Understanding and Extending Subgraph GNNs by Rethinking Their Symmetries

Fabrizio Frasca∗
Imperial College London & Twitter
ffrasca@twitter.com

Beatrice Bevilacqua∗
Purdue University
bbevilac@purdue.edu

Michael M. Bronstein
University of Oxford & Twitter
mbronstein@twitter.com

Haggai Maron
NVIDIA Research
hmaron@nvidia.com

Abstract

Subgraph GNNs are a recent class of expressive Graph Neural Networks (GNNs) which model graphs as collections of subgraphs. So far, the design space of possible Subgraph GNN architectures as well as their basic theoretical properties are still largely unexplored. In this paper, we study the most prominent form of subgraph methods, which employs node-based subgraph selection policies such as ego-networks or node marking and deletion. We address two central questions: (1) What is the upper-bound of the expressive power of these methods? and (2) What is the family of equivariant message passing layers on these sets of subgraphs?.

Our first step in answering these questions is a novel symmetry analysis which shows that modelling the symmetries of node-based subgraph collections requires a significantly smaller symmetry group than the one adopted in previous works. This analysis is then used to establish a link between Subgraph GNNs and Invariant Graph Networks (IGNs). We answer the questions above by first bounding the expressive power of subgraph methods by 3-WL, and then proposing a general family of message-passing layers for subgraph methods that generalises all previous node-based Subgraph GNNs. Finally, we design a novel Subgraph GNN dubbed SUN, which theoretically unifies previous architectures while providing better empirical performance on multiple benchmarks.

1 Introduction

Message Passing Neural Networks (MPNNs) are arguably the most commonly used version of Graph Neural Networks (GNNs). The limited expressive power of MPNNs [36, 55] has led to a plethora of works aimed at designing expressive GNNs while maintaining the simplicity and scalability of MPNNs [11, 39, 49, 30]. Several recent studies have proposed a new class of such architectures [14, 59, 61, 43, 42], dubbed Subgraph GNNs, which apply MPNNs to collections (‘bags’) of subgraphs extracted from the original input graph and then aggregate the resulting representations. Subgraphs are selected according to a predefined policy; in the most popular ones, each subgraph is tied to a specific node in the original graph, for example by deleting it or extracting its local ego-network. Subgraph GNNs have demonstrated outstanding empirical performance, with state-of-the-art results on popular benchmarks like the ZINC molecular property prediction [61, 7].

While offering great promise, it is fair to say that we still lack a full understanding of Subgraph GNNs. Firstly, on the theoretical side, it is known that subgraph methods are strictly stronger than

∗Equal contribution. Author ordering determined by coin flip.

36th Conference on Neural Information Processing Systems (NeurIPS 2022).
the Weisfeiler-Leman (WL) test [54, 39], but an upper-bound on their expressive power is generally unknown. Secondly, on a more practical level, Subgraph GNN architectures differ considerably in the way information is aggregated and shared across the subgraphs, and an understanding of the possible aggregation and sharing rules is missing. Both aspects are important: an understanding of the former can highlight the limitations of emerging architectures, a study of the latter paves the way for improved Subgraph GNNs.

**Main contributions.** The goal of this paper is to provide a deeper understanding of node-based Subgraph GNNs in light of the two aforementioned aspects. The main theoretical tool underpinning our contributions is a novel analysis of the symmetry group that acts on the sets of subgraphs. While several previous approaches [43, 14, 7] have (often implicitly) assumed that a subgraph architecture should be equivariant to independent node and subgraph permutations, we leverage the fact that node-based policies induce an inherent bijection between the subgraphs and the nodes. This observation allows us to align the two groups and model the symmetry with a single (smaller) permutation group that acts on nodes and subgraphs jointly. Other works [61, 56, 59] have (again, implicitly) recognised such node-subgraph correspondence but without studying the implications on the symmetry group, and resorting, as a result, to a partial and heuristic choice of equivariant operations.

The use of this stricter symmetry group raises a fruitful connection with Subgraph Union Networks (k-IGNs) [33, 32], a well studied family of architectures for processing graphs and hypergraphs designed to be equivariant to the same symmetry group. This connection allows us to transfer and reinterpret previous results on IGNs to our Subgraph GNN setup. As our first contribution we show that the expressive power of Subgraph GNNs with node-based policies is bounded by that of the 3-WL test. This is shown by proving that all previous Subgraph GNNs can be implemented by a 3-IGN and by leveraging the fact that the expressive power of these models is bounded by 3-WL [21, 5].

Our second contribution is the proposal of a general layer formulation for Subgraph GNNs, based on the observation that these methods maintain an \( n \times n \) representation of \( n \) subgraphs with \( n \) nodes, following the same symmetry structure of 2-IGNs (same permutation applied to both rows and columns of this representation). We propose a novel extension of 2-IGNs capturing both local (message-passing-like) and global operations. This extension easily recovers previous methods facilitating their comparison. Also, we present a number of new operations that previous methods did not implement. We build upon these observations to devise a new Subgraph GNN dubbed SUN, (Subgraph Union Network). We prove that SUN generalises all previous node-based Subgraph GNNs and we empirically compare it to these methods, showing it can outperform them.

### 2 Previous and related work

**Expressive power of GNNs.** The expressive power of GNNs is a central research focus since it was realised that message-passing type GNNs are constrained by the expressivity of the WL isomorphism test [36, 55]. Other than the aforementioned subgraph-based methods, numerous approaches for more powerful GNNs have been proposed, including positional and structural encodings [1, 45], higher-order message-passing schemes [36, 38, 10, 9], equivariant models [24, 33, 32, 53, 15, 31, 40]. We refer readers to the recent survey by Morris et al. [39] for additional details. Finally we note that, in a related and concurrent work, Qian et al. [46] propose a theoretical framework to study the expressive power of subgraph-based GNNs by relating them to the \( k \)-WL hierarchy, and explore how to sample subgraphs in a data-driven fashion.

**Invariant graph networks.** IGNs were recently introduced in a series of works by Maron et al. [33, 32, 34] as an alternative to MPNNs for processing graph and hyper-graph data. For \( k \geq 2 \), k-IGNs represent hyper-graphs with hyper-edges up to size \( k \) with k-order tensor \( \mathcal{Y} \in \mathbb{R}^{n^k} \), where each entry holds information about a specific hyper-edge. On these they apply linear \( S_n \)-equivariant layers interspersed with pointwise non-linearities. These models have been thoroughly studied in terms of: (i) their expressive power; (ii) the space of their equivariant linear layers. As for (i), IGNs were shown to have exactly the same graph separation power as the \( k \)-WL graph isomorphism test [32, 5, 21] and, for sufficiently large \( k \), to have a universal approximation property w.r.t. \( S_n \)-invariant and equivariant functions [34, 26, 47]. Concerning (ii), the work in [33] completely characterised the space of linear layers equivariant to \( S_n \) from \( \mathbb{R}^{n^k} \) to \( \mathbb{R}^{n^{k'}} \): the authors derived a basis of \( \text{bll}(k+k') \) linear operators consisting of indicator tensors of equality patterns over the multi-index set \( \{1, \ldots, n\}^{k+k'} = [n]^{k+k'} \). Albooyeh et al. [2] showed these layers can be (re-)written as sums of pooling-broadcasting operations
between elements of $\mathcal{Y}$ indexed by the orbits of the action of $S_n$ on $[n]^k$ and $[n]^{k'}$. Take, e.g., $k = k' = 2$. In this case there are only two orbits: $\{i, i\}, i \in [n]$ corresponding to on-diagonal terms, and $\{i, j\}, i \neq j \in [n]$, off-diagonal terms. According to Albooyeh et al. [2] any equivariant linear layer $L : \mathbb{R}^{n^2} \rightarrow \mathbb{R}^{n^2}$ can be represented as a composition of pooling and broadcasting operations on the elements indexed by these orbits. One example is the linear map that sums the on-diagonal elements and broadcasts the result to the off-diagonal ones: $L(\mathcal{Y})_{ij} = \sum_k \mathcal{Y}_{kk}$ for $i \neq j$, 0 otherwise. See Appendix [3] for additional details. These results particularly important as they underpin most of our theoretical derivations. Lastly, a more comprehensive coverage of IGNs can be found in [59].

Subgraph GNNs. Despite motivated by diverse premises, a collection of concurrent methods share the overarching design whereby graphs are modelled through the application of a GNN to their subgraphs. Bevilacqua et al. [7] first explicitly formulated the concept of bags of subgraphs generated by a predefined policy and studied layers to process them in an equivariant manner: the same GNN can encode each subgraph independently (DS-GNN), or information can be shared between these computations in view of the alignment of nodes across the bag [35] (DSS-GNN). Building upon the Reconstruction Conjecture [25, 52], Reconstruction GNNs [14] obtain node-deleted subgraphs, process them with a GNN and then aggregate the resulting representations by means of a set model. Nested GNNs [59] and GNN-As-Kernel models (GNN-AK) [61] shift their computation from rooted subgraphs to rooted subgraphs, effectively representing nodes by means of GNNs applied to their enclosing ego-networks. Similarly to DSS-GNNs [7], GNN-AK models may feature information sharing modules aggregating node representations across subgraphs. ID-GNNs [56] also process ego-network subgraphs, but their roots are ‘marked’ so to specifically alter the exchange of messages involving them. Intuitively, the use of subgraphs implicitly breaks those local symmetries which determine the notorious expressiveness bottleneck of MPNNs. We note that other works can be interpreted as Subgraph GNNs, including those by Papp et al. [43], Papp and Wattenhofer [42].

3 Node-based Subgraph GNNs

Notation. Let $G = (A, X)$ be a member of the family $\mathcal{G}$ of node-attributed, undirected, finite, simple graphs. The adjacency matrix $A \in \mathbb{R}^{n \times n}$ represents $G$’s edge set $E$ over its set of $n$ nodes $V$. The feature matrix $X \in \mathbb{R}^{n \times d}$ gathers the node features; we denote by $x_j \in \mathbb{R}^{d \times 1}$ the features of node $j$ corresponding to the $j$-th row of $X$. $B_{G}$ is used to denote a multisets (bag) of $m$ subgraphs of $G$. Adjacency and feature matrices for subgraphs in $B_{G}$ are arranged in tensors $A \in \mathbb{R}^{m \times n \times n}$ and $X' \in \mathbb{R}^{m \times n \times d}$. Superscript $i,(t)$ refers to representations on subgraph $i$ at the $t$-th layer of a stacking, as in $x^{i,(t)}_j$. Finally, we denote $[n] = \{1, \ldots, n\}$. All proofs are deferred to Appendices B and D.

Formalising Subgraph GNNs. Subgraph GNNs compute a representation of $G \in \mathcal{G}$ as

$$(A, X) \mapsto (\mu \circ \rho \circ \mathcal{S} \circ \pi)(A, X).$$

(1)

Here, $\pi : G \rightarrow \{G^1, \ldots, G^m\} = \{(A^1, X^1), \ldots, (A^m, X^m)\} = B_{G}^{(0)}$ is a selection policy generating a bag of subgraphs from $G$; $S = L_T \circ \ldots \circ L_1 : B_{G}^{(0)} \rightarrow B_{G}^{(T)}$ is a stacking of $T$ (node- and subgraph-) permutation equivariant layers; $\rho : (G, B_{G}^{(T)}) \rightarrow x_{G}$ is a permutation invariant pooling function, $\mu$ is an MLP. The layers in $\mathcal{S}$ comprise a base-encoder in the form of a GNN applied to subgraphs; throughout this paper, we assume it to be a 1-MLP maximally expressive MPNN such as the one in Morris et al. [35]. Subgraph GNNs differ in the implementation of $\pi$, $\mathcal{S}$ and, in some cases, $\rho$. For example, in (n-1)-Reconstruction GNNs [14], $\pi$ selects node-deleted subgraphs and $\mathcal{S}$ applies a Siamese MPNN to each subgraph independently. To exemplify the variability in $\mathcal{S}$, DSS-GNN [7] extends this method with cross-subgraph node and connectivity aggregation. More details are on how currently known Subgraph GNNs are captured by Equation (1) can be found in Appendix A.

Node-based selection policies. In this work, we focus on a specific family of node-based subgraph selection policies, wherein each subgraph is associated with a unique node in the graph. Formally, we call a subgraph selection policy node-based if it is of the form $\pi(G) = \{f(G, v)\}_{v \in V}$, for some selection function $f(G, v)$ that takes a graph $G$ and a node $v$ as inputs and outputs a subgraph $G^v$. In the following, we refer to $v$ as the root of subgraph $G^v$. We require $f$ to be a bijection and we

---

1For group $G$ acting on set $X$, the orbits of the action of $G$ on $X$ are defined as $\{G \cdot x \mid x \in X\}$. These partition $X$ into subsets whose elements can (only) reach all other elements in the subset via the group action.

2We do not consider edge features, although an extension to such a setting would be possible.
In ESAN [7] symmetries are modelled as a direct product of node and subgraph permutation groups; however, node-based policies enable the use of one single permutation group, the same as in 3-IGNs. 3-IGNs are less constrained, thus more expressive than ESAN and other Subgraph GNNs. See diagram on the right and formal statement in Section 5.

Figure 1: Symmetries of bags of subgraphs (left) and corresponding function space diagrams (right). In ESAN [7] symmetries are modelled as a direct product of node and subgraph permutation groups; however, node-based policies enable the use of one single permutation group, the same as in 3-IGNs. 3-IGNs are less constrained, thus more expressive than ESAN and other Subgraph GNNs. See diagram on the right and formal statement in Section 5.

Note that such policies produce \( m = n \) different subgraphs. Amongst the most common examples are node-deletion (ND), node-marking (NM), and ego-networks (EGO) policies. For input graph \( G \), \( f_{\text{ND}}(G, v) \) removes node \( v \) and the associated connectivity; \( f_{\text{NM}}(G, v) \) adds a special ‘mark’ attribute to \( v \)’s features (with no connectivity alterations), and \( f_{\text{EGO}(h)}(G, v) \) returns the subgraph induced by the \( h \)-hop-neighbourhood around the root \( v \). EGO policies can be ‘marked’: \( f_{\text{EGO+}(h)}(G, v) \) extracts the \( h \)-hop ego-net around \( v \) and marks this node as done by \( f_{\text{NM}} \). For convenience, we denote the class of such node-based selection policies by \( \Pi \):

**Definition 1** (Known node-based selection policies \( \Pi \)). Let \( \Sigma \) be the set of all node-based subgraph selection policies operating on \( G \). Class \( \Pi \subset \Sigma \) collects the node-based policies node-deletion (ND), node-marking (NM), ego-nets (EGO) and marked ego-nets (EGO+) of any depth: \( \Pi = \{ \pi_{\text{ND}}, \pi_{\text{NM}}, \pi_{\text{EGO}(h)}, \pi_{\text{EGO+}(h)} \mid h > 0 \} \).

**Node-based Subgraph GNNs** are those Subgraph GNNs which, implicitly or explicitly, process bags generated by node-based policies. We group known formulations in the following family:

**Definition 2** (Known node-based Subgraph GNNs \( \Upsilon \)). Let \( \Xi \subset \Xi \) collects known Subgraph GNNs when equipped with \( 1\text{-WL} \) base-encoders: \( \Upsilon = \{ (n\text{-1})\text{-Reconstr.GNN, GNN-AK, GNN-AK-ctx, NGNN, ID-GNN, DS-GNN}_{1\text{L}}, \text{DSS-GNN}_{1\text{L}} \}. \) DS-GNN\(_{1\text{L}}\), DSS-GNN\(_{1\text{L}}\) refer to DS- and DSS-GNN models equipped with any \( \pi \in \Pi \).

Importantly, all these methods apply MPNNs to subgraphs of the original graph, but differ in the way information is shared between subgraphs/nodes. In all cases, their expressive power is strictly larger than \( 1\text{-WL} \), but an upper-bound is currently unknown.

### 4 Symmetries of node-based subgraph selection policies

In an effort to characterise the representational power of node-based Subgraph GNNs, we first study the symmetry group of the objects they process: ‘bags of subgraphs’ represented as tensors \((A, \mathcal{X}) \in \mathbb{R}^{m \times n \times d} \times \mathbb{R}^{m \times n \times d} \), assuming \( n \) nodes across \( m \) subgraphs. Previous approaches [14] use two permutation groups: one copy of the symmetric group \( S_n \) models node permutations, while another copy \( S_m \) models subgraph permutations in the bag. These two were combined by a group product acting independently on the nodes and subgraphs in \((A, \mathcal{X})\). For example, Bevilacqua et al. model the symmetry as:

\[
((\tau, \sigma) \cdot (A)_{ijk} = A_{\tau^{-1}(i)\sigma^{-1}(j)\sigma^{-1}(k)}, \quad ((\tau, \sigma) \cdot (\mathcal{X})_{ijl} = \mathcal{X}_{\tau^{-1}(i)\sigma^{-1}(j)\sigma^{-1}(l)}, \quad (\tau, \sigma) \in S_m \times S_n \quad (2)
\]

Our contributions stem from the following crucial observation: When using node-based policies, the subgraphs in \((A, \mathcal{X})\) can be ordered consistently with the nodes by leveraging the bijection \( f : v \mapsto G_v \), characterising this policy class. In other words, \( f \) suggests a node-subgraph alignment inducing a new structure on \((A, \mathcal{X})\), whereby the subgraph order is not independent of that of nodes.
with the same colour. Left: the whole tensor. Middle and right: sections; elements in purple and green constitute sub-tensor $\mathcal{X}$, the remaining ones sub-tensor $\mathcal{A}$.

Figure 2: Depiction of cubed tensor $\mathcal{Y}$, its orbit-induced partitioning and the related semantics when $\mathcal{Y}$ is interpreted as a bag of node-based subgraphs, $n = 5$. Elements in the same partition are depicted with the same colour. Left: the whole tensor. Middle and right: sections; elements in purple and green constitute sub-tensor $\mathcal{X}$, the remaining ones sub-tensor $\mathcal{A}$.

...and, thus, not preserving the new structure of $(\mathcal{A}, \pi')$. Since they are restricted by a smaller set of equivariance constraints, we expect GNNs designed to be equivariant to $S_n$ to be more expressive than those equivariant to the larger groups considered by previous works (34) (see Figure 1).

We build upon this observation, along with the insight we obtain from Equation (3) is profound: it reveals that the symmetry structure of $\mathcal{X}$ matches the symmetries of second-order tensors used by $2$-IGNs.

We start by introducing a recurring, useful concept. Let $\mathcal{X}$ be two functions and such that $D_g \subseteq D_f, C_g \subseteq C_f$. We say $f$ implements $g$ (and write $f \cong g$) when $\forall x \in D_g, f(x) = g(x)$.

5 A representational bound for Subgraph GNNs

In this section we prove that the expressive power of known node-based Subgraph GNNs is bounded by $3$-WL by showing that they can be implemented by $3$-IGNs, which have the same expressive power as $3$-WL. Underpinning the possibility of IGNs to upper-bound a certain Subgraph GNN $\mathcal{N}$ in its expressive power is the ability of IGNs to (i) implement $\mathcal{N}$’s subgraph selection policy (and (ii) implement $\mathcal{N}$’s (generalised) message-passing and pooling equations $(\mu \circ \rho \circ S)$. This would ensure that whenever $\mathcal{N}$ assigns distinct representations to two non-isomorphic graphs, an IGN implementing $\mathcal{N}$ would do the same. We start by introducing a recurring, useful concept.

Definition 3 (‘implements’). Let $f : D_f \to C_f$, $g : D_g \to C_g$ be two functions and such that $D_g \subseteq D_f, C_g \subseteq C_f$. We say $f$ implements $g$ (and write $f \cong g$) when $\forall x \in D_g, f(x) = g(x)$.

More formally, $S_n$’s orbits on the indices in (3) refine the orbits of the product group in (2).
Our first result shows that 3-IGNs can implement the selection policies in class II (Definition 1), which, to the best of our knowledge, represent all known node-based policies utilised by previously proposed Subgraph GNNS.

**Lemma 4 (3-IGNs implement known node-based selection policies).** For any $\pi \in \Pi$ there exists a stacking of 3-IGN layers $M_\pi$ s.t. $M_\pi \simeq \pi$.

Intuitively, 3-IGNs start from a $\mathbb{R}^{n^2}$ representation of $G$ and, first, move to a $\mathbb{R}^{n^3}$ tensor ‘copying’ this latter along its first (subgraph) dimension. This is realised via an appropriate broadcast operation. Then, they proceed by adding a ‘mark’ to the features of some nodes and/or by nullifying elements corresponding to some edges. We refer readers to Figure 2 and Appendix B.1.2 for additional details on how nodes in each subgraph are represented in 3-IGNs. Next, we show 3-IGNs can implement layers of any model in $\mathcal{T}$.

**Lemma 5 (3-IGNs implement Subgraph GNN layers).** Let $G_1, G_2$ be two graphs in $\mathcal{G}$ and $N$ a model in family $\mathcal{T}$ equipped with Morris et al. [36] message-passing base-encoders. Let $B_1^{(t)}, B_2^{(t)}$ be bags of subgraphs in the input of some intermediate layer $L$ in $\mathcal{N}$. Then there exists a stacking of 3-IGN layers $M_L$ for which $M_L(B_1^{(t)}) = B_1^{(t+1)} = L(B_2^{(t)})$ for $i = 1, 2, 3$.

Lemmas 4 and 5 allow us to upper-bound the expressive power of all known instances of node-based Subgraph GNNS by that of 3-IGNs:

**Theorem 6 (3-IGNs upper-bound node-based Subgraph GNNS).** For any pair of non-isomorphic graphs $G_1, G_2$ in family $\mathcal{G}$ and Subgraph GNN model $N \in \mathcal{T}$ equipped with Morris et al. [36] message-passing base-encoders, if there exists weights $\Theta$ such that $G_1, G_2$ are distinguished by instance $N_\Theta$, then there exists weights $\Omega$ for a 3-IGN instance $M_\Omega$ such that $G_1, G_2$ are distinguished by $M_\Omega$ as well.

Theorem 6 has profound consequences in the characterisation of the expressive power of node-based Subgraph GNNS, as we show in the following

**Corollary 7 (3-WL upper-bounds node-based Subgraph GNNS).** Let $G_1, G_2 \in \mathcal{G}$ be two non-isomorphic graphs and $N_\Theta \in \mathcal{T}$ one instance of model $N$ with weights $\Theta$. If $N_\Theta$ distinguishes $G_1, G_2$, then the 3-WL algorithm does so as well.

**Proof idea:** If there is a pair of graphs undistinguishable by 3-WL, but for which there exists a Subgraph GNN separating them, there must exists a 3-IGN separating these (Theorem 6). This is in contradiction with the result by Geerts [21], Azizian and Lelarge [5].

### 6 A design space for Subgraph GNNS

As discussed, different formulations of Subgraph GNNS differ primarily in the specific rules for updating node representations across subgraphs. However, until now it is not clear whether existing rules exhaust all the possible equivariant options. We devote this section to a systematic characterisation of the ‘layer space’ of Subgraph GNNS.

In the spirit of the previous Section 5 where we “embedded” Subgraph GNNS in 3-IGNs, one option would be to consider all bell$(t) = 203$ linear equivariant operations prescribed by this formalism. However, this choice would be problematic for three main reasons: (i) This layer space is too vast to be conveniently explored; (ii) It includes operations involving $O(n^3)$ space complexity, impractical in most applications; (iii) The linear 3IGN basis does not directly support local message passing, a key operation in subgraph methods. Following previous Subgraph GNN variants, which use $O(n^2)$ storage for the representation of $n$ nodes in $n$ subgraphs, we set the desideratum of $O(n^3)$ memory complexity as our main constraint, and use this restriction to reduce the design space. Precisely, we are interested in modelling $S_n$-equivariant transformations on the subgraph-node tensor $X$.

#### 6.1 Extended 2-IGNs

As we have already observed in Equation 3 in Section 3 such a second order tensor $X$ abides by the same symmetry structure of 2-IGNs. We therefore gain intuition from the characterisation of linear equivariant mappings as introduced by Maron et al. [33] and propose an extension of this formalism.

$x$-WL is equivalent to $(x-1)$-FWL, i.e. the “Folklore” WL test, see Morris et al. [36].
The following result states that the ReIGN(2) generalises all known subgraph methods in \( \Upsilon \), as their layers are captured by a 2-IGN stacking. More generally, ReIGN(2) induces a ‘layer space’ for node-based Subgraph GNNs: the expanded layer space. ReIGN(2) induces (linear) layers in the same form of Equation \( \ref{eq:2-IGN} \), but where \( \square \) terms are expanded to both local and global operations, as explained. These layers can operate on any bag generated by a node-based selection policy \( \pi \), and can be combined together in ReIGN(2) stacks of the form \( \mathcal{S}_\mathcal{R} = L^{(T)} \circ \sigma \circ L^{(T-1)} \circ \sigma \circ \ldots \circ \sigma \circ L^{(1)} \), where \( \sigma \)'s are pointwise nonlinearities and \( L \)'s are ReIGN(2) layers. This allows us to define ReIGN(2) models as Subgraph GNNs in the form of Equation \( \ref{eq:ReIGN(2)} \), where \( \mathcal{S} \) is a ReIGN(2) layer stacking and \( \pi \) is node-based: \( \mathcal{R}_\pi = \mu \circ \rho \circ \mathcal{S}_\mathcal{R} \circ \pi \).

More generally, ReIGN(2) induces a ‘layer space’ for node-based Subgraph GNNs: the expanded terms in its update equations represent a pool of atomic operations that can be selected and combined to define new equivariant layers. Compared to that of 3-IGNs, this space is of tractable size, yet it recovers previously proposed Subgraph GNNs and allows to define novel interesting variants.

**Recovering previous Subgraph GNNs.** The following result states that the ReIGN(2) generalises all known subgraph methods in \( \Upsilon \), as their layers are captured by a ReIGN(2) stacking.
Theorem 8 (ReIGN(2) implements node-based Subgraph GNNs). Let $N$ be a model in family $\mathcal{Y}$ equipped with Morris et al.\cite{36} message-passing base-encoders. For any instance $N_\Theta$, there exists ReIGN(2) instance $R_\Omega$ such that $R_\Omega \cong N_\Theta$.

This shows that known methods are generalised without resorting to the $O(n^3)$ computational complexity of 3-IGNs. Figure 3 illustrates the aggregation and sharing rules used by previous Subgraph GNNs to update root and non-root nodes, and compare them with those of ReIGN(2) and 2-IGNs. We visualise these on the subgraph-node sub-tensor gathering node representations across subgraphs; here, root nodes occupy the main diagonal, non-root nodes all the remaining off-diagonal entries. As for to the 2-IGN Equations 4 and 5, the elements in these two partitions may be updated differently, so we depict them separately in, respectively, the bottom and top rows. In each depiction we colour elements depending on the set of weights parameterising their contribution in the update process, with two main specifications: (i) Elements sharing the same colour are pooled together; (ii) Triangles indicate such pooling is performed locally based on the subgraph connectivity at hand (two triangles indicate both local and global pooling ops are performed). E.g., note how DS-GNN (ii) Triangles indicate such pooling is performed locally based on the subgraph connectivity at hand.

Notably, as methods in $\mathcal{Y}$ have been shown to be strictly stronger than 2-\WL\cite{7,14,61,59,56} and 3-\WL. Nevertheless, when employing policies in $\Pi$ and 3-IGN-computable invariant pooling functions $\rho$ (as those used by models in $\mathcal{Y}$), ReIGN(2)s are upper-bounded by 3-IGNs:

**Proposition 9 (3-IGNs implement ReIGN(2)).** For any pair of non-isomorphic graphs $G_1, G_2$ in family $\mathcal{G}$, if there exist policy $\bar{\pi} \in \Pi$, parameters $\Theta$ and 3-IGN-computable invariant pooling function $\rho$ such that the ReIGN(2) instance $R_{\rho,\Theta,\bar{\pi}}$ distinguishes $G_1, G_2$, then there exist weights $\Omega$ for a 3-IGN instance $M_\Omega$ such that $G_1, G_2$ are distinguished by $M_\Omega$ as well.

This proposition entails an upper-bound on the expressive power of ReIGN(2).

**Corollary 10 (3-\WL upper-bounds ReIGN(2)).** The expressive power of a ReIGN(2) model with policy $\pi \in \Pi$ and 3-IGN-computable invariant pooling function $\rho$ is upper-bounded by 3-\WL.

We note that there may be layers equivariant to $S_n$ over $\mathbb{R}^{n^2}$ not captured by ReIGN(2). Yet, previously proposed Subgraph GNN layers do not exhaust the ReIGN(2) design space, which remains largely unexplored. One, amongst possible novel constructions, is introduced next.

### 6.2 A unifying architecture: Subgraph Union Networks

We now show how the ReIGN(2) layer space can guide the design of novel, expressive, Subgraph GNNs. Our present endeavour is to conceive a computationally tractable architecture subsuming known node-based models: in virtue of this latter desideratum, we will dub this architecture “Subgraph Union Network” (SUN). To design the base equivariant layer for SUN, we select and combine specific aggregate terms suggested by the ReIGN(2) framework:

$$x_i^{l,(t+1)} = \sigma \left( v_{\theta_1} \left( x_i^{l,(t)} + \sum_{j \sim k} x_j^{l,(t)}, \sum_j x_j^{l,(t)}, \sum_h x_j^{h,(t)}, \sum_{j \sim h} x_j^{h,(t)} \right) \right) \tag{5}$$

$$x_i^{k,(t+1)} = \sigma \left( v_{\theta_2} \left( x_i^{k,(t)} + \sum_{j \sim k} x_j^{k,(t)}, x_i^{k,(t)}, x_j^{k,(t)}, \sum_j x_j^{k,(t)}, \sum_{j \sim h} x_j^{h,(t)} \right) \right) \tag{6}$$

where $v$’s sum their inputs after applying a specific linear transformations to each term. One of the novel features of SUN is that roots are transformed by a different set of parameters ($\theta_1$) than the other nodes ($\theta_2$, see Figure 2). In practice, the first and last two terms in each one of Equations 5 and 6 can be processed by maximally expressive MPNNs\cite{36,55}, the remaining terms by MLPs. We test these variants in our experiments, with their formulations in Appendix C. SUN remains an instantiation of the ReIGN(2) framework:

**Proposition 11 (A ReIGN(2) stacking implements SUN layers).** For any SUN layer $L$ defined according to Equations 5 and 6, there exists a ReIGN(2) layer stacking $S_L$, such that $S_L \cong L$.\footnote{As a result, the architecture can mark root nodes, for example.}
Table 1: Test mean MAE on the Counting Substructures and ZINC-12k datasets. All Subgraph GNNs employ a GIN base-encoder. † This version of GNN-AK+ does not follow the standard evaluation procedure.

| Method        | Counting Substructures (MAE ↓) | ZINC (MAE ↓) |
|---------------|--------------------------------|--------------|
|               | Triangle | Tailed Tri. | Star | 4-Cycle |               |              |
| GCN [27]      | 0.4186   | 0.3248     | 0.1798 | 0.2822 | GCN           | 0.321 ± 0.009 |
| GIN [55]      | 0.3569   | 0.2373     | 0.0224 | 0.2185 | GIN           | 0.163 ± 0.004 |
| PNA [13]      | 0.3532   | 0.2648     | 0.1278 | 0.2430 | PNA           | 0.133 ± 0.011 |
| PPGN [32]     | 0.00889  | 0.0096     | 0.0148 | 0.0090 | PPGN          | 0.010 ± 0.010 |
| GNN-AK [61]   | 0.0934   | 0.0751     | 0.0168 | 0.0726 | GNN-AK        | 0.091 ± 0.011 |
| GNN-AK-CTX [61] | 0.0885  | 0.0766     | 0.0162 | 0.0668 | GNN-AK-CTX    | 0.086 ± ???   |
| GNN-AK+ [61]  | 0.0123   | 0.0112     | 0.0150 | 0.0126 | GNN-AK+       | 0.091 ± 0.011 |
| SUN (EGO)     | 0.0092   | 0.0105     | 0.0064 | 0.0140 | SUN (EGO)     | 0.083 ± 0.003 |
| SUN (EGO+)    | 0.0079   | 0.0080     | 0.0064 | 0.0105 | SUN (EGO+)    | 0.084 ± 0.002 |

Finally, we show that a stacking of SUN layers can implement any layer of known node-based Subgraph Networks, making this model a principled generalisation thereof.

**Proposition 12** (A SUN stacking implements known Subgraph GNN layers). Let \( \mathcal{N} \) be a model in family \( \Upsilon \) employing Morris et al. [36] as a message-passing base-encoder. Then, for any layer \( L \) in \( \mathcal{N} \), there exists a stacking of SUN layers \( S_L \) such that \( S_L \bowtie L \).

**Beyond SUN.** As it can be seen in Figure 3, SUN does not use all possible operations in the \( \text{ReIGN}(2) \) framework. Notably, two interesting operations that are not a part of SUN are: (i) The ‘transpose’: \( x^k_i = \nu_\theta(x^i_k) \), which shares information between the \( i \)-th node in the \( k \)-th subgraph and the \( k \)-th node in the \( i \)-th subgraph; (ii) Local vertical pooling \( x^k_i = \nu_\theta(P_{h \sim i} x^h_i) \). The exploration of these and other operations is left to future work.

### 7 Experiments

We experimentally validate the effectiveness of one \( \text{ReIGN}(2) \) instantiation, comparing SUN to previously proposed Subgraph GNNs. We seek to verify whether its theoretical representational power practically enables superior accuracy in expressiveness tasks and real-world benchmarks. Concurrently, we pay attention to the generalisation ability of models in comparison. SUN layers are less constrained in their weight sharing pattern, resulting in a more complex model. As this is traditionally associated with inferior generalisation abilities in low data regimes, we deem it important to additionally assess this aspect. Our code is also available.

**Synthetic.** Counting substructures and regressing graph topological features are notoriously hard tasks for GNNs [12, 17, 13]. We test the representational ability of SUN on common benchmarks of this kind [12, 13]. Table 1 reports results on the substructure counting suite, on which SUN attains state-of-the-art results in 3 out of 4 tasks. Additional results on the regression of global, structural properties are reported in Appendix C.

**Real-world.** On the molecular ZINC-12k benchmark (constrained solubility regression) [50, 22, 16], SUN exhibits best performance amongst all domain-agnostic GNNs under the 500k parameter budget, including other Subgraph GNNs (see Table 1). A similar trend is observed on the large-scale Molhiv dataset from the OGB [23] (inhibition of HIV replication). Results are in Table 2. Remarkably, on both datasets, SUN either outperforms or approaches HIMP [19], GSN [11] and CIN [9], GNNs which explicitly model rings. We experiment on smaller-scale TUDatasets in Appendix G, where we also compare selection policies.

---

8For GNN-AK variants [61], we run the code provided by the authors, for which the ‘context’ and ‘subgraph’ embeddings sum only over ego-network nodes.

9https://github.com/beabevi/SUN
Generalisation from limited data. In this set of experiments we compare the test performance of Subgraph GNNs when trained on increasing fractions of the available training data. Each architecture is selected by tuning the hyperparameters with the entire training and validation sets. We run this experiment on the 4-cycle counting task and the real-world ZINC-12k. We illustrate results in Figures 4a to 4c. Except for a short initial phase in the EGO policy, SUN generalises better than other Subgraph GNNs on cycle-counting. On ZINC-12k, SUN outperforms DSS-, DS-GNN and GNN-AK variants from, respectively, 20, 30 and 40% of the samples. These results demonstrate that SUN’s expressiveness is not at the expense of sample efficiency, suggesting that its modelled symmetries guarantee strong representational power while retaining important inductive biases for learning on graphs.

8 Conclusions

Our work unifies, extends, and analyses the emerging class of Subgraph GNNs. Notably, we demonstrated that the expressive power of these methods is bounded by $3$-$\text{WL}$. Towards a systematic study of models whose expressivity lies between $1$- and $3$-$\text{WL}$, we proposed a new family of layers for the class of Subgraph GNNs and, unlike most previous works on the expressive power of GNNs, we also investigated the generalisation abilities of these models, for which SUN shows considerable improvement. Appendix E lists several directions for future work, including an extension of our work to higher-order node-based policies.

Societal impact. We do not envision any negative, immediate societal impact originating from our theoretical results, which represent most of our contribution. Experimentally, our model has shown promising results on molecular property prediction tasks and strong generalisation ability in low-data regimes. This leads us to believe our work may contribute to positively impactful pharmaceutical research, such as drug discovery [20, 3].

Acknowledgments and Disclosure of Funding

The authors are grateful to Joshua Southern, Davide Eynard, Maria Gorinova, Guadalupe Gonzalez, Katarzyna Janocha for valuable feedback on early versions of the manuscript. They would like to thank Bruno Ribeiro and Or Litany for helpful discussions, Giorgos Bouritsas for constructive conversations about the generalisation experiments and, in particular, Marco Ciccone for the precious exchange on sharpness-aware optimisation and Neapolitan pizza. MB is supported in part by ERC Consolidator grant no 724228 (LEMAN). No competing interests are declared.
References

[1] Ralph Abboud, İsmail İlkan Ceylan, Martin Grohe, and Thomas Lukasiewicz. The surprising power of graph neural networks with random node initialization. In Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence (IJCAI), 2020.

[2] Marjan Albooyeh, Daniele Bertolini, and Siamak Ravanbakhsh. Incidence networks for geometric deep learning. arXiv preprint arXiv:1905.11460, 2019.

[3] Han Altae-Tran, Bharath Ramsundar, Aneesh S Pappu, and Vijay Pande. Low data drug discovery with one-shot learning. ACS Central Science, 3(4):283–293, 2017.

[4] James Atwood and Don Towsley. Diffusion-convolutional neural networks. In Advances in Neural Information Processing Systems, volume 29, 2016.

[5] Waïss Azizian and Marc Lelarge. Expressive power of invariant and equivariant graph neural networks. In International Conference on Learning Representations, 2021.

[6] Dominique Beaini, Saro Passaro, Vincent Létourneau, William L. Hamilton, Gabriele Corso, and Pietro Liò. Directional graph networks. In International Conference on Machine Learning, 2021.

[7] Beatrice Bevilacqua, Fabrizio Frasca, Derek Lim, Balasubramaniam Srinivasan, Chen Cai, Gopinath Balamurugan, Michael M Bronstein, and Haggai Maron. Equivariant subgraph aggregation networks. In International Conference on Learning Representations, 2022.

[8] Lukas Biewald. Experiment tracking with weights and biases, 2020. Software available from wandb.com.

[9] Cristian Bodnar, Fabrizio Frasca, Nina Otter, Yuguang Wang, Pietro Liò, Guido F Montúfar, and Michael Bronstein. Weisfeiler and lehman go cellular: Cw networks. In Advances in Neural Information Processing Systems, volume 34, 2021.

[10] Cristian Bodnar, Fabrizio Frasca, Yuguang Wang, Nina Otter, Guido F Montúfar, Pietro Liò, and Michael Bronstein. Weisfeiler and lehman go topological: Message passing simplicial networks. In International Conference on Machine Learning, 2021.

[11] Giorgos Bouritsas, Fabrizio Frasca, Stefanos P Zafeiriou, and Michael Bronstein. Improving graph neural network expressivity via subgraph isomorphism counting. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2022.

[12] Zhengdao Chen, Lei Chen, Soledad Villar, and Joan Bruna. Can graph neural networks count substructures? In Advances in Neural Information Processing Systems, volume 33, 2020.

[13] Gabriele Corso, Luca Cavalleri, Dominique Beaini, Pietro Liò, and Petar Veličković. Principal neighbourhood aggregation for graph nets. In Advances in Neural Information Processing Systems, volume 33, 2020.

[14] Leonardo Cotta, Christopher Morris, and Bruno Ribeiro. Reconstruction for powerful graph representations. In Advances in Neural Information Processing Systems, volume 34, 2021.

[15] Pim de Haan, Taco S Cohen, and Max Welling. Natural graph networks. In Advances in Neural Information Processing Systems, volume 33, 2020.

[16] Vijay Prakash Dwivedi, Chaitanya K Joshi, Thomas Laurent, Yoshua Bengio, and Xavier Bresson. Benchmarking graph neural networks. arXiv preprint arXiv:2003.00982, 2020.

[17] Vijay Prakash Dwivedi, Anh Tuan Luu, Thomas Laurent, Yoshua Bengio, and Xavier Bresson. Graph neural networks with learnable structural and positional representations. In International Conference on Learning Representations, 2022.

[18] Matthias Fey and Jan Eric Lenssen. Fast graph representation learning with pytorch geometric. arXiv preprint arXiv:1903.02428, 2019.
[19] Matthias Fey, Jan-Gin Yuen, and Frank Weichert. Hierarchical inter-message passing for learning on molecular graphs. In *ICML Graph Representation Learning and Beyond (GRL+)* Workshop, 2020.

[20] Thomas Gaudelet, Ben Day, Arian R Jamasb, Jyothish Soman, Cristian Regep, Gertrude Liu, Jeremy B R Hayter, Richard Vickers, Charles Roberts, Jian Tang, David Roblin, Tom L Blundell, Michael M Bronstein, and Jake P Taylor-King. Utilizing graph machine learning within drug discovery and development. *Briefings in Bioinformatics*, 05 2021. ISSN 1477-4054.

[21] Floris Geerts. The expressive power of kth-order invariant graph networks. *arXiv preprint arXiv:2007.12035*, 2020.

[22] Rafael Gómez-Bombarelli, Jennifer N. Wei, David Duvenaud, José Miguel Hernández-Lobato, Benjamín Sánchez-Lengeling, Dennis Sheberla, Jorge Aguilera-Iparraguirre, Timothy D. Hirzel, Ryan P. Adams, and Alán Aspuru-Guzik. Automatic chemical design using a data-driven continuous representation of molecules. *ACS Central Science*, 4(2):268–276, Jan 2018. ISSN 2374-7951. doi: 10.1021/acscentsci.7b00572.

[23] Weihua Hu, Matthias Fey, Marinka Zitnik, Yuxiao Dong, Hongyu Ren, Bowen Liu, Michele Catasta, and Jure Leskovec. Open graph benchmark: Datasets for machine learning on graphs. In *Advances in Neural Information Processing Systems*, volume 33, 2020.

[24] Truong Son Hy, Shubhendu Trivedi, Horace Pan, Brandon M Anderson, and Risi Kondor. Covariant compositional networks for learning graphs. *Anchorage ’19: 15th International Workshop on Mining and Learning with Graphs*, 2019.

[25] Paul J. Kelly. A congruence theorem for trees. *Pacific Journal of Mathematics*, 7(1):961–968, 1957.

[26] Nicolas Keriven and Gabriel Peyré. Universal invariant and equivariant graph neural networks. In *Advances in Neural Information Processing Systems*, volume 32, 2019.

[27] Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. In *International Conference on Learning Representations*, 2017.

[28] Devin Kreuzer, Dominique Beaini, Will Hamilton, Vincent Létourneau, and Prudencio Tossou. Rethinking graph transformers with spectral attention. In *Advances in Neural Information Processing Systems*, volume 34, 2021.

[29] Jungmin Kwon, Jeongseop Kim, Hyunseo Park, and In Kwon Choi. Asam: Adaptive sharpness-aware minimization for scale-invariant learning of deep neural networks. In *International Conference on Machine Learning*, 2021.

[30] Pan Li and Jure Leskovec. The expressive power of graph neural networks. In Lingfei Wu, Peng Cui, Jian Pei, and Liang Zhao, editors, *Graph Neural Networks: Foundations, Frontiers, and Applications*, pages 63–98. Springer Singapore, Singapore, 2022.

[31] Derek Lim, Joshua David Robinson, Lingxiao Zhao, Tess Smidt, Suvrit Sra, Haggai Maron, and Stefanie Jegelka. Sign and basis invariant networks for spectral graph representation learning. In *ICLR 2022 Workshop on Geometrical and Topological Representation Learning*, 2022.

[32] Haggai Maron, Heli Ben-Hamu, Hadar Serviansky, and Yaron Lipman. Provably powerful graph networks. In *Advances in Neural Information Processing Systems*, volume 32, 2019.

[33] Haggai Maron, Heli Ben-Hamu, Nadav Shamir, and Yaron Lipman. Invariant and equivariant graph networks. In *International Conference on Learning Representations*, 2019.

[34] Haggai Maron, Ethan Fetaya, Nimrod Segol, and Yaron Lipman. On the universality of invariant networks. In *International Conference on Machine Learning*, 2019.

[35] Haggai Maron, Or Litany, Gal Chechik, and Ethan Fetaya. On learning sets of symmetric elements. In *International Conference on Machine Learning*, 2020.
[36] Christopher Morris, Martin Ritzert, Matthias Fey, William L Hamilton, Jan Eric Lenssen, Gaurav Rattan, and Martin Grohe. Weisfeiler and leman go neural: Higher-order graph neural networks. In Proceedings of the AAAI conference on artificial intelligence, volume 33, 2019.

[37] Christopher Morris, Nils M Kriege, Franka Bause, Kristian Kersting, Petra Mutzel, and Marion Neumann. TUDataset: A collection of benchmark datasets for learning with graphs. In ICML Graph Representation Learning and Beyond (GRL+) Workshop, 2020.

[38] Christopher Morris, Gaurav Rattan, and Petra Mutzel. Weisfeiler and leman go sparse: Towards scalable higher-order graph embeddings. In Advances in Neural Information Processing Systems, volume 33, 2020.

[39] Christopher Morris, Yaron Lipman, Haggai Maron, Bastian Rieck, Nils M Kriege, Martin Grohe, Matthias Fey, and Karsten Borgwardt. Weisfeiler and leman go machine learning: The story so far. arXiv preprint arXiv:2112.09992, 2021.

[40] Christopher Morris, Gaurav Rattan, Sandra Kiefer, and Siamak Ravanbakhsh. Speqnets: Sparsity-aware permutation-equivariant graph networks. In ICLR 2022 Workshop on Geometrical and Topological Representation Learning, 2022.

[41] Mathias Niepert,Pasquale Minervini, and Luca Franceschi. Implicit mle: Backpropagating through discrete exponential family distributions. In Advances in Neural Information Processing Systems, volume 34, 2021.

[42] Pál András Papp and Roger Wattenhofer. A theoretical comparison of graph neural network extensions. arXiv preprint arXiv:2201.12884, 2022.

[43] Pál András Papp, Karolis Martinkus, Lukas Faber, and Roger Wattenhofer. Dropgnn: Random dropouts increase the expressiveness of graph neural networks. In Advances in Neural Information Processing Systems, 2021.

[44] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In Advances in Neural Information Processing Systems, volume 32, 2019.

[45] Omri Puny, Heli Ben-Hamu, and Yaron Lipman. Global attention improves graph networks generalization. arXiv preprint arXiv:2006.07846, 2020.

[46] Chendi Qian, Gaurav Rattan, Floris Geerts, Christopher Morris, and Mathias Niepert. Ordered subgraph aggregation networks. In Advances in Neural Information Processing Systems, volume 35, 2022.

[47] Siamak Ravanbakhsh. Universal equivariant multilayer perceptrons. In International Conference on Machine Learning, 2020.

[48] Yu Rong, Wenbing Huang, Tingyang Xu, and Junzhou Huang. Dropedge: Towards deep graph convolutional networks on node classification. In International Conference on Learning Representations, 2019.

[49] Ryoma Sato. A survey on the expressive power of graph neural networks. arXiv preprint arXiv:2003.04078, 2020.

[50] Teague Sterling and John J. Irwin. ZINC 15 – ligand discovery for everyone. Journal of Chemical Information and Modeling, 55(11):2324–2337, 11 2015. doi: 10.1021/acs.jcim.5b00559.

[51] Erik Thiede, Wenda Zhou, and Risi Kondor. Autobahn: Automorphism-based graph neural nets. In Advances in Neural Information Processing Systems, volume 34, 2021.

[52] Stanislaw M. Ulam. A collection of mathematical problems, volume 8. Interscience Publishers, 1960.
[53] Clément Vignac, Andreas Loukas, and Pascal Frossard. Building powerful and equivariant graph neural networks with structural message-passing. In Advances in Neural Information Processing Systems, volume 33, 2020.

[54] Boris Weisfeiler and Andrei Leman. The reduction of a graph to canonical form and the algebra which appears therein. NTI, Series, 2(9):12–16, 1968.

[55] Keyulu Xu, Weihua Hu, Jure Leskovec, and Stefanie Jegelka. How powerful are graph neural networks? In International Conference on Learning Representations, 2019.

[56] Jiaxuan You, Jonathan Gomes-Selman, Rex Ying, and Jure Leskovec. Identity-aware graph neural networks. AAAI Conference on Artificial Intelligence (AAAI), 2021.

[57] Chulhee Yun, Suvrit Sra, and Ali Jadbabaie. Small relu networks are powerful memorizers: a tight analysis of memorization capacity. In Advances in Neural Information Processing Systems, volume 32, 2019.

[58] Manzil Zaheer, Satwik Kottur, Siamak Ravanbakhsh, Barnabas Poczos, Russ R Salakhutdinov, and Alexander J Smola. Deep sets. In Advances in Neural Information Processing Systems, volume 30, 2017.

[59] Muhan Zhang and Pan Li. Nested graph neural networks. In Advances in Neural Information Processing Systems, volume 34, 2021.

[60] Muhan Zhang, Zhicheng Cui, Marion Neumann, and Yixin Chen. An end-to-end deep learning architecture for graph classification. Proceedings of the AAAI Conference on Artificial Intelligence, 2018.

[61] Lingxiao Zhao, Wei Jin, Leman Akoglu, and Neil Shah. From stars to subgraphs: Uplifting any GNN with local structure awareness. In International Conference on Learning Representations, 2022.
Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] We discussed limitations of several previous works, as well as our own model, throughout the paper as our main contribution.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] See Section 8.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes]
   (b) Did you include complete proofs of all theoretical results? [Yes] See Appendices B and D.

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] See Section 7 and Appendix G.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Appendix G.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] We report the standard deviation computed over multiple seeds for experiments on ZINC12k (Table 1), ogbg-molhiv (Table 2) and on all generalisation experiments (Figures 4a to 4c). We report the standard deviation for the “Counting Substructures” experiments (Table 1) in Appendix G.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Appendix G.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [Yes] See Appendix G.
   (c) Did you include any new assets either in the supplemental material or as a URL? [N/A]
   (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]

5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]