Leveraging Diversity to Optimize Performance in Mobile Networks

M. Zubair Shafiq
Department of Computer Science and Engineering
Michigan State University
shafiqmu@msu.edu

ABSTRACT

To cope with the rapid increase in mobile data traffic volume, mobile network operators can leverage the diversity in traffic patterns to improve network performance. In this paper, we show how can mobile network operators leverage diversity across different devices and geographical regions to improve traffic models and radio resource allocation, respectively. We conduct trace-driven simulations using data sets collected from an operational mobile network to evaluate our proposed approaches. Our experimental results indicate that diversity-aware traffic model refinements can improve the accuracy of traffic models and radio resource allocation.

Categories and Subject Descriptors

C.2.3 [Computer System Organization]: Computer Communication Networks—*Network Operations*

General Terms

Measurement, Performance

Keywords

Mobile Network; Performance

1. INTRODUCTION

Mobile network operators have globally observed an explosive increase in the volume of data traffic in recent years. According to a recent Cisco forecast [2], global mobile data traffic volume will increase 13-fold between 2012 and 2017, reaching up to 11.2 exabytes per month by 2017. The forecasted increase in mobile data traffic volume is approximately 3x faster than fixed IP traffic. This unprecedented increase in the volume of mobile data traffic is attributed to the increase in the subscriber base, improving network connection speeds, and improving hardware and software capabilities of modern smartphones. In contrast to the traditional fixed IP networks, mobile network operators are faced

with the constraint of limited radio frequency spectrum at their disposal. As the communication technologies evolve beyond 3G to Long Term Evolution (LTE), the competition for the limited radio frequency spectrum is becoming even more intense. Therefore, mobile network operators increasingly focus on optimizing different aspects of the network by customized design and management to improve key performance indicators (KPIs).

There are two major sources of diversity in mobile network traffic. First, a diverse range of devices with different hardware specifications, apps, etc. are used on modern day mobile networks [6]. Second, the nature and volume of traffic exhibits diversity across different geographical locations [7, 4]. Both of these aspects represent potential opportunities for design and optimization of mobile networks. In this work, we explore how can mobile network operators leverage the diversity to optimize performance in mobile networks.

2. PROPOSED APPROACHES & RESULTS

2.1 Device Diversity

Below, we show how can mobile network operators improve workload models by customizing them for different device types.

Prior work showed that the application distribution of Internet traffic in mobile networks is highly skewed. For instance, top 10% of the applications constitute about 99% of the flows in an operational mobile network [6]. This observation naturally leads to a Zipf-like model of the application distribution. Prior work further showed that Internet traffic volume timeseries in mobile networks exhibits strong diurnal variations. The temporal dynamics of the traffic can be modeled using a multi-ordered Markov chain model.

It is noteworthy that aggregate Internet traffic is essentially a mixture of traffic from various device types, with diverse hardware and software specifications, which exhibit vastly different traffic patterns [5]. Consequently, the application distribution and volume timeseries models can be refined for different device types for better accuracy. Since there are a large number of device types, it is infeasible to train a separate model for individual device types. Therefore, we instead cluster similar device types together and refine models for individual clusters using the following methodology. First, we aggregate the traffic from all types of devices that fall into the same cluster. Second, we normalize the cluster aggregated traffic with respect to its relative proportion in the aggregate traffic which is determined empirically.

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CoNEXT Student Workshop '13, December 9, 2013, Santa Barbara, CA, USA.
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<http://dx.doi.org/10.1145/2537148.2537149>.

Figure 1: Device type based refined models for application distribution and traffic volume timeseries

Figure 2: Effect of varying DCH→FACH timeout parameter

Finally, we model each of the aggregated and normalized traffic traces separately.

Figure 1(a) shows the Zipf-like application distribution model for a cluster of device types. The average accuracy of the refined models is better than the aggregate model. Figure 1(b) shows the plot of predictions from multi-order Markov models trained for a cluster of device types. The value of average mean-squared error (MSE) for the refined models is better than the aggregate model. More details about leveraging device diversity to improve workload models can be found in [4, 3].

2.2 Geospatial Diversity

Below, we show how can mobile network operators improve performance by tuning Radio Resource Control (RRC) state machine inactivity timers for cell sectors with distinct traffic profiles.

UEs acquire and release radio resources by transitioning to different states in their RRC state machines, which are synchronously maintained by the UEs and network [1]. Figure 2(a) shows the RRC state machine with three states: Idle, Forward Access Channel (FACH), and Dedicated Channel (DCH) – each with progressively more allocated radio resources. When a UE has some data to transfer, it is promoted to a higher energy state. Likewise, a UE is demoted to a lower energy state based on inactivity timeouts. Shorter inactivity timeouts result in more efficient radio resource utilization via more frequent state promotions. However, frequent state promotions can also result in degraded user

experience especially for delay sensitive applications such as web browsing. Therefore, RRC inactivity timers can be increased in cell sectors with more web browsing traffic to improve user experience. On the other hand, RRC inactivity timers can be reduced in cell sectors belonging to delay tolerant applications such as audio/video streaming for more efficient radio resource utilization.

To validate these ideas, we conduct trace-driven simulations of users' RRC state machine using the logs collected at Radio Network Controllers (RNCs) from an operational mobile network. For cell sectors with dominant audio/video streaming traffic, we plot CDF of idle DCH state occupation time for varying DCH→FACH RRC timeout values in Figure 2(b). We note that idle DCH state occupation time increases for larger DCH→FACH RRC timeouts. Therefore, mobile network operators can reduce RRC inactivity timeouts at cell sectors with with dominant audio/video streaming traffic to free up radio channels for accommodating additional users without affecting user experience. For cell sectors with dominant web browsing traffic, we plot CDF of state promotion delay for varying DCH→FACH RRC timeout values in Figure 2(c). We note that state promotion delay decreases for larger DCH→FACH RRC timeouts. Therefore, mobile network operators can increase the values of RRC inactivity timeouts at cell sectors with with dominant web browsing traffic to improve users' web browsing experience. More details about leveraging geospatial diversity to improve mobile network performance can be found in [6, 5].

3. REFERENCES

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