Privacy-preserving targeted mobile advertising: A Blockchain-based framework for mobile ads

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Abstract—The targeted advertising is based on preference profiles inferred via relationships among individuals, their monitored responses to previous advertising and temporal activity over the Internet, which has raised critical privacy concerns. In this paper, we present a novel proposal for a Blockchain-based advertising platform that provides: a system for privacy preserving user profiling, privately requesting ads from the advertising system, the billing mechanisms for presented and clicked ads, the advertising system that uploads ads to the cloud according to profiling interests, various types of transactions to enable advertising operations in Blockchain-based network, and the method that allows a cloud system to privately compute the access policies for various resources (such as ads, mobile user profiles). Our main goal is to design a decentralized framework for targeted ads, which enables private delivery of ads to users whose behavioral profiles accurately match the presented ads, defined by the ad system. We implement a POC of our proposed framework i.e. a Bespoke Miner and experimentally evaluate various components of Blockchain-based in-app advertising system, implementing various critical components; such as, evaluating user profiles, implementing access policies, encryption and decryption of users' profiles. We observe that the processing delay for traversing policies of various tree sizes, the encryption/decryption time of user profiling with various key-sizes and user profiles of various interests evaluates to an acceptable amount of processing time as that of the currently implemented ad systems.

Index Terms—Privacy, Advertising, Blockchain, Mobile Advertising System, Access Policy, Cryptocurrency

1 INTRODUCTION

Mobile advertising ecosystem is one of the most successful markets, in recent years, with billions of mobile devices, including smartphones, tablets, and computer tablets, and millions of mobile applications (apps) registered in various app platforms, such as Google Play Store, Apps Store etc. The advertising companies enable user tracking within apps, and hence profiling users, where user’s personal information plays an important role in ads targeting. However, significant privacy concerns are associated with it, as suggested in a number of studies [1], [2], [3], [4], [5], [6]. Other studies [7], [8] indicate, unless consumers have specifically consented to it, that they have a direct relationship between consumer attitude and their behavior, i.e. consumers’ trust in privacy of mobile advertising is positively related to their willingness to accept mobile advertising. The American ad industry, implemented self-regulated by implementing Ad-Choices1 program, which states that consumer could opt-out of targeted advertising via online choices to control ads from other networks. However, another study [9] examines that opt-out users cause 52% less revenue (hence presents less relevant ads and lower click through rates) than those users who allow targeted advertising. In addition, the authors noted that these ad impressions were only requested by 0.23% of American consumers.

Hence, the purpose of targeted advertising is to deliver most relevant ads to achieve better view/click through rates and without exposing users’ private information to the advertising companies and third party publishers/ad networks. Prior research works show the extent to which consumers are effectively tracked by a number of third parties and across multiple apps [10], mobile devices leaking Personally Identifiable Information (PHI) [11], [12], apps accessing user’s private/sensitive information through well defined APIs [13], inference attacks based on monitoring ads [6] and other data platform such as eXelate2, BlueKai3, and AddThis4 that collect, enrich and resell cookies.

There are other works on protecting user’s privacy by obfuscating user profiles5 [5], [15] and based on security techniques [2], enabling user privacy [16], [17] by suggesting design changes to Android location API based on laboratory study [18] to understand developer’s behavior. Other privacy preserving advertising systems use a mix of cryptography techniques and obfuscation mechanisms, e.g., [19], [20] and targeted mobile coupon delivery scheme using Blockchain [21]. We note that the majority of the private advertising systems have been proposed for browser based ads [22], [23], [24], [25] whereas only few works address the in-app targeted ads [2], [15], [21], [26]. Our focus in this work is to protect individual’s privacy by decoupling all direct

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1. Founded in 2010. https://optout.aboutads.info/?c=2&lang=EN
2. https://microsites.nielsen.com/daas-partners/partner/exelate/
3. https://www.oracle.com/corporate/acquisitions/bluekai/
4. https://www.addthis.com/
5. A large scale investigation of obfuscation use where authors analyze 1.7 million free Android apps from Google Play to detect various obfuscation techniques is presented in [14].
communications between apps, analytics companies, which they use for targeted advertisements, advertising systems (including third party) for their activities (both for web and apps activity) using Blockchain technology.

Blockchain is based on a distributed ledger of transactions, shared across the participating entities, and provides auditable transitions [27], where the transactions are verified by participating entities within operating network. Among the participating entities; the Miner by participating entities within operating network. Among the participating entities, shared across the participating entities, and provides apps activity) using Blockchain technology. (including third party) for their activities (both for web and

size of transactions reaches a specific block size. The process of adding a new block to the Blockchain is referred to as mining and follows a consensus algorithm, such as Proof of Work (POW) [28] and Proof of Stake (POS) [29], which ensures the security of Blockchain against malicious (Miner) users. The participating entities use the Public-Private Key pair that is used to achieve the anonymity [30]. Among various salient features of Blockchain, i.e. irreversible, auditable, updated near real-time, chronological and timestamp, which, in addition, disregards the need of a central controlling authority; thus making it a perfect choice for restricting communication between the mobile apps and the analytics/ad companies and keeping individual’s privacy.

Our main contributions in this paper include the following. We investigate the relation between the mobile apps usage and the resulting user profiles derived by a major analytics network i.e., Google AdMob. We mainly describe three states of the user profiles i.e. the user profiles that are established during when no interests are derived by the analytics services i.e. profile establishment process, the state of the profiles once apps are used that would originate interests other than the existing set of apps i.e. profile evolution process, and stable states of the profiles where subsequent use of existing set of apps have no effect over the profiles. We also determine the broad profiling rules during various processes of utilising android apps: that profiles represent an aggregation of interests generated by use of individual apps, that there is a fixed mapping of apps to sets of interests and that a minimum level of activity (in a period of up to 72h) is required to build a stable user profile. We correspondingly develop an analytical model for depicting various profiling states and rules to represent profiling processes.

Following, we design a framework for secure user profiling and Blockchain-based targeted advertising system for in-app mobile ads and the design of various critical components of advertising system, as follows: the 1. Ads Placement Server (APS) for evaluating ads according to various profile interests, hashing ads and sending hashed profiles along with corresponding ads to CS 2. Cloud System (CS) for storing hashed profiles along with corresponding ads sent by APS, in addition, maintaining a copy of user profiles 3. Cluster Head (CH) for processing ad-block requests, access control policy for various operations, such as storing user profile etc., and fetching ads from CS according to user profiles 4. System App (Miner) that sits on user’s mobile device and calculates user’s profiles, sends hashed user profile to CH, uploads user profiles on CS, and requests and delivers ads to mobile app 5. Billing Server (BS) for calculating billing for presented and clicked ads with the use of Cryptocurrency for ensuring privacy, secure payment and for compatibility with the underlying proposed advertising system over Blockchain 6. Access Control Policy implemented in Miner for holding an access control list that allows apps regarding evaluation of different operations e.g. to check whether an app is allowed to request for ads, participate in billing etc., and on CS to control access of ad-request coming from various Miners. The access policy is implemented as a policy tree that consists of matching functions for allowing access to various operations or resources and their corresponding actions.

We design the structure for various transactions for an ad-request/response block for operating within the Blockchain network e.g. block structure of an Ad-Block-Header-Request, Ad-Block-Header-Response, and Ad-Block-Structure. We design various algorithms that specify comprehensive operations of various components of the advertising system. Furthermore, we discuss various design requirements in terms of privacy, reduced overhead over (user) client, compatibility of billing with Cryptocurrency, and achieving system efficiency and component’s compatibility within the Blockchain network.

We develop an Android-based Proof of Concept (POC) implementation i.e. a Bespoke Miner for evaluating various components of Blockchain-based in-app advertising system, such as, generating public-private key pair, evaluating user profiles, encrypting user profile or decrypting the ads received from CS, implementing access policy, and its interaction with the CS. We design a detailed experimental setup that consists of Bespoke Miner and CS (a local machine for correspondence with the Bespoke Miner), following, we utilise real parameter settings obtained by extensive our real-time experiments [15], [31] (and further verified that these parameters still hold) that include various sizes of an ad, set of interests with a user profile etc. We calculate the processing delay for generating public-private key pair, encryption/decryption time of user profiling with various key-sizes and user profiles, and processing delay for traversing policies of various sizes. We observe that, using various 512, 1024, 2048, 4096 bits sizes of public-private key pairs, the Min processing time ranges from 0.005sec to 0.30sec.

Following, we calculate encryption and decryption time for user profiles with interests, randomly chosen up to 20 interests with an Avg and St.Dev of respectively 10.53 and 5.88 interests, using 1024, 2048, 4096, 8192 bits sizes of public-private key pairs and evaluate the processing delays of Avg, Min, Max, St.Dev. We observe that, for instance, the Min and Max profile encryption times with (1024, 8192) bits key sizes are respectively (0.1msec, 1.2msec) and (2.2msec, 16.3msec), with an Avg and St.Dev of (0.4msec) each and (6.0msec, 3.2msec). In addition, the decryption time evaluates to (0.001sec, 0.005msec) and (0.35sec, 1.67sec) with Avg and St.Dev of (0.002sec, 0.0009sec) and (0.8sec, and 0.36sec). Based on our observations [2], [5], we note that this is an (equivalent) acceptable amount of processing time to that of when a mobile app requests ad in the beginning of an app launch or during the app usage session.

Rest of the paper is organised as follows: Section 2 presents detailed discussion over the profiling process and formulates the problem. Section 3 presents various
components of the proposed framework for secure user profiling and Blockchain-based targeted advertising system for in-app mobile ads. In Section 4, we present the Ad-Block-Structure for an ad-request/response for operating within the Blockchain network. Details of Ad-Block operations are presented in 5, followed by experimental setup, including details of POC implementation for bespoke Miner, and experimental evaluation in Section 6. Related work is summarised in Section 7 and conclusion of our work is given in Section 8.

2 Problem Formulation

We formalise the system model that consists of the applications’ 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 Apps profiles and then show how the profiles evolve when some apps other than the initial set of apps are utilised.

2.1 Profiling

An app marketplace includes a set of $A$ mobile apps, that are commonly (e.g., in Google Play or in the Apple App store) organised within different categories. We denote an app by $a_{i,j}$, $i = 1, ..., A_j$, where $A_j$ is the number of apps that belong to an app category $\Phi_j$, $j = 1, ..., \tau$ and $\tau$ is the number of different categories in the marketplace.

A user may be characterised by a combination of apps installed on their mobile device(s), comprising a subset $S_a$ of the apps set $A$. An Apps profile $K_a$ can therefore be defined as:

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

Analytics companies (e.g., Google or Flurry) profile users by defining a set of profile interests $G$, i.e., characteristics that may be assigned to users. Interests are commonly grouped into categories, with interests $g_{k,l}, k = 1, ..., G_l$, where $G_l$ is the number of interests that belong to an interest category $\Psi_i$, $l = 1, ..., \epsilon$ and $\epsilon$ is the number of interest categories defined by the analytics company. Table 1 shows notations used in this work.

Profiling characterises the user by the combination of their interests, i.e., by a subset $S_g$ of the full interest set $G$. Google profile interests are grouped, hierarchically, under various interests categories, with specific interests. An Interests profile $I_g$ for a user can therefore be defined as:

$$I_g = \{ \{g_{k,l}, \Psi_i\} : g_{k,l} \in S_g \}$$ (2)

We note that although various types of information may be used to generate user profiles, here we focus on the interests derived from the usage of installed apps. Note that we will use the Apps profile $K_a$ and Interests profile $I_g$ respectively for calculating the Contextual and Targeted ads.

In addition, 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., Google2 presents a detailed set of various demographic targeting options for ads display, search campaigns etc. Hence, profiling also characterises users by various demographics under different options. The demographics $D$ are usually grouped into different categories, with specific options $d_{m,n}, m = 1, ..., M$ and $n = 1, ..., N$, where $M$ is the targeted demographics ranges, e.g. ‘18-24’, ‘25-34’, ‘35-44’, ‘45-54’, ‘55-64’, ‘65 or more’, and ‘Male’, ‘Female’, ‘Rather not say’, and $N$ is the number of different demographic targeting options e.g. household income, parental status, location etc. Note that for simplicity, we do not consider the user history and leave it for future work. We suggest that the profiling is done on the user side (i.e. done by the System App<sup>8</sup>, see Figure 2).

Following sub-section details derivation of Interests profile, which we call the profile Establishment process.

2.2 Mapping Rules for Profiling

We now deliberate the profiling rules as a result of utilisation of mobile apps. The advertising networks derive Interest profiles for wide range of audiences based on the collected information and accordingly target the mobile users. Note that the mapping rules outlined in this section are based on our observations [5] [31] [6].

2.2.0.1 Profile Establishment: User profile is established by using the installed apps for certain amount of time, after it has sufficient interactions with analytics services. We assume that there is a mapping of Apps profile to an Interests profile defined by Google Analytics, which is used by analytics companies to individually characterise user’s interests across the advertising ecosystem. A sample mapping is also given in [5] where we observed mapping of Apps profile to Interests profile by a series of various profiling experiments. This mapping includes the conversion of apps categories $\Phi_j$ to interest categories $\Psi_i$. This mapping converts an app $a_{i,j}$ to an interest set $S_g^{i,j}$ after a specific level of activity $t_{est}$. The $t_{est}$ is the establishment threshold i.e. time an app should be used in order to establish profile’s interests. The set $S_g^{i,j}$ derived by an app $a_{i,j}$ can be represented as a set of interests $g_{k,l}$ along with their corresponding categories $\Psi_i$:

$$S_g^{i,j} = \{ \{g_{k,l}, \Psi_i\} : g_{k,l} \in G \}$$ (3)

We note that all installed apps, from a specific mobile device, do not necessarily contribute to the profile<sup>9</sup>, in which case the $S_g^{i,j}$ is an empty set.

Finally, the resulting Interests profile $I_g$ is established as the combination of individual interests derived by each app. The Interests profile can be expressed as the union of all the interests sets $S_g^{i,j}$ derived by individual app $a_{i,j}$ in $S_a$; hence Eq. 2 can be re-written as follows:

$$I_g = \bigcup_{\forall(i,j) : a_{i,j} \in S_a} S_g^{i,j}$$ (4)

7. Demographic Targeting https://support.google.com/google-ads/answer/2580383?hl=en
8. The System App is similar to the AdMob SDK [5] that communicates with Google Analytics for deriving user profiles.
9. The full list of installed apps on an Android based phone is included in the library.db file /data/data/com.android.vending/databases/library.db
Furthermore, *System App* derives users’ demographics $S_d$ from their settings (e.g. Gmail settings) or by inferring their demographics based on their activities. We suggest that the users may 'edit' their demographics within the *System App*, i.e. similar to that by visiting Google Ad Settings\(^{10}\).

$$I_g = \bigcup_{\forall(i,j): a_{i,j} \in S_a} S_{g}^{i,j} \cup \bigcup_{\forall(m,n): m,n \in S_d} d_{m,n}$$

### 2.2.0.2 Profile Evolution

The profile is updated, and hence the *ads targeting*, each time variations in the users’ behaviour are observed; such as for a mobile user using apps that would map to interests other than the existing set of interests. Let a user uses new set of apps $S'_a$, which has no overlap with the existing set of apps $S_a$ that has created $I_g$ i.e., $S'_a \subset A \setminus S_a$.

The newly added set of apps $S'_a$ is converted to interests $g_{k,l}$ with $t_{eva}$ as evolution threshold i.e. the time required to evolve profile’s interests. Thus, an app $a'_{i,j}$ in $S'_a$ should be used for $t_{eva}$ time in order to evolve profile’s interests $S'_{g}^{i,j}$. The sets of interests $S'_{g}^{i,j}$ derived by $a'_{i,j}$ are represented as the union of all interests $I_g$, i.e. $I_g = \bigcup S'_{g}^{i,j}$. Hence, the final Interests profile, $I'_g$, after the *Evolution* process, is the combination of older interests derived during the profile *Establishment* $I_g$ and during when the profile evolves $I'_g$ and is given as:

$$I'_g = I_g \cup I'_g$$

### 2.2.0.3 Profile Development Process

We now elaborate insights of profile *Establishment* and *Evolution* processes performed by Google analytics and adopt the same strategy of profile *Development* process. In order for the *Apps profile* to establish an *Interests profile*, a minimum level of activity of the installed apps is required. Furthermore, in order to generate one or more interests, an app needs to have the AdMob SDK. This was verified by testing a total of 1200 apps selected from a subset of 12 categories, for a duration of 8 days, among which 1143 apps resulted the *Interest profiles* on all test phones indicating “Unknown”

| Symbols | Description |
|---------|-------------|
| $A$     | Set of apps in a marketplace |
| $\tau$ | Number of app categories, $\Phi_j$ is a selected category, $j = 1, ..., \tau$ |
| $S_a$   | Subset of apps installed on a user’s mobile device |
| $a_{i,j}$ | An app $a_{i,j} \in A$, $i = 1, ..., A_i, j = 1, ..., A_j$, $A_i$ is the number of apps in $\Phi_j$ |
| $K_a$   | App profile consisting of apps $a_{i,j}$ and their categories $\Phi_j$ |
| $U$     | Set of interests in Google interests list |
| $\Psi_l$ | Interest category in $U$, $l = 1, ..., \epsilon$, $\epsilon$ is the number of interest categories defined by Google |
| $S_g$   | Subset of Google interests in $U$ derived by $S_a$ |
| $I_g$   | Interest profile consisting of $g_{k,l} \in S_g$ |
| $g_{k,l}$ | An interest in $I_g$, $k \in G_g, l \in \epsilon$ |
| $S'_{g}^{i,j}$ | Set of interests derived by an app $a'_{i,j}$ |
| $D$     | The set of demographics defined by analytics companies |
| $d_{m,n}$ | Demographics options $d_{m,n} \in D$, $m = 1, ..., M$ and $n = 1, ..., N$ |
| $S_d$   | Subset of user’s demographics derived by System App |

### Table 1: List of Notations.

![Fig. 1: Profile Establishment & Evolution processes. $I_E$ is the empty profile before apps utilisation. During Stable states, *Interest profiles* $I_g$ or $I'_g$ remains the same and further activities of the same apps have no effect over the profiles.](image)
websites and ad clicks, the users’ interests are based on various norms: selection of mobile apps installed and used, (traditional) browser based profiling, ad clicks of certain categories of ads, demographics e.g. age-rank, location etc.; to create a unified user profile. User profiling and its related ads targeting expose sensitive information about users [5], [15], e.g. the target could browse through gambling websites or spends excessive time using gambling apps, revealing (including a third-party, such as the website owner) to the advertising systems that the user is a heavy gambler.

In particular, we address two privacy attacks: Legitimate user profiling by Analytics, in traditional advertising systems, these functionalities are implemented via an analytics SDK [32] for reporting user’s activities to Analytics & Ads networks, hence, observe various requests to/from mobile users. Indirect privacy attack, involves third parties that could intercept and infer user profiles based on targeted ads, since ad’s traffic is sent in clear text [6]. We presume that users do not wish to be exposed to their private interests and are willing to receive relevant ads based on their interests.

In addition, another problem being addressed where (user) clients or servers outsource their functionalities (e.g. a firewall to monitor incoming/outgoing transactions for authorising various entities to access particular service/resource) to a third party e.g. to cloud system (CS). Hence, in addition to private ads targeting, the user wishes to have private outsource functionalities where any third party, including CS, does not learn the policies implemented.

2.4 Threat Model

Our privacy goal in this work is to decouple, and hence limit the information leakage to either advertising systems or third party, (mobile) users from (advertising) servers for their interactions, hence, various functionality (i.e. policies) are implemented by cloud on their (both user’s and server’s) behalf. In addition, we limit the information leakage for various other activities e.g., tracking user’s for their activities, billing for ad presentation and ad click etc. To an extent, we emulate the "traditional" setting where the mobile user’s profiling is entirely implemented on user’s side i.e. Miner, hence revealing no information of user profiling to advertising systems. The Miner requests for corresponding encrypted ads associated with hash of profile’s interests. Hence, the CS only learns the match for some unknown (hashed profile’s interests) data along with the corresponding other (encrypted ads) data pointers, i.e. any entity in CS is assumed to be an honest-but-curious.

3 System Components

Figure 2 shows various components of proposed system.

3.1 Evaluating Advertisements

The Ad Placement Server (APS) groups advertisements according to various interest categories for targeting users with specific interests. The advertising system calculates as a similarity match between individual interests and the set of ads; where individual interests and ads are characterised by a set of keywords\(^\text{11}\). The similarity is calculated based on the \(tf \cdot idf\) metric \([33]\). We note that this strategy is not metric specific and that other similarity metrics might be used. Let \(D\) be the set of ads from all the advertisers wanting to advertise with an advertising agency. Each ad \(Ad_{l}\) is represented with a unique identifier \(ID = 1, ..., D\) and is characterised by \(\kappa_{Ad_{l}}\) keywords. Let the function \(f\) returns the set of keywords of an ad i.e. \(f(Ad_{l}) = \kappa_{Ad_{l}}\) from the pre-defined list of ads and their corresponding keywords. These set of keywords are then used by another function \(g\) for calculating an appropriate interest(s) by calculating the similarity between the ad’s keywords \(\kappa_{Ad_{l}}\) and the list of keywords of individual interests i.e. \(\kappa_{k,l}\).

\[
g(\kappa_{Ad_{l}}) = \kappa_{k,l} : \sim \left(\kappa_{k,l}, \kappa_{Ad_{l}}\right) = \max_{\forall Ad_{j} \in D} \left(\sim \left(\kappa_{k,l}, \kappa_{Ad_{j}}\right)\right)
\]

This similarity \(\sim(\kappa_{k,l}, \kappa_{Ad_{l}})\) based on \(tf \cdot idf\) is calculated as follows: Let \(t\) be a particular keyword in \(\kappa_{Ad_{l}}\) and \(d\) be the set of keywords in \(\kappa_{k,l}\); then the term frequency (occurrences of a particular keyword \(t\) in \(d\)) is \(tf_{t,d}\). The inverse document frequency of \(t\) in \(\kappa_{Ad_{l}}\) within \(d\) is calculated as \(idf_{t,d} = \log\frac{N}{df_{t,d}}\), where \(N\) is the collection of keywords of interests in Interest categories and the \(df_{t,d}\) is the document frequency that is the number of Interest categories that contain \(t\). The \(tf \cdot idf\) is then calculated as \(tf \cdot idf_{t,d} = tf_{t,d} \times idf_{t,d}\). Thus the score for \(\kappa_{Ad_{l}}\) can be calculated as:

\[
score(\kappa_{Ad_{l}}, d) = \sum_{t \in \kappa_{Ad_{l}}} tf \cdot idf_{t,d}
\]

The similarity score ranges \(0 \leq score \leq 1\) for individual ads, where an ad (or a set of ads) with highest similarity match to profile interests is calculated as a candidate ad for \(g_{k,l}\) and is assigned to particular interest i.e. \(g_{k,l} \leftarrow Ad_{T}\). Note that a single ad can be assigned to various profiling interests, hence, targeting vast majority of audience. This process is continued for entire set of advertisements. Note [31] that the served ads are either URLs of the sponsoring merchants (advertisers) or they are related to e.g. the Google Play Store apps/games\(^\text{33}\) i.e. self-advertising. Recall, an app marketplace includes a set of \(A\) mobile apps/games \(a_{i,j}\) grouped in different categories, characterised by a set of keywords i.e. \(\kappa_{i,j}\). We argue that such advertisements can either be evaluated through the \(\sim(\kappa_{k,l}, \kappa_{i,j})\) similarity metric or a direct match between the profiling Interests’ \(\Psi_{i}\) and Apps’ \(\Phi_{j}\) categories e.g. using Jaccard Index \(\frac{\Psi_{i}}{\Phi_{j}}\).

3.2 Hashing Ads and Encrypted Profile Interests

All the advertisements are associated with various profile interests, as mentioned in previous step. The advertising server now evaluates the hashes for all the interests \(g_{k,l} : \forall k \in G_{l}, l \in \epsilon\) under individual categories \(\Psi_{l}\) i.e. \(h(g_{k,l})\); in addition, the corresponding ads are encrypted (e.g. using RSA) i.e. \(Enc(Ad_{l})\). We call this dataset a 'profiling-ads'. Note that this operation is done just

\(^{11}\) The advertising agency and the advertiser agree on various keywords so as to describe advertisements.

\(^{33}\) https://play.google.com/store/apps
once during system initialisation or every time new ads are added to the system for advertising. Each hash references various set of ads e.g. \( h(y_{kl}) \to Enc(Ad_{1D1}, \ldots, Ad_{1DN}) \), which means that a user with specific \( h(y_{kl}) \) will be targeted with \( Ad_{1D1}, \ldots, Ad_{1DN} \) ads.

### 3.3 Storing profiling-ads in CS

Once the set of profiling interests and their corresponding ads (i.e. profiling-ads) are ready, the APS can upload it to Cloud Storage (CS), which is carried out through an anonymous process similar to those discussed in [34]. Note that APS need to go through the access policy mechanism to upload (store) the profiling interests and corresponding ads. For this, APS sends a request to CS for storing profiling-ads, requests the pointer to the first block \( P_b \), and the confirmation for availability of storage space. The CS evaluates access policy for APS to confirm whether the request is coming from legitimate party and to allow APS to use storage space. Once the APS is allowed to store the profiling-ads data; the CS encrypts the \( P_b \) with \( PK^+ \) and sends it to APS along with the the storage-block \( B \) i.e. the capacity of storage block within CS for saving information on physical disk for spanned organisation of storing data. Following, the APS evaluates the blocking factor \( bfr \) to calculate the number of block to be occupied by profiling-ads and sends it to the CS. Subsequent, APS decrypts the \( P_b \) with \( PK^− \) to extract the \( P_b \), creates a random ID, and starts sending profiling-ads to CS. The CS calculates the hash of the received data, compares it with the received hash, and (upon its validity) stores the profiling-ads data. Since APS needs to send (a high volume) data in several transactions; for this, the CS sends a new \( P_b \) (encrypted with the \( PK^+ \)) to APS.

### 3.4 Miner (System App)

The System App sits on a user’s devices, which performs a range of various tasks: deriving user profiles as outlined in Section 2.2, uploads hashed user profiles to CS, requests ads from CS through CH, and delivers requested ads to mobile apps while fulfilling advertising quota, discussed in detail in Section 4. The Miner processes all incoming and outgoing requests using a range of various transaction types, as discussed in Section 4.3. The Miner authorises various apps participating in profiling or requesting ads via access policy (discussed in Section 3) and authenticates various transaction types. In addition, Miner stores the list \( PK^+ \) allocated to each mobile app, which the Miner only uses to evaluate the request coming from a legitimate app (see Section 3 for details). Note that, as opposed to legacy approach towards ad request or click [2], [6], [15] i.e. encapsulating app’ name; only the app’s \( PK^+ \) is encapsulated in ad-block that ensures anonymity and privacy. Miner’s additional functions include: evaluating billing for ads, generating Genesis transaction, distributing and updating keys, forming ad-block, monitoring user’s activity for apps, updating and uploading user profiles on removal of mobile apps.

Note that, in order to calculate user profiles, the Miner communicates, similar way as AdMob SDK\(^{13}\) interacts, with installed mobile apps. We are planning an enhanced version of System App for future work aiming at user profiling (e.g. frequency of apps usage) for optimising user targeting.

### 3.5 Billing

We suggest the use of mining any Cryptocurrencies for our billing mechanism. We already proposed a billing mechanism within an advertising environment [2], using Priced Symmetric Private Information Retrieval (PSPIR) [35] that is originally proposed for private ecommerce along with polynomial commitments\(^{14}\) and Zero Knowledge Proofs (ZKP)\(^{15}\). However, we suggest the use of Cryptocurrency

\(^{13}\) https://admob.google.com/

\(^{14}\) A polynomial commitment [36] allows constant-sized commitments to polynomials (independent of their degree), where the committed value is an evaluation of this polynomial for specific inputs; consequently, only this value (rather than the polynomial coefficients) will be revealed in the opening phase.

\(^{15}\) ZKP [37] is an interactive protocol that enables one party, the prover, to prove to the verifier that a particular statement is true, while the latter learns no additional information regardless of any a priori knowledge he may posses.
for privacy, secure payment and for compatibility with the underlying proposed advertising system over Blockchain.

To enable private billing, we denote the price tags $C^\text{Ad}_{\text{pres}}$ and $C^\text{Ad}_{\text{clk}}$ respectively for ad presentation and ad click operations. The Advertiser ID$_{ID}$ buys the airtime from ad agencies for advertising their ads. To initiate Billing transaction for buying airtime; the advertiser uses her private key (PK−) and signs message with the amount of Cryptocurrency (e.g. Bitcoin) and Billing server’s address, requesting a transaction. The billing request transaction is bind with other transactions and is broadcasted to the network, where another miner validates the transaction. The process of transaction completes and the Billing server receives its portion of Cryptocurrency in her wallet. Similarly, the Miner initiates Billing transaction for ads presentations or clicks respectively by encoding the $C^\text{Ad}_{\text{pres}}$ and $C^\text{Ad}_{\text{clk}}$ price tags within Billing transaction. Note that the Miner keeps track of ads presented to a particular app in tracking-list, which is forward to CH only for those ads that were not presented until the next (e.g. 24hrs) session for the purpose of informing $\text{CS}$ about the fulfillment of advertising quota. We use the following notations for representing various symbols/entities: price tags $C^\text{Ad}_{\text{pres}}$ and $C^\text{Ad}_{\text{clk}}$ for ad presentation and click; various wallets i.e. App Developer’s wallet$_{ID_{APP}}$, Advertiser’s wallet$_{AD_{ID}}$, Billing Server’s wallet$_{BS}$; and (Bitcoin) addresses, i.e. $\text{Add}_{ID_{APP}}$, $\text{Add}_{AD_{ID}}$, $\text{Add}_{BS}$. Future work is planned for integrating complete implementation and applicability of Cryptocurrency in billing for advertising system.

### 3.6 Access Control

The Miner implements access policy (i.e. local-policy), holding an access control list that allows apps regarding evaluation of different operations e.g. to check whether an app is allowed to request for ads, billing etc. The policies are also implemented at CS (i.e. outsourcel-policy, the CS processes policies on behalf of Miner i.e. executes policy on incoming transaction requests destined for accessing various resources i.e. accessing ads) to allow access to various ads evaluated for various profile interests and to CH for processing ad-block for requesting ads from $\text{CS}$ on Miner’s behalf. Note that, instead of introducing a policy header (as suggested by [34]), we evaluate the access from various options present in the ad-block (as shown in Figure 4) for efficient access and reduced overhead.

As shown in Figure 4, we represent the policies as binary tree $T_p$ consisting of left child $l_i(T_p)$ and right child $r_i(T_p)$ along with the matching function $m(l_i(T_p))$, which is represented as an edge between different (child) nodes and the action function $a(l_i(T_p))$. The pair $(m, a)$ is a Policy. There is a list of action functions $A$ (mainly allow or disallow and route to next level of $T_p$) and the matching functions $M$ i.e. the exact policy to implement, such that $a \in A, \ m \in M$. An example set of $M$ that Miner implements are: Calculate ads quota, Apps to participate in billing, Profile establishment, Show ads within app, Apps to change public key etc. A simple example policy structure is given in Figure 3 (b) implemented at CS that consists of four pairs of distinct policies: $(l_1, a_1),$ $(l_2, a_2),$ $(l_3, a_3),$ $(l_4, a_4)$. The CS use these policies to permit Miner for requesting various actions. Here, $m_1$ is a match for evaluating Miner for its permission for requesting ad-block, likewise, $m_4$ for storing profile in CS.

We suggest to use Multi-version of access policy i.e. creating a separate copy for read ($T_p$) and modify ($T_p$) policy document. This will ensure that the read ($T_p$) copy is only accessed for reading purpose, hence, a number of transactions are allowed to access the copy of access policy. Note that the Miner has to indicate the type of transaction, as mentioned Trans. Type in Figure 4, under the Ad-Block-Structure.

### 4 Ad-Block Structure

In this section, we present the block structure for various transactions for an ad-request/response for operating within the Blockchain network.

#### 4.1 Ad Block Header Request/Response

Figure 4 presents the structure of a transaction (e.g. an ad-request) ‘Ad-Block-Header-Request’ (upper) for ad-request, ‘Ad-Block-Header-Response’ (middle) for ad-response and the ‘Ad-Block-Structure’ (lower) in a Blockchain network scenario. This block is generated by the System App, a Miner sitting in user’s mobile devices, for requesting an ad (for showing in an app) form CH. The $T_{ID}$ denotes the transaction’s unique identifier, which is the hashed value of the other fields of this transaction. Note that the first transaction (or block) is called the Genesis transaction, which lays the foundation on which additional blocks are sequentially added to form (sequential ledger by connecting current transaction with the previous transaction using $PT_{ID}$) a chain of blocks. $PT_{ID}$ represents the identifier of the previous transaction that is used for establishing connection between the current and previous transactions. The input i.e. all the request ad transactions are made to the Miner’s address, enlists all the ads that the CH has already sent to the Miner within a particular session. Note that both the CH and Miner keep track of the already served ads so that they are not presented again to user within the same session. We take the session as the time duration where user utilises a particular mobile app until she exits the

![Fig. 3: An example implementation of policy tree along with various actions (a) and a simple access policy implemented at CS for Miner (b).](image-url)
application or there is no activity for a considerable (e.g. 24hrs) time duration. The Ad-block with used “input” is then served to a different (Miner) user, which upon used by the current Miner becomes and stored in the output field.

The $ID_U^{17}$ represents (user) advertising ID that identifies user’s mobile device (detailed discussion over $ID_U$ can be found in [2]). We suggest that $ID_U$ does not change for a particular session. This will help in keeping track of ads shown to the users, in addition to, billing where app developer’s ($ID_{App}$) wallet is populated with particular amount of Cryptocurrency. Note that for simplicity we represent $ID_{App}$ both for identifying app’s developer (Developer ID) and name of the mobile app. The $Ad_{ID}$ is the ID of the advertisement shown to the user. The (mobile) Miner also keeps track of particular ads in order to fulfil ad’s advertising quota$^{18}$, Table 2 presents an example tracking of advertising quota e.g. the advertisement ‘DEF’ still needs to be presented 50% app airtime.

| Date/ time                  | Advertisement | Frequency | Served |
|-----------------------------|---------------|-----------|--------|
| 04/02/2020 10:05:52         | ABC           | 10M       | 65%    |
| 05/02/2020 01:23:41         | DEF           | 67        | 50%    |

TABLE 2: An example tracking advertising quota.

Furthermore, the Ad is the actual content of the advertisements that are presented to users within mobile apps; the contents of an ad varies over different sizes of Min ad size of 12KB, the Max size of 20KB and the Avg ad of 16KB, as observed in [2]. Similarly, $AD_{ID}$ is the advertiser’s ID of particular advertisement(s), which is used to deduct advertiser’s Bitcoin wallet (detailed discussion over billing is given in 3.5).

To enable communication in a Blockchain network, the peers of a Blockchain network require a Public-Private Key pair i.e. represented with $PK+$/$-$ in Figure 4, which is used to increase the anonymity. The Sign field contains the signature of the transaction generator (e.g. Miner (System app)) using the public-private key pair. Following illustrates to understand the exchange of data between Miner and CH (e.g., Miner sends an ad-request to CH): Miner encrypts the ad-request transaction data using CH’s public key $PK+$ and then creates a signature by taking the hash of ad-request and encrypts it using her (Miner’s) private key $PK−$. The transaction data is encrypted along with the digital signature is included in the Ad-Block-Header Request/Response. Subsequent, this transaction is broadcasted over the Blockchain network, since it is addressed to CH, hence CH starts verifying the transaction contents by decrypting the digital signature using Miner’s public key while decrypts the transaction data using her (CH’s) private key. Note that CH verifies the transaction data by comparing the ad-request hash to the hashed data in digital signature, detailed discussion can be found in [40]. We suggest to, similar to [41], store the public key in $PK+$/$-$ field for reducing the size of the transaction and for future proof transactions i.e. to prevent from malicious attacks where intruders could possibly reconstruct private key using public key.

The transactions, included in block, are being hashed by the Miner as part of the Merkle tree; the transactions stored are lead to the Merkle root stored in the block header. As mentioned in [39], the block header being part of the longest chain with Merkle root is used for different purposes, such as Simple Payment Verification (SPV), and it also speeds up the process of verifying the membership of a transaction in a block. An example Merkle tree, for 8 different ad-requests (leaf nodes represented with $Ad_{TX1}$ to $Ad_{TX8}$ on the left), including internal hashed nodes and Merkle root node is shown Figure 5. The hash value of a transaction (e.g. an ad-request) is stored in these leaf nodes; note that we presume a binary Merkle tree that has $2^{n−1}$ leaf nodes with n height. An example slice of a Merkle tree with n = 8 is also shown on the right of Figure 5. The yellow nodes are the potential hashed nodes that potentially could be pruned for reclaiming disk space, details for node pruning can be found in [39].

4.2 Ad Block Structure

The lower part of Figure 4 shows the structure of an Ad-block ‘Ad-Block-Structure’ consisting of the Ad-Block-Header Request/Response and the list of some or all recent (pending) ad-request transactions. Recall that a Miner orders the pending transactions into a block until it reaches the pre-defined block size, as mentioned, blocks in a Blockchain are connected through hashes of previous blocks.

4.3 Ad Block Transaction Types

Various types of communication done among different parties of a Blockchain are enabled via transaction, where different types of transactions are designated for various purposes. E.g. a Billing transaction is enabled for calculating billing for various ads presented in mobile apps or when the user clicks on particular ads $Ad_{ID}$, as presented in Section 3.5. Similarly, the Access, Upload, and Update transaction types are respectively used for accessing profile$^{20}$, uploading the profile, or when the user profile changes. In addition, the Request and Response transaction, as discussed above, for requesting ads from CS or response ads from CS. Furthermore, the Genesis transaction is when the Miner starts participating in Blockchain network. Note that the Genesis transaction is generated for every installed app or for every new app being installed on the device, however, grouped by the app developer $ID_{App}$. Hence, all the activities i.e. ad-request, ad-response, billing $ID_{App}$ and $AD_{ID}$ both for presented and clicked ads, and participation in profiling are chained together and are tracked for all these activities from current block to the Genesis block. In addition, a Remove transaction type is used to uninstall an app, indicating that the user might not be interested in this specific category of app and also its contribution to user

17. $ID_U$ can be reset via the Google Settings System App on Android devices.
18. This requirement comes from the advertising agency, where a particular is presented for certain frequency [31], [38].
19. The peer’s address in a Blockchain network is obtained by calculating the cryptographic hash of user’s public key e.g. in Bitcoin, the SHA–256 encryption algorithm is used for deriving user addresses [39].
20. Note that the users upload profiles to CS, as explained in Algorithm 4, which can be accessed by the user when she signs-in to another device or losses her profile.
profile. Lastly, the Monitor transaction is generated by the Miner to monitor activity of each app for various operations of ad-request, ad-response etc. Note that the transactions are secured via asymmetric encryption, digital signatures and cryptographic hash functions (e.g., SHA-256). Furthermore, the lightweight hashing [42] is employed to detect any changes in the transaction’s content.

5 Ad-Block Operations

This section presents the design requirements of a Blockchain-based mobile advertising system and the design of various algorithms describing comprehensive operations of its various components.

5.1 Design Requirements

The system is designed by taking into account various requirements: privacy, reduced overhead over (user) client, compatibility of billing with Cryptocurrency, efficiency at ad network and client.

Privacy: The underlying design uses Blockchain technology for preserving user privacy, hence various transactions are buried under the structure of Blockchain transaction for ad-request, ad-click, billing etc., hence, the ad network does not learn any information from these various operations. In traditional advertising setting, the APS establishes user profiling with the help of cookies [31] and communicates with the mobile devices for various other operations of ad presentation, click etc. However, in proposed method, the Miner constructs user profiles locally on the user device, hashes of profile interests \( g_k \), and uploads to CS or utilise it for various operations including billing. The CS learns no information about user’s interests, either during policy checking or accomplishing various operations.

Reduced overhead over (user) client: It is critical to impose marginal overhead over Miner, hence, it is made optional for user devices to participate as a Miner or request CH to construct ad-request, henceforth, the Miner sends \( h(ID_U) \) and \( h(ID_{APP}) \). However, it is crucial for Miner to evaluate various other essential operations (i.e. a trade-off between privacy and operational overheads) in order to enable a private and secure advertising system, e.g., constructing user profile and uploading to CS, keep updating the tracking-list, billing for ads, and initiating the Genesis transaction. The aim is to achieve reduced infrastructure cost, efficiency, and flexibility.

Compatibility of billing with Cryptocurrency: The biggest industries, such as travel, banking sectors, are inclined towards adapting the Cryptocurrency that will bring industries, government and community together. In addition, the number of mobile internet users have surpassed 4 billion mark [22] and is set to continue growing in the future. This proposal is an effort to adapt the Cryptocurrency in advertising system for providing a platform for embedding Cryptocurrency for billing various parties within the ad system.

Efficiency at ad network and (user) client: The Blockchain based advertising system should computa-
tionally fast with reduced computation and, in specific, communication cost. As evident in [31], in traditional in-app advertising setting using Google AdMob, a mobile app requesting an ad and the triggered action from e.g. a user click, consists of a series of different steps: The mobile app sends a POST message passing various information about the device including phone version, model, app running on phone etc.; the ad server sends ad containing web address, JavaScript, static objects; cookie for tracking user’s action; the web server associated with the ad is contacted and the landing page is downloaded and is shown to the user. Note that the mobile app developer agree on integrating ads in mobile apps by embedding ad/analytics library. It was also evident that the ads are refreshed every 15–20sec and all the above steps are followed for every single ad presentation and its associated click, hence, severely affecting throughput. This proposal reduces the communication overhead by sending a pool of ads with single ad-request transaction and locally serving ads. In addition, the APS uploads the profiling-ads set only during the system initialisation or when new advertiser is added to the system.

Following illustrates the idea behind various operations of the Blockchain-based advertising system.

5.2 The Blockchain-based Advertising System

The initial step is performed by APS via Algorithm 1. This includes evaluating profiling-ads and then uploading the profile interests g_k,l and corresponding ads Ad_{ID} to CS.

Input: g_k,l; Ad_{ID}; L_k,l
1 Run L_{k,l} = Profiling (g_k,l; Ad_{ID})
2 Run Storage (L_k,l)

Algorithm 1: Global Setup (APS)

Once the APS completes evaluating profiling-ads, it uploads this dataset to CS using Algorithm 3 requesting the pointer to the first block P_b for data storage. We assume that the storage in CS consists of various blocks of size B i.e. storage-block, where each B can accommodate numerous records, hence to evaluate various data records that could be fit in one block. The APS sends the bfr i.e. Blocking factor, to CS to accordingly reserve the storage space for profiling-ads. Following, the APS starts sending the profiling-ads and progressively asks the P_b to next available B.

The CS runs the Algorithm 7 for evaluating access permission. To initiate this process, the CS creates a read (T_p), sets s to the initial node in T_p and starts traversing through T_p. Recall an example tree-structured policy shown in Figure 3, representing k = 4 distinct policies and corresponding matching criteria m and their resultant action functions a. During the traversal, if a match is found, the corresponding action is performed, however, the policy traversal terminates whenever a leaf node is entered.

The Algorithm 4 illustrates the procedure for storing user profiles on CS, once constructed as a result of Profile development process, as explained in Section 2.1. The Miner first evaluates the cryptographic hash, using SHA–256, of individual profile’s interests and then uploads to CS using

Algorithm 2: Profiling (g_k,l; Ad_{ID})

Input: L_k,l
1 APS requests CS to store L_k,l
2 APS sends (P_b) from CS
3 if (Run Access Policy (APS)) then
4 if !(storage full) then
5 CS sends storage-block B to APS.
6 CS sends (Enc_{PK+} (P_b)) to APS
7 end
8 end
9 APS sends bfr = \left \lceil \frac{\text{len} (L_k,l)}{B} \right \rceil
10 APS Dec_{PK–} (P_b)
11 APS generates random ID
12 for i = 1,...,bfr do
13 APS sends (ID, L_k,l[i], h (L_k,l[i]), Enc_{PK+} (P_b))
14 if h (L_k,l) = CS.csec (h (L_k,l)) AND Transaction is valid then
15 CS sends (Enc_{PK+} (P_b = P_b + 1))
16 end
17 end

Algorithm 3: Storage (L_k,l), APS

Algorithm 3. In addition, the CS also evaluates Algorithm 7 to allow/disallow Miner ID_U.

The ad-request consist of various steps, as outlined in Algorithm 5 and depicted in left side of Figure 2 i.e. User Environment. The mobile app ID_APP first requests Miner for the ads to display to user; Step (1) of Figure 2. The Miner also implements an Access Policy to evaluate the ad request coming from legitimate app. Consequently, the Miner constructs an Ad-Block using Ad-Block-Header-Request by encoding ID_U, ID_APP etc., Step (2) of Figure 2. Detailed procedure for constructing Ad-Block-Header-Request
is also given in Section 4.1. Following, the Miner sends Ad-Block to CS (Step (3) of Figure 2), which the CH forwards to CS (Step (4) of Figure 2) for fetching ads according to various $g_{k,i}$ of $ID_U$. The ad-response (Step (5) of Figure 2) is encoded using Ad-Block-Header-Response as shown in Figure 4 (middle), illustrated in Section 4.1. Finally, the Miner sends the fetched ads to mobile app for display within active session (i.e. Step (7) of Figure 2).

![Algorithm 4: Profiling-Storage (Miner)](image)

The Miner corresponds to BS for billing for ad presentation and ad click operations via Algorithm 6, see Section 3.5 for detailed description of billing. In order to avoid the communication and computation overhead, we propose to periodically evaluate the billing (e.g. every 24hrs) for ad presentation through calculating the fulfillment of advertising quota. However, for ad click operation, the billing mechanism is initiated as soon as a click operation is triggered. Note that $u$ and $v$ are the proportions of billing amount (in Cryptocurrency) respectively paid to wallet$_{IDAPP}$ and wallet$_{BS}$.

![Algorithm 5: Ads-Request (Miner)](image)

![Algorithm 7: Access Policy (Node)](image)

## 6 Performance Evaluation

We now discuss our experimental evaluation i.e., the processing time for generating public-private key ($PK+/−$) pairs with various key sizes and the encryption and decryption time of advertiser’s ads with different numbers of interests along with its effect over selecting a range of public-private key sizes. Note that this wide selection of options affect the ad presentation time that include the processing time (including access policy traversing time), matching profile hashing at CS for fetching relevant ads, the transmission delay (bigger sizes of advertiser’s ads are subject to longer transmission delays), which in turn dominates the overall communication delay i.e. the response back from CS to Miner for ad request. Following, to analyze the scalability of the our proposed framework, we evaluate the processing delays for varying number of traversed rules and corresponding actions, represented with different shapes of access policy trees.

### 6.1 Experimental setup

Evaluations were performed on Intel(R) Core(TM) i7-2620M CPU @2.70GHz and 8GB or RAM; we use a Python module cryptography.hazmat.primitives.asymmetric from RSA for generating $PK+/−$ key pairs and for evaluating AES encryption/decryption time of advertiser’s ads with different sizes of ad’s contents. We generate 10,000 $PK+/−$ key pairs with a range of selection of various key sizes (i.e. 512, 1024, 2048, and 4096 bits) (i.e., we stress-test the proposed framework with continuously generating...
a total of 40,000 $PK + /-$ key pairs) and evaluate the key pair generation time. Note that the $PK + /-$ key pairs are generated once and are used for various other operations.

Following, we generate 1000 user profiles by randomly selecting up to 20 different profile interests representing users with diverse interests, equally divide them into 10 groups consisting of 100 user profiles (i.e. $P_1, P_2, \ldots, P_{10}$). Figure 9(a) shows user profile groups uniformly distributed from 1000 user profiles that consist of various profile interests with 10.53 $Avg$ interests with a $St. Dev$ of 5.88 interests. We calculate the hashes of these profiles using SHA1, SHA224, SHA256, SHA384, and SHA512 hashing schemes.

Furthermore, we generate 1000 advertiser’s ads with random sizes of between 12KB to 20KB and equally divide them into 10 groups consisting of 100 randomly chosen ads (i.e. $A_1, A_2, \ldots, A_{10}$). Figure 6 shows advertiser’s ads groups uniformly selected from 1000 ads with various sizes, with an $Avg$ size of 15943B (i.e. 15.94KB) and a $St. Dev$ of 2364B. Following, we evaluate the AES encryption/decryption time of these groups of ads with various key sizes of 512, 1024, 2048, and 4096 bits. Note that in order to encrypt ads of arbitrary length, we use hybrid encryption i.e. RSA to asymmetrically encrypt a symmetric key. To do this, we first randomly generate a symmetric encryption key using AES and encrypt the ads, then, we encrypt the AES key using $PK+$ generated with RSA and transmit both the AES-encrypted ads and RSA-encrypted AES key to the Miner. Following, to decrypt the ad’s contents, the Miner first decrypts the RSA block using $PK+$ to discover the AES symmetric key and then decrypt the symmetrically encrypted ads using AES to discover the resultant set of ads. Similarly, we construct the Ad-Block-Structure for ad-request/response by including Ad-Block-Header-Request or Ad-Block-Header-Response (by encoding $Min = 12KB, Max = 20KB, Avg = 15.94KB, St. Dev = 2364KB$ content’s sizes. $A_i = 100 ads; i = 1, \ldots, 10$).

6.2 Bespoke Miner

We develop a bespoke version of the Miner, we made significant changes to implement some of its functionalities, such as generating an ad-block, transactions with different policy requests etc., on an Android-based device. We implement Miner on Google Nexus 7, ARM Cortex-A9 Nvidia Tegra, 1GB RAM, 1.2 GHz quad-core. To implement various functionalities, first we install CyanogenMod that is a custom ROM for Android devices in order to get root access and developer capabilities. We then add support for the standard Linux utilities, in order to implement various Miner functionalities, that are not generally ported as part of the Android OS. The Android OS is equipped with Bionic C library instead of Glibc. i.e. the standard GNU C library, found on most Unix variant operating systems, which enable Android OS to achieve high performing standard C library with small memory and disk footprint. Following, we make both the Glibc and Bionic coexist on Android platform using the chroot system call in order to use Linux’s utilities; this step also enables us to create Ubuntu Linux file system, which we can run a complete Debian environment on top of the Android kernel ARM CPU support OS. These various layers of functionalities are presented in Figure 7.

Fig. 7: Runtime architecture for a bespoke Miner.

To implement a system module of access policy and to evaluate the system performance under different shapes of access trees, we set our CS to store 100, 200, \ldots, 1000 set of rules and matches with root node at random positions between $min = 1$ to $max = n$, $n = \{100, 200, \ldots, 1000\}$ representing various shapes of trees with nodes (i.e. matching rules and corresponding actions) present on both sides. E.g. for a tree of 1000 nodes with root node set to 1 or 1000 means that the entire set of matching rules and corresponding actions are present respectively on the right and left side of the root node, similarly, the set of rules and matches are equally distributed on both sides with the position of root node at position 500. We repeat this experiment for 1000
times for each of various trees of 100, 200, ..., 1000 nodes with randomly selecting root nodes at different positions. Note that for each request, in order to stress test the system, we deliberately put the matching rule for every access policy request at the leaf node of any specific tree, hence traversing the entire tree for each matching rule. We configure the Requester module (i.e. inside the Miner as depicted in Figure 7) to launch these requests, with above setting, to CS (we experiment our CS with the same specs as presented in Section 6.1), as shown at the bottom of Figure 7. The processing delay is evaluated at CS for all these experiments, along with Avg, Min, Max, St.Dev of root node placement positions and processing delays.

6.3 Experimental results

Processing delay for generating $PK+/-$: Our first evaluation is to explore the effect of $PK+/-$ key pair size over the key pair generation time. Figure 8 shows the performance in terms of processing delays evaluated to $Avg, Min, Max, St.Dev$ for generating $PK+/-$ key pair with various sizes of 512, 1024, 2048, and 4096 bits. E.g. the $Min$ and $Max$ processing time for generating 10,000 keys with key size of 512 bits respectively is 0.005sec and 0.35sec with an $Avg$ delay of 0.05sec and 0.03 St.Dev. We note that the $Avg$ power trendline results in a curve with 0.002sec slope and a 0.86 of $r-squared$ value, as the key size is increased from 512 to 4096 bits. The $Avg$ key generation delay is also written on top of each $PK+/-$ key pairs with various key sizes.

Various statistics of $Avg, Min, Max, St.Dev$ of $AES$ encryption and description processing time evaluated from 1000 advertiser’s ads with various $PK+$ sizes of 1024, 2048, 4096, 8192 bits is presented in Table 3. Furthermore, the $r-squared$ values calculated using exponential trendline $R^2 = Exp$ and power $R^2 = Pow$ are also presented that shows the relationship of increasing key size to the encryption/decryption processing time of advertiser’s ads. We note that there is a strong correlation between the $PK+$ key size and the ads’ encryption or decryption processing time. For instance, $Avg$ AES encryption processing time, the $R^2 = Exp$ and power $R^2 = Pow$ evaluated respectively to 0.8921 and 0.7663 (which also evident with high values of $St.Dev$ for both $R^2 = Exp$ and $R^2 = Pow$) showing that the encryption time exponentially increases as the key size is increased from 1024 to 8192.

Processing delay for traversing policies: To further analyze the scalability of the our proposed framework, we study the processing delay (note that this contributes to the total delay of various transactions requested by Miner or any other entity that requests CS for various services) of $Avg, Min, Max, St.Dev$ when varying the number of traversed rules among 100, 200, ..., 1000 access policy trees, for both sequential and random distribution of policy tree i.e. sequential/random root node placement. Figure 11 (b) shows the random placement of root node for policy trees, storing various nodes and matching rules of 100, 200, ..., 1000 access policy trees. We note that the root node placement, on average, perfectly follows a power distribution with $R^2 = Pow$ value of 0.99, as the tree is populated with 100 to 1000 policies and matching rules. Similarly, the $R^2 = Pow$ for $Max, St.Dev$ is also 0.99, suggesting formation of various

![Fig. 8: Processing delay for generating 40,000 PK + /− key pairs with various key sizes of 512, 1024, 2048, and 4096 bits.](image-url)
Fig. 9: Randomly generated user profile (a) with \( Min = 1, Max = 20, Avg = 10.53, St.Dev = 5.88 \) profile interests. \( P_i = 100 \) user profiles; \( i = 1, \ldots, 10 \). Processing time of hashing profiles (b) using SHA1, SHA224, SHA256, SHA384, SHA512 hashing schemes.

Fig. 10: AES Encryption time (a) to (d) and Decryption time (e) to (h) using 1024, 2048, 4096, 8192 bits of RSA \( PK+ \) key, evaluated for \( A_1, A_2, \ldots, A_{10} \) advertiser’s ads groups.

access policy with placement of root nodes at every possible positions i.e., creating every possible shape of tree by placing nodes on both sides of the access policy trees.

Figure 11 (a) shows processing delay of \( Avg, Min, Max, St.Dev \) access policy traversal delay (msec) with various access trees; note that every experiment has been repeated 1000 times. We observe that the average processing delay increases with the number of rules with a power trendline of 0.92. For instance, for a 100 and 1000 node’s policy tree, the \( Avg \) processing delay is respectively 0.0017sec and 0.0106sec; similarly, the \( Min \) processing delay varies respectively from 0.001sec to 0.005sec. Detailed statistics of root node placement and traversal delay is also given in Table 4, evaluated for \( Avg, Min, Max, St.Dev \) processing delays.

Following, we evaluate the processing delay using sequential (distribution) placement of root node (i.e. to evaluate traversal delay by placing root node at every single position e.g. 1, 2, 3, \ldots, 1000 for a tree of 1000 matching rules and their actions) and compare it with the random distribution. Figure 12 presents a CDF of processing delay with both random and sequential placement of root node; various processing delays of \( Avg, Min, Max, St.Dev \) is also given at the right side of this figure. We note that 96% of the processing delay ranges from 0.005sec to 0.014sec and 0.007sec to 0.032sec respectively for random and sequential distribution of root node placement. Overall, the sequential distribution resulted in higher processing delays as compared to random distribution. Note that these processing delay at CS can be considered acceptable i.e., close to real time performance [2], [38], both during the app/website launch time or delayed ad request.

7 Related Work

Privacy threats resulting from collecting individual’s online data i.e. direct and indirect (inferred) leakage, have been investigated extensively in literature, e.g. [1], [43], [44], [45].
TABLE 3: The Avg, Min, Max, St.Dev of AES encryption and description processing time evaluated from 1000 advertiser’s ads of various sizes with different PK+ sizes of 1024, 2048, 4096, 8192 bits.

![Latency (sec) vs number of rules traversed (x1000) for each policy tree vs number of rules traversed (x1000) for each policy tree](image)

(a) Processing delay (ms)

(b) Root node selection

Fig. 11: Avg, Min, Max, St.Dev Processing delay (ms) per policy tree vs number of rules traversed (x1000) for each policy matching requested by Miner (a) and root node placement for each set of policy trees (b).

![Policy Tree processing delay (sec) and random root node placement position (right) for policy trees of 100, 200, . . . , 1000; the exponential trendline $R^2 - Exp$ and power $R^2 - Pow$ are also presented. Each statistic is a result of 1000 experimental request.](image)

### Table 4: Avg, Min, Max, St.Dev Policy tree processing delay (sec) (left) and the random root node placement position (right) for policy trees of 100, 200, . . . , 1000; the exponential trendline $R^2 - Exp$ and power $R^2 - Pow$ are also presented. Each statistic is a result of 1000 experimental request.

including third party ad tracking and visiting [46], [47], [48], [49]. These studies have shown the prevalence of tracking on both web and mobile environments and demonstrate the possibility of inferring user’s PII, such as age, gender, relationship status, email address, etc. from their online data. The ad and analytics libraries, integrated into mobile apps, systematically collect personal information and users’ in-app activities and are more likely to leak this information to ad systems and third party tracking. The authors in [50] analyze the privacy policy for collecting in-app data by apps and study various information collected by the analytics libraries integrated in mobile apps.

**Privacy and mobile advertising:** There are number of studies that focus on privacy leakage caused by ad libraries within the mobile apps, e.g. the authors in [51] show the potential privacy and security risk by analyzing 100,000 android apps and find that majority of the embedded libraries collect private information. Another study [52] finds that majority of the used APIs within mobile apps do not implement private APIs and send private information to ad servers. The authors in [53] manually create user profiles and find that ads are vastly targeted based on fabricated profiles, in addition to, apps used and location. In our previous study [31] and in [38], the authors study various information sent to ad networks and the level of ads targeting based on communicated information, similarly, [54] investigates installed apps for leaking targeted user data. The authors in [55] studies the privacy risks collected by ad libraries across various apps installed on a single device called intra-library collision; the longitudinal analysis shows that leakage of information has increased in the following two years. Furthermore, [45] studies the level of information collected by the ad networks with the help of installed and used apps, in addition, to reverse engineer the targeted ads and investigate the collected information.

**Privacy and mobile Analytics services:** In our previous work [6], we study the user’s sensitive information leakage through the vulnerabilities in mobile analytics services by analyzing actual network traffic generated by mobile apps and reconstruct the exact user profiles of a number
of participating volunteers. We mainly carry out this study on android platform for Google Mobile Analytics and Flurry Analytics. We further study how the ads served to users can be influenced by modifying the user profiles generated by these analytics services. Another study [56] studies third-party analytics and ad libraries, and find that 60% of the paid apps contain at least one tracker that collects personal information. A similar study [32] examines how users are tracked by running android apps; they find that 57% of the apps and every participant in their study is tracked several times for sensitive information. The authors in [57] collects network traffic using ‘ICSI Haystack’ app and distinguishes between ad and analytics libraries and for collecting various information. Furthermore, the authors in [58], [59] study the distribution of third-party trackers across web and android apps and their impact on user privacy.

Analysis of third-party tracking scripts: Third-party web tracking, the practice using which websites identify and collect information about users, has been widely studied in literature, e.g. [60] develops a client side and identify 500 unique trackers and finds that majority of commercial websites are tracked by multiple parties. The authors in [61] develop a tool TrackingExcavator for longitudinal measurements of third-party web tracking 1996-2016 and finds that tracking mechanism is constantly becoming complex and widely used. An open-source privacy measurement tool ‘OpenWPM’ automatically detects and characterizes emerging online tracking behaviors. The ‘TrackingFree’ [62] provides an anti-tracking browser solution that automatically breaks the tracking chain for third-party tracking web tracking by disabling unique identifiers. Similarly, [48] analyzes the protection level offered across a wide range of web and mobile apps and evaluates their effectiveness for blocking third-party tracking. They find that more than 60% of third-party tracking services communicate in plain text.

Privacy-preserving mobile advertising: There are a number of privacy-preserving personalization and archite-

8 Conclusion

The in-app mobile advertising is growing in popularity, while the advertising companies use excellent user-tracking tools, which have raised concerns among privacy advocates. This paper presents the design of a Blockchain-based framework for advertising platform in addition to implementation of its various critical components that allows the cloud system to privately compute access policies both for mobile users and ad systems for accessing various resources, private user profiling, private billing, privately requesting ads from the advertising system based on user interests, and devising various transactions for enabling advertising operations in Blockchain. We develop POC implementation of our proposed framework and perform a thorough system evaluation and stress test its various components in order to evaluate different constraints of processing delays. Our evaluations show an acceptable amount of processing delay for performing various operations of accessing relevant ads as that of the currently implemented ad system in an actual environment.

27. https://github.com/mozilla/OpenWPM

Fig. 12: Avg, Min, Max, St.Dev Processing delay (ms) per policy tree vs number of rules traversed for rules matching requested by Miner for Random and Sequential root nodes placement.
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