MOBILE TECHNOLOGY ACCELERATION IN MULTIPLE WAY

Nirmal M. D.[1]

[1] Assist. Prof., PREC, Maharashtra, India

ABSTRACT

We give a long term and big standard study of the experience of mobile users through two popular but contrasting applications in the app world. To conduct this study, we implemented measurement framework and library, called insight, which has been deployed on these two applications that are available through apple's app store and goggle's android market. One of them, parallel kake (pk), is a popular massively multiplayer online role-playing game the other application, study smart (ss), is an educational application with over160,000 unique users. Our study spans most of the life of the pk game (more than 3 years) while our deployment with has been running for over a year now. We use insight to collect diverse information about network behaviour, application usage and footprints, platform statistics, user actions, and various factors affecting application revenues.

1. INTRODUCTION

Understanding the application experience: in the recent years, researchers have adopted various approaches to study the usage of mobile applications. Some studies have instrumented Smart phone devices of a controlled set of users to Understand application usage patterns . Other studies have deployed stand alone measurement applications for the mobile platforms. For example,3gtest uses a standalone application that allows users to run network performance tests from their current locations, while app sensor uses its own app to understand the contextual usage (e.g., time of day, location) on smart phones. The focus of this paper is quite dissimilar from such prior approaches.

We want to understand the usage pattern of a few popular apps, how it varies with different factors, such as performance of network, type of device, and application type, and the possible generalizations from our observations. To meet this goal our approach and infrastructure is quite distinct from prior published approaches.
The user's experience within an application gives multiple dimensions.

In certain cases it depends on the interaction of the network properties with application features. It also depends on the application's design . Unlike standalone measurement systems that capture various performance parameters only when users activate these processes, Insights combining network and application analytics.
Higher network latencies due to poor network performance reduced user interactivity across both applications. The impact was higher for the pk (upto 60% Reduction in interactivity), which requires real-time communication with the servers. Furthermore, poor network performance led to shorter user sessions and loss in application revenues for pk (up to 42% under bad network conditions). Thus, techniques to identify and reduce

User-perception of high network latencies (e.g., placing additional servers near regions with high cellular latency) is crucial for such developers (4). Poor cellular network performance led to an increase in wifi usage indicating that network quality affected user's choice of networks. The game users (pk) exhibited a higher preference for wifi networks (85%)compared to the educational app (69%) under poor cellular performance, indicating that choice of the network. Type is also impacted by the application.

2. GENERIC DATA LOGGED BY INSIGHT.

2.1 Session data:-

The duration of an application's usage in the foreground is denoted as a session. A session ends if the application is closed or pushed to the background.

2.2 Device information:-

Insight also records the device related information (e.g., model, platform, screen brightness, available network interfaces, signal strengths) per session.

2.3. Network data:-

Insight collects periodic network performance data by performing light-weight measurements using both tcp and udp. When a user starts the application, insight initiates a tcp connection with our measurement server(co-located with the actual application servers). The servers ends probes to the applications at a configurable interval (30seconds by default [16]) using tcp and udp packets with increasing sequence numbers. These probes elicit immediate

Responses from the application allowing computation of both udp and tcp based network latencies or round trip times (rtts). These rtts allow us the measure the quality of the network link (e.g., cellular or wifi) between the server and user device. A high value of network latency (or rtts)indicates the presence of a poor network link.

2.4. Location information:-

While the app has access to precise user location through gps/wifi, for our study we anonymize this information into coarse-grained blocks (100sq. Km. Regions, state level, or country level).

2.5. Application footprint on device:-

Insight also measures he resource overhead of the application on user devices by capturing a set of metrics. These metrics include the cpu and memory utilization by the application as well as the "battery drain rate" on the device while the application is in the fore ground. the battery drain rate is calculated per session (while the application is in foreground) by dividing the change in battery level during a session with its duration. For example, if the battery level changes from 80% to 75% during a session length of 20 minutes, the battery drain rate is (80 - 75)/ 20levels/minute, i.e., 0.25 levels/minute. The overhead of this measurement is minimal on the device as well as the application

As it is passive and performed infrequently (every 30seconds by default). Currently, we have implemented this capability only for android.

3. App specific data:-

In addition to the above generic information, insight additionally provides associate degree api to the applications to log any extra information. The appliance code calls this api sporadically to record app-specific statistics.

3.1 Analyzed datasets :-

Using insight, we've collected information for pk over a amount of over three years throughout that the sport received three major upgrades and plenty of minor updates. Compared to the current information set, the information from the study blue application (android only)is smaller in size, since we've been running insight with the application for simply over a amount of one year. We tend to use these 2datasets to produce some application specific comparisons between an mmorpg associate degreed an academic app. Table a pair of presents a outline of the half-tracked statistics.

4. Privacy implications :-

To conduct this study, we tend to had a special arrangement with our partnering package firms. In every case, we tend to developed and provided the insight library to the businesses, and they integrated our package into their application. All collected data was continually resident within the servers of the individual

Companies. Through a special nda in every case, we were provided with associate degree anonymized feed of the assorted information we tend to collected. Among information that we tend to gift during this paper, the only potentially sensitive information is user location. For the aim

Of this project, we tend to anonymized this data by mapping them to a coarse-grained block a hundred sq. Km. Area, state level, or country level, as was adequate for the analysis conferred in this paper. Associate degree correct latitude-longitude level accuracy wasn't necessary. Further, our analysis team never directly interfaced with the users or their information, and instead were restricted by special arrangements we tend to negotiated with the two firms.

5. Different Devices:-

Above Figure shows the distribution of normalized battery drain rates (levels/min) measured on the favoured devices employed by pk players. We tend to build the subsequent observations: (i) across

Different devices, the variation in drain rates is caused due to use of various elements (e.g., screen, network card)even if they need identical battery capability. As an example, the devices lg optimus, samsung galaxys epic and htc evo4g have similar memory, cpu, network capabilities and also the same battery capability of 1500 mah however have totally different drain

Rates.

How did network performance have an effect on the session lengths?

In figure sixteen, we tend to show however average user session length for pk varies with average cellular network latency for the

Session (collected exploitation insight's active measurements). We find that network performance encompasses a goodly impact on application usage—session lengths decrease with increase in network latencies i.e., users tend to play the sport for a lesser time because the network conditions worsen. A rise of network latencies from zero.3 to 0.9 seconds reduced average when do the users access these applications? However is that this

Behaviour totally different across applications?

Figure five (left) and figure five (right) show the quantity of online based mostly players (from usa local time zone) during a twenty four hour amount for pk and sb severally. It shows that the Peak range of on-line users occur at totally different times for the two applications. The foremost probably reason for this behaviour is that users choose to use these applications at completely different times Of the day. As an example, sb's peak usage is within the afternoon and nights once students study a lot of. The graph additionally shows The number of actual users truly finding out where as victimisation the application. Most on-line users at early mornings (3-6am) seem to be burning the time of day oil for studying. At alternative times, its users additionally perform alternative activities such as causation messages, making flash cards, looking knowledge etc.

We observe pk gets used the foremost at nights (9pm-11pm).further, for pk we tend to additionally realize higher population on Sundays, And a lower population on Fridays. session lengths from half-hour to twenty five minutes (16% Reduction). We tend to determined lower correlation between network Latencies and session lengths for sb (not shown here). We find that for each the applications, the amount of on-line users square measure at a minimum around 6am within the morning. This diurnal pattern was consistent across completely different countries. Application developers will use this insight for many functions. for example, early mornings (around half-dozen am) square measure favourable to schedule server downtimes and upgrades, install bug fixes or push updates, as they need smallest range of on-line users across the total day. For applications like , the time Of week info can even be accustomed schedule such server upgrades and downtimes owing to its robust correlation with application usage.

How were user interactions impacted by poor network performance?

Above figure shows the normalized number of user actions per minute (max. Of 1) as a function of the average network latency experienced during a session. We find that User interactivity (actions/minutes) declined wit han increase in network latencies for both applications. But, the decline in user interactions is much more pronounced for pk. For Example, an increase of network latency (rtts) from 300ms to900ms caused average user interactivity to drop by 40%. The same value for sb was only 7% indicating the much lower Impact of the network latency on its users. But, at higher network latencies (>= 1:4 seconds) the impact increased.

References

[1] Böhmer, b. Hecht, j. Schöning, a. Krüger, and g. Bauer. Falling Asleep with angry birds, facebook and kindle: a large scale study on Mobile application usage. Mobilehci '11.

[2] c. Chambers, w. Changfeng, s. Sahu, d. Saha, and d. Brandt. Characterizing online games.ieee ton'10.

[3] engadget. Netflix reveals android app tests that keep it running on 'Around 1000' devices daily. Http://www.engadget.com/2012/03/15/ Netflix-android-app-testing-process/.

[4] h. Falaki, r. Mahajan, s. Kandula, d. Lymberopoulos, r. Govindan, And d. Estrin. Diversity in smartphone usage.in mobisys '10.

[5] p. P. Faq. Cellular data primer. Http://www.pocketpcfaq.com/faqs/cellularprimer.htm/.

[6] j. Huang et. Al. Anatomizing application performance differences on Smartphones.in mobisys, 2010.

[7] l. Leiva, m. Böhmer, s. Gehring, and a. Krüger. Back to the app: the Costs of mobile application interruptions. Mobilehci '12.

[8] j. Manweiler, s. Agarwal, m. Zhang, r. Roy choudhury, and p. Bahl. Switchboard: a matchmaking system for multiplayer mobile games. Mobisys '11.

[9] n. Balasubramanian et al. Energy consumption in mobile phones: a Measurement study and implications for network applications. In Imc '09.

[10] a. Patro, s. Rayanchu, m. Griepentrog, y. Ma, and s. Banerjee. TheAnatomy of a large mobile massively multiplayer online game. Mobilegames '12.

[11] perblue. Parallel kingdom. Http://www.parallelkingdom.com/.

[12] a. Rahmati, c. Tossell, c. Shepard, p. Kortum, and l. Zhong. Exploring iphone usage: the influence of socioeconomic differences Onsmartphone adoption, usage and usability. Mobilehci '12.

[13] c. Shin, j.-h.hong, and a. K. Dey. Understanding and prediction of Mobile application usage for smart phones. Ubicomp '12.