# A Derandomized Sparse Johnson-Lindenstrauss Transform

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**Abstract**

Recent work of [Dasgupta-Kumar-Sarlós, STOC 2010] gave a sparse Johnson-Lindenstrauss transform and left as a main open question whether their construction could be efficiently derandomized. We answer their question affirmatively by giving an alternative proof of their result requiring only bounded independence hash functions. Furthermore, the sparsity bound obtained in our proof is improved. Our work implies the first implementation of a Johnson-Lindenstrauss transform in data streams with sublinear update time.

## 1 Introduction

The Johnson-Lindenstrauss lemma states the following.

**Lemma 1** (JL Lemma [20])**.** *For any integer $d > 0$, and any $0 < \varepsilon, \delta < 1/2$, there exists a probability distribution on $k \times d$ real matrices for $k = \Theta(\varepsilon^{-2}\log(1/\delta))$ such that for any $x \in \mathbb{R}^d$ with $\|x\|_2 = 1$,*

$$\mathbf{Pr}_A[|\|Ax\|_2^2 - 1| > \varepsilon] < \delta.$$

Several proofs of the JL lemma exist in the literature [1, 7, 11, 14, 18, 20, 24], and it is known that the dependence on $k$ is tight up to a constant factor [19] (see also Section A for another proof). Though, these proofs of the JL lemma give a distribution over *dense* matrices, where each column has at least a constant fraction of its entries being non-zero, and thus naïvely performing the matrix-vector multiplication is costly. Recently, Dasgupta, Kumar, and Sarlós [10] proved the JL lemma where each matrix in the support of their distribution only has $\alpha$ non-zero entries per column, for $\alpha = \Theta(\varepsilon^{-1}\log(1/\delta)\log^2(k/\delta))$. This reduces the time to perform dimensionality reduction from the naïve $O(k \cdot \|x\|_0)$ to $O(\alpha \cdot \|x\|_0)$, where $x$ has $\|x\|_0$ non-zero entries.

The construction of [10] involved picking two random hash functions $h : [d\alpha] \to [k]$ and $\sigma : [d\alpha] \to \{-1, 1\}$ (we use $[n]$ to denote $\{1, \ldots, n\}$), and thus required $\Omega(d\alpha \cdot \log k)$ bits of seed to represent a random matrix from their JL distribution. They then left two main open questions: (1) derandomize their construction to require fewer random bits to select a random JL matrix, for applications in e.g. streaming settings where storing a long random seed is prohibited, and (2) understand the dependence on $\delta$ that is required in $\alpha$.

We give an alternative proof of the main result of [10] that yields progress for both (1) and (2) above simultaneously. Specifically, our proof yields a value of $\alpha$ that is improved by a $\log(k/\delta)$ factor. Furthermore, our proof only requires that $h$ be $r_h$-wise independent and $\sigma$ be $r_\sigma$-wise independent for $r_h = O(\log(k/\delta))$ and $r_\sigma = O(\log(1/\delta))$, and thus a random sparse JL matrix can be represented using only $O(\log(k/\delta)\log(d\alpha + k)) = O(\log(k/\delta)\log d)$ bits (note $k$ can be assumed

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less than $d$, else the JL lemma is trivial, in which case also $\log(d\alpha) = O(\log d)$). We remark that [10] asked exactly this question: whether the random hash functions used in their construction could be replaced by functions from bounded independence hash families. The proof in [10] required use of the FKG inequality [6, Theorem 6.2.1], and they suggested that one approach to a proof that bounded independence suffices might be to prove some form of this inequality under bounded independence. Our approach is completely different, and does not use the FKG inequality at all. Rather, the main ingredient in our proof is the Hanson-Wright inequality [15], a central moment bound for quadratic forms in terms of the Frobenius and operator norms of the associated matrix.

We now give a formal statement of the main theorem of this work, which is a derandomized JL lemma where every matrix in the support of the distribution has good column sparsity.

**Theorem 2** (Main Theorem). *For any integer $d > 0$, and any $0 < \varepsilon, \delta < 1/2$, there exists a family $\mathcal{A}$ of $k \times d$ real matrices for $k = \Theta(\varepsilon^{-2}\log(1/\delta))$ such that for any $x \in \mathbb{R}^d$,*

$$\mathbf{Pr}_{A\in\mathcal{A}}[\|Ax\|_2 \notin [(1-\varepsilon)\|x\|_2, (1+\varepsilon)\|x\|_2]] < \delta.$$

*and where $A \in \mathcal{A}$ can be sampled using $O(\log(k/\delta)\log d)$ random bits. Every matrix in $\mathcal{A}$ has at most $\alpha = \Theta(\varepsilon^{-1}\log(1/\delta)\log(k/\delta))$ non-zero entries per column, and thus $Ax$ can be evaluated in $O(\alpha \cdot \|x\|_0)$ time if $A$ is written explicitly in memory. If $A \in \mathcal{A}$ is not written explicitly in memory but rather we are given a string of $\log(|\mathcal{A}|)$ representing some matrix $A \in \mathcal{A}$, then the multiplication $Ax$ can be performed in $O(\alpha \cdot \|x\|_0 + t(\alpha \cdot \|x\|_0, O(\log(k/\delta)), d\alpha, k) + t(\alpha \cdot \|x\|_0, O(\log(1/\delta)), d\alpha, 2)$ time. Here $t(s, r, n, m)$ is the total time required to evaluate a random hash function drawn from an $r$-wise independent family mapping $[n]$ into $[m]$ on $s$ inputs.*

We stated the time to multiply $Ax$ above in terms of the $t(\cdot)$ function since one can evaluate an $r$-wise independent hash function on multiple points quickly via polynomial fast multipoint evaluation. Specifically, an $r$-wise independent hash family over a finite field can consist of degree-$(r-1)$ polynomials, and a degree-$(r-1)$ polynomial over a field can be evaluated on $r-1$ points in only $O(r\log^2 r \log\log r)$ field operations as opposed to $O(r^2)$ operations [31, Ch. 10].

We also show a variant of our main result: that it is also possible to take $\alpha = \varepsilon^{-(1+o_\delta(1))}\log^2(1/\delta)$ and set $r_h = r_\sigma = O(\log(1/\delta))$. Here $o_\delta(1)$ denotes a function that goes to 0 as $\delta \to 0$ (specifically the function is $O(1/\log(1/\delta))$. This matches the best previously known seed length for JL of $O(\log(1/\delta)\log d)$ bits, and we still achieve good column sparsity.

**Implication for the streaming model.** In the turnstile model of streaming [27], a high-dimensional vector $x \in \mathbb{R}^d$ receives several updates of the form "$(i, v)$" in a stream which causes the change $x_i \leftarrow x_i + v$, where $(i, v) \in \{1, \ldots, n\} \times \{-M, \ldots, M\}$ for some positive integer $M$.

Indyk first considered the problem of maintaining a low-dimensional $\ell_2$-embedding of $x$ in the turnstile model in [17], where he suggested using a pseudorandom Gaussian matrix generated using Nisan's pseudorandom generator (PRG) [28].[1] Clarkson and Woodruff later showed that the entries can be $r$-wise independent Bernoulli for $r = O(\log(1/\delta))$ [9]. Both of these results though give an algorithm whose *update time* (the time required to process a stream update) is $\Omega(k)$. Using the matrix of [10] would give an update time of $O(\alpha)$ (in addition to the time required to evaluate the $O(\log(k/\delta))$-wise independent hash function), except that their construction requires superlinear

[1]As noted in [17], the AMS sketch of [5] does not give an $\ell_2$ embedding since the median operator is used to achieve low error probability.

($\Omega(d\alpha \log k)$) space to store the hash function. As noted in [10], it is unclear how to use Nisan's PRG to usefully derandomize their construction since evaluating the PRG would require $\Omega(k)$ time.[2] Our derandomization thus gives the first update time for $\ell_2$ embedding in data streams which is subquadratic in $1/\varepsilon$.

# 2 Related Work

There have been two separate lines of related work: one line of work on constructing JL families[3] such that the dimensionality reduction can be performed quickly, and another line of work on derandomizing the JL lemma so that a random matrix from some JL family can be selected using few random bits. We discuss both here.

## 2.1 Works on efficient JL embeddings

Here and throughout, for a JL family $\mathcal{A}$ we use the term *embedding time* to refer to the running time required to perform a matrix-vector multiplication for an arbitrary $A \in \mathcal{A}$. The first work to give a JL family with embedding time potentially better than $O(kd)$ was by Ailon and Chazelle [2]. The authors achieved embedding time $O(d \log d + k \log^2(1/\delta))$. Later, improvements were given by Ailon and Liberty in [3, 4]. The work of [3] achieves embedding time $O(d \log k)$ when $k = O(d^{1/2-\gamma})$ for an arbitrarily small constant $\gamma > 0$, and [4] achieves embedding time $O(d \log d)$ and no restriction on $k$, though the $k$ in their JL family is $O(\varepsilon^{-4} \log(1/\delta) \log^4 d)$ as opposed to the $O(\varepsilon^{-2} \log(1/\delta))$ bound of the standard JL lemma. This dependence on $1/\varepsilon$ was recently improved to quadratic by Krahmer and Ward [22], though the $\log^4 d$ factor remains. The works of Hinrichs and Vybíral [16] and later Vybíral [32] considered taking a random partial circulant matrix as the embedding matrix. This gives embedding time $O(d \log d)$ via the Fast Fourier transform, and it was shown that one can take either $k = O(\varepsilon^{-2} \log^3(1/\delta))$ [16] or $k = O(\varepsilon^{-2} \log(1/\delta) \log(d/\delta))$ [32]. Liberty, Ailon, and Singer [23] achieve embedding time $O(d)$ when $k = O(d^{1/2-\gamma})$, but their JL family only applies for $x$ satisfying $\|x\|_\infty \le \|x\|_2 \cdot k^{-1/2} d^{-\gamma}$.

None of the above works however can take advantage of the situation when $x$ is sparse to achieve faster embedding time. The first work which could take advantage of sparse $x$ was that of Dasgupta, Kumar, and Sarlós [10] who gave a JL family whose matrices all had $O(\varepsilon^{-1} \log(1/\delta) \log^2(k/\delta))$ non-zero entries per column. They also showed that for a large class of constructions, sparsity $\min\{\varepsilon^{-2}, \varepsilon^{-1}\sqrt{\log_k(1/\delta)}\}$ is necessary when $\delta = o(1)/d^2$.

Other related works include [8] and [30]. Implicitly in [8], and later more explicitly in [30], a JL family was given with column sparsity 1 using only constant-wise independent hash functions. The construction was in fact the same as in [10], but with $h$ being pairwise independent, and $\sigma$ being 4-wise independent. This construction only gives a JL family for constant $\delta$ though, since with such mild independence assumptions on $h, \sigma$ one needs $k$ to be polynomially large in $1/\delta$.

[2] The evaluation time is at least linear in the seed length, which is at least the space usage of the machine being fooled ($\Omega(k)$ space in this case).

[3] In many known proofs of the JL lemma, the distribution over matrices in Lemma 1 is obtained by picking a matrix uniformly at random from some set $\mathcal{A}$. In such a case, we call $\mathcal{A}$ a *JL family*.

## 2.2 Works on derandomizing the JL lemma

The $\ell_2$-streaming algorithm of Alon, Matias, and Szegedy [5] implies a JL family with seed length $O(\log d)$ and with $k = O(1/(\varepsilon^2\delta))$. Karnin, Rabani, and Shpilka [21] recently gave a family with seed length $(1+o(1))\log_2 d + O(\log^2(1/\varepsilon))$ also with $k = \mathrm{poly}(1/(\varepsilon\delta))$. The best known seed length for a JL family we are aware of is due to Clarkson and Woodruff [9]. Theorem 2.2 of [9] implies that a scaled random Bernoulli matrix with $\Omega(\log(1/\delta))$-wise independent entries satisfies the JL lemma, giving seed length $O(\log(1/\delta)\cdot\log d)$. In Section B, we show how to bootstrap the $r$-wise independent JL family construction to achieve seed length $O(\log d + \log(1/\varepsilon)\log(1/\delta) + \log(1/\delta)\log\log(1/\delta))$. We note that a construction which achieves this seed length for $\delta \le d^{-\Omega(1)}$ was recently achieved independently by Meka [25].

Derandomizing the JL lemma is also connected to pseudorandom generators (PRGs) against degree-2 polynomial threshold functions (PTFs) over the hypercube [12, 26]. A degree-$t$ PTF is a function $f : \{-1,1\}^d \to \{-1,1\}$ which can be represented as the sign of a degree-$t$ $d$-variate polynomial. A PRG that $\delta$-fools degree-$t$ PTFs is a function $F : \{-1,1\}^s \to \{-1,1\}^d$ such that for any degree-$t$ PTF $f$,

$$|\mathbf{E}_{z\in\mathcal{U}^s}[f(F(z))] - \mathbf{E}_{x\in\mathcal{U}^d}[f(x)]| < \delta,$$

where $\mathcal{U}^m$ is the uniform distribution on $\{-1,1\}^m$.

Note that the conclusion of the JL lemma can be rewritten as

$$\mathbf{E}_A[I_{[1-\varepsilon,1+\varepsilon]}(\|Ax\|_2^2)] \ge 1-\delta,$$

where $I_{[a,b]}$ is the indicator function of the interval $[a,b]$, and furthermore $A$ can be taken to have random $\pm1/\sqrt{k}$ entries [1]. Noting that $I_{[a,b]}(z) = (\mathrm{sign}(z-a) - \mathrm{sign}(z-b))/2$ and using linearity of expectation, we see that any PRG which $\delta$-fools $\mathrm{sign}(p(x))$ for degree-$t$ polynomials $p$ must also $\delta$-fool $I_{[a,b]}(p(x))$. Now, for fixed $x$, $\|Ax\|_2^2$ is a degree-2 polynomial over the boolean hypercube in the variables $A_{i,j}$ and thus a PRG which $\delta$-fools degree-2 PTFs also gives a JL family with the same seed length. Each of [12, 26] thus give JL families with seed length $\mathrm{poly}(1/\delta)\cdot\log d$. Also, it can be shown via the probabilistic method that there exist PRGs for degree-2 PTFs with seed length $O(\log(1/\delta) + \log d)$ (see Section B of the full version of [26] for a proof), and it remains an interesting open problem to achieve this seed length with an explicit construction. It is also not too hard to show that any JL family $\mathcal{F}$ must have seed length $\Omega(\log(1/\delta) + \log(d/k))$.[4]

Other derandomizations of the JL lemma include the works [13] and [29]. A common application of the JL lemma is the case where there are $n$ vectors $x_1,\ldots,x_n \in \mathbb{R}^d$ and one wants to find a matrix $A \in \mathbb{R}^{k\times d}$ to preserve $\|x_i - x_j\|_2$ to within relative error $\varepsilon$ for all $i,j$. In this case, one can set $\delta = 1/n^2$ and apply Lemma 1, then perform a union bound over all $i,j$ pairs. The works of [13, 29] do not give JL families, but rather give deterministic algorithms for finding such a matrix $A$ in the case that the vectors $x_1,\ldots,x_n$ are known up front.

# 3 Conventions and Notation

**Definition 3.** *For $A \in \mathbb{R}^{n\times n}$, we define the* Frobenius norm *of $A$ as* $\|A\|_F = \sqrt{\sum_{i,j} A_{i,j}^2}$.

[4] We need $|\mathcal{F}| \ge 1/\delta$ to have error probability $\delta$. Also, if $|\mathcal{F}| < d/k$, then the matrix obtained by concatenating all rows of matrices in $\mathcal{F}$ has a non-trivial kernel, implying a vector exists in the intersection of all their kernels.

**Definition 4.** *For $A \in \mathbb{R}^{n\times n}$, we define the* operator norm *of $A$ as*

$$\|A\|_2 = \sup_{\|x\|_2=1} \|Ax\|_2.$$

*In the case $A$ has all real eigenvalues (e.g. it is symmetric), we also have that $\|A\|_2$ is the largest magnitude of an eigenvalue of $A$.*

Throughout this paper, $\varepsilon$ is the quantity given in Lemma 1, and is assumed to be smaller than some absolute constant $\varepsilon_0 > 0$. All logarithms are base-2 unless explicitly stated otherwise. Also, for a positive integer $n$ we use $[n]$ to denote the set $\{1,\ldots,n\}$. All vectors are assumed to be column vectors, and $v^T$ for a vector $v$ denotes its transpose. Finally, we often implicitly assume that various quantities are powers of 2 (such as e.g. $1/\delta$), which is without loss of generality.

# 4 Warmup: A simple proof of the JL lemma

Before proving our main theorem, as a warmup we demonstrate how a simpler version of our approach reproves Achlioptas' result [1] that the family of all (appropriately scaled) sign matrices is a JL family. Furthermore, as was already demonstrated in [9, Theorem 2.2], we show that rather than choosing a uniformly random sign matrix, the entries need only be $\Omega(\log(1/\delta))$-wise independent.

We first state the Hanson-Wright inequality [15], which gives a central moment bound for quadratic forms in terms of both the Frobenius and operator norms of the associated matrix [5].

**Lemma 5** (Hanson-Wright inequality [15])**.** *Let $z = (z_1,\ldots,z_n)$ be a vector of i.i.d. Bernoulli $\pm 1$ random variables. Then for any symmetric $B \in \mathbb{R}^{n\times n}$ and integer $\ell \geq 2$ a power of 2,*

$$\mathbf{E}\left[\left(z^TBz - \mathrm{trace}(B)\right)^\ell\right] \leq 64^\ell \cdot \max\left\{\sqrt{\ell}\cdot\|B\|_F, \ell\cdot\|B\|_2\right\}^\ell.$$

**Theorem 6.** *For $d > 0$ an integer and any $0 < \varepsilon, \delta < 1/2$, let $A$ be a $k \times d$ random matrix with $\pm 1/\sqrt{k}$ entries that are $r$-wise independent for $k = \Omega(\varepsilon^{-2}\log(1/\delta))$ and $r = \Omega(\log(1/\delta))$. Then for any $x \in \mathbb{R}^d$ with $\|x\|_2 = 1$,*

$$\mathbf{Pr}_A[|\|Ax\|_2^2 - 1| > \varepsilon] < \delta.$$

**Proof.** We have

$$\|Ax\|_2^2 = \frac{1}{k}\cdot\sum_{i=1}^k \left(\sum_{(s,t)\in[d]\times[d]} x_s x_t \sigma_{i,s}\sigma_{i,t}\right), \tag{1}$$

where $\sigma$ is a $kd$-dimensional vector formed by concatenating the rows of $\sqrt{k}\cdot A$. Define the matrix $T \in \mathbb{R}^{kd\times kd}$ to be the block-diagonal matrix where each block equals $xx^T/k$. Then, $\|Ax\|_2^2 = \sigma^T T\sigma$. Furthermore, $\mathrm{trace}(T) = \|x\|_2^2 = 1$. Thus, we would like to argue that $\sigma^T T\sigma$ is concentrated about $\mathrm{trace}(T)$, for which we can use Lemma 5. Specifically, if $\ell \geq 2$ is even,

$$\mathbf{Pr}[|\|Ax\|_2^2 - 1| > \varepsilon] = \mathbf{Pr}[|\sigma^T T\sigma - \mathrm{trace}(T)| > \varepsilon] < \varepsilon^{-\ell}\cdot\mathbf{E}[(\sigma^T T\sigma - \mathrm{trace}(T))^\ell]$$

[5] [15] proves a tail bound, but it is not hard to then derive a moment bound via integration; see [12] for a direct proof of the moment bound

by Markov's inequality. To apply Lemma 5, we also pick $\ell$ a power of 2, and we ensure $2\ell \le r$ so that the $\ell$th moment of $\sigma^T T\sigma - \mathrm{trace}(T)$ is determined by $r$-wise independence of the $\sigma$ entries. We also must bound $\|T\|_F$ and $\|T\|_2$. Direct computation gives $\|T\|_F^2 = (1/k)\cdot\|x\|_2^4 = 1/k$. Also, $x$ is the only eigenvector of $xx^T/k$ with non-zero eigenvalue, and furthermore its eigenvalue is $\|x\|_2^2/k = 1/k$, and thus $\|T\|_2 = 1/k$. Therefore,

$$\mathbf{Pr}[|\|Ax\|_2^2 - 1| > \varepsilon] < 64^\ell \cdot \max\left\{\varepsilon^{-1}\sqrt{\frac{\ell}{k}}, \varepsilon^{-1}\frac{\ell}{k}\right\}^\ell, \tag{2}$$

which is at most $\delta$ for $\ell = \log(1/\delta)$ and $k \ge 4\cdot 64^2 \cdot \varepsilon^{-2}\log(1/\delta)$.[6] ■

**Remark 7.** The conclusion of Lemma 5 holds even if the $z_i$ are not necessarily Bernoulli but rather have mean 0, variance 1, and sub-Gaussian tails, albeit with the "64" possibly replaced by a different constant (see [15]). Thus, the above proof of Theorem 6 carries over unchanged to show that $A$ could instead have $\Omega(\log(1/\delta))$-wise independent such $z_i$ as entries. We also direct the reader to an older proof of this fact by Matousek [24], without discussion of independence requirements (though independence requirements can most likely be calculated from his proof, by converting the tail bounds he uses into moment bounds via integration).

# 5 Proof of Main Theorem

We recall the sparse JL transform construction of [10] (though the settings of some of our constants differ). Let $k = 28\cdot 64^2\cdot\varepsilon^{-2}\log(1/\delta)$. Pick random hash functions $h : [d] \to [k]$ and $\sigma : [d] \to \{-1, 1\}$. Let $\delta_{i,j}$ be the indicator random variable for the event $h(j) = i$. Define the matrix $A \in \{-1, 0, 1\}^{k\times d}$ by $A_{i,j} = \delta_{i,j}\cdot\sigma(j)$. The work of [10] showed that as long as $x \in \mathbb{R}^d$ satisfies $\|x\|_2 = 1$ and has bounded $\|x\|_\infty$, then $\mathbf{Pr}_{h,\sigma}[|\|Ax\|_2^2 - 1| > \varepsilon] < O(\delta)$. We show the same conclusion without the assumption that $h, \sigma$ are perfectly random; in particular, we show that $h$ need only be $r_h$-wise independent and $\sigma$ need only be $r_\sigma$-wise independent for $r_h = O(\log(k/\delta))$ and $r_\sigma = O(\log(1/\delta))$. Furthermore, our assumption on the bound for $\|x\|_\infty$ is $\|x\|_\infty \le c$ for $c = \Theta(\sqrt{\varepsilon/(\log(1/\delta)\cdot\log(k/\delta))})$, whereas [10] required $c = \Theta(\sqrt{\varepsilon/(\log(1/\delta)\cdot\log^2(k/\delta))})$. This is relevant since the column sparsity obtained in the final JL transform construction of [10] is $1/c^2$. This is because, to apply the dimensionality reduction of [10] to an arbitrary $x$ of unit $\ell_2$ norm (which might have $\|x\|_\infty \gg c$), one should first map $x$ to a vector $\tilde{x}$ by a $(d/c^2)\times d$ matrix $Q$ with $Q_{i_1 r + i_2, i_1+1} = c$ and other entries 0 for $i_1 \in \{0, \ldots, d-1\}$, $i_2 \in [1/c^2]$. Then $\|\tilde{x}\|_2 = 1$ and $\|\tilde{x}\|_\infty \le c$, and thus the set of products with $Q$ of JL matrices in the distribution of [10] over dimension $d/c^2$ serves as a JL family for arbitrary unit vectors. Thus, the sparsity obtained by our proof in the final JL construction is improved by a $\Theta(\log(k/\delta))$ factor.

Before proving our main theorem, first we note that

$$\|Ax\|_2^2 = \|x\|_2^2 + 2\sum_{(s,t)\in\binom{[d]}{2}}\left(\sum_{j=1}^{k}\delta_{s,j}\delta_{t,j}x_s x_t\right)\sigma(s)\sigma(t).$$

[6] Though our constant factor for $k$ is quite large, most likely the 64 could be made much smaller by tightening the analysis of constants in [12].

We would like that $\|Ax\|_2^2$ is concentrated about 1, or rather, that

$$Z = 2\sum_{s<t}\left(\sum_{j=1}^{k}\delta_{s,j}\delta_{t,j}x_s x_t\right)\sigma(s)\sigma(t) \tag{3}$$

is concentrated about 0. Let $\eta_{s,t}$ be the indicator random variable for the event $s \neq t$ and $h(s) = h(t)$. Then for fixed $h$, $Z$ is a quadratic form in the $\sigma(i)$ which can be written as $\sigma^T T\sigma$ for a $d \times d$ matrix $T$ with $T_{s,t} = x_s x_t \eta_{s,t}$ (we here and henceforth slightly abuse notation by sometimes using $\sigma$ to also denote the $d$-dimensional vector whose $i$th entry is $\sigma(i)$).

Our main theorem follows by applying Lemma 5 to $\sigma^T T\sigma$, as in the proof of Theorem 6 in Section 4, to show that $Z$ is concentrated about $\text{trace}(T) = 0$. However, unlike in Section 4, our matrix $T$ is not a fixed matrix, but rather is *random*; it depends on the random choice of $h$. We handle this issue by using the two lemmas below, which state that both $\|T\|_F$ and $\|T\|_2$ are small with high probability over the random choice of $h$. We then obtain our main theorem by first conditioning on this high probability event before applying Lemma 5. The lemmas are proven in Section 6 and Section 7.

Henceforth in this paper, we assume $\|x\|_2 = 1$, $\|x\|_\infty \leq c$, and $T$ is the matrix described above.

**Lemma 8.** $\mathbf{Pr}_h[\|T\|_F^2 > 7/k] < \delta$.

**Lemma 9.** $\mathbf{Pr}_h[\|T\|_2 > \varepsilon/(128 \cdot \log(1/\delta))] < \delta$.

The following theorem now implies our main theorem (Theorem 2).

**Theorem 10.**

$$\mathbf{Pr}_{h,\sigma}[|\|Ax\|_2^2 - 1| > \varepsilon] < 3\delta.$$

**Proof.** Write

$$\begin{aligned}\|Ax\|_2^2 &= \|x\|_2^2 + 2\sum_{(s,t)\in\binom{[d]}{2}} x_s x_t \eta_{s,t}\sigma(s)\sigma(t)\\ &= 1 + Z.\end{aligned}$$

We will show $\mathbf{Pr}_{h,\sigma}[|Z| > \varepsilon] < 3\delta$. Condition on $h$, and let $\mathcal{E}$ be the event that $\|T\|_F^2 \leq 7/k$ and $\|T\|_2 \leq \varepsilon/\log(1/\delta)$. By applications of Lemma 8 and Lemma 9 and a union bound,

$$\mathbf{Pr}_{h,\sigma}[|Z| > \varepsilon] < \mathbf{Pr}_\sigma[|Z| > \varepsilon \mid \mathcal{E}] + 2\delta.$$

By a Markov bound applied to the random variable $Z^\ell$ for $\ell$ an even integer,

$$\mathbf{Pr}_\sigma[|Z| > \varepsilon \mid \mathcal{E}] < \mathbf{E}_\sigma[Z^\ell \mid \mathcal{E}]/\varepsilon^\ell.$$

Since $Z = \sigma^T T\sigma$ and $\text{trace}(T) = 0$, applying Lemma 5 with $B = T$ and $2\ell \leq r_\sigma$ gives

$$\mathbf{Pr}_\sigma[|Z| > \varepsilon \mid \mathcal{E}] < 64^\ell \cdot \max\left\{\varepsilon^{-1}\sqrt{\frac{7\ell}{k}}, \frac{\ell}{128 \cdot \log(1/\delta)}\right\}^\ell. \tag{4}$$

since the $\ell$th moment is determined by $r_\sigma$-wise independence of $\sigma$. We conclude the proof by noting that the expression in Eq. (4) is at most $\delta$ for $\ell = \log(1/\delta)$. ■

**Remark 11.** In the proof Theorem 10, rather than condition on $\mathcal{E}$ we can directly bound the $O(\log(1/\delta))$th moment of $Z$ over the randomness of both $h$ and $\sigma$ simultaneously. In this case, we use the Frobenius and operator norm moments from Eq. (8) and Eq. (10) directly. This gives

$$\mathbf{Pr}_{h,\sigma}[|Z| > \varepsilon] < \varepsilon^{-\ell} \cdot 64^{\ell} \cdot \max\left\{ \left(\sqrt{\frac{6\ell}{k}}\right)^{\ell}, k \cdot \left(\frac{2\ell}{k}\right)^{\ell}, k \cdot \left(2c^2\ell^2\right)^{\ell} \right\}$$

as long as $h, \sigma$ are $\ell$-wise independent. One can then set $\ell = O(\log(1/\delta))$ and $c = O((\sqrt{\varepsilon}/\log(1/\delta)) \cdot \varepsilon^{2/\log(1/\delta)}) = O(\sqrt{\varepsilon^{1+o(1)}}/\log(1/\delta))$ to make the above probability at most $\delta$.

# 6 A high probability bound on $\|T\|_F$

In this section we prove Lemma 8.

**Proof** (of Lemma 8). Recall that for $s, t \in [d]$, $\eta_{s,t}$ is the random variable indicating that $s \neq t$ and $h(s) = h(t)$. Then, Eq. (3) implies that $\|T\|_F^2 = 2\sum_{s<t} x_s^2 x_t^2 \eta_{s,t}$. Note $\|T\|_F^2$ is a random variable depending only on $h$. The plan of our proof is to directly bound the $\ell$th moment of $\|T\|_F^2$ for some large $\ell$ (specifically, $\ell = \Theta(\log(1/\delta))$), then conclude by applying Markov's inequality to the random variable $\|T\|_F^{2\ell}$. We bound the $\ell$th moment of $\|T\|_F^2$ via some combinatorics.

We now give the details of our proof. Consider the expansion $(\|T\|_F^2)^{\ell}$. We have

$$(\|T\|_F^2)^{\ell} = 2^{\ell} \cdot \sum_{\substack{s_1,\ldots,s_\ell \\ t_1,\ldots,t_\ell \\ \forall i \in [\ell] s_i < t_i}} \prod_{i=1}^{\ell} x_{s_i}^2 x_{t_i}^2 \eta_{s_i,t_i} \tag{5}$$

Let $\mathcal{G}_\ell$ be the set of all isomorphism classes of graphs (possibly containing multi-edges) with between 2 and $2\ell$ unlabeled vertices, minimum degree at least 1, and exactly $\ell$ edges with distinct labels in $[\ell]$. We now define a map $f : \{\binom{[d]}{2}^{\ell}\} \to \mathcal{G}_\ell$ where the notation $\binom{U}{r}$ denotes subsets of $U$ of size $r$; i.e. $f$ maps the monomials in Eq. (5) to elements of $\mathcal{G}_\ell$. Focus on one monomial in Eq. (5) and let $S = \{s_1, \ldots, s_\ell, t_1, \ldots, t_\ell\}$. We map the monomial to an $|S|$-vertex element of $\mathcal{G}_\ell$ as follows: associate each $u \in S$ with a vertex, and for each $s_i, t_i$, draw an edge from the vertices associated with $s_i, t_i$ using edge label $i$.

We now analyze the expectation of the summation in Eq. (5) by grouping monomials which map to the same elements of $\mathcal{G}_\ell$ under $f$.

$$\mathbf{E}_h\left[(\|T\|_F^2)^{\ell}\right] = 2^{\ell} \cdot \sum_{G \in \mathcal{G}_\ell} \sum_{\substack{\{(s_i,t_i)\} \in \binom{[d]}{2}^{\ell} \\ f(\{(s_i,t_i)\}) = G}} \left(\prod_{i=1}^{\ell} x_{s_i}^2 x_{t_i}^2\right) \cdot \mathbf{E}_h\left[\prod_{i=1}^{\ell} \eta_{s_i,t_i}\right]. \tag{6}$$

Observe that $\prod_{i=1}^{\ell} \eta_{s_i,t_i}$ is determined by $h(s_i), h(t_i)$ for each $i \in [\ell]$, and hence its expectation is determined by $2\ell$-wise independence of $h$. Note that this product is 1 if $s_i$ and $t_i$ hash to the same element for each $i$ and is 0 otherwise. Each $s_i, t_i$ pair hash to the same element if and only if for each connected component of $G$, all elements of $S = \{s_1, \ldots, s_\ell, t_1, \ldots, t_\ell\}$ corresponding to vertices in that component hash to the same value. For the $v_G$ elements we are concerned with, where $v_G = |S|$ is the number of vertices in $G$, we can choose one element of $[k]$ for each connected component. Hence the number of possible values of $h$ on $S$ that cause $\prod_{i=1}^{\ell} \eta_{s_i,t_i}$ to be 1 is $k^{m_G}$, where $G$ has $m_G$ connected components. Each possibility happens with probability $k^{-v_G}$. Hence $\mathbf{E}_h[\prod_{i-1}^{\ell} \eta_{s_i,t_i}] = k^{m_G - v_G}$.

Also, consider the term $\prod_{i=1}^{\ell} x_{s_i}^2 x_{t_i}^2 = \prod_{i=1}^{v_G} x_{r_i}^{2\cdot\ell_i}$, where $S = \{r_i\}_{i=1}^{v_G}$, each $\ell_i$ is at least 1, and $\sum_i \ell_i = 2\ell$ ($\ell_i$ is just the degree of the vertex associated with $r_i$ in $G$). Then,

$$\prod_{i=1}^{v_G} x_{r_i}^{2\cdot\ell_i} = \left(\prod_{i=1}^{v_G} x_{r_i}^{2\cdot(\ell_i-1)}\right) \cdot \left(\prod_{i=1}^{v_G} x_{r_i}^2\right) \le \left(\prod_{i=1}^{v_G} x_{r_i}^{2\cdot(\ell_i-1)}\right) \cdot \left(\prod_{i=1}^{v_G} x_{r_i}^2\right) \le c^{2(2\ell - v_G)} \cdot \left(\prod_{i=1}^{v_G} x_{r_i}^2\right).$$

Note then that the monomials $(\prod_{i=1}^{v_G} x_{r_i}^2)$ that arise from the summation over $\{(s_i,t_i)\} \in \binom{d}{2}^{\ell}$ with $f(\{(s_i,t_i)\}) = G$ in Eq. (6) are a subset of those monomials which appear in the expansion of $(\sum_{i=1}^d x_i^2)^{v_G} = 1$. Thus, plugging back into Eq. (6),

$$\mathbf{E}_h\left[(\|T\|_F^2)^{\ell}\right] \le 2^{\ell} \cdot \sum_{G \in \mathcal{G}_\ell} \frac{c^{2(2\ell - v_G)}}{k^{v_G - m_G}}. \tag{7}$$

Note the value $\ell$ in the $c^{2(2\ell - v_G)}$ term just arose as $e_G$, the number of edges in $G$. We bound the above summation by considering all ways to form an element of $\mathcal{G}_\ell$ by adding one edge at a time, starting from the empty graph $G_0$ with zero vertices and edges. In fact we will overcount some $G \in \mathcal{G}_\ell$, but this is acceptable since we only want an upper bound on Eq. (7).

Define $F(G) = c^{2(2e_G - v_G)}/k^{v_G - m_G}$. Initially we have $F(G_0) = 1$. We will add $\ell$ edges in order by label, from label 1 to $\ell$. For the $i$th edge we have three options to form $G_i$ from $G_{i-1}$: (a) we can add the edge between two existing vertices in $G_{i-1}$, (b) we can add two new vertices to $G_{i-1}$ and place the edge between them, or (c) we can create one new vertex and connect it to an already-existing vertex of $G_{i-1}$. For each of these three options, we will argue that $n_i \cdot F(G_i)/F(G_{i-1}) \le 1/k$, where $n_i$ is the number of ways to perform the operation we chose at step $i$. This implies that the right hand side of Eq. (7) is at most $(6/k)^{\ell}$ since at each step of forming an element of $\mathcal{G}_\ell$ we have three options for how to form $G_i$ from $G_{i-1}$.

Let $e$ be the number of edges, $v$ the number of vertices, and $m$ the number of connected components for some $G_{i-1}$. In option (a), $v$ remains constant, $e$ increases by 1, and $m$ either remains constant or decreases by 1. In any case, $F(G_i)/F(G_{i-1}) \le c^4$, and $n_i < 2\ell^2$; the latter is because we have $\binom{v}{2} < 2\ell^2$ choices of vertices to connect. In option (b), $n_i = 1$, $v$ increases by 2, $e$ increases by 1, and $m$ increases by 1, implying $n_i \cdot F(G_i)/F(G_{i-1}) = 1/k$. Finally, in option (c), $n_i = v \le 2\ell$, $v$ increases by 1, $e$ increases by 1, and $m$ remains constant, implying $n_i \cdot F(G_i)/F(G_{i-1}) \le 2\ell c^2/k$. Thus, regardless of which of the three options we choose, $n_i \cdot F(G_i)/F(G_{i-1}) \le \max\{2\ell^2 c^4, 1/k, 2\ell c^2/k\}$, which is $1/k$ for $\ell = O(\log(1/\delta))$.

As discussed above, when combined with Eq. (7) this gives

$$\mathbf{E}_h[(\|T\|_F^2)^{\ell}] \le (6/k)^{\ell}. \tag{8}$$

Then, by Markov's inequality on the random variable $(\|T\|_F^2)^{\ell}$ for $\ell \ge 2$ and even, and assuming $2\ell \le r_h$,

$$\mathbf{Pr}_h[\|T\|_F^2 > 7/k] < (k/7)^{\ell} \cdot \mathbf{E}_h[(\|T\|_F^2)^{\ell}] < (6/7)^{\ell},$$

which is at most $\delta$ for $\ell = \Theta(\log(1/\delta))$. ■

## 7 A high probability bound on $\|T\|_2$

In this section we prove Lemma 9. For each $j \in [k]$ we use $\alpha_j$ to denote $\sum_{\substack{i\in[d]\\ h(i)=j}} x_i^2$.

**Lemma 12.** $\|T\|_2 \le \max\{c^2, \max_{j\in[k]} \alpha_j\}$.

**Proof.** Define the diagonal matrix $R$ with $R_{i,i} = x_i^2$, and put $S = T + R$. For each $j \in [k]$, consider the vector $v_j$ whose support is $h^{-1}(j)$, with $(v_j)_i = x_i$ for each $i$ in its support. Then $S = \sum_{j=1}^k v_j \cdot v_j^T$. Thus rank$(S)$ is equal to the number of non-zero $v_j$, since they are clearly linearly independent (they have disjoint support and are thus orthogonal) and span the image of $S$. Furthermore, these non-zero $v_j$ are eigenvectors of $S$ since $Sv_j = \alpha_j v_j$, and are the only eigenvectors of $S$ with non-zero eigenvalue since if $u$ is perpendicular to all such $v_j$ then $Au = 0$.

Now, $\|T\|_2 = \sup_{\|x\|_2=1} |x^T T x| = \sup_{\|x\|_2=1} |x^T S x - x^T R x|$. Since $S, R$ are both positive semidefinite, we then have $\|T\|_2 \le \max\{\|S\|_2, \|R\|_2\}$. $\|R\|_2$ is clearly $\|x\|_\infty^2 \le c^2$, and we saw above that $\|S\|_2 = \max_{j\in[k]} \alpha_j$. ■

**Proof** (of Lemma 9). Fix some $j \in [k]$. Define $X_i = x_i^2 \delta_{i,j}$ so that $\alpha_j = \sum_{i=1}^d X_i$. Then

$$\mathbf{E}_h[\alpha_j^\ell] = \sum_{1\le s_1,\ldots,s_\ell\le d} \mathbf{E}_h\left[\prod_{i=1}^{\ell} X_{s_i}\right] \tag{9}$$

Let $V_\ell$ be the set of length-$\ell$ vectors $v$ with non-negative integer entries such that if $r > 0$ appears as an entry of $v$, then at least one appearance of $r-1$ is in $v$ at an earlier index. Define the map $f : [d]^\ell \to V_\ell$ as follows: a vector $w \in [d]^\ell$ maps to the vector where for each $i \in [\ell]$, if $w_i$ is the $r$th distinct value (0-based indexing) to appear in $w$ then we replace $w_i$ with $r$. For example, $f((14, 1, 4, 14)) = (0, 1, 2, 0)$. We group the monomials in Eq. (9) by equal images under $f$. That is,

$$\begin{aligned}
\mathbf{E}_h[\alpha_j^\ell] &= \sum_{v\in V_\ell} \sum_{\substack{1\le s_1,\ldots,s_\ell\le d\\ f((s_1,\ldots,s_\ell))=v}} \mathbf{E}_h\left[\prod_{i=1}^{\ell} X_{s_i}\right] = \sum_{v\in V_\ell} \sum_{\substack{1\le s_1,\ldots,s_\ell\le d\\ f((s_1,\ldots,s_\ell))=v}} \left(\prod_{i=1}^{\ell} x_{s_i}^2\right) \cdot \mathbf{E}_h\left[\prod_{i=1}^{\ell} \delta_{s_i,j}\right]\\
&= \sum_{v\in V_\ell} \sum_{\substack{1\le s_1,\ldots,s_\ell\le d\\ f((s_1,\ldots,s_\ell))=v}} \left(\prod_{i=1}^{\ell} x_{s_i}^2\right) k^{-m_v} \le \sum_{v\in V_\ell} \sum_{\substack{1\le s_1,\ldots,s_\ell\le d\\ f((s_1,\ldots,s_\ell))=v}} \frac{c^{2(\ell-m_v)}}{k^{m_v}}
\end{aligned}$$

where the penultimate equality holds if $\ell \le r_h$ and $m_v$ is the number of distinct values amongst the entries of $v$. The final equality holds since, pulling out a $c^2$ term for each multiple occurrence of any $s_i$, for a fixed $v$ these terms all show up in the expansion of $(\|x\|_2^2)^{m_v}$.

Now we bound the double summation above. Begin with the empty sequence $v_0 = ()$ (in $V_0$). We will arrive at some $v_\ell \in V_\ell$ by appending an entry one at a time. In transitioning from $v_{i-1}$ to $v_i$ we can either (i) repeat an entry that already appeared in $v_{i-1}$, or (ii) add a new entry (whose identity is unique: it must be the next largest integer which has not appeared in $v_{i-1}$). For (i) there are $m_{v_{i-1}} \le \ell$ ways to choose a pre-existing integer to repeat, $i$ increases by 1, and $m_{v_i} = m_{v_{i-1}}$, and thus we gain a factor of $c^2\ell$. For (ii), there is one way to choose a new integer to appear, $i$ increases by 1, and $m_{v_i} = m_{v_{i-1}} + 1$, and thus we gain a factor of $1/k$. Since at each step we have two options to choose from (either perform (i) or (ii)), $\mathbf{E}_h[\alpha_j^\ell] \leq 2^\ell \cdot \max\{1/k, c^2\ell\}^\ell$. We then have

$$\mathbf{E}_h[\|T\|_2^\ell] \leq \mathbf{E}_h\left[\left(\max_{j\in[k]} \alpha_j\right)^\ell\right] = \mathbf{E}_h\left[\max_{j\in[k]} \alpha_j^\ell\right] \leq \sum_{j=1}^k \mathbf{E}_h[\alpha_j^\ell] \leq k \cdot 2^\ell \cdot \max\{1/k, c^2\ell\}^\ell \tag{10}$$

The lemma follows by a Markov bound with $\ell = O(\log(k/\delta))$, i.e. $\mathbf{Pr}_h[\|T\|_2 > \lambda] < \lambda^{-\ell} \cdot \mathbf{E}_h[\|T\|_2^\ell]$ and we set $\lambda = \varepsilon/(128 \cdot \log(1/\delta))$. ■

**Remark 13.** One could integrate the Bernstein inequality tail bound to obtain a moment bound which applies to $\mathbf{E}_h[\alpha_j^\ell]$ in the proof of Lemma 9. The conclusion would not improve. We chose to give an elementary proof to be self-contained.


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# Appendix

## A Optimality of Lemma 1

Jayram and Woodruff gave a proof that the $k = \Omega(\varepsilon^{-2}\log(1/\delta))$ in Lemma 1 is optimal [19]. Their proof went through communication and information complexity. We here give another proof of this fact, via some linear algebra and direct calculations.

Note that for a distribution $\mathcal{D}$, if $\mathbf{Pr}_{A\sim\mathcal{D}}[|\|Ax\|_2^2 - 1|] < \delta]$ for any $x \in S^{d-1}$, then it must be the case that $\mathbf{Pr}_{A\sim\mathcal{D}}[\mathbf{Pr}_{x\in S^{d-1}}[|\|Ax\|_2^2 - 1|]] < \delta$. The following theorem shows that no $A \in \mathbb{R}^{k\times d}$ can have $\mathbf{Pr}_{x\in S^{d-1}}[|\|Ax\|_2^2 - 1|] < \delta$ unless $k$ is at least as large as in the statement of Lemma 1.

**Theorem 14.** *If $A : \mathbb{R}^d \to \mathbb{R}^k$ is a linear transformation with $d > 2k$ and $\varepsilon > 0$ sufficiently small, then for $x$ a randomly chosen vector in $S^{d-1}$, $\mathbf{Pr}[|\|Ax\|_2^2 - 1| > \varepsilon] \geq \exp(-O(k\varepsilon^2 + 1))$.*

**Proof.** First we note that we can assume that $A$ is surjective since if it is not, we may replace $\mathbb{R}^k$ by the image of $A$. Let $V = \ker(A)$ and let $W = V^\perp$. Then $\dim(W) = k$, $\dim(V) = d - k$. Now, any $x \in \mathbb{R}^d$ can be written uniquely as $x_V + x_W$ where $x_V$ and $x_W$ are the components in $V$ and $W$ respectively. We may then write $x_V = r_V\Omega_V$, $x_W = r_W\Omega_W$, where $r_V, r_W$ are positive real numbers and $\Omega_V$ and $\Omega_W$ are unit vectors in $V$ and $W$ respectively. Let $s_V = r_V^2$ and $s_W = r_W^2$. We may now parameterize the unit sphere by $(s_V, \Omega_V, s_W, \Omega_W) \in [0,1] \times S^{d-k-1} \times [0,1] \times S^{k-1}$, so that $s_V + s_W = 1$. It is clear that the uniform measure on the sphere is given in these coordinates by $f(s_W)ds_W d\Omega_V d\Omega_W$ for some function $f$. To compute $f$ we note that

$f(s_W)$ should be proportional to the limit as $\delta_1, \delta_2 \to 0^+$ of $(\delta_1\delta_2)^{-1}$ times the volume of points $x$ so that $\|x\|_2^2 \in [1, 1+\delta_1]$ and $\|x_W\|_2^2 \in [s_W, s_W+\delta_2]$. Equivalently, $\|x_W\|_2^2 \in [s_W, s_W+\delta_2]$, and $\|x_V\|_2^2 \in [1-\|x_W\|_2^2, 1-\|x_W\|_2^2+\delta_1]$. For fixed $x_W$, the latter volume is within $O(\delta_1\delta_2)$ of the volume of $x_V$ so that $\|x_V\|_2^2 \in [s_V, s_V+\delta_1]$. Now the measure on $V$ is $r_V^{d-k-1} dr_V d\Omega_V$. Therefore it also is $\frac{1}{2}s_V^{(d-k-2)/2} ds_V d\Omega_V$. Therefore this volume over $V$ is proportional to $s_V^{(d-k-2)/2}(\delta_1 + O(\delta_1\delta_2 + \delta_1^2))$. Similarly the volume of $x_W$ so that $\|x_W\|_2^2 \in [s_W, s_W+\delta_2]$ is proportional to $s_W^{(k-2)/2}(\delta_2 + O(\delta_2^2))$. Hence $f$ is proportional to $s_V^{(d-k-2)/2} s_W^{(k-2)/2}$.

We are now prepared to prove the theorem. The basic idea is to first condition on $\Omega_V, \Omega_W$. We let $C = \|A\Omega_W\|_2^2$. Then if $x$ is parameterized by $(s_V, \Omega_V, s_W, \Omega_W)$, $\|Ax\|_2^2 = Cs_W$. Choosing $x$ randomly, we know that $s = s_W$ satisfies the distribution $\frac{s^{(k-2)/2}(1-s)^{(d-k-2)/2}}{\beta((k-2)/2,(d-k-2)/2)} ds = f(s)ds$ on $[0,1]$. We need to show that for any $c = \frac{1}{C}$, the probability that $s$ is not in $[(1-\varepsilon)c, (1+\varepsilon)c]$ is $\exp(-O(\varepsilon^2 k))$. Note that $f(s)$ attains its maximum value at $s_0 = \frac{k-2}{d-4} < \frac{1}{2}$. Notice that $\log(f(s_0(1+x)))$ is some constant plus $\frac{k-2}{2}\log(s_0(1+x)) + \frac{d-k-2}{2}\log(1-s_0-xs_0)$. If $\|x\|_2 < 1/2$, then this is some constant plus $-O(kx^2)$. So for such $x$, $f(s_0(1+x)) = f(s_0)\exp(-O(kx^2))$. Furthermore, for all $x$, $f(s_0(1+x)) = f(s_0)\exp(-\Omega(kx^2))$. This says that $f$ is bounded above by a normal distribution and checking the normalization we find that $f(s_0) = \Omega(s_0^{-1}k^{1/2})$.

We now show that both $\mathbf{Pr}(s < (1-\varepsilon)s_0)$ and $\mathbf{Pr}(s > (1+\varepsilon)s_0)$ are reasonably large. We can lower bound either as

$$\begin{aligned} s_0 \int_\varepsilon^{1/2} f(s_0)\exp(-O(kx^2))dx &\geq \Omega(k^{1/2}) \int_\varepsilon^{\varepsilon + k^{-1/2}} \exp(-O(kx^2))dx \\ &\geq \Omega(\exp(-O(k(\varepsilon + k^{-1/2})^2))) \\ &\geq \exp(-O(k\varepsilon^2 + 1)). \end{aligned}$$

Hence since one of these intervals is disjoint from $[(1-\varepsilon)c, (1+\varepsilon)c]$, the probability that $s$ is not in $[(1-\varepsilon)c, (1+\varepsilon)c]$ is at least $\exp(-O(k\varepsilon^2 + 1))$. ■

# B A JL Lemma derandomization

We give an explicit JL family with seed length $O(\log d + \log(1/\varepsilon)\log(1/\delta) + \log(1/\delta)\log\log(1/\delta))$. This seed length is always at least at least as good as the $O(\log(1/\delta)\log d)$ seed length coming from $k$-wise independence, but can be much better for some settings of parameters.

The idea is simply to graduately reduce the dimension. Consider values $\varepsilon', \delta' > 0$ which we will pick later. Define $t_j = \delta'^{-1/2^j}$. We embed $\mathbb{R}^d$ into $\mathbb{R}^{k_1}$ for $k_1 = \varepsilon'^{-2}t_1$. We then embed $\mathbb{R}^{k_{j-1}}$ into $\mathbb{R}^{k_j}$ for $k_j = \varepsilon'^{-2}t_j$ until the point $j = j^* = O(\log(1/\delta')/\log\log(1/\delta'))$ where $t_{j^*} = O(\log^3(1/\delta'))$. We then embed $\mathbb{R}^{k_{j^*}}$ into $\mathbb{R}^k$ for $k = O(\varepsilon'^{-2}\log(1/\delta'))$.

The embeddings into each $k_j$ are performed by picking a Bernoulli matrix with $r_j$-wise independent entries, as in Theorem 6. To achieve error probability $\delta'$ of having distortion larger than $(1+\varepsilon')$ in the $j$th step, Eq. (2) in the proof of Theorem 6 tells us we need $r_j = O(\log(1/\delta')/(t_j/\log(1/\delta')))$. Thus, in the first embedding into $\mathbb{R}^{k_1}$ we need $O(\log d)$ random bits. Then in the future embeddings except the last, we need $O(2^j \cdot (\log(1/\varepsilon') + 2^{-j}\log(1/\delta')))$ random bits to embed into $\mathbb{R}^{k_j}$. In the final embedding we require $O(\log(1/\delta') \cdot (\log(1/\varepsilon') + \log\log(1/\delta'))$ random bits. Thus, in total, we have used $O(\log d + \log(1/\varepsilon')\log(1/\delta') + \log(1/\delta')\log\log(1/\delta'))$ bits of seed to achieve error probability $O(\delta' \cdot j^*)$ of distortion $(1+\varepsilon')^{j^*}$. The following theorem thus follows by applying this argument with error probability $\delta' = \delta/(j^*+1)$ and distortion parameter $\varepsilon' = \Theta(\varepsilon/j^*)$.

**Theorem 15.** *For any $0 < \varepsilon, \delta < 1/2$ there exists an explicit JL family with seed length $s = O(\log d + \log(1/\varepsilon)\log(1/\delta) + \log(1/\delta)\log\log(1/\delta))$. Given a seed and a vector $x \in \mathbb{R}^d$, the embedding can be performed in polynomial time.*

**Remark 16.** *One may worry that along the way we are embedding into potentially very large dimension (e.g. $1/\delta$ may be $2^{\Omega(d)}$), so that our overall running time could be exponentially large. However, we can simply start the above iterative embedding at the level $j$ where $\varepsilon^{-2}t_j < d$.*