Making friends in life and online

Equivalence, micro-correlation and value in spatial and transpatial social networks

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***Abstract*—Social networks are increasingly constructed and maintained by online social networking tools in addition to traditional face-to-face interactions. This paper reports on how the structure of social ties established by online tools relate to those ties established by face-to-face interactions. We explore and map the social ties within a cohort of 2602 users, for whom we study the social ties mediated by both physical co-presence and Facebook. Our results suggest that the spatial social network consisting of face-to-face interactions exhibits similar characteristics to the transpatial social network consisting of Facebook ties. However, we find that individuals' involvement in each network varies considerably.**

Keywords-Social network, Facebook, Bluetooth, spatial and transpatial

I. INTRODUCTION

Social ties are increasingly constructed and maintained by social networking tools, which have enabled for meaningful social relationships to be established and maintained online. These online tools provide an alternative to the more traditional face-to-face approach of establishing and maintaining social ties. In practice, the total set of people's social ties consist of one portion maintained by face to face interactions, while another overlapping portion maintained by online tools.

Even though both face to face interactions and online tools help people establish social ties, the affordances of each modality is rather distinct. On the one hand face to face interactions can be rich communication experiences, but are strongly bound by spatial constraints. On the other hand online tools lack the richness of physical interaction, but nevertheless break away from physical constraints and allow for social interaction across space and time. Taken independently, it can be argued that face-to-face interactions help people construct *spatial* social networks, while online tools better afford *transpatial* social networks. The combination of spatial and transpatial social networks is a *fused* network that ultimately acts as individuals' platform for social engagement.

The increasing bimodality of social engagement raises important questions regarding the design of technology to support social interactions, as well as the evolving nature of social engagement. This study described in this paper sets out to address the following issues:

- **Equivalence:** To what extend do transpatial networks resemble spatial networks? On the one hand we can expect similar structure due to human nature, but on the other hand the technological capabilities may allow for new structures to evolve.
- **Micro correlation:** How do individuals position themselves in the context of both spatial and transpatial networks? Do individuals assume similar network "roles" in each network?
- **Value**: In terms of acquaintances and navigating through social ties, do transpatial networks offer greater value and opportunities than spatial networks? Does this value change in the context of fused social networks?

While a body of previous work suggests that spatial and transpatial social networks exhibit similar structural properties, they do not provide a direct comparison between the spatial and transpatial relationships for the same group of people. The study reported in this paper compares directly the spatial and transpatial networks within a cohort of 2602 people. The analysis considers the structural properties of these social ties both at the scale of the network and the individual.

This paper is structured as follows: first a body of related work is presented, and then the study is described followed by a summary of the obtained results and a discussion of the findings.

II. RELATED WORK

The concepts of spatial and transpatial networks are not new, and certainly previous work has considered the impact of information technology on social behavior. Historically, social networks have been strongly spatial with much of pre-history comprising of small groups of hunter-gatherers living and traveling together. The emergence of villages and eventually cities gave rise to neighborhoods where people living in physical proximity formed tight-knit communities.

At the same time communication technologies have achieved widespread penetration, with mobile phones and the internet leading the way in the construction and establishment of transpatial social networks. As a result, the traditional human orientation to neighborhood- and village-based groups is moving towards communities that are oriented around geographically dispersed social networks. A substantial amount of literature has focused on understanding how these technological opportunities have changed society, the way we communicate and the way we support each other [e.g. Castells, 1995].

While dystopian views of the future predicted physically isolated individuals communicating solely via technology, in fact increasing urbanization levels have surpassed 50% for the

first time in history [United Nations, 2007] hence providing unprecedented opportunities for spatial networking. Strongly situated daily activities now give rise to social networks: the workplace, the school and the cafe are all examples of locations giving rise to and fostering social networks.

Furthermore, research has highlighted a strong link between space and technology use: the more individuals talk and interact face to face, the more likely they are to communicate via technology. For instance, most phone calls and emails are between people within 50 km [Wellmann, 2001] even though these technologies can reach any part of the world.

Hence, it can be argued that while communication technologies are becoming increasingly transpatial, their use remains highly spatial. This tension raises interesting questions regarding the structure of communities and the role of technology. To gain insights on this issue, researchers are increasingly exploiting the popularity of online social networking systems such as Facebook, Dodgeball and MySpace. These platforms lend themselves to conducting research into online social behavior and social networks, for example by studying the effect of social engagement on behavior [e.g. Millen & Patterson, 2002], the issue of identity and projected identity [Lee & Nass, 2003], as well as the design of socio-technical systems [Herrmann et al., 2004]. Such work relies on the ease of collecting data online and attempts to extrapolate the analysis of online behavior to offline behavior.

Furthermore, some work has explicitly attempted to uncover the relationship between online and offline behavior. For instance, research has studied the effect of social incentives and contextual information on the use of public transportation [Booher et al., 2007], the relationship between users' profiles and their behavior [Lampe et al., 2007], the various trust issues that emerge from using such systems [Riegelsberber & Vasalou, 2007], and how such systems can help strengthen neighborhood relationships [Foth, 2006]. While such work relies on quantitative online data, the analysis of offline behavior typically relies on qualitative measures.

A number of projects have conducted research on capturing and analyzing quantitative data about offline behavior. Typically this is achieved by automatically recording people's movement and presence in urban space. Such studies rely on physical co-presence and encounter as a means for inferring the underlying spatial social networks and relationships. For instance, the Reality Mining project collected proximity, location and activity information, with proximal nodes being discovered through periodic Bluetooth scans and location information by cell tower IDs [Eagle & Pentland, 2006]. Several other groups have performed similar studies, most of which rely on Bluetooth or WiFi [Balazinska & Castro, 2003; Nicolai et al., 2005; Chaintreau et al., 2006; McNett & Voelker, 2005] to capture mobility and infer social interactions.

While a considerable body of work considers online social networks, and more recently networks of co-presence and physical encounter, to date there exists little work that directly compares the transpatial social networks captured using tools such as Facebook with the spatial social networks captured by means of detecting physical co-presence. Some evidence suggest that the structures underpinning both types of networks exhibit similar characteristics. For instance some work has identified mathematical principles such as the small-world and scaling phenomena [Barabasi & Albert, 1999; Watts & Strogatz, 1998] in a multitude of natural and man-made systems, including social networks. These structural similarities have been verified in a number of different contexts, including communities of scientific authors, actors, athletes, and students [e.g. Stogratz, 2001].

However, while such work describes properties of distinct networks, it does not provide a direct comparison between spatial and transpatial networks for the same group of people. This type of an analysis is crucial in understanding how spatial and transpatial networks merge to form individuals' platform for social engagement. A direct comparison is necessary to address issues of equivalence, individual correlation and, ultimately, value. The study described next addresses these issues by directly comparing quantitative data on the spatial and transpatial networks between the same group of people.

III. METHOD

This study collected data on the physical encounters and social ties amongst a cohort of 2602 people. For this cohort, both the spatial and transpatial social networks were captured: the spatial network was captured by recording physical encounter between members of the cohort, while the transpatial network was captured by recording their relationships on Facebook.

A. System

Data on the physical encounters of the cohort members was collected by using the Cityware application (see [Kostakos & O'Neill, 2008] for a complete description of the system). Cityware is a distributed application consisting of the following components: people's Bluetooth-enabled devices, Cityware nodes, Cityware servers, Facebook servers, and a Facebook application.

User-managed Cityware nodes are Bluetooth-enabled PCs that collect and upload information about nearby people's presence and encounter in physical space. Since Bluetooth enables the unique identification of individual devices, the software can detect when individual devices (hence users) encounter each other.

Using Facebook as a front-end to this application, users can register their personal Bluetooth devices. Hence, for each registered user the system knows their unique Bluetooth ID and their unique Facebook profile ID. A user can register multiple Bluetooth devices, hence a Facebook ID can be associated with multiple Bluetooth IDs. Unfortunately, the software cannot know whether users are being truthful about their claim to ownership of a Bluetooth device. The assumption of the software is that users indeed own and use the Bluetooth devices they claim to. Finally, use of this system is opt-in hence users willingly associate Bluetooth devices with their Facebook profile.

B. Data collection

This study reported here collected data from a cohort of 2602 Facebook users of the Cityware application. These users were recruited by advertisements on the internet, and none of them were financially rewarded. Users had been using the

Cityware application for a period of 1 to 6 months prior to the study. Initially, every cohort member's Facebook ID and Bluetooth IDs (in case users owned multiple devices) were recorded. Subsequently two data-collection sessions took place.

First, using the Cityware application data on the physical copresence of cohort members was collected over a period of one month in March 2007. This dataset captured the co-presence between individuals of the cohort by detecting instances when two individuals where sensed by a Cityware node at the same place and the same time. Hence, this dataset can be considered as a subset of all the physical encounters that actually took place between cohort members. Co-presence data regarding non-members of the cohort (e.g. members of the public) were discarded. No actual location information was recorded.

Second, at the end of the first data collection period the explicit friendship relationships between cohort members on Facebook were recorded. This data captured which of the cohort members were friends on Facebook. Due to the technical aspects of this task, the process of collecting this data lasted 10 days, since Facebook servers had to be queried for each of the possible 3.4 million pairs of cohort members.

IV. ANALYSIS

A. Data coding

The collected data were converted to three distinct social network graphs:

- **Encounter network**. To analyze the physical encounter dataset each user was represented as a node, and individuals were linked if they encountered each other at some point during the study. Users who owned multiple Bluetooth devices were still represented as a single node.
- **Facebook network.** The friendship data collected from Facebook was converted to a social network graph by representing each user as a node, and linking together users who were friends on Facebook.
- **Fused network**. A social network was constructed by merging the Encounter and Facebook networks as follows: each member of the cohort was represented as a node, and nodes were linked if the respective users where linked either in the Encounter or Facebook graphs. Hence, the fused network had three types of ties: those that resulted from a physical encounter, those that resulted from a Facebook friendship, and those that resulted from both a physical encounter and a Facebook friendship.

Conceptually, the Encounter network represents spatial networks, the Facebook network represents transpatial networks, while the Fused network represents the social environment that consists of both spatial and transpatial relationships. A visual representation of these three networks is shown in Figure 1, where each node represents a cohort member and links represent respective ties. The node and edge color varies from blue to red, indicating low betweenness (blue) or high betweenness (red) as a means of highlighting the various clusters in these networks.

B. Structural characteristics

To assess the similarities and differences between the three derived networks, their structural properties were measured. Table 1 presents the size and number of edges of each network, their density (portion of possible edges being instantiated), the size of the largest connected component of each network (core), the average number of links that each node has (degree), the longest shortest-path of each network (diameter), the average shortest-distance between all pairs of nodes (λ), and each network's transitivity (clustering coefficient).

All three networks consisted of multiple disconnected components, and cluster size refers to the size of these components. The largest component in each graph is referred to as the core. Figure 2 shows the probability distribution of cluster size for each of the three networks. The mean cluster size for the Encounter network was 1.20, for Facebook 1.27, and for the Fused network 1.36.

To identify further structural similarities in the Encounter and Facebook networks, the correlation for a number of their structural features was calculated: degree (0.68), closeness (0.46), betweenness (0.24), and clustering coefficient (0.46).

These correlations were calculated by considering all 2602 members of the cohort, and measuring their respective structural features in both the Encounter and Facebook

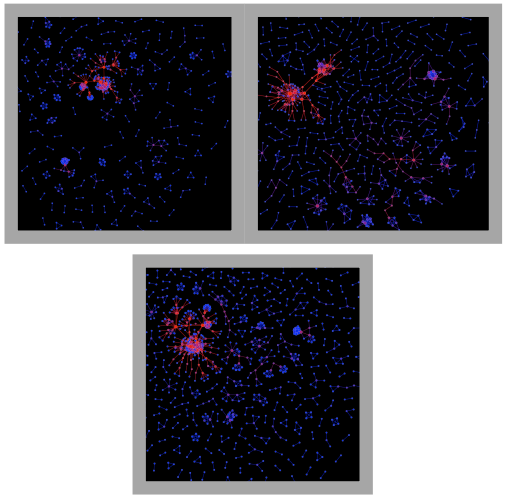

Figure 1. The Encounter network (top left), Facebook network (top right), and Fused network (bottom). The node and edge color varies, indicating low betweenness (blue) or high betweenness (red).

Network	Size	Edges	Density	Core	k	λ_{max}	λ	C
Encounter	2602	1047	0.015%	147	0.80	8	3.48	0.54
Facebook	2602	843	0.012%	101	0.65	9	3.48	0.40
Fused	2602	1481	0.022%	227	1.14	9	4.08	0.49

Table 1. Structural properties of the three derived networks: size of the network, number of edges in the network, density of edges, size of largest component (core), average degree (k), diameter of largest component (λmax), average path length (λ), and average clustering coefficient (C).

networks. For instance, the degree correlation was calculated by pairing each user's number of links in the Encounter and Facebook networks. The degree correlation is shown in Figure 3 where each member of the cohort is represented by a dot, and the vertical and horizontal axes indicate the number of links that each user had in the Encounter and Facebook datasets respectively. Note that significant overlap between the dots exists in the graph, especially for low-degree nodes. The same process was followed to calculate the correlation for closeness, betweenness and clustering coefficient.

C. *Links and triads*

To quantify the value that each type of network offers, the analysis further considered the variation and distribution of the three types of links in the Fused network. This analysis is aimed at capturing the different ways in which spatial and transpatial ties interact. Each social tie in the Fused network may be the result of a physical encounter, a Facebook friendship, or both. Figure 4 illustrates these differences by showing an excerpt of the Fused network where the ties are colored according to their type.

The relative importance of each of these three types of links was calculated by considering edge betweenness. An ANOVA test showed a significant effect of link type on link betweenness ($F(2,1478)= 18.345$, $p<0.0001$). Table 2 shows the average betweenness for each type of link in the Fused network. To further identify the effect of network fusion on individual correlation at a micro scale, a triad analysis was carried out. Table 3 shows for each of the 10 types of possible triads the observed and expected frequency of appearance, which have correlation of $R^2=0.006$. The expected frequencies were analytically calculated by assuming the same underlying network but a random distribution of link types with the relative frequency shown in Table 2. More precisely, the expected frequency for each type of triad was determined by the multinomial distribution characterized by probabilities proportional to the frequency of link types in Table 2 and the frequency of occurrence of each link type in the triad.

D. *Resilience*

The resilience of all three networks to random edge removal was assessed in order to gain an understanding of how each kind of network contributes to the overall social network. Figure 5 shows the effect of randomly removing a portion of the total edges in the networks (x-axis) on average cluster size (y-axis) in each network.

V. DISCUSSION

In our discussion we focus on the three key issues that this study set out to examine: equivalence, micro correlation, and value. In addition, we also discuss the methodological validity and present a generative random graph model that describes very well our observed data and results.

A. *Equivalence*

The Bluetooth and Facebook social networks exhibit very similar structural characteristics, suggesting that as proxies to users' actual social network they reflect similar aspects. Specifically, both networks were rather sparse with similar diameter, and both had low average degree and approximately similar average path length and clustering coefficient (see Table 1). These structural features suggest the networks are structurally similar both in terms of local characteristics (degree, clustering coefficient) as well as global characteristics (density, diameter, average path length).

It is interesting to note that while the two networks have similar characteristics, their fusion produces some interesting results. As expected, the fused network's density as well as core size significantly increase in relation to both the Bluetooth and Facebook networks. This is due to the fact that many new links are added between the same set of nodes, also evident by the increase in average degree. However, the diameter of the fused network's core does not shorten, and in fact the average path length increases. To interpret this result, we need to understand that the fused network is composed of links of three distinct types (Bluetooth, Facebook, Bluetooth+Facebook), and these types represent the effect of fusing spatial and transpatial networks. Here we observe that as users augment their traditional face-to-face spatial networks by using Facebook, they increase their local connectivity to their resulting fused network (higher average degree), but at the same time they are globally further away from everyone else in their new fused network (higher average path length) since that network is much now much larger.

We can observe just how large users' networks are by considering the cluster size we calculated in Figure 2. We note that the spatial network (Bluetooth) is made up of very small clusters even though its core is larger than the Facebook network. Overall, however, the fused network's cluster size distribution is higher and almost identical to the Facebook networks. We interpret this result as suggesting that even though spatial networks can potentially offer a bigger social circle (core size), transpatial networks offer the opportunity to be part of a larger social network overall (cluster size).

B. *Micro-Correlation*

Next we examine our networks from the perspective of each individual member of the cohort, as well as small groups (triads) within the social networks.

The correlation of individuals' structural measures between the Bluetooth and Facebook networks gives us insight into the relative similarity in which individuals experience their respective social circles, the opportunities in those networks, and their own role in those networks. In terms of local metrics we observe a relatively high correlation of degree (0.696), suggesting that user's local connection to their social network is similar in both spatial and transpatial networks, and that in general they make the same amount of relative effort to establish and maintain new links in each network. On the other hand, we observe a rather poor correlation of clustering coefficient (0.124), also known as transitivity. This suggests that the means by which users acquire new social ties (face-to-face vs. online) are rather independent in the extent to which the resulting ties are with people who are already friends themselves (ratio of open to closed triangles in the graph). The correlation of global metrics for individuals follows a similar pattern, with closeness (0.555) being higher that betweenness (0.382). These results indicate that users' relative importance in their spatial and transpatial networks varies considerably (hence the low betweenness correlation), but their relative distance to everyone in the network is more similar. This latter

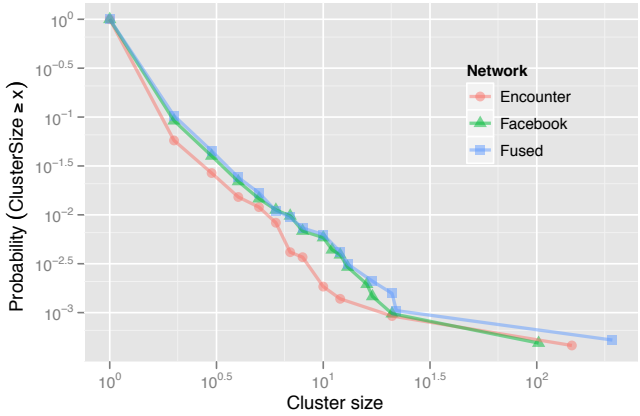

Figure 2. Probability distribution of size of individual clusters (logarithmic) for the 3 social networks (red circle: Encounter; green triangle = Facebook; blue Square = Fused).

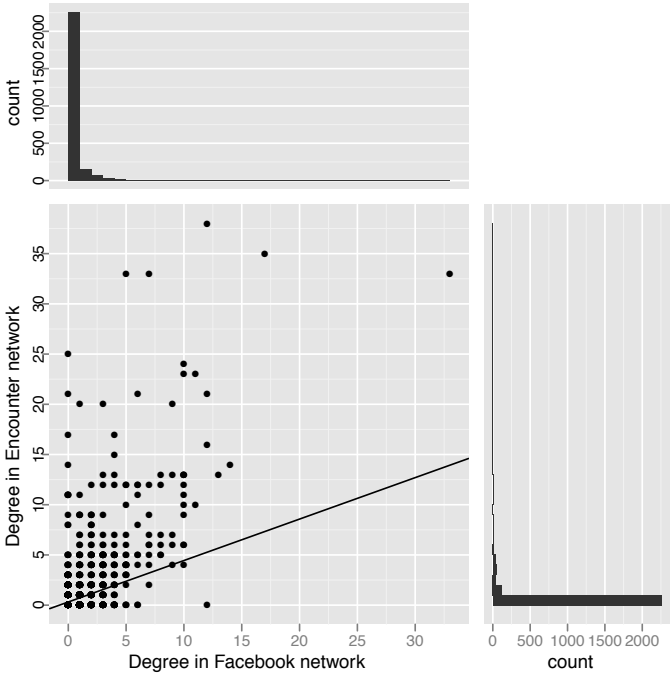

Figure 3. Correlation of number of social ties (degree) that each user in the Encounter and Facebook datasets. The histograms at the top and right indicate the spread of data points across the two axes.

Link type	Count	Mean	Std
Facebook (red)	434	2.11	1.98
Encounter (blue)	638	2.62	2.02
Fused (white)	409	1.90	1.94

Table 2. Summary statistics for link betweenness (logarithmic) in the Fused network, broken down by link type. Count: the number of links for each type of link in the Fused network. Mean: the average betweenness. Std: standard deviation.

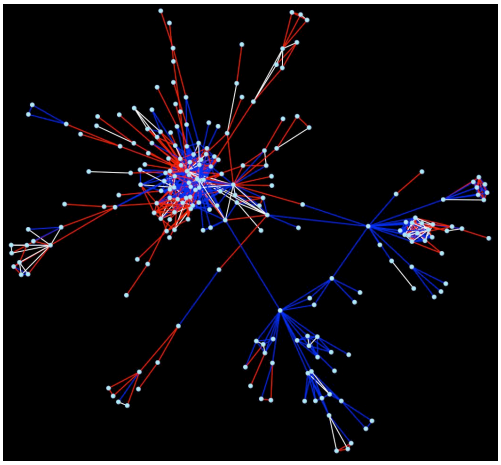

Figure 4. The core of the Fused network, with links are colored according to their type. Blue: links resulting from physical encounters; Red: links resulting from Facebook friendship; White: links resulting from both physical encounters and Facebook friendship.

	Triad	Observed	Expected	Ratio
A		220	45	4.9
B		587	171	3.4
C		650	329	2.0
D		270	211	1.3
E		103	152	0.7
F		34	54	0.6
G		85	143	0.6
H		81	349	0.2
I		43	237	0.2
J		64	447	0.1

Encounter Facebook Encounter & Facebook

Table 3. The observed and expected frequencies of the 10 types of possible triads in the Fused network, along with the ratio of observed to expected frequency.

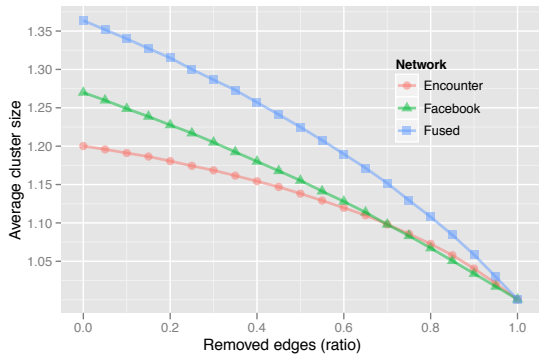

Figure 5. The effect of random edge removal on the average size of clusters in each network.

interpretation is further supported by the similar average path length of both the Bluetooth and Facebook networks.

These results indicate that some aspects of both local and global metrics appear to be similar from the perspective of individuals, while on the other hand certain local and global metrics appear to vary considerably. It is interesting to contrast this result with the global homogeneity of the Facebook and Bluetooth networks suggesting that overall the networks exhibit similar structural properties. This similarity, however, is not necessarily reflected in the way individuals utilize and experience the different ways or modalities of accessing their social networks.

In addition to individuals' structural properties, we also considered the relative frequencies of all possible types of triads (Table 3). The significant over-representation of type A triads and the fact that triads with a Facebook-only tie are under-represented is an indication that the extent to which triadic closure occurs in online social networks is less when compared to space-bound social networks, further suggesting that online ties connect individuals with low neighborhood overlap. This is verified by the fact that the clustering coefficient of the Facebook network (0.40) is lower than the Encounter network's (0.54) (Table 1), as well as the fact that the Encounter network is more resilient to random edge removal than the Facebook network (Figure 5). In conjunction with the hypothesis and conclusions of Granovetter's work on tie strength [Granovetter, 1973] (which suggest that a strong tie implies neighborhood overlap), our results indicate that online-only relationships are less likely to be "strong" and more likely to be "weak".

However, it is not clear that Granovetter's work actually does apply to online communities, since he based his hypothesis on the following arguments:

(i) If A-B and A-C ties exist, then the amount of time C spends with B depends (in part) on the amount of time A spends with B and C respectively.

(ii) Empirical evidence suggests that the stronger the tie between two individuals, the more similar they are (e.g. [McPherson *et al*, 2001]).

(iii) The theory of cognitive balance [Fritz Heider, 1958] : If strong *A-B* and *A-C* ties exist, and if *B* and *C* are aware of one another, then anything short of a positive tie between *B* and *C* would introduce a psychological strain between them.

If (i), (ii), and (iii) hold in a social network, then we would expect strong ties to also have high neighborhood overlap. However, of these arguments, only (ii) could be said to be of relevance in online relationships and the Facebook data we have collected. This is because for (i) A could spend time online with both B and C simultaneously with neither B nor C spending time with each other, and for (iii) B and C might not even be aware of the other's possibly strong relationship with A. Moreover, A might not feel the necessity to introduce B and C to each other, while in a space bound relationship she might find it beneficial to do so.

Since of Granovetter's arguments only (ii) holds in online networks, we can expect strong ties to exist with low neighborhood overlap in online communities. Hence, we argue that our finding that online-only relationships are less likely to be "strong" and more likely to be "weak" should be taken with a pinch of salt since Granovetter's hypothesis is weaker in the case of online communities.

C. Value

Next we consider the value and relative importance of the different networks and their ties. An interesting result arises when we consider the impact of the various means by which social links are established on the relative importance of those links. Here we measure a link's importance by calculating its betweenness. We found a statistically significant effect of link type on link betweenness in the fused network, indicating that links of spatial networks are more important than links of transpatial networks. More interestingly, we found that links that exist in both spatial and transpatial networks are of least importance. We believe these results further reflect the strength of weak ties hypothesis [Granovetter, 1973]. Specifically, ties that exist in both spatial and transpatial networks are most likely with close relatives or colleagues with whom we interact closely. Such ties are not globally important in the sense that they can easily be replaced by another link in the local clique. In other words, most people that a close relative or colleague knows are people that we already know. On the other hand, we observe that relationships established solely in spatial networks are likely to be of higher importance that those relationships established in transpatial networks.

To a certain extent this result may seem counter intuitive. After all, spatial networks are ultimately bound by our ability to move in space, while transpatial networks have the potential to connect us to the whole of the world in one step. Hence, how can spatial ties have higher importance (betweenness) that transpatial ties? One explanation is that spatial networks are better at mediating the establishment of new social ties. For instance, a face-to-face meeting between A and B is also an opportunity for A to meet B's friends, since physical proximity affords this kind of natural social behavior. On the other hand, online technology has possibly not matured enough to be able to provide such affordances.

An orthogonal explanation for the importance of spatial ties is that physical co-presence, as captured by Bluetooth technology, has the potential to record "familiar strangers" relationships [Paulos & Goodman, 2004]. These are the types of relationships that users possibly do not explicitly indicate as social ties, but they can potentially activate if needed. It is not clear from literature whether the strength of social ties can be classified as strong/weak/non-existent or they follow a linear scale, but if familiar stranger ties should be present they would be classified at the low end of the linear scale. It is this presence of weak ties that our methodology reflects. A further point we should also highlight is that physical co-presence facilitates the building of trust between parties while online interactions are not necessarily as effective due to the limited channels of information they support (e.g. lack of body language and subtle communication signals).

D. Methodological Validity

It is imperative to discuss the methodological validity of relying on Bluetooth and Facebook as social network proxies. In this study we were interested in capturing two distinct types of social networks: spatial and transpatial. Ideally, a single

methodology would enable us to capture data on both networks using a single proxy, and enable us to compare our data accordingly. This was not possible in our case because a single proxy does not actually exist. Hence we utilized two distinct proxies to collect data on spatial and transpatial networks. The important issue we need to address is whether the differences we have observed in our results are due to the endemic differences of the networks we are studying, or to the differences in how the proxies we used reflect the underlying networks.

The similarity of the aggregate structural features of the two networks we captured, as well as the similar degree and cluster size distributions suggest that the two proxies reflected processes of similar underlying nature. This is further supported by the fact that both global and local measures display similar properties in both cases. Since as broad communities the two networks display similar characteristics, we feel confident that our correlation analyses do indeed reflect differences and similarities in our users' perspective of their social networks.

Furthermore we note that the two datasets consisted of slightly different types of social ties: while our Facebook dataset recorded explicit friendship ties, our Bluetooth dataset recorded co-presence ties. It can be argued that this difference affected our results. A counter-argument can be made that in fact spatial networks are qualitatively different from transpatial networks, hence we should expect to have qualitatively different data. Specifically, co-presence is the crucial differentiating factor that sets apart spatial and transpatial networks, hence it is important that this is reflected in the data. While our Bluetooth data may indicate a relationship between two complete strangers who happened to be at the same place at the same time, their co-location is a significant event suggesting the possibility for social networking. As argued earlier, humans are quite adept at forming social ties with co-located individuals, and have developed a number of conversational and linguistic mechanisms such as common ground [Clarke, 1992] to facilitate this process. Furthermore, it is not clear if there exist some tie strength threshold below which no tie should be drawn between two individuals. As part of our ongoing work we are considering more qualitative metrics for Bluetooth ties, (e.g. how often they are instantiated and for how long) as a way to offer further insight into using co-presence as a social network proxy.

To further verify the validity of our collected data we developed a generative random graph model that describes the underlying processes of social networks with spatial and transpatial ties. Because our model deals with fixed number of nodes, the dynamics of new nodes joining the network are not taken into account. The model assumes a fixed number of nodes N distributed among a fixed number of locations k. These locations serve as a partition on the node set. To start the generative process, we randomly assign each node to a location. Subsequently, for each time-step the model consists of the following steps:

(a) **At each location people encounter each other randomly.** For a given location l, a number $\eta(l)$ of *encounter* links are added within l. To add each link, we pick one node at random and one node preferentially from l and join them with an encounter link.

(b) **If two people encounter each other, there is a probably that they become friends on Facebook.** or each encounter link created in the previous step, this link "upgrades" to a *fused* link with a fixed probability P_{EU}, the probability of upgrade for an encounter link.

(c) **People may become friends on Facebook even if they have not met face to face.** For the whole graph, a number η of facebook links are added. To add each of these links, we pick one node at random and one node preferentially from the network and join them with a *facebook* link.

(d) **Some Facebook friends may visit each other**. For each Facebook link created in the previous step, one of the nodes jumps to the other's location with probability P_{FU} and this link upgrades to a *fused* link. We refer to P_{FU} as the probability of upgrade for a facebook link.

(e) **People may travel to locations even if they know no-one there**. At the end of the step, each node can jump to another random location with probability P_{Jump}.

We assume that the probability of a node v being picked preferentially is proportional to a power of its degree in the encounter network (step (a)) or facebook network (step (c)), $\beta^{degree(v)}$. The number $\eta(l)$ in step (a) is assumed to be the number of successes for e trials of a binomial distribution with a probability of success $P(l)$, where e is the maximum possible number of edges between the nodes in l. Similarly the number η in step (c) is assumed to be a random variable associated with the number of successes for e trials of a binomial distribution with a probability of success $P(G)$, where e is the maximum possible number of edges between all nodes in the network G.

We ran this model using the following parameters; N =2602 (same as our dataset), k =20, P(l) = 0.0009, P_{EU} = 0.3, P(G) = 0.00001, P_{FU} = 0.01 and P_{Jump} = 0.000001, β = 1.25, Number of iterations (time-steps) = 60. The run was repeated 100 times to generate as many networks and the average triad frequency for each type of triad was calculated over these 100 networks. We found that the relative ratios of triad frequencies generated is similar to those observed in our data, with an adjusted R^2=0.965, and differ significantly from a completely random assignment (R^2=0.21). In addition, the resulting networks followed a power-law distribution of degree, just as in our data. An important difference of the model results and our recorded data is that the number of edges observed in the model results were much higher (>8500) than in our dataset (1481).

Our model is a simplified description of underlying dynamics that can generate fused networks by interweaving face-to-face with online relationships. The model describes the interweaving of face-to-face with online relationships as evident in the distribution of the relative frequency of triad types. This supports the methodological validity of relying on Bluetooth and Facebook as proxies for spatial and transpatial network proxies respectively, however our future work is on elaborating on how the model's output can be compared to collected data. Nevertheless, it is interesting to note that given the results we obtained from our model, its parameters suggest that the probability of two face-to-face friends becoming friends on Facebook is an order of magnitude greater than the probability of Facebook-only friends meeting face to face. In

addition, the high number of edges generated by our network is further evidence suggesting that our data collection methodology can collect only a subset of the actual ties (whether spatial or transpatial). Nevertheless, the ties that our methodology has collected are valid.

VI. CONCLUSION AND ONGOING WORK

Emerging technologies have the potential to act as a bridge between spatial and transpatial networks, and it is important to develop the fundamental understanding and theoretical foundations in relation to such networks. This study has provided a number of insights into the properties and relationship of spatial and transpatial social networks. Specifically, it highlights the high-level structural similarities between the two types of networks, and notes the underlying differences in how individuals take part in these social networks. Furthermore, our analysis highlights the importance of spatial networks within the grand scheme of social networks. The validity of our collected data and results is verified by a random generative model we developed, which matches with great accuracy the data we have obtained.

As part of our ongoing work we are considering more qualitative metrics for Bluetooth ties, (e.g. how often they are instantiated and for how long) as a way to offer further insight into using co-presence as a social network proxy. We are also interested in exploring appropriate static representations that fully capture the temporal behavior of the dataset. A further aspect of our ongoing work is the development of metrics to annotate the strength of social ties. Specifically, we feel that various temporal metrics can be developed to automatically assess the strength of social ties. Furthermore, such metrics can possibly be used to derive models of tie strength, and we intend to apply these models to assess the strength of online social ties.

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