

How Powerful Are Graph Neural Networks?

Xu et al 2021

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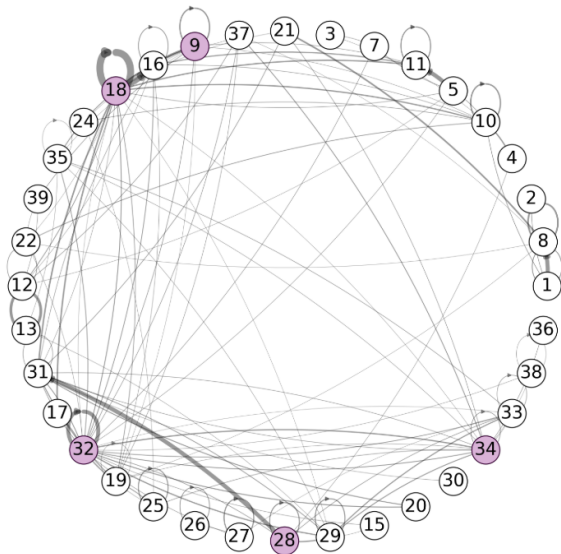
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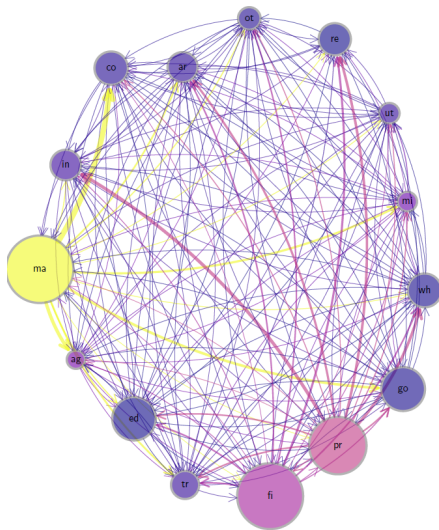
May 12th, 2025

- What Graph Neural Net(GNN) can do and cannot do?
- Empirical success but limited theoretical research
- How expressive are different GNN architectures in capturing and distinguishing graph structures?

Motivation - US and Australian economy



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Algorithm *1-WL (color refinement)*

Input: $G = (V, E, X_V)$

1. $c_v^0 \leftarrow \text{hash}(X_v)$ for all $v \in V$
2. **repeat**
3. $c_v^\ell \leftarrow \text{hash}(c_v^{\ell-1}, \{\{c_w^{\ell-1} : w \in \mathcal{N}_G(v)\}\}) \forall v \in V$
4. **until** $(c_v^\ell)_{v \in V} = (c_v^{\ell-1})_{v \in V}$
5. **return** $\{\{c_v^\ell : v \in V\}\}$

What is GNN? Setup

- $G = (V, E, X_V)$
- In the k -th layer

$$h_v^k = \text{COMBINE}^{(k)} \left(h_v^{k-1}, a_v^{(k)} \right), a_v^{(k)} = \text{AGGREGATE}^{(k)} \left(\{h_u^{k-1} : u \in \mathcal{N}(v)\} \right)$$

Looks really like the iteration step in the WL test

Key Theorem

Theorem 1

No message-passing GNN can be more powerful than the 1-WL test at distinguishing graph structure.

Theorem 2

GNN can achieve this theoretical upper bound using the GIN architecture

What is GIN?

GIN:

$$h_v^{(k)} = MLP \left(\underbrace{(1 + \epsilon)h_v^{(k-1)}}_{\text{center node}} + \underbrace{\sum_{u \in N(v)} h_u^{(k-1)}}_{\text{neighbors}} \right)$$

- The sum aggregator preserves multiset cardinality
- MLP(NN) has the universal approximation properties
- As powerful as 1-WL test

- Is 1-WL good enough? (Fail to distinguish a regular graph with n nodes)

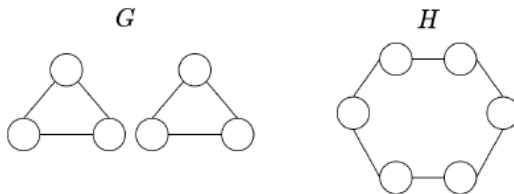


Fig. 1. Two graphs can not be distinguished by WL and 2-WL, but can be distinguished by 2-FWL.

- Difficulty lies at the tradeoff: Computational complexity and expressiveness

- Perturbations: What happens if there is a shock to one nodes? How will this shock propagates through the network
- Two network are the “same” if all or random shock has the same propagation