
- Frequency with which an ASU unit engaged with a community partner.

Query applied

Select partnerships from asu_activities where Publish_status id True and Weight >1

Following logic creation, necessary filters and data processing techniques were employed to identify partnerships having high levels of engagement. After applying all the steps as stated in the statement, the model generates a dataset with partners. Our model is developed on a Jupyter notebook utilizing the pandas library to analyze and assess our quantitative data and R Studio to visualize our results. The following sections describe our process of developing the model.

For the designed model the volume of activities significantly affects how frequently ASU Units and Community organizations appear throughout the network.If there are more number of activities then there would be high probability of repeated engagements.The majority of partnerships (90%) are single-activity partnerships, according to an analysis of activity counts per partnership. As a result, our model was structured to determine the partnership's depth. For this research, it has been assumed that more activities under the same partnership indicate a deeper level of involvement for an ASU unit with that specific campus partner. Take note that this does not suggest that all single-activity partnerships are weak; rather, it simply means that in order to use our modeling methodology, we must assign a cut-off number.



Graph Development

In social network analysis, two files have been generated as node and edge files: one indicating the actors in the network and the other indicating the involvement as well as strength across the actors. Python has been used to create a node file with a count attribute (determining the most influential campus partners and community groups) and an edge file with (The strength/relation occurrence times) by applying data processing techniques (Data cleaning, defect repairing, and formatting). Using the R language, the data are represented graphically as a graph.

The graph has three crucial parts:

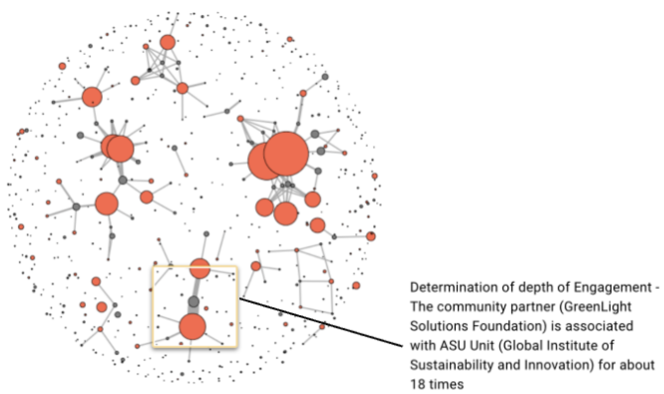
The size of the node determines whether it is huge or small depending on how actively an ASU unit or community organization is participating.

The strength of partnership among the ASU partners and its community is determined by the edges of the graph.Initially the cut-off value for determining the connection establishment between the nodes was the mean value of the edges which was 1.8. So the edges whose weight is more than 1.8 is visualized in Sociogram.

Then the connection was established based on the median value which was 0.7. So the edges whose weight is more than 1.8 is visualized in Sociogram.This established connection across all the nodes as the minimum weight was 1.

 Finally, if ASU Unit is associated with its partner more than once, then the connection has been established.Out of 1463 connections only 145 partnerships are repeated more than once.

The Width of the Edges is completely dependent on the amount of engagement a particular connection is holding. If the width is high then their engagement is also high(directly proportional)



Limitations

The purpose of this study was to explore different ways of presenting or visualizing the network partners at ASU from the Collaboratory dataset. By engineering data based on selected attributes, the breadth of community-university collaborations has been explored and analyzed.

This approach has some limitations in the research context. The first assumption is that the approach proposed here is accurate in determining the depth of partnerships. Although the techniques we employed were agreed upon by experts in the field, we do not claim that this is the only way to spot intensive partnerships in this dataset. We are convinced that the model either ignores deep partnerships or chooses ones that are not particularly intense according to conventional scoring standards. This is completely based on the attribute we choose for modeling. We will continue to improve the model over time.

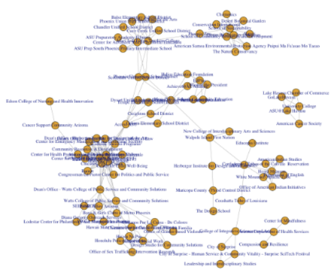
Furthermore, the volume of the data and the current state of community engagement during this research limit the scope of this study. Again, we emphasize that this study is merely the first attempt at implementing such a method or analysis of community engagement relationships. Finally, each institution that uses Collaboratory chooses a distinct deployment approach, which has an impact on Collaboratory's dataset

Conclusion and next steps

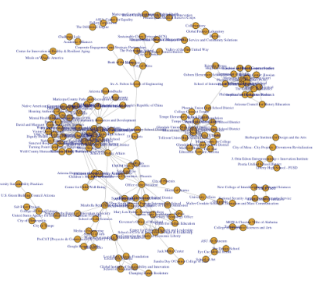
Sociogram helps data analysts see correlations and patterns in data and gives it much more meaning. Exploring these patterns allows the data analyst to focus on specific areas in the data that require attention in order to identify the importance of these areas in improving their insights ahead. Sociogram delivers actionable insights and answers many questions like - Whose contribution/engagement is higher?, Which year has more community partners? How many ASU Units have more engagements?. The sociogram was built using input from the Collaboratory dataset and the depth of the partnerships has been determined according to assumed metrics. Some of the metrics assumed are the published status, aggregated count of repeated engagement,number of activities,ASU units and their partners.This research can be further continued in various dimensions.

As an example, the longitudinal analysis of partnership establishment across years can be done using Social Network Analysis . The establishment of the network marks the beginning of ASU's collaboration with its community partner. Using this information, we compiled the network setup for each year for all the publicly released activities within a partnership. This made it possible for us to estimate the annual incoming engagements. The findings show that a key year with a huge number of relationships was the year with the highest level of engagement. The analysis for the years 2021, 2018, and 2015 with an interval of 3 years has been analyzed and its visual representation has been attached. The partnerships have been aggregated with respect to years. Out of 1463 community engagements, in the years 2021,2018, and 2015 -309, 206,20 connections have been established respectively

ASU units and Community Partners in 2015.



ASU units and Community Partners in 2018.



ASU units and Community Partners in 2021

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