A Spatiotemporal Model of Twitter Information Diffusion: An Example of Egyptian Revolution 2011

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ABSTRACT

Recent social movements demonstrate an important role of social media information diffusion in promoting social changes. Transnational information diffusion may be influenced by spatial proximity between the origin nation and other parts of the world. Proximity implies more than just physical distance. This paper develops a mathematical spatiotemporal diffusion model based on partial differential equations, called "diffusion-advection" model. The model is applied to four sets of global spatial arrangements, respectively based on geographical, ideological, economic and diaspora perspective on proximity. Twitter data on Egyptian Revolution 2011 is used for the model validation. The developed model shows an acceptable accuracy rate. Among the different definition of proximity, ideology-based arrangement (i.e., democracy) explained most effectively the spatial diffusion process over the course of the revolution, showing that different types of messages are diffused at a different pace.

Categories and Subject Descriptors

Social Media, Spatiotemporal Diffusion Model, Online Mobilization

General Terms

Information Diffusion, Spatial Diffusion, Collective Action, Partial Differential Equation, Online Social Network, Social Medium, Global Protest, Social Movement

Keywords

Social Media, Twitter, Spatiotemporal Information Diffusion, Egyptian Revolution, Protest Mobilization, Partial Differential Equation, Global Networks

1. INTRODUCTION

In responses to recent social media-assisted social movements, scholars have discussed the role of online communication in promoting social changes. Some scholars contend that social media uses change the paradigm of social movement organizing principles by mainstreaming decentralized, personalized, and spontaneous participations of large-scale global citizens [1].

Information diffusion plays a key role for the success of both action and consensus mobilization. This study contributes to social media and social movement scholarship by developing a spatiotemporal information diffusion model under two premises: First, online mobilization can be understood as a diffusion phenomenon, in line with previous scholars who adopt diffusion theoretic perspectives in social movement research (e.g. [2,3,4, 5]). More precisely, we consider the rate of information diffusion in social media to be a proxy measure of the magnitude of mobilization. Additionally, online social movements should be discussed within a larger landscape of global civil society, which is influenced by persisting international factors such as democracy rank, geographical proximity, migrant communities, and economic ties [6,7]. Drawn from the two premises, this study presents the ways in which various international relation factors may be adequately integrated into the diffusion model of social media-assisted social movements.

2. LITERATURE

2.1 Social Media and Global Movement Participation

The widespread digital media in recent decades have prompted much discussion about the strategic advantages of information and communication technologies (ICTs) in speeding up recruitment, broadening audience bases, and lowering communication costs [8, 9]. The core principle for success in ICT-driven social movements has remained consistent with old-fashioned social movements despite their differences: information diffusion is key to mobilization. As a prerequisite for successful mobilization, effective information diffusion is essential to give *salience* to protest efforts.

Social media is contributory to increase "noticeability" of other users' participation, which is crucial to form a favorable opinion climate collectively [9,10]. Also, social media assists to accumulate and share knowledge and resources, and to interconnect supportive communities [11]. Especially, in online social networks, consensus mobilization expands easily on a global scale: A local protest event may be ostensibly provincial. However, it can draw an extensive global public attention and support via social media networks. For example, during the Arab Spring protest period, a predominant portion of Twitter activities was actually made by Latin-language users [12]. This finding indicates that Twitter was a venue for global publics to express their support for the local regime changes and interact with local activists on the ground.

However, not every global citizen has an equal share of participation. Global discrepancy in social media activities reflects cross-national unevenness driven by international factors marked by pre-existing orders of world economy and geo-political systems [13]. For example, the North-South divide still exists, with citizens of affluent countries in the Northern hemisphere enjoying greater access to resources needed for global activism participation than citizens of countries in the Southern hemisphere [6,14]. A country's democracy rank is a strong predictor of citizens' involvement in transnational activism [15]. The dyadic relationship between nations such as geographic distance, bilateral trade ties, and cultural similarity may also affect the level of involvement in each other's political struggles [7]. Global migration creates diaspora communities in foreign countries, which may be prone to being mobilized when a social movement unfolds in their home country [16]. These determinants of uneven participations are likely to persist in the digital realm. After all, the pattern of transnational information flow remains largely unchanged in the Internet age [17].

While the global digital divide in activisms has been mainly discussed from institutional or organizational perspectives to this date, (e.g. relationships among non-governmental or inter-governmental organizations, and media organization-driven news flow), the discussion needs to embrace personalized forms of activisms especially rising in the social media realm. To our knowledge, existing literature has not yet fully addressed the roles international relational factors play in this personalized, ad-hoc mobilization of global publics online.

2.2 Diffusion Models of Social Movement

Existing mathematical diffusion models fall under three types: One, *threshold models* develop a mathematical procedure based on time-variant logistic function, with the time t of an individual's joining a movement depends on the individual's exposure to prior participants at time t-1 [3]. Two, *evolutionary models* is advanced from threshold models by further considering (1) effects of the exposure to protest-repressive ideas/behaviors as well as protest-inducting ones and (2) coevolving relationships among different events throughout a movement cycle [4]. Three, *event history diffusion models* are similar to the evolutionary models in that they explore the diffusion process across different events. However, even history diffusion models are different from evolutionary models in that the models involve statistical testing of relative effects of diffusion-related covariates on the rate of protest adoption, including individual attributes, infectiousness (how influential one's protest behavior is to everyone else in the system), and susceptibility (how responsive a participant is when a protest occurs) [2,5,18].

Despite insightful approaches, these models only look at temporal changes and overlook a spatial diffusion process. Although some event history modeling studies include a distance variable [18], it is treated as a covariate as opposed to a key change force. The proposed model in this paper builds on the time-variant logistic diffusion modeling by addressing spatial dimension simultaneously. We argue that spatial understanding is important because online movement participations are often transnational by nature, which involving global publics dispersed across different political, cultural, and economic contexts.

3. A MATHEMATICAL MODEL

Mathematical diffusion modeling in social sciences is mostly based on an Ordinary Differential Equation-based (ODE) logistic function, which allows researchers to explore the rate of change of a variable over time. There are some diffusion models with both external and internal factors involved. For example, Mahajan and Peterson [19] presents a number of ordinary different equation models to study the diffusion of innovations based on the early research on diffusion processes. However, the models do not incorporate spatial information. While some information cascading models over social networks such as Independent Cascade Models [20] may be insightful, they do not take into consideration external factors and only rely on the endogenous network structure.

This study develops a Partial Differential Equation-based (PDE) model instead of the ODE-based. An advantage of PDE models over the ODE is that PDE models enable to explore the rate of change not only over time but also *across spaces* [19]. PDE models have been widely used in physics, biology, and other fields to describe the process governing the diffusion of an object (e.g. sands, pollutants) or energy (e.g. heat). The PDE-based models we developed directly address a number of concerns about adapting epidemiological diffusion models to social scientific phenomena [21]. In particular, they observe that there are significant differences between information traveling in social media and the spreading of germs in that online users are exposed to information from a wide range of sources aside from the endogenous network they are connected to. Similarly, Myers et al. [22] raised the concerns about distinguishing two different diffusion processes - internal and external influence. The internal influence results from the structure of the underlying network; the external influence often comes from various out-of-network sources, such as mainstream media penetration. PDE helps to incorporate the two processes into one modeling.

Our model extends a PDE-based "diffusive-logistic" model [23], recently developed to predict news diffusion via online social networks, by adding the "advection" term. Advection term denotes the tendency of an object to move along with a discrete set of locations. By adding the advection term, we add the parameter associated with magnitude of information shift from one location to another. This location-to-location shift is treated as an external factor. The model is thus called a diffusion-advection model. By including the advection term, the model considers substances of an entity to be carried by a bulk motion of the transport medium. For example, suppose the spread of infectious disease. While the local diffusion process may occur due to autonomous and random search movements of a mosquito, wind current may also result in an "advection" movement of large masses of mosquitoes and consequently cause a quick advance of infestation [24]. Similarly, global information flow in social media can be driven by two diffusion mechanisms: one is within-local diffusion, by which individual local users share information relatively autonomously, and another is advection, which may occurs thanks to a larger global geo-political force such as democracy, immigration, physical distance, and other significant forces. Therefore, the use of diffusion-advection equations may appropriately distinguish the two mechanisms, helping understand the role of international relational forces in facilitating the spread of information during the Egyptian revolution.

For formalization, suppose that we have a series of spatial points arranged by a certain criterion, $U(x)$, as well as a set of time points, $T(t)$. Let $I = I\ (x,\ t)$ be the volume of information at location x and at time t. The mathematical formalization of the diffusion-advection model is:

$$\frac{\partial I}{\partial t} = \frac{\partial \left(d e^{-bx} \frac{\partial I}{\partial x}\right)}{\partial x} - g(x)\frac{\partial I}{\partial x} + r(t) I \left(h(x) - \frac{I}{K}\right) \quad (1)$$

Where $\frac{\partial \left(d e^{-bx} \frac{\partial I}{\partial x}\right)}{\partial x}$ in equation (1) represents the diffusion process across $U(x)$ by unexamined forces (at random).

I : the volume of dependent variable
t : time
x : locational (spatial) point
b and d: parameters associated with unknown factors that may promote the spread of I
$\partial I/\partial t$: a rate of change in I at time t
$\partial I/\partial x$: a rate of change in I at a locational point of x
$g(x)$: a parameter of advection term, which is a coefficient that determines the rate of change in I over locational points x_s. The negative sign (-) indicates that the shift of I is directed from one spatial point to the *right*-side neighbor location
$r(t)$: an intrinsic growth rate at time t, which was formulated as the decaying exponential function)
$h(x)$: a parameter representing the heterogeneity of intrinsic growth rate at location x., which is a coefficient that determines the rate of change over time within a particular location x
K : the carrying capacity (the maximum possible volume of I at a given location x)

We also set the initial function to be always equal or greater than zero, and the lower and upper boundary condition such that tweets are clustered within a single location x. Among the notations, we are the most interested in the value of advection parameter $g(x)$ because it represents the magnitude of information shifted *across locations* due to the examined force. MATLAB was used to fit the data to the model.

4. METHODS

4.1 DATA COLLECTION

Twitter public streaming API was used to collect the real-time data with a search keyword “Egypt” between January 25 and February 20th, 2011 (EST), eight times per day, for an hour per each session. Through this process, a total of 50,778 Twitter user IDs were identified. Using the identified user IDs, we developed a backtracking API to retrieve all their posted content and perform the keyword search to sort out relevant tweets. Most of tweets before January 24th were irrelevant to the revolution, and the volume of tweets decreased from February 14th. Accordingly, the time window between January 24, 2011 and February 13, 2011 was chosen for the investigation.

4.2 Message Types

To explore whether different message types show different diffusion patterns, three types of messages were defined: ad-hoc reporting, situation verifying information, and action-supportive messages, developed based on the previous literature [25,26]. We selected 5% of collected data by daily-volume based stratified sampling and had three coders categorize the selected tweets’ message type, with Cohen kappa ranged between .709 and .732 (Table 1).

Table 1. Message Types.

Type	Definition
Ad-hoc reporting	Provides firsthand observation without presenting any supporting materials; Includes an immediate update about a situation or problem *without* providing additional sources
Situation verifying	Provides information verified or supported by a third-party such as mass media, officials, governments, and advocacy organizations, or with solid supporting evidences such a photo, video, and interviews, etc.
Action supportive	Either one of the types: (1) An emotive expression of unity with the movement, a sense of belonging to protest communities, and/or opposition to the regime was included in this category; (2) Sharing of action-related skills, knowledge, or tactics. If ad-hoc reporting or verifying information comes along with the action-supportive message, we gave a priority to this category and coded the tweet as an action-supportive message.

4.3 Geo-location Classification

Tweet geo-location was manually coded based on user’s self-disclosed place cues, including profile, additional contact info available personal websites or other social media pages hyperlinked to the profile, location cues revealed via locative apps, and other cues indicative within tweet messages. Although a self-report bias is possible, we could trace 82% of the identified users’ information self-disclosed information. While we originally coded them on a country-level, we recoded by combining them into a region-level. The region-level aggregation was based on two reasons: First, the data about international relations factors – the necessary information to define proximity in this study –were not available for each single country. For example, Egypt’s bilateral economic relations were available only for a few countries. Likewise, Egyptian migration data was available only for some countries. Such data were instead available in the aggregate on a regional level. Second, many countries produced too few tweets to be reliability fitted to the model. However, the proportion of tweets from these minority countries altogether was nontrivial.

Accordingly, rather than excluding the countries that either did not allow international relations data or generated small numbers of tweets, we decided to recategorize geo-location information by abstracting them into a global regional level. As a result, eight locational points were categorized: Egypt (Origin nation), Western Europe (WE), Eastern Europe (EE), North America (NA), Latin America/the Caribbean (LA), Asia/Australasia (Asia), Middle East/North Africa (MENA), Sub-Saharan Africa (Africa).

4.4 Defining spatial proximity based on international relation factors

Egypt was the origin location x_1. To arrange spatial "proximity" of each regional point U (x_1, x_2 …x_8) from Egypt, we defined the proximity in four different ways based on each international-relation factor. First, physical proximity: a region geographically proximate to Egypt is considered to be "closer" to Egypt than the regions geographically far. Thus, the spatial arrangement based on the geographic proximity was, $U_{physical}(x)$ = {Egypt, MENA, EE, WE, Africa, NA, Asia, LA}. Second, diasporic proximity assuming that a larger migration community would induce greater contact frequencies, with the arrangement of $U_{disapora}(x)$ = {Egypt, MENA, WE, NA, Asia} (missing regions have no information). Third, economic proximity measured by bilateral economy trade ties with Egypt, $U_{economic}(x)$ = {Egypt, MENA, WE, NA, Asia, Africa, Asia, LA}. Lastly, ideological proximity, assuming that the more democratic region to be more influential to (thus "closer" to) Egyptian protesters, $U_{ideology}(x)$ = {Egypt, NA, WE, LA, EE, Asia, Africa, MENA}.

The democracy data for ideological proximity were acquired from Economist Intelligence Unit Report (2010), as a composite by averaging each country's democracy score within each region. The Egyptian International Trade Point (2010) and Migration Policy Centre (2009) provided the region-level data about economic trades and migration population. The most updated data prior to the revolution were referred.

5. RESULTS

We validated the model with 36 sub-datasets split based on three different message types, four spatial arrangements, and three time frames (3 x 4 x 3 = 36). The accuracy of the model fit was measured by the difference between the predicted value against the actual observed value as:

accuracy=1 - (|predicted value-actual value|)/(actual value) (2)

In modeling, we controlled the effect of Internet penetration on diffusion process by using the residual values as a dependent variable (*I*). Residual values were computed as the difference between observed and predicted value from the regression of the raw tweet volume on each region's Internet penetration rate. The accuracy rates ranged between 70.62% and 94.11%. PDE-based diffusion model with an average of 75% prediction accuracy has been discussed as acceptable [26].

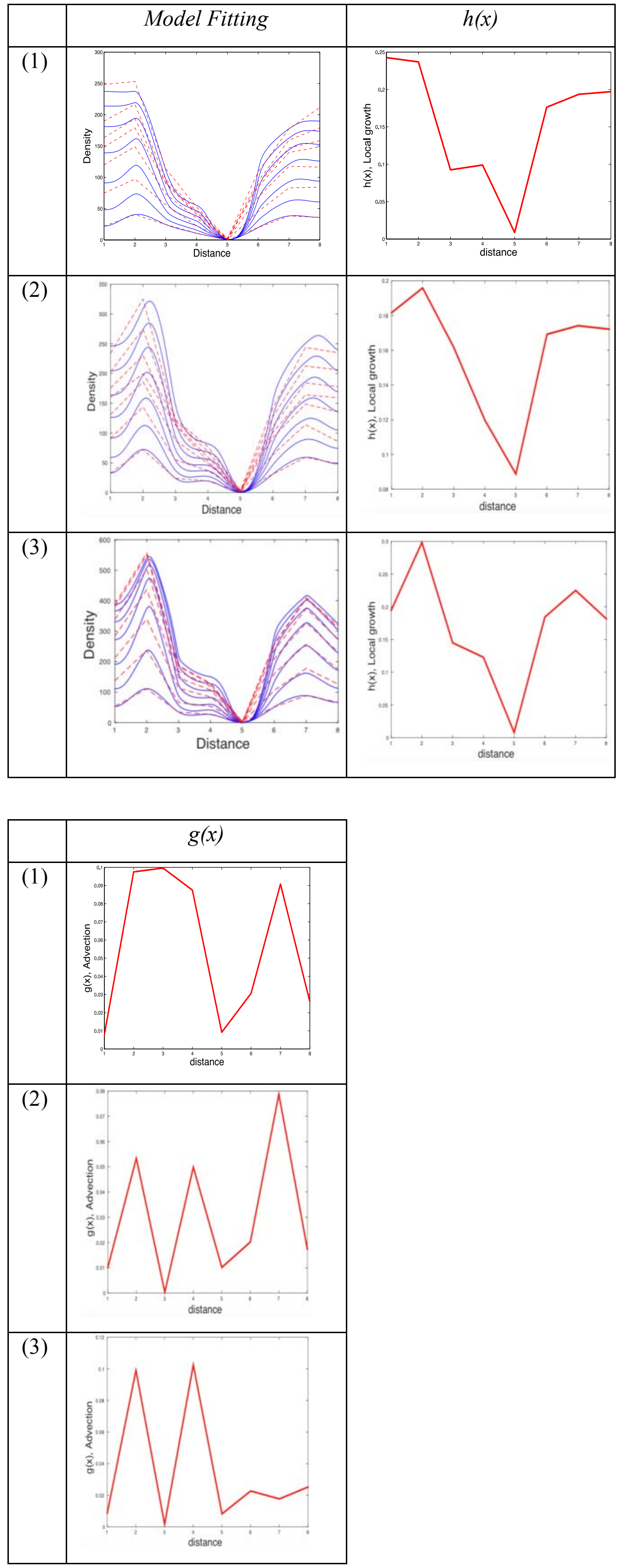

Figure 1. An example of the simulation results from the ideology proximity-based (i.e., democracy ranks) arrangement during the active protest period (2/1~2/7). (1) Ad-hoc

reporting, (2) Situation verifying messages, and (3) Action-supportive messages. Across all graphs, *X*-axis represents location points, with the origin point as Egypt. In *Model Fitting* graphs, the Y-axis represents residual tweet volume values (Density, *I*), with blue lines denoting the observed values and the red lines the best fitting value. In *h(x)* graph, Y-axis represents average coefficients of within-location diffusion rate. This is the endogenous, local growth rate. In *g(x)* graph, Y-axis represents average coefficients of cross-location diffusion rate. It is the external, advection rate. The advection value of each location is affected not only by the density of the location but also by the density of its neighboring location.

Figure 1 presents an exemplary graphical summary of model-fitting, local growth, $h(x)$, and advection tendency, $g(x)$, resulted from the ideology (democracy)-based distance arrangement. The patterns of $h(x)$ were almost parallel to the predicted lines (red dotted lines) in the model-fitting graphs, indicating that the variations of data were largely explained by the local growth within a specific location point. The addition of the advection term, however, resulted in the highest accuracy of the models, and the pattern of $g(x)$ reflected the rate of change from x to $x+1$.

To compare spatial diffusion rate among different proximity arrangements, we introduce the following weighted mean (WM) of $g(x)$. The rationale for multiplying (maximum distance +1 – x) is to give more weight to the ones that are closer to the origin (Egypt), assuming that the closer it is to Egypt the more "influential" it should be. As such:

$$WM = \sum g(x)(MaximumDistance+1-x) \quad (3)$$

The WM results suggest that the ideology proximity (i.e., *democracy-based distance* arrangement) was the most effective to address spatial spread-ability, consistently across all communication types and time windows (Table 1).

Table 1. Spatial Spread-ability: Bold is the highest values of *WM* for the advection parameter g(x).

Message	Proximity	Time Windows		
		Beginning Period (1/25~1/31)	Active Protest (2/1~2/7)	Regime Turnover (2/8~2/13)
Ad-hoc Reporting	Ideology (Democracy)	**0.98**	**2.13**	**1.74**
	Physical	0.26	0.40	0.38
	Diaspora	0.09	0.18	0.19
	Economic	0.24	0.03	0.03
Situation-verifying	Ideology (Democracy)	**0.95**	**0.98**	**0.95**
	Physical	0.32	0.40	0.31
	Diaspora	0.10	0.24	0.10
	Economic	0.30	0.03	0.32
Action-Supportive	Ideology (Democracy)	**0.95**	**1.44**	**0.68**
	Physical	0.32	0.30	0.16
	Diaspora	0.09	0.19	0.10
	Economic	0.31	0.03	0.32

In particular, the WM values for ad-hoc reporting and situation verifying messages were particularly larger during the *active protest* period (2/1 ~ 2/7) than any other time windows, implying that the transnational diffusion of protest information was more intensive during this time period. In contrast, the spread-ability of situation verifying message were relatively stable across all time periods (Figure 2).

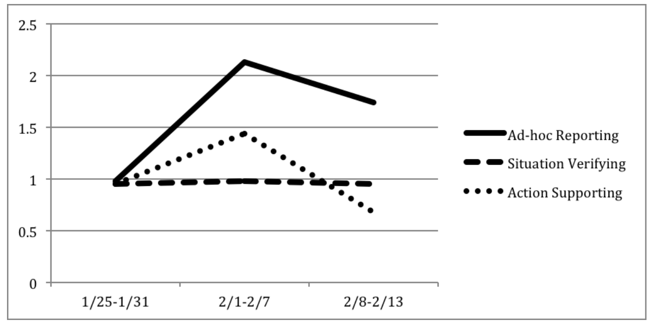

Figure 2. Comparisons of Weighed Mean of *g(x)* (WM) across different message type and time windows, when modeled by democracy-based proximity. Y-axis refers to WM values.

6. CONCLUSIONS

This paper attempts to develop a spatiotemporal diffusion model called "diffusion-advection model" to understand social movement information diffusion processes across networked global public. We developed a model under the premise that transnational social media mobilization is not disparate from existing global dynamics. To consider spatial patterns as well as temporal changes, we developed the model based on partial differential equations. We proposed to arrange spatial "proximity" between the origin protest country (Egypt) and other global regions in various ways according to their physical, ideological, economic, and diasporic relations with the origin country. The analytic focus of this study was on the spatial diffusion process, represented by the parameter associated with the advection term, *g(x)*.

While the observed data distribution was mostly explained by the local growth function – possibly because this logistic function is the baseline time-variant diffusion model –the results associated with the advection term suggest that online public's engagement from high democracy might play an important role in facilitating spatial diffusion. Interestingly, the "spread-ability" of ad-hoc reporting and action-supportive messages was particularly large during the active protest period. While these types of messages are seemingly pertinent to offline mobilization and participation, for example real-time information sharing from on-street scenes (ad-hoc reporting) and information sharing on how to coordinate offline actions (action-supportive messages), the results imply that these types of messages were actually widely exchanged across geographical boundaries. In particular, the more quickly protest ideas catch on in democratic regions the more widely they are likely to be propagated to the wider audiences. In contrast, the WM values of situation verifying messages –presumably mostly mass media coverage – remained similar across different protest time windows, suggesting that the spatial diffusion of this type of message might have been less affected by the progress of the protest. One possible explanation is that differences in the nature of information, i.e., user-generated versus media institution-originated, might affect diffusion rates in social media. For example, local, regional, and global media institutions could play a role in producing differences. Uncovering such media institutional effects is beyond the scope of this paper, calling for future research.

Some limitations must be noted: First, while democracy was found to be the dominant factor to facilitate transnational information diffusion, the results must be understood within the context where the data was collected and processed. If the data included tweets about other Arab countries' protests, or if the analyses were based on a country-level as opposed to the regional-level, geographical proximity might become more prominent than in the current results. There is a possibility of "modifiable area unit problem (MAUP)," which future studies should keep in mind. Second, this study treated external factors (proximity determinants) independently. Interdependence among the external factors may be worth considering in future research. Also, our modeling was primarily deterministic. Stochastic approach is beyond the scope of our research.

Despite some limitations, the current study presents an innovative approach to explore spatiotemporal diffusion of social movement information in social media contexts. The proximity arrangement $U(x)$, can be flexibly defined contingent on research purposes. For example, geographic/physical distance may be the default $U(x)$, when no other external influence source is known. Alternatively, mass media penetration – which has been known as an important external influence in innovation diffusion –could be another factor to define $U(x)$ if relevant data is given. Given the paucity of mathematical diffusion modeling in the scholarship of social movements and protests, the current study contributes to advance formal explorations of information diffusion patterns. As statistical or mathematical models generally do, a formal modeling allows researcher to predict the future: A model is proposed based on theories and theorems and is fitted to an existing empirical data retrospectively to validate the model accuracy. Then, the parameters computed from the empirical modeling can be applied to predict the trajectory of a similar type of events in future, for which the data may not yet available. Especially, the PDE-based model is a novel approach to information diffusion, taking advantages of simultaneously considering space and time dimensions.

7. ACKNOWLEDGMENTS

This paper is supported by the NSF grant CNS #1218212.

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