Revenue Attribution on iOS 14 using Conversion Values in F2P Games

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Abstract. Mobile app developers use paid advertising campaigns to acquire new users, and they need to know the campaigns’ performance to guide their spending. Determining the campaign that led to an install requires that the app and advertising network share an identifier that allows matching ad clicks to installs. Ad networks use the identifier to build user profiles that help with targeting and personalization. Modern mobile operating systems have features to protect the privacy of the user. The privacy features of Apple’s iOS 14 enforces all apps to get system permission for tracking explicitly instead of asking the user to opt-out of tracking as before. If the user does not allow tracking, the identifier for advertisers (IDFA) required for attributing the installation to the campaign is not shared. The lack of an identifier for the attribution changes profoundly how user acquisition campaigns’ performance is measured. For users who do not allow tracking, there is a new feature that still allows following campaign performance. The app can set an integer, so called conversion value for each user, and the developer can get the number of installs per conversion value for each campaign. This paper investigates the task of distributing revenue to advertising campaigns using the conversion values. Our contributions are to formalize the problem, find the theoretically optimal revenue attribution function for any conversion value schema, and show empirical results on past data of a free-to-play mobile game using different conversion value schemas.

1 Introduction

A famous quote in advertising comes from John Wanamaker: Half the money I spend on advertising is wasted; the trouble is, I don’t know which half [Del12]. We can group advertising channels into two groups based on the ability to measure their performance. The first group is traditional channels such as newspapers, television, radio, leaflets, billboards, or any printed media, where the advertiser does not know which users engaged with an ad. The second group is online channels such as social networks, search engines, and ad networks, which benefit from knowing which ads each user engaged. Besides the ability to track users who engaged with an ad, the internet and smartphones disrupted how companies advertise their products and services by allowing targeting of ads. If the advertiser has a profile built for the user, they can recommend a suitable ad. For example, search engines show ads to queries that express the user information needs, social networks promote products based on user interests, and mobile apps show an advertisement based on the user’s context (e.g., type of app, actions were taken).

Marketers look for online advertising channels that deliver the best return on investment (ROI). Measuring ROI requires calculating the revenue that the ads campaign brought and the money spent. For example, if a company invests $100USD in advertising an application and the users that are acquired generate revenue of $200USD, then the campaign is successful with Return on investment (ROI) 2.0. On the other hand, if it generates only $20USD, then the campaign is
not successful with ROI 0.2. To calculate the return on investment, we need to attribute the user’s revenue to the campaigns that brought them to the app. This task is known as attribution, and there are different approaches to it [HA13]. The most common attribution model in online advertising is last-click attribution, which gives all the credit to the last ad that the user engaged with [DPSP12].

Online advertising companies looking to deliver a high return on investment started building user profiles, enabling new forms of advertising optimizations where companies could target users that match more complex criteria. As the user profiles started to have more information, people became more attentive to what the companies knew about them. Various surveys [Com16, Gol18] show that people are concerned about the control that companies have over their data, and they disagree with the data collection and sharing practices of online services. Governments have taken actions to rule how companies use personal data, which led to significant legislative changes. Two of the most notable examples are the European General Data Protection Regulation (EU 2016/679) [Reg16] and the California Consumer Privacy Act of 2018 [Cal18].

Apple introduced several privacy features in their most recent devices and also on iOS 14. For instance, LEDs that indicate if the microphone and camera are on, icons showing if an application uses location data, and summarizing how an app uses the user’s data in the App Store. Besides these, the privacy feature with the most significant impact for the app developers is that users will not be trackable by default. This privacy innovation has a profound impact on how ad campaigns’ performance is measured because if a user does not allow tracking, it will not be possible to do last-click attribution as before. The following example presents an overview of what happens when users allow tracking and when they do not.

Example 1. Suppose that an application developer is promoting their app by showing a video and that a user gets interested in the ad, clicks on it, and installs the app. If the user allows tracking, an identifier is shared to attribute the install to the clicked ad; and if they spend money on the application, the app developers can attribute the revenue to the ad campaign. However, if the user does not allow tracking, the required identifier for attribution is not shared, and instead, advertising networks receive a postback with the campaign id and a conversion value when it meets certain conditions.

At a glance, the conversion values are a privacy-preserving mechanism proposed by Apple to measure an advertising campaign’s performance without disclosing the user’s identity. It is an integer between 0 and 63 that application developers assign to each user. Application developers are free to determine the user’s value. For instance, they could use revenue, in-app events, retention, or device type. Application developers see the final conversion value for each user; however, they do not know what campaign brought the user or if the user came organically. Instead, Apple reports the conversion values per campaign via postbacks once the value has not changed and associated timers have expired (See Section 2.4). The conversion values provide ad-hoc privacy protection in the “hide-in-the-crowd” sense; such as $k$-anonymity [Swe02], $l$-diversity [MKGV07], $t$-closeness [LLV07] (instead of the for instance differential privacy [DP20] which has a formal privacy guarantee).

This paper investigates various conversion value schemas in combination with revenue attribution functions (i.e., how to allocate the revenue to the networks & campaigns based on the users’ conversion values). We aim to answer the following questions: How can we attribute revenue to campaigns using the conversion value? What is the revenue attribution error for different conversion value schemas?

1.1 Contribution

Our contributions shed light on using the conversion values for attributing the revenue to the advertising campaigns. More specifically, we contribute in: i) Formalizing the problem of revenue attribution based on conversion values, ii) Finding the revenue attribution function which mini-
(a) The mobile measurement partner (MMP) uses the Identifier for Advertisers (IDFA) to identify the users that engaged with the mobile advertising campaign, and to separate those that installed the app organically (e.g., searching on the App Store). This process will remain the same for the users that allow apps A and B to track them.

(b) If the user does not allow tracking, then the attribution is done via conversion value. The conversion value postback contains various attributes about the network and campaign, but it does not have an ID for mapping the user and the advertising campaign that brought them. Application developers can track the conversion value for each user but not their origin.

Figure 1: A comparison of how attribution works when IDFA is available (left) and when it is blocked in iOS14 (right).

mizes the attribution error for any conversion value schema, and iii) Showing empirical results on past data using different conversion value schemas.

1.2 Organization

Section 2 provides the preliminaries for the conversion value and revenue attribution, while Section 3 presents the models used for attributing the revenue to campaigns and presents several conversion value schemas. In Section 4, we present our experimental results, in Section 5 we summarize the related work, and finally in Section 6 we present our conclusions.

2 Preliminaries

This section introduces the concepts and methods used in the rest of the paper, such as conversion value, Identifier for Advertisers, the last-click attribution, and user origin. Furthermore, Figure 1 presents an overview of how attribution works before and after the iOS 14 privacy features.

2.1 Last-click Attribution

App developers promote their apps in various ad networks, and because of this, a person might see ads for the same app in more than one network, which leads to the question: what was the ad that caused the install? In this paper, we focus on last-click attribution because it is the most commonly used method in online advertising [DPSP12]. Additionally, recent research observed that in the mobile gaming industry only 9.5% of the observed installs had impressions from more than one channel during a seven-day attribution window $S^{+19}$. Other approaches are first-click attribution or equal attribution of revenue to all the channels that a user had contact with [KRV16]. In addition, one could use top-down approach such as marketing mix modeling [Goo17]. However these methods are out of the scope of this paper. Handling the last-click attribution is a complex problem,
and often app developers delegate the task to attribution partners responsible for determining the last ad a user clicked.

2.2 User Origin

The origin of a user can be organic, paid advertisement, and cross-promotion. The organic users have found the app in the App Store without previously engaging with an ad, for example, by searching for the app or scrolling through a list of popular apps or non-sponsored recommendations (e.g., App Store Best of 2020). Paid advertising includes, for example, social networks, search engines, or in-app ads. Cross-promotion is similar to in-app ads, but it only occurs when the ad promotes apps from the same developers as the app which is showing the ad.

The ability to separate a user’s origin allows companies to use the revenue from paid origin users to measure the ROI. The separation of these origins allows modeling the app’s virality (i.e., organic users invited by users from the paid origin) to include a share of the organics’ revenue into the ROI calculation. This paper focuses on understanding how conversion values help attribute users’ revenue from the paid and organic origin. Cross-promotion is a particular case because application developers will know what actions the user is doing in both the source and the target app.

2.3 Identifier for Advertisers

It requires an identifier to know if a user came from a paid origin or organically. In the Apple ecosystem, the identifier is called Identifier for Advertisers (IDFA), and its purpose is to allow tracking without disclosing the user’s identity. Users in iOS14 set their preference on allowing apps to request tracking globally or per app. When tracking is disabled globally, apps will not show a pop-up requesting users if they allow tracking. When tracking is enabled globally, apps can show a pop-up to ask the user if they allow tracking, and users can accept or reject each app. The IDFA will be meaningless if the user denies tracking, and IDFA will serve its purpose only for the apps that the user allows tracking.

2.4 Conversion Value

This section explains the conversion values based on Apple’s developer documentation of the SKAdNetwork 2.0 [App20a] and updateConversionValue(:) [App20b]. The conversion value is an integer $v \in [0, 63]$ that developers can set. The conversion value is assigned for the first time when a user opens the app (i.e., not when the user installs the app). Developers can increment the value within 24h of the last update. If there has been no update within 24h, the advertiser receives knowledge of the install after a random timer of 0-24h. Even though this would allow for a 2-month time window to update the conversion value, receiving the ad campaign’s conversion value after two months is not very useful to guide advertising spend. Practically, a seven-day period seems to be a maximum delay that makes sense, with many ad networks recommending much shorter windows. Table [1] presents the binary representation of the conversion values, and such representation allows us to think of various conversion value schemas where bits represent features. We provide more details on conversion value schemas in Section [3.5].

| $v$ | bit 5 | bit 4 | bit 3 | bit 2 | bit 1 | bit 0 |
|-----|-------|-------|-------|-------|-------|-------|
| 0   | 0     | 0     | 0     | 0     | 0     | 0     |
| ... | ...   | ...   | ...   | ...   | ...   | ...   |
| 63  | 1     | 1     | 1     | 1     | 1     | 1     |

Table 1: The binary representation of the conversion value is six bits. App developers are free to determine the conversion values.
Example 2. A conversion value schema can use different bits for different things. An example of such schema would be using 2 bits to capture the days since the first opening (i.e., 00 initially, then 01, 10, 11 respectively after 1, 2, and 3 days) and 4 bits for in-app events, such as unlocking various game features.

3 Models

This section illustrates the problem, formalizes it, proposes revenue attribution models, and describes conversion value schemas. Our modeling efforts focus on finding an optimal revenue attribution function that minimizes the difference between attributing revenue using conversion values and last-click attribution with IDFA.

3.1 Problem Illustration

Initially, the app developers could distinguish between paid and organic users. Thanks to IDFA and last-click attribution, they could map the users to their origin, network, and advertising campaign. A common practice for measuring the ROI is to group users in cohorts based on their registration date, origin (e.g., paid, organic, cross-promotion), network, campaign, and country. At the cohort level, one can aggregate the cost of acquiring the users and the revenue generated from them, which helps monitor user acquisition investments’ performance.

For convenience, we define the combination of network ID \( n \) and ad campaign ID \( c \) to be \( \alpha = 100 \cdot n + c \) since Apple allows use of 100 different campaign IDs for every network. \( \beta \) denotes the total number of different network and campaign ID combinations \( 0 \leq \alpha \leq \beta - 1 \).

| User ID \( i \) | Revenue \( r^i \) | Net. ID \( n \) | Cam. ID \( c \) | \( \alpha_i \) |
|----------------|-----------------|---------------|---------------|-------------|
| 1              | 0 USD           | 4             | 05            | 405         |
| 2              | 2.99 USD        | –             | –             | \( \beta \) |
| 3              | 0 USD           | 3             | 89            | 389         |
| ...            | ...             | ...           | ...           | ...         |
| \( |U| \)        | 4.99 USD        | 1             | 71            | 171         |

(a) Available user-wise data.

| \( \alpha \) | Net. ID \( n \) | Cam. ID \( c \) | Revenue \( y^\alpha \) |
|-------------|-----------------|-----------------|------------------------|
| 000         | 0               | 00              | 245 USD                |
| 001         | 0               | 01              | 92 USD                 |
| ...         | ...             | ...             | ...                    |
| 099         | 0               | 99              | 811 USD                |
| 100         | 1               | 00              | 373 USD                |
| ...         | ...             | ...             | ...                    |
| 199         | 1               | 99              | 373 USD                |
| ...         | ...             | ...             | ...                    |
| \( \beta \) | –               | –               | 1639 USD               |

(b) Available campaign-wise organized data

Table 2: App developers can use IDFA to map users and campaigns, allowing calculating ROI per campaign.
Users who registered at least \( t \) days before the date \( d \) are denoted with \( u_i^d \in U_i^d \). If IDFA is available the data corresponding to \( u_i^d \) is a tuple (the date the app was first opened \( d_i \), the cumulative revenue \( r_i^t \) of the first \( t \) days, \( \alpha_i \)). Any other related information captured within \( U_i \) (such as event-level data), hence, the user i’s data is \( u_i^d = \{d_i, r_i^t, \alpha_i, U_i\} \), and we can see i itself as the user ID.

**Remark 1.** Note that \( d \) is at least \( t \) days after the user’s registration \( d_i \). This is necessary; otherwise, the revenue attribution would become a prediction problem (as \( r_i^t \) would be unknown). This is an important and exciting research question by itself and studied extensively [SMC87, FHL03]. On the other hand, the problem studied in this paper (i.e., revenue attribution based on conversion values) attributes actual data from the user rather than forecasted data.

Table 2 presents the initial dataset when IDFA is available. User-wise data is shown in Table 2a, and Table 2b shows the aggregated first \( t \) day revenues \( y_i^d \) for each ad network & campaign, which simplifies calculating the ROI. Note that the organic users (e.g., \( i = 2 \)) do neither correspond to any network or campaign, so we capture their corresponding revenue via \( \beta \).

When IDFA is not available, the user’s tuple \( u_i^d \) contains the same data except instead of \( \alpha_i \) the user i’s conversion value \( v_i \) will be included, i.e., \( u_i^d \in \{d_i, r_i^t, v_i, U_i\} \). The conversion value itself is computed from available user data via a conversion value schema \( f \), i.e., \( f(u_i^d \setminus \{\alpha_i\}) = v_i \). Note, \( v_i \) does depend on \( d \) and the user’s data, which might change over time. Consequently, we define \( \hat{d}_i \) which notes the last date when \( v_i \) was modified, i.e., \( \hat{d}_i = \min(d) \) s.t. \( f(u_i^d \setminus \{\alpha_i\}) = f(u_i^{d+1} \setminus \{\alpha_i\}) \).

With the iOS 14 rollout, the kind of data presented in Table 2 will not be available for the vast majority of the users, as by default, the IDFA will only be available if users give explicit system permission. Instead, app developers can use aggregate count of conversion values \( X^d \) at time \( d \), as shown in Table 3.

| User ID \( i \) | 1 | 2 | \( \cdots \) | \( |U| \) |
|----------------|---|---|-------------|--------|
| Revenue \( r_i^t \) | 0 USD | 2.99 USD | \( \cdots \) | 4.99 USD |
| \( v_i \) | 0 | 6 | \( \cdots \) | 63 |

(a) Available user-wise data.

\[
\begin{array}{cccccccccc}
\downarrow v & \downarrow \alpha \rightarrow & 000 & 001 & \cdots & 099 & 100 & \cdots & 199 & \cdots \\
0 & 19 & 420 & \cdots & 88 & 0 & \cdots & 36 & \cdots \\
1 & 355 & 107 & \cdots & 31 & 279 & \cdots & 151 & \cdots \\
2 & 329 & 22 & \cdots & 34 & 528 & \cdots & 2 & \cdots \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\
63 & 138 & 346 & \cdots & 54 & 7 & \cdots & 189 & \cdots \\
\end{array}
\]

(b) Available campaign-wise data \( X^d \).

**Remark 2.** Keep in mind that this is a simplified scenario: in real life, the \( X^d \) does not contain all the users with \( d_i \) at least \( t \) days before \( d \). Instead, \( 24 \) hours after the last modification of \( v_i \) (which happened on \( \hat{d}_i \)) plus a timer \( \tau \) that waits between \( [0, 24] \) hours to report the conversion value. Before the timer has expired this user does not contribute to \( X \) (i.e., \( u_i^d \) is not counted in \( X \) earlier than \( \tau + 1 \) day after \( \hat{d}_i \)).

Consequently, at \( d \), the app developer will have the user counts per conversion value for each campaign and network \( (x_{i, d \alpha}^d \in X^d) \). These values will be the count of users with 1) \( d_i \) at least \( t \) days before \( d \) and 2) \( \hat{d}_i \) at least a day before \( d \). Besides this, the app developers know the conversion values \( v_i \) and the revenues \( r_i^t \) for all the app users. This is illustrated in Table 3a. App
developers do not receive the conversion values for $\beta$ (i.e., organic users) but can estimate them by subtracting the number of reported conversion values to the number of installs.

### 3.2 Variable Definitions

The variables used in the paper are enlisted in Table 4. We define $U_v^d$ as the set of users with the same conversion value on $d$. We define $r_i^t$ and $g$ as the average first $t$ day revenue of this group. The function is to attribute the revenues based on the conversion value counts and the user’s data to specific campaigns and networks (i.e., $g$ approximates $y_{\alpha}$). For simplicity, we will abuse the notation by leaving out the superscript $d$ when it does not play a significant role.

| Symbol | Meaning |
|--------|---------|
| $i$    | User ID, in-between 1 and $|U^d|$. |
| $d_i$  | User’s registration date: the first time a user opens the app. |
| $t$    | Number of days for the revenue to be accumulated (e.g., 3, 7, 14, 30, 90, etc.). |
| $d$    | The date when the conversion values are reported. We assume it is at sufficiently later than any $d_i$. |
| $\alpha_i$ | User combined network and campaign ID: $\alpha = 100 \cdot n + c$. Note that $0 \leq c \leq 99$. |
| $\beta$ | The upper limit on $\alpha$ (i.e., $100 \cdot n + c < \beta$). $\alpha = \beta$ corresponds to the organic users. |
| $r_i^t$ | Accumulated revenue of the corresponding user $i$ for the first $t$ days after $d_i$. |
| $U_i$  | User features dataset (i.e., remaining information about the user). |
| $u_i^d = (d_i, r_i^t, \alpha_i, U_i)$ | User data at $d$ where campaign IDs are known (i.e., IDFA is available). |
| $v_i^d$ | Conversion value of user $i$ at $d$. Without subscript we mark the different conversion values. |
| $f(u_i^d \setminus \{\alpha_i\})$ | Conversion value schema or conversion value model (e.g., $f(u_i^d \setminus \{\alpha_i\}) = v_i^d$). |
| $\tilde{u}_i^d = (d_i, r_i^t, v_i^d, U_i)$ | User data when only conversion values are available instead of $\alpha_i$ (i.e., IDFA is not available). |
| $x_{v,\alpha}^d \in X^d$ | The count of users in $v$ bucket at $d$ corresponding to $\alpha$. |
| $\hat{U}_v^d$ | Set of all users (i.e., independently of $d_i$) with conversion value $v^d$, i.e., $\forall \tilde{u}_i \in \hat{U}_v^d : v_i = v$. |
| $\bar{r}_v^t$ | The average first $t$ days revenue of users in $\hat{U}_v^d$ at $d$, i.e., $\bar{r}_v^t = \frac{\sum_{\tilde{u}_i \in \hat{U}_v^d} r_i^t}{|\hat{U}_v^d|}$. |
| $p$    | Privacy threshold. |
| $pr_p(\cdot)$ | Privacy preserving method applied by Apple. |
| $\hat{x}_{v,\alpha}^d \in X^d = pr_p(X^d)$ | The conversion value counts after applying the privacy protection with threshold $p$. |
| $y_{\alpha}$ | Accumulated last-click attribution revenue for $\alpha$ based on the first $t$ days of the users. |
| $g_{\alpha}(\hat{U}_v^d, \hat{x}_{v,\alpha})$ | Function to attribute the revenue of $\alpha$ at $d$ based on $\hat{x}_{v,\alpha}$ as well as the user data where $v_i^d = v^d$. |

Table 4: Summary of the variables used in the paper.
3.3 Privacy Protection

The count of conversion values provides privacy protection in the form of “hide-in-the-crowd”, as the campaign information does not contain user identifiers. On the other hand, individual data could still leak when the size of a conversion value bucket is one. To overcome this problem, Apple proposed the privacy threshold \( p \), a predefined (and currently unknown) value that provides further protection without any guarantee (as far as we know). In practice, Apple will not report the count of players in the conversion values where there are less than \( p \) users, and instead, those counts will be reported as \texttt{null}. Moreover, the users with such a conversion value are not discarded. Instead, the set of conversion values is extended with \texttt{null}, i.e., \( v \in \{\texttt{null}, 0, 1, \ldots, 63\} \). This schema is formalized in Equation \( 1 \) where \( 1 \) is the indicator function, i.e., it is one of the condition insides is true, and 0 otherwise. This method relates to \( k \)-anonymity \cite{Sweeney2002}, requiring all users to be indistinguishable from at least \( k - 1 \) other users.

**Theorem 1.** The conversion value counts with the privacy thresholding mechanism \( pr_p : \mathbb{N}^{64 \times \beta} \rightarrow \mathbb{N}^{65 \times \beta} \cup \{\texttt{null}\} \) does not provide \( k \)-anonymity for \( k = p \).

\[
pr_p(X) = \hat{X} = \begin{cases} 
\hat{x}_{v,\alpha} = x_{v,\alpha} & \text{if } \sum_U 1(v_i = v) \geq p \\
\texttt{null} & \text{otherwise}
\end{cases}
\]

(1)

**Proof.** The above mechanism is not \( p \)-anonymous for \( p \geq 2 \) as the condition is not enforced on \( \hat{x}_{\text{null},\alpha} \). For instance, if there is a single user (e.g., \( i \)) with a particular conversion value (e.g., \( v_i \)), for all \( \alpha \) the values \( \hat{x}_{v,\alpha} \) is set to \texttt{null}. Moreover, if we assume that the size of all other conversion values are above \( p \), than \( \hat{x}_{\text{null},\alpha} = 0 \) for all \( \alpha \) except for \( \alpha_i \) in which case it is 1. Consequently, user \( i \) is not similar to \( p - 1 \) other users as they can be singled out.

3.4 Revenue Attribution Function

The conversion value schema \( f \) is a central part of our research, as the error metric depends on \( f \), and it is what we aim to find. Mathematically, the attribution error wrt. \( f \) is shown in Equation \( 2 \).

\[
\min_f \left[ \sum_{\alpha} \left( \sum_v g(\hat{U}_v, \hat{x}_{v,\alpha}) - y^t_{\alpha} \right)^2 \right]
\]

(2)

Although \( f \) is not explicitly visible, it defines \( \hat{U}_v \) as it contains users with \( f(u_i^d \setminus \{\alpha_i\}) = v_i^d \).

First, instead of focusing on \( f \), we show the optimal \( g \) when there is no privacy threshold for conversion values (i.e., when \( p < 2 \)). Note, that \( p = 0 \) is meaningless, while \( p = 1 \) only changes the 0 values to \texttt{null}, hence, these cases there is no real difference between \( X \) and \( \hat{X} \).

**Theorem 2.** Only based on \( \hat{U} \) (e.g., without any prior background knowledge about the distribution of users corresponding to any \( \alpha \)) and if \( p < 2 \) (i.e., we assume \( \hat{x}_{v,\alpha} = x_{v,\alpha}^d \), so there is no additional privacy protection) than independently of \( f \), the attribution function defined in Equation \( 3 \) minimizes Equation \( 2 \).

\[
g_{\alpha}(\hat{U}_v, \hat{x}_{v,\alpha}) = x_{v,\alpha}^d \cdot \bar{r}_v^d
\]

(3)

**Proof.** We show, that \( g \) in Equation \( 3 \) is the best approximation (i.e., expected value) of the unknown \( y^t_{\alpha} \) based on \( \hat{U} \), hence the equation below is minimized.

\[
\sum_{\alpha} \left( \sum_v (x_{v,\alpha} \cdot \bar{r}_v^d) - y^t_{\alpha} \right)^2
\]

(4)
The revenue $y^t_\alpha$ is the sum of revenues of the players with $\alpha_i = \alpha$. Moreover, the users $U$ can be divided into disjoint sets based on the conversion values (similarly how $\tilde{U}_v$ is defined), expressing $y^t_\alpha$ with a double summation.

$$y^t_\alpha = \frac{|U|}{\sum_{v} \mathbb{1}(\alpha_i = \alpha) \cdot t^t_i}$$

Combining this with Equation 4 we get

$$\sum_\alpha (\sum_v x_{v,\alpha} \cdot \tilde{r}^t_v - \sum_\alpha \sum_{\tilde{U}_v} \mathbb{1}(\alpha_i = \alpha) \cdot r^t_i)^2 = \sum_\alpha (\sum_v (x_{v,\alpha} \cdot \tilde{r}^t_v - \sum_{\tilde{U}_v} \mathbb{1}(\alpha_i = \alpha) \cdot r^t_i))^2$$

The above equation is minimal if the absolute elements of the summation over $\alpha$ are minimal, hence, it is enough to show this minimality for an arbitrary $\alpha$. It is trivial that $x_{v,\alpha} = \sum_{\tilde{U}_v} \mathbb{1}(\alpha_i = \alpha)$. On the other hand, when only $\tilde{U}_v$ is available (instead of $U_v$) than for any specific conversion value $v$ it is unknown which particular users $i$ is counted in $x_{v,\alpha}$. Consequently, instead of the unknown $\alpha_i$ we use a random variables noted as $\tilde{\alpha}_i$: user $i$'s origin within $\tilde{U}_v$ (i.e., with conversion value $v$) is $\alpha$ with probability $x_{v,\alpha} / |\tilde{U}_v|$.

Finally we show that the expected value of these probabilities are indeed $g$ as defined in Equation 3, hence the expected error is 0.

$$\sum_{\tilde{U}_v} \mathbb{1}(\alpha_i = \alpha) \cdot r^t_i = \sum_{\tilde{U}_v} \mathbb{E}[\tilde{\alpha}_i = \alpha] \cdot r^t_i = \sum_{\tilde{U}_v} x_{v,\alpha} / |\tilde{U}_v| \cdot r^t_i = x_{v,\alpha} \cdot \sum_{\tilde{U}_v} r^t_i / |\tilde{U}_v| = x_{v,\alpha} \cdot \tilde{r}^t_v \quad \Box$$

Now we relax our initial condition about $p$ and focus on the case when the privacy threshold is applied (i.e., when $p \geq 2$). The revenue attribution function defined in Equation 3 does not consider the null bucket, hence, we propose two attribution functions in the form of Equation 5, where $\Box$ should be filled accordingly.

$$g_\alpha(\tilde{r}^d_v, x_{v,\alpha}) = \begin{cases} \tilde{r}^d_v \cdot \hat{x}_{v,\alpha} & \text{if } \hat{x}_{v,\alpha} \neq \text{null} \\ \Box \cdot \sum_{v} \mathbb{1}(v_i = v) & \text{otherwise} \end{cases} \quad (5)$$

**Uniform Revenue Attribution (U)**

Distributing the accumulated revenue of a conversion values uniformly across all possible network and campaigns, i.e., $\frac{1}{\beta}$ should fill $\Box$ in Equation 5. This function is used as a pessimistic baseline because it does not use any information from $\hat{X}^d$.

**Null-based Revenue Attribution (N)**

Distributing the accumulated revenue of a conversion values based on the empirical distribution defined by the null bucket, i.e., $\frac{x_{\text{null},\alpha}}{\sum_{\alpha} x_{\text{null},\alpha}}$ should fill $\Box$ in Equation 5. This function is based on the ‘sum’ of the distribution corresponding to conversion values below the threshold $p$. Although we have no prior background information about the user distributions within the conversion values, we can still utilize null bucket for those below $p$.

**Theorem 3.** Only based on $\tilde{U}$ (e.g., without any prior background knowledge about the distribution of users corresponding to any $\alpha$) for any $f$, some combination of $U$ and $N$ should minimizes Equation 3.
Proof. The proof is similar to the case \( p < 2 \) with a minor modification as Equation 3 does not consider null values. It is trivial, the revenue of \( \alpha \) is under approximated if all buckets with value null are treated as 0. In other words, Equation 3 does not attribute some leftover revenue. In case \( \hat{x}_{v,\alpha} = \text{null} \), the original value could be anything between \( 0 \leq x_{v,\alpha} \leq \sum_U 1(v_i = v) \leq p - 1 \). To take this into account the value of \( x_{v,\alpha} \) can seen as a random variable denotes as \( \tilde{x}_{v,\alpha} \). For a specific \( v \) the distribution over \( \alpha \)’s itself is not as easy to formalize as in case of \( \tilde{\alpha}_i \), because while those are I.I.D. variables, \( \tilde{x}_{v,\alpha} \)’s are not independent (as their sum must be equal with \( \sum_U 1(v_i = v) \)). Luckily, for a specific conversion value \( v \) we only need the expected value, which is some probability \( \tilde{f}_v \) multiplied with the user count as shown in Equation 5.

The exact probability must be in-between the values defined by \( U \) and \( N \), as they capture the two extreme case depending on the amount of useful information contained in the null bucket. The first is when the information in the null bucket is perfect about \( v \)’s distribution. This is the case for example when \( v \) is the only conversion value with user count below \( p \), when \( N \) gives the best approximation of \( v \)’s distribution as they are identical. The second is when the information within the null bucket is useless. For instance all conversion value’s user count are below \( p \), and they corresponding distributions are completely different from each other. In this scenario \( U \) corresponds to the best unbiased approximation (i.e., uniform random guess). Hence, any information within the null bucket could be covered with a linear combination of \( U \) and \( N \).

By multiplying this expected probability with \( \tilde{f}_v \) the rest of the proof follows the proof of Theorem 2.

3.5 Conversion Value Schemas

Previously we described the revenue attribution function \( g \). This part presents various ways to define the conversion value schema \( f \), which assigns a meaning to each of the six available bits. We define three types of bits: \( T \) bits used for time, \( V \) bits used for revenue, and \( C \) bits used for a logical condition (e.g., device is tablet or smartphone, user passed tutorial, user reached a certain level). Using these bits we specify various conversion value schemas.

Day 0 event-based (EV)

Using data from \( U_i \), we encode six actions taken by the player during their first day of using the app, each taken action corresponding to one bit (e.g., passing a level the bit is 1).

Rolling Revenue (RR)

Utilizes some bits \( T \) for keeping track of the days that have passed from the first opening and bits \( V \) for bucketing the actual revenue of the player during the observation period. For the \( V \) bits, we use the observed revenue accumulated over the days captured in \( T \): the players without spend are assigned to bucket zero, and the spenders are distributed uniformly based on their revenue. For example, \( D7 \ RR \) is defined as \( TTTVVV \), where \( T \) bits capture day 0-7 and \( V \) bits are based on the current user’s spend.

Rolling in-app purchase count (RI)

Similar to the rolling revenue schema but instead of bucketing players based on their revenue it keeps count of in-app purchases, which is available in \( U_i \).

Uniform distribution (UD)

Distributing players in conversion values at random. This schema is used as a pessimistic baseline because it does not use any information of the user.
Perfect lifetime value (PV)

Uses six \( V \) bits to bucket players based on the future revenue of the player. For example, \( D30 PV \) is defined as \( VVVVVV \), where bits are based on the day 30 user’s spend. This schema is not realistic, as it uses data which is not available in practice. The schema serves as an optimistic baseline because it places players so that their revenue is very close to the conversion value’s expected revenue. We observed that the attribution error with this schema is close to zero when \( p = 1 \).

4 Experiments

This section contains the empirical results corresponding to the introduced revenue attribution functions as well as conversion value schemas.

4.1 Setup

We experimented using data from one of our main mobile games. To generate the ground truth dataset, we used six months of historical data from cohorts with revenue matured up to 90 days.

Using historical data allows us to compare the attributed revenue with the actual data from last-click attribution. We calculate the conversion value for each player in the dataset according to the schema we want to evaluate. Because neither the exact privacy threshold nor the level (e.g., globally, country-wise, etc.) is known as of now, for our experiments we use different values of \( p \) with country-level privacy protection. We build the matrix \( \hat{X}_d \) eight times separately: six for the largest countries, and two for the rest grouped randomly. For the cumulative version of matrix \( X^d \), we grouped players based on their registration week starting on Monday. The experiments were implemented in Python and ran in a single machine with 64 vCPU and 512 GB of RAM.

4.2 Attribution Results

We want to know how the various conversion value schemas presented in Section 3.5 help with revenue attribution. We experimented by backtesting on past data, which allows us to measure how closely the attribution with conversion values matches the data reported by our mobile measurement partner.

Our results are presented in Table 5. We perform experiments for all five introduced conversion value schemas \( f \) with matured accumulated revenues for 30 days, i.e., \( t = 30 \). The prefix in the abbreviations shows the number of bits used for time (e.g., \( D1 \) corresponds to \( TVVVVV \) schema). We consider both revenue attribution functions: uniform \( U \) and null-based empirical \( N \).

The attribution errors within Table 5 are normalized with the hypothetical best case \( D30 PV \) with \( U \) for every privacy parameter separately (also marked with a box). For example, in Table 5a, when \( p = 2 \), the conversion value schema \( D7 RR \) combined with \( N \) is 7% worst than the error of \( D30 PV \) with uniform revenue attribution.

Table 5 shows that the best conversion value schemas for attributing revenue use the observed user’s spend. The count of purchases also performed well. However, the event-based schema started showing better performance as \( p \) increases because a high privacy threshold applied to the revenue-based schema sets a value of \texttt{null} to players with spend.

The attribution errors within Table 5 are normalized with the hypothetical best case \( D30 PV \) with the uniform revenue attribution function for every privacy parameter separately (marked with a box). For example, in Table 5a, when \( p = 2 \), the conversion value schema \( D7 RR \) combined with empirical based revenue attribution is 7% worst than the error of \( D30 PV \) with uniform revenue attribution.

\footnotetext{Data which is available since we use past data, however, due to the limited time span of any conversion value schema, it cannot be utilized within any schema.}
Table 5: Attribution benchmark for cumulative revenue at \( t = 30 \). The shown error metric is the difference from the baseline \( D30 PV \) combined with \( U \) and marked with a box. Negative means worst than baseline and positive means better than baseline. Recall that we applied the privacy threshold using country groups in our experiments, which significantly increases privacy protection.

Table 5 shows that the best conversion value schemas for attributing revenue use the observed user’s spend. The count of purchases also performed well. However, the event-based schema started showing better performance as \( p \) increases because a high privacy threshold applied to the revenue-based schema sets a value of \textit{null} to players with spend. As expected, the baseline schema PV error was very close to zero when there was no privacy threshold, and UD was the worst. These baselines show how the performance deteriorates when placing players based on their revenue compared to uniformly random.

Figure 2 show that the attribution error increases as revenue matures. As we look into a more extended period, player behavior has more chances to diverge: some players churn, some will start and stop spending, players respond differently to the evolution of the actual game itself.

5 Related Work

This section looks at related literature concerning both privacy and revenue attribution using conversion values. However, we are not aware of any study dealing with the freshly introduced conversion values.

5.1 Privacy Related

Many privacy preserving techniques were introduced in this millennia. In 2002 \( k \)-anonymity was proposed \cite{Sweeney2002}, which was later improved by \( l \)-diversity \cite{MKGV2007}, \( t \)-closeness \cite{LLV2007}, and \( n \)-confusion \cite{ST2012}. This line of work’s main drawback is that they defined anonymity as a property of the dataset. On the other hand, in Differential Privacy \cite{Dwork2006} anonymity was defined as a property of the process. It was adopted to numerous scenarios, each requiring its own fine-tuning of the definition \cite{Dwork2020}. These approaches are widely utilized in the industry as well as by organizations like Google \cite{EPK2014}, Microsoft \cite{DKY2017}, LinkedIn \cite{KT2018}, Uber \cite{JNHS2018}, and Apple \cite{Tea2017}.

Despite of these decade long research, we found that the technique what Apple uses by the introduction of the conversion values does not satisfies any above mentioned mechanisms (although it is similar to \( k \)-anonymity). The communication around the conversion value is not transparent, which seems to be a common practice at Apple: for instance when they announced the usage of
differential privacy but without revealing crucial details of it [TKB+17]. On the other hand, it is well known that security and privacy by obscurity is never a good idea: the reason originates from cryptography, where it is always assumed that the enemy knows the system being used [Sha49].

5.2 Revenue Attribution using Conversion Values

The task of attributing revenue using conversion values is very recent. To the best of our knowledge, our work is the first scientific publications that formally investigates the task. However, related work can be found on the Web. An overview of the changes in SKAdNetwork 2.0 is presented in [Kom20] and [Seu20]. Closer to our work is [Alg20], where the authors present two approaches that rely on the user’s conversion value empirical conditional probability of belonging to a campaign. The first approach is “winner takes all”, which assigned the user to the campaign with the highest probability. The second approach is the “probabilistic attribution”, which multiplies the user’s revenue by the probability, and aggregates it at the campaign level; in fact, it can be captured via Equation 3.

6 Conclusion

This paper focuses on using conversion values to attribute revenue to advertising campaigns. The conversion values are a novel privacy-preserving method for optimizing ad campaigns introduced by Apple in SKAdNetwork 2.0 (iOS 14 and later). Instead of allowing advertisers to use IDFA by default, the user is asked for permission before it is available, impacting how MMPs attribute revenue to advertising campaigns. To the best of our knowledge, our work is the first scientific publication that formally investigates using conversion values for revenue attribution. We present an optimal revenue attribution method, and through various experiments, we shed light on how different conversion value schemas perform in revenue attribution.

Limitations & Future Works

Our work barely scratches the surface of Apple’s conversion value schema, and we hope that it motivates the industry and academia to formally investigate using conversion values in various settings. We focused on using conversion values for attributing revenue in free-to-play games where more than 95% of the players do not spend money. It is likely that the conversion value
schematics in other kind of applications (e.g., subscription, ads driven) and tasks (e.g., ads campaign optimization, real-time bidding) perform differently. The major limitation of our work is that the rules of the privacy threshold are not clear.

**The effect of Opt-In**

It is reasonable to assume that some users give permission to track in both the app that shows the ad as well as the app that gets installed. In that case, the exact network and campaign information is available. It would be possible to either try to estimate campaign revenue solely based on these users, or use the data from these users to improve the estimation that includes the opt-out users. This approximation inevitably has some error, but on the other hand, the error depends on the exact subset of users who choose to opt-in. As a result, it might be possible to reduce the attribution error by considering the difference between the empirical distribution of opt-in and opt-out users.

**Diagnosing revenue attribution**

As IDFA gets depreciated, we will not know the campaign that brought the player. We believe that a promising research area is investigating how to measure the revenue attribution quality without knowing the ground truth.

**Cardinality of the Campaigns**

Since the conversion values can be reported as nulls when the number of installs for a campaign has not reached the privacy threshold, it would be interesting to study what is the optimal number of campaigns to run to make the UA operations as efficient as possible.

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