Dear AAAI Reviewers/Committees,

RE: Algorithm Selection via Matrix Factorization (Paper ID: 771)

First of all, we would like to thank the AAAI-14 committees for giving us the opportunity to submit a substantially improved version of our paper to be considered in AAAI-15. We also thank the AAAI-14 reviewers for their constructive feedbacks.

In response to the reviewers' comments, we have revamped and made substantial improvements to our methodology for algorithm selection. For submission to AAAI-15, we propose a new ranking-based algorithm selection method that is different from the best existing algorithm selection approaches that employ either classification or regression techniques. To our best knowledge, we are the first to propose such comprehensive ranking-based algorithm selection method.

In the following, we highlight our main contributions (shown in numbers) and several major changes (summarized in bullets) that we have carried out to address the feedbacks from the AAAI-14 reviewers:

1. We develop a ranking polynomial model that can capture the rich, nonlinear interactions between problem instance and solver features. We then extend its use to model the ordering of solvers for a specific problem instance. This new model can be readily applied to handle cold-start situation (*i.e.* predicting the best k solvers for an unseen problem instance).

    - Different from our previous work (submitted to AAAI-14), we advocate a new philosophy of casting the algorithm selection problem into a more natural ranking formulation. Accordingly, we employ the appropriate loss function in developing our methodology that extends beyond the traditional classification and regression approaches.
    - From methodological standpoint, this new approach is also notably different from our previous work, which employs matrix factorization (MF) to learn an incomplete matrix of algorithm performances. Our current polynomial model no longer relies on the low-rank assumption (which is crucial for the success of MF technique) or a separate mechanism (surrogate model) for handling unseen problem instances.

2. We evaluate the efficacy of our RAS approach through extensive experiments on the SAT 2012 competition data. The results show that RAS outperforms the single-best algorithm selection method and gives competitive performance to that of the random-forest-based selection method.

    - In our current paper, we assess the efficacy of our proposed approach against the much more powerful random forest regressor, which approximates the algorithm selection method used in SATZilla (the current state-of-the-art). The results show competitive performance despite the simplicity of the approach. We believe this paves the way for a new direction for algorithm selection.

3. We devise an efficient iterative learning procedure for optimizing our proposed ranking loss function, which is derived from a sound probabilistic formulation of preferability among different solvers for a specific problem instance.

    - Specifically, we develop stochastic gradient descent (SGD) procedure that directly optimizes a ranking loss function. This is significantly different from our previous coordinate descent (CD) procedure, which is more complicated and may require more iterations to reach convergence (as pointed out by one of the reviewers). Another merit of our new SGD procedure over the previous CD method is that the former can better handle strongly correlated model parameters, which is important to capture the rich interaction between the problem instance and solver features.

Once again, we thank the AAAI-15 committees and reviewers for considering our new paper submission. We look forward to hearing from you.

Sincerely yours,

Authors of AAAI-14 Paper 771