Notes on algorithms in LeToR

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Abstract

In this note I try to list a possible number of algorithms and approaches put into practice in learning to rank based schemes. The survey is carried out form the work of author phophalia. This note is a part of an exercise carried out amongst the new introductions of habits for the year 2015. I hope this continues, and in a long term turns out to be an integral atomic part of the overall process of my research paradigm, *i.e.* note making!

1 Approaches in letor

1. **Pointwise approaches**
   (a) Regression The conventional and simple idea of ordinal regression is to map the ordinal scales into numeric values, and then solve the problem as a standard regression problem. In this approach, a document - query pair is considered in the training phase.
   (b) McRank
   (c) RankProp
2. **Pairwise approaches**
   (a) AdaBoost
   (b) RankBoost - based on adaboost algorithm
   (c) **Neural network based approaches**
      i. RankNet
      ii. LambdaRank - based on RankNet
   (d) **SVM based approaches**
      i. RankSVM [14]
3. **Listwise approaches**
   (a) ListNet (neural network based, see: 2c) - similar to RankNet

(b) LambdaMART - [10] combines MART and LambdaRank. MART is a boosted tree model in which output of the model is linear combination of the outputs of a set of regression trees. Since MART models derivatives and LambdaRank works by specifying the derivatives at any point during training.

(c) BoltzRank - It uses Boltzman distribution, [11] is to define a probability distribution over document permutations, and consider the expectation of the target performance measure under this distribution.

(d) BayesRank - It directly optimizes the Bayes Risk related to the ranking accuracy in terms of the IR evaluation measures. It uses Plackett-Luce Model as probability model of permutations. A multilayer perceptron ***neural network*** is designed for learning BayesRank with NDCG related permutation loss. 2c

(e) FRank - FRank algorithm is proposed in [13] which is based on the concept of fidelity from physics.

(f) Rank Cosine - To find the similarity between estimated output and available ground truth result, Rank Cosine approach is proposed in [14].

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