Active Reinforcement Learning for Data Preparation: Learn2Clean with Human-In-The-Loop

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ABSTRACT

Data cleaning and data preparation are challenging but necessary tasks to prevent incorrect results, biases, and misleading conclusions to be obtained from "dirty" data. For a given ML model and a dataset, a plethora of data preprocessing techniques and alternative data cleaning strategies with various configurations are available, but they may lead to dramatically different outputs with unequal result quality performances.

As illustrated in Fig. 1, data cleaning and preparation require a sophisticated sequence of tasks for the detection and elimination of a variety of intricate data quality problems (e.g., duplicates, inconsistent, missing, and outlying values). Generally, the users may not know which preprocessing methods can be applied to optimize the final results downstream. This would require executing all possible methods for each task of preprocessing, as well as all the possible combinations of the methods with different orderings and configurations. These methods can be applied to the whole or some parts of the dataset with eventual re-iterations. Data cleaning and preparation are intrinsically "AI-hard" as they can hardly be achieved by a fully automated system. AutoML approaches can optimize the hyper-parameters of a considered ML model, but they support only a limited number of preprocessing steps with by-default methods. We argue that more efforts should be devoted to proposing a principled and efficient data preparation approach to help and learn from the user in selecting the optimal sequence of data preparation tasks. Improving the quality of input data for ML and leveraging human expertise, subsequent learning performance will benefit.

As the first step in this direction, we have proposed Learn2Clean in [1], a method based on Q-Learning, a model-free reinforcement learning technique for automating data preparation.

In this paper, we present Learn2Clean+HIL, a novel contribution enhancing Learn2Clean with the "human-in-the-loop". Our exploration strategy uses active reward learning to leverage existing knowledge and user's feedback to reduce the data preparation pipeline search space. Learn2Clean+HIL selects, for a given dataset, a given ML model, and a preselected quality performance metric, the optimal sequence of tasks for preprocessing the data such that the quality metric is maximized with the help of the user.

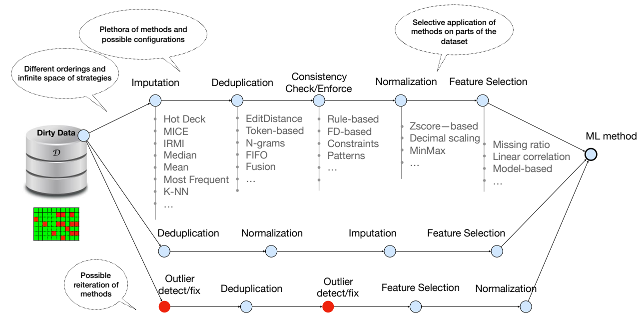

Figure 1: Challenges for building and pruning the search space of data preparation pipelines.

Recently, Alpine Meadow [2] combines an AutoML approach and a cost model to select candidate logical ML pipeline plans (as in DB query optimization). Multi-armed bandits are used to select promising logical ML pipeline plans, and Bayesian Optimization is used to fine-tune the hyper-parameters of the selected models in the search space. Although Alpine Meadow proposes an Adaptive Pipeline Selection (APS) method to find a trade-off between speed and accuracy of ML pipeline plan evaluation and returns the results progressively, the human expertise is not actually exploited for building or pruning the data preparation pipeline search space, and the user has a passive role with limited interaction. As shown in interactive data exploration [3], interactive response times can improve the rate at which insights are discovered in ML. However, human/machine interaction is not only about efficiency; it is also about quality and explainability.

This is precisely what Learn2Clean+HIL proposes in leveraging the user expertise in learning how to clean data by active reinforcement.

1. REFERENCES

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