MAXIMALLY EXPRESSIVE GNNS FOR OUTERPLANAR GRAPHS

Franka Bause, Fabian Jogl, Patrick Indri, Tamara Drucks, David Penz, Nils Kriege, Thomas Gärtner, Pascal Welke & Maximilian Thiessen

We propose a linear time graph transformation that enables the Weisfeiler-Leman test (WL) and message passing graph neural networks (MPNNs) to be maximally expressive on outerplanar graphs. Most pharmaceutical molecules correspond to outerplanar graphs. However, there are non-isomorphic outerplanar graphs, that cannot be distinguished by 1-WL. Our method relies on encoding the Hamiltonian cycle of each biconnected component and achieves maximum expressivity on outerplanar graphs.



We propose a linear time preprocessing that allows MPNNs to distinguish all outerplanar graphs.

Our approach boosts predictive performance of MPNNs on a variety of molecular benchmark datasets (see table below). The transformation is linear time, i.e., no additional computational complexity is added to the training process or inference.

Dataset \rightarrow	ZINC	MOLHIV	MOLBACE	MOLBBBP	MOLSIDER
↓ Model	MAE↓	ROC-AUC ↑	ROC-AUC ↑	ROC-AUC ↑	ROC-AUC ↑
GIN	0.168 ± 0.007	77.9 <u>+</u> 1.0	74.6 <u>+</u> 3.2	66.0 <u>+</u> 2.1	56.6 <u>+</u> 1.0
CAT+GIN	0.101 ± 0.004	76.7 <u>+</u> 1.8	79.5 ± 2.5	67.2 <u>+</u> 1.8	58.2 ± 0.9
GCN	0.184 ± 0.013	76.7 <u>+</u> 1.4	77.9 <u>+</u> 1.7	66.1 <u>+</u> 2.4	56.7 <u>+</u> 1.5
CAT+GCN	0.123 ± 0.008	77.1 ± 1.6	79.2 ± 1.5	68.3 ± 1.7	57.9 ± 1.8
GAT	0.375 <u>+</u> 0.013	76.6 <u>+</u> 2.0	81.7 <u>+</u> 2.3	66.2 <u>+</u> 1.4	58.4 <u>+</u> 1.0
CAT+GAT	0.201 ± 0.022	75.3 <u>+</u> 1.6	79.3 <u>+</u> 1.6	66.0 <u>+</u> 1.9	58.3 <u>+</u> 1.3
Dataset \rightarrow	MOLESOL	MOLTOXCAST	MOLLIPO	MOLTOX21	
Dataset → \downarrow Model	MOLESOL RMSE↓	MOLTOXCAST ROC-AUC↑		MOLTOX21 ROC-AUC↑	
		ROC-AUC ↑		ROC-AUC ↑	
↓ Model	RMSE↓	ROC-AUC ↑ 65.3 ± 0.6	RMSE↓	ROC-AUC ↑ 75.8 ± 0.7	
↓ Model GIN	RMSE ↓ 1.105 ± 0.077	ROC-AUC↑ 65.3 ± 0.6 65.6 ± 0.5	RMSE ↓ 0.717 ± 0.016	ROC-AUC↑ 75.8 ± 0.7 74.8 ± 1.0	
↓ Model GIN CAT+GIN	RMSE↓ 1.105 ± 0.077 0.985 ± 0.055	ROC-AUC 1 65.3 ± 0.6 65.6 ± 0.5 64.4 ± 0.4	RMSE ↓ 0.717 ± 0.016 0.798 ± 0.031	ROC-AUC↑ 75.8±0.7 74.8±1.0 76.4±0.3	
↓ Model GIN CAT+GIN GCN	<pre>RMSE↓ 1.105 ± 0.077 0.985 ± 0.055 1.053 ± 0.087</pre>	ROC-AUC 1 65.3 ± 0.6 65.6 ± 0.5 64.4 ± 0.4 66.2 ± 0.8	RMSE↓ 0.717 ± 0.016 0.798 ± 0.031 0.748 ± 0.018	ROC-AUC 1 75.8 ± 0.7 74.8 ± 1.0 76.4 ± 0.3 74.9 ± 0.8	
↓ Model GIN CAT+GIN GCN CAT+GCN	RMSE \downarrow 1.105 \pm 0.077 0.985 \pm 0.055 1.053 \pm 0.087 1.006 \pm 0.036	ROC-AUC 1 65.3 ± 0.6 65.6 ± 0.5 64.4 ± 0.4 66.2 ± 0.8 63.8 ± 0.8	RMSE↓ 0.717 ± 0.016 0.798 ± 0.031 0.748 ± 0.018 0.771 ± 0.023	ROC-AUC 1 75.8 ± 0.7 74.8 ± 1.0 76.4 ± 0.3 74.9 ± 0.8 76.3 ± 0.6	

A graph is outerplanar if it can be drawn in the plane without edge crossings and with all nodes belonging to the exterior face.



CAT* TRANSFORMATION

(simplified) CAT* transforms a biconnected outerplanar graph G into a modified graph $G' = CAT^*(G)$. This is done by computing the (directed) Hamiltonian cycle C of G and its reverse, creating two directed components in G'. Edges of G not included in those are added to both components with both directions each. Edges are annotated so that the HAL sequences can be recovered from the unfolding trees.



CAT TRANSFORMATION

(simplified) We define the CAT transformation by applying CAT^* to the blocks of the graph G and adding further nodes and edges. The additional nodes and edges allow to recover the orientation and location of the blocks, making non-isomorphic outerplanar graphs distinguishable by 1-WL.

> CAT(G)transformed graph G

