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# Algorithms for Sparse Random 3XOR: The Low-Density Case

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## Abstract

We present an algorithm for a variant of the 3XOR problem with lists consisting of  $n$ -bit vectors whose coefficients are drawn independently at random according to a Bernoulli distribution of parameter  $p < 1/2$ . We show that in this particular context the problem can be solved much more efficiently than in the general setting. This leads to a linear algorithm with overwhelming success probability for  $p < 0.0957$ . With slightly different parameters, this method succeeds deterministically. The expected runtime is also linear for  $p < 0.02155$  and always sub-quadratic.

**2012 ACM Subject Classification** Theory of computation → Computational complexity and cryptography; Theory of computation

**Keywords and phrases** Algorithms, 3-xor problem, random sparse 3-xor

## 1 Introduction

Given three lists  $A$ ,  $B$  and  $C$  of  $n$ -bit vectors, the 3XOR problem consists in deciding the existence of (or even finding) a triplet  $(\mathbf{x}, \mathbf{y}, \mathbf{z}) \in A \times B \times C$  such that  $\mathbf{x} \oplus \mathbf{y} \oplus \mathbf{z}$  is equal to a given target, often assumed to be zero (here the  $\oplus$  symbol represent the exclusive-OR or XOR).

In the general setting where the input lists have size  $N$  and can be arbitrary, a simple algorithm decides the existence of a 3XOR triplet in time  $\mathcal{O}(N^2)$ , but there is no known way of doing it in time  $\mathcal{O}(N^{2-\epsilon})$  for any  $\epsilon > 0$ . Dietzfelbinger, Schlag and Walzer found an algorithm that gain a poly-logarithmic factor over the quadratic algorithm [4].

3XOR can be seen as a variant of the celebrated 3SUM problem, where this time the input list items are seen as integers and we must have  $x + y + z = 0$ . Many geometric problems can be reduced to 3SUM in sub-quadratic time, and those problems are said to be 3SUM hard [6]. Although the 3XOR problem has enjoyed less interest in the complexity theory field, there exists a few such reductions. For instance, it is a fact that any  $\mathcal{O}(N^{1+\epsilon})$  algorithm for the 3XOR problem with input lists of size  $N$  would imply faster-than-expected algorithms for listing triangles in a graph [7]. In the other direction, some conditional lower-bounds have been established based on the hypothesis that 3XOR is inherently quadratic: [4] shows that the offline SETDISJOINTNESS and SETINTERSECTION problems cannot be solved in time  $\mathcal{O}(N^{2-\epsilon})$  unless 3XOR can.

Besides being a natural extension of 3SUM, the 3XOR problem has some cryptographic applications, in which the input lists consist of uniformly *random* vectors. In particular, we can mention Nandi's attack [10] against the COPA mode of authenticated encryption, or the more recent attack against the two-round single-key Even-Mansour cipher by Leurent and Sibleyras [9]. May and Both have been considering a variant of the 3XOR problem, the *approximate 3-list birthday problem*: given three lists of  $N$  uniformly random elements of  $\{0, 1\}^n$  the goal consist in finding triplets  $(\mathbf{x}, \mathbf{y}, \mathbf{z})$  in the list such that the hamming weight of  $\mathbf{x} \oplus \mathbf{y} \oplus \mathbf{z}$  is small [2].

46 Studying the 3XOR problem with uniformly random inputs seemed natural to the  
 47 cryptography community (which makes this assumption “by default”), and this led to  
 48 several algorithms gaining a polylogarithmic factor, predating [4], and often tailored to  
 49 specific input sizes [8, 11, 3]. The assumption that the input is *random* makes the problem  
 50 simpler, but it has not yet been possible to obtain a  $\mathcal{O}(N^{2-\epsilon})$  algorithm even in this simpler  
 51 case.

52 **Contributions.** In this paper, we consider an even more favorable setting, where the input  
 53 lists are both *random* and *sparse*, namely where the input bitstrings are biased towards  
 54 zero in some way. More precisely, we assume that each input bit is drawn independently  
 55 at random according to a Bernoulli distribution of parameter  $0 < p < 1/2$  — the “dense”  
 56 random case corresponds to  $p = 1/2$ .

57 We first give the probability that the input actually contains a 3XOR triplet for a given  
 58 list size  $N$  and density  $p$ . To the best of our knowledge, this result was not readily available  
 59 from the existing literature, not even in the simple “cryptographically relevant” case where  
 60  $p = 1/2$ . We then describe a new algorithm to solve the random low-density 3XOR problem  
 61 (Section 3). The main idea is to discard useless input vectors (i.e. whose Hamming weight is  
 62 above a well-chosen threshold), then search a solution using the simple quadratic algorithm.  
 63 This algorithm returns a solution with overwhelming probability in time linear in  $N$  for  
 64 small density (i.e.  $p < 0.0957$ ). A slight variation of the same algorithm can also be used to  
 65 deterministically return a solution if there is one in the input. In this case, the expected  
 66 running time of the procedure is also linear in  $N$  when  $p$  is smaller than 0.02155. The  
 67 algorithm has a time complexity of  $\mathcal{O}(N + N^e)$ , for some parameter  $e < 2$  when  $p < 1/2$ .  
 68 The evolution of this parameter  $e$  in function of  $p$  is shown in Figure 1.

69 Another relevant sparse distribution would be the “low-weight” distribution, where  
 70 bitstrings from  $\{0, 1\}^n$  of a given small weight are drawn uniformly at random. For lack of  
 71 space, we do not consider this (quite different) problem in this paper. Our main contribution,  
 72 the algorithm described in section 4, cannot be adapted to this other setting.

73 The algorithm presented in this paper has no concrete application that we are aware of,  
 74 either in cryptography or elsewhere. We nevertheless demonstrate its practical efficiency by  
 75 obtaining the —non-trivial and “sensible”— result shown in Section 5.

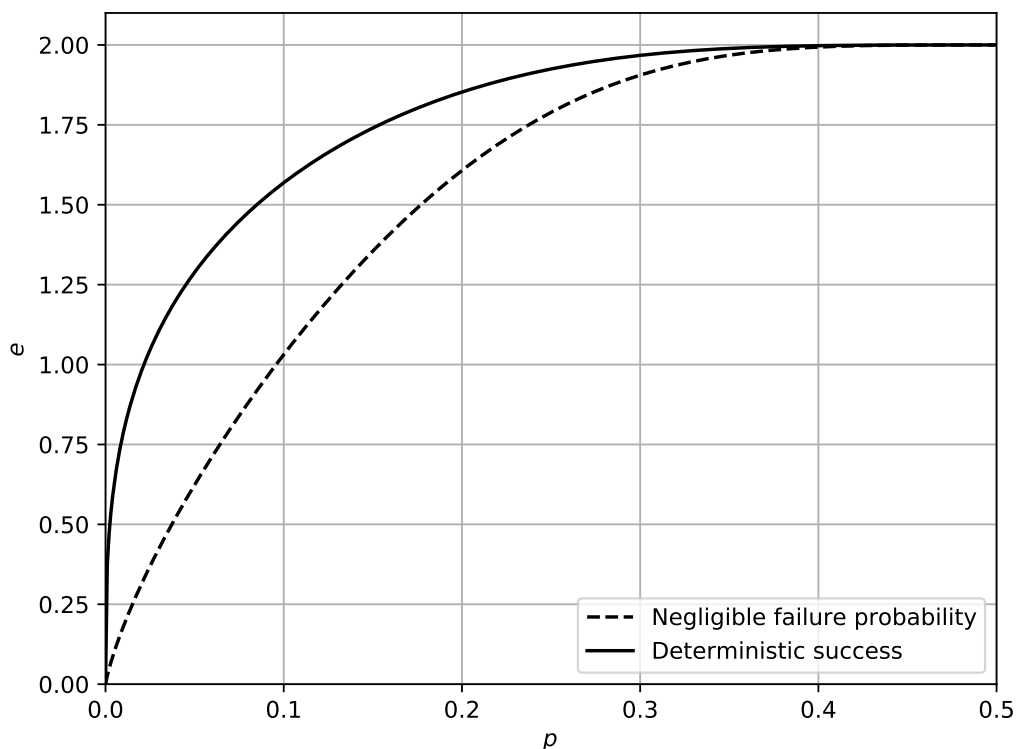
## 76 2 Preliminaries

77 Let  $\mathbf{x} = x_0x_1 \dots x_{n-1}$  be an  $n$ -bit string (we use “bit string” and “vector” as synonyms). We  
 78 denote by  $\text{wt}(\mathbf{x})$  its Hamming weight. Let  $A$  be a list ;  $|A|$  denotes the number of elements in  
 79  $A$  and  $A[i]$  denotes the  $i$ -th element. We say that  $(\mathbf{x}, \mathbf{y}, \mathbf{z})$  is a *3XOR triplet* if  $\mathbf{x} \oplus \mathbf{y} \oplus \mathbf{z} = \mathbf{0}$ .

80 We consider random instances of the problem defined as follows. Let  $\Psi$  be some probability  
 81 distribution over  $\{0, 1\}^n$ . Let  $A, B$  and  $C$  be three lists of  $N$  elements drawn independently at  
 82 random according to  $\Psi$ . A *solution* to the instance of the 3XOR problem given by  $(A, B, C)$   
 83 is a 3XOR triplet  $(\mathbf{x}, \mathbf{y}, \mathbf{z}) \in A \times B \times C$ .

84 Let  $0 < p < 1/2$  be fixed and let  $\text{Ber}_p$  the Bernoulli distribution of parameter  $p$ . In the  
 85 sequel, we focus on the sparse “low-density” distributions over  $\{0, 1\}^n$ , denoted as  $\mathcal{D}$ , where  
 86 each input bit is drawn independently from  $\text{Ber}_p$ .

87 **Bounds for Binomial Distributions.** Let  $\mathcal{B}(n, p)$  denote the binomial distribution with  
 88 parameters  $n, p$ . Let  $X \sim \mathcal{B}(n, p)$  be a binomial random variable. We make heavy use of tail  
 89 bounds, notably the Chernoff bound (1) and the tighter classical inequality (2), a proof of



■ **Figure 1** The INCREMENTAL3XOR algorithm of section 4 run in time  $\mathcal{O}(N + N^e)$  where  $e$  is shown here. With  $w_{\max} = 2nu$  (cf. theorem 3), this yields the “negligible failure probability” curve. With  $w_{\max} = n$  (theorem 6), this yields the “deterministic success” curve.

90 which can be found in [1] amongst others.

$$91 \quad \Pr(X \leq an) \leq \exp -\frac{n}{2p}(p-a)^2, \quad \text{if } \frac{k}{n} < p \quad (1)$$

$$92 \quad \Pr(X \leq an) \leq \exp -nD(a,p) \quad \text{if } a < p, \quad (2)$$

$$93 \quad \Pr(X \geq an) \leq \exp -nD(a,p) \quad \text{if } a > p,$$

94 where  $D(a,p) = a \ln \frac{a}{p} + (1-a) \ln \frac{1-a}{1-p}$  is the Kullback-Leibler divergence between an  $a$ -coin  
95 and a  $p$ -coin.  
96

97 **Computational Model.** We consider a transdichotomous word Random Access Machine  
98 (word-RAM) model. In this model, we have access to a machine in which each “memory  
99 cell” contains a  $n$ -bit word. We assume that the usual arithmetic and bit-wise operations on  
100  $n$ -bit words, as well as the comparison of two  $n$ -bit integers and memory access with  $n$ -bit  
101 addresses can be done in constant time. We also assume that obtaining the Hamming weight  
102 of an  $n$ -bit word is an elementary operation. In other terms, we assume that the machine is  
103 large enough to accommodate the instance of the problem at hand.

104 **The Quadratic Algorithm.** The simplest possible way to solve the 3XOR problem is the  
105 quadratic algorithm (shown as algorithm 1). For all pairs  $(x,y) \in A \times B$ , check if  $x \oplus y$   
106 belongs to  $C$ . Each test can be done in constant time if all entries of  $C$  have been stored in a

107 suitable data structure beforehand — for instance one could use the optimal static dictionary  
 108 of [5], or simply cuckoo hashing [12].

---

**Algorithm 1** The simple quadratic algorithm for 3XOR.

---

```

1: function QUADRATICSETUP( $C$ )
2:   Initialize a static dictionary  $\mathcal{C}$  containing all the bit strings in  $C$ 
3:   return  $\mathcal{C}$ 

4: function QUADRATIC3XOR( $A, B, \mathcal{C}$ )
5:   for  $(x, y) \in A \times B$  do
6:     if  $x \oplus y \in \mathcal{C}$  then
7:       return  $(x, y, x \oplus y)$ 
8:   return  $\perp$ 

```

---

109 The initialization of the dictionary holding  $C$  is separated from the rest, because we will  
 110 subsequently invoke QUADRATIC3XOR many times with the same  $C$ . We assume (using [5]  
 111 for instance) that QUADRATICSETUP takes time  $\mathcal{O}(|C|)$ . Then QUADRATIC3XOR( $A, B, \mathcal{C}$ )  
 112 takes time  $\mathcal{O}(|A| \times |B|)$ . The quadratic algorithm works regardless of the sparsity of the  
 113 input, and as such it does not take advantage of it. It is the only solution, up to logarithmic  
 114 factors, when the input is dense. In our case, this is the baseline that must be improved  
 115 upon.

### 116 **3** Bounds on the Existence of 3XOR Triplets

117 Suppose that  $(G, +)$  is a group (in additive notation) and assume that three lists  $A, B$  and  
 118  $C$ , each of size  $N$ , are made of group elements sampled independently at random according  
 119 to some distribution  $\Psi$ . Let  $Y$  be the random variable that counts the number of triplets  
 120  $(x, y, z) \in A \times B \times C$  such that  $x + y + z = 0$  (taken over the random choice of  $A, B$  and  $C$ ).  
 121 The expected value of  $Y$  is easy to compute, and because the average value is bounded away  
 122 from zero, a concentration bound would yield the probability that the input lists contain at  
 123 least a single “good triplet” (that sums to zero).

124 The problem is that the  $N^3$  triplets in  $A \times B \times C$  are not independent and thus classical  
 125 techniques such as the Chernoff bound do not apply. This dependence has to be accounted  
 126 for. Let  $x, y, z, u, v$  denote five independent random variable distributed according to  $\Psi$ , and  
 127 set

$$\begin{aligned}
 128 \quad \rho &= \Pr(x + y + z = 0) \\
 129 \quad \sigma &= \Pr(x + y + z = 0 \mid u + v + z = 0) \\
 130 \quad \tau &= \Pr(x + y + z = 0 \mid u + y + z = 0) \\
 131
 \end{aligned}$$

132 The following result can be specialized for any group  $G$  and any distribution  $\Psi$  by computing  
 133  $\rho, \sigma$  and  $\tau$ .

134 **► Lemma 1.**  $EY = N^3\rho$  and  $1 - N^3\rho \leq \Pr(Y = 0) \leq \frac{1}{\rho} \left( \frac{3\sigma}{N} + \frac{3\tau}{N^2} + \frac{1}{N^3} \right)$ .

135 **Proof.** Let  $X(i, j, k)$  denote the binary random variable that takes the value 1 if and only  
 136 if  $A[i] + B[j] + C[k] = 0$  (and zero otherwise), so that  $Y = \sum X(i, j, k)$ . Unless mentioned  
 137 otherwise, in this section all sums are taken over  $0 \leq i, j, k < N$ ; we omit the indices to  
 138 alleviate notations.

139 The expected value of  $Y$  is easy to determine. Because the elements of the lists are  
 140 identically distributed,  $\Pr(A[i] + B[j] + C[k] = 0)$  is independent of  $i, j$  and  $k$  and its value  
 141 is  $\rho$ . We get:

$$142 \quad \mathbb{E}Y = \mathbb{E} \sum X(i, j, k) = \sum \mathbb{E}X(i, j, k) = \sum \Pr(A[i] + B[j] + C[k] = 0) = N^3\rho.$$

143 The Markov bound yields  $1 - \mathbb{E}Y \leq \Pr(Y = 0)$ ; the less immediate part consists in  
 144 estimating  $\Pr(Y > 0)$ . Because  $Y$  is the sum of binary random variables, we are entitled to  
 145 use Ross's conditional expectation inequality [13]:

$$146 \quad \Pr(Y > 0) \geq \sum \frac{\mathbb{E}(X(i, j, k))}{\mathbb{E}(Y \mid X(i, j, k) = 1)}.$$

147 As argued above, the value of the term under the sum is independent of  $i, j$  and  $k$ , so this  
 148 boils down to:  $\Pr(Y > 0) \geq \mathbb{E}Y / \mathbb{E}(Y \mid X(0, 0, 0) = 1)$ . It remains to compute the expected  
 149 number of solutions knowing that there is at least one. This yields:

$$150 \quad \mathbb{E}(Y \mid X(0, 0, 0) = 1) = \sum \Pr(A[i] + B[j] + C[k] = 0 \mid A[0] + B[0] + C[0] = 0)$$

152 We split this sum in 8 parts by considering separately the situation where  $i = 0$ ,  
 153  $j = 0$  and  $k = 0$  (resp  $\neq 0$  for each summation index). We introduce the shorthand  
 154  $p_{ijk} = \Pr(A[i] + B[j] + C[k] = 0 \mid A[0] + B[0] + C[0] = 0)$  and we assume that  $i, j, k > 0$ .  
 155 Then the two events are in fact independent and  $p_{ijk} = \rho$ . But when at least one index is  
 156 zero, this is no longer the case; the extreme situation is  $p_{000} = 1$ . By symmetry between  
 157 the three input lists, we find that  $p_{i00} = p_{i0k} = p_{0jk}$  (this is the value we denote by  $\sigma$ ) and  
 158  $p_{i00} = p_{0j0} = p_{00k}$  (this is the value we denote by  $\tau$ ). We can now write:

$$159 \quad \begin{aligned} \mathbb{E}(Y \mid X(0, 0, 0) = 1) &= (N-1)^3\rho + 3(N-1)^2\sigma + 3(N-1)\tau + 1 \\ &= N^3\rho + 3N^2\sigma + 3N\tau + 1 - \Delta \\ 161 \quad \text{with} \quad \Delta &= (3N^2 - 3N + 1)\rho + 3(2N-1)\sigma + 3\tau \end{aligned}$$

163 The “error term”  $\Delta$  is always positive for  $N \geq 1$ . Going back to the beginning, we have:

$$164 \quad \Pr(Y > 0) \geq \frac{N^3\rho}{N^3\rho + 3N^2\sigma + 3N\tau + 1 - \Delta} \geq \frac{1}{1 + 3N^{-1}\sigma/\rho + 3N^{-2}\tau/\rho + N^{-3}/\rho}$$

166 Using the convexity of  $1/(1+x)$ , we obtain  $\Pr(Y = 0) \leq 3N^{-1}\sigma/\rho + 3N^{-2}\tau/\rho + N^{-3}/\rho$ . ◀

167 **Low-Density 3XOR.** We now specialize the result of lemma 1 to the group  $(\{0, 1\}^n, \oplus)$   
 168 with the low-density distribution  $\mathcal{D}$  (each bit is drawn independently at random according to  
 169 the Bernoulli distribution  $Ber_p$  of parameter  $p < 1/2$ ).

170 ▶ **Theorem 2.** *Let  $Y$  denote the random variable counting the number of 3XOR triplets  
 171 in  $A \times B \times C$ . The probability that a random triplet from  $A \times B \times C$  XORs to zero is  
 172  $\rho = (1-p)^n(1-2p+4p^2)^n$ , and their expected number is  $\mathbb{E}Y = N^3\rho$ . Furthermore:*

$$173 \quad 1 - \mathbb{E}Y \leq \Pr(Y = 0) \leq \frac{3}{(\mathbb{E}Y)^{1/3}} + \frac{3}{(\mathbb{E}Y)^{2/3}} + \frac{1}{\mathbb{E}Y}. \quad (3)$$

174 **Proof.** If  $a, b$  and  $c$  are random bits drawn according to  $Ber_p$ , then the probability that they  
 175 XOR to zero is  $(1-p)(1-2p+4p^2)$ . It follows that if  $\mathbf{x}, \mathbf{y}$  and  $\mathbf{z}$  are drawn according to  $\mathcal{D}$ ,  
 176 then  $\rho = \Pr(\mathbf{x} \oplus \mathbf{y} \oplus \mathbf{z} = 0) = (1-p)^n(1-2p+4p^2)^n$ .

## 6 Algorithms for Sparse Random 3XOR: The Low-Density Case

Let us compute  $\sigma = \Pr(\mathbf{x} \oplus \mathbf{y} = \mathbf{z} \mid \mathbf{u} \oplus \mathbf{v} = \mathbf{z})$ . What happens essentially depends on the hamming weight of  $\mathbf{z}$ . Both  $\mathbf{x}, \mathbf{y}$  and  $\mathbf{u}, \mathbf{v}$  have to XOR to  $\mathbf{z}$ . Two random bits drawn according to  $Ber_p$  XOR to zero with probability  $p^2 + (1-p)^2$  and their XOR to one with probability  $2p(1-p)$ . This yields (using the binomial theorem):

$$\begin{aligned} \rho\sigma &= \Pr(\mathbf{x} \oplus \mathbf{y} = \mathbf{z} \wedge \mathbf{u} \oplus \mathbf{v} = \mathbf{z}) \\ &= \sum_{k=0}^n \Pr(wt(\mathbf{z}) = k) \Pr(\mathbf{x} \oplus \mathbf{y} = \mathbf{z} \wedge \mathbf{u} \oplus \mathbf{v} = \mathbf{z} \mid wt(\mathbf{z}) = k) \\ &= \sum_{k=0}^n \binom{n}{k} p^k (1-p)^{n-k} [2p(1-p)]^{2k} [p^2 + (1-p)^2]^{2(n-k)} \\ &= [(1-p)(1-4p+8p^2-4p^3)]^n \end{aligned}$$

We move on to  $\tau = \Pr(\mathbf{x} = \mathbf{u} \oplus \mathbf{v} \mid \mathbf{z} = \mathbf{u} \oplus \mathbf{v})$ . In this context, this mostly depends on the hamming weight of  $\mathbf{u} \oplus \mathbf{v}$ . This yields (again using the binomial theorem):

$$\begin{aligned} \rho\tau &= \Pr(\mathbf{x} = \mathbf{u} \oplus \mathbf{v} \wedge \mathbf{z} = \mathbf{u} \oplus \mathbf{v}) \\ &= \sum_{k=0}^n \Pr(wt(\mathbf{u} \oplus \mathbf{v}) = k) \Pr(\mathbf{x} = \mathbf{u} \oplus \mathbf{v} \wedge \mathbf{z} = \mathbf{u} \oplus \mathbf{v} \mid wt(\mathbf{u} \oplus \mathbf{v}) = k) \\ &= \sum_{k=0}^n \binom{n}{k} [2p(1-p)]^k [p^2 + (1-p)^2]^{n-k} [p^k(1-p)^{n-k}]^2 \\ &= [(1-p)(1-3p+4p^2)]^n \end{aligned}$$

We now move on to establish (3). Because  $N = (\mathbb{E}Y)^{1/3}/\rho$ , the bound of lemma 1 can be rewritten as:

$$\Pr(Y = 0) \leq \frac{3}{(\mathbb{E}Y)^{1/3}} \frac{\sigma}{\rho^{2/3}} + \frac{3}{(\mathbb{E}Y)^{2/3}} \frac{\tau}{\rho^{1/3}} + \frac{1}{\mathbb{E}Y}.$$

We now claim that  $1/2 \leq \sigma^{3/n}/\rho^{2/n} \leq 1$  and  $1/4 \leq \tau^{3/n}/\rho^{1/n} \leq 1$  when  $0 \leq p \leq 1/2$ ; this yields the desired result. This claim follows from the facts that both values are decreasing functions of  $p$ . This can be seen by computing their derivatives (all factors are easily seen to be positive when  $0 \leq p \leq 1/2$ ):

$$\begin{aligned} \frac{\partial}{\partial p} \frac{\sigma^{3/n}}{\rho^{2/n}} &= -6 \frac{(4p^3 - 8p^2 + 4p - 1)^2 (2p^2 - 6p + 3)(1 - 2p)^2 p}{(4p^2 - 2p + 1)^6 (1 - p)^3} \\ \frac{\partial}{\partial p} \frac{\tau^{3/n}}{\rho^{1/n}} &= -6 \frac{(4p^2 - 3p + 1)^2 (4p^2 - 6p + 3)(1 - 2p)p}{(4p^2 - 2p + 1)^5 (1 - p)^2} \end{aligned}$$

203

### 4 An Algorithm for Random Low-Density 3XOR

In this section, we present a simple algorithm that solves the low-density 3XOR problem with interesting theoretical guarantees when  $p$  is small. It is always subquadratic but its most striking feature is that it succeeds with overwhelming probability in linear time when  $p$  is small enough.

First of all, because the input is random, the problem may potentially be easy to solve with low error probability without even observing the input lists, depending on  $n$ , the size and

211 the distribution of the input. In light of theorem 2, we see that if  $N$  (the size of input lists) is  
 212 exponentially smaller than  $\rho^{-1/3}$ , then “**return**  $\perp$ ” is an algorithm that has an exponentially  
 213 small probability of yielding false negatives. Alternatively, if  $N$  exponentially larger than  
 214  $(1-p)^{-n}$ , then we expect the string  $000\dots 0$  to be present in  $A, B$  and  $C$  with overwhelming  
 215 probability ; it follows that “**return**  $(0, 0, 0)$ ” is a fast algorithm with exponentially low  
 216 false positive probability. To avoid these pitfalls, our main focus is on the hard case where  
 217  $N \approx \rho^{-1/3}$ , and where the expected number of solutions in the random input lists is close to  
 218 one.

219 Let  $a, b$  and  $c$  be random bits drawn according to  $Ber_p$  conditioned to  $a \oplus b \oplus c = 0$ . The  
 220 possible combinations are 000, 011, 101 and 110. We find that

$$221 \quad u := \Pr(abc = 110 \mid a \oplus b \oplus c = 0) = p^2 / (1 - 2p + 4p^2)$$

223 The same result is attained for 101 and 011. Two out of the three non-zero options result  
 224 in a 1 bit, and therefore  $\Pr(a = 1 \mid a \oplus b \oplus c = 0) = 2u$ . It follows that if the  $(\mathbf{x}, \mathbf{y}, \mathbf{z})$  is a  
 225 triplet drawn from  $\mathcal{D}$  such that  $\mathbf{x} \oplus \mathbf{y} \oplus \mathbf{z} = 0$ , then the expected “density” of  $\mathbf{x}, \mathbf{y}$  and  $\mathbf{z}$  is  
 226  $2u$ . This is always smaller than  $p$  when  $0 < p < 1/2$ . In other terms: *random triplets drawn*  
 227 *from  $\mathcal{D}$  have density  $p$ , but random 3XOR triplets drawn from  $\mathcal{D}$  have smaller density.*

228 This observation can be exploited in a simple way: we iteratively search for 3XOR  
 229 triplets of increasing maximum weight. This yields the INCREMENTAL3XOR function (shown  
 230 as algorithm 2). It takes an additional argument  $w_{\max}$  controlling the maximum allowed  
 231 weight.  $w_{\max} = 2nu$  yields an algorithm that reveals a 3XOR triplet present in the input  
 232 with probability greater than  $1/4$ , because the median weight of both  $\mathbf{x}$  and  $\mathbf{y}$  is  $2nu$  if  
 233  $\mathbf{x} \oplus \mathbf{y} \oplus \mathbf{z} = 0$ . Setting  $w_{\max} = 2nu(1 + \epsilon)$  is enough to miss an existing solution with  
 234 exponentially small probability. With  $w_{\max} = n$ , the algorithm deterministically finds a  
 235 solution if it is present in the input, but the complexity is much higher.

---

**Algorithm 2** An “incremental” algorithm for the sparse 3XOR problem.

---

```

1: function INCREMENTAL3XOR-ONE-SIDED( $A, B, C, w_{\max}$ )
2:   for  $0 \leq j \leq w_{\max}$  do
3:     for  $0 \leq i \leq j$  do
4:        $\zeta \leftarrow$  QUADRATIC3XOR( $A_i, B_j, C$ )
5:       if  $\zeta \neq \perp$  then return  $\zeta$ 
6:   return  $\perp$ 
7: function INCREMENTAL3XOR( $A, B, C, w_{\max}$ )
8:   for  $0 \leq i \leq w_{\max}$  do ▷ Bucket sort by Hamming weight
9:      $A_i \leftarrow \{\mathbf{x} \in A \mid \text{wt}(\mathbf{x}) = i\}$ 
10:     $B_i \leftarrow \{\mathbf{y} \in B \mid \text{wt}(\mathbf{y}) = i\}$ 
11:     $\zeta_1 \leftarrow$  INCREMENTAL3XOR-ONE-SIDED( $A, B, C, w_{\max}$ )
12:     $\zeta_2 \leftarrow$  INCREMENTAL3XOR-ONE-SIDED( $B, A, C, w_{\max}$ )
13:    if both  $\zeta_1 = \perp$  and  $\zeta_2 = \perp$  then return  $\perp$  ; otherwise return the solution found.
```

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236 It is fairly obvious that `Incremental3XOR-One-Sided` only finds a 3XOR triplet  $(\mathbf{x}, \mathbf{y}, \mathbf{z})$   
 237 in the input lists if  $\text{wt}(\mathbf{x}) \leq \text{wt}(\mathbf{y}) \leq w_{\max}$ . By calling it twice, we lift the restriction that  $\mathbf{x}$   
 238 must be sparser than  $\mathbf{y}$ .

## 239 4.1 Overwhelming Success Probability

240 Choosing a small value of  $w_{\max}$  leads to smaller “filtered” instances and thus to a smaller  
 241 running time for the actual computation using the quadratic algorithm. However, if  $w_{\max}$  is



242 too small, then a potential solution present in the input might be discarded.

243 A sensible choice consists in picking  $w_{\max}$  in the range  $]2nu, np[$  — above the expected  
244 density of random 3XOR triplets so that we do not discard them, and below the density of  
245 the input lists in order to actually discard input vectors that are too heavy. In this case the  
246 algorithm succeeds with overwhelming probability as long as the original input contains at  
247 least one solution. The main contribution of this paper is the following

248 ► **Theorem 3.** *Let  $e := 2 + 6D(2p^2/(1 - 2p + 4p^2), p) / \ln(1 - p)(1 - 2p + 4p^2)$ . For all  
249  $d > e$  there is an algorithm for the random low-density 3XOR problem that runs in time  
250  $\mathcal{O}(N + N^d)$ , where  $N$  denotes the size of the input list and fails with negligible probability  
251 (in  $n$ ).*

252 We first discuss some aspects of the result. The graph of the best possible exponent  
253 ( $e$ ) is shown in Fig. 1. The exponent  $e$  increases from zero to 2 as  $p$  goes from zero to  
254  $1/2$ . Using the bisection algorithm, we find that  $e \leq 1$  when  $p \leq 0.0957$ . It follows that  
255 INCREMENTAL3XOR is *linear* in the size of the input for small  $p$ .

256 It seems that  $e \leq 2p(1 - 2 \ln p)$ ; establishing this is a fascinating endeavour that we must  
257 regrettably leave for future work. It is worth noting that the not-so-friendly expression of  
258  $e$  comes from the use of the tight binomial bound (2). It would be greatly simplified had  
259 we instead used the simpler Chernoff bound (1). However, doing so makes the result much  
260 worse for small  $p$ : it results in  $\lim e = 1$  when  $p$  goes to zero (instead of  $\lim e = 0$ ).

261 ► **Lemma 4.** *With  $w_{\max} = 2nu(1 + \epsilon)$ , if the input contains a 3XOR triplet, then INCRE-  
262 MENTAL3XOR returns  $\perp$  with probability less than  $2 \exp(-nu\epsilon^2)$ .*

263 **Proof.** Assume that the input lists contain a 3XOR triplet  $(\mathbf{x}^*, \mathbf{y}^*, \mathbf{z}^*)$ . It will be discarded  
264 if and only if the weight of either  $\mathbf{x}^*, \mathbf{y}^*$  is greater than  $w_{\max}$ . We know that the expected  
265 weight of  $\mathbf{x}^*$  and  $\mathbf{y}^*$  (and  $\mathbf{z}^*$  as well but this is irrelevant) is  $2un$ , therefore the Chernoff  
266 bound (1) shows that either has weight greater than  $2un(1 + \epsilon)$  with probability less than  
267  $\exp(-nu\epsilon^2)$ . A union bound (for  $\mathbf{x}^*$  and  $\mathbf{y}^*$ ) then ensures that the solution is discarded with  
268 probability less than  $2 \exp(-nu\epsilon^2)$ . ◀

269 ► **Lemma 5.** *Let  $T$  denote the running time of INCREMENTAL3XOR with  $w_{\max} = 2nu(1 + \epsilon)$ .  
270 Then  $ET \leq N + N^2 \exp(-2nD(2u(1 + \epsilon), p))$ .*

271 **Proof.** In the sequel, all the stated complexities must be understood “up to a constant  
272 factor”. Bucket-sorting the input lists by Hamming weight takes time  $N$ . Up to a constant  
273 factor, it is sufficient to upper-bound the running time of INCREMENTAL3XOR-ONE-SIDED.  
274 The running time of QUADRATIC3XOR on input  $(A_i, B_j, \mathcal{C})$  is upper-bounded by  $|A_i| \cdot |B_j|$ .  
275 Therefore, the total running time of INCREMENTAL3XOR is then:

$$276 \quad T = N + \sum_{j=0}^{w_{\max}} \sum_{i=0}^j |A_i| \cdot |B_j| \leq N + \left( \sum_{j=0}^{w_{\max}} |B_j| \right) \left( \sum_{i=0}^{w_{\max}} |A_i| \right)$$

277 Let  $\mathfrak{A} = \bigcup_{i=0}^{w_{\max}} A_i$  and  $\mathfrak{B} = \bigcup_{j=0}^{w_{\max}} B_j$  denote the lists of all input vectors of weight less  
278 than of equal to  $w_{\max}$ . The above inequality shows that the running-time of the algorithm is  
279 less than that of running QUADRATIC3XOR directly on  $\mathfrak{A}$  and  $\mathfrak{B}$ .

280 Let  $X \sim \mathcal{B}(n, p)$  be a (binomial) random variable modeling the weight of an input vector  
281 of density  $p$ . Such a vector belongs to  $\mathfrak{A}$  or  $\mathfrak{B}$  if its is less than or equal to  $w_{\max}$ , and  
282 this happens with probability  $s := \Pr(X \leq w_{\max})$ . Because  $w_{\max} < np$ , the binomial tail  
283 bound (2) yields the tight upper-bound  $s \leq e^{-nD(2u(1+\epsilon), p)}$ .

284 The sizes of  $\mathfrak{A}$  and  $\mathfrak{B}$  are stochastically independent random variables following a  
 285 binomial distribution of parameters  $N, s$  and their expected size is  $Ns$ . The expected  
 286 running time of the quadratic algorithm on  $\mathfrak{A}$  and  $\mathfrak{B}$  (which is an upper-bound on that of  
 287 INCREMENTAL3XOR) is therefore  $\mathbb{E}|\mathfrak{A}| \times \mathbb{E}|\mathfrak{B}| = \mathbb{E}|\mathfrak{A}| \times \mathbb{E}|\mathfrak{B}| = N^2 s^2$ . Combining this  
 288 with the upper-bound on  $s$  gives the announced result. ◀

289 We are now ready to prove theorem 3.

290 **proof of theorem 3.** Let  $d$  be a complexity exponent greater than the bound  $e$  given in  
 291 theorem 3. Let  $\epsilon > 0$  be such that

$$292 \quad d = 2 + 6 \frac{D(2u(1 + \epsilon), p)}{\ln(1 - p)(1 - 2p + 4p^2) - 3\epsilon \ln 2}.$$

293 (such an  $\epsilon$  always exist). Note that setting  $\epsilon = 0$  in this expression yields the lower-bound  
 294 exponent  $e$  of the theorem.

295 Let  $N_0 := \rho^{-1/3}$  (input lists of this size contain a single 3XOR triplet in average).  
 296 Suppose that  $N \leq N_0 2^{\epsilon n}$ , where  $N$  denotes the size of the input lists ; in this case run  
 297 INCREMENTAL3XOR with  $w_{\max} = 2un(1 + \epsilon)$ . Lemma 4 guarantees the exponentially small  
 298 failure probability while lemma 5 tells us that the expected running time  $T$  is less than  
 299  $N + N^2 \exp -nD(2u(1 + \epsilon), p)$ .

300 Set  $d' := \log_N(ET - N)$ , so that the algorithm runs in time  $\mathcal{O}(N + N^{d'})$ . A quick  
 301 calculation shows that  $d' = d$ , and the theorem is proved in this case.

302 If  $N > N_0 2^{n\epsilon}$ , then do the following : slice the input lists in chunks of size  $4N_0$  and run  
 303 INCREMENTAL3XOR with  $w_{\max} = 2un(1 + \epsilon)$  on each successive chunk until a solution is  
 304 found. Theorem 2 tells us that each chunk contain 64 3XOR triplets on average, and contain  
 305 at least one 3XOR triplet with probability greater than  $3/64$ . INCREMENTAL3XOR will  
 306 reveal an existing 3XOR triplet present in a chunk with probability greater than  $1/4$  (this is  
 307 true regardless of the value of  $\epsilon > 0$ ). Therefore, a 3XOR triplet will be found in each chunk  
 308 with probability greater than  $3/256$  ; because the the chunks are completely independent  
 309 parts of the random input, the events “INCREMENTAL3XOR finds a 3XOR triplet in chunk  $i$ ”  
 310 are independent. Therefore, the whole process fails to reveal a 3XOR triplet with probability  
 311 less than  $(1 - \frac{3}{256})^{n\epsilon}$ . The running time is  $4N \cdot N_0^{d-1}$ , which is less than  $N^d$ . ◀

## 312 4.2 Deterministic Success

313 We now study the expected behavior of INCREMENTAL3XOR algorithm with  $w_{\max} = n$ .  
 314 When  $w \geq np$ , then discarding vectors of weight greater than  $w$  does not reduce significantly  
 315 the size of the lists. Thus, all iterations with “threshold weight”  $w \geq np$  cost essentially  
 316  $\Omega(N^2)$ . It follows that if there is no 3XOR triplet in input lists (for instance, if they are  
 317 too short), then the algorithm is essentially quadratic. On the other hand, if the input  
 318 lists are so long that they contain many 3XOR triplets, then the probability that they  
 319 contain a low-weight triplet (and thus that the algorithm stops early) increases. We therefore  
 320 focus on the hardest relevant case, namely input lists of size  $N = P(n)\rho^{-n/3}$ , where  $P$   
 321 is a non-constant positive polynomial. The input lists contain on average  $P(n)^3$  3XOR  
 322 triplets and thanks to theorem 2, they contain a 3XOR triplet with probability greater than  
 323  $1 - 1/P(n)(1 + o(1))$ . The crux of the analysis is that the  $w$ -th iteration is done if and only  
 324 if the solution has Hamming weight greater than or equal to  $w$ . The expected weight of the  
 325 solution is  $2un < 2np$ , and therefore the probability that the most expensive iterations take  
 326 place is exponentially small.

327 ► **Theorem 6.** Consider input lists of size  $N = P(n)\rho^{-n/3}$  and assume that they contain  
 328 a 3XOR triplet. Then INCREMENTAL3XOR with  $w_{\max} = n$  returns a valid solution and  
 329 terminates in time  $\mathcal{O}(N + N^e)$ , where

$$330 \quad e = 2 + 3 \frac{2D\left(\frac{1}{1 + \sqrt[3]{\left(\frac{1}{p}-1\right)^2\left(\frac{1}{2u}-1\right)}}, p\right) + D\left(\frac{1}{1 + \sqrt[3]{\left(\frac{1}{p}-1\right)^2\left(\frac{1}{2u}-1\right)}}, 2u\right)}{\ln(1-p)(1-2p+4p^2)}.$$

331 The graph of  $e$  is also shown in Fig. 1. We find again that  $e \leq 1$  when  $p \leq 0.02155$ . Thus,  
 332 this unfailling algorithm is also linear for small  $p$ . It is worthwhile noting that the complexity  
 333 is significantly higher than when  $w_{\max} = 2un$ . The proof is potentially less tight, but it  
 334 seems plausible that there is a “heavy tail” effect. Theorem 6 follows from the following

335 ► **Lemma 7.** Let  $T$  denote the running time of INCREMENTAL3XOR with  $w_{\max} = n$ . Then

$$336 \quad \mathbb{E}T \leq N + 4nN^2 e^{-n[2D(x_0,p)+D(x_0,2u)]} \quad \text{where} \quad \frac{1}{x_0} - 1 = \sqrt[3]{\left(\frac{1}{p} - 1\right)^2 \left(\frac{1}{2u} - 1\right)}.$$

337 **Proof.** Let  $T_j$  denote the running time of the  $j$ -th iteration of the outer **for** loop and  $S$  the  
 338 number of iterations done when the algorithm stops (i.e. the value of  $j$  in the algorithm). As in  
 339 the proof of lemma 5, let  $\mathfrak{A}_k = \bigcup_{i=0}^k A_i$  and  $\mathfrak{B}_k = \bigcup_{j=0}^k B_j$  and we find that  $T_j \leq |\mathfrak{A}_j| \times |\mathfrak{B}_j|$ .

340 The total running time is then given by  $T = \sum_{j=0}^n [S \geq j] T_j$ . The two random variables  
 341  $[S \geq j]$  and  $T_j$  are not independent, however we claim that  $\mathbb{E}([S \geq j] T_j) \leq (\mathbb{E}[S \geq j]) T_j$   
 342 — i.e. they are negatively correlated. The point is that is that the fact that input lists  
 343 contain a “large weight” triplet  $t^*$  can only reduce the expected size of low-weight lists by at  
 344 most one, and therefore reduce the expected time needed to process them. It follows that  
 345  $\mathbb{E}T \leq \sum_{j=0}^n \Pr(S \geq j) \cdot (\mathbb{E}T_j)$ .

346 Next, let us consider two random variables following binomial distributions  $X_{2u} \sim \mathcal{B}(n, 2u)$   
 347 and  $X_p \sim \mathcal{B}(n, p)$ . From the proof of lemma 5, we know that  $\mathbb{E}T_j \leq N^2 s^2$ , where  $s =$   
 348  $\Pr(X_p \leq j)$ . In addition, following the same reasoning as in the proof of lemma 4, we have  
 349  $\Pr(S \geq j) \leq 2\Pr(X_{2u} \geq j)$ . This gives:

$$350 \quad \mathbb{E}T \leq 2N^2 \sum_{j=0}^n \Pr(X_p \leq j)^2 \Pr(X_{2u} \geq j)$$

352 Set  $\mu_j := \Pr(X_p \leq j)^2 \Pr(X_{2u} \geq j)$ . Our goal is to upper-bound the sum of the  $\mu_j$ 's. To  
 353 this end, we split the sum in three parts:

$$354 \quad \sum_{j=0}^n \mu_j \leq \sum_{j=0}^{2nu} \mu_j + \sum_{j=2nu}^{np} \mu_j + \sum_{j=np}^n \mu_j$$

355 First, we focus on the case where  $0 \leq j \leq 2nu$ . In this range,  $\Pr(X_p \leq j)$  is increasing  
 356 with  $j$  and  $\Pr(X_{2u} \geq j)$  is greater than  $\frac{1}{2}$ , therefore we find that  $\mu_j \leq 2\mu_{2nu}$  for  $0 \leq j \leq 2nu$ .  
 357 A symmetric argument shows that  $\mu_j \leq 2\mu_{np}$  for all  $np \leq j \leq n$ .

358 Let  $M$  denote the largest  $\mu_j$  for  $2nu \leq j \leq np$ . It follows from the above discussion  
 359 that this is the largest of all the  $\mu_j$ , so that their is less than  $2nM$ . We use the binomial  
 360 tail bound (2) to get an upper-bound on  $M$ . Set  $f(x) = 2D(x, p) + D(x, 2u)$ , so that  
 361  $\mu_j \leq e^{-nf(\frac{j}{n})}$  when  $2nu \leq j \leq np$ . We next seek the maximum of  $f$ , and for this we compute  
 362 its derivative:

$$363 \quad f'(x) = 2 \log \frac{x}{p} - 2 \log \frac{1-x}{1-p} + \log \frac{x}{2u} - \log \frac{1-x}{1-2u}$$

364 Solving  $f'(x_0) = 0$  reveals only one possible real solution, that satisfies:

$$365 \quad \frac{1}{x_0} - 1 = \sqrt[3]{\left(\frac{1}{p} - 1\right)^2 \left(\frac{1}{2u} - 1\right)}$$

366 It appears that  $1/x_0 - 1$  is the geometric mean of  $1/p - 1$ ,  $1/p - 1$  and  $1/(2u) - 1$ . This  
 367 implies in particular  $2u \leq x_0 \leq p$  as expected. ◀

## 368 **5 A “Sensible” Application**

369 In order to put this algorithm to the test, we forged an artificial instance of the problem.  
 370 We downloaded an XML dump of the DBLP database, and extracted all articles published  
 371 in a few selected cryptography conferences (CRYPTO, EUROCRYPT, ASIACRYPT, FSE,  
 372 PKC, CHES, SAC) as well as two journals (TOSC, TCHES). This made more than 7700  
 373 articles. For each article, we wrote down one line of text with the authors and title.

374 We considered the function (where  $\&$  denotes the bitwise AND):

$$375 \quad F(x_1, x_2, x_3, x_4) = \text{SHA-512}(x_1) \& \text{SHA-512}(x_2) \& \text{SHA-512}(x_3) \& \text{SHA-512}(x_4).$$

376 This yields 512-bit hashes with expected density  $1/16$ . SHA-512 is a secure cryptographic  
 377 hash function, so we assumed that there was no way to find inputs leading to correlated  
 378 outputs besides brute force. We looked for three quadruplets of articles such that

$$379 \quad F(x_1, x_2, x_3, x_4) \oplus F(y_1, y_2, y_3, y_4) \oplus F(z_1, z_2, z_3, z_4) = 0$$

380 With the additional constraint that all articles are distinct. There are 5775 ways to dispatch  
 381 12 items into 4 indistinguishable urns, so that with our 7700 articles, we can assemble  $2^{138.5}$   
 382 bundles of 12 publications having a chance to satisfy the above equation (of course the inputs  
 383 are correlated, and this deviates from the original problem formulation, but this is not a  
 384 serious issue). Alternatively, we may form  $2^{47}$  quadruplets of publication. With  $p = 1/16$   
 385 and  $n = 512$ , we could then expect about 40 solutions from our data set. This made us  
 386 confident that there would be at least one, but finding it does not seem so easy at first  
 387 glance.

388 Evaluating  $F$  on all the available quadruplets is not a problem (it takes 240 CPU-hours).  
 389 Trouble starts when we considered writing the list of  $2^{47}$  hashes to persistent storage: this  
 390 would require more than 9 petabytes — this is a lot, but some computing centers have that  
 391 much. However, finding the “golden” triplet of quadruplets using the quadratic algorithm  
 392 would then require  $2^{94}$  probes into a large hash table, and given mankind’s present computing  
 393 power, this does not seem feasible before the sun turns into a red giant.

394 Exploiting the sparsity of the input turns the problem into a walk in the park. The  
 395 expected weight of 3XOR triplets of density  $1/16$  is  $\approx 2.25$ . We evaluated  $F$  on all quadruplets,  
 396 but kept only the hashes with hamming weight less than or equal to 3. We thus kept 5091  
 397 candidate quadruplets, for a total storage size of 358KB. We then searched for solutions in  
 398 this restricted data set using the quadratic algorithm. This required 25 millions probes in a  
 399 hash table and was very fast.

400 We found six solutions, one of which is shown as algorithm 3. Amazingly, it contains the  
 401 name of one of the authors of the present article.

## 402 **6 Conclusion**

403 We presented a simple algorithm for the random sparse “low-density” 3XOR problem, which is  
 404 always subquadratic and can even be linear if the density is low enough. It works by reducing

---

**Algorithm 3** Demonstrating a sensible application of sparse 3XOR algorithms.
 

---

```

from hashlib import sha512

# FSE 2011
a = "Simon Knellwolf and Willi Meier: Cryptanalysis of the Knapsack Generator. (2011)"

# ASIACRYPT 2017
b = "Ran Canetti, Oxana Poburinnaya and Mariana Raykova: Optimal-Rate Non-Committing Encryption. (2017)"

# CRYPTO 2019
c = "Muhammed F. Esgin, Ron Steinfeld, Joseph K. Liu and Dongxi Liu: Lattice-Based Zero-Knowledge \
Proofs: New Techniques for Shorter and Faster Constructions and Applications. (2019)"

# FSE 2009
d = "Martijn Stam: Blockcipher-Based Hashing Revisited. (2009)"

# EUROCRYPT 1990
e = "Cees J. A. Jansen: On the Construction of Run Permuted Sequences. (1990)"

# EUROCRYPT 2013
f = 'Charles Bouillaguet, Pierre-Alain Fouque and Amandine Véber: Graph-Theoretic Algorithms for the \
"Isomorphism of Polynomials" Problem. (2013)'

# CRYPTO 2017
g = "Prabhanjan Ananth, Arka Rai Choudhuri and Abhishek Jain: A New Approach to Round-Optimal Secure \
Multiparty Computation. (2017)"

# EUROCRYPT 2001
h = "William Aiello, Yuval Ishai and Omer Reingold: Priced Oblivious Transfer: How to Sell Digital \
Goods. (2001)"

# CRYPTO 2019
i = "Navid Alamati, Hart Montgomery and Sikhar Patranabis: Symmetric Primitives with Structured \
Secrets. (2019)"

# CRYPTO 2019
j = "Shweta Agrawal, Monosij Maitra and Shota Yamada: Attribute Based Encryption (and more) for \
Nondeterministic Finite Automata from LWE. (2019)"

# EUROCRYPT 1986
k = "Christoph G. Günther: On Some Properties of the Sum of Two Pseudorandom Sequences. (1986)"

# CRYPTO 2009
l = "Susan Hohenberger and Brent Waters: Short and Stateless Signatures from the RSA Assumption. (2009)"

def H(s : str) -> int:
    """Returns the hash (SHA-512) of the string s as a 512-bit integer."""
    return int.from_bytes(sha512(s.encode('utf8')).digest(), byteorder='big')

assert (H(a) & H(b) & H(c) & H(d)) ^ (H(e) & H(f) & H(g) & H(h)) ^ (H(i) & H(j) & H(k) & H(l)) == 0

```

---

405 an instance of the “low-density” problem to several smaller instances of a “low-weight”  
 406 problem, whose sparsity is not exploited at this stage. This begs for finding new algorithms  
 407 for the “low-weight” 3XOR problem, which requires completely different techniques. This  
 408 other sparse problem is not only interesting in itself, but better algorithms would yield  
 409 even faster algorithms for the “low-density” case. This is the subject of ongoing and future  
 410 research.

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## References

- 415 1 R. Arratia and L. Gordon. Tutorial on large deviations for the binomial distribu-  
416 tion. *Bulletin of Mathematical Biology*, 51(1):125 – 131, 1989. URL: <http://www.sciencedirect.com/science/article/pii/S0092824089800527>, doi:[https://doi.org/10.1016/S0092-8240\(89\)80052-7](https://doi.org/10.1016/S0092-8240(89)80052-7).  
417  
418
- 419 2 Leif Both and Alexander May. The approximate k-list problem. *IACR Transactions on*  
420 *Symmetric Cryptology*, 2017(1):380–397, 2017.  
421
- 422 3 Charles Bouillaguet, Claire Delaplace, and Pierre-Alain Fouque. Revisiting and improving  
423 algorithms for the 3xor problem. *IACR Transactions on Symmetric Cryptology*, 2018(1):254–  
424 276, 2018.
- 425 4 Martin Dietzfelbinger, Philipp Schlag, and Stefan Walzer. A subquadratic algorithm for 3xor.  
426 In Igor Potapov, Paul G. Spirakis, and James Worrell, editors, *43rd International Symposium*  
427 *on Mathematical Foundations of Computer Science, MFCS 2018, August 27-31, 2018, Liverpool,*  
428 *UK*, volume 117 of *LIPICs*, pages 59:1–59:15. Schloss Dagstuhl - Leibniz-Zentrum für Informatik,  
429 2018. doi:10.4230/LIPICs.MFCS.2018.59.
- 430 5 Michael L. Fredman, János Komlós, and Endre Szemerédi. Storing a sparse table with  $o(1)$   
431 worst case access time. *J. ACM*, 31(3):538–544, June 1984. URL: <http://doi.acm.org/10.1145/828.1884>, doi:10.1145/828.1884.  
432
- 433 6 Anka Gajentaan and Mark Overmars. On a class of  $\mathcal{O}(n^2)$  problems in computational geometry.  
434 *Computational geometry*, 5(3):165–185, 1995.
- 435 7 Zahra Jafargholi and Emanuele Viola. 3sum, 3xor, triangles. *Algorithmica*, 74(1):326–343,  
436 2016. doi:10.1007/s00453-014-9946-9.
- 437 8 Antoine Joux. *Algorithmic cryptanalysis*. CRC Press, 2009.
- 438 9 Gaëtan Leurent and Ferdinand Sibleyras. Low-memory attacks against two-round even-mansour  
439 using the 3XOR problem. In Alexandra Boldyreva and Daniele Micciancio, editors, *Advances*  
440 *in Cryptology - CRYPTO 2019 - 39th Annual International Cryptology Conference, Santa*  
441 *Barbara, CA, USA, August 18-22, 2019, Proceedings, Part II*, volume 11693 of *Lecture Notes*  
442 *in Computer Science*, pages 210–235. Springer, 2019. doi:10.1007/978-3-030-26951-7\\_8.
- 443 10 Mridul Nandi. Revisiting Security Claims of XLS and COPA. *IACR Cryptology ePrint Archive*,  
444 2015:444, 2015.
- 445 11 Ivica Nikolić and Yu Sasaki. Refinements of the k-tree Algorithm for the Generalized Birthday  
446 Problem. In *ASIACRYPT*, pages 683–703. Springer, 2015.
- 447 12 Rasmus Pagh and Flemming Friche Rodler. Cuckoo hashing. In *European Symposium on*  
448 *Algorithms*, pages 121–133. Springer, 2001.
- 449 13 S.M. Ross. *Probability Models for Computer Science*. Elsevier Science, 2002. URL: <https://books.google.fr/books?id=fG3iEZ8f3CcC>.  
450