# Estimating True Post-Click Conversion via Group-stratified Counterfactual Inference


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## ABSTRACT

In online search and display advertising, the click-through rate (CTR) and the post-click conversion rate (CVR) are key measures of ad/campaign effectiveness. We find, however, both CTR and CVR are not always fair for advertisers to charge because of the "free-rider", referring to the user who inherently intended to make a conversion no matter with the ads promoting or not, but acted through promoted ads passingly. To tackle this problem, we propose a new measure, namely true post-click conversion rate (TCVR), to count the users who are truly affected by the ads promoting (i.e., users that made a conversion under ads, but no conversion if no ads.) under the Neyman-Rubin potential outcome framework. Theoretically, we demonstrate the advantages of our proposed TCVR for measuring ads' effectiveness compared with the CTR and CVR. In the advertising scenarios, by assuming that all users can be stratified into five groups based on their behaviors with/without ads promoting under counterfactual overview, we can clearly identify the groups of users that are truly affected by the ads promoting. Moreover, to precisely estimate the TCVR, we propose an easy but effective counterfactual model, namely Group-stratified Counterfactual Inference (GCI) algorithm, by counterfactually predicting the probability of each specific group of each unit belongs to. With empirical experiments, we demonstrate the effectiveness of our proposed counterfactual predictive model and confirm the advantages of our TCVR compared with CTR and CVR.



## CCS CONCEPTS

• **Information systems** → **Online advertising**; • **Computing methodologies** → *Supervised learning by classification.*



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## KEYWORDS

True Post-Click Conversion Rate; User Stratification Model; Online Advertising; Potential Outcome; Counterfactual Learning

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## 1 INTRODUCTION

Click-through rate (CTR) and post-click conversion rate (CVR) live the heart at many industrial systems with counterfactual overview, such as display advertising, online search and recommender systems. Taking an App advertisement from the App store as an example, based on the user behaviors (click and download) to the promoted App advertisement, both the CTR and CVR can be defined as the portion of users who clicked and downloaded the promoted App, respectively. In many online advertising systems, the CTR and CVR are key measures of ad effectiveness, hence, always be adopted for price bidding and charging from advertisers. To precisely estimate the CTR and CVR, recently, many methods have been proposed based on deep learning models. However, we find that bid price based on CTR and CVR is not fair for advertisers because there exist some users who would also click or download the advertisement even without ads promoting, and those users are counted for charging in both CTR and CVR. [17] also finds that a commercial recommender system brings a large number of click-through, where at least 75% of them would likely occur even without recommendations. Therefore, for a more fair price bidding, one needs to identify the users who are truly affected by the promoted ads (i.e., users that would make a conversion under ads, but no conversion without ads).

To clearly demonstrate the users that are truly affected by the promoted ads and show the drawbacks of the CTR and CVR, under some assumptions, we can divide all users into five groups as shown in Table 1 from a counterfactual overview using the principal stratification from causal inference literature instead of observational variables [5, 7, 11]. The stratification is based on the users' behaviors, such as exposed ($T = 0/1$, 1 for expose), clicked ($C = 0/1$, 1 for

**Table 1: *Five groups of users in advertisement scenarios with counterfactual overview.* C(T = 0) and C(T=1) refer to the click behaviors (1 for click) of users when he/she is exposed (T=1) to the promoted ad or not (T=0), respectively. And Y(T = 0) and Y(T=1) refer to the download behaviors (1 for download) of users when he/she is exposed (T=1) to the promoted ad or not (T=0), respectively.**

| Groups | C(T=0) | C(T=1) | Y(T=0) | Y(T=1) |
|---|---|---|---|---|
| A | 0 | 0 | 0 | 0 |
| B | 0 | 0 | 1 | 1 |
| C | 0 | 1 | 0 | 0 |
| D | 0 | 1 | 0 | 1 |
| E | 0 | 1 | 1 | 1 |

click) and downloaded ($Y = 0/1$, 1 for download) to the promoted App advertisement. Hence, the principal stratification is defined as a joint potential outcomes of ($C(T = 0)$, $C(T = 1)$, $Y(T = 0)$, $Y(T = 1)$). Specifically, group A refers to the non-interested users who would never click and download an advertising App no matter being exposed to the promoted App or not; group B means the users who would always download the advertising App no matter with exposure to the promoted App or not, but never click the advertisement; group C represents the users who would click the advertisement if and only if he/she is exposed to it, but they would not download the corresponding App; group D refers to the real affected users by the ads who would click and download the advertising Apps if and only if exposed to them; group E refers to the "free-rider", representing the users who would always download the advertised App no matter ads are promoted or not, and they would like to click and download if ads are promoted.

From Table 1, we know that the users who belong to group C, D and E would be counted for CTR charging from advertiser since they would click the promoted advertise (i.e., C(T=1)=1), and the users that belong to group D and E would be counted for CVR charging since they would click and download the promoted App (i.e., C(T=1)=1 and Y(T=1)=1). Exclusion of users from group C that with only click but no download makes CVR become a better way than CTR for bidding prices in some online advertising applications [14]. While the inclusion of users from group E for both CTR and CVR would lead to unnecessary payment for advertiser, since users from group E would also download the App even without advertising and promoting. The most reasonable and fair charging for advertisers should be only based on the users from group D, where advertising and promoting actually changed their behaviors (click and download) on the advertised app. How to estimate the portion of users belong to group D for fair bidding price is of paramount importance for both academic researches and real-world applications.

In this paper, we define the portion of users that belong to group D as true post-click conversion rate (TCVR), and we focus on precisely estimate TCVR for future bidding prices. The main challenge of TCVR estimation is the counterfactual problem that one can only observe users' behaviors (click and download) under one scenario (with ad exposure $T = 1$ or not $T = 0$). To address this challenge, inspired by causal literature, we therefore propose a novel Group-stratified Counterfactual Inference (GCI) model under the Neyman-Rubin potential outcome framework. Specifically, GCI model aims to predict the probability of the specific group given a user embedding. GCI learns two different distributions under treatment and control group with trainable parameters of a multi-layer perceptron. Extensive experiments on the real-world dataset indicate the existence of group D and group E.

Overall, our contributions are summarized as follow.

- We formally define the free-rider effect in the CTR and CVR model, and propose the true post-click conversion rate (TCVR) for advertising strategy optimization, which is a more reasonable strategy for the benefits of the advertisers.
- We propose a Group-stratified Counterfactual Inference (GCI) algorithm for TCVR estimation. Furthermore, we demonstrate the stability of the proposed GCI.
- We conduct analysis on real-world datasets to show the existence of group D and group E, and extensive experimental results on real-world datasets demonstrate that the proposed GCI algorithm can capture the free-rider effect.

## 2 RELATED WORK

In this section, we review the previous related work, including CTR/CVR estimation and causality based counterfactual learning.

**Click estimation and conversion estimation.** The CTR and CVR are two important measures of ad/campaign effectiveness in online search and display advertising applications. Advertisers bids for each ad request for maximizing their campaign performance (*e.g.*, CTR / CVR), and advertising systems always determine ranking score of each ads. In an App store, given a list of recommended Apps, users may click some ones and further download some of them. So the behaviors sequential pattern follows *observation* -> *click* -> *conversion*. The *clicked* samples are the positive samples of CTR prediction task, and the *conversion* samples are the positive samples of CVR prediction task.

The two tasks can always be modeled as binary classification. Logistic Regression is the most popular and effective model in advertising industry. There are several 2-order feature conjunction methods for CTR/CVR tasks, such as AutoConjunction[3]. In order to capture high order feature interactions, deep neural networks have been widely studied in the last few years, the models include Deep crossing [20] and DeepFM [9]. Recently, some counterfactual learning technologies have been studied to handle the bias problems for advertising system [6], such as propensity-free doubly robust methods for click prediction [21], direct methods for solving both position bias and selection bias[22], debias study with uniform data[12]. For jointly optimizing both CTR and CVR prediction tasks, some multi-task learning models have been proposed, like Entire Space Multi-Task Model (ESSM) [14] and Multi-gate Mixture-of-Experts (MMoE) [13]. As far as we know, our work is the first study about true post-click conversion rate (TCVR) with the potential outcome framework.

**Causality and counterfactual learning.** Causal inference is used in fields of advertisement widely, economics and marketing [2, 18]. We are mainly concerned with the impact of ad exposure on a consumer, which can help advertisers efficiently target customers.

Those methods, which combines both causal inference and machine learning algorithm, to estimate the causal effect of ad exposure is also called uplift model [10]. For example, Facebook uses to measure the advertisement effect [8].

The Neyman–Rubin causal model, is an approach to the statistical analysis of cause and effect based on the framework of potential outcomes [15]. The causal effect is the difference between the outcome variable with the treatment and without the treatment. Nowadays, more and more works adopt machine learning methods for causal effect inference, and in particular for individual-level treatment effect. [19] uses tree-based model and random forest to estimate individual treatment effect, and [16] adopts neural networks to individual treatment effect estimation.

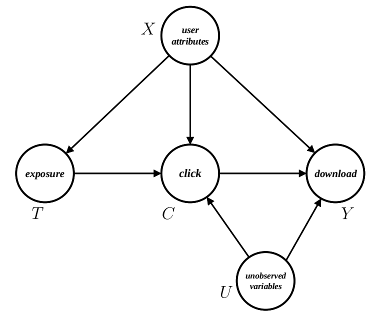


**Figure 1: Our causal diagram.**

## 3 PROBLEM AND METHODOLOGY

In this paper, we focus on how to precisely estimate the proposed TCVR for future bidding prices. Firstly, we will give a formal definition of TCVR, then propose an easy but effective counterfactual learning algorithm for TCVR estimation. Moreover, we will compare our method with traditional uplift modeling methods.

### 3.1 Problem

As shown in our causal diagram in Figure 1, we define a treatment as a random variable $T$, denoting whether a user being exposed in the target advertising App; and two potential outcomes $C(t)$ and $Y(t)$ which correspond to a specific treatment $T = t$. $C(t)$ and $Y(t)$ refer to the click and download behaviors of a user to the corresponding advertisement, respectively. In a real online recommendation system, the treatment $T$ is directly affected by users' attributes $X$, which would also affect the users' click behavior $C$ and download behavior $Y$. Fortunately, users' attributes $X$ can always be observed and collected. But users' click and download behaviors $C$ and $Y$ might be also affected by some unobserved factors $U$, such as friend's recommendation and popularity of the App.

Based on the causal diagram in Figure 1, the proposed TCVR can be formally denoted as:

$$TCVR = p(Y = 1|X, T = 1) - p(Y = 1|X, T = 0). \tag{1}$$

where $p(Y = 1|X, T = 1)$ and $p(Y = 1|X, T = 0)$ represent the probability of download ($Y = 1$) behaviors of user with treatment status as treated $T = 1$ (being exposed to a target ad) and control $T = 0$, respectively. For example, in the scenario of an online App advertisement system, the TCVR refers to the probability of a user, who would not click and download an App if not be exposed to the corresponding advertising App, to make a click and download behavior after being exposed to the App by intervention.

### 3.2 Methodology

In order to estimate TCVR unbiasedly from observational data, one has to control the impact of confounders $X$. In this paper, we propose to remove the confounding bias based on Neyman-Rubin potential outcome framework [16] in causal literature, where the following standard assumptions are needed:

**Assumption 1: Stable Unit Treatment Value.** The distribution of potential outcome for one unit is assumed to be unaffected by the particular treatment assignment of another unit, when given the observed variables.

**Assumption 2: Strong Ignorability.** The distribution of treatment is independent of potential outcome when given the observed variables.

**Assumption 3: Overlap.** Every unit has a nonzero probability to receive either treatment status when given the observed variables. Formally, $0 < p(T = 1|X) < 1$.

In this paper, we focus on the TCVR estimation under advertisement settings. Here, we need to assume following assumptions to deeply describe the relationship between advertisement exposure, click and download:

**Assumption 4: Exposure-Necessary.** Every unit cannot click the advertisement without exposure. Formally, $C(T = 0) = 0$.

**Assumption 5: Monotonicity.** The causal effect of $T$ on $Y$ is non-negative, i.e. $Y(1) \geq Y(0)$.

**Assumption 6: Exclusion.** The exposure $T$ affect download $Y$ only through click $C$, namely exposure $T$ have not direct effect on download $Y$.

Assumption 4-6 are reasonable in the advertisement setting based on the users' behaviors. All users can be categorized into five groups as shown in Table 1, then we have the following equations,

$$p(Y = 0, C = 0|T = 1, X) = p(A|X) \tag{2}$$

$$p(Y = 1, C = 0|T = 1, X) = p(B|X) \tag{3}$$

$$p(Y = 0, C = 1|T = 1, X) = p(C|X) \tag{4}$$

$$p(Y = 1, C = 1|T = 1, X) = p(D|X) + p(E|X) \tag{5}$$

$$p(Y = 1, C = 1|T = 0, X) = 0 \tag{6}$$

$$p(Y = 0, C = 1|T = 0, X) = 0 \tag{7}$$

$$p(Y = 1, C = 0|T = 0, X) = p(B|X) + p(E|X) \tag{8}$$

$$p(Y = 0, C = 0|T = 0, X) = p(A|X) + p(C|X) + p(D|X) \tag{9}$$

All left-hand side (LHS) of these equations can be estimated from observed data and the right-hand side (RHS) is the probability distribution of the five groups people. These equations are saturated, we have the following proposition:

**Proposition:** *Under assumption 1-6, the proportion of each groups is identifiable.*

Furthermore, use Eq. (5)+(3)-(6)-(8), we have:

$$p(D|X) = p(Y = 1|T = 1, X) - p(Y = 1|T = 0, X); \tag{10}$$

**Table 2: Comparison among related metrics and their corresponding probability distribution.**

| Metric | Probability Distribution |
|---|---|
| CACE of $T$ on $C$ | $p(C\|X) + p(D\|X) + p(E\|X)$ |
| CACE of $T$ on $Y$ | $p(D\|X)$ |
| LATE of $C$ on $Y$ | $\frac{p(D\|X)}{p(C\|X)+p(D\|X)+p(E\|X)}$ |
| CTR | $p(C\|X) + p(D\|X) + p(E\|X)$ |
| CVR | $p(D\|X) + p(E\|X)$ |
| TCVR | $p(D\|X)$ |
| free-rider metric | $\frac{p(E\|X)}{p(D\|X)+p(E\|X)}$ |

with Eq. (5), we have:

$$p(D|X) + p(E|X) = p(Y = 1, C = 1|T = 1, X); \tag{11}$$

with Eq. (4)+(5), we have:

$$P(C|X) + p(D|X) + p(E|X) = p(C = 1|T = 1, X) \tag{12}$$

So, we can estimate the TCVR, CTR, CVR by the estimated conditional distribution from observed data distribution as:

$$CTR(X = x) = P(C|x) + p(D|x) + p(E|x) \tag{13}$$

$$CVR(X = x) = p(D|x) + p(E|x) \tag{14}$$

$$TCVR(X = x) = p(D|x) \tag{15}$$

From Eq. 13 & 14 & 15, conceptually, we have following observations and analyses:

- CVR is fairer than CTR for advertisers to charge since CVR can exclude the users of group C that with only click but no conversion (i.e., download) from CTR. Hence, conceptually, CVR is a better way for bidding price than CTR.
- Both CTR and CVR are facing the unfair charge induced by the "free-rider" problem from users of group E, who would also make a conversion (i.e., download) even without advertising and promoting.
- By exclusion of users from group C and E, TCVR is more reasonable and fair for bidding price than CTR and CVR.

### 3.3 Comparison with uplift modeling

Uplift modeling refers to the set of techniques that a company may use to estimate the effect of advertisements on customers. For example, they estimate the conditional average causal effect (CACE) of exposure on click to maximize the number of user clicks. And all such effect can be rewritten using the probability distribution, for example, the conditional average causal effect of $T$ on $C$ and $Y$ are $p(C|X) + p(D|X) + p(E|X)$ and $p(D|X)$, respectively. And the local average treatment effect (LATE) of $C$ on $Y$ is $\frac{p(D|X)}{p(C|X)+p(D|X)+p(E|X)}$ [1].

Beyond causal effect estimation, our approach has a deeper perspective. Our method can solve more actual problems. For example, a CTR customer wants to convert to CVR, due to the change of proposing strategies, it is difficult to price. However, using our framework, we can price it by estimating the amount of TCVR in both the old and new proposing strategies.

Data scientists always estimate the causal effect of $C$ on $Y$ to measure the power of advertisement. We think there is another important metric $\frac{p(E|X)}{p(D|X)+p(E|X)}$. It measures the proportion of converts not due to the advertisement. It also measures how mature or necessary a production is. For example, this metric of daily necessities is often very low. People click this advertisement and buy this product due to their rigid demand. Even without this ad, they will still buy those products. For a mature advertisement, such as Facebook or WeChat, people click and download the advertisement just because the location is more prominent. In those situations, advertising is more like a shortcut link and powerless and we call the metric as "free-rider metric". To summarize, the relationship with existing works, some new metrics and the probability distribution of the five groups is listed in Table 2.

## 4 ESTIMATION

Group-stratified Counterfactual Inference (GCI) model under the Neyman-Rubin potential outcome framework is shown in Fig. 1. In the online advertisement scenarios, the user attributes $X$ are often observable and would affect the following decisions: (i) whether the platform decides to present the advertisement to the user, (ii) whether a user would click the advertisement, and (iii) whether a user would download the corresponding contents in the advertisements. Moreover, there exist some unobserved latent variables $U$ (e.g. friends recommendation, recreation, shopping for others) that may simultaneously affect a user's click and download behaviors.

We aim to predict the probability of whether a user would make a click and download behavior under an intervention in the treatment variable $t$ (i.e. exposure), which is formally defined as $p(y, c|t, x)$.

$$p(y, c|t, x) = p(y(t), c(t)|x) \tag{16}$$

However, the group stratification model illustrates the free-rider effect in CVR (i.e. group $E$. Traditional CVR optimized advertising strategies unavoidably take both group $D$ and group $E$ into account, which is not beneficial to advertisers.

Clearly, a better strategy is to maximize $p(D)$. However, we claim that it is hard to directly distinguish group $E$ as it is a counterfactual situation in real-world advertising systems. Finding users that belong to group $E$ requires not only the behaviors in the treated group (i.e. advertisement exposure) but also the behaviors in the control group (i.e. non-advertisement exposure).

Therefore, we summarize GCI into following two steps.

**Step1**: Estimate $p(C = c, Y = y|T = t, X = x)$.

**Step2**: Plug the estimator of $p(C = c, Y = y|T = t, X = x)$ into Eq. (2) to (9) and solve the equations.

In order to estimate $p(C = c, Y = y|T = t, X = x)$, we first apply differentiable transformation functions to learn the feature vectors from user attributes and item attributes respectively. More specifically, we assume the user embedding of a user $i$ in online advertising system to be $u_i^{user}$, which is learned from user $i$'s attribute $x_i^{user}$. It can be formalized as $u_i^{user} = h_{user}(x_i^{user})$, where $h_{user}$ is a transformation function for user embedding. Similarly, the embedding of an advertisement $j$ in online advertising systems is assumed to be $u_j^{item}$ learned from item $j$'s attribute $x_j^{item}$. It can also be formalized as $u_j^{item} = h_{item}(x_j^{item})$, where $h_{item}$ is a transformation function for advertisement embedding. Then the concatenation

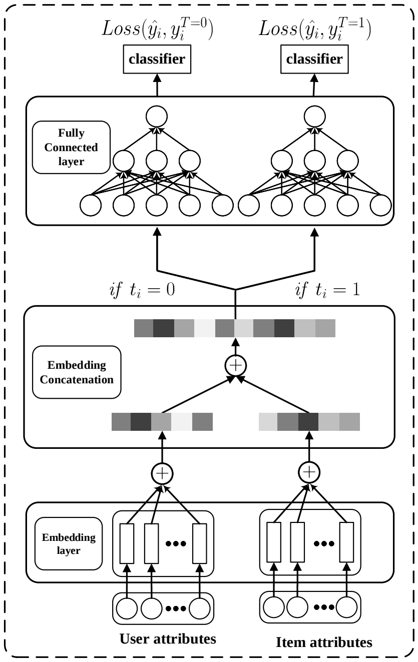


**Figure 2: The architecture of GCI, which consists of three layers. Namely, embedding layer, embedding concatenation layer and fully connected layer. Please note that $t_i$ is a binary variable, representing whether an advertisement is determined to be exposed. As we are only able to observe one result for a user $i$ and the advertisement $j$, each sample is to update model parameters on either $t = 0$ or $t = 1$.**

operation is applied to integrate $u_i^{user}$ and $u_j^{item}$. Please note that other embedding methods such as [4] could also serve as a base model for user and advertisement embedding learning.

$$\tilde{u_{i,j}} = Concat([u_i^{user}; u_j^{item}]), \tag{17}$$

where $u_{i,j}$ represents the embedding of a user $i$ and an advertisement $j$.

As we could only observe $C(T = 0)$ and $Y(T = 0)$ for units with $T = 0$, and the same for the situation when $T = 1$, the assumption 2 (i.e. strong ignorability) is necessary to make our conditional effect identifiable. For each situations (i.e. $T = 1$ and $T = 0$), we use a multi-layer perceptron to learn the integrated representations:

$$\tilde{u}_{i,j}^{(k)|T=t} = \sigma(W^{(k-1)|T=t}\tilde{u}_{i,j}^{(k-1|T=t)} + b^{(k-1)|T=t}), \tag{18}$$

where $\sigma(x) = 1/(1+exp(-x))$ is the sigmoid function, $W^{(k-1)|T=t}$ and $b^{(k-1)|T=t}$ are trainable parameters at the $(k-1)$-layer perceptron when $T = t$ and $\tilde{u}_{i,j} = \tilde{u}_{i,j}^{(0)|T=t}$.

The final final embdding are then fed into the classifier $g^{(T=t)}(\cdot)$, $y_{i,j}^{T=t} = g^{(T=t)}(\tilde{u}_{i,j}^{(k)|T=t})$, where $g^{(T=t)}(\cdot)$ is also a differentiable transformation function. Note that the dimensions of the classifier are different in the situation when $T = 0$ and $T = 1$.

Based on Eq. (1), we can estimate the TCVR by modelling $p(Y = 1|T = 1, X)$ and $p(Y = 1|T = 0, X)$. Here, we split all training data into two subset, including treated training data with $T = 1$, and control training data with $T = 0$. Then, $p(Y = 1|T = 1, X)$ and $p(Y = 1|T = 0, X)$ can be estimated by modelling $p(Y = 1|X)$ under treated training data and control training data, respectively.

According to Eq. (2)-(9), both of the two situations (i.e. $T = 0$ and $T = 1$) are the classification problems. Therefore, we minimize the cross entropy over both the treated group and the control group between the ground truth and the prediction. Therefore, when the advertisement is fixed, the objective function can be formalized as:

$$L = -\sum_{i \in \mathcal{D}_t} \hat{y}_i \log(W^{T=t} \cdot y_i^{T=t}), \tag{19}$$

where $W^{T=t}$ is the parameter of the final classifier layer, $\mathcal{D}_t$ is the set of indices in the training dataset with $T = t$. $\hat{y}_i$ and $y_i^{T=t}$ are the labels and the corresponding embeddings. Specifically, Eq.(19) could be written as $l_{T=0} = -\sum_{i \in \mathcal{D}_{T=0}} \hat{y}_i \log(W^{T=0} \cdot y_i^{T=0})$ and $l_{T=1} = -\sum_{i \in \mathcal{D}_{T=1}} \hat{y}_i \log(W^{T=1} \cdot y_i^{T=})$. The detailed architecture of our GCI algorithm is demonstrated in Figure 2.

# 5 EXPERIMENTS

In this section, we conduct extensive experiments on the real-world datasets to demonstrate the advantages of our methodology.

## 5.1 Dataset

To further validate the phenomenon of TCVR in real-world scenarios, we analyze the data of three advertising Apps from an online advertising system. In order to strictly follow the definition of the groups in the advertisement scenarios, we consider a duration of 15 days to categorize user behaviors as:

- Group A: if an advertisement is exposed to the user in the first week, but not exposed in the second week, and on the last day ($15^{th}$ day), the user did not make a conversion, then we claim that the user belongs to group A.
- Group B: If an advertisement is exposed to the user in the first week but not exposed in the second week, and on the last day, the user downloaded the corresponding App, then we claim that the user belongs to group B[1].
- Group B+E: If an advertisement is not exposed to users in the first week, so (s)he did not have chances to click or download the App, but the user installed the App from other places in the following days, hence, belonging to group B or E.
- Group C: If an advertisement is exposed to the user in the first week, and it is both exposed and clicked by the user in the second week, but on the last day the user did not download the App. We claim the user belongs to group C.
- Group D+E: if an advertisement is exposed to the user in the first week, and it is both exposed and clicked by the user in the second week, and on the last day the user downloaded the App, then we claim the user belongs to group D or E.

In real-world data, it is impossible to distinguish the users belonging to the group E from those belonging to group D, hence, we mainly demonstrate the existence of group D and group E, and give the estimation of the free-rider effect.

[1]The number of users belongs to the group B should be zero, since users download an App must with a click in our recommendation scenario.

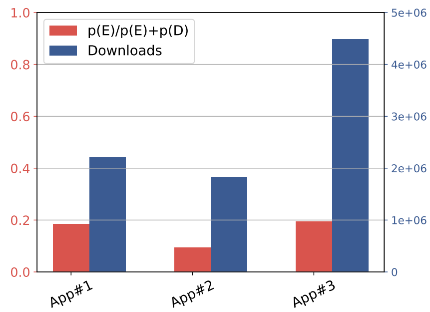


**Figure 3: The probability of free-rider metric of three apps and the corresponding number of downloads.**

**Table 3: Number of users in each group under three active app's advertisements.**

| Apps/Group | A | B+E | C | D+E | E / D+E |
|---|---|---|---|---|---|
| App#1 | 17,022 | 885 | 333 | 24,152 | 3.66% |
| App#2 | 54,205 | 585 | 553 | 40,372 | 1.44% |
| App#3 | 122,201 | 1,490 | 1,117 | 131,733 | 1.13% |

## 5.2 Experimental Results and Analyses

Overall, Table 3 summarizes the statistics of users of each group in the three advertising Apps. We can see our advertising system contains group E, which represents the users that inherently intended to download the App whether the advertising system exposes it or not. So comparing with group D, the advertisers probably do not hope to spend the payment for the advertising Apps from group E, since these users can always find ways to download the Apps. In our App advertising system, the number of users in group E is less than that of group D as shown in the column of "E/D+E" of the Table 3, one possible reason is that we can not collect all the users who belong to group E as we discussed in the last paragraph. The above analysis on real advertising data demonstrates the group E exists, and the ratios of group E are different for different advertising Apps.

Figure 3 shows the predicted free-rider metrics (i.e. $\frac{p(E)}{p(D)+p(E)}$ of three apps by GCI and the total number of downloads in recent two weeks from the online advertising system. App#1 and App#3 have $2,208,868$ downloads and $4,486,693$ downloads, respectively. If the CVR optimized strategy is employed, both App#1 and App#3 could have comparatively high prices for advertisement promotion. As for App#2, it has $1,829,707$ downloads and would pay fewer prices. However, according to the free-rider metric deduced by TCVR, it shows that mature apps would have large free-rider metrics (i.e. 0.194 for App#1 and 0.184 for App#3). Therefore, there are many users in some mature apps that shouldn't have been charged, as the contribution to downloads by these users is not the effect of the advertisement's promotion but the inherent intentions. Moreover, Figure 3 also illustrates that less well-known apps would have comparatively fewer free-rider metrics (i.e. 0.093 for App#2). This phenomenon also corresponds to the well-known fact that users are unlikely to download an unknown app only by the intentions.

# 6 CONCLUSION

In this paper, we formalize a new evaluation metric TCVR in online advertising systems to address the problem of the free-rider effect in CVR optimized advertising strategy. We point out both CTR and CVR fail to achieve a win-win situation for advertisers as the existence of the people belonging to the group D. A novel model(GCI) is proposed under a counterfactual learning framework to solve the above challenges. GCI learns the two distributions through splitting models with different trainable parameters with shared embeddings. Experimental results confirm both our analysis on reasonableness of TCVR and the effectiveness of our GCI.

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