Social Extremism

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CS 329 E Data Visualization
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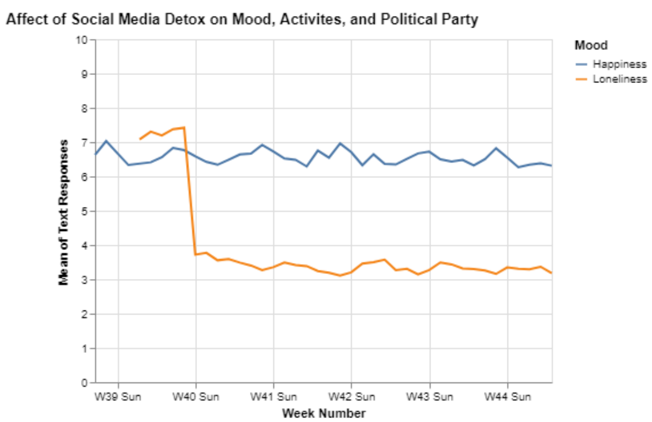
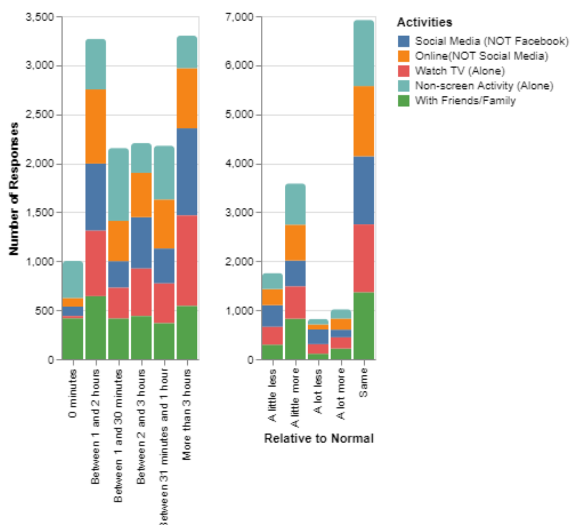
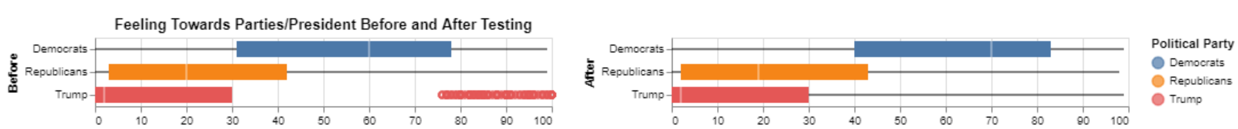






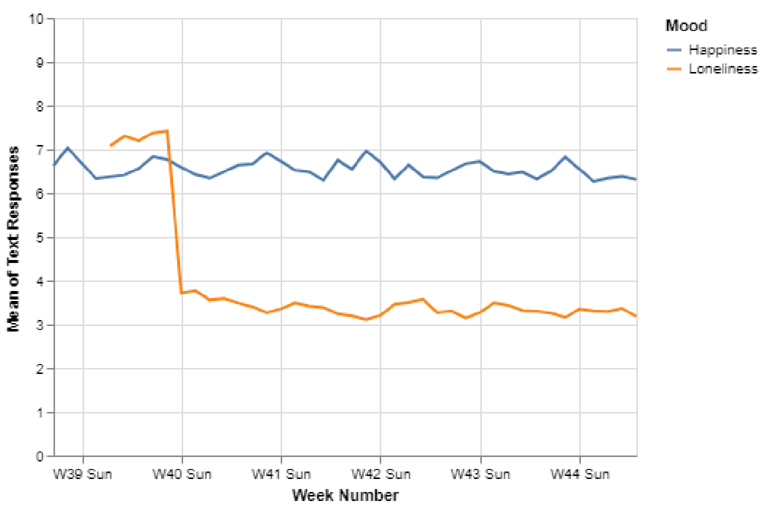
Overview: Our project ventured to look for evidence of social media technology contributing to the projection bias of our communities. Our initial interest was to investigate this phenomenon and we hoped social media had been steeped into our culture long enough that data had been gathered or studies had been done on the specifics of using the various platforms. In our search we discovered and chose a randomized study found in the American Economic Review, “The Welfare Effects of Social Media” published in March of 2020. In this study of over 2,700 individuals, social media use connected to political polarization was looked at, as well as subjective well being and activity levels of participants. Our group thought the study was recent enough and that these topics of investigation would allow some potentially great connections, being a useful data set to visualize related to our goal. Our visualizations are targeted to a public interest technologist who will be using the data to help make recommendations to government policy makers or self regulating technology companies. We chose this user because we believe bringing technologists and policymakers together is a key to surviving the rapid advancement of technology. The user is a decision maker with a deep understanding of both the policy tools available to modern society and the technologies of AI, machine learning, and algorithms that drive social media. As a conclusion, we hope our data visualizations make it easy for the user to make connections and create a safer experience online for our communities as social media grows as an influence.

Data Description: Our data consisted of 2 surveys taken at the start and end of the experiment, a list of ID’s of participants that completed the survey entirely, and a poll conducted through SMS messages which was taken daily over the course of the experiment. This data and more information on the experiment can be found here: https://www.aeaweb.org/articles?id=10.1257/aer.20190658. The start survey assigned each participant to a unique ID number, collected their general information (race and gender), and had the participants answer an array of questions regarding their opinion towards the two political parties and the president, as well as gathering information regarding their lifestyle and leisure activities that they participate in outside of Facebook. Participants were then asked to engage in a four week long detox from Facebook. During this time participants were greeted by a collection of text messages every day, were asked to describe their overall happiness and if they are experiencing feelings of loneliness on a scale from 0 to 10. Once the detoxification had been completed, the participants were once again asked how they felt towards the two main political parties and the then current president Trump. This time however, each participant was asked about the amount of time spent in their leisure activities and if it had been affected over the course of the experiment, and rate them as either: A lot less, A little less, Same, A little more, or A lot more. Using this information, we downloaded all the stata files and turned them into dataframes using pandas. From there we were able to isolate the participants that managed to complete the experiment by using only participants whose ID appeared in the ID qualified list. From there we collected the race and gender data from the survey taken at the start of the experiment, and merged each person's ID with the appropriate race and gender. We then noticed that the information in the baseline and endline survey was collected in wide form, in order to present the political opinions graph correctly we needed it converted into long form. Thus we filtered out any unnecessary information from our data frames and converted them into long form by melting them based on their ID. We used a similar technique when collecting mood data in our sms dataframe, and the leisure activity information. As a result this left us with a collection of data frames which contained the specific mood (Happy or Lonely) and the intensity of that feeling on each given day, the opinion that each person had of both political parties and Trump, and lastly the amount of time spent on leisure activities and how they changed over the course of the experiment. This provided us with all the information necessary to produce the visualizations.

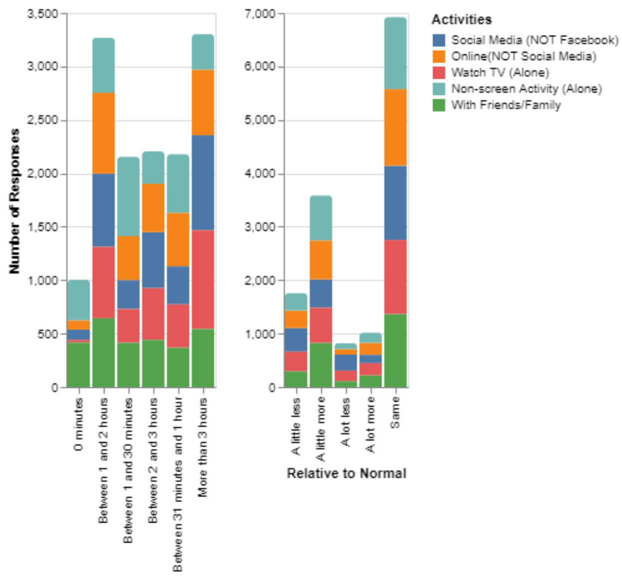
Goals and Tasks: Using the data from this large sample study of 2,743 Facebook users, our goal is to deliver information on the overall welfare of social media users in order for a public interest technologist to make informed recommendations. Our goal is for the user to access the data visualization dashboard and gather evidence about how social media affects people and communities. With this information, they can form advising recommendations and bring technologists and policymakers together. Policymakers can form legislation to regulate social media or technology companies can choose best practices in order to improve public health. Our goal is to visualize this data for our public interest technologist and give them hard evidence that helps them make an informed assessment of the way new social media technologies affect our communities, individuals, and larger social systems. Our data will be telling the story of participants who detox from social media for a period of four weeks and what affects this had on them. Our user needs to know in what ways social media affects people and measure how deep those effects are so that she can advise on prospective policy and public health recommendations. Examples of policy decisions could be to limit addictive tactics social platforms use, propose regulations on practices of platforms, or propose policies that prohibit disinformation. From the following visualizations and dashboard, our user needs to get the link between subjective wellbeing, political polarization, and activity level of social media users in order to grasp the effects of their use on their well-being.

A typical walkthrough of the user accessing our dashboard would include her taking in the information of the subjective well being of the user first in the given line chart. This visualization clearly shows a drop in loneliness after removing Facebook from a user’s daily activities. Noting that, she would move on to the activity level bar charts. Using the tool tip features that illuminate specific numbers of people, and the ability to filter by activity, Amanda can see a detailed view of how users change their activity choices without Facebook use in their daily life. A user's activity difference shows her the larger sections of the bar graph are the ones that don't have anything to do with screens. As people changed their routines, they tended to go for something that wasn't on a screen, to which she can link to her previous conclusion of the line graph that people felt less lonely. This is a positive outcome which she can detail as she creates policy ideas and advising points for her colleagues. Lastly on the dashboard, our technologist can view the effects a social media detox had on the projection bias of the user towards politics. Viewing the box plots she can see fewer outliers at the highest end leaning towards Trump after the study, showing a move towards the average. She can also note that Democrats have a higher average than Republicans and Trump before, and it increases after, showing a more blue leaning perspective after a social media detox. After gathering evidence from the visualization dashboard, our user can advise policy makers and regulators of social media technology companies on what types of harm reduction would be most effective. For example, she can propose the creation of legislation to limit the addictive tactics social platforms can use. Another route she could take would be to advise technology companies on self regulation systems they can create to reduce harms. One example would be having the companies create a policy that doesn't allow the spread of disinformation.

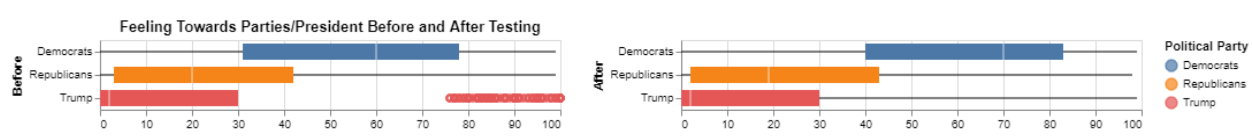
Visualization: The scenario we created revolves around a public interest technologist wanting to know the kind of effect that Facebook has on people, as well as the effect of stopping its use on mood, activities, and political bias. To fulfill that task, we employed the use of line, bar, and box plot charts. The line chart was useful for showing change over time, as the participants responded over the course of the study and the drop in loneliness happened quickly, from one day to the next.



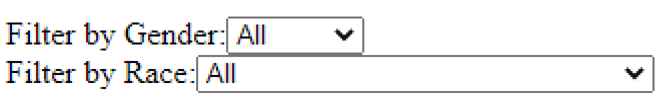
However, the data from the study over activities and political affiliation was only from the beginning and end of the study, not during. In order to effectively show the data of activities and compare the timeframes against each other, we used the timeframes as the x-axis of a bar chart. The before and after had different scales, so it would not have been effective to use a different kind of chart as it would not have shown the data in an easy to read manner.



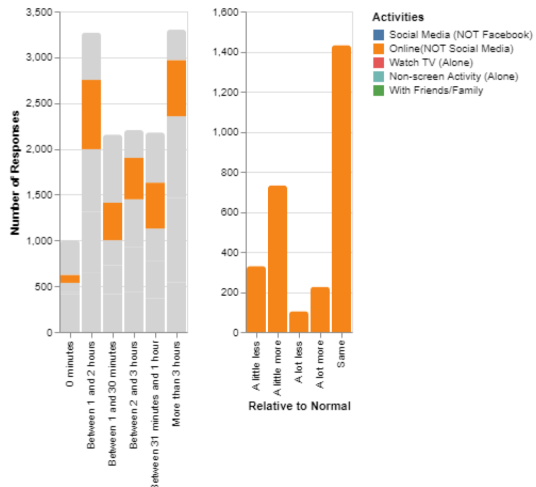
Finally, the political affiliations data was based on a 0-100 response. Since the response was such a large scale and it would be important to see the average versus the outliers, we decided to use a box plot to encode our data. It shows the average as well as the range of responses, with outliers very visibly coded so that we could see where the more controversial opinions would be sitting.



For our dashboard, the main interaction is two dropdown menus that sit below the political opinion charts. They filter all of the charts based on the respondent's race and gender. Since our user is an adviser for policymakers, the demographics of the study would be important to understand how best to go about forming policy and running for reelection.



For example, Caucasian men matched the loneliness trend of the study, but tended to spend more time online but not on social media than Caucasian women did. The bar charts have an additional layer of interactivity in that when you click on one of the activities in the left chart, it filters the data of the right chart to highlight that activity. It helps focus the user on figuring out how much the respondents changed their activities based on the detoxification portion of the study. Filtering by activity, the participants had larger trends of less screen time and more time away from screens.



All of the charts have tooltips to allow the user to find out more information. For the line chart and the left bar chart, the tooltip shows the count of respondents, with the bar chart also dividing the count between each activity segment. For the right bar chart, it shows the count and activity. For the box plot charts, the tooltip shows the maximum, median, and minimum survey result of the selected political party.

Reflection: The project has evolved as we grappled with the format the study used to survey their participants and the resulting available data. Our first idea was to look at the level of political polarization caused by social media and whether or not leaving sites like Facebook would decrease polarization. That is still present in our end product, but it's not the main focus. We found that the study also measured the mental wellness of thousands of users before, during and after a four week break from Facebook. As our data and goals changed, so did our visualizations. At first we wanted a bubble chart to show the level of polarization, but as our domain became more clear, the more we realized we couldn't use that. Our technical goals changed as well because initially we were considering targeting users who were the social media users themselves. Again, as our domain became clear about wanting to focus on mental well-being, we realized our users wouldn't be individual people wanting to know how social media was affecting their political views; it would be public health officials wanting to understand the impact that technology and especially social media had on its citizens. Our original proposal did not work, as we also wanted to include the results of a weekly test that respondents took over current events during the study. However, the way the data was collected did not work with Python or Altair in a way that would make sense or be beneficial to our user task, so we decided not to pursue it. We also had a lot of trouble with formatting and cleaning our data in a way that Pandas would accept and work with, delaying our ability to encode it into visualizations and add interactions to them. If we were to remake the project, we would want to try to fit in these test results so that we could include another visualization, as well as add interactions. For example, if you did an interval selection on the political affiliation graph it would show the mean mood responses of those people on the mood chart. I would also like to start working on the data earlier, as for this project the data processing was tedious and required a lot of reading Pandas documentation to put it in terms that would work, so having multiple people working on formatting would have resulted in an earlier finish to the data processing step.

Team Assessment: Our team members came together to create an informative dashboard and assist our user in their goals and tasks, we believe, quite successfully. Thomas contributed to researching studies that we would decide between, assisted in selecting visualizations to show our data, and worked at encoding the visualizations on Altair as well as the interactions between them. Amber contributed to researching the topic and finding the data to create a project on the effects of social media. She also created the design rough out, completing our team’s sketches for idioms. The user persona, tasks and goals are also attributed to her as well as visualization goals and idiom design along with Marcos and Thomas. Amber also took on some leadership in the project, attempting to plan and help organize our team’s goals and deadlines. Marcos contributed to finding studies, preparing the data for the visualizations, coding the visualizations, and assisting Thomas with Interactions.

Bibliography

Allcott, Hunt, Luca Braghieri, Sarah Eichmeyer, and Matthew Gentzkow. 2020. "The Welfare Effects on Social Media." *American Economic Review*, 110 (3): 629-76. https://www.aeaweb.org/articles?id=10.1257/aer.20190658