Empirical Characterization of Mobility of Multi-Device Internet Users

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Understanding the mobility of humans and their devices is a fundamental problem in mobile computing. While there has been much work on empirical analysis of human mobility using mobile device data, prior work has largely assumed devices to be independent and has not considered the implications of modern Internet users owning multiple mobile devices that exhibit correlated mobility patterns. Also, prior work has analyzed mobility at the spatial scale of the underlying mobile dataset and has not analyzed mobility characteristics at different spatial scales and its implications on system design. In this paper, we empirically analyze the mobility of modern Internet users owning multiple devices at multiple spatial scales using a large campus WiFi dataset. First, our results show that mobility of multiple devices belonging to a user needs to be analyzed and modeled as a group, rather than independently, and that there are substantial differences in the correlations exhibited by device trajectories across users that also need to be considered. Second, our analysis shows that the mobility of users shows different characteristics at different spatial scales such as within and across buildings. Third, we demonstrate the implications of these results by presenting generative models that highlight the importance of considering the spatial scale of mobility as well as multi-device mobility. More broadly, our empirical results point to the need for new modeling research to fully capture the nuances of mobility of modern multi-device users.

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1 INTRODUCTION

Understanding the mobility of users and their devices has become ever more important in the era of the mobile Internet—mobile behavior has broad implications on the design of mobile services, wireless networks, edge computing, and urban infrastructure. Over the past decade, there has been extensive work on understanding human mobility at urban scales [11, 19, 45, 48] and on modeling such mobility [10, 14, 24, 28, 30, 31, 35, 44] by using a variety of sources such as cellular, WiFi, social media check-ins, and vehicular data [16, 17, 23, 42]. This body of work has largely assumed mobile devices to be independent, an assumption that no longer holds in an era of mobile Internet users who own a multitude of devices that exhibit correlated mobility patterns. Further, prior work has analyzed or modeled mobility patterns at a single spatial scale—often that of the underlying dataset—and has not considered the impact of mobility at different spatial scales on system design.

In this paper, we focus on characterizing the mobility of modern mobile Internet users with a view to answering three questions: (1) Since modern users own multiple mobile devices, how
correlated or different are the mobility patterns exhibited by different devices belonging to the same user? (2) How do mobility patterns of devices and users vary across different spatial scales? (3) What are the implications of these findings on problems such as mobility modeling and system design? We address these research questions by conducting a large-scale study using a campus WiFi dataset from a large university campus comprising 156 buildings and 5104 WiFi access points; the four month long dataset comprises 35,699 users and 70,040 devices. We also discuss ethical considerations that arise when conducting this study (§ 3.1).

In conducting our study, this paper makes three main contributions. First, through analysis and modeling, we show that it is important to analyze the collection of each user’s devices as a group rather than treating them as independent, and also show that correlations in trajectories within such group can vary significantly across users. Second, we show that mobility characteristics of devices are different at different spatial scales. Others have observed, for example, that outdoor mobility differs from mobility of humans indoors. Given our campus data set, we quantify these differences by examining micro-scale mobility inside buildings (“intra-building scale”) and macro-scale mobility across buildings (“inter-building mobility”). Finally, we present generative models for multi-device users and mobility at multiple spatial scales and show how these models yield improvements for mobility problems such as next-location prediction and finding misplaced devices.

Key Results: Our empirical study reveals many new findings and insights. First, our analysis reveals mobility decreases with increasing spatial scales—we find 8X more mobility at intra-building (micro) scale than inter-building (macro) scale. The opposite is true for time spent at each visited

**Fig. 1. Intra and Inter-building Mobility**

**Fig. 2. Different devices of a user exhibit dissimilar trajectories**
location—inter-building visits have 2X higher stay durations than intra-building ones. Second, we find that the type of mobile device has a significant impact on its mobility—phones exhibit 3.5X more mobility in terms of locations visited per day than laptops by virtue of being smaller and more portable, implying that device type matters and should be considered when designing algorithms and systems for a mix of devices. Third, we find that different devices owned by a user exhibit moderate to strong correlations in their daily trajectories, but the degree of correlation can vary in significant ways based on the user. Finally, we find intra-building and inter-building mobility to be far more frequent, in terms of locations visited per day, than outdoor urban-scale mobility results from prior work, confirming our hypothesis that the spatial scale of mobility should be a key design consideration.

2 BACKGROUND

| Study               | Data Source  | Spatial Scale     | Multi-device users | Use case            |
|---------------------|--------------|-------------------|--------------------|---------------------|
| Tsinghua campus [51]| WiFi, SNMP, Apps | Single, flat      | No                 | Student behavior   |
| SMU campus [20, 21] | WiFi, Apps   | Single, flat      | No                 | Group/user behavior|
| Dartmouth campus [27]| Network WLAN | Single, flat      | No                 | Network optimization|
| Corporate campus [5] | Network WLAN | Single, flat      | No                 | WLAN characterization|
| Our study           | WiFi syslog  | Inter- & Intra-building | Yes             | Modeling           |

Table 1. Comparison with Prior Campus-scale Mobility Studies

In this section, we present background on characterizing human mobility using mobile devices. Humans as Nomads: Human mobile behavior is assumed to be nomadic in nature, where nomad-icity involves traveling to a location, staying at that location for a period of time, followed by travel to a new location, and so on [25]. The process of moving between two successive locations is referred to as a transition, while the stationary behavior at a location is denoted as a stationary period. The path of a mobile user over time is referred to as their trajectory.

Early work in mobile computing focused on characterizing such nomadic behavior as random walks, where the choice of the next location was random [4, 7, 36, 36]. However subsequent research showed that human activities follow daily and weekly routines, and there are significant spatial and temporal correlations as well as recurring patterns in the locations visited by mobile users [3, 14, 15, 22, 49]. These empirical characterization studies led to new modeling efforts [10, 14, 24, 28, 30, 35, 37] that employed markov models [13, 28, 28, 29, 33] as well as deep learning techniques such as recurrent neural networks (RNNs) [12, 31, 32, 39, 41] to capture these dependencies in mobility patterns. A variety of data sources have been used to drive the empirical studies as well as the subsequent modeling efforts, ranging from GPS, cellular, WiFi logs of mobile devices, social media check-in data [2, 6, 9, 16, 40, 49], as well as transportation data such as taxi logs [14, 40].

Outdoor versus Indoor Mobility: Much of the above work has focused on outdoor mobility to understand how humans move from one location to another at the spatial scale of a city or community (i.e., at urban-scales) [19, 34, 39, 46, 47]. Humans spend over 80% of their lifetime indoors [26], and indoor mobility is known to be different from outdoor mobility patterns [50, 51]. Specifically, indoor mobility is concerned with how users and their devices exhibit nomadic behavior within buildings—that is, what locations (buildings, rooms) users visit, how long they stay at each location, and the transition path between locations; since indoor movements are based on walking, we are not concerned with the velocity of transitions—unlike outdoor mobility in vehicles, for instance.

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Mobility at spatial scales: In the context of campus-scale mobility, mobility can be analyzed at two spatial scales: inter- and intra-building scales. Inter-building mobility is concerned with macro-scale mobility from one building to another; in this case, the entire building is assumed to be single spatial location and we characterize nomadic behavior in terms of time spent in a building, transition time to the next building, and so on. Intra-building mobility is concerned with micro-scale mobility inside a building—i.e., how the time spent in a single building can be further broken down into mobility across rooms or locations within that building; in this case, rooms, specific areas within the building or even access points are assumed to specific locations and mobility is viewed at the finer spatial scale across these locations. Figure 1 illustrates the inter-building and intra-building trajectories of an actual user; at inter-building scale, the trajectory reveals the sequence of buildings visited over a day and the times spent in each, while at intra-building scale, the trajectory reveals what locations were visited by the user when visiting each of those buildings.

Multi-device Users: Modern Internet users carry multiple devices. A common use case is to own a smartphone and a laptop, but many users will own more than two devices that include tablets, e-readers, and wearable smartwatches, among others. Users will use their devices differently, causing them to exhibit different mobility patterns. For example, a user may carry their phone everywhere they go while at work, but they may not take their laptop to activities such as lunch that do not require the laptop. This will cause the mobile behavior of the laptop to deviate from that of the phone even though both are owned by the same user. Thus, we distinguish between user mobility and device mobility and assume that each mobile device exhibits a distinct mobility pattern, which approximates to varying degrees of the true mobility of their owner. Further, the user’s device that exhibits the greatest mobility—often the one that the user takes with them “everywhere”—yields the best approximation of the user’s mobility. Figure 2 illustrates these differences by depicting mobile and laptop trajectory for an actual user. As shown, both devices visit the same location whenever the user brings both devices to that location; the figure shows that the user often leaves the laptop at a location but takes the phone with them when visiting other locations inside a building or even other buildings, causing trajectory deviations. The trajectories converge again when the user returns to the previous location.

Mobility in Campus Environments: Campus settings are well-suited for studying mobility for several reasons. Users in university or corporate campuses spend a significant portion of the work day working or studying in such settings. Such users tend to be tech-savvy and own a multitude of mobile devices, and campus environments tend to have ubiquitous WiFi network coverage. Finally, since a campus comprises multiple buildings, it enables mobility analysis at different spatial scales, such as intra- and inter-building characterization of mobility.

Relation to prior work on campus-scale mobility: While much prior work focuses on outdoor mobility, there have been a few campus-scale mobility characterization studies, at university campuses such as Dartmouth [18, 27], SMU [20, 21] and Tsinghua [51] and in corporate campuses [5]. However, none of these studies have examined mobility of multi-device users or that at different spatial scales. These studies do not analyze mobility at micro- and macro-scales (nor are we aware of efforts to characterize outdoor urban-scale mobility at multiple spatial scales). Further, prior studies have not focused on users with multiple mobile devices—prior work from the early 2000s was conducted in the pre-smartphone era and implicitly assumed a single device per user environment, with laptops being the primary user device[5, 27]. More recent studies [20, 21, 51] did not focus on this specific research question, and have instead focused on other issues such as crowd activities [51], group behavior [20, 21] or networking aspects [5]. Table 1 summarizes these differences.

3 DATASET AND METHODOLOGY
This section describes our dataset, followed by the methodology used in our analysis.
3.1 Campus WiFi Dataset

Our campus-scale indoor mobility study is based on WiFi data from a large university campus (name removed for double-blind review). The campus comprises 156 buildings spread over 1460 acres and is a residential campus where most undergraduate students live on campus. Wireless connectivity is available in all campus buildings and also in many outdoor spaces. The campus WiFi network consists of 5104 HP Aruba access points (APs) that are managed by seven wireless controllers. The controllers receive syslog messages of all events seen by the APs; these logs contain many types of events, of which six events types are relevant to our study: (i) association, (ii) disassociation, (iii) re-association, (iv) user authentication, (v) deauthentication, and (vi) drift events. Since the campus WiFi network uses enterprise RADIUS authentication, all user devices must first authenticate themselves before they connect to the network. Doing so generates authentication and deauthentication log messages, which allows the network to associate each device with a particular user. Once authenticated, the device can then associate with a nearby access point, which generates an association message in the event logs. If the device moves out of range or wakes up from sleep, it may generate disassociation, reassociation, or drift messages.

| Item Description         | Value                                      |
|--------------------------|--------------------------------------------|
| Duration                 | Fall 2018 (Sep-Dec)                        |
| Num. events in log       | 9.6 billion                                |
| Num. of Buildings         | 156                                        |
| Num. of APs              | 5104                                       |
| Num. of devices           | 70,040                                     |
| Num. of Student users     | 24,791                                     |
| Num. of Faculty-staff users | 5293                                    |

Table 2. Dataset Description

WiFi Logs: Each event in the log consists of a timestamp, the event type, the MAC address of the device, and the Access Point ID. In addition, authentication and deauthentication events also include the user name and user type (which can be one of student, faculty-staff, or guest). For privacy reasons, all device MAC addresses and user names are anonymized using a SHA-1 hash function. Since the location of all access points are known (in terms of the building and floor where they are deployed), each of six event types represents a “presence” event, since it indicates the presence of that device in the vicinity of the access point (and its corresponding location). The sequence of presence events generated by a device over the course of the day then reveals all the AP (and building-specific) locations visited by that device and the time spent at each location. Further, since each device must first authenticate to the network using its owner’s user ID, the owner of each device is known, which in turn reveals the collection of devices owned by each user.

This data collection has been ongoing since 2013 for various longitudinal studies. Unless specified otherwise, for computational tractability, our analysis focuses on a single university semester, namely Fall 2018, which spans from September to December 2018 (see Table 2). The event log for this one semester is over 260GB in size and contains 9.6 billion events spanning 70,040 devices, 24,791 student users and 5293 faculty-staff users.

Ethical considerations: All data collection and analysis was conducted under a set of safeguards and restrictions approved by our Institutional Review Board (IRB) and a Data Usage Agreement.
(DUA) with the campus network IT group. All MAC addresses and user names in the trace are anonymized using a strong hashing algorithm. Further, the software used to perform anonymization performs all hash-based anonymization prior to storing the data on disk (i.e., stored files only contain anonymized data) and the hash keys are known only to an IT manager and unknown to us. Our IRB protocol and DUA explicitly prohibit us from any mobility analysis that could de-anonymize users. Researchers need to undergo ethics training and sign a form consenting to these restrictions on the data. Finally, all end-users who connect to the campus WiFi network need to consent to the campus IT agreement that allows syslog data to be collected for security reasons and for aggregated analysis.

3.2 Trajectory Extraction Over Noisy Data

We now describe our methodology for extracting the mobility trajectory exhibited by each device using noisy syslog traces and validation of the generated trajectories. From the overall trace, we first extract a trace of events generated by that device using its hashed MAC address. This device-specific trace enables us to reconstruct the trajectory of the device over each day. Specifically, the timestamped presence messages reveal the sequence of locations visited by the device during each day and the time spent at each location. For students who stay on campus in residence halls, we can reconstruct a trajectory for the entire day, while for faculty, staff and student who live off-campus, we can reconstruct device trajectories for the portion of each day spent on campus. Each device trace reveals a trajectory comprising a sequence of stationary and transition periods. A stationary period indicates that the device is stationary at a particular location (by virtue of being associated with the same AP for a period of time). A transition period indicates that the device is "on the move," which is seen as a sequence of association events with different APs, each of a short time duration.

For the purpose of this study, we use a 10 minute threshold to distinguish between a stationary and transition state for a device—if a device is associated with an AP for a duration greater than 10 minutes, we label the current location as a stationary period, otherwise the location is assumed to be part of a transition period in the overall device trajectory. The 10 minute threshold was chosen after a careful analysis of the data. Figure 3 depicts the number of stationary periods (i.e., locations) visited by a device obtained for different thresholds. A smaller threshold implies that even short stays at an access point will get labeled as stationary periods. The figure depicts that the curve flattens at 10 minutes and stays flat beyond this threshold value; such a 10 minute threshold, also employed by others [24], aligns with human notions of visiting a location versus transiting through one.

Handling Noise: The trajectories extracted from raw traces will be inherently noisy. For example, mobile devices may connect to access points that not the most proximal, or “ping-pong” between nearby access points even though the user is stationary. Similarly, when the user is walking to a new location, devices may connect to distant APs in weakly connected regions or exhibit similar ping-pong switching effects. Since we are using the AP location to determine the device location, all of these effects introduce noise or spurious location changes into our extracted trajectories. To address this issues, the raw traces are subjected to a multiple filtering and smoothing steps during trajectory extraction to remove noise and obtain clean trajectories for each device. Due to space constraints, full details of these smoothing and filtering steps for data cleaning may be found in [1] (anonymous TR is available upon request through the PC chair).

Validating Trajectories: We conducted a small-scale study to validate that device trajectories derived from the WiFi dataset corresponds to the ground-truth device trajectory. To do so, we had volunteers mimic user behavior by walking with a phone to various campus buildings, spend some time inside each building, and then walk to next building and so on. The ground truth trajectory (i.e., locations and times) recorded by the user were compared to that extracted from the WiFi
log of the phone. Our validation study revealed more than 99% accuracy between the extracted locations and the ground truth for indoor locations and deviations of no more than 20-40 meters in outdoor locations when walking outside, providing confidence that our dataset enables us to study campus-scale mobility behavior. Additional details of this validation study and results may be found in [1].

3.3 Device Classification

Our WiFi logs allow us to associate a device to a user and determine all devices belonging to a user, but they do not include any information to determine the type of each device—anonymized MAC addresses alone do not reveal device type. Consequently, we develop a simple classification technique that uses the network behavior exhibited by each device to infer its device type.

First, we observe that differences in OS power management results in different network behavior during idle periods for different device types. Devices such as phones, and many tablets, tend to be powered on at all times—even when the user is not actively using the device. When these devices become idle, their network interfaces enter a low-power listen state but stay powered up (e.g., to receive push notifications, chat messages, or video calls). Hence the device continues to maintain a network presence and is periodically visible to the WiFi network. Consequently, when a user walks from one location to another, the access points along the path periodically see the presence of the device (through scans, association or disassociation messages). Of course, if the user actively uses their device when walking, the device maintains a continuous, rather than periodic, network presence along the path. Either way, the trajectory of such always-on devices is visible to the network during a location transition.

In contrast, mobile devices such as laptops tend to hibernate when not in active use (e.g., when the laptop lid is closed). The hibernate power state results in network interfaces being powered down, and the device no longer maintains a network presence while hibernating. Consequently, when a user walks with a laptop from one location to another, the device is not visible to the network during the walk and only becomes visible when a user begins using the device at the new location.

This difference in network behavior during transition periods and the resulting network visibility of the device (or lack thereof) enables us to distinguish between, and classify, always-on and hibernating devices. The most common always-on device in our current environment is a phone\(^1\) while the most common hibernating device is a laptop.

Validation: Since the above classification method is a heuristic, we conducted a small-scale study to validate its accuracy. We had a volunteer mimic actual user behavior by visiting various buildings and walking within and across buildings over a period of 3 weeks and 8 hours each day; the user used two iOS devices (phone and tablet), one android phone, and 3 laptops with MacOS, Windows and Linux. In each case, we used the daily trace from the device to classify its type using the above heuristic. We found that all devices get classified with perfect accuracy as an always-on or hibernating device when using a day long trace. The only way a laptop can get mis-classified as an always-on device is to walk with the laptop’s lid open so that it shows network presence during location transitions. However, it is highly unlikely that users will always use a laptop in this manner over multiple days, even if they occasionally walk to a location with an open laptop. Further, our analysis uses day-long traces over multiple randomly-chosen days from the 4 month dataset to

\(^1\)For privacy reasons, even partial MAC address prefixes, which reveal vendor and device type, are unavailable to us.

\(^2\)Smart watches, which are another type of always-on device, were not present in our dataset since they do not support RADIUS authentication for enterprise WiFi networks.
classify each device, which significantly reduces the chances of mis-classification. Consequently, our heuristic is able to classify devices as always-on or hibernating with high accuracy.

**Result:** We classified all devices in our WiFi log using the above method, and Table 3 depicts our results. As shown, 73.08% of all devices maintain a network presence during location transitions and are classified as always-on devices. The remaining 26.91% devices do not exhibit any presence during location transitions and are classified as hibernating devices.

For the purpose of our study, we further classify all devices belonging to each user as primary and secondary. A user’s primary device is defined as the always-on device that exhibits the greatest mobility (greatest number of stationary periods per day) across all always-on devices owned by that user. All other devices belonging to that user, whether always-on or hibernating, are defined as secondary devices. By virtue of being the user’s most mobile device, the primary device also provides the best approximation of the user’s actual mobile behavior. With a high likelihood, a user’s primary device is likely to be a mobile phone. Further, with high likelihood, a hibernating secondary device belonging to the user is likely to be a laptop. After labeling all devices as always-on and hibernating and then labeling each user’s device as primary and secondary, we see in Table 4 that 89.54% of users own a primary device. This also implies that 10.45% of our users either do not own a smartphone or do not connect their phone to the campus WiFi network. The table shows that 94.52% of our users own at least one secondary device. Since multi-device ownership is common on our campus, there is a substantial overlap between these two user groups, as discussed next.

### 4 MULTI-DEVICE USERS

In this section, we analyze the mobility of different devices owned by a user and the mobility across device types.

#### 4.1 Multi-device Ownership

To analyze device ownership, we first consider our entire longitudinal dataset spanning 2013 to 2018. Figure 4 shows the mean number of devices per user over this five year period. As shown, device ownership has grown steadily in recent years—the mean number of mobile devices per user
grew from 1.63 in 2013 to 2.04 in 2018. Next, we focus on the Fall 2018 semester used for this study and analyze multi-device ownership across broad classes of users. Figure 5 plots the probability distribution of device ownership across students, faculty-staff, and the combination of the two. The CDF shows that the majority of the users—84.4% of the students and 46.1% of faculty-staff—own two or more devices. The average student owns 2.1 devices, while the average faculty-staff user owns 1.7 devices, indicating that students own more devices, on average than other user types. This is not surprising since younger users tend to be more tech-savvy, and furthermore, a large majority of students (> 60%) stay on-campus and connect all of their devices to the networks (while faculty and staff who live off-campus may not bring all of their devices to work). Interestingly, the figure also shows that 18% of users own three or more devices, with 1.33% users owning five or more devices.

**Key Takeaway**
- Device ownership has increased steadily over time, and the typical user now owns 2.04 devices.
- 18% of the users own three devices or more.

### 4.2 Characterizing Device Mobility

To characterize the mobility of different types of devices owned by a user, we considered the primary device (i.e., the phone) and the hibernating secondary device (i.e., the laptop) for each user, which is also the common case for device ownership on our campus.

Figure 6 depicts the CDF of intra-building locations visited per day for the two device types. The CDF reveals that phones visit 35.9 intra-building locations, on average, per day, while laptops visit 10.2 locations, which yields a 3.5X more mobility for phones than laptops. More generally, since devices as laptops are less portable than phones, users will carry them to fewer locations, causing them to exhibit lower mobility—the “less portable” the device, the lower its mobility. In the future, as wearable devices such as smartwatches become common, we expect them to be even more mobile than today’s phones.

![Fig. 7. PDF of similarity scores of primary and secondary device trajectories.](image)

Recall also from Figure 2 that while the phone trajectory will often deviate from the laptop and the two will converge again when the user returns to the laptop’s location. Thus, despite having lower mobility, the laptop’s trajectory is correlated to the phone’s trajectory since both depend on the user’s mobility behavior. To understand the degree of similarity between the two, we computed the pairwise similarities in the stationary location trajectories for each user’s phone and laptop using Longest Common Subsequence (LCSS) score. We choose LCSS as a measure of similarity since it is robust to noise and can handle synchronous or random shifts of the location sequence.
Thus, small variations in trajectories do not have a large impact on the similarity measure. We compute the similarity score as a ratio of the length of LCSS to the length of the union of the primary and secondary trajectories; the higher the score the higher is the device trajectory co-relation and vice-versa. Figure 7 depicts the PDF of the similarity scores obtained for all users. The similarity scores range from 0.06-0.86, with a mean of 0.37. The plot shows that 31.9% device pairs have a weak similarity score of less than 0.3, 59.1% device pairs have a moderate similarity score between 0.3 and 0.6 and 9% device pairs have a high similarity score of 0.6 or more. Thus, more than two-thirds of the users use their phones and laptops such that the two device trajectories show moderate to strong correlations, and this behavior is true despite phones having 3.5X higher mobility than laptops. The maximum similarity score is 0.86 which indicates that even the most correlated pair of devices nevertheless see some dissimilarities in their trajectories. Our analysis shows that a user’s mobile devices should not be viewed as independent due to their moderate to strongly correlated mobility patterns. Further, these correlations vary significantly across users, which should also be considered in system design and modeling.

**Key Takeaway**
- More portable devices such as phones exhibit 3.5X more mobility in terms of location visits than laptops.
- Primary and secondary device trajectories for over two-thirds of the users show moderate to strong correlations.

5 MACRO AND MICRO-SCALE MOBILITY

In this section, we analyze mobility at macro (inter-building) and micro (intra-building) spatial scales. Unless specified otherwise, all results in this section are based on the users’ primary device.

5.1 Macro-scale Inter-building Mobility

To analyze mobility at the macro scale of entire buildings, consider the trajectory of each user’s primary device, which is a sequence of AP locations visited by that user. Since building- and floor-specific locations of each AP are known, we can assign a building label to each visited AP, and then aggregate a consecutive sequence of APs with the same building label as a single location, representing a visit to that building with a corresponding aggregated visit duration. The transformed inter-building trajectories then yield a sequence of buildings visited by each user, time spent in each building, and transitions across buildings. At this macro scale, user trajectories are only concerned with visits to buildings and transitions between buildings, but not what happens inside a building.

*Stationary period analysis:* Figure 8(a) plots the distribution of the number of buildings visited by a user over a day. The distribution reveals that the average user visits 4.1 buildings per day; highly mobile users, depicted by the 90-th percentile of the distribution, visit 9.8 buildings per day. The distribution also shows that students are more mobile than faculty and staff, with students visiting 4.4 buildings per day, on average, and faculty and staff visiting 1.2 buildings, on average. Figure 8(b) plots the distribution of the *unique* number of buildings visited by users each day (where multiple visits to a building count as a single unique location). The figure shows that a user visits 2.7 unique buildings, on average, each day, which implies users often return to their primary office building after a visit to another building or visit the same building (e.g., dining hall) multiple times per day.

Figure 9(a) shows the PDF of the time spent in each building by a user. The PDF shows that a campus user spends 109 minutes, on average, visiting a campus building. Further analysis of this distribution reveals that about 30% of building visits last less than 1.5 hours; 29% of all building visits are long visits, lasting an average of 5.8 hours, indicating that the tail of the distribution has a substantial mass. Figure 9(b) plots the total time spent in each unique building visited versus the
number of buildings visited by users each day. The figure shows that both less mobile as well as highly mobile users spend between 60 to 80% of their day in a single building, with the remainder of the day spent visiting other buildings for shorter periods. This result shows that most users spend a majority of their day in a single "home" building (e.g., office or residence hall).

Transition analysis: Next, we analyze temporal aspects of inter-building mobility by focusing on inter-building transitions. Figure 10 (a) depicts the CDF of the number of transitions per day made by campus users. Since each visit to a building must be preceded by a transition, the mean number of transitions is the same as (or, for off-campus users, one more than) the number of buildings visited, with a mean of 4.1 transitions per user per day. Figure 10(b) depicts the CDF of the duration of each inter-building transition. The figure shows that average transition time, which is usually a walk between two buildings, lasts 8.4 minutes and 6.5 minutes for students and faculty-staff users, respectively. Figure 10(c) shows the CDF of the total time spent in walking between buildings over the entire day. The figure shows that the average student spends 42.2 minutes per day walking between buildings, while the average faculty-staff user spends 16.1 minutes. Finally, Figure 10(d) depicts the CDF of the distance traveled when walking from buildings to another, and shows the average walk between campus building is 0.22 miles.
Interestingly, we also find that about 15% of all inter-building transitions on campus are loops, with the same origin and destination. Such transitions last 15 minutes, on average, and involve a walk of 0.6 miles. We believe that such transitions occur when users go for a walk during break, or walk to another building to for an errand and return to their previous building.

Figure 11(a) and (b) depicts the heatmap of the when users move between buildings. Faculty and staff users make inter-building visits at all times of the day during working hours, as shown in Figure 11(a), with a significant density of transitions during the noon lunch hour. Transition times during evenings, nights, and weekends are more diffused for these users. In contrast, Figure 11(b) shows that student transitions during weekdays are highly aligned with lecture start and end times between 8 to 6pm, and are more dispersed during other hours. The weekend transitions do not show such patterns since there are no classes on weekends.
5.2 Micro-scale Intra-building Mobility

Next, we examine intra-building mobility by characterizing micro-scale behavior of what users do while inside a building. We do so by analyzing trajectories of AP locations visited by the user’s primary device inside each building.

Figure 12(a) shows the CDFs of locations visited (i.e., stationary periods) by a user inside a building. Interestingly, our results show that students visit 8.6 locations, on average, inside a building, while faculty and staff users visit 12.1 locations. In other words, at intra-building scale, faculty and staff exhibit higher mobility (by 1.4X) than students, which can be attributed to them spending more time inside each building due to the lower inter-building mobility. Since each stationary period is preceded by a transition, Figure 12(a) also represents the mean number of transitions inside a building (not counting the final transition when the user departs from the building). Figure 12(b) shows the CDF of time spent at each location inside a building. The figure shows that students and faculty spend 37 and 40 minutes, respectively, on average, when visiting a location inside a building, indicating the mobility is similar across user types. Figure 12(c) analyzes the duration of each intra-building transition. Such transitions result from users walking inside a building to see a colleague, go to a class or meeting, or to take a restroom break. The CDF shows that the average transition within a building takes 1.5 minutes for faculty-staff and 1.48 minutes for students, which is again similar across user types.

Importantly, over the course of a day, the typical user makes 35.9 intra-building transitions across all visited buildings. Thus, we see 8X more mobility at intra-building (micro) scale than at inter-building (macro) scale, implying that mobility decreases at higher spatial scales (37.8 intra-building vs 4.1 inter-buildings locations visited). Faculty-staff users make 14.8 intra-building transitions,
while students make 37.9 transitions; in doing so, they spend 22.3 and 56 minutes walking inside buildings, respectively. Highly mobile users representing the 90-th percentile of the distribution make 59.8 intra-building transitions across all visited buildings, and spend a total of 90.4 minutes walking inside buildings.

![Fig. 13. Distribution of times spent across unique locations inside a building](image1)

![Fig. 14. Heatmap showing transitions by building type](image2)

Figure 13 plots the distribution of time spent at unique locations visited inside a building versus the number of visited locations. Unlike the inter-building scale, where users spent 60 to 80% of the time inside a single building, at inter-building scale, we find that users spend only 30 to 60% of the time at their most visited location; that number rises to 60% or greater when we consider the top three most frequented location for each user.

Finally, Figure 14 shows a heat map of when intra-building transitions occur over the day. We find that mobility patterns inside a building are highly dependent on the type of the building—an academic building sees very different intra-building mobility patterns than a residence hall. Figure 14 shows four different buildings from our overall analysis: a dining hall, a residence hall, an academic building, and an administration building. The figure shows residence hall users making intra-building transitions at all times of the day, while the academic buildings see transitions correlated with lecture start and end times as well as arrival and departure times. The dining halls see a high concentration of transitions at meal times such as breakfast, lunch, and dinner, while the administration building sees transitions during AM arrivals and PM departures and uniform mobility in-between. More broadly, we find that the type of indoor space governs the type of intra-building mobility patterns that will be seen in that space.

**Key Takeaway**

- The typical campus user visits 8.97 locations inside each building during a building visit. Over a day, a typical user visits 35.9 intra-building locations across all visited buildings.
- Users exhibit nearly 8X more mobility at intra-building scale than inter-building scale.
- While the amount of mobility decreases (by 8X) with increasing spatial scale, the time spent at each visited location increases (by a factor of 2) with increasing scale.

3Despite making fewer intra-building transition per visit, the higher number of buildings visited per day still yields an overall higher number of transitions for students.
• Unlike inter-building mobility, users do not exhibit any affinity to a single intra-building location; over 60% of the time during a building visit is spent at the three or fewer indoor locations.
• The type of indoor space governs the intra-building mobility patterns that are seen in that space.

6 MOBILITY MODELING

Our results on multi-device users and mobility spatial scales (§ 4 and 5) have several implications on system design and modeling. We present two generative models, one each for modeling multi-device user and spatial scales, that leverage the insights from our analysis.

6.1 Modeling Multi-device Users

Our analysis in §4 showed that trajectories of a user’s devices are correlated and pointed to the need to model these dependencies, rather than treating them as independent. To do so, we present a generative model that models the mobility of a group of correlated devices.

Our group model is based on a machine learning framework called multi task learning (MTL) [8] that is designed to learn multiple related tasks, while exploiting the similarities and differences between tasks. As noted in [8], doing so can improve both learning and prediction efficiency, when compared to training models separately. In our case, the task is one of predicting a device trajectory. We hypothesize that a MTL model that models a collection of correlated devices will be richer and better than modeling each device independently.

Figure 15 depicts the architecture of our MTL model. The model is initially trained using trajectories of all $k$ devices belonging to a particular user. Once trained, the model takes the trajectory of a device within that group and predicts the trajectory of the other $k - 1$ devices for that period. This is feasible since the trained model has learnt how the trajectories of devices within the group are correlated, and hence, can use the input trajectory of a device to predict the rest. As shown in 15, we use a hard parameter sharing approach with two shared layers shared between all devices and one device-specific layer per device. Note also that since all $k$ devices share the same training data samples and same feature space, our MTL problem reduces to a homogenous feature multi-label learning problem.

Such an MTL model that captures the mobility of a collection of related devices has many use cases. First, it allows a more compact method for capturing the mobility of each user. Once the model is trained for each use, we no longer need to track all of the user’s devices. Instead it is sufficient to track the mobility of a single device for that user since the model can predict the mobility behavior of the remaining devices. In the future when each user could own dozens of mobile devices, such a
group model can be powerful method to track each user’s mobility in a compact manner using a single device while still capturing the behavior of the user’s entire collection of devices.

Interestingly, it is not even necessary to use the user’s most active device, i.e., their primary device, to represent the user’s mobile behavior. A MTL model is powerful enough to take a sparse trajectory of a (secondary) device such as a laptop and predict the dense trajectory of a phone, even though the laptop may not visit many of the locations visited by the phone. MTL models can, of course, use the dense trajectory of a primary device to predict sparse trajectories of secondary devices belonging to the user.

We trained MTL models for 100 different users and device collections from our dataset; the device groups represents varying degrees of correlations in mobility patterns discussed in §4. We trained each model using data from 30 days. Once trained, we used each device belonging to a user to predict the trajectories of the remaining \(k - 1\) devices using the model, and compared the predictions to the ground-truth trajectory of those devices. As shown in table 5, the average recall for predictions made from a sparse trajectory such as laptop to a dense trajectory such as a tablet or smartphone is 82.1% while from a dense trajectory to a sparse trajectory is 95.1%. Note that this prediction accuracy is computed over a range of users with different degrees of correlations in their device trajectories. Next, we compared our group model to predictions made by individual models learnt independently for each device; each individual device model is based on a Long Short Term Memory (LSTM)-based RNN with RELU activation, MSE loss and adam optimizer. An independent device LSTM model is well-suited for using trajectory from a previous day to predict one for the present day, but it can make erroneous prediction when the user’s mobility shows non-conformance from regularly observed repeating patterns. In contrast, an MTL model is robust to such non-conforming mobility behavior since it uses the current trajectory of a device to predict those of the rest, and the non-conforming behavior is captured in the current trajectory used as model input. We carefully selected days when users had non-conforming mobility patterns and used both the MTL and individual device models to predict trajectories. As shown in Table 6, the MTL has atleast 32% points higher accuracy during non-conformance behavior when compared to the predictions made by individual models. Together, these results confirm our hypothesis that group mobility modeling is superior to individual device mobility modeling due to the highly correlated device trajectories.

### 6.2 Generative Model at Multiple Spatial Scales

Our results in §5 highlighted the importance of using an appropriate spatial scale when addressing mobility problems. In this section, we show that choice of the “correct” spatial scale can make a significant difference when addressing common mobility problems. To do so, we consider the next location prediction problem, which is a widely studied problem in mobile computing [10, 14, 32, 38]. Consider a location-aware mobile service that uses next location prediction in a campus setting to predict the next building visited by a user in order to prefetch useful information such as a list of...
current events and a building map before the user arrives at the building. Given our WiFi dataset, if device trajectories are modeled at the spatial scale of AP-level locations (i.e., intra-building scale), a next location prediction model will predict the next AP location visited by the user, which may be a location in the current building. In fact, a sequence of next $k$ AP locations need to be predicted by the model to determine the next building. As noted in §5, a user visits 9 locations, on average, inside each building, implying that a sequence of 9 next locations needs to be predicted to determine the next building, on average. On the other hand, if we model device trajectories at inter-building spatial scale, the problem of determining the next building becomes a straightforward task of predicting the next location. Clearly, the accuracy of predicting the immediate next location will be higher than a sequence of 9 future locations.

To demonstrate this difference, we use a LSTM-based RNN model to perform next location predictions both at inter-building and intra-building spatial scales. We use the LSTM model to predict a sequence of future locations. Our inter-building LSTM model is trained on past trajectories of building visits made by a group of users, while the intra-building LSTM model is trained on the same trajectories but using AP-level location visits. Both LSTM models have RELU activation, MSE loss and adam optimizer. Figure 16 depicts these models. We use the inter-building LSTM model to predict the next building visit, given the immediate past trajectory of a user. For the intra-building LSTM model, we predict a sequence of 9 next APs visited and use this sequence to determine the next building location.

As shown in Table 7, we find that the inter-building model has an mean accuracy of 92.9%, while the intra-building model has a much lower accuracy of 57.5% when trained on the same dataset containing 1500 users. Figure 17(a) and (b) show the confusion matrix of predictions made by
inter- and intra-building LSTM models, with the inter-building spatial scale model yielding better accuracy. Together, these results highlight how choice of the spatial scale can enhance the accuracy of a mobility model (here, LSTMs) when performing tasks such as next location predictions.

7 IMPLICATIONS OF OUR RESULTS

We now discuss the broader implications of our results.

Campus-scale Mobility: Overall, we find that campus-scale mobility in building depends on five key factors:

Spatial Scale: Our results show that as the spatial scale becomes coarser, the amount of mobility in terms of locations visited decreases with a corresponding increase in time spent at each visited location. We found that intra-building mobility was 8X more frequent with shorter stays at each location than inter-building mobility. Since mobility is more frequent at micro scales than macro scales, a judicious choice of the correct spatial scale is necessary when addressing system design problems, as shown in §6.

Device type: Our results indicate that less portable devices have lower mobility, since phones were found to be 3.5X more mobile than laptops. This key finding implies that all mobile devices should not be treated as equal and optimizing systems based on device type (or size-based groupings) may yield a better overall design.

Multi-device ownership: Given the prevalence of multi-device ownership, treating devices as being independent of others is no longer a reasonable approach. Our results showed that device trajectories of various devices owned by a user exhibit moderate to strong correlations but also that the degree of correlations varies considerably from user to user. Thus jointly modeling group of devices owned by a user or exploiting mobility pattern of one device to predict those of others for that user may yield better results, as shown in §6.

User behavior: Some users will naturally be more mobile than others, and this mobile behavior manifests differently at different scales. At a given scale, highly-mobile users visit several times more locations than the average user. Across spatial scales, users who visit more buildings per day are less mobile, on a per-visit basis, at the intra-building scale, since their higher inter-building mobility results in shorter stays and few intra-building location visits per building. These findings manifested themselves in our study as students being more mobile, as a group, at inter-building scales, and faculty-staff, as a group, visiting more locations per building visit at intra-building scale.

Building type: Our results show that the intra-building mobility patterns are heavily dependent on the type of the building; the functions served by a building determine how frequently and when indoor mobility will be seen. The same user will exhibit different mobile behavior in different types of buildings, which implies that mobile behavior is not just a user characteristic but also depends on the building type.

Outdoor versus Indoor Mobility: Our study reveals important differences between outdoor and indoor mobility and also some similarities. First, similar to the findings in [51], we find that mobility in buildings is far more frequent than urban-scale outdoor mobility in terms of the number of locations visited. Of course, transition times and distance traveled will naturally be smaller inside buildings than in outdoor spaces. Thus, results from outdoor mobility should not be directly employed when designing systems that will be primarily deployed and used inside buildings or on campuses. Interestingly, outdoor mobility can be viewed as a natural progression in the hierarchy from inter-building mobility, and when viewed from this standpoint, it naturally follows that mobility (in term of number of locations visited) will be lower at outdoor scales than finer indoor building scales—in line with our hierarchical spatial scale findings. A hierarchical study that combines both outdoor and indoor mobility in an integrated fashion is left to future work.
8 CONCLUSIONS AND FUTURE WORK

This paper presented an analysis and modeling of mobility of multi-device users in a university campus. Our study showed that mobility decreases with spatial scale—with 8X less mobility at inter-building scale than intra-building scale. We also found that mobility is related to device type—phones have 3.5X greater mobility than laptops. Despite these differences, devices belonging to the same user show moderate to strong correlations in mobility for the majority of the users, and the type of building has a significant influence on the frequency and timing of mobility patterns observed in it. Our generative models highlighted how these insights can be exploited to build better models to capture campus-scale user mobility patterns. Overall, our study revealed significant differences between mobility in buildings and prior results on urban-scale outdoor mobility, indicating that system designers need to carefully consider our findings when designing systems for indoor use.

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