Joint optimisation of privacy and cost of in-app mobile user profiling and targeted ads

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Abstract—Online mobile advertising ecosystems provide advertising and analytics services that collect, aggregate, process and trade rich amount of consumer's personal data and carries out interests-based ads targeting, which raised serious privacy risks and growing trends of users feeling uncomfortable while using internet services. In this paper, we address user's privacy concerns by developing an optimal dynamic optimisation cost-effective framework for preserving user privacy for profiling, ads-based inferencing, temporal apps usage behavioral patterns and interest-based ads targeting. A major challenge in solving this dynamic model is the lack of knowledge of time-varying updates during profiling process. We formulate a mixed-integer optimisation problem and develop an equivalent problem to show that proposed algorithm does not require knowledge of time-varying updates in user behavior. Following, we develop an online control algorithm to solve equivalent problem using *Lyapunov optimisation* and to overcome difficulty of solving nonlinear programming by decomposing it into various cases and achieve trade-off between user privacy, cost and targeted ads. We carry out extensive experimentations and demonstrate proposed framework's applicability by implementing its critical components using POC 'System App'. We compare proposed framework with other privacy protecting approaches and investigate that it achieves better privacy and functionality for various performance parameters.

Index Terms—Privacy, Advertising, Optimisation, Privacy aware targeted mobile advertising services, Data privacy, Cost saving

1 INTRODUCTION

The online advertising companies enable user tracking with the help of millions of mobile applications (*apps*) offered via various *app* markets, profile users and enable *targeted advertising* where user's personal information plays an important role. The advertising ecosystems connect billions of mobile devices, including smartphones, tablets, and computer tablets, with the help of various tracking technologies to collect, process and map, and disseminate user's private sensitive information. The strict laws imposed by the governments, in addition to abundance of anti-tracking tools/policies, the advertising companies are gradually obsoleting the use of third-party cookies used for *interest-based targeting*. Google announcement on Chrome's 'Cookie Apocalypse' to phase out support for third-party cookies by 2022¹, similarly, Apple² announced to update their tracking by introducing IDFA (Identification for Advertisers) opt-in overhaul, which will have significant impact over mobile *ads targeting* and *in-app* data attribution. Hence, instead of relying on third-party data, the advertisers and publishers tend towards first-party data, which has its own associated privacy concerns and will limit *targeting* vast majority of consumers. The advertisers and publishers are shifting towards maintaining data management platforms (DMPs) and demand-side platforms (DSPs) to brand their own data and measure performance in a *cookie-less* world. In addition,

users are more concerned about their data in the long term e.g. Data they leave after death (*Dad*).

An important factor in online *targeted advertising* is to deliver relevant ads to users to achieve better view/click through rates without exposing their private and sensitive information, within or outside the advertising ecosystem. In its current working mechanism, the user tracking and advertising have raised significant privacy concerns, as suggested in a number of studies [1], [2], [3], [4], [5], [6], [7]. Other works show the extent to which consumer's activities are tracked by third-parties and across multiple *apps* [8], mobile devices leaking Personally Identifiable Information (PII) [9], [10], accessing user's sensitive information via APIs [11], and profile inference attacks based on monitoring ads [12]. Research studies indicate, unless consumers have specifically consented to it, that the ad/tracking companies evaluate user behavior and tailor advertising to reach specific audiences. The American self-regulatory authority, AdChoices³ program, presents a platform for consumers to *opt-out* of *targeted ads* and tracking done by the participating companies in WebChoices, however, this would result in less revenue, in addition to, presenting less relevant ads and lower click through rates, as evident in [13].

In this paper, we mainly focus on protecting user's privacy in mobile advertising ecosystem from *profiling of specific private attributes* that is potentially used by analytics companies for tracking user's behavior, the *ads targeting* based on these attributes, and user's *apps usage behavior*. The proposed framework provides an optimal privacy preserving profile management that is, in addition to providing above user privacy, *cost effective* and achieves an optimal trade-off between *user privacy* and *targeted ads*. In particular,

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1. <https://www.adviso.ca/en/blog/tech-en/cookie-apocalypse/>
2. <https://junction.cj.com/article/button-weighs-in-what-does-apples-idfa-opt-in-overhaul-mean-for-affiliate>

3. <https://optout.aboutads.info/?c=2&lang=EN>

the private attributes during profiling process dominate user profile, which can be lowered down to reduce its dominating factor, to produce disturbance in user profile, to control *interest-based targeting*, and to control temporal change in activity-based user profiling. Similarly, the use of newly suggested *apps* can be used to flatten the usage pattern of individuals to protect temporal user's *apps* usage behavior, which would be of particular scenario when users use mobile phone during business hours. Ideally, these *apps* can be run during when there is no activity in order to achieve an average usage of *apps* to actual usage patterns. However, a major challenge is to evaluate temporal change in user profiles and *apps* usage i.e. respectively the lack of knowledge of time-varying updates in user profiles, which we classify as updates caused by *browsing history/searches*, *interactions with ads*, and the types of *apps* installed and used and *user's time-varying future apps usage behavior*.

Subsequently, using *Lyapunov optimisation*, we develop an optimal control algorithm for identifying updates in user profiles and the user's usage behavior of actual *apps* in order to capture the temporal changes during profiling process. User profiles consist of various *interests*, gathered in similar categories, that are derived based on the user's (private) behavioral activity from utilising installed *apps*, activities over web, and their interactions with ads. Our purpose is to protect attacks on privacy, via *app*-based profiling and ad-based inferencing, of selected private (that may be considered private by the user) *interest* categories in a user profile. E.g. the user may not wish the categories of gambling or porn to be presented in their profiles or to be *targeted* with relevant ads, which would of particular relevance when business devices are used for private purposes. In addition to privacy protection, which impose cost overhead by running newly suggested *apps*, the proposed framework minimises the cost introduced, termed as *resource overhead*, by bounding the use of new *apps* among various boundaries of weightages assigned to interests categories in user profiles.

Furthermore, we investigate the profiling process used by Google AdMob, a major analytics network, during *establishing* user profile and during when profile *evolves* with time, by investigating relation between mobile *apps* characteristics and the resulting profiles. We carry out extensive profiling experimentations by examining contribution of individual *apps* in a user profile, experiments with newly suggested *apps* for *apps* usage behavior protection along with evaluation of resource overheads, and evaluate effect of these experiments over user profiles; overall these experiments were run for over 5 months. Our experiments show that the mapping of interests categories can be predicted from installed and used *apps* with an accuracy of 81.4% along with the private and dominating interests categories based on user's activity over mobile device. In addition, we found that the profiling interests are selected from pre-defined set of interests categories and that the *apps* to interests mapping is deterministic, which requires specific amount of time (up to 72 hours) and certain level of activity to *establish* a user profile.

We propose various changes in 'User Environment' in a mobile advertising ecosystem i.e. we suggest 'System App' with following functionalities: It implements local user profiling based on *apps usage and user's behavior, brows-*

ing history/searches and user's interactions with ads; 'System Engine' that keeps local repository and determines newly suggested *apps*; protects user's privacy for their private sensitive attributes; Implements proposed online control algorithm for jointly optimising user privacy and associated cost. Furthermore, we implement a POC (Proof Of Concept) 'System App' of our proposed framework to demonstrate its applicability in an actual environment. As opposed to legacy advertising operations where users are tracked for their activities, the 'System App' passes anonymous *apps* usage info/statistics and generated profile to the analytics servers within advertising system. In addition, the analytics server in current advertising system only evaluates stats for *apps* usage, which are recoded for the purpose of *billing* both for ad system and *apps* developers.

Finally, we discuss the use of other privacy protection mechanisms e.g., *differential privacy*, *cryptographic approaches* etc., in the mobile advertising environment and compare the proposed framework with these privacy protection mechanisms for various performance parameters.

The paper is organised as follows: Section 2 presents background on user profiling and the ads ecosystem, proposed addressed problem, and threat model. In Section 3, we present system model and investigate the profile creation and user profiling process. Section 4 presents optimal privacy preserving system and further discusses the proposed framework. The optimal control algorithm is discussed in Section 5. Various evaluation metrics are discussed in Section 6. Section 7 discusses system evaluation, our experimental setup and results. We further discuss the applicability of proposed framework and its comparison with other privacy protection mechanisms in Section 8. Related work is presented in Section 9 and conclusion in Section 10.

2 PROBLEM FORMULATION

The Advertising and Analytic (A&A) companies rely on users' tracking data to profile and to *target* them with relevant advertisements, both 'Web & App'-based to cover vast majority of audience of diverse interests, to increase their advertising market revenue. This exposes sensitive information about users, in particular, their online behavior e.g., web browsing/serching, or when profiling is based on *apps* representing sensitive and damaging information, e.g., gambling problems indicated by a game *app*, or the mobile *apps* usage behaviors e.g. playing games or use of gambling *apps* early morning in bed or during lunch break in office hours. Following, we present the privacy issues related to profiling process for both 'Web & App' activity and *app* usage behavior, subsequently, we present the problem and threat model discussed in this paper.

2.1 User profiling

The advertising companies, e.g., Google, profile users based on information a user adds to the Google account, its estimation of user's interests based on the mobile *apps* usage and web histories, and data collected from the partnering analytics companies with Google, which effectively carry out *targeted adverting* based on the personal information extracted through various tracking technologies.

Figure 1 shows an example user profile⁴, estimated by Google⁵, which consists of demographics (e.g. gender, age-ranks) and profiling interests e.g. Action & Adventure Films. We call this an *Interests profile* with all those interests defined by A&A companies (e.g. Google) and is used by them to individually characterise user’s interests across the advertising ecosystem. Similarly, we introduce *Context profile* that is the combination of *apps* installed from various categories, e.g. Games, Entertainment, Sports etc., on a user mobile device; detailed discussion over *Context profile* is given in Section 3. We note, using our extensive experimentations [4], that *Context profile* profile is also (partly) used by the analytics companies to individually characterise user’s interests across the advertising ecosystem.

Fig. 1: An (anonymous) example user profile estimated by Google as a results of ‘Web & App’ activity.

Furthermore, the *ads targeting* is based on demographics so as to reach a specific set of potential customers that are likely to be within a specific age range, gender etc. Google⁶ presents a detailed set of various demographic *targeting* options. The demographics are usually grouped into different categories, with specific options such as age-ranges, e.g. ‘18-24’, ‘25-34’ etc., and gender e.g., ‘Male’, ‘Female’, and other demographic *targeting* options e.g. parental status, location etc. We note that this profiling is the result of interactions of user devices with AdMob SDK [4] that communicates with Google Analytics for deriving user profiles. A complete set of ‘Web & App’ activities of individual user can be found under ‘My Google Activity’⁷, which helps Google make services more useful.

Figure 2 shows various sources/platforms that Google uses to collect data and *target* users with personalised ads.

4. Google AdMob profile can be accessed through the Google Settings system app on Android-based devices; accessible through Google Settings → Ads → Ads by Google → Ads Settings.

5. Profiling interests can be found here: <https://adssettings.google.com/authenticated>.

6. Demographic Targeting: <https://support.google.com/google-ads/answer/2580383?hl=en>

7. <https://myactivity.google.com/myactivity?otzr=1>

These include a wide range of different sources enabled with tracking tools and technologies, e.g., the ‘Web & App’ activities are extracted with the help of Andoird/iOS SDKs, their interactions with Analytics servers within the Google network, cookies, conversation tracking⁸, web searches, user’s interactions with presented ads etc. Similarly, Google’s connected home devices and services⁹ rely on data collected using cameras, microphones and other sensors to provide helpful features and services¹⁰. The tracking data (up to several GBs of data), personalised for individual users, can be exported using Google Takeout¹¹ for backup or use it with a service outside of Google. This includes the data from a range Google products, such as, email conversations (including Spam and Trash emails), contacts, calendar, browsing and location history, and photos.

2.2 Entities within advertising system

Figure 3 shows a representative *in-app* mobile advertising ecosystem showing the information flow among its different parties for profiling users for enabling *targeted ads* based on ‘Web & App’ activities. User usually install a number of *apps* on their mobile devices, that are utilised with specific frequency. The mobile *apps* include analytics SDK, which directly reports user’s activity (as mentioned in above section) and sends ad requests to the analytics and ad network. Various advertising entities play important role in enabling tracking and ads dissimulation in an ad system, comprises the Aggregation, Analytics, Billing, and the Ads Placement servers. Collected tracking data is used by the Analytics server that constructs *Interests profiles* (associated with specific mobile devices and corresponding users) with specific profiling interests related to user’s (private) behavior. The *targeted ads* are served to mobile users according to their (individual) profiles. We note that other i.e., *generic ads* are also served [14]. The *Billing* server includes the functionality related to monetising *Ad impressions* (i.e. ads displayed to the users in specific *apps*) and *Ad clicks* (user action on presented ads).

2.3 Problem Statement

The problem addressed in this paper is where the A&A companies track mobile users for their activities, profile them (inferred via relationships among individuals, their monitored responses to previous advertising activity and temporal behavior over the Internet) and *target* them with ads specific to individual’s interests. The user profiling and *ads targeting* expose sensitive information about users [1], [4], e.g. the *target* could browse through medical related websites or *apps*, revealing (including a third-party, such as the website owner) to the advertising systems that the user has medical issues.

Furthermore, we address the privacy issues where an adversary (either the analytics companies examining user

8. <https://support.google.com/google-ads/answer/6308>

9. Google’s Connected Home Devices and Services: https://support.google.com/googlenest/answer/9327662?p=connected-devices&visit_id=637357664880642401-2675773861&rd=1

10. Sensors in Google Nest devices: <https://support.google.com/googlenest/answer/9330256?hl=en>

11. Your account, your data: <https://takeout.google.com/>

Fig. 2: Google’s data collection and tracking sources for targeting users with personalised ads (left) and tracking capabilities of analytics libraries enabled within mobile devices (right).

Fig. 3: The advertising system consists of user and advertising environments. Following functionalities: (1) Data collection and tracking, (2) Send tracking data to Aggregation server, (3) Forward usage info to Analytics server, (4) User profiling, (5) Send profiling info to APS, (6) Deliver targeted/generic ads, (7) Billing for Apps Developer, (8) Billing for Ad System, (9) Advertiser uploads ads, who wishes to advertise with Ad system.

activity or an intruder listening to the ad or control traffic) can determine the *app*’s usage activity e.g., someone plays games during late night or early morning and their activity is intercepted by their neighbors. The user’s *apps* usage activities can be exposed by intercepting the *apps* communi-

cation using the connected network [12], in addition, users’ activities are also exposed to the advertising systems during their interactions using ad/analytics SDKs. Figure 4 shows an example *apps* usage profile for a typical day, showing a direct threat to user’s privacy for *apps* usage.

Fig. 4: Apps usage profile for typical day showing *apps* usage activity during 24 hours.

In particular, we address three privacy attacks: **1. Legitimate user profiling** by A&A, the user profiling is implemented via an analytics SDK for reporting user’s activities to A&A companies, hence, intercepts various requests to/from mobile users. **2. Indirect privacy attack**, involves third parties that could intercept and infer user profiles based on *targeted ads*. **3. Apps usage behavioral attack** to know user’s *apps* usage activities. In the first two privacy attacks, we presume that the users do not want to expose their private interests to adversaries (including advertising agencies) and are willing to receive relevant ads based on their interests.

2.4 Threat Model

Our primary goal in this work is to achieve an *optimal privacy preserving profile management* that preserves user's privacy due to profiling interests derived via apps usage, privacy in terms of apps usage behavior, users' web history/searches, and their interactions with ads. We start by analysing and developing the profiling process, identify the dominating interests that expose user privacy and could affect ads targeting, the proportion of interests in user profile, and the apps usage activity. We further compare proposed solution and its applicability with other privacy preserving mechanisms such as differential privacy, anonymisation, randomisation, Blockchain-based solutions and crypto-based mechanisms e.g., private information retrieval) in an advertising scenario for the problems addressed in this work. Finally, we evaluate the trade-off between the achieved user privacy, cost of achieving privacy and targeted ads. Hence, in this paper, we jointly optimise the user's privacy due to profiling interests, the cost of achieving privacy, and the apps usage behavior.

3 SYSTEM COMPONENTS

We formalise the system model that consists of the apps' profiles, interests' profiles and the conversion of resulting profiles by use of applications in an app profile. In particular, we provide the insights of establishment of Interests profiles by individual apps in the Context profiles and then show how the profiles evolve when some apps other than the initial set of apps are utilised.

3.1 System Model

We denote an app by $a_{i,j}$, $i = 1, \dots, A_j$, where A_j is the number of apps that belong to an app category Φ_j , $j = 1, \dots, \phi$ and ϕ is the number of different categories in a marketplace (e.g., in Google Play or in the Apple App store). An individual app $a_{i,j}$ is characterised by a set of keywords $\kappa_{i,j}$ that includes app's category (e.g. Business, Entertainment etc.) and dictionary (specific to this particular app) keywords from its description. We represent with $\mathcal{A}$ the entire set of mobile apps in any marketplace, organised in various categories.

A user may be characterised by a combination of apps installed on their mobile device(s), comprising a subset $S_a \in \mathcal{A}$. Following, the Context profile K_a can be defined as:

$$K_a = \{\{a_{i,j}, \Phi_j\} : a_{i,j} \in S_a\} \quad (1)$$

The A&A companies, such as, Google or Flurry, partly profile and target users based on the combination of mobile apps installed on their devices i.e. Context profile. We have the following constraints on the user's Context profile:

$$\begin{aligned} 0 < n(K_a) &\leq \mathcal{A} \\ n(K_a) &\geq 1 \\ \Phi_j(a_{i,j}) &\neq 0 \\ \Phi_j &\subseteq \Phi_j ; \forall j \end{aligned} \quad (2)$$

The $n(K_a)$ is the total number of apps installed on a device, hence, using Eq. (3), it is important to make sure the $n(K_a)$ should not exceed the total number of available apps;

that a mobile device must have at least one app installed for contextual targeting; that an app $a_{i,j}$ must belong to any of the specified categories; and that the app's category is not undefined within an app market. Various important notations and their descriptions are presented in Table 1.

3.2 Representing apps in user profile

We note that the A&A companies classify users by defining a set of profiling interests $\mathcal{G}$, i.e., characteristics that may be assigned to users i.e. an Interest profile. E.g. Google profile interests¹² are grouped, hierarchically, under various interests categories, with specific interests. We denote, using $g_{k,l}$, $k = 1, \dots, G_l$, where G_l is total number of interests that belong to an interest category Ψ_l , $l = 1, \dots, \psi$. ψ is total number of interest categories defined by analytics companies. An individual interest $g_{k,l}$ consists of a set of keywords $\kappa_{k,l}$, which characterises specific interests. Following, to enable interest targeting, represents an Interests profile I_g , consists of a subset S_g of specific interests:

$$I_g = \{\{g_{k,l}, \Psi_l\} : g_{k,l} \in S_g\} \quad (3)$$

Although various types of information may be used to generate user profiles, as shown in Figure 2, however, our focus is mainly on installed and used/unused apps¹³, the history resulted from web browsing or web searches, and the clicked ads i.e. collectively described as the 'Web & Apps' activity. Similarly, other targeting criteria can also be represented in an Interest profile as a specific interest e.g. demographics, contributing analytic platforms, social media, and other Google services. An example demographics interests is also shown in Figure 1.

The targeting components are eventually grouped in Interest profile that are used for ads targeting. The Interest profiles undergo different processes e.g. the profile establishment process (i.e. the derivation of Interests profile by apps; $K_a \rightarrow I_g$) (generating a specific set of interests $S_{K_a} \{\Psi_l\}_{l=1}^{\epsilon}$ using a mapping function f i.e. $f : \Phi_j \rightarrow \Psi_l = S_{K_a} \{\Psi_l\}_{l=1}^{\psi}$), the profile evolution I'_g process (i.e. each time variations in the users' behaviour are observed), and profile development process (i.e. the minimum level of activity required to develop a stable user profile I_g^f) i.e. $I_g^f = I_g \cup I'_g$. Figure 5 shows user profiling process, detailed discussion over these various processes of user profiling can be found in [15]. Furthermore, detailed experimental evaluations over insights on profiling rules, apps usage threshold during profiling establishment, and mapping rules for Context profile to Interest profiles can be found in [4], [16].

In order to represent part (along with the dominating interest categories) of each interest category, we assign weightage to each category Ψ_l present in the final user profile I_g^f ; represented as $\eta_l(\Psi_l)$, under the following two constraints:

12. Google profile interests are listed in <https://adssettings.google.com/authenticated?hl=en>, managed under the 'How your ads are personalized'; other options and Google services can also be verified on Google Dashboard <https://myaccount.google.com/dashboard?hl=en>.

13. The list of installed apps on an Android based phone can be withdrawn using following shell command: `adb shell pm list packages`. The full list of installed apps is included in the `library.db` file `/data/data/com.android.vending/databases/library.db`.

Symbols	Description
$\mathcal{A}$	Available <i>apps</i> in a marketplace
ϕ	Total number of <i>apps</i> categories, Φ_j is a selected category, $j = 1, \dots, \phi$
S_a	Subset of <i>apps</i> installed on a user's mobile device
$a_{i,j}$	An <i>app</i> $a_{i,j} \in A, i = 1, \dots, A_j, j = 1, \dots, \phi, A_j$ is the number of <i>apps</i> in Φ_j
$\kappa_{i,j}$	Set of keywords associated with individual <i>app</i> $a_{i,j}$ including its category
K_a	App profile consisting of <i>apps</i> $a_{i,j}$ and their categories Φ_j
$\mathcal{G}$	Set of interests in Google interests list
Ψ_l	Interest category in $\mathcal{G}, l = 1, \dots, \psi, \psi$ is the number of interest categories defined by Google
S_g	Subset of Google interests in $\mathcal{G}$ derived by S_a
I_g	Interest profile consisting of $g_{k,l}, g_{k,l} \in S_g$
$g_{k,l}$	An interest in $I_g, k \in G_l, l \in \psi$
$\kappa_{k,l}$	Set of keywords associated with individual interest $g_{k,l}$ including interest category
$S_g^{i,j}$	Set of interests derived by an <i>app</i> $a_{i,j}$
f	Mapping that returns the derivation of <i>apps</i> (or history, ad's category) category to interest category
$\eta_l(\Psi_l)$	The <i>weightage</i> assigned to interest category in Ψ_l in a profile with, respectively with $\eta_l^{\min}$ and $\eta_l^{\max}$ thresholds
Π_m	Profiling components for representing <i>browsing history/searches</i>
Γ_n	Profiling components for representing <i>interactions with ads</i>
t	Time slot
$C_t(\eta_l(\Psi_l))$	Tracking change in interest category due to <i>changes in apps</i> usage
$C_t(\eta_m(\Pi_m))$	Tracking change in <i>web browsing history/searches</i>
$C_t(\eta_n(\Gamma_n))$	Tracking <i>interactions with ads</i>
$U'^\tau(K_a)$	Usage of <i>apps</i> in K_a at time slot t ; average usage of each <i>app</i> is given by $U'^\tau(K_a)$
$\eta_{l'}(\Psi_{l'})$	The <i>weightage</i> assigned to interest category generated by newly suggested <i>app</i> (s), where $l' \neq l$
S_o	Set of newly suggested <i>apps</i>
C^t	Reduction of overall user's time available by use of newly suggested <i>apps</i> to the original <i>apps</i>
R^t	Resource usage of newly suggested <i>apps</i> , in particular, R_b^t, R_c^t, R_p^t respectively represent the <i>battery consumption, communication, and processing</i> resource usage
β	Adjustable parameter to achieve trade-off between user <i>privacy</i> and <i>targeted ads</i>
R_l^t	An advertising request reported at t via ad/analytics SDK e.g. an ad request for display/ad click
ε	Adjustable parameter to achieve <i>apps</i> usage to preserve <i>privacy</i> of user's <i>app</i> usage behavior
$p(t)$	The penalty for minimising the upper bound on C^t , profiling <i>privacy</i> , and <i>apps</i> usage behavior

TABLE 1: List of Notations

Fig. 5: Profile establishment & evolution processes. I_0 is the empty profile before any activity over user device. During the *stable* states, the *Interest profiles* I_g or I_g^f remains the same and further activities of the same *apps* have no effect over the profiles [15].

$$\eta_l^{\min} \leq \eta_l(\Psi_l) \leq \eta_l^{\max} \quad \forall l \in \Psi_l | l \in \psi \quad (4)$$

$$0 < \eta_l(\Psi_l) \leq \eta_l^{\max} \quad (5)$$

Hence, *weightage* given to an interest category $\eta_l(\Psi_l)$ is within the $\eta_l^{\min}$ and $\eta_l^{\max}$ threshold *weightages*. Subsequently, the user profile is represented as, $I_g = \eta_l(\Psi_l), \forall l \in \psi$.

We note, using our extensive *profiling* experimentations [4], [16], that the set of installed *apps*, on a mobile device, do not necessarily contribute during profiling, in which case specific *apps* do not draw any interests i.e. an empty set. In addition, Eq. (5) ensures that the assigned threshold should be non-negative and cannot exceed the maximum threshold within a user profile.

Example – Assigning weightages: Let a *user* has five mobile *apps* installed on her device i.e. three from category a and one from category b and c each, respectively with the

following percentage of usage time¹⁴: $a = 20\%$, $b = 70\%$, $c = 10\%$; for simplicity we do not consider *apps* that are installed but not used, which can be assigned the lowest *weightages* e.g. $1/n(K_a)$ including system installed *apps*. The *weightage* for each category $\eta_l(\Psi_l)$ can be evaluated as follows: $\eta_l(a) = 3/5 + 20/100 = 0.8$; $\eta_l(b) = 1/5 + 70/100 = 0.9$; $\eta_l(c) = 1/5 + 10/100 = 0.3$. Hence, it requires that the user is supposed to be *targeted* with the ads related to category b with highest proportion, followed by a and c . Note that for simplicity, these *weightages* can be normalised within the range $0 - 1$; subsequently, the proportion for delivery of *targeted ads* would be: $a = 0.40$, $b = 0.45$, and $c = 0.15$.

3.3 Representing browsing history/searches and ad-interactions in a user profile

We respectively represent Π_m and Γ_n profiling components as user *history/search* and *ad-interactions* (e.g. *ad click*). Subsequently, we assign *weightages* to both these components:

$$(\eta_l^{\min}, 0) < \eta_m(\Pi_m) \leq \eta_l^{\max} \quad \forall m, \forall l \in [1, \psi] \quad (6)$$

$$(\eta_l^{\min}, 0) < \eta_n(\Gamma_n) \leq \eta_l^{\max} \quad \forall n, \forall l \in [1, \psi] \quad (7)$$

Note that the minimum threshold, on the left sides of Eq. (6) & (7) i.e. taken as a minimum of ' $\eta_l^{\min}(\Psi_l)$ ' and '0', to respectively represent its *weightage* as higher than the

¹⁴. Use `adb logcat -v threadtime` on an Android-based device to find the running time of an *app*; `threadtime` (default) is used to display the date, invocation time, tag, priority, TID, and PID of a thread issuing the message.

minimum weightage of present interests (and hence to show its importance in current *targeting* components) or lower its dominating factor to slightly higher than '0'.

Subsequently, we have the following equivalent user profile, as a representation of *weightage* of all the *targeting criteria*:

$$I_g = \eta_l(\Psi_l) + \eta_m(\Pi_m) + \eta_n(\Gamma_n) \quad (8)$$

3.4 Profile updating

An important factor in *ads targeting* is to track user's activity to find temporal changes in a user profile; hence, the *profile* and *ads targeting* is updated each time variations in user behavior is observed i.e. the *targeting criteria* result in interests other than the existing set of interests. We note that following *criteria* (but not limited to) is used to track changes in a use profile: *installation/un-installation of an app* i.e. a user uses new set of *apps* S'_a , which has no overlap with the existing set of *apps* S_a , *increase/decreases of use of an existing app*, *start use of an 'un-used' app*, *interactions with ads*, and *changes in web browsing history/searches*. Let $\eta'_l{}^{\min}$ and $\eta'_l{}^{\max}$ are new minimum and maximum threshold due to changes in *apps usage*, then following conditions may hold (provided that the *usage time* is *i.i.d* i.e. *independent and identical distributed*, with some unknown probability distribution):

$$\begin{aligned} \eta'_l{}^{\max} > \eta_l{}^{\max}; \eta'_l{}^{\min} > \eta_l{}^{\min} &\rightarrow \text{apps uninstalled} \\ \eta'_l{}^{\max} < \eta_l{}^{\max}; \eta'_l{}^{\min} < \eta_l{}^{\min} &\rightarrow \text{new apps installed} \\ \eta'_l{}^{\max} < \eta_l{}^{\max}; \eta'_l{}^{\min} < \eta_l{}^{\min} &\rightarrow \text{unused apps become used} \\ \eta'_l{}^{\max} > \eta_l{}^{\max}; \eta'_l{}^{\min} > \eta_l{}^{\min} &\rightarrow \text{used app become unused} \end{aligned} \quad (9)$$

Based on above constraints, we have the following equivalent constraint due to *changes in app activity*:

$$\eta'_l{}^{\min}(\Psi_l) \geq \min \{ \eta_l{}^{\min}, \eta'_l{}^{\min} \} \quad (10)$$

$$\eta'_l{}^{\max}(\Psi_l) \geq \max \{ \eta_l{}^{\max}, \eta'_l{}^{\max} \} \quad (11)$$

In addition, such changes in *browsing history/searches* and *interactions with ads* can also be expressed with threshold limits, as explained in next section.

3.5 Profile evolution

Furthermore, subsequent changes in a user profile (w.r.t. time t) are represented as $C_t(\eta_l(\Psi_l))$; $C_t(\eta_m(\Pi_m))$ and $C_t(\eta_n(\Gamma_n))$ respectively for changes in *apps usage*, *web browsing history/searches* and *interactions with ads*. Hence, Eq. (8) can be re-written as:

$$I_g^t = C_t(\eta_l(\Psi_l)) + C_t(\eta_m(\Pi_m)) + C_t(\eta_n(\Gamma_n)) \quad (12)$$

Since the assigned *weightages* should always be non-negative and bounded by maximum thresholds (i.e. maximum *convergence point* in specific period e.g. of every 24 hours), hence we need to make sure the following:

$$0 < C_t(\eta_l(\Psi_l)) \leq C_t^{\max}(\eta_l(\Psi_l)); \forall t, \forall l \in [1, \psi] \quad (13)$$

$$0 < C_t(\eta_m(\Pi_m)) \leq C_t^{\max}(\eta_m(\Pi_m)); \forall t \quad (14)$$

$$0 < C_t(\eta_n(\Gamma_n)) \leq C_t^{\max}(\eta_n(\Gamma_n)); \forall t \quad (15)$$

As mentioned earlier, the other profiling components, such as *history/searches* and *interactions with ads*, are also mapped to profiling interests Ψ_l , to produce a unified profile with different dominating interest categories, e.g. for *ad-interactions*: $f : \Gamma_n \rightarrow \Psi_l = S_{K_a} \{ \Psi_l \}_{l=1}^{\psi}$. We presume that all changes in user profiles are distributed with an unknown probability distribution and that these profile *weightages* are deterministically bounded by a finite constant e.g. $C_t^{\max}(\eta_m(\Pi_m))$ for web history, so that (incorporated in user profile) at time slot ' t ', Eq. (12) can be re-written, as a unified profiling interests, as:

$$I_g^t = \sum_{\forall t} C_t(\eta_l(\Psi_l)); \forall l \in \{[1, \psi], m, n\} \quad (16)$$

Similarly, the newly updated (or change in existing) interest categories are reflected in profile at ' $t + 1$ ' as: $I_g^{t+1} = I_g^t + C_{t+1}(\eta_l(\Psi_l))$. For n amount of time:

$$0 < I_g^{t+1} \leq I_g^{t+n} \quad \forall t \quad (17)$$

I_g^{t+n} is the maximum *convergence point* of a user profile i.e. the point where users are *targeted* with the most relevant ads. We envisage that this information is regularly updated, e.g. once per 24 hours, which we call *evolution threshold* i.e. the time required to *evolve* profile's interests, and is used to reflect the updated profile and fetch associated *targeted ads*:

$$\lim_{t \rightarrow \infty} \sum_{\tau=1}^t I_g^{\tau} \quad (18)$$

Recall that profile at this stage, as $t \rightarrow \infty$, due to maximum profile convergence, it contains the dominating interests $g_{k,l}$ that are considered *private* by user, and hence exposes user's privacy. Our goal is to design a control algorithm that jointly optimises user's *privacy* (both profiling and *app* usage activity at different time of the day/night, as detailed in next section) and *cost* of newly (suggested) *apps* (discussed in Section 4).

3.6 Apps usage profile

Let $U^t(K_a)$ represents the *apps* usage at time slot t (during day/night, note, for simplicity we do not consider the *app* usage time for individual *apps*). The *apps* usage behavior for every user is time-varying, e.g. some users play game/gambling *apps* during the lunch time or early in bed when she gets up, or an employee might scroll through the stocks in a broker's application during lunch break, to be exposed to her employer. We note that the user's *apps* usage activity can be intercepted from the connected network [12] or through *app's* interactions with the advertising systems [4], [14], [15]. Let $\lim_{t \rightarrow \infty} \sum_{\tau=1}^t U^{\tau}(K_a)$ denotes *app's* usage at different time slots. The *app's* usage time varies during the 24 hours for each user, which also exposes user's privacy (irrespective of the category of *app's* usage) in terms of use of *apps* during various times of the day/night.

4 OPTIMAL PRIVACY PRESERVING PROFILING

Based on the above requirements for user profiling, we now study optimal privacy preserving profile management that is *cost effective*, *preserve user's privacy due to profiling interests* and the *apps usage behavior*, in addition to, user's *web history/searches* and *interactions with ads*.

4.1 Proposed framework

Figure 6 presents detailed overview of the proposed framework, introducing changes to 'User Environment' that implements local user profiling both for *Context profile* and *Interests profiles* and further protects their privacy, presented in Section 4.2, similarly, preserves user's privacy for user's *apps usage behavior* during day/night time, detailed in Section 4.3, implemented via 'System App'. We implement these various functionalities via a Proof of Concept (PoC) mobile app; detailed discussion is given in Section 7.1. The 'System App' also implements this framework that jointly optimises the profiling process and preserves user privacy in a cost-effective way, as detailed in Sections 4.4, 4.5, and 4.6. We suggest that this framework can be integrated into AdMob SDK since the current ad ecosystem carries out user profiling and *targeted ads* via SDKs, which will require SDK modifications.

4.2 Protecting sensitive profiling interests

To protect the private interest categories i.e. sensitive to users, we select various other *apps* based on *similarity* metric [4], [16]¹⁵ to reduce the dominating private interest categories present in a user profile. This metric is calculated based on *app* keywords $\kappa_{i,j}$ using the *tf-idf* (*cosine similarity*) metric [14]. This strategy is not metric-specific hence other similarity metrics e.g., *jaccard index*, can also be used.

The newly selected candidate *apps*, which we call the *obfuscation apps* (note that in this work, we interchangeably use both 'newly suggested apps' and 'obfuscation apps'), are selected (and run for specific amount of time, as described in Eq. (23), (24), and (25)) from *apps* categories Φ_j , $j = 1, \dots, \phi$ other than the private category Φ_p ; Φ_p is considered private by users that they want to protect. The newly suggested set S_o comprises those *apps* with highest similarity to the existing set of *apps* i.e. S_a . In addition, the user may protect any number of private interests categories Ψ_p , $p = 1, \dots, \Omega$ and Ω is the set of interests categories that are *private* to the user. Furthermore, we presume that the selected *app*(s) will always generate the profiling interests other than the private profiling interest(s) i.e. $l' \neq l$.

We assign weightage $\eta_{l'}(\Psi_{l'})$ to the newly generated profiling interests, I_g^t , in order to reflect its effect over 1. *privacy* (i.e. disruption in user profile) and 2. *targeted ads* (disruption in receiving *targeted ads* based on private profiling interests, exposed to ad/analytics networks):

$$\eta_l^{\min}(\Psi_l) > \eta_{l'}(\Psi_{l'}) > 0 \quad (19)$$

15. Detailed discussion over profile *obfuscation* to achieve user privacy in an *app*-based user profiling, using various *obfuscation* strategies, can be found in [4], [16].

Cost is usually defined as the ratio of obfuscating to original data [17]. We further elaborate on *Cost* in Section 6.1.2. Recall that, beyond privacy protection, the use of these newly suggested *apps* is used to protect user privacy of *apps usage behavior* e.g., during the 24 hours period.

4.3 Control objective for apps usage behavior

As mentioned in Section 3.6, intuitively speaking, in order to achieve user privacy for *apps* usage at different time slots t of the day, the *apps* usage profile $U^t(K_a)$ needs to be 'flattened' as $t \rightarrow \infty$, as much as possible, by running additional (newly suggested *apps*, as described in above section) *apps* i.e. $U^t(K_a)$. Subsequently, the profile becomes:

$$I_g'^t = I_g^t + U^t(K_a) \quad (20)$$

Let $\overline{U^t(K_a)} = \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=1}^t U^\tau(K_a)$ represents the average *apps* usage for a user K_a , alternatively $\overline{U^t(K_a)} = \overline{C_t(\eta_l(\Psi_l))}$, $\forall l \in [1, \psi]$. In real time, at different time slots, the *apps* usage needs to be controlled with as little deviation from $\overline{C_t(\eta_l(\Psi_l))}$ as possible. Note that this is also applicable to the interests in I_g^t generated via *browsing history/searches* and *interactions with ads*, since, as mentioned earlier that $\Pi_m \rightarrow \Psi_l$ and $\Gamma_n \rightarrow \Psi_l$, in addition, using both these activities, the user devices interact with the ad/analytics networks for tracking user's activity along with their (device's) usage behavior.

Subsequently, the control objective is to minimise the variance of $\overline{U^t(K_a)}$, i.e.:

$$\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=1}^t \mathbb{E} \left\{ \left(I_g^\tau - \overline{U^{\tau}(K_a)} \right)^2 \right\} \quad (21)$$

The privacy protection in *apps usage behavior*, in addition to, *preserve user's privacy due to profiling interests*, can be achieved by using few other suggested *apps*, described in next section, for our proposed scenario.

4.4 Objective function

In this paper, we jointly optimise the user's privacy due to *profiling interests*, the *cost of running obfuscation apps*, and the *apps usage behavior*. The objective function can be expressed as:

$$\lim_{t \rightarrow \infty} \sum_{\tau=1}^t \left(\underbrace{C^\tau \eta_{l'}(\Psi_{l'})}_{\text{Cost of running obfs. apps}} + \underbrace{\beta (I_g^\tau + \eta_{l'}^\tau(\Psi_{l'}))}_{\text{Profiling privacy}} + \underbrace{\beta \left(I_g^\tau - \overline{U^{\tau}(K_a)} \right)^2}_{\text{Apps usage privacy}} \right) \quad (22)$$

Here, the β parameter is selected by user in order to achieve a trade-off between user *privacy* and *targeted ads*. Note that the selection of this parameter affects the *targeted ads* as a result of disruption in a user profile. We describe the following various scenarios for introducing (along with the number of *apps*) newly selected *apps*:

Fig. 6: The proposed advertising system with changes in user and advertising environments.

$$0 < \eta_{l'}(\Psi_{l'}) \leq \eta_l^{\min}(\Psi_l) \quad (23)$$

$$\eta_l^{\min}(\Psi_l) \leq \eta_{l'}(\Psi_{l'}) \leq \eta_l^{\max}(\Psi_l) \quad (24)$$

$$\eta_{l'}(\Psi_{l'}) \geq \eta_l^{\max}(\Psi_l) \quad (25)$$

The first scenario (i.e. Eq. (23)) introduces newly *obfuscation apps* that would introduce minimum disruption in a user profile, hence, achieves lower *privacy* and attracts higher *targeted ads*, as opposed to the last scenario, which introduces highest disruption in a user profile i.e., achieves higher *privacy* and attracts less relevant *targeted ads*. On the other hand, the middle scenario introduces medium disruption in a user profile and achieves a balance between user *privacy* and *targeted ads*. An empirical example for various scenarios is given in Figure 7. We envisage that this scenario (24) will further introduce medium operating *cost* of the selected *obfuscation apps* i.e. $C^\tau \eta_{l'}(\Psi_{l'})$.

Fig. 7: Trade-off between *privacy* and *targeted ads* achieved via various obfuscation scenarios of *Low*, *Medium*, and *High* profile (interests), respectively introducing 10%, 30%, and 80% disruption in a user profile.

4.5 Problem formulation

The optimal privacy preserving user profiling and *targeted ads* can be formulated as a dynamic optimisation problem:

$$\min \lim_{t \rightarrow \infty} \sum_{\tau=1}^t \left(C^\tau \eta_{l'}(\Psi_{l'}) + \beta (I_g^\tau + \eta_{l'}^\tau(\Psi_{l'})) + \beta (I_g^\tau - U^{\tau\tau}(K_a)) \right) \quad (26)$$

s.t. constants: (13), (14), (15), (17), (24).

An important challenge to solve this optimisation problem is to know user's temporal behavior as a combined activity of 'Web & App' i.e. the lack of knowledge of time-varying updates in a user profile. This change in temporal behavior is affected by the profiling derived by *app's usage* Eq. (13), *browsing history/searches* Eq. (14), and *interactions with ads* Eq. (15). This problem would become even more challenging when there is an irregular activity observed by a user e.g. high app's/web usage during weekends etc. Hence, we develop an optimal control algorithm, using *Lya-punov optimization*, for identifying updates in user profiles as a result of communication requests between the mobile device and the advertising system (analytics) entities, see Section 5. Recall that ad/analytics SDKs enable these requests for tracking and profiling users for their 'Web & App' activities.

4.6 Problem relaxation

To solve the optimisation problem (26), we consider its relax version using (16) to relax constraints (13), (14), and (15). The average expected change in a user profile I_g^t is given by:

$$\bar{I}_g^t = \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=1}^t \mathbb{E} \{C_t(\eta_l(\Psi_l))\} \quad (27)$$

From Eq. (16), it is clear that the profile *evolves* over time e.g. over time slot t and $t+1$ we have $I_g^t = C_{t+1}(\eta_l(\Psi_l)) +$

$C_t(\eta_l(\Psi_l))$. Hence, we take its expected values on both sides of Eq. (16) and equate it to Eq. (27), we have:

$$\sum_{\tau=1}^t \mathbb{E}\{C_t(\eta_l(\Psi_l))\} = C_{t-1}(\eta_l(\Psi_l)) + C_t(\eta_l(\Psi_l)) \quad (28)$$

Recall that $C_t(\eta_l(\Psi_l))$ is the initial *weightages* of profiling interests as the profile *evolves*. Similarly, as mentioned earlier that, these changes are bounded by finite *min* and *max* bounds i.e.:

$$C_t^{\min}(\eta_l(\Psi_l)) \leq C_t(\eta_l(\Psi_l)) \leq C_t^{\max}(\eta_l(\Psi_l)) \quad (29)$$

Divide both sides of Eq. (28) by t and take $t \rightarrow \infty$. Following:

$$\overline{I}_g^t = 0 \quad (30)$$

Consequently, we have the following relaxed version of objective function:

$$\min \lim_{t \rightarrow \infty} \sum_{\tau=1}^t \left(\frac{C^\tau \eta_{l'}(\Psi_{l'}) + \beta(I_g^\tau + \eta_{l'}^\tau(\Psi_{l'}))}{\beta(I_g^\tau - \overline{U}^{\tau}(K_a))^2} \right) \quad (31)$$

s.t. constants: (16), (17), (24).

Now the main challenge of solving objective (31) is to minimise the variance of $\overline{U}^t(K_a)$ in order to protect user's *app's usage behavior* i.e. to know all the future usage of *apps* and hence suggest the (automatic) use of newly suggested *obfuscation apps* i.e. $\overline{U}^t(K_a)$. Similar to Eq. (30), we can also show that $\overline{U}^t(K_a) = 0$ i.e. to prove that decision variable is independent of $\overline{U}^t(K_a)$. Hence, the above optimisation problem can be solved without the information of $\overline{U}^t(K_a)$ at different time slots t , as detailed below.

Proof: From Eq. (21), it can be shown that:

$$\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=1}^t \mathbb{E} \left\{ \left(\overline{U}^{\tau}(K_a) \right)^2 - 2I_g^\tau \overline{U}^{\tau}(K_a) \right\} \quad (32)$$

The above equation is independent of the choice of $\overline{U}^{\tau}(K_a)$, hence:

$$\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=1}^t \mathbb{E} \{I_g^\tau\} \quad (33)$$

As shown in Eq. (20), sum over all t , take the expectation of both sides and take $t \rightarrow \infty$, we have the following:

$$\begin{aligned} \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=1}^t \mathbb{E} \{I_g^{\tau}\} &= \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=1}^t \mathbb{E} \{I_g^\tau\} + \\ &\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=1}^t \mathbb{E} \left\{ \overline{U}^{\tau}(K_a) \right\} \\ &= \overline{I}_g^t + \overline{U}^t(K_a) \end{aligned} \quad (34)$$

From Eq. (30), we conclude:

$$\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=1}^t \{I_g^{\tau}\} = \overline{U}^t(K_a) \quad (35)$$

The relax version of our objective function in Eq. (31) can be re-written as:

$$\lim_{t \rightarrow \infty} \sum_{\tau=1}^t (C^\tau \eta_{l'}(\Psi_{l'}) + \beta(I_g^\tau + \eta_{l'}^\tau(\Psi_{l'})) + \beta(I_g^\tau)) \quad (36)$$

Note that this is an optimised version of (24) i.e. the scenario of introducing medium disruption in a user profile and it achieves balance between user *privacy* and *targeted ads*. The other scenarios of low (23) and high (25) profile disruption will have no effect over the (36) except low and high costs and trade-off between *privacy* and *targeted ads*.

5 OPTIMAL CONTROL ALGORITHM

We design a control algorithm for identifying communication requests between the mobile device and the analytics server within an advertising ecosystem, to achieve an optimal solution to (26) for identifying time varying updates in user profiles. Let R_l^t represents an advertising request reported at t via ad/analytics SDK i.e. either ad request for display/ad click in *apps/web* or web searches/hisorty; recall that a request may or may not introduce l (l is profiling interest category introduced during profile updating or *evolution*) in a user profile I_g^t , alternatively, a change in user profile with an addition of $C_t(\eta_l(\Psi_l))$ during the profile *evolution*, as described in Section 3.5. Hence:

$$R_l^t = I_g^t - C_t^{\min}(\eta_l(\Psi_l)) \quad (37)$$

Subsequently, the R_l^t is a shifted version of I_g^t and can be described as:

$$R_l^{t+1} = I_g^t + R_l^t \quad (38)$$

5.1 Lyapunov optimisation

For n requests, we have $R_l^t = R_l^1, \dots, R_l^n$, following, the quadratic *Lyapunov function* for each t is given as:

$$Q(R_l^t) = \sum_{\tau=1}^t (R_l^\tau)^2 \quad (39)$$

Similarly, the corresponding *Lyapunov drift* i.e. *drift-plus-penalty*, can be defined as:

$$\Delta R_l^t = \mathbb{E} \{Q(R_l^{t+1}) - Q(R_l^t) | I_g^t\} \quad (40)$$

To stabilize the upper bound on Eq. (36), while effective profiling process i.e. the number of interests drawn, to minimise cost of newly suggested *apps*, and to minimise the variance of $\overline{U}^t(K_a)$ for preserving user privacy of *apps usage* behavior, the control algorithm can be designed to minimise the following *drift-plus-penalty* on each time slot t :

$$\Delta R_l^t + Vp(t) \quad (41)$$

Here, $p(t)$ is the penalty for minimising the upper bound on Eq. (36) i.e. minimise $p(t) = \mathbb{E}\{C^t \eta_{l'}(\Psi_{l'}) + \beta(I_g^t + \eta_{l'}^t(\Psi_{l'})) + \beta I_g^t\}$, $V > 0$ is a non-negative parameter chosen as a desired effect of performance of trade-off over the objective function. This approach does not require the knowledge of all future events i.e. the lack of knowledge of time varying updates in a user profile and the *apps* usage behavior. Eq. (41) can be re-written as:

$$\Delta R_l^t + Vp(t) \quad (42)$$

Lemma: The upper *drift* bound. For the control policy that satisfies the constraints on Eq. (36), we have the following *drift-plus-penalty* condition holds:

$$\mathbb{E}\{\Delta R_l^t + Vp(t) | Q(R_l^t)\} \leq B + Vp'(t) - \varepsilon \sum_{\tau=1}^t (R_l^\tau) \quad (43)$$

ε is similar to β and can be controlled to achieve the average *apps* usage time to preserve privacy of user's *app* usage behavior and to achieve a trade-off between user *privacy* and *targeted ads*. $p'(t)$ is the desired *target* for the time average of $p(t)$. B can be defined as:

$$B = \frac{1}{2} \max\{C_t^{\max}(\eta_l(\Psi_l)), C_t^{\min}(\eta_l(\Psi_l))\} \quad (44)$$

$$\frac{1}{t} \sum_{\tau=1}^t \mathbb{E}\{p(\tau)\} \leq p'(t) + \frac{B}{V} + \frac{\mathbb{E}\{R_l^1\}}{Vt} \quad (45)$$

Proof: Taking expectations of both sides of above *drift-plus-penalty*, we have:

$$\mathbb{E}\{\Delta R_l^t\} + V\mathbb{E}\{p(t)\} \leq B + Vp'(t) - \varepsilon \sum_{\tau=1}^t (R_l^\tau) \quad (46)$$

$$\begin{aligned} \mathbb{E}\{R_l^t\} - \mathbb{E}\{R_l^1\} + V \sum_{\tau=1}^t \mathbb{E}\{p(\tau)\} &\leq \\ (B + Vp'(t))t - \varepsilon \sum_{\tau=0}^t \mathbb{E}\{Q(R_l^\tau)\} - \mathbb{E}\{R_l^1\} & \\ + V \sum_{\tau=0}^t \mathbb{E}\{p(\tau)\} &\leq (B + Vp'(t))t \end{aligned}$$

$$V \sum_{\tau=1}^t \mathbb{E}\{p(\tau)\} \leq p'(t) Vt + Bt + \mathbb{E}\{R_l^1\} \quad (47)$$

Dividing by Vt and rearranging terms proves the bound on average penalty, concludes the proof. ■

5.2 Control algorithm

The main objective of the control algorithm is to minimise the *drift-plus-penalty* bound subject to the constraints of (36) at each time slot t . This control algorithm optimally selects the minimum and maximum bounds over the selection of obfuscation *apps*, the rate at which these *apps* needs to run according to the variation in R_l^t and by observing the current states of I_g^t i.e. a solution to the following optimisation problem:

$$\min R_l^t + V(C^t \eta_{l'}(\Psi_{l'}) + \beta(I_g^t + \eta_{l'}^t(\Psi_{l'})) + \beta I_g^t) \quad (48)$$

s.t.

$$\begin{aligned} C_t^{\min}(\eta_l(\Psi_l)) &\leq C_t(\eta_l(\Psi_l)) \leq C_t^{\max}(\eta_l(\Psi_l)) \\ R_l^t &= I_g^t - C_t^{\min}(\eta_l(\Psi_l)) \\ I_g^t &= \sum_{\forall t} C_t(\eta_l(\Psi_l)) \forall l \in \{[1, \psi], m, n\} \end{aligned}$$

The performance of this algorithm is to achieve minimised objective during when changes occur in profiling process at t i.e. the *stable* and during the *profile development* and *profile evolution* processes, in order to solve (48) as a mixed integer non-linear programming optimisation problem. The following cases:

Stable state: Recall that during this state, no changes occur in the profiling process i.e. $C_t(\eta_l(\Psi_l)) = 0$. Hence, the optimal value of (48) is evaluated to:

$$V(C^t \eta_{l'}(\Psi_{l'}) + \beta \eta_{l'}^t(\Psi_{l'})) \quad (49)$$

Let $p(R_l^t)$ tracks the advertising requests reported at t via ad/analytics SDK during slot t , which is considered minimum i.e. $p^{\min}(R_l^t)$, during the *stable* state, hence, the $\eta_{l'}(\Psi_{l'})$ is selected as $\eta_{l'}(\Psi_{l'}) = \min\{0, \eta_l^{\min}(\Psi_l)\}$.

Profile development/evolution state: The profiling process speeds up during this state as a result of high interaction with the analytics servers. Let $p^{\min}(R_l^t)$, $p^{avg}(R_l^t)$, and $p^{\max}(R_l^t)$ respectively represents the minimum, average, and maximum; following we present various scenarios for calculating optimal value of (48):

- For $p^{\min}(R_l^t)$:
 - $\eta_{l'}(\Psi_{l'}) = \max\{0, \eta_l^{\min}(\Psi_l)\}$
- For $p^{avg}(R_l^t)$:
 - $\eta_{l'}(\Psi_{l'}) = \min\{\eta_l^{\min}(\Psi_l), \eta_l^{\max}(\Psi_l)\}$
- For $p^{\max}(R_l^t)$:
 - $\eta_{l'}(\Psi_{l'}) = \max\{\eta_l^{\max}(\Psi_l), \eta_l^{\max}(\Psi_l) + \eta_{l'}^{\max}(\Psi_{l'})\}$

Given these values, the optimal objective can be calculated as:

$$p(R_l^t) + V(C^t \eta_{l'}(\Psi_{l'}) + \beta(I_g^t + \eta_{l'}^t(\Psi_{l'})) + \beta I_g^t) \quad (50)$$

The lower values on (49) and (50) and the corresponding control values are calculated to evaluate the optimal values of our objective.

6 PERFORMANCE ANALYSIS

We now analyse the feasibility and performance of the proposed model using various evaluation metrics, in addition to, we discuss the POC implementation of our proposed model. The applicability of the proposed system is discussed in Section 8.3.

6.1 Evaluation metric

We define *utility* and further elaborate the *cost* of newly selected *apps* to provide insights on *usability* of the newly selected *apps* usage. The authors in [17] describe *utility* as the success rate for removal of private query tags i.e. the magnitude suppression of original user preferences.

6.1.1 Utility

Let $D(\eta_p(\Psi_p))$ is the dominating private interest category. We define *utility* based on two components: first, from the effectiveness of privacy protection, we use as metric the level of reduction R_p of $\eta_p(\Psi_p)$ of a selected private category Ψ_p in an *Interest profile*, achieved via newly suggested obfuscating *apps*, with $\frac{D(\eta_p(\Psi_p))}{D(\eta_l(\Psi_l))}$. Here $D(\eta_l(\Psi_l))$ is the new dominating ratio resulting from using *apps* in S_o (S_o is the new set of *apps* other than S_a ; the selection of these *apps* has been detailed in Section 4.2).

Secondly, we introduce *usability* U_s of the selected obfuscating *apps* that relates to the probability that a user would actually utilise these *apps*, rather than just install and run it for privacy protection. The U_s of an *app* $a_o \in S_o$, in regards to a user with a specific *Context profile*, as the ratio of similarity between this *app* and any of the *apps* in S_a and the maximum similarity of any other *app* from $\mathcal{A}$, not present in S_a and *apps* from the same set:

$$U_s = \min \left(\frac{\text{sim}(a_o, a_{i,p})}{\text{sim}(a_{q,r}, a_{i,p})} \right) : a_{i,p} \in S_a, a_{q,r} \notin S_a \quad (51)$$

Combining the two, the total *utility* can then be calculated as: $U_T = R_p + U_s$.

6.1.2 Cost and resource overhead

The *cost* and *resource overhead*, can be considered as equivalent terms in the context of introducing new activities, which result in usage time and other resources e.g. battery usage, however, for the sake of clarity we use two separate terms. As mentioned earlier, *cost* C is termed as a metric that relates to the reduction of overall usage time available (by use of obfuscating *apps*) to original (non-obfuscating) *apps*.

In the basic scenario where, the average introduction of newly selected *apps*, the usage of all *apps* is uniformly distributed within a time period in correspondence to $U^t(K_a)$; this is equivalent to the ratio of the number of obfuscating *apps* in S_o (that need to be installed and used to protect privacy) and the size of original *apps* set S_a . *Cost* is therefore defined as:

$$C = |S_o|/|S_a| \quad (52)$$

We consider the *resource overhead* R , to be the overall resource usage by running the newly suggested *apps*. Hence, there will be a corresponding overhead $R_{i,j}^t$ for each *app*

$a_{i,j}$ at time slot t , comprising broadly of *communication* $R_c^t(a_{i,j})$, *processing* $R_p^t(a_{i,j})$, and *battery* consumption overheads $R_b^t(a_{i,j})$.

$$R_{i,j}^t = R_c^t(a_{i,j}) + R_p^t(a_{i,j}) + R_b^t(a_{i,j}) \quad (53)$$

Following, we present further detail on resource usage and then experimentally evaluate various components (see Section 7.5) of the overall resource overhead R .

6.2 Evaluating resource use

We rely on various utilities of Android SDK¹⁶ to automate various measurements for *processing* and *battery* consumption. As an example, we execute `adb shell top -m 10` within the `Process p = Runtime.getRuntime().exec("command")` to determine *CPU* processing of each running *app*. Similarly, to evaluate *battery*'s current status, we use `adb shell dumpsys battery | grep level` command by initiating the `startActivity()` of the `Intent` utility of Android SDK. To measure this, we first charge the battery to 100% and then run the *app* for one hour, while connected to WiFi network. We envisage that running of newly suggested *apps* would be used over WiFi to reduce communication costs (specifically for users with limited mobile network packages), although, in real life scenario, users are likely to utilise *apps* (equally) on a mobile network that would results different magnitudes of resource overheads.

Similarly, we utilise the traffic captured during our experiments in order to evaluate *communication* overhead; described in Section 7.2.

In addition to above, we evaluate another resource usage overhead i.e. *storage space* consumption. This can be further classified into *installation* storage space, *cache* storage i.e. temporary stored data, e.g. cookies stored on phone, *internal data* size i.e. storage used for *apps*' files, accounts, etc., which are respectively calculated using `codeSize`, `cacheSize`, and `dataSize` of `PackageStats` package of Android SDK. Note that we automated all these through an *app*, and all the experimentation discussed in next section, using Android Debug Bridge¹⁷ of Android SDK that enables communication between a PC and connected Android devices.

7 PERFORMANCE EVALUATION

We now discuss details of various components of 'System App' implementation and experimental evaluation and further provide insights on resource overheads.

7.1 System App: The obfuscating system

We have implemented a POC 'System App' of our proposed framework. Various components are presented on left side of Figure 6 i.e. 'User Environment', which introduces changes to the user side with a range of different functionalities e.g. it implements local user profiling both for *Context profile* and *Interests profiles* (as detailed in Section 4.2), protects user's privacy for their (private) sensitive attributes,

16. <https://developer.android.com/studio>

17. <https://developer.android.com/studio/command-line/adb>

and preserves user privacy for their *apps usage* behavior (Section 4.3). In addition, it implements our proposed online control algorithm for jointly optimising user *privacy* and *cost*; presented in Section 5. To enable this functionality, a user need to install and run the ‘System App’; this approach is similar to existing *app* recommender systems, e.g. App-Brain¹⁸. The ‘System App’ acquires information about the set of currently installed *apps* on a device, interacts with user in regards to selection of private attributes to be protected. Furthermore, it evaluates the list of candidate obfuscating *apps* and presents to the user and automates the process of installation and running of these *apps*.

The ‘System App’ sends the installed *app* information to the ‘System Engine’ for calculating obfuscating *apps* and automates the installation and running of these *apps*, as shown in Figure 6. We have used various utilities of the Android SDK in our implementation. E.g., `PackageManager`¹⁹ is used to retrieve the list of installed *apps*. The meta data of the installed *apps*, such as *app* name, permissions etc., are obtained by calling the function `getInstalledApplications` (`PackageManager.GET_META_DATA`). The ‘System Engine’ evaluates obfuscating *apps* according to the criteria discussed in Section 4.2 by examining the ‘Local *app* repository’; we suggest that this repository is updated by the advertising system so that the ‘System App’ can calculate obfuscating *apps* from various *app*’s categories.

The ‘System Engine’ module forwards the list of obfuscating *apps* to the ‘System App’. Each *app* is displayed to the user as an accessible hyperlink to Google Play (or ‘Apple’s App Store’) store, which is done by invoking the `startActivity` (`new Intent(Intent.ACTION_VIEW, Uri.parse("market://details?id=" + appPackageName))`). The activity name (the *app* name that can be recognised by app market of the *app* to be installed) is specified using `appPackageName` function using the `Intent` class. These *apps* are automated and run using the `startActivity` utility of Android SDK for a specified amount of time that is required to generate new profile interests in the ad system.

7.2 Experimental setup

In this work, we mainly focus on Google AdMob²⁰ since it is the leading marketplace in mobile user profiling and has captured the online digital advertising market, however, we note that the proposed methods can be effortlessly applied to other ad/analytic networks. We carry out various experimentations for preserving profiling privacy (i.e. $I_g^t + \eta_l^t(\Psi_l)$), *apps usage* ($I_g^t - U^t(K_a)$) and evaluating various resource overheads R . To evaluate this, we select *apps* from 27 random (sample) categories; we note that Google Play store has organised *apps* into 37 (considering ‘Games’ as a single category) various categories e.g. ‘Entertainment’, ‘Lifestyle’ etc. For these experimentations, we select top 100 free *apps* from randomly chosen 27 categories and further narrow down it to 10 highest ranked *apps* from

each category. As mentioned earlier that the Google user profile is partly based on mobile *apps* usage and relevance of received ads, hence, we had to ensure that the tested *apps* receive ads.

We set a second (*mapping*) experimental setup; we select one mobile *app* from the top list of any category and run it for a period of up to 96 hours; note that this process was automated, as described above in Section 7.1. The purpose of these experiments was to evaluate *mapping* of specific *Context profile* to *Interest profile* i.e. $K_a \rightarrow I_g$, as discussed in Section 3.2. This helps in determining contribution of individual *app* in an *Interest profile*. We note that findings from these experiments help in selecting newly selected *apps* for various disturbances in user profiles i.e. achieving different trade-offs between *privacy* and *targeted ads*, as explained in Eq. (23), (25), and (24) e.g. $0 < \eta_l(\Psi_l) \leq \eta_l^{\min}(\Psi_l)$ for lower *privacy* and higher *targeted ads*. These experiments have taken around 3 months to complete for the 270 highest ranked *apps* from 27 random *apps* categories.

The ads traffic, including the control traffic exchanged for tracking/profiling purposes, was collected using `tcpdump`²¹, cleansed and saved to a local database during entire experimentations. We reset the profile²² before starting each experiment in order to make sure that the *Interest profile* is only resulting from the currently installed and actively used *apps*. In addition, we set up a phone with the same configuration however with ‘Opt-out of Ads Personalisation’ enabled in *Google Settings* system app. The purpose of this phone is to have a base reference for both newly generated user profile and received *targeted ads*. These experiments were run for all the selected categories for 24/7 for 5 months; due to practical limitations of these experiments, we only use 10 smartphones in parallel.

We also used the collected traffic from these experiments for calculating the *resource usage*; detailed in Section 6.2.

7.3 Trade-off between apps usage privacy and cost of profile disruption

Figure 8 compares the *apps* usage profile for lower and higher profile disruption by introducing lower (as shown in (a)) and higher (i.e. (b)) activity of newly suggested *apps*; note the original user profile activity is shown with rectangular boxes; already discussed in Figure 4. We first divide the time into 5 min duration bins and then record the number of ads requests in each bin (there are different number of ad requests by each *app*; as detailed in Section 7.5); each dot (in plot) in both Figures 8 (a) and (b) show the ad request frequency during the 24 hours time (shown on x-axis) and their corresponding ads requests frequency (i.e. shown on y-axis).

The newly suggested *apps* were run during various (day/night) times where there was no original (K_a) *app*’s activity e.g., during 1am–6am, as indicated in both figures. We note that, during 1am–6am with ‘lower *app* usage and low profile disruption’, newly *apps* request 27 ad (binned)

18. <https://www.appbrain.com/>

19. <https://developer.android.com/>

20. <https://apps.admob.com>

21. www.tcpdump.org

22. The profile was reset by using ‘Reset advertising ID’ option in *Google Settings* system app i.e. *Google Settings* → *Ads* → *Reset advertising ID*.

requests with a total of fetching 93 ads, while it is respectively 93 and 1323 for ‘higher *app* usage and high profile disruption’. In addition, the average number of ad requests and corresponding ads fetched were 19.6 and 60 for ‘lower *app* usage and low profile disruption’, while it was 77.6 and 809.6 for ‘higher *app* usage and high profile disruption’. Overall, there were 340 and 5068 ad requests respectively with two options of profile disruptions; note that this also has effect over various overheads, in particular, the *Communication* overhead, also discussed later in Section 7.5.

7.4 Privacy protection vs. ads distribution

Figure 9 (a) and (b) show frequency distribution of ads for lower and higher *apps* usage; the percentage of ads for presented ads in different time-bins is also shown on top of each bar. For each time bin, the presented ads were ranged from 1 to 16 ads requests, in particular, the frequency of these requests range from 1 to 9 ads requests for ‘lower *apps* usage’, which also attracted lower number of ads i.e. only 85 ads to completely *apps* usage privacy as shown in Figure 9 (a). Similarly, for ‘higher *apps* usage’, the ads requests range from 1 to 16 per time bin with an average of 32 ads for all frequency of ads, with a total of 480 ads in order to completely preserve user’s privacy. Recall that, the selection of such *apps* usages are mainly done for two purposes i.e. to protect *apps* usage privacy and to affect the *targeted* ads.

7.5 Privacy protection vs. resource use

It is reported by previous works [4], [18], and is also evident in our experimental results, that the ads (and its related tracking traffic) are the major contributor to the communication $R_c^t(a_{i,j})$ overhead. Hence, we approximate the communication cost by the traffic generated by ads and their related actions by users.

We note that, from the bandwidth viewpoint, the ads traffic is characterised by various components: The *ad refresh rate*²³ (technically it is the inter-arrival time of two consecutive ads); their correspondence with various ad/analytic servers with an advertising ecosystem; contacts with CDN for downloading various ad components e.g. images etc.; the number of objects associated with an ad along with their sizes; and communication with various servers during interactions with an ad. Table 2 shows various ad related objects and control messages, along with their sizes; determined from collected traffic traces.

During our experimentations, we examined, from collected traces, that an ad size is 16 ± 4 KBs, which (on average) contains 8–10 objects (e.g. JavaScript files, images etc.) with an average of 30–35 request/response messages. In addition, we note that *ad refresh rates* vary between 20–60 seconds²⁴, with distinct values of 20, 30, 45 and 60 seconds, which respectively to 36%, 47%, 15% and 2% of all the tested *apps*. Since the ad sizes do not vary widely, hence the communication overhead for introducing lower disturbance

in a user profile can be further minimised by selecting those *apps* that have maximum overall *ad refresh rate*; note that this information is already available with any ad network e.g. Google AdMob.

TABLE 2: The ad-related objects and control messages along with their average size in bytes.

Message Type	Size (bytes)	Message Type	Size (bytes)
200 Ok	496	POST	350
DNS Query Request	68	Ok/(PNG)	1300
GET /pagead/images	578	Ok/(GIF)	1000
DNS Query Response	334	Ok/(JPEG)	1300
Ok/(text/html)	1200	TCP reassembled PDU	1434
GET /geocode	224	no content	396
GET /simgad	252	Ok/(application/json)	240
GET /mads/gma	685	Ok/(text/javascript)	800
GET /imp	244	Ok/(text/css)	824
GET /generate_204	244	TCP Ack	66
GET /csi	595	TCP Syn	74

Figure 10 shows the distribution of bandwidth used by *apps* during our experimentations per our experimental setup, shown in Section 7.2. The proportion of *apps* that have consumed the respective bandwidths are also shown on top of each bar e.g. 26.30% of the *apps* (which corresponds to 71 *apps*) consumes a high bandwidth of 4.0–4.5MB. In addition, we note that *apps* that frequently fetch ads i.e. *apps* with *ad refresh rates* of 20 and 30 seconds, utilise an average bandwidth of 3.0–5.5MB; these *apps* represent around 70% of all the experimented *apps*. Note that the selection of such *apps* can be used for introducing higher disruption in user profiles, to attract lower *targeted* ads, and to achieve high *apps* usage privacy. The remaining 30% of the *apps* (i.e. *apps* with *ad refresh rates* of 45 and 60 seconds) utilise between 0.5–2.5MB communication bandwidth.

Subsequently, we evaluate the *processing* overhead introduced by experimented *apps*. We note that the measured CPU usage varies, although not widely, across different *apps*: the CPU-intensive *apps* such as those from the ‘Games’ category use between 25% to 30% of the CPU power; less-interactive *apps* such as *Notes* use between 15% to 20%.

Similarly, the *battery* consumption measured in our experiments shows a relatively low variations between various *apps*, with between 30% to 40% of the total battery (i.e. 100%) being used by each *app* during the measurement period.

In addition to above basic *overheads*, we evaluated *storage space* consumed by newly suggested *apps*; we mainly determined the *installation*, *data*, *cache* storage spaces. These storage spaces vary for *apps* according to their requirements e.g. a ‘language translation’ *app* might do offline text translation, hence it would require to save library files in *data* storage space quota requiring more space compared to *installation* storage space. In contrast, the *Facebook* would consume more *data* storage space to store user accounts data, search history, group settings, user timeline data etc. In addition, a *Google Maps* would take more *cache* storage space to save user’s searched places history etc. Table 3 presents few representative *apps* for combination of these storage space requirements; following we present further details.

Figures 11(a) through (c) show the distribution of *storage spaces* of the experimented *apps*; the proportion of *apps* that requires respective storage space are also shown on top of each bar. It can be observed, for *installation* storage,

23. AdMob refers this to *rate*, which is deterministic for every *app* and is configured by *apps* developer at the time of registering *apps* on Google Play store.

24. We note that supported values are 12-120 seconds in Google AdMob.

Fig. 8: Lower activity of newly suggested *apps* for lower (a) and higher (b) profile disruption.

Fig. 9: Distribution of ads by lower (a) and higher (b) *apps* usage.

Fig. 10: Bandwidth consumption (MB) calculated for ads by tested *apps* during experimentations.

that nearly half (54%) of the experimented *apps* acquires lower *storage space* i.e. 0.5MB to 10MB, while only 1.48% of these *apps* consume relatively higher *storage space* of 50–60MB. Similar observations can be found for *data* and *cache* overhead, as shown in Figures 11 (b) and (c). In conclusion, we observe that vast majority of these *apps* use a lower amount of *storage space*; e.g., 80%, 97%, and 98% of all *apps* belong to the lowest *storage space* bins, i.e. within the range of 0.5–20MB, 0.01–20MB, and 0.01–10MB storage

TABLE 3: Representative *apps* with various combination of storage space requirements.

App Names	Storage space consumed		
	Installation	Data	Cache
Youtube	117	2.57	361
Subway Surf	156	85.98	15.57
Chrome	86.88	15.46	1.53
File Manager	8.37	28.04	17.83
Foxit PDF	96.42	1.17	32.91
London City Guide	60.98	88.12	4.56
Google Play Store	93.61	7.48	22.25
Skype	62.95	28.22	13.41
Babel	51.98	14.79	0.02
English For Kids	16.45	3.55	10.81
Viber	159	17.35	0.12
Google Translate	5.53	392	2.04
Adobe Acrobat	20.91	0.47	0.22
Amazon Kindle	53.30	123.33	4.98
TripView Lite	28.21	5.92	2.09
Gmail	74.24	22.28	0.34

consumption, respectively for *installation*, *data*, and *cache* storage overheads.

8 DISCUSSION

We discuss the applicability of our framework in current advertising ecosystem, in addition to, comparing the proposed framework for various privacy protection approaches for the presented threat model.

Fig. 11: Storage space consumed by experimented *apps* for (a) *Installation* (b) *Data* and (c) *Cache*.

8.1 Protecting sensitive profiling interests via Differential privacy

The concept of *differential privacy*²⁵ was introduced in [19], a mathematical definition for privacy loss associated with any released data fetched from a database. A deeper understanding of *differential privacy* and its algorithms can be found in [20]. Let $D_1 = g_{k,l} \in S$ i.e. the set of interests in a user profile, and $D_2 = g'_{k,l} \in S_g$, where $\Psi_l \neq \Psi'_l$ and $g'_{k,l}$ is the profiling interest(s) other than the primary set of interests defined by an advertising company, Ψ_l is a selected private interests category that the user wants to protect. Subsequently, the *randomised* function K gives *differential privacy* for these two data sets as:

$$P_r [K(D_1) \in S] \leq \exp(\epsilon) \times P_r [K(D_2) \in S] \quad (54)$$

We examine the use of other privacy protection mechanisms that can also be utilised e.g. *private information retrieval*, *anonymisation*, *randomisation*, *Blockchain-based* solutions, however, we note that these solutions do not fully protect user's privacy for the presented threat model; following we provide a comparative analysis of use of various other privacy protection mechanisms.

8.2 Comparison with other privacy protection approaches

Table 4 compares various privacy protection mechanisms using different parameters, evaluated in our proposed framework. It can be observed that only the proposed mechanism of introducing newly suggested obfuscation *apps* protects user's privacy for *app's usage behavior*, since the user has to run these *apps* in order to protect usage behavior at different periods of the day/night. Similarly, an important parameter is the trade-off between *privacy* and *targeted ads*, which can only be achieved using the proposed mechanism and the *randomisation*. Furthermore, another parameter is to protect user privacy in terms of serving *targeted ads* (an *indirect* privacy attack to expose user privacy), which can also be adjusted according to user's needs i.e. 'low-relevant vs. high-relevant interest-based ads'.

8.3 Applicability of proposed framework in advertising system

Overall system functionality: The motivation for protecting user privacy is very much dependent on the way consumers use mobile *apps* and access internet; users are ever more concerned about preserving their privacy due to an enormous increase in its awareness. Such an example awareness motivation is by exposure of mass surveillance activities²⁶ and by unauthorised leaks of personal data. Hence, users have ever more interested in use of personal (bespoke) privacy tools. Thus the proposed framework is considered, inline with the current *apps* recommender and personalisation systems, that not only suggest usable newly recommended *apps* but also enable an optimised and cost effective privacy protection mechanisms. As we have seen in Section 7.3, this framework optimises the cost by selecting various number of *apps* for protecting *apps* usage privacy, protects user's private interest profile and achieves optimal trade-off between privacy protect and the *targeted ads*. Furthermore, this framework ensures that the newly recommended *apps* have an overall good *usability* to users, based on similarity metric discussed in Section 6.1.

An important user's concern is the issue related to *resource* use, we note during our *mapping* experimentation (as detailed in Section 7.2) that these experiments can help to significantly reduce the *resource* use by selecting appropriate *apps* that could (subject to availability of such *mapping* information) effectively preserve user privacy with least overhead. Using these experiments, on the average, the *communication* cost is around 3MB (for lower profile disruption) compared to 17MB for higher profile disruption, to achieve *apps* usage and profiling privacy. This would motivate users to use such strategy, in particular, those who might be on fixed mobile data plan. As discussed earlier that AdMob profiling is based on 'Web & App' activity, hence such (*mapping*) information can also be added for user's web searches/histories; although this *app*-based strategy is still applicable to protect user privacy for interest profiling as profiling is now done via both 'Web & App' activity. We envisage that such information could be made derived by approximating user profile based on various related information available, such as search/history keywords, similar to interest *mapping* discussed in Section 3.2 for K_a .

25. A C++ implementation of *differential privacy* library can be found at <https://github.com/google/differential-privacy>.

26. <http://www.theguardian.com/world/the-nsa-files>

Parameters	Proposed	Differential Privacy	Cryptographic mechanisms	Randomisation	Blockchain-based solutions
Apps usage behaviour privacy	Guaranteed	No guarantee	No guarantee	No guarantee	No guarantee
Cost C_t	Yes	Yes	Yes	Yes	Yes
Targeted ads	Minor to no relevant ads (adjustable)	Yes	Yes	Minor to no relevant ads (adjustable)	Yes
Trade-off b/w privacy and targeted ads	Yes	No	No	Yes	No
Profiling privacy	Yes	Yes	Yes	Yes	Yes

TABLE 4: Comparison of proposed framework with other privacy protection mechanisms for various performance parameters.

Server side modifications: Integrating the proposed framework within the existing advertising ecosystem would be fairly straightforward and would only require upgrading tracking and analytics mechanism of the server side i.e. we suggest the advertising system to transfer such functionalities to the client side; where the client remains honest. These changes are mainly related to *Aggregation* and *Analytics* servers; these servers would respectively receive the constructed user profile (along with anonymous *apps* usage statistics without including user’s Advertising ID) and other other statistics, e.g. ad impression/clicks etc., required by both advertising system and *apps* developers.

Client side modifications: A major change on the client side would require implementation via ‘System App’ i.e. user *profiling*, optimising user’s privacy for *targeted ads*, their *interactions with ads* and *app usage privacy* including the ‘Obfuscation engine’ for selection of newly suggested *apps*. Currently, the mobile integrates with the advertising ecosystem via SDK, hence it will mainly require modifications in client’s AdMob SDK.

Other privacy attacks: The proposed system protects users privacy against legitimate user profiling and the traffic monitoring/analysis and network surveillance both form the host advertising systems and third-party tracker/analytics. However, we did not address location-based privacy for *ads targeting* in much more detail, although this can also be handled by our privacy protection approach since the location is also added as one of the interest in user profile as part of demographics, as detailed in Section 2.1. For location specific ads, a low resolution GPS coordinates can be included in user profile to accommodate advertisers and businesses wishing to advertise to passing trade. In addition, location can be protected using other other protection mechanisms such as ‘Tor’; to use in conjunction with our system to prevent such threats.

9 RELATED WORK

In our recent work [1] we provide detailed survey on privacy leakages in profiling process, leakage of personal information by advertising platforms and ad/analytics networks, the measurement analysis of *targeted advertising* based on user’s interests and profiling context, in addition to, detailed discussion over ads delivery process in both *in-app* and *in-browser targeted ads*. We provide detailed insights on how private information is extracted and exchanged among various advertising entities e.g. between ad/analytics libraries and analytics server in an ad system,

similarly, associated privacy threats with third-party tracking, re-identification of private information and detailed overview of data and tracking sharing technologies. In addition, we compare various privacy preserving advertising systems for various capabilities, such as, the underlying architecture used, the privacy mechanisms and the deployment scenarios.

Privacy threats in *targeted advertising* have been extensively studied in literature e.g., direct and indirect (inferred) leakage of private information [3], [21], [22], [23] or third party ad tracking and visiting [24], [25], [26], [27]. These works show the prevalence of user (from their online data) tracking on both web and mobile environments and demonstrate the possibility of inferring user’s PII, such as email addresses, age, gender, relationship status, etc. The ad/analytics libraries (embedded with mobile *apps*) leak user’s personal information to ad system and (is more likely to) third party tracking, which are systematically collected by such libraries. Such example works [28], [29] study information collected by analytics libraries integrated within mobile *apps* and leaking of private information. Similarly, the authors in [30] show privacy and security risks by analysing 100,000 Android *apps* and find that majority of the embedded libraries collect and share private information. Other studies [31], [32] find that majority of the mobile *apps* do not implement private APIs and send private information to ad servers.

Recall that user profiling and *ads targeting* is carried out based on user’s activity over *apps* and internet; the authors in [33] manually create user profiles and examine that majority of *targeted ads* were based on the fabricated profiles. In our previous work [14], and later supported by another study [34], we examine various tracking information sent to the ad networks and the level of *ads targeting* based on such profiling information. Another work [23] investigates the information collected by ad networks using installed *apps* and reverse engineer the *targeted ads*. In line with above works, we also study [12] leakage of private sensitive information by examining actual network traffic through vulnerabilities in mobile analytics services, reconstruct the exact user profile of a number of participating volunteers, and further study its influence over *ads targeting*. This study was mainly for Google Mobile Analytics and Flurry Analytics. Third-party tracking also actively collect, manage and distribute user’s sensitive information, which has been widely studied in literature e.g. [26], [35], [36], [37], [38], [39] study the distribution of third-party trackers across web and Android *apps* and their impact on user privacy.

Other works [4], [15], [16], [40], [41], [42], [43], suggest the *app*-based user *profiling*, stored locally on mobile device. There are various *in-app* privacy-preserving mobile advertising and personalisation proposals, such as, Adnostic [44], Privad [45], RePriv [46], MobiAd [41], Splitx [47], ProfileGuard [4], [16]. The ProfileGuard that is an *app*-based profile obfuscation mechanism for protecting user privacy using various obfuscation strategies. Similarly, there are some other solutions that are crypto-based implementation of various techniques under Private Information Retrieval (PIR) [40] and Blockchain-based solutions [15], [48] for decentralised advertising system that enables private profiling and *targeted ads*.

This work, as opposed to our previous work [4] where it only protects user privacy by reducing dominance level of particular interests, jointly optimises *user's profiling privacy*, the *user's apps usage behavior*, and *cost* of achieving the level of privacy. We provide an online control algorithm that provides a trade-off by achieving between user *privacy* and *targeted ads*. This was achieved by optimally identifying updates in user profiles and user's *apps* usage behavior of actual *apps* by capturing temporal changes during the profiling process. We mainly address the attacks regarding *app*-based profiling, ads-based inferencing, and analysing user's behavior by sniffing network traffic of legitimate users.

10 CONCLUSION

The online mobile *targeted advertising* is growing in popularity, which at the same time has raise serious privacy concerns among individuals, enabled via the use of excellent user-tracking tools. This paper presents an optimal privacy preserving and cost-effective framework for preserving user privacy due to user profiling, ads-based inferencing and *ads targeting* and (in general) user's behavior over mobile devices. We present a dynamic optimisation framework by first examining the underlying advertising ecosystem and then provide a privacy preserving framework for temporal changes that occur in user environment in an ad ecosystem. The online control algorithm is used to detect temporal changes in user profiling based on *Lyapunov optimization* to achieve an optimal solution without requiring any knowledge of future use of mobile *apps* or temporal changes in a user profile. We carry out extensive experimentations using mobile devices of various profiles and we examine the profiling process, the privacy leakage, privacy protection and resource usage. We develop a POC 'System App' that implements critical components of the proposed framework and further discuss its applicability in an online advertising ecosystem.

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