A Novel Algorithm for Unbiased Learning to Rank

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ABSTRACT

Although click data is widely used in search systems in practice, so far the inherent bias, most notably position bias, has prevented it from being used in training of a ranker for search, i.e., learning-to-rank. Recently, a number of authors have proposed new techniques referred to as ‘unbiased learning-to-rank’, which can reduce position bias and train a relatively high-performance ranker using click data. Most of the algorithms, based on the inverse propensity weighting (IPW) principle, first estimate the click bias at each position, and then train an unbiased ranker with the estimated biases using a learning-to-rank algorithm. However, there has not been a method for pairwise learning-to-rank that can jointly conduct debiasing of click data and training of a ranker using a pairwise loss function. In this paper, we propose a novel algorithm, which can jointly estimate the biases at click positions and the biases at unclick positions, and learn an unbiased ranker. Experiments on benchmark data show that our algorithm can significantly outperform existing algorithms. In addition, an online A/B Testing at a commercial search engine shows that our algorithm can effectively conduct debiasing of click data and enhance relevance ranking.

CCS CONCEPTS

- Information systems → Learning to rank;

KEYWORDS

Learning-to-Rank, Unbiased Learning-to-Rank, LambdaMART

1 INTRODUCTION

Learning-to-rank, which refers to machine learning techniques on automatically constructing a model (ranker) from data for ranking in search, has been widely used in current search systems. Existing algorithms can be categorized into pointwise, pairwise, and listwise approaches according to the loss functions they utilize [16–18]. Among the proposed algorithms, LambdaMART is a state-of-the-art algorithm [3, 23]. The data for training in learning-to-rank is usually labeled by human assessors so far, and the labelling process is often strenuous and costly. This raises the question of whether it is possible to train a ranker by using click data collected from the same search system. Click data is indicative of individual users’ relevance judgments and is relatively easy to collect with low cost. On the other hand, it is also noisy and biased [13, 24]. Notably, the orders of documents in the search results affect users’ judgments. Users tend to more frequently click documents presented at higher positions, which is called position bias. This has been preventing the practical use of click data in learning-to-rank.

Recently a new research direction, referred to as unbiased learning-to-rank, is arising and making progress. Unbiased learning-to-rank aims at eliminating bias in click data, particularly position bias, and making use of the debiased data to train a ranker. Wang et al. [21] and Joachims et al. [14] respectively propose employing the inverse propensity weighting (IPW) principle [20] to conduct learning of an ‘unbiased ranker’ from click data. It is proved that the objective function in learning using IPW is an unbiased estimate of the risk function defined on a relevance measure (a pointwise loss). The authors also develop methods for estimating propensity (position bias) by randomization of search results online. Wang et al. [22] further develop a method for estimating propensity from click data offline. More recently Ai et al. [1] propose a method that can jointly estimate propensity and train a ranker from click data, again on the basis of IPW. In the previous work, the IPW principle is limited to the pointwise setting in the sense that propensities (position biases) are only defined on click positions.

In this paper, we address the problem of jointly estimating propensities and training a ranker from click data for pairwise learning-to-rank, particularly using a pairwise algorithm, LambdaMART. To do so, we extend the inverse propensity weighting principle to the pairwise setting, and develop a new method for jointly conducting propensity estimation and ranker training.

We give a formulation of unbiased learning-to-rank for the pairwise setting and extend the IPW principle. We define propensities as the ratio of the click probability to the relevance probability at each position, as well as the ratio of the unclick probability to
We prove that under the extended IPW principle, the objective function becomes an unbiased estimate of risk function defined on a pairwise loss function. In this way, one can learn an unbiased ranker using a pairwise ranking algorithm.

We then develop a method for jointly estimating propensities and training a ranker for pairwise learning-to-rank, called Pairwise Debiasing. The propensities (position biases) and the ranker can be iteratively learned through minimization of the same objective function, with the propensities and the ranker as optimization variables. As an instance, we further develop Unbiased LambdaMART, an algorithm of learning an unbiased ranker using LambdaMART.

Experiments on the Yahoo learning-to-rank challenge dataset demonstrate that Unbiased LambdaMART can significantly outperform the baseline algorithms in terms of all measures, for example, 3-4% improvements in terms of NDCG@1. An online A/B Testing at a commercial search engine also demonstrates that Unbiased LambdaMART can effectively conduct debiasing of click data and enhance the performance of relevance ranking at the search engine.

The contribution of this paper includes the following proposals.

- A general framework on unbiased learning-to-rank in the pairwise setting, particularly, an extended IPW.
- Pairwise Debiasing, a method for jointly estimating propensities (position biases) and training a ranker.
- Unbiased LambdaMART, an algorithm of unbiased pairwise learning-to-rank using LambdaMART.

2 RELATED WORK

In this section, we introduce related work on learning to rank, click model, and unbiased learning to rank.

2.1 Learning-to-Rank

Learning-to-rank is to automatically construct a ranking model from data, referred to as a ranker, for ranking in search. A ranker is usually defined as a function of feature vector based on a query document pair. In search, given a query, the retrieved documents are ranked based on the scores of the documents given by the ranker. The advantage of employing learning-to-rank is that one can build a ranker without the need of manually creating it, which is usually tedious and hard. Learning-to-rank is now becoming a standard technique for search.

There are many algorithms proposed for learning-to-rank. The algorithms can be categorized as pointwise approach, pairwise approach, and listwise approach, based on the loss functions in learning [16–18]. The pairwise and listwise algorithms usually work better than the pointwise algorithms [17], because the key issue of ranking in search is to determine the orders of documents but not to judge the relevance of documents, which is exactly the goal of the pairwise and listwise algorithms. For example, the pairwise algorithms of RankSVM [5, 12] and LambdaMART [3, 23] are state-of-the-art algorithms for learning-to-rank.

Traditionally, data for learning a ranker is manually labeled by humans, which can be costly. To deal with the problem, one may consider using click data as labeled data to train a ranker. Click data records the documents clicked by the users after they submit queries, and it naturally represents users’ implicit relevance judgments on the search results. The utilization of click data has both pros and cons. On one hand, it is easy to collect a large amount of click data with low cost. On the other hand, click data is very noisy and has position bias, presentation bias, etc. (Position bias means that users tend to more frequently click documents ranked at higher positions) [13, 24]. How to effectively cope with position bias and leverage click data for learning-to-rank thus is becoming an important issue.

2.2 Click Model

One direction of research on click data aims to design a click model to simulate users’ click behavior, and then estimate the parameters of the click model from data. It then makes use of the learned click model for different tasks, for example, use them as features of a ranker.

Several probabilistic models have been developed. For example, Richardson et al. [19] propose the Position Based Model (PBM), which assumes that a click only depends on the position and relevance of the document. Craswell et al. [8] develop the Cascade Model (CM), which formalizes the user’s behavior in browsing of search results as a sequence of actions. Dupret et al. [9] propose the User Browsing Model (UBM), asserting that a click depends not only on the position of a document, but also on the positions of the previously clicked documents. Chapelle et al. [7] develop the Dynamic Bayesian Network Model (DBN), based on the assumption that the user’s behavior after a click does not depend on the perceived relevance of the document but on the actual relevance of the document. More recently, Borisov et al. [2] develop the Neural Click Model, which utilizes neural networks and vector representations to predict user’s click behavior.

Click models can be employed to estimate position bias and other biases, as well as query document relevance. They are not designed only for the purpose of debiasing and thus could be suboptimal for the task. In our experiments, we use the click models for generating synthetic click data for training an unbiased learning-to-rank algorithm.

2.3 Unbiased Learning-to-Rank

Recently, a new direction in learning-to-rank, referred to as unbiased learning-to-rank, is arising and making progress. The goal of unbiased learning-to-rank is to develop new techniques to conduct debiasing of click data and leverage the debiased click data in training of a ranker.

Wang et al. [21] apply unbiased learning-to-rank to personal search. They conduct randomization to estimate query-level position bias and adjust click data for training of a ranker in personal search on the basis of inverse propensity weighting (IPW) [20]. Joachims et al. [14] theoretically prove that with the inverse propensity weighting (IPW) principle, one can obtain an unbiased estimate of a risk function on relevance in learning-to-rank. They also utilize online randomization to estimate position bias and adopt it to conduct debiasing in training of a RankSVM model. Wang et al. [22] employ a regression-based EM algorithm to infer position bias by maximizing the likelihood of click data. The estimated position
bias is then utilized in learning of LambdaMART. Recently, Ai et al. [1] design a dual learning algorithm which can jointly learn an unbiased propensity model for representing position bias and an unbiased ranker for relevance ranking, by optimizing two objective functions. Both models are implemented as neural networks. Their method is also based on IPW, while the loss function is a pointwise loss function. Our work mainly differs from the previous work in the following points:

- In previous work, propensity (position bias) is defined as the observation probability, and thus IPW is limited to the pointwise setting in which the loss function is pointwise and debiasing is performed at a click position each time. In this work, we give a more general definition of propensity, and extend IPW to the pairwise setting, in which the loss function is pairwise and debiasing is carried out at both click positions and unclick positions each time.
- In previous work, estimation of position bias either relies on randomization of search results online, which can hurt user experiences [14, 21], or resorts to separate learning of a propensity model from click data offline, which can be suboptimal to relevance ranking [1, 22]. In this paper, we propose to jointly conduct estimation of propensity and learning of a ranker through minimizing the same objective function. We further apply this framework to the state-of-the-art LambdaMART algorithm.

### 3 FRAMEWORK

In this section, we give a general formulation of unbiased learning-to-rank, for both the pointwise and pairwise settings. We also extend the inverse propensity weighting principle to the pairwise setting.

#### 3.1 Pointwise Unbiased Learning-to-Rank

In learning-to-rank, given a query document pair denoted as \( (q, d) \), the ranker \( f \) assigns a score to the document. The documents with respect to the query are then ranked in descending order of their scores. Traditionally, the ranker is learned with labeled data. In the pointwise setting, the loss function in learning is defined on a single data point \( x \).

Let \( q \) denote the query and \( D_q \) the set of documents associated with \( q \). Let \( d_i \) denote the \( i \)-th document in \( D_q \) and \( x_i \) the feature vector of \( q \) and \( d_i \). Let \( r_i^+ \) \( (r_i = 1) \) and \( r_i^- \) \( (r_i = 0) \) represent that \( d_i \) is relevant and irrelevant respectively (see Table 1). For simplicity we only consider binary relevance here and one can easily extend it to the multi-level relevance case. The risk function in learning is defined as

\[
R_{\text{point}}(f) = \int L(f(x_i), r_i^+) \, dP(x_i, r_i^+) \quad (1)
\]

where \( f \) denotes a ranker, \( L(f(x_i), r_i^+) \) denotes a pointwise loss function based on an IR measure [14] and \( P(x_i, r_i^+) \) denotes the probability distribution on \( x_i \) and \( r_i^+ \). Most ranking measures in IR only utilize relevant documents in their definitions, and thus the loss function here is solely defined on relevant documents with label \( r_i^+ \). Furthermore, the position information of documents is omitted from the loss function for notation simplicity.

Suppose that there is a labeled dataset in which the relevance of documents with respect to queries is given. One can learn a ranker \( \hat{f}_{\text{rel}} \) through the minimization of the empirical risk function (objective function) as follows.

\[
\hat{f}_{\text{rel}} = \arg \min_f \sum_{q \in D_q} \sum_{d_i \in D(q)} L(f(x_i), r_i^+) \quad (2)
\]

One can also consider using click data as relevance feedbacks from users, more specifically, viewing clicked documents as relevant documents while unclicked documents as irrelevant documents, and training a ranker with a click dataset. This is what we call ‘biased learning-to-rank’, because click data has position bias, presentation bias, etc. Suppose that there is a click dataset in which the clicks of documents with respect to queries by an original ranker are recorded. For convenience, let us assume that document \( d_i \) in \( D_q \) is exactly the document ranked at position \( i \) by the original ranker. Let \( c_i^+ (c_i = 1) \) and \( c_i^- (c_i = 0) \) represent that document \( d_i \) is clicked and unclicked in the click dataset respectively. The risk function and minimization of empirical risk function can be defined as follows.

\[
R_{\text{click}}(f) = \int L(f(x_i), c_i^+) \, dP(x_i, c_i^+) \quad (3)
\]

\[
\hat{f}_{\text{click}} = \arg \min_f \sum_{q \in D_q} \sum_{d_i \in D(q)} L(f(x_i), c_i^+) \quad (4)
\]

The loss function is defined on clicked documents with label \( c_i^+ \). The ranker \( \hat{f}_{\text{click}} \) learned in this way is biased, however.

Unbiased learning-to-rank aims to eliminate the biases, for example position bias, in the click data and train a ranker with the debiased data. The training of ranker and debiasing of click data can be performed simultaneously or separately. The key question is how to fill the gap between click and relevance, that is, \( P(c_i^+ | x_i) \) and \( P(r_i^+ | x_i) \). Here we assume that the click probability is proportional to the relevance probability at each position, where the ratio \( t_i^+ > 0 \) is referred to as propensity at a click position \( i \).

\[
P(c_i^+ | x_i) = t_i^+ P(r_i^+ | x_i) \quad (5)
\]

There are \( k \) propensity values corresponding to \( k \) positions. Propensity can be affected by different types of bias, but in this paper, we only consider position bias.
We can conduct learning of an unbiased ranker \( \hat{f}_{unbiased} \) through minimization of the empirical risk function as follows.

\[
R_{unbiased}(f) = \int \frac{L(f(x_i), c_i^+)}{t_i^+} dP(x_i, c_i^+) \tag{6}
\]

\[
= \int \frac{L(f(x_i), c_i^+)}{P(c_i^+|x_i) / P(r_i^+|x_i)} dP(x_i, c_i^+) \tag{7}
\]

\[
= \int L(f(x_i), c_i^+) dP(x_i, r_i^+) \tag{8}
\]

\[
= \int L(f(x_i), r_i^+) dP(x_i, r_i^+) = R_{rel}(f) \tag{9}
\]

\[
\hat{f}_{unbiased} = \arg \min_f \sum_q \sum_{d_i \in D_q} \frac{L(f(x_i), c_i^+)}{t_i^+} \tag{10}
\]

In (9) click label \( c_i^+ \) in the loss function is replaced with relevance label \( r_i^+ \), because after debiasing click implies relevance.

One justification of this method is that \( R_{unbiased} \) is in fact an unbiased estimate of \( R_{rel} \). This is the so-called inverse propensity weighting (IPW) principle proposed in previous work. That is to say, if we can properly estimate propensity \( t_i^+ \), then we can reliably train an unbiased ranker \( \hat{f}_{unbiased} \).

An intuitive explanation of propensity \( t_i^+ \) can be found in the following relation, under the assumption that a clicked document must be relevant (\( \epsilon^+ \Rightarrow r^+ \)).

\[
t_i^+ = \frac{P(c_i^+|x_i)}{P(r_i^+|x_i)} = \frac{P(c_i^+, r_i^+|x_i)}{P(r_i^+|x_i)} = P(c_i^+|r_i^+, x_i) \tag{11}
\]

It means that \( t_i^+ \) represents the conditional probability of how likely a relevant document is clicked at position \( i \). In previous work, \( t_i^+ \) is defined as the observation probability that the user examines the document at position \( i \) before clicking the document, which is based on the same assumption with (11). One can see that our definition of propensity is more general than that in previous work.

### 3.2 Pairwise Unbiased Learning-to-Rank

In the pairwise setting, the ranker \( f \) assigns a score to a document \( x \), and the loss function is defined on two data points \( x_i \) and \( x_j \). Traditionally, the ranker is learned with labeled data.

Let \( q \) denote a query. Let \( d_i \) and \( d_j \) denote the \( i \)-th and \( j \)-th documents with respect to query \( q \). Let \( x_i \) and \( x_j \) denote the feature vectors from \( d_i \) and \( d_j \) as well as \( q \). Let \( r_i^+ \) and \( r_j^+ \) represent that document \( d_i \) and document \( d_j \) are relevant and irrelevant respectively. Let \( L_q \) denotes a set of document pairs \( (d_i, d_j) \) where \( d_i \) is relevant and \( d_j \) is irrelevant. For simplicity we only consider binary relevance here and one can easily extend it to the multi-level relevance case. The risk function and the minimization of empirical risk function are defined as

\[
R_{rel}(f) = \int L(f(x_i), r_i^+, f(x_j), r_j^-) dP(x_i, r_i^+, x_j, r_j^-) \tag{12}
\]

\[
\hat{f}_{rel} = \arg \min_f \sum_q \sum_{(d_i, d_j) \in L_q} L(f(x_i), r_i^+, f(x_j), r_j^-) \tag{13}
\]

where \( L(f(x_i), r_i^+, f(x_j), r_j^-) \) denotes a pairwise loss function.

One can consider using click data to directly train a ranker, that is, to conduct "biased learning-to-rank". Let \( c_i^+ \) and \( c_j^- \) represent that document \( d_i \) and document \( d_j \) are clicked and unclicked respectively. Let \( L_q \) denotes a set of document pairs \( (d_i, d_j) \) where \( d_i \) is clicked and \( d_j \) is unclicked. The risk function and minimization of empirical risk function can be defined as follows.

\[
R_{click}(f) = \int L(f(x_i), c_i^+, f(x_j), c_j^-) dP(x_i, c_i^+, x_j, c_j^-) \tag{14}
\]

\[
\hat{f}_{click} = \arg \min_f \sum_q \sum_{(d_i, d_j) \in L_q} L(f(x_i), c_i^+, f(x_j), c_j^-) \tag{15}
\]

The ranker \( \hat{f}_{click} \) is however biased.

Similar to the pointwise setting, we consider dealing with position bias in the pairwise setting and assume that the click probability is proportional to the relevance probability at each position and the unclick probability is proportional to the irrelevance probability at each position. The ratios \( t_i^+ > 0 \) and \( t_j^- > 0 \) are referred to as propensities at a click position \( i \) and an unclick position \( j \).

\[
P(c_i^+|x_i) = t_i^+ \ P(r_i^+|x_i) \tag{16}
\]

\[
P(c_j^-|x_j) = t_j^- \ P(r_j^-|x_j) \tag{17}
\]

There are \( 2k \) propensity values corresponding to \( k \) positions.

We can conduct learning of an unbiased ranker \( \hat{f}_{unbiased} \), through minimization of the empirical risk function as follows.

\[
R_{unbiased}(f) = \int \frac{L(f(x_i), c_i^+, f(x_j), c_j^-)}{t_i^+ \cdot t_j^-} dP(x_i, c_i^+, x_j, c_j^-) \tag{18}
\]

\[
= \int \int \frac{L(f(x_i), c_i^+, f(x_j), c_j^-)dP(c_i^+, x_i) dP(c_j^-, x_j)}{P(c_i^+|x_i) P(c_j^-|x_j)} \tag{19}
\]

\[
= \int \int L(f(x_i), c_i^+, f(x_j), c_j^-)dP(r_i^+, x_i) dP(r_j^-, x_j) \tag{20}
\]

\[
= R_{rel}(f) \tag{21}
\]

\[
\hat{f}_{unbiased} = \arg \min_f \sum_q \sum_{(d_i, d_j) \in L_q} \frac{L(f(x_i), c_i^+, f(x_j), c_j^-)}{t_i^+ \cdot t_j^-} \tag{23}
\]

In (18) it is assumed that relevance and click at position \( i \) are independent from those at position \( j \). In (21), click labels \( c_i^+ \) and \( c_j^- \) are replaced with relevance labels \( r_i^+ \) and \( r_j^- \) because after debiasing click implies relevance and unclick implies irrelevance.

One justification of this method is that \( R_{unbiased} \) is an unbiased estimate of \( R_{rel} \). Therefore, if we can accurately estimate the propensities, then we can reliably train an unbiased ranker \( \hat{f}_{unbiased} \). This is an extension of the inverse propensity weighting principle to the pairwise setting.

Propensity \( t_i^+ \) has the same explanation as that in the pointwise setting. An explanation of propensity \( t_j^- \) is that it represents the reciprocal of the conditional probability of how likely an unclicked document is irrelevant at position \( j \), as shown below.

\[
t_j^- = \frac{P(c_j^-|x_j)}{P(r_j^-|c_j^-|x_j)} = \frac{1}{P(r_j^-|c_j^-|x_j)} \tag{24}
\]
It is under the assumption that an irrelevant document must be unclicked (r− ⇒ c−), which is equivalent to (c+ ⇒ r+). Note that t− cannot be defined as the 'unobservation probability' at position j and it is in fact not a probability.

4 APPROACH

In this section, we present Pairwise Debiasing as a method of jointly estimating propensities and training a ranker for pairwise learning-to-rank. Furthermore, we describe Unbiased LambdaMART as an algorithm of pairwise unbiased learning-to-rank.

4.1 Learning Strategy

We first give a general strategy for pairwise unbiased learning-to-rank.

A key issue of unbiased learning-to-rank is to accurately estimate propensity. Previous work either relies on randomization of search results online, which can hurt user experiences [14, 21], or resorts to a separate learning of model of propensity from click data offline, which can be suboptimal to the ranker [1, 22]. In this paper, we propose to simultaneously conduct estimation of propensity and learning of a ranker offline through minimizing the following empirical risk function (objective function).

\[
\min_{f, t^+, t^-} \mathcal{L}(f, t^+, t^-) = \min_{f, t^+, t^-} \sum_{q \in \mathcal{D}_q} \sum_{(d_i, d_j) \in I_q} \frac{L(f(x_i), c^+_i, f(x_j), c^-_j)}{t^+_i \cdot t^-_j} + ||t^+||_p^p + ||t^-||_p^p
\]

\[
= \min_{f, t^+, t^-} \sum_{q \in \mathcal{D}_q} \sum_{(d_i, d_j) \in I_q} \frac{L(f(x_i), c^+_i, f(x_j), c^-_j)}{t^+_i \cdot t^-_j} + \sum_{i} ||t^+_i||_p^p + \sum_{j} ||t^-_j||_p^p
\]

\[
s.t. \ t^+_i = 1, t^-_j = 1
\]

where f is a ranker, t+ and t− are propensities at all positions, L is a pairwise loss function, ||·||_p^p denotes L_p regularization. The propensities of the first position are fixed at one, which are defined as constraints of optimization. Here p ∈ [0, +∞) is a hyperparameter. The higher the value of p is, the more regularization we impose on the propensities.

In the objective function, the propensities t+ and t− are inversely proportional to the pairwise loss function \(L(f(x_i), c^+_i, f(x_j), c^-_j)\), and thus the learned propensities will be high if the losses on those pairs of positions are high in the minimization. The propensities are regularized and constrained to avoid a trivial solution of infinity.

It would be difficult to directly optimize the objective function in (27). We adopt a greedy approach to perform the task. Specifically, for the three optimization variables f, t+, t−, we iteratively optimize the objective function \(\mathcal{L}\) with respect to one of them with the others fixed; we repeat the process until convergence.

4.2 Estimation of Propensities

Given a fixed ranker, we can estimate the propensities at all positions. There are in fact closed form solutions for the estimation.

The partial derivative of objective function \(\mathcal{L}\) with respect to propensity \(t^+\) is

\[
\frac{\partial \mathcal{L}(f^+, t^+, (t^-)^*)}{\partial t^+_i} = \sum_{q} \sum_{(d_i, d_j) \in I_q} \frac{L(f^+(x_i), c^+_i, f^+(x_j), c^-_j)}{-t^-_j^p \cdot (t^-_j)^{p-1}} + p \cdot (t^-_j)^{p-1}
\]

Thus, we have

\[
\text{arg min } t^+_i \mathcal{L}(f^+, t^+, (t^-)^*) = \left[ \sum_{q} \sum_{(d_i, d_j) \in I_q} \frac{L(f^+(x_i), c^+_i, f^+(x_j), c^-_j)}{p \cdot (t^-_j)^{p-1}} \right]^{\frac{1}{p}}
\]

In (31) the result is normalized to ensure that the propensity at the first position is 1.

Similarly, we have

\[
\text{arg min } t^-_j \mathcal{L}(f^+, t^+, (t^-)^*) = \left[ \sum_{q} \sum_{(d_i, d_j) \in I_q} \frac{L(f^+(x_i), c^+_i, f^+(x_j), c^-_j)}{p \cdot (t^-_j)^{p-1}} \right]^{\frac{1}{p}}
\]

In this way, we can estimate the propensities \(t^+\) and \(t^-\) in one step given a fixed ranker \(f^+\). Note that the method here, referred to as Pairwise Debiasing, can be applied to any pairwise loss function, and even any pointwise loss function.

4.3 Learning of Ranker

Given fixed propensities, we can learn an unbiased ranker. The partial derivative of \(\mathcal{L}\) with respect to f can be written in the following general form.

\[
\frac{\partial \mathcal{L}(f^+, t^+, (t^-)^*)}{\partial f} = \sum_{q} \sum_{(d_i, d_j) \in I_q} \frac{1}{(t^+_i)^{p} \cdot (t^-_j)^p} \frac{\partial L(f^+(x_i), c^+_i, f(x_j), c^-_j)}{\partial f}
\]

We employ the state-of-art pairwise learning-to-rank algorithm LambdaMART to train a ranker. LambdaMART [4, 23] employs gradient boosting or MART [10] and the gradient function of the loss function called lambda function. Given training data, it performs minimization of the objective function using the lambda function.

In LambdaMART, the gradient \(\lambda_i\) of document \(d_i\) is calculated using all pairs of the other documents with respect to the same query.

\[
\lambda_i = \sum_{j \neq i} \lambda_{ij} = \sum_{j \neq i} \lambda_{ji}
\]

\[
\lambda_{ij} = \frac{-\sigma}{1 + e^{\sigma(f(x_i) - f(x_j))}} |\Delta Z_{ij}| \tag{34}
\]

where \(\lambda_{ij}\) is the lambda gradient defined on a pair of documents \(d_i\) and \(d_j\), \(\sigma\) is a constant with a default value of 2, \(f(x_i)\) and \(f(x_j)\) are the scores of the two documents given by LambdaMART, \(\Delta Z_{ij}\)

\[\text{The derivation is based on the fact } p \in (0, +\infty). \text{ The result is then extended to the case of } p = 0.\]
denotes the difference between NDCG[11] scores if documents \( d_i \) and \( d_j \) are swapped in the ranking list.

Following the discussion above, we can make an adjustment on the lambda gradient \( \tilde{\lambda}_t \) with the estimated propensities

\[
\tilde{\lambda}_t = \sum_{(d_i,d_j) \in I} \tilde{\lambda}_{ij} - \sum_{(d_j,d_i) \in I} \tilde{\lambda}_{ji}
\]  

(36)

\[
\tilde{\lambda}_{ij} = \frac{\lambda_{ij}}{(t_i^+)^r \cdot (t_j^-)^r}
\]  

(37)

Thus, by simply replacing the lambda gradient \( \lambda_i \) in LambdaMART with the adjusted lambda gradient \( \tilde{\lambda}_i \), we can reliably learn an unbiased ranker with the LambdaMART algorithm. We call the algorithm Unbiased LambdaMART.

Estimation of propensities in (31) and (32) needs calculation of the loss function \( L_{ij} = L(f(x_i), c_i^+, f(x_j), c_j^-) \). For LambdaMART the loss function can be derived from (35) as follows.

\[
L_{ij} = \log(1 + e^{-\sigma(f(x_i) - f(x_j))})|\Delta z_{ij}|
\]  

(38)

### 4.4 Learning Algorithm

The learning algorithm of Unbiased LambdaMART is given in Algorithm 1. The input is a click dataset \( D \). The hyper-parameters are regularization parameter \( p \) and total number of boosting iterations \( M \). The output is an unbiased ranker \( f \) and estimated propensities at all positions \( t^+, t^- \). The algorithm iteratively trains a ranker and estimates propensities. Algorithm 1 gives the details.

**Algorithm 1 Unbiased LambdaMART**

**Require:** click dataset \( D = \{(q,D_q,C_q)\}; hyper-parameters \( p,M \);

**Ensure:** unbiased ranker \( f \); propensities \( t^+ \) and \( t^- \);

1. Initialize all propensities as 1;
2. for \( m = 1 \) to \( M \) do
3. for each query \( q \) and each document \( d_i \) in \( D_q \) do
   4. Calculate \( \tilde{\lambda}_t \) with \( (t^+)^r \) and \( (t^-)^r \) using (36) and (37);
5. end for
6. Re-train ranker \( f \) with \( \tilde{\lambda} \) using LambdaMART algorithm
7. Re-estimate propensities \( t^+ \) and \( t^- \) with ranker \( f^+ \) using (31) and (32)
8. end for
9. return \( f, t^+, t^- \);

### 5 EXPERIMENTS

In this section, we present the results of two experiments on our proposed algorithm Unbiased LambdaMART. One is an experiment on a benchmark dataset, along with empirical analysis on the effectiveness and robustness of the algorithm, and the other is an online A/B testing at a commercial search engine.

#### 5.1 Experiment on Benchmark Data

We first made use of the Yahoo! learning-to-rank challenge dataset\(^1\) to conduct an experiment. The Yahoo dataset is a benchmark dataset for learning-to-rank [6]. It consists of feature vectors extracted from query-document pairs assigned with manually annotated relevance labels at five levels.

There is not click data associated with the Yahoo dataset. We followed the procedure proposed in [1] to automatically generate click data from the learning-to-rank data. In total, there were 2 million query sessions generated. We were able to reproduce almost the same results as reported in [1]. We chose NDCG at position 1, 3, 5, 10 and MAP as evaluation measures.

**5.1.1 Click Data Simulation.** The click data generation process is as follows. We first train a ranker (original ranker) with a proportion of labeled data, and then create a ranking list of documents for each query with the ranker. Next, we simulate a user’s behavior and generate clicks on the ranking lists using a click model. A RankSVM model is trained as the original ranker using 1% of the training data. The Position Based Model (PBM) proposed in [19] is exploited as the click model. PBM assumes that the user decides to click a document according to probability \( P(c_i^+) = P(o_i^+)P(r_i^+) \). The probability of observation \( P(o_i^+) \) is calculated from the position bias values obtained from an eye-tracking experiment as reported in [13]. The probability of relevance \( P(r_i^+) \) is calculated by

\[
P(r_i^+) = \epsilon + (1 - \epsilon) \frac{2^{y} - 1}{2^{y_{\text{max}}} - 1}
\]

where \( y \in [0, 4] \) represents a relevance level and \( y_{\text{max}} \) is the maximum level of 4 in the dataset. The parameter \( \epsilon \) represents click noise due to that irrelevant documents \( (y = 0) \) are incorrectly perceived as relevant documents \( (y > 0) \), which is set as 0.1 by default.

**5.1.2 Baseline Methods.** We made comprehensive comparisons between our method and the baselines. The baselines were created by combining the state-of-the-art debiasing methods and learning-to-rank algorithms. There were six debiasing methods. To make fair comparison, the same click dataset was utilized for all debiasing methods. The number of positions was set to 10.

**Randomization:** The method, proposed by Joachims et al. [14], uses randomization to infer the observation probabilities as position biases. We randomly shuffled the rank lists and then estimated the position biases as in [1].

**Regression-EM:** The method, proposed by Wang et al. [22], directly estimates the position biases using a regression-EM model.

**Dual Learning Algorithm:** The method, proposed by Ai et al. [1], jointly learns a ranker and conducts debiasing of click data. The algorithm implements both the ranking model and the debiasing model as deep neural networks.

**Pairwise Debiasing:** Our proposed debiasing method can conduct debiasing when combined with a pairwise learning-to-rank algorithm. In this experiment, we set the hyper-parameter \( p \) as 0.

**Click Data:** In this method, the raw click data without debiasing is used to train a ranker, whose performance is considered as a lower bound.

**Labeled Data:** In this method, human annotated relevance labels are used as data for training of ranker, whose performance is considered as an upper bound.

There were three learning-to-rank algorithms.

**DNN:** A deep neural network was implemented as a ranker, as in [1]. We directly used the code provided by Ai et al.\(^2\).

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\(^1\) http://webscope.sandbox.yahoo.com

\(^2\) https://github.com/QingyaoAi/Dual-Learning-Algorithm-for-Unbiased-Learning-to-Rank
Table 2: Comparison of different unbiased learning-to-rank methods.

| Ranker    | Debiasing Method               | MAP  | NDCG@1  | NDCG@3  | NDCG@5  | NDCG@10 |
|-----------|--------------------------------|------|---------|---------|---------|---------|
| LambdaMART| Labeled Data (Upper Bound)     | 0.854| 0.745   | 0.745   | 0.757   | 0.790   |
|           | Pairwise Debiasing             | 0.836| 0.717   | 0.716   | 0.728   | 0.764   |
|           | Regression-EM [22]             | 0.830| 0.685   | 0.684   | 0.700   | 0.743   |
|           | Randomization                  | 0.827| 0.669   | 0.678   | 0.690   | 0.728   |
|           | Click Data (Lower Bound)       | 0.820| 0.658   | 0.669   | 0.672   | 0.716   |
| DNN       | Labeled Data (Upper Bound)     | 0.831| 0.677   | 0.685   | 0.705   | 0.737   |
|           | Dual Learning Algorithm [1]    | 0.828| 0.674   | 0.683   | 0.697   | 0.734   |
|           | Regression-EM                  | 0.829| 0.676   | 0.684   | 0.699   | 0.736   |
|           | Randomization                  | 0.825| 0.673   | 0.679   | 0.693   | 0.732   |
|           | Click Data (Lower Bound)       | 0.819| 0.637   | 0.651   | 0.667   | 0.711   |
| RankSVM   | Labeled Data (Upper Bound)     | 0.815| 0.631   | 0.649   | 0.675   | 0.707   |
|           | Regression-EM                  | 0.815| 0.629   | 0.648   | 0.674   | 0.705   |
|           | Randomization [14]             | 0.810| 0.628   | 0.644   | 0.672   | 0.707   |
|           | Click Data (Lower Bound)       | 0.811| 0.614   | 0.629   | 0.658   | 0.697   |

**RankSVM**: We directly used the Unbiased RankSVM Software provided by Joachims et al.\(^{3}\), with hyper-parameter \(C\) being 200.

**LambdaMART**: We implemented Unbiased LambdaMART by modifying the LambdaMART tool in LightGBM [15]. The total number of trees was 300, learning rate was 0.05, number of leaves for one tree was 31, feature fraction was 0.9, and bagging fraction was 0.9.

In summary, there were 13 baselines to compare with our proposed Unbiased LambdaMART algorithm. Note that Dual Learning Algorithm and DNN are tightly coupled. We did not combine Pairwise Debiasing with RankSVM and DNN, as LambdaMART is a more powerful algorithm.

5.1.3 Experimental Results. Table 2 summarizes the results. We can see that our method of Unbiased LambdaMART (LambdaMART + Pairwise Debiasing) significantly outperforms all the other baseline methods. In particular, we have the following findings:

- Our method of LambdaMART+Pairwise Debiasing achieves better performances than all the state-of-the-art methods in terms of all measures. For example, in terms of NDCG@1, our method outperforms LambdaMART+Regression-EM by 3.2%, outperforms DNN+Dual Learning by 4.3%, and outperforms RankSVM+Randomization by 8.9%.
- Pairwise Debiasing works better than the other debiasing methods. When combined with LambdaMART, Pairwise Debiasing outperforms Regression-EM by 3.2%, outperforms Randomization by 4.8% in terms of NDCG@1.
- LambdaMART trained with human labeled data achieves the best performance (upper bound). An unbiased learning-to-rank algorithm can still not beat it. This indicates that there is still room for improvement in unbiased learning-to-rank.
- When trained with Click Data, the performance of LambdaMART decreases significantly and gets closer to those of RankSVM and DNN. This implies that a sophisticated algorithm like LambdaMART is more sensitive to position bias.

\(^{3}\) https://www.cs.cornell.edu/people/tj/svm_light/svm_proprank.html

Figure 1: Average positions after re-ranking of documents at each original position by different debiasing methods with LambdaMART.

Figure 2: Propensities (position biases) at click and unclick positions estimated by Unbiased LambdaMART.

5.2 Empirical Analysis

In addition, we conducted two studies to verify how effectively Unbiased LambdaMART can reduce position bias, and how robustly Unbiased LambdaMART can deal with different types of click behavior.
whether the performance improvement by Unbiased LambdaMART is indeed from reduction of position bias.

We first identified the documents at each position given by the original ranker. We then calculated the average positions of the documents at each original position after re-ranking by Pairwise Debiasing and the other debiasing methods, combined with LambdaMART. We also calculated the average positions of the documents after re-ranking by their relevance labels, which is the ground truth. Ideally, the average positions by the debiasing methods should get close to the average positions by the relevance labels. Figure 1 shows the results.

One can see that the curve of LambdaMART + Click Data (in grey) is away from that of relevance labels or ground truth (in brown), indicating that directly using click data without debiasing can be problematic. The curve of Pairwise Debiasing (in orange) is the closest to the curve of relevance labels, indicating that the performance enhancement by Pairwise Debiasing is indeed from effective debiasing.

Figure 2 shows the propensities (position bias) for click and unclick positions given by Unbiased LambdaMART. The result indicates that both the propensities at click positions and propensities at unclick positions monotonically decrease, while the former decrease at a faster rate than the latter. The result exhibits how Unbiased LambdaMART can reduce position biases in the pairwise setting.

5.2.2 Robustness of Unbiased LambdaMART. Unbiased LambdaMART assumes that the bias of a document only depends on its position, which is an approximation of user click behavior in practice. The Cascade Model [9], on the other hand, assumes that the user browses the search results in a sequential order from top to bottom, which may more precisely model user behavior. We therefore analyzed the robustness of our proposed Unbiased LambdaMART by using simulated click data from both the Position Based Model and Cascade Model, and studied whether regularization of position biases (propensities) affects performance.

For the Cascade Model, there is a probability $\phi$ that the user is satisfied with the result after clicking the document. If the user is satisfied, he / she will stop searching; and otherwise, there is a probability $\beta$ that he / she will examine the next result and there is a probability $1 - \beta$ that he / she will stop searching. In our experiment, we set $\phi$ as half of the relevance probability and used the default value of $\beta$, i.e., 0.5.

We compared Unbiased LambdaMART (LambdaMART + Pairwise Debiasing) with LambdaMART + two different debiasing methods, including Regression-EM, Randomization, and also the Click Data without debiasing on the new dataset. Again, we found that Unbiased LambdaMART significantly outperforms the baselines, indicating that Pairwise Debiasing is indeed an effective method.

Figure 3 shows the results of the methods in terms of NDCG@1. For Unbiased LambdaMART, it gives the results under different hyper-parameter values. For comparison, the results based on data generated from Position Based Model is also given. Table 3 shows the improvements in click ratios by Unbiased LambdaMART in online A/B testing.

Next, we evaluated the performance of Unbiased LambdaMART by deploying it at a commercial search engine. We conducted an A/B testing to compare the performances of Unbiased LambdaMART and LambdaMART + Click Data.

The click data over two days at the search engine, including queries, document ranking lists, and clicks of documents, was used to train the above two rankers. There were totally 19,592,854 query sessions. We then conducted A/B testing using the two rankers for seven days, over 12,320,000 query sessions. As evaluation measures, top click ratios were used, which are the percentage of sessions having first click at top 1, 3, or 5 positions among all sessions. In this experiment, we set the hyper-parameter $p$ as 1, i.e., we conducted $L_1$ regularization to have tighter control on debiasing.

As is shown in Table 3, Unbiased LambdaMART can significantly outperform LambdaMART + Click Data. It increases the click ratios
at positions 1,3,5 by 2.64%, 1.21% and 0.80%, respectively, which are all statistically significant (p-values < 0.05). It represents a significant enhancement of relevance ranking for this search engine.

6 CONCLUSION

In this paper, we have proposed a general framework for pairwise unbiased learning-to-rank, including the extended inverse propensity weighting (IPW) principle. We have also proposed a method called Pairwise Debiasing to jointly estimate propensities (position biases) and train a ranker by directly optimizing the objective function within the framework. We develop a new algorithm called Unbiased LambdaMART as application of the method. Experimental results show that Unbiased LambdaMART achieves significantly better results than the existing methods, and is effective in a real-world search system.

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