Orbit-Equivariant Graph Neural Networks ICLR 2024

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Some Graph Theory

Similarity

An automorphism of G is a permutation σ on G satisfying $\sigma \cdot G = G$. Nodes $v, w \in V(G)$ are *similar* if there is an automorphism σ of G such that $\sigma(v) = w$. Similar nodes form equivalence classes called *orbits*.



Figure: Graph with nodes colored by orbit.

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Structural Inductive Biases

Equivariance

Node-labelling function f on a domain D closed under permutation is equivariant if $f(\sigma \cdot G) = \sigma \cdot f(G)$ holds for all $G \in D$ and permutations σ on V(G).



Figure: Example of an equivariant function f.

The Limits of Equivariance



Figure: Non-equivariant molecular transformation that increases lipophilicity (LogP), where the nodes are labelled with the atom type, without positional information.

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The Limits of Equivariance



Figure: Non-equivariant molecular transformation that increases lipophilicity (LogP), where the nodes are labelled with the atom type, without positional information.

Proposition 1

Let f be an equivariant node-labelling function and let G be a labelled graph in its domain. If $v, w \in V(G)$ are similar, then $f(G)_v = f(G)_w$.

Definition 1

A node-labelling function f on domain D closed under permutation is **orbit-equivariant** if, for all labelled graphs $G \in D$, permutations σ on V(G), and orbits $r \in R(G)$, it holds that $\{\!\!\{f(\sigma \cdot G)_{\sigma(v)} \mid v \in r\}\!\!\} = \{\!\!\{f(G)_v \mid v \in r\}\!\!\}.$

Orbit-Equivariance in the Hierarchy of Graph Functions

Not all orbit-equivariant functions are equivariant:



Figure: An orbit-equivariant function that is not equivariant.

Proposition 2

All equivariant functions are orbit-equivariant, but not vice-versa. There exist node-labelling functions which are not orbit-equivariant.

Proposition 3

If f is orbit-equivariant and max-orbit(f) = 1, then f is equivariant.



Figure: A node-labelling function with max-orbit = 1 that is not equivariant.

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Non-equivariant GNN Architectures



Figure: Architecture for constructing orbit-equivariant GNNs.

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Model Expressivity

Theorem 2

The expressivity of our proposed models is as follows, where for a class of models X, the claim "X is not equivariant" means that "there exists $f \in X$ such that f is not equivariant":

- 1. Unique-ID-GNNs are not orbit-equivariant and, for any fixed n, can approximate any node-labelling function $f : G_n \to \mathbb{R}^n$, where G_n is the set of graphs with $\leq n$ nodes.
- 2. RNI-GNNs are equivariant in expectation and, for any fixed n, can approximate any equivariant function $f : G_n \to \mathbb{R}^n$ with probability arbitrarily close to 1. They can approximate some non-equivariant and orbit-equivariant functions with probability arbitrarily close to 1, but there exist RNI-GNNs which, with probability arbitrarily close to 1, are not orbit-equivariant.

Theorem 2

The expressivity of our proposed models is as follows, where for a class of models X, the claim "X is not equivariant" means that "there exists $f \in X$ such that f is not equivariant":

- Orbit-Indiv-GNNs are not equivariant but are orbit-equivariant on graphs whose orbits are distinguishable by orbit-1-WL. For any m ∈ Z⁺, there exist Orbit-Indiv-GNNs f with max-orbit(f) > m.
- m-Orbit-Transform-GNNs f are not equivariant but are orbit-equivariant on graphs whose orbits are distinguishable by orbit-1-WL. They have max-orbit(f) ≤ m and there exist m-Orbit-Transform-GNNs f with max-orbit(f) = m.

Datasets



Figure: Molecular transformation.

- **Bioisostere** swap out some atoms in a given molecule to achieve minimal lipophilicity. This is an important factor in drug design.
- Alchemy-Max-Orbit-*m* based off Alchemy dataset, designed to test model performance for orbits of increasing sizes.

Table: Mean and standard deviation of final model accuracy percentage on the test datasets.

Dataset	Model	Graph Accuracy	Orbit Accuracy	Node Accuracy
Bioisostere (cross-entropy loss)	GCN Unique-ID-GCN RNI-GCN Orbit-Indiv-GCN	$52.4 \pm 6.37 \\ 66.1 \pm 5.13 \\ 63.6 \pm 4.29 \\ 69.9 \pm 4.68 \\ 57.4 \pm 6.42 \\ 69.9 \pm 6.42 \\ $	$\begin{array}{c} 92.9 \pm 1.14 \\ 94.5 \pm 0.97 \\ 93.9 \pm 0.86 \\ \textbf{95.4 \pm 0.63} \\ \textbf{95.4 \pm 0.63} \end{array}$	$\begin{array}{c} 94.4 \pm 0.79 \\ 95.6 \pm 0.62 \\ 95.1 \pm 0.76 \\ \textbf{96.1} \pm 0.76 \\ \textbf{96.3} \pm 0.49 \\ \textbf{96.4} \end{bmatrix}$
Alchemy- Max-Orbit-2 (orbit-sorting cross-entropy)	2-Orbit- Transform Unique-ID-GCN RNI-GCN Orbit-Indiv-GCN 2-Orbit-Transform	57.1 ± 6.43 20 ± 4.57 0 ± 0 51.9 \pm 4.38 47.9 ± 6.45	$\begin{array}{c} 93 \pm 0.99 \\ \hline 79.9 \pm 2.01 \\ 74.5 \pm 1.7 \\ \textbf{87.5 \pm 1.78} \\ 86.8 \pm 1.53 \end{array}$	$\begin{array}{c} 94.1 \pm 0.79 \\ 77 \pm 1.52 \\ 75.2 \pm 1.66 \\ \textbf{90.6 \pm 1.12} \\ 85.1 \pm 1.66 \end{array}$
Alchemy- Max-Orbit-6 (orbit-sorting cross-entropy)	Unique-ID-GCN RNI-GCN Orbit-Indiv-GCN 6-Orbit-Transform	$\begin{array}{c} 66.8 \pm 7.15 \\ 44.9 \pm 7.19 \\ \textbf{83.4 \pm 4.22} \\ 10.6 \pm 4.14 \end{array}$	$\begin{array}{c} 84.8 \pm 2.97 \\ 78.5 \pm 3.39 \\ \textbf{88.9 \pm 2.71} \\ 71.2 \pm 2.47 \end{array}$	$\begin{array}{c} 95.4 \pm 1.07 \\ 91.4 \pm 1.47 \\ \textbf{97.1 \pm 1.46} \\ 87.6 \pm 1.08 \end{array}$

Results



Figure: Graph accuracy with standard error on the test datasets across all models using orbit-sorting cross-entropy: Bioisostere (left), Alchemy-Max-Orbit-2 (center), and Alchemy-Max-Orbit-6 (right).

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- Orbit-equivariance can be generalized to other data structures besides graphs.
- Designing optimal bioisosteres is complex and deserves further investigation.
- Identification of other problems that require non-equivariant and orbit-equivariant models to solve.
- Finally, design better orbit-equivariant GNNs to solve such problems.

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