# NP IS AS EASY AS DETECTING UNIQUE SOLUTIONS 

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Communicated by R.M. Karp
Received August 1984
Revised January 1986


#### Abstract

For every known NP-complete problem, the number of solutions of its instances varies over a large range, from zero to exponentially many. It is therefore natural to ask if the inherent intractability of NP-complete problems is caused by this wide variation. We give a negative answer to this question using the notion of randomized polynomial time reducibility. We show that the problems of distinguishing between instances of SAT having zero or one solution, or of finding solutions to instances of SAT having a unique solution, are as hard as SAT, under randomized reductions. Several corollaries about the difficulty of specific problems follow. For example, computing the parity of the number of solutions of a SAT formula is shown to be NP-hard, and deciding if a SAT formula has a unique solution is shown to be $\mathrm{D}^{\mathrm{p}}$-hard, under randomized reduction. Central to the study of cryptography is the question as to whether there exist NPproblems whose instances have solutions that are unique but are hard to find. Our result can be interpreted as strengthening the belief that such problems exist.


## 1. Introduction

Several authors have observed that, among most known NP-complete problems, reductions can be found that preserve the number of solutions [3, 15, 18]. Such reductions are called parsimonious reductions. A characteristic of each such NPcomplete problem is that its instances have widely varying numbers of solutions. Their number may be zero, one, several, or exponentially many. It is natural to ask whether the inherent difficulty in solving NP-complete problems is caused by this wide variation.

In this paper we give a negative answer to this question, in the following sense. Let $A$ be any NP-complete problem to which satisfiability is parsimoniously reducible. Let $\# A(x)$ denote the number of solutions to instance $x$. For each Boolean

[^0]predicate $Q$, define the problem $\mathrm{UA}_{\mathrm{Q}}$ :
\[

\mathrm{UA}_{Q}(x)= $$
\begin{cases}0 & \text { if } \# A(x)=0 \\ 1 & \text { if } \# A(x)=1 \\ Q(x) & \text { if \# } A(x)>1\end{cases}
$$
\]

Our main result is that there is a randomized polynomial time reduction from $A$ to $\mathrm{UA}_{Q}$ that is valid for any predicate $Q$. This shows that if there is a random polynomial-time (i.e., RP) decision procedure that gives the correct answer on instances of $\boldsymbol{A}$ having zero or one solution, and an arbitrary answer on the remaining instances, then NP=RP.

Equivalently, we prove that the following 'promise problem' [10] is NP-hard, under randomized reductions (see Corollary 3.4):

Input: an instance $x$ of $A$,
Output: a solution to $x$,
Promise: $\# A(x)=1$.
A procedure for this problem is required to give the correct answer only if $\# A(x)=1$. It must, however, halt on each input.

Via our theorem, we can establish for several problems for the first time that they are NP-hard, under randomized polynomial-time reductions. Let $A$ be as defined above. Then Parity- $A$, which gives the parity of the number of solutions of an instance of $A$, is NP-hard. The problem of computing the permanent of a ( 0,1 )matrix $\bmod k$, for any $k$ which is not an exact power of 2 , is NP-hard.

One further motivation for studying $\mathrm{UA}_{Q}$ is that every problem in UP is polynomial time reducible to it (for any $Q$ ). UP is the class of sets recognized by nondeterministic polynomial-time Turing machines that for all inputs have either zero or one solution. The class appears to be especially relevant in cryptography and has been studied before [ $8,11,12,14,19]$. Note that it is not known whether, for any $Q$, USAT $_{Q}$ is itself a member of UP. Hence, our proof does not show the existence of a hard problem in UP.

As remarked earlier, most of the known polynomial-time reductions among NP-complete problems are parsimonious. For reducing SAT to USAT ${ }_{Q}$, this is exactly the property that our reducibility should not have. Instead, we shall use a randomized reduction. Such reductions have been used in the past for classifying the complexity of certain NP problems which have not yielded to proofs of NPcompleteness in the standard sense [1,2,22]. Our reduction is of the following kind: We shall say that a problem $A$ is reducible to $B$ by a randomized polynomial-time reduction if there is a randomized (coin flipping) polynomial-time Turing machine $T$, and a polynomial $p$, such that:
(1) $\forall x[x \notin A \rightarrow T[x] \notin B]$. (Even though the output of $T$, on input $x \notin A$, may depend on the coin flips, it will definitely not be in $B$.)
(2) $\forall x[x \in A \rightarrow T[x] \in B$ with probability at least $1 / p(|x|)]$.

Define RP to be the class of sets accepted by randomized Turing machines with one-sided error. In particular, $A \in R P$ if there is a randomized Turing machine $T$ such that:
(1) $\forall x[x \notin A \rightarrow T$ rejects $x]$.
(2) $\forall x\left[x \in A \rightarrow T\right.$ accepts $x$ with probability at least $\left.\frac{1}{2}\right]$.

Notice that if, in the above definition, " $\frac{1}{2}$ " is replaced by " $[p(|x|)]^{-1 "}$, for any polynomial $p$, we still obtain the same class. Clearly, if $A$ is reducible to $B$ by a randomized polynomial-time reduction and if $B \in R P$, then $A \in R P$.

In the remainder of this paper we shall take the conjunctive normal form SAT itself as representative of the class of NP-complete problems parsimoniously interreducible with it. Hence, our main result can be stated as follows.

Theorem 1.1. There is a randomized polynomial-time reduction from SAT to USAT $_{Q}$ that is valid for any predicate $Q$.

## Corollary 1.2. If, for some predicate $Q$, $U_{S A T}^{Q} \in \mathrm{RP}$, then $\mathrm{NP}=\mathrm{RP}$.

Our technique can be used to establish certain problems to be complete in the class $D^{p}$ [13]. In particular, it can be shown that UniQue SAT, the problem of determining whether a formula has exactly one solution or not, is complete in $D^{p}$ under randomized polynomial reduction. This contrasts with the result of Blass and Gurevich [4] that states that completeness here does not hold under any deterministic reduction that relativizes.

## 2. The proof

We shall show that for any $Q$ there is a randomized polynomial-time reduction from SAT to $\mathrm{USAT}_{\mathbf{Q}}$. The idea of the reduction is the following: given instance $f$ of SAT we will successively conjoin constraints to $f$ to obtain a series of formulae $f_{1}, \ldots, f_{n}$ that will have decreasing numbers of solutions. We shall prove that if $f$ is satisfiable, then with probability at least $\frac{1}{4}$ one of these formulae will have a unique solution. Hence, if we pick one of these formulae at random it will have a unique solution with probability at least $(4 n)^{-1}$. On the other hand, if $f$ is not satisfiable, then each of these formulae will be unsatisfiable, including the randomly chosen one.
Since we do not know what the solutions of $f$ are, we will pick constraints at random from a suitable set. Ideally, we would like to knock out each solution independently with a certain probability. This is not possible with only polynomially many random choices. Surprisingly, the use of GF[2] inner products with polynomially few $\{0,1\}$ vectors suffices. This use can be viewed as an application of universal hash functions [5]. Such inner products have been used previously in complexity theory by Sipser [16] and Stockmeyer [17].

We shall view truth assignments to the variables $x_{1}, \ldots, x_{n}$ as $n$-dimensional $\{0,1\}$ vectors from the vector space GF[2] ${ }^{n}$. The solutions to $f$ form a set of vectors from this space $\{0,1\}^{n}$. For $u, v \in\{0,1\}^{n}$ we denote by $u \cdot v$ the inner product over GF[2] of $u$ and $v$.

First we observe the following:
Lemma 2.1. If $f$ is any CNF formula in $x_{1}, \ldots, x_{n}$ and $w_{1}, \ldots, w_{k} \in\{0,1\}^{n}$, then one can construct in linear time a formula $f_{k}^{\prime}$ whose solutions $v$ satisfy $f$ and the equations $v \cdot w_{1}=\cdots=v \cdot w_{k}=0$. Furthermore, one can construct a polynomial-size CNF formula $f_{k}$ in variables $x_{1}, \ldots, x_{n}, y_{1}, \ldots, y_{m}$ for some $m$ such that there is a bijection between solutions of $f_{k}$ and $f_{k}^{\prime}$, defined by equality on the $x_{1}, \ldots, x_{n}$ values.

Proof. It is sufficient to show the lemma for $k=1$. Then, $f_{1}^{\prime}$ is

$$
f \wedge\left(x_{i_{1}} \oplus x_{i_{2}} \oplus \cdots \oplus x_{i j} \oplus 1\right)
$$

where $\oplus$ denotes exclusive-or and $i_{1}, \ldots, i_{j}$ are the indices of the $x_{i}$ that have values 1 in $w$. Also, $f_{1}$ is the CNF equivalent of the formula

$$
\begin{aligned}
f \wedge & \left(y_{1} \Leftrightarrow x_{i_{1}} \oplus x_{i_{2}}\right) \wedge\left(y_{2} \Leftrightarrow y_{1} \oplus x_{i_{3}}\right) \\
& \wedge \cdots \wedge\left(y_{j-1} \Leftrightarrow y_{j-2} \oplus x_{i_{j}}\right) \wedge\left(y_{j-1} \oplus 1\right) .
\end{aligned}
$$

The intuition behind our main theorem can be explained as follows. Let $S$ be any subset of $\{0,1\}^{n}$. Define the sets

$$
S_{1}=\{v \mid v \in S, v \cdot w=0\} \quad \text { and } \quad S_{1}^{\prime}=\{v \mid v \in S, v \cdot w=1\} .
$$

The surprising fact is that if we pick $w$ randomly, then any $S$ will be partitioned in this way into roughly equal halves with high probability. By letting $S$ be the set of solutions of $f$, choosing $w_{1}, \ldots, w_{k}$ at random and constructing $f_{k}$ we obtain a formula with roughly $2^{-k}|S|$ solutions.

The randomized polynomial-time reduction of Theorem 1.1 from SAT to USAT $_{Q}$ is simply the following: Given an instance $f$ of SAT, randomly choose an integer $k$ from $\{1, \ldots, n\}$, randomly choose vectors $w_{1}, \ldots, w_{k} \in\{0,1\}^{n}$, and output $f_{k}$.

The phenomenon that a random $w$ partitions $S$ into about equal halves is expressed by the following result from [21].

Theorem 2.2. For all $\varepsilon>0$ there exists a constant $\alpha>1$ such that for all $x \geqslant 1$ if $S \subseteq\{0,1\}^{n}$ with $|S| \geqslant n^{\alpha x}$, then the probability that either $\left|S_{1}\right|$ or $\left|S_{1}^{\prime}\right|$ is smaller than $\left(\frac{1}{2}-\varepsilon\right)|S|$ is less than $n^{-x}$.

While this result is sufficient to establish Theorem 1.1, it does not yield the simplest proof. Sharp bounds on the tails of the distribution are not necessary, while bounds applying to all sizes $|S|$ are advantageous. Mark Jerrum observed that the following remarkably precise statement is true and easily proved.

Cheorem 2.3. If $S \subseteq\{0,1\}^{n}-\left\{0^{n}\right\}, w_{1}, \ldots, w_{n}$ are randomly chosen from $\{0,1\}^{n}$ and $S_{i}$ is defined as

$$
\left\{v \mid v \in S, v \cdot w_{1}=v \cdot w_{2}=\cdots=v \cdot w_{i}=0\right\}
$$

then the expectation and variance of $S_{i}$ are as follows:

$$
E\left(\left|S_{i}\right|\right)=2^{-i}|S| \quad \text { and } \quad V\left(\left|S_{i}\right|\right)=2^{-i}\left(1-2^{-i}\right)|S| .
$$

Sharper bounds still on the required probabilities can be established by a direct argument due to Michael Rabin. The main idea is to dispense with discussing the ;ize of $S_{i}$ and do induction on its rank. We shall restrict ourselves to giving this last argument which is encapsulated in Theorems 2.4 and 2.5. The final conclusions are he following.

Theorem 2.4. Let $S \subseteq\{0,1\}^{n}$. Suppose $w_{1}, \ldots, w_{n}$ are chosen at random, for each $i \leqslant n$, $S_{i}=\left\{v \mid v \in S, v \cdot w_{1}=\cdots=v \cdot w_{i}=0\right\}$ and $P_{n}(S)$ is the probability that, for some $i \leqslant n$, $S_{i} \mid=1$. Then:
(i) $P_{n}(S) \geqslant \frac{1}{4}$;
(ii) if $w_{1}, \ldots, w_{n}$ are chosen to be linearly independent in addition, then $P_{n}(S) \geqslant \frac{1}{2}$.

Clearly, Theorem 1.1 follows directly from either one of the above two statements. in order to prove them, we first state and prove the following.

Theorem 2.5. Let $S \subseteq\{0,1\}^{n}, S \neq \emptyset$. Randomly choose vectors $w_{1}, w_{2}, \ldots$ from $\{0,1\}^{n}$. Define $H_{i}=\left\{v \mid v \cdot w_{i}=0\right\}, S_{0}=S$, and $S_{i}=S \cap H_{1} \cap \cdots \cap H_{i}$. Then:

$$
P(S) \stackrel{\text { def }}{=} \operatorname{Prob}\left(\exists i\left|S_{i}\right|=1\right) \geqslant \frac{1}{2} .
$$

Proof. Let $T_{k}=\min \{P(S)\}$, where $S$ ranges over all nonempty sets with $\operatorname{rank}(S) \leqslant k$. We shall show by induction on $k$ that $T_{k} \geqslant 2^{k-1} /\left(2^{k}-1\right)$.

For $k=0$ we have $S=\left\{0^{n}\right\}$ and $T_{0}=1$. If $k=1$, then $|S| \leqslant 2$ and $T_{1}=1$. Assume he statement true for all $0 \leqslant m \leqslant k-1$, and let $\operatorname{rank}(S)=k$. A nonsingular linear ransformation on $\{0,1\}^{n}=\mathrm{GF}[2]^{n}$ permutes the vectors as well as hyperplanes of $\underset{\mathrm{J} F}{\mathrm{~F}}[2]^{n}$. We may therefore assume w.l.o.g that $\left\{e_{1}, \ldots, e_{k}\right\} \subseteq S$, where $e_{i}$ is the $i$ th mit vector, and these vectors span $S$.
A hyperplane $H=\{v \mid v \cdot w=0\}$ satisfies $\operatorname{rank}(S \cap H)<k$ iff $w \notin 0^{k}\{0,1\}^{n-k}$. There are $2^{n}-2^{n-k}$ such vectors $w$. Also, $e_{i} \notin S \cap H$ for all $1 \leqslant i \leqslant k$ iff $w \in 1^{k}\{0,1\}^{n-k}$. If ${ }_{i} \in S \cap H$ for some $i$, then certainly $S \cap H \neq \emptyset$. Hence, the probability that $S \cap H \neq \emptyset$, elative to the event that $\operatorname{rank}(S \cap H)<k$, satisfies

$$
\begin{equation*}
\operatorname{Prob}(S \cap H \neq \emptyset \mid \operatorname{rank}(S \cap H)<k) \geqslant 1-\frac{2^{n-k}}{2^{n}-2^{n-k}}=\frac{2^{k}-2}{2^{k}-1} \tag{1}
\end{equation*}
$$

When randomly choosing $w_{1}, w_{2}, \ldots$, we encounter with probability 1 an index $j$ such that $\operatorname{rank}\left(S \cap H_{1} \cap \cdots \cap H_{j}\right)<k$. Let $i$ be the smallest such index, thus $S \cap H_{1} \cap \cdots \cap H_{i-1}=S$, and $H_{i}$ satisfies $\operatorname{rank}\left(S \cap H_{i}\right)<k$. By (1), the probability that $S \cap H_{i} \neq \emptyset$ is at least $\left(2^{k}-2\right) /\left(2^{k}-1\right)$, thus

$$
T_{k} \geqslant T_{k-1} \frac{2^{k}-2}{2^{k}-1} \geqslant \frac{2^{k}-2}{2^{k-1}-1} \frac{2^{k}-2}{2^{k}-1}=\frac{2^{k-1}}{2^{k}-1} .
$$

Proof of Theorem 2.4. (i) Clearly, $P_{n}(S) \geqslant P(S) \operatorname{Prob}\left(H_{1} \cap \cdots \cap H_{n}=\left\{0^{n}\right\}\right)$. Now, $H_{1} \cap \cdots \cap H_{n}=\left\{0^{n}\right\}$ iff the vectors $w_{1}, \ldots, w_{n}$ are linearly independent. The probability of that is

$$
\left(2^{n}-1\right)\left(2^{n}-2\right) \cdots\left(2^{n}-2^{n-1}\right) / 2^{n^{2}} \geqslant \frac{1}{4} .
$$

Hence, $P_{n}(S) \geqslant \frac{1}{2} \times \frac{1}{4}$. To obtain the claimed constant of $\frac{1}{4}$ we consider the cases of $0^{n} \in S$ and $0^{n} \notin S$ separately. In these two cases,

$$
\begin{aligned}
& P_{n}(S) \geqslant \operatorname{Prob}\left(H_{1} \cap \cdots \cap H_{n}=\left\{0^{n}\right\}\right) \geqslant \frac{1}{4} \text { and } \\
& P_{n}(S) \geqslant P(S) \operatorname{Prob}\left(\operatorname{rank}\left(H_{1} \cap \cdots \cap H_{n-1}\right)=1\right) \geqslant \frac{1}{2} \times \frac{1}{2},
\end{aligned}
$$

respectively.
(ii) Satisfaction of the condition " $\exists i\left|S_{i}\right|=1$ " by the random process only depends on the indices $i_{1}(=1), i_{2}, \ldots, i_{n}$ for which strictly

$$
H_{i_{1}} \supset H_{i_{1}} \cap H_{i_{2}} \supset \cdots \supset H_{i_{1}} \cap \cdots \cap H_{i_{n}}=\left\{0^{n}\right\} .
$$

Therefore, $P(S)$ equals

$$
\operatorname{Prob}\left(\exists i\left|S_{i}\right|=1 \mid H_{1} \supset H_{1} \cap H_{2} \supset \cdots \supset H_{1} \cap \cdots \cap H_{n}=\left\{0^{n}\right\}\right) .
$$

Also, if $0^{n} \notin S$, then it suffices to go down to $H_{n-1}$ since now $\left|S \cap H_{1} \cap \cdots \cap H_{n-1}\right| \leqslant 1$. Hence, by choosing $w_{1}, \ldots, w_{n}$ to be linearly independent we get a process utilizing just $n$ hyperplanes and achieving the same bound of $\frac{1}{2}$ as $P(S)$.

## 3. Applications

By deterministic polynomial-time reductions from USAT $_{Q}$, we can show for several problems for the first time that they are NP-hard under randomized poly-nomial-time reductions. Let $A$ by any NP-complete problem to which SAT is parsimoniously reducible and define $\mathrm{UA}_{Q}$ as in Section 1.

Corollary 3.1. For any choice of $Q, \mathrm{UA}_{Q}$ is NP -hard, under randomized reductions.
Important examples of $\mathrm{UA}_{\mathbf{Q}}$ are the following, defined for each positive integer $k$ :

$$
\#_{k} A(x)= \begin{cases}0 & \text { if \#A(x)=0 mod } k \\ 1 & \text { if } \# A(x) \neq 0 \bmod k\end{cases}
$$

Corollary 3.2. For any $k>1, \#_{k} A$ is NP-hard, under randomized reductions.
For the following problem, testing for the existence of solutions is in $\mathbf{P}$ (by a reduction to finding perfect matchings in bipartite graphs); yet, counting solutions $\bmod k$ is hard.

Corollary 3.3. For any $k>1$ that is not an exact power of two, computing the permanent $\bmod k$ of a $(0,1)$-matrix is NP-hard, under randomized reductions.

Proof. [20, Lemmas 3.1, 3.2, and 3.3] give a transformation from a SAT formula $f$ to a $(0,1)$-matrix $B$ such that $\operatorname{Perm}(B)$ equals \# $\operatorname{SAT}(f) \cdot 4^{t} \bmod k($ where $t$ is a polynomial-time computable function of $f$ ). Hence, \# $\operatorname{SAT}(f)=0 \bmod k$ iff $\operatorname{Perm}(B)=0 \bmod k$.

Corollary 3.4. Consider the problem of finding solutions to instances of SAT with the relaxation that for instances having no solution or more than one solution the output can be arbitrary (the algorithm still has to terminate). This problem is NP-hard under randomized reductions.

Proof. For any instance of this problem (i.e., with the arbitrariness resolved) there is some $Q$ such that $U S A T_{Q}$ reduces to it trivially. Apply this problem to an instance $f$ of SAT and output 1 or 0 according to whether the output is a solution of $f$.

By self-reducibility, the converse of the above also holds.
The next application, due to Selman, identifies a problem to be complete in the class $\mathrm{D}^{\mathrm{p}}$ introduced by Papadimitriou and Yannakakis [13],

$$
\mathrm{D}^{\mathrm{p}}=\left\{L_{1}-L_{2} \mid L_{1}, L_{2} \in \mathrm{NP}\right\} .
$$

The problem Unique SAT is defined as follows: Given an instance of SAT, does it have a unique solution?

Corollary 3.5. Unique SAT is complete in $\mathrm{D}^{\mathrm{p}}$ under randomized polynomial-time reductions.

Proof. In [13] it was shown that the following problem SAT-UNSAT is complete for $\mathrm{D}^{\mathrm{P}}$ : Given a pair ( $f_{1}, f_{2}$ ) of formulae in CNF, determine whether it is the case that " $f_{1}$ is satisfiable but $f_{2}$ is not". We achieve the required randomized reduction by transforming ( $f_{1}, f_{2}$ ) to $f_{1}^{\prime} \wedge f_{2}^{\prime}$ as follows: $f_{2}^{\prime}$ is such that it has exactly one more solution than $f_{2}$ has (see [4]). $f_{1}^{\prime}$ is obtained from $f_{1}$ exactly as $f_{k}$ in Theorem 1.1. The variables of $f_{1}^{\prime}$ and $f_{2}^{\prime}$ are made distinct.

Our final application involves the problem of Approximate Counting. Sipser and Gacs [16] show that this problem is solvable by a randomized polynomial-time TM with a SAT oracle. Our hash function yields a simpler proof. Once again, this result seems to be the best achievable; Stockmeyer [17] shows an oracle relative to which this problem is not in $\Delta_{2}^{\mathrm{p}}$.

Corollary 3.6. For any $\varepsilon>0$ there is a randomized polynomial-time TM with a SAT oracle, which given a SAT formula foutputs a number $k$ such that $(1-\varepsilon) \cdot \# f \leqslant k \leqslant$ $(1+\varepsilon) \cdot \# f$ with probability at least $1-\varepsilon$.

Proof. As in Theorem 1.1, we obtain $f_{1}, \ldots, f_{n}$ from $f$. Using the SAT oracle, we determine $i$ such that $\# f_{i}>0$ and $\# f_{i+1}=0$, and output $2^{i}$. The corollary follows from Theorem 2.3 and standard methods for reducing the probability of error in polynomial time.

## 4. Open problems

The obvious open problem is whether there are deterministic reductions from SAT to USAT $_{Q}$, for each $Q$. Blass and Gurevich [4] give an oracle relative to which UniQue SAT is not complete in $D^{p}$ under deterministic reductions. On the other hand, a deterministic reduction from SAT to Unique SAT will make Unique SAT complete in $\mathrm{D}^{\mathrm{P}}$. Therefore, any deterministic reduction that relativizes could not work for reducing SAT to Unique SAT.

We have shown that Parity SAT is NP-hard under randomized reductions. The problem is clearly in PsPace; however, we would like to determine where in the hierarchy it lies.

A possible direction for further work is to try to narrow the gap between plausible cryptographic functions and NP-completeness. An ideal cryptographic function would have exactly ohe solution but it would be NP-hard to find the solution. The following question may be a more tractable first step: Find an NP-complete problem in which for some fixed polynomial $p(n)$ the instances either have no solution, or the number of solutions of an instance of size $n$ is in the range [ $s(n), t(n)$ ], where $t(n) / s(n) \leqslant p(n)$. In this regard it is known that not all NP-complete problems are parsimoniously reducible from SAT. Graph edge-coloring is a natural counterexample [7]. Whether the number of solutions of all NP-complete problems is nevertheless polynomial-time interreducible (i.e., whether NP-completeness implies \# P completeness) is also open.

## Acknowledgment

We are thankful to Umesh Vazirani for several valuable comments.

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[^0]:    * Supported by National Science Foundation under Grant MCS-83-02385.
    ** Supported by the National Science Foundation under Grants MCS-81-21431, BCR-85-03611 and an IBM Faculty Development Award. Present affiliation: AT\&T Bell Laboratories, Murray Hill, NJ 07974, U.S.A.

