Abstract
In this paper, we introduce SparsePIR, a single-server keyword private information retrieval (PIR) construction that enables querying over sparse databases. At its core, SparsePIR is based on a novel encoding algorithm that encodes sparse database entries as linear combinations while being compatible with important PIR optimizations including recursion. SparsePIR achieves response overhead that is half of state-of-the art keyword PIR schemes without requiring long-term client storage of linear-sized mappings. We also introduce two variants, SparsePIRg and SparsePIRc, that further reduces the size of the serving database at the cost of increased encoding time and small additional client storage, respectively. Our frameworks enable performing keyword PIR with, essentially, the same costs as standard PIR. Finally, we also show that SparsePIR may be used to build batch keyword PIR with halved response overhead without any client mappings.

1 Introduction
Private information retrieval (PIR) [21] is an important cryptographic primitive that allows a client to retrieve entries from a public database without revealing the client’s entry of interest. Due to its strong privacy guarantees, PIR is a critical building block for many practical applications including advertisements [36], anonymous communication [7, 10, 46, 52], contact discovery [12, 27], device enrollment [4], media consumption [38], password leak checks [8] and route navigation [65].

PIR has been studied in two settings with a single server [17, 25, 34, 37, 45, 47, 55, 56, 63] or multiple, non-colluding servers [13, 21, 29, 30, 35]. PIR schemes in the multi-server setting are, typically, more efficient. However, they rely on stronger trust assumptions between different organizations that may be difficult to materialize. In our work, we will focus on single-server PIR.

The standard PIR problem considers databases that are n-entry arrays. The client’s goal is to retrieve the i-th entry in the array without revealing index i to the server holding the public database. Unfortunately, in most practical applications, databases more closely resemble key-value pairs where users want to retrieve the value associated to a certain key. For example, we can think of data sets like contact lists, videos, websites, etc. To address this, keyword PIR [20] was introduced where databases consist of key-value pairs and a client wishes to retrieve the value associated with a certain key.

A naive solution for keyword PIR is to replicate mappings from keys to array indices that need to be stored by all clients. To query, a client uses the mapping to determine the array index storing the entry associated to the query key and uses a standard PIR scheme. Unfortunately, this requires the client to store mappings that are linear in the database size. Chor et al. [20] presented a multiple round solution introducing additional overhead. Another solution to keyword PIR utilizes cuckoo hashing [8] in a single round, but results in 2x response overhead compared to standard PIR. A recent work [50] builds one-round keyword PIR using constant-weight equality operators. However, this scheme requires significantly more communication and computation than recent PIR schemes. In the current state of affairs, moving from standard PIR to keyword PIR requires increasing roundtrips, doubling the response size or large long-term client storage. None of these choices are appealing. This paper addresses this inefficiency.

Our Contributions. We present SparsePIR that is a framework for building keyword PIR from a standard
SparsePIR word PIR [50]. We also introduce SparsePIR. The main benefit of very slight increase in computation compared to standard lattice-based PIR should also enable faster storage of < 11.2 KB. In summary, we show that key-near optimal encoding size with small additional client by up to 20% in exchange for more time to encode the decrease the encoding size and, thus, computation time that has identical request and response sizes are identical to the underlying standard PIR schemes without any additional client storage. As a result, SparsePIR halves the response size compared to the cuckoo hashing keyword PIR approach [8]. The only slight drawback of SparsePIR is a small increase in the server computation costs. For databases with one million 256-byte entries, SparsePIR built on Spiral [51] halves response sizes from 42 KB to 21 KB compared to the cuckoo hashing approach [8] using Spiral. In exchange, SparsePIR uses only 2% more server computation. We also show that SparsePIR uses 2-12x smaller communication and at least 10x less computation than constant-weight keyword PIR [50]. We also introduce SparsePIR² that has identical request and response overhead as SparsePIR. The main benefit of SparsePIR² is that we can further decrease the encoding size and, thus, computation time by up to 20% in exchange for more time to encode the database. Finally, we introduce SparsePIR² that achieves near optimal encoding size with small additional client storage of < 11.2 KB. In summary, we show that keyword PIR requires no additional communication and a very slight increase in computation compared to standard PIR. Furthermore, we believe any future improvements to standard lattice-based PIR should also enable faster keyword PIR schemes using our frameworks. Figure 1 presents a comparison of keyword PIRs. Finally, we show that we can build batch keyword PIR schemes using any of our SparsePIR algorithms with small response sizes.

2 Preliminaries

We denote vectors \( \mathbf{v} \) as column vectors and \( \mathbf{v}^\top \) as row vectors. We denote the \( i \)-th entry of \( \mathbf{v} \) by \( v[i] \). For two vectors \( \mathbf{a} \) and \( \mathbf{b} \) in \( \{0, 1\}^n \), we denote the dot product operator as \( \mathbf{a} \cdot \mathbf{b} = \sum_{i=1}^{n} a[i] \cdot b[i] \). For a matrix \( \mathbf{M} = [\mathbf{M}_1 \ldots \mathbf{M}_m] \), we denote the dot product \( \mathbf{a} \cdot \mathbf{M} = [\mathbf{a} \cdot \mathbf{M}_1 \ldots \mathbf{a} \cdot \mathbf{M}_m] \). For any database consisting of key-value pairs \( D = \{(k_1, v_1), \ldots, (k_n, v_n)\} \), we denote \( D[k] \) to be the standard operation to access the value associated with \( k \) in the database \( D \). If \( k = k_i \) for some \( i \in [n] \), then \( D[k] = v_i \). If \( k \neq k_i \) for all \( i \in [n] \), then \( D[k] = \perp \).

Next, we present definitions of PIR and batch PIR. Formal definitions may be found in the full version.

PIR. We will restrict ourselves to single-server, one-round schemes. A keyword PIR scheme consists of algorithms \( \Pi = (\text{Init}, \text{Encode}, \text{Query}, \text{Answer}, \text{Decrypt}) \). \text{Init} initializes all crypto keys and \text{Encode} enables preparing a database for queries. The client runs \text{Query} and \text{Decrypt} to create a request and compute an answer from the server’s response. The server runs \text{Answer} to create a response from the client’s request. For correctness, the client should retrieve the correct value associated with the queried key. In terms of privacy, the server should not learn information about the client’s queried key.

Batch PIR. In this setting, clients query a batch of \( \ell \geq 1 \) query keys to retrieve all \( \ell \) associated values. A batch keyword PIR consists of the same four algorithms \( \Pi = (\text{Init}, \text{Encode}, \text{Query}, \text{Answer}, \text{Decrypt}) \). For correctness, the scheme should return all \( \ell \) associated values correctly. In terms of privacy, the server should not learn any information about the client’s set of queried keys.

3 Keyword PIR over Sparse Databases

3.1 State-of-the-Art PIR Schemes

We start by revisiting the current state-of-the-art PIR schemes [6–9, 33, 51, 54, 57] that utilize leveled fully homomorphic encryption (FHE) built on the Ring Learning with Errors (RLWE) assumption [49].

Fully Homomorphic Encryption. Most leveled FHE schemes relying on RLWE (such as [15, 16, 31]) share similar mathematical structures. These FHE schemes are based on a cyclotomic ring \( R = \mathbb{Z}[x]/(x^N + 1) \) where \( N \) is the degree of the polynomials. \( N \) is also commonly referred to as the ring dimension. Plaintext values are encoded as polynomials in the ring \( R_\alpha = R/\alpha R \) where the integer \( \alpha \) is referred to as the plaintext modulus. Ciphertexts consist of two polynomials from the ring \( R_\beta = R/\beta R \) for some integer \( \beta \). The secret key \( s \) in these FHE schemes will be polynomials in \( R \) with very small coefficients. An encryption of a plaintext polynomial \( pt \) will look like \((r, r \cdot s + e + pt)\) where \( r \) is a uniformly
random element from $R_{p}$, $s$ is the secret key and $e$ is the noise polynomial where each coefficient is typically small and drawn from a truncated Gaussian distribution. To decrypt a ciphertext $(c_{1}, c_{2})$, one will compute $c_{2} - (c_{1} \cdot s) = e + pt$. As long as the noise polynomial $e$ remains small, the plaintext $pt$ can be retrieved by rounding to remove $e$.

FHE schemes allow homomorphic operations over ciphertexts. PIR schemes generally rely upon three core operations: ciphertext-ciphertext addition, ciphertext-plaintext multiplication and ciphertext-ciphertext multiplication. The costs and noise growth of these operations are quite different. Typically, ciphertext-ciphertext addition is the most efficient, ciphertext-plaintext multiplication is a bit more expensive and ciphertext-ciphertext multiplication is the worst of the three.

**Query-Independent PIR Parameters.** Following prior works [8, 9, 51, 54], we will consider the model where the client uploads query-independent parameters to the server. These parameters will be used by the server to process all future requests sent by the client. At a high level, these public parameters enable the server to operate over FHE ciphertexts efficiently. We assume that these parameters are sent by the client to the server in an “offline” phase before any queries are performed.

**Recursion.** A common technique in standard PIR is to utilize recursion introduced in [45] that represents the $n$-entry array database as a hypercube of dimensions $d_{1} \times d_{2} \times \ldots \times d_{z}$, where the product of the dimensions is at least $n$, $d_{1} \cdot d_{2} \cdot \ldots \cdot d_{z} \geq n$. To query an entry, the client will generate $z$ indicator vectors $v_{1} \in \{0,1\}^{d_{1}}, \ldots, v_{z} \in \{0,1\}^{d_{z}}$ where each $v_{i}$ has zeroes everywhere except for a one indicating the location of the entry with respect to the dimension $d_{i}$. The benefit of this representation is that querying for an entry only requires uploading an encrypted bit vector of length $d_{1} + \ldots + d_{z}$ that can be substantially smaller than $n$. For example, if we set $d_{1} = \sqrt{n}$ and $d_{2} = \sqrt{n}$, the total bit length $2\sqrt{n}$. An unfortunate side note is that recursion introduces the need for ciphertext-ciphertext multiplication. The majority of PIR works aim to achieve recursion while obtaining better trade-offs between communication and computation. In our work, we will present keyword PIR schemes whose constructions will utilize recursion to reduce communication. We note there are other important PIR techniques such as compression and oblivious expansion (see the full version). However, unlike recursion, they end up being easier to fit into our framework.

**Building on a PIR Scheme.** Our constructions will be frameworks that can be built upon FHE based PIR schemes, which are the most common ones today. In other words, one can view our constructions as transforming standard PIR schemes into keyword PIRs that can handle sparse databases. We will assume a standard PIR scheme $\Pi_{PIR} = (\text{Init}, \text{Query}, \text{Answer}, \text{Decrypt})$ with the following properties:

- The underlying PIR scheme will represent any $m$-element database as a hypercube with dimensions $d_{1} \times \ldots \times d_{z}$. Our framework will be parameterized by the dimensions $(d_{1}, \ldots, d_{z})$ that may depend on $n$.
- The $\Pi_{PIR}.\text{Init}$ algorithm produces client key $ck$ and server key $sk$ (i.e., query-independent parameters).
- The $\Pi_{PIR}.\text{Query}$ algorithm receives $z$ vectors of length $d_{1}, \ldots, d_{z}$ that it will homomorphically encrypt and upload to the server. For standard PIR, these $z$ vectors are indicator vectors representing the query index in each dimension. As compression and oblivious expansion can handle arbitrary Hamming weight vectors (see the full version for more details), we assume that $\Pi_{PIR}$ can receive arbitrary vectors for the first $d_{1}$-length vector.
- The $\Pi_{PIR}.\text{Answer}$ algorithm receives an encoding $E$, a two-dimensional matrix of size $d_{1} \times \lceil m/d_{1} \rceil$, and homomorphic encryptions of vectors $v_{1}, \ldots, v_{z}$. The $\Pi_{PIR}.\text{Answer}$ algorithm will perform the standard PIR algorithm of applying $v_{1}$ to $E$ to obtain a $\lceil m/d_{1} \rceil$ vector, arrange the vector into a $d_{2} \times \lceil m/(d_{1}d_{2}) \rceil$ matrix and apply $v_{2}$ to obtain a vector of size $\lceil m/(d_{1}d_{2}) \rceil$, and repeat this process for all $z$ dimensions.
- The $\Pi_{PIR}.\text{Decrypt}$ algorithm receives the server’s response and produces a decrypted answer. We will assume that the answer was already decoded from the decrypted plaintext polynomial into a string.

### 3.2 Warm-Up: Keyword PIR without Recursion

To start, we consider a simplified setting where we will utilize an underlying PIR scheme $\Pi_{PIR}$ that does not use recursion. In other words, we will represent the encoded database $E$ as a vector of length $d_{1} = m$. For this setting, we do not care if the query vector can be represented succinctly and we will be content with uploading an encrypted version of a linear number of values. In future sections, we will fix this issue to enable recursion. However, we choose to start from this simplified setting as it illuminates some of the ideas that we will use in our more efficient constructions.

**Representing Key-Value Pairs.** For any pair $(k, v)$ of a key and a value, we will represent them in the following way. For some hash key $K$, we denote $\text{rep}(K, k, v)$ as the hash evaluation of $k$ concatenated with $v$. In more
detail, \( \text{rep}(K, k, v) = F(K, k) \parallel v \) where we denote \( \parallel \) as concatenation. We assume the representation length is fixed for all \( (k, v) \). For convenience, we will assume that \( \text{rep}(K, k, v) \) is small enough to be uniquely represented in \( \mathbb{Z}_\alpha \) where \( \alpha \) is the plaintext modulus and each \( \text{rep}(K, k, v) \) will be stored into one ciphertext. We will discuss later how to handle the setting when larger values and packing multiple values into a ciphertext.

Using our representation, we note that one can distinguish representations of different key-value pairs. For different keys \( k_1 \neq k_2 \), the resulting representations will be different \( \text{rep}(K, k_1, v) \neq \text{rep}(K, k_2, v) \) except with negligible probability as the representations are the same only when \( F(K, k_1) = F(K, k_2) \). If the hash output is sufficiently long, these collisions do not occur in practice.

### Encoding the Database

Let \( K_r \) be the hash key used to generate representations of key-value pairs. Throughout this section, we will assume that all operations are done in \( \mathbb{Z}_\alpha \) where \( \alpha \) is the plaintext modulus. We will associate each key \( k \in K \) with a uniformly random subset of \( S_k \subseteq [m] \) that will be randomly generated. The goal is to arrange the encoding \( E \) such that for any database \( D = \{(k_1, v_1), \ldots, (k_n, v_n)\} \) and for any integer \( i \in [n] \),

\[
\sum_{x \in S_k} E[x] = \text{rep}(K_r, k_i, v_i)
\]

where \( S_k \) is the random subset associated with key \( k_i \). For convenience, we can denote the set \( S_k \) using a vector \( v_k \) such that \( v_k[x] = 1 \) only when \( x \in S_k \). We can re-write the above equation as the dot product:

\[
v_k \cdot E = \sum_{x \in S_k} E[x] = \text{rep}(K_r, k_i, v_i).
\]

To construct the encoded database \( E \), we note that the above represents \( n \) systems of equations that need to be satisfied. We can view each \( v_k^T \) to be the \( i \)-th row of a \( n \times m \) matrix \( M \). We also denote the vector \( y \) such that the \( i \)-th entry is the \( i \)-th value, \( y[i] = \text{rep}(K_r, k_i, v_i) \). Therefore, we must find a vector \( E \in \mathbb{F}^m \) satisfying:

\[
\begin{bmatrix}
v_{k_1}^T \\
v_{k_2}^T \\
\vdots \\
v_{k_n}^T
\end{bmatrix} \cdot E = M \cdot E = y = \begin{bmatrix}
\text{rep}(K_r, k_1, v_1) \\
\text{rep}(K_r, k_2, v_2) \\
\vdots \\
\text{rep}(K_r, k_n, v_n)
\end{bmatrix}.
\]

In other words, we can generate a correct encoding \( E \) of the database \( D = \{(k_1, v_1), \ldots, (k_n, v_n)\} \) as long \( M \cdot E = y \) has a solution, i.e. \( M \) has full row rank. Intuitively, increasing the number of columns in \( M \), denoted by \( m \), will also increase the probability that it has full row rank. However, this has the affect of also increasing the size of the encoded database \( E \in \mathbb{F}^m \). Therefore, we would like to pick \( m \) in such a way that \( M \) has full row rank with high probability while minimizing the size of the encoding.

### Decoding an Entry

From the above encoding scheme, we note that decoding an entry is pretty straightforward. For any query key \( k \), the client will randomly generate the vector \( v_k \). The client also computes the hash evaluation \( F(K_r, k) \). Using our PIR scheme without recursion, the client uploads an encrypted version of \( v_k \). The PIR scheme continues without change and the client will eventually receive the dot product \( v_k \cdot E \) in plaintext. The client will parse this result as \( a \parallel b \). If \( a = F(K_r, k) \), then the client returns \( b \) as the retrieved value. Otherwise, when \( a \neq F(K_r, k) \), then the client returns \( \perp \).

If \( k = k_i \) for some \( (k_i, v_i) \in D \), then we know that \( v_k \cdot E \) will be exactly \( F(K_r, k_i) \parallel v_i \) enabling retrieval of \( v_i \). On the other hand, suppose that \( k \notin D \). Then, we know that \( a \neq F(K_r, k) \) meaning the client returns the right response (except with negligible probability of collisions).

#### Quick Comparison with Prior Approaches

In the above, we only needed to retrieve a single ciphertext, which was the dot product response. On the other hand, cuckoo hashing required retrieving two entries. Furthermore, the above approach ensures that the number of entries is very close to linear. We have also ensured minimal error growth as no additional homomorphic operations are performed. This shows us that we are heading in the right direction, although there are still several problems that need to be resolved.

### Problems with this Approach

While the above approach is very promising, it has two significant problems that we outline below and solve in later sections:

1. As discussed earlier, we considered a simplified setting of PIR that does not utilize recursion. Unfortunately, PIR without recursion ends up requiring linear communication. Most state-of-the-art PIR schemes utilize recursion to represent the database using a hypercube with dimensions \( d_1 \times \ldots \times d_z \) such that \( d_1 \cdot \ldots \cdot d_z \geq n \). In our scheme, we chose each row vector \( v_k \) to be uniformly random, which cannot be represented in any succinct manner using recursion.

2. A second, more subtle, issue is that computing a solution to the system of linear equations \( M \cdot E = y \) is very expensive. The best possible algorithm for solving a general linear system would already be quadratic in the size of the database \( n \).
3.3 Partition-Based Keyword PIR

At a high level, both problems from the prior construction resulted from the fact that the random matrix $M$ was very dense with many non-zero entries. The expected number of non-zero entries was $nm/2$, so it is not surprising that finding a solution would require at least quadratic time. Furthermore, as each row vector has, on average, $m/2$ non-zero entries, it is not surprising that any representation of the row vector must also be large. We present our construction SparsePIR that deals with the issues from the previous section to obtain an efficient keyword PIR.

**High-Level Idea of Partitioning.** To solve this problem that row vectors have high density, we will use the idea of partitioning where we aim to break down the problem into smaller sub-problems. To do this, we will aim to embed the random vector into only the first dimension used in recursion. We will assume that the underlying PIR scheme uses recursion and represents the database as $d_1 \times \ldots \times d_s$ hypercube.

At a high level, we will create $b = (1 + \varepsilon)n/d_1$ partitions where each part will be size $d_1$. We will choose the value of $\varepsilon$ later through experimentation. On input of database $D = \{(k_1, v_1), \ldots, (k_n, v_n)\}$ that we wish to encode, we will assign the $n$ key-value pairs to the $b$ partitions uniformly at random. Therefore, the expected number of key-value pairs in each part is $n/b = d_1/(1 + \varepsilon) < d_1$. As a result, we have now reduced the problem to efficiently encoding databases of size $O(d_1)$.

Within each part $P_i$, we will essentially repeat the construction from Section 3.2. Consider the $i$-th part $P_i = \{(k_1, v_1), \ldots, (k_{|P_i|}, v_{|P_i|})\}$. We will generate $M_i$ that is a $|P_i| \times d_1$ matrix where each entry is uniformly chosen from $\{0, 1\}$. In particular, the $i$-th row is generated randomly using $K_2$ and key $k$. We compute $y_i = [\text{rep}(K_r, k_1, v_1) \ldots \text{rep}(K_r, k_{|P_i|}, v_{|P_i|})]$. Finally, we solve the linear system $M_i \cdot \mathbf{e}_i = y_i$ and obtain the encoding $\mathbf{e}_i$ for part $P_i$.

To build the final encoded database $E$, we put each of $\mathbf{e}_1, \ldots, \mathbf{e}_b$ as column vectors in $E$ to construct a $d_1 \times b$ matrix. Note, the cost to solve the linear system in each part is $O(d_1)$, and the total time across all $b = O(n/d_1)$ parts is $O(n \cdot d_1^2)$. For small values of $d_1$, this is much more efficient than approach in Section 3.2.

To query for a key $k$, the client will compute $i = F_1(K_1, k)$ to determine the partition associated with $k$. Next, the client randomly generates the associated random vector using hash key $K_2$ and $k$ that we denote $v_1$. This will be the vector uploaded for the first dimension of PIR. Suppose that the server applied $v_1$ to the first dimension of $E$. Note, the result is $[v_1 \cdot \mathbf{e}_1 \ldots v_1 \cdot \mathbf{e}_b]$. As $k$ is assigned to the $i$-th partition, the only entry needed to be retrieved is $v_1 \cdot \mathbf{e}_i$. Therefore, this reduces to performing a standard PIR query over a $b$-entry array with recursion dimensions $d_2 \times \ldots \times d_s$. We formally present the above ideas in our SparsePIR construction below.

**Encoding the Database.** The encoding algorithm SparsePIR is formally presented in Algorithm 2 that utilizes the partitioning ideas that were discussed previously. Our algorithms are also portrayed pictorially in Figure 2. Recall that the algorithm receives a database $D = \{(k_1, v_1), \ldots, (k_n, v_n)\}$ as input and must output parameters for decoding and an encoding of the database. The encoding is parameterized by $\varepsilon$ where $b = (1 + \varepsilon)n/d_1$ is the number of parts in the partitioning.

First, the algorithm samples three hash keys: $K_1, K_2$ and $K_r$. The first key $K_1$ will be used to generate the random partitioning of the database into $b$ bins such that $F_1(K_1, \cdot) \in \{0, \ldots, b - 1\}$. The second key $K_2$ will be used to generate the random row vectors within each partition where $F_2(K_2, \cdot) \in \{0, 1\}$. $K_r$ is used to generate representations $\text{rep}(K_r, k, v)$ of key-value pairs $(k, v)$.

For any input database $D = \{(k_1, v_1), \ldots, (k_n, v_n)\}$, the next step is to partition the $n$ key-value pairs into the $b$
Next, we compute the end, we note that produce an encoding $E$ is placed into the $K$ is a vector with $i$ is a vector with $b$ are outlined in Algorithms 5, 6 of retrieving the $K$ is a vector with $2$ is able decoding the value associated with query key $k$ (if it exists).

The first step is to compute $F_1(K_1, k)$ to compute the partition associated with $k$. Suppose that $k$ was associated with the $i$-th part. The next step is to compute $F_2(K_2, k || *)$ for all $x \in [d_1]$ to obtain the random bit vector of length $d_1$. The above bit vector will be $v_1$. Next, suppose we applied the first layer of the server’s response algorithm in standard PIR schemes that utilize recursion. Note, that the result is $[v_1 \cdot e_1 \ldots v_z \cdot e_b]$. Furthermore, as we know that $k$ was assigned to the $i$-th part, we only need to retrieve the $i$-th column containing the entry $v_1 \cdot e_i$. In other words, the rest of the problem becomes a standard PIR query of retrieving the $i$-th entry from an array with $b$ entries. To do this, we encode the index $i$ using the standard PIR query over a database of dimensions $d_2 \times \ldots \times d_z$.

Algorithm 2 SparsePIR.Encode algorithm

Input: $D = \{(k_1, v_1), \ldots, (k_n, v_n)\}$: database
Output: $(\text{prms}, E)$: parameters and encoding
Sample hash keys $K_1, K_2$ and $K_r$

$b \leftarrow (1 + \epsilon)n/d_1$
$m \leftarrow (1 + \epsilon)n$
$P_i \leftarrow 0, \ldots, P_b \leftarrow 0$

for $i = 1, \ldots, n$ do ▷ Partition database
    $j \leftarrow F_1(K_1, k_i)$
    $P_{j+1} \leftarrow P_{j+1} \cup \{(k_i, v_i)\}$

for $j = 1, \ldots, b$ do
    $e_j \leftarrow \text{GenerateEncode}(K_2, K_r, P_j)$
    $\text{prms} \leftarrow (K_1, K_2, K_r)$
    $E \leftarrow [e_1, \ldots, e_b]$
return $(\text{prms}, E)$

Algorithm 3 RandVector algorithm

Input: $(K_2, k)$: the hash key and database key.
Output: $v_k$: a randomly generated vector.
$v_k \leftarrow [0]^d$

for $i = 1, \ldots, d_1$ do
    $v_k[i] \leftarrow F_2(K_2, k || i)$
return $v_k$

Algorithm 4 GenerateEncode algorithm

Input: $(\text{prms}, K_2, k_r, P)$: hash keys and a part.
Output: $e$: an encoding of the part.
$M \leftarrow []$ as empty array
$y \leftarrow []$ as empty array
for $(k, v) \in P$ do
    Append $\text{RandVector}(K_2, k)^T$ to $M$ as row.
    Append $\text{rep}(K_r, k, v)$ to $y$.
$e \leftarrow \text{SolveLinearSystem}(M, y)$
return $e$

Algorithm 5 SparsePIR.Query algorithm

Input: $(\text{prms}, ck, k)$: parameters and the query key.
Output: $(st, req)$: temporary state and request.
$b \leftarrow (1 + \epsilon)n/d_1$
Parse $\text{prms} = (K_1, K_2, K_r)$
$v_1 \leftarrow \text{RandVector}(K_2, k)$
$j \leftarrow F_1(K_1, k)$
for $i = 2, \ldots, b$ do ▷ Generate encoding of $j$
    $j_i \leftarrow [j / [b / d_1]]$
    $v_i \leftarrow [0]^{d_i}$
    $v_i[j_i + 1] \leftarrow 1$
    $b \leftarrow [b / d_1]$
    $j \leftarrow j \mod b$
$(st_{\text{PIR}}, \text{req}) \leftarrow \Pi_{\text{PIR}}.\text{Query}(ck, v_1, \ldots, v_z)$
return $(st_{\text{PIR}}, k, \text{req})$
SparsePIR. Answer algorithm

Input: \((\text{prms}, \text{sk}, E, \text{req})\): parameters, server key, encoded databases and the request.
Output: \(\text{resp}\): the response to the request.
Algorithm 6

\[
\text{resp} \leftarrow \text{SparsePIR}.\text{Answer} (\text{sk}, E, \text{req})
\]

return \(\text{resp}\)

SparsePIR. Decrypt algorithm

Input: \((\text{prms}, \text{ck}, \text{st}, \text{resp})\): parameters, client key, temporary state and response.
Output: \(v\): output value
Algorithm 7

\[
\text{Parse prms as } (K_1, K_2, K_r)
\]

\[
\text{Parse st as } (\text{st}_{\text{PIR}}, k)
\]

\[
x \leftarrow \text{SparsePIR}.\text{Decryp}t (\text{ck}, st_{\text{PIR}}, \text{resp})
\]

\[
\text{Parse x as } (id, v)
\]

if \(id = F(K_r, k)\) then

\[
\text{return } v
\]

else

\[
\text{return } \perp
\]

Packing

Throughout this section, we assumed that \(\text{rep}(K_r, k, v)\) fit into \(\mathbb{Z}_\alpha\) where \(\alpha\) is the plaintext modulus and each representation was stored in a single ciphertext. We show how to handle arbitrary length values and efficiency improvements using packing. We will represent \(\text{rep}(K, k, v)\) as a base-\(\alpha\) string with \(L = \lfloor \log_\alpha (|\text{rep}(K, k, v)|) \rfloor\) characters in \(\mathbb{Z}_\alpha\). We repeat the above encoding algorithm for each part \(P_i\) to obtain \(L\) encodings \(e_1^i, \ldots, e_L^i\) using the same matrix \(M_i\). The resulting encoding is: 
\[
E = [e_1^1, \ldots, e_L^1, \ldots, e_1^i, \ldots, e_L^i].
\]

If \(L > N\), we encode each row of \(E\) using \(b \cdot [L/N]\) plaintext polynomials where each tuple \((e_1^i, \ldots, e_L^i)\) uses \(\lfloor L/N \rfloor\) polynomials. When \(L \leq N\), we can encode \(\lfloor N/L \rfloor\) values into a single polynomial meaning each row of \(E\) is encoded using \(\lfloor b/\lfloor N/L \rfloor \rfloor\) polynomials.

Re-sampling and Optimizations

The encoding algorithm of SparsePIR fails (outputs \(\perp\)) when any of the smaller linear systems doesn’t have a solution. In practice, rather than terminating, the encoding would simply re-sample new hash keys \(K_1\) and \(K_2\) and try to encode the database again. In our implementation, this will also be the case. However, we show that one may optimize the re-sampling step. The naive approach would be to re-sample both \(K_1\) and \(K_2\), which is unnecessary.

Recall that \(K_1\) partitions the \(n\) key-value pairs into \(b\) parts. If any single part \(P_i\) receives too many items, the associated linear system \(M_i \cdot e = y\) will not have a solution. In this case, we do not need to even generate \(M_i\). Therefore, we try to sample \(K_1\) until the resulting partition does not over-assign items to any part. Once a good \(K_1\) is found, we fix it. Afterwards, we only keep re-sampling \(K_2\) until all randomly generated matrices have full row rank.

Handling Database Updates

In most applications, the database \(D\) will periodically change. Our encoding algorithm does not enable incremental updates to add/remove entries. If the database changes, the encoding must be run again. To handle database updates, new encoded databases may be generated. As we will show in Section 7, the encoding is concretely efficient to enable creating encoded databases every few minutes.

3.4 Efficiently Solvable Matrices

For SparsePIR, we have been generating random matrices such that each entry is chosen to be uniformly random from \(\{0, 1\}\). The state-of-the-art algorithm for solving general linear systems for practical sizes of \(n\) require at least quadratic (and, typically, near-cubic) time. This is unsurprising as the expected number of non-zero entries in these matrices is \(n^2/2\).

To circumvent this issue, SparsePIR utilized partitioning to guarantee that the generated linear systems were very small in size. Recall that each of the \(O(n/d_1)\) parts involves solving a linear system of size \(O(d_1^2)\), which takes \(O(d_1^3)\) time using Gaussian elimination algorithm. As long as we chose \(d_1\) to be small, then the overall encoding algorithm required \(O(n \cdot d_1^2)\) time that was rel-
We show that there are ways to generate such random matrices that admit efficiently solvable linear systems. It turns out that core algorithm of generating random matrices such that the associated linear system can be solved efficiently is a well-studied area (see [22, 53, 60, 61, 64] and references therein as some examples). For our work, we will utilize the random band matrix constructions of Dietzfelbinger and Walzer [28] that satisfy the requirements needed by our keyword PIR schemes.

Random band matrices are constructed such that each row vector will consist of a short band of length \( w \). The short band will be a uniformly random \( w \)-bit vector. All entries outside of the band will be zero. The location of the short band is chosen uniformly at random. Dietzfelbinger and Walzer [28] showed that for matrices of dimension \((1 - \gamma)n \times n\) for some constant \( 0 < \gamma < 1\), if the band parameter is chosen as \( w = O(log n / \gamma) \), then the resulting random matrix has full row rank with high probability. To solve the associated linear system, one will first sort the rows by the starting location of the non-zero band of length \( w \). Next, one can employ Gaussian elimination in a very efficient manner. At a high level, Gaussian elimination only needs to consider columns within the \( w \)-length band for each row. Therefore, Gaussian elimination requires only \( O(n/\gamma^2) \) time. In Figure 4, we present a diagram depicting random band matrices and the Gaussian elimination algorithm.

**Encoding the Database.** We modify our construction SparsePIR to utilize random band matrices to improve the efficiency of our encoding algorithm for larger values of \( d_1 \). In particular, we only need to modify the RandVector and SolveLinearSystem sub-routines. The new sub-routines may be found in Algorithm 8 and 9. The rest of the encoding algorithm remains unchanged.

**Decoding an Entry.** We note that the decoding algorithm remains identical except that we utilize the new RandVector algorithm.

**Encoding Running Time Analysis.** Finally, we show that the usage of random band matrices improves the running time of the encoding algorithm and enables using large values of \( d_1 \). Previously, solving a linear system for each of the \( O(n/d_1) \) parts took \( O(d_1^3) \) using Gaussian elimination. Utilizing the random band matrix constructions, we can reduce this down to \( O(d_1) \) (ignoring constant factors of \( \varepsilon \) for now), which makes the total encoding time only \( O(n) \). As a result, we can now consider arbitrary values of \( d_1 \) as the encoding algorithm will not grow significantly as \( d_1 \) increases in size.

### 4 Extending Partition Based Keyword PIR

In the partition based keyword PIR, each of the \( n \) keywords was randomly assigned to one of \( b = (1 + \varepsilon)n/d_1 \) partitions of size \( d_1 \). This allowed us to treat each partition as a small independent linear system and solve it separately, making the scheme highly efficient.

However, partition based keyword PIR suffers from a major problem: at most \( d_1 \) keywords can be assigned to a single partition. This means that \( \varepsilon \) has to be big enough for this to happen with high probability. Section 7 shows that for \( n = 2^{20} \) and \( d_1 = 128 \), \( \varepsilon \) has to be at least 0.38. Throughout the rest of this section and the next one, we will consider the example of \( d_1 = 128 \) as all prior concretely efficient PIR schemes (including [8, 9, 51, 54]) use \( d_1 \geq 128 \). It turns out that smaller values of \( d_1 \) are more difficult (see Section 7). Therefore, considering \( d_1 = 128 \) is effectively the most difficult setting.

Looking back, the two motivations behind the partition based keyword PIR were the inefficiency of solving a large random linear system and recursion incompatibility of the generated random vectors. The first issue can be

---

**Algorithm 8** RandVector algorithm

**Input:** \((K_2, k)\): the hash key and database key.

**Output:** \( v_k \): a randomly generated vector.

```plaintext
/* F_3 outputs elements in \{0, \ldots, d-\gamma \}. */
\( p \leftarrow F_3(K_2, k \ | \ "position") \)
\( v_k \leftarrow [0]^{d_1} \)
for \( i = 1, \ldots, w \) do
  \( v_k[p+i+1] \leftarrow F_2(K_2, k \ | \ i) \)
return \( v_k \)
```

**Algorithm 9** SolveLinearSystem algorithm

**Input:** \((M, y)\): band matrix and values to solve for.

**Output:** \( e \): solution to the linear system \( M \cdot e = y \).

Sort rows of \( M \) and \( y \) according to first non-zero entry of \( M \)
Execute Gaussian elimination to get \( e \)
```
return \( e \)
```
Figure 4: The left matrix is a random band matrix with 4 rows and band width $w = 5$. The middle matrix is the intermediate step of the Gaussian elimination that sorts rows by band location. The final matrix shows that Gaussian elimination only considers a small subset of entries.

Figure 5: A two dimensional representation of a database of 9 elements and an example LHS of the combined linear system. Each column of the database corresponds to a partition. The gray bands all lie strictly inside a partition and are recursion compatible, while the red band spans partition 1 and partition 2 and is recursion incompatible.

Recall that partition based keyword PIR allowed us to view each partition as an independent linear system. Another equivalent way to formulate this is to combine these independent linear systems and form a single system as in Figure 5. Pictorially, each partition corresponds to a contiguous range of $d_1$ variables (and columns in the matrix). In Figure 5, notice that the gray bands all lie strictly inside a partition and do not span multiple partitions - this is the crucial property that allowed the row vectors to be recursion compatible in the partition based keyword PIR. On the other hand, the red band spans partition 1 and partition 2 and is not recursion compatible. However, a band spanning multiple partitions is not really fundamentally problematic; it is just that such random band is more likely to be recursion incompatible than not. The main idea behind the new construction is to artificially modify these spanning bands to be recursion compatible, with the hope that the new band matrices remain "random recursion PIR protocol.

Warmup: Two Dimensional Recursion. To motivate our construction, we will start off with constructing recursion compatible band matrices for the two dimensional recursion PIR protocol.
Extending to Higher Dimensions

We will start by focusing on hypercube representation in the form $d_1 \times d \times \cdots \times d$, i.e., all subsequent dimensions after the first are equal.

In the context of PIR, one useful way of visualizing a hypercube of this form is as a $d_1 \times d^d$ matrix, where each column corresponds to a first dimension slice (of size $d_1$) and the column indices correspond to base $d$ representations of the "coordinates" of the first dimension slices in the $d^d$ space. In the context of partition based keyword PIR, each column can be viewed as a partition (numbered from 0 to $d^d - 1$). Selecting partition $i$ is equivalent to transforming $i$ to its base $d$ representation and naturally mapping the $j$th digit to the corresponding indicator vector for the $j + 1$th dimension.

In the two dimensional recursion case, for bands that spanned two partitions, we had to construct the second dimension vector to indicate that we wanted to select those two partitions. This could be done in a straightforward manner by turning on bits at positions corresponding to the partition numbers in the query vector.

However, such naive approach no longer works if we move on to higher dimensions. For example, suppose we embed the database in Figure 5 and Figure 6 on to a hypercube of dimensions $3 \times 2 \times 2$. The partitions (columns) are numbered 002, 012, 102, 112 in base two (the last partition will correspond to empty entries in this case). The green band spans partition 012 and partition 102, but we can no longer construct recursion compatible query vectors (unlike the two dimensional case).

To get around this, we make the following observation: we can construct recursion compatible query vectors for selecting two partitions as long as the Hamming distance between the base $d$ representation of the two partition numbers is 1. Indeed, we can observe that there is no problem of selecting partition 002 and 012 - simply send vector $[1 0]$ for the second dimension and $[1 1]$ for the third dimension. Similarly, if we want to select partition 102 and 112, we can send vector $[0 1]$ for the second dimension and $[1 1]$ for the third dimension.

In fact, we can see that this observation is applicable to an arbitrary hypercube structure of dimensions $d_1 \times d_2 \times \cdots \times d_d$. If we represent the partition numbers in mixed bases $(d_2, \ldots, d_d)$, then we can select the two partitions as long as the Hamming distance between the two partition numbers is 1.

This motivates the following construction: in the linear system, permute the order of the variables in such a way that adjacent partition numbers have Hamming distances 1. This way, all bands that span two adjacent
partitions in the linear system will be recursion compatible. In particular, we can use mixed-radix Gray code [43] to construct this permutation. After permuting the variables according to the Gray code, we have to reverse the order of odd indexed partition variables as in the two dimensional case to ensure that the first dimension remains recursion compatible. Figure 7 shows an example construction. Note that the last partition 112 can be ignored while solving the linear system, and will correspond to empty entries in the database. We point out that this composition of permutations does not require extra storage on the client side, as computing the nth Gray code can be done efficiently on the fly without requiring extra space.

Our experimental evaluation shows that SparsePIRc is able to reduce ε and is practically efficient. For example, for \( n = 2^{20} \) and \( d_1 = 128 \), SparsePIRc is able to reduce ε from 0.38 to 0.1, a significant improvement over naive partition based keyword PIR.

5  Keyword PIR with Client Storage

In SparsePIR, if \( d_1 + 1 \) items were assigned to any single part then the associated linear system would not have a solution. In practice, we needed slightly less than \( d_1 \) items to make sure the solution exists with high probability thus not requiring too much resampling. We would have exact partitioning if all the parts have slightly less than \( d_1 \) items. We present SparsePIRc, an enhancement of SparsePIR with client-side storage, achieving exact partitioning and thus minimal encoded database size at the cost of storing moderate amounts of extra information in the decoding parameter. We provide more detailed algorithms and justification for the choice of client storage in the full version of this paper.

Explicit Exact Partitioning. One very expensive way of exactly partitioning is for the client to receive and explicitly store the assignment of \( n \) items to the \( n/d_1 \) parts requiring \( n \log(n/d_1) \) bits. When \( n = 2^{20} \) and \( d_1 = 128 \), this would require 1.6 MB, which is quite large.

Exact Partitioning via Boundaries. Our main idea is to first sort the hashed outputs of the \( n \) keywords and then evenly split them into \( n/d_1 \) parts. The client stores the \( n/d_1 \) partition boundary values that separate the parts, \( B_0, B_1, \ldots, B_{n/d_1}, B_{n/d_1+1} \). All items in the \( i \)-th part are contained in the interval \([B_{i-1}, B_i]\). For convenience, we will assume \( B_0 \) to be the smallest possible hash output and \( B_{n/d_1+1} \) to be the largest hash output. The list \( B \) becomes part of prms at setup time. During query time, the client hashes the key \( k \) and finds the interval \([B_{i-1}, B_i]\) containing the hash output. Then, the client determines key \( k \) belongs to the \( i \)-th part. This only requires \( O(n/d_1 \log U) \) bits where \( U \) is range of \( F(K_r, k_i) \). For \( n = 2^{20}, d_1 = 128, |U| = 2^{64} \), then this requires 64 KB.

Truncation of Boundaries. For our next improvement, we note that it is not necessary to store the full boundary value. Instead, we can set most of the least significant bits of boundary values to zero and truncate them since we need \( B_i \) only to be precise enough to distinguish it from the neighboring keyword hash value to maintain exact partitioning. This can reduce the \( \log U \) bits used to represent each boundary. For example, when \( n = 2^{20} \) and \( d_1 = 128 \), we see that approximately 25 bits are necessary through experimentation (see the full version for more details). For the concrete example of \( n = 2^{20} \) and \( d_1 = 128 \), this reduces client storage by 60% to 25 KB.

Compression for Persistent Storage. Furthermore, we show that one can further compress the boundary values when storing in persistent storage. In particular, we can store the differences between boundaries as opposed to the boundaries themselves. Additionally, we can apply standard compression techniques for variable length encodings. This can reduce the client storage to less than 11.2 KB for \( n = 2^{20} \) and \( d_1 = 128 \). However, we note that this compression must be decompressed to be able to handle queries (so the client must use 25 KB of temporary storage when performing queries).

Discussion about Client Storage Size. While the client storage of SparsePIRc consists of \( O(n/d_1) \) boundary values, the practical client storage is very small. In the concrete example above of \( n = 2^{20} \) and \( d_1 = 128 \), the resulting client storage is \( \approx 11 \) KB. If we consider a practical database size used in prior works (such as [8–10]) of \( n = 2^{20} \) 256-byte entries, we note that the client storage is equivalent to 0.004% of the total database size (or 43 entries). Furthermore, the client storage is independent of the size of each entry. For larger entries, the client storage is an even smaller percentage of the database. Furthermore, the client storage is smaller for larger values of \( d_1 \). For example, \( n = 2^{20} \) and \( d_1 = 1024 \) requires only 1.8 KB of client storage amounting to 0.0006% of the total database (or 7 entries).

Comparison with SparsePIRc and SparsePIR. We note that SparsePIRc and SparsePIRc obtain near-optimal database sizes in different ways. SparsePIRc requires large encoding times to create the database. In contrast, SparsePIRc requires long-term client storage. If large encoding times are tolerable (i.e., databases may be created in the background before serving), one should choose SparsePIRc. If long-term client storage is reasonable, then one can choose SparsePIRc. If neither slow encoding times or long-term client storage are acceptable, one can simply use SparsePIR instead. See Section 7 for
experimental comparisons between the three options.

6 Batch Keyword PIR

In this section, we show that our techniques can be extended to batch settings where a client wishes to query a batch of $\ell \geq 1$ queries at one time. Clearly, there is a trivial approach of performing $\ell$ independent PIR queries, but this ends up being very inefficient. The goal in the batch setting is to design techniques that enable performing batch queries more efficiently.

Revisiting State-of-the-Art Batch PIR. To date, the most practically efficient approach to constructing batch PIR schemes arises from the framework introduced by Angel et al. [9] that utilizes cuckoo hashing to encode both the database and queries. We note that the original framework was designed for doing batch PIR over an $n$-entry array. The framework did not consider batch keyword PIR over sparse databases. However, we will present the framework with respect to the keyword setting and point out where the framework is inefficient when querying sparse databases.

At a high level, the servers utilizes $t$ random hash functions $H_1, \ldots, H_t$ to encode a database $D = \{(k_1, v_1), \ldots, (k_n, v_n)\}$. We assume that the $t$ hash functions are shared between all clients and the server. The server will replicate each entry in the database $t$ times and assign them into $b_{CH}$ buckets as follows. For each $(k_i, v_i)$, the server assigns the $(k_i, v_i)$ to the $t$ buckets according to the $t$ hash function evaluations $H_1(k_i), \ldots, H_t(k_i)$. The resulting encoding consists of a total $t \cdot n$ key-value pairs across $b_{CH}$ buckets.

For the query algorithm, suppose the client receives a batch of $\ell \geq 1$ queries $(q_1, \ldots, q_{\ell}) \in \mathcal{K}^\ell$. For convenience, it is typically assumed that $\ell$ queries are distinct. If not, the client may de-duplicate locally, perform a batch PIR query for a distinct set of keys and then replicate the blocks as needed to produce the correct answer. The client uses the $t$ hash functions, $H_1, \ldots, H_t$, to perform cuckoo hashing that allocates each $q_i$ into exactly one of the $b_{CH}$ buckets specified by the $t$ hash functions $H_1(q_i), \ldots, H_t(q_i)$. Cuckoo hashing guarantees that each of the $b_{CH}$ buckets is assigned at most one of $\{q_1, \ldots, q_{\ell}\}$. Finally, the client performs $b_{CH}$ keyword PIR queries into each of the $b_{CH}$ buckets to retrieve the assigned query key (or an arbitrary index if no query key was assigned). We further discuss the necessity of keyword PIR later.

The last step is to pick concrete parameters of the cuckoo hashing scheme: $t$ and $b_{CH}$. This is an important step as bad parameters can cause a large portion of queries to fail. Note, if a set of $\ell$ query keys $\{q_1, \ldots, q_{\ell}\}$ cannot be allocated according to cuckoo hashing, then the client’s query will fail. Angel et al. [9] suggested picking $t = 3$ and $b_{CH} = 1.5\ell$ using the experimental evaluation of prior works [19, 59] showing that the concrete failure probability is very small.

This approach achieves much better computational efficiency compared to the trivial approach of performing $\ell$ keyword PIR queries. The trivial approach would require performing $O(n \cdot \ell)$ overhead as each keyword PIR query would require linear overhead. On the other hand, this framework requires only $O(n)$ server computation as only one keyword PIR query is performed per bucket and the total bucket size is $3n$.

Prior Approaches to underlying Keyword PIR. The above framework essentially reduces a batch PIR query for $\ell$ keys into $1.5\ell$ keyword PIR queries into $1.5\ell$ buckets whose total size is $3n$. We note that the framework requires keyword PIR even if database was an array and the database’s keys were $k_1 = 1, \ldots, k_n = n$. Each of the $1.5\ell$ buckets is a database whose keys are a subset of $[n]$. To retrieve the value associated with any key $q \in [n]$ from a bucket, one must use keyword PIR.

To perform keyword PIR, Angel et al. [9] proposed several different options. The simplest approach was for the client to download a direct mapping from each array entry to the physical index within each bucket (or a compressed version using Bloom filter or similar data structures). These approaches would require linear storage on the client side that may be expensive. Furthermore, for databases with small values, these maps may be almost as large as the database. Instead, Angel et al. [9] proposed a very clever trick that enables a client to derive the mapping using the original $t$ hash functions that are shared between the server and the client. The client can simply repeat the server’s allocation process to compute the mapping. Therefore, the client can re-create the mapping without large long-term storage.

Going back to batch keyword PIR, we note that the above trick of the client repeating the server’s allocation process cannot be used. The key observation is that, for standard PIR, the client knows that the database’s keys are exactly $k_1 = 1, \ldots, k_n = n$. Therefore, the client can repeat the server’s allocation process identically. When the database’s keys are from a sparse universe, the client no longer knows the exact keys that appear in the database. Therefore, the client cannot compute the mapping without knowing the keys present in the database.

Replacing the Keyword PIR. To construct batch keyword PIR schemes, it seems like we must use a true keyword PIR as the trick of succinctly generate client maps can no longer be used. Prior to our work, previous key-
word PIR schemes incurred significant additional client storage, doubling response sizes or multiple roundtrips compared to standard PIR.

We show that our SparsePIR families of keyword PIR schemes enable significantly more efficient batch keyword PIR schemes. We obtain SparseBatchPIR by plugging our keyword PIR schemes into the framework of Angel et al. [9], whose communication is identical to batch PIR schemes over $n$-entry arrays. This is a 2x improvement over using any prior keyword PIR scheme that does not require long-term client storage of linear-sized mappings. We present a comparison of batch (keyword) PIR schemes in Figure 8. In Section 7, we experimentally evaluate our new batch keyword PIR schemes showing significant improvements.

7 Experimental Evaluation

7.1 Implementation

We implemented SparsePIR, SparsePIR$^e$ and SparsePIR$^c$ in C++ on top of several open source PIR schemes: OnionPIR [3] and Spiral [5]. To compare, we also implement the keyword PIR cuckoo hashing framework of Ali et al. [8] on top of the same PIR schemes. We also implement SparseBatchPIR using the framework of Angel et al. [9]. In total, our implementations required around 2000 lines of codes. We plan to open source our implementations in the near future.

FHE Parameter Selection. Our SparsePIR families of frameworks were constructed carefully to ensure minimal noise growth. As a result, we can directly use the parameters of the underlying standard PIR scheme. The only exception to this is the plaintext modulus, which we round down to the closest prime.

Cuckoo Hashing Optimization. In our cuckoo hashing keyword PIR implementations, we use the optimization that empty entries will be skipped. As empty entries are represented using 0, they can be skipped during server processing. To our knowledge, this optimization was never presented elsewhere. Without this, SparsePIR would actually have better computation as cuckoo hashing keyword PIR needs $(2 + \varepsilon)n$ entries while our frame-works use strictly less than $2n$ entries.

Experimental Setup. Our experiments are conducted with machines that are Ubuntu PCs with 12 cores, 3.7 GHz Intel Xeon W-2135 and 64 GB of RAM. We use the AVX2 and AVX-512 instruction sets with SIMD instructions enabled. All our experiments use single-thread execution. Reported results are the average of at least 10 experimental trials with standard deviation less than 10% of the means. Monetary costs are computed using Amazon EC2 pricing of t2.2xlarge instances [2] of $0.09 per GB of outbound traffic and $0.014 per CPU hour at the time. We do not report client times as they are very small (see [8, 9, 51]). Following prior works, we define rate as the ratio of the retrieved record size to the response size.
We choose our parameters to accommodate the recursion compression algorithm. SparsePIR ε empirical results, we can choose appropriate values of band parameter for random band linear systems. Similarly, we choose offsets between the computation time and the solvability of for all our experiments, which seem to provide good trade-offs.

For SparsePIR, see Figure 9 and Figure 10 for the time to create an encoding of a database of n key-value pairs into a serving database of size \((1 + \epsilon)n\).

For SparsePIR and SparsePIRε, we choose band parameter \(w \in [50, 60]\) for all our experiments, which seem to provide good trade-offs between the computation time and the solvability of the random band linear systems. Similarly, we choose band parameter \(w \in [85, 120]\) for SparsePIRε. From these empirical results, we can choose appropriate values of \(\epsilon\). In Figure 11, we compare SparsePIR, SparsePIRε and SparsePIRc in terms of the trade-offs between \(\epsilon\) and the client storage. For SparsePIRc, we used bzip2 for the compression algorithm.

7.2 SparsePIR Family Parameters

We choose our parameters to accommodate the recursion dimensions of prior works. Recall OnionPIR [54] used \(d_1 = 128\) dimensions and Spiral [51] used \(d_1 = 512\). Recall that our frameworks encode a database of \(n\) key-value pairs into a serving database of size \((1 + \epsilon)n\).

For SparsePIR and SparsePIRε, see Figure 9 and Figure 10 for the time to create an encoding of size \((1 + \epsilon)n\). For SparsePIR, we choose band parameter \(w \in [50, 60]\) for all our experiments, which seem to provide good trade-offs between the computation time and the solvability of the random band linear systems. Similarly, we choose band parameter \(w \in [85, 120]\) for SparsePIRε. From these empirical results, we can choose appropriate values of \(\epsilon\). In Figure 11, we compare SparsePIR, SparsePIRε and SparsePIRc in terms of the trade-offs between \(\epsilon\) and the client storage. For SparsePIRc, we used bzip2 for the compression algorithm.

7.3 Comparisons

Cuckoo Hashing Keyword PIR. Figure 12 compares the cuckoo hashing [8] and our families of SparsePIR frameworks applied to various PIR protocols. SparsePIR exhibits clear advantage over the cuckoo hashing framework on the response size and the rate. This is expected because cuckoo hashing framework requires the server to send two ciphertexts, while SparsePIR sends only one ciphertext. Cuckoo hashing framework has a slight advantage in computation cost with the optimization of skipping empty entries. However, the small additional server computation time is a worthwhile trade-off for the substantial improvement in the response size as evidenced in the reduced server costs. Due to packing, we obtain smaller \(\epsilon\) for smaller entries (e.g. 256 bytes).

We note that both SparsePIRε and SparsePIRc can reduce the server computation compared to SparsePIR because of the small \(\epsilon\) both encoding schemes can achieve.

Constant-Weight Keyword PIR. In Figure 13, we compare SparsePIR with keyword PIR using constant-weight equality operators [50] using their open source implementation [1]. We observe that SparsePIR framework instantiated on the Spiral protocol outperforms constant-weight keyword PIR for both communication and computation, demonstrating the benefits of SparsePIR. Our experiments use similar settings as [50] with 16-bit keyword lengths and database sizes of \(2^{10}, 2^{12}\) and \(2^{14}\).

Batch Keyword PIR. In Figure 14, we present experiments for batch keyword PIR using the batch PIR framework of Angel et al. [9]. As the underlying keyword PIR, we use the cuckoo hashing framework [8] and our SparsePIR framework. We use Spiral as the blackbox PIR protocol for both frameworks. We run our experiments on \(2^{20}\) 288-byte entries, which are also used in [9]. We used \(\tau = 3\) hash functions and the number of buckets to be \(1.5\ell\) where \(\ell\) is the batch size. We observe that SparsePIR halves response size and reduces server costs.

<table>
<thead>
<tr>
<th>(d_1)</th>
<th>SparsePIR</th>
<th>SparsePIRε</th>
<th>SparsePIRc</th>
</tr>
</thead>
<tbody>
<tr>
<td>128</td>
<td>(\epsilon) 0.38</td>
<td>0.1</td>
<td>&lt; 0.03</td>
</tr>
<tr>
<td>Client Storage</td>
<td>0 B</td>
<td>0 B</td>
<td>11.1 KB</td>
</tr>
<tr>
<td>512</td>
<td>(\epsilon) 0.18</td>
<td>0.06</td>
<td>&lt; 0.03</td>
</tr>
<tr>
<td>Client Storage</td>
<td>0 B</td>
<td>0 B</td>
<td>3.4 KB</td>
</tr>
<tr>
<td>1024</td>
<td>(\epsilon) 0.12</td>
<td>0.05</td>
<td>&lt; 0.03</td>
</tr>
<tr>
<td>Client Storage</td>
<td>0 B</td>
<td>0 B</td>
<td>1.8 KB</td>
</tr>
</tbody>
</table>

Figure 11: Comparisons of SparsePIR, SparsePIRε and SparsePIRc of achievable \(\epsilon\) for \(n = 2^{20}\) elements.
### Table 1: Comparison of PIR Protocols

<table>
<thead>
<tr>
<th>Database</th>
<th>Onion CH-PIR</th>
<th>Onion SparsePIR</th>
<th>Onion SparsePIR&lt;sup&gt;c&lt;/sup&gt;</th>
<th>Onion SparsePIR&lt;sup&gt;c&lt;/sup&gt;</th>
<th>Spiral CH-PIR</th>
<th>Spiral SparsePir</th>
<th>Spiral SparsePIR&lt;sup&gt;g&lt;/sup&gt;</th>
<th>Spiral SparsePIR&lt;sup&gt;c&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>2&lt;sup&gt;20&lt;/sup&gt; × 256 B</td>
<td>Query Size</td>
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<td>63 KB</td>
<td>63 KB</td>
<td>63 KB</td>
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<tr>
<td>Response Size</td>
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<td>127 KB</td>
<td>127 KB</td>
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<tr>
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<td>3.04 s</td>
<td>3.10 s</td>
<td>3.05</td>
<td>1.41 s</td>
<td>1.44 s</td>
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<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>0.006</td>
<td>0.012</td>
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<tr>
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<td>$0.000027</td>
<td>$0.000029</td>
<td>$0.000028</td>
<td>$0.000091</td>
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<tr>
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<tr>
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<td>127 KB</td>
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<tr>
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<tr>
<td>Response Size</td>
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<tr>
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<td>17.32 s</td>
<td>15.14 s</td>
<td>15.10 s</td>
<td>4.93 s</td>
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</table>

Figure 12: Comparison of cuckoo hashing (CH) and SparsePIR frameworks for various PIR protocols.

in exchange for small increase in computation.

### 8 Related Work

**Early PIR Schemes.** Single-server PIR was introduced by Kushilevitz and Ostrovsky [45]. Several follow-ups built PIR using number-theoretic assumptions [25,47,56] and the phi-hiding assumption [17, 34].

**Lattice-based PIR.** In recent years, many works studied practically efficient PIR schemes using lattice-based homomorphic encryption as first done in [6] with many follow-ups including [7–10,33,51,57].


**Batch PIR.** Several works [11,37,40,42,48] have studied batch PIR with the goal of efficiently querying multiple records at once. Recent works [9, 10] introduced probabilistic batch codes that are the most efficient batch PIR frameworks to date.

**Multi-Server PIR.** A long line of work has also studied PIR with multiple, non-colluding servers. Early work considered information-theoretic security [21, 29, 30]. Recent work showed concretely efficient constructions using function secret sharing [13, 35, 39].

**Other PIR Variants.** The notion of PIR with preprocessing was introduced by Beimel et al. [11] where the server holds a public hint string. This was also studied as doubly-efficient PIR [14, 18] with sub-linear online time using strong obfuscation assumptions.

Stateful PIR introduced by Patel et al. [58] allows clients to compute query-independent hints in an offline phase to help speed up online queries that was also studied in [54]. A recent line of work starting with Corrigan-Gibbs and Kogan [24] presented constructions with sub-linear online times. Multiple works have further studied the topic [23, 26, 41, 44, 62, 66].

### 9 Conclusions

In this paper, we proposed SparsePIR, SparsePIR<sup>g</sup> and SparsePIR<sup>c</sup>, frameworks that build keyword PIR from lattice-based standard PIR schemes. Our schemes reduce the response size by at least 2x compared to prior keyword PIR constructions. In essence, our frameworks show that keyword PIR may be built with identical communication and computation costs as standard PIR. We also show our keyword PIR frameworks may also be used to also halve the response overhead of batch keyword PIR.

### References

Figure 13: Comparison of SparsePIR and constant-weight (CW) keyword PIR with 16-bit keyword length [50].


Figure 14: Comparison of cuckoo hashing [8] and SparsePIR keyword PIR frameworks with Spiral [51] for batch PIR queries. The database size is $2^{20}$ 288-byte entries. The reported numbers are the amortized cost of retrieving a single entry.


