1. Proofs

Lemma 1. Let $\text{MESSAGE}_φ^{(\ell)}$ and $\text{UPDATE}_φ^{(\ell)}$ be Lipschitz continuous functions with Lipschitz constants $k_1$ and $k_2$, respectively. If, for all $v \in V$, the inputs are close to the exact input, i.e. $\|\tilde{h}_v^{(\ell-1)} - h_v^{(\ell-1)}\| \leq \delta$, and the historical embeddings do not run too stale, i.e. $\|\tilde{h}_v^{(\ell-1)} - \tilde{h}_v^{(\ell-1)}\| \leq \epsilon$, then the output error is bounded by

$$\|\tilde{h}_v^{(\ell)} - h_v^{(\ell)}\| \leq \delta k_2 + (\delta + \epsilon) k_1 k_2 |N(v)|.$$ 

Proof. By triangular inequality, it holds that $\|\tilde{h}_v^{(\ell-1)} - h_v^{(\ell-1)}\| \leq \delta + \epsilon$. Since both $\text{MESSAGE}_φ^{(\ell)}$ and $\text{UPDATE}_φ^{(\ell)}$ denote Lipschitz continuous functions with Lipschitz constants $k_1$ and $k_2$, respectively, it further holds that for any $x, y$:

$$\|\text{MESSAGE}_φ^{(\ell)}(x) - \text{MESSAGE}_φ^{(\ell)}(y)\| \leq k_1 \|x - y\|$$
$$\|\text{UPDATE}_φ^{(\ell)}(x) - \text{UPDATE}_φ^{(\ell)}(y)\| \leq k_2 \|x - y\|$$

Furthermore, the Lipschitz constants for the aggregations $\sum_{x \in X} x$, $\frac{1}{|X|} \sum_{x \in X} x$ and $\max_{x \in X} x$ are given as $|X|$, 1 and 1, respectively. Then,

$$\|\text{UPDATE}_φ^{(\ell)}(\tilde{h}_v^{(\ell-1)}, \bigoplus_{w \in N(v)} \text{MESSAGE}_φ^{(\ell)}(\tilde{h}_w^{(\ell-1)})) - \text{UPDATE}_φ^{(\ell)}(h_v^{(\ell-1)}, \bigoplus_{w \in N(v)} \text{MESSAGE}_φ^{(\ell)}(h_w^{(\ell-1)}))\|$$

$$\leq k_2 (\delta + |N(v)| (k_1 (\delta + \epsilon))) = \delta k_2 + (\delta + \epsilon) k_1 k_2 |N(v)|.$$

Theorem 2. Let $f_φ^{(L)}$ be a $L$-layered GNN, containing only Lipschitz continuous $\text{MESSAGE}_φ^{(\ell)}$ and $\text{UPDATE}_φ^{(\ell)}$ functions with Lipschitz constants $k_1$ and $k_2$, respectively. If, for all $v \in V$ and all $\ell \in \{1, \ldots, L-1\}$, the historical embeddings do not run too stale, i.e. $\|\tilde{h}_v^{(\ell)} - h_v^{(\ell)}\| \leq \epsilon^{(\ell)}$, then the final output error is bounded by

$$\|\tilde{h}_v^{(L)} - h_v^{(L)}\| \leq \sum_{\ell=1}^{L-1} \epsilon^{(\ell)} k_1^{L-\ell} k_2^{L-\ell} |N(v)|^{L-\ell}.$$ 

Proof. For layer $\ell = 1$, the inputs do not need to be estimated, i.e. $\delta^{(0)} = \|\tilde{h}_v^{(0)} - h_v^{(0)}\| = 0$, and, as a result, the output is exact, i.e. $\delta^{(1)} = \|\tilde{h}_v^{(1)} - h_v^{(1)}\| = 0$. With $\|\tilde{h}_v^{(1)} - h_v^{(1)}\| \leq \epsilon^{(1)}$, it directly follows via Lemma 1 that the approximation error of layer $\ell = 2$ is bounded by $\|\tilde{h}_v^{(2)} - h_v^{(2)}\| \leq \epsilon^{(1)} k_1 k_2 |N(v)| = \delta^{(2)}$. Recursively replacing

$$\delta^{(\ell)} = \delta^{(\ell-1)} k_2 + (\delta^{(\ell-1)} + \epsilon^{(\ell-1)}) k_1 k_2 |N(v)|$$

in $\|\tilde{h}_v^{(L)} - h_v^{(L)}\| \leq \delta^{(L-1)} k_2 + (\delta^{(L-1)} + \epsilon^{(L-1)}) k_1 k_2 |N(v)|$ (cf. Lemma 1) yields

$$\|\tilde{h}_v^{(L)} - h_v^{(L)}\| \leq \sum_{\ell=1}^{L-1} \epsilon^{(\ell)} k_1^{L-\ell} k_2^{L-\ell} |N(v)|^{L-\ell}.$$ 

\qed
Proposition 3. Let $f_\theta^{(L)} : \mathcal{V} \rightarrow \mathbb{R}^d$ be a $L$-layered GNN as expressive as the WL test in distinguishing the $L$-hop neighborhood around each node $v \in \mathcal{V}$. Then, there exists a graph $A \in \{0, 1\}^{[|V|] \times |V|}$ for which $f_\theta^{(L)}$ operating on a sampled variant $\tilde{A}$, $\tilde{a}_{v,w} = \begin{cases} \frac{|N(v)|}{|N(v)|}, & \text{if } w \in \tilde{N}(v) \\ 0, & \text{otherwise} \end{cases}$, produces a non-equivalent coloring, i.e., $\tilde{c}_v^{(L)} \neq \tilde{c}_w^{(L)}$ while $c_v^{(L)} = c_w^{(L)}$ for nodes $v, w \in \mathcal{V}$.

Proof. Consider the colored graph $A$ and its sampled variant $\tilde{A}$ as shown on the right. Here, it holds that $h_v^{(1)} = h_w^{(1)}$ while $\tilde{h}_v^{(1)} \neq \tilde{h}_w^{(1)}$.

Lemma 4. Let $\|h_v^{(\ell-1)} : v \in \mathcal{V}\|$ be a countable multiset such that $\|h_v^{(\ell-1)} - h_w^{(\ell-1)}\| > 2(\delta + \epsilon)$ for all $v, w \in \mathcal{V}$, $h_v^{(\ell-1)} \neq h_w^{(\ell-1)}$. If the inputs are close to the exact input, i.e., $|\|h_v^{(\ell-1)} - h_w^{(\ell-1)}\| - \delta|$, and the historical embeddings do not run too stale, i.e., $|\tilde{h}_v^{(\ell-1)} - \tilde{h}_w^{(\ell-1)}| \leq \epsilon$, then there exist $\text{MESSAGE}^{(\ell)}_\theta$ and $\text{UPDATE}^{(\ell)}_\theta$ functions, such that

$$\|f_\theta^{(\ell)}(\tilde{h}_v^{(\ell-1)}) - f_\theta^{(\ell)}(h_v^{(\ell-1)})\| \leq \delta + \epsilon$$

and

$$\|f_\theta^{(\ell)}(h_v^{(\ell-1)}) - f_\theta^{(\ell)}(h_w^{(\ell-1)})\| > 2(\delta + \epsilon + \lambda)$$

for all $v, w \in \mathcal{V}$, $h_v^{(\ell-1)} \neq h_w^{(\ell-1)}$ and all $\lambda > 0$.

Proof. Define $\phi : \mathbb{R}^d \rightarrow \mathbb{R}^d$ as the Voronoi tessellation induced by exact inputs $\{h_v^{(\ell-1)} : v \in \mathcal{V}\}$:

$$\phi(x) = h_v^{(\ell-1)} \quad \text{if } \|x - h_v^{(\ell-1)}\| \leq \|x - h_w^{(\ell-1)}\| \quad \text{for all } v \neq w \in \mathcal{V}$$

Furthermore, we know that there exists $\text{MESSAGE}^{(\ell)}_\theta$ and $\text{UPDATE}^{(\ell)}_\theta$ functions so that $f_\theta^{(\ell)}$ is injective for all countable multisets (Zaheer et al., 2017; Xu et al., 2019; Morris et al., 2019; Maron et al., 2019). Therefore, it holds that $|f_\theta^{(\ell)}(\phi(h_v^{(\ell-1)})) - f_\theta^{(\ell)}(\phi(h_w^{(\ell-1)}))| = 0 \leq \delta$. Since $\{h_v^{(\ell-1)} : v \in \mathcal{V}\}$ is countable and $f_\theta^{(\ell)}$ is injective, there exists a $\alpha > 0$ such that $|f_\theta^{(\ell)}(\phi(h_v^{(\ell-1)})) - f_\theta^{(\ell)}(\phi(h_w^{(\ell-1)}))| > \alpha$ for all $v, w \in \mathcal{V}$, $h_v^{(\ell-1)} \neq h_w^{(\ell-1)}$. Due to the homogeneity of $\| \cdot \|$, it directly follows that there must exists $\alpha > 0$ so that

$$|\alpha f_\theta^{(\ell)}(\phi(h_v^{(\ell-1)})) - \alpha f_\theta^{(\ell)}(\phi(h_w^{(\ell-1)}))| > \alpha \kappa \geq 2(\delta + \epsilon + \lambda)$$

for all $v, w \in \mathcal{V}$, $h_v^{(\ell-1)} \neq h_w^{(\ell-1)}$ and all $\lambda > 0$.

Theorem 5. Let $f_\theta^{(L)}$ be a $L$-layered GNN in which all $\text{MESSAGE}^{(\ell)}_\theta$ and $\text{UPDATE}^{(\ell)}_\theta$ functions fulfill the conditions of Lemma 4. Then, there exists a map $\phi : \mathbb{R}^d \rightarrow \Sigma$ so that $\phi(\tilde{h}_v^{(\ell)}) = c_v^{(\ell)}$ for all $v \in \mathcal{V}$.

Proof. Define $\phi : \mathbb{R}^d \rightarrow \Sigma$ as the Voronoi tessellation induced by exact outputs $\{h_v^{(L)} : v \in \mathcal{V}\}$:

$$\phi(x) = c_v^{(L)} \quad \text{if } \|x - h_v^{(L)}\| \leq \|x - h_w^{(L)}\| \quad \text{for all } v \neq w \in \mathcal{V}$$

Since each GNN layer $f_\theta^{(\ell)}$ is injective for exact inputs, we know that such a function needs to exist (Xu et al., 2019; Morris et al., 2019). Therefore, it is sufficient to show that there exists a $\delta^{(L)} > 0$ so that $\|h_v^{(L)} - h_w^{(L)}\| \leq \delta^{(L)}$ and $\|h_v^{(L)} - h_w^{(L)}\| > 2\delta^{(L)}$ for all $v, w \in \mathcal{V}$, $h_v^{(L)} \neq h_w^{(L)}$. Following upon Theorem 2, we know that $\|h_v^{(1)} - h_w^{(1)}\| = 0$. Due
to Lemma 4, it holds that \( \| \tilde{h}_v^{(2)} - h_v^{(2)} \| \leq \epsilon(1) \). The next layer introduces an increased error, i.e., \( \| \tilde{h}_v^{(2)} - h_v^{(2)} \| \leq \epsilon(1) + \epsilon(2) \), and to compensate, we set \( \lambda^{(2)} = \epsilon(2) \) so that \( \| h_v^{(2)} - h_w^{(2)} \| > 2(\epsilon(1) + \epsilon(2)) \) for all \( v, w \in \mathcal{V}, h_v^{(L)} \neq h_w^{(L)} \). By recursively applying Lemma 4 with \( \lambda^{(t)} = \epsilon^{(t)} \), it immediately follows that \( \| h_v^{(L)} - h_w^{(L)} \| \leq \sum_{t=1}^{L-1} \epsilon^{(t)} = \delta(L) \), and \( \| h_v^{(L)} - h_w^{(L)} \| > \sum_{t=1}^{L-1} 2 \epsilon^{(t)} \) for all \( v, w \in \mathcal{V}, h_v^{(L)} \neq h_w^{(L)} \).

2. Algorithm

Our GAS mini-batch training algorithm is given in Algorithm 1:

**Algorithm 1 GAS Mini-batch Execution**

\[
\begin{align*}
\text{Input: } & \text{ Graph } \mathcal{G} = (\mathcal{V}, \mathcal{E}), \text{ input node features } H^{(0)}, \text{ number of batches } B, \text{ number of layers } L \\
\{B_1, \ldots, B_B\} & \leftarrow \text{SPLIT}(\mathcal{G}, B) \\
\mathcal{V}_b & \leftarrow \bigcup_{v \in B_b} \mathcal{N}(v) \cup \{v\} \quad \forall b \in \{1, \ldots, B\} \\
\mathcal{G}_b & \leftarrow \mathcal{G}[\mathcal{V}_b] \quad \forall b \in \{1, \ldots, B\} \\
\text{for } & B_b \in \{B_1, \ldots, B_B\} \text{ do} \\
\text{for } & \ell \in \{1, \ldots, L-1\} \text{ do} \\
& h_v^{(\ell)} \leftarrow f_{\theta}^{(\ell)}(h_v^{(\ell-1)}, \{h_w^{(\ell-1)} : w \in \mathcal{N}(v)\}) \quad \forall v \in B_b \\
& \text{PUSH}(\ell)(h_v^{(\ell)}) \quad \forall v \in B_b \\
& h_w^{(\ell)} \leftarrow \text{PULL}(\ell)(w) \quad \forall w \in B_b \setminus B_b \\
\text{end for} \\
& h_v^{(L)} \leftarrow f_{\theta}^{(L)}(h_v^{(L-1)}, \{h_w^{(L-1)} : w \in \mathcal{N}(v)\}) \quad \forall v \in B_b \\
\text{end for}
\end{align*}
\]

3. GNN Operators

We briefly recap the details of all graph convolutional layers used in our experiments. We omit final non-linearities and edge features due to simplicity.

**Graph Convolutional Networks (GCN)** use a symmetrically normalized mean aggregation followed by linear transformation (Kipf & Welling, 2017)

\[
h_v^{(\ell)} = \sum_{w \in \mathcal{N}(v) \cup \{v\}} \frac{1}{c_{w,v}} \mathbf{W} h_w^{(\ell-1)},
\]

where \( c_{w,v} = \sqrt{\text{deg}(w) + 1} \sqrt{\text{deg}(v) + 1} \).

**Graph Attention Networks (GAT)** perform an anisotropic aggregation (Veličković et al., 2018)

\[
h_v^{(\ell)} = \sum_{w \in \mathcal{N}(v) \cup \{v\}} \alpha_{w,v} \mathbf{W} h_w^{(\ell-1)},
\]

where normalization is achieved via learnable attention coefficients

\[
\alpha_{w,v} = \frac{\exp \left( \text{LeakyReLU} \left( a^\top \left[ \mathbf{W} h_v^{(\ell-1)}, \mathbf{W} h_w^{(\ell-1)} \right] \right) \right)}{\sum_{k \in \mathcal{N}(v) \cup \{v\}} \exp \left( \text{LeakyReLU} \left( a^\top \left[ \mathbf{W} h_v^{(\ell-1)}, \mathbf{W} h_k^{(\ell-1)} \right] \right) \right)}.
\]
Approximate Personalized Propagation of Neural Predictions (APPNP) networks first perform a graph-agnostic prediction of node labels, i.e. $h_v^{(0)} = \text{MLP}(x_v)$, and smooth initial label predictions via propagation afterwards (Klicpera et al., 2019)

$$h_v^{(\ell)} = \alpha h_v^{(0)} + (1 - \alpha) \sum_{w \in \mathcal{N}_v} \frac{1}{c_{w,v}} h_w^{(\ell-1)},$$

where $\alpha \in [0,1]$ denotes the teleport probability and $c_{w,v}$ is defined as in GCN. Notably, the final propagation layers are non-trainable, and predictions are solely conditioned on node features (while gradients of model parameters are not).

Simple and Deep Graph Convolutional Networks (GCNII) extend the idea of APPNP to a trainable propagation scheme which leverages initial residual connections (Chen et al., 2020)

$$h_v^{(\ell)} = \alpha Wh_v^{(0)} + (1 - \alpha) \sum_{w \in \mathcal{N}_v(v)} \frac{1}{c_{w,v}} Wh_w^{(\ell-1)},$$

and $W$ makes use of identity maps, i.e. $W \leftarrow (1 - \beta)I + \beta W$ for $\beta \in [0,1]$.

Graph Isomorphism Networks (GIN) make use of sum aggregation and MLPs to obtain a maximally powerful GNN operator (Xu et al., 2019)

$$h_v^{(\ell)} = \text{MLP}_\theta \left( (1 + \epsilon) h_v^{(\ell-1)} + \sum_{w \in \mathcal{N}_v(v)} h_w^{(\ell-1)} \right),$$

where $\epsilon \in \mathbb{R}$ is a trainable parameter in order to distinguish neighbors from central nodes.

Principal Neighborhood Aggregation (PNA) networks leverage multiple aggregators combined with degree-scalers to capture graph structural properties (Corso et al., 2020)

$$h_v^{(\ell)} = W_2 \left[ h_v^{(\ell-1)}, \bigoplus_{w \in \mathcal{N}_v(v)} W_1 \left[ h_w^{(\ell-1)}, h_v^{(\ell-1)} \right] \right],$$

where

$$\bigoplus = \left[ \begin{array}{c} \frac{1}{s(\text{deg}(v),1)} \\ \frac{1}{s(\text{deg}(v),-1)} \end{array} \right] \otimes \begin{bmatrix} \text{mean} \\ \text{min} \\ \text{max} \end{bmatrix},$$

with $\otimes$ being the tensor product and

$$s(d, \alpha) = \left( \frac{\log(d+1)}{\log|V| \sum_{v \in V} \log(\text{deg}(v)+1)} \right)^\alpha$$

denoting degree-scalers.

4. PyGAS Programming Interface

To highlight the ease-of-use of our framework, we showcase the necessary changes to convert a common GCN architecture (Kipf & Welling, 2017) implemented in PYTORCH GEOMETRIC (Fey & Lenssen, 2019) (cf. Listing 1) to its corresponding scalable version (cf. Listing 2). In particular, our model now inherits from ScalableGNN, which takes care of creating all history embeddings (accessible via self.histories) and provides an efficient concurrent history access pattern via push_and_pull(). Notably, the forward() execution method of our model now takes in the additional n_id parameter, which holds the global node index for each node in the current mini-batch. This assignment vector is necessary to push and pull the intermediate mini-batch embeddings to and from the global history embeddings.
Table 1. Inter-/intra-connectivity ratio for real-world datasets with different mini-batch sampling strategies. Utilizing METIS heavily minimizes inter-connectivity between mini-batches, which reduces history accesses and tightens approximation errors in return.

| Sampling Scheme | CORA     | CITESEER | PUBMED   | COAUTHOR-CS | COMPUTER | AMAZON-PHOTO | WIKI-CS |
|-----------------|----------|----------|----------|--------------|----------|--------------|---------|
| Random          | 1.33     | 1.24     | 3.17     | 6.81         | 9.94     | 9.05         | 5.61    | 5.85    |
| METIS           | 0.14     | 0.02     | 0.52     | 2.77         | 2.26     | 2.27         | 1.03    | 1.12    |
|                  | CLUSTER  | PATTERN  | REDDIT   | PPI          | FLICKR   | YELP         | ogbn-arxiv | ogbn-products |
| Random          | 36.64    | 51.02    | 6.58     | 6.79         | 1.82     | 6.74         | 3.02    | 26.18   |
| METIS           | 1.57     | 1.61     | 6.50     | 1.27         | 1.07     | 2.52         | 0.48    | 1.94    |

from torch_geometric.nn import GCNConv

class GNN(Module):
    def __init__(self, in_channels, hidden_channels, out_channels, num_layers):
        super(GNN, self).__init__()
        self.convs = ModuleList()
        self.convs.append(GCNConv(in_channels, hidden_channels))
        for _ in range(num_layers - 2):
            self.convs.append(GCNConv(hidden_channels, hidden_channels))
        self.convs.append(GCNConv(hidden_channels, out_channels))

    def forward(self, x, adj_t):
        for conv, history in zip(self.convs[:-1], self.histories):
            x = conv(x, adj_t).relu()
            x = self.push_and_pull(history, x, n_id)
        return self.convs[-1](x, adj_t)

Listing 1. Full-batch GCN (Kipf & Welling, 2017) model within PYTORCH GEOMETRIC (Fey & Lenssen, 2019).

from torch_geometric.nn import GCNConv
from torch_geometric_autoscale import ScalableGNN

class GNN(ScalableGNN):
    def __init__(self, num_nodes, in_channels, hidden_channels, out_channels, num_layers):
        super(GNN, self).__init__(num_nodes, hidden_channels, num_layers)
        self.convs = ModuleList()
        self.convs.append(GCNConv(in_channels, hidden_channels))
        for _ in range(num_layers - 2):
            self.convs.append(GCNConv(hidden_channels, hidden_channels))
        self.convs.append(GCNConv(hidden_channels, out_channels))

    def forward(self, x, adj_t, n_id):
        for conv, history in zip(self.convs[:-1], self.histories):
            x = conv(x, adj_t).relu()
            x = self.push_and_pull(history, x, n_id)
        return self.convs[-1](x, adj_t)

Listing 2. Mini-batch GCN (Kipf & Welling, 2017) model within PYTORCH GEOMETRIC (Fey & Lenssen, 2019) and our proposed PyGAS framework. ■ denotes lines that require changes, while ■ refers to newly added lines. Only minimal changes are required to auto-scale GCN (or any other model) to large graphs.

5. Additional Ablation Studies

We report additional ablation studies to further strengthen the motivation of our GAS framework:
Table 2. Ablation study for a 4-layer GIN (Xu et al., 2019) model on the CLUSTER dataset (Dwivedi et al., 2020). Combining both GAS techniques help in resembling full-batch performance for expressive models with highly non-linear message passing phases.

|                       | Accuracy |
|-----------------------|----------|
|                       | Training | Validation | Test |
| Full-batch Baseline   | 60.49    | 58.17      | 58.49 |

| Minimizing Inter-Connectivity | Enforcing Lipschitz Continuity |
|-------------------------------|--------------------------------|
| GAS                           |                                 |
| ✓                             | x                              |
| ✓                             | ✓                              |
| 55.66                         | 54.86                          |
| 58.97                         | 57.79                          |
| 60.67                         | 58.21                          |
| 55.15                         | 57.82                          |
| 58.51                         |                                 |

Table 3. Dataset statistics.

| Dataset       | Task          | Nodes  | Edges  | Features | Classes | Label Rate |
|---------------|---------------|--------|--------|----------|---------|------------|
| Small-scale   | multi-class   | 2,708  | 5,278  | 1,433    | 7       | 5.17%      |
| CORA          | multi-class   | 3,327  | 4,552  | 3,703    | 6       | 3.61%      |
| CITESEER      | multi-class   | 19,717 | 44,324 | 500      | 3       | 0.30%      |
| PUBMED        | multi-class   | 18,333 | 81,894 | 6,805    | 15      | 1.64%      |
| COAUTHOR-CS   | multi-class   | 34,493 | 247,962| 8,415    | 5       | 0.29%      |
| COAUTHOR-PHYSICS | multi-class   | 13,752 | 245,861| 767      | 10      | 1.45%      |
| AMAZON-COMPUTER | multi-class   | 7,650  | 119,081| 745      | 8       | 2.09%      |
| AMAZON-PHOTO  | multi-class   | 11,701 | 215,863| 300      | 10      | 4.96%      |
| CLUSTER       | multi-class   | 1,406,436| 25,810,340| 6    | 6  | 83.35%  |
| REDDIT        | multi-class   | 232,965| 11,606,919| 602   | 41  | 65.86%  |
| PPI           | multi-label   | 56,944 | 793,632| 50      | 121   | 78.86%   |
| FLICKR        | multi-class   | 89,250 | 449,878| 500     | 7     | 50.00%   |
| YELP          | multi-label   | 716,847| 6,977,409| 300   | 100  | 75.00%   |
| ogbn-arxiv    | multi-class   | 169,343| 1,157,799| 128   | 40   | 53.70%   |
| Large-scale   | multi-class   | 2,449,029| 61,859,076| 100  | 47   | 8.03%    |

Minimizing Inter-Connectivity Between Batches. We make use of graph clustering methods (Karypis & Kumar, 1998; Dhillon et al., 2007) in order to minimize the inter-connectivity between batches, which minimizes history accesses and therefore increases closeness and reduces staleness in return. To evaluate this impact in practice, Table 1 lists the inter-/intra-connectivity ratio of all real-world datasets used in our experiments, both for randomly sampled mini-batches as well as for utilizing METIS partitions as mini-batches. Notably, applying METIS beforehand reduces the overall inter-/intra-connectivity ratio by a factor of 4 on average, which results in only a fraction of history accesses. Furthermore, most real-world datasets come with inter-/intra-connectivity ratios between 0.1 and 2.5, leading to only marginal runtime overheads when leveraging historical information, as confirmed by our runtime analysis.

Analysis of Gains for Obtaining Expressive Node Representations. Next, we highlight the impacts of minimizing the inter-connectivity between mini-batches and enforcing Lipschitz continuity of the learned function in order to derive expressive node representations. Here, we benchmark a 4-layer GIN model (Xu et al., 2019) on the CLUSTER dataset (Dwivedi et al., 2020), cf. Table 2. Notably, both solutions achieve significant gains in training, validation and test performance, and together, they are able to closely resemble the performance of full-batch training. However, we found that Lipschitz continuity regularization only helps in non-linear message passing phases, while it does not provide any additional gains for linear operators such as GCN (Kipf & Welling, 2017).

6. Datasets

We give detailed statistics for all datasets used in our experiments, cf. Table 3, which include the following tasks:

1. classifying academic papers in citation networks (CORA, CITESEER, PUBMED) (Sen et al., 2008; Yang et al., 2016)
2. categorizing computer science articles in Wikipedia graphs (WIKI-CS) (Mernyei & Cangea, 2020)
3. predicting active research fields of authors in co-authorshop graphs (COAUTHOR-CS, COAUTHOR-PHYSICS) (Shchur et al., 2018)
4. predicting product categories in co-purchase graphs (AMAZON-COMPUTER, AMAZON-PHOTO) (Shchur et al., 2018)
5. identifying community clusters in Stochastic Block Models (CLUSTER, PATTERN) (Dwivedi et al., 2020)
6. predicting communities of online posts based on user comments (REDDIT) (Hamilton et al., 2017)
7. classifying protein functions based on the interactions of human tissue proteins (PPI) (Hamilton et al., 2017)
8. categorizing types of images based on their descriptions and properties (FLICKR) (Zeng et al., 2020)
9. classifying business types based on customers and friendship relations (YELP) (Zeng et al., 2020)
10. predicting subject areas of ARXIV Computer Science papers (ogbn-arxiv) (Hu et al., 2020)
11. predicting product categories in an AMAZON product co-purchasing network (ogbn-products) (Hu et al., 2020)

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