

7 Conclusion

Using active learning to build adaptive questionnaire trees is the promising approach to address the cold-start problem in recommender systems. The performance of questionnaire trees can be improved by splitting the nodes in a finer-grained fashion, i.e. one child node per each possible rating (including the "Unknown" answer).

As the future work, we plan to use other data sets, in which the maximum rating is higher than 5. For example, in EachMovie, the range of ratings is from one to six, or in IMDb, it is from one to ten. The hypothesis is that opting for the higher number of splits, i.e. 7-way and 11-way splits respectively, may lead to a better accuracy. On the other hand, there might be limitation in the accuracy gained by increasing the number of splits. One needs to verify this hypothesis.

References

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