Occupied with Place: Exploring Twitter Resistance Networks

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Abstract
From Tehran Square to Gezi Park, Twitter is an emergent tactic of protestors in the public square. Our work utilizes the theoretical framework of contentious politics and its human geographic extension as a framework for examining the role of “place” in Twitter-based networks of resistance. We examine Twitter traffic about local instantiations of Occupy Wall Street across eight cities. The study addresses mutual communications between Twitter participants in hashtags related to each of these local instantiations. This work explores the role of place as a constitutive component of these networks. To do so, we employ descriptive statistical and chi-square tests to examine the significance of user-defined metadata regarding place to the exchanges between users within a network. We conclude that place matters and point to future directions in computational and traditional qualitative analysis, spatial-temporal studies of social media, and the effects of locational propinquity for network development.

Keywords: place, social network analysis, social media, contentious politics, geography


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1 Introduction
Social media platforms are increasingly utilized as tools to enable and engage in public protest. Twitter is one such social media platform that is gaining attention as a tool in protestors’ repertoire of contention, or the toolkit of strategies and tactics used to resist oppression (Tarrow, 2011). Beginning with Tunisia in the Arab Spring of 2011, and followed by the Spanish indignados, Occupy Wall Street, (Gerbaudo, 2012) and most recently protests trending in Turkey, Twitter is used to organize, enable, report protest activities and increase the visibility of protester solidarity. In short, Twitter is a place to exchange information (Kwak et al., 2010). As an increasingly present condition of protest, services like Twitter are thus of increasing importance to the ways in which oppression can be challenged and thus worthy of careful interdisciplinary conversation.

Information scientists and geographers have much to teach one another. Geographic Information Science (Goodchild, 1992) is dedicated to the treatment of explicitly spatial information, often at the expense of other forms. Information scientists have a stronger grasp on the multitude of ways in which information can be treated, but largely leave spatial and place-based interpretations to their geographic brethren. A third group, human geographers, would argue that aspects of space and place are inherently more than simply the location of a person, but the socio-historical relations between everything that constitutes our notions of place. It is time to break down disciplinary walls and begin collaborating.

Geographic explanations of Twitter have largely relied on traditional geographic information, such as the latitude/longitude coordinates embedded in a tweet’s metadata. However, geography is much more than Cartesian location. Goodchild (2008) argues that geographic information in the form of Cartesian location can be derived from a number of heterogeneous, often confusing, user-generated data sources.
Moreover, more qualitative approaches to geographic information science suggest ways in which we can spatially consider issues of place not just as Cartesian location, but as the socio-historical construction of contested spaces (Knigge and Cope, 2006). Thus geography is more than just “where a person is,” but includes one’s relationship to the geographic spaces, cities, neighborhoods, and communities in which we live. Unfortunately, socio-historical construction is not a metadata field in Twitter data.

Human geography, in essence, highlights place as something more than location. An individual’s relationship to place is multi-faceted, socio-historical, and not necessarily bound to Cartesian space. These relational notions of space open the possibility for considering non-Cartesian modes of geographic information, such as a user’s place-based identity. This paper intentionally divorces a person’s relation to place from geographic location. We suggest that this is a beginning step in conceptualizing geographic relationships within information that are not tightly coupled to coordinate systems.

The Occupy Wall Street protests (hereafter “Occupy”) are one example of activists utilizing Twitter to mobilize, motivate, and acquire resources. Twitter metadata offer both a location (in the form of latitude/longitude coordinates) and a self-identified “place” in the user profile data. The formation of Occupy networks around place-based identity occurred via hashtags, such as #OccupyDenver. This offers a unique opportunity to examine a user’s self-identification with a place in conjunction with their discussions about that place. When the place listed in a user’s profile matches the place in the hashtag of their tweet, e.g. Denver and #OccupyDenver, we refer to this as place congruence, irrespective of their location. As such, examining Twitter in the context of Occupy offers uniquely geographic insights about the use of Twitter within social movements in the formation of interest networks (Hemsley & Mason, 2013) related to contentious politics.

This exploratory work examines the role of place in the formation of networks of contention, or the structural relationships between persons with a shared interest in urban protest activities. We utilize McAdam et. al’s theoretical framework of contentious politics (2001) and its later conceptual extension by geographers (Leitner and Miller, 2007; Leitner et al., 2008; Martin et al., 2003) to justify the point of entry for our analysis. We employ statistical methodology drawn from social network analysis (SNA) (Wasserman and Faust, 1994) to understand what the role of users self-identifying with a place has on their communicative practices within these networks of contention. We find that they are, but that the magnitude of the effect varies spatially across different urban interest networks.

Through these findings, we offer the following contributions: 1) previously lacking empirical evidence for geographers’ conceptualized links between network structure and contentious politics; 2) advancing information analytic techniques to consider place as more than merely latitude/longitude coordinates; and 3) an approach for studying within and among multiple Twitter-augmented networks of contentious politics. These results provide empirical evidence of place’s role in communicative interactions among individuals. This points to exciting opportunities for studies of organizational formation, political participation, social network analysis, and the increasing role of social media platforms in the creation of the city.

2 Literature

Three conceptually overlapping literatures inform our work. First, studies of the geographies of user-generated data make heavy use of Cartesian location while theorists push for the extension of this work “beyond the geotag” (Crampton et al., 2013). Second, the relationships among individuals in communicative networks are examined in network theory and social network analysis. Finally, the theoretical framework of contentious politics (McAdam et al., 2001, 1996) and its conceptual extension by geographers demands an attention to the relational spaces of networks. Taken together, these literatures highlight the need for empirical studies at the intersection of place, communicative networks, and politics of resistance, which we address at the conclusion of this section.
2.1 Geographies of user-generated data

Studies of user-generated geographic information lean heavily on the location of users as represented by latitude/longitude coordinate metadata. In geography, theorists are beginning to implore that we move “beyond the geotag,” or latitude/longitude coordinates, to consider other ways in which place and space are implicated in the creation of user-generated data.

Geographic information is more than topology, boundaries, and point locations. Goodchild (2008) argues that the future of geographic information science lies with the ability to derive geographic information from rapidly changing user-generated sources of data. Human geographers are pressing those in this field to move “beyond the geotag” (Crampton et al., 2013) to examine representations of place that cannot be cartographically represented. To date, nascent research on the geographies of user-generated data almost entirely rely on the study of latitude/longitude-based point locations of users.

Geographers treat Twitter as an instantiation of the “geoweb” or “geospatial web” (Scharl and Tochtermann, 2007). This broad rubric posits the geoweb as web 2.0-styled user generated content that contains locational metadata, generally in the form of geotags. Empirical studies of the geoweb relate the conditions of the user’s location to other attributes of place. The spatial distribution of Google Maps placemarks created following Hurricane Katrina mirror the spatial distributions of race brought about by deeply inscribed structural inequalities (Crutcher and Zook, 2009). Similarly, research shows that Wikipedia editors writing about the global south are frequently located in the global north (Graham and Zook, 2011), suggesting that digital representations will reproduce existing arrangements of inequality. The tie here to place extends beyond the locations of participants to include the context of those locations.

Geographically-informed studies of Twitter also exhibit a reliance on latitude/longitude coordinate metadata. Geographic information science is quickly integrating Twitter data into its studies. Tweets have been used to correlate topic models with the location of fast food establishments (Ghosh and Guha, 2013), observed as reproductions of existing spatial, temporal, and socioeconomic patterns (Li et al., 2013), or used in mapping the multiple interpretations of Syria with respect to place (Stefanidis et al., 2013). Non-geographers have used network analysis to suggest that Twitter @-mention networks are best modeled against airplane traffic data (Takhteyev et al., 2012). And within geography, Stephens & Poorthius (Forthcoming) relate geographic distance to the strong and weak ties posited by Granovetter (1973), tying geographic studies back into those of network theory.

But these studies still rely on locational metadata rather than other attributes of place despite the flaws inherent in geotagged Twitter data. The accuracy of geotag coordinates varies widely, from several meters for GPS and up to several thousand for triangulation via a cellular network (Li et al., 2013). Moreover, locations derived from IP lookup are only as accurate as the databases from which they pull data (Li et al., 2013). Finally, only 1-2% of tweets are geotagged, thus hardly representative of Twitter traffic as a whole. Thus, locational data associated with Twitter is adequate for low-resolution studies but may not be appropriate for a conceptualization that treats networks as more granular, relational spaces. Considering place rather than location allows us to include contextual information by proxy, such as the relationship, history, and meanings with which users self-identify by means of the presentation of a user profile.

2.2 Network Theory: Where is Place?

The unfolding of place and sited resistance occurs through the process of “everyday living,” or the multiple, often banal, exchanges among actors (Certeau 1984). These processes enable resistance in the face of oppressive structures. There are multiple processes by which this occurs, but we argue that the exchange of information via Twitter is among them. The city and the public square unfold as places of contention, at least in part, through the ties formed among actors communicating about these places via a social media platform.
Network theorists study the structure and process of these networks – how they form, how actors relate, and the emergent social processes enabled by them – through social network analysis (SNA). SNA is a methodology that supports the measurement and analysis of network structure (Butts, 2008; Wasserman and Faust, 1994). Network structure is defined as “the observed set of ties linking the members of a population” (Watts, 2004, p. 48). We conceptualize one set of such ties to be communications between Twitter users with the topology of these ties comprising a network structure. Network theorists tie the attributes of actors within a network to that network’s structure. For instance, political blogs with similar ideological affiliations share homophilious and often identical content (Nahon and Hemsley, 2011, 2013). Also, the geographic propinquity and contextual environment of actors are contributing components to the formation of networks (McPherson et al., 2001). More recent work on Twitter has extended this work to show that communication between Occupy protestors located within the same state tends to be on topics of a local nature, and that interstate communication is more often related to the main stream media or focuses on a few individuals (Conover, Ferrara, Menczer, & Flammini, 2013; Conover, Davis, et al., 2013). This, however, focuses the object of inquiry as locational ties rather than the place-based identity characteristics of those that comprise the network. The structural formation of networks is owed at least in part to the attributes of the actors within it.

Durable networks formed around shared interest likely contribute to a place’s capacity for contentious politics. Interest networks, or networks that form around topically similar content, can evolve into durable relations where actors engage in collaboration and collective action (Hemsley and Mason, 2013). While the topic of interest and the related communication network may be ephemeral, some ties among actors may have durability beyond the life of the topic. These invocations brought about through actors’ “everyday living” around place and protest-based interest networks form durable relationships that contribute not only to Occupy-related events, but have the potential to shape future contentious politics in a given place. Thus network theory is an integral component of the emergence of social media platforms as tools in the repertoire of contention.

2.3 Contentious Politics and the Geographic Extension

The theoretical framework of contentious politics (McAdam et al., 2001, 1996; Tarrow, 2011, 1998; Tilly and Tarrow, 2007; Tilly, 2003) is ideal for analyzing Occupy Wall Street. McAdam, Tilly, and Tarrow separate contentious politics from the study of “social movements” by highlighting the non-institutional interactions between groups making interest-based claims (2001). This framework suggests that the study of Occupy Wall Street need not be a study of a movement per se, but conforms more closely to the heterogenous claims being made among different Occupy locations. The interaction was certainly non-institutional, using occupation and protests alongside of Twitter and other social media platform based communications as tools in the repertoire of contention (Tilly and Tarrow, 2007).

Geographers’ extension of the contentious politics framework highlights the spatial dimension to illustrate resistance across difference conceptualizations of place’s role in politics of resistance. This includes the comparison of activism across global and local scales (Kurtz, 2003; Martin, 2007), neighborhood or community-based organizing (Elwood, 2008, 2006; Martin, 2007), institutional hierarchies (Leitner et al., 2008; Martin et al., 2003) and place-framing, the legitimization of an agenda by constituting place identity through communicative framing (Martin, 2003). Occupy drew inspiration from international resistances that formed in the place of the public squares of Tehran and Spain. Occupy was a national phenomenon locally instantiated in the individual public squares of their associated cities, but representative of lessons learned at the local, national, and global scales.

Leitner et al. (2008) challenges human geographers to move away from scale as the sole arbiter of what makes contentious politics “spatial” and consider other spatial dimensions such as the relational spaces of networks. This comes at a time when researchers outside of geography have recognized technology’s role
in constructing social structures that can be described in terms of networks (Castells, 1996; Latour, 2005). Thus Twitter-exchanges mark a particular bounding of the Occupy Wall Street activities that allow us to leverage a framework of contentious politics using these communicative, placed networks. The newest extensions of literature along these lines encourage us to examine these relational network dynamics as they relate to place-framing (Pierce et al., 2011), power formation (Nicholls, 2009), and protest (Castells, 2012).

The networked nature of protest (Castells, 2012) is alive and well on Twitter. Mainstream media lauded the role of Twitter in the “Arab Spring” revolutions earlier in 2011 (Howard and Hussain, 2011; Khondker, 2011). González-Bailón et al. (2011) examine the ways protestors are recruited through online Twitter networks and Gerbaudo (2012) examined Twitter activity across the Arab Spring, the work of the Spanish indignados, and even Occupy Wall Street more broadly. As Gerbaudo (2012) notes, while Twitter plays an important role in the development and deployment of networked protest activity it is still greatly overshadowed by the work of more traditional protest in popular media. Looking at Occupy specifically, Nahon et al. (2013) suggest that Twitter users employed tweeted news, information, and wishes of solidarity to protestors within Occupy Wall Street. Twitter acts as a communicative platform-based augmentation to networks of contention.

2.4 Exploring Intersections

We identify a gap of empirical studies at the theoretical intersection of literature about the geographies of user-generated data, social network analysis, and the geographic extended conceptualization of the theoretical framework of contentious politics. Studies involving geographies of user-generated data are over-reliant on geolocation through latitude/longitude coordinates. Studies with a network-theory based approach are frequently treated aspatially. However, geographers studying contentious politics call us to consider the roles of space and place in relational networks, as these networks undergird new modes of resistance. While we have theoretical framings suggesting that place plays a formative role in digital media, there is a lack of empirical work that confirms the role of place in networks of contention. This work serves to fill that gap by answering the following research questions:

1. Networks are made visible through the communicative exchanges among people. If people self-identify with a place (on their profile) and then identify a tweet with the same place (a condition that we will refer to as place congruence), in what ways does this condition affect their communicative practices in these networks of contention?

2. In what ways is the role of place congruence similar and different among the multiple networks of contentious politics of Occupy?

3 Methods

We employ statistical techniques in this exploratory study in order to explore the relationship between a user’s self-represented place and network formation while drawing from geographers’ conceptualization of contentious politics. Each of the parts of our two-level analysis corresponds to one of our research questions. For the first question, we examine the role of place within in-network communications by employing a network variance model drawn from SNA methods. For our second research question, we treat each network as a unit of analysis and employ case study techniques (Yin, 2008). Our networks are comprised of users (individuals, shared accounts, or automated accounts) who interacted on Twitter using specific city-based protest activity hashtags (e.g. #OccupyDenver, #OccupyHouston, etc.) between October 19th and November 19th, 2011.

3.1 MR-QAP Model

The interactions among Twitter users and their related attributes (e.g., place) are fundamental to our work as factors in the formation of resistance networks. SNA models are used to describe how social distance
between actors is related to the degree to which those actors exhibit similar behavior (Christakis and Fowler, 2011), how relationship types shared by actors influence the exchange of novel information (Granovetter, 1973) and how connection characteristics relate to influencing behavior (Barash et al., 2012; Brown and Reingen, 1987; González-Bailón et al., 2011). Thus, SNA’s focus on the relationships that constitute a network is well suited to analyzing the self-representation of place as a constitutive component of these networks.

We use a network variance model to address our first research question. Specifically, we use multiple regression quadratic assignment procedure (MR-QAP) as outlined by Krackhard (Krackhardt, 1988, 1988). The unit of analysis for this type of regression is the dyad, or pairing of individuals within the network who may or may not interact. This is apt for our work as we are exploring whether or not users being in-place is related to their linking to each other. Additionally, MR-QAP models have been shown to be robust for network datasets where sets of dyads cannot be assumed to be independent (Dekker, Krackhardt, & Snijders, 2003; Krackhardt, 1987, 1988).

In this type of regression each variable is a matrix and the coefficients are estimated using ordinary least squares (OLS), and their significance is tested against a reference distribution generated via a Monte Carlo permutation of the model’s matrix variables. All of the analysis is done using the SNA package for R, which uses the Double-Semi-Partialing (DSP) method for MR-QAP developed by Dekker et al. (2007). DSP employs a residual permutation method wherein an initial regression is run to calculate the residuals, which are then repeatedly permuted and entered into the model. The resulting coefficients form the reference distribution for each estimated coefficient. This approach has been found to be robust against confounding variables that might not be included in the model (Dekker et al., 2007).

Each of the 8 cases in this study is a place-based Twitter communication network that is constructed from and limited to tweets with one of these hashtags: #OccupyCincinnati, #OccupyAtlanta, #OccupyDenver, #OccupyMemphis, #OccupyHouston, #OccupySLC, #OccupyOrlando, and #OccupyPortland. So for tweets to be included in our Denver network, they must contain the hashtag #OccupyDenver. These Occupy cities were selected with the intention of representing varied network sizes and geographic location to increase reliability. A map displaying the ratio of tweets within a hashtag to the total tweets within the dataset is seen in Figure 1.

![Figure 1: Ratio of tweets within an occupy hashtag to total tweets within entire dataset.](image)

Each of our networks is further bound by only including tweets that contain an @-mention. An @-mention is a feature of the Twitter platform that directs a tweet to another user by placing an @ in front of the user handle in the text of the tweet. Users are alerted by the platform when they are @-mentioned by another.
@-mentions also occur when a user “retweets,” or shares, another user’s tweets. The text of such a tweet contains the prefix “RT” followed by the @-mention of the user whose tweet is being shared.

By taking a @-mention as a communication between user accounts, we use tweets as communication trace data that form the links, or arcs, between users. This is known as an “arc sample method,” which takes relations rather than nodes as the sample for analysis (Butts, 2008). @-mention communication networks have been constructively employed to study political polarization within Twitter (Conover et al., 2011).

We further focus on interaction among users by only including users (and their links) who have been mentioned at least once and who have mentioned someone else at least once. This narrows the network to those individuals engaging with one another and helps reduce (but not eliminate) broadcast-style spam in the datasets.

We represent the final network as a matrix and capture the direction of the communication (e.g., the frequency at which A @-mentions B as well as B @-mentions A). This directed, valued network forms the dependent variable in our MR-QAP model. Note that the model specification is the same for each of the place-based networks, detailed here:

\[
E_{Y_{ij}} = \theta_0 + \theta_1 X_{1ij} + \theta_2 X_{2ij} + \theta_3 X_{3ij} + \varepsilon
\]

Each of the variables is in matrix form and is constructed as follows:

**Y**: A directed, valued network comprising links that represent @-mention interactions in a given place-based network bound by an Occupy-city hashtag (e.g., #OccupyDenver).

**β 1**: The first variable is a dichotomous matrix representing cases where two users are both place congruent, meaning their user-defined profile listed place matched the place-based hashtags of their tweets (see discussion below for the place related data used to construct this matrix). For example, given users A, B, and C, where A & B are place congruent, cells A-B and B-A will contain a 1, while A-C, C-A, B-C and C-B will contain a zero. The estimated coefficient, if significant, represents the increase in tie strength (or the number of @-mentions) and addresses our first research question.

**β 2**: Users who reciprocate in communication have a higher likelihood of communicating in general (Steglich et al., 2006). We control for this reciprocity effect with a mutual-tie, dichotomous, symmetric network. Cells that contain the integer 1 correspond to users who have @-mentioned one another. Otherwise, the cells contain a zero. As above, if the estimated coefficient is significant, the coefficient represents the increase in tie strength.

**β 3**: Twitter users who have large followings produce a disproportionate amount of retweeted content (Hu et al., 2012; Kwak et al., 2010). Since retweets are a form of an @-mention, we include this variable to control for this effect. In this matrix, the value of the cells in each column are the number of followers for the user represented by that column. For example, if user-A has 200 followers, then the cells in user-A’s column contain 200. Wasserman and Faust refer to these as expansiveness and popularity effects (1994), or more recently, receiver effects (Nahon and Hemsley, 2011). We expect this variable to be both significant and positive. The estimated coefficient for this variable can be interpreted by noting that a unit change in X3 (followers) increases tie strength in the @-mention network by the estimated coefficient.

In the model notation E represents the expected value of Y and ε represents the model residuals.

### 3.2 Quantitatively exploring case similarities and differences

We explore similarities and differences among networks by treating each network as an independent unit of analysis, or case. We utilize a case study approach, outlined by Yin (2008), in identifying patterns related to the concept of place congruence. Our case selection supports analytic generalization by representing varied network sizes and geographic locations across 8 different Occupy place-based networks.
Case study methodology usefully frames our analytical approach. Our explorations make use of several heterogeneous techniques. Yin identifies “the case study’s unique strength as its ability to deal with a full variety of evidence,” (2008, p.11) and as such offers a methodological framework for this study. This analysis utilizes descriptive statistics about each network, data visualizations that foreground comparisons among networks, and the variance in the results from our MR-QAP model. Thus a case study approach is particularly suited to evaluate multi-modal evidence across network structures.

Particular to our model, we find the amount of variance that place congruence affords among each of the networks. We re-run all of the regression models (see above) without $\beta_1$ – the place congruent variable – and find the difference in the adjusted R2. We employ a partial F-test to verify that the difference in variance is significant (Ott and Longnecker, 1993).

3.3 Data

Our data is drawn from a corpus of Occupy related tweets collected and maintained by the Social Media Lab at the University of Washington (somelab.net). The full data set contains over 160 million tweets collected from October 19th, 2011 to June 30th, 2012 using Twitter’s streaming application programming interface (API). The streaming API provides a continuous “stream” of tweets that match a given set search terms. As long as one of the terms is matched in the text, hashtags, @-mentions, or URLs of a tweet, Twitter streams the tweet to our collection system. Along with the tweet text, Twitter returns metadata fields such as a tweet timestamp, the number people who follow the user, as well as the location and place of the user.

Twitter offers two pieces of locational metadata with each tweet if the user changed her settings (opted-in) to provide them. First, Twitter’s “location” field is tied to latitude/longitude coordinates (a “geotag”). Location is gathered either through granular cell phone tower triangulation, or through GPS. Second, Twitter’s “place” field is derived from these coordinates to determine the user’s city, state, or country. In the case of a non-GPS enabled device, the “place” of the user is determined by comparing the IP of the user’s device against a geo-IP database. This means that our generalization of a “geotag” or Twitter’s definition of “place” is not as accurate as frequently portrayed, and that the two cannot be treated as spatially equivalent to one another.

Twitter also allows a user to define her own place as a user-defined text field. While this is not necessarily an accurate representation of a user’s physical location (Stephens and Poorthius, Forthcoming), we argue that this field is indicative of a user’s self-perceived relationship to a place. People may not reliably update their accounts with the most current information, or perhaps identify themselves as living in a hometown rather than a temporary location, such as studying at a university. For our work, this is more than acceptable. We are interested in relative location as opposed to actual Cartesian location. The user’s activities tied to their affective relationship to place remain relevant in the process of that city’s network formation. A geotag would likewise not necessarily capture a user’s relational ties to a location (e.g., loyalty to a hometown’s sports team or family and friends).

This Occupy dataset is notable among other Twitter datasets for the proliferation of place-based hashtags (e.g. #occupydenver or #occupyhouston). We therefore identify users as “place congruent” when their user-defined place matched the place-based hashtags of their tweets. So for #occupydenver, if the user profile contained “Denver” anywhere in the user-defined place field, that user would be “place congruent.”

For this exploratory work, we used tweets from October 19th to November 19th that contained any of our 8 Occupy city hashtags. Table 1 provides descriptive information for each network, including the total number of tweets and users in the dataset, followed by the number of tweets with an @-mention. The columns labeled “Nodes” and “Links” provide the number of users and links in the networks after filtering. The column labeled “Place congruence” represents the number of users who specifically list a place in their profile that matches the network location. To find matches we use a regular expression using the city name.
A map displaying the ratio of tweets deemed to be place congruent to the total tweets within a given hashtag is seen in Figure 1.

<table>
<thead>
<tr>
<th>City \ Descriptives</th>
<th>Tweets</th>
<th>Users</th>
<th>@mentions</th>
<th>Nodes</th>
<th>Links</th>
<th>Place Congruence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cincinnati</td>
<td>1124</td>
<td>560</td>
<td>601</td>
<td>58</td>
<td>60</td>
<td>17</td>
</tr>
<tr>
<td>Memphis</td>
<td>1864</td>
<td>814</td>
<td>1227</td>
<td>86</td>
<td>205</td>
<td>19</td>
</tr>
<tr>
<td>Salt Lake</td>
<td>5937</td>
<td>2027</td>
<td>4629</td>
<td>275</td>
<td>1191</td>
<td>80</td>
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<tr>
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<td>6114</td>
<td>1700</td>
<td>4268</td>
<td>353</td>
<td>1410</td>
<td>64</td>
</tr>
<tr>
<td>Orlando</td>
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<td>2148</td>
<td>4799</td>
<td>293</td>
<td>1241</td>
<td>79</td>
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<tr>
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<td>11897</td>
<td>24611</td>
<td>1671</td>
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<td>292</td>
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<tr>
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<td>12715</td>
<td>40457</td>
<td>2170</td>
<td>14326</td>
<td>219</td>
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<td>17644</td>
<td>62425</td>
<td>3437</td>
<td>26092</td>
<td>953</td>
</tr>
</tbody>
</table>

Table 1: Descriptives by City

Figure 2: Ratio of place congruent tweets to total tweets within an occupy hashtag.

3.4 Limitations

There are a few limitations of this exploratory work we wish to highlight. First, we store the user-defined place listed in the profile and the number of followers for each user as derived from the tweet metadata. If users in our set tweeted more than once, their location and follower count may change over the course of time. In cases where a user changed their location over the course of our study period, we included users as place congruent if they matched once. We used the average follower count across all tweets for a given user. Second, it is worth noting that a user’s place is not always associated with a particular city, but a neighborhood within that city. Likewise, users may use a colloquial reference to their city (e.g., “Mile High City” for Denver). Expanding matching criteria for place to include these users as “place congruent” is planned in future work.

4 Findings

Place congruence is significant in all eight of our models, as shown in table 2. However, the effect is not large. In Memphis, for example the place congruence effect only accounts for 0.035% of each link. Our
control variable for mutual ties is also significant in all of the networks, but our control for receiver effects (users having a tendency to @-mention people with many followers) was not significant in the smaller networks and showed a wide range in terms of its effect. The difference in R2 values between model 1 (the full model) to model 2 (without place congruence) is also significant for all networks, as shown in Table 2. These values are small, but consistent with the statistical behavior of a variable standing in as a proxy for complex processes.

<table>
<thead>
<tr>
<th>City Model</th>
<th>Place congruence</th>
<th>Mutual tie</th>
<th>†Receiver follower</th>
<th>R²</th>
<th>Mod 1 Adj-R²</th>
<th>Mod 2 Adj-R²</th>
<th>∆Adj-R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cincinnati***</td>
<td>0.040**</td>
<td>0.985***</td>
<td>-0.591</td>
<td>0.403</td>
<td>0.402</td>
<td>0.395</td>
<td>0.0066***</td>
</tr>
<tr>
<td>Memphis***</td>
<td>0.035*</td>
<td>0.970***</td>
<td>-4.065</td>
<td>0.289</td>
<td>0.289</td>
<td>0.287</td>
<td>0.0019***</td>
</tr>
<tr>
<td>Salt Lake***</td>
<td>0.037**</td>
<td>0.978***</td>
<td>0.328*</td>
<td>0.213</td>
<td>0.213</td>
<td>0.207</td>
<td>0.0062***</td>
</tr>
<tr>
<td>Houston***</td>
<td>0.016**</td>
<td>0.987***</td>
<td>2.178*</td>
<td>0.323</td>
<td>0.323</td>
<td>0.322</td>
<td>0.0012***</td>
</tr>
<tr>
<td>Orlando***</td>
<td>0.029**</td>
<td>0.987***</td>
<td>0.556*</td>
<td>0.265</td>
<td>0.265</td>
<td>0.262</td>
<td>0.0024***</td>
</tr>
<tr>
<td>Atlanta***</td>
<td>0.004**</td>
<td>0.998***</td>
<td>0.185**</td>
<td>0.145</td>
<td>0.145</td>
<td>0.145</td>
<td>0.0002***</td>
</tr>
<tr>
<td>Denver***</td>
<td>0.014**</td>
<td>0.996***</td>
<td>0.252*</td>
<td>0.142</td>
<td>0.142</td>
<td>0.142</td>
<td>0.0007***</td>
</tr>
<tr>
<td>Portland***</td>
<td>0.003**</td>
<td>0.998***</td>
<td>0.118**</td>
<td>0.130</td>
<td>0.130</td>
<td>0.129</td>
<td>0.0003***</td>
</tr>
</tbody>
</table>

*p ≤ 0.05, ** p ≤ 0.01, *** p ≤ 0.001; † For ease of reading, we multiply these coefficients by 10 million

Table 2: Findings by City

Our model, including place congruence, explains a larger amount of variance for networks with fewer nodes. Figure 3 plots the amount of variance explained by place congruence against the number of nodes in each network. This suggests that our model, on the whole, performs better for networks with fewer nodes.

Figure 3: Change in R² by Network Size. Amount of variance explained by place congruent against network size.

We also explored the relationship between place congruent variance and other network measurements, such as network density, centralization, and density (Wasserman and Faust, 1994). Place congruence is not related to density or centralization in our dataset, whereas networks with larger diameters appear to also have a lower place congruence effect. This is consistent with our finding regarding the relationship between network size and place congruence.
The amount of variance explained by the place congruence variable also changes when measured temporally. We divided each place based network into four week-long datasets, and ran our fully specified regression on each dataset. Somewhat surprisingly, place congruence was not significant for the first week of any network, but remained significant in all networks at the second week and after. Additionally, the R2 for smallest networks increased over time while for the larger networks it declined (see figure 4).

![Figure 4: Change in Model 1 R2 by Network Size Over Time. Change in model R2 over time for each network. Network size shown as circle size.](image)

Interestingly, we find that the amount of variance due to place congruence is stable over time. That is, while the model on the whole performed more poorly as networks grew and time passed, the performance of the place congruence variable stayed consistent over time, with the exception of Salt Lake City and Cincinnati. We regressed the model without place congruence against all weeks, for all networks. Figure 6 provides a plot showing the amount of variance explained by place congruence for each network, for each week.

![Figure 5: Variance explained by place congruence. Change in variance due to place congruence. Network size shown as circle size.](image)
5 Discussion
We find that in networks of contentious politics, place matters. That is to say place congruence is a constitutive component of the formation of resistance networks. The small variance explained by our independent variable for users being place congruent comes as no surprise; conceptually, place-congruence-as-attribute stands in as a proxy for the myriad of attributes that comprise place, such as demographics, interpersonal relationships, history, governmental and community organizations, and any host of other unknowns. To relate this back to the theory of contentious politics, it is clear that self-identified place is a constituent component of these emergent networks.

But we also note that the degree to which place matters differs among our city-based networks and is related to the size and diameter of the network. Together this suggests that place congruence matters more in smaller, less complex networks. This complexity is likely, at least in part, found in the multidimensionality of place represented here by a user-defined proxy.

Place is a surprisingly consistent factor over time, while the role of well-established factors in network formation (reciprocation and receiver effects) declines over time. But as the city networks grow over time, the models overall explain less variance. This suggests that the networks, and the factors that drive their growth, become more complex over time. As the amount of variance due to place congruence remains fairly stable, we suggest there may be a core set of actors who remained committed throughout our 4 week sample.

Place is more than just a self-representation through a field of metadata. This initial foray suggests that seeking further contextual qualities of place would lead to a more robust model. Other modes of inquiry will be needed to ascertain the processes through which place asserts itself in contentious politics, but our work provides evidence to justify further work in this area. We suggest mixed methods approaches, including computational topic modeling and qualitative interviews, for ascertaining contextual qualities of these information exchanges that can be attributed to place. Topic modeling will offer us contextual information regarding the discussion within a placed hashtag, giving us a way to move beyond rote metadata fields through the development of novel mixed methods approaches for including context computationally. Finally, examining the ways in which protestors are co-located in place and converse across place-based hashtags might further inform our understanding of the exchange of information during protest activities.

6 Conclusion
In this paper we argue that place, as conceptualized by human geographers as essentially more than raw location to include contextual and socio-historical factors, is a useful analytic focus for researchers in information science. To accomplish this, we examined eight city-based Twitter networks, each a local instantiation of Occupy Wall Street, through the lenses of contentious politics and network theory. Our methodological approach employs social network analysis coupled with a quantitative case study approach to explore the role of place in the formation of resistance networks.

Each network is conceptualized as an independent case, comprised of users who mention each other on Twitter and include a city-based hashtag (e.g. #OccupyDenver, #OccupyHouston, etc.) between October 19th and November 19th, 2011. Our case selection supports analytic generalization by representing varied network sizes and geographic locations across the U.S. This approach allows us to examine the role of place within each network as well identify patterns among our networks.

We find that place is a constitutive component of these resistance networks, but that the amount of variance due to place in a network depends on characteristics of the network such as its size and complexity. We also find that the effect of place, in terms of variance explained, remains stable over time while established factors, such as reciprocation and receiver effects due to users have high follower counts, decline in the degree to which they add explanatory power to the model.
This work fills an empirical gap at the intersection of human geography, network theory, and contentious politics by highlighting the usefulness of social network analysis to geographic studies and by demonstrating the importance of place in the formation of networks of resistance. Our methodological contribution suggests contextualized and nuanced considerations of place may be fundamental to network formation through social media.

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