Do animated graphs increase the effectiveness of email-based event recruitment at Yale?

A Final Project for S&DS315

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December 11th, 2020

Introduction

The coronavirus pandemic has affected nearly every aspect of the Yale student experience. Most notably, classes have been moved onto Zoom, but students are still learning. It is what takes place beyond the classroom that is of particular interest: extracurricular participation. The traditional activities bazaar was held virtually, with clubs making online booths; however, due to the lack of in-person recruitment tactics, such as food events, welcome meetings, and getting to know club members through socials, clubs needed to get creative in how they marketed to the incoming first-year class.

The Yale Entrepreneurial Society and the Yale Undergraduate Consulting Group, for example, sent out mass emails to the student body in hopes of increasing attendance at their recruitment events. In an online environment, email appeared to be the best approach to connecting with Yalies.

But what kind of email will get the most attendance? To find out, we ran a randomized field experiment with to compare the efficacy of static and animated email graphics. We developed a new club on campus, the Yale Society for Civic Engagement, and invited the entire first-year class to attend our virtual election watch party.

We randomized 1265 first-years into one of four treatments: 1) two static graphs (control group), 2) one static graph and one animated graph, 3) one animated graph and one static graph, and 4) two animated graphs. In the end, we found no statistically significant difference in the RSVP rate between the various assignments.

This paper will answer our research question: Does graphic animation effect email-based event recruitment efficacy? We will cover our hypotheses, treatments and outcomes, analysis and interpretation of data, limitations of our experiment, and a concluding discussion about our results.

Hypotheses

It stands to reason that the design of the graph that gets the most response should be the one that is the most attractive. Literature on the use of data visualization testifies that animated graphics can be exciting ways to show trends in data with multiple dimensions. Robertson, et al confirm "[trend animation] is the fastest technique for presentation and participants find it enjoyable and exciting", but they also found that the motion can occasionally lead to participant confusion (Robertson et al. 2008).

Insofar as the graphs we are animating are straightforward bar and line charts, we think that the tradeoff in confusion is minimal compared to the increased attention-getting ability of the animation. The application of our research is not to increase understanding of information, but to increase event attendance by getting subjects to read an email. If a viewer as drawn in by the animated graph, we expect them to continue reading through the email, and to be more likely to RSVP.

Therefore, we hypothesize that the treatment group shown two animated graphs in the body of the recruitment email will yield the greatest share of event RSVPs. The treatment groups with one animated and one static graph will yield the second greatest share of event RSVPs. And the control group shown two static graphs will yield the least share of event RSVPs.

https://pubmed.ncbi.nlm.nih.gov/18988980/#:~:text=Animation%20has%20been%20used%20to%20show%20trends%20in%

Methods

The purpose of this project was to discover if animated graphics lead to an increase in signups. We had four different treatment groups:

1. A static line graph of voter turnout rates for the midterm and presidential elections from 1880 to the present.

2. An animated line graph of voter turnout rates for the midterm and presidential elections from 1880 to the present

3. Static bar graph of registered voters and turnout among racial lines in 2016

4. Animated bar graph of registered voters and turnout among racial lines in 2016

These graphics were generated with the `ggplot2` and `showtext` packages, with the `gganimate` and `magick` packages in R to convert the static images into animated plots.[1] The voter turnout trends since 1880 in the line graph was taken from the United States Elections Project, and the trends by race seen in the bar graphs came from the U.S. Census Bureau.

When deciding how to place people in certain treatment groups, we used a simple random sample. We used a random number generator to equally place the same number of people in each group. There are many statistical concepts that we could have used to increase our precision, but decided that it was not necessary. For example, we could have used blocked random assignment, which is arranging of experimental units in groups that are similar to one another, but we did not see any covariates that could play a factor in affecting our results.

We used Mailchimp and the Mailchimp API (through the `chimpr` package in R) to contact students and track several important variables like the email open rate, the time of opening, whether students opened the email twice, and whether the students clicked the link for the Google Form where they could sign up for our "event."

We then ran a balance check across residential colleges and whether students are on leave, followed by two checks for treatment noncompliance. Finally, we ran our main analyses to study whether any treatments had a significant effect on form sign-ups. We specifically ran a set of t-tests with Bonferroni corrections search for differences across the four treatment groups, and then ran a linear regression with only the static-only and animated-only groups.

Results

Treatment noncompliance

As we see in the following two figures, treatment noncompliance was unexpectedly a problem for our research design. Because the subject line of the emails were the same across all four treatment groups and each email was sent at the same time, we did not expect any difference to appear across the four treatment groups in terms of treatment receipt. However, as the chart below shows, the treatment group receiving an email with

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[1]An annoying issue was had in formatting, where custom fonts implemented via the `showtext` package somehow made random frames distorted in the `gganimate`d plots. These frames were manually removed and then the `magick` package was used to stitch the remaining frames back together, with the end result being a GIF that misses a few frames and therefore could have appeared rocky. After watching both sets of GIFs several times I decided this was a negligible issue.

an animated bar chart and a static line chart opened the initial email at a much lower rate than the other three treatment groups. Just as confusingly, this trend disappears in the follow-up email.

We aren't sure what happened here; as some classmates noted in their final project presentation, Yale SIS or Gmail could have labeled our email as spam in this case and many students may not have received the treatment. This still would not explain why only one treatment group was marked as spam, or why this did not happen with our follow-up emails. We proceed onward with a grain of salt at the ready, and limit our study from here to specifically those candidates that opened at least one email.

Tracking email open rates across our campaigns
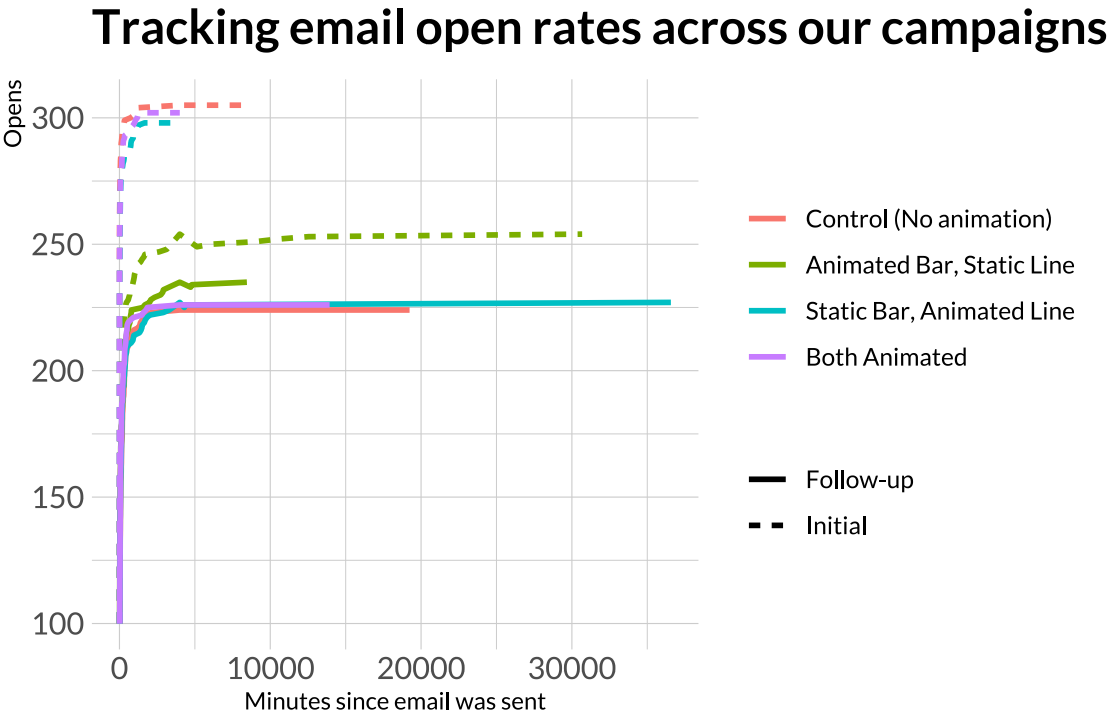
Some initial summary statistics in Table 1 and Figure 2 show the far bigger "weakness" of our study: engagement with the email to fill out the form was far too low to be able to discern a statistically significant test of whether animated graphics assist with event registration. We present three metrics here of engagement: whether students returned to the email a second time, whether students clicked on the form, whether they actually filled out the form. Only the metric of whether the students actually filled out the form would be relevant for a club aiming to boost event registration.

As we see from these statistics, although a number of people returned to either email a second time, far fewer people actually clicked on the form and an even smaller number of people filled out the form. Trends from the three metrics also do not match each other, given the animated bar and static line treatment grop opened the follow-up email a second time at a noticeably lower rate than other groups but had the highest percentage of form clicks and form fills.

Going further with a set of pairwise t-tests with Bonferroni corrections, we confirm our suspicions that there is no significant difference in form response rates across all four treatment groups. A linear regression using just the control group that received only static images and the both-animated group, which performs a similar test without the Bonferroni correction, returns a similar result that animations did not have a significant impact on event registration, be it positive or negative, compared to emails without graphics.

Table 1: Summary of Response Statistics Across Treatment Groups

	Treatment Group	Opened either email a second time	Form click rate	Form fill rate
1	Control (No animation)	49.72%	0.95%	0.76%
2	Animated Bar, Static Line	33.13%	2.53%	0.82%
3	Static Bar, Animated Line	44.19%	0.63%	0.19%
4	Both Animated	46.21%	0.32%	0.19%

Table 2: P-values from pairwise comparisons using t-tests, pooled SD, and Bonferroni corrections

	Comparison Group	Control (No animation)	Animated Bar, Static Line	Static Bar, Animated Line
1	Animated Bar, Static Line	1	NA	NA
2	Static Bar, Animated Line	1	0.8995	NA
3	Both Animated	1	0.892	1

Table 3: Model-based comparison among just animated and static (control) treatment groups.

	Dependent variable:
	'Fill rate'
'Treatment group = 'Both Animated	−0.006
	(0.004)
Constant	0.008**
	(0.003)
Observations	1,057
R^2	0.002
Adjusted R^2	0.001
Residual Std. Error	0.069 (df = 1055)
F Statistic	1.803 (df = 1; 1055)
Note:	*p<0.1; **p<0.05; ***p<0.01