Reinforcement Learning To Rank With Coarse-grained Labels

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1 Introduction

Ranking lies at the core of many Information Retrieval (IR) tasks including web search [13, 35] and recommender system [49, 50, 55, 56]. Learning to rank (LTR) typically applies machine learning techniques for ranking [12, 24, 31, 34, 37, 43, 53–55, 57]. One of the popular approaches is to use Supervised Learning [7, 9, 12] with document-level relevance annotation data [31] to optimize ranking metrics [20, 42] such as normalized Discounted Cumulative Gain (nDCG), or Expected Reciprocal Rank (ERR). While this method has been proven effective, one of the main drawbacks is that in order to construct the loss function based on these metrics, the model requires fine-grained labels, i.e. the explicit relevance judgements of each query-document pair. On the one hand, such labels can often be expensive to attain (e.g. the high cost of human annotations) or suffer from different biases, e.g. trust bias and quality-of-context bias for click logs [22, 23]; on the other hand, myopically optimizing ranking metrics hand-crafted from those fine-grained labels may not always serve the ultimate goal of the ranking systems (e.g. user satisfaction and engagements) directly.

Compared to fine-grained labels, coarse-grained labels, such as query reformation, second search result page examination, user scroll patterns, are abundant and can be easily collected from search logs to generate large-scale training data [15, 22, 23, 29]. Some of recent works study the usage of RL algorithms in LTR task [31, 37, 43, 46, 47, 60]. While the Supervised Learning approach requires fine-grained labels to compute the evaluation metrics and construct the loss function, certain RL-algorithms, such as policy gradient, can directly use rewards from the environment to update the RL-based model with coarse-grained labels as rewards.

Existing research in Reinforcement Learning to Rank can be generally categorized into two learning methods: step-wise learning and SERP-level learning. In step-wise learning, the ranking of each query-document pair. On the one hand, such labels can often be expensive to attain (e.g. the high cost of human annotations) or suffer from different biases, e.g. trust bias and quality-of-context bias for click logs [22, 23]; on the other hand, myopically optimizing ranking metrics hand-crafted from those fine-grained labels may not always serve the ultimate goal of the ranking systems (e.g. user satisfaction and engagements) directly.

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Existing research in Reinforcement Learning to Rank can be generally categorized into two learning methods: step-wise learning and SERP-level learning. In step-wise learning, the ranking of documents is a sequence of actions in which the model selects the appropriate document for the position in the ranklist [43, 47]. Thus, a ranklist containing N documents results from N discrete ranking time steps. While this approach utilizes the discreteness of classical RL (i.e., only picking one action per time step), it also requires fine-grained document-level reward. Here, we pay more focus on situations where such reward is unavailable. SERP-level learning, on the other hand, returns a ranklist corresponding to a query in each time step [31, 37]. To be more specific, in contrast

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We conduct the experiments on two well-established public LTR datasets. While existing works of RL in LTR mainly focus on improving the performance of the model, we are more interested in seeing whether training RL model without fine-grained data can also deliver good performance in the LTR task.

In this work, we implement four different RL models, namely, Policy Gradient Rank (PGRank), Top-K Off-policy Correction for Reinforcement Learning (REINFORCE), Deep Deterministic Policy Gradient (DDPG), Batch Constrained Deep Q-Learning (BCQ). Because of the lack of real-world search logs, we first simulate coarse-grained labels from explicit fine-grained labels, then use them to train RL algorithms and report the performance. We compare these results to the classical DNN algorithms trained with fine-grained labels. We use two variants of DNN with different loss functions, i.e. CrossEntropy loss [2, 6] and LambdaRank loss [6, 42]. We conduct the experiments on two different public LTR datasets, Yahoo! LETOR [10] and MSLR-10K [32]. Based on the result, we find that the RL-based algorithms are still less effective than the classical approach for ranking tasks. Nevertheless, with more research, it could act as a good alternative for scenarios where the fine-grained labels are not available.

The rest parts of this paper are organized as follows: we first discuss the related works in §2; then cover our methods (§3) including the problem formulation (§3.1) and details of RL algorithms we adopt (§3.2). We cover the experimental details in §4 and analyze the results in §5. Finally, we conclude this work in §6.

2 Related Work

In this section we briefly existing works on reinforcement learning and its application in learning-to-rank (§2.1); then we discuss the comparison between coarse-grained labels and fine-grained labels in LTR (§2.2).

2.1 Reinforcement Learning to Rank

Reinforcement Learning has been an established field of research with applications ranging from playing video games to robotics and autonomous systems [3]. In recent years, deep RL has received considerable attention in the IR community with research in Recommender System [12, 46, 58, 59], Advertisement [8], and Relevance Feedback [30]. Some works have also studied RL for LTR tasks. They often formulate LTR as a Markov Decision Process (MDP) [4]. For example, Wei et al. [43] formulate the ranking task as MDP and leverage step-wise learning to build RL models for document ranking. Xu et al. [48] adopt the approach and implement a pairwise policy gradient approach to improve the ranking performance further. Singh and Joachims [37] propose the PG Rank model, which tries to improve the fairness of learning-to-rank models with RL methods. However, to the best of our knowledge, there has been limited research in RL with coarse-grained labels for LTR tasks, i.e. to directly construct effective ranking models with rewards collected on SERP-level. One representative work is from Oosterhuis and de Rijke [31]. They propose to train the RL model for LTR task with SERP-level rewards. However, from the perspective of RL model designs, their model is similar to PG Rank from Singh and Joachims [37]. Our work is different from [31] as we explore multiple different RL algorithms including PG Rank and aim to draw a comprehensive comparison between these RL models for this specific application scenario.

2.2 Coarse-grained Labels vs Fine-grained Labels

In this work, we investigate the usage of coarse-grained labels, including session-level labels [19] and SERP-level labels [31]. Existing works mostly adopt fine-grained labels (document-level) to train LTR models. Explicit relevance judgements can be expensive to attain [11]. Works including [22, 23, 32] have been proposed to utilize implicit feedbacks in search sessions such as clicks, user dwell time and purchases. Although abundant labels can be generated from these implicit feedbacks, they still suffer from intrinsic bias including position bias, trust bias and quality-of-context bias. Various unbiased LTR algorithms have been proposed to mitigate these biases. Perhaps a better strategy is to bypass these intrinsic problems existed in fine-grained labels and use coarse-grained labels. Oosterhuis and de Rijke [31] make the attempt to train LTR model with SERP-level reward. Coarse-grained labels, however, are not limited to SERP-level labels. Other implicit feedbacks such as query reformulation, second search result page examination and user scroll patterns can also be seen as coarse-grained labels. Hu et al. [19] propose to use session-level rewards to train reinforcement LTR model; they propose a session-level MDP to use user behaviors within session to dynamically rank items. However, as we have no access to real world search logs, we can not directly compare with their model. Instead, we use a similar approach as [31], i.e. to simulate SERP-level labels from document-level relevance judgements and utilize these simulated coarse-grained labels to train our LTR model. Our work can be further extended to utilize other coarse-grained labels discussed above.

3 Methods

In this section, we first introduce the problem formulation, i.e. LTR as a Markov Decision Process (MDP) in §3.1; then we detail the RL algorithms we use in this work (§3.2).

3.1 Problem Formulation

Our goal is to investigate whether we can train an RL model with coarse-grained SERP-level rewards to effectively rank documents given query q. Following existing works on RL for LTR [19, 31, 37], we formulate the process of ranking a collection of documents given query \( q \in Q \) as a Markov Decision Process (MDP). We adapt the document-level MDP to work with SERP-level reward. The RL model for LTR task can be formulated as a tuple \( (\mathcal{R}, S, P, R, \pi, \gamma)^2 \) representing states, actions, transition, reward, and policy, respectively, where:

- **Ranklist** \( \mathcal{R} \): the list of documents constructed by the agent w.r.t. the query \( q \).

\(^2\text{Note that here we just denote reward from ranklist with } R \text{ to align with other notations, and we use reward in the rest parts of the paper.}\)
Table 1: A summary of notations

| Symbol | Description |
|--------|-------------|
| \(q, Q\) | query, queries set |
| \(d, D\) | document, documents set |
| \(x^q_i\) | the input feature vectors of all query-document pairs in the candidate set, i.e. SERP-level feature vector |
| \(R, R_i\) | ranklist, rank position |
| \(\pi, \pi_0\) | policy, learned policy parameterized by \(\theta\) |
| \(\gamma\) | discount factor for future rewards, \(0 \leq \gamma \leq 1\) |
| \(k\) | number of documents in a ranklist |
| \(n\) | number of queries in a batch |
| \(h(x)\) | the ranking scoring function for input \(x\), parameterized by \(\theta\), universal for all models |

- **States** \(S\): a continuous state space that describe the environment. In our problem setting, we use the input feature vectors of all query-document pairs in the candidate set as state \(S\).

- **Actions** \(A\): the action space of agent. In SERP-level ranking, \(A\) usually consists the whole document collection \(D\).

- **Transitions** \(P(S_{t-1}, R, S_t) \rightarrow [0, 1]\): the state transition probability which map one state \(t-1\) to the next state \(t\) conditioned on the ranklist \(R\). Since we focus on directly constructing a whole ranklist, we do not implement transition in our experiment.

- **Rewards** \(R\): the reward the agent received after constructing a ranklist. For example, the reward could be user signals such as click, user dwell time, query reformulation, predicted user satisfaction or other implicit feedback collected from the current SERP [23].

- **Policy** \(\pi\): the learned target policy which chooses the ranklist \(r\) given state \(S\) to maximize the reward.

- **\(\gamma\)**: the discount factor for future reward.

The goal of the model is to learn the policy \(\pi\) which maximizes the reward \(R\) from ranklist \(R\) w.r.t. the search query \(q\).

### 3.2 RL Algorithms

We walk through the details of RL algorithms we adopt in this work. A summary of common notations can be found in Table 1.

#### 3.2.1 PG Rank [37]

PG Rank first utilizes a Plackett-Luce model to extract the ranking policies. Given a scoring model \(h_\theta\) with learnable parameter \(\theta\), an input \(x^q_i\), the output of the model is the scores vector of size \(k\):

\[
h_\theta(x^q) = \left( h_\theta(x^q_1), h_\theta(x^q_2), ..., h_\theta(x^q_k) \right)
\]

(1)

Based on this score vector, we can derive the \(\pi_\theta(R | q)\) of a ranklist \(R = (R_1, R_2, ..., R_k)\) using the Plackett-Luce model as follow:

\[
\pi_\theta(R | q) = \prod_{i=1}^{k} \frac{\exp \left( h_\theta(x^q_{R_i}) \right)}{\sum_{j=1}^{k} \exp \left( h_\theta(x^q_{R_j}) \right) + \ldots + \exp \left( h_\theta(x^q_{R_k}) \right)}
\]

(2)

where \(R_i\) is the \(i\)-th rank on the ranklist \(R\). The parameters \(\theta\) are updated using policy gradient technique:

\[
\nabla_\theta U (\pi_\theta | q) = \nabla_\theta \mathbb{E}_{R \sim \pi_\theta}(R | q) \cdot \text{reward}
\]

(3)

\[
= \mathbb{E}_{R \sim \pi_\theta}(R | q) [\nabla_\theta \log \pi_\theta(R | q) \cdot \text{reward}]
\]

(4)

where \(U (\pi_\theta | q)\) is the user utility of a policy \(\pi_\theta\) given a query \(q\) and is often measured with ranking metrics such as nDCG or ERR. In the same work [37], the authors also introduced a baseline for variance reduction and entropy regularization technique to balance between exploitation and exploration. However, within the scope of this work, we only focus on using coarse-grained label to train a ranking model instead of balancing exploitation and exploration. Thus we do not include these techniques.

#### 3.2.2 Deep Deterministic Policy Gradient (DDPG) [28]

DDPG combines both Q-learning and policy gradients to train an RL model. DDPG consists of two models: Actor and Critic. For ranking, the Actor Model \(A = h(\cdot)\), parameterized by \(\theta\) is a policy network that takes the input state representing the feature vectors of all the query-document pairs in the candidate set and outputs a ranklist. The Critic Model \(Q\), parameterized by \(\theta_Q\) is a Neural Network that takes the action and the state as input and computes the Q-value. For the Critic, we need to fix the Actor model \(h_\theta(x)\), and optimize \(\theta_Q\) by minimizing the following loss function:

\[
J_Q = \frac{1}{n} \sum_{x^q \in \mathcal{B}} \left( Q(x^q, h(x^q)) - \left( \text{reward}_q + \gamma \cdot Q_{\text{target}}(x^{q+1}, h_{\text{target}}(x^{q+1})) \right) \right)^2
\]

(5)

where \(x^q\) is the SERP-level feature vector for all the relevant documents w.r.t. the query, and \(x^{q+1} = (x^q_1 || x^q_2 || ... || x^q_k)\) and || denotes concatenation. We will illustrate how we create training batches in Section 4.1. For the Actor \(h_\theta(\cdot)\), we fix \(\theta_Q\) during computation and optimize \(\theta\) by maximizing the following objective function:

\[
J_h = \frac{1}{n} \sum_{x^q \in \mathcal{B}} Q(x^q, h(x^q))\]

(6)

where \(\mathcal{B}\) denotes the batch. Here, the input to the Q network is the concatenation of \(x^q\) and \(h_\theta(x^q)\). \(h_\theta(x^q)\) is the output of the Actor network and is the same as Eq. 1 with an additional \(\tanh(\cdot)\) activation function on top of it. The \(Q_{\text{target}}\) and the \(h_{\text{target}}\) in Eq. 5 are the snapshots of the main networks. These networks contain the parameters of the main networks from a few previous iterations. Periodically, these networks will receive a soft update where only a fraction (usually small) of the main networks’ parameters \(\theta\) are transferred over in the following manner:

\[
\theta_{\text{target}} \leftarrow (1 - \tau) \theta_A + \tau \theta_{\text{target}}
\]

\[
\theta_Q \leftarrow (1 - \tau) \theta_Q + \tau \theta_Q
\]

(7)

where \(\tau\) is a scale hyperparameter and is usually chosen to be close to 1 (e.g. 0.99).

After we train the parameters set, i.e. \(\theta_Q\) and \(\theta\), we derive the policy \(\pi\) as the Actor model as:

\[
\pi_\theta(R | q) = h_\theta(x^q)
\]

(8)

Then we construct the ranklist with this policy.
We should note this \( \tau \) where \( \delta \) variance generated from the Generative model.\[ \]

Perturbation model: \( \xi_\phi(S, R, \Phi) \) adds noise ranged in \([-\Phi, \Phi]\) to the ranklist \( R \) generated by \( G_\omega(S) \). The model is updated as follow:

\[
J_\phi = \sum_{(x^q, R) \in B} Q_\phi \left( x^q, R + \xi_\phi (x^q, R, \Phi) \right)
\]

where \( B \) is the data batch, and \( x^q \) is the input feature vectors to be used as state \( S \).

Two Q-networks: \( Q_\theta_1(S, R) \) and \( Q_\theta_2(S, R) \) serve as Critic networks. In order to compute the temporal difference \( \delta \) for the two networks, first we generated \( m \) ranklists using Generative model \( G_\omega \) and after that, we perturb the ranklist with the Perturbation model \( \xi_\phi \); finally, we computed the temporal difference as follows:

\[
\delta = \max_{R_i} \left[ \lambda \min_{j=1,2} Q_{\theta_j} (x^q, R_i) + (1 - \lambda) \max_{j=1,2} \right. \left. Q_{\theta_j} (x^q, R_i) \right]
\]

where \( \theta_j \) is a different set of parameters compared to the scoring model \( h_\theta \). Then the overall objective function is:

\[
y = \text{reward} + \alpha \cdot \delta
\]

where \( \alpha \) is a scalar to control the effect of estimated temporal difference \( \delta \). This step is to penalize the high-variance estimates in regions of uncertainty [16]. We can update the Critic networks and the perturbation network by:

\[
J_{\theta_j} = \arg \min_{\theta_j} \sum_{(x^q, R) \in B} \left( y - Q_{\theta_j} (x^q, R) \right)^2
\]

\[
J_\phi = \arg \max_\phi \sum_{(x^q, R) \in B} Q_{\phi} (s, a + \xi_\phi (x^q, R, \Phi))
\]

\[
J_{\theta_j} = \tau \cdot J_{\theta_j} + (1 - \tau) \cdot J_{\phi}
\]

\[
J_{\phi} = \tau \cdot J_{\phi} + (1 - \tau) \cdot J_{\phi}
\]

where \( \tau \) is used to control the update step. The algorithm policy is derived by jointly considering Critic networks, perturbation model and generative model:

\[
\pi_\theta(R|S) = \arg \max_{x^q + \xi_\phi (x^q, R, \Phi)} \left\{ x^q \sim G_\omega(x^q) \right\}
\]

where \( G_\omega(x^q) \) denotes the perturbed input feature vector; and we use this policy to construct the ranklists.

Top-k Off-Policy Correction for a REINFORCE Model [12, 44].

REINFORCE [12] based on the classical policy-gradient-based REINFORCE algorithm [44] is a RL algorithm originally designed for e-commerce recommendation with implicit feedback [18, 33, 50, 51]. The original algorithm consists of two models: a historical policy model \( \beta \) which generates the historical policy, and a neural model that generates the policy \( \pi_\theta \). Here we should note that the original paper [12] utilizes users’ logged implicit feedback resulted from historical policies \( \beta \). However, in our experiments, we assume no historical search logs and learn the ranking model from scratch. Therefore we opt to not implement the historical model \( \beta \) and make corresponding changes to the rest parts of the model.

Given a scoring model \( h_\theta (\cdot) \) with learnable parameters and input \( x^q \), the output of the model is the same as Eq. 1. We can compute the policy to sample one document \( d \), i.e. \( \pi_\theta(d | q) \), using the score vector as follows:

\[
\pi_\theta(d | q) = \exp \left( \frac{h(x^q_d)}{\tau} \right) \sum_{k=1}^{K} \exp \left( \frac{h(x^q_k)}{\tau} \right)
\]

where \( h(x^q_i) \) is the score for the document at rank \( R_i \) in the ranklist, and \( \tau \) is the temperature hyperparameter used to smooth the gradients.

To create the ranklist \( R \) with \( k \) documents, the algorithm independently samples documents according to the policy \( \pi_\theta \) and them remove duplicate. We denote the policy for creating a ranklist as \( \Pi_\theta \), and it can be computed by:

\[
\Pi_\theta (R | q) = \prod_{d \in D_q} \pi_\theta (d | q)
\]

where \( D_q \) is the candidate documents set corresponding to query \( q \) after sampling. We should note that above policy is different from the Plackett-Luce model defined in Eq. 2; the above policy will perform sampling with replacement while Plackett-Luce model will perform sampling without replacement. For example, when selecting the third document for a ranked list, the first two will be excluded in the denominator of Eq. 2. Thus one of the limitation of this approach is that the equation does not account for the probability of a document being duplicated. Then we can optimize the parameters of the policy network with the following objective function:

\[
\max_{\theta} \sum_{d \in D_q} \left[ a_\theta(d|q) \cdot \text{reward} \nabla_\theta \log a_\theta(d | q) \right]
\]

where the probability of document \( d \) appear in rank position \( i \) given query \( q \) is computed as

\[
a_\theta(d|q) = 1 - (1 - \pi_\theta(d | q))^i
\]

and \( \pi_\theta \) is computed by Eq. 15.

4 Experimental Setup

We cover the details of experimental setup in this section.
Table 2: A summary of the dataset statistics.

| Dataset            | Yahoo! LETOR | MSLR-10k |
|--------------------|--------------|----------|
| #Queries           | 29,921       | 10,000   |
| #Documents         | 701k         | 122k     |
| #Average assessed documents/query | 23 | 123 |
| #Features          | 700          | 136      |
| Relevance Scale    | 0-4          | 0-4      |

4.1 Dataset

We conduct experiments using two datasets Yahoo! Learning to Rank Collection (set 1) and MSLR-WEB10K (set 1). Each dataset contains the query IDs as well as the features of each query-document pair. The statistic for the two dataset is reported in Table 2. For both dataset, we only use 136 features. To train the baseline model, DDPG, BCQ, we sample 256 queries per batch for 10,000 training steps. When we train PG Rank, we follow the training procedure similar to the original paper and train on the entire dataset for 1000 epochs.

4.2 Evaluation and Implementation Details

4.2.1 Baseline Models.
Our goal is to see if RL algorithms trained with coarse-grained session level rewards can perform competitively with a deep neural model trained with fine-grained labels. Thus the following baseline models are trained with fine-grained labels.

We utilize two baselines models: Oracle-CrossEntropy and Oracle-LambdaRank. For both models, we use the same neural network structure as in Ai et al. [1]. The structure is a three-layer neural network with 512, 256 and 128 neurons in each layer, respectively. After that, an ELU activation is added:

\[ ELU(x) = \begin{cases} x, & \text{if } x \geq 0 \\ e^x - 1, & \text{if } x < 0 \end{cases} \]

The only difference between two models is in the objective function. In the Oracle-CrossEntropy model, we first define the attention allocation \( a_j^y \) on document \( d \) in a ranked list of documents should be,

\[ a_j^y = \frac{y_j}{\sum_{j \in [R]} y_j} \]  

where \([R]\) denotes the size of ranklist \( R \), and \( y_j \) is the relevance judgement of item \( d \) at position \( R_j \). Similarly, the baseline model computes the parameterized attention using the ranking score,

\[ a_j^y = \frac{h_\theta(x_j)}{\sum_{j \in [R]} h_\theta(x_j)} \]

Finally, the loss function is formulated as a CrossEntropy loss:

\[ L = -\sum_{x_i \in D} a_j^y \log(a_j^y) \]  

In the Oracle-LambdaRank model, the loss function is formulated as

\[ L = \sum_{i=1}^{k} \sum_{j: y_j < y_i} \Delta nDCG(i, j) \log_2 \left( 1 + \Phi \right) \]

where \( s_i \) and \( s_j \) are the scores of candidate documents predicts by the ranking scoring model, \( \Delta nDCG(i, j) \) is the absolute difference between the nDCG values when two document \( i \) and \( j \) are flipped. We optimize the two baseline models with Adam optimizer [25]. For both Oracle-CrossEntropy and Oracle-LambdaRank, our implementations are based on the ULTRA framework [2, 41].

4.2.2 RL models.
We implement the four RL models with PyTorch; we use the same DNN model architecture described in §4.2.1. With the output scores from DNN models, we use the loss and objectives described in Section 3.2 to train parameters in DNN models. We use Adam optimizer [25] for all these RL models. We experiment with different learning rates from \( 1 \times 10^{-4} \) to \( 1 \times 10^{-5} \). The \( \gamma \) discount factor for future reward is set at 0.99. We set the \( \tau \) hyper parameter in Eq. 7 to 0.001. The \( \Phi \) value in Eq. 10 is set to 0.05 and the \( \lambda \) in Eq. 12 is set to 0.75 similar to the original BCQ paper implementation.

4.2.3 Simulated coarse-grained labels.
To simulate the coarse-grained SERP-level reward for the RL models, we use the ground truth labels in this dataset to compute the nDCG score of the ranklist produced by the models. We then block the gradient from the computation of the nDCG and use this as a reward to update the model. This is to simulate the feedback from the session.

4.2.4 Evaluation.
Yahoo! LETOR and MSLR-WEB10K come with train, validation and test sets. We train all models on the provided train set and use validation set to tune the hyperparameters. We report the model performance on the testset. We use two standard ranking metrics: normalized Discounted Cumulative Gain (nDCG) [21] and the Expected Reciprocal Rank (ERR) [11], to measure the performance of each algorithm. nDCG is a metric based on the theory of information gain while ERR is constructed based on the model of users’ web search satisfaction. We select the ranking models with the best performance on the validation set according to nDCG@10 during training. All experiments are repeated for five times. We report the average metric values scores for the top 1, 3, 5, and 10 results. We conduct the Fisher randomization test [38] with \( p \leq 0.05 \) confidence level.

5 Result & Analysis

5.1 Performance Comparison (RQ1)
In this section, we try to analyze the effectiveness of RL algorithms with coarse-grained labels for learning to rank. Specifically, we tries to answer two research questions:

RQ1: Can RL-based algorithms using coarse-grained labels as rewards achieve competitive performance compared to the baseline Oracle-DNN model?

RQ2: Do RL-based algorithms for LTR task suffered from generalization problem due to extrapolation error [16, 36]?

We report the result comparison between the four RL models and the baseline in Table 3. Overall, the two baseline models trained with fine-grained relevance labels outperform all the other RL algorithms with DNN model. When we examine the four RL algorithms

1https://webscope.sandbox.yahoo.com/
2https://github.com/ULTR-Community/ULTRA
3https://pytorch.org/
Table 3: Results of RL models compare to baseline DNN on different dataset; we highlight the best model among baselines and RL models, respectively. All baseline models outperform the RL models with Fisher randomization test at 0.05 level.

(a) Testing performance of RL models compare to baseline DNN on Yahoo! LETOR

| Models/Metrics       | nDCG@1 | ERR@1 | nDCG@3 | ERR@3 | nDCG@5 | ERR@5 | nDCG@10 | ERR@10 |
|----------------------|--------|-------|--------|-------|--------|-------|---------|--------|
| Oracle-CrossEntropy  | 0.665  | 0.335 | 0.672  | 0.413 | 0.693  | 0.435 | 0.739   | 0.444  |
| Oracle-LambdaRank    | 0.667  | 0.336 | 0.678  | 0.417 | 0.695  | 0.438 | 0.742   | 0.454  |
| REINFORCE            | 0.357  | 0.130 | 0.417  | 0.217 | 0.466  | 0.249 | 0.555   | 0.275  |
| DDPG                 | 0.502  | 0.212 | 0.556  | 0.314 | 0.670  | 0.343 | 0.670   | 0.363  |
| BCQ                  | 0.377  | 0.145 | 0.434  | 0.233 | 0.483  | 0.265 | 0.570   | 0.289  |
| PG Rank              | 0.607  | 0.332 | 0.613  | 0.399 | 0.655  | 0.406 | 0.725   | 0.423  |

(b) Testing performance of RL models compare to baseline DNN on MSLR-WEB10K

| Models/Metrics       | nDCG@1 | ERR@1 | nDCG@3 | ERR@3 | nDCG@5 | ERR@5 | nDCG@10 | ERR@10 |
|----------------------|--------|-------|--------|-------|--------|-------|---------|--------|
| Oracle-CrossEntropy  | 0.360  | 0.169 | 0.381  | 0.251 | 0.392  | 0.277 | 0.418   | 0.298  |
| Oracle-LambdaRank    | 0.381  | 0.203 | 0.385  | 0.279 | 0.398  | 0.302 | 0.421   | 0.321  |
| REINFORCE            | 0.179  | 0.073 | 0.204  | 0.126 | 0.220  | 0.149 | 0.257   | 0.173  |
| DDPG                 | 0.142  | 0.048 | 0.157  | 0.087 | 0.174  | 0.107 | 0.207   | 0.129  |
| BCQ                  | 0.149  | 0.063 | 0.169  | 0.112 | 0.184  | 0.133 | 0.215   | 0.156  |
| PG Rank              | 0.177  | 0.162 | 0.181  | 0.160 | 0.212  | 0.174 | 0.240   | 0.171  |

Table 4: Training performances of RL models compare to baselines on Yahoo! LETOR; we highlight the best model among baselines and RL models, respectively. All baseline models outperform the RL models and the improvement is significant with Fisher randomization test at 0.05 level.

| Models/Metrics       | nDCG@1 | ERR@1 | nDCG@3 | ERR@3 | nDCG@5 | ERR@5 | nDCG@10 | ERR@10 |
|----------------------|--------|-------|--------|-------|--------|-------|---------|--------|
| Oracle-CrossEntropy  | 0.761  | 0.415 | 0.783  | 0.493 | 0.814  | 0.527 | 0.857   | 0.543  |
| Oracle-LambdaRank    | 0.769  | 0.417 | 0.787  | 0.498 | 0.820  | 0.534 | 0.873   | 0.546  |
| REINFORCE            | 0.569  | 0.356 | 0.641  | 0.433 | 0.684  | 0.458 | 0.781   | 0.486  |
| DDPG                 | 0.691  | 0.409 | 0.754  | 0.517 | 0.788  | 0.539 | 0.791   | 0.561  |
| BCQ                  | 0.598  | 0.351 | 0.662  | 0.429 | 0.701  | 0.462 | 0.761   | 0.491  |
| PG Rank              | 0.698  | 0.436 | 0.720  | 0.487 | 0.771  | 0.503 | 0.830   | 0.517  |

in the two datasets, we can see that the performance varies from one to another. In the Yahoo! LETOR dataset, PG rank achieves the highest performance among the four algorithms. Next is DDPG, followed by BCQ and REINFORCE. However, in MSLR-WEB10K, REINFORCE achieves the best performance. Following REINFORCE is PG Rank, BCQ, and then DDPG. Interestingly, PG Rank has the highest performance differences between the two datasets compared to other algorithms. Even though we do not clearly explain this phenomenon, we have three speculations:

First, features in each dataset could impact the performance of these models. Compared to MSLR-WEB10K, it could be that the features presented in Yahoo! LETOR are of higher quality and more suitable for training with coarse-grained relevance labels.

Secondly, it is worth noticing that in Yahoo!LETOR dataset, there are approximately 23 documents per query, while for MSLR-WEB10K, there are an average 122 documents per query. The considerable difference between the two action pools may contribute to the performance drop for these algorithms. The intuition is that it is harder to train the RL algorithms when the action pool is very large. However, more analysis and experiments will be needed to verify this hypothesis.

Finally, it should be noted that Yahoo! LETOR dataset has almost tripled the number of queries compared to MSLR-10K. Since PG Rank is trained on the entire a dataset for each training step, this could explain the different between the performance of this algorithms between the two datasets.

To summarize from Table 3, at the current state, RL models trained on coarse-grained labels are not comparable to DNNs trained with ground-truth labels. However, the performance of PG Rank on Yahoo! LETOR dataset suggests that with better model design and feature selections, RL algorithms could serve as a good substitute in scenarios where we do not have fine-grained relevance labels.

5.2 Generalization Problem (RQ2)

Previous works [16, 17] suggest that one of the main issues that contribute to generalization problem in RL is that there is a mismatch between training data and testing data. Formally, this is called extrapolation error. While this error is more prevalent in
off-policy RL, it could still be relevant even with on-policy training for LTR tasks because new documents are being added to the web every day, which causes the distribution to be constantly changed. To investigate this issue, we report the training performance and compare it to the testing performance of the four RL algorithms and report the result in Figure 1 and Table 4.

From the result, we can see a clear disparity between the training performance compared to the testing results for all four models. There are about 20% performance differences between training and testing results among all RL models. However, DNN models only suffered from about 10% differences. While it is expected that the training performance is higher than testing performance, the differences between the two performances in RL models are significant. If this was to be deployed in a real environment, it could negatively affect users’ browsing experience. How to balance exploration and exploitation is a crucial problem to solve. There have been currently few research attempts to tackle the issue [5, 14, 16, 36, 45]. However, they are not implemented for the LTR task. Thus, a possible research direction in the future could be solving the generalization error for RL algorithms on the LTR task.

6 Conclusion and Future Work

In this paper, we implemented four RL algorithms trained with coarse-grained SERP-level rewards and compared the result with two baseline models, a three layers MLP trained using CrossEntropy loss, and on trained with LambdaRank both used fine-grained ground truth labels. The empirical result illustrates that these RL algorithms still need more work before they can perform competitively with the current approaches using loss functions that directly optimize using evaluation metrics calculated using ground truth labels. We also discussed the generalization problem in classical RL task still exist and could be more pervasive in LTR task. We should note this work is far from a comprehensive investigation on RL algorithms for LTR. A natural extension of this work would be to design more comprehensive experiments to verify the actual reasons that lead to the performance drop of RL algorithms. The next step would be to design a RL model that could have competitive performance compare to DNN approach.

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