# SUPPLEMENT TO "BIDIMENSIONAL LINKED MATRIX FACTORIZATION FOR PAN-OMICS PAN-CANCER ANALYSIS"

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#### APPENDIX A: MODULE ENUMERATION

As the default representation of model (6) in the main article, set  $K = (2^I - 1)(2^J - 1)$  and let  $\mathbf R$  and  $\mathbf C$  enumerate all possible modules as follows. For  $k = 1, \ldots, K$ , let  $\mathbf R[\cdot, k]$  be the I-digit binary representation for  $k \mod (2^I - 1) + 1$ , where mod gives the modulo (remainder) operator. For  $k = 1, \ldots, K$ , let  $\mathbf C[\cdot, k]$  give the J-digit binary representation for  $\lceil k/(2^I - 1) \rceil$ , where  $\lceil \cdot \rceil$  gives the ceiling operator.

#### APPENDIX B: PROOFS

## **B.1.** Proof of Proposition 1.

PROOF. Let  $\{\hat{\mathbf{S}}^{(k)}_{::}\}_{k=1}^K \in \mathbb{S}_{\hat{\mathbf{X}}}$  be a minimizer of the objective function  $f(\cdot)$ . Assume a violation of condition 1., wherein  $\lambda_{k'} \geq \lambda_k$ . Consider another minimizer  $\{\tilde{\mathbf{S}}^{(k)}_{::}\}_{k=1}^K$ , where  $\tilde{\mathbf{S}}^{(k)}_{::} = \mathbf{0}$  and  $\tilde{\mathbf{S}}^{(k')}_{::} = \hat{\mathbf{S}}^{(k)}_{::} + \hat{\mathbf{S}}^{(k')}_{::}$ , and all other modules are equal. Then, using the triangle inequality,

$$f(\{\hat{\mathbf{S}}_{..}^{(k)}\}_{k=1}^{K}) - f(\{\hat{\mathbf{S}}_{..}^{(k)}\}_{k=1}^{K}) = \lambda_{k} ||\hat{\mathbf{S}}_{..}^{(k)}||_{*} + \lambda_{k'} ||\hat{\mathbf{S}}_{..}^{(k')}||_{*} - \lambda_{k} ||\hat{\mathbf{S}}_{..}^{(k)} + \hat{\mathbf{S}}_{..}^{(k')}||_{*}$$

$$\geq \lambda_{k} ||\hat{\mathbf{S}}_{..}^{(k)}||_{*} + \lambda_{k'} ||\hat{\mathbf{S}}_{..}^{(k')}||_{*} - \lambda_{k} (||\hat{\mathbf{S}}_{..}^{(k)}||_{*} + ||\hat{\mathbf{S}}_{..}^{(k')}||_{*})$$

$$\geq \lambda_{k} ||\hat{\mathbf{S}}_{..}^{(k)}||_{*} + \lambda_{k'} ||\hat{\mathbf{S}}_{..}^{(k')}||_{*} - \lambda_{k} (||\hat{\mathbf{S}}_{..}^{(k)}||_{*}) - \lambda_{k'} ||\hat{\mathbf{S}}_{..}^{(k')}||_{*})$$

$$= 0,$$

and thus there is a solution in which module k is 0, regardless of the data  $X_{...}$ .

Now assume a violation of condition 2., wherein  $\lambda_k \geq \sum_{j \in \mathcal{I}_k} \lambda_j$ . Let  $\widehat{\mathbf{S}}^{(k)} = \sum_{j \in \mathcal{I}_k} \widehat{\mathbf{S}}^{j\prime}_{...}$ , where  $\widehat{\mathbf{S}}^{j\prime}_{...}$  contains the submatrix of  $\widehat{\mathbf{S}}^{(k)}_{...}$  corresponding to  $\mathbf{R}[\cdot,j]$  and  $\mathbf{C}[\cdot,j]$  and  $\mathbf{0}$  otherwise. Consider another decomposition  $\{\widetilde{\mathbf{S}}^{(k)}_{...}\}_{k=1}^K$ , where  $\widetilde{\mathbf{S}}^{(k)}_{...} = \mathbf{0}$  and  $\widetilde{\mathbf{S}}^{(j)}_{...} = \widehat{\mathbf{S}}^{(j)}_{...} + \widehat{\mathbf{S}}^{(j)\prime}_{...}$  for all  $j \in \mathcal{I}_k$ . Then,

$$\begin{split} f(\{\hat{\mathbf{S}}_{..}^{(k)}\}_{k=1}^{K}) - f(\{\hat{\mathbf{S}}_{..}^{(k)}\}_{k=1}^{K}) &= \lambda_{k} ||\hat{\mathbf{S}}_{..}^{(k)}||_{*} + \sum_{j \in \mathcal{I}_{k}} \lambda_{j} ||\hat{\mathbf{S}}_{..}^{(j)}||_{*} - \sum_{j \in \mathcal{I}_{k}} \lambda_{j} ||\hat{\mathbf{S}}_{..}^{(j)}| + \hat{\mathbf{S}}_{..}^{(j)}||_{*} \\ &\geq \lambda_{k} ||\hat{\mathbf{S}}_{..}^{(k)}||_{*} + \sum_{j \in \mathcal{I}_{k}} \lambda_{j} ||\hat{\mathbf{S}}_{..}^{(j)}||_{*} - \sum_{j \in \mathcal{I}_{k}} \lambda_{j} ||\hat{\mathbf{S}}_{..}^{(j)}||_{*} \\ &= \lambda_{k} ||\hat{\mathbf{S}}_{..}^{(k)}||_{*} - \sum_{j \in \mathcal{I}_{k}} \lambda_{j} ||\hat{\mathbf{S}}_{..}^{(j)}||_{*} \\ &\geq \lambda_{k} ||\hat{\mathbf{S}}_{..}^{(k)}||_{*} - \sum_{j \in \mathcal{I}_{k}} \lambda_{j} ||\hat{\mathbf{S}}_{..}^{(k)}||_{*} \\ &\geq 0, \end{split}$$

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and thus there is a solution in which module k is 0, regardless of the data X..

## **B.2.** Proof of Proposition 4.

PROOF. We show that  $\lambda_k = \sqrt{\mathbf{R}[\cdot,k] \cdot \mathbf{M}} + \sqrt{\mathbf{C}[\cdot,k] \cdot \mathbf{N}}$  satisfies the necessary conditions of Proposition ??. For condition 1., note that  $\sqrt{\mathbf{R}[\cdot,k] \cdot \mathbf{M}} + \sqrt{\mathbf{C}[\cdot,k] \cdot \mathbf{N}} > \sqrt{\mathbf{R}[\cdot,j] \cdot \mathbf{M}} + \sqrt{\mathbf{C}[\cdot,j] \cdot \mathbf{N}}$ .

For condition 2., note that

$$\begin{split} \sum_{j \in \mathcal{I}_k} \sqrt{\mathbf{R}[\bullet, j] \cdot \mathbf{M}} + \sqrt{\mathbf{C}[\bullet, j] \cdot \mathbf{N}} &\geq \sqrt{\sum_{j \in \mathcal{I}_k} \mathbf{R}[\bullet, j] \cdot \mathbf{M}} + \sqrt{\sum_{j \in \mathcal{I}_k} \mathbf{C}[\bullet, j] \cdot \mathbf{N}} \\ &= \sqrt{r \cdot \mathbf{R}[\bullet, k] \cdot \mathbf{M}} + \sqrt{c \cdot \mathbf{C}[\bullet, k] \cdot \mathbf{N}} \\ &> \sqrt{\mathbf{R}[\bullet, k] \cdot \mathbf{M}} + \sqrt{\mathbf{C}[\bullet, k] \cdot \mathbf{N}} \end{split}$$

**B.3. Proof of Proposition 5.** Lemmas 1 and 2 below are used to establish Proposition 5.

LEMMA 1. Take two decompositions  $\{\hat{\mathbf{S}}^{(k)}_{\boldsymbol{\cdot}}\}_{k=1}^K \in \mathbb{S}_{\hat{\mathbf{X}}}$  and  $\{\tilde{\mathbf{S}}^{(k)}_{\boldsymbol{\cdot}}\}_{k=1}^K \in \mathbb{S}_{\hat{\mathbf{X}}}$ , and assume that both minimize the structured nuclear norm penalty:

$$f_{pen}(\{\hat{\mathbf{S}}_{::}^{(k)}\}_{k=1}^{K}) = f_{pen}\left(\{\tilde{\mathbf{S}}_{::}^{(k)}\}_{k=1}^{K}\right) = \min_{\mathbb{S}_{\hat{\mathbf{X}}}} f_{pen}(\{\mathbf{S}_{::}^{(k)}\}_{k=1}^{K}).$$

Then, for any  $\alpha \in [0, 1]$ ,

$$||\alpha \hat{\mathbf{S}}_{..}^{(k)} + (1-\alpha) \tilde{\mathbf{S}}_{..}^{(k)}||_{*} = \alpha ||\hat{\mathbf{S}}_{..}^{(k)}||_{*} + (1-\alpha) ||\tilde{\mathbf{S}}_{..}^{(k)}||_{*}$$

for k = 1, ..., K.

PROOF. Because  $\mathbb{S}_{\hat{\mathbf{X}}}$  is a convex space and  $f_{\text{pen}}$  is a convex function, the set of minimizers of  $f_{\text{pen}}$  over  $\mathbb{S}_{\hat{\mathbf{X}}}$  is also convex. Thus,

$$f_{\mathrm{pen}}\left(\{\alpha\hat{\mathbf{S}}_{\boldsymbol{\cdot\cdot}}^{(k)}+(1-\alpha)\tilde{\mathbf{S}}_{\boldsymbol{\cdot\cdot}}^{(k)}\}_{k=1}^K\right)=\min_{\mathbb{S}_{\hat{\boldsymbol{\cdot}}}}f_{\mathrm{pen}}(\{\mathbf{S}_{\boldsymbol{\cdot\cdot}}^{(k)}\}_{k=1}^K).$$

The result follows from the convex property of the nuclear norm operator, which implies that for any two matrices of equal size  $\hat{\bf A}$  and  $\hat{\bf A}$ ,

(1) 
$$||\alpha \hat{\mathbf{A}} + (1-\alpha)\tilde{\mathbf{A}}||_* \le \alpha ||\hat{\mathbf{A}}||_* + (1-\alpha)||\tilde{\mathbf{A}}||_*.$$

Applying (1) to each additive term in  $f_{pen}$  gives

(2) 
$$f_{\text{pen}}\left(\left\{\alpha\hat{\mathbf{S}}_{..}^{(k)} + (1-\alpha)\tilde{\mathbf{S}}_{..}^{(k)}\right\}_{k=1}^{K}\right) \leq \alpha f_{\text{pen}}\left(\left\{\hat{\mathbf{S}}_{..}^{(k)}\right\}_{k=1}^{K}\right) + (1-\alpha)f_{\text{pen}}\left(\left\{\tilde{\mathbf{S}}_{..}^{(k)}\right\}_{k=1}^{K}\right)$$
$$= \min_{\mathbb{S}_{sc}} f_{\text{pen}}\left(\left\{\mathbf{S}_{..}^{(k)}\right\}_{k=1}^{K}\right).$$

Because  $\{\alpha \hat{\mathbf{S}}_{\boldsymbol{\cdot}}^{(k)} + (1-\alpha) \tilde{\mathbf{S}}_{\boldsymbol{\cdot}}^{(k)}\}_{k=1}^K \in \mathbb{S}_{\hat{\mathbf{X}}}$ , the inequality in (2) must be an equality, and it follows that the inequality (1) must be an equality for each penalized term in the decomposition.

LEMMA 2. Take two matrices  $\hat{\mathbf{A}}$  and  $\tilde{\mathbf{A}}$ . If  $||\hat{\mathbf{A}} + \tilde{\mathbf{A}}||_* = ||\hat{\mathbf{A}}||_* + ||\tilde{\mathbf{A}}||_*$ , and  $\mathbf{UD}_+\mathbf{V}^T$  is the SVD of  $\hat{\mathbf{A}} + \tilde{\mathbf{A}}$ , then  $\hat{\mathbf{A}} = \hat{\mathbf{U}}\hat{\mathbf{D}}\hat{\mathbf{V}}^T$  where  $\hat{\mathbf{D}}$  is diagonal and  $||\hat{\mathbf{A}}||_* = ||\hat{\mathbf{D}}||_*$ , and  $\tilde{\mathbf{A}} = \mathbf{U}\tilde{\mathbf{D}}\mathbf{V}^T$  where  $\tilde{\mathbf{D}}$  is diagonal and  $||\tilde{\mathbf{A}}||_* = ||\tilde{\mathbf{D}}||_*$ .

PROOF. Here we use the fact that the spectral norm is dual to the nuclear norm (Fazel et al., 2001). That is, if  $\sigma_1(\mathbf{Z})$  is the maximum singular value of  $\mathbf{Z}$  (i.e., the spectral norm), then

$$||\mathbf{A}||_* = \sup_{\sigma_1(\mathbf{Z})=1} \langle \mathbf{Z}, \mathbf{A} \rangle.$$

Thus,

(3) 
$$\sup_{\sigma_1(\mathbf{Z})=1} \langle \mathbf{Z}, \hat{\mathbf{A}} + \tilde{\mathbf{A}} \rangle = \sup_{\sigma_1(\mathbf{Z})=1} \langle \mathbf{Z}, \hat{\mathbf{A}} \rangle + \sup_{\sigma_1(\mathbf{Z})=1} \langle \mathbf{Z}, \tilde{\mathbf{A}} \rangle.$$

By the properties of the SVD,

(4) 
$$\langle \mathbf{U}\mathbf{V}^T, \tilde{\mathbf{A}} \rangle + \langle \mathbf{U}\mathbf{V}^T, \hat{\mathbf{A}} \rangle = \langle \mathbf{U}\mathbf{V}^T, \hat{\mathbf{A}} + \tilde{\mathbf{A}} \rangle = \sup_{\sigma_1(\mathbf{Z})=1} \langle \mathbf{Z}, \hat{\mathbf{A}} + \tilde{\mathbf{A}} \rangle.$$

By (3) and (4),

(5) 
$$\langle \mathbf{U}\mathbf{V}^T, \tilde{\mathbf{A}} \rangle + \langle \mathbf{U}\mathbf{V}^T, \hat{\mathbf{A}} \rangle = \sup_{\sigma_1(\mathbf{Z})=1} \langle \mathbf{Z}, \hat{\mathbf{A}} \rangle + \sup_{\sigma_1(\mathbf{Z})=1} \langle \mathbf{Z}, \tilde{\mathbf{A}} \rangle.$$

Because  $\mathbf{U}\mathbf{V}^T \in \{\mathbf{Z} : \sigma_1(\mathbf{Z}) = 1\}$  it follows that

$$\langle \mathbf{U}\mathbf{V}^T, \hat{\mathbf{A}} \rangle \leq \sup_{\sigma_1(\mathbf{Z})=1} \langle \mathbf{Z}, \hat{\mathbf{A}} \rangle \ \ \text{and} \ \ \langle \mathbf{U}\mathbf{V}^T, \tilde{\mathbf{A}} \rangle \leq \sup_{\sigma_1(\mathbf{Z})=1} \langle \mathbf{Z}, \tilde{\mathbf{A}} \rangle,$$

and so (5) implies

$$\langle \mathbf{U}\mathbf{V}^T, \hat{\mathbf{A}} \rangle = \sup_{\sigma_1(\mathbf{Z})=1} \langle \mathbf{Z}, \hat{\mathbf{A}} \rangle = ||\hat{\mathbf{A}}||_*,$$

and similarly  $\langle \mathbf{U}\mathbf{V}^T, \tilde{\mathbf{A}} \rangle = ||\tilde{\mathbf{A}}||_*$ . Let  $\tilde{\mathbf{U}}\tilde{\mathbf{D}}\tilde{\mathbf{V}}^T$  give the SVD of  $\tilde{\mathbf{A}}$ . Note that

$$\langle \mathbf{U}\mathbf{V}^T, \tilde{\mathbf{U}}\tilde{\mathbf{D}}\tilde{\mathbf{V}}^T \rangle = \text{Tr}(\mathbf{V}\mathbf{U}^T\tilde{\mathbf{U}}\tilde{\mathbf{D}}\tilde{\mathbf{V}}^T) = \text{Tr}(\mathbf{V}^T\tilde{\mathbf{V}}\mathbf{U}^T\tilde{\mathbf{U}}\tilde{\mathbf{D}}),$$

and

$$\mathrm{Tr}(\mathbf{V}^T\tilde{\mathbf{V}}\mathbf{U}^T\tilde{\mathbf{U}}\tilde{\mathbf{D}}) = ||\tilde{\mathbf{A}}||_* = \sum_i \tilde{\mathbf{D}}[i,i]$$

if and only if  $\mathbf{V}^T \tilde{\mathbf{V}} \mathbf{U}^T \tilde{\mathbf{U}}[i,i] = 1$  where  $\tilde{\mathbf{D}}[i,i] > 0$ . It follows that the left and right singular vectors of A that correspond to non-zero singular values must also be singular vectors of  $\hat{\bf A} + \hat{\bf A}$ . By an analogous argument, the left and right singular vectors that correspond to non-zero singular values in  $\hat{A}$  must also be singular vectors of  $\hat{A} + \hat{A}$ . 

Proposition 5 is a direct corollary of Lemmas 1 and 2, as Lemma 1 implies  $||\hat{\mathbf{S}}_{::}^{(k)}|$  $|\tilde{\mathbf{S}}_{\mathbf{n}}^{(k)}||_* = ||\hat{\mathbf{S}}_{\mathbf{n}}^{(k)}||_* + ||\tilde{\mathbf{S}}_{\mathbf{n}}^{(k)}||_*$  for each k, and then Lemma 2 implies the result.

#### **B.4.** Proof of Theorem 1.

PROOF. Take two decomposition  $\{\hat{\mathbf{S}}^{(k)}_{...}\}_{k=1}^K$  and  $\{\tilde{\mathbf{S}}^{(k)}_{...}\}_{k=1}^K$  that satisfy properties 1., 2., and 3. of Theorem 1; we will show that  $\{\hat{\mathbf{S}}^{(k)}_{...}\}_{k=1}^K = \{\tilde{\mathbf{S}}^{(k)}_{...}\}_{k=1}^K$ . For each  $k=1,\ldots,K$ , write  $\hat{\mathbf{S}}^{(k)}_{...} = \mathbf{U}^{(k)}\hat{\mathbf{D}}\mathbf{V}^{(k)T}$  and  $\hat{\mathbf{S}}^{(k)}_{...} = \mathbf{U}^{(k)}\hat{\mathbf{D}}^{(k)}\mathbf{V}^{(k)T}$  as in Proposition ??. Then, it suffices to show that  $\hat{\mathbf{D}}^{(k)}[r,r] = \tilde{\mathbf{D}}^{(k)}[r,r]$  for all k,r.

First, consider module k = 1 with  $\mathbf{R}[\cdot, 1] = [1 \ 0 \ \cdots \ 0]^T$  and  $\mathbf{C}[\cdot, 1] = [1 \ 0 \ \cdots \ 0]^T$ . By way of contradiction, assume  $\hat{\mathbf{D}}^{(1)}[1,1] > 0$  and  $\tilde{\mathbf{D}}^{(1)}[1,1] = 0$ . The linear independence of  $\{\mathbf{V}_{i}^{(k)}[\bullet,r]:\hat{\mathbf{D}}^{(k)}[r,r]>0\}$  and  $\{\mathbf{V}_{i}^{(k)}[\bullet,r]:\tilde{\mathbf{D}}^{(k)}[r,r]>0\}$  implies that

$$\text{row}(\mathbf{X}_{\bullet}) = \text{span}\{\mathbf{U}_{\bullet}^{(k)}[\bullet, r] : \hat{\mathbf{D}}^{(k)}[r, r] > 0\} = \text{span}\{\{\mathbf{U}_{\bullet}^{(k)}[\bullet, r] : \hat{\mathbf{D}}^{(k)}[r, r] > 0\}.$$

Thus,  $\mathbf{U}^{(1)}[\cdot,1] \in \operatorname{span}\{\{\mathbf{U}^{(k)}[\cdot,r]: \tilde{\mathbf{D}}^{(k)}[r,r]>0\}$ , and it follows from the orthogonality of  $\mathbf{U}^{(1)}[\cdot,1]$  and  $\{\mathbf{U}^{(1)}[\cdot,r],r>1\}$  that

$$\mathbf{U}_{\boldsymbol{\cdot}}^{(1)}[\boldsymbol{\cdot},1] \in \operatorname{span}\{\{\mathbf{U}_{\boldsymbol{\cdot}}^{(k)}[\boldsymbol{\cdot},r]: \tilde{\mathbf{D}}^{(k)}[r,r]>0 \text{ and } k>1\}.$$

Moreover, because  $\mathbf{U}_i^{(1)} = \mathbf{0}$  for any i > 1 and  $\{\mathbf{U}_i^{(k)}[\cdot,r]: \tilde{\mathbf{D}}^{(k)}[r,r] > 0\}$  are linearly independent it follows that

(6) 
$$\mathbf{U}_{\bullet}^{(1)}[\bullet, 1] \in \text{span}\{\mathbf{U}_{\bullet}^{(k)}[\bullet, r] : \tilde{\mathbf{D}}^{(k)}[r, r] > 0, \ k > 1, \text{ and } \mathbf{R}[i, k] = 0 \text{ for any } i > 1\}.$$

Note that (6) implies  $\mathbf{U}_1^{(1)}[{}^{}_{},1]\in \mathrm{row}(\mathbf{X}_{12}+\cdots+\mathrm{row}(\mathbf{X}_{1J}),$  however, this is contradicted by the linear independence of  $\mathbf{U}_1^{(1)}[{}^{}_{},1]$  and  $\{\mathbf{U}_i^{(k)}[{}^{}_{},r]:\hat{\mathbf{D}}^{(k)}[r,r]>0,k>1\}.$  Thus, we conclude that  $\tilde{\mathbf{D}}^{(1)}[1,1]>0$  implies  $\tilde{\mathbf{D}}^{(1)}[1,1]>0$ . Analogous arguments show that  $\tilde{\mathbf{D}}^{(k)}[r,r]>0$  if and only if  $\tilde{\mathbf{D}}^{(k)}[r,r]>0$  for any pair (r,k). It follows that  $\{\mathbf{U}_i^{(k)}[{}^{}_{},r]:\hat{\mathbf{D}}^{(k)}[r,r]>0\}$  are linearly independent for  $i=1,\ldots I$ , and  $\{\mathbf{V}_j^{(k)}[{}^{}_{},r]:\hat{\mathbf{D}}^{(k)}[r,r]>0\}$  are linearly independent for  $j=1,\ldots,J$ . Thus,

$$\sum_{k=1}^{K} \mathbf{U}_{\boldsymbol{\cdot}}^{(k)} (\hat{\mathbf{D}}^{(k)} - \tilde{\mathbf{D}}^{(k)}) \mathbf{V}_{\boldsymbol{\cdot}}^{(k)T} = \sum_{k=1}^{K} \hat{\mathbf{S}}_{\boldsymbol{\cdot}}^{(k)} - \tilde{\mathbf{S}}_{\boldsymbol{\cdot}}^{(k)} = \mathbf{X}_{\boldsymbol{\cdot}} - \mathbf{X}_{\boldsymbol{\cdot}} = \mathbf{0}$$

implies that  $\hat{\mathbf{D}}^{(k)}[r,r] = \tilde{\mathbf{D}}^{(k)}[r,r]$  for all k, r.

#### REFERENCES

Fazel, M., Hindi, H., Boyd, S. P., et al. (2001). A rank minimization heuristic with application to minimum order system approximation. In *Proceedings of the American control conference*, volume 6, pages 4734–4739. Citeseer.