# STRATEGIES FOR PRE-TRAINING GRAPH NEURAL NETWORKS

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## ABSTRACT

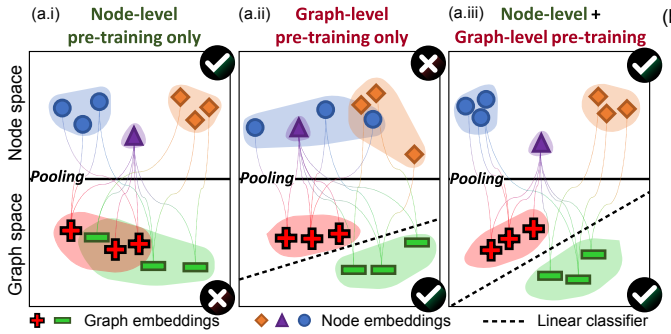
Many domains in machine learning have datasets with a large number of related but different tasks. Those domains are challenging because task-specific labels are often scarce and test examples can be distributionally different from examples seen during training. An effective solution to these challenges is to pre-train a model on related tasks where data is abundant, and then fine-tune it on a downstream task of interest. While pre-training has been effective for improving many language and vision domains, pre-training on graph datasets remains an open question. Here, we develop a strategy for pre-training Graph Neural Networks (GNNs). Crucial to the success of our strategy is to pre-train an expressive GNN at the level of individual nodes as well as entire graphs. We systematically study different pre-training strategies on multiple datasets and find that when ad-hoc strategies are applied, pre-trained GNNs often exhibit negative transfer and perform worse than non-pre-trained GNNs on many downstream tasks. In contrast, our proposed strategy is effective and avoids negative transfer across downstream tasks, leading up to 11.7% absolute improvements in ROC-AUC over non-pre-trained models and achieving state of the art performance.

## 1 INTRODUCTION

Deep transfer learning, where a model trained on some tasks is re-purposed on a different related task, has been immensely successful in computer vision (He et al., 2016; Krizhevsky et al., 2012) and language modeling (Devlin et al., 2018; Peters et al., 2018; Mikolov et al., 2013). Pre-training is an effective approach to transfer learning and can potentially provide a solution to the following two fundamental challenges with learning on graph datasets (Pan & Yang, 2009; Hendrycks et al., 2019): First, task-specific labeled data can be extremely scarce. This problem is exacerbated in important graph datasets from scientific domains, such as chemistry and biology, where data labeling (*e.g.*, biological experiments in a wet laboratory) is resource- and time-intensive (Zitnik et al., 2018). Second, graph data from real-world applications often contain out-of-distribution samples, meaning that graphs in the training set are structurally very different from graphs in the test set. Out-of-distribution prediction is common in real-world datasets, for example, it occurs when one wants to predict chemical properties of a brand-new, just synthesized molecule, which is different from all molecules synthesized so far, and thereby different from all molecules in the training set.

However, pre-training on graph datasets remains a hard challenge; there is currently no systematic investigation of pre-training for prevailing machine learning methods that operate on graphs, *i.e.*, Graph Neural Networks (GNNs) (Kipf & Welling, 2017; Hamilton et al., 2017a; Ying et al., 2018b; Xu et al., 2019; 2018). Thus, we do not know what pre-training strategies are effective and how effective they are on hard real-world datasets. This is especially important because transfer learning in certain scientific domains has had rather mixed results. Several key studies (Xu et al., 2017; Ching et al., 2018; Wang et al., 2019) have shown that successful transfer learning is not only a matter of increasing the size of a labeled dataset. Instead, it requires substantial domain expertise to carefully select examples and properties that are correlated with the downstream task of interest. Otherwise, the transfer of knowledge from a related task that has already been learned to a new task can harm generalization, which is known as negative transfer (Rosenstein et al., 2005).

**Present work.** In this paper, we focus on pre-training as an approach to transfer learning in GNNs. Our work presents two key contributions. (1) We conduct the first systematic large-scale investigation of strategies for pre-training GNNs. For that, we build two large new pre-training datasets, which we will share with the community: a chemistry dataset with 2 million graphs and a biology dataset




(b) Categorization of our pre-training methods

| | Node-level | Graph-level |
|---|---|---|
| **Attribute prediction** | Attribute Masking | Supervised Attribute Prediction |
| **Structure prediction** | Context Prediction | Structural Similarity Prediction |

Figure 1: **(a.i)** When only node-level pre-training is used, nodes of different shapes (semantically different nodes) can be well separated, however, node embeddings are not composable, and thus resulting graph embeddings (denoted by their classes, $+$ and $-$) that are created by pooling node-level embeddings are not separable. **(a.ii)** With graph-level pre-training only, graph embeddings are well separated, however the embeddings of individual nodes do not necessarily capture their domain-specific semantics. **(a.iii)** High-quality node embeddings are such that nodes of different types are well separated, while at the same time, the embedding space is also composable. This allows for accurate and robust representations of entire graphs and enables robust transfer of pre-trained models to a variety of downstream tasks. **(b)** Categorization of pre-training methods for GNNs. Crucially, our methods, *i.e.*, Context Prediction, Attribute Masking, and graph-level supervised pre-training (Supervised Attribute Prediction) enable both node-level and graph-level pre-training.

with 395K graphs. We also show that large datasets are crucial to investigate pre-training and that existing benchmark datasets are too small to evaluate pre-training in a statistically reliable way. (2) We develop a principled pre-training strategy for GNNs and demonstrate its effectiveness and its ability for out-of-distribution generalization on hard transfer-learning problems.

(1) In our systematic study, we show that pre-training GNNs does not always help. Ad-hoc pre-training strategies can lead to negative transfer on many downstream tasks. Strikingly, a seemingly strong pre-training strategy (*i.e.*, graph-level multi-task supervised pre-training using a state-of-the-art graph neural network architecture for graph-level prediction tasks) only gives marginal performance gains. Furthermore, this strategy even leads to negative transfer on many downstream tasks (2 out of 8 molecular datasets and 12 out of 40 protein prediction tasks). We find that effective pre-training of GNNs is challenging, especially on hard transfer learning problems.

(2) We develop an effective strategy for pre-training GNNs. The key idea is to use easily accessible node-level information and encourage GNNs to capture domain-specific knowledge about nodes and edges. This idea is crucial to be able to generate graph-level representations (which are obtained by pooling node representations) that are robust and transferable to diverse downstream tasks (Figure 1). Empirically, our pre-training strategy used together with an expressive GNN yields state-of-the-art results on benchmark datasets and completely avoids negative transfer in all downstream tasks we tested. It significantly improves generalization performance across downstream tasks, yielding up to 7.2% (resp. 11.7%) higher average ROC-AUC scores than non-pre-trained GNNs, and up to 4.1% (resp. 6.1%) higher average ROC-AUC scores compared to GNNs with the extensive graph-level multi-task supervised pre-training. Furthermore, we find that highly expressive GNN architectures (*e.g.*, Graph Isomorphism Network (Xu et al., 2019)) benefit most from pre-training, and that pre-training GNNs leads to orders-of-magnitude faster training and convergence in the fine-tuning stage.

## 2 Preliminaries on Graph Neural Networks

We first formalize supervised learning of graphs and provide an overview of GNNs (Gilmer et al., 2017). Then, we briefly review methods for unsupervised graph representation learning.

**Supervised learning of graphs.** Let $G = (V, E)$ denote a graph with node feature vectors $X_v$ for $v \in V$ and edge feature vectors $e_{uv}$ for $(u, v) \in E$. Given a set of graphs $\{G_1, \ldots, G_N\}$ and their labels $\{y_1, \ldots, y_N\}$, the task of graph supervised learning is to learn a representation vector $h_G$ that helps predict the label of an entire graph $G$, $y_G = g(h_G)$.

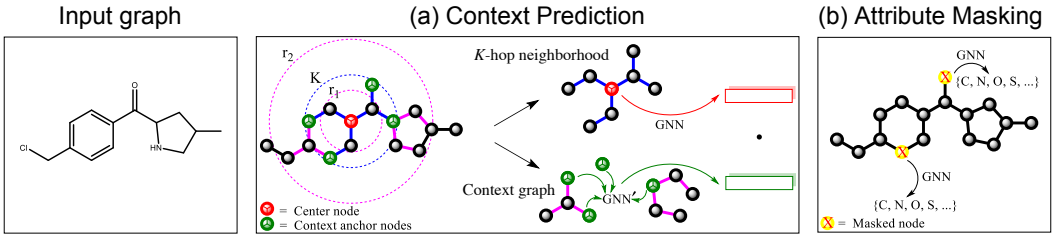



Figure 2: Illustration of our node-level methods, Context Prediction and Attribute Masking for pre-training GNNs. **(a)** In Context Prediction, the subgraph is a $K$-hop neighborhood around a selected center node, where $K$ is the number of GNN layers and is set to 2 in the figure. The context is defined as the surrounding graph structure that is between $r_1$- and $r_2$-hop from the center node, where we use $r_1 = 1$ and $r_2 = 4$ in the figure. **(b)** In Attribute Masking, the input node/edge attributes (*e.g.*, atom type in the molecular graph) are randomly masked, and the GNN is asked to predict them.

**Graph Neural Networks (GNNs)**. GNNs use the graph connectivity as well as node and edge features to learn a representation vector (*i.e.*, embedding) $h_v$ for every node $v \in G$ and a vector $h_G$ for the entire graph $G$. Modern GNNs use a neighborhood aggregation approach, where representation of node $v$ is iteratively updated by aggregating representations of $v$'s neighboring nodes and edges (Gilmer et al., 2017). After $k$ iterations of aggregation, $v$'s representation captures the structural information within its $k$-hop network neighborhood. Formally, the $k$-th layer of a GNN is:

$$h_v^{(k)} = \text{COMBINE}^{(k)}\left(h_v^{(k-1)}, \text{AGGREGATE}^{(k)}\left(\left\{\left(h_v^{(k-1)}, h_u^{(k-1)}, e_{uv}\right) \colon u \in \mathcal{N}(v)\right\}\right)\right), \quad (2.1)$$

where $h_v^{(k)}$ is the representation of node $v$ at the $k$-th iteration/layer, $e_{uv}$ is the feature vector of edge between $u$ and $v$, and $\mathcal{N}(v)$ is a set neighbors of $v$. We initialize $h_v^{(0)} = X_v$. To obtain the entire graph's representation $h_G$, the READOUT function pools node features from the final iteration $K$,

$$h_G = \text{READOUT}\big(\{h_v^{(K)} \mid v \in G\}\big). \quad (2.2)$$

READOUT is a permutation-invariant function, such as averaging or a more sophisticated graph-level pooling function (Ying et al., 2018b; Zhang et al., 2018).

**Node representation learning.** There is rich literature on unsupervised representation learning of *nodes* within graphs, which broadly falls into two categories. In the first category are methods that use local random walk-based objectives (Grover & Leskovec, 2016; Perozzi et al., 2014; Tang et al., 2015) and methods that reconstruct a graph's adjacency matrix, *e.g.*, by predicting edge existence (Hamilton et al., 2017a; Kipf & Welling, 2016). In the second category are methods, such as Deep Graph Infomax (Veličković et al., 2019) that train a node encoder that maximizes mutual information between local node representations and a pooled global graph representation. All these methods encourage nearby nodes to have similar embeddings and were originally proposed and evaluated for node classification and link prediction. This, however, can be sub-optimal for graph-level prediction tasks, where capturing *structural* similarity of local neighborhoods is often more important than positional information (You et al., 2019; Rogers & Hahn, 2010; Yang et al., 2014).

## 3 Strategies for Pre-training Graph Neural Networks

At the technical core of our pre-training strategy is the notion to pre-train a GNN *both* at the level of individual nodes as well as entire graphs. This notion encourages the GNN to capture domain-specific semantics at both levels, as illustrated in Figure 1 (a.iii). This is in contrast to straightforward but limited pre-training strategies that either only use pre-training to predict properties of entire graphs (Figure 1 (a.ii)) or only use pre-training to predict properties of individual nodes (Figure 1 (a.i)).

In the following, we first describe our node-level pre-training approach (Section 3.1) and then graph-level pre-training approach (Section 3.2). The methods, when considered together, give rise to a pre-training strategy that can capture domain-specific semantics at both network scales. We describe the full pre-training strategy in Section 3.3.

### 3.1 NODE-LEVEL PRE-TRAINING

For node-level pre-training of GNNs, our approach is to use unlabeled data, which is often easily accessible, and use the natural graph distribution to capture domain-specific knowledge/regularities in the graph. Next, we propose two self-supervised methods, Context Prediction and Attribute Masking. Both methods exploit the natural graph distribution but do so in complementary ways.

#### 3.1.1 CONTEXT PREDICTION: EXPLOITING DISTRIBUTION OF GRAPH STRUCTURE

In Context Prediction, we exploit the distribution of graph structure. To do that, we leverage subgraphs and predict their surrounding graph structures. Our goal is to pre-train a GNN so that it maps nodes with similar surrounding structures to nearby embeddings (Rubenstein & Goodenough, 1965; Mikolov et al., 2013).

**Neighborhood and context graphs.** For every node $v$, we define $v$'s neighborhood and context graphs as follows. The *neighborhood* of node $v$ is a $K$-hop neighborhood of $v$, meaning that the neighborhood contains all nodes and edges that are at most $K$-hops away from $v$ in the graph. This is because a $K$-layer GNN aggregates information across the $K$-th order neighborhood of $v$, and thus node embedding $h_v^{(K)}$ depends on nodes that are at most $K$-hops away from $v$. We define *context graph* of node $v$ as graph structure that surrounds $v$'s neighborhood. The context graph is described by two hyperparameters, $r_1$ and $r_2$, and it represents a subgraph that is between $r_1$-hops and $r_2$-hops away from $v$ (*i.e.*, it is a ring of width $r_2 - r_1$). Examples of neighborhood and context graphs are shown in Figure 2 (a). We require $r_1 < K$ so that some nodes are shared between the neighborhood and the context graph, and we refer to those nodes as *context anchor nodes*.

**Encoding context into a fixed vector using an auxiliary GNN.** Directly predicting the context graph is intractable due to the combinatorial nature of graphs. This is different from natural language processing, where words come from a fixed and finite vocabulary. To enable context prediction, we encode context graphs as *fixed-length vectors*. To this end, we use an auxiliary GNN, which we refer to as *context GNN*. As depicted in Figure 2 (a), we first apply the context GNN (denoted as GNN$'$ in Figure 2 (a)) to obtain node embeddings in the context graph. We then average embeddings of *context anchor nodes* to obtain a fixed-length context embedding. For node $v$ in graph $G$, we denote its corresponding context embedding as $c_v^G$.

**Learning via negative sampling.** We use negative sampling (Mikolov et al., 2013; Ying et al., 2018a) to jointly learn the main GNN and the context GNN. The main GNN encodes neighborhoods to obtain node embeddings. The context GNN encodes context graphs to obtain context embeddings. In particular, the learning objective of Context Prediction is a binary classification of whether a particular neighborhood and a particular context graph belong to the same node:

$$\sigma\left(h_v^{(K)\top} c_{v'}^{G'}\right) \approx \mathbf{1}\{v \text{ and } v' \text{ are the same nodes}\}, \tag{3.1}$$

where $\sigma(\cdot)$ is the sigmoid function, and $\mathbf{1}(\cdot)$ is the indicator function. We either let $v' = v$ and $G' = G$ (*i.e.*, a positive neighborhood-context pair), or we randomly sample $v'$ from a randomly chosen graph $G'$ (*i.e.*, a negative neighborhood-context pair). We use a negative sampling ratio of 1 (one negative pair per one positive pair), and use the negative log likelihood as the loss function. After pre-training, the main GNN is retained as our pre-trained model.

**Relation to existing methods.** A number of recent works have explored how node embeddings generalize across tasks (Jaeger et al., 2018; Zhou et al., 2018; Chakravarti, 2018; Narayanan et al., 2016). However, all of these methods use distinct embeddings for different neighborhoods/contexts and do not share any parameters. Thus, they are inherently transductive, cannot transfer between datasets, cannot be fine-tuned in an end-to-end manner, and cannot capture large and diverse neighborhoods/contexts due to data sparsity. Here we address all these challenges. Another line of work uses random-walks and defines context as surrounding nodes, not surrounding structures (Grover & Leskovec, 2016; Perozzi et al., 2014). Consequently, existing methods capture positional information of nodes rather than their neighboring structure information, the latter being more suitable for graph-level prediction (Yang et al., 2014; Rogers & Hahn, 2010).

#### 3.1.2 ATTRIBUTE MASKING: EXPLOITING DISTRIBUTION OF GRAPH ATTRIBUTES

In Attribute Masking, we exploit the data distribution by learning how node and edge attributes are distributed over graph structure.

**Masking node and edges attributes.** We develop Attribute Masking pre-training method, which works as follows. First, we mask node/edge attributes and then we let GNNs predict those attributes based on neighboring structure (Devlin et al., 2018). Figure 2 (b) illustrates our proposed method when applied to a molecular graph. We randomly mask input node/edge attributes, for example atom types in molecular graphs, by replacing them with special masked indicators. We then apply GNNs to obtain the corresponding node/edge embeddings (edge embeddings can be obtained as a sum of node embeddings of the edge's end-nodes). Finally, a linear model is applied on top of embeddings to predict a masked node/edge attribute.

Our node and edge masking strategies are especially beneficial in richly-annotated graphs from scientific domains. For example, (1) in molecular graphs, the node attributes correspond to atom types, and capturing how they are distributed over the graphs enables GNNs to learn simple chemistry rules such as valency, as well as potentially more complex chemistry phenomenon such as the electronic or steric properties of functional groups. Similarly, (2) in protein-protein interaction (PPI) graphs, the edge attributes correspond to different kinds of interaction between a pair of proteins. Capturing how these attributes distribute across the PPI graphs enables GNNs to learn how different interactions relate and correlate with each other.

### 3.2 Graph-level Pre-training

We aim to pre-train GNNs to generate useful graph embeddings composed of the meaningful node embeddings obtained by methods in Section 3.1. Our goal is to ensure both node and graph embeddings are of high-quality; consequently, graph embeddings are robust and transferable across downstream tasks, as illustrated in Figure 1 (a.iii).

As shown in Figure 1 (b), there are two options for graph-level pre-training: (1) making predictions about domain-specific attributes of entire graphs (*e.g.*, supervised labels), or, (2) making predictions about graph structure, *e.g.*, graph edit distance (Bai et al., 2019) or graph structure similarity (Navarin et al., 2018). As the graph-level representation $h_G$ is directly used for fine-tuning on downstream prediction tasks, it is desirable to directly encode domain-specific information into $h_G$. Here we use the first option and consider a practical method to pre-train graph representations; graph-level multi-task supervised pre-training to jointly predict a diverse set of supervised graph labels. This is analogous to massive multi-task supervised pre-training on ImageNet (Krizhevsky et al., 2012), which predicts a set of object categories. Specifically, we apply linear classifiers on top of graph representations to jointly predict graph properties, where each property corresponds to a binary classification task. The actual graph-level supervised tasks and datasets are in Section 4.1.

### 3.3 Overview: Pre-training GNNs and Fine-tuning for Downstream Tasks

Altogether, our pre-training strategy is to first perform node-level self-supervised pre-training (Section 3.1) and then graph-level multi-task supervised pre-training (Section 3.2). When GNN pre-training is finished, we fine-tune the GNN for downstream tasks. Specifically, we add randomly-initialized linear classifiers on top of graph-level representations to predict downstream graph labels. The full model, *i.e.*, the pre-trained GNN and downstream linear classifiers, is subsequently fine-tuned in an end-to-end manner. Time-complexity analysis is provided in Appendix F.

## 4 Experiments

We thoroughly compare our pre-training strategy with two strong baselines: (i) extensive supervised multi-task pre-training on relevant graph-level tasks, and (ii) node-level self-supervised pre-training.

### 4.1 Datasets

We consider two domains; molecular property prediction in chemistry and protein function prediction in biology, and we build two new large datasets, which we release and share with the community.

**Pre-training datasets.** For the chemistry domain, we use 2 million unlabeled molecules sampled from the ZINC15 database (Sterling & Irwin, 2015) for node-level self-supervised pre-training. For graph-level multi-task supervised pre-training, we use a preprocessed ChEMBL dataset (Mayr et al., 2018; Gaulton et al., 2011), containing 456K molecules with 1310 kinds of diverse and extensive biochemical assays. For the biology domain, we use 395K unlabeled protein ego-networks derived

from PPI networks of 50 species (*e.g.*, humans, yeast, zebra fish) for node-level self-supervised pre-training. For graph-level multi-task supervised pre-training, we use 88K labeled protein ego-networks to jointly predict 5000 *coarse-grained* biological functions (*e.g.*, cell apoptosis, cell proliferation).

**Downstream classification datasets.** For the chemistry domain, we considered classical graph classification benchmarks (MUTAG, PTC molecule datasets) (Kersting et al., 2016; Xu et al., 2019) as our downstream tasks, but found that they are too small (188 and 344 examples for MUTAG and PTC) to evaluate different methods in a statistically meaningful way (see Appendix B for the results and discussion). Because of this, as our downstream tasks, we decided to use 8 larger binary classification datasets contained in MoleculeNet (Wu et al., 2018), a recently-curated benchmark for molecular property prediction. The dataset statistics are summarized in Table 2. For the biology domain, we compose our PPI networks from Zitnik et al. (2019), consisting of 88K proteins from 8 different species, where the subgraphs centered at a protein of interest (*i.e.*, ego-networks) are used to predict their biological functions. Our downstream task is to predict 40 *fine-grained* biological functions[1] that correspond to 40 binary classification tasks. In contrast to existing PPI datasets (Hamilton et al., 2017a), our dataset is larger and spans multiple species (*i.e.*, not only humans), which makes it a suitable benchmark for evaluating out-of-distribution generalization. Additional details about datasets and features of molecule/PPI graphs are in Appendices C and D.

**Dataset splitting.** In many applications, conventional random split is overly optimistic and does not simulate the real-world use case, where test graphs can be structurally different from training graphs (Wu et al., 2018; Zitnik et al., 2019). To reflect the actual use case, we split the downstream data in the following ways to evaluate the models' *out-of-distribution generalization*. In the chemistry domain, we use *scaffold split* (Ramsundar et al., 2019), where we split molecules according to their scaffold (molecular substructure). In the biology domain, we use *species split*, where we predict functions of proteins from new species. Details are in Appendix E. Furthermore, to prevent data leakage, all test graphs used for performance evaluation are removed from the graph-level supervised pre-training datasets.

### 4.2 Experimental Setup

**GNN architectures.** We mainly study Graph Isomorphism Networks (GINs) (Xu et al., 2019), the most expressive and state-of-the-art GNN architecture for graph-level prediction tasks. We also experimented with other popular architectures that are less expressive: GCN (Kipf & Welling, 2016), GAT (Veličković et al., 2019), and GraphSAGE (with mean neighborhood aggregation) (Hamilton et al., 2017b). We select the following hyper-parameters that performed well across all downstream tasks in the validation sets: 300 dimensional hidden units, 5 GNN layers ($K = 5$), and average pooling for the READOUT function. Additional details can be found in Appendix A.

**Pre-training.** For Context Prediction illustrated in Figure 2 (a), on molecular graphs, we define context graphs by setting inner radius $r_1 = 4$, and on PPI networks, we use $r_1 = 1$. For both molecular and PPI graphs, we let outer radius $r_2 = r_1 + 3$, and use a 3-layer GNN to encode the context structure. For Attribute Masking shown in Figure 2 (b), we randomly mask 15% of node (for molecular graphs) or edge attributes (for PPI networks) for prediction. As baselines for node-level self-supervised pre-training, we adopt the original Edge Prediction (denoted by EdgePred) (Hamilton et al., 2017a) and Deep Graph Infomax (denoted by Infomax) (Veličković et al., 2019) implementations. Further details are provided in Appendix G.

### 4.3 Results

We report results for molecular property prediction and protein function prediction in Tables 1 and 2 and Figure 3. Our systematic study suggests the following trends: **(1)** Overall, Table 1 shows that our pre-training strategy used together with an expressive GNN architecture achieves the best performance across all benchmarks and domains, outperforming non-pre-trained model by a large margin. **(2)** The strong baseline strategy that performs extensive graph-level multi-task supervised pre-training of GNNs on large-scale datasets gives surprisingly limited performance gain and yields negative transfer on many downstream tasks (2 out of 8 datasets in molecular prediction, and 12 out of 40 tasks in protein function prediction. See shaded cells of Table 2, and highlighted region in the middle panel of Figure 3). **(3)** Further, we find that another baseline strategy, which performs node-level self-supervised pre-training, also gives limited performance improvement and is comparable to the

[1]Fine-grained labels are harder to obtain than coarse-grained labels; the latter are used for pre-training.

| | Chemistry | | | Biology | | |
|---|---|---|---|---|---|---|
| | Non-pre-trained | Pre-trained | Gain | Non-pre-trained | Pre-trained | Gain |
| GIN | 67.0 | **74.2** | **+7.2** | $64.2 \pm 1.4$ | $\mathbf{75.9 \pm 0.8}$ | **+11.7** |
| GCN | **68.9** | 72.2 | +3.4 | $64.5 \pm 0.8$ | $71.8 \pm 1.8$ | +7.3 |
| GraphSAGE | 68.3 | 70.3 | +2.0 | $65.6 \pm 1.3$ | $69.4 \pm 0.8$ | +4.2 |
| GAT | 66.8 | 60.3 | -6.5 | $\mathbf{67.6 \pm 0.9}$ | $73.5 \pm 2.4$ | +6.9 |

Table 1: **Test ROC-AUC (%) performance of different GNN architectures with and without pre-training.** Without pre-training, the less expressive GNNs give slightly better performance than the most expressive GIN because of their smaller model complexity in a low data regime. However, with pre-training, the most expressive GIN is properly regularized and dominates the other architectures. For results split by chemistry datasets, see Table 4 in Appendix H. Pre-training strategy for chemistry data: Context Prediction + Graph-level supervised pre-training; pre-training strategy for biology data: Attribute Masking + Graph-level supervised pre-training.

| Dataset | | BBBP | Tox21 | ToxCast | SIDER | ClinTox | MUV | HIV | BACE | **Average** |
|---|---|---|---|---|---|---|---|---|---|---|
| # Molecules | | 2039 | 7831 | 8575 | 1427 | 1478 | 93087 | 41127 | 1513 | / |
| # Binary prediction tasks | | 1 | 12 | 617 | 27 | 2 | 17 | 1 | 1 | / |
| Pre-training strategy | | Out-of-distribution prediction (scaffold split) | | | | | | | | |
| Graph-level | Node-level | | | | | | | | | |
| – | – | $65.8 \pm 4.5$ | $74.0 \pm 0.8$ | $63.4 \pm 0.6$ | $57.3 \pm 1.6$ | $58.0 \pm 4.4$ | $71.8 \pm 2.5$ | $75.3 \pm 1.9$ | $70.1 \pm 5.4$ | 67.0 |
| – | Infomax | $\mathbf{68.8 \pm 0.8}$ | $75.3 \pm 0.5$ | $62.7 \pm 0.4$ | $58.4 \pm 0.8$ | $69.9 \pm 3.0$ | $75.3 \pm 2.5$ | $76.0 \pm 0.7$ | $75.9 \pm 1.6$ | 70.3 |
| – | EdgePred | $67.3 \pm 2.4$ | $76.0 \pm 0.6$ | $64.1 \pm 0.6$ | $60.4 \pm 0.7$ | $64.1 \pm 3.7$ | $74.1 \pm 2.1$ | $76.3 \pm 1.0$ | $79.9 \pm 0.9$ | 70.3 |
| – | AttrMasking | $64.3 \pm 2.8$ | $76.7 \pm 0.4$ | $64.2 \pm 0.5$ | $61.0 \pm 0.7$ | $71.8 \pm 4.1$ | $74.7 \pm 1.4$ | $77.2 \pm 1.1$ | $79.3 \pm 1.6$ | 71.1 |
| – | ContextPred | $68.0 \pm 2.0$ | $75.7 \pm 0.7$ | $63.9 \pm 0.6$ | $60.9 \pm 0.6$ | $65.9 \pm 3.8$ | $75.8 \pm 1.7$ | $77.3 \pm 1.0$ | $79.6 \pm 1.2$ | 70.9 |
| Supervised | – | $68.3 \pm 0.7$ | $77.0 \pm 0.3$ | $64.4 \pm 0.4$ | $62.1 \pm 0.5$ | $57.2 \pm 2.5$ | $79.4 \pm 1.3$ | $74.4 \pm 1.2$ | $76.9 \pm 1.0$ | 70.0 |
| Supervised | Infomax | $68.0 \pm 1.8$ | $77.8 \pm 0.3$ | $64.9 \pm 0.7$ | $60.9 \pm 0.6$ | $\mathbf{71.2 \pm 2.8}$ | $\mathbf{81.3 \pm 1.4}$ | $77.8 \pm 0.9$ | $80.1 \pm 0.9$ | 72.8 |
| Supervised | EdgePred | $66.6 \pm 2.2$ | $\mathbf{78.3 \pm 0.3}$ | $\mathbf{66.5 \pm 0.3}$ | $\mathbf{63.3 \pm 0.9}$ | $70.9 \pm 4.6$ | $78.5 \pm 2.4$ | $77.5 \pm 0.8$ | $79.1 \pm 3.7$ | 72.6 |
| Supervised | AttrMasking | $66.5 \pm 2.5$ | $77.9 \pm 0.4$ | $65.1 \pm 0.3$ | $\mathbf{63.9 \pm 0.9}$ | $\mathbf{73.7 \pm 2.8}$ | $\mathbf{81.2 \pm 1.9}$ | $77.1 \pm 1.2$ | $80.3 \pm 0.9$ | 73.2 |
| Supervised | ContextPred | $\mathbf{68.7 \pm 1.3}$ | $\mathbf{78.1 \pm 0.6}$ | $65.7 \pm 0.6$ | $62.7 \pm 0.8$ | $\mathbf{72.6 \pm 1.5}$ | $\mathbf{81.3 \pm 2.1}$ | $\mathbf{79.9 \pm 0.7}$ | $\mathbf{84.5 \pm 0.7}$ | **74.2** |

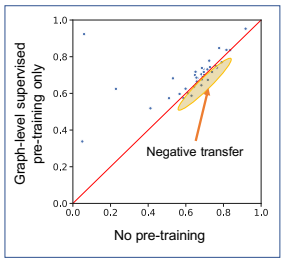
Table 2: **Test ROC-AUC (%) performance on molecular prediction benchmarks using different pre-training strategies with GIN.** The rightmost column averages the mean of test performance across the 8 datasets. The best result for each dataset and comparable results (*i.e.*, results within one standard deviation from the best result) are bolded. The shaded cells indicate negative transfer, *i.e.*, ROC-AUC of a pre-trained model is worse than that of a non-pre-trained model.

graph-level multi-task supervised pre-training baseline. **(4)** Our pre-training strategy of combining graph-level multi-task supervised and node-level self-supervised pre-training completely avoids negative transfer in all downstream datasets that we tested. Further, it gives significantly better generalization performance than the two baseline strategies. **(5)** Compared with gains of pre-training achieved by GIN architecture, gains of pre-training using less expressive GNNs (GCN, GraphSAGE, and GAT) are smaller and can sometimes even be negative (Table 1). This finding confirms previous observations (*e.g.*, Erhan et al. (2010)) that using an expressive model is crucial to fully utilize pre-training, and that pre-training can even hurt performance when used on models with limited expressive power. **(6)** Beyond generalization improvement, Figure 4 shows that our pre-trained models achieve orders-of-magnitude faster training and validation convergence than non-pre-trained models. We observe that pre-trained models require less than 10 epochs to achieve the best validation performance, whereas non-pre-trained models require nearly 100 epochs. This result is true across all the datasets we used, as shown in Figure 5 in Appendix I.

**Chemistry.** The results in Table 2 show that our Context Prediction + Graph-level multi-task supervised pre-training strategy gives the most promising performance, leading to an increase in average ROC-AUC of 7.2% over non-pre-trained baseline and 4.2% over graph-level multi-task supervised pre-trained baseline. On the HIV dataset, where a number of recent works (Wu et al., 2018; Li et al., 2017; Ishiguro et al., 2019) have reported performance on the same scaffold split and using the same protocol, our best pre-trained model (ContextPred + Supervised) achieves state-of-the-art performance. In particular, we achieved a ROC-AUC score of 79.9%, while best-performing graph models in Wu et al. (2018), Li et al. (2017), and Li et al. (2017) had ROC-AUC scores of 76.3%, 77.6%, and 76.2%, respectively.

We also report performance on classic benchmarks (MUTAG, PTC molecule datasets) in Appendix B. However, as mentioned in Section 4.1, the extremely small dataset sizes make these benchmarks unsuitable to compare different methods in a statistically reliable way.

| Pre-training strategy | | Out-of-dist. |
|---|---|---|
| Graph-level | Node-level | (species split) |
| – | – | 64.2 ±1.4 |
| – | Infomax | 63.6 ±1.2 |
| – | EdgePred | 66.1 ±1.5 |
| – | ContextPred | 64.8 ±1.3 |
| – | AttrMasking | 64.3 ±1.4 |
| Supervised | – | 69.8 ±2.2 |
| Supervised | Infomax | 71.7 ±1.8 |
| Supervised | EdgePred | 72.9 ±1.2 |
| Supervised | ContextPred | 74.3 ±0.9 |
| Supervised | AttrMasking | **75.9 ±0.8** |



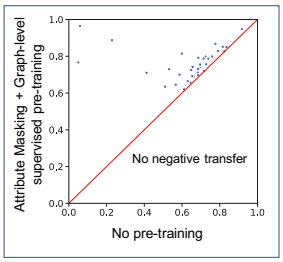




Figure 3: **Test ROC-AUC of protein function prediction using different pre-training strategies with GIN. (Left)** Test ROC-AUC scores (%) obtained by different pre-training strategies, where the scores are averaged over the 40 fine-grained prediction tasks. **(Middle and right):** Scatter plot comparisons of ROC-AUC scores for a pair of pre-training strategies on the 40 *individual* downstream tasks. Each point represents a particular individual downstream task. **(Middle):** There are many *individual* downstream tasks where graph-level multi-task supervised pre-trained model performs worse than non-pre-trained model, indicating negative transfer. **(Right):** When the graph-level multi-task supervised pre-training and Attribute Masking are combined, negative transfer is completely avoided across all 40 downstream tasks.

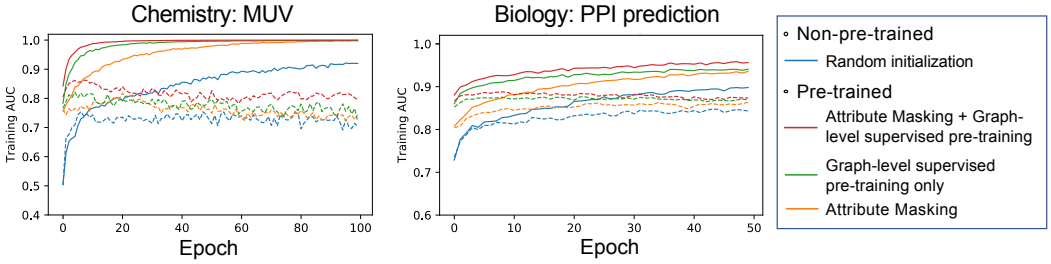



Figure 4: **Training and validation curves of different pre-training strategies on GINs.** Solid and dashed lines indicate training and validation curves, respectively.

**Biology.** Figure 3 shows that our Attribute Masking + Graph-level multi-task supervised pre-training strategy achieves superior generalization performance compared to other baselines *across almost all* 40 downstream prediction tasks. In particular, our strategy improves average ROC-AUC by 11.7% over non-pre-trained baseline and 6.1% over graph-level multi-task supervised pre-trained baseline.

## 5 Conclusions and Future Work

We developed a novel strategy for pre-training GNNs. Crucial to the success of our strategy is to consider both node-level and graph-level pre-training in combination with an expressive GNN. This ensures that node embeddings capture local neighborhood semantics that are pooled together to obtain meaningful graph-level representations, which, in turn, are used for downstream tasks. Experiments on multiple datasets, diverse downstream tasks and different GNN architectures show that the new pre-training strategy achieves consistently better out-of-distribution generalization than non-pre-trained models.

Our work makes an important step toward transfer learning on graphs and addresses the issue of negative transfer observed in prior studies. There are many interesting avenues for future work. For example, further increasing generalization by improving GNN architectures as well as pre-training and fine-tuning approaches, is a fruitful direction. Investigating what pre-trained models have learned would also be useful to aid scientific discovery (Tshitoyan et al., 2019). Finally, it would be interesting to apply our methods to other domains, *e.g.*, physics and material science, where many problems are defined over graphs representing interactions of *e.g.*, atoms and particles.

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# A DETAILS OF GNN ARCHITECTURES

Here we describe GNN architectures used in our molecular property and protein function prediction experiments. For both domains we use the GIN architecture (Xu et al., 2019) with some minor modifications to include edge features, as well as center node information in the protein ego-networks.

As our primary goal is to systematically compare our pre-training strategy to the strong baseline strategies, we fix all of these hyper-parameters in our experiments and focus on relative improvement directly caused by the difference in pre-training strategies.

**Molecular property prediction.** In molecular property prediction, the raw node features and edge features are both 2-dimensional categorical vectors (see Appendix C for details), denoted as $(i_{v,1}, i_{v,2})$ and $(j_{e,1}, j_{e,2})$ for node $v$ and edge $e$, respectively. Note that we also introduce unique categories to indicate masked node/edges as well as self-loop edges. As input features to GNNs, we first embed the categorical vectors by

$$\begin{aligned} h_v^{(0)} &= \mathrm{EmbNode}_1(i_{v,1}) + \mathrm{EmbNode}_2(i_{v,2}) \\ h_e^{(k)} &= \mathrm{EmbEdge}_1^{(k)}(j_{e,1}) + \mathrm{EmbEdge}_2^{(k)}(j_{e,2}) \quad \text{for } \ k = 0, 1, \ldots, K-1, \end{aligned}$$

where $\mathrm{EmbNode}_1(\cdot)$, $\mathrm{EmbNode}_2(\cdot)$, $\mathrm{EmbEdge}_1^{(k)}(\cdot)$, and $\mathrm{EmbNode}_1^{(k)}(\cdot)$ represent embedding operations that map integer indices to $d$-dimensional real vectors, and $k$ represents the index of GNN layers. At the $k$-th layer, GNNs update node representations by

$$h_v^{(k)} = \mathrm{ReLU}\left(\mathrm{MLP}^{(k)}\left(\sum_{u \in \mathcal{N}(v) \cup \{v\}} h_u^{(k-1)} + \sum_{e=(v,u): u \in \mathcal{N}(v) \cup \{v\}} h_e^{(k-1)}\right)\right), \tag{A.1}$$

where $\mathcal{N}(v)$ is a set of nodes adjacent to $v$, and $e = (v, v)$ represents the self-loop edge. Note that for the final layer, i.e., $k = K$, we removed the ReLU from Eq. (A.1) so that $h_v^{(k)}$ can take negative values. This is crucial for pre-training methods based on the dot product, *e.g.*, Context Prediction and Edge Prediction, as otherwise, the dot product between two vectors would be always positive.

The graph-level representation $h_G$ is obtained by averaging the node embeddings at the final layer, i.e.,

$$h_G = \mathrm{MEAN}(\{h_v^{(K)} \mid v \in G\}). \tag{A.2}$$

The label prediction is made by a linear model on top of $h_G$.

In our experiments, we set the embedding dimension $d$ to 300. For MLPs in Eq. (A.1), we use the ReLU activation with 600 hidden units. We apply batch normalization (Ioffe & Szegedy, 2015) right before the ReLU in Eq. (A.1) and apply dropout (Srivastava et al., 2014) to $h_v^{(k)}$ at all the layers except the input layer.

**Protein function prediction.** The GNN architecture used for protein function prediction is similar to the one used for molecular property prediction except for a few differences. First, the raw input node features are uniform (denoted as $X$ here) and second, the raw input edge features are binary vectors (see Appendix D for the detail), which we denote as $c_e \in \{0, 1\}^{d_0}$. As input features to GNNs, we first embed the raw features by

$$\begin{aligned} h_v^{(0)} &= X \\ h_e^{(k)} &= W c_e + b \quad \text{for } \ k = 0, 1, \ldots, K-1, \end{aligned}$$

where $W \in \mathbb{R}^{d \times d_0}$ and $b \in \mathbb{R}^d$ are learnable parameters, and $h_v^{(0)}, h_e^{(k)} \in \mathbb{R}^d$. At each layer, GNNs update node representations by

$$h_v^{(k)} = \mathrm{ReLU}\left(\mathrm{MLP}^{(k)}\left(\mathrm{CONCAT}\left(\sum_{u \in \mathcal{N}(v) \cup \{v\}} h_u^{(k-1)}, \sum_{e=(v,u): u \in \mathcal{N}(v) \cup \{v\}} h_e^{(k-1)}\right)\right)\right), \tag{A.3}$$

| Dataset | | MUTAG | PTC |
|---|---|---|---|
| # Molecules | | 188 | 344 |
| # Binary prediction tasks | | 1 | 1 |
| Prvious results | | Cross validation split | |
| WL substree (Douglas, 2011) | | $90.4 \pm 5.7$ | $59.9 \pm 4.3$ |
| Patchysan (Niepert et al., 2016) | | $92.6 \pm 4.2$ | $60.0 \pm 4.8$ |
| GIN (Xu et al., 2019) | | $89.4 \pm 5.6$ | $64.6 \pm 7.0$ |
| Pre-training strategy | | Cross validation split | |
| Graph-level | Node-level | | |
| – | – | $89.3 \pm 7.4$ | $62.4 \pm 6.3$ |
| – | Infomax | $89.8 \pm 5.6$ | $65.9 \pm 3.9$ |
| – | EdgePred | $91.9 \pm 7.0$ | $66.5 \pm 5.7$ |
| – | Masking | $91.4 \pm 5.0$ | $64.4 \pm 7.3$ |
| – | ContextPred | $92.4 \pm 7.1$ | $68.3 \pm 7.8$ |
| Supervised | – | $90.9 \pm 5.8$ | $64.7 \pm 7.9$ |
| Supervised | Infomax | $90.9 \pm 5.4$ | $63.0 \pm 9.3$ |
| Supervised | EdgePred | $91.9 \pm 4.2$ | $63.5 \pm 8.2$ |
| Supervised | Masking | $90.3 \pm 3.3$ | $60.9 \pm 9.1$ |
| Supervised | ContextPred | $92.5 \pm 5.0$ | $66.5 \pm 5.2$ |

Table 3: **10-fold cross validation accuracy (%) on classic graph classification benchmarks using different pre-training strategies with GIN.** All the previous results are excerpted from Xu et al. (2019).

where $\mathrm{CONCAT}(\cdot, \cdot)$ takes two vectors as input and concatenates them. Since the downstream task is ego-network classification, we use the embedding of the center node $v_{\mathrm{center}}$ together with the embedding of the entire ego-network. More specifically, we obtain graph-level representation $h_G$ by

$$h_G = \mathrm{CONCAT}\left(\mathrm{MEAN}(\{h_v^{(K)} \mid v \in G\}), h_{v_{\mathrm{center}}}^{(K)}\right). \tag{A.4}$$

**Other GNN architectures.** For GCN, GraphSAGE, and GAT, we adopt the implementation in the Pytorch Geometric library (Fey & Lenssen, 2019), where we set the number of GAT attention heads to be 2. The dimensionality of node embeddings as well as the number of GNN layers are kept the same as GIN. These models do not originally handle edge features. We incorporate edge features into these models similarly to how we do it for the GIN; we add edge embeddings into node embeddings, and perform the GNN message-passing on the obtained node embeddings.

## B EXPERIMENTS ON CLASSIC GRAPH CLASSIFICATION BENCHMARKS

In Table 3 we report our experiments on the commonly-used classic graph classification benchmarks (Kersting et al., 2016). Among the datasets Xu et al. (2019) used, MUTAG, PTC, and NCI1 are molecule datasets for binary classification. Out of these three, we excluded the NCI1 dataset, because it misses edge information (*i.e.*, bond type) and therefore, we cannot recover the original molecule information, which is necessary to construct our input representations described in Appendix C.

For fair comparison, we used exactly the same evaluation protocol as Xu et al. (2019), *i.e.*, report 10-fold cross-validation accuracy. All the hyper-parameters in our experiments are kept the same in the main experiments except that we additionally tuned dropout rate from $\{0, 0.2, 0.5\}$ and the batch size from $\{8, 64\}$ at the fine-tuning stage.

While the pre-trained GNNs (especially those with Context Prediction) give competent performance, all the accuracies (including all the previous methods) are within a standard deviation with each other, making it hard to reliably compare different methods. As Xu et al. (2019) has pointed out, this is due to the extremely small dataset size; a validation set at each fold only contains around 19 to 35 molecules for MUTAG and PTC, respectively. Given these results, we argue that it is necessary to use larger datasets to make reliable comparison, so we mainly focus on MoleculeNet (Wu et al., 2018) in this work.

## C DETAILS OF MOLECULAR DATASETS

**Input graph representation.** For simplicity, we use a minimal set of node and bond features that unambiguously describe the two-dimensional structure of molecules. We use RDKit (Landrum et al., 2006) to obtain these features.

- Node features:
  - Atom number: [1, 118]
  - Chirality tag: {unspecified, tetrahedral cw, tetrahedral ccw, other}
- Edge features:
  - Bond type: {single, double, triple, aromatic}
  - Bond direction: {–, endupright, enddownright}

**Downstream task datasets.** 8 binary graph classification datasets from Moleculenet (Wu et al., 2018) are used to evaluate model performance.

- **BBBP.** Blood-brain barrier penetration (membrane permeability) (Martins et al., 2012).
- **Tox21.** Toxicity data on 12 biological targets, including nuclear receptors and stress response pathways (Tox21).
- **ToxCast.** Toxicology measurements based on over 600 in vitro high-throughput screenings (Richard et al., 2016).
- **SIDER.** Database of marketed drugs and adverse drug reactions (ADR), grouped into 27 system organ classes (Kuhn et al., 2015).
- **ClinTox.** Qualitative data classifying drugs approved by the FDA and those that have failed clinical trials for toxicity reasons (Novick et al., 2013; AACT).
- **MUV.** Subset of PubChem BioAssay by applying a refined nearest neighbor analysis, designed for validation of virtual screening techniques (Gardiner et al., 2011).
- **HIV.** Experimentally measured abilities to inhibit HIV replication (HIV).
- **BACE.** Qualitative binding results for a set of inhibitors of human $\beta$-secretase 1 (Subramanian et al., 2016).

## D DETAILS OF PROTEIN DATASETS

**Input graph representation.** The protein subgraphs only have edge features.

- Edge features:
  - Neighbourhood: {True, False}
  - Fusion: {True, False}
  - Co-occurrence: {True, False}
  - Co-expression: {True, False}
  - Experiment: {True, False}
  - Database: {True, False}
  - Text: {True, False}

These edge features indicate whether a particular type of relationship exists between a pair of proteins:

- Neighbourhood: if a pair of genes are consistently observed in each other's genome neighbourhood
- Fusion: if a pair of proteins have their respective orthologs fused into a single protein-coding gene in another organism
- Co-occurrence: if a pair of proteins tend to be observed either as present or absent in the same subset of organisms
- Co-expression: if a pair of proteins share similar expression patterns
- Experiment: if a pair of proteins are experimentally observed to physically interact with each other

- Database: if a pair of proteins belong to the same pathway, based on assessments by a human curator
- Text mining: if a pair of proteins are mentioned together in PubMed abstracts

**Datasets.** A dataset containing protein subgraphs from 50 species is used (Zitnik et al., 2019). The original PPI networks do not have node attributes, but contain edge attributes that correspond to the degree of confidence for 7 different types of protein-protein relationships. The edge weights range from 0, which indicates no evidence for the specific relationship, to 1000, which indicates the highest confidence. The weighted edges of the PPI networks are thresholded such that the distribution of edge types across the 50 PPI networks are uniform. Then, for every node in the PPI networks, subgraphs centered on each node were generated by: (1) performing a breadth first search to select the subgraph nodes, with a search depth limit of 2 and a maximum number of 10 neighbors randomly expanded per node, (2) including the selected subgraph nodes and all the edges between those nodes to form the resulting subgraph.

The entire dataset contains 394,925 protein subgraphs derived from 50 species. Out of these 50 species, 8 species (arabidopsis, celegans, ecoli, fly, human, mouse, yeast, zebrafish) have proteins with GO protein annotations. The dataset contains 88,000 protein subgraphs from these 8 species, of which 57,448 proteins have at least one positive coarse-grained GO protein annotation and 22,876 proteins have at least one positive fine-grained GO protein annotation. For the self-supervised pre-training dataset, we use all 394,925 protein subgraphs.

We define *fine-grained protein functions* as Gene Ontology (GO) annotations that are leaves in the GO hierarchy, and define *coarse-grained protein functions* as GO annotations that are the immediate parents of leaves (Ashburner et al., 2000; Consortium, 2018). For example, a fine-grained protein function is "Factor XII activation", while a coarse-grained function is "positive regulation of protein". The former is a specific type of the latter, and is much harder to derive experimentally. The GO hierarchy information is obtained using GOATOOLS (Klopfenstein et al., 2018). The supervised pre-training dataset and the downstream evaluation dataset are derived from the 8 labeled species, as described in Appendix E. The 40-th most common *fine-grained* protein label only has 121 positively annotated proteins, while the 40-th most common *coarse-grained* protein label has 9386 positively annotated proteins. This illustrates the extreme label scarcity of our downstream tasks.

For supervised pre-training, we combine the train, validation, and prior sets described previously, with the 5,000 most common coarse-grained protein function annotations as binary labels. For our downstream task, we predict the 40 most common fine-grained protein function annotations, to ensure that each protein function has at least 10 positive labels in our test set.

## E DETAILS OF DATASET SPLITTING

For molecular prediction tasks, following Ramsundar et al. (2019), we cluster molecules by scaffold (molecular graph substructure) (Bemis & Murcko, 1996), and recombine the clusters by placing the most common scaffolds in the training set, producing validation and test sets that contain structurally different molecules. Prior work has shown that this *scaffold split* provides a more realistic estimate of model performance in prospective evaluation compared to random split (Chen et al., 2012; Sheridan, 2013). The split for train/validation/test sets is 80%:10%:10%.

In the PPI network, *species split* simulates a scenario where we have only high-level *coarse-grained* knowledge on a subset of proteins (prior set) in a species of interest (human in our experiments), and want to predict *fine-grained* biological functions for the rest of the proteins in that species (test set). For species split, we use 50% of the protein subgraphs from human as test set, and 50% as a prior set containing only coarse-grained protein annotations. The protein subgraphs from 7 other labelled species (arabidopsis, celegans, ecoli, fly, mouse, yeast, zebrafish) are used as train and validation sets, which are split 85% : 15%. The effective split ratio for the train/validation/prior/test sets is 69% : 12% : 9.5% : 9.5%.

## F TIME COMPLEXITY OF PRE-TRAINING.

The time complexity of all the pre-training methods are at most linear with respect to the number of edges, which is as efficient as ordinary message-passing in GNNs, and thus, incurs little computational

| Dataset | | BBBP | Tox21 | ToxCast | SIDER | ClinTox | MUV | HIV | BACE | **Average** |
|---|---|---|---|---|---|---|---|---|---|---|
| # Molecules | | 2039 | 7831 | 8575 | 1427 | 1478 | 93087 | 41127 | 1513 | / |
| # Binary prediction tasks | | 1 | 12 | 617 | 27 | 2 | 17 | 1 | 1 | / |
| Configuration | | Out-of-distribution prediction (scaffold split) | | | | | | | | |
| Architecture | Pre-train? | | | | | | | | | |
| GIN | No | 65.8 ±4.5 | 74.0 ±0.8 | 63.4 ±0.6 | 57.3 ±1.6 | 58.0 ±4.4 | 71.8 ±2.5 | 75.3 ±1.9 | 70.1 ±5.4 | 67.0 |
| GIN | Yes | 68.7 ±1.3 | **78.1 ±0.6** | **65.7 ±0.6** | **62.7 ±0.8** | **72.6 ±1.5** | **81.3 ±2.1** | **79.9 ±0.7** | **84.5 ±0.7** | **74.2** |
| GCN | No | 64.9±3.0 | 74.9±0.8 | 63.3±0.9 | 60.0±1.0 | 65.8±4.5 | 73.2±1.4 | 75.7±1.1 | 73.6±3.0 | 68.9 |
| GCN | Yes | **70.6±1.6** | 75.8±0.3 | **65.3±0.1** | 62.4±0.5 | 63.6±1.7 | 79.4±1.8 | 78.2±0.6 | 82.3±3.4 | 72.2 |
| GraphSAGE | No | 69.6±1.9 | 74.7±0.7 | 63.3±0.5 | 60.4±1.0 | 59.2±4.4 | 72.7±1.4 | 74.4±0.7 | 72.5±1.9 | 68.3 |
| GraphSAGE | Yes | 63.9±2.1 | 76.8±0.3 | 64.9±0.2 | 60.7±0.5 | 60.7±2.0 | 78.4±2.0 | 76.2±1.1 | 80.7±0.9 | 70.3 |
| GAT | No | 66.2±2.6 | 75.4±0.5 | 64.6±0.6 | 60.9±1.4 | 58.5±3.6 | 66.6±2.2 | 72.9±1.8 | 69.7±6.4 | 66.8 |
| GAT | Yes | 59.4±0.5 | 68.1±0.5 | 59.3±0.7 | 56.0±0.5 | 47.6±1.3 | 65.4±0.8 | 62.5±1.6 | 64.3±1.1 | 60.3 |

Table 4: **Test ROC-AUC (%) performance on molecular prediction benchmarks with different GNN architectures.** The rightmost column averages the mean of test performance across the 8 datasets. For pre-training, we applied Context Prediction + graph-level supervised pre-training.

overhead. Also, there is almost no memory overhead as we transform data (e.g., mask input node/edge features, sample the context graphs) on-the-fly.

## G FURTHER DETAILS OF THE EXPERIMENTAL SETUP

**Optimization.** All models are trained with Adam optimizer (Kingma & Ba, 2015) with a learning rate of 0.001. We use Pytorch (Paszke et al., 2017) and Pytorch Geometric (Fey & Lenssen, 2019) for all of our implementation. We run all pre-training methods for 100 epochs. For self-supervised pre-training, we use a batch size of 256, while for supervised pre-training, we use a batch size of 32 with dropout rate of 20%.

**Fine-tuning.** After pre-training, we follow the procedure in Section 3.3 to fine-tune the models on the training sets of the downstream datasets. We use a batch size of 32 and dropout rate of 50%. Datasets with multiple prediction tasks are fit jointly. On the molecular property prediction datasets, we train models for 100 epochs, while on the protein function prediction dataset (with the 40 binary prediction tasks), we train models for 50 epochs.

**Evaluation.** We evaluate test performance on downstream tasks using ROC-AUC (Bradley, 1997) with the validation early stopping protocol, *i.e.*, test ROC-AUC at the best validation epoch is reported. For datasets with multiple prediction tasks, we take the average ROC-AUC across all their tasks. The downstream experiments are run with 10 random seeds, and we report mean ROC-AUC and standard deviation.

## H COMPARISON OF PRE-TRAINING WITH DIFFERENT GNN ARCHITECTURES

Table 4 shows the detailed comparison of different GNN architectures on the chemistry datasets. We see that the most expressive GIN architectures benefit most from pre-training compared to the other less expressive models.

## I ADDITIONAL TRAINING AND VALIDATION CURVES

**Training and validation curves.** In Figure 5, we plot training and validation curves for all the datasets used in the molecular property prediction experiments.

**Additional scatter plot comparisons of ROC-AUCs.** In Figure 6, we compare our Context Prediction + graph-level supervised pre-training with a non-pre-trained model and a graph-level supervised pre-trained model. We see from the left plot that the combined strategy again completely avoids negative transfer across all the 40 downstream tasks. Furthermore, we see from the right plot that additionally adding our node-level Context Prediction pre-training almost always improves ROC-AUC scores of supervised pre-trained models *across the 40 downstream tasks*.

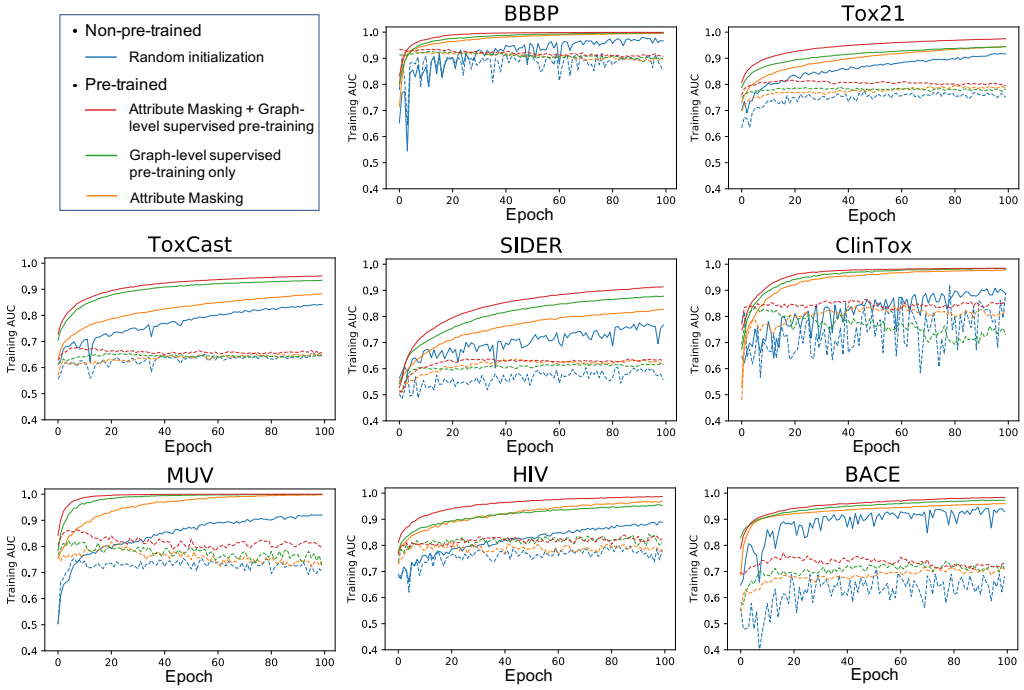


Figure 5: **Training and validation curves of different pre-training strategies.** The solid and dashed lines indicate the training and validation curves, respectively.

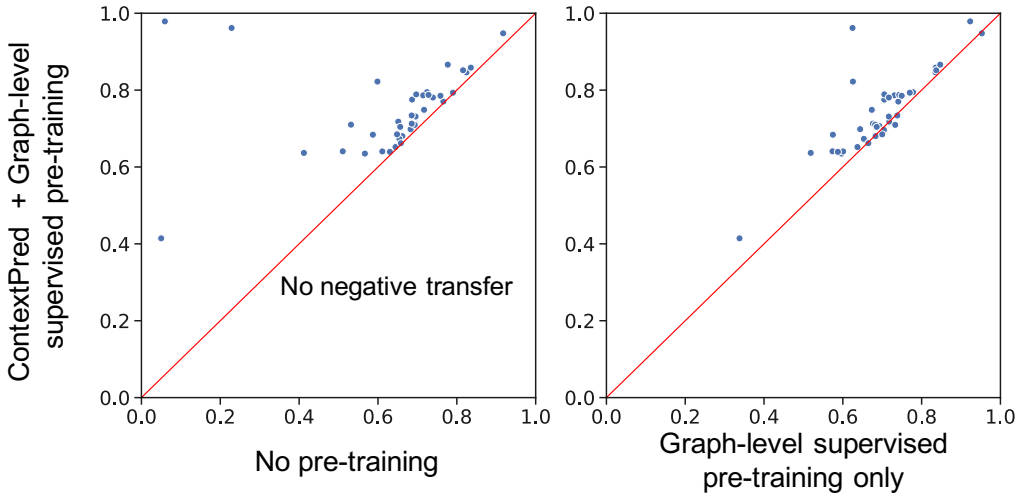


Figure 6: **Scatter plot comparisons of ROC-AUC scores of our Context Prediction + graph-level supervised pre-training strategy versus the two baseline strategies (non-pre-trained and graph-level supervised pre-trained) on the 40 individual downstream tasks of predicting different fine-grained protein function labels.**