COBRA: A Framework for the Analysis of Realistic Mobility Models

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***Abstract*—The future global Internet is going to have to cater to users that will be largely mobile. Mobility is one of the main factors affecting the design and performance of wireless networks. Mobility modeling has been an active field for the past decade, mostly focusing on matching a specific mobility or encounter metric with little focus on matching protocol performance. This study investigates the adequacy of existing mobility models in capturing various aspects of human mobility behavior (including communal behavior), as well as network protocol performance. This is achieved systematically through the introduction of a framework that includes a multi-dimensional mobility metric space. We then introduce COBRA, a new mobility model capable of spanning the mobility metric space to match realistic traces. A methodical analysis using a range of protocol (epidemic, spray-wait, Prophet, and Bubble Rap) dependent and independent metrics (modularity) of various mobility models (SMOOTH and TVC) and traces (university campuses, and theme parks) is done. Our results indicate significant gaps in several metric dimensions between real traces and existing mobility models. Our findings show that COBRA matches communal aspect and realistic protocol performance, reducing the overhead gap (w.r.t existing models) from 80% to less than 12%, showing the efficacy of our framework.**

I. Introduction

Mobility modeling, analysis and simulation are essential to the design and evaluation of mobile networking protocols, services and applications. What is lacking, however, is a benchmarking framework for mobility evaluation, which can systematically assess comprehensive metrics to aid in the characterization and meaningful comparison of these models. Furthermore, the main purpose of these models is the realistic evaluation of protocol performance, which should be an integral part of the framework. Recently, a new generation of mobile networking protocols has been introduced based on communal and structural congruity aspects of mobile users [7], [9], [4]. Such aspects have not been considered in mobility modeling conventionally, and it is important for the benchmarks to include these new aspects and metrics of human mobility. The main challenges lie in introducing and assessing mobility models that capture all these metrics simultaneously in a realistic (matching traces and protocol performance) and practical manner (amenable to large-scale simulations). Particularly, we attempt to answer the following questions: *i.* Which aspects of behavior do current mobility models capture (or fail to capture) and to what degree? *ii.* How can a model be purposefully designed to capture the various metrics of mobility at will? *iii.* How does capturing mobility metrics reflect in the ability to capture realistic protocol performance?

This study re-visits the area of mobility modeling for the purpose of mobile network evaluation, and introduces a multi-dimensional mobility metric space to accurately characterize and benchmark mobility models. The metrics are classified into individual (e.g., spatio-temporal preferences), pair-wise (e.g., encounter based) and collective (e.g., group, community) metrics. In addition to these protocol-independent metrics, a systematic method is adopted to evaluate and compare protocols performance across models and real traces.

Next, a new mobility model is introduced. The salient feature of the new model is capturing the ***CO***llective ***B***ehavior based on ***R***ealistic ***A***spects of human mobility (*COBRA*). The construction of this model attempts to explicitly capture individual, pair-wise, and group mobility metrics, while maintaining scalability and manageability during simulations. COBRA is then thoroughly analyzed using framework guidelines. Once the benchmarking framework is in place and the mobility model is defined, the study passes through two phases. First, a systematic protocol-independent analysis is performed to characterize the mobility metrics of real traces, COBRA, and a set of existing mobility models. Extensive traces from several university campuses, conferences, offices, and theme parks† are used. In addition, several mobility models are evaluated including random direction [2], time-variant community (TVC) [8], and SMOOTH [14]. The latter two models are based on real traces and have been shown to capture several important characteristics of mobility. Second, a protocol-dependent analysis is performed, using several key opportunistic protocols; including epidemic routing [22], spray-and-wait [18] and prophet [12], to evaluate the accuracy by which the models match the protocol performance over network traces. Furthermore, the support for behavior-aware protocols; such as profile-cast [7], bubble rap [9] is discussed. The results of our analyses clearly show the shortcomings of existing mobility models over several mobility metrics.

Interestingly, the systematic approach to designing COBRA to account for the various mobility metrics also achieves a very close match in all the protocol performance metrics (for all the evaluated protocols), thus closing the significant gap in mobility and protocol evaluation. Specifically, the results have shown that COBRA is 90% accurate in demonstrating the similarity patterns observed in real traces. Also, it closely matches the protocol performance (85%-95%) on all different metrics. Contributions of this work are manifold:

1) introducing a systematic mobility benchmarking method, including a multi-dimensional mobility met-

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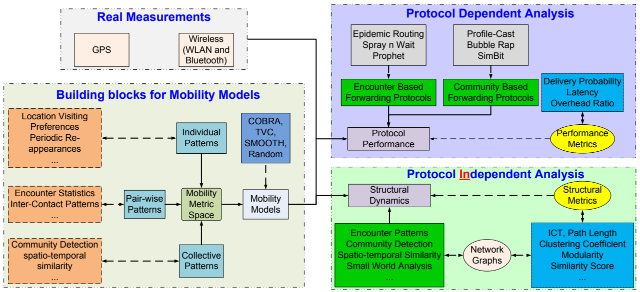


Fig. 1. Framework for analysis and modeling of human contact networks.

ric space and a framework for thorough mobility and protocol performance analysis,

2) introducing a new mobility model to capture multiple mobility metrics simultaneously. We also plan to release the model implementation and benchmark scenarios as part of this study.
3) characterizing and quantifying the metric gaps in existing mobility models,
4) providing a comprehensive evaluation of performance of DTN protocols over the various models and traces.

The rest of this paper is outlined as follows. In Section II, we introduce the mobility framework and multi-dimensional mobility metric space. In Section III, we introduce a new mobility model, COBRA. In Section IV and V, we extensively perform protocol-independent analysis and protocol-dependent analysis respectively, and finally conclude this paper in Section VI.

II. The Mobility Framework

Future mobile services, applications, and message dissemination paradigms will be influenced by behavior-driven human mobility. For example, spatio-temporal preferences of humans (e.g., such as going to sports complex and music concerts) will provide insight into their likings and diurnal activities, which can be used for customized services and advertisements. Also, opportunistic communication techniques rely on varying human mobility characteristics (such as inter-contact time and social structures) to efficiently transfer messages in the network. Since mobility and social dynamics impact the performance of routing protocols, it is of critical importance to examine constituent factors that identify such characteristics and evaluate models that use them. As shown in Figure 1, the proposed framework consists of four major components: *I.* Real measurements, *II.* Building block for mobility models, *III.* Mobility characterization using protocol-independent analysis, and *IV.* Mobility characterization using protocol-dependent analysis. More details will be provided on each of these blocks throughout this paper. These blocks constitute systematic guidelines for developing future models, generic evaluation of protocol-independent metrics such as similarity and community structures, as well as network protocols analysis. Next we describe components of the framework.

A. *Real measurements:*

In order to study the accuracy of mobility models it is imperative to compare them against real measurements [11], [1]. In the framework, we use real measurements to analyze the effectiveness of mobility models.

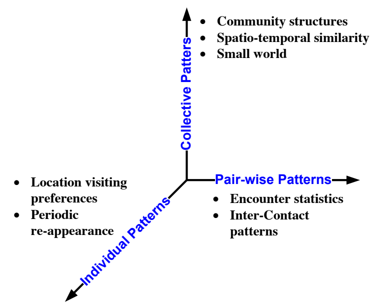


Fig. 2. Multi-dimension behavioral metric space for human mobility.

B. *Building blocks for mobility models:*

We propose a multi-dimensional mobility metric space that expresses various aspects of human mobility. Each of the dimensions consist of a set of metrics that help to capture specific features. Next, we discuss this metric space.

Owing to the complexity of understanding the human behavioral preferences, we represent them through *Multi-dimensional Mobility Metric Spaces* as shown in Figure 2. The design of these dimensions make ways to classify commonly used quantitative metrics of human behavior that follows naturally from the understanding of existing mobile services and protocols. These services and protocols rely on spatio-temporal mobility, location-based services, individual patterns, encounters, and communal behavior. The three dimensions are *i.* individual mobility, *ii.* pair-wise mobility, and *iii.* collective mobility patterns. Next, we discuss these dimensions in detail.

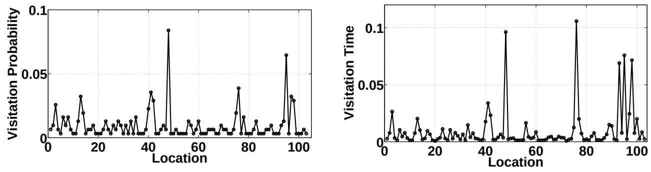
1) Individual Mobility Patterns: Individual patterns focus on independent behavior of the mobile users over space and time. Two related important metrics have been observed by Hsu et. al in [8]. The first is a spatial metric to capture the location visiting preferences measured by the percentage of time a mobile user spends at a given location. The second is a temporal metric to capture the periodic reappearances measured by the probability of visiting the same location after a time gap. Other metrics include speed and pause time. We evaluate these patterns in Section IV-C.

2) Pairwise Mobility Patterns: Pairwise patterns are observed between two encountering mobile users and reflect various statistical aspects of encounter patterns. They provide an insight into opportunities to exchange messages in encounter-based protocols [3]. Encounter metrics include number and duration distribution of encounters, and inter-contact time.

3) Collective Mobility Behavior Patterns: To capture the community dynamics, metrics that assess the similarity of users are introduced, in addition to clustering mechanisms based on modularity [16]. Metrics include similarity and cluster size distributions. We evaluate the accuracy of several mobility models in replicating these metrics in Section IV-F.

C. *Protocol-independent mobility analysis:*

In the context of communicating across wireless networks, recent services, protocols, and models have started to exploit the structural dynamics of human social connectivity [4], [8]. These macroscopic structures (such as communities, etc.) have been found favorable for the design of efficient opportunistic protocols [7], [9]. They go beyond the simple one-to-one



(a) (b)

Fig. 3. Probability distribution of location visitation and time

interaction (inter-contact patterns) to showcase the complex longitudinal patterns of how people meet, how often and for how long [17]. Thus, desirable models should accurately replicate such structures (via synthetic traces). To this end, we propose protocol-independent analysis of mobility models that involve examining dynamic properties such as spatio-temporal similarity, clustering, and community structures. They are evaluated through metrics such as modularity [16], similarity scores [20], and clustering coefficient.

D. Protocol dependent mobility analysis

The main purpose of mobility models is to simulate realistically identical performance of protocols and services. We identify two types of routing protocols *i)* Encounter based *ii)* Community based forwarding protocols. Encounter based forwarding protocols such as epidemic routing [22] utilizes human encounters as an opportunity to transfer messages. While, community based forwarding protocols such as Bubble Rap [9] benefit from structural dynamics (communities, etc.) of human mobility to perform message dissemination. The framework recommends to evaluate such protocols through performance metrics such as delivery ratio, latency, etc. [10].

The discussed mobility analysis framework focuses on multi-dimensional aspect of human mobility that a earlier model should demonstrate. In the subsequent sections, we will use this framework for evaluating current mobility models and routing protocol analysis.

III. COBRA

Today, mobility models have ventured from replicating features of pure stochastic systems such as random walk to more sophisticated ones, which involve demonstrating realistic human behavior and mobility patterns. It's preferable for them to be data-driven and be able to generate synthetic traces that are comparable to real measurements. Also, models should demonstrate identical protocol performance likewise the reality. Protocols such as Profile-cast [7] and Bubble-rap [9] harness the underlying structural dynamics of human communal behavior to transmit messages. For that purpose, models' generated traces should reflect such dynamics that we evaluate using community detection. [16]. However, previous studies show that vast majority of mobility models are inadequate to depict realistic patterns [6], [20], [21], [19]. These findings strongly motivates the need to re-visit mobility modeling to depict accurate human behavioral characteristics and network performance. We design ***CO***llective ***B***ehavior based on ***R***ealistic ***A***spects of human mobility (***COBRA***) keeping in mind the limitation imposed by the predisposition of modeling a specific type of stochastic distribution. Instead, we take a natural approach by attempting to encapsulate realistic human behavioral mobility features through explicit *spatio-temporal*

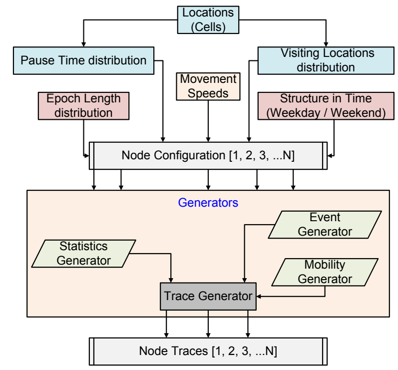


Fig. 4. COBRA architecture

synchronization of finite set of key activities. That include orderly distribution of location visitation, structure in time (pause time, weekday and weekend behavior, and offline/online patterns), movements speeds, and social ties. In general, human mobility can be pictured through a set of locations visited during a particular time. The idea fundamental to COBRA is to explicitly synchronize the events (not done in earlier models) leading up to the visit to these locations at a particular time interval for respective mobile users. For example, COBRA attempts to model the periodic visitation patterns of mobile users attending lectures in a classroom (location). As a result, this approach naturally helps to model human mobility and test discussed metrics. More details are available here [5].

Design Details

In this section, we describe the design of COBRA in more details. The block diagram of COBRA is shown in Figure 4. The model components involve time structure and pause time, visitation location, epoch length distribution, event and mobility generator, and a trace generator. The model provides flexibility to independently configure each node's spatio-temporal patterns, thereby capturing the heterogenous behavioral pattern and mobility at will. This makes COBRA distinct from other models and helps to capture the richness otherwise evident only in real measurements. We start with location visitation patterns of nodes that is the probability distribution of frequencies of their visits to a set of locations. This approach helps to capture skewed (heavily visited) as well infrequently visited locations, shown in Figure 3(a). For example, a mobile user regularly goes to office, but once in a while (say weekend) goes to grocery store. In that sense the probability to visit office is much higher than stores. In the simulation setting, each location is a square geographical area (cell) with constant edge length. Next, the duration of time a node spends in moving to a location is defined by epoch length. It starts from the end point of the previous location's epoch and is generated from an exponential distribution equal to the size of location. The offline behavior of the node is thus defined as the travel time from one epoch to another, measured through a speed and a direction (angle) movement for the chosen location. A roaming epoch is also defined when node roams around the whole simulation area during some epoch, by assigning an additional location that corresponds to the whole simulation. Basically, a node chooses a new location probability and epoch, and continues to move in that direction with a chosen speed. After each epoch, the node remains stationary in that location for the pause time drawn from the distribution,

TABLE I. DETAILS OF WIRELESS MEASUREMENTS

Campus	# Users	Duration	Settings
Dartmouth	300	Fall 2007	WiFi, Campus
Infocom	41	3 days	Bluetooth, Conference
IBM Watson	1300	Fall 2006	WiFi, Office
Theme Park[1]	825	5 days	GPS, Attractions
Univ. of Florida	700	Fall 2008	WiFi, Campus
USC	300	Fall 2007	WiFi, Campus

an example is shown in Figure 3(b). As evident from both the figures, there are few locations that are frequently visited with large pause times. In addition to that, we also gather periodicity, which provides flexibility to create multiple time periods with different locations and variable settings. The time periods are essentially the periodicities that are present in the human mobility. For example, a weekly periodicity can be going to work during the weekdays and spending weekend at home, or attending classroom lectures three times a week, etc. The epoch lengths and pause time therefore depend on the time periodicity. The model is data-driven and generates synthetic traces that can be compared against real measurements using metrics discussed in the framework section. We model time dependent location selection process through Markov chains that maintain the spatio-temporal heterogeneity of individual nodes in the simulation area.

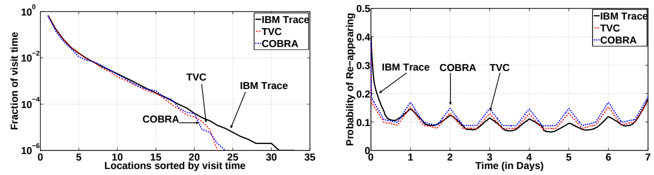
IV. PROTOCOL INDEPENDENT ANALYSIS

In this section, we perform protocol independent analysis on several mobility models, including COBRA and on real world measurements. The purpose of this study is to compare the accuracy of models against reality in capturing human structural dynamics and; to validate COBRA and test it's superiority over other models. While several metrics are mentioned in the framework, we focus our study on *i)* Similarity in mobile societies, *ii* Encounter Statistics, *iii)* Clustering based on Modularity. We start with discussing real world measurements and existing mobility models.

A. Measurements

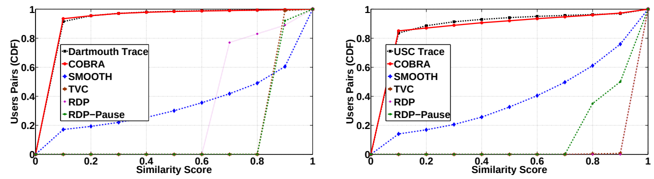
We have used six different types of measurements from varied sources that include university campuses, offices, conferences, and theme parks. These measurements are shown in Table I and are publicly available at [11], [1] except theme parks measurements. These measurements are categorized as:

- Spatio-Temporal Measurements: These are WiFi usage measurements that are collected from several university campuses and offices and exceeded in size and number by many orders compared to others.
- Encounter Measurements: These measurements are collected using devices with bluetooth scanning functionality. They capture explicit user-user encounters and its duration.
- GPS Measurements: These measurements log geo-coordinate footprints of guests in theme parks and the GPS locations accuracy was taken every two minutes on average, when the satellite signals were available. More details are available in [23].



(a) (b)

Fig. 5. (a) Location visitation patterns. (ii) Periodic re-appearance.



(a) Dartmouth-Similarity (b) USC-Similarity

Fig. 6. Distribution of Similarity

B. Mobility Models Studied

We use available mobility models and evaluate them through the metrics proposed in the framework. These mobility models have shown to capture human behavioral dynamics such as spatial and temporal preferences. For baseline comparison, we have used a variant of random mobility model. The models include: *i)* Time-Variant Community Model, *ii)* SMOOTH, *iii)* Random Direction model. While there are several models, we did our best to select ones that showed an edge over others [4], [13], [15].

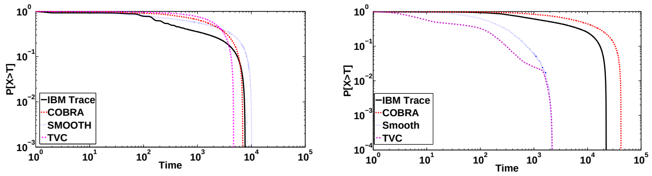
C. Analysis of Spatio-Temporal Preferences

In reality, there exists a non-homogenous behavior of mobile users in both space and time. In general two important metrics: *i)* Location visiting preferences, *ii)* periodic-reappearances are important in capturing such behavior [8]. In Figure 5, we show the plots for metrics exhibited in real measurements as well as in the synthetic measurements of both TVC and COBRA model. We see that TVC and COBRA were able to accurately capture the above metrics. In addition to that COBRA was able to capture *average node degree, the hitting time and the meeting time* (not shown for page limits). Since other models are not designed to replicate these characteristics, we are unable to study them at this point of time.

D. Similarity in Mobile Societies

We examine the distribution of similarity values among node pairs as proposed in [7], [20]. We show the results of similarity distribution for Dartmouth and USC in Figure 6. We find a range of scores exists that capture the heterogenous behavior among user pairs in real measurements. For example, in Dartmouth, 90% of pairs have scores less than 0.6 and for USC 85% have a score less than 0.5. The analysis of user pairs generated from the models show that COBRA is very accurate in demonstrating the distribution of similarity scores akin to the reality. While TVC and variants of random models show that 90% users have a similarity score of 0.85 and 0.8 respectively for Dartmouth and USC, which largely deviate from the reality. Since SMOOTH is designed to demonstrate power-law distribution of encounters, we find this is the main reason that it is able to distribute the similarity patterns somewhere in the middle, alas deviating from the reality.

[1]Analysis is done while working at Disney Research, Zürich, 2012.



(a) Infocom'05 - ICT (b) IBM Watson -ICT

Fig. 7. Inter contact time distribution

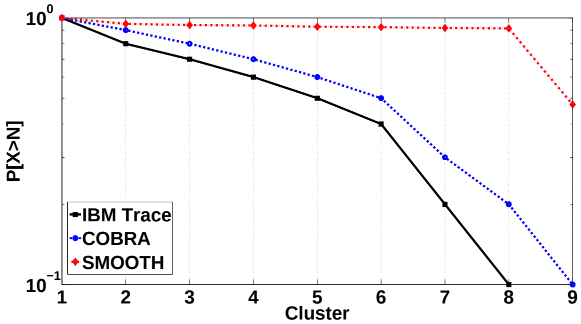


Fig. 8. Modularity based clustering distribution for IBM

E. Analysis of Human Encounter Statistics

In [3], authors proposed an important set of encounter statistic metrics that include inter-contact times (ICT), encounter frequencies, and encounter durations, which are critical in analyzing transfer opportunities between wireless devices carried by humans. They have also established these statistics exhibit power-law and exponential decay dichotomy that helps in studying the impact of human mobility on forwarding protocol performance in opportunistic networks. We have extensively analyzed these metrics in real world and synthetic measurements (from mobility models) to study the accuracy of later in demonstrating real human mobility patterns. In view of page limit, we show the ICT results only for Infocom and IBM Watson measurements in Figure 7. In case of Infocom measurements, SMOOTH, TVC, and COBRA accurately demonstrate ICT patterns as evident in real measurements. This make sense for SMOOTH and TVC, which previously had shown to capture power-law and exponential decay dichotomy [8], [14]. However, in case of IBM measurements (where the distribution of ICT is not power-law and exponential decayed dichotomy), only COBRA demonstrates the accuracy. This analysis indicates the scalability and benefit of adopting COBRA where the underlying human encounter statistics do not necessarily follow a power-law and exponential decay dichotomy (e.g [23]).

F. Community Detection through Modularity Optimization

In order for models to imitate reality, it is important that they should reproduce real world social and structural dynamics of human behavior mobility. We use modularity optimization [16] to detect structural dynamics of mobile societies (communities) in real world and synthetic measurements (from mobility models). The divisive algorithm has detected eight communities in IBM Watson measurements and nine in COBRA and SMOOTH generated measurements. Furthermore, we find that cluster sizes and membership follow a power-law distribution that is also captured by COBRA. However, in case of SMOOTH the community memberships are evenly distributed within clusters and largely deviate from the reality. In case of TVC and RDP, we detect only one community.

In this section, we have examined protocol independent metrics that capture human behavioral patterns. Our results indicate that current models largely deviate from the reality and are inadequate in synthesizing human mobile societies. However, COBRA has accurately replicated all the examined statistics indicating it's easy adoption and scaling to any kind of scenario. Next, we investigate protocol dependent metrics and compare the performance of routing protocols.

V. Protocol Dependent Analysis

Here, we compare the network protocol performance of mobility models (including COBRA) to the performance achieved with the real measurements. We divide this analysis into two parts. First we examine the performance of encounter based forwarding protocols (e.g., epidemic routing) and then of community based forwarding protocols (e.g., Bubble rap). For a fair analysis, we use the same set of traces that we have generated for protocol independent analysis. We benchmark protocol performance on the following three criteria: *i)* Delivery probability, *ii)* Latency, and *iii)* Overhead ratio. We use ONE simulator [10] to run this protocol performance analysis.

A. Encounter based Forwarding Protocol Analysis

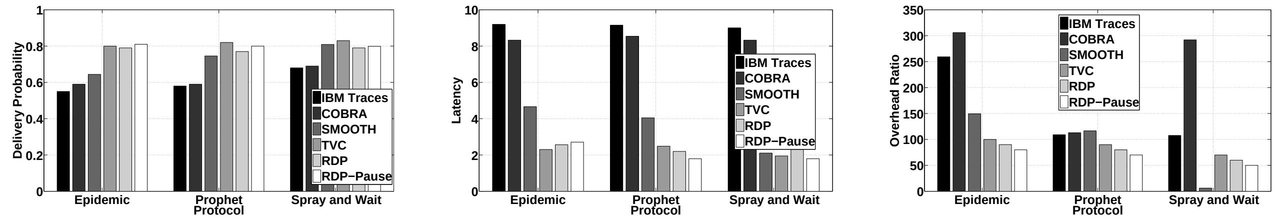
We evaluate three different encounter based forwarding protocols: *i)* Epidemic Routing, *ii)* Spray and Wait, and *iii)* Prophet for real and model generated measurements of IBM Watson and Dartmouth in Figure 9. In broad terms, COBRA is found to perform better than other models on all three metrics. Overall, COBRA's delivery ratio performance deviates less than 5% to reality, while other models on an average deviate more than 40%. Similarly, COBRA's latency differ less than 6% and overhead ratio less than 10% to the reality. Surprisingly, other models' latency and overhead on an average deviate more 66% and 80% respectively to the reality.

B. Community based Forwarding Protocol Analysis

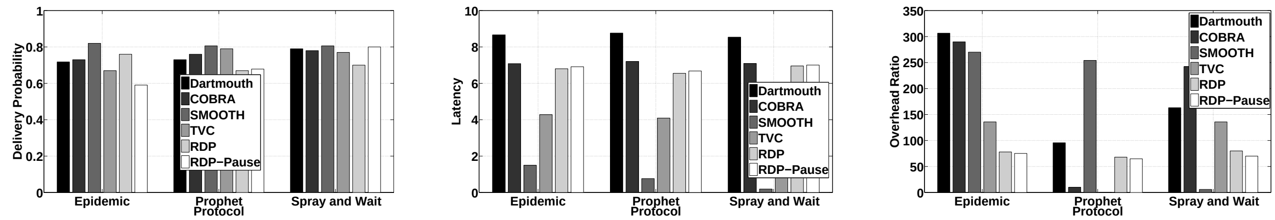
We study the performance of Bubble Rap routing protocol to examine the usefulness of mobility models in utilizing human community dynamics to transfer the messages in opportunistic settings [9]. We show the results of community based forwarding protocol for real and model generated measurements of IBM Watson in Figure 10. The protocol performance of COBRA in case of delivery probability differ by less than 6%, latency by less than 2%, and overhead by less than 10% to the real measurements. On the other hand other models' delivery probability on average deviate more than 10%, latency more than 60%, and overhead by more than 45% to the reality. These results indicate that COBRA is superior at demonstrating heterogeneous interactions among individuals and their communities for social message forwarding purposes.

VI. Conclusion

In this paper, we proposed a new framework for the analysis of data-driven human mobility models that included a multi-dimensional mobility metric space to measure individual, pair-wise, and community metrics. In addition, it has systematic guidelines for protocol dependent and independent analysis of mobility models. We also proposed COBRA, a new mobility model that captures the *CO*llective *B*ehavior

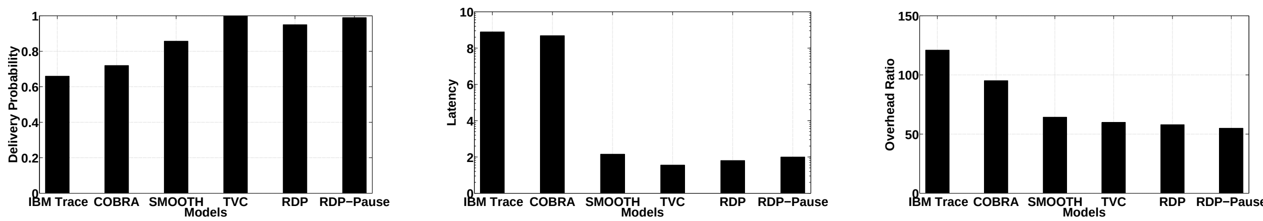


(a) IBM, Delivery Probability (b) IBM, Latency (c) IBM, Overhead Probability



(d) Dartmouth, Delivery Probability (e) Dartmouth, Latency (f) Dartmouth, Overhead Ratio

Fig. 9. Results for encounter based forwarding protocol analysis



(a) IBM Watson, Delivery (Top 30%) (b) IBM Watson, Latency (c) IBM Watson, Overhead Ratio

Fig. 10. Results for community based forwarding protocol analysis

based on *R*ealistic *A*spects of human mobility. Later on, we demonstrated the ability of COBRA in replicating several protocol independent metrics such as spatio-temporal preferences akin to the real measurements. Also, COBRA performance is closer to the reality than other models of its class for several networking protocols. Particularly, COBRA's encounter based protocol performance fared well by more than 80% to other models. It was also superior to other models at demonstrating community based protocols (less than 10% deviation). In summary, our work showed a need for a systematic mobility testing framework, which we achieved in this work. With COBRA, we were able to bridge the gap between current models and human behavioral mobility modeling. Finally, we hope this work will set standards of mobility evaluation.

REFERENCES

[1] Ahmed Helmy. MobiLib: Community-wide Library of Mobility and Wireless Networks Measurements, 2008.

[2] Tracy Camp, Jeff Boleng, and Vanessa Davies. A survey of mobility models for ad hoc network research. *WCMC*, 2002.

[3] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, and J. Scott. Impact of human mobility on the design of opportunistic forwarding algorithms. In *INFOCOM*, 2006.

[4] Elizabeth M. Daly and Mads Haahr. Social network analysis for routing in disconnected delay-tolerant manets. In *MobiHoc*, 2007.

[5] Gautam S. Thakur, Ahmed Helmy. COBRA: A Framework for the Analysis of Realistic Mobility Models, 2012.

[6] T. Hossmann, T. Spyropoulos, and F. Legendre. Putting contacts into context: mobility modeling beyond inter-contact times. In *MobiHoc*, 2011.

[7] W. Hsu, D. Dutta, and A. Helmy. CSI: A paradigm for behavior-oriented profile-cast services in networks. *Ad Hoc Networks*, 2011.

[8] Wei-Jen Hsu, T. Spyropoulos, K. Psounis, and A. Helmy. Modeling spatial and temporal dependencies of user mobility in wireless mobile networks. *Networking, IEEE/ACM Transactions on*, 2009.

[9] Pan Hui, Jon Crowcroft, and Eiko Yoneki. Bubble rap: social-based forwarding in delay tolerant networks. In *MobiHoc*, 2008.

[10] Ari Keränen, Jörg Ott, and Teemu Kärkkäinen. The ONE Simulator for DTN Protocol Evaluation. In *SIMUTools*, 2009.

[11] David Kotz, Tristan Henderson, and Ilya Abyzov. CRAWDAD data set dartmouth/campus, December 2004.

[12] Anders Lindgren, Avri Doria, and Olov Schelén. Probabilistic routing in intermittently connected networks. *SIGMOBILE MCCR*, 2003.

[13] Alessandro Mei and Julinda Stefa. Swim: A simple model to generate small mobile worlds. *Infocom*, 2009.

[14] Aarti Munjal, Tracy Camp, and William C. Navidi. Smooth: a simple way to model human mobility. In *MSWiM*, 2011.

[15] Mirco Musolesi and Cecilia Mascolo. A community based mobility model for ad hoc network research. In *REALMAN*, 2006.

[16] M. E. J. Newman. Modularity and community structure in networks. *PNAS*, 103(23):8577–8582, 2006.

[17] Mukund Seshadri, Sridhar Machiraju, Ashwin Sridharan, Jean Bolot, Christos Faloutsos, and Jure Leskove. Mobile call graphs: beyond power-law and lognormal distributions. In *KDD*, 2008.

[18] Thrasyvoulos Spyropoulos, Konstantinos Psounis, and Cauligi S. Raghavendra. Spray and wait: an efficient routing scheme for intermittently connected mobile networks. In *ACM WDTN*, 2005.

[19] G. Thakur, U. Kumar, A. Helmy, and W. Hsu. On the efficacy of mobility modeling for DTN evaluation: Analysis of encounter statistics and spatio-temporal preferences. In *IEEE IWCMC*, 2011.

[20] Gautam S. Thakur, Ahmed Helmy, and Wei-Jen Hsu. Similarity analysis and modeling in mobile societies: the missing link. In *CHANTS*, 2010.

[21] Gautam S. Thakur, Udayan Kumar, Wei-Jen Hsu, and Ahmed Helmy. Gauging human mobility characteristics and its impact on mobile routing performance. *Int. J. Sen. Netw.*, 11(3):179–191, April 2012.

[22] Amin Vahdat and David Becker. Epidemic routing for partially-connected ad hoc networks. *CoRR*, 2000.

[23] V. Vukadinovic and S. Mangold. Opportunistic wireless communication in theme parks: a study of visitors mobility. In *CHANTS*, 2011.