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Geographical Variability as a Determinant of Large-scale Network Structure*

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It is a well-established result that the marginal probability of a social tie between two persons declines with geographical distance for a wide range of social relations (see, e.g., Bossard, 1932; Zipf, 1949; Festinger et al., 1950; Hägerstrand, 1967; Freeman et al., 1988; Latané et al., 1995; McPherson et al., 2001). While often regarded as a mere curiosity, others have argued that this relationship is a critical determinant of social structure (Mayhew, 1984). Indeed, Butts (2003) has shown that under fairly weak conditions, spatial structure is adequate to account for the vast majority of network structure (in terms of total entropy) at large geographical scales.

Spatial Network Models

The simplest family of network models to incorporate this notion is the family of spatial Bernoulli graphs, defined by pmfs of the form

$$\Pr\left(Y = y \,|D\right) = \prod_{\{i,j\}} B\left(Y_{ij} = y_{ij} \,|\mathcal{F}\left(D_{ij}, \theta\right)\right), \qquad (1)$$

where Y is the (random) graph adjacency matrix, D is a matrix of inter-vertex distances, B is the Bernoulli pmf, and $\mathcal{F}$ is a function taking distances into the $[0, 1]$ interval (parameterized by real vector θ). In this context, $\mathcal{F}$ is referred to as a *spatial interaction function*, and can be interpreted directly as providing the marginal probability of a tie between two randomly selected individuals at some given distance. It can immediately be observed that this family is a special case of the inhomogeneous Bernoulli graphs (w/pmf $\Pr(Y = y|\Phi) = \prod_{ij} B(Y_{ij} = y_{ij}|\Phi_{ij})$), with parameter matrix Φ given by $\Phi_{ij} = \mathcal{F}(D_{ij}, \theta)$. Models of this form have been studied in the context of geographical distances by Butts (2002); Hipp and Perrin (2009); Butts and Acton (2011), and are closely related to the latent space models of Hoff et al. (2002); Handcock et al. (2007). They can also be viewed as special cases of the family of gravity models (Haynes and Fotheringham, 1984), which have been used for several decades in the geographical literature to model interaction between areal units. Butts (2006) has further shown that the spatial Bernoulli graphs can be written as a special case of a more general curved exponential family of graph distributions. By defining canonical parameters $\eta\left(\theta, d\right) = \mathrm{logit}\mathcal{F}\left(d, \theta\right)$, we may write the pmf for adjacency matrix Y with support $\mathcal{Y}$ as

$$\Pr\left(Y = y \,|D, \theta, \psi\right) \propto \exp\left[\sum_{\{i,j\}} \eta(\theta, D_{ij}) y_{ij} + \psi^T t(y)\right], \qquad (2)$$

where $\psi \in \mathbb{R}^p$ and $t : \mathcal{Y} \mapsto \mathbb{R}^p$ are respective vectors of parameters and sufficient statistics. The incorporation of additional statistics (via t) allows for the combination of both spatial and non-spatial effects (e.g., endogenous triangulation, as explored in recent work by Daraganova and Pattison (2007)).

Implications for Cross-Sectional Structure

Employing this model family with population data from the U.S. Census, we have explored the impact of geographical variability on the structure of large-scale interpersonal networks. A basic observation regarding the distribution of humans across geographical space is that this distribution is extremely heterogeneous. Even leaving aside the contrast between inhabited lands and uninhabited oceans (comprising the majority of Earth's surface area), settlements are typically concentrated in a small set of regions having desirable geological, hydrological, and resource access properties. Within these regions, the resulting settlements are of extremely uneven size, distribution, and structure (Zipf, 1949; Brakman et al., 1999; White et al., 2008). Contrary to the intuition of an evenly inhabited Earth, then, humans are distributed unevenly across a wide range of geographical scales. This variability has important consequences for network structure.

As expected, the wildly unequal distribution of population across space leads to dramatic differences in local connectivity and tie volume. This is graphically illustrated in Figure 1, which shows simulated ties among individuals in blocks near the center of Cookeville, TN based on a model calibrated to data on friendship ties. While activity is present throughout the region, the intense clustering of persons in blocks like that near the center of the figure creates a corresponding social cluster whose members have both higher mean degree and who are on average more cohesively connected than those in nearby blocks. Even at scales on the order of 1km, we thus expect to see substantial heterogeneity in structural characteristics that are driven in part by geographical variation.

The unequal concentration of tie volume can have subtle implications for cohesion. For instance, Figure 2 shows the convex hulls covered by members of cohesively connected subsets of the 2-core of the Cookeville, TN network. We have shown that such groups develop relatively suddenly when a sufficiently large area exceeds a characteristic threshold density; the location of large cores "covering" the high-density regions of the figure is emblematic of this behavior. Such spatially large cohesive sets are of potential interest for theories such as those of Sampson et al. (1997), which relate to the

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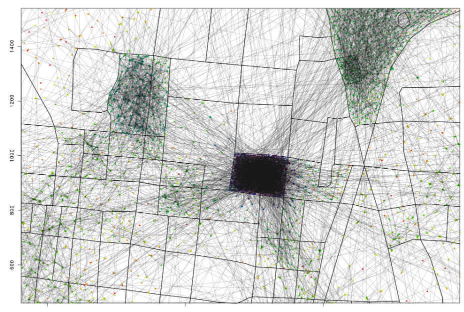

Figure 1: Detail of Edge Structure (Quasi-random Placement, Friendship Model), Cookeville, TN

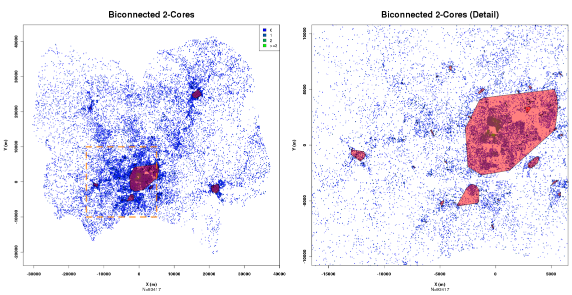

Figure 2: Spatial structure of cohesive components, Cookeville TN MSA (uniform placement, Friendship SIF). Shaded regions indicate convex hulls of membership locations for biconnected sets of k-core members, with pink shading indicating 2-cores, and green indicating 3-cores. Right-hand panel shows detail of dotted area.

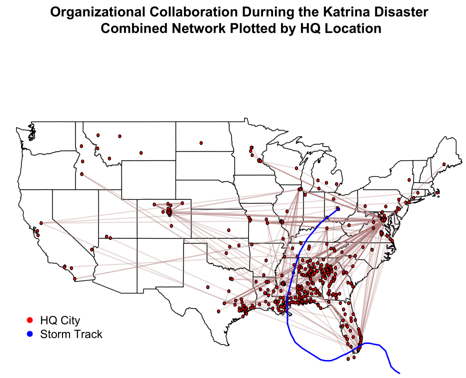

Figure 3: Katrina EMON, with organizations placed by HQ location; blue line depicts storm track.

ability of social groups to monitor and control activities within a given area. Models of the kind studied here suggest a relatively sharp boundary between the conditions under which such cohesion is feasible, and those under which it is not.

Implications for Network Dynamics

It should be emphasized that the effects of geographical variability are in no way limited to the static case. For instance, we have also investigated the role of geography in shaping the emergent multi-organizational network (EMON) of collaborative relationships that formed in response to the 2005 Hurricane Katrina disaster. Figure 3 depicts the headquarter locations of the 1,577 organizations mobilized within the first 13 days following storm formation, with edges connecting those organizations who were observed collaborating on response related tasks during the period. As shown by Butts and Acton (2011), pre-disaster headquarter location is a strong influence on tie formation, even given the dynamic nature of the network.

This marginal relationship does not tell the whole story, however. Modeling of the dynamics of the Katrina EMON reveals that factors such as proximity to the evolving storm track (Figure 3, blue curve) were important predictors of mobilization in the disaster, with immediate effects on tie formation. Thus, not only was the distribution of organizational headquarter locations important as a general factor encouraging or inhibiting collaboration (in the sense of a global propinquity effect), but this distribution was also consequential in determining which particular organizations were mobilized at any given time (and, hence, which pairs of organizations were *available* for collaboration). Where networks emerge in response to events that are localized in time and space, the geographical properties of the events themselves become significant influences on network structure. These influences may manifest themselves both in effects on the propensity of actors to form or dissolve ties, and on the likelihood that particular actors will be active in the first place (a powerful and generally underappreciated determinant of network structure).

Summary

Our experiments with extrapolative network simulation using detailed population data have shown that spatial variability exerts substantial influence on network structure at the settlement level. The highly uneven density of population within typical settlements results in "lumpy" networks that are characterized by regions of differential local connectivity, spatially correlated gradients of expected degree and core number, and other such properties. At small spatial scales, then, we predict that the character of the local structural environment will – for many types of relations – depend heavily on local population distribution.

While spatial heterogeneity does induce substantial within-network heterogeneity, we also observe that geography drives many aggregate network properties in a predictable way. For the relatively proximate relations we have examined in our work, properties such as aggregate mean degree, edge length, and local clustering can be well-predicted by the mean nearest-neighbor distance, together with SIF-specific factors. This implies that, for these sorts of relations, it should be possible to predict differences in a number of aggregate structural properties from fairly basic features of the underlying social geography.

The study of geographical effects on network dynamics is still in its infancy, owing in large part to a lack of available data. However, we have found in studying cases such as the Katrina EMON that the spatial distribution of both actors and external stimuli (e.g., an evolving hazard) can shape tie formation and the dynamic composition of the vertex set. It is clear that both types of effects will need closer study before their impact on network evolution can be well-understood.

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Towards Web-Scale Geo-Semantic Crowd Discovery

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Introduction and Opportunity

There is a growing need to fundamentally advance research for enabling a new generation of applications for monitoring, analyzing, and distilling information from the prospective web of real-time content that reflects the current activity of the web's participants. Highly-dynamic real-time social systems like Twitter, Facebook, and Google Buzz have already published terabytes of real-time human "sensor" data in the form of status updates. Coupled with growing location-based social media services like Gowalla, Foursquare, and Google Latitude, we can see unprecedented access to the activities, actions, and trails of millions of people, with the promise of deeper and more insightful understanding of the emergent collective knowledge ("wisdom of the crowds") embedded in these activities and actions. Toward the goal of web-scale social media mining and inference, our lab (http://infolab.tamu.edu) is pursuing a set of related research activities, two of which are briefly described here: (i) Identifying and tracking the evolution of semantic crowds; and (i) Social media location estimation.

Identifying and Tracking the Evolution of Semantic Crowds

First, we believe that "crowd-based" information holds the key to effective modeling and understanding of the real-time web. A single user action—for example, posting a picture of a smoke plume to Flickr—though perhaps interesting itself, does not convey a strong community or social-based importance to the user action. In contrast, a flurry of activity associated with a "crowd" is a strong indicator of an emergent online phenomenon that may be worth identifying and directing to interested users. We refer to these ad-hoc collections of users that reflect the real-time interests and affiliations of users as semantic crowds. Unlike the more static and perhaps staler group-based membership offered on many social networks, semantic crowds are naturally organic and reflect highly-temporal group affiliation.

Identifying coherent crowds in real-time from the massive scale of the real-time web across a collection of non-obviously connected user actions is a major challenge. Considering Twitter alone, there are potentially 100s of millions of active users inserting new messages into the system at a high-rate. Concretely, we consider three overlapping crowd perspectives: (i) communication-based, reflecting groups of users who are actively messaging each other, e.g., users coordinating a meeting; (ii) location-based, reflecting groups of users who are geographically bounded, e.g., users posting messages from

Houston, Texas; and (iii) interest-based, reflecting groups of users who share a common interest, e.g., users posting messages about a presidential debate. While each of these crowd perspectives can be studied separately, in many cases it will be important to study cross-cutting crowds, e.g., users in Houston (location-based), messaging each other (messaging-based) about a local fire (interest-based). In addition to identifying a crowd at a point-in-time, we must additionally track the crowd over time as users join, crowds merge, and disband (as in Figure 1).

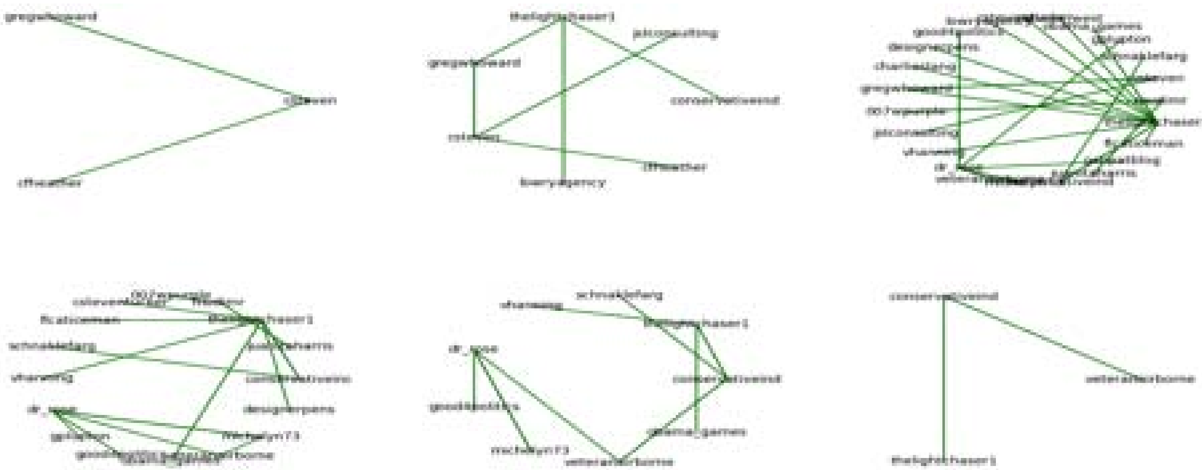

Figure 1: Example crowd growth and dispersal over 6 hours on July 23, 2010

Social Media Location Estimation

Second, the potential of social media as a medium for geospatial and temporal research is potentially limited by the aversion of participants to engage in and use location-revealing technologies. The increasing popularity of location-based social media (including Facebook Places, Google Latitude, Foursquare, etc.) belies the slowness of the vast majority of social media users to adopt geospatial features. To illustrate, in a random sample of over 1 million Twitter users, we find that only 26% of users have listed a location as granular as a city name and that fewer than 0.42% of all tweets actually use geotags. To overcome this location sparsity problem and to support our overall objectives of web-scale social media mining, we believe it is necessary to develop novel algorithms for automatically estimating a user's location through an analysis of the publicly-available data in a user's profile and the social media community itself. By relying only on publicly-available data, these algorithms can be generalized across social media sites and future human-powered sensing systems for providing accurate and reliable location estimation without requiring expensive or proprietary data from system operators or privacy-sensitive data from users.

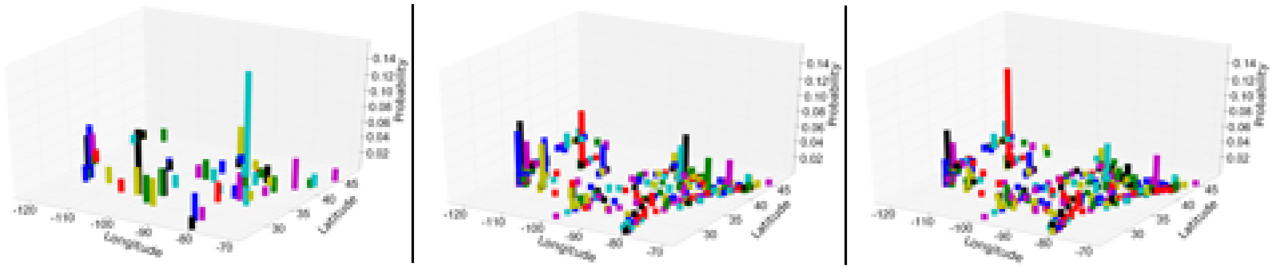

Figure 2: Example: Location Estimation Convergence as Number of Tweets Increases

As an illustration, we have built a simple probabilistic model that estimates the likelihood of a user in a particular location "emitting" a word. By aggregating over all of the words that a particular user posts (e.g., on Twitter), we can infer the user's most likely location. In essence, the hope is that as a user continues to tweet, more location-sensitive information is "leaked" which can be used to refine the user's location estimation. We find that the location estimates converge quickly (needing just 100s of tweets), placing 51% of Twitter users within 100 miles of their actual location. Figure 2 illustrates the increasingly refined geo-location estimate for a test user with an actual location in Salt Lake City, converging after only 500 tweets.

By augmenting the enormous human-powered sensing capabilities with algorithmically-derived location information, this framework can overcome the sparsity of geo-enabled features in these services and bring enhanced scope and breadth to emerging location-based personalized information services. This in turn could lead to even broader applications of social media in time-critical situations such as emergency management and tracking the diffusion of infectious diseases.

Social Network Interaction among Nested Sets in Dynamic Contexts: Disaster Operations as a Laboratory for Social Change

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Disaster operations represent a classic laboratory for the study of social network interactions that are constrained by both space and time and that involve multiple modes of communication. Further, these interactions vary significantly at different levels of authority, capacity, and severity of damage to the affected community. At each level of operation, differences in resources, number of skilled personnel, extent of prior knowledge, and experience affect significantly the frequency and type of interactions among organizations in a given community as well as access to outside sources of assistance, and potential strategies for reducing risk and minimizing losses.

One means of extending theories of social network interaction to incorporate the constraining effects of space, time, and different modes of communication on organizational interaction is to address these problems through the lens of complex, adaptive systems. From this perspective, a system is composed of multiple subsystems, many of which include sub-subsystems, nested inside one another, but sharing common goals. These "nested sets" can easily be identified in large-scale disaster operations. For example, in Haiti, the primary actors in delivering public services to quake-shattered Haiti was a set of large, powerful, NonGovernmental Organizations (NGOs) that drew resources from an international donor base and created an organizational operations environment that functioned largely in parallel to, rather than with, the Haitian Government. While the Haitian Government was struggling to resume its limited and fragile delivery of public services, it was heavily outspent and surpassed in performance by international NGOs operating largely in English, instead of the language of the country, French. The inability to track exactly who was doing what tasks in which regions of Haiti now ten months after the earthquake reveals the critical importance of spatial analysis. The interdependence of the tasks that were performed . . . or not performed . . . and the consequences of both types of action shows the key spatial and temporal relationships among actions taken or not taken.

Three streams of literature inform the study of social network interaction in complex systems. First, the Institutional Analysis and Development (IAD) framework proposed by Elinor Ostrom (2005) acknowledges the interaction of social units at different scales of operation within the same broadly defined social system. By identifying a domain of action, for example, disaster preparedness, response, and recovery, Ostrom notes that different "action arenas" will likely emerge in response to an urgent event at different times and places in an ongoing social process. Within those arenas of action, different "action situations" will emerge that require different response operations that are appropriate to that specific community or context. Ostrom's framework can be used to study the complex problem of interacting "nested sets" in which a given stressor, e.g. an earthquake, triggers action in different geographic locations and generates a cascading effect of failure or informed response in a social and engineered environment.

Second, the concept of "distributed cognition" (Hutchins, 1995) holds that, in complex operations, no single person, unit, or organization has all of the knowledge and skills necessary to manage that operation successfully. Rather, knowledge is generated by multiple persons, units, organizations sharing their perspectives and essentially creating new knowledge that supports informed action to achieve the shared goal. Recognition of the distributed nature of relevant information to support rapid response to disaster events is critical to mobilizing informed, timely response and recovery.

Third, the concepts and measurement underlying "dynamic network analysis" (Carley, 2006, 2001) are central to understanding the complex interactions among organizations of different sizes, scopes of action, and access to resources that characterize disaster operations. Networks of action mobilize, shift, change, and adapt . . . or fail to do so . . . under the changing requirements of a severely damaged community following disaster. Understanding this process and seeking to provide timely, valid information to guide action in damaged environments represents a challenging set of technical and organizational tasks. These three concepts can be integrated through the design and development of a "knowledge commons" (Hess and Ostrom, 2006) that can be developed as an ongoing source of timely, valid information to support action. The critical aspect of a knowledge commons is that information is not only organized around a shared set of goals and actions, but that it is updated and revised as its users gain a better understanding of the problems they encounter. The "knowledge commons" does not perform merely as a database of stored, static information. Rather, it includes the entire process of eliciting information from users, formatting it for readily accessible information exchange to relevant users, and updating the knowledge base as conditions and requirements change in a dynamic environment. The task of creating a knowledge commons for specific domains of organizational action involves both spatial and temporal constraints. The critical difference is that the knowledge commons is designed to support collective action, not simply to inform individual actors. By informing collective action, this process also generates new knowledge in the process.

As government agencies and organizations move to record their operations logs through electronic means, the process creates new sources of data that can be analyzed in ways that document changing patterns of action and interaction among organizations participating in response operations. These electronic logs and situation reports, given appropriate permissions for access to researchers, provide an important source of information for analysis. Such records provide more reliable data to analyze points at which networks of action are effective or fail.

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Relational ontologies, power relations and media convergence

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My interest in this field of intellectual endeavour is situated at the intersection of geography and media and cultural studies. In particular, I am interested in the ways in which digital social networks and other convergent media, including Google Earth, Facebook and Twitter, are shaping everyday experiences of space and place in dynamic and complex ways and the potential of these technologies for forging social transformation and new modes of cultural citizenship, particularly among marginalized populations in the global South and elsewhere.

The development of media geography (geography's engagement with media and cultural studies) and the spatial turn within media and cultural studies potentially enable the two most vibrant subdisciplines of geography, namely critical cultural geography, on the one hand, and GIS and geospatial technologies, on the other, to find points of intersection and areas of mutual collaboration. A growing body of literature by a number of scholars including Crampton, Dodge, Goodchild, Graham, Kitchin, Sui, Kwan, and Zook attests to this development. The theoretical barriers to such collaboration are also well documented and geographers have highlighted the influence of different philosophical traditions and understandings of the concept of ontology. I would like to contribute three main themes that I feel are pertinent in terms of developing interdisciplinary research on the spatio-temporal constraints of social networks.

Social networks are actor-networks. It is important to consider the difficulties which arise when social networks are modelled using techniques developed to model infrastructural or biological networks. The complex, dynamic and shifting spatialities of social networks are potentially less amenable to algorithmic calculation. This is a particularly difficult problem given that the media effects argument (i.e., the idea that media have measurable and therefore predictable effects) has been deeply challenged. Media "effects" if they exist are also multidirectional, with users shaping media just as media shape users. Similarly, distance and proximity are themselves relational outcomes without any fixed and measurable status. Even if distance and proximity can be measured in minutes or kilometres, these measurements usually matter less than the level of connectivity. Social networks should therefore be understood as actor-networks in which outcomes, including distance and proximity, are relational and therefore often unpredictable. How can we account for the (sudden) enrolment of new actants? How can we account for the moments in which media consumers suddenly become media producers? How could computer models account for the fluidity and dynamism of user driven creativity which constantly creates new limitations or disrupts old ones? What might GIScience, in its attempts to understand the spatio-temporal constraints of social networks, look like if it started to move towards relational and non-essentialist ontologies, embracing the insights from STS and ANT?

Social networks are embedded in power relations. The new media environment and the development of digital social networks are clearly providing new forms of connectivity which overcome to some extent the constraints posed by time and space. It is clear that convergent media technologies such as YouTube, Twitter, Facebook, Google Earth and cell phones are being used in socially and politically transformative ways in many places and by a range of differentially situated users, including people who are socially and economically marginalized or who are working to contest marginalization (e.g., indigenous peoples, immigrant communities, disenfranchised voters, civil society organizations in the global south). Users are however constrained by a range of proprietary regimes, the digital divide, affordability and access to the technology, the rapidity of technological change and the ways in which information can be lost and buried in the Web 2.0 environment and thus lose or fail to gain social or political effectivity. In part, this unevenness comes about because digital social networks, like any social networks, are embedded in complex and shifting relations of power, shaped by gender, class, race/ethnicity, geographic location, and access to technology, which are necessarily contested. Furthermore, while new media technologies facilitate new possibilities for connection and social transformation, they also facilitate new modes of surveillance and monitoring that are not always benign. The disciplines of geography and anthropology have recently been subject to substantial controversy, given the growing linkages between military geospatial applications and geographic and anthropological research (human terrain mapping, the controversies surrounding the Bowman expeditions). So how do we gain understanding of the spatial-temporal constraints of social networks while remaining cognizant of shifting power relations? Could a more topological approach enable us to get to grips with the power relations of social networks?

Digital social networks exist in a convergent media environment. Digital social networks (the Internet, GIS) are converging with other media in complex ways. On the one hand, the digital social networks which form for example around "old" media such as television drama show many similarities and continuities with the face to face discussions which prior to the Web 2.0 environment took place in workplaces and other sites of everyday face-to-face interaction, although they take place across vastly enlarged spatial and temporal frames. On the other, phenomena such as reader-generated visualizations and mash-ups, which find their way into established newspapers' online content have dramatically transformed the ways in which we read and use "newspapers." Both of these convergent media forms clearly overcome a number of spatial and temporal constraints in that people can participate over much larger time-spaces, can do so with a range of media platforms (Internet, television, cell phones, radio etc), can interact with a greater number and diversity of people, and leave digital traces of themselves over time which others might pick up in important ways. Consequently, the interactions become less fleeting and the network potentially more robust and resilient. While crowd-sourced data are sometimes used by media corporations to enhance profits, media content becomes more user driven and is potentially more resonant with the social, political and cultural investments in such media by users/viewer participants. However, the Web 2.0 environment creates its own constraints and limitations, which include the fragmentation of the media environment (a phenomenon that co-exists with media convergence) and the potential excess of information that users face. How might the concept of media convergence inform the debates which are under discussion at this meeting? What are the points of connection and distinction between the concepts of media convergence and meta-network? How might the established scholarship in media and cultural studies on media convergence and on everyday life inform our understandings of the spatio-temporal constraints in social networks?

Influence Propagation in Adversarial Social Network—Impact of Space and Time

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The goal of a major DoD project (Minerva), currently underway at Arizona State University, is mapping the diffusion and influence of counter-radical Muslim discourse across various parts of the world. The project team include Social Scientists, Ethnographers, Mathematicians and Computer Scientists. Data collection and analysis for the project is being carried out by the team members in four different continents—North America, Europe (Germany, France, Britain), Africa (Niger) and Asia (Indonesia). The objective is to map the size, scope, and spectrum of the social, religious, and political characteristics of radical/counter-radical Muslim networks in Southeast Asia, West Africa, and Western Europe. As a part of this study, we have collected over 800,000 documents from Indonesian web sites and with assistance from the Social Scientists in our team, identified organizations engaged in radical and counter radical activities. Based on agreement and disagreement of their beliefs and practices, we constructed a multi-graph where the nodes represent radical/counter-radical/neutral organizations and a labelled edge represents agreement/disagreement between them. Utilizing this graph, we plan to understand *influence propagation mechanism through these networks and devise strategies to isolate the radical organizations and minimize their influence*.

Social Network Theory provides the framework within which studies on influence propagation through social media can be undertaken. Due to its application in many different domains, influence propagation through Social Networks has emerged as an important area of research in recent times and a significant amount of research in *influence propagation model* has been carried out in sociology, economics and computer science communities [1, 5, 7, 8, 10–13, 15]. Models such as *linear threshold* [5, 14], *independent cascade* [4, 9] and *decreasing cascade model* [8] have been studied in the computer science community and their effectiveness evaluated. *However, all these models do not take into account presence of an adversary in the social network, whose goal is to prevent diffusion of ideas that an opponent is trying to promote.*

We illustrate the point with the help of a simple example. Suppose that the Coca-Cola company comes up with a new Coke (NewCoke) and attempts to sell its product through viral marketing in a social network, such as Facebook, with the slogan *"NewCoke is great."* The influence propagation models studied so far, such as *linear threshold*, *independent cascade* and *decreasing cascade model* provide means to identify the nodes that are *more influential* than others, so that influencing these "important" nodes will result in larger acceptance of the idea that "NewCoke is great" in the social networking community.

However, if Pepsi, an adversary of Coke, wants to confront Coke in an attempt to contain spreading of Coke's message with its own *"Pepsi is better,"* the models such as *linear threshold*, *independent cascade* and *decreasing cascade model* do not have any mechanism to capture impact of adversaries in the influence propagation model. Clearly, influence propagation will be significantly different in *absence* or *presence* of an active adversary.

The adversarial scenario discussed here cannot be modeled by the known diffusion techniques for an important reason. In the traditional diffusion models, each node *u* in the social network is in one of following two states: (i) *u* has adopted innovation *I* and (ii) *u* has not adopted innovation *I* but *u* is open to the idea of adoption. In presence of an adversary who is not only trying to dissuade *u* adopting innovation *I* but actively trying to persuade *u* to adopt a competing innovation *J*. In this case, each node *u* in the social network graph can be in one of following three states: (i) *u* has adopted innovation *I*, (ii) *u* has adopted innovation *J*, and (iii) *u* has not adopted has not adopted innovation *I* or *J* but is open to the idea of adopting either one of them. This scenario can be visualized by coloring the nodes of the social network graph $G = (V,E)$) with *blue* if they adopted *I*, with *red* if they adopted *J* and with *green* if they have not adopted either *I* or *J*, but open to the idea of adopting either *I* or *J*. As the diffusion process progresses over time, by observing changing color of the nodes of the graph, one can infer if innovation *I* (or *J*) is being adopted by the members of the social network $G = (V,E)$.

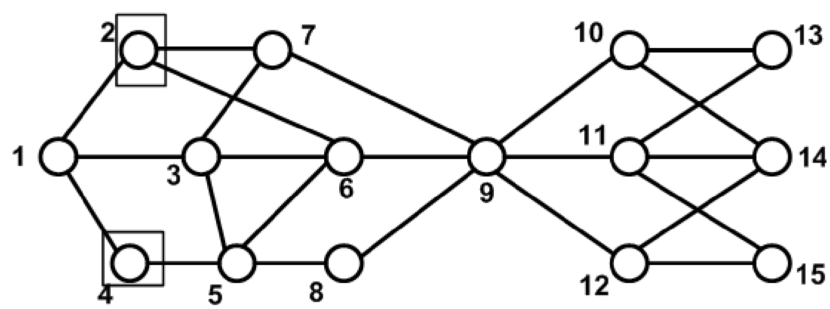

Figure 1: Adversarial diffusion blocking network

The main reason why traditional models of innovation diffusion is inadequate to capture the adversarial scenario is the following. In the traditional models of diffusion, the nodes are either blue or green and green nodes can be used in the diffusion process to change the color of a node from green to blue. As discussed in the previous paragraph, in the adversarial scenario, the colors assigned to the nodes may be blue, green or red. It may be noted that in this case, a red node *will not allow* diffusion of a blue stream through it. Consider the network shown in the Figure 1. Suppose that initially (i.e., at $t = 0$), only two nodes in the network are colored red or blue—the node 2 is colored blue and the node 4 is colored red (the remaining nodes are all green). As the diffusion process progresses over time, more and more nodes change their color from green to blue or green to red. At some point of time during the diffusion process the node 9 will be colored either red or blue.

Once the node 9 changes its color from green to say, blue, it will not allow the diffusion of red color through it to the any node to its right side. Accordingly, the nodes 10 through 15 will never have an opportunity to turn red, and most likely the entire right side of the node 9 will eventually turn blue. The traditional models of diffusion have no mechanism to capture this aspect of an adversarial scenario.

From the discussion in the preceding paragraphs, it is clear that current models of innovation diffusion are inadequate to capture some key features of an adversarial scenario and new models are needed. The complexity of the problem is further acerbated by two additional dimensions - *time* and *space*. In Figure 2 we present some results of our analysis of the data collected as part of the Minerva project. The figure shows how influence of various radical and counter-radical groups evolved over time and space in Indonesia.

As discussed earlier, studies on influence propagation model in adversarial scenario is fairly limited, and studies on influence propagation model in adversarial scenario that evolves over time and space is almost non-existent. Currently, we are exploring mathematical modeling tools, such as a *Markov decision process, Pebbling Games* [2, 6] and *Petri Nets* [3] as possible candidates. However, none of these tools seem to be able to capture the complexity and nuances of this challenging problem. Clearly, further research is essential to study the impact of time and space on influence propagation model. From that perspective, the proposed meeting could not possibly have come at a more appropriate time.

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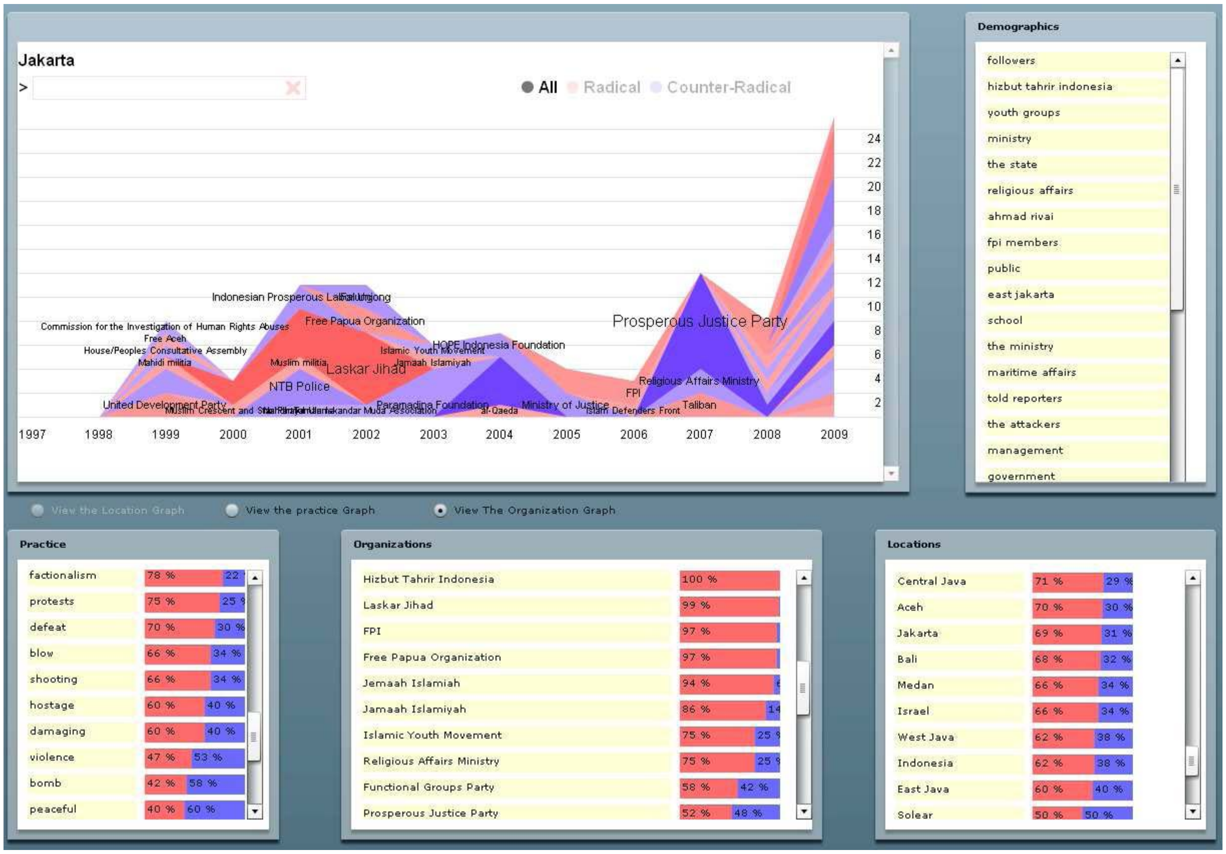

Figure 2: Influence of radical and counter-radical groups as they evolve over time and space in Indonesia

Spatiality, temporality, and contexts: Geosocial data as evidence of social interactions and networks

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My interest in and contributions to this specialist meeting stem from two strands of my past research: my long-term focus on the use of geospatial technologies at the grassroots, by laypersons; and more recent work on volunteered geographic information and qualitative GIS.

From these perspectives, I read the call for participation as implicitly pointing to the latest in a series of developments through which the Internet has dramatically altered human communication and social networks: The rising use of online social networking sites, especially those that include a geographic component. Specifically, I refer to services that document network members' presence in or preferences for particular places or locations (as in FourSquare's "check in" function), or that enable geolocating of user-generated content shared through a social networking service (as in Twitter's geoAPI). As these services have proliferated and the data streams flowing from them exponentially increased, there is growing interest in how these data might be used for a variety of purposes—improving real-time emergency response, investigating new forms of social life and social capital, or fighting terrorism to name a few.

Using these new forms of socio-spatial data will require understanding their unique characteristics, especially as compared to more conventionally-sourced and represented geospatial data. I would argue that these new forms of geosocial data—by which I mean data from social networking that have a geographic component—illustrate some of the fundamentally different spatio-temporal characteristics of social networks/interactions in the age of Web 2.0 and the geoweb and introduce some new challenges with respect to how we can understand social networks and interactions vis-à-vis space and time.

With respect to space, working with geosocial data is complicated by the fact that these data may encode two kinds of spatialities simultaneously—(primary) digital or virtual interactions and connections, as well as (secondary) documentation of embodied or interpersonal interactions in the "real" world. For researchers, this introduces all sorts of complexities. The first is a primary form of data, the second a secondary form. Both types may be present within a single data set (geo-tagged tweets, for example, could be either kind). Within a single social group, both kinds of interactions may be occurring with mutual influence on the content of both and the social ties that emerge from them. At an epistemological level, these issues are rooted in a basic hybridity of geosocial data: these data both *represent* and *constitute* social networks and they do so in both *virtual* and *material* worlds.

Another key challenge with respect to the spatiality of geosocial data is rooted in a tension between how social networks or interactions are represented and analyzed, and the richer ways that they exist in the world. That is, many of the metrics used for social network analysis are explicitly spatial—centrality, between-ness, closeness, cohesion, density, reach, etc—and they are represented and analyzed using Cartesian and arithmetic representations. Yet these approaches always give us somewhat abstracted, a-contextual, or flattened representations of the more complex social world. This is not to suggest that since these metrics should be rejected because they cannot get at the full sense of a social network and interaction. Rather, I suggest we must ask how these metrics might be enriched, or new ones explored, to allow us to get a richer sense of contemporary social networks. For starters, computational social science, scientific information visualization, semantic web research, and GIScience ontologies work would all seem to hold some promise for analyzing complex, unstructured, and shifting relationships and interactions.

With respect to their temporality, data from geosocial networking introduce new opportunities and challenges. One fundamental issue is the tension between the durability of a digital data artifact—perhaps "true" at the moment it was created—and ongoing changes in the social world.

A social connection mediated through an online social network leaves a durable digital trace that becomes separated in time from the moment when it was created, and at some time X in the future, may no longer exist, or may not have the same content and meaning to its members. A pressing issue then, is to understand what principles, social and computational, might help us assess how reliable geosocial data may over time, if we are using them as evidence of social interactions or networks.

Finally, a basic challenge to understanding social networks and interactions through geosocial data is the inevitably abstracted nature of digital data and digitally-mediated interactions and their removal from immediate embodied times/places. User-generated and social networking data will always suffer a certain degree of de-contextualization. Yet I would argue that context is critical to interpretation and understanding what these data are telling us. That is, relatively a-contextual techniques will easily highlight spatio-temporal patterns and anomalies in the data, yet we will almost certainly need to re-construct something about context if we are to understand and interpret the meaning of these patterns and anomalies.

For instance, we may discern that thousands of members of a geosocial networking service of a particular age or place of residence 'checked in' from the downtown area during large public gatherings after a recent election, yet what does this tell us about the nature of the political event that might or might not be occurring and the motivations of those present? Context is also essential to interpreting whether a spatio-temporal anomaly in the data is cause for concern. If my elderly grandfather deviates from his usual space-time trajectory, what other events or conditions must also be present before I become concerned that something is amiss? I would argue that if we can develop systematic ways of exploring the geosocial data themselves, their richness, volume, and quotidian nature may enable us to get at some of these contextual issues, with an eye toward more robust interpretation and explanation.

The Impact of Displaced Persons on US Army Conflict and Stability Operations

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During periods of conflict and instability in nations, there is often an associated flow of displaced populations. This flow can be confined within national boundaries, or move across them. The spatial extent of displaced population migration may be determined by physical, ethnic, or cultural factors instead of (or in addition to) political ones. In all situations, there will be active social networks among the displaced persons created and maintained by physical proximity and the limits of any available communication technology. There will also be active social networks between the migrants and people remaining in their home area. If the entire home area population has been displaced, there will remain networks between the migrants and relatives or friends in other locations. In addition to serving as a communication medium, these networks can function to transfer remittances and other economic services. They can also provide a system for planning and communicating activities designed to impede "enemy" progress in conflict areas.

For the US military, being able to track the displaced populations and understand their ties to others in the new settlement area, to relatives and friends outside both the new area and the home area, and contacts left behind at the point of diaspora origin has a positive impact on operations in both conflict and stability-enhancing environments. Data related to these networks could assist in answering questions in research areas such as:
Migration patterns in conflict areas:

- Who moves in and out?
- How long do displaced populations stay in camps?
- Is it a series of camps on their way "home" or do they stop along the way as opportunity presents itself? If so, what does this mean for tribal ties?
- What kind of movement data can soldiers collect and how can they utilize it in planning?
- How useful are academic migration studies in determining which groups of people are moving?

Migrations patterns in areas with active US military stability operations:

- What kinds of alternative data sources can be used to map or anticipate population movement?
- What is the time lag for displaced populations to recognize positive changes in the home area and begin to consider returning?

- How is this time lag affected by distance? By means of communication among the displaced population and contacts in other areas?

Post-conflict reconstruction operations:

- What percentage of the migrant population can be expected to return to the home area?
- At what rate will they return?
- How far away is "too far" for a return stream?
- If a group chooses to remain outside the home area, how do the tentative social networks developed between the migrant population and the new local population get expanded?
- Over time, does the physical distance from the home area lead to decay of the network between those in the new location and those in the old? If so, at what rate does this decay occur?
- Do these changes occur to a different extent or at a different rate if the "new" settlement location is inside or outside the home area national boundaries?

I am also interested in modifications to the cultural heritage of the displaced population as it relates to physical manifestations of that culture. To what degree is the displaced population tied to the cultural in the area they have left? If a group resettles away from the home area, to what degree does their new settlement replicate the specific architecture and spatial use patterns of their point of origin? What is the role of social networks in maintaining a culture that is spatially removed from its heartland?

I look forward to gaining insight from the other meeting participants that may assist in developing methods for answering these questions.

The power of dynamic spatial and temporal characterization in social networks

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Abstract

Social networks tend to form topically around shared subjects, affiliations, events and causes. They assemble and disperse and their boundaries in space and time depend on their topical viability. Physical and temporal distance are of lesser or greater importance in different communities.

Social networks, like all networks, compete for resources. They require some form of presence, effort or participation. The investment that people make in social networks depends on the visibility and relative importance of the network topics to potential participants.

Time and space provide us with a convenient and shared backdrop for understanding dynamic social networks but traditional spatial and temporal boundaries are often replaced by domain specific references to regions, events and schedules. Community specific notions of space and time and their relative importance are needed to understand changing network topology.

Introduction

When understanding the dynamics of a social network, it is important to understand the bonds that unite a particular social community. In different communities, the notion of "half time," polling day or religious service can replace traditional temporal patterns. Religious, trading and familial patterns break down traditional political boundaries in the spatial domain. The temporal and spatial patterns are often driven by the shared context, key events and semantics of the community members.

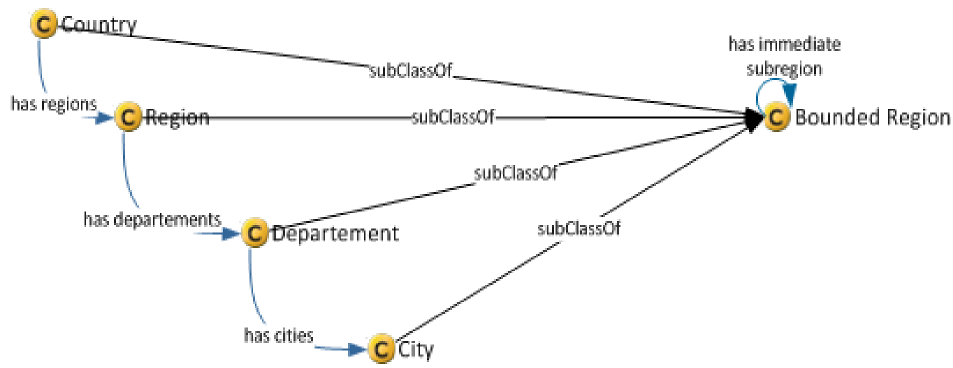
By using generalized models for space and time and focusing on capture of events that preserve time and place, context and semantics of the specific social networks can be incorporated and the traditional backdrop of more familiar space and time presentations can be used with community specific perspectives thus facilitating a better understanding of regionalization and cadence in different networks.

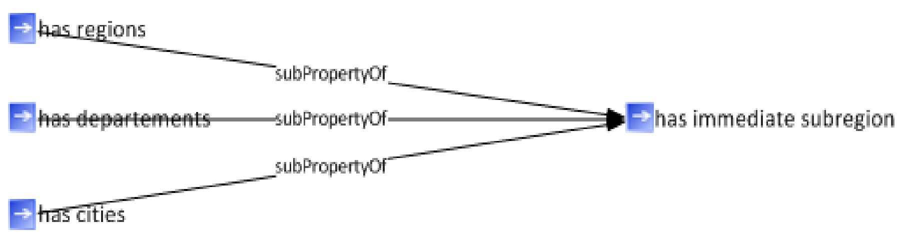
Space: A Generalized Bounded Region Ontology

A very general bounded region ontology lets different communities view space in different ways. Regions can be of any size or shape and are often defined dynamically by their properties. Events can re-shape regions and containment can change over time.

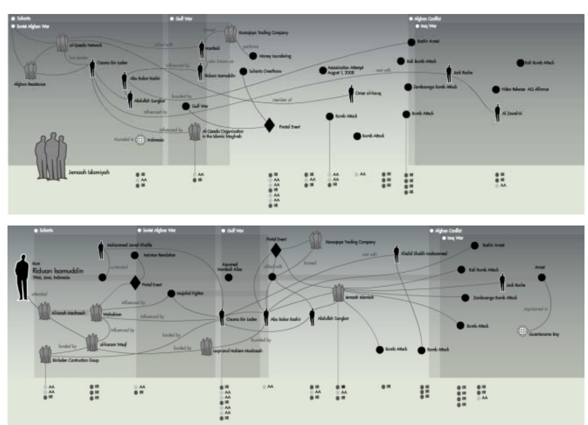
A bounded region is defined by its community and known physical locations are mapped into the more general region based models.

The ontology itself is very simple; a single class and a small number of interconnected relationships. It is sufficient to address the ideas of containment or nested regions and relate regions to more traditional political boundaries. When used with an event driven schedule ontology, it paints a picture of spatial temporal change in a network.





A generalized schedule ontology complements the bounded region ontology. It allows different communities to define key temporal events in community or subject specific ways. The presentation below shows a traditional timeline with different subjects of interest (in this case, a group and a person) where the temporal events are adjusted for the community specific interests.



Using events in lieu of specific properties allows capture, contextualization and spatial/temporal reasoning that is otherwise difficult. Representations that are based in the present (is employed by, is member of, etc.) instead of event based (with start and end) limit understanding of change in both time and place. Event based representations allow derivation of current state from different perspectives and can facilitate understanding of changes in the state of a social (and other) networks.

Social networks are, by their nature, constantly moving in time and space. Participants and roles change, people move, outside events drive participation changes. However, understanding of the network dynamics can be easily understood if general event driven spatial and temporal models are used to describe activity.

Guided Spatial Search in Digital Maps

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In less than a decade, online social networks have risen to become some of the most popular sites on the Internet (Cosenzo 2010). Leveraging user-generated relationship linkages, such sites facilitate casual communication among friends and those with similar interests. The massive popularity of social networks has driven their evolution to include more diverse relationship types, such as business-to-business, business-to-consumer, teacher-to-student, and others. The ancillary effect of the derived social graph is the ability to automate recommendations from linked individuals' attribute similarities; such recommendation systems often provide the sites' sustaining business model via targeted advertising (Mitra and Baid 2009).

While a great deal of research has been conducted on the nature of the social graph (Barabasi 2003; Watts 2003), less work has been undertaken on such graphs' spatiotemporal embedding. That is, how does the "real world" affect network capabilities and what are the nature and magnitude of those impacts? For example, users in transit likely engage differently with the network than those sitting at a desktop computer. Similarly, since users may not be connected at all times to retain linkages, most social network communication is asynchronous. A message sent from one user to their connections will not be received simultaneously because not all participate in real time. Even with increasingly prevalent mobile clients, asynchronous communication is likely to persist in Web-based social networks due to imperfect hardware infrastructure and varying user interest.

Many goals and tasks performed by social structures require specific spatiotemporal configurations. The positional arrangement of groups, such as sport teams, military units, and nuclear families, may allow prediction of underlying linkages and functions. The pursuit of a general approach for disentangling social network relationships and goals based on spatiotemporal configuration might be built upon Hägerstrand's (1970) notions of Time Geography.

The initial undertaking presumably would be to census and classify social tasks. These activities might include food gathering, defense building, shelter construction, child rearing, and so on. Each task would then by defined by their common, associated spatiotemporal signatures. Such an inventory may eventually lead to better characterization of networks that do not include a social structure's entire population, allowing position and role prediction of off-network and hidden individuals. Given the mathematical properties of social graphs, such questions could be framed conceptually or solved as a set of operations research optimization problems.

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Position Paper

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The position papers submitted for the meeting raise a fascinating array of issues, ranging from representation and analysis to the social context. I would like to focus on two issues that seem to me not to have received much attention in the papers, but to be important in addressing the topic of the meeting.

Inference from spatiotemporal pattern

Geographers have long been interested in phenomena distributed in space and time, and in making inferences from pattern to process. Every dynamic process leaves a characteristic footprint or pattern on the Earth's surface, from which it is possible to infer process, though subject to the problem of equifinality, or the tendency of multiple processes to produce identical patterns. Some of the most compelling examples concern disease, and inferences about the causal mechanisms that have been derived from the spatial patterns of disease morbidity. Many of these studies have been carried out without explicit respect to time, either because data were available only in cross-sectional form, or because of the difficulties of visualizing and making inferences from truly spatiotemporal data. This situation is changing rapidly, however, because of the rapid growth in new spatiotemporal data sources and tools. Time adds much useful information and allows us to come closer to inferences about cause.

Applied to the specific topic of this specialist meeting, this logic implies that one can study spatiotemporal patterns to infer the existence and operation of social networks, and to build models of their structure. Applied to the data collected by Tilley on the Swing Rebellion of 1832 in England, for example, it suggests that we can learn about the structure of social networks in this pre-Internet age by observing the spatiotemporal diffusion of the rebellion's events. Geographers might distinguish in this example between spatial diffusion, in which news travels from person to person through physical interaction, and hierarchical diffusion, in which the contemporary print media were able to reach large numbers of people roughly simultaneously. The spatiotemporal pattern suggests that diffusion was initially spatial and then hierarchical.

Proximity provides the key to distinguishing spatial from hierarchical diffusion, since under spatial diffusion an event must be close to at least one prior event. Proximity can be modeled using a variety of distance-decay functions, including the negative exponential, which unlike negative powers has the advantage of being both well-behaved and supported by sound theory. Hierarchical diffusion can also be expected to display effects of proximity, though in this case the relevant distance is that between the producer and the consumer of media. Electronic communication, starting with the telegraph in the mid 1800s, has the potential to remove the effects of proximity entirely, driving the parameter of the negative exponential function to zero. Nevertheless there is abundant evidence that proximity effects persist in many instances of electronic communication, for a variety of reasons.

While the literature includes many instances of both hierarchical and spatial diffusion, I am not aware of any attempts to combine them in a single model, though this seems essential if we are to theorize about diffusion in an Internet-based world. One way to do this would be by mixing two pdfs, one the negative exponential of traditional spatial diffusion, and the other the uniform distribution implied by perfect communication. It would be interesting to do this within the context of a spatial interaction model, where the origin and destination mass terms can be included. Another approach would be through a small-world network model, which includes both forms of interaction.

Digital representation of embedded networks

The analysis and modeling of phenomena embedded in space and time has received an enormous boost in the past four decades. GPS, remote sensing, and GIS combine to provide an abundance of data, many of them born digital, and allow easy manipulation and sharing. A GIS today is capable of virtually any systematic operation on spatial data, and has been described as a new medium of communicating what is known about the surface and near-surface of the planet. However almost all attention in the development of GIS has been directed to maps, and the map remains a powerful metaphor for the contents of a GIS database. Maps are very efficient ways of showing what exists at each point in a mapped section of the Earth's surface, and humans are adept at connecting the dots to infer the existence of lines and areas, and to associate annotation with these features. However maps are not ideal media for communicating spatiotemporal information, since maps are inherently static once printed. Video addresses this problem, but is similarly limited in being able to display only one color at any point at any time.

Information about social networks embedded in space and time falls into the category of *binary* geographic information, or information about *pairs* of locations. Connections, interactions, flows, and movements all are of this nature, replacing the unary form $<\mathbf{x},z>$ with the binary form $<\mathbf{x}_1,\mathbf{x}_2,z>$. In the object-oriented paradigm that now dominates the design of GIS databases, such information would typically appear in association classes, since it qualifies the relationship between two features rather than the properties of a single feature. Visualization of binary geographic information remains a hard problem. We see this in the "fish-tank" views that assign the third (vertical) dimension to time in displaying large numbers of tracks, creating a confusing mass of lines that are difficult to interpret. New methods of measuring the similarity of tracks, and clustering them, may provide some clarity, but the appropriate metrics of similarity may be hard to define.

Interests (Position) Related to Spatial-Temporal Constraints on Social Networks

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Currently, I have three specific areas of interest related to the topic of spatial-temporal constraints on social (and other) networks. However, I work numerous other projects where an improved ability to analyze seamlessly across network and spatial-temporal context would be valuable.

Host Population Networks: The first of these specific areas is the geographic and temporal representation of "host populations" and the political, economic and social networks of these populations in locations where U.S. is interested in improved governance and stability, and increased local economic capability. In recent years, U.S. security policy has recognized the need to nurture and enhance governance in all nations across the globe, because of the global threats posed by individuals and groups operating in under-governed and ungoverned regions and nations. The U.S. and U.S. allies operating in these regions and nations need to better understand the motivations, perspectives, and alliances between individuals and groups in local populations, and to "model" the complex reactions of these communities. Specifically, we wish to better parse our understanding of how the various economic, social, religious and political networks at work in these host populations will each react to changes and potential actions within these regions (and external to these regions). Understanding these social networks are important for both populations and individuals that remain in their locations of origin, and those that are displaced to new "communities" but who maintain strong "network" ties across geographic and even temporal distances.

Understanding the social networks in local and displaced situations involves accurate and detailed spatial and temporal information about populations, but data available from census and published sources is often sparse in these regions. However, the desired information is resident in the local populations. Constraints in obtaining and accurately applying this "social networks" data include all the issues associated with crises and conflict areas – mistrust, access to individuals, safety, access to local data sources, language barriers, place name confusion, and the cultural "opaqueness" of important but hard to articulate network relationships.

Defense Sustainability Knowledge Network: The second specific area of interest has do with effectively growing a "network" of connections across the U.S. Department of Defense (and other related organizations) related to sustainability (the Defense Sustainable Knowledge Network).

Social networks facilitate building "culture" or shared behaviors and beliefs in spatially distant communities. Organizations, including large organizations like the U.S. Army, advance the use of social networking tools to reduce costs in operations and to nurture cultural ties across the geographically dispersed soldiers, civilians and families that are part of the Army. The Army has units and personnel in essentially every time zone on the planet—in scores of locations, so capabilities that link those with common interests across these physical spaces are of great value for an organization that builds upon cultural cohesion among soldiers and the civilians and families supporting these soldiers.

A number of factors, however, limit the effectiveness of social networks in building and sustaining communities and an improved understanding of how these factors operate, including:

- Security constraints that limit the exchange between the "internal" and external elements of the community
- Access, bandwidth and security constraints that prohibit the use of some types of social media
- The complexity of a very hierarchical and vertical organization "facilitating" horizontal interactions across the community, and uncertainty about what communications are actionable.
- Concerns that social interactions are vulnerable to monitoring by adversaries
- Difficulty of "like minded" elements of the community finding one another and establishing common ground, because of the diversity of locations and organizational elements across a very large organization
- Ingrained behaviors of individuals—with limited exposure (and willingness to gain exposure) to social network resources.

There have been several efforts provide social network tools to members of this diverse community, most with limited success. So, this challenge related to: 1) examining current and changing interactions across this community to better understand if these constraints (or others) are limiting interactions, 2) identifying in spatial-temporal, organizational and functional dimensions as to how sustainability interactions are occurring and where they are constrained, and 3) modeling how various additional resources might improve this "defense sustainability knowledge network.

Protection and Projection Nodes for Global Networks: Historically, all military organizations locate their military assets in key locations that serve to protect vital proximate assets and/or to project military forces to where they are needed. US bases were first placed where there were threats—in the early years of the colonies along coastlines and key navigable rivers, then along the routes of wagons and trains as the nation grew westward. Finally, bases and troops were located where airports, railways and highways and seaports could facilitate rapid "projection" of power to wherever needed. Space and time are important considerations in these locational considerations—what is the range of protection from our military bases, and how long does it take to project forces to the perimeter of their ranges?

As modes of transportation and communication transform, as weapons systems project globally and in the space around the globe, and as known vulnerabilities to attacks multiply, there is a growing need to examine the range of networks, and the crossing nodes of these networks, where US military should allocate its limited protection and projection resources. These "networks" include multiple types of communications infrastructure, space infrastructure, power infrastructure, transportation infrastructure. Key spatial factors include space imagery surveillance, various infrastructures extent and range and key nodes, and the types of protection and projection needed for these infrastructures. All these factors also have a temporal dimension. A goal, related to this issue, is to dynamically identify ideal "nodes" from multiple network in terms of spatial, temporal and network characteristics.

Time Use Investment and Expenditures in Social Networks

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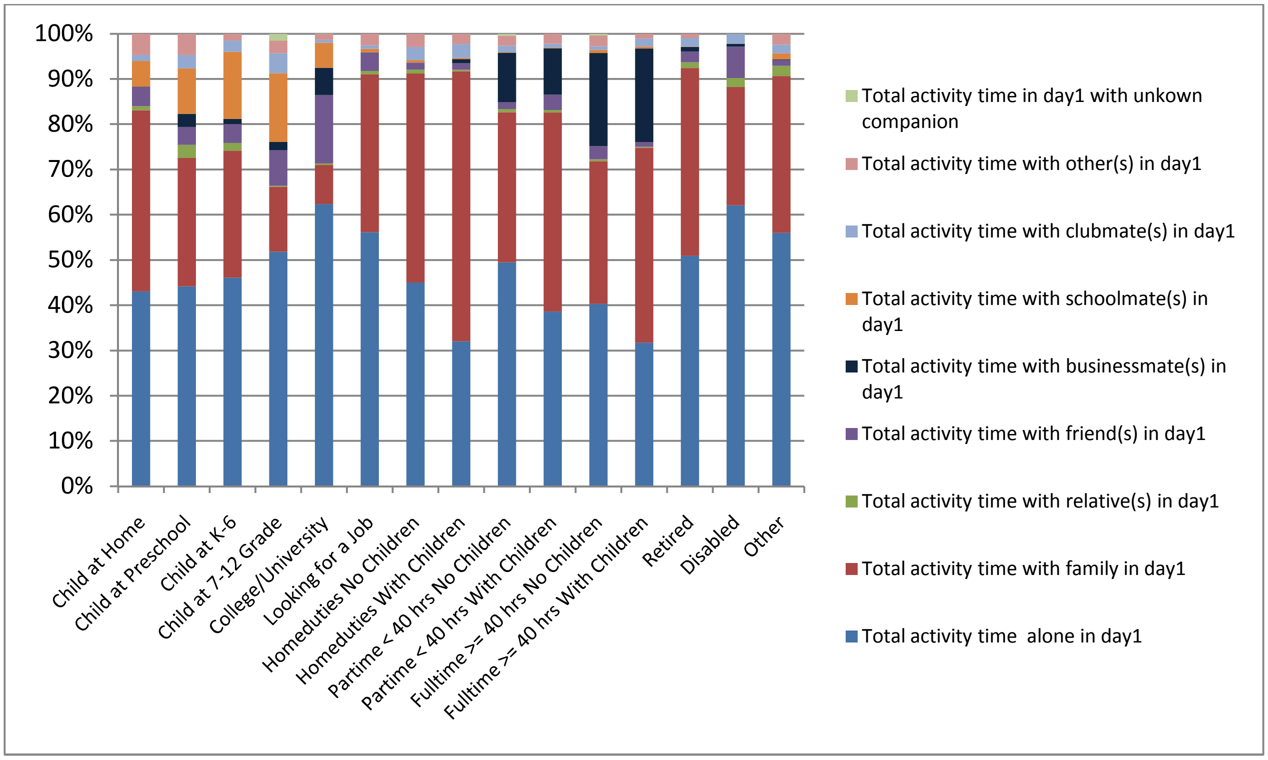
In this presentation I use Brofenbenner's Person-Process-Context-Time (PPCT) model and two-day time use diary data to first identify social network types based on reported activities, travel, and the types of persons with whom and for whom these activities and travel were completed. The data used are from a time use two-day diary of 1471 persons collected between November 2002 and May 2003 in Centre County, Pennsylvania. In their time use diaries respondents provided a detailed record of each activity they completed in each day, the persons with whom they completed each activity as well as for whom they participated in each activity. The social networks identified by the respondents include immediate family, relatives, friends, schoolmates, businessmates, clubmates (members of a society or church), and all other. Measures of investment and expenditures in social networks include the number of episodes in a day, and the amount of time allocated to activities per day. These two measures (episodes and amount of time allocated) are classified by the amount of time allocated to activities at home, work, school, and elsewhere to examine the "placial" nature of social network investments. They are also classified by the persons with whom these activities are conducted and for whom these activities are conducted offering additional insights. A third measure considered is an estimate of the social network size based on the number of persons that each respondent interacts with per day in each of the social networks defined above.

To illustrate major changes but also stability over a person's life and following a life course perspective, respondents are classified in 15 mutually exclusive groups that follow age graded stages and they also include groups of persons that may have experienced major turning points or other dramatic events inhibiting mobility. In this way we can study the possible evolution in activity engagement within social networks. One of the most important findings confirmed in this analysis are the role of home as the place (or critical node) where many of the social networks are accessed from and most activities can take place at. Also, persons at different life cycle stages are active in a multitude of social networks but with different time expenditures and mix of interactions that are a function of their social role. This is something we should expect to see in other situations such as online communication. Figure 1 displays an example of the analysis findings. In the presentation I will provide an overview of the findings emphasizing the spatio-temporal constraints for specific life cycle stages and discuss issues of network identification and classification, measurement of contacts and intensity of relations based on these time use data, and expand the discussion to include the use of telecommunication to access social networks.



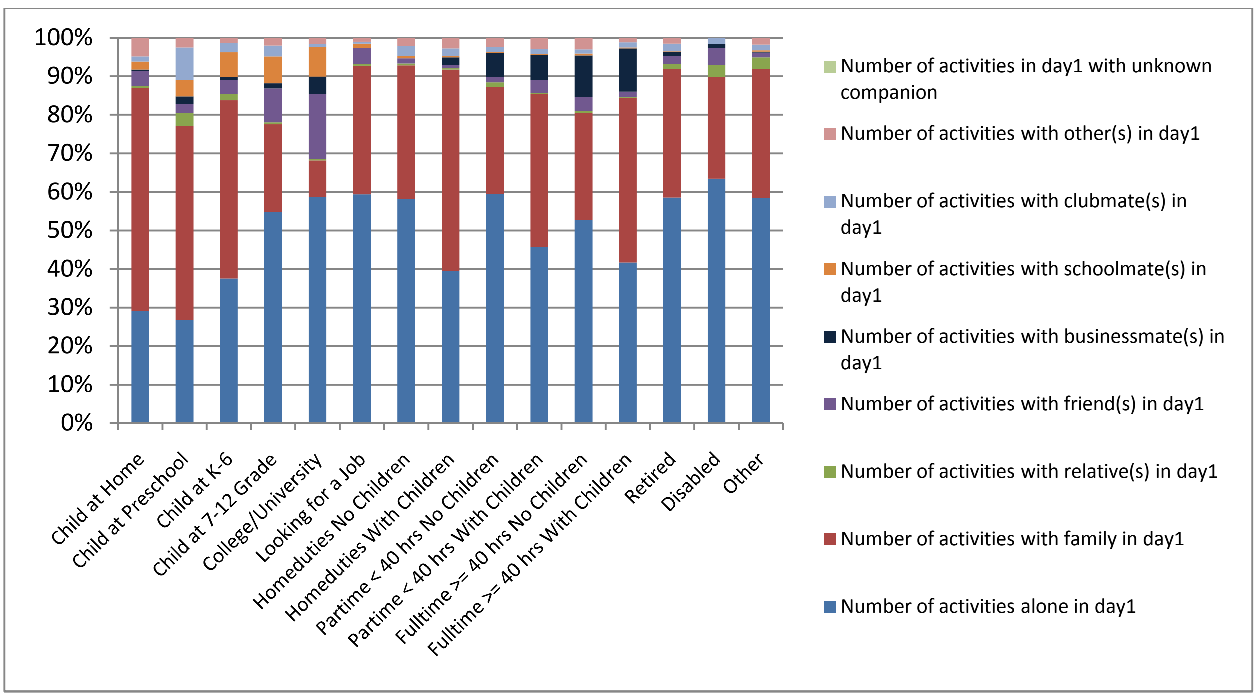


Figure 1. Amount of Time and Episodes Per Day by (Expanded) Lifecycle Stage

Place and Spatio-temporal Constraints on Social Networks

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My interest in spatio-temporal constraints on social networks is twofold. First and foremost, I am focused on what can be learned about *places* from mining and understanding spatio-temporal constraints on social networks. For instance, how do we define a "local user" in the context of an online knowledge creation-oriented social network? [2] How do we communicate the degree of "localness" to a content consumer? My colleagues and I are also working toward applying this research in novel systems and applications. Second, I am a Ph.D. student in human-computer interaction with a background in geography and close ties to the fields of communication, psychology, and sociology. As a result, I have been involved in many brainstorming sessions in which questions arise about spatio-temporal constraints on social networks. I thus very much appreciate the need for additional research in this area, as well as increased communication between the multitudes of interested disciplines.

Techniques for understanding places in the context of spatio-temporal constraints on social networks require additional research in many areas. There are of course many theoretical questions left unanswered. We have thus far limited our theoretical exploration of these questions to the concept of "localness." For instance, in [2], we found that the people who define place descriptions in knowledge creation social networks are not necessary those most "local" to the described place. We hypothesized that this phenomenon may be due to network effects dominating spatial effects. We also noticed a difference in the "localness" of content when different spatio-temporal constraints were placed on these networks.

Our experiments have also increased our interest in developing technologies that truly understand spatio-temporal constraints on social networks. Web 2.0's dominant model of zero-dimensional point spatial footprint representations that are ignorant spatial relationships (i.e. the First Law of Geography [6]) is highly flawed [4]. This paradigm will have to be retired for models and systems with much greater understanding of geography within a social context. In particular, technology that at a fundamental level recognizes the two-dimensional, fuzzy, and socially-defined nature of footprints (i.e., [5]) will be required.

Interdisciplinarity Issues

I am a computer science Ph.D. student with a Masters in geography who works with many researchers in communication, sociology, and psychology. As a result, I am frequently reminded of the vital importance of spatial science to network science through consultations and brainstorming sessions. It is obvious that much work needs to be done integrating relevant core theory from different disciplines. For instance, how does time geography [1] relate to existing work on social location-based services? Many opportunities are being missed because of this disciplinary disconnect [3]. In particular, I have found that the spatial science developed through decades of research in the discipline of geography goes largely ignored in many academic contexts. As a result, I am especially excited to see geographers take such an active role in this specialist meeting.

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Defining and Using Types of Relationships in Social Networks

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My interest in the specialist meeting on spatio-temporal constraints on social networks is in the interaction between the relationships between real-world interactions and online social networks. I am particularly interested in how those real-world relationships can act as the grounding for social networks. Evidently, key relationships—such as best friends—are often reflected in current social networks, yet hard to distinguish from other, potentially loose contacts in a user's social network. Hence, there seems to be a mapping mechanism form real-world to online relationships, where some information is lost on the way. This loss is partly caused by the implementation of the social networks, which only allow for certain, fixed types of relationships. Spatio-temporal relationships between users, combined with other information (message exchange, participation in events, etc.) could be used to disambiguate these relationships. In order to do so, the following research questions need to be dealt with:

1. *What is the ontology of relationships in online social networks?* We need an understanding of the different types of relationships that can be found in online social networks, independent of the actual implementation. The spatio-temporal aspects of these user type definitions can act as anchors when mapping from the real-word to online social networks, and between different networks.
2. *What information is lost when going from real-world to online relationships?* Social networks typically only allow for very coarse distinction between types of contacts. Evidently, this results in a loss of information, as the diverse types of relationships between people are reduced to a small number of online contact types. Vice versa, some online relationships do not have a correspondency in the real world. Defining the offset between offline and online networks will allow us to understand the information loss when mapping one to the other, and give us clues on how space and time can be used to refine the mappings.
3. *How can real-world identities allow us to translate between different social networks?* Identity is an inherently spatio-temporal concept, as any member of a social networks is somewhere during some activity within the network. The number of online communities that allow users to disclose their current location is rapidly growing. Location information thus becomes an important indicator for the integration of different online social networks, which is required for a higher-level, implementation-independent analysis.

4. *How can spatio-temporal media be used in this process?* Geotags have become standard metadata in photo communities, and their use is constantly increasing as more and more cameras and mobile phones are equipped with GPS chips. More recently, social networks enabled users to tag people in their uploaded pictures, who can be unambiguously identified via their ID or URL within the network. Together, these pictures allow for the detection of collocation of users at a certain point in time, which could be used to further disambiguate the relationships within network and develop a more fine-grained classification.
5. *How can such information be used in online communities?* Trust and reputation are currently being investigated as proxies for data quality for collaboratively generated content; in [1], we have discussed this issue for a community-generated gazetteer. However, the degree to which findings on trust and reputation from the social sciences [2] translate to online communities largely defines how useful they will be as proxies for data quality. A more detailed understanding of the mapping process (see question 2) is required to judge the practicability of such approaches.

Insights on these questions bear great potential to improve online interaction, especially when users collaboratively create content. Privacy, however, is an obvious issue in such research. What we can infer from social networks should therefore not only be explored from an academic perspective, i.e., what we can learn from the massive datasets collected by online social networks, but also with the ethic implications in mind. Particularly, it should be discussed what kinds of conclusions the operators of such social networks can draw on a larger scale, having access to all data of all users.

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Harvesting Geospatial Knowledge from Online Social Networks

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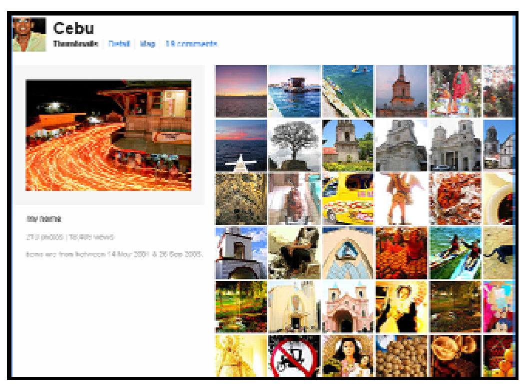
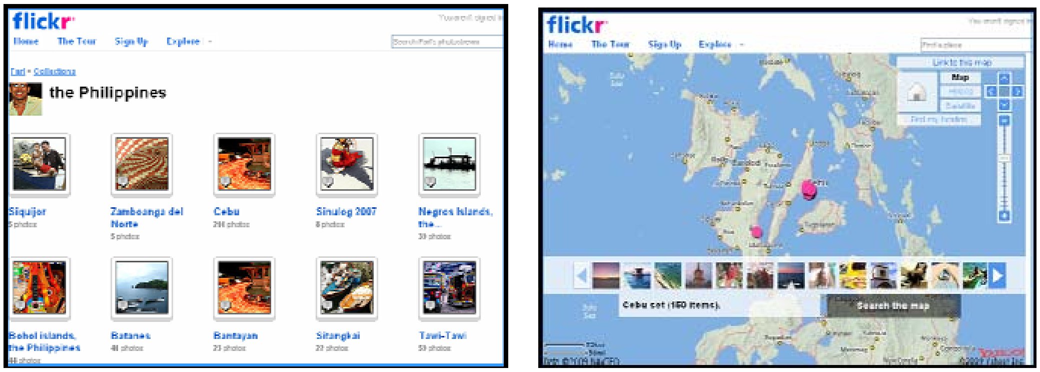
Social Web has moved knowledge production from the hands of the experts and professionals to the masses. Today online social networking sites, such as Twitter, Facebook, YouTube, and Flickr, allow ordinary people not only to create massive quantities of new data, but also organize it, use it, and share it with others. Unlike earlier information technologies, the Social Web exposes social activity, allowing each person to observe and be influenced by the actions of others in real time. How will such real-time, many-to-many communication change how we discover, use, and manage information? And how will it transform society and how we solve problems? My research addresses these questions by developing methods to harvest social knowledge.

Consider a gazetteer, for example, Geonames.org, which compiles geospatial knowledge within a directory of places and place names, often organizing it hierarchically within taxonomy of geospatial concepts. Such gazetteers have been useful for creating geo-aware applications and integrating geospatial knowledge. However, since gazetteers are manually and painstakingly created by an expert or a small group of experts, they are rarely complete or comprehensive, do not reflect the variety of views, and fail to keep up with our changing ideas about places.

(a)



(b)



(b) (d)

Figure 1*: Examples of data and metadata created by a Flickr user. (a) Tags assigned to an individual image (geotags are not shown), (b) images in the set "Cebu", (c) sets in a collection called "the Philippines" created by the user, (d) geotagged images in the "Cebu" set displayed on the map.*

Social Web has given ordinary people the ability to organize information, including geospatial information. A person can annotate content they create, whether a photograph, a blog post, or a tweet, with descriptive labels known as tags, attach geographic coordinates to it, or organize it hierarchically within personal directories. These annotations help people browse content or retrieve specific items at a later date. While an individual's annotation expresses her particular worldview, collectively social annotation provides valuable evidence for harvesting social knowledge. My group is developing machine learning methods [Plangprasopchok et al., 2010a; 2010b] to combine annotations created by many individuals into a common hierarchy, a *folksonomy*, that reflects how a community organizes knowledge [Plangprasopchok & Lerman, 2009].

Error! Reference source not found.(a) shows an image on *Flickr*, along with metadata associated with it, which includes descriptive tags. *Flickr* allows users to group photos in folder-like *sets*, and group sets in *collections*. The image in Error! Reference source not found.(a) was grouped with other images taken around the Philippine province of Cebu in an eponymous set (Error! Reference source not found.(b)). This and sets devoted to other places around Philippines were grouped together in a collection called "the Philippines" (Error! Reference source not found.(c)). In addition to tags, users can attach geospatial metadata to photos. Error! Reference source not found.(d) shows geotagged images (purple dots) in the "Cebu" set on a map.

While geospatial knowledge expressed by a single user may be noisy, ambiguous, and incomplete (e.g., points in Fig. 1(d) only cover a small portion of Cebu), combining data from many different people will provide more accurate knowledge. We have developed a method that aggregates geotagged content created by thousands of users of the social photo-sharing site Flickr to learn geospatial concepts and relations between them [Intagorn et al., 2010]. Our method leverages geo-referenced data to represent and reason about places. We have evaluated the learned geospatial relations by comparing them to a reference ontology provided by GeoNames.org. Our approach achieves good performance and also learns novel relations that do not appear in the reference gazetteer. Such folksonomies may eventually aid people in searching, browsing, visualizing, managing, and personalizing information. In addition to learning folksonomies, we have extended machine learning methods to learn better topic models of annotated documents [Plangprasopchok and Lerman, 2007; 2010]. We showed that these methods help us exploit social annotation to discover relevant new information sources more effectively than a search engine [Plangprasopchok and Lerman, 2007; Ambite et al., 2009].

What we learn from social annotation is often surprising. For example, some Flickr users annotate spider with the term "insect," as shown in Fig. 1, and Disneyland with "LA." Technically, they are wrong, since spiders, in possession of eight legs, are certainly not insects, and Disneyland is not even a part of Los Angeles County, much less the city of Los Angeles. Though it may be wrong, this information is still useful. If you want to find images of spiders, sometimes you will have to look under "insects." Likewise, if you are traveling to Los Angeles with children, you better know about Disneyland. This type of *folk knowledge* is often at odds with expert-generated knowledge expressed in formal taxonomies, but you need folk knowledge to make the most of social information.

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Spatio-temporal footprints in online social networks

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Society is comprised of many different types of social networks on various levels. Social networks play a critical role in achieving goals and solving problems. While traditional social networks only existed within a very limited geographical distance (*e.g.*, villages) constrained by temporal factors, modern technology—especially the growth of the Internet and cell phones—has greatly reduced the spatio-temporal limitations on human communication. People who live on different continents in different time zones can interact with each other using phones, emails, and websites. Particularly, online social networks provide an effective channel to enhance existing social networks and to initiate new ones. Facebook, for example, offers services to create profiles, add friends, and exchange information. Twitter, on the other hand, provides a platform to share and discover "what is happening right now?" Social network websites have been an alternative and complementary form of social networks with a growing number of users.

Human activities usually take place in particular locations at specific times within a social network; the activities in online social networks may reflect activities in the physical world. For instance, people may comment on an event that they are currently experiencing, such as a football game or a fire. I am interested in the spatio-temporal footprints inferred from the data created in online social networks, using Twitter as an example.

The study on the temporal patterns of tweets as related to the spatial distribution of tweets may shed light on people's daily activities. From tweet analysis we may collect data on places people have been to, how long they stay at a particular place, *etc*. For smart phone users, Tweet contents may provide a real-time record of people's activity episodes that is even more accurate than a travel diary recorded from memory recall. Besides, this data collection is non-intrusive, so subjects don't need to write down purposely what they are doing and at what time, because the time of a tweet is recorded automatically by the online service. Traditionally, travel behavior is usually studied using travel diaries that are a part of a travel survey—which is very expensive in terms of time and labor. On the other hand, online social networks provide a possible channel to collect data on people's daily activities and to study activity-based modeling without circulating questionnaires. Although data collected from online social networks provide a promising way to study travel behavior, we also need to note that it is not randomly designed and the studied sample is self-selective. Therefore, it is also interesting to study the relationship between tweet users and their socioeconomic characteristics, such as age, gender, income, occupation, *etc.*

Who are frequent users of online social networks?

Who are likely to disclose their locations and activities?

Are tweet activities different between people in large cities and rural areas?

How is the distribution of tweets related to land use within an area?

How is the tweet pattern correlated to socioeconomic characteristics?

How is the distribution of tweets within a day, on different days of a week, and around a major event?

Do young people tweet more?

Do people in big cities tweet more?

Is the number of tweets related to the type of jobs or life style?

Harnessing Massive, Crowdsourced Data for Intelligent Decision Making

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Advanced social media, smart phones, and mobile technologies enable unprecedented capabilities for a layman to act as a data collection sensor. Crowdsourced data present arduous challenges for their utilization in disaster relief: they are noisy, unstructured, informal, massive, and unpredictable; and great opportunities such as timely updates, immense coverage, and most of all, collective wisdom. In this presentation, we will introduce an ongoing project—ACT (ASU Coordination Tracker) for Disaster Relief. Using disaster relief efforts as examples, we will elaborate the obstacles of employing crowdsourced data, and illustrate how to turn raw data to usable information for intelligent decision making by innovatively analyzing and processing crowdsourced data. ACT is an inclusive, open-source platform that is aimed to seamlessly integrate with state-of-the-art systems and tools such as social network analysis, multi-agent modeling, visual analytics, etc.; and with new functions necessary for logistics, planning, and response coordination.

What else do we want to know about social networks?

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What is common to all networks and what is unique to particular network types? Are we looking at the sorts of networks that matter? Can we answer questions about membership dynamics in significant types of networks?

Humans live in relation to each other. Sometimes they live in strong relationship, sometimes in weak relationship. Families, friendships, business partnerships, transnational organizations, political parties, clans and tribes, swim teams, charities, drug cartels, and organized crime are all forms of human relatedness, ensuring that the members of these networks are more strongly tied to each other in some time and place than to other networks at the same time and place.

Social network analysis should facilitate understanding of variables governing where and when members enter each network, how, when, and where a network expands and contracts, how relationships alter dynamically within a network, how multiple networks might share members, which network has the strongest claim to member loyalty at any given time, and how networks start and end. Given the number of relationships most people have, an understanding is needed about when a repetitive pattern (buying coffee at the same Starbucks on Thursdays) reaches the level of a relationship in a network. People are usually proximal to multiple networks, but are unlikely to consider themselves in network with all of them. What level of connectedness/role/function is needed before a person is part of a network? What types of boundaries are recognized by people that cause them to see themselves as members of one network, but not another-even if they contact it frequently? (Is an older sister a member of a crime gang if a younger brother who takes her to lunch occasionally is a member?)

With the development of online social media sites and the accessibility of digital data associated with these sites, methods and concepts for visualizing, measuring, and describing network strength and organization have blossomed. A large number of metrics and strategies for characterizing online social media networks have been developed, usually extending graph theory and its focus on links and nodes to individuals who come in contact with each other. This methodology needs to be enhanced to answer questions about the dynamic nature of network creation and membership.

Key to creating a general approach to networks is a better understanding of the varied types of relationship within networks (Wilson et al, 2009). Social network research needs to expand its focus to a range of types of networks and begin to compare and contrast the nature of relationships and roles within each of network. Analyzing the spatial and temporal aspects of networks can provide insight into the patterns of network membership, roles, and involvement not apparent from link and node analysis.

Potential Spatial constraints on Networks: Are networks constrained by space?

While the Internet has changed the impact of physical distance, proximity is well accepted throughout the social sciences as having an effect on strength of relationship. A considerable body of information exists that suggests that the closer individuals are to each other spatially, the more likely they will be close in a network (Scellato et al, 2010). An underlying geographic tenet is that near things are more related to each other than far things (Tobler, 1970). Unfortunately, social network analyses are seldom spatially enabled, so the potential of spatial relationship to add information about strength of relationship is unexplored. Part of the challenge is finding social network datasets that are spatially tagged. However, even with appropriate datasets, a number of complex challenges exist in adding spatial information to social networks. One of the problems is scale (Olson and Carley, 2010, Goodchild and Gopal, 2005). Selecting an appropriate geographic scale for a network may involve smaller aggregate areas for some nodes and relationships and larger for others. An exploratory spatial data analysis methodology for accurate selection of spatial scale for network analysis needs to be developed. Once spatial scale is selected, it is possible to add existing topographic or other spatial data to the node and link network representation to begin to explore aspects of the network. It becomes possible to ask such questions as whether networks with equal numbers of members and large spatial extent function the same as networks with smaller spatial extent. It also becomes possible to understand whether there is a relationship between type/effectiveness of network and place or type of member and place.

Although network analysis looks at all links between nodes, spatial analysis might look extensively at the spatial pattern of each node's closest links. Early work examining individual spatial distributions suggest that some nodes have circular spatial network distributions while others are linear. In some cases these distributions conform to elevation, road, and telecommunications features, but in other cases there appear to be additional variables determining individual node network patterns. This type of effect is only apparent when social networks are spatially enabled and are enhanced with additional geospatial data. Other challenges emerge when considering the display of networks with extensive near and far nodes since the scale of the nodes may be different than the spatial extent that is spanned. Additional challenges include understanding how to evaluate networks when some percentage of the attached nodes are spatially enabled and others are not. When is a form of interpolation permissible and when should data be treated as spatially unknown? How should spatially enabled networks with untagged nodes be displayed to allow accurate analytic interpretation? It is possible that some of the existing social media datasets using IP addresses as spatial analogues or actual declared locations might be used to create test sets to resolve some of these issues. For example, removing a percentage of the spatial information from a tagged network might provide additional understanding of the potential error involved in varied strategies of network display and analysis when only a proportion of the network is spatially enabled. It is also possible that additional spatial information such as

Census data might be used to increase insight into network relationships, network formation, and network distribution/development.

Temporal Challenges: What dynamic patterns are unique to particular networks and what patterns are repeated in all social networks?

Social networks are temporally dynamic, but most often treated as though they are static. Members join, participate, and leave and affect the shape and strength of the network and its relationships. Adding temporal analysis to social network analysis is likely to provide additional information about the strength of relationships and the importance of nodes to a network. Questions about the growth of networks, length of time to become a significant network node, lifespan of varied network types, and other network dynamics might be framed and answered differently if temporal aggregation into appropriate discrete units accompanies network analysis. However the same issue of scale is present with temporal tagging. Issues of how often a network should be sampled and how this is determined are currently unresolved. Understanding the temporal patterns of a network involves temporal exploratory data analysis and selection of statistically significant patterns for analysis. Jointly applying temporal exploratory data analysis and spatial exploratory data analysis may have statistical interactions and implications not yet articulated in the literature.

Integration of Network, Spatial, and Temporal Visualization:

Each network domain is likely to have an optimal method of data display and exploration. Providing a view of each element of a network, its relationships, its spatial extent and characteristics of place, and its temporal pattern is likely to be essential if the interaction of network, place, and time are to be understood.

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A new framework to define Familiar Strangers in online social networks: spacio-temporal challenges

A proposal from the DARSI (ADSNI) project team:

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Abstract

With the exponential growth of social networks of Internet the identity of an individual has become numerical and thus diffused in both time and space dimensions. We cannot ignore that online social network has become a new platform for people to communicate and interact with each other. In our study we propose to focus on the Familiar Stranger notion in order to adapt it to virtual communities such as online social networks and micro-blogging platforms. Familiar Strangers are critical in the understanding of our society (as they can become friend easily) and interesting for a lot of improvement of our community. In this study we propose to adapt and improve the actual formalization of Familiar Stranger applied to Social Networks by injecting both time and spatial constraint. This framework opens on some applications such as identifying the set of Familiar Strangers (FS) of a given micro-blogger in twitter.

Introduction

S. Milgram introduced in 1972 the definition of the concept of Familiar Stranger (FS) (Milgram 1977). Our Familiar Stranger is a person whose face is familiar to us but with whom we do not have direct interaction. An example of our FSs are people who take the same bus with us everyday, who we encounter repeatedly but without direct interaction (e.g. talking). Typically they are not our friends, but they are more likely to become our friends, as explained by S. Milgram. They look familiar to us and they share some common characteristics (hobbies, interests, etc.) with us. Recent studies have attempted to formalize some algorithms for Familiar Strangers detection (Agarwal, et al. 2009). The starting point of these algorithms is the building of a reference set of attributes named "Goal". In this work we present a new framework that revisits the definition of this set to better take into account spatial-temporal constraints. The first section of this paper presents the current definition of familiar stranger and discusses its limitations. Then in section 2 we propose a new definition that takes into account time and space. Finally section 3 presents the challenges of such approach.

1-Familiar Stranger definition on graphs

A social network can be modeled by a graph G(N,E,A) where N is a set of nodes (persons) linked by edges from the set E (relationships). Each node has a subset of attributes from a collection of attributes A={characteristics, hobbies, interests, ...}. Considering a graph G representing a social network the notion of Familiar stranger is defined as follows:

Definition 1[(Agarwal, et al. 2009)**]:**
The set of nodes T_u, FS of a node u respect two conditions:
- Stranger condition (H1):$\forall\, w \in T_u, edge(w,u) = 0$
- Familiar condition (H2):

$\forall\, w \in T_u, A_w \cap \gamma \neq \emptyset \; and \; \gamma \cap A_u = \gamma$,
Where:
$edge(w,u)$ *is a Boolean function revealing the existence of a link between nodes* w *and* u
A_u *is the set of attributes of a node* u
γ *is the Goal for the detection subset of attributes.*

Depending on the purpose, the detection of Familiar Stranger can be time consuming, especially if one wants to detect all the familiar strangers of any node without any limitation. A first approach can be to fix a Goal that is a subset of attributes (Academic, Arts, Business, News, Political, Geographical location, etc.) and to look for nodes that share the same attributes (H2) but that are not directly connected (H1). Each approach will therefore focalize on the way to search these individuals in the graph with some extensions of the concept. For more details about current techniques of detection and applications of this concept, the reader can refer to (Paulos et Goodman 2004, Perez, et al. 2010). Although the goal (as defined above) can contain attributes in relation with geographical location and activities over time, it does not take into account time and space constrains such as the geographical notions of neighborhood, proximity, distance, and their consistency over time.

2- A New approach to compute FS detection

Since no conditions imply directly a geographical distance between a person and his FS, we propose to improve the definition 1 with the geographical criteria that could approach the sociological definition of S.Milgram. (Liben-Nowell, et al. 2005) analyzes the relation between friendship and location of individuals. His study was about the LiveJournal social network. He concludes that one of the best approaches to link the geographical location with friendship in the network has to take into account a Rank Based parameter. This parameter is computed as the number of persons connected to the network that appear (based on geographical position) between two persons *u* and *v*.
Defining the rank as:

$$rank(u,v) = \{w \in N \mid d(u,w) \; < d(u,v) \},$$

where $d(u,v)$ is the Euclidian distance between u and v. The probability for u to interact with v on the online social network is the inverse of the rank:

$$Pr[(u,v) \in E] = \frac{1}{|rank(u,v)|}$$

This probability can be directly related to the location criterion of S.Milgram that is "an individual who is recognized from regular geographical position". We can consider that two persons are more likely to be familiar if they have a high probability to interact. This justifies the fact that two familiar strangers have a high probability to interact and that for example they can share the same way of moving from home to work. If the

Figure 1. Snapshots of the sub-community of a given network

probability $Pr[(u,v) \in E]$ is high, $|rank(u,v)|$ is low and thus there are few people who at the time of observation network, are located (geographically) between us. Therefore U is more likely to notice the presence (or recognized from regular activities) of V (figure 1). We propose to add a second "familiar condition" (H2.2) to the Familiar Stranger formulation in order to better fit with the original sociological concept.

Definition 2:
The set of Familiar Strangers F_u of a given node u respect three conditions:

- Stranger condition (H1): $\forall\ \mathrm{w} \in \mathrm{F_u}, \mathrm{edge(w,u)} = 0$
- Familiar conditions:
  (H2.1) $\forall\ \mathrm{w} \in \mathrm{F_u}, \mathrm{A_w} \cap \gamma \neq \emptyset$ and $\gamma \cap \mathrm{A_u} = \gamma$
  (H2.2) $\forall\ \mathrm{w} \in \mathrm{F_u}, \mathrm{Pr[(u,w) \in E]} \geq \mathrm{K}$

Where:
*K is the **familiarity threshold.***

As illustration, we provide in figure 1, two snapshots of the sub-community of a given network that have been captured at two different periods on the same geographical area. For convenience we have not displayed the links between the individuals. At the opposite of case (b), V shares his regular activities with less people in case (a) and therefore he is more likely to be "identified" by U.

3- Application and Challenges of this approach

We end this study by discussion some key issues emerging in the application of such framework.

Data collection

In order to compute the detection of Familiar Stranger, one needs to access a huge amount of data on the network (Relations,Messages,Location, etc.). The extraction of these data can be done through the APIs (Application Programming Interfaces) provided by some online social networks. These APIs provide a set of methods and documentation in order to extract, store, update (over the time) and analyze data in the limit of privacy level granted by users. The Graph G is built by extracting topology (friends, followers) and attributes are generated from messages, profiles with statistical text-mining methods like tf-idf (Tan 1999, D\"{o}rre, Gerstl et Seiffert 1999). We propose to apply our Familiar Stranger Detection Algorithm on the Graph of the twitter micro-blogging platform. For more information on the twitter API the reader can refer to www.apiwiki.twitter.com. One can notice that some extractions and network analysis have been previously done on twitter and other online social networks (Java, et al. 2007, Mislove, et al. 2007). We choose Twitter because it is used worldwide and it proposes geolocation services. For example when a user updates a new status the status can be geotagged with longitude and latitude of the user location. Figure 2 shows a status extracted in xml format with the

```
1  <user>
2    <id>Permanent unique id referencing a user</id>
3    <name>User specified name for a saved search</name>
4    <...
5    ....
6    ....>
7    <status>
8      <created_at>UTC timestamp of status creation</created_at>
9      <id>Permanent unique id referencing a status</id>
10     <text>Status body</text>
11     <source>Application that sent a status web/iphone/android</source>
12     <geo>Object that may contain GeoRSS or GeoJSON data for a point</geo>
13   </status>
14 </user>
15
```

Figure 2. Xml sample file of a user and status data associated timestamp and geotag on line 8 and 12.

Fast algorithm to compute the familiar stranger

The proposed framework is quite simple, since one can follow the public timeline of twitter through the API (i.e receive new statuses of public users), we propose to apply a FS detection every time that the targeted user (Node u) publishes a new geotagged tweet. Then we store in a list (F_u) the nodes that respect the 3 conditions of definition 2. However one of the obvious difficulties that may appear is the online extraction and time data. Due to combinatorial explosion issues one needs high speed processors and a high storage capacity to perform such an algorithm.

Conclusion

We have proposed a framework to improve the adaptation of the concept of Familiar Stranger to social network of Internet by adding Spatio-Temporal constraints. This proposal, specifically adapted for online social networks, attempts to better fit the sociological requirements as postulated by S. Milgram in his first studies. The resulting detection algorithm can be applied to any social networks or microblogging platforms that support geolocation APIs.

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Using Human Movement Data to Derive Dengue Virus Transmission Networks

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Movement patterns and social structure play an important role in modulating human-vector contact rates, affecting transmission dynamics, and the spread and persistence of vector-borne pathogens. For dengue virus (DENV), limited dispersal range of its day-biting vector, *Aedes aegypti*, points to movement of viremic humans as a plausible explanation for the rapid spread of infection across urban environments. We used field data from spatially-explicit semi-structured interviews (SSI) and GPS data-loggers to derive contact networks of individual humans for DENV transmission in Iquitos, Peru. We obtained movement data for 300 participants and expressed their contact network as an undirected bipartite graph representing the locations participants had in common as a consequence of their routine movements. Different measures of network topology were estimated for the full contact network and "key sites" network containing only those locations where exposure to *Ae. aegypti* is most likely (houses and schools). Places where participant's spent the most time outside their home were other residential locations (71% of total time); markets and stores (18%); parks, cemeteries, and recreational areas (3%); and hospitals and health posts (2%). Average degree of a participant (number of locations visited) increased with age from an average (SD) of 2.8 (1.1) for 3–8 year olds to 7.1 (4.3) for 45–69 year olds. The derived key-sites network had a main component with 69% of all the participants, indicating a high degree of connectivity at residential locations. Current targeted vector control programs focus on neighboring homes within 100 m of a diagnosed dengue case's house. Our quantitative empiric contact networks indicate that residential exposure can occur beyond 100 m of a person's home and are consistent with the notion that movement of viremic people is a prime driver of rapid DENV propagation in urban environments.

Position Paper

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Social networks are ubiquitous in contemporary times as we live in a mobile information society. Digital, internet-based social networks change human behavior. Some examples include: more time looking at electronic displays, more feelings of friendship, less privacy, different ways to travel, changes in world views and distribution of information. While some networks such as Facebook have seen great international success, one may interact with the network purely in a virtual environment. Others can require interactions in the physical environment such as LinkedIn and CouchSurfing. Hence these hybrid networks have different spatio-temporal constraints as they bridge the gap between the virtual and physical worlds. In addition they require variety of social skills from their users and methods used to analyze these networks differ from social networks with only digital interactions.

Geographic visualization techniques and time geography (Hägerstrand 1970) are valuable when combined with social networks. They are used for assessing critical nodes and trails as well as social capital (Pultar *et al.* 2010). An individual with high social capital signifies a critical node in a social network. The constraints of time geography are also a useful starting point for working with spatio-temporal restrictions and the sharing or flow of ideas and information.

Social networks combining virtual and physical worlds create a rich data source for social network studies. In the CouchSurfing (CS) network members from all continents provide each other with a free place to stay. Whether it be a couch, bed, or floor space this hospitality exchange network has created a new, emerging form of connection. Initially users contact each other virtually with a message through the Internet. Once a meeting time and place has been established members meet face to face. After the guest leaves both the host and guest return to the virtual world to leave references for each other. This influences their social capital and how well they will be able to utilize the social network in the future. Hence a critical node in the CS network is one that has high capital and good references, but do they have to play both roles (guest and host) in order to be the most trustworthy? Does one role in the social network have more of an effect than the other? What about the geographical distribution of their connections within the network?

The Internet is a key component of CS and its ability to function. This social network integrates multiple levels of networks such as transportation, data, and communication networks. Mass media affects the network in critical ways. Publications in blogs or widely read periodicals add to the popularity of the network increasing membership. Similarly, mass media depicting a dangerous place for travelers causes a decrease in tourism for a destination and hence the usage levels of a hospitality network.

There is a wealth of crowd-sourced data in the CS network. Members contribute volunteered geographic information (VGI, Goodchild 2007) in their profiles including

- Current city of residence
- Places to travel in the future
- Places traveled in the past
- Placed lived in the past

Additional data is available in the references users leave such as available activities near a host's location (Pultar and Raubal 2009). Thus there is a variety of data mining possible here that leads to changes in the way people travel. How trustworthy are these sources? If a member claims they explored caves with their host, how do we determine the level of uncertainty in this information? A member's social capital and reputation within the network are initial indicators for establishing uncertainty.

The field of social networks is quite interesting and rapidly changing as popularity moves from Friendster to MySpace to Facebook. New networks are created often with some services even allowing an individual to make their own social network in less than sixty seconds such as http://www.ning.com. The spatio-temporal constraints vary between social networks but some concepts such as making connections and sharing information are present in all the networks. These threads that tie together the multitude of social networks make for an exciting workshop to discuss the past, present, and future of social networks.

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Position paper for workshop on "Spatio-Temporal Constraints on Social Networks"

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Life in our mobile information society depends strongly on the interaction between networks, such as data and communication networks, transportation networks, and social networks. Space and time function as the major constraints for individual networks as well as for various network combinations. Examples are local area networks, which are bound to a spatio-temporal region; public transportation networks, which are spatio-temporally constrained and may connect to other nearby public transportation networks; and social and real-time information networks, such as Facebook[1] and Twitter[2], which are subject to potential access restrictions for a particular space and time (e.g., "China Blocks Access To Twitter, Facebook After Riots"[3]).

Spatio-temporal constraints impact social networks in different ways:

- They serve as *accessibility constraints* to a social network, e.g., scientist networks for citizens of a particular country that work abroad.
- They impact the *social capital* of the members of a social network, e.g., Couchsurfing, a worldwide network for making connections between travelers and the local communities they visit[4] (Pultar *et al.* 2010).
- They serve as *dynamic participation constraints* in services such as shared-ride trip planning (Raubal *et al.* 2007), whose members may form a social network by rating each other.

It is interesting to note that the constraints work both ways. The examples clearly demonstrate that spatio-temporal constraints impact social networks but social constraints also impact spatiotemporal networks.

Investigating spatio-temporal constraints on social networks (and vice versa!) involves different research questions, such as:

- How can we formally represent social and other networks in Geographic Information Services in order to allow for an impact analysis of spatio-temporal constraints? How should the results of such analysis be presented to the users of these systems?

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[1] http://www.facebook.com/
[2] http://twitter.com/
[3] http://techcrunch.com/2009/07/07/china-blocks-access-to-twitter-facebook-after-riots/
[4] http://www.couchsurfing.org/

- Is there a need for novel analysis frameworks that closely tie the spatial, temporal, and social components together or is a spatio-temporal extension to social network analysis sufficient?
- How can we quantify the impact of one network change on other networks? There seems to be a feedback loop, for example, spatio-temporal constraints impact social networks and in turn social constraints from such networks impact spatio-temporal networks.
- How can we best visualize different network levels and the impact of spatio-temporal constraints to offer users visual decision support?
- What are the critical applications where spatio-temporal constraints have a large impact on social networks? Which data sets are publicly available so that they can be used for benchmark testing?

Answers to these questions will help in the design of geospatial and social services that allow users to understand the impact of spatio-temporal constraints and network changes on social (and other) networks and offer optimal decision support in areas such as electronic tourism, agent-based collaboration (Raubal and Winter 2010), or transportation infrastructures.

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Spatial Decisions as Social Context

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Location-based services and social networks

The design of location-based social network services has been mainly driven by access to novel types of data and the opportunities these data offer to improve existing location-based services or to design completely novel ones (see the ACM SIGSPATIAL Workshops on Location-based Social Networks in 2009 and 2010). There is a need for research that advances our understanding of the networks underlying such services. This concerns networks in which social relations are explicitly specified as well as implicit social networks that are defined as networks of people showing similar spatial behaviour or sharing similar spatial interests even though they are not necessarily personally acquainted, for instance, the students of a university or the participants of a frequent flyer program.

Spatial and temporal constraints are relevant even for the most elementary service, a buddy finder which informs the mobile user when some friend happens to be close to his or her geographic position. Such a location disclosure service makes two assumptions (1) the importance of face to face contacts which the service sets out to establish, and (2) the availability of data about explicit social relations, namely, the list of the user's friends. Many location-based services, however, abandon one or both of the assumptions. Social serendipity services still facilitate face to face contacts but they do so between individuals who do not necessarily know each other suggesting contacts on the basis of similar interests. In contrast, geographic recommender systems offer services that neither make use of explicit social relations nor establish face to face contacts. They identify geo-referenced data objects that might be of interest to the user based on information about the past choices of that user and the choices made by the user community. We argue that spatial and temporal constraints are especially important for services which exploit implicit social relations.

Geographic Recommendations

In our research group, we have studied spatial constraints on social networks primarily in the context of collaborative filtering approaches to geographic recommender systems. Geographic recommendations are based on a heuristic principle: people who agreed in the past in their spatial choices are likely to do so in the future. Different approaches to geographic recommender systems take different types of choices into account, for instance, travel destinations of the users, shops they visit, or—as in our research—the objects the users photograph. Data crawled from web-based collections of geo-referenced images shows that the choice of places at which tourists take photographs is characterized by a power law relationship between popularity rank and image frequency. Typically, one to five sites in a city are photographed by almost everybody while the other sites attract only the interest of a few visitors (see Fig.1, Schlieder 2007, Matyas & Schlieder 2009)

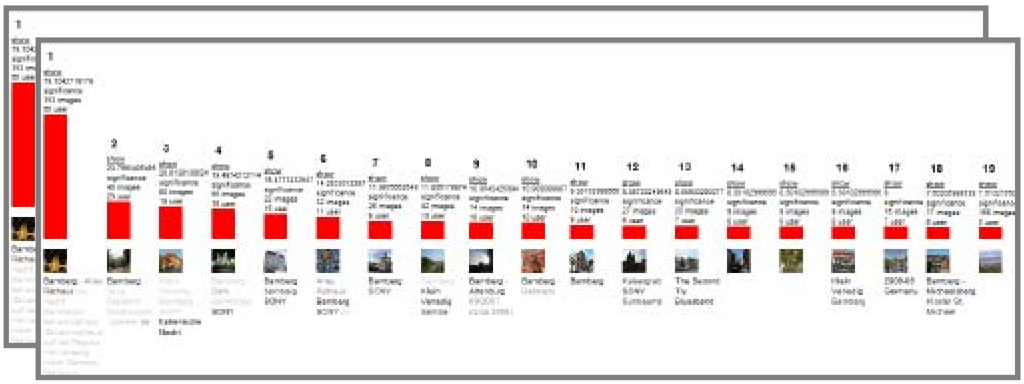

Figure 1. Exponentially decreasing touristic interest in urban places

Comparing the choices of different users, we found, that the differences in frequency need to be taken into account (Schlieder & Matyas 2009). A good predictor for geographic recommendations consists in spatial decisions adopted by only few users. Fig. 2 shows the places two tourists photographed. The fact that the users agreed on rarely photographed sights (rank 9, 12, 20, and 42) is much more informative than the fact that they both photographed the most popular sight (rank 1).

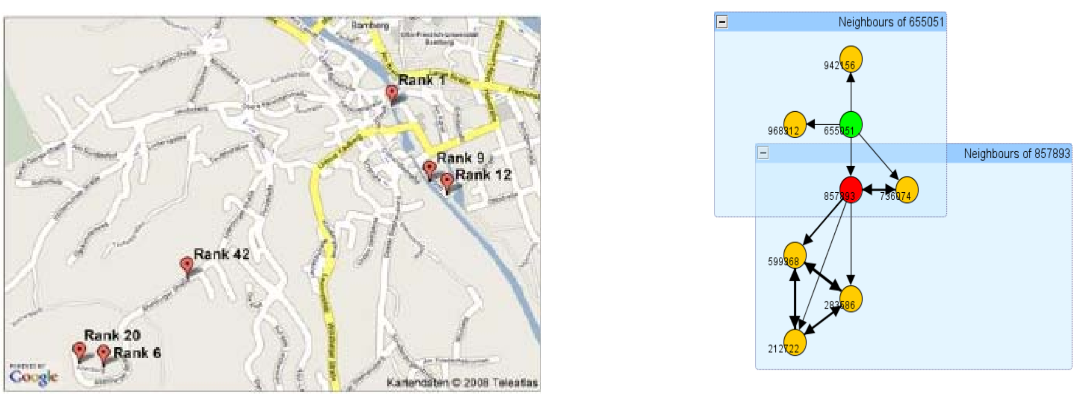

Figure 2. Places where two users agreed in their spatial decisions and part of the implicit social network arising by grouping users that take similar spatial decisions

Similarities in spatial decisions translate into a grouping of the users—an implicit social relation. We found that a k-nearest neighbour grouping often produces asymmetric relations in our data sets in the sense that a user *A* belongs to the set of the *k* users most similar to user *B* while *B* not being among the *k* users most similar to *A*. Asymmetry means that it is easier to predict the behaviour of B given the behaviour of A than vice versa.

Implicit Social Relations: Research Issues

We hold that successful spatial information services of the Social Web such as geographic recommender systems will have to focus on the long tail of the frequency distribution, that is, on individual differences. Open research issues include the following:

- Which types of user behaviour are best predicted by similarities of spatial decisions? Which other data sources provide the most valuable complementary information?
- Which models of temporal sequences of actions are most appropriate? How do levels of spatial granularity interact with spatial decisions (e.g., countries visited vs. cities visited)?
- How do displacements in groups constrain spatial decisions (e.g., being on the same plane vs. participating in the same frequent flyer program)?
- How do we model individual differences in the conceptualization of geographic places, for instance, the images associated with a city?

Recently, we have started to study another type of services that build upon implicit social relations, namely confirmation mechanisms for reports of events gathered in crowd sourcing networks (Schlieder & Yanenko 2010). A report about an event is confirmed by a report stating the same facts and being spatially and temporally close to the first. We argue that social network data should be used in situations affected by social biases. In such a case, a report is best confirmed by a report from an observer with a contrary perspective, a different stake holder. This raises yet another research issue, namely that of modeling the structure and dynamics of information flows in stakeholder networks.

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Relevance of Time Geography to Spatio-Temporal Constraints on Social Networks

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Hägerstrand's time geography examines human activities under various constraints in a space-time context (Hägerstrand, 1970). Space and time are connected through the concept of *space-time path* that tracks an individual's sequence of activities at different locations over time. The *space-time prism* concept, on the other hand, delimits a feasible spatio-temporal opportunity space that an individual could conduct his/her activities under capability, authority, and coupling constraints. Although time-geographic concepts were developed mainly for human activities in physical space, these concepts are relevant and applicable to human activities in virtual space enabled by information and communication technologies (ICT) such as the Internet and mobile phones. For example, people who do not have access to a smartphone face more capability constraints on social networking than those who have a smartphone with an unlimited data plan. Different social networks often have their own policies on user access, information sharing, among others. These are examples of authority constraints. Instant chats still require all parties involved be available online at the same time, which represent a coupling constraint. It is clear that time-geographic concepts have potential of helping us gain better understanding of spatio-temporal constraints on social networks. However, some classical time-geographic concepts need to be modified and extended to accommodate the changing nature and characteristics of human activities and interactions in virtual space. Among many possible directions of extending time-geographic concepts for studying spatio-temporal constraints on social networks, I would like to focus on the following challenges in this position paper:

(a) Interconnected Physical and Virtual Spaces: Physical space and virtual space are not independent from each other. They interact and influence each other. For example, time zones around the world certainly place some constraints on online social networks as people still need to sleep. Although ubiquitous computing and communication have been discussed for years, we are not there yet (or may never be there due to considerations other than technology). Locations of information and communication infrastructure in physical space can influence where we can have access to activities in virtual space. On the other hand, interactions with other people via online social networks can shape our activities and schedules in physical space. Our understanding of these interactions between physical space and virtual space is rather limited. The constraint concept and a space-time context suggested in time geography can help us formulate a spatio-temporal framework for studying how human activities in physical space constrain their online social networking activities and vice versa.

(b) Use Time-Geographic Concepts to Analyze Individual Spatio-Temporal Constraints on Social Networking Activities: Many social network sites (e.g., Facebook) offer information such as user names and date/time of postings. Such information could be used to build space-time paths of social networking activities and interactions. With recent progress in space-time GIS research based on time-geographic concepts, it is feasible to manage, analyze, and visualize individual activities and interactions in both physical and virtual spaces (Shaw et al. 2008, Shaw and Yu 2009, Yu and Shaw 2008). Online chats and postings among friends can be represented as virtual links among the space-time paths of involved parties. We can then visualize and analyze the spatio-temporal activity patterns of individuals as well as the spatio-temporal interaction patterns among individuals. Such studies could help shed light on the operation of spatio-temporal constraints and their effects on social networks at both individual and group levels. Alternatively, we could conduct surveys to collect data of both physical and virtual activities from individuals and then construct a space-time GIS database involving both physical and virtual activities. This would permit researchers to investigate mutual interactions (including spatio-temporal constraints) among online social networking activities, other virtual activities, and physical activities.

(c) Linkages between Virtual Locations and Physical Locations: Hägerstrand (1970) discussed the concept of *bundle* within the context of coupling constraints. An individual forms a bundle with other individuals and/or entities when they need to be coupled together to perform a specific activity. This concept is directly applicable to social networks, except that they are bundled at a virtual location rather than at a physical location. This brings up an important consideration of linking virtual locations with physical locations since social networks are tied to both locations. For example, a message posted on Facebook may lead to a get-together among a group of friends at a physical place if their spatio-temporal constraints defined by Hägerstrand's space-time prism concept permit them to be at that location during a specific time period. Some important research questions include, for example, the definition and representation of virtual locations. We could argue that locations of nodes and links in a virtual network are not relevant according to a topological perspective. This is true if we only are interested in the connectivity and flows between different nodes on social networks. However, when we chat with a friend who is 1,000 miles away, we are unlikely to suggest "let's meet at a nearby Starbuck store an hour from now." It therefore is important to consider the research needs of analyzing topological relationships on a meta-network versus research needs of understanding spatial-temporal constraints at the individual and small group levels that time geography could make valuable contributions.

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Computational Modeling of Spatio-temporal Social Networks: A Time-Aggregated Graph Approach

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Introduction

Social computing is transforming on-line spaces with popular applications such as social-networking (e.g., Facebook), collaborative authoring (e.g., Wikipedia), social bargain-hunting (e.g., Groupon), etc. Spatio-temporal constraints are becoming a critical issue in social computing with the emergence of location-based social-networking, Volunteered Geographic Information (Goo 07, Elw 08), Participative Planning (Elw 08, Fis 01), etc. Location-based social networks (e.g., foursquare.com and the "Places Check-in" feature on Facebook) facilitate socialization with nearby friends at restaurants, bars, museums, and concerts. Volunteered Geographic Information (e.g., Wikimapia, OpenStreetMap, Google MyMaps) allows Internet users to participate in generation of geographic information. Traditional computational models for social networks are based on graphs [Fre 06, Was 94, Nrc 03, Cro 09], where nodes represent individual actors (e.g., persons, organizations) and edges represent relationship ties (e.g., communication, financial aid, contracts) between actors. Such graph models are used to assess centrality and the influence of actors (e.g., measures such as degree, reach, "between-ness," bridge), as well as community structure (e.g., measures such as cohesion, clustering, etc.). Statistical properties such as skewed degree distribution are modeled by random graphs [New 02, Nrc 03], where each node-pair has a connecting edge with independent probability *p*, which may depend on factors such as geographic distance [Won 05].

However, traditional graph and random graph models are limited in addressing spatio-temporal questions such as change (e.g., how is trust or leadership changing over time? who are the emerging leaders in a group? what are the recurring changes in a group?), trends (e.g., what are the long-term and short-term trends in network size or structure? what are the exceptions to the long-term trend?), duration (e.g., how long is the tenure of a leader in a group? how long does it take to elevate the level of trust such as a relationship changing from visitor to friend?), migration, mobility and travel (e.g., interplay between travel behavior and size/structure of social networks [Tim 06]). This position paper explores time-aggregated graph models to support computational tools to address such questions.

Background

"A social network is a social structure made up of individuals (or organizations) called "nodes," which are tied (connected) by one or more specific types of interdependency, such as friendship, kinship, common interest, financial exchange, dislike, sexual relationships, or relationships of beliefs, knowledge or prestige" [Wik 10]. Network formation theories bring up the principle of homophily [McP 01] (i.e. birds of a feather flock together) and differentiate between two types, namely, baseline and in-breeding. Baseline homophily [Fel 81] refers to the limited social pool available to individuals for tie formation due to foci of activities, demographics, etc. In-breeding homophily models additional constraints due to gender, religion, social class, education, personality, etc.

Spatio-temporal constraints (e.g., geographic space, travel, schedules and diurnal cycles) play a major role in determining baseline homophily due to reasons like opportunity and minimization of cost and effort [Deb 69]. Survey research on student housing communities [Ath 73, Mok 04] and Torontonian personal communities [Wel 88] have provided evidence on the role of geographic spaces. For example, [Wel 88] noted that about 42% of "frequent contact" ties lived within a mile of a typical person. Computational simulation based on agent-based models [Cro 09], game-theory and cost-benefit analysis [Joh 00] as well as spatially embedded random graphs and distance-decay based edge probabilities [Won 05] have reproduced many properties of social networks including small-world properties (e.g., graph diameter), short average geographic distances, community structures, low tie density, etc.

Traditionally, social network research has had a relatively small amount of data from infrequent longitudinal surveys and computer simulations. However, the recent popularity of social computing on the Internet is providing large and frequently-sampled spatio-temporal social interaction datasets. These may facilitate better understanding of social network formation and the role that spatio-temporal constraints play, in the face of opportunities to interact with distant actors via Internet based social networking applications. This development also highlights a central role for computation and computational models, not only to scale up to the large and growing data volumes, but also to address new spatio-temporal social questions related to change, trends, duration, mobility, and travel.

Time-Aggregated Graphs

Given a spatio-temporal social network dataset and analysis questions, a computational model provides a representation to not only specify the dataset and questions, but also design data-structures and algorithms for addressing the questions. The model should be able to scale as large datasets are becoming available from Internet based social computing services with a large number of actors and a large number of time-points.

There are several challenges associated with modeling such a network. The model should be able to accommodate changes and compute results consistent with the existing conditions both accurately and simply. Furthermore, for quickly answering frequent queries such as tracking recurring changes in a group, fast algorithms are required for computing the query results. Sufficient support for the design of correct and efficient algorithms should therefore be provided by the model. The need for computational efficiency conflicts with the requirement for expressive power of the model and balancing these two conflicting goals is challenging.

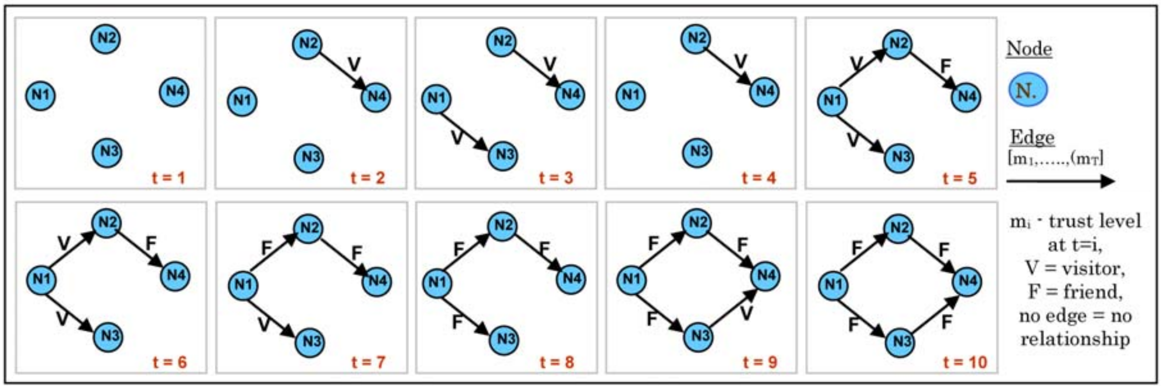

Figure 1: A Time-series of Snapshots for a trust Network for time instants 1 through 10

Dynamic networks are often modeled using a time-series of snapshots [Tan 07, Lah 08] of actors and their relationships. For example, Figure 1 shows a time-series of snapshots of a trust network for time instants, t = 1 to t = 10. Three levels of trust are exhibited in Figure 1, where an absent edge indicates that there is no trust relationship, an edge with V indicates a visitor trust relationship and an edge with F indicates friendship, which is a stronger relationship than visitor. For example, (N1, N3) have no trust relationship at t = 1, 2, and 4, a visitor relationship at t = 3, 5, 6, and 7 and a friend relationship at t = 8, 9, and 10. Due to duplication of information about nodes and edges across snapshots, the scalability of snapshot time-series model is limited in answering longitudinal questions such as how long it takes a relationship to evolve from visitor to friend. Storage and thus computational cost increases linearly with the number of time-points.

An alternative is the time aggregated graph (TAG) model [Geo 06], which has provided scalable algorithms for temporal questions in transportation networks [Geo 08]. Figure 2 shows a time aggregated graph that is based on the trust network of Figure 1. Each edge has a time series (enclosed in square brackets). For example, the trust relationship for the edge (N1, N3) for all instants within the time interval under consideration are aggregated into a time series [-,-,V,-,V,V,V,F,F,F]; the entry '-' indicates that the edge is absent at the time instants t = 1, t = 2 and t = 4.

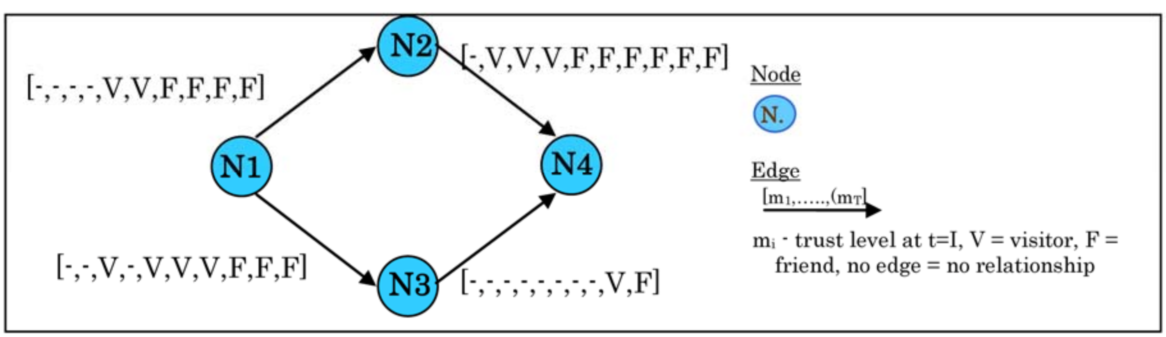

Figure 2: A Time Aggregated Graph for a Trust Network for time instants 1 through 10

With the time aggregated graph model, the longitudinal behavior is captured for each edge (or node). Time aggregated graphs do not replicate information about nodes and edges across time-points. This reduces storage cost as well as computational costs. It also consolidates time-series information to make it easier to answer cross snapshot questions such as how long it takes for a relationship to evolve from visitor to friend. For example, in Figure 3, it takes 2 units for edge (N1, N2), 3 units for edge (N2, N4), 4 units for edge (N1, N3) and 1 unit for edge (N3, N4) with an average of (2 + 3 + 4 + 1) / 4 = 2 units, for a relationship to evolve from visitor to friend. Answering this duration question in snapshot model takes more effort due to the need to repeatedly go from one snapshot to the other.

Discussion

Time-Aggregated Graphs has the potential to be a general representation of temporal evolution of relationships, whose snapshots were traditionally modeled as graphs. Thus, it may help address questions about individual relationships over longer time-frames by providing a representation for relevant datasets. For example, consider social network datasets representing *friend-of* relationships among people. Currently, graph representations are used to model a static (e.g., time-snapshot) view of social relationships to explore questions like centrality (e.g., leaders), and cohesiveness of communities. In contrast, TAG may support a direct representation of a "friend-of" relationship over long time periods to address questions related to changes in and evolution of centrality (e.g., emerging leaders) and group cohesiveness (e.g., increasing, diminishing). We welcome collaboration towards identifying datasets and use-cases to evaluate the potential of TAG to address spatio-temporal questions about social networks.

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A Geographic Conceptual Framework for Understanding the Spatio-Temporal Constraints on Social Networks

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In much the same way as web search engines provide instant access to the retrospective web of previously crawled and indexed content, rapidly expanding social computing services are a catalyst for what is known as the prospective web, with constantly modified real-time content that reflects the current activity of the web's participants. As an integral part of the prospective web, social media is quickly becoming social sensors that broadcast signals at both individual and societal levels. The explosive growth and diffusions of locative social media and the spatial turn in media studies, coupled with the communicational turn in geography, are providing us a golden opportunity to study social media and social networking from geographic perspectives. As the first step, I am interested in contributing a geographic conceptual framework for understanding spatio-temporal constraints on social networks. This framework will be developed by synthesizing the insights gained from the spatial turn in media studies (Falkheimer, and Jansson, 2006) and the communicational turn in geography (Adams, 2009).

For this workshop, I have made the initial attempt to piece together such a comprehensive framework (Figure 1). This synthetic framework is influenced by Gregory's (1994) earlier writings and Adams' (2009) recent effort to synthesize the literature. Embedded in our framework are a myriad of ideas developed by both geographers and scholars in other disciplines. Page limit makes it impossible to elaborate the framework in detail, but it suffices to highlight the key components that can shed light on many of issues stated in the workshop call for papers.

Following Adams' (2009) lead, I argue that geographic studies on the new social media should incorporate perspectives of space & place (the horizontal dimension of Figure 1) and coding/representation and spatial organization (the vertical dimension of Figure 1). As Sack (1980) and Casey (1998) have so cogently argued, conceptualizations of space and place have a rich history and do not lend themselves for easy summary. According to Tuan (1977), space has often been associated by geographers with freedom, movement, distance, potential, and abstraction whereas place often implies confinement, stability, proximity, meaning, and the concrete. In the context of media and communication, Adams (2009) argues for the dual process of both space-making and place-making—pace implies patterns, flows, and ideals of public life while place implies territory, daily routines, and ideals of personal identity & privacy.

According to this framework, space, place, and media are mutually constituted, as Adams (2009) observed that "without space and place as the (a) priori frameworks for experience communication is meaningless, yet without communication we would not be able to conceive of space and place (p. 5)." The double Mobius strip at the center of the figure is used to signify the mutual constitution among space, place, and media. When media is examined from both space and place perspectives, four core set of themes can be raised, i.e., media in spaces (I), spaces in media (II), places in media (III), and media in places (IV).

According to the preliminary framework, the dialectical relationship between media and spaces is examined via the relational view and processes of transduction. The relationship between places and media is studied via the performative view and the processes of structuration. Spaces and places in media are socially integrated via a diverse scheme of coding and representation which can be linked to co-presence in time and space that contributes to time-space compression and routinization. Media in spaces and places are technically integrated to shape the spatial organization via absence in time and space that leads to time-space distantiation. This is a hybrid framework because space and place serve both as the container (providing the context for social media, top half of the figure) and the contained (produced by the content of social media, bottom half of the figure).

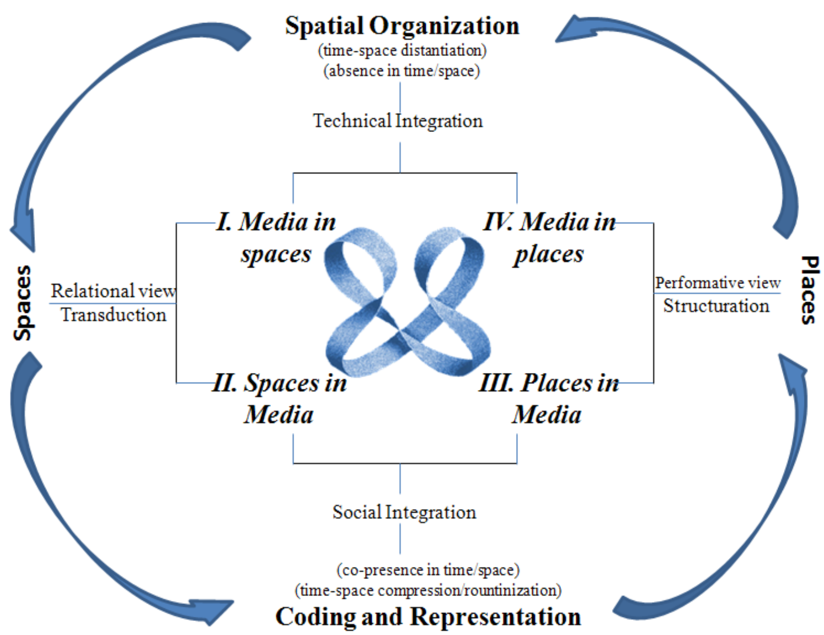

Figure 1. Conceptual framework for studying geographies of social media [Developed based upon synthesis and expansion of ideas in Adams (2009) and Gregory (1994)]

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Linking Local Communities of Interest into Networks of Communities

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There are several common organizing principles for online communities, notably people, places, and topics. Notable examples include: Facebook and Twitter organize around people, Foursquare organizes around places, and PatientsLikeMe and CNet organize around topics. Of course, these are only a few examples. Moreover, few communities organize solely around any one principle. Most topic-oriented sites support social interaction. Social services like Twitter can—with proper filtering and interfaces—be useful sources for topical information. And some sites combine a local geographic and topic orientation. This is the space my work is situated in and extends.

Our research group created and maintains Cyclopath, a site for bicyclists (topic) in the Twin Cities metropolitan area (place). Geographic place scopes the system: the interactive map covers the seven county metropolitan area. Bicycling defines the content of the system: the network of roads and trails used by cyclists along with various annotations relevant to the activity of cycling. Cyclopath also enables several forms of social interaction:

- Cyclopath is a wiki, so users can interact around the revision history by providing comments for their revisions and giving feedback on other users' revisions.
- Cyclopath includes a built-in discussion space. Users may (if they choose to) *geolink* messages in the forum to objects on the map (places, regions, or road/trail segments).

From one perspective, bicycling is an intensely local, geographically constrained area: cyclists ride mostly close to their homes. It also is a knowledge intensive activity, and one of the best and most frequently consulted sources of knowledge about riding is other local cyclists (Priedhorsky and Terveen, 2008). Thus, it is natural for a bicycling online community to focus on a single geographic area, as Cyclopath does for the Twin Cities. However, we are expanding Cyclopath to cover other geographic areas. As we do so, our strategy is to add more distinct local instances (we already have created one for another the Denver / Boulder metro area, which currently is in closed alpha testing). However, bicyclists also have a lot in common, regardless of where they live, such as interest in new bicycles and gear, training regimens, ways to coexist safely with cars, etc. Further, different Cyclopath instances use the same software, so Cyclopath system knowledge, e.g., of editing policies and interface tools, transfers across instances.

Therefore, as we develop new Cyclopath instances, we have a potential opportunity to investigate the types of social interaction and knowledge sharing that are constrained by geographic bounds and those that are not. We have made design decisions and are developing interaction techniques that will let us conduct studies to address these issues. We have made user identities global across all instances, meaning a single person can log in to any instance under the same identity. We also have encouraged experienced Twin Cities Cyclopath users to help out with the startup process in Denver. We are observing this process informally currently by analyzing usage data and monitoring discussion forums. We will first examine differences between the roles played by local and non-local people in a Cyclopath instance.

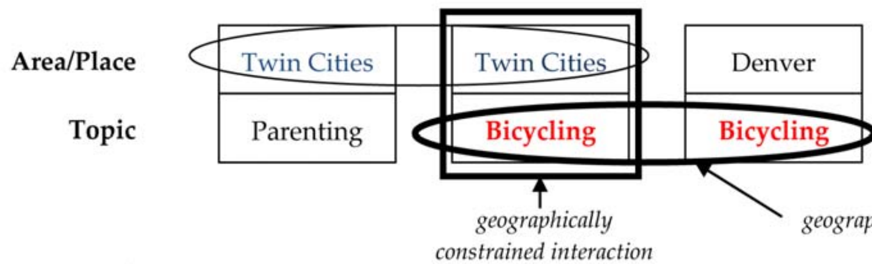
We will create new algorithms and interface mechanisms to support the roles we observe. For example, discussion topics in Cyclopath already can be *geolinked*, i.e., associated with geographic objects such as a trail or area of interest. We will augment geolinking with geographic filtering, letting users specify discussion viewing preferences like "Only show me discussions that are not geolinked or that are linked to objects within 20 miles of my region of interest." This mechanism will let different geographically local communities that share an interest (e.g., bicycling or parenting) share a common discussion forum, yet let users see only those topics that are relevant to them.

We then plan a set of natural experiments to investigate which types of tasks and patterns of social interaction take place mostly within a local community and which span community boundaries.

- We will examine how people use the geolinking and geofiltering features of discussions. Will it enable local communities to share local information within their scope, while reaching beyond their boundaries for general topic-related information? We will analyze usage of these features, the structure and content of the discussions that result, then follow up with surveys and interviews as appropriate.
- As we create new instances of Cyclopath, we will explicitly invite members from established instances to participate in the new instances, sharing general bicycling information as well as knowledge about the Cyclopath system. We will investigate a number of key issues, including:
  - How much time do "long distance" users devote to a new local instance?
  - Do they take on different roles in the two instances? For example, do they contribute more content in their "home" instance and do more "community maintenance" work (Bryant et al. 2005; Panciera et al. 2010) in the "away" instance?
  - How do things change over time? For example, do "long distance" users take a prominent role early in the lifecycle of a new instance, then step back as the new instance matures?
  - How are "long distance" users affected by their participation in a remote instance? Do they decrease their participation in their home instance while they participate in a new one? And after their participation in the new instance declines (as we assume it will), will their participation in their home instance be different than it was before their participation in the remote instance?

Note that bicycling is just one topic domain—we could substitute other domains and make the same observations and carry out the same types of research. We intend to do just that, focusing first on the domain of parenting, which we think is an exciting domain for social media research. As a demographic, parents' needs and requirements for social computing technology are not widely studied; therefore, work in this context may reveal new requirements for the technology. Further, research shows that social networks play a crucial role in parental decision making. Third, parents need both very local ("which indoor play space is best to take my toddler to get some exercise on this rainy day?") and completely general ("How do I get my toddler to sleep through the night?") knowledge.

Finally, as the figure below suggests, we also could hold geographic area constant and substitute in a new topic, and see which social interactions are constrained by and which cross topic boundaries.



Framework for studying constraint of geography and topic social interaction

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Homophily as Constraint & Opportunity

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Space–time homophily suggests that many activities are local, in some sense. Localness is a type of constraint that is susceptible of exploitation. In this circumstance techniques such as multidimensional scaling can often yield locational coordinates. It may then be possible to analyze flows of information, or the movement of people, etc, using the space-time coordinates that describe where these events are positioned in this homophilyic environment. The localness of such events implies the possibility of estimating partial derivatives in time and space. If this is valid then a further suggestion is that one can interpret these as gradients, i.e., space-time vectors. An interpolation in space-time of individual vectors can then be performed to obtain a quasi-continuous vector field. The vector field, if it is a gradient field, will be curl free, a situation that should be tested. Integration, in the mathematical sense, of the vector field can then give one a scalar potential. This potential is of course determined only up to a constant of integration. And the potential should be that its gradient coincides with the original vectors; an iteration may be necessary to obtain this result. The final potential forms a compact description of the event situation.

Another possibility comes to mind. Geographic positions can be specified using metrical location names φ (latitude) and λ (longitude). Many analysis procedures relating situations given in the form of matrices (social networks or pairs of texts) use a measure or index of similarity to impute locations (via MDS for example) in, usually, Euclidean space and thus assign coordinates u and v. When both of these spatial locations are so indexed there exists a one-to-one association between the φ, λ and the u, v names. So we can postulate $u = f_1(\varphi, \lambda)$ and $v = f_2(\varphi, \lambda)$, or $\varphi = f_3(u, v)$ and $\lambda = f_4(u, v)$, and also the inverses thereto. Interpolation of these functions to continuous fields allows estimates of the four partial derivatives from which Tissot's indicatrix (a.k.a. the strain tensor) can be calculated yielding information on the several (angular, areal, distance) distortions induced by the mapping transformations. Extension to space - time events using (non-Einsteinian) φ, λ, t and u, v, w units can lead to similar three dimensional properties and analysis.

Space –Time Cliques

Numerous indices and statistics have been developed in conjunction with two-way arrays. At the same time such data tables are increasingly available at several instances in time. One such example are from–to tables of geographic movement such as the several decades (1935–1940, 1949–1950, 1955–1960, 1965–1970, 1975–1980, 1985–1990, 1990–2000) of US

Census Bureau state-to-state migration tables. Another example can be seen in the regional input/output tables over time. I suspect that network indices have been developed or implemented for the analysis of such sequences, but I am not familiar with any. This needs to be looked at.

The Promise and Challenges of Social Media in Public Health and Medicine

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"Measure what is measurable, and make measurable what is not so."

Gallileo Gallilei (1564–1642)

The utilization of social media platforms including Twitter, Facebook & mobile continues to grow rapidly world-wide. Professionals and laypersons have adopted these communication and information platforms. Public Health providers may be both generators and professional consumers of content distributed through social media networks.

The consideration of how social media can be leveraged by providers to improve the Public's Health should incorporate data-driven, evidence-based measures. This is particularly true in environments where resources are scarce and there are competing priorities of known benefit and duty.

There are a number of ways in which social media are currently implemented in Public Health. These frameworks can impact the data compiled & analyses conducted. Social media examples posted by Public Health professionals to social media platforms include:

- Txt4Baby is the largest mobile health system in the United States with more than 101 thousand participants, according to HHS's CTO Todd Park
- In study of fifteen facebook diabetes communities 66% of posts were personal experiences and 27% were promotions for treatments according to Lisa Gualtieri
- As of Oct. 19, 871 hospitals have 2,259 social media sites, according to Ed Bennett's Hospital Social Network List
- Social media can be a resource for education and engagement via Jan Gurley, MD in Doc Gurley's "Recette de La Vie" docgurley.com.

There is a rich literature, ongoing research, policies and practice regarding the importance of social factors and health. Research incorporating the specific impacts of contemporary social media technologies per se is at a relatively early stage.

This gap presents an important limitation to understanding spatial-temporal factors in Public Health. The breadth and strength of social factors research linked to policies, standards and outcomes offer key resources moving forward.

There are a number of ways in which social media are implemented in Public Health. These frameworks can impact the data compiled & inform the analyses conducted.

There are many interesting and important questions to consider regarding spatial-temporal factors of social media and public health. These include:

- Which robust public health assessment methods and tools can be implemented to conduct spatial-temporal analyses of social media data?

- How can existing epidemiologic and statistical methods be extended to program and policy evaluation and outcome measures?
- What are the metrics of success and failure?
- Given similar issues and circumstances, what makes a particular social media instance more efficacious?
- What best practices can be identified to engage the broadest number of stakeholders in leveraging these dynamic resources?
- Which of these hold the greatest likelihood of being incorporated into existing workflows?
- What are the human subjects issues and ethical conduct responsibilities of this research and adoption of these technologies?

Social media are as old as human speech, with air being the medium through which sound waves propagate observes Mayo Clinic social media leader, Lee Aase. These dynamic tools and the spatial-temporal analysis challenges they pose are contemporary opportunities to improve the Public's health.

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The Principle of Complexity Management Networks

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Norbert Wiener speculated that the complex networks in the social and life sciences behave differently from, but not in contradiction to, those in the physical sciences with control emanating from the flow of information not from the flow of energy[1]. The significance of this observation cannot be overstated. In the physical world: cars roll down hill, traveling from higher to lower potential energy; an apple pie cools off, heat flows from the hot apples to the cooler room; hot air rises, being buoyed from the region of more dense to the less dense air. The force laws and therefore control in physical phenomena are a consequence of the negative gradients of energy potentials. Wiener's speculation implied that the force laws and therefore control in social phenomena do not follow the negative gradients of energy potentials but rather they follow gradients due to changes of information. This is Wiener's rule.

The Wiener rule remained speculation for over sixty years and it was only with the recent scientific activity to develop a science of networks that a form of the rule was proved true. This proof relies on generalizing some of the fundamental ideas of non-equilibrium statistical physics[2]. The science of thermodynamics explains the movement of heat and other irreversible phenomena in the physical world. Statistical physics seeks to explain thermodynamic formalism from the microscopic dynamics of physical systems. On the space and time scales we live our lives the laws of thermodynamics and statistical physics are familiar and seem to encapsulate our experience into a few simple intuitive principles. The dynamics of society's complex networks are a very different matter, however. Predicting the ups and downs of the stock market may have an analogy with Brownian motion, where a heavy particle is buffeted about by a fluid of lighter particles, but we cannot predict the average behavior of a stock's price the way we can the position of the heavy particle.
As the networks in which we are immersed become increasingly complex a number of apparently universal properties begin to emerge. One of those properties is a version of Wiener's rule having to do with how complex networks, perhaps involving phenomena assigned to very different disciplines, exchange information with one another.

The complexity of networks is herein quantified by inverse power-law distributions and consequently by their power-law index. But because of the ubiquity of such inverse power-law networks the imposed restriction is not overly severe. Now we consider two such

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[1] N. Wiener, *Proc. New York Acad. Sci.* (1948).

[2] G. Aquino, M. Bologna, P. Grigolini and B.J. West, "Beyond the death of linear response theory: criticality of the 1/-noise condition," *Phys. Rev. Lett.* **105**, 040601 (2010).

networks exchanging information: two people actually talking to one another; a patient's body talking to a physician during a physical examination; the music of a symphony orchestra influencing an audience member. Each complex network has its own characteristic exponent and the efficiency of the information transfer is determined by the relative values of the power-law indices.

One measure of the information transfer between two complex networks is the cross-correlation between the output of a complex network P and that of a complex network S being perturbed by P. In the figure the asymptotic cross-correlation function normalized to one is graphed as a function of the power-law indices of the two networks to form the cross-correlation cube. This cube displays a number of remarkable properties: 1) When the power-law indices are both equal to two there is an abrupt jump from zero correlation to perfect consensus; the spectrum associated with this exchange is exactly 1/f . 2) The upper plateau indicates that when P is non-ergodic $1<\mu p<2$ and S is ergodic $2<\mu s<3$ the time intervals between stimulating P-events are very short and the time intervals between unperturbed S-events are much longer. Consequently more S-events occur in response to the P-events than occur naturally and therefore the greater information in the P network dominates the process producing complete correlation between stimulus and response. This region of the cube can explain why a leaky faucet keeps a person awake at night. 3) The lower plateau indicates that when P is ergodic $2<\mu p<3$ and S is non-ergodic $1<\mu s<2$ the time intervals between P-events are much longer than that between the naturally occurring S-events. The S-events therefore disrupt the stimuli so there is no detectable response asymptotically and the information-rich S network washes out the influence of the stimulus. This effect occurs in habituation where after a short time we no longer smell a strong odor or hear the monotonous speaker[3].

How a complex network responds to perturbation by another complex network is determined by which of the two networks has the greater information and the Principle of Complexity Management (PCM) embodied in the cross-correlation cube[4].

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[3] B.J. West and P. Grigolini, "Habituation and 1/f-Noise," *Physica A* 389, 5706–5718 (2010).

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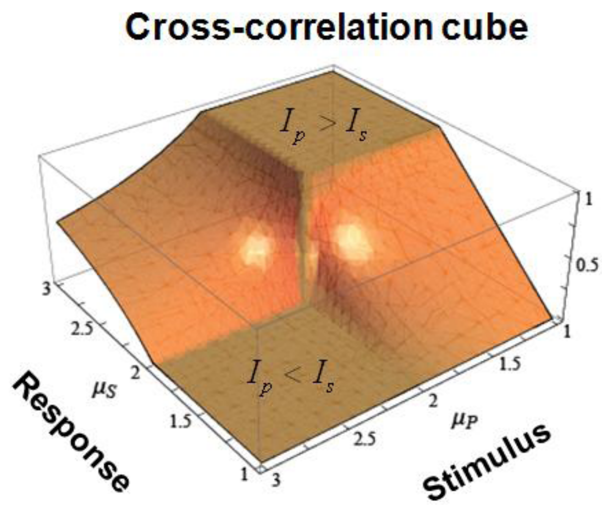

The cross-correlation cube and PCM. The asymptotic cross-correlation function is graphed as a function of the two power-law indices of the responding network S and the stimulating network P.

Wiener's rule described the influence of the stimulus as it appears on the upper plateau region of the cross-correlation cube where the information in the stimulus exceeds that in the response. In all regions except the lowest one the weak stimulus significantly modifies the properties of the responding network. In the upper plateau region the stimulus actually dominates the properties of the response and reorganizes it, just as Wiener predicted. However Wiener's rule is now part of PCM.

PCM quantifies Wiener's rule by introducing a measure of information in complex networks allowing us to compare the level of information in interacting networks. This measure is determined by the power-law index of the inverse power-law distribution and a generalization of linear response theory that in combination enabled us to construct the cross-correlation cube to determine the degree of asymptotic influence one network has on another. In this way the 1/f variability of stimuli is found to "resonate" with the human brain, as when we are entranced by music or irritated by a dripping faucet. Thus, there is a mathematical proof of Wiener's rule and its extension to the Principle of Complexity Management.

Social Media and Meta-Networks for Crisis Mapping: Collaboratively Building Spatial Data for Situation Awareness in Disaster Response and Recovery Management

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After a disaster strikes, answers to questions like, "Who is hurt?" and "Where is the hardest hit area?" may not be so easy to answer. Either while ongoing or after a disaster has occurred, too often the worst hit areas are not detected quickly enough. Due to a lack of awareness, this poses an even greater problem in rural or in the more isolated areas where communications have either failed, worked intermittently on a good day or are absent. No databases may exist providing geographic data on these more isolated or rural areas. The two earlier questions identify the problems this position paper tackles: (1) how do you identify impact zones and then once identified, (2) how do you populate a database with spatial data? Disaster assessment and situational awareness is required to support response and recovery efforts. Locals need to know where to go for help and responders need to know where to go to help those in need. A common site can be created for all stakeholders proving access to a map where anyone can use and access the map anytime and anyone can add information to the map anytime.

Searching for Signals

In AI there's the concept of "active learning," in which a supervised learning procedure requests samples from regions of the sample space where it has too little data. In monitoring some system (e.g., a network) for trouble, the absence of signals from some part of the system can indicate a failure there. Interspersed information will produce less data and may be a trigger indicating the system or someone to take a more in-depth look. So in a disaster, if messages are coming in from everywhere but some spots, maybe the damage is worse in those spots, and they merit investigation.

Crowd-sourcing and Crisis Mapping

In many rural areas and many underdeveloped areas there are not adequate databases on such things as vulnerable areas or locations adequate for temporary shelter. Only the locals may know this information. What one wants is a collaborative spatial data system such as Wikimapia where any participant can *pin* given symbols and text explanations along with other valuable information (videos, pics, links to sites) to a given site even if someone trained has to go around to locals who don't have the use of the web to collect the locations and what characterizes them.

The recent rain and wind storms that nearly destroyed but also flooded the tent sites where large numbers of Haiti refugees were stranded after a year has gone by, is one example as there was no real data to even base the decisions of where to locate other camp sites.

Crisis mapping as such can be the result of technological support given *volunteerism* and the acquisition of spatial data through crowd-souring. Information can be added to the map anytime and by anybody. Hospitals and temporary shelters can be identified by those who know the area best, the locals while data integrity issues are handled by those dedicated to support the system itself. Trained personnel using social media along with mobile technology and other web based methods of communication can help fill the gaps in missing data whereby real time crisis mapping can create and provide geo-spatial information for time critical response needs.

The Power of Social Media

In a single Tweet, more information can be provided building a very informative crisis map. A picture, video or link to another document (or two) can be sent along with a Tweet. Additionally, if the geoLocation device is turned on, other information is stamped with the 140 character blog. The Twitter account name, time, source of technology (TweetDeck, Droid, etc), and the longitude and latitude is sent making it such that the information is immediately mapped and available for real time decision making. People can build the streets where locals can identify buildings and shelters and other information that is needed. This information can be recorded and added to the data layers.

Conclusion

Building the capability to gather geospatial intelligence anywhere, anytime using social media along with web 2.0 technologies in a real time environment can provide feasible solutions to real problems that exist not only locally (The Conference Center, Katrina, New Orleans, 2005) but also globally (Haiti Earthquake, Pakistan Floods and now preparing for the Cholera outbreak in Haiti). By utilizing methods such as what was described here, ad hoc information can be created to help manage the unexpected. Collaboration among stakeholders provides a visual interpretation of data, crisis mapping offering decision makers and victims a way building collective intelligence from a grassroots effort. By creating such a tool, responders can better take care of the needs of the vulnerable population and victims.

More-than-Human Contact, Conspicuous Mobility, and the Digital Frontier

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mother: "Who's Tyler?"
daughter: "That's my new boyfriend."
mother: "When were you going to tell me?"
daughter: "Well, I put it on Facebook!"

Not only have social networking technologies provided alternative modes of interaction among individuals, but these technologies are increasingly shifting more traditional ways in which individuals interact in everyday life. This has implications for human contact, and therefore impacts all aspects of contemporary social life—government, politics, the interpersonal, kinship, work environments, artistic expression, health and wellness, informational media, entertainment, *etc.* A "more-than-human contact" has emerged, where mediation has become the norm, where the concept of "human-computer-human interaction" is excessively repetitive. Human interaction is always already digitally mediated.

My interest in more-than-human contact is, of course, rooted in my own implication in these new mediations. I entered the academy as the "GIS Wars" were cooling, and the question of the role of GIS in Geography was seemingly answered, resolved. My graduate study worked to design and develop an Internet-based public-participation spatial decision-support system. My dissertation research examined the use of mobile, spatial technologies in the mapping of community interests, by community residents. And my more recent work examines the emergence of spatial media—more specifically the tensions around framing this emergence as neogeographic and/or as volunteered geographic information.

A materialist-turn within social-cultural geography leaves GIScientists well-positioned to demonstrate how spatial data about everyday life can be utilized to better understand spatial practices, specifically mobility. By drawing the concept of the "more-than-human" from recent work within non-representational theories[1], a reinvigorated critical GIScience can examine spatiotemporal interaction as mediated by digital, spatial technologies. More-than-human contact assumes that contact is always already interdigitated—that the technological and the social are fused in contemporary society. Informed by the figuration of the cyborg and broader literature in technoculture[2], the concept of more-than-human contact enables our recognition of the multiple objects that, according to Sherry Turkle[3],

[1] Whatmore, 2006; Lorimer, 2005; see also, Anderson and Harrison, 2010.
[2] Wilson, 2009; Haraway, 1991, 1997; Hayes, 1999, 2005; Halberstam and Livingston, 1995.
[3] Turkle, 2007.

evoke the human condition. These digital objects have become part of our everyday lives, whether we like it or not. Our ability to have contact with others—to respond—necessitates their inclusion.

Spatial media have provided a more recent spatial twist on social networking. Online information from the crowd can be georeferenced; photo-sharing sites and micro-blogging tools enable their users to attach their current location to posts. And with the introduction of location-based services, networking giants like Facebook (with Places) and search giants like Google (with Latitude) are finding new ways to connect people with and through place.

These spatial media developments are generally not originating from departments of geography within the academy. These activities, of individuals producing geographic data and applications, have fallen under the term: neogeography[4]. Where 2.0, an O'Reilly Media Inc. conference is one such gathering of self-described neogeographers that has held six meetings since 2005. In a 317-person sample of the over 900 registered attendees of the Where 2.0 conference in 2010, nearly 72 percent represented private business, including behemoths like Microsoft, Google, and ESRI as well as recent start-ups. The prospect of developer announcements that might change the face of social media businesses attracted a number of attendees from news organizations. Nearly 12 percent of attendees were journalists or media managers. Less than 5 percent was from the government sector and nearly 1.5 percent was from nonprofits. Only 8.5 percent of attendees were academics, a third of which were students. Critical GIScientists must remain attentive to the pulse of these developments, particularly as they invoke a kind of locational awareness that is primarily motivated by corporate profit.

The question becomes, then, how do academic geographers enter in to these developments? How do *we* re-implicate ourselves? My own approach has been to continue to invest in what I have termed a "vigilant openness" towards this technology—to approach it in non-deterministic ways while remaining cautious of the multiple co-implications. In doing so, I want to develop two concepts to help understand the spatio-temporal constraints on social networking. The first, "conspicuous mobility," recognizes that many location-based services (LBS) for mobile devices cater to those who want to make known, or publish, their location and movement to those in their social network. However, the second, "digital frontier," notes that the use of LBS for social networking is a limited activity. Those at the margins of this movement in social-spatial networking constitute a digital frontier—where opportunities exist to alter the motivations and practices of mobile spatial data collection and publishing. It is at this digital frontier that I see great promise for a potentially radical neogeography—to leverage the increasing proliferation of Internet-based social media towards important social-economic and environmental objectives.

[4] Turner, 2006.

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Position Paper: Responsive social networks

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Introduction

The research idea presented here contributes to the effort to make social and other kinds of networks more responsive to events happening in geographic space. Consider the scenario of a wild-fire developing in a populated region, where neighbors begin to communicate with each other using cell phones and social networking software such as Facebook. As the fire develops and moves, traditional central and hierarchical means of communication and control break down, but others need to be alerted. The network of communications between neighbors needs to develop in parallel with the development of the fire, so that information is shared and appropriate actions are taken. There may also be the need for some time-critical, collaborative activities, such as the creation of a dynamic map, so that the entire group can see the boundaries and properties of the fire as it develops. All these activities will be facilitated by the development of a network of communications that is responsive to changing needs. The development of such a model is the focus of this research.

Outline of the model

Figure 1 shows the basic idea. A spatially embedded network evolves to meet changing needs. The figure shows the state of the network at two moments in time, as it responds to the movement of a front of some event of interest. The dark filled nodes represent active nodes, and the unfilled nodes are quiescent. As the front moves, the network needs to track the movement, and so the pattern of active-quiescent nodes changes, as does the edge configuration. We say that the dynamic network is responsive to the movement of the front. In this case the nodes are stationary.

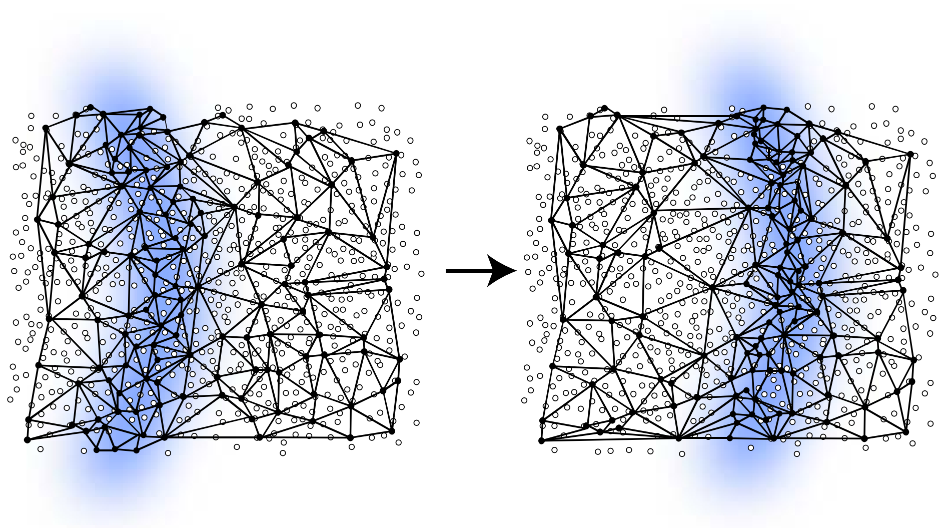

Figure 1: Network responding to movement of a front

Formally, we assume a directed graph embedded in space-time. Because of temporal auto-correlation, we model this as a temporal sequence of spatially embedded graphs. We also note that because of spatial auto-correlation, two spatially close nodes are more likely to be connected than two distant nodes.

There are several forms that responsiveness can take.

- Nodes are created and deleted
- Nodes transpose awake-asleep
- Nodes move
- Edges are created and deleted
- Edge weights change
- Nodes' spatial embeddings change
- Edges' spatial embeddings change

There is also the issue of to what the network is aimed to be responsive. We assume for this work that the network is responding to a dynamic field - a pattern of variation of a scalar or vector quantity over a surface (assumed to be part of the surface of the Earth). Another possibility might be responsiveness to the changes to a collection of spatial objects (e.g., points, regions).

Approach

We have already done extensive work on sensor networks responding to dynamic fields. We have constructed a model of spatial change [2,5,9] and constructed algorithms for detecting basic changes, particularly qualitative and topological changes, in a decentralized manner [1,3,4,6,7,8]. That is, the determination of change is computed entirely within the network, with no external controller. We aim to extend this approach to the problems described above. Our focus is on models and algorithms, and our principal domains of interest are in volunteered geographic information in time-critical and emergency situations.

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The Constraints and Benefits of Space and Time in Digital Social Networks

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I highlight three key issues related to integrating the constraints and benefits of space and time in digital social networks. They are (1) selecting the appropriate space-time scale of analysis; (2) integrating space and time within existing theories of strong/weak social ties; and (3) recognizing that software is an actor.

Finding the appropriate space-time scale of analysis

Bringing space and time into social analysis necessarily means that we must deal with the modifiable areal unit problem or boundary issues. In short, how do we define the space-time units in which social action takes place? This is a long standing issue for Geography but working with digital social networks creates a range of new problems and opportunities. These include:

- How accurate and precise is the spatial data associated with social networks? If it is user provided, how confident are we in this volunteered data?
- Can we use spatial data to create internally generated and defined spatial units? Can we use these organically defined regions instead of traditionally defined ones?
- How does scale affect the way in which space interacts with social networks? For example, does physical proximity matter a lot up to 25 km (the metropolitan level) and then its importance dramatically drops off? In other words, how is the relationship between physical distance and social networks kinked?
- How do existing physical networks of transportation and trade as well as historical ties of colonialism, language and culture, kink space in social networks?

The appearance of large and comprehensive data sets (e.g., University of Tartu's data on the location of all mobile phone calls within Estonia over the past six years) provides the means for putting these questions to task.

Theorizing Space and Time in Social Ties

Related to the previous issue of appropriate scale is how we theorize space and time in social networks. While the concepts of strong and weak ties in social action are well established, I feel it is worth revisiting how they relate to space and time. We have moved beyond simply equating physical proximity with strong ties but there is clearly a relationship albeit complex, multifaceted and with scalar effects. At this point I am thinking in terms of a typology of three binary variables based on sociability (strong and weak), physical distance (proximate and remote) and time (synchronous and synchronous). A weak, proximate, synchronous tie would be saying hello to an acquaintance on the way to work. A weak, proximate, asynchronous tie could be user generated Google placemarks in augmented reality. Directionality and power are other possibilities and clearly variables need not be restricted to only two values.

Sociability	Strong		Weak	
Physical	Proximate	Remote	Proximate	Remote
Time				
Timely (Synchronous)				
Timeless (Asynchronous)				

Software as an actor

Although software code is often viewed as an objective means/tool for a wide range of human activity it is also an actor and determines what is allowed and what is denied. At the most basic level it is the codification of rules and decisions made by human actors and as AI develops, its own agency increases. Code is based on selective decisions (e.g., valuing security over openness) which creates a politics of code that is often overlooked. For example, the structure of the TCP/IP protocol laid the foundation for an extremely decentralized Internet. In contrast, the code behind virtual worlds and social networking tools is closed and proprietary. This both increases user lock-in and creates barriers for researchers interested in studying these emerging social phenomenons.

As increasing amounts of digital social activities take place via proprietary networks the challenge of measuring them is ever changing. While the digitized and coded nature of online social interaction provide the means for collecting social network data, many key parts of the social metaverse are operated in a fashion that confounds researchers. For example, Pete Warden was able to gather data on Facebook connections (in accordance with the rules set out by their robots.txt file) but due to threatened legal action ended up destroying the collected data (http://petewarden.typepad.com/searchbrowser/2010/04/how-i-got-sued-by-facebook.html). Even Twitter which provides garden hose and fire hose feeds of Tweets does not specify the way in which these feeds are generated, calling into question basic assumptions needed for research, i.e., selecting a randomized sample. Other issues such as privacy and access are also tied to the structure of code.

Because digital social networks are increasing interconnected with the material, e.g., Foursquare, Facebook Places, the power of code is manifest in how space and time interacts with social networks. As such, code is both the enabling and limiting factor in the creation of the metaverse, making its politics an important subject for researchers. Efforts by private actors to exert control over code for their own self-interests are continuous. Commons based coding—a TCP/IP for the metaverse—may be one way of dealing with this issue.

Specialist Meeting:
Spatio-Temporal Constraints on Social Networks

Upham Hotel, Santa Barbara
December 13–14, 2010

The impact of the Internet on human communication and the organization of social networks has been profound, greatly reducing the effects of distance and time differences. Strong spatial and temporal constraints persist, however, because of the importance of human contact and the spatial and temporal context of human actions. Recent research in social networks that places them in a meta-network context (multi-node, multi-link, multi-level) paves the way for exploring spatial and temporal effects. Yet to date only very preliminary efforts have been made to develop appropriate theory and models, or to calibrate them with the abundant data sources that are now available. This two-day workshop organized by the Center for Spatial Studies at the University of California, Santa Barbara, will bring together specialists drawn from the many disciplines with interest in these issues, including computer and information science, geography, mathematics, spatial statistics, and social network analysis. The workshop will assess the current state of the art, identify and prioritize a research agenda, and begin the development of an international community of collaborating scholars working on these issues.

The specialist meeting of approximately 30 participants will be held at the Upham Hotel in downtown Santa Barbara, and is being convened by an organizing committee chaired by Michael F. Goodchild, UCSB, and Kathleen M. Carley, Carnegie Mellon University. The meeting will include plenary presentations by invited experts, and ample time for small-group discussion of the issues, following a model developed more than 20 years ago by the National Center for Geographic Information and Analysis and refined in more than 40 such meetings.

The meeting will assess the current state of the art, flesh out a research agenda, and foster an international network of collaborating scholars. Specific questions to be addressed include:

- What is the current state of knowledge with respect to spatiotemporal constraints on social networks and information flows, particularly from a meta-network perspective?
- How can theories of social network interaction be extended to incorporate the constraining effects of space, time, the Internet, and mass media?
- Can probability distributions be developed for networks or network metrics that are parameterized by spatial and temporal separation?
- What rich sources of data can be found to calibrate and parameterize these new models?
- What new metrics and models can be developed for assessing critical nodes, groups, and trails in and through networks that take spatio-temporal constraints, the Internet, and mass-media effects into account?
- Can we develop novel methods for visualizing the operation of spatio-temporal constraints and their effects on the flow of ideas and information through meta-networks?
- What methods of inference are appropriate for detection of spatio-temporal and network constraints in crowd-sourced data, and what are appropriate metrics of uncertainty?

To respond to this Call for Participation, please send a two-page resumé and a two-page position paper discussing your interest in these issues to **Michael F. Goodchild, good@geog.ucsb.edu** by Sept 30, 2010.

Participants will be selected by the organizing committee and notified by Oct 15.

Funding to cover travel and accommodation costs may be available.