A New Algorithm for Finding Closest Pair of Vectors

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Abstract

Given $n$ vectors $x_0, x_1, \ldots, x_{n-1}$ in $\{0, 1\}^m$, how to find two vectors whose pairwise Hamming distance is minimum? This problem is known as the Closest Pair Problem. If these vectors are generated uniformly at random except two of them are correlated with Pearson-correlation coefficient $\rho$, then the problem is called the Light Bulb Problem. In this work, we propose a novel coding-based scheme for the Closest Pair Problem. We design both randomized and deterministic algorithms, which achieve the best-known running time when the minimum distance is very small compared to the length of input vectors. When applied to the Light Bulb Problem, our algorithms yields state-of-the-art deterministic running time when the Pearson-correlation coefficient $\rho$ is very large.

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1 Introduction

We consider the following classic Closest Pair Problem: given $n$ vectors $x_0, x_1, \ldots, x_{n-1}$ in $\{0, 1\}^m$, how to find the two vectors with the minimum pairwise distance? Here the distance is the usual Hamming distance: $\text{dist}(x_i, x_j) = |\{k \in [m] : (x_i)_k \neq (x_j)_k\}|$, where $(x_i)_k$ denotes the $k$th component of vector $x_i$. Without loss of generality, we assume that $d_{\text{min}} = \text{dist}(x_0, x_1)$ is the unique minimum distance and all other pairwise distances are greater than $d_{\text{min}}$.

The Closest Pair Problem is one of the most fundamental and well-studied problems in many science disciplines, having a wide spectrum of applications in computational finance, DNA detection, weather prediction, etc. For instance, the Closest Pair Problem recently finds the following interesting application in bioinformatics. Scientists wish to find connections between Single Nucleotide Polymorphisms (SNPs) and phenotypic traits. SNPs are one of the most common types of genetic differences among people, with each SNP representing a variation in a single DNA block called nucleotide [22]. Screening for most correlated pairs of SNPs has been applied to study such connections [10, 14, 17, 35]. As the number of SNPs in humans is estimated to be around 10 to 11 million, for problem size $n$ of this size, any improvement in running time for solving the Closest Pair Problem would have huge impacts on genetics and computational biology [35].

In theoretical computer science, the Closest Pair Problem has a long history in computational geometry, see e.g. [39] for a survey of many classic algorithms for the problem. The naive algorithm for the Closest Pair Problem takes $O(n^2)$ time. When the dimension $m$ is a constant, either in the Euclidean space or $\ell_p$ space, the classic divide-and-conquer based algorithm runs in $O(n \log n)$ time [13]. Rabin [38] combined the floor function with randomization to devise a linear time algorithm. In 1995, Khuller and Matias [30] simplified Rabin’s algorithm to achieve the same running time $O(n)$ and space complexity $O(n)$. Golin et al. [25] used dynamic perfect hashing to implement a dictionary and obtained the same linear time and space bounds.

When the dimension $m$ is not a constant, the first subquadratic time algorithm for the Closest Pair Problem is due to Alman and Williams [4] for $m$ as large as $\log^{2-o(1)} n$. The algorithm is built on a recently developed framework called polynomial method [46, 47, 4]. In particular, Alman and Williams firstly constructed a probabilistic polynomial of degree $O(\sqrt{n \log 1/\epsilon})$ which can compute the MAJORITY function on $n$ variables with error at most $\epsilon$, then applied the polynomial method to design an algorithm which runs in $n^{2 - 1/O(s(n) \log^2 s(n))}$ time where $m = s(n) \log n$, and computed the minimum Hamming distance among all red-blue vector pairs through polynomial evaluations. In a more recent work, Alman et al. [3] unified Valiant’s fast matrix multiplication approach [42] with that of Alman and Williams’ [4]. They constructed probabilistic polynomial threshold functions (PTFs) to obtain a simpler algorithm which improved to randomized time $n^{2 - 1/O(\sqrt{s(n) \log^3 s(n)})}$ or deterministic time $n^{2 - 1/O(s(n) \log^2 s(n))}$.

The Light Bulb Problem. A special case of the Closest Pair Problem, the so-called Light Bulb Problem, was first posed by Valiant in 1988 [43]. In this problem, we are given a set of $n$ vectors in $\{0, 1\}^m$ chosen uniformly at random from the Boolean hypercube, except that two of them are non-trivially correlated (specifically, have Pearson-correlation coefficient $\rho$, which is equivalent to that the expected Hamming distance between the correlated pair is $\frac{1-\rho}{2} m$), the problem then is to find the correlated pair.

Patuiri et al. [37] gave the first non-trivial algorithm, which runs in $O(n^{2 - \log(1+\rho)})$. The well-known locality sensitive hashing scheme of Indyk and Motwani [27] performs slightly worse than Patuiri et al.’s hash-based algorithm. More recently, Dubiner [19] proposed a Bucketing Coding algorithm which runs in time $O(n^{\frac{2}{3}+\rho})$. As $\rho$ gets small, all these three algorithms have running time $O(n^{2-O(\rho)})$. Comparing the constants in these three algorithms, Dubiner achieves the best constants, which is $O(n^{2-2\rho})$, in the limit of $\rho \to 0$. Asymptotically the same bound was also achieved by May and Ozerov [32], in which the authors
used algorithms that find Hamming closest pairs to improve the running time of decoding random binary linear codes.

In a recent breakthrough result, Valiant [42] presented a fast matrix multiplication based algorithm which finds the “planted” closest pair in time $O\left(n^{\frac{1}{\omega^2}} \cdot \log\left(\frac{m}{\epsilon}\right)\right)$ with high probability for any constant $\epsilon, \rho > 0$ and $m > n^{\frac{1}{\omega^2}}$, where $\omega < 2.373$ is the exponent of fast matrix multiplications. The most striking feature of Valiant’s algorithm is that $\rho$ does not appear in the exponent of $n$ in the running time of the algorithm. Karppa et al. [29] further improved Valiant’s algorithm to $n^{1.582}$. Both Valiant and Karppa et al. achieved runtime of $n^{2 - O(1)}$ for the Light Bulb Problem, which improved upon previous algorithms that rely on the Locality Sensitive Hashing (LSH) schemes. The LSH methods based algorithm only achieved runtime of $n^{2 - O(\epsilon)}$ for the Light Bulb Problem.

We remark that all the above-mentioned algorithms (except May and Ozerov’s work) that achieve state-of-the-art running time are based on either involved probabilistic polynomial constructions or impractical $O(n^\omega)$ fast matrix multiplications or both. Moreover, these algorithms are all randomized in nature while our approach yields simple and practical randomized as well as deterministic algorithms.

### 1.1 Our approach

We propose a simple, error-correcting code based scheme for the Closest Pair Problem. Apart from achieving the best running time for certain range of parameters, we believe that our new approach has the merit of being simple, and hence more likely being practical as well. In particular, neither complicated data structure nor fast matrix multiplication is employed in our algorithms.

The basic idea of our algorithms is very simple. Suppose for concreteness that $x_0$ and $x_1$ is the unique pair of vectors that achieve the minimum distance. Our scheme is inspired by the extreme case when $x_0$ and $x_1$ are identical vectors. In this case, a simple sort and check approach solves the problem in $O(mn \log n)$ time: sort all $n$ vectors and then compute only the $n - 1$ pairwise distances (instead of all $\binom{n}{2}$ distances) of

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1. **Algorithm 1: General Idea of Main Algorithm**

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input: A set of $n$ vectors $x_0, \ldots, x_{n-1}$ in $\{0, 1\}^m$ and $d_{\text{min}}$

output: Two vectors and their distance

1. generate a binary code $C \subseteq \{0, 1\}^m$
2. pick a random $y \in \{0, 1\}^m$
3. for $j \leftarrow 0$ to $n - 1$ do
4.  | decode $y + x_j$ in $C$, and denote the resulting vector by $\tilde{x}_j$
5. end
6. sort $\tilde{x}_0, \ldots, \tilde{x}_{n-1}$
7. for each of the $n - 1$ pairs of adjacent vectors in the sorted list do
8.  | compute the distance between the two original vectors.
9. end
10. output the pair of vectors with the minimum distance and their distance
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1Subquartic fast matrix multiplication algorithms are practical only for Strassen-based ones [12, 26]. Even though the recent breakthrough results [40, 49, 23] achieve asymptotically faster than Strassen’s algorithm [41], however, these algorithms are all based on Coppersmith-Winograd’s algorithm [16], and to the best of our knowledge, there are no practical implementations of these trilinear based algorithms.
adjacent vectors in the sorted list. Since the two closest vectors are identical, they must be adjacent in the sorted list and thus the algorithm would compute their distance and find them. This motivates us to view the input vectors as received messages that were encoded by an error correction code and have been transmitted through a noisy channel. As a result, the originally identical vectors are no longer the same, nevertheless are still very close. Directly applying the sort and check approach would fail but a natural remedy is to decode these received messages into codewords first. Indeed, if the distance between $x_0$ and $x_1$ is small and we are lucky to have a codeword $c$ that is very close to both of them, then a unique decoding algorithm would decode both of these two vectors into $c$. Now if we “sort” the decoded vectors and then “check” the corresponding original vectors of each adjacent pair of vectors, the algorithm would successfully find the closest pair. How to turn this “good luck” into a working algorithm? Simply try different shift vectors $y$ and view $y + x_i$ as the input vectors, since the Hamming distances are invariant under any shift. The basic idea of our approach is summarized in Algorithm 1.

Figure 1 illustrates the effects “bad” shift vectors and “good” shift vectors on the decoding part of our algorithm.

Figure 2 illustrates what happens if we sort the vectors directly and why sorting decoded vectors works.

Making the idea of decoding work for larger minimum pairwise distance involves balancing the parameters of the error-correcting code so that it is efficiently decodable as well as having appropriate decoding radius. The decoding radius $r$ should have the following properties. On one hand, $r$ should be small to ensure that there is a codeword $c$ such that only $x_0$ and $x_1$ will be decoded into $c$ (therefore $x_0$ and $x_1$ will be adjacent in the sorted array and hence will be compared with each other). On the other hand, we would like $r$ to be large so as to maximize the number of “good” shift vectors which enable both $x_0$ and $x_1$ decoding to the same codeword. As a result, our algorithms generally perform best when the closest pair distance is very small.

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2 Actually, we only need to “check” when the two adjacent decoded vectors are identical.
1.2 Our results

Our simple error-correcting code based algorithm can be applied to solve the Closest Pair Problem and the Light Bulb Problem.

1.2.1 The Closest Pair Problem

Our main result is the following simple randomized algorithm for the Closest Pair Problem.

**Theorem 1.1 (Main).** Let \( x_0, x_1, \ldots, x_{n-1} \) in \( \{0, 1\}^m \) be \( n \) binary vectors such that \( x_0 \) and \( x_1 \) is the unique pair achieving the minimum pairwise distance \( d_{\text{min}} \) (and the second smallest distance can be as small as \( d_{\text{min}} + 1 \)). Suppose we are given the value of \( d_{\text{min}} \) and let \( \delta \triangleq d_{\text{min}} / m \). Then there is a randomized algorithm running in \( O(n \log^2 n \cdot 2^{(1-\kappa_Z(\delta)-\delta)m} \cdot \text{poly}(m)) \) which finds the closest pair \( x_0 \) and \( x_1 \) with probability at least \( 1 - 1/n^2 \). The running time can be improved to \( O(n \log^2 n \cdot 2^{(1-\kappa_{GV}(\delta)-\delta)m} \cdot \text{poly}(m)) \), if we are given black-box decoding algorithms for an ensemble of \( O(\log m/\epsilon) \) binary error-correcting codes that meet the Gilbert-Varshamov bound.

Here \( \kappa_{GV}(\delta) \) and \( \kappa_Z(\delta) \) are functions derived from the Gilbert-Varshamov (GV) bound and the Zyablov bound respectively (see Section 2.1.5 for details).

The running time of our algorithm depends on — in addition to the number of vectors \( n \) — both dimension \( m \) and \( \delta \triangleq d_{\text{min}} / m \). To illustrate its performance we choose two typical vector lengths \( m \), namely those corresponding to the Hamming bound\(^3\) and the Gilbert-Varshamov (GV) bound\(^4\) and list the exponents \( \gamma' \) in the running time of the GV-code version of our algorithm as a function of \( d_{\text{min}} \) (in fact \( \delta \)) in Table 1. Here,

\(^3\)The Hamming bound, also known as the sphere packing bound, specifies an upper bound on the number codewords a code can have given the block length and the minimum distance of the code.

\(^4\)The GV bound is known to be attainable by the random codes.
we write the running of the algorithm as \( \tilde{O}(n^{\gamma'}) \), where \( \tilde{O} \) suppresses any polylogarithmic factor of \( n \). One can see that our algorithm runs in subquadratic time when \( \delta \) is small, or equivalently when the Hamming distance between the closest pair is small.

In the setting of \( m = \epsilon \log n \) for some not too large constant \( \epsilon \), Alman et al. [3] gave a randomized algorithm which runs in \( n^{2-1/\tilde{O}(\sqrt{\log n}^{3/2})} \) time for the Closest Pair Problem. As it is very hard to calculate the hidden constant in the exponent of their running time, it is impossible to compare our running time with theirs quantitatively. However, as the running time of Alman et al. is of the form \( n^{2-g(c)} \) for some function \( g \), it is reasonable to believe that our algorithms run faster when the minimum distance is small enough.

**Deterministic algorithm.** By checking all shift vectors up to certain Hamming weight, our randomized algorithm can be easily derandomized to yield the following.

**Theorem 1.2.** Let \( x_0, x_1, \ldots, x_{n-1} \in \{0, 1\}^m \) be \( n \) binary vectors such that \( x_0 \) and \( x_1 \) is the unique pair achieving the minimum pairwise distance \( d_{\text{min}} \) (and the second smallest distance can be as small as \( d_{\text{min}} + 1 \)). Suppose we are given the value of \( d_{\text{min}} \) and let \( \delta = d_{\text{min}} / m \). Then there is a deterministic algorithm that finds the closest pair \( x_0 \) and \( x_1 \) with running time \( O(n \log n \cdot 2^{H_2(1-\kappa_{GV}(\delta))m} \cdot \text{poly}(m)) \), where \( H_2(\cdot) \) is the binary entropy function. Moreover, if we are given as black box the decoding algorithm of a random Varshamov linear code with block length \( m \) and minimum distance \( d_{\text{min}} + 1 \), then the running time is \( O(n \log n \cdot 2^{H_2(1-\kappa_{GV}(\delta))m} \cdot \text{poly}(m)) \).

**Searching for \( d_{\text{min}} \).** If we remove the assumption that \( d_{\text{min}} \) is given, our algorithm can be modified to search for \( d_{\text{min}} \) first without too much slowdown; more details appear in Section [4].

**Theorem 1.3.** Let \( x_0, x_1, \ldots, x_{n-1} \in \{0, 1\}^m \) be \( n \) binary vectors such that \( x_0 \) and \( x_1 \) is the unique pair achieving the minimum pairwise distance \( d_{\text{min}} \). Then for any \( \epsilon > 0 \), there is a randomized algorithm runs in \( O(\epsilon^{-1}n \log^2 n \cdot 2^{1-\kappa_{GV}((1+\epsilon)\delta)-\delta H_2(\frac{1-\epsilon}{2})m} \cdot \text{poly}(m)) \) which finds the \( d_{\text{min}} \) (and the pair \( x_0 \) and \( x_1 \)) with probability at least \( 1 - 1/n \). The running time can be improved to \( O(\epsilon^{-1}n \log^2 n \cdot 2^{1-\kappa_{GV}((1+\epsilon)\delta)-\delta H_2(\frac{1-\epsilon}{2})m} \cdot \text{poly}(m)) \), if we are given black-box decoding algorithms for an ensemble of \( O(\log^2 n / \epsilon) \) binary error-correcting codes that meet the Gilbert-Varshamov bound.

**Gapped version.** Intuitively, if there is a gap between \( d_{\text{min}} \) and the second minimum distance, the Closest Pair Problem should be easier. This is reminiscent of the case of the \( \epsilon \)-Approximate NNS Problem versus the NNS Problem. However, as we still need to find the *exact* solution to the Closest Pair Problem, the situation here is different.

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**Table 1:** Running time of our algorithm when vector length \( m \) meets the Hamming bound and GV bound

| \( \delta \) | length of vector \((m/\log n)\) | exponent (\( \gamma' \)) | length of vector \((m/\log n)\) | exponent (\( \gamma' \)) |
|---|---|---|---|---|
| 0.01 | 1.0476 | 1.0742 | 1.0879 | 1.0770 |
| 0.025 | 1.1074 | 1.1591 | 1.2029 | 1.1728 |
| 0.05 | 1.2029 | 1.2844 | 1.4013 | 1.3313 |
| 0.075 | 1.2999 | 1.4021 | 1.6242 | 1.5024 |
| 0.1 | 1.4013 | 1.5171 | 1.8832 | 1.6949 |
| 0.125 | 1.5090 | 1.6316 | 2.1909 | 1.9170 |
Theorem 1.4 (Gapped version). Let $x_0, x_1, \ldots, x_{n-1}$ in $\{0,1\}^m$ be $n$ binary vectors such that $x_0$ and $x_1$ is the unique pair achieving the minimum pairwise distance $d_{min}$. Suppose we are given the values of $d_{min}$ as well as the second minimum distance $d_2$. Let $\delta \overset{\text{def}}{=} d_{min}/m$ and $\delta' \overset{\text{def}}{=} d_2/m$. Then there is a randomized algorithm running in $O(n \log^2 n \cdot 2^{(1-\kappa_2)(\delta') - \gamma - (1-\delta)H_2(\frac{\delta' - \delta}{2(1-\delta)}) \cdot \text{poly}(m)})$ which finds the closest pair $x_0$ and $x_1$ with probability at least $1 - 1/n^2$. Moreover, the running time can be further improved to $O(n \log^2 n \cdot 2^{(1-\kappa_{GV})(\delta') - \gamma - (1-\delta)H_2(\frac{\delta' - \delta}{2(1-\delta)}) \cdot \text{poly}(m)})$, if we are given the black box access to the decoding algorithm of an $(m, K, d)$-code which meets the Gilbert-Varshamov bound.

Our gapped version algorithm uses $d_2/2$ instead of $d_{min}/2$ as the decoding radius. This, however, does not always give improved running time as illustrated in Figure 3. In Figure 3, we set $\delta' = (1+\epsilon)\delta$ and write the running time as $O(n \log^2 n \cdot 2^{\gamma m} \cdot \text{poly}(m))$ for both the gapped version (the blue line) and the non-gapped version (the green line). One can see that the gapped version performs better only when $\epsilon$ is small enough.

1.2.2 The Light Bulb Problem

Applying our algorithms for the Closest Pair Problem to the Light Bulb Problem easily yields the following.

Theorem 1.5. There is a randomized algorithm for the Light Bulb Problem which runs in time

$$O(n \cdot \text{poly}(\log n)) \cdot 2^{(1-\kappa_2(\frac{1-\rho}{2}) - \frac{1-\rho}{2}) \gamma m \cdot \log n \cdot \frac{1+o(1)}{\rho^2}},$$

and succeeds with probability at least $1 - 1/n^2$. The running time can be further improved to

$$O(n \cdot \text{poly}(\log n)) \cdot 2^{(1-\kappa_{GV}(\frac{1-\rho}{2}) - \frac{1-\rho}{2}) \gamma m \cdot \log n \cdot \frac{1+o(1)}{\rho^2}},$$

if we are allowed a one-time preprocessing time of $n^2 773/\rho^2$ to generate the decoding lookup table of a random Gilbert’s $(m, K, (1-\rho)m/2)$-code. Similar results can also be obtained for deterministic algorithms.

Our deterministic algorithm for the Light Bulb Problem is, to the best of our knowledge, the only deterministic algorithm for the problem. Moreover, we believe that our algorithms are very simple and therefore are likely to outperform other complicated ones for at least not too large input sizes.
1.3 Related work

The Nearest Neighbor Search problem. The Closest Pair Problem is a special case of the more general Nearest Neighbor Search (NNS) problem, defined as follows. Given a set \( S \) of \( n \) vectors in \( \{0, 1\}^m \), and a query point \( q \in \{0, 1\}^m \) as input, the problem is to find a point in \( S \) which is closest to \( q \). The performance of an NNS algorithm is usually measured by two parameters: the space (which is usually proportional to the preprocessing time) and the query time. It is easy to see that any algorithms for NNS can also be used to solve the Closest Pair problem, as we can try each vector in \( S \) as the query vector against the remaining vectors in \( S \), and output the pair with minimum distance.

Most early work on this problem is for fixed dimension. Indeed, when \( m = 1 \) the problem is easy, as we can just sort the input vectors (which in this case are numbers), then perform a binary search to find the closest vector to the input query. For \( m \geq 2 \), Clarkson [15] gave an algorithm with query time polynomial in \( m \log n \), and space complexity \( O(n^{m/2}) \). Meiser [33] designed an algorithm which runs in \( O(m^5 \log n) \) time and uses \( O(n^{m+\epsilon}) \) space for arbitrary \( \epsilon > 0 \). By far, all efficient data structures for NNS have dimension \( m \) appear in the exponent of the space complexity, a phenomenon commonly known as the curse of dimensionality.

This motivates people to introduce a relaxed version of Nearest Neighbor Search called the \( \epsilon \)-Approximate Nearest Neighbor Search (\( \epsilon \)-Approximate NNS) Problem in the 1990s. The problem now is, for an input query point \( q \), find a point \( p \) in \( S \) such that the Hamming distance is:

\[
dist(p, q) \leq (1 + \epsilon) \min_{p' \in S} \text{dist}(p', q).
\]

We call such a \( p \) as an \( \epsilon \)-approximate nearest neighbor of input query \( q \).

The \( \epsilon \)-Approximate NNS Problem has been studied extensively in the last two decades. In 1998, Indyk and Motwani [27] used a set of hash functions to store the dataset such that if two points are close enough, they will have a very high probability to be hashed into the same buckets. As a pair of close points have higher probability than a pair of far-apart points to fall into the same bucket, the scheme is called locality sensitive hashing (LSH). The query time of LSH is \( O(n^{1/\epsilon}) \), which is sublinear, and the space complexity of LSH is \( O(n^{1+1/\epsilon}) \), which is subquadratic. After Indyk and Motwani introducing the locality sensitive hashing, there have been many improvements on the parameters under different metric spaces, such as \( \ell_p \) metric [31, 18, 6, 36, 34]. Recently, Andoni et al. [8] gave tight upper and lower bounds of time-space trade-offs for hashing based algorithms for the \( \epsilon \)-Approximate NNS Problem. This is the first algorithm that achieves sublinear query time and near-linear space, for any \( \epsilon > 0 \). For many results on the Approximate NNS problem in high dimension, see e.g. [7] for a survey. Some algorithms for the low dimension problem are surveyed in [9].

Recently, Valiant [42] leveraged fast matrix multiplication to obtain a new algorithm for the \( \epsilon \)-Approximate NNS Problem that is not based on LSH. The general setting of Valiant’s results is the following. Suppose there is a set of points \( S \) in \( m \)-dimensional Euclidean (or Hamming) space, and we are promised that for any \( a \in S \) and \( b \in S \), \( \langle a, b \rangle < \alpha \), except for only one pair which has \( \langle a, b \rangle \geq \beta \) (which corresponds to the closest pair), and \( \beta \) is known as the Pearson-correlation coefficient), for some \( 0 < \alpha < \beta < 1 \). Valiant’s algorithm finds the closest pair in \( n^{2-\omega} + \omega \log \alpha \log \beta m^{O(1)} \) time, where \( \omega \) is the exponent for fast matrix multiplication (\( \omega < 2.373 \)). Notice that, if the Pearson-correlation coefficient \( \beta \) is some fixed constant, then when \( \alpha \) approaches 0 the running time tends to \( n^{2-\omega} \), which is less than \( n^{1.62} \). Valiant applied his algorithms to get improved bounds\(^5\) for the Learning Sparse Parities with Noise Problem, the Learning \( k \)-Juntas with

\(^5\) All these results are due to the fact that Valiant’s algorithms are much more robust to weak correlations than other algorithms.
Noise Problem, the Learning $k$-Juntas without Noise Problem, and so on. More recently, Karppa et al. [29] improved upon Valiant’s algorithm and obtained an algorithm that runs in $n^{2c} + O(\log \frac{n}{m \epsilon})$ $m^{O(1)}$ time.

Note that in general algorithms for the $\epsilon$-Approximate NNS Problem can not be used to solve the Closest Pair Problem, as the latter requires to find the exact solution for the closest pair of vectors.

Decoding Random Binary Linear Codes. In 2015, May and Ozerov [32] observed that algorithms for high dimensional Nearest Neighbor Search Problem can be used to speedup the approximate matching part of the information set decoding algorithm. They designed a new algorithm for the Bichromatic Hamming Closest Pair problem when the two input lists of vectors are pairwise independent, and consequently obtained a decoding algorithm for random binary linear codes with time complexity $2^{0.097n}$. This improved upon the previously best result of Becker et al. [11] which runs in $2^{0.102n}$.

The Bichromatic Hamming Closest Pair problem. In fact, the problem studied in [4, 3, 32] is the following Bichromatic Hamming Closest Pair Problem: we are given $n$ red vectors $R = \{r_0, r_1, \ldots, r_{n-1}\}$ and $n$ blue vectors $B = \{b_0, b_1, \ldots, b_{n-1}\}$ from $\{0, 1\}^m$, and the goal is to find a red-blue pair with minimum Hamming distance. It is easy to see that the Closest Pair Problem is reducible to the Bichromatic Hamming Closest Pair Problem via a random reduction. On the other hand, our algorithm for the Closest Pair Problem can also be easily adapted to solve the Bichromatic Hamming Closest Pair Problem as follows. Run the decoding part of our algorithm on both sets $R$ and $B$ to get $\tilde{R} = \{\tilde{r}_0, \tilde{r}_1, \ldots, \tilde{r}_{n-1}\}$ and $\tilde{B} = \{\tilde{b}_0, \tilde{b}_1, \ldots, \tilde{b}_{n-1}\}$, sort $\tilde{R}$ and $\tilde{B}$ separately (without comparing the orginal vectors for adjacent pairs in the sorted lists), then merge the two sorted lists into one, and compute the distance between the original vectors for each red-blue pair of vectors that are compared during the merging process. On the other hand, the Bichromatic Closest Pair Problem is unlikely to have truly subquadratic algorithms under some mild conditions. Assuming the Strong Exponential Time Hypothesis (SETH), for any $\epsilon > 0$, there exists a constant $c$ such that when the dimension $m = c \log n$, then there is no $2^{o(m)} \cdot n^{2-\epsilon}$-time algorithm for the Bichromatic Closest Pair Problem [4, 11, 48].

1.4 Organization

The rest of the paper is organized as follows. Preliminaries and notations that we use throughout the paper are summarized in Section 2. In Section 3, we present our main decoding-based algorithms for the Closest Pair Problem, assuming the minimum pairwise distance is given. We then show how to get rid of this assumption in Section 4. In Section 5, we apply our new algorithms to study the Light Bulb Problem. Finally, we conclude with several open problems in Section 6.

2 Preliminaries

Let $m \geq 1$ be a natural number, we use $[m]$ to denote the set $\{1, \ldots, m\}$. All logarithms in this paper are base 2 unless specified otherwise.

The binary entropy function, denoted $H_2(p)$, is defined as $H_2(p) = -p \log p - (1 - p) \log(1 - p)$ for $0 \leq p \leq 1$.

Let $\mathbb{F}_q$ be a finite field with $q$ elements and $m \geq 1$ be a natural number. If $x \in \mathbb{F}_q^m$ is an $m$-dimensional vector over $\mathbb{F}_q$ and $i \in [m]$, then we use $(x)_i$ to denote the $i^{th}$ coordinate of $x$. The Hamming distance between two vectors $x, y \in \mathbb{F}_q^m$ is the number of coordinates at which they differ: $\text{dist}(x, y) = |\{i \in [m]: x_i \neq y_i\}|$.

Our algorithms therefore do not give improved bounds for these learning problems in the general settings.

When $q = 2$, we use $\mathbb{F}_2$ and $\{0, 1\}$ interchangeably throughout the paper.
distance of \((x)_i \neq (y)_i\). For a vector \(x \in \mathbb{F}^m\) and a real number \(r \geq 0\), the Hamming ball of radius \(r\) around \(x\) is \(B(x, r) = \{y \in \mathbb{F}^m : \text{dist}(x, y) \leq r\}\). The weight of a vector \(x\), denoted \(\text{wt}(x)\), is the number of coordinates at which \((x)_i \neq 0\). The distance between two vectors \(x\) and \(y\) is easily seen to be equal to \(\text{wt}(x - y)\).

### 2.1 Error correcting codes

**Definition 2.1** (Error correcting codes). Let \(\mathbb{F}_q\) be a finite field with \(q\) elements, and let \(m \geq 1\) be a natural number. A subset \(C\) of \(\mathbb{F}_q^m\) is called an \((m, K, d)_q\)-code if \(|C| = K\) and for any two distinct vectors \(x, y \in C\), \(\text{dist}(x, y) \geq d\). The vectors in \(C\) are called codewords of \(C\), \(m\) the block length of \(C\), and \(d\) the minimum distance of \(C\).

Normalized by the block length \(m\), \(\kappa(C) \overset{\text{def}}{=} \log_q K/m\) is known as the rate of \(C\) and \(\delta(C) \overset{\text{def}}{=} d/m\) is known as the relative distance of \(C\). If \(C\) is a linear subspace of \(\mathbb{F}_q^m\) of dimension \(k\), the code is called a linear code and denoted by \([m, k, d]_q\). It is convenient to view such a linear code as the image of an encoding function \(E : \mathbb{F}_q^k \rightarrow \mathbb{F}_q^m\), and \(k\) is called message length of \(C\). This can be generalized to non-linear codes as well where we view \(\lceil \log_q K \rceil\) as the effective message length. We usually drop the subscript \(q\) when \(q = 2\).

**Definition 2.2** (Covering radius). Let \(C \subseteq \mathbb{F}_q^m\) be a code. For any \(x \in \mathbb{F}_q^m\), define the distance between \(x\) and \(C\) to be \(\text{dist}(x, C) \overset{\text{def}}{=} \min_{y \in C} \text{dist}(x, y)\). (clearly, \(\text{dist}(x, C) = 0\) if and only if \(x\) is a codeword of \(C\).) The covering radius of a code \(C\), denoted \(R(C)\), is defined to be the maximum distance of any vector in \(\mathbb{F}_q^m\) from \(C\), i.e., \(R(C) = \max_{x \in \mathbb{F}_q^m} \text{dist}(x, C)\).

#### 2.1.1 Unique decoding

Given an \((m, K, d)\)-code \(C\), if a vector (aka received word) \(x \in \mathbb{F}_q^m\) is at a distance \(r \leq \lceil d/2 \rceil\) from some codeword \(w\) in \(C\), then by triangle inequality, \(x\) is closer to \(w\) than any other codewords in \(C\). Therefore \(x\) can be uniquely decoded to the codeword \(w \in C\). Such a decoding scheme\(^7\) is called unique decoding (or minimum distance decoding) of code \(C\), and we shall call \(\lceil d/2 \rceil\) the (unique) decoding radius of \(C\).

#### 2.1.2 Gilbert-Varshamov bound and Gilbert’s greedy code

The Gilbert-Varshamov bound asserts that there is an infinite family of codes \(C\) (essentially random codes or even random linear codes meet this bound almost surely) that satisfy \(\kappa(C) \geq 1 - H_2(\delta(C))\). In particular, the following greedy algorithm of Gilbert\(^8\) finds a (non-linear) binary code \(C\) of block length \(m\) and minimum distance \(d\) and satisfies that \(\frac{1}{m} \log K \geq 1 - H_2(d/m) - \epsilon\) for any \(\epsilon > 0\) for all sufficiently large \(m\). Start with \(S = \mathbb{F}_2^m\) and \(C = \emptyset\); while \(S \neq \emptyset\), pick any element \(x \in S\), add it to \(C\) and remove all the elements in \(B(x, d)\) from \(S\). We denote such a code by \(\text{GV}_{m, d}\).

We will need the following simple facts about \(\text{GV}_{m, d}\)

**Lemma 2.3.** The greedy algorithm of Gilbert can be implemented to run in \(O(2^m)\) time, and produces a decoding lookup table that supports constant time unique decoding. That is, for any \(x \in \mathbb{F}_2^m\), if there is a
codeword \( w \in GV_{m,d} \) with \( \text{dist}(x, w) \leq \left\lfloor \frac{d-1}{2} \right\rfloor \), then the lookup entry of \( x \) is \( w \); otherwise the entry is a special symbol, say, \( \perp \). Moreover, the code \( GV_{m,d} \) constructed by Gilbert’s greedy algorithm satisfies that \( R(GV_{m,d}) \leq d \).

2.1.3 Reed-Solomon codes

**Definition 2.4** (Reed-Solomon codes). Let \( \mathbb{F}_q \) be finite field, \( k \) and \( m \) be integers satisfying \( k \leq m \leq q \). The encoding function for Reed-Solomon code from \( \mathbb{F}_k \) to \( \mathbb{F}_m \) is the following: First pick \( m \) distinct elements \( \alpha_1, \ldots, \alpha_m \in \mathbb{F}_q \); on input \( (a_0, a_1, \ldots, a_{k-1}) \in \mathbb{F}_k \), define a degree-\( k \) polynomial \( P : \mathbb{F}_q \rightarrow \mathbb{F}_q \) as \( P(x) = \sum_{i=0}^{k-1} a_i x^i \); finally output the evaluations of \( P(x) \) at \( \alpha_1, \ldots, \alpha_m \), i.e. the codeword is \( (P(\alpha_1), \ldots, P(\alpha_m)) \). We will denote such a code by \( \text{RS}_{q,m,k} \).

**Theorem 2.5.** The Reed-Solomon code defined above is an \([m, k, m-k+1]_q\) linear code.

**Theorem 2.6** ([45]). There exists an efficient unique decoding algorithm for Reed-Solomon codes which runs in time \( \text{poly}(m, \log q) \).

Reed-Solomon codes are optimal in the sense that they meet the Singleton bound, which states that for any linear \([m, k, d]_q\)-code, \( k \leq m - d + 1 \).

2.1.4 Concatenated codes

The most commonly used way to transform a nice code which has constant rate and constant relative distance over a large alphabet to a similarly nice code over binary is concatenation, which was first introduced by Forney [21].

**Definition 2.7** (Concatenated codes). Let \( C_1 \) be an \((m_1, K_1, d_1)_Q\)-code and let \( C_2 \) be an \((m_2, K_2, d_2)_q\)-code with \( K_2 \geq Q \). Then the code obtained by concatenating \( C_1 \) with \( C_2 \), denoted by \( C = C_1 \circ C_2 \), is an \((m, K, d)_q\)-code defined as follows. Let \( \phi \) by any mapping from \( \mathbb{F}_Q \) onto \( \mathbb{F}_q \). Then the codewords of \( C_1 \circ C_2 \) are obtained by replacing each element in \( \mathbb{F}_Q \) of any codeword \( w = ((w)_1, \ldots, (w)_{m_1}) \in C_1 \) with the corresponding codeword in \( C_2 \) defined by \( \phi \); namely \( C = \{ \phi((w)_1) \circ \ldots \circ \phi((w)_{m_1}) : w \in C_1 \} \), where each \( \phi((w)_j) \) consists of \( m_2 \) elements in \( \mathbb{F}_q \) and \( \circ \) denotes string concatenation. Note that each codeword in \( C \) is an element in \( \mathbb{F}_q^{m_1m_2} \) and there are \( K_1 \) such codewords, therefore \( m = m_1m_2 \) and \( K = K_1 \). Usually \( C_1 \) is called the outer code and \( C_2 \) is called the inner code.

It is well-known that the minimum distance of \( C \) is \( d_1d_2 \), and the rate of \( C \) is \( \kappa(C) = \kappa(C_1)\kappa(C_2) \). Another useful fact is that \( C \) can be efficiently decoded as long as both \( C_1 \) and \( C_2 \) can be efficiently decoded.

**Fact 2.8.** Suppose \( C_1 \) is an \((m_1, K_1, d_1)_Q\)-code with a decoding algorithm \( A_1 \) running in \( p_1(m_1, \log Q) \) time, \( C_2 \) is an \((m_2, K_2, d_2)_q\)-code, where \( K_2 \geq Q \), and a decoding algorithm \( A_2 \) running in \( p_2(m_2, \log q) \) time. If \( C \) is the concatenated code \( C = C_1 \circ C_2 \), and then there is a decoding algorithm \( A \) for \( C \) which run in time \( p_1(m_1, \log Q) + m_1p_2(m_2, \log q) \) by first decoding \( m_1 \) received words of \( C_2 \) each consisting of \( m_2 \) elements in \( \mathbb{F}_q \), and then decode the \( m_1 \) concatenated elements in \( \mathbb{F}_q \) as a received word of \( C_1 \).

2.1.5 Codes used in our algorithms

Some of the codes to be employed in our algorithm are a family of codes constructed by concatenating Reed-Solomon codes with certain binary non-linear Gilbert’s greedy codes meeting the Gilbert-Varshamov
bound. It is well-known that concatenated codes such constructed can be made to meet the so-called Zyablov bound\footnote{In fact, a stronger bound called Blokh-Zyablov bound can be achieved by applying multilevel concatenations (see e.g. \cite{20} for a detailed discussion on multilevel concatenations of codes); however, as the improvement is minor, we only use single level concatenation in our code constructions to make the algorithms simpler.}

\[\kappa(C) \geq \max_{0 < \kappa(C_2) < 1-H_2(\delta(C))} \kappa(C_2) \left( 1 - \frac{\delta(C)}{H_2^{-1}(1 - \kappa(C_2))} \right) \tag{1}\]

Suppose we want a binary \((m, K, d)\)-code for our algorithms, where \(m\) and \(d\) are fixed and our goal is to maximize \(K\), conditioned on that the code is efficiently decodable. We pick a Reed-Solomon code \(C_1 = RS_{q,m_1,k_1}\) and a Gilbert’s greedy code \(C_2 = GV_{m_2,d_2}\) with the following constraints: \(m_1m_2 \leq m\) (\(m_1m_2\) should be as close to \(m\) as possible), \(d_1d_2 \geq d\), \(K_2 = 2^{m_2\kappa(C_2)} \geq q > m_1\), and \(2^{m_2} \leq poly(m_1)\). It is easy to check that there are large ranges of values for \(m_1\) and \(m_2\), and optimizing the choice of \(d_2\) (and therefore \(\delta(C_2)\)) makes our concatenated code \(C = C_1 \circ C_2\) both meets the Zyablov bound in Eqn. (1) and can be decoded in \(poly(m)\) time.

We will denote the maximum rate as a function of the relative distance \(\delta\) given by the Zyablov bound by \(\kappa_Z(\delta)\), and similarly denote the maximum rate given by the Gilbert-Varshamov bound by \(\kappa_{GV}(\delta)\) (i.e. \(\kappa_{GV}(\delta) = 1 - H_2(\delta)\)). Note that \(\kappa_Z(\delta) \leq \kappa_{GV}(\delta)\) for all \(0 \leq \delta \leq 1\), and the reason we use codes achieving only \(\kappa_Z(\delta)\) is because such codes can be generated and decoded in \(poly(m)\) time.

### 2.2 The closest pair problem

Given \(n\) vectors \(x_0, x_1, \ldots, x_{n-1}\) in \(\{0, 1\}^m\), the Closest Pair Problem is to find two vectors whose pairwise Hamming distance is minimum. For ease of exposition and without loss of generality, we will assume throughout the paper that there is a unique pair, namely \(x_0\) and \(x_1\), that achieves the minimum pairwise distance \(d_{\text{min}}\). We will use \(d_2\) to denote the second minimum pairwise distance, where \(d_2 \geq d_{\text{min}} + 1\). In the most general case, we do not make any assumption about \(m, d_{\text{min}}\) or \(d_2\).

### 3 Main Algorithm for the Closest Pair Problem

We now present our Main Algorithm for the Closest Pair Problem. For ease of exposition, we make a somewhat unnatural assumption that the value of \(d_{\text{min}}\) is given. However, as we show in Section 4, the algorithm can be modified to get rid this assumption, with only a slight slowdown in running time.

**Theorem 3.1** (Non-gapped version). Let \(x_0, x_1, \ldots, x_{n-1}\) in \(\{0, 1\}^m\) be \(n\) binary vectors such that \(x_0\) and \(x_1\) is the unique pair achieving the minimum pairwise distance \(d_{\text{min}}\) (and the second smallest distance can be as small as \(d_{\text{min}} + 1\)). Suppose we are given the value of \(d_{\text{min}}\) and let \(\delta = d_{\text{min}}/m\). Then there is a randomized algorithm running in \(O(n \log^2 n \cdot 2^{(1-\kappa_Z(\delta)-\delta)m} \cdot poly(m))\) which finds the closest pair \(x_0\) and \(x_1\) with probability at least \(1 - 1/n^2\).

**Proof.** Our Main Algorithm for the Closest Pair problem is described in Algorithm 2 and the decoding subroutine \(\text{Dec}(C, r, x)\) is illustrated in Algorithm 5. Note that we choose the minimum distance of \(C\) to be \(d_{\text{min}} + 1\), hence the decoding radius of \(C\) is \(d_{\text{min}}/2\) (without loss of generality, assume that \(d_{\text{min}}\) is even).

For the correctness of the algorithm, first note that our algorithm will output the correct minimum distance if and only if \(x_0\) is ever compared against \(x_1\) for computing pairwise distance, and this happens if and
only if \( x_0 \) and \( x_1 \) are adjacent in the sorted array after decoding. A sufficient condition for the latter is that the decoded vectors of \( x_0 \) and \( x_1 \) are identical and they are different from any other decoded vectors.

How many shift vectors \( y \in \{0, 1\}^m \) in Algorithm 2 satisfy this condition? We will call such vectors good vectors. Denote the set of vectors lying at the “middle” between \( x_0 \) and \( x_1 \) by

\[
\text{MID} = \{ z \in \{0, 1\}^m : \text{dist}(x_0, z) = \text{dist}(z, x_1) = d_{\text{min}}/2 \}.
\]

Note that any vector \( y \) that shifts a vector \( z \in \text{MID} \) to a codeword \( c \in C \) would be a good vector. To see this, first note that after such a shift, \( y + z \) is a codeword in \( C \), and both \( y + x_0 \) and \( y + x_1 \) lie within the decoding radius of \( y + z \), and therefore will be decoded to \( y + z \). Moreover, the shifted vector of any other input vector \( y + x_i \), \( 2 \leq i \leq n - 1 \), lies outside the decoding radius of \( y + z \). This is because if it does, then by triangle inequality and the fact that the decoding radius of \( C \) is \( d_{\text{min}} \),

\[
\text{dist}(x_0, x_i) = \text{dist}(y + x_0, y + x_i) \\
\leq \text{dist}(y + x_0, y + z) + \text{dist}(y + z, y + x_i) \\
\leq d_{\text{min}}/2 + d_{\text{min}}/2 = d_{\text{min}},
\]

contradicting our assumption that \( x_0 \) and \( x_1 \) is the unique pair achieving the minimum distance.

How many such good vectors? There are in total \( \binom{d_{\text{min}}}{\lfloor d_{\text{min}}/2 \rfloor} \) vectors in MID, and all their pairwise distances are at most \( d_{\text{min}} \). Let \( c_1, c_2 \) be two distinct codewords in \( C \). By our choice of the minimum distance of \( C \), \( \text{dist}(c_1, c_2) > d_{\text{min}} \). Consider any two distinct vectors \( z_1 \) and \( z_2 \) in MID. Clearly applying these two shift vectors to the same codeword gives two distinct vectors, namely \( c_1 + z_1 \) and \( c_1 + z_2 \). Moreover, applying two distinct vectors in MID to two distinct codewords also results in two distinct shift vectors, because

\[
\text{dist}(c_1 + z_1, c_2 + z_2) = \text{wt}(c_1 + c_2 + z_1 + z_2) > 0,
\]

since \( \text{wt}(c_1 + c_2) \geq d > d_{\text{min}} \) but \( \text{wt}(z_1 + z_2) = \text{dist}(z_1, z_2) \leq d_{\text{min}} \).

Recall that \( C \) is a \((m, K, d)\)-code and hence there are \( K \) codewords in \( C \). It follows that there are in total \( K \cdot \binom{d_{\text{min}}}{\lfloor d_{\text{min}}/2 \rfloor} \) good vectors of this kind. Therefore

\[
\Pr(\text{a random } y \text{ succeeds in finding the closest pair}) \geq \frac{K \cdot \binom{d_{\text{min}}}{\lfloor d_{\text{min}}/2 \rfloor}}{2^m},
\]

and hence repeatedly selecting

\[
2 \ln n \cdot \frac{2^m}{K \cdot \binom{d_{\text{min}}}{\lfloor d_{\text{min}}/2 \rfloor}} = O \left( \log n \cdot \sqrt{2^m \frac{2^m}{2^{2\kappa Z(\delta)m} m^{2\delta/m}}} \right) = O(2^{(1 + \kappa Z(\delta) - \delta)m} m^{1/2} \log n)
\]

independent \( y \)’s will succeed with probability at least \( 1 - 1/n^2 \).

Finally, note that each choice of shift vector \( y \) requires \( n \cdot \text{poly}(m) \) time decoding as well as \( O(n \log n \cdot m) \) sorting and comparing adjacent vectors, so the total running time of the algorithm is \( O(n \log^2 n \cdot 2^{(1 - \kappa Z(\delta) - \delta)m} \cdot \text{poly}(m)) \).

If we assume further that a decoding algorithm for some binary \((m, K, d)\)-code \( C \) which meets the Gilbert-Varshamov bound is given as a black box, then the running time in Theorem 3.1 can be improved to \( O(n \log^2 n \cdot 2^{(1 - \kappa_{GV}(\delta) - \delta)m} \cdot \text{poly}(m)) \). Note that this is not a totally unrealistic assumption, as for
as well as the second minimum distance $d$ code of block length $m$
most interesting settings, $m = c \log n$ for some small constant $c$. Therefore, greedily searching for a binary code of block length $m$ that meets the Gilbert-Varshamov bound is tantamount to running an $O(n^c)$ time preprocessing, which can be reused for any problem instance with the same vector length and minimum closest pair distance.

If there is a gap between $d_2$ and $d_{\text{min}}$ (this roughly corresponds to the approximate closest pair problem in [42]), then we can improve the running time of the Main Algorithm in Theorem 3.1 by exploiting an error correcting code with larger decoding radius.

**Theorem 3.2 (Gapped version).** Let $x_0, x_1, \ldots, x_{n-1}$ in $\{0, 1\}^m$ be $n$ binary vectors such that $x_0$ and $x_1$ is the unique pair achieving the minimum pairwise distance $d_{\text{min}}$. Suppose we are given the values of $d_{\text{min}}$ as well as the second minimum distance $d_2$. Let $\delta \overset{\text{def}}{=} d_{\text{min}}/m$ and $\delta' \overset{\text{def}}{=} d_2/m$. Then there is a randomized algorithm running in $O(n \log^2 n \cdot 2^{1 - \kappa \delta}(\delta')^{\delta - (1 - \delta)H_2(\frac{\delta' - \delta}{2(1 - \delta)})} \cdot \text{poly}(m))$ which finds the closest pair $x_0$ and $x_1$ with probability at least $1 - 1/n^2$. Moreover, the running time can be further improved to $O(n \log^2 n \cdot 2^{1 - \kappa \delta_G(\delta')}(\delta')^{\delta - (1 - \delta)H_2(\frac{\delta' - \delta}{2(1 - \delta)})} \cdot \text{poly}(m))$, if we are given the black box access to the decoding
algorithm of an \((m, K, d)\)-code which meets the Gilbert-Varshamov bound.

**Proof.** The proof follows a similar structure as the proof of Theorem \(3.1\). The main difference is now we pick a binary error correcting code of minimum distance \(d_2 + 1\), thereby decoding radius \(r = d_2/2 = \frac{1}{2} \delta/m\) (once again, for simplicity, we assume \(d_2\) is even).

Accordingly, the “middle point” set is now defined as

\[
\text{MID}_G = \{z \in \{0, 1\}^m : \text{dist}(x_0, z) \leq r \text{ and dist}(x_1, z) \leq r\}.
\]

We now give a lower bound on the size of \(\text{MID}_G\).

Without loss of generality, we assume \(x_0 = 0^m\) and let \(T = \{i \in [m] : (x_1)_i = 1\}\). Clearly \(|T| = d_{\min}\).

Let \(i = |\{k \in T : (z)_k = 0\}|\) and \(j = |\{k \in [m] \setminus T : (z)_k = 1\}|\). Then \(\text{dist}(x_0, z) \leq r\) is equivalent to \(d_{\min} - i + j \leq r\), and \(\text{dist}(x_1, z) \leq r\) is equivalent to \(i + j \leq r\). Therefore

\[
|\text{MID}_G| = \sum_{i+j \leq r} \sum_{d_{\min} - i + j \leq r} \binom{d_{\min}}{i} \binom{m - d_{\min}}{j} \geq \binom{d_{\min}/2}{i} \binom{m - d_{\min}}{r - d_{\min}/2} = \Theta \left( \frac{2^{\delta m} \cdot 2^{(1-\delta)H_2(\frac{s'-\delta}{2})}}{\sqrt{(1-\delta)m}} \right).
\]

The rest of the proof is identical to that of Theorem \(3.1\) and therefore is omitted. \(\square\)

### 3.1 A deterministic variant of the Main Algorithm

One can turn our randomized Main Algorithm into a deterministic one by exhaustively searching for all possible shift vector \(y \in F_2^n\). A simple observation is that it is sufficient to check for all vectors in the Hamming ball of radius equals to the covering radius of the code \(C\).

**Theorem 3.3.** Let \(x_0, x_1, \ldots, x_{n-1}\) in \(\{0, 1\}^m\) be \(n\) binary vectors such that \(x_0\) and \(x_1\) is the unique pair achieving the minimum pairwise distance \(d_{\min}\) (and the second smallest distance can be as small as \(d_{\min}+1\)). Suppose we are given the value of \(d_{\min}\) and let \(\delta = \frac{d_{\min}}{m}\). Then there is a deterministic algorithm that finds the closest pair \(x_0\) and \(x_1\) with running time \(O(n \log n \cdot 2^{H_2(1-\kappa_{GV}(\delta))m} \cdot \text{poly}(m))\). Moreover, if we are given as black box the decoding algorithm of a random Varshamov linear code with block length \(m\) and minimum distance \(d_{\min}+1\), then the running time is \(O(n \log n \cdot 2^{H_2(1-\kappa_{GV}(\delta))m} \cdot \text{poly}(m))\).

**Proof.** Let \(\delta = \frac{d_{\min}}{m}\). It is well-known that for any linear \([m, k, d]\)-code \(C\), the covering radius of \(C\) satisfies that \(R(C) \leq m - k\). It follows that for Reed-Solomon code \(RS_{q, m, k}\), \(R(RS) \leq m - k < d\). We can either generate a random linear Varshamov code \(44\) similar to that described in Section \(2.1.5\) that meets the Gilbert-Varshamov bound and concatenate it with a Reed-Solomon code so that the resulting binary code is a linear code. Then the covering radius of this concatenated code satisfies that \(R(C) \leq (1 - \kappa_{z}(\delta))m\). Or, if preprocessing is allowed, we may simply generate a random linear Varshamov code of block length \(m\), whose covering radius satisfies that \(R(C) \leq (1 - \kappa_{GV}(\delta))m\).

Now the deterministic algorithm for finding the closest pair is similar to the Main Algorithm, except that instead of picking random shift vector \(y\), the algorithm checks every \(y \in B(0^m, R(C))\). It follows directly that the running time of the algorithm is \(O(n \log n \cdot \text{poly}(m) \cdot \text{Vol}(B(0^m, R(C))))\). Here \(\text{Vol}(B(0^m, R(C)))\)
denotes the number of vectors within the Hamming ball $B(0^m, R(C))$, which is $2^{H_2(1-\kappa_Z)}m$ for the concatenated code, or $2^{H_2(1-\kappa_{GV})}m$ for the random Varshamov linear code.

The correctness of the algorithm follows that, by the same argument of the correctness of Algorithm 2, any vector $z \in \text{MID}$ is at most $R(C)$ away from some codeword $c \in C$, namely $\text{dist}(z, c) = \text{wt}(z + c) \leq R(C)$. When vector $z + c$, which lies in $B(0^m, R(C))$, is chosen as the shift vector, $x_0$ and $x_1$ will be the only two vectors decoded to $c$, therefore the algorithm successfully finds the closest pair.

We remark that our covering radius argument seems to be too rough, as there are many vectors in MID. Getting a more efficient deterministic algorithm, or derandomizing the Main Algorithm is an interesting open question of combinatorics in nature.

4 Searching for the Minimum Distance

In this section we show how to remove the assumption that the value of $d_{\text{min}}$ is given to the Main algorithm. Basically we show that one can use a binary-search like procedure to find $d_{\text{min}}$ without too much slowdown of the Main Algorithm. Our key observation is that, although the decoding radius is chosen to be $d_{\text{min}}/2$ in the Main Algorithm, actually we can relax this requirement: indeed, any decoding radius between $d_{\text{min}}/2$ and $d_{\text{min}}$ works.

**Lemma 4.1.** The Main Algorithm works (with worse running time) as long as the binary error correcting code used has decoding radius $r = \lfloor \frac{d_{\text{min}}-1}{2} \rfloor$ satisfying $\frac{1}{2}d_{\text{min}} \leq r \leq d_{\text{min}}$.

**Proof.** The proof is similar to the proof of Theorem 3.1, but we slightly generalize the original definition of MID as follows. Let

\[ \text{MID}_1 = \{ z \in \{0, 1\}^m : \text{dist}(x_0, z) = r \text{ and } \text{dist}(x_1, z) = d_{\text{min}} - r \}, \]

let

\[ \text{MID}_2 = \{ z \in \{0, 1\}^m : \text{dist}(x_1, z) = r \text{ and } \text{dist}(x_0, z) = d_{\text{min}} - r \}. \]

and finally let $\text{MID}' = \text{MID}_1 \cup \text{MID}_2$.

Clearly the set $\text{MID}'$ is non-empty. The key point is that any vector $y$ that shifts some vector $z \in \text{MID}'$ to a codeword $c \in C$ must be a \textit{good} vector, following a similar argument as in the proof of Theorem 3.1. The running time of the algorithm can also be calculated similarly.

Our algorithm for finding $d_{\text{min}}$ is illustrated in Algorithm 4. The correctness of Algorithm 4 follows from two simple facts: first, Algorithm 2 can never return a value less than $d_{\text{min}}$; second, when $d_{\text{min}}/2 \leq r \leq d_{\text{min}}$, by Lemma 4.1 and Theorem 3.1, Algorithm 2 returns the correct value of $d_{\text{min}}$ (with high probability).

In fact, to make our algorithm more efficient, for any $\epsilon > 0$, we can search with decoding radius $r = 1, [1 + \epsilon], (1 + \epsilon)^2, \ldots$. Note that by Lemma 4.1 the maximum value we will ever try is $(1 + \epsilon)d_{\text{min}}/2$. As the running time of Algorithm 2 is monotone increasing with respect to the decoding radius $r$, so in order to bound the running time of searching for $d_{\text{min}}$, it suffices to bound the running time of Algorithm 2 for $r = (1 + \epsilon)d_{\text{min}}/2$. Following a similar analysis as in the proof of Theorem 3.1,

\[ |\text{MID}'| \geq |\text{MID}_1| = \left( \frac{d_{\text{min}}}{(1 + \epsilon)d_{\text{min}}/2} \right). \]
Algorithm 4: Searching for $d_{\text{min}}$

**input**: A set of $n$ vectors $x_0, \ldots, x_{n-1}$ in $\{0, 1\}^m$

**output**: The minimum pairwise distance $d_{\text{min}}$

1. $r \leftarrow 1$
2. while true do
3.    run Algorithm 1 with $d = r$;
4.    if the minimum distance $d_{\text{min}}$ returned in Algorithm 2 is at most $2r$
5.       then
6.          return $d_{\text{min}}$;
7.       else
8.          $r \leftarrow (1 + \epsilon)r$;
9.      end
10. end

Therefore,

$$\Pr(\text{a random } y \text{ succeeds in finding the closest pair}) \geq \frac{K \cdot \left( \frac{d_{\text{min}}}{(1+\epsilon)d_{\text{min}}/2} \right)}{2^m} = \Theta \left( \frac{2^{\kappa_Z((1+\epsilon)\delta) m/2} H_2(1+\epsilon) \delta m}{\sqrt{\delta m} 2^m} \right).$$

As the binary search calls at most $\log_{(1+\epsilon)} d_{\text{min}} < \log_{(1+\epsilon)} m = O(\log m/\epsilon)$ times Algorithm 2, we therefore have the following theorem.

**Theorem 4.2.** Let $x_0, x_1, \ldots, x_{n-1}$ in $\{0, 1\}^m$ be $n$ binary vectors such that $x_0$ and $x_1$ is the unique pair achieving the minimum pairwise distance $d_{\text{min}}$. Then for any $\epsilon > 0$, there is a randomized algorithm running in:

$$O(\epsilon^{-1} n \log^2 n \cdot 2^{(1-\kappa_Z((1+\epsilon)\delta)-\delta H_2(1+\epsilon))m} \cdot \text{poly}(m)),$$

which finds the $d_{\text{min}}$ (as well as the closest pair $x_0$ and $x_1$) with probability at least $1 - 1/n$. The running time can be improved to:

$$O(\epsilon^{-1} n \log^2 n \cdot 2^{(1-\kappa_{GV}((1+\epsilon)\delta)-\delta H_2(1+\epsilon))m} \cdot \text{poly}(m)),$$

if we are given black-box decoding algorithms for an ensemble of $O(\log m/\epsilon)$ binary error correcting codes that meet the Gilbert-Varshamov bound.

## 5 The Light Bulb Problem

In this section, we apply our new algorithms for the Closest Pair Problem to a special case of it, namely the Light Bulb Problem.

In the Light Bulb Problem, we are given $n$ sequences of bit strings $X_0, X_1, \ldots, X_{n-1}$. All bits are generated independently, uniformly at random from $\{0, 1\}$, except that two strings, say $X_0$ and $X_1$, are...
generated with non-zero linear correlation \( \rho \); that is, independently for each \( i \), \( \Pr((X_0)_i = (X_1)_i) = \frac{1+\rho}{2} \) and \( \Pr((X_0)_i \neq (X_1)_i) = \frac{1-\rho}{2} \). The problem is to find this correlated pair of sequences.

First note that we may assume the Pearson correlation \( \rho \) is positive, as there is a simple randomized reduction from the negative \( \rho \) case to the positive \( \rho \) case: given an instance of the Light Bulb Problem with \( \rho < 0 \) randomly pick \( n/2 \) sequences and flip all the bits in these sequences. Then with probability 1/2, the correlated pair become \(-\rho\) correlated.

To apply our algorithms for the Closest Pair Problem to the Light Bulb Problem, the following theorem provides a randomized reduction from the latter to the former.

**Theorem 5.1.** If we pick \( m = \frac{4 \ln 2 \log n}{\rho^2} (1+o(1)) \) bits at random from \( X_0, X_1, \ldots, X_{n-1} \) to obtain \( n \) vectors \( x_0, x_1, \ldots, x_{n-1} \) in \( \{0,1\}^m \), then with constant probability, \( x_0 \) and \( x_1 \) is the unique closest pair among these \( n \) vectors.

**Proof.** For each pair of vectors \( x_i \) and \( x_j \), \( 0 \le i < j \le n-1 \), define \( m \) indicator random variables \( \{(I_{i,j})_k\}_{k \in [m]} \) such that \( (I_{i,j})_k = 1 \) if and only if \( (x_i)_k \neq (x_j)_k \). Note that for any pair \( i < j \), \( \{(I_{i,j})_k\}_{k \in [m]} \) are \( m \) independent and identically distributed random variables, and \( \text{dist}(x_i, x_j) = \sum_{k \in [m]} (I_{i,j})_k \). Specifically, \( \Pr((I_{0,1})_k = 0) = \frac{1+\rho}{2} \) and \( \Pr((I_{0,1})_k = 1) = \frac{1-\rho}{2} \); and \( \Pr((I_{i,j})_k = 0) = \Pr((I_{i,j})_k = 1) = 1/2 \) for all other \( i < j \) pairs.

Note that each pairwise distance \( \text{dist}(x_i, x_j) \) is a binomial random variable. In particular, \( \text{dist}(x_0, x_1) \) is a \( B(m, \frac{1-\rho}{2}) \) random variable and all others are \( B(m, 1/2) \) random variable.

**Fact 5.2** ([28]). Binomial distribution \( B(n, p) \) has median \( \lfloor np \rfloor \) or \( \lceil np \rceil \).

Let \( d_t \overset{\text{def}}{=} \mathbb{E}(\text{dist}(x_0, x_1)) = (1-\rho)m/2 \). Then by Fact 5.2, \( \Pr(\text{dist}(x_0, x_1) \ge d_t) \le 1/2 \).

On the other hand, for any other pair \( x_i \) and \( x_j \),

\[
\Pr(\text{dist}(x_i, x_j) < d_t) = \Pr(\text{dist}(x_i, x_j) < \mathbb{E}(\text{dist}(x_i, x_j)) - \rho m/2) \\
< e^{-\rho m^2/2m} = e^{-m\rho^2(1-o(1))/2} \\
\le \frac{1}{2m^2},
\]

by a simple application of the Chernoff bound (e.g. Theorem A.1.1 in [5]). Now applying a union bound over all \( x_i \) and \( x_j \) pairs, we have that with probability at least 1/4, \( \text{dist}(x_0, x_1) < d_t \) and for all other pairs \( \text{dist}(x_i, x_j) \ge d_t \), i.e., \( x_0 \) and \( x_1 \) is the unique closest pair among these \( n \) vectors. \( \square \)

Note that Theorem 5.1 implies that if we sample \( m = \frac{4 \ln 2 \log n}{\rho^2} (1+o(1)) \) bits from the \( n \) random sequences, then with constant probability, we get an instance of the Closest Pair Problem with \( d_{\min} < (1-\rho)m/2 \). Combining Theorem 5.1 with Theorem 5.5, we obtain the following

**Theorem 5.3.** There is a randomized algorithm for the Light Bulb Problem which runs in time

\[
O(n \cdot \text{poly}(\log n)) \cdot 2^{(1-\kappa_2)(\frac{1-\rho}{2})-\frac{1-\rho}{2}} \frac{4 \ln 2 \log n}{\rho^2} (1+o(1))
\]

and succeeds with probability at least \( 1 - 1/n^2 \). The running time can be further improved to

\[
O(n \cdot \text{poly}(\log n)) \cdot 2^{(1-\kappa_{GV})(\frac{1-\rho}{2})-\frac{1-\rho}{2}} \frac{4 \ln 2 \log n}{\rho^2} (1+o(1)),
\]

if we are allowed a one-time preprocessing time of \( n^{2.773}/\rho^2 \) to generate the decoding lookup table of a random Gilbert’s \((m, K, (1-\rho)m/2)\)-code.
Numerical calculations show that our new algorithm performs better than the improved Valiant’s fast matrix multiplication algorithm [29] (which runs in $n^{1.582}$) when $\rho \geq 0.9967$ (equivalently when $\delta < 0.0016$). Moreover, if an $n^{2.773/\rho^2}$-time preprocessing is allowed, then our algorithm runs faster for all $\rho \geq 0.9310$ (equivalently for all $\delta < 0.0345$).

6 Concluding Remarks and Open Problems

We propose a simple approach, namely a decoding-base method, to solve the classic Closest Pair Problem. Our results leave open several interesting questions.

Valiant’s fast matrix multiplication method [42] for the Light Bulb Problem is the only known algorithm that makes good use of the availability of larger amount of data. Is there a way to leverage the data size to improve the running time of our decoding approach? Another interesting open question is to study the Closest Pair Problem in the streaming model, as many real-life situations — such as in cyber security — of the problem are in fact in this setting.

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