Sensing and Using Social Context

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We present online algorithms to extract social context: Social spheres are labeled locations of significance, represented as convex hulls extracted from GPS traces. Colocation is determined from Bluetooth and GPS to extract social rhythms, patterns in time, duration, place, and people corresponding to real-world activities. Social ties are formulated from proximity and shared spheres and rhythms. Quantitative evaluation is performed for 10+ million samples over 45 man-months. Applications are presented with assessment of perceived utility: *Socio-Graph*, a video and photo browser with filters for social metadata, and *Jive*, a blog browser that uses rhythms to discover similarity between entries automatically.

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1. INTRODUCTION

Technology, contrary to the forecasts, has helped drive up the pace of life and engendered dislocation. One telling example is the "connection technology" of the Internet that has in many cases increased social disconnection [Dreyfus 2001]. Various attempts at hybrid communities whose lives are mediated both in the real and online worlds have sprung up in response (e.g., www.meetup.com). An encoded version of real-life social context would be useful in bridging the gap with the virtual in a variety of applications. Computation has a role to play here as it has become increasingly mobile and, concurrently, sensor-rich. Technologies such as Smartphones, PDAs, Ultramobile PCs, Digital Cameras, and MP3 players form a spectrum between traditional computers and appliances, but often have similar sensing capabilities (e.g., traditional media, such as images, audio, and video, together with radio technologies, such as Bluetooth, RFID, WIFI, and global positioning, and indicators of physicality, such as accelerometers, thermometers, and infrared). The resulting tide of digital detritus these sensors provide presents opportunities for truly multimodal multimedia research. But representing and structuring these heterogeneous signals, from heterogeneous devices, and inherently noisy sensors and behaviours, remains a challenge.

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We define three aspects of social context useful for a variety of applications that need a representation of the situated, social life of a user, and extract them unobtrusively from GPS and Bluetooth sensors:

—*Social spheres* are labeled geo-spatial locations of significance to a user. We cluster GPS traces, represent them as convex hulls, and label as Home, Work or Other. Social spheres are where we go.

—*Social rhythms* are latent pursuits of daily life giving rise to repeated occurrences among the dimensions of people, social sphere, and time. We cluster on various projections of this multidimensional space to discover and represent activities by constraints inherent to them. Social rhythms characterize what we do.

—*Social ties* are the relationships a user has with others. We formulate a measure of tie strength based on time spent with a person, weighted by the nature of the spheres of the interaction, and also characterize the nature of ties based on the type of social rhythms shared. Social ties capture who we know.

We detail work on a corpus of data from 8 users, comprising 10+ million GPS and Bluetooth samples over a period of 45 man-months. The utility of social context is demonstrated with two novel applications: a personal media browser for photos, videos, and movies that uses social metadata for media filtering, and a blog browsing application, which automatically augments navigation with similarity measures based on social rhythms implicitly linked by blog entries. We present qualitative feedback from user studies of each.

We address limitations of previous work and provide a number of other novel contributions here:

—Methods for (i) iterative discovery, refinement, and deletion of places in the rich representation of convex hull, (ii) detection of copresence of users and subsequent cross-interpolation of sensor data, and (iii) representation and discovery of social rhythms at different resolutions

—Formulation of social tie nature using social rhythms

—Innovative application of social rhythms to blogging

The significance of this work lies in its direct relevance to the underlying social aspect of creation, use and access of media. Applications that seek to support a real-life facet to tele-mediated relationships of whatever type will benefit from techniques for structuring data coming from sensors embedded in daily life. For example, semi-automatic calendaring or collaboration tools, information discovery and personalized advertising, media browsing and sharing, demographic tools (market research and surveillance), and context-sensitive device management, to name a few.

The rest of the article is as follows. Related work is discussed in Section 2. Section 3 describes experiment setup and data preparation, including cross-interpolation of sensor data via co-presence. Sections 4, 5, and 6 provide definitions, algorithms and discussion of results for social spheres, rhythms, and ties, respectively. Section 7 contains example applications of social context: *Socio-graph*, a social-context aware media browser, and *Jive*, a blog transformer that aids navigation using social rhythms. Each includes a user study aimed at assessing perceived utility of social context to the respective application. Section 8 concludes the paper and discusses avenues for future research aimed at improving the extraction or use of social context.

2. RELATED WORK

This work makes contributions in the areas of representation and extraction of (i) significant locations and visitation patterns from embodied life, (ii) interactions among people, and demonstrates their utility with novel (iii) media browsing applications. We will briefly detail relevant work in each of these areas.

2.1 Locations and behavior

Extraction and representation of locations of significance has received much attention in recent years. Work on GPS signals has focused mainly on handling the inherent noise and sparseness of data, whereas celltower ID and WIFI suffer from lower resolution. Difficulties comparing and evaluating approaches point to the underlying problem of defining *significance* generically.

Ashbrook and Starner [2003] use a variant of K-means clustering with multiple radii to discover locations at multiple resolutions. Kang et al. [2004] improve upon this by assigning points from sequential traces into clusters based on a distance threshold followed by filtering out those clusters below a time threshold, but data sparseness remains problematic. Zhou et al. [2005] deal with missing data with a density and join-based spatio-temporal clustering algorithm. We use interpolation to attenuate missing data, and use accumulation of stays over a day to achieve robustness to fragmentation in time. These approaches represent locations with centroid-radius pairs and spatial or temporal weightings, whereas we represent locations as convex hulls as a better approximation to underlying GPS traces.

Nurmi and Koolwaaij [2006] compare algorithms for clustering on cell location, where absolute positioning is seeded by GPS coordinates from a server if available. They cite social identity theory as motivation, noting the tie between the notion of a role and a place. But role to place can be a many-to-many relationship. Social rhythms as defined here correlate loosely with role, and thus provide an index beyond place alone.[1]

Clarkson [2002] extracts “life patterns” from wearable sensors. Early experiments were focused on clustering signatures of panoramic video and audio features, and then developed into situation classification methods. Situation space is then discretized to understand an individual’s transitions through the day.

Hariharan and Toyama [2004] analyze and predict behaviors from GPS signals obtained from handheld devices by 2 subjects over 2 years. Both Markov and non-Markov models are used for training location histories. Their results show the shortcomings of rigid Markov assumptions about real data, and problems arising from a lack of large training datasets. They conclude that “for identifying typical patterns” non-Markovian models are sufficient.

2.2 Interactions—the Social Dimension

Sensors that allow inference of proximity of users or explicit interaction, like Bluetooth and audio, provide the foundation for social analyzes.

Choudhury and Basu [2004] collect sensor data that are predictors of natural interactions using a wearable “sociometer,” a packaged sensor configuration that records nearby people (IR), speech and motion. Markov models are used for feature extraction and mutual information to discover interaction between streams. An influence model captures turn-taking in conversation, but limited interaction dynamics are modelled.

Reality Mining [Eagle 2005] examines human behavior dynamics using mobile phone logs of Bluetooth, celltower ID, calls, application usage, and phone status, with manual self-surveys. Generative graphical models and eigen decomposition are used to understand individual behavior and interactions. Locations are analyzed in a coarse resolution over home, work, other, and network metrics are used to describe interactions. They acknowledge that strict, graphical models such as Markov networks work for small sets of behaviors, but have trouble coping with the sometimes sparse and nonstrict nature of recurrences of patterns in such data. They propose eigenbehaviors as a solution, and perform a SVD on a (# days $\times$ # hours) matrix, in which each entry is mapped to one of home, work or other. However,

[1]Location alone is an insufficient index for many applications; diverse activities may be folded into the same location. Jones et al. [2004] note that people and routine are equally important.

the strict nature of the matrix requirement for eigenvalue decomposition makes it cumbersome for large amounts of incremental data. SVD decomposition is also a rigid interpretation at one resolution, and thus inflexible for application across other richer attributes of rhythms such as duration, topic, resolution etc.

Ratti et al. [2005] look at very large scale user patterns. Cellphones and related services are used to extract intensity and traffic migration as footprints to understand when people called, for how long and where they moved. This data drives visualisation of patterns of people and movement across cities, providing a powerful urban cartography tool.

These works are the closest to ours in spaces other than multimedia. We break away from rigid Markov assumptions or even structured SVD decompositions to cope with the special nature of social spaces as related to multimedia: the lack of rigid patterns, except in the most simplest of cases, the violation of the Markov assumption especially in relation to long term data, the continuous and incremental nature of data and the variability in resolution in time. All the current methods will perform poorly in this case.

2.3 Social Context Applied to Media Browsing and Sharing

Multiuser frameworks provide an ideal base to develop applications for media sharing or browsing augmented with social context. We focus here on work for which media communication and consumption is central.

Davis et al. [2005] implement a web photo sharing application. The work aims to facilitate photo sharing with mobile phones by pooling metadata, including spatial (Celltower ID, GPS, Static Bluetooth), temporal (network served time), and social context (copresent users via Bluetooth), and recording those whom a user shares photos with. They tackle a specific question: “Who—do I want to share this photo with?”[2]

Naaman et al. [2004] present PhotoCompas alongside a survey to examine the usefulness of contextual metadata for photo search and recall. Time and location metadata seed the harvesting of further metadata from databases or Web services, such as weather, temperature, light atmosphere, and season. They conclude that context involving location and people is useful for browsing photos, both explicitly manifest in an interface, and potentially implicit to relevance ranking. Subsequent work [Naaman et al. 2005] studies patterns of reoccurrence and cooccurrence of people in manually annotated photo collections as estimators for short-list suggestions for further annotation. A number of the estimators use algorithms of PhotoCompas to generate sets of semantically related photos, for example, by location or event. Cooccurrence per event or location is a kind of social tie strength, sampled per media item creation. That is, a photo provides the occasion for annotation which is required to calculate a cooccurrence weighting. We assume persistent Bluetooth discovery logs or GPS traces, which provide a denser sampling to estimate of social ties, with the disadvantage of requiring an, albeit unobtrusively, instrumented actor.

Zunjarwad et al. [2007] explore collaborative annotation of events, which take many facets as metadata, such as who, what, where, text, and images. They note image classifiers often fail to distinguish the different contexts from which similar textual annotations have come, and seek to supply that context through social-network-derived correlations. Annotations are recommended as a function of global similarity, cooccurence of event facet terms, and trust, where the latter is defined in the narrow sense that if a user can provide high quality annotations, they are a trustworthy annotator. Their experiment

[2]A subproject [Nair and Davis 2005] involved propagating copresence derived from Bluetooth devices seen at photo capture time. Data is sparse (7352 photos originally tagged with copresence metadata) compared to that resulting from our context of continuous logging (over a million device discoveries).

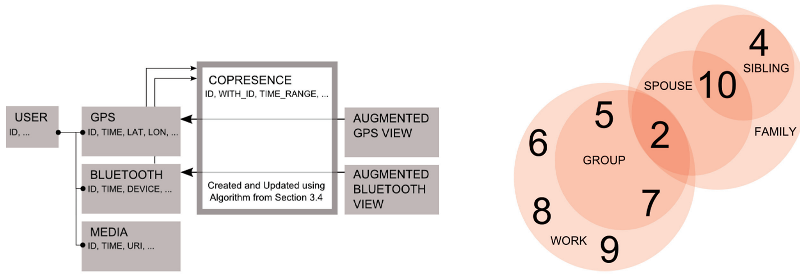


Fig. 1. a) Simplified data model. Tables to the left correspond to real data, the right to data derived from copresence; b) Venn diagram of user relationships.

is initial, and uses a Web interface for the creation and annotation of events and their facets, but provides an interesting framework which might be complemented by social spheres (where), copresence (who), and social tie measures (as an automatic alternative to the manual assignment of a trust vector for all users in the network).

It is worth mentioning here the work of Counts and Geraci [2005]. They implement and evaluate a prototype Web-based social networking system called *Trace*. Trace begins with copresence at a real-world social event and uses it as a seed for the creation and extension of a social network. Following an event, participants are emailed photos and links to profile pages of attendees. Usage logs indicated connections were made between users who didn't interact at the event, and deduce that close proximity peer-peer copresence detection would not suffice, and note GPS and Bluetooth logging as possible solutions. While they gather copresence information manually, they envisage a setting assumed in our work of automated copresence detection, and likewise aim to augment online networks with context from embodied life.

3. INFRASTRUCTURE AND DATA PROCESSING

Here we present our data model, and discuss pragmatic issues regarding experiment apparatus and user behaviors on data collection. We detail two complementary approaches to cleaning and augmenting data: single user noise removal and interpolation, and data sharing in our multiuser context. We finish by summarizing the makeup of the user group and their collected data.

3.1 Data Model and Quality

The core of our data model is a user. A user has GPS fixes and Bluetooth device discoveries, both indexed by time. These signals ideally correspond to the user's global location and explicit colocation with another device, respectively, and are prevalent sensing technologies. Additionally, each user has associated media items, such as photos, videos, and blog entries, which are indexed by URI, and have an associated creation timestamp. Media items are indexed with a view to applications like those presented in Section 7, which demonstrate the utility of sociometric measures derived from wireless sensors. Figure 1(a) contains a simple schema of the data model. WIFI access point IDs and signal strength are also associated with a user, as they are useful for localization, but are not used further in this work. Ideally, for a given user, we would have GPS fixes and complete Bluetooth neighbourhood discovery 24/7, and an index for every piece of media created.

Both technological and behavioral factors result in data of quality lower than the ideal mentioned above. Data can be missing due to power loss, from battery depletion or intentional power-off, line of sight (GPS), incomplete polling (Bluetooth), and software and hardware failure. Additionally, a user may be unwilling to carry a sensing device at all times, or to certain locations. GPS signal quality is also degraded by local geographic anomalies, such as signal reflection from nearby buildings, compounded by satellite configuration, and device-dependent quirks, such as variable dead reckoning of lost signal. Media items may also be created using a range of devices, making difficult the construction of a unified index.

3.2 Experiment Apparatus and User Group

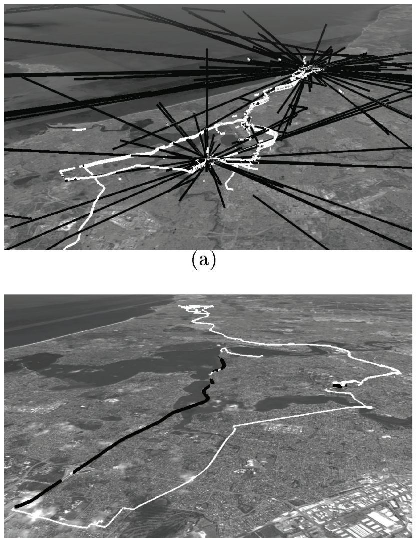
Our experiment apparatus consists of 8 mobile devices: a Sony Vaio U71 ultramobile PC (UMPC), two Sony Vaio UX UMPCs, two iPAQ h2210 PDAs, and three iPAQ hw6965 smartphones. All are equipped with GPS and Bluetooth capabilities, and most have embedded image, audio, and video capture. They represent a range of form factors, battery life, computational power, and motivational aspects (e.g., a smartphone is a drop-in replacement for a user's existing cell phone). Placelab logs all radio protocols (GPS, WIFI and Bluetooth) on UMPCs, and GPS only on the iPAQs. Bluetooth is logged on the iPAQs with custom software, and together the logging applications are scheduled by a watchdog process that also logs device usage (memory, battery, charge etc.). The watchdog also schedules uploads of logs and media via a client-side executable and server-side PHP, and does so automatically whenever a connection to the repository is possible (e.g., cradled device or wireless network detected). Uploaded items are routinely imported into an SQLite database and all subsequent processing accesses data and stores results via the SQLite API.

A user group was informally solicited from among friends, colleagues and family members. We obtained a user group this way, rather than via a general call, as we foresaw the study would at times be a burden, given that our setup overreaches current technology (e.g., managing smartphone battery life), and any extra motivation would be useful. We also desired a group with a variety of relationships within the constraints of our size limit. The final experiment involved a set of 8 users, not counting pilot users or those who were subsequently unwilling to participate. User relationships are summarized as Venn diagrams in Figure 1(b).

3.3 Data Preprocessing: Single User Noise Removal and Interpolation

Raw GPS traces are first filtered of noise. It is hard to model given the variety of sources indicated above plus the nonuniform characteristics of GPS receivers in our range of devices (e.g., the smartphones sacrifice signal quality for increased rate of position fix). We experimented with machine learning approaches to noise filtering, using position and its derivatives together with quality information available in NMEA sentences, which led us to adopt a simpler mechanism based on physical constraints. Successive points are subject to velocity and acceleration reality checks and removed if they violate them. Figure 2(a) is an example signal in white, with filtered noise colored black. Noticeable is the star-patterned noise centered on two locations.

Recovery of missing signal is first attempted with an interpolation heuristic to determine if a user is stationary at a given position. If a trace disappears and reappears within a time threshold, and within a distance threshold of the last position, the user is inferred to have remained at the last-seen position for the duration. This approach was demonstrated in previous work [Adams et al. 2006]. The vertical GPS trace at the center of Figure 3(c) is an example of interpolation. The thresholds used in this work were 15 hours and 150 meters, which recovered over night periods where some users turned devices off, and the distance covered in a car in the time it took to obtain a cold GPS fix. It should be noted that 150 meters is not the effective resolution, but the threshold at which an intervening period is clipped back to the last seen location, which is typically on entry to a building. The second method of recovering missing signal, via copresence, becomes possible in a multiuser context.



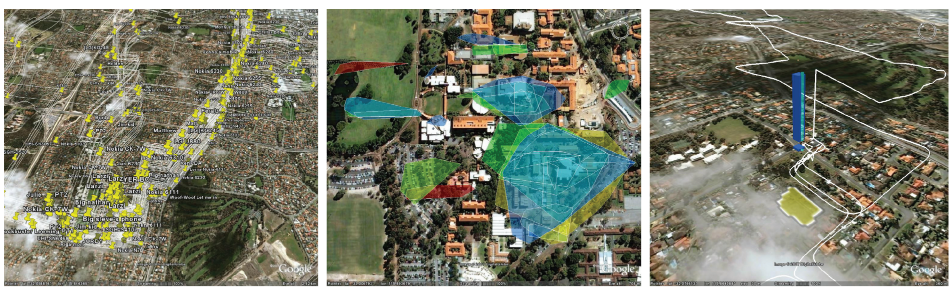
(a)

(b)

User	Raw	Filtered	Interpolated	Shared	Copresence	Borrowed
2	16.20	16.10	158.52	170.18		
4	0.84	0.83	12.29	12.29		N/A
5	10.78	10.56	36.72	45.02		
6	53.50	53.02	93.17	95.27		
7	4.22	4.10	27.10	30.19		
8	0.09	0.09	0.42	3.01		
9	5.3	5.27	22.30	23.85		
10	28.77	28.22	84.56	85.06		

(c)

Fig. 2. Processing GPS traces: a) Noise filtering (black); b) Shared GPS (black) via copresence; c) Results in *packed* days.



(a) (b) (c)

Fig. 3. a) GPS traces and Bluetooth discovery 'cloud', time mapped to altitude; b) Convex hull locations for multiple users; c) A stay comprised of a location, start time, duration, and people.

3.4 Data Preprocessing: Data Sharing via Copresence

Our multiuser, heterogeneous device setting creates both the need and opportunity to share sensor information among users. Different devices have varying strengths and different users varying behaviors. For example, UMPCs can have longer battery life at full power or are able to perform more complex processing, but being more bulky are not carried as much as smartphones (which are primarily an always-on connection device).

We first infer copresence directly from either absolute colocation via (interpolated) GPS, within a spatial tolerance, or Bluetooth device discovery, within a temporal tolerance. Copresence is then propagated among users up to a given number of hops. Spatial and temporal thresholds are proportionally related to resolution; That is, higher thresholds allow users further away to be considered copresent. Hops further effectively constrain the search space in terms of these parameters. Algorithm complexity is $O(NU^2)$ worst case, where N is the number of GPS or Bluetooth samples, and U is the number of users in the database. For very large user sets, a number of mitigating policies could be employed:

(i) In an incremental setting, N can be reduced arbitrarily (e.g., processing logs a day at a time); (ii) copresences falling outside the time range of the currently considered sample can be culled, resulting in complexity $O(UV)$, where V is the number of others copresent with the user on average; and finally (iii) a hard limit to the number of propagations can be applied. With our small set of 8 users, we use 10 hops, spatial threshold of 150m, and temporal window of 1 minute, effectively maximising recall for our small set. Processing time for 10 million samples (GPS fixes with variable duration plus Bluetooth device discoveries) is under a minute on desktop hardware *without* culling. Larger user sets or denser copresence would call for much smaller parameter values.

Copresence can be viewed as a junction through which other information can pass. We pass not only copresence (generating a fully spanned copresence network subject to the parameters mentioned above), but also location information if a user has missing data. If more than one donor is available, the user with the longest GPS range donates their information to the user. Other policies that, say, preferred higher signal quality to duration could be used. Figure 2(b) depicts an example of GPS data shared through copresence. The user's existing GPS traces, in white, have been augmented with signal shared from another user, in black. This example is a shared trip where one device lost GPS line of sight, but indicated its presence via Bluetooth. The device with line of sight patched the other's missing data. Single user interpolation performed again on the augmented data.

3.5 Data Collection

At time of writing, the database of 2.1GB has accumulated GPS logs, including interpolated periods, of 378 days, covering a total period of about 1360 days, and 1.1 million Bluetooth device discoveries, plus discovered places, stays, copresence etc., discussed later. Figure 3(a) depicts 4 months of GPS traces and Bluetooth discovery "cloud" for one user to give a feel for the data. Figure 2(c) contains statistics on the phases of GPS data processing for the 8 users. The Raw, Filtered, and Interpolated columns correspond to single user data, Section 3.3; The Shared column is the result of data sharing and (re)interpolation, Section 3.4. Copresence uses colour coded pie charts to indicate who a user is copresent with by proportion, and simlarly, Borrowed depicts who a user shares data from. GPS figures are in *packed* days, that is, include only actual sample spans.

Consider the example of User 2 from Figure 2(c). Raw GPS signal amounts to 16.20 days, which drops slightly to 16.10 after being filtered of noise. Single user interpolation takes the total of all spanned periods to 158.52. Interpolation typically boosts the total significantly as it recovers extended periods indoors, such as when the user is at home or work. Another 11.66 days are obtained via borrowing signal from copresent users, making a total of 170.18 days (collected over a period of 18 months, only 5 of which included copresence detection). User 2 is copresent most often with User 5, a close colleague, and then with User 10, his spouse! User 2 also borrows most data from User 5. It is also easy to see, for example, that Users 4 and 10 have little linkage with the network of users, as indicated in Figure 1(b).[3] Borrowed GPS data appears marginal in raw terms, but its utility will depend on its application. In particular, the GPS data obtained by sharing is by definition at times that are potentially most useful: when other users are present.

Data sharing raises the issue of privacy. A user might not mind a friend knowing they were present at an event, but draw the line at revealing their whereabouts before the event. For this study users were told data collected would be accessible to the authors and application evaluators. In general, an acceptable balance between privacy and functionality would probably be best achieved via a trusted 3rd-party broker and opt-in invitation protocol, such as that used by exiting social network services.

[3]It is also easy to determine which user donated the most data, user 5 (25% of all shares). Metrics like this obtainable in a "trusted broker" setting are vital to the viability of presence sharing applications according to Cox et al. [2006].

Ludford et al. [2007] include privacy considerations specific to location-based information, noting it to be an open, complex problem.

All subsequent extraction of spheres, rhythms and ties is applied to the data output from the processing detailed in the above sections.

4. SOCIAL SPHERES: LOCATIONS OF SIGNIFICANCE

Recall our definition of social spheres as labeled geo-spatial locations of significance to a user. Location is useful knowledge. For media management, it is a useful index of recall [Naaman et al. 2004]; it maps loosely to role(s) [Nurmi and Koolwaaij 2006] (e.g., at home I am a father, but at the shops, a consumer), which may be used to provide proactive device behavior, as well as forming the basis of relational metrics (e.g., social tie strength, Section 6). We cluster GPS traces "cleaned" and augmented by the processes we have detailed, and represent discovered spheres as convex hulls, and label them as either Home, Work or, Other using heuristics. Our motivation for using a richer representation for location, a convex hull, is the desire to preserve subtle differences in cluster shapes in a compact, efficiently updatable manner over time. For example, adjacent buildings can coincide with markedly different roles or activities, such as an office and a cafe, and preservation of these distinctions provides a better foundation for subsequent analyzes than representations with lower degrees of freedom, such as bounding boxes or centroid-radius pairs.

In the following we introduce the notion of places and stays, frame their extraction as an incremental, density-based clustering problem, present some heuristics for labeling places as Home, Work, or Other, and finally present algorithm performance for the set of 8 users.

4.1 Clustering GPS Traces to Discover Places and Stays

A *place* is an approximation of a real-world area visited by a user, as evidenced by his or her GPS traces. We represent the area characterizing a place as a convex hull of latitude-longitude pairs. We also store indices of a user's particular idiosyncratic use of a place, including total time spent there, time (UTC) of their last stay, and number of stays. Hence, for a user a:

$$place(a) = \{\mathsf{cvhull}, \mathsf{totalduration}, \mathsf{lastseen}, \mathsf{numstays}\}.$$

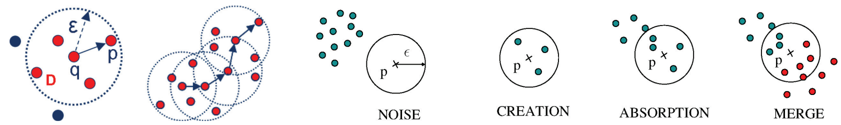
A *stay* is a period of time spent at a discovered place, and is characterized by the start time and duration of the visit, together with the set of people copresent at any time during the stay (as detected with the process of Section 3.4). Stays are the unit of clustering to discover social rhythms, detailed in Section 5.

$$stay(a) = \{\mathsf{place}, \mathsf{time}, \mathsf{duration}, \mathsf{people}\}.$$

Two speed thresholds are applied separately to GPS traces to obtain places at two resolutions: the first filters out all points not approximately stationary, while the second filters out points above slow walking speed. These filters are only used for place and stay discovery. The second pass was added after initial experiments found areas connected by travel on foot to be a useful index of recall. For example, a visit to a park or shopping mall (Use of the coarser resolution will also depend on the particular application).[4] To determine if a user is staying at a place, points are tested for inclusion within the smaller convex hulls obtained with the first threshold, and then the latter.

We adapt an incremental version of DBSCAN [Ester et al. 1996] to extract places from streaming data. DBSCAN has the threefold advantage of being deterministic, tractable for large datasets, and able

[4]Extension to a finer resolution, such as might be obtained from WIFI or Bluetooth [Krumm and Horvitz 2004], would be valuable. For example, within the building, am I in my office or at the water cooler?



(a) (b) (c)

Fig. 4. DBSCAN: a) Directly density reachable; b) Density reachable; c) Insertion of a point p (adapted [Ester et al. 1998]).

to discover clusters of arbitrary shape. DBSCAN is a density-based clustering algorithm founded upon three key concepts: directly density reachable, density reachable, and density connected. It requires a pair of parameters (ϵ, D), where ϵ is used to draw a perimeter around a point p to form its neighboring set $N(p \mid \epsilon)$ and D serves as a threshold to test if two points p and q are *directly density reachable*, see Figure 4(a). Two points p and q are called *density reachable* if there is a sequence of points $\{p_1, \ldots, p_l\}$ that links them, see Figure 4(b); and finally p is called *density connected* to q if we can find a point o that is density reachable from both p and q. DBSCAN then seeks to form clusters that are maximal in density-connectedness. For this work, $\epsilon = 0.001$, which corresponds to 60 meters, more than double typical accuracy of GPS, and $D = 300$, approximately the number of samples gathered in 5 minutes.

Incremental DBSCAN [Ester et al. 1998] also uses the above density concepts but operates incrementally. Assume all points prior to the arrival a new point have been clustered. The essential step in IncDBSCAN is insertion of a new point p. This requires a list of points q that need to be updated upon the arrival of p. Let Ω and $\Omega^+ = \{\Omega \cup p\}$ be the set of points before and after p is inserted, respectively. Recall that a point p is a core point wrt Ω, denoted by the propositional statement $C(p, \Omega \mid \epsilon, D)$, if the number of points in its neighbour set $N(p \mid \epsilon)$ computed based on Ω is greater than D. Then, the set of points to be updated upon the arrival of p is:

$$UpdateSeed(p) = \{q \mid C(q, \Omega^+), \exists h : C(h, \Omega^+) \vee \neg C(h, \Omega) \vee q \in N(h \mid \epsilon)\}.$$

In other words, it is the set of core points after the arrival of p that are affected. That is, only these points need to be refined. This set can also be computed efficiently if for each existing point we also store the number of its neighboring points, as only for those points q that become core points after the insertion of p (i.e., $q \in N(p \mid \epsilon)$ and $|N(q \mid \epsilon)| = D - 1$) should we do another neighbor query to determine UpdateSeed(p). With an R*-tree structure, querying neighbors takes $O(\log N)$ and thus the insertion step will takes $O(\log N)$ on average where N is the total number of points. Updates seeded by point p fall into four classes: Noise, Creation, Absorption and Merge, as shown in Figure 4(c). Ester et al. [1998] show theoretically, and we have verified empirically, that IncDBSCAN yields the same results as offline DBSCAN.

Convex hull descriptions of clusters are maintained and updated incrementally using techniques from computational geometry [de Berg et al. 2000] whenever a point is added to a cluster (Absorption and Merge cases), or computed from scratch (Creation). Informally, we divide an existing convex hull into a sequence of pie pieces counterclockwise by maintaining the list of points sorted by order of angles. When a new point p arrives, a search is performed to find the corresponding pie p belongs to and the convex hull is updated accordingly. Binary trees are used for convex hulls, and thus update and search for inclusion are $O(\log m)$, where m is number of vertices.

To give an idea of the performance in mobile devices, we ran our incremental algorithms on a Sony Vaio U71 UMPC with GPS data obtained from User 2. For 42K points it took less than 0.4s on average to update a new point (In fact, after filtering high-speed points, the number to be processed in a day is rarely above 22K). Given GPS fixes are logged every 1.4s, the algorithms are suited to resource-constrained mobile devices and the streaming nature of radio sensor data. The implemented point insertion algorithm does not make use of the time ranges of interpolated data, but artificially breaks them into many individual GPS fixes. An improved cluster update method will insert a single point representing the interpolated range once only, update cluster duration with its time range, and result in at least an order of magnitude speed up. An example of place extraction with convex hull description is shown in Figure 3(b), which shows a number of convex hulls extracted for different users for a section of the data. Without the use of the convex hull, the spatial descriptions would be coarse and cause different locations to be merged into each other.

4.2 Labeling Places

So far we have extracted static representations of places visited by a user, plus attributes derived from the history of the user's appearance at those places. We now label those places with socially semantic categories. That is, beyond anonymous coordinates on a map, what significance does a place hold in the web of a user's social life? This will provide the necessary building blocks for further inference about social context.

We choose to label places from the set *Home*, *Work*, or *Other*, as it is a widely applicable trichotomy [Nippert-Eng 1995],[5] and offers potential for inferring about the nature of activities or relationships carried on there. We use a heuristic that demonstrates surprising effectiveness, but is by no means the final word on this classification task.

The algorithm attempts to discover the place corresponding to Home or Work by applying a time filter, $\tau(x_i)$, to GPS fixes, x_i, to obtain only those in the assumed appropriate time ranges, and returns the cluster with maximal duration. To detect Home we specify that $\tau_{home}(x_i)$ is true iff x_i is collected before 7 a.m. or after 7 p.m. Similarly, $\tau_{work}(x_i)$ is set to 8 a.m.–11 a.m. and 1 p.m.–4 p.m. on a weekday.

A more sophisticated classifier might handle varying user profiles, such as having many part-time jobs, a nighttime job, or even no job at all, by using fundamental assumptions about the need for sleep or socialization, and try alternate hypotheses about temporal patterns. Urban zoning information, such as can be obtained from GIS services, might provide valuable input. A complementary approach could represent places as nodes in a graph with edges as travel routes between places. Home is often a decision point, and would appear as a hub in such a graph, detectable by graph measures like centrality.

4.3 Social Sphere Discovery Results and Observations

We are unable to evaluate performance against a complete ground truth due to the scope of the study: it would require users to keep a diary of every movement with a resolution of minutes for months at a time. We settled, therefore, with assessing false positive rates absolutely, and false negative rates via unprompted user memory, which can be patchy. Each user was given a GoogleEarth file (KML format) containing discovered social spheres, by default labeled Unknown. Each sphere was then examined and labeled appropriately if the user recognized it as a location of significance (For example, a coffee shop is labeled, whereas traffic lights are not). Any spheres labeled Unknown after this process are viewed as false positives. There were no reported false negatives for spheres at which logging occurred; however, it is likely some users have a small number of unreported false negatives.

Referring to Figure 5, the users with the highest Unknown counts are User 2 and 6. User 2's false positives come from unfiltered noise (6) and car parks (4). The spheres derived from noise consist of (anomalous) convex hulls of only 1, 2, or 3 vertices. The car parks achieve sufficient cluster duration in cases where the device was turned off and left in the car, for convenience, and GPS was subsequently interpolated for the entire period the car was parked. User 6 went on holidays for 2 weeks during data

[5]Mashups with the increasing amount of online location-indexed information, such as text and images provided by Google Earth Community, will make for useful social markup from different perspectives. Ludford et al. [2007] characterize locations in a multi-user setting by number of bookmarks, duration of stay, and content of associated personal reminders.

User	Detected	Unknown	Home (τ_{home} hours)		Work (τ_{work} hours)	
2	101	10	$\surd$	(1053)	$\surd$	(276)
4	37	0	$\surd$	(58)	$\surd$	(12)
5	20	3	$\surd$	(387)	$\surd$	(43)
6	121	18	$\surd$	(453)	$\surd$	(107)
7	29	2	$\surd$	(91)	$\surd$	(106)
8	4	0	$\times$	(0)	$\surd$	(6)
9	55	0	$\surd$	(74)	$\surd^{\dagger}$	(26)
10	45	0	$\surd$	(471)	$\surd^{\ddagger}$	(218)

†User 9 works from home 2-3 days a week, and Home is 2nd candidate for Work at 21 hrs

‡User 10 is a stay-at-home Mum: Home and Work are correctly detected as the same

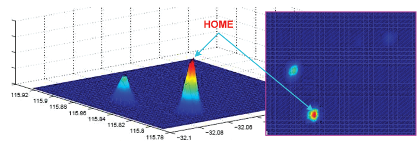


Fig. 5. Social sphere discovery: (left) Results; (right) Example discovery of Home for User 2.

collection to an unfamiliar city. Because he was a tourist, his movements consisted of many fragmented stays at places not always easy to recall. We note spheres can be refined based on total duration spent there. Significance of a sphere is user and application dependent, but unknown places tend to cluster at the tail and can be pruned with thresholds corresponding to differing confidence levels.

All homes and workplaces were discovered with the algorithm of Section 4.2, barring only the home of User 8, which is due to the small amount of data collected for him, exacerbated by a daily routine of starting late and working late. Figure 5 depicts the heaviest cluster arising from $\tau_{home}(x_i)$ for User 2, labeled home.

5. SOCIAL RHYTHMS: ACTIVITIES OF DAILY LIFE

In this section, we define and motivate social rhythms, frame their extraction as a multidimensional clustering problem, and investigate an initial lifestyle measure based on rhythms.

5.1 Definition

Pursuits of daily life, such as work, holiday-making, or shopping, give rise to more or less prominent patterns of where and when we go, and with whom we spend time. These patterns in the multidimensional space of people, place and time, we term social rhythms.[6] Different projections of this space uncover different patterns, which are signatures arising from pursuits that lie latent within them. These signatures reflect real-world constraints inherent to the pursuit. For example, rhythms characterized by repeated start time or duration often indicate a constraint imposed by an institutional timetable or felt expectation, such as Work [Gehl 1987]; repeated duration can also indicate structure inherent to an activity—a basketball game might be timetabled at various start times, but is always 40 minutes long; rhythms formed by similarity of people present arise from activities constrained by who *must* attend, such as the choir at both practice and performance; rhythms comprised of repeated place can indicate the presence of a resource (animal, mineral, vegetable, or even intangible) that is a necessary component of an activity tied to a location, and consequently draws the user to that location, such as the requirement of a pool for swimming lessons. Table I contains examples of the kinds of pursuits that correspond to different signature types.

Social rhythms do not define an activity to the degree of high-level textual label, such as is the case with work aimed at (usually supervised) classification of highly specific situations (e.g., "restaurant dining" [Kern and Schiele 2003]). High-level classification is useful in a number of contexts, but is difficult and typically limited in scope due to the number of user or group-specific assumptions and/or small number of classes required to achieve acceptable performance, the requirement of a supervised training period, or the sheer dynamism of embodied life. Social rhythm classification remains, rather,

[6]Social rhythms are analogous to *projects,* defined as "coherent, logically interconnected sets of actions" [Carrasco and Miller 2006]. In that work, a "social project generates a series of activity and travel episodes," which are analogous to our stays.

Table I. Rhythm Detection as a Combinatorial Clustering Process by Folding in Certain Dimensions

Time	Location	Duration	People	Rhythm Type	Example
√	√	√	×	timetable-, place-bound, structured	Regularly scheduled office meetings, tutorial classes
√	√	×	×	timetable-, place-bound, unstructured	"Shopping", visit scrapbooking shop on Sat morning at 8.00 a.m., sometimes for class (3 hours), to buy (30 mins), and to browse (1 hour)
√	×	√	×	timetable-bound, structured	Mum's group meeting, different homes, for an hour on Tuesdays
×	√	√	×	place-bound, structured	Exercise, 45 minutes at same gym with varying start time
√	×	√	√	timetable-, people-bound, structured	Dinner date, couple goes to different restaurants at about 8.00 p.m. for roughly an hour
×	√	√	√	place-, people-bound, structured	Swimming lessons, Dad and son at pool for 45 mins with shifting start time

at the level of signature type, leaving it to the user to close the semantic gap for a *timetable-bound, structured rhythm* in their own unique context to the label "chess club event" or "skydivers' outing."

5.2 Approach

Stays, as defined in Section 4.1, contain our sensed correspondants to the dimensions of people, place and time. Stays can be viewed as a vector, geometrically spanning a multidimensional space $\mathfrak{S}$, where each axis corresponds to a contributing element.

We cast social rhythm extraction as a multidimensional stay clustering task and use DBSCAN [Ester et al. 1996]. Multidimensional DBSCAN (M-DBSCAN) requires only that the distance function be a metric.[7] Rhythm extraction is thus a problem of clustering stays detected for each user by *folding* in certain dimensions. If n is the number of dimensions, there are $\binom{1}{n} + \binom{2}{n} + \cdots + \binom{n}{n} = (2^n - 1)$ different ways to perform clustering, which grows exponentially with n. Even for a small values of $n = 4$ or 5 the number of configurations is undesirably large for this setting. Therefore, Table I presents a subset of all possible configurations of more readily interpretable rhythms in terms of the constraints. We consider rhythm extraction for this subset below.

We note the stay attribute *time* is open to many different interpretations. For example, is 5 p.m. considered the same time regardless of day of the month or week? Are weekdays to be differentiated from weekends? Are Mondays to be considered the same, or the 3rd Monday of each month? A multidimensional clustering framework allows investigations of different resolutions and distinctions.

5.3 Behavioral Rhythms

We first consider patterns arising from a user's movements in place and time, termed behavioral rhythms. Consideration of patterns of who a user spends time with, termed relational rhythms, are postponed till Section 5.4. Rhythms are first delineated into Rare and Frequent, and the latter are further classified as either Timed or Flexible. Each of these classes has different attributes in terms of usefulness as an item of recall and corresponding latent pursuits.

5.3.1 *Rare and Frequent.* Behavioral rhythms are extracted by clustering using place and/or time, but not people, rows 1 to 4 of Table I. The notion of rarity is relative. A rhythm is classified frequent if

[7] Recall that a function $\mu()$ is a metric if it is positive definite and symmetric and possesses triangle inequality properties.

	Rare		Frequent		Timed		Flexible
User	#	Recall	#	Recall	#	Recall	
2	63	0.92	16	1.00	75/48	1.00	45/38
4	21	0.75	5	1.00	0/0	×	6/5
5	8	0.78	11	1.00	46/34	1.00	41/16
6	88	1.00	14	1.00	12/0	1.00	29/27
7	19	1.00	6	1.00	43/30	1.00	21/10
8	3	×	1	×	0/0	×	2/1
9	21	1.00	10	1.00	11/9	1.00	20/13
10	30	0.55	8	0.67	6/1	1.00	15/14

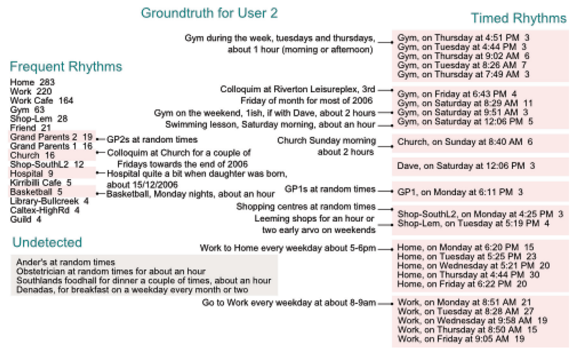


Fig. 6. Behavioral rhythms: (left) Results; (right) Example rhythms detected for User 2 with stay frequency.

the number of stays in the cluster is above a threshold, R_m, during a sliding time window, R_d; otherwise, it is classed as rare. For example, a frequent rhythm of visiting a cafe near work might become rare after a change of job, whereupon the user only meets old workmates occasionally.

We encounter the same difficulty in obtaining complete ground truth here as that expressed in Section 4.3. We solicited ground truth prior to and after presenting the user with rhythms discovered by the system, and evaluate using this hybrid ground truth. Users responded to the initial request with natural language responses such as "often, sometimes, once, or twice," and were mapped to rare or frequent accordingly, with further consultation if necessary. Quantitative results for rare and frequent rhythm discovery with parameters $R_m = 3$ and $R_d = 180$ days are presented in Figure 6(a).[8] As expected, the number of rare rhythms is much higher than frequent (averages of 31.6 and 8.9 respectively). Recall rates for frequent rhythms is also higher than for rare, due to the comparitive ease with which they are remembered. As with social sphere results, it is assumed there are a small number of false negatives not indicated by the users. Figure 6(b) presents examples of behavioral rhythms extracted for User 2 to give a feel for the results.

In the context of information retrieval, such as the media browsing applications presented in Section 7, rare rhythms have high specifying power (e.g., in search of a photo, a rhythm that corresponds to rare "dinner dates" will rapidly shrink search scope), but frequent rhythms are perhaps more immediately recalled given the relatively large portion of a user's life they represent (e.g., "I took the photo when we were shopping").

5.3.2 *Timed and Flexible.* We now consider nuancing the rhythms classed as frequent based on their time characteristics, motivated by the importance of *punctuality* or lack of it in shaping one's life patterns: arriving at work on time, dropping your child at childcare, etc. Rhythms that display little variation in start time are termed Timed, and are often signatures of pursuits bounded by institutional timetables and/or inherently structured activities, such as work or community meetings. We detect them by clustering on stays constrained by day of the week and approximate start time, and either place or duration. Any rhythm in Table I including start time is termed Timed.

On the flip side, the absence of recurring punctuality often signifies an underlying pursuit engaged in during free time, which may or may not relate to institutional schedules and timetables. We term these Flexible rhythms. Such pursuits might be spontaneous (such as the decision to jog) or lack structure that dictates duration (e.g., fishing, where duration might depend on the catch). Any clustering parameterizations in Table I not using time are termed Flexible.

[8]Note that we were unable to obtain rhythm groundtruth from User 8.

M-DBSCAN clustering for timed and flexible rhythms is controlled by two parameters (in addition to those delineating a frequent rhythm): allowed variation in starting time, π_{time_relax}, and duration, π_{dur_relax}, for two stays to be directly density reachable. Unless stated otherwise, $\pi_{time\_relax} = 15$ mins and $\pi_{dur\_relax} = 15$ mins, set by the sorted k-dist graph method suggested by Ester et al. [1996]. Examples of detected timed rhythms appear in Figure 6(b), with results reported in Figure 6(a), where the number of detected rhythms is represented by a pair (x/y), which are results without and with considering duration respectively.

5.4 Relational Rhythms

Social life is *interactive* in nature: hanging out with relatives, friends, or working with colleagues. Who is or is not present with a user can be a signature of the type of pursuit engaged in. Rhythms that include copresence we term Relational. Relational rhythms are clustered using similar settings to timed and flexible rhythms but with added constraints on colocated people, rows 5 and 6 of Table I. Clustering parameterizations in Table I that include people are examples of relational rhythms. Table II contains results for relational rhythms constrained by place, any day of the week, and starting time with $\pi_{time\_relax} = 15$ minutes. Each cell (i, j) reports the number of relational rhythms shared by users i and j, followed by examples.

Note that Table II is asymmetric. Recall that places, and hence stays, are user specific. Hence rhythms built atop these are also user specific. For example, User 2 has 3 specific places connected with the university, whereas User 10 has 2. Thus User 2's stays at the university may be more fragmented than User 10's, which will effect clustering performed on those stays.

Relational rhythms allow some inference about the nature of interpersonal relationships. For example, *where* do two actors share rhythms—Home, Grandparents, Parks, or Work? For example, User 2 shares timed rhythms with both User 10 and User 5, but those with User 5 occur exclusively at Work, whereas those with User 10 are more spread. Users $\{2, 5, 6, 7, 8, 9\}$ are colleagues with a high proportion of rhythms occurring at work, with the exception of the shared anomaly, Heathcote, a social gathering. This is explored further in Section 6.

5.5 Lifestyle Measures Based on Social Rhythms

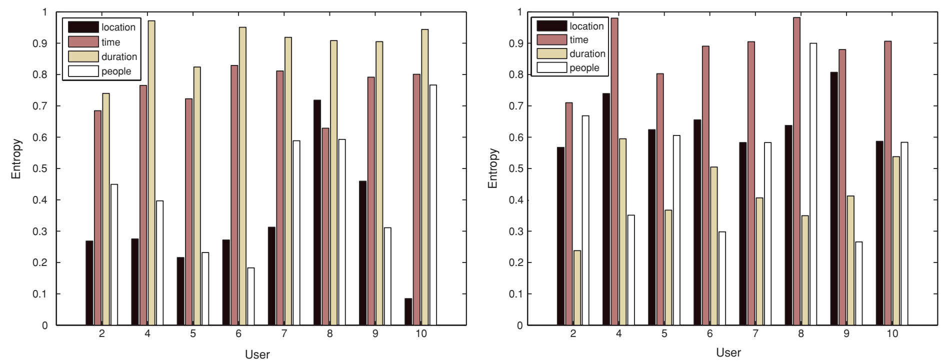
Social rhythms provide a basis for formulating measures of the kinds of activities a person engages in. For example, is a person run by the clock? Do they tend to choose activities for the nature of the activity, or the people who can be involved? Below we present results of calculating entropy on each dimension for a user. The resulting vector characterizes a user's predictability of each dimension on his mix of activities.

Figures 7(a) and (b) plot entropy on each dimension for all users. Entropy is calculated across all clusters on normalized total duration (i.e., sum of duration for all stays in a cluster), and number of stays in each cluster, respectively. So for location, for example, entropy by count is higher for greater diversity in the location of stays, *regardless* of the amount of time spent there, whereas entropy by duration takes time spent into account. These, and all subsequent, calculations are performed on a 5-month subset of the data with maximal devices being carried in parallel.

It is interesting to observe that User 10 has the lowest entropy on location, being a stay-at-home Mom; User 9 has the highest, having a working week split between home and the university campus. Observations regarding the people dimension must be tentative given the small number of users, but we note that User 10 has the highest entropy on people by duration, stemming from the fairly even split of time alone and with User 2; Users 2 and 7 are involved in a number of projects at work, and therefore see more people, and the lowest, User 6, doesn't collaborate with any of the other users in the study. User 8 has by far the smallest amount of data, and his probabilities, and hence, entropies, are severely skewed. This might be attenuated by interpolating over periods of missing data with synthetic data, as mentioned in the future work of Eagle and Pentland [2006]. The amount of data for most users does not allow it, but

Table II. Relational Rhythms Result Matrix: Each Cell(i, j) Contains the Total Number of Shared Rhythms from User i's Perspective, and a Description for a Small Sample

	2	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2	x	7 GP1 2:53PM Basketball 5:00PM Home 5:25PM	21 Bookmark 9:11AM ParkLake 4:17PM	18 Heathcote 5:47PM Work-314 9:47AM Bookmark 9:32AM	16 Work 9:59AM Home 12:47PM Heathcote 5:47PM	15 Work 10:07AM Bookmark 9:38AM Heathcote 5:47PM	13 Work 12:38PM Heathcote 5:47PM Guild 1:02PM	22 Home 5:19PM GP2 6:11PM Church 8:37AM
4	4 Home 2:53PM Church 7:57AM Fam 4:12PM	x	3 Home 2:20PM Fam 4:12PM Stadium 4:42PM	0	0	0	0	0
5	9 Build314 4:27PM Bookmark 9:11AM ParkLake 4:17PM	2 Build314 8:57AM Unknown 4:14PM	x	19 Build314 9:49AM Bookmark 9:32AM Deli 12:36PM	22 Build314 9:41AM ParkLake 4:17PM Unknown 3:52PM	14 Build314 1:08PM Build314 9:07AM Build314 3:37PM	13 Build314 9:01AM Bookmark 9:26AM Deli 1:00PM	0
6	18 Work-B314 8:05AM Heathcote 5:31PM Lawn 12:14PM	0	11 Work-B314 8:05AM Lawn 12:14PM Work-B314 12:23PM	x	9 Work-B314 8:32AM Heathcote 5:31PM Work-B314 12:46PM	18 Heathcote 5:31PM Work-B314 9:13AM	7 (all at Work)	0
7	30 Work 9:23AM Home 5:21PM ParkLake 4:17PM	0	28 (all at Work)	21 Work-B314 7:10AM HeathCote 4:54PM Work-B314 8:16AM	x	13 HeathCote 4:54PM Work-B314 1:40PM Work-B314 8:41AM	8 (all at Work)	0
8	10 (all at Work)	0	7 (all at Work)	4 (all at Work)	9 (all at Work)	x	2 (all at Work)	0
9	10 (all at Work)	0	8 (all at Work)	3 (all at Work)	4 (all at Work)	2 (all at Work)	x	0
10	22 Home 8:43PM Church 8:52AM SouthBeach 5:23PM	0	0	0	0	0	0	x



(a) (b)

Fig. 7. Single User Entropy by Dimension: a) by total duration of stays in each cluster, and b) by count of stays in each cluster.

entropy plotted in time might form the basis of interesting indices. For example, we plotted location and time entropy for User 2 with a month window, at increments of a week, and found edges coinciding with a holiday period.

6. SOCIAL TIES: INTERPERSONAL RELATIONSHIPS

Social context, in addition to place and activity, includes interpersonal relationships. Social tie is an abstract term used to characterize a particular aspect of such a relationship. Social ties are of great interest to social scientists, and can constitute the link structures of social networks, an area of study that has exploded in popularity in recent times. The complexity of interpersonal relationships has made for a plurality of social tie types. For example, Mika and Gangemi [2004] provide a partial list of tie facets defined and studied in the social science literature 26 items long.

We focus on two types of tie: an approximation of relationship *strength*, and the more subjective notion *closeness*.[9] We formulate strength as a function of proximity (or, how much time user A spends with user B), weighted by ascribing more or less significance to the social spheres it occurs within. For *closeness,* we present some initial investigative indicators.

6.1 Relationship Strength from Proximity

We require an estimate of a user's interaction with others. There are many ways this can be estimated, such as detection of presence through audio, colocated GPS, active RFID, and so on. We focus on physical proximity, but note virtual proximity or interaction via information communication technologies (ICTs), like Instant Messaging, email or even web documents [Mika 2004], is an important input to social tie strength.

Regardless of the technique used to assess copresence, we fomalize tie strength with respect to user i as follows: Let user i be observed over a set of S sampled periods,[10] and let l_i be the social sphere of this user at sample s. Then let p_i denote the Boolean presence of another actor j in sample s,

[9]For example, The Connected Lives Project elicited two categories of closeness, *close* and *somewhat close*. Close people were those with whom respondents "discuss important matters with" or "regularly keep in touch with," whereas somewhat close people were "more than just casual acquaintances, but not 'very close'."

[10]The decision to use frequency of stays vs. duration will be application specific. Marsden and Campbell [1984] note "frequency as a measure of strength will tend systematically to overestimate the strength of ties between persons who are neighbors or coworkers, while the use of duration as a measure of strength will overestimate the strength of ties between relatives."

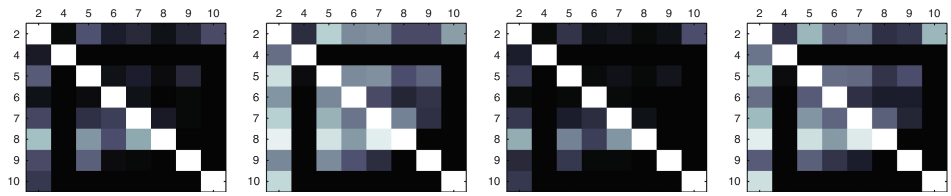


Fig. 8. Social tie by proximity: a) by duration, equal weights, b) by count, equal weights, c) by duration, weighted spheres, and d) by count, weighted spheres. Stronger ties are lighter.

1 denoting present and 0 not present. To account for the relative importance of spheres when users interact (e.g., depending on the application, home might be more socially significant than the dry cleaners), we introduce ω_L, a weight expressing the relative significance of sphere l_i. Social tie strength T between actors i and j is defined as:

$$T(i, j) = \frac{1}{N_{i,S}} \sum_{s=1}^{S} p_i(s, j)\omega_L(l_i(s)), \tag{1}$$

where $N_{i,S}$ is a normalizing constant for actor i over the sample set. $T = 1$ is interpreted as "actor j is always with i" for the sample set, and $T = 0$ as "j is never seen with i." It can be noted T is not commutative, by virtue of the weights, reflecting that the strength of a bond from one person's point of view isn't necessarily shared by the other.

Relationships carried on at familiar places imbue those places with a derivative significance, and those places in turn may imbue continuing or new relationships carried on there with significance reciprocally. One option for generating sphere weights is to use a media-flavored approach: the significance of a sphere is proportional to how much media is captured there. Let l_m be 1 if media item m was created at sphere i, and M be the total number of media items captured in sample set S at all spheres. Then, ω_L is defined as:

$$\omega_L(i) = \frac{1}{M} \sum_{m=1}^{M} l_m(m, i). \tag{2}$$

Social ties used in the media browser Socio-Graph are calculated this way (Section 7.1). Other possibilities for calculating sphere significance include sphere type, such as Home or Work cumulative time spent there, or even the kind of social rhythms that occur there (e.g., spheres that host Flexible rhythms might be weighted higher). Weighting schemes will depend most on the immediate application of the tie strength approximation, but whatever the flavour of ω_L, the assumption is that time spent together is a coarse indicator of significance of the relationship, and social spheres factor this.

Here we make a few observations on tie strength calculated on our data set. Figure 8 includes matrices of social tie strength, $T(i, j)$, mapped on a log scale to a color gradient. Each row is calculated from a single user's logs, which gives rise to the observed asymmetry. Black indicates lowest strength (never proximate), white highest (always proximate). Figures 8(a) and (b) are for $T(i, j)$ calculated with unit sphere weights. User 2 has approximately equal tie with User 5 by duration, a close collaborator at work, and User 10, his spouse, but the tie is stronger with User 5 by count, as predicted by Carrasco and Miller [2006]. Figures 8(c)&(d) are for $T(i, j)$ calculated with weights ascribing a higher significance to Home (3) and Other (2), over Work (1). Accordingly, User 2's ties with Users 10 and 5 become about equal by count, and stronger with User 10 by duration. $T(i, j)$ is affected by the distribution of logging times,

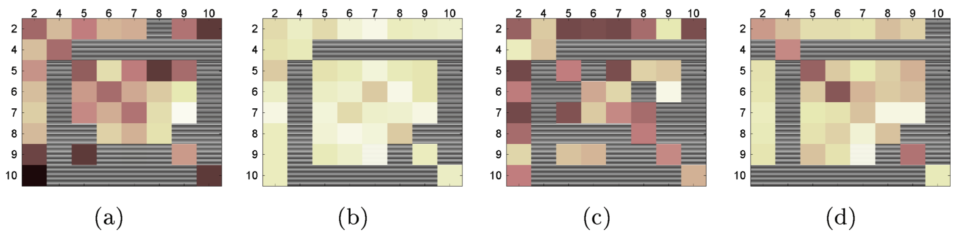


Fig. 9. Joint entropy of users: a) location, b) time, c) duration by counts, and d) people. Darker indicates a dimension is more important in bringing two users together. Horizontal lines indicate insufficient data.

as exemplified by User 8: He has consistently higher tie strengths with work colleagues, a product of his small and work-skewed data set.

6.2 Indicators of Closeness

Tie strength, as previously formulated, does not make use of the approximation of activities supplied by social rhythms. Intuitively, the kinds of activities two people share ought to provide a valuable insight into the closeness of their relationship. That is, proximity is useful, but the *reason* for it might be even more useful.

6.2.1 *A Reciprocal Measure: Joint Entropy.* A natural extension of single user measure based on rhythms of Section 5.5 is *joint* entropy on dimensions. This is a symmetric measure that treats the copresence of x and y as a new actor.[11] Given users x and y, joint entropy is:

$$H(x, y) = -\sum_{x,y} p_{x,y} \log(p_{x,y}), \tag{3}$$

where $p_{x,y}$ is calculated by duration of stays in each cluster. Stays are recreated from scratch, such that x and y are *strictly* copresent (i.e., if y leaves, the stay is terminated at that point). The definition of stays in Section 4.1 required only that another user be present at any point during it to be registered as present.

Figure 9 presents a matrix of $H(x, y)$ normalized to lie between 0 and 1 for each dimension, from user x's data. The lower the entropy, the darker the colour, indicating that dimension plays a greater role in bringing two people together. For example, User 2 and User 10 are low entropy on location but high on time of day; They see each other at various times, but home is often the shared location. User 2 and User 5 collaborate according to a timetable, indicated by the dark shade of cell (2, 5).

6.2.2 *A Nonreciprocal Measure: Presence of User Y with Respect to User X's Timed Rhythms.* Ego-centered networks are often studied in social science, and pose questions such as: how does actor x perceive his relationship with actor y? In our terminology, we could ask: how does actor y fit into actor x's social rhythms? The time and location dimensions of our experiment are strongest (duration being noisy, and people sparse), so we formulate an asymmetric measure by way of demonstration.

First we generate timed rhythms for user x according to Section 5.3.2, with $\pi_{min\_stays} = 1$ to include lone stays. Next we partially rank the resulting rhythms to the number of stays in each cluster. The largest cluster is ranked 1, and those rhythms with equal stays are ranked equally. For example, clusters of a single stay are all pooled with equal, lowest rank. Given this reference ranking of social rhythms in time for user x, we now calculate a measure of how user y appears in them. If user y is present in

[11] $H(x, y)$ is not strictly symmetric in this context. That is, $H(x, y)$ doesn't necessarily equal $H(y, x)$, as discrepancies arise from likely differences in social spheres for each user. Recall that social spheres are discovered per user, based on the their GPS data.

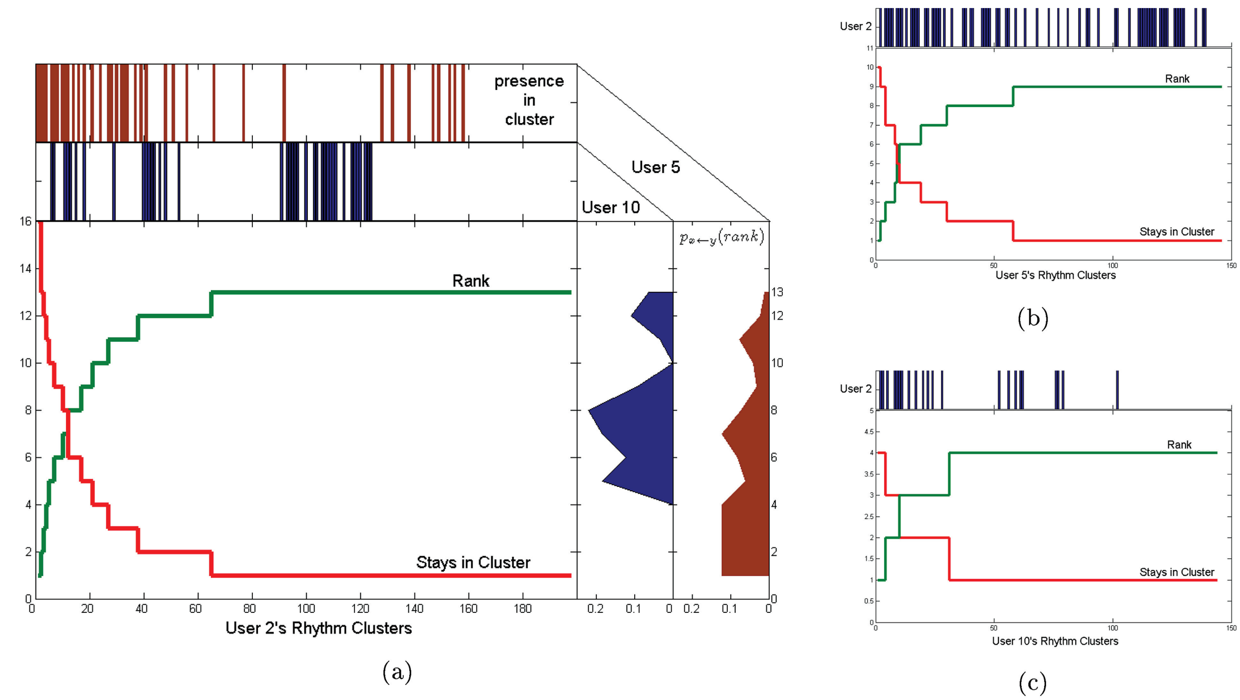


Fig. 10. Presence of User Y with respect to User X's time rhythms: a) Stays per cluster and rank for User 2's timed rhythms, with presence in a cluster indicated for Users 5 & 10 (top), and and (right); b) Stays per cluster and rank for User 5's timed rhythms, with presence in a cluster indicated for User 2 (top); c) Stays per cluster and rank for User 10's timed rhythms, with presence in a cluster indicated for User 2 (top).

any of the stays in a cluster at a given rank, it is interpreted as user y sharing that rank of timed social rhythm.[12] From the list of shared ranks we generate a pdf, $p_{x\leftarrow y}(rank)$, where the weight of each rank corresponds to the proportion of rhythm clusters user y appears in, and finally calculate median rank, $med(p_{x\leftarrow y})$, which provides the average type of user x's timed rhythms in which user y appears, and rank entropy, $H(p_{x\leftarrow y})$, which characterizes how scattered across all of x's rhythms y's presence is. For example, for a user y who only sees user x in his activities strongly tied to a timetable, $med(p_{x\leftarrow y})$ will be closer to 1, whereas for a relationship whose context is impromptu from x's point of view, $med(p_{x\leftarrow y})$ will be closer to user x's maximum rank. Different application contexts might call for different emphases and different choices for each component of the measure, such as a weighted ordinal mean that takes the number of rhythms at a given rank into account, or even avoids ranking altogether.

Figure 10 plots ranked timed rhythms for users, together with the presence of other users in those rhythms. $med(p_{2\leftarrow 5}) = 4$ and $H(p_{2\leftarrow 5}) = 0.94$, indicating User 5 is toward the timed end of User 2's 13 rhythm ranks with even spread. Conversely, $med(p_{5\leftarrow 2}) = 5$ and $H(p_{5\leftarrow 2}) = 0.86$, which puts User 2 slightly towards the untimed end of User 5's 9 rhythm ranks from his perspective. $med(p_{2\leftarrow 10}) = 7$ and $H(p_{2\leftarrow 10}) = 0.76$, shows User 10's relationship to be both more untimed and less scattered from User 2's perspective. Conversely, $med(p_{10\leftarrow 2}) = 1$ and $H(p_{10\leftarrow 2}) = 1.0$, which is due to User 10's home rhythms being her most timed, which is not mirrored as strongly by User 2 (i.e., the variation of User

[12]The choice to consider a rank shared if there is any copresence during any rhythm is to preserve the significance of rare events, which would be drowned by the amount of time encapsulated by timed rhythms if a time-weighted measure were used.

2's time of arrival at home causes fragmentation of rhythms occurring at home, pushing them to higher ranks).

Measures like these might provide a cheap alternative or supplement to expensive data collection techniques, such as surveys and interviews. For example, The Connected Lives Project [Hogan et al. 2005] obtained data by survey including time and place fixity. Carrasco and Miller [2006] use this data to discover inputs to the latent variable *propensity* to perform social activities. Propensity is influenced by personal attributes (e.g., income, age, live with partner), social network composition (e.g., numbers of immediate family, neighbors, work mates), and ICT interaction (e.g., email and IM frequency). It is, in turn, measured by three dependent variables: tie strength (*closeness* here, strong or weak), social activity types (hosting/visiting or bars/restaurants) and frequency (once a week or between a week and a month). For example, they found a positive correlation between people living with a partner and hosting or visiting (at homes), and a negative correlation with meeting in public places like bars and restaurants: if *living with partner* is known, and activity types and frequency are estimated from sensor data, closeness can be cheaply estimated.

7. APPLICATIONS THAT LEVERAGE SOCIAL CONTEXT

Encoded social context can drive applications requiring representation of embodied social life, and are conceivably useful in a range of application domains, including automated media annotation and sharing, diarizing and collaboration tools, to name a few. We choose two examples of automated media annotation and browsing and perform user studies aimed at examining their comprehensibility and perceived usefulness.

7.1 Personal Media Browsing with Socio-Graph

The first application is a novel media browser called *Socio-Graph*, which aims to demonstrate the utility of social context metadata for the task of personal media exploration and sharing. It does this by explicitly supporting navigation in the common terms of the who, what, where and when. Specifically, it is a multiuser spatio-temporal browser with the ability to render images, video, and movies (structured for flexible delivery and containing cinematic and content annotation, detailed in previous work [Adams and Venkatesh 2005, 2006]) in a unified environment, and filter media items on time, position, labeled significant place, shared places, presence of actor, and social tie strength by proximity.

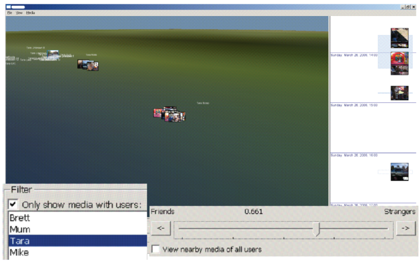
For many users their awareness of specific media items is with reference to a comprehensive, if imperfect, mental model built from memories.[13] But in a typical browsing session this wealth of contextual knowledge must be mapped to the indices natively supported by the browser, such as folder, time, or raw latitude and longitude. In the absence of perfect memory, this mapping is nontrivial. Socio-Graph uses social spheres, copresence, and social ties, and derived structures, as ready-made mappings from a user's contextual knowledge to raw media indices.[14]

We now briefly consider core design parameters for Socio-Graph and resulting implementation choices, before presenting our user study.

7.1.1 *Nonexpert Users.* The context of personal media browsing means we can not make strong assumptions about user proficiency. The number of types of media visualization and interaction is thus kept to a minimum. Media items are displayed from a 3D, first-person point of view in the main pane, which allows traversal to any global coordinate à la GoogleEarth. A linear timeline view accompanies this in a pane to the right. Translation and zoom, able to deal with volume of items while providing a

[13] Westermann and Jain [2007] focus on events, and "users' eventcentricity," and make it their primary datastructure.

[14] This can be viewed as an instance of aligning the software's 'structure or paths' with the user's [Rice et al. 2001], thus promoting the 'disappearance of the interface' [Norman 1999].



Question	Mean	Median
General response to Socio-Graph		
I like this media browser	3.4	3
This browser is easy to use	2.9	3
I am satisfied with the media organization	3.1	3
A month from now, I would still be interested in using this browser	3.6	4
Rate Socio-Graph's social context filters		
Social tie strength	3	3
Location	3.9	4
Shared place	3.3	3
Actor presence	3.9	4
Event	3.4	4

Fig. 11. Socio-Graph: (left) Filtering on copresent user and social tie strength. Media clustered in time at a significant place signals an event; (right) User study feedback, 0 - Strongly disagree, 4 - Strongly agree.

measure of orientation [Raskin 2000], are supported in both time and space views with the same mouse gestures. Double-clicking selects an item, and if it is time-based, clicking again plays it. No annotation effort is assumed; the more the user carries a device and uses it to capture media, the better the social context indices. Socio-Graph aims for a minimum number of widgets [Lee and Smeaton 2002]. Figure 11 contains a screen shot of Socio-Graph.

7.1.2 *Support for Goal-Directed Browsing by Multiple Paths.* Often a user has a particular media item or set of items in mind, and the browsing activity equates to a search. Such a search often mimics the mental activity of ransacking memories, amassing evidence, and drilling down to the particular, sought after memory. As noted earlier, social context, such as who was present or where an event was, is often a prominent means to recall. Socio-Graph supports this kind of search by allowing social context to be used as filters on displayed media items: Spatial and temporal filtering are provided by the field of view and timeline scope; social spheres are labeled on the map; display of media from actors who share a social sphere with the user can be on or off; actor presence at media capture can be specified to be any sub-set; and media can be thresholded on the user's social tie strength with its owner. This matrix of filters can be aggregated to mimic the process of amassing of evidence mentioned above. Media items entering or leaving the query set due to filter changes fade in and out dynamically, allowing the user to play with configurations and observe their effects. A choice of filters also allows the user to choose those corresponding to the most salient memories associated with the sought after media. For example, queries expressing the following intentions can be formulated with the simple interactions detailed below: Find Media... Taken at home in the previous month; Owned by anyone from the party I missed; or From the last family outing to the park near the city.

7.1.3 *Support for Casual, Entertainment-Oriented Browsing.* Personal media browsing is often a casual, entertainment-oriented activity. In this context, serendipity, the possibility of stumbling upon unlooked for items, is a desirable trait [Rice et al. 2001, p. 226]. The first-person metaphor adopted by Socio-Graph, involving a location, orientation and zoom level, offers a unified view on the entire media repository, and affords many opportunities for uncovering unlooked for media as the user traverses space. Additionally, the hidden interplay between social tie strength and shared place, two filters that can potentially work against each other, makes for a level of unpredictability. For example, adding shared places viewing relaxes the tie strength threshold at the current place in view if the initial result set is very small.

7.1.4 *Media Aquisition and Index Extraction.* A user imports photos, videos, and movies in the aforementioned format. Time of creation for each item is extracted from the EXIF header of JPEGs and thumbnails of videos created with digital cameras. Movie creation time is obtained from the file

Table III. Comparative Ability to Achieve Tasks. Values are Mean Ranking

Question	PhotoMesa	Picasa	Socio-Graph
Find media containing someone you don't know well or haven't seen recently	2.1	2.5	1.3
Find a photo of a {house, smile, special occasion}	1.8	2.2	2.0
Find media from an event that you weren't at	2.2	2.5	1.3

creation time stamp of the first shot. Media items are tagged with position and actor presence when available. If an (interpolated) position is not available for the exact creation time of a media item, a widening neighborhood in time is searched. For this study, a maximum search range of 30 minutes was used. Media items are tagged with any actors detected present in the 15 minute sample in which its creation time falls. No attempt has been made to improve this annotation using coarser resolutions than 15 minutes or confidence values of actor presence. Media items without position are indexed on the timeline only and rendered in the main pane when selected.

Media clustered in time and/or location have been recognized as signatures of *events* [Graham et al. 2002; Cooper et al. 2005; Pigeau and Gelgon 2005]. We cluster timestamps agglomeratively with hard-wired cutoff at 1 hour, while noting that dynamic navigation of the entire cluster tree within Socio-Graph is desirable. The cut-off was set with an aim to preserve microevents; for example, the cluster of photos of cutting the cake *within* the party event. Euclidean distance of time represented as seconds since an origin was used, and experiments found distance between cluster centroids performed best by cophenetic distance. Events are displayed as blue bands in the timeline pane.

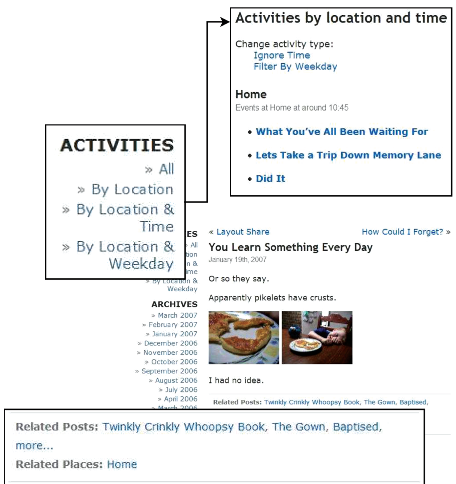
Socio-Graph was developed in tandem with a similar study to that detailed in Section 3, a pilot study with an overlap of 3 users. The chief difference was a lack of Bluetooth logs. Consequently, actor presence is derived from diary study groundtruth taken by a user as part of the audio presence detection component of that work. Social sphere weightings for the calculation of social tie by proximity is calculated from the number of media capture instances at a given sphere, as per Equation (2).

7.1.5 *User Study*. A comparative user study was undertaken to evaluate Socio-Graph. It included 7 users, 5 male, 2 female, diverse in life situation, age, and computer competency. The media repository used was from the pilot study mentioned previously and contained 514 items (452 photos, 38 videos, 24 movies). Three users from this study owned media in the repository, and the remaining 4 users were acquainted to some degree with all owners of media in the repository. Each was given a quick introduction to Socio-Graph, as well as PhotoMesa and Picasa 2, followed by time to play with each, and finally a handful of assigned tasks. Figure 11 contains responses to general question about the browser, borrowed from the user study of Appan and Sundaram [2004], together with those concerning the usefulness of its social context filters. Table III lists responses ranking the three browsers at assigned tasks.

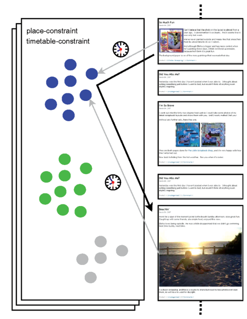
Interaction strategies for Socio-Graph varied among users. Common traits included initial choice of compass orientation, followed by cycles of diving in and out to inspect media. Where media for a given filter was clustered too densely for the spatial view to be clear, they were pulled apart by zooming within the timeline.

Figure 11 shows the reaction to Socio-Graph, and the possibility of filtering with social context, to be very positive. Curiously, both females in the study were ambivalent about the browser's ease of use. In one case, further comments indicated the zoom metaphor, while uniform in space and time, to be perceived as complex. This user also happened to be a retiree with little computer experience.

Table III indicates Socio-Graph was clearly preferred for tasks 1 and 3; however, there was more confusion over task 2. This stemmed from the much larger variety of search strategies employed. While tasks 1 and 3 were both a short step away from formulation in terms of the social context supported by Socio-Graph, task 2 could be performed by hunting for a visual match (e.g., faces, groups of people),



(a)



(b)

Question		
Read blog(s) regularly	Yes 36%	
Know the user	Yes 36%	
Rate implicit 1(useless)→ 5(helpful)	Mean 3.6	Med. 3
Rate explicit 1(useless)→ 5(helpful)	Mean 4.6	Med. 5
Prefer **T**axonomic or **E**nglish label	T 91%	E 9%
Would like this facility	Yes 100%	

(c)

Fig. 12. Jive: (a) Navigation augmented with "Related Posts" from implicit similarity, and side-panel with links to entries about explicit rhythm types with example; (b) Implicit similarity between blog entries via social rhythms; (c) User study feedback.

best supported by PhotoMesa and Picasa, specific dates (e.g., birthdays, Christmas), best supported by PhotoMesa and Socio-Graph, or specific people (e.g., babies), best supported by Socio-Graph.

7.2 Blog with Jive

The second application focuses on the ubiquitous blog. Blogs are an inherently serial genre, but non-linear browsing behaviors are often exhibited. Frequent use of manually maintained *categories* (e.g., "Holidays" or "Scrapping") attest to this. In our demonstration application, named *Jive* (conjuring the notion of navigating by rhythm), each blog entry is treated as an item of media. Timestamps of photo(s) contained in an entry are used to anchor it in the user's signal stream, and hence social rhythms. Similarity metrics derived from the users rhythms are used to navigate to entries about similar events or on similar days.

Figure 12(b) depicts a typical interentry link generated by an underlying social rhythm. On the left of the figure are stay clusters generated for a place-constrained, timetable-constrained dimension folding. On the right is a sequence of blog entries, two of which have photos that associate them with stays that have been clustered. If the user begins navigating the blog from the topmost entry, the other entry referring to an instance of a similar social rhythm appears as a linked entry. This is a kind of Query by Example (QBE), with social rhythms providing an *implicit* similarity measure. Our similarity measure is a function of all social rhythms, and awards a higher score to more constraining clusterings. Entries with more photos from a rhythm also accrue a higher score, which can be viewed as increased confidence in inferring the presence of a topic when a strongly associated term has higher frequency. Notably, the user may not be aware of why these entries have been deemed similar. For an *explicit* use of social rhythm categories, Jive collects all entries discovered in one or more social rhythm types and allows the user to navigate parameter space. For example, in order to find entries that refer to, say, swimming lessons, the user can specify location-bound, people-bound, structured activities (with variable starting time each term), and peruse the entries grouped by this criterion.

Figure 12(a) is a screen shot of Jive. Links to similar entries are calculated and injected directly into the blog, and placed above the existing category links. Explicit navigation is entered via the top of the sidebar, and then the user is able to turn the dimensions on or off, and sort the resulting clustered entries via underlying rhythm frequency.

To demonstrate Jive we obtained User 10's (a regular blogger) permission to use the portion of her blog that overlapped with the experiment period. The blog also includes photos contributed by User 2 (her spouse), and in those cases, User 2's rhythms are also used to aid navigation. A user study was undertaken to gain insight into whether users felt implicit social rhythm enabled navigation added to the utility or pleasure of browsing the blog,[15] and secondly, whether browsing by explicit social rhythm was comprehensible. Users were emailed Jive along with some background information about the idea, instructions on how to run the application, and a questionnaire to fill in. Figure 12(c) reports the results of the qualitative user study for 11 users. Users were also invited to submit comments.

Explicit search by social rhythm proved comprehensible (reflected in the preference for the taxonomic label), more so than the simple related posts links, where a couple of users wanted a clearer idea of in what sense entries were related. Explicit search was also perceived as being more useful (median of 5), but this result may be skewed by the large portion of computing students in the study. One user commented that listing entries in social rhythm clusters gave an interesting overview of the organization of the blog.

8. CONCLUSION

Mobile computing has increased the number and diversity of sensors carried by people during their daily activities. As the information age continues to extend its reach beyond the desktop and into embodied life, "organizing the world's [online] information" is no longer sufficient to filter the information blitz to a humane level. Paradoxically, this technology often requires humans to behave like computers. Tools for indexing social context are needed to support applications that push cognitive load from grey matter back to the CPU, such as social-context-aided calendaring and collaboration, information discovery and personalized advertising, media browsing and sharing, context-sensitive device management, and privacy and trust measures.

We have used GPS and Bluetooth sensors to infer about real-world places of significance to a user, patterns among the dimensions of place, people and time, reflective of activities, and measures of interpersonal relationships among users. Our approach proved apt to the noisy and sparse nature of real-life data. These constructs have demonstrable utility for navigating personal media, including photos and videos, and blog archives, and have a potential role in the social scientist's toolkit as cheap estimators of social variables. Incremental versions of the algorithms are suited to resource-constrained mobile devices, which often serve as media capture appliances, making a nice fit with media managment applications.

Richer representations of social context are needed to capture varying scale: Room-level localization for detection of micro-social spheres (e.g., cubicle, water cooler), and context for day-level rhythms, such as "*home→work→shops→home* is a standard *work day*." Many more sensed properties can be used, and shared if implied by copresence. Fusion of real-world social context with online presence, for example, via metadata such as GPS tags, will make for a rich array of indices with which to tame information overload.

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[15]Entertainment value of media applications like this often takes precedence over task-related metrics [Rodden and Wood 2003].

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