Valence-based homophily on Twitter: Network Analysis of Emotions and Political Talk in the 2012 Presidential Election

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Abstract
This study integrates network and content analyses to examine valence-based homophily on Twitter or the tendency for individuals to interact with those expressing similar valence. During the 2012 federal election cycle, we collected Twitter conversations about 10 controversial political topics and mapped their network ties. Using network analysis, we discovered clusters—subgroups of highly self-connected users—and coded messages in each cluster for their expressed positive-to-negative emotional valence,

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level of support or opposition, and political leaning. We found that valence-based homophily successfully explained the selection of user interactions on Twitter, in terms of expressed emotional valence in their tweets or support versus criticism to an issue. It also finds conservative voices to be associated with negatively valenced clusters and vice versa. This study expands the theory of homophily beyond its traditional conceptualization and provides a new understanding of political-issue interactions in a social media context.

Keywords
2012 Election, emotional valence, homophily, political talk, social networks, Twitter

因为情感趋同所以选择推特上的人互动。

Social media spaces are becoming increasingly popular for several forms of political communication, such as partisan debates or praise for a candidate (Raine, 2012; Raine et al., 2012). The prevalence of political talk in these networked spaces has been gauged, and others have looked at the reasons users engage in these conversations (Jones et al., 2002; Joyce and Kraut, 2006). However, from content to social context, patterns of connections and disconnections in Twitter political talk remain understudied by network analyses and political talk scholarship. Furthermore, studies in this vein have not looked at how these brief political messages are phrased with respect to their emotional valence. Recognizing the growing literature that documents the important role emotions play in political conversations (Baek et al., 2012; Yu et al., 2008), this study draws from the theory of homophily as a basis for the selection of peers for political talk on Twitter and extends that theoretical concept to include emotional valence as a criterion for selection.

The theory of homophily asserts that relationships between similar individuals occur more frequently than those among dissimilar people (McPherson et al., 2001). Among many other contexts, homophily was found to describe political conversations (Huckfeldt and Sprague, 1995) and online political discussions on Twitter (Himelboim, Smith and Shneiderman, 2013). Despite the documented role emotions play in persuasive political communication, the phenomenon of homophily based on emotional valence expressed in political discussions has remained theoretically and empirically understudied. 句式

This study's contribution is threefold. First, it bridges an existing gap in the homophily literature, which has so far essentially ignored the role of emotions in peer-selection. Second, it identifies the affective social environment in which political decision-making may occur. Third, it introduces a novel methodology for examining emotions in political communication on Twitter. This research integrates network and content analyses to identify affective homophily in Twitter activity related to 10 salient 2012 US election issues.

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Emotions and political communicaiton

Dimensions of emotional response

While emotional valence has consistently been conceptualized as the single most "dominant" dimension of emotion (Fishbein and Ajzen, 1975; Morris, 2012), discrete emotions

are differentiated on two other dimensions, together referred to as the "emotional triad" (Percy, 2012): subjective feeling (emotional valence), physiological arousal, and motor expression. These three dimensions have been repeatedly observed, often in the context of dimensions of emotional responses to persuasion, with somewhat different labels, such as Holbrook and Batra's (1987) "pleasure, arousal, and dominance." In his review of theories of emotion and affect in marketing communications, Morris (2012) recognized these dimensions as representing emotional facets of connotative or subjective meaning: "evaluative, activity, and potency" (Osgood et al., 1957).

Emotional valence—positive and negative affect—has consistently emerged as two dominant categorizations of emotional response (Diener et al., 1985; Russell, 1983) and is considered here as a primary indicator of affective responses. Affect is often seen as a summary judgment stored in memory and is typically defined as a valence "tag," which is typically positive or negative (Fiske and Pavelchak, 1986). Bargh et al. (1992) argued that prior emotional tagging of stimuli can elicit the emotional cue as an evaluation on even subliminal presentation of those stimuli. Marcus (1991) suggested that evaluations arising from emotional processes can, in turn, influence emotional expression, thoughts, decisions, and political behaviors in ways that are distinct from cognitively based processes. Ladd and Lenz (2008) showed that emotions reflect an evaluative judgment, such as likes and dislikes that are independent from attention and habit.

Dillard and Seo (2013) argued that positively valenced emotions result when information is considered both relevant and goal-congruent, while negatively valenced emotions are generated by relevant but goal-incongruent information. These assessments are not necessarily mutually exclusive. Thus, summary evaluative judgments are often treated as a simple singular mutually exclusive valence assessment, such as positive or negative, like or dislike (McGraw et al., 1991). Others posit conceptual independence between positive and negative feelings, allowing for emotional responses of "mixed" valence (Dillard and Seo, 2013). A valence-based approach to emotions focuses on the effects of positive, negative, and mixed feeling states.

However, Percy's (2012) dimensions included physiological arousal and motor expression, not just emotional valence. In this article, we posit that the fact of participation in an online network establishes a particular issue as relevant (or sufficiently arousing) to motivate a valenced response. We, therefore, view expressed support or opposition to a political issue as indicative of the "motor expression" dimension (perhaps captured by the terms approach–avoidance, dominance–resistance, aggressive–assertive, and offense–defense). Thus, while we focus on variations in emotional valence across online networks, we do not ignore the other two dimensions of the "emotional triad" in our hypotheses and research questions. We will now explore these dimensions in the context of political communication.

Emotional valence in political communication

It has long been argued by political and social scientists that politics is the expression of personal emotions (Lasswell, 1930). Emotional valence has been shown to be meaningful in understanding political communication. Emotional appeals are perceived as dealing with highly polarized attributes or topics (Fishbein and Ajzen, 1975). Gunther and

Thorson (1992) found messages bearing more positive emotion to be more persuasive. Tinkham and Weaver Lariscy (1994) found that negative content is more memorable and more complex than a positive message. Baek et al. (2012) found that online conversations possess more negative than positive emotions, while others found positive emotions to dominate political conversations (Yu et al., 2008) and messages posted by political candidates in Europe (Tumasjan et al., 2010). The affective component of attitudes has predictive power in matters of interest to political science, such as voting (Kenney and Rice 1988; Rahn et al., 1990).

The expression of opposition and support is also central to political expression. News coverage of political issues, including elections, is often framed by the media in terms of support and opposition (Kleinnijenhuis et al., 2007). The viewpoint that expression of support is "positively valenced" and criticisms or opposition is "negatively valenced" for political actors or issues has been widely supported (Beck et al., 2002; Kahn and Kenney, 2002; Kepplinger et al., 1991). Yet, we suggest that these relationships do in fact tag two distinct dimensions of emotion, as we view expressed support or opposition to a political issue as indicative of the "motor expression" dimension, distinct from the valence dimension. The extent to which they are "oblique" or even positively correlated remains open. We, therefore, suggest that the expression of opposition and support may provide another layer of understanding to our focus on emotional valence or "affect" in political discussions.

Social media activity is based on interpersonal interactions. However, little scholarly research exists about the relational value of emotional political messages in the user-generated content of social media. The specific language of these tweets and updates is often figurative, which can make interactions more relatable according to Reyes et al. (2012). This can enhance the social interaction, the context of this content, especially when an online discussion revolves around ideological or issue-based subjects. The theory of homophily provides the much needed relational theoretical context.

Homophily

Homophily is a theory that asserts that "a contact between similar people occurs at a higher rate than among dissimilar people" (McPherson et al., 2001: 416). It captures a key characteristic of naturally occurring social networks and depicts a mechanism through which "distance in terms of social characteristics translates into network distance" (McPherson et al., 2001: 416). Put simply, homophily suggests that similar individuals will be socially closer to one another than dissimilar people.

Homophily has been documented in the literature for almost a century. Early studies showed homophily based on demographic characteristics such as age, sex, race, and education (Bott, 1928; Loomis, 1946) and psychological characteristics such as intelligence, attitudes, and aspirations (Almack, 1922; Richardson, 1940). Studies show that homophily characterizes the selection of peers across a range of relationships, such as marriage (Kalmijn, 1998), friendship (Verbrugge, 1977), and mere contact (Wellman, 1996). Finally, homophily was also found in political behavior and beliefs (Huckfeldt and Sprague, 1995; Knoke, 1990).

Homophily in social media spaces

The literature suggests that homophily often characterizes computer-mediated social interactions. Adamic and Glance (2005) found political bloggers preferred sending hyperlinks to blogs with similar political orientation. Examining the political interaction on Twitter around major topics of the 2010 Midterm Elections, Himelboim et al. (2013) found that Twitter users preferred interacting with users with similar political views. Skopek et al. (2011) examined an online dating platform and found education, primarily among women, to be the dominant dimension of homophily. In a study on Myspace, Thelwall (2009) found support for homophily based on ethnicity, religion, age, country, marital status, attitude toward children, sexual orientation, and reasons for joining Myspace. Aral et al. (2009), who examined an instant messaging network, found that homophily—namely, shared backgrounds and tastes between friends—explained almost half of the perceived behavioral contagion. La Fond and Neville (2010) have also found evidence of homophily on Facebook.

The affective component in homophily is understudied, but not neglected. Thelwall (2010) found a weak association between the level of emotions given and received on the social network site Myspace—this indicates homophily for both positive and negative sentiments. Twitter identified Subjective Well-Being to be assortative across the Twitter social network. This study, then, found support for happiness-based homophily.

This study, nonetheless, identifies message valence as an attribute lacking in the literature about homophily in political communication. It posits the possibility that feeling consistency of valence—that is, affect-based homophily—might characterize online communication networks. In other words, we suggest here that similarities in expressed valence can explain the patterns of political interaction on social media. Suggestive of this phenomenon are findings that mood similarity between message and receiver is positively related to more central (but biased) information processing (Fazio, 1995). One must not overlook the seminal work of Festinger (1957) and Heider (1946, 1958) that suggested a motive of consistency among affective relationships (both personal and interpersonal): between thought and feeling, thought and behavior, and feeling and behavior. Within this framework, it seems viable that there is a firm basis for positing emotional homophily in online communication networks.

Twitter as a social network: a conceptual framework

Broadly speaking, a social network is a structure created by social actors, such as individuals and organizations, when links are formed among them. Social network literature suggests focusing on relational ties among social entities and on patterns and implications of these relationships (Wasserman and Faust, 1999). On Twitter, social networks are formed between users and their relationships through following, a form of subscription to other's Twitter messages, mentions, and replies.

A social networks theoretical framework—and subsequently, network analysis—is, therefore, a viable approach to the study of homophily. As discussed earlier, homophily leads to short network distance among similar groups of individuals (McPherson et al., 2001). Social networks capture social interactions and provide a conceptual framework

for understanding homophily in terms of the grouping of similar others. We, therefore, suggest a network cluster as a core concept for the study of homophily in social media. Clusters refer to subgroups in a network in which nodes are substantially more connected to one another than to nodes outside that subgroup, leading to a shorter distance among users within the same cluster (Carrington et al., 2005). This allows us to examine whether valence-based homophily can explain Twitter political interactions. Individuals in a cluster are expected to be more similar to one another in terms of expressed valence than to those outside their cluster. If valence expressed in tweets in a given cluster is not similar, that contradicts valence-based homophily and subsequently the following hypotheses. The first research hypothesis is as follows:

> H1. Emotional valence expressed by messages within a given network cluster will be associated primarily with one part of the emotional valence spectrum (i.e. positive, negative, or neutral affect).

McPherson et al. (2001) suggest that homogeneity of a network on some characteristic is a source or outcome of social processes. In an attempt to go beyond simply demonstrating affective similarities among self-selected groups of individuals, we question whether valence is topic-dependent. Specifically, it has been documented that some topics are more likely than others to evoke political polarity in online discussions (Himelboim et al., 2013). We therefore ask the following question:

> R1. Is the emotional valence of the network clusters (positive, negative, or neutral/mixed) associated with topic of discussion?

Political conversations, as discussed earlier, are often heated and emotional (Baek et al., 2012; Tumasjan et al., 2010; Yu et al., 2008). Political attitudes can, therefore, provide context for valence-based homophily. Clusters of users, expressing similar valence, may also be associated primarily with a certain political attitude. Considering that political behavior and attitude-based homophily have long been documented (Adamic and Glance, 2005; Huckfeldt and Sprague, 1995; Knoke, 1990), the second hypothesis is as follows:

> H2. The emotional valence of the message clusters will be associated with the extent to which messages in the cluster express a position on the political ideological spectrum (i.e. conservative to liberal).

Indeed, if network clusters show distinct affective valences, it would be unclear whether support or opposition to an issue would be equivalent to a positive or negative response to it. For example, in a discussion about abortion, users may express pro-choice or pro-life positions. Each of these could be coded as positively valenced emotions, yet they express diametrically opposed policy positions (pro-life as opposition to abortion rights and pro-choice as support of these rights). Percy (2012) notes a similar, but more mundane, example of a toothpaste brand that claims to "whiten teeth," which he notes is actually "… a benefit claim reflective of a negative motivation such as problem removal"

(p. 75). In order to better understand valence-based homophily, then, the following question examines at some depth the valence characteristics of the major network clusters (positive, negative, and neutral) as a predictor of their expressed issue opposition or support.

> *R2.* Is the emotional valence of the message clusters related to the extent to which messages in the cluster express support or opposition to the discussed issue?

Method

Data

Twitter usernames, user statistics (e.g. profile description and URL, number of followers), their topic-related tweets, and the relationships among these users (follow, mention, and reply) were captured for key election issues. Based on the *New York Times*' taxonomy of the top issues for the 2012 elections (economy, world, health, social issues, and the planet), the researchers identified specific topics for each main issue (e.g. immigration as an attribute to the overarching social issues category). The issues were the following: Bin Laden, economy, energy, gay marriage, health, immigration, Medicare/Medicaid, oil/gas, women, and abortion. Data were collected using NodeXL's Twitter Search importer (Hansen et al., 2010), which identifies the most recent Twitter users who conversed about each topic (up to 1500 users per data collection). To ensure the relevance of the tweets for each dataset for the elections, we composed the Boolean search strings that were used to collect the data, so it requests users who posted messages about a topic (e.g. women) together with at least one election-specific keyword: Romney, Obama, vote, elections, or campaign. Each data collection (i.e. each topic) was carried out in the same way, requesting users who posted tweets using at least one of the election-specific keywords AND a topic keyword. Data were collected weekly for 7 weeks on each Tuesday evening for each of the topics during the time period immediately leading up to the election (starting on Tuesday, 25 September 2012). The last dataset was collected on Monday, 5 November 2012, so that data also came before Election Day. A total of 70 datasets were collected.

Measurements

Network analysis. Using NodeXL, the network was created by users who follow, mention, and reply to one another; each dataset was mapped. We identified clusters of relatively more connected groups of users in the topic-networks using the Clauset–Newman–Moore algorithm (Clauset et al., 2004), which is included in the NodeXL software. We selected this algorithm for its ability to analyze large network datasets and efficiently find subgroups. This algorithm uses edge betweenness as a metric to identify the boundaries of communities. Each user, then, is classified into the best fit group (cluster), in terms of the interconnectivity among users. The major clusters were identified by ordering clusters by size in descending order. The clusters identified using the algorithm above were generally very small, typically leaving very
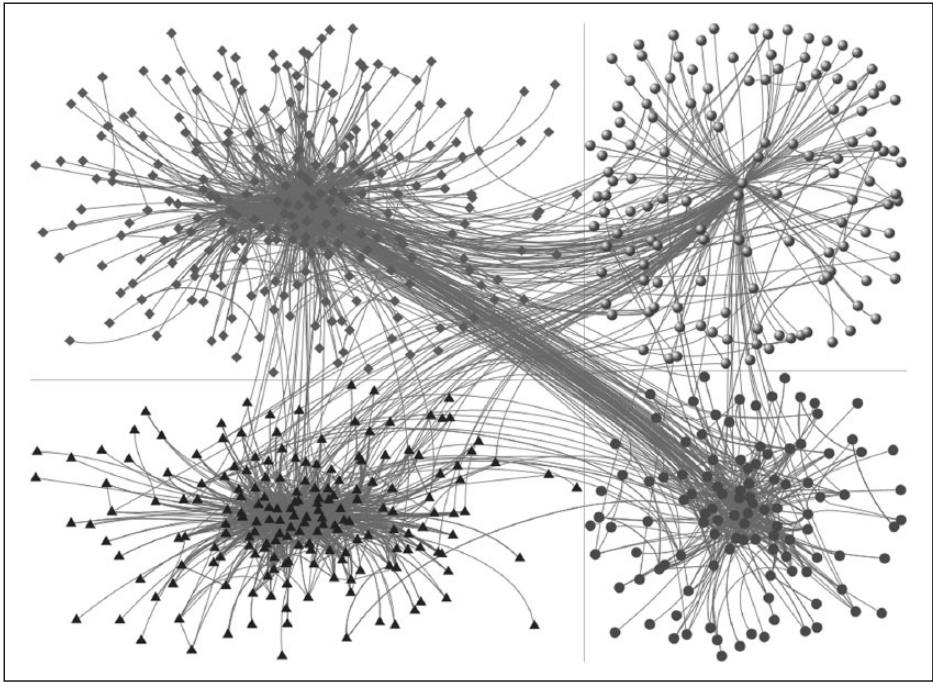
Figure 1. Network clusters (an example from the 9-25 Gay Marriage topic-network).
The election-related conversation about gay marriage on Twitter produces four major clusters, as this figure shows. Each user appears as a node in the figure (sphere, diamond, square, or triangle, depending on the cluster). Two users are connected to one another if they interact, by ways of following, mentioning, or replying to one another. Users in each cluster expressed primarily one side of the emotional spectrum (i.e. positive or negative emotion). The heavy links run across the two negative clusters (top-left and bottom-right). Although more than one cluster included users who primarily tweeted negative content, these two clusters were still strongly connected.

few large ones. If no clear drop in cluster size was identified, the top three clusters were selected, as in the majority of datasets a drop in size was recorded after the top three clusters. See Figure 1 for illustration of network clusters.

In total, 232 nontrivial clusters were identified. These interactive nodes became the unit of analysis for our further investigation of the relevance of emotion (valence) as a basis for defining taxonomy of Twitter networks. Each tweet was also judged by coders with respect to a number of mood states applying those identified by Lorr and Wunderlich (1988), each possessing an identifiable *valence* (positive, neutral, and negative), as described in detail in the next paragraph. Then, for each of the 232 first-order networks, the proportions of positive, neutral, and negative tweets were calculated. These proportions were summarized and encoded into a transformed dataset to indicate three proportionate characterizations of each network cluster. Similar data transformations designed to correspond to the network (rather than the tweet) as the unit of analysis were made for other content-coded variables, including issue position and political ideology. These later-transformed variables were relevant in developing profiles of valence-based

network clusters. Finally, each network cluster was characterized by the proportion of messages that corresponded to the emotional states and political ideology in question.

Content analysis. This study applied a Berelson-type quantitative content analysis to assess only manifest content, which followed the variable definitions from a specific codebook and required extensive training among coders to ensure reliability. Although clusters are the primary unit of analysis for this study, the individual content in each tweet within the cluster was thought to provide a greater context to understanding emotion. In addition to the cluster units examined in network analysis, this study also employed a traditional content analysis of each of the items within each cluster. In particular, the tweets and user data associated with those tweets were content analyzed from 232 main clusters. Given the sheer cumulative quantity of tweets in the analysis across all 232 main clusters, random sampling was applied to identify 15% of tweets and associated content (Twitter user data) within each of the 10 issue attributes (e.g. immigration, unemployment). This proportion of analyzed content is in accordance with Kaid and Wadsworths' (1989) assertion that only 15–20% of content need be content analyzed before results become repetitious and effort efficiency declines. A total of 12,814 items were identified for content analysis, which included 7090 tweets from 5724 users.

The content analysis portion included two sections: content analysis of the tweet itself and analysis of the Twitter user who posted the tweets in the clusters. For both portions, only manifest content was coded (Berelson, 1952), and coders were instructed to not infer meaning beyond what was present in the tweet. A team— consisting of six coders—underwent extensive training on the coding process and the codebook. Coding differences were reconciled throughout the coding process to ensure accuracy. Cohen's Kappa was used to compute inter-coder reliability and was found to be acceptable at .87.

Coding categories for the tweet messages examined what was said and how it was said. Each message was reviewed for the following categories: *Tweet type* such as RT (whether the message is a re-tweet) or MT (whether the message was noted by the poster to be a modified tweet), *ideology of tweet* (liberal, moderate or no ideology, conservative, or unable to determine), and *support* (oppositional, supportive, mix, or doesn't take sides/NA) in tweets. *Valence* in each tweet was also coded (tone as being positive, negative, or neutral) for each of the five top *issues* (economy, world, health, social issues, and planet). Strict definitions were written for each coding category and item within to ensure coder consistency during the process. Although some have found success in computer-assisted sentiment analysis in social media (Thelwall et al., 2012), given that these units in this study were human coded for topic and emotion, this was the case for sentiment as well.

For coding user data, information from the user's self-provided Twitter profile was coded. Here, coders reviewed the self-posted "biography" or description text the user provided about himself or herself. It should be noted that the researchers understood through a pilot test of the cluster datasets that tweets may be posted by organizations and may not always be posted by a single person. As such, the coding scheme was developed to allow for differentiation between single users or organizational user profiles. Coding categories for the user-level data were as follows: *type* (person,

politician/political campaign, media organization, other organization, or unable to determine), *political ideology* (Democrat, Republican, Independent, or not specified), and *gender* (male, female, organization, or unable to determine). Berelson's (1952) approach of only examining manifest content was adhered to here as well, and it was not uncommon for users to communicate these variables very openly (e.g. LextasticMe's profile proclaimed "Lots of kids, SAHM, liberal DEM, other stuff, not debating jack w you. Go 'Noles" or LaTicaChica's profile which said "Hispanic Conservative, Republican, Christian, Mom of two awesome daughters, wife and teacher"). When coders did not have enough information to make a correct determination about type, ideology, or gender, the coder was instructed to select the "unable to determine" option. Adhering to the Berelson (1952) approach to content analysis, only manifest content was considered.

K-Means cluster analysis. For addressing the hypotheses and the research question, our 232 network clusters were examined as the unit of analysis for the purpose of further grouping them into emotional valence categories and also for validating and profiling those dimensions. In order to prepare them as broader units of analysis, each network cluster was encoded with respect to the portion of tweets that was emotionally positive, negative, or neutral in valence; oppositional and supportive with respect to topic; as well as its topical distribution. Then, using this initial set of network clusters as units of analysis, a nonhierarchical cluster analysis procedure (K-Means analysis, using SPSS) examined both a two- and three-cluster solution, employing the emotional valence distributions as criteria for deriving the clusters. While the two-cluster solution was acceptable, the three-cluster solution was considered the most appropriate because (1) it produced more precise classification results in the validation procedure and (2) it was considered the most theoretically meaningful, based on the fact that three proportional categories of emotional valence (positive, neutral, or negative) for each network served as the input variables.

After examining the effective separation of the three clusters and interpreting their meaning, a multiple discriminate analysis was conducted as a validation procedure to predict the overall goodness of fit of the three-cluster solution. These procedures enabled assessment of H1. Then (in order to answer RQ1, H2, and RQ2), several criterion validity analyses of the three-cluster solution were conducted. These analyses resulted in further explication of the cluster profile, thus completing all stages of the clustering procedure (Hair et al., 1998).

It should be noted that the term "cluster" is used by two different statistical procedures here, which can be confusing for the reader. In network analysis, the Clauset–Newman–Moore algorithm was used to identify *network clusters*, a subgroup of Twitter users that are densely interconnected to one another. Using the network clusters as the unit of analysis, a very different statistical procedure, *K-Means cluster analysis*, was applied to identify clusters of network clusters, based on the emotions used in the tweets in each network cluster. For clarity in reporting the findings, this research uses the term *network clusters* to describe the units of analysis resulted by the network analysis; the term *cluster analysis* here is used when referring to the *K-Means cluster analysis*, and the resulted clusters are referred to as *clusters*.

Findings

A total of 70 datasets created 70 topic-Twitter networks. A sample of 15% of tweets and 15% of users were coded. Of the total 7557 users that were coded, 75.3% were individual users, 5.0% were organizations, 2.8% were media organization, 1.1% were politicians or users associated with the political campaign, and the rest were coded as "other." More than 1 in 10 (12.3%) users in the sample self-described themselves as democrats or liberals, 18.1% as republicans or conservatives, 1.7% as independent, and the rest were not specific regarding their political orientation. Almost a fifth (17.7%) of the users in the sample were male, 20.7 were female, and the rest did not indicate their gender.

The initial Twitter network clusters were originally assembled according to the Clauset–Newman–Moore algorithm, which included 10 topics as well as other cognitive and typing characteristics. This first-order network clustering procedure produced 232 nontrivial communication networks, which were clearly differentiated by topic. It can be somewhat confusing that the term "cluster" is used by the two different analyses. A network cluster is identified through a network cluster analysis, which becomes the unit of analysis here. A K-Means cluster analysis is used to allow patterns of emotions expressed in clusters to present themselves. To increase clarity, then, "network cluster" is used *in this section* to describe the densely interconnected subgroups of twitter users, while "cluster" (as in "three-cluster solution," for instance) is used to report K-Means cluster analysis–related results.

H1. Emotional valence expressed by messages within a given network cluster will be associated primarily with one part of the emotional valence spectrum (i.e. positive, negative, or neutral affect).

Findings supported H1. Since a cluster defines the social boundaries of users' self-selection of peers, a network cluster was used as the unit of analysis. A K-Means cluster analysis resulted in a parsimonious cluster solution consisting of three emotional Twitter network clusters. Next, a discriminant analysis was calculated in which the clustering variables (negative, neutral, and positive emotion/valence) were used to predict membership in the three network clusters. The three-cluster solution produced an extremely accurate prediction of actual valence membership: 95.7% of originally grouped cases were correctly classified. A classification of these results is shown in Table 1.

Further insight into the classification of Clusters 1, 2, and 3 as neutral, negative, and positive, respectively, is revealed in Table 2, which looks at mean valence scores for each of the three network clusters. These means are actually mean proportion (percentages) values of coded valence values attributed to each tweet within a communication network. The distribution of mean valence values across network clusters indicates clearly that Cluster 1 is dominated by tweets of neutral valence, Cluster 2 has predominantly negative valence, and Cluster 3 is dominated by positive valence among Twitter networks.

The results of the three-cluster solution indicate that the three-cluster centers differ from each other significantly ($p < .001$). The descriptive statistics also give clear insight into the meaning of each cluster: Cluster 1 consists of Twitter networks of predominantly neutral valence, while Clusters 2 and 3 are, respectively, negative and positive.

Table 1. Classification table from discriminant analysis: valence distribution of tweets in network as predictors of network cluster membership.

		Predicted group membership[a]			
		Neutral	Negative	Positive	Total
Actual	Neutral	37	8	2	47
count	Negative	0	144	0	144
	Positive	0	0	41	41
Actual %	Neutral	78.7	17.0	4.3	100.0
	Negative	0	100.0	0	100.0
	Positive	0	0	100.0	100.0

[a]Of the original grouped cases, 95.7% were correctly classified.

Table 2. Network cluster taxonomy based on valence: interpretation of three-cluster solution.

Clustering variables (mean % valence values)

Cluster number	Neutral	Negative	Positive	Size
1	51.62	12.23	12.43	47
2	14.58	80.73	17.46	144
3	8.27	7.05	70.11	41

Significance testing of differences between cluster centers

Variable	Mean square	df	F value	Significance	Partial Eta square
Neutral	2.902	2	73.816	.000	.392
Negative	11.480	2	394.801	.000	.775
Positive	6.652	2	406.121	.000	.780

df: degree of freedom.

The results of the cluster analysis indicate that the three-cluster solution produces a taxonomy of network clusters that clearly differentiate among those with neutral valence, negative valence, and positive valence, thus supporting H1, which predicted that messages expressed in a given cluster are associated with a position on the emotional spectrum. The presence of a "neutral" cluster suggests that not all Twitter networks are positively or negatively valenced, although all are still appropriately characterized as occupying a position on the emotional continuum (see Table 3).

R1.   Is the emotional valence of the network clusters (positive, negative, or neutral) predictive of the way message topics are distributed across them?

Table 3. Criterion validity of three-cluster solution: valenced network cluster membership as a determinant of cluster profile characteristics.

	Clustering profile			F value	Significance
	Neutral (mean %)	Negative (mean %)	Positive (mean %)		
Issue position					
Opposition	26.02	68.82	53.01	77.419	.000
Support	16.33	10.04	53.79	73.852	.000
Mixed	4.59	3.82	7.15	1.757	ns
Neither	27.53	17.29	10.61	7.736	.001
Political ideology					
Liberal	24.49	25.76	67.25	25.923	.000
Conservative	14.44	29.64	7.42	11.548	.000
Unclear	31.04	39.66	19.62	5.470	.005
None expressed	6.63	4.90	5.70	.360	ns

ns: not significant.

Three second-order clusters based on emotion (valence) emerged, as described earlier, representing not only a parsimonious set of networks (neutral, negative, and positive valence) but also a set of clusters that vary in content over 10 topical areas. It is relevant, then, to ask whether or not topical areas are spread evenly or disproportionately across the valence categories. In order to answer this final exploratory research question, a contingency table of valence by topic was calculated and showed significant patterns of association ($\chi^2 = 62.984$, degree of freedom [df] = 18, $p < .001$). Each topical area constituted about 10% of the total number of networks, representing raw numbers of networks ranging from 18 to 24. One topic, Osama bin Laden, exhibited disproportionately high neutral valence, and several others (Medicare, immigration) exhibited both higher positive and negative valence than neutral. Gay issues showed disproportionately high proportions of positive-valence networks and disproportionately low proportions that were negative valence. Other topics (the economy, health, oil/gas, and women's issues) were proportionately represented within each of the valence categories. Thus, valence of network clusters varies by topic in a way that may confound or moderate some of the findings reported above regarding criterion validity. Further investigations of valence-based clusters within separate topical areas could further the extent to which our results are generalizable.

> *H2.* The emotional valence of the message clusters will be associated with the extent to which messages in the cluster express a position on the political ideological spectrum (i.e. conservative to liberal).

Table 3 provides data that support H2, which predicted that the valence of the network clusters would predict their political ideology. As can be seen, positive-valence network clusters are predominantly liberal. Negative-valence networks are statistically more

conservative in their political ideology, but to a much lesser extent. Those that are unclear ideologically are concentrated in the neutral or negative cluster of networks. The absence of ideological content is spread equally across the emotional spectrum.

> *R2.* Is the emotional valence of the message clusters related to the extent to which messages in the cluster express support or opposition to the discussed issue?

Using valence as a basis for clustering network clusters, results reported in Table 3 suggest that opposition or support issue positions expressed in the Twitter networks are meaningfully predicted by their membership in a cluster of a particular valence. As the data clearly show, oppositional issue positions are primarily found in the negative-valence cluster, while supportive issue positions are concentrated in the positive-valence cluster. Mixed (or conflicted) issue positions occur evenly across clusters of different valence. Finally, network clusters that express neither opposition nor support issue positions (do not express a position) are predominantly found within the neutral/mixed emotional cluster. An exploratory analysis of these relationships considered whether or not controlling for political ideology (examined directly in H2) as a covariate would reduce or eliminate the observed relationships between emotional valence and political support/opposition. Ideology was not found to be an explanatory antecedent variable. In fact, political ideology helped explain extraneous variance in the issue support/opposition variables, making the observed statistical relationships somewhat "stronger." This finding is consistent with the notion that the distinct dimensions of emotion (valence, arousal, and motivational) nevertheless form an oblique, rather than an orthogonal, spatial, or dimensional structure.

Discussion

This study builds on the theory of homophily and successfully explains patterns of interactions among users for political conversation, based on commonality in expressed emotions. Twitter users preferred to interact with others, with whom they share message valence (positive, negative, or neutral) and the supportive nature of messages (support, opposition, or neither). We next discuss the contribution of these findings to the theory of homophily and the literature about the role of emotions in political communication. Conclusions are then offered with a discussion of the methodological contribution of this study.

Almost a decade of research about homophily indicates that individuals interact with others who are similar to them in terms of attitudes, values, religion, activities, and some socio-demographic characteristics (McPherson et al., 2001). This study makes a theoretical contribution to the rich body of knowledge by adding an affective dimension. Garrett (2009) describes selective exposure to news sources that reinforces one's political opinions as "echo chambers." Our findings indicate the formation of "affective echo chambers," where users interact with "like-minded" others, exposing themselves primarily to messages with similar valence—positive, natural, or negative.

The emergence of homogeneous affective echo chambers indicates an individual desire for consistency among affective relationships, as Festinger (1957) and Heider

(1946, 1958) posited more than half a century ago. Self-exposure to like-minded individuals and information sources has led scholars to worry that such fragmented interactions would lead to divided groups that are increasingly homogeneous (Sunstein, 2006; Van Alstyne and Brynjolfsson, 1996). This study adds to the illustrations of the role of emotions in the formation of political attitudes. These findings may raise a concern that online political conversations reinforce one's political opinion indirectly through its affective response to a given issue. Findings also indicate that network clusters (hereby, clusters) with an overall oppositional tone were associated more with negative-valence clusters, while supportive clusters overlapped more often with positive-valence clusters.

This study also contributes to the growing literature about the relation between emotions and political ideology. Network clusters where liberal ideology characterized the posted content were primarily positive in valence. Clusters with conservative-leaning content, in contrast, were more likely to overlap with the negative-valence clusters. The outcome of the elections reinforced this relationship between political ideology and pre-election emotions. Interestingly, clusters characterized by politically unidentified messages overlapped primarily with the negative and neutral clusters. This may be an indication of the discomfort associated with uncertain political leanings.

In terms of methodological contribution, the current research uses a cluster—self-selected subgroups of users who interact with one another—as a unit of analysis. As Twitter users often re-tweet messages from others, users in a cluster are likely to be exposed to not only those they selected to be exposed to directly but also others they may be exposed to indirectly. The proposed methodology then allows researchers to expand the study of homophily beyond direct social interactions. Furthermore, a network analysis of large social media data, like the one used in this study, holds advantages over other methods, such as surveys, as this examines actual self-selection of social peers, rather than self-reports.

Limitations

This study holds several limitations. First, researchers are limited to interactions through a single social media space. Interacting face-to-face, individuals may be more inclined to interact with others who express different emotions. This limitation can be addressed by employing different methods, such as surveys and focus groups. Furthermore, valence-based approaches face one obvious shortcoming: they fail to specify whether different, discrete emotions of the same valence differentially influence judgments and choices. In the context of this study, it would be helpful to know whether homophily explains interactions based on more specific emotions, such as fear and anger. Finally, the political ecology in the time of data collections may have affected the results. A future study may examine whether these findings change during other election cycles.

Conclusion

This study contributes to the growing interest in two key areas of political communication: role of emotions and the use of social media. Expanding the theory of homophily to

include valence, findings offer novel insights for understanding the process underlying peer-selection in political communication in online spaces.

Acknowledgements

Funding

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