

## Matrix Concentration Derivations

Instructor: Sham Kakade

## 1 Introduction

Let  $X \in \mathbb{R}^{d_1 \times d_2}$  be a random matrix. In many settings, we are interested in the behavior of either:

$$\left\| \frac{1}{n} \sum_{i=1}^n X_i - \mathbb{E}[X] \right\|_{\text{F}} \leq ?, \quad \left\| \frac{1}{n} \sum_{i=1}^n X_i - \mathbb{E}[X] \right\|_2 \leq ?$$

where each  $X_i$  is sampled i.i.d. from some distribution. Here,  $\|\cdot\|_2$  denotes the spectral norm (the largest eigenvalue) and  $\|\cdot\|_{\text{F}}$  denotes the Frobenius norm.

The following theorem provides a high probability bound on these quantities.

**Theorem 1.1.** Assume that  $X_i \in \mathbb{R}^{m \times n}$  are sampled i.i.d. Let  $d = \min\{d_1, d_2\}$ .

- (Spectral Norm) Suppose  $\|X\|_2 \leq M$  almost surely. Then with probability greater than  $1 - \delta$ ,

$$\left\| \frac{1}{n} \sum_{i=1}^n X_i - \mathbb{E}[X] \right\|_2 \leq 6M \sqrt{\frac{1}{n}} \left( \sqrt{\log d} + \sqrt{\log \frac{1}{\delta}} \right).$$

- (Frobenius Norm) Suppose  $\|X\|_{\text{F}} \leq M$  almost surely. Then with probability greater than  $1 - \delta$ ,

$$\left\| \frac{1}{n} \sum_{i=1}^n X_i - \mathbb{E}[X] \right\|_{\text{F}} \leq 6M \sqrt{\frac{1}{n}} \left( 1 + \sqrt{\log \frac{1}{\delta}} \right).$$

## 1.1 Concentration and Strong-smoothness

Throughout we let  $\mathcal{X}$  be a Euclidean vector space equipped with an inner product  $\langle \cdot, \cdot \rangle$ . We also work with a norm  $\|\cdot\|$  over  $\mathcal{X}$  (and this norm need not be the one induced by  $\langle \cdot, \cdot \rangle$ ).

**Definition 1.2.** A function  $f : \mathcal{X} \rightarrow \mathbb{R}$  is  $\beta$ -strongly smooth w.r.t. a norm  $\|\cdot\|$  if  $f$  is everywhere differentiable and if for all  $x, y$  we have

$$f(x + y) \leq f(x) + \langle \nabla f(x), y \rangle + \frac{1}{2} \beta \|y\|^2$$

We now point out the role of strong smoothness in proving certain concentration results. In particular, we are interested in the behavior of a function  $f(\sum_{i=1}^n Z_i)$  where  $Z_i$  is a martingale difference sequence. The following simple lemma bounds the expectation of this quantity.

**Lemma 1.3.** [Juditsky and Nemirovski; 08] Suppose that  $Z_i$  is a martingale difference sequence (where  $Z_i \in \mathcal{X}$ ) and that  $\|Z_i\| \leq M_i$  almost surely. Also, suppose that  $f^2$  is  $\beta$ -strongly smooth w.r.t. a norm  $\|\cdot\|$  on  $\mathcal{X}$  and that  $f(\mathbf{0}) = 0$ .

$$\mathbb{E} f \left( \sum_{i=1}^n Z_i \right) \leq \sqrt{\frac{1}{2} \beta \sum_{i=1}^n M_i^2}$$

*Proof.* By smoothness we have:

$$\begin{aligned}
\mathbb{E}f^2\left(\sum_{i=1}^n Z_i\right) &\leq \mathbb{E}f^2\left(\sum_{i=1}^{n-1} Z_i\right) + \mathbb{E}\left\langle \nabla f^2\left(\sum_{i=1}^{n-1} Z_i\right), Z_n \right\rangle + \frac{1}{2}\beta\mathbb{E}\|Z_n\|^2 \\
&= \mathbb{E}f^2\left(\sum_{i=1}^{n-1} Z_i\right) + \mathbb{E}\left[\left\langle \nabla f^2\left(\sum_{i=1}^{n-1} Z_i\right), \mathbb{E}[Z_n|Z_1, \dots, Z_{n-1}] \right\rangle\right] + \frac{1}{2}\beta\mathbb{E}\|Z_n\|^2 \\
&\leq \mathbb{E}f^2\left(\sum_{i=1}^{n-1} Z_i\right) + 0 + \frac{1}{2}\beta X_n^2
\end{aligned}$$

where we have used that  $Z_n$  is a martingale difference sequence. Proceeding recursively and using that  $f(\mathbf{0}) = 0$ , we have that:

$$\mathbb{E}f^2\left(\sum_{i=1}^n Z_i\right) \leq \frac{1}{2}\beta \sum_{i=1}^n M_i^2$$

and proof is completed by Jensen's inequality.  $\square$

To obtain concentration, we can directly appeal to Hoeffding-Azuma if  $f$  is a norm. However, note that in the following lemma we do not require  $f^2$  to be strongly smooth (which is useful for the case of the spectral norm, which is not strongly smooth).

**Lemma 1.4.** *Let  $f$  be a norm. Suppose that  $Z_i$  are independent (where  $Z_i \in \mathcal{X}$ ) and that  $f(Z_i) \leq M_i$  almost surely. Then with probability greater than  $1 - \delta$ ,*

$$f\left(\sum_{i=1}^n Z_i\right) \leq \mathbb{E}f\left(\sum_{i=1}^n Z_i\right) + \sqrt{8 \log \frac{1}{\delta} \sum_{i=1}^n M_i^2}$$

*Proof.* Using that  $f$  is a norm,

$$\left| f\left(\sum_i Z_i\right) - f\left(\sum_{i \neq j} Z_i + Z'_j\right) \right| \leq f(Z_j) + f(Z'_j)$$

for all  $Z_1, \dots, Z_n$ , and  $Z'_j$ . Since the distribution over  $Z_i$ 's are independent, this implies (Doob's) martingale  $D_j = \mathbb{E}[f(\sum_{i=1}^n Z_i) | Z_j, \dots, Z_1]$  satisfies the bounded difference property:

$$|D_j - D_{j-1}| \leq 2M_j.$$

The result now follows from Hoeffding-Azuma.  $\square$

## 1.2 Matrix Concentration Proofs

The Schatten  $q$ -norm is defined as:

$$\frac{1}{2}\|X\|_{S(q)}^2 := \frac{1}{2}\|\sigma(X)\|_q^2$$

where  $\sigma(X)$  is the singular values of  $X$  and  $\|\cdot\|_q^2$  is the usual  $L_q$ -norm. The function  $f^2$ :

$$f^2(X) = \frac{1}{2}\|X\|_{S(q)}^2$$

is  $(q-1)$ -strongly smooth, as shown in [Juditsky and Nemirovski; 08] (for  $q \geq 2$ ).

Note that the spectral norm  $\|\cdot\|_2$  is just the Schatten  $\infty$ -norm  $\|\cdot\|_{S(\infty)}$  and the Frobenius norm  $\|\cdot\|_F$  is just the Schatten 2-norm  $\|\cdot\|_{S(2)}$ .

*Proof.* For the spectral norm case, note that our assumption that  $\|X\|_{S(\infty)} \leq M$  (almost surely) implies  $\|X\|_{S(q)} \leq d^{1/q}M$  (almost surely). Let  $Z_i = X_i - \mathbb{E}[X]$ . By convexity of norms and Jensen's inequality,  $\|\mathbb{E}[X]\|_{S(q)} \leq \mathbb{E}[\|X\|_{S(q)}] \leq d^{1/q}M$ . So we have that  $\|Z_i\|_{S(q)} \leq 2d^{1/q}M$  (almost surely). Hence, by Lemma 1.3:

$$\mathbb{E} \left\| \sum_{i=1}^n Z_i \right\|_{S(\infty)} \leq \mathbb{E} \left\| \sum_{i=1}^n Z_i \right\|_{S(q)} \leq \sqrt{4(q-1)nd^{2/q}M^2}$$

and choosing  $q = \log d$

$$\mathbb{E} \left\| \sum_{i=1}^n Z_i \right\|_{S(\infty)} \leq 2Me\sqrt{n \log d}$$

Now let us apply Lemma 1.4 with  $f$  as the spectral norm  $\|\cdot\|_{S(\infty)}$ . Here, we have that  $\|Z_i\|_{S(\infty)} \leq 2M$  (almost surely), and our first claim follows.

For the Frobenius norm case, again let  $Z_i = X_i - \mathbb{E}[X]$ . Then by convexity of norms and Jensen's inequality,  $\|\mathbb{E}[X]\|_{S(2)} \leq \mathbb{E}[\|X\|_{S(2)}] \leq M$ . So we have that  $\|Z_i\|_{S(2)} \leq 2M$  (almost surely). Hence, by Lemma 1.3:

$$\mathbb{E} \left\| \sum_{i=1}^n Z_i \right\|_{S(2)} \leq \sqrt{4nM^2}$$

Using Lemma 1.4 with this norm and  $\|Z_i\|_{S(2)} \leq 2M$ , we have our second claim. □

## Acknowledgements

These notes are from discussions with Ambuj Tewari and Shai Shalev-Schwartz. Also, they borrow heavily from ideas in [Juditsky and Nemirovski; 08].