NLocalSAT: Boosting Local Search with Solution Prediction

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\section*{Abstract}

The boolean satisfiability problem is a famous NP-complete problem in computer science. An effective way for this problem is the stochastic local search (SLS). However, in this method, the initialization is assigned in a random manner, which impacts the effectiveness of SLS solvers. To address this problem, we propose NLocalSAT. NLocalSAT combines SLS with a solution prediction model, which boosts SLS by changing initialization assignments with a neural network. We evaluated NLocalSAT on five SLS solvers (CCAnr, Sparrow, CPSparrow, YalSAT, and probSAT) with problems in the random track of SAT Competition 2018. The experimental results show that solvers with NLocalSAT achieve $27\% \sim 62\%$ improvement over the original SLS solvers.

\section{Introduction}

Boolean satisfiability (also referred to as propositional satisfiability and abbreviated as SAT) is the problem to determine whether there exists a set of assignments for a given boolean formula to make the formula evaluate to true. SAT is widely used in solving combinatorial problems, which are generated from various applications, such as program analysis \cite{harris2010}, program verification \cite{leino2010}, and scheduling \cite{kasi2013}. These applications first reduce the target problem into a SAT formula and then find a solution using a SAT solver. However, the SAT problem has proven to be NP-complete \cite{cook1971}, which means that algorithms for solving SAT problems may need exponential time in the worst case. Therefore, many techniques have been proposed to increase the efficiency of the search process of SAT solvers.

The state-of-the-art SAT solvers can be divided into two categories, CDCL (Conflict Driven Clause Learning) solvers and SLS (Stochastic Local Search) solvers. CDCL solvers are based on the deep backtracking search, which assigns one variable each time and backtracks when a conflict occurs. On the other hand, SLS solvers initialize an assignment for all variables and then find a solution by constantly flipping the assignment of variables to optimize some score.

Over the last few years, artificial neural networks have been widely used in many problems \cite{edwards2010, simonyan2015, edwards2016}. The boolean satisfiability problem is a famous NP-complete problem in computer science. An effective way for this problem is the stochastic local search (SLS). However, in this method, the initialization is assigned in a random manner, which impacts the effectiveness of SLS solvers. To address this problem, we propose NLocalSAT. NLocalSAT combines SLS with a solution prediction model, which boosts SLS by changing initialization assignments with a neural network. We evaluated NLocalSAT on five SLS solvers (CCAnr, Sparrow, CPSparrow, YalSAT, and probSAT) with problems in the random track of SAT Competition 2018. The experimental results show that solvers with NLocalSAT achieve $27\% \sim 62\%$ improvement over the original SLS solvers.

In this paper, we propose NLocalSAT, which is the first method that uses a neural network to boost SLS solvers and the first off-line method to boost SAT solvers with neural networks. Different from NeuroCore which induces large overhead to CDCL by an on-line prediction \cite{selsam2019}, NLocalSAT uses the prediction in an off-line way. In this method, the neural network is computed only once for each SAT problem.

In our proposed method, we first train a neural network to predict the solution space of a SAT problem. Then, we combine SLS solvers with the neural network by modifying the solvers' initialization assignments under the guidance of the output of the neural network. Such combination induces limited overhead, and it can easily be applied to SLS solvers. Furthermore, we evaluated SLS solvers, and NLocalSAT solves $27\% \sim 62\%$ more problems than the original SLS solvers. Such experimental results show the effectiveness of NLocalSAT.

\textbf{Contributions} (1) We train a neural network to predict the solution of a SAT problem. (2) We propose a method to boost SLS solvers by modifying its initialization of assignments

\textsuperscript{1}The on-line prediction means to predict every certain interval in CDCL.
with the guidance of predictions of the neural network. (3) To the best of our knowledge, we are the first to combine the SLS with a neural network model and we are the first to propose an off-line method to boost SAT solvers with a neural network.

2 Approach

Figure 1 shows an overview of our model, NLocalSAT. Our model combines a neural network and an SLS solver. Given a satisfiable input formula, the neural network is to output a candidate solution and the solver is to find a final solution with the guidance of the neural network. For an input formula, we first transfer it into a formula graph, which is further fed to a graph-based neural network for extracting features. Then, different from previous works, where the neural network is to predict the satisfiability of the whole problem in NeuroSAT and to predict whether the variable is in the unsatisfiable core in NeuroCore, the neural network in NLocalSAT outputs a candidate solution for the formula by a multi-layer perceptron after the neural network. We use this candidate solution to initialize the assignments of an SLS SAT solver to guide the search process.

2.1 Formula Graph

To take the structural information of an input formula into consideration, we first transfer it into a formula graph. A general boolean formula can be any expressions consisting of variables, conjunctions, disjunctions, negations, and constants. All boolean formulas can be reduced into an equisatisfiable conjunctive normal form (CNF) with linear length in linear time [Tseitin, 1983]. In a CNF, a SAT problem is a conjunction of clauses \( C_1 \land C_2 \land \cdots \land C_n \). Each clause is a disjunction of literals (i.e., variables and negated variables) \( C_i = L_{i1} \lor L_{i2} \lor \cdots \lor L_{in} \), where \( L_{ij} = x_k \) or \( L_{ij} = \neg x_k \). In this paper, we assume that all SAT problems are in CNFs.

A SAT problem \( S \) in the CNF can be seen as a bipartite graph \( G = (C, L, E) \), where \( C \) (clause set of \( S \)) and \( L \) (literal set of \( S \)) are the node sets of \( G \) and \( E \) is the edge set of \( G \). \((c, l)\) is in \( E \) if and only if the literal \( l \) is in the clause \( c \). \( A \) is the adjacent matrix of the bipartite graph \( G \). The element \( A_{ij} \) of the adjacent matrix equals to one when there is an edge between node \( i \) and node \( j \), otherwise 0. For example, \((x_1 \lor x_2) \land \neg(x_1 \land x_3)\) is a boolean formula. This boolean formula can be converted into \((x_1 \lor x_2) \land (\neg x_1 \lor \neg x_3)\) in the conjunctive normal form. The bipartite graph for this problem is shown in Figure 2. The adjacency matrix for this graph is

\[
A = \begin{pmatrix}
1 & 0 & 1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 1
\end{pmatrix}.
\]

2.2 Graph-Based Neural Network

The graph-based neural network aims to predict the candidate solution for a SAT problem. The network consists of a gated graph convolutional network to extract structural information about the graph and a two-layer perceptron to predict the solution.

Gated Graph Convolutional Network

Inspired by NeuroSAT [Selsam et al., 2019], we use a similar gated graph convolutional network (GGCN) to extract features of variables. The gated graph convolutional network (GGCN) takes the adjacency matrix as the input and outputs the features of each variable extracted from the graph.

In a SAT problem, the satisfiability is not influenced by the names of clauses and literals (e.g., the satisfiability of two formulas \((x_1 \lor x_2), (x_3 \lor x_4)\)). To use this property, for an input formula graph \( G \), we initialize each clause \( c_i \in G \) as a vector \( e_{\text{init}} \in \mathbb{R}^d \), each literal \( l_i \in G \) as another vector \( l_{\text{init}} \in \mathbb{R}^d \), where \( d \) is the embedding size and \( d \) is set to 64 in this paper. These vectors are further fed to GGCN to extract structural information in the graph.

Each iteration of GGCN is an update for the vectors of these nodes where each node updates its vector by taking its neighbors’ information (vectors). Formally, at the \( t \)-th iteration, the detailed computations for clause \( c \) and literal \( l \) are represented by

\[
c_t = \text{LSTMCell}(c_{t-1}, \sum_{l' \in G} \hat{A}_{cl} l'_{t-1}) \tag{1}
\]

\[
l_t = \text{LSTMCell}(l_{t-1}, \sum_{c' \in G} \hat{A}_{c'l} c'_{t} + \neg l_{t-1}) \tag{2}
\]

Here, \( \hat{A} \) is a normalized adjacency matrix for the graph (the detailed computation is presented in Equation 3). \( l'_t \) and \( c'_t \) denote the vector of the literal \( l' \) and clause \( c' \) at the \( t \)-th iteration. \( \neg l_t \) is the vector of the negated literal of \( l \) at the \( t \)-th iteration. \( c_0 = c'_0 = e_{\text{init}}, l_0 = l'_0 = l_{\text{init}} \). The LSTMCell is a long short-term memory (LSTM) unit with layer normalization.

We use normalization in convolution to improve scalability. Because in a SAT problem, there can be any number of nodes adjacent to one, so if we simply add all vectors together, the summation is unbounded. We use symmetrical normalization

\[
\hat{A} = S_1^{-1/2} AS_2^{-1/2}, \tag{3}
\]
where \( S_1 \) and \( S_2 \) are the diagonal matrices with summation of \( A \) in columns and rows. In the implementation, a small number \( (10^{-6}) \) is added to the diagonal elements of \( S_1 \) and \( S_2 \) to avoid division by zero.

We apply the GGCG layer of 16 iterations on the initial value and get a vector containing structural information about each literal. Then, the two vectors for a literal and its negation are concatenated for each variable.

Two-layer Perceptron
After applying GGCG, vectors of nodes contain structural information of literals. A two-layer perceptron MLP with hidden 512 size is applied on the vector for each variable to extract classification information from the structural information. Through a softmax function, we get the probability for the variable to be true.

\[
P(v = \text{TRUE}) = \text{softmax} \{ W_2 \text{ReLU} [W_1 (1_v : 1_{\neg v}) + b_1] + b_2 \} \tag{4}
\]

where \( W_1, W_2, b_1, b_2 \) are weights and biases for the two perceptrons and the colon indicates the connection of two vectors.

Loss Function
Our model is trained by minimizing the cross-entropy loss against the ground truth. For the predicted variables \( g \), \( v \) is the ground truth of \( v \).

\[
\text{Loss} = - \sum_{i=1}^{n} [g(v_i) \log(P(v = \text{TRUE})) + (1 - g(v_i)) \log(P(v = \text{FALSE}))], \tag{5}
\]

where \( g(v_i) \) denotes the ground truth of \( v_i \).

2.3 Training Data
The goal of our network is to predict the solution to the SAT problem, so we should generate training data for SAT problems with solution labeling. Due to the scarcity of SAT Competition data, using additionally generated small SAT instances could help provide thorough training. We generate two training datasets and train our model in order. Our model is first pretrained with a large number of generated small SAT instances. We generate tens of millions of small SAT instances with solution labeling because these small problems are easy to solve. Such large amounts of data can make the training process more effective and avoid overfitting. These small instances can help our network better learn structural information. Then, our model is fine-tuned on a dataset generated from SAT Competitions. By finely tuning on the dataset from SAT Competition instances, our model can learn specific information in the field and learn to predict the solution on large instances.

Small Generated Instances
We generate small instances containing 10 to 20 variables by a random generator. The number of clauses is 2 to 6 times the number of variables. Each clause contains 3 variables with the probability of 0.8 and 2 variables with the probability of 0.2. Each clause is generated randomly by randomly selecting variables or negated variables from the problem.

After the generation of problems, we solve these problems with a complete backtracking solver. We drop those unsatisfied problems because our model only learns to predict the solution of a satisfiable SAT problem. However, there can be more than one solution for a specific SAT instance, which can confuse the neural network. We depend on the solution space to tackle this problem. The solver maintains a counter for each variable and each negated variable. In the solving process, the solver explores all solutions instead of stopping after one specific solution. When the solver finds a solution, the counters of literals in the solution will increase by 1. When the whole search process finishes, the solver reports for each variable whether the variable itself or its negated form appears more in the solutions. If the variable itself appears more, we label this variable as 1. If the negated variable appears more, we label this variable as 0. We use this value as training labeling for the variable.

After data generation, we pretrain \( \text{NLocalSAT} \) on these small instances. In the implementation, small data instances have higher overhead during model training, so we combine several instances into one larger batch. Since our model is independent of the order of variables, we can simply combine two or more instances via concatenating edges and labels of these instances.

SAT Competition Instances
To train our model on larger instances, we generate training data from SAT problems in random tracks of SAT Competitions. We use a SAT solver to get one solution for each problem. Problems that are not solved by the solver will be removed. We then use the solution as labeling in the training data.

Training on GPU requires more memory than evaluation. So, if the problem is too large to fit in the memory of our GPU during training, we will cut these problems into smaller ones. Let us denote the largest number of variables that can fit into the memory of our GPU as \( N_L \). For every large instance, we first get a solution \( S_0 \) with a SAT solver. Then, we sample \( N_L \) variables \( X_0 \) from all variables. For one clause \( c \) in the original SAT problem, if \( c \) contains no literals from \( X_0 \), the clause is removed. If \( c \) is not satisfied on \( X_0 \) after removing literals that are not from \( X_0 \), the clause is also removed. Clauses with only one literal are also removed to prevent the problem from being too easy. Otherwise, the clause \( c \) remains in the problem. If the sampling generates a problem with too few clauses, the problem is removed because this will lead to too many solutions.

2.4 Combination with Local Search
Stochastic local search algorithms can be considered as an optimization process. The solver flips the assignments of variables to maximize some total score. For example, we can use the number of clauses that evaluate to true as the score. When the score reaches the number of clauses, the problem is solved. Algorithm 1 shows a general algorithm in a local search solver.
was evaluated on problems in the random track of SAT Competition 2012, 2013, 2014, 2016, 2017 (denoted as Dataset\_small) and a dataset with random tracks of SAT Competitions in 2018 (denoted as Dataset\_eval) with 255 SAT instances in total. We found that there are several duplicate problems in 2018 and previous years, so we removed them from the training and validation datasets to ensure problems in the Dataset\_eval are generated with different random seeds with those in Dataset\_comp. So, it’s almost impossible to have isomorphic problems between these two datasets. However, there will be some similar substructures between the training set and the test set, so that neural networks can predict by learning these substructures.

The Dataset\_comp and the Dataset\_eval both contain two categories of problems, i.e., uniformly generated random SAT problems (denoted as Uniform) [Heule, 2018] and hard SAT problems generated with a predefined solution (denoted as Predefined) [Balyo and Chrpa, 2018].

3.2 Pretraining

In Dataset\_small, we generated about $2.5 \times 10^7$ small problems and combined them into about $4 \times 10^6$ batches with about ten thousand variables each as our pretraining dataset. We generated 200 batches in the same approach with different random seeds as validation data during pretraining.

We trained our model to converge using the ADAM [Kingma and Ba, 2015] optimizer with its default parameters by minimizing the cross-entropy of predicted values and label values on Dataset\_small. After pretraining, the precision on the validation dataset is 98%, i.e., the network can predict correctly 98% of variables

### Algorithm 2 Initialization of variables using neural network values

**Data:** Probability $p_0$, Assignment of variables assignment, Neural network predictions $N$

```
for i < number of variables do
    if rand() < $p_0$ then
        assignment[i] ← $N[i]$
    else
        assignment[i] ← $\neg N[i]$
end if
end for
```

3. Experiments

3.1 Datasets

Our model was trained on a dataset with generated problems with small SAT instance (denoted as Dataset\_small) and a dataset with problems in random tracks of SAT Competitions in 2012, 2013, 2014, 2016, 2017 (denoted as Dataset\_comp) (The competition of SAT in 2015 was called SAT Race 2015. There was no random track in SAT Race 2015). Our model was evaluated on problems in the random track of SAT Competition in 2018 (denoted as Dataset\_eval) with 255 SAT instances in total. We found that there are several duplicate problems in 2018 and previous years, so we removed them from the training and validation datasets to ensure problems in the Dataset\_eval are generated with different random seeds with those in Dataset\_comp. So, it’s almost impossible to have isomorphic problems between these two datasets. However, there will be some similar substructures between the training set and the test set, so that neural networks can predict by learning these substructures.

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### Algorithm 3 A general algorithm for stochastic local search solvers with NLocalSAT (The underlined code is the different part from the original solvers)

**Data:** SAT problem $P$

```
N ← predicting solution of $P$ by NLocalSAT;
while End condition not reached do
    S ← initialize assignment with $N$;
    while Restart condition not reached do
        if $P$ evaluate to true under $S$ then
            Return $S$;
        end if
        l ← Select a variable by some heuristics;
        Flip($S$, $l$);
    end while
end while
```

In SLS solvers, it is not counter-intuitive that the initial assignment has a great impact on whether it can quickly find a solution, because there can be many local minima in the problem and badly initialized assignments near a local optimum can cause the SLS solvers to get stuck. Intuitively, the closer to the solution of the problem, the less likely it is to encounter local minima. In order to avoid falling into the local optimum, these solvers restart the searching process by reassigning new random values to variables after a period of time without a score increase. However, most of the existing SLS solvers initialize assignments in a random manner. Random generation of initial values can explore more space for the SAT problem. However, if the distance between initial values and solution values is too large, the solver is more likely to fall into a local optimum.

We propose a new initialization method using the output of our neural network. Before starting the solver, we run our neural network to predict a solution. We replace the initialization function with our neural initialization, where, instead of randomly generating 0 or 1, the function assigns the predicted values to a variable with a probability of $p_0$ and assigns the negation of the predicted value with a probability of $1 - p_0$. This neural-initialization function keeps the assignment with a probability of $p_0$ to explore near the candidate solution and explores new solution space with a probability of $1 - p_0$ in case that the neural networks’ prediction is wrong. The initialization process is shown in Algorithm 2. Algorithm 3 shows the architecture of our modified SLS solvers. Note that our neural network model is executed only once for one SAT problem. Though the cost of computing a neural network is high, the cost of calling a neural network only once is acceptable, which consumes 0.1 seconds to tens of seconds depending on the size of the problem.
whose solution space is larger on these small SAT problems.

3.3 Training

We used Dataset\textsubscript{comp} as the training dataset and the validation dataset. We loaded the pretrained model and continued to train with the same optimizer and loss function. After training, the precision on the validation dataset is 95%.

3.4 Evaluation

We tested our proposed method on five recent SLS solvers, i.e., CCAnr [Cai et al., 2015], Sparrow [Balint and Fröhlich, 2010], CPSparrow, YalSAT [Biere, 2016], probSAT [Balint and Schöning, 2014]. These solvers have performed very well among SLS solvers on random tracks of SAT Competitions in recent years. CCAnr is an SLS solver proposed in 2015 to capture structural information on SAT problems. CCAnr is a variant of CCSat [Cai and Su, 2013]. CCAnr performs better on all tracks of SAT Competitions than CCSat. Sparrow is a clause weighting SLS solver. CPSparrow is a combination of Sparrow and a preprocessor Coprocessor [Balint and Manthey, 2013]. CPSparrow is the best pure SLS solver in the random track of SAT Competition 2018. YalSAT is the champion of the random track of SAT Competition 2017.

Due to the strong randomness of SLS solvers, the experiments for SLS solvers were performed three times with three different random seeds and then aggregated the results.

We evaluated these original solvers and those modified with NLocalSAT on Dataset\textsubscript{eval}. We also evaluated three other solvers MapleLCMDistChronoBT [Ryvchin and Nadel, 2018], gluHack, and Sparrow2Riss [Balint and Manthey, 2018] under the same set. MapleLCMDistChronoBT and Sparrow2Riss are the champions of SAT Competition 2018 in the main track and the random track. gluHack is the best CDCL solver of SAT Competition 2018 in the random track. MapleLCMDistChronoBT is a CDCL solver with recently proposed techniques to improve performance such as chronological backtracking [Nadel and Ryvchin, 2018], learned clause minimization [Luo et al., 2017], and so on. Sparrow2Riss is a combination of Coprocessor, Sparrow, and a CDCL solver Riss.

We set up a timeout limit to 1000 seconds. Solvers failed to find a solution within the time limit will be killed immediately. Our experiments were performed on a work station with an Intel Xeon E5-2620 CPU and a TITAN RTX GPU. During our experiment, the time for initialization of the GPU environment was ignored but the time of the GPU computation was included in the total time.

4 Results

4.1 Number of Problems Solved

Table 1 shows the number of problems solved in 1000 seconds time limit. Each row represents a tested solver. The experiments of SLS solvers are performed three times to reduce the randomness of results. Each number in the rows of SLS solvers is the average and the standard deviation of results in the three experiments. Each column in the table represents a category of problems in the dataset. The number in parentheses indicates the total number of problems in the category. Dataset\textsubscript{eval} contains unsatisfiable problems [Heule, 2018]. However, no solvers reported unsatisfiability on any problems within the time limit. So, the solved problems in Table 1 are all satisfiable ones.

The experimental result shows that solvers with NLocalSAT solve more problems than the original ones. CCAnr, Sparrow, CPSparrow, YalSAT, and probSAT with NLocalSAT solve respectively 41%, 30%, and 27%, 62%, and 62% more problems than the original solvers. This improvement has been shown in Predefined problems and in Uniform problems on Sparrow and CPSparrow. Sparrow with NLocalSAT and CPSparrow with NLocalSAT solve more problems than all other solvers including the champions on SAT Competition 2018. Sparrow2Riss is a combination of a preprocessor, an SLS solver, and a CDCL solver, thus showing good performance, but the SLS solvers with NLocalSAT still outperforms Sparrow2Riss. CDCL solvers perform well on Predefined problems and NLocalSAT can help to improve performance particularly on this category, from which we can conclude that NLocalSAT can improve particularly on those problems, on which CDCL solvers perform well. NLocalSAT may capture some structural information to boost SLS solvers on these problems.

4.2 Time of Solving Problems

Figure 3 shows the relationship between the number of problems solved and time consumption comparing solvers with NLocalSAT and without NLocalSAT. In this figure, we can see that some simple problems which are solved within 1 second with the original solver need more solving time with NLocalSAT than the original solver. This is because the neural network computation takes a certain amount of time before the solver starts and this time is especially noticeable for simple problems. But on hard problems, our modifications can improve the solver significantly.

Table 2 compares the average running time with the timeout penalty (PAR-2) between different solvers. The PAR-2 running time of problems that are not solved by the solver in the time limit is twice of the time limit (i.e., 2000 seconds in our experiments). The PAR-2 score was used in previous
SAT Competitions. Values in this table show that solvers with \textit{NLocalSAT} are slightly slower on easy problems but much faster on hard problems, particularly, on \textit{Predefined}. Solvers with \textit{NLocalSAT} can find a solution faster than those without \textit{NLocalSAT} on most problems, i.e., solvers with \textit{NLocalSAT} are more effective than the original ones.

5 Related Work

Recently, several studies have investigated how to make use of neural networks in solving NP-complete constraint problems. There are two categories of methods to solve NP-complete problems using neural networks. The first category of methods is end-to-end approaches using end-to-end neural networks to solve problems, i.e., given the problem as an input, the neural network outputs the solution directly. In these methods, the neural network can learn to solve the problem itself [Amizadeh \textit{et al.}, 2019; Galassi \textit{et al.}, 2018; Selsam \textit{et al.}, 2019; Xu \textit{et al.}, 2018; Prates \textit{et al.}, 2019]. However, due to the accuracy and structural limitations of neural networks, the end-to-end methods can only solve small problems. The other category of methods is heuristic methods that treat neural networks as heuristics [Balunovic \textit{et al.}, 2018; Li \textit{et al.}, 2018; Selsam and Björner, 2019]. Among these methods, traditional solvers work with neural networks together. Neural networks generate some predictions, and the solvers will use these predictions as heuristics to solve the problem. Constraints in the problems can be maintained in the solver, so these methods can solve large-scale problems. Our proposed method (i.e., \textit{NLocalSAT}) belongs to the second category, heuristic methods, so \textit{NLocalSAT} can be used for larger instances than those end-to-end methods. Balunovic \textit{et al.} [Balunovic \textit{et al.}, 2018] proposed a method to learn a strategy for Z3, which greatly improves the efficiency of Z3. Li \textit{et al.} [Li \textit{et al.}, 2018] proposed a model on solving maximal independent set problems with a tree search algorithm. NeuroCore [Selsam and Björner, 2019] is a method to improve CDCL solvers with predictions of unsat-cores. None of these methods is used to boost stochastic local search solvers with solution predictions and none of these is an offline method to boost SAT solvers. The training data used in \textit{NLocalSAT} are solutions of problems or solution space distribution of problems, which is also different from previous works, where NeuroSAT uses the satisfiability of problems and NeuroCore uses unsat-core predictions.

6 Conclusion and Future Work

This paper explores a novel perspective of combining SLS with a solution prediction model. We propose \textit{NLocalSAT} to boost SLS solvers. Experimental results show that \textit{NLocalSAT} significantly increases the number of problems solved and decreases the solving time for hard problems. In particular, Sparrow and CPSparrow with our proposed \textit{NLocalSAT} perform better than state-of-the-art CDCL, SLS, and hybrid solvers on the random track of SAT Competition 2018.

\textit{NLocalSAT} can boost SLS SAT solvers effectively. With this learning-based method, we may build a domain-specific SAT solver without expertise in the domain by training \textit{NLocalSAT} with SAT instances from the domain. It is also interesting to further explore building domain-specific solvers with \textit{NLocalSAT}.
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