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A NOTE ON COLUMN SUBSET SELECTION

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ABSTRACT. Given a matrix $U$, using a deterministic method, we extract a "large" submatrix of $	ilde{U}$ (whose columns are obtained by normalizing those of $U$) and estimate its smallest and largest singular value. We apply this result to the study of contact points of the unit ball with its maximal volume ellipsoid. We consider also the paving problem and give a deterministic algorithm to partition a matrix into almost isometric blocks recovering previous results of Bourgain-Tzafriri and Tropp. Finally, we partially answer a question raised by Naor about finding an algorithm in the spirit of Batson-Spielman-Srivastava’s work to extract a "large" square submatrix of "small" norm.

1. INTRODUCTION

Let $U$ a $n \times m$ matrix, the stable rank of $U$ is given by
$$srank(U) = \frac{\|U\|_2^2}{\|U\|_{HS}^2},$$
where $\|U\|_{HS}$ denotes the Hilbert-Schmidt norm of $U$ and $\|U\|_2$ the operator norm of $U$ seen as an operator from $l^2_m$ to $l^2_n$. Denoting $\tilde{U}$ the matrix whose columns are obtained by normalizing those of $U$, our aim is to extract almost $srank(U)$ number of linearly independent columns of $\tilde{U}$ and estimate the smallest and the largest singular value of the restricted matrix.

This problem is closely related to the restricted invertibility where only an estimate on the smallest singular value is needed. The restricted invertibility was first studied by Bourgain-Tzafriri \cite{BourgainTzafriri}

\textbf{Theorem A.} Given an $n \times n$ matrix $T$ whose columns are of norm one, there exists $\sigma \subset \{1, \ldots, n\}$ with $|\sigma| \geq d_n \|T\|_2^2$ such that $\|T_\sigma x\|_2 \geq c \|x\|_2$ for all $x \in \mathbb{R}^\sigma$, where $d, c > 0$ are absolute constants and $T_\sigma$ denotes the restriction of $T$ onto the columns in $\sigma$.

In \cite{Vershynin}, Vershynin extended this result for any decomposition of the identity, whereas the previous result was valid for the canonical decomposition. Moreover the size of the restriction depended on the Hilbert-Schmidt norm of the operator. Precisely, Vershynin proved the following:

\textbf{Theorem B.} Let $Id = \sum_{j \leq m} x_j x_j^t$ and let $T$ be a linear operator on $l^2_n$. For any $\varepsilon \in (0, 1)$ one can find $\sigma \subset \{1, \ldots, m\}$ with
$$|\sigma| \geq (1 - \varepsilon) \frac{\|T\|_{HS}^2}{\|T\|_2^2}$$
such that
$$c(\varepsilon) \left( \sum_{j \in \sigma} a_j^2 \right)^{\frac{1}{2}} \leq \left\| \sum_{j \in \sigma} a_j T x_j \right\|_2 \leq C(\varepsilon) \left( \sum_{j \in \sigma} a_j^2 \right)^{\frac{1}{2}}$$
for all scalars $(a_j)$.

Vershynin applied this result to the study of contact points. The normalization on the vectors $T x_j$ is crucial for the applications and the dependence on $\varepsilon$ plays an important role. Spielman-Srivastava \cite{SpielmanSrivastava} generalized the restricted invertibility principle (Theorem A) for any decomposition of the identity without the normalizing factors appearing in Vershynin’s result and improved the dependence on $\varepsilon$. In \cite{SpielmanSrivastava}, we unified the two previous results obtaining a good dependence on $\varepsilon$ for any normalizing factors. However this result deals only with the lower
bound and doesn’t give any information on the norm of the restricted matrix. Our aim here, is
to improve Vershynin’s result obtaining simultaneously a restricted invertibility principle and
an estimate on the norm of the restricted matrix. Our proof uses ideas of the method of Batson-
Spielman-Srivastava ([1], [14], see also [18] for related topics).

The main result of this paper is the following:

**Theorem 1.1.** Let \( U \) be an \( n \times m \) matrix and denote by \( \tilde{U} \) the matrix whose columns are the
columns of \( U \) normalized. For all \( \varepsilon < 1 \), there exists \( \sigma \subset \{1, \ldots, m\} \) of size
\[
|\sigma| \geq (1 - \varepsilon)^2 \frac{\|U\|_{\text{HS}}^2}{\|U\|^2}
\]
such that
\[
\frac{\varepsilon}{2 - \varepsilon} \leq s_{\min} (\tilde{U}_\sigma) \leq s_{\max} (\tilde{U}_\sigma) \leq \frac{2 - \varepsilon}{\varepsilon}
\]
In other terms, for all \((a_j)_{j \in \sigma}\)
\[
\frac{\varepsilon}{2 - \varepsilon} \left( \sum_{j \in \sigma} a_j^2 \right)^{\frac{1}{2}} \leq \left\| \sum_{j \in \sigma} a_j \frac{U e_j}{\|U e_j\|_2} \right\|_2 \leq \frac{2 - \varepsilon}{\varepsilon} \left( \sum_{j \in \sigma} a_j^2 \right)^{\frac{1}{2}}.
\]

Note that the lower bound problem is the restricted invertibility problem treated in [13] and
[18] while the upper bound problem is related to the sparsification method and the Kashin-
Tzafriri column selection theorem [8] treated respectively in [1] and [18]. Our idea is to merge
the two algorithms together to get the two conclusions simultaneously. The heart of these
methods is the study of the evolution of the eigenvalues of a matrix when perturbated by a rank
one matrix.

In the regime where \( \varepsilon \) is close to one, the previous result yields the following:

**Corollary 1.2.** Let \( U \) be an \( n \times m \) matrix and denote by \( \tilde{U} \) the matrix whose columns are the
columns of \( U \) normalized. For all \( \varepsilon < 1 \), there exists \( \sigma \subset \{1, \ldots, m\} \) of size
\[
|\sigma| \geq \frac{\varepsilon^2}{9} \frac{\|U\|_{\text{HS}}^2}{\|U\|^2}
\]
such that
\[
1 - \varepsilon \leq s_{\min} (\tilde{U}_\sigma) \leq s_{\max} (\tilde{U}_\sigma) \leq 1 + \varepsilon
\]
In other terms, for all \((a_j)_{j \in \sigma}\)
\[
\left( \sum_{j \in \sigma} a_j^2 \right)^{\frac{1}{2}} \leq \left\| \sum_{j \in \sigma} a_j \frac{U e_j}{\|U e_j\|_2} \right\|_2 \leq \left( \sum_{j \in \sigma} a_j^2 \right)^{\frac{1}{2}}.
\]
Where \((e_j)_{j \leq m}\) denotes the canonical basis of \( \mathbb{R}^m \).

This result is also related to the problem of column paving that is partitioning the columns
into sets such that each of the corresponding restrictions has "good" bounds on the singular
values, in particular such that the singular values are close to one. We will show how our Theo-
rem allows us to recover a result of Tropp [16] (and of Bourgain-Tzafriri [2]) dealing with this
problem, using our deterministic method instead of the probabilistic methods used previously.

In a survey [11] on Batson-Spielman-Srivastava’s sparsification theorem, Naor asked about
giving a proof of another theorem of Bourgain-Tzafriri [2], which is stronger than the restricted
invertibility, using tools from Batson-Spielman-Srivastava’s method. The theorem in question is the following:

**Theorem C** (Bourgain-Tzafriri). There is a universal constant \( c > 0 \) such that for every \( \varepsilon < 1 \) and \( n \in \mathbb{N} \) if an operator \( T : \mathbb{R}^n \rightarrow \mathbb{R}^n \) satisfies \( \langle Te_i, e_i \rangle = 0 \) for all \( i \in \{1, \ldots, n\} \) then there exists a subset \( \sigma \subseteq \{1, \ldots, n\} \) satisfying \( |\sigma| \geq c\varepsilon^2 n \) and \( \|R_{\sigma}TR_{\sigma}^*\| \leq \varepsilon \|T\| \).

Using our result, we will be able to give a deterministic algorithm to solve this problem for symmetric matrices.

The paper is organized as follows: in section 2, we prove our main result, in section 3 we give applications to the local theory of Banach spaces and compare it with Vershynin’s result. In section 4, we prove column paving results and finally in section 5 we answer Naor’s question.

2. **Proof of Theorem 1.1**

Note \( k = |\sigma| = (1 - \varepsilon)^2 \frac{\|U\|_{HS}^2}{\|U\|_F^2} \) and

\[
A_k = \sum_{j \in \sigma} s_j \left( \tilde{U}e_j \right) \left( \tilde{U}e_j \right)^t,
\]

where \( s_j \) are positive numbers which will be determined later. Since our aim is to find \( \sigma \) such that the smallest singular value of \( \tilde{U}_{\sigma} \) is bounded away from zero and its largest one is upper bounded, it is equivalent to try to construct the matrix \( A_k \) such that \( A_k \) has \( k \) eigenvalues bounded away from zero and bounded from above and to estimate the weights \( s_j \). Our construction will be done step by step starting from \( A_0 = 0 \). So at the beginning, all the eigenvalues of \( A_0 \) are zero. At the first step we will try to find a vector \( v \) among the columns of \( \tilde{U} \) and a weight \( s \) such that \( A_1 = A_0 + svv^t \) has one nonzero eigenvalue which have a lower and upper bound. Of course the first step is trivial, since for whatever column we choose the matrix \( A_1 \) will have one eigenvalue equal to \( s \). At the second step, we will try to find a vector \( v \) among the columns of \( \tilde{U} \) and a weight \( s \) such that \( A_2 = A_1 + svv^t \) has two nonzero eigenvalues for which we can update the lower and upper bound found in the first step. We will continue this procedure until we construct the matrix \( A_k \).

For a symmetric matrix \( A \) such that \( b < \lambda_{\min}(A) \leq \lambda_{\max}(A) < u \), we define:

\[
\phi(A, b) = \text{Tr} \left( U^t \left( A - b. Id \right)^{-1} U \right) \quad \text{and} \quad \psi(A, u) = \text{Tr} \left( U^t \left( u. Id - A \right)^{-1} U \right)
\]

For \( l \leq k \), we denote by \( b_l \) the lower bound of the \( l \) nonzero eigenvalues of \( A_l \) and by \( u_l \) the upper bound i.e \( A_l \prec u_l.Id \) and has \( l \) eigenvalues \( > b_l \). We also note

\[
\phi = \phi(A_0, b_0) = - \frac{\|U\|_{HS}^2}{b_0} \quad \text{and} \quad \psi = \psi(A_0, u_0) = \frac{\|U\|_{HS}^2}{u_0},
\]

where \( b_0 \) and \( u_0 \) will be determined later.

As we said before, we want to control the evolution of the eigenvalues so we will make sure to choose a "good" vector so that our bounds \( b_l \) and \( u_l \) do not move too far. Precisely, we will fix this amount of change and denote by \( \delta \) for the lower bound and \( \Delta \) for the upper bound i.e at the next step the lower bound will be \( b_{l+1} = b_l - \delta \) and the upper one \( u_{l+1} = u_l + \Delta \). We will choose these two quantities as follows:

\[
\delta = (1 - \varepsilon) \frac{b_0}{k} \frac{\|U\|_F^2}{\|U\|_{HS}^2} \quad \text{and} \quad \Delta = (1 - \varepsilon) \frac{u_0}{k} \frac{\|U\|_F^2}{\|U\|_{HS}^2}
\]
Our choice of $\delta$ is motivated by the fact that after $k$ steps we want the updated lower bound to remain positive but not too small due to some obstructions in the proof. In this case the final lower bound will be

$$b_k = b_{k-1} - \delta = \ldots = b_0 - k\delta = \varepsilon b_0$$

The choice of $\Delta$ is motivated by the fact that we don’t want the upper bound to move too far from the initial one and as for $\delta$ we have some obstruction on taking its value too small. The final upper bound will be

$$u_k = u_{k-1} + \Delta = \ldots = u_0 + k\Delta = (2 - \varepsilon)u_0$$

**Definition 2.1.** We will say that a positive semidefinite matrix $A$ satisfies the $l$-requirement if the following properties are verified:

- $A \prec u_l. Id$.
- $A$ has $l$ eigenvalues $> b_l$.
- $\phi(A, b_l) \leq \phi$.
- $\psi(A, u_l) \leq \psi$.

In order to construct $A_{l+1}$ which has $l + 1$ nonzero eigenvalues larger than $b_{l+1}$ and such that $\phi(A_{l+1}, b_{l+1}) \leq \phi(A_l, b_l)$, we may look at the algorithm used for the restricted invertibility problem ([13], [18]) and more precisely, at the condition needed on the vector $v$ to be chosen:

**Lemma 2.2.** If $A_l$ has $l$ nonzero eigenvalues greater than $b_l$ and if for some vector $v$ and some positive scalar $s$ we have

$$G_l(v) := - v^t (A_l - b_{l+1}. Id)^{-2} v \cdot \|U\|^2 - v^t (A_l - b_{l+1}. Id)^{-1} v \geq \frac{1}{s}.$$ 

Then $A_{l+1} = A_l + svv^t$ has $l + 1$ nonzero eigenvalues all greater than $b_{l+1}$ and $\phi(A_{l+1}, b_{l+1}) \leq \phi(A_l, b_l)$.

Now, in order to construct $A_{l+1}$ which has all its eigenvalues smaller than $u_{l+1}$ and such that $\psi(A_{l+1}, u_{l+1}) \leq \psi(A_l, u_l)$ we may look at the algorithm used for the sparsification theorem [1] or the Kashin-Tzafriri column selection theorem (see Theorem 4.2 [18]):

**Lemma 2.3.** If $A_l \prec u_l. Id$ and if for some vector $v$ and some positive scalar $s$ we have

$$F_l(v) := \frac{v^t (u_{l+1}. Id - A_l)^{-2} v}{\psi(A_l, u_l) - \psi(A_l, u_{l+1})} \cdot \|U\|^2 + v^t (u_{l+1}. Id - A_l)^{-1} v \leq \frac{1}{s}.$$ 

Then denoting $A_{l+1} = A_l + svv^t$, we have $A_{l+1} \prec u_{l+1}. Id$ and $\psi(A_{l+1}, u_{l+1}) \leq \psi(A_l, u_l)$.

The proof of these two lemmas makes use of the Sherman-Morrison formula.

For our problem, we will need to find a vector $v$ satisfying (1) and (2) simultaneously. For that we need to merge these two conditions in one equation:

**Lemma 2.4.** If $A_l \prec u_l. Id$ has $l$ eigenvalues greater than $b_l$ and if for some vector $v$ we have

$$F_l(v) \leq G_l(v)$$

Then taking any $s$ such that $F_l(v) \leq \frac{1}{s} \leq G_l(v)$, then $A_{l+1} = A_l + svv^t$ satisfies the $(l + 1)$-requirement.

**Remark 2.5.** Since $A_{l+1}$ has $l+1$ nonzero eigenvalues while $A_l$ had only $l$ nonzero eigenvalues, then the vector $v$ chosen is linearly independent with the eigenvectors of $A_l$. Therefore one can see that $\text{Ker}(A_{l+1}) \subset \text{Ker}(A_l)$ and $\dim \left[\text{Ker}(A_{l+1})\right] = \dim \left[\text{Ker}(A_l)\right] - 1$. 
Proposition 2.6. Let \( A_l \) satisfying the \( l \)-requirement. If \( b_0 \) and \( u_0 \) satisfy

\[
(4) \quad b_0 \leq \frac{\varepsilon u_0}{2 - \varepsilon}
\]

then there exists \( i \leq m \) and a positive number \( s_i \) such that \( A_{i+1} = A_i + s_i \left( \tilde{U} e_i \right) \cdot \left( \tilde{U} e_i \right)^t \) satisfies the \((l+1)\)-requirement.

Proof. According to Lemma 2.4, it is sufficient to find \( i \leq m \) such that \( F_l \left( \tilde{U} e_i \right) \leq G_l \left( \tilde{U} e_i \right) \) and then take \( s_j \) such that

\[
(5) \quad F_l \left( \tilde{U} e_i \right) \leq \frac{1}{s_j} \leq G_l \left( \tilde{U} e_i \right)
\]

Since \( F_l \) and \( G_l \) are quadratic forms, it is equivalent to find \( i \leq m \) such that \( F_l \left( U e_i \right) \leq G_l \left( U e_i \right) \).

For that, it is sufficient to prove

\[
(6) \quad \sum_{j \leq m} F_l \left( U e_j \right) \leq \sum_{j \leq m} G_l \left( U e_j \right)
\]

Before estimating \( \sum_{j \leq m} F_l \left( U e_j \right) \), let us note that

\[
\psi(A_l, u_l) - \psi(A_l, u_{l+1}) = \text{Tr} \left[ U^t (u_{l+1} \cdot Id - A_l)^{-1} U \right] - \text{Tr} \left[ U^t (u_l \cdot Id - A_l)^{-1} U \right]
\]

\[
\geq \Delta \text{Tr} \left[ U^t (u_{l+1} \cdot Id - A_l)^{-2} U \right]
\]

Replacing this in \( F_l \) we get

\[
\sum_{j \leq m} F_l \left( U e_j \right) = \sum_{j \leq m} \frac{e_j^t U^t (u_{l+1} \cdot Id - A_l)^{-2} U e_j}{\psi(A_l, u_l) - \psi(A_l, u_{l+1})} \cdot \|U\|^2 + \sum_{j \leq m} e_j^t U^t (u_{l+1} \cdot Id - A_l)^{-1} U e_j
\]

\[
\leq \frac{\|U\|^2}{\Delta} + \psi
\]

Now we may estimate \( \sum_{j \leq m} G_l \left( U e_j \right) \). We denote by \( P_l \) the orthogonal projection onto the image of \( A_l \) and \( Q_l \) the orthogonal projection onto the kernel of \( A_l \). Note that \( \forall l \leq k \) we have the following

\[
(7) \quad b_l \leq \delta \frac{\|Q_l U\|^2_{\text{HS}}}{\|U\|^2}
\]

Since \( Q_0 = Id \), this fact is true at the beginning by our choice of \( \delta \). Taking in account Remark 2.5 at each step \( \|Q_l U\|^2_{\text{HS}} \) decreases by at most \( \|U\|^2 \) so that the right hand side of (7) decreases by at most \( \delta \). Since at each step we replace \( b_l \) by \( b_{l+1} \), (7) remains true.

Since \( Id = P_l + Q_l \) and \( P_l, Q_l, A_l \) commute we can write

\[
\text{Tr} \left[ U^t (A_l - b_{l+1} \cdot Id)^{-2} U \right] = \text{Tr} \left[ U^t P_l (A_l - b_{l+1} \cdot Id)^{-2} P_l U \right] + \text{Tr} \left[ U^t Q_l (A_l - b_{l+1} \cdot Id)^{-2} Q_l U \right]
\]

\[
= \text{Tr} \left[ U^t P_l (A_l - b_{l+1} \cdot Id)^{-2} P_l U \right] + \frac{\|Q_l U\|^2_{\text{HS}}}{b_{l+1}^2}
\]
Doing the same decomposition for \( \phi_t(A_t) \) we get
\[
\phi(A_t, b_t) = \text{Tr} \left[ U^t P_t (A_t - b_t. Id)^{-1} P_t U \right] + \text{Tr} \left[ U^t Q_t (A_t - b_t. Id)^{-1} Q_t U \right]
\]
\[
= \text{Tr} \left[ U^t P_t (A_t - b_t. Id)^{-1} P_t U \right] - \frac{\|Q_t U\|_{HS}^2}{b_t} \\
:= \phi^P(A_t, b_t) + \phi^Q(A_t, b_t)
\]

Denote \( \Lambda_t = \phi(A_t, b_t) - \phi(A_t, b_{t+1}) \) and \( \Lambda_t^P, \Lambda_t^Q \) the corresponding decompositions onto the image part and the kernel part as above. As we did before, we have \( \Lambda_t = \Lambda_t^P + \Lambda_t^Q \) and
\[
\Lambda_t^P = \text{Tr} \left[ U^t P_t (A_t - b_t. Id)^{-1} P_t U \right] - \text{Tr} \left[ U^t P_t (A_t - b_{t+1}. Id)^{-1} P_t U \right] \\
= \delta \text{Tr} \left[ U^t P_t (A_t - b_t. Id)^{-1} (A_t - b_{t+1}. Id)^{-1} P_t U \right] \\
\geq \delta \text{Tr} \left[ U^t P_t (A_t - b_{t+1}. Id)^{-2} P_t U \right]
\]

Using (7) we have
\[
\Lambda_t^Q = -\frac{\|Q_t U\|_{HS}^2}{b_t} + \frac{\|Q_t U\|_{HS}^2}{b_{t+1}} = \frac{\delta \|Q_t U\|_{HS}^2}{b_t b_{t+1}} \geq \frac{\|U\|^2}{b_{t+1}}
\]

Looking at the previous information, we can write
\[
\sum_{j \in m} G_t (U e_j) = -\frac{\text{Tr} \left[ U^t (A_t - b_{t+1}. Id)^{-2} U \right]}{\Lambda_t} \cdot \|U\|^2 - \text{Tr} \left[ U^t (A_t - b_{t+1}. Id)^{-1} U \right]
\]
\[
= -\frac{\text{Tr} \left[ U^t P_t (A_t - b_{t+1}. Id)^{-2} P_t U \right] + \frac{\|Q_t U\|_{HS}^2}{b_{t+1}}}{\Lambda_t} \cdot \|U\|^2 - \phi_t(U) \\
\geq -\frac{\Lambda_t^P + \Lambda_t^Q \left[ \frac{1}{\delta} + \frac{1}{b_{t+1}} \right]}{\Lambda_t} \cdot \|U\|^2 + \Lambda_t - \phi_t(U) \\
\geq -\frac{\Lambda_t^P}{\delta} - \frac{\|U\|^2}{b_{t+1}} + \Lambda_t^Q - \phi \\
\geq -\frac{\|U\|^2}{\delta} - \phi
\]

Until now we have proven that
\[
\sum_{j \in m} G_t (U e_j) \geq -\frac{\|U\|^2}{\delta} - \phi \quad \text{and} \quad \sum_{j \in m} F_t (U e_j) \leq \frac{\|U\|^2}{\Delta} + \psi
\]

So in order to prove (6), it will be sufficient to verify

(8) \[
\frac{\|U\|^2}{\Delta} + \psi \leq -\frac{\|U\|^2}{\delta} - \phi
\]

Replacing in (8) the values of the corresponding parameters as chosen at the beginning, it is sufficient to prove
\[
\frac{(2 - \varepsilon) \|U\|_{HS}^2}{u_0} \leq \varepsilon \|U\|_{HS}^2
\]
which is after rearrangement condition (4). \( \square \)
Keeping in mind that \( k = (1 - \varepsilon)^2 \frac{\|U\|_{2s}}{\|U\|_1^2} \), we are ready to finish the construction of \( A_k \). We may iterate Proposition 2.6 starting with \( A_0 = 0 \). Of course, \( A_0 \) satisfies the 0-requirement so by the proposition we can find a column vector and a corresponding scalar to form the 1-requirement. Once again we use the proposition to construct \( A_2 \) satisfying the 2-requirement. We can continue with this procedure as long as the corresponding lower bound \( b_1 \) is positive (which is the case for \( b_k \)). So after \( k \) steps we have constructed \( A_k = \sum_{j \in \sigma} s_j (\tilde{U} e_i) \cdot (\tilde{U} e_i)^t \) satisfying the \( k \)-requirement which means that
\[
A_k \prec u_k Id = (1 - 2\varepsilon) u_0 \text{ and } A_k \text{ has } k \text{ eigenvalues bigger than } b_k = \varepsilon b_0.
\]
Now it remains to estimate the weights \( s_j \) chosen. This will be done by a trivial calculation:

**Lemma 2.7.** For any \( l \leq k \) and any unit vector \( v \) we have
\[
G_l(v) \leq \frac{1}{\varepsilon b_0} \quad \text{and} \quad F_l(v) \geq \frac{1}{(2 - \varepsilon) u_0}.
\]

**Proof.** Write again \( Id = P_l + Q_l \) and notice that \( \frac{\psi(A_l - b_{l+1} Id)}{\phi(A_l, b_l) - \phi(A_l, b_{l+1})} \) and \( v^t P_l (A_l - b_{l+1} Id)^{-1} P_l v \) are positive then we have
\[
G_l(v) \leq -v^t (A_l - b_{l+1} Id)^{-1} v \leq -v^t Q_l (A_l - b_{l+1} Id)^{-1} Q_l v \leq \frac{\|Q_l v\|_2^2}{b_{l+1}} \leq \frac{\|v\|_2^2}{b_k} \leq \frac{1}{\varepsilon b_0}
\]
Now since \( \frac{v^t (u_{l+1} Id - A_l)^{-1} v}{\psi(A_l, u_l) - \psi(A_l, u_{l+1})} \geq 0 \) then
\[
F_l(v) \geq v^t (u_{l+1} Id - A_l)^{-1} v \geq v^t (u_k Id)^{-1} v \geq \frac{1}{(2 - \varepsilon) u_0}.
\]

The weights \( s_j \) that we have chosen satisfy (5) and therefore by the previous lemma
\[
\forall i \leq k, \quad \varepsilon b_0 \leq s_j \leq (2 - \varepsilon) u_0
\]
Back to our problem note that
\[
\tilde{U}_\sigma \tilde{U}_\sigma^t = \sum_{j \in \sigma} (\tilde{U} e_i) \cdot (\tilde{U} e_i)^t
\]
and therefore
\[
\frac{1}{(2 - \varepsilon) u_0} A_k = \frac{1}{(2 - \varepsilon) u_0} \sum_{j \in \sigma} s_j (\tilde{U} e_i) \cdot (\tilde{U} e_i)^t \leq \tilde{U}_\sigma \tilde{U}_\sigma^t \leq \frac{1}{\varepsilon b_0} \sum_{j \in \sigma} s_j (\tilde{U} e_i) \cdot (\tilde{U} e_i)^t = \frac{1}{\varepsilon b_0} A_k
\]
Transferring the properties of \( A_k \), we deduce that \( \tilde{U}_\sigma \tilde{U}_\sigma^t \leq \frac{(2 - \varepsilon) u_0}{\varepsilon b_0} Id \) and \( \tilde{U}_\sigma \tilde{U}_\sigma^t \) has \( k \) eigenvalues greater than \( \frac{\varepsilon b_0}{(2 - \varepsilon) u_0} \).
This means that
\[
\frac{\varepsilon b_0}{(2 - \varepsilon) u_0} Id \prec \tilde{U}_\sigma \tilde{U}_\sigma^t \leq \frac{(2 - \varepsilon) u_0}{\varepsilon b_0} Id
\]
Taking \( b_0 = \frac{\varepsilon u_0}{2 - \varepsilon} \) in order to satisfy (4) we finish the proof of Theorem 1.1.

3. **APPLICATION TO THE LOCAL THEORY OF BANACH SPACES**

As for the restricted invertibility principle where one can interpret the result as the invertibility of an operator on a decomposition of the identity, we will write the result in terms of a decomposition of the identity. This will be useful for applications to the local theory of Banach spaces since by John’s theorem [7] one can have a decomposition of the identity formed by contact points of the unit ball with its maximal volume ellipsoid.
Proposition 3.1. Let $I\!d = \sum_{i \leq m} y_i y_i^t$ be a decomposition of the identity in $\mathbb{R}^n$ and $T$ be a linear operator on $l^2$. For $\varepsilon < 1$, there exists $\sigma \subset \{1, \ldots, m\}$ such that

$$|\sigma| \geq (1 - \varepsilon)^2 \frac{\|T\|_{HS}^2}{\|T\|^2}$$

and for all $(a_j)_{j \in k}$,

$$\frac{\varepsilon}{2 - \varepsilon} \left(\sum_{j \in k} a_j^2\right)^{\frac{1}{2}} \leq \left\| \sum_{j \in k} a_j \frac{T y_j}{\|T y_j\|_2} \right\|_2 \leq \frac{2 - \varepsilon}{\varepsilon} \left(\sum_{j \in k} a_j^2\right)^{\frac{1}{2}}.$$ 

Proof. Let $U$ be the $n \times m$ matrix whose columns are $T y_j$. Therefore we can write

$$UU^t = \sum_{j \leq m} (T y_j) \cdot (T y_j)^t = T T^t.$$ 

We deduce that $\|U\|_{HS} = \|T\|_{HS}$ and $\|U\| = \|T\|$. Applying Theorem 1.1 to $U$, we find $\sigma \subset \{1, \ldots, m\}$ such that

$$|\sigma| \geq (1 - \varepsilon)^2 \frac{\|T\|_{HS}^2}{\|T\|^2}$$

and for all $(a_j)_{j \in \sigma}$,

$$\frac{\varepsilon}{2 - \varepsilon} \left(\sum_{j \in \sigma} a_j^2\right)^{\frac{1}{2}} \leq \left\| \sum_{j \in \sigma} a_j \frac{U e_j}{\|U e_j\|_2} \right\|_2 \leq \frac{2 - \varepsilon}{\varepsilon} \left(\sum_{j \in \sigma} a_j^2\right)^{\frac{1}{2}}.$$ 

Noting that $\frac{U e_j}{\|U e_j\|_2} = \frac{T y_j}{\|T y_j\|_2}$, we finish the proof.

This result improves the dependence on $\varepsilon$ in comparison with Vershynin’s result [17]. While Vershynin proved that $(T y_j)_{j \in \sigma}$ is $c(\varepsilon)$-equivalent to an orthogonal basis, the value of $c(\varepsilon)$ was of the order of $\varepsilon^{-c \log(\varepsilon)}$. Here our sequence is $(4 \varepsilon^{-2})$-equivalent to an orthogonal basis.

In the regime where $\varepsilon$ is close to one, the previous proposition yields the following:

Corollary 3.2. Let $I\!d = \sum_{i \leq m} y_i y_i^t$ a decomposition of the identity in $\mathbb{R}^n$ and $T$ a linear operator on $l^2$. For $\varepsilon < 1$, there exists $\sigma \subset \{1, \ldots, m\}$ such that

$$|\sigma| \geq \frac{\varepsilon^2 \|T\|_{HS}^2}{9\|T\|^2}$$

and for all $(a_j)_{j \leq k}$,

$$(1 - \varepsilon) \left(\sum_{j \leq k} a_j^2\right)^{\frac{1}{2}} \leq \left\| \sum_{j \leq k} a_j \frac{T y_j}{\|T y_j\|_2} \right\|_2 \leq (1 + \varepsilon) \left(\sum_{j \leq k} a_j^2\right)^{\frac{1}{2}}.$$ 

The two previous results can be written in terms of contact points, let us for instance write the case of $T = I\!d$. If $X = (\mathbb{R}^n, \|\cdot\|)$ where $\|\cdot\|$ is a norm on $\mathbb{R}^n$ such that $B_2^n$ is the ellipsoid of maximal volume contained in $B_X$, then by John’s theorem one can get an identity decomposition formed by contact points of $B_X$ with $B_2^n$. Applying Proposition 3.1 we get the following:

Proposition 3.3. Let $X = (\mathbb{R}^n, \|\cdot\|)$ where $\|\cdot\|$ is a norm on $\mathbb{R}^n$ such that $B_2^n$ is the ellipsoid of maximal volume contained in $B_X$. For $\varepsilon < 1$, there exists $x_1, \ldots, x_k$ contact points of $B_X$ with $B_2^n$ such that

$$k \geq (1 - \varepsilon)^2 n.$$
and for all \((a_j)_{j \leq k}\),

\[
\frac{\varepsilon}{2 - \varepsilon} \left( \sum_{j \leq k} a_j^2 \right)^{\frac{1}{2}} \leq \left\| \sum_{j \leq k} a_j x_j \right\|_2 \leq \frac{2 - \varepsilon}{\varepsilon} \left( \sum_{j \leq k} a_j^2 \right)^{\frac{1}{2}}.
\]

In other terms, we can find a system of almost \(n\) contact points which is \((\frac{4\varepsilon^{-2}}{\varepsilon})\)-equivalent to an orthonormal basis. Looking at the lower bound, this gives a proportional Dvoretzky-Rogers factorization \([6]\) with the best known dependence on \(\varepsilon\).

If we are willing to give up on the fact of extracting a large number of contact points, we can have a system of contact points which is \((1 + \varepsilon)\)-equivalent to an orthonormal basis. For that we write the previous proposition in the regime where \(\varepsilon\) is close to 1.

**Corollary 3.4.** Let \(X = (\mathbb{R}^n, \| \cdot \|)\) where \(\| \cdot \|\) is a norm on \(\mathbb{R}^n\) such that \(B_2^n\) is the ellipsoid of maximal volume contained in \(B_X\). For \(\varepsilon < 1\), there exists \(x_1, \ldots, x_k\) contact points of \(B_X\) with \(B_2^n\) such that

\[
k \geq \frac{\varepsilon^2 n}{9}
\]

and for all \((a_j)_{j \leq k}\),

\[
(1 - \varepsilon) \left( \sum_{j \leq k} a_j^2 \right)^{\frac{1}{2}} \leq \left\| \sum_{j \leq k} a_j x_j \right\|_2 \leq (1 + \varepsilon) \left( \sum_{j \leq k} a_j^2 \right)^{\frac{1}{2}}
\]

Applying proposition 3.3, we get the following corollary:

**Corollary 3.5.** Let \(X = (\mathbb{R}^n, \| \cdot \|)\) where \(\| \cdot \|\) is a norm on \(\mathbb{R}^n\) such that \(B_2^n\) is the ellipsoid of maximal volume contained in \(B_X\). For \(\varepsilon < 1\), there exists \(x_1, \ldots, x_k\) linearly independent contact points of \(B_X\) with \(B_2^n\) such that

\[
k \geq (\sqrt{2} - 1)^4 \varepsilon^2 n
\]

and for any \(i \leq k\),

\[
\sum_{j \neq i} \langle x_j, x_i \rangle^2 \leq \varepsilon
\]

**Proof.** Let \(\varepsilon < 1\) and denote \(\alpha = (\sqrt{2} - 1)^2\). Apply proposition 3.3 with \((1 - \alpha \varepsilon)\) in order to find a system of linearly independent contact points \((x_j)_{j \leq k}\) such that

\[
A_k = \sum_{j \leq k} x_j x_j^t \leq \left( \frac{1 + \alpha \varepsilon}{1 - \alpha \varepsilon} \right)^2 Id
\]

For \(i \leq k\),

\[
\langle A_k x_i, x_i \rangle = 1 + \sum_{j \neq i} \langle x_j, x_i \rangle^2 \leq \left( \frac{1 + \alpha \varepsilon}{1 - \alpha \varepsilon} \right)^2
\]

The conclusion follows by a trivial calculation. \(\square\)

### 4. Column Paving

Extracting a large column submatrix reveals to be useful since the extracted matrix may have better properties. First results in this direction were given by Kashin in \([9]\), and others followed improving or dealing with different properties (see \([1], [2], [8], [10], [16]\)). One can also be interested in partitioning the matrix into disjoint sets of columns such that each block has "good" properties. Obtaining a constant number of blocks (independent of the dimension) turns out to be a difficult problem and many conjectures concerning this were given previously (see \([4]\)).
The previous algorithms for extraction used probabilistic arguments and Grothendieck’s factorization theorem. Here we propose a deterministic algorithm to achieve the extraction, we apply our main result iteratively in order to partition the matrix into blocks on each of them we have good estimates on the singular values.

**Definition 4.1.** Let \( U \) a \( n \times m \) matrix. We will say that \( U \) is standardized if all its columns are of norm 1.

Note that when \( U \) is standardized we have \( \|U\|_{\text{HS}}^2 = m \) and \( \|U\| \geq 1 \). Applying Theorem 1.1 to a standardized matrix, we get the following proposition:

**Proposition 4.2.** Let \( U \) a \( n \times m \) standardized matrix. For \( \varepsilon < 1 \), there exists \( \sigma \subset \{1, \ldots, m\} \) with
\[
|\sigma| \geq \frac{(1 - \varepsilon)^2 m}{\|U\|^2}
\]
such that
\[
\frac{\varepsilon}{2 - \varepsilon} \leq s_{\min}(U_\sigma) \leq s_{\max}(U_\sigma) \leq \frac{2 - \varepsilon}{\varepsilon}
\]

In the regime where \( \varepsilon \) is close to one, the previous proposition yields an almost isometric estimation:

**Corollary 4.3.** Let \( U \) a \( n \times m \) standardized matrix. For \( \varepsilon < 1 \), there exists \( \sigma \subset \{1, \ldots, m\} \) with
\[
|\sigma| \geq \frac{\varepsilon^2 m}{9\|U\|^2}
\]
such that
\[
1 - \varepsilon \leq s_{\min}(U_\sigma) \leq s_{\max}(U_\sigma) \leq 1 + \varepsilon
\]

**Proposition 4.4.** Let \( U \) a \( n \times m \) standardized matrix. For \( \varepsilon < 1 \), there exists a partition of \( \{1, \ldots, m\} \) into \( p \) sets \( \sigma_1, \ldots, \sigma_p \) such that
\[
p \leq \frac{\|U\|^2 \log(m)}{(1 - \varepsilon)^2}
\]
and for any \( i \leq p \),
\[
\frac{\varepsilon}{2 - \varepsilon} \leq s_{\min}(U_{\sigma_i}) \leq s_{\max}(U_{\sigma_i}) \leq \frac{2 - \varepsilon}{\varepsilon}
\]

**Proof.** Apply Proposition 4.2 to \( U \) in order to get \( \sigma_1 \) verifying
\[
|\sigma_1| \geq \frac{(1 - \varepsilon)^2 m}{\|U\|^2}
\]
such that
\[
\frac{\varepsilon}{2 - \varepsilon} \leq s_{\min}(U_{\sigma_1}) \leq s_{\max}(U_{\sigma_1}) \leq \frac{2 - \varepsilon}{\varepsilon}
\]
Now note that \( U_{\sigma_1^c} \) is a \( n \times |\sigma_1| \) standardized matrix and \( \|U_{\sigma_1^c}\| \leq \|U\| \) and apply Proposition 4.2 to \( U_{\sigma_1^c} \) in order to get \( \sigma_2 \subset \sigma_1^c \) verifying
\[
|\sigma_2| = \frac{(1 - \varepsilon)^2 |\sigma_1^c|}{\|U\|^2} = \frac{(1 - \varepsilon)^2}{\|U\|^2} \left[ 1 - \frac{(1 - \varepsilon)^2}{\|U\|^2} \right] m
\]
Doing this procedure \( p \) times, the number of remaining columns is
\[
\left( 1 - \frac{(1 - \varepsilon)^2}{\|U\|^2} \right)^p m
\]
So in order to cover all the columns, we need to take \( p \) such that
\[
\left( 1 - \frac{(1 - \varepsilon)^2}{\|U\|^2} \right)^p m < 1
\]
By a trivial calculation, it is sufficient to take \( \frac{\|U\|^2 \log(m)}{(1 - \varepsilon)^2} \) blocks.

In the regime where \( \varepsilon \) is close to one, the previous proposition yields a column partition with almost isometric blocks. This recovers a result of Tropp (see Theorem 1.2 in [16]), which follows results of Bourgain-Tzafriri [2], with a deterministic method.

**Corollary 4.5.** Let \( U \) a \( n \times m \) standardized matrix. For \( \varepsilon < 1 \), there exists a partition of \( \{1, ..., m\} \) into \( p \) sets \( \sigma_1, ..., \sigma_p \) such that
\[
p \leq \frac{9\|U\|^2 \log(m)}{\varepsilon^2}
\]
and for any \( i \leq p \),
\[
1 - \varepsilon \leq s_{\min}(U_{\sigma_i}) \leq s_{\max}(U_{\sigma_i}) \leq 1 + \varepsilon
\]

The number of blocks here depends on the dimension. The challenging problem is to partition into a number of blocks which does not depend on the dimension. This would give a positive solution to the paving conjecture (see [4] for related problems).

5. **Extracting square submatrix with small norm**

In this section, we will show how using our main result we can answer Naor’s question [11]: find an algorithm, using the Batson-Spielman-Srivastava’s method [1], to prove Theorem C [2]. However, we will be able to do this only for symmetric matrices.

**Proposition 5.1.** Let \( T \) a \( n \times n \) symmetric matrix with 0 diagonal. For any \( \varepsilon < 1 \), there exists \( \sigma \subset \{1, ..., n\} \) of size
\[
|\sigma| \geq \frac{(\sqrt{2} - 1)^4 \varepsilon^2 n}{2}
\]
such that
\[
\|P_{\sigma}TP_{\sigma}^*\| \leq \varepsilon\|T\|
\]

**Proof.** Denote \( A = T + \|T\|.Id \), then \( A \) is a positive semidefinite symmetric matrix so we may take \( U = A^{\frac{1}{2}} \). First note that since \( T \) has 0 diagonal then
\[
\|Ue_i\|^2 = \langle Ue_i, Ue_i \rangle = \langle Ae_i, e_i \rangle = \|T\|
\]
Therefore \( \tilde{U} = \frac{U}{\|T\|^2} \) is a standardized matrix. Moreover \( \|\tilde{U}\|^2 = 2 \).

Denote \( \alpha = (\sqrt{2} - 1)^2 \) and apply Proposition 4.2 with \( 1 - \alpha\varepsilon \) to find \( \sigma \subset \{1, ..., n\} \) of size \( \frac{\alpha^2 \varepsilon^2 n}{2} \) such that
\[
\frac{1 - \alpha \varepsilon}{1 + \alpha \varepsilon} \leq s_{\min}(\tilde{U}_{\sigma}) \leq s_{\max}(\tilde{U}_{\sigma}) \leq \frac{1 + \alpha \varepsilon}{1 - \alpha \varepsilon}
\]
This means that
\[
\left( \frac{1 - \alpha \varepsilon}{1 + \alpha \varepsilon} \right)^2 . Id_{\sigma} \leq (\tilde{U}_{\sigma})^* \cdot (\tilde{U}_{\sigma}) \leq \left( \frac{1 + \alpha \varepsilon}{1 - \alpha \varepsilon} \right)^2 . Id_{\sigma}
\]
Recall that \( \tilde{U}_{\sigma} = \tilde{U} P_{\sigma}^* \) and \( \tilde{U}^* \cdot \tilde{U} = A\|T\|^2 \). Therefore by the choice of \( \alpha \)
\[
(1 - \varepsilon)\|T\|.Id_{\sigma} \leq P_{\sigma}AP_{\sigma}^* \leq (1 + \varepsilon)\|T\|.Id_{\sigma}
\]
which after rearrangement gives
\[
-\varepsilon\|T\| \leq P_{\sigma}TP_{\sigma}^* \leq \varepsilon\|T\|
\]
and finishes the proof.

Iterating the previous result, we obtain by a deterministic method the strongest result on the paving problem which is due to Bourgain-Tzafriri (see also [15]) that is every zero-diagonal matrix of size $n \times n$ can be paved with at most $O(\log(n))$ blocks. Once again, we are able to achieve this for symmetric matrices.

**Proposition 5.2.** Let $T$ a $n \times n$ symmetric matrix with 0 diagonal. For any $0 < \varepsilon < 1$, there exists a partition of $\{1, \ldots, n\}$ into $k$ subsets $\sigma_1, \ldots, \sigma_k$ such that

$$k \leq \frac{2 \log(n)}{(\sqrt{2} - 1)^4 \varepsilon^2}$$

and for any $i \leq k$,

$$\|P_{\sigma_i} TP_{\sigma_i}^*\| \leq \varepsilon \|T\|$$

**Proof.** As before denote $A = T + \|T\|.Id$ and $U = A^{\frac{1}{2}}$. Note $\tilde{U} = \frac{U}{\|T\|^2}$ the standardized matrix. Applying Corollary 4.5, we have a column partition for which we do on each block as we did in the previous proposition. The result follows easily. □

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