A Case Study on Fundraising Analytics at Memorial Sloan Kettering Cancer Center

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ABSTRACT
Since 2006, analysts have worked with fundraisers and IT colleagues to use data to inform strategy in fundraising at Memorial Sloan Kettering Cancer Center (MSK). This case study reviews a range of projects undertaken over the years, and proposes a variety of potential future applications of data science to the field.

1. BACKGROUND

1.1 Memorial Sloan Kettering Cancer Center
As one of the world's premier cancer centers, Memorial Sloan Kettering Cancer Center is committed to exceptional patient care, leading-edge research, and superb educational programs. The close collaboration between our physicians and scientists is one of our unique strengths, enabling us to provide patients with the best care available today as we work to discover more effective strategies to prevent, control, and ultimately cure cancer. Our education programs train future physicians and scientists. The knowledge and experience they gain at Memorial Sloan Kettering has an impact on cancer treatment and the biomedical research agenda around the world.

1.2 Philanthropy at MSK
The Campaign for Memorial Sloan Kettering has raised more than $3.3 billion over the last twelve years for the priorities of the Center, including $380 million last year alone. Philanthropy accounts for roughly 14% of the Memorial Sloan Kettering budget each year, and provides essential capital infusions to fund major building and research initiatives. The Center regularly appears in the top echelon of the *Philanthropy 400*[1] hospital and medical center category.

MSK is unusual in the breadth of its fundraising operation. Roughly 4.5 million people have contributed to the Campaign since its inception in 2002. As with most things, a Pareto distribution is in effect, with the great majority of the funds being given by a small fraction of that total. To date, there are several gifts of more than $100 million included in the campaign total, including most recently, the gift to found the Marie-Josée and Henry R. Kravis Center for Molecular Oncology.[2]

1.3 Analytics in Fundraising at MSK
In 2006, MSK initiated a new strategic unit in its fundraising operation whose goal was to apply data science broadly across the operation. The application of these methods to fundraising is not precisely new. Direct response marketing efforts have applied rigorous analytics to decision making in that arena for decades, and this application continues to be essential to our mass-market efforts to recruit and engage donors.

However, while direct response is important for recruiting new donors for the coming decades and stewarding loyal planned giving donors, the bulk of any given year's success depends on the identification and cultivation of donors at all levels, including those at the multi-million dollar level. Initially, the

[1] http://philanthropy.com/section/Philanthropy-400/237/

[2] http://www.mskcc.org/pressroom/press/landmark-gift-100-million-marie-josee-and-henry-r-kravis-foundation-will-support-groundbreaking-approach-precisi

Analytics group's focus was on creating a process to identify donors with the potential to give major gifts. As the analytics effort at MSK developed, the scope of the group's responsibilities broadened beyond identification projects to strategic applications of data and technology for planning and implementation across the operation. The group now consists of four analysts, with deep collaborations in IT and with fundraisers and managers.

2. AREAS OF INQUIRY

When freed from the old question of mail response, the variety of opportunities for application of data science to fundraising explodes. Any and all projects that observe the makeup and behavior of the many segments of the donor populations can be strategically applied to recruit and engage donors in MSK's mission. A number of current projects are described below, organized according to our efforts to observe the nature of the donor population, identify donors who would be most likely to be responsive to particular fundraising efforts, inform strategy, and measure results.

2.1 Observation

Traditionally, donor engagement strategies are organized according to different gift ranges and communications methods. For example, strategies have been developed to appeal to donors of gifts of less than $1,000, or donors of gifts of more than $25,000. Alternatively, strategies have been developed to communicate with donors in the mail vs. online. These segmentation approaches tend to organize donors according to a framework that is convenient for the organization's internal structure, rather than the nature and needs of the diverse donor population.

Taking a different tack, the philosophy underpinning many of these projects is to take a bird's eye view of the donor population and attempt to observe clusters of donors who are similar to each other, and allow the similarities and differences in donor demographics and behavior to guide our engagement efforts.

2.1.1 Multi-channel Donor Demographics

In this example, Development Analytics collaborated with the marketing team to characterize donors who give solely online, offline, or through multiple channels. This type of analysis allows for segmentation of giving populations in order to create targeted programs and engagement strategies based on available transactional, behavioral, and socio-economic data.

In Figure 1, the age distribution of three different populations is compared: one group that has given both through online and offline channels, a second group that has made two gifts or more, with all gifts only made online, and a third group of donors who have made at least two gifts with all gifts made offline. (Offline gifts are generally made through the mail.) Multi-channel donors tend to be younger than offline only donors, and online only donors are generally the youngest of the three groups.

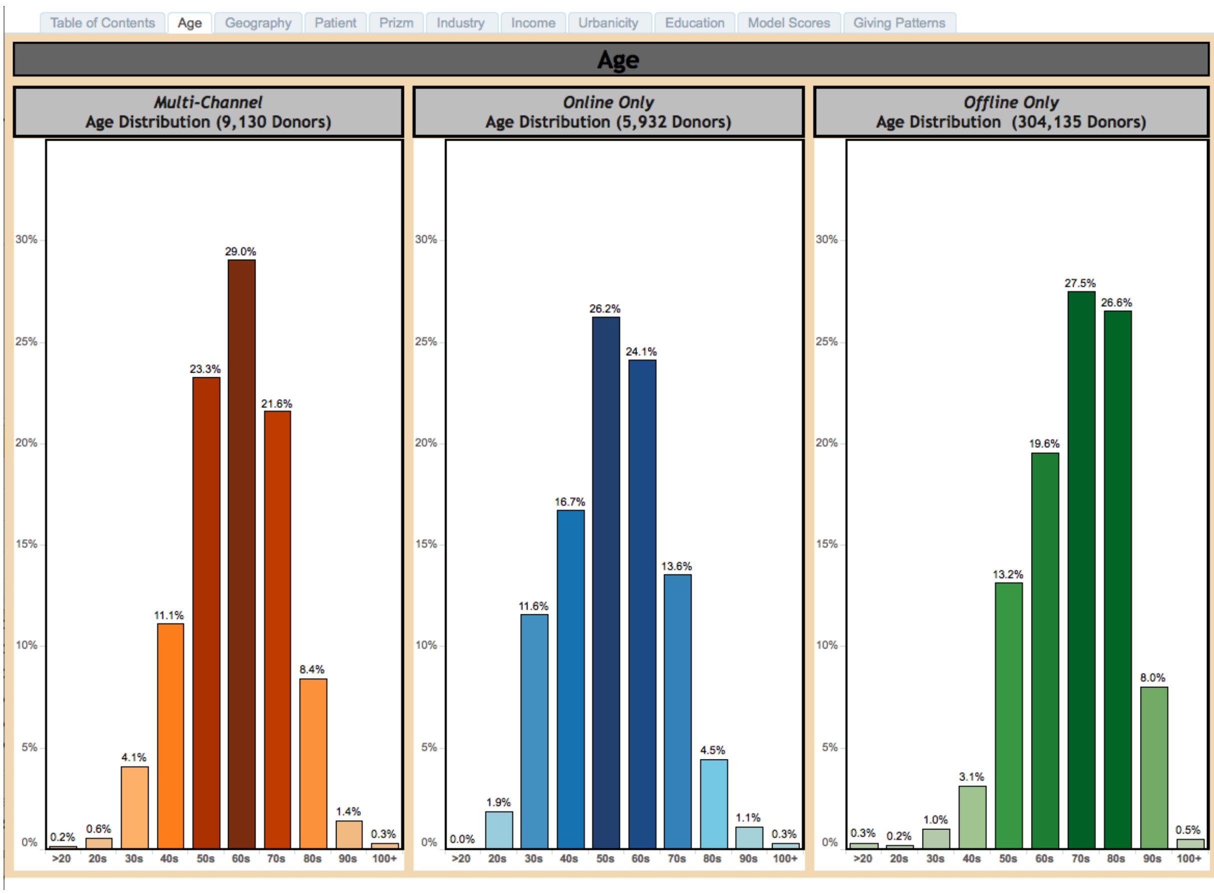


Figure 1: Comparison of Age Distributions

This analysis is repeated for geographic variables, giving patterns, and qualities derived from Nielsen Claritas Prizm segments[3] to give a multi-dimensional view of the three different groups of donors. Fundraisers can then use this information to tailor the communications they send via different media to the audiences in question.

2.1.2 *Stewarding Bequest Donors: Age at Last Gift*

Donors who make bequests to MSK are generally deeply loyal donors who have given many small gifts to the Center over the course of years. Many of these donors also live to be quite elderly. The planned giving fundraisers are faced with a dilemma. Given that many donors stop giving years before they pass away, when should the Center stop communicating with them? On the one hand, these are important donors who care about the Center and may have left bequests. It would be unfortunate and impolite to cut off the relationship prematurely. On the other hand it is wasteful and sometimes painful for donors' families if the Center continues to communicate with the donor after their passing as if they were alive.

Using data gathered during the administration of past estate gifts, the Analytics group plotted the following graphs showing the age of estate donors at the time of their last gift against the age of estate donors at the time of their death. Based on this information, it appears reasonable to contact elderly donors up to four years after their last gift. The team was also able to recommend mailing rules that suggested if a donor has not given in four years and is over a certain age, there is a high likelihood they are deceased and should not receive communications from MSK.

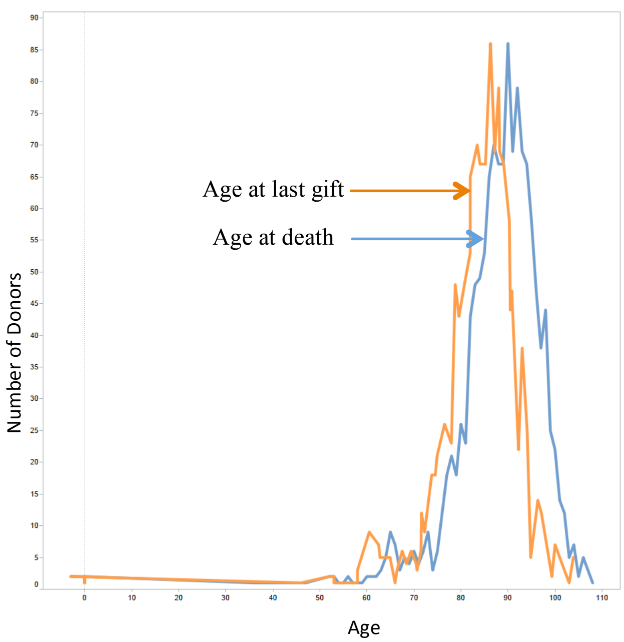


Figure 2. Age at last gift vs. age at death for determining planned giving communication rules

[3] http://www.claritas.com/MyBestSegments/Default.jsp

2.2 Identification

2.2.1 *Predictive Modeling*

For 44% of donors who ultimately give $1 million or more, their first gift to MSK is under $1,000. Yet 1.7 million of our active donors have a first gift of less than $1,000. Using predictive modeling techniques, we have identified and successfully upgraded thousands of new major gift-level prospects, with several having made gifts of more than $1 million.

Using classification techniques (usually logistic regression is the winning algorithm), the group has built a variety of models to score donors on their likelihood to give at various levels and in various ways. Examples include: likelihood to give a single gift of $50,000 or more, likelihood to make a realized bequest of $25,000 or more, and likelihood to become a Cycle for Survival participant.

These models have been highly reliable – backtesting results are reported in Table 1. Each row shows the percentage of new donors who satisfy the target conditions for the specific model and scored in the top 5% of the file when the model was created.

Table 1. Model Backtesting Results

Model	Successes in Top 5% of Scored File
Major Gifts ($50K+ Gift)	68%
Annual Giving ($1 - $25K)	60%
Planned Giving (bequest)	77%

As donors exhibit new behavior in the form of giving or engagement, our automated feeds use the data to update the model results, allowing fundraisers to see changes in the data and use it directly in their decision-making.

2.2.2 *Clustering*

The group has also experimented with unsupervised clustering methodologies to divide the pool of constituents into clusters defined by the donors' similarities in the database rather than the department's self-imposed business logic. These initial experiments confirmed that clusters can be identified that have significantly different expected

lifetime value from each other. The clusters show promise as a method to personalize communications and streamline investment.

2.3 Strategy

The team's collaborative work with fundraisers, management, marketing, and IT puts it in a unique position to identify undetected opportunities that may contribute to long-term fundraising strategy.

2.3.1 *Regional Experiments*

The Center's broad base of supporters is concentrated in the greater New York City metropolitan area and on the coasts of Florida. However, there are pockets of donors spread throughout the country. In an effort to investigate the viability of programs focused on areas outside of MSK's core geographic areas, and to test the impact of a personalized outreach strategy, Analytics collaborated with the Annual Giving program to implement a controlled experiment.

Over the course of three years, the Annual Giving group reached out personally to donors in several regions. In each case, the donors received a personal letter from a fundraiser, inviting the donor to an event that was expected to take place in the area shortly. The fundraiser followed up with a telephone call, and spoke with the donor if possible. If the donor could not be reached, a voicemail message was left. The calls were stewardship calls, focused on thanking the donor for previous giving and reaching out to continue the relationship between the donor and the Center. There was no direct solicitation in the outreach plan.

Donors were selected for the experiment using the Annual Giving model, which scores donors on their likelihood to give a gift between $1,000 and $25,000. In each region, a group of 1,000 donors was selected by model scores. Then 200 of these were randomly removed from the experiment group to serve as a control. After sufficient time had elapsed, the change in giving was compared between the experiment group and the control group.

Results in all locations supported the classic fundraising belief that increased personalized contact results in higher giving. In all cases, donors who were contacted increased their giving over the experiment period more than the control group. The results in Chicago and California are good examples.

In Chicago, the average gift and total amount given by the contacted group was more than twice what they would have given if they had not been contacted. The project could show that it brought in more than $62,000 that would not otherwise have been received.

In California, the total raised from the contacted group was more than 3.5 times what the control indicates they would have given if they had not been contacted. This experiment was particularly dramatic as the experiment took place in early 2008, as the California economy was struggling. In fact, giving by all of these donors went down during the experiment period as compared with the previous year. Giving from members of the control group plummeted 70%. However, giving by members of the contacted group only went down by 38%.

Without the context of the control group's results, the whole effort would have appeared a failure – a 38% decrease in giving only shows as a success when compared with the 70% decline in the control group. Despite the decline, it follows that nearly $36,000 was raised as a result of the group's personalized outreach that would not have otherwise been received.

2.3.2 Forecasting

Since 2009, the Analytics group has been forecasting cash results for the fundraising operation at the end of the coming year. As with many organizations, a very large percentage of MSK donations are received during the last two weeks of December. Since MSK is on a calendar fiscal year, the end of the year is quite suspenseful. To give management a sense of the progress being achieved during the year, the Analytics team forecasts results periodically.

Using historical cash giving totals reaching back to 1976, the team builds a data file broken out into donor types: individuals, foundations, corporations, and estates. The individuals are then further broken out into gift ranges: totals from gifts of up to $1,000, between $1,000 and $24,999, between $25,000 and $1 million, and between $1 million and $10 million. Gifts larger than $10 million are not included.

Using time series forecasting algorithms provided by SAS, each series is forecasted to the end of the current year and the end of the next year. The full, unsegmented series is also forecasted. ARIMA models using stock market indices as covariates have also been estimated. In the case of the segmented series, each segment's forecast is then added to the others to form a total forecast for gifts of up to $10 million for the current and coming year.

These results have been very successful, coming within 2% of the final total each year. Generally the most accurate forecast has come from the sum of the segmented forecasts. The stock market indices seem to adjust the results too low to be accurate. If our leadership is aware of potential gifts of more than $10 million that are expected, they would add them to the forecast – these are not included in the statistical exercise due to the low sample size and the high impact on the total.

2.3.3 Feasibility

In 2014, as the economic environment was finally recovering from the financial crisis, the team studied the untapped potential of the donor population and estimated potential revenue that could be expected given a variety of input scenarios over the next ten years. The result is a model that combines forecasting, fundraiser prospect portfolio optimization, and scenario analysis methodologies to identify an expected revenue range based on performance indicators and selection of strategic options.

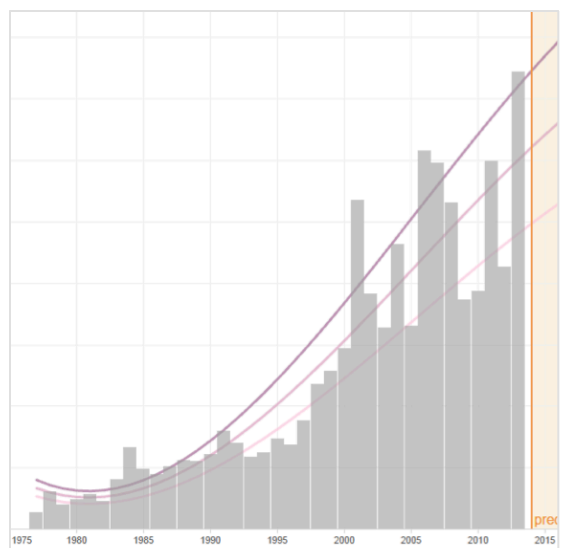


Figure 3. Low, medium, and high forecasts were estimated from forty years of giving data.

Statistical forecasts similar to the previous section were estimated for gifts below $50,000. Then the team estimated the range of potential outcomes that would result if the fundraising operation hired various numbers of fundraisers who would concentrate on the largest gifts.

These scenarios depended upon defining a "strike zone" of current donors with the financial potential to make very large gift as well as very high major gift model scores. Using historical yield rates calculated based on giving as a fraction of a donor's financial capability, the team estimated the amount a fundraiser could expect to raise from a pool of specific high quality prospective major gift donors.

Fundraisers with tenure at MSK of four years or more are observed to have higher yield rates. Using this timing, the relevant yield, and the financial capability of the pool of prospective donors, a range of different potential results were calculated based on various staffing ramp up scenarios. These results were then combined with the forecasts for smaller gifts to estimate a reasonable range for expected fundraising results over the next decade.

2.4 Metrics

2.4.1 Direct Mail Impact

In the area of program evaluation, the team's broad-based, long-run perspective enables it to provide a comprehensive view of the impact of a program on the overall fundraising effort.

For example, by taking a long-term, system-wide view of the direct response program, we were able to track the flow of donors from acquisition by direct mail through giving at the various high-end gift levels, often years later. (In fact, for donors whose first gift is under $1,000, it takes a median of 10 years to go from a donor's first gift to their first gift of more than $1,000.)

The team was able to show that many donors who began their relationship with the Center through the direct mail program have become contributors to our fundraising programs on a higher level over the long term. In fact, more than 14,000 donors who were acquired by the direct mail program ultimately gave a gift of more than $1,000.

Looking forward at donors with potential to be future major gift donors, 83% of donors in the top 5% of major gift model scores were acquired by direct mail. Recognizing this goal in addition to short-run fundraising response and renewal, the direct mail program is using the model scores for major and planned giving to target the acquisition of donors who score highly on their likelihood to make these particularly valuable gifts.

2.4.2 Program Evaluation with Retroactive Comparison Groups

While it would be optimal to be able to design controlled experiments as described above for all our programs, this is not always practical. Faced with the need to determine whether our annual giving fundraisers are making a difference with the groups of donors they have cultivated, the team built retroactive comparison groups to provide context.

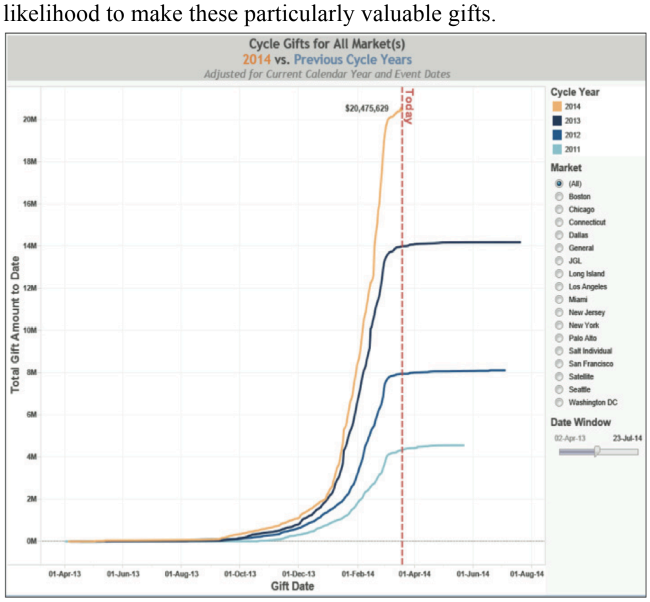
In order to achieve this, a group of donors not addressed by any program outside of direct mail ("unassigned donors") were assembled, one at a time, by identifying one unassigned donor for each assigned donor with as many characteristics in common as possible. The two donors would have similar model scores, be from the same region, and have similar giving histories. After each unassigned individual has been identified, that group forms a comparison group to assess the differences in donation activity between the assigned and the unassigned groups. This produces a rough picture of the impact of the contact made by the fundraiser.

2.4.3 Cycle for Survival Event Dashboards

Visual analytics are a key element in our fundraising operation to effectively deploy metrics on program performance and provide ongoing data-driven evaluation directly to management and front-line staff. Development Analytics develops dashboard visualizations that take the place of tables, lists, and reports to allow effective and efficient interpretation of data that is automatically updated on a daily basis.

The example in Figure 4 shows two views from the dashboard used by the Cycle for Survival team to monitor progress through the event's fundraising season. Cycle for Survival is an indoor cycling fundraising event that brings teams of riders together to raise money to benefit research on rare cancers[4]. The participants reach out to their extended network to raise money, then on the day of the event, join their teams to ride in half hour increments.

There are several key metrics that the group needs to monitor



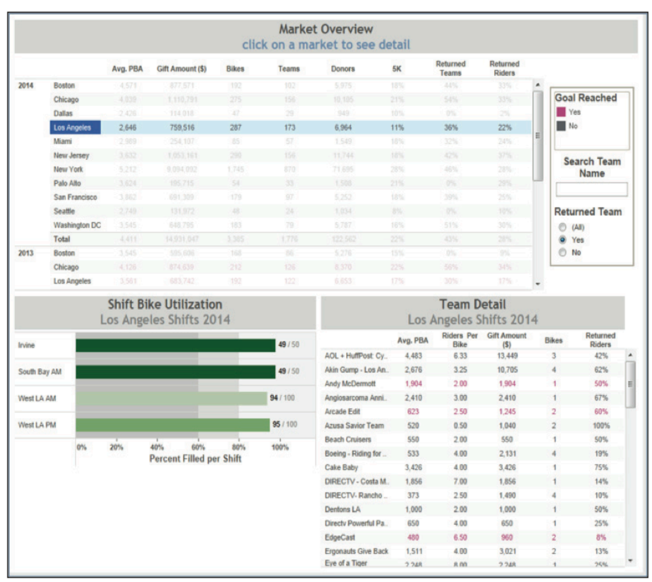


Figure 4. Cycle for Survival Event Dashboards

[4] www.cycleforsurvival.org

throughout the season. Initially, Cycle fundraisers are focused on recruiting teams of riders and filling the bikes reserved for the event. As the season moves forward, the focus shifts to helping teams and riders raise as much money as possible.

Since the event is capacity constrained (there are a finite, determined number of bikes available), the ultimate success of the event is determined by filling all the bikes with teams and riders, then maximizing the teams' per bike fundraising average.

The dashboards track these key metrics for each market where the event is held, as well as reporting aggregate totals for fundraising compared to a similar time frame in previous years. They update automatically overnight with the newest data from the previous day.

3. AREAS OF POTENTIAL

In presenting the team's work at the *Workshop on Data Science for Social Good*, we hope to broaden the understanding our data science colleagues have of the complexity and variety of questions to be addressed in this arena. It would be valuable to get feedback on potential improvements to existing projects or new avenues that could be explored. Some ideas being developed are described below.

3.1 Networks

Variables that seek to approximate the connections between donors in the MSK fundraising database already demonstrate the potential for predictive power, including family and friend relationships to other donors and various connections to the Center, including engagement via events or planned giving. Social network analysis would seem to have great potential to add to our predictive efforts. Measures of network centrality could form new model variables.

Passionate donors with powerful networks could be engaged to inspire their connections to give and recruit other new donors to support the Center. Influential donors could be ambassadors for the mission on social media and through other modes of social discourse.

In addition to social network analysis, text and sentiment mining appear to have some potential in this arena. As people are inspired to discuss our mission publicly, can we identify and steward people who are passionate about our cause? When we are interacting with our donors, can we mine the notes in our database to understand anything new about the nature and status of the relationship?

3.2 Pathways

What are the common pathways a donor takes through his or her relationship with the Center? Do they start as a patient or a caregiver? Do they attend events, make donations, raise money for research? Can clusters of donors be identified and supported who take similar paths? Sequence and associate rules might have potential here. Also, how should we think about churn in the context of (hopefully) recurring giving? Is there an opportunity to prevent a lapse in donation and support donor loyalty?

3.3 Time

One area the team has only touched on marginally so far is looking at time in the context of the donor experience. Considering the churn questions above – at what point after a gift should the Center consider that a donor has lapsed? Is there a point where preventative action should be taken?

Can we estimate time to next gift? Would survival analysis be useful? How would our likelihood models be altered if we brought in the element of time? Are there improvements that these projects could bring to our forecasts and feasibility estimates?

3.4 Motivation

Why do donors give? Are there different clusters that could be identified as having different motivations? Can we tailor our appeals and strategies to our various constituencies with an eye toward promoting action in the fight against cancer?

There are opportunities to bring market research to bear on the messages and segmentation strategies pursued at MSK. Online tools and data, as they become available, present a whole new world of opportunities for personalized communication. How can our donors be organized in order to communicate with each individual in as personal a way as possible, given the constraints of time and funding?

In summary, Development Analytics is critical to MSK's strategy to recruit and steward the passionate people who will support its mission for years to come. There are still many questions to be addressed; any input the community of data scientists can provide will be greatly appreciated.

4. ACKNOWLEDGEMENTS

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