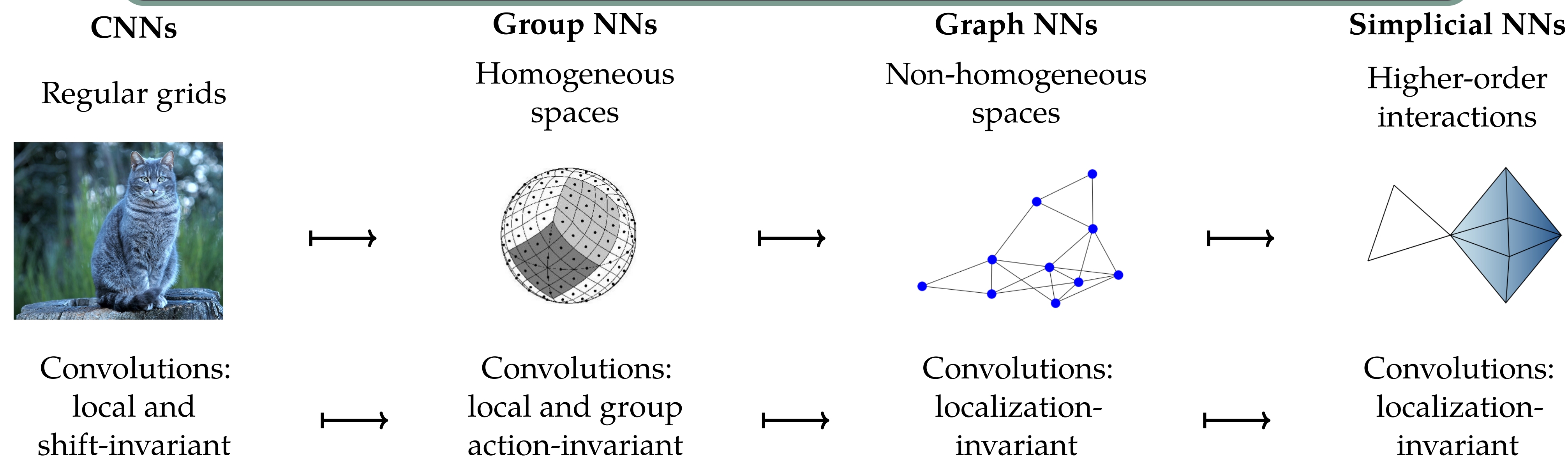


SIMPLICIAL NEURAL NETWORKS

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Convolution: a way to exploit the space's structure



Basic building blocks of a space: simplices



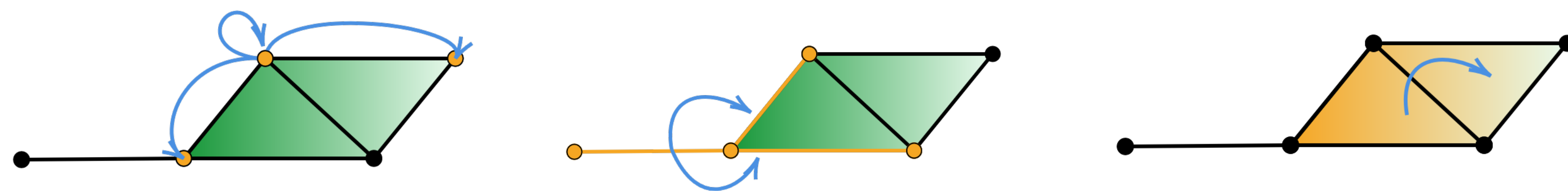
Laplacians for simplicial complexes

The graph Laplacian can be extended to Laplacians for simplices of any dimension k [1]. The k -Laplacian can be interpreted as a function propagating values of functions on the k -simplices. These functions are called k -cochains, x_k .

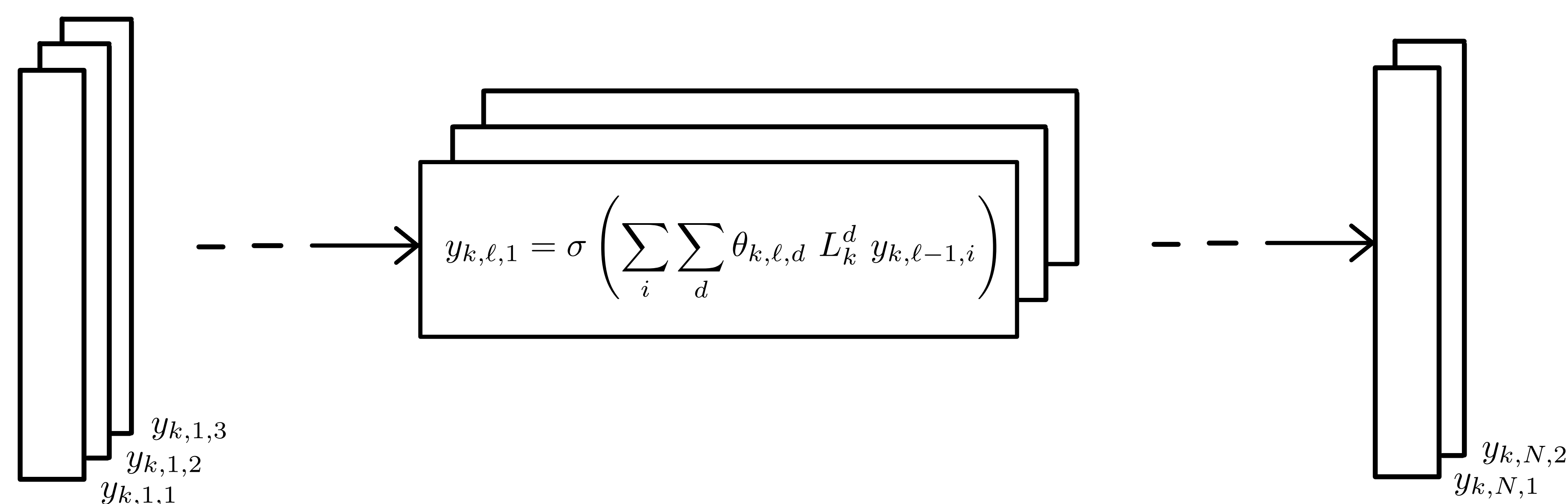
L_0 : Graph Laplacian
 $y_0 = L_0 x_0$

L_1 : 1-Laplacian
 $y_1 = L_1 x_1$

L_2 : 2-Laplacian
 $y_2 = L_2 x_2$

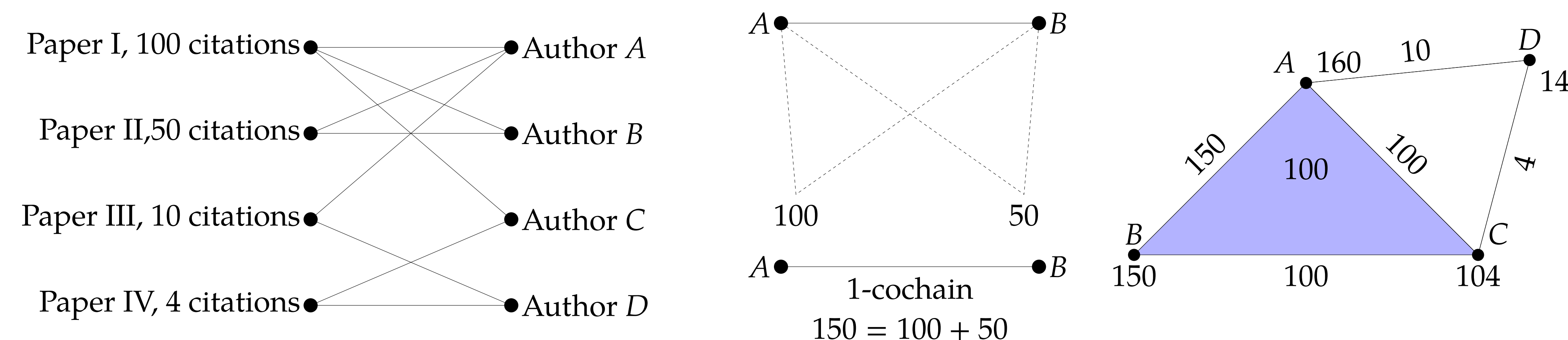


Simplicial Neural Networks (SNNs)



- Linear cost: convolutions are sparse matrix-vector multiplications.
- $O(1)$ weights to be learned.
- d -localizing: no interaction between simplices that are more than d hops apart.

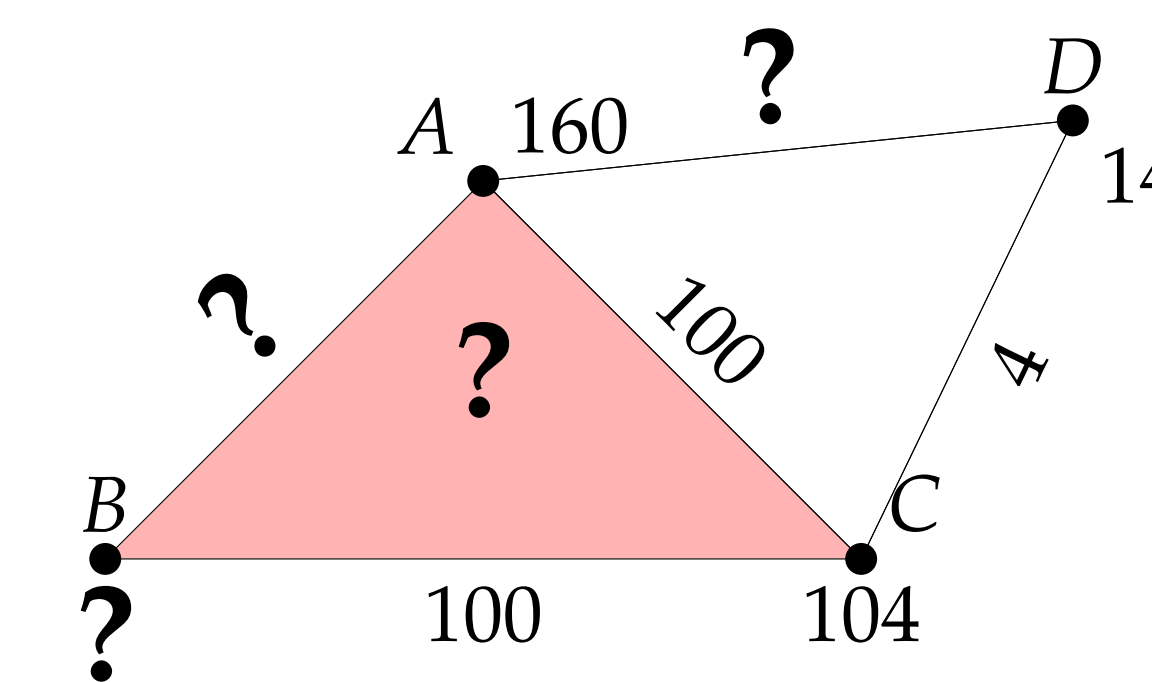
Coauthorship complex: from a bipartite graph to a complex



Predicting missing citations on the coauthorship complex

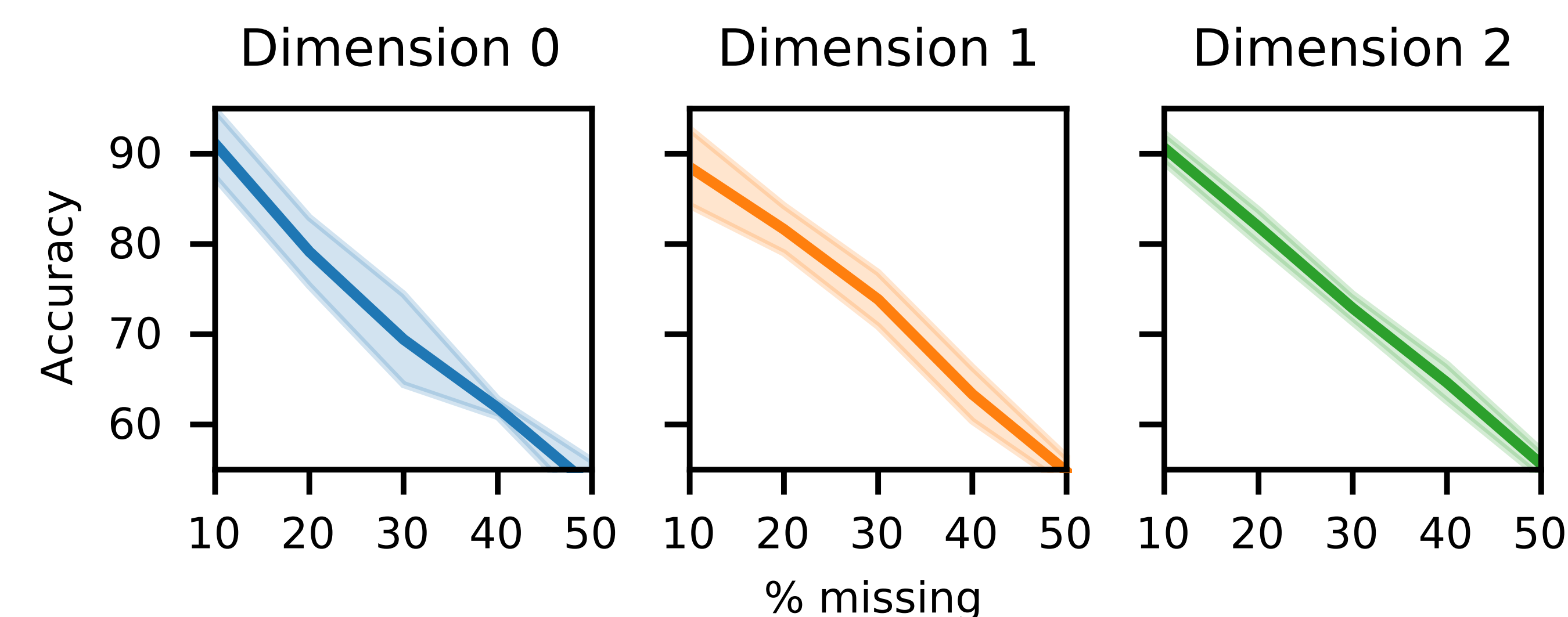
Data

Coauthorship complexes are built from the Semantic Scholar dataset [2] where missing citations are introduced at random on the k -cochains ($k = 1, 2, 3$) at five rates: 10%, 20%, 30%, 40%, and 50%.



First Results

Mean accuracy \pm standard deviation over 5 samples in imputing missing citations.



Performance of baselines: mean accuracy \pm standard deviation over 5 samples for 30% missing citations.

Method	Dimension 0	Dimension 1	Dimension 2
Global Mean	3.30 \pm 0.82	5.75 \pm 1.28	2.96 \pm 0.49
Global Median	7.78 \pm 2.70	10.44 \pm 1.00	12.50 \pm 0.63
Neighbors Mean	11.88 \pm 5.29	24.15 \pm 1.85	27.38 \pm 1.18

Code: https://github.com/stefaniaebli/simplicial_neural_networks

References

- [1] D. Horak and J. Jost, *Spectra of combinatorial Laplace operators on simplicial complexes*, Adv. in Math. 2013.
- [2] W. Ammar et al., *Construction of the Literature Graph in Semantic Scholar*, <https://www.semanticscholar.org/paper/09e3cf5704bcb16e6657f6ceed70e93373a54618>.