

Coloring Graphs and Beyond

Joint work with Soheil Anbouhi

Abdullah Naeem Malik

Department of Mathematics
College of Arts and Sciences
Florida State University

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Weisfeiler-Lehman Test [WL68]

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Definition

A **coloring** of a (undirected) graph $G = (V, E)$ is a function $c : V \rightarrow \mathbb{N}$.

Weisfeiler-Lehman Test [WL68]

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Basic idea

start with $c(v) = c^{(0)}(v)$, and
 $c^{(t+1)}(v) = \text{hash}(c^{(t)}(v), \{\{c^{(t)}(w) : w \in N(v)\}\})$ [WL68]

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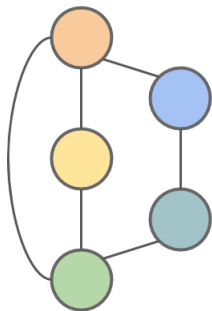
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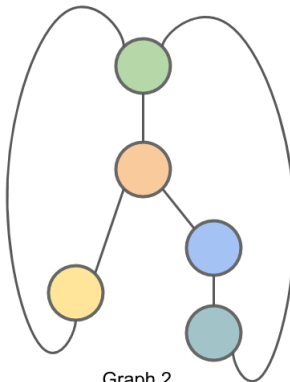
Weisfeiler-Lehman Test

If two graphs have different colorings, then the graphs are not isomorphic. Test is inconclusive if coloring of graphs is the same [MBHSL19]

Weisfeiler-Lehman Test [WL68]



Graph 1

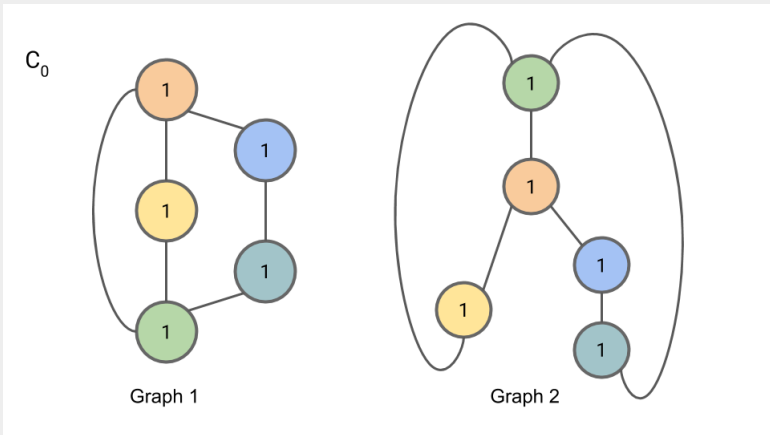


Graph 2

Source:

<https://davidbieber.com/post/2019-05-10-weisfeiler-lehman-isomorphism-test/>

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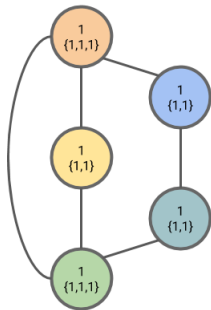


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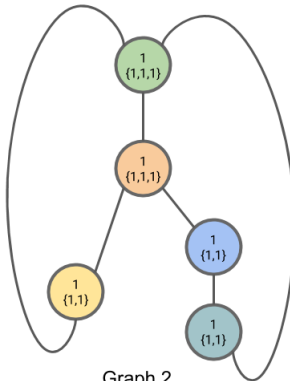
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Weisfeiler-Lehman Test [WL68]

L_1



Graph 1

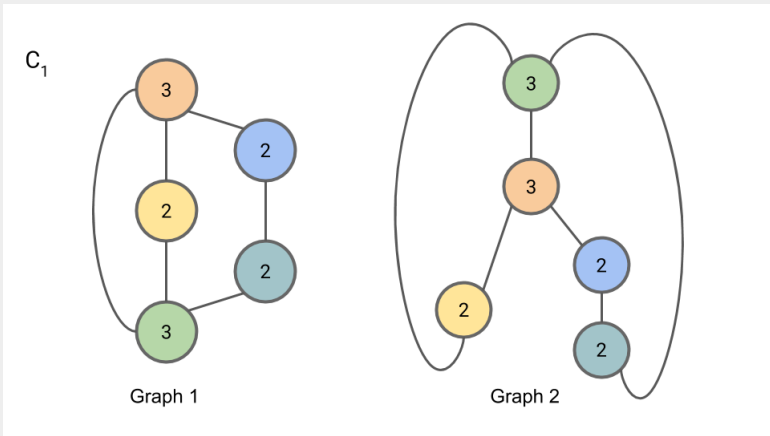


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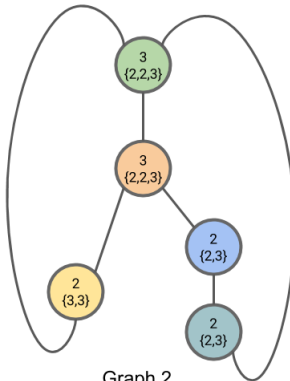
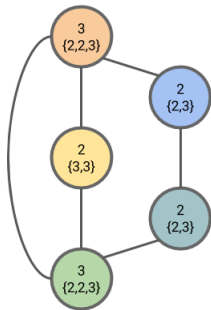


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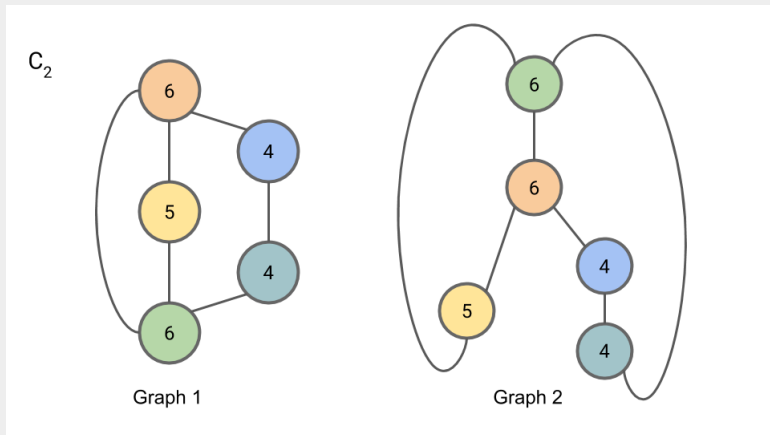
L_2



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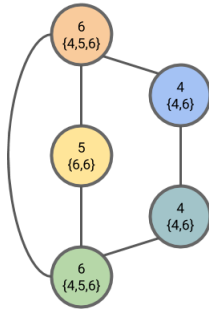


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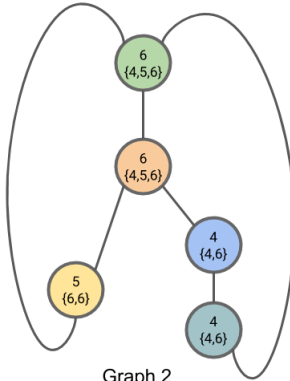
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Weisfeiler-Lehman Test [WL68]

L_3



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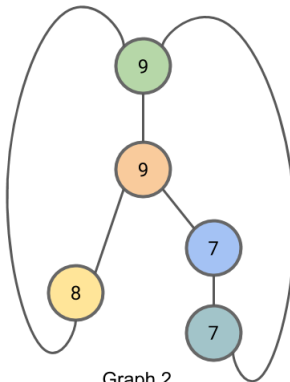
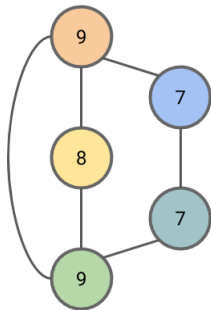
Graph 2

Source:

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Weisfeiler-Lehman Test [WL68]

C_3



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Weisfeiler-Leman Algorithm [WL68]

Recall..

A **coloring** of a graph $G = (V, E)$ at iteration t is a function $c^{(t)} : V \rightarrow \mathbb{N}$. A (perfect) **hashing** is any injective function.

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Algorithm Weisfeiler-Leman (WL) or Naive vertex refinement [WL68]

- 1: **Input:** (V, E, X_V) Here, $x_v \in \mathbb{Z}_2^d$
 - 2: $c^{(0)}(v) \leftarrow \text{hash}(x_v)$
 - 3: **while** $c^{(t)}(v) = c^{(t+1)}(v) \forall v \in V$ **do**
 - 4: $c^{(t+1)}(v) \leftarrow \text{hash}(c^{(t)}(v), \{\{c^{(t)}(w) : w \in N(v)\}\})$
 - 5: **Output:** $c^{(T)}(v) \forall v \in V$
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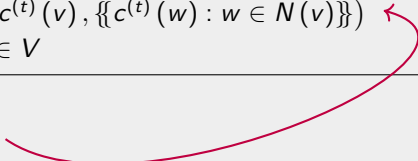
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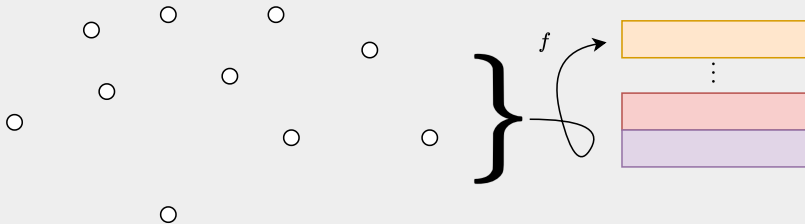
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Secretly message passing!



Neural Networks



Message passing in Graph Neural Networks

Message passing in Graph Neural Networks

$$x_v^{(k+1)} = \text{COMBINE} \left(x_v^{(k)}, \text{AGGREGATE}^{(k+1)} \left(\left\{ x_u^{(k)} : u \in N(v) \right\} \right) \right)$$

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$$F^{out} = \psi \circ ((AW + I) F).$$

$$\psi : \mathbb{R} \longrightarrow \mathbb{R}$$

Examples of Message Passing

$$\begin{array}{l} \text{AGGREGATE} \\ \text{MAX} \left(\left\{ \sigma \left(W_1 \cdot x_u^{(k)} \right) \right\}, u \in N(v) \right) \\ W_1 \cdot \text{MEAN} \left(x_u^{(k)}, u \in N(v) \cup \{v\} \right) \end{array}$$

$$\begin{array}{l} \text{COMBINE} \\ W_2 \cdot \left[x_v^{(k)}, a_v^{(k+1)} \right] \\ \sigma \left(\left\{ W_2 \cdot a_v^{(k+1)} \right\} \right) \end{array}$$

Ref
GraphSAGE[HYL17]
GCN[KW08]

Message passing in Graph Neural Networks

How powerful are graph neural networks?[MBHSL19, XHLJ18]

Theorem

Let G_1 and G_2 be any two non-isomorphic graphs. If a graph neural network $f : \mathcal{G} \rightarrow \mathbb{R}^d$ maps G_1 and G_2 to different embeddings, the Weisfeiler-Leman graph isomorphism test also decides G_1 and G_2 are not isomorphic. Converse holds if COMBINE and AGGREGATE are injective[XHLJ18].

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Proof sketch

Compare

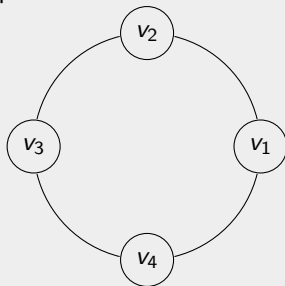
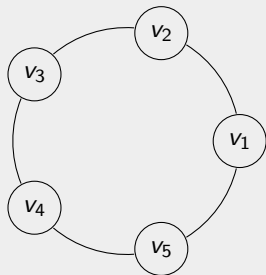
$$x_v^{(k+1)} = \text{COMBINE} \left(x_v^{(k)}, \text{AGGREGATE}^{(k+1)} \left(\left\{ x_u^{(k)} : u \in N(v) \right\} \right) \right)$$

with

$$c^{(t+1)}(v) = \text{hash} \left(c^{(t)}(v), \left\{ c^{(t)}(w) : w \in N(v) \right\} \right)$$

Limits of WL Test

WL Test fails to distinguish the following graphs:



k -Weisfeiler-Leman Algorithm

Algorithm k -Weisfeiler-Leman (k -WL)

- 1: **Input:** (V, E, X_V) Here, $x_v \in \mathbb{Z}_2^d$
2: $c(\vec{v}) = c^{(0)}(\vec{v}) \leftarrow \text{hash}(x_{\vec{v}})$
3: **while** $c^{(t)}(\vec{v}) = c^{(t+1)}(\vec{v}) \forall \vec{v} \in V^k$ **do**
4: $c_i^{(t+1)}(\vec{v}) \leftarrow \{\{c^{(t)}(\vec{w}) : w \in N_i(\vec{v})\} \forall \vec{v} \in V^k$
5: $c^{(t+1)}(\vec{v}) \leftarrow \text{hash}(c^{(t)}(\vec{v}), c_1^{(t+1)}(\vec{v}), \dots, c_k^{(t+1)}(\vec{v})) \forall \vec{v} \in V^k$
6: **Output:** $c^{(T)}(\vec{v}) \forall \vec{v} \in V^k$
-

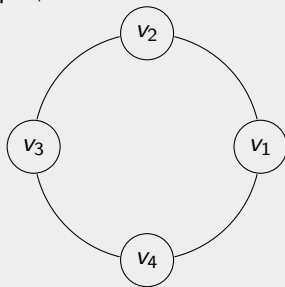
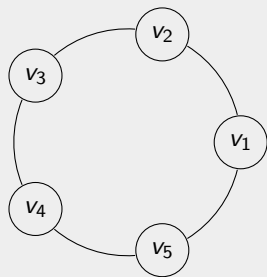
where $\text{hash}(x_{\vec{v}}) = \text{hash}(x_{\vec{w}})$ iff **(a)** $x_{v_i} = x_{w_i}$ and **(b)** $(v_i, v_j) \in E$ iff $(w_i, w_j) \in E$.

N.B.: $N_i(\vec{v}) = \{(v_1, \dots, v_{i-1}, u, v_{i+1}, \dots, v_k) : u \in V\}$.

Weisfeiler-Leman Hierarchies

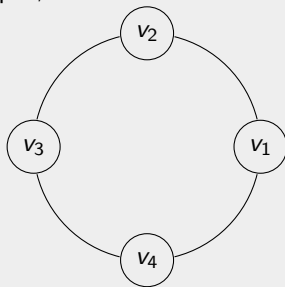
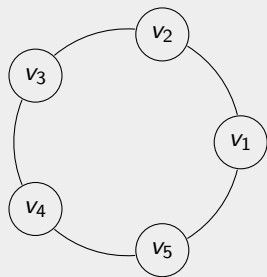
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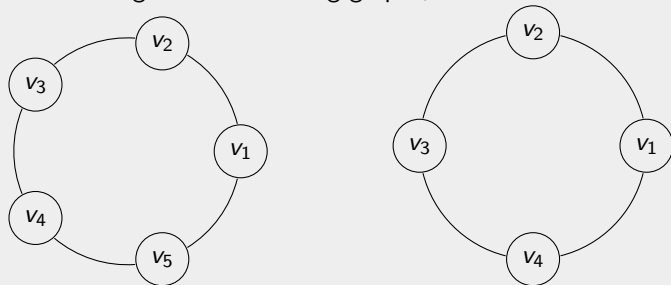
WL Test fails to distinguish the following graphs, whereas 5-WL does not:



k -WL is strictly weaker than $(k + 1)$ -WL [HV21]

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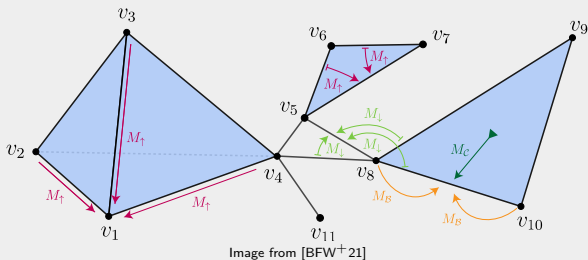
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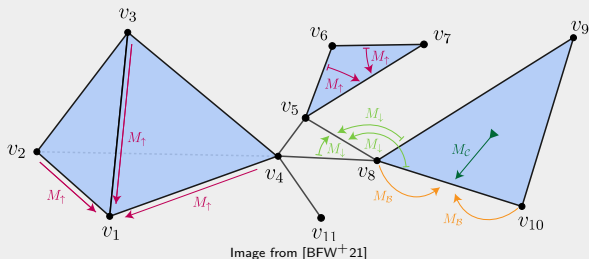
However.. for every k , there is an infinite family of graphs for which the k -WL test fails [CFI92]

Message Passing on Simplicial Complexes



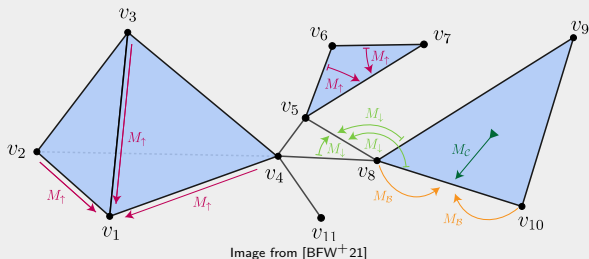
Simplicial WL [BFW⁺21]: $c^{t+1}(\sigma) = \text{hash of coloring at } t \text{ of } \sigma \text{ and..}$

Message Passing on Simplicial Complexes



Simplicial WL [BFW⁺21]: $c^{t+1}(\sigma)$ = hash of coloring at t of σ and.. coloring of its upper-neighbors, lower-neighbors, boundaries and coboundaries.

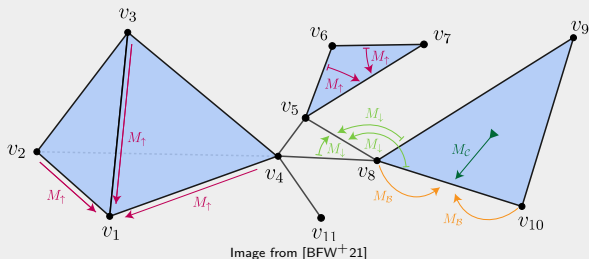
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SWL is strictly stronger than 3-WL[BFW⁺21]

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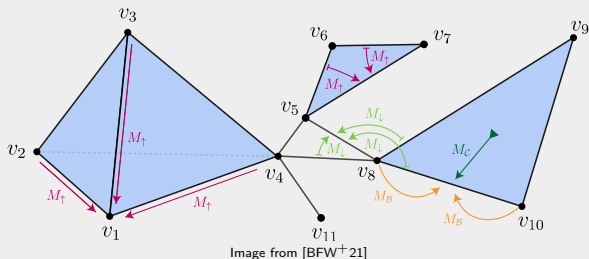
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Lemma

For each $k \leq n$ and $a : V(G)^k \rightarrow \mathbb{N}$ and $c : \mathcal{K} \rightarrow \mathbb{N}$, where $\dim \mathcal{K} = n$, SWL is strictly stronger than k -WL.

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Lemma

For each $k \leq n$ and $a : V(G)^k \rightarrow \mathbb{N}$ and $c : \mathcal{K} \rightarrow \mathbb{N}$, where $\dim \mathcal{K} = n$, SWL is (almost) strictly stronger than k -WL.

Can we get better directions?

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Algorithm Directed Weisfeiler-Leman (DWL)[MG21]

1: **Input:** (V, E, X_V)

Here, $x_v \in \mathbb{Z}_2^d$

2: $c(v) = c^{(0)}(v) \leftarrow \text{hash}(x_v)$

3: **while** $c^{(t)}(v) = c^{(t+1)}(v) \forall v \in V$ **do**

4: $c^{(t+1)}(v) \leftarrow \text{hash} \left(\begin{array}{c} c^{(t)}(v), \{\{c^{(t)}(w) : w \in N_{\text{in}}(v)\}\}, \\ \{\{c^{(t)}(u) : w \in N_{\text{out}}(u)\}\} \end{array} \right)$

5: **Output:** $c^{(T)}(v) \forall v \in V$

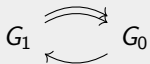
DWL is strictly stronger than WL[BFW⁺21]

Yes, we can



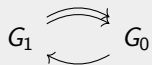
Directed Graph

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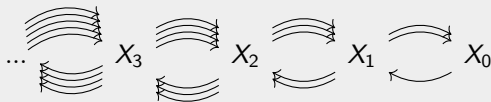


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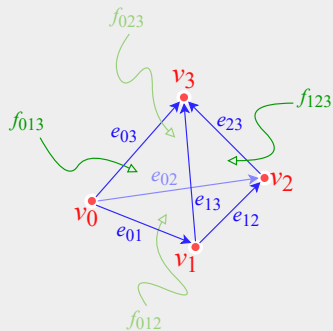
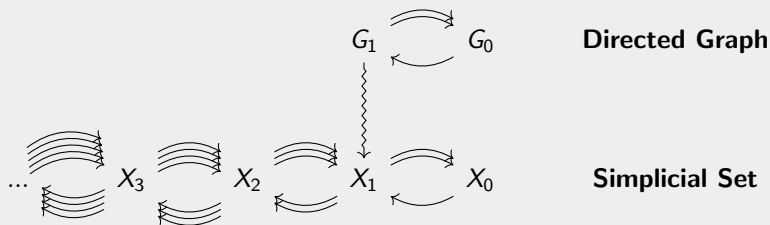


Directed Graph



Simplicial Set

Yes, we can



$$v_0, v_1, v_2, v_3 \in X_0$$

$$e_{01}, e_{02}, e_{03}, e_{12}, e_{13}, e_{23} \in X_1$$

$$f_{012}, f_{013}, f_{023}, f_{123} \in X_2$$

$$g_{0123} \in X_3$$

Simplicial Set WL

- Assign all simplices of every dimension of two simplicial sets the same initial color.

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Update rules for SSWL

$c^{t+1}(\sigma)$ = hash of coloring at t of σ and coloring of its

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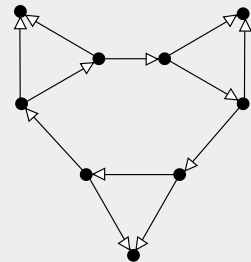
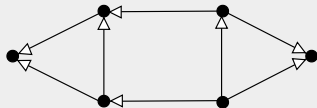
$c^{t+1}(\sigma)$ = hash of coloring at t of σ and coloring of its i -th boundaries, i -th coboundaries, i -th upper-neighbors and i -th lower-neighbors for $0 \leq i \leq k$ whenever $\sigma \in X_k$

Simplicial Set Weisfeiler-Leman Algorithm

SSWL is strictly stronger than SWL[BFW⁺21]

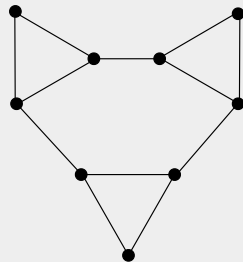
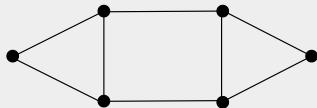
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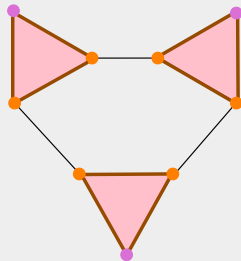
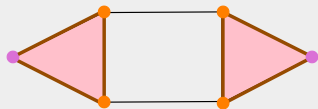
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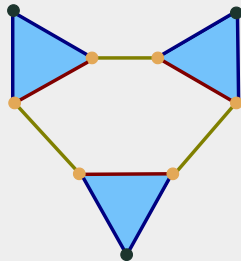
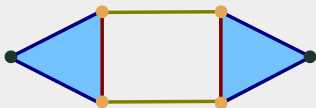
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Message Passing with Higher Dimensional Data

Summary:





$DWL \sqsubset WL$
 \sqsubset
3 $-WL$
 \sqsubset
 SWL

Message Passing with Higher Dimensional Data


Summary:

DWL	\square	WL
\sqcup		\sqcup
$?$		$k\text{-}WL$
\sqcup		\sqcup
$SSWL$	\square	SWL

References I

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Thank you!