Understanding Data Traffic Behaviour for Smartphone Video and Audio Apps

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***Abstract*—This poster is the first known attempt towards traffic engineering for smart-phone audio and video apps – it seeks to report network traffic characteristics, like packet size distribution, traffic burstiness and self-similarity in data traffic. We consider different candidate apps from three different groups – interactive apps, buffered apps and streaming apps, collect packet traces for three months with four customized Android smart-phones, and then analyze their internal patterns. We observe significant differences in traffic characteristics among various application groups, which can be explored in the future for the development of network level service provisioning and traffic management mechanisms.**

I. Introduction

With fast penetration of smart-phones during the last few years, a large number of applications, popularly known as apps, have emerged to provide different services to the users. Data traffic generated by the smart-phone apps contribute significantly to the load at the Internet backbone. While network traffic engineering is absolutely important for Internet Service Providers (ISP) to ensure service differentiation and proper network management, data traffic from smart-phone apps show different characteristics compared to conventional wired and wireless network traffic. There are mainly two reasons behind this. First, majority of the smart-phone apps use small size packets with low data generation rate, although a few traffic hungry apps (like video apps) contribute to the majority of the traffic load [1]. Second, the conventional multimedia and streaming applications use HTTP tunneling to transfer the data [2]. As a consequence, although the *long term evolution* (LTE) for cellular networking standard defines different classes of services over guaranteed bit rate (GBR) and non-GBR bearers, like voice, video streaming, interactive video etc., it is difficult to identify the traffic classes because of the best effort envelope enforced by HTTP tunneling over almost all the app generated data traffic.

In this poster, we consider multiple candidate smart-phone apps, primarily from four different traffic classes - streaming video, interactive video, streaming audio and interactive audio, and analyze their traffic characteristics. We observe that different traffic classes exhibit distinct features in their traffic characteristics which can be explored in the future to develop service differentiation and network management applications.

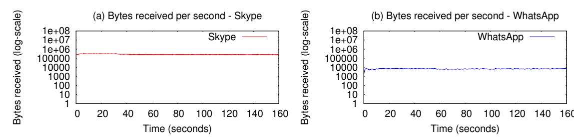

Fig. 1. Traffic Distribution for Interactive Apps Traffic

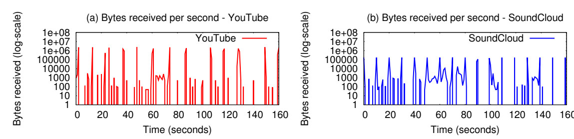

Fig. 2. Traffic Distribution for Buffered Apps Traffic

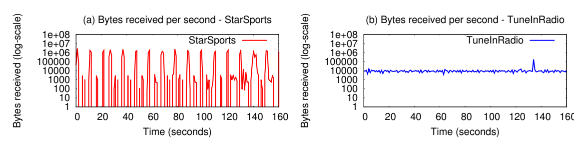

Fig. 3. Traffic Distribution for Streaming Apps Traffic

II. Traffic Analysis

In this study, we consider the major traffic hungry applications - the audio and video apps. We have classified the audio and video apps into three categories: (a) interactive (Skype video and WhatsApp audio), (b) buffered (YouTube and SoundCloud), and (c) streaming (StarSports and TuneIn-Radio). We have conducted a three month data collection activity from multiple such apps, through 6 volunteers and with Motorola Moto X 2^{nd} generation Android mobile phones. The total trace is 10 GB in size. During trace collection, we have logged the associated events, like start time and end time for inset advertisements. We analyze the traffic traces using three parameters: (a) periodicity of the data traffic distribution, (b) packet size distribution, and (c) self-similar nature of the traffic pattern. The observed results are as follows.

A. Periodicity of Data Traffic Distribution

Fig. 1, Fig. 2 and Fig. 3 display the traffic pattern distributions (bytes received with respect to time) for interactive,

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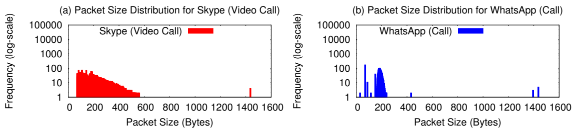

Fig. 4. Packet Size Distribution for Interactive Apps Traffic

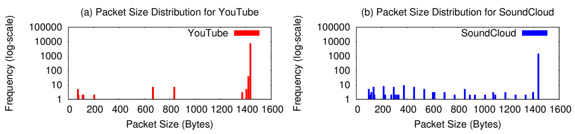

Fig. 5. Packet Size Distribution for Buffered Apps Traffic

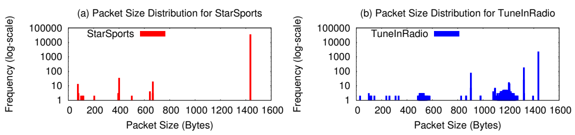

Fig. 6. Packet Size Distribution for Streaming Apps Traffic

buffered and streaming video apps, respectively. From the visual trace itself, we can identify that different types of apps generate different traffic patterns. While interactive apps show constant bit-rate smooth data traffic with respect to time, buffered video and audio apps exhibit periodic traffic bursts. On the other hand, streaming video and streaming audio show different characteristics in traffic pattern – while streaming video traffic is bursty and hence periodic, streaming audio generates a smooth bytes/sec pattern with respect to time.

B. Packet Size Distribution

Fig. 4, Fig. 5 and Fig. 6 exhibit the packet size distribution for interactive, buffered and streaming apps, respectively. We observe that, for both interactive video and audio apps, the packet sizes are small – for video, it is less than 600 bytes, and for audio, it is less than 200 bytes. For buffered video apps, most of the packet sizes are closer to the network's maximum transmission unit (MTU) (around 1400 bytes in this case), whereas, for audio apps, packet sizes are uniformly spread in the pre-MTU region, although a large number of packets have size closer to the MTU. We get an interesting observation for streaming apps. For video streaming app, majority of the packet sizes are closer to MTU; but for streaming audio app, packet sizes are spread in the pre-MTU region, making a few local clusters. In summary, we observe that for buffered video, buffered audio and streaming video apps, data packet sizes can be clustered towards a closer value of the MTU, but for other type of audio and video apps, a significant number of small size packets exist.

C. Self-Similarity

Next we study self-similarity for different app traffic using periodogram power spectrum density [3], as shown in Fig. 7 and Fig. 8. Self-similarity indicates that the traffic shows

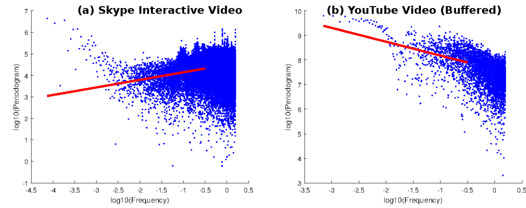

Fig. 7. Periodogram for Video Traffic

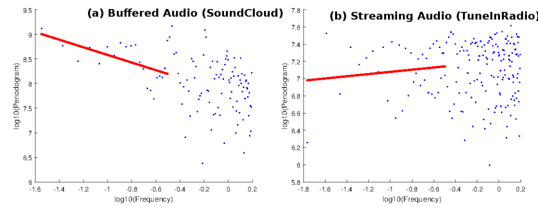

Fig. 8. Periodogram for Audio Traffic

"burstiness" and the burst size is time-scale invariant. By fitting a least-square line using just the least 20% of every frequency, we obtain slope estimates, which result in *Hurst parameter* [3] estimations of 0.3239 and 0.7819 respectively for Skype and YouTube (video apps), whereas 0.8877 and 0.4361 for SoundCloud and TuneInRadio (audio apps). Estimated *Hurst Parameter* values close to 0.73 indicate that the traffic is self-similar; therefore, we observe that both buffered audio and buffered video traffic are self-similar. However, although streaming video is self-similar, streaming audio does not show self-similarity in traffic distribution. In case of interactive audio and video apps, traffic from both the categories are not self-similar.

III. Conclusion

In this poster, we report the internal traffic characteristics and traffic patterns for popular smart-phone video and audio apps. From the analysis of a large data set, we show that traffic characteristics can be used as a distinctive feature to group the apps into traffic classes, like streaming, buffered and interactive. A major problem associated with service differentiation techniques in mobile devices is the segregation of traffic flows originating from different apps using unique signatures – the insights about app traffic provided in this poster can be used as the building blocks of such signatures. This is an initial attempt, and in future we seek to extend this analysis for a large set of apps with a target to develop end-to-end network services.

References

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