

Supplementary Material for Generalized Domain-Adaptive Dictionaries

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1. Optimization

The final optimization problem is given as:

$$\{\mathbf{D}^*, \tilde{\mathbf{P}}^*, \tilde{\mathbf{X}}^*\} = \arg \min_{\mathbf{D}, \tilde{\mathbf{P}}, \tilde{\mathbf{X}}} \mathcal{C}_1(\mathbf{D}, \tilde{\mathbf{P}}, \tilde{\mathbf{X}}) + \lambda \mathcal{C}_2(\tilde{\mathbf{P}})$$

$$\text{s.t. } \mathbf{P}_i \mathbf{P}_i^T = \mathbf{I}, i = 1, \dots, M \text{ and } \|\tilde{\mathbf{x}}_j\|_1 \leq T_0, \forall j \quad (1)$$

where,

$$\mathcal{C}_1(\mathbf{D}, \tilde{\mathbf{P}}, \tilde{\mathbf{X}}) = \|\tilde{\mathbf{P}}\tilde{\mathbf{Y}} - \mathbf{D}\tilde{\mathbf{X}}\|_F^2 + \mu \|\tilde{\mathbf{P}}\tilde{\mathbf{Y}} - \mathbf{D}\tilde{\mathbf{X}}_{\text{in}}\|_F^2 + \nu \|\mathbf{D}\tilde{\mathbf{X}}_{\text{out}}\|_F^2, \quad (2)$$

$$\mathcal{C}_2(\tilde{\mathbf{P}}) = -\text{trace}((\tilde{\mathbf{P}}\tilde{\mathbf{Y}})(\tilde{\mathbf{P}}\tilde{\mathbf{Y}})^T). \quad (3)$$

1.1. Proposition 1:

There exists an optimal solution $\mathbf{P}_1^*, \dots, \mathbf{P}_M^*, \mathbf{D}^*$ to equation (1), which has the following form:

$$\mathbf{P}_i^* = (\mathbf{Y}_i \mathbf{A}_i)^T \forall i = 1, \dots, M \quad (4)$$

$$\mathbf{D}^* = \tilde{\mathbf{P}}^* \tilde{\mathbf{Y}} \tilde{\mathbf{B}} \quad (5)$$

Proof:

Form for \mathbf{D}^* : First we will show the form for \mathbf{D}^* . We can decompose \mathbf{D}^* into two orthogonal components as follows:

$$\mathbf{D}^* = \mathbf{D}_{\parallel} + \mathbf{D}_{\perp} \quad (6)$$

$$\text{where, } \mathbf{D}_{\parallel} = (\tilde{\mathbf{P}}\tilde{\mathbf{Y}})\tilde{\mathbf{B}}, \mathbf{D}_{\perp}^T(\tilde{\mathbf{P}}\tilde{\mathbf{Y}}) = \mathbf{0} \quad (7)$$

for some $\mathbf{B} \in \mathbb{R}^{\sum_{i=1}^M N_i \times K}$. Substituting the value of \mathbf{D}^* into the value of $\mathcal{C}_1(\mathbf{D}, \tilde{\mathbf{P}}, \tilde{\mathbf{X}})$, we get for the three terms of \mathcal{C}_1 , ignoring the multiplicative constants μ, ν :

$$\begin{aligned} \text{First Term} &= \text{trace}((\tilde{\mathbf{P}}\tilde{\mathbf{Y}} - \mathbf{D}\tilde{\mathbf{X}})^T(\tilde{\mathbf{P}}\tilde{\mathbf{Y}} - \mathbf{D}\tilde{\mathbf{X}})) \\ &= \text{trace}(\tilde{\mathbf{Y}}^T \tilde{\mathbf{P}}^T \tilde{\mathbf{P}} \tilde{\mathbf{Y}} + \tilde{\mathbf{Y}}^T \tilde{\mathbf{P}}^T \mathbf{D}_{\parallel} \tilde{\mathbf{X}} + \tilde{\mathbf{X}}^T \mathbf{D}_{\parallel}^T \mathbf{D}_{\parallel} \tilde{\mathbf{X}} + \tilde{\mathbf{X}}^T \mathbf{D}_{\perp}^T \mathbf{D}_{\perp} \tilde{\mathbf{X}}) \\ &\geq \text{trace}(\tilde{\mathbf{Y}}^T \tilde{\mathbf{P}}^T \tilde{\mathbf{P}} \tilde{\mathbf{Y}} + \tilde{\mathbf{Y}}^T \tilde{\mathbf{P}}^T \mathbf{D}_{\parallel} \tilde{\mathbf{X}} + \tilde{\mathbf{X}}^T \mathbf{D}_{\parallel}^T \mathbf{D}_{\parallel} \tilde{\mathbf{X}}). \end{aligned} \quad (8)$$

$$\begin{aligned} \text{Second Term} &= \text{trace}((\tilde{\mathbf{P}}\tilde{\mathbf{Y}} - \mathbf{D}\tilde{\mathbf{X}}_{\text{in}})^T(\tilde{\mathbf{P}}\tilde{\mathbf{Y}} - \mathbf{D}\tilde{\mathbf{X}}_{\text{in}})) \\ &= \text{trace}(\tilde{\mathbf{Y}}^T \tilde{\mathbf{P}}^T \tilde{\mathbf{P}} \tilde{\mathbf{Y}} + \tilde{\mathbf{Y}}^T \tilde{\mathbf{P}}^T \mathbf{D}_{\parallel} \tilde{\mathbf{X}}_{\text{in}} + \tilde{\mathbf{X}}_{\text{in}}^T \mathbf{D}_{\parallel}^T \mathbf{D}_{\parallel} \tilde{\mathbf{X}}_{\text{in}} + \tilde{\mathbf{X}}_{\text{in}}^T \mathbf{D}_{\perp}^T \mathbf{D}_{\perp} \tilde{\mathbf{X}}_{\text{in}}) \\ &\geq \text{trace}(\tilde{\mathbf{Y}}^T \tilde{\mathbf{P}}^T \tilde{\mathbf{P}} \tilde{\mathbf{Y}} + \tilde{\mathbf{Y}}^T \tilde{\mathbf{P}}^T \mathbf{D}_{\parallel} \tilde{\mathbf{X}}_{\text{in}} + \tilde{\mathbf{X}}_{\text{in}}^T \mathbf{D}_{\parallel}^T \mathbf{D}_{\parallel} \tilde{\mathbf{X}}_{\text{in}}). \end{aligned} \quad (9)$$

$$\begin{aligned} \text{Third Term} &= \text{trace}(\mathbf{D}\tilde{\mathbf{X}}_{\text{out}})^T(\mathbf{D}\tilde{\mathbf{X}}_{\text{out}}) \\ &= \text{trace}(\tilde{\mathbf{X}}_{\text{out}}^T \mathbf{D}_{\parallel}^T \mathbf{D}_{\parallel} \tilde{\mathbf{X}}_{\text{out}} + \tilde{\mathbf{X}}_{\text{out}}^T \mathbf{D}_{\perp}^T \mathbf{D}_{\perp} \tilde{\mathbf{X}}_{\text{out}}) \\ &\geq \text{trace}(\tilde{\mathbf{X}}_{\text{out}}^T \mathbf{D}_{\parallel}^T \mathbf{D}_{\parallel} \tilde{\mathbf{X}}_{\text{out}}) \end{aligned} \quad (10)$$

The equality is reached when $\mathbf{D}_{\perp} = \mathbf{0}$. Hence, the form of \mathbf{D}^* is:

$$\mathbf{D}^* = \tilde{\mathbf{P}}\tilde{\mathbf{Y}}\tilde{\mathbf{B}}.$$

Form for \mathbf{P}_i^* : For each $i = 1, \dots, M$, \mathbf{P}_i^* can be decomposed as:

$$\mathbf{P}_i^* = \mathbf{P}_{\parallel,i} + \mathbf{P}_{\perp,i} \quad (11)$$

$$\text{where, } \mathbf{P}_{\parallel,i} = (\mathbf{Y}_i \mathbf{A}_i)^T, \mathbf{P}_{\perp,i} \mathbf{Y}_i = \mathbf{0}. \quad (12)$$

Let $\tilde{\mathbf{P}}_{\parallel} = [\mathbf{P}_{\parallel,1}, \dots, \mathbf{P}_{\parallel,M}]$ and $\tilde{\mathbf{P}}_{\perp} = [\mathbf{P}_{\perp,1}, \dots, \mathbf{P}_{\perp,M}]$. Substituting the value for \mathbf{D}^* into cost terms, we can write the terms of \mathcal{C}_1 as:

$$\begin{aligned} \text{First Term} &= \|\tilde{\mathbf{P}}^* \tilde{\mathbf{Y}} (\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})\|_F^2 \\ &= \|(\tilde{\mathbf{P}}_{\parallel} + \tilde{\mathbf{P}}_{\perp}) \tilde{\mathbf{Y}} (\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})\|_F^2 \\ &= \|\tilde{\mathbf{P}}_{\parallel} \tilde{\mathbf{Y}} (\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})\|_F^2 \\ &= \text{trace}(\tilde{\mathbf{P}}_{\parallel} \tilde{\mathbf{Y}} (\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}) (\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})^T \tilde{\mathbf{Y}}^T \tilde{\mathbf{P}}_{\parallel}^T). \end{aligned} \quad (13)$$

$$\begin{aligned} \text{Second Term} &= \|\tilde{\mathbf{P}}^* \tilde{\mathbf{Y}} (\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}})\|_F^2 \\ &= \|(\tilde{\mathbf{P}}_{\parallel} + \tilde{\mathbf{P}}_{\perp}) \tilde{\mathbf{Y}} (\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}})\|_F^2 \\ &= \|\tilde{\mathbf{P}}_{\parallel} \tilde{\mathbf{Y}} (\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}})\|_F^2 \\ &= \text{trace}(\tilde{\mathbf{P}}_{\parallel} \tilde{\mathbf{Y}} (\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}}) (\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}})^T \tilde{\mathbf{Y}}^T \tilde{\mathbf{P}}_{\parallel}^T). \end{aligned} \quad (14)$$

$$\begin{aligned}
\text{Third Term} &= \|\tilde{\mathbf{P}}^* \tilde{\mathbf{Y}}(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})\|_F^2 \\
&= \|(\tilde{\mathbf{P}}_{\parallel} + \tilde{\mathbf{P}}_{\perp})\tilde{\mathbf{Y}}(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})\|_F^2 \\
&= \|\tilde{\mathbf{P}}_{\parallel}\tilde{\mathbf{Y}}(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})\|_F^2 \\
&= \text{trace}(\tilde{\mathbf{P}}_{\parallel}\tilde{\mathbf{Y}}(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})^T\tilde{\mathbf{Y}}^T\tilde{\mathbf{P}}_{\parallel}^T). \quad (15)
\end{aligned}$$

The cost term, \mathcal{C}_2 can be written as:

$$\begin{aligned}
\mathcal{C}_2(\tilde{\mathbf{P}}) &= -\text{trace}((\tilde{\mathbf{P}}\tilde{\mathbf{Y}})(\tilde{\mathbf{P}}\tilde{\mathbf{Y}})^T) \\
&= -\text{trace}(((\tilde{\mathbf{P}}_{\parallel} + \tilde{\mathbf{P}}_{\perp})\tilde{\mathbf{Y}})((\tilde{\mathbf{P}}_{\parallel} + \tilde{\mathbf{P}}_{\perp})\tilde{\mathbf{Y}})^T) \\
&= -\text{trace}((\tilde{\mathbf{P}}_{\parallel}\tilde{\mathbf{Y}})(\tilde{\mathbf{P}}_{\parallel}\tilde{\mathbf{Y}})^T). \quad (16)
\end{aligned}$$

Putting all the terms together, the overall objective function becomes:

$$\begin{aligned}
&\text{trace}(\tilde{\mathbf{P}}_{\parallel}\tilde{\mathbf{Y}}((\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})^T + \mu(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}}) \\
&(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}})^T + \nu(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})^T - \lambda\mathbf{I})\tilde{\mathbf{Y}}^T\tilde{\mathbf{P}}_{\parallel}^T) \\
&= \text{trace}(\tilde{\mathbf{A}}_T\tilde{\mathbf{K}}((\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})^T + \mu(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}}) \\
&(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}})^T + \nu(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})^T - \lambda\mathbf{I})\tilde{\mathbf{K}}\tilde{\mathbf{A}}). \quad (17)
\end{aligned}$$

It can be seen that from equation (17), that the cost function is independent of $\mathbf{P}_{\perp,i}$, hence it can be safely set to be 0. Hence,

$$\mathbf{P}_i^* = (\mathbf{Y}_i\mathbf{A}_i)^T.$$

2. Updating $\tilde{\mathbf{A}}$

Using Proposition 1, optimization problem equation (1) becomes:

$$\{\tilde{\mathbf{A}}^*, \tilde{\mathbf{B}}^*, \mathbf{X}^*\} = \arg \min_{\tilde{\mathbf{A}}, \tilde{\mathbf{B}}, \tilde{\mathbf{X}}} \mathcal{C}_1(\tilde{\mathbf{A}}, \tilde{\mathbf{B}}, \tilde{\mathbf{X}}) + \lambda\mathcal{C}_2(\tilde{\mathbf{A}})$$

$$\text{s.t. } \mathbf{A}_i^T\mathbf{K}_i\mathbf{A}_i = \mathbf{I}, \quad i = 1, \dots, M \text{ and } \|\tilde{\mathbf{x}}_j\|_1 \leq T_0, \forall j. \quad (18)$$

Here, we assume that $(\tilde{\mathbf{B}}, \tilde{\mathbf{X}})$ are fixed. Then, the optimization for $\tilde{\mathbf{A}}$ can be solved efficiently. We have the following proposition.

3. Proposition 2:

The optimal solution of equation (18) when $(\tilde{\mathbf{B}}, \tilde{\mathbf{X}})$ are fixed is:

$$\begin{aligned}
\{\mathbf{G}^*\} &= \arg \min_{\mathbf{G}} \text{trace}[\mathbf{G}^T\mathbf{H}\mathbf{G}] \\
\text{s.t. } \mathbf{G}_i^T\mathbf{G}_i &= \mathbf{I} \quad \forall i = 1, \dots, M \quad (19)
\end{aligned}$$

where,

$$\begin{aligned}
\mathbf{H} &= \mathbf{S}^{\frac{1}{2}}\mathbf{V}^T((\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})^T + \mu(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}}) \\
&(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}})^T + \nu(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})^T - \lambda\mathbf{I})\mathbf{V}\mathbf{S}^{\frac{1}{2}} \quad (20)
\end{aligned}$$

Proof:

Let,

$$\tilde{\mathbf{K}} = \mathbf{V}\mathbf{S}\mathbf{V}^T,$$

$$\begin{aligned}
\tilde{\mathbf{H}} &= \mathbf{S}^{\frac{1}{2}}\mathbf{V}^T((\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}})^T + \\
&\mu(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}})(\mathbf{I} - \tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{in}})^T + \nu(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})(\tilde{\mathbf{B}}\tilde{\mathbf{X}}_{\text{out}})^T \\
&- \lambda\mathbf{I})\mathbf{V}\mathbf{S}^{\frac{1}{2}},
\end{aligned}$$

and

$$\mathbf{G} = \mathbf{S}^{\frac{1}{2}}\mathbf{V}^T\tilde{\mathbf{A}}.$$

Substituting into equation (17), we get the required form of the optimization.