# Beware of layer dependency: when the type of your device impacts your web traffic

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## ABSTRACT

Mobile devices are everywhere nowadays but little is known about the way they differ from traditional non-mobile devices in terms of usage and the characteristics of the web traffic they generate. In this paper, we propose a first study of the differences that exist between mobile and non-mobile Web traffic seen from the lorgnette of a university campus network. The study is performed at different levels starting from users' behavior to transport protocol configurations. Our main findings are that mobile users often browse websites tailored to their devices. They show a significant adoption of Apps to browse the web and a preference for multimedia content. The different way of conceiving the web for mobiles is reflected at the HTTP and TCP levels with much less HTTP redirections and abrupt TCP connection terminations. Interestingly, mobile traffic carries larger contents and have larger TCP flows than non-mobile traffic. By cross-analysis of protocols and users' behavior, we explain why TCP flows in mobile traffic are larger than those of non-mobiles.


## 1. INTRODUCTION

The Internet evolves continually from many aspects including scope, complexity, applications, etc. Thus, understanding traffic characteristics carried by current network is an essential step to manage the network efficiently and effectively. Traffic analysis has allowed for example in the past to evaluate the impact of Peer-to-Peer (P2P) applications on the revenues and costs (CAPEX and OPEX) of ISPs. The understanding of the P2P traffic and its real impact on the underlaying network was the only way to conciliate P2P and ISPs [4, 23]. Similarly, when users massively adopted smartphones, some mobile operator networks got overloaded [1]. The colossal infatuation with connected mobile devices was hardly predictable making network provisioning hazardous. Still, mobile devices are now at the origin of a significant part of the global Internet traffic and are obtaining new application fields everyday [11]. So it is essential to understand how people use mobile devices and what is their impact on the traffic to better conceive network technologies and more efficiently design applications well suited to the new mobile usages.

What characterizes mobiles is the small size of their screen and their simplified user interfaces, in addition to their mobility. These appealing features are fostering creativity and enabling new types of applications. There is no doubt that the usage of mobiles is different from non-mobile ones but the impact on the traffic they generate is largely unknown. In this paper, we provide a first answer to this question from the viewpoint of their web traffic. By web traffic we mean all traffic carried by the HTTP protocol, whether coming from browsers or other applications. The choice of HTTP traffic is for its importance in Internet traffic [7, 17], its generality, and the diversity of applications it supports. Mobile web is indeed a popular design choice (i.e., web vs. naive code) in the mobile application development area [9] and Gember et al. showed that HTTP traffic accounts more than 95% of total traffic in mobile environment [14].

Previous studies such as [18, 12, 24] pinpoint that Apps are common in mobile usage while [15, 18, 12, 24, 10] show that mobile devices clearly target multimedia content. In a first attempt, [15] and [18] underline that mobile transfers are slightly larger than non-mobile ones. On the contrary, [14] observed larger flows in non-mobiles. Shaikh et al. proposes a model for mobile traffic in [22]. There is however a lack of an integrated and multi-level study that provides a comprehensive understanding of mobile traffic. In this paper, we propose a first attempt to solve this issue by comparing the two types of devices in terms of their usage and the traffic they generate from an original environment where mobile and non-mobile devices are used jointly, at the same time, on the same network, and by the same users.

Our study is based on a full packet payload traffic trace that we collected from a Korean university campus network with about 3,000 users and that contains a large mixture of mobiles and non-mobiles.

We focus on the web traffic and study all its facets (i.e., user behavior, HTTP, TCP, server placement) to understand the differences between mobile and non-mobile usages. We make several interesting observations that can be summarized as follows. First, we observe that users browse different categories of websites on their mobile devices than on their non-mobile devices and that websites are tailored to their devices with specific composition. This dissimilarity has direct impact on the underlying protocols with less HTTP redirections and less frequent abrupt TCP connection termination (i.e., RST) on mobiles. Second, and even though mobile traffic shows more multimedia content than the non-mobile one, there is no particular topological change in the spatial distribution of IP addresses, as servers in both environments are mostly hosted in the same few and very localized Korean datacenters. Third, we give a particular attention to TCP flow sizes of mobiles and non-mobiles. Similar to [18], we observe that not only the sizes of contents but also the sizes of TCP flows sizes are larger in mobile traffic. However, and by applying a cross-layer measurement analysis, we find that the difference in user behavior between mobile and non-mobile devices and the fact that web pages are tailored to mobile devices are behind this phenomenon of larger TCP flow sizes in mobile traffic.

This paper is structured in the following way. Sec. 2 details our methodology. Sec. 3 compares mobile and non-mobile traffic from four different facets (i.e., user behavior, HTTP, TCP, server placement), then Sec. 4 digs into the difference in TCP flow sizes between both web usages. Sec. 5 establishes the link between user behavior and HTTP traffic. Finally, the paper is concluded in Sec. 6 along with future research perspectives.

# 2. METHODOLOGY

In this section we describe the methodology we follow for the analysis and comparison of mobile and non-mobile web traffic from the complementary social and technological aspects. Our study is based on our own packet trace captured at the border router of a university campus network in Korea. We describe our dataset and its characteristics and we explain how we have processed the trace for the purpose of the analysis.

## 2.1 Dataset

We collected a full packet trace from Pohang University of Science and Technology (POSTECH) campus network in South Korea. The trace covers all HTTP connections during a 24-hour period on Thursday, November 1, 2012. The residential area covers roughly 3,000 users connected to Internet with Ethernet and WiFi. Therefore, the trace contains HTTP traffic generated by a variety of devices including mobiles, laptops, and desktops, used by the same set of users, hence allowing us to confront the HTTP traffic they generate within the same networking, professional, and social environment. The total volume of the collected trace is 1.3 TB with $3.08\times10^7$ TCP flows and $2.53 \times 10^7$ HTTP request/response pairs. As we are in presence of a full packet trace, we can fully exploit all available information related to the HTTP traffic such as user and website information, TCP flow status, or even server placement. In particular, the richness of the trace makes it possible to replay the same experiments as in [18], and in addition, to apply the cross-layer analysis to understand the reason why TCP flows are larger in mobile traffic.

As our analysis requires deep packets inspection, we ignored encrypted web traffic (i.e., HTTPS) which surprisingly accounts for less than 1% of the total traffic and thus only considered HTTP traffic on TCP port 80 initiated by hosts from inside the campus to web servers outside.

## 2.2 Data processing

For application level (i.e., HTTP) and TCP level analysis, we extracted HTTP and TCP flow information with BRO [20]. We extended BRO logs with the SHA-1 HTTP response body signature (to uniquely identify and verify contents) as well as the capacity of extraction of every HTTP header. To be able to analyze the composition of web pages, we composed from the packet trace the set of all objects having the MIME type *text/html* thanks to the standard BRO feature and parsed these objects with our own static analysis tool based on HTML anchors. For user behavior level analysis, we used the K9 Web Protection tool [6] that identifies the socioeconomic category of a website from its URL. Further details on the extra data analysis processes, except BRO, will be given later along the presentation of the observations.

## 2.3 Classification of mobile traffic

We define *mobile* as any hand-held device (e.g., smartphone, tablet); all other devices (e.g., laptops, desktops) are denoted by the term *non-mobile*. To classify traffic into mobile and non-mobile, we rely on the user-agent field in the HTTP header. Most often, the user-agent field contains web client information such as OS, browser platform, and browser engine. We extracted these information with the user-agent parser described in [2]. By proceeding this way, we automatically classified 87% of the total HTTP request/response pairs. For the rest, we manually inspected the traffic, and found it to have either an empty user-agent field or a proprietary user-agent value. After a thorough manual inspection of all unknown user-agent values, we identified 477 distinct user-agent strings [1] for applications that are with no doubt used by either mobiles or non-mobiles, hence allowing their safe classification into each type of devices. By accounting for these particular well-identified user-agent strings, we have increased the volume of classified HTTP traffic to 91%. We ignore the remaining 9% presenting misleading user-agent field.

## 2.4 Limitations of the dataset

End hosts in POSTECH residential area are behind network address translators (NAT) making impossible to identify end users or devices without violating end-users' privacy. Therefore, we limit ourselves to general observations that are NAT independent. Our trace is also very localized in terms of time and geography. However, by covering a 24-hour period of a large campus network traffic during a normal workday, our conclusions can be assumed to apply to other days as well. We verified this conjecture with a partial 1-hour trace that we captured on Tuesday, March 26, 2013 at peak hour. As for the geographical limitation to a Korean university, our trace contains traffic from websites used worldwide and captures the activity of students and academics that are closer than others to their counterparts in the rest of the world, hence increasing the representativeness of our dataset. The trace is also limited to the traffic carried on the campus, but mobiles can also connect to Internet via a cellular network to which unfortunately we don't have access. Thus, we did not evaluate the part of mobile traffic transported on the campus over 3G/4G but only the mobile traffic of WiFi, and we compared this latter one to the traffic of non-mobiles over the same network. Despite its inherent limitations, we believe our dataset is still rich enough to shed light on the web traffic properties when end users have access to mobiles and non-mobiles in the same environment (i.e., how do they use mobile and non-mobile devices when they are on the campus and can access the Internet with either type of devices).

# 3. OBSERVATIONS

## 3.1 User behavior

Mobile and non-mobile devices are different in their shape, their graphical user interface, and their software, in addition to the rich sensing features the former ones provide. We investigate in this section whether these differences impact the characteristics of websites users consult. We observe that indeed web usages on the two types of devices are actually different both in terms of applications' nature and browsed content.

[1] Available at http://tinyurl.com/c4caczr/

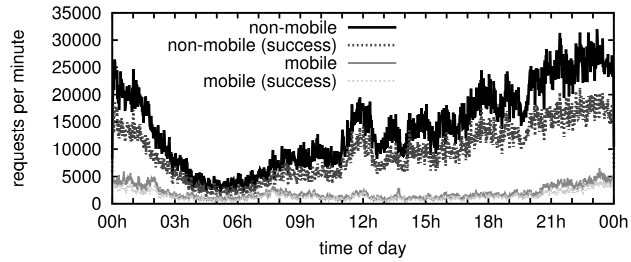


**Figure 1: HTTP requests per minute.**

To give a context to our dataset, Fig. 1 shows the daily evolution of the minute-averaged HTTP request rate for mobiles and non-mobiles. As usually observed for residential area, the maximum load is measured the evening and early night with more than 30,000 (resp. 6,000) requests per minute for non-mobiles (resp. mobiles). The one order of magnitude difference between mobiles and non-mobiles does not mean that mobiles are used less than non-mobiles in general. Our packet trace only accounts for the WiFi traffic of mobiles, while they can potentially use their cellular connectivity to access the web as well. Nevertheless, mobiles still represent a notable fraction of our dataset proving that mobile traffic is not strictly bound to cellular networks. Apart from the scale, there is no noticeable daily pattern difference between mobiles and non-mobiles.

A particularity of HTTP is that the answer to a request is not always the requested content in a successful way, but can instead be some meta information such as redirection to another URL or an error. In Fig. 1 we then plot, with the curves labeled `success`, the request rate if we only consider the successfully answered requests. The figure shows that a significant part of requests are not directly answered and this phenomenon is more present for non-mobile traffic. We present a more comprehensive study of this difference in Sec. 3.2. For now, and unless stated otherwise, we only consider successfully responded requests (i.e., HTTP status code 200).

An interesting question is to determine how much the type of a device influences the characteristics of web contents effectively consumed by end users. To answer this question, we define a *content* as being the body part of the HTTP response (i.e., all HTTP related information removed). Unfortunately, in the web, contents are not bound to any particular name, so to determine the equality of two contents we consider their binary signature made by hashing the content with SHA-1 and MD5. Two contents are equal if they have the same binary signature, otherwise they are different. Using this definition, only 2% of contents are shared between mobiles and non-mobiles but they account for 16.6% of the

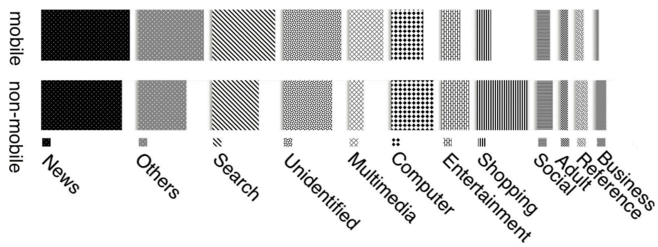


**Figure 2: Socioeconomic classification of websites.**

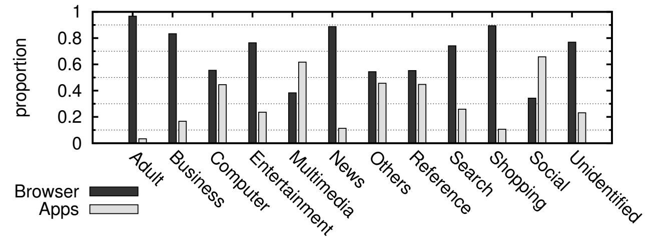


**Figure 3: Proportion of Apps usage on mobiles per socioeconomic category.**

total volume of the trace (16.8% for non-mobiles and 15.2% for mobiles). The average size of these shared contents is similar to the global average size of all contents in the trace. Therefore, the factor 8 between their frequency and the total volume they produce is only the result of their higher popularity. However, if we consider, for instance, the top 10% most popular contents in both mobile and non-mobile traffic (i.e., 3571 and 9375 contents, respectively), only 4.5% of the shared contents appear in these two top lists. It means that, in general and independently of what users do, contents consumed on mobiles and non-mobiles are different.

Our trace confirms that content popularity follows a power-law distribution. Furthermore, using a maximum likelihood estimator, the best fit to a Zipf distribution is almost the same in both environments, with a decay parameter of 0.825 for non-mobiles and 0.824 for mobiles, and a fitting error below 0.1%. Even though content demand popularity follows similar distributions, this does not mean that popular contents themselves are the same as we have seen earlier. Nevertheless, for the anecdote, the most popular content in mobiles and non-mobiles is the same and is the 1x1 pixel GIF image commonly used to track users and websites' browsing [19].

The raw study of contents shows that they differ between mobiles and non-mobiles but it does not help to understand if contents differ just because they are adjusted for mobile technologies (e.g., adjust the size of a picture to be smaller, touch screen adaptation of a website...) or if they come from different categories of websites. With Fig. 2 we classify visited websites from a socioeconomic viewpoint. We use the K9 Web Protection tool [6] to obtain such classification. K9 is a proxy that classifies every HTTP request it passes through it into a set of predefined categories. To classify websites of the trace, we extracted all the distinct HTTP hosts and sent an HTTP request to them via a K9 instance. As we can see in the figure, there exist clear differences in user behavior when they browse the Internet with the two types of devices. The news category is the most prominent for both mobiles and non-mobile devices with almost the same proportion. On the contrary, shopping is seldom on mobiles while it is common on non-mobile devices. The multimedia category on its side, including video streaming, is more popular on mobiles than on non-mobile devices. This difference, combined with the adaptation of websites to the technology of the end-user device, explains the small proportion of common contents between mobiles and non-mobiles. We believe this first observation on the socioeconomic usage difference between the two types of devices is important to understand the main characteristics of the web traffic they generate and to dimension networks and web services in an appropriate way.

In addition to influencing usage patterns, the device technology also influences the nature of applications used to access web contents, as summarized in Fig. 3. More than 95% of traffic is generated with standard web browsers (e.g., Microsoft Internet Explorer) on non-mobiles, the rest being generated with specific applications such as video players or antivirus without any particular trend. On the contrary, while more than half of the web traffic is still generated with browsers on mobiles (i.e., 63%), there is a significant proportion of mobile web traffic that is the result of using Apps (i.e., 37%). This ratio is even higher for some traffic categories, with for example more than 65% of the mobile social networking traffic and 61% of the mobile multimedia traffic driven by such Apps. On the contrary, mobile users seldom use Apps for news (i.e., 11%) or shopping (i.e., 10%). These two latter examples show that the popularity of a category is independent of the existence of Apps for it. Indeed, news is the most popular category in mobile environment even though users seldom use Apps to read them while shopping is not frequent on mobiles. It would be useful to know why shopping, common on non-mobiles, is not common on mobiles as well. The absence of well designed Apps and the inconvenience of mobile screens for shopping can be behind this phenomenon.

Finally, HTTP transfers can be aborted at anytime

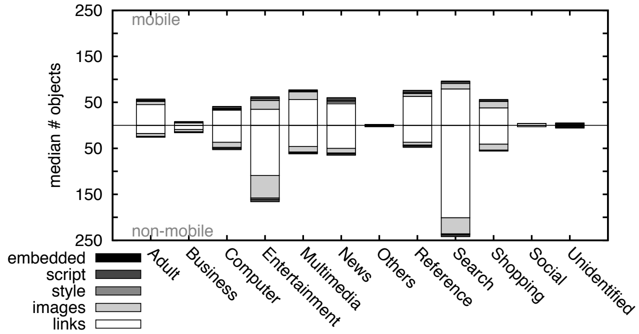


**Figure 4: Breakdown of object types by category.**

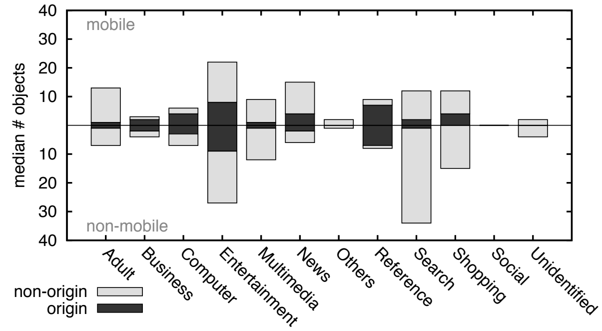


**Figure 5: Breakdown of non-clickable objects origin by category.**

either because users stop them or because the connection is lost [22]. One can expect a higher connection abortion rate on mobiles as they are more likely to lose their network connectivity while moving. To quantify this rate, we compare the content length advertised by the server in the HTTP response header with the length of the content effectively downloaded. We are unable to determine the expected size of the downloads in 32% of non-mobile cases and 36% of mobile ones. For the rest, and surprisingly enough, the ratio of aborted connections is almost the same, even slightly higher on non-mobile devices with 1.9% rate compared to 1.6% on mobiles. HTML pages are the most concerned by these abrupt terminations in both cases. Interestingly, and in both cases, 14% of transfers are longer than expected and mostly correspond to Ajax or assimilated technology.

In summary, we have seen a close content popularity distribution in both environments with a small amount of common content. We have also seen an important usage of Apps on mobiles. All this suggests that content producers care about the type of the end-user device and specialize their websites accordingly, which is in line with the observations made in [8].

## 3.2 Impact on web technologies

Sec. 3.1 shows an important usage of Apps on mobiles, as opposed to browsers which are more generic web tools. It also shows some divergence in term of socioeconomic usage. In this section, we determine how these differences impact web page composition (i.e., HTML) and retrieval (i.e., HTTP) thanks to a static analysis of the HTML pages in our packet trace and HTTP logs issued by BRO.

**Methodology.** To determine how web pages are composed, we follow the same approach as in [8] which consists in counting and categorizing objects that appear in HTML pages. We define an *object* as an entity that is referred to inside an HTML page but that is not defined in the page itself. An object is then retrieved with a distinct HTTP request. For instance, a script defined entirely in the HTML page is not an object. To ease the presentation, we group objects into 5 categories: (*i*) *links* that correspond to *clickable* objects; (*ii*) *images*; (*iii*)*styles*; (*iv*) *scripts*; and (*v*) *embedded* that correspond to applets, frames, and audio/videos streams.

In addition to the types of objects, we consider their origins as well. An *origin* object is hosted on the same server as the HTML page referencing it. On the contrary, a *non-origin* object is hosted on a separate server. So that, an origin object can potentially use the same persistent HTTP connection as the HTML page, while a non-origin object cannot do the same.

To determine the *composition* of web pages in terms of objects, we extract every web page as described in Sec. 2. We maintain only one copy of each page, identified with its signature, and extract objects' types and origins using our HTML parser.

**Observations.** Fig. 4 shows the breakdown of the median of the number of objects per object type, grouped by category for mobiles and non-mobiles. Pages are mostly composed of links indicating that they are interactive. In general, non-mobile web pages have more objects than mobile ones, which confirms that web pages are optimized according to their targeted devices. However, pages in multimedia and reference categories have more objects on mobiles. Also, images constitute most of the non-clickable objects with a median between 7 to 12 images per page, directly followed by stylesheets, showing that the visual rendering of pages is important in general. We don't see any particular reason for the difference of composition in the multimedia category. Nonetheless, for the reference category, a weather forecast App is particularly popular (30% of the transfers in the category) and uses pages composed of more objects than usually observed on non-mobiles. Obviously, the search category is the one with the most objects with

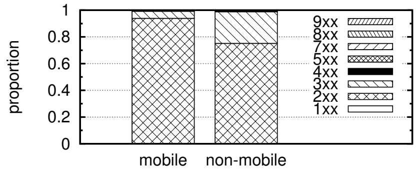


**Figure 6: Breakdown of HTTP status code**

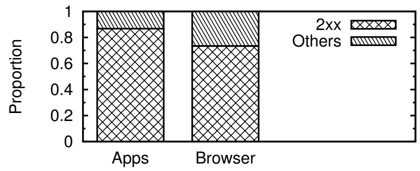


**Figure 7: Success rate of apps and browsers**

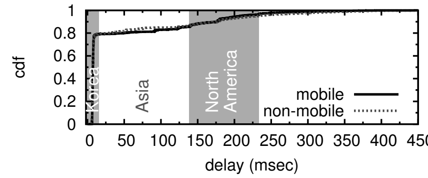


**Figure 8: Delay cdf**

in particular a large number of links.

Fig. 5 shows the origin of non-clickable objects per category on mobiles and non-mobiles. In most of the cases, there are more non-origin objects than origin ones, which has negative impact on web page loading time [8]. As one can expect, objects in search engines and portals are mostly non-origin as by nature they reference external sites. On the contrary, the reference category being specialised and directory oriented mostly points to objects obtained internally. In general, there is no notable difference in the origin of objects between mobiles and non-mobiles, except that non-mobile pages have more objects than mobile ones.

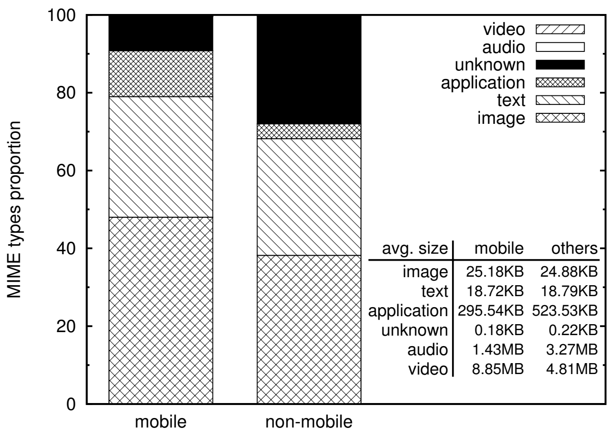


**Figure 9: Breakdown of mime types**

Fig. 9 gives the breakdown of mime types observed in all downloads, separated between mobiles and non-mobiles. Mime types are provided by the HTTP servers and indicate to the clients the type of content they are receiving. There are 5 different mime types in the trace: *image*, *text*, *application*, *audio*, and *video*. The image type is the most prominent with up to 48% of transfers on mobiles and 38% on non-mobiles, followed by the text type such as HTML pages in 30% of the cases. The application mime type is the third most popular on mobiles but only forth on non-mobiles. In both environments, application related transfers are mostly opaque byte streams. However, XML is the second class of applications with 3% of the transfers, while it is less than 1% on non-mobiles. This can be caused by Apps that tend to use XML more frequently than generic websites. Another important difference is that flash is anecdotal on mobiles with less than 0.3% of the total volume of transfers. Finally, less than 8% of transfers do not specify any mime type on mobiles while no less than 28% of transfers do not specify the mime type for non-mobiles, suggesting that web pages and Apps designed for mobiles benefit from a more careful design.

Surprisingly, downloaded objects are generally larger on mobiles than on non-mobiles with 40 KB on average on mobiles and only 30 KB on non-mobiles, mostly due to the higher frequency of images. Even text objects are slightly larger on mobiles (20 KB) than on non-mobiles (19 KB). As a matter of fact, HTTP response header length is similar in both environments, so non-mobile transfers suffer from more HTTP overhead than mobile ones with a median value of 10% for the former and 6% for the latter. Thus, transfers are more efficient on mobiles in terms of HTTP overhead. Content size distributions is summarized in Fig. 12. We will revisit this observation later in the paper and explain how our thorough and cross-layer analysis of Internet traffic can help understanding its root causes.

Fig. 7 shows the breakdown of HTTP status code with the distinction between mobiles and non-mobiles. The main status codes [13] are of the form *2xx* and correspond to successfully responded requests. On the contrary, *3xx* status codes indicate that further action (i.e., redirection) is needed to fulfill the requests. There is a clear success rate difference with 93% of success in the case of mobiles and only 75% for non-mobiles. The difference comes from redirections (i.e., *3xx*) that are more common on non-mobiles with 23% prevalence compared to only 5% on mobiles. This difference can be interpreted by Apps which are more common on mobile devices. Fig. 6 shows different success rate (i.e., proportion of HTTP *2xx*) between Apps and browsers. Apps have 86.71% of success rate while standard browsers have 73.47% of it. From Sec. 3.1 we know that significant proportion of mobile web traffic is generated as the result of using Apps (i.e., 37%) while only small portion of traffic is generated by Apps in non-mobile case (i.e., 5%). Unlike standard browsers, Apps usually hide URIs to users. They lead users to exact locations of contents and this also reduce the number of invalid requests requests (i.e., *4xx*) in the mobile environment, with only 0.8% of prevalence on mobiles, while it is 1.1% on non-mobiles. Consequentially, higher utilization of Apps which have higher success rate mobiles results higher proportion of HTTP *2xx* in mobiles.

To summarize, web pages are composed differently for mobile and non-mobile devices. As mobiles have smaller screens, pages are in general composed of less objects but contain more images. In addition, as mobile web pages are frequently retrieved with Apps without an explicit usage of URI, HTTP redirections and errors are less encountered on mobiles.

### 3.3 Effects on TCP and server placement

Previous sections show that mobiles differ from non-mobiles by their utilization of Apps and their access to tailored websites, and that these differences have impact on the HTTP protocol. In this section, we go deeper in the stack and study the impact on TCP and on the placement of the web servers. The study at this level is useful for network operators to understand the potential shift in their traffic caused by the introduction of mobiles.

**TCP flow statistics.** To see the impact of mobile and non-mobile usages on TCP, we first compare the distributions of TCP flow duration in Fig. 10 and size in Fig. 11. Fig. 11 shows no significant difference in the upstream direction and the globally small upstream volume indicates that devices seldom upload large documents to servers. On the contrary, Fig. 11 shows that downstream non-mobile TCP flows are generally smaller than in the case of mobile devices, which can partially be explained by the propensity for downloading smaller contents on non-mobiles. However, the understanding of why flow sizes vary much depends on so many other factors, that we devote an entire section to it (Sec. 4) addressing that subject and trying to understand its root causes. Despite that flows are globally smaller on non-mobiles, they tend to last longer which can be explained by the higher frequency of redirections that do not significantly increase overall flow size but that slow down the reception of the actual content.

Similarly to TCP flow size and duration, we observe that TCP session termination method significantly differs between mobiles and non-mobiles. Indeed, and as we highlight in Sec. 3.2 that the number of aborted HTTP connections is slightly higher on non-mobiles, Fig. 13 shows that abrupt TCP session terminations (i.e., RST) are also more frequent on non-mobiles (24.1% vs 11.7%). The fact that mobiles have simpler user interfaces (e.g., no stop or refresh button or address bar) can explain this difference. In other words and in line with the observation made in [21], the graphical user interface of the device has impact on the user's behavior and on the underlying TCP connections.


**Figure 13: TCP session termination method.**

**Server placement.** One important question is how content providers deploy their web servers for mobiles and non-mobiles. In particular, we are interested in the topological overlap between the two sets of servers. We determine the topological position of each server by mapping its IP address to the autonomous system (AS) advertising it. We establish the IP-to-AS mapping from RouteViews BGP feed [3]. Our trace contains IP addresses originated by 2,885 distinct ASes (963 for mobiles and 2,640 for non-mobiles). Among them, only 844 appear on both mobiles and non-mobiles (91.8% of the ASes observed on mobiles and 33.5% on non-mobiles). Even though this number of ASes is small in comparison with the 45,000 ASes advertised in the Internet, it shows an interesting trend. Indeed, these 844 common ASes are behind 99.8% and 98.6% of mobile and non-mobile traffic in our trace, respectively, showing a high localization degree of servers on the topology. However, apart from the few very popular ASes, there is no clear correlation between the popularity of common ASes in each environment. For instance, an AS can be at the same time popular on mobiles and not popular on non-mobiles. Unfortunately, the originating AS is not enough to determine the geographical spread of servers, so we estimate the round-trip delay to each AS as measured by the time difference between TCP SYN and SYN+ACK packets. Fig. 8 shows the TCP delay distribution and the possible locations of the web servers. No clear difference is observed between mobiles and non-mobiles. As Fig. 8 highlights, most of the servers are hosted within 6 ms radius of the university, which corresponds to the location of major Korean datacenters, hence showing a very high regional localization of servers. These observations indicate that even though the usage of mobiles and non-mobiles is different, as well as the traffic they generate when seen at different levels, their servers are mostly hosted by the same ASes and at the same locations. This confirms the general trend to host services on very large and commercial cloud and data-center providers and to push

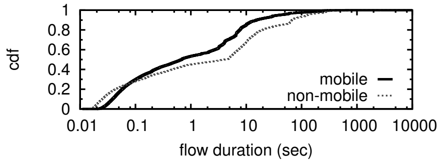


**Figure 10: TCP flow duration cumulative distribution.**

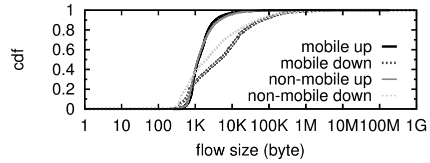


**Figure 11: TCP flow size cumulative distribution.**

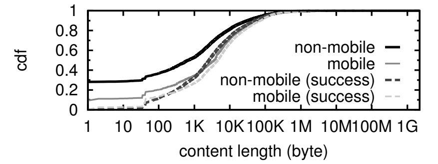


**Figure 12: Content length cumulative distribution.**

content by Content-Delivery Networks very close to the end-users consuming them.

# 4. LAGER FLOWS IN MOBILE

## 4.1 Observations on TCP flow

In the previous sections, we have pinpointed to discrepancies between contents downloaded via HTTP on mobiles and non-mobiles. We have noticed average size difference for TCP flows, with mobile devices behind larger downloads on average. Similar observation has been in previous work as [15, 18] but a general analysis is still missing. While it is straightforward that content size affects flow size, it cannot be considered as the only factor. In this section, we show that these are all the discrepancies discovered between mobiles and non-mobiles in the previous sections that actually impact the average size of TCP flows. This confirms the interest of our methodology based on cross-layer analysis to understand the root causes of an observation when it comes to a complex system as the Internet web access.

From Sec. 3.3 we know that TCP flow size generated by mobiles are slightly larger than those generated by non-mobiles, especially download stream showed this phenomenon distinctly.

It is not sufficient to find the causes of larger flows in mobile defend on TCP level information. As a matter of fact, the vast majority of flows are too large to justify the difference in the way the TCP stack is implemented (e.g., TCP options). It means that the deviation of TCP flow size characteristics between mobiles and non-mobiles comes from the payload. The payload is composed of HTTP traffic, so we have to jump one layer up in the stack to understand why TCP flows are larger on mobiles.

## 4.2 HTTP influence on TCP

The difference in TCP flow size can be affected by three factors. The first factor is the actual amount of data transported, including meta information. The second factor is very specific to the HTTP protocol and is called *persistent connection* [13]. Without persistent connection, each HTTP request/response pair uses a dedicated TCP connection. On the contrary, when HTTP persistence is in use, a single TCP connection can transport several HTTP request/response pairs. Therefore, if a client requests multiple objects using a persistent connection, the underlying TCP flow will be larger than in the simple case of one request/response per TCP connection. The last factor is HTTP compression. HTTP data can be compressed.

We can approximate the average TCP flow size as follows:

$$S_{flow} = \sum_{N} \big( (P \cdot R + (1 - P)) \cdot S_{content} + H_{http} \big) + H_{tcp/ip} \cdot \#\{packts\}, \quad (1)$$

where $P$ and $R$ are compression probability and compression factor respectively. $S_{content}$ is larger in the download direction for mobiles. The content length $S_{content}$ refers the actual size of downloaded contents not the content-length (compressed size if compression is in use) advertised by server. $H_{http}$ are the average volume of content carried by an HTTP request/response and volume of meta information (i.e., the HTTP header). $N$ denotes the average number of HTTP request/response pairs in a persistent HTTP connection and $H_{tcp/ip} \cdot \#\{packet\}$ is the average volume of TCP/IP headers that belongs to the flow. Because all these factor are making a TCP flow in HTTP download stream, it is impossible to say that a sole metric results larger flow in mobile even though individual metric affects TCP characteristics.

For the sake of the comparison with Fig. 11 and understanding effects of all factors of HTTP, we measure $S_{flow}$, $R$, $P$, $S_{content}$, $H_{http}$, $H_{tcp/ip}$, average number of packets in a flow according to the different HTTP response available in our dataset, and distinguish mobiles from non-mobiles. Table 1 summarize our observations made in previous section.

**Table 1: HTTP metrics influencing TCP flow size**

| Download direction | Mobile | | Non-mobile |
|---|---|---|---|
| HTTP header length ($H_{http}$) | 318.30B | ≈ | 298.63B |
| TCP/IP header length ($H_{tcp/ip}$) | 71.82B | ≈ | 73.13B |
| Content length ($S_{content}$) | 63.96KB | > | 36.67KB |
| Compression factor ($R$) | 0.79 | > | 0.69 |
| Compression probability | 0.18 | > | 0.16 |
| Persistent rate ($N$) | 1.47 | < | 2.01 |
| Number of packets per flow | 72.49 | > | 57.74 |
| Flow size ($S_{flow}$) | 96.21KB | > | 75.21KB |

Table 1 shows that HTTP and TCP/IP header size are similar between mobiles and non-mobiles. These similarities comes from the fact that HTTP and TCP/IP headers are not issued by client devices but servers and these values rarely affect TCP flow size. Content length shows obvious difference in particular. However, mobile content size, which is almost two time bigger than non-mobile ones, cannot explain relatively small difference in flow size precisely. As also shown in Table 1, the persistence rate is less on mobiles (1.47 vs. 2.01 for non-mobiles). Intuitively, high persistence rate leads high TCP flow size however these values are in opposition with the fact that download flow sizes are larger on mobiles. Finally, mobiles showed high compression factor and compression probability than non-mobiles. Flow size is proportional to compression factor but in inverse proportion to compression probability.

This leads to a conclusion that none of the values listed in Table 1 cannot explain the difference of behavior between mobiles and non-mobiles alone. All in all, the combination of HTTP header, actual content size, TCP/IP header overhead, compression of HTTP contents, and persistent connection make us able to explain the reason why TCP flow sizes are different between mobiles and non-mobiles. The combination of all the metrics impact the size of TCP flows. However, this analysis still does not explain the very reason why these metrics are different between mobiles and non-mobiles. The next section answers this question by considering web page composition and user behavior.

# 5. ESCAPE FROM HTTP

The analysis of TCP and HTTP reveals that solely relying on protocol information can yield to a superficial understanding of what is observed as it can be influenced by external factors (e.g., different protocol stack). In particular, user behavior is an important factor to consider while analyzing web traffic. In this section, we study the highest level of the protocol stack to infer the influence that user behavior has on the network traffic to infer the user behavior influence on the network traffic.

## 5.1 Factors affecting HTTP header length

The content of the HTTP request/response header depends on how the HTTP client and server libraries are implemented. This implementation is directly influenced by the device and its operating system [16]. For HTTP response header, there is no difference between mobiles and non-mobiles as we see in previous section. The similarity of HTTP header between mobiles and non-mobiles in the download direction is because HTTP response headers are generated by web servers that do not make distinction between mobiles and non-mobiles when they reply to client's request yielding no significant difference in HTTP response header.

**Table 2: Comparison of the average HTTP request header length according to device and browser type.**

| | Mobile | | Non-mobile |
|---|---|---|---|
| Apps. | 313.89B | | 209.70B |
| Standard browser | 682.84B | | 774.46B |
| Total | 552.76B | $<$ | 747.81B |

HTTP request header length showed difference between different devices (i.e., 552.76 B in mobiles and 747.81 B in non-mobiles). It is influenced by the applications used by the user to access web contents as we show next. In case of mobiles, there is a significant proportion of HTTP traffic that is the result of using Apps (i.e., 37%). On the contrary, more than 95% of traffic is generated with standard web browsers (e.g., Internet Explorer) on non-mobiles. While standard web browsers are built for general purpose of web browsing, Apps are tailored for their particular services, thus HTTP header format in Apps is simpler and shorter than standard web browsers. The higher usage of Apps on mobiles causes shorter header length at the upload stream. Table 1 summarizes average HTTP request header length generated by different devices and browser types. One interesting observation is that mobile standard browser (e.g., mobile Safari) and non-mobile standard browser (e.g., Safari) show similar request header length which implies the way how they generate HTTP request message don't have significant difference.

## 5.2 Factors affecting content length

Mobiles have larger content size ($S_{content}$) in the download direction. HTTP request method cannot explain this difference because this request method is similar for both types of device. To answer the root cause of larger content size on mobiles, we have to go back and investigate the composition of downloaded contents (i.e., content size and type).

Fig. 9 gives the breakdown of MIME types observed in all downloads as well as the average size for each of them.

The difference in breakdown of MIME types can be explained by user behavior and how webpages are composed. In Sec. 3.1, there exist clear differences user behavior when they brows Internet with different of devices. Socioeconomic classification of websites shows distinct composition according to device type. Different classes of websites have their own characteristics in terms of webpage composition and webpages for mobile devices also have different composition (Fig. 4). This leads different breakdown of MIME types in mobiles and non-mobiles.

### 5.3 Factors affecting the persistence of HTTP connections

We need to understand the reason why persistent rate ($N$) is not the same in both environments. Using persistent connections reduces the number of signaling packets as it mutualizes the overhead of TCP handshake among several HTTP exchanges. In some cases, it can also speed up downloads as the TCP flow tend to be more often in its steady state (e.g., not in slow-start mode). It can be only used when the objects to download are located on the same server. The difference in persistence rate is related to how web pages are composed, similarly to content size as shown in Sec. 5.2. Indeed, and as we explained in Sec. 3.2, web pages requested by mobiles refer to less origin objects than web pages requested by non-mobiles. Thus, the chance to leverage persistent connections is lower with mobiles, reducing the value of persistent rate for them.

### 5.4 Factors affecting HTTP compression

HTTP compression provides better transmission speed and available bandwidth utilization. HTTP compression is affected by both client and web server. One factor affecting HTTP compression is compression function built in clients. A client specifies compression methods supported by itself using *accept-encoding* field when it requests a content from a web server. Standard browsers support popular compression method such as *gzip* and *deflate* both in mobiles and non-mobiles. Therefore, standard browsers request compressed content most of their requests regardless of device type (98.39% in mobile browsers 97.99% in non-mobile ones) and and this rarely affects to servers' compression. Apps request uncompressed contents more frequently than browsers especially non-mobile Apps request compress contents only with 30.22% of probability while mobile Apps has 85.37%. Web servers compress HTTP data before send it to the client if compression is supported by clients.

**Table 3: Compression probabilities of MIME**

| MIME | Compression probability |
|---|---|
| text | 0.46 |
| application | 0.02 |
| unknown | 0.02 |
| image | 0.01 |
| audio | 0.00 |
| video | 0.00 |

The main factor of HTTP compression is content's MIME type. Although a client can specify whether it accept compressed contents or not, the main agent of HTTP compression is web server and the server's decision is dependent on MIME type of contents. Table 3 shows different compression probability according MIME type. All MIME types have very low probability (less then 0.02) except text type. Web severs compress contents considering gain from compression. The gain from compression is small when contents are already in compressed format (e.g., jpeg image, mp3 audio, mpeg video). Thus, different compression probabilities in mobile and non-mobile are influenced by different breakdown of MIME types in both environments and user behavior as explained in Sec. 5.2.

Users utilize their devices in different ways due to their different characteristics such as shape of devices and available software, and this directly affects the underlying layers. It is important to broaden the scope of traffic studies.

## 6. CONCLUSION

In this paper, we propose the first multilevel analysis of the differences between mobile and non-mobile web traffic. Using full-packet trace from a Korean university campus network, we find that websites browsed by mobiles are tailored to them (i.e., composed of less objects) and that mobile users often use Apps. However, web sites appearance is still important on both mobiles and non-mobiles with a large usage of images and styles. Mobile users also consume more multimedia contents but seldom practice shopping on their devices. These differences are directly reflected at the HTTP and TCP layer with less HTTP redirections on mobiles and more abrupt TCP flow termination on non-mobiles.

We also explain how the characteristics of TCP are affected by higher network protocols (i.e., application protocol layer) and even some factors not directly linked with protocols such as user behavior. We first confirm the larger TCP flow size in mobile traffic, then we relate it to observations made by analyzing the traffic trace at the HTTP level. However, we identify that user behavior seriously explain the larger TCP flow in mobile traffic. Users utilize their devices in different ways due to their different characteristics such as shape and available software and this directly affects the underlying layers.

An anonymized copy of the dataset behind this study is made available via `http://tinyurl.com/c4caczr`. In the close future, we plan to study in further details the way users interact with their devices and conceive long term traffic demand models taking into account discrepancies between mobile and non-mobile usages.

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