Leveraging Relationships in University Fundraising: An Analysis of Faculty Advisee Groups and Alumni Networks

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ABSTRACT Fundraising is based on relationship building, yet university fundraisers often underuse data about alumni connections to faculty and to other alumni. Fundraising offices have not prioritized collecting relationship data; and so, despite its importance, this information is often missing, hidden, or inaccessible. However, the discrepancy underscores an opportunity. This project used a combination of recommender systems, network graphing, and data visualization to help a university fundraising department discover and leverage its network of alumni and post-docs. The project resulted in two dashboards, one focused on faculty advisee groups and the other an alumni network map. The advisee group dashboard made it easy for fundraising analysts to see each faculty advisor's alums and post-docs, compare the philanthropy of the groups, and strategize about potential fundraising initiatives. The network map helped identify previously unknown connections between engaged alumni and their unengaged peers, based on shared student experiences. This information led to new strategies for connecting with alumni who had been difficult to engage. Together, the dashboards enabled the department to take advantage of more relationship-based fundraising opportunities. The project demonstrated the value of treating fundraising not just as an art, but as a data-driven science.

KEYWORDS fundraising, philanthropy, donor, relationships, alumni, higher education, college, university, faculty advisors, advisees

JOURNAL OF ADVANCEMENT ANALYTICS VOLUME 2 | 2022

DOI: 10.7560/JAA202

Fundraising professionals have long recognized the importance of relationship building in their work. Fundraisers spend much of their time visiting and getting to know prospective donors and their interests, helping move these prospects toward a gift. However, giving can also be impacted by other types of relationships, such as a donor's peer-to-peer network and relationships with campus administrators and faculty (Frisby et al., 2019; King, 2016).

The focus on personal connections should not imply a disregard for data. In the last decade, data science has risen to join prospect research and prospect management as one of the three pillars of prospect development, the analytical and "strategic arm of an organization's fundraising operation" (Apra Board of Directors, 2014). Today's fundraising data scientists are finding ways of quantifying seemingly qualitative factors like engagement, connection, and relationships, typically using scoring systems and predictive models.

Data science takes many forms in fundraising, and some departments are venturing into using more advanced techniques like recommender systems and network analysis. These topics surface at industry conferences, with presenters recently offering sessions such as "Using Recommender Systems to Identify Prospect Interests" and "Using Social Network Analysis to Analyze and Influence Alumni Giving" (Cherry, 2019; Schaffmaster, 2019). At many universities though, data science is a new role, and organizations struggle to fully invest the resources required to support its expansion. Still, data scientists can add great value by beginning to creatively apply such techniques.

In the following client-based project, I investigated how the fundraising industry can benefit from combining the tools of visualization, recommender systems, and network analysis to strategically leverage relationships. A team of university fundraising researchers originally wanted to identify fundraising opportunities with groups of alumni and postdocs who shared the same faculty advisor. The client's fundraisers frequently asked for lists of individuals associated with a particular advisor, and there was an organizational belief that there were missed philanthropic opportunities from this population.

I addressed this issue through an analysis of the philanthropic capacity and engagement of the advisee groups, which supports fundraising goals in several ways. Importantly, the analysis can inform the creation of fundraising initiatives that are made in honor of a professor, thereby showcasing which advisors have a big and committed enough network to support such efforts. Analysis also helps identify faculty advisors who may be particularly good at building engaged, philanthropic alumni communities, so the client can further investigate what these professors are doing differently.

The project expanded to identifying and mapping out relationships between the wider pool of alumni. While the client organization tracks relationship data in the database, it is largely based on public board memberships. There is a lack of available data in the system on which students may have interacted while on campus. To redress this gap, I included a content-based recommendation program to identify shared experiences among alumni, based on criteria like their years on campus, student activities, and faculty advisee group. The results serve to discover alumni with overlapping activities who may therefore know each other.

Together, the project's two components (the advisee dashboard and the alumni map) help answer several questions important to the fundraising researchers:

1. Who are each faculty advisor's alums and post-docs and are they donating?
2. Which advisee groups have the greatest philanthropic potential?
3. What fundraising opportunities exist based on the advisee group data?
4. Which alumni know each other, and how can fundraisers use those relationships to promote additional giving?

LITERATURE REVIEW

The scholarly literature on educational philanthropy is spread across different subject areas and can be challenging to synthesize. In 2017, the founding editor of *Philanthropy & Education* commented on the difficulty of gaining a complete understanding of the field's research and theoretical frameworks. He described the interdisciplinary nature of the work, noting that scholars publish in many different venues across disciplines, professions, and applied fields. He further explained that much of the research is never published because authors compete for space in journals on broader topics, and because dissertations are commonly written by active fundraising professionals who are too busy to go through the publishing process (Drezner, 2017). Therefore, research on a specific fundraising topic is often meager and hidden among articles from fields as diverse as psychology, biology, business, and education.

Indiana University approved the nation's first School of Philanthropy in 2012, and its founding dean expressed a similar sentiment at the time. As he explained, "Everyone who teaches in philanthropic studies has a home somewhere else," and early critics "didn't see enough intellectual basis to justify creating a school" (West, 2012). Fortunately, there is a trend toward increased academic research, and as the fundraising industry becomes more professionalized and analysts further integrate quantitative methods into their work, the field is transforming from an art to a combination of art and science. Yet, the current project incorporates not just topics from higher education fundraising, but also from several areas of data science. A thorough review of the literature involves exploring studies and discussions on subjects including faculty fundraising, peer-to-peer fundraising and social networks, recommender systems, and industry practices.

Faculty Fundraising

Researchers have studied different aspects of faculty fundraising, one of the more prominent of which is the impact of deans, who are often expected to participate in promoting philanthropy. Still, an article as recent as 2018 declared, "There is sparse empirical research on deans in general and on their fundraising role in particular," even though the role's fundraising expectation has been commonplace since the early 2000s (Hunsaker & Bergerson, 2018). The research that does exist is sometimes based on a handful of qualitative interviews at a single university, and thus may have limited generalizability. However, since the current project does not reveal decisively the underlying reasons that some faculty advisors' alumni are more philanthropic than others, the existing research may help point to areas the client can further explore. For example, Hunsaker and Bergerson (2018) found that deans struggle with fundraising because of a lack of training, a need for stronger partnerships with fundraising staff, unrealistic dollar goals, limited time, and conflicting priorities. The client's faculty advisors likely face similar challenges, and in some cases the advisors are deans.

In the Hunsaker and Bergerson (2018) study, the interviewees also emphasized the importance of relationship development in fostering philanthropy. Because deans and other faculty members interact with students while they are on campus, it would be useful to know how those relationships affect giving once the students graduate and become prospective alumni donors. Intuitively, one would expect that positive faculty interactions would correlate with increased giving. In speaking of deans, faculty, and other employees, the author of a paper focused on law schools expressed this idea saying, "By treating students well, grading on time, answering e-mail and phone calls, . . . and other similar work, every law school employee becomes a fundraiser" (Matasar et al., 2008). Research supports this idea. Pumerantz (2005) studied the California State University system, noting from his interviews that "it is the experiences the alumni had while they were students and the connections with faculty and staff that have the greatest impact on alumni giving." He also revealed that the most successful programs had a university president or chancellor who instilled a sense of family loyalty. The importance of the familial leader could have implications for the current project if it translates to the leadership of faculty over their advisee groups. Another study focused specifically on journalism and communication students found that alumni satisfaction with the quality of their education was predictive of giving (Tsao & Coll, 2004). At research universities like the client organization, faculty advisors are an important part of the educational experience.

However, the relationship between faculty and their students does not need to end when students receive their diploma. In studying black colleges, Gasman (2005) noted that faculty can support fundraising efforts by acting "as a connection point between fund-raising staff and alumni," and that "simply taking an interest in students after they graduate may steer them toward giving." Frisby et al. (2019) came to similar conclusions in their recent study of alumni interactions with faculty, which focused on instructor rapport and memorable messages. The results suggested that continuing rapport after graduation may be more important than rapport during the student's time on campus. In their discussion, the authors advocated for alumni relations offices to "effectively leverag[e] positive relationships faculty may have already built with students," and asserted that "faculty members should engage with former students to maximize the positive results of those relationships rather than fundraising and development offices initiating contact" (Frisby et al., 2019). Collectively, these studies point to the importance of faculty relationships in promoting alumni giving behavior and provide support for the current project as an area worthy of further analysis.

In thinking about the relationship between faculty and advisees, it is important to recognize that these groups are not mutually exclusive. In exploring the client's data, I originally believed I was looking at a bipartite network, which would include a set of faculty linked to a separate set of advisees. However, some faculty advisors are alumni, meaning they fall into both categories. They have a set of students they have advised, but they also are linked to their own faculty advisors. In 2013, a study investigated how giving is affected when a person has the dual identities of being both an alum and a faculty member. The authors made comparisons between faculty and staff who are alumni and those who are not, finding that the non-alumni are more affected by the level and length of their employment (Borden et al., 2013). However, since the current project focuses on advisee giving, and all advisees are alums, the more relevant comparison would be between alumni faculty and alumni who are not faculty. While the article does not address that topic, it includes some useful points about organizational identification as a theoretical framework for understanding the level of connection people have to an organization. A sense of oneness with the organization typically increases giving likelihood for alumni, and the insider information gained from also serving as faculty can positively or negatively affect that feeling. The client university should consider these effects when reviewing advisee groups with members who have multiple affiliations.

Social Networks and Fundraising

A number of studies discuss the power of peer pressure and social influence on giving. Chapman et al. (2019) observed a "champion effect" in peer-to-peer giving, whereby giving is influenced more by the person doing the asking than by the specific charity or cause. Individuals who "identified more with their selected charity, and who took more actions to solicit donations, signal their personal investment, and signal the efficacy of the charity, raised more money" (Chapman et al., 2019). Scharf and Smith (2016) reported similar findings that donors are at least partly motivated by their relationship with the fundraiser. They attribute this phenomenon to relational altruism, meaning that donors are motivated to support a member of their network—in this case, the fundraiser. For the current project, when the client reviews the relationship map, they will need to carefully select volunteer alumni fundraisers from the network using the insights from these studies. Alumni who have strong peer relationships and who are good at conveying their own commitment to the university are likely to be more effective fundraisers.

Network analysis and relationship mapping are rarely mentioned in the fundraising literature and appear to focus more on philanthropy from foundations and corporations. For example, a study investigated nonprofit networks through board member overlap, mostly finding that greater connectedness is associated with increased success in attracting grants (Faulk et al., 2016). However, some studies have explored social networks and individual giving. A recent study focused on celebrity philanthropy in China noted that philanthropic behavior is embedded in social networks (Yang et al., 2019). The researchers conducted a network analysis to examine how a celebrity's position in a network relates to giving, finding greater philanthropic engagement in the network's center. There again seemed to be a peer pressure effect, with increased likelihood of celebrity giving if others in the network were philanthropic. There may be cultural differences, but the study offers good ideas regarding questions to ask when analyzing a network of potential philanthropists. However, the client's primary business need in the current project focuses more on discovering relationship connections than on analyzing the structural components of the network.

Recommender Systems

The most relevant research regarding the recommender piece of this project focuses on the similarity calculation. The project requires comparing pairs of alumni to determine the individuals' level of similarity. Cosine similarity is a standard way of comparing the distance between two vectors, and it does so by measuring the angle between them. However, it has limitations. Li and Han (2013) explained that cosine similarity is generally biased by terms with higher frequencies, and does not put much emphasis on the number of shared terms.

The latter issue has important implications for the current project, as the client is specifically interested in basing the similarity calculation on the number of campus experiences that alumni share. Li and Han experimented with several variants of the cosine similarity measure and found that a weighted distance formula better accounted for the number of shared and unshared terms in text classification problems. Clearly, matching the purpose and underlying logic of a recommendation project with the calculations used is of consequence.

Given the emphasis on similarity, it is important to note that the literature points to potential pitfalls when recommender systems use such metrics. Barasz et al. (2016) demonstrated that "people sensibly expect others to like similar products, but erroneously expect others to dislike dissimilar ones." For example, a movie goer may like watching documentaries and action movies, but outsiders assume that a single person would be unlikely to enjoy both since the genres are so different. This research suggests that a content-based recommender would miss the dissimilar subset of a person's preferences. Of course, the current project focuses on similarity between people rather than products, but even in that case there are possible challenges. While people often form relationships with friends who are like themselves, a phenomenon known as homophily, Altenburger and Ugander (2018) explored the variation between members of a network. The researchers found that in some cases people make connections with others who are not like themselves in certain aspects, though this is often tied to an unexpected similarity between friends of friends. The recommender for the current project only calculates similarity between immediate connections, but it is useful to know that more complex network interactions exist.

Prospect Development Industry Practices

Much of the industry discussion about relationship mapping has focused on tools (Apra, 2018–2021). However, the relevant tools depend on what the analyst means by "relationship mapping," and that meaning varies. Some analysts are interested in bolstering their relationship data through data appends or vendors who help uncover relationships. RelSci is commonly mentioned, either as a standalone product or accessed through iWave. Customers like its user-friendly platform and believe that there is not another comparable tool, but note that it is pricey, the information is sometimes outdated, and the relationships are mostly limited to prospects who are board directors and company insiders. A second group of analysts seek tools that can visualize a network. NodeXL, an Excel add-in, is the most frequently mentioned free resource, but paid options such as Kumu and Prospect Visual have also been referenced. A third focus has been on geographic mapping of prospects to identify neighbors. Suggested tools have included Excel, Tableau, the Mapquest API, Google Maps via a Google Enterprise account, and ResearchPoint's Bing Maps add-on. Across the different use cases additional company names have surfaced, though it is often unclear which purpose they best fulfill. These vendors include Aidentified, WealthQuotient, Advizor/Pursuant, WealthX, S&P Capital IQ, BoardEx, WealthInsight, and DonorSearch's Inner Circle. Tool selection should take into account whether the fundraising department intends to map internal versus external relationships and whether the focus is on individual versus organizational records.

Regardless of the tool, the aim of relationship mapping is to increase fundraising revenue by empowering fundraisers to use relationships strategically in their work. The knowledge helps fundraisers successfully land meetings through warmer introductions. It also informs volunteer recruitment, event invitations, and board nominations.

DATA COLLECTION AND METHODOLOGY

While the project touched on many data science concepts and techniques, there were three primary methods at the project's core: data visualization, recommender systems, and network mapping. Each one served a useful purpose in addressing the project objectives.

Data visualization is a means of communication. It is the conduit through which data are turned into meaningful insights, connecting information with decision makers. Good visualizations enable viewers to quickly see important messages and patterns so they can act, and the best displays are linked to specific goals that are aligned with the organization's strategic objectives (Ioana et al., 2014). I used dashboards because they provide a space to present several charts in a compact end product, and they serve as a useful way of organizing information with a common purpose. The fundraising researchers were interested in multiple questions about advisee groups, and a dashboard solution allowed them to interact with the data, dig further into the answers, and ask additional questions.

Recommender systems can help suggest products, people, or services that may be of interest to a user. I opted to include a relationship recommender in this project as a way of comparing the similarity of alumni experiences, with the goal of identifying alumni who interacted and may be acquainted. I reviewed several recommender approaches, and found the content-based recommender most applicable. It focuses directly on the similarity of two items, which aligned with my purpose of comparing two people's overlapping student experiences. If one alum had many experiences in common with a second alum, the second was recommended as a possible relation of the first. Other approaches, including collaborative filtering, did not translate as clearly to the current project or would have relied too heavily on the quality of the current relationship data, which was insufficient.

Given fundraising's emphasis on relationships, a network map was a natural choice for this project. As important as relationships are, fundraisers were underusing relationship data because this information was not easily accessible. In the best-case scenario, they could pull a list of names linked to an individual, but there was no way of looking at how that person fit into the bigger network of donors and alumni. The database contained much information about student activities, sports, dorm affiliations, and research groups, but it was difficult to see how this information connected people. I chose a network map as a way of uncovering and displaying these intersections so the information could inform prospect strategies. By leveraging internal data, a network map can act as a sort of automated peer screening, bringing previously unknown relationships to the attention of the fundraisers. As a visualization, network mapping also promotes the communication of relationship data by presenting it in an easily consumable, actionable format.

Tool Selection

Each method required at least one data science tool. For data visualization, a few prominent options existed, including Tableau, QlikView, Power BI, and Excel. However, Tableau was the clear choice for this project, mainly because it already served as the client's data platform. The software was already installed, and there were no additional costs to use it.

The dashboards' audience was familiar with Tableau and understood how to interact with its features, so training could focus on the content of each dashboard rather than on the tool. That said, Tableau does not lend itself easily to network graphing, at least in terms of the data setup. Other tools specifically designed for network visualizations were briefly considered, such as Kumu, but would have required a potentially lengthy approval process, and time restrictions did not allow for that.

For the relationship recommender, I chose Python as the programming language and used a Jupyter notebook to better organize the code. While it is likely possible to use other statistical programming languages such as R for this process, Python made sense because the concept was based on code used in the University of Wisconsin data science program's Prescriptive Analytics course, which used Python (Banik, 2018). It was easier to translate the example content-based recommender to the current project by remaining in the same language.

In moving to the network graph, I switched to R Studio to define the coordinates. I have experience using a couple of its network analysis packages, igraph and statnet (Luke, 2015), and have previously presented at a conference about using R to build networks in Tableau. I did weigh the benefits of keeping all the code in Python, but felt I had greater flexibility and stronger knowledge in R. Like Jupyter, R Studio is open source and free, so that was an additional benefit in selecting these tools for the project. Both also facilitate reproducible results.

Data Collection

Source Data. The client organization used a standard fundraising CRM as its internal database, and the data for this project came from that system. While the internal database supported both parts of this project, the advisee group dashboard relied on a separate data pull from the network map dashboard because the two focused on different kinds of information. For the advisee group dashboard, the data represented faculty advisors and the alumni and post-docs they advised. Each row contained a unique faculty advisor/advisee combination. Because advisees could have multiple advisors, the same alum or post-doc could appear on multiple rows, once for each advisor he or she had. The main components of this dataset included:

- faculty advisor name and ID
- advisee name and ID
- advisee philanthropy metrics
- advisee biographical, prospect, gift, and wealth data

There were several philanthropy metrics. The first, RFM, stands for recency, frequency, and monetary value. RFM considers the timing of the donor's last gift, the number of gifts made, and the amount given. It is a common way of gauging giving behavior and segmenting donors. The second metric was velocity, which is a measure of whether a donor's giving is accelerating. The data also contained a donor flag, which allowed for calculating two additional metrics, donor proportion and donor count, when the data were aggregated to the faculty advisor level in the dashboard. I describe the calculation of the philanthropy metrics in more detail in the methodology section. Examples of the biographical, prospect, gift, and wealth data include geographic location, the prospect's stage in the cultivation cycle and assigned fundraiser, giving totals, and capacity rating. All columns were produced using an SQL query.

The source data for the second part of the project focused on producing a list of alumni along with their campus experiences and recorded relationships. This dataset served as the starting point for the process that passed through the recommender system and ultimately created the network map. The dataset's purpose was to provide the recommender with the information necessary to compare alumni experiences. Here, each row represented a unique alumnus, as the comparisons happened on an alum-to-alum basis. This structure required aggregating the alum's data points into a list for each column. As an example, consider student activities. The alum may have several student activities on record, and in the underlying database table, there is a separate row for each activity. When I pulled the data, I combined all the alum's student activities into a list, so that they could be stored on one row. Figure 1 shows this process.

However, knowing that two people shared an activity is not enough information. The timing of the activity matters in determining whether two alums interacted. If one was on the basketball team in the 1970s and the second in the 1990s, there is little reason to believe they have a relationship. For this reason, I also concatenated each activity with a year. Because activity dates are unreliable and often missing in the system, the client opted to estimate the years based on the alum's graduation date. Most undergrads take around four years to graduate, so I tagged each activity with the graduation year and the preceding three years. Figure 2 shows how the data was transformed to include the year estimates.

Alum A	Basketball
Alum A	Band
Alum A	Biology Club

Alum A	Basketball, Band, Biology Club

FIGURE 1. Formatting the activity data. Figure by author.

Alum ID	Graduation Year	Activity
Alum A	2001	Basketball
Alum A	2001	Band
Alum A	2001	Biology

Alum ID	4th year activities	3rd year activities	2nd year activities	1st year activities
Alum A	Basketball-2001 Band-2001 Biology Club-2001	Basketball-2000 Band-2000 Biology Club-2000	Basketball-1999 Band-1999 Biology Club-1999	Basketball-1998 Band-1998 Biology Club-1998

FIGURE 2. Example of year tagging. Figure by author.

I used similar list aggregations and year tagging for the alum's sports, dormitory affiliations, and advisee groups. Lastly, I added in known relationships by combining the ID numbers of the two connected individuals; that way, both would have the same concatenated ID tag in their data and the recommender would recognize it as something they had in common. These relationships were not tagged with years, as they were relevant regardless of when they began. All columns were pulled using an SQL query, and the main components for the complete dataset included:

- alum name and ID
- list of activities for each year
- list of sports for each year
- list of advisee groups for each year
- lists of known relationships

The client and I also considered using employment and event overlap to factor in data beyond the student experience. However, employment dates were sparse, and I had concerns over the size of certain employers. Many alumni were academics working in large universities where it would be unrealistic to assume that everyone at the organization knows everyone else. Similarly, it only would have been reasonable to include small events as large events do not imply strong connections between attendees. These criteria were left for a future enhancement because of the additional complications.

Data-Collection Challenges

Data science students frequently hear that gathering and cleaning data is the most time-intensive part of a project (Yan & Davis, 2019), and that was true in this case as well. I encountered multiple data-collection challenges. First, the data quality was sometimes lacking. I saw alumni linked as having relationships with deleted records and alumni linked to themselves. Data were often missing or incomplete. For example, the client understood that not all post-docs had records, and not all faculty advisor relationships were recorded. Student activity data were inconsistent, and some sports appeared to have multiple codes for the same team, or no distinction between the men's and women's teams. Dates were often unavailable. Several cleanup and data enhancement efforts took place during the project to help address a few of these issues.

Second, the structure of the data posed problems. To make data more accessible, the client had flattened out versions of some of the underlying tables, known as views and materialized views. These data sources typically had one row for each person, making it easy to pull data by individual. However, most of the data I required did not have relevant views and was structured such that there were multiple rows for the same person, as described in the student activity example in the last section. These factors complicated the collection process, as data needed to be aggregated into lists and combined in atypical ways.

Methodology to Create and Use the Two Dashboards

The two dashboards each had its own methodology, which resulted in distinct products. I did consider integrating them as multiple tabs on the same Tableau workbook. That option would have made sense if the network map represented advisee groups, but ultimately that was not the path I took. Since they focused on different populations, I kept the dashboards separate.

Advisee Group Dashboard. In terms of getting the data to Tableau, the process was simple for the advisee group dashboard. The query pulling the data was embedded in Tableau as the data source, so there was a direct connection to the database. However, I did initially write and test the query in SQL Developer, which is why I have included an additional intermediary step in Figure 3.

I selected four philanthropy metrics for inclusion in this dashboard, and the first two were RFM and velocity. For the purposes of this project, I calculated RFM as a 30-point score, with each of the three components (recency, frequency, and monetary value) receiving up to 10 points. For each component, it is common to assign scores based on percentages, such as the top 10% of donors receiving a 10, those in the top 20% receiving a 9, and the top 30%, an 8. Rather than using equally sized percentage blocks, though, I looked at where there were natural cut points in the data, such as considering the gift level categories. Fundraising researchers focus their attention on the very top donors, so a more granular separation at the highest levels was necessary. For example, only the top 2% of alumni received the highest monetary score. For velocity, I calculated its value as the average giving amount over the last three years divided by the average over the last five years. This formula came from speaking with industry experts and reviewing conference materials on the topic (Cato, 2015; Eichinger, 2020; Pelletier, 2020).

The remaining two philanthropy metrics were straightforward and only applied at the advisee group level. One was the donor proportion and the other was the donor count. The proportion is a calculation of the number of advisees in the group who are donors out of the total number of advisees in the group. The count is simply the number of donors. Both metrics were meant to help the fundraising researchers assess the viability of a fundraising initiative with the group. The proportion helped them see if the group was collectively engaged and already primed to give. The count helped determine whether there were enough members to support an initiative.

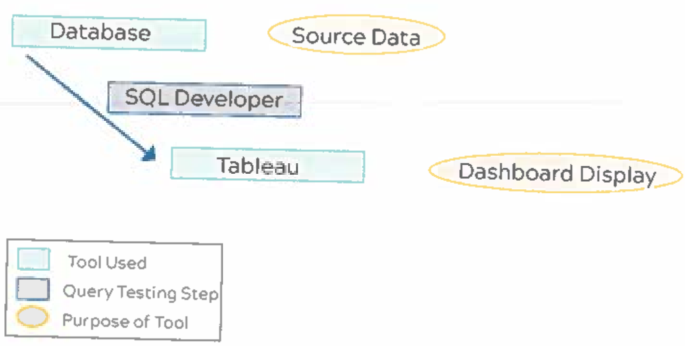

FIGURE 3. Process for creating the advisee group dashboard.
Figure by author.

Data interpretation requires a context. I could report on a metric, but users need more than the number. They need to know whether the number is good or bad. For this reason, I included references to the overall average for each metric. That way, users could have a better understanding of where a score falls relative to the other scores. Later in the project, I revised the initial metrics charts to use boxplots, which better showed an advisee group's position in the overall distribution, rather than compared to a single point.

I also wanted to create a simple way for users to tell almost instantly whether an advisee group warrants further attention. Staff face competing demands and need ways to save time and focus on priority areas. Design must therefore facilitate quick decision making. To make that possible, I created a four-star system, similar to a Yelp rating. Each star corresponded to one of the philanthropic metrics, and the star was filled with color if the metric was above average. Using the stars, fundraising staff could quickly identify when to spend time on a group, and when to move on to another one.

Additionally, there were a group of decisions around the dashboard's functionality. I added filters because they provided flexibility for asking different questions of the data. Often the fundraising researchers were most interested in the wealthier subset of alumni and post-docs, and the filters allowed for targeting the analysis to these individuals. I also made the underlying, unaggregated data exportable. While visualizations have many benefits, spreadsheets still had a place in the client's work, and the combination of data options best suited the project objectives. It enabled a high-level analysis to identify possible areas of opportunity, followed by a more detailed review of individual donors.

Network Map Dashboard. Translating the source data into a meaningful dashboard display was a much more involved process for the relationship map, as seen in Figure 4.

The process began with the source data pulled using SQL Developer. The result was a CSV file, which was read into a Jupyter notebook. The notebook contained the Python code for the recommender system, which calculated and scored the similarity of alumni pairs, based on their shared experiences. If two alumni lived in the same dorm at the same time, or were in the same student club, or played on the same sports team, it is logical to conclude

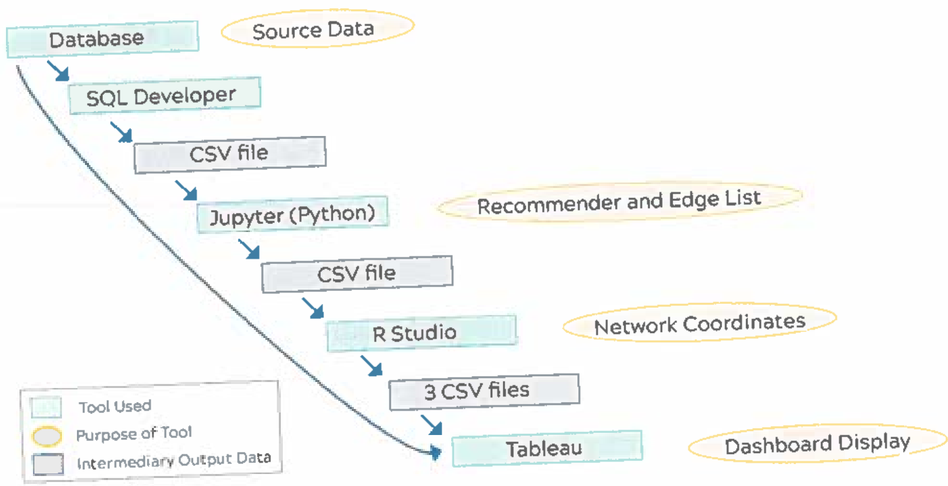

FIGURE 4. Process for creating the network map dashboard. Figure by author.

that they interacted and are possible acquaintances or friends. This phase resulted in a second CSV file, this one containing the list of uncovered alumni relationships. In network analysis, the list of relations is known as an edge list, and here it served as the data source for an R Studio program that assigned coordinates to the network of alumni. The coordinates defined the position of each alum in the network map. That list of coordinates was one of three files output from R Studio. The second was a filtered version of the original edge list. The third, called the bridge file, helped format the final combined data into a structure that Tableau could use. I joined these three files in Tableau to form the data source supporting the network map dashboard. These last few steps closely followed Jim Knippenberg's 2017 YouTube video on building a Tableau network graph, although I used R Studio in place of Python to generate the map's coordinates. In Figure 4, there is one final line connecting the database directly with the Tableau dashboard, as one of the database views was joined to the CSVs in the Tableau data source. The purpose was to bring in some basic biographical, prospect, giving, and wealth info for the alumni and their relations.

Several key decision points occurred as the data progressed through the phases, the first of which involved the recommender's similarity calculation. Each alum's campus activities were combined into a string "soup," which the recommender could compare and score, with the results stored in a matrix. I originally planned to use cosine similarity for comparing the alumni. It is a common method for determining similarity in a content-based recommender, and it measures the angle between the two vectors associated with the alumni pair (Li & Han, 2013). However, when I looked at the results, the strength of the relationships seemed counterintuitive. Alumni pairs with the same number of items in common were not necessarily receiving the same score. I found that the differences in the alumni experiences influenced the scores too much. For example, if a pair of alumni shared two activities in common, but one had three other unshared activities, that would return a different result than if there were two activities in common and five unshared activities. That outcome may be useful in other scenarios, but not for this project. Many daily commitments in college go unrecorded, so it did not feel reasonable to assume that alums with more unshared activities were busier and thus had weaker relationships in their shared activities. Outside activity need not take away from the friendship experienced in a shared affiliation.

For this reason, I looked for alternatives to cosine similarity. I briefly considered Euclidian distance, which calculates a straight-line distance between points in Euclidean space. However, this measure is affected by the length of the vectors, once again meaning that the scores would be influenced by the number of unshared experiences. Ultimately, I decided on a straightforward additive measure, and created a function that simply counted the number of overlapping activities. In this manner, I could completely ignore the unshared experiences, as desired. I considered weighting some of the criteria, such as placing more emphasis on known relationships, but decided to keep the initial iteration less complicated. This decision aligned with advice I received about starting smaller and scaling up after there is additional evidence of the project's continued value (M. Pawlus, personal communication, June 8, 2020).

Another important decision occurred while preparing the data for the network map. The network's population changed several times over the course of the project and required clarification from the client. I settled on using a single map that focused on relationships between alumni who were already connected to the client organization and those who were not yet connected but were wealthy enough to give a major gift. This approach best promoted the strategic purpose of discovering relationships that help the client connect with unengaged individuals. I identified the two groups using prospects stages, with alumni in later stages of the cultivation cycle coded as having a relationship with the client organization, and alumni in earlier stages coded as unconnected to the organization.

After deciding on a population, I also needed to choose a layout for the network. There are several algorithms that produce network layouts, such as circle, sphere, random, and Fruchterman-Reingold. I chose the Fruchterman-Reingold option, as it is a force-directed layout, which tends to place related nodes near each other and prevent excessive line crossings (Fruchterman & Reingold, 1991). Such graphs are often aesthetically pleasing and easier to read. It is the default option and commonly used in practice. I used a seed to make the randomly generated layout reproducible and tested different seeds to view a collection of possible layouts. I aimed for one with the points evenly spread out and a shape that was more symmetrical.

On the dashboard itself, the key decisions mostly involved functionality. It was important for the user to be able to find a specific alum on the map, so I included a search box and a highlight feature. While the network visualization was an essential part of the dashboard, the client was also used to drilling down and exporting details about the individuals represented on dashboards, so I added an exportable list of the selected alum's relations. I wanted users to quickly identify key players on the map, so I associated the size of the nodes with the number of relations, a measure of degree centrality. Alumni with more connections would therefore appear larger on the map. I also attempted to associate the relationship strength with the thickness of the lines (edges), so that extra emphasis would be on stronger relationships. However, the distinctions were not noticeable enough without increasing the thickness to a level that interfered with the overall readability of the graph.

Since the relationships represented potential connections rather than confirmed ones, the client needed to see the shared experiences of each alumni pair as part of the dashboard. This information explained why two people might know each other and provided the evidence for their bond. It made it easier for the fundraising analysts to review the results, factor in their own knowledge about campus groups, and weigh the likelihood that alumni pairs truly were connected. Therefore, I took extra efforts later in the project to go back and collect a human readable version of the string soup that contained the overlapping alumni experiences. The original version used field codes that were indecipherable to end users. The dashboard became much more useful because of this change.

FINDINGS/RESULTS

The Advisee Group Dashboard

The advisee group dashboard is displayed in Figure 5. The dashboard contained three main sections and a couple of global filters. Note that I have modified some labels and numbers for confidentiality reasons.

The dashboard facilitated two ways of approaching the advisee group information. The first is when the user does not have a specific advisor in mind, but is seeking to identify

FIGURE 5. Image of the advisee group dashboard. Figure by author.

groups that are more philanthropic. The line graph served this purpose. It showed the top 10 advisors with the most philanthropic groups, based on whichever of the four philanthropy metrics was selected. The overall average was included above the chart to provide context. There were several user settings related to the chart. The first allowed the user to filter out advisee groups that were not of interest, so those groups no longer appeared in the results. For example, it would make sense to exclude groups that already had a recent fundraising initiative, or those for which the advisor is not receptive to the idea. The "Select a Metric" option let the user choose between the four philanthropy metrics, so he or she could see the results by RFM, velocity, donor proportion, or donor count. This setting provided alternative ways of comparing group philanthropy. The final setting, "Select Ranks," enabled the user to shift to the next set of 10 advisors, so the user could easily access information for up to the top 50 advisee groups.

The second way of approaching the information is when the user wants to explore the philanthropy of a specific advisor's group. The user may start with this information, or the user might become interested in an advisor after interacting with the line graph. The two bottom sections of the dashboard supported the analysis of a specific advisee group, with the left section addressing the high-level questions. For the selected advisor, the boxplots showed how that group's average compared to the distribution of averages across the advisee groups, and it made this comparison for each of the four philanthropy metrics. The four stars served as a quick indicator of whether the group was doing well on the metrics, as each star was lit with color if the group was above average and greyed out if the group was below average. The colors in this section were consistent with the colors in the line graph, such that RFM was always teal, velocity green, the donor proportion purple, and the donor count blue. Finally, the bottom right section provided the detail on the selected group's members. The user could scroll through to see the advisees' names, wealth, and individual giving history, or the user could export the list to Excel for greater flexibility in sorting the information.

Two global filters controlled the population represented on the dashboard. The filters both enabled the fundraising researchers to restrict the data based on the wealth level of the advisees. While low-level annual giving is important, the researchers' work generally focused on potential donors who can make more sizable gifts. The first filter set the minimum number of wealthy advisees per group. For example, if the user set the value to 5, then the dashboard charts would only include advisee groups that have at least five members at the major gift level. Zero was the default and meant that none of the groups was excluded. Since the first filter was doing the exclusions at the group level, the second filter worked at the individual level. When set to yes, the "Major Gift Prospect Flag" filter excluded all advisees who did not have a high enough wealth rating.

Objectives Fulfilled. In requesting the advisee group dashboard, the fundraising researchers first wanted to answer the question, "Who are each faculty advisor's alums and post-docs and are they donating?" The bottom right spreadsheet-like section directly fulfilled this need. Users could ask about any advisor, living or deceased, and immediately see the resulting list of advisees, along with each advisee's philanthropy. The dashboard also addressed the question, "Which advisee groups have the greatest philanthropic potential?" The line graph served as a ranking of the best groups according to each metric. Together, the dashboard's components aimed to answer the deeper question, "What fundraising opportunities exist based on the advisee group data?" The dashboard informed decisions about opportunities like honoring a professor with a named scholarship fund or starting a collective effort to support a research area similar to the group's work. The dashboard findings indicated which groups had a large and philanthropic enough network to support such efforts. The results also helped identify key group members whose participation was needed for success.

The Network Map Dashboard

The network map is displayed in Figure 6. This image represents what the users would see before making any selections. Again, I modified some details to protect confidentiality.

The dots on the map represent alumni, and the grey lines connecting them indicate relationships. The dots are either blue or a brownish orange. The blue dots correspond to the unengaged alumni, and the orange dots to alumni who are already engaged. The client wants to reach the blue dots by using the orange dots as connectors. The sizing of each dot

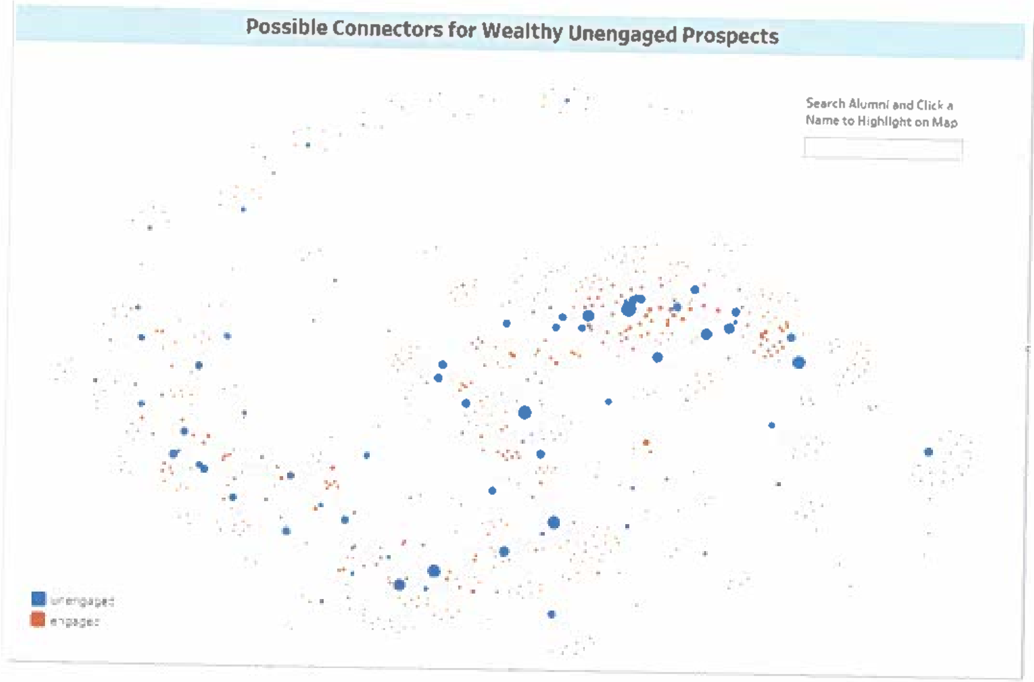

FIGURE 6. Image of the network map dashboard without selections. Figure by author.

is based on the number of connections the alum has (the number of degrees), which is why dots in dense parts of the map tends to be larger.

The map provided a high-level view of the connections between the engaged alumni and their unengaged peers. Users could see that some connectors were able to reach multiple target alumni, while others only had one connection. Similarly, some target alumni were connected to many engaged alums, so there were multiple possible avenues for reaching them.

Most of the map's value came from interacting with it. When users hovered over the dots in the map, pop-up boxes (tooltips) appeared that displayed the alum's name and ID, wealth rating, and prospect stage. Hovering over the lines produced pop-ups showing the shared experiences for each connected pair. These pop-up features allowed users to understand whom the points represented. However, the fundraising researchers often had a name in mind already, and it could take a while to locate somebody on the map if the user had to mouse around until stumbling upon the alum of interest. To avoid that issue, I added a search box near the top of the dashboard. The user could enter a name or ID, select from the resulting list, and the alum would become highlighted on the map. This functionality is demonstrated in Figure 7, in which a user has searched for Jane.

Once the user located Jane on the map, clicking on her dot generated Jane's picture and the list of her relations, as seen at the bottom of the dashboard. The detail information included each relation's name and ID, campaign giving, and the experiences he or she shared with the selected alum, in this case Jane. The list was exportable, and the resulting spreadsheet included additional biographical, prospect, and wealth data about the relations to

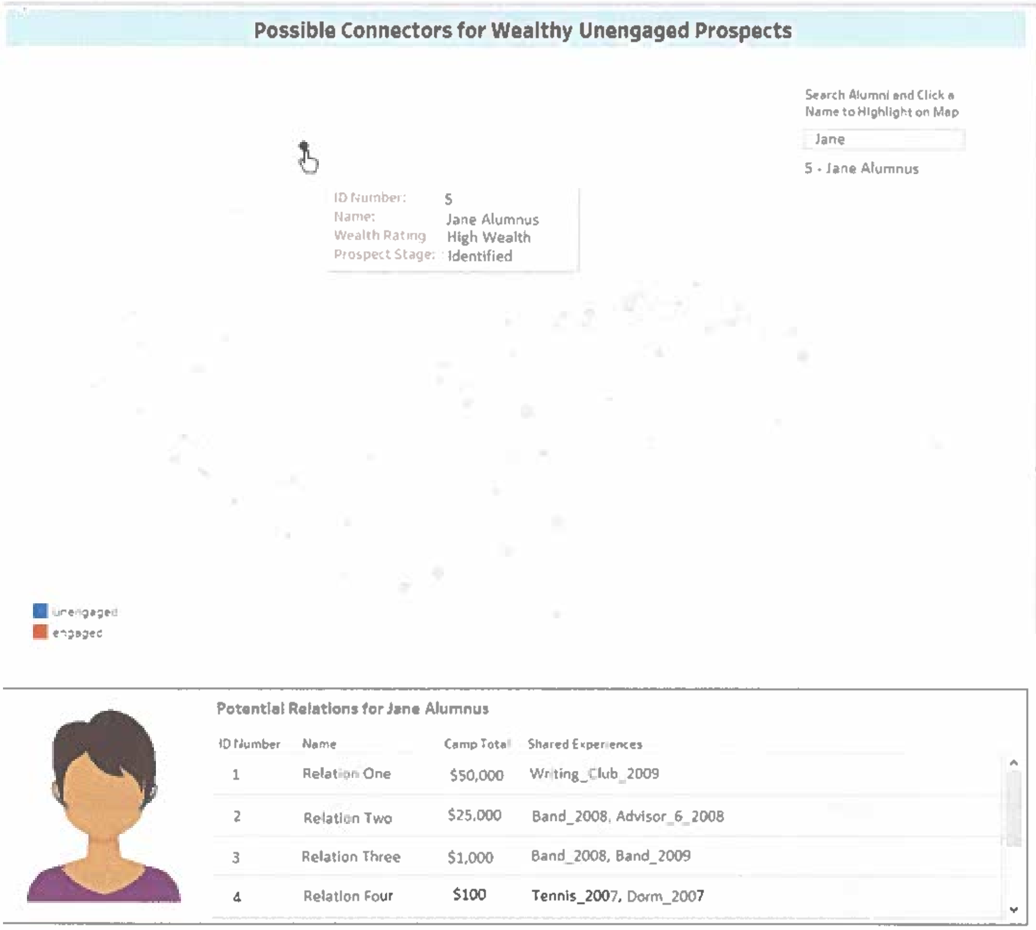

FIGURE 7. Image of the network map dashboard with selections. Figure by author.

help inform the user's review. It also included the strength of the relationship, based on the number of shared activities, though it is not yet clear whether more shared activities really corresponds to deeper relations.

Objectives Fulfilled. The network map helped answer the question "Which alumni know each other and how can fundraisers use those relationships to promote additional giving?" I found that even the wealthiest unengaged alumni have relationships with potential connectors. These relationships provided a basis for discussing new strategies to move these prospects forward in the cultivation cycle. When I demonstrated the dashboard to the client's fundraising analysts, they already started thinking about which relations were most invested in the organization and how existing conversations with those alums could include discussions about how best to connect with their peers.

As an example, consider Jane's relations. In reviewing that list, the fundraising researchers recognized the second relation's name and knew from their work experience that frontline fundraisers regularly talk with him. I will call the relation Matt. Matt was a consistent donor with a passion for his alma mater. The researchers could notify the fundraisers who were assigned to Jane and Matt about the potential relationship, so the fundraisers could ask Matt about Jane the next time they speak with him. The fundraisers might ask him if he feels comfortable encouraging Jane to donate to a fund or attend a campus event. They might ask if he knows what areas of campus would interest her most. The dashboard's findings consisted of the collective set of these kinds of relationships and discussion points that helped build engagement and thus promote philanthropy. As noted in the literature review, it matters who asks Jane to commit her time or money (Chapman et al., 2019). The insights from this dashboard enabled the client to find the right people to make those asks.

DISCUSSION

Each dashboard has a clear focus, and I expect the client to continue using the information to better understand its fundraising opportunities. However, information is only valuable if staff act on it. It is not enough to know which advisee groups are philanthropic, or which alums are connected. Those insights must have a direct effect on decision making. Therefore, I recommend the client pay extra attention to how they will implement the results. They should consider whether the fundraising researchers will proactively search for opportunities, and if so, how they can best transfer that information to frontline fundraisers in a way that encourages the fundraisers to use it. If the process will be more reactive, the researchers should still understand how fundraisers ultimately use the results and follow up with them to hear whether the advisee group initiatives and alumni outreach efforts are successful.

Sometimes inaction comes from not knowing where to start. On both the advisee group dashboard and the network map, the fundraising researchers should use wealth and philanthropy data to help prioritize efforts. The dashboards provide a great deal of new information that was previously unknown, but the insights are not all equally useful. I recommend sharing information that has the greatest likelihood of producing successes, and that which is most impactful, first. The successes build trust and demonstrate that the tools have value. On the network map, I also recommend looking first at connectors who can reach multiple unengaged alums, because one conversation with the connector might lead to several gifts.

The dashboards should spark conversations with internal groups, too. Data do not always give a complete picture, and sometimes the numbers need to be supplemented with qualitative interviews. For example, the advisee group dashboard shows which advisee groups are especially philanthropic, but it does not tell the researchers why those groups are so committed. Staff should consider asking faculty advisors for their thoughts on why some groups are more engaged, as the discussions may reveal things these professors are doing differently. Communication is important between the fundraising researchers and the frontline fundraisers as well. Fundraisers can help validate the accuracy of the network map criteria, because they speak with the connectors, directly learning which suggested connections are real.

The network map treats shared activities as an indication of a relationship. Some staff may question that logic, as it is likely unrealistic to think that everyone in the same activity, or living in the same dorm, or working under the same advisor has a strong bond with everyone else in the group. However, even if the alumni pair are not close friends, shared experiences provide them with a common ground that could be leveraged into a gift conversation. While I definitely do not remember everyone who lived in my college dorm, I do remember many of our traditions. Those kinds of memories help create rapport and often spark positive feelings about the college. As such, they serve as an opening to discuss giving back and helping current students.

That said, the network map and its relationship recommender come with an important ethical caveat. It is crucial to consider the implications for diversity. With the singular focus on similarity, the recommender may lead to fundraising practices that discourage diverse individuals from interacting. The recommender suggests people who shared experiences on campus, and therefore is likely to bring together like-minded individuals. Some student clubs are based on race or ethnicity, religious affiliations, and sexual orientation. Others are based on hobbies or areas of study. In all these cases, the recommender would connect people who are the same in some way. The system could inadvertently separate groups of alumni who are different, but most universities aim to enhance diversity, not stifle it.

There are already examples of how using a friendship-based networking approach harms nonprofit diversity. Nonprofit boards are notoriously uniform, with BoardSource finding that "90 percent of chief executives and 84 percent of board members report as Caucasian" (2017). Board recruitment often involves asking the current members to recommend people they know. They tend to recommend people who are like themselves, because their networks largely contain people like themselves. Automated peer-screenings likely also suffer from this problem. Therefore, the client should take extra care in how it uses the recommended relationships and make additional efforts to promote diversity when engaging campus alumni.

While the project is applicable to other universities looking to engage with their alumni and advisee groups, the methods may become more challenging for large organizations with sizable alumni communities. The relationship map may not scale well and may appear too dense unless additional filtering is applied. When student groups are large, there is also less chance that any two alumni in the group truly know each other well or relate to the experience in the same way. Finally, this project and others like it are dependent on the quality and robustness of the organization's data.

DIRECTIONS FOR FUTURE RESEARCH

It would be beneficial to further automate and integrate the data preparation steps. Currently, the process is clunky, requiring a series of different CSV files, software tools, and programming languages. The network data immediately become static and have no simple way of receiving regular refreshes without a manual update. This extra continued maintenance takes up valuable resources like developer time. Therefore, one next step is to explore TabPy and Rserv, two tools that help integrate Python and R Studio directly in Tableau. These tools may allow for dynamic data and greater automation, though that functionality is unconfirmed.

The similarity calculation is another area for possible improvement in future iterations of the network map, and there are several ways to enhance it. First, weighting the calculation's criteria would likely make the network results more useful. Currently there is no distinction in the map between relationships that are known and those that are educated guesses. A weighting could better emphasize the known connections. Second, the client has already discussed several criteria they may want to add when considering shared activities. These factors include overlapping employment and overlapping event attendance. The factors were excluded from the current project to keep the first iteration simple, and because employment and event attendance have additional data-collection challenges, as described in the methodology section. However, they could prove valuable if these hurdles are overcome. Finally, the client should review the existing criteria in more detail to confirm that the selected activities reflect groups that truly foster relationships. The similarity calculation assumes that alumni who share activities know each other, but this assumption does not always hold. For example, if a student club is too large or does not meet frequently, it may be better to exclude it as most members are unlikely to remember each other.

Other assumptions are worth checking as well. The current map assumes all individuals spend four years on campus, but this reasoning is flawed for graduate students. It is an overestimate for master's students, and an underestimate for doctoral students. It would also fail to accurately reflect the timeframe for post-docs if they are included, since their positions typically last two to three years. Ideally, the client would update the logic to handle each subgroup differently. The number of years tagged would depend on the person's affiliation. Directly addressing missing and incomplete data would also improve the accuracy of the relationships and their dates, so the client should consider forming partnerships across campus that promote the ethical sharing of data.

There are additional types of networks that could be mapped. For example, the network might represent fundraisers and the potential donors they have contacted. If some donors are contacted by multiple fundraisers, that would be obvious on the map. It might indicate collaboration between fundraisers or staff disregarding policies about whom they can contact. Another option is using maps to analyze event attendance, either with attendees linked to their events, or event attendees linked directly to each other. Also, it still might make sense to map the alums of a specific advisee group if one is selected for a fundraising initiative.

The current project only scratched the surface of what is possible with network data. It primarily aimed to produce relationship connections, answering the question, "Who might this person know?" However, social network analysis offers tools for analyzing the structure of the whole network, investigating clusters, and identifying people with important positions within the system. The client may want to explore these techniques in the future to get a more holistic understanding of the alumni network.

Lastly, the client is becoming increasingly interested in predictive modeling. As predictive scores become available, the client could consider incorporating them into the advisee group dashboard in place of the more descriptive metrics, which would better allow fundraising researchers to target groups having many members with a high likelihood of giving.

CONCLUSION

Relationships influence giving. Fundraisers understand this principle, and yet, the industry has not placed enough emphasis on using data to uncover and leverage those relationships. Through an analysis of advisee groups and the shared campus experiences of alumni, this project demonstrated that data science techniques can transform common fundraising data points into relationship knowledge that supports actionable fundraising strategies. Taken together, the two dashboards encourage fundraisers to unlock the power of relationships while working toward ambitious fundraising goals. Effective relationship building now becomes both an intuitive and a data-driven process.

The project's promising results should inspire other organizations to consider their own relationship data. Across higher education, relationships are the foundation of major gift fundraising, and many colleges and universities could discover their own opportunities by better understanding the networks that support them. While many schools do not have the resources to hire the expansive data science teams sometimes seen in the business world, relationship-based projects of any size can have meaningful impacts. Also, project leaders need not do it alone. The current project tapped into the prospect development community for advice, and other organizations can also find mentorship through industry associations and listservs. Such collaborations expand and empower the data science capabilities we do have.

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