Towards Detecting and Mitigating Smartphone Habits

Poster: Towards Detecting and Mitigating Smartphone Habits

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ABSTRACT

Smartphones have the potential to produce new habits, i.e., habitual phone usage sessions consistently associated with explicit contextual cues. Despite there is evidence that habitual smartphone use is perceived as meaningless and addictive, little is known about what such habits are, how they can be detected, and how their disruptive effect can be mitigated. In this paper, we propose a data analytic methodology based on association rule mining to automatically discover smartphone habits from smartphone usage data. By assessing the methodology with more than 130,000 smartphone sessions collected in-the-wild, we show evidence that smartphone use can be characterized by different types of complex habits, which are highly diversified across users and involve multiple apps. To promote discussion and present our future work, we introduce a mobile app that exploits the proposed methodology to assist users in monitoring and changing their smartphone habits through implementation intentions, i.e., "if-then" plans where if's are contextual cues and then's are goal-related behaviors.

CCS CONCEPTS

• **Human-centered computing** → **Smartphones**; **Empirical studies in ubiquitous and mobile computing**; User models; • **Computing methodologies** → *Machine learning*.

KEYWORDS

Habits, Smartphone Addiction, Digital Wellbeing, Association Rules, Implementation Intentions

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1 INTRODUCTION AND MOTIVATION

Smartphones have become an integral part of our daily lives. As smartphone use increases dramatically, however, so do concerns about the negative impact of overusing technology [7]. News providers extensively talk about "digital wellbeing", and researchers are starting to explore new ways of assessing and overcoming what they call "smartphone addiction." The same smartphone users often perceive the excessive use of their devices as problematic [4]. Even if the addiction framing may not be appropriate for widespread and everyday behaviors like mobile devices use, there is scientific evidence that the excessive usage of smartphones and online services can be a source of distraction [3], mental health problems [6], and poor social interaction [8]. Prior work, in particular, has already shown that "Short-duration, Isolated, Reward-Based" (SIRB) phone use is associated with habit-driven experiences, which erode users' intentions [11] and make them feel a loss of autonomy over their own behavior [9]. A habit is defined as a consistent repetition of a behavior in the presence of stable contextual cues that increases the automaticity of that behavior [5]. With smartphones, habits can be further defined as automated phone usage sessions associated with explicit contexts [11]. Prior research that aims at understanding smartphone habits, however, typically analyzes very *simple* recurrent patterns in mobile usage data, by comparing application uses across all users [11]. In our work, we challenge such an elementary characterization by introducing a data analytic methodology based on association rules to automatically discover complex smartphone habits from smartphone usage data. By assessing the methodology over more than 130,000 phone usage sessions collected in-the-wild, we show evidence that smartphone use can be characterized by different types of complex habits, highly diversified across users and that involve multiple applications. To promote discussion and present our future work, we also introduce a mobile app that exploits the proposed methodology to assist users in monitoring and changing their smartphone habits through implementation intentions, i.e., "if-then" plans where if's are contextual cues and then's are specific goal-related behaviors.

2 DETECTING SMARTPHONE HABITS

A Data Analytic Methodology for Detecting Smartphone Habits

To automatically discover complex smartphone habits from phone usage data, we adopt a methodology based on association rule mining (Figure 1). Association rules are an exploratory data mining technique to mine correlations among data. We use them to represent smartphone habits, i.e., correlations between contextual cues and the usage of one or more apps. Following the original definition of Agrawal et al. [1], the problem of association rule mining is defined as follows. Let $I = \{i_1, i_2, ..., i_n\}$ be a set of n binary attributes called items, and $D = \{t_1, t_2, ..., t_m\}$ a set of m transactions called database. Each transaction in D has a unique transaction ID and contains a subset of the items in I. A rule is defined as an implication of the form $X \implies Y$, where $X, Y \subseteq I$. The two terms of a rule are known as itemsets, and are named *antecedent* and *consequent*, respectively.

Within the methodology, user's mobile usage data is firstly preprocessed to build phone usage sessions, i.e., sessions that start when the screen is turned on and end when the screen is turned off. Through the Context Aggregation phase (Figure 1), then, sessions are aggregated with contextual information. The methodology is generic and can be easily extended to work with different contexts. In our work, we preliminary considered for each session: a) the *period*, i.e., working day or holiday, b) a 2-hour *time-slot* c) the *user-location* and d) the *user-activity*. The aggregated sessions are transformed (Data Transformation phase) into a transactional Vector Space Model (VSM) representation, depicted in Figure 2. Each aggregated session is a transaction $t_i \in D$ modeled as a binary vector representing mobile applications and contextual information. In each vector cell, the value 1 means the presence of an item, be it a context or a used app, in the corresponding transaction, while the value 0 represents the absence of an item in that transaction. The resulting transactional dataset D is finally used to mine association rules, i.e., habits, through the Apriori algorithm [2] (Rules Extraction phase). For each user, promising association rules are extracted by using common metrics for association rules evaluation, namely support, confidence, and lift.

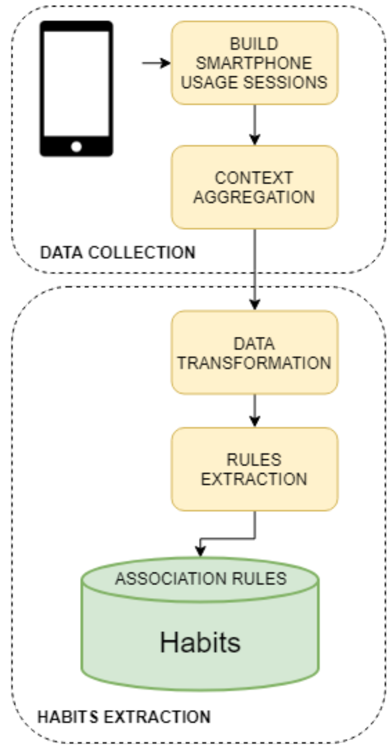


Figure 1: The data analytic methodology we devised to automatically discover complex smarthphone habits from smartphone usage data. The methodology is based on association rule mining.

Detecting Habits from Real-World Data

We assessed the data analytic methodology by applying it over more than 130,000 smartphone sessions collected in an in-the-wild study with 35 users [10]. Consistent differences emerged among users for what concerns the number of retrieved rules: some users had no habits at all, while others demonstrated more than 100 complex habits, i.e., habits that involve multiple contextual cues and used apps ($M = 21$, $SD = 19.56$). Furthermore, the type of the used apps were different across users. Not surprisingly [9], habits including messaging apps and social networks were very common, and strongly characterized the phone use of all users. Other habits, e.g., those including games and music apps, were instead peculiar to some specific users, only. Overall, by analyzing the structure of the retrieved rules, we found 3 main habit categories:

- *Context Habits* are represented by association rules that model a strong correlations between contextual cues and mobile apps, where the period, the time slot, the user activity and/or the user location trigger the usage of one or more apps. An example is $\{$*working day*, *10-12 AM*, *work*$\} \implies \{$*Facebook*$\}$.

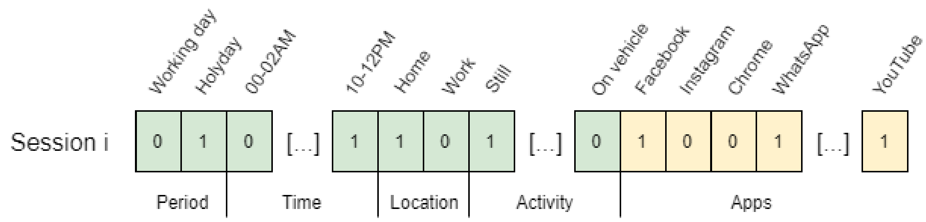


Figure 2: An example of an aggregated phone usage session transformed in a transactional format. In each entry, the value 1 means the presence of the item in the corresponding transactional session, and the value 0 represents the absence of an item in that session. Items involve contextual information (green boxes) and used apps (yellow boxes).

Table 1: The 10 most promising association rules in terms of lift, support, and confidence extracted for the the user U34.

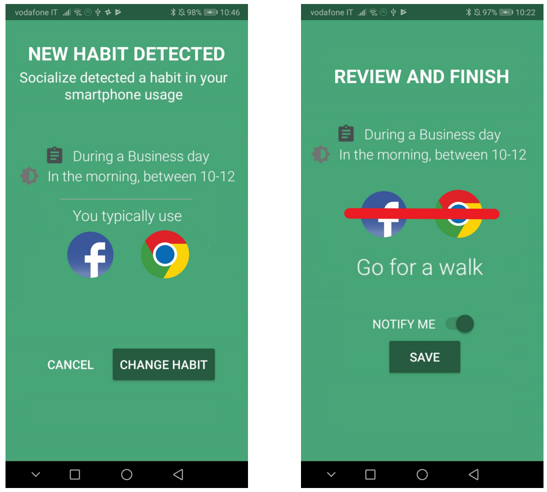
id	antecedents	consequents	category	lift	supp	conf
R1	{12-02 PM, on vehicle}	{Spotify}	Context Habit	7.30	0.02	0.46
R2	{12-02 PM, on vehicle, Spotify}	{Instagram}	App-Context Habit	2.40	0.02	0.70
R3	{12-02 PM, Instagram}	{WhatsApp}	App-Context Habit	1.80	0.02	0.51
R4	{home, still}	{WhatsApp, Instagram}	Context Habit	1.60	0.03	0.18
R5	{06-08 AM}	{Instagram}	Context Habit	1.41	0.04	0.41
R6	{06-08 AM, home, still}	{Instagram}	Context Habit	1.41	0.02	0.41
R7	{04-06 AM, home, still}	{Instagram}	Context Habit	1.37	0.02	0.40
R8	{home, still}	{Clash Royal}	Context Habit	1.34	0.02	0.10
R9	{WhatsApp}	{Instagram}	App Habit	1.31	0.10	0.38
R10	{still}	{Gangstar 4}	Context Habit	1.17	0.03	0.05

- *App Habits* are represented by association rules that model a strong correlation between mobile apps, only, where the usage of a given app spurs the usage of of one or more other apps. An example is $\{\mathit{WhatsApp}\} \implies \{\mathit{Twitter, Facebook}\}$.
- *App-Context Habits* are represented by hybrid association rules, where the usage of a specific app in a given context spurs the usage of one or more other apps. An example is $\{\mathit{02\text{-}04\ PM, work, Slack}\} \implies \{\mathit{Chrome, Instagram}\}$.

To exemplify the retrieved results, Table 1 reports the 10 most promising association rules in terms of lift, support, and confidence extracted for the the user U34. From the rules, we can easily glimpse her habits. In the morning, especially at home, the user typically uses Instagram (R5, R6, and R7). The 2 *Context Habits* R6 and R7, in particular, occur when U34 is still: we can reasonably speculate that one of the first thing the user does when she wakes up is to check her Instagram timeline. Instead, R1 and R2, a *Context* and an *App-Context Habit*, respectively, describe how U34 uses her smartphone between 12 and 02 PM when she is on a vehicle: she checks Instagram and listens to some music from Spotify. The same user also demonstrates other habits related to messaging, social, and gaming applications. R3, R4, and R9 confirm that, as for the majority of the users, also U34 is susceptible to habits that involve messaging services and social networks in the same phone sessions. Finally, R8 and R10 characterize two *Context Habits* of U34 related to gaming: she typically plays Gangstar 4 and Clash Royal when she is still, especially at home.

3 MITIGATING SMARTPHONE HABITS

Besides better characterizing smartphone use, we believe that targeting smartphone habits is fundamental to improve the effectiveness of contemporary "digital wellbeing" tools. Existing solutions that assist users in limiting smartphone usage are in fact mainly focused on supporting self-monitoring, i.e., tracking user's behavior and receiving feedback, and they are not effective in the long term [10]. By proving users with the possibility of understanding and changing their (unwanted) smartphone habits, "digital wellbeing" tools could support behavior change by ensuring its long-term effect [5]. As part of our ongoing activities, we have developed Socialize, an Android "digital wellbeing" mobile app. Socialize implements our data analytic methodology, and it allows users to dynamically monitor and change their smartphone habits through implementation intentions. When the app detects a smartphone habit (e.g., using Facebook and Chrome during a business day between 10-12 AM, Figure 3a), the user has the possibility to define an alternative behavior (e.g., go for a



(a) Detecting Habits **(b) Changing Habits**

Figure 3: Socialize is able to detect and notify smartphone habits by using the data analytic methodology presented in this paper along with the context-aware functionality of smartphones (Figure 3a). With Socialize, users can change a smartphone habit by defining an alternative behavior to be associated with the habit's contextual cues (Figure 3b).

walk, Figure 3b) to be associated with the habit's contextual cues. When the contextual cues are detected, Socialize can optionally send a notification to the user to remember the defined alternative behavior. Furthermore, if the smartphone continues to be used in the same habitual way, Socialize sends a warning that motivates the user in respecting her goal. Socialize is available on the Google Play Store[1]: we are currently collecting data to further asses the effectiveness of our habit detection approach, and to evaluate whether implementation intentions are a viable way for changing smartphone habits.

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