Query Dependent Ranking for Information Retrieval Based on Query Clustering

Pwint Hay Mar Lwin, Nan Sai Moon Kham
University of Computer Studies, Yangon
pwinthaymarlwin.phml@gmail.com,moonkhamucsy@gmail.com

Abstract

Ranking is the central problem for information retrieval (IR), and employing machine learning techniques to learn the ranking function is viewed as a promising approach to IR. In information retrieval, the users' queries often vary a lot from one to another. However most of existing approaches for ranking do not explicitly take into consideration the fact that queries vary significantly along several dimensions. In this paper we will take into account the diversity of query type by clustering the queries. Instead of deriving a single function, this system attempt to develop several ranking functions based on the resulting query clusters in the sense that different queries of the same cluster should have similar characteristics in terms of ranking. So, for each query cluster, there will be its associated ranking model. To rank the documents for a new query, the system first find the most suitable cluster for that query and produce the scoring results depend on that cluster. The effectiveness of the system will be tested on LETOR, publicly available benchmark data set.

1. Introduction

Many applications have ranking as the central issue, such as information retrieval, collaborative filtering, expert finding, data mining, and anti web spam. Recently, "learning to rank" has been one of the most popular research topics in the areas of information retrieval and search engines. When applied to document retrieval, the task of learning to rank is to construct a ranking function for a search engine.

An effective ranking framework is the core component of any information retrieval system and several ranking functions emerged including the Boolean model, the vector space model [7] and BM25. They have the advantage of being fast and produce reasonably good results. When more features become available, however, incorporating them into these models is usually difficult since it requires a significant change in the underlying model. Recently machine learning techniques have also been applied to ranking model construction and supervised learning to rank algorithms can help overcome that limitation. Several methods for learning to rank have been developed. Typical methods include RankSVM [9], RankBoost [5] [6], RankNet [1], and some improved methods such as MHR [4], AdaRank10], and ListNet [4].

Using a single ranking model may not be appropriate, particularly for web search, since queries vary largely in multiple facets, for example, queries can be navigational, informational, or transactional. These various types of query difference make it difficult to build a single general ranking function for all kinds of queries. This is because the diverse feature impacts on ranking relevance with respect to difference queries. In this paper we will consider the query diversity in ranking by clustering the queries and derive separate model for each cluster.

The rest of this paper is organized as follows. In Section 2, background theory of the learning to rank method is described. Related work is presented in Section 3. Section 4 presents the proposed system framework. In section 5, the dataset and evaluation methods that will be used to determine the performance of the system are described. Finally, Section 6 presents conclusion of the paper.

2. Background Theory

Learning to rank is a new and popular topic in the areas of information retrieval and search engines.

The general framework of learning to rank [15] is described in Figure.1. A number of queries and their corresponding retrieved data are given. The ranks of the data are also provided. Partition the data set into several subsets, some subsets as training set, some as a validation set, and others as a testing set. The training set will be used to learn the ranking model M, the validation set to tune the parameters, and the test set to report the ranking performance of M. In the learning phase, the objective is to construct a ranking model M, which yields the best results in ranking of the training data. After that, the ranking model M tunes the parameters on the basic of performance measure of the results of the validation set. In the ranking phase, the model M returns a ranking list of retrieved results corresponding to the given query in descending order of the relevance scores.

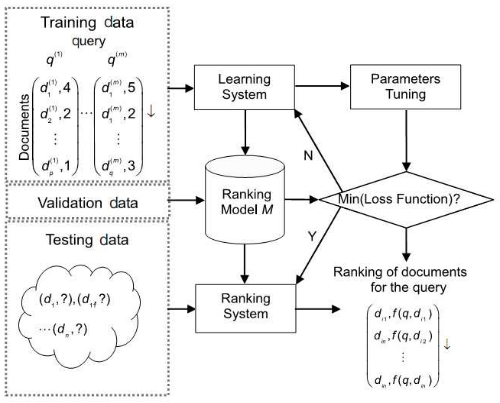


Figure 1. Architecture of the proposed system

3. Related Work

Jiang Bian et.al [2] proposed the divide and conquers approach for ranking specialization. They divided the problem of learning one single ranking model for all training queries into a set of sub-problems for learning multiple models. They also proposed global loss function to learn multiple ranking models simultaneously. For a new query, the ranking result is produced by combining the corresponding ranking results of the models whose corresponding query topic hold the H highest correlation values with that new query.

Somnath Banejee et.al[3] proposed a local learning algorithm based on new similarity measure between queries. Firstly, they defined the principal components for each query. After that, they used an offline method to cluster queries base on their proposed similarity measure and train a model for each cluster. When a test query is entered, they used the model from the most similar cluster.

Weijian Ni et.al [13] developed a query dependent ranking approach. In their approach, the ranking model of each query consists of a generalizable model and a specific model. During the learning stage, the generalizable and specific models are learned through using structural risk minimization (SRM) inductive principle. At the inference stage, for each new query, several of the most favorable specific models learned from training queries are used to generate its adaptable ranking model.

Lian-Wang Lee et.al [11], also proposed a new framework for query-dependent ranking. They generated individual ranking models from each training queries. When a new query is asked, the retrieved documents of the new query are ranking according to their scores given by a ranking model which is a weighted combination of the models of similar training queries.

Xiubo Geng et.al [8] developed query-dependent ranking by using K-Nearest Neighbor (KNN) method. They create a ranking model for a given query by using the labeled neighbors of the query in the query feature space and then rank the documents with respect to the query using that model.

4. Proposed System

Figure.2 shows the architecture of the proposed system.

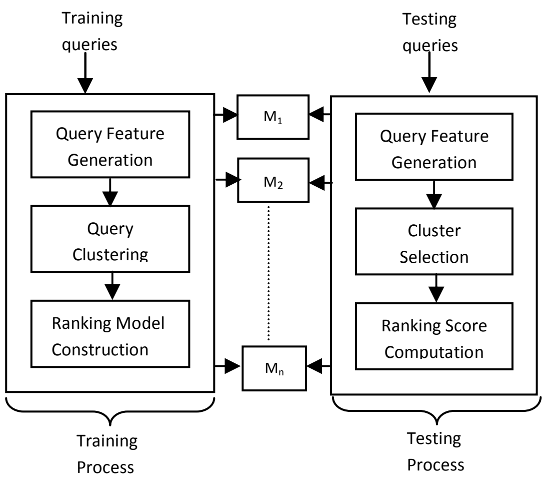


Figure 2. Architecture of the proposed system

4.1. Training Phase

Training phase consists of query feature generation, query clustering and ranking model construction.

4.1.1. Query feature generation

In order to achieve high accuracy, query features used in the method are important. A query is associated with a list of retrieved documents, each of which can be taken as an observation about the query. In this system, to extract query features for each query, the system use top few documents retrieved by existing ranking model. The system use BM25 as a reference model [2]. For each query $q \in Q$ in the training data, the system find top T documents $D_q = \{d^1, d^2, d^3 \ldots d^T\}$ for q. We use the ranking features of these documents to extract the features of the query. Each document $d^i \in D_q$ is represented with n ranking features $d^i_x = \{ d^i_{x1}, d^i_{x2} \ldots, d^i_{xn}\}$. To represent q in a feature space we aggregate the ranking features of all documents in D_q. We use the mean and variance of ranking features values as follow:

For each $q \in Q$,

$$\mu_{x_j}(q) = \frac{\sum_{i=1}^{T} d^i_{x_j}}{T} \qquad (1)$$

Where d^i_{xj} means the jth feature value of ith document for query q.

For each $q \in Q$,

$$\sigma^2_{x_j} = \sum_{i=1}^{T} \frac{\left(d^i_{x_j} - \mu_{x_j}(q)\right)^2}{T} \qquad (2)$$

So we can define the query q in terms of aggregated mean and variance values of each feature over q's top T retrieved documents.

4.1.2. Query Clustering

After the query features are generated, we employ the k-means clustering algorithm to obtain the query clusters.

K-means is a well-known partitioning method. Objects are classified as belonging to one of k groups, k is chosen a priori. Cluster membership is determined by calculating the centroid for each group and assigning each object to the group with the closest centroid.

In a general sense, a k-partitioning algorithm takes as input a set S of objects and an integer k, and outputs a partition of S into subsets $S_1, \dots, S_k$. Let x_r^i be the rth element of S_i, □ S_i □ be the number of elements in S_i, and $d(x_r^i, x_s^i)$ be the distance between x_r^i and x_s^i. The sum of squares criterion is defined by the cost function:

$$C(S_i) = \sum_{r=1}^{|S_i|} \sum_{x=1}^{|S_i|} (d(x_r^i, x_s^i))^2 \tag{3}$$

In particular, k-means works by calculating the centroid of each cluster S_i, denoted x^{-i}, and optimizing the cost function:

$$C(S_i) = \sum_{r=1}^{|S_i|} (d(x^{-i}, x_r^i))^2 \tag{4}$$

The goal of the algorithm is to minimize the total cost:

$$C(S_i) + \cdots + C(S_i) \tag{5}$$

4.1.3. Model Construction

The system create separate model for each query cluster. To construct a ranking model for each cluster the system adopts RankSVM.

Ranking SVM is a generalization of classical SVM formulation that learns over pairwise preferences, rather than binary labeled data. Instead pairwise preferences can implicitly encode the structure of ranking problems, and therefore learning an SVM over such pairwise preferences is typically more effective when used for ranking since its objective function tends to more in line with standard information retrieval metrics, such as precision, mean average precision and F1 score, which is the harmonic mean of precision and recall.

Formally, the ranking SVM is formulated as a quadratic programming problem that has the following form:

$$\min \frac{1}{2} \|w^2\| + C \sum_{i,j} \varepsilon_{i,j}$$

$$\text{subject to } (w.x_i - w.x_j) \geq 1 - \varepsilon_{ij} \quad \forall (i,j) \in \rho$$

$$\varepsilon_{ij} \geq 0 \qquad \forall (i,j) \in \rho \tag{6}$$

Where w is the weight vector being fit, ρ is the set of pair-wise preferences used for training, and C is a tunable parameter that penalizes misclassified input pairs. Once a weight vector w is learned, we can score the documents for unseen queries. These scores can then be used to rank documents.

4.2. Testing Phase

In the testing process, the most suitable cluster for the test query is identified by finding the closest centric c. To find the closest centroid for the test query the system use the Euclidian distance.

$$c^* = \arg\min(dist(t, x^{-i})) \tag{7}$$

where x^{-i} is the centroid of ith cluster and i=1,2,…k.

$$dist(x^{-i}, t) = \sqrt{(x_1^{-i} - t_1)^2 + (x_2^{-i} - t_2)^2 + \cdots + (x_n^{-i} - t_n)^2} \tag{8}$$

After the closest cluster is found, the system retrieves the model with respect to that cluster and produces the ranking results for the test query by using the retrieved model. Figure 3 describe the algorithm of the proposed system.

```
Training algorithm
Input: a set of training query $Q_{train}$= {$q_1$,$q_2$,$q_t$} together with
associated documents $D_{Qtrain}$= {$d_1^{(q_i)}$, $d_2^{(q_i)}$,… $d_n^{(q_i)}$} with
relevant judgments $Y_{qi}$={$y_1^{(q_i)}$, $y_2^{(q_i)}$,… $y_n^{(q_i)}$}, number of
clusters k.
Output: k ranking models associated with k clusters.

1.$Q_{feature}$ $\leftarrow$ generate-query-feature ($Q_{train}$ , $D_{Qtrain}$)
//$Q_{feature}$={$q_1$,$q_2$,…$q_t$}.
(i) for each query $q_i \in Q_{train}$, find the mean and variance values
of the ranking features values of the documents associated with
the query $q_i$.
(ii) represent query $q_i$ with generated feature vector.

2. C $\leftarrow$ k-means-clustering (k,$Q_{feature}$)

3.M $\leftarrow$ develop-model(C,$C_{train}$)// M=($M_1$,$M_2$,$M_k$)

(i)for each query cluster $c_i \in C$, develop ranking models using
the training data associated with the cluster $c_i \in C$.

Testing algorithm
Input: $q_{test}$, one of the query-document pairs in the testing set, k
clusters, k ranking models associated with k cluster.
Output: ranked list of documents for the test query.

1.$q_{tfeature}$ $\leftarrow$ generate-query-feature ($q_{test}$,$D_{qtest}$)

(i) find the mean and variance values of the ranking features
values of the documents associated with the query $q_{test}$.

(ii) represent query $q_{test}$ with generated feature vector.

2. c* $\leftarrow$ find cluster(C,$q_{tfeature}$)

(i) for each cluster $c_i \in C$, find the centroid and choose the
cluster whose centroid is closest to $q_{tfeature}$.

(3) ranklist $\leftarrow$ ($D_{qtest}$, $M_{c*}$)

(i)produce ranking results using the model $M_{c*}$
```

Figure 3. Architecture of the proposed system

5. Dataset and Performance Metric

The system will be evaluated on the LETOR benchmark dataset. The evaluation tools provided by LETOR are utilized to evaluate the effectiveness of the proposed system.

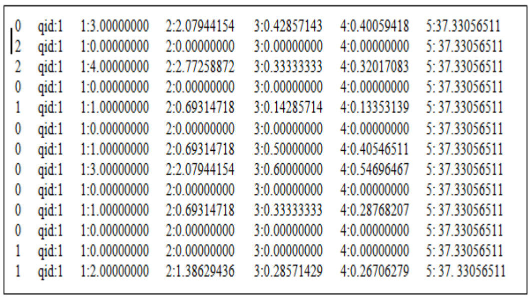
5.1. Dataset

The system will be evaluated on TREC 2003, TREC 2004 and OHSUMED, which are included in LETOR 3.0 dataset [12]. The statistics of the datasets from the LETOR 3.0 is described in table 1.

Table 1. Statistics of the datasets from LETOR

	Queries	Rel: levels	features
TREC 2003	350	2	64
TREC 2003	225	2	64
OHSUMED	106	3	45

Figure 4 shows the sample data from LETOR.



```
0  qid:1  1:3.00000000  2:2.07944154  3:0.42857143  4:0.40059418  5:37.33056511
2  qid:1  1:0.00000000  2:0.00000000  3:0.00000000  4:0.00000000  5: 37.33056511
2  qid:1  1:4.00000000  2:2.77258872  3:0.33333333  4:0.32017083  5: 37.33056511
0  qid:1  1:0.00000000  2:0.00000000  3:0.00000000  4:0.00000000  5: 37.33056511
1  qid:1  1:1.00000000  2:0.69314718  3:0.14285714  4:0.13353139  5: 37.33056511
0  qid:1  1:0.00000000  2:0.00000000  3:0.00000000  4:0.00000000  5: 37.33056511
0  qid:1  1:1.00000000  2:0.69314718  3:0.50000000  4:0.40546511  5: 37.33056511
0  qid:1  1:3.00000000  2:2.07944154  3:0.60000000  4:0.54696467  5: 37.33056511
0  qid:1  1:0.00000000  2:0.00000000  3:0.00000000  4:0.00000000  5: 37.33056511
0  qid:1  1:1.00000000  2:0.69314718  3:0.33333333  4:0.28768207  5: 37.33056511
0  qid:1  1:0.00000000  2:0.00000000  3:0.00000000  4:0.00000000  5: 37.33056511
1  qid:1  1:0.00000000  2:0.00000000  3:0.00000000  4:0.00000000  5: 37.33056511
1  qid:1  1:2.00000000  2:1.38629436  3:0.28571429  4:0.26706279  5: 37. 33056511
```

Figure 4. Sample data from LETOR

5.2. Evaluation Measures

The system will be evaluated using three common IR evaluation measures supported by LETOR.

1. Precision

For a given query, its precision of the top n results of the ranking lists is defined as:

$$P@n = \frac{\#relevant\ results\ in\ top\ n\ results}{n} \tag{9}$$

2. Mean Average Precision (MAP)

Given a query, its average precision can be computed as follows:

$$AP(q) = \frac{\sum_{i=1}^{n} P@n \cdot rel(n)}{\#total\ relevant\ results\ for\ the\ query} \quad (10)$$

where N is the number of retrieved documents and rel (n) is either 1 or 0, indicating that nth document is relevant or not to the query. MAP for a set of queries is the mean of the average precision scores for each query.

$$MAP = \frac{\sum_{q=1}^{Q} AP(q)}{Q} \quad (11)$$

where Q is the number of queries.

2. Normalized Discounted Cumulative Gain (NDCG)

For a query, the NDCG of its ranking list at position m is calculated as follows:

$$NDCG(n) = Z_n \sum_{j=1}^{n} \frac{2^{r(j)}-1}{\log(1+j)} \quad (12)$$

where r (j) is the rating of the jth document in the ranking list, and the normalization constant Z_n is chosen so that the perfect list gets a NDCG score of 1.

To compare the performance of our approach we will use RankSVM as a baseline method and conduct training over all the training queries to learn one single ranking model. Then we will examine the effectiveness of using separate models over single model. For each of the datasets in LETOR 3.0, we will conduct 5-fold cross-validation experiments, using the default partitions in LETOR.

6. Conclusion

This paper proposes a framework for query-dependent ranking model. In this system, instead of learning a single model for all training queries, individual model is developed for each query group that consists of the subset of training queries which have the similar features for ranking. Since the diverse feature impacts on ranking relevance with respect to different queries, the result produces by a single ranking function, while indicating good ranking relevance for a certain type of queries may not be able to achieve similar performance for other type of queries. By using separate model for each query cluster we can use separate features and training data for learning the ranking model for each query cluster. Therefore, we can apply useful information of the similar queries and avoiding negative effect of dissimilar ones. So we can achieve better ranking performance than a single model approach for each query cluster without hurting others. On the other hand, it may use only a small part of training data for learning each model; it may cause declining accuracy due to the lack of enough training examples. The evaluation will be done on LETOR bench mark data set.

References

[1]B. Chris, S. Tal, R. Erin, L. Ari, D. Matt, H. Nicole, H. Greg , "Learning to rank using Gradient Descent", Proceeding of the 22nd International Conference on Machine learning, Bonn, Germany, 2005.

[2]B. Jiang, L. Xin, L. Fan, Z. Zhaohui, Z. Hongyuan , "Ranking Specialization for web search: A Divide-and-Conquer Approach by using Topical RankSVM", WWW 2010, Raleigh, North Carolina, USA, April 26-30.

[3]B.Somnath, D.Avinava , M. Jinesh, C. Soumen, "Efficient and accurate local learning for ranking", copyright 2009 ACM.

[4]C. Zhe, Q. Tao, L.Tie-Yan, T. Ming-Feng, L.Hang, "Learning to Rank: From Pairwise Approach to Listwise Approach" , Proceedings of 24th International Conference on Machine Learning, Corvallis, 2007.

[5]D. Kevin , K. Katrin, "Learning to rank with partially-labeled data", SIGIR'08, Singapore , July20–24,2008.

[6]F. Yoav, I. Raj, E. S. Robert, "an efficient boosting algorithm for combining preferences",

Journal of machine learning research 4 (2003) 933-969.

[7] G.Salton, M.J.McGill, "Introduction to Modern Information Retrieval"

[8]G. Xiubo, L. Tie-Yan, Q .Tao, "Query Dependent Ranking Using K-Nearest Neighbor", SIGR'08, Singapore, July 20-24, 2008

[9]H. Ralf, G. Thore, O. Klaus, "Large Margin Rank Boundaries for Ordinal Regression"

[10]Jun Xu, Hang Li, "AdaRank: A Boosting Algorithm for Information Retrieval", SIGR'07, July 23-27, 2007 ,The Netherlands.

[11]L. Lian-Wang, J. Jung-Yi, W. ChunDer, L. Shie-Jue, "A Query-Dependent Ranking approach for search engines",2009 Second international workshop on Computer Science and Engineering.

[12] L.Tie-Yan, X.Jun, Q.Tao, X.Wening, L.Hang , "LETOR: Benchmark Dataset for Research on Learning to Rank for Information Retrieval".

[13]N. Weijian, H. Yalou, X. Maoqiang, "A Query Dependent Approach to Learning to Rank for Information Retrieval" , The Ninth International Conference on Web-Age Information Management, copyright 2008 IEEE.

[14]Q. Tao, L. Tie-Yan, L. Wei, Z. Xu-Dong, W. De-Sheng, L. Hang, "Ranking with multiple hyperplanes" SIGR'07, The Netherlands,July 23-27, 2007.

[15]S. Heli, H. Jianbin, F. Boqin, "QoRank:A Query-Dependent Ranking Model Using LSE-Based Weighted Multiple Hyperplanes Aggregation for Information Retrieval", INTERNATIONAL JOURNAL OF INTELLIGENT SYSTEMS, VOL.26,73–97(2011).