

Appendix A

The vectorization procedure of convex optimization problem in decision matrix \mathbf{H}

$$\begin{aligned} \min_{\mathbf{H}} \quad & \|\mathbf{H}\mathbf{Y}\|_F \\ \text{s.t.} \quad & \mathbf{H}\mathbf{G}^y = \mathbf{J}_{uu}^{1/2} \end{aligned}$$

to convex optimization problem in \mathbf{h}_δ is described (Alstad et al., 2009). We write

$$\mathbf{H} = \begin{bmatrix} h_{11} & h_{12} & \dots & h_{1n_y} \\ h_{21} & h_{22} & \dots & h_{2n_y} \\ \vdots & \vdots & \ddots & \vdots \\ h_{n_u 1} & h_{n_u 2} & \dots & h_{n_u n_y} \end{bmatrix} = [\mathbf{h}_1 \quad \mathbf{h}_2 \quad \dots \quad \mathbf{h}_{n_y}] = \begin{bmatrix} \tilde{\mathbf{h}}_1^T \\ \tilde{\mathbf{h}}_2^T \\ \vdots \\ \tilde{\mathbf{h}}_{n_u}^T \end{bmatrix}$$

where

$$\begin{aligned} \mathbf{h}_j &= j^{\text{th}} \text{ column of } \mathbf{H}, \mathbf{h}_j \in \mathbb{R}^{n_u \times 1} \\ \tilde{\mathbf{h}}_j &= j^{\text{th}} \text{ row of } \mathbf{H}, \tilde{\mathbf{h}}_j \in \mathbb{R}^{n_y \times 1} \end{aligned}$$

The transpose must be included because all vectors including $\tilde{\mathbf{h}}_i$ are column vectors.

Similarly, let $\mathbf{J}_{uu}^{1/2} = [\mathbf{j}_1 \quad \mathbf{j}_2 \quad \dots \quad \mathbf{j}_{n_u}]$.

We further introduce the long vectors \mathbf{h}_δ and \mathbf{j}_δ ,

$$\mathbf{h}_\delta = \begin{bmatrix} \tilde{\mathbf{h}}_1 \\ \tilde{\mathbf{h}}_2 \\ \vdots \\ \tilde{\mathbf{h}}_{n_u} \end{bmatrix} = \begin{bmatrix} h_{11} \\ h_{12} \\ \vdots \\ h_{1n_y} \\ h_{21} \\ h_{22} \\ \vdots \\ h_{2n_y} \\ h_{n_u1} \\ h_{n_u2} \\ \vdots \\ h_{n_un_y} \end{bmatrix} \in \mathbb{R}^{n_un_y \times 1}$$

$$\mathbf{j}_\delta^T = [\mathbf{j}_1^T \quad \mathbf{j}_2^T \quad \dots \quad \mathbf{j}_{n_u}^T] \in \mathbb{R}^{n_un_u \times 1}$$

and the large matrices

$$\mathbf{G}_\delta^T = \begin{bmatrix} \mathbf{G}^{y^T} & 0 & 0 & \dots \\ 0 & \mathbf{G}^{y^T} & 0 & \dots \\ \vdots & \vdots & \vdots & \ddots \\ 0 & 0 & \dots & \mathbf{G}^{y^T} \end{bmatrix}, \quad \mathbf{Y}_\delta = \begin{bmatrix} \mathbf{Y} & 0 & 0 & \dots \\ 0 & \mathbf{Y} & 0 & \dots \\ \vdots & \vdots & \vdots & \ddots \\ 0 & 0 & \dots & \mathbf{Y} \end{bmatrix}$$

$$\text{Then, } \mathbf{H}\mathbf{Y} = \begin{bmatrix} \tilde{\mathbf{h}}_1^T \mathbf{Y} \\ \tilde{\mathbf{h}}_2^T \mathbf{Y} \\ \vdots \\ \tilde{\mathbf{h}}_{n_u}^T \mathbf{Y} \end{bmatrix} \text{ and for the frobenius norm the following equal-}$$

ities apply.

$$\begin{aligned} \|\mathbf{H}\mathbf{Y}\|_F^2 &= \left\| \begin{bmatrix} \tilde{\mathbf{h}}_1^T \mathbf{Y} \\ \tilde{\mathbf{h}}_2^T \mathbf{Y} \\ \vdots \\ \tilde{\mathbf{h}}_{n_u}^T \mathbf{Y} \end{bmatrix} \right\|_F^2 = \left\| \begin{bmatrix} \tilde{\mathbf{h}}_1^T \mathbf{Y} & \tilde{\mathbf{h}}_2^T \mathbf{Y} & \dots & \tilde{\mathbf{h}}_{n_u}^T \mathbf{Y} \end{bmatrix} \right\|_F^2 \\ &= \|\mathbf{h}_\delta^T \mathbf{Y}_\delta\|_F^2 = \|\mathbf{h}_\delta \mathbf{Y}_\delta^T\|_F^2 = \mathbf{h}_\delta^T \underbrace{\mathbf{Y}_\delta \mathbf{Y}_\delta^T}_{\mathbf{F}_\delta} \mathbf{h}_\delta = \mathbf{h}_\delta^T \mathbf{F}_\delta \mathbf{h}_\delta \end{aligned}$$

Because $\mathbf{H}\mathbf{G}^y = \mathbf{J}_{uu}^{1/2}$ where $\mathbf{J}_{uu}^{1/2}$ is symmetric matrix, we have $\mathbf{H}\mathbf{G}^y = \mathbf{G}^{y^T} \mathbf{H}^T = \mathbf{J}_{uu}^{1/2}$ and

$$\left[\mathbf{G}^{y^T} \tilde{\mathbf{h}}_1 \quad \mathbf{G}^{y^T} \tilde{\mathbf{h}}_2 \quad \dots \quad \mathbf{G}^{y^T} \tilde{\mathbf{h}}_{n_u} \right] = [\mathbf{j}_1 \quad \mathbf{j}_2 \dots \mathbf{j}_{n_u}] \implies \mathbf{G}_\delta^T \mathbf{h}_\delta = \mathbf{j}_\delta$$