The Indoor Predictability of Human Mobility: Estimating Mobility with Smart Home Sensors

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Abstract—Analyzing human mobility patterns is valuable for understanding human behavior and providing locationanticipating services. In this work, we theoretically estimate the predictability of human movement for indoor settings, a problem that has not yet been tackled by the community. To validate the model, we utilize location data collected by ambient sensors in residential settings. The data support the model and allow us to contrast the predictability of various groups, including singleresident homes, homes with multiple residents, and homes with pets.

Index Terms—prediction, compression, human mobility, smart homes

I. INTRODUCTION

Studying human movement patterns helps researchers to understand human behavior. If human movement can be anticipated, this information can improve intelligent services that are provided by smart cities and smart homes [1]. One question that has captured the attention of researchers is determining how predictable human motion is. Given the ability to collect massive amounts of geolocation data, researchers have formalized models of large-scale outdoor human movement, population migration, and epidemics. These advances lead to improvements in city planning, traffic engineering, public health, and communication.

On the other hand, sensing indoor human mobility offers untapped potential to model behavior patterns. Indoor activities occupy most of our daily routine. According to the Environmental Protection Agency, Americans spend up to 89% of their time indoors, 69% specifically inside residences [2]–[4]. Using ambient sensors, researchers can continuously monitor the locations and activities of building occupants without requiring resident effort or behavior change [5], [6]. Discovering indoor mobility patterns facilitates providing mobility-aware services and automatic detection of abnormal behaviors. In buildings with multiple inhabitants, accurate prediction of each individual's movements is also key to tracking and responding to each person's needs.

In this work, we investigate the theoretical limit of the predictability of indoor human mobility. This investigation is accompanied by quantification of the effect of multiple

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TABLE I EXCERPT OF SENSOR EVENTS COLLECTED IN SMART HOME M3

Time Tag	Sensor ID	Message	
2016/12/27 7:44:58	BedroomADoor	ON	
2016/12/27 7:44:59	BedroomAArea	ON	
2016/12/27 7:45:01	BedroomADoor	OFF	
2016/12/27 7:45:05	BedroomAArea	OFF	
2016/12/27 7:45:08	KitchenAArea	ON	
2016/12/27 7:45:09	BedroomAArea	ON	
2016/12/27 7:45:11	HallwayB	ON	
2016/12/27 7:45:13	BedroomAArea	OFF	
2016/12/27 7:45:14	BedroomAArea	ON	
2016/12/27 7:45:15	BedroomAArea	OFF	
2016/12/27 7:45:15	HallwayB	OFF	

residents and pets on prediction accuracy. We also assess the performance of existing mobility prediction models.

We empirically validate our theoretical analysis by analyzing 140 million motion sensor readings recorded in 117 CASAS smart homes. In these homes, ambient sensors including passive infrared (PIR) motion sensors, magnetic door sensors, and contact-based item sensors, are deployed to track residents and their interaction with objects in the home. The sensor map for a sample smart home site, home m3, is shown in Figure 1.

Whenever the state of the sensor changes due to resident activity, the sensor sends a message to the smart home gateway, and the message is uploaded to a central database. Each sensor message is a three-tuple containing the time of the observation, the sensor identifier that observed the resident movement, and the state of the sensor. Table I shows an excerpt of sensor messages collected in one smart home testbed. Because a "deactivate" message (OFF for motion sensors, CLOSE for magnetic door sensors, and PRESENT for item sensors) always follows an "activate" message (ON for motion sensor, OPEN for magnetic door sensor, and ABSENT for item sensors), we only analyze the "activate" messages. Data are continuously collected in these environments while residents perform their normal daily routines.

II. HUMAN MOBILITY

Human mobility has been the subject of investigation in many fields, but the advent of mobile computing has opened



Fig. 1. Floor plan and sensor positions in a sample smart home (home m3).

the door to creating statistical models based on passivelyobserved movement patterns. In their seminal work, Song et al. [7] formulated an upper bound on outdoor human mobility predictability by entropy rate estimation. In this study, geolocation data are obtained from cell tower logs. Here, an individual's location is identified by the closest mobile tower each time they use a phone. Data are then extrapolated to form a continuous hourly record for estimating the entropy rate. Based on Fano's inequality, the authors concluded that the potential predictability of human mobility could be as high as 93%. This early study ignited a series of follow-up work [8]–[13] that replicate the outdoor mobility experiments using data collected from high-resolution GPS, embedded sensors on mobile devices, and wireless signal strengths to understand mobility predictability at various spatial and temporal resolutions. However, Smith et al. [11] noticed that, in geolocation data, each individual only visits a small fraction of all locations. As a result, the upper bound claimed by Song et al. [7] is an overestimate, an observation that is echoed by Xu et al. [14], and the actual limits could be 11-24% lower.

A limitation of earlier investigations is that the geolocation data monitors only outdoor human movement. Understanding outdoor movement supports analysis of viruses, city planning, and management of resources. Unfortunately, the theoretical bound of indoor human mobility predictability is a subject that has not received this same level of investigation. Understanding indoor movement is also valuable. Researchers have used such information to detect changes in a person's health [15], identify possible in-home security threats [16], design proactive behavior interventions [17], and provide residentaware home automation [18]. Predicting future resident locations is a central task of smart homes: thus researchers have proposed algorithms to model the indoor mobility of residents [19]. For example, Gopalratnam and Cook [20] proposed an online Lempel-Ziv sequence prediction algorithm, Active LeZi, which converges to 47% accuracy for predicting indoor locations using one month of smart home data. Alam et al. [21] introduced SPEED, an algorithm that predicts future events through a partial match, and reported 88.3% accuracy in predicting next sensor events over one month. Jayarajah and Misra [22] used WiFi logs on an urban campus to monitor indoor activities and observed an 87% predictability across building sections (e.g., classroom, food outlet, meeting space). Minor et al. [23] introduced a structured prediction algorithm that forecasted the times of upcoming activities with a MAE of 16 minutes, although this was not applied to movement prediction.

To analyze movement in smart homes with multiple residents, Ghasemi and Pouyan create a Markov chain that maps states to indoor sensors. This Markov model is used to predict the next location of each resident [24]. Doty et al. [25] further improve smart home state estimation by introducing flag hidden Markov models that contain a finite-state Markov chain as well as a structured observation process wherein a subset of states emit flags (i.e., observations) while other states are unmeasured. Lin and Cook [26] analyze the Markov order that best fits behavior observed by smart home sensors. While the focus of this paper is on deriving an upper bound on indoor mobility predictability rather than providing a best fit of smart home data, researchers including Begleiter et al. [27], Dimitrakakis [28], and Bejerano [29] have contributed several additional methods for improving prediction methods with variable-order models.

As an alternative method to model smart home behavior, Roy et al. [30] model the movement of smart home residents as actions taken in a multi-agent stochastic game. Thus, the mobility of all residents, characterized by a policy (i.e., the probability of a state-action pair), can be learned using a Nash H-learning algorithm. These authors reported 90% prediction accuracy for residents and 40% accuracy for visitors based on smart home data recorded over three weeks. These works are complementary to our analysis. However, they cannot be directly compared because we focus on the theoretical bound of indoor human movement predictability.

III. ENTROPY RATE AND PREDICTABILITY

The goal of this research is to investigate the theoretical bound for the predictability of indoor human mobility in realworld settings. Here we present the relationship between predictability and entropy rate estimated from actual smart home empirical data, using alternative computational approaches.

As introduced in Section I, the indoor locations of smart home residents are identified by ambient sensor messages. A person's indoor trajectory, T, is represented as a series of sensor messages, $\{X_i\}_{i \in \mathbb{Z}}$, where X_i is the *i*th sensor message in the trajectory. We define indoor mobility prediction as prediction of the next sensor message activated by the smart home resident(s) based on their past trajectories. In the case of multiple residents, we initially consider predicting the next sensor message caused by any of the residents at the site, without attempting to identify which of the residents was responsible for the message. Using this method, multipleresident prediction can thus be viewed as prediction of a single, more "complex" resident in the building. The upper bound of the predictability of indoor mobility can be calculated by estimating the entropy rate of the underlying stationary stochastic process [7].

A. Entropy Rate and Predictability

We assume that ambient sensor-detected resident trajectory inside a building can be modeled by a stationary stochastic process $\mathcal{X} = \{X_1, X_2, \ldots, X_n\}$, where X_i is a random variable representing the *i*th sensor message. For smart home data, the values of each variable X_i are the identifiers of activated sensors, representing the location of a smart home resident at time *i*. The entropy rate, $H(\mathcal{X})$, measures the average conditional entropy $H(X_{n+1}|X_n, X_{n-1}, \ldots, X_1)$ when *n* approaches infinity, as shown in Equation 1. This rate can also be interpreted as the growth of the information contained in the trajectory compared to the length of the trajectory.

$$H(\mathcal{X}) = \lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} H(X_{i+1} | X_i, \dots, X_1)$$
(1)

The most powerful prediction model for indoor mobility, characterized by the conditional probability distribution $f(X_{n+1}|T_n)$, would predict the next sensor message (at time n+1) based on the complete past history of resident trajectories (for times 1 through n). Here, X_{n+1} represents the next sensor message, and T_n represents the past history of resident trajectory up to time step n. The maximum predictability Π^{max} , defined as the prediction accuracy of the next sensor message averaged over the entire observed sequence, can be formulated according to Equation 2. In this equation, $P(T_i)$ represents the probability at time *i* of having observed a particular resident trajectory T_i .

$$\Pi^{max} = \lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} \sum_{T_i} \sup_{X_{i+1}} f(X_{i+1}|T_i) P(T_i)$$
(2)

Given an observed trajectory T_i , a predictive estimator $g(T_i) = \hat{X}_{i+1}$ will output an estimated value of \hat{X}_{i+1} . The probability of the estimator's error is then defined as the probability that the estimate does not match the actual next sensor message, X_{i+1} , or $P_e(T_i) = P(\hat{X}_{i+1} \neq X_{i+1})$. Fano's inequality, which relates information lost in a noisy channel to the probability of predictive error [31], states that

$$H_b(P_e(T_i)) + P_e(T_i)\log_2(N) \ge H(X_{i+1}|T_i)$$
(3)

In Equation 3, $H_b(P)$ is the binary entropy function shown in Equation 4 and N represents the number of possible messages that could be observed (number of sensors in the home).

$$H_b(P) = -P\log_2 P - (1-P)\log_2(1-P)$$
(4)

Given the conditional entropy $H(X_{i+1}|T_i)$, Fano's inequality guarantees a lower bound of the probability of error $P_e(T_i)$, and thus an upper bound of the predictability $\Pi(T_i) = 1 - P_e(T_i)$. We can represent the left side of Equation 3 as a function $\Pi(T_i)$, expressed in Equation 5.

$$H_F(\Pi(T_i)) = H_b(1 - \Pi(T_i)) + (1 - \Pi(T_i))\log_2 N \quad (5)$$

Based on the concavity of $H_F(\Pi(T_i))$, we can associate the maximum predictability Π^{max} with the entropy rate of the underlying stationary stochastic process by applying Jensen's inequality, as shown in Equation 9.

$$H(\mathcal{X}) = \lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} H(X_{i+1} | X_i, \dots, X_1)$$
(6)

$$= \lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} \sum_{T_i} H(X_{i+1}|T_i) P(T_i)$$
(7)

$$\leq \lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} \sum_{T_i} H_F(\Pi(T_i)) P(T_i)$$
(8)

$$\leq H_F\left(\lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^n \sum_{T_i} \Pi(T_i) P(T_i)\right) \tag{9}$$

$$=H_F(\Pi^{max})\tag{10}$$

According to Equation 10, given the entropy rate of the underlying stochastic process, the upper bound of predictability of the sequence can be calculated numerically.

B. Estimating Entropy Rate

Having established the association between entropy rate and predictability, the key challenge is to reliably estimate the entropy rate from empirical data with a universal coding method. The entropy rate, defined in Equation 1, is the conditional entropy of the future random variable as the length of the random process approaches infinity. Due to the limited sample size of our empirical data, we implement multiple entropy rate estimators to ensure the consistency of entropy rate estimation.

Previous work by Song et al. [7] and Smith et al. [11] used an entropy rate estimator based on Limpel-Ziv data compression, proposed by Kontoyiannis et al. [32]. In this approach, let $\mathcal{X} = \{X_i\}$ be a stationary ergodic process with entropy rate $H(\mathcal{X}) > 0$. We can then state:

$$\lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} \frac{\Lambda_i^i}{\log_2 n} = \frac{1}{H(\mathcal{X})}$$
(11)

In Equation 11, Λ_i^k is the length of the shortest substring starting at position *i* that does not appear as a continuous substring of the previous *k* symbols.

The entropy rate can also be estimated using the code length after compressing the data. Let $R(T_n)$ denote the size in bits of a sequence $T_n = \{X_n, X_{n-1}, \ldots, X_1\}$ after performing data compression. Takahira et al. verify that the code length per unit, $r(n) = \frac{1}{n}R(T_n)$, is always larger than the entropy rate $H(\mathcal{X})$ [33]. Additionally, provided the stochastic process is stationary and ergodic, a universal text compressor guarantees that the encoding rate converges to the entropy rate. Thus, we estimate the entropy rate by calculating data compression. In our experiments, we compare several stateof-the-art data compressors for this process. Specifically, we select 7-zip deflate (an implementation of Lempel-Ziv 77 [34] with Huffman coding), 7-zip LZMA (an optimized version of LZ77), and 7-zip PPMD (a lossless data compression using prediction by partial matching [35]).

Though all of the above approaches will converge to the true entropy rate, the accuracies of the estimates differ and are affected by the data sample size. To demonstrate the differences between the estimators and contrast the estimated values with the true entropy rate, we generated a state sequence of 10,000,000 time steps based on a second-order Markov chain with 20 states, where the probability of the current state is dependent on the previous 2 states. The state transition probabilities of the second-order Markov chain, characterized by $P(X_{i+1}|X_i, X_{i-1})$, are generated randomly. Thus, the true entropy rate of the synthetic state sequence (i.e., the entropy of the simulated second-order Markov chain) can be calculated based on the entropy rate definition shown in Equation 12.

$$H(\mathcal{X}) = H(X_{i+1}|X_i, X_{i-1})$$

= $\sum_{x_i, x_{i-1}} P(x_i, x_{i-1}) H(X_{i+1}|x_i, x_{i-1})$ (12)

In Equation 12, $P(x_i, x_{i-1})$ is the stationary probability distribution of state sequence $\{x_i, x_{i-1}\}$, and $H(X_{i+1}|x_i, x_{i-1})$ is the entropy of random variable X_{i+1} given the values of the previous two states.

In Figure 2 (top), we plot the entropy rates based on sequence size. For this plot we compare multiple established methods including the LZ77 deflate (H^{LZ77}), LZMA (H^{LZMA}) and PPMD (H^{PPMD}) algorithms, as well as the estimator defined in Equation 11 (H^{est}). Figure 2 (bottom) plots the corresponding predictability of each estimator. To put the results in perspective, we also include the random entropy (H^{rand}) , temporally-uncorrelated entropy (H^{unc}) , and entropy rate (H^{mc}) , of a first-order Markov chain fitted to the synthetic sequence. The random entropy $H^{rand} = \log_2 N$ represents the maximum amount of possible information content in any sequence of N states. The uncorrelated entropy H^{unc} assumes that there is no temporal correlation between consecutive random variables in the random process. In other words, the sensor message at each time step is independently drawn from a probability distribution $P(X_i)$. Thus, H^{unc} can be calculated according to Equation 13, where $P(X_i)$ can be estimated by counting the occurrences of each observable symbol.

$$H^{unc} = -\sum_{X_i} P(X_i) \log_2 P(X_i)$$
(13)

The Markov chain-based entropy rate H^{mc} assumes that the state sequence can be modeled by a Markov chain, characterized by the conditional probability of state transition $P(X_{i+1}|X_i)$. Based on the empirical data, the transition probability can be estimated by maximizing the likelihood of the observed sequence. Thus, the entropy rate of the constructed Markov chain can be calculated according to Equation 14 [31]. Here, $P(X_i)$ is the stationary state distribution of the Markov chain, calculated by solving Equation 15.

$$H^{MC} = -\sum_{X_{i+1}, X_i} P(X_i) P(X_{i+1}|X_i) \log_2 P(X_{i+1}|X_i)$$
(14)



Fig. 2. Entropy rate (top) and predictability (bottom) estimated from synthetic data generated by a second-order Markov chain.

$$P(X_i) = \sum_{X_j} P(X_i | X_j) \;\forall j \tag{15}$$

In Figure 2, the true entropy rate (the red dashed line) is calculated according to Equation 12. As shown, all estimators $(H^{LZ77}, H^{LZMA}, H^{PPMD})$, and H^{est}) converge to the true entropy rate as the sequence length increases. Among the estimators based on the compressed code length (H^{LZ77}, H^{LZMA}) , and H^{PPMD}), PPMD yields the tightest upper bounds and fastest convergence. Due to the dictionary size, the entropy rates reported by those estimators are higher than the actual process entropy rate. Comparatively, H^{est} provides

the most accurate estimate among all of the tested entropy rate estimators. However, H^{est} may undershoot when there is not enough data, leading to an over-estimated predictability. The estimators based on compressed code length are guaranteed to be an upper bound to the actual entropy rate.

The entropy rate of any stochastic process with an alphabet size of 20 should lie between the random entropy H^{rand} (4.33 in this example), indicating that the process is entirely random, and 0, indicating that the process is fully deterministic. The second-order Markov model has an actual entropy rate of 1.35, and thus a corresponding predictability of 83.51%. The entropy rates estimated by H^{est} and H^{PPMD} are 1.52 and

1.60, resulting in an error of predictability of 3.5% and 4.01%, respectively. Since the synthetic data in this example is generated by a second-order Markov chain, a first-order Markov chain is not sufficient to capture patterns in the data. As a result, entropy rate H^{MC} calculated by fitting a first-order Markov chain to the synthetic data is 3.58, much higher than the actual entropy rate of the second-order Markov chain or the estimates reported by H^{est} and H^{PPMD} .

Additionally, the predictability estimated by H^{MC} is more than 30% lower than estimates derived from H^{est} or H^{PPMD} . Compared to H^{MC} , the temporally-uncorrelated entropy H^{unc} is less powerful for capturing regularities in the synthetic data. Quantitatively, the predictability corresponding to the uncorrelated entropy is close to a fully-random sequence, which is more than 40% lower than the first-order Markov chain, and about 80% lower than the predictability calculated from the actual entropy of the sequence. In this example, the random entropy $H^{rand} = 4.33$ sets the upper bound of the information contained in any data sequence with 20 symbols (the number of states in this case). The random entropy can only be achieved if, at any time step, each state is equally probable, meaning $P(X_i) = 1/20$. Thus, the average predictability of such a random stochastic process equals 0.05, as shown in Figure 2.

IV. PREDICTABILITY OF INDOOR HUMAN MOBILITY

In the previous section, we investigated a formal method to determine the theoretical limits of indoor human mobility predictability in real-life settings. Here, we validate our theoretical formulations based on sensor message data collected from 117 smart homes, characterized in Table II. We collected these data from participants using the CASAS Smart Home in a Box technology [6], [36]. Residents in the smart homes performed their normal daily routines while ambient sensors collected data. Data collection in these homes ranged from 2 weeks to over 11 years. Among these homes, 45 smart homes have ≥ 2 residents and 14 of these include pets. The remainder of the 72 smart homes are single-resident, 10 of which include pets. Many of these datasets, as well as the code, are available online¹.

Since the estimated entropy rate accuracy is affected by the data sample size, we start by establishing the relationship between entropy rate estimators and the length of the recorded message sequence. For all of the evaluations, the estimators are trained separately from a random initialization for each home. Figure 3 plots the estimated entropy rates (top) and the corresponding predictability (bottom) against the number of sensor messages. In this example, the sensor messages were collected in a home with multiple residents, home m3, over 6 months. This home was chosen because it houses multiple residents (making the data complex). Furthermore, ground truth resident labels are provided for a subset of this home's data, associating each sensor message with a corresponding resident ID. To provide a time reference in the graphs, the plots include red vertical lines indicate the first, second, third, and fourth weeks, as well as the second, third, and sixth months, on a log scale. Entropy rates in Figure 3 are estimated using the code length of the compressed data based on the LZ77 (deflate) (H^{LZ77}) , LZMA (H^{LZMA}) , and PPMD (H^{PPMD}) algorithms, as well as the entropy rate estimator H^{est} defined in Equation 11. The results are compared against random entropy H^{rand} , uncorrelated entropy H^{unc} , and the entropy rate H^{mc} calculated by fitting a first-order Markov chain to the sensor messages. The predictabilities plotted in Figure 3 are calculated according to Equation 10. Since there are 25 sensors in home m3, the size of alphabet N in Equation 10 is 25.

Among the entropy rate estimators $(H^{LZ77}, H^{LZMA}, H^{PPMD})$ and H^{est} , H^{est} provides the lowest estimates. In the figure, H^{est} oscillates when there is not enough data, and stabilizes after consuming two months of data. Based on such observations, we acknowledge that the entropy rate reported by H^{est} is the best approximation to the true entropy rate of the underlying stochastic process that generates the observed human trajectories. As shown in Figure 3, the upper bound of indoor mobility predictions in this home converges to 79.3% according to the entropy rate estimated by H^{est} . If a first-order Markov model is used to predict the next sensor message triggered by the residents living in the smart home, the prediction accuracy, according to the entropy rate H^{mc} , is 67.5%, indicating that an improvement of 11.8% can potentially be achieved.

By repeating the above experiment for each smart home, we calculated the predictability upper bound of each home. Figure 4 summarizes the upper bounds of resident mobility predictability using entropy estimator H^{est} . Homes with single residents are shown in red and multi-resident homes are colored blue. Homes with pets as well as human residents are indicated with a star symbol. The indoor mobility of residents in some of these homes exhibits high orders of regularity, where the prediction accuracy of resident movement exceeds 95%. As expected, these occur in single-resident homes with no pets. On the contrary, in many multi-resident smart homes, the predictability is much lower and, in some cases, drops below 65%.

A. Homes with Multiple Residents

To further explore the effect of multiple residents and pets on indoor mobility predictability, we pictorially compare predictability between a single resident smart home and a multiresident smart home. Figure 5 shows two resident trajectories that are subsets of the collected sensor data. One trajectory is recorded in a single-resident smart home (home s4) and the other is recorded in a multi-resident smart home (home m3). In the single-resident trajectory recorded in home s1, the resident generally triggers sensors along the path as the individual moves from one part of the home to another. In this case, the next sensor message is expected to be strongly correlated to the previous sensor message. In multi-resident home m3, the merged (dual-resident) trajectory is indicated by red arrows.

¹Links to code and datasets are online at http://casas.wsu.edu

$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Site	Sensors	Residents	Messages	Weeks	Site	Sensors	Residents	Messages	Weeks
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	m1	27	2	1,178,506	54	m2	42	2	6,826,679	236
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	m3	25	2-3	1,378,574	31	m4	70	2	18,944,701	614
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	m5	36	2-3	973,349	52	m6	19	2	1,155,121	31
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	m7	22	2	1,550,683	132	m8	17	2-3	980,093	10
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	m9	39	2-3	409,115	23	m10	47	2-3	176,412	8
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	m11	22	2-3	2,144	2	m12	37	2-3	129,213	6
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	m13	35	2-3	60,377	13	m14	60	2-3	426,996	13
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	m15	40	2-3	236,637	8	m16	51	2-3	293,211	10
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	m17	24	2	153,603	10	m18	27	2	228,634	10
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	m19	22	2	376,708	10	m20	30	2	840,649	16
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	m21	30	2	377,391	13	m22	35	2	1,432,718	80
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	m23	36	2	70,066	3	m24	27	2	249,987	10
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	m25	19	2	307,187	10	m26	25	2	284,137	11
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	m27	36	2	220,960	14	m28	24	2	324,905	12
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	m29	34	3	472,826	15	m30	30	2	114,684	4
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	m31	30	2	249,387	14	b1	27	2	328,260	9
	b2	33	2	437,733	23	b3	25	3	784,428	21
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	b4	20	2	120,469	4	b5	27	4	594,493	13
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	b6	19	2	423,214	14	b7	21	2	242,491	10
	b8	33	2	311,322	15	b9	21	2	288,301	13
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	b10	30	3	1,431,903	24	b11	30	3	599,925	19
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	b12	30	2	249,289		b13	32	2	528,142	15
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	b14	35	2	63,146	6	pl	20	1	1,509,615	82
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	p2	31		207,690	12	p3	29	1	224,022	10
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	p4	18	1	/59,/50	51	p5	20	1	3,884,561	220
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	po	20	1	011,724	18	p/	30	1	290,800	14
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	ро 10	25	1	280,749	10	p9	10	1	469,511	21
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	°2	33	1	285 207	26	s1 •3	32	1	256 301	20
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	52 s4	10	1	630 517	54	- 55 - 5	20	1	56 720	20
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	54 56	34	1	2 583 713	02	sJ •7	30	1	2 300 510	146
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	s8	21	1	2,583,715	299	\$9	33	1	2,355,515	118
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	\$10	30	1	3 154 735	276	\$11	39	1	2 028 153	169
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	s12	33	1	3,395,594	269	\$13	27	1	5,393,455	239
816 29 1 $1,117,701$ 73 817 26 1 $3,778,629$ 273 818 20 1 $818,002$ 51 819 19 1 $205,246$ 24 $s20$ 16 1 $385,107$ 44 $s21$ 25 1 $2,991,898$ 153 $s22$ 27 1 $1,528,537$ 223 $s23$ 20 1 $906,345$ 100 $s24$ 28 1 $438,681$ 31 $s25$ 16 1 $845,371$ 85 $s26$ 18 1 $12,299$ 22 $s27$ 32 1 $2,460,714$ 220 $s28$ 17 1 $1,654,459$ 178 $s29$ 17 1 $1,161,989$ 181 $s30$ 20 1 $4,323,961$ 175 $s31$ 20 1 $1,715,885$ 98 $s32$ 26 1 $371,175$ 27 $s33$ 14 1 $1,379,134$ 211 $s34$ 20 1 $1,155,121$ 211 $s35$ 15 1 $1,681,679$ 207 $s36$ 18 1 $217,944$ 8 $s37$ 25 1 $116,878$ 14 $s38$ 24 1 $280,500$ 12 $s39$ 32 1 $168,677$ 9 $s44$ 17 1 $888,745$ 60 $s45$ 17 1 $2,745,749$ 28 $s46$ 19 1 $532,1015$	s14	33	1	3.423.249	309	\$15	20	1	298.254	21
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	s16	29	1	1.117.701	73	s17	26	1	3.778.629	273
$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	s18	20	1	818.002	51	s19	19	1	205.246	24
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s20	16	1	385,107	44	s21	25	1	2,991,898	153
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s22	27	1	1,528,537	223	s23	20	1	906,345	100
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s24	28	1	438,681	31	s25	16	1	845,371	85
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s26	18	1	12,299	22	s27	32	1	2,460,714	220
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s28	17	1	1,654,459	178	s29	17	1	1,161,989	181
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s30	20	1	4,323,961	175	s31	20	1	1,715,885	98
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s32	26	1	371,175	27	s33	14	1	1,379,134	211
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s34	20	1	1,155,121	211	s35	15	1	1,681,679	207
s38 24 1 280,500 12 s39 32 1 267,881 12 s40 20 1 86,996 10 s41 22 1 364,617 9 s42 28 1 287,873 14 s43 23 1 565,153 20 s44 17 1 888,745 60 s45 17 1 2,745,749 28 s46 19 1 5,321,015 61 s47 19 1 9,768,315 90 s48 17 1 773,010 67 s49 19 1 439,836 43 s50 22 1 395,083 20 s51 30 1 596,031 20 s52 17 1 316,837 20 s53 21 1 185,086 19 s54 20 1 517,534 15 s55 26 1 285,168 10 s56 31 1 311,815 12 s57 29 <t< td=""><td>s36</td><td>18</td><td>1</td><td>217,944</td><td>8</td><td>s37</td><td>25</td><td>1</td><td>116,878</td><td>14</td></t<>	s36	18	1	217,944	8	s37	25	1	116,878	14
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s38	24	1	280,500	12	s39	32	1	267,881	12
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s40	20	1	86,996	10	s41	22	1	364,617	9
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	s42	28	1	287,873	14	s43	23	1	565,153	20
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	s44	17	1	888,745	60	s45	17	1	2,745,749	28
s48 1/ 1 7/3,010 67 s49 19 1 439,836 43 s50 22 1 395,083 20 s51 30 1 596,031 20 s52 17 1 316,837 20 s53 21 1 185,086 19 s54 20 1 517,534 15 s55 26 1 285,168 10 s56 31 1 311,815 12 s57 29 1 254,952 10 s58 30 1 700,171 22 s59 23 1 611,557 19 s60 36 1 468,679 10 s61 36 1 134,012 11	s46	19		5,321,015	61	s47	19		9,768,315	90
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s48	17		773,010	67	s49	19		439,836	43
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	s50	17		395,083	20	\$51	30		596,031	20
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	SJ2	20		510,85/	20	833	21	1	103,080	19
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	\$J4 •56	20		317,334	13	833	20	1	200,108	10
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	\$50	30	1	700 171	12	\$57	29	1	611 557	10
300 1 $700,077$ 10 501 50 1 $154,012$ 11	s50 s60	36	1	468 670	10	\$59	36	1	13/ 012	19
s62 19 17,986 12	s62	19	1	117 986	12	301	50	1	154,012	11

 TABLE II

 Summary of the Smart Home Datasets Used for Evaluation

The actual paths of each resident, identified as R1 and R2, are shown with dotted green arrows and dotted blue arrows, respectively. In multi-resident smart homes, given that sensor messages are not mapped to specific residents, the combined movement is more complex and, therefore, more difficult to predict. As a result, we expect that the predictability of resident

mobility is lower in multi-resident settings when compared to the single-resident scenario. According to the statistics shown in Figure 6, the predictability limit of resident mobility in single-resident homes averages 81.86%, while the upper bound of mobility predictability in multi-resident settings is 74.40%, approximately 7.46% lower on average.



Fig. 3. Entropy rate (top) and corresponding upper bounds of predictability (bottom) estimated based on sensor messages recorded in a sample smart home (home m3).

In addition to the uncertainty caused by multiple residents, pets in the household can also trigger ambient sensors and cause the creation of sensor messages. Because of their smaller mass, some pets do not consistently trigger passive infrared motion sensors, causing what appears to be a "teleporting" effect. This causes an increase in data noise and an overall decrease in predictability. In the experiments, we studied the predictability limits of smart homes with pets in comparison with the smart homes without pets. Based on these results, we found that the decrease in the predictability of indoor mobility caused by pets is 3% in both single-resident and

multi-resident scenarios. Specifically, the predictability limit for single resident homes with pets averages 79.00% and multi-resident homes with pets averages 72.10%.

Because of the inherent difficulty in associating sensor messages with specific individuals in multi-resident scenarios, a simple Markov chain is commonly used to construct a human mobility model based on recorded sensor messages for these situations [24]. A Markov chain conditions the probability distribution of the next sensor message only on the previous sensor message. To model multi-resident movement, we initially fit a first-order Markov chain to the recorded data



Fig. 4. Scatter plot of the entropy (top) and predictability (bottom) of resident mobility estimated in each smart home as a function of the number of sensors in the home. Single resident smart homes are represented as red circles, and multi-resident smart homes are represented in blue. A star marker indicates that the household includes pets.



Fig. 5. Example of resident trajectories observed in a single-resident smart home (home s4, left) and a multi-resident smart home (home m3, right).

and calculated both entropy rates and associated predictability. In Figure 6, we average these values across all single-resident homes without pets, multi-resident homes without pets, single-resident homes with pets, and multi-resident homes with pets. We also compute and plot the theoretical upper bound on predictability for these house categories. In single-resident cases where there are no pets in the household, we found that the predictability of the first-order Markov chain is 6% below the theoretical upper bound of the estimated predictability, while in multi-resident homes or smart homes with pets, the predictability is closer to 8% below the theoretical limit.

We note that the multi-resident homes exhibit the greatest variability in number of residents as well as overall movement patterns. At any particular point in time, the number of residents in these spaces can vary from 0 to 4+. As the number of residents increases, so may the randomness observed in the sequence. Based on the above results, there is certainly room for improvement in constructing more representative mobility models than are found in first-order Markov chains, especially in multi-resident settings.

One possible improvement to consider is employing methods to track multiple resident movements within a smart home



Fig. 6. Comparison of resident mobility predictability with/without multiple residents and with/without pets.

and use this information to disaggregate the combined sensor data time series into separate components. If such a method can effectively track each resident, then we can analyze each resident separately. We explore this idea by utilizing GAMUT, a smart home multi-resident tracking algorithm [?]. Based on analyzing the aggregated sensor stream, GAMUT associates each sensor reading with a corresponding resident. To do this, the algorithm maps sensors onto a latent space using a technique borrowed from word embeddings [37]. Just as words with similar meanings can be mapped close together in a latent space, so GAMUT maps sensors to a latent space such that the distance between a pair of sensors in that space reflects how often one sensor in the pair generates a reading soon after the other.

To track multiple residents based on observed sensor readings, a Gaussian mixture probability density filter is used to model each resident's likely movements. The model needs to account for possible movements within the home as well as cases when a resident enters or leaves, false readings due to noise, and reading caused by more than one resident moving together. Ultimately, a sensor reading is assigned to a resident that yields the highest likelihood. Based on the probability hypothesis density of the residents through time, GAMUT also estimates the number of residents that are in the space at any given time. From this information, one time series containing sensor readings corresponding to movements for r residents is automatically split into r time series, one per resident. This method yielded association accuracies of 0.82 for a home with 2 residents and 0.80 for a home with 4 residents. In these homes, external staff manually annotated 12 days of sensor readings with corresponding resident identifiers to provide ground truth labels. The results of this analysis are included in Figure 6 and show that neither the estimated predictability nor the Markov-modeled predictability exhibit much deviation from the original approach of modeling multiple residents as a single complex entity.

B. Staypoints

Our analysis so far focused on all movements that a resident makes within a home. A separate but related consideration is the predictability of a resident's intended location destinations. For example, if the resident is heading from the kitchen to an office area, sensors will generate readings along the path between the origin and destination locations. These intermediate locations may be more geometrically constrained (e.g., sensors in doorways and along hallways) and thus boost predictability.

To assess intended location predictability, we filter the original data to only consider "staypoints", or sensor-observed regions where the resident stays for at least one minute before moving to another location. The results for staypoint analysis of single-resident homes is shown in Figure 6. As the graph indicates, predictability is lower for staypoint locations than for all locations. The drop in predictability occurs for both the estimated predictability and the predictability of the Markov model.

C. Sensor Resolution

In this section, we analyze the observed impact of varying spatio-temporal sensor resolution on movement predictability. Resolution differences are very apparent when comparing indoor and outdoor mobility. A notable difference between outdoor and indoor mobility tracking is the data resolution. Outdoor analyses based their findings on hourly reports with spatial resolutions varying from 10 meters [8] to 3 kilmeters [7]. In the case of our indoor analysis, the mobile sensors update their state every 1.25 seconds and the spatial resolution is 1 meter. Lin et al. [8] note that a trade-off exists between predictability and spatial resolution, thus the observed difference in resolutions indicates that indoor predictability will likely be higher than outdoor predictability. Another factor in comparing these sources of information is that the smart home sensors provide constant monitoring. In contrast, Lin et al. and Song report up to 25% and 80% missing locations, respectively. Such missing information introduces uncertainty into the empirical estimates.

An important consideration for the practical application of predictability analysis is to observe the impact of spatial sensor resolution on mobility predictability. To provide insight on the relationship between spatial resolution and predictability, we simulate a lower spatial resolution by aggregating individual sensors and their readings into just one "simulated" sensor for each room or region of the home. On average, we are replacing three sensors in the original data with one sensor in the aggregated data. The results are shown in Figure 6. As the graph indicates, the predictability of both single resident homes and multiple resident homes increases as the sensor resolution decreases. This experiment assumes that there are still no gaps in coverage, just less precision for monitoring movement. As a result, there are fewer states to model and predict, thus simplifying the prediction problem.

D. Sensor Reliability

We note that the empirical results discussed here are subject to sensor error. For PIR motion sensors, error can originate from multiple sources. In some homes, there may be gaps in coverage. As a result, residents may move to locations that are not reflected in the sensor message sequence. Occasionally, motion sensors can generate false positive messages when hit with heat from an outside source such as a laser printer or baseboard heater. We estimated these errors occurred fewer than 0.05% of the days that were monitored. More commonly, sensor messages may be lost due to communication errors. In the CASAS smart homes, these are alerted as "radio errors". Such errors occurred on less than 0.45% of the monitored days.

Some of the errors due to ambient sensors could be corrected by fusing multiple sensor sources [38], such as fusing ambient sensor data with that of wearable and object sensors. Each data source is faced with challenges including sensor noise, participant non-compliance, and gaps in coverage. However, fusing data from multiple sources can harness the strengths of the individual sensor modalities to compensate for the weaknesses of others.

V. CONCLUSIONS

In this study, we investigated the limits of predictability for indoor human mobility. We examined multiple methods for modeling this predictability and provided evidence to support the models based on sensor messages collected from 117 smart homes. In single-resident smart homes, we found that the upper bound of the prediction accuracy for the next sensor message averages 83%. With the presence of multiple people in the smart home, the predictability lowers on average by 11%. If pets are present in smart homes, the predictability decreases by approximately 3% for both single-resident and multi-resident settings.

Although deriving a predictive model for a particular resident is beyond the scope of this paper, the above results provide an expectation of mobility prediction performance in real-world deployments. For applications that rely on the prediction of resident movement trajectories, developers can make more educated design decisions to achieve an improved user experience based on the statistical limits of mobility prediction performance.

Moreover, we can use the difference between the theoretical limits of predictability and the prediction accuracy of a particular mobility model as a quantitative absolute measurement of the performance of the mobility model. In the experiments, we assessed the performance of Markov chain-based mobility model in both single-resident and multi-resident settings. In terms of predictability, we found that the performance of Markov chain models is approximately 6% lower than the theoretical upper bound in single resident settings and 11% lower in multi-resident settings. The results indicate that more representative models could be developed for indoor human mobility, especially in multi-resident homes. To construct a mobility model that achieves a performance above the theoretical limit of predictability, information in addition to the residents' past trajectory, such as the time of day, the day of the week, and the length of resident stay at specific locations, will be needed.

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