Automatic Construction of Parallel Portfolios via Explicit Instance Grouping

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Abstract

Simultaneously utilizing several complementary solvers is a simple yet effective strategy for solving computationally hard problems. However, manually building such solver portfolios typically requires considerable domain knowledge and plenty of human effort. As an alternative, automatic construction of parallel portfolios (ACPP) aims at automatically building effective parallel portfolios based on a given problem instance set and a given rich design space. One promising way to solve the ACPP problem is to explicitly group the instances into different subsets and promote a component solver to handle each of them. This paper investigates solving ACPP from this perspective, and especially studies how to obtain a good instance grouping. The experimental results showed that the parallel portfolios constructed by the proposed method could achieve consistently superior performances to the ones constructed by the state-of-the-art ACPP methods, and could even rival sophisticated hand-designed parallel solvers.

1 Introduction

It has been widely observed in many problem domains [Xu et al., 2010; Tang et al., 2014] that there is no universal optimal solver dominating all other solvers on all problem instances. Instead, different solvers perform well on different problem instances. Thus a natural idea is to combine those complementary solvers together to achieve a better overall performance. Typical examples include algorithm selection methods [Rice, 1976; Xu et al., 2008; Kotthoff, 2016] which try to select the best solver for every single problem instance before solving it, and adaptive solvers such as adaptive parameter control [Karafotias et al., 2015], reactive search [Battiti et al., 2008] and hyper-heuristics [Burke et al., 2013] which seek to dynamically determine the best solver setting while solving a problem instance. In principle, all these methods need to involve some mechanisms (e.g., selection or scheduling) to appropriately allocate computational resource to different solvers.

Recently parallel portfolios [Gomes and Selman, 2001; Tang et al., 2014; Lindauer et al., 2017] as another paradigm of simultaneously utilizing several sequential solvers, have attracted more and more research interest. While solving a problem instance, parallel portfolios run all the component solvers in parallel until the first of them solves it; thus the performance of a parallel portfolio is always the best performance achieved by its component solvers. Different from algorithm selection and adaptive solvers, parallel portfolios do not necessarily require any extra resource allocation since each involved component solver is simply assigned with the same amount of resource. Moreover, the rapid growth of parallelism in computational power [Gepner and Kowalik, 2006] makes such parallel solving strategy more and more critical for solving computationally hard problems. However, the manual construction of parallel portfolios is non-trivial. Specifically, identifying (or designing) a set of relatively uncorrelated sequential solvers which are complementary to each other still requires relatively significant domain knowledge [Xu et al., 2010].

Recently [Lindauer et al., 2017] proposed using automatic construction of parallel portfolios (ACPP) as a first step towards tackling parallel portfolio construction. The goal of ACPP is to automatically construct a parallel portfolio based on the rich design space induced by a highly parametrized sequential solver or a set of them. More formally, let $I$ and $P$ denote the configuration space of the parameterized solvers and the given set of problem instances, respectively. The parallel portfolio with $k$ component solvers could be denoted as a $k$-tuple, i.e., $P = (c_1, ..., c_k)$, in which $c_i \in C$ is an individual configuration and represents the $i$-th component solver of $P$. The goal is to find $c_1, ..., c_k$ from $C$, such that the performance of $P$ on $I$ according to a given metric $m$ is optimized.

There are three key ACPP methods, namely GLOBAL, PARHYDRA and CLUSTERING, in which GLOBAL and PARHYDRA are both proposed by [Lindauer et al., 2017] while CLUSTERING is adapted by [Lindauer et al., 2017] from ISAC [Kadioglu et al., 2010] for comparison. Generally, these methods can be divided into two categories. GLOBAL belongs to the first category, which considers ACPP an algorithm configuration problem by directly treating $P$ as a parameterized solver. By this means pow-

1 Although ISAC is an automatic portfolio construction method for algorithm selection, its basic idea is also applicable to ACPP. See [Lindauer et al., 2017] for more details.
erful automatic algorithm configurators such as ParamILS [Hutter et al., 2009], GGA [Ansótegui et al., 2009], irace [Ansótegui et al., 2009] and SMAC [Hutter et al., 2011] could be directly applied to configure $P$ (GLOBAL uses SMAC in [Lindauer et al., 2017]). The key issue of GLOBAL is that its scalability is limited since the size of the configuration space of $P$, i.e., $|C|^k$, increases exponentially with the number of the component solvers, i.e., $k$. The other two methods, PARHYDRA and CLUSTERING, solve the ACPP problem from the perspective of instance grouping. That is, they explicitly or implicitly promote different component solvers of $P$ to handle different subsets of problem instances, with the goal that the resulting component solvers would be complementary to each other. More specifically, starting from an empty portfolio, PARHYDRA proceeds iteratively and in the $i$-th iteration it uses an algorithm configurator (also SMAC) to configure $c_i$ to add to the current portfolio, i.e., $(c_1, ..., c_{i-1})$, such that the performance of the resulting portfolio, i.e., $(c_1, ..., c_{i-1}, c_i)$, is optimized. In other words, in each iteration PARHYDRA intrinsically aims to find a solver that can improve the current portfolio to the best extent. Since the greatest chance of the current portfolio getting improved is on those problem instances which cannot be solved satisfactorily, thus while PARHYDRA configuring the $i$-th component solver $c_i$, the configurator would actually promote $c_i$ to handle those intractable instances to the current portfolio $(c_1, ..., c_{i-1})$. Compared to PARHYDRA, CLUSTERING adopts a more explicit way to group instances. It clusters the problem instances in a given (normalized) instance feature space and then independently configures (using SMAC) a component solver on each instance cluster. The advantage of PARHYDRA and CLUSTERING is that they keep the size of the configuration space involved in each algorithm configuration task as $|C|$. The main issue of PARHYDRA is that its intrinsic greedy mechanism may cause stagnation in local optima. To alleviate this problem, [Lindauer et al., 2017] makes a modification to PARHYDRA by allowing simultaneously configuring several component solvers in each iteration. The resulting method is named PARHYDRA$_b$, where $b$ ($b \geq 1$) is the number of the component solvers configured in each iteration. PARHYDRA and GLOBAL could be both seen as special cases of PARHYDRA$_b$, with $b = 1$ and $b = k$ respectively. It is conceivable that the choice of $b$ is very important for PARHYDRA$_b$ since the tendency to stagnate in local optima would increase as $b$ gets smaller, while the size of the configuration space involved in each configuration task in PARHYDRA$_b$, i.e., $|C|^b$, would grow exponentially as $b$ gets larger. However, in general the best value of $b$ may vary across different scenarios, and for a specific scenario it is very hard to determine a good choice of $b$ in advance.

For methods based on explicit instance grouping such as CLUSTERING, obviously the quality of the instance grouping is crucial. A good instance grouping should meet at least one requirement: The instances that are grouped together should be similar in the sense that in the configuration space $C$ there exist same good configurations for them. CLUSTERING uses the distances in the normalized feature space to characterize such similarity. Although the problem features have been proved very useful for modeling the relationship between problem instances and solvers (e.g., algorithm selection), some practical issues still exist while applying CLUSTERING to ACPP. Specifically, the used instance features as well as the normalization of the features would greatly influence the final clustering results. However, determining appropriate choices of them is very hard since accurate assessment of the cluster quality relies on completely constructed portfolios.

In this paper, we investigate further solving the ACPP problem based on explicit instance grouping. Specifically, we propose a new ACPP method named parallel configuration with instance transfer (PCIT)\footnote{Here “parallel configuration” means that the configuration processes of the component solvers are independent of each other and thus could be conducted in parallel.}, which explicitly divides the instances into different subsets and configures a component solver on each subset. The most novel feature of PCIT is its dynamic instance transfer mechanism. Unlike CLUSTERING which determines the instance grouping in advance and then keeps it fixed through the whole process, during portfolio construction PCIT would dynamically adjust the instance grouping by transferring instances between different subsets. The instance transfer is conducted with the goal that the instances which share the same high-quality configurations (in the configuration space $C$) would be grouped together, such that the complementarity between the component solvers configured on different subsets would be favourably enhanced. The experimental results showed that the parallel portfolios constructed by PCIT could achieve consistently superior performances to the ones output by the existing ACPP methods, and could even rival the state-of-the-art hand-designed parallel solvers.

2 Proposed Method

The basic idea of PCIT is simple. Although it is hard to obtain an appropriate instance grouping at one stroke, it is possible to gradually improve an instance grouping. PCIT adopts a random splitting strategy to obtain an initial grouping: that is, the instances are evenly and randomly divided into $k$ subsets. It is conceivable that the quality of random instance grouping is not guaranteed at all since there is no guidance involved in the grouping procedure. Consider a simple example where instance set $I = \{ins_1, ins_2, ins_3, ins_4\}$, configuration space $C = \{\theta_1, \theta_2\}$, $ins_1, ins_2$ shares the high-quality configuration $\theta_1$ and $ins_3, ins_4$ shares the high-quality configuration $\theta_2$. Obviously the appropriate grouping for this example is $\{ins_1, ins_2\} \{ins_3, ins_4\}$, which would lead algorithm configurator to output $\theta_1$ and $\theta_2$ on the first and the second subset respectively, thus producing the optimal portfolio $P = \{\theta_1, \theta_2\}$. Random splitting strategy may fail on this example if it happens to split $I$ as $\{ins_1, ins_3\} \{ins_2, ins_4\}$ or $\{ins_1, ins_4\} \{ins_2, ins_3\}$, which could cause algorithm configurator to output the same component solver i.e., $(\theta_1, \theta_1)$ or $(\theta_2, \theta_2)$, on both subsets.

The key point here is that if the problem instances grouped together do not share the same high-quality configurations,
then the cooperation between the component solvers configured on these subsets would be much affected, thus limiting the quality of the final output parallel portfolio. To handle this issue, PCIT employs an instance transfer mechanism to improve the instance grouping during the construction process by transferring instances between different subsets. More specifically, as the configuration process of a component solver on a subset proceeds, if the algorithm configurator cannot manage to find a common high-performance configuration for every instance in the subset but only some of them, then it can be inferred that these intractable instances may correspond to different high-quality configurations (in the configuration space $C$) from others. It is therefore better to transfer these instances to other subsets that are more suitable to them.

PCIT conducts the instance transfer with the help of incumbent configurations (i.e., the best configurations found by the algorithm configurator). In each subset, the instances which cannot be solved satisfactorily by the corresponding incumbent are identified as the ones that need to be transferred, and the target subset of each transferred instance is determined according to how well the incumbent on the candidate subset could perform on the instance. In essence, the incumbent on a subset can be seen as a common special characteristic of those “similar” instances (in the sense they share the same high-quality configurations) within the subset, and PCIT uses it to identify those “dissimilar” instances and find better subsets for them. In each subset, the performance of the incumbent on each instance could be obtained from the rundata collected from the configuration process. However, while determining the target subsets for the transferred instances, how well the incumbents on the candidate subsets would perform on the transferred instances are unknown. One way to obtain these performances is to actually test these incumbents on the transferred instances, which however would introduce considerable additional computational costs. To avoid this, PCIT builds empirical performance models (EPM) [Hutter et al., 2014] based on the collected rundata to predict these performances.

2.1 Algorithm Framework

The pseudo-code of PCIT is given in Algorithm 1. The main difference between PCIT and the existing methods (e.g., GLOBAL and CLUSTERING) is that in PCIT the portfolio construction process is divided into $n$ (we always set $n = 4$ in this paper) sequential phases (Lines 3-13 in Algorithm 1). The first $(n-1)$ phases serve as adjustment phases, in each of which the instance grouping is adjusted (Line 12) once the configuration procedures in the first phase are finished. The last phase is the construction phase in which the component solvers of the final portfolio are configured on the obtained subsets with a large amount of time. In fact, the time consumed for the configuration processes in the last phase amounts to the sum of the time consumed for the configuration processes in the first $(n-1)$ phases (Lines 4-8). One thing which is not detailed in Algorithm 1 for brevity is that, on each subset, to keep the continuity of the configuration processes across successive phases, the incumbent configuration obtained in the previous phase is always used to initialize the configuration procedure in the next phase.

Algorithm 1: PCIT

Input: parameterized solvers with configuration space $C$; number of component solvers $k$; instance set $I$; performance metric $m$; configurator $AC$; number of independent runs of portfolio construction $r_{pc}$; time budget for configuration process $t_{c}$; time budget for validation process $t_{v}$; number of stages $n$; features $F$ for all instances in $I$

Output: parallel portfolio $(c_{1}, \ldots, c_{k})$

1: for $i := 1 \ldots r_{pc}$ do
2: Randomly and evenly split $I$ into $I_{1}, \ldots, I_{k}$
3: for $phase := 1 \ldots n$ do
4: if $phase = n$ then
5: $t \leftarrow \frac{t_{c}}{2(n-1)}$
6: else
7: $t \leftarrow \frac{t_{c}}{2(n-1)}$
8: end if
9: for $j := 1 \ldots k$ do
10: Obtain component solver $c_{j}$ by running $AC$ on configuration space $C$ on $I_{j}$ using $m$ for time $t$
11: end for
12: $I_{1}, \ldots, I_{k} \leftarrow \text{InsTransfer}(I_{1}, \ldots, I_{k}, c_{1}, \ldots, c_{k}, F)$
13: end for
14: $P_{t} \leftarrow (c_{1}, \ldots, c_{k})$
15: end for
16: Validate each of $P_{1}, \ldots, P_{r_{pc}}$ on $I$ using $m$ for time $t_{v}$
17: Let $P$ be the portfolio which achieved the best validation performance
18: return $P$

Another important difference between PCIT and the existing methods lies in the way of obtaining reliable outputs. For existing methods, the uncertainty of the portfolio construction results mainly comes from the randomness of the output of the algorithm configurator (especially when the given parametrized solvers are not deterministic). Thus for each specific algorithm configuration task, typically they conduct multiple independent runs of the algorithm configurator (with different random seeds), and then validate the configurations produced by these runs to determine the output one. For PCIT, in addition to the randomness mentioned above, a greater source of uncertainty is the randomness of the initial instance grouping results. One way to handle both of them is to perform multiple runs of portfolio construction (with different initial instance groupings), and in each construction process the algorithm configurator is also run for multiple times for each configuration task. In this paper, to keep the design simple, we only allow repeated runs of portfolio construction and rely on the validation to ensure the reliability of the final output (Lines 16-18 in Algorithm 1).

PCIT can be easily performed in parallel. First, different portfolio construction runs (Lines 1-15 in Algorithm 1) can be executed in parallel, and second, during each construction run the configuration processes for different component solvers (Lines 9-11 in Algorithm 1) can also be executed in parallel.
2.2 Instance Transfer

As shown in Algorithm 2, the instance transfer procedure first builds an empirical performance model (EPM) based on the rundata collected from all the previous algorithm configuration processes (Line 1). More specifically, the rundata is actually records of runs of different solver configurations on different instances, and each run can be represented by a 3-tuple, i.e., \((\text{config}, \text{ins}, \text{result})\). The exact implementation of EPM here is the same as the one in SMAC [Hutter et al., 2011], which is a random forest that takes as input a solver configuration \(\text{config} \) and a problem instance \(\text{ins}\) (represented by a feature vector), and predicts performance of \(\text{config} \) on \(\text{ins}\). The performances of the incumbent configuration on instances in each subset are obtained by querying the corresponding runs in rundata \(R\) (Line 2). After collecting all of them, the median value is used to identify the instances which will be transferred (without loss of generality, we assume a smaller value is better for \(m\)) (Line 3). Then these instances are examined one by one in a random order (Lines 7-22), for each examined instance the target subset is determined according to three rules (Line 13): 1) Both the source subset and the target subset will not violate the constraints on the subset size after the instance is transferred; 2) The predicted performance on the instance is not worse on the target subset; 3) The target subset is the one with the best predicted performance among the ones satisfying 1) and 2). The subset size constraints, i.e., the lower bound \(L\) and the upper bound \(U\) in Algorithm 2 are set to prevent the occurrence of too large or too small subsets. In this paper \(L\) and \(U\) are set as \(\lceil (1 \pm 0.2) \frac{|I|}{k} \rceil\), respectively. Since the sizes of the subsets keep changing during the instance transfer process, there is a possibility that an instance, which was examined earlier and at that time no target subset satisfying the above conditions was found, has a satisfactory target subset later. To handle this situation, instances which are not successfully transferred will be examined again in the next round (Line 26), and the whole procedure will be terminated (Lines 23-25) if there is no instance which needs to be transferred, or there is no successful transfer in a round (Lines 7-22).

2.3 Computational Costs

The computational costs of ACPP methods are mainly composed of two parts: the costs of configuration processes and the costs of validation. For PCIT, the total CPU time consumed is \(r_{pc} \cdot k \cdot (t_c + t_v)\) (the small overhead introduced by instance transfer in PCIT is ignored here). Similarly, for GLOBAL and CLUSTERING, it is \(r_{ac} \cdot k \cdot (t_c + t_v)\), where \(r_{ac}\) is the number of independent runs of algorithm configurator (for each configuration task). For PARHYDRA\(_b\), the consumed CPU time is \(r_{ac} \cdot \sum_{i=1}^{m} [i \cdot b \cdot (t_{cb} + t_{vb})]\), where \(t_{cb}\) and \(t_{vb}\) refer in particular to the configuration time budget and the validation time budget used in PARHYDRA\(_b\) (See [Lindauer et al., 2017] for more details).

Algorithm 2: InsTransfer

\(R\) is the run data collected from all the previous algorithm configuration processes. \(L\) and \(U\) are the lower bound and the upper bound of the size of a subset, respectively.

**Input:** instance subsets \(I_1, \ldots, I_k\), incumbent configurations \(c_1, \ldots, c_k\), instance features \(F\)

**Output:** instance subsets \(I_1, \ldots, I_k\)

1: Build an EPM based on \(R\) and \(F\)
2: For each instance \(ins\) in each subset, obtain the performance of the corresponding incumbent configuration on it from \(R\), denoted as \(P(ins)\)
3: Let \(v\) be the median value of all \(P(ins)\) across all subsets, and the instances with bigger values than \(v\) are identified as the ones which need to be transferred, denoted as \(T\)
4: while true do
5: \(T\)success \(\leftarrow\) \\(\varnothing\)
6: \(T\)remaining \(\leftarrow\) \\(\varnothing\)
7: while \(T\) \(\neq\) \(\varnothing\) do
8: Randomly select an instance \(ins\) from \(T\) and let \(I_s\) and \(c_s\) be the subset containing \(ins\) and the corresponding incumbent configuration, respectively
9: \(T \leftarrow T \setminus \{ins\}\)
10: For each incumbent configuration \(c\) of \(c_1, \ldots, c_k\), use EPM to obtain the predicted performance of \(c\) on \(ins\), denoted as \(E(c)\)
11: Sort \(c_1, \ldots, c_k\) according to the goodness of \(E(c_1), \ldots, E(c_k)\), denoted as \(c_\pi(1), \ldots, c_\pi(k)\)
12: for \(j := 1 \ldots k\) do
13: if \(E(c_\pi(j)) \leq E(c_s) \&\& |I_\pi(j)| < U \&\& |I_s| > L\) then
14: \(I_s \leftarrow I_s \setminus \{ins\}\), \(I_\pi(j) \leftarrow I_\pi(j) \cup \{ins\}\)
15: \(T\)success \(\leftarrow T\)success \(\cup\) \{\(ins\)\}
16: break
17: end if
18: end for
19: if \(ins \notin T\)success then
20: \(T\)remaining \(\leftarrow T\)remaining \(\cup\) \{\(ins\)\}
21: end if
22: end while
23: if \(T\)success \(=\) \(\varnothing\) \&\& \(T\)remaining \(=\) \(\varnothing\) then
24: break
25: end if
26: \(T \leftarrow T\)remaining
27: end while
28: return \(I_1, \ldots, I_k\)

3 Empirical Study

We conducted experiments on two widely studied domains, SAT and TSP. Specifically, we used our method to build parallel portfolios based on a training set, and then compared them with the ones constructed by the existing methods, on an unseen test set.
3.1 Experimental Setup

Portfolio Size and Performance Metric

We set the number of component solvers to 8 (same as [Lindauer et al., 2017]), since 8-core (and 8-thread) machines are widely available now. The optimization goal considered here is to minimize the time required by a solver to solve the problem (for SAT) or to find the optimum of the problem (for TSP). In particular, we set the performance metric to Penalized Average Runtime–10 (PAR-10) [Hutter et al., 2009], which counts each timeout as 10 times the given cutoff time. The optimal solutions for TSP instances were obtained using Concorde [Applegate et al., 2006], an exact TSP solver.

Scenarios

For each problem domain we considered constructing portfolios based on a single parameterized solver and based on multiple parameterized solvers, resulting in four different scenarios. For brevity, we use SAT/TSP-Single/Multi to denote these scenarios. Table 1 summarizes the used instance sets, cutoff time, and base parameterized solvers in each scenario. Except in SAT-Multi we reused the settings from [Lindauer et al., 2017], in the other three scenarios we all used new settings which had never been considered before in the literature of ACPP. We especially note that this was the first time the ACPP methods were applied to TSP. Settings in SAT-Multi are the same as the ones in [Lindauer et al., 2017]: 1) Instance set obtained from the application track of the SAT’12 Challenge were randomly and evenly split into a training set and a test set, and to ensure the computational costs for portfolio construction would not be prohibitively large, the cutoff time used in training (180s) was smaller than the one used in testing (900s, same as the SAT’12 challenge); 2) The parameterized solvers in SAT-Multi (the configuration space C contains 150 parameters in total, including a top-level parameter used to select a base solver) were the 8 sequential solvers considered by [Wotzlaw et al., 2012] when designing portfolioUZK, the gold medal winning solver in the parallel track of the SAT’12 Challenge. In SAT-Single, we chose instances from the benchmark used in the parallel track of the SAT’12 Challenge. In SAT-Single, the base solver used from the original benchmark (containing 5000 instances) and divided them evenly for training and testing. We chose Riss6 [Manthey et al., 2016], the gold medal winning solver of this track, as the base solver. Since Riss6 exposes a large number of parameters, we selected 135 parameters from them to be tunable while leaving others as default. For TSP-Single and TSP-Multi we used a same instance set. Specifically, we used the portgen and the portgen generators from the 8th DIMACS Implementation Challenge to generate 1000 “uniform” instances (in which the cities are randomly distributed) and 1000 “clustering” instances (in which the cities are distributed around different central points). The problem sizes of all these generated instances are within [1500, 2500]. Once again, we divided them evenly for training and testing. The base solver used in TSP-Single was LKH version 2.0.7 [Helsgaun, 2000] (with 35 parameters), one of the state-of-the-art inexact solver for TSP. In TSP-Multi, in addition to LKH, we included another two powerful TSP solvers, GA-EAX version 1.0 [Nagata and Kobayashi, 2013] (with 2 parameters) and CLK [Applegate et al., 2003] (with 4 parameters), as the base solvers, resulting in a configuration space containing 43 parameters (including a top-level parameter used to select a base solver).

Competitors and Time Budgets

Besides PCIT, we implemented GLOBAL, PARHYDRA_1, and CLUSTERING (with normalization options including linear normalization, standard normalization and no normalization), as described in [Lindauer et al., 2017] for comparison. For all considered ACPP methods here, SMAC version 2.10.03 [Hutter et al., 2011] was used as the algorithm configurator. Since the performance of SMAC could be often improved when used with the instance features, we gave SMAC access to the 126 SAT features used in [Hutter et al., 2011], and the 114 TSP features used in [Kotthoff et al., 2015]. The same features were also used by PCIT (for transferring instances) and CLUSTERING (for clustering instances). To make the comparisons fair, the total CPU time consumed by each method was kept almost the same. The detailed setting of time budget for each method is given in Table 2. To validate whether the instance transfer in PCIT is useful, we included another method, named PCRS (parallel configuration with random splitting), in the comparison. PCRS differs from PCIT in that it directly configures

| Instance Set | Cutoff Time | Base Solvers |
|--------------|-------------|--------------|
| SAT-Single   | From the SAT 16 Competition Agile Track, 2000 instances (1000 for training, 1000 for testing) | 60s | Riss6 [Manthey et al., 2016] |
| SAT-Multi    | From the SAT 12 Challenge Application Track, 600 instances (300 for training, 300 for testing) | 180s(900s) | 8 solvers considered by [Wotzlaw et al., 2012] |
| TSP-Single   | Same as TSP-Multi | 20s | LKH |
| TSP-Multi    | 2000 instances containing 1000 “uniform” ones and 1000 “clustering” ones generated using the generators from the DIMACS TSP Challenge (1000 for training, 1000 for testing) | 20s | LKH |

Table 1: Summary of the used instance sets, cutoff time, base parameterized solvers and configuration space size in each scenario.

| Scenario | Instance Set | Cutoff Time | Base Solvers |
|----------|--------------|-------------|--------------|
| SAT-Single | From the SAT 16 Competition Agile Track, 2000 instances | 60s | Riss6 [Manthey et al., 2016] |
| SAT-Multi | From the SAT 12 Challenge Application Track, 600 instances | 180s(900s) | 8 solvers considered by [Wotzlaw et al., 2012] |
| TSP-Single | Same as TSP-Multi | 20s | LKH |
| TSP-Multi | 2000 instances containing 1000 “uniform” ones and 1000 “clustering” ones | 20s | LKH |

Table 2: Detailed time budget (in hours) for each method in each scenario. In the experiments \( r_{pc} \) (for PCIT) and \( r_{ac} \) (for GLOBAL, PARHYDRA_1, and CLUSTERING) were both set to 10. The 3-tuple in each cell represents (configuration time budget, validation time budget, total CPU time). Given the same configuration budget, the same validation budget and \( r_{pc} = r_{ac} \), PCIT, GLOBAL and CLUSTERING would consume the same amount of CPU time (see Section 2.3). Thus \( M \) group is used to represent these methods for brevity. For PARHYDRA_1, the configuration budget was set to grow linearly with b, same as [Lindauer et al., 2017].
the final portfolios on the initial random instance grouping and involves no instance transfer. The time budgets for PCRS were the same as PCIT.

Baselines
For each scenario, we identified a sequential solver as the baseline by using SMAC to configure on the training set and the configuration space of the scenario.

Experimental Environment
All the experiments were conducted on a cluster of 5 Intel Xeon machines with 60 GB RAM and 6 cores each (2.20 GHz, 15 MB Cache), running Centos 7.5.

3.2 Results
We tested each solver (including the ACPP portfolios and the baseline) by running it on each test instance for 3 times, and reported the median performance. The obtained number of timeouts (#TOS), PAR-10 and PAR-1 are presented in Table 3. For CLUSTERING and PARHYDRA0, we always reported the best performance achieved by their different implementations. To determine whether the performance differences between these solvers were significant, we performed a permutation test (with 100000 permutations and significance level \( p = 0.05 \)) to the (0/1) timeout scores, the PAR-10 scores and the PAR-1 scores. Overall the portfolios constructed by PCIT achieved the best performances in Table 3. In SAT-Single, SAT-Multi and TSP-Single, it achieved significantly and substantially better performances than all the other solvers. Although in TSP-Multi, the portfolio constructed by PARHYDRA0 obtained slightly better results than the one constructed by PCIT (however the performance difference is insignificant), as aforementioned, the appropriate value of \( b \) varied across different scenarios (as shown in Table 3) and for a specific scenario it was actually unknown in advance (in TSP-Multi it was 2). Similarly, as shown in Table 3 the best normalization strategy for CLUSTERING also varied across different scenarios. Compared to the portfolios constructed by PCRS, the ones constructed by PCIT consistently obtain much better results, which verified the effectiveness of the instance transfer mechanism of PCIT. Finally, all the ACPP methods here could build portfolios that obtained much better results than the baselines, indicating the great benefit by combining complementary configurations obtained from a rich design space.

To further evaluate the portfolios constructed by PCIT, we compared them with the state-of-the-art manually designed parallel solvers. Specifically, we considered the ones constructed for SAT. We chose Priss6 [Manthey et al., 2016] to compare with the one constructed in SAT-Single, since Priss6 is the official parallel version of Riss6 (the base solver in SAT-Single). For the same reason, we chose PfolioUZK [Wotzl, et al., 2012] (the gold medal winning solver of the parallel track of the SAT’12 Challenge) to compare with the one constructed in SAT-Multi. Finally, we chose Pingeleng (version bbc) [Biere, 2016], the gold medal winning solver of the parallel track of the SAT’16 Competition, to compare with both. Note that all the manually designed solvers considered here have implemented far more advanced solving strategies (e.g., clause sharing) than only independently running component solvers in parallel. In the experiments the default settings of these solvers were used and the same statistical tests as before were conducted. As shown in Table 3 on SAT-Single test set, the portfolio constructed by PCIT achieved much better results than others. This may be because the parallel solvers considered here are not designed for the type of these instances (obtained from the SAT’16 Competition Agile track, which is for simple fast SAT solvers with low overhead), which on the other hand demonstrates the wide applicability of ACPP methods. It is impressive that, on SAT-Multi test set, the portfolio constructed by PCIT (regardless of its simple solving strategy) obtained slightly better results than pfolioUZK, and could reach the performance level of the more state-of-the-art Pingeleng. Such results imply that the portfolios constructed by PCIT may be a good staring point for designing more powerful parallel solvers.

4 Conclusion
In this paper we proposed a novel ACPP method which utilized an instance transfer mechanism to improve the quality of the instance grouping. The experimental results verified the effectiveness of the proposed method. Directions of future work include extending the proposed method to use parallel solvers as base solvers, and investigating solving ACPP from the perspective of subset selection.

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The performance of a solver is shown in boldface if it was not significantly different from the best performance (according to a permutation test with 100 000 permutations and significance level \( p = 0.05 \)). For CLUSTERING and PARHYDRA\(_b\), the best performance achieved by their different implementations is reported and the corresponding implementation option, i.e., the choice of \( b \) for PARHYDRA\(_b\), and the normalization strategy (“None” for no normalization, “Linear” for linear normalization and “Standard” for standard normalization) for CLUSTERING, is also reported.

### Table 3: Results on the test set in the four scenarios.

The name of the ACPP method is used to denote the portfolios constructed by it. The performance of a solver is shown in boldface if it was not significantly different from the best performance (according to a permutation test with 100 000 permutations and significance level \( p = 0.05 \)).

|                | SAT-Single PAR-10 | PAR-1 | SAT-Multi PAR-10 | PAR-1 | TSP-Single PAR-10 | PAR-1 | TSP-Multi PAR-10 | PAR-1 |
|----------------|-------------------|-------|------------------|-------|-----------------|-------|-----------------|-------|
| Baseline       | 383               | 238   | 31               | 71    | 2275            | 358   | 565             | 118   |
| PCRS           | 234               | 152   | 26               | 44    | 1435            | 247   | 110             | 31    |
| PCTI           | **181**           | **119** | **24**            | **35** | **1164**      | **219** | **87**           | **24** |
| GLOBAL         | 230               | 149   | 25               | 46    | 1495            | 253   | 224             | 53    |
| PARHYDRA\(_b\) | 235 b=4          | 151   | 24               | 40 b=1           | 1326 | 246      | 107 b=1        | 29    |
| CLUSTERING     | 227 None          | 146   | 23               | 43 None           | 1415 | 254      | 121 Linear      | 31    |
|                |                   |       |                  |                   |      |         | 99 Linear       | 28    |

### Table 4: Test results of parallel solvers on the test set of SAT-Single and SAT-Multi.

The performance of a solver is shown in boldface if it was not significantly different from the best performance (according to a permutation test with 100 000 permutations and significance level \( p = 0.05 \)).

|                | SAT-Single PAR-10 | PAR-1 | SAT-Multi PAR-10 | PAR-1 |
|----------------|-------------------|-------|------------------|-------|
| PCIT           | **181**           | **119** | **21**            | **35** | **1164**      | **219** |
| Prais6         | 225               | 146   | 25               | -     | -              | -     |
| PfolioUZK      | -                 | -     | -                | -     | -              | -     |
| Plinegling-bbc | 452               | 276   | 32               | -     | -              | -     |

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