Hierarchical Denoising Entire Space Multi-Task Model for Post-Click Conversion Rate Prediction with Noisy Labels

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Abstract

The post-click Conversion Rate (CVR) prediction plays a pivotal role in industrial recommender systems, directly serving as a decisive factor for ranking strategies and revenue optimization. While Entire Space Multi-Task Models (e.g., ESMM) have become the dominant framework by effectively addressing sample selection bias and data sparsity, they rely heavily on the assumption that the observed click and conversion labels perfectly reflect user preferences. In real-world scenarios, however, observed data is inevitably contaminated by label noise. Crucially, within the entire space modeling framework, this noise exhibits a complex hierarchical structure, where the superimposition of noise from antecedent click labels and subsequent conversion labels results in conventional single-task denoising methods being ineffective.

To bridge this gap, we propose HiDe-ESMM (Hierarchical Denoising Entire Space Multi-Task Model), a unified framework designed to systematically mitigate hierarchical label noise. First, adopting the loss correction paradigm, we derive a statistically unbiased CTCVR loss via backward correction and identify the requisite noise rates based on the weak separability assumption. Second, to alleviate the numerical instability inherent in the unbiased loss approach, we introduce a robust forward correction strategy as an efficient alternative and theoretically prove the consistency of its optimal solution with the optimal solution on clean data. Extensive experiments on one semi-synthetic dataset and two real-world industrial datasets demonstrate that HiDe-ESMM significantly outperforms state-of-the-art baselines, validating its robustness in handling hierarchical noisy labels.

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CCS Concepts

• **Information systems → Recommender systems**.

Keywords

Recommender systems, Noisy label learning, Post-click conversion rate prediction

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1 Introduction

Recommender systems (RS) serve as the fundamental engine for modern e-commerce platforms [17, 18, 41, 44], effectively bridging the gap between massive item pools and specific user interests by providing accurate personalized recommendations [29, 30, 37, 42]. Within these systems, user interaction typically unfolds along a sequential decision path: Impression → Click → Conversion [38]. This decision path naturally gives rise to two fundamental prediction tasks: Click-Through Rate (CTR) estimation [46] for the initial stage, and Post-click Conversion Rate (CVR) estimation [32] for the subsequent stage. Formally, CTR is defined as the probability of a user clicking on the item following an impression [45], while CVR is defined as the probability that a user performs a conversion action conditioned on the occurrence of a click event [8, 13, 28, 35, 40]. Accurate predictions of CTR and CVR are indispensable, as they directly determine the platform's profitability and serve as the cornerstone for advanced ranking strategies.

Unlike CTR models, which are trained and inferred on the same entire impression space, traditional CVR models suffer from two critical issues: sample selection bias (SSB) and data sparsity (DS) [20]. Specifically, SSB is due to the distribution of click events and the

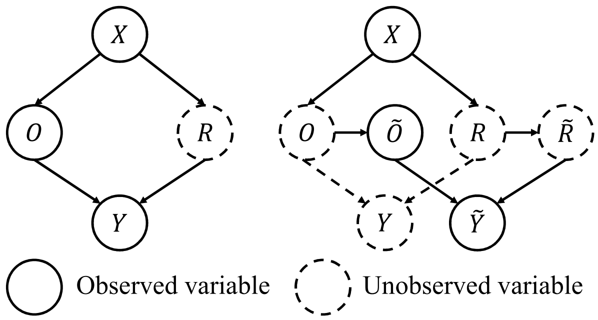

Figure 1: Data generation process of clean (left) and noisy (right) data distribution. X represents the feature vector, O represents the click event, R represents the post-click conversion event, Y represents the observed click-through & conversion event, and $\tilde{O}$, $\tilde{R}$, $\tilde{Y}$ are their noisy counterparts. Note that in the right panel, only the noisy $\tilde{Y}$ can be observed because the clean Y is unobservable since O is unobservable.

entire impression space (our target) being different. Furthermore, since conversion events are significantly less than click events, the training data for CVR estimation is much scarcer than that for CTR, resulting in the DS problem. To alleviate these challenges, methods such as the Entire Space Multi-Task Model (ESMM) [20] were proposed to model the sequential pattern over the entire impression space, establishing themselves as the dominant paradigm.

Despite the significant success of these entire space modeling approaches, they typically rely on the assumption that observed user behaviors or labels accurately reflect users' true preferences. However, in real-world industrial scenarios, this assumption is often violated, as the observed data is inevitably contaminated by label noise, which is a critical factor that has not been systematically considered in existing entire-space modeling frameworks. This noise arises from several sources such as erroneous or careless preference selection [22], attacks by malicious agents [5], and various other outcome measurement errors such as delayed feedback [12]. Failing to account for such pervasive noise forces the model to overfit to erroneous signals, thereby significantly degrading the performance of both CTR and CVR prediction tasks.

More critically, within the specific framework of entire space modeling, this label noise exhibits a unique and complex hierarchical structure. Since direct modeling of CVR over the entire impression space is infeasible, standard approaches, such as ESMM, resort to estimating the CVR indirectly by modeling the joint probability of Click-Through & Conversion Rate (CTCVR) via the probability chain rule (i.e., $pCTCVR = pCTR \times pCVR$) [20]. Consequently, the label noise in the CTCVR task is not isolated but rather represents a superimposition of noise patterns from both the click stage and the conversion stage. As illustrated in Figure 1, the observed CTCVR labels are derived from potentially corrupted click and conversion events, meaning that a corrupted signal in either stage propagates to the final CTCVR target. This compounded noise renders the denoising process significantly more intricate and we show that the CTCVR loss can not be unbiasedly estimated using the approaches proposed in independent single-task learning scenarios [12].

To systematically mitigate the hierarchical label noise inherent in entire-space post-click conversion prediction, we propose a novel framework named HiDe-ESMM (**Hi**erarchical **De**noising **E**ntire **S**pace **M**ulti-Task **M**odel). We first derive a theoretically grounded unbiased CTCVR loss, demonstrating that its risk estimator remains unbiased even under the superposition of corrupted antecedent click labels and subsequent conversion labels. We identify the requisite noise transition matrices via the standard weak separability assumption [12, 21], which posits the existence of "perfectly positive" and "perfectly negative" samples within the impression space. Then, we employ the widely adopted loss correction technique [12, 23] to derive an unbiased CTR loss under noisy clicks and establish a unified denoising framework over the entire impression space by integrating this CTR loss with our proposed CTCVR loss. Further, we notice that while theoretically unbiased, the direct implementation of such unbiased loss may suffer from numerical instability arising from the inversion of ill-conditioned noise matrices [1, 23]. To address this limitation, we further propose a robust alternative strategy based on forward correction [23]. Although this correction method does not strictly guarantee unbiasedness in all scenarios, we theoretically prove that its optimal solution converges to that trained on the clean data under mild assumptions. Finally, extensive experiments on one semi-synthetic dataset and two real-world industrial datasets validate the superiority of our proposed approach.

The main contributions of this paper are summarized as follows:

- **Hierarchical Denoising Framework**: We identify the hierarchical label noise problem in the entire space CVR prediction task and propose HiDe-ESMM, a unified multi-task learning framework. To the best of our knowledge, this is the first work to systematically address the superposition of noise from both click and conversion stages within the entire space modeling paradigm.
- **Theoretical Guarantees**: We derive a unbiased CTCVR loss. Furthermore, to mitigate the numerical instability of the inversion of noise matrices, we propose a robust forward correction strategy and theoretically prove the consistency of its optimal solution with the noise-free counterpart.
- **Empirical Effectiveness**: We conduct extensive experiments on one semi-synthetic dataset and two real-world industrial datasets. The results demonstrate that HiDe-ESMM significantly outperforms state-of-the-art baselines, validating its robustness and effectiveness in handling hierarchical label noise.

2 Preliminaries

Let $\mathcal{U} = \{u_1, u_2, \ldots, u_m\}$ be the set of m users, $\mathcal{I} = \{i_1, i_2, \ldots, i_n\}$ be the set of n items, and $\mathcal{D} = \mathcal{U} \times \mathcal{I}$ be the set of all user-item pairs. Denote $\mathbf{O}$ as the click matrix where each element $o_{u,i} \in \{0, 1\}$ indicates the occurrence of the click event between user u and item i, $\mathbf{Y}$ as the observed conversion (click-through&conversion) matrix where each element $y_{u,i} \in \{0, 1\}$ indicates the occurrence of the conversion event between user u and item i, and $\mathbf{R}$ as the post-click conversion matrix where each element $r_{u,i} \in \{0, 1\}$ indicates the occurrence of the conversion event if user u clicked item i. With this definition, the relationship between these 3 matrices can be described using an element-wise matrix product as:

$$\mathbf{Y} = \mathbf{O} \cdot \mathbf{R}. \tag{1}$$

Denote $x_{u,i}$ as the feature vector of user u and item i, then in the ideal case where all post-click conversion events are observed, e.g. $\mathbf{O} = \mathbf{1}$ and $\mathbf{Y} = \mathbf{R}$, the CVR prediction model $f(x_{u,i}; \theta_{CVR})$, parameterized by θ_{CVR}, can be trained by minimizing the ideal loss:

$$\mathcal{L}_{ideal}(\theta_{CVR}) = \frac{1}{|\mathcal{D}|} \sum_{(u,i) \in \mathcal{D}} \delta(r_{u,i}, \hat{r}_{u,i}), \tag{2}$$

where δ denotes prediction error of $r_{u,i}$ and $\hat{r}_{u,i} := f(x_{u,i}; \theta_{CVR})$ denotes the predicted $r_{u,i}$. We adopt the binary cross entropy loss for δ throughout this paper:

$$\delta(r_{u,i}, \hat{r}_{u,i}) = -r_{u,i} \log \hat{r}_{u,i} - (1 - r_{u,i}) \log(1 - \hat{r}_{u,i}). \tag{3}$$

However, in real recommendation scenarios, users only click on a few items, which means only a part of the post-click conversion events are observed. In this case, a naive approach [7, 24] estimates the ideal loss using observed $r_{u,i}$ as:

$$\mathcal{L}_{Naive} = \frac{1}{|\mathcal{O}|} \sum_{(u,i) \in \mathcal{D}} o_{u,i} \delta(r_{u,i}, \hat{r}_{u,i}), \tag{4}$$

where $|\mathcal{O}| = \sum_{(u,i) \in \mathcal{D}} o_{u,i}$. The problem with $\mathcal{L}_{Naive}$ is that $\mathbb{E}\mathcal{L}_{Naive} \neq \mathcal{L}_{ideal}$ due to data sparsity and sample selection bias [27]. To solve this problem, ESMM [20] proposed to model CVR indirectly by direct modeling of $\mathbf{O}$ and $\mathbf{Y}$ using the chain rule as:

$$\mathbb{P}(r_{u,i} = 1) = \mathbb{P}(r_{u,i} = 1 | o_{u,i} = 1) = \frac{\mathbb{P}(y_{u,i} = 1)}{\mathbb{P}(o_{u,i} = 1)}, \tag{5}$$

where $\mathbb{P}(y_{u,i} = 1)$ (i.e. CTCVR) and $\mathbb{P}(o_{u,i} = 1)$ (i.e. CTR) can all be unbiasedly estimated through the entire impression space $\mathcal{D}$ using the corresponding loss:

$$\mathcal{L}_{CTR}(\theta_{CTR}) = \frac{1}{|\mathcal{D}|} \sum_{(u,i) \in \mathcal{D}} \delta(o_{u,i}, \hat{o}_{u,i}), \tag{6}$$

$$\mathcal{L}_{CTCVR}(\theta_{CTR}, \theta_{CVR}) = \frac{1}{|\mathcal{D}|} \sum_{(u,i) \in \mathcal{D}} \delta(y_{u,i}, \hat{y}_{u,i}). \tag{7}$$

where $\hat{o}_{u,i} := f(x_{u,i}; \theta_{CTR})$ is the predicted CTR and $\hat{y}_{u,i} = \hat{o}_{u,i} \cdot \hat{r}_{u,i}$.

3 Proposed Methods

In this section, we describe our proposed method. We first define the noisy data generation process and related assumptions. Then we formulate the unbiased CTCVR loss and prove its theoretical properties. Third, we discuss how to estimate the noisy rate based on the weak separability assumption and overall HiDe-ESMM algorithm. Finally, we propose the alternative forward correction approach to deal with the numerical instability of the unbiased loss approach.

3.1 Problem Formulation

Let $\tilde{\mathbf{O}}$ denote the observed noisy click matrix where each element $\tilde{o}_{u,i} \in \{0, 1\}$ indicates the observed noisy click event between user u and item i. Similarly, let $\tilde{\mathbf{R}}$ as the noisy post-click conversion matrix where $\tilde{r}_{u,i} \in \{0, 1\}$ indicates the noisy occurrence of the conversion event if user u clicked item i and $\tilde{\mathbf{Y}}$ as the observed noisy conversion (click-through&conversion) matrix. To model the noisy data generation process, we further make the following assumption.

Assumption 1. *Given user u and item i, the noise generation process are independent for the click event and the post-click conversion event, i.e.* $\tilde{o}_{u,i} \perp\!\!\!\perp \tilde{r}_{u,i} | x_{u,i}$. *Further, in case of noisy click events and post-click conversion events, the observed noisy click-through&conversion event is generated as*

$$\tilde{\mathbf{Y}} = \tilde{\mathbf{O}} \cdot \tilde{\mathbf{R}}.$$

An illustration of this data generation process is given in the right panel of Figure 1. Further let $\mathbb{P}(\tilde{o}_{u,i} = 0 | o_{u,i} = 1) = \tau_{01}$ and $\mathbb{P}(\tilde{o}_{u,i} = 1 | o_{u,i} = 0) = \tau_{10}$ denote the false negative rate and false positive rate for the click event and $\mathbb{P}(\tilde{r}_{u,i} = 0 | r_{u,i} = 1) = \rho_{01}$ and $\mathbb{P}(\tilde{r}_{u,i} = 1 | r_{u,i} = 0) = \rho_{10}$ denote the false negative rate and false positive rate for the post-click conversion event respectively, with $\tau_{01} + \tau_{10} < 1$ and $\rho_{01} + \rho_{10} < 1$. Then, the unbiased CTR loss $\bar{\mathcal{L}}_{CTR}$ can be derived directly as [12, 23]:

$$\bar{\mathcal{L}}_{CTR} = -\tilde{o}_{u,i} \cdot \bar{\delta}(1, \hat{o}_{u,i}) - (1 - \tilde{o}) \cdot \bar{\delta}(0, \hat{o}_{u,i}), \tag{8}$$

where

$$\bar{\delta}(0, \hat{o}_{u,i}) = \frac{(1 - \tau_{01}) \cdot \delta(0, \hat{o}_{u,i}) - \tau_{10} \cdot \delta(1, \hat{o}_{u,i})}{1 - \tau_{01} - \tau_{10}}, \tag{9}$$

$$\bar{\delta}(1, \hat{o}_{u,i}) = \frac{-\tau_{01} \cdot \delta(0, \hat{o}_{u,i}) + (1 - \tau_{10}) \cdot \delta(1, \hat{o}_{u,i})}{1 - \tau_{01} - \tau_{10}}, \tag{10}$$

which satisfies $\mathbb{E}_{\mathbf{O}}\mathcal{L}_{CTR} = \mathbb{E}_{\tilde{\mathbf{O}}}\bar{\mathcal{L}}_{CTR}$. However, a similar approach can not be applied directly for constructing the unbiased CTCVR loss $\bar{\mathcal{L}}_{CTCVR}$. To see why, we first note that the direct construction of $\bar{\mathcal{L}}_{CTCVR}$ needs the noise rate, denoted by $\nu_{01} = \mathbb{P}(\tilde{y}_{u,i} = 0 | y_{u,i} = 1)$, and $\nu_{10} = \mathbb{P}(\tilde{y}_{u,i} = 1 | y_{u,i} = 0)$. Then it is easy to show that:

$$\nu_{01} = 1 - (1 - \tau_{01})(1 - \rho_{01}), \tag{11}$$

and

$$\nu_{10} = \frac{\mathbb{P}(\tilde{y}_{u,i} = 1) - \mathbb{P}(\tilde{y}_{u,i} = 1 | y_{u,i} = 1)\mathbb{P}(o_{u,i} = 1)\mathbb{P}(r_{u,i} = 1)}{1 - \mathbb{P}(o_{u,i} = 1)\mathbb{P}(r_{u,i} = 1)}. \tag{12}$$

We can see that while ν_{01} can be estimated using τ_{01} and ρ_{01}, ν_{10} can not be estimated directly since $\mathbb{P}(r_{u,i} = 1)$ is the target being optimized by ν_{10} itself, which arises the needs to propose a new unbiased loss for the CTCVR prediction task.

3.2 Unbiased CTCVR Loss

In this section, we deduce the unbiased loss $\bar{\mathcal{L}}_{CTCVR}$. We first denote $\delta_1 = \delta(1, \hat{y}_{u,i}) = -\log \hat{y}_{u,i}$ and $\delta_0 = \delta(0, \hat{y}_{u,i}) = -\log(1 - \hat{y}_{u,i})$, which means the clean CTCVR loss for user-item pair (u, i) defined in Equation (7) is given by:

$$\delta(y_{u,i}, \hat{y}_{u,i}) = y_{u,i} \cdot \delta_1 + (1 - y_{u,i}) \cdot \delta_0. \tag{13}$$

Taking expectation over the click space gives:

$$\mathbb{E}_o \delta(y_{u,i}, \hat{y}_{u,i}) = P^o_{u,i} \cdot r_{u,i} \cdot \delta_1 + (1 - P^o_{u,i} \cdot r_{u,i}) \cdot \delta_0, \tag{14}$$

where $P^o_{u,i} = \mathbb{P}(o_{u,i} = 1)$.

Next, we formulate the noisy CTCVR loss $\bar{\delta}(\tilde{y}_{u,i}, \hat{y}_{u,i})$ as:

$$\bar{\delta}(\tilde{y}_{u,i}, \hat{y}_{u,i}) = \tilde{y}_{u,i} \cdot \bar{\delta}_1 + (1 - \tilde{y}_{u,i}) \cdot \bar{\delta}_0. \tag{15}$$

Taking expectation over the noisy click space gives:

$$\mathbb{E}_{\tilde{o}} \bar{\delta}(\tilde{y}_{u,i}, \hat{y}_{u,i}) = P^{\tilde{o}}_{u,i} \cdot \tilde{r}_{u,i} \cdot \bar{\delta}_1 + (1 - P^{\tilde{o}}_{u,i} \cdot \tilde{r}_{u,i}) \cdot \bar{\delta}_0, \tag{16}$$

where $P^{\tilde{o}}_{u,i} = \mathbb{P}(\tilde{o}_{u,i} = 1)$. Next, to better formulate the noise generation process, we introduce two indicator variables $I^{10}_{u,i}$ and $I^{01}_{u,i}$ where $I^{10}_{u,i}$ represents the flip event $\tilde{r}_{u,i} = 1, r_{u,i} = 0$ and $I^{01}_{u,i}$ represents the flip event $\tilde{r}_{u,i} = 0, r_{u,i} = 1$, which means we have:

$$\tilde{r}_{u,i} = I^{10}_{u,i} + (1 - I^{10}_{u,i} - I^{01}_{u,i}) r_{u,i}. \tag{17}$$

Then, the noisy CTCVR loss can be written as:

$$\begin{aligned} \mathbb{E}_{\tilde{o}} \bar{\delta}(\tilde{y}_{u,i}, \hat{y}_{u,i}) =& P^{\tilde{o}}_{u,i} \cdot (I^{10}_{u,i} + (1 - I^{10}_{u,i} - I^{01}_{u,i}) r_{u,i}) \bar{\delta}_1 & (18)\\ &+ (1 - P^{\tilde{o}}_{u,i} \cdot (I^{10}_{u,i} + (1 - I^{10}_{u,i} - I^{01}_{u,i}) r_{u,i})) \bar{\delta}_0 & (19) \end{aligned}$$

and we take expectation over the flipping event we get:

$$\begin{aligned} \mathbb{E}_{\tilde{o}, \tilde{r}|r} \bar{\delta}(\tilde{y}_{u,i}, \hat{y}_{u,i}) =& P^{\tilde{o}}_{u,i} \cdot (\rho_{10} + (1 - \rho_{10} - \rho_{01}) r_{u,i}) \bar{\delta}_1 \\ &+ (1 - P^{\tilde{o}}_{u,i} \cdot (\rho_{10} + (1 - \rho_{10} - \rho_{01}) r_{u,i})) \bar{\delta}_0. \end{aligned} \tag{20}$$

Thus, to ensure unbiasedness, we set up and solve the system of equations for different values of $r_{u,i}$ in Equations (14) and (20):

$$P^{\tilde{o}}_{u,i} \cdot (1 - \rho_{01}) \cdot \bar{\delta}_1 + (1 - P^{\tilde{o}}_{u,i} \cdot (1 - \rho_{01})) \bar{\delta}_0 = P^{o}_{u,i} \delta_1 + (1 - P^{o}_{u,i}) \delta_0 \tag{21}$$

$$P^{\tilde{o}}_{u,i} \cdot \rho_{10} \cdot \bar{\delta}_1 + (1 - P^{\tilde{o}}_{u,i} \cdot \rho_{10}) \cdot \bar{\delta}_0 = \delta_0. \tag{22}$$

By solving the system of Equations (21) and (22), we can derive the analytical solutions for $\bar{\delta}_1$ and $\bar{\delta}_0$ in terms of δ_1 and δ_0. Then, by substituting these expressions into Equation (15), the final unbiased CTCVR loss function is obtained as follows:

$$\begin{aligned} \bar{\mathcal{L}}_{CTCVR} =& \sum_{(u,i) \in \mathcal{D}} \tilde{y}_{u,i} \cdot \left\{ \frac{\left[-P^{o}_{u,i} + P^{\tilde{o}}_{u,i} (1 - (1 - P^{o}_{u,i}) \rho_{10} - \rho_{01}) \right] \delta_0}{P^{\tilde{o}}_{u,i} (1 - \rho_{10} - \rho_{01})} \right. \\ &+ \left. \frac{\left[P^{o}_{u,i} (1 - P^{\tilde{o}}_{u,i} \rho_{10}) \right] \delta_1}{P^{\tilde{o}}_{u,i} (1 - \rho_{10} - \rho_{01})} \right\} + (1 - \tilde{y}_{u,i}) \cdot \left\{ \frac{\left[1 - (1 - P^{o}_{u,i}) \rho_{10} - \rho_{01} \right] \delta_0}{1 - \rho_{10} - \rho_{01}} \right. \\ &- \left. \frac{\left[P^{o}_{u,i} \rho_{10} \right] \delta_1}{1 - \rho_{10} - \rho_{01}} \right\}. \end{aligned} \tag{23}$$

3.3 Estimation of the Noise Rates

As we can see, the calculation of $\bar{\mathcal{L}}_{CTR}$ and $\bar{\mathcal{L}}_{CTCVR}$ relies on the value of τ_{10}, τ_{01}, ρ_{10} and ρ_{01}, which are usually to be estimated from the observed data. In this paper, we adopt the widely adopted weak separability assumption [12, 21], which states that the following relationships holds:

$$\inf_{(u,i) \in \mathcal{D}} \mathbb{P}(o_{u,i} = 1) = 0 \quad \text{and} \quad \sup_{(u,i) \in \mathcal{D}} \mathbb{P}(o_{u,i} = 1) = 1, \tag{24}$$

$$\inf_{(u,i) \in \mathcal{D}} \mathbb{P}(r_{u,i} = 1) = 0 \quad \text{and} \quad \sup_{(u,i) \in \mathcal{D}} \mathbb{P}(r_{u,i} = 1) = 1. \tag{25}$$

This assumption means that for each of the click-through event and the post-click conversion event, there exist "perfectly positive" and "perfectly negative" samples among the entire user-item pairs. This is a reasonable assumption since it only requires at least one click/not click event and one post-click conversion event are reliable, without knowing which one they are, which is easy to meet in real-world recommendation scenarios.

Algorithm 1: Proposed HiDe-ESMM method.

Input: Pretrained CTR model g_o and CVR model g_r on the noisy data; Datasets $\mathcal{D}$; Prediction model $f(\theta_{CTR})$ and $f(\theta_{CVR})$.

```
Randomly initialize θ_CTR, θ_CVR;
Estimate τ10, τ01, ρ10, ρ01 according to Equations (26)
  and (27) using g_o and g_r;
while not convergent do
    for number of steps for training the prediction model do
        Sample a batch of user-item pairs u, i from D;
        Calculate L̄_CTR + L̄_CTCVR according to Equation (8)
          and Equation (23);
        Optimize θ_CTR and θ_CVR by minimizing
          L̄_CTR + L̄_CTCVR;
    end
    Epoch ← Epoch + 1;
end
```

Output: $f(\theta_{CTR})$ and $f(\theta_{CVR})$.

If this assumption holds, existing works [12, 19] demonstrated that given $\tau_{10} + \tau_{01} < 1$ and $\rho_{10} + \rho_{01} < 1$, let:

$$(u^{<}_{o}, i^{<}_{o}) = \arg\min_{(u,i) \in \mathcal{D}} \mathbb{P}(\tilde{o}_{u,i} = 1), (u^{>}_{o}, i^{>}_{o}) = \arg\max_{(u,i) \in \mathcal{D}} \mathbb{P}(\tilde{o}_{u,i} = 1),$$

$$(u^{<}_{r}, i^{<}_{r}) = \arg\min_{(u,i) \in \mathcal{D}} \mathbb{P}(\tilde{r}_{u,i} = 1), (u^{>}_{r}, i^{>}_{r}) = \arg\max_{(u,i) \in \mathcal{D}} \mathbb{P}(\tilde{r}_{u,i} = 1),$$

which yields:

$$\tau_{01} = 1 - \mathbb{P}(\tilde{o}_{u^{>}_{o}, i^{>}_{o}} = 1) \quad \text{and} \quad \tau_{10} = \mathbb{P}(\tilde{o}_{u^{<}_{o}, i^{<}_{o}} = 1), \tag{26}$$

$$\rho_{01} = 1 - \mathbb{P}(\tilde{r}_{u^{>}_{r}, i^{>}_{r}} = 1) \quad \text{and} \quad \rho_{10} = \mathbb{P}(\tilde{r}_{u^{<}_{r}, i^{<}_{r}} = 1). \tag{27}$$

Thus, we can easily estimate τ_{10}, τ_{01}, ρ_{10} and ρ_{01} by fitting CTR and CVR prediction models on the noisy observed data. Pseudo code for the entire training process is provided in Algorithm 1.

3.4 Generalization Bound of the Unbiased CTCVR Loss

In this section, we further discuss the generalization property of the proposed unbiased CTCVR loss. The Generalization bound of the proposed denoised CTCVR loss is given by the following theorem.

Theorem 1. *Given $\hat{\rho}_{01}$ and $\hat{\rho}_{10}$ with $\hat{\rho}_{01} + \hat{\rho}_{10} < 1$, suppose $\delta(r_{u,i}, \hat{r}_{u,i})$ is L_r-Lipschitz in $\hat{o}$, $\delta(o_{u,i}, \hat{o}_{u,i})$ is L_o-Lipschitz in $\hat{r}$, and $\bar{\delta}(\tilde{o}_{u,i}, \hat{o}_{u,i}) \leq C_o$, $\bar{\delta}(\tilde{r}_{u,i}, \hat{r}_{u,i}) \leq C_r$ for all o, r, then with probability $1-\eta$, the difference between the optimal prediction loss $\mathcal{L}^{*}_{\text{CTCVR}}\left(\hat{\boldsymbol{Y}}, \boldsymbol{Y}\right)$ and the empirical unbiased loss $\hat{\bar{\mathcal{L}}}_{CTCVR}$ is bounded by:*

$$\begin{aligned} &\text{Bias}\left[\hat{\bar{\mathcal{L}}}_{\text{CTCVR}}\right] + 4 \cdot L_o L_r \frac{1 - \rho_{01}}{1 - \rho_{10} - \rho_{01}} \cdot R(\mathcal{F}) \\ &+ (C_o + C_r + 4 L_o L_r) \cdot \frac{1 - \rho_{01}}{1 - \rho_{10} - \rho_{01}} \cdot \sqrt{\frac{2 \log(4/\eta)}{|\mathcal{D}|}}, \end{aligned}$$

where $R(\mathcal{F})$ represents the empirical Rademacher complexity and the Bias term is given by:

$$\text{Bias}\left[\hat{\tilde{\mathcal{L}}}_{\text{CTCVR}}\right] = \frac{1}{|\mathcal{D}|}\left|\sum_{(u,i):r_{u,i}=1}\left((\omega_{11}-1)\,\ell_{u,i}^{(1)} + \omega_{01}\ell_{u,i}^{(0)}\right) + \sum_{(u,i):r_{u,i}=0}\left(\omega_{10}\ell_{u,i}^{(1)} + (\omega_{00}-1)\,\ell_{u,i}^{(0)}\right)\right|,$$

where:

$$\ell_{u,i}^{(1)} = P_{u,i}^{\tilde{o}}\cdot(1-\hat{\rho}_{01})\bar{\delta}_1 + (1-P_{u,i}^{\tilde{o}}\cdot(1-\hat{\rho}_{01}))\bar{\delta}_0,$$
$$\ell_{u,i}^{(0)} = P_{u,i}^{\tilde{o}}\cdot\hat{\rho}_{10}\bar{\delta}_1 + (1-P_{u,i}^{\tilde{o}}\cdot\hat{\rho}_{10})\bar{\delta}_0,$$
$$\omega_{11} = \frac{1-\rho_{01}-\hat{\rho}_{10}}{1-\hat{\rho}_{01}-\hat{\rho}_{10}},\quad \omega_{01} = \frac{\rho_{01}-\hat{\rho}_{01}}{1-\hat{\rho}_{01}-\hat{\rho}_{10}},$$
$$\omega_{10} = \frac{\rho_{10}-\hat{\rho}_{10}}{1-\hat{\rho}_{01}-\hat{\rho}_{10}},\quad \omega_{00} = \frac{1-\hat{\rho}_{01}-\rho_{10}}{1-\hat{\rho}_{01}-\hat{\rho}_{10}}.$$

Proof. Due to the page limitation, we list the idea of Theorem 1 proof, which is in four stages.

- We decompose the true CTCVR risk into our empirical corrected risk, a bias term due to estimated noise rates ($\hat{\rho}_{01}, \hat{\rho}_{10}$), and a uniform deviation term.
- By taking the conditional expectation of the corrected loss under the true noise model, we derive those explicit bias coefficients ω; this bias vanishes when estimates are accurate.
- We bound the deviation via symmetrization. The Rademacher complexity for the product function class $\hat{y} = \hat{o}\cdot\hat{r}$ is controlled using the contraction principle, where the Lipschitz constants of the clean CTCVR label, given the underlying CTR and CVR losses, is upper-bounded by L_oL_r factor. The scaling factor $(1-\rho_{01})/(1-\rho_{10}-\rho_{01})$ emerges from the inverse of the noise transition matrix used in the backward correction.
- McDiarmid's inequality [25] provides the concentration term, which shares the same noise-dependent factor. Thus, the bound reflects the increased estimation difficulty under stronger label noise but guarantees consistency given accurate noise-rate estimates and sufficient data.

□

3.5 Forward correction

The proposed HiDe-ESMM method is theoretically unbiased. However, the optimization of the proposed unbiased loss may suffer from numerical instability due to its complex format and the inversion of ill-conditioned noise matrices [1, 23]. Thus, we propose a robust alternative by leveraging the widely adopted forward correction technique [15, 16, 36]. To derive the proposed method, we first note that with τ_{10}, τ_{01}, ρ_{10} and ρ_{01} defined in Section 3.1, we have:

$$\mathbb{P}(\tilde{r}_{u,i}=1) = \rho_{10}\mathbb{P}(r_{u,i}=0) + (1-\rho_{01})\mathbb{P}(r_{u,i}=1), \tag{28}$$
$$\mathbb{P}(\tilde{o}_{u,i}=1) = \tau_{10}\mathbb{P}(o_{u,i}=0) + (1-\tau_{01})\mathbb{P}(o_{u,i}=1), \tag{29}$$

which means:

$$\begin{aligned}\mathbb{P}(\tilde{o}_{u,i}=1) &= \tau_{10} + (1-\tau_{10}-\tau_{01})\mathbb{P}(o_{u,i}=1),\\ \mathbb{P}(\tilde{r}_{u,i}=1) &= \rho_{10} + (1-\rho_{10}-\rho_{01})\mathbb{P}(r_{u,i}=1),\end{aligned} \tag{30}$$

and consequently:

$$\mathbb{P}(\tilde{y}_{u,i}=1) = \mathbb{P}(\tilde{o}_{u,i}=1)\mathbb{P}(\tilde{r}_{u,i}=1). \tag{31}$$

Thus, if $\hat{o}_{u,i}$ and $\hat{y}_{u,i}$ are predictions for the clean CTR and CTCVR, the corresponding predictions, $\hat{o}_{u,i}^N$ and $\hat{y}_{u,i}^N$, for the noisy CTR and CTCVR respectively can be obtained as:

$$\hat{o}_{u,i}^N = \tau_{10} + (1-\tau_{10}-\tau_{01})\cdot\hat{o}_{u,i}, \tag{32}$$

and

$$\hat{y}_{u,i}^N = \hat{o}_{u,i}^N\cdot(\rho_{10} + (1-\rho_{10}-\rho_{01})\cdot\hat{r}_{u,i}), \tag{33}$$

where $\hat{r}_{u,i}$ is the prediction for the clean CVR from the CVR tower in ESMM. Therefore, the forward correction loss for CTR and CTCVR predictions training on the noisy data can be constructed using $\hat{o}_{u,i}^N$ and $\hat{y}_{u,i}^N$ as:

$$\tilde{\mathcal{L}}_{CTR} = \frac{1}{|\mathcal{D}|}\sum_{(u,i)\in\mathcal{D}}\delta(\tilde{o}_{u,i},\hat{o}_{u,i}^N), \tag{34}$$

$$\tilde{\mathcal{L}}_{CTCVR} = \frac{1}{|\mathcal{D}|}\sum_{(u,i)\in\mathcal{D}}\delta(\tilde{y}_{u,i},\hat{y}_{u,i}^N), \tag{35}$$

where $\tilde{y}_{u,i} = \tilde{o}_{u,i}\cdot\tilde{r}_{u,i}$.

Pseudo code for forward correction approach is given in Algorithm 2. Theoretically, there is no unbiasedness guarantee for $\tilde{\mathcal{L}}_{CTR}$ and $\tilde{\mathcal{L}}_{CTCVR}$. However, we demonstrate through the following theorem that if τ_{10}, τ_{01}, ρ_{10} and ρ_{01} are correctly specified, the optimal model parameters that minimize $\mathbb{E}\tilde{\mathcal{L}}_{CTR}$ and $\mathbb{E}\tilde{\mathcal{L}}_{CTCVR}$ on the noisy data are the same as the model parameters minimize the original loss defined in Equation (7) on the clean data.

Theorem 2. *Given τ_{10}, τ_{01}, ρ_{10} and ρ_{01}. Let $\hat{o}_{u,i} = f(x_{u,i};\theta_{CTR})$, $\hat{o}_{u,i}^N = f(x_{u,i};\tilde{\theta}_{CTR})$, $\hat{r}_{u,i} = f(x_{u,i};\theta_{CVR})$ and $\hat{r}_{u,i}^N = f(x_{u,i};\tilde{\theta}_{CVR})$. Suppose $\mathcal{L}_{CTR}$, $\mathcal{L}_{CTCVR}$, defined in Equation (7), are calculated over* $\mathbf{O},\mathbf{Y}$ *using $\hat{o}_{u,i}$, $\hat{y}_{u,i}$ and $\tilde{\mathcal{L}}_{CTR}$, $\tilde{\mathcal{L}}_{CTCVR}$, defined in Equation (35), are calculated over $\tilde{\mathbf{O}},\tilde{\mathbf{Y}}$ using $\hat{o}_{u,i}^N$, $\hat{y}_{u,i}^N$. Suppose the cross-entropy loss is adopted. Then for the CTR prediction task, we have:*

$$\theta_{CTR}^* = \tilde{\theta}_{CTR}^*, \tag{36}$$

where $\theta_{CTR}^* = \arg\min_{\theta_{CTR}}\mathbb{E}\mathcal{L}_{CTR}$ and $\tilde{\theta}_{CTR}^* = \arg\min_{\theta_{CTR}}\mathbb{E}\mathcal{L}_{CTR}$. Furthermore, if $\theta_{CTR} = \tilde{\theta}_{CTR} = \theta_{CTR}^*$, then for the CTCVR prediction task, we have:

$$\theta_{CVR}^* = \tilde{\theta}_{CVR}^*, \tag{37}$$

where $\theta_{CVR}^* = \arg\min_{\theta_{CVR}}\mathbb{E}\mathcal{L}_{CTCVR}$ and $\tilde{\theta}_{CVR}^* = \arg\min_{\theta_{CVR}}\mathbb{E}\mathcal{L}_{CTCVR}$.

Proof. We provide a proof sketch here.

Remind our notation that $P_{u,i}^o = \mathbb{P}(o_{u,i}=1)$, $P_{u,i}^{\tilde{o}} = \mathbb{P}(\tilde{o}_{u,i}=1)$ and let $P_{u,i}^r = \mathbb{P}(r_{u,i}=1)$, $P_{u,i}^{\tilde{r}} = \mathbb{P}(\tilde{r}_{u,i}=1)$. Then consider the clean CTR loss for user u and item i given by:

$$\delta(o_{u,i},\hat{o}_{u,i}) = -o_{u,i}\log\hat{o}_{u,i} - (1-o_{u,i})\log(1-\hat{o}_{u,i}), \tag{38}$$

the expectation is given by:

$$\mathbb{E}\delta(o_{u,i},\hat{o}_{u,i}) = -P_{u,i}^o\log f(x_{u,i};\theta_{CTR}) - (1-P_{u,i}^o)\log(1-f(x_{u,i};\theta_{CTR})). \tag{39}$$

Taking derivative of $\mathbb{E}\delta(o_{u,i},\hat{o}_{u,i})$ w.r.t. $f(x_{u,i};\theta_{CVR})$ and setting the partial derivative to 0 gives:

$$f(x_{u,i};\theta_{CTR}) = P_{u,i}^o, \tag{40}$$

Algorithm 2: Proposed HiDe-ESMM method using forward correction.

Input: Pretrained CTR model g_o and CVR model g_r on the noisy data; Datasets $\mathcal{D}$; Prediction model $f(\theta_{CTR})$ and $f(\theta_{CVR})$.

Randomly initialize $\theta_{CTR}, \theta_{CVR}$;
Estimate τ_{10}, τ_{01}, ρ_{10}, ρ_{01} according to Equation (26) and Equation (27) using g_o and g_r;
while *not convergent* **do**
  for *number of steps for training the prediction model* **do**
    Sample a batch of user-item pairs u, i from $\mathcal{D}$;
    Get clean CTR prediction $\hat{o}_{u,i} = f(x_{u,i}; \theta_{CTR})$ and CTCVR prediction $\hat{y}_{u,i} = f(x_{u,i}; \theta_{CTR}) \cdot f(x_{u,i}; \theta_{CVR})$;
    Correct the prediction to get $\hat{o}^N_{u,i}$ using Equation (32) and $\hat{y}^N_{u,i}$ using Equation (33);
    Calculate $\tilde{\mathcal{L}}_{CTR} + \tilde{\mathcal{L}}_{CTCVR}$ according to Equation (35);
    Optimize θ_{CTR} and θ_{CVR} by minimizing $\tilde{\mathcal{L}}_{CTR} + \tilde{\mathcal{L}}_{CTCVR}$;
  end
  $Epoch \leftarrow Epoch + 1$;
end

Output: $f(\theta_{CTR})$ and $f(\theta_{CVR})$.

which means the optimal parameter θ^*_{CTR} that minimize $\mathbb{E}\mathcal{L}_{CTR}$ solves the system of equations:

$$f(x_{u,i}; \theta^*_{CTR}) = P^o_{u,i} \quad \forall (u,i) \in \mathcal{D}. \tag{41}$$

Similarly, we can derive that the optimal parameter $\tilde{\theta}^*_{CTR}$ that minimize $\mathbb{E}\tilde{\mathcal{L}}_{CTR}$ also solves the system of equations:

$$f(x_{u,i}; \tilde{\theta}^*_{CTR}) = P^o_{u,i} \quad \forall (u,i) \in \mathcal{D}, \tag{42}$$

which means $\theta^*_{CTR} = \tilde{\theta}^*_{CTR}$ and completes the first part of the proof.

Following the same procedure, we can derive the optimal solutions for θ_{CVR} and $\tilde{\theta}_{CVR}$. Specifically, the expectation of the clean CTCVR loss for user u and item i is given by:

$$\begin{aligned}\mathbb{E}\delta(y_{u,i}, \hat{y}_{u,i}) = &- P^o_{u,i} P^r_{u,i} \log \hat{o}_{u,i} \cdot f(x_{u,i}; \theta_{CVR}) &(43)\\ &- (1 - P^o_{u,i} P^r_{u,i}) \log(1 - \hat{o}_{u,i} \cdot f(x_{u,i}; \theta_{CVR})), &(44)\end{aligned}$$

which gives the optimal solution satisfying:

$$f(x_{u,i}; \theta^*_{CVR}) = \frac{P^o_{u,i} P^r_{u,i}}{\hat{o}_{u,i}} = P^r_{u,i}, \tag{45}$$

if we choose $\theta_{CTR} = \theta^*_{CTR}$ and the optimal solution $\tilde{\theta}^*_{CVR}$ satisfies:

$$f(x_{u,i}; \tilde{\theta}^*_{CVR}) = (\frac{P^{\tilde{o}}_{u,i} P^{\tilde{r}}_{u,i}}{\hat{o}^N_{u,i}} - \rho_{10})/(1 - \rho_{10} - \rho_{01}) = P^r_{u,i} \quad \forall (u,i) \in \mathcal{D}, \tag{46}$$

if we choose $\tilde{\theta}_{CTR} = \tilde{\theta}^*_{CTR} = \theta^*_{CTR}$. Thus, we get $\theta^*_{CVR} = \tilde{\theta}^*_{CVR}$, which completes the proof. □

4 Semi-Synthetic Experiments

4.1 Dataset and Pre-Processing

To evaluate how accurately the proposed denoised loss function $\tilde{\mathcal{L}}_{CTCVR}$ estimates the true CTCVR loss $\mathcal{L}_{CTCVR}$ under the influence of noisy click-through and post-click conversion actions, we conducted experiments using the MovieLens-100K (ML-100K) dataset. The whole ML-100K dataset is assumed to be the impression space. Following existing works [6, 12, 24], the data generation process is described as follows. We first employed Matrix Factorization (MF) to fill in the missing values of the original five-scale preference matrix $P = [p_{u,i}], p_{u,i} \in \{1, 2, 3, 4, 5\}$. Then we generated the true conversion probabilities. We sorted the matrix entries and divided them into five proportions $(g_1, g_2, g_3, g_4, g_5)$. We assigned discrete conversion probabilities $p^r_{u,i} \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$ to these segments sequentially to establish the true conversion probability matrix. Then, we sample the binary true conversion matrix $\mathbf{R}$ as:

$$r_{u,i} \sim Bern(p^r_{u,i}), \forall (u,i) \in \mathcal{D}, \tag{47}$$

where $Bern(\cdot)$ denotes the Bernoulli distribution and the corresponding noisy conversion matrix $\tilde{\mathbf{R}}$ is obtained by flipping each item in $\mathbf{R}$ with noise rate ρ_{10} and ρ_{01} respectively.

Next, we use P to generate the click probability as $p^o_{u,i} = \alpha^{\min(4, 6 - p_{u,i})}$ for each user-item pair and the binary true click matrix $\mathbf{O}$ as:

$$o_{u,i} \sim Bern(p^o_{u,i}), \forall (u,i) \in \mathcal{D}, \tag{48}$$

and the corresponding noisy click matrix $\tilde{\mathbf{O}}$ is obtained by flipping each item in $\mathbf{O}$ with noise rate τ_{10} and τ_{01} respectively.

We adopted six distinct methods to generate the prediction matrix of the post-click conversion rate $\hat{\mathbf{R}}$ [12]:

- **ROTATE**: If the true probability $r_{u,i} > 0.1$, the prediction is reduced by 0.2; if $r_{u,i} = 0.1$, it is flipped to 0.9.
- **SKEW**: Sample predictions from a Gaussian distribution $N(\mu = r_{u,i}, \sigma = (1 - r_{u,i})/2)$, clipped to the range $[0.1, 0.9]$.
- **CRS**: Apply a threshold such that the prediction is set to 0.2 if $r_{u,i} \leq 0.6$, otherwise the prediction is set to 0.6.
- **ONE**: Start with the true probability matrix but introduce specific distortions by randomly flipping a total of $|\{(u,i)|r_{u,i} = 0.9\}|$ entries to 0.9 with original probabilities of $r_{u,i} = 0.1$.
- **THREE**: Same as **ONE**, but flipping with original probabilities $r_{u,i} = 0.3$ instead.
- **FIVE**: Same as **THREE**, but flipping with original probabilities $r_{u,i} = 0.5$ instead.

At last, we use the following equation to generate the prediction matrix of the click rate $\hat{\mathbf{O}}$:

$$1/\hat{o}_{u,i} = (1 - \beta)/p^o_{u,i} + \beta/p_e, \tag{49}$$

where $p_e = |\mathcal{D}|^{-1} \sum_{(u,i) \in \mathcal{D}} o_{u,i}$ and β is randomly chosen from $[0, 1]$ to introduce noise.

We use the absolute relative error (RE) to evaluate the estimation accuracy of the proposed unbiased loss. Specifically, $RE(\mathcal{L})$ for a specific loss function $\mathcal{L}$ is defined as:

$$RE(\mathcal{L}) = |\mathcal{L}((\hat{R}, \hat{O}), (\tilde{R}, \tilde{O})) - \mathcal{L}_{CTCVR}|/\mathcal{L}_{CTCVR}, \tag{50}$$

where $\mathcal{L}_{CTCVR}$ is the ideal CTCVR loss calculated using the clean data as defined in Equation (7). The smaller the RE, the more accurate the estimation.

Table 1: RE of $\mathcal{L}_{CTCVR}$ on ML-100K dataset with $\tau_{10} = 0.2$, $\tau_{01} = 0.2$, $\rho_{10} = 0.2$ and $\rho_{01} = 0.2$.

	ROTATE	SKEW	CRS	ONE	THREE	FIVE
Naive	0.0846±0.0004	0.2533±0.0013	0.4950±0.0019	0.3857±0.0013	0.3905±0.0015	0.3983±0.0015
Denoise_R	0.0691±0.0005	0.1355±0.0018	0.2917±0.0023	0.1974±0.0017	0.1963±0.0022	0.1989±0.0020
HiDe_EST	0.0111±0.0007	0.0129±0.0009	0.0273±0.0019	0.0162±0.0010	0.0163±0.0008	0.0158±0.0009
HiDe	0.0003±0.0002	0.0007±0.0005	0.0011±0.0008	0.0008±0.0003	0.0008±0.0003	0.0009±0.0004

4.2 Result Interpretation

We compare four different losses and the results are summarized in Table 1 where the *Naive* method simply calculate the CTCVR loss based on Equation (35), *HiDe* denotes our proposed CTCVR loss using the true value of τ_{10}, τ_{01}, ρ_{10}, ρ_{01} while *HiDe_EST* denotes our proposed CTCVR loss using the estimated $\hat{\tau}_{10}$, $\hat{\tau}_{01}$, $\hat{\rho}_{10}$, $\hat{\rho}_{01}$. To further demonstrate the impact of the hierarchical noise to the CTCVR loss under the entire space modeling scenario, we also present the *Denoise_R* loss, which only denoise the noise in the conversion labels while omit the noise in the click labels.

From Table 1 we can draw three conclusions. First, our proposed HiDe-ESMM method gives the lowest RE that is close to 0 while the Naive loss has the largest RE in all the scenarios, verifying the importance of addressing the noise in real applications and the unbiasedness of the proposed HiDe-ESMM method. Second, the HiDe_EST method is close to the HiDe method in all the scenarios. This result demonstrates the robustness of our proposed HiDe-ESMM method in real applications where the true value of the noise rates are unknown while the estimates are used instead. Third, the Denoise_R method has a significantly larger RE than the HiDe_EST method in all the scenarios. This result reveals that omitting the noise in click events may not achieve satisfied denoising performance by simply denoising the noise post-click events. This finding further emphasizes the importance of our proposed hierarchical denoising method when there exist different levels of label noise in CTCVR modeling.

4.3 In-depth Analysis

To rigorously examine the impact of noise magnitude on the proposed unbiased loss, we evaluate the RE by varying all noise rates (τ_{10}, τ_{01}, ρ_{10} and ρ_{01}) within the range of $\{0.1, 0.15, 0.2, 0.25, 0.3\}$. The results are illustrated in Figure 2. The results reveal a sharp deterioration in the performance of Naive and Denoise_R methods as noise increases, evidenced by a dramatic surge in RE. In contrast, our proposed unbiased loss consistently remains near zero across all noise levels, further substantiating its denoising capability. Moreover, the marginal increase in the RE of the HiDe_EST loss is significantly lower than that of the competing methods, verifying the exceptional robustness of the HiDe-ESMM framework.

5 Real-World Experiments

5.1 Dataset

We conducted real-world experiments on two datasets, one publicly available and one private industrial dataset. We introduce these two dataset as follows.

Table 2: Summary statistics of ALI-CCP and Industrial datasets.

	# Train	# Click	# Conv	# Test	# Click	# Conv
ALI-CCP	42.3M	1.6M	8.8K	43.0M	1.7M	9.2K
Industrial	11.5M	2.9M	0.16M	3.5M	0.88M	46.6K

Public dataset: We validated our method on the widely adopted ALI-CCP dataset [20, 26, 27]. This large-scale dataset comprises more than 80 million samples with diverse features and provides sequential ground-truth labels for both click and conversion events.

Industrial dataset: We further conducted validation experiments on an Industrial dataset collected from Tencent's affiliate advertising platform [26]. This dataset comprises samples characterized by 50 discrete feature fields, capturing comprehensive user, item, and interaction information. Following standard industrial practices, the dataset spans five consecutive days of logs, which are temporally partitioned into a training set (first four days) and a test set (the last day). We summarize the statistics of both datasets in Table 2.

5.2 Experiment Protocol

5.2.1 Baselines. We compare our method with the following methods, including:

- Debiased methods, which primarily focus on mitigating the SSB problem: **Multi-IPS** [38], **Multi-DR** [38], **IPS** [24], **SNIPS** [24], **DR-JL**[31], **MRDR** [6], **DR-BIAS** [2], **DR-MSE** [2], **DR-GPL** [47], **TDR-CL** [8], **IPS-V2** [11], **DR-V2** [11], **AKBDR** [14];
- Denoised methods, which aim to denoise the post-click conversion labels but fail to consider the noise in the antecedent click labels: **OME-IPS**[12], **OME-DR** [12];
- Entire space modeling methods, which focus on estimating CVR over the entire impression space within a multi-task framework: **ESMM** [20], **ESCM^2-IPS** [27], **ESCM^2-DR** [27], **AECM** [39], **DCMT** [48], **DDPO** [26], **EVI** [3].

5.2.2 Experiment setups. In this paper, we employed an MLP with hidden layer sizes of [64, 32] for both the CTR and CVR prediction towers within the entire space modeling framework, as well as for the imputation model in some of the baselines. We implemented the unbiased loss and the forward correction approach based on the model architecture of ESCM^2 to demonstrate the denoising power of our proposed HiDe-ESMM. We used Adam as the optimizer for all methods. All experiments were run on Pytorch with NVIDIA GeForce RTX TITAN V as the computational resource. Following

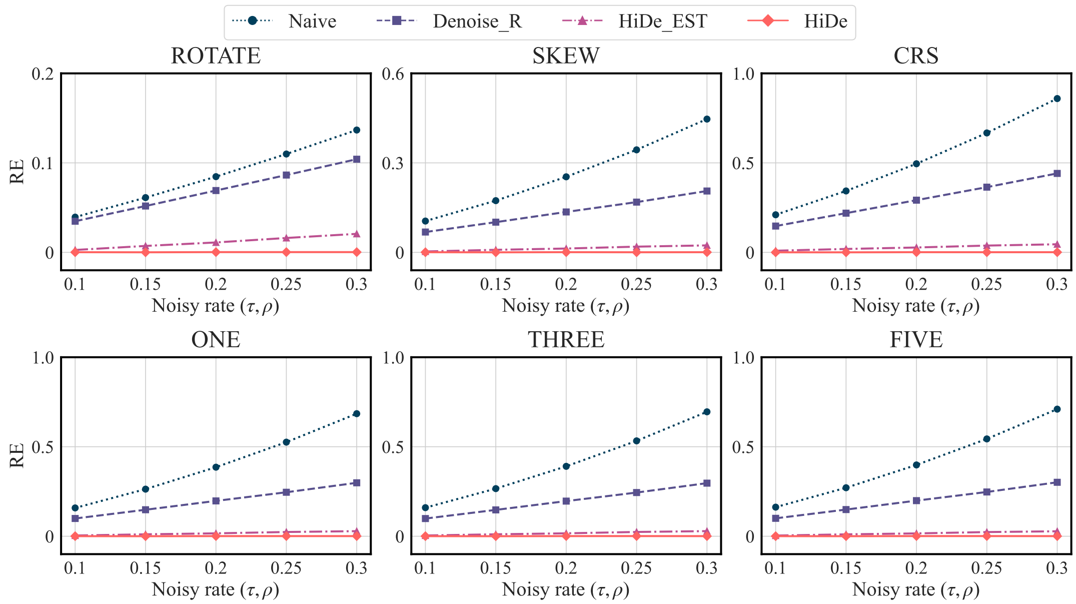

Figure 2: RE Comparison of $\mathcal{L}_{CTCVR}$ with different value of τ and ρ.

Table 3: Performance on AUC and KS on the test set of ALI-CCP and Industrial dataset. The best results are bolded and the best baseline is underlined. * means statistical significant under p < 0.05 using pairwise t-test.

Method	ALI-CCP						Industrial					
	CVR		CTR		CTCVR		CVR		CTR		CTCVR	
	AUC	KS	AUC	KS	AUC	KS	AUC	KS	AUC	KS	AUC	KS
IPS	0.6331	0.1921	0.6056	0.1494	0.6389	0.1986	0.8486	0.5696	0.6049	0.1604	0.8515	0.5658
SNIPS	0.6328	0.1932	0.6103	0.1561	0.6393	0.1984	0.8489	0.5668	0.6044	0.1610	0.8506	0.5615
DR-JL	0.6362	0.1983	0.6055	0.1487	0.6368	0.1953	0.8478	0.5663	0.6083	0.1658	0.8508	0.5665
Multi-IPS	0.6266	0.1824	0.5841	0.1358	0.6289	0.1789	0.8472	0.5697	0.6069	0.1589	0.8501	0.5647
Multi-DR	0.6293	0.1876	0.5328	0.0827	0.5671	0.1186	0.8232	0.5368	0.5131	0.0325	0.8211	0.5266
MRDR	0.6316	0.1928	0.5939	0.1296	0.6245	0.1792	0.8480	0.5716	0.6059	0.1607	0.8479	0.5594
DR-BIAS	0.6353	0.1989	0.5970	0.1364	0.6234	0.1754	0.8438	0.5661	0.6040	0.1573	0.8431	0.5549
DR-MSE	0.6272	0.1829	0.5643	0.0832	0.6287	0.1871	0.8470	0.5693	0.6073	0.1627	0.8481	0.5579
DR-GPL	0.6356	0.1979	0.6055	0.1487	0.6364	0.1944	0.8479	0.5663	0.6083	0.1658	0.8508	0.5667
TDR-CL	0.6278	0.1889	0.6029	0.1447	0.6347	0.1965	0.8438	0.5641	0.6077	0.1619	0.8488	0.5658
IPS-V2	0.6281	0.1865	0.6116	0.1576	0.6314	0.1949	0.8478	0.5699	0.6056	0.1599	0.8507	0.5651
DR-V2	0.6319	0.1936	0.6151	0.1624	0.6316	0.1959	0.8478	0.5641	0.6033	0.1577	0.8486	0.5628
AKBDR	0.6287	0.1870	0.6041	0.1468	0.6201	0.1726	0.8450	0.5669	0.6051	0.1568	0.8502	0.5672
OME-IPS	0.6243	0.1855	0.6103	0.1595	0.6285	0.1935	0.8431	0.5646	0.6034	0.1636	0.8507	0.5620
OME-DR	0.6319	0.1973	0.6161	0.1637	0.6322	0.1980	0.8479	0.5697	0.6054	0.1588	0.8462	0.5656
ESMM	0.6249	0.1807	0.6137	0.1615	0.6340	0.1958	0.8467	0.5704	0.6084	0.1637	0.8514	0.5688
ESCM2-IPS	0.6276	0.1845	0.6064	0.1496	0.6331	0.1932	0.8479	0.5674	0.6045	0.1593	0.8502	0.5671
ESCM2-DR	0.6391	0.2041	0.6116	0.1565	0.6362	0.2034	0.8501	0.5681	0.6094	0.1616	0.8518	0.5642
AECM	0.6269	0.1854	0.5256	0.0437	0.6281	0.1880	0.8468	0.5652	0.5701	0.1126	0.8478	0.5656
DCMT	0.6242	0.1774	0.6089	0.1535	0.6246	0.1883	0.8500	0.5701	0.6050	0.1599	0.8521	0.5660
DDPO	0.6112	0.1624	0.6096	0.1545	0.6115	0.1664	0.8483	0.5661	0.6096	0.1689	0.8517	0.5610
EVI	0.6323	0.1923	0.6168	0.1607	0.6320	0.2016	0.8475	0.5698	0.6088	0.1608	0.8496	0.5651
HiDe-ESMM-B	0.6435	0.2067	**0.6258***	**0.1783***	**0.6522***	0.2161	0.8513	0.5712	**0.6131***	**0.1705***	0.8547	0.5712
HiDe-ESMM-F	**0.6490***	**0.2152***	0.6249	0.1760	0.6488	**0.2189***	**0.8530***	**0.5736***	0.6122	0.1667	**0.8569***	**0.5770***

previous studies [3, 26, 27], we prefixed the training parameters for all the models. Specifically, the learning rate was set to 1e-3, weight decay was set to 1e-5 for all the methods. The embedding size was set to 5 and the batch size was set to 8192 for both **ALI-CCP** and **Industrial** datasets. Following the previous studies [27], we employ two widely used evaluation metrics, AUC and KS score, to assess the denoising performance of our model, where KS score quantifies a model's maximum separation power between the two classes at an optimal threshold.

5.3 Performance Comparison

We validate the effectiveness of our proposed framework through two specific implementations, namely **HiDe-ESMM-B**, utilizing the denoised loss described in Equations (8) and (23), and **HiDe-ESMM-F**, leveraging the forward correction strategy detailed in Section 3.5. The comprehensive performance comparison of our methods against various baselines is reported in Table 3. As observed, our approach demonstrates dominant performance on both the **ALI-CCP** and **Industrial** datasets, yielding significant improvements across all CVR, CTR, and CTCVR prediction tasks compared to the baselines. These results not only confirm the pervasive existence of label noise in both click and post-click conversion events but also highlight the critical importance of our unified denoising framework in addressing these hierarchical biases within entire-space modeling methods for real-world applications.

5.4 In-Depth Analysis

To further substantiate the effectiveness of the proposed HiDe-ESMM framework in enhancing existing entire-space models, we conduct experiments applying both HiDe-ESMM-B and HiDe-ESMM-F strategies using ESMM and ESCM^2-DR as backbones. The results are visualized in Figure 3. Two key observations can be drawn from these results. First, incorporating the denoising mechanism, whether via the unbiased loss or forward correction, consistently boosts CVR prediction performance. Second, and more importantly, this improvement in CVR is accompanied by dramatic gains in both CTR and CTCVR metrics. This synchronous improvement provides empirical evidence that accurate CVR estimation is intrinsically grounded in robust CTR and CTCVR predictions, thereby emphasizing the necessity of jointly denoising both tasks in real-world applications.

5.5 Ablation Study

In this section, we evaluate a variant denoised objective that we term as the Standard-Approach. Specifically, this method directly utilizes the noisy rates ν_{10} and ν_{01} (defined in Equations (11) and (12)) to denoise the CTCVR loss, adopting a structure identical to the CTR loss described in Equation (8). The empirical results are presented in Table 4, from which we draw the following conclusions. First, the Standard-Approach achieves comparable CTR performance to HiDe-ESMM due to their shared denoising mechanism on CTR prediction task. However, its CTCVR performance degrades significantly. This stems from a critical circular dependency where estimating ν_{10} requires the true probability $\mathbb{P}(r_{u,i} = 1)$, which is approximated by the initially unstable CVR tower. This creates a detrimental loop where erroneous early predictions compromise the noise rate estimation, hindering convergence, which is a limitation effectively circumvented by our HiDe-ESMM.

Table 4: Model performance comparison on ALI-CCP using different approaches to construct the unbiased loss.

	CVR		CTR		CTCVR	
	AUC	KS	AUC	KS	AUC	KS
Standard-Approach	0.6324	0.1916	**0.6260**	**0.1793**	0.6429	0.2050
HiDe-ESMM-B	**0.6435**	**0.2067**	0.6258	0.1783	**0.6522**	**0.2161**

6 Related Work

CVR prediction is a fundamental task in recommender systems [7, 10, 33, 34, 43]. Traditional CVR models trained solely on clicked samples suffer from two intrinsic challenges: Sample Selection Bias (SSB) and Data Sparsity (DS) [20]. To alleviate SSB, Doubly Robust (DR) estimators, such as DR-JL [31], MRDR [6], DR-BIAS [2] and Multi-DR [38] have been widely applied. Alternatively, the Entire Space Multi-task Model (ESMM) [20] addresses both issues by modeling CVR indirectly using CTCVR and CTR over the entire space via the decomposition $pCTCVR = pCTR \times pCVR$. Subsequent works have further refined this paradigm. ESCM^2 [27] incorporates regularizers to tackle inherent biases, while approaches like DDPO [26] and EVI [3] introduce auxiliary tasks to enhance performance. However, these methods universally operate under the assumption of clean labels, overlooking the inevitable label noise in real-world data [9, 14]. This oversight forces models to overfit erroneous signals, which is a critical limitation our framework addresses by explicitly modeling hierarchical noise.

Learning with noisy labels (LNL) represents a critical challenge in robust machine learning. Training models on such noisy data can lead to poor generalization and unreliable performance [4]. Among established solutions, loss correction has emerged as a prominent approach due to its rigorous theoretical guarantees [19]. The core mechanism of this approach involves modifying the optimization objective, either by correcting the loss function via backward correction [12] or adjusting the model predictions via forward correction [23], to ensure that the empirical risk estimator remains statistically unbiased or consistent despite label corruption. Typically, an estimated transition matrix [15] is used to model the noisy label generation process. However, these methods are tailored for independent single-task classification. They are fundamentally insufficient for entire space CVR prediction, where the target label (CTCVR) is a composite of two sequential variables (click and conversion). This unique hierarchical structure implies that the observed noise is a superposition of errors from both stages, leading to ineffectiveness of conventional single-task denoising techniques without adaptation.

7 Conclusion

In this paper, we proposed HiDe-ESMM, a unified denoising framework designed to mitigate the hierarchical label noise inherent in entire space multi-task modeling approaches. By leveraging the loss correction paradigm, we derived a statistically unbiased CTCVR loss via backward correction and a consistent forward correction strategy, utilizing the weak separability assumption to estimate the requisite noise rates. Through extensive experimentation on one semi-synthetic dataset and two real-world industrial datasets, HiDe-ESMM consistently demonstrates superior performance across CVR,

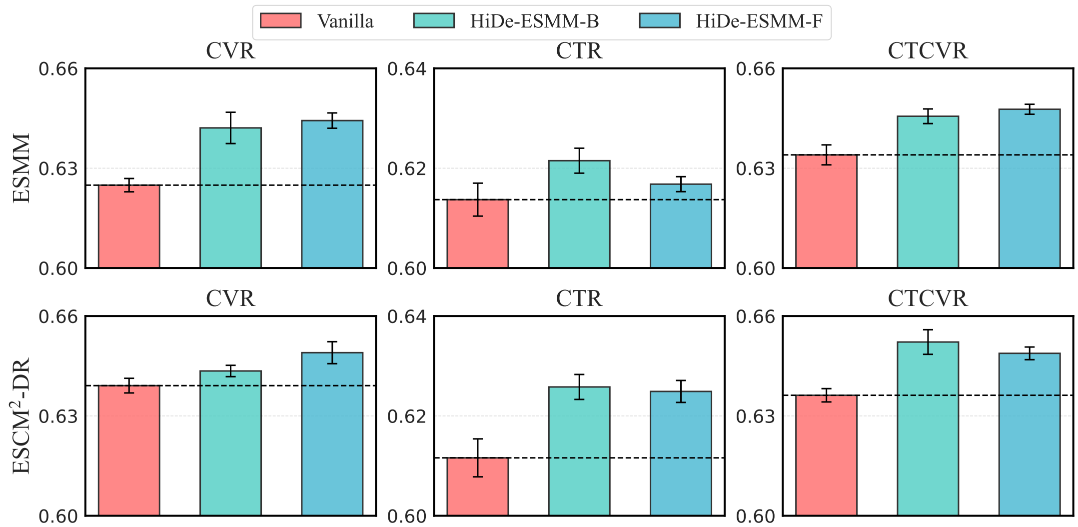

Figure 3: AUC performance using different base model structures.

CTR, and CTCVR prediction tasks compared to state-of-the-art baselines.

Despite these significant improvements, there remain avenues for further exploration. First, regarding computational efficiency, while both our forward and backward correction strategies enable the model to directly output clean predictions during inference without additional cost, the current framework relies on a pre-trained prediction network to estimate noise rates during training, which inevitably increases overall training time. Exploring end-to-end joint learning approaches that simultaneously estimate noise rates and optimize the prediction models presents a promising direction to enhance efficiency. Second, our current framework relies on the widely adopted weak separability assumption and class-dependent noise to estimate noise rates. While theoretically sound, these assumptions may not perfectly encapsulate the intricate noise patterns present in highly dynamic real-world scenarios. Future work could consider integrating instance-dependent noise modeling or other advanced noise estimation methods into our proposed hierarchical denoising framework to capture more complex noise patterns in dynamic environments and achieve broader adaptability.

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