
Random Conic Pursuit for Semidefinite Programming: Supplementary Materials

Ariel Kleiner
 Computer Science Division
 University of California
 Berkeley, CA 94720
 akleiner@cs.berkeley.edu

Ali Rahimi
 Intel Research Berkeley
 Berkeley, CA 94720
 ali.rahimi@intel.com

Michael I. Jordan
 Computer Science Division
 University of California
 Berkeley, CA 94720
 jordan@cs.berkeley.edu

Theorem 2. *Let $X^* \succ 0$ be a fixed positive definite matrix, and let $x_1, \dots, x_n \in \mathbb{R}^d$ be drawn i.i.d. from $\mathcal{N}(0, \Sigma)$ with $\Sigma \succ X^*$. Then, for any $\delta > 0$, with probability at least $1 - \delta$,*

$$\min_{X \in \mathcal{F}_n^x} \|X - X^*\| \leq \frac{1 + \sqrt{2} \log \frac{1}{\delta}}{\sqrt{n}} \cdot \frac{2}{e} \sqrt{|\Sigma X^{*-1}|} \left\| (X^{*-1} - \Sigma^{-1})^{-1} \right\|_2$$

Proof of Theorem 2. We wish to bound the tails of the random variable

$$\min_{\gamma_1 \dots \gamma_n \geq 0} \left\| \sum_{i=1}^n \gamma_i x_i x_i - X^* \right\|. \quad (1)$$

We first simplify the problem by eliminating the minimization over γ . Define a function $\gamma(x; X^*) : \mathbb{R}^d \rightarrow \mathbb{R}_+$ that satisfies

$$\mathbb{E}_{x \sim \mathcal{N}(0, \Sigma)} \gamma(x) x x' = X^*. \quad (2)$$

The choice

$$\gamma(x) = \frac{\mathcal{N}(x|0, X^*)}{\mathcal{N}(x|0, \Sigma)} = |\Sigma|^{1/2} |X^*|^{-1/2} \exp \left(-\frac{x'(X^{*-1} - \Sigma^{-1})x}{2} \right) \quad (3)$$

works, since $\mathbb{E}_{x \sim \mathcal{N}(0, \Sigma)} \gamma(x) x x' = \mathbb{E}_{x \sim \mathcal{N}(0, X^*)} x x' = X^*$. Setting sub-optimally the coefficients γ_i to $\gamma(x_i)$ gives

$$\min_{\gamma \geq 0} \left\| \sum_{i=1}^n \gamma_i x_i x_i' - X^* \right\| \leq \left\| \frac{1}{n} \sum_{i=1}^n \gamma(x_i) x_i x_i' - \mathbb{E} \gamma(x) x x' \right\| \quad (4)$$

$$= \left\| \frac{1}{n} \sum_{i=1}^n z_i - \mathbb{E} z \right\|. \quad (5)$$

So it suffices to bound the tails of the deviation of an empirical average of i.i.d. random variables $z_i := \gamma(x_i) x_i x_i'$ from its expectation, $\mathbb{E} z = X^*$. We proceed using McDiarmid's inequality.

The scalar random variables $\|z_i\|$ are bounded because for all x , we have:

$$\|z\| = \|\gamma(x) x x'\| = \|x x'\| |\Sigma|^{1/2} |X^*|^{-1/2} \exp \left(-\frac{x'(X^{*-1} - \Sigma^{-1})x}{2} \right) \quad (6)$$

$$\leq |\Sigma|^{1/2} |X^*|^{-1/2} \|x\|_2^2 \exp \left(-\frac{\lambda_{\min}(X^{*-1} - \Sigma^{-1}) \|x\|_2^2}{2} \right) \quad (7)$$

$$\leq \frac{2|\Sigma|^{1/2} |X^*|^{-1/2}}{e \lambda_{\min}(X^{*-1} - \Sigma^{-1})} \quad (8)$$

$$= \frac{2}{e} |\Sigma|^{1/2} |X^*|^{-1/2} \left\| (X^{*-1} - \Sigma^{-1})^{-1} \right\|_2 \quad (9)$$

$$=: \Delta. \quad (10)$$

Equation (8) follows because the function $f(y) = ye^{-\alpha y}$ is bounded above by $\frac{1}{e\alpha}$.

The expectation of $\left\| \frac{1}{n} \sum_{i=1}^n z_i - \mathbb{E} z \right\|$, whose tails we wish to bound, is the standard deviation of $\frac{1}{n} \sum_{i=1}^n z_i$, and can be bounded in the standard way in a Hilbert space:

$$\left(\mathbb{E} \left\| \frac{1}{n} \sum_{i=1}^n z_i - \mathbb{E} z \right\| \right)^2 \leq \mathbb{E} \left\| \frac{1}{n} \sum_{i=1}^n z_i - \mathbb{E} z \right\|^2 = \frac{1}{n} (\mathbb{E} \|z\|^2 - \|\mathbb{E} z\|^2), \quad (11)$$

which yields

$$\mathbb{E} \left\| \frac{1}{n} \sum_{i=1}^n z_i - \mathbb{E} z \right\| \leq \frac{\Delta}{\sqrt{n}}. \quad (12)$$

Using Equations (5) and (12), and the fact that $\|z_i\| \leq \Delta$, McDiarmid's inequality gives

$$\Pr \left[\min_{\gamma \geq 0} \left\| \sum_{i=1}^n \gamma_i x_i x'_i - X^* \right\| > \frac{\Delta}{\sqrt{n}} + \epsilon \right] \quad (13)$$

$$\leq \Pr \left[\left\| \frac{1}{n} \sum_{i=1}^n z_i - \mathbb{E} z \right\| > \frac{\Delta}{\sqrt{n}} + \epsilon \right] \quad (14)$$

$$\begin{aligned} &\leq \Pr \left[\left\| \frac{1}{n} \sum_{i=1}^n z_i - \mathbb{E} z \right\| > \mathbb{E} \left\| \frac{1}{n} \sum_{i=1}^n z_i - \mathbb{E} z \right\| + \epsilon \right] \\ &\leq \exp \left(-\frac{n\epsilon^2}{2\Delta^2} \right). \end{aligned} \quad (15)$$

In other words, for any $\delta > 0$, with probability at least $1 - \delta$,

$$\min_{\gamma \geq 0} \left\| \sum_{i=1}^n \gamma_i x_i x'_i - X^* \right\| < \frac{\Delta}{\sqrt{n}} \left(1 + \sqrt{2} \log \frac{1}{\delta} \right). \quad (16)$$

□