

Abstract

All around the world, people are using social media platforms like Twitter to express opinions on policy and communicate information on the novel coronavirus (COVID-19). In this project, I explore the sentiment of American tweets from six different cities regarding the pandemic and associated political grievances. I examine the three metropolitan areas that displayed the lowest vote share for President Trump in the 2016 election, and compare them with the three cities that exhibited the highest vote share for President Trump during the 2016 election. Since the declaration of the global pandemic, researchers have since used data sources like Twitter to test public opinion toward subjects like reopening and policy reactions. My research focuses more on how regions of differing political opinions may feel different emotions about varying topics relating to the pandemic. I found that tweets collected from each city did not vary in amount of each emotion I analyzed; however, when more fully interpreted, the content of these tweets differed across liberal versus conservative discourses.

Introduction

- On March 11, 2020, the World Health Organization officially declared 2019-nCoV a global pandemic
- The U.S. leads in new cases and deaths as of Summer 2020 as a result of a relatively slow response to the WHO's warning and inconsistently enforced CDC guidelines [Yamey & Gonsalves, 2020]
- One way to analyze public perception of the virus and preventative measures stems from social media and Twitter [Pollett & Rivers, 2020], [Ahmed et. Al., 2020]
- The pandemic has become increasingly politicized, and assessing perception of politics and the pandemic may show geographical trends considering the upcoming 2020 presidential election [Bavel et. Al., 2020]

Research question:

- How might conservative discourses affect how people feel about the coronavirus differently than liberal discourses?
- How is the politicization of COVID-19 affecting how people feel about the virus (are current events and politics influencing sentiment)?

Methods

- This project pulls from several data sources, most of which coming out of the R package, 'rtweet' and Twitter's developer portal

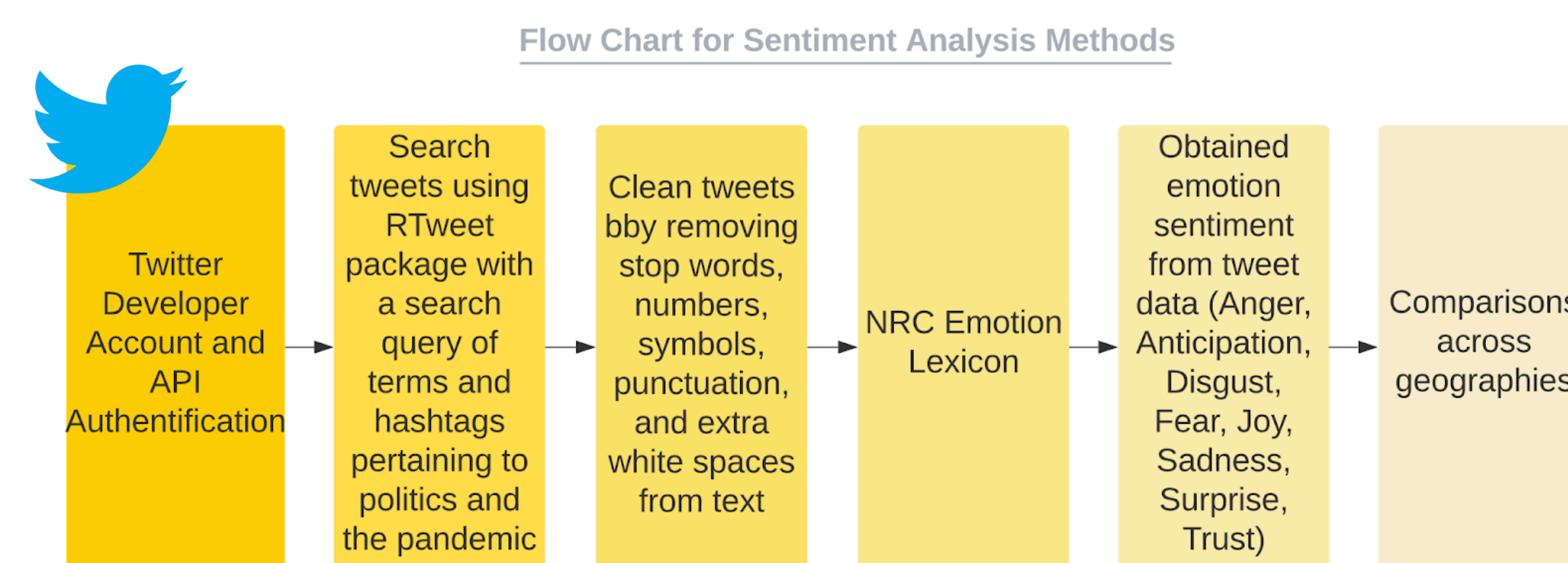


Figure 1. This flow chart illustrates my process once in RStudio.

Results

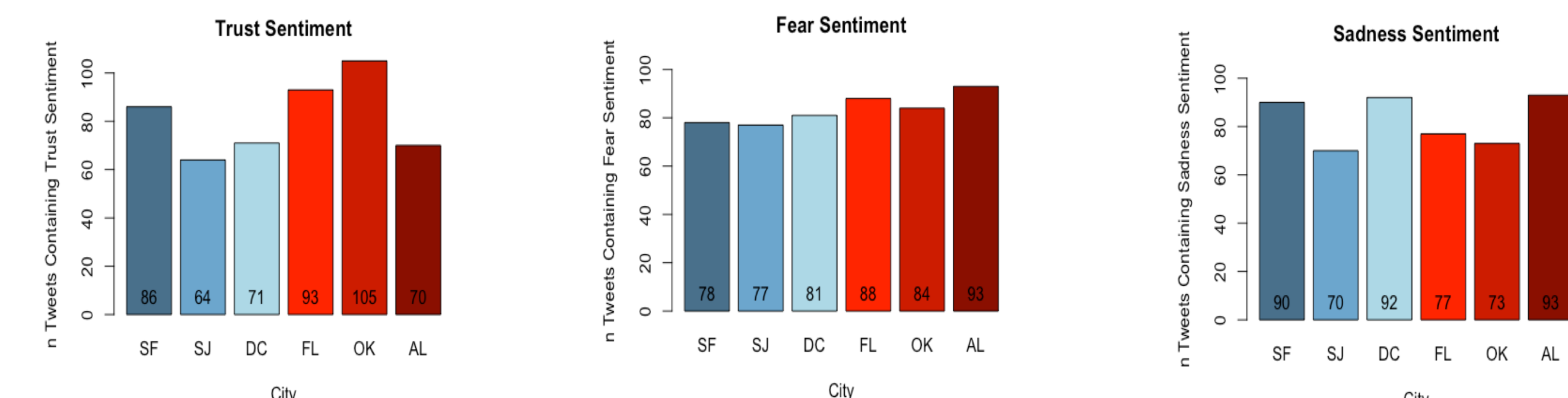


Figure 2. The three sentiments with highest n tweets are broken down across each city. The darker color across the blue and red bars represents a more partisan metropolitan area.

Word	Place	Sentiment	Full Text
Black	DC	Negative and sadness	"Black residents make up 74% -- or 424 out of 571-- of #COVID19 fatalities in DC. That's 5.9x higher for black residents than white. MPD continues to put Black lives at risk by refusing to mandate mask wearing for all @DCPoliceDept officers. #MPDwithoutPPE https://t.co/1DpT55OxEk"
Black	DC	Negative and sadness	"DC's Black community has been hardest hit by COVID19: 424 of 571 deaths were of Black residents. Black ppl also face the greatest police presence, putting them at the highest risk when police officers refuse to wear masks. #MPDwithoutPPE #WearAMaskMPD https://t.co/1DpT55OxEk"
Black	DC	Negative and sadness	"@MayorBowser we agree that wearing a mask is very effective against preventing the spread of #COVID19. So why not make ALL @dcpolicedept officers wear one? https://t.co/1DpT55OxEk #MPDwithoutPPE https://t.co/Qphw5Wzb"
Black	DC	Negative and sadness	"Many tenure-track Black faculty members experience inordinate difficulties when looking for housing, a situation that COVID-19 has only exacerbated (opinion) https://t.co.tt2zNtZvkW"
Black	SJ	Negative and sadness	"Diversity job openings fell nearly 60% after the coronavirus. Then came the Black Lives Matter protests. https://t.co/lfu9MRmdq"

Table 2. This table makes up all tweets that contain the word, "black," in reference to the Black Lives Matter movement. These tweets have a high n due to a large amount of retweets per each original.

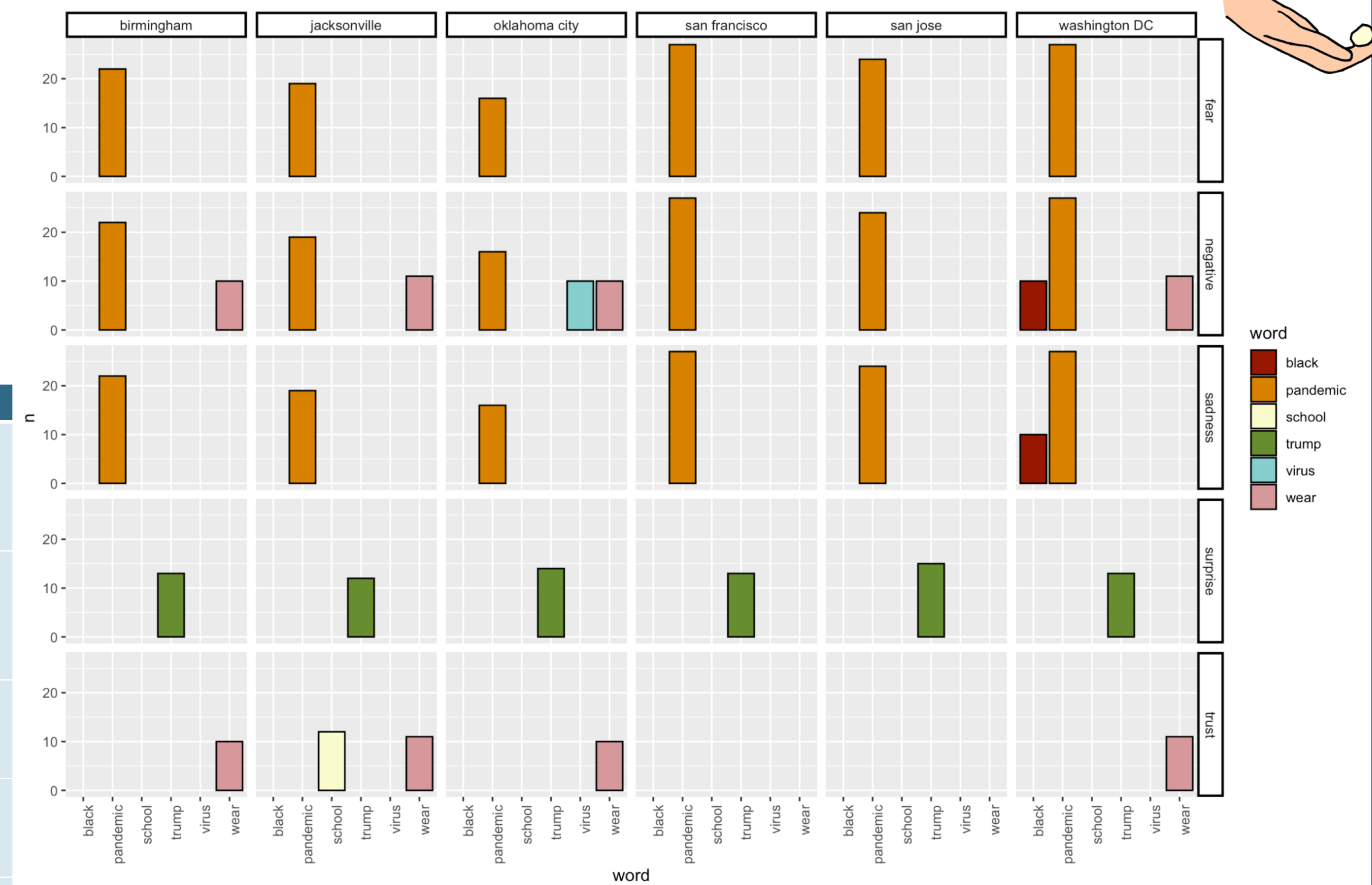


Figure 3. This graph outlines the six words across all tweets that were used more than 10 times. These six words fall into the five sentiments on the right side of the graph, sorted by the NRC Lexicon.

- Only the 'Fear' sentiment shows a statistically significant difference in means of n tweets across liberal and conservative cities
- Sentiment across the other seven emotions did not differ per political affiliation
- All three conservative cities displayed negative and trusting sentiment toward the word 'wear'
- Only Washington, D.C. exhibits a high amount of tweets regarding the Black Lives Matter movement, and San Jose put out a smaller number of similar tweets
- All three conservative cities express trusting sentiment toward schools and schools reopening (subjects not present in the search query). These cities all show a high variety of users expressing opinions on schools, whereas only a total of 3 tweets relevant to schools stem from the liberal cities (all of which being from news agencies)

Discussion

- When looking at the full text of the Washington, D.C. tweets, the tweets express concern toward the black community's extreme vulnerability in Washington, D.C. considering police officers refusing to wear masks and a disproportionate percentage of COVID-19 fatalities come from the black community
- Republican geographies may feel more negative toward wearing a mask, whereas Washington, D.C. feels equally negative sentiment toward wearing a mask as users feel toward racial disparity highlighted in the Black Lives Matter movement
- During COVID-19, everyone looks for something to blame likely as a way to, "justify," this tragedy [Baker, 2020]. This blame materializes into political current events such as the fight for racial equality, the subject of reopening schools, wearing masks, etcetera, adding to the politicization of the pandemic.

Significance and Next Steps

- Analyzing the content of sentiment on social media as opposed to simply amount of each emotion may prove to be more meaningful in comparing different groups of users
- Politicization of COVID-19 affects public sentiment toward the virus, and placement of this sentiment varies across political affiliation
- Future work:**
 - I look forward to further analyzing socio-political pressures during the pandemic as the 2020 presidential election ensues
 - I hope to take into account a multitude of variables beyond geography, examining more completely factors such as user age and profession
 - I also aim to obtain a premium Twitter API to conduct a time series data analysis

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