While China has become the biggest online market in the world with around 1 billion internet users, Baidu runs the world largest search engine who serves hundreds of millions of daily active users and responding billions queries per day. To handle the diverse query requests from users at web-scale, Baidu has done tremendous efforts in understanding users’ queries, retrieve relevant contents from a pool of trillions of webpages, and rank the most relevant webpages on the top of results. Among these components used in Baidu search, learning to rank (LTR) plays a critical role and we need to timely label an extremely large number of queries together with relevant webpages to train and update the online LTR models. To reduce the costs and time consumption of queries/webpages labeling, we study the problem of \textit{Active Learning to Rank} (active LTR) that selects unlabeled queries for annotation and training in this work. Specifically, we first investigate the criterion – \textit{Ranking Entropy} (RE) characterizing the entropy of relevant webpages under a query produced by a sequence of online LTR models updated by different checkpoints, using a Query-By-Committee (QBC) method. Then, we explore a new criterion namely \textit{Prediction Variances (PV)} that measures the variance of prediction results for all relevant webpages under a query. Our empirical studies find that RE may favor low-frequency queries from the pool for labeling while PV prioritizing high-frequency queries more. Finally, we combine these two complementary criteria as the sample selection strategies for active learning. Extensive experiments with comparisons to baseline algorithms show that the proposed approach could train LTR models achieving higher Discounted Cumulative Gain (i.e., the relative improvement $\Delta DCG_4=1.38\%$) with the same budgeted labeling efforts.

\section{INTRODUCTION}

Baidu has established herself as the world largest Chinese search engine who serves hundreds of millions of daily active users and handling billions of queries per day. Till now, Baidu has archived more trillions of webpages for search. In addition to webpages and data resources, Baidu has invented a number of most advanced technologies for search, ranging from language models for content understanding \cite{wang2022domain}, domain-specific recommendation \cite{li2022domain, liu2022domain}, online query-Ads matching for sponsored search \cite{tong2022sponsored, xiong2022online}, and software/hardware co-designed infrastructures \cite{yang2022software, xiao2022hardware} for handling web-scale traffics of online search.

Generally, ranking the retrieved contents plays a critical role in a search engine, where learning to rank (LTR) is a standard workhorse. To achieve better ranking performance, we need to use a large amount of annotated data to train a LTR model. However, it is extremely expensive and time-consuming to label the ranks of relevant webpages for every query \cite{lu2022efficient}. To address this issue, active learning \cite{settles2012active, zhu2022active} to pickup a small number of most informative queries and relevant webpages for labeling is requested.

In this paper, inspired by uncertainty-based active learning methods, we present a simple yet effective approach to active learning for ranking. First, we investigate \textit{Ranking Entropy} (RE), which characterizes the uncertainty of the ranking for every relevant webpage under a query using a Query-By-Committee (QBC) method \cite{dou2020query}. Intuitively, RE could discover queries with ranking uncertainty — i.e., the predicted ranks of webpages in a query are indistinguishable using the LTR model. However RE is also biased in favor of the low-frequency queries, i.e., the queries are less searched by users, as their are no sufficient supervisory signals (e.g., click-throughs) to train LTR models for fine predictions. The bias to the low-frequency queries would not bring sufficient information gain to LTR training.

To alleviate this problem, we study yet another criterion – \textit{Prediction Variance (PV)}, which refers to the variances of rank prediction results among all relevant webpages for a query. Intuitively, we assume a query pairing to multiple webpages that have clearly...
distinguished orders of ranking as a query with high diversity. We further assume the variance of rank prediction results would faithfully characterize the variance of ground truth rank labels—i.e., the diversity of webpages in a query. We thus propose to use PV as a surrogate to the diversity of webpages in a query. Please refer to Section 3 for detailed comparisons and empirical analysis with real data.

More specifically, we report our practices in using above two criteria to design queries selection strategies for active learning. We conducted comprehensive empirical studies on these two criteria using realistic search data. The empirical studies shows that the use of RE results in the bias to the low-frequency queries, while the use of PV leads to the potential over-fittings to the high-frequency queries. When incorporating low-frequency queries (less searched queries) in labeling, the active learner might not be able to train LTR models well, due to the lack of supervisory signals (e.g., click-throughs) to distinguish the webpages for the queries. In contrast, when using high-frequency queries (hot queries) in labeling, the active learner might not be able to adapt the out-of-distribution queries. Please see also in Sections 3.2 and 3.3 for the details of the criterion and empirical observations.

Finally, extensive experiments with comparisons to baseline algorithms show that the proposed approach (i.e., the combination of RE and PV) could train LTR models achieving higher accuracy with fewer webpages labeled. Specifically, we have made contributions as follows.

- We study the problem of active learning for ranking in Baidu search engine, where we focus on selecting queries together with relevant webpages for annotations to facilitate LTR models training and updates. And we deploy the system in Baidu search engine.

- In the context of Baidu search, we first consider a commonly-used uncertainty metrics for active learning of LTR, namely Ranking Entropy (RE). We find the use of RE could be biased by the frequency of queries, i.e., low-frequency queries normally have higher RE scores, as LTR models usually have not been well trained to rank webpages in such queries due to the lack of supervisory signals. To de-bias RE, we propose to study yet another diversity-based criteria—Prediction Variance (PV) that may favor high-frequency queries and are highly correlated to the true label variance of webpages under the query. In this way, we combine the two criteria for additional performance improvements.

- We conduct extensive experiments, showing that our proposed approach is able to significantly improve the performance of LTR in the context of Baidu search. Specifically, we compare our proposals (the combination of RE and PV) with a wide range of sample selection criteria for active learning, including random pickup, expected loss prediction (aka ELO-DCG) [16]. The comparisons show that our proposals outperform other criteria, which discovers 43% more validate training pairs and improves DCG (e.g., \(\Delta_{DCG4}=0.35\%\sim1.38\%\) in offline experiments and \(\Delta_{DCG4}=0.05\%\sim0.35\%\) in online experiments) using the same budgeted labeling efforts under fair comparisons.

Note that in this work, we focus on the low-complexity criteria of sample selection in active learning for LTR. There also exists some sample set selection algorithms [17, 18] for active learning in the high-order polynomial or even combinatorial complexity over the number of unlabeled samples, which is out of the scope of this paper as we intend to scale-up active learning of LTR with large-scale unlabeled queries and webpages.

2 Related Works

The goal of active learning (AL) is to select the most informative samples in the unlabelled data pool for annotation to train a model [19]. Generally, AL models are able to achieve similar performance but use fewer annotated data points. To select the most informative samples for labeling, two categories of methods, i.e., diversity-aware criteria and uncertainty-aware criteria, for sample selection have been studied. The diversity-aware methods [20, 21] measure the diversity of every subset of unlabeled samples and select the sample set with top diversity for labeling. While diversity-aware methods work well on the small datasets, they might fail to scale-up over large datasets due to the needs of subset comparisons and selections. The uncertainty-aware methods [23–28] screen the pool of unlabeled samples and select samples with top uncertainty in the context of training model (e.g., LTR models here) for labeling. While uncertainty-aware methods could easily scale-up over large datasets due to the low complexity, a wide variety of uncertainty criteria have been proposed, such as Monte Carlo estimation of expected error reduction [29], distance to the decision boundary [30, 31], margin between posterior probabilities [32], and entropy of posterior probabilities [33–35].

Discussion. The most relevant works to this study are [16, 36–38]. As early as 2010, Long et al. [16, 36] proposed the expected loss optimization (ELO) framework, which selects and labels most informative unlabelled samples for LTR, and incorporate a predictor for discounted cumulative gain (ELO-DCG) to estimate the expected loss of given queries and documents. The work [37] further confirmed ELO with DCG could work well with any rankers at scale and deliver robust performance. Cai et al. [38] followed the settings of ELO and extended DCG through incorporating the kernel density of queries, so as to balance sample distribution and the model-agnostic uncertainty for sample selection. Compared to above studies, this work revisits the problem of active learning for LTR at web-scale of 2020s, and we study new metrics of uncertainty for queries selection with online LTR performances reported and data analyzed in the context of Baidu search.

3 Practical Active Learning to Rank for Web Search: Sample Selection Criteria and Empirical Studies

In this section, we first review the system design of active learning to rank (Active LTR) for web search, then present our proposed selection criteria for active learning with empirical observations.
As shown in Figure 1, given a search query, denoted as \( q \), a user, the search engine frequently first retrieves all relevance webpages, denoted as \( \{w_1, w_2, \ldots \} \), from the dataset and sorts the top-\( K \) relevant webpages for the best user reading experience through ranking. To rank every webpage under the query, the search engine pairs every webpage with the query to form a query-webpage pair, e.g., \( (q, w) \), and then extracts features from \( (q, w) \), denoted as the feature vector \( (x_q, x_w) \), where \( x_q \) denotes query-relevant features and \( x_w \) denotes webpage-relevant features, and adopts the learning to rank (LTR) model to predict the ranking score, e.g., \{bad, fair, good, excellent, perfect\} \(^1\) at Baidu Search using \( (x_q, x_w) \).

To train the LTR model, the search engine usually collects the Historical Search Queries \( Q = \{q_1, q_2, \ldots \} \) and archives relevant webpages \( W = \{w_1, w_2, \ldots \} \), where \( w_{i, j} \) denotes the \( j \)th webpage associates with \( q_i \). To scale-up the active LTR on trillions of webpages/queries while ensuring the timeliness of search engine, our active learning system (red path in Figure 1) periodically picks up NEW queries appeared within the last ONE month i.e., \( S \subset Q \), pairs every selected query in \( S \) with retrieved webpages and extracts feature vectors to form the unlabeled datasets denoted as \( T = \{(x_{q_i}, x_{w_{i, 1}}), (x_{q_i}, x_{w_{i, 2}}), \ldots \} \). Finally, the search engine recruits annotators to label \( T \) and re-trains the LTR model with annotated data.

### 3.2 Sample Selection Criteria for Active LTR

In this section, we present the two criteria proposed for active learning to rank webpages.

\(^1\)For human annotations, labels 0, 1, 2, 3, 4, 5 denote bad, fair, good, excellent and perfect, respectively.

#### 3.2.1 Ranking Entropy (RE)

Uncertainty is one of the most popular criteria in active learning and Query-By-Committee (QBC) \(^1\) approach has been widely applied to estimate the uncertainty scores of the unlabelled data. In this paper, we apply QBC to compute the Ranking Entropy (RE) of each webpage. Normally, there are \( M \) models \( \{h_m(x_q, x_w) | m = 1, \ldots, M \} \) to constitute a committee. Given the representation of a query-webpage pair \( (x_{q_i}, x_{w_{i,j}}) \in T \), the committee would provide a set of scores \( S_{i,j} = \{h_m(x_{q_i}, x_{w_{i,j}}) | m = 1, \ldots, M \} \). Then, for any two webpages \( w_{i,U}, w_{i,V} \) associate to \( q_i \), we can easily calculate the probability that webpages \( w_{i,U} \) is ranked higher than \( w_{i,V} \) under query \( q_i \), denoted as the probability of \( P_{i,U} > P_{i,V} \), i.e.,

\[
P_{i,U} > P_{i,V} = \frac{1}{1 + \exp \left( -\frac{\pi_m(x_{q_i}, x_{w_{i,U}}) + \pi_m(x_{q_i}, x_{w_{i,V}})}{\delta} \right)},
\]

where \( \pi \) denotes the temperature and \( P_{i,U} > P_{i,V} \) denotes that \( w_{i,U} \) is more relevant than \( w_{i,V} \) under query \( q_i \).

Similar to SoftRank \(^1\), we can obtain the distribution over ranks based on the probabilities calculated by Eq. (1). We define the initial rank distribution of the \( k \)th webpage \( w_{i,J} \) as \( \pi_{i,J} \), the distribution over ranks is updated using Eq. (1).


distribution and the ranking in the last step will be the final ranking distribution. The computing procedure is shown in Alg. 1, where one webpage is added to the list for comparison in each step and the ranking distribution is updated using Eq. (1).

For each webpage \( w_{i,j} \), we can obtain a set of ranking distributions \( \{P_{i,J}^{1/r}(r) | m = 1, \ldots, M; r = 1, \ldots, N_i \} \) using Alg. 1, where \( N_i \) denotes the number of webpages associate with \( q_i \). Finally, for every query-webpage pair with the feature vector \( (x_{q_i}, x_{w_{i,j}}) \in T \), we use the average distribution over the committee to compute its entropy score as follow

\[
P_{i,J}^k = \frac{1}{M} \sum_{m=1}^{M} \pi_{i,J}^{1/m}(r),
\]

\[
E_{i,j} = -\sum_{r=1}^{N_i} p_{i,j}(r) \log_2 p_{i,j}(r).
\]

Note that the goal of this paper is to select queries, hence, for a query \( q_i \), we employ the average entropy of the webpages \( \{w_{i,j} | j = 1, \ldots, N_i \} \) that associate with \( q_i \), i.e.,

\[
RE(q_i) = \frac{1}{N_i} \sum_{j=1}^{N_i} E_{i,j}.
\]

Higher \( RE(q_i) \) refers to larger uncertainty in ranking results across the LTR models in the committee. Active learners are expected to pickup queries with large \( RE(q_i) \), for \( q_i \in Q \), for annotation and training.

#### 3.2.2 Prediction Variance (PV)

In our work, we assume a query, pairing to multiple webpages that are with clearly distinguished orders of ranking, as a query with high diversity. While the true
Algorithm 1: Ranking Distribution

```python
# Pseudo code in Python
Data: \{p_i^m(w_{i,u} > w_{i,v})|u,v = 1, \cdots, N_i; u \neq v\}
Result: \{p_i^m[w = 1, \cdots, N_i]\}

for v in range(N_i) do
  p_i^m[v] = 1, 0, \cdots, 0 \# N_i elements
  p_{tmp} = 0, \cdots, 0 \# N_i elements
  \pi_v = \{p_i^m(w_{i,u} > w_{i,v})\}
  for u in range(1, N_i) do
    if r == 0 then
      \alpha = 0
    else
      \alpha = p_i^m[r - 1]
    end
    p_{tmp}[r] = p_i^m[r] \ast \pi_v[u - 1] + \alpha \ast (1 - \pi_v[u - 1])
  end
  p_i^m = p_{tmp}
end
```

orders of ranking could be obtained through human annotations (i.e., labeling every webpage under the query using scores of five levels 0, 1, 2, 3, and 4 in this work), we propose to use the rank prediction results of a trained LTR model to measure such diversity. Given a checkpoint of the online GBRank [40] model, we propose to adopt the variance of predicted ranking scores (namely Prediction Variance (PV)) to measure the diversity of webpages for the query.

Similar to RE, we also use the predictions of the committee to compute the prediction variance. Given the outputs of the committee \( S_{i,j} = \{h_m(x_{q_i}, x_{w_{ij}})\}_{m = 1, \cdots, M} \), the prediction variance of a query \( q_i \) with \( N_i \) retrieved webpages can be computed using the following equations:

\[
\mu_m(q_i) = \frac{1}{N_i} \sum_{j=1}^{N_i} h_m(x_{q_i}, x_{w_{ij}}),
\]

\[
STD_m(q_i) = \sqrt{\frac{1}{N_i} \sum_{j=1}^{N_i} \left( h_m(x_{q_i}, x_{w_{ij}}) - \mu_m(q_i) \right)^2},
\]

Finally, we calculate the prediction variance \( PV(q_i) \) as follows:

\[
PV(q_i) = \frac{1}{M} \sum_{m=1}^{M} STD_m(q_i).
\]

For active learning, we assume queries with large prediction variance, i.e., higher \( PV(q_i) \) for \( q_i \in Q \), as the candidates for annotation and training.

### 3.3 Empirical Studies on Proposed Criteria for Active LTR

While the first criterion Ranking Entropy (RE) directly measures the uncertainty of ranking results under a query (either due to the defects of learned models or simply the difficulty to rank), we now hope to validate whether the second proposed criterion Prediction Variance (PV) could characterize the diversity of webpages in a query and how PV improve LTR. We conduct empirical studies based on 1000 realistic query data drawn from the validation set, and hope to test two hypotheses as follows.

- **Does PV characterize the variance of human-annotated ground truth ranking scores for LTR?** Here to test our hypothesis, we fetch a past checkpoint of the online LTR model in Baidu search, and use the model to predict the ranking scores for every webpage in the 1000 queries. Note that, such 1000 queries are obtained from the validation set and have no overlapped with the queries used for training the LTR model. In Figure 2(a), we plot the scatter points of LV (label variance) versus PV with Pearson correlation \( Corr = 0.59 \) and \( p \)-value < 0.05. In this way, we can conclude that PV significantly correlates to the variance of human-annotated ground truth ranking scores (LV) and faithfully characterizes the difficulty to rank of every query.

- **Does PV correlate to the information gain of query selection for LTR?** Yet another hypothesis in our mind is that selecting queries with high diversity of webpages for annotations could bring more information gain to LTR. We thus need to correlate LV and PV with certain information measures of queries. In this study, we use a measure namely Best DCG4—referring to the estimate of the upper bound of DCG4 that uses the human-annotated ground truth ranking scores as the prediction results of ranking. Intuitively, the Best DCG4 reflects to the optimal DCG4 that could be achieved by any algorithms. The correlation studies have been done and illustrated in Figures 2(b) and (c). The significance could be found in the correlations between LV and Best DCG4 and the correlations between PV and Best DCG4. The observations suggest that queries with higher diversity in webpages usually are more informative for LTR, no matter the diversity was measured by LV or PV.

Based on above two observations, we could conclude that (1) PV could faithfully characterize LV (label variance – the diversity of webpages), though PV was estimated using the prediction results of a model, and (2) a query with higher LV or PV usually is more informative for LTR, since LTR models are normally trained using pairwise or listwise loss and a small LV leads to small loss values and gradients.

### 3.4 Combined Criteria

To be simple, we use the weighted sum of RE and PV as the acquisition function in active learning. For each query \( q_i \in Q \), the acquisition function is

\[
f(q_i) = RE(q_i) + \alpha \ast PV(q_i),
\]

where \( \alpha \) is a hyper-parameter to balance ranking uncertainty and webpage variance. We select the queries that have the largest values of \( f(q_i) \) in each cycle of active learning.

### 4 EXPERIMENTS

In this section, we present the results of experiments, where we first introduce the results of offline experiments, then figure out
4.1 Offline Experiments and Results

In this section, we present the details of offline experiments with introductions to the setups and results.

4.1.1 Setups. First, we split the dataset (15,000 queries and each query has 60 relevant webpages on average) into training set (14,000 queries) and validation set (1,000 queries). In the beginning of active learning, we randomly select \( N_0 \) queries from the training set as the base and in each cycle of active learning, we set the batch size \( b_s = 100 \), i.e., we select 100 queries from the pool (the rest of the training set) using the acquisition function \(^2\). The quota is 2,000 queries, i.e., we run active learning for 20 cycles. We also conduct ablation studies on the value of \( \alpha \) in Eq. (9), where \( \alpha = \{0.5, 1.0, 1.5\} \). We set the number of committee \( M \) to 9, i.e., 9 variants of GBRank with different numbers of trees (100, 300, 500) and maximum depth (1, 3, 5).

\(^2\) The reason for using \( b_s = 100 \) is that annotating the relevant scores are expensive and time-consuming. We can only annotate 500 queries per day and in the following offline experiments we also consider \( b_s = 500 \).

4.1.2 Offline results. Here, we first present the statistical characteristics of selected queries (with webpages retrieved) for annotations, then introduce the details about the valid query-webpage pairs. To evaluate the performance of a LTR model, we use Discounted Cumulative Gain (DCG), computing as follows:

\[
DCG_K = \sum_{k=1}^{K} \frac{G_k}{\log_2(k + 1)},
\]

where \( G_k \) denotes the weight assigned to the webpage’s label at position \( k \). A higher \( G_k \) indicates that the webpage is more relevant to the query. Also, a higher \( DCG_K \) indicates a better LTR model. In this paper, we consider the DCG of top 4 ranking results, i.e., \( DCG_4 \). In addition, we consider another important metric – the percentage of the irrelevant webpages in top \( K \), which is computed as follows:

\[
R_{01} = \frac{N_{01}}{K},
\]

where \( N_{01} \) denotes the number of the irrelevant webpages\(^3\). Obviously, a lower \( R_{01} \) indicates a better LTR model. Also, we consider \( R_{01} \) in top 4 in this paper.

There are two baselines for comparison, the first one random selection and the second one is ELO-DCG\([16]\) – an uncertainty-based active learning method for ranking.

\(^3\) We consider the webpages with labels of 0 and 1 as irrelevant webpages.
formed from annotation results for training. Finally, we present the performance improvements of proposed criteria in comparisons to baseline criteria, such as ELO-DCG [16, 36].

The distribution of selected queries. Fig. 3 shows the distribution over categories of 1,000 selected queries. Category 0 is composed of the most frequent queries, while category 9 contains the least frequent (only one time in the one-month search log) queries. For random selection, we randomly select 100 queries from each category. Compared with random selection, Label Variance (LV) prefers relatively frequent queries, such as categories 2-4, but selects fewer low-frequency queries in categories 7-9, indicating that the webpages associated with low-frequency queries have similar human annotations. PV performs similar in high-frequency queries but selects much fewer low-frequency queries. By contrast, RE selects the most low-frequency queries. However, it is difficult to construct enough training pairs if there are too many low-frequency queries, since irrelevant webpages dominate these queries. In Fig. 4(c), we demonstrate the distribution of labels, where we use 1,000 randomly selected queries to obtain the statistics. Obviously, label 0 dominates low-frequency queries leading to difficulties in constructing training pairs for GBRank, hence, we need to balance the number of selected queries in each category and RE+PV is able to achieve the goal (see Fig. 4(f)). Interestingly, the existing work – ELO-DCG [16, 36] is in favor of high-frequency queries. Generally, Baidu search engine can well handle high-frequency queries to satisfy user’s demands and selecting more high-frequency queries cannot benefit the gain of Baidu search.

Looking at Fig. 4, where we present the distribution of labels over categories. For random selection, one observation is that low-frequency queries have more webpages with label 0. In addition, the distributions of labels for each category are different and unbalanced. Using more webpages with label 0 is able to provide more training pairs composed of irrelevant and relevant webpages, which could reduce the percentage of irrelevant webpages in top K ranking results. However, too many webpages with similar labels could reduce the number of valid training pairs, hurting ranking quality. By contrast with random selection, ELO-DCG [16, 36] selects more webpages with label 2 since it prefers low-frequency queries that have more relevant (label 2, 3, 4) webpages. Though ELO-DCG [16, 36] can select more relevant webpages, the diversity among webpages for each query is relatively low. While RE performs in an opposite way, selecting more webpages with label 0, which also lacks diversity among webpages. Intuitively, if the webpages of a query have the same label, then it is difficult to rank them, i.e., higher uncertainty. Moving on to Fig. 4 (d-f) (LV, PV and RE+PV), the distribution of labels are more balanced, indicating the webpages are diverse. On one hand a higher diversity score could result in more training pairs, on the other hand only considering diversity selects more queries that the trained model can easily rank the associated webpages and these queries cannot further improve the ranking model. On the contrary, RE+PV is able to balance diversity and uncertainty, selecting more useful and informative queries.

The number of training pairs. For GBRank [40] that uses pairwise loss, the number of training pairs is crucial. With more training pairs fed to the training procedure, LTR models are expected to deliver better performance. Table 1 presents the number of pairs obtained using different approaches. We can easily conclude that the proposed approach is able to obtain more training pairs compared with random selection and the existing work – ELO-DCG [16, 36]. In terms of the number of valid pairs composed of two webpages with different human annotated labels, random selection...
Let’s first pay attention to base 100 – the top two sub-figures in Fig. 5. The proposed approach RE+PV achieves better performance than random selection and ELO-DCG [16, 36]. We can see that using RE+PV selected queries to train GBRank, DCG4 raises faster than its counterparts, such as random selection, ELO-DCG and RE. Compared with random selection, the relative improvement of DCG4 ranges from 0.35% to 1.38% using RE+PV. And compared to the existing work ELO-DCG [16, 36], the proposed RE+PV boosts

### Table 1: The number of training pairs obtained by using different criteria and the relative improvement compared with random selection. If two webpages associate with a query have different labels, then they constitute a valid pair. Neg-pos pair denotes that a pair is composed of an irrelevant and a relevant webpages. We use each approach to select 1,000 queries to obtain the statistics.

| Criterion                  | # valid pairs | # neg-pos pairs |
|----------------------------|---------------|-----------------|
| Random                     | 764,527       | 534,500         |
| ELO-DCG [16]               | 959,228 (25%) | 598,555 (12%)  |
| LV                         | 1,039,474 (36%) | 757,492 (42%)  |
| PV                         | 979,051 (28%) | 704,621 (32%)  |
| RE                         | 823,411 (8%)  | 562,464 (5%)   |
| Ours (RE+PV)               | 1,091,176 (43%) | 803,723 (50%)  |
| RE+LV(upper bound)         | 1,149,083 (50%) | 827,133 (55%)  |

LTR Performance Comparisons. In this experiments, we use the valid query-webpage pairs obtained by various strategies to train LTR models (GBRank models with cross-entropy loss) and compare the ranking quality of these LTR models on our validation dataset of 1,000 queries. The ranking quality is measured using DCG. Fig. 5 shows the comparison among different approaches.

Figure 5: The relative improvements of DCG4 (i.e., ΔDCG4) and R01 (i.e., ΔR01) compared with using random selection in each active learning cycle with the same budget. Top: the base set is composed of 100 queries. Bottom: the base set is composed of 500 queries.
DCG4 by at least 0.37%. While random selection outperforms ELO-DCG and RE when selecting more training data. The possible reason is that ELO-DCG and RE are biased by query frequency, e.g., ELO-DCG prefers high-frequency queries, whereas RE is in favor of low-frequency queries. Interestingly, ELO-DCG and RE perform similar to each other, though the distributions of the selected queries are different. Looking at PV and LV that are related to the diversity among webpages, both outperform random selection in most cycles. When it comes to R01 (top-right sub-figure in Fig. 5), the proposed RE+PV also achieves competitive performance compared with its counterparts. E.g., R01 drops by at most 6.31% compared to random selection. Although ELO-DCG is able to obtain higher DCG4 scores at the beginning of AL cycles, it performs even worse considering the metric R01. The reason is that ELO-DCG selects more webpages with label 2 but less webpages with label 0, hence, it is difficult for GBRank to distinguish irrelevant webpages.

Moving on to base500 (bottom sub-figures in Fig. 5), our proposed approach – RE+PV also achieves higher DCG4 than random selection and ELO-DCG [16, 36]. The relative improvement of DCG4 is at most 0.84% compared to random selection. Moreover, R01 shows decreases in most cycles, e.g., in cycle 9, R01 drops by 3.76% using RE+PV.

We also present the relative improvement of the average DCG4 over AL cycles for each category in Table 2. We can easily find that most AL approaches obtain better performance on high-frequency queries compared with random selection, e.g., for category 0, using RE, RE+0.5PV and RE+LV boost DCG4 by 1.13% compared with random selection in the scenario of base100. DCG4 also increases by 0.42% using ELO-DCG [16, 36] for category 0 since ELO-DCG selects more high-frequency queries (see Fig.3). By contrast, for low-frequency queries, the performances of different approaches vary, e.g., DCG4 for category 9 obtained by ELO-DCG drops by 0.74% compared with random selection, whereas DCG4 obtained by our proposed approach – RE+PV is 1.23% higher than using random selection. Interesting, the performances of using bs = 100 and bs = 500 on category 3 are different. We can see that the test models except for PV and RE outperform random selection when using bs = 100, while they are inferior to random selection when bs = 500. The possible reason is that for the queries belong to category 3, it is difficult to annotate the relevance scores, resulting in many noisy labels, and selecting more queries introduces more noisy labels, hence the performance reduces when using bs = 500.

Table 2: The relative improvement of average DCG4 (i.e., ΔDCG4) over all active learning cycles compared with random selection. The red numbers represent the relative increases, the blue numbers are the relative decreases and the bold numbers are the highest relative improvements.

| base | Method       | Categories based on frequency | All         |
|------|--------------|------------------------------|-------------|
|      |              | 0   | 1       | 2   | 3  | 4   | 5 | 6     | 7  | 8 | 9   |                 |
|      | ELO-DCG      | 0.42%| 0.14% | 0.52% | 0.39% | 0.39% | 0.17% | 0.36% | 0.54% | 0.28% | 0.48% | 0.09% |
|      | LV           | 0.28%| 0.29% | 0.22% | 0.86% | 0.75% | 0.55% | 0.27% | 0.66% | 0.24% | 0.12% | 0.35% |
|      | PV           | 0.05%| 0.07% | 0.15% | 0.08% | 0.42% | 0.27% | 0.36% | 0.66% | 0.12% | 0.62% | 0.35% |
|      | RE           | 1.13%| 0.57% | 0.22% | 0.31% | 0.31% | 0.93% | 0.18% | 0.18% | 0.00% | 1.44% | 0.74% |
|      | RE+0.5PV     | 1.13%| 0.29% | 0.15% | 0.86% | 0.76% | 0.45% | 0.36% | 0.85% | 0.48% | 0.62% | 0.52% |
| 100  | RE+PV        | 0.57%| 0.43% | 0.00% | 0.86% | 1.18% | 0.36% | 0.82% | 1.14% | 0.96% | 1.23% | 0.78% |
|      | RE+1.5PV     | 0.35%| 0.22% | 0.30% | 0.70% | 1.43% | 0.36% | 0.45% | 1.42% | 1.06% | 0.60% | 0.61% |
|      | RE+LV        | 1.13%| 0.29% | 0.45% | 0.23% | 1.35% | 0.10% | 0.64% | 0.85% | 0.60% | 0.00% | 0.61% |

Figure 6: The online performance. We only report the relative improvement with p-value < 0.05 over the baseline. Left: the performance based on DCG4. Right: the performance based on R01.

4.2 Online Experiments and Results

To report the online performance of our proposals, we carried out an A/B Test with real-world web traffics. Note that online test is expensive and time-consuming, so we only compare our proposed model with the existing baseline that employs random selection in Baidu search engine.

---

4For the queries belong to category 0, it is easy to annotate since many webpages are highly relevant to the queries. Likewise, we can easily annotate queries belong to category 9, since the webpages are irrelevant to queries.
4.2.1 A/B Test Setups. We used 0.6% real-world web traffics on Baidu search engine to conduct the A/B test, where the 0.6% traffics have been randomly partitioned into two folders (0.3%) each to evaluate the performance of our proposals (RE+PV) and random selection respectively. This online A/B test lasted for 13 days/cycle. In each cycle, we use our proposed approach to select 500 queries from the historical query pool composed of hundreds million queries and each query has 100 retrieved webpages. Then we filter out the pornographic webpages and the webpages forbidden by government, resulting in around 60 webpages for each query. After that, we hire people to annotate the relevance scores and each query-webpage pair has at least 6 scores annotated by different workers. Finally, our expert annotator will evaluate the quality of annotations to make sure that the accuracy is higher than 85% and then we use the weighted sum of the scores as the final label to train our LTR model. Similar to the offline experiments, we also calculate \( \Delta DC^4 \) and \( \Delta R^0 \) between the two methods based on the ground-truth annotation results.

As we have mentioned, we can only label 500 queries per day, hence, in the online experiments we use the \( b_t = 500 \). Also, note that our query pool is composed hundreds million historical queries, therefore, the selection criteria should be as simple as possible, otherwise, our cluster cannot handle the selection in a few hours. Moreover, since we need to update the LTR model everyday, and to avoid some unexpected influences on the search engine, we just use the 0.6% traffic to test the proposed approach.

4.2.2 Online Performance. The comparison is shown in Fig. 6, where we only present the relative improvements. Compared to random selection, the proposed RE+PV is able to boosts \( DC^4 \) in all cycles and the largest relative improvement is around 0.35% when considering all queries. We also compare RE+PV to random selection on low-frequency queries (categories 7, 8, 9) and \( DC^4 \) increases by at most 0.85%, indicating that the proposed approach benefit low-frequency query search. In terms of \( R^0 \), our proposed approach – RE+PV can also reduce the percentage of irrelevant webpages in the top \( K \) results, e.g., \( R^0 \) decreases by at most 1.9% considering all queries, while it drops by at most 2.6% on low-frequency queries. Basically, the online performance are consistent with our offline results and the proposed active learning approach outperforms with the baseline.

5 CONCLUSION

In this work, we revisited the problem of active learning for ranking webpages in the context of Baidu search, where the key problem is to establish the training datasets for learning to rank (LTR) models. Given trillions of queries and relevant webpages retrieved for every query, the goal of active learning is to select a batch of queries for labeling and trains the current LTR model with the newly-labeled datasets incrementally, where the labels here refer to the ranking score of every webpage under the query. To achieve the goals, for every query, this work proposed two new criteria – Ranking Entropy (RE) and Prediction Variances (PV) that could measure the uncertainty of the current LTR model to rank webpages in a query and the diversity of ranking scores for webpages in a query respectively. Specifically, RE estimates the entropy of relevant webpages under a query produced by a sequence of online LTR models updated by different checkpoints, using a Query-By-Committee (QBC) method, while PV estimates the variance of prediction results for all relevant webpages under a query. Our experimental observations find that RE may pop low-frequency queries from the pool for labeling while PV prioritizing high-frequency queries more. Further, the estimate of PV significantly correlates to the diversity of true ranking scores of webpages (annotated by human) under a query and correlates to the information gain of LTR. Finally, we combine these two complementary criteria as the sample selection strategies for active learning. Extensive experiments with comparisons to baseline algorithms show that the proposed approach could train LTR models achieving higher DCG (i.e., \( DCG_4 = 0.35\% - 1.38\% \) in offline experiments, \( DCG_4 = 0.05\% - 0.35\% \) in online experiment) using the same budgeted labeling efforts, while the proposed strategies could discover 43% more valid training pairs for effective training.

REFERENCES

[1] Yu Sun, Shuohuan Wang, Yukun Li, Shikun Feng, Xuyi Chen, Han Zhang, Xin Tian, Danxiant Zhu, Hao Tian, and Hua Wu. Ernie: Enhanced representation through knowledge integration. arXiv preprint arXiv:1904.09223, 2019.
[2] Yu Sun, Shuohuan Wang, Yukun Li, Shikun Feng, Hao Tian, Hua Wu, and Haifeng Wang. Ernie 2.0: A continual pre-training framework for language understanding. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 8968–8975, 2020.
[3] Jizhou Huang, Shiqiang Ding, Haifeng Wang, and Ting Liu. Learning to recommend related entities with serendipity for web search users. ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP), 17(3):1–22, 2018.
[4] Jizhou Huang, Wei Zhang, Yaming Sun, Haifeng Wang, and Ting Liu. Improving entity recommendation with search log and multi-task learning. In Proceedings of the 27th International Joint Conference on Artificial Intelligence, pages 4107–4114, 2018.
[5] Jizhou Huang, Haifeng Wang, Wei Zhang, and Ting Liu. Multi-task learning for entity recommendation and document ranking in web search. ACM Transactions on Intelligent Systems and Technology (TIST), 1(3):1–24, 2020.
[6] Miao Fan, Yibo Sun, Jizhou Huang, Haifeng Wang, and Ying Li. Meta-learning spatial-temporal poi auto-completion for the search engine at baidu maps. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, pages 2822–2830, 2021.
[7] Miao Fan, Jiacheng Guo, Shuai Zhu, Shuo Miao, Mingming Sun, and Ping Li. Mobius: towards the next generation of query-ad matching in baidu’s sponsored search. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 2509–2517, 2019.
[8] Tan Yu, Yi Yang, Yi Li, Xiaodong Chen, Mingming Sun, and Ping Li. Combo-attention network for baidu video advertising. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 2474–2482, 2020.
[9] Jian Qian, Shiding Lin, Wei Qi, Yong Wang, Bo Yu, and Song Jiang. Sda: Software-defined accelerator for large-scale dnn systems. In 2014 IEEE Hot Chips 26 Symposium, pages 1–23, 2014.
[10] Weijie Zhao, Jingyuan Zhang, Deping Xie, Yulei Qian, Ronghai Jia, and Ping Li. Ashon: Ctr prediction model training on a single node. In Proceedings of the 28th ACM International Conference on Information & Knowledge Management, pages 319–328, 2019.
[11] Jian Ouyang, Mijung Noh, Yong Wang, Wei Qi, Yin Ma, Caoghai Gu, SoonGon Kim, Ki-il Hong, Wang-Keun Bae, Zhihiao Zhao, et al. Baidu kunlun an ai processor for diversified workloads. In 2020 IEEE Hot Chips 32 Symposium, pages 1–18, 2020.
[12] Burr Settles. From theories to queries: Active learning in practice. In Active Learning and Experimental Design Workshop In conjunction with AISTATS 2010, pages 1–18. JMLR Workshop and Conference Proceedings, 2011.
[13] Burr Settles. Active learning literature survey. 2009.
[14] Siyu Huang, Tianyang Wang, Haoyi Xiong, Jun Huan, and Dejing Dou. Semi-supervised active learning with temporal output discrepancy. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 3447–3456, 2021.
[15] Yoav Freund, H Sebastian Seung, Eli Shamir, and Naftali Tishby. Selective sampling using the query by committee algorithm. Machine learning, 28(2):133–168, 1997.
[16] Bo Long, Jiang Bian, Olivier Chapelle, Ya Zhang, Yoshiyuki Inagaki, and Yi Chang. Active learning for ranking through expected loss optimization. IEEE transactions
on knowledge and data engineering, 27(5):1180–1191, 2014.

[17] Kai Wei, Rishabh Iyer, and Jeff Bilmes. Submodularity in data subset selection and active learning. In International Conference on Machine Learning, pages 1954–1963. PMLR, 2015.

[18] Steve Hanneke and Liu Yang. Minimax analysis of active learning. J. Mach. Learn. Res., 16(12):3487–3602, 2015.

[19] David A Cohn, Zoubin Ghahramani, and Michael I Jordan. Active learning with statistical models. JAIR, 4:129–145, 1996.

[20] Hieu T Nguyen and Arnold Smeulders. Active learning using pre-clustering. In ICML, page 79, 2004.

[21] Yuhong Guo. Active instance sampling via matrix partition. In NIPS, pages 802–810, 2010.

[22] Ozan Sener and Silvio Savarese. Active learning for convolutional neural networks: A core-set approach. In ICLR, 2018.

[23] Ashish Kapoor, Kristen Grauman, Raquel Urtasun, and Trevor Darrell. Active learning with gaussian processes for object categorization. In ICCV, pages 1–8, 2007.

[24] Zheng Wang and Jieping Ye. Querying discriminative and representative samples for batch mode active learning. TKDD, 9(3):1–23, 2015.

[25] Nicholas Roy and Andrew McCallum. Toward optimal active learning through monte carlo estimation of error reduction. pages 441–448, 2001.

[26] Simon Tong and Daphne Koller. Support vector machine active learning with applications to text classification. JMLR, 2(Nov):45–66, 2001.

[27] Klaus Brinker. Incorporating diversity in active learning with support vector machines. In ICML, pages 59–66, 2003.

[28] Dan Roth and Kevin Small. Margin-based active learning for structured output spaces. In ECML, pages 413–424, 2006.

[29] Yarin Gal, Riashat Islam, and Zoubin Ghahramani. Deep Bayesian active learning with image data. arXiv preprint arXiv:1703.02910, 2017.

[30] Simon Tong and Daphne Koller. Support vector machine active learning with applications to text classification. JMLR, 2(Nov):45–66, 2001.

[31] Mustafa Bilgic and Paul N Bennett. Active query selection for learning rankers. In Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval, pages 1033–1034, 2012.

[32] Wenbin Cai, Muhao Zhang, and Ya Zhang. Active learning for ranking with sample density. Information Retrieval Journal, 19(2):123–144, 2015.

[33] Michael Taylor, John Guiver, Stephen Robertson, and Tom Minka. Softrank: optimizing non-smooth rank metrics. In Proceedings of the 2008 International Conference on Web Search and Data Mining, pages 77–86, 2008.

[34] Zhaohui Zheng, Keke Chen, Gordon Sun, and Hongxuan Zha. A regression framework for learning ranking functions using relative relevance judgments. In Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval, pages 287–294, 2007.