

Supplemental Material to Dual-Path Distillation: A Unified Framework to Improve Black-Box Attacks

1 The derivation of Eq. (8)

As described in Section 3.1, the gradient of the efficient-attack loss with respect to the searching direction \mathbf{u} (we denote \mathbf{u}_i by \mathbf{u} for simplicity) can be approximated as

$$\widehat{\mathbf{g}}_{\mathbf{u}} \approx -\frac{\eta}{qq_v} \sum_{j=1}^{q_v} h(\mathbf{x}', \mathbf{u}, \alpha) h(\mathbf{x}' + \alpha\mathbf{u}, \mathbf{v}_j, \alpha\beta) \mathbf{v}_j. \quad (\text{S1})$$

Here, we give the detailed derivation of Eq. (S1) as follows. In this paper, we define two functions $h(\mathbf{x}', \mathbf{u}, \alpha) = \frac{f(\mathbf{x}' + \alpha\mathbf{u}) - f(\mathbf{x}')}{\alpha}$ and $\phi(\mathbf{u}) = h(\mathbf{x}', \mathbf{u}, \alpha) \mathbf{g}_{\mathbf{x}}^{\top} \mathbf{u}$ which are used in the derivation. According to these definitions, we have

$$\begin{aligned} \widehat{\mathbf{g}}_{\mathbf{u}} &= -\frac{\eta}{qq_v} \sum_{j=1}^{q_v} \frac{\phi(\mathbf{u} + \beta\mathbf{v}_j) - \phi(\mathbf{u})}{\beta} \mathbf{v}_j \\ &= -\frac{\eta}{qq_v} \sum_{j=1}^{q_v} (h(\mathbf{x}', \mathbf{u} + \beta\mathbf{v}_j, \alpha) \mathbf{g}_{\mathbf{x}}^{\top} (\mathbf{u} + \beta\mathbf{v}_j) - h(\mathbf{x}', \mathbf{u}, \alpha) \mathbf{g}_{\mathbf{x}}^{\top} \mathbf{u}) \frac{\mathbf{v}_j}{\beta} \end{aligned} \quad (\text{S2})$$

$$\begin{aligned} &= -\frac{\eta}{qq_v} \sum_{j=1}^{q_v} (h(\mathbf{x}', \mathbf{u} + \beta\mathbf{v}_j, \alpha) \mathbf{g}_{\mathbf{x}}^{\top} \mathbf{u} - h(\mathbf{x}', \mathbf{u}, \alpha) \mathbf{g}_{\mathbf{x}}^{\top} \mathbf{u} + \beta h(\mathbf{x}', \mathbf{u} + \beta\mathbf{v}_j, \alpha) \mathbf{g}_{\mathbf{x}}^{\top} \mathbf{v}_j) \frac{\mathbf{v}_j}{\beta} \\ &\approx -\frac{\eta}{qq_v} \sum_{j=1}^{q_v} \mathbf{g}_{\mathbf{x}}^{\top} \mathbf{u} (h(\mathbf{x}', \mathbf{u} + \beta\mathbf{v}_j, \alpha) - h(\mathbf{x}', \mathbf{u}, \alpha)) \frac{\mathbf{v}_j}{\beta} \end{aligned} \quad (\text{S3})$$

$$\approx -\frac{\eta}{qq_v} \sum_{j=1}^{q_v} \mathbf{g}_{\mathbf{x}}^{\top} \mathbf{u} \left(\frac{f(\mathbf{x}' + \alpha\mathbf{u} + \alpha\beta\mathbf{v}_j) - f(\mathbf{x}')}{\alpha} - \frac{f(\mathbf{x}' + \alpha\mathbf{u}) - f(\mathbf{x}')}{\alpha} \right) \frac{\mathbf{v}_j}{\beta} \quad (\text{S4})$$

$$\approx -\frac{\eta}{qq_v} \sum_{j=1}^{q_v} \mathbf{g}_{\mathbf{x}}^{\top} \mathbf{u} \left(\frac{f(\mathbf{x}' + \alpha\mathbf{u} + \alpha\beta\mathbf{v}_j) - f(\mathbf{x}' + \alpha\mathbf{u})}{\alpha\beta} \right) \mathbf{v}_j$$

$$\approx -\frac{\eta}{qq_v} \sum_{j=1}^{q_v} \mathbf{g}_{\mathbf{x}}^{\top} \mathbf{u} h(\mathbf{x}' + \alpha\mathbf{u}, \mathbf{v}_j, \alpha\beta) \mathbf{v}_j \quad (\text{S5})$$

$$\approx -\frac{\eta}{qq_v} \sum_{j=1}^{q_v} \frac{f(\mathbf{x}' + \alpha\mathbf{u}) - f(\mathbf{x}')}{\alpha} h(\mathbf{x}' + \alpha\mathbf{u}, \mathbf{v}_j, \alpha\beta) \mathbf{v}_j \quad (\text{S6})$$

$$\approx -\frac{\eta}{qq_v} \sum_{j=1}^{q_v} h(\mathbf{x}', \mathbf{u}, \alpha) h(\mathbf{x}' + \alpha\mathbf{u}, \mathbf{v}_j, \alpha\beta) \mathbf{v}_j.$$

Here Eq. (S2) uses the definition of ϕ . And the definition of h is utilized in Eq. (S4) and Eq. (S5). Because $\beta \ll 1$, we neglect $\beta h(\mathbf{x}', \mathbf{u} + \beta\mathbf{v}_j, \alpha) \mathbf{g}_{\mathbf{x}}^{\top} \mathbf{v}_j$ in Eq. (S3). The term $\mathbf{g}_{\mathbf{x}}^{\top} \mathbf{u}$ in Eq. (S6) is approximated by finite difference method since $\mathbf{g}_{\mathbf{x}}^{\top} \mathbf{u} = D_{\mathbf{u}} f(\mathbf{x}') = \frac{f(\mathbf{x}' + \alpha\mathbf{u}) - f(\mathbf{x}')}{\alpha}$, where $D_{\mathbf{u}} f(\mathbf{x}')$ is the directional derivative of f at a point \mathbf{x}' in the direction of a vector \mathbf{u} .

2 The derivation of Eq. (21)

To simplify the loss Eq. (21) introduced in Section 3.3, we employ the assumption that is also used in [1]. In detail, we assume that all eigenvectors of \mathbf{C} have the same eigenvalues, that is, $\mathbf{C} = \sum_{i=1}^D \lambda \mathbf{p}_i \mathbf{p}_i^{\top}$, where \mathbf{p}_i is the i^{th} eigenvector.

According to [1], we have $\text{trace}(\mathbf{C}) = 1$ and $\|\mathbf{p}_i\|_2 = 1$. It implies that we have $\lambda = \frac{1}{D}$. This yields

$$\begin{aligned} \min \ell(\hat{\mathbf{g}}_{\mathbf{x}}) &= -\frac{(\mathbf{g}_{\mathbf{x}}^T \mathbf{C} \mathbf{g}_{\mathbf{x}})^2}{\left(1 - \frac{1}{q}\right) \mathbf{g}_{\mathbf{x}}^T \mathbf{C}^2 \mathbf{g}_{\mathbf{x}} + \frac{1}{q} \mathbf{g}_{\mathbf{x}}^T \mathbf{C} \mathbf{g}_{\mathbf{x}}} \\ &= -\frac{\left(\mathbf{g}_{\mathbf{x}}^T \frac{1}{D} \sum_{i=1}^D \mathbf{p}_i \mathbf{p}_i^T \mathbf{g}_{\mathbf{x}}\right)^2}{\left(1 - \frac{1}{q}\right) \mathbf{g}_{\mathbf{x}}^T \frac{1}{D} \sum_{i=1}^D \mathbf{p}_i \mathbf{p}_i^T \frac{1}{D} \sum_{j=1}^D \mathbf{p}_j \mathbf{p}_j^T \mathbf{g}_{\mathbf{x}} + \frac{1}{q} \mathbf{g}_{\mathbf{x}}^T \frac{1}{D} \sum_{i=1}^D \mathbf{p}_i \mathbf{p}_i^T \mathbf{g}_{\mathbf{x}}} \end{aligned} \quad (\text{S7})$$

$$\begin{aligned} &= -\frac{\left(\mathbf{g}_{\mathbf{x}}^T \frac{1}{D} \sum_{i=1}^D \mathbf{p}_i \mathbf{p}_i^T \mathbf{g}_{\mathbf{x}}\right)^2}{\left(1 - \frac{1}{q}\right) \mathbf{g}_{\mathbf{x}}^T \frac{1}{D^2} \sum_{i=1}^D \sum_{j=1}^D \mathbf{p}_i \mathbf{p}_i^T \mathbf{p}_j \mathbf{p}_j^T \mathbf{g}_{\mathbf{x}} + \frac{1}{qD} \mathbf{g}_{\mathbf{x}}^T \sum_{i=1}^D \mathbf{p}_i \mathbf{p}_i^T \mathbf{g}_{\mathbf{x}}} \\ &= -\frac{\left(\mathbf{g}_{\mathbf{x}}^T \frac{1}{D} \sum_{i=1}^D \mathbf{p}_i \mathbf{p}_i^T \mathbf{g}_{\mathbf{x}}\right)^2}{\left(1 - \frac{1}{q}\right) \mathbf{g}_{\mathbf{x}}^T \frac{1}{D^2} \sum_{i=1}^D \mathbf{p}_i \mathbf{p}_i^T \mathbf{g}_{\mathbf{x}} + \frac{1}{qD} \mathbf{g}_{\mathbf{x}}^T \sum_{i=1}^D \mathbf{p}_i \mathbf{p}_i^T \mathbf{g}_{\mathbf{x}}} \end{aligned} \quad (\text{S8})$$

$$\begin{aligned} &= -\frac{\left(\frac{1}{D} \sum_{i=1}^D \mathbf{g}_{\mathbf{x}}^T \mathbf{p}_i \mathbf{p}_i^T \mathbf{g}_{\mathbf{x}}\right)^2}{\left(1 - \frac{1}{q}\right) \frac{1}{D^2} \sum_{i=1}^D \mathbf{g}_{\mathbf{x}}^T \mathbf{p}_i \mathbf{p}_i^T \mathbf{g}_{\mathbf{x}} + \frac{1}{qD} \sum_{i=1}^D \mathbf{g}_{\mathbf{x}}^T \mathbf{p}_i \mathbf{p}_i^T \mathbf{g}_{\mathbf{x}}} \\ &= -\frac{\frac{1}{D^2} \left(\sum_{i=1}^D (\mathbf{g}_{\mathbf{x}}^T \mathbf{p}_i)^2\right)^2}{\left(1 - \frac{1}{q}\right) \frac{1}{D^2} \sum_{i=1}^D (\mathbf{g}_{\mathbf{x}}^T \mathbf{p}_i)^2 + \frac{1}{qD} \sum_{i=1}^D (\mathbf{g}_{\mathbf{x}}^T \mathbf{p}_i)^2} \\ &= -\frac{\frac{1}{D^2}}{\left(1 - \frac{1}{q}\right) \frac{1}{D^2} + \frac{1}{qD}} \sum_{i=1}^D (\mathbf{g}_{\mathbf{x}}^T \mathbf{p}_i)^2 \\ &= -\frac{q}{D + q - 1} \sum_{i=1}^D (\mathbf{g}_{\mathbf{x}}^T \mathbf{p}_i)^2. \end{aligned}$$

Here, we use eigenvectors to represent \mathbf{C} in Eq. (S7) and the property, $\mathbf{p}_i^T \mathbf{p}_j = \mathbb{1}_{i=j}$, is used in Eq. (S8), where $\mathbb{1}_{i=j}$ is the indicator function.

References

- [1] Shuyu Cheng, Yinpeng Dong, Tianyu Pang, Hang Su, and Jun Zhu. Improving black-box adversarial attacks with a transfer-based prior. *NeurIPS*, 2019.