## **Author Correction for**

# TensorProjection Layer: A Tensor-Based Dimension Reduction Method in Deep Neural Networks

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October 2025

# Correction for Equation (11)

The authors found that in the published paper, the derivative

$$\frac{\partial \operatorname{vec}(G_k)}{\partial \operatorname{vec}(M_k)}$$
, where  $G_k = M_k^{-1/2}$ ,

was not correct. The corrected expression is given by (1). This correction does **not** affect the numerical results, since all experiments used automatic differentiation and did not rely on the analytical backpropagation formula.

Let

$$H_k = M_k^{1/2} \quad \Rightarrow \quad G_k = H_k^{-1},$$

where each  $G_k, H_k, M_k \in \mathbb{R}^{q_k \times q_k}$  and  $M_k$  is symmetric positive definite.

We aim to find the Jacobian via the chain rule:

$$\frac{\partial \operatorname{vec}(G_k)}{\partial \operatorname{vec}(M_k)^\top} = \frac{\partial \operatorname{vec}(G_k)}{\partial \operatorname{vec}(H_k)^\top} \frac{\partial \operatorname{vec}(H_k)}{\partial \operatorname{vec}(M_k)^\top}.$$

#### Step 1: Relation between $G_k$ and $H_k$

From  $G_k H_k = I_{q_k}$ , we have

$$G_k(\Delta H_k) + (\Delta G_k)H_k = O.$$

Then

$$\Delta G_k = -G_k(\Delta H_k)H_k^{-1} = -G_k(\Delta H_k)G_k.$$

Vectorizing both sides gives

$$\operatorname{vec}(\Delta G_k) = -(H_k^{\top} \otimes G_k) \operatorname{vec}(\Delta H_k),$$

so that

$$\frac{\partial \text{vec}(G_k)}{\partial \text{vec}(H_k)^{\top}} = -(H_k^{\top} \otimes G_k) = -(H_k^{-1} \otimes H_k^{-1}) = -(M_k^{-1/2} \otimes M_k^{-1/2}). \tag{1}$$

### Step 2: Relation between $H_k$ and $M_k$

Since  $H_k^2 = M_k$ , we have

$$\Delta M_k = H_k(\Delta H_k) + (\Delta H_k)H_k.$$

Using the identity  $vec(AXB) = (B^{\top} \otimes A) vec(X)$ ,

$$\operatorname{vec}(\Delta M_k) = (I_{q_k} \otimes H_k) \operatorname{vec}(\Delta H_k) + (H_k \otimes I_{q_k}) \operatorname{vec}(\Delta H_k)$$
$$= (I_{q_k} \otimes H_k + H_k \otimes I_{q_k}) \operatorname{vec}(\Delta H_k).$$

Hence,

$$\frac{\partial \operatorname{vec}(H_k)}{\partial \operatorname{vec}(M_k)^{\top}} = \left(I_{q_k} \otimes H_k + H_k \otimes I_{q_k}\right)^{-1}.$$
 (2)

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#### Step 3: Chain rule

Combining (1) and (2),

$$\begin{split} \frac{\partial \operatorname{vec}(G_k)}{\partial \operatorname{vec}(M_k)^\top} &= \frac{\partial \operatorname{vec}(G_k)}{\partial \operatorname{vec}(H_k)^\top} \frac{\partial \operatorname{vec}(H_k)}{\partial \operatorname{vec}(M_k)^\top} \\ &= -(H_k^{-1} \otimes H_k^{-1}) \big(I_{q_k} \otimes H_k + H_k \otimes I_{q_k}\big)^{-1}. \end{split}$$

Substituting  $H_k = M_k^{1/2}$  gives the corrected result:

$$\frac{\partial \operatorname{vec}(G_k)}{\partial \operatorname{vec}(M_k)^{\top}} = -(M_k^{-1/2} \otimes M_k^{-1/2}) (I_{q_k} \otimes M_k^{1/2} + M_k^{1/2} \otimes I_{q_k})^{-1}.$$
(1)

#### Invertibility remark

The matrix

$$I_{q_k} \otimes M_k^{1/2} + M_k^{1/2} \otimes I_{q_k}$$

is invertible if and only if  $M_k$  is positive definite, since its eigenvalues are  $\{\sqrt{\lambda_i} + \sqrt{\lambda_j}\}_{i,j}$ , where  $\lambda_i$  are the eigenvalues of  $M_k$ .