# **AutoPBO: LLM-powered Optimization for Local Search PBO Solvers**

Jinyuan Li<sup>1, 2</sup>, Yi Chu<sup>3</sup>, Yiwen Sun<sup>4</sup>, Mengchuan Zou<sup>1</sup>, Shaowei Cai<sup>1, 2\*</sup>

<sup>1</sup>Key Laboratory of System Software, Institute of Software, Chinese Academy of Sciences, Beijing, China
<sup>2</sup>School of Computer Science and Technology, University of Chinese Academy of Sciences, Beijing, China
<sup>3</sup>Institute of Software, Chinese Academy of Sciences, Beijing, China
<sup>4</sup>School of Data Science, Fudan University, Shanghai, China
lijy@ios.ac.cn, chuyi2020@iscas.ac.cn, ywsun22@m.fudan.edu.cn, zoumc@ios.ac.cn, caisw@ios.ac.cn

#### Abstract

Pseudo-Boolean Optimization (PBO) provides a powerful framework for modeling combinatorial problems through pseudo-Boolean (PB) constraints. Local search solvers have shown excellent performance in PBO solving, and their efficiency is highly dependent on their internal heuristics to guide the search. Still, their design often requires significant expert effort and manual tuning in practice. While Large Language Models (LLMs) have demonstrated potential in automating algorithm design, their application to optimizing PBO solvers remains unexplored. In this work, we introduce AutoPBO, a novel LLM-powered framework to automatically enhance PBO local search solvers. We conduct experiments on a broad range of four public benchmarks, including one real-world benchmark, a benchmark from PB competition, an integer linear programming optimization benchmark, and a crafted combinatorial benchmark, to evaluate the performance improvement achieved by AutoPBO and compare it with six state-of-the-art competitors, including two local search PBO solvers NuPBO and OraSLS, two complete PB solvers PBO-IHS and RoundingSat, and two mixed integer programming (MIP) solvers Gurobi and SCIP. AutoPBO demonstrates significant improvements over previous local search approaches, while maintaining competitive performance compared to state-of-the-art competitors. The results suggest that AutoPBO offers a promising approach to automating local search solver design.

#### 1 Introduction

Pseudo-Boolean Optimization (PBO) plays an important role in solving a wide range of combinatorial problems (Boros and Hammer 2002), which seeks an assignment of values to a set of Boolean variables that optimizes a linear objective function under Pseudo-Boolean (PB) constraints. Due to its powerful expressiveness and the convenience to make use of properties of boolean variables, PBO has demonstrated broad applicability across various domains, including VLSI design, economic modeling, computer vision, and manufacturing optimization (Wille, Zhang, and Drechsler 2011; Zhang et al. 2011; Roussel and Manquinho 2021).

Along with the wide usages of the PBO problem in industrial and application domains, solving the PBO is then a non-negligible topic. However, the solving of PBO is a challenging task as the problem is NP-hard (Buss and Nordström 2021). In previous studies, the solving methods can be divided into two classes: complete methods and incomplete methods. The complete methods solves the problem to optimal and proves the optimality, while incomplete methods do not guarantee to compute the optimal assignment but try to compute good solutions in a short time.

Research on complete methods for solving PBO has developed multiple approaches. First, since PB constraints can be naturally treated as 0-1 linear constraints, mixed-integer programming (MIP) solvers such as SCIP (Bestuzheva et al. 2021) and Gurobi (Gurobi Optimization, LLC 2021) can be directly applied to solve PBO problems. Second, by translating PB constraints into conjunctive normal form (CNF), the problem can be solved using SAT solvers based on Conflict-Driven Clause Learning (CDCL), including MINISAT+ (Eén and Sörensson 2006), Open-WBO (Martins, Manquinho, and Lynce 2014), and NaPS (Sakai and Nabeshima 2015). Beyond these, advanced methods have been developed for more efficient PBO solving. The cutting planes technique, which goes beyond the resolution power of CDCL, is implemented in solvers like sat4j (Le Berre and Parrain 2010) and RoundingSat (Elffers and Nordström 2018, 2020; Devriendt et al. 2021). Additionally, the implicit hitting set (IHS) method has been successfully adapted to PBO in solvers such as PBO-IHS (Smirnov, Berg, and Järvisalo 2021; Smirnov, Berg, and Järvisalo 2022).

Complete algorithms often struggle with large-scale instances, leading to the development of incomplete approaches, among which local search stands out as a representative strategy (Lei et al. 2021; Chu et al. 2023; Zhou et al. 2023). The first notable solver *LS-PBO* (Lei et al. 2021) introduced a weighting scheme and a scoring function that jointly handle hard and soft constraints. Several key extensions followed: *DeciLS-PBO* (Jiang et al. 2023) enhanced the framework by incorporating unit propagation; *NuPBO* (Chu et al. 2023) proposed enhanced scoring functions and weighting schemes; and *DLS-PBO* (Chen et al. 2024) implemented dynamic scoring functions. Additionally, *OraSLS* (Iser, Berg, and Järvisalo 2023) utilizes a oracle mechanism to guide the local search approach in PBO.

The efficiency of local search solvers heavily relies on internal heuristics to guide the search process. In the past,

<sup>\*</sup>Corresponding author

many works on designing different algorithmic components such as weighting scheme and score functions have been proposed, as in (Thornton 2005; Cai and Su 2013; Cai et al. 2014; Cai and Lei 2020; Lei et al. 2021; Chu, Cai, and Luo 2023; Chu et al. 2024). However, those works are based on human-designed techniques and designing these heuristics often demands substantial expert effort and manual tuning in practice. On the other hand, recent developments on the LLM-based algorithm design start a new paradigm of algorithm design and show the capability of large language models (LLMs) in automating algorithm design. However, the application of LLMs to building PBO solvers remains unexplored, presenting a promising direction for future research.

Current works on automated algorithm design for combinatorial optimization problems are mainly on designing evolutionary algorithms for specific problems or optimizing heuristics in simple solvers. FunSearch (Romera-Paredes et al. 2024) pioneered the integration of pretrained LLMs with evolutionary search, initiating heuristic discovery through iterative code generation. Then, EoH (Liu et al. 2024) extends this paradigm through dual-representation evolution, and ReEvo (Ye et al. 2024) introduces a structured reflection mechanism to guide evolutionary search. What is more, AutoSAT (Sun et al. 2024, 2025) focus on optimizing heuristics in SAT solvers, AlphaEvolve (Novikov et al. 2025) pushes the paradigm further by ensembling LLMs with automated evaluators in an evolutionary loop, enabling the discovery of entire algorithmic codebases.

The works on automated heuristic design for the general form problem (i.e. problems with general constraints types, such as Integer Programming, Pseudo Boolean Optimization, etc) is rare, and current approaches of designing heuristics for specific types of problems face critical limitations in this scenario: 1) the general-problem solver usually have complex structure with various algorithm components, and thus results in long-context of source codes, being much more sophisticated than evolutionary algorithms for specific types of problems; 2) A general form problem usually allows a wide range of types of constraints rather than specific types of problems normally has quite limited and known types of constraints, making the heuristics design for these two scenarios quite different. Thus, the algorithm design for the general form optimization problem is still challenging, and to our knowledge, there is no prior work on the LLM-driven automated design for PBO solver.

We consider the automated optimization for local search solvers of the PBO problem. Specifically, we consider to enhance the existing state-of-the-art local search solver for PBO by leveraging the power of LLM. We try to address the above challenges by designing methods from three considerations:1) Enhancing LLMs' comprehension of solver codes with complex structures; 2) Reducing errors or invalid modifications during code generation; 3) Improving the solver's efficiency by optimizing its algorithm as a composition that involves multiple functions.

In this work, we design a novel LLM-powered framework to automatically enhance PBO local search solvers. We propose a multi-agent system integrated with a greedy search strategy, enabling closed-loop, feedback-driven op-

timization. Furthermore, we introduce a structuralized local search PBO solver *StructPBO*, with a clearer structure of codes, that could be used as an input for automatic optimization frameworks. This design helps LLMs to effectively comprehend and optimize PBO-specific search algorithms and was adopted in our system.

Bring the above ideas together, we design our *AutoPBO* framework to automatically enhancing local search solvers of PBO. Experimental results demonstrate that *AutoPBO* significantly improves the performance of local search PBO solvers, offering a promising approach to automating local search solver design.

## 2 Preliminaries

# 2.1 Pseudo-Boolean Optimization

A linear pseudo-Boolean (PB) constraint is expressed as:  $\sum_{j=1}^{n} a_j l_j \triangleright b$ , where  $a_j, b \in \mathbb{Z}$  are integer coefficients, b is the threshold,  $\triangleright \in \{=, >, \geq, <, \leq\}$  is a relational operator, and each  $l_j$  is a literal (either a Boolean variable  $x_i$  or its negation  $\neg x_i$ ).

In this work, we assume all PB constraints are in the normalized form  $\sum_{j=1}^{n} a_j l_j \geq b$  with  $a_j, b \in \mathbb{N}_0^+$  (non-negative integers). This assumption is without loss of generality since all PB constraints can be converted to this form by expressing equalities as inequality pairs and applying the identity  $x_i = 1 - \neg x_i$  to ensure non-negative coefficients (Roussel and Manquinho 2021).

An assignment  $\alpha$  is a mapping from variables to  $\{0,1\}$ . A PB constraint c is *satisfied* under  $\alpha$  if the inequality  $\sum_{j=1}^n a_j l_j \geq b$  holds; otherwise, c is *violated*. The *violation degree* of c under  $\alpha$ , denoted viol(c), quantifies how far c is from being satisfied:  $viol(c) = \max\left(0, b - \sum_{j=1}^n a_j l_j\right)$ , which is zero if c is satisfied, and otherwise measures the shortfall. A *PB formula F* is a conjunction of PB constraints, and an assignment that satisfies all constraints in c is called a *feasible solution*.

A pseudo-Boolean optimization (PBO) instance consists of a PB formula F together with a linear Boolean objective function  $\sum_{j=1}^n e_j l_j + d$ , where  $e_j \in \mathbb{N}^+$  and  $d \in \mathbb{Z}$ . Since all PB constraints must hold, they are treated as *hard constraints*. For any assignment  $\alpha$ , its objective value is denoted as  $obj(\alpha)$ . A feasible solution  $\alpha_1$  is considered superior to another solution  $\alpha_2$  if  $obj(\alpha_1) < obj(\alpha_2)$ . The objective of PBO is to identify a feasible assignment  $\alpha$  that minimizes  $obj(\alpha)$ .

#### 2.2 Local Search for PBO

The local search is a general algorithmic paradigm fo solving combinatorial optimization problems. It typically begins with an initial solution and iteratively explores the neighborhood of the current solution, seeking an improved candidate solution. If such a solution is found, it replaces the current one; otherwise, the search either terminates or employs strategies to escape local optima. The process continues until a stopping criterion is met, such as reaching a maximum number of iterations, a time limit, or a satisfactory solution quality threshold.

In a typical local search process of PBO, given an instance F, the local search algorithm starts from an initial solution  $\alpha$ , then iteratively modifies  $\alpha$  by selecting variables heuristically and applying corresponding **operators** (e.g., the flip operator in pseudo-Boolean optimization) until a feasible solution is found. An operation is obtained when an operator is specified with a variable, and it is easy to see there could be multiple operations for generating a new solution. During this process, **scoring functions** evaluate candidate operations, prioritizing operations that are likely to improve solution quality. An important factor normally included in scoring functions is the weights of constraints. A **weighting scheme** is adopted to compute the weights of constraints in the scoring function, representing the importance of the constraints.

In general, for greedy variable flipping, PBO local search (LS) algorithms employ a scoring function integrated with the weights of constraints. Let w(c) denote the weight of a hard constraint c, and w(o) denote the weight of the objective function o. For instance, in LS-PBO, the penalty for a constraint c is defined as  $penalty(c) = w(c) \times viol(c)$ , and the penalty for the objective function under the current assignment  $\alpha$  is  $penalty(o) = w(o) \times obj(\alpha)$ . In NuPBO, a smoothed penalty method is proposed to balance the viol values across constraints. Specifically, for a hard constraint c, the penalty function is redefined as:  $penalty(c) = \frac{w(c) \times viol(c)}{smooth(c)}$  where smooth(c) represents a smoothing coefficient derived from constraint properties. Similarly, for the objective function o, the penalty is adjusted to:  $penalty(o) = \frac{w(o) \times obj(\alpha)}{smooth(o)}$ ; with smooth(o) often calculated as the average of the objective function's coefficients. Across these algorithms, the hard score hscore(x)of a variable x quantifies the reduction in the total penalty of all hard constraints when x is flipped. The soft score oscore(x) measures the reduction in the objective function's penalty after flipping x. The scoring function of x is defined as score(x) = hscore(x) + oscore(x), a linear combination of the hard and soft scores.

# 3 A New Structuralized Local Search PBO Solver: StructPBO

As we mentioned in Section 1, previous studies on automated algorithm design usually focus on combinatorial optimization problems with known types and usually result in simple-architecture algorithms, which are quite different from general form problem solvers that have complex structures. Notably, the Local Search PBO solvers typically employ advanced programming techniques and multiple algorithmic components in the code to achieve high efficiency in finding high-quality solutions within a short time period. Thus, it is still challenging for LLMs to process the codes of general problem solvers.

In our preliminary experiments, using LLMs to generate a PBO solver from scratch under the EoH mechanism resulted in local search algorithms that were limited to basic scoring functions and random perturbation stages (see Appendix A). Furthermore, when attempting to optimize existing Lo-

#### Algorithm 1: the structPBO solver

```
Input: PBO instance F, cutoff time cutof f.
  Output: The best solution \alpha^* found and its objective
            function value obj^*, or "No solution found".
1 \ \alpha^* := \varnothing, \quad obj^* := +\infty;
2 \alpha := InitializeAssignment();
  while elapsed time < cutoff do
      if \alpha is feasible and obj(\alpha) < obj^* then
           // Update best solution and
           its objective function value
          \alpha^* := \alpha, \quad obj^* := obj(\alpha);
5
      for each variable x do
6
          hscore(x) := \Delta Penalty_{hard}(x);
7
          oscore(x) := \Delta Penalty_{obj}(x);
8
          score(x) :=
            CalculateScore(hscore(x), oscore(x));
      if D := \{x | Score(x) > 0\} \neq \emptyset then
10
           // A variable is picked
          accordingly
11
          x := PickBestVariable(D);
      else
12
           // Stuck in a local optimum
          UpdateWeights(F);
13
           // A variable is picked
          according to
           local-optima-escaping
          heuristics
          x := PickEscapeVariable(F);
      \alpha := \alpha with x flipped;
16 if \alpha^* \neq \emptyset then return \alpha^* and obj^*;
17 else return No solution found;
```

cal Search PBO solvers using established solver optimization frameworks (see Appendix A), the high complexity and tight coupling of the codebase led to a significant increase in syntactic errors and logical inconsistencies in the LLM-generated code.

To address these problems, we propose a predefined, structured Local Search PBO Solver framework named *StructPBO*. Aligning the basic components of local search routine, we defines the functionalities of different parts of a local search solver and build a structuralized solver *StructPBO*, following the SOTA PBO local search solver *NuPBO* (Chu et al. 2023).

As presented in Algorithm 1, a local search solver maintains a complete assignment (line 2). During the search, it keeps track of the best solution found (lines 4-5) and returns it when the termination condition is reached (lines 16-17). The effectiveness of the proposed local search PBO solver lies in its heuristic-driven variable selection mechanism, which hinges on the interplay between dynamic constraint weighting and penalty-based scoring functions, designed to systematically navigate the search space while balancing constraint satisfaction and objective optimization (lines 6-15). Specifically, for each variable x, the algorithm

evaluates flip candidates through a composite score (line 9) that combines hscore(x) and oscore(x) – the respective penalty reductions for hard constraints and objective optimization (lines 7-8), where penalties are weighted according to constraint criticality. This weighting adapts dynamically: during feasibility-seeking phases, hard constraints dominate through exponentially higher weights, while objective constraints gain influence when approaching optimality. When trapped in local optima (line 13), the solver strategically updates these weights to escape stagnation. The resulting score-driven variable selection (lines 10-15) thus automatically shifts focus between constraint repair and objective improvement based on real-time search progress.

In this paper, we work on a structuralized local search framework that defines seven functions which are independently implemented:

- InitializeAssignment: Heuristically generates an initial complete assignment
- **Penalty\_hard**: Heuristically computes the hard constraint penalty reduction
- Penalty\_obj: Heuristically computes the objective penalty reduction
- CalculateScore: Heuristically combines hard and soft penalties into a dynamic composite score
- **PickBestVariable**: Heuristically selects the most promising variable
- UpdateWeights: Heuristically selects the most promising variable
- PickEscapeVariable: Heuristically identifies variables for diversification when stagnation is detected

This modular architecture enables isolated function optimization while maintaining global coherence through our convergence mechanism described in Section 4.3.

#### 4 The Automated Optimization Framework

For automating the optimization of codes for local search solver of PBO, we propose a LLM-based multi-agent framework, named *AutoPBO*. Our framework is based on three types of agents and a greedy-based iterative method to achieve a better performance solver.

As illustrated in Figure 1, our framework begins by loading a local search PBO solver, then a number of iterative code optimizing rounds are launched. In each round, we perform several distinct and independent code modifications work, each modification work is realized by the three LLM agents collaboratively. After an optimization round, several versions of code are generated and then a greedy-based selection strategy is applied to select the most effective version for the next iteration. By repeating, the framework ultimately generates the resulting solver.

#### 4.1 Optimization by Multiple Agents

There are three specialized LLM agents in our framework, each of which has its own functionality and distinct roles, i.e., the Code Optimization Planner, Code Editor, and Modification Evaluator. Each of them serves different functionalities in our framework as follows:

- Code Optimization Planner: Analyze key code segments to recognize the function targeted for modification and generate modification plans.
- Code Editor: Realize the code modification to improve the code, following the advice generated by the Code Optimization Planner.
- Modification Evaluator: Evaluate the modified code and generate advice for future improvement.

Those three agents operate through an automated cycle of modification plan generation, code edit iteration, and dynamic evaluation.

A code optimization round is consist of two phases: the planning phase and the editing phase. In the planning phase, the Code Optimization Planner Agent identifies possible optimization ways and generates preliminary improvement plans, such as "Dynamic Score Ratios: Adjust h\_score\_ratio and s\_score\_ratio dynamically based on the current state of the search (e.g., increase the weight of hard constraints when the solution is infeasible", "Include a term that considers the age of the variable (time since last flip) to encourage diversification and escape local optima", etc. The details of the implementations of the Code Optimization Planner is presented in Section 4.2.

The editing phase is built by interactions of the Code Editor and the Modification Evaluator, for multiple times. The Code Editor Agent performs the actual work of code modifications and runs for multiple times in the editing phase. Initially, it modifies the code modifications with the optimization plans provided by the Code Optimization Planner as input, and generates the first version of the code. It identifies if the modification has actual significant meanings, by excluding trivial modifications such as variable re-naming, parameter changing, etc. An actual compilation and running of the code is also performed at this time, to collect information such as the existence of compilation errors or running information.

The running information and the evaluation results from the Modification Evaluator will then be sent to the code Editor as feedback for the next modification. This interaction will be performed by the Code Editor, Modification Evaluator several times, resulting in a final version of code for the current code optimization round.

In the following, we will first present the implementation of different agents, then introduce the greedy-based iterative methods on top of code optimization rounds, which jointly form our whole optimization framework for PBO local search solver.

#### 4.2 Implementation of Agents

The three agents are implemented by different prompt, which are designed following the principles proposed by OpenAI's foundational guidelines(OpenAI 2023), we have developed a structured prompt to implement different functionalities for them.

Our prompt includes A *Role* set to the agent, the *Tasks* definitions, the *Tips* to provide suggestions and the complete PBO solver code appended at the end to ensure all agents share the same context. All three agents share a common

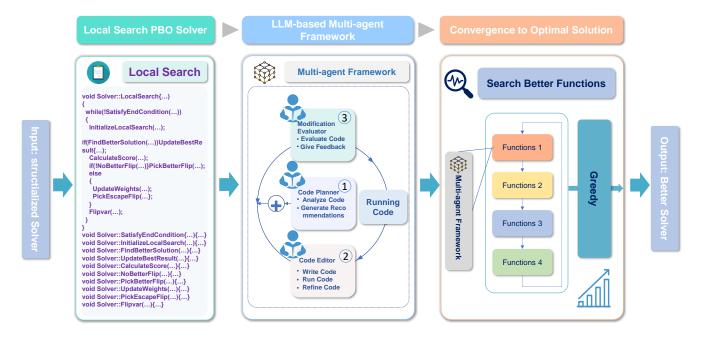


Figure 1: Architecture of AutoPBO. With a structuralized local search PBO solver as input, AutoPBO implements greedy strategy to optimize heuristic functions iteratively. For each iteration, AutoPBO employs the original solver code to instantaneously create an understanding and recommendations for heuristic functions, subsequently engages in code generation and performance assessment by three agents. Upon completion, AutoPBO returns the optimal solver code.

*Role* configuration as a solver researcher attempting to improve the heuristics in a PBO solver. This foundational *Role* description establishes the professional identity and overarching objective for each agent in the optimization process. *Tasks* and *Tips* of every agent are shown in Table 1.

#### 4.3 Convergence to Optimal Solution

As illustrated in Figure 1, we implement an iterative greedy algorithm that progressively constructs the improved solver through three steps:

• Code Optimization Round: Agents optimize one function at a time, while keeping others functions fixed. For example, we first generate multiple optimized versions of the UpdateWeights function through LLM agents, then select the best-performing version before proceeding to optimize CalculateScore. Implementation Process is that the LLM agents first generate multiple optimized versions of the function as illustrated in 4.1. Then our framework automates the following workflow: it constructs solver instances for each function version, runs these solvers in parallel on certain dataset, and automatically collects their outputs—including feasibility status (Feasible or Infeasible) and objective values(obj) across all test instances. Finally, the framework determines the best-performing version through automatic comparison by tallying the total feasible solutions (Feasible count) and the number of instances where a solver's obj outperforms StructPBO (Win count), selecting the version that achieves the highest count on both metrics.

- Modification Propagating: The selected optimal function (e.g., improved UpdateWeights) is immediately integrated into *StructPBO*. Subsequent optimizations (e.g., CalculateScore refinement) are then performed on this updated *StructPBO*.
- Iterative Improvement: This process repeats until all target functions are optimized.

This approach addresses the inherent dependency between functions. Consider the interaction between UpdateWeights and CalculateScore: The scoring function in CalculateScore must reflect the latest clause weights from UpdateWeights to properly prioritize constraint satisfaction. If we independently optimize both functions and combine their best versions, the scoring mechanism might ignore updated weight distributions, leading to inconsistent optimization behavior. Our greedy strategy prevents such conflicts by enforcing sequential adaptation - the improved CalculateScore automatically adapts to the newly integrated UpdateWeights through Modification Propagating.

Together with these three steps and the three agents involved, we iteratively improve our code, trying to get a better performance solver.

# 5 Experiments

In this section, we introduce the experimental settings and present extensive experiments on 4 PBO benchmarks. First, we evaluate the effectiveness of *AutoPBO* as a framework for enhancing baseline solvers, demonstrating that it consistently improves performance across multiple benchmarks.

Agent	Tasks	Tips
Code Optimization Planner	Comprehensively analyzing all key code segments     Proposing possible modification manners	<ol> <li>Complete review of all relevant code sections</li> <li>Generation of both practical and theoretically promising proposals</li> <li>Strict JSON format adherence</li> </ol>
Code Editor	Phase 1: 1. Precise interpretation of Planner's description 2. Directional suggestions for code changes Phase 2: 1. Analyze experimental outcomes 2. Produce superior code versions	Phase 1: 1. Preserve original function signatures 2. Prevent undefined variable introduction 3. Guarantee differentiation from previous codes Phase 2: 1. Maintain code formatting 2. Avoid redundant modifications
Code Modification Evaluator	1. Evaluation and classification of outputs	Thorough syntax verification     Comparative analysis for meaningful improvements     Categorical classification

Table 1: Agent Tasks and Tips Overview

Second, we compare *AutoPBO* with state-of-the-art PBO solvers to highlight its strong competitiveness. Finally, in Appendix A we provide variance analysis through repeated experiments to demonstrate the statistical stability of *AutoPBO*'s performance.

#### 5.1 Settings

**Environment** Our PBO solver is implemented in C++, while the interface for interacting with LLMs is developed in Python. The solver is compiled using g++ 9.4.0. All experiments are performed on an Ubuntu 20.04.4 LTS server, which is equipped with two AMD EPYC 7763 processors. Each processor operates at a base frequency of 2.45 GHz. The server is configured with 1TB of RAM. For all experiments, the DeepSeek<sup>1</sup> LLM is employed.

**Benchmarks and Datasets** We evaluate *AutoPBO* on four widely-used PBO benchmarks, comprising 47 datasets in total. For each dataset, we randomly split the instances into training and test sets with a 1:1 ratio. The training set is used to generate the enhanced solver via *AutoPBO*, while the test set is reserved for final evaluation. Detailed instance information is provided in Code & Data Appendix. A summary is provided below:

- PB16: The OPT-SMALLINT-LIN benchmark from the 2016 pseudo-Boolean competition, comprising 1600 diverse instances from multiple categories. Following the categorization in (Smirnov, Berg, and Järvisalo 2021), we divide PB16 into 42 datasets based on their applications.
- MIPLIB: A benchmark of 0-1 integer linear programming problems, containing 267 instances of various types, as introduced in (Devriendt et al. 2021).<sup>3</sup>
- CRAFT: A collection of 1025 crafted combinatorial problems with small integer coefficients, also from (Devriendt

et al. 2021).4

Real-world: A benchmark set containing three application-driven problems: the Minimum-Width Confidence Band Problem (MWCB, 24 instances), the Seating Arrangements Problem (SAP, 21 instances), and the Wireless Sensor Network Optimization Problem (WSNO, 18 instances). All problem descriptions, encodings, and instances are from (Lei et al. 2021).<sup>5</sup>

**State-of-the-art Competitors.** We compare *AutoPBO* with 6 state-of-the-art solvers, including 2 incomplete solver (*i.e.*, *NuPBO* and *OraSLS*) and 4 complete solvers. The 4 complete solvers include 2 PB solvers (*i.e.*, *PBO-IHS* and *RoundingSat*) and 2 MIP solvers (*i.e.*, *Gurobi* and *SCIP*):

- *NuPBO* (Chu et al. 2023): The state-of-the-art local search solver for solving PBO.
- *OraSLS* (Iser, Berg, and Järvisalo 2023): a recent oracle-based SLS algorithm for PBO, which improves upon previous pure SLS approaches.
- PBO-IHS (Smirnov, Berg, and Järvisalo 2022): A PBO solver that utilizes the implicit hitting set approach and building upon *RoundingSat* (Elffers and Nordström 2018).
- *RoundingSat* (Devriendt et al. 2021): A PBO solver combining core-guided search with cutting planes reasoning.
- Gurobi (Gurobi Optimization, LLC 2021): One of the most powerful commercial MIP solvers (Version 12.0.2).
   The default configuration is used, along with a single thread.
- SCIP (Gamrath et al. 2020): One of the fastest non-commercial solvers for MIP (Version 8.0.4).

**Performance Metrics** In our experiments, *AutoPBO* first generates optimization strategies on the training set with a 60-second cutoff time. Then, each solver performs one run

<sup>&</sup>lt;sup>1</sup>We utilize the DeepSeek-R1 as default in this paper.

<sup>&</sup>lt;sup>2</sup>http://www.cril.univ-artois.fr/PB16/bench/PB16-used.tar

<sup>&</sup>lt;sup>3</sup>https://zenodo.org/record/3870965

<sup>4</sup>https://zenodo.org/record/4036016

<sup>5</sup>https://lcs.ios.ac.cn/\%7ecaisw/Resource/LS-PBO/

Benchmark	Str	uctPBO	AutoPBO			
Deficilitation	#win	$avg\_score$	#win	$avg\_score$		
Real-world	17	0.9962	29	0.9998		
CRAFT	488	0.9472	513	0.9474		
MIPLIB	101	0.8450	112	0.8598		
PB16	697	0.8272	775	0.8447		
Total	1303	0.8738	1429	0.8849		

Table 2: *AutoPBO* vs *StructPBO* Performance Comparison (By Benchmark)

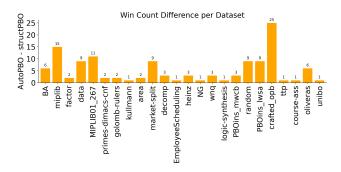


Figure 2: #win differences between AutoPBO and StructPBO. Each bar represents AutoPBO's #win minus StructPBO's #win. Positive values (orange bars) indicate AutoPBO's advantage.

within a given cutoff time (300 seconds) on every instance in the testing set for evaluation. We record the cost of the best solution found by solver  $S_j$  on instance  $I_k$ , denoted as  $sol_{S_j}I_k$ . The cost of the best solution found among all solvers in the same table on instance  $I_k$  is denoted as  $best_{I_k}$ .

Following previous research on PBO, we measure the performance of each solver using two metrics:

- #win: the number of instances where the corresponding  $best_{I_k}$  can be obtained by solver S on  $B_i$  (i.e., the number of winning instances).
- $avg\_score$ : in our experiments, the competition score of solver  $S_j$  on instance  $I_k$  is represented by  $score_{S_jI_k} = \frac{best_{I_k}+1}{sol_{S_jI_k}+1}$ , which measures the gap between  $sol_{S_jI_k}$  and  $best_{I_k}$ . If solver  $S_j$  could not report a solution on instance  $I_k$ , then  $score_{S_jI_k} = 0$ . We use  $avg\_score$  to denote the average competition score of a solver on a dataset.

For each of the above two metrics, if a solver obtains a larger metric value on a dataset, then the solver exhibits better performance on the dataset. The results highlighted in **bold** indicate the best performance for the corresponding metric.

#### 5.2 Results

**Improvements of Local Search PBO solver** We first evaluate AutoPBO on top of StructPBO across 47 datasets from 4 benchmarks. Figures 2 and 3 present the datasets with changes in #win and  $avg\_score$  respectively along with the

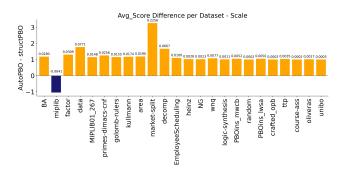


Figure 3:  $avg\_score$  differences between AutoPBO and StructPBO. Each bar represents AutoPBO's  $avg\_score$  minus StructPBO's  $avg\_score$  (AutoPBO - StructPBO). Positive values (orange bars) indicate AutoPBO's higher  $avg\_score$ , while negative values (dark-blue bars) indicate StructPBO's higher  $avg\_score$  (after non-linear scaling for better visibility).

magnitude of these changes. *AutoPBO* demonstrates consistent performance gains: improving #win on 24 datasets and avg\_score on 23 datasets, with only a single case of marginal degradation in avg\_score. This consistent nonnegative trend confirms that *AutoPBO* not only avoids harming performance but also delivers significant gains on nearly half of the datasets across all benchmarks.

Table 2 provides a benchmark-level comparison between AutoPBO and StructPBO in terms of both #win and score. Across all 4 benchmarks, AutoPBO demonstrates consistent improvements, raising the total number of #win and increasing the overall  $avg\_score$ .

These benchmark-level results highlight the generality and robustness of *AutoPBO*.

Competitive Results of *AutoPBO* We conduct a comprehensive comparison between *AutoPBO* and state-of-the-art solvers, as shown in Table 3. To ensure fair comparison, we performed parameter tuning for *PBO-IHS*, *RoundingSat*, *OraSLS*, and *NuPBO* on each dataset. The tuning scripts and final parameter configurations are documented in Code & Data Appendix. The experimental results demonstrate that *AutoPBO* outperforms all open-source solvers in both #win and avg\_score. Notably, *AutoPBO* shows competitive performance compared to the commercial solver *Gurobi*.

At the dataset level (see Appendix A), AutoPBO achieves the highest #win on 31 out of 47 datasets and obtains the best  $avg\_score$  on 32 datasets. The complete per-dataset comparison reveals that AutoPBO consistently delivers robust performance across diverse problem types.

# 6 Conclusions and Future Work

This paper is devoted to develop a novel LLM-powered framework to automatically enhance PBO local search solvers. First, we introduced our structuralized local search PBO solver framework. Furthermore, we configured multiple LLM agents and employed a greedy strategy to generate an optimized and efficient solver. Experimental results

	Gurobi		SCIP		PBO-IHS-Tuned		RoundingSat-Tuned		OraSLS-Tuned		NuPBO-Tuned		AutoPBO	
Benchmark	#win	$avg\_score$	#win	$avg\_score$	#win	$avg\_score$	#win	$avg\_score$	#win	$avg\_score$	#win	$avg\_score$	#win	$\overline{avg\_score}$
Real-world	3	0.5319	0	0.1417	0	0.3503	0	0.0000	2	0.3322	19	0.9956	26	0.9977
CRAFT	479	0.9783	289	0.8337	277	0.7959	302	0.8341	406	0.9620	454	0.9447	460	0.9449
MIPLIB	101	0.8313	33	0.5625	55	0.7051	47	0.7619	53	0.7236	74	0.8259	73	0.8367
PB16	680	0.8461	353	0.5974	513	0.7542	397	0.5297	529	0.8026	600	0.8190	624	0.8204
Total	1263	0.8836	675	0.6660	845	0.7555	746	0.6442	990	0.8404	1147	0.8668	1183	0.8687

Table 3: Multi-Solver Performance Comparison (By Benchmark)

demonstrate that AutoPBO can improve the efficiency of local search PBO solver to a very high level.

In the future, we will integrate advanced LLM technologies into more general solvers to enhance their flexibility and performance. For instance, techniques like retrieval-augmented generation (RAG) could help LLM generating correct modifications. We will also enhance other solvers such as MIP solvers using LLM-based framework. This approach would enable faster modifications and more efficient solver customization.

#### References

Bestuzheva, K.; Besançon, M.; Chen, W.-K.; Chmiela, A.; Donkiewicz, T.; Van Doornmalen, J.; Eifler, L.; Gaul, O.; Gamrath, G.; Gleixner, A.; et al. 2021. The SCIP optimization suite 8.0. *arXiv preprint arXiv:2112.08872*.

Boros, E.; and Hammer, P. L. 2002. Pseudo-boolean optimization. *Discrete applied mathematics*, 123(1-3): 155–225.

Buss, S.; and Nordström, J. 2021. Proof complexity and SAT solving. In *Handbook of Satisfiability*, 233–350. IOS Press.

Cai, S.; and Lei, Z. 2020. Old techniques in new ways: Clause weighting, unit propagation and hybridization for maximum satisfiability. *Artificial Intelligence*, 287: 103354.

Cai, S.; Luo, C.; Thornton, J.; and Su, K. 2014. Tailoring local search for partial MaxSAT. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 28.

Cai, S.; and Su, K. 2013. Local search for boolean satisfiability with configuration checking and subscore. *Artificial Intelligence*, 204: 75–98.

Chen, Z.; Lin, P.; Hu, H.; and Cai, S. 2024. ParLS-PBO: A Parallel Local Search Solver for Pseudo Boolean Optimization. *arXiv preprint arXiv:2407.21729*.

Chu, Y.; Cai, S.; and Luo, C. 2023. NuWLS: Improving local search for (weighted) partial MaxSAT by new weighting techniques. In *Proceedings of AAAI 2023*, volume 37, 3915–3923.

Chu, Y.; Cai, S.; Luo, C.; Lei, Z.; and Peng, C. 2023. Towards more efficient local search for pseudo-boolean optimization. In 29th International Conference on Principles and Practice of Constraint Programming (CP 2023), 12–1.

Chu, Y.; Li, C.; Ye, F.; and Cai, S. 2024. Enhancing MaxSAT Local Search via a Unified Soft Clause Weighting Scheme. In *In Proceedings of SAT 2024*, volume 305, 8:1–8:18.

Devriendt, J.; Gocht, S.; Demirovic, E.; Nordström, J.; and Stuckey, P. J. 2021. Cutting to the Core of Pseudo-Boolean

Optimization: Combining Core-Guided Search with Cutting Planes Reasoning. In *Proceedings of AAAI 2021*, 3750–3758.

Eén, N.; and Sörensson, N. 2006. Translating pseudo-boolean constraints into SAT. *Journal on Satisfiability, Boolean Modeling and Computation*, 2(1-4): 1–26.

Elffers, J.; and Nordström, J. 2018. Divide and Conquer: Towards Faster Pseudo-Boolean Solving. In Lang, J., ed., *Proceedings of IJCAI 2018*, 1291–1299.

Elffers, J.; and Nordström, J. 2020. A Cardinal Improvement to Pseudo-Boolean Solving. In *Proceedings of AAAI 2020*, 1495–1503.

Gamrath, G.; Anderson, D.; Bestuzheva, K.; Chen, W.-K.; Eifler, L.; Gasse, M.; Gemander, P.; Gleixner, A.; Gottwald, L.; Halbig, K.; Hendel, G.; Hojny, C.; Koch, T.; Le Bodic, P.; Maher, S. J.; Matter, F.; Miltenberger, M.; Mühmer, E.; Müller, B.; Pfetsch, M. E.; Schlösser, F.; Serrano, F.; Shinano, Y.; Tawfik, C.; Vigerske, S.; Wegscheider, F.; Weninger, D.; and Witzig, J. 2020. The SCIP Optimization Suite 7.0. Technical report, Optimization Online.

Gurobi Optimization, LLC. 2021. Gurobi Optimizer Reference Manual.

Iser, M.; Berg, J.; and Järvisalo, M. 2023. Oracle-based local search for pseudo-boolean optimization. In *ECAI 2023*, 1124–1131. IOS Press.

Jiang, L.; Ouyang, D.; Zhang, Q.; and Zhang, L. 2023. DeciLS-PBO: an Effective Local Search Method for Pseudo-Boolean Optimization. arXiv preprint arXiv:2301.12251.

Le Berre, D.; and Parrain, A. 2010. The Sat4j library, release 2.2. *Journal on Satisfiability, Boolean Modeling and Computation*, 7(2-3): 59–64.

Lei, Z.; Cai, S.; Luo, C.; and Hoos, H. 2021. Efficient local search for pseudo boolean optimization. In *Theory and Applications of Satisfiability Testing—SAT 2021: 24th International Conference, Barcelona, Spain, July 5-9, 2021, Proceedings 24*, 332–348. Springer.

Liu, F.; Xialiang, T.; Yuan, M.; Lin, X.; Luo, F.; Wang, Z.; Lu, Z.; and Zhang, Q. 2024. Evolution of Heuristics: Towards Efficient Automatic Algorithm Design Using Large Language Model. In the 41st International Conference on Machine Learning.

Martins, R.; Manquinho, V.; and Lynce, I. 2014. Open-WBO: A modular MaxSAT solver. In *International Conference on Theory and Applications of Satisfiability Testing*, 438–445. Springer.

- Novikov, A.; Vũ, N.; Eisenberger, M.; Dupont, E.; Huang, P.-S.; Wagner, A. Z.; Shirobokov, S.; Kozlovskii, B.; Ruiz, F. J.; Mehrabian, A.; et al. 2025. AlphaEvolve: A coding agent for scientific and algorithmic discovery. *arXiv preprint arXiv:2506.13131*.
- OpenAI. 2023. OpenAI API Documentation.
- Romera-Paredes, B.; Barekatain, M.; Novikov, A.; Balog, M.; Kumar, M. P.; Dupont, E.; Ruiz, F. J.; Ellenberg, J. S.; Wang, P.; Fawzi, O.; et al. 2024. Mathematical discoveries from program search with large language models. *Nature*, 625(7995): 468–475.
- Roussel, O.; and Manquinho, V. 2021. Pseudo-Boolean and cardinality constraints. In *Handbook of satisfiability*, 1087–1129. IOS Press.
- Sakai, M.; and Nabeshima, H. 2015. Construction of an ROBDD for a PB-Constraint in Band Form and Related Techniques for PB-Solvers. *IEICE Transactions on Information & Systems*, 98-D(6): 1121–1127.
- Smirnov, P.; Berg, J.; and Järvisalo, M. 2021. Pseudoboolean optimization by implicit hitting sets. In *27th International Conference on Principles and Practice of Constraint Programming (CP 2021)*, 51–1. Schloss Dagstuhl-Leibniz-Zentrum für Informatik.
- Smirnov, P.; Berg, J.; and Järvisalo, M. 2022. Improvements to the Implicit Hitting Set Approach to Pseudo-Boolean Optimization. In *Proceedings of SAT 2022*, 13:1–13:18.
- Sun, Y.; Ye, F.; Chen, Z.; Wei, K.; and Cai, S. 2025. Automatically discovering heuristics in a complex SAT solver with large language models. *arXiv preprint arXiv:2507.22876.*
- Sun, Y.; Ye, F.; Zhang, X.; Huang, S.; Zhang, B.; Wei, K.; and Cai, S. 2024. Autosat: Automatically optimize sat solvers via large language models. *arXiv preprint*.
- Thornton, J. 2005. Clause weighting local search for SAT. *Journal of Automated Reasoning*, 35: 97–142.
- Wille, R.; Zhang, H.; and Drechsler, R. 2011. ATPG for Reversible Circuits Using Simulation, Boolean Satisfiability, and Pseudo Boolean Optimization. In 2011 IEEE Computer Society Annual Symposium on VLSI, 120–125.
- Ye, H.; Wang, J.; Cao, Z.; Berto, F.; Hua, C.; Kim, H.; Park, J.; and Song, G. 2024. Reevo: Large language models as hyper-heuristics with reflective evolution. *Advances in neural information processing systems*, 37: 43571–43608.
- Zhang, Y.; Hartley, R.; Mashford, J.; and Burn, S. 2011. Superpixels via pseudo-Boolean optimization. *International Conference on Computer Vision, International Conference on Computer Vision*.
- Zhou, W.; Zhao, Y.; Wang, Y.; Cai, S.; Wang, S.; Wang, X.; and Yin, M. 2023. Improving local search for pseudo boolean optimization by fragile scoring function and deep optimization. In 29th International Conference on Principles and Practice of Constraint Programming (CP 2023), 41–1.

	Real	l-world	CF	RAFT	MI	PLIB	PB16		
Solver	$Win(\mu \pm \sigma)$	$Score(\mu \pm \sigma)$	$Win(\mu \pm \sigma)$	$Score(\mu \pm \sigma)$	$Win(\mu \pm \sigma)$	$Score(\mu \pm \sigma)$	$Win(\mu \pm \sigma)$	$Score(\mu \pm \sigma)$	
Gurobi	$3.3 \pm 0.6$	$0.523 \pm 0.013$	$\textbf{479.0} \pm \textbf{0.0}$	$\textbf{0.978} \pm \textbf{0.000}$	$\textbf{102.0} \pm \textbf{1.0}$	$\textbf{0.839} \pm \textbf{0.008}$	$\textbf{680.7} \pm \textbf{0.6}$	$\textbf{0.846} \pm \textbf{0.001}$	
SCIP	$0.0 \pm 0.0$	$0.145 \pm 0.005$	$288.7 \pm 0.6$	$0.834 \pm 0.000$	$41.3 \pm 16.2$	$0.561 \pm 0.010$	$358.0 \pm 7.0$	$0.601 \pm 0.007$	
PBO-IHS-Tuned	$0.0 \pm 0.0$	$0.351 \pm 0.001$	$276.7 \pm 0.6$	$0.793 \pm 0.005$	$55.0 \pm 0.0$	$0.710 \pm 0.004$	$514.7 \pm 1.5$	$0.753 \pm 0.002$	
RoundingSat-Tuned	$0.0 \pm 0.0$	$0.000 \pm 0.000$	$301.7 \pm 1.5$	$0.834 \pm 0.000$	$46.7 \pm 0.6$	$0.762 \pm 0.000$	$397.3 \pm 0.6$	$0.529 \pm 0.001$	
OraSLS-Tuned	$2.0 \pm 0.0$	$0.340 \pm 0.013$	$406.0 \pm 0.0$	$0.962 \pm 0.000$	$51.3 \pm 1.5$	$0.723 \pm 0.001$	$529.3 \pm 0.6$	$0.801 \pm 0.001$	
NuPBO-Tuned	$19.0 \pm 1.0$	$0.996 \pm 0.001$	$454.0 \pm 0.0$	$0.945 \pm 0.000$	$71.7 \pm 2.1$	$0.823 \pm 0.003$	$601.7 \pm 1.5$	$0.818 \pm 0.001$	
AutoPBO	$\textbf{25.3} \pm \textbf{1.2}$	$\textbf{0.997} \pm \textbf{0.000}$	$460.0 \pm 0.0$	$0.944 \pm 0.001$	$70.7 \pm 2.1$	$0.836 \pm 0.001$	$624.7 \pm 1.2$	$0.819 \pm 0.001$	

Table 4: Solver Stability Analysis Across Experiments

# **A Extended Experimental Results**

## A.1 Statistical Analysis of Repeated Experiments

To ensure the reliability and reproducibility of our experimental results, we conducted multiple independent runs of our experiments to evaluate the stability of solver performance across different conditions.

For each benchmark category (Real-world, CRAFT, MIPLIB, and PB16), we calculated the mean  $(\mu)$  and standard deviation  $(\sigma)$  of both win counts and average scores across the experimental runs. The coefficient of variation (CV =  $\sigma/(\mu) \times 100\%$ ) was used as a measure of relative variability to assess the consistency of each solver's performance.

Our statistical analysis reveals that most solvers demonstrate excellent stability across repeated experiments. AutoPBO shows particularly consistent performance with CV values mostly below 5% for both win counts and scores across all benchmark categories. For instance, in the Real-world benchmark, AutoPBO achieves a win count of  $25.3 \pm 1.2$  (CV = 4.6%) and a score of  $0.997 \pm 0.000$  (CV = 0.0%), indicating highly stable performance. Similarly, other solvers like Gurobi, PBO-IHS-Tuned, and RoundingSat-Tuned also exhibit low variability, with most CV values remaining under 3%.

The low variance observed across multiple experimental runs confirms that our results are not artifacts of specific random initializations or environmental conditions, but rather reflect the genuine algorithmic performance of each solver. This statistical validation strengthens the reliability of our comparative analysis and supports the robustness of our experimental conclusions.

#### A.2 Detailed Experimental Results

Tables 5 and 6 present the detailed per-dataset evaluation results of AutoPBO across all 47 datasets, extending the benchmark-level analysis in Section 5.2. These comprehensive results demonstrate that AutoPBO consistently outperforms StructPBO while maintaining competitive performance against state-of-the-art solvers. Specifically, AutoPBO achieves superior performance in both #win and  $avg\_score$  metrics across diverse problem types, further validating its robust performance.

Dataset	StructPBO #win	AutoPBO #win	StructPBO avg_score	AutoPBO avg_score
BA	5	11 (+6)	0.9820	1.0000 (+0.0180)
EmployeeSche	8	9 (+1)	0.8789	0.8889 (+0.0100)
MIPLIB01_267	101	112 (+11)	0.8450	0.8598 (+0.0148)
NG	14	15 (+1)	0.9977	1.0000 (+0.0023)
PBOins_lwsa	1	10 (+9)	0.9949	0.9999 (+0.0050)
PBOins_mwcb	7	10 (+3)	0.9945	0.9997 (+0.0052)
PBOins_wsno	9	9	1.0000	1.0000
area	13	15 (+2)	0.9810	1.0000 (+0.0190)
areaDelay	15	15	1.0000	1.0000
bounded_golo	9	9	0.4444	0.4444
course-ass	2	3 (+1)	0.9998	1.0000 (+0.0002)
crafted_opb	488	513 (+25)	0.9472	0.9474 (+0.0002)
cudf	11	11	0.5455	0.5455
data	30	39 (+9)	0.4452	0.5223 (+0.0771)
decomp	2	5 (+3)	0.9333	1.0000 (+0.0667)
domset	8	8	1.0000	1.0000
dt-problems	30	30	1.0000	1.0000
factor	86	88 (+2)	0.8756	0.9066 (+0.0310)
fctp	16	16	0.1250	0.1250
featureSubsc	10	10	1.0000	1.0000
flexray	5	5	0.4000	0.4000
frb	20	20	1.0000	1.0000
garden	4	4	1.0000	1.0000
golomb-ruler	6	8 (+2)	0.6433	0.6589 (+0.0156)
graca	10	10	1.0000	1.0000
•	4	4	1.0000	1.0000
haplotype heinz	20	23 (+3)	0.6494	0.6522 (+0.0028)
kullmann	3		0.9826	
		4 (+1)		1.0000 (+0.0174)
logic-synthe	36	37 (+1)	0.9989	1.0000 (+0.0011)
market-split	11	20 (+9)	0.3244	0.5500 (+0.2256)
milp	17	17	0.7059	0.7059
minlplib	49	49	1.0000	1.0000
miplib	36	51 (+15)	0.7706	0.7665 (-0.0041)
mps	2	2	1.0000	1.0000
oliveras	57	63 (+6)	0.9975	0.9992 (+0.0017)
pbfvmc-formu	11	11	1.0000	1.0000
poldner	3	3	1.0000	1.0000
primes-dimac	75	77 (+2)	0.8077	0.8332 (+0.0255)
radar	6	6	1.0000	1.0000
random	13	22 (+9)	0.7725	0.7727 (+0.0002)
routing	8	8	1.0000	1.0000
synthesis-pt	5	5	1.0000	1.0000
trarea_ac	5	5	1.0000	1.0000
ttp	3	4 (+1)	0.9965	1.0000 (+0.0035)
unibo	17	18 (+1)	0.3886	0.3889 (+0.0003)
vtxcov	8	8	1.0000	1.0000
wnq	4	7 (+3)	0.9895	0.9971 (+0.0076)
Total	1303	1429 (+126)	0.8738	0.8849 (+0.0110)

Table 5: AutoPBO vs StructPBO Performance Comparison (By Dataset)

	G	urobi	S	SCIP	PBO-	IHS-Tuned	Round	ingSat-Tuned	Oras	SLS-Tuned	NuP	BO-Tuned	Au	toPBO
Dataset	#win	$avg\_score$		$avg\_score$				$avg\_score$		$avg\_score$	#win	avg_score	#win	ava_score
BA	13	0.9995	0	0.2554	0	0.8295	0	0.0000	1	0.8780	0	0.9676	3	0.9830
EmployeeSc	7	0.7579	1	0.0000	2	0.5786	1	0.0000	6	0.8195	8	0.8789	9	0.8889
MIPLIB01_2	101	0.8313	33	0.5625	55	0.7051	47	0.7619	53	0.7236	74	0.8259	73	0.8367
NG	11	0.9466	0	0.0000	0	0.8847	0	0.0000	0	0.9176	7	0.9847	7	0.9847
PBOins_lws	0	0.0811	0	0.0000	0	0.0000	0	0.0000	0	0.0000	3	0.9957	9	0.9997
PBOins_mwc	2	0.8082	0	0.1080	0	0.6113	0	0.0000	0	0.2956	9	0.9950	10	0.9970
PBOins_wsn	1	0.7144	0	0.3599	0	0.4305	0	0.0000	2	0.7871	7	0.9962	7	0.9962
area	15	1.0000	8	0.8974	10	0.9265	14	0.9892	10	0.9430	13	0.9769	14	0.9949
areaDelay	15	1.0000	0	0.8691	8	0.9690	14	0.9957	6	0.9683	15	1.0000	15	1.0000
bounded_go	5	0.5215	3	0.2753	4	0.6140	2	0.0000	7	0.6610	3	0.2561	3	0.3172
course-ass	3	1.0000	1	0.7863	1	0.9871	2	0.9998	2	0.9976	2	0.9998	3	1.0000
crafted_op	479	0.9783	289	0.8337	277	0.7959	302	0.8341	406	0.9620	454	0.9447	460	0.9449
cudf	6	0.5455	6	0.5455	10	0.9987	6	0.5455	4	0.3636	6	0.5455	6	0.5455
data	42	0.6591	13	0.1445	13	0.3422	18	0.3950	19	0.5079	16	0.4398	17	0.4517
decomp	1	0.7381	0	0.7788	0	0.3150	0	0.0000	0	0.9355	1	0.9206	5	1.0000
domset	1	0.9872	0	0.9035	0	0.9774	0	0.0000	0	0.9269	7	0.9993	8	1.0000
dt-problem	30	1.0000	30	1.0000	30	1.0000	16	0.5333	24	0.8000	30	1.0000	30	1.0000
factor	96	0.9583	96	0.9583	96	0.9583	96	0.9583	96	0.9583	96	0.9583	87	0.9006
fctp	16	0.1250	15	0.1211	14	0.0000	14	0.0000	16	0.1250	16	0.1250	16	0.1250
featureSub	3	0.9869	0	0.7037	10	1.0000	10	1.0000	10	1.0000	10	1.0000	10	1.0000
flexray	5	0.4000	5	0.4000	5	0.4000	5	0.4000	3	0.0000	5	0.4000	5	0.4000
frb	2	0.9966	0	0.9880	0	0.9942	0	0.9808	0	0.9922	20	1.0000	20	1.0000
garden	3	0.9057	1	0.8628	3	0.7500	2	0.9256	2	0.9050	4	1.0000	4	1.0000
golomb-rul	6	0.6599	5	0.5486	8	0.7300	1	0.0000	7	0.6667	4	0.5707	3	0.5740
graca	10	1.0000	0	0.0098	9	0.9997	10	1.0000	10	1.0000	10	1.0000	10	1.0000
haplotype	4	1.0000	0	0.3886	3	0.9931	4	1.0000	4	1.0000	4	1.0000	4	1.0000
heinz	18	0.6515	8	0.3848	15	0.6131	14	0.5739	14	0.5598	18	0.6487	19	0.6487
kullmann	2	0.8196	0	0.3577	2	0.8122	0	0.0000	1	0.6816	3	0.9817	4	1.0000
logic-synt	36	0.9986	12	0.8932	35	0.9459	23	0.9250	25	0.0010	36	0.9989	37	1.0000
market-spl	20	0.5500	11	0.8932	9	0.0130	9	0.1705	12	0.3659	11	0.2544	11	0.3186
milp	17	0.8235	5	0.2727	9	0.5556	10	0.1705	13	0.6964	7	0.2344	7	0.5389
minlplib	38	0.9972	9	0.2727	14	0.7229	12	0.9620	10	0.9612	36	0.9197	36	0.9994
miplib	52	0.8946	16	0.3904	25	0.6048	5	0.0000	27	0.7191	25	0.7028	28	0.7099
	1	1.0000	2	1.0000	0	0.8824	2	1.0000	2	1.0000	2	1.0000	20	1.0000
mps oliveras	47	0.7930	21	0.4640	47	0.8322	47	0.8998	70	1.0000	42	0.9790	41	0.9800
pbfvmc-for	10	0.7930	1	0.5562	0	0.5031	2	0.4258	3	0.5180	11	1.0000	11	1.0000
poldner	3	1.0000	2	0.9841	3	1.0000	3	1.0000	3	1.0000	3	1.0000	3	1.0000
primes-dim	73	0.8205	57	0.6871	68	0.7436	10	0.0000	72	0.8290	70	0.8073	73	0.8329
radar	6	1.0000	0	0.0871	6	1.0000	2	0.9770	3	0.8290	6	1.0000	6	1.0000
random	22	0.7727	6	0.5740	22	0.7727	22	0.7727	22	0.7727	13	0.7725	22	0.7727
routing	8	1.0000	5	0.6250	8	1.0000	8	1.0000	8	1.0000	8	1.0000	8	1.0000
synthesis-	5	1.0000	3	0.0230	5	1.0000	5	1.0000	3	0.9869	5	1.0000	5	1.0000
trarea_ac	5	1.0000	2	0.9743	3	0.9704	0	0.0000	3	0.9636	5	1.0000	5	1.0000
	1	0.7154	1	0.9822	0	0.9704	0	0.0000	1	0.9636	2	0.9894	4	1.0000
ttp unibo	16	0.7134	8	0.7040	13	0.9290	8	0.0000	10	0.3394	8	0.9894	8	0.3161
vtxcov	5	0.4833	0	0.1142	3	0.4908	0	0.0000	0	0.3881	8	1.0000	8	1.0000
	1	0.9993	0	0.0000	0	0.9572	0	0.0000	0	0.3860	4	0.9895	7	0.9995
wnq Total	1263	0.9719	675	0.6660	845	0.9372	746	0.6442	990	0.3800			1183	0.8687
Total	1203	0.0030	0/3	0.0000	043	0.7333	740	0.0442	J 990	0.0404	1147	0.8668	1103	0.808/

Table 6: Multi-Solver Performance Comparison (By Dataset)