Adversarial Learning-to-Rank Based on Variational Divergence Minimization
変分ダイバージェンスの最小化による敵対的ランキング学習

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Learning-to-rank has been intensively studied and has brought significant value to many fields. The information retrieval (IR) community has experienced a flourishing development of learning-to-rank methods, such as *pointwise* methods, *pairwise* methods and *listwise* methods. However, the previous studies mainly focused on supervised datasets with complete information, where relevance labels are known for all items, such as MSLR-WEB30K and Yahoo!LETOR. To address this problem, some recent studies appeal to use an adversarial training framework, in which two models (generator and discriminator) compete with each other during learning. Unfortunately, there are still many open issues. In the conventional adversarial learning-to-rank method, the difficulty of stable learning has been reported as a problem, and there are no studies that has examined the effect of each divergence on adversarial learning-to-rank. Motivated by the aforementioned open issues, we propose a variational divergence estimation framework using f-divergence minimization approach on adversarial learning-to-rank. In addition, for a stable learning, we modified training algorithm which took a single gradient update on both the generator and discriminator for each iteration step, and in the pairwise method, we used weighted sampling and sampling based on the probability obtained from the Bradley-Terry model. Based on the variational divergence estimation framework, we explore how to perform pointwise and pairwise adversarial learning-to-rank, respectively.

To demonstrate the effectiveness of the proposed approach, we conduct a series of experiments using multiple benchmark collections, such as MQ2008, MQ2008-semi, MSLR-WEB30K and Yahoo!LETOR. The experimental results demonstrate that: 1) The proposed framework for adversarial learning-to-rank shows better performance than the baseline approach based on either pointwise or pairwise model. This is probably because the single-step gradient method and the sampling method in the pairwise model have stabilized the learning. 2) We observed that the optimal divergence for learning in adversarial learning-to-rank is affected by the number of features in the dataset used for learning.

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