Masters Thesis
Investigations on Backbone Computation

Eberhard Karls Universität Tübingen
Mathematisch-Naturwissenschaftliche Fakultät
Wilhelm-Schickard-Institut für Informatik
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Jonas Bollgrün, `jonas.bollgruen@posteo.de`, 2019

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Betreuer/Gutachter: Prof. Dr. Wolfgang Küchlin, Universität Tübingen
Zweitgutachter: Prof. Dr. Michael Kaufmann, Universität Tübingen

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Jonas Bollgrün (Matrikelnummer 3353424), September 9, 2019

Abstract

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1 Introduction

introduction

wofür brauche ich backbones

wer hat sich damit beschäftigt

welche paper waren relevant

wie ist die thesis strukturiert,

was wurde in den sechs monaten gemacht

hab prefbones erfunden

haben prefbones paper rausgesucht

was kann ich mit prefbones noch so anstellen

wie sehen die praktischen nutzen der prefbones varianten aus.

introduction soll aus perspektive vor dem schreiben geschrieben werden (absichten)

1.1 Disambiguation

1.1.1 Terminology

This thesis is an investigation on the calculation of backbones for boolean formulas in conjunctive normal form (or CNF in short). A CNF formula F is a conjunction of a set of clauses $C(F)$, meaning that all of these clauses have to be satisfied to satisfy the formula. A clause c in turn is a disjunction of a set of literals, meaning at least one of said literals must be fulfilled. A literal l can be defined as the occurence of a boolean variable v which may or not be negated and to fulfill such a literal, it's variable must be assigned $\perp$ for negated literals and $\top$ for those literals without negation. The same variable can occur in multiple clauses of the same formula but must have the same assignment in all occurences, either ($\perp$) or ($\top$). A complete assignment of all variables of F (written as $Var(F)$) that leads to the formula being fulfilled is called a model. A formula for which no model can be found is called unsatisfiable. Any set of assignments that is sufficient to satisfy a formula is called an implicant and if has no subset that isn't itself an implicant it is called a primeimplicant. The variables that do not occur in an implicant are called optional.

When we want to know whether a model M satisfies a formula F, clause c or literal l, we write $F\langle M\rangle \rightarrow \{\top, \perp\}$ or $c\langle M\rangle$ and $l\langle M\rangle$ respectively. The result is $\top$ if the assignment satisfies what it is applied to or $\perp$ if it doesn't.

The exact terminology can differ depending on the paper and project that you read. A formula can be called a problem and the assignment of a variable can be called it's phase. Sometimes assignment and literal are used interchangeably, as they

both consist of a variable and a boolean value. Clauses can also be called constraints and sometimes sentences. A synonym for a formula, clause or literal being fulfilled is it being satisfied. Models can also be called solutions of formulas. The terminology for $\top$ or $\bot$ can be (T, F), $(true, false)$ or $(1, 0)$.

The backbone is a formula specific set of literals that contains all literals that occur in every model of said formula. We can also say that a variable is not part of the backbone, if neither it's positive or it's negative assignment is in the backbone. If we have an unsatisfiable formula, it's backbone can be considered undefinable, which is why this thesis concerns itself only with satisfiable CNF formulas.

For the context of CNF formulas, on which this thesis focuses, the term "subsumption" should to be explained. A clause c_1 subsumes another clause c_2 of the same formula, if and only if $c_1 \subseteq c_2$, in prose if all the literals that occur in c_1 also occur in c_2[1]. If c_1 subsumes c_2 in formula F then this means that you can remove c_2 from F because in terms of satisfying models, $F \backslash \{c_2\}$ is equivalent to F as $\{c_1\}$ is equivalent to $\{c_1, c_2\}$. This is because in this case an assignment that satisfies c_1 also satisfies c_2 automatically. There is no possible assignment that satisfies clause c_1 that doesn't satisfy it's subsuming clause c_2.

1.1.2 CDCL

All the methods to generate a backbone of a formula F that are described in this thesis essentially rely on calculating various models of F, so it makes sense to describe a method to do that as well. The current state-of-the-art algorithm to do this is the *Conflict Driven Clause Learning* algorithm, or *CDCL* for short. This algorithm was first published as "*GRASP*" in [PMSS03].

Here a *CDCL table* is used as a special dataset, to store the state of the SAT solver. This table stores the succession of assignments with four values for each assignment.

- The *level* of the assignment. This level increases with each decision and starts at 0, where unit assignments before any decision are stored.

- The affected variable.

- The value that the variable was assigned to.

- The reason for the assignment. This can be one of two cases, either *Unit* or *Decision*.
  Unit assignments happen, when a clause has all but one of it's literals unsatisfied. Since all clauses have to be satisfied for a CNF formula to be satisfied, that last literal must be assigned a value that satisfies it and it's clause. Entries in the

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[1] One can filibuster whether c_1 would have to be a true subset of c_2. If a formula has two occurences of the exact same clause, then one of the occurences would be redundant, so the same rule could be applied here as well. In practice it makes more sense to filter out duplicates of clauses before running any computation on the formula. Similarly, you can safely drop all clauses where both literals of the same variable occur, as that clause would be satisfied in each and every possible model.

CDCL table that refer to a unit assignment also store a reference to the clause that required the assignment. A clause that fulfills the above condition and requires an assignment can be called a *unit clause* or that it *is unit*.
Decisions happen when no clause is in the unit state. In theory, in this case you are free to pick any variable and assign it either $\top$ or $\bot$.

The purpose of unit assignments is to reduce the search space. The solving process for a formula can be modeled as the traversal of a search tree, where each node corresponds to an individual assignment and every leaf node to a complete assignment that might be satisfying or not[2]. However, given that you can stop to search once a single clause is unsatisfied, you can disqualify many branches of the tree early, for example when the assignments in your tree path so far require some additional assignment for some clause, which would be a *unit clause*. Going the other way in the tree at that particular node will never result in a satisfying model.

The solver will now fill the table with assignments, unit assignments if possible or decisions otherwise, until one of two things happens. Either the formula became satisfied[3] in which case we can return the assignments that are stored in the table.

The other possibility is that you run into a contradiction. Here a unit clause requires that a variable is assigned a value b, but it is already assigned $\neg b$. If the assignments have a reason (a unit clause), then some of the variables in these clauses must be assigned differently(since they were unit then), so we can connect the reasons for our conflict to other assignments. Repeating this we sometimes meet decisions instead of unit clauses as reason. Collecting these decisions, we end with the precise combination of assignment decisions that resulted in the conflict.

F:= {(¬c),(a,e),(b,¬d),(b,c,d)}

Level	Var	Value	Reason
0	c	$\bot$	{¬c}
1	a	$\bot$	Decision
1	e	$\top$	{a,e}
2	b	$\bot$	Decision
2	d	$\bot$	{b,¬d}
2	d	$\top$	{b,c,d}
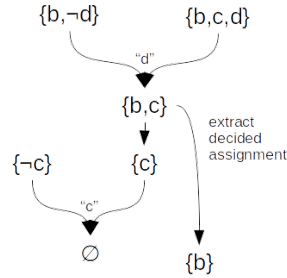
Figure 1.1: Example of a resolution. Shown is a formula, the content of the CDCL table at the point of conflict in variable d and the resolution graph.

This process of following assignments through their reasons is called *resolution* and can be briefly explained with the following formula:

$$r_\lambda(c_1, c_2) = (c_1 \setminus \{\lambda\}) \cup (c_2 \setminus \{\neg\lambda\})$$

The resolvent r consists of all literals of the two clauses that are resolved, where in this case c_1 contains λ and c_2 contains $\neg\lambda$. This precondition is given in this case,

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[2] Sadly the size of such a tree makes it impractical to actually implement sat solving like this.

[3] In this case only an implicant is returned. If you want a complete model, you can keep making decisions until all variables are assigned and return the assignments after that. However once you have an implicant, you are free to assign the remaining variables to anything you want, as the formula is already satisfied and further assignments cannot change that.

because c_1 is the reason for the assignment of λ to $\top$ and c_2 the reason for assigning λ to $\bot$.

Figure 1.1 shows this with an example, where a conflict in variable d happened. First the clauses $\{b, \neg d\}$ and $\{c, b, d\}$ are resolved over the variable d. Then b is extracted for the learned clause, as it's reason was a decision and not a unit clause. Finally $\{c\}$ and $\{\neg c\}$ are resolved over c, resulting in the empty set. The learned clause is $\{b\}$. An alternative resolution scheme would leave literals that stem from decisions in the working set until the end, but here they are extracted on first extraction. Otherwise, these literals would be inspected multiple times.

Once collected, this set of decisions must be taken back, by reversing the assignmnents up until the first of these decisions, as this path through the search tree results in a conflict and will not end in models.

We also add the clause to our formula as a *learned clause*. This clause serves to prevent the particular combination of assignments that led to our conflict. The resulting formula will still be completely equivalent to before. It merely stores the information that we gained through analysis of our conflict to prevent it from happening again.

However it is also possible that we end up with reasons for assignments that do not end in a decision. This would mean that all reasons were axiomatic assignments, for example when a formula contains a clause with only a single literal in it [4] . In this case the formula implies a contradiction and the clause that we would learn from this would be empty, unsatisfiable.

Concerning the decisions, depending on the particular formula, it is possible that some assignments make it easier to solve the formula than others and some decisions might lead to a completely unsatisfied clause where all of it's literals are unsatisfied. A lot of research has been done to prevent this by setting up heuristics that try to pick a variable and corresponding assignment that would lead to a satisfying model without complications. For this you would typically measure how often the variable was involved in conflicts and prefer to decide on such difficult variables. It is assumed that difficult formulas are so because of individual difficult variables. If you decide on these early, you have a 50-50 chance that you either found the correct assignment or at least learned a useful clause from a conflict.

As is usually done in literature, calls to sat solvers such as CDCL in code listings are written as $(outc, v) = SAT(F)$. Here, two values are returned. $outc$ is a boolean value that simply states whether F was satisfiable to begin with. Only if it equals to $\top$, the second return parameter v can have a meaningful value, which would be the model that was found and satisfies F. In some of the algorithms listed in this thesis, one of the return parameters is not used at all. In that case I write $(\_, v) = SAT(F)$ or $(outc, \_) = SAT(F)$ to indicate that either $outc$ or v is discarded.

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[4] A simple example: A formula contains the two clauses $\{a\}$ and $\{\neg a\}$. Resolving these two results in the empty set.

Algorithm 1: CDCL ALGORITHM

Input: A formula *F* in CNF
Output: A CDCL table which implies an implicant for *F*, or ⊥ if *F* is not
        satisfiable

1   *level* ← 0
2   *table* ← *emptyList*
3   **while** 1 **do**
4   *table.pushAll*(*F.getUnits*())
5   **if** ∃ *conflicting assignment* **then**
6   **if** *level* = 0 **then**
7   **return** ⊥
8   **else**
9   *level* ← *backtrackAndLearn*(*F, table*)
10   **else if** *F is fulfilled* **then**
11   **return** *table*
12   **else**
13   *level* + +
14   *l* ← *any free variable*
15   *l.assign*(*either* ⊤ *or* ⊥)
16   *table.pushDecision*(*l*)

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2 Base Algorithms

The algorithms that I investigated for this thesis can be grouped very broadly into two approaches, which I will describe in the following two sections.

2.1 Enumeration algorithms

2.1.1 Model Enumeration

A simple definition of the backbone is that it is the intersection of all models of it's formula. If a literal is not part of the backbone, there must exist a model that contains the negation of that literal. Therefore if we had a way to iterate over every single model of the formula and, starting with the set of both literals for every variable and removing every literal from that set that was missing in one of these models, that set would end up being the backbone of the formula. [MSJL10] as well as [JLMS15] list an algorithm that does exactly this.

Algorithm 2: ENUMERATION-BASED BACKBONE COMPUTATION

Input: A satisfiable formula F
Output: Backbone of F, v_r

1   $v_r \leftarrow \{x | x \in Var(F)\} \cup \{\neg x | x \in Var(F)\}$
2   **while** $v_r \neq \emptyset$ **do**
3      $(outc, v) \leftarrow SAT(F)$
4   **if** $outc = \bot$ **then**
5         $return\ v_r$
6      $v_r \leftarrow v_r \cap v$
7      $\omega_B \leftarrow \bigvee_{l \in v} \neg l$
8      $F \leftarrow F \cup \omega_B$
9   **return** v_r

Here, found models are prevented from being found again by adding a blocking clause of said model and the algorithm terminates once all models are prohibited and the formula became unsatisfiable through this.

2.1.2 Upper Bound Reduction

Clearly, calculating every single model of a formula leaves room for optimization. Most models of a common boolean formula differ by small, independent differences

that can just as well occur in other models. Therefore the intersection of only a handful of models can suffice to result in the backbone, as long as these models are chosen to be as different as possible. This was achieved in [JLMS15] as is described in algorithm 3.

Algorithm 3: Iterative algorithm with complement of backbone estimate

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Input: A satisfiable formula F

Output: Backbone of F, v_r

1   $(outc, v_r) \leftarrow SAT(F)$
2   **while** $v_r \neq \emptyset$ **do**
3      $bc \leftarrow \bigvee_{l \in v_r} \neg l$
4      $(outc, v) \leftarrow SAT(F \cup \{bc\})$
5   **if** $outc = \bot$ **then**
6          $return\ v_r$
7      $v_r \leftarrow v_r \cap v$
8   **return** v_r

It generates an upper bound v_r of the backbone by intersecting found models and inhibits this upper bound instead of individual models. This blocking clause is much more powerful, because it enforces not only that a new model is found, but also that this new model will reduce the upper bound estimation of the backbone in each iteration.

This is because what remains after the intersection of a handful of models, are the assignments that were the same in all these models and from that we make a blocking clause that prohibits the next model to contain that particular combination of assignments. The next model will then have to be different from all previous models for at least one of the variables in the blocking clause to satisfy it.

Eventually v_r will be reduced to the backbone. This can be easily recognized, because the blocking clause of the backbone or any of it's subsets makes the formula unsatisfiable, except in the case that the formulas backbone would be empty.

Note that it is not particularly important for the algorithm whether the blocking clauses remain in F or get replaced by the next blocking clause, because the new blocking clause bc_{i+1} always subsumes the previous one bc_i, meaning that every solution that is prohibited by bc_{i+1} is also prohibited by bc_i and $F \cup \{bc_i, bc_{i+1}\}$ is equivalent to $F \cup \{bc_{i+1}\}$ concerning the set of models.

This algorithm is implemented in the Sat4J library under the designation *IBB*, except that prime implicants are used instead of models. For specifics on these, see chapter 3.1.1.

2.2 Iterative algorithms

2.2.1 Testing every literal

Alternatively, you can define the backbone as all literals that occur with the same assignment in all models of it's problem, which implies that enforcing a backbone literal to it's negation should make the formula unsatisfiable. This definition already leads to a simple algorithm that can calculate the backbone, by checking both assignments of every literal for whether it would make the formula unsatisfiable, see algorithm 4. This algorithm is referenced in [MSJL10]

Algorithm 4: ITERATIVE ALGORITHM (TWO TESTS PER VARIABLE)

Input: A satisfiable formula F in CNF
Output: All literals of the backbone of F v_r

1   $v_r \leftarrow \emptyset$
2   **for** $x \in Var(F)$ **do**
3     $(outc_1, \_) \leftarrow SAT(F \cup \{x\})$
4     $(outc_2, \_) \leftarrow SAT(F \cup \{\neg x\})$
5     $assert(outc_1 = \top \vee outc_2 = \top)$ `// Otherwise F would be unsatisfiable`
6   **if** $outc_1 = \bot$ **then**
7       $v_r = v_r \cup \{\neg x\}$
8       $F = F \cup \{\neg x\}$
9   **else if** $outc_2 = \bot$ **then**
10    $v_r = v_r \cup \{x\}$
11    $F = F \cup \{x\}$

12 **return** v_r

The two calls to the *SAT* function return a pair which consists first of whether the given function was satisfiable at all and, secondly, the found model, which in this case is discarded. There is no good algorithm that can tell whether a boolean formula is satisfiable or not without trying to find a model for said formula, but we can use it to greatly improve the algorithm above by combining this approach with that of the enumeration algorithms.

2.2.2 Combining with Enumeration

First observe that any model of F would already reduce the set of literals to test by half, because for every assignment missing in the model, we know that it cannot be part of the backbone, so there is no need to test it.

This can be repeated with every further model that we find. The following algorithm 5 is another one that is listed in both [MSJL10] and [JLMS15] and is implemented in the Sat4J library as BB[1].

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[1]With the exception of using prime implicants instead of models, similar to the *IBB* algorithm.

Algorithm 5: ITERATIVE ALGORITHM (ONE TEST PER VARIABLE)

Input: A satisfiable formula F in CNF
Output: All literals of the backbone of F v_r

1   $(outc, v) \leftarrow SAT(F)$
2   $\Lambda \leftarrow v$
3   $v_r \leftarrow \emptyset$
4   **while** $\Lambda \neq \emptyset$ **do**
5     $l \leftarrow pick\ any\ literal\ from\ \Lambda$
6     $(outc, v) \leftarrow SAT(F \cup \{\neg l\})$
7   **if** $outc = \bot$ **then**
8       $v_r \leftarrow v_r \cup \{l\}$
9       $\Lambda \leftarrow \Lambda \setminus \{l\}$
10      $F \leftarrow F \cup \{l\}$
11   **else**
12       $\Lambda \leftarrow \Lambda \cap v$

13   **return** v_r

Note that both possible results of the call to the sat solver are converted to useful information. In the else branch, the formula together with the blocked literal l was still solvable. In this case v is still a valid model for F, so we can search through it to look for more assignments that don't need to be checked. Note that here v must contain $\neg l$, as it was enforced. Therefore l will be removed from Λ in this case as well.

In the other case, we identified l as a backbone literal. In that case it will be added to the returned set, removed from the set of literals to test and, lastly, added to the problem F, which increases performance in subsequent solving steps. However it would be even better, not only to reuse the learned backbone literals, but all learned clauses.

It is possible to apply the concept of preferences described in section 2.3 to the iterative algorithms listed here. However, this is less beneficial than adding it to the enumeration approach of *IBB*, because in the *BB* algorithm many sat calls are supposed to return *UNSAT* to positively identify an assignment as backbone. However, this case does not give us a model, so the extra effort of trying to find a more valuable model is often wasted here.

Another difficulty with the *BB* algorithm in comparison to *IBB* is that here it is more difficult to reuse learned clauses. These are based on a subset of the clauses in F. Their existence is virtual so to speak, implied through these base clauses but difficult to find. Adding more clauses to the formula does not remove a learned clause, as the set of base clauses is untouched. At most it might be possible to subsume it with another learned clause. However if a clause is removed from F, it might be that the learned clause is no longer implied through the formula, therefore making it invalid.

Example: Using the iterative approach on formula $F = \{(a,b,c)\}$ together with blocking clause $(\neg a)$ implies the clause (b,c). CDCL would learn this clause if it were configured to assign $\bot$ in every decision and assign $\top$ only through unit implications. This learned clause must be discarded. Otherwise when we test with the blocking clause $(\neg b)$, together with (b,c) it would imply (c), making c a backbone of F, which it clearly isn't.

2.3 Preferences

The previous approaches still leave much of their efficiency to chance. Theoretically the solver might return models with only the slightest differences from each other, when other models could reduce the set of backbone candidates much more. For example the blocking clause can be satisfied with only one literal in it being satisfied, but if we were to find a model that satisfies all literals in the blocking clause, we can immediately tell that the backbone is empty and we would be finished. So it would be a good approach for backbone computation if we could direct our sat solver to generate models that disprove as many of the literals in the blocking clause as possible. Precisely this has been described by [PJ18], but has also been proposed much earlier by [Kai01].

[PJ18] describe an algorithm called $BB - PREF$ or $Prefbones$, which makes use of a slightly modified SAT solver based on CDCL, which is called $prefSAT$ in the algorithm below. It can be configured with a set of preferred literals $prefs$. As already stated, when the CDCL algorithm reaches the point where it has the freedom to decide the assignment of a variable, it consults a heuristic that tries to predict the best choice of variable and assignment to reach a model. Instead, $prefSAT$ uses two separate instances of these heuristics h_{pref} and h_{tail}, which by themselves may work just as the single heuristic used in the ordinary CDCL solver. The key difference in $prefSAT$ is, that h_{pref}, which contains the literals in $prefs$, is consulted first for decisions, and only when all variables with a preferred assignment are already assigned, h_{tail} is used to pick the most important literal.

Algorithm 6: BB-PREF: BACKBONE COMPUTATION USING PREF-SAT

Input: A satisfiable formula F in CNF
Output: All literals of the backbone of F, v_r

1   $(\_, v_r) \leftarrow SAT(F)$
2 **Repeat**
3     $prefs \leftarrow \{\neg l : l \in v_r\}$
4     $(\_, v) \leftarrow prefSAT(F, prefs)$
5   **if** $v \supseteq v_r$ **then**
6   **return** v_r // No preference was applied
7     $v_r \leftarrow v_r \cap v$

This algorithm also differs from *IBB* in that it does not add blocking clauses, and that is also why it cannot use the case when *F* becomes unsatisfiable to terminate the algorithm. Instead it relies on the preferences to be taken into account. Except for the case where a formula has only one model, CDCL must make at least one decision. That decision must come from h_{pref}, except for the case that CDCL learned axiomatic assignments for all variables in *prefs*. Depending on whether the learned value for the variables in *prefs* contradicts all preferences it may take another call to *prefSAT*, but at the latest then no more changes will happen to v_r and the algorithm terminates. The return condition also covers the case when the backbone turns out to be empty, because then v_r was reduced to $\emptyset$ and that is a subset of every set.

Note that the algorithm was written slightly different from what is listed in [PJ18] to make the relation with common enumeration algorithms more apparent and also make it easier to read.

The return condition makes this algorithm inflexible, as the preferences have to be taken into account without exception. If not, a model might be returned that terminates the algorithm prematurely, because it did not properly test a variable assignment, instead taking a shortcut to save time in the calculation of a model. Since the purpose of this thesis was to experiment with solvers and I was interested in the concrete effects of preferences by themselves on the backbone computation, I created a variation of Prefbones, that uses the previous approach of upper bound reduction, adding a blocking clause to *F* in every iteration and terminating when *F* would become unsatisfiable. This made the preferences algorithmically completely optional and allowed to experiment with many variations on the concept. Coincidentally, the added blocking clause happens to be the exact same set as that of the preferred variables.

Algorithm 7: BB-PREF: BACKBONE COMPUTATION USING PREF-SAT AND BLOCKING CLAUSE

Input: A formula *F* in CNF
Output: All literals of the backbone of *F*, v_r

1   $(\_, v_r) \leftarrow SAT(F)$
2   **Repeat**
3     $bc \leftarrow \bigvee_{l \in v_r} \neg l$
4     $F \leftarrow F \cup \{bc\}$
5     $prefs \leftarrow \{\neg l : l \in v_r\}$
6     $(outc, v) \leftarrow prefSAT(F, prefs)$
7   **if** $outc = \perp$ **then**
8   **return** v_r
9     $v_r \leftarrow v_r \cap v$

Later in the results section I will show how this variant faired against the previous algorithm from [PJ18].

3 Optimizations

The following chapter elaborates on methods to enhance the algorithms that were described in the previous chapter. Depending on the particular combination of algorithm and enhancement, applying the optimization can be be considered a no brainer. However, experimental results show that this is not true without exception and in individual cases we will give thoughts why that is. Other improvements can only be applied to some algorithms due to the data that is available.

3.1 Model Reduction

The algorithms described in section 2 all boil down to testing for each variable whether there exist two models where one assigns the variable to $\top$ and the other to $\bot$. This section describes two strategies to reduce the model that is returned by the sat solver to a subset that tells us more for the purpose of calculating a backbone. Both methods are essentially about using implicants instead of models.

Having a single implicant I that leaves some variables optional immediately tells us, that every possible combination of assignments of the optional literals can make a model, if we just add the assigned literals in I. You could say that an implicant implies a large set of models.

Without any further information, a single implicant I tells us, that every one of the optional variables in it cannot be part of the backbone.

Starting with complete models, implicants can be subsets of other implicants, by removing more and more assignments that are not essential. This way you will eventually reach an implicant where all of it's assignments are required and removing any literal from it, would leave some clause unsatisfied. This would be called a prime implicant I_π.

3.1.1 Prime Implicant

[DFLBM13] describes an algorithm that allows to calculate the prime implicant from a model in linear time over the number of literal occurrences in the formula. This algorithm works best if you generate the model of a variable with the CDCL algorithm for multiple reasons.

First, it takes advantage of data structures that you also need in a good implementation of CDCL, namely a lookup from each variable to all clauses that contain either literal of that variable. In CDCL this lookup table improves the performance of unit propagation, because you can check exactly the set of clauses that might be affected

by the assignment to determine whether one of the clauses has become exhaustively unsatisfied or implies another assignment[1]. Here, the lookup is used to determine whether a literal is required in the implicant that you are in the process of generating, by looking for clauses that only contain a single satisfying literal anymore, which then must be part of the prime implicant. You can even reuse the watched literals[2] of the clauses, however you would have to change the way in which the propagate, since you take assignments away instead of adding them.

The second fit with CDCL is that it not only generates a model, but also a table containing information on how that model was generated. This information can be used in this algorithm to reduce the number of literals that need to be checked on whether they are required in the resulting prime implicant. You can quickly generate the input I_r by going through the table generated by CDCL and noting down every assignment that happened through unit propagation. These must be part of the prime implicant because to have been assigned through unit propagation at some point in time there must have been a clause that required that particular assignment.

The only assignments that you really have to test here are those that were decisions. Additionally, you can avoid many decided assignments if you configure your CDCL SAT solver to stop once the formula is satisfied instead of stopping once every variable was assigned. Once the formula is satisfied, no more assignment is necessary, so all further ones are arbitrary decisions that are not necessary in the implicant.

It is sufficient to go over the remaining set of assignments only once each. After having determined that a literal is required to satisfy the formula, it cannot become optional later. After all, for this the algorithm would have to add assignments instead of taking them away. And after having discarded a literal from our implicant it cannot become required again. For this to happen we would have to drop a literal from our implicant where that was the last one that satisfied some particular clause. This fits the description of a required literal and we do not drop those.

Since the same model could be calculated in different ways by CDCL depending on the particular order in which the variables in it were assigned values, the partition between decided assignments and unit assignments can be different for the same model. Therefore, this method can give you different prime implicants for the same model depending on the CDCL table that you use. Additionally, the order in which you check the decided literals can also make a difference.

The function $Req(I_m, l, c)$ tells, whether the assignment l in the implicant I_m is required to satisfy c. In other words, is l the only literal in I_m that also occurs in c.

3.1.2 Rotations

There is a model reduction method that is even more powerful than calculating the prime implicant. Even better, the concept is much simpler than calculating the prime

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[1] The unit case

[2] These are used in CDCL to determine and store the information on whether a clause is satisfied, unsatisfied, unit or neither of them. This is done by having two pointers that rest on unassigned literals in each clause. In this algorithm you can let these pointers rest on satisfying literals.

Algorithm 8: Base approach to compute a prime implicant

Input: A formula F, a model I_m, I_r containing some required literals in I_m

Output: I_r, reduced to a primeimplicant of F, being a subset of I_m

1 **while** $\exists l \in I_m \backslash I_r$ **do**

2   **if** $\exists c \in F : Req(I_m, l, c)$ **then**

3          $I_r \leftarrow I_r \cup \{l\}$

4   **else**

5          $I_m \leftarrow I_m \backslash \{l\}$

6 **return** I_r

---

implicant.

Any model of a CNF formula can contain multiple implicants and even prime implicants[3] , so if we could find out from only a single model M_0 of F, which of these literals occured in all implicants that that model covered, with each model we could reduce the set of backbone candidates even more than with just one of it's prime implicants.

Doing this is actually pretty simple. Instead of generating a small set of various prime implicants, you check for each assignment a in M_0, whether it is required in M_0, by checking whether $(M_0 \backslash a)$ is still an implicant that satisfies F. If so, we know that a is not part of the backbone, because we found an implicant without it. This approach was described in [JLMS15].

You can do this reduction faster if you make use of the lookup table described in the previous subsection, where each literal is mapped to the set of clauses where it occurs. After all, you already know that M_0 satisfies F, so it is sufficient to check only the clauses that contain the tested literal a, whether they are satisfied in a different way in $M_0 \backslash \{a\}$. Unaffected clauses must still be satisfied without a.

Additionally, if you happen to use a computation strategy, where you have a set of positively identifed backbone literals (for example an iterative algorithm as described in section 2.2, or when you make use of axiomatic literals as described in the next section), then of course these don't have to be tested either.

The benefit of this approach depends on the particular example. If the individual models of a formula contain very few primeimplicants or even only one, then looking for rotatable literals might not give a benefit over calculating the prime implicants. However formulas where individual models contain many prime implicants with large differences, the benefit can be extreme. See section 5 for experimental results.

---

[3]As an example imagine any formula with only clauses of size two, where the first literals are disjunct from the second literals. This formula has at least two prime implicants I_1 and I_2 that you can generate by collecting either the first literal of every clause for I_1 or the second literal for I_2. Since the literals in I_1 are disjunct from those in I_2, you can build a model of the combination of I_1 and I_2.

Algorithm 9: LITERAL ROTATION IN MODELS

Input: A formula F, a model M
Output: R, the required literals of all implicants in M

1 $R \leftarrow \emptyset$
2 **for** $a \in M$ **do**
3 $\quad I_a \leftarrow M \backslash a$
4 $\quad$ **if** $\exists c \in F : c \langle I_a \rangle = \bot$ **then**
5 $\quad \quad R \leftarrow R \cup \{a\}$

6 **return** R

3.2 Cheap Identification of backbone literals

This section describes various ways that allow you to recognize backbone literals without an additional satisfiability check. Knowing these backbone literals early can speed up the individual calls to the SAT solver, because enforcing the backbone literals prevents the solver from trying to find solutions containing the negation of backbone literals, which by definition don't exist.

3.2.1 Axiomatic literals

The most straightforward method to quickly identify backbone literals is to scan the formula for clauses with only a single literal. Since these clauses have only one possible way to become satisfied, that assignment must be used in every model of the formula and is therefore backbone.

Additionally you should check the CDCL table that your solver creates. If you look at this table you might find variable assignments through unit implication which happened before any decision. This includes all assignments from the paragraph above, but also those that are implied through these[4].

It makes sense to do this check after every sat computation, as every different way that leads to a different model brings different learned clauses, that may sometimes consist of a single literal.

An expansion on this would be to look for pairs of clauses (a,b), $(a, \neg b)$ for any two variables of the formula. The only way to fulfill this pair of clauses is to assign a to $\top$[5]. This scheme can theoretically be applied to any clause size, but then you would require a quadratically increasing number of clauses to determine a backbone which would first increase computation time and secondly decrease the chance that the necessary set of clauses was available.

TODO was ist mit gelerntem auf basis von assumptions

---

[4]Example: Formula $\{\{a\}, \{\neg a, b\}\}$ has the backbone $\{a, b\}$, but only a is immediately obvious.
[5]Which fits the resolution formula described in section 1.1.2

3.2.2 Unit Implication

yadayada

bedingung: damit c hier angewandt werden kann müssen alle literale darin backbone sein und $n_c - 1$ davon müssen bekannt sein.

We have tested this method in two solvers, *BB* and a variant of *PrefBones* that learns backbone literals only from clause learning as described in the previous subsection. This clearly showed that this method requires a critical mass of already known backbone literals to have a benefit, because as already stated, if there even exists a clause in F where this method can be applied, you need to know the $n_c - 1$ other backbone literals in c beforehand.

The learned backbone literals alone can rarely supply this, before the *PrefBones* algorithm terminates from other conditions. However the iterative approach of the *BB* solver, testing every yet unidentified literal individually, is much faster at providing positively identified backbone literals that you need to imply other backbone literals through unit implication.

3.2.3 Implication through Cooccurrence

Another method to recognize backbone literals from other ones is described in [WBX$^+$16] and the rationale goes as follows:

Lemma 1 Given a backbone literal a and another literal b. If b occurs in all clauses that also contain a, then $\neg b$ must be part of the backbone.

Proof: Assuming $\neg b$ was not in the backbone, then there would have to exist a model that contained b. Given that all clauses that contain b also contain a, a cannot be part of the backbone.

In other words, if we determine a new backbone literal, and all clauses that contain it also contain another literal, then we can add the negation of the latter to our backbone set.

bisschen dazu schreibseln. Diskussion unit case ist ja auch selten

refinedEssentials benchmark hat selten überhaupt irgendwelche damit festgestellt, höchstens 4, bei zwischen 200 und 400 variablen dimacs-hanoi5 hat 47

tabelle zum vergleich zwischen normalen KBB und KBB mit cooccurrence hinklatschen (je datei, nur implizierte backbone literale)

TODO überlegen, ob es sinnmacht überhaupt zwei variablen zu haben die in denselben klauseln auftauchen

3.3 Assumptions

A sub problem of calculating backbones is to calculate a backbone under an assumption. This means, that we actually want to know the Backbone of $F \cup \{l\}$ where F is our base formula and l is some variable of F.

File	n_{unit}	n_{coocc}
brock400-2.cnf	0	0
dimacs-hanoi5.cnf	1465	47
grieu-vmpc-s05-25.cnf	565	0
grieu-vmpc-s05-27.cnf	142	0
johnson8-2-4.cnf	0	0
fla-barthel-200-2.cnf	33	0
fla-barthel-200-3.cnf	43	0
fla-barthel-220-1.cnf	149	0
fla-barthel-220-2.cnf	0	0
fla-barthel-220-4.cnf	0	0
fla-barthel-240-2.cnf	61	0
fla-qhid-320-2.cnf	0	0
fla-qhid-320-5.cnf	283	2
fla-qhid-340-2.cnf	310	0
fla-qhid-340-3.cnf	309	3
fla-qhid-340-4.cnf	301	4
fla-qhid-360-1.cnf	326	0
fla-qhid-360-5.cnf	321	0
fla-qhid-380-1.cnf	344	2
fla-qhid-400-3.cnf	366	0
fla-qhid-400-4.cnf	359	0
smallSatBomb.cnf	0	0

Table 3.1: Comparison of number of back-bone literals identified through cooccurrence in comparison to the number identified through unit implication.

The most straightforward way to implement this is to simply call the sat solver that we use with the same assumptions every time. However depending on the way that assumptions are implemented in your solver, the set of learned clauses may have to be discarded or at least filtered. Reusing learned clauses is very useful when you calculate a backbone through repeating calls to the SAT solver, as table 5.2 shows.

We can implement assumptions in two ways, either as added clauses or as decisions above root level. This section discusses which should be preferred when designing a sat solver that should also be a good backbone generator.

4 Experiments with Preferences

As is mentioned in [PJ18], the concept of preferences has not experienced much research as of yet. That is why I experimented a lot with various modifications on the concept for the purpose of this thesis.

All of the following modifications were implemented ontop of algorithm 7 (*PB*1). Algorithm 6 (PB0) depends on that all available preferences are taken into account strictly, so there is not much space to experiment there without making the algorithm unreliable.

4.1 Forgetting preferences

During the course of solving a CNF formula with the CDCL algorithm, many assignment conflicts occur which must be resolved through backtracking. This means that some assignments need to be taken back. Looking at this from the other direction, it can very well happen, that the same variable can occur in decisions multiple times over such a calculation. If a variable assignment is even slightly involved in a conflict, then, lacking any further knowledge, it is a good strategy to simply try it's negation in the future. It is not guaranteed, but simply more likely that the other assignment resolves the conflict that occurred with the previous assignment.

The default way in that preferences are implemented stands in the way of this. If you tell the SAT solver to always assign the same boolean value to a specific variable, then the strategy above cannot be applied. That is why I have implemented an option to *PB*1 where preferences are forgotten after the first time when they are taken into account. This means that when a variable is selected for a decision, it is removed from the primary heap that is consulted first for this selection[1].

The secondary heap always contains all used variables for selection, but in the default configuration where preferences are not forgotten the preferred variables would already be assigned at the point in time when it is consulted. Here this means, that once a preference was forgotten, the associated variables can still occur in decisions after they were reverted through backtracking and can potentially be assigned a different value.

The most important effect of this strategy is, that the solver quickly falls back to his default behaviour when it turns out that the formula is difficult to solve when

---

[1] In the Sat4J library, what decides the order of decisions and what decides the value assigned in these decisions are actually two separate data structures. This means that this removal must be written in two separate places.

preferences for the resulting model are to be taken into account.

It is quite likely that a formula contains models that are relevant for the backbone, because they contain the only occurence of some literal. However, if they contradict the current set of preferred literals in many other places, giving these preferences to the SAT solver can actually make it difficult to find said model.

4.2 Subsets

During benchmarking it showed itself, that all solvers that did not employ any preferences at all were the fastest ones when it came to difficult formulas. So it might be interesting to test some algorithm that can be configured with a floating point number, where a ground value of 0.0 would be equivalent to having no preferences at all and then allowing to enable preferences in very small increments.

The simplest way to do this would be to restrict the number of preferences that could be set for each SAT call. The parameter above is multiplied with the number of variables in the formula and then the number of preferred literals is pruned in each iteration to have at most that size, without of course discarding the set of assignments that has yet to be tested.

Aside from the straightforward implementation, I also created a variant, where extra care is taken to use different subsets for the preferences for each sat call. To do this, all preferences given to the SAT solver are remembered and not picked again until all of them were tried once. At this point the memory of previously used preferences is cleared so that it builds up again.

4.3 Nudging

The previous approach to scalable preferences still works against the decision heuristic because before the SAT solver even starts, the preferred variables are chosen. What subset of the preferred variables would be easiest for the solver to take into account cannot be said upfront. Therefore it should be much more efficient to "nudge" the existing decision heuristic in the direction of the preferences while it's running.

To do this, I implemented a different kind of preference strategy. Here, similar to the previous method, you can pass a floating point number f between 0.0 and 1.0 in addition to the set of preferred variables. When a decision happens in the CDCL algorithm, the selection heuristic sorts all variables by an activity value, which is typically based on how often it was involved in conflicts. Then the resulting array is scanned, beginning with the variable with the lowest activity until one is found that is not yet assigned.

Here this activity value is multiplied with $1 - f$ during this sorting step where a variable is preferred. Therefore, if you pass 0 as value for f, the order that is returned from sorting the activities would be completely unaffected. Very small values of f would only affect the selection heuristic if a preferred value was already deemed

very important but only in second or third place with a small distance to the first one.

However, this factor f can only influence the order of variables for decisions. Which value is then assigned can not be weighted[2]. That is why the default strategy for deciding the phase was left in place.

The purpose of this scheme was to see, whether benefits of preferences would rise up faster than the drawbacks with very low values of f.

---

[2]Except if there was a heuristic for that, which can give a confidence value

5 Results

5.1 Tested Backbone algorithms

The following section lists the results for various backbone implementations. As this thesis focuses on the preferences approach, which is also not as thoroughly examined as other approaches, most of these variants are slight modifications of algorithm 7, where preferences are combined with blocking clauses.

The first two algorithms are *BB* (as listed in algorithm 5) and *IBB* (algorithm 3). The next algorithm (designated as *KBB*) is a variant of *BB* that whenever a backbone literal was identified through iterative testing, unit implication as described in subsection 3.2.2 is used on the set of known backbone literals, trying to identify more backbone literals in a cheap way[1]. The following variant *KBB(Pref)* additionally adds preferences to *KBB*. Both differ further from *BB*, in that they reduce their model not to a prime implicant, but to the required assignments in said model. TODO KBB benutzt Rotationen (keine primimplikanten). reiner effekt der unit implikation verfälscht. Problem?

Next is the original *bb − pref* (see algorithm 6) as described in [PJ18], designated as *PB0*, followed by my own variant of *Prefbones* that uses blocking clauses (see algorithm 7). However by default it contains two optimizations.

- Instead of intersecting models, the result of the sat call is refined to a prime implicant. The results for the case where this optimization was omitted can be seen in *PB1(model)*.

- Preferences are *forgetting*. There is a test with this omitted as well, namely *PB1(noAmnes)*.

The algorithms after that can also be described as slight modifications of *PB1*.

- *PB1(invert)* is a variant where the preferences are inverted, resulting in the sat solver trying to reproduce already found solutions.

- *PB1x* simply deactivates the preferences. Algorithmically this makes *PB1x* the same is *IBB*.

- *PB1a* removes the effect of selection order from the preferences. However, when one of the preferred literals is assigned, the assigned phase is chosen from the preferences.

---

[1] Note that optimisations such as this one were sometimes implemented in a simple, brute-force manner for the sake of time. Here the number of easily identified literals in combination with the pure calculation time is more interesting than the overall time that includes the unit search time.

- *PB1b* is the opposite of *PB1a*. The assigned value to a preferred literal is left to underlying heuristics, but preferred literals are picked for decisions.

- *PB1c* is configured in a way that only a handful of preferences are set in any point in time. It can be configured with a parameter $f \in]0..1]$. The maximum number of preferred assignments in *PB1c* is the number of variables in the formula multiplied with f. However, the particular order in which the subset is chosen is linear beginning at the first literal, so the set of preferences is often very similar over different sat calls.

- To alleviate this, *PB1d* contains an additional mechanism to ensure that the chosen subset of preferences is as different as possible in every sat computation.

- *PB1e* takes learned literals into account. These are put into set called bb_{sub}, which always contains a lower bound of the backbone. This allows two things. First you can omit preferences that would go against required backbone assignments, which would unnecessarily waste time. Secondly, you can add another abort condition. Instead of only stopping once the blocking clause makes the formula unsatisfiable, here you can also compare the backbones lower bound (bb_{sub}) with it's upper bound, which would be the intersection of previously found implicants. You can stop, once both upper and lower bound are the same and it is sufficient to compare their size to do this. This approach can potentially save the last sat computation. TODO: unter umständen behält der sat solver sowieso gelernte literale, dann hätten andere präferenzen eh keinen effekt.

- *PB1f* expands upton *PB1e* by initially running two satcalls, where one always assigns decided literals to $\top$ and the other to $\bot$.

PB2 employs a different way to implement preferences. Instead of having a preferred and a remainder set of literals and first exhausting the preferred set, here only one order is set up. However the activity values that determine the order are manipulated by applying a constant factor f to those literals that are preferred. The underlying idea is, that two variables are an equally good choice for a decision if their activity values are close, but if we have to pick one of the two, the one that is preferred is definitely to better. TODO problem mit ansatz ist, dass durch bevorzugte phase, präferenz trotzdem hart ist.

PB3 reduces the models not to a prime implicant but to the set of required literals as described in section 3.1.2.

5.2 SAT Competition Benchmark

For the first benchmark, I collected a set of 71 files from a SAT competition TODO welcher. The SAT competitions generally use problems that are difficult to solve compared to other problems of the same file size. This is in order to encourage

development of solving strategies that reliably have good performance and not only for most of them. To save time during benchmarking, those files that took longer than around one minute for a single model computation were excluded, resulting in files that are generally around 30 kilobytes large. Additionally, problems where the duration for backbone computation averaged below one second were excluded, because here the small differences in the measurements could just as well be explained with external factors like the CPU throttling for a short time. To get meaningful testresults for such files, multiple testpasses should be conducted.

The averaged time to compute the backbones of these 71 testfiles can be seen in 5.1. To prove that various computation strategies are implemented as good as possible[2], the second column shows the time that was only spent in the sat solver.

Taking a look at this table, we can quickly see that for these instances, all solver that employed preferences as part of their algorithm performed much worth than those that did not[3].

IBB hatte bug, darum bessere leistung von pb1x vgl IBB

zweite tabelle zeigen, wenn blocking clause nicht entfernt wurde

	t_{full}	t_{sat}	n_{sat}
BB	25.767	25.765	275
IBB	27.086	27.07	7
KBB	25.454	25.29	42
KBB(pref)	54.729	54.619	39
PB0	57.177	57.175	5
PB1	131.063	131.061	5
PB1(noAmnes)	171.183	171.182	4
PB1(model)	116.853	116.852	6
PB1x	18.564	18.562	8
PB1a	154.091	154.089	7
PB1b	144.028	144.026	6
PB1c(50%)	119.571	119.569	6
PB1c(5%)	141.334	141.332	6
PB1d(50%)	131.602	131.6	6
PB1d(5%)	148.734	148.732	6
PB1e	143.675	142.621	6
PB1f	224.335	224.334	6
PB2(50%)	228.267	228.264	8
PB2(5%)	182.26	182.258	8
PB2(0.5%)	165.892	165.89	8
PB3	157.297	157.249	5

Table 5.1: Averages of 71 testfiles taken from sat competitions. The columns indicate: The full time that the calculation took in seconds; The time that was spent in the sat solver; The number of sat calls (all three values are averages).

5.2.1 Importance of reusing learned clauses

Table 5.2 shows a comparison of individual benchmarks to highlight the importance of reusing learned clauses. While working with the *Sat4J* library I noticed that the *IBB* backbone algo-

---

[2]e.g. no noteworthy timeloss during setup of preferences
[3]Which would be *BB*,*IBB*,*KBB* and *PB1x*

rithm was accidentally configured in a way that learned clauses would always be discarded between SAT computations. However, these learned clauses are still valid in later iterations of the *IBB* algorithm. The only difference that the formula goes through during this algorithm, is that the blocking clause that ensures a new model repeatedly looses some of it's literals. As long as the set of solutions for a formula is only reduced, the learned clauses of that formula stay valid.[4]

The information contained in learned clauses is very valuable, as it prevents the solver from repeating invalid combinations of assignments that might even be likely to occur again. But if already learned clauses can guide the SAT solver away from possible conflicts, it could ideally return a model without any backtracking.

5.2.2 Comparison of PB0 with PB1

Table 5.1 shows a strong performance difference between PB0 and PB1.

TODO grieu beispiel rauspicken (letzter sat call)

stammt daher, dass zuletzt unsat errechnet wird. vonThore hat das problem nicht (selten überhaupt eine millisekunde gebraucht für letzten aufruf)

5.2.3 Benefits of unit implication

This subsection evaluates the effects of trying to recognize backbone literals through unit implication as described in section 3.2.2. Table 5.4 shows individual performance differences between the *BB* solver supplied by Sat4J and

File	t_{keep}	$t_{discard}$
brock400-2.cnf	0.233	0.252
dimacs-hanoi5.cnf	1.41	1.596
grieu-vmpc-s05-25.cnf	71.945	78.964
grieu-vmpc-s05-27.cnf	554.52	648.697
fla-barthel-200-2.cnf	0.634	6.019
fla-barthel-200-3.cnf	0.619	2.16
fla-barthel-220-1.cnf	2.511	9.572
fla-barthel-220-2.cnf	7.497	17.759
fla-barthel-220-4.cnf	2.24	14.113
fla-barthel-240-2.cnf	3.632	50.552
fla-komb-200-3.cnf	0.236	0.301
fla-komb-200-5.cnf	0.114	0.276
fla-qhid-320-1.cnf	6.61	6.575
fla-qhid-320-2.cnf	9.227	101.17
fla-qhid-320-5.cnf	7.861	7.962
fla-qhid-340-2.cnf	11.922	13.688
fla-qhid-340-3.cnf	11.796	17.157
fla-qhid-340-4.cnf	9.454	9.297
fla-qhid-360-1.cnf	39.998	39.797
fla-qhid-360-5.cnf	10.698	10.849
fla-qhid-380-1.cnf	189.895	249.003
fla-qhid-400-3.cnf	83.098	130.834
fla-qhid-400-4.cnf	55.213	52.811
smallSatBomb.cnf	0.011	0.022

Table 5.2: Backbone computation time of the *IBB* algorithm, once with keeping learned clauses (t_{keep}) and once discarding learned clauses between every sat call($t_{discard}$)

---

[4]Example: With a formula without any clauses but three variablesyy *a*,*b* and *c* you can create eight models. With only the clause {*a*} in your formula you can have four models, with only the clause {*a* ∨ *b*} you can have 6 models, with only the clause {*a* ∨ *b* ∨ *c*} you can have 7 models.

File	$t_{BB}(n_{sat})$	$t_{KBB}(n_{sat})$	n_{unit}	$n_{backbone}$
brock400-2.cnf	0.041(254)	0.038(254)	0	0
fla-komb-400-3.cnf	1276.712(381)	1241.124(45)	336	379
dimacs-hanoi5.cnf	1.944(1931)	1.836(281)	1650	1931
vonThore42.cnf	0.018(398)	0.014(51)	345	346
grieu-vmpc-s05-27.cnf	261.091(678)	281.083(536)	142	677
fla-komb-360-4.cnf	14.937(337)	14.936(45)	292	333
fla-qhid-360-1.cnf	74.964(355)	76.032(29)	326	355
grieu-vmpc-s05-25.cnf	182.837(625)	179.914(51)	574	625
fla-qhid-360-5.cnf	20.678(350)	20.892(29)	321	349
fla-barthel-220-4.cnf	3.553(32)	2.741(32)	0	6
9012345.cnf	4.181(1483)	6.734(813)	670	1478
fla-barthel-220-2.cnf	8.183(23)	8.109(23)	0	4
1098765.cnf	1.208(938)	1.291(493)	444	921
smallSatBomb.cnf	0.013(26)	0.012(19)	7	9

Table 5.4: Benchmark results for a selection of files with a focus on the benefit of unit implication. Rows indicate: The number of backbone literals identified through unit implication; the actual number of backbone literals; Calculationtime and number of sat calls of the solvers *KBB* (using unit implication) and *BB* (not doing unit implication, otherwise the same).

my *KBB* solver for comparison, as well as the backbone's size and the number of backbone literals identified through unit implication. The time columns also contain the number of sat calls that were comitted.[5]

The results drunter und drüber, auf einzeldateien eingehen

Begründungsvermutung: Hauptzeit geht für wenige schwierige Literale drauf, die nicht per unit implikation gefunden werden können. Könnte experimentell festgestellt werden, dur

reine sat zeit von kbb wurde auch gemessen: verlust durch suche liegt bei 0

	t_{full}	t_{sat}	t_{last}	n_{sat}
PB0	1005.756	1005.753	810.946	3
PB1	6741.638	6741.635	6594.098	2
IBB	584.737	584.619	TODO	2

Table 5.3: Comparison of runtime of file $grieu - vmpc - s05 - 27$. t_{last} shows the time that the very last sat call took.

---

[5]Most of the performance differences in table 5.4 can be explained with other reasons than actual algorithmic differences. $fla - barthel - 220 - 4.cnf$ for example should not be faster with *KBB* since here no backbone literal was determined through unit propagation. However I was able to reproduce this performance difference just through the order of what was called first, i.e. if the two solvers are called the other way around the timings are so as well. A possible explanation could be a power saving feature in modern processors.

5.2.4 Benefits of forgetting preferences

schlechte ergebnisse von PB1c (0.05) vgl run2 mit run3 (run3 hat kein default vergessen)

5.3 Industrial benchmark

Another benchmark I applied on the various backbone algorithms was a formula for a real world application from the automobile industry. The purpose of this formula F_{conf} was to describe a product in the context of options or features available to the customer. Some of these options can be combined, others exclude or require each other. Most of the variables in F_{conf} correspond to a boolean parameter that is set to $\top$ if the associated feature is requested by the customer. If the formula would become unsatisfiable under such assumptions equal to the requested configuration, then the combination of these features would be impossible. F_{conf} further contains a small set of additional variables to model more complex relationships between options.

	t_{calc}(sec)	t_{sat}(sec)	NSatCalls
BB	11.117	7.235	159545
IBB	6.353	2.316	15748
KBB	13.747	2.11	15266
PB0	3.659	1.469	6531
PB1	3.918	1.611	6531
PB1(amnes)	4.067	1.682	6531
PB1(model)	2.148	1.59	6531
PB1x	7.596	2.94	15748
PB1a	5.096	2.112	9335
PB1b	7.754	3.199	15248
PB1c	5.376	2.248	9680
PB1c(5%)	7.026	2.693	13955
PB1d	4.464	1.804	7386
PB1e	3.524	1.354	6387
PB1f	3.603	1.526	6369
PB2	8.341	3.457	15752
PB2(5%)	8.313	3.484	15752
PB2(0.5%)	8.364	3.529	15752
PB3	3.872	1.204	4471

Table 5.5: First execution of industry application. Values are not averaged, but summed up over 407 different benchmarks.

The particular use case that I examined was to find the implications in the formula, i.e. if a customer requests feature a, would he also have to pick feature b. A primitive way to calculate this would be to iterate over all possible pairs of features [6] and check for satisfiability of F_{conf} under the condition that a is $\top$ and b is $\bot$. If this was unsatisfiable, then a would imply b. However, with 407 literals to choose from, you would have to do 82,621 sat calls.

A more efficient approach is to only go over the 407 options once and for each variable a of them calculate the backbone of $F_{conf} \cup \{a\}$ or in other words F_{conf} under

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[6]Minus permutations and pairs with the same feature twice

the assumption *a*. If a feature *b* occurs in all models when *a* is assumed, then *a* implies *b* in some way.

Table 5.5 lists experimental results with the same set of algorithms that were run on the files from the sat competition. After analyzing performance results, I try to give a specialized algorithm that is optimized for this particular benchmark.

We immediately see, that preferences give a much greater benefit than in the benchmark with the files from the sat competition. However there are some more things that stand out:

- The fastest algorithm overall is the one that does not reduce the models at all. The number of sat calls is even exactly the same as that of that variant with prime implicant reduction. However the time that was spent in the sat solver is very similar to that execution with prime implicant reduction (*PB*1), so the difference must be the time that was spent to reduce the model and the benefit, namely the number of optional literals in the prime implicant, was very small.

- However, the fastest implementation when it comes to pure sat solver time as well as number of sat calls, was *PB*3, which differs from the others in that it uses literal rotation to reduce models instead of prime implicant computation. Apparantly the models that occur in this formula contain many different prime implicants with little distance to the model.
  A previous variant of this algorithm took around 250 seconds to compute overall. This version did not use the lookup from literal to containing clauses (as described in later paragraphs in section section 3.1.2), but iterated over all clauses in the formula. Such a drastic effect of an efficient implementation did not occur for the sat competition benchmark.
  This has primarily two reasons. First, the number of sat calls per instance is twice as much in this benchmark compared to those from the sat competitions[7], therefore the model reduction happens twice as often. Secondly, the formula of this benchmark is much larger than those from the sat competition, with the filesize being around twenty times as large. Therefore there are much more clauses to search through.

- The two algorithms in third place of overall computation time were *PB*1*e* and *PB*1*f*. Both of these make use of learned literals so appearantly the backbone literals in this formula are easy to identify by checking the set of literals that the solver learns when it computes new models.
  In fact, on inspection, all literals that later turn out to be part of the backbone occur in this set after the very first sat call(with an exception of the forced literal, which can be extracted by searching the formula for clauses with only one literal).

- Another noteworthy algorithm is the *KBB* algorithm that uses unit implication to identify backbone literals. The implementation of this algorithm was based

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[7]The 4471 calls span over 407 problem instances.

on that of the *BB* algorithm and here the number of sat calls with *KBB* is a tenth of the number in the case of *BB*. However this advantage is not expressed equally strong when it comes to the time spent in the sat solver(around a fourth), which means that the identification through calculating a new model can sometimes be more efficient than regularly checking unit implications.
The overall computation time is even worse in comparison, meaning that the benefit through cheap backbone literal identification is less than the time that it takes to check the clauses for the unit case. It may be possible that this method requires an improved implementation. The search for clauses where the unit implication for backbone literals applies could be implemented in a similar way as was used to calculate required and rotatable assignments, using the lookup from variables to clauses where they occur (see section 3.1.2)

verbesserungen: - nicht brute force klauseln prüfen, sondern anhand des index für watched literal propagation (notiz: monoclauses werden in sat4j nicht gelernt. Sollten stattdessen eh als assumptions übergeben werden) - nur die literale rotieren die in der obermenge verbleiben - Außerdem: "bugfix" erzwungenes literal trat nicht in gelernten auf. - präferenzen nutzen

besonderheiten: - absolut alle backbone literale sind nach dem ersten sat aufruf gelernt. (*mit technischen besonderheiten, nur wenn man blocking clauses nimmt und dann ausgenommen die in der blocking clause)

Line 5 bis Line 8 do while breche ab sobald nix neues gefunden wird. unitImplied gibt nur neue zurück

besondere bedeutung für diesen benchmark: wiederverwendung von gelernten klauseln über unterschiedliche literale

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Algorithm 10: SPECIALIZED ALGORITHM FOR INDUSTRIAL APPLICATION

Input: A satisfiable formula F in CNF
Output: All literals of the backbone of F

1   $(outc, mdl, learnt) \leftarrow SAT(F)$
2   $bb_u \leftarrow required(mdl, F)$
3   $bb_l \leftarrow learnt$
4   **while** $bb_l \neq bb_u$ **do**
5   **do**
6        $unitBackbones \leftarrow unitImplied(F, bb_l)$
7        $bb_l \leftarrow bb_l \cup unitBackbones$
8   **while** $unitBackbones \neq \emptyset$
9      $blocker \leftarrow \bigvee_{l \in bb_u} \neg l$
10     $prefs \leftarrow \{\neg l : l \in bb_u\}$
11     $(outc, mdl, learnt) \leftarrow prefSAT(F \cup blocker \cup bb_l, prefs)$
12   **if** $\neg outc$ **then**
13   **return** bb_u
14     $bb_l = bb_l \cup learnt$
15     $bb_u = bb_u \cap required(mdl, F, bb_l)$
16 **return** bb_u

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