Donor Mining as a Socio-technical System and the Ethics of Using It In Competition Amongst Nonprofit Organizations

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Data mining is a set of analysis techniques that has become increasingly popular in recent years, as companies realize the numerous benefits that come from data-driven work. This set of techniques includes traditional analysis, AI, machine learning, and statistical analysis. One sector that is beginning, more and more, to reap the benefits of this process is nonprofit organizations. As both the number of nonprofits and donation amounts increase, each nonprofit is fighting to retain their current donors and pull in new donors (Urban Institute National Center for Charitable Statistics, 2020). When data mining is used specifically to attract or retain donors, the term *donor mining* can be used to be more specific. As a tightly coupled paper with the technical work being done for the Children's Inn at the National Institute of Health, donor mining will first be examined as a socio-technical system. The social construction of technology (SCOT) framework will be used to examine how society has shaped this technology. Next, the ethics of how nonprofits can (and do) use donor mining to compete with one another will be examined from several ethical viewpoints including consequentialism and deontology. While this paper does not argue for or against nonprofits using these techniques, this paper attempts to bring in different viewpoints on this emerging topic in order to educate nonprofits who may be considering delving into this new technique for donor retention and attraction.

COMPETITION IN THE NONPROFIT SPACE

Competition in the nonprofit sector for resources, namely donations, has been increasing steadily in recent years. According to the National Center for Charitable Statistics (2020), there was a 4.5 percent growth in the number of nonprofits registered with the Internal Revenue Service from 2006 to 2016, and an almost 16 percent increase in total charitable giving in the United States. Although the increase in giving is larger than that of the number of organizations, the market for nonprofits is becoming increasingly competitive as each organization tries to stand out from similar nonprofits and attract new donors. Some studies have shown that although the average revenue per nonprofit is increasing, the median is decreasing, indicating a potential disproportionate distribution of funds (Beaton & Hwang, 2017). Because of this, each nonprofit organization must find a way to retain their current donors, as well as attract potential new donors. As Beaton and Hwang (2017) describe it, a larger pie is being cut into more and more pieces, and solicitation is the way to increase one's piece of the pie (p. 216). Barman (2002) explains that nonprofits will try to differentiate themselves to make themselves stand out in the nonprofit market (p. 1192).

One such method is data mining, a technique that "uses statistical analysis, artificial intelligence, and machine learning technologies to identify patterns that could not be found by manual analysis alone" (Wang et al., 2010, p. 43). With data mining, organizations can more easily and accurately identify individuals with a high propensity to give, making it an approach that has been becoming increasingly popular among nonprofits. As Maclaughlin states "The future is data driven, and companies and governments both know it… When nonprofits focus on converting data into information and insights, value is created" (p. 13). As stated by Bopp et. al. (2017), "Researchers have identified many benefits of using technology for data-driven practices, including ... the creation of competitive advantage" (p. 3609). Yet, although there is evidence that data-driven decision making can save money and help organizations work more efficiently (Maclaughlin, 2016), Lenczner and Phillips (2012) discuss the fact that many nonprofits will not see the value in this type of work, and also lack the resources to be able to incorporate such practices into their systems. This is where concern about equal access arises. Clements (2014) outlines how the costs of data mining add up quickly, and nonprofits will often outsource their data mining efforts as they often do not have the resources in-house. This can be costly as well, and smaller nonprofits are put in a difficult position. If they do not have the funds upfront to pursue donor mining, they will lose out on the effectiveness, the cost-saving properties, and the value-added that donor mining brings. This may put them at an even greater disadvantage in the future, when the larger nonprofit organizations who could perform donor mining have reaped the benefits.

SCOT AS APPLIED TO DONOR MINING

In this paper, the main STS framework examined in conjunction with donor mining will be social construction of technology, as introduced by Bijke, Bonig, and van Oost (1970). The basis of the SCOT framework is that every technology is shaped by society, and evolves over time to fit into society. There are four basic tenants of SCOT that must be clearly understood and defined with respect to a technology. The first is interpretive flexibility, or the idea that different groups or individuals will inherently perceive and interact with a technology differently. The second is relevant social groups, the groups that will either directly or indirectly interact with the technology. The first two pillars work directly together, as the unique interpretations are what define the social groups. The third tenant is closure, or the idea that when the social groups begin to agree on the interpretation of a technology, and the interpretative flexibility has been reduced, the technology has reached closure. The final tenant, stabilization, is similar to closure, but is within each social group. A technology has become stable when a social group's definition and interpretation of it is consistent. With these four tenants in place, one can examine a technology through the lens that society is more powerful than technology, and will shape its growth over time.

SCOT can easily be applied to donor mining, and for ease of explanation, the Children's Inn (CIN) at the National Institute of Health (NIH) will be used as an example. Serving more than 1,500 children each year, CIN is a place for families with children participating in research at the NIH to stay without cost (https://childrensinn.org/learn-more/). To stay competitive in the nonprofit space, CIN is attempting to discover insights about their current donor database using data mining techniques. Figure 1 shows an overview for the SCOT depiction of donor mining used at CIN, and while generalized, it proves to be a sufficient example for explaining how SCOT can be used to depict donor mining. Some of the relevant social groups, like CIN patients and the NIH, are specific to CIN, but the others are applicable to any nonprofit using donor mining.

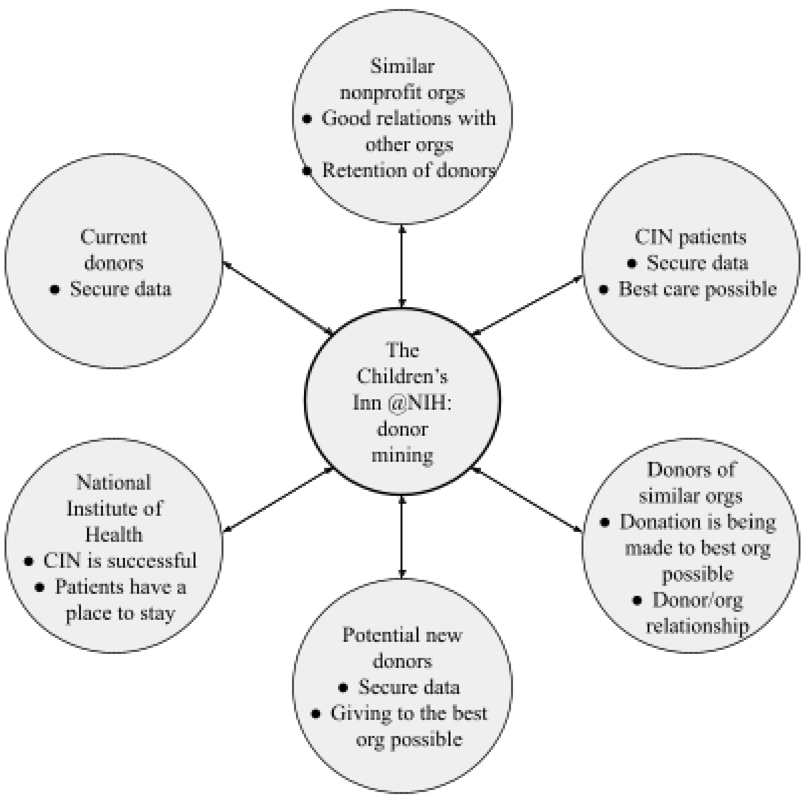

Figure 3: SCOT depiction of the Children's Inn at NIH using donor mining. The Children's Inn must understand what each stakeholder values and what each could gain and/or lose from CIN employing donor mining. (Adapted by Hammonds from Carlson, 2009).

The first is current donors, whose data is inevitably being used to perform data mining techniques. Many people may not even be aware of data being collected in the first place, much less being used in other organizations' marketing efforts (Fowler, 2020). This ethical dilemma is one that will not be examined in this paper, but this social group is critical to the success of the technology, as they are able to pull their funding if they do not approve of the spending of the nonprofit. Since donor mining is an expensive proposition, this could cause a nonprofit to no longer be able to use the technology if enough members of this social group discontinue their donations. There are other ethical issues in play with donor mining which will not be fully discussed in this discussion, such as the increasing disempowerment within nonprofits when data is used to drive decisions, as they often drift away from their missions and goals in the process of using data to move forward (Bopp et al., 2017, p. 3609). van Wel & Royakkers (2004) also bring up the issue of de-individualism, which can occur "[w]hen the judgement and treatment of people is based on patterns resulting from web-data mining" (p. 131). While these ethical issues are important, they are also not the focus of this paper.

The next relevant social group is potential new donors of the nonprofit. In addition to the privacy issues mentioned with the previous group, this group has the goal of giving to the best nonprofit possible, and a nonprofit effectively using donor mining may be better positioned to pull potential new donors than organizations who do not. This is because a nonprofit using data mining techniques will most likely have a higher proportion of each dollar raised going to the actual cause, as well as a higher return on investment (ROI). The third social group is the donors of similar nonprofits, which is a very similar group to the potential new donor group. As discussed with previous social groups, this social group will want their data to be secure, will want to be giving to the best organizations possible, and will want to maintain a healthy donor-nonprofit relationship. Donor mining can affect all three of these things, as it can tell a nonprofit the best methods to interact with each type of donor, effectively making those relationships stronger.

The final social group, and most relevant to this discussion, is similar nonprofit organizations. Nonprofits often share lists of donors and other information, so retaining good relationships with similar organizations is very important in this space. Even though these lists are purchased by number of names, an organization can choose not to sell its list should it feel as though it is being used against them. Each organization has the same goal of attempting to retain all of their donors. Donor mining can potentially increase retention if used, and so this may hurt the retention of other organizations. There are definitely some donors who will give to many organizations, even (or especially) if those organizations are very similar in their missions, while other donors choose to focus their donations on just a couple of nonprofits they feel are doing the best work.

The interpretation of donor mining by each of these groups is highly varied. In a case study done in the education sector examining data mining being performed on data from computer science students, it was acknowledged how much work had to be taken to obtain personal data of the students to begin with (Ihantola et. al., 2015). Beyond that, those performing the case study examined how the findings provided by the data mining could have a significant effect on the students' perceptions of their educational worth as well as the relationships they had with their peers (Ihantola et. al., 2015). Although the findings of data mining performed by nonprofits are often not published in the same way, if this was to be the case, it would certainly put strain on the donor-nonprofit relationship, as many data mining models "score" donors in terms of propensity to give and to be a high-level giver. Some of the donor groups, unless they have given a donation to a nonprofit specifically to perform donor mining, probably do not even know what data analysis processes are occurring behind the scenes to obtain and retain donors. On the other side, the nonprofits themselves are slowly starting to understand the power of data mining techniques (MacLaughlin, 2016). Some may know what donor mining is, while it may be a foreign concept to others. It is certainly possible that nonprofits using donor mining and those not using it may be two separate relevant social groups, or it is possible that the technology has not yet stabilized. The technology has certainly not reached a point of closure, most likely due to the fact that it is so new. When all social groups are similarly informed about the technology, then closure could be examined in more detail, but at this point in time, closure will not be seen soon.

ETHICAL EXAMINATION OF NONPROFITS USING DONOR MINING

Some ethical considerations considering data mining generally were brought forward in the discussion of SCOT, but the issue that will be examined in more detail is whether or not nonprofits should be able to use donor mining, acknowledging that it has significant benefits but is not easily accessible, especially for small or underfunded nonprofit organizations. Of course, competition is natural, so some may argue that those nonprofits strong enough to perform data mining must have survived in the nonprofit space this long for a certain reason, and the advantage they have now is deserved. However, this way of thinking discourages new competition, not just in the nonprofit sector, but in any market. New nonprofits should be encouraged to be formed without being afraid that they will have no means of competing with larger organizations because of unequal access to data-driven techniques.

Looking at this first dilemma from different ethical viewpoints, consequentialism and deontology will both be used to examine this question. Consequentialism is the viewpoint that any potential action should be evaluated, as its name suggests, by its consequences (Sinnott-Armstrong, 2019). That is to say, each action should be examined to determine what would result in the highest net "good" in the outcome, even if there are parts of the outcome that are bad. A consequentialist would most likely argue that if data mining is the only thing setting various nonprofits apart in terms of which ones survive, and there are new nonprofits potentially doing better (or more efficient in terms of money going to the actual cause) work than existing ones, those new nonprofits should have the same access to those valuable resources. This is because if the consequence is nonprofits doing the best or most efficient work fail to exist, then the maximum "good" is not being achieved. In the mind of a consequentialist, just because one nonprofit has the resources to successfully perform data mining, that does not mean they should do so, especially if it means taking donors away from "better" organizations. Of course, it can be difficult to determine if one nonprofit is better than another, but consequentialists would likely thoroughly examine this in order to figure out which are bringing about the most good in the world.

Deontologists, in comparison to consequentialists, believe that the choices themselves behind the actions should be evaluated to determine if they are morally "Right" under a series of rules (Alexander & Moore, 2020). Deontology differs from consequentialism in that the consequences do not matter at all in the decision, only the decision itself. Deontologists might argue that the action of using data mining is not in and of itself unethical, and although the consequences of those practices may be that larger and better-funded nonprofits survive, that consequence is not relevant to the ethical argument. There is nothing morally wrong with the action of performing data mining in a nonprofit. However, if the intention behind the action is to take donors away from other nonprofit organizations, it becomes a more difficult ethical question. If the action is performed with the belief that one's nonprofit is truly doing work that aligns more with the "Right" under one's moral beliefs, then it would be morally permissible. Otherwise, deontologists may choose to take the view that the action is ethically immoral.

There are also those who argue that there is an easy solution to this problem: that data scientists, much like lawyers, doctors, and others, should feel obligated to perform some pro bono work for nonprofits that cannot otherwise afford their services. Patterson et. al. (2020) explain that professionals who undertake pro bono work "experience positive feelings that engender their good intentions to help the underprivileged, those in need and society more generally," arguing that there certainly are benefits for those fortunate enough to have the option to perform this work. Data scientists have not long been one's first thought when it comes to pro bono work, but Perlich (2014) explains that as an emerging field with high value, data scientists have begun to perform work for social good more and more. Yet this raises another ethical question: is pro bono work unjust? Does each person not have a right to wages, and why should those in certain fields be expected to give up some of those wages for general social good? However, there may be a reason that society generally thinks of certain fields when it comes to pro bono work. Those fields are expensive for people to purchase services from, and therefore generally pay well to those employed in those fields. If services are too expensive for everyone to have access to, individuals can make the choice to give up some of their services for free. Consequentialists and deontologists would most likely both agree that pro bono work is not unethical, as long as the individual has the choice to participate and is not forced to do so by their larger company. Consequentialists would believe that because the outcome is that those without access to services now have access, it is morally correct to participate in pro bono work. Deontologists would argue that as long as an individual is choosing to participate for the correct reasons (they want to help and it is not simply a marketing move to make themselves or their company look better), it is also morally permissible. So perhaps pro bono data science work is a feasible option for some nonprofits moving forward, but it still does not solve the larger ethical question.

CONCLUSION

It may take some time for more data to be created concerning just how much value donor mining can add to a nonprofit, as it is still a relatively new technology. Although it has proven to be very lucrative for other companies, and should be just as effective for nonprofits, there is currently not much data to back this up (although my capstone team is attempting to prove, at least for a single nonprofit, just how much money could be saved by using these methods). Nonprofits, however, should be aware of the fact that should they pursue these methods, similar nonprofits may not have the in-house expertise or the funds to discover data-driven insights. They must consider how they may have unfair advantages if they are able to use data mining techniques, and the sector as a whole will surely, over time, come to a consensus as the technology reaches closure as to how best to fairly incorporate this technology into the sector.

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