

# $\mathcal{N}$ -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

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

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

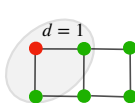
## Question:

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

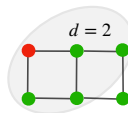
Colouring nodes



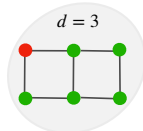
Local  
neighbourhood



$N_1(v)$

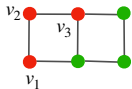


$N_2(v)$

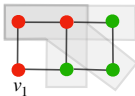


$N_3(v)$

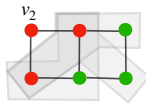
Colouring k-tuples



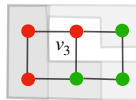
Global  
neighbourhood



$N_1(\vec{v})$



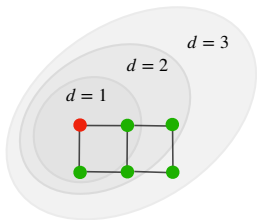
$N_2(\vec{v})$



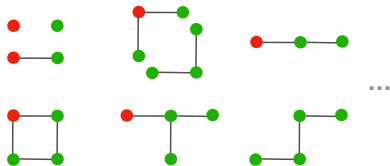
$N_3(\vec{v})$

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

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



$d$ -hop neighbourhoods

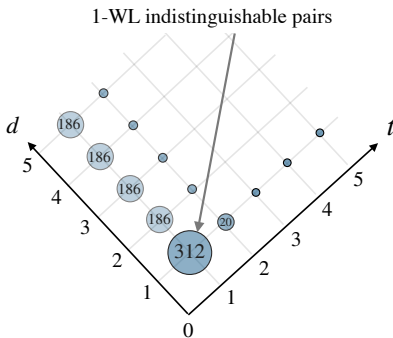


$t$ -order induced subgraphs

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

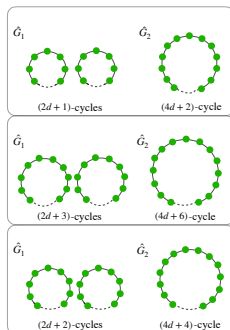
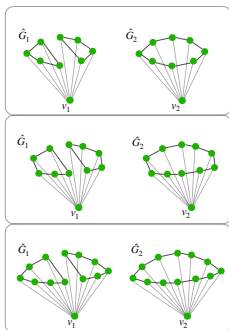
# Main Ideas in Proofs (1)

**Theorem:**  
(Strong Hierarchy)

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

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

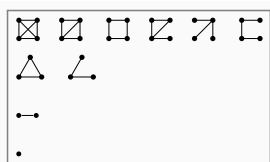
We prove strictness of hierarchies by constructing counterexample graphs.



**Theorem:**  
(Equivalence)

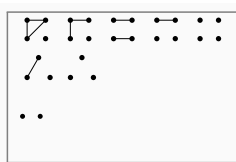
$$\mathcal{N}^c(t, d)\text{-WL} \equiv \mathcal{N}(t, d)\text{-WL}$$

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



subgraph counts

implies  
 $\rightarrow$



subgraph counts



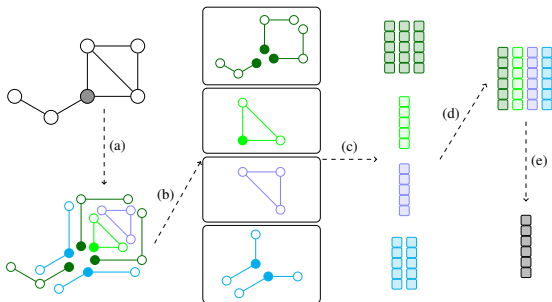
# k-WL Hierarchy vs $\mathcal{N}$ -WL Hierarchy

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

$\mathcal{N}(t, d)$ -WL	$\mathcal{N}^c(t, d)$ -WL
$n$	$n$
$\binom{a^d}{t}$	$\text{subset}(\sum_{q=1}^t \binom{a^d}{q}, 1)$
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.



$$h_u^{(l+1)} = \text{COMBINE}\left(h_u^{(l)}, \text{AGG}_{(i,j) \in I_t \times J_d}^N \left( \text{AGG}_{S \in S_u^{(l)}(i,j)}^T \left( \text{POOL}(S) \right) \right) \right)$$



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