

# A Full Derandomization of Schönig's $k$ -SAT Algorithm

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## Abstract

Schönig [7] presents a simple randomized algorithm for  $k$ -SAT with running time  $O(a_k^n \text{poly}(n))$  for  $a_k = 2(k-1)/k$ . We give a deterministic version of this algorithm running in time  $O((a_k + \epsilon)^n \text{poly}(n))$ , where  $\epsilon > 0$  can be made arbitrarily small.

## 1 Introduction

In 1999, Uwe Schönig [7] gave an extremely simple randomized algorithm for  $k$ -SAT. Ten years on, the fastest algorithms for  $k$ -SAT are only slightly faster than his, and far more complicated. His algorithm works as follows: Let  $F$  be a  $(\leq k)$ -CNF formula over  $n$  variables. Start with a random truth assignment. If this does not satisfy  $F$ , pick an arbitrary unsatisfied clause  $C$ . From  $C$ , pick a literal uniformly at random, and change the truth value of its underlying variable, thus satisfying  $C$ . Repeat this reassignment step  $O(n)$  times. If  $F$  is satisfiable, this finds a satisfying assignment with probability at least

$$\left(\frac{k}{2(k-1)}\right)^n.$$

By repetition, this gives a randomized  $O^*(1.334^n)$  algorithm for 3-SAT, an  $O^*(1.5^n)$  for 4-SAT, and so on (we use  $O^*$  to suppress polynomial factors in  $n$ ). Shortly after Schönig published his algorithm, Dantsin, Goerdt, Hirsch, Kannan, Kleinberg, Papadimitriou, Raghavan and Schönig [2] (henceforth *Dantsin et al.* for the sake of brevity) came up with a *deterministic* algorithm that can be seen as an attempt to derandomize Schönig's algorithm. We say *attempt* because its running time is  $O^*((2k/(k+1))^n)$ , which is exponentially slower than Schönig's. For example, this gives an  $O^*(1.5^n)$  algorithm for 3-SAT and  $O^*(1.6^n)$  for 4-SAT. Subsequent papers have improved upon this running time, mainly focusing on 3-SAT: Dantsin et al. already improve the running time for 3-SAT to  $O(1.481^n)$ , Brueggemann and Kern [1] to  $O(1.473^n)$ , Scheder [6] to  $O(1.465^n)$ , and Kutzkov and Scheder [4] to  $O^*(1.439^n)$ . All improvements suffer from two drawbacks: First, they fall short of achieving the running time of Schönig's randomized algorithm, and second, they are all fairly complicated. In this paper, we give a rather simple deterministic algorithm with a running time that comes arbitrarily close to Schönig's, thus completely derandomizing his algorithm. We also show how to derandomize Schönig's algorithm for constraint satisfaction problems, which are a generalization of SAT, allowing more than two truth values.

## 1.1 Notation

We use the notational framework introduced in [8]. We assume an infinite supply of propositional *variables*. A *literal*  $u$  is a variable  $x$  or a complemented variable  $\bar{x}$ . A finite set  $C$  of literals over pairwise distinct variables is called a *clause* and a finite set of clauses is a *formula* in CNF (Conjunctive Normal Form). We say that a variable  $x$  *occurs* in a clause  $C$  if either  $x$  or  $\bar{x}$  are contained in it and that  $x$  occurs in the formula  $F$  if there is any clause where it occurs. We write  $\text{vbl}(C)$  or  $\text{vbl}(F)$  to denote the set of variables that occur in  $C$  or in  $F$ , respectively. We say that  $F$  is a  $(\leq k)$ -CNF formula if every clause has size at most  $k$ . Let such an  $F$  be given and write  $V := \text{vbl}(F)$ .

A (*truth*) *assignment* is a function  $\alpha : V \rightarrow \{0, 1\}$  which assigns a Boolean value to each variable. A literal  $u = x$  (or  $u = \bar{x}$ ) is *satisfied* by  $\alpha$  if  $\alpha(x) = 1$  (or  $\alpha(x) = 0$ ). A clause is *satisfied* by  $\alpha$  if it contains a satisfied literal and a formula is *satisfied* by  $\alpha$  if all of its clauses are. A formula is *satisfiable* if there exists a satisfying truth assignment to its variables.

If  $\alpha$  and  $\beta$  are two truth assignments over a set  $V$  of variables, then their (*Hamming*) *distance*  $d_H(\alpha, \beta)$  is defined to be the number of variables  $x \in V$  where  $\alpha(x) \neq \beta(x)$ , i.e.  $d_H(\alpha, \beta) := |\{x \in V \mid \alpha(x) \neq \beta(x)\}|$ . For a given assignment  $\alpha$ , we denote the set of all assignments  $\beta$  with Hamming distance at most  $r$  from  $\alpha$  by  $B_r(\alpha) := \{\beta : V \rightarrow \{0, 1\} \mid d_H(\alpha, \beta) \leq r\}$  and call this the *Hamming ball of radius  $r$  centered at  $\alpha$* .

Formulas can be manipulated by permanently assigning values to variables. If  $F$  is a given CNF formula and  $x \in \text{vbl}(F)$  then assigning  $x \mapsto 1$  satisfies all clauses containing  $x$  (irrespective of what values the other variables in those clauses are possibly assigned later) whilst it truncates all clauses containing  $\bar{x}$  to their remaining literals. We will write  $F^{[x:=1]}$  to denote the formula arising from doing just this, or equally  $F^{[u:=1]}$  where  $u$  is a literal and we mean to assign the underlying variable the value necessary to satisfy  $u$ . If  $\beta$  is a partial assignment, i.e., defined on a subset of  $\text{vbl}(F)$ , then  $F^{[\beta]}$  denotes the formula we obtain from  $F$  by permanently setting the variables from those subset to their respective values under  $\beta$ .

## 1.2 Previous Work

Both Schönig’s algorithm and its deterministic versions can be seen as not attacking SAT directly, but rather a parametrized local search problem:

**Promise-Ball- $k$ -SAT:** Given a  $(\leq k)$ -CNF formula  $F$  over  $n$  variables, an assignment  $\alpha$  to these variables, a natural number  $r$ , and the promise that the Hamming ball  $B_r(\alpha)$  contains a satisfying assignment. Find any satisfying assignment to  $F$ .

Let us clarify what we mean by saying “Algorithm  $A$  solves PROMISE-BALL- $k$ -SAT”: If  $F$ ,  $\alpha$ , and  $r$  are as described above, i.e., if  $B_r(\alpha)$  contains a satisfying assignment, then  $A$  must return *some* satisfying assignment. We do not require this assignment to lie in  $B_r(\alpha)$ , however. On the other hand, if  $F$  is unsatisfiable, or  $B_r(\alpha)$  contains no satisfying assignment, the behavior is unspecified. Of course, since we can quickly check any purported assignment that the algorithm outputs, we can assume the algorithm always either returns a satisfying assignment or **failure**.

Schönig’s original randomized algorithm for PROMISE-BALL- $k$ -SAT as described in the introductory section, henceforth called **Schönig**, repeatedly selects any clause unsatisfied under  $\alpha$ , then randomly picks a literal from that clause and flips the underlying

variable's value. The algorithm gives up if a satisfying assignment has not been encountered by the time  $O(n)$  steps have been performed (it is well-known and easy to check that  $n/(k-2)$  correction steps are sufficient to achieve optimal efficiency).

**Lemma 1** (Schöning [7]). *Let  $F$  be a  $(\leq k)$ -CNF formula,  $\alpha$  a truth assignment to its variables, and  $r \in \mathbb{N}$ . If there is a satisfying assignment in  $B_r(\alpha)$ , then with probability at least  $(k-1)^{-r}$ , Schöning returns a satisfying assignment. By repetition, this gives a Monte-Carlo algorithm for PROMISE-BALL- $k$ -SAT with running time  $O^*((k-1)^r)$ .*

Schöning turns this lemma into an algorithm for  $k$ -SAT by choosing the assignment  $\alpha$  uniformly at random from all  $2^n$  truth assignments:

**Theorem 2** (Schöning [7]). *There is a randomized algorithm that runs in polynomial time and finds a satisfying assignment of  $F$  with probability*

$$\left(\frac{k}{2(k-1)}\right)^n,$$

*provided  $F$  is satisfiable.*

*Proof.* Let  $\alpha^*$  be a satisfying assignment of  $F$  and let  $\alpha$  be an assignment chosen uniformly at random from  $\{0,1\}^n$ . For each  $0 \leq r \leq n$ , the probability that the Hamming distance  $d_H(\alpha, \alpha^*)$  is  $r$  is  $\binom{n}{r}/2^n$ . In this case, Schöning's random walk returns a satisfying assignment with probability at least  $(k-1)^{-r}$ . The overall success probability thus is at least

$$\sum_{r=0}^n \binom{n}{r} 2^{-n} (k-1)^{-r} = \left(\frac{k}{2(k-1)}\right)^n,$$

and the running time is clearly polynomial.  $\square$

By repeating the above algorithm, one obtains a Monte-Carlo algorithm for  $k$ -SAT of running time  $O^*((2(k-1)/k)^n)$ .

## Deterministic Algorithms

What about deterministic algorithms? Dantsin et al. [2] give a simple recursive algorithm for PROMISE-BALL- $k$ -SAT running in time  $O^*(k^r)$ : If  $\alpha$  satisfies  $F$ , we are done. Otherwise, if  $r = 0$ , we can return **failure**. If  $r \geq 1$  and  $\alpha$  does not satisfy  $F$ , we let  $C$  be an unsatisfied clause. There are at most  $k$  literals in  $C$ , thus there are at most  $k$  possibilities to locally change  $\alpha$  so as to satisfy  $C$ . We recursively explore each possibility, decreasing  $r$  by 1 (see Algorithm 1 for the details). The next achievement of Dantsin et al. is to show how a deterministic algorithm for PROMISE-BALL- $k$ -SAT can be turned into a deterministic algorithm for  $k$ -SAT:

**Lemma 3** (Dantsin et al. [2]). *If algorithm  $A$  solves PROMISE-BALL- $k$ -SAT in time  $O^*(a^r)$ , then there is an algorithm  $B$  solving  $k$ -SAT in time  $O^*\left(\left(\frac{2a}{a+1}\right)^n\right)$ . Furthermore,  $B$  is deterministic if  $A$  is.*

Their algorithm to prove the lemma constructs a so-called covering code  $\mathcal{C} \subseteq \{0,1\}^n$  with the property that every assignment  $\alpha \in \{0,1\}^n$  has a codeword  $\gamma \in \mathcal{C}$  at a suitably small Hamming distance from  $\alpha$ . Schöning's randomized selection of an initial assignment is turned deterministic by iterating through all codewords  $\gamma \in \mathcal{C}$  and solving PROMISE-BALL- $k$ -SAT around each of them. Provided that the formula is satisfiable,

one choice of  $\gamma \in \mathcal{C}$  will be sufficiently close to a satisfying assignment for the subsequent local search to succeed.

The recursive algorithm for PROMISE-BALL- $k$ -SAT of Dantsin et al. has running time  $O^*(k^r)$ . Therefore Lemma 3 gives a running time of  $O^*((2k/(k+1))^n)$ . For  $k = 3$ , clever branching rules have been designed to improve upon the  $O^*(3^r)$  bound, leading to the respective improvements on deterministic running times mentioned in the first paragraph of this paper.

### 1.3 Our Contribution

Our contribution is to give a deterministic algorithm solving PROMISE-BALL- $k$ -SAT in a running time that gets arbitrarily close to that of the Monte-Carlo algorithm in Lemma 1.

**Theorem 4.** *For every  $\epsilon > 0$ , there exists a deterministic algorithm which solves the problem PROMISE-BALL- $k$ -SAT in time  $O((k-1+\epsilon)^r)$ .*

Combining this theorem with Lemma 3 proves our main theorem:

**Theorem 5.** *For every  $\epsilon > 0$ , there is a deterministic algorithm solving  $k$ -SAT in time  $O^*\left(\left(\frac{2(k-1)}{k} + \epsilon\right)^n\right)$ .*

Before jumping into technical details, let us sketch the main idea of our improvement for  $k = 3$ . Let  $F$  be a 3-CNF formula and  $\alpha$  some assignment. Suppose  $F$  contains  $t$  pairwise disjoint clauses  $C_1, \dots, C_t$ , all of which are unsatisfied by  $\alpha$ . We let Schöning’s random walk algorithm process these clauses one after the other: In each clause  $C_i$ , it picks one literal randomly and satisfies it. Thus, of all  $3^t$  possibilities to choose one literal in each  $C_i$ , it chooses one uniformly at random. Let  $\alpha^*$  be an assignment satisfying  $F$ . With probability at least  $3^{-t}$ , Schöning’s random walk chooses in each  $C_i$  a literal that  $\alpha^*$  satisfies. In this case, the distance from  $\alpha$  to  $\alpha^*$  decreases by  $t$ . However, with much bigger probability, roughly  $2^{-t/3}$ , the random walk chooses the “correct” literal in  $2t/3$  clauses  $C_i$  and a “wrong” literal in the remaining  $t/3$ . In this case, the distance from  $\alpha$  to  $\alpha^*$  decreases by  $t/3$ . This is the power of Schöning’s algorithm: It hopes to make a modest progress of  $t/3$ , which is much more likely than making a progress of  $t$ . Our key observation is that this choice of Schöning can be derandomized: There is a set of (roughly)  $2^{t/3}$  choices which literal to satisfy in each  $C_i$ , such that at least one of them makes a progress of at least  $t/3$ .

## 2 The Algorithm

To begin with, we will formally state the recursive algorithm by Dantsin et al. [2] solving PROMISE-BALL- $k$ -SAT in time  $O^*(k^r)$ .

**Proposition 6.** *Algorithm 1 solves BALL- $k$ -SAT in time  $O^*(k^r)$*

*Proof.* The running time is easy to analyze: If  $F$  is a  $(\leq k)$ -CNF formula, then each call to `searchball` causes at most  $k$  recursive calls. To see correctness of the algorithm, we proceed by induction on  $r$  and suppose that  $\alpha^*$  satisfies  $F$  and  $d_H(\alpha, \alpha^*) \leq r$ . Let  $C$  be the clause selected in line 6. Since  $\alpha^*$  satisfies  $C$  but  $\alpha$  does not, there is at least one literal  $u \in C$  such that  $\alpha^*(u) = 1$  and  $\alpha(u) = 0$ . Let  $\alpha' := \alpha^*[u := 0]$ . We observe that  $d(\alpha, \alpha') \leq r - 1$  and  $\alpha'$  satisfies  $F^{[u:=1]}$  (although not necessarily  $F$ ). Therefore the induction hypothesis ensures that the recursive call to `searchball`( $F^{[u:=1]}$ ,  $\alpha$ ,  $r - 1$ ) return `true`.  $\square$

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**Algorithm 1** searchball(CNF formula  $F$ , assignment  $\alpha$ , radius  $r$ )

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1: if  $\alpha$  satisfies  $F$  then
2:   return true
3: else if  $r = 0$  then
4:   return false
5: else
6:    $C \leftarrow$  any clause of  $F$  unsatisfied by  $\alpha$ 
7:   for  $u \in C$  do
8:     if searchball( $F^{[u:=1]}$ ,  $\alpha$ ,  $r - 1$ ) = true then
9:       return true
10:    end if
11:  end for
12:  return false
13: end if

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**Proposition 7.** *Suppose  $F$  is a  $(\leq k)$ -CNF formula,  $\alpha$  a truth assignment to its variables, and  $r \in \mathbb{N}$ . If every clause in  $F$  that is unsatisfied by  $\alpha$  has size at most  $k - 1$ , then searchball( $F, \alpha, r$ ) runs in time  $O^*((k - 1)^r)$ .*

*Proof.* The key observation is that if all clauses in  $F$  that are not satisfied by  $\alpha$  have at most  $k - 1$  literals, then the same is true for any formula of the form  $F^{[u:=1]}$ . Therefore, any call to searchball entails at most  $k - 1$  recursive calls.  $\square$

## 2.1 $k$ -ary Covering Codes

Before explaining our algorithm, we make a combinatorial detour to  $k$ -ary covering codes, which will play a crucial role in our algorithm.

The set  $\{1, \dots, k\}^t$  looks similar to the Boolean cube  $\{0, 1\}^t$  in many ways. For example, it is endowed with a Hamming distance  $d_H$ : For two elements  $w, w' \in \{1, \dots, k\}^t$ , we define  $d_H(w, w')$  to be the number of coordinates in which  $w$  and  $w'$  do not agree. There are also balls: We define

$$B_r^{(k)}(w) := \{w' \in \{1, \dots, k\}^t \mid d_H(w, w') \leq r\} .$$

What is the volume of such a ball? Well, there are  $\binom{t}{r}$  possibilities to choose the set of coordinates in which  $w$  and  $w'$  are supposed to differ, and for each such coordinate, there are  $k - 1$  ways in which they can differ. Therefore,

$$\text{vol}^{(k)}(t, r) := |B_r^{(k)}(w)| = \binom{t}{r} (k - 1)^r .$$

We are interested in the question how many balls  $B_r^{(k)}(w)$  we need to cover all of  $\{1, \dots, k\}^t$ . Note that by symmetry,  $w \in B_r^{(k)}(v)$  iff  $v \in B_r^{(k)}(w)$  for any  $v, w \in \{1, \dots, k\}^t$ .

**Definition 8.** *Let  $t \in \mathbb{N}$ . A set  $\mathcal{C} \subseteq \{1, \dots, k\}^t$  is called a code of covering radius  $r$  if*

$$\bigcup_{w \in \mathcal{C}} B_r^{(k)}(w) = \{1, \dots, k\}^t .$$

*In other words, for each  $w' \in \{1, \dots, k\}^t$ , there is some  $w \in \mathcal{C}$  such that  $d_H(w, w') \leq r$ .*

The following lemma is an adaptation of a lemma by Dantsin et al. [2], only for  $\{1, \dots, k\}^t$  instead of the Boolean cube  $\{0, 1\}^t$ .

**Lemma 9.** *For any  $t, k \in \mathbb{N}$  and  $0 \leq r \leq t$ , there exists a code  $\mathcal{C} \subseteq \{1, \dots, k\}^t$  of covering radius  $r$  such that*

$$|\mathcal{C}| \leq \left\lceil \frac{t \ln(k) k^t}{\binom{t}{r} (k-1)^r} \right\rceil$$

*Proof.* The proof is probabilistic. Let  $m := \lceil (t \ln(k) k^t) / (\binom{t}{r} (k-1)^r) \rceil$  and build  $\mathcal{C}$  by sampling  $m$  points from  $\{1, \dots, k\}^t$ , uniformly at random and independently. Fix an element  $w' \in \{1, \dots, k\}^t$ . We calculate

$$\Pr[w' \notin \bigcup_{w \in \mathcal{C}} B_r^{(k)}(w)] = \left(1 - \frac{\text{vol}^{(k)}(t, r)}{k^t}\right)^{|\mathcal{C}|} < e^{-|\mathcal{C}| \text{vol}^{(k)}(t, r) / k^t} \leq e^{-t \ln(k)} = k^{-t}.$$

By the union bound, the probability that there is any  $w' \notin \bigcup_{w \in \mathcal{C}} B_r^{(k)}(w)$  is at most  $k^t$  times the above expression, and thus smaller than 1. Therefore, with positive probability,  $\mathcal{C}$  is a code of covering radius  $r$ .  $\square$

## 2.2 A Deterministic Algorithm for Promise-Ball- $k$ -SAT

We will now describe our deterministic algorithm. First it chooses a sufficiently large constant  $t$ , depending on the  $\epsilon$  in Theorem 4, and computes a code  $\mathcal{C} \subseteq \{1, \dots, k\}^t$  of covering radius  $t/k$ . Since  $k$  and  $t$  are constants, it can afford to compute an optimal such code. We estimate its size using Lemma 9 and the following approximation of the binomial coefficient:

**Proposition 10** (MacWilliams, Sloane [5], Chapter 10, Corollary 9). *For  $0 \leq \rho \leq 1/2$  and  $t \in \mathbb{N}$ , it holds that*

$$\binom{t}{\rho t} \geq \frac{1}{\sqrt{8t\rho(1-\rho)}} \left(\frac{1}{\rho}\right)^{\rho t} \left(\frac{1}{1-\rho}\right)^{(1-\rho)t}$$

We apply this bound with  $\rho = 1/k$ :

$$\binom{t}{t/k} \geq \frac{1}{\sqrt{8t}} k^{t/k} \left(\frac{k}{k-1}\right)^{(k-1)t/k} = \frac{k^t}{\sqrt{8t}(k-1)^{(k-1)t/k}}.$$

Together with Lemma 9, we obtain, for  $t$  sufficiently large:

$$|\mathcal{C}| \leq \left\lceil \frac{t \ln(k) k^t}{\binom{t}{t/k} (k-1)^{t/k}} \right\rceil \leq \frac{t^2 k^t (k-1)^{(k-1)t/k}}{k^t (k-1)^{t/k}} \leq t^2 (k-1)^{t-2t/k}.$$

The algorithm computes this constant-size code and stores it for further use. It then calls a recursive procedure that does the real stuff. That procedure first greedily constructs a maximal set  $G$  of pairwise disjoint unsatisfied  $k$ -clauses of  $F$ . That is,  $G = \{C_1, C_2, \dots, C_m\}$ , the  $C_i$  are pairwise disjoint, each  $C_i$  in  $G$  is unsatisfied by  $\alpha$ , and each unsatisfied  $k$ -clause  $D$  in  $F$  shares at least one literal with some  $C_i$ .

At this point, the algorithm considers two cases. First, if  $m < t$ , it enumerates all  $2^{km}$  truth assignments to the variables in  $G$ . For each such assignment  $\beta$ , it calls

`searchball`( $F^{[\beta]}$ ,  $\alpha$ ,  $r$ ) and returns `true` if at least one such call returns `true`. Correctness is easy to see: At least one  $\beta$  agrees with the promised assignment  $\alpha^*$ , and therefore  $\alpha^*$  still satisfies  $F^{[\beta]}$ . To analyze the running time, observe that for any such  $\beta$ , the formula  $F^{[\beta]}$  contains no unsatisfied clause of size  $k$ . This follows from the maximality of  $G$ . Therefore, Proposition 7 tells us that `searchball`( $F^{[\beta]}$ ,  $\alpha$ ,  $r$ ) runs in time  $O^*((k-1)^r)$ , and therefore this case takes time  $2^{km}O^*((k-1)^r)$ . Since  $m < t$ , and  $t$  is a constant, this is  $O^*((k-1)^r)$ .

The second case is more interesting: If  $m \geq t$ , the algorithm chooses  $t$  clauses from  $G$  to form  $H = \{C_1, \dots, C_t\}$ , a set of pairwise disjoint  $k$ -clauses, all unsatisfied by  $\alpha$ . At this point, our code will come into play, but first we introduce some notation: For  $w \in \{1, \dots, k\}^t$ , let  $\alpha[w]$  be the assignment obtained from  $\alpha$  by flipping the value of the  $w_i^{\text{th}}$  literal in  $C_i$ , for  $1 \leq i \leq t$ . To do this, the algorithm has to choose a fixed but arbitrary ordering on  $H$  as well as on the literals in each  $C_i$ . Note that  $\alpha[w]$  satisfies exactly one literal in each  $C_i$ , for  $1 \leq i \leq t$ . Strictly speaking  $\alpha[w]$  depends not only on  $w$ , but also on  $H$ , so we should write  $\alpha[H, w]$  instead of  $\alpha[w]$ . However, as long as  $H$  is understood, we write  $\alpha[w]$ .

Let us give an example. Suppose  $\alpha$  is the all-0-assignment,  $t = 3$  and  $H = \{(x_1 \vee y_1 \vee z_1), (x_2 \vee y_2 \vee z_2), (x_3 \vee y_3 \vee z_3)\}$ . Let  $w = (2, 3, 3)$ . Then  $\alpha[w]$  is the assignment that sets  $y_1, z_2$ , and  $z_3$  to 1 and all other variables to 0.

Consider now the promised satisfying assignment  $\alpha^*$  with  $d_H(\alpha, \alpha^*) \leq r$ . We define  $w^* \in \{1, \dots, k\}^t$  as follows: For each  $1 \leq i \leq t$ , we set  $w_i^*$  to  $j$  such that  $\alpha^*$  satisfies the  $j^{\text{th}}$  literal in  $C_i$ . Since  $\alpha^*$  satisfies at least one literal in each  $C_i$ , we can do this, but since  $\alpha^*$  possibly satisfies multiple literals in  $C_i$ , the choice of  $w^*$  is not unique. Note that in any case  $d(\alpha[w^*], \alpha^*) = d(\alpha, \alpha^*) - t \leq r - t$ .

We could now iterate over all  $w \in \{1, \dots, k\}^t$  and call `searchball`( $F, \alpha[w], r-t$ ). This would essentially be what `searchball` does and would yield a running time of  $O^*(k^r)$ , i.e., no improvement over Dantsin et al. Therefore, we do not do this. Instead, we let our code  $\mathcal{C}$  play its crucial role: Rather than recursing on  $\alpha[w]$  for each  $w \in \{1, \dots, k\}^t$ , we recurse only for each  $w \in \mathcal{C}$ . By the properties of  $\mathcal{C}$ , there is some  $w' \in \mathcal{C}$  such that  $d_H(w', w^*) = t/k$ . Observe what happens when we go from  $\alpha$  to  $\alpha[w']$ : For at most  $t/k$  coordinates  $i$ , we have  $w'_i \neq w_i^*$ . For those coordinates, switching the  $w_i^{\text{th}}$  literal of  $C_i$  in the assignment  $\alpha$  *increases* the distance to  $\alpha^*$ . On the other hand, there are at least  $t - t/k$  coordinates  $i$  where  $w'_i = w_i^*$ , and switching the  $w_i^{\text{th}}$  literal of  $C_i$  for such an  $i$  *decreases* the distance to  $\alpha^*$ . We conclude that the distance increases at most  $t/k$  times and decreases at least  $t - t/k$  times. Therefore

$$d_H(\alpha[w'], \alpha^*) \leq d_H(\alpha, \alpha^*) + t/k - (t - t/k) \leq r - (t - 2t/k).$$

Writing  $\Delta := (t - 2t/k)$ , the procedure calls itself recursively with  $\alpha[w]$  and  $r - \Delta$  for each  $w \in \mathcal{C}$  and at least one call will be successful. Let us analyze the running time: We cause  $|\mathcal{C}|$  recursive calls and decrease the complexity parameter  $r$  by  $\Delta$  in each step. This is good, since  $|\mathcal{C}|$  is only slightly bigger than  $(k-1)^\Delta$ . We conclude that the number of leaves in this recursion tree is at most

$$|\mathcal{C}|^{r/\Delta} \leq (t^2(k-1)^\Delta)^{r/\Delta} = \left((k-1)t^{2/\Delta}\right)^r.$$

Since  $t^{2/\Delta}$  goes to 1 as  $t$  grows, the above term is, for sufficiently large  $t$ , bounded by  $(k - 1 + \epsilon)^r$ . This proves Theorem 4. We summarize the whole procedure in Algorithm 2.

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**Algorithm 2** `searchball-fast`( $k \in \mathbb{N}$ ,  $(\leq k)$ -CNF formula  $F$ , assignment  $\alpha$ , radius  $r$ , code  $\mathcal{C} \subseteq \{1, \dots, k\}^t$ )

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1: if  $\alpha$  satisfies  $F$  then
2:   return true
3: else if  $r = 0$  then
4:   return false
5: else
6:    $G \leftarrow$  a maximal set of pairwise disjoint  $k$ -clauses of  $F$  unsatisfied by  $\alpha$ 
7:   if  $|G| < t$  then
8:     for each assignment  $\beta$  to the variables in  $G$  do
9:       if searchball( $F^{[\beta]}$ ,  $\alpha$ ,  $r$ ) = true then
10:        return true
11:      end if
12:    end for
13:   else
14:      $H \leftarrow \{C_1, \dots, C_t\} \subseteq G$ 
15:     for  $w \in \mathcal{C}$  do
16:       if searchball-fast( $F, \alpha[H, w], r - (t - 2t/k)$ ) = true,  $\mathcal{C}$  then
17:        return true
18:      end if
19:    end for
20:   end if
21: end if
22: return false

```

---

### 3 Constraint Satisfaction Problems

Constraint Satisfaction Problems, short CSPs, are generalizations of SAT, allowing more than two truth values. Formally, suppose there is a set  $V = \{x_1, \dots, x_n\}$  of  $n$  variables, each of which can take on a value in  $\{1, \dots, d\}$ . A *literal* is an expression of the form  $(x_i \neq c)$  for  $c \in \{1, \dots, d\}$ . A constraint is a disjunction of literals, for example

$$(x_1 \neq 7 \vee x_2 \neq 5 \vee x_3 \neq d) .$$

A CSP formula finally is a conjunction of constraints. We call it a  $(d, \leq k)$ -CSP formula if its variables can take  $d$  values and each constraint has at most  $k$  literals. An assignment  $\alpha$  to the variables  $V$  is a function  $\alpha : V \rightarrow \{1, \dots, d\}$  and can be represented as an element from  $\{1, \dots, d\}^n$ . We say  $\alpha$  satisfies the literal  $(x_i \neq c)$  if, well,  $\alpha(x_i) \neq c$ . It satisfies a constraint if it satisfies at least one literal in it, and it satisfies a CSP formula if it satisfies each constraint in it. Finally,  $(d, \leq k)$ -CSP is the problem of deciding whether a given  $(d, \leq k)$ -CSP formula has a satisfying assignment. Note that  $(2, k)$ -CSP is the same as  $k$ -SAT. Also,  $(d, \leq k)$ -CSP is NP-complete except the following three cases: (i)  $d = 1$ , (ii)  $k = 1$ , (iii)  $d = k = 2$ . Cases (i) and (ii) are trivial problems, and (iii) is 2-SAT, which is solvable in polynomial time (well-known, not difficult to show, but still not trivial).



For the cases where  $(d, \leq k)$ -CSP is NP-complete, what can we do? Iterating through all  $d^n$  assignments constitutes an algorithm solving  $(d, k)$ -CSP in time  $O^*(d^n)$ . Schöningg's algorithm [7] is much faster:

**Theorem 11** (Schöningg [7]). *There is a randomized Monte-Carlo algorithm solving  $(d, \leq k)$ -CSP in time*

$$O^* \left( \left( \frac{d(k-1)}{k} \right)^n \right).$$

Again, for  $d = 2$  this is the running time of Schöningg for  $k$ -SAT. In his original paper [7], Schöningg describes how his algorithm seamlessly generalizes to arbitrary domain sizes  $d \geq 2$ : in each correction step, after a variable to reassign has been selected at random, another random choice is made among the  $d - 1$  values it may be changed to. The subsequent analysis in [7] also extends to this case.

However, there is a more direct way to reduce the  $(d, \leq k)$ -CSP for  $d > 2$  to the Boolean problem which is then able to use any  $k$ -SAT algorithm as a black box: we simply select for each variable, uniformly at random and independently from the other variables, 2 out of the  $d$  possible values in the domain. Any satisfying assignment survives this restriction with probability exactly  $(2/d)^n$  and thus any  $k$ -SAT algorithm with success probability  $p^n$  generalizes to a  $(d, \leq k)$ -CSP algorithm with success probability  $(2p/d)^n$ . When plugging in Schöningg for  $k$ -SAT, we obtain Theorem 11.

In order to generalize our deterministic variant to arbitrary domain sizes, we will choose the simple route and derandomize the aforementioned reduction instead of trying to rework the whole analysis from the previous section, with the additional advantage that the result scales for any further improvement on the running time for deterministic  $k$ -SAT.

**Theorem 12.** *There exists a deterministic algorithm having running time  $O^*((d/2)^n)$  which takes any  $(d, \leq k)$ -CSP  $F$  over  $n$  variables and produces  $l = O^*((d/2)^n)$  Boolean  $(\leq k)$ -CNF formulas  $\{G_i\}_{1 \leq i \leq l}$  such that  $F$  is satisfiable if and only if there exists some  $i$  such that  $G_i$  is satisfiable.*

Using the  $k$ -SAT algorithm we developed in the previous section, we then immediately get the derandomization of Theorem 11.

**Corollary 13.** *For every  $\epsilon > 0$ , there is a deterministic algorithm solving  $(d, \leq k)$ -CSP in time*

$$O^* \left( \left( \frac{d(k-1)}{k} + \epsilon \right)^n \right).$$

*Proof of Theorem 12.* We start with a useful definition. A *2-box* in  $\{1, \dots, n\}^d$  is a set of the form  $B := P_1 \times \dots \times P_n$ , where  $P_i \subseteq \{1, \dots, d\}$  and  $|P_i| = 2$ . A 2-box can be seen as a subcube of  $\{1, \dots, d\}^n$  of side length 2 and full dimension. A *random 2-box* is a 2-box sampled uniformly at random from all 2-boxes in  $\{1, \dots, d\}^n$ : This can be done by sampling each  $P_i$  independently, uniformly at random from all  $\binom{d}{2}$  pairs in  $\{1, \dots, d\}$ . As mentioned above, the probability that any fixed satisfying assignment of  $F$  lies within a random 2-box is  $(2/d)^n$ .

In order to derandomize this technique, we need to deterministically cover  $\{1, \dots, d\}^n$  with 2-boxes, in a fashion very similar to the covering codes used by Dantsin et al. [2]:

**Lemma 14.** *Let  $d, n \in \mathbb{N}$ . There is a set  $\mathcal{B}$  of 2-boxes in  $\{1, \dots, d\}^n$  such that*

$$\bigcup_{B \in \mathcal{B}} B = \{1, \dots, d\}^n$$

and

$$|\mathcal{B}| \leq \left(\frac{d}{2}\right)^n \text{poly}(n) .$$

Furthermore,  $\mathcal{B}$  can be constructed in time  $O(|\mathcal{B}|)$ .

Given this lemma, our algorithm is complete: It first constructs such a suitably small set  $\mathcal{B}$  of 2-boxes, and then, for each 2-box  $P_1 \times \dots \times P_n = B \in \mathcal{B}$ , outputs a  $(\leq k)$ -CNF formula arising from  $F$  by restricting the domain of the  $i^{\text{th}}$  variable to the values in  $P_i$ . This finishes the proof of the theorem.  $\square$

It remains to prove the lemma.

*Proof of Lemma 14.* Note that if  $d$  is an even number, the proof is easy. For  $1 \leq j \leq d/2$ , define  $P^{(j)} = \{2j-1, 2j\}$ . Each element  $w \in \{1, \dots, d/2\}^n$  defines the 2-box

$$B_w := P^{(w_1)} \times \dots \times P^{(w_n)}$$

and clearly

$$\bigcup_{w \in \{1, \dots, d/2\}^n} B_w = \{1, \dots, d\}^n .$$

The difficulty arises if  $d$  is odd. As Dantsin et al. [2], we first show the existence of a suitable set of 2-boxes, and then use a block construction and an approximation algorithm to obtain a construction.

**Lemma 15.** *For any  $n, d \in \mathbb{N}$ , there is a set  $\mathcal{B}$  of 2-boxes such that  $|\mathcal{B}| \leq \lceil n \ln(d)(d/2)^n \rceil$  such that  $\bigcup_{B \in \mathcal{B}} B = \{1, \dots, d\}^n$ .*

*Proof.* The proof works exactly like the proof of Lemma 9. We sample  $\lceil n \ln(d)(d/2)^n \rceil$  many 2-boxes independently, uniformly at random and show that with positive probability, the resulting set has the desired properties.  $\square$

To prove Lemma 14, we have to derandomize the probabilistic argument we have just seen. For this, we choose a sufficiently large constant  $b$ , set  $n' := n/b$  and construct an instance of SET-COVER: The ground set is  $\{1, \dots, d\}^{n'}$  and the sets are all 2-boxes therein, of which there are  $\binom{d}{2}^{n'} \leq d^{2n'}$ . We know from Lemma 15 that there is a cover of 2-boxes of size  $\lceil n \ln(d)(d/2)^n \rceil$ . There is a greedy algorithm for SET-COVER (see Hochbaum [3] for example) achieving an approximation ratio of  $O(\log N)$ , where  $N$  is the size of the ground set. Since in our case  $\log N = \log(d^{2n'}) = O(n')$ , this algorithm will give us a set  $\mathcal{B}$  of 2-boxes covering  $\{1, \dots, d\}^{n'}$  of size

$$|\mathcal{B}| \in O\left((n')^2 \left(\frac{d}{2}\right)^{n'}\right) .$$

How much time do we need to construct  $\mathcal{B}$ ? The greedy algorithm is polynomial in the size of its instance, which is  $O(d^{2n'})$ , thus it takes time  $O(d^{2Cn'})$  for some constant  $C$ . By choosing  $b$  large enough, we can make sure that  $d^{2Cn'} = d^{2Cn/b}$  is smaller than the running time we are aiming at. Finally, we obtain a set of 2-boxes in  $\{1, \dots, d\}^n$  by

“concatenating” the boxes in  $\mathcal{B}$ : We identify a tuple  $(B_1, \dots, B_b) \in \mathcal{B}^b$  with the 2-box  $B_1 \times \dots \times B_b$ , and therefore  $\mathcal{B}^b$  is a set of 2-boxes covering  $\{1, \dots, n\}$ , and

$$|\mathcal{B}|^b \leq O \left( \left( (n')^2 \left( \frac{d}{2} \right)^{n'} \right)^b \right) = O \left( \left( \frac{n}{b} \right)^{2b} \left( \frac{d}{2} \right)^n \right) = \left( \frac{d}{2} \right)^n \text{poly}(n).$$

This is a set of 2-boxes covering  $\{1, \dots, d\}^n$  of the desired size, finishing the proof of Lemma 14.  $\square$

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