

Supplementary Materials for EVD-Dualdating based Online Subspace Learning

1. Proof of Theorem 1

Proof.

$$F^T F = \begin{bmatrix} C^T C & C^T D & C^T B \\ D^T C & D^T D & D^T B \\ B^T C & B^T D & B^T B \end{bmatrix} = X_F + \sigma^2 I_{n+m}.$$

Then,

$$X_F = F^T F - \sigma^2 I_{n+m} = \begin{bmatrix} C^T C - \sigma^2 I_{n-p} & C^T D & C^T B \\ D^T C & D^T D - \sigma^2 I_p & D^T B \\ B^T C & B^T D & B^T B - \sigma^2 I_m \end{bmatrix}.$$

Since $\text{rank}(X_F) = k$, it follows that:

$$\begin{aligned} \text{rank}(C^T C - \sigma^2 I_{n-p}) &= k_C \leq k, \\ \text{rank}(D^T D - \sigma^2 I_p) &= k_D \leq k, \\ \text{rank}(B^T B - \sigma^2 I_m) &= k_B \leq k. \end{aligned}$$

Let the EVDs of $C^T C - \sigma^2 I_{n-p}$, $D^T D - \sigma^2 I_p$, and $B^T B - \sigma^2 I_m$ are:

$$\begin{aligned} C^T C - \sigma^2 I_{n-p} &= V_C \begin{bmatrix} \Lambda'_C \\ 0 \end{bmatrix} V_C^T, \\ D^T D - \sigma^2 I_p &= V_D \begin{bmatrix} \Lambda'_D \\ 0 \end{bmatrix} V_D^T, \\ B^T B - \sigma^2 I_m &= V_B \begin{bmatrix} \Lambda'_B \\ 0 \end{bmatrix} V_B^T, \end{aligned}$$

where $\Lambda'_C = \Sigma_C^2 - \sigma^2 I_{k_C}$, $\Lambda'_D = \Sigma_D^2 - \sigma^2 I_{k_D}$, $\Lambda'_B = \Sigma_B^2 - \sigma^2 I_{k_B}$ and $\Sigma_C \in \mathbb{R}^{k_C \times k_C}$, $\Sigma_D \in \mathbb{R}^{k_D \times k_D}$, $\Sigma_B \in \mathbb{R}^{k_B \times k_B}$ are from the singular values of C , D and B .

So the SVDs of C , D , and B can be written as:

$$\begin{aligned} C &= U_C \begin{bmatrix} \Sigma_C \\ \sigma I_{t_C} \end{bmatrix} V_C^T = \begin{bmatrix} U_{Ck_C} & U_{Cl} \end{bmatrix} \begin{bmatrix} \Sigma_C \\ \sigma I_{t_C} \end{bmatrix} \begin{bmatrix} V_{Ck_C} & V_{Cl} \end{bmatrix}^T, \\ D &= U_D \begin{bmatrix} \Sigma_D \\ \sigma I_{t_D} \end{bmatrix} V_D^T = \begin{bmatrix} U_{Dk_D} & U_{Dl} \end{bmatrix} \begin{bmatrix} \Sigma_D \\ \sigma I_{t_D} \end{bmatrix} \begin{bmatrix} V_{Dk_D} & V_{Dl} \end{bmatrix}^T, \\ B &= U_B \begin{bmatrix} \Sigma_B \\ \sigma I_{t_B} \end{bmatrix} V_B^T = \begin{bmatrix} U_{Bk_B} & U_{Bl} \end{bmatrix} \begin{bmatrix} \Sigma_B \\ \sigma I_{t_B} \end{bmatrix} \begin{bmatrix} V_{Bk_B} & V_{Bl} \end{bmatrix}^T, \end{aligned}$$

where $U_{Ck_C} \in \mathbb{R}^{d \times k_C}$, $U_{Cl} \in \mathbb{R}^{d \times t_C}$, $U_{Dk_D} \in \mathbb{R}^{d \times k_D}$, $U_{Dl} \in \mathbb{R}^{d \times t_D}$, $U_{Bk_B} \in \mathbb{R}^{d \times k_B}$, $U_{Bl} \in \mathbb{R}^{d \times t_B}$, $t_C = \text{rank}(C) - k_C$, $t_D = \text{rank}(D) - k_D$, $t_B = \text{rank}(B) - k_B$.

Then,

$$\begin{aligned}
& \begin{bmatrix} V_C \\ V_D \\ V_B \end{bmatrix}^T X_F \begin{bmatrix} V_C \\ V_D \\ V_B \end{bmatrix} \\
&= \begin{bmatrix} \begin{bmatrix} \Lambda'_C \\ 0 \end{bmatrix} & V_C^T C^T D V_D & V_C^T C^T B V_B \\ V_D^T D^T C V_C & \begin{bmatrix} \Lambda'_D \\ 0 \end{bmatrix} & V_D^T D^T B V_B \\ V_B^T B^T C V_C & V_B^T B^T D V_D & \begin{bmatrix} \Lambda'_B \\ 0 \end{bmatrix} \end{bmatrix} = \begin{bmatrix} \Lambda'_C & 0 & S_1 & S_2 & S_5 & S_6 \\ 0 & 0 & S_3 & S_4 & S_7 & S_8 \\ S_1^T & S_3^T & \Lambda'_D & 0 & S_9 & S_{10} \\ S_2^T & S_4^T & 0 & 0 & S_{11} & S_{12} \\ S_5^T & S_7^T & S_9^T & S_{11}^T & \Lambda'_B & 0 \\ S_6^T & S_8^T & S_{10}^T & S_{12}^T & 0 & 0 \end{bmatrix}.
\end{aligned}$$

Because X_F is symmetric positive semidefinite and $\text{rank}(X_F) = k$, according the determination condition of a symmetric positive semidefinite matrix, there exists a k -order principal minor is positive, and the determinant of arbitrary $(k+1)$ -order principal minor is zero. It follows that $S_2 = 0, S_3 = 0, S_4 = 0, S_6 = 0, S_7 = 0, S_8 = 0, S_{10} = 0, S_{11} = 0, S_{12} = 0$, and $k_C + k_D + k_B = k$.

Thus, we have

$$\begin{aligned}
\begin{bmatrix} U_{Ck_C} \Sigma_C & \sigma U_{Cl} \end{bmatrix}^T \begin{bmatrix} U_{Dk_D} \Sigma_D & \sigma U_{Dl} \end{bmatrix} &= \begin{bmatrix} S_1 & 0 \\ 0 & 0 \end{bmatrix}, \\
\begin{bmatrix} U_{Ck_C} \Sigma_C & \sigma U_{Cl} \end{bmatrix}^T \begin{bmatrix} U_{Bk_B} \Sigma_B & \sigma U_{Bl} \end{bmatrix} &= \begin{bmatrix} S_5 & 0 \\ 0 & 0 \end{bmatrix}, \\
\begin{bmatrix} U_{Dk_D} \Sigma_C & \sigma U_{Dl} \end{bmatrix}^T \begin{bmatrix} U_{Bk_B} \Sigma_B & \sigma U_{Bl} \end{bmatrix} &= \begin{bmatrix} S_9 & 0 \\ 0 & 0 \end{bmatrix},
\end{aligned}$$

which lead to

$$\begin{aligned}
U_{Ck_C} &\perp U_{Dl}, U_{Cl} \perp U_{Dk_D}, U_{Cl} \perp U_{Dl}, \\
U_{Ck_C} &\perp U_{Bl}, U_{Cl} \perp U_{Bk_B}, U_{Cl} \perp U_{Bl}, \\
U_{Dk_D} &\perp U_{Bl}, U_{Dl} \perp U_{Bk_B}, U_{Dl} \perp U_{Bl}.
\end{aligned}$$

Let \hat{U}_A be an orthonormal basis of

$$\mathcal{L} \left(\begin{bmatrix} U_{Ck_C} & U_{Dk_D} \end{bmatrix} \right) \cap \mathcal{L}^\perp \left(\begin{bmatrix} U_{Cl} & U_{Dl} \end{bmatrix} \right),$$

where $\mathcal{L}(\cdot)$ denotes the column space of a matrix, and $\mathcal{L}^\perp(\cdot)$ denotes the orthonormal complement.

Obviously, $\text{rank}(\hat{U}_A) \leq k$, so in order to construct the first k eigen vectors, we append a few mutually orthogonal vectors from U_{Cl} and U_{Dl} to \hat{U}_A . Divide U_{Cl} and U_{Dl} into two parts, $U_{Cl} = \begin{bmatrix} U_{Cl}^{A1} & U_{Cl}^{A2} \end{bmatrix}$, $U_{Dl} = \begin{bmatrix} U_{Dl}^{A1} & U_{Dl}^{A2} \end{bmatrix}$, satisfying that the first k eigen vectors of A are

$$U_{Ak} = \begin{bmatrix} \hat{U}_A & U_{Cl}^{A1} & U_{Dl}^{A1} \end{bmatrix}.$$

Then, we have

$$AA^T = \hat{A}\hat{A}^T + \sigma^2 U_{Cl}^{A2} U_{Cl}^{A2T} + \sigma^2 U_{Dl}^{A2} U_{Dl}^{A2T},$$

which leads to

$$EE^T = \hat{E}\hat{E}^T + \sigma^2 U_{Cl}^{A2} U_{Cl}^{A2T} + \sigma^2 U_{Dl}^{A2} U_{Dl}^{A2T},$$

Similarly, let \hat{U}_E be an orthonormal basis of $\mathcal{L}([U_{Ck_C} \ U_{Bk_B}])^\perp$, divide U_{Cl} and U_{Bl} into two parts, $U_{Cl} = [U_{Cl}^{E1} \ U_{Cl}^{E2}]$, $U_{Bl} = [U_{Bl}^{E1} \ U_{Bl}^{E2}]$, then the first k singular vectors of E are

$$U_{Ek} = [\hat{U}_E \ U_{Cl}^{E1} \ U_{Bl}^{E1}].$$

Assuming that the intersection of U_{Cl}^{A2} and U_{Cl}^{E1} is U_{Cl}^I (null or non-null), it can be written that $U_{Cl}^{A2} = [U_{Cl}^I \ U_{Cl}^A]$, $U_{Cl}^{E1} = [U_{Cl}^I \ U_{Cl}^E]$. Let $\text{rank}(U_{Cl}^C) = k_s$, the following holds

$$\begin{aligned} & U_{Ek}^T U_{Cl}^{A2} U_{Cl}^{A2T} U_{Ek} \\ &= [\hat{U}_E \ U_{Cl}^{E1} \ U_{Bl}^{E1}]^T U_{Cl}^{A2} U_{Cl}^{A2T} [\hat{U}_E \ U_{Cl}^{E1} \ U_{Bl}^{E1}] \\ &= \begin{bmatrix} 0 & \begin{bmatrix} U_{Cl}^I{}^T \\ U_{Cl}^A{}^T \end{bmatrix} \end{bmatrix} \begin{bmatrix} U_{Cl}^I & U_{Cl}^E \end{bmatrix} \begin{bmatrix} 0 \end{bmatrix}^T \begin{bmatrix} 0 & \begin{bmatrix} U_{Cl}^I{}^T \\ U_{Cl}^A{}^T \end{bmatrix} \end{bmatrix} \begin{bmatrix} U_{Cl}^I & U_{Cl}^E \end{bmatrix} \begin{bmatrix} 0 \end{bmatrix} \\ &= \begin{bmatrix} 0 & & \\ & I_{k_s} & \\ & & 0 \end{bmatrix}_{k \times k}, \end{aligned}$$

$$\begin{aligned} & U_{Ek}^T U_{Dl}^{A2} U_{Dl}^{A2T} U_{Ek} \\ &= [\hat{U}_E \ U_{Cl}^{E1} \ U_{Bl}^{E1}]^T U_{Dl}^{A2} U_{Dl}^{A2T} [\hat{U}_E \ U_{Cl}^{E1} \ U_{Bl}^{E1}] = 0_{k \times k}. \end{aligned}$$

So

$$U_{Ek}^T EE^T U_{Ek} = U_{Ek}^T \hat{E} \hat{E}^T U_{Ek} + \sigma^2 \begin{bmatrix} 0 & & \\ & I_{k_s} & \\ & & 0 \end{bmatrix}_{k \times k}.$$

Finally, we can conclude that

$$\text{best}_k(S_E) = \text{best}_k(\hat{S}_E).$$

completing the proof. □