Comparing Wireless Network Usage: Laptop vs Smart-Phones

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1. INTRODUCTION

The proliferation of smart-phones has been simply unprecedented. Unlike laptops, smart-phones have a much smaller form factor, are ultra mobile, include a rich set of sensors (e.g., location, motion), and are tightly coupled with the users. These factors pose a fundamental question regarding the characteristics in mobile users' on-line behavior for these devices, and how their differences (vs laptops) impact networking protocols and services.

Several existing research studies (mobility models [1], behavior models [2]) have been parametrized/designed using real WLAN traces, assuming that movement detected in the traces is indicative of real user movement. The vast majority of the devices in these traces have been laptops. For recent traces, with the presence of always-on mobile devices (smart-phones), we are able to study mobility more accurately, and at a finer granularity. Several fundamental questions are raised: Will the usage be any different? Do we need to revisit the mobility models? The goal of this work is to study difference in the usage characteristics of smart-phones and laptops to shed light on the preceding questions. The main challenges in our study include the collection of extensive recent traces, the classification of mobile devices, and the analysis of various behavioral metrics on a large-scale. To the best of our knowledge, this is the first work that compares laptops and smart-phone on the basis of wireless network usage and behavior.

The result of our analysis shows significant differences between usage of smart-phones and laptops. The differences include shorter session durations for smart-phones (by 67% as compared to laptops), higher number of sessions per day (2 times that of laptops) and visiting new location (3 times that of laptops). We find that these differences are significant and will allow researchers to create better models and future services.

Categories and Subject Descriptors

C.2.m [**Computer Communication Networks**]: Miscellaneous

MobiCom'13, September 30–October 4, Miami, FL, USA.
ACM 978-1-4503-1999-7/13/09.
http://dx.doi.org/10.1145/2500423.2504586.

MAC	Start Time	Duration	AP/Location
00:11:22:33:44:55	01 Jun 2011 21:00:51	3000secs	CS_buildingAP1
11:22:33:44:55:66	01 Sept 2011 21:01:30	10secs	ECE_buildingAP2
01:02:03:04:05:06	01 Sept 2011 22:11:00	200secs	MSL_buildingAP1
10:20:30:40:50:60	01 Sept 2011 22:15:30	600secs	MACA_buildingAP1

Table 1: Wireless Association Trace sample after Processing (MAC address are faux to protect privacy)

Keywords

Network usage, laptop, smart-phone, mobile device

General Terms

Measurement

2. RELATED WORKS

The majority of work on data-driven analysis of mobile networks uses traces from Crawdad [3] and MobiLib [4] that do not include smart-phones. Recently, a handful of works studied smart-phone usage. Authors in [5] compared browsing behavior differences between laptops and smart-phones. Their results indicate that smart-phones abort a large portion of video streaming which the authors feel is due to inadequate browser caching in smart-phones. Another work [6] focuses on discovering why smart-phones are more pervasive in terms of usage. Authors in [7] study the use of smart-phone and laptop/pc in business environment and find that smart-phones can make employees work overtime due to ubiquitous access to office emails. Smart-phone use by non-mobile business user is studied here [8]. Researchers studied the confidence a user has in sending/accessing private information over smart-phones [9]. The above studies show some usage difference between smart-phones and laptops. However, to the best of our knowledge, this study is the first to compare the usage differences based on network access and mobility patterns.

3. DATA SET

In this work we analyze wireless association traces collected at University of Florida (UF) from Sept. 2011 to Dec. 2011. For each wireless association, there is : 1. MAC address of the device associating, 2. Time of the association, 3. Duration of the association and 4. Name of Wireless Access Point (AP), as shown in Tab. 1. The MAC address is used as a unique identifier of a device throughout the trace (here we assume that very few users change the MAC address of their devices). In this trace period almost 120K unique devices make more than 46 Million associations. There are 1700 unique Access Points throughout the campus.

Identification of Smart-phones and Laptops: In the WLAN association trace we collected (Tab. 1), there is no explicit 'device type' information to allow classification of devices into laptops or smart-phones, and the MAC addresses are partially anonymized. However, the manufacturer of

Make	Smart-phone	Laptop
Apple	12485	4121
Rim	1495	
Samsung	2292	
HTC	2096	
Murata	469	
Motorola	405	
Huawei	49	
Sony Ericcson	9	
Asus		392
Intel		14781
HP		82
LiTE-ON		4530
Atheros		23
Total	19300	23929

Table 2: Number of devices detected as Smart-phone and Laptops along with the manufacturers

the wireless network card can be inferred (i.e., identified uniquely) from the first 3 octets of a MAC address (a.k.a. the Organizationally Unique Identifier - OUI), which were kept intact in our trace even after anonymization.

There are several manufacturers that either make only smart-phones (e.g., HTC, RIM, Nokia) or only laptops (e.g., Asus, Dell, HP, Lenovo) but not both (and if they do, the market share in the other segment was less than 1% until the end of the trace period in 2011). However, there are manufacturers such as Apple and Samsung that manufacture both. To distinguish between smart-phones and laptops coming from the same manufacturer, we conduct a user survey where users of different smart-phones were asked to give the first 3 octets of their WiFi MAC address.

The assumption here is that a manufacturer will not use the same MAC address range for both smart-phones and laptops. This assumption is reasonable, since WiFi cards used in laptops are different from those used in smart-phones, thus they are manufactured separately. Hence assigning MAC addresses from the same range may call for unnecessary collaboration and is not commonly practiced. In our survey we did not find any overlapping MAC address ranges between laptops and smart-phones. In our survey, we provide detailed instructions for finding and sharing the MAC address for iOS, Android, and Windows phone OS.

A total of 95 responses were received for our survey that provided us with 30 unique MAC address ranges. These surveys were conducted from Dec 2011 to Jan 2012. Tab. 2 gives the details of our classification.

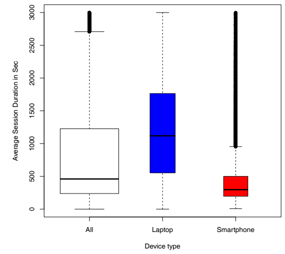
4. ANALYSIS

In this section, we present our results and analysis based on the processing of the traces. The analysis is divided into three main parts based on the temporal, spatial and load characteristics (details [10]). First, we discuss the temporal characteristics, including the overall average duration of sessions for both devices and the session start (i.e., initiation) times in terms of time-of-day. Second, we investigate the spatial aspects with analysis of the number of unique APs visited, the location predictability of users, and the radius of gyration (RG) to estimate the centroid of the user's movements. Finally, we analyze the load characteristics with the number of session made per day by each device kind.

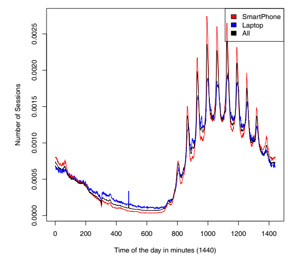
The metrics are evaluated mainly for three sets (i.e., categories) of traces; the first includes 19,300 smart-phones, the second includes 23,929 laptops, and the third includes 120K devices overall. Note that we are interested in analyzing and comparing the mobility during on-line activity (i.e., not physical mobility), which is faithfully captured by WLAN traces.

4.1 Average Session Duration

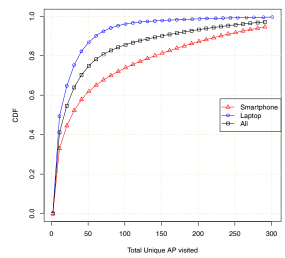
Average session duration can be used to distinguish between the amounts of time spend on-line by different devices. It may also be indicative of user activities. To compute this



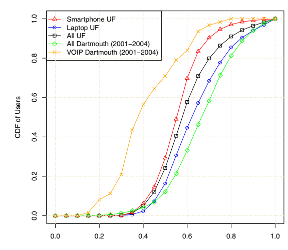
(a) Average Session Duration per user. For clarity the plot only shows average session duration less than 3000 sec



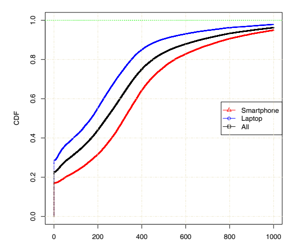
(b) PDF for session starts in minutes



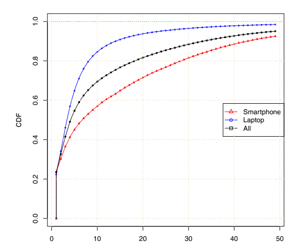
(c) CDF for unique APs visited for entire trace period. Graph is clipped at 300 APs for clarity



(d) CDF of Predictability using Markov O(2) predictor



(e) CDF of Radius of Gyration



(f) CDF for number of sessions per day. Clipped at 50 session for clarity

Figure 1: Analysis Metrics

metric we calculate the average session duration for each of the devices in different categories. The results are plotted in Fig. 1a. We find that an average session for a laptop user is 1900 sec long (∼31 min) and that of a smart-phone user is 630 sec (∼10 min). This indicates that laptop users on average have 3 times longer sessions than a smart-phone user. The session duration for all devices is 1222 sec (∼20 min).

4.2 Session start time

For each category of devices, we look at the PDF of starting a session with respect to time (in minutes). To measure this empirical metric we create 1440 bins denoting the total number of minutes in a day. Each bin contains the normalized number of sessions that start during that respective minute. Fig. 1b shows the PDFs for each device category. It is interesting to note that the PDF of session is low from 0 to 800 mins (12am to 1pm) and then it starts to rise. Another interesting feature on this graph is the presence of 10 spikes between 800 and 1400 minutes. These 10 spikes correlate with 10 hours and occur whenever the class period changes. The spikes are more prominent for smart-phone users than laptop users during class breaks. We note that between two adjacent spikes (i.e., during classes) the probability of laptops starting a session is greater than smart-phones. In-between classes there is a gap of 15 mins which makes smart-phones the easily accessible device for quick browsing and work needs, thus the spikes in smart-phone usage. However, during class, laptops provide most of the browsing, class material access and other work needs so there is a higher probability of sessions created by laptops in the periods between the spikes. This metric, yet again shows us the temporal usage differences between smart-phones and laptops.

4.3 Unique APs Visited

The number of unique APs visited through the trace period can tell us about the mobility experienced by these devices. Questions such as what kind of device is more mobile can be partially answered by this metric (APs remain at fixed location, accessing more unique AP implies visiting more unique locations). Fig. 1c displays the CDF of number of unique AP visited. We note that approximately 50% of the laptop users visit less than 12 unique APs, however, for smart-phone users this number is 28. The average number of unique APs accessed by laptops is 26 where that of smart-phones is 75 (almost 3 times the number visited by laptops). We also note that barely 1% of laptop users visit more than 200 unique APs, whereas there are at least 13% smart-phone users visit more than 200 unique APs (max is 600 which is approximately 1/3 of the total number of APs).

4.4 Predictability

Many applications utilize prediction to achieve functionality (or improve performance), including caching, paging, resource allocation, and capacity planning. Here we look at the user location predictability of these devices. The predictor attempts to predict the next AP that the device will access next, given the history of AP accesses. We use a Markov O(2) predictor (considers past two locations). Earlier studies [10] find this as the best predictor. Predictability results are shown in Fig. 1d. We observe 7% difference in the average prediction accuracy between the laptops and smart-phones, with smart-phones being harder to predict. To show a more fundamental trend that is evolving over the years [1], we add two more curves on this particular graph (Fig. 1d) that include prediction accuracy of the always-on voice-over-IP (VoIP) devices and regular WLAN devices collected from Dartmouth college during from 2001 to 2004 ([11]). As we can see the gap between the prediction accuracy difference between always-on devices (e.g., VoIP devices and smart-phones) and laptops has closed significantly (down from 30% to 7%). On plausible trend could be that users are migrating more predictable activities (traditionally done on laptops) to the more capable smart-phones. We have yet to do a thorough investigation on this cause but intend to work on this in the future.

4.5 Radius of Gyration

Radius of Gyration (RG) measures the standard deviation between a user's movements and the user's center of mass which is the centroid of all the user's movements. A higher RG indicates the user going farther away from the center of mass. Comparing average RG of smart-phone users with laptop users can point out the mobility differences based on the area that they have traveled. Since actual coordinates of AP were not available, we used the Geo-coordinates of the buildings (centroid) to represent the location of the APs. Hence we would not be able to distinguish distance traveled inside buildings. Fig. 1e shows the CDF of RG for smart-phones and laptops. On average, a laptop user travel 255 meters from the center of mass, whereas a smart-phone user travels 449 meters which is almost twice the distance covered by laptop user.

4.6 Number of Sessions per Day

The number of sessions per day is indicative of the load a wireless device puts on the network systems including dhcp, authentication, dynamic configuration change of APs, etc. This metric is also related to temporal characteristic of the wireless device. Fig. 1f shows the empirical CDF comparing laptops and smart-phones. We find that only 15% of the laptop user make 10 or more session per day, however, more than 40% of smart-phones make more than 10 sessions a day. Also the average number of sessions per day for laptops is 7 where as it is 16 for smart-phones (almost twice that of laptops).

5. CONCLUSION

In this paper we study the changing patterns of network usage between laptops and smart-phones. We analyze four month long traces that consist of 120K unique devices and among those devices we selected two subsets of data each consisting of approximately 20K unique devices of laptops and smart-phones respectively. The method we introduced for device classification is systematic, robust and repeatable. We investigated three main sets of metrics with respect to temporal, spatial and load characteristics.

This is the first study we are aware of to investigate the spatio-temporal differences between smart-phones and laptops based on large-scale WLAN trace analysis. It is evident from our study that these differences are dramatic, both in time and space, and warrant further research. More importantly, the behavioral shift from laptops to smart-phones (and other devices, e.g., tablets) is likely to grow at a faster pace in the future. This calls for the re-evaluation of existing mobility and network behavioral models and the protocols affected by those models (e.g., prediction, routing, caching). More so, perhaps the re-design of such models and protocols is needed based on new data-driven approaches. In our future work, we plan to conduct further analysis of net-flow traces to provide another perspective on the difference between smart-phones and laptops from a traffic and flow points of view.

6. REFERENCES

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[1] A complete evolution study is out of scope of this paper, and is addressed in more details in [11] over a period of 10 years.