

Real Negatives Matter: Continuous Training with Real Negatives for Delayed Feedback Modeling

Siyu Gu*, Xiang-Rong Sheng*, Ying Fan, Guorui Zhou, Xiaoqiang Zhu
 {wushang.gsy,xiangrong.sxr,fanying.fy,guorui.xgr,xiaoqiang.zxq}@alibaba-inc.com
 Alibaba Group
 Beijing, China

ABSTRACT

One of the difficulties of conversion rate (CVR) prediction is that the conversions can delay and take place long after the clicks. The delayed feedback poses a challenge: fresh data are beneficial to continuous training but may not have complete label information at the time they are ingested into the training pipeline. To balance model freshness and label certainty, previous methods set a short waiting window or even do not wait for the conversion signal. If conversion happens outside the waiting window, this sample will be duplicated and ingested into the training pipeline with a positive label. However, these methods have some issues. First, they assume the observed feature distribution remains the same as the actual distribution. But this assumption does not hold due to the ingestion of duplicated samples. Second, the certainty of the conversion action only comes from the positives. But the positives are scarce as conversions are sparse in commercial systems. These issues induce bias during the modeling of delayed feedback. In this paper, we propose **DE**layed **FE**edback modeling with **R**eal negatives (**DEFER**) method to address these issues. The proposed method ingests real negative samples into the training pipeline. The ingestion of real negatives ensures the observed feature distribution is equivalent to the actual distribution, thus reducing the bias. The ingestion of real negatives also brings more certainty information of the conversion. To correct the distribution shift, **DEFER** employs importance sampling to weigh the loss function. Experimental results on industrial datasets validate the superiority of **DEFER**. **DEFER** have been deployed in the display advertising system of Alibaba, obtaining over 6.0% improvement on CVR in several scenarios. The code and data in this paper are now open-sourced¹.

CCS CONCEPTS

• **Information systems** → **Computational advertising**.

¹<https://github.com/gusuperstar/defer.git>

*Both authors contributed equally to this research.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Woodstock '18, June 03–05, 2018, Woodstock, NY

© 2018 Association for Computing Machinery.

ACM ISBN 978-1-4503-XXXX-X/18/06...\$15.00

<https://doi.org/10.1145/1122445.1122456>

KEYWORDS

Delayed Feedback, Continuous Learning, Display Advertising

ACM Reference Format:

Siyu Gu*, Xiang-Rong Sheng*, Ying Fan, Guorui Zhou, Xiaoqiang Zhu. 2018. Real Negatives Matter: Continuous Training with Real Negatives for Delayed Feedback Modeling. In *Woodstock '18: ACM Symposium on Neural Gaze Detection*, June 03–05, 2018, Woodstock, NY. ACM, New York, NY, USA, 9 pages. <https://doi.org/10.1145/1122445.1122456>

1 INTRODUCTION

Display advertising has involved the use of the internet as a medium to obtain website traffic and deliver marketing messages [3, 6, 8, 27, 28]. Cost-per-conversion (CPA) is a widely used performance-dependent payment model in display advertising, where advertisers bid for predefined conversion actions, such as purchases and adding items to the cart. The systems then convert the bids to effective cost per mille (eCPM) depending on the predicted CVR. Thus, estimating accurate CVR is of importance for a competitive advertising system.

In display advertising, the data distribution is dynamically shifting due to the special events, change of active advertisers, ad campaigns, and users. To catch up with the distribution shift, the model often updates continuously to keep fresh [12, 16]. Most industrial systems adopt continuous training for click-through rate (CTR) and CVR prediction: the training pipeline waits for a time window before assigning a label to the sample. If a click or conversion happens within the window, it will be labeled as positive, else as negative. Samples are then ingested into the training pipeline.

However, different from CTR prediction modeling, there exists a severe **delayed feedback** problem in CVR prediction modeling: the conversion action may occur hours or days later. For samples clicked near the training timing, it might be mistakenly labeled as a negative due to the conversion waiting time being too short. Thus, although benefited from real-time training, a short waiting time window introduces *fake negatives* [12], which are referred to as incorrectly labeled negative samples, while a long window keeps the correctness but loses freshness.

Previous methods [12, 24] address delayed feedback for continuous training by redesigning the data pipeline and loss function. To ensure the model training on the fresh data stream, they set a short window to wait for some immediate conversions or even don't wait for any delayed conversion at all. If the actual conversion does not occur within the waiting window, the corresponding sample will be labeled as a negative one and ingested into the training pipeline. Then once the conversion happens, the same data will be duplicated and ingested into the training pipeline with a positive label. The duplication provides more certainty of the conversion action. Since there exists a disparity between the observed distribution and the

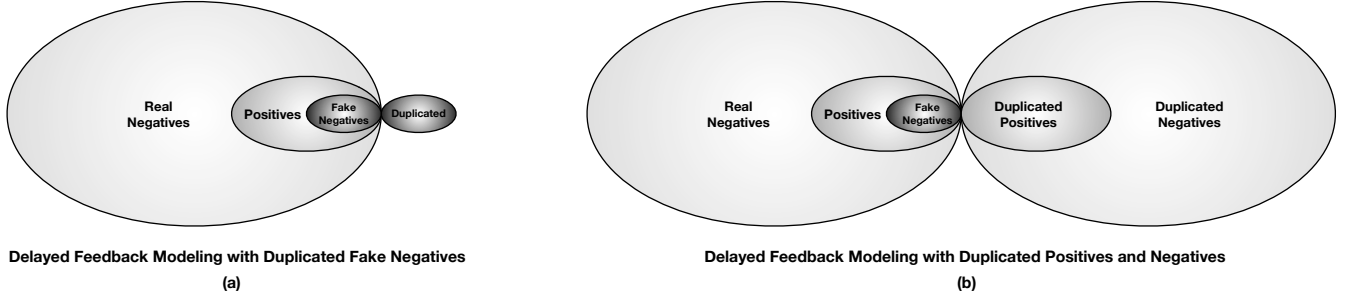


Figure 1: (a): Data pipeline of previous online delayed feedback methods, which duplicate fake negative samples with positive labels. (b) Data pipeline of the proposed method. The proposed method duplicate both positives and real negatives. After the duplication, the feature distribution remains the same as the actual distribution.

actual distribution, importance sampling methods are employed to weigh the loss function. However, previous methods still have some issues. First, the ingestion of duplicated positives changes the feature distribution. But these methods assume the observed feature distribution remains the same, which increases the bias. Second, the certainty of the conversion action only comes from the scarce positive labels, making the model hard to learn and perform well.

In this paper, we propose **DE**layed **FE**edback modeling with **R**eal negatives (**DEFER**) for online CVR prediction, which tackles the previous issues by ingesting duplicated real negatives. Concretely, negatives that the conversions do not occur eventually will be duplicated and ingested into the training pipeline. The ingestion of duplicated samples ensures that the observed feature distribution $q(\mathbf{x})$ is equivalent to the actual $p(\mathbf{x})$, thus reducing the bias. Moreover, the ingestion of real negatives provides more label certainty, facilitating the modeling of delayed feedback. With the ingestion of real negatives, the proposed DEFER method employs importance sampling to correct the distribution shift. Since the delay time of real negatives equals to the maximum delay time of positive samples, the model freshness is unlikely to be affected a lot by the real negatives but bring more label certainty to the training algorithm. Experimental results on industrial datasets validate the effectiveness of the proposed DEFER approach. We also illustrate that the ingestion of real negatives can consistently improve previous online delayed feedback methods.

Apart from the proposed method for online CVR prediction, we also share our practices on deployment for commercial platforms with different conversion *attribution mechanisms* and business demands. The attribution mechanism is the mechanism used to assign credit for a conversion [12, 23]. The attribution mechanism includes an attribution window: a conversion is attributed to a click only if it occurred within this time window. We split the deployment setting with different attribution windows and business demand into 3 types and give the corresponding solution. (1) For business scenarios with a short attribution window, e.g., 1 day, we employ continuous training with the proposed DEFER method. (2) For business scenarios with a long attribution window, e.g., 7 days, the ingestion of duplicated samples may increase additional infrastructure cost on maintaining data caches. We set a window shorter than the attribution window to approximate the duplicated samples.

We empirically found the approximation can achieve comparable performance for scenarios with a long attribution window. (3) Although continuous training is better for CVR prediction, in some industrial scenarios, the model is trained on data of a long duration daily or weekly considering the business requirements and resource consumption of real-time updates. Here, we refer to this paradigm as offline training. Offline training loses freshness but have more correct labels. In this situation, continuous training methods are not suitable. For commercial platforms that cannot deploy continuous training, we also give an offline training solution to address the delayed feedback problem which has been proved to be useful in some scenarios of our display advertising system.

The main contributions of this paper are summarized as follow:

- We stress the importance of real negatives in continuous CVR training. The real negatives are duplicated and ingested into the training pipeline. The ingestion of real negatives eliminates the bias in feature distribution introduced by the duplication of positive samples, which is ignored by previous methods. Moreover, it provides more certain information about the conversion signals, facilitating the modeling of delayed feedback. We further develop an importance sampling method to model the CVR.
- We conduct experiments on industrial datasets and deploy the algorithm in the display advertising system of Alibaba. The consistent superiority validates the efficacy of DEFER and the ingestion of real negatives consistently improves previous delayed feedback methods. During online experiments, the deployment of the proposed method obtains over 6.0% CVR improvement in several scenarios. The code and data for the experiments are now publicly available.
- We share our deployment experiences for commercial platforms with different conversion attribution mechanisms and production budgets. Continuous training and offline training practices are both shared. The practical experience gained in our deployment generalizes to other setups and is thus of interest to both researchers and industrial practitioners.

2 RELATED WORK

Some previous works on CVR prediction do not focus on the delayed feedback problem [13, 14, 17, 19]. These method are not trained continuously and ignore the falsely labeled negatives. For example,

if the model is trained on 30 day data and the attribution window is 7 days (the delay between a click and a conversion can never be more than 7 days), then the labels of the negative samples from the last 7 days may be incorrect since the conversion may happen in the future. Note that the negative label is much more likely to be incorrect if the click has just happened.

2.1 Delayed Feedback Models

In display advertising, the distribution is dynamically changing due to the change of active advertisers, ad campaigns and users. For example, when new ad campaigns are added to the system, models built on past data may not perform as well on those new ad campaigns. To capture the change in data, machine learning models should be updated continuously to keep fresh. To this end, during training, a waiting window can be set: the conversion is attributed to a click once it occurred within this waiting window. Then the fresh samples can be ingested by the training algorithm for continuous training. However, the continuous learning manner may introduce more falsely labeled negative samples (fake negatives) due to the short window. To correct the bias introduced by the fake negatives, delayed feedback models [2, 26] are proposed. The importance of delayed feedback modeling is first emphasized by DFM [2]. In DFM, a negative is treated as unlabeled samples since the conversion has not happened yet. Besides predicting the CVR, DFM also introduces a second model that captures the expected delay between the click and the conversion and assumes the delay distribution follows the exponential distribution. These two models are trained jointly. Note that delayed feedback modeling is also closely related to survival time analysis [5] that studies the distribution of survival times. In practice, the exponential assumption may be violated. To address this issue, Yoshikawa and Imai [26] propose a non-parametric delayed feedback model for CVR prediction that represents the distribution of the time delay without assuming a parametric distribution.

Ktena et al. [12] also adopt a continuous training scheme by ingesting all samples with a negative label initially. If a positive engagement occurs, this sample will be duplicated with positive label and ingested to the training algorithm for the second time. Hence, the biased observed data distribution consists of all samples from the actual data distribution labeled as negatives and the original positive samples. To learn the model from the biased distribution, Ktena et al. [12] proposes two loss function FNW and FNC utilizing importance sampling Bottou et al. [1], Sugiyama et al. [21] to handle the distribution shift. Instead of labeling all samples as negative initially, Yasui et al. [25] propose a feedback shift importance weighting algorithm, in which the model waits for the real conversion in a certain time interval. However, it does not allow the data correction, i.e., duplicated positive samples even a conversion event took place in the future. To find a trade-off between the delay in model training and the fake negative rate, ESDFM [24] models the relationship between the observed conversion distribution and the true conversion distribution.

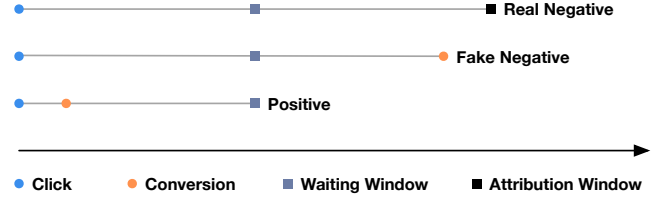


Figure 2: Illustration of the real negative, fake negative and positive. Here, the waiting window is referred to as the time interval between the click time and the time samples ingested into the training pipeline. A real negative is the sample that the conversion does not occur. A fake negative is the sample the conversion occurs outside the waiting window but within the attribution window. A positive is the sample that the conversion occurs within the waiting window.

2.2 Delayed Bandits

There are also some bandit algorithms [10, 18, 22] that investigate the delayed feedback modeling. The objective of these bandit algorithm is to make sequential decisions in order to minimize the cumulative regret. Joulani et al. [10] analyze the effect of delay on the regret of online learning algorithms and shows that the delay increases the regret in a multiplicative way in adversarial problems, and in an additive way in stochastic problems. Pike-Burke et al. [18] study the problems of bandits with delayed, aggregated anonymous feedback. Vernade et al. [22] investigate the stochastic delayed bandit setting and provided a complete analysis under the assumption that the distribution of the delay is known.

3 PRELIMINARY

In this section, we first give a brief introduction about the background of online CVR modeling. Then we introduce how previous methods address the delay feedback issue for CVR prediction.

3.1 Background

In CVR prediction, the model takes input as $(\mathbf{x}, y) \sim (X, Y)$, where \mathbf{x} is the feature and $y \in \{0, 1\}$ is the conversion label. The goal of CVR prediction is to learn a function f with parameter θ that minimize the the generalization error on sample drawn from this data distribution:

$$\mathbb{E}_{(\mathbf{x}, y) \sim (X, Y)} [\ell(\mathbf{x}, y; f_{\theta}(\mathbf{x}))], \quad (1)$$

where ℓ is the loss function.

As the conversion may delay, some of the samples are incorrectly labeled as negatives by traditional supervised learning methods. Denote the duration between the conversion and click as z . If the sample will not have conversion eventually, $z = +\infty$. Let w_1, w_2 be the length of the waiting window and attribution window, respectively ($w_2 > w_1$). As shown in Figure 2, there exist three types of samples in delayed feedback modeling:

- **Real negatives** ($z > w_2$). Real negatives are samples that the conversion does not occur.
- **Fake negatives** ($w_1 < z < w_2$). Fake negatives are samples that the conversion does not occur at the training timing

and are incorrectly labeled as negatives due to the waiting window being too short.

- **Positives** ($z < w_1$). Positives have the conversion action inside the waiting window.

Note that fake negatives are also positive samples but the conversion don't occur inside the waiting window. A naive strategy to reduce the number of fake negatives is to wait for a sufficiently long window to ensure most of the labels are correct. However, in display advertising systems, the data distribution is dynamically changing, e.g., new ad campaigns are added to the systems. To capture the change in data, CVR models should update continuously. As such, it needs to balance between model freshness and label certainty. Previous methods address this problem by setting a short waiting window to wait for the immediate conversions. To correct the label noise, fake negatives are duplicated with a positive label as soon as the engagement takes place [12]. The duplicated samples are ingested into the training pipeline. Hence as shown in Figure 1 (a), the observed distribution contains four parts: real negatives, positives, fake negatives, and duplicated samples that are the duplication of fake negatives but with positive labels. Since directly training with the fake negatives may mislead the direction of optimization, previous methods develop various methods to correct the distribution shift.

3.2 Fake Negative Weighted

Due to the disparity between the observed distribution and actual distribution, importance sampling is adopted to correct the distribution shift. Ktena et al. [12] proposes fake negative weighted (FNW) approach.

The loss function of CVR prediction can be written as:

$$\begin{aligned}
 L &= \mathbb{E}_{(\mathbf{x}, y) \sim p} \ell(\mathbf{x}, y; f_\theta(\mathbf{x})) \\
 &= \iint p(\mathbf{x}) q(y|\mathbf{x}) \frac{p(y|\mathbf{x})}{q(y|\mathbf{x})} \ell(\mathbf{x}, y; f_\theta(\mathbf{x})) d\mathbf{x} dy \\
 &\approx \iint q(\mathbf{x}) q(y|\mathbf{x}) \frac{p(y|\mathbf{x})}{q(y|\mathbf{x})} \ell(\mathbf{x}, y; f_\theta(\mathbf{x})) d\mathbf{x} dy \\
 &= \mathbb{E}_{(\mathbf{x}, y) \sim q} \frac{p(y|\mathbf{x})}{q(y|\mathbf{x})} \ell(\mathbf{x}, y; f_\theta(\mathbf{x})),
 \end{aligned} \tag{2}$$

where q is the biased observed distribution. Due to the ingestion of duplicated positive samples, the observed feature distribution $q(\mathbf{x})$ is not equivalent to the actual feature distribution $p(\mathbf{x})$. FNW assumes that $p(\mathbf{x}) \approx q(\mathbf{x})$, which may introduce additional bias to the delayed feedback modeling.

In FNW, no waiting window is set and samples are immediately ingested with negative labels. As soon as the user engages with the ad, the same data point will be presented to the model with a positive label. Hence we can get: $q(\mathbf{x}|y=0) = p(\mathbf{x})$, $q(\mathbf{x}|y=1) = p(\mathbf{x}|y=1)$, and $q(y=0) = \frac{1}{1+p(y=1)}$. The probability of observing

a conversion in the biased distribution is:

$$\begin{aligned}
 q(y=1|\mathbf{x}) &= \frac{q(y=1)q(\mathbf{x}|y=1)}{q(y=1)q(\mathbf{x}|y=1) + q(y=0)q(\mathbf{x}|y=0)} \\
 &= \frac{\frac{p(y=1)}{1+p(y=1)} p(\mathbf{x}|y=1)}{\frac{p(y=1)}{1+p(y=1)} p(\mathbf{x}|y=1) + \frac{1}{1+p(y=1)} p(\mathbf{x})} \\
 &= \frac{p(y=1)p(\mathbf{x}|y=1)}{p(y=1)p(\mathbf{x}|y=1) + p(\mathbf{x})} \\
 &= \frac{p(y=1|\mathbf{x})}{1 + p(y=1|\mathbf{x})}.
 \end{aligned} \tag{3}$$

Similarly, the probability of observing a negative sample in the biased distribution can be computed as:

$$q(y=0|\mathbf{x}) = \frac{1}{1 + p(y=1|\mathbf{x})}. \tag{4}$$

By replacing Equation 3 and Equation 4 in Equation 2, the loss function can be rewritten as:

$$\begin{aligned}
 L &= - \sum_{\mathbf{x}, y} y(1 + p(y=1|\mathbf{x})) \log f_\theta(\mathbf{x}) \\
 &\quad + (1 - y)p(y=0|\mathbf{x})((1 + p(y=1|\mathbf{x})) \log(1 - f_\theta(\mathbf{x})))
 \end{aligned} \tag{5}$$

Since $p(y=1|\mathbf{x})$ cannot be accessed, FNW replaces it with the model estimate f_θ and stops the gradient propagation through it during training.

3.3 Fake Negative Calibration

Fake negative calibration (FNC) learns a function that directly estimates the biased distribution q . Then FNC obtains the function $p(y=1|\mathbf{x})$ by the following calibration:

$$p(y=1|\mathbf{x}) = \frac{q(y=1|\mathbf{x})}{1 - q(y=1|\mathbf{x})} \tag{6}$$

4 DELAYED FEEDBACK MODELING WITH REAL NEGATIVES

In this section, we present the proposed method, DELayed FEEdback modeling with Real negatives (DEFER) in detail. We first introduce the designed data pipeline in DEFER, which duplicates real negatives to correct the distribution shift. Based on the designed data pipeline, DEFER use importance sampling to correct the distribution shift. Other methods can also be trained with the real negatives and we derive the corresponding loss functions. Finally, we share our deployment experiences for commercial platforms with different conversion attribution mechanisms and production budgets.

4.1 Data Stream

As mentioned above, previous continuous training methods ingest fake negative samples to catch the freshness at the expense of noisy signals. To introduce more certainty conversion information, duplicated samples are ingested and importance sampling is developed to correct the distribution shift. However, these methods have some issues. First, the duplicated samples change the feature distribution. The approximation $q(\mathbf{x}) \approx p(\mathbf{x})$ may introduce additional bias. Moreover, all certain information of the conversion action comes from the positive labels, which are scarce in CVR prediction. This makes the model hard to learn and perform well. To reduce

the bias without hurting the freshness, we ingest both the duplicated positive samples and duplicated real negatives to the training pipeline.

Concretely, in the redesigned data pipeline, we let each sample have a waiting window w_1 to wait for the conversion signal. The waiting window can be the same for all samples or sample-specific. The reason to use a sample-specific window is that different products have different delay distributions. For example, expensive products have longer expected conversion times than cheap products, thus need a longer window to wait for the conversion signal. One strategy to set the sample-specific window is to define multiple window length and train a multi-class classification model $p_{\text{length}}(w_1|\mathbf{x})$ and predict the waiting window length as:

$$w_1 = \arg \max_w p_{\text{waiting}}(w|\mathbf{x}). \quad (7)$$

Samples that have conversion in this window are labeled as positive samples and samples that do not have conversion are fake negatives or real negatives. For those fake negatives, if the conversion occurs later in the attribution window, we will ingest this sample with a positive label into the pipeline. For those real negatives that the conversion does not occur finally, we will also duplicate and ingest them into the training pipeline. The duplication brings more certainty information of the conversion signal. Thus, there are four kinds of samples in the proposed method, as shown in Figure 1 (b), the real negatives, positives, fake negatives, and duplicated samples with the real label (can either be positive or negative).

4.2 Loss Function

Due to the disparity between the observed distribution and the actual distribution, the proposed method uses importance sampling to correct the distribution shift. With the ingestion of duplicated samples, we can get $q(\mathbf{x}) = p(\mathbf{x})$ and the joint probability $q(\mathbf{x}, y = 0)$ can be computed as:

$$q(\mathbf{x}, y = 0) = p(\mathbf{x}, y = 0) + \frac{1}{2}p(\mathbf{x}, y = 1, z > w_1). \quad (8)$$

The conditional probability $q(y = 0|\mathbf{x})$ can be written as:

$$\begin{aligned} q(y = 0|\mathbf{x}) &= \frac{q(\mathbf{x}, y = 0)}{q(\mathbf{x})} \\ &= \frac{p(\mathbf{x}, y = 0) + \frac{1}{2}p(\mathbf{x}, y = 1, z > w_1)}{p(\mathbf{x})} \\ &= p(y = 0|\mathbf{x}) + \frac{1}{2}p_{dp}(\mathbf{x}) \end{aligned} \quad (9)$$

where $p_{dp}(\mathbf{x}) = p(\mathbf{x}, y = 1, z > w_1|\mathbf{x})$ is the probability of \mathbf{x} being a fake negative. Similarly, $q(y = 1|\mathbf{x})$ can be written as:

$$q(y = 1|\mathbf{x}) = p(y = 1|\mathbf{x}) - \frac{1}{2}p_{dp}(\mathbf{x}). \quad (10)$$

Then according to Equation 2, we can compute the importance sampling weights for \mathbf{x} as:

$$\begin{aligned} \frac{p(y = 0|\mathbf{x})}{q(y = 0|\mathbf{x})} &= \frac{p(y = 0|\mathbf{x})}{p(y = 0|\mathbf{x}) + \frac{1}{2}p_{dp}(\mathbf{x})} \\ \frac{p(y = 1|\mathbf{x})}{q(y = 1|\mathbf{x})} &= \frac{p(y = 1|\mathbf{x})}{p(y = 1|\mathbf{x}) - \frac{1}{2}p_{dp}(\mathbf{x})}. \end{aligned} \quad (11)$$

Thus, the importance weighted CVR loss function can be formulated as:

$$\begin{aligned} L &= - \sum_{\mathbf{x}, y} y \frac{p(y = 1|\mathbf{x})}{p(y = 1|\mathbf{x}) - \frac{1}{2}p_{dp}(\mathbf{x})} \log f_{\theta}(\mathbf{x}) \\ &\quad + (1 - y) \frac{p(y = 0|\mathbf{x})}{p(y = 0|\mathbf{x}) + \frac{1}{2}p_{dp}(\mathbf{x})} \log(1 - f_{\theta}(\mathbf{x})). \end{aligned} \quad (12)$$

Since $p(y = 1|\mathbf{x})$, $p(y = 0|\mathbf{x})$ cannot be accessed, we replace $p(y = 1|\mathbf{x})$, $p(y = 0|\mathbf{x})$ with the model estimate $f_{\theta}(\mathbf{x})$ and $1 - f_{\theta}(\mathbf{x})$, respectively. For $p_{dp}(\mathbf{x})$, we train a classifier f_{dp} to predict the probability of \mathbf{x} being a fake negative. As in [12], we stop the gradient propagation through the importance weight. Therefore, Equation 13 can be rewritten as:

$$\begin{aligned} L &= - \sum_{\mathbf{x}, y} y \left[\frac{f_{\theta}(\mathbf{x})}{f_{\theta}(\mathbf{x}) - \frac{1}{2}f_{dp}(\mathbf{x})} \right] \log f_{\theta}(\mathbf{x}) \\ &\quad + (1 - y) \left[\frac{1 - f_{\theta}(\mathbf{x})}{1 - f_{\theta}(\mathbf{x}) + \frac{1}{2}f_{dp}(\mathbf{x})} \right] \log(1 - f_{\theta}(\mathbf{x})), \end{aligned} \quad (13)$$

where $[\cdot]$ means the stop gradient operation.

4.3 Variants

For other methods, like FNW and FNC, the duplicated real negatives can also be ingested to improve learning. We derive the corresponding loss function for FNW and FNC.

4.3.1 *FNW*. For FNW, we have

$$\begin{aligned} q(y = 1|\mathbf{x}) &= \frac{p(y = 1|\mathbf{x})}{1 + p(y = 1|\mathbf{x}) + p(y = 0|\mathbf{x})} \\ &= \frac{p(y = 1|\mathbf{x})}{2} \end{aligned} \quad (14)$$

$$\begin{aligned} q(y = 0|\mathbf{x}) &= \frac{1 + p(y = 0|\mathbf{x})}{1 + p(y = 1|\mathbf{x}) + p(y = 0|\mathbf{x})} \\ &= \frac{1 + p(y = 0|\mathbf{x})}{2} \end{aligned} \quad (15)$$

Then we have

$$\begin{aligned} \frac{p(y = 1|\mathbf{x})}{q(y = 1|\mathbf{x})} &= 2 \\ \frac{p(y = 0|\mathbf{x})}{q(y = 0|\mathbf{x})} &= \frac{2p(y = 0|\mathbf{x})}{1 + p(y = 0|\mathbf{x})} \end{aligned} \quad (16)$$

Finally, the loss function is reformulated as

$$\begin{aligned} L &= - \sum_{\mathbf{x}, y} 2y \log f_{\theta}(\mathbf{x}) \\ &\quad + (1 - y)p(y = 0|\mathbf{x}) \left(\frac{2p(y = 0|\mathbf{x})}{1 + p(y = 0|\mathbf{x})} \right) \log(1 - f_{\theta}(\mathbf{x})) \end{aligned} \quad (17)$$

4.3.2 *FNC*. Similarly, for FNC, we have

$$p(y = 1|\mathbf{x}) = 2q(y = 1|\mathbf{x}) \quad (18)$$

4.4 Production Settings of Real Negatives

In display advertising, different business scenarios often set different attribution window according to the distinct user behaviors. For example, in Alibaba, some business scenarios set 1 day as the attribution window while some business scenarios set 7 days as the attribution window. It is notable that the delay time of real negatives is equal to the maximum delay time of positive samples.

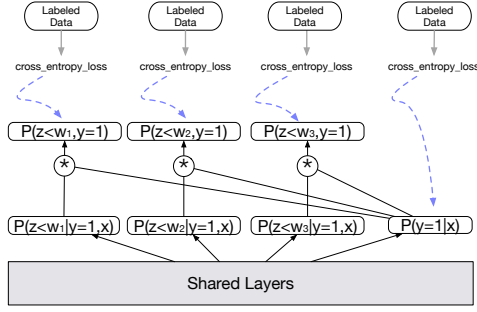


Figure 3: The proposed offline model which uses multi-task learning to improves generalization by leveraging the information contained in the conversion time. One of the head predicts $p(y = 1|x)$, the probability of whether the click will eventually convert. Others predict whether the conversion will occurs within the predefined time windows w_1, w_2, w_3 .

hence the model freshness is unlikely to be affected hugely by the real negatives but brings more label certainty to the training algorithms. For business scenarios with a long conversion window, the ingestion of duplicated samples may increase additional infrastructure cost of maintaining data caches. As such, we approximate the real negatives by setting a shorter window w_3 ($w_1 < w_3 < w_2$) for scenarios with long conversion window. Samples that do not have conversion before w_3 are approximated as real negatives and ingested into the training algorithm. For business scenarios with short attribution window, we employ no approximation and ingest the real negatives. In other words, we divide the online delayed feedback modeling into 2 settings, short attribution and long attribution window. For the first one, we use the model above directly. For the second one, we let the real negative samples be ingested after a time window w_3 ($w_1 < w_3 < w_2$). Similarly, w_3 can be fixed for all samples or predicted by a multi-class classification model:

$$w_3 = \arg \max_w p_{\text{attribution}}(w|x). \quad (19)$$

4.5 Offline Training Method

For commercial platforms that apply offline training, we also propose an approach that has been proved to be useful in some scenarios of our display advertising system.

As shown in Figure 3, the proposed offline approach uses multi-task learning to improves generalization by leveraging the information contained in the conversion time. Concretely, the model has $N + 1$ heads on top of the shared bottom layers. One of the head predicts the probability of whether the click will eventually convert, denoted as $p(y = 1|x)$. Others predict whether the conversion will occurs within the predefined time windows w_1, w_2, \dots, w_N :

$$p(z < w_n, y = 1|x) = p(z < w_n|y = 1, x) * p(y = 1|x). \quad (20)$$

Table 1: Statistics of Criteo and Taobao-30days dataset.

Datasets	#Users	#Items	#Features	#Conversions	#Samples	average CVR	Duration
Criteo	-	5443	17	3.6 million	1.59 million	0.2269	60 days
Taobao-30days	2 million	6.5 million	11	12 million	116 million	0.1034	30 days

Denote y_n the label that whether the sample has conversion in w_n , the loss function can be written as:

$$L = - \sum_n \sum_x y_n \log p(z < w_n, y = 1|x) - \sum_n \sum_x (1 - y_n) \log(1 - p(z < w_n, y = 1|x)) - \sum_x y \log p(y = 1|x) - \sum_x (1 - y) \log(1 - p(y = 1|x)). \quad (21)$$

Since samples that near the end of training date may not have all $N + 1$ labels, we only update the corresponding parameters according to the observed labels. For a sample, if the predefined w_n, \dots, w_N windows have not reached, we only update the parameters through $p(y = 1, z < w_1|x), \dots, p(y = 1, z < w_{n-1}|x)$ using observed labels while block the parameters of other heads. Note that $p(y = 1|x)$ will also be updated through the gradient of $p(y = 1, z < w_1|x), \dots, p(y = 1, z < w_{n-1}|x)$. For example, assuming the attribution window as 7 days, we set 1 day, 3 days, 5 days as three time windows. If there is a sample clicked at the 4th day from the last, we only update the parameters from $p(z < w_1, y = 1|x), p(z < w_2, y = 1|x)$. For samples clicked before the 7th day from the last, all the parameters are updated simultaneously.

5 EXPERIMENTS

We evaluate the efficacy of DEFER in this section. We begin by introducing the setup including the used industrial datasets, construction of data stream, evaluation metrics and compared methods in Sec. 5.1. The results and discussion are elaborated in Sec. 5.2. We also investigate the effect of window size in Sec. 5.3. Experimental results on production environment and our experience in deploying the model are shown in Sec. 5.4.

5.1 Setup

Datasets We experiment with two industrial datasets for evaluation. The characteristics of these datasets are shown in Table 1.

- **Criteo dataset**² is used for our experiments. Criteo dataset contains more than 15 million Criteo live traffic data for 60 days. Most of the features are categorical and the continuous features have been made categorical through appropriate quantization. It also includes the timestamps of the clicks and those of the conversions.
- **Taobao-30days dataset.** The real traffic logs for 30 days are collected from the display advertising system of Alibaba. We sub-sample 20% of the negatives and 1% of the users. The sampled dataset contains about 120 million samples. For this problem, the conversion is attributed to the last click in a

²<https://labs.criteo.com/2013/12/conversion-logs-dataset/>

Table 2: Performance comparisons of different models on Criteo and Taobao-30days dataset. Oracle is the upper bound on the best achievable performance as there are no delayed conversions. Bold indicates top-performing method.

Datasets	Criteo						Taobao-30days					
Metrics	AUC	PRAUC	NLL	RI-AUC	RI-PR-AUC	RI-NLL	AUC	PRAUC	NLL	RI-AUC	RI-PR-AUC	RI-NLL
Pre-trained	0.8075	0.5811	0.5425	0.00%	0.00%	0.00%	0.6087	0.6142	0.7693	0.00%	0.00%	0.00%
Vanilla-NoDup	0.7989	0.5794	0.6149	-24.29%	-2.70%	-47.20%	0.6395	0.6442	0.7754	68.44%	75.38%	-4.85%
Vanilla-NoWin	0.8347	0.6189	0.4302	76.84%	60.00%	73.21%	0.6368	0.6395	0.7444	62.44%	63.57%	19.81%
Vanilla-Win	0.8348	0.6251	0.4079	77.12%	69.84%	87.74%	0.6427	0.6474	0.6756	75.56%	83.42%	74.54%
Vanilla-RN	0.8351	0.6266	0.4562	77.97%	72.22%	56.26%	0.6446	0.6496	0.6707	79.78%	88.94%	78.44%
FNC	0.8347	0.6189	0.4659	76.84%	60.00%	49.93%	0.6368	0.6395	0.7196	62.44%	63.57%	39.54%
FNC-RN	0.8370	0.6299	0.4103	83.33%	77.46%	86.18%	0.6411	0.6447	0.6710	72.00%	76.63%	78.20%
FNW	0.8348	0.6262	0.4006	77.12%	71.59%	92.50%	0.6440	0.6477	0.6589	78.44%	84.17%	87.83%
FNW-RN	0.8372	0.6326	0.3970	83.90%	81.75%	94.85%	0.6458	0.6499	0.6592	82.44%	89.70%	87.59%
ES-DFM	0.8373	0.6347	0.3956	84.18%	85.08%	95.76%	0.6453	0.6476	0.6560	81.33%	83.92%	90.14%
DEFER	0.8394	0.6367	0.3943	90.11%	88.25%	96.61%	0.6483	0.6497	0.6550	88.00%	89.20%	90.93%
Oracle	0.8429	0.6441	0.3891	100.00%	100.00%	100.00%	0.6537	0.6540	0.6436	100.00%	100.00%	100.00%

period of 7 days. The dataset has 6 groups of user features and 5 groups of item features.

Data Stream We divide all datasets into two parts to simulate the continuous training paradigm. The first part of data is used for pre-training the model to obtain a good initialization for continuous training. Note that in case of label leaking, we set the labels as 0 if the conversion occurs in the second part of the data. The models are then trained and evaluated on the second part. According to the click timestamp in the datasets, we divide the second part of data into multiple pieces, each of which contains data of one hour. Following the online training manner of industrial systems, we train models on the t -th hour data and test them on the $t + 1$ -th hour. The reported metrics are the weighted average across different hours on streaming data.

Evaluation Metrics AUC, PR-AUC and negative log likelihood (NLL) are adopted for evaluation on offline dataset.

- AUC [4] is a widely used metric in CTR and CVR prediction task [12, 14, 20, 29, 30], which denotes the probability that a positive sample is ranked higher than a negative sample.
- Area under the Precision-Recall Curve (PR-AUC) is shown to be more sensitive than AUC in the case where there are a lot more negative samples than the positive samples.
- Negative log likelihood (NLL) is a standard measure of a probabilistic model's quality [7]. It is sensitive to the absolute value of the predictions [2].

We also compute the relative improvement of each model over the pre-trained model. Denote RI-AUC the relative improvement of AUC, RI-AUC_{DEFER} can be computed as:

$$\text{RI-AUC}_{\text{Defer}} = \frac{\text{AUC}_{\text{Defer}} - \text{AUC}_{\text{Pre-trained}}}{\text{AUC}_{\text{Oracle}} - \text{AUC}_{\text{Pre-trained}}} \times 100\%,$$

where $|\text{AUC}_{\text{Oracle}} - \text{AUC}_{\text{Pre-trained}}|$ means how much we can improve over the pre-trained model and $|\text{AUC}_{\text{Defer}} - \text{AUC}_{\text{Pre-trained}}|$ means how much DEFER improves over the pre-trained model. Note that the closer the relative improvement to 100%, the better the method performs. The relative improvement of PR-AUC (RI-PR-AUC) and NLL (RI-NLL) are computed similarly.

For online A/B testing, we report the CVR. The online CVR reflects the actual performance that determines which approach is the most suitable for the system.

Compared Methods In order to evaluate the performance of the proposed DEFER approach, the following methods are implemented and compared:

- **Pre-trained:** The pre-trained model is trained on the data before the streaming data.
- **Vanilla-NoDup:** Vanilla-NoDup is the online learning model trained on streaming data with a waiting window but without duplicated samples. A sample that has conversion in the waiting window is labeled as positive, else as negative.
- **Vanilla-NoWin:** This method is trained on streaming data without waiting window. Samples are immediately ingested with negative labels and then insert a positive duplication when conversion happens.
- **Vanilla-Win:** Vanilla-Win is trained on streaming data with a waiting window. The positive samples are duplicated and ingested after the window.
- **Vanilla-RN:** Vanilla-RN is also trained on streaming data with a waiting window. Positives and real negatives are duplicated and ingested after the window.
- **FNW** [12]: FNW is trained on the same streaming data as Vanilla-NoWin. The loss function is the importance weighted loss.
- **FNW-RN:** Compared with FNW, FNW-RN additionally uses the duplicated real negatives.
- **FNC** [12]: FNC is trained on the same streaming data as Vanilla-NoWin.
- **FNC-RN:** Compared with FNC, FNC-RN additionally use the duplicated real negatives.
- **ES-DFM** [24]: ES-DFM is trained on the same streaming data as Vanilla-Win. The loss function is the ES-DFM loss.
- **DEFER:** The proposed DEFER method is trained on the same streaming data as Vanilla-RN but with the proposed loss function.

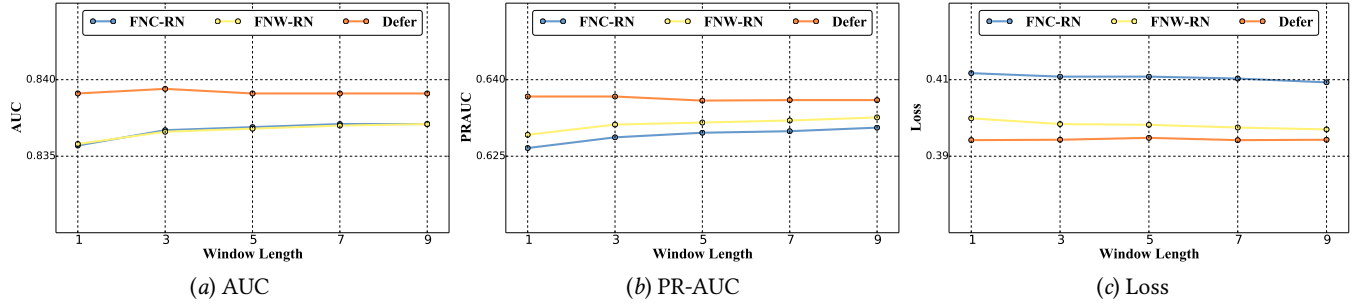


Figure 4: The effect of different window length for approximating the real negatives.

- **Oracle:** The oracle can access the true label, i.e., it can look into the future to determine if there will be a conversion. This is the upper bound on the best achievable performance as there are no delayed conversions for oracle.

Note that all Vanilla- $\{\cdot\}$ methods use the vanilla log loss function while FNW, FNW-RN, ESDFM, and DEFER use the importance weighted loss function. FNC and FNC-RN are trained with the vanilla log loss function but apply the probability calibration.

Implementation Details We implement the CVR model as a deep neural network. The features are transformed to embedding vectors firstly and then fed to fully-connected layers. The hidden units are fixed for all models with hidden size $\{256, 256, 128\}$. The activation functions are Leaky ReLU [15]. For each hidden layer, we also apply batch normalization [9] to accelerate the model training. All methods are trained with Adam [11] for optimization. Following ES-DFM [24], the waiting window z_1 is set as 0.25 hour. To give a fair comparison, all hyper-parameters are tuned carefully for all compared methods. For methods that use the real negatives, the window z_3 to approximate the real negatives is also tuned fairly and we report the results at the best window length.

5.2 Results

We evaluate all approaches on the Criteo and Taobao-30days dataset. The result is reported in Table 2. Except for the close PRAUC compared with FNW-RN on Taobao-30days, the proposed method almost consistently outperforms other approaches on all performance metrics, which validates the effectiveness of DEFER. We analyze the results from various aspects.

Continuous training with duplicated samples contributes to the performance lift. It is notable that all continuous training methods, except for Vanilla-NoDup, outperform the pre-trained method, especially on NLL. Compared with FNW and FNC, Vanilla-NoDup performs poorly since positives outside the waiting window are not corrected, making the observed distribution deviate much from the actual distribution. These results demonstrate the importance of continuous training on real-time samples and duplicated samples. We also notice that Vanilla-Win is better than Vanilla-NoWin, which suggests **the waiting window in the training pipeline is crucial** as it provides more label correctness. The comparison between FNW and ES-DFM also indicates the importance of the waiting window.

Note that all methods using the duplicated real negatives (Vanilla-RN, FNC-RN, FNW-RN, DEFER) achieve better performance than

the counterpart methods trained without the real negatives (Vanilla-Win, FNC, FNW, ES-DFM). **The consistent superiority validates the effectiveness of ingesting real negatives** as it reduces the bias and introduces more certain conversion information. We also notice that the Vanilla-NoDup performs worse on Criteo than on Taobao-30days, which result from the different conversion distributions. On Criteo, the delayed feedback is more serious, where only 35% conversions happen in 0.25 hours. By contrast, about 55% conversions take place in 0.25 hours on Taobao-30days. This also validates the importance of duplicating samples with real labels when facing severely delayed feedback.

The comparison between Vanilla-NoWin, FNC, and FNW indicates **the necessity of designing appropriate loss functions**. The gap between Vanilla-Win and ES-DFM and the gap between Vanilla-RN and DEFER also validate the effect of importance sampling to correct the distribution shift. Finally, the relative metrics among Oracle, Pre-trained, and DEFER demonstrate that the gap is narrowed down by the proposed method significantly.

5.3 Analysis of Window Length z_3

A short window for approximating the real negatives can reduce the cost of maintaining data caches but could also introduce fake negatives. We study the effect and sensitivity of different window length z_3 for approximating the real negatives.

To this purpose, FNW-RN, FNC-RN, and DEFER are trained with $z_3 = \{1, 3, 5, 7, 9\}$ days on the Criteo dataset. As shown in Figure 4, DEFER achieves the best performance with window length $z_3 = 3$, while FNW-RN and FNC-RN achieve the best performance with $z_3 = 9$. Note that all evaluation metrics of the three methods stay stable with window lengths longer than 3 days. The results suggest that we can approximate the real negatives with a relatively short window length. It can also be inferred that the freshness of the training data is already captured when the samples are firstly ingested into the training pipeline. The duplicated samples mainly help eliminate the bias in the observed distribution and reduce the uncertainty. Since the ingestion of real negatives with long window length improve little but consume much more resources, we can choose a suitable short window in industrial practice.

5.4 Deployment

5.4.1 Online Serving with Continuous Training. To verify the effectiveness of our continuous training method, we conduct experiments on 2 scenarios of the display advertising system of Alibaba.

In both scenarios, the goal of the CVR model is to estimate the probability of *Adding To Cart* and the attribution window of conversion is 1 day. Compared with the pre-trained model, we observe 8.5% improvement on CVR during the online A/B testing. The model has been successfully deployed into production, serving the main traffics for these scenarios.

5.4.2 Online Serving with Offline Training. We evaluate the proposed multi-task approach on a scenario of our display advertising system that uses offline training. The goal of CVR prediction is to estimate the probability of *Purchase* and the attribution window of conversion is 7 days. The model is trained on data of 30 days and test on the data of the following date. The AUC of the proposed approach and the baseline model using vanilla log loss are 0.8385 and 0.8347 respectively. During the online A/B testing, we observe 6% improvement on CVR. The model has also been successfully deployed into production, serving the main traffic.

6 CONCLUSION

In this paper, we have investigated the problem of online delayed feedback modeling. Compared with previous approaches, the proposed DEFER ingests duplicated real negatives without changing the original feature distribution. The ingestion of duplicated real negatives provides more label correctness, facilitating the modeling of delayed feedback. With the ingestion of real negatives, DEFER further employs importance sampling to correct the distribution shift. Apart from the proposed method for online CVR prediction, we also share our deployment experiences for commercial platforms with different conversion attribution mechanisms and budgets. Experiment result on industrial dataset validates the superiority of the proposed methods. Up to now, the proposed methods have been successfully deployed in the display advertising system of Alibaba. The practical experience gained in our deployment generalizes to other setups, thus of interest to both researchers and industrial practitioners.

7 ACKNOWLEDGMENTS

We appreciate the helpful discussion as well as the support for experiments from Jia-Qi Yang.

REFERENCES

- [1] Léon Bottou, Jonas Peters, Joaquin Quiñero Candela, Denis Xavier Charles, Max Chickering, Elon Portugaly, Dipankar Ray, Patrice Y. Simard, and Ed Snelson. 2013. Counterfactual Reasoning and Learning Systems: the Example of Computational Advertising. *Journal of Machine Learning Research* 14, 1 (2013), 3207–3260.
- [2] Olivier Chapelle. 2014. Modeling delayed feedback in display advertising. In *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. 1097–1105.
- [3] David S Evans. 2009. The online advertising industry: Economics, evolution, and privacy. *Journal of economic perspectives* 23, 3 (2009), 37–60.
- [4] Tom Fawcett. 2006. An introduction to ROC analysis. *Pattern Recognit. Lett.* 27, 8 (2006), 861–874.
- [5] Laurence L. George. 2003. The Statistical Analysis of Failure Time Data. *Technometrics* 45, 3 (2003), 265–266.
- [6] Avi Goldfarb and Catherine Tucker. 2011. Online Display Advertising: Targeting and Obtrusiveness. *Marketing Science* 30, 3 (2011), 389–404.
- [7] Trevor Hastie, Jerome H. Friedman, and Robert Tibshirani. 2001. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer.
- [8] Xinran He, Junfeng Pan, Ou Jin, Tianbing Xu, Bo Liu, Tao Xu, Yanxin Shi, Antoine Atallah, Ralf Herbrich, Stuart Bowers, and Joaquin Quiñero Candela. 2014. Practical Lessons from Predicting Clicks on Ads at Facebook. In *Proceedings of the 8th International Workshop on Data Mining for Online Advertising*. ACM, 5:1–5:9.
- [9] Sergey Ioffe and Christian Szegedy. 2015. Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift. In *Proceedings of the 32nd International Conference on Machine Learning*. Vol. 37. 448–456.
- [10] Pooria Joulani, András György, and Csaba Szepesvári. 2013. Online Learning under Delayed Feedback. In *Proceedings of the 30th International Conference on Machine Learning*. Vol. 28. 1453–1461.
- [11] Diederik P. Kingma and Jimmy Ba. 2015. Adam: A Method for Stochastic Optimization. In *Proceedings of the 3rd International Conference on Learning Representations*.
- [12] Sofia Ira Ktena, Alykhan Tejani, Lucas Theis, Pranay Kumar Myana, Deepak Dilipkumar, Ferenc Huszár, Steven Yoo, and Wenzhe Shi. 2019. Addressing Delayed Feedback for Continuous Training with Neural Networks in CTR Prediction. In *Proceedings of the 13th ACM Conference on Recommender Systems*. 187–195.
- [13] Kuang-chih Lee, Burkay Orten, Ali Dasdan, and Wentong Li. 2012. Estimating Conversion Rate in Display Advertising from Past Performance Data. In *Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. 768–776.
- [14] Xiao Ma, Liqin Zhao, Guan Huang, Zhi Wang, Zelin Hu, Xiaoqiang Zhu, and Kun Gai. 2018. Entire Space Multi-Task Model: An Effective Approach for Estimating Post-Click Conversion Rate. In *Proceedings of the 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*. 1137–1140.
- [15] Andrew L Maas, Awni Y Hannun, and Andrew Y Ng. 2013. Rectifier nonlinearities improve neural network acoustic models. In *Proceedings of the 30th International Conference on Machine Learning*. Vol. 30. 3.
- [16] H. Brendan McMahan. 2011. Follow-the-Regularized-Leader and Mirror Descent: Equivalence Theorems and L1 Regularization. In *Proceedings of the 14th International Conference on Artificial Intelligence and Statistics*. Vol. 15. 525–533.
- [17] Aditya Krishna Menon, Krishna Prasad Chitrapura, Sachin Garg, Deepak Agarwal, and Nagaraj Kota. 2011. Response Prediction Using Collaborative Filtering with Hierarchies and Side-Information. In *Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 141–149.
- [18] Ciara Pike-Burke, Shipra Agrawal, Csaba Szepesvári, and Steffen Grünewälder. 2018. Bandits with Delayed, Aggregated Anonymous Feedback. In *Proceedings of the 13th International Conference on Machine Learning*. Vol. 80. 4102–4110.
- [19] Römer Rosales, Haibin Cheng, and Eren Manavoglu. 2012. Post-Click Conversion Modeling and Analysis for Non-Guaranteed Delivery Display Advertising. In *Proceedings of the 5th International Conference on Web Search and Web Data Mining*. Eytan Adar, Jaime Teevan, Eugene Agichtein, and Yoelle Maarek (Eds.). 293–302.
- [20] Xiang-Rong Sheng, Liqin Zhao, Guorui Zhou, Xinyao Ding, Binding Dai, Qiang Luo, Siran Yang, Jingshan Lv, Chi Zhang, and Xiaoqiang Zhu. 2021. One Model to Serve All: Star Topology Adaptive Recommender for Multi-Domain CTR Prediction. *CoRR* abs/2101.11427 (2021). arXiv:2101.11427 <https://arxiv.org/abs/2101.11427>
- [21] Masashi Sugiyama, Shinichi Nakajima, Hisashi Kashima, Paul von Büna, and Motoaki Kawanabe. 2007. Direct Importance Estimation with Model Selection and Its Application to Covariate Shift Adaptation. In *Advances in Neural Information Processing Systems* 20. 1433–1440.
- [22] Claire Vernade, Olivier Cappé, and Vianney Perchet. 2017. Stochastic Bandit Models for Delayed Conversions. In *Proceedings of the 33rd Conference on Uncertainty in Artificial Intelligence*, Gal Elidan, Kristian Kersting, and Alexander T. Ihler (Eds.).
- [23] Jun Wang, Weinan Zhang, and Shuai Yuan. 2017. Display Advertising with Real-Time Bidding (RTB) and Behavioural Targeting. *Foundations and Trends® in Information Retrieval* 11, 4-5 (2017), 297–435.
- [24] Jia-Qi Yang, Xiang Li, Shuguang Han, Tao Zhuang, De-Chuan Zhan, Xiaoyi Zeng, and Bin Tong. 2020. Capturing Delayed Feedback in Conversion Rate Prediction via Elapsed-Time Sampling. *CoRR* abs/2012.03245 (2020).
- [25] Shota Yasui, Gota Morishita, Komei Fujita, and Masashi Shibata. 2020. A Feedback Shift Correction in Predicting Conversion Rates under Delayed Feedback. In *Proceedings of The Web Conference 2020*. 2740–2746.
- [26] Yuya Yoshikawa and Yusaku Imai. 2018. A Nonparametric Delayed Feedback Model for Conversion Rate Prediction. *CoRR* abs/1802.00255 (2018).
- [27] Weinan Zhang, Shuai Yuan, and Jun Wang. 2014. Optimal Real-time Bidding for Display Advertising. In *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. 1077–1086.
- [28] Weinan Zhang, Tianxiong Zhou, Jun Wang, and Jian Xu. 2016. Bid-aware Gradient Descent for Unbiased Learning with Censored Data in Display Advertising. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 665–674.
- [29] Guorui Zhou, Na Mou, Ying Fan, Qi Pi, Weijie Bian, Chang Zhou, Xiaoqiang Zhu, and Kun Gai. 2019. Deep Interest Evolution Network for Click-Through Rate Prediction. In *Proceedings of the 33rd AAAI Conference on Artificial Intelligence*. Honolulu, Hawaii, USA, 5941–5948.
- [30] Guorui Zhou, Xiaoqiang Zhu, Chenru Song, Ying Fan, Han Zhu, Xiao Ma, Yanghui Yan, Junqi Jin, Han Li, and Kun Gai. 2018. Deep interest network for click-through rate prediction. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. ACM, 1059–1068.