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Towards Disentangling Relevance and Bias in Unbiased Learning to Rank

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ABSTRACT

Unbiased learning to rank (ULTR) studies the problem of mitigating various biases from implicit user feedback data such as clicks, and has been receiving considerable attention recently. A popular ULTR approach for real-world applications uses a two-tower architecture, where click modeling is factorized into a relevance tower with regular input features, and a bias tower with bias-relevant inputs such as the position of a document. A successful factorization will allow the relevance tower to be exempt from biases. In this work, we identify a critical issue that existing ULTR methods ignored - the bias tower can be confounded with the relevance tower via the underlying true relevance. In particular, the positions were determined by the logging policy, i.e., the previous production model, which would possess relevance information. We give both theoretical analysis and empirical results to show the negative effects on relevance tower due to such a correlation. We then propose three methods to mitigate the negative confounding effects by better disentangling relevance and bias. Empirical results on both controlled public datasets and a large-scale industry dataset show the effectiveness of the proposed approaches.

KEYWORDS

Unbiased Learning to Rank; Multitask Learning; Observation Bias

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1 INTRODUCTION

Learning to rank (LTR) is critical for many real-world applications such as search and recommendations [15]. In real-world applications, implicit feedback from user logs such as clicks are used to

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train ranking models. Though easily available in a large scale, implicit feedback has various kinds of biases, such as position bias. Unbiased Learning To Rank (ULTR) has drawn much attention recently due to its promise to mitigate such biases [3].

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Roughly speaking, there are two categories of approaches for ULTR. The first category is the counterfactual approaches that are mainly based on the Inverse Propensity Scoring (IPS) method [2, 12, 14, 26]. These approaches require knowing the bias or observation propensities in advance, but they are not available necessarily. The second category covers click modeling approaches that achieve relevance estimation through factorized models trained to predict clicks. This type of approaches do not have such prerequisites. In this paper, we focus on the second category, and in particular, the two-tower additive models, which are popular in practice [5, 10, 11, 30] due to their simplicity and effectiveness.

In the two-tower models, one tower takes regular input features to model unbiased relevance predictions, and another tower takes bias-related features, such as position and platform (e.g., mobile vs desktop) to estimate the non-uniform probability user would observe the results. We thus use bias and observation interchangeably in this paper. The outputs of these two towers are added together to explain logged user feedback during offline training, and only the unbiased prediction tower is effectively used during online serving. Two-tower additive models are easy to implement, interpret, and follow the Position Based Model (PBM) click model [6, 22] to model user behaviors, which assumes that bias learning is independent of true relevance. Ideally, the factorization will cleanly separate relevance and biases into their respective towers.

However, we argue that such assumption is unrealistic in practice. The key issue ignored in the literature is that the relevance tower and observation tower are confounded by true relevance in terms of causal inference [17]. As shown in Figure 1, the logged display position of an item was actually determined by the logging policy, i.e., the previous deployed ranker, which is likely correlated with true relevance. Thus, bias features and relevance features are both correlated with true relevance, which violates the independence assumption of observation and relevance signals. Overlooking such correlations between relevance features and observation features can be detrimental to the relevance tower to be served. Consider

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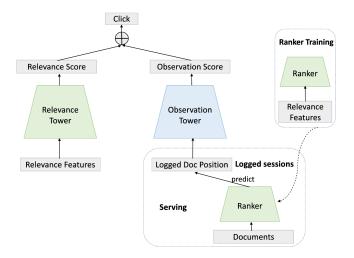


Figure 1: An illustration of the two tower additive model ULTR framework. The input of the observation tower is generated from a ranker trained to learn relevance.

the extreme case where the logged positions were from a perfect relevance model, then the observation tower can potentially absorb *all* relevance information during two-tower model learning and explain the clicks perfectly. The resulted relevance tower, on the other hand, can be completely random and thus useless.

In this paper, we study the confounding effect both theoretically and empirically. We perform controlled semi-synthetic experiments with different relevance-entangling levels by injecting different percentages of ground-truth information into the logging policy, and examine a wide range of cases, from relevance-agnostic to total relevance-deterministic position data. The findings align with our intuition - the more correlated the bias and relevance are, the less effective the relevance tower is. We further propose three methods to mitigate the negative confounding effect to improve the relevance tower performance, including (1) an adversarial training method to disentangle the relevance information from the observation tower, (2) a dropout algorithm that learns to zero-out relevance-related neurons in the observation tower, and (3) a mixture mechanism that forcefully controls the contributions of the two towers to model observed feedback. We show that all the proposed methods can potentially disentangle the relevance and bias by mitigating the confounding issue with different strengths and weaknesses.

In summary, the contributions of our work are three-fold:

- We identify and analyze the confounding effect between relevance and bias in ULTR, which may bring detrimental effects to real-world ranking systems.
- We propose three methods to mitigate this issue to disentangle relevance and bias and show promising results in both controlled semi-synthetic and real-world industry datasets.
- We provide a theoretical analysis on why the confounding factors can negatively affect relevance model learning, and on why our methods work.

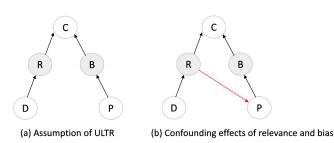


Figure 2: The causal graphs of click modeling. *C*-click, *R*-true relevance, *B*-bias, *P*-position, *D*-regular item features. Grey circles indicate unobserved latent variables. White circles indicate observed variables.

2 RELATED WORK

The two-tower model family for ULTR has been widely explored in both industry and academia community. PAL [10] is the pivot work that introduces the two-tower model to the research community. Zhao et al. [30] uses the two-tower model for recommending which video to watch on YouTube. Haldar et al. [11] applies a two-tower model on Airbnb search. Wu et al. [28] adapts a two tower model for news feed recommendation ranking with a rich set of bias features. Zhuang et al. [31] considers surrounding items in the observation model. Yan et al. [29] enriches two-tower models with more expressive interactions and click models, and is orthogonal to our work. To the best our knowledge, no prior work discusses the confounding effect in the formulation.

Another closely related family of methods for ULTR, Inverse Propensity Scoring (IPS) based methods [1, 2, 14, 16, 20, 25–27], follow the same Position Based Model assumption (except for very few recent works, like [24]). In this work, we focus on the discussion of two-tower models due to their popularity, but the discussed concerns may generalize to some IPS-based methods since they follow the same assumptions. For example, Wang et al. [27] performs an EM procedure between relevance and observation propensity model. Though the goal was to estimate propensity, the confounding between these two models persists and the propensity estimation can be negatively affected. Studying the confounding effect in these methods is left for future work.

Zhao et al. [30] uses a dropout operation in their two-tower model, which may look similar to one of our proposed methods. However, the dropout was treated as a heuristic in [30] and they do not concern about the confounding effect - their dropout is added to the input layer of the bias tower with the goal to learn a default position representation. Thus, the motivation and methodology are quite different from ours, as our main question is on the confounding effect and how to disentangle relevance and bias in a better way.

3 THE PROBLEM

In this section, we describe the general formulation of the popular two-tower models and their key assumptions, and identify the confounding effect that can negatively affect the learning process.

3.1 General Assumption

As shown in Figure 2, in the two-tower model, a relevance-observation factorization is assumed for the click behavior. The click probability of an item *i* can be factorized into two factors: the relevance of the item, and the observation probability of the item. The relevance of the item is assumed to be only related to the item features x_i and its interaction with the query *q*. The observation modeling is assumed to be only related to display properties, e.g., position p_i . We can then formulate the click probability of item i as:

$$P(c_i = 1 | x_i, p_i) = \psi(f(r(x_i)), g(o(p_i))),$$
(1)

where *r* and *o* are encoders that map x_i and p_i into scalars. *f* and *g* are univariate transformation functions that compute the relevance scores and observation scores. ψ is a transformation that fuses relevance scores and observation scores into click scores. Such formulation is expected to be bias-aware and to learn a position-agnostic relevance representation when the relevance encoder *r* is taken alone.

3.2 The Confounding Problem

The position-agnostic relevance learning is based on the assumption that relevance and observation are independent, which allows us to factorize them. However, p_i is the logged position of an item in previous servings, where we have a ranker to rank items based on their predicted relevance r':

$$p_i = |j|r'(x_j) > r'(x_i), \text{ for } j \text{ in } [1, n]|$$
(2)

where $r'(x_i)$ is the relevance score for the item x_i . The position p_i is obtained by computing all the *n* relevance scores associated with a query and sorting results by their scores in the descending order.

We can see from Equation 2 that the position p_i is determined by the estimated relevance in the logging policy. To what level the position reflects the true relevance depends on how the rank r' is correlated with the true relevance. In an extreme case when r' is a perfect ranker, the position would also be a perfect indication of relevance. In this case, the two-tower model would find an obvious shortcut during learning: the simple integer position index is a lot more important to learn compared to the heavy (query, doc) features. Such learning behavior can be detrimental to the relevance tower learning.

A simple way to mitigate confounding bias is to perform online randomization experiments and gather data with logged position that is not confounded with relevance. However, it is not practical as randomization experiments hurt user experience significantly and real-world ranking systems usually need a lot of data to train. We focus on logged biased datasets in our methods bleow.

4 METHODS

In this section, we introduce three ways to disentangle relevance and observation learning. The high-level idea is to control or unlearn the relevance information in the observation tower. We describe the model details below.

4.1 DNN Architecture

We describe the backbone two-tower DNN architecture shared by all our methods.

Input Representation. Each tower of the two-tower model takes one type of input. The relevance tower processes relevance-related features while the observation tower handles observation-related features. The relevance input can be represented as a concatenation of various types of feature vectors depending on the data. We refer to the concatenated representation for item *i* as x_i . The observation features (an integer position index in the simplest case) are mapped to a embedding vector. If the observation tower input contains multiple features, we concatenate them in a similar way to relevance features. We still denote the observation input features as p_i by slightly abusing the notation.

Relevance Tower. The relevance tower takes one item at a time. In this paper, we instantiate the relevance tower as a feed-forward neural network (FFN) r whose parameters are denoted as θ_{rel} . Each layer of the network is fully connected with the ReLU activation.

$$r(x_i) = FFN(x_i; \theta_{rel}) \tag{3}$$

Observation Tower. The observation tower takes a similar design to the relevance tower. In this paper, we instantiate the observation tower as a feed-forward neural network *o* whose parameters are denoted as θ_{obs} . Each layer of the network is fully connected with the ReLU activation.

$$o(p_i) = FFN(p_i; \theta_{obs}) \tag{4}$$

Here, p_i is the logged ranking result of item 1...*n* by the serving ranker that is deployed in the production system.

Training. The model is trained with the sigmoid cross entropy loss supervised by user clicks. We denote the predicted click probability as \hat{c}_i ,

$$\hat{c}_i = \psi(r(x_i), o(p_i)), \tag{5}$$

where the interaction function ψ is specific to each method as shown below. With ground-truth click as c_i , we can optimize the following cross-entropy loss:

$$\mathcal{L}_{click} = -\sum_{i=1}^{n} [c_i \log(\hat{c}_i) + (1 - c_i) \log(1 - \hat{c}_i)].$$
(6)

4.2 Gradient Reversal

The main issue we want to fix is the confounding relevance learned in the observation tower from the observation features. Inspired by research in adversarial learning and domain adaptation [7], we design a gradient reversal approach with a simple intuition - Machine learning models learn from the supervision by backpropagating the gradient from a loss. Reversely, it could unlearn from the supervision by backpropagating the negative of the gradient.

In this method, the main click prediction is obtained as the additive model,

$$\psi(r, o) = \operatorname{sigmoid}(r + o). \tag{7}$$

In our case, we want to remove the unreliable relevance information contained in the observation tower. So we add an extra relevance prediction task for the observation tower. We feed the observation tower output through a gradient reversal layer followed by a dense layer. The output o^{rev} of the dense layer on top of the sharing hidden layers of the observation tower is treated as its relevance prediction. We pass this output through a gradient reverse (GradRev) layer and supervise this task by an adversarial label, y^{rev} , that contains

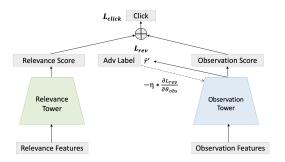


Figure 3: An illustration of the gradient reversal method. The adv label provides supervision for the observation tower's gradient reversal task. The gradient of this task would be multiplied by a negative scaling factor η in back-propagation.

relevance-related signals, e.g., ranker predictions or clicks. In the forward pass, the GradRev layer conducts an identity mapping of the input. In backpropagation, the layer reverses the gradient from the following layer, scales it by a hyperparameter η , and backpropagates it to the observation tower.

$$\mathcal{L}_{rev} = \sum_{i=1}^{n} (y_i^{rev} - \text{GradRev}(o^{rev}(p_i), \eta))^2.$$
(8)

 y_i^{rev} is the adversarial label. The total loss to be optimized is then the sum of \mathcal{L}_{click} and \mathcal{L}_{rev} .

Figure 3 gives an illustration of this method. We tried three different adversarial labels to prove the method's generality across scenarios. (1) Ground truth relevance label: this setting is mainly used for the ablation study as true relevance is usually not available in user logs. (2) Click: we directly use user click as the adversarial label. (3) Relevance tower prediction: the two towers play a minimax game as in GAN. We will compare these choices in detail in Section 6.5.

4.3 **Observation Dropout**

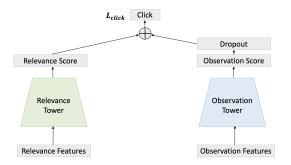


Figure 4: Graphic illustration of the observation dropout method. A dropout layer is added to the observation score.

Another perspective of the confounding issue is a classic shortcut learning problem common in neural networks [8, 9, 13]. The taxonomy, shortcut, refers to the scenario when the learned decision rule relies on superficial correlation rather than the intended intrinsic features. For example, in image classification, the classifier may learn to use the background of an object, instead of the object itself for classification [9]: A cow can be recognized if it appears in a typical cow-background like grass or barns, but it may be classified correctly if put into an unexpected background like a beach. This behavior is analogous to our case where the two-tower model learns relevance from the position of the document rather than the (query, doc) features.

Neural networks take shortcut because they find some unrobust features useful to cheaply optimize the target function. One intuitive way of discouraging such behavior is to make the shortcut features less useful for the target, e.g., by adding some random noise to the shortcut features.

Following this intuition, we discourage the shortcut learning behavior by zero-out some neurons in the observation tower. Ideally, we want to only masked out relevance-related neurons which gives better interpretability and possibly better performance guarantee. However, we find a simple dropout layer [23] above the observation tower works well emperically in experiments:

$$\psi(r, o) = \text{sigmoid}(r + \text{Dropout}(o, \tau)),$$
 (9)

where τ is the dropout probability.

4.4 Tower Mixture

In this method, we control the contribution that each tower can make towards prediction in a mixture model. The mixture model assumes the observed implicit feedback is resulted from a mixture of relevance and observation factors and it allows to control the contribution from each factor. The intuition is to control the contribution of the observation tower in the learning process so the relevance tower is less likely to be dominated. Concretely, we assign a weight λ to the observation tower, and $1 - \lambda$ to the relevance tower.

$$\psi(r, o) = \lambda \operatorname{sigmoid}(o(p_i)) + (1 - \lambda)\operatorname{sigmoid}(r(x_i))$$
(10)

The weight λ plays a throttling role for the observation tower when explaining clicks. Similar techniques have been explored in various domains in the literature, such as natural language processing and recommender systems, to control the contribution of different model components [19, 21]. We will analyze the role of λ for the training process in Section 5.

5 THEORETICAL ANALYSIS

In this section, we give a qualitative theory to rationalize how above methods reduce the confounding effect in the observation tower.

5.1 Problem formulation

Without loss of generality, we denote relevance related features as \vec{x}^R , and observation bias related features, such as positions and/or some relevance features [31], as \vec{x}^O , so that the click probability depends on the combined features as,

$$P(C=1|\vec{x}^R, \vec{x}^O) = P_{rel}(\vec{x}^R) \times P_{obs}(\vec{x}^O)$$
(11)

Let's assume that we could perfectly model the click above with DNN models with the two-tower architecture with click probability,

$$\hat{c} = f_{\theta}(\vec{x}^R) \times g_{\varphi}(\vec{x}^O), \tag{12}$$

where θ and φ are the training parameters of the relevance tower and the observation bias tower, respectively.

As such, there is a set of parameters θ^* and ϕ^* so that $f_{\theta^*}(\vec{x}^R) = p_{rel}(\vec{x}^R)$ and $g_{\phi^*}(\vec{x}^O) = p_{obs}(\vec{x}^O)$ for any $\{\vec{x}^R, \vec{x}^O\}$. It is then straightforward to show that (θ^*, ϕ^*) optimize the average of the total loss on clicks in Eq.(6),

$$\langle \mathcal{L}^t \rangle = -\int dP^t(\vec{x}^R, \vec{x}^O) \left[p(C=1) \log(\hat{c}) + p(C=0) \log(1-\hat{c}) \right],$$
(13)

where $dP^t(\vec{x}^R, \vec{x}^O)$ denotes the probability measure at $\{\vec{x}^R, \vec{x}^O\}$ of the logged data generated from the previous model *t*.

It's also easy to show that the corresponding model f_{θ^*} also optimizes the average relevance metrics like NDCG,

$$\langle \mathcal{M} \rangle = \int dP(\vec{x}^R) m(p_{rel}(\vec{x}^R), f_\theta(\vec{x}^R)), \qquad (14)$$

where the metric function $m(y, \hat{y})$ is optimal when the model prediction is equal to the ground truth label, $\hat{y} = y$. Similar to above, $dP(\vec{x}^R)$ denotes the marginal probability measure of the ranking candidates near \vec{x}^R .

5.2 Confounding effect

As we have discussed, in real-world data log, there exists a nontrivial correlation between positions and relevance features, in other words, $dP^t(\vec{x}^R, \vec{x}^O) \neq dP(\vec{x}^R)dP(\vec{x}^O)$. In the following, we will show and define how this correlation could negatively impact the two-tower model performance.

We denote the marginal probability measure $dP(\vec{x}^R)$ is nonzero in the input space \mathbb{R} , similarly, $dP(\vec{x}^O)$ is nonzero in the input space \mathbb{O} . In the following, we assume \mathbb{R} and \mathbb{O} are continuous differentiable domains for deep neural networks. For example, they could be representations or numerical positions extended to the real numbers.

CONJECTURE 1. For the correlated \vec{x}^R and \vec{x}^O , we then have the joint probability measure $dP^t(\vec{x}^R, \vec{x}^O)$ nonzero on the input space \mathbb{X}^t , which must be a subset of $\mathbb{R} \otimes \mathbb{O}$, i.e. $\mathbb{X}^t \subseteq \mathbb{R} \otimes \mathbb{O}$.

THEOREM 2. If there is a parameter set different from the ground truth set (θ^*, φ^*) minimizing the loss function $\langle \mathcal{L}^t \rangle$ in Eq.(13) on the input domain which is a strict subset of $\mathbb{R} \otimes \mathbb{O}$, then there exists a continuous set of parameter sets minimizing $\langle \mathcal{L}^t \rangle$: $\exists \Theta = \{(\theta, \varphi) | \langle \mathcal{L}^t(\theta, \varphi) \rangle =$ $\langle \mathcal{L}^t(\theta^*, \varphi^*) \rangle \} \supset \{(\theta^*, \varphi^*)\}$ s.t. $\forall \varepsilon > 0$ and $\forall (\theta, \varphi) \in \Theta$, $\exists (\theta', \varphi') \neq$ (θ, φ) s.t. $||(\theta', \varphi') - (\theta, \varphi)|| < \varepsilon$ and $(\theta', \varphi') \in \Theta$, if $\exists (\theta, \varphi) \neq$ (θ^*, φ^*) s.t. $\langle \mathcal{L}^t(\theta, \varphi) \rangle = \langle \mathcal{L}^t(\theta^*, \varphi^*) \rangle$.

PROOF. Assuming there is another parameter set, $(\theta_1, \varphi_1) \neq (\theta^*, \varphi^*)$, minimizing the average total loss in Eq.(13), $\langle \mathcal{L}^t(\theta_1, \varphi_1) \rangle = \langle \mathcal{L}^t(\theta^*, \varphi^*) \rangle$. It's easy to see that $\langle \mathcal{L}^t(\theta_1, \varphi_1) \rangle = \langle \mathcal{L}^t(\theta^*, \varphi^*) \rangle$ if and only if $f_{\theta_1}(\vec{x}^R)g_{\varphi_1}(\vec{x}^O) = p_{rel}(\vec{x}^R)p_{obs}(\vec{x}^O)$ for $\forall \{\vec{x}^R, \vec{x}^O\} \in \mathbb{X}^t$. Let's say $f_{\theta_1}(\vec{x}^R)g_{\varphi_1}(\vec{x}^O) = p_{rel}(\vec{x}^R)p_{obs}(\vec{x}^O)$ on \mathbb{X}_1 so that $\mathbb{X}^t \subseteq \mathbb{X}_1 \subset \mathbb{R} \otimes \mathbb{O}$. Due to the continuity of the Deep neural network on parameters (θ, φ) , there must exist a neighbor (θ_2, φ_2) in any close vicinity of (θ_1, φ_1) so that $f_{\theta_2}(\vec{x}^R)g_{\varphi_2}(\vec{x}^O) = p_{rel}(\vec{x}^R)p_{obs}(\vec{x}^O)$ on \mathbb{X}_2 with $\mathbb{X}_1 \subseteq \mathbb{X}_2 \subseteq \mathbb{R} \otimes \mathbb{O}$, where the second equal sign is true if and only if $(\theta_2, \varphi_2) = (\theta^*, \varphi^*)$.

PROPOSITION 3. The relevance metrics are suboptimal for the parameters in the loss optimal set different from the ground truth (θ^*, φ^*) .

PROOF. $\langle \mathcal{M} \rangle$ is maximal if and only if $f_{\theta}(\vec{x}^R) = p_{rel}(\vec{x}^R) = f_{\theta^*}(\vec{x}^R)$ for $\forall \vec{x}^R \in \mathbb{R}$, as $\frac{\delta^2}{\delta f_{\theta}(\vec{x}^R)^2} m(p_{rel}(\vec{x}^R), f_{\theta}(\vec{x}^R)) < 0$ at $f_{\theta^*}(\vec{x}^R)$. For a non-constant function $f_{\theta}(\vec{x}^R)$, its value does not equal to $f_{\theta^*}(\vec{x}^R)$ for $\forall \vec{x}^R \in \mathbb{R}$ if $\theta \neq \theta^*$. So for any $(\theta, \varphi) \in \Theta \setminus \{(\theta^*, \varphi^*)\}, \langle \mathcal{M}(\theta) \rangle < \langle \mathcal{M}(\theta^*) \rangle$.

POSTULATE 4. Click dependence on the confounding features are easier to be fitted with neural network model in the observation tower g_{φ} than in the relevance tower f_{θ} , so that when optimizing the twotower model Eq.(12), so that the model converges to a parameter set $(\theta^{\text{sub}}, \varphi^{\text{sub}}) \neq (\theta^*, \varphi^*)$ with $\langle \mathcal{L}(\theta^{\text{sub}}, \varphi^{\text{sub}}) \rangle = \langle \mathcal{L}(\theta^*, \varphi^*) \rangle$.

COROLLARY 5. The relevance metric $\langle \mathcal{M} \rangle$ is suboptimal for a twotower model trained on the clicks generated from correlated relevance and observation bias satisfying the above Postulate 4: $\langle \mathcal{M}(\theta^{rmsub}) \rangle < \langle \mathcal{M}(\theta^*) \rangle$.

PROOF. Applying Theorem 2 and Proposition 3 to Postulate 4, we can derive the above Corollary.

5.3 Application to Our Methods

Given that the correlation in the relevance inputs \vec{x}^R and the observation inputs \vec{x}^O degrades the two-tower model performance on the relevance metrics, we will discuss how each of our method could help recover the relevance predictions of the two-tower models.

PROPOSITION 6 (DROPOUT METHOD). Given a dropout rate τ , the model converges to an optimum $(\theta_{\tau}, \varphi_{\tau}) \in \Theta$ different from $(\theta^{\text{sub}}, \varphi^{\text{sub}})$ when $\tau > 0$. The relevance metrics $\langle \mathcal{M}(\theta_{\tau}) \rangle$ can be optimized at $\tau^* \in [0, 1]$ s.t. $\langle \mathcal{M}(\theta_{\tau^*}) \rangle \geq \langle \mathcal{M}(\theta^{\text{sub}}) \rangle$.

To prove the above Proposition 6, we first need to show,

LEMMA 7. Parameters (θ, φ) optimizing the average loss function with a dropout $\tau > 0$ also optimize the original loss function $\langle \mathcal{L} \rangle$ in Eq.(13): $\Theta^{dropout} = \{(\theta_{\tau}, \varphi_{\tau}) | 0 \le \tau < 1\} \subseteq \Theta$.

PROOF. By variation at $\{\vec{x}^R, \vec{x}^O\}$, we can see that the average loss is optimized only when $p(C = 1 | \vec{x}^R, \vec{x}^O) = \vec{c}^{\tau} = f_{\theta_{\tau}}(\vec{x}^R)g_{\varphi_{\tau}}(\vec{x}^O)$ for $\forall \{\vec{x}^R, \vec{x}^O\} \in \mathbb{X}^t$. So $(\theta_{\tau}, \varphi_{\tau}) \in \Theta$.

LEMMA 8. For the set of parameters optimizing the dropout method, $\Theta^{dropout}$, the optimal relevance performance must be better or at least as good as the performance of the vanilla two-tower model: $\sup_{\Theta^{dropout}} \langle \mathcal{M}(\theta_{\tau}) \rangle \geq \langle \mathcal{M}(\theta^{sub}) \rangle.$

PROOF. It's straightforward to show that there exists $\theta \in \Theta^{\theta}$ with $\langle \mathcal{M}(\theta) \rangle > \langle \mathcal{M}(\theta^{sub}) \rangle$, as $\theta^* \in \Theta^{\theta}$ and $\langle \mathcal{M}(\theta^*) \rangle > \langle \mathcal{M}(\theta^{sub}) \rangle$ in Corollary 5. So if there exists such a $\theta \in \Theta^{dropout}$, the greater sign would be satisfied. On the other hand, $\theta_{\tau=0} = \theta^{sub} \in \Theta^{dropout}$ by definition, so the equal sign would be satisfied if no such a θ with better relevance metric belongs to $\Theta^{dropout}$.

Based on Lemma 7 and Lemma 8, we can easily derive Proposition 6, which guarantees that we can find a two-tower model with a relevance performance as good or better. In practice, by dropping out the observation tower prediction, to which the model overly attributes the dependence of confounding features, we move the converging optimum in the direction towards the ground truth optimum. The trained model is thus able to approach to a parameter set with relevance ranking performance closer to the ground truth f_{θ^*} .

PROPOSITION 9 (GRADIENT REVERSAL METHOD). Given a gradient reverse coefficient η , the model converges to an optimum $(\theta_{\eta}, \varphi_{\eta}) \in \Theta$ different from $(\theta^{\text{sub}}, \varphi^{\text{sub}})$ when $\eta > 0$. The relevance metrics $\langle \mathcal{M}(\theta_{\eta}) \rangle$ can be optimized at $\eta^* \in [0, \infty)$ s.t. $\langle \mathcal{M}(\theta_{\eta^*}) \rangle \geq \langle \mathcal{M}(\theta^{\text{sub}}) \rangle$.

Proposition 9 can be derived similarly as Proposition 6. And similar to Proposition 6, Proposition 9 guarantees the relevance performance of the gradient reversal method equal or better than that of the vanilla two-tower model. In the situation that the vanilla model over-depends on the confounding features in the observation tower. Reversed gradients hinder the learning of such dependence, and thus lead to the relevance performance closer to the ground truth f_{θ^*} for $\eta^* > 0$.

PROPOSITION 10 (TOWER MIXTURE METHOD). Optimal relevance tower performance of the tower mixture method is as good or better than the biased baseline model trained without observation features: $\max_{\lambda} \langle \mathcal{M}(\theta_{\lambda}) \rangle \geq \langle \mathcal{M}(\theta_{\lambda=0}) \rangle.$

PROOF. Apparently, when $\lambda = 1$, only the observation tower is trained, where the relevance tower performance is just the lower bound of a random ranker, so that $\langle \mathcal{M}(\theta_{\lambda}) \rangle \geq \langle \mathcal{M}(\theta_{\lambda=1}) \rangle$ for $\forall \lambda \in [0, 1]$. On the other end, when $\lambda = 0$, the tower mixture model is just the biased single tower model without any position input. So $\max_{\lambda} \langle \mathcal{M}(\theta_{\lambda}) \rangle \geq \langle \mathcal{M}(\theta_{\lambda=0}) \rangle \geq \langle \mathcal{M}(\theta_{\lambda=1}) \rangle$.

Apparently, the tower mixture method is different from either the observation dropout or the gradient reversal method. There is no guarantee from the Proposition 10 that the models trained from the tower mixture model could do better than the vanilla two-tower model. On the other hand, we could see that the click probability contribution from the observation tower contribution is capped by the hyperparameter λ . When the relevance and the position are highly correlated, top items have very high click probabilities, thus cannot be fully explained by the observation tower. This fraction $1-\lambda$ of observed clicks can only be explained by the relevance tower prediction. Non-zero λ in fact serves as a filter on the high relevance items to train the relevance tower. This intuitively explains why the relevance tower could show good performance when trained on the clicks generated from highly correlated relevance and position.

Despite that all the above proofs rely on the strong assumptions of the perfect solvability of the DNN models to the relevance and observation functions and continuity of the input space, relaxing these assumptions still allows most of the conclusions to be valid in practice as we test in our experiments.

6 EXPERIMENTS

In this section, we discuss our experiment setting and validate our methods on two public learning to rank datasets with synthetic clicks and a dataset from industry with logged user clicks.

6.1 Methods

We compare the following methods on both semi-synthetic datasets and the real-world dataset.

- Biased baseline (Biased): A single tower feed-forward neural network model that takes only the regular (query, doc) features trained to predict the biased clicks. No observation-bias related features are included.
- Two Tower Additive Model (**Baseline**): An unbiased model that consists of two towers of feed-forward neural networks: a relevance tower takes regular (query, doc) features to model relevance predictions and the other observation tower takes observation-bias related features like positions. The outputs of both towers are added together to predict user click behavior.
- Gradient Reversal (**Grad**): The two-tower baseline with a gradient reversal layer is applied to the relevance head added to the observation tower. See method details in Sect. 4.2. In the results below, we always present the results from using clicks as the adversarial labels. Results for other adversarial labels are discussed in the Ablation study in Sect. 6.5.
- Observation Dropout (**Drop**): The two-tower baseline with a dropout layer applied to the output of the observation tower. See method details in Sect. 4.3.
- Tower Mixture (**Mix**): A two-tower model that combines the predictions of the relevance tower and the observation tower in a weighted sum. See method details in Sect. 4.4.

6.2 Preparation of Semi-synthetic Datasets

LTR Datasets. We use Yahoo Learning to Rank Set1 (Yahoo) [4] and MSLR-WEB30K Fold1 (Web30k) [18] to benchmark our methods. Yahoo contains 19944 training queries, 2994 validation queries, and 6983 test queries. Each query is associated with 20 documents on average. Each query-doc contains 700 dense features. Web30k contains 30K queries, divided into train, validation, test set with a ratio of 3:1:1. Each query on average has 120 documents, with 136 dense features for each query-doc pair. Both datasets are labeled with 5-grade relevance judgement from 0 to 4.

Logging Policy. Our goal is to understand how the confounding between relevance and observance modeling would affect relevance learning, and how we can mitigate such effects. Toward this goal, we design logging policies to generate observation features of different quality in terms of their correlation with the relevance, and test their effects on the relevance learning in two-tower models by measuring the relevance tower performance. We discuss our steps to generate the logging positions and clicks.

Intuitively, observation is mostly entangled with relevance when the positions are fully determined by ground-truth relevance scores. So we consider an oracle logging by ranking all the documents of each query based on their relevance scores. We expect such setting would guarantee the worst relevance tower performance. At the other end, the observation bias is least entangled with relevance when the input positions are randomly shuffled despite the querydoc features. We expect such setting would set the upper bound for the relevance tower performance. We also interpolate the cases between the extremes using a mixture of relevance-based ranking and random shuffling.

In particular, we examine 5 different logging policies in our experiments using the methods described above. For each document d_i , we have a ground-truth relevance label, y_i , and a random noise, n_i , extracted from a uniform distribution in [0,4]. We assign a weight w to y_i , and (1-w) to n_i . We rank all the documents of a query based on the descending order of a weighted sum score $s_i = wy_i + (1-w)n_i$ and use the rank as the logged position p_i for d_i .

- Oracle: *w* = 1.0
- L1: w = 0.8
- L2: *w* = 0.6
- L3: *w* = 0.2
- Random: w = 0.0

Generating Synthetic Clicks. Given the logged positions, we then use a common position bias click model to simulate user clicks, similar to previous studies [22]. Click probability is given by the product of relevance score and observation probability. The observation probability is assumed to be only related to its position p_i as:

$$P(O_i = 1|p_i) = \frac{1}{p_i}$$
(15)

Once a document is examined, user will click based on its relevance label, y_i , but with certain noise, ϵ , in the decision. We consider the click probability that users find a document relevant as:

$$P(R_i = 1|y_i) = \epsilon + (1 - \epsilon) \frac{2^{y_j} - 1}{2^{y_{max}} - 1}$$
(16)

where $y_{max} = 4$ is the maximum relevance score in the datasets and ϵ is the noise constant, which we set as 0.1. The click probability of a document of relevance y_i appearing at position p_i is:

$$P(c_i = 1|y_i, p_i) = P(O_i = 1|p_i) \times P(R_i = 1|y_i)$$
(17)

6.3 Results of Semi-synthetic Datasets

We evaluate the relevance performance of two-tower models by checking the NDCG@5 of the relevance tower predictions on the ground-truth relevance label y_i . Main results are shown in Table 1.

First, compared to the Random case with independent relevance and position, the baseline two-tower model performance degrades as the logging policy involves more and more relevance information from L3 to Oracle. This phenomenon aligns with our hypothesis that the confounding between relevance and observation learning has negative effects on the relevance tower.

On the contrary, the biased model with no position input show improving performance, as the more correlation between relevance and position leads to more clicks and thus more information in the synthetic clicks. But in all cases, the biased model performance is always significantly worse than the two-tower model upper bound obtained from the independent relevance and position.

Focusing on the three methods we proposed to disentangle the correlations in two-tower models, we observe that all three methods have improvements over the baseline. Especially, we find the larger improvements in the proposed models when the observation feature is more correlated with the relevance: The improvement goes up to 4.7% in Yahoo as the logging policy is perfectly correlated with the relevance. The best performance of each method stays close to the

Table 1: Relevance prediction performance on Yahoo LTR and Web30k, measured by NDCG@5 of utility label. Best results are bolded. Significant improvement ($\alpha = 0.05$) of the method over the Baseline is marked by upperscript *.

Dataset	Logging	Biased	Baseline	Grad	Drop	Mix
	Oracle	0.7048	0.6836	0.7126^{*}	0.7157*	0.7086*
Yahoo	L1	0.7038	0.6831	0.7149^{*}	0.7159*	0.7119*
	L2	0.6929	0.7058	0.7162^{*}	0.7169*	0.7108*
	L3	0.6837	0.7140	0.7147*	0.7145	0.7144
	Random	0.6630	0.7179	0.7189	0.7199*	0.7117
	Oracle	0.4191	0.3333	0.4159*	0.4118^{*}	0.3999*
Web30k	L1	0.3984	0.2939	0.4221^{*}	0.4087^{*}	0.3903*
	L2	0.3878	0.3166	0.4334^{*}	0.4130^{*}	0.4001^{*}
	L3	0.3880	0.3524	0.4119*	0.4222^{*}	0.4036*
	Random	0.3860	0.4103	0.4140	0.4056	0.4114

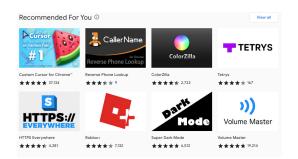


Figure 5: An example of Chrome Web Store user interface.

two-tower model upper bound rather independent of the logging policy.

Comparing the disentangling methods, we notice the Observation Dropout method consistently give the best result across different logging policies in Yahoo, and the Gradient Reversal method can achieve on par, or marginally worse performance. While in Web30k, the Gradient Reversal method consistently outperform the Observation Dropout method. The Tower Mixture method is in general less effective than the other two on both datasets.

6.4 Results of Industrial Dataset

Dataset. We also test the methods on the Chrome Web Store (CWS) dataset, which contains logged display history of Chrome Web Store Homepage (see Fig. 5 for the user interface) and user behaviors including both click and install. The dataset contains several relevance-related features, e.g., average recent rating, and several observation-related features, e.g., layout index, including both numerical and categorical features, the latter of which will be mapped into an embedding before fed into the neural network model. The logs are collected for one month over the October (27 days) and November (3 days) in 2021. We train models with the October's logs only on logged clicks and test the performance on the November's logs. As we do not have ground-truth relevance labeled for CWS, we evaluate the relevance tower predictions on both logged clicks and installs using both NDCG metric and NDCG metric corrected with the Inverse Propensity Scores, (IPS NDCG), where the IPS is calculated with the average clicks at a give position. We summarized the results in Table 2.

Results. From Table 2, we observe that all three methods improves the relevance tower performance over the vanilla two-tower baseline, bringing around 1.3% improvement, which is considered significant in the production setting. This indicates that the confounding effects could be general in real-world user logs and our proposed methods could further boost the real-world two-tower models in such situations.

6.5 Ablation Study

Adversarial Label Study. For the gradient reversal methods, we study how the choice of adversarial labels affects the method efficacy. Given the fact that real production logs usually do not contain the ground-truth relevance label, we experiment several alternatives, including clicks (Click), predicted relevance score (Prediction) by a pre-trained relevance tower. We compare them with the model trained with ground-truth utility (Utility) as the adversarial label, which is the case considered as the upper-bound for the gradient reversal method. From Table 3, we find that the three adversarial labels achieve comparable performance without any of them getting an obvious edge. This observation indicates that the method is rather robust to the choice of the adversarial labels. This promises the applicability of the method in wide scenarios when the groundtruth relevance labels are not available.

Sensitivity Study. We analyze the sensitivity of the Gradient Reversal method and the Observation Dropout method against their hyper-parameters, as illustrated in Figure 6 and Figure 7 for Yahoo. For the Gradient Reversal method, shown in Figure 6, the performance generally increases with a larger gradient scaling factor and takes optimal around 0.6 to 0.8, when the input position becomes strongly correlated with the relevance in Oracle and L1. At the same time, the performance is rather less sensitive to the choice of the gradient scaling factor in the range we test when the correlation becomes weak, as in L3. Observation Dropout performance, shown in Figure 7, presents a non-monotonic dependence on the dropout rate: the model takes optimal performance between a dropout rate

Table 2: Relevance prediction performance on CWS, measured by NDCG@5, and IPS NDCG@5 of installs and clicks. Best results are bolded. Significant improvement ($\alpha = 0.05$) of the method over the Baseline is marked by upperscript *.

Model	I	nstall	Click		
Model	NDCG	IPS-NDCG	NDCG	IPS-NDCG	
Biased	0.3135	0.3077	0.5045	0.4884	
Baseline	0.3108	0.3066	0.4945	0.4825	
Grad	0.3144	0.3104*	0.5050	0.4890	
Drop	0.3150*	0.3103	0.5056*	0.4901 [*]	
Mix	0.3143	0.3090	0.5008	0.4861	

Table 3: Performance comparison for the gradient reversal
method on Yahoo, given different adversarial labels.

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Logging	Utility	Click	Prediction
Oracle	0.7150	0.7126	0.7165
L1	0.7128	0.7149	0.7092
L2	0.7186	0.7162	0.7149
L3	0.7150	0.7147	0.7151
Random	0.7179	0.7189	0.7200

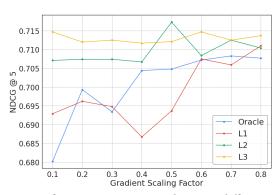


Figure 6: Performance comparison between different gradient scaling rates for the gradient reversal method.

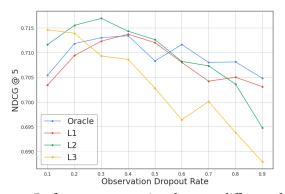


Figure 7: Performance comparison between different observation dropout rates for the observation dropout method.

of 0.2 and 0.5. The other trend we observe is that the more correlation between the position and the relevance in the logging policy, we need to search for a larger dropout rate α on the observation tower prediction to optimally disentangle them.

Method Combination. Finally, we study the effects of combining our proposed tricks. In Table 4, we show the combination of the proposed methods in the oracle setting, compared to the best score we achieved using a single method. We can see Drop + Grad can get on par or even slightly improve the performance by 0.5%. Grad + Mix can bring around 0.2% improvement. Drop + Mix would render a 4.3% performance drop. This result aligns with our theoretical analysis: the Dropout method and the Gradient Reversal method can be unified in the same framework and thus may work additively. But simply combining the Tower Mixture method may just be harmful.

Table 4: Performance comparison to the best numbers using Oracle as logging policy on Yahoo.

Drop+Grad	Drop+Mix	Grad+Mix
+0.5%	-4.3%	+0.2%

7 CONCLUSION

In this work, we reexamine the factorization assumption in unbiased learning to rank frameworks. We empirically show that the confounding between relevance modeling and observation bias modeling can hurt relevance predictions in semi-synthetic datasets. We also propose three effective methods, gradient reversal, observation dropout, and mixture, to alleviate the negative effects. We demonstrate that the proposed methods can achieve superior performance compared to baseline two-tower model in two semisynthetic datasets and a real-world dataset. Lastly, we theoretically show why the confounding issue could hurt model performance and how our methods work.

Interesting future directions include, (1) a more explainable dropout method to only zero-out relevance-related neurons, and (2) the confounding issue in textual and multi-modal ranking tasks beyond the dense numerical (query,doc) features.

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