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Functional Context Awareness: Measuring and Utilizing Context Dependency of Android Mobile Usage

Mrs. Swati Shivaji Gore[1], Mrs. Prachi A. Joshi[2]

Department of Computer Science and Engineering, Marthawada Shikshan Prasark Mandal's Deogiri Institute of Engineering & Management Studies, Aurangabad, Maharashtra, India[1]

Assistant Professor, Department of Computer Science and Engineering, Marthawada Shikshan Prasark Mandal's Deogiri Institute of Engineering & Management Studies, Aurangabad, Maharashtra, India[2]

Abstract: Contextual data brings new open doors for productive and compelling applications and services on mobile devices. A wide variety of examinations have abused context dependency, i.e. relationships in the middle of the context (s) and outcome, to achieve enormous, evaluated performance, A range of applications and services. This work generally needs to manage the difficulties of many contextual sources, resulting in inadequate data preparation and the difficulties of context sensors starved by energy. On a regular basis, they address these difficulties in a particular and specially designated application. We offer mobile application planners and analysts from these weights by providing a systematic way to cope with these challenges. More precisely, we 1) characterize and measure the contextual dependence of three types of mobile use (by site, phone calls and application usage) in a free mode of demand, but viable, Possible application. 2) Adapt to the condition of evaluation of the state of evaluation when managing various contextual sources effectively. 3) Introduce Android based Smart Context to meet the energy challenge by choosing from among the sources of context while guaranteeing a basic accuracy for each estimate. Our review and discoveries depend on the usage and context follows the collection, in reality, of the different Android client settings. We show findings with respect to the context dependence of three types of mobile usage of different clients, but our philosophy and the lessons we learn can quickly be extended to different kinds of use and, in addition, the assets of frame. Our findings control the improvement of contextual frameworks and highlight the difficulties and assumptions regarding the contextual dependence of mobile use.

Keywords: Mobile computing, mobile applications, human factors.

I. INTRODUCTION

Context is usually been misunderstood as to provide much more usability to mobile applications and services, such as client cooperation [5], substance adjustment [3], [4] and moreover the important one i.e. data transfer [6], [7]. Context has additionally been widely misused to give improved framework proficiency and execution, for example, for energy administration [8], [9] and system choice [10]. These highlight the misuse of dependence on the context of mobile use and mobile assets for particular purposes, and show remarkable, evaluated, performance resumes. Cutting edge mobile frameworks, for example, cell phones and tablets are as of now an essential piece of our lives. They are computationally capable as well as have a rich ability to sense their outside and inside environment. Like the definition by Schilit et al. in [1], we allude to the last referred to state of these situations on the whole as context. Dependency on context may be substantially classified as an consolidated arrangement of much stricter or more probabilistic variant of tenets and relations are in the middle of context(s) and the result.

Context mindful frameworks regularly need to manage two principal difficulties.

In the first place, the management of various sources of context is trying; Due to the scourge of dimensionality [11], considering them essentially as a multidimensional vector results from an inadequate preparation set. Second, the liberal use of context can quickly deplete the battery of devices, because some context sensors are incredibly generous. In order to respond to the insufficiency test, the existing work regularly constrains the quantity of contextual sources, for example To one [8] or two [9], and / or use specially named or basic answers to join various context sources, Eg [ten]. To address the energy challenge, they often use impromptu plans in one or more of these ways: to reduce the recurrence of access to an exorbitant context [12], [13], [14], stay away from them in The set [10], [12], [13], or replacing them with another context [15], [16], [17], [18].

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Specific methodologies specifically called and applied to these difficulties imply that the authors must describe and evaluate another response for each contextual system. In addition, before planning and evaluating their application or administration, its creators can simply understand their outcome. Our work is freed in this way. We give a methodological answer for using different and different context wells while dealing with their energy costs. We give a formal but pragmatic sense of context dependency, which gives an understanding of the execution of applications while remaining the agnostic of application. We measure the context dependence of three central types of mobile usage using our LiveLab dataset (http://livelab.recg.rice.edu). LiveLab is a phenomenal set of real-life context and usage is followed by several different Android clients over a year [19]. The mobile use we focus on is through sites, phone calls and application usage. We use contextual data from sensors embedded in the phone (ie constant clock, cell ID, accelerometer and GPS) and, in addition, the last state of use Known to the phone (ie, application, web and phone use). Yet our system and the lessons learned can be communicated to another context and use. Specifically, we make four remarkable commitments to assess and measure dependency on the context of mobile use.

We analyse the accuracy of the estimate in the light of the most extreme a posterior estimate (MAP) as a free thinker of the application, but downwards, a measure of context dependence, For example, entropy as a measure of vulnerability and pseudo R square as a measure of connection, the accuracy of the estimate provides reasonable knowledge about the execution of many potential applications While remaining a rationalist application. To allow the effective calculation of the return probabilities, we present and examine the execution of some structures ordering and grouping context estimates in a predetermined number of classes, for incessant and discrete context sources. In addition, we address the test of the unavailability of information during the comparison in order to manage with several wells of contextual merge systems.

Secondly, we introduce a progression of fascinating discoveries with respect to the contextual dependence of mobile use, as follows:

1) The adequacy of a varied context fluctuates while taking into account the use to be assessed, and the quantity of acknowledged reactions. Yet, joining various sources of context reveals their consolidated quality.

2) We find that, despite the fact that the different context sources are in need, the Bayesian mix works well to combine the contextual data.

3) Dependence on the context of use generally remains consistent, notwithstanding the length of one to three months, rather than the full 12 months. This indicates that a little dataset would be adequate for context mindfulness.

4) Monitored so that binning can, in an extraordinary way, build estimation accuracy, a large number of tests in each class or receptacle, while enabling the embellishment of the boxes.

5) Even if the clients are diverse in their use, we can indicate a considerable contextual dependence among all of them.

Third, we display Android based Smart context, a system to powerfully or statically improve the expense/precision tradeoffs of context mindfulness, while guaranteeing a base exactness for every estimation occasion. Android based Smart context exploits the classifier blend calculations we have investigated that have minimal overhead. We demonstrate that by using energy hungry context just at unverifiable times, Android based Smart context can accomplish an estimation precision inside 1% of the greatest conceivable exactness, while fundamentally diminishing energy costs by 60% or more.

Fourth, we exhibit and assess a few specimen applications that profit by context dependency of mobile use. These applications highlight the viable estimate of the accuracy of the estimate as a measure of context dependence and verify the viability of the context to evaluate the use. Our best performing systems, i.e. utilizing Supervised and Bernoulli Bayesian, reliably beat regular non-context-based strategies.

II. RELATED WORK

In addition, characterize context dependency as an arrangement of strict or probabilistic norms and the relationships between context (s) and outcome. Others outline and execute systems for detecting and handling context data [31],[32]. Baldauf [33] researches the issue by concentrating on telephone call use, and demonstrate that call terms, and accordingly their energy utilization, are context subordinate. In addition, Eagle and Pentland demonstrated that the use of gadgets is sure to be organized and not surprising[37]. The clear value of a context can be at most significant and extended to the point that numerous analysts can be clearly outlined and the actual structure can be outlined for the particular assignment of detecting and preparing context [31], [32], [33]. Our work presents a methodological response for the use of different and different context wells while treating their energy expenditure and displays a formal meaning of context dependence and in addition down to earth routines to figure it. We usually refrain from actually concentrating on some solitary application or that of administration, yet we give functional understanding into the relationship between context dependency and the execution accomplishments of individual applications. Various late research have managed decreasing the expense of getting context. This work confirms the energy productivity test in the attentive context, but normally focuses on single and / or static application. They utilize one or a greater amount of the accompanying three strategies to decrease energy cost, while holding satisfactory execution.

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To begin with, decreasing occurrence, as in [12], [13], [14] decreases the recurrence of tests of energy-starved context sensors. Secondly, sensor substitution uses a context of lower energy cost than energy hunger, as in [10], [12], [13]. Third: the elimination of the sensors attempts to use a subset of sensors. We take the third approach in Smart Context based on Android, but not at all like the past work that attention on and exploit the properties of a particular application, for example, action identification [15], [16]], [18], we give a non-specific structure to framework architects to progressively or statically advance expenditure exchanges / focus attention to context. A wider problem of choosing the best subset of sensors, also referred to as perceptions or indicators, has been the focus of many years of exploration into consciousness research groups and counterfeit operations. This work focuses on the advancement of data, often characterized by a joint entropy or data collection (delta entropy). It is the usual practice to use the aborted arrangement (close to sight) to this problem of determination [40], [38], [39], with insured limits of execution, due to the complexity of the Management of the discovery of the ideal arrangement [28], [29], [30].

Krause and Guestrin [40], have utilized and adjusted the estimation and precision rather than picking up actual data. A typical ease sensor utilized for recognizing movement is the accelerometer. With accelerometer as the primary detecting source, movement acknowledgment is generally figured as a classification issue where the preparation information is gathered with experimenters wearing one or more accelerometer sensors in a certain period. Different sorts of classifiers can be prepared and looked at regarding the precision of classification [19, 20, 21 7, 8, 9]. For instance, more than 20 human exercises including strolling, staring at the TV, running, extending thus on can be perceived with genuinely high precision [11]. While it is still not clear what sort of classification calculations works the best, a large portion of the current works require accelerometer sensor(s) to be introduced on pre-identified position(s) close human body. One approach to make the detecting process less prominent is to utilize the o®-the-rack mobile devices such that no outside sensors are required. A few works have been directed by utilizing the item mobile phones as stages [22, 23, 24, 25, 26, 27]. CenceMe [24] empowers individuals from interpersonal organizations to impart their detecting vicinity to their buddies" in a protected way. The main objective is to utilize the framework and process that is coordinated and in addition outside sensors to catch the clients' status as far as movement, attitude, propensities and environment. A CenceMe model has been made accessible on Facebook, and the execution and assessment of the CenceMe application has additionally been talked about [25]. So also, Sensay" [23] is a context-mindful mobile telephone and uses information from various sources to powerfully change PDA ring tone, ready sort, and in addition decide clients' un-interruptible states.

III. PROPESED SYSTEM

Android based Smart Context,a framework to dynamically or statically optimize the cost/accuracy tradeoffs of context awareness, while ensuring a minimum accuracy for each estimation event. Android based Smart Context, takes advantage of the classifier combination algorithms I have explored that have little overhead. We show that by utilizing energy hungry context only at uncertain times.

Smart Android-based context can achieve 1% accuracy as accurately as possible, while significantly reducing energy costs by 60% or more. These applications highlight the practical value of estimation accuracy as a measure of context dependence and demonstrate the effectiveness of context in estimating usage. Our most effective methods, namely the use of Binning Supervised and the Bayesian combination of Bernoulli, systematically outperform common, non-context-based methods. Smart background based on Android, the operation consists of two main steps. The first is to determine the classification of contextual sources. In order to keep processing costs under control, this classification must be calculated beforehand, but it can always be static or depends on the context information obtained at any stage. In the next section, we show that a static solution is practical and efficient. In this case, the classification must be done only once. The second step is the combination of the energy context.

dynamically for each estimation event depending on the demands and commitments of the application or contextual service. Once classification is determined, the energy context combination works as follows. For each ranking event, Smart Context based on Android, begins to combine several sources of contextual information one by one in the command determined in the first step. This can be done with minimal overhead and for any combination of contextual sources, as explained below. Energy aware combination of context

After running the classifier combination with each additional context source, it checks the criteria of the requesting application or service for that estimation event. In the evaluation presented here, a fixed minimum estimate accuracy is used for each estimation event. However, the application or service may establish a different accuracy requirement for each estimation event, or even consider the expected cost of accessing the next context source to determine when to resolve with the current estimate accuracy and stop accessing more Sources of context. Based on Android Smart Context, it ensures the accuracy of the target estimate for each estimation event, as long as it is possible to achieve that accuracy, while not spending any excess cost on acquiring unnecessary context. In other words, under some conditions, no additional costly context is used, while in more uncertain conditions, based on Android Smart Context, you can use up all available context sources.

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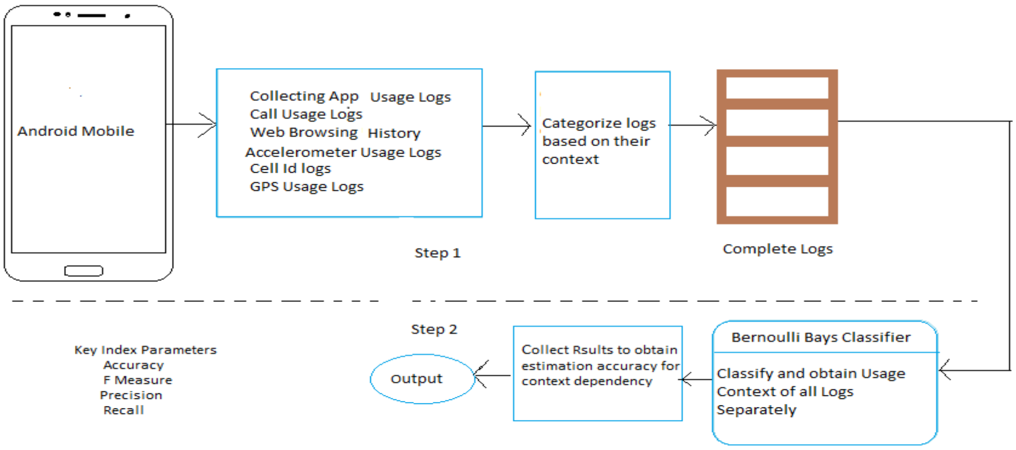

Figure 1: Proposed System Architecture

Combining multiple sources
Once the ranking is determined, the energy aware combination of context works as follows. For each classification event, Android based Smart Context, starts combining multiple sources of context information one by one, in the ordering determined in step one

Combinations of Context
By observing the performance of the three types of usage, we can see that combination methods are very useful when a number of meaningful context sources are present. The max rule consistently outperforms the mean-rule for our data. The mean-rule is known to perform well when classifiers are noisy and highly dependent. Therefore, we conclude that that different context sources are likely not noisy or highly dependent. The surprising fact that Bayes often outperforms other combinations is another indicator that our context sources are either not highly (conditionally) dependent, and/or their dependencies are distributed evenly. On the other hand, even though we use Laplace Correction to reduce the impact of data sparseness, the performance of Bayes is reduced when there are more bins (with fewer samples and therefore more noise). Indeed, it is well known that Bayes is highly susceptible to noise.
This is especially notable in web usage. We note that as expected, and as confirmed by the traces (not shown), treating multiple context sources in a multidimensional manner results in virtually no improvement in estimation accuracy. This is unsurprising, as even with only 10 context bins, there were less than 1 percent of samples in any given context.
More importantly, most samples belonged to bins that each contained less than 0.1 percent of samples.

Ranking Mobile Context
Android based Smart Context, is based upon the greedy method described in the earlier section, guaranteeing a performance bound of (1 _ 1=e). However, the performance guarantee requires two assumptions. First, the costs of context sources (observations) must be independent from each other. Indeed, mobile context sources typically have independent energy costs, as was our case. Second, the sub modularity or diminishing returns property must hold for our utility function (estimation accuracy). While this appears a reasonable assumption, it is necessary to verify it. It is necessary to show that the estimation accuracy gain resulting from adding (combining) any context source decreases if more context sources were known (combined) beforehand. Note that since Android based Smart Context, assumes that free context is always utilized, it is necessary to verify the sub modularity only among costly context. Shows the estimation accuracy gain for Cell ID, acceleration, and GPS location. Therefore, we conclude that the greedy approach works well for context awareness.

In this case, the best ordering is obtainable by ranking the context sources according to their cost effectiveness. In this case, the cost effectiveness of each context source is the marginal estimation accuracy increase divided by its expected energy cost. The expected energy cost can be pre-measured by the system designer, as in our case, or can be measured automatically in software as in. The energy costs of acquiring context on the Android 3GS are presented in Table 2.
The estimation accuracy of each context source is shown in. The resulting ranking is shown in Table 2. Note that due to the often significant difference in the energy cost of context sources on mobile devices, their ranking becomes close to the order of their energy cost.
Finally, we note that due to the relatively limited number of costly context sources on mobile devices, it is also possible to simply perform a thorough search, calculating the performance of Android based Smart Context, under all possible orderings of context sources.

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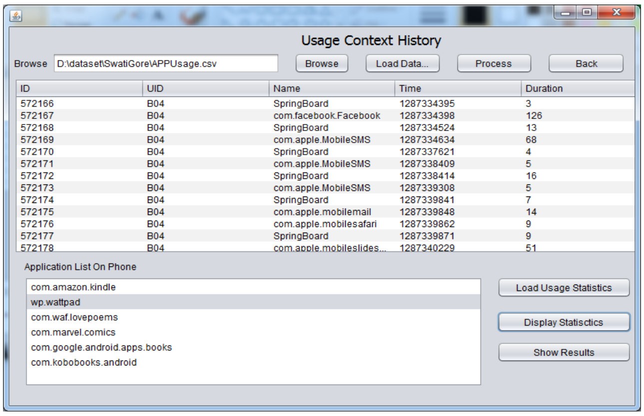


Figure 2 : Screenshot Application Usage Context

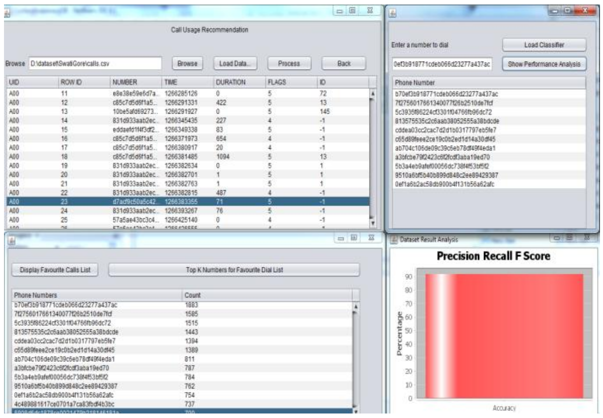


Figure 3 : Screenshot Call Usage Context

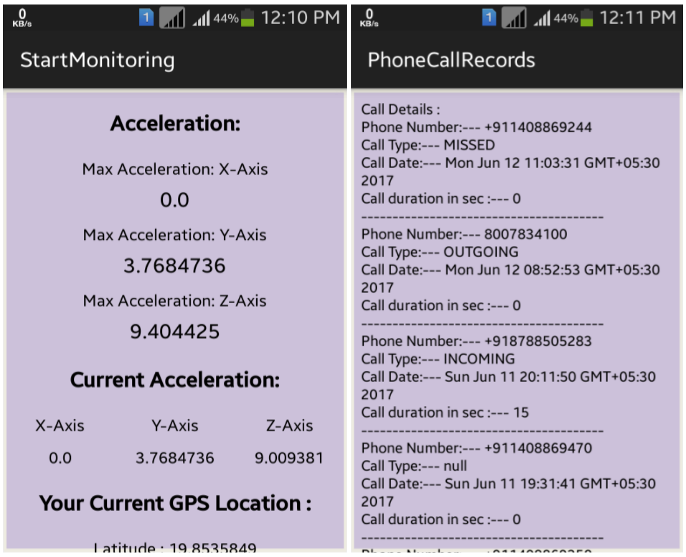


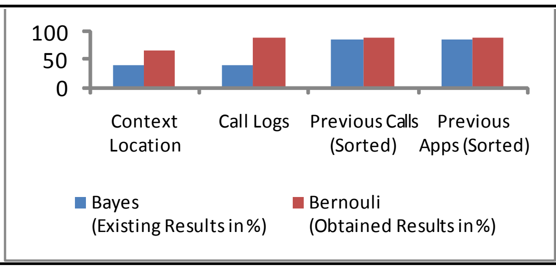
Figure 4 : Screenshots From App

Figure 5: Energy Usage of Android Phone

Table 1 : Classifier Comparison

Classifiers	Context Location	Call Logs	Previous Calls (Sorted)	Previous Apps (Sorted)
Bayes (Existing Results in %)	40	39	88	86
Bernouli (Obtained Results in %)	68	89.45	91.66	91

Graphical Presentation of Classifier comparison



IV. CONCLUSION

We have found that 1) it is important to keep up a sensible number of usage tests in every class, i.e. no under ten, and break even with recurrence discretization of single dimension context accomplishes this. 2) Classifier combination systems can address the information meager condition challenge while using various context sources, and Bayesian combination works best, despite the fact that the contexts are needy. 3) Individualized administered keeping so as to bin incredibly enhances estimation precision a more examples in every receptacle while permitting the fine embellishment of canisters. At long last, despite the fact that the vitality expense of some context sources can be a generous test for context based applications. We address this test through the Smart-Context structure, which guarantees utilizing just as much context sources to meet a base exactness set by the application creator for every estimation occasion.

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