



MOORE

Death to Buckets:

Toward More Profitable and Satisfying Segmentation

Introduction

You've probably used the bucket analogy to explain the need for donor acquisition:

- You have a bucket full of donors.
- The bucket has holes in it.
- If you want your water level to rise (i.e., get more revenue), you must fill the bucket faster than water is leaking out.

Simple and easily understood. But our buckets are very leaky. Eighty percent of first-time donors won't become second-time donors within a year. Almost 40% of multi-year donors won't give again.¹ At the current rate, our donor files will be halved in the next decade, on average.² Our buckets have too many holes.

Maybe our donor buckets leak because we insist on putting donors in buckets.

You know the buckets. Lapsed versus active. Single versus multi. Digital versus mail. \$100+ versus under \$100. Generations versus other generations.

Each bucket does a job, trying to pick the things that are most like each other and exclude the things that are most unlike each other. But they do that job so poorly.

It's time to kill the buckets. It's time to embrace the genius of the "and".

Any one data point is a poor predictor. But all of them together—transactional *and* consumer *and* behavioral *and* historical *and* demographic *etc.*—can create a rich model that helps you better acquire, keep, and upgrade donors. And the human brain can only keep track of so many categories at once; this is best done with algorithms.

Consumer marketers are doing this already to make us buy things. Only when we get rid of the bucket will we be able to grasp the relevance that makes our buckets less leaky and puts us on a par with those who want to sell things, not impacts.

We'll talk about the pitfalls that befall us as we work to create a one-on-one relationship with our donors and potential donors. Then we'll discuss what an ideal solution looks like in theory. And, to show that this isn't just complaining about the current segmentation regime, we'll talk about how this has been implemented this in both acquisition and donor communications with reaped rewards.

¹ Fundraising Effectiveness Project (2020). 2019 Q4 Report. Retrieved September 16, 2020, from <https://afpfp.org/reports/>.

² Ellinger, N. (2019, March 18). Three Scenarios for The Future of Individual Giving. Retrieved September 16, 2020, from <http://agitator.thedonorvoice.com/three-scenarios-for-the-future-of-individual-giving/>.

The Challenges of Donor Segmentation

While we'll address five major segmentation issues here, they are only the tip of the iceberg. Each of these, and more, make it difficult to segment your donor file accurately, so most donors go through an organization undifferentiated from any other donor. We'll talk about each challenge, then discuss a better way forward.

1. Lack of segmentation begins at the beginning: the cultivation fallacy

We direct marketers think we are superior to mass marketers. And we are. They spend their money on Super Bowl ads, billboards, and radio spots that promote alcohol to the 30% of Americans who don't drink, meat products to the 5% of Americans who are vegetarian or vegan, and political candidates to the 40-60% who thinks that candidate would destroy us all.

And we are superior—that's all a waste of money—but not by as much as we would like to think. We do have screening criteria for who comes into our organization, but they are very broad:

- Outside list acquisition means they donated to a specific organization
- Traditional co-ops mean they likely donated to several organizations
- Unattributed digital gifts mean they found you and liked that one offer
- DRTV means they put their hand in the air to support you

But beyond the self-selection of supporting you and the channel in which they chose to do it, you know little else about that person. That means that donors come in the door as a largely undifferentiated and undifferentiable mass.

Many are OK with this because they believe in the cultivation fallacy: that continual, consistent communication will turn the members of this horde into satisfied, productive loyal donors. It does happen, but it's the exception rather than the rule. We're hoping to have happy long-term relationships with donors by having the same first date with donors over and over again...

And over and over and over again. Everyone gets the standard welcome messaging, even though it could be turning off your loyal donors.³ Everyone gets the email newsletter and the full diet of emails whether they open them or not. Everyone is included in the standard renewal campaigns for the first 6, 12, 18, or however many months, regardless of how likely they are to donate.

³ Ellinger, N. (2017, December 14). Killing the One-Size-Fits-All Onboard. Retrieved September 16, 2020, from <https://agitator.thedonorvoice.com/killing-the-one-size-fits-all-onboard/>.

In doing so, we are Procrustes, the hotelier from hell of Greek myth. He had a bed where passersby could spend the night. If they were too short to fit the bed, they would be stretched to fit it; if they were too tall, they would have the “excess” lopped off. Our introduction to the organization is one-size-fits-no-one: too much for some, too little for others, too generic for everyone.

Relationships are fostered through increasing depth, not breadth. Each communication needs to talk to each donor in a way that speaks to them, not to the mass, lest we become like the aforementioned alcohol, meat, and political merchants who don't know who is who in their appeals.

2. Lack of meaningful data

This lack of differentiation among donors at the outset, and beyond, is because we don't have meaningful data about a donor. Let's take four donors to a disease organization on the same day:

- She's a researcher working on your disease. You featured some of her research in your newsletter and she was reminded to give you a donation.
- She was diagnosed with the disease you are working to eradicate. She found tips on management and coping on your web site and wanted to show her appreciation.
- A favorite high school teacher of his just passed away. The obit said in lieu of flowers to donate to your organization. He did, knowing he wouldn't be able to travel back for the funeral.
- She got a person in the office Secret Santa drawing and, knowing little about him other than his mother suffers from the disease, donated in his name.

Four different donors. Four very different reasons for giving. Four extremely different likelihoods of ever giving again.

And yet your database will record them all as a \$50 donor on December 3rd. They'll all be part of the same cohort, same appeals, and same messaging unless someone does something unexpected like giving again or dying. (With poor data systems, this latter option may not even be sufficient.)

We cluster based on transaction because it's the data we know. This is referred to as the streetlight effect, going back to the old joke where a man has lost his keys and is searching under a streetlight. A passerby helps look for a while and finally asks whether he's sure he lost them under the streetlight. The man says "no, I lost them in the park, but here's where the light is." We use the data we have, not the data we would want in an ideal world.

This leads to inadvisable conclusions that a donor who donated 23 months and 28 days ago is fundamentally different from one who donated 24 months and 2 days ago. One goes in the active (or shallowly lapsed) bucket; the other goes into the lapsed bucket. And yet, if these donors have everything else in common, their trajectory will be much more similar than our disease sufferer and our Secret Santa donors above.

Fortunately, these data exist: additional transactional data, demographics, life events, self-expressed data, behavioral data, prior relationships with your organization and more. We can use them to break these buckets. We can learn more about our donors and differentiate among them in intelligent ways. Our doing so will make them happier and us happier with the results.

3. Organizational challenges

Sometimes the data you need exist but they are locked away in that hardest of all places to access: your own organization. Let's leave aside for now the technical challenges of getting all your internal databases to talk to each other; those are significant, but not insurmountable. Rather, there are institutional barriers to getting critical information about donors by people who misunderstood '80s movies and thought the snot that said "that's on a need-to-know basis and you don't need to know" was the hero.

While there are few silver linings to the COVID-19 pandemic, one of those very few slivers of hope is that it has given lie to some people's siloed thinking. To wit, pre-pandemic, event managers would talk about "their donors"; if you were to get your grubby direct marketing paws on them, there would be blackout dates, limits on how many times you could communicate with these donors, and more. That's if you were negotiating with an open-minded events person. The closed-minded ones just say no.

Then, COVID-19. Organizations, faced with no revenues from event donors, wisely decided to open the doors to direct marketing for these donors. Turns out, some of them were donors to the event, not the organization. And some of them were donors to the organization, not the event.

The people in this latter group should always have been asked for more in different ways. They wanted to help but were prevented from doing so because of internal rules. Those rules that assumed the event person knew best didn't benefit the organization; it lost out on revenue. They didn't benefit the donor; the donor wasn't able experience the joy of giving in the ways they found beneficial. It probably didn't even benefit the event donor gatekeeper.

Further, it prevented the organization from having a full view of that donor. Some donors are event and direct marketing donors, but a poor system view of that donor prevented you from soliciting, thanking, and receipting that person correctly.

This is not just for events. It's likely that volunteers and former volunteers to your organization are significantly more likely to give. But if the direct marketer doesn't have that information, they can't include that in the model, match that name to those on outside lists, or give that person the personalized treatment they deserve when they are solicited.

For hospitals, grateful patients are a rich source of potential donors. Unfortunately, the farther they get from their treatment, the less likely they are to donate. One hospital found that every 30 days that passed before a solicitation went out after the patient's first visit dropped response rate by 30%. Every 30 days that passed before a solicitation went out after the patient's final visit cut response rates in half.⁴ While the treatment side of the hospital is right to be concerned about patient privacy, they are wrong that HIPAA would prevent information sharing, as it allows for demographic data, health insurance status, dates of service, general department of treatment, outcome information, and who treated the person to be shared.⁵ When this information is not shared, it not only cuts off donors who are potentially the best prospects, it prevents you from being sensitive to the person's treatment and experience in your communication.

You need a system that can cut through the technological barriers and can prove the value of a customized donor journey for each donor to help keep those who would erect fundraising silo at bay.

⁴ Chuan, A., Kessler, J. B., & Milkman, K. L. (2018). Field study of charitable giving reveals that reciprocity decays over time. *Proceedings of the National Academy of Sciences*, 115(8), 1766-1771.

⁵ Association of American Medical Colleges. (2014, April). *When Federal Privacy Rules and Fundraising Desires Meet: An Advisory on the Use of Protected Health Information in Fundraising Communications*. Retrieved September 21, 2020, from https://www.aamc.org/system/files/c/3/376966-hipaa_advisory.pdf

4. Failures of single variables, intuition, and violating Simpson's Paradox

"Four blind men went to the zoo and visited the elephant. One blind man touched its side and said, 'The elephant is like a wall.' The next blind man touched its trunk and said, 'The elephant is like a snake.' The next blind man touched its leg and said, 'The elephant is like a column.' The last blind man touched its tail and said, 'The elephant is like a broom.' Then the four blind men started to fight, each one believing that his opinion was the right one. Each only understood the part he had touched; none of them understood the whole."⁶

Many will tell you there is an ideal way to segment your file that goes beyond transactional information. In fact, they will tell you the best way, possibly the only way, to segment your file with just one variable. And it just so happens that this usually corresponds to the variable they have for sale:

- F2F canvassing organizations talk about age as *the* predictive variable of whether a sustaining donor will, in fact, sustain.
- Wealth screeners talk about how knowing how much wealth someone has will predict whether they will give that wealth to you.
- Organizations that sell surveys will tell you that only zero-party data from donors' mouths is valuable.
- Email marketing systems make it easy (OK, easy-ish) to stop sending emails to those who haven't opened in a while.

All these variables are predictive. And yet they are all only part of the elephant. Older donors, wealthy donors, survey answerers, and email openers all behave differently from the young, poor, shy, and email-shy. And these are only four of literally hundreds of variables that can make a difference.

It makes more sense to look at donors in their totality than to think only about the elephant's trunk, differentiate only on the trunk, and swear by the trunk. And it's more predictive of their future behavior, whether it's information you have before they are acquired or after.

Even a one-variable segmentation, however, is an improvement on intuition to segment and dictate communications. This often elevates anecdote and stereotype to the level of truism. It leads to rules like "don't email the mail donors; they are old

⁶ Mitchell, S. (1976). *Dropping Ashes on the Buddha*. Grove Press: New York, NY.

and don't get email" or "all people with Hispanic-sounding last names should get our Spanish language materials," which are as unsuccessful as they are arbitrary.

Mixing one-variable thinking and intuition together, some segmenters would take one bit of data about results—say, females respond better than males overall—and try to apply it to each subgroup.

This brings up an interesting statistical paradox called Simpson's Paradox. This has nothing to do with Homer, Marge, Lisa, Bart, and Maggie. Simpson's paradox is a statistical oddity where the whole of a sample can go one direction while all subgroups go the other direction.

Let's take an example of retention with rounded numbers to make the math easy.

In year one, you have:

	New donors	Multi-year donors	Total
Total from previous	100,000	100,000	200,000
Retained	25,000	75,000	100,000
Retention rate	25%	75%	50%

You do two things correctly: you invest in acquisition to bring in new donors and you invest in retention to keep the ones you have. So in year two, you have:

	New donors	Multi-year donors	Total
Total from previous	200,000	100,000	300,000
Retained	60,000	80,000	140,000
Retention rate	30%	80%	47%

Your retention rate went up for both new donors and multi-year donors, but your total retention went down because of the composition of your file.

So going back to our "females respond better than males, overall" example, you might be making a mistake to prefer women over men in your segmentation because it could be that in most RFM-based segments, males outperform females.

This shows the complexity of good segmentation. Not only is it based on multiple variables and rationales, not hunches, but it also requires a strong statistical understanding to do right.

5. Big buckets

Linda and Susan are both donors to your disease organization. That's where the similarity ends.

Linda has the disease your organization fights. She used your resources to learn about the disease and beat it back. She's volunteered to help others with this disease and with healthy living education. She's been a walk captain for you. She's donated 70 times in over 20 years of giving, offline and online, with steadily increasing gift amounts. She last gave \$40 four months ago.

Susan had a distant uncle who passed from the disease you treat. She gave once when he passed away three years ago, then forgot about you. About five months ago, she gave \$30 again.

Should these donors be in the same segment? Certainly not.

Linda models as someone deserving of a different treatment, possibly with a different offer—monthly giving, planned giving, or other upgraded giving. Susan is a coin flip to make another gift, at best.

Yet through the lens of traditional recency, frequency, and monetary value (RFM) analysis, they are both 4-6 month, \$25-49.99, multi donors.

As marketing professor Mark Ritson put it, “If your segment is populated by different people who want different things, it is not a segment. It's a joke and so are your skills as a marketer.”⁷

Yet that's what we do when our buckets obscure things like demographics, experience with the organization, volunteering, cause connection, and more. Our buckets are full of people who want different things.

The solution is to create an appeal—in acquisition or for donors—that treats every person as an individual and builds up from there. It means additional information is needed and extra effort going into modeling but is a better solution for you and for your donors.

⁷ Ritson, M. (2017, June 26). Mark Ritson: Only crap marketers mistake stereotypes for segments. Retrieved September 17, 2020, from <https://www.marketingweek.com/mark-ritson-stereotypes-segmentation/>.

The Solution in Theory

The difference in a post-segmentation world starts at point of acquisition. People acquired from list rentals or traditional co-op are *acquired*. Next generation co-op donors are *chosen*.

They are chosen not because they give to a bunch of nonprofits. That's still part of the equation, but it's no longer the whole equation. Rather, potential donors are chosen based on their overall fit to your organization based on all available data: behavioral, consumer, demographic, historical, and, yes, transactional.

Each bit of data makes the model that much more predictive. For example, literature reviews of peer-reviewed studies found that age, education, religion, means of solicitation⁸, sex/gender, family composition, and income⁹ are all predictive variables in whether someone will give or not. And that's before you ever consider previous giving to other organizations, previous giving to your organization, volunteer history, and connection to the cause that we know are all predictive.

You might say that these can't all possibly be used to segment your file or your prospects. Even if you had only two types of these 11 different variables, you'd have over two thousand different segments.

This would work and would be a good step forward to segmenting your file on the path to abandoning buckets altogether on your way toward an individualized predictive model.

A predictive model looks to predict an outcome, laying odds on each potential possibility. In our case, we're looking to predict whether someone will donate.

The segmentation you were using was a predictive model: It predicted that your 4-6 month, \$25-49.99, multi donors would have a response rate of 7% and an average gift of \$41 because that's what that segment had last year.

It just wasn't a very good model. It assumed that Linda and Susan were both 7% likely to give a donation, although Linda was much higher and Susan much lower. You would be wasting money if you had the same communication strategy for both donors.

⁸ Bekkers, R, Wiepking P. (2011) Who gives? A literature review of predictors of charitable giving part one: religion, education, age and socialisation. Voluntary Sector Review. 2011;2(3):337-65.

⁹ Wiepking, P, Bekkers, R. (2012) Who gives? A literature review of predictors of charitable giving. part two: Gender, family composition and income. Voluntary Sector Review. 2012;3(2):217-45.

That's why we advocate for individual, not segment, level predictions. Instead of arguing that this big bucket of dissimilar people will have the same likelihood of donating, it starts with the person and their particular probability of donating.

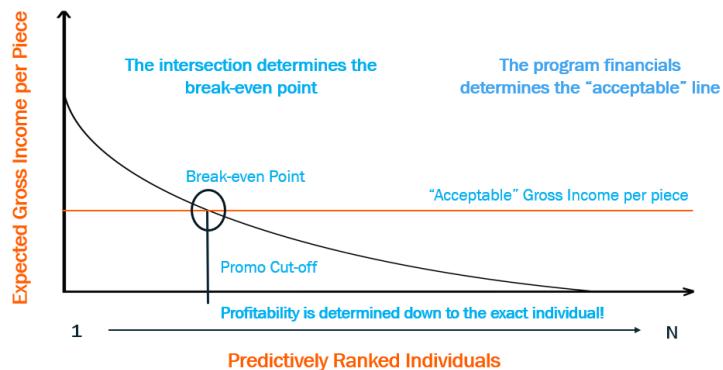
We can start by doing this by hand. Let's say you *had* to get someone to donate to your appeal. Maybe you'd start with your mom, who has a 99% chance of donating if you write her a letter (there's a 1% chance that she thinks it's from Publisher's Clearing House). If you had to get 20 people to donate, #20 is probably your flaky cousin Robert, where there's a 50/50 shot he'll donate if you text him to remind him.

Your task with your communications, however, is to line up the 1,000, 10,000, 100,000, or 1,000,000 people most likely to donate. At this point, even the most robust virtual Rolodex is used up; it's time to use technology to predict likelihood of giving.

An individual-level predictive model for donations does exactly what you were doing by hand *en masse*: putting people in order in their likelihood of taking the action you wanted them to do. If you wanted to mail 250,000 people an acquisition appeal, it would be able to tell that person #250,000 in line's chance of donating is .54339% and you would do better to mail her than person #250,001 who has a mere .54338% chance of donating.

Because of this, individual-level predictions done well will always, **always**, perform better than segmentation. Even if you got your buckets down to two people each, a predictive model should be able to tell you the difference between those two people given sufficient individual data.

In fact, this hopefully makes the idea of "I want to mail 250,000 people" as antiquated. You now can replace this with "I want to mail everyone who is predicted to return net positive value within two years" or "I want to advertise to everyone where the revenue of the campaign will exceed the cost." Since you have a prediction about every donor or potential donor, you can project where that line is and base your campaigns on likely results, rather than budgets that could leave you with too little investment or wasted spend.



The way a good individual-level predictive model can rank order your file or prospect lines so thoroughly is through machine learning. Once upon a time, you might have taken all your data points and dumped them into Excel or your statistical analysis package of choice and run a regression analysis. This would have given you a best fit line, a prediction of the amount of error in your model, and a statement of what variables were predictive and in which direction. Not bad.

But a statistical analysis's goal isn't to make predictions about the future; it's about discovering relationships between variables of the past. Thus, techniques like regression are good at discovering when someone goes uniformly in one direction, but not when something must be just the right amount: not too much and not too little.

An example: Let's say you water your lawn when it doesn't rain and, when you forget, your lawn suffers. If you fed the data from this experiment—lawn health, rain, and sprinkler use—into a statistical analysis like regression, it would tell you:

- Watering your lawn is good; the more you have of that, the better
- Rain is good; the more you have of that, the better
- Therefore it would be good for your lawn if you watered your lawn day and night without end, even when it is already raining

Even worse, if you took its advice and flooded out your lawn, you could feed that data back into the regression analysis and it would reply that there was now no relationship between rain, water, and lawn health. The data that would be clear to you and me—you should only water when it isn't raining—would make no sense to a regression analysis.

Therefore we've graduated to machine learning for more sophisticated predictive modeling. Instead of a statistical approach that seeks the relationships among variables, a machine learning approach seeks to predict the future, single-minded in its focus. Thus, machine learning is judged on how well it has solved a problem, in this case predicting response. It's also iterative; as it gets additional data, it will incorporate that into its view of the world, using it to continually improve its predictions.

The Solution in Practice

All this theory is nice, but does it work in practice?

Yes. Machine learning makes better predictions than regression analysis. In one study, machine learning combined with powerful neural networks was able to predict almost 90% of the error in United States charitable giving using only population, personal income, education level, unemployment rate, poverty, and charitable giving in a previous year.¹⁰ This bested two other regression-based models. It shows that artificial intelligence and machine learning beat other segmentation approaches when applied to a donor population.

The difference is even more stark when applied to an acquisition file, as there is no organization-specific donation information to work from. For example, a higher education institution applied machine learning to its acquisition files. They found that they could have mailed only 26% of its acquisition file and still brought in more than 85% of its new donors.¹¹

Some look at this and see incredible cost savings. But we prefer to think of it as a reinvestment strategy. Picture what you could do if you had three-quarters of your acquisition budget back and you only had to bring in 15% of your target number of donors. Those are funds you can put into a best mail acquisition cohort, increasing lapsed donor reactivation, and/or other channels entirely. This type of optimization means your first dollar, last dollar, and every dollar in between is spent to maximize your program instead of marketing to people who either will not donate to you or do not need the reminder.

In short, artificial intelligence and machine learning can create great advantages for you when they are applied to building your files and lists from the bottom-up, not the top-down. Only when every individual is their own bucket can you get the best donors and prospects from across your buckets and silos and maximize your fundraising investment in direct marketing.

¹⁰ Farrokhvar, L., Ansari, A., & Kamali, B. (2018). Predictive models for charitable giving using machine learning techniques. *PloS one*, 13(10), e0203928. Retrieved September 17, 2020, from <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6169901/>.

¹¹ Ye, L. (2017). *A Machine Learning Approach to Fundraising Success in Higher Education*. Retrieved September 17, 2020, from https://dspace.library.uvic.ca:8443/bitstream/handle/1828/8028/Liang_Ye_MSc_2017.pdf