# *Flutes* vs. *Cellos*: Analyzing Mobility-Traffic Correlations in Large WLAN Traces

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***Abstract*—Two major factors affecting mobile network performance are *mobility* and *traffic* patterns. Simulations and analytical-based performance evaluations rely on models to approximate factors affecting the network. Hence, the understanding of mobility and traffic is imperative to the effective evaluation and efficient design of future mobile networks. Current models target either mobility or traffic, but do not capture their interplay. Many trace-based mobility models have largely used pre-smartphone datasets (e.g., AP-logs), or much coarser granularity (e.g., cell-towers) traces. This raises questions regarding the relevance of existing models, and motivates our study to revisit this area. In this study, we conduct a multi-dimensional analysis, to *quantitatively* characterize mobility and traffic spatio-temporal patterns, for laptops and smartphones, leading to a detailed integrated mobility-traffic analysis. Our study is *data-driven*, as we collect and mine capacious datasets (with 30TB, 300k devices) that capture all of these dimensions. The investigation is performed using our systematic (*FLAMeS*) framework. Overall, dozens of mobility and traffic features have been analyzed. The insights and lessons learnt serve as guidelines and a first step towards future *integrated mobility-traffic models*. In addition, our work acts as a stepping-stone towards a richer, more-realistic suite of *mobile test scenarios* and *benchmarks*.**

## I. Introduction

Human mobility has been studied extensively and many models have been derived. The spectrum ranges from simple synthetic mobility models to complex trace-based models, capturing different properties with varying degrees of accuracy [1], [2]. Similarly, network traffic has been studied increasingly for wireless networks: for rather stationary users (as in WLANs) (e.g., [3], [4]) and potentially mobile users as for cellular networks (e.g., [5], [6]). Such analyses range from metrics such as flow count, sizes, and traffic volume to service usage (e.g., visited web sites, backend services).

Both mobility and network usage, characterize different aspects of human behavior. In this sense, we have a *mobility plane* and a *(network) traffic plane*. In reality, these two planes are likely interdependent. Human mobility may be influenced by network activity; for example, a person slowing down to read incoming messages. Also, network activity may be influenced by mobility and location; stationary users may produce/consume more data than those walking, and people may use different services in different places [7].

In earlier studies, this interdependence has not been widely considered, and models for both mobility and network traffic planes have been developed and evaluated largely in isolation. For example, when evaluating mobile systems' performance, traffic generation generally follows regular patterns, drawn from common simple distributions (e.g., exponential or uniform), while assuming neither transmission nor reception of data impacts mobility. Simply observing people walking while staring at (or reacting to) their smartphones suggests, however, that such interdependencies need to be captured properly. Understanding the mobility-traffic interplay is imperative to the effective evaluation and efficient design of future mobile algorithms ranging from user behavior prediction and caching, to network load estimation and resource allocation.

In this paper, we take a stab at understanding the interconnection of the mobility and traffic planes. To do this properly, we need to consider the nature of mobile devices people use: one class of devices is merely intended for stationary use, typically while the user is seated—this primarily holds for laptop computers, dubbed ***cellos***. In contrast, another class—'on-the-go' smartphones, which we refer to as ***flutes***—lend themselves to truly mobile use[1]. We focus our analysis on these two classes because they have been around long enough to have extensive datasets to build upon. We stipulate that the interconnection of the mobility and traffic is modulated by the device(s) a mobile user is carrying. Therefore, we follow two main lines of investigation: we develop a framework to differentiate between cellos and flutes, and study both the mobility and traffic patterns for each of those types.

Specifically, the main goal of this paper is to quantitatively investigate the following questions in-depth: *(I) How different are mobility and traffic characteristics across device types, time and space? (II) What are the relationships between these characteristics? (III) Should new models be devised to capture these differences? And, if so, how?*

To answer these questions, a multi-dimensional (comparative) analysis approach is adopted to investigate mobility and traffic spatio-temporal patterns for flutes and cellos. We drive our study with capacious datasets (30TB+) that capture all the above dimensions in a campus society, including over 300k devices (Sec. IV). A systematic *F*ramework for *L*arge-scale *A*nalysis of *M*obil*e* *S*ocieties (*FLAMeS*) is devised for this study, that can also be used to analyze other multi-sourced data in future studies. Our main contributions include:

1) *Integrated mobility-traffic analyses* (Sec. VII): This study is the first to quantify the correlations of numerous

[1]Throughout, we use *flutes* for *smartphones*, and *cellos* for *laptops*.



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features of mobility and traffic simultaneously. This can identify gaps in existing mobile networking models, and reopen the door for future impactful work in this area.

2) *Flutes vs. Cellos analysis* (Sec. V–VI): The device type classification presented here, is an important dimension to understand. This is particularly relevant as new generations of portable devices are introduced, that are different than laptops, traditionally considered in earlier studies.
3) *Systematic multi-dimensional investigation framework* (Sec. III): *FLAMeS* provides the scaffolding needed to process, in multiple dimensions, many features of large sets of measurements from wireless networks, including AP-logs and NetFlow traces. This systematic method can apply to other datasets in future studies.

## II. Related work

To characterize mobility and network usage, existing studies have covered various aspects, including human mobility, device variation, and dataset analysis.

**Human Mobility**: Given its importance in various research areas, human mobility has received significant attention. We refer the reader to [1], [2] for surveys of mobility modeling and analysis. For spatial-temporal patterns, [8] and [9] reveal the regularity and bounds for predicting human mobility using cellular logs. A recent study highlighted the importance of combining different datasets to study various features simultaneously [10]. Our observations are similar to [8], [9], which reaffirms the intrinsic properties of human mobility, despite differences in granularity and population across datasets. To advance the understanding of human mobility, we integrated different datasets to correlate mobility and network traffic.

**Device Variation**: Usage and traffic patterns of different device types have been studied from various perspectives ([11], [12], [13], [14], [15], [16]). However, those findings are based on classifications that rely on either MAC addresses or HTTP headers solely. The former is rather limited and the latter may have serious privacy implications and are often unavailable. In [17], authors use packet-level traces from 10 phones and application-level monitoring from 33 Android devices to analyze smartphone traffic. Although this allowed fine-grained measurements, the approach is invasive and limited in scalability, leading to small sample sizes and restricted conclusions. They also do not compare the traffic of smartphones with that of "stop-to-use" wireless devices (i.e. cellos) nor do they measure spatial metrics. The study in [18] analyzes 32k users on campus, and focuses on multi-device usage. It notes differences between laptops and smartphones in packets, content, and time of usage. That work targets device usage patterns and security, while we study mobility and wireless traffic correlations. In our method, the combination of MAC and NetFlow allowed us to classify majority of observed devices while preserving users' privacy.

**Dataset Analysis**: A recent work on WLAN traces [19] revealed surprising patterns on increases of long-term mobility entropy by age, and the impact of academic majors on students' long-term mobility entropy. The authors of [7] investigated correlations and characteristics of web domains accessed by users and their locations, based on NetFlow and DHCP logs from a university campus in 2004. They propose a simulation paradigm with data-driven parameters, producing realistic scenarios for simulations. However, that study uses data from pre-smartphone era and does not distinguish between device types. It also does not analyze the relation between mobility and traffic. On both WiFi and cellular networks, the authors of [20] performed an in-depth study on smartphone traffic, highlighting the benefits and limitations of using MPTCP. Distributions of flow inter-arrival time (IAT) and arrival rate at APs of "static" flows were analyzed (e.g., Exp, Weibull, Pareto, Lognormal) in [21]. Lognormal was found to best fit the flow sizes, while at small time scales (i.e. hourly), IAT was best described by Weibull but parameters vary from hour to hour. We analyze flows on a much larger scale, newer dataset including smartphones, and identify Lognormal distribution as the best fit for flow sizes, and beta as best for IAT, regardless of device type. The study in [22] analyzed ISP traces with 9600 cellular towers and 150K users in Shanghai, and mapped timed traffic patterns to urban regions. It provided insight into mobile traffic patterns across time, location and frequency. This work is complementary to ours, as we provide a much finer scope analyzing campus WLAN traces.

## III. Systematic multi-dimensional analysis

To methodically analyze statistical characteristics and correlations in multiple dimensions, we introduce the *FLAMeS* framework (Fig. 1). The main components include: I. Data collection and pre-processing, II. Flutes vs. cellos mobility and traffic analysis, and III. Integrated mobility-traffic analysis.

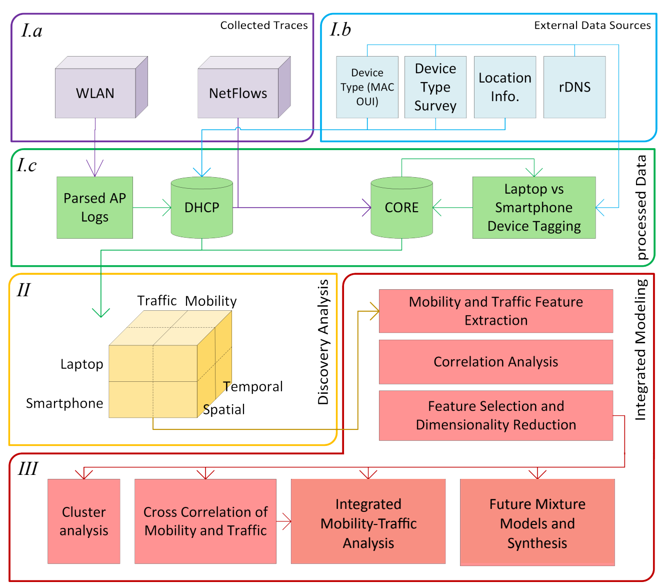



Fig. 1: *FLAMeS* system overview.

The two main purposes of this work are to understand and **quantify** the *gaps between flutes and cellos*, and the *interaction between the mobility and traffic dimensions*. Individual mobility and traffic analyses for flutes and cellos are conducted in Sections V and VI, respectively, with detailed reporting for spatio-temporal features showing significant gaps. In Sec. VII, the most important mobility and traffic features are identified and their correlation quantified.

## IV. Experimental setup and datasets

We drive our framework with large-scale datasets from multiple sources, capturing the mobility and traffic features in different dimensions. In this section, we introduce the two data sets and their preprocessing, and present the device type classification into flutes and cellos.

The *input datasets* in this study are specifically chosen to capture: 1. location, mobility and network traffic information, 2. smartphone and laptop devices, 3. spatio-temporal features, and 4. scale in number of devices and records. The total size is >**30TB**, consisting of two main parts: WLAN Access Point (AP) logs, and Netflow records (details in Tables I, II). [2]

### A. WLAN AP logs

These logs are collected from 1760 APs in 138 buildings over 479 days on a university campus, and contain association and authentication events from 316k devices in 2011-2012. It contains over 555M records, with each record including the device's MAC and assigned IP addresses, the associated AP and a timestamp. Locations of the APs are approximated by the building locations where they are installed, i.e., (longitude, latitude) of Google Maps API. To validate this, we fetched 8000 mapped APs around the campus area from a crowd-sourced service, *wigle.net*. For the 130 matched APs in 42% of buildings (i.e., 58 bldgs), all were less than 200m from their mapped location; an error of less than 1.5% of the campus area. This is very reasonable for our study purposes.

### B. NetFlow logs

Over **76 billion** records of NetFlow traces were collected from the same network, over 25 days in April 2012. A *flow* is defined as a consecutive sequence of packets with the same transport protocol, source/destination IP and port number, as identified by the collecting gateway router. An example of major Netflow data fields is presented in Table II.

The NetFlow records are matched with the wireless associations (from the AP logs) using the dynamic MAC-to-IP address mapping from the DHCP logs. We refer to the result as *CORE* dataset (Table I). They are also augmented with location and website information using reverse DNS (rDNS)[3].

TABLE I: Summary of datasets. B=billion.

| | # Records | | Traffic Vol. (TB) | | # MAC | |
|---|---|---|---|---|---|---|
| | DHCP | CORE | TCP | UDP | WLAN | CORE |
| *Flutes* | 412.0 M | 2.13 B | 56.18 | 4.50 | 186.0 K | 50.3 K |
| *Cellos* | 101.0 M | 4.20 B | 73.85 | 12.90 | 93.2 K | 27.1 K |
| Total | 557.5 M | 6.53 B | 134.39 | 17.61 | 316.0 K | 80.0 K |

[2]Data collected using proper procedures. It does not contain *PII*.

[3]Dataset merging and system details in appendix I & II [23].

### C. Device type classification

To classify devices into flutes and cellos, we utilize several observations and heuristics. To start, note that a device manufacturer (with OUI) can be identified based on the first 3 octets of the MAC address[4]. Most manufacturers produce one type of device (either laptop or phone), but some produce both (e.g., Apple). In the latter case, OUI used for one device type is not used for another. We conducted a survey to help classify 30 MAC prefixes accurately. Using OUI and survey information, we identify and label 46% of the total devices (90k cellos and 56k flutes). Then, from the NetFlow logs of these labeled devices, we observe over 3k devices (92% of which are flutes) contacting *admob.com*; an ad platform serving mainly smartphones and tablets (i.e. flutes). This enables further classification of the remaining MAC addresses. Finally, we apply the following heuristic to the dataset: (1) obtain all OUIs (MAC prefix) that contacted *admob.com*; (2) if it is unlabeled, mark it as a flute. Overall, over 270k devices were labeled (180k as flutes), covering 86% of the devices in AP logs and 97% in NetFlow traces, a reasonable coverage for our purposes. Out of $\approx 80k$ devices in the NetFlow logs, $\approx 50$K are flutes and $\approx 27$K cellos.

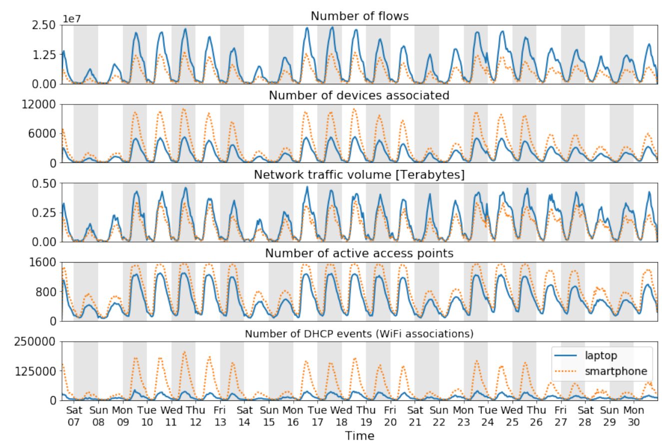



Fig. 2: Time series for 25 days of combined AP-NetFlow Core traces

Fig. 2 shows the temporal plot for the combined traces over 25 days, after device classification. Throughout, the number of flows and total traffic volume is clearly higher for cellos, even with an overall higher number of flutes connected. Also note the device activities in a *diurnal* and *weekly* cycles, with the peaks occurring during weekdays, as expected. Wed, 25th, was the last day of classes, explaining the decline in network activity afterwards. This plot motivates our analyses for *flutes* vs *cellos*, over *weekends* vs *weekdays*, in this study.

## V. Mobility analysis

This section covers the *temporal* and *spatial* mobility analyses. For all metrics, unless otherwise noted, we investigate 479 days. A summary of studied metrics and their most significant statistical values are presented in Tab. III along with mean and median ratios for comparison. From that list, we further

[4]MAC address randomization does not affect our association trace.

TABLE II: NetFlow (top) and AP logs/DHCP (bottom) sample data

| Start time | Finish time | Duration | Source IP | Destination IP | Protocol | Source port | Destination port | Packet count | Flow size |
|---|---|---|---|---|---|---|---|---|---|
| 1334332274.912 | 1334332276.576 | 1.664 | 173.194.37.7 | 10.15.225.126 | TCP | 80 | 60482 | 157 | 217708 |

| User IP | User MAC | AP name | AP MAC | Lease begin time | Lease end time |
|---|---|---|---|---|---|
| 10.130.90.3 | 00:11:22:33:44:55 | b422r143-win-1 | 00:1d:e5:8f:1b:30 | 1333238737 | 1333238741 |

TABLE III: General results for mobility. Upper values are for weekdays and lower ones for weekends (in red color). **LJM**: maximum jump [m]; **DIA**: diameter [m]; **TJM**: total trajectory length [m]; **GYR**: radius of gyration [m]; **BLD**: no. uniq. buildings; **APC**: access point count; **PDT**: time spent at preferred building [minutes]; **DLT**: total session time at each building.

| | Flutes (F) | | | Cellos (C) | | | Ratio (C/F) | |
|---|---|---|---|---|---|---|---|---|
| | $\mu$ | *mdn* | $\sigma$ | $\mu$ | *mdn* | $\sigma$ | $\mu$ | *mdn* |
| **LJM** | 435 | 296 | 813 | 178 | 1 | 624 | 0.409 | **0.003** |
| | 350 | 168 | 683 | 97 | 1 | 312 | 0.277 | 0.006 |
| **DIA** | 549 | 411 | 874 | 195 | 1 | 642 | 0.355 | **0.002** |
| | 425 | 179 | 739 | 107 | 1 | 338 | 0.252 | 0.006 |
| **TJM** | 1582 | 707 | 2336 | 378 | 1 | 1444 | 0.239 | **0.001** |
| | 1036 | 279 | 1793 | 252 | 1 | 1766 | 0.243 | 0.004 |
| **GYR** | 396 | 290 | 2725 | 321 | 191 | 3265 | 1.102 | 1.019 |
| | 330 | 248 | 1368 | 178 | 65.1 | 1800 | 1.247 | 1.4 |
| **BLD** | 5.4 | 3 | 5.6 | 1.8 | 1 | 2.1 | 0.811 | 0.659 |
| | 2.8 | 2 | 4.1 | 1.5 | 1 | 1.8 | 0.539 | 0.262 |
| **APC** | 11.8 | 6 | 13.3 | 3.7 | 2 | 4.8 | 0.333 | 0.333 |
| | 7.2 | 4 | 8.8 | 3 | 2 | 3.8 | 0.536 | 0.5 |
| **PDT** | 225 | 161 | 219 | 248 | 164 | 254 | 0.314 | 0.333 |
| | 223 | 135 | 272 | 278 | 189 | 292 | 0.417 | 0.5 |
| **DTL** | 316 | 235 | 302 | 316 | 217 | 305 | 1 | 0.92 |
| | 326 | 247 | 308 | 316 | 221 | 309 | 0.97 | 0.89 |

investigate in this section those metrics that show the most interesting or non-trivial differences between *flutes* and *cellos*.

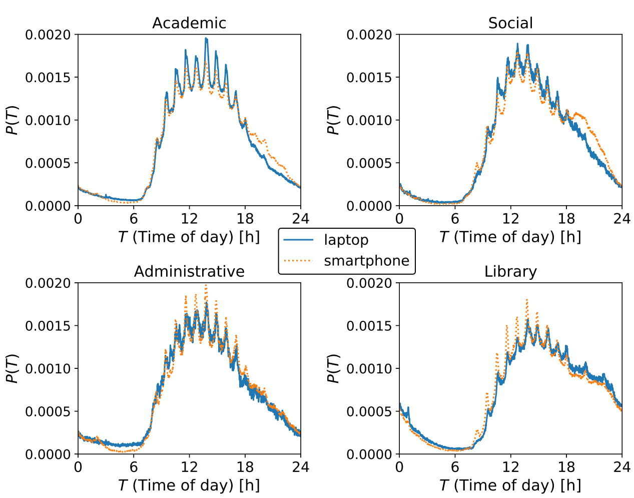



Fig. 3: PDF Session start over time of the day.

### A. Session start probability

A session is defined as the period between WLAN associations. The distributions of session start times across the day for four building categories are depicted in Fig. 3. The start times of the Sessions match the periodic beginning of classes, but mainly in *Academic* buildings, where users move mostly at the start and end of classes. In these places, activity drops sharply for *cellos* at 5pm, with considerable *flutes* activity until 8pm. For *Social* and *Library* buildings, *the probability of new sessions remains higher for a few more hours into the evening, and the times users tend to leave are more spread out*. We do not make similar observation during weekends, which is expected when the day is, unlike weekdays, not governed by a class schedule. For most visitors, the session start distributions show a smooth shape and no significant differences between device types (omitted for brevity).

### B. Radius of gyration

This metric, $GYR$, captures the size of the geospatial dispersion of a device's movements, denoted by $r_g$ and computed as $r_g = \frac{1}{N}\sum_{k=1}^{N}(\vec{r_k} - \vec{r_s})^2$, where $\vec{r_1}, ..., \vec{r_N}$ are positional vectors of a device and $\vec{r_s}$ is its center of gravity.

Grouping devices by their $r_g$ after six months of observation, we look at its evolution since the first time they are observed. Unsurprisingly (cf. [8]), after an initial transient period of about one week, this value stabilizes even across different semesters (not shown).

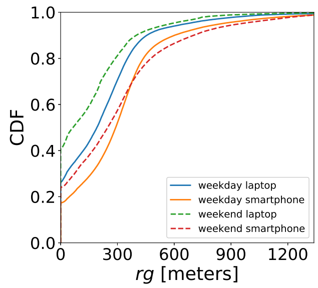
We split the traces into weekdays and weekends, presenting the distributions in Fig. 4a. For *cellos*, we notice a substantial reduction in their overall mobility whereas, for *flutes*, this difference is not so pronounced. This might be due to students having fewer activities on weekends, a tendency to study at a single building like a library, or just not carry their cellos; we will revisit this aspect in Sec. VII. *Flutes*, being "always-on" devices, are able to capture movements at pass-by locations, dining areas, and bus stops and thus are better suited to capture the fine-granular mobility of their users than cellos.

Despite the 8.1km$^2$ area of the campus (approximate radius of 1.42km), buildings with related fields of study (e.g. Fine Arts) are fairly clustered. Computing the distance between the k-nearest neighboring buildings, for $k = 22$ and $k = 9$ (average number of visited buildings for *flutes* and *cellos*) the median distances are 295m and 172m, respectively. Due to their focus on classes, attending students have limited area of activity on weekdays, which explains the observed *radius of gyration*.

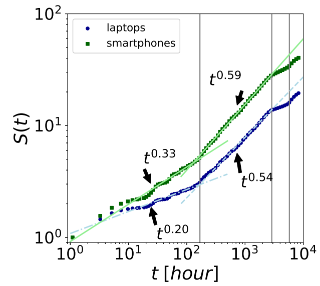
We also evaluated: (1) *diameter* $DIA$, the longest distance between any pair of $\vec{r_k}$ points; (2) *max jump* $LJM$, the longest distance between a pair of consecutive $\vec{r_k}$ points; and (3) *total trajectory length* $TJM$, the sum of all trips made by a device. The distributions of these metrics are similar to *Radius of Gyration* and therefore not shown. Table III summarizes the most significant statistical values for these metrics.

### C. Visitation preferences and interests

We count the number of unique buildings visited by a user, $BLD$, and define a *preferred building* as the location where a device has spent most of its time in a given day, measured in minutes and referred to as $PDT$. We approximate the latter by the formula $t_b = \sum_{k=1}^{N_b} S_k$, where $t_b$ is the time spent, $N_b$ the total number of sessions and $S_1 ... S_N$ the time duration of *each*




(a)




(b)

Fig. 4: (a) Radius of gyration ($rg$ for the device types). (b) Visited locations $S(t)$. Vertical lines at 7, 120 and 240 days.

*session* at a building $b$, here referred as $DLT$. Interestingly, cellos have slightly longer stays but both have medians around 2:40 hours. The similarity of the distributions, combined with a lower number of visited locations indicate that cellos are used mostly when users remain longer periods at places.

Fig. 4b highlights the differences between *flutes* and *cellos* on the required time $t$ to visit $S(t)$ locations. *After an initial exploration period of one week the rates of new visits change similarly for both device types, and new exploration rates show up at 120 and 240 days.* These could be explained by the weekly schedules of the university as well as the usual length of a lecture term ($\approx 4$ months).

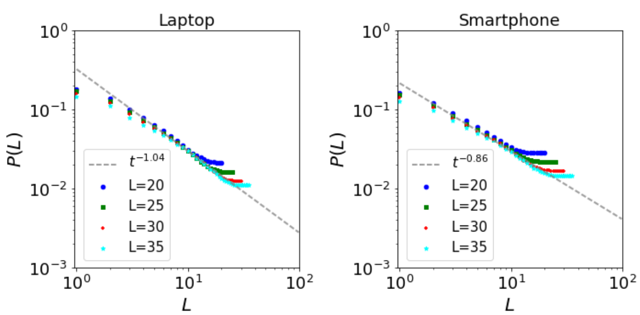



Fig. 5: Zipf's plot on $L$ visited access points.

We also consider the number of unique APs a device associates with, $APC$, which provides a finer spatial resolution than the building level. Furthermore, the probability of finding a device at its *L-th* most visited access point is shown in Fig. 5. When taking buildings as aggregating points for location, the values become $L^{-1.36}$ for *cellos* and $L^{-1.16}$ for *flutes*. These approximations validate previous work on human mobility [8], yet highlight differences between device types.

## D. Sessions per building

To study AP utilization over time, we look at the session duration distribution, or session duration dispersal kernel P(t), depicted in Fig. 6. The smaller inner plots represent the same metric, limited to four types of buildings.

We noted that the five-minute spikes correspond to default idle-timeout for the used WiFi routers. On the other hand, the *knees* at 1 and 2 hours could be explained by the typical duration of classes. They are only noticeable at Academic buildings (shown inside inner plots) and during weekdays (not shown). This leads us to conclude that despite the differences in distributions of device types, *flutes* and *cellos* present *certain similarities in their usage, such as during classes*. To differentiate *pass-by* access points, we examine all sequences of three unique APs where all session durations are lower than 5 minutes (typical idle-timeout). We observed these APs clustered at buildings that also had major bus stops nearby.

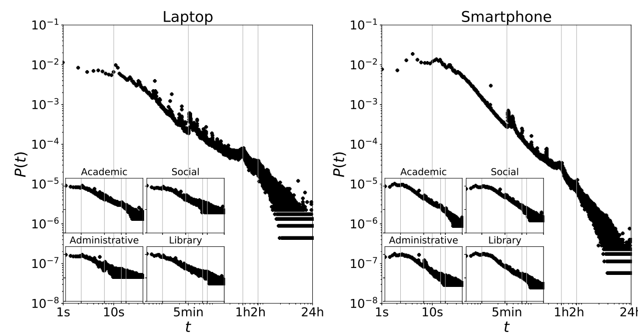
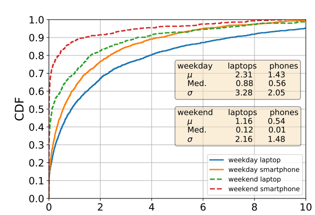


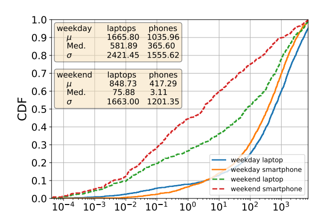

Fig. 6: Probability $P(t)$ of session duration $t$.

## VI. Traffic analysis

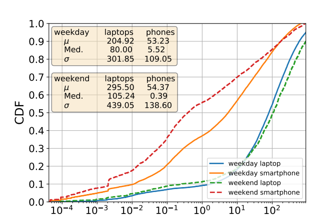
In this section, we compare different *traffic* characteristics, across *device types*, *time* and *space*. For this purpose, we start with statistical characterization of *individual* flute and cello flows. Next, we measure how these flows, *put together*, affect the network patterns across APs and buildings. Finally, *user behavior* is analyzed by monitoring weekly cycles, data rates, and active durations. By quantifying *temporal* and *spatial* variations of traffic across device types, we make a case for new models to capture such variations based on the most relevant attributes. Table IV summarizes the results.



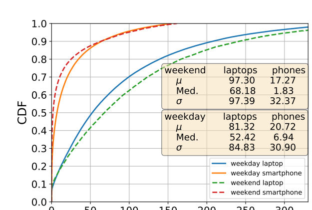

(a) Packet processing rate of APs (millions per day)




(b) Traffic load of APs (MB per day, log-scale)




(c) User data consumption (MB per day, log-scale)




(d) User active time (minutes per day)

Fig. 7: Distribution plots

### A. Flow-level statistical characterization

We compare the following distributions using maximum likelihood estimation (MLE) and maximizing goodness-of-fit estimation: Gaussian, Exponential, Gamma, Weibull, Logistic, Beta and Lognormal[5].

*1) Size:* Flow size is the sum of bytes for all packets within a single flow. On weekdays, average *size of individual flute flows* is $> 2x$ **larger** *than cello flows* (2070 vs. 822 bytes), while median is $> 4x$ **larger** (678 vs. 142 bytes). There are no significant changes on weekends.

The average packet size within a single flow also provides insight into packet-level behavior of services on mobile devices. We notice that the average *packet size of flute flows* is $\approx$**50% larger** *than that of cellos* (212 vs 144 bytes on weekdays, 205 vs 142 on weekends). Comparing weekdays and weekends, median size of flute packets drops on weekends whereas it remains *the same* for cellos. In fact, comparing cello flows on weekdays and weekends shows *no significant difference* in terms of average packet size (p-value$>$ .05). Despite smaller flows, the average cello generates *2.7 times traffic* as an average flute because the average cello is responsible for *3.7 as many flows* as a flute. Analyzing distributions of flow size and average packet size in our datasets shows that *Lognormal* distribution is the best fit, with varying parameters for each device type (More details in Sec. IV of [23] for details).

*2) Packets:* This metric is the count of packets within each flow. The mean and median packet counts per flow are 7.06 and 5 in flutes and 3.64 and 2 in cellos, during weekdays. The means drop slightly on weekends. Packet counts per flow match the *Lognormal* distribution well for flows of both device types. The average flute flow is bigger in size and has *more packets* (with higher variance) but there are *fewer* flows coming from these devices. This is analyzed further for TCP/UDP flows (Sec. VI-A5).

*3) Runtime:* Flow runtime is the period of time the flow was active (equal to a flow's $finishtime - starttime$). Flute flows have a mean and median of 1868ms and 128ms respectively on weekdays, while these numbers are 1639ms and 64ms for cellos. Both device types show increase in means during weekends (flutes by 204 and cellos by 164), indicating that although there are fewer devices online during weekends, they are more active. The low medians in either group corresponds to many *short-lived* flows with few packets, showing little variation across device type, time or space.

*4) Inter-arrival times (IAT):* Median of the flow *IAT*[6] at APs is 6ms for cello flows and 4ms in case of flutes, on weekdays (similar on weekends), which suggests that the majority of APs handle flows from either device type at nearly the same rate. However, average *IAT* is $\approx$ 143ms for flute and $\approx$ 78ms for cello flows, as there are more cellos with very high rate of flows. Flow *IAT* in our datasets matches a **beta** distribution well (See appendix IV in [23]) with a *very high estimated kurtosis* and *skewness* (estimated at 58 & 6.9 respectively). The high estimated kurtosis illustrates that there are *infrequent extreme values*, which explains the observed highly elevated standard deviation of *IAT*. Higher average IAT of flutes, combined with the higher standard deviation compared to cellos (596 vs 284), shows that *flutes face more extreme periods of inactivity, which can be caused by higher mobility and packet loss.*

*5) Protocols:* TCP accounts for *78.5%* of cello flows (**84.6% of bytes**) and *98.2%* of flute flows (**91.6% of bytes**). The higher presence of UDP in cellos is reasonable, considering that UDP applications (e.g., multi-player games, video conferencing and file sharing) are more likely to be used with cellos. Comparing the number of packets in flows, in case of TCP, the average number of packets in cello flows is almost half that of a flute flow (4.6 vs 8.8), and the average packet size of flutes is 22% higher than that of cellos. This supports our earlier observation regarding the bigger flow sizes of flutes. However, for UDP, the two device types are similar in terms of average packet count per flow (2.5 for cellos & 2.87 for flutes) and average packet size (119 for both). This conforms to low latency requirements of many UDP applications.

Given these differences, traffic classification using machine learning [26] could benefit from considering device types to train models. We investigate this in Sec. VII-B.

After establishing the similarities and differences of flows, the next step is to evaluate whether the individual variations in flows lead to different *aggregate traffic behaviors* from viewpoint of the network.

### B. Network-centric (spatial) analysis

We examined the load of APs in all buildings on a daily basis to provide insight into differences from the viewpoint of the network. For each AP, we calculate flow metrics for every weekday and weekend.We focus our analysis on the first three weeks of NetFlow traces to avoid significant user behavior change during exams period, as already shown in Fig. 2.

First, we measure the daily packet and flow arrival rates at APs. The median flow rates are $42k$ and $20k$ per weekday for cellos and flutes respectively (7.5k and 0.5k on weekends). The average number of cello packets processed daily by APs is **1.6 times higher** than flute packets (Fig. 7a). Each AP handles, on average during weekdays, $\approx 27$ *cello packets per second* and $\approx 17$ *flute packets per second*, dropping to $\approx 13.5$ and $\approx 6.25$ on weekends. This indicates that, during the weekends, a high percentage of access points are not utilized, with *60% of APs seeing no flute flows* and *70% receiving no cello flows*. However, *at least one AP in >80% of buildings sees traffic*, supporting observations of less mobility during weekends.

Next, we look at traffic volume. On average weekdays, 90% of APs handle < $5GB$ of cello traffic ($2.5GB$ on weekends), whereas the same percentage handles < $3GB$ of flute traffic ($1GB$ on weekends) (Fig. 7b). Flutes are more mobile, visit a higher number of unique APs and have bigger flow sizes but they are still responsible for *less overall network load.*

[5]For distribution comparison, significance threshold $p - value$ is set at .05.

[6]IAT is important in simulation and modeling of networking protocols, traffic classification [24], congestion control and traffic performance [25]. Our flow-level IAT analysis can also be used for measuring delay and jitter effects.

Thus, the individual differences of flute and cello flows result in *heterogeneous aggregate traffic patterns* in time (different days) and space (APs at different buildings)[7]. With that established, in order to take steps towards modeling and simulation, we also need to analyze the behavior of users.

### C. User behavior (temporal) analysis

Here, we measure traffic patterns from a user-centric perspective. We identified gaps in diurnal and weekly cycles (Fig. 2) as well as traffic flow features of individual *users* including data consumption, packet rates, and network activity duration.

*1) Data consumption:* Fig. 7c shows daily data consumption, with 90% of cellos consuming **< 700MB** and 90% of flutes using **< 200M** on weekdays. Surprisingly, for cellos on campus during weekends, average data consumption is even higher whereas data consumption of flutes drops sharply.

*2) Packet rate:* On weekdays, cellos on average generate **≈318K packets**, while flutes only average **≈84K packets** per day. On weekends, the few on-campus cellos see greatly increased number of packets, with an average daily packet rate of $\approx 495$K. Weekend flutes also have a modestly *increased* packet count, with an average of $\approx 96$K flows.

*3) Active duration:* Total active time of devices serves well to demonstrate the differences between time spent online by users of different device types. We rely on NetFlow to measure **'active'** time instead of AP association time. This allows us to distinguish user's *idle* presence in the network from its *activity* periods. Cellos have **4x** average active time compared to flutes in our traces ($\approx 81$ vs $\approx 21$ min on weekdays, $\approx 97$ vs $\approx 17$ min on weekends). Overall, 90% of cellos are active for <**3.5h** and 90% of flutes are active for <**1h** (Fig. 7d). As evident in various metrics, the cellos appearing on weekends are more active than the average cello on weekdays.

Overall, the data consumption of flutes seems to be *more bursty* in nature, with **bigger** flows and **lower active duration**. This could be due to more intermittent usage of flutes and also bundling of network requests to save battery on these devices. In addition, there are fewer devices on campus during weekends, but those remaining devices are more active and consume more data than average.

## VII. Integrated mobility-traffic analysis

We study the relation between mobility and network traffic features, examine whether their *fusion* provides a case for the necessity of *integrated mobility-traffic models*, and introduce steps towards such models (Sec. VII-B).

### A. Feature engineering

To simplify analysis and interpretation, and reduce dimensionality, we identify the most important features. First, we study the relationships among variables from *mobility* and *traffic* dimensions separately. Then, from this subset of combined features, we investigate whether clusters of user devices appear in the dataset. For this, we use correlation feature selection (*CFS* [27]), to obtain uncorrelated features,

[7]A more in-depth analysis is presented in appendix IV [23].

TABLE IV: Traffic features used for integrated mobility-traffic analysis (per device, per day; see Fig. 8 for abbreviations). Upper values are for weekdays and lower ones for weekends (in red).

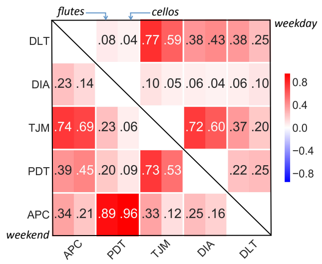
| | Flutes (F) | | | Cellos (C) | | | Ratio (C/F) | |
|---|---|---|---|---|---|---|---|---|
| | $\mu$ | ***mdn*** | $\sigma$ | $\mu$ | ***mdn*** | $\sigma$ | $\mu$ | ***mdn*** |
| TBY | 96.77 | 11.47 | 194.52 | 373.08 | 144.68 | 554.54 | 3.85 | **12.61** |
| [MB] | 80.96 | 0.86 | 195.15 | 448.87 | 180.23 | 623.86 | 5.54 | 209.56 |
| ABY | 5.48 | 0.74 | 14.02 | 15.67 | 7.34 | 25.81 | 2.85 | **9.91** |
| | 4.54 | 0.15 | 14.16 | 18.06 | 8.34 | 28.71 | 3.97 | 55.6 |
| SBY | 10.56 | 1.57 | 23.76 | 30.59 | 13.77 | 49.82 | 2.89 | **8.77** |
| | 8.09 | 0.13 | 21.48 | 33.21 | 15.42 | 53.39 | 4.10 | 118.61 |
| TAT | 1,330 | 388.6 | 2,517 | 5,123 | 3,003 | 6,444 | 3.85 | 7.73 |
| | 1,059 | 90.89 | 2,497 | 5,883 | 3,861 | 6,934 | 5.55 | 42.48 |
| AAT | 63.14 | 27.97 | 86.69 | 188.26 | 166.93 | 138.70 | 2.98 | 5.96 |
| | 50.60 | 12.98 | 85.27 | 206.89 | 184.17 | 156.53 | 4.08 | 14.18 |
| TFC | 7.2 | 1.7 | 15.61 | 33.5 | 17.1 | 60.10 | 4.65 | **10.05** |
| [K] | 5.7 | 0.3 | 15.01 | 38.5 | 20.6 | 88.52 | 6.75 | 68.66 |
| SFC | 515.6 | 177.3 | 907.7 | 1,640 | 1,181 | 2,081 | 3.18 | 6.66 |
| | 361.05 | 30.18 | 796.6 | 1,673 | 1,215 | 2,098 | 4.63 | 40.27 |
| RUB | 0.05 | 0.00 | 0.19 | 0.07 | 0.00 | 0.22 | 1.4 | N/A |
| | 0.06 | 0.00 | 0.22 | 0.08 | 0.00 | 0.23 | 1.33 | N/A |
| RUF | 0.07 | 0.00 | 0.18 | 0.12 | 0.02 | 0.22 | 1.71 | N/A |
| | 0.09 | 0.00 | 0.22 | 0.13 | 0.02 | 0.24 | 1.44 | N/A |
| AIT | 3.36 | 2.24 | 3.59 | 3.40 | 2.45 | 3.51 | 1.01 | 1.09 |
| | 2.95 | 1.74 | 3.60 | 3.18 | 2.27 | 3.39 | 1.07 | 1.3 |
| SIT | 5.22 | 3.44 | 5.50 | 5.14 | 3.18 | 5.28 | 0.98 | 0.92 |
| | 4.09 | 1.98 | 5.06 | 4.72 | 2.79 | 4.96 | 1.15 | 1.41 |

but highly correlated to the classification. Finally, we quantify correlations between mobility and traffic metrics (See abbreviations in Fig. 8). Pearson correlation is shown in the figures.

*1) Mobility:* The *CFS* algorithm was run on 8 features (in Sec. V), and kept only *5* (to be used in the cross-dimension analysis). Fig. 8a visualizes the linear dependence between mobility features, comparing flutes and cellos on weekdays and weekends. Close inspection reveals temporal correlation relationships. For example, for cellos on weekdays, there is a **strong** correlation $(0.96)$ between preferred building time (*PDT*) and time of network association (*DLT*), but weak correlation $(0.1)$ on weekends, suggesting that most of weekend online time is spent at preferred buildings (e.g., libraries).

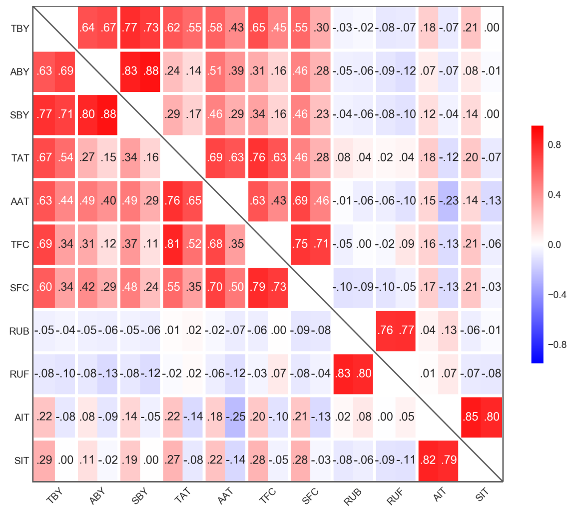
*2) Traffic:* We extract statistical measures for traffic metrics (Sec. VI) per device per day. The *CFS* algorithm was run on 19 features, reducing them to 11. A summary of these metrics is provided in Table IV. The correlations are depicted in Fig. 8b. The analysis shows us that average number of packets and bytes are positively correlated, but negatively correlated with variance of bytes and uncorrelated with IAT. Average IAT (*AIT*) seems to be mostly independent from other traffic features, but as *AIT* increases, its standard deviation (*SIT*) also greatly increases which could be due to device mobility; bearing further investigation on traffic-mobility interactions. Interestingly, active time is *weakly correlated* with number of flows and packets, which shows that users who remain online longer are *not* necessarily consuming traffic at a high rate. Examining weekdays and weekends, correlation trends among traffic features remain similar for either device type.

*3) Cross-dimension:* Studying correlations across mobility and traffic dimensions, based on subsets of features selected by *CFS*, is a solid step towards an integrated mobility-traffic model. Results are presented in Fig. 9. We find that as the numbers of unique APs/buildings visited (*APC*, *BLD*) *increase*,




| Abbr. | Description |
|---|---|
| APC | AP Count (unique) |
| PDT | Preferred building $\Delta t$ |
| TJM | Total (sum) jumps |
| DIA | Diameter of mobility |
| DLT | Delta time (time of network association) |

(a) Mobility




(b) Traffic

| Abbr. | Description |
|---|---|
| TBY | Total flow bytes |
| ABY | Avg. flow bytes |
| SBY | Std. flow bytes |
| TAT | Total active time |
| AAT | Avg. active time |
| TFC | Total flow count |
| SFC | Std. flow counts |
| RUB | UDP bytes / total bytes |
| RUF | UDP flows / total flows |
| AIT | Avg. IAT |
| SIT | Std. IAT |

Fig. 8: Correlation plots for (a) *mobility* and (b) *traffic* features. Each cell's left half is for flutes and right half is for cellos, the upper right triangle is for weekdays and the lower left for weekends.

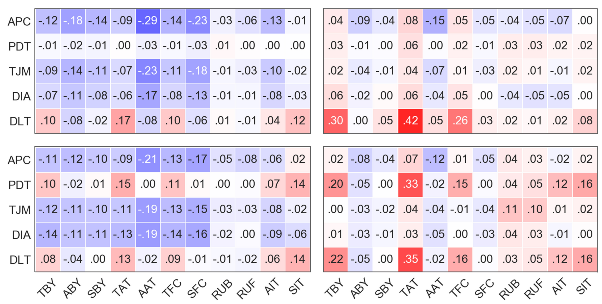



Fig. 9: Correlation plots of mobility vs. traffic on weekdays (top) vs. weekends (bottom) for flutes (left) and cellos (right).

the average active time (*AAT*), and total and std. of flow counts (*TFC* and *SFC*) *decrease* markedly (significant negative correlation). Surprisingly, there is no noticeable change in total traffic consumed with change in *APC*, suggesting bundling of more packets in flute flows. (Similar correlation between mobility diameter and the above traffic features) Average IAT (*AIT*) of flutes also rises slightly as mobility metrics *decrease*; for cellos this correlation is almost *nonexistent*. This reinforces our *"stop-to-use"* categorization; cellos are movable but are not active in transit. To sum, *flutes score high on mobility metrics*, have an overall lower flow count and network traffic but produce bigger flows on average. For cellos, on weekends the more time spent at preferred buildings the higher the total active time (*TAT*) and flow counts; this effect exists to a lesser degree for flutes. On weekdays, such correlation does not exist.

## B. Steps towards modeling

Here we present our steps towards an integrated mobility-traffic model, with various applications in simulation and protocol design. We utilize daily mobility and traffic features of users during a week. First, we examine how different mobility and traffic features are for flutes and cellos using machine learning. Second, we investigate whether natural convex clusters of users appear in the dataset. These steps verify that the differences of mobility and traffic characteristics across device types are *significant*. We also find that *combining mobility* ***and*** *traffic* makes this distinction even more *clear*. Finally, mixture models are used to model and synthesize simulated data points of each device type, finding that the accuracy the mixture model *increases* when trained on *combined* features.

1) Supervised classification: Having shown significant differences throughout this study, we used support vector machines (SVM) on different subsets of features to examine the feasibility of device type inference as well as the relationship between mobility and traffic characteristics. These sets include mobility and traffic features *separately*, then *combined*, and then combined with *weekend/weekday labels*. Using *solely mobility features* achieves ≈65% accuracy, while *traffic features alone*, obtains ≈79% accuracy. Using all mobility and traffic variables *combined*, the trained model achieves ≈81% accuracy. Then, as the **combined** feature set is extended to include *weekdays and weekends* independently, accuracy increases to ≈86%. This suggests that users' behavior (both flutes and cellos) is *more distinguishable* when looking at **combined** mobility and traffic features; especially when *temporal* features such as weekdays are considered separately from weekends. We note that such behavior gaps are *not* the same for both device types and a model should to take that into account.

2) Unsupervised clustering: To investigate natural convex clusters, we used K-means algorithm. Using *mobility features only*, the best mean silhouette coefficient is achieved on k=2 and 4. However, cluster sizes are highly skewed and at k=2, $\approx 60\%$ of devices are correctly clustered. *Traffic features alone*, at k=2, results in $\approx 81.2\%$ accuracy. **Combining** mobility and traffic, *increases* the accuracy to $\approx 81.5\%$. While some flutes and cellos are similar in terms of mobility and traffic, the clusters of the combined features clearly illustrate **two distinct modes** (especially in *traffic*) and the *high homogeneity* of the clusters hints at *disjoint sets of behaviors* in mobility and traffic dimensions, governed by the device type.

3) Mixture model: To take a step towards synthesis of traces based on our datasets, we trained Gaussian mixture models (GMM) on *combined mobility and traffic features*. From the combined model ($CM$), we acquired simulated samples. We used Kolmogorov-Smirnov (KS) statistic to compare the simulated samples with the real data and found that $CM$ is able to capture the behaviors of each device type. (Average KS statistic of features is $\approx 0.15$ **for flutes** and $\approx 0.14$ **for cellos**. More details in appendix V [23].) Importantly, the combined model produces samples whose *traffic* features match the original data **better**, compared with training a GMM *on traffic features alone* (based on KS statistic), hinting at a key relationship between mobility and traffic. However, comparing mobility features of $CM$ with a GMM trained on mobility features alone shows no improvement.

Overall, this suggests that there is significant potential for an ***integrated mobility-traffic model*** that captures the differences and ***relationships*** of features, across ***device types***, ***time*** *and* ***space***. We leave detailed comparison of combined modeling with separate modeling of mobility and traffic for future work.

## VIII. Conclusion

In this study, we mine large-scale WLAN and NetFlow logs from a campus to answer: *(I) How different are mobility and traffic characteristics across device types, time and space? (II) What are the relationships between these characteristics? (III) Should new models be devised to capture these differences? And, if so, how?* We build *FLAMeS*, a framework for systematic processing and analysis of the datasets. Using MAC address survey, OUI matching and web domain analysis, we categorized devices: **flutes** (*"on-the-go"*) and **cellos** (*"stop-to-use"*). We then study a multitude of mobility and traffic metrics, comparing flutes and cellos across time and space. On average, flutes visit twice as many APs as cellos, while cellos generate ≈2x more flows. However, flute flows are 2.5x larger in size, with ≈2x the number of packets. The best fit distribution for location preference is **Zipfian**, for flow/packet sizes is **Lognormal**, and for flow IAT at APs is **beta**. Furthermore, flute traffic drops sharply on weekends whereas many cellos remain active. Across mobility and traffic dimensions, we spot a negative correlation for flutes between mobility and flow duration but negligible correlation with traffic size; for cellos, this effect is less pronounced. We find a negative correlation with APs visited and active time, particularly for flutes. However, no correlation exists between APs visited and traffic for cellos. We *quantified* correlations *across both mobility and traffic*. Finally, we applied machine learning and trained a mixture model to synthesize data points and verified that the **combined** mobility-traffic features capture the *differences* in metrics ***better*** than *either mobility or traffic separately*. Many of our findings are not captured by today's models, and they provide insightful guidelines for the design of evaluation frameworks and simulations models. Hence, this study answered the questions posed, introduced a strong case for newer models, and provided our first step towards a future integrated mobility-traffic model.

**Acknowledgments**: We thank Alin Dobra for help in the computing cluster, and the anonymous reviewers for useful feedback. Mostafa Ammar suggested the term *'cello mobility'*. Partial funding was provided by NSF 1320694 at Univ. of Florida, August-Wilhelm Sheer fellowship at Technical University-Munich, and Aalto Univ.

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