

Universal Invariant and Equivariant GNNs [1]

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Introduction

Universal Approximation

Universal Approximation Theorem

MLPs with a single hidden layer are universal approximators

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- ▶ Maron et al. [2] showed certain invariant GNNs are universal approximators of invariant continuous functions on graphs

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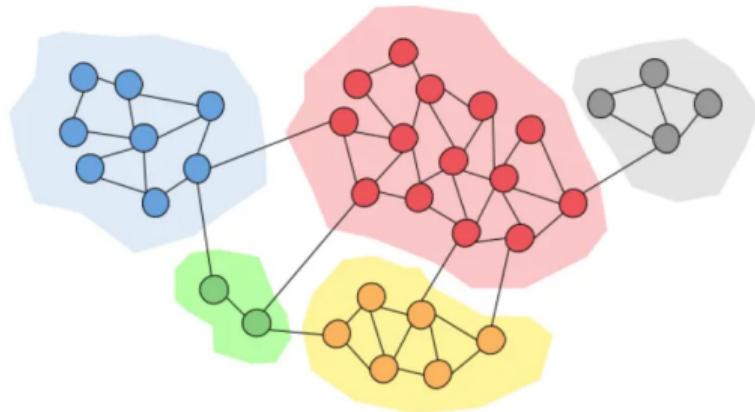
- ▶ Maron et al. [2] showed certain invariant GNNs are universal approximators of invariant continuous functions on graphs
- ▶ **Are equivariant GNNs universal approximators of equivariant continuous functions on graphs?**

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Equivariance vs Invariance

- Community detection

$$G = (V, E) \quad y : V \rightarrow \{1, \dots, C\}$$

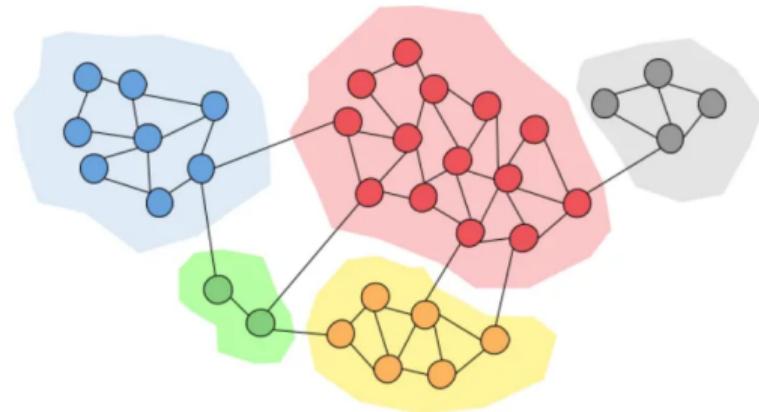


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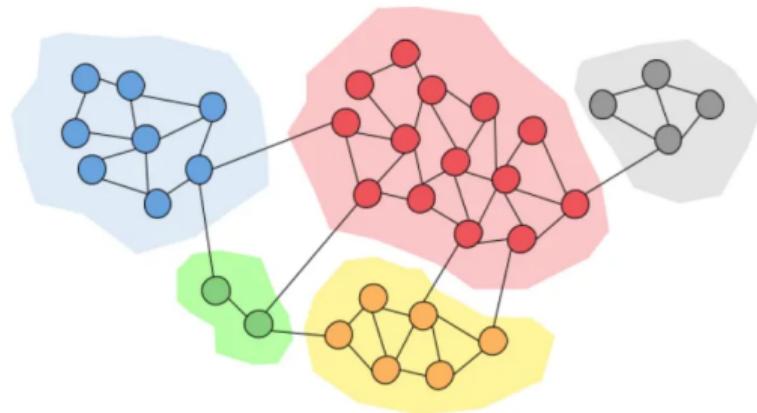


Equivariance vs Invariance

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$$G = (V, E) \quad y : V \rightarrow \{1, \dots, C\}$$

- Recommender Systems
- State Prediction



One-Layer GNN

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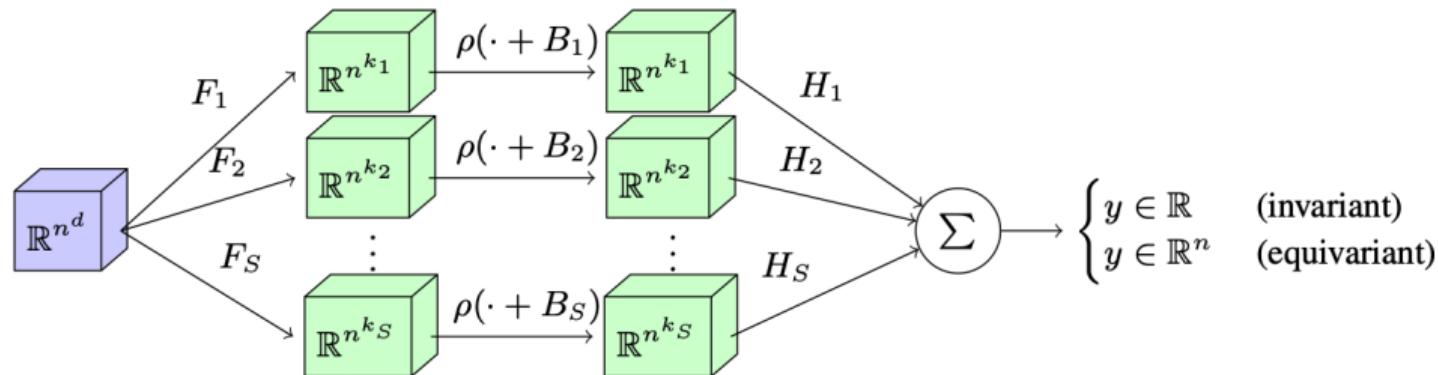
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- $B_s = \sigma B_s$: equivariant Bias

Model of GNN



Number of parameters

- ▶ Maron et al. [3] showed $f: \mathbb{R}^{n^k} \rightarrow \mathbb{R}^{n^\ell}$ lives in vector space of dimension $b(k + \ell)$

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- ▶ GNN described by a single set of parameters can be applied to graphs of any size
- ▶ We want to show that a GNN approximates a continuous function uniformly well for several n at once

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Proof for Invariant Case

Proof Idea: Dense subsets

- If $\mathcal{A} \subset \mathcal{B}$ is dense in \mathcal{B} , then $\forall b \in \mathcal{B}, \forall \epsilon > 0, \exists a \in \mathcal{A}$ such that $\|a - b\| < \epsilon$

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- ▶ Show class of invariant 1-layer GNNs is dense in space of real-valued
continuous invariant functions on graphs

Alternate Proof for [2]

Show class of invariant 1-layer GNNs is dense in space of real-valued continuous invariant functions on graphs

- Equivalence class of isomorphic graphs

$$\mathcal{G}_{\text{inv}} := \left\{ \mathcal{O}(G); G \in \mathbb{R}^{n^d} \text{ with } n \leq n_{\max}, \|G\| \leq R \right\}$$

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Isomorphism

G_1, G_2 isomorphic if $G_1 = \sigma \star G_2$

Invariance

$$f(G_1) = f(\sigma \star G_2) = f(G_2)$$

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- ▶ $\mathcal{O}(G) := \{\sigma \star G; \sigma \in \mathcal{O}\}$

Edit Distance

- Graph edit distance

$$d_{\text{edit}}(\mathcal{O}(G_1), \mathcal{O}(G_2)) := \min_{(o_1, o_2, \dots, o_k) \in \mathcal{P}(G_1, G_2)} \sum_{i=1}^k c(o_i)$$

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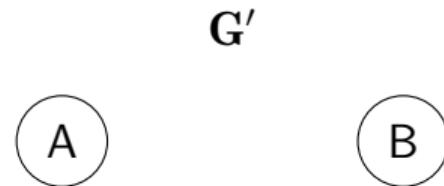
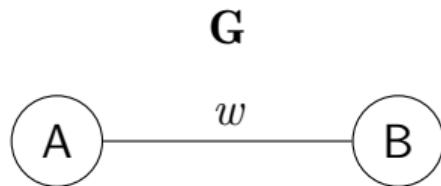
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 - ▶ $c(\text{edge_weight_modification}) = |w - w'|$

Edit Distance Example

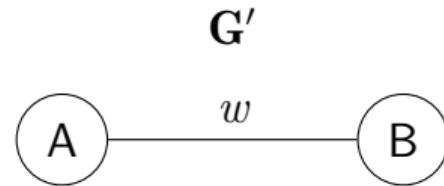
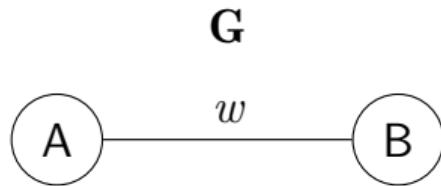


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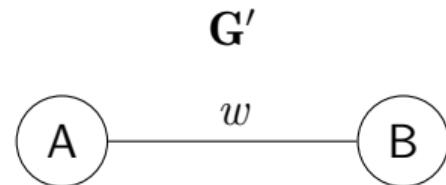
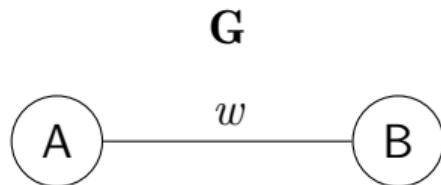
cost accumulated: c

Edit Distance Example



cost accumulated: $c + w$

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$$d_{\text{edit}}(G, G') = c + w$$

Edit Distance Observations

Assume $d_{\text{edit}}(\mathcal{O}(G_1), \mathcal{O}(G_2)) < c$. Then the following hold:

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- This shows any continuous invariant function is *uniformly* well-approximated by a GNN on \mathcal{G}_{inv}

Stone-Weierstrass Theorem

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Hausdorff

Separate points have separate neighborhoods

✓ all metric spaces are Hausdorff

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 - Therefore $G \mapsto \mathcal{O}(G)$ is continuous

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Subalgebra

a vector subspace closed under the multiplication of vectors

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Separability

For all $x \neq y$ in X , there exists $f \in A$ such that $f(x) \neq f(y)$

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For two distinct classes of isomorphic graphs in \mathcal{G}_{inv} ($\mathcal{O}(G_1) \neq \mathcal{O}(G_2)$), there is a class of 1-layer GNNs $f \in \mathcal{N}_{\text{inv}}^{\otimes}$ with $f(\mathcal{O}(G_1)) \neq f(\mathcal{O}(G_2))$.

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- Proof by contradiction and graphs G_1, G_2 are permutations of each other if $f(\mathcal{O}(G_1)) = f(\mathcal{O}(G_2))$ for $f \in \mathcal{N}_{\text{inv}}^{\otimes}(\rho_{\text{sig}})$

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Wrapping up Theorem 1

- So far proved $\mathcal{N}_{\text{inv}}^{\otimes}(\rho_{\text{sig}})$ is dense in $\mathcal{C}(\mathcal{G}_{\text{inv}}, d_{\text{edit}})$
- Can go from $\mathcal{N}_{\text{inv}}^{\otimes}(\rho_{\text{sig}})$ to $\mathcal{N}_{\text{inv}}(\rho)$
- Show $\mathcal{N}_{\text{inv}}(\rho)$ dense in $\mathcal{N}_{\text{inv}}^{\otimes}(\rho_{\text{sig}})$
- Have re-proved results from [2] but without fixing n

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Proof for Equivariant Case

Equivariant Case

- Isomorphic graphs aren't equivalent anymore

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Equivariance

For isomorphic G_1, G_2 , ($G_1 = \sigma \star G_2$) we have

$$f(G_1) = f(\sigma \star G_2) = \sigma \star f(G_2) \neq f(G_2)$$

Equivariant Case

- ▶ Isomorphic graphs aren't equivalent anymore
- ▶ So define

$$\mathcal{G}_{\text{eq}} := \left\{ G \in \mathbb{R}^{n^d}; n \leq n_{\max}, \|G\| \leq R \right\}$$

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- H_s equivariant output operators

Theorem 2

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Classical Stone-Weierstrass theorem doesn't apply!

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Solution

Define specialized version of Stone-Weierstrass theorem for equivariant functions

Stone-Weierstrass for equivariant functions

- ▶ Additional condition: self-separability
- ▶ $f(G)$ can have different values on different coordinates
- ▶ Rest of the proof similar to invariant case

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