

# Sheaf Neural Networks on SPD Manifolds: Second-Order Geometric Representation Learning

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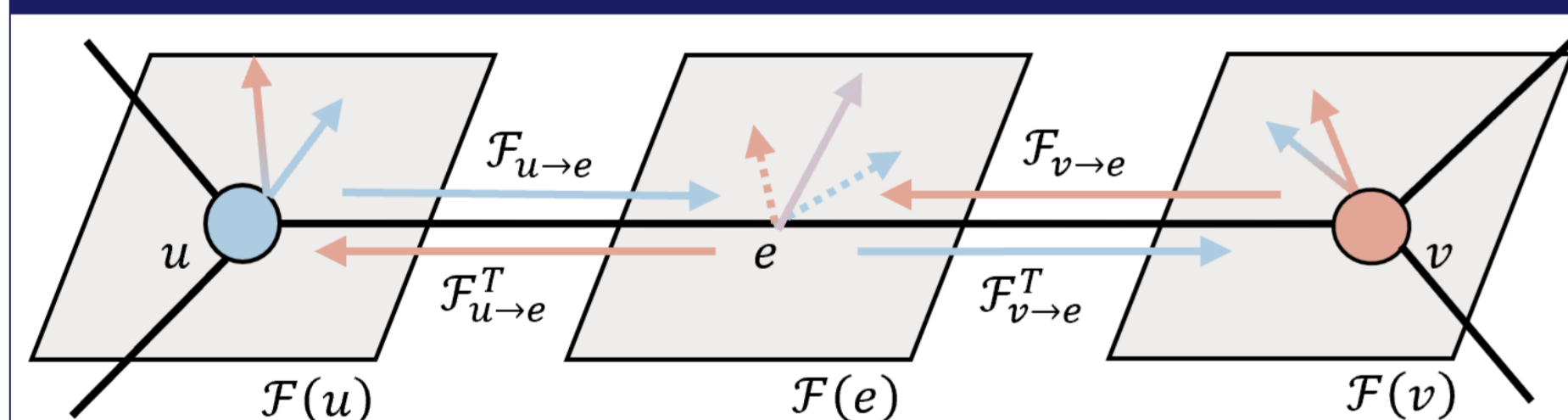
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## Motivation

- **Why sheaf?** Standard GNNs share one information-combination rule across all edges; sheaves make it **edge-specific**.
- **Why SPD stalks?** Existing Sheaf NNs use vector stalks, but second-order geometry is **matrix-valued**  $\rightarrow SPD_n$  (**symmetric positive definite manifold**).
- **Our solution:** First sheaf neural network native on  $SPD_n$  with Lie group structure  $\rightarrow$  well-posed operators & **strictly more expressive**.
- **Why is it hard?**  $SPD_n$  has **no** vector subtraction, Euclidean adjoint, or classical sheaf Laplacian.
- **Core problem:** How do we construct SPD counterparts of  $\delta, \delta^T, L$  that play the same role as classical sheaf neural network operators?

## Sheaf Neural Network



### Cellular sheaf:

- Vector space (stalk)  $F(u)$  and  $F(v)$
- Linear **restriction map**  $F_{v \to e}: F(u) \rightarrow F(e)$

**Coboundary operator** measures *local inconsistency*:  $\delta(x)_e = F_{v \to e}x_v - F_{u \to e}x_u$

**Sheaf Laplacian**:  $L_{\mathcal{F}} = \delta^T \delta$

**Sheaf neural network:**

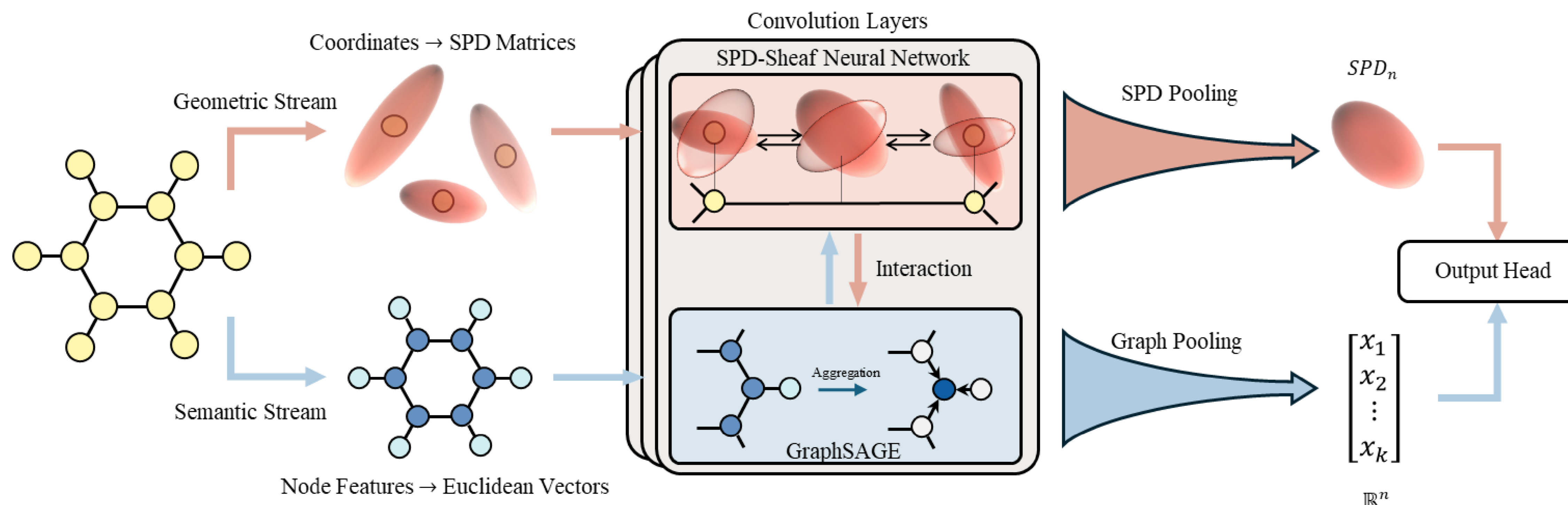
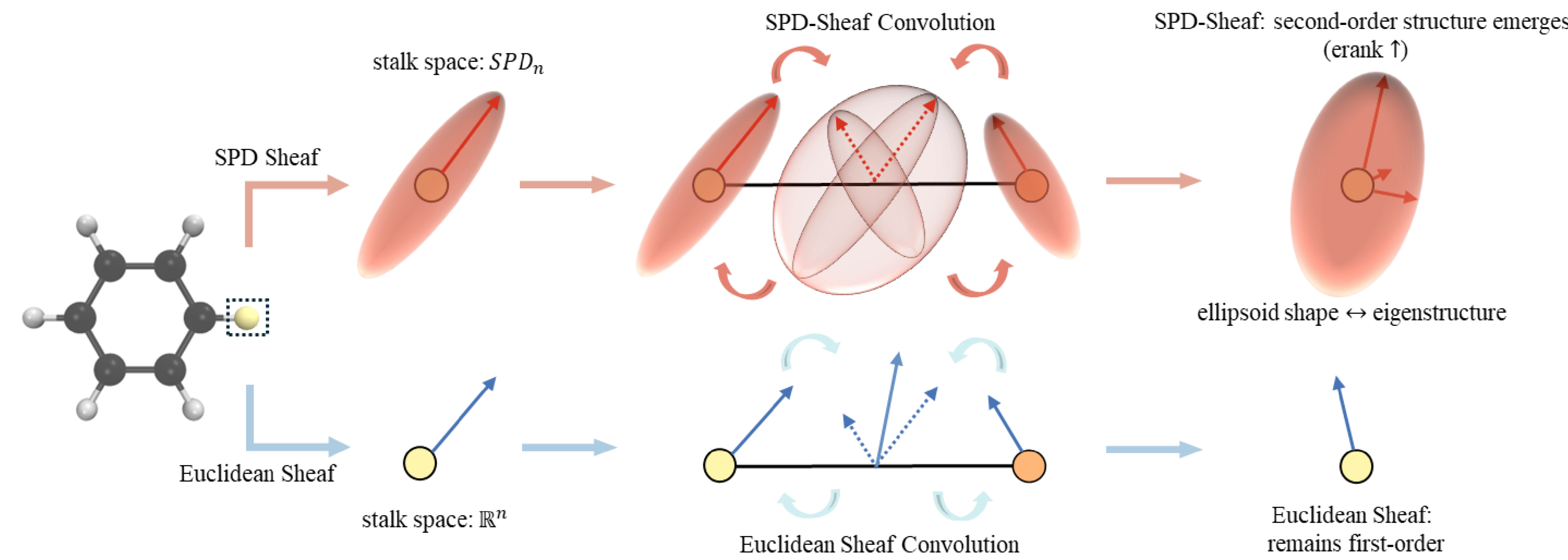
$$H^{(l+1)} = \sigma((I - L_{\mathcal{F}})H^{(l)}W^{(l)})$$

## Lie Group Structure on SPD

$$P \odot Q := \exp(\log P + \log Q)$$

forms an **Abelian lie group** with identity  $I_n$  and inverse  $P^{-1} = \exp(-\log P)$

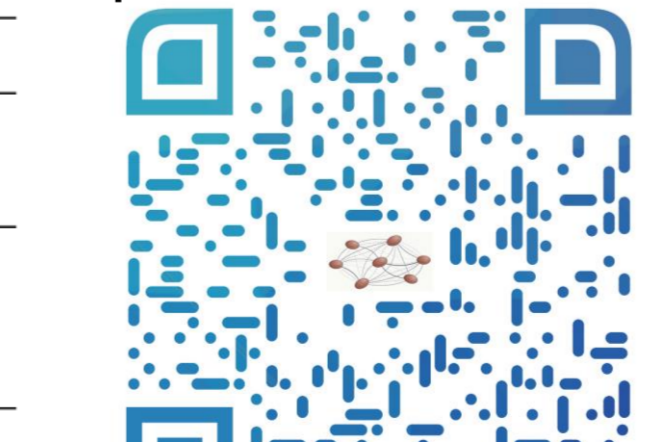
## Method Overview



## Experiments on MoleculeNet

Model	BACE	BBBP	ClinTox	SIDER	Tox21	HIV	MUV
No. molecules	1,513	2,039	1,478	1,427	7,831	41,127	93,808
No. avg atoms	65	46	50.58	65	36	46	43
No. tasks	1	1	2	27	12	1	17
D-MPNN	80.9 <sub>0.6</sub>	71.0 <sub>0.3</sub>	90.6 <sub>0.7</sub>	57.0 <sub>0.7</sub>	75.9 <sub>0.7</sub>	77.1 <sub>0.5</sub>	78.6 <sub>1.4</sub>
AttentiveFP	78.4 <sub>2.2</sub>	66.3 <sub>1.8</sub>	84.7 <sub>0.3</sub>	60.6 <sub>3.2</sub>	78.1 <sub>0.5</sub>	75.7 <sub>1.4</sub>	78.6 <sub>1.5</sub>
N-GramRF	77.9 <sub>1.5</sub>	69.7 <sub>0.6</sub>	77.5 <sub>4.0</sub>	66.8 <sub>0.7</sub>	74.3 <sub>0.9</sub>	77.2 <sub>0.4</sub>	76.9 <sub>0.2</sub>
PretrainGNN	84.5 <sub>0.7</sub>	68.7 <sub>1.3</sub>	87.5 <sub>2.7</sub>	65.5 <sub>0.7</sub>	75.8 <sub>0.9</sub>	78.7 <sub>0.4</sub>	74.8 <sub>0.2</sub>
GROVE <sub>base</sub>	82.1 <sub>0.7</sub>	70.0 <sub>1.1</sub>	81.2 <sub>3.0</sub>	64.8 <sub>0.6</sub>	74.3 <sub>0.1</sub>	62.5 <sub>0.9</sub>	67.3 <sub>1.8</sub>
GROVE <sub>large</sub>	81.0 <sub>1.4</sub>	69.5 <sub>0.1</sub>	76.2 <sub>3.7</sub>	65.4 <sub>0.1</sub>	73.5 <sub>0.1</sub>	68.2 <sub>1.1</sub>	67.3 <sub>1.8</sub>
GraphMVP	81.2 <sub>0.9</sub>	72.4 <sub>1.6</sub>	79.1 <sub>2.8</sub>	63.9 <sub>1.2</sub>	75.9 <sub>0.5</sub>	77.0 <sub>1.2</sub>	77.7 <sub>0.6</sub>
MolCLR	82.4 <sub>0.9</sub>	72.2 <sub>2.1</sub>	91.2 <sub>3.5</sub>	58.9 <sub>1.4</sub>	75.0 <sub>0.2</sub>	78.1 <sub>0.5</sub>	79.6 <sub>1.9</sub>
GEM	85.6 <sub>1.1</sub>	72.4 <sub>0.4</sub>	90.1 <sub>1.3</sub>	67.2 <sub>0.4</sub>	78.1 <sub>0.1</sub>	80.6 <sub>0.9</sub>	81.7 <sub>0.5</sub>
Mol-GDL	86.3 <sub>1.9</sub>	72.8 <sub>1.9</sub>	96.6 <sub>0.2</sub>	83.1 <sub>0.2</sub>	79.4 <sub>0.5</sub>	80.8 <sub>0.7</sub>	67.5 <sub>1.4</sub>
Uni-Mol	85.7 <sub>0.2</sub>	72.9 <sub>0.6</sub>	91.9 <sub>1.8</sub>	65.9 <sub>1.3</sub>	79.6 <sub>0.5</sub>	80.8 <sub>0.7</sub>	82.1 <sub>1.3</sub>
SMPT	87.3 <sub>1.5</sub>	73.3 <sub>0.3</sub>	92.7 <sub>0.2</sub>	67.6 <sub>0.9</sub>	79.7 <sub>0.1</sub>	<b>81.2</b> <sub>0.1</sub>	82.2 <sub>0.8</sub>
SchNet	73.7 <sub>0.9</sub>	70.8 <sub>1.4</sub>	97.8 <sub>0.3</sub>	83.1 <sub>0.0</sub>	72.4 <sub>0.2</sub>	68.8 <sub>0.1</sub>	68.2 <sub>0.6</sub>
EGNN	79.4 <sub>2.3</sub>	72.1 <sub>2.0</sub>	98.6 <sub>0.5</sub>	83.2 <sub>0.1</sub>	74.5 <sub>0.3</sub>	70.4 <sub>0.2</sub>	68.6 <sub>0.5</sub>
<b>SPD-Sheaf (Ours)</b>	<b>89.0<sub>1.4</sub></b>	<b>77.4<sub>2.7</sub></b>	<b>99.4<sub>0.2</sub></b>	<b>84.3<sub>0.4</sub></b>	<b>80.1<sub>0.7</sub></b>	<b>80.9<sub>0.7</sub></b>	<b>82.3<sub>1.4</sub></b>

Paper:



Group:



## SPD-Valued Sheaf Theory

**SPD sheaf:** SPD-valued stalk  $\mathcal{F}(v) = \mathcal{F}(e)$ ;

restriction map (**isometry**):

$$F_{v \to e}(P) = M_{ve} P M_{ve}^T \text{ with } M_{ve} \in O(n)$$

**SPD coboundary** ( $\delta(\sigma \odot \tau) = \delta\sigma \odot \delta\tau$ ):

$$(\delta\sigma)_e = \exp(\log(F_{v \to e}(\sigma_v)) - \log(F_{u \to e}(\sigma_u)))$$

**SPD Pairing:**  $\langle X, Y \rangle := g_n(\log X, \log Y)$

**Adjoint Operator:**  $(\delta^T \tau)_v =$

$$\exp(\sum_{v \to e} (-1)^{I(v,e)} M_{ve}^T (\log \tau_e) M_{ve})$$

satisfying  $\langle \delta\sigma, \tau \rangle = \langle \sigma, \delta^T \tau \rangle$

**SPD Sheaf Laplacian:**  $L_{\mathcal{F}} = \delta^T \delta$

$$(L_{\mathcal{F}} X)_v = \exp\left(\sum_{(v,u)=e} (-1)^{I(v,e)} M_{ve}^T (\log(F_{v \to e} X_v) - \log(F_{u \to e} X_u)) M_{ve}\right)$$

**Hodge-type Decomposition for SPD-valued Sheaves:**  $\ker L_{\mathcal{F}} = \ker \delta$

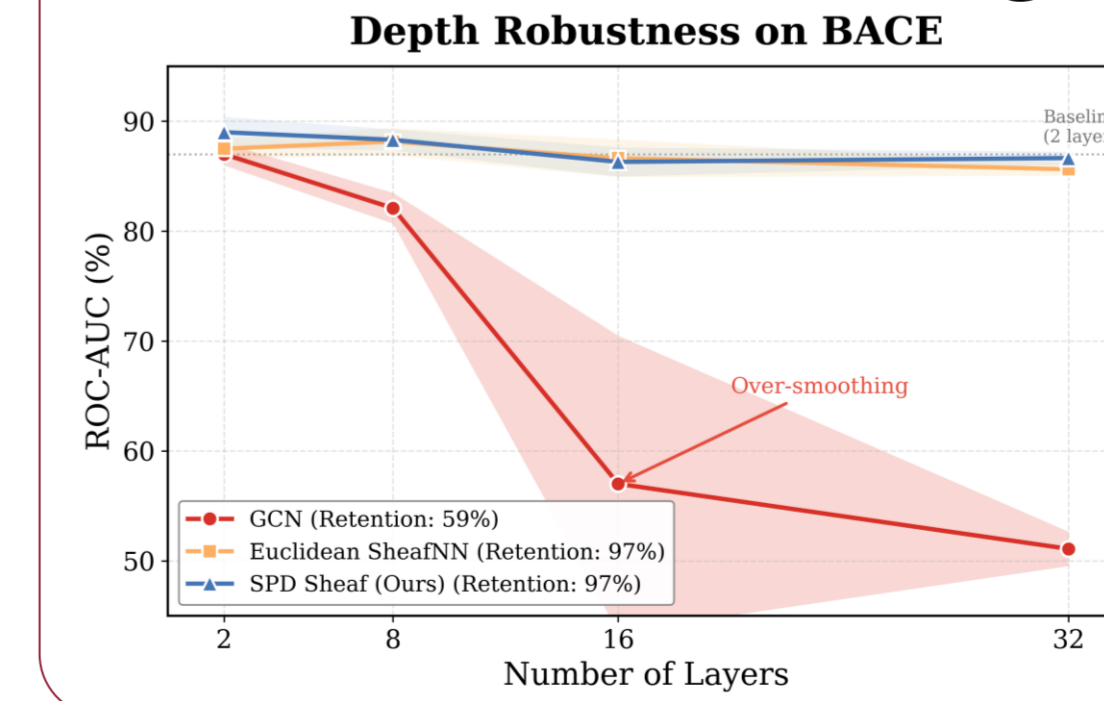
**Euclidean-to-SPD Embedding:**  $\Phi_\varepsilon(x) = xx^T + \varepsilon I_n$

**Strict generalization:**  $\phi'(\ker L_{\text{Euclidean}}) \subsetneq \ker(L_{\text{SPD}})$

**SPD-Sheaf convolution:**  $X_v^{(l+1)} = \sigma(X_v^{(l)} \odot (L_{\mathcal{F}}^{(l)} X^{(l)}))_v$

## Analysis

**Depth robustness: 97%**  
performance at 32 layers  $\rightarrow$   
resists **over-smoothing**



**Second-order emergence:** SPD-Sheaf lifts erank-1 SPD matrix to full-erank, **boundary (first-order)  $\rightarrow$  interior (second-order)** of  $SPD_n$

Dataset	Layers	Initial Erank	Final Erank	$\Delta$ Erank	$\lambda_2$ : Init $\rightarrow$ Final
BACE	2	1.00	2.28	+1.28	0.00 $\rightarrow$ 1.16
BBBP	2	1.00	2.16	+1.16	0.00 $\rightarrow$ 1.15
SIDER	2	1.00	2.22	+1.22	0.00 $\rightarrow$ 1.14
ClinTox	5	1.00	1.83	+0.83	0.00 $\rightarrow$ 1.32
HIV	5	1.00	1.87	+0.87	0.00 $\rightarrow$ 1.42
Tox21	7	1.00	1.75	+0.75	0.00 $\rightarrow$ 1.46
MUV	7	1.00	1.72	+0.72	0.00 $\rightarrow$ 1.55

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