Erika Fox

Extracting and Analyzing User Comments to Expose How Americans Respond to Gun Violence: A Computational Social Science Study

Advised by Professor Alicia Simmons and Professor Michael Hay

6/10/2019-8/02/2019

LDA Topic Model Code on GitHub: https://github.com/efoxcolgate/LDA/blob/master/LDA.py

INTRODUCTION

A journalist's word choice is crucial. When covering a shocking news story, the words they choose are blown up to the striking headlines that have the power to devastate the country. The wording used in news stories, also known as framing, influences the way citizens choose to respond to tragedies. However, until now, there has been little to no evidence that indicates just how powerful an article's frames can be. This study seeks to discover the press's impact on public opinion about gun violence by taking advantage of the news sphere's most modern state of evolution: internet news. The internet has taken the press's sphere for debate function to a whole other level, as it provides a virtual sphere for disagreement along with nearly unlimited access to information for discussion (Papacharissi, 2002). Not only have social media platforms such as Facebook, Twitter and Instagram enabled political participants to project their beliefs to millions of people, but news agencies such as the New York Times have created comment sections on their articles. In these comment sections, readers can react to the news and to the comments of other readers. These comment sections are changing the nature of news spheres of debate. They have made the process more interactive and more collaborative. In fact, comment sections on news articles have brought news consumption into a brand new state, a state with a many-to-many information flow instead of the traditional one-to-many information flow.

Instead of news platforms just putting their content out there as they would when news articles were restricted to the more physical newspaper medium, online publications allow for their audience to contribute to what is exposed to other news consumers by commenting. Now when news consumers go to inform themselves on current events, they don't only rely on the journalist content to shape their opinion and understanding of events and their subsequent issues, but they are now subject to the influence of commenters as well. The many-to-many information flow is one of the most important defining characteristics of New Media. This term refers to mass communication on the internet, which is commonly associated with uncertainty as to how the networks are forever changing human interactivity. However, this study takes advantage of this online mass communication in an effort to find out just how much journalistic content can affect what users might bring up in the comments. How do different writing styles/selection of frames used by the journalists impact the opinions of individual audience members as reflected in the comment sections? By closely analyzing both frames and audience response, this study aims to begin to answer the questions we have about news in the age of new media using sociological content analysis and computational natural language processing methods. The study will look specifically at news articles and comments that cover mass shootings. This country has recently experienced an increased awareness of this type of event, and news coverage has played a crucial part in that and how Americans have come to understand and respond to the tragedies. For the ambition of understanding as much about American mass shootings as possible for a study of this length, both Parkland's Marjory Stoneman Douglas (MSD) High School shooting of 2018 and the Las Vegas Massacre at the Route 91 Harvest Festival of 2018 will be considered. Because these two events are similar in nature but come from completely different circumstances, it should be telling to see how they differ in representations in the press and possibly in audience response as a result. Yes, some of the differences in how the shootings are covered will come from differences between the events themselves and not as much from their frames, but the comparison of these two bodies of news coverage should tell us a lot about which event aspects inspire which kinds of political conversation in the comment sections. I will be looking for the same categories of frames in each while still accounting for their differences. Would a shooting that occurred at a Country Music Festival inspire more journalists to bring up more discussions about gun control? Would a shooting perpetrated by a troubled teen in a high school inspire more journalists and their commenters to discuss mental health? This study could start to tell us which frames used by journalists are the most effective. Which frames cause the audience to be the most vocal in the comments? Will some frames appear in the comments regardless if they are used in its corresponding article? Are there any frames that are more successful in starting productive political conversations?

RESEARCH QUESTION

1) How are the implications of news framing reflected in the comments of New York Times articles on the Las Vegas Massacre at the Route 91 Harvest Festival and the Parkland Marjory Stoneman Douglas High School Shooting?

a) What is the nature of users' comments about online news articles about mass shootings? What topics are discussed?

b) How does the population of comments vary across case characteristics? How do discussion topics differ between the Las Vegas Massacre and the Parkland Shooting?

BACKGROUND

Conceptualization of Frames

Framing is the process of selecting some aspects of reality and making them salient, while directing attention away from other aspects. Frames are present anywhere, especially in press systems, but these frames still remain a "scattered conceptualization" (Entman, 1993; see also Zhou & Moy 2007). Frames can be considered a mode of interpretation for citizens to come to understand the information they are provided about the civic issues they need to know about. In the article "Communication and Opinion", Donald Kinder (1998) explains that frames are to issues in a similar way that stereotypes are to political candidates. This conceptualization of frames implies that they are oversimplified conceptions of a certain issue. Word selections made by journalists often prompt audiences to oversimplify what is really going on and to conceptualize complex social issues with only a fraction of the big picture. The way an issue is framed reflects what aspects are central or peripheral in the public's eyes. For example, in the case of gun violence in the United States, the frames present in the news coverage of such a tragic event could mean the difference between an audience member coming to understand a shooting as the fault of a single gunman or of a shortage of gun regulations in this country.

Implications of Framing

The process of framing in the American press system has implications for audience members' understanding and opinions about the world. Journalists cannot help but to only portray a fragment of reality when reporting on current affairs. As everyday Americans who are only exposed to a small percentage of the country's ground on any given day, we rely on these fragments of reality to fuel what we can imagine about the world and its public issues (Kinder 1998). As the providers of these tiny fragments of reality, journalists play a crucial role in determining how Americans come to understand political issues. The world's most acclaimed journalists such as Ann Curry are aware of this responsibility, as she hinted in her recent interview with NPR: "[A journalist's] job is to help people with good information" (Curry, 2018). However, even the best, most unbiased information might still be told with frames depending on which parts of the whole picture a certain journalist decides to focus on in their articles that are short enough for the public to be willing to read. This puts a large amount of power in the hands of journalists, as they are the ones who determine what frames are available to citizens. In other words, they may be responsible for much of how American's think about the events that they cover. This sense of power of the press has been around for a long time, as Lipperman wrote first in 1922 about how Americans must come to depend on others for their information about current affairs. However, just how much power these journalists have has been debated since the beginning of the study of this subject. For instance, JT Klapper, an early researcher on this topic, famously declared in 1960 that mass communication has "minimal effects" on public opinion. While this declaration might have been true to the evidence that was available at the time, the last 60 years of the press' evolution and an increase of understanding of how citizens interact with news have proven the claim to be mistaken (Kinder, 1998). Because the press has such a strong ability to tell us what to think about and even which aspects of each issue belong to our central cognitive processes as opposed to our peripheral cognitive processes, we know that frames can have powerful influence over public opinion. Even so, certain questions on the topic still remain. How do citizens choose which frames to read and how do they make them their own (Kinder, 1998)? To what extent have frames contributed to polarization in American politics? **How are the implications of news framing reflected in the comments of New York Times articles on the Las Vegas Massacre and the Parkland High School Shooting?**

Internet News (New Media's Impact on American News Consumption)

The term "New Media" refers to mass communication that relies on digital means of distribution, and often consists of interactivity between the distributor and the distributor's audience. This includes that many-to-many information flow that was described in the introduction to this paper. The internet is the setting for new media, and the decentralized communications that come with it. There is no debate that this new media communication is largely unknown terrain, and news on the internet is no exception. However, we can still speculate about what major affects new media has on news consumption. It is generally agreed upon that the traditional way to consume news is to receive a physical newspaper on one's doorstep every morning from a subscription, or to just read whatever physical news (including newspapers, magazines...) that is readily available. This "traditional" method of news consumption usually consists of readers sticking to just one source, or in other words, one set of frames. However, the digitalization of news has brought about a new level of agency for news consumers, as it allows them to switch from one news source to another in seconds, without any extra cost or the need to get up from where they are sitting. With this newfound ability, news consumers are no longer confined to just one set of frames in a single news source, and instead are free to explore an unlimited amount of other sources until they find the one they like the best. Of course, there are advantages in this development in that citizens can now expand their scope of knowledge about the rest of the world and its current affairs. Citizens can also see more than one set of frames in this way, and inform themselves on more aspects of the reality they are reading about. However, there are consequences with this online news selection process in that some news consumers may browse until they find a source whose frames focus only on certain pieces of the whole reality that they relate to or agree with the most, and then close themselves off from the rest. This kind of behavior may lead to a more polarized society, in that strong opinions on either side of a public issue can continuously reaffirm and strengthen their beliefs through their news consumption, while simultaneously blocking themselves off from any sources that may be favored by the other side of the debate (Tewksbury & Rittenberg, 2012). Social media networks such as Twitter and Facebook can easily have the same effect, in that their algorithms curate media for their users to consume. The internet has made it easier for media to spread information and reinforce beliefs, and in some cases these features have even made it vulnerable to exploitation by meddlers trying to change the course of the American democracy (Ness, 2019). However as much as the internet can be used as a weapon, it can be used as a tool. In this study it will be used as a tool to extract user comments in order to understand their nature, and public opinion about mass shootings, but the possibilities don't end there.

The Internet as a Platform for Political Discussion

In addition to the process of citizens subliminally selecting news sources for their frames, the level of interactivity (many-to-many information flow) included with a particular news source may also be a huge attracting factor for certain audiences, in that this additional layer of participation makes for a more satisfying news experience (Tewksbury & Rittenberg, 2012). Experts have been discussing the internet's potential for becoming a sphere for political debate since around the 1990's when it became more widespread as a means for social interactions. With the introduction of chatrooms, there was plenty of speculation by experts of whether these spaces would become a platform for political disagreement (Wojcieszak & Mutz, 2009). Sure enough, even online spaces that are by no means intended for political discussions frequently become hosts for interested users to express their opinions and stances as well. There are definitely some positive and negative sides to this ability of online political discussion. On the positive side, it encourages more discussion of issues and has the potential to get more Americans actively involved and interested in the country's politics. On the negative side, it has the potential to polarize our political climate in that many impressionable citizens get exposed to the strong opinions of others online everyday instead of getting informed from a selection of unbiased news sources. Additionally, we know that our behavior changes online. In "The Online Disinhibition Effect" (2004), John Suler explains that social interactions that humans undergo without their bodies present can have different effects. He notes that online, "some people self-disclose or act out more frequently or intensely than they would in person”, and goes on to explain six factors that contribute to this change in behavior, including invisibility and anonymity. Applying these changes and intensified interactions to political discussions online could be a lot to handle. Political discussions that occur online are often more aggressive and less compassionate than ever before. (Arendholz, 2013). For the purposes of this study, I will be analyzing political discussion that is housed in the comments of New York Times articles.

The New York Times Comment Section

While the lack of embodiment in online conversations may cause more aggression and less compassion in the way humans interact with each other, little aggression can be expected to be found in the New York Times comments due to something they have that many chatrooms do not: comment monitoring. NYT can choose not to display certain comments if they are offensive or too extreme, as well as choose which comments get displayed at the top to be the most frequently seen (these comments are decorated with a “NYT’s pick” icon). The Times even provides a little bit of information on their website of what they want to see from their commenters: “We are interested in articulate, well-informed remarks that are relevant to the article. We welcome your advice, your criticism and your unique insights into the issues of the day.” Because of this structure, this study may lack exposure to some of the more aggressive ideas left by commenters. However, these comment sections still have the potential to provide us with the answers to our questions, and show us what the New York Times considers to be “well-informed” and “relevant”. It was discovered during the sampling process that only about half of New York Times articles have comment sections. The New York Times says on its website that they are not able to open up comments for every article because of their limiting monitoring process, however it is not clear how they select which articles get to have comments and which ones do not. Maybe some articles were deemed too sensitive for users to be discussing, or too controversial to allow potentially angry readers to express their opinions on that page.

The Media Coverage of Gun Massacres in America

Since the Columbine High School shooting of 1999, the American press systems have adopted somewhat of a routine when it comes to how instances of gun violence are covered in the media, regardless of how the internet has changed news consumption since then. This routine consists of immediate near-complete domination of the media, usually beginning with live updates from the scene and then continuing to take up at least half of most news TV networks' airtime (Schildkraut & Elsass, 2018). Gun tragedies routinely dominate the agenda setting of written news as well, as the New York Times alone released over 130 articles following the Sandy Hook shooting of 2012, and around 170 articles following the Columbine shooting in 1999 (Schildkraut & Muschert, 2014). This news coverage is crucial for American citizens, because as noted before, this journalism is their only link to the rest of the world, and for most, this coverage is the most they will ever be affected by a mass shooting in their lifetime. In this dramatic amount of gun massacre coverage, a vast variety of frames can be found across journalists as there seems to be some disagreement on what issues relating to these gun crimes should be the most salient in the minds of those who are yet to be informed on a massacre. As described by Schildkraut and Elsass (2018), some of the most central issues that are addressed include the gun control vs the right to bear arms debate, as well as the mental health of perpetrators. Many people tend to agree that mental health is an issue regarding the perpetrators of these crimes and should be addressed, and most don't fail to attribute guns as a topic of interest regarding mass shootings. However, there is a strict divide between political affiliations regarding just how guns should be handled as a response to gun crimes. While some think it would be better to increase accessibility to guns with the mentality that the only way to stop a bad guy with a gun is with a good guy with a gun, others would prefer to restrict gun access as much as possible, especially for those with a history of mental health issues. These are the common frames that have been blamed over and over again for variation in public opinion, understandably so since one can imagine how this type of coverage could indirectly tell their audience what aspects of each case of gun violence to think about. Not only that, but it has been discovered that there is a heightened sense of interest in the media coverage of gun violence in comparison to any other type of coverage. All kinds of news networks have reported a surge in their audience interest when it comes to these shooting stories (Schildkraut & Elsass, 2018). While it may be difficult to pinpoint the reasoning why, whether it be an increased fear of crime, some kind of morbid curiosity, or something else, these implications of the framing of gun violence should not be ignored. Finally, although the media has developed a routine for the coverage of mass shootings, the extent to which each tragic instance of gun violence is covered is not always exactly the same. In an analysis, Schildkraut and Elsass (2018) pointed out that the higher the death toll of the event, the more attention it tends to gather. This study may further show how the coverage varies across two shootings of different magnitudes and circumstances.

EVENTS OF INTEREST

The following are the facts of the Las Vegas Massacre and the Parkland Shooting cases, the two events whose coverage and comments will be analyzed for this study. The facts have been compiled from a sample of ten New York Times articles from each event, as well as some additional sources.

<u>Las Vegas, Nevada; Route 91 Harvest Festival</u>

On October 1st, 2017, a crowd of about 22,000 people gathered at the Route 91 Harvest Festival to watch country musician Jason Aldean perform. Shortly into the performance, the sound of gunfire interrupted the concert, sparking chaos. The gunman, Stephen Paddock, released gunfire onto the crowd from the 32nd floor of the Mandalay Bay Resort and Casino, several hundred feet away from the victims. The gunfire lasted for nine to eleven minutes, killing 58 people and injuring more than 500. Stephen Paddock was identified to be a 64-year-old man from Mesquite, Nevada, but his motive for this mass murder is still unknown. Police officers on the scene were able to contact Paddock alive, but by the time they breached the hotel room from which he was firing, he was dead due to suspected suicide. Along with Paddock, 23 weapons were found in that hotel room including multiple semi-automatic rifles. Investigators later uncovered that Paddock checked into the hotel room on September 25th, about five days before he released fire. He reportedly had five bags with him. On September 26th, Paddock brought six more bags up to his room and wired $50,000 to the Philippines. His girlfriend Marilou Danley was visiting family there at the time but is not thought to have been involved with the crime. According to Daily Mail, she feared that Paddock wanted to break up with her because he not only sent her large amounts of money but also paid for her plane ticket to the Philippines. By the time the day of the attack arrived, Paddock had sent another $50,000 to the Philippines, demanded a new hotel room with a “better view”, brought four more bags up to the hotel and spent an estimated total of 18 hours gambling. Less than an hour before he fired the first shots on the Las Vegas Village, the venue of the country music festival, he deadbolted the doors to the crime scene. He then opened fire and made history by inducing the deadliest mass shooting in modern American history. The distant sounds of gunfire prompted performer Jason Aldean to run from the stage in a panic. Concert goers ran for their lives doing their best to keep themselves and their loved ones safe. During their frenzy of panic, they witnessed their fellow concertgoers drop dead and incapacitated all around them. Many victims were injured by the force of the crowd, shrapnel, or barbed wire as well as bullets during their attempt at escaping. Many of the concert-goers helped transport people to hospitals in their personal vehicles. By the end of the night, the total death count was 59 people, including gunman Paddock. A huge wave of grief was spread throughout the United States for this was the second “worst” mass shooting in a row, following the Orlando Pulse Night Club shooting the year prior. Americans mourned the victims all over the country and lined up immediately to donate blood in order to help survivors. President Trump publicly addressed the tragedy on October 2nd calling it an “act of pure evil”. He then announced that he would be flying to Las Vegas within the next couple days to be with the victims and their families.

<u>Parkland, Florida; Marjory Stoneman Douglas High School</u>

On February 14th, 2018, a normal day at Marjory Stoneman Douglas High School was interrupted by the sound of the second fire alarm for the day. Some teachers were reportedly suspicious around the idea of two fire drills in one day, and told their students to take shelter, lockdown style, in their classrooms. These suspicions were almost immediately confirmed with the sound of an AR-15 automatic rifle firing throughout the school's hallways. The shooting lasted for about six minutes. The massacre resulted in the death of 17 people, a football coach, an athletic director, a geography teacher, and 14 young students. Additionally, 17 people were non-fatally injured, although five of those injuries were life-threatening. The majority of the shooting reportedly occurred in the freshman wing of the building. The gunman of the crime was identified to be a former student of the high school, 19 year old Nikolas Cruz. Cruz was reportedly some sort of outcast during his time at Marjory Stoneman Douglas. Unlike most mass shootings, the shooter managed to escape the scene alive by blending into the fleeing crowds. About an hour after his crime, he was taken into custody and treated for "labored breathing" at the local ER. As a part of the investigation of this case, police discovered cell phone footage of Cruz on the day of his crime. Notable lines from the footage include: "My goal is [to kill] at least 20 people" and "You will all know my name". In the wake of this record breaking school shooting (in terms of number of victims), there was an increase of anger amongst young people for the cause of gun control. Most famously, surviving teen Emma Gonzalez spoke out about the tragedy, begging politicians to stop offering prayers and condolences, but to take action instead. The massacre inspired the "March for Our Lives" organized protest that occurred in many locations across the country on March 24, 2018.

<u>Historical Context and Differences to Consider</u>

Because I am going to be comparing the news coverage and the corresponding comments of these two events, it seems necessary to touch on where these events fit into the political climate of the time, and how this context could influence what I might expect to see in the news coverage. Mass shootings aren't a modern invention but they have been more or less on the American radar since 1999, when Columbine occurred. However, 2016's Orlando Pulse Nightclub shooting served as a little bit of a wakeup call for many in that this was the first "worst" mass shooting to occur in almost 10 years, topping the 32 fatalities from the Virginia Tech Massacre of 2007 with a high death count of 49. The shock of this new "worst" shooting in 2016 came 4 years after the shock of the Aurora (12 victims) and Sandy Hook (27 victims) shootings of 2012. Countless other shootings have occurred before and after 2012 as well. However, the Orlando shooting was especially timely in that the June shooting had many Americans thinking about guns (whether they wanted to protect their rights to own a gun or if they supported gun reform) going into the 2016 election. The Las Vegas Massacre, one of the cases of interest this study, became the next "worst" mass shooting the following year, within months of the change of office in the White House. The political context for these two events, Orlando and Las Vegas, were probably pretty influential in how Americans chose to react to the tragedies, in that they were already experiencing a time of political shifting. However, by the time the Parkland shooting occurred, it is likely that much of this political energy had already fizzled out.

METHODS (Part One: Content/Frame Analysis)

Article Sampling

For the purpose of this study, a total of 20 articles from the New York Times were analyzed. The sample was evenly split between the two shootings, with 10 articles that covered the Las Vegas shooting and 10 articles that covered the Parkland shooting. The sampling process consisted of downloading narrowly refined results from the NexusUni database. The queries used were the keywords “Las Vegas” for the Las Vegas shooting and “Parkland” for the Parkland shooting. Both searches were refined to only yield results from newspapers, and more specifically, from the New York Times. Additionally, the search results were restricted to a small time frame, namely the first two days after the event, which translates to October 2nd-3rd, 2017 for Las Vegas and February 15-16th, 2018 for Parkland. These results were then compiled into two Microsoft Excel documents and screened for relevance to this research. For an article to be considered relevant, it could have either covered the shooting directly, or any of its subsequent events (flywheels). The minimum word count for the articles was 500 words. The articles then needed to be checked to see if they had comment sections, which many of them did not. In fact after this parameter was applied I was brought down to only 6 articles for the Parkland shooting (down from 43 results) and needed to extend its time frame an extra day, bringing its window up to February 15-17th, 2018. This brought us to a total selection of 10 eligible articles for Parkland (down from 67 results). Las Vegas yielded a total of 13 eligible articles from its original time frame (down from 58 results). These logistics confirm that these two shootings did not receive equivalent coverage, in that Las Vegas, the more deadly event, appears to have been covered much more thoroughly given that it yielded more eligible results from a shorter time period than

Parkland. With these final selections, those 10 articles for Parkland became the sample for that event. For Las Vegas, 10 out of those 13 articles were randomly selected.

The full sample is as follows. From now on in this paper, individual articles will be referred to by their ArticleID:

Las Vegas Articles			
ArticleID	Citation	Word Count	Number of Comments
1	KEN BELSON, JENNIFER MEDINA and RICHARD PÉREZ-PEÑA. (October 2, 2017 Monday). A Burst of Gunfire, a Pause, Then Carnage in Las Vegas That Would Not Stop. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5PNY-K7F1-DXY4-X0TD-00000-00&context=1516831.	1839	440
2	The New York Times. (October 2, 2017 Monday). Multiple Weapons Found in Las Vegas Gunman's Hotel Room. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5PNY-K7F1-DXY4-X0TB-00000-00&context=1516831.	1933	5507
3	KEVIN ROOSE. (October 2, 2017 Monday). After Las Vegas Shooting, Fake News Regains Its Megaphone; The Shift. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5PNY-K7F1-DXY4-X0X3-00000-00&context=1516831.	1186	296
4	ROSS DOUTHAT. (October 3, 2017 Tuesday). Why Gun Control Loses, and Why Las Vegas Might Change That; Op-Ed Columnist. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5PNY-K7F1-DXY4-X0YY-00000-00&context=1516831.	969	1446
5	NICHOLAS KRISTOF. (October 2, 2017 Monday). Preventing Mass Shootings Like the Vegas Strip Attack; Op-Ed Columnist. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5PNY-K7F1-DXY4-X0V3-00000-00&context=1516831.	899	2420
6	ROXANE GAY. (October 3, 2017 Tuesday). No More Shootings That Follow the Rules; Contributing Op-Ed Writer. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentIt	921	698

	em:5PNY-K7F1-DXY4-X11N-00000-00&context=1516831.		
7	JENNIFER MEDINA, RICHARD PÉREZ-PEÑA and ADAM GOLDMAN. (October 3, 2017 Tuesday). Meticulous Planning by Las Vegas Gunman Before He Opened Fire. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5PNY-K7F1-DXY4-X126-00000-00&context=1516831.	1718	938
8	TIFFANY HSU. (October 2, 2017 Monday). Las Vegas Shooting Underscores Hotel Security Choices. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5PNY-K7F1-DXY4-X0VF-00000-00&context=1516831.	814	45
9	STEVE ISRAEL. (October 2, 2017 Monday). Nothing Will Change After the Las Vegas Shooting; Op-Ed Contributor. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5PNY-K7F1-DXY4-X0WR-00000-00&context=1516831.	1068	3134
10	THE NEW YORK TIMES. (October 3, 2017 Tuesday). Gunman's Girlfriend Arrives in U.S. and Is Expected to Be Questioned; Live Briefing. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5PNY-K7F1-DXY4-X0Y8-00000-00&context=1516831.	2243	1847
Parkland Articles			
ArticleID	Citation		
11	NATALIE PROULX and KATHERINE SCHULTEN. (February 15, 2018 Thursday). Resources for Talking and Teaching About the School Shooting in Florida. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5RN8-HC51-DXY4-X07N-00000-00&context=1516831.	4130	12
12	By RICHARD FAUSSET and SERGE F. KOVALESKI; Richard Fausset reported from Parkland, and Serge F. Kovaleski from New York. Reporting was contributed by Nick Madigan from Fort Lauderdale, Fla.; Audra D.S. Burch and Neil Reisner from Parkland; Frances Robles from San Juan, P.R.; and Jonah Engel Bromwich, Steve Eder and Patricia Mazzei from New York. Kitty Bennett contributed research.. (February 16, 2018 Friday). Florida Shooting Suspect Displayed Flashes of Rage And Other Warning Signs. *The New York Times.* Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5RND-9F91-JBG3-609M-00000-00&context=1516831.	1679	1197
13	Julie Turkewitz, Patricia Mazzei and Audra D. S. Burch. (February 15, 2018 Thursday). Suspect Confessed to Police That He Began Shooting Students 'in the Hallways'. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5RND-6BJ1-JBG3-604R-00000-00&context=1516831.	2237	1124

14	By DAN BARRY; Alan Blinder contributed reporting.. (February 16, 2018 Friday). A Horror Story Is Replaying as America Reloads. *The New York Times.* Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5RND-9F91-JBG3-607H-00000-00&context=1516831.	1260	809
15	ALEXANDRIA SYMONDS and RAILLAN BROOKS. (February 16, 2018 Friday). Reporting on a Mass Shooting, Again. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5RNG-P931-DXY4-X132-00000-00&context=1516831.	989	7
16	By AUDRA D. S. BURCH and PATRICIA MAZZEI; Audra D.S. Burch reported from Parkland, and Patricia Mazzei from New York. Reporting was contributed by Maggie Astor, C.J. Chivers, Niraj Chokshi, Matthew Haag, Serge Kovaleski, Matt Stevens and Daniel Victor from New York, and Adam Goldman from Washington. Doris Burke contributed research.. (February 15, 2018 Thursday). Horror at Florida School; Ex-Student Held. *The New York Times.* Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5RN6-C311-DXY4-X4CM-00000-00&context=1516831.	1299	4128
17	By KATIE BENNER, PATRICIA MAZZEI and ADAM GOLDMAN. (February 17, 2018 Saturday). Warned About Suspect, F.B.I. Didn't Act. *The New York Times.* Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5RNM-8M11-JBG3-6313-00000-00&context=1516831.	1037	1832
18	GREGORY GIBSON. (February 17, 2018 Saturday). A Message From the Club No One Wants to Join; Opinion. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5RNP-K561-DXY4-X3JM-00000-00&context=1516831.	1224	402
19	MAUREEN DOWD. (February 17, 2018 Saturday). Appeasing the Trigger Gods; Op-Ed Columnist. *The New York Times* . Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5RNT-1MG1-JBG3-64KS-00000-00&context=1516831.	964	739
20	By BRET STEPHENS. (February 17, 2018 Saturday). To Repeat: Repeal the Second. *The New York Times.* Retrieved from https://advance.lexis.com/api/document?collection=news&id=urn:contentItem:5RNM-8M11-JBG3-634D-00000-00&context=1516831.	878	1002

You might notice that although I had a desired word count for the articles, the comment counts for these articles range from 7 to 5507. As of now there's no telling why some articles attract way more comments than others, but that is a question that some content analysis may be able to answer. The comment totals are 16,771 comments for the Las Vegas sample and 11,252 for the Parkland sample. That's a total of 28,023 comments to analyze for this study.

Content Analysis/Definition of Frames

The sample of 20 articles were imported into the content analysis software MAXQDA for frame analysis. There, the articles were thoroughly scanned for frames as characterized into four primary frame categories and a total of 14 secondary frame categories. The primary frames consisted of ATTRIBUTION OF RESPONSIBILITY, CONFLICT, HUMAN INTEREST, and MORALITY. The secondary frames for ATTRIBUTION OF RESPONSIBILITY included "Stephen Paddock/Nikolas Cruz", "Police/FBI Negligence", "Assault Rifles", and "Lack of Gun Control". For CONFLICT, the secondary frames were "Right to Bear Arms vs. Gun Control", "Americans vs. the NRA", "Democrats vs. Republicans", "Mental Health", and "Hotel/Concert/School Security". The secondary frames for HUMAN INTEREST were "Accounts of Grievances/Trauma" and "Humanization of Stephen Paddock/Nikolas Cruz". Finally, the secondary frames for MORALITY were "Thoughts and Prayers", "Unity for Action" and "Demoralization".

Definition of Frames:

ATTRIBUTION OF RESPONSIBILITY

The following secondary frames characterize the different ways by which the sample of articles placed blame for the occurrences of these gun tragedies.

- <u>Stephen Paddock/Nikolas Cruz:</u> The majority of articles with this frame are the ones that stick mostly to the facts of the case, and note factually that Paddock and

Cruz are the ones who committed their respective crimes. However, these articles do not usually provide much more information about what motivated or enabled them to commit their crimes, and in doing so they may be indirectly dismissing any possibility that the American government or any social forces could be responsible for yet another mass shooting. Some of the articles with this frame gave a little bit more context around the character of Paddock or Cruz, often using mental illness as their reasoning for placing the responsibility on the gunman.

- <u>Police/FBI Negligence:</u> Many of the articles explain the FBI/Police activity surrounding the events but some of them portray the forces in a negative way, such as by suggesting that the FBI failed to act upon a tip they were given or did not do a thorough enough background check that could have prevented the shooting.
- <u>Assault Rifles:</u> Many of the articles made sure to highlight that legally purchased semi-automatic rifles were used in the massacres and made it possible for a large amount of people to be killed in just a short amount of time. Some of these articles go as far as to make comments along the lines of "there is no good reason for any American to own a semi-automatic weapon".
- <u>Lack of Gun Control:</u> In the aftermath of mass shootings, the media often prompts their audiences to think about gun laws. The articles with this frame are the ones that say or imply that the mass shooting could have been prevented with tighter gun laws (any guns, not just assault rifles).

CONFLICT

The following secondary frames categorize the different types of perceived conflicts/problems to solve that existed in the aftermath of these shootings.

- <u>Right to Bear Arms vs. Gun Control:</u> The articles with this frame discuss how the country should address the gun-debate in the most general sense in the wake of a mass shooting. These articles do more than simply attribute the responsibility of the shooting to a lack of gun control laws, instead they provide a commentary on whether or not that is the right step at the right time for the country to take.
- <u>Americans vs. the NRA:</u> Many of the articles depicted the gun debate to be a struggle between the NRA and the rest of Americans. Most of these articles portray the NRA as a villain that Americans need to overcome in order to achieve the regulations they desire.
- <u>Democrats vs. Republicans:</u> The articles with this frame discuss the gun-debate like most conflict frames for this study, but this particular variation applies to the articles that describe this debate by stating the case of either or both polarized political parties.
- <u>Mental Health:</u> A few of the articles discuss the mental health of the perpetrators and speculate about what should be done to address these mental health issues in order to prevent future mass shootings. Additionally, some articles address how the shooting might affect the mental health of survivors or community members.

- Concert/Hotel/School Security: Some of the articles mention or discuss weaknesses in security that allowed for the shootings to happen and propose solutions.

HUMAN INTEREST

The following secondary frames characterize the ways in which the articles attempt to spark an empathetic response in their audiences when they inform them about the mass shootings.

- Accounts of Grievance/Trauma: Many of the articles include quotes or stories that describe the emotions that the shooting brought about. Some of the quotes are from victims describing what is was like to be on the scene of the crime or how the experience has affected them. Some of the quotes are from loved ones of victims, describing what it was like to fear for their lives or not have them return home. There are also a few quotes from the president or other officials provided.
- The Humanization of Stephen Paddock/Nikolas Cruz: The articles characterized under this secondary frame include more insight into the lives of the perpetrators, possibly inspiring the audience to feel empathetic towards the less-than-perfect lives they had leading up to their crimes.

MORALITY

The articles with MORALITY frames are the ones that have any indication of a perceived ethically correct way for the country to move forward in the aftermath of the shooting.

- Thoughts and Prayers: After tragedies in the US, Americans often take the stance that it may be too soon for any related political discussions and instead offer thoughts and prayers to those who were affected by the shooting. Many of the articles either take this stance or at least bring it up.
- Unity for Action: Many of the articles demand that the country must spring into action to prevent future instances of Gun Violence.
- Demoralization: Some of the articles are self-aware that the coverage of mass shootings is repetitive and so are instances of gun-violence. The articles with the demoralization frame often say that the shootings should, but won't spark change.

DESCRIPTION OF FRAMES

The content analysis of the two samples of articles resulted in a total of 95 frames, with 48 for Las Vegas and 47 for Parkland. Here is a break down of the results by shooting and primary codes:

Attribution of Responsibility Codes	Las Vegas	Parkland
Stephen Paddock/Nikolas Cruz	5	6
Lack of Gun Control	4	5
Assault Rifles	6	6
FBI/Police Negligence	3	3
Total	18	20

Conflict Codes	Las Vegas	Parkland
Right to Bear Arms vs. Gun Control	2	5

Americans vs. NRA	3	2
Democrats vs. Republicans	3	2
Mental Health Issues	2	1
Concert/Hotel/School Security	5	1
Total	15	11

Human Interest Codes	Las Vegas	Parkland
Accounts of Grievance/Trauma	4	4
Humanization of Stephen Paddock/Nikolas Cruz	3	4
Total	7	8

Morality Codes	Las Vegas	Parkland
Thoughts and Prayers	3	1
Unity for Action	4	2
Demoralization	1	5
Total	8	8

<u>Comparing the Results: Las Vegas vs. Parkland</u>

As the tables express, there are many areas where the shootings yielded similar results (within one frame), supporting the popular hypothesis that the media has a routine when it comes to covering mass shootings. These areas with more consistent results include the attribution of responsibility and the human interest categories. This might hint to us that these two categories of frames are more important to what makes this said "media routine" so consistent. However, there are other areas that show more disparity in how the two events were covered, the conflict and morality frame categories. This result seems about right, in that over time as tragic events continue to happen, our morality changes and that has effects on how we deal with conflict. For the conflict frames, the most disparity between the two events happens with the “Right to Bear Arms vs. Gun Control” and the “Concert/Hotel/School Security” frames. For the “Right to Bear Arms vs. Gun Control” frame, Parkland has more frames. For the “Concert/Hotel/School Security” frame, Las Vegas has more frames. There is not an obvious explanation for the disparity here. In both events, guns (including assault rifles) were utilized as the crime’s weapon, and the weapon(s) was not necessarily any more significant in Parkland’s case than it was in Las Vegas’. Similarly, there is no apparent reason why hotel or concert security (for Vegas) should be more important than school security (Parkland), even though that is what seems to be the case with this sample of articles. When we analyze the comments we can see to what extent the commenters agree with this disparity by the topics they choose to bring up in response. For morality frames, the results are uneven for all three subcategories. For the “Thoughts and Prayers” and “Unity for Action” frames, Las Vegas had a higher number. For the “Demoralization” frame, Parkland had a higher number. These disparities only give us some insight on how the coverage of the two shootings differed. Only the comments can tell us if the audience response differs as well as a result.

IMPLICATIONS OF FRAMING

Hypotheses on how these articles may impact public opinion

Attribution of Responsibility Frames:

The way these articles chose to attribute responsibility for these tragic events may be the most impactful on public opinion. Where the blame is placed could be extremely influential on how an audience comes to understand an event, and therefore how they believe the event should be addressed. For instance, if we were to assume that a certain reader only knows the information that they have read from the New York Times, and they only read articles with the “Stephen Paddock/Nikolas Cruz” frame, they may not think to consider the other factors that could have contributed to the mass shooting. Instead, these readers may be more likely to react with sadness and disbelief that one man committed such a crime. Some of those readers could also form opinions around the danger of individuals with mental health. Take one of the Parkland articles for example, when discussing how teachers should address the shooting in their classrooms, the article “Resources for Talking and Teaching About the School Shooting in Florida” written by Natalie Proulx and Katherine Schulten emphasized that teachers should be “reminding students to report warning signs of mental health issues and possible threats to an adult”. This message can have extremely damaging effects because of the way it implies that any students with mental health issues are dangerous and are “potential threats” to the school. On the other hand, if some readers only read articles that attributed a “Lack of Gun Control” responsible for the events, those readers would supposedly be more likely to want to fight for gun regulations. As for the “Assault Rifles” frame, readers will likely react in a similar way than those who were exposed to the “Lack of Gun Control” frame, as both frames blame the legality of guns in some way. However, I think that when I start to look at some comments in response to these articles, I will see more people addressing a ban on assault rifles in particular instead of all guns in general. This way, readers would be advocating for a way to decrease death counts in America in a less controversial way, in that the ban of assault rifles and not all guns feels more like a compromise. This idea is appealingly shared with this quote from one of the Las Vegas articles, “Nothing Will Change After The Las Vegas Shooting” written by Steve Israel: “Democrats would offer amendments to prevent people on the terrorist watch list from purchasing firearms. A no-brainer, I thought. If you’re too dangerous to board a plane, you’re too dangerous to buy an assault weapon, a common-sense position shared by over 80 percent of Americans”.

Finally, there were several articles that chose to put the blame on “FBI/Police Negligence”. Articles such as “Warned About Suspect, FBI Didn’t Act”, a Parkland article by Katie Benner, Patricia Mazzei and Adam Goldman, describe instances where the FBI or Police probably could have done something more to prevent the shooting. The article writes: “The FBI received a tip last month from someone close to Nikolas Cruz that he owned a gun and had talked of committing a school shooting, the bureau revealed Friday, but it acknowledged that it had failed to investigate.” The audiences of these articles could end up more outraged about the FBI than any other issue that is often discussed in the aftermath of a mass shooting.

Conflict Frames:

The conflict frames in my sample can be sorted into two main types, the ones that relate to the gun-debate and the ones that don’t. Because the gun-debate is such a prominent thing for newspapers to discuss in the wake of a shooting, there is a variety of ways that journalists choose to depict that particular conflict. For this study, this variation was represented by the “Right to Bear Arms vs. Gun Control”, “Americans vs. the NRA” and the “Democrats vs. Republican” frames. Whichever frame is used to depict the gun-debate could influence the audience’s interpretation of who the real villain in the fight against gun violence. For example, the articles that frame the conflict as “Americans vs. the NRA” could leave some of the more impressionable audience members with the belief that in the fight for gun-control, the NRA is their demon opponent. This point is illustrated in one of the Parkland articles, “Appeasing the Trigger Gods” by Maureen Dowd, when she describes Donald Trump’s ambitions to negotiate with the NRA: “He said that he would hop in his limo and go to the NRA headquarters in suburban Virginia and stay as long as it took to make a deal, noting that there were some points where both sides in the debate could agree.” The quote implies that the organization has more political power than the president and government. On the other hand, articles that frame the conflict as “Democrats vs. Republicans” just perpetuate the idea that in order for people to get their way in our democracy, they must make sure that their political party is the one with the most power. Regardless, the frames of “Conflict” in my sample of articles influence how the audience perceives the conflict between gun laws in our current political climate and in result can have an impact on how citizens go about getting what they want. The articles may either inspire them to challenge/protect the NRA’s power or try harder to have their party dominate in leadership positions. There are also the articles with the “Right to Bear Arms vs. Gun Control” frame, which depict the gun-debate more generally. The audience of those articles are also likely to have a political response.

In addition to the conflict frames that characterize the different ways that the media depicted the gun-debate, there were the “Mental Health” and the “Concert/Hotel/School Security” frames. Although these frames were less prominent, they could still affect what the audience perceives as important issues to address in the wake of a mass shooting, and possibly even distract the audience from the gun-debate. For instance, one of the Parkland articles, "Suspect Confessed to Police That He Began Shooting Students 'in the Hallways'" by Julie Turkewitz, Patricia Mazzei and Audra D. S. Burch, wrote that "Trump announced he would visit Parkland and work with the nation's governors 'to help secure our schools, and tackle the difficult issue of mental health'. But he made no mention of guns." Quotes such as this one could have a similar damaging effect than the Stephen Paddock/Nikolas Cruz attribution of responsibility frame where the nation could start to believe that anyone with mental health issues has violent tendencies. For the Security frames, more articles discussed hotel security in regards to the Las Vegas shooting than articles that addressed school security in regards to the Parkland shooting. This may be because the Parkland coverage so heavily focused on the gun-debate, but this probably means that very few people were concerned with increasing school security after that event, or at least less people were concerned about school security after Parkland than people were concerned about hotel security after Las Vegas.

Human Interest Frames:

The appeal in using human interest frames in an article is to connect those who will only experience mass shootings by its media coverage to those who have been directly affected by capturing the human element of the story. By sharing the experiences of people involved in mass shootings with their readers, journalists can trigger certain empathetic emotions in their audience that will impact how they continue to conceptualize the tragedies. These emotions can be positive or negative, and could have a significant impact on how an individual chooses to react to a story. The human interest frames were sorted into two main secondary codes, "Accounts of

Grievance/Trauma" and "The Humanization of Stephen Paddock/Nikolas Cruz". The articles that fit into the "Accounts of Grievance/Trauma" category often included quotes from survivors of the shooting. For example, the Vegas article "A Burst of Gunfire, a Pause, Then Carnage in Las Vegas That Would Not Stop" by Ken Belson, Jennifer Medina and Richard Perez-Pena writes: " Down below at the Route 91 Harvest Festival, Melissa Ayala, 41, was drinking and laughing with four friends from California when they heard the gunfire, which at first they thought was fireworks. Then a man near her fell with a bullet wound to his neck. 'There was blood pouring everywhere,' she said." This form of storytelling that is highly present in the coverage of mass shootings is intended to help the reader imagine what it must have been like to have been in a vulnerable position such as in the crowd at the Route 91 Harvest Music Festival or present at Marjory Stoneman Douglas High School. In other words, these human elements of reality help audiences to feel the same pain and anger that the survivors do, which could result in an increased amount of them wanting to react in a similar way, which is often to make sure that it never happens again. On the other hand, some articles use alternative forms of human interest, such as the ones that fit into the "Humanization of Stephen Paddock/Nikolas Cruz" category. As described earlier where the frames are defined, the coverage of both shootings contained some frames where journalists chose to include some insight into the life of the perpetrator. These two frame categories have the potential to influence the audience in different ways, whether they are more likely to empathize with the victims, possibly encouraging them to spring into action to prevent gun violence, or if they feel a little bit of empathy towards Stephen Paddock and/or Nikolas Cruz in the sad lives they must have led that have propelled them to do such terrible things. The readers that are more receptive to the humanization of the perpetrator could also be more likely to be the ones to send thoughts and prayers to the victims and claim that there is not a lot anyone can do to prevent tragedies like these.

Digging a little deeper though, even within the category that humanizes the perpetrator, I mentioned before that I noticed that the frames that humanized Nikolas Cruz differed from the frames that humanized Paddock, possibly because Cruz is still alive to tell a story and Paddock is not. While Paddock's frames had more focus on his upbringing, Cruz's frames more often discussed his expulsion of Marjory Stoneman Douglas and his mental health. Both types of frames depict the perpetrator as a troubled man, but it is possible that the different ways in which the coverage conveys this could have implications on the public opinion regarding them.

Morality Frames:

Last but not least, the morality frames characterize the ways in which the coverage subliminally or explicitly suggests how the country should move on after these mass shootings whether that be "Thoughts and Prayers", "Unity for Action" or "Demoralization". Since this frame is defined around its allusion to action or inaction, morality frames could have very impactful implications on how audiences react to news. It is not terribly difficult to imagine how an article telling their audience to not sit back in silence and take action such as in the "Unity for Action" frame could inspire people to take action. Or how an article that extends thoughts and prayers out to the victims of the shootings such as in "Thoughts and Prayers" could inspire the audience to be the same. The "Demoralization" frame which is growing in prominence the more often these tragedies occur could have a similar obvious effect, in that it could prompt audiences to feel demoralized as well that there will never be any changes made in order to prevent mass shootings in the future. These different takes on Morality should not be taken lightly by readers.

METHODS (Part 2: Automated Data Extraction and Analysis)

Data Extraction

After the content analysis of the 20 articles was complete, thousands of comments needed to be extracted using the New York Times API. The New York Times API is available for anyone to use and its intended purpose is to "encourage innovation for collaboration" (https://developer.nytimes.com/faq#a3) . The way it works is to register an "App" in order to get an API key that allows you to enter a command into a web browser in order to extract data. The New York Times provides many APIs, including ones that extract data on New York Times articles, NYT Best Sellers, movie reviews and more. For this project, the Community API, the API that extracts user comments from articles, was the one that was going to be the most handy. However, around the time that I was going to start collecting data for this project, this Community API was "DEPRECATED" which meant that its algorithm was disapproved. The website noted that a new version was in the works, but the current version seemed to be not only disapproved of but completely unusable. I sent an email to the developers and crossed my fingers that they could help me, but in the meantime I started to gear up to use Twitter tweets instead. However, almost a week later, I did hear from the NYT developers, informing me that they had updated their website with a beta version of the API. Typically, if an algorithm is in a "beta" version, that means that it is only available to a small number of people for testing. Even though this may mean that the algorithm I used for data extraction was not as perfect as it could have been, I'm still very lucky that the NYT developers allowed me to use it. This beta API worked by plugging two values into an html command, including a URL and an Integer value. The URL would be the web address of each NYT article, and the Integer would indicate which comments I wanted to extract, as the API would return comments in batches of 25. For example, the input "0" would return the first 25 comments, the input "25" would return the second 25 comments, and so on. An example of an html input to the community API would look something like this: https://api.nytimes.com/svc/community/v3/user-content/url.json?api-key=z2YMruN1az0mrM0P9sez7T0JEhQHxZjH&offset=0&url=https://www.nytimes.com/2017/10/02/business/hotel-security-las-vegas.html , where the Integer input is "0" (offset=0) and the url is "https://www.nytimes.com/2017/10/02/business/hotel-security-las-vegas.html" (url=https://www.nytimes.com/2017/10/02/business/hotel-security-las-vegas.html).

Now that I had a method of extracting data, my next step was to organize the outputs the API would give me in a less overwhelming format.

Data Organization

A call to the NYT API would return data in JSON, which is a javascript file format. The data comes in the form of a dictionary (a python data structure) that contains some copyright information, some metadata about the call itself, and finally the comments, which comes as a list (another python data structure) of more dictionaries. Each comment is provided its own dictionary that includes just about anything you would want to know about a comment. Below is a screen grab from my python code that lists all the aspects of the comment data that are included

```
dict_keys(['commentID', 'status', 'commentSequence', 'userID', 'userDisplayName', 'userLocation', 'userTitle', 'userU
RL', 'picURL', 'commentTitle', 'commentBody', 'createDate', 'updateDate', 'approveDate', 'recommendations', 'replyCou
nt', 'replies', 'editorsSelection', 'parentID', 'parentUserDisplayName', 'depth', 'commentType', 'trusted', 'recommen
dedFlag', 'permID', 'isAnonymous'])
```

in one dictionary. As you can see, information such as the userDisplayName, commentTitle and commentBody are all included.

In order to get the data ready for analysis, I first needed to get all the data I extracted into one place, instead of having a different JSON file for each 25 comment batch from all 20 articles (with around 28,000 comments, that would be about 1,120 JSON files!). My goal was to get this data down to just two files, one for Las Vegas and one for Parkland. I first wrote a for loop to automate the API calls. I then decided to organize the data into a smaller dictionary to make the data more accessible. Although I could have chosen to narrow down the data any way I wanted, I decided to start with a simple list of dictionaries where each entry only contained: a) the ID of the article (as mapped out in the sample chart on pages 13-15) b) the body of the comment c) a number to keep track of the comment count. This small number of aspects were chosen for a text analysis of the comments. The comment title might have been useful to include as well, but I left it out for simplicity and for the fact that the majority of the comment titles are just "<br\\//>".

The New York Times put a maximum quota on their API in order to project their companies data. This means that the API will not allow you to write code that extracts their data at a rate any higher than 10 calls a minute. This meant that in order to extract the data I had to include a sleep command of 6 seconds in between calls of 25 comments in order to avoid hitting that quota. This detail made my code that would normally take just a couple seconds to run, take 45 minutes (for each event).

Here is a screengrab of the code that did this organizing (compiler: Jupyter):

```
In [*]: import json
        import requests

        comdata=[]
        vegasurl={
        "https://www.nytimes.com/2017/10/02/us/las-vegas-shooting-live-updates.html":440,
        "https://www.nytimes.com/2017/10/02/us/las-vegas-shooting.html":5507,
        "https://www.nytimes.com/2017/10/02/business/las-vegas-shooting-fake-news.html":296 ,
        "https://www.nytimes.com/2017/10/03/opinion/vegas-gun-control-shooting.html":1446,
        "https://www.nytimes.com/2017/10/02/opinion/mass-shooting-vegas.html":2420 ,
        "https://www.nytimes.com/2017/10/03/opinion/vegas-shooting-gun-control-paddock.html":628 ,
        "https://www.nytimes.com/2017/10/03/us/las-vegas-gunman.html":938,
        "https://www.nytimes.com/2017/10/02/business/hotel-security-las-vegas.html":45,
        "https://www.nytimes.com/2017/10/02/opinion/gun-control-vegas-shooting.html":3135 ,
        "https://www.nytimes.com/2017/10/03/us/las-vegas-shooting-live-updates.html":1847
        }

        artID=0
        comment=0;
        from time import sleep

        for url in vegasurl.keys(): #loop through all the urls
            num=0
            print("UPDATING .        "+url)
            artID+=1
            while(num<vegasurl.get(url)): #all the calls to get all the comments
                response = requests.get("https://api.nytimes.com/svc/community/v3/user-content/url.json?api-key=z2YMruN1az0mrM(
                vegas=(json.loads(response.text))
                results=vegas.get('results')
                comments=results.get('comments') #list of comments at each call
                cid=0
                for com in comments:
                    comdata.append({'articleID':artID,'comBody':comments[cid].get('commentBody'),'com#':comment})
                    comment+=1
                    cid+=1
                sleep(6)
                num+=25
            print(comdata)
            with open('vegasCommentsFOX.txt', 'w') as outfile:
                json.dump(comdata, outfile)
```

As well as creating master files for both the Parkland and Vegas comment datasets, I also ended up creating individual files for each article and their comment bodies as well. I uploaded every file I made to GitHub as a gist in the json format so I could easily have my topic model access them with a URL address. This file separation and formatting is what allowed me to use the topic model to reveal the results of each article and its comments.

LDA Topic Modeling

After some experimentation with different NLP techniques and sample code, the most success seemed to come with something called Latent Dirichlet Allocation (LDA) Topic Modeling. This statistical modeling tool allowed me to discover abstract “topics” that occur in both my sample of articles and their corresponding comment sections. I cruised the internet looking at many different samples of code that implement this kind of algorithmic tool, and eventually by picking and choosing pieces from several different sources plus some experimentation on my own I was able to build my unique version of a LDA topic model that worked well for this project and with the json files that I had uploaded to github for use. My topic model used Python code and many of its packages, including Gensim, Pandas, Numpy and Spacy, to read through documents that I would input into the model. Once I ran the code, the model would generate a given number of topics based off of the words that it found. The way that the topic model creates these topics is a complicated and somewhat abstract process, but the best way to explain it is that the code looks through all the words in the text and identifies topics based off of different groups of words that frequently occur in close proximity to each other, while simultaneously using the data that the natural language processing package (gensim) provides in order to inform the algorithm about which words frequently occur together elsewhere on the internet or in the world. I instructed the algorithm to disregard "stop words" such as "the" and "and" before the topics were generated. I also included code that would consider bigrams and trigrams as topic keywords as well, which means that for instance, if one of the topics involved the second amendment, instead of returning "second" and "amendment" as different words, my code would figure out that those two are part of one term and would return it as "second_amendment". The topics are composed of about 10 keywords each, and most of the time those 10 terms are pretty descriptive of what that particular topic represents in the document. To use the example from the University of Chicago's Computing for the Social Science's page (https://cfss.uchicago.edu/notes/topic-modeling/), imagine running the topic model on the following set of phrases:

1. I ate a banana and spinach smoothie for breakfast.
2. I like to eat broccoli and bananas.
3. Chinchillas and kittens are cute.
4. My sister adopted a kitten yesterday.
5. Look at this cute hamster munching on a piece of broccoli

If you were to ask for two topics in return, you might receive an output that looks like this:

Topic 0: .30 broccoli, .15% bananas, .10 breakfast, .10 munching, …

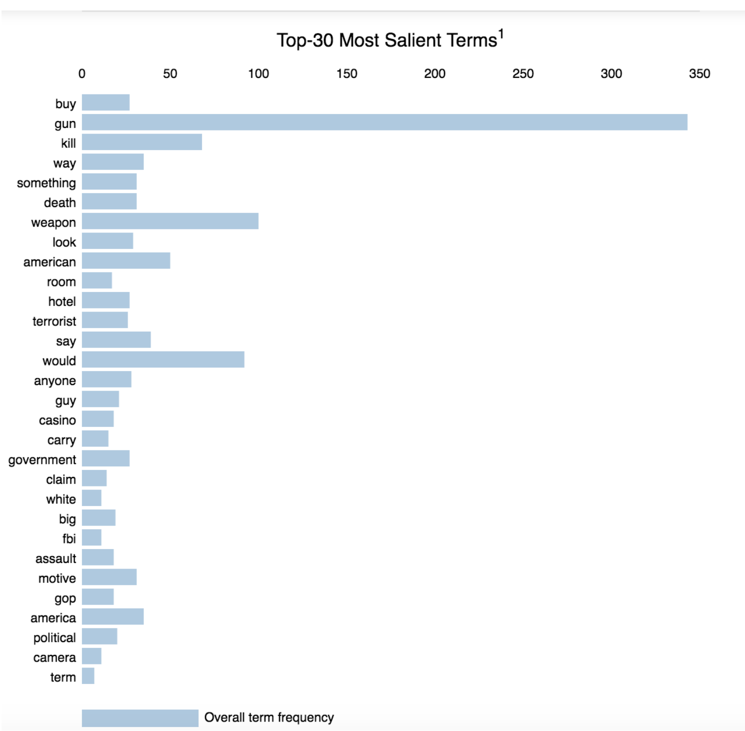
Topic 1: .20 chinchillas, .20 kittens, .20 cute, .15 hamster, …

From this output we would likely infer here that topic 0 is about munching on a snack or breakfast- perhaps of a banana or broccoli, and that topic 1 is about cute animals. This example is idealistic in that the topics it returns are pretty clear and we can tell by manually looking at the text that these two topics pretty thoroughly describe it. However, it shouldn't come as much of a surprise that analyzing the text of 20 news articles that cover mass shootings and their comments requires a little bit more thinking. Although I have read each article closely, there is no obvious number of topics to ask the algorithm for, and even after that is decided, the 10 word topics are more strenuous to interpret. Luckily, another one of my LDA sources, Machine Learning Plus (https://www.machinelearningplus.com/nlp/topic-modeling-gensim-python/), provided some advice on how to choose an optimal number of topics. This source gave me some information about how to implement the pyLDAvis's interactive charts to accompany the topics in the model's output. After I implemented this code, I had a model that would return the following things for each body of text I provided it with (as explained using the example of the Las Vegas article, article 7's comment section output):

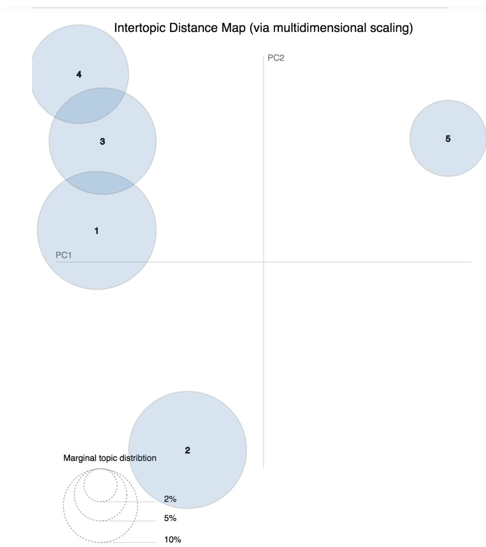
```
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/erikafox/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

```
[(0,
  '0.021*"gun" + 0.012*"weapon" + 0.011*"people" + 0.011*"time" + '
  '0.007*"right" + 0.007*"go" + 0.006*"need" + 0.006*"many" + 0.005*"nra" + '
  '0.005*"would"'),
 (1,
  '0.025*"gun" + 0.009*"people" + 0.009*"kill" + 0.009*"would" + '
  '0.007*"american" + 0.005*"death" + 0.005*"time" + 0.005*"america" + '
  '0.005*"weapon" + 0.005*"want"'),
 (2,
  '0.021*"gun" + 0.007*"go" + 0.006*"make" + 0.006*"nra" + 0.005*"want" + '
  '0.005*"would" + 0.005*"people" + 0.005*"law" + 0.005*"get" + '
  '0.004*"weapon"'),
 (3,
  '0.025*"gun" + 0.009*"people" + 0.006*"would" + 0.006*"control" + '
  '0.006*"nra" + 0.006*"time" + 0.005*"many" + 0.005*"go" + 0.005*"law" + '
  '0.004*"take"'),
 (4,
  '0.019*"gun" + 0.006*"weapon" + 0.006*"buy" + 0.006*"would" + 0.006*"make" + '
  '0.005*"time" + 0.005*"say" + 0.005*"way" + 0.004*"something" + '
  '0.004*"look"')]
```

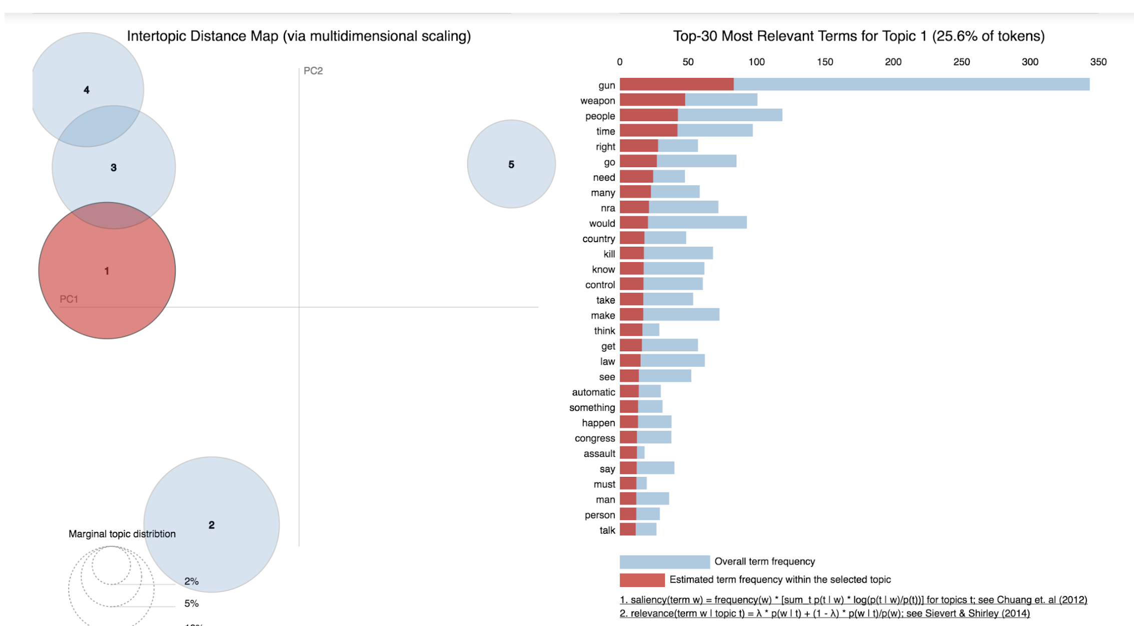
The LDA topic model's abstract topics, each consisting of 10 words, numbered 0-4.



pyLDAvis output: salience chart, a bar graph showing which terms show up the most frequently in the document.



pyLDAvis output: intertopic distance map, used to determine the quality of the topics. Each bubble represents a topic, and the bigger the bubble, the more prevalent the topic in the text. The most ideal outputs would have bubbles that are spread out evenly across the four quadrants.



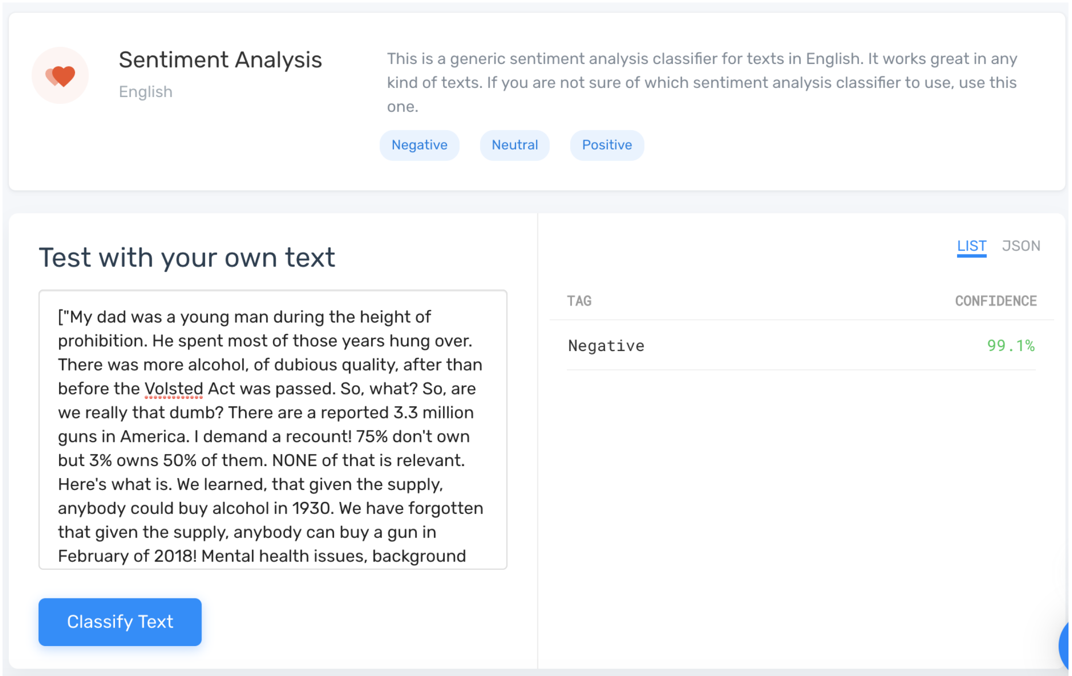
The pyLDAvis charts are interactive in that when you click on any of the topic bubbles on the intertopic distance map, a bar graph would be provided that shows which terms were the most relevant for that particular topic. Here is what that looks like for topic 1 from the comment section of article 7.

After some intuition about the size of the text bodies I was using, how many topics I expected to see in the articles, and some experimentation with the distribution of the bubbles in the intertopic distance maps, I settled on using 5 topics for this project. See above, the sample output that I have just provided was generated using 5 topics.

By comparing these charts that the topic model would return on each individual article to the topic model output of its comment section, I could tell how the topic makeup between the two text bodies differed and could begin to speculate about how these differences (or similarities) can help me answer my research question.

Sentiment Analysis Model

Although the LDA topic model can tell us a lot about these articles and their comments, one thing that it can't tell us is the tone of the comments. That's why an additional program, a sentiment analysis model, would be beneficial to the data analytics process for this project. To build this program, I set out to use the same strategy I used when I built my LDA topic model, which was to cruise the internet for resources and to build a program using the elements I liked the most off of a couple different sources, and then adding some of my own. I ended up with a program that I adapted using the nltk package's movie_review corpus that appeared to work okay, but not well enough for me to be satisfied with the model. Turns out that analyzing comments in response to gun violence is a little bit more complicated than analyzing the sentiment of movie reviews. This is probably due to the fact that many comments in response to gun violence are highly passionate and include a mix of tones. For instance, a comment might say something like: “This event of gun violence is a terrible and shameful tragedy. These innocent people did not deserve to die these untimely, horrible deaths. We must take action and reform our gun laws! Background checks can be so beneficial to our wonderful country”. This comment would be very difficult to generate an accurate reading on because it contains so many powerful emotion words. Unfortunately, comments like these are just a margin of error that we might just have to live with for this project. Moving forward, I came across a code company known as MonkeyLearn. This company has a sentiment analysis model that they make available for use by developers with the registration of an API key, similar to the way that the New York Times API requires developers to register an API key in order to extract data. I was able to use MonkeyLearn’s API to implement a python program that would give a sentiment reading on all of my comments individually and then return percentages to describe how many of the comments in the overall body were positive, negative or neutral. However, automating the model, I quickly discovered (much to my dismay) that the algorithm worked beautifully, but I was very limited on how many queries I could make. Just like how the New York Times API limited my data extraction to 10 calls per minute, MonkeyLearn has a limitation where developers can only make 300 calls a month for free. If you need more queries, you can upgrade and pay $300 a month for up to 10,000 queries (per month). For this project, I would need at least 23,000 queries. The next upgrade option after that required me to fill out a questionnaire describing my use case, which I did, but after a week of not hearing back, I figured it was time to move on from this accurate yet not affordable nor practical automation option. However, as my search continued I came up with two more options that seem to work better than my original homemade model. The first of those two still includes MonkeyLearn’s fancy sentiment analysis algorithm, just without the detailed comment by comment automation. On their website, the company provides a built in application where you can input text and then ask it to classify it for you. MonkeyLearn's intention with including this application is to allow users to test out their algorithm before they include in their program like the way I did initially. Though it still would have been preferable to use this algorithm as a part of a python program to look at each comment individually, inputting the entire comment body for each article into this online application has a similar effect. I would just receive a more general result for the sentiment of the entire comment body, instead of generating percentages of the makeup of the different types of sentiments in the comments. This single result would represent which sentiment describes the majority of the comments in the body, which along with confidence rating it returns, should tell us all I really need to know for the sake of this project. I can even go as far as using another python program to filter the comment body before inputting it into this application. For example, if I wanted to know the sentiment around the term "gun" in the comments, I could use python to produce a list of only the comments that mentioned "gun" on a particular article, and then use the MonkeyLearn application to tell me which sentiment characterizes that body of comments.



MonkeyLearn's Online Application: *https://app.monkeylearn.com/main/classifiers/cl_pi3C7JiL/*

Additionally, I was able to build a sentiment analysis model that worked exclusively with the Twitter API for the processing of twitter data. When you extract tweets from twitter using this API, the sentiment of each tweet is included in a dictionary along with its text. The program I built with this allowed me to see the percentage of positive/negative tweets that match a query that I would input to it. Though I can't run this program on my New York Times article comments, it could still be interesting to see how public opinion around the Parkland and Las Vegas shootings was represented on Twitter.

RESULTS AND INTERPRETATION OF DATA

After running the LDA model on every article in my sample as well as all of their comment sections, I was left with over 200 topics to interpret as well as many, many bar graphs. All of this information has so much potential to tell us about how the media coverage of mass shootings impacts public opinion, and there are endless possibilities when it comes to how to interpret this data to the point where it would simply be impossible to consider every piece for a study of this length. However, the following is a description of what I was able to observe from this data. Keep in mind that when discussing articles, articles 1-10 are Las Vegas articles and articles 11-20 are Parkland articles.

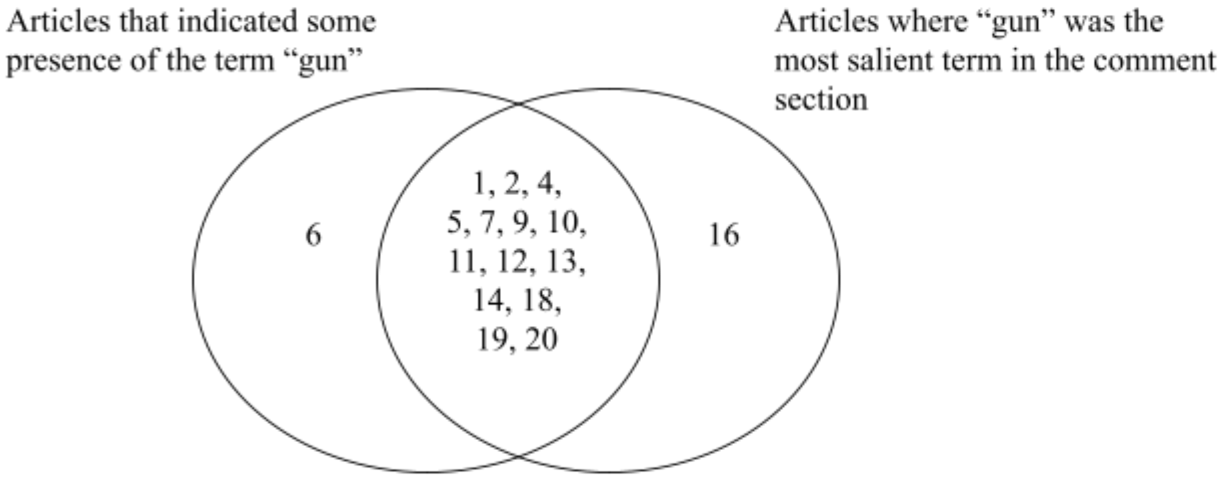
<u>The Salience of "Gun" Terms in the Comments and Articles</u>

The most overwhelming result was that "gun" was the most salient term in the comments section of 15/20 articles. This result clearly showed in the salience charts that the LDA topic model returned. However, even though most of the articles' comment sections had "gun" as the most salient term in their bar graphs, this was not the case with the text of the actual articles. Only three of those articles had it appear as the #1 most salient term: articles 9, 18, and 20. Less than half of the articles, 9/20, had "gun" appear in the salience graph at all. Some more of the articles had "gun" appear as a word in one or more of its topics even if the term did not appear in the chart: articles 2, 4, 5, 6, 14 and 19. Articles 1 and 12 were the only articles where the term "gun" appeared in the overall salience chart but was not included as a word in any of its 5 topics. The "gun" term appeared in both the bar graph and as a topic word in articles 7, 9, 10, 11, 13, 18, and 20. That adds up to a total of 15 articles that showed the prevalence of the "gun" term in the text of the article itself in one or both ways. The 15 articles that yielded the term "gun" as the most salient term in the comments and the 15 articles that showed the prevalence of the same term in some way in their own text line up almost perfectly, meaning that these are all the same articles with the exception of articles 6 and 16. Article 16 was an oddball in that the article itself exhibited no prevalence of the "gun" term, yet the term still showed up as the most salient in that article's comment section. And while almost 100% of articles that showed any evidence of the term "gun" in the topic model results for the article text yielded a comment section with "gun" as the most salient term, article 6 was the only article where "gun" appeared as a topic word for the article text (though it wasn't extremely salient, nor did it appear on the bar graph) but did not have the term dominate the comment section. However, despite being absent from the chart, "gun" was still not completely absent from article 6's comments, as it appeared as a word in the comment section's topics. That leaves us with only 4 more articles where "gun" did not dominate the comments: articles 15, 17, 3 and 8. Articles 8, 15 and 17 did not have any evidence of "gun" in the article results but it appeared in the topics of the comment results (though it wasn't the most salient). Articles 3 was the only article that did not have "gun" appear in any of its results, for both the article and the comments.

Article ID	"Gun" appears in the chart of most salient terms for article	"Gun" is **the most** salient term in the chart of most salient terms for article	"Gun" appears in article topics	"Gun" appears in the chart of most salient terms for comment section	"Gun" is **the most** salient term in the chart of most salient terms for comment section	"Gun" appears in comment topics
1	●			●	●	●
2			●	●	●	●
3						
4			●	●	●	●
5			●	●	●	●
6			●			●
7	●		●	●	●	●
8				●		●
9	●	●	●	●	●	●
10	●		●	●	●	●
11	●		●	●	●	●
12	●			●	●	●
13	●		●	●	●	●
14			●	●	●	●
15						●
16				●	●	●
17				●		●
18	●	●	●	●	●	●
19			●	●	●	●
20	●	●	●	●	●	●

Because “gun” was the most used word in the comment sections of a whopping 75% of my article sample, it is pretty clear that that term is the most potent when it comes to opinion formation in the wake of mass shootings. This result tells us that of the issues that gun violence often brings up, whether that’s the mental health of the perpetrator/victims, the security of the venue, or the battle between democrats versus republicans on potential policy changes, the ones that center around the guns themselves are the most prominent in online discussion, or at least within the comments on my New York Times articles. What the saliency of the “gun” term does not yet tell us is the tone or side of the arguments from the comments that generated this result, but I will dive more into that later. For now, we’ll speculate about the trends of the saliency of the word “gun” in my articles and comments to see if an explanation can be found as to which frames within the articles themselves are surefire ways to get the audience riled up about gun issues, and what are the seemingly few frames that manage to avoid this domination of the gun debate.

My results suggest that if articles were to discuss “guns” at all, at any level of saliency, the term would dominate the comment section. In other words, if the word “gun” was in the article at least once, you could be almost certain that it would be the most salient term in the comments. After running the LDA topic model on all 20 of my articles and their comment sections, I found that there were exactly 15 articles that showed some prevalence of the term “gun” and exactly 15 comment sections that had “gun” as the most salient term. These two sets of 15 articles align almost exactly- in that of the 15 articles that showed some prevalence of the term guns, 14 of those were also part of that group where the article’s comment sections were dominated by “gun”, and vice versa. See the venn diagram:



As you can see, 14/15 times (93%), if the article mentioned “gun”, then “gun” was the most salient term in the comments. This suggests that whenever readers see the word gun in the media coverage of gun violence, it is almost sure to stay in their mind. But what about the times where it doesn’t? What happened with article 6, where readers saw the term in the article but did not discuss it as much in the comments? Or with article 16, where readers had a lot to say about guns in the comments but the article did not seem to say much about the topic? In order to try and gain a more in depth understanding of the uses of and responses to the “gun” term in gun violence media, let’s take a closer look at the articles that don’t fit the mode- a.k.a. those 6 articles that either did not have some mention of “gun” in the article or have the “gun” term completely dominate the comment section.

The Outlying Articles: articles 6, 16, 8, 15, 17, and 3

Article 6- Some prevalence of “gun” in the article (appeared as a topic word but not as one of the most salient terms) but the term did not dominate the comment section.

Article	“Gun”	“Gun” is **the**	“Gun”	“Gun”	“Gun” is **the**	“Gun”

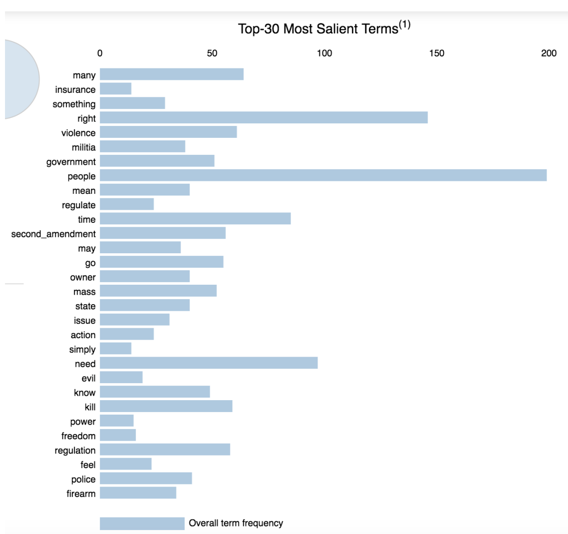
ID	appears in the chart of most salient terms for article	**most** salient term in the chart of most salient terms for article	appears in article topics	appears in the chart of most salient terms for comment section	**most** salient term in the chart of most salient terms for comment section	appears in comment topics
6			●			●

The actual title of article 6 is “No More Shootings that Follow the Rules”. It is a Las Vegas article from October 3rd, 2017. The frames that I found in this article’s text during my initial content analysis with MAXQDA include “Lack of Gun Control” and “FBI Negligence” for attribution of responsibility codes, “Right to Bear Arms vs. Gun Control” and “Americans vs. the NRA” for conflict codes, “Thoughts and Prayers” and “Unity for Action” for morality codes, and “Accounts of Grievances” for a human interest code. With 7 codes, this article was one of the most heavily framed articles in my sample. Because of its higher number of frames, this is an article that I would expect to be more likely to shape some opinions of readers. As you can tell from its variety of frames, this article covered a lot of ground in relation to the Las Vegas Massacre. However, the article primarily structured itself around the “Lack of Gun Control” and the “Right to Bear Arms vs. Gun Control” frames, using those as sort of a thesis statement while many of the other frames were more supportive. The “Unity for Action” was heavily present as well, as the article doesn’t simply vent that lack of gun control is an issue, but instead it actually lays out a strong argument for how gun regulation is a necessity just like speed regulation on our highways. In the LDA topic model’s output for the article, you can see these topics represented.

Article 6’s Topics	[(0, '0.036*"gun" + 0.026*"regulate" + 0.026*"time" + 0.021*"control" + '	(1, '0.019*"say" + 0.019*"way" + 0.019*"hand" + 0.019*"formal" +	(2, '0.026*"word" + 0.020*"american" + 0.014*"mass" + 0.014*"strength" + '	(3, '0.022*"rule" + 0.022*"weapon" + 0.022*"access" + 0.022*"need" + '	(4, '0.022*"right" + 0.022*"store" + 0.015*"gun" + 0.015*"vegas" +

	'0.021*"talk" + 0.016*"many" + 0.011*"terrorist" + 0.011*"protect" + ' '0.011*"act" + 0.011*"shoe"')	0.019*"clean" + ' '0.003*"word" + 0.003*"strength" + 0.003*"vegas" + 0.003*"would" + ' '0.003*"heartbreake "')	'0.014*"life" + 0.014*"gun" + 0.014*"vegas" + 0.014*"demoralize" + ' '0.014*"heartbreake" + 0.014*"would"')	'0.022*"people" + 0.015*"gun" + 0.015*"follow" + 0.015*"regulation" + ' '0.015*"week" + 0.015*"regulate"')	0.015*"say" + ' '0.015*"follow" + 0.015*"background " + 0.015*"call" + 0.015*"stand" + ' '0.015*"buy"')

Topic 0 clearly represents the article's "Unity for Action" frame with the words "gun", "regulate", "time" and "control" and "talk". This result solidifies that this article's call to action is its most important part. However, this first topic includes the word "gun", which is surprising to see because this article does not match the trend we have seen before where any mention of the word "gun" in the article translates to complete domination of the word in the comments 93% of the time. What makes this article different? To answer this, we need to look at what the commenters are talking about instead.



Article 6's comment section topics	[(0, '0.009*"people" + 0.009*"gun" + 0.007*"right" + 0.007*"many" + ' '0.007*"weapon" + 0.006*"need" + 0.006*"make" + 0.005*"mass" + '	(1, '0.024*"gun" + 0.011*"people" + 0.011*"right" + 0.008*"would" + ' '0.008*"weapon" + 0.007*"violence" + 0.006*"militia" + 0.006*"kill" + ' '0.006*"need" +	(2, '0.045*"gun" + 0.011*"people" + 0.009*"right" + 0.008*"weapon" + ' '0.006*"would" + 0.006*"make" + 0.006*"control" + 0.005*"regulation" + '	(3, '0.032*"gun" + 0.013*"people" + 0.011*"weapon" + 0.010*"control" + ' '0.008*"would" + 0.008*"law" + 0.007*"time" + 0.007*"need" + 0.006*"get" + '	(4, '0.011*"gun" + 0.008*"people" + 0.006*"time" + 0.005*"weapon" + ' '0.005*"american" + 0.004*"go" + 0.004*"nra" + 0.004*"second_ame ndment" + '

	'0.005*"government" + 0.005*"something"')	0.006*"mean"')	'0.005*"stop" + 0.005*"american"')	'0.006*"make"')	'0.004*"state" + 0.004*"may"')

Between the topics that the model generated for article 6's comment section and the salience chart, this data is unusual. In the topics we can see the term "gun" represented in similar ways that we have seen it represented in many of the other articles, but this time the term does not appear on the chart of the 30 most salient terms. Instead, the terms that beat it out for the most salient include words such as "people", "right", "government", and most strikingly, "action", "regulate", and "regulation". The use of these words by commenters suggests that they are responding to the "Unity for Action" frame in this article. The idea that this article was able to talk about guns and have its audience thinking more about the actions to take around guns instead of just the guns themselves could be groundbreaking. This call-to-action type of journalism might be more effective in molding an audience's understanding than we originally thought.

The sentiment analysis of these comments can offer more information as to how the audience responded to this particular article. I used MonkeyLearn's online application to analyze the entire comment body first, and then I did secondary analyses with only all the comments that include "gun", and another with only all the comments that include "regulate" or "regulation". For the entire comment body, the result was "Negative" with a 98.2% confidence percentage. This near-perfect confidence rating shows that the vast majority of the comment body had a negative tone. For just the comments that included "gun" in the text, the result was "Positive" with a 56.9% confidence rating. This huge decrease in confidence from the entire comment body's result indicates that the sentiment around "guns" is much more variant- though possibly leaning more on the positive side. Finally, the result for the comments that mention "regulate" or "regulation" was "Negative" with a 94% confidence rating. This result aligns more with the result of the overall comment section, in that it is still negative, just with a lower level of confidence. To me, this suggests that some of the commenters were more optimistic in their comments about regulation, but for the most part it seems that the general audience has a more negative tone- whether they are angry that they haven't seen action yet, saddened by the news of this event, or passionately disagreeing with the idea of gun regulation. As for the "Positive" sentiment around guns in these comments, it is a little bit harder to speculate about what exactly is going on there. While it is possible that those commenters are gun enthusiasts, within the context of this article it is more likely that they are speaking with a more optimistic tone towards action. I did one more test where I ran the sentiment analysis application on just the comments that include "action", and the result seems to support that idea in that it was "Positive" with 83.1% confidence.

Article 16- No apparent prevalence of "gun" in the article, yet "gun" is the most salient term in the comments.

Article ID	"Gun" appears in the chart of most salient terms for article	"Gun" is **the most** salient term in the chart of most salient terms for article	"Gun" appears in article topics	"Gun" appears in the chart of most salient terms for comment section	"Gun" is **the most** salient term in the chart of most salient terms for comment section	"Gun" appears in comment topics
16				●	●	●

The actual title of article 16 is “Horror at Florida School; Ex-Student Held”. It is a Parkland article from February 15th, 2018. The frames that I found in this article’s text during my initial content analysis with MAXQDA include “Nikolas Cruz” and “Assault Rifles” for attribution of responsibility codes, as well as “Humanization of Cruz” and an “Account of Trauma” for human interest codes. There were no clear morality or conflict codes present in the article, as it mostly focused on the experience of the victims as well as the implementation of the perpetrator’s plan to shoot up the Parkland high school. The topics that my topic model generated reflected these ideas nicely. They are the following:

Article 16’s topics	(0, '0.029*"say" + 0.029*"student" + 0.015*"dead" + 0.015*"gunman" + ' '0.015*"sheriff" + 0.015*"gunshot" + 0.008*"backpack" + 0.008*"coach" + ' '0.008*"deputy" + 0.008*"wallet"')	(1, '0.016*"school" + 0.016*"area" + 0.016*"teacher" + 0.016*"say" + ' '0.009*"include" + 0.009*"child" + 0.009*"treat" + 0.009*"boyar" + ' '0.009*"die" + 0.009*"evan"')	(2, '0.044*"say" + 0.024*"school" + 0.018*"student" + 0.015*"cruz" + ' '0.015*"authority" + 0.015*"fire" + 0.012*"high" + 0.009*"sheriff" + ' '0.009*"israel" + 0.009*"alarm"')	(3, '0.062*"school" + 0.028*"student" + 0.021*"say" + 0.014*"parent" + ' '0.014*"shooting" + 0.011*"teacher" + 0.011*"gard" + 0.011*"high" + ' '0.011*"state" + 0.008*"cruz"')	(4, '0.021*"school" + 0.015*"local" + 0.014*"student" + 0.014*"cruz" + ' '0.008*"hotel" + 0.008*"parent" + 0.008*"arm" + 0.008*"die" + 0.008*"screen" ' '+ 0.008*"sprint"')

These topics are exactly what I would expect to get for an article that has a heavy focus on human interest framing. Notice how 4 out of 5 of these topics include the word “say”, which is possibly the most common word used by journalists when they are providing someone’s account of the story. So what are these topics saying? Topic 0 has the words “say”, “student”, “dead”, and “gunman”, so I might infer that since this is the first and most prominent topic, this one represents a more general account of what happened in Parkland. Topic 1 also includes the word “say”, but it also includes the words “Evan”, “Boyar”, “school”, “area” and “child” which together indicate that this is a topic that refers to the account of Dr. Evan Boyar that the article includes about how the child victims were treated in three different area hospitals after the school shooting. The third topic seems to be referring to what Sheriff Israel had to say about the school shooting and the student who committed that crime, Nikolas Cruz, and so on. So if this article is so focused on sharing the human elements of the Parkland shooting with the reader, how come the most used word in the comments is gun? What are they responding to and exactly what are they saying about guns? What is their tone? We can look at the topic model results for the comments to get some insight.

Article 16’s comment section topics	(0, '0.036*"gun" + 0.010*"school" + 0.009*"nra" + 0.008*"weapon" + 0.008*"need" ' '+ 0.007*"get" + 0.007*"people" + 0.007*"control" + 0.006*"child" + ' '0.006*"country"')	(1, '0.030*"gun" + 0.012*"school" + 0.011*"nra" + 0.009*"weapon" + ' '0.009*"shooting" + 0.008*"people" + 0.007*"country" + 0.006*"time" + ' '0.006*"mass" + 0.006*"right"')	(2, '0.012*"gun" + 0.011*"school" + 0.006*"prayer" + 0.006*"kid" + 0.006*"time" ' '+ 0.006*"many" + 0.006*"would" + 0.005*"know" + 0.005*"nra" + 0.004*"take"')	(3, '0.018*"gun" + 0.014*"school" + 0.012*"child" + 0.011*"people" + ' '0.010*"prayer" + 0.007*"day" + 0.007*"american" + 0.007*"thought" + ' '0.007*"go" + 0.006*"would"')	(4, '0.033*"gun" + 0.011*"people" + 0.008*"time" + 0.007*"would" + 0.005*"child" ' '+ 0.005*"right" + 0.005*"nothing" + 0.005*"problem" + 0.004*"control" + ' '0.004*"need"')

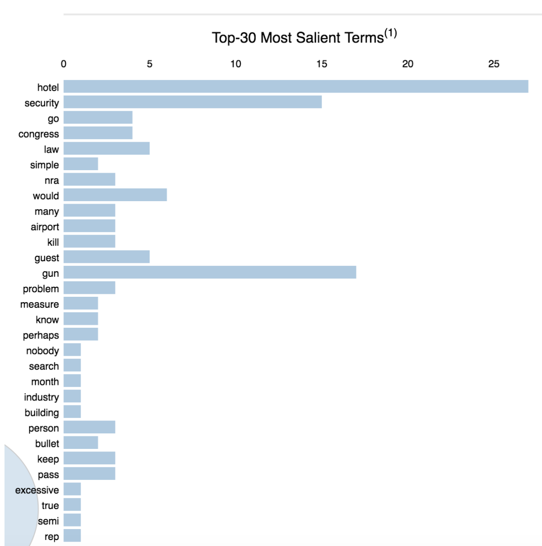
Despite the article saying practically nothing about guns (though it does include that an AR-15 assault rifle was the weapon used), every topic that my topic model yielded from the comment section includes “gun” as the first word. This result is overwhelming and baffling. What are the readers saying? The topics provide some information about what context the commenters are using “gun” (and any other word for that matter) in. Topic 0 contains terms “gun”, “nra”, “need”, and “control”, so I might infer that this topic represents readers who are arguing in favor of gun control, attributing the NRA as an obstacle that that cause needs to overcome. Topic 1 has a lot of overlap with Topic 0 in that the first 4 words are the same, but then there is some variation in the words that follow. This second topic confirms that many of the arguments that people have made in response to this article have had something in reference to the NRA. NRA is a term for the third topic as well. The same inference can be made about the term “school” in that that is the second most prominent term in the comments other than “gun” itself. This article was the only one from my sample where there was very little evidence of the term gun in the actual article but had the term dominate the comments. Although it may be difficult to pinpoint why this occurred, my hypothesis would have to be that even though this article didn’t mention guns, it did not have to because guns were already on the minds of most of the readers. This could be because of a number of reasons, it’s a possibility that since this article was released on the first day after the shooting, many of the readers came to read this article immediately after reading one about guns. It’s also a possibility that Americans are pre-wired to respond to mass shootings with their gun pleas- regardless if they are for or against. Although it is possible that there is something about the human interest style that might have prompted some audience members to bring up the gun debate, it isn’t clear and I did not have that experience myself when I read the article. However, it only takes a small number of people to get the ball rolling in an online comment section.

As far as the tone of these comments go, we can use the MonkeyLearn application to retrieve some more information about the nature of this comment section. The overall comment section resulted “Negative” sentiment with 98.2% confidence. When I ran the application on just the comments from the article that mention “gun”, I got “Negative” again, this time with a 97.9% confidence. The decrease in confidence rating from all of the comments to just the gun comments indicates that there may be more positive comments about guns in proportion to other topics. Finally, the application returned “Negative” with 76.6% confidence for the comments that include “NRA”, which indicates that there are some more positive comments about the NRA as well.

Article 8- *No apparent prevalence of "gun" in the article, yet "gun" is one of the top 30 most salient terms in the comments (but not the #1 most salient).*

Article ID	"Gun" appears in the chart of most salient terms for article	"Gun" is **the most** salient term in the chart of most salient terms for article	"Gun" appears in article topics	"Gun" appears in the chart of most salient terms for comment section	"Gun" is **the most** salient term in the chart of most salient terms for comment section	"Gun" appears in comment topics
8				●		●

The actual title of article 8 is "Las Vegas Shooting Underscores Hotel Security Choices". It is a Las Vegas article from October 2nd, 2017. When I did my initial content analysis with MAXQDA, I only found one frame in this article, the conflict frame "Hotel Security". This article's LDA data was similar to article 16's where the article itself does not appear to discuss guns at all, but the term is still highly present in the comments. Although, unlike article 16, gun is not the #1 most salient term in the comments, even though it is up there as the term still makes the chart of the most salient terms (it ranks #2, beneath #1 "hotel" but before #3 "security").



Article 8's comment section's salience chart

Article 8 is certainly one of the more focused articles from my sample, in that instead of including a variety of details from the event it centers itself around one of the shooting's flywheels: hotel security. This strategy of focusing on just one particular flywheel seems to have been effective in that there appears to be more commenters that have discussed hotel security as the article intended instead of an influx of readers that got distracted somehow with the gun debate. Although there aren't as many with this one as there were with some articles, there's still a significant amount of people that chose to discuss guns in the comments. However, if you look at the topics for the comment section, you can see that most of the time "gun" appears, it is paired with the terms "hotel" and "security". This may show that some of those "gun" commenters are still on topic.

Article 8's topics	(0, '0.034*"hotel" + 0.014*"say" + 0.014*"security" + 0.014*"country" + ' '0.008*"hospitality" + 0.008*"practice" + 0.008*"bay" + 0.008*"mandalay" + ' '0.008*"target" + 0.008*"resort"')	(1, '0.015*"walking" + 0.015*"network" + 0.015*"coverage" + 0.015*"set" + ' '0.015*"update" + 0.015*"bellman" + 0.015*"constantly" + 0.015*"give" + ' '0.015*"order" + 0.015*"first"')	(2, '0.028*"hotel" + 0.021*"say" + 0.014*"security" + 0.014*"hospitality" + ' '0.008*"firearm" + 0.008*"guest" + 0.008*"company" + 0.008*"manhattan" + ' '0.008*"detective" + 0.008*"retire"')	(3, '0.027*"hotel" + 0.027*"say" + 0.027*"security" + 0.014*"system" + ' '0.014*"even" + 0.014*"room" + 0.008*"upscale" + 0.008*"people" + ' '0.008*"hospitality" + 0.008*"continue"')	(4, '0.049*"hotel" + 0.044*"say" + 0.017*"security" + 0.017*"employee" + ' '0.017*"firearm" + 0.012*"room" + 0.012*"procedure" + 0.012*"pay" + ' '0.012*"gunman" + 0.012*"bring"')

Article 8's comment section topics	(0, '0.029*"hotel" + 0.026*"security" + 0.019*"gun" + 0.011*"would" + ' '0.011*"many" + 0.008*"issue" + 0.008*"carry" + 0.008*"state" + ' '0.008*"vegas" + 0.008*"design"')	(1, '0.041*"hotel" + 0.022*"security" + 0.013*"gun" + 0.011*"would" + ' '0.011*"check" + 0.009*"carry" + 0.009*"firearm" + 0.007*"law" + ' '0.007*"guest" + 0.007*"safety"')	(2, '0.026*"hotel" + 0.013*"security" + 0.013*"go" + 0.007*"airport" + ' '0.007*"kill" + 0.007*"perhaps" + 0.007*"nra" + 0.007*"month" + 0.007*"know" ' '+ 0.007*"guest"')	(3, '0.020*"gun" + 0.020*"hotel" + 0.009*"take" + 0.009*"weapon" + ' '0.009*"people" + 0.009*"keep" + 0.007*"let" + 0.007*"security" + ' '0.007*"assault" + 0.007*"drive"')	(4, '0.023*"gun" + 0.019*"congress" + 0.015*"law" + 0.012*"simple" + ' '0.008*"hotel" + 0.008*"problem" + 0.008*"luggage" + 0.008*"person" + ' '0.008*"excessive" + 0.008*"piece"')

The sentiment reading on the aggregate comment section for this article was "Negative" with 98.4% confidence. For only the comments that include "gun", the reading was "Negative" with 76.6% confidence. For only the comments that include "hotel" and "security", the reading was "Negative" with 97.7% confidence. This sentiment for hotel security seems to be pretty accurate, however it doesn't represent the different types of negative comments that make up the aggregate collection. For example, one commenter may be speaking negatively about the hotel security that allowed Paddock to get over 23 weapons up to his room, while another may be negatively criticizing other commenters who choose to blame the shooting on the hotel.

Article 15- *No apparent prevalence of "gun" in the article, and "gun" is not the most salient term in the comments. However, the term is still present enough to be a topic word.*

Article ID	"Gun" appears in the chart of most salient terms for article	"Gun" is **the most** salient term in the chart of most salient terms for article	"Gun" appears in article topics	"Gun" appears in the chart of most salient terms for comment section	"Gun" is **the most** salient term in the chart of most salient terms for comment section	"Gun" appears in comment topics
15						●

The actual title of article 15 is "Reporting on Mass Shooting, Again". It is a Parkland article from February 16th, 2018. The only prominent frame that I found in this article's text during my initial content analysis with MAXQDA is "Demoralization" for a morality frame. It is important to note that this article had a very small amount of comment data to work with- only 7 comments were left on this article. This could mean that the article itself did not inspire as many comments due to its content, or it could just be that this article did not get as much exposure to readers. Whatever the case may be, this article was another that focused on just one aspect of the shooting. This time, it's the Parkland shooting's demoralizing quality. The article also comments on the media's routine in covering mass shootings. Below are the topics for article 15. You can notice that there are some words in these topics that represent the article's discussion of the press's media routine for mass shootings with the words "story", "say", "editor", "reporter", "journalist" and more, but the demoralization frame is not as clearly represented.

Article 15's topics	(0, '0.023*"hour" + 0.023*"story" + 0.016*"say" + 0.016*"editor" + 0.016*"work" ' '+ 0.016*"reporter" + 0.016*"start" + 0.009*"time" + 0.009*"shooting" + ' '0.009*"team"')	(1, '0.025*"say" + 0.017*"team" + 0.017*"nobody" + 0.017*"wear" + ' '0.017*"graphic" + 0.017*"journalist" + 0.017*"feel" + 0.017*"role" + ' '0.009*"desk" + 0.009*"start"')	(2, '0.015*"time" + 0.015*"cover" + 0.015*"react" + 0.015*"routine" + ' '0.015*"story" + 0.015*"come" + 0.015*"make" + 0.008*"shooting" + ' '0.008*"confirm" + 0.008*"begin"')	(3, '0.019*"say" + 0.015*"desk" + 0.015*"begin" + 0.015*"news" + 0.010*"day" + ' '0.010*"social" + 0.010*"medium" + 0.010*"time" + 0.010*"report" + ' '0.010*"reporter"')	(4, '0.028*"shooting" + 0.023*"time" + 0.019*"shoot" + 0.019*"go" + 0.014*"mass" ' '+ 0.010*"report" + 0.010*"ask" + 0.010*"national" + 0.010*"lacey" + ' '0.010*"say"')

The demoralization frame does not appear to be represented in the topics of the comments either, but neither does the article's discussion of the mass shooting media routine. Because this comment section was such a small pool of data, this doesn't tell us too much, but this output is still interesting to consider. However, I do speculate that if this article had more comments, "gun" would have been more salient. Even as of now, the most salient term in this comment section was "weapon".

Article 15's comment section topics	(0, '0.033*"man" + 0.025*"gun" + 0.025*"time" + 0.025*"young" + 0.017*"mass" + ' '0.017*"murder" + 0.017*"something" + 0.017*"op" + 0.017*"submit" + '	(1, '0.045*"weapon" + 0.023*"gun" + 0.023*"control" + 0.016*"legislation" + ' '0.016*"industrial" + 0.016*"shooting" + 0.016*"inspection" + 0.009*"box" + ' '0.009*"well" +	(2, '0.025*"go" + 0.025*"thought" + 0.025*"prayer" + 0.025*"nra" + ' '0.025*"turmoil" + 0.025*"tweet" + 0.025*"trump" + 0.004*"gun" + 0.004*"man" '	(3, '0.005*"weapon" + 0.005*"gun" + 0.005*"get" + 0.005*"control" + 0.005*"time" ' '+ 0.005*"shooting" + 0.005*"inspection" + 0.005*"industrial"	(4, '0.020*"time" + 0.020*"point" + 0.020*"get" + 0.020*"would" + 0.020*"thank" ' '+ 0.020*"police" + 0.020*"department " +

	'0.017*"school"')	0.009*"mass"')	'+ 0.004*"would"')	+ 0.005*"man" ' '+ 0.005*"legislation"')	0.011*"become" + 0.011*"hear" + ' '0.011*"god"')

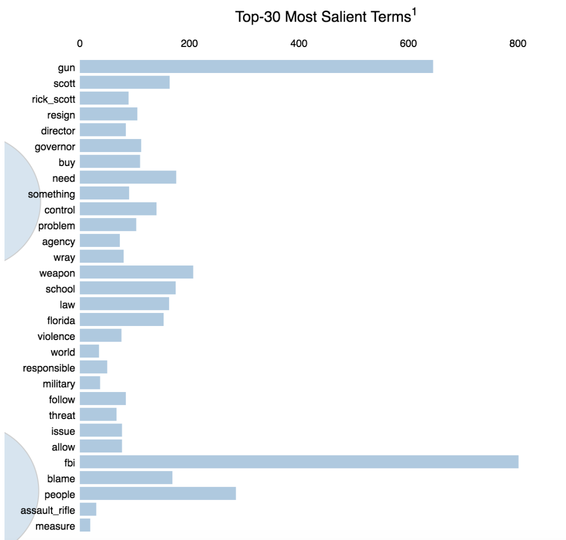
Article 17-*No apparent prevalence of "gun" in the article, and "gun" is not the most salient term in the comments. However, the term is still present enough to be a topic word.*

Article ID	"Gun" appears in the chart of most salient terms for article	"Gun" is **the most** salient term in the chart of most salient terms for article	"Gun" appears in article topics	"Gun" appears in the chart of most salient terms for comment section	"Gun" is **the most** salient term in the chart of most salient terms for comment section	"Gun" appears in comment topics
17				●		●

The actual title of article 17 is "Warned About Suspect, F.B.I. Didn't Act". It is a Parkland article from February 17th, 2018. The frames that I found in this article's text during my initial content analysis with MAXQDA include "Nikolas Cruz" and "FBI Negligence" for attribution of responsibility frames. There were no other types of frames that were prominent in this article. This is an article that seemed to focus heavily on placing blame for the Parkland shooting. Nikolas Cruz was a troubled teen, and there were warning signs that this article says that the FBI should have picked up on. In the topics and salience chart of the comment sections, we can tell that this got people talking.

Article 17's topics	(0, '0.025*"bureau" + 0.019*"attack" + 0.019*"also" + 0.013*"russian" + ' '0.013*"month" + 0.013*"say" + 0.013*"investigation"	(1, '0.028*"say" + 0.028*"friday" + 0.021*"cruz" + 0.021*"sheriff" + ' '0.021*"israel" + 0.015*"year" + 0.015*"office" +	(2, '0.029*"bureau" + 0.024*"say" + 0.024*"cruz" + 0.020*"school" + 0.020*"tip" ' '+ 0.010*"friday" + 0.010*"law" +	(3, '0.034*"say" + 0.025*"trump" + 0.015*"former" + 0.010*"cruz" + ' '0.010*"bureau" + 0.010*"statement" + 0.010*"something" +	(4, '0.013*"field" + 0.013*"could" + 0.013*"say" + 0.013*"make" + 0.013*"attack" ' '+ 0.013*"come" + 0.013*"aware" +

	+ 0.013*"election" + ' '0.013*"know" + 0.013*"shooting"')	0.015*"make" + ' '0.015*"public" + 0.015*"act"')	0.010*"nikolas" + 0.010*"commit" + ' '0.010*"last"')	0.010*"public" + ' '0.010*"wray" + 0.010*"behavior"'	0.013*"time" + 0.013*"first" + ' '0.013*"threat"')



Article 17's comment section's salience chart

Article 17's comment section topics	(0, '0.031*"fbi" + 0.009*"would" + 0.009*"gun" + 0.007*"trump" + 0.007*"people" ' '+ 0.007*"get" + 0.006*"tip" + 0.006*"school" + 0.006*"weapon" + ' '0.006*"many"')	(1, '0.022*"gun" + 0.018*"fbi" + 0.011*"people" + 0.008*"make" + 0.007*"blame" + ' '0.006*"buy" + 0.006*"control" + 0.005*"trump" + 0.005*"kill" + ' '0.005*"weapon"')	(2, '0.028*"fbi" + 0.010*"gun" + 0.009*"trump" + 0.008*"governor" + ' '0.008*"rick_scott" + 0.008*"florida" + 0.008*"resign" + 0.008*"scott" + ' '0.007*"director" + 0.007*"go"')	(3, '0.031*"gun" + 0.012*"fbi" + 0.010*"weapon" + 0.010*"scott" + 0.010*"people" ' '+ 0.009*"need" + 0.008*"law" + 0.007*"nra" + 0.006*"control" + 0.006*"get"')	(4, '0.025*"gun" + 0.019*"fbi" + 0.009*"school" + 0.007*"blame" + 0.007*"would" ' '+ 0.006*"people" + 0.006*"do" + 0.006*"something" + 0.006*"could" + ' '0.006*"trump"')

The most salient term in this comment section was "FBI" which shows that the audience of this article really responded to the article's frame of placing blame on the bureau, even though by looking at the topics for this article (above), there was more going on that could have been a conversation piece as well (especially in the first topic, where you can tell the article was discussing Russian interference with the key words "Russian", "investigation" and "election"). This excess of comments regarding the FBI seem to be the one reason why "gun" did not reach the number one spot for saliency in this article's comment section, as it still appears as the second most salient term. An interesting thing is happening in the topics with these two terms though, both "FBI" and "gun" appear in all five topics, which implies that the majority of the time that the term "FBI" pops up, the "gun" term isn't too far behind. I speculate this to mean that in this comment section, the commenters that are mentioning "gun" are still are not distracted of off topic. Instead, they are simply including it with their more relevant comment regarding the FBI. It is still unclear why "gun" would come up in the comments of this article, but it seems to be a trend that when it comes to mass shootings, "guns" are on the minds of the public already and it takes more of a force to deter readers from this topic than it does to put or keep them on it. As far of the tone of these comments, MonkeyLearn's sentiment analysis reading for the aggregate comment section was "Negative" with 67.9% confidence. For only the comments that mention "FBI", the reading "Negative" with 89.4% confidence. For the comments that mention "gun", the reading was also "Negative" with 67.9% confidence. This could mean that a lot of the negativity in this comment section is centered more around the FBI than the other topics, in that the confidence reading shot up in comparison to the readings of both the aggregate comment section and the comments that mention "gun". The fact that only the comments that mention "gun" and the entire comment section generated the exact same reading is stunning to me, in that it seems to be that the "gun" comments are pretty representative of the tone in the overall comment section. As far as the relationship between the "gun" and "fbi" terms in this comment section, it seems like the negativity the two terms generate are often related. Many of the comments rebut the idea that the FBI could be more at fault for the Parkland shooting than guns could be. Some of the commenters were angry that this article seemed to be distracting their audience away from what they thought was really important in the wake of the violence, such as placing the blame on weapons and opting for gun control.

Article 3- *No apparent prevalence of "gun" in the article or its comments.*

Article ID	"Gun" appears in the chart of most salient terms for article	"Gun" is **the most** salient term in the chart of most salient terms for article	"Gun" appears in article topics	"Gun" appears in the chart of most salient terms for comment section	"Gun" is **the most** salient term in the chart of most salient terms for comment section	"Gun" appears in comment topics
3						

The actual title of article 3 is "After Las Vegas Shooting, Fake News Regains Its Megaphone;The Shift". It is a Las Vegas article from October 2nd, 2017. When I did my initial content analysis with MAXQDA, I only found one frame in this article, the attribution of responsibility frame "FBI Negligence". This article stood out to be since the very beginning of this project, because it's the one that seems to branch off the most from the others in terms of topic. The article has very little description of the event itself, but instead focuses on the instances of fake news that occurred in the wake of the massacre. However, even though the article might seem off topic, it still qualifies as a valid article for this study because this fake news drama is certainly one of the Las Vegas Shooting's flywheels, and it definitely had a lot of potential to influence how America remembers and understands the tragedy. By taking a look at the article and comment section topics for article 3, you can definitely see some alignment, indicating that this article was successful in generating the conversations that it intended to start. Consequently, less readers got distracted by discussions about the gun debate in the comments.

Article 3's topics	[(0, '0.014*"news" + 0.014*"facebook" + 0.013*"make" + 0.013*"platform" + ' '0.013*"time" + 0.013*"information" + 0.007*"appear" + 0.007*"company" + ' '0.007*"malicious" + 0.007*"often"')	(1, '0.027*"news" + 0.016*"misinformation" + 0.016*"facebook" + 0.016*"story" + ' '0.012*"platform" + 0.012*"spread" + 0.012*"company" + 0.012*"make" + ' '0.012*"appear" + 0.008*"medium"')	(2, '0.011*"news" + 0.011*"shoot" + 0.011*"link" + 0.011*"liberal" + ' '0.011*"organization" + 0.011*"trump" + 0.011*"man" + 0.011*"mass" + ' '0.011*"org" + 0.011*"may"')	(3, '0.020*"spend" + 0.020*"top" + 0.011*"story" + 0.011*"identify" + ' '0.011*"right" + 0.011*"site" + 0.011*"chan" + 0.011*"troll" + ' '0.011*"message" + 0.011*"contingent"')	(4, '0.033*"facebook" + 0.020*"news" + 0.013*"post" + 0.013*"platform" + ' '0.010*"user" + 0.010*"shooter" + 0.010*"story" + 0.010*"fix" + ' '0.010*"company" + 0.010*"ad"')

Article 3's comment section topics	(0, '0.026*"news" + 0.013*"fake" + 0.011*"facebook" + 0.009*"people" + ' '0.008*"fact" + 0.008*"problem" + 0.007*"story" + 0.006*"source" + ' '0.006*"site" + 0.006*"get"')	(1, '0.020*"news" + 0.008*"facebook" + 0.007*"fake" + 0.006*"right" + ' '0.005*"people" + 0.005*"social_media" + 0.005*"time" + 0.005*"get" + ' '0.005*"would" + 0.005*"information"')	(2, '0.037*"news" + 0.015*"fake" + 0.011*"social_media" + 0.010*"get" + ' '0.009*"people" + 0.008*"make" + 0.008*"facebook" + 0.007*"american" + ' '0.006*"source" + 0.005*"company"')	(3, '0.012*"news" + 0.012*"facebook" + 0.008*"people" + 0.007*"social_media" + ' '0.006*"fake" + 0.005*"lie" + 0.005*"time" + 0.005*"right" + 0.004*"fact" + ' '0.004*"interest"')	(4, '0.008*"facebook" + 0.006*"people" + 0.006*"pay" + 0.005*"algorithm" + ' '0.005*"make" + 0.005*"company" + 0.005*"news" + 0.004*"see" + 0.004*"would" ' '+ 0.004*"dollar"')

When it comes to the sentiment of article 3's comment section, the reading for the overall section was "Negative" with 99.8% confidence. When inputting just the comments that contain the word "news", the result was "Negative" with 74.9% confidence. Seems like most Americans are not fans of fake news.

<u>The Trends in "Gun" Term Salience- Discussion</u>

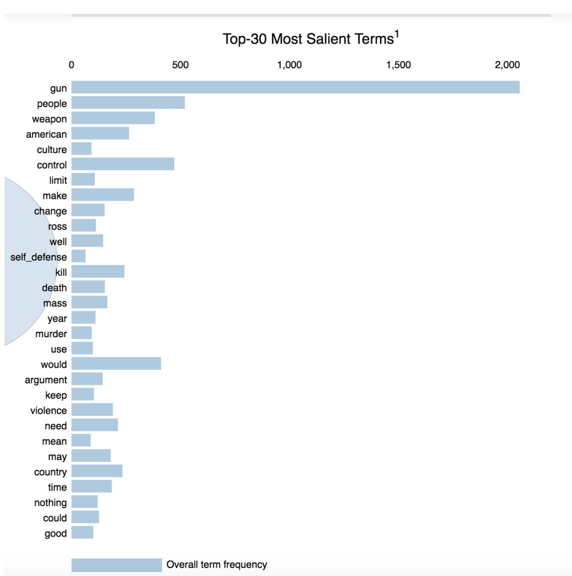
The overwhelming dominance of "gun" terms in the comment sections of the articles in my sample tell us that "guns" may be the most influential topic when it comes to how Americans come to understand and remember mass shootings in this country, but the preceding analyses of the outlying articles in terms of "gun" prevalence tell us even more. Of those six articles that don't fit the 14 article mode of having some mention of "gun" in the article itself translate to complete dominance of the term in the comment section, four of them did not have any mention at all of "gun" in the article itself but still had it appear in the comment sections. Those articles consist of articles 8, 15, 16 and 17. Of those four, only article 16 had "gun" as the #1 most salient term in the comment section. Among those other three I discovered another trend, they were each one of the four articles that were more focused on just one aspect of the event's story, meaning that there was only one type of frame found in the article during my initial content analysis with MAXQDA. For instance, article 8 only had the conflict frame "Hotel Security", article 15 only had the morality frame "Demoralization", and article 17 only had attribution of responsibility frames, more specifically "Nikolas Cruz" and "FBI Negligence". The fourth article of this kind was the one article that had no mention of "gun" in either the article or comments (article 3). In summary, most of the articles simply showed that when journalists bring up the topic of guns, the audience is quick to pick up on that topic in the comments. However, if journalists focus their point a little bit more, perhaps by narrowing in on a discussion about hotel/school security or something else, then it seems as if they could have a little bit more control over what their audience's takeaways are from their writing. One more thing though, even though these focused articles seem more productive in generating the right kind of conversations in the comment sections, they can only be effective if they are popular articles, and judging by the comment counts of these articles that does not always seem to be the case for these. Article 8 has only 45 comments, Article 15 has just 7 comments, and article 17 has 1832 comments. With the exception of article 17, these three articles might be hinting that audiences are less drawn to articles that narrow in on just one major aspect of the story. However, article 17 shows that this might not be the case, or if it is, there's a way around it.

Other Topics of Interest in Gun Violence Coverage

Up until this point, I have almost exclusively been discussing my results in terms of conversations about guns, and this is because my results showed an unexpected dominance of "gun" terms amongst my sample's comment sections. When I say unexpected, I don't mean that I didn't expect lots of readers to have guns on their mind, but I mean that I had expected to see some more representation of some of the other issues that are commonly associated with mass shootings as well. In my literature review prior to this study and from my own personal experience, I know that some other issues that are associated with mass shootings include mental health (could be referring to the troubled life of a perpetrator or the recovery of the community that was affected by the shooting), the security of schools and events, the power of the National Rifle Association (NRA) and more. However, while these other issues tend to get overshadowed by the predisposition of many Americans to discuss guns in response to these tragedies, these other issues aren't absent from my sample. As mentioned before, article 8, one of the Las Vegas articles, actually almost purely focused on "hotel security", and that article was clearly successful in generating conversations about that particular topic as can be seen in its LDA results. As far as the issues of mental health and the disputed power of the NRA go, I saw representation in different forms. The NRA topic was sprinkled into comment sections of 17/20 articles, but it was rarely highly salient and there didn't seem to be much of a trend as to when it was brought up by commenters. However, it was always present in the comments of the articles with the "Americans vs. the NRA" frame. On the other hand, mental health appeared in the LDA results only twice, or three times if you count the keyword "sick" in the comment section results for one of the Las Vegas articles. The other two articles were from the Parkland sample and more explicitly included mental health as bigram terms, once as "mental_illness" and the other time as "mental_health". Before faced with these results, I had speculated that more Parkland articles would generate discussions of mental health than Las Vegas articles. This is because of some of the elements of the Parkland case, in that it occurred in a high school as opposed to a concert and that the perpetrator Nikolas Cruz is still alive and therefore more vulnerable to receive character attacks. All three of those articles included the"Humanization of Stephen Paddock/Nikolas Cruz" frame in the article's initial MAXQDA content analysis, which gives a little bit of a hint as to what might inspire readers to discuss mental illness. When readers are exposed to more details of the perpetrator's life, they are more likely to look for more personal factors that could have propelled the shootings to occur such as mental health. I ran sentiment analysis tests to see if those results could provide a little more insight to how commenters feel about mental health. For the Las Vegas article (article 10) that had "sick" as one of its keywords, the result for the aggregate comment section was "Negative" with 99.9% confidence. For only the comments on article 10 that include "sick", the reading was also "Negative", with 88.9% confidence. For the first Parkland article (article 12) that had "mental_illness" as a keyword, the result for the aggregate comment section was "Negative" with 86.5% confidence, and for just the articles that included “mental illness”, the result was “Negative” with 95.6% confidence. For the second Parkland article (article 13) that had “mental_health” as a keyword, the result for the aggregate comment section was “Negative” with 74% confidence, and for just the articles that included “mental health, the result was “Negative” with 92.5% confidence. I also experimented a little bit between these two Parkland articles because I was confused as to how the keyword came out as “mental_health” in one article and as “mental_illness” in another. Both articles have plenty of occurrences of each bigram term, but my LDA topic model seems to have found more of a cohesive topic word in each of the two article’s respective bigrams for the subject. This could also be an instance where commenters are subliminally shaping their word choices based off of words they see other commenters using.

“Piggyback” Commenters

Going off of the difference between the salience of the terms “mental_health” vs. “mental_illness” as described in the previous section, I believe that there may be several instances in these comment sections where the commenter’s responses are largely influenced by the word choice of other commenters in addition to the frames used by the journalist. This definitely plays into that many-to-many information flow that characterizes internet news, in that readers are subject to the influence of not just the source but also anyone else who happens to have shared their opinion on the article as well. For example, the topics that come up in my LDA model to describe what commenters are discussing come from conversations, and conversations must begin with some comment somewhere. In a comment section, it only takes one person to say something that inspires a response from someone else before those two comments spiral into an entire thread of lots of comments, all discussing the same thing. This natural trend in comment section conversations could also describe how biases exist within the comment sections, in that a right-wing comment might inspire lots of left-wing arguments in response and vice versa. These patterns can explain some of the salience and topics results that I got from my sample too. Taking the “mental_health” vs. “mental_illness” bigram terms as an example, I believe that piggyback commenting goes beyond subject matter, but could apply to word choice as well. In that case it seems that someone started a conversation using “mental health” in one article and someone else started a conversation using “mental illness” in another, and in responses to those original comments, other commenters continued the same word trends. This also applies for articles like Article 4, for example where “weapon” showed up as a highly salient term in addition to the “gun” term. In the case of gun violence, the terms “gun” and “weapon” can more or less be used interchangeably, but the reason why we may see the “weapon” term at different saliencies throughout the article sample most likely has to do with this piggybacking theory.



Article 4’s comment section’s LDA topic chart

Parkland vs. Las Vegas

By now we have gone through all of the LDA topic model results and have seen lots of trends in the comment data that provide us with many insights of how readers might be processing the sample of the articles as a whole, but here I will summarize how the samples from the two separate events compare to each other. Recall that there was a mode in the data, which I characterized as the 14 articles where any presence of the term "gun" translated into complete dominance of that term in the comment section. Coincidentally, those six articles that did not fit the mode were evenly distributed amongst the two cases with three outlying articles from each one. To consider the other differences between the two cases, we need to recall the MAXQDA content analysis results and how they differed. The biggest differences were in the conflict and morality categories, more specifically with the "Right to Bear Arms vs. Gun Control", "Concert/Hotel/School Security", "Thoughts and Prayers", "Unity for Action" and "Demoralization" frames. We've already extensively explored how the gun debate influenced audience response across the entire sample of articles, so I will start with the "Concert/Hotel/School Security" frame. In the MAXQDA results, Las Vegas showed a higher concentration of this frame which means that in my article sample, the New York Times exhibited a higher emphasis on hotel (concert security never came up) security than school security. However, the topic model results of the comments did not reflect that at all. For the Las Vegas results, only two of the comment sections had "hotel" show up as a topic keyword, articles 1 and 8. The audience showed way more concern for the safety of their schools with their comments on Parkland articles. For the Parkland results, 9 out of 10 articles included "school" as a topic word for their comment sections. This disparity shows that sometimes it does not matter what the articles actually say, the audience is going to bring up the issues that are on their mind, and in the case of Parkland, the audience had a lot of concern for schools. I can even imagine that some of the responses that mention “school” may include commentary on the lack of discussion about school security in the Parkland articles.

Next, there is the disparity between the morality frames for the two events. Parkland, the more recent of the two events showed more “Demoralization”. This confirms the common sense idea that as time goes on and more tragedies occur, the public gets more and more demoralized. Las Vegas showed some more optimism towards a better future with more “Unity for Action” frames. Again, it’s easy to imagine why this may be the case, because the Parkland shooting occurred so soon after Las Vegas that journalists might have felt too repetitive repeatedly writing about the same actions that their audience should take in the wake of the shootings. Las Vegas also had a higher number of “Thoughts and Prayers” frames. However, even though the articles showed this disparity in morale between the two cases, there isn’t much evidence within the LDA results that indicates whether the audience’s response consists of the same distribution of morality frames. It seems as if both cases inspired pretty even amounts of each morality frame in the comment sections. I will mention though that article 6, that one article with the most clear call to action that seemed to get the most people talking, was a Las Vegas article.

A Note on the Sentiment Analysis Results

You might have noticed that among the sentiment analysis results that I have reported, the overwhelming majority of them are “Negative”. Although I have included some speculation about what the difference in some of the confidence percentages could mean about the sentiment of the data, the only thing this result really tells us is that the American public feels negatively about mass shootings. Unfortunately, this is not new information.

CONCLUSION

<u>What We've Learned</u>

The most certain result to come out of this study is the fact that public opinion when it comes to American mass shootings revolves around guns and where one stands within the gun debate, whether they choose to be an advocate for tighter gun restrictions or to protect their right to bear arms at all costs. I found that 93% of the time, when an article brings up a discussion about guns, that frame will be the one that the audience remembers and responds to regardless of what other frames are present in the article. The only article from my sample that brought up a gun conversation yet exhibited more prominence of another frame in the comments had commenters discussing "regulation" and "action" for a safer America. Even the articles that did not bring up the gun conversation explicitly still often had commenters discussing the gun debate in the comments. This result shows us that issues that center around "gun" terms are the most central to the cognitive processes of the American public in that they often bring it up for no apparent reason simply because that is what is on their minds. This frequent discussion of the gun debate is not a bad thing, especially since several of the comment sections that discussed this particular topic contained productive conversations that could even inspire readers to take action to make a change of how guns are handled in the USA. However, this study doesn't only show that "guns" are the most important topic to the public, it also shows just how hard the topic is to avoid amongst readers in response to mass shooting articles. Because of this, if a journalist ever wanted to start a conversation in response to a shooting that doesn't center around guns, they would have to be very smart about how they framed their article. In other words, studies such as this one can begin to inform journalists on how to frame their articles in order to have more control over what message their audience receives from their writing. I found that the articles that really focused in on just one aspect of the story (one frame category) were more successful in starting those intended conversations, such as articles 3 and 8, which had the audience discussing fake news and hotel security, respectively, instead of guns. Finally, this research should make the public more aware of how news coverage impacts their understanding of gun violence. Perhaps the study of the implications of news coverage can someday get us all on the same page, to the point where we can address issues most efficiently.

Pitfalls of this Study

Even though this research can tell us a lot about the media's impact on public opinion, this study was far from perfect. A number of this study's aspects could have caused some margin of error.

- Sampling of Articles: Although I tried to make the article sampling process as random and unbiased as possible, I believe it is possible that my sample could have added a bit of skew into my results due to my parameter where I required that all of my articles have comment sections. Clearly, the presence of a comment section was crucial for this study, but the requirement narrowed down my sample pool more than I initially thought it would. It ended up being the case where my sample was less random, and instead my sample consisted only of the articles that had comment sections. Because I don't have an explanation from the New York Times as of why some articles have comment sections and why some others do not, I can't really speculate how this detail could have affected my results. However, because of the observation that comment sections make for a more satisfying an interactive experience for news consumers, I can consider the idea that the commenters in my sample are the more engaged readers.

- LDA Topic Modeling: Although my version of the LDA topic model worked out really well for the purposes of this study, it is still a branch of Natural Language Processing (NLP) which means that we have to accept that it is not a perfect algorithm. Just like how humans often differ in how they come to understand natural language, we must assume that this model understands language differently too. This technology is forever developing and I think that even in a few years if you were to do this study with updated technology, you could find out even more.
- Sentiment Analysis: Similarly to the LDA topic model, sentiment analysis is a developing NLP technology. However, for this specific study there were more issues than just that. The resources for sentiment analysis are not as developed as they are for LDA topic modeling, and because of that my "homemade" sentiment analysis model was not satisfactory for the purposes of this study. That is partially because the sentiment of comments in response to gun violence are typically far more complicated than what most sentiment analysis models are designed to process, in that commenters often use a mix of sentiments to prove their point (ex. "It's incredible how the people of Las Vegas have come together to move on after this unthinkable act of violence and destruction"). This issue propelled me to make use of a commercially available program with my aggregate

texts. That method seemed to be the most effective, but even then the program's results told us nothing about stance. The program could only inform us on tone.

- Comment Bots: "Bots", also referred to as "Internet Robots" or "Web Crawlers" are automated instances of code that attempt tasks all over the internet. Bots can be good or malicious, but the bottom line is that these bots are everywhere. Recently it was estimated that these internet bots even outnumber humans, making up an estimated 56% of all internet traffic (WIRED). Because of their prominence and often malicious tendencies, bots are always a concern when conducting any sort of research with internet data. For this study specifically, Social Bots are a concern. Social Bots are agents that sometimes exert themselves autonomously into comment sections or social platforms for the purpose of communicating with humans in order to influence public opinion. The New York Times is certainly a platform from which opinions are formed, which makes it vulnerable to become a target for some of those malicious bots. However, the website notes that it has taken action to prevent this from happening, by requiring users to register before commenting: "We ask you to complete the simple NYTimes.com registration process to ensure that you are a "real" person and that you accept our terms and conditions. The registration process serves to facilitate the development of our online community, and ensure that members take responsibility for their writings.".

Moving Forward

In the introduction to this study, I explained that the ever changing nature of news and how the media impacts public opinion inspires many questions regarding how comments can contribute to the formation of opinions and what those comments can tell us about the implications of news media. This study only begins to answer these questions. While this study has provided some possible answers as to how the implications of news framing are reflected in the comments of the New York Times articles on mass shootings by studying their nature, topics, tone, and differences between the two cases, the findings are not the end all be all solutions. Studies like this one should continue to be conducted to find out more, using different samples of articles, more advanced technology, and more. There are also so many other ways to explore this type of data. Perhaps in a future study, instead of comparing two different events of similar nature like this one did, we could compare articles and comment sections from two different news platforms of different biases. For example, The New York Times is typically a left-leaning agency. It could be very informative to see how the results of a right-leaning agency would compare. This type of research has the potential to answer some other questions as well, such as “Do individual users’ comments vary across articles?” or “Do individual users’ comments vary across case characteristics?”. Even more could be discovered if we expanded the study of public opinion beyond just the data from news sites, and used data from social media sites such as Twitter as well. I previously mentioned that I was able to build a sentiment analysis model for Tweets, which makes this method even more accessible. The possibilities for how to continue the search for complete understanding of public opinion are endless, but we have to start somewhere. As of now, this research should make the public more aware of how news coverage impacts their understanding of gun violence. Perhaps the study of the implications of news coverage can someday get us all on the same page, to the point where we can these address issues most efficiently.

References

Arendholz, J. 2013. *(in)appropriate online behavior: A pragmatic analysis of message board relations*. Amsterdam;Philadelphia;: John Benjamins Publishing Company.

Highfield, Tim. 2016. *Social Media and Everyday Politics*. Polity Press.

E. M. Kerr, S. 2018. *Gun violence prevention?: The politics behind policy responses to school shootings in the united states*. Cham: Springer International Publishing.

Fallahi, Carolyn R. 2016. “Social Media and News Coverage as Vicarious Exposure.” *The Wiley Handbook of the Psychology of Mass Shootings*, by Laura Wilson, Wiley-Blackwell 136–152.

Griffith, Keith. 2018. “Las Vegas Gunman's Girlfriend Told Investigators He Was 'Unable to Perform'.” *Daily Mail Online*, Associated Newspapers

Kinder, Donald R. 1998. "Communication and Opinion." *Annual Review of Political Science* 1:167-197.

Ness, Susie. 2019. *Divided We Stand: The Nature and Prevalence of Fascist Politics in the United States' Partisan Press*. Sociology Honors Thesis

Papacharissi, Z. 2002. The virtual sphere: The internet as a public sphere. *New Media & Society*, *4*(1), 9–27.

Sastry, Anjuli, and Sam Sanders. 2018. “Ann Curry On Journalism, Her PBS Series And Working On The 'Today' Show.” with guest Ann Curry, NPR.

Schildkraut, Jaclyn, and H. Jaymi Elsass. 2016. “The Influence of Media on Public Attitudes.” *The Wiley Handbook of the Psychology of Mass Shootings*, by Laura Wilson, Wiley-Blackwell 117–135.

2019. “Sentiment Analysis by MonkeyLearn”. *MonkeyLearn Inc. https://app.monkeylearn.com/main/classifiers/cl_pi3C7JiL/*

Suler, J. 2004. The online disinhibition effect. *CyberPsychology & Behavior, 7*(3), 321-326.

Tewksbury, David and Jason Rittenberg. 2012. *News on the Internet: Information and Citizenship in the 21st Century*. New York: Oxford University Press.

2019. “The New York Times Developer Network”. https://developer.nytimes.com.

2018. “Topic Modeling in Python with Gensim.” *Machine Learning Plus*, www.machinelearningplus.com/nlp/topic-modeling-gensim-python/.

Wojcieszak, M., & Mutz, D. 2009. Online groups and political discourse: Do online discussion spaces facilitate exposure to political disagreement? *Journal of Communication, 59*(1), 40-U9.

Zhou, Yuqiong and Patricia Moy. 2007. "Parsing Framing Processes: The Interplay between Online Public Opinion and Media Coverage." *Journal of Communication* 57(1):79-98.