Addressing Exposure Bias in Uplift Modeling for Large-scale Online Advertising

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***Abstract*—Uplift modeling is an important task for online advertising and marketing. Advertisers rely on accurate modeling of the uplift effect to formulate, plan and implement their advertising and marketing strategies. Therefore, the capability of effective and efficient uplift modeling is essential for advertising platforms to attract and satisfy their customers (i.e., advertisers). In practical advertising applications, uplift modeling focuses on the estimation of the uplift effect caused by ad exposure. It is not a trivial task to estimate such causal impact of ad exposure at the individual level. In this paper, we propose an end-to-end approach for explicit uplift modeling, using data collected from Random Control Trials (RCTs) in large-scale real-world advertising platforms. More specifically, we first introduce the Explicit Uplift Effect Network (EUEN) to explicitly model the uplift effect and demonstrate its advantages in uplift modeling. Then for the exposure uplift effect modeling, we further propose the Explicit Exposure Uplift Effect Network (EEUEN), which can correct the exposure bias for uplift modeling. We evaluate our proposed approach with both public data sets as well as data sets collected from our advertising platform. The significant improvements with respect to various performance metrics demonstrate the advantages of our approach[1].**

***Index Terms*—Treatment Effect, Uplift Modeling, Randomized Controlled Trials, Exposure Value, Online Advertising**

I. Introduction

The measurement and optimization of advertisement uplift effect are important tasks in digital brand marketing [16, 8]. The uplift effect is often defined as the increment of user conversion, i.e., the conversion difference (or uplift ratio) between users with ad exposure and users without ad exposure. The main challenge for uplift modeling is how to quantify and estimate the real uplift effect of ad exposure. To measure uplift effect, two homogeneous groups of traffic (i.e., user access records) are often constructed so that users in one group (i.e., treatment group) will be exposed to ad content and users in the other group (i.e., control group) will be blocked from the ads. Such homogeneous groups can be constructed with pre-delineated user crowds and randomized controlled trials (RCTs) [7]. However, implementing RCTs in real-world advertising platform is challenging for several reasons. First, estimation of uplift effect often has resource constraints [10]. Control traffic may result in lost of revenue of advertising platform due to wasting opportunities for ad impression. Second, industrial advertising platform has many operational requirements, which can affect the exposure priority of different ads. As a consequence, the quality of RCT data depends on the position of RCT mechanism in the overall pipeline of advertising allocation [8, 15, 7].

[1]Our code and data will be shared once the paper can be made public.

Furthermore, there are still challenges for accurately measuring uplift effect even with large-scale RCT mechanism. Due to the complicated modern websites and mobile applications, there might be hidden yet significant biases in the ad allocation process and the subsequent RCT data. Particularly, some users in the treatment group may not get real ad exposure due to various technical issues. Without correcting such biases, directly comparing the ad effects between treatment and control groups will result in inaccurate uplift effect estimation. Indeed, if ad exposure is failed for a significant proportion of treatment traffic, the bias correction can be a daunting challenge. Therefore, we need to consider when and where the RCT mechanism should be used in the allocation pipeline to alleviate potential biases, and meanwhile, to correct the inevitable non exposure bias of treatment group.

Recently various uplift modeling approaches have been proposed to address these challenges [5, 13, 6]. However, the estimation of uplift effect usually proceeds in a multi-stage framework [1, 23]. The first stage is to model the potential outcomes from treatment and control group separately. Then, these fitted models of potential outcomes are plugged into a downstream estimator for uplift estimation. Such multi-stage approaches are not ideal for large-scale online advertising platform due to requirements on efficiency and accuracy. Overall, although advanced and improved modeling approach is vital for many operational and managerial tasks in online advertising, these existing methods cannot provide an end-to-end and explicit model of uplift effect with the aforementioned exposure bias corrected.

In this paper, we propose an end-to-end framework for uplift effect modeling based on data collected from RCTs. To get homogeneous groups for measuring the uplift effect, the RCT mechanism is deployed as the last step of our advertising allocation pipeline so that all advertising campaigns provided to the RCTs are competitive. The important advantage of deploying the RCT mechanism to the end of the allocation process is that it can greatly increase the proportion of effective traffic in the RCT groups (e.g., more users in the treatment group can be exposed to competitive ad content). Meanwhile, such a design has better guarantee of group homogeneity with independent operational conditions of other components in the allocation process. Then, to estimate the uplift effect from the RCT data, we propose a novel approach, the Explicit Uplift Effect Network (EUEN), for the estimation of individual causal effect. We show that our explicit approach to uplift modeling is more suitable for large-scale advertising platform.

Specifically, to correct the exposure bias, our approach partitions treatment group into two parts, one with real exposure (treat-exposed) and the other without exposure (treat-unexposed). Similarly, there are counterfactual exposure part (control-exposed) and real non-exposure part (control-unexposed) in the control group, which are homogeneous with the treat-exposed and treat-unexposed parts, respectively. The key idea in our approach is to measure the exposure uplift effect by comparing treat-exposed group and control-exposed group. To learn the exposure uplift effect, we introduce the Explicit Exposure Uplift Effect Network (EEUEN) as an end-to-end approach with efficient online inference.

Our contributions in this paper are summarized as follows:

- We propose an end-to-end framework for modeling the uplift effect of large-scale online advertising. As shown in Figure 1, we use online RCTs as the last component of advertisement allocation pipeline to obtain homogeneous trial groups. The RCT mechanism supports multi-cell experiment, i.e., simultaneous uplift modeling of multi (brand) advertising campaigns. With the RCT data, we propose a novel method to estimate the uplift effect, which is more effective and efficient through explicit modeling designs.
- We consider the real uplift effect only after the user is exposed to the ad content. According to the theoretical design of RCT groups with homogeneity orthogonality, the real control group should also include non exposure samples similar with those in the treatment group. This observation inspires us to redesign the measurement method to accurately quantify the exposure uplift effect with EEUEN, an extended end-to-end approach to explicit uplift modeling.
- To the best of our knowledge, our paper is the first attempt to model the uplift effect for online advertising by jointly learning an explicit estimation function and addressing the important exposure bias in the treatment group. The joint learning can better exploit complex and inter-correlated user behaviors and allow efficient real-time inference in supporting industrial applications. Our approach can also quantify the advertising performances in a more reliable way in supporting managerial decisions by correcting the exposure bias.
- To evaluate the learning performance of exposure uplift effect, we formulate an improved evaluation metric, AUUCE, based on the Area Under Uplift Curves (AUUC) [6, 7]. We show that the proposed metric can reliably measure modeling performance of exposure uplift effect with extensive experiments.

Our work has been used in the online advertising platform for a large-scale video and e-commerce platform. The new methods and implementations have been supporting our managers and brand advertisers with various demands in accurate modeling of the exposure uplift effect.

II. Related Work

A. Advertising Effect Measurement

Early work to understand the casual effect of advertising relied on casual measurement with observational studies [25]. Generally, observational studies of online advertising are sensitive to various selection biases [3]. Due to the lack of homogeneous groups, measuring the causal effect of advertising accurately with observational studies is difficult [14, 8]. In principle, adopting large-scale randomized controlled trials (RCTs) can improve the measurement of advertising effectiveness [4]. As mentioned by Gordon et al. [8], although an online advertising platform can adopt RCTs, it is still difficult to ensure that traffic in treatment group will all be exposed to the ad content due to issues such as frequency filtering, request timeout, and system failure. However, few previous works considered how to fix such issues for reliable measurement of ad effects when the traffic in treatment group cannot meet the ideal exposure expectation.

B. Uplift Modeling

Uplift modeling aims to estimate individual treatment effect (ITE), or the **uplift effect** in this paper, for online advertising platforms [5]. Existing approaches usually build two independent models for potential outcomes of treatment group and control group separately, then estimate the uplift effect as the difference between the outputs of the two models [9, 24, 11, 1]. In addition to such two-model approaches, the single-model approach of uplift modeling can concatenate the treatment and covariates as the modeling features, then apply standard supervised learning algorithms for uplift effect estimation [17]. For instance, Athey et al. [1] used regression tree to estimate heterogeneous treatment effect. Meta-learners such as X-learner [13] has also been used for uplift effect estimation by considering the imbalance and heterogeneous propensity between groups. In this paper, we aim to explicitly model the uplift effect with an end-to-end framework.

With recent advances of deep learning methods, Shalit et al. [22] designed the Counterfactual Regression (CFR) method by extending the two-model approach for uplift effect estimation. The CFR method can regularize the distributions of shared representations learned from two different groups to be similar by minimizing the maximum mean discrepancy or the Wasserstein distance between the representation distributions. To capture the uncertainty in the counterfactual distributions, Yoon et al. [27] adopted the Generative Adversarial Networks (GAN), and proposed the GANITE, which consists of a counterfactual block and an uplift effect block, for uplift effect estimation. Recently, neural networks have been used to model the treatment assignment propensity and estimate the potential outcome [18, 23]. Overall, these works use neural networks to improve estimation performance, but rarely consider how to design an end-to-end approach to explicitly model the exposure uplift effect.

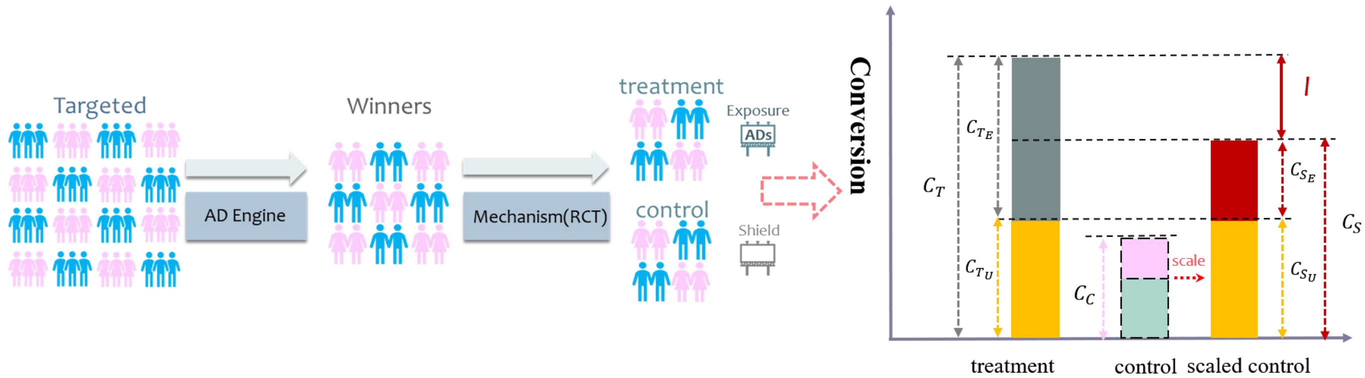


Fig. 1: Our uplift modeling is based on the Randomized Control Trials (RCTs). For each advertising campaign, we randomly block the allocated impressions for the control group. The proportion for ad blocking depends on the potential loss of revenue and any requirements from the advertisers.

III. Problem Statement

A. Uplift Effect Estimation

We study the uplift modeling as a causal inference problem based on two important concepts: potential outcome and causal effect [21]. Assuming the data is generated independently and identically: $(x_i, y_i, t_i, e_i) \overset{\text{i.i.d}}{\sim} \mathcal{P}$, where $\mathcal{P}$ is the joint data distribution. The modeling input $x_i \in \mathbb{R}^d$ contains processed and embedded covariates about the user and the ad. The modeling outcome $y_i \in \{0, 1\}$ is the potential outcome: $y_i = 1$ if the user has interaction or conversion with the product, and $y_i = 0$ if otherwise. The indicator $t_i \in \{0, 1\}$ is the intervention marker to represent treatment assignment, i.e., $t_i = 1$ if and only if the subject (e.g., an user) is assigned to the treatment (e.g., an ad exposure). Finally, the indicator $e_i \in \{0, 1\}$ is the exposure status: $e_i = 1$ if and only if the ad exposure is confirmed.

Consider a data set of observations $D = \{x_i, y_i, t_i, e_i : i = 1, \cdots, N\}$ for modeling the uplift effect. Let $y_i(0)$ denote the outcome of the i-th instance when the traffic is assigned to the control group, and $y_i(1)$ is the outcome when the traffic is assigned to the treatment group. The uplift effect of the i-th instance without considering the exposure bias is defined as $\tau(x_i) = y_i(1) - y_i(0)$. The well-known challenge to estimate such uplift effect is that, since t_i is either 0 or 1, we can only observe one outcome:

$$y_i = y_i(t_i) = t_i \cdot y_i(1) + (1 - t_i) \cdot y_i(0) = \begin{cases} y_i(0) & t_i = 0 \\ y_i(1) & t_i = 1 \end{cases},$$

where the counterfactual outcome $y_i(1 - t_i)$ cannot be observed, and thus it is impossible to obtain $\tau(x_i)$ directly.

One typical solution is to use the Conditional Average Treatment Effect (CATE) [13, 28] as an unbiased uplift effect estimator. The CATE estimator is defined as:

$$\begin{aligned}\tau(x_i) =& \mathbb{E}[Y(1) - Y(0) | X = x_i] \\ =& \mathbb{E}[Y | T = 1, X = x_i] - \mathbb{E}[Y | T = 0, X = x_i] \\ =& \mu_t(x_i) - \mu_c(x_i).\end{aligned}$$

The two potential outcomes are defined as:

$$\begin{aligned}\mu_t(x_i) &= \mathbb{E}[Y | T = 1, X = x_i], \\ \mu_c(x_i) &= \mathbb{E}[Y | T = 0, X = x_i].\end{aligned}$$

Here, we use X, Y, and T as random variables for input covariates, potential outcome, and treatment indicator, respectively. The CATE estimation depends on the assumption of conditional independence or unconfoundedness [20], such that T is independent of Y given X. Such assumptions are usually justified when the data set D is collected from RCTs, with which, we can estimate the uplift effect by learning the potential outcomes.

B. Exposure Uplift Effect Estimation

However, uplift effect estimation faces many practical challenges even with RCTs. For instance, the actual uplift effect of exposure is of great concern to advertisers. Measuring the uplift effect by comparing outcome difference between the treatment group and the control group might be inaccurate if the exposure bias is not properly adjusted. In general, it is more difficult to model the real uplift effect of exposure than to model the effect difference due to treatment decisions.

1) Exposed Subgroups for Exposure Uplift Effect: In practice not all the traffic in the treatment group can be exposed to the ad content in the uplift experiment based on RCT mechanism. Since ad exposure is the real factor that causes the uplift effect, we only want to compare the difference between the exposure subgroups of treatment and control groups to estimate the real exposure uplift effect. Therefore, we define treat-exposed and control-exposed subgroups, where the exposure subgroup of control group is a counterfactual subgroup and cannot be observed directly. The exposure uplift effect of our interest comes from treat-exposed subgroup.

Let N_T and N_C represent the size of the treatment group and control group, respectively. Let $\alpha = N_T / N_C$ be the scale coefficient, then the scaled conversions in control group can be expressed as $C_S = \alpha \cdot C_C$ where C_C is the size of the conversions in control group as shown in the far right part of Figure 1. Note that, the conversions of treatment group C_T consists of conversions of treat-exposed (C_{T_E}) and treat-unexposed (C_{T_U}) subgroups. We use C_{S_E} and C_{S_U} to characterize the counterfactual scaled conversions of control-exposed and control-unexposed subgroups, respectively. As aforementioned, the counterfactual subgroups are not directly constructed by RCTs.

With RCTs, unexposed parts are considered equal, i.e., $C_{T_U} = C_{S_U}$. Therefore, the incremental conversion ratio between the treatment and scaled control groups is:

$$Uplift = \frac{C_{T_E} - C_{S_E}}{N_T} = \frac{C_T - \alpha \cdot C_C}{N_T}.$$

However, our real objective is to estimate the exposure uplift effect based on the exposure subgroups:

$$Uplift_E = \frac{C_{T_E} - C_{S_E}}{N_{T_E}} = Uplift / \frac{N_{T_E}}{N_T},$$

where N_{T_E} is the size of treat-exposed subgroup and $\frac{N_{T_E}}{N_T}$ represents the exposure probability.

2) Estimation of Exposure Uplift Effect: Section III-B1 introduces how to measure the exposure uplift effect at ad level. Our goal is to estimate the exposure uplift effect expectation at individual level with our uplift modeling framework. Define $\omega(x_i) = \Pr(e_i = 1|X = x_i)$ as the exposure probability function, which can only be observed and learned based on the data of the treatment group. Once learned, we use the same exposure probability function to construct the counterfactual subgroups in the control group. We use $\widetilde{\omega}(\cdot) = 1 - \omega(\cdot)$ for simplicity. We define $P_T(X, E) = \mathbb{E}(Y|T = 1, E, X)$ to represent the conversion probability in treatment group, and $P_C(X, E) = \mathbb{E}(Y|T = 0, E, X)$ for the control group. Then, it follows that:

$$\mathbb{E}[Y|T = 1, X] = \omega(X) \cdot P_T(X, 1) + \widetilde{\omega}(X) \cdot P_T(X, 0),$$

$$\mathbb{E}[Y|T = 0, X] = \omega(X) \cdot P_C(X, 1) + \widetilde{\omega}(X) \cdot P_C(X, 0).$$

For unexposed part, we have $P_T(X, 0) = P_C(X, 0)$, therefore:

$$\begin{aligned}\tau(X) &= \mathbb{E}[Y|T = 1, X] - \mathbb{E}[Y|T = 0, X]\\ &= \omega(X) \cdot [P_T(X, 1) - P_C(X, 1)] = \omega(X) \cdot \tau_e(X).\end{aligned}$$

Here the exposure uplift effect are defined as:

$$\tau_e(X) = P_T(X, 1) - P_C(X, 1).$$

Then it follows straightforwardly that:

$$\mu_t(X) = \mu_c(X) + \omega(X) \cdot \tau_e(X).$$

Our paper develops an effective framework to learn the functions $\tau(X)$ and $\tau_e(X)$. We focus on real exposure uplift effect and propose to learn the uplift effect explicitly with an end-to-end approach to the modeling of the uplift effect for large-scale online advertising.

IV. The Proposed Framework

According to Section III, the conversion in the treatment group can be formalized as $\mu_t(X) = \mu_c(X) + \tau(X) = \mu_c(X) + \omega(X) \cdot \tau_e(X)$. Following this formulation, we propose the EUEN and the EEUEN, where both $\tau(X)$ and $\tau_e(X)$ are explicitly modeled and estimated. To the best of our knowledge, our paper is the first attempt to model the uplift effect for online advertising by jointly learning the explicit function $\tau(X)$ and $\tau_e(X)$ as well as addressing the important exposure bias in the treatment group with the exposure probability function $\omega(X)$. The joint learning can better exploit complex and inter-correlated user behaviors and allow efficient real-time inference in supporting industrial applications. Our approach can also quantify the advertising performances in a more reliable way in supporting managerial decisions by correcting the exposure bias.

A. Overview: Features, Embedding Layers, and Networks

As shown in Figure 2a and Figure 2b, each network consists of several sub-networks following the Multi-Layer Perceptron (MLP) paradigm with activation functions such as Exponential Linear Unit (elu). As shown at the bottom gray rectangle part, for sparse features (e.g., categorical information) in our data, we use embedding layer with four feature fields: context field (e.g., network status, app name), user behavior field (e.g., click and purchase history), user profile field (e.g., age, gender), and candidate ad field (e.g., ad and brand information). The one-hot encodings of each feature will be projected into a fixed-size dense vector, via the so-called embedding process. After concatenating the embedding results into field representations, the representations of all feature fields are concatenated as the input vectors to the network. Dense features (e.g., numerical information) are directly used as part of the input.

B. Explicit Uplift Effect Network

Explicit uplift modeling. As shown in Figure 2a, we learn the control conversion probability μ_c and the uplift effect τ with two sub-networks, respectively. The final output takes the sum of μ_c and τ, i.e., $\mu_t = \mu_c + \tau$, as the conversion probability of the treatment group. The fact that our approach can explicitly learn uplift effect τ is a distinguish feature in comparison with previous methods for uplift modeling. Meanwhile, as we will elaborate in the following, the two sub-networks are learned jointly with a unified objective function.

Joint learning with two sub-networks. Our optimization process can be formulated as joint training of the two sub-networks:

$$\hat{\theta}_\lambda = \arg\min_\theta \mathcal{J}(\theta) + \lambda \cdot \mathcal{L}(\theta),$$

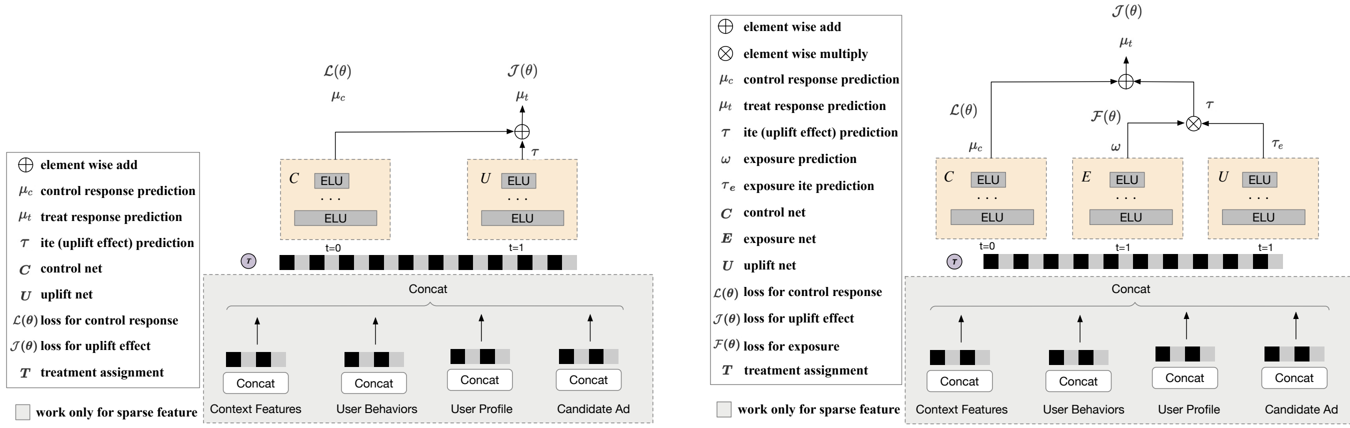
where θ is the set of modeling parameters in the functions $\mu_c(X)$ and $\tau(X)$. The loss function $\mathcal{J}(\theta)$ is for learning the conversion of treatment group, and $\mathcal{L}(\theta)$ is the loss function for learning conversion of control group. The hyper-parameter $\lambda > 0$ is used to balance the two losses. Specifically:

$$\mathcal{J}(\theta) = \sum_i t_i \cdot [y_i - (\tau(x_i) + \mu_c(x_i))]^2,$$

$$\mathcal{L}(\theta) = \sum_i (1 - t_i) \cdot [y_i - \mu_c(x_i)]^2.$$

Training process of EUEN. We will update the sub-network with output $\mu_c(\cdot)$ using samples and conversion $Y(0)$ as the learning target in control group ($t_i = 0$). Here the loss function $\mathcal{L}(\theta)$ will work to update the parameters of the sub-network in the left part, and the parameters for the shared feature embedding layer at the bottom part, as shown in Figure 2a.

Sub-network in the right part will be updated with each sample in treatment group ($t_i = 1$), using conversion $Y(1)$ as the learning target. The loss function $\mathcal{J}(\theta)$ will work to update the parameters of the whole network including the two sub-networks and the shared feature embedding layer. Note that, since the learning of $Y(1)$ is not an independent or direct network output, but a sum of two explicit outputs $\mu_c(X)$ of conversion prediction in control group and $\tau(X)$



(a) EUEN

(b) EEUEN

Fig. 2: The structures of EUEN and EEUEN, where the gray rectangle with ELU description represents the fully connected layer with Exponential Linear Unit (elu) as the activation function.

of uplift effect. We will show advantages of such joint and explicit learning of the uplift effect in experiments.

C. Explicit Exposure Uplift Effect Network

The architecture of EEUEN. Next, we develop a novel model specifically to model the exposure uplift effect. As shown in Figure 2b, we simultaneously learn the control conversion probability μ_c, the exposure uplift effect τ_e, and the exposure probability ω with three sub-networks. Estimation of conversion probability of the treatment group then takes a combination of these three explicit outputs as $\mu_t = \mu_c + \tau_e \cdot \omega$.

Joint learning of EEUEN with three sub-networks. The optimization process can be formulated as joint training of the three sub-networks:

$$\hat{\theta}_{\lambda,\gamma} = \arg\min_{\theta} \mathcal{J}(\theta) + \lambda \cdot \mathcal{L}(\theta) + \gamma \cdot \mathcal{F}(\theta),$$

where $\lambda > 0$ and $\gamma > 0$ are hyper-parameters. The loss function $\mathcal{J}(\theta)$ is for learning conversion of treatment group, and $\mathcal{L}(\theta)$ is the loss function for learning conversion of control group. Moreover, $\mathcal{F}(\theta)$ is the loss function for learning exposure propensity of treatment group. Specially, we define:

$$\mathcal{J}(\theta) = \sum_i t_i \cdot [y_i - (\tau_e(x_i) \cdot \omega(x_i) + \mu_c(x_i))]^2,$$

$$\mathcal{F}(\theta) = -\sum_i t_i \cdot [e_i \cdot \log \omega(x_i) + (1 - e_i) \cdot \log(1 - \omega(x_i))].$$

Note that the loss function $\mathcal{L}(\theta)$ is the same as defined in Section IV-B.

Training process of EEUEN. The training process of EEUEN is different from that of EUEN due to the estimation of the two functions $\omega(X)$ and $\tau_e(X)$. First, We will update the sub-network in the far left part with output $\mu_c(X)$ in the same way as that of Section IV-B we update EUEN, as shown in Figure 2b.

Second, the middle sub-network will be updated with each sample in treatment group ($t_i = 1$), which uses real exposure label $E(1)$ as learning target. The loss function $\mathcal{F}(\theta)$ will work to update the parameter of this middle sub-network, and the parameters for the shared feature embedding layer at the bottom part.

Finally, sub-network in the far right part will be updated with each sample in treatment group ($t_i = 1$), which uses conversion $Y(1)$ as learning target. The loss function $\mathcal{J}(\theta)$ will work to update the parameter of the whole network including the three sub-networks and the shared feature embedding layer. Note that, since the learning of $Y(1)$ is not independent direct network output, but a combination of three explicit outputs $\mu_c(X)$ of conversion prediction in control group, $\omega(X)$ of exposure propensity estimation in treatment group, and $\tau_e(X)$ of exposure uplift effect if the ad is treated and exposed, which makes the exposure uplift effect directly and explicitly expressed and learned.

V. Experimental Results

A. Data sets

We use real-world and large-scale data collected from RCTs on marketing and advertising platforms, where the ad exposure signal is included to support our experiments. The following two data sets are used for our experiments.

1) CRITEO-UPLIFT1: The CRITEO-UPLIFT1 [7] data was collected from RCTs at population level for several uplift tests. The data consists of 25 million samples. Each sample consists of 12 dimensional numerical features (i.e., dense features), one treatment indicator, and two labels (i.e., visit and conversion). The exposure ratio in the treatment group is only 4.13%, which may affect accurate estimation of exposure uplift effect due to the lack of sufficient exposure.

2) EC-LIFT: [2] We collect the data through online RCTs for 5 days on our real-world brand advertising platform, which serves billion-scale visits per day. The sample label inspected whether there is action (e.g., visit) within 7 days after the traffic request time. We make a reasonable sampling of the collected data to form the EC-LIFT data set, which consists of over 425 million samples. In addition to necessary indicators and labels, we collect anonymized user features (e.g., user behavior history), ad features (e.g., ID, category), and additional contextual features. The exposure ratio in the

[2]We will release this data set after publication of this paper.

TABLE I: Dataset Summary

Dataset	CRITEO-UPLIFT1	EC-LIFT
Size	25,309,483	425,272,339
Ratio of Treatment to Control	5.48:1	2.92:1
Exposure Ratio in Treatment	4.13%	65.37%
Average Visit Ratio	4.132%	2.99%
Average Conversion Ratio	0.229%	0.146%
Average Relative Uplift(visit)	68.7%	429%
Average Uplift(visit rate)	1.80%	3.05%
Average Exposure Uplift(visit rate)	43.4%	4.67%
Conversion target	visit	visit
Fields/Type	12/dense	25/sparse category

treatment group is 65.37%, which is much higher than that of CRITEO-UPLIFT1 data.

The data summaries are shown in Table I. As shown in the table, the two data sets have quite different exposure ratio. Indeed, extreme low exposure ratio in the treatment group will affect the accuracy of the exposure uplift effect measurement, especially when the number of exposure subgroup is not large enough. For example, in data set CRITEO-UPLIFT1, if we use the method in [16] to measure the relative exposure uplift effect, the denominator in the calculation will be negative, which is incorrect by definition. Therefore, in our EC-LIFT data, the RCT mechanism used in our work has largely ensured the high exposure ratio, so that we can expect better performance of exposure uplift effect modeling.

B. Evaluation metrics

1) **Metric for uplift effect modeling:** We use the area under uplift curves (AUUC) [6, 7] and qini coefficients [19, 2] to measure the performance of uplift effect models. For an uplift model $\hat{u}$, we assume the data $D = \{x_i, y_i, t_i, e_i : i = 1, \cdots, N\}$ has been sorted, such that $\hat{u}(x_1) \geq \hat{u}(x_2) \geq \cdots \geq \hat{u}(x_N)$. Then for the treatment group, we count the number $N_T(D,k) = \sum_{i=1}^{k} [\![t_i = 1]\!]$ and the conversions $R_T(D,k) = \sum_{i=1}^{k} [\![y_i = 1, t_i = 1]\!]$ of the top k instances, respectively. Similarly for the control group, $N_C(D,k) = \sum_{i=1}^{k} [\![t_i = 0]\!]$ and $R_C(D,k) = \sum_{i=1}^{k} [\![y_i = 1, t_i = 0]\!]$. Note that $[\![\cdot]\!]$ is the Iverson bracket, which transforms logical statement in the brackets to one if the statement is true, and zero otherwise. We define:

$$\phi(k) = \frac{N_T(D,k) + N_C(D,k)}{N_T + N_C},$$

and the the conversion rate gain:

$$V(k) = (\frac{R_T(D,k)}{N_T(D,k)} - \frac{R_C(D,k)}{N_C(D,k)}) \times \phi(k).$$

For convenience, we set $V(0) = 0$. Finally, we calculate AUUC as:

$$AUUC = \frac{1}{2N} \sum_{k=1}^{N} [V(k) + V(k-1)].$$

The definition based on top k estimations can be efficiently approximated to compute large amount of results by aggregating the sorted results into groups. Specifically, we can divide the sorted results into M parts of the same size p so that $Mp = N$. Then we get the approximated AUUC:

$$AUUC \approx \frac{1}{2M} \sum_{m=1}^{M} [V(m \cdot p) + V((m-1) \cdot p)].$$

Finally, the qini coefficient is defined as:

$$QINI = AUUC - AUUC_{rand},$$

where AUUC$_{rand}$ is the AUUC of a model sorting the data randomly:

$$AUUC_{rand} = \frac{1}{2}(\frac{R_T}{N_T} - \frac{R_C}{N_C}).$$

2) **Metric for exposure uplift effect modeling:** As mentioned in Section III-B1, the relationship between exposure uplift effect and uplift effect is $Uplift_E = Uplift \times \frac{N_T}{N_{T_E}}$. Since the metric AUUC is derived from uplift effect $Uplift$ as a cumulative value to measure the performance of uplift models, for the evaluation of exposure uplift effect of an uplift model, it is natural to consider the exposure factor in AUUC calculation. Therefore, we revise AUUC and define AUUCE for exposure uplift effect to measure the performance of exposure uplift model. For exposure part in treatment group, the exposure coefficient of top k is calculated as $\xi(k) = \frac{N_T(D,k)}{N_{T_E}(D,k)}$, therefore we can compute the exposure conversion rate gain as:

$$\begin{aligned} V_E(k) &= (\frac{R_T(D,k)}{N_T(D,k)} - \frac{R_C(D,k)}{N_C(D,k)}) \times \frac{N_T(D,k)}{N_{T_E}(D,k)} \times \phi(k) \\ &= V(k) \times \xi(k). \end{aligned}$$

Again, we set $V_E(0) = 0$ and AUUCE can be calculated as:

$$AUUCE = \frac{1}{2N} \sum_{k=1}^{n} [V_E(k) + V_E(k-1)],$$

which measures the area below the curve of the exposure conversion uplift gain $V_E(k)$.

Similarly we can approximate AUUCE for large-scale results by aggregating the sorted results into M groups with the same size p:

$$AUUCE \approx \frac{1}{2M} \sum_{m=1}^{M} [V_E(m \cdot p) + V_E((m-1) \cdot p)].$$

The corresponding qini coefficients based on AUUCE is calculated as:

$$QINIE = AUUCE - AUUCE_{rand},$$

where AUUCE$_{rand}$ is calculated as:

$$AUUCE_{rand} = \frac{\xi(N)}{2} \times (\frac{R_T}{N_T} - \frac{R_C}{N_C}).$$

3) **Example for AUUC and AUUCE:** Suppose we sort the data records with respect to the model estimations and divide the data into $M = 5$ groups of the same size. Let $N_T = 1000$, $N_C = 200, R_T = 100, R_C = 10$, then $N = N_T + N_C = 1200$, and $p = N/M = 240$. For the M groups, assuming that $N_T(D) = \{220, 440, 640, 820, 1000\}$, $N_C(D) = \{20, 40, 80, 140, 200\}$, $R_T(D) = \{33, 59, 80, 90, 100\}$, $R_C(D) = \{1, 2, 4, 7, 10\}$, then $\phi = \{0.2, 0.4, 0.6, 0.8, 1.0\}$, $V = \{0.02, 0.0336, 0.045, 0.048, 0.05\}$. Follow the definition we can calculate $AUUC = 0.0343$, $AUUC_{rand} = 0.025$, and $QINI = 0.0093$.

Similarly, to calculate AUUCE, suppose that we have $N_{T_E} = 700$ and $N_{T_E}(D) = \{140, 280, 420, 560, 700\}$, then we can calculate that $\xi = \{1.57, 1.57, 1.52, 1.46, 1.43\}$. It follows that $V_E = \{0.0314, 0.05275, 0.0684, 0.07008, 0.0715\}$, and then we can calculate $AUUCE = 0.05168$, $AUUCE_{rand} = 0.0357$, and $QINIE = 0.01598$.

By comparing AUUC and AUUCE, we can see that by correcting the exposure bias, AUUCE can better reflect the performance of the underlying uplift effect estimations. In this paper, we use both to investigate various modeling approaches. Since AUUC$_{rand}$ and AUUCE$_{rand}$ are constant on the same data set, we will just focus on the QINI and QINIE as the main evaluation metrics.

C. Comparison methods

We compare EUEN and EEUEN with current approaches designed for uplift effect modeling with neural networks based on the QINI metric for uplift effect modeling and the QINIE metric for exposure uplift effect modeling. Note that QINI and QINIE are based on AUUC and AUUCE, respectively. Since AUUC$_{rand}$ and AUUCE$_{rand}$ are fixed for the same data set, we only report QINI and QINIE as the main evaluation criterion. We will discuss more details in our result analyses.

Tarnet [22, 23] is a two-head network for uplift effect learning without any group balance learning design, which can be seen as a network based on T-learner[13]. This method is used as the baseline to evaluate the relative improvements of all methods.

CFRNet [22] is a neural network like Tarnet, but considering the group balance learning by adding a distance constrained regular term to feature representation.

GANITE [27] is motivated by the possibility that the uncertainty in the counterfactual distributions can be captured using a Generative Adversarial Nets (GAN). It consists of a generator for counterfactual outcomes learning, a discriminator for group propensity and an inference block for conversion learning.

Dragonnet [23] is based on Tarnet with neural networks. The model considers the group propensity learning and implements some regularization in estimating potential treatment outcomes to study the uplift effects.

CEVAE [18] is a model based on Variational Autoencoders (VAE). The model adopts neural networks to model treatment assignment propensity and follows the causal structure of inference with proxies.

D. Setup

All experiments are implemented with TensorFlow[3] and the same computing environments[4]. We use different strategies to setup the empirical studies for the two data sets.

[3] https://www.tensorflow.org

[4] A distributed cluster with 4 parameter servers, 8 (CRITEO-UPLIFT1) / 16 (EC-LIFT) workers, and 16 CPU cores and 61 GB memory for each node.

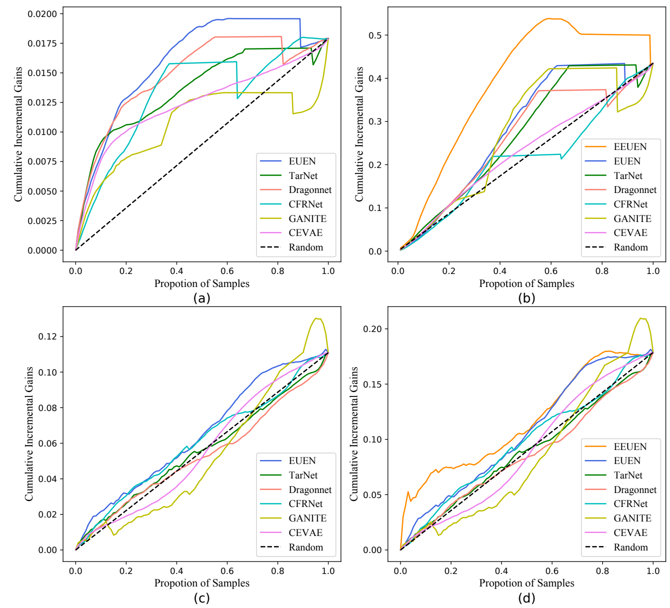


Fig. 3: The performance of difference models. AUUC related curve (a, c), AUUCE related curve (b, d). Data set CRITEO-UPLIFT1 (a, b), EC-LIFT (c, d).

1) CRITEO-UPLIFT1: We use the *visit* label as the target to model uplift effect, and randomly split the data with ratio 80/20% for training and testing, respectively. All the dense features in training set are normalized with 0 mean and 1 standard deviation, and then the features in the testing set are normalized with the same mean and standard deviation as the training set. The embeddings of sparse features will be learned in our methods. The bottom layer size is set to 64 for input feature vectors, and three layers are used for all sub-networks in the most models. We use Adam [12] as the optimizer with learning rate as $0.001/8$, where eight distributed workers are used for TensorFlow computation. We conduct experiments for ten times per model and then report average performance and important statistics.

2) EC-LIFT: We use independent training set and testing set through time division, where training set is selected from the day 1 to the day 4, and testing set is selected from the day 5. The bottom layer size for feature embedding is set to 512 and four layers are used for all sub-networks in all models. We still use Adam as the optimizer with learning rate as $0.001/16$ and sixteen workers. We conduct experiments for five times per model and report statistics based on all results.

More details about our implementation and parameters for reproducing our results will be shared together with our source codes once the paper is published.

E. Result

Model performance. The results in Table II and Table III show that our models perform well in different scenarios for uplift modeling. In comparison with other models, our proposed model EUEN has significant advantages due to the effectiveness of explicit modeling. In addition, Table III shows that, to model the real exposure uplift effect, it is necessary

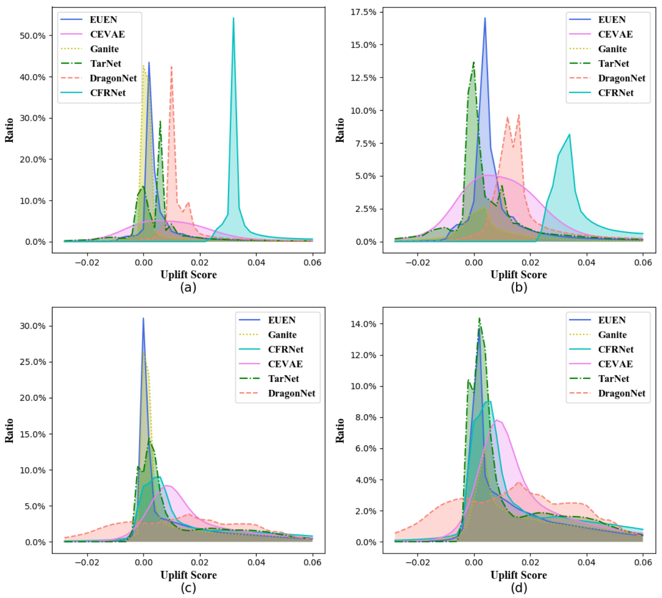


Fig. 4: The distribution of estimated uplift scores before (a, c) and after (b, d) removing noise values on CRITEO-UPLIFT1 (a, b) and EC-LIFT (c, d).

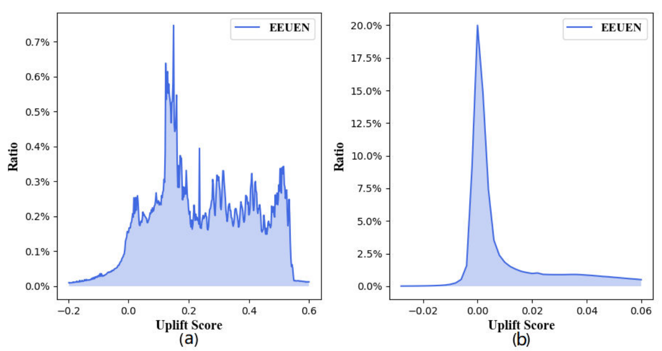


Fig. 5: The estimated uplift score distribution of the EEUEN. CRITEO-UPLIFT1 (a), which some aggregation points are removed. EC-LIFT (b).

TABLE II: Comparison of QINI, where the AUUC$_{rand}$ of CRITEO-UPLIFT1 and EC-LIFT are 91.3×10^{-4} and 81.3×10^{-4} respectively. Values in bold indicate the best performance in comparison with the baseline TarNet.

Models	CRITEO-UPLIFT1 QINI mean±std(10^{-4})	CRITEO-UPLIFT1 QINI Gains(%)	EC-LIFT QINI mean±std(10^{-4})	EC-LIFT QINI Gains(%)
EUEN*	**62.2±1.53**	**21.7**	**54.6±0.66**	**20.53**
TarNet	51.1±4.11	-	45.3±22.4	-
CFRNet	49.9±5.92	-2.35	46.6±24.2	2.87
GANITE	11.7±1.93	-77.1	37.3±13	-17.66
DragonNet	58.2±9.84	13.89	36.9±85.6	-18.54
CEVAE	45.5±4.01	-10.96	44.9±1.32	-0.88

to take ad exposure into account. Our model EEUEN can improve QINIE which measure the performance in exposure uplift modeling compared with other models without considering the exposure bias. The uplift curves shown in Figure 3

TABLE III: Comparison of QINIE, where the AUUCE$_{rand}$ of CRITEO-UPLIFT1 and EC-LIFT are 2217×10^{-4} and 138×10^{-4} respectively. Values in bold indicate the best performance compared with the baseline TarNet.

Models	CRITEO-UPLIFT1 QINIE mean±std (10^{-4})	CRITEO-UPLIFT1 QINIE Gains(%)	EC-LIFT QINIE mean±std (10^{-4})	EC-LIFT QINIE Gains(%)
EEUEN*	**939±60.8**	**121.99**	**132±2.87**	**59.04**
EUEN*	620±24.1	46.57	105±1.07	26.51
TarNet	423±113	-	83±6.84	-
CFRNet	404±34.2	-4.49	89±6.83	7.23
GANITE	-303±363	-171.63	78±24.3	-6.02
DragonNet	520±186	22.93	80±17.2	-3.61
CEVAE	260±99.3	-38.53	85±4.58	2.41

demonstrate that the modeling performance changes with the proportion of samples, and our models exhibit consistent advantages in AUUC and AUUCE curves on both data sets.

In order to further investigate the performance of the EEUEN method for the uplift modeling, we evaluate the QINI performance of $\tau_e(X)$ and $\tau_e(X) \cdot \omega(X)$. As shown in Table IV, the multiplication approach achieves results similar to that of EUEN on both data sets in Table II. This observation demonstrates the flexible design and better comprehensive performance of the EEUEN method. However, without correcting the exposure bias, the performance of $\tau_e(X)$ is significantly worse. Therefore, this paper develops the EEUEN model by considering the exposure bias and demonstrates its improved performance in Table III for modeling exposure uplift effect.

TABLE IV: The QINI of different estimation functions.

Datasets	CRITEO-LIFT1 mean±std (10^{-4})	EC-LIFT mean±std (10^{-4})
$\tau_e(X)$	53.7±1.92	47.4±0.68
$\omega(X) \cdot \tau_e(X)$	64.8±3.28	52.5±0.26

R-square analysis. We analyze the R-square of the predicted mean value and the lift value after sorting them according to the predicted value and dividing them into 20 sub bins with the same sample size. As shown in Table V and Table VI, most of the models can capture the expected patterns in the estimation of uplift effect. For exposure uplift effect, the performance of CRITEO-UPLIFT1 is relatively poor, while the performance of EC-LIFT is still very good. This can be caused by the extremely low exposure ratio in the CRITEO-UPLIFT1 data, where considerable amount of noise can affect the modeling of real exposure uplift effect. These observations show that correcting exposure bias and sufficient exposure records are both very important to measure the real exposure uplift effect.

Distribution of model estimations. Another analysis is the distribution of model estimations. As shown in Figure 4, the estimations of most models are very concentrated, except for CEVAE. Due to its modeling design, CEVAE estimate approximately follows normal distribution. Also, there is no obvious concentration intervals in the results of Dragonnet on the EC-LIFT data set. The estimation distribution of EEUEN is shown in Figure 5. For CRITEO-UPLIFT1 data, the EEUEN estimation distribution is reasonably flat except few outliers. For EC-LIFT data, the EEUEN estimation distribution has a small concentrated interval but is mostly flat elsewhere. In practice, a flat estimation distribution with few concentration intervals is of great interest to support decision optimization tasks for online advertising. Our models as well as other methods can be further improved by incorporating the desired distribution patterns as regularization terms or constraints in the learning process.

Analysis of propensity learning. For those models (i.e., TarNet, GANITE, CEVAE and DragonNet) relying on propensity learning to make a balance for more accurate uplift modeling, we check the learnability of treatment assignment. It turns out that propensity learning achieves a low AUC about 0.58 in CRITEO-UPLIFT1 and about 0.76 in EC-LIFT. The later is relatively higher mostly due to the rich and consistent information about users and ads in our EC-LIFT data where we run the RCTs for relatively longer periods. Overall, these results show that the treatment assignment cannot be accurately learned all the time, especially in dynamic and large-scale online environments. With the data collected by RCTs, we propose not to solely rely on the learning of treatment propensity for uplift modeling. For instance, in this paper, we consider joint and explicit learning of the uplift effect by correcting significant biases.

TABLE V: R^2 between predicted and observed uplift effect.

Models	CRITEO-UPLIFT1	EC-LIFT
EUEN*	0.922	0.989
TarNet	0.449	0.983
CFRNet	0.972	0.975
GANITE	0.240	0.946
DragonNet	0.938	0.806
CEVAE	0.800	0.965

TABLE VI: R^2 between predicted and observed exposure uplift effect.

Models	CRITEO-UPLIFT1	EC-LIFT
EEUEN*	0.017	0.981
EUEN*	0.020	0.989
TarNet	0.000	0.973
CFRNet	0.118	0.966
GANITE	0.062	0.946
DragonNet	0.035	0.802
CEVAE	0.173	0.966

F. Discussion

Uplift modeling with real-world and large-scale ad data is an important task for online advertising. Particularly, for the exposure uplift effect, we need to pay close attention to the effect difference between the ad exposure and non exposure, so we need to redesign our modeling strategy to support the estimation of exposure uplift effect. In comparison with previous methods without considering the exposure effect, our solution can effectively model the exposure uplift effect with good performances according to our comprehensive results.

Scalability and flexibility. We design the EUEN and EEUEN to model the (exposure) uplift effect to support large-scale online advertising applications. In fact, both EUEN and EEUEN adopt joint learning and sparse feature embedding component to enhance scalability. For example, the embedding layers can explicitly distinguish the ‘exposed’ contexts and ‘unexposed’ contexts for differential representation learning of the relevant features. At the same time, it allows better attention learning for sequential features, such as Transformer [26]. For the problem of propensity learning and group balance mentioned in Section II-B, we can introduce it into the underlying input and modify it in the target design. Overall, these extensible methods can be combined flexibly to support various interesting research and application tasks.

Simplicity and efficiency for online inference. Real-world advertising platform has strict requirement on responsive time in production (e.g less than 10ms per request). Our EUEN and EEUEN models only need the uplift sub-network to support real-time inference of the uplift score, which greatly reduces the operational complexity. With our implementation, each request takes about 1ms in our advertising system. To achieve such simplicity and efficiency, we model the uplift effect with the end-to-end function τ explicitly, and the final model for online inference is very lightweight in implementation.

Business implications and extensions. This paper mainly focuses on explicit and exposure uplift modeling by addressing the group homogeneity bias. Our contributions are important for practical and long-term RCT designs. For instance, we show that the RCT should be implemented as the very last component of the advertisement allocation pipeline. In view of the state-of-the-art research on causal effect and uplift modeling, we plan to further consider practical problems encountered in the actual industrial scenarios to extend our work. For example, one direction is to combine the attention mechanism to better learn from informative and sequential features. Meanwhile, for the problem of sparse and extremely unbalanced treatment outcomes, we can optimize the model by introducing auxiliary learning tasks to correct biases in the unbalanced data. In terms of methodology, we can adopt recent advances in multi-task learning to simultaneously estimate the important functions in our model.

VI. Conclusion

In this paper, we first propose an effective model, EUEN, for explicit modeling of the uplift effect in large-scale online advertising and marketing. To correct the exposure bias, we then propose an extended model, EEUEN, for modeling the real exposure uplift effect. Finally, we evaluate our approaches with real-world data and metrics such as QINI and QINIE to study the exposure uplift effect. The significant improvements in our results clearly show the effectiveness and advantages of our approaches. Overall, this paper develops novel and effective models to investigate exposure uplift effect for online advertising and marketing applications.

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