Supplementary Material for Global Gated Mixture of Second-order Pooling for Improving Deep Convolutional Neural Networks

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1 Relationship between Parametric SOP and Covariance of Multivariate Generalized Gaussian Distribution

Here, we show our parametric second-order pooling (SOP) shares similar philosophy with estimation of covariance by assuming features are sampled from a generalized multivariate Gaussian distribution with zero mean. Firstly, our parametric SOP takes the following form:

$$\mathbf{\Sigma}(\mathbf{Q}_j) = \mathbf{X}^T\mathbf{Q}_j\mathbf{X} = (\mathbf{P}_j\mathbf{X})^T(\mathbf{P}_j\mathbf{X}), \tag{1}$$

where $\mathbf{Q}_j$ is a learnable matrix, and $\mathbf{Q}_j$ is a symmetric positive definite matrix, which has a unique decomposition $\mathbf{Q}_j = \mathbf{P}_j^T\mathbf{P}_j$. Given a set of $\mathbf{X} \in \mathbb{R}^{L\times d} = \{\mathbf{x}_1, \dots, \mathbf{x}_L\}$, their generalized multivariate Gaussian distribution with zero mean [5] can be represented as

$$p(\mathbf{x}_l; \widehat{\mathbf{\Sigma}}; \delta; \varepsilon) = \frac{\Gamma(d/2)}{\pi^{d/2}\Gamma(d/2\delta)2^{d/2\delta}}\frac{\delta}{\varepsilon^{d/2}|\widehat{\mathbf{\Sigma}}|^{1/2}}\exp\left(-\frac{1}{2\varepsilon^{\delta}}(\mathbf{x}_l\widehat{\mathbf{\Sigma}}^{-1}\mathbf{x}_l^T)^{\delta}\right), \tag{2}$$

where ε and δ are parameters of scale and shape, respectively; $\widehat{\mathbf{\Sigma}}$ is covariance matrix, and Γ is a Gamma function. Under maximum likelihood criterion, given δ and ε, covariance matrix $\widehat{\mathbf{\Sigma}}$ can be estimated by:

$$\arg\min_{\widehat{\mathbf{\Sigma}}} \sum_{l=1}^{L}(\mathbf{x}_l\widehat{\mathbf{\Sigma}}^{-1}\mathbf{x}_l^T)^{\delta} + N\log|\widehat{\mathbf{\Sigma}}|. \tag{3}$$

As shown in [1, 6], the objective function in Eq. (3) can converge to a stationary point by using iterative reweighed methods, whose j-th iteration has the following form:

$$\widehat{\mathbf{\Sigma}}_j = \frac{1}{L}\sum_{l=1}^{L}\frac{Ld}{\mathbf{q}_l^j + (\mathbf{q}_l^j)^{1-\delta}\sum_{k\neq j}(\mathbf{q}_k^j)^{\delta}}\cdot\mathbf{x}_l^T\mathbf{x}_l, \;\; \mathbf{q}_l^j = \mathbf{x}_l\widehat{\mathbf{\Sigma}}_{j-1}\mathbf{x}_l^T. \tag{4}$$

Let $f_j(\mathbf{x}_l) = \frac{Ld}{\mathbf{q}_l^j + (\mathbf{q}_l^j)^{1-\delta}\sum_{k\neq l}(\mathbf{q}_k^j)^{\delta}}$, we have

$$\widehat{\mathbf{\Sigma}}_j = \mathbf{X}^T\widehat{\mathbf{G}}_j\mathbf{X} = (\widehat{\mathbf{R}}_j\mathbf{X})^T(\widehat{\mathbf{R}}_j\mathbf{X}), \tag{5}$$

where $\widehat{\mathbf{G}}_j$ and $\widehat{\mathbf{R}}_j$ are diagonal matrices, and their diagonal elements are $\{f_j(\mathbf{x}_1)/L, \dots, f_j(\mathbf{x}_L)/L\}$ and $\{\sqrt{f_j(\mathbf{x}_1)/L}, \dots, \sqrt{f_j(\mathbf{x}_L)/L}\}$, respectively. Comparing Eq. (1) with Eq. (5), it is evident that,

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in each iteration, our parametric SOP learns a full matrix $\mathbf{P}_j$, while iterative reweighted methods [1, 6] learn the diagonal $\widehat{\mathbf{R}}_j$.

According to Eq. (5), iterative reweighted methods can be accomplished by J iterations:

$$\widehat{\mathbf{\Sigma}} = (\widehat{\mathbf{R}}_T \cdots \widehat{\mathbf{R}}_1 \mathbf{X})^T (\widehat{\mathbf{R}}_T \cdots \widehat{\mathbf{R}}_1 \mathbf{X}), \tag{6}$$

Correspondingly we can learn a sequence of parameters $\mathbf{Q}_j$, $\{j = 1, \ldots, J\}$ for our parametric SOP, i.e.,

$$\mathbf{\Sigma} = (\mathbf{P}_T \cdots \mathbf{P}_1 \mathbf{X})^T (\mathbf{P}_T \cdots \mathbf{P}_1 \mathbf{X}). \tag{7}$$

Since $\mathbf{P}_j\mathbf{X}$ can be conveniently implemented using 1×1 convolution, our parametric SOP can be transformed into learning multiple sequential 1×1 convolution operations following by computation of SOP. Eqs. (5)and (7) clearly show our parametric SOP and covariance of multivariate generalized Gaussian distribution share the similar form.

2 Details of Matrix Square Root of Covariance Based on Newton-Schulz Iteration [2]

Let $\mathbf{A}_0 = \mathbf{\Sigma}$ and $\mathbf{B}_0 = \mathbf{I}$, according to Newton-Schulz iteration [2], we have

$$\mathbf{A}_{\tilde{j}} = \frac{1}{2}\mathbf{A}_{\tilde{j}-1}(3\mathbf{I} - \mathbf{B}_{\tilde{j}-1}\mathbf{A}_{\tilde{j}-1}); \;\; \mathbf{B}_{\tilde{j}} = \frac{1}{2}(3\mathbf{I} - \mathbf{B}_{\tilde{j}-1}\mathbf{A}_{\tilde{j}-1})\mathbf{B}_{\tilde{j}-1}, \tag{8}$$

where $\mathbf{A}_{\tilde{J}}$ and $\mathbf{B}_{\tilde{J}}$ will converge to $\mathbf{\Sigma}^{\frac{1}{2}}$ and $\mathbf{\Sigma}^{-\frac{1}{2}}$ after $\tilde{J}$ iterations, respectively. However, Eq. (8) requires norm of $(\mathbf{I} - \mathbf{\Sigma})$, i.e., $\|\mathbf{I} - \mathbf{\Sigma}\| < 1$. The recently proposed method [4] introduces pre-normalization (i.e., $\tilde{\mathbf{\Sigma}} = \frac{1}{\mathrm{tr}(\mathbf{\Sigma})}\mathbf{\Sigma}$) and post-compensation operations (i.e., $\mathbf{Z} = \sqrt{\mathrm{tr}(\mathbf{\Sigma})}\mathbf{A}_{\tilde{J}}$) for Newton-Schulz iteration in Eq. (8), and develop a back-propagation (BP) algorithm based on matrix back-propagation method [3] for end-to-end learning. Specifically, given the loss function l, BP for post-compensation can be achieved by

$$\frac{\partial l}{\partial \mathbf{A}_{\tilde{J}}} = \sqrt{\mathrm{tr}(\mathbf{\Sigma})}\frac{\partial l}{\partial \mathbf{Z}}; \;\; \frac{\partial l}{\partial \mathbf{\Sigma}}\Big|_{\mathrm{post}} = \frac{1}{2\sqrt{\mathrm{tr}(\mathbf{\Sigma})}}\mathrm{tr}\Big(\Big(\frac{\partial l}{\partial \mathbf{Z}}\Big)^T\mathbf{A}_{\tilde{J}}\Big)\mathbf{I}. \tag{9}$$

Let $\dfrac{\partial l}{\partial \mathbf{B}_{\tilde{J}}} = 0$, for $\tilde{j} = \tilde{J}, \ldots, 2$, BP of Newton-Schulz iteration can be accomplished with

$$\begin{aligned}
\frac{\partial l}{\partial \mathbf{A}_{\tilde{j}-1}} &= \frac{1}{2}\Big(\frac{\partial l}{\partial \mathbf{A}_{\tilde{j}}}\Big(3\mathbf{I} - \mathbf{A}_{\tilde{j}-1}\mathbf{B}_{\tilde{j}-1}\Big) - \mathbf{B}_{\tilde{j}-1}\frac{\partial l}{\partial \mathbf{B}_{\tilde{j}}}\mathbf{B}_{\tilde{j}-1} - \mathbf{B}_{\tilde{j}-1}\mathbf{A}_{\tilde{j}-1}\frac{\partial l}{\partial \mathbf{A}_{\tilde{j}}}\Big) \\
\frac{\partial l}{\partial \mathbf{B}_{\tilde{j}-1}} &= \frac{1}{2}\Big(\Big(3\mathbf{I} - \mathbf{A}_{\tilde{j}-1}\mathbf{B}_{\tilde{j}-1}\Big)\frac{\partial l}{\partial \mathbf{B}_{\tilde{j}}} - \mathbf{A}_{\tilde{j}-1}\frac{\partial l}{\partial \mathbf{A}_{\tilde{j}}}\mathbf{A}_{\tilde{j}-1} - \frac{\partial l}{\partial \mathbf{B}_{\tilde{j}}}\mathbf{B}_{\tilde{j}-1}\mathbf{A}_{\tilde{j}-1}\Big).
\end{aligned} \tag{10}$$

When $\tilde{j} = 1$, we have

$$\frac{\partial l}{\partial \tilde{\mathbf{\Sigma}}} = \frac{1}{2}\Big(\frac{\partial l}{\partial \mathbf{A}_1}\Big(3\mathbf{I} - \tilde{\mathbf{\Sigma}}\Big) - \frac{\partial l}{\partial \mathbf{B}_1} - \tilde{\mathbf{\Sigma}}\frac{\partial l}{\partial \mathbf{A}_1}\Big). \tag{11}$$

Finally, BP of pre-normalization can be computed as

$$\frac{\partial l}{\partial \mathbf{\Sigma}} = -\frac{1}{(\mathrm{tr}(\mathbf{\Sigma}))^2}\mathrm{tr}\Big(\Big(\frac{\partial l}{\partial \tilde{\mathbf{\Sigma}}}\Big)^T\mathbf{\Sigma}\Big)\mathbf{I} + \frac{1}{\mathrm{tr}(\mathbf{\Sigma})}\frac{\partial l}{\partial \tilde{\mathbf{\Sigma}}} + \frac{\partial l}{\partial \mathbf{\Sigma}}\Big|_{\mathrm{post}}. \tag{12}$$

Eq. (12) is the gradient of loss function l with respect to $\mathbf{\Sigma}$, which is used to achieve BP for matrix square root of covariance. Readers can refer to [4] for more details.

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