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# Geometric Conditions for Subspace-Sparse Recovery

## Supplementary Material

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## Appendices

### A. Proof of Lemma 2

**Lemma.** *If the inlier dictionary  $\Phi \in \mathbb{R}^{n \times M}$  has full column rank, then the set of dual points,  $\mathcal{D}(\Phi)$ , contains exactly  $2^M$  points specified by  $\{\Phi(\Phi^\top \Phi)^{-1} \cdot \mathbf{u}, \mathbf{u} \in U_M\}$ , where  $U_M := \{[u_1, \dots, u_M], u_i = \pm 1, i = 1, \dots, M\}$ .*

*Proof.* It can be seen in the proof of Theorem 2 that there are possibly at most  $2^M$  dual points in the case where  $\Phi$  is of full column rank. So in order to prove the result, it is enough to show that the set  $\{\Phi(\Phi^\top \Phi)^{-1} \cdot \mathbf{u}, \mathbf{u} \in U_M\}$  contains  $2^M$  points, and each of them is a dual point.

To show that there are  $2^M$  different points, notice that  $U_M$  has  $2^M$  points, so we are left to show that for any  $\mathbf{u}_1, \mathbf{u}_2 \in U_M$  with  $\mathbf{u}_1 \neq \mathbf{u}_2$ , it has  $\Phi(\Phi^\top \Phi)^{-1} \mathbf{u}_1 \neq \Phi(\Phi^\top \Phi)^{-1} \mathbf{u}_2$ . This can be easily established by noticing that  $\text{rank}(\Phi(\Phi^\top \Phi)^{-1}) = \text{rank}(\Phi) = M$ , i.e.,  $\Phi(\Phi^\top \Phi)^{-1}$  is also of full rank, so its null space contains only the origin.

Now we show that  $\Phi(\Phi^\top \Phi)^{-1} \mathbf{u}_0$  is a dual point for any  $\mathbf{u}_0 \in U_M$ . Denote  $\eta_0 = \Phi(\Phi^\top \Phi)^{-1} \mathbf{u}_0$ . By definition, we need to show that  $\eta_0$  is an extreme point of the set  $\mathcal{K}^\circ(\pm \Phi) = \{\eta \in \mathcal{R}(\Phi) : \|\Phi^\top \eta\|_\infty \leq 1\}$ . First,  $\eta_0$  is in  $\mathcal{K}^\circ(\pm \Phi)$  because  $\|\Phi^\top \eta_0\|_\infty = \|\mathbf{u}_0\|_\infty = 1$ . Second, suppose there are two points,  $\eta_1, \eta_2 \in \mathcal{K}^\circ(\pm \Phi)$ , such that

$$\eta_0 = (1 - \lambda)\eta_1 + \lambda\eta_2 \quad (1)$$

for some  $\lambda \in (0, 1)$ , we need to show that it must be the case that  $\eta_1 = \eta_2$ . Notice that the columns of  $\Phi(\Phi^\top \Phi)^{-1}$  span the space  $\mathcal{R}(\Phi)$  and that  $\eta_1, \eta_2 \in \mathcal{K}^\circ(\pm \Phi) \subseteq \mathcal{R}(\Phi)$ , there exists  $\mathbf{x}_1, \mathbf{x}_2$  such that  $\eta_i = \Phi(\Phi^\top \Phi)^{-1} \mathbf{x}_i, i = 1, 2$ . Then by using (1), it has

$$\Phi(\Phi^\top \Phi)^{-1} \mathbf{u}_0 = (1 - \lambda)\Phi(\Phi^\top \Phi)^{-1} \mathbf{x}_1 + \lambda\Phi(\Phi^\top \Phi)^{-1} \mathbf{x}_2,$$

and by left multiplying  $\Phi^\top$ , we have

$$\mathbf{u}_0 = (1 - \lambda)\mathbf{x}_1 + \lambda\mathbf{x}_2. \quad (2)$$

Now, consider the equation for each entry separately in (2), i.e.,  $[\mathbf{u}_0]_i = (1 - \lambda)[\mathbf{x}_1]_i + \lambda[\mathbf{x}_2]_i$ , where  $i$  indexes an entry in the vector. The left hand side, being  $\pm 1$ , is an extreme point of the set  $[-1, 1]$ , while the right hand side is the convex combination of two points in  $[-1, 1]$ , so it necessarily has that  $[\mathbf{x}_1]_i = [\mathbf{x}_2]_i$ . This is true for all entries  $i$ , so  $\mathbf{x}_1 = \mathbf{x}_2$ , thus  $\eta_1 = \eta_2$ , which shows that  $\eta_0$  is indeed an extreme point.  $\square$

### B. Proof of Theorem 14

**Theorem.** *Given a dictionary  $\Pi$ . If it has  $\mu(\Pi) < \frac{1}{2M-1}$ , then for any partition of  $\Pi$  into  $\Phi$  and  $\Psi$  where  $\Phi$  has  $M$  columns, it has  $\text{rank}(\Phi) = M$  and that PRC and DRC hold.*

*Proof.* If  $\mu(\Pi) < 1/(2M - 1)$ , then it must have  $\text{rank}(\Phi) = M$ , this is an established result in sparse recovery. In the following, we show that PRC holds.

We start by giving an upper bound on  $R(\mathcal{K}^\circ(\pm \Phi))$ . From Lemma 2, given any  $\eta \in \mathcal{K}^\circ(\pm \Phi)$  where  $\eta \neq 0$ , it can be written as  $\eta = \Phi(\Phi^\top \Phi)^{-1} \mathbf{u}$  for some  $\mathbf{u} \neq 0$  with  $\|\mathbf{u}\|_\infty \leq 1$ . Thus,

$$\|\eta\|_2^2 = \eta^\top \eta = \mathbf{u}^\top (\Phi^\top \Phi)^{-1} \mathbf{u} \leq M \cdot \frac{\mathbf{u}^\top (\Phi^\top \Phi)^{-1} \mathbf{u}}{\mathbf{u}^\top \mathbf{u}}.$$

Denote  $\lambda_{\max}(\cdot), \lambda_{\min}(\cdot)$  to be the maximum and minimum eigenvalue of a symmetric matrix, respectively. We get

$$\begin{aligned} \|\eta\|_2^2 &\leq M \cdot \max_{\mathbf{u} \neq 0} \frac{\mathbf{u}^\top (\Phi^\top \Phi)^{-1} \mathbf{u}}{\mathbf{u}^\top \mathbf{u}} \\ &= M \cdot \lambda_{\max}(\Phi^\top \Phi)^{-1} = \frac{M}{\lambda_{\min}(\Phi^\top \Phi)}. \end{aligned}$$

Notice that  $\Phi^\top \Phi$  is very close to identity matrix, i.e., its diagonals are 1 and the magnitude of each off-diagonal entry is bounded above by  $\mu(\Pi)$ . By using Gersgorin's disc theorem,  $\lambda_{\min}(\Phi^\top \Phi) \geq 1 - (M - 1)\mu(\Pi)$ , so

$$\|\eta\|_2^2 \leq \frac{M}{1 - (M - 1)\mu(\Pi)}.$$

As a consequence,  $R(\mathcal{K}^o(\pm\Phi)) \leq \sqrt{\frac{M}{1-(M-1)\mu(\Pi)}}$ .

In the second step, we give an upper bound for the right hand side of PRC. By definition,

$$\mu(\Psi, \mathcal{R}(\Phi)) = \max_{\substack{\eta \in \mathcal{R}(\Phi), \\ \|\eta\|_2=1}} \|\Psi^\top \eta\|_\infty.$$

We thus need to bound  $\|\Psi^\top \eta\|_\infty$  for any  $\eta \in \mathcal{R}(\Phi)$  with  $\|\eta\|_2 = 1$ . Consider the optimization program

$$\mathbf{x}^* = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \eta = \Phi \mathbf{x}.$$

and its dual program

$$\max_{\omega} \langle \omega, \eta \rangle \quad \text{s.t.} \quad \|\Phi^\top \omega\|_\infty \leq 1.$$

The strong duality holds since the primal problem is feasible, and the objective of the dual is bounded by  $\|\omega\|_2 \|\eta\|_2 \leq R(\mathcal{K}^o(\pm\Phi))$ . Consequently, it has  $\|\mathbf{x}^*\|_1 \leq R(\mathcal{K}^o(\pm\Phi))$ . This leads to

$$\begin{aligned} \|\Psi^\top \eta\|_\infty &= \|\Psi^\top \Phi \mathbf{x}^*\|_\infty \leq \|\Psi^\top \Phi\|_\infty \|\mathbf{x}^*\|_1 \\ &\leq \mu(\Pi) R(\mathcal{K}^o(\pm\Phi)), \end{aligned}$$

in which  $\|\cdot\|_\infty$  for matrix treats the matrix as a vector.

Now we combine the results from the above two parts.

$$\begin{aligned} \mu(\Psi, \mathcal{R}(\Phi)) &\leq \mu(\Pi) R(\mathcal{K}^o(\pm\Phi)) \\ &= r(\mathcal{K}(\pm\Phi)) (\mu(\Pi) R(\mathcal{K}^o(\pm\Phi)))^2 \\ &\leq r(\mathcal{K}(\pm\Phi)) \frac{M}{1-(M-1)\mu(\Pi)}, \end{aligned}$$

in which

$$\frac{M}{1-(M-1)\mu(\Pi)} = 1 + \frac{\mu(\Pi)(2M-1)-1}{1-(M-1)\mu} < 1,$$

thus  $\mu(\Psi, \mathcal{R}(\Phi)) < r(\mathcal{K}(\pm\Phi))$ , which is the PRC.  $\square$

## References