CSI: A Paradigm for Behavior-oriented Profile-cast Services in Mobile Networks

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***Abstract*—We propose profile-cast, a novel behavior-oriented service representing a new paradigm of communication in mobile networks. Our study is motivated by the tight user-network coupling in future mobile societies. In such a paradigm, messages are sent to sender-specified behavioral profiles, instead of explicit IDs. Our paper provides a systematic framework in providing such services in two phases.**

First, user behavioral profiles are constructed based on traces collected from two large wireless networks, and their spatio-temporal stability is analyzed. Our analysis shows that user *behavioral profiles* **are surprisingly stable. The similarity of the behavioral profile of a user to its future behavioral profile is above 0.75 for one week, remaining above 0.6 for five weeks, while the correlation coefficient of the similarity metrics between a user pair at different time instants is above 0.62 for a week, remaining above 0.5 for two weeks. This stable implicit relationship discovered between mobile users based on their** *behavioral profiles* **can be further utilized to provide a service for message delivery and resource discovery in various network environments.**

Second, we provide a detailed protocol design for the profile-cast service, named *CSI*, in the challenged opportunistic network architecture. We provide a fully distributed solution utilizing *behavioral profile space* **gradients and small world structures to selectively diffuse the information across the network towards the intended target recipients. Leveraging stability in user behaviors, the two modes of *CSI* protocol both achieve good performance comparing with the optimal protocols. For** *CSI:Target mode***, the delivery ratio is more than 94% comparing with delay-optimal 1-path protocol, with less than 47% more delay. Comparing with the overhead-optimal protocol, *CSI:T* shows more than 94% delivery ratio, less than 5% more overhead, and less than 11% more delay. For** *CSI:Dissemination mode***, comparing with the delay-optimal protocol, is has more than 98.5% delivery ratio under less than 32% more delay. *CSI:D* shows less than 7% more transmission overhead but at least 60% less delay comparing with the transmission overhead-optimal protocol. It also significantly outperforms variants of epidemic and random walk schemes.**

We believe that our new profile-cast paradigm will act as an enabler of multiple new services in mobile societies, and is potentially applicable in server-based, heterogeneous or infrastructure-less wireless environments.

I. Introduction

We envision future networks that consist of numerous ultra portable devices delivering highly personalized, context-aware services to mobile users and societies. Such scenarios elicit strong, tight-coupling between user behavior and the network. Users' mobility and on-line activities significantly impact wireless link characteristics and network performance, and at the same time, the network performance can potentially influence user activities and behavior. Such a tight user-network coupling provides a rich set of opportunities and poses several challenges. On one hand, fundamental understanding of the mobile user behavior becomes crucial to the design and analysis of future mobile networks. On the other hand, novel services can now be introduced and utilize such a coupling to effectively navigate mobile societies, providing efficient information dissemination, search and resource discovery.

In this paper, we propose a novel behavior-driven communication paradigm, that we call profile-cast, to enable a new class of services in mobile societies. In addition, we design a protocol, called *CSI*, with a set of schemes to realize profile-cast in intermittently connected mobile networks. Current communication paradigms, including unicast and multicast, require explicit identification of destination nodes (through node IDs or group membership protocols), while directory services *map* logical, interest-specific queries (e.g., reaching people who visit libraries often) into destination IDs where parties are then connected using behavior-oblivious protocols. The power and scalability of such conventional paradigms might be quite limited in the context of future, highly dynamic mobile networks, where it is desirable in many scenarios to support implicit membership based on user behavior or interest. In such scenarios, membership in interest groups is not explicitly expressed by users, it is rather implicitly and autonomously inferred by network protocols based on the past *behavioral profiles* of users. This removes the dependence on third parties (e.g. directory lookup), maintenance of group membership (e.g., in multicast) or the need to flood user interests to the whole network, and minimizes delivery overhead to uninterested users.

Applying such a behavior-driven paradigm in mobile networks poses several research challenges. First, how can user behavior be captured and represented adequately? Second, is user behavior stable enough to enable meaningful prediction of future behavior with a short history? How can such services be provided when the interest or behavior cannot be centrally monitored and processed? And finally, can we design privacy-preserving services in this context?

To address these questions we propose a systematic framework with two phases 1) *behavioral profile* extraction by analyzing large-scale empirical data sets and investigating the stability of user behavior, and 2) leverage the *behavioral profiles* for service design – We use the implicit structure in user behaviors to guide message and query dissemination given a target profile.

Specifically, we first analyze network activity traces and design a summary of user *behavioral profiles* based on the *mobility preferences*. This is captured using the eigen vectors of the association matrix representation of users' mobility history. We find that the similarity of the *behavioral profile* for a given user to its future profile is high, above 0.75 for eight days and remains above 0.6 for five weeks. The surprising observation is that, the similarity metric between a pair of users predicts their future similarity reasonably well. The correlation coefficient between their current and future similarity metrics is above 0.7 for four days, and remains above 0.5 for fifteen days.

The above observations demonstrate that the *behavioral profile* we design is an intrinsic property of a given user and a valid representation of the user for a good period of time into the future. We refer to this phenomenon as the *stability* of user *behavioral profiles*, which can be used to map the users into a high dimensional *behavioral space*. The *behavioral space* is defined as a space where each dimension reflects a particular interest. For example, when we consider mobility preferences, each dimension represents the fraction of time a user spends at a given location (or, in other words, the *interest* of a user towards this location). The position of a user in such a space reflects its characteristics in terms of the dimensions we select to construct the *behavioral space*, and the distances between users in this space quantify how similar they are with respect to the *behavioral profile* we construct. We then design a new protocol, in which a *target profile* is used to replace network IDs to indicate the intended receiver(s) of a message (i.e., those with *matching behavioral profiles* to the target profile chosen by the sender are the intended receivers.). It is a ***C***ommunication protocol in mobile networks based on the ***S***tability of the user *behavioral profile* to discover the receivers ***I***mplicitly, abbreviated as ***CSI***. We present the details of the *CSI* protocol with two modes of operation under the over-arching *profile-cast* paradigm: the *target mode (CSI:T)* and the *dissemination mode (CSI:D)*. The *target mode* is used when the *target profile* is specified in the same context as the *behavioral profile* (i.e., the *target profile* is in terms of *mobility preferences*). The *dissemination mode*, on the other hand, is used when the *target profile* is de-coupled from mobility preferences.

We show that our *CSI* protocols perform very close to the oracle-based optimal schemes assuming global knowledge of the future and improve significantly over the baseline and existing dissemination protocols. For the *CSI:T mode*, comparing with the optimal 1-path protocol, our protocol achieves more than 94% delivery ratio with less overhead (less than 84% to the optimal 1-path), and less than 47% more delay. Comparing with the overhead-optimal protocol, our protocol has less than 5% more overhead and comparable (no more than 11% more) delay. For the *CSI:D mode*, our protocol features delivery ratio more than 98% while the delay of *CSI:D* is about 32% more than the delay-optimal. Comparing with the transmission overhead-optimal protocol, *CSI:D* can be adjusted to have similar (less than 7% more) transmission overhead, but much lower (up to 150% less) delay.

Our Contributions

(1) We introduce the notion of multi-dimensional *behavioral space*, and devise a representation of user *behavioral profiles* to map users into the *behavioral space*. Our study is the first to establish conditions for stability of the relationship between mobile network users on university campuses in this space.

(2) We propose *profile-cast*, a new communication paradigm delivering messages based on user profiles. The target profile can even be independent of the context of the *behavioral profile* we use to construct the *behavioral space*, while still leveraging the stability of the *behavioral profile* to deliver the messages efficiently.

(3) We design *CSI*, an efficient dissemination protocol utilizing the stability of *behavioral profiles* and SmallWorld in mobile societies, then empirically evaluate and validate the efficacy of our proposal using large-scale traces from university campuses.

The outline of the rest of the paper is as follows. We discuss the related work in section II and important background in section III. This is followed by an analysis to understand the stability of user *behavioral profile* in section IV. We further discuss the potential usages of this understanding in section V and design our *CSI* protocols in section VI as an example. We evaluate the performance of *CSI* protocols in section VII. Finally, we discuss some finer points in section VIII and conclude in section IX.

II. Related Work

We conduct the first detailed systematic study on the spatio-temporal stability of user behaviors in mobile societies, a new dimension that has not been considered before. We lay the foundation of this work on a solid analysis of empirical user behaviors, enabled by extensive collections of user behavioral traces. Many of them can be found in the archives at [1], [2]. Our effort on the extraction of *behavioral profiles* and behavior-based user classification is related to the reality mining project [16] and the work by Hsu et al. [4] and Ghosh et al. [20]. We leverage the representation of mobility preference matrix defined by us in [4], which reveals more detailed user behavior than the five categories representation used in the reality mining [16] and the presence/absence encoding vector used by Ghosh et al. [20].

Applications of user traces analysis can be classified into two different environments – in a centralized environment where a global view of the information about all users is available, or in a decentralized environment where each user has limited knowledge about other users. In centralized trace analysis, the capability of classifying users based on their mobility preferences [4] or periodicity [19] could potentially lead to applications such as behavior-aware advertisements or better network management. While understanding user behavior for these applications has its own merit, applications in centralized scenario (where user behaviors are collected, processed and mined at an aggregation point) are not our major focus in the paper.

The major application considered in this paper is to design a message dissemination scheme in decentralized environments. While several previous works exist in the delay tolerant network field, most of them (e.g. [3], [5], [17], [6], [10]) consider one-to-one communication pattern based on network identities. The objective considered is to deliver messages efficiently and promptly, given a *destination node ID*. In this paper, we consider a different communication paradigm to use the *intrinsic behavioral profiles* of users, instead of extrinsic, user-behavior independent network IDs, as the destination for messages. Our paradigm is motivated by the tight coupling between users and their mobile devices in future mobile networks, and the possibility of leveraging existing patterns in user behavior to improve decentralized communication, as we will show later.

The one-to-many communication targeted at a behavioral group presented in this paper is a new paradigm in decentralized environments. Some of the previous work assume existing infrastructure: PeopleNet [18] uses specialized geographic zones for queries to meet. The queries are delivered to randomly chosen nodes in the corresponding zone through the infrastructure. Others (e.g., [17], [10]) rely on persistent control message exchanges (e.g., the delivery probability) for each node to learn the structure of the network, even when there is no on-going traffic. From the design point of view, our approach differs from them by avoiding such persistent control message exchanges to achieve better power efficiency, an important requirement in decentralized networks.

The spirit of our design is somewhat similar to the work by Daly et al. [6], in which each node learns the structure of the network locally and uses the information for message forwarding decisions. They use the SmallWorld network structure [7] which often exists in mobile network users (as has been investigated in [14], [9]) and push the message toward nodes with high centrality to improve the chance of delivery. However, the learning process still involves control message exchanges about past encounters, even in the absence of actual data traffic. Our work, on the other hand, relies on the intrinsic *behavioral profile* of individual nodes to "position" themselves in the *behavioral space* in a localized and fully distributed manner, without exchanging encounter history between nodes. The use of user *behavioral profiles* to understand the structure of the space is similar to the mobility space routing by Leguay et al. [3] and the utility-based routing by Costa et al. [8]. The major differences between this work and [3], [8] are two fold: First, we design the *CSI:D mode*, in which the target profile does not have to be related to the *behavioral profile* based on which the message dissemination decisions are made. Second, we also provide a non-revealing option, via a privacy-preserving mechanism in our protocol, thus no node has to explicitly reveal its *behavioral profile* or interests to others, as opposed to [3], [8].

The work presented in this paper significantly enhances the capability of our preliminary profile-cast protocol presented in [15], where the focus is on sending messages to users with similar *behavioral profile* to the sender. In this paper we allow the sender to specify a *target profile* to decouple the *behavioral profile* of the sender from the destination profile in the message in the *CSI:T mode*. We further enhance the capability of the message dissemination scheme, allowing a *target profile* to be specified in contexts orthogonal to the *behavioral profile* based on which we measure the similarity between users (in the *CSI:D mode*).

III. Background

A. Mobility-based User Behavior Representation

We represent mobile user behavior of a given user using the *association matrix* as illustrated in Fig. 1. In the matrix, each row vector describes the percentage of time the user spends at each location on a day, reflecting the importance

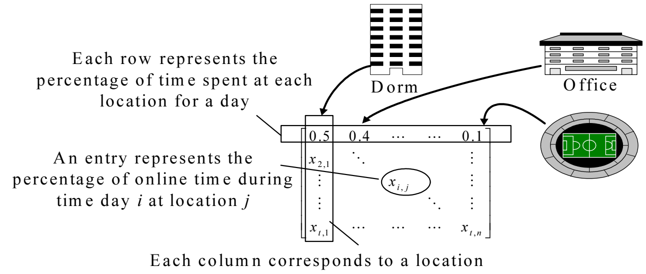


Fig. 1. Illustration of the association matrix to describe a given user's location visiting preference.

of the locations to the user[1]. In [4] it has been shown that the *location visiting preferences* can be leveraged to classify users of wireless networks on university campuses. For a given user, the singular value decomposition (SVD) [21] is applied to its *association matrix* M, such that

$$M = U \cdot \Sigma \cdot V^T, \tag{1}$$

where a set of *eigen-behavior* vectors summarizing the important trends in the original matrix M, $v_1, v_2, ..., v_{rank(M)}$, can be obtained from rows of matrix V^T, with their corresponding singular values, σ_1, σ_2, ..., $\sigma_{rank(M)}$ on the diagonal of matrix Σ. The weight, or the relative importance of how much power from the original matrix M each *eigen-behavior* vector captures, is calculated by

$$w_i = \frac{\sigma_i^2}{\sum_{j=1}^{Rank(M)} \sigma_j^2}. \tag{2}$$

This set of vectors is referred to as the *behavioral profile* of the particular user, denoted as $BP(M)$. We have shown that, based on realistic mobile user behaviors collected from large-scale university traces [12], [13], a small set of *behavioral profile* vectors is adequate to capture the major trend in the association matrix for a long period[2] [4]. Thus, the *behavioral profiles* form a succinct, effective representation of user's behavioral pattern.

Furthermore, we have shown that the *behavioral profile* representation provides a computational efficient way to compare the mobility trend of two users [4]. The *behavioral similarity* metric between two users' association matrices A and B is defined based on their *behavioral profiles*, vectors a_i's and b_j's and the corresponding weights, as

$$Sim(BP(A), BP(B)) = \sum_{i=1}^{rank(A)} \sum_{j=1}^{rank(B)} w_{a_i} w_{b_j} |a_i \cdot b_j|, \tag{3}$$

which is essentially the weighted cosine similarity between the two sets of *eigen-behavior* vectors.

B. Traces

In this paper, we seek a realistic, deep understanding of user behavioral patterns by analyzing semester/quarter-long user

[1]While there may be numerous other representations of user behavior, we shall show that this representation possesses desirable characteristics for the purposes of this study. Further investigation of other representations is a subject of future work.

[2]Specifically, for more than 99% of users, seven vectors or less are adequate to capture 90% or more power in their association matrices.

TABLE I
FACTS ABOUT STUDIED TRACES

Trace source	USC [12]	Dartmouth [13]
Time/duration of trace	2006 spring semester	2004 spring quarter
Start/End time	01/25/06-04/28/06	04/05/04-06/04/04
Unique locations	137 buildings	545 APs/ 162 buildings
Unique MACs analyzed	5,000	6,582

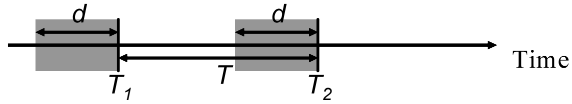


Fig. 2. Illustration: consider the trailing d days of behavioral profile at time points that are T days apart.

behavioral logs collected from operational campus networks from public trace archives [1], [2]. We present results based on two data sets from the University of Southern California (USC) [12] and the Dartmouth College (Dartmouth) [13]. The details of the data sets are listed in Table I.

We choose to use WLAN traces as they are the largest user behavioral data sets available. The information available from these anonymized traces contains many aspects of the network usage (e.g., time-location information of the users by tracking the association and disassociation events with the access points, amount of traffic sent/received, etc.). The richness in user behavioral data poses a challenge in *representing* the user behavior in a meaningful way, such that the representation not only reveals an intrinsic, stable *behavioral profile* of a user, but the identified *behavioral profile* also leads to practical applications. We show in this paper that the *location visiting preferences* (which is only a subset of the user behavioral data) is a stable attribute for both individual users and the relationship between users. This property will prove quite valuable to the design of efficient message dissemination schemes, which we empirically validate using the above traces.

IV. UNDERSTANDING SPATIO-TEMPORAL CHARACTERISTICS OF USER BEHAVIORAL PROFILES

In this section we introduce our analysis of user behavioral patterns and its significance on the service design. While previous works on user classification based on long-term behavioral trend [4], [20], [19] are useful and in line with our goal, the stability of such classification over time has not been studied systematically. In particular, the short-term behavior of a user may deviate significantly from the *norm*, and the *stability* of user *behavioral profiles* is a decisive factor for whether it can be leveraged to represent the user's future behavior. In this section we investigate the following questions: (1) How long of behavioral history do we need to classify a user? and (2) How much does the behavior of a given user and its relationship with other users change with respect to time?

We consider the effect of the amount of past history (of user behavior) on the obtained *behavioral profiles*. Each user uses the location visiting preference vectors in the past d days to

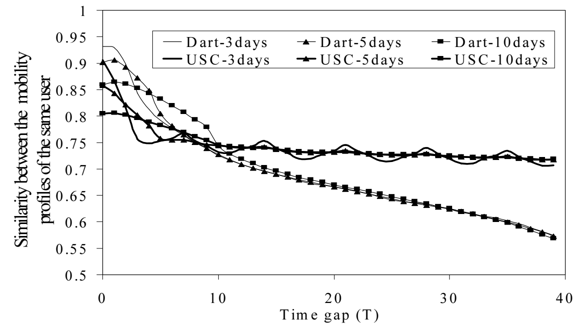


Fig. 3. Similarity metrics for the same user at time gap T apart.

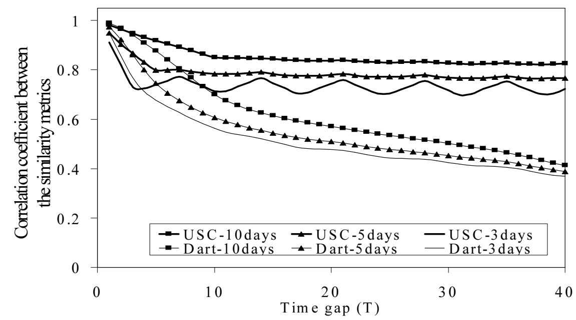


Fig. 4. Correlation coefficient of the similarity metrics between the same user pair at time gap T apart.

summarize the behavior in the most recent history – the user retains d location visiting preference vectors for these days, organize them in a matrix, and use singular value decomposition to obtain the *behavioral profile*, as described in section III-A. We seek to understand how d influences the representation and similarity calculations. More specifically, we look into two important aspects: (1) Whether the representation of a given user is stable across time, and (2) whether the relationships between user pairs remain stable as time evolves.

We first consider the stability of the representation of a given user. Considering two points in time that are T days apart, we obtain the *behavioral profiles* for the same user at both end points, using the logs of the trailing d days ending at those end points, as illustrated in Fig. 2. Then we use the similarity metric defined in Eq. (3) to compare how stable a user's *behavioral profile* is to one's former self after T days elapse. The average results with various values of the time gap, T, and considered behavioral history, d, are shown in Fig. 3. We notice that, even if we collect a short history of user behavior (say $d = 3$), the representation is similar to the behavior of the user for a long time into the future. When we consider $T = 35$ days (five weeks) apart, the behavioral profiles from the same user still show high similarity, at about 0.6. The amount of history used does not influence the result too much when the considered T is large enough to avoid overlaps in the used behavioral history (i.e., when $T > d$). We conclude that on university campuses, the *behavioral profile* as defined in Section III-A for a given user is stable, i.e., it remains highly similar for the same user across time. One interesting note is that, when the *behavioral profile* includes only part of a week ($d < 7$), the similarity of the user to its former self shows a weekly pattern (i.e., when T is an integer multiple of seven, the similarity peaks). This trend is particularly pronounced in the USC trace.

Second, we try to quantify how the behavioral similarity between the same pair of users varies with time. For this part, we use Eq. (3) to calculate the similarity between two users, A and B, at two points in time, $Sim_{T_1}(A, B)$ and $Sim_{T_2}(A, B)$, where T_1 and T_2 are T days apart. We perform this calculation to all user pairs, and then calculate the correlation coefficient of the similarity metrics obtained after a T-day interval, as

$$r = \frac{\sum_{\forall A,B}(X - \overline{X})(Y - \overline{Y})}{NS_X S_Y}, \tag{4}$$

where $X = Sim_{T_1}(A, B)$ and $Y = Sim_{T_2}(A, B)$, and the notations $\overline{X}$ and S_X denote the average of X obtained from all user pairs and its standard deviation, respectively. N is the total number of user pairs. The correlation coefficient quantifies how stable the relationship between user pairs is. We repeat the calculation for all pairs of users with various d and T values to arrive at Fig. 4. We observe that the similarity metrics between user pairs correlate reasonably well if the considered time periods are not far apart. For T smaller than one week, the correlation coefficient is above 0.62. This indicates, once the similarity between a pair of user is obtained, it remains a reasonable predictor for their mutual relationship for some time period into the future. Although the reliability of the stale similarity data decreases with respect to time, the current similarity of a user pair remains moderately correlated to their future similarity, in the time range up to several weeks. The correlation is above 0.4 for up to five weeks.

The investigation establishes that the user behavioral profile is a stable feature of the users – the representation of an individual user and the relationship between users are well correlated with the past history for the near future. Thus we map the *behavioral profile* to a virtual *behavioral space* [3], in which each user's behavior is quantified as a high dimensional point[3]. The mutual similarity metric between users is a function of their respective positions in this space. In this paper, when we say two users are *similar*, it means they are *close* in the *behavioral space* (i.e., the *distance* between the two users is small). We also use the term *neighborhood of a node* to refer to the other nodes that are *similar* to this particular node in the *behavioral space*.

V. The Profile-cast Communication Paradigm

Profiling users based on stable behaviors is a fundamental step to understand human behavior. Motivated by the stability of user *behavioral profiles*, we introduce a *profile-cast communication paradigm* where we use *user behavioral profiles*, instead of network IDs, to represent the destination(s) for messages in this new paradigm. We envision that such a novel approach has several benefits.

First, it enables behavior-aware message delivery in the network without mapping attributes to network IDs. As each user maintains its *behavioral profile*, it is now possible to deliver announcements about sports events on campus towards sports enthusiasts (e.g., people who visit the gym often) or advertise a performance at the school auditorium to the regular attendees of such events. The key advantage here is to avoid the need to maintain a directory service mapping user behaviors to their IDs, which provides design and privacy challenges in highly dynamic mobile networks.

Second, it facilitates the discovery of nodes with certain behavior patterns. Consider, for example, in the message ferry [11] architecture where nodes with high mobility move messages across the network to facilitate the communication between otherwise disconnected nodes. One can choose a target profile that reflects a mobility profile and thus eliminate the need for knowing the identity of the ferry beforehand or enforcing this mobility pattern on a controlled node. Alternatively, users that possess the desired mobility pattern can be discovered dynamically and serve as ferries.

Our *profile-cast communication paradigm* is applicable in several architectures. In the *centralized server-based architecture*, user profiles could be collected and stored at a data repository, and mined for user classification (e.g., [4], [19]), abnormality detection, or targeted advertisements. In the *cellular networks*, the low-bandwidth channel between the users and the infrastructure can be leveraged to exchange *behavioral profiles* and match users (e.g., [18]). In this paper, however, we consider *decentralized infrastructure-less networks*, and focus on how stable *behavioral profiles* are used for better message dissemination. We name the protocols designed for this scenario as *CSI*, since it is a *C*ommunication scheme based on the *S*table, *I*mplicit structure in mobile networks.

VI. Protocol Design

In this section, we first present our assumptions and design requirements for the *CSI* protocols. We then discuss the design of the *CSI* protocols based on in-depth understanding of the relationship between similar *behavioral profiles* and encounter events.

A. Assumptions and Design Requirements

We assume that each node profiles *its own behavioral pattern* by keeping track of the visiting durations at different locations and summarizing the *behavioral profile* using the technique discussed in III-A. This is an individual effort by each node involving no inter-node interactions. This can be done by the nodes over-hearing the beacon signals from the fixed access points in the environment to find out its current location. Note that, the use of these beacon signals is only for the node to profile its own behavior – they are not used to help the communication in our protocols (we will re-visit detailed points of this assumption in section VIII). Also, for ease of understanding, we assume in this section that nodes are willing to send their *behavioral profiles* to other nodes when needed. A privacy-preserving mechanism that eliminates this operation is introduced and discussed in section VIII.

The goal of our *CSI* protocol is to reach a group of nodes matching with the target profile specified by the sender, under the following performance requirements: (1) The protocol should be scalable, in particular not being dependent on a centralized directory to map target profiles to user identities. (2) It should work in an efficient manner and avoid transmission and storage overhead when possible. Also, it should avoid

[3]The dimension of the *behavioral space* is the same as the *mobility preference vector* representation, typically in the order of a hundred for these two campuses.

control message exchanges in the absence of data traffic. (3) The syntax of the target profile should be flexible, allowing the target profile in a different context from the *behavioral profiles* we use to represent the users. (4) The operation of the protocol should be flexible to allow tradeoff between various performance metrics. And finally, (5) the design should be robust and help in protecting user privacy.

We design two modes of operation for the *CSI* protocol under the above requirements. (a) When the target profile is in the same context as the *behavioral profile* (in our example, since the *behavioral profile* is a summary of user mobility, this corresponds to the scenario when the target profile describes users that *move* in a particular way), the *CSI:Target mode (CSI:T)* should be used. We note that for *CSI:T* the *behavioral profile* (in terms mobility) can sometimes be used to infer other social aspects of the users, such as affiliations or even interests (e.g., people who visit the gym often should like sports in general). Such inferences expand the scenarios in which *CSI:T* can be used. (b) When making such inferences of target user *behavioral profiles* is not possible (hence *CSI:T* is not applicable), *CSI:D* provides a more generic option. When the target profile is irrelevant to the context of the *behavioral profile* (e.g., when I want to send to everyone interested in movies on campus), the *CSI:Dissemination mode (CSI:D)* should be used.

The major challenge involved in the design process is that each node is only aware of the *behavioral profile* of itself. Furthermore, we require no persistent control message exchanges for the nodes to "learn" the structure of the network proactively when they have no message to send. Nodes only compare their *behavioral profiles when they are involved in message dissemination*. Based on this very limited knowledge about the *behavioral space*, a node should predict how useful a given encounter opportunity is in terms of achieving the fore-mentioned requirements. Since encounter events may occur sporadically in sparse, opportunistic networks, nodes must make this decision for each encounter event independent of other encounter events (that may occur long before or after the current one under consideration). Such a heuristic must rely on the understanding of the relationship between nodal *behavioral profiles* and encounters, which we discuss next.

B. Relationship between Behavioral Profiles and Encounters

We now analyze the relationship between user *behavioral profiles* and a key event for user-to-user communication in an infrastructure-less network – *encounters*. *Encounters* in mobile networks refer to events when users move within the radio range of each other and direct communication between the involved devices is possible. In this paper, based on the WLAN traces, we assume that when two users visit the *same location* (i.e., access point) during overlapped time intervals, they *encounter* with each other.

While it seems intuitive that users visiting similar locations should encounter with each other with higher probability, this is *not obvious* on university campuses. Students and faculty have their own schedules, and they may rarely encounter due to the difference in their schedules (i.e., they might be in the same building at different times). Hence we investigate the relationship between *behavioral profiles* and encounter events, first as a sanity check of our intuition, and more importantly, to understand the relationship between the *behavioral profiles* and various aspects of the encounter events (e.g., the encounter probabilities, encounter durations, etc.). This helps to reveal the *implicit structure* existing in mobile network users, which is the key to the design of the *CSI* protocols presented later.

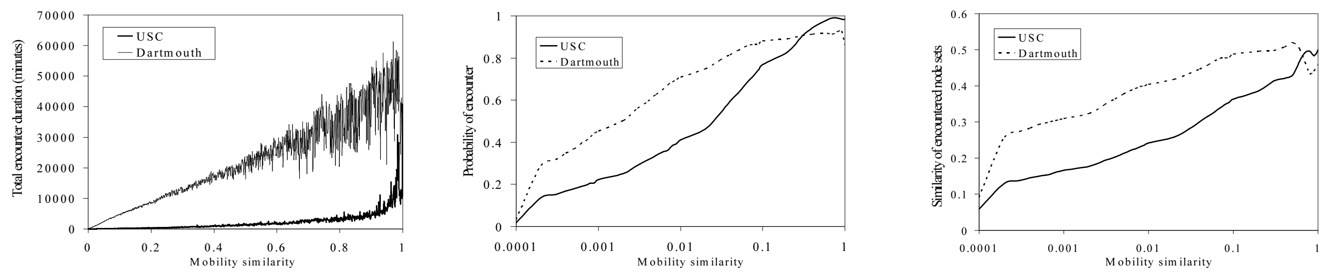
We classify all node pairs into different bins based on their behavioral similarity metric (as defined in Eq. (3)), and obtain various characteristics of encounter events as a function of the pair-wise behavioral similarity. In Fig. 5 (a), we show the aggregate encounter time duration between an average pair of nodes given the behavioral similarity. In Fig. 5 (b), we show the probability for a given node pair to encounter with each other, given their similarity. Combining these two graphs, we see that **if two users are similar in behavioral profiles, they are much more likely to encounter, and the total time they encounter with each other is much longer – an indication that nodes with** *similar behavioral profiles* **indeed are more likely to have better opportunities to communicate.** When two users are similar enough (with behavioral similarity larger than 0.3), they are almost guaranteed to encounter at some point (with probability above 0.9). However, we note that some "random" encounter events happen between dissimilar users. For users with very low (almost zero) similarity, the probability for them to encounter is not zero, although such encounter events are much less reliable (i.e., they occur with much shorter durations, see Fig. 5 (a)).

In Fig. 5 (c) we further compare the behavioral similarity of node A and B versus the sets of nodes A and B encounter. We denote the set of nodes A encounters with as $E(A)$. The similarity of the two sets of nodes is quantified by $|E(A) \cap E(B)|/|E(A) \cup E(B)|$, where $|\cdot|$ is the cardinality of the set. This graph shows, **as two nodes are increasingly similar, there is a larger intersection of nodes they encounter. On the flip side of the coin, when an unlikely encounter event between** *dissimilar nodes* **occurs, it helps both nodes to gain access to a very different set of nodes, which they are unlikely to encounter directly.**

The above findings relate to the SmallWorld encounter patterns between mobile users [14]. The key features of SmallWorld networks [7] are high clustering coefficient and low average path length. In the mobile user behavior we analyze in this section, people with similar behavior form "cliques". The "random" encounter events between dissimilar nodes build *short-cuts* between these cliques to shorten the distances between any two nodes. We leverage these properties in our protocol design, discussed next.

C. CSI:Target Mode

In the *CSI:Target mode (CSI:T)*, the sender specifies the *target profile (TP)* for the recipients using the same format and semantics as that of the user *behavioral profile*, i.e., in our case the *TP* is a summarized *mobility preference* vector (i.e., the percentage of times the target node(s) visit various locations). The sender also specifies a threshold value, th_{sim}, as the similarity threshold for a node to be an *intended receiver* (i.e., if a given user A has $Sim(BP(A), TP) > th_{sim}$, node A belongs to the group of *intended receivers*.). This threshold is set by the sender according to the desired degree of similarity to the TP. The TP and the threshold, th_{sim}, are included in the message header of the message.



(a) Total encounter duration. (b) Encounter probability. (c) Similarity of encountered node sets.

Fig. 5. Relationship between the similarity in behavioral profiles and other quantities.

For example, we could reach people who like sports by sending messages to those who visit the gym regularly. This criteria could be set up by specifying the *TP* as a vector with only one 1 corresponding to the gym location (hence only time spent at this location is considered), and a threshold for the percentage of time a user spends at the gym to be considered as a "frequent visitor". Note that this value could be set according to the needs of the message sender. If one wants to consider time spent at multiple locations (e.g., several libraries) in aggregation, one can also specify a *TP* with multiple 1's (refer to Eq. (3), the inner product operation in the similarity calculation naturally combines these corresponding entries).

We first discuss the intuition behind the design of the *CSI:T mode* using Fig. 6 as an illustration. As per section VI-B, to deliver messages to receivers defined by a given *TP* in the *behavioral space*, one way is to gradually move the message towards nodes with increasing *similarity* to the *TP* via encounters, in the hope that such transmissions will improve the probability of encountering the intended receivers and shorten the delay before such encounters occur. Finally, when the message reaches a node *close* to the *TP* (in the *behavioral space*), most nodes that encounter frequently with this node are also similar to *TP*. Hence, the message should be spread to other nodes in the *neighborhood* (in the *behavioral space*) of the node.

There are two phases in the operation, as shown in the pseudo-code in Algorithm 1, the *gradient ascend phase* and the *group spread phase*. (1) Starting from the sender, if node A currently holding the message is not an intended receiver (i.e., $Sim(BP(A), TP) < th_{sim}$), it works in the *gradient ascend phase*, otherwise it works in the *group spread phase*. (2) In the *gradient ascend phase*, for each encountered node, the current message holder asks for the *behavioral profile* of the other node, and if the other node is more similar to the TP in the *behavioral space*, the responsibility of forwarding the message is passed to this node. One can imagine that these similarities form an inherent *gradient* for the message to follow and reach the close neighborhood of the *TP* in the *behavioral space*, hence the name *gradient ascend phase*. Note that, up to this point, there is only one copy of the message in the network – these intermediate nodes who are not similar to the TP only forward the message once. (3) When the message reaches a node with similarity larger than th_{sim} to the *TP*, the *group spread phase* starts. This intended receiver holds on to the message, and requests the *behavioral profiles* from nodes it encounters. If they are also intended receivers, copies of the messages will be delivered to them. All intended receivers, after getting the message, continue to work in the *group spread phase*. Although multiple copies of the message are generated in the *group spread phase*, it is triggered only when the message is close to the *TP*, thus most of the encounter events and inquiries will occur among the *intended receivers*, reducing unnecessary overhead.

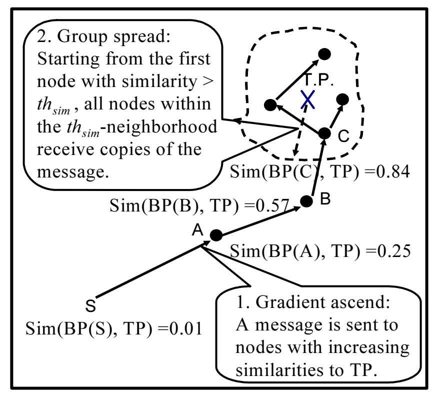


Fig. 6. Illustration of the *CSI:T* protocol: 1. Gradient-ascend: One copy of the message follows increasing similarity gradient to reach the neighborhood of the target profile, then triggers 2. Group spread.

D. CSI: Dissemination Mode

In the *CSI:Dissemination mode (CSI:D)*, there does not exist a direct relationship between the target profiles of the recipients and their measured *behavioral profiles*. One example is to reach people who like movies on campus. If there are no movie theaters on campus, the measured *behavioral profiles* (i.e., mobility preference) cannot be used to infer such interest. This situation is illustrated in Fig. 7. There appears to be little insight provided by the similarities between the nodal *behavioral profiles* to guide message propagation, as the intended receivers in this case may be scattered in the *behavioral space*, and the relationship between the target profile and the *behavioral profile* cannot be quantified. Although it is always possible to reach most users through epidemic routing[5], this leads to high overhead, and requires all nodes in the network to keep a copy of the message. The objective of *CSI:D mode* is to reduce the numbers of message copies transmitted and stored in the network, yet make it possible for most nodes to get a copy quickly, if they are the intended receivers.

We first discuss the intuition behind the design of the *CSI:D mode*, using Fig. 8 as an illustration. From section VI-B, **since**

/* $BP(A)$: *Behavioral profile* **of node** A */
/* T: **Maximum life time of the message** */
if *node* A *has the message* **then**
  if $Sim(BP(A), TP) > th_{sim}$ **then**
    Initiate *Group_spread*();
  else
    Initiate *Gradient_ascend*();

Gradient_ascend(){
while *the message is not sent* **do**
  foreach *node* E *encountered* **do**
    Get $BP(E)$ from E;
    if $Sim(BP(E), TP) > Sim(BP(A), TP)$ **then**
      Send message to E;
      Delete message;
  if *message is in network longer than* T **then**
    Delete message;
}
Group_spread(){
foreach *node* E *encountered* **do**
  Get $BP(E)$ from E;
  if $Sim(BP(E), TP) > th_{sim}$ **then**
    Send message to E;
  if *message is in network longer than* T **then**
    Delete message;
}

Algorithm 1: Algorithm for the *CSI:T mode*

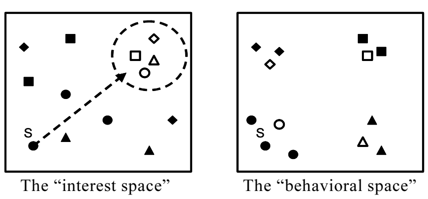


Fig. 7. Illustration of the *CSI:D* protocol. Left chart: The goal is to send a message to a group of nodes with a similar characteristic in the *interest space* (white nodes in the circle). Right chart: However, they may not be similar to each other in the *behavioral space* (nodes with the same legend represent similar nodes in the *behavioral space*).

the nodes with high similarity in their *behavioral profiles* **are almost guaranteed to encounter, there is really no need for each of them to keep a copy and disseminate the message. Electing a few** *message holders* **within a group of similar nodes would suffice.** This intuition leads to the construction of our message dissemination strategy for *CSI:D*. We aim to have only one *message holder* among the nodes who are similar in their *behavioral profiles* (or equivalently, pick only one *message holder* within a *neighborhood* in the *behavioral space*. In Fig. 7, this corresponds to having only one message holder from each group of nodes with the same legend). We add the message holders carefully to avoid overlaps in the encountered nodes among message holders. This is achieved as follows. As suggested by Fig. 5 (c), we should **select nodes that are very** *dissimilar* **in their** *behavioral profiles* **to achieve low overlaps.** Recall that dissimilar node pairs still encounter with non-zero probability, our design philosophy is to leverage these “random” encounter events as *short-cuts* to navigate

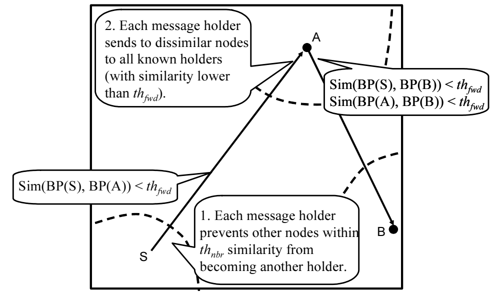


Fig. 8. Illustration of the *CSI:D* protocol. The idea is to select the message holders in a non-overlapping fashion to cover the entire *behavioral space*.

through the *behavioral space* efficiently, hopping across the space to reach dissimilar nodes with relatively few message transmissions. Such a design philosophy is also related to the SmallWorld human network structure – a message will reach an intended receiver shortly once it has reached someone in the receiver's “clique”.

The pseudo-code for *CSI:D* is given in Algorithm 2. (1) The sender itself starts as the first message holder in the network. (2) Each message holder attempts to strategically add additional message holders in the network. When it encounters with other nodes, it asks for the *behavioral profile* of the other node to be considered as a potential additional message holder. Each message holder keeps a list of the *behavioral profiles* of all known message holders[4], and the new node has to be dissimilar to all known holders (with the similarity metric lower than a forwarding threshold, th_{fwd}) to be added as a new message holder. (3) If, on the other hand, this node is similar to the message holder (i.e., within a neighbor threshold th_{nbr}), it uses a single bit to remember that there is a message holder in its neighborhood and propagates this information to other nodes within the th_{nbr}-neighborhood, defined as all nodes with similarity value higher than th_{nbr} to the message holder. This bit is used to prevent excessive message holders in the same neighborhood, even if some nodes have not encountered with the message holders directly. (4) When holders encounter, they update each other with the *behavioral profiles* of the known holders list, to gain a better view of the existing message holders in the network. (5) If two similar holders encounter, one of them should cease to be a holder to reduce duplicates.

Each message holder is responsible for disseminating the actual message to the intended receivers. The message holders sends the *TP* specified by the sender in the message to the encountered nodes. If the encountered node is an intended receiver, the full message will be transferred.

VII. Evaluation Results

In this section, we perform extensive evaluation of the *CSI* protocols, based on the derived encounters between users from the two empirical traces. We compare the performance of our proposal with two flavors of oracle-based protocols with the objectives of optimizing delay or overhead, to understand where the *CSI* protocols stand with respect to the optimum.

[4]Note this list does not necessarily contain all holders in the network. Message holders that are added by a particular message holder are not known to other holders until they meet and sync the lists.

```
/* BP(A): Behavioral profile of node A */
/* H_i(A): The i-th known holder of node A */
/* holder_in_group(A): If A knows there is a
   message holder in its neighborhood */
/* T: Maximum life time of the message */
if node A is a message holder then
    foreach node E encountered do
        Get BP(E);
        if E is not a holder then
            if Sim(BP(E), BP(H_i(A))) < th_fwd ∀i and
            holder_in_group(E) = false then
                Elect E as an holder;
                Add BP(E) to holder list;
                Send the message;
                Send BP(H_i(A)), ∀i;
            else if Sim(BP(E), BP(H_i(A))) > th_nbr
            for any i then
                Let E set holder_in_group(E) = true;
        else
            if Sim(BP(E), BP(A)) > th_nbr then
                A ceases to be a holder;
            else
                Sync holder lists between node A and E;
    if message is in network longer than T then
        Delete message and related data structure;
else if holder_in_group(A) = true then
    foreach node E encountered do
        Get BP(E);
        if Sim(BP(A), BP(E)) > th_nbr then
            Let E set holder_in_group(E) = true;
    if message is in network longer than T then
        Delete related data structure;
```

Algorithm 2: Algorithm for *CSI:D mode*.

We also compare *CSI* to epidemic routing [5] and variants of random walk[5]. In all the simulation cases, we split the traces into two halves, use the first half to obtain the behavioral profiles for all users, and then use the second half of the trace to evaluate the protocols.

A. CSI: Target Mode (CSI:T)

1) Evaluation setup: In the scenario of *CSI:T mode*, the sender specifies the *TP* and a threshold of similarity th_{sim}. If a node shows a similarity metric higher than th_{sim} to the *TP*, it is an intended receiver. In our evaluation, we use the top-10 dominant *behavioral profiles*[6] (i.e., the *behavioral profiles* exhibited by the most number of users, typically in the order of hundreds) in our traces as the *TP*s, and for each *TP* we randomly pick 100 users as the senders generating messages targeting at the *TP*. We use the threshold $th_{sim} = 0.8$ as the transition point between the *gradient ascend phase* and the *group spread phase*[7].

We compare our *CSI:T* protocol with several other protocols discussed below.

(1) The *epidemic routing* [5] is a message dissemination scheme with simplistic message-forwarding rules: all nodes that have received the message send copies further to all other nodes who have not received the message yet.

(2) The *random walk (RW)* protocol generates several copies of the message from the sender, and each copy is passed around among all nodes in a random fashion, until the hop count reaches a pre-set TTL value.

(3) The *group spread only* is a simplified version of our *CSI:T* protocol. It uses only the *group spread phase*, i.e., the original sender holds on to the message until it encounters a node that is more similar than th_{sim} to the *TP*, when it skips the *gradient ascend phase* and enters the *group spread phase* directly.

(4) We also consider three theoretical protocols that require global knowledge of the future. (4.1) The *delay-optimal* protocol sends copies of the message only to the nodes which lead to the fastest delivery to the targeted receivers, and no one else. This is the oracle-based optimal protocol achievable if one has perfect knowledge of the future, and serves as the upper bound for performance (in terms of delay). (4.2) The *overhead-optimal* protocol, on the other hand, minimizes the number of transmission counts using the knowledge of future encounter events. This protocol delivers messages to all reachable receivers under the minimum possible transmission count. The pseudo-code we use for these two optimal protocols is summarized in Algorithm 3. Notice this is basically a generalized version of the Dijkstra algorithm, with a different metric (i.e., delay or transmission count) used in either protocol. (4.3) The *optimal 1-path* protocol is an oracle-based protocol to leverage the fastest path to deliver the message to the neighborhood of the *TP* – Using the knowledge of the future encounter events, it identifies the node that could receive the message the earliest among all intended receivers, and finds the path taken from the sender to reach this particular node. The *optimal 1-path* protocol then uses this path to deliver one copy of the message to the neighborhood of the intended receiver group. Once a copy of the message is delivered to the th_{sim}-neighborhood to the *TP*, it follows the same *group spread phase* as in *CSI:T*. This is the optimal performance (upper bound) for the family of protocols delivering one copy of message to the neighborhood of the target profile, if one chooses a good (shortest delay) path – note that this shortest-delay path may not always follow an increasing gradient of similarities to the *TP*.

Performance metrics We compare these message dissemination schemes with respect to three important performance metrics: *delivery ratio*, *average delay*, and *transmission overhead*. The *delivery ratio* is defined as the percentage of the intended receivers (those with similarity greater than th_{sim} to the TP) actually receive the message. We account for the transmission overhead as *the total number of messages sent* in the process of delivery. See more discussions on the additional overhead of exchanging the *behavioral profiles* later in section VIII-A.

[5]The CSI could not be directly compared with existing routing schemes (e.g., [17], [3], [6], [10]) in DTN as most of them have a different routing objective: reaching a particular network ID.

[6]We have also experimented with other target profiles, such as rarely visited locations on campuses or profiles that contain a combination of several locations, and the results are similar to those presented in this section.

[7]We have also tried various values of th_{sim} and the results are similar to what we show here.

```
/* done[i]: if the metric for node i is finalized                          */
/* metric[i]: current best metric to reach node i                          */
/* from[i]: the previous hop of node i                                     */
/* reach_time[i]: time node i receives the message                         */
/* s: the source node                                                      */
/* candidate: current node under consideration, from
   which all other "unfinished" nodes could
   potentially improve the metric                                          */
forall Node i do
    set done[i] = false;
    set metric[i] = inf.;
    set from[i] = null;
    set reach_time[i] = inf.;
set done[s] = true;
set metric[s] = 0;
set reach_time[i] = sendtime;
set candidate = s;
while candidate ≠ null do
    foreach node k that done[k] = false do
        foreach Encounter event between candidate and
        k after reach_time[candidate] do
            if Message delivery from candidate to k
            improves (reduces) metric[k] then
                Modify metric[k];
                set reach_time[k] =
                Encounter_event_time;
                set from[k] = candidate;
    forall Node k such that done[k] = false and
    metric[k] ≠ inf. do
        Find node m with minimum metric[m];
        if m ≠ null then
            set candidate = m;
            set done[m] = true;
        else
            set candidate = null;
```

Algorithm 3: Algorithm for the oracle-based optimal protocols. The metric under consideration is delay in the delay-optimal protocol, and number of transmissions in the overhead-optimal protocol.

2) Evaluation results: We show the normalized performance metrics with respect to that of *epidemic routing* (the relative performance for each protocol assuming *epidemic routing* is 1.0) and its 95% confidence intervals in Fig. 9. We first observe, among all compared protocols, our *CSI:T* leads to a high delivery ratio (0.96 for USC, 0.94 for Dartmouth) with very small overhead (0.02 for USC, 0.018 for Dartmouth). We summarize the comparisons as follows.

(1) The *epidemic routing* leads to the highest overhead while its aggressiveness also results in the highest possible delivery ratio and the lowest possible delay. Notice that our *CSI:T* has close delivery ratio to the *epidemic routing* but very low overhead.

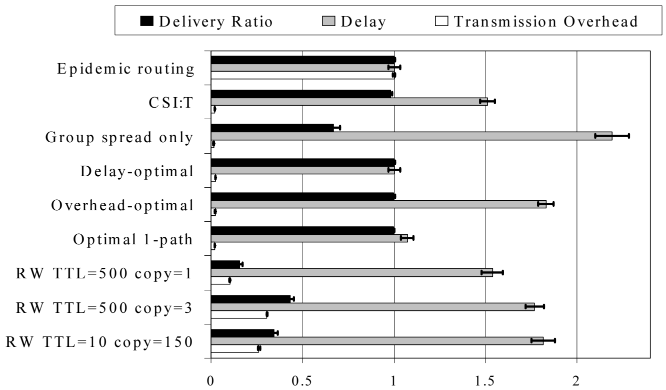
(2) The *random walks* do not work well regardless the number of copies and the value of TTL, with delivery ratio lower than 45% in all cases and high delay. Since the *random walk* does not transmit messages using the guidance from user *behavioral profile*, it wastes a lot of transmissions without sending the message towards the right nodes.

(3) For the simplified version of *CSI:T*, *group spread only*, the delay is longer and the delivery ratio is lower than our *CSI:T* protocol, and the difference is quite significant. This validates the need for the *gradient ascend phase* before the *group spread phase*. We will further investigate this phenomenon later.

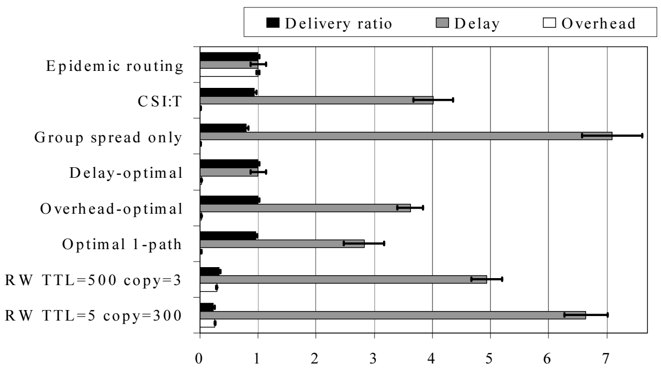
(4) Comparing with the optimal protocols with future knowledge, we see that there is really not much room for the *CSI:T* protocol to improve in terms of the delivery ratio and the overhead. (4.1) Specifically, *CSI:T* has more than 94% of delivery ratio and uses *less than* 84% overhead of the *delay-optimal* strategy. The delay, on the other hand, has some room for improvement. The key reason of this difference (in terms of delay) is that our *gradient ascend phase* generates only one copy of message from the sender and it moves towards the TP following strictly ascending similarity, while the *delay-optimal* protocol generates as many copies as needed to achieve the lowest delay for each node. (4.2) When comparing with the *overhead-optimal* protocol, we observe that the overhead *CSI:T* incurs is about the same (with less than 5% difference) as the *overhead-optimal* protocol, and the delay is less in the USC case (by 20%) but slightly more in the Dartmouth case (by 11%). Base on the above comparisons, our *CSI:T* protocol does well in terms of overhead and delivery ratio, even compared to the optimal protocols with perfect information of the intended receivers and future encounter events. (4.3) Finally, comparing with the *optimal 1-path*, which delivers one copy of the message to the neighborhood of the TP using the best (fastest) path based on the knowledge of the future encounters, our *CSI:T* has 1.40 and 1.47 times more delay, for USC and Dartmouth, respectively. This calls for a further investigation of selecting good path(s) from the sender to the TP, which we leave out for future work.

The average performance metrics shown above provide adequate comparison between protocols, but do not reveal the detailed differences of the protocol performance under different scenarios. To achieve this, we analyze the performance metrics by splitting the simulation cases into categories, depending on the original similarity metric between the sender's *behavioral profile* and the *TP*, $Sim(BP(S), TP)$. By the split statistics shown in Fig. 10, we see why the *gradient ascend phase* is needed to improve the delivery ratio and reduce the delay. When we use only the *group spread phase*, and the sender is dissimilar from the *TP*, it takes a longer time before any encounter event happens directly between the sender and anyone in the neighborhood of the *TP*, if it happens at all – hence the delay is longer, and the delivery ratio is lower. The introduction of the *gradient ascend phase* in *CSI:T* is thus crucial for these senders who are dissimilar from the TP to achieve good performance.

Comparing the differences between two versions of random walks, few long threads and many short threads, reveals an interesting difference. The concept that leads to the difference is illustrated in Fig. 11. Many short threads are better if the sender is close to the *TP*, in terms of both delivery ratio and delay, as the sender generates a lot of threads to "occupy" the neighborhood – since the threads are short, and similar users encounter more frequently, they are likely to stay in the neighborhood, even if the *random walk* does not make forwarding decisions based on *behavioral profile* similarity at

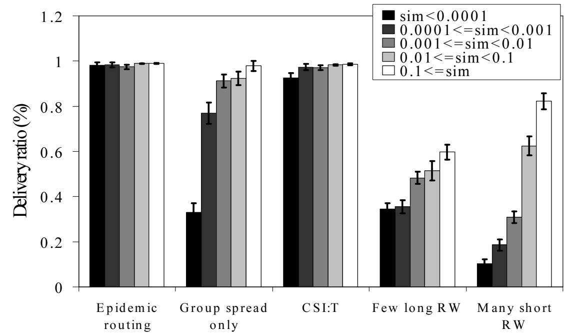


(a) USC.

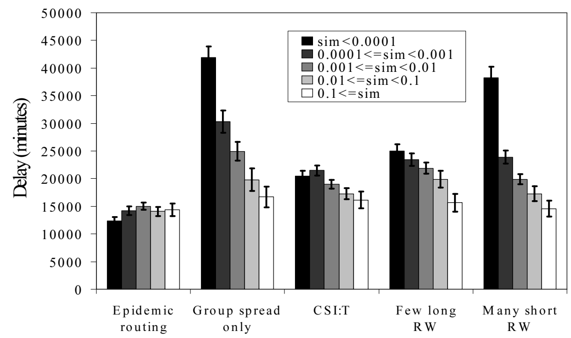


(b) Dartmouth.

Fig. 9. Performance comparison of *CSI:T* to other protocols.



(a) Delivery ratio.



(b) Average delay.

Fig. 10. Split performance metrics of *CSI:T* based on the similarity between the sender and the target profile (for USC trace).

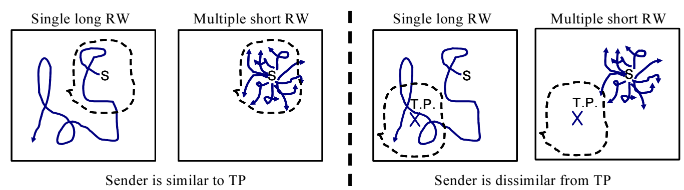


Fig. 11. Illustration for the comparison between one long random walk and many short random walks.

all. This phenomenon is also observed in our earlier work [15]. By contrast, if the sender is far away from the *TP*, long random walk threads provide a higher chance of moving close to the *TP*, while short threads provide less hope. **Our *CSI:T* protocol successfully leverages the implicit relationship between behavioral profile similarity and encounters detailed in section VI-B to improve the message delivery when the sender is dissimilar to the target profile. This highlights the power of incorporating the understanding of user behaviors in the profile-cast paradigm.**

B. CSI: Dissemination Mode (CSI:D)

1) Evaluation setup: In the scenario of *CSI:D mode*, the target profile specified by the sender is not used to determine to where the message should be sent in the *behavioral space*. Hence, the protocol seeks to keep one copy in every neighborhood in the *behavioral space*. In our evaluation, we start from 1000 randomly selected users as the senders. Since the target profile of the intended receivers can be orthogonal to the *behavioral profile*, we create the scenario for evaluation by randomly selecting 500 nodes as the intended receivers for each sender, and consider the average performance. We vary the two thresholds, th_{fwd} and th_{nbr} in our *CSI:D mode* protocol proposed in VI-D, to adjust the aggressiveness of the forwarding scheme. Setting lower values for both thresholds, we expect, would lead to fewer message holders. Furthermore, the existence of a message holder now prevents nodes in a larger neighborhood from becoming message holders. This provides for less aggressive operation and forwarding, thus leading to lower delivery ratio and more delay, but incurring less overhead.

We compare various parameter settings of our *CSI:D mode* with two baseline protocols, (1) the *epidemic routing* and (2) the *random walk*. *Epidemic routing* again serves as the baseline for comparison. In the *random walk*, the visited nodes along the walks become message holders and they will later disseminate the messages further when encountering with the intended receivers. We also compare *CSI:D* with two oracle-based optimal protocols, (3.1) the *delay-optimal* and (3.2) the *Tx-optimal*. The *delay-optimal* protocol again assumes global view of the network and the knowledge of the future. Every node in the network knows who the intended receivers are, and sends the messages to other nodes only if they lead to the fastest delivery of the message to one of the receivers. The *Tx-optimal* (transmission optimal) protocol sends the message to other nodes only if they lead to the delivery of the message to one of the receivers with minimum number of transmissions, considering all possible ways to reach the receivers given future encounter events. In both optimal protocols, the intermediate nodes (i.e., non-receivers) keep a copy of the message as they have to store it for future transmission(s).

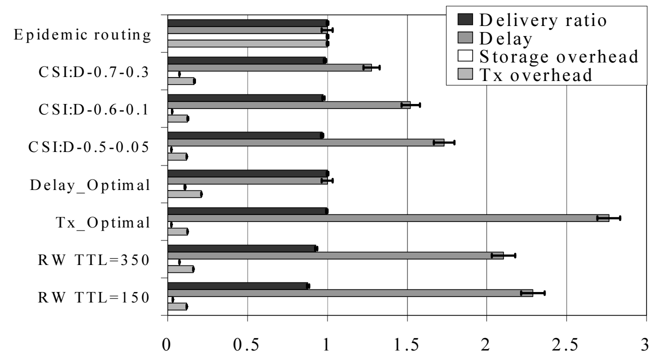
Performance metrics The performance metrics we consider are *delivery ratio*, *average delay*, *transmission overhead*, and, in addition, *storage overhead*. Here the *transmission overhead* refers to the total number of transmissions to spread the message to holders and to deliver them to the intended receivers. The *storage overhead* is the number of eventual message holders that remain in the network after our scheme is stabilized (recall that some message holders may decide to cease performing the task if another message holder is found with similar *behavioral profile* in *CSI:D*). This is the overall amount of storage space consumed by the nodes collectively to deliver the message[8]. In the *epidemic routing* protocol, all nodes that receive the message hold on to the message for future transmissions (there is no distinction between the message holder and a regular node), hence the transmission overhead and the storage overhead are the same.

2) Evaluation results: In Fig. 12 we show the average result of 1000 simulation cases with 95% confidence interval. We use the legend *CSI:D*-th_{fwd}-th_{nbr} for our *CSI:D* scheme. (1) Comparing with the *epidemic routing*, our protocol saves a lot of transmission and storage overhead. It is possible to use only about 7.2% strategically chosen nodes as the message holder and reach the intended receivers with little extra delay (about 32% more), when $th_{fwd} = 0.3$ and $th_{nbr} = 0.7$. The delivery ratio is almost perfect, no lower than 98.5%. On the other hand, if one desires further reduction of the overhead, setting lower threshold values provides a way to trade-off more delay and less delivery ratio for less overhead, e.g., setting $th_{fwd} = 0.05$ and $th_{nbr} = 0.5$ cuts the transmission overhead to less than 30% of the previous parameter setting. The *delivery ratio* is still more than 96.7% with this less aggressive parameter setting, and the *storage overhead* is as low as 2.2%.

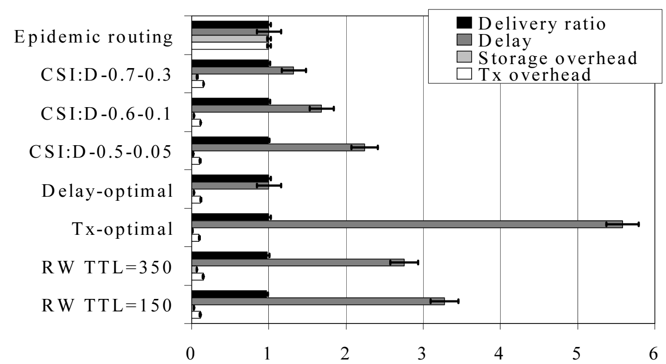
(2) For the *random walks*, we have configured the TTL values to have similar overhead to the *CSI:D* (i.e., compare RW TTL=350 with *CSI:D*-0.7-0.3 and RW TTL=150 with *CSI:D*-0.6-0.1). We notice that although the delivery ratio of the *random walk* is also very good (1.5% to 10% inferior to the corresponding *CSI:D*), thanks to the non-zero encounter probability between dissimilar nodes, its delay is much longer than the corresponding *CSI:D* (between 50% to 108% more). This is because the *random walk* does not leverage the implicit structure of the *behavioral space* to select the message holders wisely, as *CSI:D* does. The *random walk* leaves copies within the same neighborhood of the original sender with higher probability, as similar nodes are more likely to encounter (i.e., the *random walk* will not "leave the neighborhood" in a small number of hops). Hence, for *random walks* there exists significant overlap between the nodes encountered by the selected message holders, and the intended receivers that are dissimilar to these holders have to wait for a long time before some "random" encounter events occur to receive the message, resulting in the longer delay.

(3) Finally, we compare the *CSI:D* protocol with the optimal

[8]Typically, only about a couple dozens of message holders drop the message in the simulation cases in our *CSI:D* protocol. Even if we have accounted for the temporarily invested storage, it adds less than 1% additional storage overhead.



(a) USC.



(b) Dartmouth.

Fig. 12. Performance comparison of *CSI:D* to other protocols.

protocols. We point out that with aggressive parameter settings (e.g., *CSI:D*-0.7-0.3), the delay of the *CSI:D* is not much more than the *delay-optimal* protocol (by 27% to 32%). When the *CSI:D* is set to reduce overhead (e.g., *CSI:D*-0.5-0.05), its transmission overhead is very similar to (less than 7% more than) the *Tx-optimal* but the delay is much better, by 60% and 150% for USC and Dartmouth, respectively.

The performance of *CSI:D protocol* again shows the power of incorporating user behaviors in protocol design. By careful evaluation of behavioral similarity and selective message holder assignment, it is possible to achieve good delivery ratio and delay with much less overhead. Our *CSI:D* not only significantly out-performs the baseline protocols, but also shows reasonably close delay and transmission overhead when comparing with the corresponding optimal protocols.

VIII. Discussion

In this section, we further discuss some detailed issues regarding the additional overhead incurred by the *CSI* protocols, and a privacy-preserving option to eliminate the need for users to explicitly reveal their *behavioral profiles*.

A. Additional Overhead

In addition to the message transmission and storage, in our proposed *CSI* protocols, due to the need for exchanging and maintaining the *behavioral profiles*, there is some additional overhead.

Overhead for exchanging the behavioral profiles We identify some additional components on top of the actual message transmissions when the encounter events between mobile nodes are used for message dissemination. Some of the components are common to *any* message dissemination schemes, and the others are unique to our *CSI* protocols.

- The common overhead for all the message dissemination schemes considered in infrastructure-less mobile networks includes the neighbor-discovery beacon signals for nodes to discover each other when they encounter, and the exchange of a list of "messages seen" to avoid receiving duplicated messages from different nodes. This type of overhead is a function of the encounter pattern itself and is independent of the actual protocol used. We ignore these common factors in our analysis.
- Exchanging the *behavioral profiles* for the evaluation of mutual similarity is an additional component that exists only in our *CSI* protocols. However, the *behavioral profile* is sent only if a node has message(s) to send[9]. Thus, comparing with the protocols that require proactive, persistent exchanges of control messages (e.g., encounter probability vectors in ProPHET [17]), qualitatively, *CSI* has lower overhead, especially when the volume of traffic is low in the network. Furthermore, thanks to the repetitive pattern in our daily lives, a small set of vectors and their corresponding weights are sufficient to summarize user behaviors [4]. It is worthwhile to pay this small overhead to achieve the reduction of actual message transmission counts as we see in section VII, especially if the message size is much larger than the *behavioral profiles*. This is usually true as messages are transferred in a bigger unit (i.e., a "bundle") in DTNs.
- The actual message size has to be augmented with the *TP* as well. This is a constant overhead, and it can be reduced if the target vector is "sparse" (e.g., if the *TP* considers only the visits to the gym exclusively, there is only one 1 in the vector. Instead of adding a vector $(0, ..., 0, 1, 0, ...)$ in the header, the vector can be encoded (i.e., by specifying (gym, 1)) to save space.).
- In the *CSI:D mode*, the message holders have to exchange the list of *behavioral profiles* of known holders. This happens only between a small subset (less than 8%) of the nodes, and the exchange is necessary only when there is a difference in the lists. To further alleviate this, two nodes can compare their known holder lists using a hash value, and exchange only the difference.

Overhead for maintaining the behavioral profiles In order to maintain the behavioral profiles, nodes have to keep track of their visiting time to various locations. Note this does not require a node be aware of all possible locations in the environment – it has to keep track of only the locations it visited. When two nodes exchange the behavioral profiles, each entry in the behavioral profile contains only a subset of locations with annotations for these locations (e.g., Node A specifies (library, gym) = (0.8, 0.2) while node B specifies (library, computer lab) = (0.4, 0.6)). The nodes will take a union of the location sets when comparing their similarities (e.g., in the previous example, when node A sends the behavioral profile to B, B will convert the profiles to $BP(A)$: (library, gym, *computer lab*) = (0.8, 0.2, 0) and $BP(B)$: (library, *gym*, computer lab) = (0.4, 0, 0.6) before comparing). The required storage on each node is minimal, as we show about three to five days of summarized *mobility preference* is sufficient to establish a stable *behavioral profile* for the users in section IV.

In addition, if the beacon signals from locations are not available, it is possible to use the mutual encounter vectors as the behavioral descriptors for the nodes – nodes who move similarly should have similar encounter sets. In this sense, we could replace the representation to be totally independent of the infrastructure. The relationship between the two representations (i.e., location preference vectors versus encounter vectors) is a subject for future investigation.

B. Privacy Issues

While the profile-cast message dissemination paradigm achieves good performance with significant overhead reduction, it also raises user privacy concerns. In some cases, individuals may not want to reveal their own behavior. We discuss privacy-preserving options of our *CSI* protocols below.

First we emphasize that the original design of *CSI* presented in section VI inherently possesses a privacy-preserving feature: we only use a small subset of user behavior (specifically, the mobility preference) in the *behavioral profile*, and with the singular value decomposition, we reveal only the summarized trend, not detailed location visiting events for the user (e.g., the exact time and duration a user visits various locations). In addition, the *behavioral profiles* are exchanged only between nodes, not stored in any public directory, and the *behavioral profile* exchanges happen only when a given node is involved in message dissemination.

We can further reduce the *behavioral profile* exchanges in the *CSI* scheme, and hence help to further preserve privacy as follows. For the *CSI:T mode*, when nodes encounter, instead of exchanging their *behavioral profiles*, the node with a message to send would first send to the other node the *TP* of the message and its similarity score to the *TP*. The other node locally calculates its similarity to the *TP* and decides whether to request for the actual message. **This completely removes the need for behavioral profile exchanges in** *CSI:T mode*.

For the *CSI:D mode*, when two nodes encounter, instead of asking the other node to send its *behavioral profile*, the message holder sends the list of known holder's *behavioral profiles*. Since this list does not contain the *identities* of the known message holders, distributing it does not pose a privacy threat[10]. If the other node decides to become a message holder, instead of immediately sending its *behavioral profile* back to the old message holder, the new holder requests for the message but silently adds its *behavioral profile* to its own holder list, and delays the dissemination for a later holder profile list exchange. This prevents the old message holder from linking the *behavioral profile* and the *identity* of the new holder.

Finally, as a last resort, privacy-minded individuals can always opt-out of the service, and we expect this would not

[9]The privacy-preserving operation introduced in the next section further eliminates *behavioral profile* exchange.

[10]When there are multiple holders on the list, it is not possible to tell which *behavioral profile* corresponds to the holder sending out the list.

impact the performance severely, as it has been shown that the encounter pattern between nodes in mobile networks is rich enough to sustain up to 40% of nodes opting out before observing a performance degradation [14]. Opt out options shall be evaluated more thoroughly in our future work.

IX. Conclusion and Future Work

In this paper, we propose a novel profile-cast paradigm in which user *behavioral profiles*, instead of their *identities*, are used to represent targets of communication. We first represent user mobility by the *association matrix* and summarize it using singular value decomposition techniques. The *behavioral profile* we obtain displays high stability even when using data for only several days. The *behavioral profile* remains highly similar for the same user across time, and the similarity metrics between two users are well-correlated for the time span of weeks.

The analysis lays the foundation for the design of *CSI* protocols, which highlight the applicability and efficiency of the profile-cast paradigm in infrastructure-less mobile networks. It meets the design goals outlined in section VI-A with respect to efficiency, flexibility and privacy preserving properties. The *CSI* protocols perform closely to the delay-optimal protocols (with 94% or more delivery ratio and less than 83% of overhead; in *CSI:T* the delay is less than 47% more than the *optimal 1-path*, in *CSI:D* the delay is less then 32% more than the *delay-optimal*) and show significant improvement over behavior-oblivious protocols.

We are working towards an implementation of the *CSI* schemes based on mobile devices and consider a real-world evaluation. One key issue for further study is to adapt our protocol to a more privacy-preserving operation, and improve its resistance to spamming (e.g., include a reputation system). We are also considering different applications of *behavioral profiles*, including targeted advertising via our *CSI* schemes.

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