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Sparsity Lower Bounds for Dimensionality Reducing Maps

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Abstract

We give near-tight lower bounds for the sparsity required in several dimensionality reducing linear maps. First, consider the Johnson-Lindenstrauss (JL) lemma which states that for any set of n vectors in $\mathbb{R}^d$ there is a matrix $A \in \mathbb{R}^{m\times d}$ with $m = O(\varepsilon^{-2}\log n)$ such that mapping by A preserves pairwise Euclidean distances of these n vectors up to a $1\pm\varepsilon$ factor. We show that there exists a set of n vectors such that any such matrix A with at most s non-zero entries per column must have $s = \Omega(\varepsilon^{-1}\log n/\log(1/\varepsilon))$ as long as $m < O(n/\log(1/\varepsilon))$. This bound improves the lower bound of $\Omega(\min\{\varepsilon^{-2}, \varepsilon^{-1}\sqrt{\log_m d}\})$ by [Dasgupta-Kumar-Sarlós, STOC 2010], which only held against the stronger property of distributional JL, and only against a certain restricted class of distributions. Meanwhile our lower bound is against the JL lemma itself, with no restrictions. Our lower bound matches the sparse Johnson-Lindenstrauss upper bound of [Kane-Nelson, SODA 2012] up to an $O(\log(1/\varepsilon))$ factor.

Next, we show that any $m\times n$ matrix with the k-restricted isometry property (RIP) with constant distortion must have at least $\Omega(k\log(n/k))$ non-zeroes per column if $m = O(k\log(n/k))$, the optimal number of rows of RIP matrices, and $k < n/\operatorname{polylog} n$. This improves the previous lower bound of $\Omega(\min\{k, n/m\})$ by [Chandar, 2010] and shows that for virtually all k it is impossible to have a sparse RIP matrix with an optimal number of rows.

Both lower bounds above also offer a tradeoff between sparsity and the number of rows.

Lastly, we show that any oblivious distribution over subspace embedding matrices with 1 non-zero per column and preserving distances in a d dimensional-subspace up to a constant factor must have at least $\Omega(d^2)$ rows. This matches one of the upper bounds in [Nelson-Nguyễn, 2012] and shows the impossibility of obtaining the best of both of constructions in that work, namely 1 non-zero per column and $\tilde{O}(d)$ rows.

1 Introduction

The last decade has witnessed a burgeoning interest in algorithms for large-scale data. A common feature in many of these works is the exploitation of data sparsity to achieve algorithmic efficiency, for example to have running times proportional to the actual complexity of the data rather than the dimension of the ambient space it lives in. This approach has found applications in compressed sensing [CT05,Don06], dimension reduction [BOR10,DKS10,KN10,KN12,WDL+09], and numerical linear algebra [CW12, MM12, MP12, NN12]. Given the success of these algorithms, it is important to understand their limitations. Until now, for most of these problems it is not known how far one

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can reduce the running time on sparse inputs. In this work we make a step towards understanding the performance of algorithms for sparse data and show several tight lower bounds.

In this work we provide three main contributions. We give near-optimal or optimal sparsity lower bounds for Johnson-Lindenstrauss transforms, matrices satisfying the restricted isometry property for use in compressed sensing, and subspace embeddings used in numerical linear algebra. These three contributions are discussed in Section 1.1, Section 1.2, and Section 1.3, respectively.

1.1 Johnson-Lindenstrauss

The following lemma, due to Johnson and Lindenstrauss [JL84], has been used widely in many areas of computer science to reduce data dimension.

Theorem 1 (Johnson-Lindenstrauss (JL) lemma [JL84])**.** *For any $0 < \varepsilon < 1/2$ and any $x_1, \dots, x_n$ in $\mathbb{R}^d$, there exists $A \in \mathbb{R}^{m \times d}$ with $m = O(\varepsilon^{-2} \log n)$ such that for all $i, j \in [n]$*[1]*,*

$$\|Ax_i - Ax_j\|_2 = (1 \pm \varepsilon)\|x_i - x_j\|_2.$$

Typically one uses the lemma in algorithm design by mapping some instance of a high-dimensional computational geometry problem to a lower dimension. The running time to solve the instance then becomes the time needed for the lower-dimensional problem, plus the time to perform the matrix-vector multiplications Ax_i; see [Ind01, Vem04] for further discussion. This latter step highlights the importance of having a JL matrix supporting fast matrix-vector multiplication. The original proofs of the JL lemma took A to be a random dense matrix, e.g. with i.i.d. Gaussian, Rademacher, or even subgaussian entries [Ach03, AV06, DG03, FM88, IM98, JL84, Mat08]. The time to compute Ax then becomes $O(m \cdot \|x\|_0)$, where x has $\|x\|_0 \le d$ non-zero entries.

A beautiful work of Ailon and Chazelle [AC09] described a construction of a JL matrix A supporting matrix-vector multiplication in time $O(d \log d + m^3)$, also with $m = O(\varepsilon^{-2} \log n)$. This was improved to $O(d \log d + m^{2+\gamma})$ [AL09] with the same m for any constant $\gamma > 0$, or to $O(d \log d)$ with $m = O(\varepsilon^{-2} \log n \log^4 d)$ [AL11, KW11]. Thus if $\varepsilon^{-2} \log n \ll \sqrt{d}$ one can obtain nearly-linear $O(d \log d)$ embedding time with the same target dimension m as the original JL lemma, or one can also obtain nearly-linear time for any setting of ε, n by increasing m slightly by polylog d factors.

While the previous paragraph may seem to present the end of the story, in fact note that the "nearly-linear" $O(d \log d)$ embedding time is actually much worse than the original $O(m \cdot \|x\|_0)$ time of dense JL matrices when $\|x\|_0$ is very small, i.e. when x is sparse. Indeed, in several applications we expect x to be sparse. Consider the bag of words model in information retrieval: in for example an email spam collaborative filtering system for Yahoo! Mail [WDL$^+$09], each email is treated as a d-dimensional vector where d is the size of the lexicon. The ith entry of the vector is some weighted count of the number of occurrences of word i (frequent words like "the" should be weighted less heavily). A machine learning algorithm is employed to learn a spam classifier, which involves dot products of email vectors with some learned classifier vector, and JL dimensionality reduction is used to speed up the repeated dot products that are computed during training. Note that in this scenario we expect x to be sparse since most emails do not contain nearly every word in the lexicon. An even starker scenario is the turnstile streaming model, where the vectors x may receive coordinate-wise updates in a data stream. In this case maintaining Ax in a stream given some update of the form "add v to x_i" requires adding vAe_i to the compression Ax stored in memory. Since $\|e_i\| = 1$, we would not like to spend $O(d \log d)$ per streaming update.

[1] Here and throughout this paper, $[n]$ denotes the set $\{1, \dots, n\}$.

The intuition behind all the works [AC09, AL09, AL11, KW11] to obtain $O(d \log d)$ embedding time was as follows. Picking A to be a scaled sampling matrix (where each row has a 1 in a random location) gives the correct expectation for $\|Ax\|_2^2$, but the variance may be too high. Indeed, the variance is high exactly when x is sparse; consider the extreme case where $\|x\|_0 = 1$ so that sampling is not even expected to see the non-zero coordinate unless $m \geq d$. These works then all essentially proceed by randomly preconditioning x to ensure that x is very well-spread (i.e. far from sparse) with high probability, so that sampling works, and thus fundamentally cannot take advantage of input sparsity. One way of obtaining faster matrix-vector multiplication for sparse inputs is to have sparse JL matrices A. Indeed, if A has at most s non-zero entries per column then Ax can be computed in $O(s \cdot \|x\|_0 + m)$ time. A line of work [Ach03, Mat08, DKS10, BOR10, KN10, KN12] investigated the value s achievable in a JL matrix, culminating in [KN12] showing that it is possible to simultaneously have $m = O(\varepsilon^{-2} \log n)$ and $s = O(\varepsilon^{-1} \log n)$. Such a sparse JL transform thus speeds up embeddings by a factor of roughly $1/\varepsilon$ without increasing the target dimension.

Our Contribution I: We show that for any $n \geq 2$ and any $\varepsilon = \Omega(1/\sqrt{n})$, there exists a set of n vectors $x_1, \ldots, x_n \in \mathbb{R}^n$ such that any JL matrix for this set of vectors with $m = O(\varepsilon^{-2} \log n)$ rows requires column sparsity $s = \Omega(\varepsilon^{-1} \log n / \log(1/\varepsilon))$ as long as $m = O(n/\log(1/\varepsilon))$. Thus the sparse JL transforms of [KN12] achieve optimal sparsity up to an $O(\log(1/\varepsilon))$ factor. In fact this lower bound on s continues to hold even if $m = O(\varepsilon^{-c} \log n)$ for any positive constant c.

Note that if $m = n$ one can simply take A to be the identity matrix which achieves $s = 1$, and thus the restriction $m = O(n/\log(1/\varepsilon))$ is nearly optimal. Also note that we can assume $\varepsilon = \Omega(1/\sqrt{n})$ since otherwise $m = \Omega(n)$ is required in any JL matrix [Alo09], and thus the $m = O(n/\log(1/\varepsilon))$ restriction is no worse than requiring $m = O(n/\log n)$. Furthermore if all the entries of A are required to be equal in magnitude, our lower bound holds as long as $m \leq n/10$.

Before our work, only a restricted lower bound of $s = \Omega(\min\{1/\varepsilon^2, \varepsilon^{-1}\sqrt{\log_m d}\})$ had been shown [DKS10]. In fact this lower bound only applied to the *distributional JL problem*, a much stronger guarantee where one wants to design a distribution over $m \times d$ matrices such that any fixed vector x has $\|Ax\|_2 = (1 \pm \varepsilon)\|x\|_2$ with probability $1 - \delta$ over the choice of A. Indeed any distributional JL construction yields the JL lemma by setting $\delta = 1/n^2$ and union bounding over all the $x_i - x_j$ difference vectors. Thus, aside from the weaker lower bound on s, [DKS10] only provided a lower bound against this stronger guarantee, and furthermore only for a certain restricted class of distributions that made certain independence assumptions amongst matrix entries, and also assumed certain bounds on the sum of fourth moments of matrix entries in each row.

It was shown by Alon [Alo09] that $m = \Omega(\varepsilon^{-2} \log n / \log(1/\varepsilon))$ is required for the set of points $\{0, e_1, \ldots, e_n\}$ and $d = n$ as long as $1/\varepsilon^2 < n/2$. Here e_i is the ith standard basis vector. Simple manipulations show that, when appropriately scaled, any JL matrix A for this set of vectors is $O(\varepsilon)$-*incoherent*, in the sense that all its columns $v_1, \ldots, v_n$ have unit ℓ_2 norm and the dot products $\langle v_i, v_j \rangle$ between pairs of columns are all at most $O(\varepsilon)$ in magnitude. We study this exact same hard input to the JL lemma; what we show is that any such matrix A must have column sparsity $s = \Omega(\varepsilon^{-1} \log n / \log(1/\varepsilon))$.

In some sense our lower bound can be viewed as a generalization of the Singleton bound for error-correcting codes in a certain parameter regime. The Singleton bound states that for any set of n codewords with block length t, alphabet size q, and relative distance r, it must be that $n \leq q^{t-r+1}$. If the code has relative distance $1 - \varepsilon$ then $t - r \leq \varepsilon t$, so that if $t \geq 1/\varepsilon$ the Singleton bound implies $t = \Omega(\varepsilon^{-1} \log n / \log q)$. The connection to incoherent matrices (and thus the JL lemma), observed in [Alo09], is the following. For any such code $\{C_1, \ldots, C_n\}$, form a matrix $A \in \mathbb{R}^{m\times n}$ with $m = qt$. The rows are partitioned into t chunks each of size q. In the ith column of A, in the jth chunk we put a $1/\sqrt{t}$ in the row of that chunk corresponding to the symbol $(C_i)_j$, and we put zeroes everywhere else in that column. All columns then have ℓ_2 norm 1, and the code having relative distance $1 - \varepsilon$ implies that all pairs of columns have dot products at most ε. The Singleton bound thus implies that any incoherent matrix formed from codes in this way has $t = \Omega(\varepsilon^{-1}\log n/\log q)$. Note the column sparsity of A is t, and thus this matches our lower bound for $q \le \mathrm{poly}(1/\varepsilon)$. Our sparsity lower bound thus recovers this Singleton-like bound, without the requirement that the matrix takes this special structure of being formed from a code in the manner described above. One reason this is perhaps surprising is that incoherent matrices from codes have all nonnegative entries; our lower bound thus implies that the use of negative entries cannot be exploited to obtain sparser incoherent matrices.

1.2 Compressed sensing and the restricted isometry property

Another object of interest are matrices satisfying the restricted isometry property (RIP). Such matrices are widely used in compressed sensing.

Definition 2 ([CT05, CRT06b, Can08])**.** *For any integer $k > 0$, a matrix A is said to have the k-restricted isometry property with distortion δ_k if $(1-\delta_k)\|x\|_2^2 \le \|Ax\|_2^2 \le (1+\delta_k)\|x\|_2^2$ for all x with $\|x\|_0 \le k$.*

The goal of the area of compressed sensing is to take few nonadaptive linear measurements of a vector $x \in \mathbb{R}^n$ to allow for later recovery from those measurements. That is to say, if those measurements are organized as the rows of some matrix $A \in \mathbb{R}^{m\times n}$, we would like to recover x from Ax. Furthermore, we would like do so with $m \ll n$ so that Ax is a *compressed* representation of x. Of course if $m < n$ we cannot recover all vectors $x \in \mathbb{R}^n$ with any meaningful guarantee, since then A will have a non-trivial kernel, and $x, x+y$ are indistinguishable for $y \in \ker(A)$. Compressed sensing literature has typically focused on the case of x being sparse [CRT06a, Don06], in which case a recovery algorithm could hope to recover x by finding the sparsest $\tilde{x}$ such that $A\tilde{x} = Ax$.

The works [Can08, CRT06b, CT05] show that if A satisfies the $2k$-RIP with distortion $\delta_k < \sqrt{2} - 1$, and if x is k-sparse, then given Ax there is a polynomial-time solvable linear program to recover x. In fact for any x, not necessarily sparse, the linear program recovers a vector $\tilde{x}$ satisfying

$$\|x - \tilde{x}\|_2 \le O(1/\sqrt{k}) \cdot \inf_{\|z\|_0 \le k} \|x - z\|_1,$$

known as the ℓ_2/ℓ_1 *guarantee*. That is, the recovery error depends on the ℓ_1 norm of the best k-sparse approximation z to x.

It is known [BIPW10, GG84, Kaš77] that any matrix A allowing for the ℓ_2/ℓ_1 guarantee simultaneously for all vectors x, and thus RIP matrices, must have $m = \Omega(k\log(n/k))$ rows. For completeness we give a proof of the new stronger lower bound $m = \Omega(\log^{-1}(1/\delta_k)(\delta_k^{-1} k\log(n/k) + \delta_k^{-2}k))$ in Section 5, though we remark here that current uses of RIP all take $\delta_k = \Theta(1)$.

Although the recovery $\tilde{x}$ of x can be found in polynomial time as mentioned above, this polynomial is quite large as the algorithm involves solving a linear program with n variables and m constraints. This downside has led researchers to design alternative measurement and/or recovery schemes which allow for much faster sparse recovery, sometimes even at the cost of obtaining a recovery guarantee weaker than ℓ_2/ℓ_1 recovery for the sake of algorithmic performance. Many of these schemes are iterative, such as CoSaMP [NT09], Expander Matching Pursuit [IR08], and several others [BI09, BIR08, BD08, DTDlS12, Fou11, GK09, NV09, NV10, TG07], and several of their running times depend on the product of the number of iterations and the time required to multiply by A or A^* (here A^* denotes the conjugate transpose of A). Several of these algorithms furthermore apply A, A^* to vectors which are themselves sparse. Thus, recovery time is improved significantly in the case that A is sparse. Previously the only known lower bound for column sparsity s for an RIP matrix with an optimal $m = \Theta(k \log(n/k))$ number of rows was $s = \Omega(\min\{k, n/m\})$ [Cha10]. Note that if an RIP construction existed matching the [Cha10] column sparsity lower bound, application to a k-sparse vector would take time $O(\min\{k^2, nk/m\})$, which is always $o(n)$ and can be very fast for small k. Furthermore, in several applications of compressed sensing m is very close to n, in which case an $\Omega(n/m)$ lower bound on column sparsity does not rule out very sparse RIP matrices. For example, in applications of compressed sensing to magnetic resonance imaging, [LDP07] recommended setting the number of measurements m to be between 5-10% of n to obtain good performance for recovery of brain and angiogram images. We remark that one could also obtain speedup by using structured RIP matrices, such as those obtained by sampling rows of the discrete Fourier matrix [CT06], though such constructions require matrix-vector multiplication time $\Theta(n \log n)$ independent of input sparsity.

Another upside of sparse RIP matrices is that they allow faster algorithms for encoding $x \mapsto Ax$. If A has s non-zeroes per column and x receives, for example, turnstile streaming updates, then the compression Ax can be maintained on the fly in $O(s)$ time per update (assuming the non-zero entries of any column of A can be recovered in $O(s)$ time).

Our Contribution II: We show as long as $k < n/\operatorname{polylog} n$, any k-RIP matrix with distortion $O(1)$ and $m = \Theta(k \log(n/k))$ rows with s non-zero entries per column must have $s = \Omega(k \log(n/k))$. That is, RIP matrices with the optimal number of rows must be dense for almost the full range of k up to n. This lower bound strongly rules out any hope for faster recovery and compression algorithms for compressed sensing by using sparse RIP matrices as mentioned above.

We note that any sparsity lower bound should fail as k approaches n since the $n \times n$ identity matrix trivially satisfies k-RIP for any k and has column sparsity 1. Thus, our lower bound holds for almost the full range of parameters for k.

1.3 Oblivious Subspace Embeddings

The last problem we consider is the oblivious subspace embedding (OSE) problem. Here one aims to design a distribution $\mathcal{D}$ over $m \times n$ matrices A such that for any d-dimensional subspace $W \subset \mathbb{R}^n$,

$$\mathbb{P}_{A \sim \mathcal{D}}(\forall x \in W \ \|Ax\|_2 \in (1 \pm \varepsilon)\|x\|_2) > 2/3.$$

Sarlós showed in [Sar06] that OSE's are useful for approximate least squares regression and low rank approximation, and they have also been shown useful for approximating statistical leverage scores [DMIMW12], an important concept in statistics and machine learning. See [CW12] for an overview of several applications of OSE's.

To give more details of how OSE's are typically used, consider the example of solving an overconstrained least-squares regression problem, where one must compute $\operatorname{argmin}_x \|Sx - b\|_2$ for some $S \in \mathbb{R}^{n \times d}$. By overconstrained we mean $n > d$, and really one should imagine $n \gg d$ in what follows. There is a closed form solution for the minimizing vector x, which requires computing the Moore-Penrose pseudoinverse of S. The total running time is $O(nd^{\omega-1})$, where ω is the exponent of square matrix multiplication.

Now suppose we are only interested in finding some $\tilde{x}$ so that

$$\|S\tilde{x} - b\|_2 \le (1+\varepsilon) \cdot \operatorname{argmin}_x \|Sx - b\|_2.$$

Then it suffices to have a matrix A such that $\|Az\|_2 = (1 \pm O(\varepsilon))\|z\|_2$ for all z in the subspace spanned by b and the columns of A, in which case we could obtain such an $\tilde{x}$ by solving the new least squares regression problem of computing $\operatorname{argmin}_{\tilde{x}} \|AS\tilde{x} - Ab\|_2$. If A has m rows, the new running time is the sum of three terms: (1) the time to compute Ab, (2) the time to compute AS, and (3) the $O(md^{\omega-1})$ time required to solve the new least-squares problem. It turns out it is possible to obtain such an A with $m = O(d/\varepsilon^2)$ by choosing, for example, a matrix with independent Gaussian entries (see e.g. [Gor88,KM05]), but then computing AS takes time $\Omega(nd^{\omega-1})$, providing no benefit.

The work of Sarlós picked A with special structure so that AS can be computed in time $O(nd\log n)$, namely by using the Fast Johnson-Lindenstrauss Transform of [AC09] (see also [Tro11]). Unfortunately the time is $O(nd\log n)$ even for sparse matrices S, and several applications require solving numerical linear algebra problems on sparse matrix inputs. For example in the Netflix matrix where rows are users and columns are movies, and $S_{i,j}$ is some rating score, S is very sparse since most users rate only a tiny fraction of all movies [ZWSP08]. If $\text{nnz}(S)$ denotes the number of non-zero entries of S, we would like running times closer to $O(\text{nnz}(S))$ than $O(nd\log n)$ to multiply A by S. Such a running time would be possible, for example, if A only had $s = O(1)$ non-zero entries per column.

In a recent and surprising work, Clarkson and Woodruff [CW12] gave an OSE with $m = \text{poly}(d/\varepsilon)$ and $s = 1$, thus providing fast numerical linear algebra algorithms for sparse matrices. For example, the running time for least-squares regression becomes $O(\text{nnz}(A) + \text{poly}(d/\varepsilon))$. The dependence on d, ε was improved in [NN12] to $m = O(d^2/\varepsilon^2)$. The work [NN12] also showed how to obtain $m = O(d^{1+\gamma}/\varepsilon^2)$, $s = O(1/\varepsilon)$ for any constant $\gamma > 0$ (the constant in the big-Oh depends polynomially on $1/\gamma$), or $m = (d\,\text{polylog}\, d)/\varepsilon^2$, $s = (\text{polylog}\, d)/\varepsilon$. It is thus natural to ask whether one can obtain the best of both worlds: can there be an OSE with $m \approx d/\varepsilon^2$ and $s = 1$?

Our Contribution III: In this work we show that any OSE such that all matrices in its support have m rows and $s = 1$ non-zero entries per column must have $m = \Omega(d^2)$ if $n \ge 2d^2$. Thus for constant ε and large n, the upper bound of [NN12] is optimal.

1.4 Organization

In Section 2 we prove our lower bound for the sparsity required in JL matrices. In Section 3 we give our sparsity lower bound for RIP matrices, and in Section 4 we give our lower bound on the number of rows for OSE's having sparsity 1. In Section 5 we give a lower bound involving δ_k on the number of rows in an RIP matrix, and in Section 6 we state an open problem.

2 JL Sparsity Lower Bound

Define an ε-incoherent matrix $A \in \mathbb{R}^{m\times n}$ as any matrix whose columns have unit ℓ_2 norm, and such that every pair of columns has dot product at most ε in magnitude. A simple observation of [Alo09] is that any JL matrix A for the set of vectors $\{0, e_1, \dots, e_n\} \in \mathbb{R}^n$, when its columns are scaled by their ℓ_2 norms, must be $O(\varepsilon)$-incoherent.

In this section, we consider an ε-incoherent matrix $A \in \mathbb{R}^{m \times n}$ with at most s non-zero entries per column. We show a lower bound on s in terms of ε, n, m. In particular if $m = O(\varepsilon^{-2} \log n)$ is the number of rows guaranteed by the JL lemma, we show that $s = \Omega(\varepsilon^{-1} \log n / \log(1/\varepsilon))$ as long as $m < n/\operatorname{polylog} n$. In fact if all the entries in A are either 0 or equal in magnitude, we show that the lower bound even holds up to $m < n/10$.

In Section 2.1 we give the lower bound on s in the case that all entries in A are in $\{0, 1/\sqrt{s}, -1/\sqrt{s}\}$. In Section 2.2 we give our lower bound without making any assumption on the magnitudes of entries in A. Before proceeding further, we prove a couple lemmas used throughout this section, and also later in this paper. Throughout this section A is always an ε-incoherent matrix.

Lemma 3. *For any $x \ge 2\varepsilon$, A cannot have any row with at least $5/x$ entries greater than $\sqrt{x}$, nor can it have any row with at least $1/x$ entries less than $-\sqrt{x}$.*

Proof. For the sake of contradiction, suppose A did have such a row, say the jth row. Suppose $A_{j,i_1}, \dots, A_{j,i_N} > \sqrt{x}$ for some $x \ge 2\varepsilon$, where $N \ge 5/x$ (the case where they are each less than $-\sqrt{x}$ is argued identically). Let v_i denote the ith column of A. Let u_i be v_i but with the jth coordinate replaced with 0. Then for any $k_1, k_2 \in [N]$

$$\langle u_{i_{k_1}}, u_{i_{k_2}} \rangle \le \langle v_{i_{k_1}}, v_{i_{k_2}} \rangle - x \le \varepsilon - x \le -x/2.$$

Thus we have

$$0 \le \left\| \sum_{j=1}^{N} u_{i_j} \right\|_2^2 \le N - xN(N-1)/4,$$

and rearranging gives the contradiction $1/x \ge (N-1)/4 > 1/x$. ■

Lemma 4. *Let s, q, r be positive reals with $q/r \ge 2$ and $s \le q/e$. Then if $s \ln(q/s) \ge r$ it must be the case that $s = \Omega(r/\ln(q/r))$.*

Proof. Define the function $f(s) = s \ln(q/s)$. Then $f'(s) = \ln(q/(es))$ is increasing for $s \le q/e$. Then since $q/r \ge 2$, for $s = cr \ln(q/r)$ for constant $c > 0$ we have the equality $s \ln(q/s) = cr/\ln(q/r) \ln((q/r)\ln(q/r)) = (c + o_{q/r}(1)) r \ln(q/r)$, where the $o_{q/r}(1)$ term goes to zero as $q/r \to \infty$. Thus for c sufficiently small we have that the $c + o_{q/r}(1)$ term must be less than 1, so in order to have $f(s) \ge r$, since f is increasing we must have $s = \Omega(r/\ln(q/r))$. ■

2.1 Sign matrices

In this section we consider the case that all entries of A are either 0 or $\pm 1/\sqrt{s}$ and show a lower bound on s in this case.

Lemma 5. *Suppose $m < n/10$ and all entries of A are in $\{0, 1/\sqrt{s}, -1/\sqrt{s}\}$. Then $s \ge 1/(2\varepsilon)$.*

Proof. For the sake of contradiction suppose $s < 1/(2\varepsilon)$. There are ns non-zero entries in A and thus at least $ns/2$ of these entries have the same sign by the pigeonhole principle; wlog let us say $1/\sqrt{s}$ appears at least $ns/2$ times. Then again by pigeonhole some row j of A has $N = ns/(2m)$ values that are $1/\sqrt{s}$. The claim now follows by Lemma 3 with $x = 1/\sqrt{s}$. ■

We now show how to improve the bound to the desired form.

Theorem 6. *Suppose $m < n/10$ and all entries of A are in $\{0, 1/\sqrt{s}, -1/\sqrt{s}\}$. Then $s \ge \Omega(\varepsilon^{-1}\log n/\log(m/\log n))$.*

Proof. We know $s \ge 1/(2\varepsilon)$ by Lemma 5. Let $t = 2\varepsilon s \ge 1$. Every v_i has $\binom{s}{t}$ subsets of size t of non-zero coordinates. Thus by pigeonhole there exists a set of t rows $i_1, \ldots, i_t$ and $N = n\binom{s}{t}/(2^t\binom{m}{t})$ columns $v_{j_1}, \ldots, v_{j_N}$ such that for each row all entries in those columns are $1/\sqrt{s}$ in magnitude and have the same sign (the signs may vary across rows). Letting u_j be v_j but with those t coordinates set to 0, we have

$$\langle u_{j_{k_1}}, u_{j_{k_2}}\rangle = \langle v_{j_{k_1}}, v_{j_{k_2}}\rangle - t/s \le \varepsilon - t/s \le -t/(2s).$$

Thus we have

$$0 \le \left\|\sum_{k=1}^{N} u_{j_k}\right\|_2^2 \le N - tN(N-1)/(4s)$$

so that rearranging gives

$$s \ge t(N-1)/4 = (t/4)\cdot\left(\frac{n\binom{s}{t}}{2^t\binom{m}{t}} - 1\right) \ge (t/4)\cdot(n(s/(2em))^t - 1).$$

Suppose $s < c\varepsilon^{-1}\log n/\log(2em/n)$ for some small constant c so that $n(s/(2em))^t \ge 2$. Then

$$s \ge (tn/8)\cdot(s/(2em))^t.$$

Thus

$$\frac{\varepsilon n}{4} = \frac{tn}{8s} \le \left(\frac{2em}{s}\right)^t.$$

Taking the natural logarithm of both sides gives

$$s\ln\left(\frac{2em}{s}\right) \ge \frac{1}{2\varepsilon}\ln\left(\frac{\varepsilon n}{4}\right).$$

Define $q = 2em$, $r = \varepsilon^{-1}\ln(\varepsilon n/4)/2$. Then $s \le q/e$, since $s \le m$. By [Alo09] we must have $m = \Omega(\varepsilon^{-2}\log n/\log(1/\varepsilon))$, so $q/r \ge 2$ for ε smaller than some fixed constant. Thus by Lemma 4 we have $s = \Omega(r/\ln(q/r))$. The theorem follows since $\log(\varepsilon m/\log n) = \Theta(m/\log n)$ since $m = \Omega(\varepsilon^{-2}\log n/\log(1/\varepsilon))$ [Alo09]. ■

Corollary 7. *Suppose $m \le \mathrm{poly}(1/\varepsilon)\cdot\log n < n/10$ and all entries of A are in $\{0, 1/\sqrt{s}, -1/\sqrt{s}\}$. Then $s \ge \Omega(\varepsilon^{-1}\log n/\log(1/\varepsilon))$.*

2.2 General matrices

We now consider arbitrary sparse and nearly orthogonal matrices $A \in \mathbb{R}^{m\times n}$. That is, we no longer require the non-zero entries of A to be $1/\sqrt{s}$ in magnitude.

Lemma 8. *Suppose $m < n/(20\ln(1/2\varepsilon))$. Then $s \ge 1/(4\varepsilon)$.*

Proof. For the sake of contradiction suppose $s < 1/(4\varepsilon)$. We know by Lemma 3 that for any $x \geq 2\varepsilon$, no row of A can have more than $5/x$ entries of value at least $\sqrt{x}$ in magnitude and of the same sign. Define $S_i = \{j : A_{i,j}^2 \geq 2\varepsilon\}$. Let S_i^+ be the subset of indices j in S_i with $A_{i,j} > 0$, and define $S_i^- = S_i \backslash S_i^+$. Let X denote the square of a random positive value from S_i^+. Then

$$\sum_{j \in S_i^+} A_{i,j}^2 = |S_i^+| \cdot \mathbb{E}X = |S_i^+| \cdot \int_0^1 \mathbb{P}(X > x)\, dx \leq 2\varepsilon |S_i^+| + \int_{2\varepsilon}^1 \frac{5}{x} dx = 2\varepsilon |S_i^+| + 5\ln(1/2\varepsilon).$$

By analogously bounding the sum of squares of entries in S_i^-, we have that the sum of squares of entries at least $\sqrt{2\varepsilon}$ in magnitude is never more than $2\varepsilon|S_i| + 10\ln(1/2\varepsilon)$ in the ith row of A, for any i. Thus the total sum of squares of all entries in the matrix less than $\sqrt{2\varepsilon}$ in magnitude is at most $2\varepsilon(ns - \sum_i |S_i|)$. Meanwhile the sum of all other entries is at most $2\varepsilon(\sum_i |S_i|) + 10m\ln(1/2\varepsilon)$. Thus the sum of squares of all entries in the matrix is at most $2\varepsilon ns + 10m\ln(1/2\varepsilon) < n/2 + 10m\ln(1/2\varepsilon)$, by our assumption on s. This quantity must be n, since every column of A has unit ℓ_2 norm. However for our stated value of m this is impossible since $10m\ln(1/2\varepsilon) < n/2$, a contradiction. ■

We now show how to obtain the extra factor of $\log n / \log(1/\varepsilon)$ in the lower bound.

Lemma 9. *Let $0 < \varepsilon < 1/2$. Suppose $v_1, \ldots, v_n \in \mathbb{R}^m$ each have $\|v\|_2 = 1$ and $\|v\|_0 \leq s$, and furthermore $|\langle v_i, v_j\rangle| \leq \varepsilon$ for $i \neq j$. Then for any $t \in [s]$ with $t/s > C\varepsilon$, we must have $s \geq t(N-1)/(2C)$ with*

$$N = \left\lceil \frac{n}{2^t \binom{m}{t}\binom{2(s+t)}{t}} \right\rceil, \qquad C = 2/(1 - 1/\sqrt{2}).$$

Proof. We label each vector v_i by its *t-type*, defined in the following way. The t-type of a vector v_i is the set of locations of the t largest coordinates in magnitude, as well as the signs of those coordinates, together with a rounding of those top t coordinates so that their squares round to the nearest integer multiple of $1/(2s)$. In the rounding, values halfway between two multiples are rounded arbitrarily; say downward, to be concrete. Note that the amount of ℓ_2 mass contained in the top t coordinates of any v_i after such a rounding is at most $1 + t/(2s)$, and thus the number of roundings possible is at most the number of ways to write a positive integer in $[2s + t]$ as a sum of t positive integers, which is $\binom{2s+2t}{t}$. Thus the total number of possible t-types is at most $2^t\binom{m}{t}\binom{2(s+t)}{t}$ ($\binom{m}{t}$ choices of the largest t coordinates, 2^t choices of their signs, and $\binom{2(s+t)}{t}$ choices for how they round). Thus by the pigeonhole principle, there exist N vectors $v_{i_1}, \ldots, v_{i_N}$ each with the same t-type such that $N \geq \left\lceil n/(2^t\binom{m}{t}\binom{2(s+t)}{t})\right\rceil$.

Now for these vectors $v_{i_1}, \ldots, v_{i_N}$, let $S \subset [n]$ of size t be the set of the largest coordinates (in magnitude) in each v_{i_j}. Define $u_{i_j} = (v_{i_j})_{[n]\backslash S}$; that is, we zero out the coordinates in S. Then for $j \neq k \in [N]$,

$$\begin{aligned}
\langle u_{i_j}, u_{i_k}\rangle &= \langle v_{i_j}, v_{i_k}\rangle - \sum_{r \in S} (v_{i_j})_r (v_{i_k})_r \\
&\leq \varepsilon - \sum_{r \in S} (v_{i_j})_r ((v_{i_j})_r \pm 1/\sqrt{2s}) \\
&\leq \varepsilon - \sum_{r \in S} \left((v_{i_j})_r^2 - |(v_{i_j})_r|/\sqrt{2s}\right)
\end{aligned}$$

$$\leq \varepsilon - \|(v_{i_j})_S\|_2^2 + \sqrt{t/(2s)} \cdot \left\|(v_{i_j})_S\right\|_2$$
$$\leq \varepsilon - \left(1 - \frac{1}{\sqrt{2}}\right) t/s. \tag{1}$$

The last inequality used that $\|(v_{i_j})_S\|_2 \geq \sqrt{t/s}$. Also we pick t to ensure $t/s > 2\varepsilon/(1-1/\sqrt{2})$ so that the right hand side of Eq. (1) is less than $-((1-1/\sqrt{2})/2)t/s = -Ct/s$. The penultimate inequality follows by Cauchy-Schwarz. Thus we have

$$\left\|\sum_{j=1}^{N} u_{i_j}\right\|_2^2 = \sum_{j=1}^{N} \|u_{i_j}\|_2^2 + \sum_{j\neq k} \langle u_{i_j}, u_{i_k}\rangle$$
$$\leq N - C(t/s)N(N-1)/2 \tag{2}$$

However we also have $\|\sum_j u_{i_j}\|_2^2 \geq 0$, which implies $s \geq C(N-1)t/2$ by rearranging Eq. (2). ■

Theorem 10. *There is some fixed $0 < \varepsilon_0 \leq 1/2$ so that the following holds. Let $1/\sqrt{n} < \varepsilon < \varepsilon_0$. Suppose $v_1, \ldots, v_n \in \mathbb{R}^m$ each have $\|v\|_2 = 1$ and $\|v\|_0 \leq s$, and furthermore $|\langle v_i, v_j\rangle| \leq \varepsilon$ for $i \neq j$. Then $s \geq \Omega(\varepsilon^{-1}\log n/\log(m/\log n))$ as long as $m < O(n/\ln(1/\varepsilon))$.*

Proof. By Lemma 8, $4\varepsilon s \geq 1$. Set $t = 7\varepsilon s$ so that Lemma 9 applies. Then by Lemma 9, as long as $2^t\binom{m}{t}\binom{2(s+t)}{t} \leq n/2$,

$$7\varepsilon n = \frac{tn}{s} \leq 4C \cdot 2^t \binom{m}{t}\binom{2(s+t)}{t}$$
$$\leq 4C \cdot \left(\frac{8e^2 m}{49\varepsilon^2 s}\right)^{7\varepsilon s},$$

where C is as in Lemma 9. Taking the natural logarithm on both sides,

$$\ln(7\varepsilon n/(4C)) \leq (7\varepsilon s)\ln\left(\frac{8e^2 m}{49\varepsilon^2 s}\right)$$

In other words,

$$s \geq \frac{\ln(7\varepsilon n/(4C))}{7\varepsilon \ln\left(\frac{8e^2 m}{49\varepsilon^2 s}\right)}.$$

Define $r = \ln(7\varepsilon n/(4C))/(7\varepsilon)$, $q = 8e^2 m/(49\varepsilon^2)$. Thus we have $s\ln(q/s) \geq r$. We have that $s \leq q/e$ is always the case for $\varepsilon < 1/2$ since then $q/e \geq m$ and we have that $s \leq m$. Also note for ε smaller than some constant we have that $q/r > 2$ since $m = \Omega(\log n)$ by [Alo09]. Thus by Lemma 4 we have $s \geq \Omega(r/\ln(q/r))$. Using that $\ln(\varepsilon n) = \Theta(\log n)$ since $\varepsilon > 1/\sqrt{n}$, and that $2^t\binom{m}{t}\binom{2(s+t)}{t} \leq (8e^2 m/(49\varepsilon^2 s)) \leq n/2$ for our setting of t when $s = o(\varepsilon^{-1}\log n/\log(m/(\varepsilon^{-1}\log n)))$ gives $s = \Omega(\varepsilon^{-1}\log n/\log(\varepsilon^{-1}m/\log n))$. Since $m = \Omega(\varepsilon^{-2}\log n/\log(1/\varepsilon))$ [Alo09], this is equivalent to our lower bound in the theorem statement. ■

Corollary 11. *Let ε, m, s be as in Theorem 10. Then $s = \Omega(\varepsilon^{-1}\log n/\log(1/\varepsilon))$ as long as $m \leq \mathrm{poly}(1/\varepsilon) \cdot \log n < O(n/\ln(1/\varepsilon))$.*

Remark 12. From Theorem 10, we can deduce that for constant ε, in order for the sparsity s to be a constant independent of n, it must be the case that $m = n^{\Omega(1)}$. This fact rules out very sparse mappings even when we significantly increase the target dimension.

3 RIP Sparsity Lower Bound

Consider a k-RIP matrix $A \in \mathbb{R}^{m \times n}$ with distortion δ_k where each column has at most s non-zero entries. We will show for $\delta_k = \Theta(1)$ that s cannot be very small when m has the optimal number of rows $\Theta(k \log(n/k))$.

Theorem 13. *Assume $k \geq 2$, $\delta_k < \delta$ for some fixed universal small constant $\delta > 0$, $m < n/(64 \log^3 n)$. Then we must have $s = \Omega(\min\{k \log(n/k)/\log(m/(k \log(n/k))), m\})$.*

Proof. Assume for the sake of contradiction that $s < \min\{k \log(n/k)/(64 \log(m/s)), m/64\}$. Consider the ith column of A for some fixed i. By k-RIP, the ℓ_2 norm of each column of A is at least $1 - \delta_k > 1/2$, so the sum of squares of entries greater than $1/(2\sqrt{s})$ in magnitude is at least $1/4$. Therefore, there exists a scale $1 \leq t \leq \log s$ such that the number of entries of absolute value greater than or equal to $2^{(t-3)/2}/\sqrt{s}$ is at least $2^{-t-1}s/t^2$. To see this, let $|S|$ be the set of rows j such that $|A_{j,i}| \geq 1/(2\sqrt{s})$. For the sake of contradiction, suppose that every scale $1 \leq t \leq \log s$ has strictly fewer than $2^{-t-1}s/t^2$ values that are at least $2^{(t-3)/2}/\sqrt{s}$ in magnitude (note this also implies $|S| < s/4$). Let X be the square of a random element of S. Then

$$\sum_{j \in S} A_{j,i}^2 = |S| \cdot \mathbb{E}X = |S| \cdot \int_0^\infty \mathbb{P}\left(X > x\right) dx < \frac{1}{16} + \int_{1/4s}^\infty \mathbb{P}\left(X > x\right) dx < \frac{1}{16} + \sum_{t=1}^\infty \frac{2^t}{8s} \cdot \frac{s}{2^{t+1}t^2} < \frac{1}{4},$$

a contradiction. Let a pattern at scale t be a subset of size $u = \max\{2^{4-t}s/k, 1\}$ of $[m]$ along with u signs. There are $\binom{2^{-t-1}s/t^2}{u}$ patterns P where $A_{v,i}^2 \geq 2^{t-3}/s$ for all $v \in P$ and the signs of $A_{v,i}$ match the signs of P.

There are $2^u\binom{m}{u}$ possible patterns at scale t. By an averaging argument, there exists a scale t, and a pattern P such that the number of columns of A with this pattern is at least $z = n\binom{2^{-t-1}s/t^2}{u}/((\log s)2^u\binom{m}{u})$. Consider 2 cases.

Case 1 ($z \geq k$): Pick an arbitrary set of k such columns. Consider the vector v with k ones at locations corresponding to those columns and zeroes everywhere else. We have $\|v\|_2^2 = k$ and for each $j \in P$, we have

$$(Av)_j^2 \geq k^2 2^{t-3}/s.$$

Thus,

$$\|Av\|_2^2 \geq uk^2 2^{t-3}/s \geq 2k.$$

This contradicts the assumption that $\|Av\|_2^2 \leq (1 + \delta_k)\|v\|_2^2$.

Case 2 ($z < k$): Consider the vector v with z ones at locations corresponding to those columns and zeroes everywhere else. We have $\|v\|_2^2 = z$ and for each $j \in P$, we have $(Av)_j^2 \geq z^2 2^{t-3}/s$. Consider 2 subcases.

Case 2.1 ($u = 1$): Then $z = \frac{n 2^{-t-2}s/t^2}{(\log s)m}$, so

$$\|Av\|_2^2 \geq z^2 2^{t-3}/s \geq \frac{2^{-5}n/t^2}{(\log s)m} \cdot z \geq 2z. \tag{3}$$

This contradicts the assumption that $\|Av\|_2^2 \leq (1 + \delta_k)\|v\|_2^2$.

Case 2.2 ($u = 2^{4-t}s/k$): . We have

$$\begin{aligned}
z =& \frac{n\binom{2^{-t-1}s/t^2}{u}}{(\log s)2^u\binom{m}{u}} \\
\geq& \frac{n}{\log s}\left(\frac{s}{t^2 2^{t+2}em}\right)^u \\
\geq& \frac{n}{\log s}2^{-(\log(m/s)+\log e+t+2+2\log t)2^{4-t}s/k} \\
\geq& \frac{n}{\log s}2^{-(\log(m/s)+\log e+t+2+2\log t)2^{4-t}\cdot\log(n/k)/(64\log(m/s))} && (4) \\
\geq& \frac{n}{\log s}(k/n)^{1/4} && (5) \\
\geq& k. && (6)
\end{aligned}$$

Eq. (4) follows from $s < k\log(n/k)/(64\log(m/s))$. Eq. (5) follows from the fact that $f(t) = (\log(m/s) + \log e + t + 2 + 2\log t)2^{-t}$ is monotonically decreasing for $t \geq 1$. Indeed,

$$\begin{aligned}
f'(t) &= 2^{-t}\left(-\ln 2(\log(m/s) + \log e + 2 + t + 2\log t) + \frac{2}{t\ln 2} + 1\right) \\
&\leq 2^{-t}\left(-9\ln 2 - t\ln 2 + \frac{2}{t\ln 2} + 1\right) \\
&\leq 0.
\end{aligned}$$

Eq. (6) follows since $k < n/\log^{4/3} n < n/\log^{4/3} s$, which holds since $k \leq m \leq n/(64\log^3 n)$. This contradicts the assumption of Case 2 that $z < k$.

Thus we have $s \geq \min\{k\log(n/k)/(64\log(m/s)), m/64\}$ as desired. If $s \geq m/64$ we are done. Otherwise we have $s \geq k\log(n/k)/(64\log(m/s))$. Define $q = m$, $r = k\log(n/k)/64$. Thus we have $s\log(q/s) \geq r$. We have $q/r \geq 2$ for δ_k smaller than some constant by Theorem 20, and we have $s < q/e = m/e$ since we assume we are in the case $s < m/64$. Thus by Lemma 4 we have $s = \Omega(r/\ln(q/r))$, which completes the proof of the theorem. ∎

Corollary 14. *When $k \geq 2$, $\delta_k < \delta$ for some universal constant $\delta > 0$, and the number of rows $m = \Theta(k\log(n/k)) < n/(32\log^3 n)$, we must have $s = \Omega(k\log(n/k))$.*

Remark 15. The restriction $m = O(n/\log^3 n)$ in Theorem 13 was relevant in Eq. (3). Note the choice of t^2 in the proof was just so that $\sum_t 1/t^2$ converges. We could instead have chosen $t^{1+\gamma}$ and obtained a qualitatively similar result, but with the slightly milder restriction $m = O(n/\log^{2+\gamma} n)$, where $\gamma > 0$ can be chosen as an arbitrary constant.

4 Oblivious Subspace Embedding Sparsity Lower Bound

In this section, we show a lower bound on the dimension of very sparse OSE's.

Theorem 16. *Consider d at least a large enough constant and $n \geq 2d^2$. Any OSE with matrices A in its support having m rows and at most 1 non-zero entry per column such that with probability at least $1/5$, the lengths of all vectors in a fixed subspace of dimension d of $\mathbb{R}^n$ are preserved up to a factor 2, must have $m \geq d^2/214$.*

Proof. Assume for the sake of contradiction that $m < d^2/214$. By Yao's minimax principle, we only need to show there exists a distribution over subspaces such that any fixed matrix A with column sparsity 1 and too few rows would fail to preserve lengths of vectors in the subspace with probability more than 4/5.

Consider the uniform distribution over subspaces spanned by d standard basis vectors in $\mathbb{R}^n$: $e_{i_1}, e_{i_2}, \ldots, e_{i_d}$ with $i_1, \ldots, i_d \in \{1, \ldots, n\}$. Let $a(i)$ be the row of the non-zero entry in column i of A and $b(j)$ be the number of non-zeroes in row j. We say i *collides with* j if $a(i) = a(j)$. Let the set of *heavy* rows be the set of rows j such that $b(j) \geq \frac{n}{10m}$.

If we pick $i_1, \ldots, i_d$ one by one. Conditioned on $i_1, \ldots, i_{t-1}$, the probability that $a(i_t)$ is heavy is at least $\frac{9}{10} - \frac{d}{n} \geq \frac{4}{5}$. Therefore, by a Chernoff bound, with probability at least 9/10, the number of indices i_t such that $a(i_t)$ are heavy is at least $3d/4$.

We will show that conditioned on the number of such i_t being at least $3d/4$, with probability at least 9/10, two such indices collide. Let $j_1, \ldots, j_{3d/4}$ be indices with $b(a(j_t)) \geq \frac{n}{10m}$. Conditioned on $a(j_1), \ldots, a(j_{t-1})$, the probability that j_t does not collide with any previous index is at most

$$1 - \sum_{u=1}^{t-1} b(a(j_u))/(n-t+1) + (t-1)/(n-t+1) \leq e^{-\sum_{u=1}^{t-1} b(a(j_u))/n + 2(t-1)/n} \leq e^{-(t-1)/(10m) + 2(t-1)/n}.$$

Thus, the probability that no collision occurs is at most $e^{(-(3d/4)^2/(40m)) + ((3d/4)^2/n)} < 1/10$. In other words, collision occurs with probability at least 9/10. When collision occurs, the number of non-zero entries of AM, where M is the matrix whose columns are $e_{i_1}, \ldots, e_{i_d}$, is at most $d-1$ so it has rank at most $d-1$. Therefore, with probability at least 4/5, A maps some non-zero vector in the subspace to the zero vector (any vector Mx for $x \in \ker(AM)$) and fails to preserve the length of all vectors in the subspace. ■

5 Lower Bound on Number of Rows for RIP Matrices

In this section we show a lower bound on the number of rows of any k-RIP matrix with distortion δ_k. First we need the following form of the Chernoff bound.

Theorem 17 (Chernoff bound)**.** *Let $X_1, \ldots, X_n$ be independent random variables each at most K in magnitude almost surely, and with $\sum_{i=1}^n \mathbb{E}X_i = \mu$ and $\mathrm{Var}\left[\sum_{i=1}^n X_i\right] = \sigma^2$. Then*

$$\forall\ \lambda > 0,\ \Pr\left[\left|\sum_{i=1}^n X_i - \mu\right| > \lambda\sigma\right] < C \cdot \max\left\{e^{-c\lambda^2}, (\lambda K/\sigma)^{-c\lambda\sigma/K}\right\}$$

for some absolute constants $c, C > 0$.

This form of the Chernoff bound can then be used to show the existence of a large error-correcting code with high relative distance.

Lemma 18. *For any $0 < \varepsilon \leq 1/2$ and integers k, n with $1 \leq k \leq \varepsilon n/2$, there exists a q-ary code with $q = n/k$ and block length k of relative distance $1 - \varepsilon$, and with size at least*

$$\min\left\{e^{C'\varepsilon^2 n}, e^{C'\varepsilon k \log\left(\frac{\varepsilon n}{2k}\right)}\right\}$$

for some absolute constant $C' > 0$.

Proof. We take a random code. That is, pick

$$N = \min\left\{e^{C\varepsilon^2 n}, e^{C\varepsilon k \log\left(\frac{\varepsilon n}{2k}\right)}\right\}$$

codewords with alphabet size $q = n/k$ and block length k, with replacement. Now, look at two of these randomly chosen codewords. For $i = 1, \ldots, k$, let X_i be an indicator random variable for the event that the ith symbol is equal in the two codewords. Then $X = \sum_{i=1}^k X_i$ is the number of positions at which these two codewords agree, and $\mathbb{E}X = k^2/n \le \varepsilon k/2$ and $\mathrm{Var}[X] \le k^2/n$. Thus by the Chernoff bound,

$$\mathbb{P}(|X| > \varepsilon k) < C \cdot \max\left\{e^{-c\varepsilon^2 n}, e^{-c\varepsilon k \log\left(\frac{\varepsilon n}{2k}\right)}\right\}.$$

Therefore by a union bound, a random multiset of N codewords has relative distance $1 - \varepsilon$ with positive probability (in which case it must also clearly be not just a multiset, but a set). ■

Before proving the main theorem of this section, we also need the following theorem of Alon [Alo09].

Theorem 19 (Alon [Alo09]). *Let $x_1, \ldots, x_N \in \mathbb{R}^n$ be such that $\|x_i\|_2 = 1$ for all i, and $|\langle x_i, x_j\rangle| \le \varepsilon$ for all $i \ne j$, where $1/\sqrt{n} < \varepsilon < 1/2$. Then $n = \Omega(\varepsilon^{-2}\log N/\log(1/\varepsilon))$.*

Theorem 20. *For any $0 < \delta_k \le 1/2$ and integers k, n with $1 \le k \le \delta_k n/2$, any k-RIP matrix with distortion δ_k must have $\Omega\left(\min\{n/\log(1/\delta_k), (k/(\delta_k \log(1/\delta_k)))\log(n/k)\}\right)$ rows.*

Proof. Let $C_1, \ldots, C_N$ be a code as in Lemma 18 with block length $n/(k/2)$ and alphabet size $k/2$ with

$$N \ge \min\left\{e^{C\delta_k^2 n}, e^{C\delta_k k \log\left(\frac{\delta_k n}{k}\right)}\right\}.$$

Consider a set of vectors $y_1, \ldots, y_N$ in $\mathbb{R}^n$ defined as follows. For $j = 0, \ldots, k/2 - 1$, we define $(y_i)_{2jn/k + (C_i)_j} = \sqrt{2/k}$, and all other coordinates of y_i are 0. Then we have $\forall i\ \|y_i\|_2 = 1$, and also $0 \le \langle y_i, y_j\rangle \le \delta_k$ for all $i \ne j$, and thus $2 - 2\delta_k \le \|y_i - y_j\|_2^2 \le 2$. Since y_i is $k/2$-sparse and $y_i - y_j$ is k-sparse for all i, j, we have for any k-RIP matrix A with distortion δ_k

$$\forall i\ \|Ay_i\|_2 = 1 \pm \delta_k, \qquad \forall i \ne j\ \|Ay_i - Ay_j\|_2^2 = (1 \pm \delta_k)^2 \cdot (2 \pm 2\delta_k) = 2 \pm 9\delta_k.$$

Thus if we define $x_1, \ldots, x_N$ by $x_i = Ay_i/\|Ay_i\|_2$, then the x_i satisfy the requirements of Theorem 19 with inner products at most $O(\delta_k)$ in magnitude. The lower bound on the number of rows of A then follows. ■

It is also possible to obtain a lower bound on the number of rows of A in Theorem 20 of the form $\Omega(\delta_k^{-2} k/\log(1/\delta_k))$. This is because a theorem of [KW11] shows that any such RIP matrix with $k = \Theta(\log n)$, when its column signs are flipped randomly, is a JL matrix for any set of n points with high probability. We then know from Theorem 19 that a JL matrix must have $m = \Omega(\delta_k^{-2}\log n/\log(1/\delta_k))$ rows, which is $\Omega(\delta_k^{-2} k/\log(1/\delta_k))$.

Corollary 21. *Suppose $1/\sqrt{n} \le \delta_k \le 1/2$ and $A \in \mathbb{R}^{m\times n}$ is a k-RIP matrix with distortion δ_k. Then $m = \Omega(\log^{-1}(1/\delta_k) \cdot \min\{k\log(n/k)/\delta_k + k/\delta_k^2, n\})$.*

6 Future Directions

For several applications the JL lemma is used as a black box to obtain dimensionality-reducing linear maps for other problems. For example, applying the JL lemma with distortion $O(\delta_k)$ on a certain net with $N = O\binom{n}{k} \cdot O(1/\delta_k)^k$ vectors yields a k-RIP matrix with distortion δ_k [BDDW08]. Note in this case, for constant δ_k, the number of rows one obtains is the optimal $\Theta(\log N) = \Theta(k\log(n/k))$. Applying the distributional JL lemma with distortion $O(\varepsilon)$ to a certain net of size $2^{O(d)}$ yields an OSE with $m = O(d/\varepsilon^2)$ rows to preserve d-dimensional subspaces (see [CW12, Fact 10], based on [AHK06]).

Applying the JL lemma in this black-box way using the sparse JL matrices of [KN12] yields a factor-ε improvement in sparsity over using a random dense JL construction, with for example random Gaussian entries. However, some examples have shown that it is possible to do much better by not using the JL lemma statement as a black box, but rather by analyzing the sparsity required from the constructions in [KN12] "from scratch" for the problem at hand. For example, the work [NN12] showed that one can have column sparsity $O(1/\varepsilon)$ with $m = O(d^{1+\gamma}/\varepsilon^2)$ rows in an OSE for any $\gamma > 0$, which is much better than the column sparsity $O(d/\varepsilon)$ that is obtained by using the sparse JL theorem as a black box.

We thus pose the following open problem in the realm of understanding sparse embedding matrices better. Let $\mathcal{D}$ be an OSNAP distribution [NN12] over $\mathrm{R}^{m\times n}$ with column sparsity s. The class of OSNAP distributions includes both of the sparse JL distributions in [KN12], and more generally an OSNAP distribution is characterized by the following three properties where A is a random matrix drawn from $\mathcal{D}$:

- All entries of A are in $\{0, 1/\sqrt{s}, -1/\sqrt{s}\}$. We write $A_{i,j} = \delta_{i,j}\sigma_{i,j}/\sqrt{s}$ where $\delta_{i,j}$ is an indicator random variable for the event $A_{i,j} \neq 0$, and the $\sigma_{i,j}$ are independent uniform ± 1 r.v.'s.
- For any $j \in [n]$, $\sum_{i=1}^{m} \delta_{i,j} = s$ with probability 1.
- For any $S \subseteq [m] \times [n]$, $\mathbb{E}\prod_{(i,j)\in S} \delta_{i,j} \le (s/m)^{|S|}$.

Given a set of vectors $V \subset \mathbb{R}^n$, what is the tradeoff between the number of rows m and the column sparsity s required for a random matrix A drawn from an OSNAP distribution to preserve all ℓ_2 norms of vectors $v \in V$ up to $1 \pm \varepsilon$ simultaneously, with positive probability, as a function of the geometry of V? We are motivated to ask this question by a result of [KM05], which states that for a set of vectors $V \subseteq \mathbb{R}^n$ all of unit ℓ_2 norm, a matrix with random subgaussian entries preserves all ℓ_2 norms of vectors in V up to $1 \pm \varepsilon$ as long as the number of rows m satisfies

$$m \ge C\varepsilon^{-2} \cdot \left(\mathbb{E}_g \sup_{x\in V} |\langle g, x\rangle|\right)^2, \tag{7}$$

where $g \in \mathbb{R}^n$ has independent Gaussian entries of mean 0 and variance 1. The bound on m in [KM05] is actually stated as $C\varepsilon^{-2}(\gamma_2(V, \|\cdot\|_2))^2$ where γ_2 is the γ_2 functional, but this is equivalent to Eq. (7) up to a constant factor; see [Tal05] for details. Note Eq. (7) easily implies the $m = O(d/\varepsilon^2)$ bound for OSE's by letting V be the unit sphere in any d-dimensional subspace, and also implies $m = O(\delta_k^{-2} k \log(n/k))$ suffices for RIP matrices by letting V be the set of all k-sparse vectors of unit norm.

Note that the resolution of this question will not just be in terms of the γ_2 functional. In particular, for constant δ_k we see that $m, s = \Theta((\gamma_2(V))^2)$ is necessary and sufficient when V is the set of all unit norm k-sparse vectors. Even increasing m to $\Theta((\gamma_2(V))^{2+\gamma})$ does not decrease the lower bound on s by much. Meanwhile for V a unit sphere of a d-dimensional subspace, we can simultaneously have $m = O((\gamma_2(V))^{2+\gamma}/\varepsilon^2)$, and $s = O(1/\varepsilon)$ not depending on $\gamma_2(V)$ at all.

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