

4. SOLUTION OF RPCA-EWC

For convenience, the subscripts of parameters are ignored. Specifically, let $\mathbf{P}_0^* = \mathbf{P}_{\mathcal{M}_{K-1}}$, $\mathbf{X}_2 = \tilde{\mathbf{X}}_{2,K}$, $\mathbf{\Omega} = \zeta_K \mathbf{\Omega}_{\mathcal{M}_{K-1}}$. The formula (12) in the paper can be described as follows:

$$\begin{aligned} \mathcal{J}(\mathbf{P}) &= \mathcal{J}_K(\mathbf{P}) + \zeta_K \mathcal{J}_{loss}(\mathbf{P}, \mathbf{P}_0^*) \\ &= \|\mathbf{X}_2 - \mathbf{X}_2 \mathbf{P} \mathbf{P}^T\|_F^2 + \|\mathbf{P} - \mathbf{P}_0^*\|_{\mathbf{\Omega}}^2 \end{aligned} \quad (\text{S9})$$

The formula (S9) can be reformulated as

$$\mathcal{J}(\mathbf{P}) = \text{tr}(\mathbf{P}^T \mathbf{\Omega} \mathbf{P}) - \text{tr}(\mathbf{P}^T \mathbf{X}_2^T \mathbf{X}_2 \mathbf{P}) - 2\text{tr}(\mathbf{P}^T \mathbf{\Omega} \mathbf{P}_0^*) + \underbrace{\{\text{tr}(\mathbf{X}_2^T \mathbf{X}_2) + \text{tr}(\mathbf{P}_0^{*T} \mathbf{\Omega} \mathbf{P}_0^*)\}}_{\text{constant}} \quad (\text{S10})$$

Let $G(\mathbf{P}) = \text{tr}(\mathbf{P}^T \mathbf{\Omega} \mathbf{P}) - 2\text{tr}(\mathbf{P}^T \mathbf{\Omega} \mathbf{P}_0^*)$, $H(\mathbf{P}) = \text{tr}(\mathbf{P}^T \mathbf{X}_2^T \mathbf{X}_2 \mathbf{P})$. Thus, $\mathcal{J}(\mathbf{P}) = G(\mathbf{P}) - H(\mathbf{P}) + \text{constant}$. The minimization of (S10) is equivalent to

$$\begin{aligned} \min_{\mathbf{P}} \quad & G(\mathbf{P}) - H(\mathbf{P}) \\ \text{s.t.} \quad & \mathbf{P}^T \mathbf{P} = \mathbf{I} \in \mathbb{R}^{l \times l} \end{aligned} \quad (\text{S11})$$

Because $G(\mathbf{P})$ and $H(\mathbf{P})$ are convex, the objective function (S11) is actually DC programming problem [3], [4]. DC programming includes linearizing and solving the convex functions as follows [5].

Assume that \mathbf{P}_i is the solution at i th iteration, we approximate the second part $H(\mathbf{P})$ by linearizing

$$H_i(\mathbf{P}) = H(\mathbf{P}_i) + \langle \mathbf{P} - \mathbf{P}_i, \mathbf{U}_i \rangle$$

As the subgradient $\mathbf{U} \in \partial H(\mathbf{P}) = 2\mathbf{X}_2^T \mathbf{X}_2 \mathbf{P}$, let $\mathbf{U}_i = 2\mathbf{X}_2^T \mathbf{X}_2 \mathbf{P}_i$. Then, (S11) is approximated by

$$\mathbf{P}_{i+1} \doteq \arg \min_{\mathbf{P}^T \mathbf{P} = \mathbf{I}} G(\mathbf{P}) - \langle \mathbf{P}, \mathbf{U}_i \rangle$$

Because $\mathbf{\Omega}$ is semidefinite, let $\mathbf{\Omega} = \mathbf{L}^T \mathbf{L}$ and \mathbf{L} is the triangle matrix [5]. Thus, we can get

$$\begin{aligned} & G(\mathbf{P}) - \langle \mathbf{P}, \mathbf{U}_i \rangle \\ &= \text{tr}(\mathbf{P}^T \mathbf{\Omega} \mathbf{P}) - 2\text{tr}(\mathbf{P}^T \mathbf{\Omega} \mathbf{P}_0^*) - 2\text{tr}(\mathbf{P}^T \mathbf{X}_2^T \mathbf{X}_2 \mathbf{P}_i) \\ &= \langle \mathbf{L} \mathbf{P}, \mathbf{L} \mathbf{P} \rangle - 2\langle \mathbf{L} \mathbf{P}, \mathbf{L} \mathbf{P}_0^* \rangle + (\mathbf{L}^T)^{-1} \mathbf{X}_2^T \mathbf{X}_2 \mathbf{P}_i \\ &= \|\mathbf{Z}_i - \mathbf{L} \mathbf{P}\|_F^2 - \|\mathbf{Z}_i\|_F^2 \end{aligned} \quad (\text{S12})$$

where $\mathbf{Z}_i = \mathbf{L} \mathbf{P}_0^* + (\mathbf{L}^T)^{-1} \mathbf{X}_2^T \mathbf{X}_2 \mathbf{P}_i$ is constant at $(i+1)$ th iteration [5]. Then, (S12) is equivalent to [5], [6]

$$\mathbf{P}_{i+1} = \arg \min_{\mathbf{P}^T \mathbf{P} = \mathbf{I}} \|\mathbf{P} - \mathbf{L}^T \mathbf{Z}_i\|_F^2 \quad (\text{S13})$$

Let $\mathbf{Y}_i = \mathbf{L}^T \mathbf{Z}_i = \mathbf{\Omega} \mathbf{P}_0^* + \mathbf{X}_2^T \mathbf{X}_2 \mathbf{P}_i$. According to the lemma in [6], we can obtain that $\mathbf{P}_{i+1} = \mathbf{W}_i \mathbf{I}_{m_2, l} \mathbf{V}_i^T$, where $\mathbf{W}_i \in \mathbb{R}^{m_2 \times m_2}$ and $\mathbf{V}_i \in \mathbb{R}^{l \times l}$ are left and right singular values of the singular vector decomposition of \mathbf{Y}_i [5]. m_2 is the dimension of \mathbf{X}_2 and l is the number of principal components. The procedure is summarized in Algorithm 2 in the paper.