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I. Introduction

On June 12, 2016, the United States woke up to headlines of a massacre at the Pulse nightclub in Orlando. With 52 dead it became the largest mass shooting on US soil since the Virginia Tech Massacre in 2007. Omar Mateen, a Muslim man, claimed allegiance to ISIS and attacked a gay nightclub on Latinx night with legally purchased, semi-automatic weapons, all during the most divisive presidential campaign season I had witnessed. It was a deeply complex, political, and at the time confusing, instance of mass violence that had the nation scrambling for explanations and solutions.

At the time, I was working on ways to quantitatively capture political discourse on Twitter in relation to the coming election. I spent my days on Twitter exploring political conversations and observing the language Twitter users employed to tweet about issues. What language was in a tweet when a user tweeted about immigration? How nuanced and subtle can the language within a tweet be and still be recognizable as relating to an issue? I observed tweets, Twitter users, and the ecosystem of Twitter so we could begin to quantify the conversation. Yet, On June 12, Orlando became the top priority, and all other projects stalled. Orlando was going to be a huge moment in the election, it seemed, and we had to put all our efforts into capturing it.

I observed Twitter looking for trends in language to best capture Orlando conversation. It was all Twitter users were talking about for days, but finding the patterns within the nuanced Tweets was different than any topics I had studied before. For rather than two frames defining the sides to an argument (pro-life/pro-choice, anti-immigration/pro-immigration), Twitter users offered many competing and intersecting frames. It was difficult to gauge what Twitter users
were talking about in relation to Orlando, for they developed many complex frames and argued for them with heavy emotions. It was difficult to measure what was the highest priority or the most salient frame.

Of course the Orlando shooting incited heavy emotional responses and debate from the US and Twitter. Orlando acted as a focusing event. It shocked the public, and with that shock created fear and a desire to find a solution. But did all mass shootings look like this on social media? Each group framed Orlando in a way that identified the cause of the shooting and how to stop future shootings from happening, but they did it with panic in their tone and frantic, occasionally attacking language. How did frames function on Twitter after mass shootings? And how do they correlate with polarization on this platform? Do they exacerbate it? Create hostile environments? Or perhaps bring opposing groups together? Does this frantic, panicked sprint to frame and solve the issue lead to depolarization or larger consensus on Twitter?

To explore these questions, I brought together my little experience in data analytics, machine learning, social media, and political science to create a method to observe what frames form on Twitter after a mass shooting, who argues what frames, and who shares information? In the first chapter, I break down the significance and history of framing and polarization. The second chapter dives into the method of my data collection and analysis. The next three chapters are case studies of mass shootings. In the final chapter, I consider the findings and implications of this work.
II. Framing and Polarization: A Literature Review

Introduction
In this thesis I analyze three mass shootings with different frames. Though each incident was violent and resulted in many deaths by similar if not by the same means, I expect that in the wake of each shooting, Twitter users will use language to frame the shootings differently. Then, based on my inclinations from working with on Orlando, I hope to explore the possibility that different frames of shootings correlate with polarity patterns of Twitter users. To explore this, I measure what topics frame the conversation after each shooting, and who is sending tweets that contribute to those topics.

To give my work more context, I will briefly review and explain the relevance of framing and focusing events before diving into the different frames that are relevant to my case studies. I will explain polarization in the public sphere, and how I predict focusing events and more specifically, how they are framed, will correlate with polarization patterns on Twitter.

Framing
There is extensive work analyzing media framing of political issues as well as how that framing influences policy and public opinion over time.¹ Entman defines framing as “the process of

culling a few elements of perceived reality and assembling a narrative that highlights connections among them to promote a particular interpretation. Frames guide the audience to interpret an issue in a certain way that generally promotes their agenda, be it political, economic, or social. They are often designed by a person in a position of power. Issues with multiple frames are controversial, and issues with almost opposite frames, polarizing.

For framing to be effective, the audience must be primed to absorb the narrative that is framed. Priming, or the act of increasing the importance and salience of specific aspects of the issue that is being framed, ensures that the public is focused on the issue and deems it not only worthy of their attention, but important and urgent enough that they have the responsibility to pay attention, be informed, and develop an opinion on the issue. The media can prime the audience to receive a frame by focusing an abnormal or extraordinary amount of attention on the issue at hand. The audience can also prime other members of the audience by continuously discussing one subject. These methods increase the issue’s perceived importance and relevance, and promotes more discussion of the subject, growing its salience. Once primed and searching to form an opinion,

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4 Entman, “Framing Bias.”


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the audience is influenced to see the issue through the frame.

Fully developed framing performs four functions. First, the frame defines the problem.\(^6\) For example, in the wake of a mass shooting the problem is quite glaring, for shocking and violent deaths should not be a fear of any American citizen. Next, the framer performs a causal analysis.\(^7\) The cause can be identified as an issue of gun control, terrorism, immigration, crime, hate, or other factors. Third, the framer makes subtle or not-so-subtle moral judgments and massages his or her language to suggest that the frame chosen is morally correct.\(^8\) For example, gun rights and gun control both use language that suggests defense, such as “defend our constitutional right to bear arms” and “defend our lives and children by regulating guns.” The flip side of either frame then could read as “give everyone guns” and “restrict our freedoms.” A clearer example, perhaps, outside of the gun debate is in the classic pro-choice/pro-life binary in the reproductive health debate.\(^9\) Finally, the framer promotes a remedy that often contributes to a political agenda.\(^10\)

Often politicians or journalists, individuals with power and influence, develop frames. Journalists can frame topics in order to incite drama or excitement, with the intention of improving hits, supporting a politician, and so forth. A politician who is funded by a gun lobby can frame mass shootings to support his agenda. The refrain of the right, “the only way to stop a

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\(^6\) Entman, “Framing Bias.”

\(^7\) Ibid.


\(^9\) Diakopoulos, “Identifying and Analysing Moral Evaluation Frames.”

\(^10\) Entman, “Framing Bias”
bad guy with a gun, is a good guy with a gun,” bolsters the Second Amendment and individual rights, suggesting that for a safer nation, we must ensure that there are enough guns to protect citizens. Not all framing is deceitful and negative, but it all builds a narrative that promotes an agenda, be the motivations altruistic or not.

Boydstun et al. identify three main traits that are consistent across frames. First, they argue that the selected frames are “contingent on the institutional venue and political/economic context.” Second, frames evolve over time in relation to the debate that surrounds the frame. For mass shootings, this trait is especially salient as the conversation is driven by a collective mourning in the first days after the event before quickly becoming politicized. Finally, frames spread, “contagion like,” throughout the public sphere, via social media, mass media, institutions, casual conversation, and so forth. I will touch more on this aspect in the polarization section of this chapter.

The audience proliferates frames through their social and formal networks. Of course, framing is not necessarily unidirectional. Journalists and politicians do not exclusively create frames that influence the public. Rather, the public can develop frames that influence the media and political

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13 Boydstun, “Tracking the Development of Media Frames.”
15 Boydstun, “Tracking the Development of Media Frames.”
16 Entman, “Framing Bias.”
actors. Focusing events allow citizens “to observe and evaluate government in action” and critique it in a way that forces the government to adapt to the needs of the governed.\textsuperscript{17}

Curated and intentional language is the foundation of framing.\textsuperscript{18} And though the words may seem to have no inherent political meaning, “they attain meanings in their own historical and discursive settings through a long process of repetitive, selective, and careful usage within specific contexts.”\textsuperscript{19} Natural language processing, it seems, can act as a useful tool to measure the salience of frames on social media, and I use it as a tool to measure the rates words occur in tweets and link those words to frames with long and political histories.

I am concerned in this thesis primarily with the frames the audience latches onto and how different frames of mass shootings correlate with the polarization on Twitter. I recognize that social media is not contained in a vacuum, but rather interacts heavily with media, prominent figures, and other external influencers. For this reasons, I hope to not suggest that the frames shared on Twitter were organically formed by the Twitter user as if they received all of the important facts, and all of those facts presented in an unbiased way. Furthermore, because of Twitter users’ (and all humans) reputational fears and a desire to maintain or gain social capital, I hope to also not suggest that what we measure on Twitter is an accurate, inclusive, or


\textsuperscript{18} Newman, Benjamin and Todd Hartman, “Mass Shootings and Public Support for Gun Control.” \textit{British Journal for Political Science} doi:10.1017/S0007123417000333

\textsuperscript{19} Boydstun, “Tracking the Development of Media Frames.”


complete representation of public opinion. I am simply identifying the frames on Twitter. For future work, I hope to continue to analyze how frames are born in the wake of mass shootings on different media and how they travel and influence one another. For now, I will focus primarily on identifying the frames that form around mass shootings on Twitter after a shooting and how they correlate with polarization in the Twittersphere over time.

**Focusing Events**

In this study I observe the frames applied to focusing events specifically through case studies. Focusing events are unique in the political sphere, for they are “sudden shocks” to the political system that can lead to policy change and affect mass polarization. Focusing events unveil an issue that might have been hidden before, a policy or regulation flaw, security risk, etc. and must increase (almost always negative) attention around a public issue yielding in political debate. A focusing event is “sudden, relatively rare, reasonably defined as harmful or revealing the possibility of potentially greater future harms, inflicts harms or suggests potential harms that are or could be concentrated on a definable geographical area or community of interest, and that is known to policy makers and the public virtually simultaneously.”

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22 Birkland, “Focusing Events.”

Research shows that violent, man-made and natural tragedies such as the assassination of President John F. Kennedy, Hurricane Katrina, and the 9/11 terrorist attacks all act as focusing events, for they “highlight the need for legislative action by providing a stark example of why a particular policy proved ineffectual or out of line with public opinion.” Distant threats, threats to the nation, and personal threats or displays of vulnerability can all be focusing events, but they are received differently and carry different weights based on the audience's proximity to the event.

For this paper, my case studies are three mass shootings that act as focusing events for an array of social problems as a single individual inflicts death on a mass scale. For this reason, mass shootings have a different influence on public discourse, policy, and public opinion than something such as the assassination of JFK or Hurricane Katrina. The perceived risk is greater in instances of mass, sudden, man-caused death than in a single death or in natural disasters, which cultivates panic and a different form of debate. My work draws no conclusions on perceived risk after each focusing event, but does show aspects of each mass shooting that correlate with framings of risk. I elaborate more on these implications in the conclusion.

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24 Sears 1965; Sheatsley and Feldman 1964; Sheatsley and Feldman 1965.
26 Huddy and Feldman 2011; Jacobson 2007; Smith, Rasinski, and Toce 2001; Traugott et al. 2002
27 Birkland, “Focusing Events.”
Frames in Case Studies

Mass shootings are framed by a variety of narratives depending on the context of the shooting and who is doing the framing. To begin, I first review some of the frames used in these three case studies.

Many of these frames are not mutually exclusive. For example, some of the frames I outline below bleed into each other, and others such as the Security/Gun Rights frame are completely inseparable from one another and act as one frame. I have organized the frames to have a sort of tree structure where one frame feeds others. For example, below I outline Terrorism, War on Terror/Islamic Terrorism, and Domestic Terrorism. Terrorism is the trunk that supports the smaller branches of War on Terror/Islamic Terrorism and Domestic Terrorism. Any frame that is a War on Terror/Islamic Terrorism frame or a Domestic Terrorism frame is also a Terrorism frame. However, not all Terrorism frames act as War on Terror/Islamic Terrorism or Domestic Terrorism frames. I will break this concept down further in my Methods chapter when I discuss topics and how topics fit into the following frames.

Terrorism
Arguably the frame in this study with the most deep and political history is Terrorism. There is no single, universally-accepted definition of terrorism. For example, the US Patriot Act of 2001 and the FBI have definitions of terrorism that do not align. The US Patriot Act defines terrorism as “any crime committed with the use of any weapon or dangerous device,” when the intent of the crime is determined to be the endangerment of public safety or substantial property damage.
rather than for “mere personal monetary gain,” while the FBI and Department of Defence require political coercion for a violent act to be defined as a terrorist act.\textsuperscript{29} States define terrorism differently as well, for mass violence is the only prerequisite for an act to be a terrorist act in Nevada.\textsuperscript{30} Furthermore, the word “terrorism” is often used as an attention grabber by politicians or the media to draw attention and cause fear,\textsuperscript{31} framing it as more scary than a mere crime.

Miller argues that “terrorism and the media are entwined in an almost inexorable, symbiotic relationship”—the media are drawn to the nature of the shock of a terror story and the revenue it promises, and terror is dependent on the media’s proliferation of terrorist content. Ahmed writes, “Maximum impact of an act of terrorism comes from the widespread media coverage, which creates a climate of fear among the population, focusing government attention, economic resources, and military resources on fighting a ‘War on Terror.’”\textsuperscript{32} Though Ahmed specifically focuses on the War on Terror, his claim is more general. Terror relies heavily on the media, and how those acts are framed and who sees them is perhaps more important to the terrorist than the act itself.

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\item \textsuperscript{29}“Terrorism” FBI, \url{https://www.fbi.gov/investigate/terrorism}.
\item “How the US Patriot Act Redefines Domestic Terrorism” ACLU, \url{https://www.aclu.org/other/how-usa-patriot-act-redefines-domestic-terrorism}.
\item “The US Patriot Act, Preserving Life and Liberty” Justice.gov, \url{https://www.justice.gov/archive/ll/highlights.htm}.
\item \textsuperscript{30}“Nevada Revised Statutes, “Act of Terrorism” defined” Justia US Law, \url{https://law.justia.com/codes/nevada/2015/chapter-202/statute-202.4415/}
\item \textsuperscript{31}RETURN TO
\end{itemize}
\end{footnotesize}
Terrorism can encapsulate each of our three case studies. However, the Terrorism frame has many layers. For instance, a terrorist act could be one of Domestic Terrorism, International Terrorism, Radical Leftist Terrorism, Radical Islamic Terrorism, and so forth. Yet, regardless of the type of terrorism, the language of terrorism always incites a different reaction than language of Crime in the US. So, to try to capture when an issue is framed as any kind of terror attack, I created the broad topic of Terrorism. It classifies a tweet as relating to Terrorism whenever it uses language such as “terrorist” or “terrorism.” Then, to capture the nuances of terrorism, I created more granular terrorism topics as well such as Domestic Terrorism and Radical Islamic Terrorism to identify if the tweet can fit into a granular, specific form of terrorism.

Domestic Terrorism
Domestic Terrorism, or homegrown terrorism, is any act of terrorism on a country committed by someone who shares the same citizenship as the victims rather than by some international organization. Mass shootings are often framed as acts of Domestic Terrorism when the shooter expresses clear political motives but is an American, often from the radical political left or the radical political right. For example, violent acts committed by the Environmental Liberation Front are often defined and framed as acts of Domestic Terrorism. This frame is usually used in clear cut cases of explicit politically-motivated violence rather than mass violence. Framers often look to federal law to define terrorism and are hesitant to use language of terrorism if there is not an expressed political motive.

33 Ahmed, “The Emotionalization of the ‘War on Terror’”
War on Terror/Islamic Terrorism
In the US, terrorism has become almost synonymous with Islamic Terrorism. The government has built the Islamic Terrorism frame and narrative around 9/11, and conflict between the US and Iraq or the Middle East more generally acts as the foundation for this frame. The repetition of the tight juxtaposition of Islam and terror has lead Americans, whether they be government officials, journalists, or everyday citizens to see a relationship and causal connection between Islam and terror that is not based in logic, but is rather an emotional and affective response.

Reese and Lewis argued that the press and media internalized the government’s focus on the link between Islam and terror. The media framed terror attacks as within the “War on Terror,” and juxtaposed images terror attacks with Islam so the audience saw a direct relationship between the two. Curated to elicit a powerful emotional and affective response, these images guide the audience to entangle terrorism and Islam so closely and deeply that they believe terrorism and Islam go hand in hand. After 9/11, rhetoric such as this lead to the invasion of Iraq and the new beginning of an “Us versus Them, or the United States versus Islam that created animosity between East and West.” This language and imagery cultivated a new fear of Muslim terrorists from a fear of terrorism. Terror has become synonymous to Muslim violence. Powell explains, “coverage of those terrorist events revealed a pattern of media coverage of terrorism in which

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38 Powell, “Framing Islam.”
fear of international terrorism is dominant, particularly as Muslims/Arabs/Islam working
together in organized terrorist cells against a ‘Christian America,’ while domestic terrorism is
cast as a minor threat that occurs in isolated incidents by troubled individuals. “

Jackson breaks down how the Radical Islamic Terrorism frame is constructed: (a) define the
attacks as exceptional tragedies and assigned America a victim status; (b) construct them as acts
of war rather than as crimes or mass murders; (c) describe them in ways that allow them to fit
into other preexisting popular meta-narratives, such as the Pearl Harbor attack; and (d) construct
them as national attacks as opposed to local (New York) violence. 

With this frame, the audience supports drastic and aggressive measures, such as the war with Iraq and the Muslim travel ban.
This is the most common and specific Terrorism frame.

Hate Crime
Our final terror frame is the Hate Crime frame. A hate crime is an often violent crime motivated
by racial, sexual, or other forms of prejudice. Many acts of terror are performed with the intent
of gaining an audience’s attention, often a government, and the victims of the physical act are
arbitrarily chosen to best suit the main goal. Hate crimes, however, are usually inflicted upon the
groups they hope to influence rather than a random victim, and they hope inflict fear and harm a
group because of their race, religion, and so forth.

Perhaps the most prevalent form of terror in the United States and the least documented, the
history of hate crimes in the US is dark and hidden. The FBI, in an attempt to accurately gauge

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39 Powell, Framing Islam.”
40 Jackson, Writing the War on Terror.
the frequency of hate crimes in the US, has begun measuring the annual occurrence of hate crimes by state and city. However, the data is given voluntarily. States that are good about reporting their rates, such as California and New Jersey, report many hate crimes annually. Still, often in the deep south, states report zero hate crimes per year. States hide hate crimes, and some, like South Carolina, have no hate crime laws.

Overall, observing the pattern, the public is often hesitant to explicitly talk about hate crimes, explicitly argue the frame of Hate Crime, or admit the attack was a Hate Crime and motivated by racism, homophobia, and so forth. However, in this study, if tweets reference racism, islamophobia, homophobia in tweets relating to the attack, I consider the frame to be a Hate Crime frame.

Immigration
The immigration frame is simple and is only applied to shooters who are either first-generation immigrants or whose family is. The only shooting that is framed in terms of immigration in this study is the Orlando shooting, for Omar Mateen’s parents immigrated from Afghanistan. And although Mateen was born in the United States, many blamed the US’s immigration policies for the mass shooting. However, this frame is intimately linked with the War on Terror/Islamic Terrorism frame, for if his family had not immigrated from a Middle Eastern or Muslim country, perhaps the frame would not have been prominent. Furthermore, because Trump devoted much of his campaign to immigration policy, the frame was bolstered further.

43 Middlebrook, “Hate Crime Tracking in the US”
44 Middlebrook, “Hate Crime Tracking in the US”
However, immigration is never a major frame within these shootings.

Crime
Some scholars have identified the crime frame as the counter to the Terrorism frame. For instance, in a study directly comparing the Ft. Hood shooting and the DC Navy Yard shooting, two mass shootings at similar locations, where military personnel died, Aysel Morin found them to be framed completely differently. Morin argues that Major Nidal Malik Hasan, the Ft. Hood shooter, was labelled an Islamic terrorist while Aaron Alexis, the DC Navy Yard shooter, was deemed a criminal. Yet rather than analyzing the framing of the Alexis shooting as “Crime,” Morin focuses on other, more granular frames that I classify through topics like Mental Health. Because I have made topics for the more granular frames rather than the large, Crime frame, crime language rarely registers in my classifiers. Rather, the frames that compose this crime frame, such as Mental Illness, register.

Gun Control
Gun control, often a frame born from the political left, defines the problem displayed in mass shootings as the accessibility of guns in the United States. This frame explains that guns, especially semi-automatic such as AR-15s, the type of weapon most commonly used in mass shootings, are only useful for violence and murder. This frame implies that without access to such weapons, the perpetrators wouldn’t be able to commit such heinous crimes--guns cause

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45 Morin, “Framing Terror.”
46 Morin, “Framing Terror.”
mass shootings. The Left offers the solution of more gun control to save lives and prevent mass shooting in the future.

Security/Gun Rights
The political right recognizes that unjustified deaths from mass shootings are a problem, but to counter the Gun Control argument, they explain that there are not enough guns distributed among the public to prevent mass shootings. Within the Security frame, their refrain, “guns don’t kill people, people kill people” suggests that there will always be people who want to commit these mass murders. 47 This frame is often tied tightly with the Mental Health frame, suggesting that there are always going to be those who are mentally ill and violent who will commit murder. Regulation, they explain, will not stop someone who is determined to commit a mass shooting from getting a gun illegally. Rather, they suggest that a “good guy with a gun” is the only way to stop a “bad guy with a gun.” 48 Their solution is to arm teachers, pastors, and so forth. While armed, if met with a mass shooter the shooter will be stopped by the “good guy with a gun.”

Gun Rights correlates strongly with this frame. The Gun Rights frame generally is reactionary to the Gun Control frame. Many, predominantly on the Right, recognize the Left’s response to mass shootings as strict gun control. The gun rights advocates feel as if their second amendment rights will be taken away, and therefore begin to advocate to protect this right. Generally, this leads

48 “I believe that the only thing that stops a bad guy with a gun, is a good guy with a gun.” Fox News, https://twitter.com/foxnews/status/983299745195216897?lang=en

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them to become so entangled in the “good guy with a gun” rhetoric that they are impossible to separate. Therefore, I have merged the Security and Gun Rights frames into one frame.

Mental Health
Another frame that is often linked with the Security frame is the Mental Health frame. In the words of Metzl and MacLeish who break down mental illness, mass shootings, and the politics of firearms, those who frame mass shootings as a Mental Health issue suggest that (1) mental illness causes gun violence, (2) psychiatric diagnosis can predict gun crime, (3) shootings represent the deranged act of mentally ill loners, and (4) that gun control will not prevent mass shootings. In instances where a gunman has shown no prior mental health illness, the framers suggest that the shooter must have had a mental health “break” or was moving through life undiagnosed. In cases where the shooter was diagnosed, the blame of the mass shooting falls completely on that illness. They suggest that if someone who is mentally ill decides to commit a mass shooting, nothing could prevent it.

Sometimes associated with this frame is the claim that US culture is to blame for the perpetrator’s violence. Some who use this frame suggest that violence in media, violent movies, violent video games and so forth perpetuate the drive to commit violent acts.

Thoughts and Prayers

Here is an example tweet that I will reference again in the Charleston chapter. @mikachu247 shared her disgust for the Charleston shooting. And though expressing disgust could be seen as a political act in itself, I do not classify it as such, for almost all Twitter users expressed sadness and grief at these events. This tweet received no classification.

However, I do classify Thoughts and Prayers as political and have made it a topic and frame. The language of Thoughts and Prayers is active, an explicit expression of hopefulness and condolences towards, most generally, the victims and all those affected. This active engagement with the event is in contrast with those who simply speak about the event and their distaste for it. Furthermore, there is a history of political actors, media outlets, and the general public responding to mass shootings with “thoughts and prayers” that has created its own political discourse. For example, on Twitter, in academia, and in mass media, a typical response to a politician tweeting something like, “Our thoughts and prayers are for the victims of today’s tragic shooting” is “Thoughts and prayers are not enough”.

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Marke Leibovich, “Do Politicians’ Thoughts and Prayers Mean Anything?” The New York Times Magazine,
Case Studies

I have chosen the following as case studies: the Charleston Church Shooting, the Orlando Pulse Nightclub Shooting, and the Las Vegas Shooting. To choose my case studies, I first pulled together a pool of mass shootings. I classified a mass shooting as any shooting that resulted in 3 or more deaths in the US. Next, the shooting needed to actually act as a national focusing event. Events that were impactful locally would not bring in constructive or useful data from Twitter with the method used. To be a national focusing event, it had to be seen as nationally significant, and shocking, and the event had to take up major time and space on media outlets. In order for the data to be meaningful, I chose events that, most likely, many Twitter users had exposure to. This way, if the data showed that people tweeted less after one shooting than another, it would not be a question of whether the Twitter users knew that the shooting happened or had exposure to it. This eliminated many shootings from the pool that did not have the characteristics of a focusing event.

Next, I looked at the media and government’s framing of each shooting. For the sake of this study, I wanted shootings that had all different frames. However, they had to be close in time to one another. For example, to compare a shooting from 2009 with one from 2015 would have distorted results, for Twitter has grown significantly between those years and the results would not be comparable with so few case studies. Similarity in impact was also important. A shooting that killed few is not easily comparable to a shooting that killed many. Yet, impact is a difficult measure, for a shooting that killed few could be just as large a focusing event as one that killed many depending on how shocking or how the media and government portrays...
it. For this reason I included Charleston. Framed as a hate crime, it was comparable in media significance to the other two even though fewer died in that attack than Vegas or Orlando. For these reasons and in order to observe frames on Twitter, I chose these three shootings for their differences which promised some variance of frames and polarization across shootings.

Polarization
In this study, I hope to observe how the different frames of each shooting correlate with the level of political polarization on Twitter in the two weeks after the shooting. Cass R. Sunstein explains in “The Law of Group Polarization” that individuals naturally gravitate towards others with whom they identify and form groups. Even on platforms like Twitter, a platform that has little structure or regulation, people gravitate towards those who perhaps have similar opinions, experiences, senses of humor, or in this case, political opinions. Once roughly formed, groups self select to become more homogenous. Members of that group “follow” those who are similar, and their feed gradually becomes homogeneous as they filter out and “unfollow” those who are do not conform to the group. Their feed, then, reflects ideas and arguments in-line with the group’s ideology. Gradually, members shift closer together and become more loyal to that group. They conform to one another. Yet, when multiple groups develop around opposing ideologies of the same debate, they begin to define themselves in opposition to the other group. As a result, the group moves further away from the opposition. They polarize as a result, and members of the
group move towards an extreme.\textsuperscript{52} The extreme point they gravitate towards is generally in whatever direction they leaned towards already.\textsuperscript{53}

Sunstein identifies two principal mechanisms underlying group polarization: social influences on behavior, and cascades. Social influences on behavior reflect the tendency for people to believe and do what they think other relevant people believe and do. For example, when someone expresses their opinion on Twitter, there is an external informational component that directs others within that group, saying that they should have this opinion too. Observers receive a signal about what makes sense to believe or do when they watch those they respect express their beliefs.\textsuperscript{54} For example, if I followed a politician because I valued their stance on abortion and respected their opinion, and if they offered another opinion on a different subject, say immigration, I would be more inclined to form that similar opinion because I already respected and valued their voice. This trend pushes groups to become homogenous not around just one position, but many.\textsuperscript{55} Within the groups, conformity dominates, and the majority of individuals hope to be just like the people they deem relevant and important.\textsuperscript{56}

The second mechanism, although not always present or necessary in group polarization, is informational and reputational cascades. When someone in a group is unsure, if they do not have a concrete opinion formed on an issue, they do not know what action to take, or they feel they do

\textsuperscript{53}Ibid.
\textsuperscript{54}Ibid.
\textsuperscript{55}Ibid.
\textsuperscript{56}Ibid.
not know enough about an issue, they rely on “information provided by the statements or actions of others.” Sunstein gives the following example from Lisa Anderson and Charles Holt’s study of information cascades about toxic waste dumps:

If A is unaware whether abandoned toxic waste dumps are in fact hazardous, he may be moved in the direction of fear if B seems to think that fear is justified. If A and B believe that fear is justified, C may end up thinking so too, at least if she lacks independent information to the contrary. If A, B, and C believe that abandoned hazardous waste dumps are hazardous, D will have to have a good deal of confidence to reject their shared conclusion.

The result of this process, they explain, “can be to produce cascade effects, as large groups of people end up believing something - even if that something is false simply because other people seem to believe it too.” Within the groups that participate in polarization, local conformity plays a massive role, to the point where the entire group will believe the same things whether they are true or not, and take the same actions for informational or reputational reasons. As Sunstein explains, “like polarized molecules, group members become even more aligned in the direction they were already tending.”

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57 Ibid.
59 Ibid.
60 Sunstein, “The Law of Group Polarization.”
Many factors play into this gradual shift towards the extreme. Social comparison, similar to reputational social influences, play a key role. People want to be perceived positively and to perceive themselves positively by those they deem relevant, who often are in their group.\textsuperscript{61} When they observe what others in the group believe and how they act, they compare themselves to them. Then, they move towards the dominant position, which in turn, shifts the entire group towards a more extreme view. The point of reference has shifted from the middle of all groups, from the political moderate, to the middle of one’s respective group. And, when one compares themselves to an external group and defines themselves in terms of that external group (in the case of political parties), polarization increase.\textsuperscript{62}

Personal factors play into an individual’s probability of taking part in group polarization. The more politically literate an individual is, the more likely they are to push towards the extreme ends.\textsuperscript{63} One common sense piece of polarization is that those with the most persuasive arguments bring others into their groups. Individuals perceive those who state their views with a “high degree of confidence” or have novel arguments to be more convincing.\textsuperscript{64} Conversely, when an issue has been in the public eye and discussed extensively for a long period of time, opinion movement is less likely.\textsuperscript{65}

\textsuperscript{61}Ibid.
\textsuperscript{62}Ibid.
\textsuperscript{63}Kahan, Dan M. “What is the ‘Science of Science Communication?’” \textit{Journal of Science Communication} 14, no. 3 (2015)
\textsuperscript{64}Ibid.
\textsuperscript{65}Brown
Mass shootings seem to be distinctive as focusing events. Barbera, in his piece, “Tweeting from Left to Right”, analyzed Twitter discourse on twelve issues: six that he deemed political, six coded as non-political. He found that nonpolitical events such as the Super Bowl and Oscars were depolarized, with Twitter users interacting across party lines. In comparison, on events such as elections, Twitter users were highly polarized. The Newtown shooting proved distinct from both that of the standard political and non-political events: It started out highly depolarized, but polarized over time as the conversation turned from mourning to a political debate. Discussion around US intervention in Syria produced the reverse pattern, at first highly politicized but then depolarizing over time.

Social influences and cascades shift because of focusing events, suggesting that polarization could end or reverse in light of new and shocking information given to the public through the framing of focusing events. Mass shootings are focusing events that dominate mass media, legislatures, and the public’s attention for extended periods of time. Do they have common patterns of Twitter discourse? And are the ways in which they are framed correlate either with polarization or depolarization? These are the central questions I investigate in this thesis. In the next chapter I explain the processes of gathering and analysing the Twitter data to observe frames on Twitter.

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67 Ibid.
68 Ibid
70 Sunstein, “The Law of Group Polarization”
III. Method

Background

The Media Lab

The Media Lab of the Massachusetts Institute of Technology designs technologies with the intention of aiding humans to create a better future. Within the Media Lab, the Laboratory for Social Machines (LSM) develops data science methods to analyze societal trends for positive social impact. Using natural language processing, network science, and machine learning, the group maps the intersection of news, entertainment, and media nationally to better understand the interaction of media and behavior. A partnership between Twitter and LMS sparked the project, Electome, which tracked the news and social media discussion around the 2016 presidential campaigns. The Lab’s exclusive access to Twitter’s firehose, every historical and real-time tweet, gave the group the opportunity to develop a machine learning algorithm to label individual tweets and accounts based on topic and tone. From this data, LSM has mapped the Twittersphere based on political standing of accounts, topics discussed, and sharing of information.71

To break down Twitter’s firehose into those component parts, the tweets must pass through a processing pipeline. The pipeline ingests all real time tweets and passes them through text processing modules daily. In addition, at any time the Lab can bring forth historical tweets to

be classified. My project takes the algorithms developed for Electome, removes them from the 2016 campaign discussion, and applies them to man-made tragedies, or mass shootings. For this project, I collected historic tweets and collected data the day of and the two weeks after each event, Orlando (June 12, 2016 - June 26, 2016), Charleston (June 17, 2015 - July 1, 2015), and Las Vegas (October 1, 2017 - October 14, 2017).

Data Analysis
To find frames on Twitter, recognize who is arguing these frames, and observe the polarization patterns associated with the frames, my analysis then must answer a series of questions: 1) What is each tweet about and who is tweeting it? 2) Who is tweeting articles, what articles are they sharing, and in what networks? 3) How much of the discourse is isolated? In this chapter, I will explain the methods I’ve used to try to answer these questions. First, I identify what each tweet is about by building topic classifiers. Next, I identify who is tweeting by classifying Twitter users by demographic attributes. Then, I identify what articles are shared on Twitter and by whom. To identify frames, I use the tweet classifier to quantitatively measure what is dominating the conversation for each of the demographics identified by the ideology classifier. To give the frames context, I look at other topics that correlate with the frame, but do not dominate the conversation. I find groups that form by the urls they share and observe how they polarize. After aggregating the data to a digestible form, I am able to measure the volume of tweets. I then can compare across shootings and explore patterns of framing and polarization across my cases.

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Classifiers

Topic Classification
Twitter estimates that there are more than half a billion tweets sent out daily. To classify and collect relevant tweets about an event, each individual tweet must be sifted through a series of text processing models and filtered into a specific bucket. In order to capture almost all tweets relating to each event, I made event-specific classifiers using a precise list of mass shooting seed terms. These lists included event-specific terms including hashtags, single words, and phrases (e.g., #orlandoshooting, #pulsenightclubshooting, “pulse night club”) as well as the names of those involved, including victims and perpetrators. We also included if-then statements of the name of the location along with shooting terms (e.g., if both orlando and shooting).

Next, after being classified as relating to a specific shooting, each tweet is sifted through a series of text processing models to identify the topic of the tweet. To label the tweet with a topic, I made another series of topic classifiers using a list of terms. For example, the topic Gun Rights includes terms such as “2A” and #endgunviolence. I chose a list of topics that were often used in discussions surrounding the shootings the week after the shooting. The topics include Gun Issues, LGBTQ Issues, Hate Crimes, Terror, Immigration, Foreign Policy, Justice, Racial Issues, and Politics.

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73 Vijayaraghavan, Prashanth, Soroush Vosoughi, and Deb Roy. (2016)
74 Vijayaraghavan, Prashanth, Soroush Vosoughi, and Deb Roy. (2016)
75 Vijayaraghavan, Prashanth, Soroush Vosoughi, and Deb Roy. (2016)
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Granularity of Topics
Topics as broad as I’ve outlined above (Gun Issues, LGBTQ Issues, Terror, etc.), naturally have many layers and component parts. Many tweets about a mass shooting reference Gun Issues, and those tweets fall into the Gun Issues bucket. However, when we break the topics down into their component parts, or subtopics, we can identify what tweets are referencing more specifically in relation to the shooting. Within the topic Gun Issues, I created subtopics ranging from policy issues, such as Gun Laws and Second Amendment Rights (#2A, “second amendment”, #gunrights, etc.) to the objects themselves in Weapons (“gun(s)”, “rifle(s)”, “semiautomatic”, etc.). I did the same for the other topics as well, though some have more subtopics than others. By developing these subtopics, we created a filter that labels a tweet and drops it into a bucket granular enough that we can identify what specifically a twitter user chooses to comment on after a mass shooting.

Shortfalls of the Topic Model
Tweets often have multiple topics. For instance, a tweet about Orlando can reference Gun Issues, LGBTQ Issues, and Terror: “I’ll never forget he blamed guns, instead of calling the Orlando shooting a radical Islamic attack on the #LGBTQ.” When the machine takes in a tweet, it identifies the probability a single tweet is about a certain topic. However, many tweets touch on multiple topics. For instance, the machine could identify that a tweet is about Terrorism, the Second Amendment, and Hillary Clinton. In that instance, the tweet would be counted towards every subtopic once, making it count multiple times. For this reason, the volume of all tweets
after a shooting appears smaller than the volume of all topic classified tweets. I made the
decision to not classify one tweet as only one topic because it would have distorted the tweets I
am analyzing.

### Demographic Classification

In a similar fashion to the topic classifiers, our demographic classifier recognizes patterns within
Twitter and drops accounts that fit these patterns into demographic buckets.\(^7\) Our demographic
classifier can identify a user’s gender, age, political orientation, and location.\(^8\) An account will
be classified as either male or female, younger than thirty, between thirty and sixty, or older than
60 years old, left or right leaning, and living in one of four regions in the US.\(^9\) However, for
this project, I classify only political ideology.

Just like the topic classifier, the demographic classifier will label an account with “none” if it
cannot identify the account’s demographic. The machine cannot identify a user if there is not
enough information or the identity does not fit cleanly into any bucket. For example, regarding
an account’s political ideology, the account would be labeled “none” if the machine cannot
classify it, suggesting it is not a politically active account or it is moderate and doesn’t fit into
either liberal or conservative bucket.\(^10\) If the classifier is 60% confident in its classification, it

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\(^8\) Vijayaraghavan, Prashanth, Sorouch Vosoughi, and Deb Roy. (2017)

\(^9\) Vijayaraghavan, Prashanth, Sorouch Vosoughi, and Deb Roy. (2017)

\(^10\) Vijayaraghavan, Prashanth, Sorouch Vosoughi, and Deb Roy. (2017)
will classify the account as either Right or Left. If it is less than 60% confident, it will classify it as Unknown.

Tweet History and Manual Political Ideology Classification

The demographic classifier observes each account’s tweet history to identify political orientation. Three politically literate individuals manually annotated a list of 1000 Twitter accounts. Journalists, celebrities, politicians, companies and so forth were excluded from the list to attempt to accurately represent the average Twitter user. We labeled each account’s political ideology on a 5 point scale, 1 for the most liberal, 3 for moderate, and 5 for the most conservative accounts. To accurately determine each account’s political ideology, we read at least the most recent 100 tweets from each account. Based on their opinions on different partisan issues both economic and social (such as healthcare, taxes, welfare, immigration, racial issues, and so forth) we estimated their ideological stance.

With this annotation, in a similar manner as the topic models, we trained the machine to identify and learn from the language patterns of each account. From this baseline 1000 accounts, the machine learned to identify the political ideology of active, politically engaged accounts on Twitter. Spam accounts or accounts that do not participate politically at all or rarely are excluded from this group. For purposes of accuracy, we simplified the machine’s findings to a binary
system. The nuances of a ideological spectrum were lost when labelling accounts. However, the machine accurately identifies if an account is right or left leaning, or if an account is “unknown,” suggesting it is either moderate or did not offer enough information for the machine to identify it.

URL Classification
In order to annotate and understand what is happening on Twitter during the two weeks after the shooting, I needed to give the tweets context. I needed to see what news had been released, be it policy related, new information about the shooter, or law enforcement reports in short time increments. Given the nature of these events, the tweets in the hours and days after the event changed hour by hour. Similarly, mass media reports of the events evolved rapidly and changed direction many times after some shootings. Articles reflecting on the event but written months or years after the event do not capture this frantic tone. To get an accurate vision of what the environment was like on social media the two weeks after a shooting, I had to identify, classify, and analyze the articles that were shared on Twitter over time in brief increments.

URL Scraping
After all tweets pass through the initial shooting filter and are dropped into the shooting buckets, we scrape them for URLs. “Scraping” text online means we deploy code that reads the text and searches for designated targets, like language patterns or symbols, and store them on a file to be analyzed. Scraping can be used to count the number of times a single word, a phrase, or piece of punctuation occurs in all articles from a source. The source could be a news provider’s archives, academic articles published online, and so forth. This system is easily translated to our Twitter

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data and can scrape tweet text. We used a scraper that targets URLs within tweets. Then, we pulled all the tweets with URLs and observed them independently from tweets without URLs. Though we looked at URL containing tweets independently from each mass shooting tweet bucket, we did not exclude them from our analysis of all tweets relating to that shooting. Rather, we identified tweets with URLs, observed and analyzed them separately from tweets, and then dumped them back into the mass shooting tweet bucket to analyze all mass-shooting-related tweets.

URL Classifiers
After we isolated the URL-containing tweets, we began to classify the URLs within the tweets. First, we recognized that many URLs were not sharing information we could digest at a large scale. For instance, many URLs were links to images or videos. In this project, I did not incorporate any imaging processing. Though images such as memes and photographs of events hold a lot of information, language is both more informative and easily processable at large scales. Research shows that conservative social media users use video to express their opinion and sight sources more than liberal users, so this is a bias in my data that should be kept in mind. Furthermore, we excluded urls that began with: twitter.com, facebook.com, youtube.com, linkis.com, google.com, and dmm.com. These link lead to other social media statuses, videos, or content that we chose not to include in this analysis. When pulling urls, we hoped that they would hold information relevant to the shooting from some verified or legitimate information source.

Once the URL-containing tweets were pulled, we broke down the URL to label the tweet with a
source and an article headline. For instance, if the Tweet shared this URL:

http://www.foxnews.com/politics/2016/06/18/orlando-massacre-prompts-some-in-lgbt-communit
y-to-come-out-for-trump.html, we would automatically identify that it was from Fox News and that the headline was, “Orlando Massacre Prompts Some in LGBT Community to Come Out for Trump.” At this point, I manually classified each article. I took into account the source and its historical patterns of being liberal or conservative, as well as the article itself and how strongly it leaned left or right.

Next, we rated the articles based on the number of shares per day. For example, if a FoxNews article was shared 103 times, an Atlantic article was shared 95 times, and a CNN article was shared 30 times on June 12, they would be ranked in that order for first, second, and third most shared article in shooting related tweets on June 12. For the sake of simplicity and to avoid redundancy, when looking for context around the tweet-volume fluctuations I focused on the top shared articles in the shooting related tweets.

Volume of Original Tweets and Retweets
In this study, we look at two volumes of tweets: original tweets, and tweets including retweets. For each case study, I compare the total volume of original tweets as well as total volume of original tweets and retweets. To look at original tweets allows us to observe what users write when they create an original thought. However, when we include retweets, the volume of tweets increases up to tenfold. Because users often retweet far more often than they tweet (except for influencers or accounts with tens to hundreds of thousands of followers i.e. Hillary Clinton), I assume retweets are more representative of the actual distribution of conversation on Twitter.

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Furthermore, looking at original tweets exclusively makes our data susceptible to bots. Bots are automated accounts built to spread ideas on social media rapidly. Bots do not retweet, but only send out original tweets and hundreds at a time. It is interesting to compare what tweets bots are tweeting versus what tweets real users are tweeting, and I hope to observe this in the next iteration of this project.

**Frames**

For this thesis, I operationalize framing of these events by the topic classifiers and the relative frequency different topics occur among tweets of the Left and Right. To identify the frames of the shooting, I measure the distribution of a political group’s tweets among my topics. Based on the percent of the conversation devoted to each topic, I determine whether it acts as a topic, a frame, or a major frame. To be classified as a frame, a topic such as Gun Control needs to make up at least 10% of the tweets of that political group, the Left or Right. To be classified as a major frame, a topic must make up 20% of the tweets of that political group. If a topic receives less than 10% of the conversation, it is merely a topic. If a topic receives less than 1% across demographics, I dropped it from the analysis.

I also include topics that do not constitute frames, but rather give the frames context. For example, Racism is a topic, but not a frame in itself. Rather, it gives the Hate Crime frame context. Political Institutions and political actors such as Trump and Hillary are also topics that are not frames in themselves, but that give the tweets and frames context. For instance, if I identify Mental Health as a frame, for it makes up more than 10% of the tweets of those on the
Left, but Hillary also makes up 10% of Left tweets, Hillary is not a frame, but rather gives the Mental Health frame context, suggesting that there could be a correlation in tweets between Mental Health issues and Hillary.

My Topics

I have made the topics so they fall under the frames I listed in the previous chapter. Most are self explanatory. For instance, if a tweet is classified as Gun Control, it clearly means that that tweet frames the shooting with the Gun Control frame. However, as I explained in the previous chapter, some are more broad. For example, I have created the Topics Terrorism as well as Domestic Terrorism, Radical Islamic Terrorism, and so forth. Terrorism will encompass all Domestic Terrorism and Radical Islamic Terrorism tweets, but the opposite would not be true.

I have included the list here: Weapons, Gun Rights, Gun Control, Institutions, Self Defense, Terrorism, Radical Islamic Extremism, Domestic Terrorism, Foreign Relations, LGBTQ, Thoughts & Prayers, Hate Crime, White Supremacy, Antisemitism, Islamophobia, Homo/transphobia, Racism, Xenophobia, Sexism, Islam, Christianity, Judaism, Hinduism, Sikhism, Mental Health, Slang Terms for Mental Health, Professional Mental Health terms, Civil Rights, Race & Ethnicity, Blacklivesmatter and Police Brutality, Trump, Hillary, Bernie, Obama, Republican, Democrat, Institutions, Political Correctness, Ignorance, Censorship, Visa, ICE, Wall, Undocumented Immigrants, DREAMer, Pathway to Citizenship, Sanctuary Cities, Amnesty, DAPA/DACA, Refugees, Deportation, Syrian Refugee Crisis, Background Check
This list is not comprehensive. For instance, I included topics such as Judaism and Antisemitism, Hinduism, Sikhism, more granular topics on immigration such as ICE and Mass Deportation. However, none of these topics registered at or above 1% of the conversation for any shooting, so I have excluded them from my analysis. Furthermore, my lists were not comprehensive and did not catch every type of conversation. For example, the Confederate flag debate was noticeably missing from my topics when I analyzed the Charleston data. However, I have captured some of that conversation and how it was framed through other topics, such as Racism and White Supremacy.

Networks and Clusters
The final step of my data analysis is observing how Twitter users cluster and polarize on social media networks. In this study, a cluster is a group of accounts that are not necessarily linked by a follower-followee relationship, but share some habit or trait, such as pattern or opinion. For instance, a cluster could be composed of a series of individuals that share the same article on social media, that follow the same account such as a political candidate’s account, or that tweet using similar language patterns. Twitter users tend to build their own clusters by filtering accounts into and out of their network. These decisions by the individual contribute to echo chambers and have allowed users to fall into a feedback loop or echo chamber. They tweet an

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opinion, share an article, or retweet a friend and are often fed back that same opinion from their curated network.\(^{83}\)

Infamously, the United States’ politically opinionated social media users have taken part in a wave of intense clustering on social media that has lead to echo chambers. Scholars have argued that echo chambers such as these have contributed to the historical and unprecedented level of polarization and spread of misinformation taking place in the U.S. today.\(^{84}\) In Electome, the project which preceded and paved the way for this one, we focused primarily on the two largest and most recognizable groups in the 2016 presidential race: conservative leaning and liberal leaning users. We classify accounts using these same groups, the Right and Left, but grow networks differently.

In this project, I hope to understand how information is shared across my three cases. I look at what clusters form by the urls shared by users. Each node, or dot, on the graphs I provide in the following chapters is a user that has shared a url in their tweet. It is colored based on my political ideology classifier. Then, each edge, or line connecting two nodes, is denoting two nodes that have shared the same url. For instance, if I shared a NY Times article, there would be an edge between my node and every other node that has shared the same article. An edge between two nodes becomes heavier the more urls the two nodes share in common. With this technique and with our demographic classification, we can see when Right and Left accounts


\(^{84}\)Vicario (2016).
share the same information and when they are isolated from one another. How often are users sharing the same article, and in turn, spreading the same information? Thus in this study I operationalize polarization by the extent of information-sharing across Right and Left users. In this study I show who makes up the clusters, when clusters are predominantly homogenous or heterogenous, how often clusters in a shooting are completely isolated from other clusters (i.e., how densely packed is the network graph), and the extent to which these characteristics of clusters vary across cases.

Conclusion
Every component of the data analysis that I’ve outlined above contributes to the story of a mass shooting. For each, I compare the similarities and differences in topics (framing) and in clustering (polarization). I then analyze these differing patterns and try to make sense of them.

To begin, I look at the Charleston Church shooting in South Carolina on June 17, 2015.
IV. Charleston

Context

In the evening of Wednesday, June 17, 2015, the Emanuel AME (African Methodist Episcopal Church) was meeting for their weekly bible study. Among the thirteen people in attendance was the pastor, and South Carolina state senator Clementa C. Pinckney. They were joined by an unfamiliar face, that of Dylann Roof, a white man who asked specifically for Pinckney and sat next to him.\(^{85}\)

The study moved forward as planned, and Roof sat quietly as others interpreted the scripture. A little while in, however, Roof began arguing with the group, disagreeing with their interpretations aggressively. After almost an hour with the group, as they bowed their heads to pray, Roof pulled a Glock 41 from his fanny pack and aimed it at one of the participants, Sandy Jackson. Tywanza Sanders, Sandy’s nephew, pleaded with Roof, and asked him why he was doing this.\(^{86}\) He tried to stop Roof.

Roof responded, "I have to do it. You rape our women and you're taking over our country. And you have to go."\(^{87}\) He said he was going to shoot everyone, and Sanders dove in front of Jackson to save her. Sanders was the first person shot. As the participants dove for protection, Roof


\(^{86}\) Ibid.

\(^{87}\) Ibid.
continued to shoot them while shouting racial epithets. He reloaded his gun 5 times. Sander’s mother and niece survived while pretending to be dead.

Roof saw Sander’s mother, asked if she was shot, and when she said no explained, "Good, 'cause we need someone to survive, because I'm gonna shoot myself, and you'll be the only survivor."

He pulled the trigger on his gun but realized he was out of ammunition. Then, he got in his car and fled. 88

After images of Roof and his car were spread through the media, a civilian identified the shooter and called the police. Roof was apprehended at a traffic stop. Within the car, Roof had a list of several churches, a confederate flag, a burned US flag, a gun, an empty ammunition box, and a scope attachment for the gun. 89 The police immediately labelled the attack a hate crime. 90

Unlike the rest of the shooters we look at, Roof survived. He was taken to prison and put on trial. At the state level, he was charged and convicted of 9 counts of murder, 3 counts of attempted murder, and possession of a weapon during the commission of a violent crime. He was sentenced to life imprisonment. 91 At the federal level, he was convicted with 9 counts of a hate crime act resulting in death, 3 counts of a hate crime act involving an attempt to kill, 9 counts of obstruction of exercise of religion resulting in death, 3 counts of obstruction of exercise of

88 Ibid.
89 Ibid.
religion involving an attempt to kill and use of a dangerous weapon, nad 9 counts of use of a firearm to commit murder during and in relation to a crime of violence. He showed only pride for his actions and was sentenced to death on January 10th, 2017.

Trends in Data

Charleston’s total volume of tweets spiked early on and steadily declined throughout the two weeks following. The only time the conversation spiked again was on June 26, for at the memorial service, President Obama gave a eulogy and sang Amazing Grace. The song went viral.

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Where the Vegas and Orlando had close to 50 people and many more injured, Charleston was much smaller with only 9 dead. However, Dylann Roof had a clear and explicit motive. This event was quickly defined as a hate crime by law enforcement and the media. Unlike Orlando and Las Vegas, there was little room for interpretation. Of the top articles shared on Twitter after the shooting, all reference the church as a historically black institution and acknowledge the violence as racially motivated. Although the context of Charleston arguably leaves less room for interpretation than the two other cases I will analyze, I nevertheless observe some significant patterns in how this event was framed by Twitter users.

Of all the tweets analyzed, 40% were classified, suggesting that 40% of all tweets had some political edge. What do the others look like? Here’s one tweet that is not classified:

In comparison here’s a tweet that was classified as relating to Race & Ethnicity, Racism, and Terrorism:

In this example, @quanmon seems to have politicized the shooting with his tweet while @mikachu247 was shared her disgust at the event. And though expressing disgust could be seen as a political act in itself, I do not classify it as such, for almost all Twitter users expressed sadness and grief in the wake of mass shootings.
Of the 4 million original tweets collected after the Charleston shooting, I sampled 28,872 original tweets. From those original tweets, there was a total of 89,328 retweets, or three times as many retweets as there were tweets. Of the 40% of Tweets that are classified and the 50% of Retweets that are classified, Table 1 shows the distribution of tweets and retweets between those the machine and I classified as left of center, right of center, or unknown, and the topics that they reference.

The first, most obvious and interesting pattern is the disparity of volume of tweets between the Left and Right. While Tweets from the Left make up 52% of all original tweets around Charleston, the Right only makes up 8.7%. When we look at retweets, the disparity shifts to 63.3% of all retweets and 19.13% for the Left and Right, respectively. For this shooting, the Left participated and tweeted originally 5 times as often as the right, and retweeted 3 times as often. The Right simply did not participate at the same rate as the Left.

Next, Christianity dominates as a major frame. However, this massive topic reflects the term “church” being in the Christianity topic, and the shooting was widely named the Charleston Church Shooting. A frame did develop around a rumor that Charleston was framed as a hate crime against Christians and Christianity by Fox News. Yet, it is impossible to measure the impact of that frame with the topic being skewed by the term “church.”

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93David Garcia, "And Boston was attack on Marathons. Fox Spins Charleston Shooting As Hate Crime Against Christians, Via @AddInfoOrg" June 18, 2015, https://twitter.com/DavidArtGar/status/611658097392680961.
Surprisingly, Gun Control made up 41% of Right retweets. However, because the Right was pulling from such a small pool of retweets (10,193 classified retweets), a single ideology classifier mistake distorted the results. Stephen King was incorrectly classified as Right, and his tweet, “Too many closed minds on gun control. Worse, far too many PROUDLY closed minds. Meanwhile, the American shooting gallery remains open.” was pulled into the sample and correctly classified as gun control. This one mistake, in such a small number of tweets, completely skewed the results. It had gotten 3,981 retweets, suggesting that it made up almost the entire 41% Right, Gun Control retweets. Similarly, Weapons registered as a frame coming from the Right, but very little explicit Gun Control, Gun Deaths, or Gun Rights language was used suggesting this stemmed mostly from the single mistake.

After acknowledging the mistakes of the Christianity frame and the incorrect Gun Control frame, we can observe the more true frames of the Charleston shooting: Race & Ethnicity, Racism, and Terrorism all acted as frames when measured from Left original tweets, taking 14%, 11%, and 11% of the conversation, respectively. This pattern continued into retweets, but Racism jumped dramatically from 11% to 30% of Left tweets. Although Hate Crime was not a registered topic, Racism drove the conversation coming from the Left, suggesting that though they did not use explicit hate crime language, they recognized and discussed openly the racial implications of the attack. None of these frames registered in Right tweets except for Race & Ethnicity in original tweets with 11%. This suggests that they neither talked about the racial implications of the attack explicitly nor did they acknowledge it as a Hate Crime. Rather, because it registered under Race
& Ethnicity, it talked about race without any hate language, suggesting they only talked about the shooting as executed by a white man in a black church.

Although Domestic Terrorism never claimed enough of the conversation to be recognized as a frame, Terrorism more generally was a frame of the Left. Because this frame registered, it suggests the Left interpreted this as an act of Terrorism as well as a racially motivated hate crime. However, surprisingly, White Supremacy never registered as a frame and only gained 3% of original Left tweets at its most registered level. Race was talked about so explicitly by the left regarding the victims, but the perpetrator’s motivations were rarely framed as acts of White Supremacy, suggesting the Left only focused on the results of racism rather than the white supremacy that lead to that racism. In other words, the Left seemed to see that racism was an issue and lead to the deaths of 9 black church goers, yet Left users rarely if ever explicitly used language identifying white supremacy as the issue. Though racism is tied tightly to white supremacy, for an event to be framed as an act of white supremacy rather than an act of racism perhaps could yield different political and social outcomes.
Table 1: Distribution of total volume of Charleston the portion of total shows how the conversation was distributed between Blue, Red, and Unknown users. The first column of each demographic shows original Tweets, the second Retweets. None, the first topic, represent tweets that the machine did not label. Because None made up 60% of original tweets and 50% of retweets, the portion of topics represented here are the percent of tweets that were classified, excluding None Tweets.

<table>
<thead>
<tr>
<th>CHARLESTON</th>
<th>Right</th>
<th>Unknown</th>
<th>Left</th>
</tr>
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<tr>
<td></td>
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<td>Original Tweets</td>
<td>Original Tweets</td>
</tr>
<tr>
<td>Portion of total</td>
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<tr>
<td>white supremacy</td>
<td>1.47%</td>
<td>0.60%</td>
<td>2.58%</td>
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</tbody>
</table>
One key current event to note that I did not measure was the conversation around the raised confederate flag on South Carolina grounds at the state house. Sorting through the data, tweets that referenced the confederate flag alone were not classified. However, a large portion of tweets referencing the confederate flag reference it in a political way that my classifiers catch. For example, tweets such as these two go unclassified by my classifiers, and the confederate flag conversation does not register, and therefore does not contribute to my measure of the portion of tweets about Racism, White Supremacy, or Institutions even if it should. Yet, for tweets like those by @tyceUF, they will be caught by the Race & Ethnicity classifier and the Hate Crime classifier. However, I did miss a significant portion of the political conversation in the wake of Charleston from this mistake.

It is important and relevant to note, as well, that within this shooting, Democrats and Republican officeholders rarely registered as topics. Of course, Trump and Hillary were not quite relevant at this time in 2015. Yet, Obama rarely and inconsistently (across original tweets and retweets) registered as a frame. Political Institutions also were not quite relevant. This suggests that though
Charleston was politicized and both the Left and Right talked about it in political contexts, they did not explicitly link the failings of politicians or political institutions to the attack.

**Polarization**

After identifying these frames, we next wish to observe the polarization of Twitter users who sent tweets relevant to Charleston in the two weeks after the shooting. In Figure 1, I show the entire graph of users pulled from the sample 28,872 tweets, a total sample of 24,614 users, suggesting that the users tweeted at a rate of about 1.17 tweets per user. Of these users, 50.8% or 12,504 users shared a url link. Predictably, the nodes are overwhelmingly blue, suggesting that the political Left shared far more articles than the Right. To share more articles suggests that the Left is more often citing news articles, blogs, op-eds, and so forth that relate to the shooting. Rather than just stating one’s opinion, to share a url attempts to share a source and cite either the Twitter user’s fact or from where they derived their opinion. Along with having more tweets classified by topic, for this reason I argue that sharing articles politicizes the shooting. And though we see in Figure 1 that red nodes are speckled among the blue, the largest clusters are dominated by blue nodes.
Figure 1: In this network graph, I show the entire graph of users pulled from the sample 28,872 tweets, a total sample of 24614 users, suggesting that the users tweeted an average of 1.17 times. Of these users, 50.8% shared a url link.
Figure 2: In Figure 2, we zoom in on the largest cluster. Here we can see that the vast majority of nodes are blue, yet there are a few red nodes sprinkled in. The most shared link was the petition to remove the confederate flag: http://petitions.moveon.org/sign/remove-the-confederate-3
Figure 3: Figure 3 looks at the large number of nodes that share only a few edges with other nodes. These nodes are predominantly blue as well. These urls are generally links to smaller publications, blog stories, or articles that are about the shooting but did not go viral for example, an ABC news article of the story of the Good Samaritan who called 911 when they spotted Dylann Roof at the gas station.
Within the sample tweets, there were 10,112 urls shared, meaning that 80% of the urls shared were shared once. The average number of edges per node was 7.75. This means that for every user that shared an article, on average, 7.75 other users shared the same article. Because so many articles were shared and the average edges per node was so low, the majority of articles were not shared between many users. The virality of this shooting was low. Instead, it seems as though most of the discussion occurred in small clusters with new urls shared in each cluster, explaining the thin density of the network graph. In general, Twitter users did not share the same information when tweeting about Charleston nor did they share information with anyone outside of their ideological group.

In Figure 2, we zoom in on the largest cluster. Here we can see that the vast majority of nodes are blue, yet there are a few red nodes sprinkled in. The most shared link was the petition to remove the confederate flag: http://petitions.moveon.org/sign/remove-the-confederate-3. The next most popular articles are 2) an Iron Den Forum post about the Charleston shooting, 3) an Esquire article about the shooting, and 4) a CNN article.

Figure 3 looks at the large number of nodes that share only a few edges with other nodes. These nodes are predominantly blue as well. These urls are generally links to smaller publications, blog stories, or articles that are about the shooting but did not go viral. For example, an ABC news

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96 “Shooting Suspect in Custody after Charleston Massacre”

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article of the story of the Good Samaritan who called 911 when they spot Dylann Roof at the gas station.

This network graph shows clear polarization. Clusters form tightly around one another and rarely share edges with nodes outside of that cluster. This suggests that though many users shared articles during Charleston, they did not share them across party lines. In this bar chart, I show quantitatively how polarized these networks are. Each node is given a score from 0 to 1. If the node only shares edges with blue nodes, the node receives a score of 0. If it only shares edges with red nodes, it receives a score of 1. Though there are users who have scores closer to .5, the graph shows a clear slant. The vast majority are blue nodes, or Left users, that only share articles with other Left users. The Right barely shares articles at all.

Conclusion
Charleston was a hate crime that Twitter recognized and framed as having racial motives, but rarely used hate crime language explicitly. In this context, only 40% of all tweets were politicized, and the Left tweeted vastly more often than the Right. The Left framed the shooting as one motivated by racism, where Racism was 30% of the conversation. Neither Race &

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Ethnicity nor Racism was a frame from the Right when observing retweets. Rather, Thoughts & Prayers was the only frame offered by the right. Terrorism was barely a frame, and only one from the Left. Domestic Terrorism never registered far above 1% of the conversation.

Charleston was a deeply polarized event, with there being little if any shared urls between red and blue users. However, it is difficult for the Left to have shared similar articles with the Right, because the Right barely tweeted and barely shared any urls. On top of there being little shared information between Left and Right users, there was little shared information between the Left. Because there were so many articles, so few were shared multiple times (20%), and the average node had only 7.75 edges, clusters were isolated and rarely shared the same urls with those outside of their cluster, even if they were classified as having the same political ideology. In this case study, we see little shared information.
V. Orlando

Context
On Saturday, June 12, 2016 in Orlando, Florida, Pulse nightclub was having “Latin Night”, a night to honor the intersection of the latinx and lgbtq communities of Orlando. As one of the most famous gay clubs in Orlando on one of their more popular nights, Pulse was packed with a racially diverse range of over 300 patrons ranging from teens to middle aged adults.

In the early morning hours, Omar Mateen entered the nightclub. Official investigative updates from FBI Tampa report that at 2:02 a.m., Orlando police received reports that shots had been fired in the club. By 2:08, officers from various law enforcement agencies entered Pulse and engaged the shooter. By 2:18, the Orlando Police Department’s Special Weapons and Tactics (SWAT) team arrived and initiated a full “call-out” and began working to end the hostage situation. At 2:35, the shooter had his first contact with a 911 operator from inside Pulse:

*Orlando Police Dispatcher (D):* Emergency 911, this is being recorded.

*Omar Mateen (M):* In the name of God the Merciful, the beneficent [Arabic]

D: What?

M: Praise be to God, and prayers as well as peace be upon the prophet of God [Arabic]. I wanna let you know, I’m in Orlando and I did the shootings.

D: What’s your name?

M: My name is I pledge of allegiance to Abu Bakr al-Baghdadi of the Islamic State.

D: Ok, What’s your name?

M: I pledge allegiance to Abu Bakr al-Baghdadi may God protect him [Arabic], on behalf of the Islamic State.

D: Alright, where are you at?

M: In Orlando.

D: Where in Orlando?

[End of call.]
In the next hour, Mateen engaged in three more conversations with the OPD’s Crisis Negotiation Team ranging from 3 to 16 minutes. Within these conversations, the attacker identified himself as an Islamic soldier, pledged his allegiance to ISIL, and told the negotiator to tell America to stop bombing Syria and Iraq. Those US bombings and attacks on Iraq and Syria, he explained, is why he “is out here right now.”

Mateen continued to talk to the Crisis Negotiation Team and threatened to “ignite” a van full of bombs and vest bombs outside of the club as well as vests like those “used in France,” which we assumed to be a reference to the terror attacks in France that had occurred in the not-so-distant past. He praised the brothers responsible for the Boston Marathon Bombing, and continued to threaten, “In the next few days, you’re going to see more of this type of action going on.”

Between 4:21 and 5:00 am, victims were slowly evacuated by the OPD. At 5:02, the team began to breach a wall with explosive and armored vehicles to enter the premises. By 5:15, Mateen was shot multiple times in a direct confrontation with the police, and was killed.97

At the time, this shooting was the largest, most deadly mass shooting in United States history, surpassing the shooting at Virginia Tech in 2007. In the attack, Matten murdered 49 of the club’s patrons (39 died at the scene, 11 were pronounced dead in the hospital) and injured 58 more. The youngest person to die was 18, the oldest 50.

Orlando had a spike in tweets at the beginning of the two weeks, but fell as a slower rate with larger, more irregular spikes than Charleston. I sampled a total of 25,778 original tweets and 158,025 retweets, 6 times the number of original tweets.

Unlike the other shootings I analyze in this thesis, Orlando occurred during the presidential campaigns of the 2016 election. The Twittersphere was already alive with political debate when Orlando happened, making the conversation abnormally federal-politics heavy. For example, Democrats and Republicans are two of the most common topics with Orlando, but they barely registered at Vegas and Charleston. This can get confusing, for some of my topics are
Republicans and Democrats—meaning Republican and Democratic candidates and officeholders—but I also analyze Left and Right users. When in this analysis I use Republican or Democrat, I am referring to the topic of either Republicans or Democrats, meaning officeholders and candidates from either party, such as Trump or Clinton. When referring to the demographic of those tweeting, I use Left-Right, blue-red language.

When Mateen struck, it was becoming more certain that Hillary Clinton and Donald Trump were going to be the respective Democratic and Republican candidates for the 2016 presidential election. Politics was a huge leader in the conversation surrounding the shooting on Twitter. This election was particularly controversial and engaged with social media platforms like Twitter at an unprecedented rate, for Donald Trump used Twitter as his primary platform for public communication. Trump was referenced in 52.7% of original tweets, completely dominating the conversation. Among retweets, Trump was huge in the conversation among all three demographics, Left, Right, and Unknown, equally at 47% of retweets. Left and Right also tweeted at the same rate for Orlando, suggesting they both participated in the conversation equally.

Unlike Charleston and Vegas, the vast majority of Orlando tweets were classified 94%. This suggests that almost all of the tweets had some political edge. Below is one of the very few tweets that was not classified as relating to any topic:
Though a tweet about Gov. Bobby Jindal has some obvious political motives, I didn’t capture them, for I did not include Bobby Jindal as a term. On the other hand, here is a tweet classified as Hillary, Politically Correct, and Terrorism:

This suggests that the vast majority of the tweets around Orlando are politically oriented, and even many of those that were not classified could have some political edge.
The first interesting trend in the Orlando data, as I suggested before, is the prevalence of political party and political candidate topic tweets. Donald Trump’s topic held 47% of the Right, Left, and Unknown groups. Hillary, on the other hand, fell far behind. The Left rarely referenced her; Hillary was only a topic in 8.6% of Left retweets. Yet, the Hillary topic still acted as a major topic among Unknown and Right users. The Left talked about the Right’s candidate much more than they talked about their own. The Right, however, talked about their own candidate often, yet also managed to talk about the Left’s candidate frequently.

On a similar note, the Right’s tweets and retweets were classified as having a Democrat topic (30.13%) far more than they were classified as having a Republican topic (11.58%). The Left’s tweets, as well, were classified as having a Republican topic (45.10%) far more than they were classified as having a Democrat topic (5.70%). In regard to talking about politics, it seems as if each side, Left and Right, used the Orlando shooting as ammunition to attack or critique the other side. Unknown users stayed neutral, retweeting about Republicans (12.23%) and Democrats (12.41%) at the same rate.

Across the board, LGBTQ Issues accounted for about 10-20% of the conversation. However, Hate Crime never registered at even 1% for any of the demographics. After the shooting, rumors spread about Mateen’s motivations in choosing an LGBTQ club as a target. And though he was rumored to be homophobic or gay himself, no reports of his sexuality have been verified nor have evidence been shown that he had intentions of committing a hate crime. Yet, debate spread across the Twittersphere about the importance of calling this attack a hate crime along with a
terrorist attack. Obama himself identified the attack as “an act of terror and an act of hate.” However, Twitter never latched onto Orlando as a hate crime, and only talked about LGBTQ issues as facts about the event, who the victims were, where it happened, not the motivation.

Gun Control language, on the other hand, acted as a frame for the Left, making up 18.10% of tweets and 21.09% of retweets. For Unknown users, Gun Control acted as a frame as well, making up 13.63% of original tweets and 11.33% of retweets. The Right, however, did not reference Gun Control at the same rate. Any Gun Control only acted as a frame for original tweets, but fell off for retweets. Gun Deaths and Gun Rights also did not register. Weapons, however, registered as a topic quite consistently across demographics between 16-18%, with a significant rise for Left retweets at 23.67%. This suggests that Twitter users were talking about guns, talking about bullets, semi-automatic weapons, and so forth, but not using explicit language such as “ban”, “control”, “restriction”, “rights”, etc.

Terrorism registered as a frame across all political ideologies, and a major frame for the Right in original tweets (29.49%) and retweets (34.24%) as well as for Unknown users at 22.58% of retweets. All demographics of Twitter user classified and framed the event as an act of terrorism, yet they classified it as different forms of terrorism. For example, Radical Islamic Extremism

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Table 1: Distribution of total volume of Orlando tweets. The Portion of Tweets shows how the conversation was distributed between Blue, Red, and Unknown users. The first column of each demographic shows original Tweets, the second Retweets. None, the first topic, represent tweets that the machine did not label. The portion of topics represented below the None row are the percent of tweets that were classified excluding None Tweets.

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<thead>
<tr>
<th>Orlando</th>
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<tr>
<td></td>
<td>Original Tweets</td>
<td>Retweets</td>
<td>Original Tweets</td>
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<td>Portion of Tweets</td>
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<td>Radical Islamic Extremism</td>
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registered as a frame for the Right, almost a major frame, and Islam measured as a major frame.

For the Left, however, neither Radical Islamic Extremism nor Islam registered as frames.

Domestic Terrorism never registered at 1% or higher for any user group. Finally, Thoughts & Prayers registered the least often of all of the shootings with Orlando.

Polarization

As with the other shootings, I look next at Polarization. In Figure 1, we show the entire network of users who shared Orlando related tweets. Of all the 25,778 tweets, there was a total sample of 16,348 users, suggesting they tweeted at a rate of 1.67 per user, the highest tweet rate for all of the shootings. Of these users, 58%, or 9,488, shared a url linking to an article related to Orlando. Of all the shootings this was the largest portion of users to share a link along with their tweet.

The top shared Right url was a link to a Clash Daily post titled, “Dear CNN: Orlando Terrorist Muslim Registered Democrat Targeted Gays,” along with two other articles from Fox News and PJMedia titled, “Orlando Massacre Prompts Some LGBT Community to Come Out for Trump,” and “I’m a Gay Activist, and After Orlando, I HaveSwitched My Vote to Trump.”

“I’m a Gay Activist, and After Orlando, I’m Switching My Vote to Trump,” PJMedia.com, pjmedia.com/trending/2016/06/12/gay-activist-after-orlando-trump-voter/
The top Left url was a Huffington Post article and a TIME article citing Trump’s “humble brag” after the shooting, along with Vanity Fair and the Hill articles citing how the GOP blocked a vote on LGBT rights days after the shooting.

This network graph looks radically different from the one for Charleston. Right away, one can recognize that finding clear clusters is more difficult than it was in Charleston. The polarization is significantly lower in Orlando than in Charleston, showing that blue and red nodes, or the Left and Right, share the same articles. Furthermore, Left and Right, red and blue, both shared urls at the same rate, unlike Charleston, where the Left was the only group participating in the Twitter conversation. Overall, the Orlando network graph is equally dispersed among blue and red nodes.

In Figures 2 and 3, we zoom in on blue and red clusters. We can see that though the graph is polarized and there are clear blue and red tinted clusters, each cluster has the opposite color sprinkled throughout the cluster.

“Donald Trump Tweets Disgusting Humble Brag After Orlando Massacre” HuffingtonPost, www.huffingtonpost.com/entry/donald-trump-orlando_us_575d92e6e4b0e39a28addbe6
“Donald Trump Faces Backlash for Tweets After Shooting” Time, time.com/4365411/orlando-shooting-donald-trump-tweet-congrats/

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Figure 1: For Orlando, we pulled a sample of 25,778 tweets, a total sample of 16348 users, suggesting that the users tweeted at a rate of about 1.67 to 1, the highest tweet rate of all the shootings. Of these users, 58% shared a url link. In this network graph, I show the entire graph of users pulled from the sample that shared a link, a total of 9,488 users.
Figure 2: In Figure 2, we zoom in on a blue cluster. Here we can see that the vast majority of nodes are blue, yet there are a few red nodes sprinkled in. The most shared link was the petition to remove the confederate flag: [http://petitions.moveon.org/sign/remove-the-confederate-3](http://petitions.moveon.org/sign/remove-the-confederate-3)
Figure 3: Figure 3 looks at a red cluster. Though the cluster is tightly red and polarized, blue is highlighted throughout as well. Edges context from within the cluster outside to many other clusters, blue and red, as well. We can also see the small cluster of grey, unknown users in the top right corner.
Orlando is also more densely packed than Charleston. In this sample of Orlando related tweets, there were 4,135 URLs shared, meaning that only 50% of urls shared were shared once. The average number of nodes per cluster was 34.04, meaning when a user shared a url, on average there were 34 other users that shared that same url. Where Charleston had clouds of nodes floating outside the largest cluster with only a few edges, those isolated, tiny clusters are almost nonexistent in the Orlando graph. Rather, even nodes that only have one edge usually share that edge with a node more deeply ingrained in the cluster. This suggests that urls in Orlando were more condensed and shared than the other shootings.

We can see in this bar chart the quantitative analysis of this polarization. As I’ve explained, if a node is rated 0.0, it means it only shares edges with blue nodes. If a node is given a rating of 1.0, it only shares edges with red nodes. For Charleston we saw majorly polarized networks, with almost all of the nodes being either classified as 0.0 or 1.0. With Orlando, though 0.0 and 1.0 nodes make up a large portion of the bar chart, there are also many nodes at other points. Similarly though the network graph has clear clusters dominated by blue and red nodes, there is far more mixing of red and blue in the Orlando graphs as compared to those for Charleston.
Conclusion

Twitter users, overall, politicized Orlando heavily, placing it squarely in the middle of the presidential elections. Using that federal, political party and political candidate language, Twitter users seemed to use Orlando to focus on the opposite party and opposite candidate--except for the Right who talked about Trump just as often as the Left.

From my observations and measurements, Orlando was framed by the Left as Terrorism. But Left users rarely used language that recalled the War on Terror, Islamic Terrorism, or even Domestic Terrorism. Rather, they referenced Terrorism broadly, and focused more heavily on the Gun Control frame. The Right, on the other hand, framed this event as an act of Terrorism, and one of Radical Islamic Extremism. They referenced Islam at a rate of 20% of Tweets, suggesting that language referencing Islam gives their Orlando frames further context. Orlando was also talked about in the context of LGBTQ Issues by both sides, but neither hate crime nor homo/transphobic language was used.

The Left and Right participated in the conversation equally, shared urls at the same rate, and shared the same articles far more often than after Charleston. Though there were clear clusters that had blue and red tints, suggesting there was polarization, the majority of users shared articles with users of other political ideologies.
Furthermore, there was a small number of articles that were shared widely in Orlando, while Charleston had many articles that were not shared widely. And, users who shared articles about Orlando shared articles with an average of 34 other users, making Orlando much more densely packed than Charleston. This suggests that Orlando users clusters were much less defined than Charleston users, and those less-defined clusters shared similar urls with each other, within and across political ideological lines.

However, though users seemed less polarized in Orlando by my measure of url shares, the Left and Right took opposing stances and framed Orlando differently. This measure of polarization does not measure interaction, but rather shared information and url shares. Perhaps users did share more of the same urls in Orlando than after Charleston, but perhaps it was purely the same information, facts that users agreed on, but facts they framed differently. This shows a flaw in my measure, for the frames show a Left and Right at war and opposing each other, where my network graph shows interaction and shared urls. This suggests that shared urls do not suggest any ideological bridge was built.
VI. Vegas

Context

On September 28th, 2017, Stephen Paddock checked into the Mandalay Bay Resort and Casino in Las Vegas, Nevada. He had specifically requested one large suite, a living room, kitchen, and separate bedroom had floor to ceiling windows with “uninterrupted views of the Las Vegas Strip.” Over the course of three days, Paddock left and returned to the resort incrementally with an excess of 10 suitcases. He stayed up all night gambling for two nights and was generous with tips, but reported to have a “god complex,” expecting the staff to serve quickly.

At 10:06pm, on the 32nd floor of the resort, Paddock smashed the window of his room with a hammer. When Mandalay Bay security guard Jesus Campos, responding to the break, knocked on his door, Paddock shot through the door and killed him. Looking down on the Route 91 Harvest festival into a crowd of 22,000 people, Paddock began to fire.

The first stretch of fire did not disrupt the Harvest Festival concert. Many in the crowd and the performer thought there were merely firecrackers and fireworks being released during one of the final songs. The audience began to stir as members of the crowd noticed some around them fall, but the show continued. Thirty-six seconds after the first round of automatic fire, Paddock began unloading a second round. The crowd began to panic and take cover.

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100 “What Happened Inside the Shooter’s Suite in the Mandalay Hotel” CNN

101 “Stephen Paddock, Las Vegas shooter, called hotel security before rampage”, CBS News,
After a third and fourth round, with a cumulative of more than 900 shots fired, muffled gunfire heard in a video at the scene suggested more rounds were fired within the hotel room. Officers arrived seven minutes after the shooting started, and Paddock took his own life. Less than a year and a half after Orlando, Vegas became the worst mass shooting on American soil with 59 dead and 851 wounded.

Trends in the Data

Unlike Orlando, Vegas occurred on the night of the 1st around 10pm, explaining the data’s start at zero and quick spike. Out of all of our shootings, Vegas has the largest volume of Tweets over the two week period, with over 4 million original tweets about the event. On top of having the largest total volume of original tweets, Vegas had the biggest spike in tweets and the quickest
decline. I sampled a total of 27,000 original tweets relating to Las Vegas and 100,000 retweets. Vegas had the fewest tweets that fell into one of my classification buckets, with 65% of tweets being classified as “none”. For example, the following tweet received no classification:

Megan @MeganDuffy_x · 3 Oct 2017
Heart is broken reading about the victims of Las Vegas 😞

This tweet, by contrast, would be classified as Race & Ethnicity and Terrorism:

Tsitsi Dangarembga @efie41209591 · 2 Oct 2017
Las Vegas - they’re calling it a mass shooting instead of a terrorist attack, that’s code for “the shooter was white” right? @fentsemokale

96% of Orlando’s tweets are classified and 50% of Charleston, but only 35% of Vegas tweets are classified. The relatively low percentage of classified tweets suggests that Twitter users were tweeting significantly less about political issues than they were in the other two shootings. They were not referencing Terrorism, Race & Ethnicity, Gun Control, Gun Rights, or any other topic at a comparable rate to Charleston or Orlando. Furthermore, Vegas users were the least likely to share URLs. Out of all of their tweets, only 13% contained URLs compared to Charleston’s 50% and Orlando’s 60%.
Table 1: Distribution of total volume of Vegas tweets. The Portion of Tweets shows how the conversation was distributed between Left, Right, and Unknown users. The first column of each demographic shows original Tweets, the second Retweets. None, the first topic, represent tweets that the machine did not label. The portion of topics represented below the None row are the percent of tweets that were classified excluding None Tweets. Vegas was the least politicized of all the events, with None classifying 65% of all tweets, and up to 70% of Unknown Retweets. This suggests that only 35% of original tweets were politically oriented.

<table>
<thead>
<tr>
<th>Vegas</th>
<th>Right</th>
<th>Unknown</th>
<th>Left</th>
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<tr>
<td></td>
<td>Original Tweets Retweets</td>
<td>Original Tweets Retweets</td>
<td>Original Tweets Retweets</td>
</tr>
<tr>
<td>Portion of Tweets</td>
<td>38.70% 39.80%</td>
<td>24.97% 22.59%</td>
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<td>none</td>
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<td>74.72% 71.20%</td>
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<td>2.15% 0.87%</td>
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<td>1.59% 0.57%</td>
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<td>3.32% 12.57%</td>
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<tr>
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<td>3.71% 2.78%</td>
<td>3.32% 4.52%</td>
</tr>
<tr>
<td>Gun Control</td>
<td>9.22% 7.56%</td>
<td>13.20% 19.28%</td>
<td>14.43% 20.07%</td>
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<tr>
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<td>6.56% 1.56%</td>
<td>5.72% 4.47%</td>
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<td>1.59% 0.46%</td>
<td>2.22% 1.77%</td>
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<td>Hillary</td>
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<td>Islam</td>
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<td>Obama</td>
<td>1.99% 4.33%</td>
<td>0.71% 0.69%</td>
<td>1.13% 0.48%</td>
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<tr>
<td>Professional</td>
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<td>0.49% 4.44%</td>
<td>0.30% 0.07%</td>
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<tr>
<td>Race &amp; Ethnicity</td>
<td>4.06% 1.48%</td>
<td>4.29% 2.66%</td>
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<td>0.20% 0.05%</td>
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<td>1.76% 0.78%</td>
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<td>Terrorism</td>
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<tr>
<td>Thoughts &amp; Prayers</td>
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<td>5.73% 19.16%</td>
<td>6.52% 8.12%</td>
</tr>
<tr>
<td>Trump</td>
<td>22.21% 15.54%</td>
<td>20.62% 7.08%</td>
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</tr>
<tr>
<td>Weapons</td>
<td>28.35% 25.15%</td>
<td>41.36% 54.53%</td>
<td>39.55% 36.57%</td>
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</table>
Left and Right Twitter tweeted at the same rate, each making up about 40% of the total Vegas conversation. For original tweets, 30% of the Left and the Right’s tweets were classified, and for retweets 35% and 40% of the Right and Left’s tweets were classified, respectively, suggesting the two sides were equally likely to frame the event in political terms.

As with Orlando, Trump was a major topic for both the Left and Right at the same rates for original tweets. But he was a minor topic when we observe retweets. The Trump topic was not nearly as major in Vegas as it was in Orlando at its highest point making up 20% of original tweets for the Left and Right. Hillary, predictably, fell off of the charts. Institutions made up a large portion of the conversation and was a major topic for the Left at 27.43%. This suggests that the Left referenced some political institution or office 30% of the time while talking about the Vegas shooting, most likely expressing grief or criticism of legislation for not changing gun policy. The Left framed Vegas as an issue of Gun Control, just making the cut as a major frame at 20.07% of the conversation. Weapons was also a major frame and was referenced in 36.57% of tweets, suggesting that though they only talked about Gun Control explicitly 20% of the time, they referenced the weapon used almost twice as often.

The Right also framed the shooting in terms of Weapons, but it only made up about 25% of the discourse. They did not talk about the weapons in terms of control, rights, deaths, or even how Paddock bought the guns. I included the term “bump stock” in weapons, which was a large topic of discourse on the Right and Left. Thoughts & Prayers registered as a frame. Surprisingly, Radical Islamic Extremism and Foreign Relations registered as frames as well. Shortly after
Vegas, ISIS claimed Stephen Paddock and the shooting as their own. The Right did frame the shooting as an attack by ISIS, mostly in the beginning of the discourse after the event. Though those rumors were eventually squashed, the Right framed the event in this light.

In Vegas, Terrorism became a frame for the Left as well. However, it was a highly contested frame, and not one associated with Islam or ISIS. The Terrorism classifies as a frame at 13.5% of the Left’s tweets, but Radical Islamic Extremism, Islam, and Foreign Relations never registered above 5%, suggesting they rarely correlate the two in Vegas. Where the Right pushed the frame that Vegas was an act motivated by ISIS, the Left questioned why it was not seen as a terror attack in of itself. A common headline from the Left questioned why Vegas was not framed as a terror attack, for it instigated terror in the general public and was an event of mass violence. Many cited the federal definitions of terror that require an act of violence to have an explicit political motive. Without a clear motive in Vegas, it was not federally defined as a terror attack. However, Nevada state law classified it as a terror attack. The law defines an act of terrorism as "Any act that involves the use of violence intended to cause great bodily harm or death to the general population." It seems as though the Left worked to frame the Vegas shooting as a terror attack to suggest the US should not treat events like Orlando and Vegas so differently.

Furthermore, many argued, because Stephen Paddock was white and not Muslim, he was not classified as a terrorist but rather as being a “lone wolf” or having “lost his mind.” The Left in particular argued that this is a privilege of race and religion, that when committing an act of terror, a white man will be labelled crazy and a “lone wolf,” but a Muslim man would be labeled
a terrorist. They argue that Americans feel an intrinsic fear and threat of Muslim people that they do not feel with white people, making them label such act like Orlando as ones of International Terrorism or Radical Islamic Extremism though it may more accurately be described as a Domestic Terror attack.

However, noticeably absent from the topics analysis is Domestic Terrorism and Mental Health. Not once did Domestic Terrorism register at 1%, and no language regarding Mental Health, be it slang, or more professional terms, registered as a frame. The term “lone wolf” is within the slang topic that never registered above 3%. Racism never reached above 7%, and white supremacy did not register once about 1%.

**Polarization**

In this network graph, we look at the entire network of Las Vegas related tweets. For Vegas, I pulled a sample of 27,000 tweets, and of those tweets, there were 22,605 accounts, suggesting an average tweet rate of 1.19. Of those users, only 13.7% shared urls, the lowest rate of each case study, further bolstering my observation that Vegas was the least politicized of all the shootings.

Zooming in, we look at the largest cluster of users in Figure 2. Interestingly, though there are blue and red nodes within the cluster, the vast majority have an Unknown political classification, meaning they result in a grey node. Though Vegas is highly polarized, it seems as though the majority of shared information is shared by those with an Unknown political ideology. As a reminder, the Unknown ideology group are those who the machine was not 60% or more.
confident in its classification, suggesting that they are either moderate or rarely post political content.

Next, in Figure 3, we can see there is a large cloud of nodes that share only a few edges with other nodes, or none at all. There are slightly more blue nodes than red, for Left leaning users shared articles at a higher rate than Right leaning. Because there are so few edges between nodes, this suggest that there was little url sharing among Twitter users after Vegas. Small clusters with only a few edges between a few nodes suggest that each user in that cluster has shared a url with few other shares, perhaps a small article, a blog post, or link to an obscure website.

The top url shared in Vegas was a Gofundme for the victims of Vegas. The next top shared articles are all from left leaning publications: a New York Times piece, a Guardian piece, a Washington Post article, CNN, and NBC all reporting on the shooting. After these pieces, the next top shared urls are an Independent piece framing the shooting as organized by ISIS, and a Fox News article on a CBS lawyer who said the Vegas victims deserved it, for the majority of concert goers likely were gun rights advocates.

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102 “Las Vegas Victims’ Fund” GoFundMe, https://www.gofundme.com/dr2ks2-las-vegas-victims-fund

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Figure 1: In this network graph, we look at the entire network of Las Vegas related tweets. For Vegas, we pulled a sample of 27,001 tweets, and of those tweets, there were 22,605 accounts, suggesting an average tweet rate of 1.19. Of those users, 3,099 shared urls, meaning only 13.7% of users shared urls, the lowest rate of each case study.
Figure 2: Zooming in, in this chart we look at the main cluster of users. Interestingly, though there are blue and red nodes within the cluster, the vast majority have an unknown political classification, meaning they result in a grey node.
Figure 3: Figure 3 looks at the large number of nodes that share only a few edges with other nodes, or none at all. These nodes are predominantly blue as well. These urls are generally links to smaller publications, blog stories, or articles that are about the shooting but did not go viral.
In the Vegas sample there was a total number of 8,118 different urls shared. With an of 10 nodes per user, there were many different urls shared, and few viral urls. Each user stayed within a small cluster and shared the same url as only a few users, meaning many different narratives could accompany the Vegas shooting rather than a few dominating ones.

As a reminder, this bar chart represents the polarity of those who shared articles on Twitter. A rating of 0.0 means the node shared edges with only blue nodes and a rating of 1.0 means the node only shared edges with red nodes.

Again, Vegas is highly polarized, much more so than Orlando, and the Left shared more urls than the Right, though not as extreme as in Charleston.

**Conclusion**

The Left and Right tweeted about Vegas at the same rate, but used different frames. The Left framed the event as an issue of Gun Control and Terrorism, while the Right framed it as a act of Terrorism while citing the Weapon used. However the types of terrorism the Left and Right framed the shooting as were radically different. The Right framed the event as an act of Radical Islamic Terrorism after ISIS tried to claim the act as their own. The Left, on the other hand, used this event as an opportunity to argue that it was an act of terrorism though the perpetrator was not Muslim. From this event, it seemed
as though the Left hoped to critique the public’s tendencies to privilege white people by suggesting white mass murderers are “lone wolves” and not to be feared as deeply as Muslim murderers, in turn contributing to islamophobic tendencies and racial biases.

The Left and Right were highly polarized and rarely shared information. Furthermore, through the network graphs we can see that the Vegas url sharing was highly isolated. There were many tiny clusters that shared no edges outside of their own cluster, suggesting that yes, these groups were polarized, but also only sharing the same information as a few other users.
VII. Conclusion

Findings

Participation in Twitter Discourse and Political Agenda
One clear difference between each shooting was who was tweeting. After Charleston, the Right tweeted at a much slower rate than the Left. When they did tweet, they primarily used language such as Thoughts & Prayers. Out of the tweets they sent, a small portion were politicized or had any political angle or reference. It seemed that no one dared send tweets at all, let alone political ones. However, the Left quickly politicized the event and drove the discourse. The Right shared urls at a low rate, while the Left cited their sources and shared information through urls after the attack. Vegas showed a similar pattern, though not at the same rate.

From this pattern, there seems to be a correlation between participation and the tweeter’s political agenda. In other words, the political Left and Right on Twitter tend to tweet about an event when a frame that has been constructed around the event contributes to their political agenda. If no such frame exists, the Twitter users can simply not tweet about the event, or not acknowledge that there are any political implications of the event. For example, in Charleston, 1) the shooter was a white supremacist, 2) he used a handgun he legally purchased to 3) commit a hate crime against black people 4) in a church. There seemed to be no way the Right could build a frame that contributed to their agenda. If anything, to acknowledge this as a political event
would only give fuel to the fire of the Left to build frames that tore down the Right agenda. The Right chose to not participate in the discourse, but instead offered condolences for a sad incident.

On the other hand, when we observe Orlando, it is clear that multiple frames can be born from the event. Both the Right and Left participated equally, and both pushed different frames that were in line with their political agenda. The Right argued that Terrorism, and specifically Radical Islamic Extremism was the main issue at hand. They argued this frame while also talking about Donald Trump and the Democrats. The Left, on the other hand, argued that Terrorism was the main problem exposed by Orlando, and Guns along with it. They tweeted their frame in the context of Donald Trump and Republicans. It seems as though both the Left and Right used Orlando to either argue for or against Donald Trump, and against the opposing political party. Orlando presented the opportunity for both parties to create a frame around the event that bolsters their own political agenda.

Finally, Vegas was not highly politicized by either side. The Right, in this instance, had few frames to make, except to try to frame this as an event funded by ISIS. The Left tweeted slightly more than the Right and focused on Terrorism and Guns, but did not tweet, or at least, tweet politically at the same rate as Orlando. Something about Vegas made them apathetic, and something about Orlando, passionate.

This shows that Orlando was a special case out of the three studies. Orlando incited more emotion and passion from both the Left and Right, which I imagine is tied tightly with the threat.
felt by Orlando compared to the threat felt by greater America after Charleston and Vegas. I believe this threat is directly correlated with the frame of the event and America's fear of Muslim violence and complacency with white violence.

Shared Information
In this study, I measured shared information by url shares in network graphs. The fewer urls that are shared, and the more widely the few urls reach, the more consolidated and consistent the narrative is around the shooting. In other words, the less urls that are circling the Twittersphere, the more likely that a user coming across a url will take in the same information as another user. This shared information creates a shared reality. A shared reality and shared truth is essential to depolarization. If facts cannot be agreed upon, consensus cannot be reached or productive dialogue. Alternatively, if two groups absorb different or opposite information and believe opposing facts to be true, it will further push the groups to the extremes. These differing realities make individuals within the group more skeptical and less trusting of those outside of the group. They will only take in and deem valid information from those who they see as relevant and important within their own group. Without any external fact checks, the narratives can continue to spiral further from the opposing group’s narrative, pushing the groups to opposite extremes, contributing to further group polarization.

In Vegas and Charleston, there was very little shared information. The groups were highly polarized by political ideology. Yet, even within a political ideology, there was little information shared. For both shootings, there were many tiny clusters as opposed to large clusters of nodes.
This suggests that there were many, varying sources of information, and not necessarily any shared reality or truth.

By my measure, Orlando had the most shared information by far, and both Left and Right participated equally. This suggests that though there were competing frames in Orlando, the Right and Left were interacting and sharing similar information, similar realities, and a similar truth, contributing to Orlando’s lack of polarization.

However, this presupposes that most individual urls contain new or opposing information. Different urls do not necessarily suggest multiple truths or realities. Rather, a url could offer the same facts and information framed the same way as many other urls. Measuring information sharing through url shares has limitations, for it overestimates the number of opposing realities. Perhaps the majority of urls gave the same information after a shooting, or perhaps they gave contradicting information. For the next iteration, I hope to restructure the information sharing method and how I operationalize information sharing.

Polarization

Vegas and Charleston were deeply polarized by my measure. As a reminder, I operationalize polarization by measuring the frequency of url shares within or across groups. Shares predominantly in one cluster suggests polarization, shares outside of the cluster suggest depolarization. Group polarization in political discourse leads to gridlock, groups falling more into their views, and pushing towards the extreme. Orlando, however, was not deeply polarized on the network graph. Yet, the opposing frames presented by the Left and Right would suggest
deep polarization. My network graphs do not represent interaction, but shared information and a shared reality. It does not suggest that they depolarize through interaction, but through some shared truth. One characteristic of group polarization is the groups believing in different facts. So, perhaps to believe in the same facts but to argue them differently and to use different frames is a step towards depolarization. This suggests that shared urls do not claim any ideological bridge was built, but rather reality is shared.

Interaction across party lines in Orlando was regular, and information shared between the Right and Left. But why? I offer two possible explanations:

1) Because Orlando was during the presidential election, the Right and Left were already interacting with each other more often.

2) The Right and Left depolarize when there is a larger, outside perceived threat to unite against.

Unfortunately, because of the few case studies I look at and the methods I use, I am unable to offer an answer with certainty. If the first were true, this study would show that during presidential elections, polarization decreases as interaction between the Left and Right increases on Twitter.

However, if the second were to be true, perhaps new and intentional frames of mass shootings could effectively decrease polarization after the event. For example, Terrorism has a deep, political history in the US tied tightly to media. In the US, Terrorism has become equated to
Islamic Terrorism and is deeply feared, for with each attack America as a whole is victimized. Each individual is attacked. However, with mass shootings perpetrated by “lone wolves”, no such frame exists. Rather, it is a tragedy that is unlikely to be a recurring threat, for the man dies or goes to jail. To alter the mass shooting frame so that each American is a victim that will be threatened by this in the future (i.e. Parkland: March for Our Lives), the same emotion and political participation would be seen on Twitter in instances like Charleston or Vegas as they were for Orlando.

Limitations

Case Studies
Because I looked at only three case studies with radically different frames, it is difficult to recognize patterns across the shootings, for the factors that came into play were different with each case. For example, the fact that Orlando was during the 2016 presidential campaigns could have made the tweets much more political than they would have been had it been outside of election season. Furthermore, Charleston had only 9 deaths, while Vegas had 58. If the number of deaths influences the volume or politicization of tweets, it would skew the results. Though these case studies were chosen by design for their differences, measures could be taken to improve the method.

In order to more accurately recognize if the frame of the event correlates with the polarization, we would need to compare shootings that were as similar as possible in all other regards. A good example of this method is Aysel Morin who compares the DC Navy Yard Shooting with the Ft.
Hood Shooting and could conclude that the demographic of the shooter influences the frame.\textsuperscript{104} With more shootings, I would be able to draw more substantial conclusions.

**Operalization of Polarization and Information Sharing**

As I have suggested above, operalization of information shares through url shares can overestimate the number of shared, for not all urls show different information from one another. However, I do stand behind operalization of polarization as url shares. Though url shares do not necessitate interaction between users, it suggests that those users have a common belief or view. Perhaps more subtle than a retweet or reply, observing url shares could look at how often people respected or found valuable the same information online across parties.

We see through my measure of Orlando’s depolarization, that when there is a perceived external threat larger than the US political divide, a threat to both the Left and Right, interaction and depolarization could occur. Perhaps this could apply to focusing events and highly polarized issues more broadly. By changing the opposition each group is defined by from the opposing political party to some external, greater threat, my observations suggest that polarization would decrease as it did in Orlando. Therefore, one powerful way to decrease polarization is to alter the frame to mirror that of the War on Terror, but with Guns or mass violence. To make America as a whole a single, collective victim could allow a break in grid-lock to solve a problem that leads to death on a such a massive scale.

\textsuperscript{104} Morin, “Framing Terror.”
Victims of the Shootings

Charleston
Cynthia Hurd, 54
Rev. Clementa Pinckney, 41
Tywanza Sanders, 26
Sharonda Singleton, 45
Rev. DePayne Middleton-Doctor, 49
Rev. Daniel Simmons, 74
Susan Jackson, 87
Ethel Lance, 70
Myra Thompson, 59

Orlando
Stanley Almodovar III, 23
Amanda L. Alvear, 25
Oscar A. Aracena Montero, 26
Rodolfo Ayala Ayala, 33
Antonio Davon Brown, 29
Darryl Roman Burt II, 29
Angel Candelario-Padro, 28

Hughes 95
Juan Chavez Martinez, 25
Luis Daniel Conde, 39
Cory James Connell, 21
Tevin Eugene Crosby, 25
Deonka Deidra Drayton, 32
Simón Adrian Carrillo Fernández, 31
Leroy Valentin Fernandez, 25
Mercedez Marisol Flores, 26
Peter Ommy Gonzalez Cruz, 22
Juan Ramon Guerrero, 22
Paul Terrell Henry, 41
Frank Hernandez, 27
Miguel Angel Honorato, 30
Javier Jorge Reyes, 40
Jason Benjamin Josaphat, 19
Eddie Jamoldroy Justice, 30
Anthony Luis Laureano Disla, 25
Christopher Andrew Leinonen, 32
Alejandro Barrios Martinez, 21
Brenda Marquez McCool, 49
Gilberto R. Silva Menendez, 25
Kimberly Jean Morris, 37
Akyra Monet Murray, 18
Luis Omar Ocasio Capo, 20
Geraldo A. Ortiz Jimenez, 25
Eric Ivan Ortiz-Rivera, 36
Joel Rayon Paniagua, 32
Jean Carlos Mendez Perez, 35
Enrique L. Rios, Jr., 25
Jean Carlos Nieves Rodríguez, 27
Xavier Emmanuel Serrano-Rosado, 35
Christopher Joseph Sanfeliz, 24
Yilmary Rodríguez Solivan, 24
Edward Sotomayor Jr., 34
Shane Evan Tomlinson, 33
Martin Benitez Torres, 33
Jonathan A. Camuy Vega, 24
Juan Pablo Rivera Velázquez, 37
Luis Sergio Vielma, 22
Franky Jimmy DeJesus Velázquez, 50
Luis Daniel Wilson-Leon, 37
Jerald Arthur Wright, 31
Las Vegas
Hannah Lassette Ahlers, 34
Heather Lorraine Alvarado, 35
Dorene Anderson, 49
Carrie Rae Barnette, 34
Jack Reginald Beaton, 54
Stephen Richard Berger, 44
Candice Ryan Bowers, 40
Denise Burditus, 50
Sandra Casey, 34
Andrea Lee Anna Castilla, 28
Denise Cohen, 58
Austin William Davis, 29
Thomas Day, Jr., 54
Christiana Duarte, 22
Stacee Ann Etcheber, 50
Brian S Fraser, 39
Keri Galvan, 31
Dana Leann Gardner, 52
Angela C Gomez, 20
Rocio Guillen, 40
Charleston Hartfield, 34,
Christopher Hazencomb, 44
Jennifer Topaz Irvine, 42
Teresa Nicol Kimura, 38
Jessica Klymchuk, 34
Carly Anne Kreibaum, 34
Rhonda M LeRocque, 42
Victor L Link, 55
Jordan McIldoon, 24
Kelsey Breanne Meadows, 28
Calla-Marie Medig, 28
James Melton, 29
Patricia Mestas, 67
Austin Cooper Meyer, 24
Adrian Allan Murfitt, 35
Rachael Kathleen Parker, 33
Jennifer Parks, 36
Carolyn Lee Parsons, 31
Lisa Marie Patterson, 46
John Joseph Phippen, 56
Melissa V Ramirez, 26
Jordyn N Rivera, 21
Quinton Robbins, 20
Cameron Robinson, 28
Tara Ann Roe, 34
Lisa Romero-Muniz, 48
Christopher Louis Roybal, 28
Brett Schwanbeck, 61
Bailey Schweitzer, 20
Laura Anne Shipp, 50
Erick Silva, 21
Susan Smith, 53
Brennan Lee Stewart, 30
Derrick Dean Taylor, 56
Neysa C Tonks, 46
Michelle Vo, 32
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