

A Thesis

entitled

A Context-Aware Approach  
to Android Memory Management

by

Srinivas Muthu

Submitted to the Graduate Faculty as partial fulfillment of the requirements for the  
Masters of Science Degree in Engineering

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The University of Toledo  
December 2015

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Smartphones are ubiquitous and operate in diverse environments. Hence, they are well suited to utilize contextual information in enhancing the behavior of their applications. However, the potential of context analysis is not fully utilized by Android devices. The Android operating system caches the processes of recently-used applications in memory, so that they can be loaded quickly should the user request them again. We postulate that incorporating context information can improve this caching scheme. As a proof of concept, we set up an experiment that comprised of twenty volunteers (Android smartphone users) and compared the cache hit ratios of the default scheme with a default-context hybrid scheme. This hybrid scheme incorporated information from the user's calendar in determining which processes were cached. To accomplish this task, each volunteer installed an Android application that parses their calendar for contextual clues and generates a list of applications that the user is likely to use. This list is then combined with the default list (that Android generates through recency of usage) to determine the cache hit ratios of the hybrid scheme. Finally, we use the data collected from the experiment to show why the hybrid scheme is more efficient and on a broader level, that context analysis is beneficial in enhancing the user experience.

To my parents who have always put my needs ahead of theirs.

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I would like to thank all my friends and family for supporting me throughout my time here at UT but I would like to especially mention Sandy Stewart for everything she has done for me. This page is not enough to expound on the details but it suffices to say I would not be here without her and she is like a second mother to me.

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# List of Abbreviations

RAM .....	Random Access Memory
CHR .....	Cache Hit Ratio
OS .....	Operating System
AOSP .....	Android Open Source Project
APK .....	Android Package
APMD .....	Android Powered Mobile Device
CBP .....	Cached Background Process
OEM .....	Original Equipment Manufacturer
ADB .....	Android Debug Bridge
UID .....	Unique Identifier
OOM .....	Out Of Memory
API .....	Application Programming Interface
USA .....	United States of America
UI .....	User Interface
PPMCC .....	Pearson Product Moment Correlation Coefficient
CI .....	Confidence Interval

# List of Symbols

✓ ..... Represents a check mark indicating that a particular item has been checked or in a different context, whether the checked item is correct

# Preface

This thesis is original, unpublished, independent work by the author, Srinivas Muthu under the tutelage of Dr. Jackson Carvalho.

# Chapter 1

## Introduction

### 1.1 Problem

By default, every Android application runs in its own Linux process [34]. When a smartphone that runs on Android is active, the RAM contains all the active processes [3] and services [2]. In addition, it also contains cached background processes. These processes are kept in memory so that in the event the user clicks any of the corresponding applications, they can be loaded onto the screen quickly, thereby enhancing the user experience. Consequently, it is in Android's best interests to maximize the chances of the user requesting one of these applications. Currently, Android uses recency of usage to determine which applications get cached. To elaborate, the most recently used applications are cached as cached background processes. Therefore, the problem at hand is determining whether there is a better caching scheme, and whether contextual information can be influential in such a scheme.

### 1.2 Proposed Solution

We postulate that incorporating context information can lead to a better caching scheme. In our case, we utilize context by looking into the user's calendar, to try and predict which applications the user is likely to use in the near future. This leads to

three possible caching schemes:

- Default Scheme (based on caching recently used applications)
- Context Scheme (based on caching applications predicted by reading the user's calendar)
- Default-Context Hybrid Scheme (based on caching applications from both groups)

We measured the efficiency of each scheme in order to determine the best one. We set up an experiment comprised of twenty Android smartphone users, to measure the cache hit ratios of each scheme. We developed an Android application that parsed the user's calendar and generated a list of applications, likely to be used by the user. Additionally, it collected the basic cache metrics (cache hit, cache miss, cache hit ratio) for each scheme. We thoroughly analyzed the data collected and the summarized the results.

### 1.2.1 Assumptions

We have made the following assumptions:

- For the purpose of this thesis, the user's context is obtained through reading the user's calendar.
- All the research volunteers own an Android smartphone that operates at API (Application Programming Interface) Level 21 and above [41].
- Each volunteer authorized the application to access their calendar.

Chapter 4 elaborates on why volunteers require API level 21 and above. Android mandates that the user authorize all permissions for third-party applications to access their data, during installation.

## 1.3 Checking Applications in RAM

Every Android smartphone user is capable of checking the processes that currently reside in physical memory. The Application Manager, which is part of the Settings application, shows a list of running processes and cached background processes. Additionally, it breaks down the composition of RAM usage (Figure 1-1) by system applications and user installed applications.

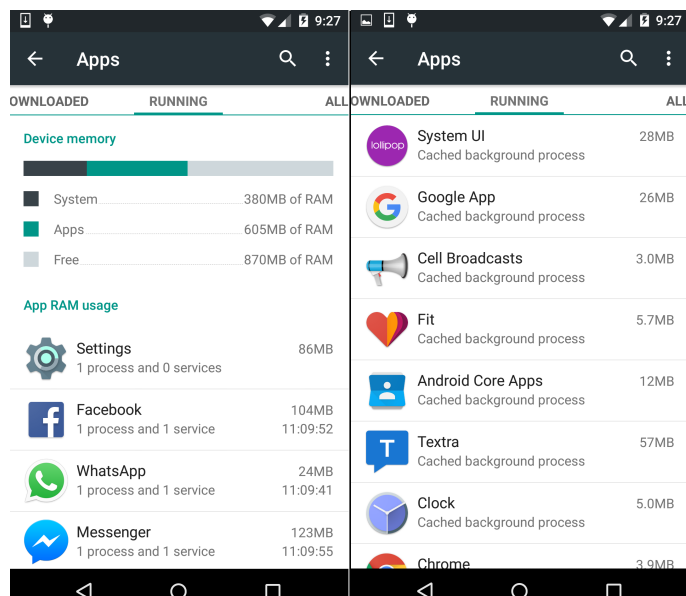


Figure 1-1: Left - List of Running Applications (Active Processes and Services)  
Right - List of Cached Background Processes

## 1.4 Organization of Thesis

Several works in the past have focused on context-aware applications and ways to observe user behavior patterns. We will explore some these works and how this contextual data was put to use in Chapter 2. In Chapter 3, we will take a look at some of the challenges in collecting cache metrics, such as detecting the applications in memory, detecting when the user clicks a new application, whether to approach the



problem at the user level or the system level, to list a few. Chapter 4 elaborates on the setup of the experiment and analyzes the design of the application used to collect these metrics. We dive into the data and summarize the results in Chapter 5. We also investigate how certain supplementary factors could explain the distribution of data. In Chapter 6, we discuss some of the shortcomings of this thesis and conclude the thesis with Chapter 7. Finally, chapter 8 talks about scope for future work and explores some of the possibilities of directly adding to this thesis.

# Chapter 2

## Related Work

### 2.1 Early Studies in Context-Aware Computing

Dey, Abowd and Salber, in their 2001 paper titled *A conceptual framework and a toolkit for supporting the rapid prototyping of context-aware applications* laid out the foundation, and in many ways, a standardized framework for building context-aware applications. When this paper was published, mobile phones were becoming mainstream devices and were no longer confined to the hands of a few. By definition, more people were mobile and the devices they carried with them had the potential to utilize contextual information gathered from the surroundings, in ways that desktops could not do, due to their stationary nature. Dey et al. defined context as any information that characterizes a situation related to the interaction between humans, applications and the surrounding environment. They opined that the state of research in context-awareness was inadequate for three main reasons:

- The notion of context was ill-defined.
- There was a lack of conceptual models and methods to help drive the design of context-aware applications.
- No tools were available to jump-start the development of context-aware appli-

cations.

They focused their efforts on the pieces of context that could be inferred automatically from sensors in a physical environment and produced Context Toolkit [6], a conceptual framework that supported the rapid development of context-aware applications. It is important to keep in mind that at the time this paper was published, the notion of what we refer to as a smartphone was non-existent. This is evident from the fact that most APMD (Android Powered Mobile Device)(s) have built-in sensors that measure motion, orientation, and various environmental conditions. These sensors are capable of providing raw data with high precision and accuracy, and are useful in monitoring three-dimensional device movement or positioning, or changes in the ambient environment near a device [7]. These conditions make APMD(s) very suitable for utilizing contextual information and translating that potential into a better user experience. We utilize this feature of APMD(s) to propose ways to improve user experience by incorporating contextual information in managing its physical memory.

## 2.2 Context Patterns in Application Usage

Several works have attempted to collect user behavior data and they have accomplished this in unique ways. Hannu Verkasalo, in his 2007 paper titled *Contextual Patterns in Mobile Service Usage*, analyzes how mobile services are used in different contexts [4]. Usage contexts were divided into *home*, *office* and *on the move*. A specialized algorithm tracked user's location patterns over a period of time, to determine whether the user was at home or at work. Furthermore, changes in location data revealed whether the user was in transit between home and work. There was a correlation between the mobile services requested by the user and the user's physical location, which enabled the algorithm to understand the user's context quite well (Figure 2-1). It was also observed that certain services were requested more during

the weekends as opposed to certain others being requested more during the weekdays i.e. days with office hours.

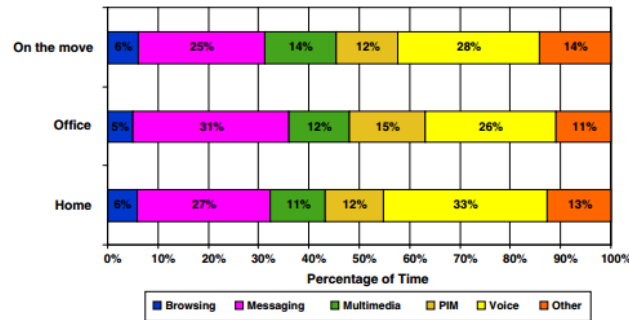


Figure 2-1: Mobile Services Requested at Various Times of the Day

## 2.3 Context Phone

Mika Raento, Antti Oulasvirta, Renaud Petit, and Hannu Toivonen, in their paper titled *ContextPhone: A Prototyping Platform for Context-Aware Mobile Applications*, proposed that mobile phones are well suited for context aware computing due to an intimate relationship between the user and the phone [5]. Their primary goal was to provide context as a resource and in order to accomplish that, developed a *ContextPhone* which comprised of four components (Figure 2-2):

- Sensors that acquire contextual data (such as location data from GPS)
- Communication Services (such as SMS, MMS to list a few)
- Customizable Applications (that can replace existing applications)
- System Services (such as background services for error logging)

It is important to observe that this paper came out in 2005, two years before the first version of Android was even launched. Yet, their fundamental point of focus is

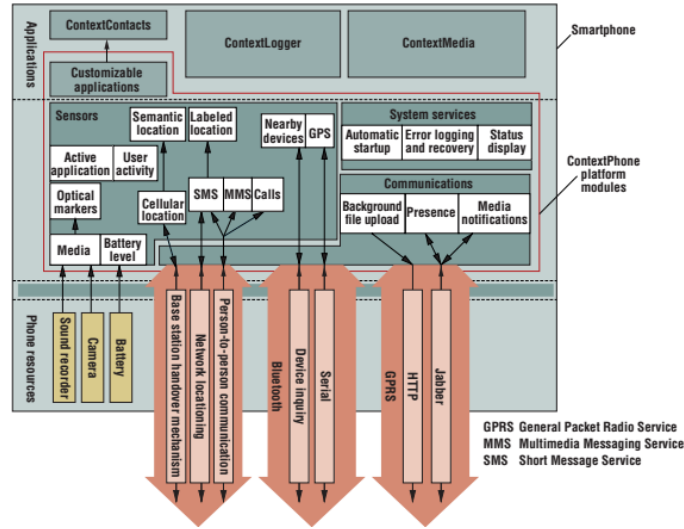


Figure 2-2: The ContextPhone platform; Four interconnected components : sensors, system services, communication services, and customizable applications facilitate communication with the outside world.

still relevant in how we can use context as a powerful resource. Their point about the necessity of customizable applications, that are needed for context information to be relevant, perfectly applies to this thesis. The Android OS which is open sourced as AOSP (Android Open Source Project), is as customizable as it can get when it comes to modifying mobile components, and by extension, the user experience with APMD(s). To be specific, it facilitates ways to gather information needed to compute the efficiency of the cache, such as the list of processes currently residing in memory and the current foreground application, among others. We could also modify the caching mechanism and build our own custom distribution of the Android OS. It would be impossible to collect and/or modify such information on any other mobile OS (such as Apple's iOS).

## 2.4 Using Context Information for Authentication

Dey et al. established a framework for collecting contextual data and Verkasalo and Raento et al. have shown how user behavior can be analyzed through sensors and other modules that gather contextual information. Shi et al.'s paper, titled *Implicit Authentication through Learning User Behavior*, demonstrates a similar approach in collecting behavioral data of the user but differs in how it puts that information to use. They have devised a model to implicitly authenticate smartphone users based on their behavioral patterns. The user's usage patterns are collected (for e.g. how many calls a user makes a day, how many times user's location changes (Figure 2-3) etc.) and this information is used in building a user model [8].

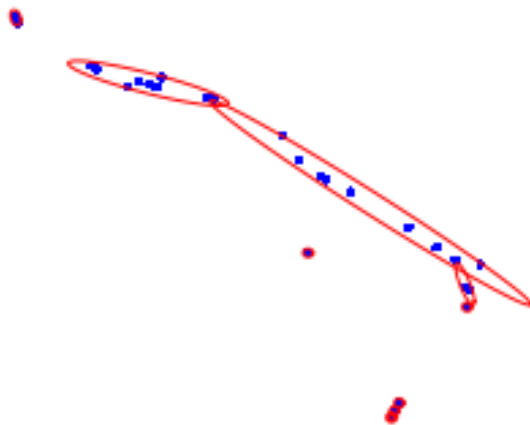


Figure 2-3: The blue dots represent the users traces in a two-hour epoch over multiple days, and the red ellipses represent the clusters fitted. The major two directional clusters correspond to the users trajectory on a highway

Once the user model is built and the profile completed, the algorithm can determine the likelihood of a random user of the phone not being the owner of the phone (the one whose user model was profiled).

As demonstrated by Shi et al., there are numerous ways contextual information can come in handy. In our case, we propose a default-context hybrid caching scheme,

for caching application components in memory, that operates by looking into the user's calendar for contextual information.

# Chapter 3

## Metrics of Interest

### 3.1 Introduction

Now that we have laid the foundation for using contextual information to influence which processes Android caches in memory, we need to establish the metrics that need to be collected in order to measure the efficiency of the existing caching scheme and the proposed caching scheme. The following section addresses the metrics we need.

### 3.2 What are the desired metrics?

#### 3.2.1 Hits, Misses, Hit Ratio & Latency

Alan Jay Smith defines Cache as a high speed buffer that holds items in current use [9]. In our context, Android holds application components (such as processes) as CBP (Cached Background Process)(s) in memory. As previously discussed, CBP(s) do not take up processor time, they are merely cached for quick application startup, should the user request that particular application. A cache hit is a state in which data requested for processing by a component or application, is found in the cache memory. It is a faster means of delivering data to the processor, as the cache already contains the requested data [10]. When applied to our scenario, a cache hit would



represent a situation wherein the user requests (clicks) an application that currently resides in memory, either as an active process (including services) or as a CBP (Figure 3-1).

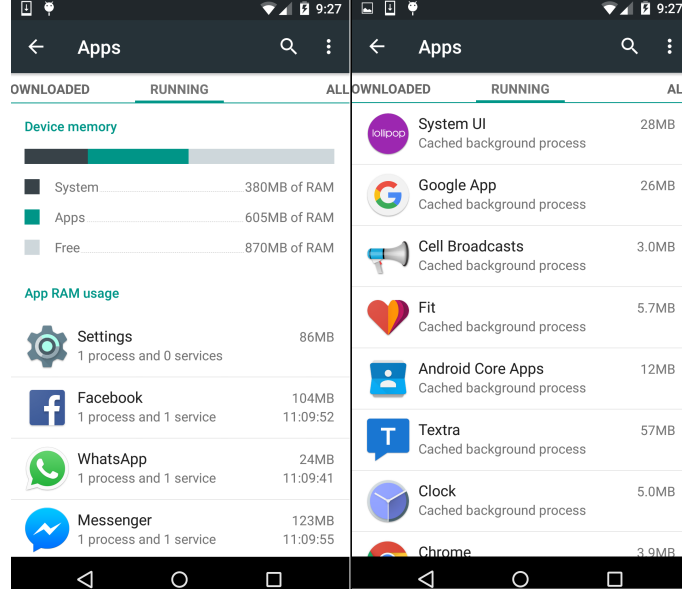


Figure 3-1: Given this snapshot of the RAM, if the user clicks on say, the Messenger application (active process) or the Clock application (CBP), it would result in a Cache Hit

A cache miss is a state where the data requested for processing, by a component or application is not found in the cache memory [11]. When applied to our scenario, a cache miss would represent a situation wherein the user requests (clicks) an application that currently does not reside in memory, either as an active process (including services) or as a CBP (Figure 3-2).

CHR (Cache Hit Ratio) is defined as the ratio of cache hits to the overall number of requests (total of cache hits and cache misses).

$$OverallNumberOfRequests = CacheHits + CacheMisses \quad (3.1)$$

$$CHR = \frac{CacheHits}{OverallNumberOfRequests} \quad (3.2)$$

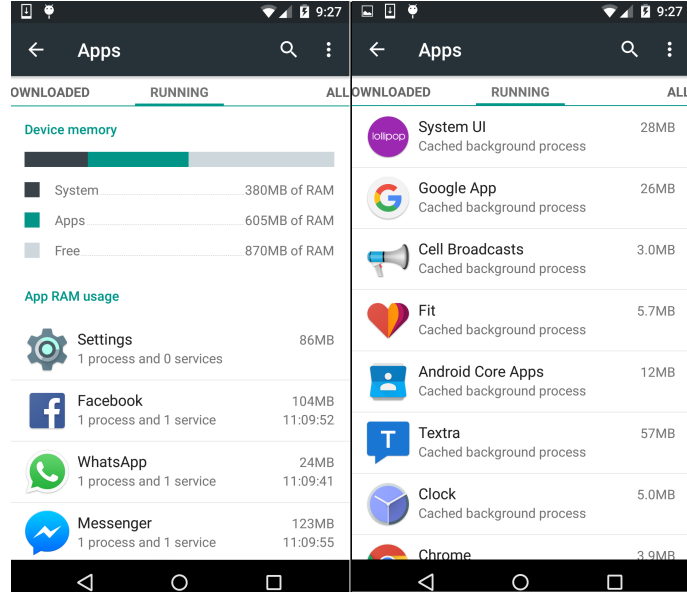


Figure 3-2: Given this snapshot of the RAM, if the user clicks on say, the Google Drive application (process not in memory), it would result in a Cache Miss

$$CHR'(In\%) = CHR * 100 \quad (3.3)$$

There are two primary figures of merit of a cache [9]:

- Latency
- CHR

The latency of a cache describes how long after requesting a desired item, the cache can return that item (in the case of a cache hit). In our scenario, processes are cached in RAM. Therefore, even if the number of processes cached in memory increases, there will hardly be any difference in the time it takes to fetch a requested item (application component), as they all reside in RAM which by definition supports random access. Latency is more of a factor in caches that are located further away from physical memory (such as L1 and L2 caches).

The CHR of a cache describes how often a searched-for item is actually found in the cache. The higher the CHR, the better the cache is. When applied to our

context, a high CHR results in more application components being fetched from memory, rather than disk, which in turn results in quicker application startup times. This improvement in startup speed results in an enhanced user experience.

### **3.2.2 Caching Schemes Under Consideration**

Now that we have determined the fundamental metrics we need, let us analyze the various caching schemes under consideration.

#### **3.2.2.1 Optimal Caching Scheme**

The most efficient caching scheme would always have the requested item in cache. In our case, the ideal scheme would be one that ensures that every application the user requests, resides in memory. This optimal result is referred to as Belady's optimal algorithm [12] or the clairvoyant algorithm. Since it is generally impossible to predict the exact behavior of the user, this is not implementable in practice. The practical minimum can be calculated only after experimentation, and one can compare the effectiveness of the actually chosen caching scheme against Belady's, as a benchmark.

#### **3.2.2.2 Recency of Usage**

This caching scheme primarily relies on recency of application usage and this is the default scheme Android currently uses. Android caches application components in memory as CBP(s) and associates each with a time-stamp. If the memory gets too full, it starts removing the least recently used CBP(s) first and depending on how direly low the memory is, it may not stop killing processes until even the active foreground application (the one user is interacting with) is removed [3], although this situation is extremely rare in practice and only results in the case of malfunctioning applications that leak memory. The Settings application can give the user clues about which CBP(s) were recently used. Clicking on an application that is currently not

in memory results in that application being cached as a CBP near the top of the list. This suggests that the CBP(s) displayed by the Settings application are roughly sorted by their time-stamp from most recently used to least recently used (Figure 3-3).

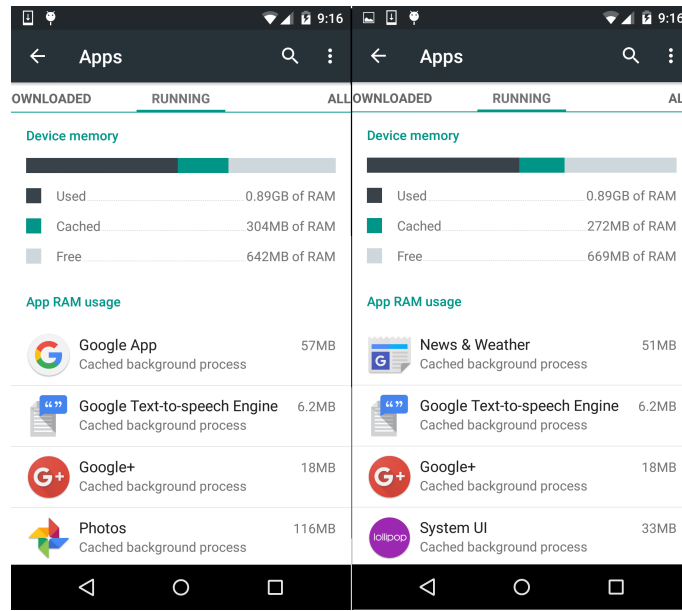


Figure 3-3: The image to the left describes the snapshot of the CBP(s) as displayed to the end-user by the Settings application. The image to the right displays the snapshot of the CBP(s) after the end-user requests for the News and Weather application. Note that the News and Weather application will not be cached as a CBP until the user is done interacting with it, as up until that point, it will reside in memory as an active process.

It is worth noting that a perfect implementation of this caching scheme requires a time-stamp on each reference, and the OS needs to keep a list of items ordered by the time-stamp. This implementation may be deemed too expensive in certain cases especially if the frequency of memory references is high. The common practice is to approximate the behavior of this scheme [13].

### **3.2.2.3 Frequency of Usage**

This caching scheme relies on the frequency of application usage as opposed to the recency of application usage. To elaborate, the most frequently used applications would be cached as CBP(s) in memory. This could be a really good alternative to the default recency-based scheme, given the tendency of most smartphone users to stick with the same set of popular applications and use them in rotation [15]. Under these circumstances, the frequency of a select few applications would be really high and would always be cached in memory, as they are requested often. Frequency based caching scheme is sometimes combined with a recency-based caching scheme to form a frequency-recency hybrid [14].

### **3.2.2.4 Random**

Much like the name suggests this caching scheme would randomly select an application and cache it in memory as a CBP. This scheme does not require keeping any information about the access history. For its simplicity, it has been used in ARM processors [16]. When applied to our scenario, it does not seem like a viable option, mainly because there is no benefit in randomly caching applications in memory.

### **3.2.2.5 Default-Context Hybrid**

So far we have analyzed the standard caching schemes that focus on caching items that were either accessed recently, frequently, or in other ways that analyze past behavior. Our approach combines the applications that Android caches through a recency of usage scheme, with a separate context-analyzer module that reads the user's calendar and predicts which applications the user is likely to use. When the user requests an application, the combined set of applications (default applications based on recency and the list of predicted applications) is used as the base to compute whether a cache hit or a cache miss occurred. We will analyze in detail how each

module functions but before that, we need to examine two things:

- Whether Android can pro-actively cache application components in memory.
- Which applications will be removed from memory when it runs too low.

**Pro-actively Adding CBP(s)** In order for the proposed Default-Context Hybrid (henceforth referred to as Hybrid) caching scheme to work, there must be a provision for the Android OS to pro-actively cache application components in memory as CBP(s). Presuming that the context-analyzer module does its job and suggests a list of applications the user might use in the near future, there must be a mechanism for Android to utilize that information and pro-actively cache these applications in RAM as CBP(s). This mechanism can be verified at the user level through a small experiment. As previously mentioned, the Settings application provides a visual interface for the list of active processes and services running in memory and the CBP(s) that reside in memory at any moment in time. As part of the experiment, each and every CBP was forcefully removed from the cache (there is provision to do this at the user level (Figure 3-4)).

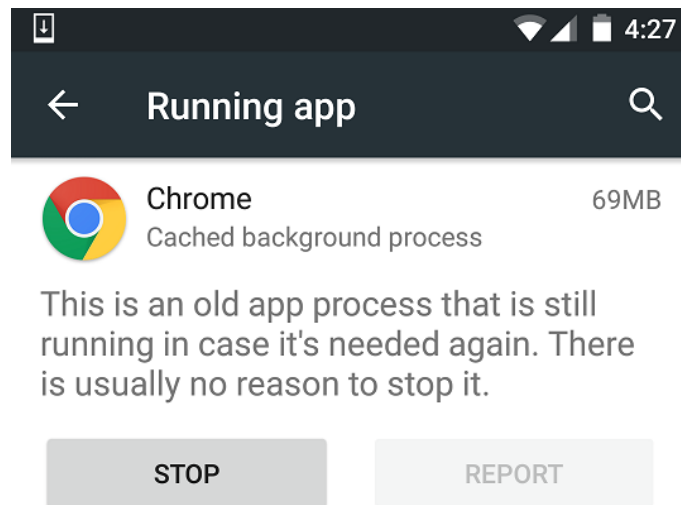


Figure 3-4: Pressing the *STOP* button removes the CBP from memory

Once each CBP was removed, the phone was untouched for three minutes. After three minutes, when the Settings application was launched to look at the list of CBP(s), it was not empty. Instead, there were several CBP(s), some of which were previously removed and some of which were not in the list to begin with (Figure 3-5).

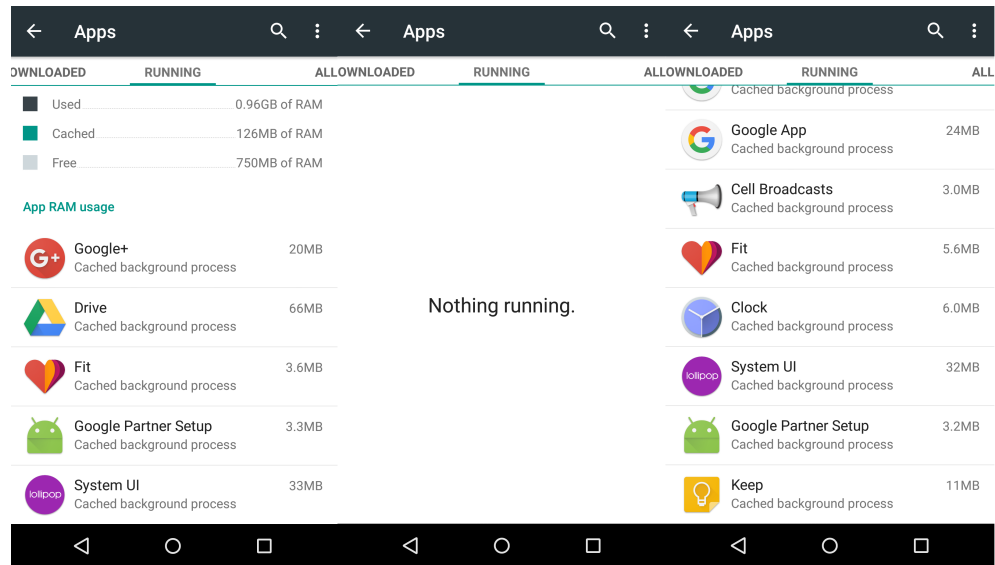


Figure 3-5: The leftmost image shows the snapshot of the CBP(s) before forceful deletion. After each and every CBP was removed manually, the screen displayed is shown in the middle image. The image farthest to the right shows the repopulated list of CBP(s), 3 minutes after the middle image was taken. This demonstrates Android's ability to utilize free RAM space and pro-actively cache CBP(s)

This indicates that Android pro-actively caches applications that were not in memory to begin with, as CBP(s). This is also the reason why task killer applications fell out of favor [17]. This demonstrates that not only does Android provide a mechanism to pro-actively cache applications in memory, it already does so. The applications suggested by the Hybrid scheme can be introduced into the memory as CBP(s) in the same way. This is discussed in Chapter 8.

**Prioritizing Applications in Hybrid Scheme** The Hybrid scheme would involve storing as CBP(s), both default application components cached by Android's recency-

based scheme and the application components of the list of applications obtained from analyzing the user’s calendar. So the question now becomes, who gets kicked out when memory is running low? Since the applications inferred from user’s contextual information do not have a recency associated with them, the overall list of CBP(s) cannot be prioritized based on recency of usage. A simple solution is to prioritize the CBP(s) obtained from the list of suggested applications over the default ones i.e. all the default CBP(s) are removed from memory before the CBP(s) cached as a result of context inference. Alternatively, the CBP(s) with the least memory footprint can be prioritized i.e. the most memory-heavy CBP(s) are removed first. While this approach releases memory quickly, it does not take into account the likelihood of application usage in the immediate future.

### 3.2.3 Supplementary Data

We have talked about the fundamental metrics involved in measuring the efficiency of any caching scheme, namely cache hits, cache misses and CHR. We explored potential candidates for serving as the caching scheme in managing the list of CBP(s) cached in memory. There are other subtle measurements that are not as significant as the fundamental metrics but are important nonetheless, as they shed light on certain attributes of the experiment. They are listed below:

- Number of Installed Applications
- Number of Unique Applications Requested (Clicked)
- Number of Calendar Entries During the Course of the Experiment
- Phone Model
- Android OS Version

These are elaborated upon in Chapter 5 under the demographic data section.



## 3.3 Challenges

Now that we have established what the desired metrics are, let us examine some of the challenges in collecting them.

### 3.3.1 Deciding Between System vs User Level Approach

Firstly, we need to determine whether to approach the problem from a user level perspective or not. Attempting to solve the problem i.e. collecting the aforementioned metrics at the user level would involve building Android applications to gather relevant data. On the other hand, approaching the problem from a system level would involve altering the source code of the Android OS (facilitated by AOSP) and recompiling it to build our own custom distribution, much like the CyanogenMod community [18]. It is easier to solve the problem (if possible) at the user level for two reasons:

- The complexity involved in altering OS source code is significantly higher compared to writing Android applications.
- It would be significantly harder to convince potential research volunteers to reboot their smartphones with a custom distribution of the Android OS as opposed to asking them to install an Android application.

Given that it is beneficial to gather relevant data at the user level, we need to identify the complexities involved and determine whether they are solvable at the user level. In order to effectively determine which caching scheme is ideal for caching CBP(s) in memory, we need to identify whether the following problems can be approached from a user level perspective:

- Getting the list of processes currently in memory ✓

- Knowing when a new process is launched by the user ✓
- Reading the User's Calendar ✓

We will inspect in detail, why and how we need to solve these problems (and others) in the next section. The '✓' indicates that they are indeed solvable at the user level and do not require system level changes.

### 3.3.2 Getting Processes in Memory

Let us first address why it is necessary to get the list of processes that reside in memory. In our scenario, we are trying to determine the most efficient caching scheme among the following:

- Default Recency based Scheme
- Pure Context Scheme (Applications will be cached solely based on context inference)
- Default-Context Hybrid (or simply Hybrid)

In order to determine which scheme is most efficient, we need the ability to measure CHR data, and by extension, if and when a cache hit or miss occurs. We can only determine if a cache hit occurred if we had access to the list of processes in the cache i.e. the active processes and the CBP(s) in memory. The *ActivityManager* class in Android provides two relevant helper methods [19]:

- *getRunningTasks()*
- *getRunningAppProcesses()*

Unfortunately, as of Android 5.0, it has become increasingly difficult to get a list of applications running in memory. *getRunningTasks()* has been deprecated and

*getRunningAppProcesses()* has been killed (It only returns the requesting application rather than all applications running in memory). An alternate solution is to use the *UsageStatsManager* class [20]. However, it requires special permission from the user in the Settings application and some OEM (Original Equipment Manufacturers)(s) have removed this setting explicitly, rendering this solution unreliable. The best solution involves using the ADB (Android Debug Bridge) shell to retrieve the desired information which can then be parsed into a suitable list of processes residing in memory. ADB is a versatile command line tool that enables communication with an APMD. It is a client-server program that includes three components [21]:

- A client, which runs on the APMD. The client can be invoked from a shell by issuing an ADB command.
- A server, which runs as a background process on the APMD. The server manages communication between the client and the ADB daemon running on the APMD.
- A daemon, which runs as a background process on the APMD.

The ADB provides a Unix shell that can be used to run a variety of commands on the APMD. The command binaries are stored in the APMD's file system at */system/bin/* [22]. We obtain the list of processes residing in memory by running the *toolbox* command [26] in the shell. The Android *toolbox* command encapsulates the functionality of many common Linux commands (and some special Android commands) into a single binary [23]. Of these, we are most interested in the *toolbox* and *ps* commands as they provide a direct window into the processes residing in memory.

With the help of *libsuperuser* library, which provides a convenient framework to run shell commands [24] and the *AndroidProcess* library which provides a framework to parse the process-related shell outputs [25], the following algorithm (Algorithm 1) was written to obtain a list of processes residing in memory (active processes and

CBP(s)). It is worth noting that this list corresponds to the list of processes displayed by the Settings application (Figure 3-1) as part of the running applications and CBP screens, and that the Settings application has system privileges that third party Android applications do not.

**Result:** LIST Process

INITIALIZE LIST Process - processes

LIST String - stdout — Shell.SH.run("toolbox ps -p -P -x -c")

Integer myPid — android.os.Process.myPid()

```
for String line : stdout do
|   INITIALIZE Process - process
|   if process matches APP-ID-PATTERN then
|   |   if (process.ppid EQUAL TO myPid)
|   |   |   OR (process.name EQUAL TO "toolbox") then
|   |   |   |   CONTINUE
|   |   else
|   |   |   ADD TO processes - process
|   |   end
|   else
|   |   CONTINUE
|   end
end
```

RETURN processes;

**Algorithm 1:** In the above algorithm, *Process* is a custom data structure that parses the output format of the *toolbox ps* command. Its class structure is discussed in Chapter 4. The *APP-ID-PATTERN* is a regular expression that maps to application ID patterns for the Android OS in versions 5.0 and above. Each process is added to a result list that is returned by the algorithm. Note that the requesting application represented by *myPid* (discussed in 4.4) and *toolbox* related processes represented by process names that match *toolbox*, are not added to the result.

### 3.3.3 Obtaining the Foreground Application

In order to update the CHR metric, we need the ability to detect new cache hits and cache misses. A new cache hit/miss occurs when there are new application requests i.e. changes in the foreground application. Before we analyze how to detect change in the foreground application, we first need a way to obtain the current foreground application. Had we approached this problem at the system level, we could have made use of system level privileges such as listening to a new screen-touch by the user and detecting which application was launched, but this is not possible from a third party user-level application. Fortunately, there is a workaround to detecting the foreground application at the user level. We obtain every process currently running in memory and through a process of elimination, obtain the process associated with the foreground application. To elaborate, the foreground application has certain unique properties in its process name, UID (Unique Identifier) and other fields, that can be utilized to eliminate processes that are not associated with the current foreground application. The following algorithm (Algorithm 2) illustrates this process.

**Result:** Foreground Application

INITIALIZE LIST *files* — LIST */proc* File

**for** *File file : files* **do**

**if** *file IS A DIRECTORY* **then**

        | CONTINUE

**end**

*pid* — *file.getName()*

*cgroup* — FILE READ (*/proc/%d/cgroup*)

*cpuSubSystem*, *cpuAccountSubSystem* — *cgroup*

**if** *cpuAccountSubSystem ENDS WITH pid OR cpuSubSystem ENDS*

*WITH bg\_non\_interactive* **then**

            | CONTINUE

**end**

*cmdline* — FILE READ (*/proc/%d/cmdline*)

*uid* — PARSE FROM *cpuAccountSubSystem*

**if** *cmdline CONTAINS com.android.systemui OR uid BETWEEN 1000*

*AND 1038* **then**

            | CONTINUE

**end**

*oomAdj* — FILE READ (*/proc/%d/oom\_score\_adj*)

*oomScore* — FILE READ (*/proc/%d/oom\_score*)

**if** *LOWEST oomScore AND oomAdj EQUAL TO 0* **then**

        | RETURN *cmdline*

**end**

**end**

**Algorithm 2:** This algorithm obtains the current foreground process i.e.

the process associated with the application that the user is  
interacting with.

Firstly, all files with path */proc* are obtained and each iterated over, to find the foreground application. We eliminate file directories as these are of no concern to us. If the CPU account sub-system ends with *pid*, it is not an application process and is thus eliminated. Similarly, if the CPU sub-system ends with *bg\_non\_interactive*, it is a background process and is eliminated as well. The application stored in *cmdline* is a potential candidate for the foreground application and is the right choice, as long as it clears four more hurdles:

- *cmdline* does not contain *com.android.systemui*
- *uid* does not lie between 1000 and 1038
- *oomAdj* i.e. the OOM (Out Of Memory) adjustment level [27] equals 0
- *oomScore* is the lowest among all iterated values

If *cmdline* contains *com.android.systemui* or if *uid* lies between 1000 and 1038, it is a system application and is thus eliminated from consideration. The crucial attribute of the foreground application is that it has the lowest OOM score of all applications. When the Android OS is running too low on memory, it is the job of the Linux OOM killer [28] to sacrifice one or more processes in order to free up memory for the system, when all else fails. A low OOM score indicates that the process is less likely to be killed and that it is lower on the OOM killer's radar. The process with the lowest OOM score is the foreground process as it is of paramount importance not to remove the process the end-user is interacting with, unless as a last resort. This unique property of the foreground process enables us to distinguish it from the rest of the pool.



### 3.3.4 Updating the Statistics

So far, we have established ways to collect the list of processes in memory and the foreground application. The next step is to figure out a way to update the metrics when the user requests new applications. The rate at which the end-user toggles between applications varies from person to person. It also depends on the level of usage. For instance, there are times when the end-user is actively using their APMD and others when the APMD is idle or switched off. Therefore it is hard to predict when there could be a potential change in the foreground application. There is no inherent mechanism for user-level applications to detect third party application launches (That privilege is reserved for system level processes). Therefore, our solution comprises of starting a service [2] that retrieves the current foreground process (Algorithm 2) and the current list of processes residing in memory (Algorithm 1) every second. If there is a change detected in the foreground process (compared to the last second), then the cache metrics are updated. The time interval of one second is chosen as it is deemed to be reasonably accommodative of the average time it takes an end-user to switch from one application to another. The design of the service and the corresponding application is discussed in Chapter 4. The following algorithm (Algorithm 3) illustrates the process of updating the cache metrics.

**Result:** Update Cache Metrics

```
for EACH SECOND do
    newForegroundApp — getNewForegroundApp()
    currentListOfProc — getListOfProcesses()
    if newForegroundApp EQUALS oldForegroundApp then
        | CONTINUE
    end
    if oldListOfProc CONTAINS newForegroundApp then
        | cacheHit++
    else
        | cacheMiss++
    end
    updateMetrics()
    oldListOfProc — newListOfProc
    oldForegroundApp — newForegroundApp
end
```

**Algorithm 3:** This algorithm retrieves the foreground application and checks if it has changed since the last second. If it has, it verifies whether it was a cache hit or a cache miss and updates the cache metrics. Finally, it updates the old foreground application and the previous list of processes to the current one, so that the next iteration uses these values as the base.

### 3.3.5 Backing Up the Data

Previously, we discussed the mechanism by which the background service updates the cache metrics. The other aspect of this issue is storing this data. Before we inspect how to store the data, let us discuss the necessity for such a provision. Our background service is designed to run throughout the duration of the experiment and retrieve the foreground application and the list of processes in memory every second.

This results in its OOM score increasing i.e. its likelihood of getting killed by the Linux OOM killer [28], which would result in a loss of data. It is worth noting that the OOM killer selects the *best* process to kill which is decided by the combination of how long a process has been running and how much memory would be released if the process is killed. Even though our process scores poorly on the time duration aspect, it takes up relatively low memory compared to some of the other common background processes (Figure 3-6).

Android provides several options for saving persistent application data. There are five ways to accomplish this task [29]:

- Shared Preferences - It is used in cases where primitive data needs to be stored in Key Value pairs.
- Internal Storage - It is used to store private data on device memory.
- External Storage - It is used to store public data on shared external storage
- SQLite Databases - They are used to store structured data in a relational database.
- Network Connection - It is used to store data over the Internet.

For our scenario, Internal Storage is the best fit as it keeps the data private to the application and since the data is quite primitive (cache hits and misses), we do not need SQLite databases or network connections. The data is written to a file every minute. That way, we do not have to constantly perform I/O operations from the service and in the worst case scenario (the application is stopped), fifty nine seconds of Cache data would be lost, which is relatively a small amount of time. Algorithm 3 can be tweaked to incorporate the file write operation (Algorithm 4).

**Result:** Update Cache Metrics AND Write to File

```
for EACH SECOND do  
  ...  
  ...  
  updateMetrics()  
  if END OF MINUTE then  
    | writeMetricsToFile()  
  end  
  ...  
  ...  
end
```

**Algorithm 4:** In addition to updating the metrics every second, it also writes the data to internal storage every minute. Any time the application is closed and launched again the metrics are initialized with the values in file.

### 3.3.6 Reading the User’s Calendar

To compute the CHR of the Hybrid scheme, we need the ability to obtain the list of events from the user’s calendar and the ability to parse that information to come up with a list of suggested applications. We will discuss the parsing aspect in the next segment and focus on finding a way to read the user’s calendar. The solution to this problem is quite simple, Google provides a public API [30] to obtain access to the user’s calendar information, including the list of events. We query the calendar every four hours (for events occurring in that four hour period) and feed the data (events list) into a module that parses the information and produces a suggested list of applications (Algorithm 5).

**Result:** Update Cache Metrics, Write to File AND Update List of Suggested Applications

```
for EACH SECOND do
  ...
  ...
  updateMetrics()
  if END OF MINUTE then
    | writeMetricsToFile()
  end
  if END OF 4 HOURS then
    | updateListOfSuggestedApplications()
  end
  ...
  ...
end
```

**Algorithm 5:** In addition to updating the metrics every second and writing them to file every minute, it also updates the list of applications suggested by the Calendar Parser (discussed in next segment)

The following algorithm (Algorithm 6) illustrates our implementation of the module that queries the user's calendar.

**Result:** Get List of Events from Calendar

INITIALIZE List *result*

List *allEvents* — QUERY *content://com.android.calendar/events*

**for** *EACH event IN allEvents* **do**

**if** *event.startTime()* IS WITHIN 4 hours FROM NOW **then**

        | *result.add(event)*

**end**

**end**

RETURN *result*

**Algorithm 6:** This algorithm obtains all events in the user’s calendar that start within 4 hours from the time of the algorithm invocation.

### 3.3.7 Parsing the Calendar Information

We have examined the mechanism behind reading the user’s calendar, thereby solving one half of the puzzle. The other half is utilizing this information to compute the Hybrid scheme’s metrics. In order to achieve that, we need to build a module that parses the list of events obtained from reading the calendar and suggests a list of applications. Every event in the user’s calendar is split into individual keywords and a predetermined mapping between keywords and applications builds this list. The keyword-application mapping is determined by a two factors:

- There is a default application [42] that directly maps to the keyword.
  - For instance the keyword *mail* is mapped to the *GMail* application, which is the default e-mail application in APMD(s).
  - Similarly the keyword *call* is mapped to the *Google Dialer* application, which is the default application to make and receive calls.

- Additionally, when the Google Play Store [32] is searched with the keyword, the top result is mapped to it.
  - For instance, when the Play Store was searched with the keyword *skype*, Skype application was the top result. Once it is verified that Skype is part of the installed applications [33], it is added to the list of suggested applications.

Finally, if there are no events in the user's calendar for the four hour period, then the list of suggested applications is populated with a maximum of ten default applications. These default applications are derived from the ten most popular Android applications in USA (United States of America) [31]. Out of these ten applications, every application that the user has installed in their APMD will be added to the default list (resulting in a maximum of ten).

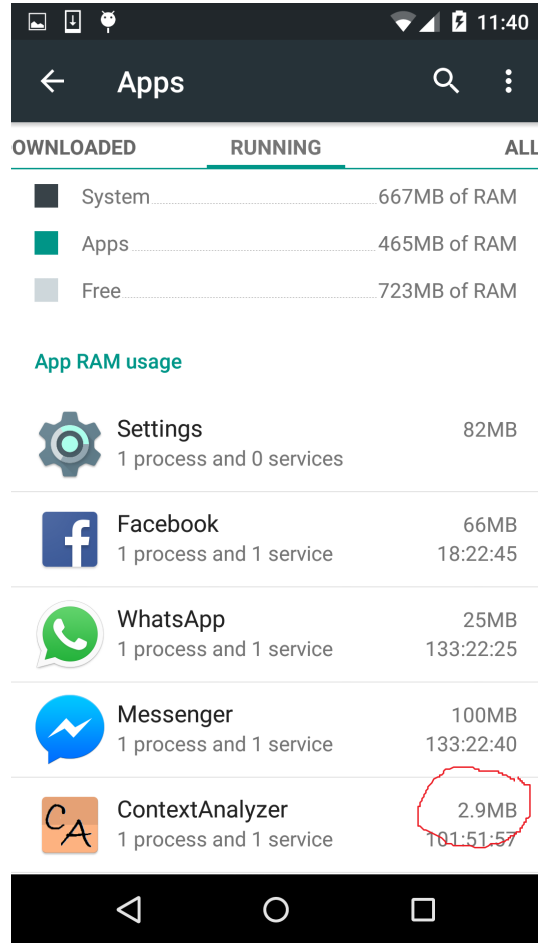


Figure 3-6: *ContextAnalyzer* is our custom Android application that reads the user's calendar and collects cache metrics. The service mentioned in the diagram is the background service that updates the metrics every second. We will discuss the design of this application in Chapter 4. It is worth noting that the memory footprint of the application is quite low. This is not to suggest that it will not get killed by the OOM killer (as its longevity is still a factor), which is why we are backing the data up.



# Chapter 4

## Experiment Setup and Application Design

### 4.1 Introduction

In the previous chapter, we examined the metrics we needed to analyze the best caching scheme for caching application components in memory as CBP(s). We looked into some of the common caching schemes and analyzed some of the challenges in collecting the metrics needed to determine if contextual information can help better the CHR of the Hybrid approach. To analyze the efficiencies of the default recency-based approach and the Hybrid approaches, an Android application, namely *ContextAnalyzer*, was developed to collect the desired cache metrics. It was installed in the APMD(s) of research volunteers. We will dissect *ContextAnalyzer*'s design in Section 4.4.

### 4.2 Eligibility for Volunteers

The following criteria had to be met to qualify as a research volunteer:

- The volunteer must own an APMD with Android OS version greater than 5.0

(Lollipop and above).

- The volunteer must be willing to install a third party application on their APMD.

The algorithm that obtains the list of processes currently residing in memory (Section 3.3.2) and the algorithm that retrieves the current foreground application (Section 3.3.3) do not apply to Android OS versions below 5.0, hence the necessity for APMD(s) with OS versions that are Lollipop and above.

#### 4.2.1 Addressing Privacy Concerns

Since the research volunteers had to install a third party application (*ContextAnalyzer*), it was crucial to address any privacy concerns that arose. In order to gain the trust of the volunteers, we adopted a policy of full transparency and took the following measures:

- We fully explained to each volunteer, the nature of the data we were collecting i.e. cache metrics.
- We open sourced the Android application [35] in case the volunteers wanted to verify that there were no nefarious activities going on in the background.
- We did not automatically store the cache metrics in a server. Instead, we asked the volunteers to send us the data in order to convey the message that we were not collecting any private data that the volunteers were not aware of.

Although the aforementioned points address the privacy issues, we realize that divulging the nature of the experiment has the potential to bias the volunteers in their APMD usage. We explore this aspect in detail in Chapter 8.

### 4.3 Process and Duration of Experiment

A total of twenty volunteers signed up and installed the application. Each volunteer had the application running for a minimum of 7 days and a maximum of 12 days. A 7 day minimum was enforced to ensure that the monitoring period included both weekdays and weekends. This accounted for any difference in usage patterns among the volunteers during the weekends. The link to the APK (Android Package) file was posted online [40] and each volunteer downloaded and installed the application as a third-party application. In this context, the term third-party refers to the fact that the Android application was not downloaded from the Google Play store. The volunteers were instructed not to manually stop the application for the duration of the experiment [36].

### 4.4 Context Analyzer Design

*ContextAnalyzer* computes the metrics for both the default scheme and the Hybrid scheme. In order to accomplish this, *ContextAnalyzer* reads the user’s calendar (Section 3.3.6) and produces a list of applications that the user is likely to use. For the sake of simplicity, let us refer to this list as the calendar list. It also reads the list of processes residing in memory (Section 3.3.2). Let us refer to this list as the memory list. Given this information, every application that the user requests falls into one of four categories:

- The application is present in neither list.
- The application is present in memory list but not the calendar list.
- The application is present in calendar list but not the memory list.
- The application is present in both lists.

If the application is present in neither list, it results in an overall cache miss. To elaborate, an overall cache miss implies that neither the list of processes in memory (cached by the default recency-based caching scheme) nor the list of applications predicted by reading the calendar, contained the requested application. If the application was present only in memory list, it results in an overall cache hit and a suggested cache miss i.e. the Hybrid scheme would have still had a hit but it was not present in the list of applications suggested by the calendar list. If the application was present only in the calendar list, it results in an overall cache hit and a suggested-exclusive cache hit, implying that the hit is solely a result of the calendar list's suggestion. This metric is important as it reveals the significance of the list of applications suggested exclusively by the calendar list. Finally, if the application was present in both lists, it results in an overall cache hit and suggested non-exclusive cache hit, implying that the hit would have occurred regardless of whether the application was present in the calendar list or not. The following snapshot (Figure 4-1) illustrates *ContextAnalyzer's* UI (User Interface).

It is worth noting that *ContextAnalyzer* collects sufficient data to compute the CHR of three distinct caching schemes:

- Hybrid Scheme
- Pure Prediction Scheme
- Default Scheme

Since it collects the overall cache hits and overall cache misses, it is quite straightforward to see how it would compute the CHR of the Hybrid scheme.

$$HybridCHR = \frac{OverallHits}{OverallHits + OverallMisses} \quad (4.1)$$

The total hits for the pure prediction approach can be obtained by summing the

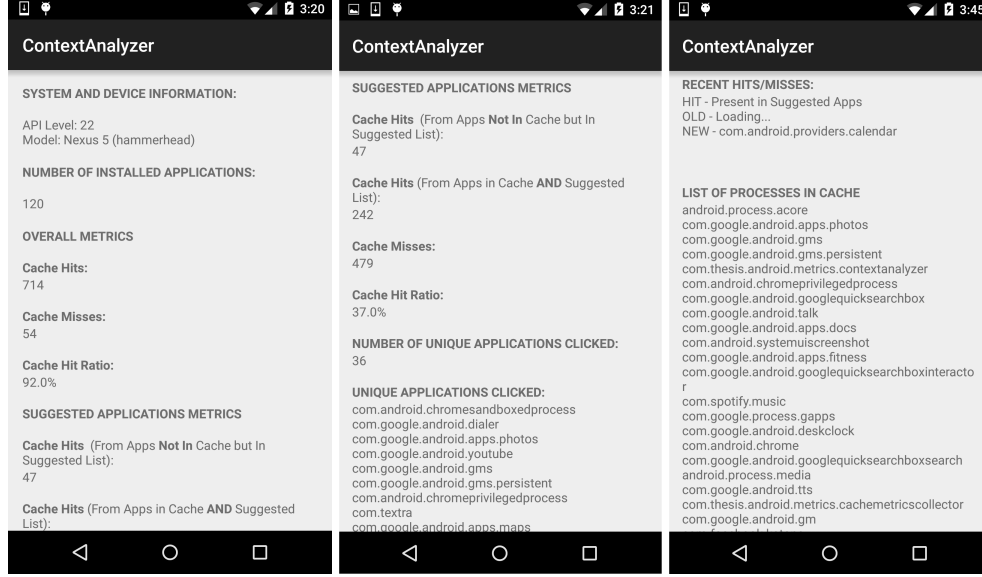


Figure 4-1: The images to the left, middle and right represent the top, middle and bottom portions of the UI, respectively. Note that the Cache Hits in the Suggested Applications Metrics section is divided into suggested-exclusive and suggested non-exclusive. In addition to the cache metrics, it also displays some supplementary data such as the number of unique applications clicked, phone model, OS version and the number of installed applications. These details are discussed in Chapter 5 and are presented as demographic data. Finally, it also displays recent cache hits/misses, memory list and the calendar list purely for the user's benefit. It is not used in data analysis in any way.

suggested-exclusive hits and the suggested non-exclusive hits as their total comprises of all the hits that resulted due to the calendar list. The application also collects the suggested misses, therefore the CHR for the pure prediction approach can be easily obtained.

$$TotalSuggestedHits = SuggestedExclusiveHits + SuggestedNonExclusiveHits \quad (4.2)$$

$$PurePredictionCHR = \frac{TotalSuggestedHits}{TotalSuggestedHits + SuggestedMisses} \quad (4.3)$$

The total hits and misses for the default scheme can be derived from the data that *ContextAnalyzer* directly collects. Since it collects the overall cache hits (that includes default cache hits) and the suggested-exclusive cache hits, the default cache hits can be obtained by computing their difference:

$$DefaultHits = OverallHits - SuggestedExclusiveHits \quad (4.4)$$

Alternatively, we can obtain the default-exclusive cache hits by computing the difference of the overall misses and the suggested misses. This can then be added to suggested non-exclusive cache hits to obtain the total cache hits for the default scheme.

$$DefaultExclusiveHits = SuggestedMisses - OverallMisses \quad (4.5)$$

$$DefaultHits = DefaultExclusiveHits + SuggestedNonExclusiveHits \quad (4.6)$$

Every application click that results in a suggested-exclusive cache hit would by extension, also result in a default cache miss. Additionally, every application click that results in an overall cache miss would also result in a default cache miss. Therefore the sum of these two fields would give us the default cache misses.

$$DefaultCacheMisses = OverallCacheMisses + SuggestedExclusiveCacheHits \quad (4.7)$$

The CHR for the default scheme can be computed using the following equation:

$$DefaultCacheHitRatio = \frac{DefaultCacheHits}{DefaultCacheHits + DefaultCacheMisses} \quad (4.8)$$

We have established that the application collects sufficient data to compute all the necessary metrics for the three caching schemes. Let us inspect the design of this application. *ContextAnalyzer* comprises of the following modules:

- The main Activity [1]
- A background Service [2]
- Process Manager
- Calendar Reader
- Calendar Parser

The main Activity is the heart of the application. It is responsible for launching the application and creating a background service. The background service retrieves the list of processes in memory and the current foreground application. The background service is bound to the Activity i.e. its life-cycle is tied to that of the Activity's [36]. It is for this reason that the volunteers are instructed not to forcefully close *ContextAnalyzer* for the duration of the experiment as that would destroy the service along with the Activity and all metric collection would stop. The Process Manager module contains a *Process* data structure that encapsulates a running process and all of its

attributes (name, user identifier, process identifier to list a few). It also contains the algorithm that fetches the list of processes residing in memory. The background service launches a separate thread that invokes this algorithm every second, to compute the cache metrics and update the UI. It also has the additional task of obtaining the calendar list from the Calendar Parser. The Calendar Parser gets the list of calendar events from the Calendar Reader and produces the calendar list (that the service consumes). The Calendar Reader queries the user’s Calendar API and obtains the list of events for the next four hours. The following class diagram (Figure 4-2) illustrates *ContextAnalyzer*’s design.

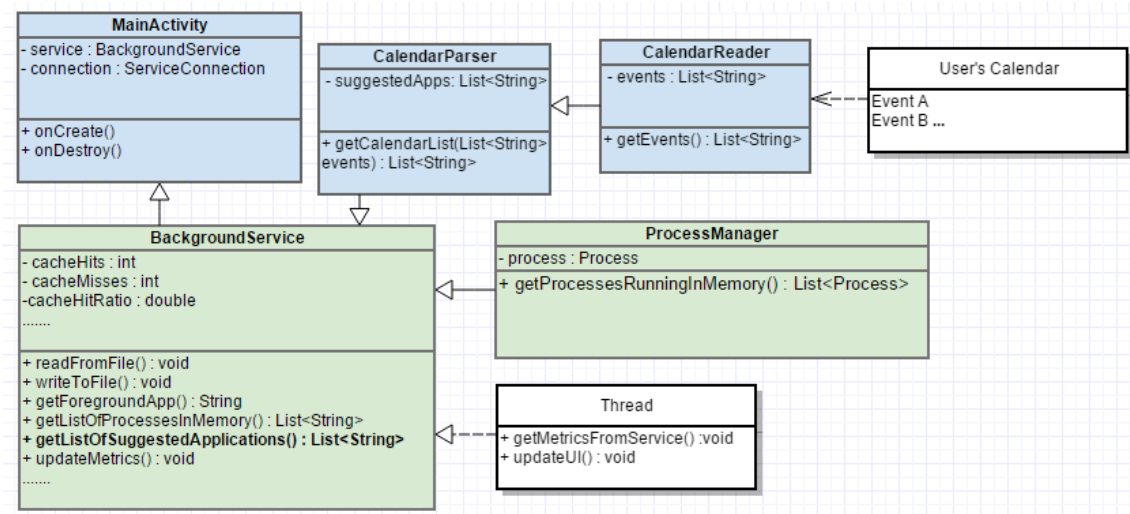


Figure 4-2: Context Analyzer Class Diagram

*ContextAnalyzer* was developed using Android Studio [37] and the source code was uploaded on Github [35]. The class diagram was built using Gliffy [38]. The APK file was uploaded on our Github I/O page [39][40].



# Chapter 5

## Data Analysis and Results

### 5.1 Introduction

In Chapter 3, we examined some of the challenges in collecting the data we needed and in the previous chapter, we analyzed *ContextAnalyzer*'s design and how the experiment was setup. In this chapter, we will inspect the data we collected from each volunteer and compare the CHR(s) of each caching scheme (Default, Context & Default-Context Hybrid). The following section elaborates on the volunteer demographic and the subsequent sections analyze the cache data. Finally, we verify whether our results are statistically significant using a Paired T test [44] and examine the points of weaknesses of this experiment.

### 5.2 Demographic Data

Our experiment comprised twenty volunteers, all of whom were male college students between the ages of nineteen and twenty three. The most common APMD used by the volunteers was the Nexus 5 [45], and SM-G900T (Samsung Galaxy S5) [46] was the least common one. Every volunteer satisfied the Android OS version prerequisite as they all ran Android 5.1 (LOLLIPOP\_MR1) [47]. There were three other metrics collected from the volunteers that can be classified as demographic data:

- Number of Installed Applications (Measured at start of the experiment)
- Number of Unique Applications Clicked (During the course of the experiment)
- Number of Calendar Entries (During the course of the experiment)

### 5.2.1 Total Installed Applications

The minimum number of installed applications among the volunteers was 120. The maximum number of applications installed by any volunteer was 374. The average number of installed applications was 295. The following chart (Figure 5-1) illustrates this distribution.

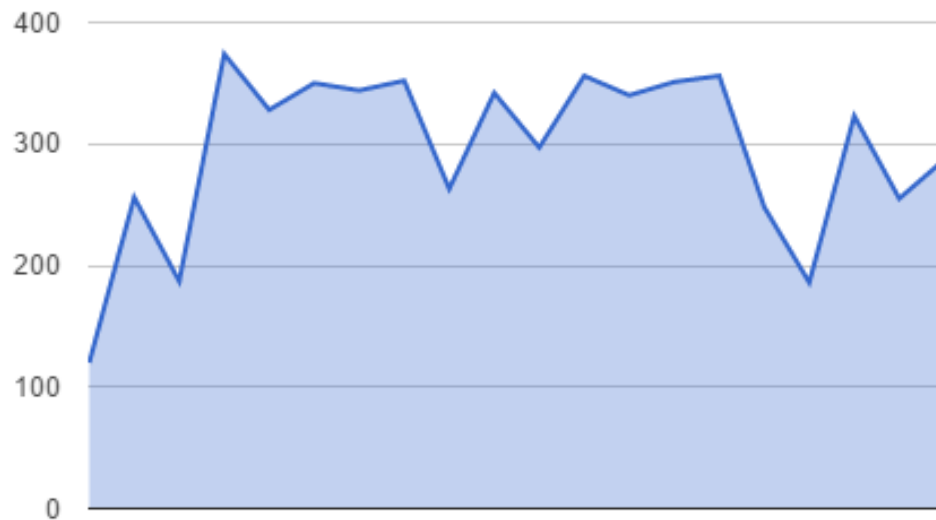


Figure 5-1: This chart illustrates the distribution for the number of installed applications (measured at the start of the experiment), among the 20 volunteers.

Even though, it is a good indicator of the number of applications a user is likely to use, a better indicator would be the number of unique applications requested by a user. We look at this metric next.

### 5.2.2 Unique Applications Clicked

The maximum number of unique applications requested by any volunteer was 56, with an average of roughly 46. The following chart (Figure 5-2) illustrates this distribution. We'll examine the effects of this distribution, and see if there are any correlations with an increase in CHR, later in the chapter.

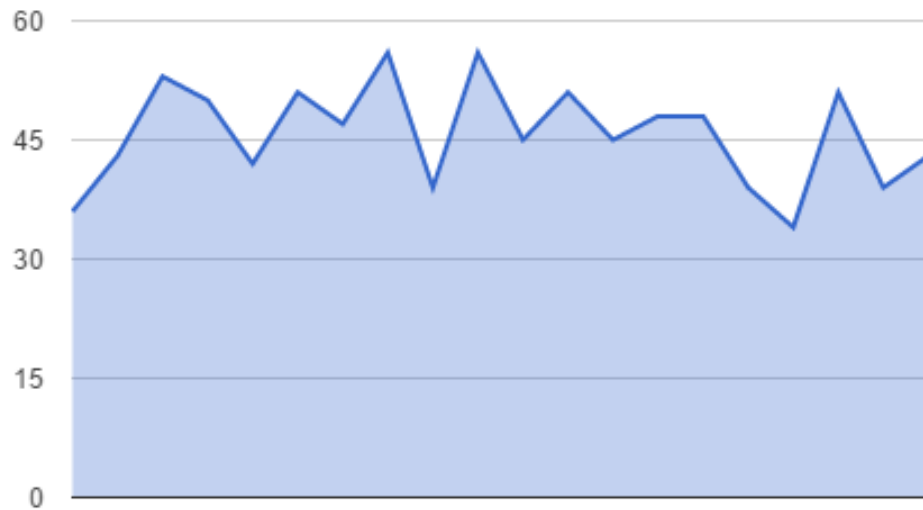


Figure 5-2: This chart illustrates the distribution for the number of unique applications requested during the course of the experiment, among the 20 volunteers.

### 5.2.3 Calendar Entries

The minimum number of calendar entries among the volunteers was 11. The maximum number of entries entered in the calendar by any volunteer was 43. The average number of calendar entries was roughly 25. The following chart (Figure 5-3) illustrates this distribution. We'll analyze the implications of this distribution in Section 5.5.

So far, we have analyzed the distribution for the number of installed applications, the number of unique applications clicked and the total number of calendar entries

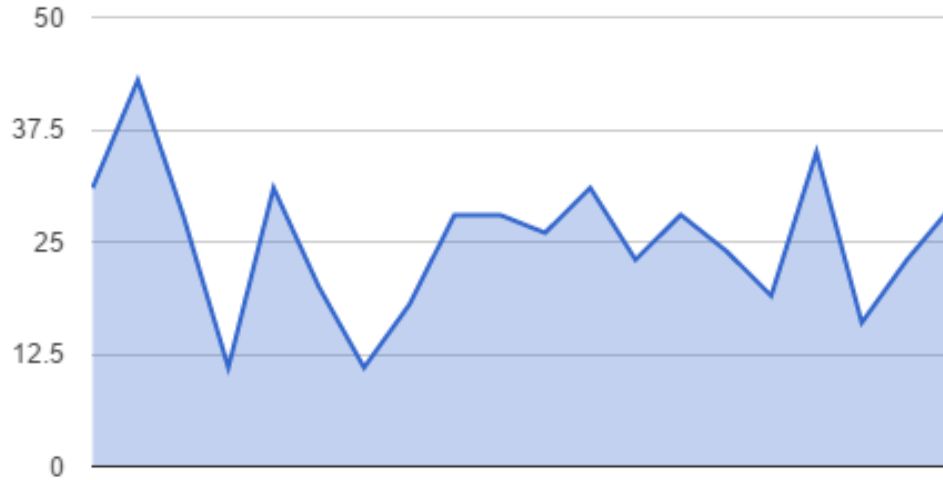


Figure 5-3: This chart illustrates the distribution for the number of calendar entries during the course of the experiment, among the 20 volunteers.

during the course of the experiment. In the next section, we will examine the  $\text{CHR}(s)$  of each caching scheme and whether there is a correlation between these metrics and the efficiency of certain caching schemes.

### 5.3 Experiment Results

The data collected by the *ContextAnalyzer* application provides the metrics to measure the efficiencies of three caching schemes (Section 4.4):

- Context Scheme
- Default Scheme
- Default-Context Hybrid Scheme

Let us analyze the data from each scheme. Since the absolute number of cache hits and cache misses vary depending on frequency of smartphone usage, the only relevant metric is the CHR for each scheme. We will examine the  $\text{CHR}(s)$  in percentages for each caching scheme.

### 5.3.1 Context Scheme

The maximum CHR recorded by any volunteer for this scheme was 37.39%. However, this is not representative of the average case. The mean CHR for the context scheme was 18.47% with a standard deviation of 7.67% and a variance of 58.75. The minimum recorded CHR was 5.92% suggesting that in the worst case, roughly 1 in 16 application requests resulted in a cache hit. The median CHR was 17.35%. The following box plot (Figure 5-4) illustrates this distribution.

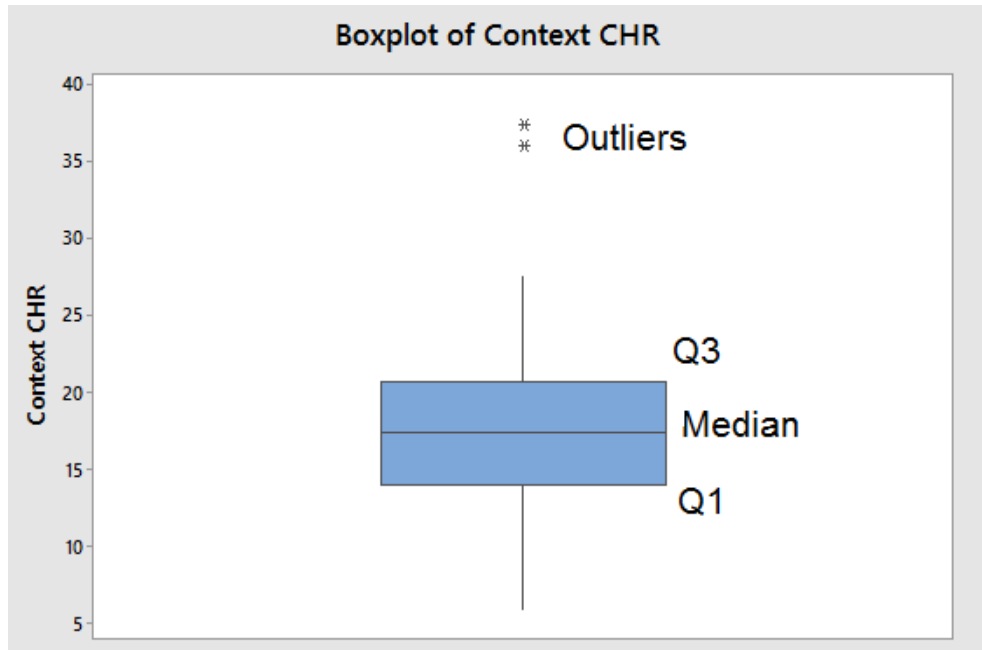


Figure 5-4: This box plot illustrates the distribution for the CHR(s) in the context scheme, among the 20 volunteers. It is worth noting that 25% of the volunteers had a CHR of 14.05% or less i.e. the Q1 value is 14.05%. Similarly, 75% of the volunteers had a CHR of 20.68% or below indicating that the third quartile value or Q3 is 20.68%. Note that the two outlier values are indicated by the asterisk symbol at the very top. On a side note, this box plot was generated using Minitab, a statistical software package [48].

The average CHR was 18.47% i.e. roughly 4 in 5 application requests resulted in a cache miss. While it is better than nothing, it remains to be seen whether the default scheme or the default-context hybrid scheme can put up better numbers.

### 5.3.2 Default Scheme

The maximum CHR recorded by any volunteer for this scheme was 93.19%. However, this is not representative of the average case. The mean CHR for the default scheme was 79.17% with a standard deviation of 13.87% and a variance of 192.37. The minimum recorded CHR was 46.52% suggesting that in the worst case, less than 1 in 2 application requests resulted in a cache hit. The median CHR was 84.04%. The following box plot (Figure 5-5) illustrates this distribution.

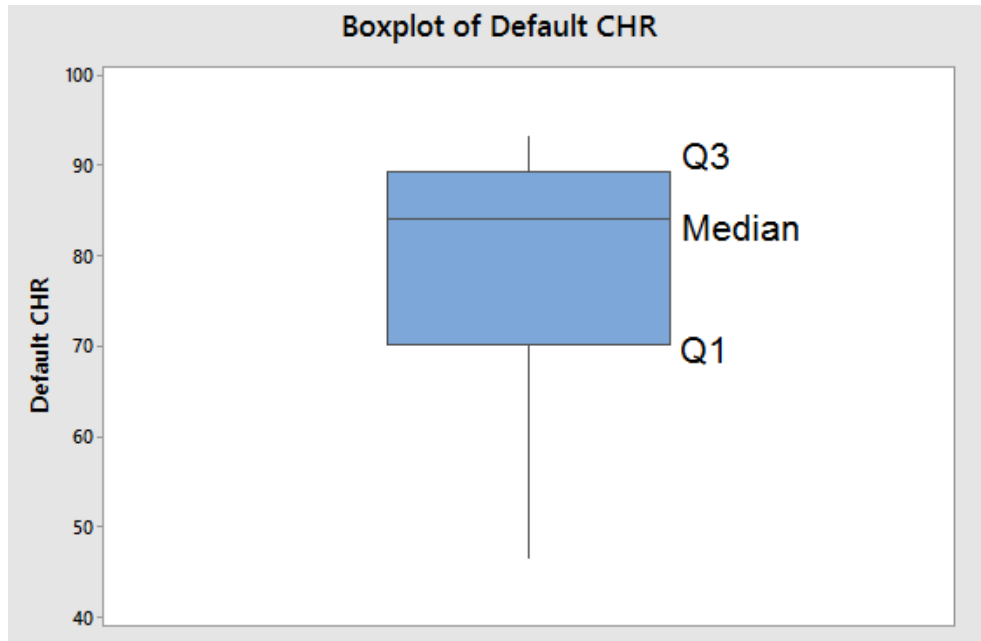


Figure 5-5: This box plot illustrates the distribution for the CHR(s) in the default scheme, among the 20 volunteers. It is worth noting that 25% of the volunteers had a CHR of 70.28% or less i.e. the Q1 value is 70.28%. Similarly, 75% of the volunteers had a CHR of 89.34% or below indicating that the third quartile value or Q3 is 89.34%. This box plot was generated using Minitab as well [48].

The average CHR was 79.17% i.e. roughly 4 in 5 application requests resulted in a cache hit. To put that in perspective, it is more than 4 times the average CHR of the context scheme. Let us see if the hybrid scheme can improve these numbers.

### 5.3.3 Default-Context Hybrid Scheme

The maximum CHR recorded by any volunteer for this scheme was 95.62%. However, this is not representative of the average case. The mean CHR for the hybrid scheme was 83.50% with a standard deviation of 12.39% and a variance of 153.49. The minimum recorded CHR was 53.48% suggesting that in the worst case, less than 1 in 2 application requests resulted in a cache miss. The median CHR was 88.48%. The following box plot (Figure 5-6) illustrates this distribution.

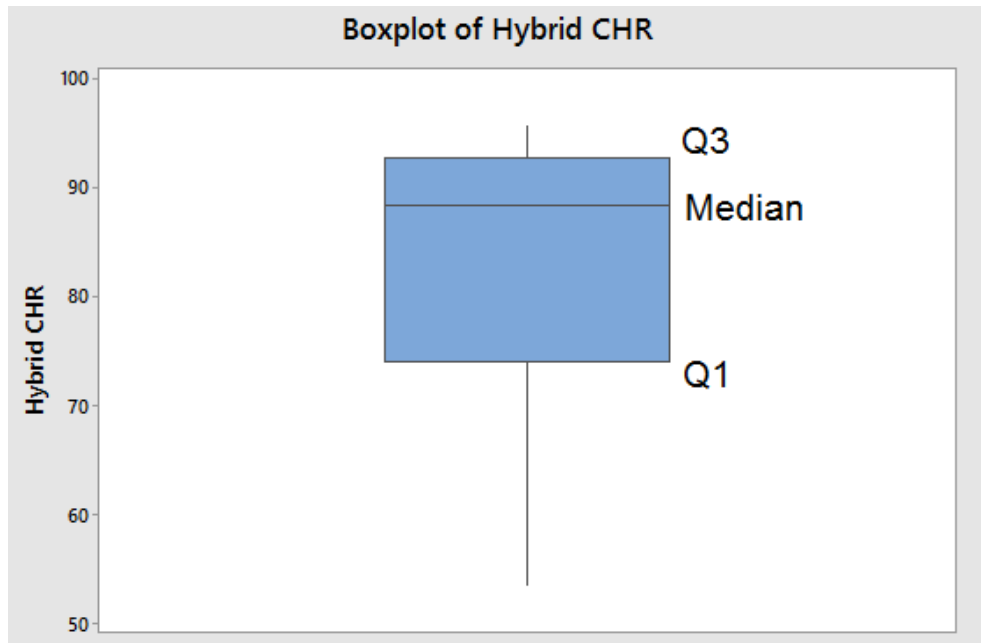


Figure 5-6: This box plot illustrates the distribution for the CHR(s) in the hybrid scheme, among the 20 volunteers. It is worth noting that 25% of the volunteers had a CHR of 73.97% or less i.e. the Q1 value is 73.97%. Similarly, 75% of the volunteers had a CHR of 92.73% or below indicating that the third quartile value or Q3 is 92.73%. This box plot was generated using Minitab as well [48].

The average CHR was 83.50% i.e. roughly more than 4 in 5 application requests resulted in a cache hit. It is worth noting that the hybrid scheme's average CHR is 4.33% more than that of the default scheme, hinting at an improvement in efficiency. In the next section, we will examine if this increase in CHR is statistically significant,

by performing a paired t test [44].

## 5.4 Significance Testing

In any experiment or observation that involves drawing a sample from a population, there is always the possibility that an observed effect could have occurred due to sampling error alone [49][50]. In order to prove that the increase in CHR for the hybrid scheme is statistically significant, we performed a paired t test using every [hybrid CHR, default CHR] pair collected over the duration of the experiment (Figures 5-7, 5-8).

Before the test is performed, two things need to be determined:

- Null Hypothesis
- Significance Level

The null hypothesis refers to a general statement or a default position that there is no relationship between two measured phenomena [51]. In our case, the null hypothesis would state that there is no difference in the means between the CHR(s) of the default and the hybrid schemes. Our objective is to perform a paired t test and determine the validity of the null hypothesis, and by extension, the statistical significance of our data. Significance level is the probability of rejecting the null hypothesis given that it is true [52]. By convention, the significance level is set to 0.05 (5%), implying that it is acceptable to have a 5% probability of incorrectly rejecting the null hypothesis. The *p-value* is defined as the probability of obtaining a result equal to or more statistically extreme than what was actually observed, assuming that the null hypothesis is true [53]. Therefore, if the paired t test produces a p-value less than the significance level i.e. the probability of obtaining more extreme results is less than the probability of incorrectly rejecting the null hypothesis, then the results



are statistically significant and the null hypothesis can be rejected. The results of the paired t test are shown in Figure 5-9.

Given that the *p-value* is less than the significance level (0.05), there is strong evidence to reject the null hypothesis. Furthermore, a 95% CI (Confidence Interval) [54] between 2.97% & 5.70% indicates the lower and upper bound for the true average increase in CHR (If the study were conducted with a larger population). Therefore, it is reasonable to conclude that the increase in CHR between the two caching schemes is not due to sampling error and is statistically significant. In the next section, we will examine potential correlations between the cache hit ratios and some of the demographic data.

## 5.5 Correlation with Demographic Data

### 5.5.1 Calendar Usage

Let us examine if there is a correlation between an increase in CHR and the extent of calendar usage. We compute the PPMCC (Pearson Product Moment Correlation Coefficient) [53] for the increase in CHR and the number of calendar entries for each volunteer (Figure 5-10).

The results of the PPMCC computation (computed using Minitab [48]) were the following:

- A PPMCC value of 0.467
- A p-value of 0.038

If we assume the significance level to be 0.05, then a p-value of 0.038 (less than significance level) corroborates the statistical significance of our PPMCC. A PPMCC value of 0.467 signifies a modest positive correlation. Therefore, it is reasonable to

conclude that an increase in CHR from the default to hybrid scheme is consistent with an increase in calendar usage among the test subjects. The following fitted line plot (Figure 5-11) illustrates this linear correlation.

### 5.5.2 Number of Unique Applications Requested

Let us examine if there is a relationship between the number of unique applications a user requests over the course of the experiment, and an increase in the cache hit ratio. We compute the PPMCC [53] for the increase in CHR and the number of unique applications requested for each volunteer (Figure 5-12).

The results of the PPMCC computation (using Minitab [48]) were the following:

- A PPMCC value of  $-0.437$
- A p-value of 0.054

If we assume the significance level to be 0.05, then a p-value of 0.054 (approximately equal to the significance level) corroborates the statistical significance of our PPMCC. A PPMCC value of  $-0.437$  signifies a modest negative correlation. Therefore, it is reasonable to conclude that an increase in CHR from the default to hybrid scheme is consistent with a decrease in the number of unique applications requested among the test subjects. However, it is worth noting that the p-value is within the margin of error compared to a 0.05 significance level. The following fitted line plot (Figure 5-13) illustrates this negative correlation.

Default CHR	Hybrid CHR	Increase in CHR
86.4385	92.6489	6.2104
86.9565	92.7536	5.7971
92.4403	95.6233	3.1830
89.0110	90.5220	1.5110
90.5523	93.4593	2.9070
80.7309	86.0465	5.3156
92.9806	93.3045	0.3240
46.5190	53.4810	6.9620
49.4186	61.0465	11.6279
72.2656	76.5625	4.2969
69.6221	73.1105	3.4884
87.7514	91.0420	3.2907
82.6786	85.8929	3.2143
69.5918	71.2245	1.6327
85.4054	89.4595	4.0541
61.0656	65.3689	4.3033
76.5625	87.5000	10.9375
93.1944	94.1667	0.9722
89.4444	92.4074	2.9630
80.7432	84.4595	3.7162

Figure 5-7: The data listed in this table illustrates the relative increase in CHR between the default and hybrid schemes for each volunteer. This data is used as the input for the paired t test to measure its statistical significance.

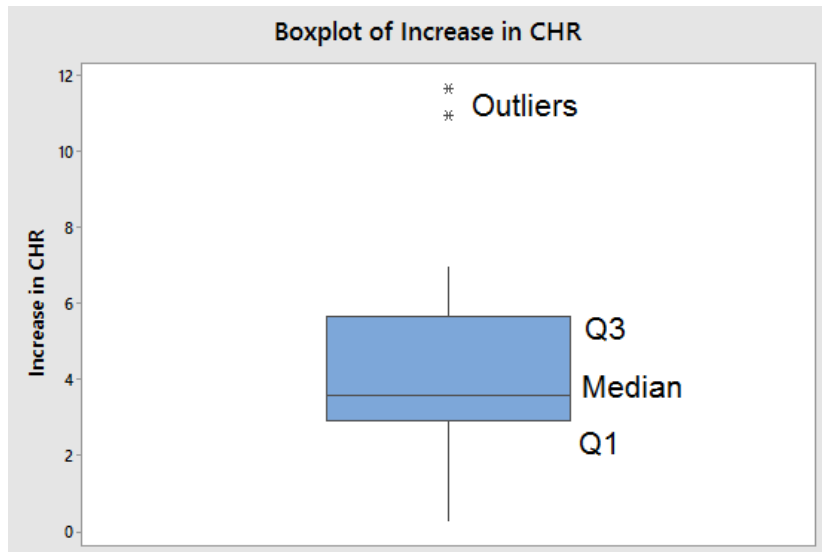


Figure 5-8: This box plot illustrates the increase in CHR from the default to hybrid scheme for each of the 20 volunteers. Note that the two outliers are indicated by the asterisk symbol at the very top.

## Paired T-Test and CI: Hybrid CHR, Default CHR

Paired T for Hybrid CHR - Default CHR

	N	Mean	StDev	SE Mean
Hybrid CHR	20	83.50	12.39	2.77
Default CHR	20	79.17	13.87	3.10
Difference	20	4.335	2.918	0.652

95% CI for mean difference: (2.970, 5.701)

P-Value = 0.000

Figure 5-9: This image illustrates the results of a paired t test conducted with the data listed in Figure 5-7. The paired t test was conducted using Minitab [48].

Calendar Entries	Increase in CHR
31	6.2104
43	5.7971
28	3.1830
11	1.5110
31	2.9070
20	5.3156
11	0.3240
18	6.9620
28	11.6279
28	4.2969
26	3.4884
31	3.2907
23	3.2143
28	1.6327
24	4.0541
19	4.3033
35	10.9375
16	0.9722
23	2.9630
29	3.7162

Figure 5-10: This table illustrates the data used to compute the correlation between increase in CHR and the number of calendar entries entered by each volunteer for the duration of the experiment.

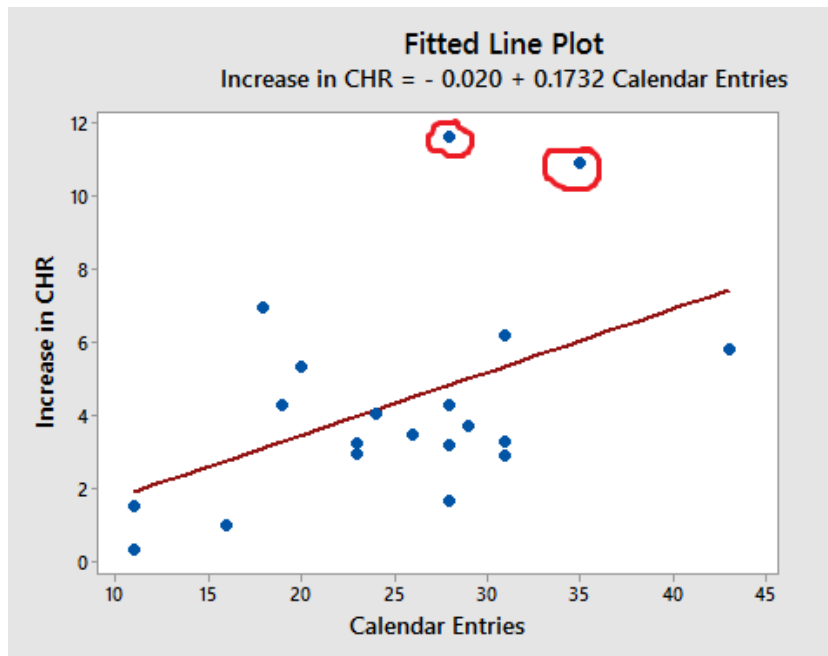


Figure 5-11: This fitted line plot illustrates the linear correlation between increase in CHR and calendar usage. Note that the two outliers are marked at the top with red circles.

Unique Apps Clicked	Increase in CHR
36	6.2104
43	5.7971
53	3.1830
50	1.5110
42	2.9070
51	5.3156
47	0.3240
56	6.9620
39	11.6279
56	4.2969
45	3.4884
51	3.2907
45	3.2143
48	1.6327
48	4.0541
39	4.3033
34	10.9375
51	0.9722
39	2.9630
43	3.7162

Figure 5-12: This table illustrates the data used to compute the correlation between increase in CHR and the number of unique applications requested by each volunteer for the duration of the experiment.

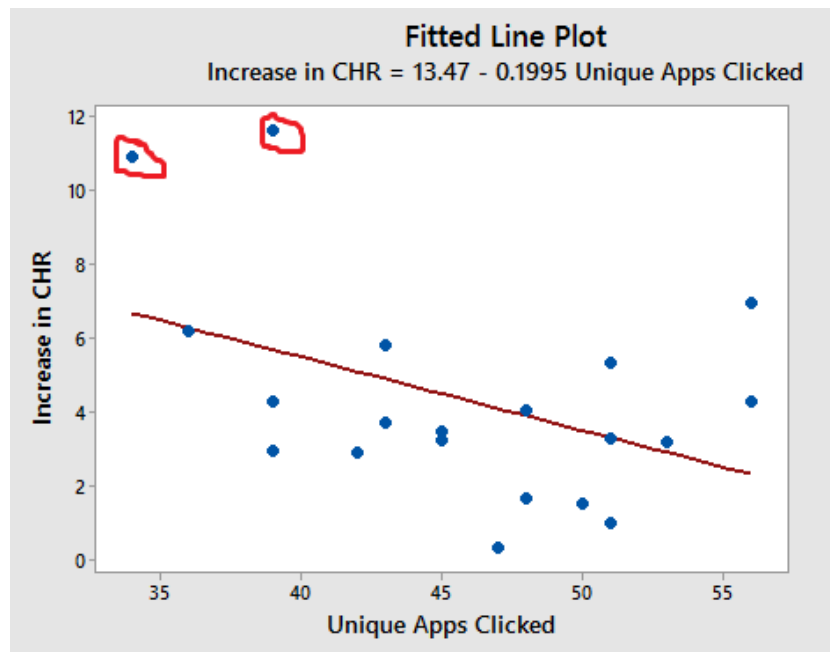


Figure 5-13: This fitted line plot illustrates the negative correlation between increase in CHR and number of unique applications requested over the course of the experiment. Note that the two outliers are marked at the top with red circles.



# Chapter 6

## Points of Weakness

While the data demonstrates that incorporating context analysis improves the efficiency of the default caching scheme, there are certain factors that could affect the validity of this thesis:

- The experiment comprised only twenty volunteers which is a relatively low sample size.
- The volunteers were instructed to use their calendar applications but real-world users may or may not use their calendar application. However, if the users were aware of the benefits in using the calendar under a hybrid scheme, that may change.
- The entries in the calendar may not be indicative of the application that the user might use during that calendar event.
- Not all applications can be mapped to keywords obtained from calendar entries. For instance, while *call* can be directly mapped to the Caller application, there are no keywords that come to mind for the Camera application.
- Since the calendar is only queried every four hours, change in event descriptions within a four hour period are not captured by our application. However, this is

merely a design decision and the frequency can be increased to account for this issue.

- If the volunteer requests two applications within a span of a second (highly unlikely but theoretically possible), then our application would only count the cache hit/miss from the second request as the thread only checks for a new foreground application every second.
- The lack of diversity in our volunteer demographic could have influenced the data. Given that all research volunteers were male college students, the rate of smartphone usage was quite high. It would have been conducive to gather volunteers of all ages and gender.
- Due to our policy of full transparency, the volunteers were aware of the type of data being collected. Even though there was no inherent motivation for any of the volunteers to intentionally skew the cache metrics, theoretically they had the ability to do so.
- The volunteers were instructed not to close the application for the duration of the experiment but this was not enforced. Technically, a volunteer could have selectively closed the application for certain times of the day resulting in an inaccurate monitoring period. However, they had no motivation to do so as no personal information was being collected.

# Chapter 7

## Conclusion

The typical user is not facing a desktop machine in the relatively predictable office environment anymore. Smartphones are well suited to utilize contextual information in enhancing the behavior of their applications. However, the full potential of context analysis is not harnessed by Android devices. Currently, the Android OS caches application components in memory, based on recency of application usage. We have demonstrated that incorporating context information improves the efficiency of this caching scheme. For this purpose, we set up an experiment comprising of twenty volunteers. We developed an Android application to measure the cache metrics of both the default recency-based caching scheme and a default-context hybrid scheme, which in addition to relying on recency of usage, parsed the user's calendar for contextual clues. We analyzed the data and proved that on an average, the hybrid scheme had a significantly higher cache hit ratio. By virtue of its superior efficiency, the hybrid scheme would result in a lower startup time for relatively more applications, thereby enhancing the overall user experience.

# Chapter 8

## Future Work

In addition to the user’s calendar, other sources of information can be utilized to obtain context. These days, most APMD(s) have built-in sensors that measure motion, orientation, and various environmental conditions. These sensors are capable of providing raw data with high precision and accuracy, and are useful in monitoring three-dimensional device movement or positioning, or changes in the ambient environment near a device [7]. Information from multiple sensors can significantly improve the reliability of contextual data. Shi et al.’s work focused on constructing a user behavior model [8] based on analyzing user behavior. A similar approach can be used to predict the list of applications the user is likely to use in the immediate future. Currently the calendar parser relies on predetermined mapping between keywords and applications. This can be improved upon by learning the user’s preferences. If the user predominantly requests an application, associated with a particular event in the calendar, then the mapping can be altered by learning the user’s preferences. Finally, this thesis merely verifies whether a caching scheme that incorporates context information is more efficient than the default recency-based scheme. The next step would be to implement this caching scheme by building a custom distribution of the Android OS, facilitated by the AOSP [43].

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