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Structure and Dynamics of a Charitable Donor Co-Attendance Network

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Abstract*—The dynamics of charitable donor co-attendance networks can help fundraisers assess and improve fundraising outcomes. To improve understanding of donor-giving patterns, this study examines a large, multi-year network describing the co-attendance of donors at charitable fundraising events. We analyze the dynamics of co-attendance networks based on their topological structure, shift in node characteristics, and various network properties. Among other results, we observe a 76% increase in giving value for donors that showed increased centrality rank over nonoverlapped snapshots. In the data we examined, 19.14% of the donors whose giving increased and 16.24% of donors that remained in the same giving range exhibited increased co-attendance with high-capacity donors, whereas none of the donors that shifted to a lower class exhibited increased co-attendance with high-capacity donors over the periods, potentially illustrating a positive peer effect on donors. Some similarity was also observed in the giving characteristics of donors who co-attend events, with a 0.211 assortativity coefficient for the giving class of donors as a characteristic of donors when considering network dynamics using a rolling window size of 3 years. This is followed by analyzing the group-level similarities that reveal an interlinked clique of communities with diverse sizes. Our results show that large communities have a higher fraction of wealthy donors.

***Index Terms*—Fundraising, Charitable donations, Network dynamics, Co-attendance networks**

I. Introduction

Fundraising campaign events for charitable organizations provide opportunities for donors and staff to reinforce social connections and foster new collaborations. The presence of fellow donors has been observed to encourage others to donate during fundraising events amplify the impact of fundraising campaigns [6], [14]. To better understand the dynamics of charitable donor networks and the relationship between network structure and charitable giving, we analyze real data from a large private research university in the United States. Our dataset spans several years and includes information about donations made by individuals, their primary relationship (e.g., alumni or their parents), and events attended by those individuals(Section III). Using this information, we construct a co-attendance network, where nodes denote donors and edges indicate whether donors have attended at least one fundraising event together.

Our analysis here reflects the type of data typically available to a large charity; we note that other interactions (such as friendships) not captured in this dataset affect giving, but are unobserved by the charitable organization. Staff for charitable organizations can leverage the impact of attendance by creating engaging campaign experiences that encourage collaborations, leading to more successful fundraising outcomes.

At a high level, the goals of our analysis are to analyze aspects of donor-attendance networks that relate to fundraising outcomes. We examine the structural and characteristic attributes of donors in the dynamic co-attendance network, with a particular focus on donors who are present for multiple nonoverlapped time windows, and correlate these attributes to shifts in giving levels. We additionally examine the extent of homophily in the network and its variation over time, as well as the community dynamics related to giving patterns. We analyze the extent to which the fundraising outcomes for an attendance network vary from a nonattendance network of donors for lifetime and annual giving distributions. To understand similarities in characteristics of co-attendees, we inspect the assortative mixing in the network. We test homophily with respect to giving amounts and the giving class of each donor in the network.

Our results show positive low-moderate assortativity values, with a maximum of 0.211. We then examine if the position of a node affects giving by observing the centrality scores. We find that more than half of the donors (retained in nonoverlapped windows) exhibited increased centrality scores and 76% of these exhibited increased giving. Whereas, more than half that decreased or maintained the same centrality score had a decreased giving. Next, we measure the extent to which they increased their giving by examining the change in giving class memberships of donors over multiple nonoverlapped windows. We observe that 41.37% shifted to higher giving levels, 37.53% remained in the same giving class, and 21.1% moved to a lower giving class.

Out of the donors that shifted to higher giving classes, 19.12% exhibited increased co-attendance with high-capacity

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donors (donors above the sixtieth percentile) and 16.4% of those that remained in the same giving class between the two periods exhibited increased co-attendance with high-giving donors. In contrast, *none* of the donors that shifted to lower giving classes exhibited an increase in co-attendance with high-giving donors. This highlights the relationship between network properties of donors and increased fundraising outcomes.

To further understand if there is segregation among donors, we perform community analysis by generating communities from these attendance networks. We observe that large communities have a greater fraction of above-median and high-giving donors.

While a large body of research focuses on what motivates a person to donate by analyzing personal attributes and interactions of the network [5], [14], [20], there is little research that examines the scope of utilizing event attendance networks for assessing fundraising outcomes. Several other works focus on using the promised lifetime giving value [13]. The research of using a time-evolving network's structural aspects and features is yet to be fully explored. This study provides implications and reasoning for the various time-evolving network analyses that can be examined on donor event attendance networks.

This paper is structured as follows: In Section II, we describe related work on charitable networks and donations. In Section III, we describe the properties of the dataset. Next, in Section IV, we give an overview of our methodology. Section V gives results of our analysis, and we discuss these results in Section VI. Concluding thoughts are presented in Section VII.

II. Related Work

Extant research on charitable donation networks has examined various aspects of donor properties, including the donor dyad relationships [12], [16] and personal attributes of donors like gender, age, and income [18]. Three primary types of relationships are donor-donor dyads, donor-solicitor dyads, and donor-recipient dyads [18]. It has been observed that donor-donor dyads tend to exhibit high homophily with respect to giving: that is, people often tend to give donations in similar amounts as their peers [8], [10]. Such studies [18] have analyzed similarities in personal characteristics such as gender, area of residence, income, and relationship with the neighboring node – friend/colleague that increases their giving [18].

Charitable donations can be increased with interactive and effective communications between a donor and a solicitor. People donate more when they are solicited by similarities with the fund-raisers [3]. Sometimes, the donor tends to give more donations to an organization that they are more connected to [4], [17]. Examples include alumni donating to their university or people donating to nonprofit organizations for causes that they believe in. In summary, most research finds a positive social influence among similar individuals in donor–solicitor, and donor–recipient dyads. However, in donor–donor dyads, the effects of social influence on charitable giving are mixed where an individual's giving can positively or negatively be affected by another's giving.

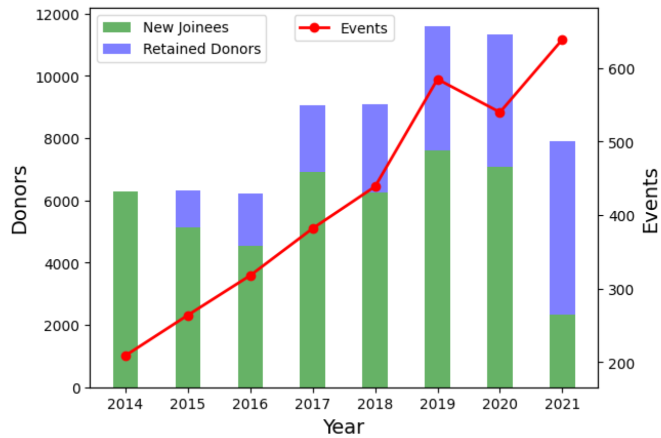

Fig. 1. Growth of donors and events organized in period 2014-2021

A large body of literature uses network properties to detect the influence of donors on one another, particularly on social media [5], [14], [20]. (In contrast, our study examines real-world connections.) A study on network structure shows that a Twitter campaign network's size and decentralization, as well as prosocial cultural norms, are positively related to the average donation amount per day [19]. A similar study on Twitter data shows that having more online followers increases the success rate of a fundraising campaign emphasizing the extent to which social connections matter [7]. Another interesting finding is that authority and centrality within internal social connections positively impact the number of funders and campaign progress [7]. It was also observed that social connection variables enhance prediction algorithms for funding outcomes. Finally, it was found that external social connections have a stronger impact on funding outcomes compared to internal social connections.

There is an abundance of research that develops predictive models for efficient fund-raising in charitable organizations [11]. Research has been conducted to predict the likelihood of giving (propensity) of a donor [15] immediately after an event, and then this binary classification has been extended to predicting the amount that the donor would give predicted from past data. Organizational attachments resulting from alumni status and employee appointment as a faculty or staff member have been hypothesized to impact individuals' donation propensities, including giving likelihood and potential gift amount [2].

III. Dataset Description and Statistics

The study dataset describes a collection of donors who donated varying amounts to the events and donations not associated with any event. The dataset contains more than 46,175 unique givers, for over 3000 events spanning the years 2014 to 2021 organized by the large private research university. This data is collected by the university and is

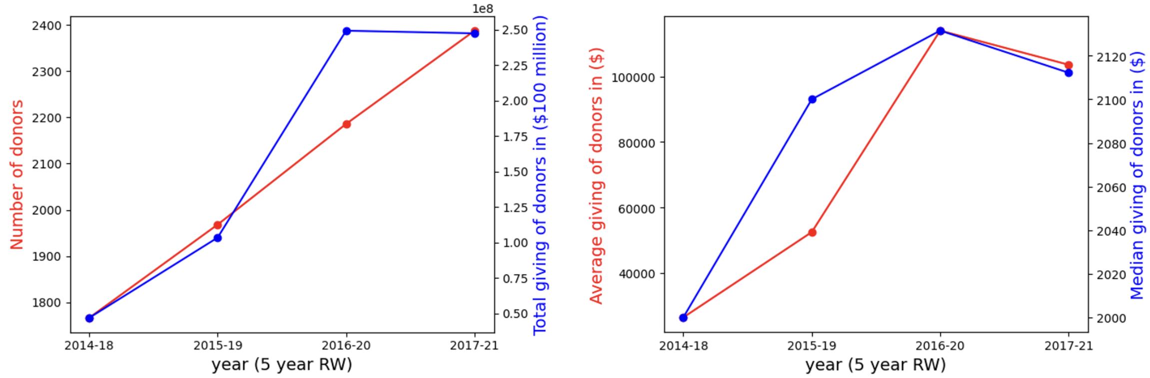

Fig. 2. Giving statistics (including only donors who gave at least $500).

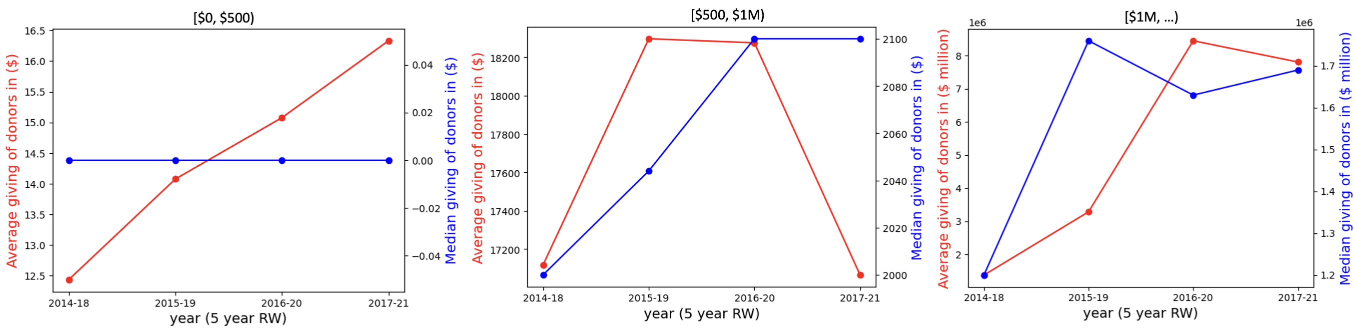

Fig. 3. Giving statistics across donor classes.

sponsored by the staff. Events organized by the university include meetings, fundraising event campaigns, alumni engagement programs, and many others. Some of these events are focused on networking and organizing lectures that are solely for fostering collaborations. The donations received by the university are used for endowments, scholarships, and funding various facilities for the university. Fig. 1 shows the retained (existing) donors and newly joined donors for each year starting from the year 2014 to 2021. We see that each year the events draw a similar number of new donors and with time there is an increase in the number of retained donors. Fig. 1 also provides the number of unique events organized each year. We see that the number of events increases with time. The donors have varying primary constituencies with the University. These relationships include alumni, students, parents or spouses of students/alumni, staff, and others. For this analysis, we focus on two types of giving: lifetime giving, which includes an individual's promised donation amount, and the actual amount given each year.

To observe changes in basic dataset properties over time, we first consider overlapped rolling window sizes of 5 years. Properties are shown in Fig. 2. This figure depicts the number of donors from 2014 to 2021, the average/median giving amount per donor, and the total giving. We see a steep increase in total distribution during 2016-2020, a period that includes the Covid pandemic. The reason behind this could be wider participation in virtual campaign events during the pandemic.

In Fig. 3, we divide donors into classes based on giving amounts, and present average/median giving within each class. The first subplot corresponds to the class of donors whose donations are at most $500, we observe that the median is 0, which implies that more than half of these attendees are nondonors. The second subplot corresponds to the class of donors who donated in the range $500 to $1M$. Finally, the third subplot represents the class of donors who donated over a million dollars. In this plot, we observe that the median increases drastically in the period 2016-2020.

In the remainder of our study, based on discussion with the university office of charitable giving, we carry out all analyses on donors who donated at least $500. The statistics of this filtered data are present in Table I represents the dataset details for all donations, irrespective of the donation amount for the rolling window of 5 years (2017-2021).

As shown in Fig. 4, we observe that the degree distribution for the 2017-2021 co-attendance network of donors is a heavy-tailed distribution. This holds across all periods.

IV. Network Construction

Our primary goal in this study is to examine the relationship between the network properties of an individual in the dataset and that individual's giving levels. Analysis of longitudinal network data can assess whether the donation amounts increase, decrease, or remain stable over time. This information

TABLE I
NETWORK OF DONORS

Properties	**Network Type**	
	Everyone	***Nonstaff Only***
Nodes	7687	6546
Edges	644k	340k
Average Clustering Coefficient	0.787	0.803
Max events attended by a pair	19	15
Fraction of Alumni	0.77	0.818
Fraction of Parent/Former Parent	0.074	0.08
Fraction of Friend	0.075	0.087

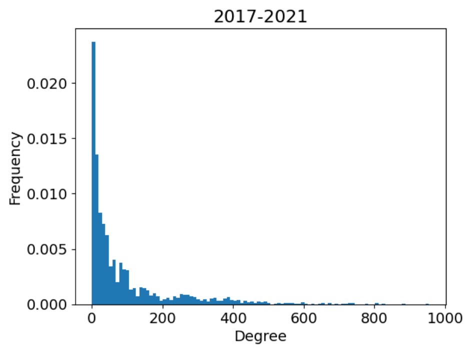

Fig. 4. Degree distribution of donor co-attendance network

can be used to evaluate the effectiveness of fundraising campaigns or external factors that may have influenced donations.

We construct weighted network snapshots over varying window sizes, with and without a decay function applied to the edge (depending on what is being evaluated). The weight update is given by (1).

$$W_{ij}^t = N_{ij}^t + \frac{W_{ij}^{t-1}}{2^d} \tag{1}$$

In (1) W_{ij}^t represents the weight on edge connecting nodes i and j. In each time slice of the window, represented by t the weight of each edge is updated with the number of events that i and j co-attend in that time slice represented by N_{ij}^t and is summed up with the old weight decayed by a magnitude of 2^d where d indicates the time since the last co-attended event, in years. The impact of an existing edge's weight on the updated weight is reduced from the previous year and is halved every time slice because we are more interested in the impact of recent co-attendance than the previous.

V. ANALYSIS

In this section, we highlight key findings of our study that offer insights for assessing fundraising based on network co-attendance. We examine the interplay between event participation and giving and the structural properties of the co-attendance network, and gain insights into the mechanisms that may prompt increased giving behavior.

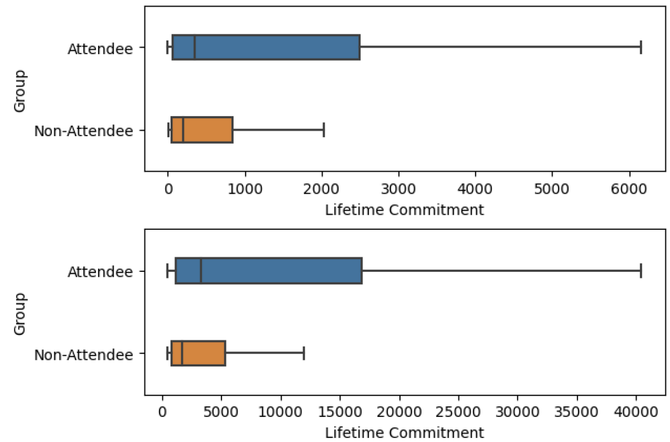

Fig. 5. Box plot for attendees' and nonattendees' donations $> \$0$ and $>= \$500$

A. *Event attendance is associated with higher levels of giving.*

Before analyzing network structure, we first examine the impact of event attendance on the donor giving value and compare it to the giving distribution of nonattendees.

The box plot in Fig. 5 shows that event attendance has an impact on the giving amount. When we consider the box plot of all donors including staff by removing the outliers, we observe that attendees have a higher giving distribution than nonattendees. This observation is much more evident for larger amounts as observed in the second subplot with donations of at least 500$. To test the statistical significance we have the following null and alternative hypotheses.

Hypothesis 1 (H1): *The average and median giving of attendees and nonattendees are exactly the same.*

Hypothesis 2 (H2): *The average and median giving of attendees is larger than nonattendees.*

The distribution is skewed, due to the presence of a large fraction of low-givers and fewer high-givers as shown in Fig. 5 (lifetime and number of donors in statistics section). Therefore, we use the Mann-Whitney U test [9] to test the significance of the giving distributions of attendees and nonattendees for the network consisting of staff and nonstaff. For this test, we randomly draw 1000 samples from attendees and nonattendees distribution to perform the nonparametric two-sided p-test. The p-value is less than 0.05 (close to 0.00) for both tests. Therefore, we can reject our null hypothesis, and accept our alternative hypothesis.

We then repeat a similar procedure to check the difference between the yearly distributions of attendees and nonattendees. We observe that the difference is statistically significant in all years except 2014 and 2016 as shown in Table II. To get a better sense of the outcomes of the two categories we plot the average and median distributions of the giving data by using bootstrapped samples as shown in Fig. 6 for mean distribution and Fig. 7 for median distribution.

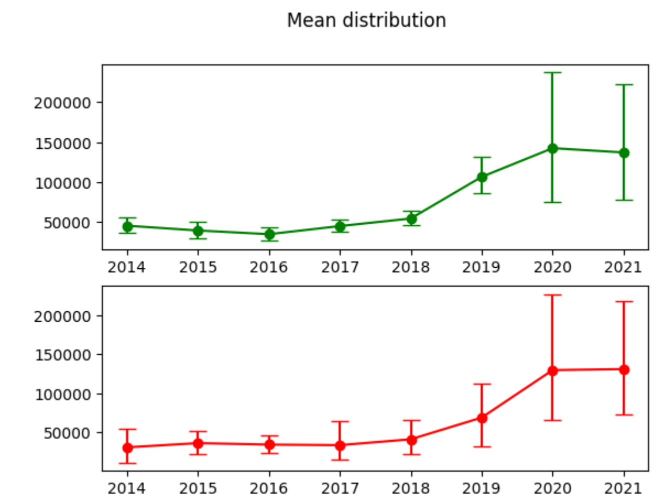

Fig. 6. Comparison of the mean distribution of event attendees and nonattendees annually. In this figure, The green plot represents the distribution of event attendees and the red plot represents the distribution of nonattendees

The giving data is bootstrapped annually by random sampling and calculating sample distributions' average and median values. These are used for finding the low and high values for marking the 95% confidence intervals in the plots shown in Fig. 6 for mean distribution and Fig. 7 for median distribution.

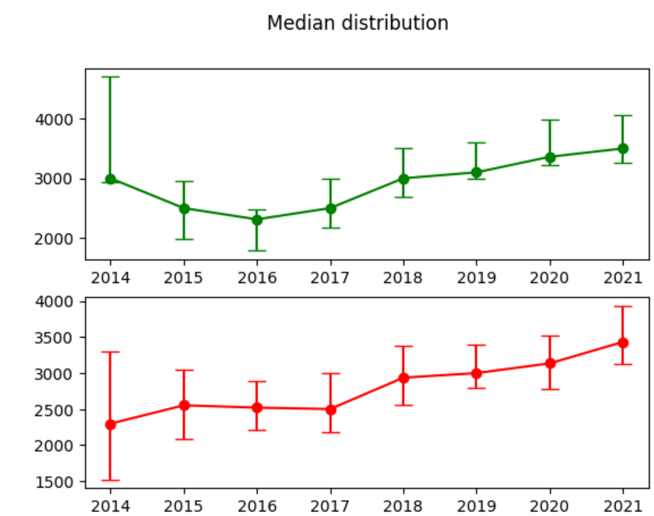

Fig. 7. Comparison of the median distribution of event attendees and nonattendees annually. In this figure, The green plot represents the distribution of event attendees and the red plot represents the distribution of nonattendees

Having established that participation has an impact on the effectiveness of fundraising, we move on to identifying similarities in donor characteristics of this network.

B. Giving homophily

Our first network task is to establish whether giving homophily is present in the network: that is, whether neighbors tend to give similar amounts. To do this, we measure the assortativity of the network, which indicates the preference for nodes to attach to others that have similar characteristics. We perform our tests on overlapped windows of 3 years, using the decay function described in Section IV. We choose a shorter window size to reflect more recent similarities in characteristics.

TABLE II
MANN-WHITNEY U TEST

Year	p-value for mean	p-value for median
2014	< 0.001	0.63
2015	< 0.001	< 0.001
2016	0.16	< 0.001
2017	0.001	< 0.001
2018	< 0.001	< 0.001
2019	< 0.001	< 0.001
2020	< 0.001	< 0.001
2021	0.02	0.01

TABLE III
ASSORTATIVITY COEFFICIENT FOR OVERLAPPED WINDOWS

Period	Raw	5-Class	2-Class
2014-2016	0.005	0.060	0.0806
2015-2017	0.016	0.148	0.150
2016-2018	0.030	0.211	0.170
2017-2019	0.005	0.106	0.124
2018-2020	0.031	0.098	0.139
2019-2021	0.042	0.109	0.159

We compute assortativity with respect to three values: first, the giving value (Raw assortativity); second; the giving class within the 5-classes $[\$500, \$1000]$, $(\$1000, \$5000]$, $(\$5000, \$10000]$, $(\$10000, \$50000]$, $(\$50000, ...)$; and a binary attribute describing whether the donor gave above or below the median giving value for that time period.

Results are shown in Table III. We observe that for all three computations, assortativity is consistently small but positive, indicating that individuals have a slight tendency to attend events with others of similar giving status. Of the three tests, the final (assortativity of above/below median status) gives the highest assortativity value for nearly all periods.

C. Donor behavior across time

Next, we examine variations in donor behavior from the 2014-2017 period to the 2018-2021 period. We construct network snapshots for these two periods (no decay), excluding staff members.

First, we examine if the shift in the structural position of the network is related to giving. For this examination, we use centrality measures of the scores. We rank the nodes based on weighted eigenvector and degree centrality scores.

We observe that of the donors retained between the two periods, *more than half (53%)* have an increased weighted eigenvector and degree centrality rank. An increase in degree or eigenvector centrality implies, respectively, that a node is increasingly attending more/larger events or events with other high-centrality nodes. We observe that 76% of donors that had an increased rank exhibited increased giving. Additionally, *more than half* of the donors (54%) that had a decreased or equal rank displayed a decrease in giving.

In addition to examining the percentage of increased giving, it is important to ascertain the extent to which their donations have amplified. For example, a donor who donated in the hundreds in the first period and donated in the thousands in the second period marks a major change in the donor's behavior. For this second analysis, we label each node according to the five giving classes described earlier.

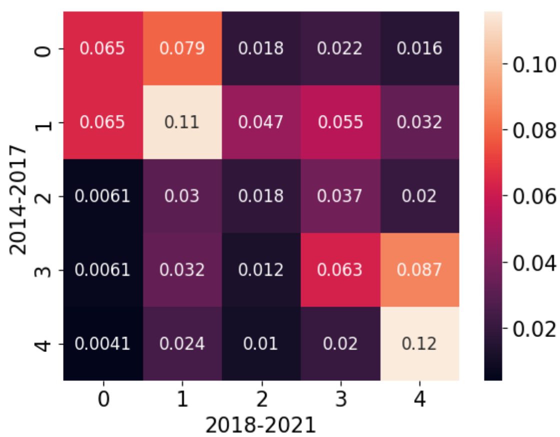

Fig. 8. Fraction of shift in donors between giving classes

We observe from Fig. 8 that a total of 37.53% of people remained in the same giving class between the two periods. A total of 41.37% of people shifted from a lower class to a higher class. We notice that the percentage in shift of donors to upper classes is greater than the percentage retained in the same class. Also, 8.7% of donors shifted from class 3 to class 4 between the first to second periods and contributes to 14.67% of donors in class 4 in the second period.

Additionally, 19.12% of those who shifted to a higher giving class and 16.24% of donors that remained in the same class exhibited increased co-attendance with high-capacity donors. In contrast, *none* of the donors that shifted to lower classes exhibited increased co-attendance.

At this point, we begin to gain an understanding of changes in behavior at the individual level. Sometimes, this behavior can be driven by other factors such as group-level characteristics. For our next analysis, we examine the community characteristics.

D. Understanding the collective behavior of co-attendees

For this analysis, we run the Louvain community detection algorithm [1] on the 5-year overlapping window donor co-attendance networks, with edges decayed as described in Section IV. In Fig. 9 we provide a visualization of the communities formed from the donor-attendance network for the period 2017-2021. Each node is a community of donors that attend events together. The size of the node represents the number of donors in that community. The intensity of the green color represents the average giving of each community. The community sizes range from 2 to 500 and the average giving amount per community ranges from \$55 to \$272000. Communities of size 2 with no connections to the rest of the network are not shown.

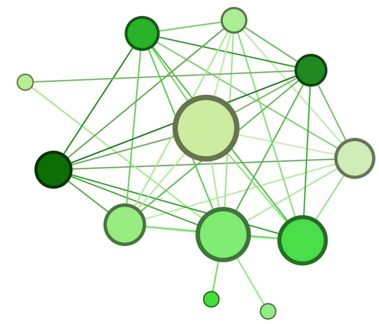

Fig. 9. Communities for a snapshot of 5 years (2017-2021). Here, each node represents a community. The intensity of green color marks the average giving of that community. The size of each community is represented by the size of its node. An edge connecting two communities marks the external edges between the communities and is not weighted as we are inspecting co-attendance and not the interaction.

From this plot, we observe that there is a clique of communities that marks strong participation. We see segregated communities and donors that link two communities. We also notice the communities that are a part of this clique are moderate to large communities.

In Fig. 10, we show the fraction of individuals in a community who give more than the global median versus the size of the community. Interestingly, the correlation between community size and the fraction of above-median capacity donors increases gradually and is nearly 0.5 in the last two periods. Further, from Fig. 11 we note that the community sizes tend to increase over the years, indicating more close-knit participation.

VI. Discussion

First, we note that the university fundraising team was successful in arranging engaging events, as the participation of donors grew with time, as seen in Fig. 1. We also observe that donors increased their giving with time, as seen in Fig. 2. As suggested by the increase in total, average and median giving distributions over the rolling time windows, the fundraising team likely was able to utilize their own professional network connections and attract more high-giving donors with time. This is meaningful because our analysis suggests a statistically significant relationship between event attendance and donors' giving. After discussion with the fundraising team, possible reasons for the steep increase in average and total giving in the time period 2016-2020 could be that the donors gained more trust in the fundraising team, the growth in nonalumni donors, and the opportunity for virtual campaign events during the Covid pandemic.

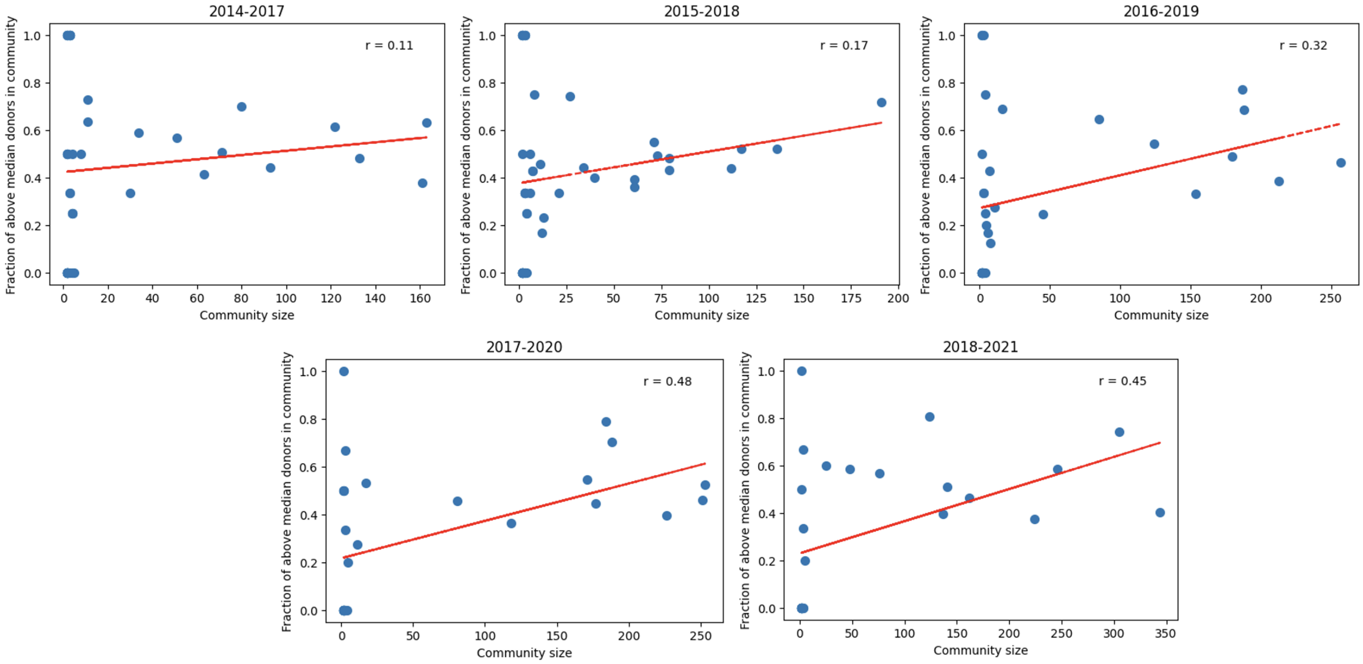

Fig. 10. Fraction of above-median givers vs. community size for a rolling window of 4 years (2014-2021).

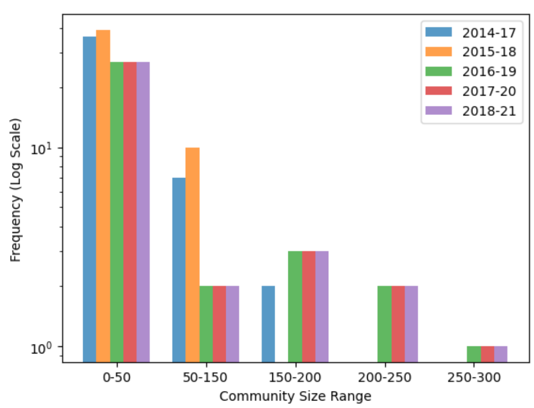

Fig. 11. Increase in frequency of larger communities with time

We then identify the similarities in characteristics of individuals. Our results show a slight but positive assortativity of co-attendees with respect to their giving values. A low to moderate assortativity in co-attendance is beneficial for fundraising networks, and suggests that event organization and placement of attendees is successful. If the assortativity was very high, it would result in segregated components, which would limit the access of low donors to eventually interact with high donors. Former studies have shown that when donors witness others making contributions or pledging support, it can create a positive peer pressure effect by feeling compelled to match or exceed the generosity of their fellow attendees, resulting in higher overall donation amounts [10], [17]. Having no access to high donors would hinder new connections and diminish the positive pressure effect.

Because we see similarities between co-attendees, it is crucial to assess how donor characteristics change with time. For our analysis, we discovered that 76% of donors that had a increased rank also showed increase in giving amounts, and more than half of donors that displayed an equal or lesser rank between the periods decreased their giving (recall that this does not include university staff members). Increased centralities indicate that donors are actively co-attending more events or are in the vicinity of other high-centrality donors. Next from Fig. 8 we inspect the shift in giving class of the donor and its relationship with co-attendance. We observe that 41.37% donors increased their giving class, and 37.53% donors were retained in the same class. We observe that 35% that remained in the same class or shifted to a upper giving class showed an increased co-attendance with high-giving donors, while none of the donors that shifted to lower class exhibited increased co-attendance. By analyzing the shift in central donors, fundraisers can maximize peer-peer fundraising and tailor their recognition efforts to effectively engage with high-centrality donors.

Finally, we conclude our study with an analysis of the collective group characteristics of donors. Analyzing the donor-attendee communities helps organizations examine donor engagement and identify major donor prospects. This information can be used to strengthen relationships and maximize event impact. We provide a structural visualization of communities of co-attendees shown in Fig. 9. We observe a clique of communities. This implies that donors actively attend events and are connected to key donors that act as bridges between two communities. This clique can be a source to spread awareness and foster additional connections.

From Fig. 10, we observe that the correlation between fraction of above-median donors and community size increases with time. Next, from Fig. 11, we observe increased community sizes over the years, indicating larger and more tightly-knit participation of donors over time. From discussion with the fundraising staff, a possible explanation is that larger communities have varying donors that benefit from resources such as business opportunities, and professional networks. Individuals who have gained from these resources may feel a sense of gratitude and a desire to give back to the community that provided them with such advantages [8]. Nevertheless, not all high-giving donors come from large communities, and factors such as moral values, experiences, and interests also play a role in philanthropic decisions.

There are two important limitations of our work. First, we cannot distinguish between causation and correlation: it is not clear whether the network properties of a donor cause certain giving outcomes, whether some other property of the individual leads to those network properties and giving outcomes, or whether giving outcomes lead to certain network properties. Second, it is possible, or even likely, that many network structures that are not present in the dataset have a major influence on giving. In our future work, we plan further exploration (through conversations with the fundraising office) of these questions.

VII. Conclusion

This study highlights the potential of utilizing donor co-attendance networks for understanding fundraising outcomes. We show that event attendance has a strong correlation with donor giving. We identified that there is a low-moderate similarity in co-attendees giving characteristics. We then identified that donors who occupied central positions had increased giving and increased co-attendance over the periods increased their giving class membership. We also looked at group-level similarities and found that with time larger communities have a higher proportion of high-giving donors. The community structure also revealed strong interlinks that are beneficial for maximizing the effectiveness of their resource allocation strategies.

This study contributes to the body of knowledge on assessing fundraising outcomes by utilizing the dynamics of the co-attendance network. By analyzing the dynamic network of 46,175 donors over 8 years we found that about 13% of donors were retained throughout the eight years. Moreover, only 4% of the retained donors exhibited increased giving and 35% of these exhibited increased co-attendance with high-capacity donors.

Such a subset of donors can be used to understand the change in behavior and what influenced their increase in donation. We can further study their interactions by inspecting their email communications, peer interactions, and demographical aspects. Similarly, one can also analyze the interactions of donors who exhibited a decrease in donation amounts over the years. Analysis of event attendance can be used for performance tracking and benchmarking, and for developing tailored strategies. This work can also be extended to a time-series forecasting model that predicts the amounts given by donors, utilizing network properties and demographics.

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