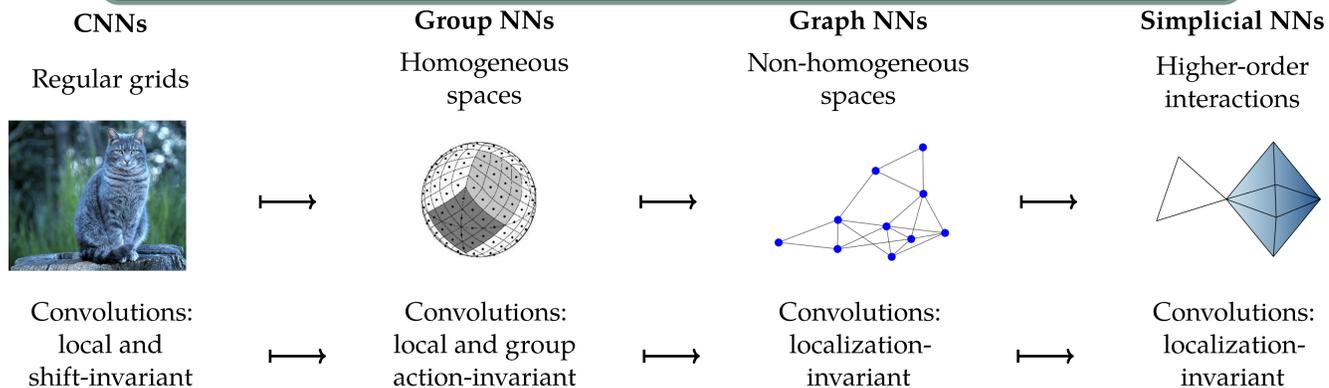


SIMPLICIAL NEURAL NETWORKS

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Convolution: a way to exploit the space's structure



Basic building blocks of a space: simplices



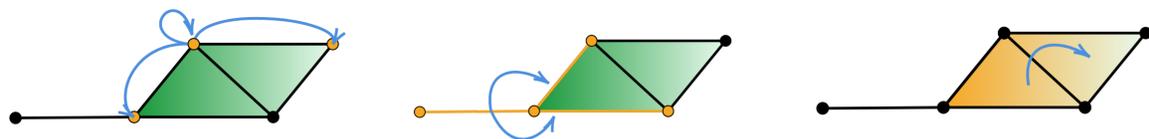
Laplacians for simplicial complexes

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 .

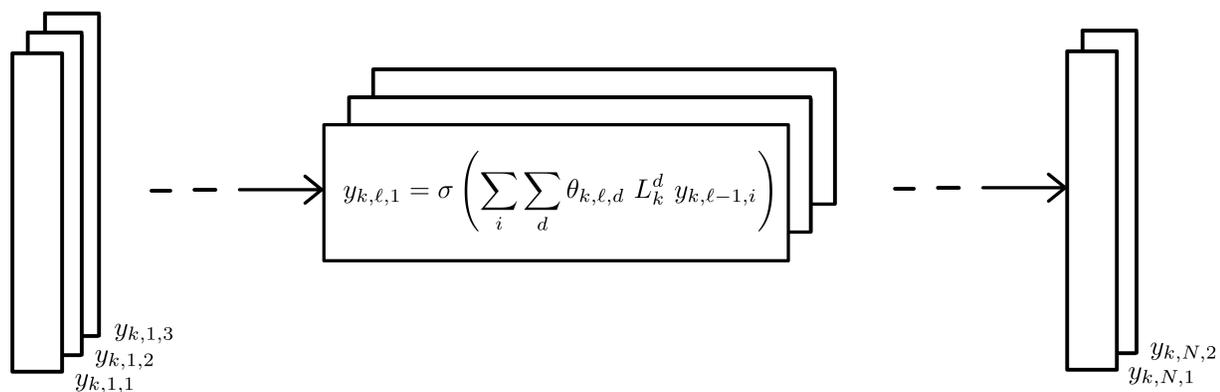
L_0 : Graph Laplacian
 $y_0 = L_0 x_0$

L_1 : 1-Laplacian
 $y_1 = L_1 x_1$

L_2 : 2-Laplacian
 $y_2 = L_2 x_2$

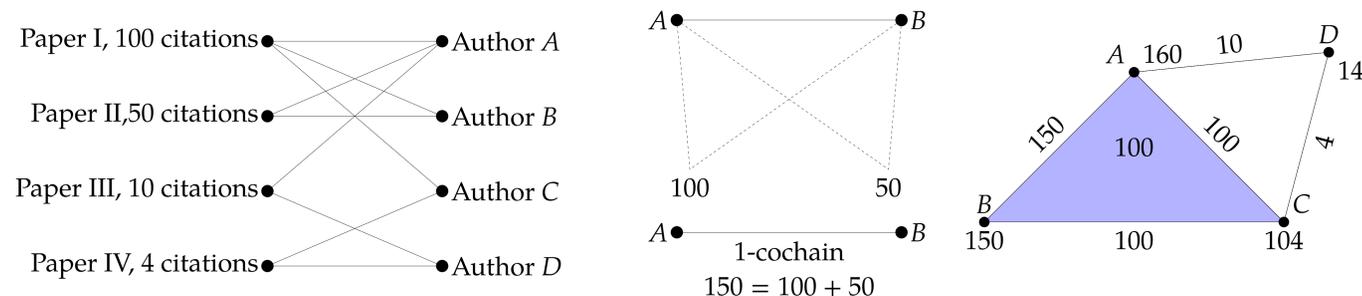


Simplicial Neural Networks (SNNs)



- 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.

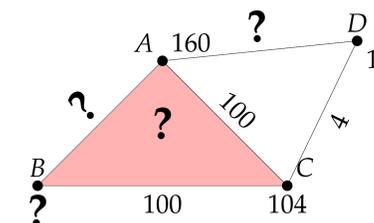
Coauthorship complex: from a bipartite graph to a complex



Predicting missing citations on the coauthorship complex

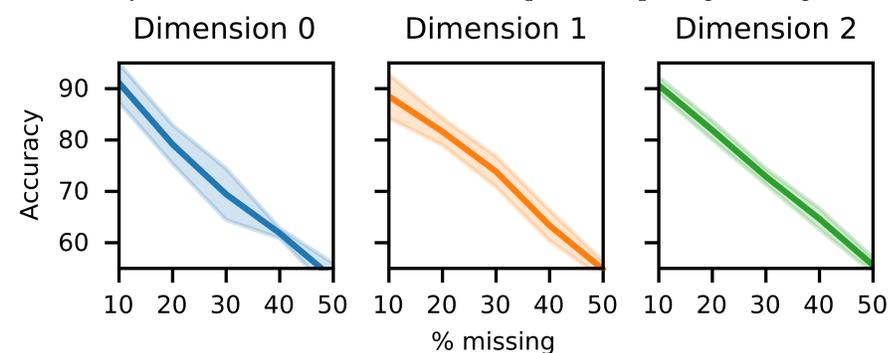
Data

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 ± 0.82	5.75 ± 1.28	2.96 ± 0.49
Global Median	7.78 ± 2.70	10.44 ± 1.00	12.50 ± 0.63
Neighbors Mean	11.88 ± 5.29	24.15 ± 1.85	27.38 ± 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>.