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# New Applications of the Incompressibility Method: Part II

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## Abstract

The incompressibility method is an elementary yet powerful proof technique. It has been used successfully in many areas [8]. To further demonstrate its power and elegance we exhibit new simple proofs using the incompressibility method.

## 1 Introduction

The incompressibility of individual random objects yields a simple but powerful proof technique: *the incompressibility method*. This method is a general purpose tool that can be used to prove lower bounds on computational problems, to obtain combinatorial properties of concrete objects, and to analyze the average complexity of an algorithm. Since the early 1980's, the incompressibility method has been successfully used to solve many well-known questions that had been open for a long time and to supply new simplified proofs for known results. A survey is [8].

The purpose of this paper is pragmatic, in the same style as [9, 7]. We want to further demonstrate how easy the incompressibility method can be used, via a new collection of simple examples. The proofs we have chosen to be included in [7] and here are not difficult ones. They are from diverse topics and most of these topics are well-known. Some of our results are new (but this is not important), and some are known before. In all cases, the new proofs are much simpler than the old ones (if they exist).

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## 2 Kolmogorov Complexity and the Incompressibility Method

We use the following notation. Let  $x$  be a finite binary string. Then  $l(x)$  denotes the *length* (number of bits) of  $x$ . In particular,  $l(\epsilon) = 0$  where  $\epsilon$  denotes the *empty word*.

We can map  $\{0, 1\}^*$  one-to-one onto the natural numbers by associating each string with its index in the length-increasing lexicographical ordering

$$(\epsilon, 0), (0, 1), (1, 2), (00, 3), (01, 4), (10, 5), (11, 6), \dots \quad (1)$$

This way we have a binary representation for the natural numbers that is different from the standard binary representation. It is convenient not to distinguish between the first and second element of the same pair, and call them “string” or “number” arbitrarily. As an example, we have  $l(7) = 00$ . Let  $x, y, \in \mathcal{N}$ , where  $\mathcal{N}$  denotes the natural numbers. Let  $T_0, T_1, \dots$  be a standard enumeration of all Turing machines. Let  $\langle \cdot, \cdot \rangle$  be a standard one-one mapping from  $\mathcal{N} \times \mathcal{N}$  to  $\mathcal{N}$ , for technical reasons chosen such that  $l(\langle x, y \rangle) = l(y) + O(l(x))$ .

Informally, the Kolmogorov complexity, [10], of  $x$  is the length of the *shortest* effective description of  $x$ . That is, the *Kolmogorov complexity*  $C(x)$  of a finite string  $x$  is simply the length of the shortest program, say in FORTRAN (or in Turing machine codes) encoded in binary, which prints  $x$  without any input. A similar definition holds conditionally, in the sense that  $C(x|y)$  is the length of the shortest binary program which computes  $x$  on input  $y$ . Kolmogorov complexity is absolute in the sense of being independent of the programming language, up to a fixed additional constant term which depends on the programming language but not on  $x$ . We now fix one canonical programming language once and for all as reference and thereby  $C()$ . For the theory and applications, as well as history, see [8]. A formal definition is as follows:

DEFINITION 1 Let  $U$  be an appropriate universal Turing machine such that

$$U(\langle \langle i, p \rangle, y \rangle) = T_i(\langle p, y \rangle)$$

for all  $i$  and  $\langle p, y \rangle$ . The *conditional Kolmogorov complexity* of  $x$  given  $y$  is

$$C(x|y) = \min_{p \in \{0,1\}^*} \{l(p) : U(\langle p, y \rangle) = x\}.$$

The unconditional Kolmogorov complexity of  $x$  is defined as  $C(x) := C(x|\epsilon)$ .

It is easy to see that there are strings that can be described by programs much shorter than themselves. For instance, the function defined by  $f(1) = 2$  and  $f(i) = 2^{f(i-1)}$  for  $i > 1$  grows very fast,  $f(k)$  is a “stack” of  $k$  twos. Yet for each  $k$  it is clear that  $f(k)$  has complexity at most  $C(k) + O(1)$ .

By a simple counting argument one can show that whereas some strings can be enormously compressed, the majority of strings can hardly be compressed at all. For each  $n$  there are  $2^n$  binary strings of length  $n$ , but only  $\sum_{i=0}^{n-1} 2^i = 2^n - 1$  possible shorter descriptions. Therefore, there is at least one binary string  $x$  of length  $n$  such that  $C(x) \geq n$ . We call such strings *incompressible*. It also follows that for any length  $n$  and any binary string  $y$ , there is a binary string  $x$  of length  $n$  such that  $C(x|y) \geq n$ .

DEFINITION 2 For each constant  $c$  we say a string  $x$  is  $c$ -incompressible if  $C(x) \geq l(x) - c$ .

Strings that are incompressible (say,  $c$ -incompressible with small  $c$ ) are patternless, since a pattern could be used to reduce the description length. Intuitively, we think of such patternless sequences as being random, and we use “random sequence” synonymously with “incompressible sequence.” It is possible to give a rigorous formalization of the intuitive notion of a random sequence as a sequence that passes all effective tests for randomness, see for example [8].

How many strings of length  $n$  are  $c$ -incompressible? By the same counting argument we find that the number of strings of length  $n$  that are  $c$ -incompressible is at least  $2^n - 2^{n-c} + 1$ . Hence there is at least one 0-incompressible string of length  $n$ , at least one-half of all strings of length  $n$  are 1-incompressible, at least three-fourths of all strings of length  $n$  are 2-incompressible,  $\dots$ , and at least the  $(1 - 1/2^c)$ th part of all  $2^n$  strings of length  $n$  are  $c$ -incompressible. This means that for each constant  $c \geq 1$  the majority of all strings of length  $n$  (with  $n > c$ ) is  $c$ -incompressible. We generalize this to the following simple but extremely useful *Incompressibility Lemma*.

LEMMA 1 *Let  $c$  be a positive integer. For each fixed  $y$ , every set  $A$  of cardinality  $m$  has at least  $m(1 - 2^{-c}) + 1$  elements  $x$  with  $C(x|y) \geq \lfloor \log m \rfloor - c$ .*

PROOF. By simple counting. □

As an example, set  $A = \{x : l(x) = n\}$ . Then the cardinality of  $A$  is  $m = 2^n$ . Since it is easy to assert that  $C(x) \leq n + c$  for some fixed  $c$  and all  $x$  in  $A$ , Lemma 1 demonstrates that this trivial estimate is quite sharp. The deeper reason is that since there are few short programs, there can be only few objects of low complexity.

DEFINITION 3 A *prefix set*, or prefix-free code, or prefix code, is a set of strings such that no member is a prefix of any other member. A prefix set which is the domain of a partial recursive function (set of halting programs for a Turing machine) is a special type of prefix code called a *self-delimiting* code because there is an effective procedure which reading left-to-right determines where a code word ends without reading past the last symbol. A one-to-one function with a range that is a self-delimiting code will also be called a self-delimiting code.

A simple self-delimiting code we use throughout is obtained by reserving one symbol, say 0, as a stop sign and encoding a natural number  $x$  as  $1^x0$ . We can prefix an object with its length and iterate this idea to obtain ever shorter codes:

$$E_i(x) = \begin{cases} 1^x0 & \text{for } i = 0, \\ E_{i-1}(l(x))x & \text{for } i > 0. \end{cases} \quad (2)$$

Thus,  $E_1(x) = 1^{l(x)}0x$  and has length  $l(E_1(x)) = 2l(x) + 1$ ;  $E_2(x) = \lg_1(l(x))x$  and has length  $l(E_2(x)) = l(x) + 2l(l(x)) + 1$ . We have for example

$$l(E_3(x)) \leq l(x) + \log l(x) + 2 \log \log l(x) + 1.$$

Define the pairing function

$$\langle x, y \rangle = E_2(x)y \quad (3)$$

with inverses  $\langle \cdot \rangle_1, \langle \cdot \rangle_2$ . This can be iterated to  $\langle \langle \cdot, \cdot \rangle, \cdot \rangle$ .

In a typical proof using the incompressibility method, one first chooses an individually random object from the class under discussion. This object is effectively incompressible. The argument invariably says that if a desired property does not hold, then the object can be compressed. This yields the required contradiction. Then, since most objects are random, the desired property usually holds on average.

### 3 Number of Strings of Maximum Complexity

A simple counting argument shows that for every  $n$  there is at least one string  $x$  of length  $n$  such that  $C(x|n) \geq n$  and a string  $y$  of length  $n$  such that  $C(y) \geq n$ . In fact, we can do much better. With respect to the prefix version  $K(\cdot)$  of Kolmogorov complexity reference [4] gives an elegant proof that the number strings of length  $n$  that have maximal prefix complexity (also known as self-delimiting complexity or program-size complexity) is  $\Omega(2^n)$ .<sup>1</sup>

The purpose of this section is analyse this matter in detail with respect to  $C(\cdot)$  complexity. The situation is different from prefix-complexity because here we have a simple constructive upper bound. We also want to determine how large the  $C(\cdot)$ -complexity in fact can get (and how many such strings there are). That these matters are not mere curiosities but can be used to obtain meaningful results are shown in [7].<sup>2</sup>

**THEOREM 1** *There is a constant  $d > 0$  such that for every  $n$  there are at least  $\lfloor 2^n/d \rfloor$  strings  $x$  of length  $n$  with  $C(x|n) \geq n$  (respectively,  $C(x) \geq n$ ).*

**PROOF.** It is well-known that there is a constant  $c \geq 0$  such that for every  $n$  there is a string  $x$  of length  $n$  such that  $C(x|n) \leq n + c$ . Hence for every  $n$  and every  $x$  of length  $l(x) \leq n - c - 1$  we have  $C(x|n) < n$ . Consequently, there are at most  $2^n - 2^{n-c}$  programs of length  $< n$  available as shortest programs for the strings of length  $n$  (there are  $2^n - 1$  potential programs and  $2^{n-c} - 1$  thereof are already taken). Hence there are at least  $2^{n-c}$  strings  $x$  of length  $n$  with  $C(x|n) \geq n$ .  $\square$

**THEOREM 2** *There are constants  $c, d > 0$  such that for every large enough  $n$  there are at least  $\lfloor 2^n/d \rfloor$  strings  $x$  of length  $n - c \leq l(x) \leq n$  with  $C(x|n) > n$  (respectively,  $C(x) > n$ ).*

**PROOF.** For every  $n$  there are equally many strings of length  $\leq n$  to be described and potential programs of length  $\leq n$  to describe them. Since some programs do not halt for

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<sup>1</sup>Prefix complexity makes its brief and only appearance in this paper here; for more details check out [8]. We remark that the prefix complexity  $K(x)$  is typically larger than  $C(x)$  and in fact for every  $n$  there are  $x$  such that  $K(x) = n + K(n) + O(1)$ . This is larger than  $C(x)$  which is upper bounded by  $n + O(1)$ . With respect to the the related question for  $C(x)$  complexity [4] states: “An earlier, unpublished version of this result was obtained more than twenty years ago in connection with  $[C(\cdot)]$ . . . the proof shows that a number is large because it is random.”

<sup>2</sup>The history of interest and reinvention of these curious but useful facts makes it useful to archive them. Theorems 1, 2 were independently proved by two of us [HB,PV] in June 1995, and Theorem 1 was also independently found by both M. Kummer and L. Fortnow. This was not published but appears as Exercise 2.2.6 in [8]. Of course, the cited reference [4] giving the result for the prefix-complexity  $K(\cdot)$  precedes all of this.

every large enough  $n$  there exists a string  $x$  of length at most  $n$  such that  $n < C(x|n) \leq l(x) + c$  and a string  $y$  of length at most  $n$  such that  $n < C(y) \leq l(y) + c$ .

Let there be  $m \geq 1$  such strings. Given  $m$  and  $n$  we can enumerate all  $2^{n+1} - m - 1$  strings  $x$  of length  $\leq n$  and complexity  $C(x|n) \leq n$  by dovetailing the running of all programs of length  $\leq n$ . The lexicographic first string of length  $\leq n$  not in the list, say  $x$ , is described by a program  $p$  giving  $m$  in  $\log m$  bits plus an  $O(1)$ -bit program to do the decoding of  $x$ . Therefore,  $\log m + O(1) \geq C(x|n) > n$  which proves the theorem for the conditional case. The unconditional result follows similarly by padding the description of  $x$  up to length  $n + c'$  for a constant  $c'$  and adding the description of  $c'$  to program  $p$  describing  $x$ . This way we can first retrieve  $c'$  from  $p$  and then retrieve  $n$  from the length of  $p$ .  $\square$

REMARK 1 This shows that there are lots of strings  $x$  that have complexity larger than their lengths. How much larger can this get? While the theorems above are invariant with respect to the choice of the particular reference universal Turing machine in the definition of the Kolmogorov complexity, the excess of maximal complexity over the length depends on this choice.

For example, we can easily choose a reference universal Turing machine that has no halting programs of odd length, or such that it has no halting programs of length  $i \bmod 100$  for  $i = 0, \dots, 98$ . In such a case there are many  $x$ 's that have complexity at least  $l(x) + 100$ . In the opposite extreme, given an appropriate universal Turing machine  $U$  we can transform it into a universal Turing machine  $U'$  such that  $U'(1p) = p$  and  $U'(0p) = U(p)$  for all  $p$ . Taking  $U'$  as reference universal Turing machine we clearly have  $C(x) \leq l(x) + 1$  for all  $x$ . Consequently, for every  $n$  the shortest programs of strings of length  $< n$  have length at most  $n$ . This means that there are at most  $2^{n+1} - 2^n = 2^n$  strings available of length at most  $n$  to serve as shortest programs for strings of length  $n$ .

By definition of  $U'$  the Theorem 2 means that at least  $\Omega(2^n)$  strings of length  $n$  are used as shortest programs for strings of length  $n - 1$ , while by definition of  $U'$  at least  $2^n/2$  strings of length  $n$  are used as (not necessarily shortest) programs for strings of length  $n - 1$ . Consequently, at most  $2^n/2$  strings  $x$  of length  $n$  have complexity  $C(x) = n$  and at least  $\Omega(2^n)$  strings  $y$  of length  $n$  have complexity  $C(y) = n + 1$ . There are no strings  $z$  of length  $n$  that have complexity  $C(z) > n + 1$ .

## 4 Average Time for Boolean Matrix Multiplication

We begin with a simple (almost trivial) illustration of average-case analysis using the incompressibility method. Consider the problem of multiplying two  $n \times n$  boolean matrices  $A = (a_{i,j})$  and  $B = (b_{i,j})$ . Efficient algorithms for this problem have always been a very popular topic in the theoretical computer science literature due to the wide range of applications of boolean matrix multiplication. The best worst-case time complexity obtained so far is  $O(n^{2.376})$  due to Coppersmith and Winograd [5]. In 1973, O'Neil and O'Neil devised a simple algorithm described below which runs in  $O(n^3)$  time in the worst case but achieves an average time complexity of  $O(n^2)$  [12].

**Algorithm** QuickMultiply( $A, B$ )

1. Let  $C = (c_{i,j})$  denote the result of multiplying  $A$  and  $B$ .
2. For  $i := 1$  to  $n$  do
3.     Let  $j_1 < \dots < j_m$  be the indices such that  $a_{i,j_k} = 1$ ,  $1 \leq k \leq m$ .
4.     For  $j := 1$  to  $n$  do
5.         Search the list  $b_{j_1,j}, \dots, b_{j_m,j}$  sequentially for a bit 1.
6.         Set  $c_{i,j} = 1$  if a bit 1 is found, or  $c_{i,j} = 0$  otherwise.

An analysis of the average-case time complexity of QuickMultiply is given in [12] using simple probabilistic arguments. Here we give an analysis using the incompressibility method.

**THEOREM 3** *Suppose that the elements of  $A$  and  $B$  are drawn uniformly and independently. Algorithm QuickMultiply runs in  $O(n^2)$  time on the average.*

**PROOF.** Let  $n$  be a sufficiently large integer. Observe that the average time of QuickMultiply is trivially bounded between  $O(n^2)$  and  $O(n^3)$ . By the Incompressibility Lemma, out of the  $2^{2n^2}$  pairs of  $n \times n$  boolean matrices, at least  $(n-1)2^{2n^2}/n$  of them are  $\log n$ -incompressible. Hence, it suffices to consider  $\log n$ -incompressible boolean matrices.

Take a  $\log n$ -incompressible binary string  $x$  of length  $2n^2$ , and form two  $n \times n$  boolean matrices  $A$  and  $B$  straightforwardly so that the first half of  $x$  corresponds to the row-major listing of the elements of  $A$  and the second half of  $x$  corresponds to the row-major listing of the elements of  $B$ . We show that QuickMultiply spends  $O(n^2)$  time on  $A$  and  $B$ .

Consider an arbitrary  $i$ , where  $1 \leq i \leq n$ . It suffices to show that the  $n$  sequential searches done in Steps 4 – 6 of QuickMultiply take a total of  $O(n)$  time. By the statistical results on various blocks in incompressible strings given in Section 2.6 of [8], we know that at least  $n/2 - O(\sqrt{n \log n})$  of these searches find a 1 in the first step, at least  $n/4 - O(\sqrt{n \log n})$  searches find a 1 in two steps, at least  $n/8 - O(\sqrt{n \log n})$  searches find a 1 in three steps, and so on. Moreover, we claim that none of these searches take more than  $4 \log n$  steps. To see this, suppose that for some  $j$ ,  $1 \leq j \leq n$ ,  $b_{j_1,j} = \dots = b_{j_{4 \log n},j} = 0$ . Then we can encode  $x$  by listing the following items in a self-delimiting manner:

1. A description of the above discussion.
2. The value of  $i$ .
3. The value of  $j$ .
4. All bits of  $x$  except the bits  $b_{j_1,j}, \dots, b_{j_{4 \log n},j}$ .

This encoding takes at most

$$O(1) + 2 \log n + 2n^2 - 4 \log n + O(\log \log n) < 2n^2 - \log n$$

bits for sufficiently large  $n$ , which contradicts the assumption that  $x$  is  $\log n$ -incompressible.

Hence, the  $n$  searches take at most a total of

$$\begin{aligned}
& \left( \sum_{k=1}^{\log n} (n/2^k - O(\sqrt{n \log n})) \cdot k \right) + (\log n) \cdot O(\sqrt{n \log n}) \cdot (4 \log n) \\
& < \left( \sum_{k=1}^{\log n} kn/2^k + O(\log^2 n \sqrt{n \log n}) \right) \\
& = O(n) + O(\log^2 n \sqrt{n \log n}) \\
& = O(n)
\end{aligned}$$

steps. This completes the proof.  $\square$

## 5 Average Complexity of Finding the Majority

Let  $x = x_1 \cdots x_n$  be a binary string. The *majority bit* (or simply, the *majority*) of  $x$  is the bit (0 or 1) that appears more than  $\lfloor n/2 \rfloor$  times in  $x$ . The majority problem is that, given a binary string  $x$ , determine the majority of  $x$ . When  $x$  has no majority, we must report so.

The time complexity for finding the majority has been well studied in the literature (see, *e.g.* [1, 2, 3, 6, 13]). It is known that, in the worst case,  $n - \nu(n)$  bit comparisons are necessary and sufficient [2, 13], where  $\nu(n)$  is the number of occurrences of bit 1 in the binary representation of number  $n$ . Recently, Alonso, Reingold and Schott [3] studied the average complexity of finding the majority assuming the uniform probability distribution model. Using quite sophisticated arguments based on decision trees, they showed that on the average finding the majority requires at most  $2n/3 - \sqrt{8n/9\pi} + O(\log n)$  comparisons and at least  $2n/3 - \sqrt{8n/9\pi} + \Theta(1)$  comparisons.

In this section, we consider the average complexity of finding the majority and prove a pair of upper and lower bounds tight up to the first major term, using simple incompressibility arguments.

We start by proving an upper bound of  $2n/3 + O(\sqrt{n \log n})$ . The following standard tournament algorithm is needed.

**Algorithm** Tournament( $x = x_1 \cdots x_n$ )

1. If  $n = 1$  then return  $x_1$  as the majority.
2. Elseif  $n = 2$  then
  3. If  $x_1 = x_2$  then return  $x_1$  as the majority.
  4. Else return “no majority”.
5. Elseif  $n = 3$  then
  6. If  $x_1 = x_2$  then return  $x_1$  as the majority.
  7. Else return  $x_3$  as the majority.

8. Let  $y = \epsilon$ .
9. For  $i := 1$  to  $\lfloor n/2 \rfloor$  do
10. If  $x_{2i-1} = x_{2i}$  then append the bit  $x_{2i}$  to  $y$ .
11. If  $\lfloor n/2 \rfloor$  is even then append the bit  $x_n$  to  $y$ .
12. Call  $\text{Tournament}(y)$ .

**THEOREM 4** *On the average, algorithm Tournament requires at most  $2n/3 + O(\sqrt{n \log n})$  comparisons.*

**PROOF.** Let  $n$  be a sufficiently large number. Again, since algorithm Tournament makes at  $n$  comparisons on any string of length  $n$ , by the Incompressibility Lemma, it suffices to consider running time of Tournament on  $\log n$ -incompressible strings. Let  $x = x_1 \cdots x_n$  be a  $\log n$ -incompressible binary string. For any integer  $m \leq n$ , let  $\sigma(m)$  denote the maximum number of comparisons required by algorithm Tournament on any  $\log n$ -incompressible string of length  $m$ .

We know from [8] that among the  $\lfloor n/2 \rfloor$  bit pairs  $(x_1, x_2), \dots, (x_{2\lfloor n/2 \rfloor - 1}, x_{2\lfloor n/2 \rfloor})$  that are compared in step 10 of Tournament, there are at least  $n/4 - O(\sqrt{n \log n})$  pairs consisting of complementary bits. Clearly, the new string  $y$  obtained at the end of step 11 should satisfy

$$C(y) \geq l(y) - \log n - O(1)$$

Hence, we have the following recurrence relation for  $\sigma(m)$ :

$$\sigma(m) \leq \lfloor m/2 \rfloor + \sigma(m/4 + O(\sqrt{m \log n}))$$

By straightforward expansion, we obtain that

$$\begin{aligned}
\sigma(n) &\leq \lfloor n/2 \rfloor + \sigma(n/4 + O(\sqrt{n \log n})) \\
&\leq n/2 + \sigma(n/4 + O(\sqrt{n \log n})) \\
&\leq n/2 + (n/8 + O(\sqrt{n \log n})/2) + \sigma(n/16 + O(\sqrt{n \log n})/4 + O(\sqrt{(n \log n)/4})) \\
&= n/2 + (n/8 + O(\sqrt{n \log n})/2) + \sigma(n/16 + (3/4) \cdot O(\sqrt{n \log n})) \\
&\leq \dots \\
&\leq 2n/3 + O(\sqrt{n \log n})
\end{aligned}$$

□

Now we prove a lower bound which differs from the above upper bound only by  $O(\sqrt{n \log n})$ .

**THEOREM 5** *Every algorithm requires at least  $2n/3 - O(\sqrt{n \log n})$  comparisons to find the majority, on the average.*

PROOF. Consider an arbitrary majority finding algorithm  $A$ . Again, let  $n$  be a sufficiently large number and  $x = x_1 \cdots x_n$  a log  $n$ -incompressible binary string. Without loss of generality, we assume that  $A$  never makes redundant comparisons, *i.e.* if the relationship between bits  $x_i$  and  $x_j$  can be inferred from the previous comparisons, then  $A$  will not compare  $x_i$  with  $x_j$  again. It will be useful to think of the comparisons of  $A$  as partitioning the bits  $x_1, \dots, x_n$  of  $x$  into “clusters” where each cluster contains all the bits whose relationships to each other have been established. Let  $C_1, \dots, C_p$  be the clusters formed when  $A$  terminates. For each cluster  $C_i$ , let  $w(C_i)$ , called the weight of  $C_i$ , denote the absolute value of the difference between the number of 0’s and the number of 1’s in  $C_i$ . Clearly, in order for algorithm  $A$  to be correct, there must be a unique cluster  $C_i$  such that

$$w(C_i) > \sum_{j \neq i} w(C_j).$$

(Otherwise how can the algorithm declare the majority)

We first claim that for each cluster  $C_i$ , its weight  $w(C_i) \leq O(\sqrt{n \log n})$ . Suppose that  $C_i$  contains  $m$  bits  $x_{i_1}, \dots, x_{i_m}$ , listed in the order that they were first compared. Clearly, given the algorithm  $A$ , the bits in the clusters  $C_1, \dots, C_p$ , listed in the order that they were first compared, encode the string  $x$ . Since the total number of the bits is  $n$  and  $C(x) \geq n - \log n$ , we have  $C(x_{i_1} \cdots x_{i_m}) \geq m - \log n - O(1)$ . Hence, from the results in [8] we know that the numbers of 0’s and 1’s in these bits differ by at most  $O(\sqrt{m \log n}) \leq O(\sqrt{n \log n})$ .

Suppose that  $A$  makes a total of  $k$  comparisons. In order to relate  $k$  to the Kolmogorov complexity of the string  $x$ , we re-encode  $x$  by listing the following information in the self-delimiting form:

1. The above discussion and the algorithm  $A$ .
2. For each of the  $k$  comparisons made by  $A$ , a bit indicating the outcome of the comparison. This gives rise to a string  $y$  of length  $k$ .
3. For each cluster  $C_i$ , a bit indicating the value of the lowest indexed bit in  $C_i$ .

Since  $A$  does not make redundant comparisons, the length of the above description is at most  $n + \log n + O(1)$ . Hence,

$$k + p = l(y) + p = n \pm \log n \pm O(1)$$

Thus,  $C(y) \geq k - 2 \log n$ . Again, by the results in [8], we claim that at most  $k/2 + O(\sqrt{k \log n})$  of the  $k$  comparisons identify pairs of complementary bits.

Observe that for any cluster  $C_i$ , in order for the weight  $w(C_i)$  to equal zero, at least one of the comparisons that form  $C_i$  must involve complementary bits. Hence, from the above discussion, the number of clusters with zero weight is at most  $k/2 + O(\sqrt{k \log n})$ . Since the maximum weight of a cluster is  $O(\sqrt{n \log n})$ , we have

$$p - k/2 - O(\sqrt{k \log n}) \leq O(\sqrt{n \log n})$$

Since  $p \geq n - k - O(1)$ , we obtain

$$n - k - O(1) - k/2 - O(\sqrt{k \log n}) \leq O(\sqrt{n \log n})$$

That is,

$$k \geq 2n/3 - O(\sqrt{k \log n}) - O(\sqrt{n \log n}) = 2n/3 - O(\sqrt{n \log n}).$$

□

## 6 Communication Complexity

Consider the following communication complexity problem (for definitions see the book by Kushilevitz and Nisan [11]). Initially, Alice has a string  $x = x_1, \dots, x_n$  and Bob has a string  $y = y_1, \dots, y_n$  with  $x, y \in \{0, 1\}^n$ . Alice and Bob use an agreed-upon protocol to compute the inner product of  $x$  and  $y$  modulo 2

$$f(x, y) = \sum_{i=1}^n x_i \cdot y_i \pmod{2}$$

with Alice ending up with the result. We are interested in the minimal possible number of bits used in communication between Alice and Bob in such a protocol. Here we prove a lower bound of  $n - 1$ , which is almost tight since the trivial protocol where Bob sends all his  $n$  bits to Alice achieves this bound. In [11] it is shown that the lower bound is in fact  $n$ . We also show an  $n - O(1)$  lower bound for the average-case complexity and a  $n - 1 + \log(1 - \epsilon)$  lower bound for randomized algorithms (private coins) that output the correct answer with probability at least  $1 - \epsilon$ .

**THEOREM 6** *Assume the discussion above. Every protocol computing the inner product function requires at least  $n - 1$  bits of communication.*

**PROOF.** Fix a communication protocol  $P$  that computes the inner product. Let  $A$  be an algorithm that we describe later. Let  $z$  be a string of length  $2n$  such that  $C(z|A, P, n) \geq 2n - 1$ . Let  $z = x_1 \dots x_n y_1 \dots y_n$ . Let Alice's input be  $x = x_1 \dots x_n$  and Bob's input be  $y_1 \dots y_n$ . Assume without loss of generality that  $f(x, y) = 0$  (the innerproduct of  $x$  and  $y$  is 0 modulo 2).<sup>3</sup> Run the communication protocol  $P$  between Alice and Bob ending in a state where Alice outputs that  $f(x, y)$  is 0. Let  $C$  be the sequence of bits sent back and forth. Note that  $P$  can be viewed as a tree with  $C$  a path in this tree [11]. Hence  $C$  is self-delimiting. Consider the set  $S$  defined by

$$S := \{a : \exists b \text{ such that } P(a, b) = 0 \text{ and induces conversation } C, a, b \in \{0, 1\}^n\}.$$

Given  $n, P$  and  $C$ , we can compute  $S$ . Let the cardinality of  $S$  be  $l$ . The strings in  $S$  form a matrix  $M$  over  $\text{GF}(2)$  with the  $i$ th row of  $M$  corresponding to the  $i$ th string in  $S$  (say in lexicographic ordering). Since for every  $a \in S$  it holds that  $f(a, y) = 0$  it follows that  $y$  is an element of the Null space of  $M$  ( $y \in \text{Null}(M)$ ). Application of the Null space Theorem from linear algebra yields:

$$\text{rank}(M) + \dim(\text{Null}(M)) = n. \tag{4}$$

---

<sup>3</sup>By symmetry there are precisely  $2^{2n-1}$  strings  $z = xy$   $l(x) = l(y) = n$  with inner product  $x, y$  equal 0. There are only  $2^{2n-1} - 1$  programs of length less than  $2n - 1$ . Hence there must be a  $z$  as required.

Since the cardinality of  $S$  is  $l$  and we are working over  $\text{GF}(2)$  it follows that the rank of  $M$  is at least  $\log(l)$  and by (4) it follows that  $\dim(\text{Null}(M)) \leq n - \log(l)$ . The following is an effective description of  $z$  given  $n$  and the reconstructive algorithm  $A$  explained below:

1.  $C$ ;
2. the index of  $x \in S$  using  $\log(l)$  bits; and
3. the index of  $y \in \text{Null}(M)$  with  $n - \log(l)$  bits.

The three items above can be concatenated without delimiters. Namely,  $C$  itself is self-delimiting, while from  $C$  one can generate  $S$  and hence compute  $l$ . From the latter item one can compute the binary length of the index for  $x \in S$ , and the remaining suffix of the binary description is the index for  $y \in \text{Null}(M)$ . From the given description and  $P, n$  the algorithm  $A$  reconstructs  $x$  and  $y$  and outputs  $z = xy$ . Consequently,  $C(z|A, P, n) \leq l(C) + \log l + (n - \log l)$ . Since we have assumed  $C(z|A, P, n) \geq 2n - 1$  it follows that  $l(C) \geq n - 1$ .  $\square$

We can improve this lower bound to  $n$  as follows:

**THEOREM 7** *Assume the discussion above. There exists a constant  $c$  such that for all  $m$  there is an  $n$  ( $2m - c \leq 2n \leq 2m$ ) such that every protocol computing the inner product function of two  $n$ -bit strings requires at least  $n$  bits of communication.*

**PROOF.** Using a similar argument as in Theorem 2 there is a constant  $c$  such that for every  $m$  we can choose  $z$  of length  $2n$  ( $2m - c \leq 2n \leq 2m$ ) with associated inner product 0 and  $C(z|A, P, n) \geq 2n$ . The remainder of the proof is the same as above.  $\square$

Approximately the same lower bound holds for the average-case communication complexity of computing the inner product of two  $n$ -bit strings:

**THEOREM 8** *The average communication complexity of computing the inner product of two  $n$ -bit strings is at least  $n - O(1)$  bits.*

**PROOF.** There are exactly  $2^{2n-1}$  strings  $z$  of length  $2n$  such that  $z = xy$ ,  $l(x) = l(y) = n$  and inner product of  $x$  and  $y$  modulo 2 equals 1. For such  $z$  define  $\bar{z} = \bar{x}\bar{y}$  as  $z$  but with the first bit of  $x$  and the first bit of  $y$  changed so that the inner product of the resulting strings  $\bar{x}$  and  $\bar{y}$  equals 0.  $C(\bar{w}|n) = C(w|n) + O(1)$  for every  $w \in \{z, x, y\}$ . Let  $\delta(n)$  be a function and choose in the proof above  $C(z|A, P, n) \geq 2n - \delta(n)$ . By simple counting there are at least

$$2^{2n}(1 - 1/2^{\delta(n)}) \tag{5}$$

such  $z$ 's. If the above inner product associated with  $z$  equals 1 then the inner product associated with  $\bar{z}$  equals 0 and  $C(\bar{z}|A, P, n) \geq 2n - \delta(n) - O(1)$

Hence we can apply the proof of the previous theorem for all  $z$  with randomness deficiency at most  $\delta(n)$  as follows:

- If  $z$  has an associated inner product 0 then the proof as above yielding  $l(C_z) \geq n - \delta(n)$  where  $C_z$  is the communication sequence associated with the computation with input  $z$ .

- If  $z$  has associated inner product 1 then the proof as above to  $\bar{z}$  yielding  $l(C_{\bar{z}}) \geq n - \delta(n) - O(1)$ .

There are at least  $2^{2n}(1 - 1/2^{\delta(n)})$  strings  $z$  of length  $2n$  with  $C(z|A, P, n) \geq 2n - \delta(n)$ . Altogether we obtain that the average communication complexity is

$$\begin{aligned}
\sum_{z \in \{0,1\}^{2n}} \Pr(z) l(C_z) &= 2^{-2n} \sum_{z \in \{0,1\}^{2n}} l(C_z) \\
&\geq 2^{-2n} \sum_{\delta(n)=1}^n \sum_{z \in \{0,1\}^n \& C(z|A, P, n) = 2n - \delta(n)} l(C_z) \\
&\geq 2^{-2n} \sum_{\delta(n)=1}^n 2^{2n} \frac{1}{2^{\delta(n)}} (n - \delta(n) - O(1)) \\
&= \sum_{\delta(n)=1}^n \frac{n}{2^{\delta(n)}} - \sum_{\delta(n)=1}^n \frac{\delta(n) + O(1)}{2^{\delta(n)}} \\
&\geq n - O(1).
\end{aligned}$$

This proves the theorem. □

A similar proof establishes a lower bound of about  $n$  bits for the communication complexity of equality of the strings held by both parties.

**THEOREM 9** *The communication complexity of a randomized protocol using private coins computing the inner product of two  $n$ -bit strings that outputs the correct answer with probability at least  $1 - \epsilon$  is at least  $n - 1 + \log(1 - \epsilon)$  bits.*

**PROOF.** The proof is similar to that of the deterministic lower bound. Assume that Alice and Bob compute probabilistically, that is, they can each flip a private fair coin (whose output does not depend on the input) and decide their next step depending on the result of the coin flip, and the error rate of their computation is  $\epsilon$ . Because for each pair of inputs, there is  $1 - \epsilon$  chance to output the correct result, there must exist a coin flipping sequence such that using it Bob and Alice output the correct result for  $1 - \epsilon$  portion of the inputs. Fix such a sequence  $R$ . Out of such  $2^{2n}(1 - \epsilon)$  strings of length  $2n$ , choose  $z$  such that

$$C(z|A, P, R, n) \geq 2n - 1 + \log(1 - \epsilon).$$

Such  $z$  exists according to Lemma 1. Then we proceed as before in the deterministic case to show that Alice and Bob must communicate

$$n - 1 + \log(1 - \epsilon)$$

bits to compute  $f(x, y)$ , where  $z = xy$ ,  $|x| = |y| = n$ . □

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