Parameter Setting in SAT Solver using Machine Learning Techniques

Filip Beskyd and Pavel Surynek[a]
Faculty of Information Technology, Czech Technical University, Thákurova 9, 160 00 Praha 6, Czech Republic

Keywords: SAT Problem, Boolean Satisfiability, Solver, Graph Structure, Machine Learning, Heuristic Parameter Tuning.

Abstract: Boolean satisfiability (SAT) solvers are essential tools for many domains in computer science and engineering. Modern complete search-based SAT solvers represent a universal problem solving tool which often provide higher efficiency than ad-hoc direct solving approaches. Over the course of at least two decades of SAT related research, many variable and value selection heuristics were devised. Heuristics can usually be tuned by single or multiple numerical parameters prior to executing the search process over the concrete SAT instance. In this paper we present a machine learning approach that predicts the parameters of heuristic from the underlying structure of the input SAT instance.

1 INTRODUCTION

The Boolean satisfiability (SAT) problem, the task of finding a truth-value assignment of a given Boolean formula, is one of the fundamental computer science problems (Biere et al., 2009). Concretely; the SAT problem was the first one to be proven to belong to the NP-Complete class of problems (Cook, 1971). Major direct use-cases of SAT come from industries such as software testing (Dennis et al., 2006), automated planning (Kautz and Selman, 1992), hardware verification (Gupta et al., 2006) or cryptography (Soos et al., 2009), as well as many other. Moreover, many other problems of computer science are often reduced to SAT.

Standard and in practice often used way of solving a given problem is to compile it, in some way, to a concrete SAT instance which is then given to another program as an input, so called a SAT Solver. The SAT solver solves the instance and answers whether there exists a truth-value assignment by which it can be satisfied or not, with the concrete proof, that is either variables assignment which satisfy the formula or conflict.

There exist many solvers to the SAT problem. Solvers are divided into two major groups, **local search** and **systematic search** solvers. This work is focused on systematic search solvers based on the Conflict-driven clause-learning (CDCL) algorithm (Marques Silva and Sakallah, 1996) whose implementations come as variants of the Minisat (Niklas Eén, 2004) solver.

CDCL SAT solvers have witnessed dramatic improvements in their efficiency over the last 20 years, and consequently have become drivers of progress in many areas of computer science such as formal verification (Newsham et al., 2015). There is a general agreement that these solvers somehow exploit structure inherent in industrial instances due to the clause learning mechanism and its cooperation with variable and value selection heuristics.

Typically, implementations of CDCL SAT solvers have many parameters, such as variable decay, clause decay and frequency of restarts, which need to be set prior to the solver being executed. Depending on how various parameters are set for an input instance often has significant impact on the running time of the solver. Hence it naturally makes sense to try to set these parameters automatically.

The paper is organized as follows: in Section 3 we introduce related works, Section 4 states which parameters will be tuned and briefly explains their meaning, Section 5 measures the impact of each parameter on solving time, Section 6 presents how we applied machine learning to our problem and finally in Section 7 we evaluate our machine learning parameter setting in various benchmarks.

[a] https://orcid.org/0000-0001-7200-0542

Beskyd, F. and Surynek, P.
Parameter Setting in SAT Solver using Machine Learning Techniques.
DOI: 10.5220/0010910200003116
In *Proceedings of the 14th International Conference on Agents and Artificial Intelligence (ICAART 2022) - Volume 2*, pages 586-597
ISBN: 978-989-758-547-0; ISSN: 2184-433X

2 CONTRIBUTION

In this work we apply **machine learning** techniques (Mitchell, 1997) to predict the values for the parameters of SAT solver which reduce solving time, based on the type of an input instance. This step is motivated among else by notion that many instances for a fixed domain are in some way similar thus formula's hidden structure will be similar as well.

For example the structure of most industrial SAT instances are vastly different from the structure of the random SAT instances (Ansótegui et al., 2012) or instances constructed for planning problems, and these are different from instances encoding puzzles like the pigeon-hole problem. Problems that belong to the same class tend to have similar structure within the class and specific values of the parameters work better for them, than having the default parameter setting globally for every instance.

Our contribution presented in this paper consists in:

1. Visual summary of dependencies of solving time on setting of various parameters of the SAT solver.
2. Extending the set of usual features extracted by SAT solvers from instances, by computing graph related features on clause graph (CG), and variable–clause graph (VCG), which ought to better capture the underlying structure of the instance.
3. Building a machine learning mechanism based on the extended set of features that sets the SAT solver's parameters according to the input instance.

3 RELATED WORK

3.1 Portfolio Solver: SatZilla

SatZilla (Xu et al., 2008) is a portfolio solver, which won many awards in SAT Competition (SAT,). It introduced new approach of using many other solvers (portfolio) in the background. The solvers are used as-is, and SatZilla does not have any control over their execution.

Machine learning was previously shown to be an effective way to predict the runtime of SAT solvers, and SatZilla exploits this. It uses machine learning to predict hardness of the input instance, and then based on this prediction select a solver from its portfolio which will be assigned to solve the problem. This works because different solvers are better for different types of instances. Predicting hardness of an instance is done by first extracting various features from the input.

To train the model, SatZilla will first compute some features on training set of problem instances and run each algorithm in the portfolio to determine its running times. When the new input instance comes, it computes its features. These are then used as input for predictive model which predicts the best solver to be used. That particular solver is then used to solve instance.

3.2 Parameter Tuning: AvatarSat

AvatarSat (Ganesh et al., 2009) is a modified version of Minisat 2.0 which introduced two key novelties.

First one is that it used machine learning to determine the best parameter settings for each SAT formula.

Second novelty in AvatarSat is the "course correction" as it dynamically "corrects" the direction in which solver is searching. Modern SAT solvers store new learnt clauses and drop input clauses during the search, which can change the structure of the problem considerably. AvatarSat's argument is that the optimal parameter settings for this modified problem may be significantly different from the original input problem.

Input SAT instances are classified using 58 different features of SAT formulas such as ratio between variables and clauses, number of variables, number of clauses, positive and negative literal occurrences etc.

AvatarSat is tuning only two parameters, `-var-decay` and `-rinc`, nine values for the first one and three for the second one, so the number of examined configurations is 27.

3.3 Iterated Local Search

The key idea underlying iterated local search is to focus the search not on the full space of all candidate solutions but on the solutions that are returned by some underlying algorithm, typically a local search heuristic. (Lourenço et al., 2010)

Iterated local search is a local search algorithm that optimizes parameters but only one dimension at a time, it is a one-dimensional variant of hill climbing.

In (Pintjuk, 2015) author has used this algorithm for MiniSat's parameter tuning. There was not feature extraction approach as in AvatarSat, SatZilla and this paper, but it was an attempt to tune SAT solvers parameters and therefore we mention his solution in this chapter. Results were measured only on factorization problem instances.

4 TUNED PARAMETERS

We will tune the following heuristics settings of MiniSat solver as these have the most significant impact on the solver's running time.

- `-var-decay` the VSIDS's decay factor
- `-cla-decay` the clause decay factor
- `-rfirst` base restart interval
- `-rinc` restart interval increase factor

4.1 VSIDS

VSIDS is an abbreviation of *variable state independent decaying sum*. VSIDS has become a standard choice for many popular SAT solvers, such as MiniSat (Niklas Eén, 2004) which we employed as default solver for this paper.

The main idea of VSIDS heuristic is to associate each variable with an *activity*, which signifies a variable's frequency of appearing in recent conflicts via the mechanism of *bump* and *decay*.

Bump is a number which is incremented by 1 every time this variable appears in conflict.

Decay factor $0 < \alpha < 1$ is a number by which each of the variable's activity is multiplied after each conflict and thus decreased.

4.2 Clause Decay

In MiniSat, similar principle as in VSIDS is applied to clauses. When a learnt clause is used in the conflict analysis, its activity is incremented. Inactive clauses are periodically removed from the *learnt clauses database* (Niklas Eén, 2004). Since a set of unsatisfiable clauses generates many conflicts, and therefore many conflict clauses, the high activity of a clause can be seen as a potential sign of unsatisfiability. (D'Ippolito et al., 2010)

4.3 Restart Frequency

Frequency of restarts in MiniSat is determined by two parameters, the *base restart interval* and *restart interval increase factor*. One round of search will take as long until the search encounters given number of conflicts *L*. For example, `minisat(120)` will be searching space of assignments as long as it reaches count of conflicts equal to 120. After that, the algorithm will pause, determine new number of needed conflicts to force next restart, and continue searching.

Number of needed conflicts to restart *L* is determined as follows:

$$L = \texttt{restart\_base} \cdot \texttt{restart\_inc\_factor}^{\#restarts}.$$

5 IMPACT OF PARAMETERS

The term "structure", due to its vagueness, leaves much room for interpretation, though, and it remains unclear how this structure manifests itself and how exactly it should be exploited. (Sinz and Dieringer, 2005)

However, research has advanced since then, and nowdays the structure of some instances can be exploited.

Base idea of this paper comes from (Ansótegui et al., 2012), where it was shown that industrial instances exhibit "hidden structures" based on which solver is learning clauses during search. In (Pipatsrisawat and Darwiche, 2007) researchers have shown that formulas with good community structure tend to be easier to solve.

Variables form logical relationships and we hypothesize that VSIDS exploit these relationships to find the variables that are most "constrained" in the formula. The logical relationship between variables are concretized as some variation of the variable incidence graph (VIG). (Liang, 2018)

Our idea is to exploit this fact, so we will construct three types of graphs which are representing each instance, compute various properties of this graph which will be used as features for machine learning, in addition to standard features of the instance like number of variables, clauses, their ratios etc.

This section is dedicated to present results of our initial data exploration. We performed several observations on four different classes of problems, on which we observe how the solver's parameters affect then number of conflicts, and thus solving time.

5.1 Classes of Selected SAT Instances

In this paper we limited ourselves to the following SAT problem's **structurally diverse** classes, for which we expected different demands on parameters.

- Random SAT/UNSAT
- Pigeonhole problem
- Planning
  - $n^2 - 1$ problem
  - Hanoi towers
- Factorization

Random SAT/UNSAT are instances of 3-SAT problem, generated randomly. This class of problems if used as benchmark in SAT competition, this the category's name is *RANDOM*.

Pigeonhole problem involves showing that it is impossible to put $n+1$ pigeons into n holes if each pigeon must go into a distinct hole. It is well known that for this combinatorial problem there is no polynomial-sized proof of the unsatisfiability. (Haken, 1984) Combinatorial problems are part of SAT competition benchmarks as well, known as *CRAFTED*. We chose pigeonhole problem as one representative, because it can be generated easily with random starting positions with fixed size.

As **Planning** problems representatives we chose problem known as $n^2 - 1$ *problem*, or in its fixed size $(n = 4)$ form *Lloyd's fifteen*. We generated numbered tiles order randomly, and aggregated these instances always within fixed size, E.g., we never combined problem of size 4x4 with 5x5. Another representative of planning is Hanoi towers problem, this problem is not possible to "randomize" because initial state is always given, we included this problem to observe whether it will exhibit similarities to our other planning problem.

Factorization problem is problem of determining whether a big number is a prime. It is an example of *INDUSTRIAL* instance from SAT competitions.

5.2 Correlation of Number of Conflicts and Solving Time

For the initial dataset building process, it is necessary to find close to optimal solver parameters for which the solving time is lowest possible.

Because some harder instances take several tens of seconds to solve, it would be unfeasible to generate dataset from solving each of these instances by brute force search on grid of parameter values, thus we decided to build this dataset from small instances from SATLIB. These instances are usually solved within fraction of second by Minisat solver, but this approach comes with a trade-off, it is hard to capture real solving time, because for these small instances overhead can outweigh useful computation time.

Solving time varies a bit with every run and solving time captured by MiniSat also includes several system-originated factors which are not desired. However, computation is deterministic with fixed initial random seed, so it is natural to use number of conflicts as other metric instead of actual solving time.

Scatter plot in Figure 1 shows strong correlation between the number of conflicts and solving time on randomly selected instances from SATLIB. As an implication of this observation it is correct to use conflict count as measurement of performance of the parameters instead of time.

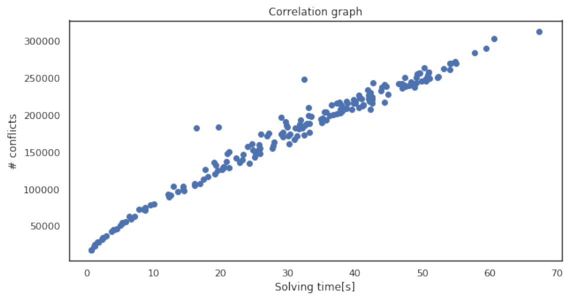


Figure 1: Correlation between number of conflicts and solving time.

5.3 Observed Parameters

Following subsections illustrate how number of conflicts depends on selected parameters for each of aforementioned problem classes. Note that axes do not have same values in each of the examples. Before we made these plots we first analyzed which intervals should we chose to discretize. E.g. we observed that *variable decay* parameter for values in $(0, 0.4)$ always yielded bad results so we excluded those and only examined $[0.4, 1)$. We have omitted label of vertical axis, and it will always be **number of conflicts**.

Following plots in this section were first aggregated by different random seeds, and then aggregated per many instances of the same size.

5.3.1 Variable Decay

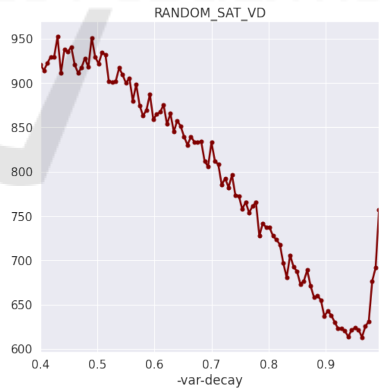


Figure 2: Variable decay on random SAT instances.

For random satisfiable instances shown in Figure 2 it seems that variable decay at around 0.95 gives best results. For unsatisfiable instances the plot is slightly "smoother", this is likely because the solver has to search entire space so there are not many backjumps which would cut "heavy" branches.

From Figure 3 it seems that factorization instances require `-var-decay` close to 1. Unsatisfiable variant (prime numbers) is smoother with the same result.

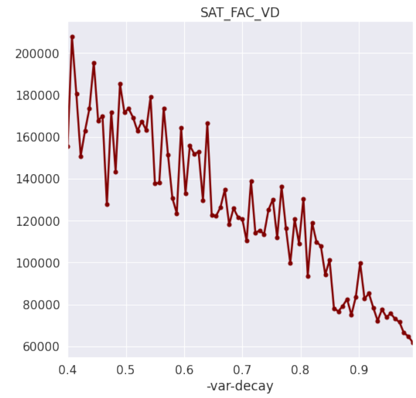
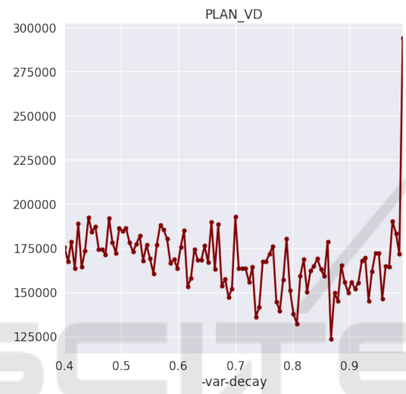
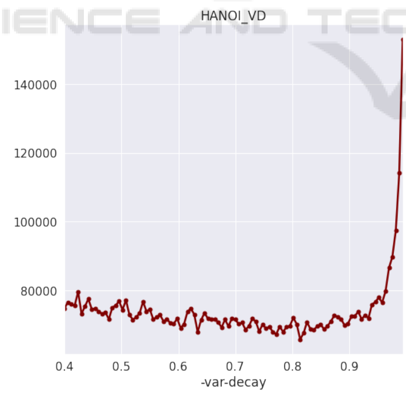


Figure 3: Variable decay on factorization instances.



(a) n^2-1 problem instances.



(b) Hanoi tower planning.

Figure 4: Variable decay on planning instances.

Figure 4 shows that planning instances are very different from previous instances. As `-var-decay` increases from 0.9 higher number of conflicts rises rapidly, this may be signaling that planning instances have variables which are more-less independent, because setting variable decay factor close to value of 1, effectively means algorithm will decay activity of variables very slowly.

Behavior of pigeonhole problem instances was identical to factorization.

5.3.2 Clause Decay

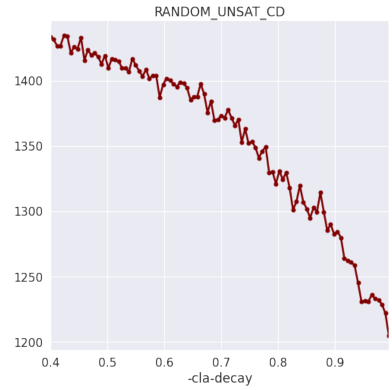
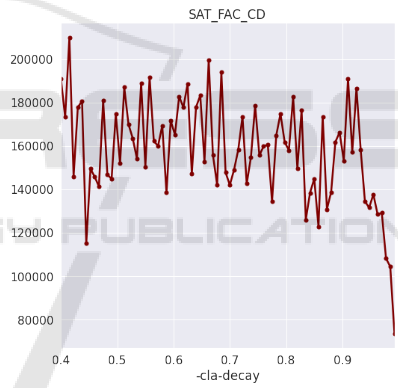
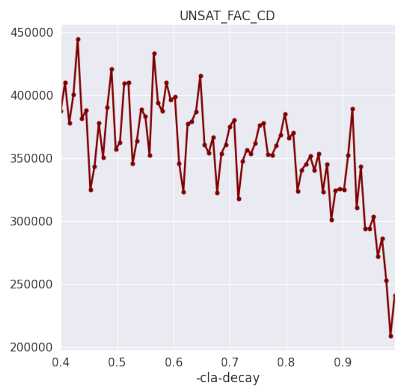


Figure 5: Clause decay on random SAT instances.

Figure 5 shows that it is best to set `-cla-decay` to value very close to 1 for random instances.



(a) Satisfiable.



(b) Unsatisfiable.

Figure 6: Clause decay on factorization instances.

Same conclusion can be seen in Figure 6 for factorization instances, but the trend starts to decrease significantly at the value of 0.93.

For planning instances, we did not observe any dependency, leading us to conclusion that `-cla-decay` parameter does not have significant impact.

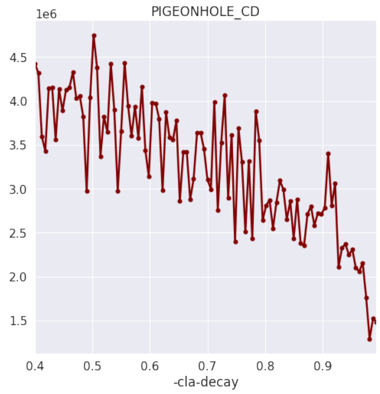


Figure 7: Clause decay on pigeonhole instances.

For pigeonhole problem, Figure 7 shows similar course as for random and factorization instances.

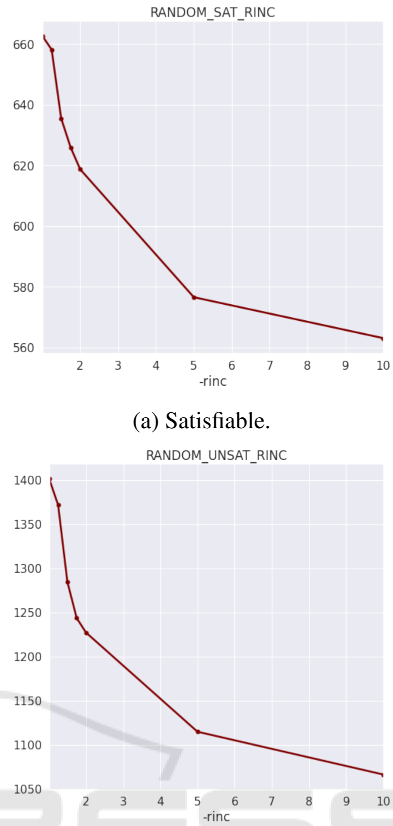
5.3.3 Restart Interval Increase Factor

In Figure 8, higher value seems to be better for random instance, but important note is that the instances on which we performed these aggregations are of smaller size than in SAT competitions (SAT,). For those, these plots could look very different. We hypothesize that for big instances smaller value of this parameter would be better, because if the value is too high, it might mean that longer the solver is running, the interval until next restart will be too high, so the much needed restart would not happen in very long time.

In Figure 9, for not prime instances it was unclear what value could be suitable, prime instances show that values above 10 seems to be fastest.

For planning instances, it is clear from Figure 10 that lower values yield faster solving. There is raising trend, but we think this is dependent on instance size. Lower value means more frequent restarts, that is suggesting that solver is often in local optima, which eventually will not lead to solution and the restart is needed. Hanoi tower problem also required very small value, dependency on this parameter was almost linear.

Plot in Figure 11 shows that for value 5 and higher impact of this parameter does not yield any significant improvement. Higher values are preferred for pigeonhole problem, this means that the problem demands less restarts because it is likely doing useful work, in



(a) Satisfiable.

(b) Unsatisfiable.

Figure 8: Restart interval increase factor on random SAT instances.

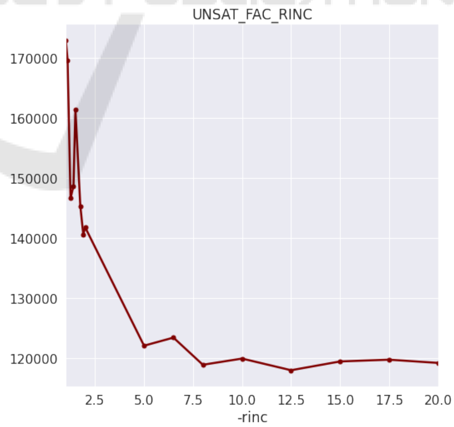


Figure 9: Restart interval increase factor on factorization instances.

other words, the path to solution is narrow so there are not many branches which lead to local optima.

5.3.4 Restart Interval Base

Figure 12 shows that initial restart interval around 200 conflicts seems best for both satisfiable and unsatisfi-

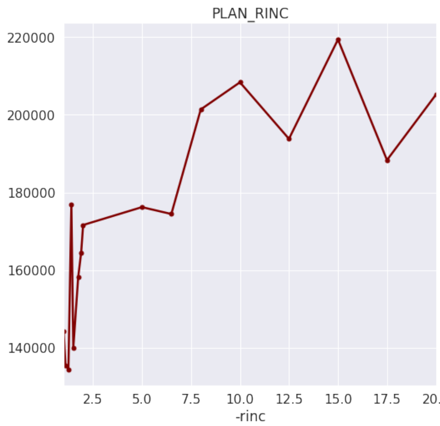


Figure 10: Restart interval increase factor on planning instances.

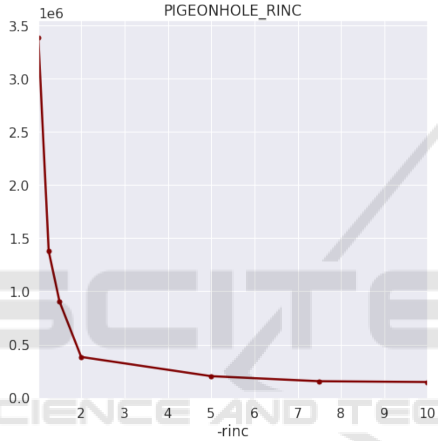


Figure 11: Restart interval increase factor on pigeonhole instances.

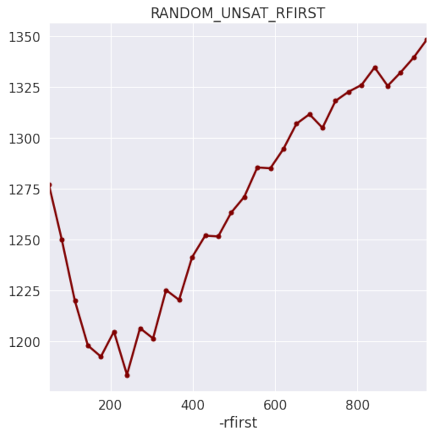


Figure 12: Restart interval base on random SAT instances.

able random instances, this is dependent on the size of the problem.

We did not observe any dependency of `-rfirst` factorization instances.

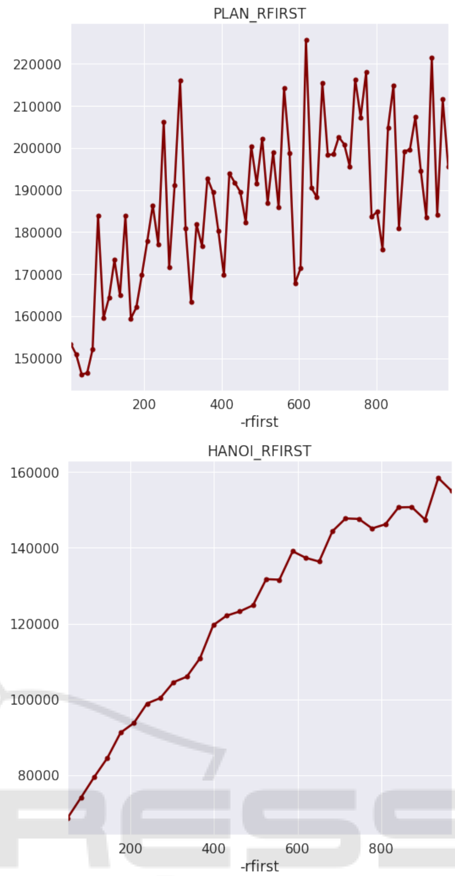


Figure 13: Restart interval base on planning instances.

Both plots in Figure 13 contain increasing trend despite plot lines are quite different, so for planning instances smaller initial interval is to be preferred, and thus more frequent restarts.

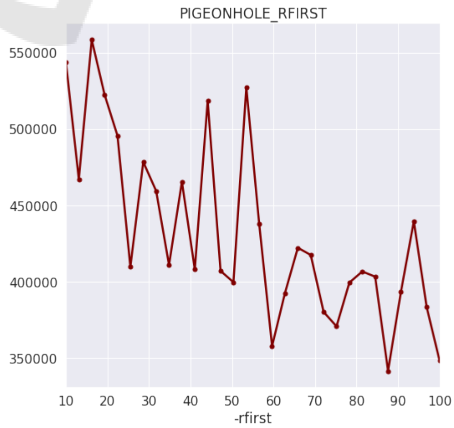


Figure 14: Restart interval base on pigeonhole instances.

Decreasing trend in Figure 14 suggests that less frequent intervals perform better for pigeonhole instances, this further confirms the hypothesis made with restart increase factor in previous section.

5.4 Implications for Parameter Tuning

The results show that there are some dependencies among parameters and solving time, thus it makes sense to try and implement machine learning system to set these parameters automatically depending on input instance.

It is debatable whether we should include parameter `-cla-decay` in the list of parameters which will be learned by machine learning technique, since for all classes of instances value close to 1 was best. We included this parameter nevertheless.

The parameter `-rnd-freq` we will not include in our experiments, because our prior analysis has shown that it has no impact, and it is best to set this parameter's value to 0.

We used grid-search to find optimal parameters. For each instance, we prepared the grid of parameters to be evaluated. The intervals of values in this grid were those, which appeared promising. For example, for random SAT instances we searched the space of `-var-decay` $\in [0.8, 0.95]$ and `-rfirst` $\in [50, 400]$, because we noticed that values from these intervals yielded best results.

6 PARAMETER TUNING

In this section we will describe each of the components of the process of parameter tuning for MiniSat solver.

Starting with overview of features extracted from SAT instances which try to describe the structure of the instance as closely as possible.

Next stage is to prepare a dataset for machine learning technique.

In comparison to related works in Section 3, we took a different path in stage of actual learning, instead of treating this problem as classification task, where features are used for classifying each instance into class of the problem it most likely belong to, and only then set parameter values, which are predetermined for each class; we will directly predict values. Thus the dataset constructed will have n features, where n is number of extracted features, and four target features (parameters: `-var-decay`, `-cla-decay`, `-rinc`, `-rfirst`). Thus, the approach we implemented is doing an multi-output regression.

6.1 SAT Instance Features

6.1.1 Basic Formula Features

By basic features we mean characteristics of the instance which were used in SatZilla's (Xu et al., 2008) feature extractor which we have used with an option `-base`.

6.1.2 Structural Features

To extract structural features of a SAT problem instance, we have decided to use three common types of graph representations of a formula as defined next.

Definition 6.1. *Variable graph (VG)* has a vertex for each variable and an edge between variables that occur together in at least one clause.

Definition 6.2. *Clause graph (CG)* has vertices representing clauses and an edge between two clauses whenever they share a negated literal.

Definition 6.3. *Variable-clause graph (VCG)* is a bipartite graph with a node for each variable, a node for each clause, and an edge between them whenever a variable occurs in a clause.

From the input instance we construct each VG, CG and VCG, which correspond to constraint graphs for the associated *constraint satisfaction problem (CSP)*. Thus, they encode the problem's combinatorial structure. (Bennaceur, 2004)

For these three types of graphs, we used basic node degree statistics from (Xu et al., 2008).

Additionally, we computed several graph properties which we thought could help describe instance's structure more closely, and at the same time are not too much time expensive.

- Variable graph features
  - diameter
  - clustering coefficient
  - size of maximal independent set (approx.)
  - node redundancy coefficient
  - number of greedy modularity communities
- Clause graph
  - clustering coefficient
  - size of maximal independent set (approx.)
- Variable-clause graph
  - latapy clustering coefficient
  - size of maximal independent set (approx.)
  - node redundancy coefficient
  - number of greedy modularity communities

The VG is usually smallest in terms of number of nodes, thus we could compute more properties on this graph, such as modularity communities and diameter.

In contrast CG is the biggest graph (there are more clauses than variables) and thus we limited the number of features extracted from this graph to only two, relatively easy–to–compute features.

VCG has the highest number of nodes among these three types of graphs ($|Vars| + |Clauses|$), but as defined earlier, it is a bipartite graph and some of the features are easier to compute on bipartite graph than on standard graph.

6.2 Constructed Dataset

Constructing training dataset for learning consists of few steps.

For each instance we ran SatZilla's feature extractor, then ran our extractor and combined the computed features into one sample.

We determined the optimal values for every parameter of MiniSat for the given instance, using the brute-force *grid search*.

Final step of compiling single sample for the dataset was to add the corresponding optimal parameters to the data row of extracted features.

6.2.1 Extraction Complexity

Building variable graph BUILDVG is $O(n^2)$, it iterates over every clause and then over every literal in that clause. Building variable clause graph has the same complexity as VG. Building Clause graph is the most expensive operation, for every pair of clauses, that is $O(n^2)$ operation, it checks for intersection of literals. Intersection of two sets is quadratic in worst case, thus the complexity of BUILDCG is $O(n^4)$.

6.3 Learning

As underlying machine learning technique we have chosen random forest, as this is multi-output regression and also data are from four distinctive classes which have different optimal parameter demands, and we believe random forest suits best for this task.

7 EVALUATION

This section presents the results achieved, it is evident that the tuned parameters outperform MiniSat defaults.

All plots of this section only show pure solving time, time spent computing features was excluded.

All instances are pre-processed by SatELite instance pre-processor (Eén and Biere, 2005) which is very fast and the time spent preprocessing can be neglected in any evaluations.

In the following plots there are two columns for each instance next to each other. Blue columns are performances on tuned parameters, green ones on the default MiniSat's parameters. Instances are sorted by number of conflicts yielded by default parameter.

7.1 Performance on Training Instances

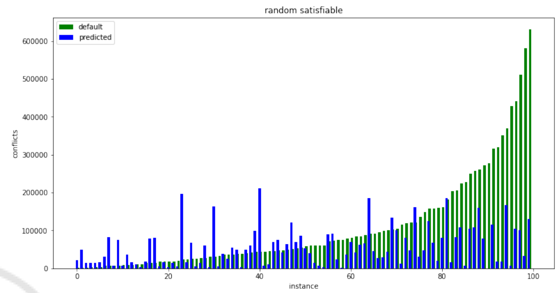


Figure 15: 100 Training instances, random, satisfiable.

Instances used for training are from SATLIB, they have constant number of variables, 250 before preprocessing.

In Figure 15 it can be seen that tuned parameters (blue), are faster for some of the instances but in fact slower for those instances that can be solved very fast with default parameters, those are instances which are solved within single digit number of restarts.

This is probably because the model tends to choose wider restart interval (in comparison to default's value of 2, which is quite low), because it was also trained on the factorization instances, which require less frequent restarts. On those random instances which take considerable time to solve by default parameters, the efficiency rises dramatically, and thus tuned parameters should be used on random instances which have larger number of variables, because for small instances default parameters perform better.

This could be fixed by including random instances of different sizes in the training set, so the model could adapt to the size of the instance better, for example, for small instances restart frequency should be also much smaller.

For every random unstatisfiable instance from training set (SATLIB) the tuned parameters are much faster.

This plot proves that it is worth tuning solver's parameters in particular for unsatisfiable instances. There is a slight correlation between heights of green

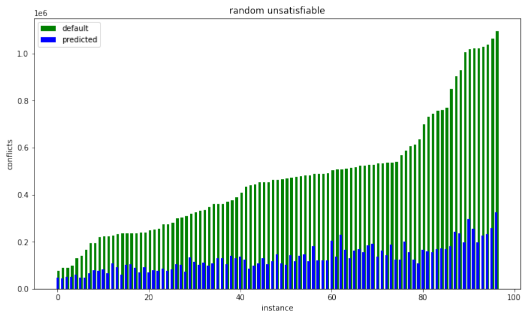


Figure 16: 97 Training instances, random, unsatisfiable.

and blue bars on the graph, unlike for random satisfiable instances.

The hardest instances are from so called *phase transition* which is a ratio of clauses to variables around value 4.26, so roughly 4x more clauses than variables.

The computation of features is very fast for random instances as they have balanced ratio of clauses and variables.

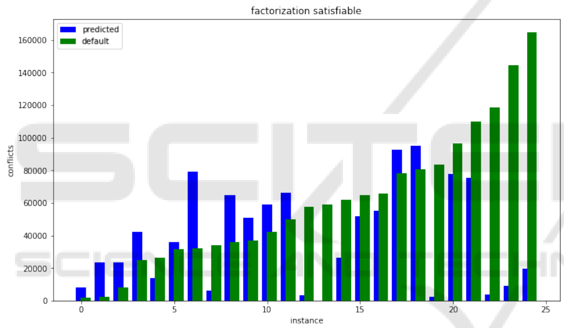


Figure 17: 25 Training instances, factorization, satisfiable (not prime numbers).

12/25 satisfiable instances were actually slower with tuned parameters but 10 of them were easy instances. This may seem a bit disturbing result as first sight, but our hypothesis is that the cause of it, is lack of easier instances of this type of problem in the training dataset as first half of the plot shows. On the second half of the graph it can be observed that for harder instances, only two instances are slightly slower. We would say, for harder instances these results are positive.

The model does not distinguish well between hard and easier instances, and as a result it is predicting restart frequency parameters similarly for both harder and easier instances.

Another possibility can be that there is no information to be captured from the graph structure about how hard the instance will be.

Majority of eight out of ten instances are favoring tuned parameters, for two easiest instances the default

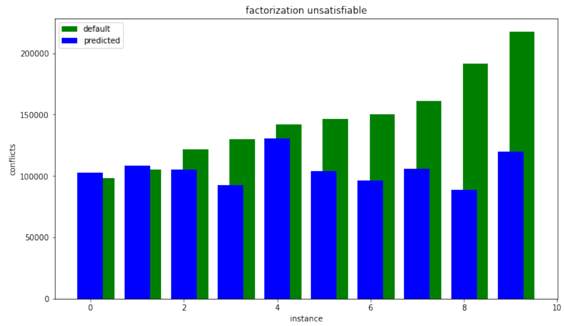


Figure 18: 10 Training instances, factorization, unsatisfiable (prime numbers).

parameters perform better but only by a tiny bit of 500-1000 conflicts less which is small enough count to be neglected.

The improvement is only moderate, nowhere near the improvement observed on random unsatisfiable instances.

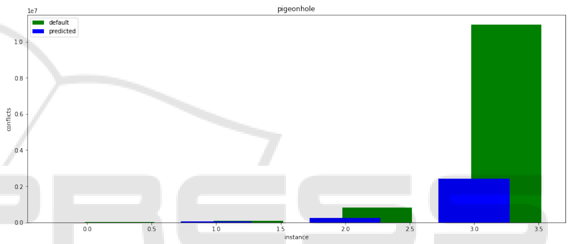


Figure 19: Training instances, pigeonhole problem.

First two bars are insignificant, but on remaining the big improvement can be seen. Even though the training dataset contained only these four instances of pigeonhole problem (because higher order of this problem is very difficult and it was infeasible to perform grid-search on many parameters values), the model was able to predict values correctly.

This might mean that the structure of this instance is vastly different from all the other instances from classes.

7.2 Performance on Testing Instances

As a testing set for random instances we generated instances randomly but with 300 variables in comparison to SATLIB's 250, to observe whether the model will be able to predict values correctly also for instances which are much harder than the ones it was trained on.

Plot shows very good results, so this verify my hypothesis, that even model trained on smaller instances can perform good on bigger.

For harder instances (second half of the plot), there is only one instance which takes almost twice as

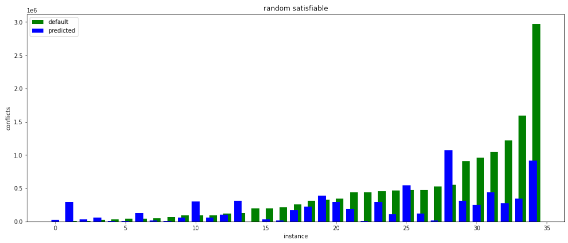


Figure 20: 36 Testing instances, random, satisfiable.

much with tuned parameters as with the default ones.

This is probably because the structures of the random instances are homogeneous regardless of their size.

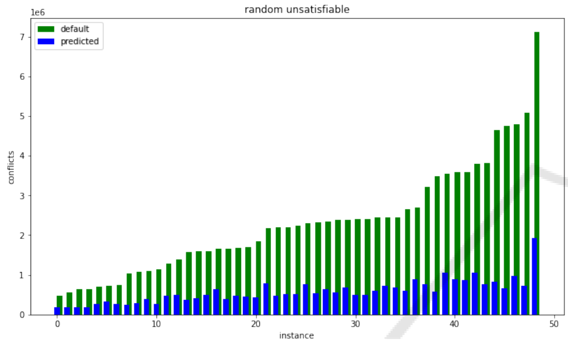


Figure 21: 60 Testing instances, random, unsatisfiable.

Observed results are remarkable, all instances are faster on tuned parameters by at least 2x, on some instances, mostly harder ones, 3x faster.

The key takeaway is that the parameter tuning is very effective way to improve SAT solvers performance on unsatisfiable instances.

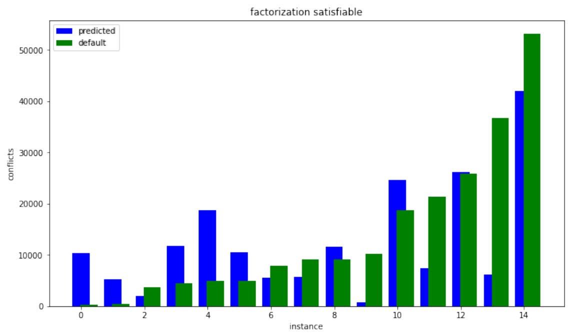


Figure 22: 15 Testing instances, factorization, satisfiable.

Similar results as on training set can be seen here for factorization, satisfiable instances. Performance is better on harder instances, from harder instances only one is outperformed by default settings. Easier instances are solved faster by default settings, most likely because of low base restart interval.

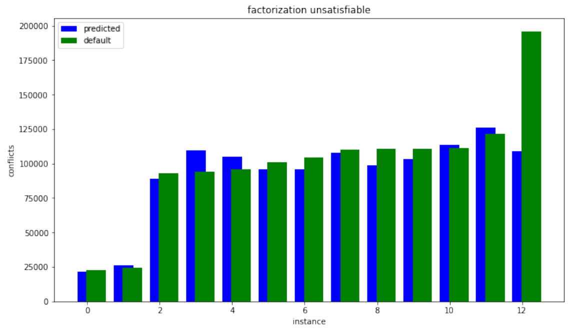


Figure 23: 13 Testing instances, factorization, unsatisfiable.

For testing set we picked 2 easy instances, which can be seen as first 2 bars, then a few average hard instances and one very hard, the last bar.

For easy instances there is no improvement, for medium instances predicted parameters give steadily 100000 conflicts, worth noting is that, the same is for instances in the training set. For hard instance number of conflicts is also close to 100000, and almost 2x speedup can be seen. Tuned parameters perform more less the same as default ones but we hypothesize that, that as hardness of the instances increase the speedup would get more significant with it.

7.3 Planning Instances

It is unfortunate that we were unable to train the model for planning problems. This is due to computational burden that we encountered later, in the process of extracting features.

Constructing clause graph which is usually very big due to the nature of planning instances and computing features on it was not feasible.

If we were to start over, we would not include clause graph for planning instances, and focus more on graph properties of corresponding VG and VCG graphs.

8 CONCLUSIONS

We have shown that a dependency of SAT solver's solving time on its parameters exists. This has been fully illustrated in our experimental evaluation, on a set of four, structurally diverse SAT instances.

The dependencies were measured with five of the MiniSat's parameters concerning heuristics and restart policy.

The most significant dependencies were observed on random SAT instances exhibiting dependency on four parameters. Except the planning instances, every other class has shown dependency on clause decaying factor. Each of the studied classes were dependent on the restart frequency.

The dependency has been utilized for automated settings of MiniSat's parameters using machine learning based on features extracted from graphs derived from the input instance.

We evaluated how predicted parameters perform on both training set and testing set.

Significant improvement of running time has been achieved with predicted parameters for all types of instances except the planning class. The most positive achievement was tuning parameters for unsatisfiable random SAT instances, where for significant number of instances tested we achieved up to 3x speedup.

As a suggestion for a future work, we plan to focus on computing features of VG and VCG and leave CG out as it is very computationally expensive and often causes feature extractor execution time to outweigh actual solving time.

ACKNOWLEDGEMENTS

This research has been supported by GAČR - the Czech Science Foundation, grant registration number 22-31346S.

REFERENCES

Sat competition website. http://www.satcompetition.org/.

Ansótegui, C., Giráldez-Cru, J., and Levy, J. (2012). The community structure of sat formulas. In Cimatti, A. and Sebastiani, R., editors, *Theory and Applications of Satisfiability Testing – SAT 2012*, pages 410–423. Springer.

Bennaceur, H. (2004). A comparison between sat and csp techniques. *Constraints*, 9:123–138.

Biere, A., Biere, A., Heule, M., van Maaren, H., and Walsh, T. (2009). *Handbook of Satisfiability: Volume 185 Frontiers in Artificial Intelligence and Applications*. IOS Press, NLD.

Cook, S. A. (1971). The complexity of theorem-proving procedures. In *Proceedings of the Third Annual ACM Symposium on Theory of Computing*, STOC '71, page 151–158, New York, NY, USA. Association for Computing Machinery.

Dennis, G., Chang, F. S.-H., and Jackson, D. (2006). Modular verification of code with sat. In *Proceedings of the 2006 International Symposium on Software Testing and Analysis*, ISSTA '06, page 109–120, New York, NY, USA. Association for Computing Machinery.

D'Ippolito, N., Frias, M., Galeotti, J. P., Lanzarotti, E., and Mera, S. (2010). Alloy+hotcore: A fast approximation to unsat core. volume 5977, pages 160–173.

Eén, N. and Biere, A. (2005). Effective preprocessing in sat through variable and clause elimination. In Bacchus, F. and Walsh, T., editors, *Theory and Applications of Satisfiability Testing*, pages 61–75. Springer.

Ganesh, V., Singh, R., Near, J., and Rinard, M. (2009). Avatarsat: An auto-tuning boolean sat solver.

Gupta, A., Ganai, M. K., and Wang, C. (2006). Sat-based verification methods and applications in hardware verification. In Bernardo, M. and Cimatti, A., editors, *Formal Methods for Hardware Verification*, pages 108–143. Springer.

Haken, A. (1984). *The Intractability of Resolution (Complexity)*. PhD thesis, USA. AAI8422073.

Kautz, H. and Selman, B. (1992). Planning as satisfiability. pages 359–363.

Liang, J. H. (2018). *Machine Learning for SAT Solvers*. PhD thesis, University of Waterloo.

Lourenço, H., Martin, O., and Stützle, T. (2010). *Iterated Local Search: Framework and Applications*, volume 146, pages 363–397.

Marques Silva, J. P. and Sakallah, K. A. (1996). Grasp-a new search algorithm for satisfiability. In *Proceedings of International Conference on Computer Aided Design*, pages 220–227.

Mitchell, T. M. (1997). *Machine Learning*. McGraw-Hill.

Newsham, Z., Lindsay, W., Ganesh, V., Liang, J. H., Fischmeister, S., and Czarnecki, K. (2015). Satgraf: Visualizing the evolution of sat formula structure in solvers. In *International Conference on Theory and Applications of Satisfiability Testing (SAT)*, Austin, USA. Springer, Springer.

Niklas Eén, N. S. (2004). Theory and applications of satisfiability testing: 6th international conference, sat, santa margherita ligure, italy, may 5-8, 2003, selected revised papers, chapter an extensible sat-solver. *Springer*, pages 502–518.

Pintjuk, D. (2015). Boosting sat-solver performance on fact instances with automatic parameter tuning.

Pipatsrisawat, K. and Darwiche, A. (2007). A lightweight component caching scheme for satisfiability solvers. In Marques-Silva, J. and Sakallah, K. A., editors, *Theory and Applications of Satisfiability Testing – SAT 2007*, pages 294–299. Springer.

Sinz, C. and Dieringer, E.-M. (2005). Dpvis – a tool to visualize the structure of sat instances. In Bacchus, F. and Walsh, T., editors, *Theory and Applications of Satisfiability Testing*, pages 257–268. Springer.

Soos, M., Nohl, K., and Castelluccia, C. (2009). Extending sat solvers to cryptographic problems. In Kullmann, O., editor, *Theory and Applications of Satisfiability Testing - SAT 2009*, pages 244–257. Springer.

Xu, L., Hutter, F., Hoos, H. H., and Leyton-Brown, K. (2008). Satzilla: Portfolio-based algorithm selection for sat. *J. Artif. Intell. Res.*, 32:565–606.