Online Learning to Rank with List-level Feedback for Image Filtering

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Abstract. Online learning to rank (OLTR) via implicit feedback has been extensively studied for document retrieval in cases where the feedback is available at the level of individual items. To learn from item-level feedback, the current algorithms require certain assumptions about user behavior. In this paper, we study a more general setup: OLTR with list-level feedback, where the feedback is provided only at the level of an entire ranked list. We propose two methods that allow online learning to rank in this setup. The first method, PGLearn, uses a ranking model to generate policies and optimizes it online using policy gradients. The second method, RegLearn, learns to combine individual document relevance scores by directly predicting the observed list-level feedback through regression. We evaluate the proposed methods on the image filtering task, in which deep neural networks (DNNs) are used to rank images in response to a set of standing queries. We show that PGLearn does not perform well in OLTR with list-level feedback. RegLearn, instead, shows good performance in both online and offline metrics.

Keywords: Online learning to rank · Image retrieval · Implicit feedback

1 Introduction

Image search concerns a large portion of modern search engine systems [31, 32]. In this paper, we focus on the image filtering task, a special case of image search, which aims at identifying relevant images given a standing query [2, 5]. We are particularly interested in scenarios that are characterized by a fixed set of information needs and a set of images that needs to be ranked against each of those needs, e.g., video surveillance with a fixed visual vocabulary [3], (visual) reputation monitoring [4], or visual information discovery services such as Pinterest¹ etc.

How can we use state-of-the-art online learning to rank (OLTR) methods to learn to improve performance on the image filtering task? The image filtering task poses a number of challenges for modern OLTR methods. First, previous OLTR methods are mostly based on a typical text search setup, where

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features are textual similarities between query and document, e.g., BM25 and TF-IDF [23]. How to learn and rank images by pixel features online is still an open question. Second, in many specific instances of the image filtering task, the feedback from which one has to learn is not available at the level of individual items but only at the level of the entire result list [33]. Think, in particular, of scenarios such as user satisfaction in mobile search, or with intelligent assistants, where feedback comes from a potentially diverse set of user interactions, e.g., user gestures, search dialogues [17, 30], and where large volumes of feedback can only be acquired at the level of an entire ranked list of items.

More specifically, then, the problem that we address in this paper is how can we develop OLTR methods for image filtering that learn from list-level feedback? In OLTR, we aim to constantly improve the underlying ranking model based on an incoming stream of user feedback such as clicks. A range of online learning to rank (OLTR) techniques have been proposed in the literature [9, 19, 25, 26, 35, 38]. The methods proposed so far only operate with item-level feedback, such as knowing whether a particular item is clicked or not, which allows us to assess the quality of an individual item. Since user feedback is biased [14, 36], to get rid of the bias, OLTR algorithms with item-level feedback either require additional assumptions, e.g., the cascading assumption [18], or a certain level of randomization [19, 38]. As a result, algorithms of the first group are limited by the assumptions they require, and algorithms of the second group potentially hurt the user experience during the early stages of learning [19].

Unlike item-level feedback, list-level feedback measures the quality of ranked lists directly, such that a ranked list of higher quality receives more clicks on average than a ranked list of lower quality. Learning from list-level feedback allows the algorithm to avoid debiasing procedures used by item-level based algorithms. And, clearly, item-level feedback can be turned into list-level feedback (but not vice versa). Meanwhile, from the point of learning to rank (LTR), list-wise methods generally performs better than point-wise methods [20, 23].

The challenge of list-level OLTR is that a ranked list consists of multiple items (e.g., 5 images), but the obtained feedback is a single value (e.g., abandonment). To learn a ranking model in this scenario, we need to compute the contribution of individual items to the list-level feedback. We propose two methods to do so. The first method, PGLearn, takes a policy gradient point of view and considers each ranked list as an action and optimizes the policy that chooses the best action given a user’s query based on the observed reward (i.e., list-level feedback). The second method, RegLearn, uses regression to directly learn to combine individual item relevance scores to predict the observed list-level feedback. Then, RegLearn employs back-propagation to update the underlying ranking model that produces the relevance scores. In order to learn from pixel features, we choose a deep neural network (DNN) as the underlying ranking model for both RegLearn and PGLearn.

We simulate the image filtering task on the MSCOCO dataset [22] and consider nDCG@k (the ideal setup) and CTR@k (the noisy setup) as list-level feedback. Our experimental results show that PGLearn performs poorly when the
list size is larger than 2 while RegLearn is able to train a good underlying ranking model with larger lists.

In summary, the main contributions of this paper are the following:
1. We propose two methods, PGLearn and RegLearn, which allow online learning of ranking models in scenarios where only list-level feedback is available.
2. We evaluate the proposed methods on the image filtering task and show that RegLearn has superior performance compared to PGLearn, especially when the list size increases.

2 Related work

Online learning to rank. Most previous work on OLTR either formulates the OLTR problem as a multi-armed bandits (MAB) problem [18, 19, 25, 38] or as a Dueling Bandit Gradient Descent (DBGD) problem [9, 20, 28, 35]. MAB-type algorithms rank items by an item-wise estimator that estimates the probability of an item being clicked. This type of algorithms only use item-level feedback and are not generalized across different queries.

DBGD has been proposed by Yue and Joachims [35] and learns a ranking function by gradient descent via interleaved comparisons. Schuth et al. [26] extend DBGD to learn from multileaved comparisons and propose a more effective algorithm: Multileave Gradient Descent. Since both interleaved and multileaved comparison methods require item-level clicks to infer the preference for ranked lists over others, DBGD-type algorithms cannot be extended to learn from list-level feedback.

In contrast to DBGD-type algorithms, we propose two OLTR algorithms to directly learn from list-level feedback.

Image retrieval based on implicit feedback. There is a growing number of studies on LTR for image retrieval that exploit user behavior. Jain and Varma [13] use click data as a pseudo-relevance signal to train a re-ranking model and also use PCA and Gaussian Process regression to address the sparsity problem of click data in image search. Yu et al. [34] simultaneously use visual features and click features to learn a ranking model. O’Hare et al. [24] extract user behavior features such as hover-through rate and demonstrate that combining these features with content features can yield significant improvements on relevance estimation compared to purely content-based features. However, to train an LTR framework using these features, a manually annotated dataset is needed.

In contrast to the work listed above, we propose an OLTR method for image search that is based on list-level feedback. To the best of our knowledge, we are the first to do so.

3 Method

In this section, we first present the notation and our general OLTR framework (Section 3.1). Then, we propose two algorithms for OLTR with list-level feed-
back. The first, PGLearn, is based on policy gradients \cite{15} (Section 3.2). The second, RegLearn, is based on linear regression (Section 3.3).

Algorithm 1 OLTR framework

Input: SERP size $k$ and exploration rate $\epsilon$.

1: for $t \leftarrow 1, 2, \ldots$ do
2: $q_t \leftarrow \text{receive query}(t)$ // Receive a query from a user.
3: $s_i \leftarrow f(x_i; q_t)$ for $\forall x_i \in X$ // Score image candidates by the ranking function $f(x; q_t)$.
4: $l_t \leftarrow \text{generate results}([s_i]_{i=1}^n, k, \epsilon)$ // Generate ranked list $l_t$ with $\epsilon$-greedy exploration.
5: Show $l_t$ to the user and receive the list-level feedback $r_l$.
6: Update $f(x; q_t)$ // We update the ranking function by the proposed PGLearn and RegLearn, respectively.
7: end for

3.1 Notation and framework

In our image filtering task, we have a set of standing queries $Q = \{q_i\}_{i=1}^m$ and a set of images $X = \{x_i\}_{i=1}^n$. The goal is to rank image candidates with respect to a given standing query. We use $f(x; q)$ to denote the score assigned to an image $x$ by a ranking model given a query $q$, $\theta$ to denote the parameters of the ranking function $f(x; q)$, $l$ and $r(l)$ to denote a ranked list and its list-level feedback, respectively.

In OLTR, a little exploration helps to increase the performance of an online algorithm [9]. But too much exploration may hurt the user experience. In this paper, the $\epsilon$-greedy policy is chosen to balance exploration and exploitation. With the $\epsilon$-greedy policy, an algorithm ranks image candidates randomly with probability $\epsilon$ (exploration), while with probability $1-\epsilon$ the algorithm ranks image candidates based on the scores produced by the underlying DNN (exploitation).

Figure 1 provides a high-level overview of PGLearn and RegLearn. The inputs are ranked image lists. In this paper, both algorithms use a deep neural network (DNN) as the underlying ranking model to score images for a given query. Each DNN has $m$ outputs which is the same size as the number of standing queries. And a query $q$ is encoded by a one-hot vector with size $m$. Hence, each output of DNN is the score of the image given the corresponding query. The general online learning to rank framework is provided as pseudo-code of in Algorithm 1.

In the rest of this section, we explain PGLearn and RegLearn in more detail, respectively.

3.2 PGLearn

The first proposed OLTR algorithm is PGLearn, which is based on policy gradients in reinforcement learning [15]. It aims to estimate the probability of the
Fig. 1: Structure of the proposed algorithms for OLTR with list-level feedback. First, each input image receives a relevance score from the underlying ranking mode. Then, these scores are transformed either using softmax in PGLearn or weighted sum in RegLearn. Finally, PGLearn outputs a Plackett-Luce distribution, while RegLearn directly predicts list-level feedback.

ranked list given a query. Shown in Figure 1, a shared weight DNN is employed to predict a relevance score for every image given a query. Then, the scores are transformed into probabilistic outputs via a softmax layer. PGLearn uses these probabilities to estimate the probability distribution over actions, i.e., ranked lists of images in our case. To get the probability of a ranked list, we follow the Plackett-Luce model \[7\] and compute this probability as follows:

\[
PL(l \mid q, X) = \prod_{i=1}^{k} \frac{\exp(f(x_i; q))}{\sum_{m=i}^{k} \exp(f(x_m; q))}.
\]

PGLearn identifies the best ranked list by choosing the one with the highest probability. However, the action space is very large, namely \(O(k!)\), where \(k\) is the size of a list. Again, we follow the Plackett-Luce model and sample without replacement from a probability distribution over the set of images, similar to [12]. Importantly, finding the best ranked list becomes infeasible as the list size increases.

In the training phase, PGLearn learns the underlying ranking model, i.e., a DNN, by maximizing the expected reward over the whole action space:

\[
L(\theta) = \mathbb{E}_{q,l}[r(l, q)].
\]

PGLearn computes the gradients as follows:

\[
\nabla_\theta L(\theta) = \sum_q P(q) \sum_l \nabla_\theta (PL_\theta(l \mid q) \cdot r(l, q))
\]

\[
= \sum_q P(q) \sum_l \frac{PL_\theta(l \mid q)}{PL_\theta(l \mid q)} \cdot \nabla_\theta PL_\theta(l \mid q) \cdot r(l, q)
\]

\[
= \mathbb{E}_{q,l}[\nabla_\theta \log PL_\theta(l \mid q) \cdot r(l, q)].
\]
Then, we approximate the derivative by sampling, for example using a single
Monte Carlo sample, which is a standard procedure in policy gradients [15].
Finally, we use back propagation to train the underlying DNN.

3.3 RegLearn

In contrast to PGLearn, which estimates the probability of a ranked list, the
second proposed algorithm, RegLearn, aims at directly estimating the quality,
i.e., the reward, of a ranked list given a query. Specifically, RegLearn directly
predicts the list-level feedback $r(l)$ of a ranked list $l$ for a given query $q$.

As shown in Figure 1, given a ranked list with $n$ images, RegLearn employs $n$
DNNs, each of which shares the weights, to score all the images. Then, RegLearn
sums up the scores output by DNNs with some discounted weights to approx-
imate the feedback $\hat{r}(l)$. More precisely, RegLearn approximates the feedback
as follows: $\hat{r}(l) = \sum_{i=1}^{n} w_i f(x_i, q)$, where $w = \{w_1, \ldots, w_n\}$ are the discounted
weights of positions. These $w$ are regarded as the last layer (the discounted sum-
mation layer) in Figure 1 and are learned during training. Finally, the $L^2$-loss is
used to optimize the underlying DNN and the above-mentioned weights:

$$L(r(l), \hat{r}(l)) = \frac{1}{2} (r(l) - \hat{r}(l))^2.$$ 

(4)

Since the discounted weights $w$ just mentioned are the last layer of the whole
network structure and the $L^2$-loss is differentiable, the error can be back prop-
agated to the underlying DNN.

4 Experimental setup

Our experiments are designed to answer three research questions: (RQ1) Can
RegLearn and PGLearn learn from the ideal feedback, i.e. nDCG@k? (RQ2) How
would different levels of noise in the feedback signal affect the performance of
RegLearn? (RQ3) Can RegLearn learn the discounted weights $w$ while learning
the ranking function?

Dataset. We conduct experiments on the MSCOCO image dataset [22]. In the
MSCOCO dataset, each image contains at least one object, where an object can
be seen as a category the image belongs to or a query the image is relevant to,
and so an image is relevant to one or more queries. More precisely, MSCOCO
contains 2.5 million labeled objects in 328k images chosen from a set of 80
objects. In our image filtering setup, this translates into 80 standing queries and
328k images to rank. We train our models on the training set of MSCOCO.
Since the test set of MSCOCO does not have labels, we test our methods on the
validation set of MSCOCO.
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Table 1: Overview of the click configurations.

| configuration | p(a|R) | p(a|IR) |
|---------------|-------|--------|
| perfect       | 1.0   | 0.0    |
| locating      | 0.95  | 0.05   |
| entertaining   | 0.9   | 0.4    |

Online learning simulation. Evaluating the ability of an online algorithm requires a sequence of user requests (queries) and user feedback. The ideal setup is to run algorithms on the real online systems and interact with real users. However, online experiments are expensive. In contrast, simulation experiments, which are cheaper, are widely used to evaluate the ability of online algorithms [8, 10] [19, 21]. In this paper, we use the following procedure to simulate OLTR:

1. Given a randomly chosen standing query, a set of candidate images is selected randomly, such that at least one of the selected images is relevant to the query. This is a general setup in OLTR [19, 38].
2. We use ResNet [6] to produce a relevance score for each selected image.
3. Before passing an image to ResNet, we apply VGG-Net preprocessing to rescale the image and obtain random crops so as to avoid overfitting [27].
4. The list-level feedback of the ranked list is then simulated.
5. The user feedback is used by PGLearn and RegLearn to update the ranking model, namely ResNet.

Since we focus on the image filtering scenario with a finite set of queries, the same query appears multiple times in the training and test set. Every image appears in only one of the two sets (training or test).

In order to avoid updating ResNet frequently and to take advantage of parallelized computations, the above procedure is performed in batches. Each batch contains 100 queries, which are processed in parallel. We update ResNet after we collect feedback for all 100 queries in a batch. In terms of hyperparameters, we use a learning rate of $10^{-4}$ together with the Adam optimizer [16]. We also use batch normalization [11] with a decay of 0.997 and epsilon of $10^{-5}$ which are the default setups in ResNet [6].

List-level feedback. We use two types of list-level feedback: nDCG@$k$ and CTR@$k$, where $k$ is the number of positions. nDCG@$k$ is a widely used metric in ranking tasks [3] [9] [26]; it measures the quality of a ranked list. It is an ideal and deterministic feedback for OLTR but it is not clear how to transfer real world feedback to nDCG scores. We conduct experiments with nDCG@$k$ feedback to determine whether RegLearn and PGLearn are able to learn from list-level feedback. Obviously, if they could not learn from nDCG@$k$ feedback, they certainly would not learn from noisy feedback, which widely exists in online interactive search systems [35, 37]. For a more realistic setup, we choose CTR@$k$ as another type of list-level feedback, which is easily obtained from users and contains more noise. In experiments, we choose $k = 2$ and 5, which are important in commercial search systems [30, 37].
Click simulation. For the click feedback based experiments, we use the Position Based Model (PBM) [4] to simulate clicks. This configuration is different from the Dependent Click Model (DCM) [4] based configurations, i.e., perfect, navigational and informational configurations [9], which are widely used in the online text retrieval simulation. The reason that we choose PBM instead of DCM in the paper is twofold: 1. Recent user studies show that users do not always check the highest ranked images [29, 31, 33], so DCM does not exactly fit for the image retrieval task. 2. The image retrieval scenario is more complex than the text retrieval scenario [29, 31, 32]. Particularly, there is no certain order in positions with which users browse a search engine result page.

The PBM consists of two sets of parameters: examination and attraction probabilities [4]. For the examination probabilities, we learn the PBM of the Yandex click logs using PyClick and obtain the examination probabilities of the top 5 positions as follows: 0.999, 0.959, 0.761, 0.592 and 0.457.

For the attraction probabilities, we follow the configurations used by Hofmann et al. [9] and design three configurations, i.e., perfect, locating and entertaining, to transfer the relevance labels in the MSCOCO dataset into attraction probabilities. Table 1 provides an overview of the configurations. The feedback in the perfect configuration is deterministic, where users always and only click relevant images. This configuration aims at upper bounding the performance with click feedback. The other configurations are designed to mimic two types of user behavior in image search, i.e., “locate” and “entertain,” as proposed by Xie et al. [32]. In the locating configuration, a user tries to find certain images that match some requirements, so he or she has a high probability to click relevant images and a low probability to click irrelevant images. In the entertaining configurations, instead of finding certain images, users want to kill time by browsing the search results, so their click behaviors tend to be noisy. All in all, the noise level in three configurations follows this order: perfect” < “locating” < “entertaining.”

Skyline. Since all previous OLTR algorithms require item-level feedback, we do not compare PGLearn and RegLearn with any baseline. However, to calibrate their performance, we design a skyline for the comparison. The skyline we choose is based on RegLearn, but the last layer is the predefined discounted weights and not updated during training. More precisely, for the different types of list-level feedback, either the discounted weights in nDCG or the examination probability of a PBM are input to RegLearn as prior knowledge. Since RegLearn is informed about the importance of each position in this way, it should learn a high quality ranking model. We call the skyline OracleLearn.

Exploration. To explore the ranking space, all the algorithms are combined with two types of \(\epsilon\)-greedy policy with \(\epsilon = 0.1\) and \(\epsilon = 1\). The setting \(\epsilon = 1\) means that the algorithm always explores the ranking space, which may lead to the best

\[https://academy.yandex.ru/events/data_analysis/relpred2011\]
\[https://github.com/markovi/PyClick\]
Fig. 2: Online performance (average nDCG@k) of different combinations of learning methods (PGLearn, RegLearn and OracleLearn) and exploration rate (ε = 0.1 and ε = 1). Higher is better. Best viewed in color.

Evaluation measures. We have two types of evaluation: online and offline. In online evaluation, we care about the user experience during the whole online training phase. Both the past and current performances of the algorithm should be considered when choosing the online metric. We use the average cumulative nDCG@k of ranked lists as the online metric, which is computed as follows:

\[ nDCG_{@k}(T) = \frac{1}{T} \sum_{t=1}^{T} nDCG_{@k}(l_t) \]

where \( T \) is the number of steps and \( nDCG_{@k}(l_t) \) is the nDCG@k of the ranked list \( l_t \).

In offline evaluation, we care about the final quality of OLTR algorithms, which is measured by nDCG@k on a left out test set. To measure the offline performance, we randomly choose 150 batches each containing 100 queries from the test set. Then, we compute the average nDCG@k over these 15,000 queries. To determine whether differences between the best performance and the others are significant, we use a two-tailed Student’s t-test with \( p < 0.05 \).
Table 2: Offline nDCG@k scores obtained on the test set of MSCOCO. The best results are marked in boldface. Statistically significant losses against the best result per row are indicated by *. We report the standard deviation in the subscripts.

<table>
<thead>
<tr>
<th></th>
<th>PGLearn</th>
<th>RegLearn</th>
<th>OracleLearn (skyline)</th>
</tr>
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<tbody>
<tr>
<td>k = 2</td>
<td>ϵ = 1</td>
<td>ϵ = 0.1</td>
<td>ϵ = 1</td>
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<tr>
<td></td>
<td>0.926_{0.02}^*</td>
<td>0.946_{0.02}^*</td>
<td>0.846_{0.18}^*</td>
</tr>
<tr>
<td>k = 5</td>
<td>ϵ = 1</td>
<td>ϵ = 0.1</td>
<td>ϵ = 1</td>
</tr>
<tr>
<td></td>
<td>0.607_{0.05}^*</td>
<td>0.624_{0.05}^*</td>
<td>0.564_{0.18}^*</td>
</tr>
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</table>

ing with ϵ-greedy with ϵ = 0.1 and ϵ = 1 during the online training. We run experiments with 40k batches, which contain 4M queries in total.

We see that all algorithms with ϵ = 1 (pure exploration) have the worst performance since the output is just a randomly ranked list. OracleLearn_ϵ=0.1 outperforms others in both the k = 2 and k = 5 cases. For k = 2, PGLearn_ϵ=0.1 performs close to OracleLearn_ϵ=0.1 and outperforms RegLearn_ϵ=0.1. But when k becomes larger, i.e., for k = 5, PGLearn_ϵ=0.1 is hardly better than generating random output and loses to RegLearn_ϵ=0.1 with a large gap. The huge difference in the behavior of PGLearn_ϵ=0.1 in the two cases is caused by the fact that policy gradient tends to converge to suboptimal policies without a good estimate of the reward [15]. We approximate the derivate (Eq. 3) by Monte Carlo sampling. When the action space is small, e.g., O(2!) for k = 2, Monte Carlo sampling can easily sample all actions and then return a good estimation of the rewards, so we get a good approximation of the derivate. But when the action space is large, e.g., O(5!) for k = 5, Monte Carlo sampling can hardly sample the whole action space and then the estimation of rewards is biased and the approximation of the derivate is inaccurate. Given the fact that the SERP size can be larger than 5, where PGLearn_ϵ=0.1 may perform even worse, RegLearn_ϵ=0.1 is a better choice for the online image filtering task than PGLearn_ϵ=0.1 and we omit PGLearn from further considerations.

**Offline performance.** We report the offline performance of the algorithms trained with nDCG@k feedback in Table 2. The values reflect the quality of user experiences after the training. For k = 2, OracleLearn_ϵ=1 and RegLearn_ϵ=0.1 have the best offline performance. Different from the online results, where PGLearn_ϵ=0.1 outperforms RegLearn_ϵ=0.1, RegLearn_ϵ=0.1 outperforms PGLearn_ϵ=0.1 significantly with the offline metric. We hypothesize that even for k = 2 the action space is too large for the Monte Carlo sampling, used by PGLearn, to fully estimate the action reward and the good online performance may be the effect of overfitting the training dataset. For a longer list, e.g., with k = 5, OracleLearn_ϵ=0.1 outperforms others. RegLearn_ϵ=0.1 does not keep up with OracleLearn_ϵ=0.1. That is, RegLearn_ϵ=0.1 is about 0.015 lower than OracleLearn_ϵ=0.1 in term of nDCG@5. Again, PGLearn performs poorly.

The offline evaluation indicates that, with the proper exploration policy, RegLearn can learn to combine the individual scores to predict list-level feedback, and then train a good ranking model, especially with short lists, e.g. k = 2.
Fig. 3: Online performances (average nDCG@5) of RegLearn$_{\epsilon=0.1}$ and OracleLearn$_{\epsilon=0.1}$ with three different click configurations. Higher is better. Best viewed in color.

However, pure exploration, i.e., $\epsilon = 1$, is harmful to RegLearn. This is because RegLearn cannot get any position information through pure exploration, which randomly shuffles the results during the training phase. On the other hand, PG-Learn performs poorly when $k = 5$, which is consistent with the online results. Together with the online performance, the answer to RQ1 is that RegLearn can learn from list-level feedback and PG-Learn can learn from the list-level feedback with small list sizes. Because of the poor performance of PG-Learn when $k > 2$, we leave it out of our later experiment with click feedback.

**Online performance with click feedback.** To answer RQ2, we conduct experiments on RegLearn$_{\epsilon=0.1}$ and OracleLearn$_{\epsilon=0.1}$ with click feedback. Here, Oracle-Learn has the prior knowledge of the examination probabilities. We omit the results of $k = 2$, because the difference between the examination probabilities of the first two positions is fairly small, only 0.04. We choose $\epsilon$-greedy with $\epsilon = 0.1$, since pure exploration ($\epsilon = 1$) hurts the performance of RegLearn.

Shown in Fig. 3 with the perfect and locating configurations, the performances (average nDCG@5) of RegLearn$_{\epsilon=0.1}$ go from $0.59 \pm 0.01$ and $0.61 \pm 0.02$ to $0.67 \pm 0.01$ and $0.66 \pm 0.00$, respectively. However, with the entertaining configuration, RegLearn$_{\epsilon=0.1}$ fails to learn a ranking function. Note that the entertaining configuration is the most noisy one. This result indicates that RegLearn$_{\epsilon=0.1}$ can learn from noisy feedback, but the performance of RegLearn$_{\epsilon=0.1}$ drops down as the level of noise increases. If the feedback is too noisy, as witnessed in, e.g., the entertaining configuration, RegLearn$_{\epsilon=0.1}$ may fail to learn a ranking model.

When it comes to the OracleLearn$_{\epsilon=0.1}$, we see that it learns a ranking function with all three configurations, since the three lines in the right plot of Figure 3 climb up alone the number of batches. This result indicates that the performances of RegLearn can be boosted by integrating the prior knowledge of user behavior.
Learning discounted weights. To answer RQ3, we analyze the discounted weights, $w$, learned by RegLearn$_{\epsilon=0.1}$, i.e., the discounted weights in nDCG and the examination probabilities in a PBM. Figure 4 shows the results with different setups, where the “ground truth” is the true $w$ in nDCG and click setup, respectively.

For the nDCG feedback setup, the learned $w$ by RegLearn$_{\epsilon=0.1}$ is close to the ground truth, and the Euclidean distance 4 to the ground truth is 0.079. When it comes to the click feedback setup, with the less noisy configurations, i.e., the perfect and locating configurations, RegLearn$_{\epsilon=0.1}$ learns the correct order of the importance of positions. However, because of the noise in feedback, the Euclidean distances from learned $w$ to the ground truth are 0.231 and 0.372, respectively. Moreover, RegLearn$_{\epsilon=0.1}$ fails to learn the examination probabilities with the entertaining configuration, the most noisy configuration.

In summary, the answer to RQ3 is that RegLearn$_{\epsilon=0.1}$ can learn the proper discounted weight $w$ from the ideal or little noisy feedback, but cannot learn a proper $w$ from the most noisy feedback, i.e., entertaining click feedback.

6 Conclusion

This paper has shown two novel ways to use list-level feedback for OLTR: PG-Learn and RegLearn. They can both back propagate the loss to the underlying ranking model. The main findings are that RegLearn with $\epsilon$-greedy, with $\epsilon = 0.1$, is a good choice for the OLTR task in the image filtering setup.

One of the interesting future directions is to adopt different types of exploration strategy to PG-Learn and RegLearn, since the experiments have demonstrated that proper exploration helps to boost offline performance, while, with pure exploration, $\epsilon = 1$, RegLearn fails to train the underlying ranking model. We hypothesize that an alternative exploration policy may help to increase the performance of RegLearn.

4 We consider the learned weights as a 5-dimensional vector.
Code and data

To facilitate reproducibility of the results in this paper, we are sharing the code and data used to run the experiments in this paper at [https://github.com/chang-li/dcgnet](https://github.com/chang-li/dcgnet).

Bibliography


