























Figure 5: The variants of PRFM and LambdaFM based on various pairwise loss functions.

to a set of well-known ranking loss functions. Furthermore, we have built a family of PRFM and LambdaFM algorithms, shedding light on how they perform in real tasks. In our evaluation, we have shown that LambdaFM largely outperforms state-of-the-art counterparts in terms of four standard ranking measures, but underperforms PRFM methods in terms of AUC, known as a binary classification measure.

LambdaFM is also applicable to other important ranking tasks based on implicit feedback, e.g., personalized microblog retrieval and learning to personalize query auto-completion. In future work, it would be interesting to investigate its effectiveness in these scenarios.

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