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To Guess or to Think? Hybrid Algorithms for SAT (Extended Abstract) *

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Complete algorithms for solving propositional satisfiability fall into two main classes: backtracking search (e.g., the Davis-Putnam Procedure [1]) and resolution (e.g., the original Davis-Putnam Algorithm [2] and Directional Resolution [4]). Backtracking may be viewed as a systematic "guessing" of variable assignments, while resolution is inferring, or "thinking". Experimental results show that "pure guessing" or "pure thinking" might be inefficient. We propose an approach that combines both techniques and yields a family of hybrid algorithms, parameterized by a bound on the "effective" amount of resolution allowed. The idea is to divide the set of propositional variables into two classes: *conditioning* variables, which are assigned truth values, and *resolution* variables, which are resolved upon. We report on preliminary experimental results demonstrating that on certain classes of problems hybrid algorithms are more efficient than either of their components in isolation.

The well-known Davis-Putnam Procedure (DP) is a backtracking algorithm enhanced by unit resolution at each level of the search. Directional Resolution (DR)[4] is a variable-elimination algorithm similar to adaptive-consistency for constraint satisfaction. Its worst-case time and space complexity is exponential in *induced width*, w^*, of the interaction graph of a propositional theory. The time complexity of DP is worst-case exponential in the number of variables, while its space complexity is linear. However, on average DP is relatively efficient, while DR's average complexity is close to its worst-case. Consequently, DR is significantly less efficient than DP when applied to uniformly generated 3-cnfs having large w^*, while outperforming DP by many orders of magnitude when applied to theories with bounded w^* [4]. This time- and space-wise complementary behavior of the two algorithms prompted the idea of combining DP and DR.

We propose a family of hybrid algorithms, called *Dynamic Conditioning + DR (DCDR)*, parameterized by a bound, b, that controls the balance between resolution and backtracking. Given b, the algorithm DCDR(b) selects a subset of conditioning variables, or *cutset*, C_b, such that w^* of the resulting (conditional) theory does not exceed b. The hybrid algorithm searches the space of truth assignments for the conditioning variables and resolves upon the rest of the

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variables. Dividing the set of variables into the cutset and resolution variables is accomplished during run time, i.e. dynamically. We have also experimented with a static version of the algorithm (for details see the full paper available through *http://www.ics.uci.edu/˜irinar*). We show that the time complexity of both algorithms is $O(exp(c+b))$, where c is the largest cutset size encountered during run time.

We tested DCDR(b) on *uniform k-cnfs* and on structured problems having bounded w^*, such as (k,m)-trees. A *(k,m)-tree* is a tree of cliques, each having $k+m$ nodes, where k is the size of intersection between each two neighboring cliques. We observed three different behavior patterns depending on $w*$ (see Figure 1): 1. on problems having large w^*, such as uniform 3-cnfs around the 50% solvable crossover point (the transition region from satisfiable to unsatisfiable problems), the time complexity of DCDR(b) is similar to DP when b is small (obviously, a bound $b=-1$ does not allow any resolution, making DP equivalent to DCDR(-1)), however, when b increases, the CPU time for DCDR(b) grows exponentially; 2. theories having very small w^* (such as (k,m)-trees with $k \leq 4, m \leq 6$) are easier for DCDR(b) with a large b, since DCDR(b) coincides with DR for $b \geq w^*$; 3. on (k,m)-trees with larger clique size, we observed an intermediate region of b's values yielding a faster algorithm than both DP and DR. The averages for uniform 3-cnfs are computed on 100 problem instances, while for (k,m)-trees we ran only 25 experiments per point. We therefore view our results as preliminary. However, they indicate the general promise of the approach.

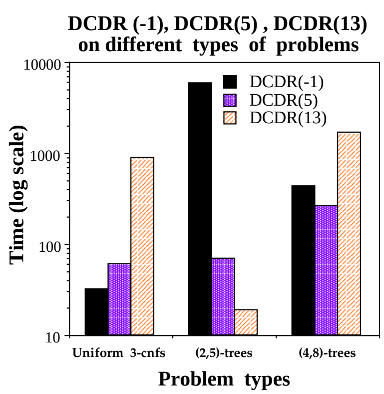

Figure 1

We see that w^* provides a reasonable predictor of b. When $w*$ is very large, we choose $b \leq 1$; when w^* is very small (less than 4), we choose large b; for intermediate levels of $w*$ it is better to choose a bounded level of b. The algorithms having b in the range of 5 to 8 seem promising, since they behave similarly to DP on uniform instances, to DR for small w^*, while for intermediate values of w* they exploit the benefits of both DP and DR. The hybrid algorithms trade space for time [3], and output a compiled theory from which a portion of the solution set rather than one solution can be generated in linear time.

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