Information Diffusion and Opinion Change during the *Gezi Park Protests*: Homophily or Social Influence?

Ersin Dincelli
University at Albany, SUNY
Albany, NY 12222, USA
edincelli@albany.edu

Yuan Hong
University at Albany, SUNY
Albany, NY 12222, USA
hong@albany.edu

Nic DePaula
University at Albany, SUNY
Albany, NY 12222, USA
ndepaula@albany.edu

ABSTRACT

Growth in online, opinion-rich sources of information, such as social networking websites, microblogs, and discussion forums, makes it possible for information to spread and reach others more easily than ever. During social movements the diffusion of ideas on these online platforms, along with other factors, may influence users' decision of what to think or who to support. This paper develops a study to investigate the effects of homophily mechanism as it may impact individuals' opinions and, in particular how opinions about a certain event change over time through mimicry and conformity. In this paper we present a Twitter dataset of communication during the *Gezi Park Protests* that took place in Turkey in 2013. We also present preliminary results based on text analysis and future steps for testing the effects of homophily mechanism.

Keywords

Social movement, protest, homophily, social influence, social media, political participation, user behavior, Twitter.

INTRODUCTION

We have been witnessing massive social movements and protests that use social media as a common communication tool, in particular Facebook and Twitter. The perceived importance of social media in these situations have led many governments to censor their use in order to slow and diminish the diffusion of collective action (Howard, Agarwal, & Hussain, 2011). The prevalence and nature of these social networks have also led researches to examine their effects on information diffusion and political communication phenomena, to name a few (Borge-Holthoefer et al., 2011; Centola, 2010; Conover et al., 2013). In the contexts of political protests these tools have been used to communicate ideas, organize activities, and show support and opposition to the events (Choudhary, Hendrix, Lee, Palsetia, & Liao, 2012; Tufekci & Wilson, 2012). However, explanations about information diffusion

and reasons for political opinion expression have been less explored.

Observations of Twitter communication during the Gezi Park protests of 2013 led us to hypothesize that individuals may change their initial political opinion after realizing the opinion of their peers or other members of their social groups on a particular event. Given the characteristics of Turkish society—collectivist (e.g., loyalty within the group), high uncertainty avoidance (e.g., anxiety about future), and power distance characteristics (e.g., dependent, hierarchical, expectance of control) (Hofstede, 1980)—individuals are likely to be more careful with their online postings for fear of reprimand. Moreover, individuals in such societies may also express their political position online in order to ensure to other members of their groups their position on a particular issue, and therefore be secure from punishment or minimize anxiety about their future.

A previous study on the Gezi Park Protests found interesting patterns in the communication about the event: as time passed the control of new information as well as the influence of users was more equally shared among the Twitter population discussing the issue (Varol, Ferrara, Ogan, Menczer, & Flammini, 2014). However, the study failed to explain the causes of these changes. While we do not propose at this time to investigate all of the dynamics of Twitter communication we would like to show and explain if and why certain individuals were influenced by others in their opposition or agreement.

The structure of the Twitter network allows us to observe the spread of both positive and negative opinions towards the Gezi Park Protests and the possible network effects. We view the spread of positive and negative references to the Gezi Park Protests as a type of information diffusion. One of the main issues in studying information diffusion, however, is distinguishing between *social influence* (where a node or user influences or causes an outcome on its connected nodes) from *homophily* (where shared characteristics of nodes correlate with the outcomes at question) (Easley & Kleinberg, 2010). In other words, whereas social influence refers to the effects of the network on the adoption of a particular opinion, for example,

homophily suggests that the sharing of the opinion is based on other shared characteristics of the nodes.

In this study we conceptualize opinion adoption as a type of information diffusion. We hypothesize the opinions of individuals regarding the Gezi Park Protests expressed on Twitter will be affected by the group or cluster they belong to. In the following sections we present theories about homophily and social influence and how they may impact political opinion. We then test the performance of automated sentiment classification for and explain how we may carry out a study to distinguish the homophily and social influence aspects of opinion formation from Twitter data.

LITERATURE REVIEW

It is generally understood that individuals tend to associate themselves with similar others—what is known as *homophily*. Individuals that share the same race and ethnicity, for example, are more likely to be associated in marriages and also to form weaker ties of friendship (McPherson, Smith-Lovin, & Cook, 2001). Lazarsfeld and Merton (1954) suggested two types of homophily: those based on *status*, which includes sociodemographic dimensions such as race and class; and *value,* which refers to believes, attitudes or personal preferences that shape our behavior.

Status characteristics such as race and sex are relatively immutable. Therefore, associations among people of the same sex and race, for example, may be inferred to have been *caused by* these shared characteristics. Studies on homophily often focus on these characteristics as determinants of association. Value characteristics are more difficult to note for their homophily effects. That is because value characteristics are adopted by individuals and may be later rejected by the same individual.

Rice and Aydin (1991) suggest that social entities that are connected to the same group of people are likely to exhibit similarity and they could even mimic each other through interactions in their network. Features specific to social media such as *follow*, *like*, and *retweet* could be used to identify people who are connected to the same network and carry the same ideology by interacting with similar others (Fang, Hu, Li, & Tsai, 2013). On Twitter, individuals have been observed to associate themselves and form networks with others that share similar political positions (Halberstam & Knight, 2014; Mousavi & Gu, 2015), suggesting the presence of homophily effects. However, work in social influence network theory (Friedkin, 2006) has also argued that individuals who have an initial opinion or behavior react to information disseminated in a social network they belong to and could decide to adjust their original opinion or behavior accordingly.

Moreover, both internal and external factors affect the process of information diffusion in social movements (Strang & Soule, 1998). The internal factors refer to

influence and information flowing within the network at question. Examples of internal influence include influence from strong ties, in which individuals attempt to conform to their groups positions or characteristics; as well as through weak ties where influence is more based on the discovery and knowledge that others adopt a particular position or opinion (Strang & Soule, 1998). External sources of influence are also important to note, but are not internal to the network themselves, such as mass media and policy.

We know that ideas can diffuse through social media within a short time frame in events such as social movements (Varol et al., 2014). However, the distribution of conflicting opinions and the effects of network structures are less clear (Leskovec, Huttenlocher, & Kleinberg, 2010). We suggest two processes for analyzing Twitter data that would help us understand the mechanisms: (1) discovering the opinion of each participant and examining the opinion change over time by building a data mining model applicable to social movements and (2) examining the interactions among individuals with negative and positive opinions and how the structure of the social movement network changes over time based on opposing opinions using social network analysis.

The Gezi Protests

Starting as an environmental protest to oppose the government's urban development plan on May 27, 2013, spontaneous protests spread across Turkey against a number of issues and the general situation of the government and society (Göle, 2013). These protests, referred to by the name of the park from which it started, *Gezi Park*, reached thousands of anti-government sympathizers quickly. Using social media, both the protesters and the supporters of the government created a *synthetic* division in the society: a group in general opposition to the current ruling party; and another in favor. This societal division can be observed in the communication of Twitter, where references to the protests were captured via hashtags. These references contained a diversity of commentary, many of which expressed positive and negative opinions about the protest and reflected a particular political positioning on the issue.

METHODOLOGY

Twitter messages (tweets) contain sentiment that may reflect particular ideas, such as political opinions (Tumasjan, Sprenger, Sandner, & Welpe, 2010), and can capture large scale social trends (O'Connor, Balasubramanyan, Routledge, & Smith, 2010). As previously stated, this work is interested in examining the effects of homophily on the diffusion of opinions in a particular social movement. Therefore, we collected and analyzed the tweets posted during the first month of the Gezi Park Protests.

There are a number of steps that need to be carried out first to conduct this analysis. First, a dataset must be obtained

which presents (1) the opinions of the actors (marked with + and - based on their opinions) across time; and (2) relationships between each actor so that the network structure can be evaluated. Protest communication and network linkages may be observed and extracted from Twitter. However, the polarity of the opinion of each individual is not determined in the dataset. Given the large amount of data, we test the efficiency of automated sentiment analysis for this dataset.

Data Collection
In our study, Twitter API and a set of PHP scripts were integrated to acquire the protest related tweets. The tweets were identified based on three keywords that were used by both the protesters and pro-governments. Those type of *common* keywords would allow us to capture tweets from two different crowds with opposing ideas at the same time: (1) *Gezi*, the name of the park the protests started and centered around and (2) *Taksim*, the town the park is located, were chosen as they were location specific words, and (3) *capulcu*, meaning marauder or looter was chosen as it was used to disparage and refer to the protesters. However, this last term was also reclaimed and used widely by protesters to label themselves.

Since Twitter API gives limited access to historical Twitter data (about 15 tweets for each day for each keyword search), we first collected a preliminary set of random tweets using Twitter API and the mentioned keywords: 1,465 tweets posted by 1,176 unique Twitter users during the first month of the protests. Then, we expanded the preliminary dataset by scraping all the daily tweets posted by those 1,176 users over the first month of the protests. Our second dataset includes 211,450 tweets from those 1,176 Twitter users.

Data Features
In addition to the full text of each tweet, we collected various other attributes for both the users and tweets. The user related attributes include user ID, username, total number of tweets posted by the user, total number of people the user is following, the user's number of followers, the user's number of favorites, and the user's join date to Twitter. The tweet related attributes include tweet ID, full text of the tweet, time and date the tweet was posted, number of times the tweet was favorited and retweeted, and location the tweet was posted (if available).

Preliminary Data Analysis
Sentiment analysis can automate the identification of the positive and negative opinions of a particular subject (Pang & Lee, 2008). In order to test the effectiveness/efficiency of automated classification algorithms we conducted a manual content analysis to identify the sentiments of the tweets in a preliminary dataset (1,465 tweets from 1,176 users). This was used as a training dataset for benchmarking the classification algorithms and to allow the automated

Category	# of Tweets	Percentage
Positive	883	60.27%
Negative	197	13.45%
Neutral	348	23.75%
Irrelevant	37	2.53%

Table 1. Preliminary dataset (spanning one month).

classification of the expanded dataset (211,450 tweets from the same 1,176 users).

More specifically, the tweets in our preliminary dataset were categorized by a native Turkish speaker with four different labels based on their content/opinion in the message. As shown in Table 1, these tweets were tagged with *Positive* (pos), *Negative* (neg), *Neutral* (neu), and *Irrelevant* (irr) tags:

- **Positive:** Tweets that support the protest.
- **Negative:** Tweets that are against the protest or supporting pro-governments.
- **Neutral:** Tweets that are relevant to the protest but not particularly positive or negative. This category included news articles or statements from news agencies, newspapers, or users who were reporting the ongoing situation without picking a particular side (e.g., by the use of specific hashtags or meanings either with positive or negative sentiment) or posts that asked for information about ongoing situation.
- **Irrelevant:** Tweets that include the particular keywords we used to scrape the data but were irrelevant to the protest. Only 2.53% of the tweets were irrelevant in the preliminary dataset.

We have also considered sarcastic tweets. We checked the profile of the user to determine his/her attitude in the case of sarcasm and tagged the message accordingly.

Initial Findings
Figure 1 demonstrates the time series proportions of three opinion types over the first month of the protest (May 27-June 26, 2013) in the training dataset only (note that the category *irr* was skipped as it did not change over time).

We observe a large number of tweets supporting the protest at the beginning. However, the proportion of positive tweets followed a downward trend and dropped as low as 39.5% over the first month of the protests. The proportions of negative, as well as the neutral, tweets followed an upward trend over time. Our initial findings show that there was a prominent change in the proportion of opinions over time.

This phenomenon can be explained by a few simple considerations. Since the protests began as a reactionary activity against government actions, this group was the one that first emerged online. However, as opposing groups came online to present their opinion and defend their cause,
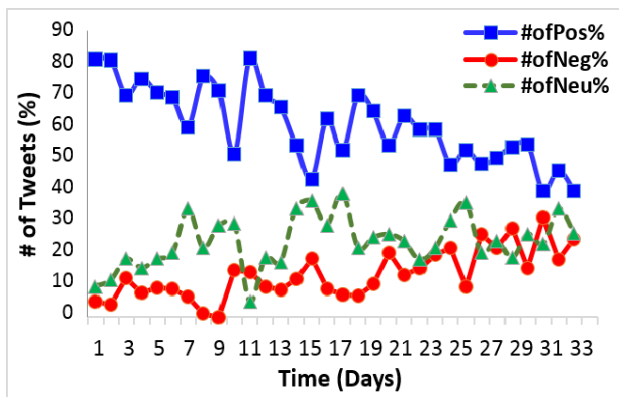
Figure 1. Time series proportions of three different opinions over the first month of the protests.

the ratio of positive and negative reactions became more equal. The trend in neutral opinions are perhaps more interesting. Their increase over time may be explained by noting that at first individuals communicating about the protest were likely those with higher concerns and knowledge about the issue. As the issue became popularized, a larger population, with many individuals not strongly opinionated on either side, began to also make references to the protests, as they participated in the same communication medium.

Table 2 presents the results of precision, recall, and F1-score drawn from the Naïve Bayes (NB), J48, and the Sequential Minimal Optimization (SMO) classifiers for three different opinions. In addition, Support Vector Machine (SVM) returns similar results and IBk performs worse than other classifiers. The best result for classification of positive messages is from SMO. Negative classification does not perform very well with these standard algorithms. Although the precision of SMO is good, its recall and F1-scores are not. Similar results are obtained from the other algorithms. This indicates that a modified classifier algorithm should be developed that considers features of this protest or more generally of social movements.

Classifier	Category	Precision	Recall	F1-Score
NB	Positive	.75	.692	.72
	Negative	.556	.5	.526
	Neutral	.867	1	.929
J48	Positive	.706	.923	.8
	Negative	.667	.4	.5
	Neutral	.923	.923	.923
SMO	Positive	.75	.923	.828
	Negative	.75	.3	.429
	Neutral	.813	1	.897

Table 2. Classifier training results.

Ongoing Data Analyses

After tagging the full dataset, our ongoing studies for opinion chance and homophily mechanism will include:

(1) Performing a trend analysis for three different opinions. The estimated parameters in regression analyses can help us further understand the opinion change at different times and accurately predict opinion change at any time. Regression analyses will be conducted to predict the trends of three different opinions respectively.

(2) Exploring how different online activities (e.g., retweeting a message) influence the homophily mechanism. We will first attribute the options to the corresponding Twitter accounts and then perform time series analysis to discover the sequential patterns of the online activities. For instance, we can identify the association between retweeting another user's message and option change right after retweeting, as well as the correlation between the options of two Twitter accounts involved in retweeting.

(3) Conducting analyses to study how popular citizens and agencies (e.g., celebrities and media reports) impact the homophily mechanism, which will be done by constructing a social network based on the main actors followed and their tweets that were retweeted or liked. Similarly, correlation or association analysis is expected to learn such homophily effect.

Both contagions via social influence and homophilous diffusions are represented by correlations between network structure and individual outcomes (Aral, Muchnik, & Sundararajan, 2009). As Aral et al. (2009) have summarized the empirical patterns used to show the effect of social influence and contagion in networks are: (1) *assortative mixing*—exemplified by correlations of outcomes among linked nodes; and (2) *temporal clustering*—temporal interdependence of outcomes among liked nodes (p. 21544). However, while these patterns may demonstrate social influence they may also be evidence of homophily. That is to say, the shared outcomes observed may not be done simply to contagion effects but may be reflective of existing characteristics of individuals adopting the particular outcomes. For our study, in order to account for homophily effects, we may adopt a framework of matched sample estimation which may control for confounding factors and address selection bias (Aral et al., 2009).

CONCLUSION

Homophily is the tendency of individuals to associate themselves with similar others on a social network. We develop a study to test homophily mechanism during a particular social protest, in order to examine how certain groups and network characteristics influence opinion formation and change over time. In this brief paper we report on the preliminary steps of data gathering, automated opinion classification, and future steps for testing the effects of homophily mechanism. Traditional algorithms

performed moderately well for some of the opinion classification, but we believe specific algorithms need to be developed for automated sentiment analysis in this particular context.

REFERENCES

Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences, 106*(51), (pp. 21544-21549).

Borge-Holthoefer, J., Rivero, A., García, I., Cauhé, E., Ferrer, A., Ferrer, D., . . . Ruiz, G. (2011). Structural and dynamical patterns on online social networks: The Spanish May 15th movement as a case study. *PLoS One, 6*(8), e23883.

Centola, D. (2010). The spread of behavior in an online social network experiment. *Science, 329*(5996), (pp. 1194-1197).

Choudhary, A., Hendrix, W., Lee, K., Palsetia, D., & Liao, W.-K. (2012). Social media evolution of the Egyptian revolution. *Communications of the ACM, 55*(5), (pp. 74-80).

Conover, M. D., Davis, C., Ferrara, E., McKelvey, K., Menczer, F., & Flammini, A. (2013). The geospatial characteristics of a social movement communication network. *PLoS One, 8*(3), e55957.

Easley, D., & Kleinberg, J. (2010). *Networks, Crowds, and Markets: Reasoning About a Highly Connected World.* New York: Cambridge University Press.

Fang, X., Hu, P. J.-H., Li, Z., & Tsai, W. (2013). Predicting adoption probabilities in social networks. *Information Systems Research, 24*(1), (pp. 128-145).

Friedkin, N. E. (2006). *A Structural Theory of Social Influence*. New York: Cambridge University Press.

Göle, N. (2013). Gezi-anatomy of a public square movement. *Insight Turkey, 15*(3), (pp. 7-14).

Halberstam, Y., & Knight, B. (2014). *Homophily, group size, and the diffusion of political information in social networks: Evidence from Twitter*. National Bureau of Economic Research, NBER Paper No. 20681. Retrieved August 9, 2016 from http://www.nber.org/papers/w20681

Hofstede, G. (1980). *Culture's Consequences: International Differences in Work-Related Values*. London, UK: Sage Publications, Inc.

Howard, P. N., Agarwal, S. D., & Hussain, M. M. (2011). When do states disconnect their digital networks? Regime responses to the political uses of social media. *The Communication Review, 14*(3), (pp. 216-232).

Lazarsfeld, P. F., & Merton, R. K. (1954). Friendship as a social process: A substantive and methodological analysis. In *Freedom and Control in Modern Society*. London, UK: Octagon Books.

Leskovec, J., Huttenlocher, D., & Kleinberg, J. (2010). Signed networks in social media. *Proceedings of the 28th Conference on Human Factors in Computing Systems* (*SIGCHI '10*) (pp. 1361-1370). Atlanta, GA: ACM.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology, 27*, (pp. 415-444).

Mousavi, R., & Gu, B. (2015). *The effects of homophily in Twitter communication network of U.S. house representatives: A dynamic network study*. Retrieved August 7, 2016 from http://ssrn.com/abstract=2666052

O'Connor, B., Balasubramanyan, R., Routledge, B. R., & Smith, N. A. (2010). From tweets to polls: Linking text sentiment to public opinion time series. *Proceedings of the 4th International AAAI Conference on Weblogs and Social Media (ICWSM '10)* (pp. 122-129). Washington DC.

Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval, 2*(1-2), (pp. 1-135).

Rice, R. E., & Aydin, C. (1991). Attitudes toward new organizational technology: Network proximity as a mechanism for social information processing. *Administrative Science Quarterly, 36*(2), (pp. 219-244).

Strang, D., & Soule, S. A. (1998). Diffusion in organizations and social movements: From hybrid corn to poison pills. *Annual Review of Sociology*, 24. (pp. 265-290).

Tufekci, Z., & Wilson, C. (2012). Social media and the decision to participate in political protest: Observations from Tahrir Square. *Journal of Communication, 62*(2), (pp. 363-379).

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. (2010). Predicting elections with twitter: What 140 characters reveal about political sentiment. *Proceedings of the 4th International AAAI Conference on Weblogs and Social Media (ICWSM '10)* (pp. 178-185).

Varol, O., Ferrara, E., Ogan, C. L., Menczer, F., & Flammini, A. (2014). Evolution of online user behavior during a social upheaval. *Proceedings of the 2014 ACM Conference on Web Science (WebSci '14)* (pp. 91-90).