Characterizing and clustering neighborhoods in a multi-neighborhood local search algorithm

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Abstract

We consider a multi-neighborhood local search framework with a large number of possible neighborhoods. Each neighborhood is accompanied by a weight value which represents the probability of being chosen at each iteration. These weights are fixed before the algorithm runs, and can be tuned by off-the-shelf off-line automated algorithm configuration tools (e.g., SMAC). However, the large number of parameters might deteriorate the tuning tool's efficiency, especially in our case where each run of the algorithm is not computationally cheap, even when the number of parameters has been reduced by some intuition. In this work, we propose a systematic method to characterize each neighborhood's behaviours, representing them as a feature vector, and using cluster analysis to form similar groups of neighborhoods. The novelty of our characterization method is the ability of reflecting changes of behaviours according to hardness of different solution quality regions based on simple statistics collected during any algorithm runs. We show that using neighborhood clusters instead of individual neighborhoods helps to reduce the parameter configuration space without misleading the search of the tuning procedure. Moreover, this method is problem-independent and potentially can be applied in similar contexts.

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1. Introduction

This work has been accepted and presented at the Learning and Intelligent OptimizatioN Conference 2016 (Dang & De Causmaecker, 2016).

Because optimization algorithms are usually highly parameterized, algorithm parameter tuning/configuration is an important task. Given a distribution of problem instances, we need to find parameter configurations that optimize a predefined performance measure over the distribution, such as mean of optimality gap. For the last fifteen years, automated algorithm configuration has been extensively studied (Hoos, 2012). General-purpose automated algorithm configuration tools such as SMAC (Hutter et al., 2011) and irace (López-Ibánez et al., 2011) have been successfully applied in several studies.

In this work, we consider the parameter tuning problem of a multi-neighborhood local search algorithm (Wauters et al., 2015), which consists of a large number of neighborhoods. The algorithm is the winner of the Verolog Solver Challenge 2014 (Heid et al., 2014). At each iteration, a neighbor solution is generated by a randomly chosen neighborhood with a probability defined by a weight value in the range of [0,1]. Weights of all neighborhoods are fixed before the algorithm runs, and are considered as algorithm parameters. Given a set of six (large) instances provided by the challenge, automated algorithm configuration tools can be used to tune the algorithm parameters. However, the large number of parameters might deteriorate the tuning tool's efficiency, especially in our case where each run of the algorithm is not computationally cheap (600 seconds per run for each instance). A potential solution is to cluster neighborhoods into groups and assign a common weight value parameter to each. It can help to reduce the algorithm configuration space, hoping to

make use of available tuning budgets more efficiently. The key question raised while doing such a clustering is how to characterize each neighborhood behaviours over a set of instances and represent them as a feature vector. In this paper, we propose a method to do so. This method is problem-independent and does not depend on any specific local search. Moreover, it can be done during stages of algorithm development, e.g., testing, manual/automated tuning. After the characterization, a high-dimensional low-sample-size clustering method (Bouveyron et al., 2007) is applied. The number of clusters is automatically chosen by the clustering method using Bayesian Information Criteria. In our case study, there are 42 neighborhoods, and after the characterization and clustering, 9 groups are formed. Experiment results showed that this reducing number of groups (hence tuned parameters) significantly improve tuning performance.

2. Experimental results

We applied the automated tuning tool SMAC (Hutter et al., 2011) to three configuration scenarios:

- original: the original 42 neighborhoods are treated independently, i.e., there is a weight value parameter for each neighborhood
- basic: neighborhoods are grouped into 28 groups using some knowledge from the algorithm developers' expertise.
- clustered: the 9 clusters of neighborhoods generated from our characterization method are used.

We carried out 18 runs of SMAC on each scenario. Each one has a budget of 2000 algorithm runs (13.9 CPU days). Due to the large CPU time each SMAC run requires, we use the shared-model-mode offered by SMAC with 10 cores (walltime is reduced to 1.39 days), and take the configuration which has the best training performance as the final one. Mean of optimality gaps (in percentage) on the instance set is used as tuning performance measure. The best algorithm configuration from each SMAC run is evaluated using test performance, which is the mean of optimality gaps obtained from 30 runs of the configuration on the instance set (5 runs/instance). *Paired t-tests* conducted on the two pairs (clustered, original) and (clustered, basic) give $p - values$ of 0.00216206 and 0.009258918 respectively, indicating statistical significance. These results show that clustering results obtained from the proposed characterization method does help to reduce the parameter configuration space without misleading the search of the tuning.

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