

\mathcal{N} -WL: A New Hierarchy of Expressivity for Graph Neural Networks

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k -Weisfeiler-Lehman (k -WL) hierarchy is a theoretical framework for graph isomorphism tests

\leftrightarrow but not practically useful when $k \geq 3$!

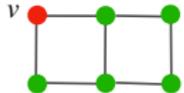
- GIN \equiv 1-WL [Xu et al., 2019]
- Many expressive GNNs go beyond 1-WL

Question:

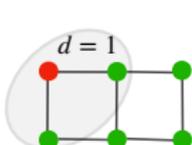
Is k -WL hierarchy a good yardstick for measuring expressivity of GNNs?

Colouring nodes

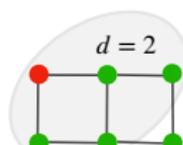
v



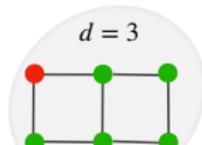
Local
neighbourhood



$N_1(v)$



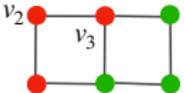
$N_2(v)$



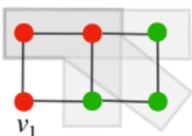
$N_3(v)$

Colouring k-tuples

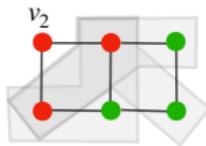
v_2



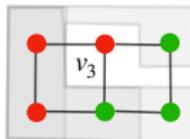
Global
neighbourhood



$N_1(\vec{v})$



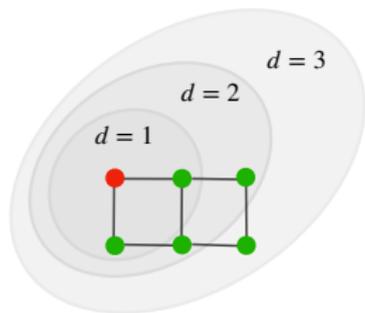
$N_2(\vec{v})$



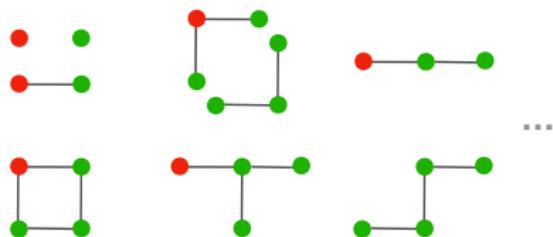
$N_3(\vec{v})$

$\vec{v} = \{v_1, v_2, v_3\}$

\mathcal{N} -WL hierarchy computes node coloring via t -order induced subgraphs within d -hop neighbourhoods.



d -hop neighbourhoods

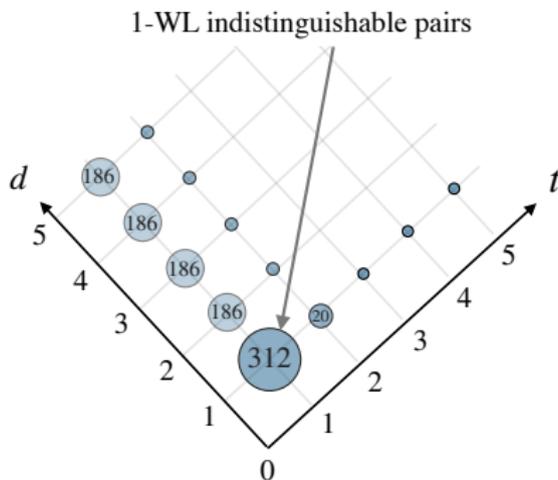


t -order induced subgraphs

A Simple Experiment

A graph isomorphism test on 312 pairs of simple graphs of 8 vertices:

- *None-or-all*: none by 1-WL but all by 3-WL
- *Progressive*: varying with d and t by \mathcal{N} -WL



Increasing the order of induced subgraphs, the expressive power increases
– *Not surprising*

Theorem:
(Weak Hierarchy) $\mathcal{N}^-(t, d)\text{-WL} \subsetneq \mathcal{N}^-(t+1, d)\text{-WL}$

Increasing the hops of neighbourhood, the expressive power may decrease
– *Surprising but can be fixed*

Theorem:
(Strong Hierarchy) $\mathcal{N}(t, d)\text{-WL} \subsetneq \mathcal{N}(t+1, d)\text{-WL}$
 $\mathcal{N}(t, d)\text{-WL} \subsetneq \mathcal{N}(t, d+1)\text{-WL}$

Induced connected subgraphs remain the same expressive power
– *Surprising but can be proved*

Theorem:
(Equivalence) $\mathcal{N}^c(t, d)\text{-WL} \equiv \mathcal{N}(t, d)\text{-WL}$

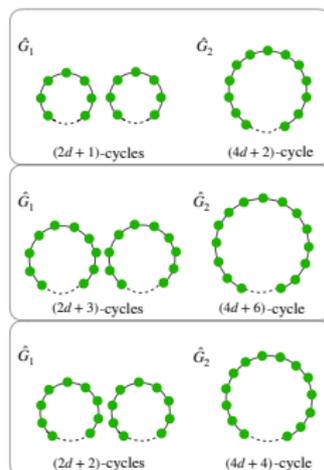
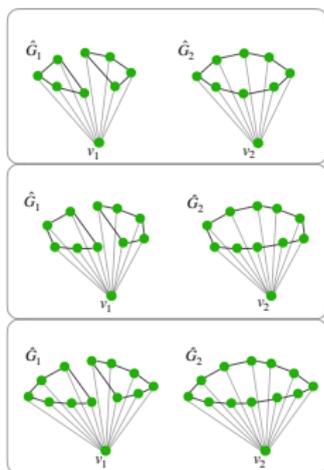
Main Ideas in Proofs (1)

Theorem:
(Strong Hierarchy)

$$\mathcal{N}(t, d)\text{-WL} \subsetneq \mathcal{N}(t+1, d)\text{-WL}$$

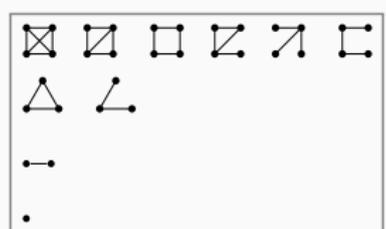
$$\mathcal{N}(t, d)\text{-WL} \subsetneq \mathcal{N}(t, d+1)\text{-WL}$$

We prove strictness of hierarchies by constructing counterexample graphs.



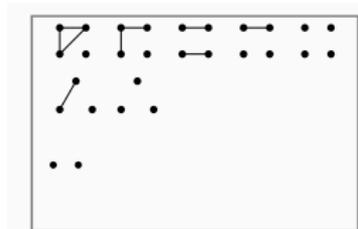
Theorem:
(Equivalence) $\mathcal{N}^c(t, d)\text{-WL} \equiv \mathcal{N}(t, d)\text{-WL}$

Our proof is based on Kocay's Vertex Theorem [Kocay, 1982].



subgraph counts

implies
 \rightarrow



subgraph counts

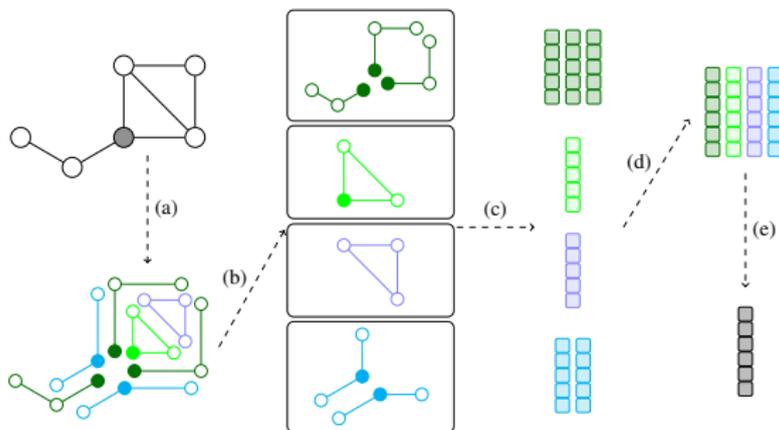
k-WL Hierarchy vs \mathcal{N} -WL Hierarchy

	k-WL	δ -k-LWL	(k, s)-LWL	(k, c)(\leq)-SETWL
#Coloured objects	n^k	n^k	subset(n^k, s)	subset($\sum_{q=1}^k \binom{n}{q}, c$)
#Neighbour objects	$n \times k$	$a \times k$	$a \times k$	$n \times q$
Δ Coloured objects	k-tuples	k-tuples	k-tuples	$\leq k$ -sets
Δ Neighbour objects	k-tuples	k-tuples	k-tuples	\dots
Sparsity awareness	\times	\checkmark	\checkmark	

$\mathcal{N}(t, d)$ -WL	$\mathcal{N}^c(t, d)$ -WL
n	n
$\binom{a^d}{t}$	subset($\sum_{q=1}^t \binom{a^d}{q}, 1$)
nodes	nodes
t-sets	$\leq t$ -sets
\times	\checkmark

Theorem: $1\text{-WL} \equiv \mathcal{N}(1, 1)\text{-WL} \equiv \mathcal{N}^c(1, 1)\text{-WL}$

Graph Neighbourhood Neural Network (G3N) instantiates the ideas of \mathcal{N} -WL algorithms for graph learning.



$$h_u^{(l+1)} = \text{COMBINE} \left(h_u^{(l)}, \text{AGG}_{(i,j) \in \mathcal{I}_t \times \mathcal{J}_d}^N \left(\text{AGG}_{S \in \mathcal{S}_u^{(l)}(i,j)}^T \left(\text{POOL}(S) \right) \right) \right)$$



Kocay, W. L. (1982).

Some new methods in reconstruction theory.

In *Combinatorial Mathematics IX*, pages 89–114. Springer.



Xu, K., Hu, W., Leskovec, J., and Jegelka, S. (2019).

How powerful are graph neural networks?

In *International Conference on Learning Representations (ICLR)*.

Thank You