

# Mathematics of Information

Spring semester 2022

## Solutions to Problem Set 8

### Problem 1 Equivalent Expression for the Restricted Isometry Constants.

It follows directly from the definition that  $\delta_s$  is the smallest number  $\tilde{\delta} \geq 0$  such that

$$\left| \|Ax\|_2^2 - \|x\|_2^2 \right| \leq \tilde{\delta},$$

for all  $s$ -sparse  $x \in \mathbb{C}^N$  with  $\|x\|_2 \leq 1$ . Therefore

$$\begin{aligned} \delta_s &= \sup_{\substack{x \in \mathbb{C}^N \\ \|x\|_2 \leq 1}} \sup_{s\text{-sparse}} \left| \|Ax\|_2^2 - \|x\|_2^2 \right| = \sup_{\substack{S \subset [N] \\ \#(S) \leq s}} \sup_{\substack{x \in \mathbb{C}^S \\ \|x\|_2 \leq 1}} \left| \|Ax\|_2^2 - \|x\|_2^2 \right| \\ &= \sup_{\substack{S \subset [N] \\ \#(S) \leq s}} \sup_{\substack{x \in \mathbb{C}^S \\ \|x\|_2 \leq 1}} \left| \left\langle (A_S^H A_S - \text{Id}) x, x \right\rangle_{\mathbb{C}^S} \right| \\ &= \sup_{\substack{S \subset [N] \\ \#(S) \leq s}} \left\| A_S^H A_S - \text{Id} \right\|_2, \end{aligned}$$

where in the last line we used the fact that  $A_S^H A_S - \text{Id}$  is hermitian.

### Problem 2 Properties of the Restricted Isometry Constants.

- a) For every  $\mathbf{x} \in \mathbb{C}^N$ , which is a 1-sparse vector, there exists  $i \in \{1, \dots, N\}$  and  $x_i \in \mathbb{C}$  nonzero such that

$$\mathbf{x} = (0, \dots, 0, x_i, 0, \dots, 0)^T.$$

Therefore,  $\delta_1$  is the smallest  $\delta \geq 0$  such that

$$(1 - \delta)|x_i|^2 \leq \|A_i\|_2^2 |x_i|^2 \leq (1 + \delta)|x_i|^2,$$

for all  $i \in \{1, \dots, N\}$  and  $x_i \in \mathbb{C}$  nonzero, where  $A_i$  denotes the  $i$ -th column of  $A$ . Since, by assumption, the columns of  $A$  are normalized, we have  $\|A_i\|_2 = 1$ , for all  $i \in \{1, \dots, N\}$ . Therefore,  $\delta_1$  is the smallest  $\delta \geq 0$  such that

$$(1 - \delta) \leq 1 \leq (1 + \delta),$$

that is,  $\delta_1 = 0$ .

- b) We know from Problem 1, that the restricted isometry constant  $\delta_2$  can be equivalently expressed as

$$\delta_2 = \sup_{\substack{i,j \in \{1, \dots, N\} \\ i \neq j}} \left\| A_{\{i,j\}}^H A_{\{i,j\}} - \text{Id} \right\|_2,$$

where  $A_{\{i,j\}}$  is the matrix obtained by retaining only the columns  $i$  and  $j$  of  $A$ . A little computation shows that

$$A_{\{i,j\}}^H A_{\{i,j\}} - \text{Id} = \begin{pmatrix} \|A_i\|_2^2 & \langle A_j, A_i \rangle \\ \langle A_i, A_j \rangle & \|A_j\|_2^2 \end{pmatrix} - \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}.$$

Using that the columns of  $A$  are normalized yields

$$A_{\{i,j\}}^H A_{\{i,j\}} - \text{Id} = \begin{pmatrix} 0 & \langle A_j, A_i \rangle \\ \langle A_i, A_j \rangle & 0 \end{pmatrix},$$

which is a matrix with eigenvalues  $\pm |\langle A_i, A_j \rangle|$ . Therefore, the operator norm of this matrix being equal to its largest eigenvalue, we get

$$\delta_2 = \max_{\substack{i,j \in \{1, \dots, N\} \\ i \neq j}} |\langle A_i, A_j \rangle|,$$

which, by definition, is the coherence of the matrix  $A$ .

- c) As  $\text{supp}(u) \cap \text{supp}(v) = \emptyset$ , we must have  $\langle u, v \rangle = 0$ . Let us now define the support set  $S := \text{supp}(u) \cup \text{supp}(v)$ , which has cardinality  $\#S = 2s$ . We thus have

$$\begin{aligned} |\langle Au, Av \rangle| &= |\langle A_S u, A_S v \rangle| \\ &= \left| \langle A_S^H A_S u, v \rangle - \langle u, v \rangle \right| \\ &= \left| \langle (A_S^H A_S - \text{Id}) u, v \rangle \right|. \end{aligned}$$

Now using consecutively Cauchy-Schwarz and the definition of the operator norm gives

$$|\langle Au, Av \rangle| \leq \left\| (A_S^H A_S - \text{Id}) u \right\|_2 \|v\|_2 \leq \left\| A_S^H A_S - \text{Id} \right\|_2 \|u\|_2 \|v\|_2,$$

which, using the result of Problem 1, yields the desired result

$$|\langle Au, Av \rangle| \leq \delta_{2s} \|u\|_2 \|v\|_2.$$

### Problem 3 Restricted Orthogonality (Exam 2020/2021, Problem 1).

- a) It follows directly from the definition of  $\theta_{s,t}$  that  $\theta_{s,t}$  is the smallest number  $\tilde{\theta} \geq 0$  such that

$$\left| \frac{|\langle Au, Av \rangle|}{\|u\|_2 \|v\|_2} \right| \leq \tilde{\theta},$$

for all disjointly supported  $s$ -sparse and  $t$ -sparse vectors  $u \in \mathbb{C}^N \setminus \{0\}$  and  $v \in \mathbb{C}^N \setminus \{0\}$ , respectively. Therefore,

$$\begin{aligned}
\theta_{s,t} &= \max_{\substack{u,v \in \mathbb{C}^N \text{ disjointly } s, t\text{-sparse,} \\ \|u\|_2 = \|v\|_2 = 1}} |\langle Au, Av \rangle| \\
&= \max_{\substack{S,T \subset \{1,\dots,N\}, S \cap T = \emptyset, \\ |S| \leq s, |T| \leq t}} \max_{\substack{u \in \mathbb{C}^{|S|}, v \in \mathbb{C}^{|T|}, \\ \|u\|_2 = \|v\|_2 = 1}} |\langle Au, Av \rangle| \\
&= \max_{\substack{S,T \subset \{1,\dots,N\}, S \cap T = \emptyset, \\ |S| \leq s, |T| \leq t}} \max_{\substack{u \in \mathbb{C}^{|S|}, v \in \mathbb{C}^{|T|}, \\ \|u\|_2 = \|v\|_2 = 1}} |\langle A_S u, A_T v \rangle| \\
&= \max_{\substack{S,T \subset \{1,\dots,N\}, S \cap T = \emptyset, \\ |S| \leq s, |T| \leq t}} \max_{\substack{u \in \mathbb{C}^{|S|}, v \in \mathbb{C}^{|T|}, \\ \|u\|_2 = \|v\|_2 = 1}} |\langle (A_T^H A_S) u, v \rangle|.
\end{aligned} \tag{1}$$

Note that for every  $S, T \subset \{1, \dots, N\}$  with  $S \cap T = \emptyset$ ,  $|S| \leq s$ ,  $|T| \leq t$  and  $u \in \mathbb{C}^{|S|}$ ,  $v \in \mathbb{C}^{|T|}$  with  $\|u\|_2 = \|v\|_2 = 1$ , the Cauchy–Schwarz inequality yields

$$|\langle (A_T^H A_S) u, v \rangle| \leq \|(A_T^H A_S) u\|_2 \|v\|_2 = \|(A_T^H A_S) u\|_2.$$

On the other hand,  $A_T^H A_S \in \mathbb{C}^{|T| \times |S|}$  and hence  $(A_T^H A_S) u \in \mathbb{C}^{|T|}$ . Therefore, if  $(A_T^H A_S) u \neq 0$ ,  $v = (A_T^H A_S) u / \|(A_T^H A_S) u\|_2$  satisfies  $v \in \mathbb{C}^{|T|}$  with  $\|v\|_2 = 1$ , and we get

$$\begin{aligned}
|\langle (A_T^H A_S) u, v \rangle| &= |\langle (A_T^H A_S) u, (A_T^H A_S) u / \|(A_T^H A_S) u\|_2 \rangle| \\
&= \frac{\|(A_T^H A_S) u\|_2^2}{\|(A_T^H A_S) u\|_2} = \|(A_T^H A_S) u\|_2.
\end{aligned}$$

Hence,

$$\max_{\substack{u \in \mathbb{C}^{|S|}, v \in \mathbb{C}^{|T|}, \\ \|u\|_2 = \|v\|_2 = 1}} |\langle (A_T^H A_S) u, v \rangle| = \max_{\substack{u \in \mathbb{C}^{|S|}, \\ \|u\|_2 = 1}} \|(A_T^H A_S) u\|_2 = \max_{\substack{u \in \mathbb{C}^{|S|}, \\ \|u\|_2 \leq 1}} \|(A_T^H A_S) u\|_2.$$

Combining this with (1), we obtain

$$\begin{aligned}
\theta_{s,t} &= \max_{\substack{S,T \subset \{1,\dots,N\}, S \cap T = \emptyset, \\ |S| \leq s, |T| \leq t}} \max_{\substack{u \in \mathbb{C}^{|S|}, \\ \|u\|_2 \leq 1}} \|(A_T^H A_S) u\|_2 \\
&= \max_{\substack{S,T \subset \{1,\dots,N\}, S \cap T = \emptyset, \\ |S| \leq s, |T| \leq t}} \|A_T^H A_S\|_2.
\end{aligned}$$

- b) Let  $u, v \in \mathbb{C}^N$  be disjointly supported  $s$ -sparse and  $t$ -sparse vectors, respectively, let  $S := \text{supp}(u) \cup \text{supp}(v)$ , and let  $u_S, v_S \in \mathbb{C}^{|S|}$  be the restrictions of  $u, v \in \mathbb{C}^N$  to  $S$ . Since  $u$  and  $v$  have disjoint supports, we have  $\langle u_S, v_S \rangle = 0$  and hence

$$|\langle Au, Av \rangle| = |\langle A_S u_S, A_S v_S \rangle - \langle u_S, v_S \rangle| = |\langle (A_S^H A_S - I_{|S|}) u_S, v_S \rangle|.$$

Applying the Cauchy–Schwarz inequality and the relation

$$\|u_S\|_2 \|A_S^H A_S - I_{|S|}\|_2 = \|u_S\|_2 \max_{\substack{x \in \mathbb{C}^{|S|}, \\ \|x\|_2 \leq 1}} \|(A_S^H A_S - I_{|S|}) x\|_2 \geq \|(A_S^H A_S - I_{|S|}) u_S\|_2,$$

we get

$$|\langle Au, Av \rangle| \leq \|(A_S^H A_S - I_{|S|})u_S\|_2 \|v_S\|_2 \leq \|A_S^H A_S - I_{|S|}\|_2 \|u_S\|_2 \|v_S\|_2.$$

Based on the lemma in the problem statement and using  $\|u_S\|_2 = \|u\|_2$ ,  $\|v_S\|_2 = \|v\|_2$ , this allows us to conclude that

$$|\langle Au, Av \rangle| \leq \delta_{s+t} \|u\|_2 \|v\|_2,$$

which, in turn, proves

$$\theta_{s,t} \leq \delta_{s+t}.$$

c) i) Note that each  $j \in T$  belongs to exactly  $s$  sets  $S_i$ , so that

$$u = \frac{1}{s} \sum_{i=1}^t u_{S_i} \quad \text{and} \quad \|u\|_2^2 = \frac{1}{s} \sum_{i=1}^t \|u_{S_i}\|_2^2.$$

ii) Using c)i) and the triangle inequality, we get

$$\begin{aligned} |\langle Au, Av \rangle| &\leq \frac{1}{s} \sum_{i=1}^t |\langle Au_{S_i}, Av \rangle| \leq \frac{1}{s} \sum_{i=1}^t \theta_{s,r} \|u_{S_i}\|_2 \|v\|_2 \\ &= \theta_{s,r} \frac{1}{s} \left( \sum_{i=1}^t \|u_{S_i}\|_2 \right) \|v\|_2, \end{aligned} \tag{2}$$

where in the second inequality we used that  $u_{S_i}$  and  $v$  are disjointly supported  $s$ -sparse and  $r$ -sparse vectors, respectively. Moreover, note that the Cauchy-Schwarz inequality yields

$$\left( \sum_{i=1}^t \|u_{S_i}\|_2 \right)^2 \leq \left( \sum_{i=1}^t \|u_{S_i}\|_2^2 \right) \left( \sum_{i=1}^t 1 \right) = t \left( \sum_{i=1}^t \|u_{S_i}\|_2^2 \right).$$

This together with (2) and subproblem (c)(i) yields

$$\begin{aligned} |\langle Au, Av \rangle| &\leq \theta_{s,r} \frac{\sqrt{t}}{s} \left( \sum_{i=1}^t \|u_{S_i}\|_2^2 \right)^{1/2} \|v\|_2 \\ &= \theta_{s,r} \sqrt{\frac{t}{s}} \|u\|_2 \|v\|_2. \end{aligned}$$

#### Problem 4 Johnson-Lindenstrauss with sub-Gaussian Matrices.

Let  $\mathbf{a}_j^T$  be the  $j$ -th row of  $\mathbf{A}$ , and set  $X_j := \frac{\sqrt{k}}{\|\mathbf{u}\|} \mathbf{a}_j^T \mathbf{u}$ . Note that

$$\mathbf{a}_j^T \mathbf{u} = \sum_{i=1}^n \mathbf{a}_{i,j} \mathbf{u}_i$$

is a linear combination of independent sub-Gaussian random variables. We first prove that it implies that  $X_j$  is a sub-Gaussian random variable with parameter 1. Using the definition of a sub-Gaussian random variable, together with the independence of the  $\{\mathbf{a}_{i,j}\}_{1 \leq i \leq n}$ , we have

$$\begin{aligned} \mathbb{E} \left[ e^{\lambda X_j} \right] &= \mathbb{E} \left[ e^{\lambda \sum_{i=1}^n \frac{\sqrt{k}}{\|\mathbf{u}\|} \mathbf{a}_{i,j} \mathbf{u}_i} \right] \\ &= \prod_{i=1}^n \mathbb{E} \left[ e^{\frac{\lambda \sqrt{k} \mathbf{u}_i}{\|\mathbf{u}\|} \mathbf{a}_{i,j}} \right] \\ &\leq \prod_{i=1}^n e^{\frac{\lambda^2 k \mathbf{u}_i^2}{2 \|\mathbf{u}\|^2} \frac{1}{k}} \\ &= e^{\frac{\lambda^2}{2}}, \end{aligned}$$

for all  $\lambda \in \mathbb{R}$ . Therefore,  $X_j$  is indeed a sub-Gaussian random variable with parameter 1. Now, taking  $\lambda \in (0, 1/2)$ , and applying Markov's inequality, we obtain

$$\begin{aligned} \mathbb{P} \left[ \|\mathbf{A}\mathbf{u}\|^2 \geq (1 + \epsilon) \|\mathbf{u}\|^2 \right] &= \mathbb{P} \left[ \sum_{j=1}^k X_j^2 \geq (1 + \epsilon)k \right] \\ &= \mathbb{P} \left[ e^{\lambda \sum_{j=1}^k X_j^2} \geq e^{\lambda(1+\epsilon)k} \right] \\ &\leq e^{-\lambda(1+\epsilon)k} \mathbb{E} \left[ e^{\lambda \sum_{j=1}^k X_j^2} \right] \\ &= e^{-\lambda(1+\epsilon)k} \left( \mathbb{E} \left[ e^{\lambda X_1^2} \right] \right)^k. \end{aligned}$$

Using that  $X_1$  is a sub-Gaussian random variable with parameter 1, it satisfies  $\mathbb{E} \left[ e^{\lambda X_1^2} \right] \leq \frac{1}{\sqrt{1-2\lambda}}$ , and therefore, it holds that

$$\mathbb{P} \left[ \|\mathbf{A}\mathbf{u}\|^2 \geq (1 + \epsilon) \|\mathbf{u}\|^2 \right] \leq \left( \frac{e^{-2\lambda(1+\epsilon)}}{1-2\lambda} \right)^{k/2}.$$

Taking the particular value  $\lambda = \frac{\epsilon}{2(1+\epsilon)}$ , we obtain

$$\mathbb{P} \left[ \|\mathbf{A}\mathbf{u}\|^2 \geq (1 + \epsilon) \|\mathbf{u}\|^2 \right] \leq ((1 + \epsilon)e^{-\epsilon})^{k/2} < e^{-k \frac{\epsilon^2 - \epsilon^3}{4}},$$

where the last inequality comes from the relation

$$1 + \epsilon < e^{\epsilon - (\epsilon^2 - \epsilon^3)/2}. \quad (3)$$

Repeating the arguments above, we can also prove that

$$\mathbb{P} \left[ \|\mathbf{A}\mathbf{u}\|^2 \leq (1 - \epsilon) \|\mathbf{u}\|^2 \right] < e^{-k \frac{\epsilon^2 - \epsilon^3}{4}}.$$

Finally, applying the union bound yields the desired result

$$\begin{aligned} \mathbb{P} \left[ \left| \|\mathbf{A}\mathbf{u}\|^2 - \|\mathbf{u}\|^2 \right| \geq \epsilon \|\mathbf{u}\|^2 \right] &= \mathbb{P} \left[ \|\mathbf{A}\mathbf{u}\|^2 \leq (1 - \epsilon) \|\mathbf{u}\|^2 \right] + \mathbb{P} \left[ \|\mathbf{A}\mathbf{u}\|^2 \geq (1 + \epsilon) \|\mathbf{u}\|^2 \right] \\ &< 2e^{-(\epsilon^2 - \epsilon^3)k/4}. \end{aligned}$$

Remark: We conclude this problem by providing an explicit proof of the inequality (3). We need to prove that, for all  $0 < \epsilon < 1$ , it holds that

$$1 + \epsilon < e^{\epsilon - (\epsilon^2 - \epsilon^3)/2}.$$

Taking logarithm on both sides, we equivalently wish to prove

$$\log(1 + \epsilon) < \epsilon - (\epsilon^2 - \epsilon^3)/2.$$

A Taylor expansion yields

$$\begin{aligned} \epsilon - \frac{\epsilon^2}{2} + \frac{\epsilon^3}{2} - \log(1 + \epsilon) &= \epsilon - \frac{\epsilon^2}{2} + \frac{\epsilon^3}{2} + \sum_{n=1}^{\infty} \frac{(-\epsilon)^n}{n} \\ &= \frac{\epsilon^3}{2} - \frac{\epsilon^3}{3} + \sum_{n=4}^{\infty} \frac{(-\epsilon)^n}{n} \\ &= \frac{\epsilon^3}{2} - \frac{\epsilon^3}{3} + \sum_{n=2}^{\infty} \frac{\epsilon^{2n}}{2n} - \frac{\epsilon^{2n+1}}{2n+1} \\ &= \frac{\epsilon^3}{6} + \sum_{n=2}^{\infty} \frac{2n(1 - \epsilon) + 1}{2n(2n+1)} \epsilon^{2n} > 0. \end{aligned}$$

Where the last inequality is obtained by observing that we have a sum of positive terms when  $0 < \epsilon < 1$ . This is the desired result.

## Problem 5 Random Matrices (Exam 2020, Problem 1).

a) i) We have

$$\sum_{j=1}^N \tilde{\mu}_j^2 = \sum_{j=1}^N \max_{k \in [N]} |\langle g_k, h_j \rangle|^2 \geq \sum_{j=1}^N |\langle g_1, h_j \rangle|^2 = \|g_1\|_2^2 = 1,$$

where we used the fact that  $\{h_j\}_{j=1}^N$  is an orthonormal basis for  $\mathbb{C}^N$ .

ii) Let  $\mathbf{t}$  be a random variable taking values in  $[N] := \{1, 2, \dots, N\}$  and distributed according to  $\tilde{\mathcal{P}}$ . We then have

$$\kappa^{-1} = \min_{j \in [N]} p_j \tilde{\mu}_j^{-2} \leq p_{\mathbf{t}} \tilde{\mu}_{\mathbf{t}}^{-2}.$$

Taking the expectation of both sides with respect to  $\mathbf{t}$  yields  $\kappa^{-1} \leq \mathbb{E}_{\mathbf{t} \sim \tilde{\mathcal{P}}} [p_{\mathbf{t}} \tilde{\mu}_{\mathbf{t}}^{-2}]$ .

iii) We have

$$\begin{aligned} \kappa^{-1} &\leq \mathbb{E}_{\mathbf{t} \sim \tilde{\mathcal{P}}} [p_{\mathbf{t}} \tilde{\mu}_{\mathbf{t}}^{-2}] = \sum_{j=1}^N \mathbb{P}_{\mathbf{t} \sim \tilde{\mathcal{P}}}(\mathbf{t} = j) \cdot p_j \tilde{\mu}_j^{-2} \\ &= \sum_{j=1}^N \frac{\tilde{\mu}_j^2}{\tilde{\mu}_1^2 + \dots + \tilde{\mu}_N^2} p_j \tilde{\mu}_j^{-2} = \frac{1}{\tilde{\mu}_1^2 + \dots + \tilde{\mu}_N^2} \underbrace{\sum_{j=1}^N p_j}_{=1} = \frac{1}{\tilde{\mu}_1^2 + \dots + \tilde{\mu}_N^2}, \end{aligned}$$

and hence  $\kappa \geq \sum_{j=1}^N \tilde{\mu}_j^2$ . Moreover, equality holds if and only if

$$\min_{j \in [N]} p_j \tilde{\mu}_j^{-2} = \mathbb{E}_{\mathbf{t} \sim \tilde{\mathcal{P}}} \left[ p_{\mathbf{t}} \tilde{\mu}_{\mathbf{t}}^{-2} \right].$$

This is the case if and only if the random variable  $p_{\mathbf{t}} \tilde{\mu}_{\mathbf{t}}^{-2}$  is constant, i.e., there exists a  $c \in \mathbb{R}$  such that  $p_j \tilde{\mu}_j^{-2} = c$ , for  $j \in [N]$ . If this is the case, then, using that  $\mathcal{P}$  is a probability distribution, we have

$$c \sum_{k=1}^N \tilde{\mu}_k^2 = \sum_{k=1}^N p_k = 1,$$

and thus  $p_j = c \tilde{\mu}_j^2 = \left( \sum_{k=1}^N \tilde{\mu}_k^2 \right)^{-1} \tilde{\mu}_j^2$ , for all  $j \in [N]$ , i.e.,  $\mathcal{P} = \tilde{\mathcal{P}}$ .

b) i) We have

$$\begin{aligned} \mathbb{E} \left[ |\langle x, Y_\ell \rangle|^2 \right] &= \mathbb{E} \left[ \langle x, Y_\ell \rangle \overline{\langle x, Y_\ell \rangle} \right] = \mathbb{E} \left[ \sum_{k, k'=1}^N A_{\ell k} x_k \overline{A_{\ell k'} x_{k'}} \right] \\ &= \sum_{k, k'=1}^N x_k \overline{x_{k'}} m^{-1} \mathbb{E}_{\mathbf{t} \sim \mathcal{P}} \left[ p_{\mathbf{t}}^{-1} \langle g_k, h_{\mathbf{t}} \rangle \overline{\langle g_{k'}, h_{\mathbf{t}} \rangle} \right] \\ &= \sum_{k, k'=1}^N x_k \overline{x_{k'}} m^{-1} \sum_{j=1}^N p_j \cdot p_j^{-1} \langle g_k, h_j \rangle \overline{\langle g_{k'}, h_j \rangle} \\ &= \sum_{k, k'=1}^N x_k \overline{x_{k'}} m^{-1} \left\langle \sum_{j=1}^N \langle g_k, h_j \rangle h_j, g_{k'} \right\rangle \\ &= \sum_{k, k'=1}^N x_k \overline{x_{k'}} m^{-1} \underbrace{\langle g_k, g_{k'} \rangle}_{=\delta_{kk'}} = m^{-1} \|x\|_2^2 = m^{-1}, \end{aligned}$$

and so  $\mathbb{E}[X_\ell] = \mathbb{E}[|\langle x, Y_\ell \rangle|^2] - \frac{1}{m} = 0$ . Next, for  $\ell \in [m]$ , applying the Cauchy-Schwarz inequality and  $|\langle g_j, h_{\mathbf{t}_\ell} \rangle| \leq \tilde{\mu}_{\mathbf{t}_\ell}$  yields

$$\begin{aligned} |\langle x, Y_\ell \rangle|^2 &\leq \left( \sum_{j \in \text{supp}(x)} |A_{\ell j}|^2 \right) \|x\|_2^2 = \sum_{j \in \text{supp}(x)} m^{-1} p_{\mathbf{t}_\ell}^{-1} |\langle g_j, h_{\mathbf{t}_\ell} \rangle|^2 \\ &\leq \sum_{j \in \text{supp}(x)} m^{-1} p_{\mathbf{t}_\ell}^{-1} \tilde{\mu}_{\mathbf{t}_\ell}^2 = s m^{-1} p_{\mathbf{t}_\ell}^{-1} \tilde{\mu}_{\mathbf{t}_\ell}^2 \leq s m^{-1} \kappa, \end{aligned}$$

and so

$$|X_\ell| \leq \max \left\{ |\langle x, Y_\ell \rangle|^2, \frac{1}{m} \right\} \leq m^{-1} \max \{ s \kappa, 1 \} = s m^{-1} \kappa,$$

where the second inequality follows from  $\kappa \geq \sum_{j=1}^N \tilde{\mu}_j^2 \geq 1$ . Finally, we estimate

$$\begin{aligned} \mathbb{E} \left[ |X_\ell|^2 \right] &= \mathbb{E} \left[ |\langle x, Y_\ell \rangle|^4 \right] - \frac{2}{m} \mathbb{E} \left[ |\langle x, Y_\ell \rangle|^2 \right] + \frac{1}{m^2} \\ &\leq s m^{-1} \kappa \mathbb{E} \left[ |\langle x, Y_\ell \rangle|^2 \right] - \frac{2}{m} \mathbb{E} \left[ |\langle x, Y_\ell \rangle|^2 \right] + \frac{1}{m^2} \\ &= s m^{-1} \kappa \frac{1}{m} - \frac{2}{m} \frac{1}{m} + \frac{1}{m^2} < s m^{-2} \kappa, \end{aligned}$$

for all  $\ell \in [m]$ , as desired.

ii) We have

$$\|Ax\|_2^2 - 1 = \sum_{\ell=1}^m |\langle x, Y_\ell \rangle|^2 - 1 = \sum_{\ell=1}^m X_\ell,$$

and thus obtain using Bernstein's inequality

$$\begin{aligned} \mathbb{P}\left(\left|\|Ax\|_2^2 - 1\right| \geq t\right) &= \mathbb{P}\left(\left|\sum_{\ell=1}^m X_\ell\right| \geq t\right) \leq 2 \exp\left(-\frac{t^2/2}{m \cdot sm^{-2}\kappa + sm^{-1}\kappa \frac{t}{3}}\right) \\ &\leq 2 \exp\left(-\frac{t^2/2}{sm^{-1}\kappa + \frac{1}{3}sm^{-1}\kappa}\right) = 2 \exp\left(-\frac{3t^2m}{8s\kappa}\right), \end{aligned}$$

for  $t \in (0, 1)$ , as desired.