

Poznań University of Technology

**On SAT information content,
its polynomial-time solvability
and fixed code algorithms**

M.Drozdowski

Research Report RA-01/23

2023

Institute of Computing Science, Piotrowo 2, 60-965 Poznań, Poland

On SAT information content, its polynomial-time solvability and fixed code algorithms

M.Drozdowski

Institute of Computing Science, Poznań University of Technology,
Piotrowo 2, 60-965 Poznań, Poland

Abstract

Amount of information in SAT is estimated and compared with the amount of information in the fixed code algorithms. A remark on SAT Kolmogorov complexity is made. It is argued that SAT can be polynomial-time solvable, or not, depending on the solving algorithm information content.

Keywords: computational complexity, information theory.

1 Introduction

A number of observations can be made in relation to the performance of algorithms solving combinatorial problems and the amount of information they hold:

- In [3] a connection between entropy of the Markov chains representing behavior of simulated annealing algorithms and the convergence of the expected objective function value has been made for maximum 3-SAT problem.
- In [8] it is argued that there is a link between the fraction of problem instances achieving certain histogram of values and the entropy of the histogram.
- In evolutionary optimization it is widely accepted rule of thumb that with growing population diversity and size, the chances of producing high quality solutions improve. Intuitively, such populations have more information.
- There is a notion of a graph *hard-to-color* for a certain algorithm in graph node coloring [5, 6]. A graph that is hard-to-color is colored by the considered algorithm with more colors than the optimum. There are examples of graphs hard-to-color for many deterministic algorithms. Random sequential algorithm visits graph nodes in a random sequence and assigns to a node the

lowest feasible color. For random sequential algorithm no hard-to-color graph exists, and hence, this algorithm cannot deterministically fail. Ominously, this algorithm is connected to a source of randomness, that is, a source of unlimited amount of information.

The notations used in this paper are summarized in Tab.1. Search version of SAT problem is defined as follows:

SAT – SEARCH VERSION

INPUT: sums $k_j, j = 1, \dots, m$, of binary variables, or their negations, chosen over a set of n binary variables x_1, \dots, x_n . The input data is SAT instance I . Let $|I|$ denote instance I size, i.e., length of the string encoding I according to some reasonable rule.

REQUEST: Find the assignment of values 0/1 to binary variables x_1, \dots, x_n , i.e. vector \bar{x} of n 0/1 values, such that the conjunction of the clauses $F(I, \bar{x}) = \prod_{j=1}^m k_j$ is 1. If such a vector does not exist then signal \emptyset .

If the binary vector \bar{x} such that $F(I, \bar{x}) = 1$ exists then we will be saying that I is a "yes" instance. Otherwise I is a "no" instance. The input sums k_j will be alternatively referred to as clauses. If clauses k_j comprise exactly three variables we will say that it is a 3-SAT problem instance.

Definition 1 *Fixed code algorithm is an algorithm which is encoded in limited number of immutable bits.*

Thus, a fixed code algorithm does not change its code during the runtime. Furthermore, it has no access to a source of randomness and is deterministic. Let $|A|$ denote the size of algorithm A code in bits.

Postulate 2 *Information is not created ex nihilo by fixed code algorithms.*

Postulate 3 *An algorithm to solve a problem must be capable of representing at least the same amount of information as the amount of the information in the problem.*

Definition 4 *Truly random bit sequence (TRBS) is a sequence of bits, that no bit can be computed on the basis of the other bits.*

Thus, for a TRBS of length N it is not possible to compute the i th bit on the basis of bits $\{1, \dots, N\} \setminus \{i\}$. In effect, a TRBS cannot be compressed, and the only way to represent it is to store it in its whole entirety on N bits.

Postulate 5 *Truly random bit sequences exist.*

2 SAT Polynomial-time Solvability

SAT can be solved in $O(|I|)$ time by referring to precomputed solutions. In more detail, the search for a precomputed solution of I can be conducted in a binary tree with $2^{|I|}$ leaves and $2^{|I|} - 1$ internal nodes using pointers (addresses) of length $|I| + 1$ to arrive at the leaves. An internal node holds two pointers to its successors. A leaf holds an answer to a SAT solution (\bar{x} or \emptyset). The data-structure has size $O(2^{|I|}|I|)$ because it has $2^{|I|+1} - 1$ nodes each holding at most $2(|I| + 1)$ bits.

The tree can be traversed top-down in $O(|I|)$ time. Thus, *SAT can be solved in polynomial time*, at least in principle, provided that an algorithm for SAT has unlimited (precisely, exponential in $|I|$) amount of information.

3 Amount of Information in SAT

Let Σ^+ be a set of strings encoding instances of SAT using some reasonable encoding scheme e over alphabet Σ . An empty string $\epsilon \notin \Sigma^+$. SAT-search is an example of a search problem, while search problems are string relations [4]:

Definition 6 *A search problem Π is a string relation*

$$R[\Pi, e] = \left\{ (a, b) : \begin{array}{l} a \in \Sigma^+ \text{ is the encoding of an instance } I \in D_{\Pi} \text{ and} \\ b \in \Sigma^+ \text{ is the encoding of a solution } s \in S_{\Pi}(I) \\ \text{under coding scheme } e \end{array} \right\},$$

where $S_{\Pi}(I)$ is a set of solutions for instance I of Π .

Thus, SAT can be thought of as a mapping from strings a representing instances to strings b representing solutions. Each string a is either encoding a "yes" instance, or not. In the former case an n -bit solution \bar{x} must be provided by the mapping. In the latter case a string representing $S_{SAT}(I) = \emptyset$ must be provided. If the a string is not encoding any SAT instance, then such a case can be represented in the same way as a negative answer \emptyset . In order to encode each (a, b) pair of the relation representing SAT it is necessary to have an equivalent of a graph arc from string a to its solution b . Such an arc requires $|I| + n$ bits of information which is at least $\Omega(|I|)$ bits. There are $2^{|I|}$ strings of some size $|I|$. Since it is necessary to at least distinguish whether

b strings represent \emptyset or \bar{x} , at least $\Omega(2^{|I|})$ bits of information are necessary to encode SAT as string relation $R[SAT, e]$.

An algorithm solving problem Π must represent a mapping from the instances to the solutions. The mapping requires a certain number of bits to be represented. This information must be provided in the input instance and the algorithm to solve the *problem* because information is not created ex nihilo in fixed code algorithms. Note that an algorithm solves a problem if it provides an answer *for each* input instance [4]. The amount of information in a fixed code algorithm A solving SAT and in the input instance I is $|I| + |A|$ bits. Since $|A|$ is constant and for sufficiently large $|I|$, the instance and the algorithm together have less information than $\Omega(2^{|I|})$ bits necessary to represent SAT as a string relation. However, it is still possible that SAT is encoded in fewer than $\Omega(2^{|I|})$ bits. Hence, the above consideration does not preclude existence of some more compact representation of SAT. In other words, SAT could possibly be expressed in a size smaller than $|I| + |A|$ bits, for some fixed code algorithm A .

Theorem 7 *The amount of information in SAT grows exponentially with instance size.*

Proof. Assume there are n variables and $4n$ clauses in 3-SAT. Let there be 4 clauses $k_{i1} = x_a + x_b + \widetilde{x}_i, k_{i2} = \bar{x}_a + x_b + \widetilde{x}_i, k_{i3} = x_a + \bar{x}_b + \widetilde{x}_i, k_{i4} = \bar{x}_a + \bar{x}_b + \widetilde{x}_i$ for each $i = 1, \dots, n$. \widetilde{x}_i denotes that variable x_i is with or without negation. No valuing of x_a, x_b makes the four clauses simultaneously equal 1. The four clauses may simultaneously become equal 1 only if $\widetilde{x}_i = 1$. Satisfying formula $F = k_{i1}k_{i2}k_{i3}k_{i4} \dots k_{n4}$ depends on valuing of variables \widetilde{x}_i for $i = 1, \dots, n$. Depending on whether x_i is negated or not there can be 2^n different ways of constructing formula F , thus leading to 2^n different "yes" instances with 2^n different solutions. Variables x_a, x_b are chosen such that $a \neq b$ and $a, b \neq i$. Since there are $(n-1)(n-2)/2$ possible pairs a, b for each i , it is possible to generate pairs a, b satisfying the above conditions for $n \geq 3$.

We are now going to calculate the number of different "yes" instances as a function of instance size $|I|$. Suppose the uniform cost criterion [1] is assumed, then each number has value limited from above by constant K . The length of the encoding of the instance data is $|I| = 4n \times 3 \log K + \log K = 12n \log K + \log K$ because it is necessary to record the number of variables in $\log K$ bits, each binary variable induces 4 clauses of length $3 \log K$. Negation

of a variable, or lack thereof, is encoded on one bit within $\log K$. Consequently, the number of possible unique solutions is $2^n = 2^{(|I| - \log K)/(12 \log K)} = 2^{|I|/(12 \log K)} 2^{-1/12}$, which is $\Omega(2^{d_1 |I|})$, where $d_1 = 1/(12 \log K) > 0$ is constant.

Assume logarithmic cost criterion [1], then the number of bits necessary to record n is $\lfloor \log n \rfloor + 1$, and $\lfloor \log n \rfloor + 2$ bits are needed to encode the index of a variable and its negation, or lack thereof. Length of the encoding string is $|I| = 12n(\lfloor \log n \rfloor + 2) + \lfloor \log n \rfloor + 1 \leq 15n \log n = dn \ln n$, for $n > 2^{2^4}$ and $d = 15/\ln 2 \approx 21.6404$. An inverse function of $(cx \ln x)$, for some constant $c > 0$, is $\frac{x}{c}/W(\frac{x}{c})$, where W is Lambert W -function [7]. Lambert W function for big x can be approximated by $W(x) = \ln x - \ln \ln x + O(1)$. Given instance size $|I|$, we have $n \geq \frac{|I|}{d}/W(\frac{|I|}{d}) \approx \frac{|I|}{d}/(\ln \frac{|I|}{d} - \ln \ln \frac{|I|}{d} + O(1)) \geq \frac{|I|}{d}/(2 \ln \frac{|I|}{d}) \geq \frac{|I|}{d}/(2 \ln |I| - 2 \ln d) \geq |I|/(2d \ln |I|)$, for sufficiently large $|I|$. Note that $|I|$, $dn \ln n$, $\frac{x}{c}/W(\frac{x}{c})$ are increasing in n, x . Thus, by approximating $|I|$ from above we get a lower bound of n after calculating an inverse of the upper bound of $|I|$. The number of possible unique solutions is $2^n \geq 2^{|I|/(d_2 \ln |I|)}$ where $d_2 = 2d$. Observe that $2^{|I|/(d_2 \ln |I|)}$ exceeds any polynomial function of $|I|$ for sufficiently large $|I|$, because for a polynomial function $O(|I|^k)$, $\ln(|I|^k) < |I|/(d_2 \ln |I|)$ with $|I|$ tending to infinity.

Consider a truly random bit sequence (TRBS) of length 2^n . Assume that $j = 1, \dots, 2^n$ is one of the instances of 3-SAT constructed in the above way. Let $j[i]$ for $i = 1, \dots, n$ be the i -th bit of j binary encoding. If bit j of the TRBS is equal to 1 we set variables \tilde{x}_i such that $\tilde{x}_i = j[i]$ satisfies clauses k_{1i}, \dots, k_{4i} . For example, if $j[i] = 1$, then \tilde{x}_i is written as x_i . Thus, if bit j of the TRBS is equal to 1 then a "yes" instance is constructed. Conversely, if $j = 0$ then at least one variable x_i in the corresponding clauses k_{1i}, \dots, k_{4i} is set inconsistently, i.e., \tilde{x}_i appears in k_{1i}, \dots, k_{4i} both with negation and without. Hence, if bit j of the TRBS is equal to 0, the j -th instance constructed in the above way becomes a "no" instance. Note that in this way the TRBS of length 2^n was encoded in 3-SAT search problem. The amount of information in 3-SAT grows at least in the order of $\Omega(2^{d_1 |I|})$ for uniform ($\Omega(2^{|I|/(d_2 \ln |I|)})$, for logarithmic) cost criterion. \square

4 On Consequences

Note that by Theorem 7, SAT problem has amount of information that grows at least exponentially with the size of the input instances. This information cannot be reduced because a TRBS of size exponentially growing with in-

stance size is put in SAT.

Proposition 8 *Fixed code algorithm is not capable of representing SAT in polynomial time.*

Proof. The amount of information that can be produced by the polynomial-time algorithm running in time $p(|I|)$, where p is a polynomial, is $|I| + |A| + p(|I|) \log(p(|I|))$, where $|I| + |A|$ is the instance and algorithm information, while $p(|I|) \log(p(|I|))$ bits of information come from the progress of time because $p(|I|)$ values of time can be recorded on $\log(p(|I|))$ bits. It is still less information than comprised in SAT. \square

Observation 9 *Problems in class **NP** have more information than their Kolmogorov complexity.*

Proof. Note that by Theorem 7 information content of SAT grows exponentially with the size of the instance because sufficiently long TRBS can be injected in SAT. For some given number of variables n a TRBS of length 2^n can be placed in SAT. However, the minimum amount of information required to represent SAT is at most $\log n + |E| + |V|$, where E is an algorithm that enumerates all input instances and all solutions according to some SAT instance encoding scheme, while V is the fixed code algorithm capable of verifying if a given solution for I is correct. Given n , it is possible to enumerate all strings encoding SAT. For example, SAT instance may be encoded as a sequence of values: (n, m, k_1, \dots, k_m) . Since each variable can be used with or without negation in clauses k_i , the number of possible clauses is $m \leq 2^{2n}$ which can be encoded in $2n$ bits. Each clause can be encoded as a sequence of n bit pairs representing at position $i = 1, \dots, n$: 00_i or 01_i – variable x_i is absent in the current clause, 10_i – variable x_i is present in the current clause as x_i , 11_i – variable x_i is present in the current clause as \bar{x}_i . Thus, each clause can be encoded in $2n$ bits. All clauses of the instance can be encoded in $2nm \leq 2n \times 2^{2n}$ bits. The whole SAT instance can be encoded as a binary number of length $\log n + 2n + 2n \times 2^{2n}$ bits. All possible values of this number can be enumerated by a constant information size Turing machine adding 1 to a binary-encoded number recorded on the tape. Similarly it is possible to enumerate all 2^n potential solutions of a SAT instance with n variables. Thus, a fixed code algorithm E enumerating all input instances and all solutions exists. Algorithm V exists because $\text{SAT} \in \text{NP}$, and all problems in **NP**

have algorithms verifying given solutions in polynomial time. Hence, SAT as a string relation can be reconstructed by enumerating all input instances and choosing the correct answer by use of algorithm V .

On the one hand, Kolmogorov complexity of SAT is at most $\log n + |E| + |V|$. On the other hand, SAT has $\Omega(2^n)$ incompressible bits. By the example given in Theorem 7 SAT has $\Omega(2^{d_1|I|})$ (uniform criterion) or $\Omega(2^{|I|/(d_2 \ln |I|)})$ (logarithmic criterion) incompressible bits, while Kolmogorov complexity of SAT is $\log(d_1|I|) + |E| + |V|$ (uniform) or $\log(|I|/(d_2 \ln |I|)) + |E| + |V|$ (logarithmic criterion). Since by Cook's theorem SAT is a foundation of all **NP**-complete problems, the above observations can be extended to all problems in class **NP**. \square

The discrepancy between these two numbers can be explained by the existence of algorithm V and the fact that information is created by the progress of time, the process of solution enumeration and filtering by algorithm V . Informally, SAT has exponential compression efficiency and SAT is information-inflated by solutions enumeration and verification.

Acknowledgments

I thank Joanna Berlińska, Małgorzata Sterna and Piotr Formanowicz for discussing with me in the earlier stages of this consideration [2].

References

- [1] A.Aho, J.E.Hopcroft, J.D.Ullman, The Design and Analysis of Computer Algorithms, Addison-Wesley Publishing Company, Reading MA, 1974
- [2] M.Drozdowski, On polynomial-time solvability and fixed code size algorithms, Research Report RA-06/16, Institute of Computing Science, Poznań University of Technology, 2016 <http://www.cs.put.poznan.pl/mdrozdowski/rapIn/MD-RA-6-16.pdf>
- [3] M.Fleischer, S.H.Jacobson, Information Theory and the Finite-Time Behavior of the Simulated Annealing Algorithm: Experimental Results, INFORMS Journal on Computing 11(1), Winter 1999.

- [4] M.R.Garey, D.S.Johnson, *Computers and Intractability: A guide to the theory of NP-completeness*, Freeman, San Francisco, 1979.
- [5] M.Kubale (ed.), *Graph Colorings*, American Mathematical Society, Providence, Rhode Island, 2004. (I used Polish version: *Optymalizacja dyskretna. Modele i metody kolorowania grafów*, WNT, Warszawa, 2002).
- [6] K.Manuszewski, *Grafy algorytmicznie trudne do kolorowania*, Ph.D. Thesis, Gdańsk University of Technology, 1997.
- [7] Eric W. Weisstein, Lambert W-Function, MathWorld—A Wolfram Web Resource. [accessed in September 2015]. <http://mathworld.wolfram.com/LambertW-Function.html>
- [8] D.H.Wolpert, W.G. Macready, No Free Lunch Theorems for Optimization, *IEEE Trans. on Evolutionary Computation* 1(1), April 1997.

Version 3. January 1, 2024. Previous version is here.

Table 1: Summary of notations.

$ A $	Size of algorithm A in bits according to some reasonable encoding rule
D_{Π}	set of instances for problem Π
F	$F = \prod_{j=1}^m k_j$ conjunction of clauses k_j
$F(I, \bar{x})$	value of F for instance I and bit assignment \bar{x}
I	instance of a problem
$ I $	instance size, i.e., length of the string encoding instance I according to some reasonable encoding rule (e.g. numbers encoded at base greater or equal 2)
k_j	j th clause of SAT instance, for $j = 1, \dots, m$
n	number of variables in the SAT problem
m	number of clauses in the SAT problem
$S_{\Pi}(I)$	set of solutions for instance I of search problem Π
x_i	i th variable in SAT problem, for $i = 1, \dots, n$
\tilde{x}_i	i th variable x_i with or without negation
\bar{x}	vector of n binary values, alternatively n -bit unsigned integer