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Resonant Moments in Media Events: Discursive Shifts, Agenda Control, and Twitter Dynamics in the First Clinton-Trump Debate

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Live-tweeting has emerged as a popular hybrid media activity during broadcasted media events. Through second screens, users are able to engage with one another and react in real time to the broadcasted content. These reactions are dynamic: they ebb and flow throughout the media event as users respond to and converse about different memorable moments. Using the first 2016 U.S. presidential debate between Hillary Clinton and Donald Trump as a case, this paper employs a temporal method for identifying resonant moments on social media during televised events by combining time series analysis, qualitative (human-in-the-loop) evaluation, and a novel natural language processing tool to identify discursive shifts before and after resonant moments. This analysis finds key differences in social media discourse about the two candidates. Notably, Trump received substantially more coverage than Clinton throughout the debate. However, a more in-depth analysis of these candidates' resonant moments reveals that discourse about Trump tended to be more critical compared to discourse associated with Clinton's resonant moments.

Keywords: televised presidential debates, media events, discursive shift analysis, Twitter dynamics, time series, natural language processing

Televised presidential debates have long been a fixture of electoral campaigns in the United States, offering rare opportunities to see candidates compete on the same stage for an extended period and enabling direct comparisons. The advent of social media, however, has altered the way audiences watch debates and engage with them. Now, viewers are able to discuss, dissect, and react to media events in real time on social media, a second-screening phenomenon that enables horizontal communication between members of the viewing audience and arguably changes the television-viewing experience (Shah et al., 2015; Vaccari et al., 2015). The relationship between media events and social media activity is of growing interest to social scientists, especially as it relates to civic engagement and attention (Williams & Gonlin, 2017; Zheng & Shahin, 2020). However, existing research relies heavily on panel surveys and experimental designs to track second-screening activity, which provides an incomplete picture of the nature of audience engagement, particularly as it concerns real-time dynamics.

To address this gap in scholarship, we conceptualize and operationalize resonant moments during political media events, in this case a televised presidential debate, by exploring periods of heightened social media activity during the first 2016 U.S. presidential debate between Hillary Clinton and Donald Trump. In our analysis, we are especially interested in identifying resonant moments. Drawing from the pre-social media era concept of "defining moments," proposed by Clayman (1995), a resonant moment is defined as "a single compelling remark or interactional exchange [that] becomes the primary focus of attention as it is extensively replayed, quoted, paraphrased, referred to, and discussed" (p. 119) in and through *social media* by an attentive public. Digital platforms—and social media in particular—allow audiences to provide feedback about broadcasted events and engage in synchronous conversational exchange. Audiences, therefore, can create resonant moments on one medium about another medium's content, making resonant moments a hybrid media phenomenon (Chadwick, 2017). Resonant moments are culturally consequential because they shape conversations both during and after media events (Freelon & Karpf, 2015) and may define events in collective memory (Tan, Peng & Smith, 2018).

Our approach for identifying and studying resonant moments on social media utilizes several methods, including time series, qualitative analysis, and a natural language processing (NLP) approach, to describe how word usage around the debate shifts on Twitter during resonant moments. This strategy allows us to identify resonant moments through social media discourse during key points of the debate. Applied to presidential debate discourse here, our technique can be used to study a much broader range of social media conversations about public events.

Presidential Debates, Social Media, and Second-Screening

As media events, presidential debates are high-stakes moments of collective attention involving political performances by candidates who are keenly aware of their scrutinizing audience (Schroeder, 2008). Characterized as both a gladiatorial contest of ideas or an extended press conference, presidential debates are media spectacles wherein candidates joust for stage dominance by deploying rhetorical maneuvers and nonverbal behaviors (Bucy et al., 2020). While presidential debates are often guided by pre-defined questions and subjects, the candidates frequently go off-topic, switching attention to other issues in hopes of gaining an advantage over an opponent (Boydstun et al., 2013a). Competing for agenda control - i.e., focusing on favorable topics while avoiding topics that favor opponents - is a common practice among competing rivals (Riker, 1996), particularly when a topic that a candidate "owns" is deemed important by the public at the time (Ansolabehere & Iyengar, 1994).

Digital communication platforms afford new venues to investigate debate discourse dynamics and the interplay between the dual screens of television and social media. Rather than evaluating presidential debates in isolation, contemporary viewers interpret candidates' performances through the broader media ecology (Tsfati, 2003), including post-debate spin in news media coverage (Fridkin, Kenney, Gershon & Serignese, 2008), the in-person reactions of other viewers (Fein, Goethls, & Kugler, 2007), and, increasingly, social media discourse (Hawthorne, et al., 2013).

During the 2012 U.S. presidential debates, about one in five debate viewers engaged in second-screening—watching debates on one screen while simultaneously scrolling or posting on social media, via a second screen—with 18 to 34-year-olds engaging at the highest rate (Gottfried et al., 2016: p. 8). A 2018 Nielsen survey of U.S. adults found 45% of the respondents reported using a digital device "very often" or "always" when watching TV. Because second screeners are reacting to the first screen during televised events, moments of heightened social media activity are likely to focus on "real-time" occurrences transpiring during the debate.

The Case

Our analysis focuses on the first 2016 U.S. presidential debate between Democratic nominee Hillary Clinton and Republican nominee Donald Trump, which took place on September 26, 2016 at Hofstra University. It was moderated by Lester Holt, anchor of NBC Nightly News. Over 84 million Americans tuned in across 13 television channels, making it the most watched debate in U.S. history (Stelter, 2016). Millions more watched the debate on YouTube and other streaming services (Spangler, 2016). The 90-minute debate covered six broad topics: the economy, trade, the federal deficit, race relations and policing, foreign policy, and the candidates' experience (Burns & Flagenheimer, 2016). With over 17.1 million interactions on Twitter, the first 2016 debate was also "the most-tweeted debate" (Jarvey, 2016) since the platform's inception, and remains so even after the 2020 presidential debates (Brown, 2020). Tweets mentioning either candidate (Trump or Clinton) were at their highest on the days of the presidential debates relative to the rest of the election cycle (Coyne, 2016).

Social Media Resonant Moments

In this study, we use social media activity to explore how certain debate moments become especially memorable for audiences. These defining moments (Clayman, 1995) on social media, which we call resonant moments, involve an exchange of information between the political candidates on the stage and the active audience of prosumers—consumers of televised content and producers of social media messages (Axel & Schmidt, 2011) which, in this case, are about the televised presidential debate they are witnessing.

Resonant moments during debates can be induced in two ways. The first is by the candidates: they can say something that gains immediate traction on social media. Naturally, debating candidates hope to have a memorable performance that receives favorable coverage and amplifies pro-candidate messages (Cornfield, 2017; Shah et al., 2016). Part of the memorability of their performance hinges on being able to make salient and notable comments (Clayman, 1995). However, this strategy is not always effective. Worse yet, a candidate may make comments that are widely shared but negatively perceived. In fact, most debate-defining moments tend to be zingers and gaffes (Freelon & Karpf, 2015). Second, resonant moments can be induced by members of the digital media audience, who may tweet something compelling that circulates widely, independent of what is discussed in the debate. Though audience-driven moments are worth exploring in future research, this study is focused on the former: candidate-induced resonant moments.

Previous studies of debate highlights have relied on relatively arbitrary procedures or post-hoc news coverage to identify resonant moments (e.g., Freelon & Karpf, 2015; Shah et al., 2015). Such an approach, while meaningful, carries the risk of conflating post-debate spin and anecdotal accounts with other empirical indicators of real-time resonance. Another way these real-time dynamics may manifest is through language mimicry between the rhetoric of the candidates on stage and the discourse on social media about the debate. In cognitive linguistics, Pennebaker's theory of language style matching posits that communicators harmonize one another's word patterns (2011). Though language style matching is less studied in mass communication contexts, the increasing interactions between content across platforms invites an opportunity to apply language style matching to understand cross-platform discourse. Our analysis adopts this approach by empirically identifying moments during the debate where spikes in engagement occur on Twitter and then tracking language shifts over the corresponding time periods.

We argue there are two useful attributes of social media discourse for identifying resonant moments. First, during resonant moments, there is generally a brief spike in media activity (Lin, Keegan, Margolin, & Lazer, 2014). When studying media events, scholars have often relied on heightened social media activity to justify their selection of resonant moments (e.g., Freelon & Karpf, 2015; Giglietto, Ariteri, Gemini, & Orefice, 2016). Second, when resonant moments occur, audiences may harmonize their language with the discourse used by candidates. In other words, we should be able to identify a resonant moment by the increased in-platform activity and the discursive shift. Indeed, when something important happens on television, tweets posted at the time often discuss the subject of that moment, either repeating what was said, evaluating it, or circulating humorous interpretations of real-time performances (Robertson, Dutton, Ackland & Peng, 2019).

Detecting Events and Moments

Our effort to identify resonant moments builds on previous approaches to detecting events and moments of heightened engagement. Event detection studies have employed a range of computational strategies, including natural language processing (NLP) and network analysis (e.g., Qian et al., 2019; Zhao et al., 2017). Other reviews of event detection have also noted the usefulness of machine learning techniques broadly (Saeed et al., 2019). Though computational scholars have traditionally used news stories in event detection analysis, in recent years there has been increasing use of social media content, particularly Twitter, as a plausible source for event detection (Hossny & Mitchell, 2018). Providing an overview of such strategies applied to Twitter data, Hasan et al. (2018) highlight NLP approaches, such as topic modeling, as well as studies focusing on “bursty terms.” One analytical advantage of social media over, say, survey data, is the ability to look at highly granular moments in time, as Twitter post timestamps are recorded at the millisecond level. However, there are also disadvantages: relative to other text data, social media discourse is rife with spelling and grammatical errors as well as colloquial language that make it difficult to use NLP tools such as part-of-speech tagging.

Thus far, event detection strategies have focused on crises, emergencies, and major breaking news events such as natural disasters (Huang et al., 2021), economic developments, (e.g., Jacobs & Hoste, 2020), and public health threats (Feldman et al., 2019). The events studied in this body of literature tend to be unexpected; after all, there is no need to detect events that are planned, known, and promoted in advance. As such, event detection strategies are rarely applied to planned events such as congressional hearings, sporting events, award shows, and debates.

A handful of studies about event detection have also utilized these methods to study key timepoints *within* an event. Rather than detecting events across a broader time horizon, these studies focus on moments of heightened activity during an event itself, which can be useful to understanding both planned and unplanned media events. For example, Arachie et al. (2020) identify “sub-events” by clustering noun-verb pairs. However, studies identifying short “moments” (e.g., less than 5 minutes) are rare and often rely on human annotation (e.g., Monfort et al., 2019).

We advance this literature by studying resonant moments within a presidential debate using both time series and NLP methods. The consideration of temporal dynamics is most closely aligned with event detection methods using burst detection algorithms (Kleinberg, 2003), which identify "bursts" of activity as state-changes within a time series. In other words, discourse can change states, from being less bursty to more bursty (i.e., active) for some time. The concept of a change in "state" (i.e., bursty versus non-bursty activity) is similar to, but longer than, the more circumscribed resonant moments we study, which we expect to appear and disappear quickly as the audience of a live-tweeted event moves onto other topics. A resonant moment is less a consistent state than a quick and passing blip—the equivalent of a sound bite (see Bucy & Grabe, 2007).[1]

Methodology

We employ a mixed-methods approach, combining time series analysis to identify resonant moments induced by a televised media event with natural language processing to study the discourse shifts occurring during a highly viewed presidential debate.

Detecting Events and Moments

Social media data. To collect tweets posted during the first 2016 U.S. presidential debate, we purchased from GNIP, Twitter's data provider, a full corpus of tweets mentioning either "Clinton" or "Trump," but not both, during the debate, which took place on September 26, 2016 from 9:00 p.m. to 10:30 p.m. EDT. Previous studies have used this method to collect an efficient corpus of debate tweets (Bucy et al., 2020). From this social media data, we constructed two time series: one of Twitter mentions of Clinton and one of Twitter mentions of Trump.

Debate Transcript. Since this analysis is focused on resonant moments in response to the candidates during the debate over time, we prepared the debate transcript by manually parsing it into 30-second increments. For each 30-second segment, two coders documented who was speaking at the time (Clinton, Trump, the moderator, or some combination). The timestamp of the

[1] For a more empirical comparison of these methods, please see Appendix A.

tweet was aligned to the timestamp of the debate transcript segment by matching the timestamp of the two data layers across several key points: the start of the debate, the end of the debate, and when the moderator asked a question. This final dataset included 178 30-second segments.

Time Series Analysis

To identify spikes in live-tweeting discourse about the debate, we perform an outlier analysis using the package <tsoutliers> (López-de-Lacalle, 2016). This package identifies outliers in a univariate time series using two steps. First, an ARIMA model is constructed to determine the data-generating process of the time series. For each time point, we then forecast what the data would look like using the ARIMA model. When an actual timepoint's data at time t deviates significantly from the forecasted time point, then that time point is said to have an outlier. As we have two time series—Twitter mentions of Clinton and Twitter mentions of Trump—we perform two separate outlier analyses, one focusing on each candidate. Since we are specifically looking for increases in expressive attention, we consider only positive outliers as potential resonant moments.

Transcript

After identifying when positive outliers occurred, we turned to the transcript to understand what occurred in the debate prior to and around the time of the activity spike. Our window of analysis for exploring the debate discourse is two and a half minutes prior to and 30 seconds after the resonant moment. When analyzing the debate transcript, we focus specifically on the subject matter and the speaker's language use at the time. This approach allows us to find a broad inventory of resonant moments throughout the debate, including those that were not highlighted in media coverage and which researchers might not have considered otherwise.

Identifying Discursive Shifts

To study the changes in discourse during the debate, we introduce a method to identify discursive shifts—changes in word use—between the pre-resonant and post-resonant moments of a media event. This is made possible by recent advancements in NLP, which leverages the value of neural network-based algorithms that learn efficient vector representations for words (Ling, Dyer, Black & Trancoso, 2015). In many modern NLP applications, words are represented as points in an N-dimensional space and semantic relationships between words (for example, analogies) are quantified using distance measures like the L2 distance and cosine similarity. Research using these algorithms has typically relied on large-sized generic bodies of text (e.g., Wikipedia), as larger datasets are required to train neural network-based algorithms that are able to capture a wide range of semantic possibilities for words represented in vector form.

Recent work in computational linguistics has applied word embeddings to smaller-sized datasets (such as vocabularies in a debate) by shifting the space of generic word embeddings (see Sarma, Liang, & Sethares, 2018). In this approach, three sets of word embeddings are obtained for a single vocabulary of words, with each encoding for different information about the same word. A generic embedding is obtained from off-the-shelf methods like word2vec (Mikolov et al., 2013) or GloVe (Pennington et al., 2014) that are trained on a large generic corpus such as Wikipedia. A second set of Domain Specific (DS) word embeddings is then obtained by either retraining word2vec/GloVe on a target data domain or using LSA (Deerwester et al., 1990). In the LSA approach, a documents-by-words ($d \times N$) matrix of word counts is constructed. Then, a SVD/dimensionality reduction step is performed, followed by projecting the left singular vectors onto the k largest singular values to obtain k dimensional word embeddings for the N words.

Once the generic and DS embeddings are obtained, they are combined to create the Domain Adapted (DA) embedding. This new embedding is obtained using KCCA (Kernel Canonical Correlation Analysis), which finds the nonlinear mapping that maximizes the statistical correlations between the generic and DS embeddings. Thus, the DA embedding combines the strengths of the large generic embedding with the specificity and targeted nature of the DS embedding. Sarma et al. (2018) demonstrate that DA embeddings perform particularly well on sentiment analysis tasks applied to modestly-sized target domains.

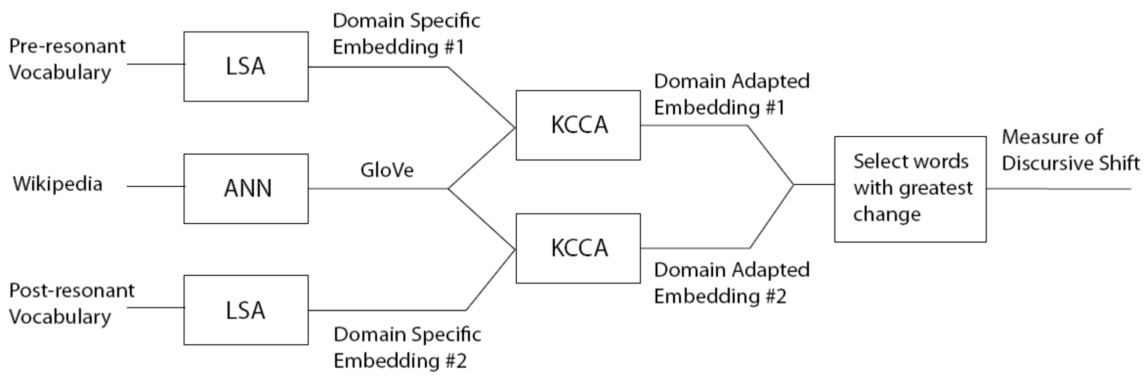

Figure 1. Discursive shift analysis data pipeline.

The methodological innovation in this paper is to combine two such DA embeddings. The data pipeline is shown in Figure 1. First, we tokenize texts from tweets before and after the resonant moment and construct two sets of vocabularies corresponding to the before and after vocabularies. These are the two Domain Specific embeddings shown in the figure. The two DS embeddings are separately combined with GloVe (the large-scale generic embedding) using KCCA to create the two DA embeddings. Then, we select all words that are common among the two DA vocabularies and measure how similar/different they are by calculating the L2 distance between the pre- and post-vector representations of each word. The interpretation of a large L2 distance is that words are being used in different ways, whereas words with a small distance have essential similarity. Thus, we can numerically extract the N words with the greatest change (we use $N = 100$), providing an automated method of investigating the shift in meaning. Sarma et al. (2018) show that using the L2 distance yields words that not only shift numerically but that are significant in their shift across domains. In the debate data, the technique is applied to two chronologically ordered corpora, thus the shift is temporal. In other applications, the two vocabularies might be from different geographical regions or writings from different authors.

Results

The first 2016 debate was 1 hour and 29 minutes long, producing 178 data points at 30-second increments. Figure 2 displays the time series of mentions for Clinton and Trump.

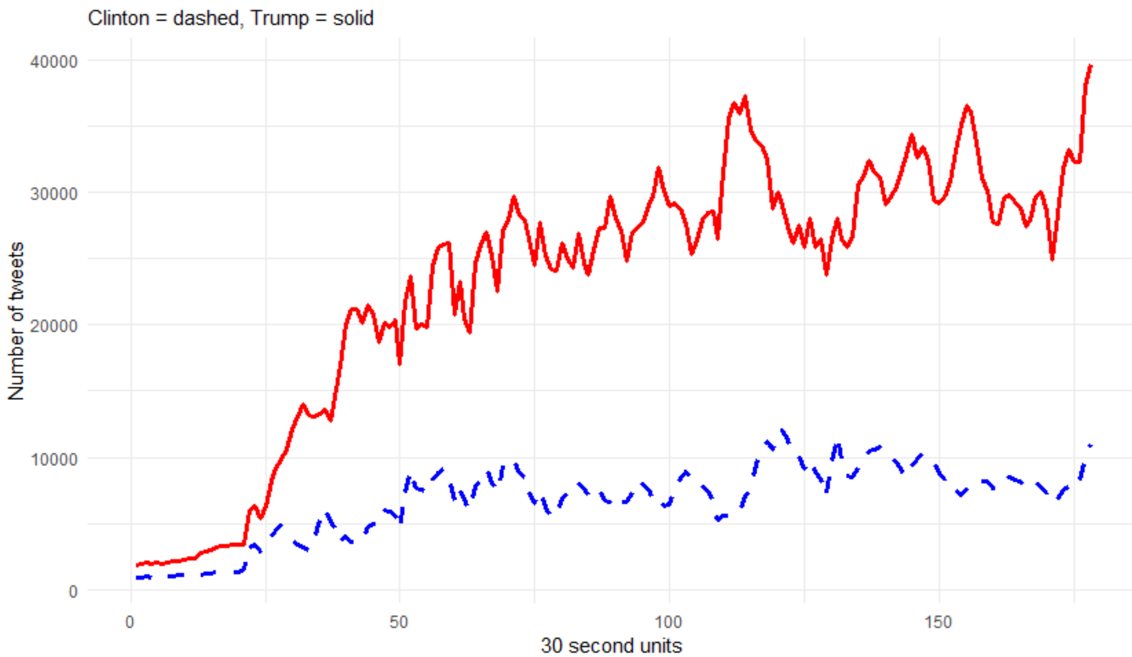

Figure 2. Time series of attention to Clinton versus attention to Trump

To diagnose the data-generating properties of each candidate's Twitter count, we build two auto-regressive integrated moving-average (ARIMA) models, using the R package <forecast>. To select the optimal model, we used the Bayesian Information Criterion, which yielded an (0,1,1) ARIMA model for Twitter attention to Trump (BIC = 3109.361) and an (0,1,1) ARIMA model for Twitter attention to Clinton (BIC = 2948.52).[2]

Identifying Temporal Outliers in Social Media Discourse

Rather than relying solely on human coders to identify resonant moments, we apply a time series outlier analysis first proposed by Chen & Liu (1993) to reveal resonant moments.

[2] Results of an ARFIMA suggested a fractional integration approaching 1. Treating the integrated component as fractional did not improve the BIC; we therefore chose to present the more parsimonious model.

Results of the outlier analysis identify eight time series outliers. For Clinton, there are four positive outliers. The first occurs around 25:18 to 25:48[3] (coefficient = 2432.50, *t value* = 5.37, $p < 0.01$). The second occurs around 39:18 to 39:48 (coefficient = 3378.01, *t value* = 9.09, $p < 0.01$). The third is between 1:12:18 to 1:12:48 (coefficient = 1048.00, *t value* = 4.20, $p < 0.01$). And finally, the fourth is between 1:14:48 to 1:15:18 (coefficient = 1789.88, *t value* = 3.11, $p < 0.01$). Figure 3a displays Clinton's positive outliers identified using this strategy.

There are four positive outliers for Trump. The first occurs between 42:18 and 43:48. The second happens between 46:18 and 47:18. The third is between 1:09:18 and 1:09:48. The fourth occurs between 1:22:48 and 1:23:18. Figure 3b displays Trump's positive outliers identified using this strategy.

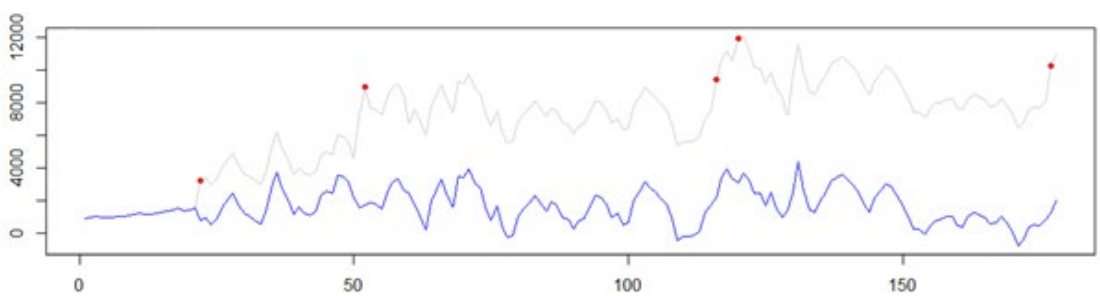

Figure 3a. Outlier detection in the Clinton time series

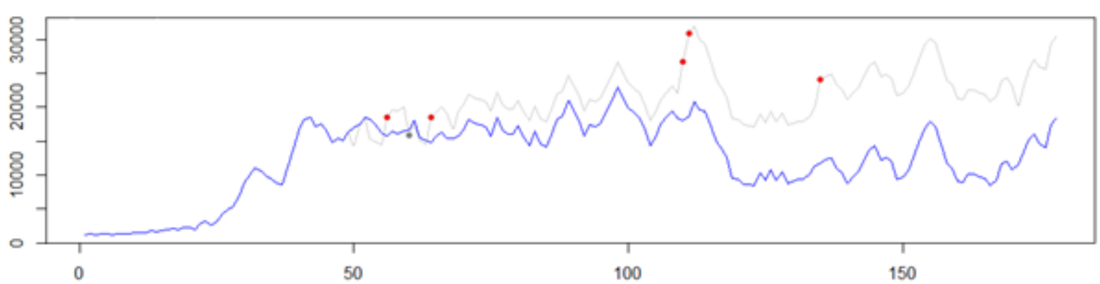

Figure 3b. Outlier detection in the Trump time series

[3] All timestamps referring to the debate are identified by the number of minutes and seconds that elapsed since the start of the moderator asking the first question to the candidates.

Identifying Temporal Outliers in Social Media Discourse

To identify whether these time series outliers actually reflect resonant moments induced by a candidate, we turn to the debate transcript. To understand these potential resonant moments in more detail, we examined the candidate's performative discourse in the eight aforementioned time segments. In the Clinton series, the following outliers were identified:

1) When Clinton said, "Donald thinks that climate change is a hoax perpetrated by the Chinese" (25:37-25:49).
2) When the moderator asked a question about Trump's tax returns (39:48:23-40:09). Because this event was induced by the moderator's question and not from either of the candidates, it was removed from subsequent analysis.
3) The third outlier occurred when Clinton quoted First Lady Michelle Obama ("When they go low, we go high") regarding the Birther scandal (1:11:59-1:12:16).
4) The last outlier happened during Clinton's response to a question about cybersecurity (1:42:10-1:42:18). In her response, Clinton spoke about threats from independent hackers and cyberattacks from other countries, explicitly identifying Russia as a threat.

In the Trump series, the following outliers were identified:

1) At the end of Trump's remarks regarding his taxes, and as Clinton began her response (42:38-43:10).
2) Following a back and forth that included remarks about Clinton's email scandal, when Trump uses the word "braggadocious" regarding his income: "I have a tremendous income. And the reason I say that is not in a braggadocious way" (46:28-46:33).
3) When Trump answered a question about the Birther scandal, stating: "I figured you'd ask the question tonight, of course. But nobody was caring much about it. But I was the one that got him to produce the birth certificate. And I think I did a good job" (1:09:28-1:09:36).
4) When Trump attributed the formation of ISIS to Clinton: "Well, President Obama and Secretary Clinton created a vacuum the way they got out of Iraq […] once they

got in, the way they got out was a disaster. And ISIS was formed" (1:22:08-1:22:22).

Testing for Discursive Shifts in Resonant Moments

To analyze the discursive shifts, we examined tweets posted two minutes before and two minutes after each of the seven candidate-induced resonant moments. For each moment, there were two corpora: tweets in the pre-resonant moment and tweets in the post-resonant moment. Tweets from these 14 corpora were tokenized, and unique vocabularies were constructed for each corpus. The final vocabularies were constructed by retaining words that appeared at least twice across all the tweets from the pre- and post- resonant moment corpora.

Words were ranked as "most different" in use by measuring the L2 distance between the domain-adapted vector embedding for a given word from the pre-vocabulary and the corresponding embedding for the same word in the post-vocabulary. Word embeddings for words in the pre- and post- vocabularies were obtained via the Kernel CCA projection method described in Sarma et al. (2018). Tables 1 and 2 show words that changed the most between pre-resonant and post-resonant vocabularies. In addition to the L2 distance, we measured the cosine similarity to calculate other words that are most similar to top words. We then compared these words to a list of words used in the debate, and related synonyms, to better understand whether the post-resonant vocabularies reflected the debate discourse. For a full list of these words, please see Appendix D.

In the seven resonant moments, several of the words with the greatest L2 distance in the pre-resonant and post-resonant moment were employed directly by a candidate during that time or were relevant to the resonant moment being discussed. For example, in Clinton's first resonant moment (focusing on climate change), words related to her statement were among those that shifted the most, including "climate," "change," "hoax," and "China." This makes sense, as tweets about climate change in the pre-resonant corpus focused on policies, such as this Sierra Club tweet: "Here's what we know even before #debatenight: @HillaryClinton is running on the best climate platform in history." By contrast, tweets about climate change in the post-resonant corpus focused on what Clinton said. For example, one Twitter user posted: "Now hitting him on climate change.

Clinton is going for the jugular early. #debatenight." Many tweets in the post-resonant moment corpus also quoted Clinton's remarks, which is a markedly different context from how climate change was referenced in the pre-resonant moment.

Table 1. Words with the greatest post-resonant moment shifts, Clinton 2016.

	"Donald thinks that climate change is a hoax perpetrated by the Chinese"		"When they go low, we go high"		Cybersecurity	
	Word	Δ L2 Distance	Word	Δ L2 Distance	Word	Δ L2 Distance
1	blah	47.95	nothing	57.57	nothing	61.44
2	made	41.93	response	56.66	high	41.52
3	fuck	39.47	**high**	47.37	well	38.51
4	said	38.71	line	44.96	back	37.39
5	**green**	38.06	**go**	38.61	election	33.89
6	**climate**	37.57	history	37.44	time	32.60
7	**energy**	36.32	**they**	37.33	they	32.59
8	looks	36.28	record	35.89	senator	31.87
9	again	35.19	really	34.23	also	31.73
10	real	33.80	hurtful	33.45	prepare	30.50
11	because	33.71	vote	33.07	drop	28.67
12	sexist	33.68	lester	31.75	watching	28.04
13	**change**	33.54	low	31.67	movement	27.98
14	**hoax**	33.38	went	31.64	birth	27.84
15	important	32.93	**Obama**	31.26	business	27.40
16	please	32.21	Barack	31.12	literally	26.99
17	bush	32.07	better	30.77	them	26.87
18	**China**	30.65	there	30.75	hurtful	25.41
19	those	30.48	watching	30.30	issue	25.00
20	does	29.69	prepare	29.41	there	24.94

Note. Bolded words are either from a candidate's quote or the debate topic at the time of the viral moment.

Similarly, the words with the greatest differences in Clinton's second resonant moment were related to Clinton's use of Michelle Obama's quote, such as "response," "high," "go," "hurtful," and "low"; or, they were related to the Birther scandal (the debate topic at the time), like Obama and Barack. However, during the cybersecurity moment, no words with the greatest discursive shifts had to do with cybersecurity. Although there was heightened social media activity during this time, social media discourse may not have been focusing on what the candidates in the debate were saying.

Table 2. Words with the greatest post-resonant moment shifts, Trump 2016.

	Trump taxes		braggadocious		Birther scandal		Clinton “created” ISIS	
	Word	Δ L2 Distance	Word	Δ L2 Distance	Word	Δ L2 Distance	Word	Δ L2 Distance
1	**paying**	80.42	wrong	102.62	healing	43.71	**iraq**	103.84
2	bubble	79.22	iraq	101.83	wasn’t	36.56	wrong	100.95
3	discur	75.57	should	73.67	ever	30.48	internet	94.33
4	**smart**	73.88	take	62.94	take	29.96	hacker	86.05
5	talk	71.58	china	57.53	much	29.13	take	70.37
6	obama	69.45	there	53.07	**born**	28.77	china	59.39
7	**federal**	66.49	security	51.86	**lying**	28.09	really	49.59
8	**income**	64.52	really	51.56	even	27.75	**america**	47.04
9	think	58.67	talking	45.79	here	26.63	they	45.31
10	shit	57.66	**money**	45.33	profiling	26.37	does	45.03
11	rates	56.64	wants	45.02	years	26.25	**security**	43.57
12	water	54.00	racial	44.28	first	26.03	year	43.08
13	down	53.32	only	41.38	produced	25.80	racial	42.96
14	ugly	51.61	plan	41.30	very	24.95	talking	42.82
15	make	51.54	even	41.00	**chicago**	24.31	wants	41.49
16	golf	51.42	better	40.14	politicians	24.23	very	38.46
17	need	51.41	maybe	39.66	white	23.78	better	37.95
18	interest	50.03	endorse	38.90	must	23.57	even	37.48
19	**crook**	48.75	lost	36.91	communities	23.41	russia	35.39
20	**tax**	48.43	**international**	36.15	vote	23.38	jacking	34.81

Note. Bolded words are either from a candidate’s quote or the debate topic at the time of the viral moment.

For Trump, the words with the greatest L2 distance difference between the pre- and post-resonant moment were related to topics Trump discussed. However, unlike Clinton’s first two resonant moments, they were not necessarily words used by Trump verbatim. Rather, they were critiques or words tangential to what Trump was talking about. For example, Trump did not explicitly mention countries in these resonant moments, but social media did discuss countries like China and Iraq, which Trump mentions at other points in the debate. In the “Trump taxes” moment, words with the greatest discursive shift included topic-specific terms like paying, federal, and tax, but also negative descriptors like “shit,” “ugly,” and “crook.” Similarly, in the last Trump moment, where he states that Clinton in essence created ISIS, one noteworthy word that appears in the post-resonant moment corpus was the word "wrong." One explanation for this is that live-tweeters were correcting or negatively reacting to Trump's comments in real-time.

When identifying the most commonly used words in the pre- and post-resonant moment corpora, very similar words would be revealed, including hashtags and generic terms like "president," "prepared," and "debate." By contrast, the top keywords in the post-resonant moment corpora differed from their pre-resonant moment equivalents. For example, in the post-resonant moment corpus for the Birther scandal (in the Trump time series), the words "birther" and "racist" were among the top ten words in the post-resonant moment, but not in the pre-resonant moment.

Discussion

Our analysis of multiple media platforms during the first 2016 U.S. presidential debate highlights the value of studying resonant moments as a cross-platform phenomenon. Notably, our analysis highlights the substantially greater focus on Trump relative to Clinton, as exemplified in Figure 1. This suggests that Trump received an outsized amount of attention. Even when Clinton was able to produce resonant moments, Trump still exceeded her in terms of who the audience discussed. One contributing factor may be the Trump campaign's sophisticated understanding of the hybrid media ecology (Wells et al., 2020).

However, both candidates were able to produce resonant moments, as shown by our outlier analysis. Our descriptive discursive shift analysis also shows social media conversation coalesced around important key words related to the debate rhetoric during these times. However, the nature of these key words may depend on the candidate. For Clinton, these terms tended to be specifically related to the topics being discussed in the debate, whereas for Trump, words with the greatest pre-/post-resonant moment shift were broader and more negative, including terms like "crook," "lying," and "wrong," which may reflect 'real-time" critiques of the candidate.

This analysis makes several contributions to the literature on discursive shifts in second screening activity around planned media events. Conceptually, we define and operationalize the notion of resonant moments during planned media events. Our analysis finds a range of ways in which social media audiences discuss salient debate moments, from repeating what candidates said on the debate stage to providing evaluative judgements of the politicians' statements.

Methodologically, we utilize a mixed-methods strategy to identify and study resonant moments. Our approach combines time series analysis to identify outliers in Twitter activity, with a human-in-the-loop qualitative analysis to identify the rhetoric the candidates were using at the time. We then use a natural language processing (NLP) technique to explore what was going on in the discourse during resonant moments. Though these methods have often been used separately in the event detection literature (e.g., Chae, et al., 2012; Kleinberg, 2003; Monfort et al., 2019; Ward, Beger, Cutler, Dickenson, Dorff, & Radford, 2013), the combination of multiple methods allows us to both identify these resonant moments and study the discourse when they happen. This granular and more audience-centered approach may also yield events not considered by pundit commentary or subsequent media coverage.

We find that audience-defined resonant moments during the first 2016 U.S. presidential debate varied greatly in topic, including insults (e.g., Clinton's remark that Trump believes "climate change is a hoax" or Trump's remark that Clinton and Obama's policies created ISIS), references to other well-known political messages (Clinton's use of "When they go low, we go high"), and scandals (e.g., Trump's taxes or the Birther scandal). Discursive shift analysis demonstrates that social media responses to these moments were not always positive, underscoring the lack of control that candidates have over expression discussing them on social media. Compared to Clinton, discourse during Trump's moments did not shift around the specific words he used but brought out more negative sentiments related to the debate's topic.

Our descriptive findings align with Boydstun et al's (2013a, 2013b) agenda control theory. However, the discursive shift analysis descriptively shows that discourse from live tweeting audiences varies. For example, when Clinton quoted Michelle Obama, the quote was repeatedly shared, sometimes on its own and sometimes in reference to the debate. When Trump discussed his taxes, some of his words (such as "federal," "income," "tax," and "smart") can be seen in the words with the greatest post-resonant moment shifts. However, we also see words like "lying" and "shit," which represent broader critical commentary occurring following the resonant moment.

While it is possible for researchers to manually identify resonant moments during the debate, an empirically grounded and audience-oriented approach such as this can reveal resonant moments that pundits may not have anticipated. For example, we would not have considered Clinton's second resonant moment, in which she quoted Michelle Obama ("When they go low, we go high") since it was not an original comment. Yet, this was a meaningful moment for people tweeting during the debate, as evidenced by the heightened activity around Clinton's name and the discursive shift. After the debate, Clinton continued to use this quote on the campaign trail (Fraser-Champong, 2016), indicating that her campaign believed the phrase resonated with audiences.

Another advantage of this method, which puts audience in the center of the discussion, is its ability to detect more transient resonant moments, which attracted the attention of social media users but normally would not be noticed as a point of interest by political analysists or scholars. For example, discourse about Clinton increased when she criticized Trump for thinking that climate change was a Chinese hoax. This moment, which occurred early in the debate, was quickly eclipsed by other debate topics. However, after the debate, at least one Twitter user (the senior White House correspondent for Bloomberg, Jennifer Jacobs) identified it as a debate highlight: "Clinton's peak Twitter mentions: 1. Prepared for debate/presidency 2. Bait with tweet/can't handle nuclear 3. He thought climate change hoax" (JenniferJJacobs 2016).

Beyond its application to study resonant moments, the discursive shift analysis procedure can be used in many context (Sarma et al., 2018). It is worth noting this method is especially useful when the researcher has a sense about what discourse would shift—for example, in this case, we speculated that the social media discourse would shift to language used during the debate. Although the interpretation may be more difficult when the researcher is unsure of how the discourse would shift, we argue that discursive shift analysis can also be supplemented with other natural language processing methods, including supervised machine learning and unsupervised methods such as topic modeling.

As with any study, there are several limitations to this analysis. For one, we did not analyze tweets beyond the immediate pre- and post-resonant moment, which limits the scope of our analysis. Additionally, our data collection strategy did not include tweets referencing both candidates. In this study, we were interested in moments that each candidate dominated the online discourse, and the language associated with those instances. Future analyses can expand on this work by studying the overall corpora, which would likely reveal other outliers. Additionally, since we focus on the audience's impression of the media event, we are unable to detect or distinguish resonant moments induced by social media users from those created by the candidates, or the interplay of the two. Lastly, while we conducted time series analysis to detect attention spikes during the debate, there might have been resonant moments that did not pass our threshold and thus were left out, creating a potential for Type II error.

We also encourage future scholars to study whether resonant moments tend to generate more positive or negative tweets, for our analysis suggests candidate-induced resonant moments are not necessarily linked to message control and may even reflect negative reactions. Our discursive shift analysis showed that social media audiences may pivot to using negative words about the debate; this may also be the case for other live-tweeted media events, such as sporting events and award shows.

Resonant moments can also be studied in tandem with other event detection strategies. For example, resonant moment detection can be used with event detection methods to study whether bursty stages in social media activity produce more resonant moments than non-bursty stages. While our analysis focuses specifically on Twitter activity, additional work can study how television or print news media reacted to these debates, comparing the trifecta of debate rhetoric, news coverage, and social media activity. Experiments should also be designed to assess whether political attitudes or intentions change as a result of exposure to the second screen during these moments. Finally, future studies should explore the visual elements of resonant moments to assess the kinds of gestures and expressions used during particularly memorable candidate exchanges.

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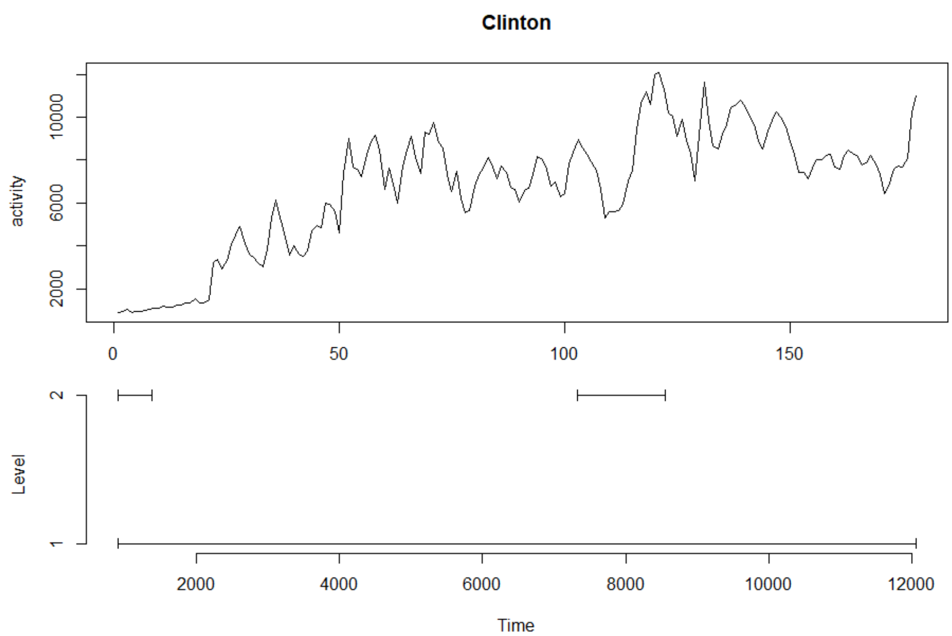
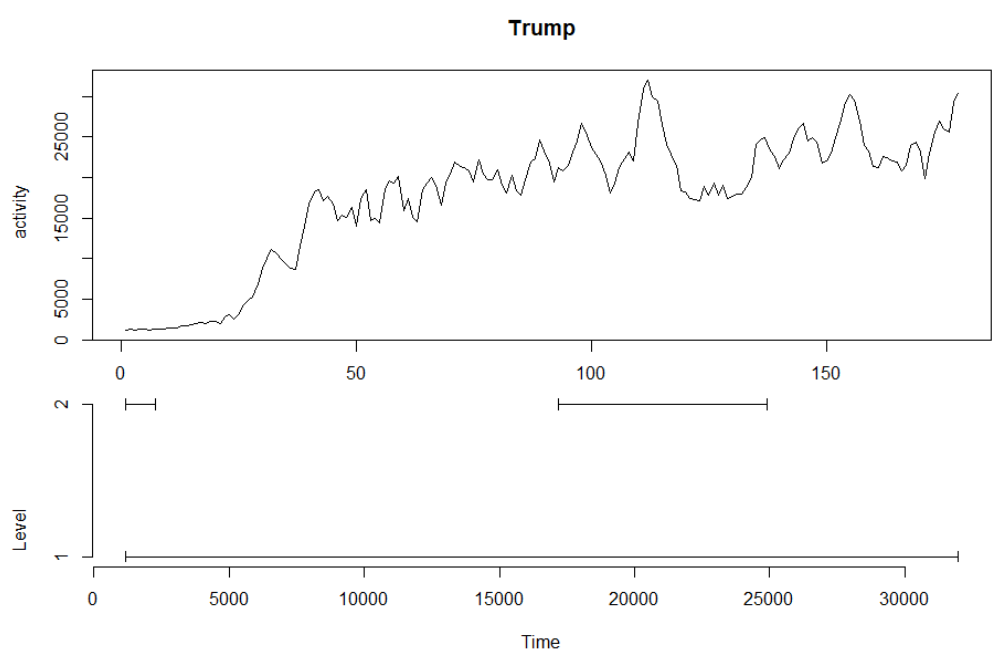
Appendix

Appendix A: Burst Detection

We compared our analysis to Kleinberg's burst detection algorithm using the <bursts> package in R (Binder, 2014). Burst detection is especially useful for identifying when a time point is at a different "state" than another time point within a series. The analysis suggests that activity was "more bursty" (i.e., reaching a second level) at the beginning of the debate and later in the debate for both Clinton and Trump, with the later bursts lasting longer (particularly for Trump).





Appendix B: Debate Words

Clinton 1: Climate Change Hoax

1. climate
2. change
3. hoax
4. perpetrated
5. chinese
6. china
7. natural
8. energy
9. green
10. carbon
11. atmosphere
12. environment
13. thinks
14. lying
15. clinton
16. trump

Clinton 2: Clinton Quotes Michelle Obama

1. low
2. high
3. go
4. they
5. obama
6. michelle
7. flotus
8. hillary
9. quote
10. line
11. dnc
12. speech
13. clinton

Clinton 3: Cybersecurity

1. cyber
2. security
3. defense
4. warfare
5. adversaries
6. securing
7. america
8. attack
9. fight
10. behind
11. putin
12. russia
13. china
14. clinton

Trump 1: Trump taxes

1. tax
2. return
3. audit
4. irs
5. federal
6. income
7. paying
8. habit
9. response
10. publish
11. smart
12. trump

Trump 2: “braggadocious”

1. braggadocious
2. tremendous
3. income
4. money
5. underleveraged
6. business
7. tax
8. international
9. foreign
10. debt
11. trump

Trump 3: Birther Scandal

1. obama
2. barack
3. lie
4. birth
5. born
6. scandal
7. certificate
8. citizenship
9. presidency
10. illegitimate
11. kenya
12. chicago
13. hawaii
14. trump

Trump 4: Clinton “created” ISIS

1. iraq
2. isis
3. america (or US)
4. army
5. military
6. opposed
7. critic
8. record
9. wrong
10. international
11. foreign
12. powers
13. national
14. security
15. clinton
16. trump

Appendix C: Analysis of top retweeted tweets

To compare our method to a simpler strategy, we examine whether our resonant moments could have been identified just by studying the top retweeted tweets in the dataset. The figure below shows the number of retweets that the top 10 retweeted tweets received throughout the debate. This analysis tended to favor tweets that occurred at the beginning of the debate because they had more time to be retweeted—as a result, tweets posted later in the evening received fewer retweets despite overall activity being higher during the later half of the debate.