Abstract

Recommender Systems (RSs) are software tools and techniques that are used to produce *recommendations* for the users of a certain application in such a way that the recommendations generated are likely to be liked by the users. Popular examples of applications that use RSs include Amazon, Netflix, Spotify, and Youtube. To support the wide-spread use of RSs, a variety of open-source tool-kits have been developed. While research studies show that different algorithms work well for different recommendation scenarios and with varying data-set characteristics, it has also been pointed out that the same recommendation algorithms implemented from different tool-kits can produce significantly different results. Recommendation algorithms typically have *hyper-parameters* that can be used to change their behaviour. Tuning the hyper-parameters according to the recommendation scenario can effectively improve the performance of any such algorithm. Even so, RS tool-kits generally lack hyper-parameter optimization (HPO) methods.

On the other hand, the AutoML community has proposed many solutions to solve the problem of *Combined Algorithm Selection and Hyper-parameter optimization*. AutoML tools like Auto-sklearn [1] often use advanced HPO methods like Bayesian optimization to find the "best" algorithm and hyper-parameters for a machine learning problem. Inspired by the AutoML community, Auto-CaseRec, a novel Automated Recommender System framework is presented. Given a data set, Auto-CaseRec allows the usage of advanced HPO techniques to produce the "best" combination of algorithm and hyper-parameters. Experimentation with 5 tests each across 2 data sets in 2 recommendation scenarios: Item Recommendation and Rating Prediction show that Auto-CaseRec always outperforms the individual best recommendation algorithm with unmodified hyper-parameters. We hope that Auto-CaseRec will become a standard tool in the RS community.