

Show me the Money: Measuring Marketing Performance in F2P Games using Apple's App Tracking Transparency Framework

Frederick Ayala-Gómez*
fayala@bn-mobile.com



Ismo Horppu*
ihorppu@zynga.com



Erlin Gülbenkoğlu
erlin.gulbenkoglu@rovio.com



Vesa Siivola
vesa.siivola@rovio.com



Balázs Pejó
pejo@crysys.hu



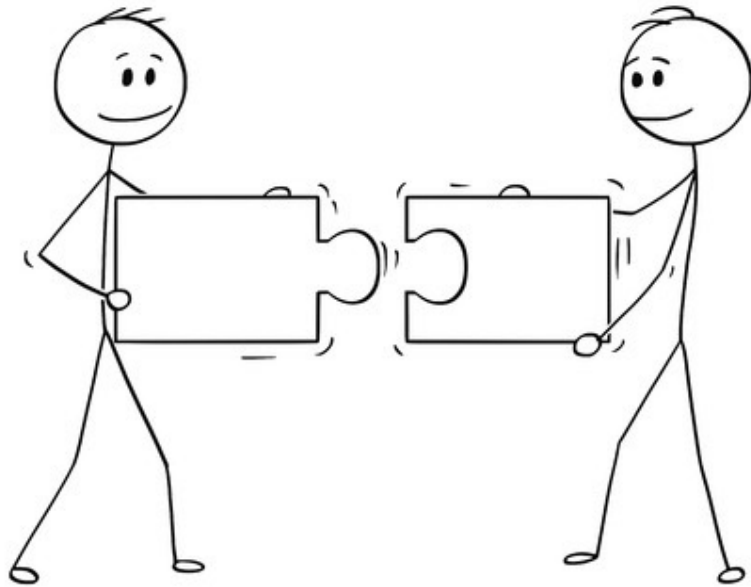
* The author's current institution for contacting purposes. The research was done while at Rovio.

Introduction: Growing the user base



- Mobile apps grow their user base by spending in advertising.
- The goal is to keep the user acquisition activities profitable.
- Revenue attribution assigns revenue to an ad campaign.
- Comparing the revenue obtain advertising campaigns versus the spend helps keeping track of which campaigns are profitable.
- Monitoring ROI is done at cohort level rather than user level.

Motivation: Identifiers for advertising



- Comparing revenue and spend has been possible thanks to attribution methods such as last-click attribution.
- Last-click attribution:
 - Assigns the origin of the user to the last campaign the user clicked or saw.
 - Requires advertising identifiers that allows linking clicks and installs.
- The advertising identifiers have created a big concern on how much data can be collected and linked to profiles for advertising.

Motivation: Privacy innovations



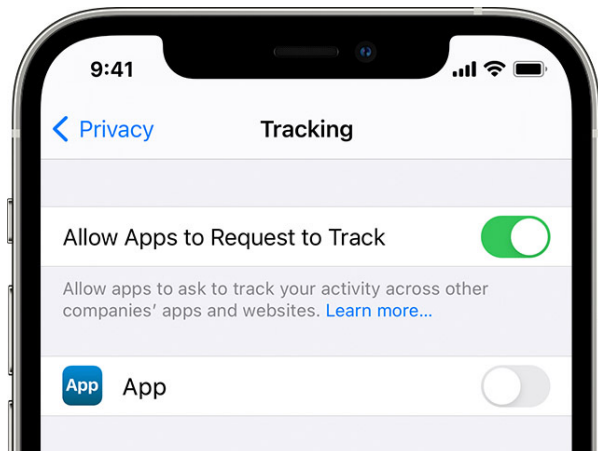
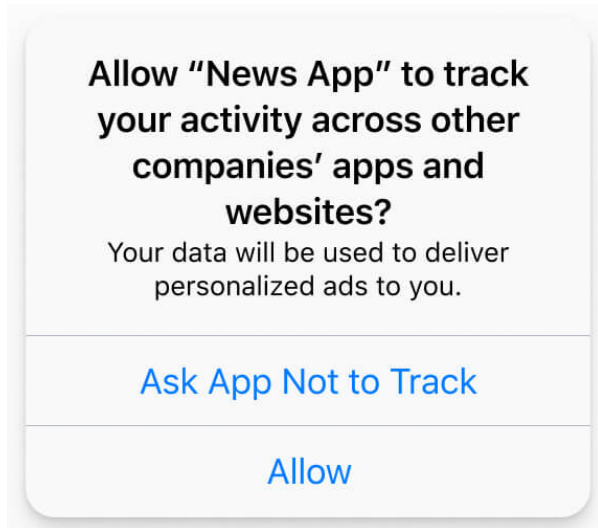
- Starting iOS 14.5+, Apple allows users to choose privacy on advertisement tracking.
- The lack of identifiers for advertising (IDFA) disrupts traditional mechanisms for attributing revenue to advertising campaigns.
- Online advertising has been operating under low uncertainty when it comes to tracking revenue and spend.
- This privacy innovation affects how marketing teams operate advertising campaigns on iOS.

Motivation: Impact to advertisement



- Various advertising networks reported impact in their revenue during their earnings calls of 2021 Q3.
- Reasons:
 - Lack of tools to measure ROI
 - Campaign optimization algorithms less effective
- Undoubtedly, marketing teams need a way to measure the performance of marketing campaigns under the new privacy preserving mechanisms.

What are the changes?



- Starting iOS14.5+, users can reject sharing any identifier for advertising purposes
- Without identifiers for advertisement, there is no way to connect the app installs to the advertising campaigns.
- For users that do not allow tracking, the campaign performance is reported via the SkAdNetwork and App Tracking Transparency framework.
- App developers receive post-backs containing conversion values.

What are conversion values?

Bit 5	Bit 4	Bit 3	Bit 2	Bit 1	Bit 0	Conversion Value
0	0	0	0	0	0	0
0	0	0	0	0	1	1
0	0	0	0	1	0	2
0	0	0	0	1	1	3
0	0	0	1	0	0	4
...
1	1	1	1	1	1	63

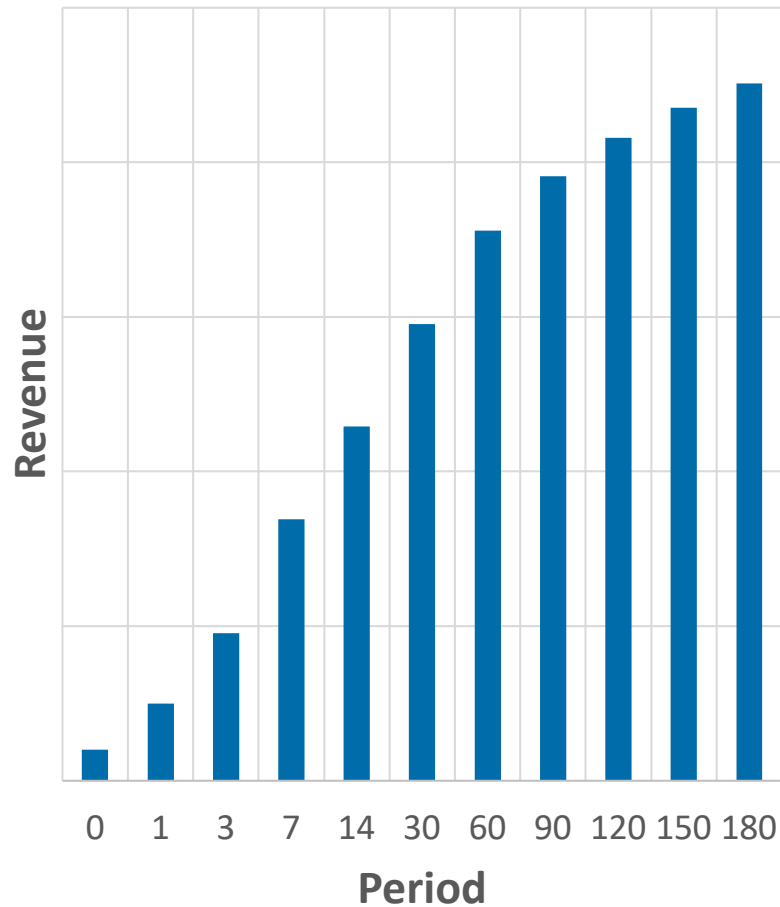
- A conversion value is as an integer between 0 and 63 that developers define following a set of rules (see [Apple's documentation](#)).
- Users that do not allow tracking will appear as if they would have come organically to the application.
- Conversion values follow last-click attribution and is the only reliable mechanism for it (e.g., fingerprinting is not allowed).
- Under certain circumstances that Apple is not disclosing, the conversion values will be reported as *null* to protect the user's privacy.

Privacy Protection

$$pr_p(X) = \hat{X} = \begin{cases} \hat{x}_{v,\alpha} = \begin{cases} x_{v,\alpha} & \text{if } \sum_U \mathbb{1}(v_i = v) \geq p \\ \text{null} & \text{otherwise} \end{cases} \\ \hat{x}_{\text{null},\alpha} = \sum_v \mathbb{1}(\hat{x}_{v,\alpha} = \text{null}) \cdot x_{v,\alpha} \end{cases} \quad (1)$$

- In the lack of open rules, we interpret the conversion value mechanism to be like k-anonymity, which requires all users to be indistinguishable from at least $k - 1$ other users.
- On the other hand, it does not warranty privacy because the condition is not enforced on $\hat{x}_{\text{null},\alpha}$
- Keep in mind that this is our interpretation, and that the real definition is not disclosed.

Revenue attribution using conversion values



- When we talk about revenue attribution, we mean translating the reported counts of conversion values to revenue.
- We focus on attributing revenue to cohorts.
- A cohort is a group of users that started using the app at the same time.
- Looking at how much revenue the cohorts have generated at a certain period (e.g., 7, 14, 30 days) provide early signals to determine if the cohort will generate enough money to cover the investment or not.

Proposed Method

➤ The attribution error minimization problem is defined as:

$$\min_f \left[\sum_{\alpha} \left(\sum_v g \left(\tilde{U}_v^d, \hat{x}_{v,\alpha}^d \right) - y_{\alpha}^t \right)^2 \right] \quad (2)$$

➤ Independently of the conversion value scheme f , the function g that minimizes equation (2) when there is no privacy threshold (i.e., $p = 1$) is the product of the count of conversion value by the average revenue of users with such a conversion values.:

$$g_{\alpha} \left(\tilde{U}_v^d, x_{v,\alpha}^d \right) = x_{v,\alpha}^d \cdot \bar{r}_v^t \quad (3)$$

Proposed Method

- When there is a privacy threshold (i.e., $p \geq 2$) we need to account for the *null* conversion value.
- We propose two attribution formulas:

$$g_{\alpha}(\tilde{U}_v^d, x_{v,\alpha}) = \begin{cases} \bar{r}_v^t \cdot \hat{x}_{v,\alpha} & \text{if } \hat{x}_{v,\alpha} \neq \text{null} \\ \bar{r}_v^t \cdot h(\cdot) \cdot \sum_U \mathbb{1}(v_i = v) & \text{otherwise} \end{cases} \quad (4)$$

- Where $h(\cdot)$ can be:
 - Uniform Revenue Attribution (**U**): Distributes revenue uniformly across networks and campaigns.
 - Null-based Revenue Attribution (**N**): Distribute the revenue based on the empirical distribution of *null* values.
- **Let's look at an example!**

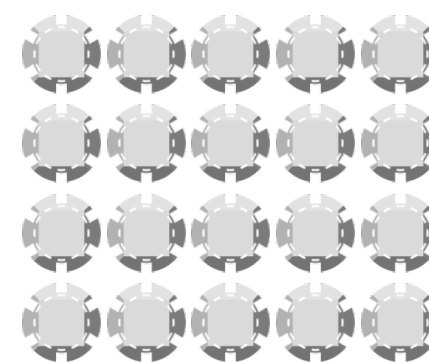
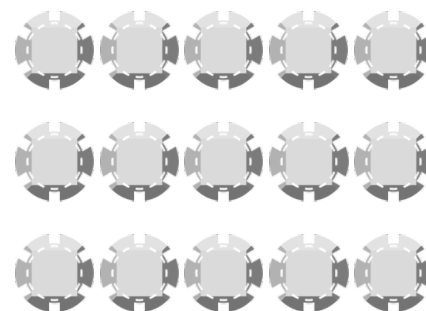
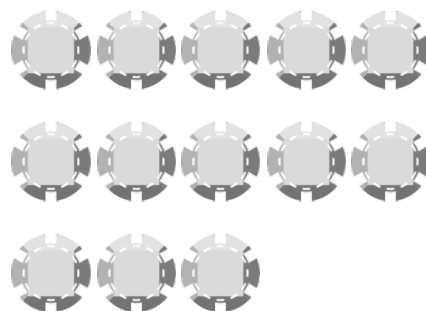
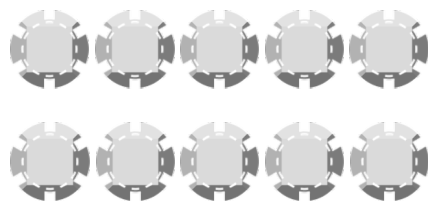
Network 1

Network 2

Network 3

Organic

CV0



CV1



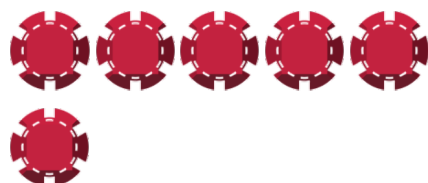
CV2



CV3



CV null



👉 Organic CVs are estimated

Avg. Revenue per CV		
Conversion Value (CV)	Day 7	
0	\$	0.02
1	\$	0.15
2	\$	0.50
3	\$	1.00

Count of Conversion Values			
Network 1	Network 2	Network 3	Organic Estimated
10	13	15	20
5	2	2	2
2	4	1	4
1	2	3	3

Avg. Revenue per CV	
Conversion Value (CV)	Day 7
0	\$ 0.02
1	\$ 0.15
2	\$ 0.50
3	\$ 1.00

Count of Conversion Values			
Network 1	Network 2	Network 3	Organic Estimated
10	13	15	20
5	2	2	2
2	4	1	4
1	2	3	3

	Revenue Attribution			
	Network 1	Network 2	Network 3	Organic
Revenue CV1	\$ 0.23	\$ 0.30	\$ 0.35	\$ 0.46
Revenue CV2	\$ 0.75	\$ 0.30	\$ 0.30	\$ 0.30
Revenue CV3	\$ 1.00	\$ 2.00	\$ 0.50	\$ 2.00
Revenue CV4	\$ 1.00	\$ 2.00	\$ 3.00	\$ 3.00
Known CVs revenue	\$ 2.98	\$ 4.60	\$ 4.15	\$ 5.76

Count of CV

* Average Revenue =

↓

Avg. Revenue per CV	
Conversion Value (CV)	Day 7
0	\$ 0.02
1	\$ 0.15
2	\$ 0.50
3	\$ 1.00

Count of Conversion Values			
Network 1	Network 2	Network 3	Organic Estimated
10	13	15	20
5	2	2	2
2	4	1	4
1	2	3	3

	Revenue Attribution			
	Network 1	Network 2	Network 3	Organic
Revenue CV1	\$ 0.23	\$ 0.30	\$ 0.35	\$ 0.46
Revenue CV2	\$ 0.75	\$ 0.30	\$ 0.30	\$ 0.30
Revenue CV3	\$ 1.00	\$ 2.00	\$ 0.50	\$ 2.00
Revenue CV4	\$ 1.00	\$ 2.00	\$ 3.00	\$ 3.00
Known CVs revenue	\$ 2.98	\$ 4.60	\$ 4.15	\$ 5.76

Count of CV
* Average Revenue = ↓

Totals	D7 Revenue
Total revenue	\$ 30.00
Known CVs revenue	\$ 17.48
Pending attribution	\$ 12.52

<- Known from all the revenue of the users

Avg. Revenue per CV	
Conversion Value (CV)	Day 7
0	\$ 0.02
1	\$ 0.15
2	\$ 0.50
3	\$ 1.00

Count of Conversion Values			
Network 1	Network 2	Network 3	Organic Estimated
10	13	15	20
5	2	2	2
2	4	1	4
1	2	3	3

	Revenue Attribution			
	Network 1	Network 2	Network 3	Organic
Revenue CV1	\$ 0.23	\$ 0.30	\$ 0.35	\$ 0.46
Revenue CV2	\$ 0.75	\$ 0.30	\$ 0.30	\$ 0.30
Revenue CV3	\$ 1.00	\$ 2.00	\$ 0.50	\$ 2.00
Revenue CV4	\$ 1.00	\$ 2.00	\$ 3.00	\$ 3.00
Known CVs revenue	\$ 2.98	\$ 4.60	\$ 4.15	\$ 5.76

$\frac{\text{Total Revenue} - \text{Revenue Known CVs}}{\text{Total nulls}}$ ↓

null	\$ 0.74
-------------	---------

$\frac{\text{Network nulls}}{\text{Total nulls}} =$ ↓

Total nulls	6	2	4	5
null distribution	0.35	0.12	0.24	0.29

↓ = total null count * null average revenue * null distribution

null CVs revenue	\$ 4.42	\$ 1.47	\$ 2.94	\$ 3.68
-------------------------	---------	---------	---------	---------

Totals	D7 Revenue
Total revenue	\$ 30.00
Known CVs revenue	\$ 17.48
Pending attribution	\$ 12.52

<- Known from all the revenue of the users

Avg. Revenue per CV	
Conversion Value (CV)	Day 7
0	\$ 0.02
1	\$ 0.15
2	\$ 0.50
3	\$ 1.00

Count of Conversion Values			
Network 1	Network 2	Network 3	Organic Estimated
10	13	15	20
5	2	2	2
2	4	1	4
1	2	3	3

	Revenue Attribution			
	Network 1	Network 2	Network 3	Organic
Revenue CV1	\$ 0.23	\$ 0.30	\$ 0.35	\$ 0.46
Revenue CV2	\$ 0.75	\$ 0.30	\$ 0.30	\$ 0.30
Revenue CV3	\$ 1.00	\$ 2.00	\$ 0.50	\$ 2.00
Revenue CV4	\$ 1.00	\$ 2.00	\$ 3.00	\$ 3.00
Known CVs revenue	\$ 2.98	\$ 4.60	\$ 4.15	\$ 5.76

$\frac{\text{Total Revenue} - \text{Revenue Known CVs}}{\text{Total nulls}}$ ↓

null	\$ 0.74
-------------	---------

$\frac{\text{Network nulls}}{\text{Total nulls}} =$ ↓

Total nulls	6	2	4	5
null distribution	0.35	0.12	0.24	0.29

Count of CV * Average Revenue = ↓
= total null count * null average revenue * null distribution

null CVs revenue	\$ 4.42	\$ 1.47	\$ 2.94	\$ 3.68
-------------------------	---------	---------	---------	---------

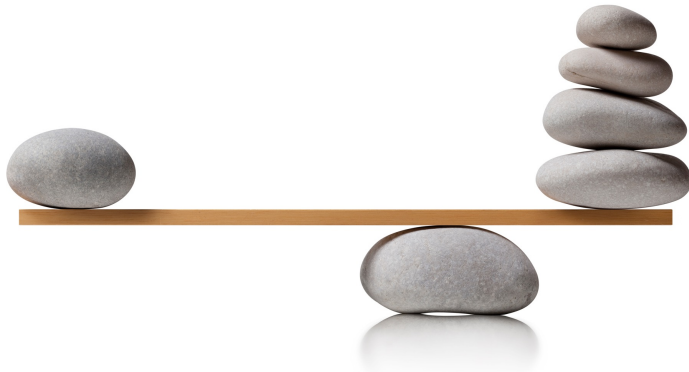
Totals	D7 Revenue
Total revenue	\$ 30.00
Known CVs revenue	\$ 17.48
Pending attribution	\$ 12.52
Attributed Revenue	\$ 30.00

<- Known from all the revenue of the users

✓ Matches the total revenue

Network Revenue	\$ 7.40	\$ 6.07	\$ 7.09	\$ 9.44
------------------------	---------	---------	---------	---------

Experiments



- Using historical data allows us to compare the attributed revenue with the actual data from last-click attribution:
 - Back tested on historical data of a globally launched free-to-play game.
 - More than 500K paid players.
 - Organic and 213 paid campaigns across seven networks.
- Conversion value schemas:
 - Day 0 event-based (**EV**)
 - Rolling Revenue & Rolling Purchase Count (**RR & RI**)
 - Uniform distribution (**UD**)
 - Perfect lifetime value (**PV**)

Results

- ✓ When there is no privacy threshold the error with baseline schema using D30 PV is smaller than all others, and UD performs the worst.
- ✓ As p increases, the D0 event-based and Uniform Distributed schemas' performance gets closer to the rest of the schemas.
- ✓ Using a more extended period than the first 24 hours of gameplay reduces the attribution error.
- ✓ RR and RI work well if enough players are spending during the observed period.
- ✓ Empirical results suggest that schemas that separate spenders and non-spenders and group users based on their spending are the most helpful for revenue attribution.

Conclusions



- ✓ Our work formalizes and investigate the conversion values for revenue attribution rigorously.
- ✓ We find the optimal revenue attribution function that does not depend on the conversion value scheme.
- ✓ We shed light on how different conversion value schemas perform in revenue attribution.
- ✓ Separating spenders and non-spenders and then grouping users based on their spending gives the lowest error in revenue attribution.

Thanks! If you have questions please reach out:

Show me the Money: Measuring Marketing Performance in F2P Games using Apple's App Tracking Transparency Framework

Frederick Ayala-Gómez*
fayala@bn-mobile.com



Ismo Horppu*
ihorppu@zynga.com



Erlin Gülbenkoğlu
erlin.gulbenkoglu@rovio.com



Vesa Siivola
vesa.siivola@rovio.com



Balázs Pejó
pejo@crysys.hu



* The author's current institution for contacting purposes. The research was done while at Rovio.