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## **1** ▶ Operator monotonicity

a) Show that the logarithm is operator monotone by the integral representation:

$$\log(a) = \int_0^\infty [(1+x)^{-1} - (a+x)^{-1}] dx, \quad \text{for } a > 0.$$

b) Let  $f: \mathbb{R}^{n \times n} \to \mathbb{R}$  be defined as  $f(B) = \operatorname{trace}(\exp(B))$ . Prove that f is operator monotone, i.e., if  $A, B \in \mathbb{R}^{n \times n}$  and  $B - A \in \mathbb{R}^{n \times n}$  are symmetric positive semidefinite matrics, then  $f(A) \leq f(B)$ .

## 2 ► Largest eigenvalue of sum of symmetric independent matrices

Let  $X_1, \ldots, X_s$  be symmetric independent random matrices. Prove that

$$\mathbb{E}\left[\lambda_{\max}\left(\sum_{i=1}^{s} X_{i}\right)\right] \leq \inf_{\theta>0} \frac{1}{\theta} \log \operatorname{trace}\left(\exp\left(\sum_{i=1}^{s} \log\left(\mathbb{E}e^{\theta X_{i}}\right)\right)\right).$$

Hint: combine the proof and the Lemma from Lecture 4 slide 6.

## **3** ► Matrix sparsification

Let  $A \in \mathbb{R}^{m \times n}$  be a matrix. In this question, we design and analyze a sampling approach for approximating A by a sparse matrix.

- a) Express A as a sum of mn matrices, each with at most one nonzero entry.
- b) Show how to construct an unbiased estimator X of A by uniform sampling.
- c) Define

$$\tilde{X}_s = \frac{1}{s} \sum_{k=1}^s X_i$$
 where each  $X_i$  is an independent copy of  $X$ .

For  $\epsilon \in [0, 1]$ , using the Matrix Bernstein inequality to give an upper bound on the number of s needed to obtain

$$\mathbb{E}\left[\|\tilde{X}_s - A\|_2\right] \le 2\epsilon \|A\|_2.$$

d) Define the probability mass

$$p_{ij} = \frac{1}{2} \left[ \frac{|a_{ij}|^2}{\|A\|_F^2} + \frac{|a_{ij}|}{\|A\|_{\ell_1}} \right]$$
 for  $i = 1, ..., m$  and  $j = 1, ..., n$ .

Here,  $\|\cdot\|_{\ell_1}$  is the entrywise  $\ell_1$  norm, i.e  $\|A\|_{\ell_1} := \sum_{i=1}^m \sum_{j=1}^n |a_{ij}|$ . Using the Matrix Bernstein inequality to provide a bound on the number s of samples needed to achieve  $\mathbb{E}\left[\|\tilde{X}_s - A\|_2\right] \le 2\epsilon \|A\|_2$ . Express the result in terms of the stable rank of A.

e) Implement both procedures and apply them to the RBF kernel matrix, i.e., for h > 0,

$$a_{ij} = \exp(-\|x_i - x_j\|_2^2/(2h))$$
 for  $i, j = 1, ..., n$ 

associated with randomly generated  $x_1, \ldots, x_n$ , uniformly drawn from the unit cube  $[0,1]^d$ . Plot the sampling distribution of the spectral norm error as a function of the number s of samples.