GAPTUNE: LEARNING GRAPH PROMPTS FROM SOURCE–TARGET CONTEXT GAPS

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ABSTRACT

Graph prompting adapts *graph neural networks* (GNNs) pretrained on source graphs to target applications with few trainable parameters. Recent methods introduce feature, topology, and message prompts, but how source–target context gaps should inform local prompt values remains underexplored. In a controlled prompt-transfer study with a frozen GNN, we find that prompt transferability is associated with source–target context shifts in node representations and messages. Motivated by this association, we propose GAPTUNE, a graph prompting framework that learns local prompts from context gaps in source-available and source-free settings. Source observations are obtained from pretraining graphs when available or approximated by responses to compact model-inverted proxy graphs. Shared learnable queries pool the frozen GNN's unprompted initial node states and layer-wise messages into paired source and target contexts, whose differences supply prompt values. Local relevance weights and shared signed gates combine these values into task-supervised local prompts. Our analysis establishes gap-dependent prompt bounds, task-compatible symmetries, and conditional prediction stability under source-context approximation for a fixed adapted predictor. Experiments against 12 prompting baselines on 9 target datasets and 4 tasks show task-dependent transfer gains. Joint gap-valued prompts outperform equally parameterized free values on four ablation targets, with benefits depending on insertion locations and graph shifts.

1 INTRODUCTION

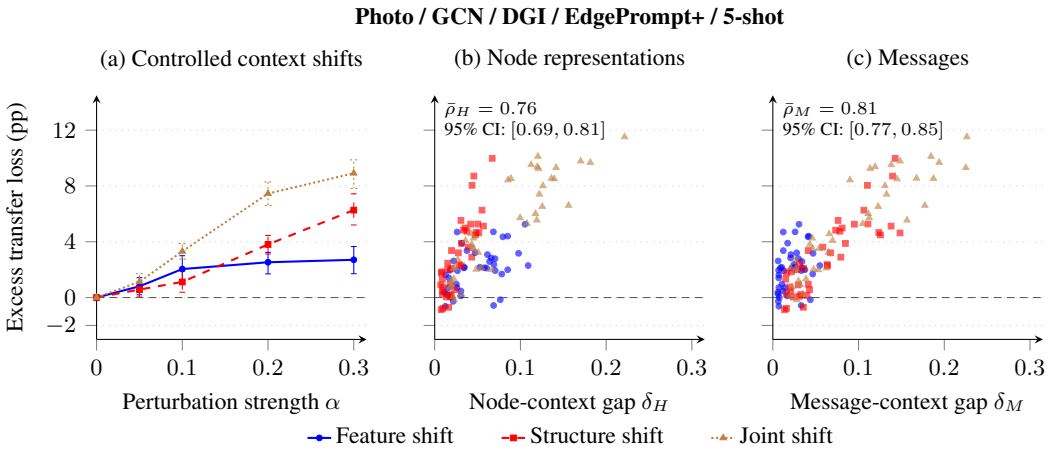

Figure 1: Source–target context shifts and prompt transferability. (a) Mean excess transfer loss; (b,c) its association with node- and message-context gaps over 120 repetition–condition pairs. Intervals are 95% repetition-bootstrap intervals; $\bar{\rho}$ is the mean within-repetition Spearman correlation.

Graph prompting adapts *graph neural networks* (GNNs) pretrained on source graphs to target applications by learning a small number of task-specific parameters while keeping the pretrained GNN frozen (Fang et al., 2023; Fu et al., 2025a;c). However, target graph contexts can differ even when

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the source GNN is frozen: node attributes and neighborhood structure can change the information processed by the same GNN (Yan et al., 2024). Beyond prompt placement, this raises a question: *what source–target information should determine local prompt values?*

Existing methods address the pretraining–task mismatch through task reformulation (Sun et al., 2022; Liu et al., 2023; Sun et al., 2023) or introduce feature, representation, topology, and message prompts (Fang et al., 2023; Yu et al., 2024; Fu et al., 2025b;a). Instance-conditioned prompts and learnable message prototypes tailor adaptation to target nodes and neighborhoods (Li et al., 2025; Yu et al., 2025; Chen et al., 2026), while distribution-aware methods address graph shifts through spectral alignment or hop-specific adaptation (Yan et al., 2024; Chen et al., 2025). We investigate a complementary design: *use explicitly modeled source–target context gaps to supply local prompt values*. This separates prompt values from their insertion locations and local composition.

We use *graph context* to describe patterns in node states and messages under a frozen GNN. To examine prompt transferability, we conduct a controlled 5-shot node-classification study on Photo (Shchur et al., 2018) with EdgePrompt+ (Fu et al., 2025a) and a frozen GCN (Kipf & Welling, 2017) pretrained using DGI (Veličković et al., 2019) (Figure 1). Target views introduce feature, structure, or joint perturbations while preserving node identities, labels, and the feature coordinate system. We compare source-transferred and target-trained prompts using fresh heads fitted on the same target support; their accuracy difference, centered on a same-context control, defines *excess transfer loss*. This loss increases with perturbation strength and correlates with independently measured node- and message-context gaps ($\bar{\rho}_H = 0.76$, $\bar{\rho}_M = 0.81$), motivating explicit context comparisons. Appendix A gives the protocol, uncertainty, and single-configuration scope.

We propose GAPTUNE, a graph prompting framework that constructs local prompts from paired context gaps without node correspondence or equal graph sizes (Figure 2). Shared learnable queries pool unprompted initial node states and layer-wise messages into paired contexts, whose differences supply prompt values. Object-dependent relevance weights and shared signed gates compose these gaps, and a second pass injects the resulting node and message prompts without changing the frozen GNN or topology. Source-available GAPTUNE+ uses pretraining graphs; source-free GAPTUNE uses compact model-inverted proxies and retained pretrained components. Target labels train the queries, relevance maps, gates, and head without a gap-minimization objective, and final pooled source contexts replace source or proxy graphs at inference.

Our analysis establishes gap-dependent prompt bounds, task-compatible symmetries, and conditional prediction stability under source-context approximation for a fixed adapted predictor. Experiments compare 12 prompting baselines on 9 target datasets spanning node classification, link prediction, graph classification, and graph regression. Cross- and same-dataset experiments show task-dependent transfer gains. Joint gap-valued prompts outperform free values on four ablation targets, with insertion and controlled-shift studies revealing the limits of this advantage.

2 RELATED WORK

Graph prompting. GPPT and GraphPrompt connect pretraining and downstream tasks through shared prediction templates (Sun et al., 2022; Liu et al., 2023), while All-in-One combines task reformulation with prompt graphs and meta-learned initialization (Sun et al., 2023). GPF adds a shared feature prompt, and GPF+ learns node-dependent mixtures of prompt vectors (Fang et al., 2023). GraphPrompt+ extends prompting across layers (Yu et al., 2024); GraphTOP rewires topology (Fu et al., 2025b), while UniPrompt fuses a learnable weighted nearest-neighbor graph with the original topology through bootstrapped updates (Huang et al., 2025). IA-GPL, SUPT, and ProNoG condition prompts on instances, subgraphs, and non-homophilic patterns, respectively (Li et al., 2025; Lee et al., 2026; Yu et al., 2025). At the message level, EdgePrompt adds shared prompts and EdgePrompt+ learns edge-dependent mixtures (Fu et al., 2025a); MAGPrompt also reweights neighbor messages (Nguyen & Nguyen, 2026). MTG learns message prototypes (Chen et al., 2026), and LR-GMP uses low-rank message-prompt representations (Wang et al., 2026a). These methods motivate distinguishing prompt placement and target-side conditioning from the source–target information used to construct prompt values.

Graph adaptation under distribution shifts. GCOPE learns coordinators for multi-domain pretraining (Zhao et al., 2024), and GraphControl adds target attributes as conditions to models pre-

trained on graph structure (Zhu et al., 2024). IGAP addresses graph-signal and graph-structure gaps through spectral prompting without source graphs (Yan et al., 2024). DAGPrompT combines low-rank adaptation with hop-specific prompts (Chen et al., 2025), while GP2F fuses a frozen branch with an adapter-based branch (He et al., 2026). GFMate combines labeled target support with unlabeled test data for test-time prompt tuning (Jiang et al., 2026). SFGAR adapts a task-specific source predictor through pseudo-source reconstruction and unlabeled-target adversarial alignment (Yang et al., 2026); OGMM generates graphs to merge multiple pretrained predictors (Wang et al., 2026b). GAPTUNE instead constructs gap-valued prompts for one frozen GNN with labeled target support; Appendix D.4 distinguishes the source-free comparison settings.

3 METHODOLOGY

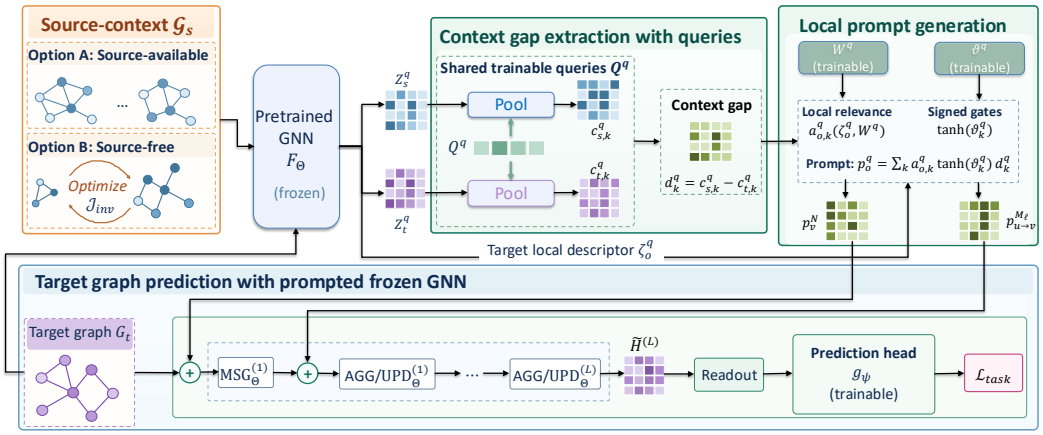

Figure 2: Overview of GAPTUNE.

GAPTUNE uses two passes of a frozen GNN (Figure 2): an unprompted pass supplies context observations and local descriptors, and a prompted pass makes predictions. Shared queries pool source and target observations into paired contexts, whose differences supply prompt values. Local relevance and shared signed gates combine these values into node and message prompts, trained with the task head through target supervision. Source observations come from pretraining or proxy graphs, with only their final pooled contexts retained at inference.

3.1 PROBLEM FORMULATION

For an attributed graph $G = (V, E, X)$ with node set $V \neq \varnothing$, edges E, and features X, an L-layer pretrained GNN F_Θ computes unprompted messages and node states (Wu et al., 2021):

$$\bar{m}_{u\to v}^{(\ell)} = \text{MSG}_\Theta^{(\ell)}(G, \bar{H}^{(\ell-1)})_{u\to v}, \tag{1}$$

$$\bar{h}_v^{(\ell)} = \text{UPD}_\Theta^{(\ell)}\left(\bar{h}_v^{(\ell-1)}, \text{AGG}^{(\ell)}\{\bar{m}_{u\to v}^{(\ell)} : u \in \mathcal{N}(v)\}\right). \tag{2}$$

Here, $\bar{H}^{(\ell)}$ collects node states, $\mathcal{N}(v)$ contains the neighbors sending messages to v, and $\bar{h}_v^{(0)}$ is the initial continuous state after any frozen input embedding. The bar denotes an unprompted quantity, MSG constructs structurally weighted messages, AGG combines the messages received by a node, and UPD uses the aggregate and the previous state to compute its next state.

Given labeled targets $\mathcal{D}_t^{\text{lab}} = \{(G_i, o_i, y_i)\}_{i=1}^n$, we learn prompt parameters Φ and a task head g_ψ:

$$\min_{\Phi,\psi} \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}_{\text{task}}\big(g_\psi\big(r_{o_i}(G_i;\Theta,\Phi)\big), y_i\big), \qquad \Theta \text{ fixed.} \tag{3}$$

o_i is a node, an edge, or a subgraph; y_i is its classification or regression target, and r_o is its prompted representation after a task-appropriate readout. Both forward passes use deterministic evaluation of the frozen GNN and stored normalization statistics. Checkpoint-compatible features make subtraction well-defined, but equal widths do not establish semantic alignment; Appendix B.11 analyzes coordinate mismatch and task-directed gap use.

3.2 SOURCE AND TARGET CONTEXT OBSERVATIONS

Observation type $q \in \mathcal{I} = \{N, M_1, \ldots, M_L\}$ denotes initial node states or layer-wise messages:

$$z_v^N = \bar{h}_v^{(0)}, \qquad z_{u\to v}^{M_\ell} = \bar{m}_{u\to v}^{(\ell)}. \tag{4}$$

Each $z_o^q \in \mathbb{R}^{d_q}$ matches its insertion dimension, and $\mathcal{O}_q(G)$ contains all nodes or directional messages receiving prompts, including unlabeled and unpooled instances.

Source-available observations. We encode the pretraining graphs $\mathcal{G}_s$ and each target graph G separately with the same unprompted GNN and form the label-free collections

$$\mathcal{Z}_s^q = \{z_{s,i}^q\}_{i=1}^{n_s^q}, \qquad \mathcal{Z}_t^q(G) = \{z_{t,i}^q\}_{i=1}^{n_t^q}. \tag{5}$$

Here, n_s^q and n_t^q count the source and target observations of type q retained for context pooling; they need not equal the numbers of objects receiving prompts. A label-independent selection rule may bound collection sizes without changing the neighborhoods used to compute responses. Target collections are graph-specific, not pooled across a minibatch. In same-dataset adaptation, the gap compares the pooled pretraining reference with a prediction subgraph; it need not indicate a dataset-level distribution shift.

Source-free observations. When $\mathcal{G}_s$ is unavailable, model inversion constructs compact proxy graphs (Wang et al., 2026b). For graph or generator parameters ω, initialization or latent input ξ, and retained pretrained components or statistics $\mathcal{A}_{\mathrm{pre}}$, it solves

$$\omega^\star \approx \arg\min_{\omega}\ \mathbb{E}_\xi\left[\mathcal{J}_{\mathrm{inv}}\big(\widehat{G}_\omega(\xi); F_\Theta, \mathcal{A}_{\mathrm{pre}}\big)\right]. \tag{6}$$

After optimization, $\widehat{\mathcal{G}}_s = \{\widehat{G}_{\omega^\star}(\xi_b)\}_{b=1}^B$ denotes the collection of B generated proxy graphs. Encoding this collection with the frozen GNN supplies the source observations:

$$\mathcal{Z}_s^q = \mathrm{Responses}_q(F_\Theta, \widehat{\mathcal{G}}_s). \tag{7}$$

$\mathrm{Responses}_q$ extracts the node states or messages needed for source-context approximation, without requiring recovery of the full source distribution. For the two transfer checkpoint types, source-free construction requires input gradients and a retained edge scorer or contrastive projection. Appendix B.8 defines the objectives; optimization details are provided in our code.

In both settings, source observations remain fixed during prompt learning, whereas their query-weighted summaries are learnable. Source or proxy graphs are not inserted into the target graph. Both passes follow the same data-access and split conventions as the baselines; context extraction uses no downstream labels. Type q is active only when both observation collections are nonempty; otherwise, all its prompts are zero.

3.3 SHARED QUERIES FOR PAIRED GRAPH CONTEXTS

Each type has K_q queries $Q^q = \{q_k^q \in \mathbb{R}^{d_q}\}_{k=1}^{K_q}$, shared between source and target but not across types. For fixed $\varepsilon, \tau_c > 0$, set $\nu(z) = z/\sqrt{\|z\|_2^2 + \varepsilon^2}$ and pool each nonempty side $a \in \{s, t\}$:

$$\pi_{a,k,i}^q = \frac{\exp((q_k^q)^\top \nu(z_{a,i}^q)/\tau_c)}{\sum_{j=1}^{n_a^q} \exp((q_k^q)^\top \nu(z_{a,j}^q)/\tau_c)}, \tag{8}$$

$$c_{a,k}^q = \sum_{i=1}^{n_a^q} \pi_{a,k,i}^q z_{a,i}^q, \qquad d_k^q = c_{s,k}^q - c_{t,k}^q. \tag{9}$$

Observation normalization limits magnitude effects in attention, ε handles zero responses, and τ_c and query norms control attention sharpness. Queries are not unit-normalized; pooled values and gaps retain their original coordinates and magnitudes. Shared queries pair contexts without node correspondence, while separate normalizations allow source and target weights to differ. Task gradients update queries through both summaries. Identical source and target observations give zero gaps, so topology-only shifts can change message prompts while leaving node-input prompts zero.

3.4 Local Prompt Generation and Injection

Local relevance and signed contributions. Unprompted encodings provide the local descriptors

$$\begin{aligned}\zeta_v^N &= [\bar{h}_v^{(0)} \,\|\, \bar{h}_v^{(L)}],\\ \zeta_{u\to v}^{M_\ell} &= [\bar{h}_u^{(\ell-1)} \,\|\, \bar{h}_v^{(\ell-1)} \,\|\, \bar{m}_{u\to v}^{(\ell)}].\end{aligned} \tag{10}$$

Here, $\|$ denotes concatenation. The node descriptor combines initial and final states, while message descriptors distinguish the sender from the receiver even when link prediction is undirected. For $e_q = \dim(\zeta_o^q)$, learnable relevance vectors $W^q = \{w_k^q \in \mathbb{R}^{e_q}\}_{k=1}^{K_q}$, gates $\vartheta^q \in \mathbb{R}^{K_q}$, and fixed temperature $\tau_p > 0$, we define

$$a_{o,k}^q = \frac{\exp((w_k^q)^\top \nu(\zeta_o^q)/\tau_p)}{\sum_{j=1}^{K_q} \exp((w_j^q)^\top \nu(\zeta_o^q)/\tau_p)}, \tag{11}$$

$$p_o^q = \sum_{k=1}^{K_q} a_{o,k}^q \tanh(\vartheta_k^q) d_k^q, \qquad o \in \mathcal{O}_q(G). \tag{12}$$

The softmax over queries assigns each object nonnegative weights summing to one, so the descriptor selects a mixture while the gaps supply its values. The signed gates are shared across objects of type q, allowing a gap contribution to be preserved, reversed, or suppressed. Locality therefore comes from object-dependent mixtures, not independent signs for every object–gap pair. Only the target task supervises this construction, with no free prompt values or gap-minimization objective. Gaps supply value directions; relevance and signed gates determine their local use.

Prompted propagation. A second pass adds node prompts once to the initial continuous states:

$$\widetilde{h}_v^{(0)} = \bar{h}_v^{(0)} + p_v^N. \tag{13}$$

Each layer adds message prompts to native messages from prompted states before applying the original aggregation and update operators:

$$m_{\Theta,u\to v}^{(\ell)} = \mathrm{MSG}_\Theta^{(\ell)}(G, \widetilde{H}^{(\ell-1)})_{u\to v}, \tag{14}$$

$$\widetilde{m}_{u\to v}^{(\ell)} = m_{\Theta,u\to v}^{(\ell)} + p_{u\to v}^{M_\ell}, \tag{15}$$

$$\widetilde{h}_v^{(\ell)} = \mathrm{UPD}_\Theta^{(\ell)}\left(\widetilde{h}_v^{(\ell-1)}, \mathrm{AGG}^{(\ell)}\{\widetilde{m}_{u\to v}^{(\ell)} : u \in \mathcal{N}(v)\}\right). \tag{16}$$

Message prompts enter after structural weighting and before aggregation, without changing topology or pretrained parameters. State-dependent attention is recomputed from prompted states, while prompts use fixed unprompted observations and descriptors rather than recursive regeneration.

3.5 Task-Native Prediction and Optimization

Prediction. For final prompted states $\widetilde{h}_v = \widetilde{h}_v^{(L)}$, the readouts are

$$r_o(G) = \begin{cases} \widetilde{h}_v, & o = v,\\ [\widetilde{h}_u + \widetilde{h}_v \,\|\, \widetilde{h}_u \odot \widetilde{h}_v], & o = \{u, v\},\\ |V|^{-1} \sum_{v\in V} \widetilde{h}_v, & o = G. \end{cases} \tag{17}$$

Here, $\odot$ denotes element-wise multiplication, and each candidate link is an unordered pair $\{u, v\}$. The edge readout satisfies $r_{\{u,v\}}(G) = r_{\{v,u\}}(G)$, while graph averaging is invariant to node order. Candidate links need not be message-passing edges. An affine head $g_\psi(r) = W_\psi r + b_\psi$ produces logits or regression outputs, using cross-entropy for multiclass targets, binary cross-entropy for binary or multilabel targets, or a regression loss.

Optimization. We optimize $\Phi = \{Q^q, W^q, \vartheta^q\}_{q\in\mathcal{I}}$ and ψ using Eq. 3, with detached observations and descriptors but differentiable context pooling and prompted propagation. Every update recomputes contexts from the current queries. Source pooling may be shared across graphs, but target pooling is graph-specific. Inversion finishes before adaptation; the validation-selected checkpoint is restored before retaining source contexts (Algorithm 1). Zero-initialized gates make the initial prompted pass identical to the unprompted encoder, while distinct query and relevance rows permit specialization as the gates change.

Inference and cost. We store source-empty flags and the final pooled source contexts:

$$C_s^\star = \left\{ c_{s,k}^q(Q^{q\star}; \mathcal{Z}_s^q) : \; q \in \mathcal{I}, \; n_s^q > 0, \; 1 \le k \le K_q \right\}. \tag{18}$$

With fixed queries, these summaries replace repeated source pooling; inference needs only the new target graph, not source graphs, proxy graphs, or further inversion. This replacement is exact for the retained queries and source observations; it introduces no additional approximation beyond the source bank itself. Prompt parameters number $\sum_q K_q(d_q + e_q + 1)$, excluding the head; retained source contexts need $\sum_q K_q d_q$ scalars, independent of source graph size. Appendix C.10 reports measured costs and query-count dependence; Appendix D.2 specifies observation sampling.

Same-dataset adaptation. Node and edge queries use induced subgraphs retaining their prediction objects and labels (Sun et al., 2023); graph tasks use complete graphs. The pretraining reference and prediction graph can have different contexts within one dataset, whereas identical observation collections yield zero prompts (Proposition B.1).

3.6 Theoretical Properties

We establish gap-supported prompt bounds, task-compatible symmetries, and conditional stability, with proofs and operator interpretations in Appendix B.

Proposition 3.1 (Bounded gap-supported prompts)**.** *For active q and $o \in \mathcal{O}_q(G)$,*

$$p_o^q \in \operatorname{span}\{d_1^q, \ldots, d_{K_q}^q\}, \qquad \|p_o^q\|_2 \le \max_k \|d_k^q\|_2. \tag{19}$$

If observation norms are bounded by C_q on both sides, then $\|p_o^q\|_2 \le 2C_q$.

Proposition 3.2 (Task-compatible symmetries)**.** *Suppose the pretrained GNN has equivariant node and directional-message operators, invariant neighborhood aggregation, and observation selection commuting with node relabeling. The prompted GNN is equivariant, and a shared classification or regression head preserves node equivariance, endpoint-exchange invariance for links, and graph-level invariance in Eq. 17.*

Proposition 3.3 (Conditional prediction stability)**.** *Fix the target graph, unprompted observations and descriptors, learned parameters, and active types. If $\max_k \|\widehat{c}_{s,k}^q - c_{s,k}^q\|_2 \le \epsilon_q$, then source-context replacement obeys the following prompt bound:*

$$\|\widehat{P}^q - P^q\|_{\max,2} \le \epsilon_q. \tag{20}$$

Here, $P^q = \{p_o^q\}_{o \in \mathcal{O}_q(G)}$ and $\|B\|_{\max,2} = \max_o \|B_o\|_2$, with value zero for empty collections. For $P = \{P^q\}_{q \in \mathcal{I}}$, let $f_o(P) = g_\psi(r_o(G; P))$ be the logits or regression outputs. If f_o is separately Lipschitz in each P^q, with constants $\kappa_{o,q}$ valid along all intermediate type-wise replacements, then

$$\|f_o(\widehat{P}) - f_o(P)\|_\infty \le \sum_{q \in \mathcal{I}} \kappa_{o,q} \epsilon_q. \tag{21}$$

Inactive observation types contribute zero to both the prompt and output perturbation bounds.

Implications. A classification margin exceeding twice the output bound preserves the predicted class; for regression, the bound limits the change in absolute error per coordinate. Appendix B.9 relates context error to observation distance; these fixed-predictor guarantees do not establish inversion quality or generalization. Proposition B.5 characterizes task-loss descent through the shared gates: gap directions must interact with the task gradient, not merely have large magnitudes. The span restriction is therefore an inductive bias rather than an expressivity advantage over free values, motivating separate tests of values, insertion locations, and shift strength.

4 Experiments

4.1 Experimental Setup

We compare 12 prompting baselines on 9 datasets and 4 tasks, with 7 scratch-trained GNNs as separate references (Fu et al., 2025a; Fang et al., 2023). Cross-dataset transfer uses

ZINC/GCN/EdgePred and PubMed/GIN/GraphCL checkpoints with 100-dimensional inputs obtained by SVD reduction or padding (Zhao et al., 2024). GAPTUNE uses proxy source contexts and GAPTUNE+ uses pretraining graphs; both retain the baseline data splits. We use *5-shot* and *100-shot* settings: single-label classification has k training examples per class, graph regression has k training graphs, and multi-label and link prediction retain their task-specific support partitions. Baseline configurations follow their official implementations, and all methods share the task-specific data and evaluation conventions in Appendix D.1; implementation and optimization details are provided in our code. We report accuracy, ROC-AUC, and MAE as 5-run mean±sample standard deviation. Each run selects its adaptation checkpoint on validation performance before recording the test score. All same-dataset prompting methods search the same 7×6 architecture–objective grid and report their best observed test mean with the corresponding sample standard deviation.

4.2 EXPERIMENTAL RESULTS

Table 1: Cross-dataset adaptation at 5-shot settings. Each block repeats the architecture-matched scratch control from Table 2. Bold/underline mark the best/second test means, including scratch.

Methods	Homophilic graphs: E-commerce **Photo** NC / Acc. ↑	Homophilic graphs: Academic **ogbn-arxiv** NC / Acc. ↑	Homophilic graphs: Academic **DBLP** LP / AUC ↑	Heterophilic graphs: Transport **Airports** NC / Acc. ↑	Heterophilic graphs: Web **Chameleon** NC / Acc. ↑	Heterophilic graphs: Web **Cornell** LP / AUC ↑	Graph-level tasks: Chemistry **QM7b** GR / MAE ↓	Graph-level tasks: Chemistry **ToxCast** GC / AUC ↑	Graph-level tasks: Vision **MNIST** GC / Acc. ↑
Source dataset: ZINC, GNN: GCN, Pretraining: EdgePred									
GCN (scratch)	77.08$_{\pm 1.52}$	22.86$_{\pm 1.72}$	54.94$_{\pm 0.45}$	32.51$_{\pm 3.89}$	28.79$_{\pm 4.71}$	58.29$_{\pm 8.87}$	5.59$_{\pm 0.28}$	48.76$_{\pm 0.98}$	21.08$_{\pm 0.72}$
All-in-One	54.80$_{\pm 3.20}$	14.85$_{\pm 1.35}$	52.74$_{\pm 0.88}$	36.92$_{\pm 3.94}$	27.41$_{\pm 3.55}$	52.41$_{\pm 7.84}$	15.42$_{\pm 4.50}$	46.99$_{\pm 1.81}$	24.73$_{\pm 3.10}$
EdgePrompt	53.48$_{\pm 5.90}$	8.62$_{\pm 2.10}$	51.86$_{\pm 0.72}$	30.54$_{\pm 4.66}$	25.98$_{\pm 3.27}$	54.28$_{\pm 8.46}$	29.68$_{\pm 3.12}$	49.92$_{\pm 1.24}$	18.62$_{\pm 3.75}$
EdgePrompt+	59.86$_{\pm 5.15}$	11.24$_{\pm 2.32}$	52.47$_{\pm 0.68}$	31.88$_{\pm 5.12}$	27.62$_{\pm 3.10}$	55.61$_{\pm 8.92}$	25.71$_{\pm 2.61}$	50.90$_{\pm 1.45}$	21.46$_{\pm 2.67}$
GPF	55.21$_{\pm 4.87}$	9.16$_{\pm 1.88}$	51.13$_{\pm 0.77}$	29.45$_{\pm 4.53}$	26.71$_{\pm 2.94}$	52.86$_{\pm 8.17}$	40.18$_{\pm 4.31}$	51.65$_{\pm 1.11}$	16.08$_{\pm 4.12}$
GPF+	61.32$_{\pm 4.51}$	12.05$_{\pm 2.01}$	52.08$_{\pm 0.70}$	30.76$_{\pm 4.14}$	28.40$_{\pm 2.81}$	54.19$_{\pm 7.62}$	34.62$_{\pm 3.08}$	47.74$_{\pm 1.75}$	20.54$_{\pm 3.35}$
GPPT	39.72$_{\pm 4.42}$	4.11$_{\pm 1.55}$	50.45$_{\pm 1.10}$	28.17$_{\pm 3.70}$	23.84$_{\pm 3.60}$	51.72$_{\pm 8.20}$	45.63$_{\pm 8.75}$	50.10$_{\pm 0.30}$	16.80$_{\pm 2.55}$
GraphPrompt	47.64$_{\pm 3.11}$	5.73$_{\pm 1.26}$	51.21$_{\pm 0.76}$	28.83$_{\pm 3.96}$	24.53$_{\pm 4.72}$	52.27$_{\pm 7.66}$	31.72$_{\pm 3.40}$	43.84$_{\pm 1.98}$	21.77$_{\pm 2.41}$
GraphPrompt+	52.15$_{\pm 4.39}$	5.21$_{\pm 1.41}$	51.84$_{\pm 0.74}$	29.58$_{\pm 3.72}$	25.18$_{\pm 4.15}$	53.06$_{\pm 8.50}$	25.42$_{\pm 3.30}$	42.15$_{\pm 2.49}$	20.31$_{\pm 2.25}$
ProNoG	48.53$_{\pm 3.48}$	5.71$_{\pm 1.26}$	51.54$_{\pm 0.81}$	27.61$_{\pm 3.21}$	24.33$_{\pm 3.57}$	53.81$_{\pm 8.03}$	34.44$_{\pm 5.94}$	42.82$_{\pm 2.73}$	20.54$_{\pm 2.79}$
IGAP	70.84$_{\pm 4.32}$	20.72$_{\pm 2.91}$	54.46$_{\pm 0.69}$	35.61$_{\pm 3.89}$	31.92$_{\pm 3.02}$	59.18$_{\pm 8.11}$	12.36$_{\pm 1.66}$	49.29$_{\pm 1.50}$	23.68$_{\pm 2.33}$
MTG	68.93$_{\pm 4.01}$	19.15$_{\pm 2.78}$	54.08$_{\pm 1.34}$	36.74$_{\pm 3.71}$	33.51$_{\pm 2.88}$	57.86$_{\pm 7.94}$	10.72$_{\pm 1.42}$	51.49$_{\pm 1.69}$	25.16$_{\pm 2.06}$
SUPT	66.77$_{\pm 3.78}$	17.64$_{\pm 3.54}$	53.28$_{\pm 0.71}$	35.09$_{\pm 3.80}$	32.24$_{\pm 2.75}$	56.34$_{\pm 7.73}$	14.08$_{\pm 1.88}$	51.81$_{\pm 2.28}$	24.84$_{\pm 2.13}$
GAPTUNE	75.12$_{\pm 3.61}$	22.43$_{\pm 2.45}$	55.15$_{\pm 0.62}$	38.21$_{\pm 3.43}$	35.19$_{\pm 2.56}$	60.48$_{\pm 7.05}$	11.38$_{\pm 1.31}$	52.68$_{\pm 1.88}$	26.28$_{\pm 1.91}$
GAPTUNE+	**77.86**$_{\pm 3.44}$	**23.91**$_{\pm 2.28}$	**55.82**$_{\pm 0.57}$	**39.74**$_{\pm 3.21}$	**36.47**$_{\pm 2.39}$	**61.92**$_{\pm 6.83}$	**5.42**$_{\pm 1.18}$	**53.18**$_{\pm 1.63}$	**27.63**$_{\pm 1.79}$
Source dataset: PubMed, GNN: GIN, Pretraining: GraphCL									
GIN (scratch)	71.84$_{\pm 1.52}$	17.86$_{\pm 1.31}$	55.91$_{\pm 0.82}$	35.18$_{\pm 3.08}$	29.01$_{\pm 3.20}$	61.91$_{\pm 4.48}$	41.65$_{\pm 5.39}$	45.97$_{\pm 2.36}$	26.79$_{\pm 2.20}$
All-in-One	67.22$_{\pm 2.84}$	26.80$_{\pm 0.77}$	53.26$_{\pm 0.77}$	31.98$_{\pm 3.28}$	31.26$_{\pm 2.94}$	58.42$_{\pm 8.94}$	48.74$_{\pm 10.20}$	53.32$_{\pm 3.47}$	20.97$_{\pm 4.55}$
EdgePrompt	61.68$_{\pm 3.76}$	22.94$_{\pm 1.31}$	53.21$_{\pm 0.82}$	31.46$_{\pm 4.14}$	27.82$_{\pm 3.42}$	54.69$_{\pm 8.67}$	72.51$_{\pm 8.63}$	47.72$_{\pm 1.61}$	20.64$_{\pm 3.48}$
EdgePrompt+	63.74$_{\pm 3.50}$	24.36$_{\pm 1.52}$	53.78$_{\pm 0.78}$	32.80$_{\pm 4.01}$	29.33$_{\pm 3.30}$	55.76$_{\pm 8.32}$	68.39$_{\pm 7.95}$	49.16$_{\pm 1.07}$	22.17$_{\pm 2.84}$
GPF	64.31$_{\pm 3.12}$	23.71$_{\pm 1.42}$	53.08$_{\pm 0.70}$	31.18$_{\pm 4.00}$	28.72$_{\pm 3.18}$	53.41$_{\pm 8.55}$	82.63$_{\pm 9.41}$	48.78$_{\pm 1.44}$	20.08$_{\pm 3.97}$
GPF+	65.42$_{\pm 3.33}$	24.75$_{\pm 1.68}$	53.46$_{\pm 0.74}$	31.73$_{\pm 3.72}$	29.11$_{\pm 2.96}$	54.36$_{\pm 8.10}$	76.28$_{\pm 8.54}$	47.62$_{\pm 1.55}$	21.66$_{\pm 3.20}$
GPPT	41.84$_{\pm 4.63}$	17.53$_{\pm 3.85}$	51.04$_{\pm 1.09}$	29.62$_{\pm 3.15}$	24.40$_{\pm 2.77}$	52.18$_{\pm 8.77}$	96.42$_{\pm 16.74}$	51.02$_{\pm 0.81}$	18.31$_{\pm 2.62}$
GraphPrompt	58.09$_{\pm 3.84}$	14.18$_{\pm 1.69}$	52.74$_{\pm 0.84}$	30.62$_{\pm 4.21}$	24.88$_{\pm 4.18}$	53.22$_{\pm 9.17}$	73.55$_{\pm 8.81}$	45.31$_{\pm 2.99}$	22.95$_{\pm 2.86}$
GraphPrompt+	60.77$_{\pm 4.21}$	13.05$_{\pm 1.82}$	53.11$_{\pm 0.81}$	31.46$_{\pm 3.95}$	25.53$_{\pm 3.88}$	54.01$_{\pm 8.74}$	69.24$_{\pm 8.26}$	42.28$_{\pm 2.71}$	21.37$_{\pm 2.72}$
ProNoG	62.02$_{\pm 2.86}$	22.19$_{\pm 1.63}$	53.28$_{\pm 0.77}$	33.29$_{\pm 4.40}$	27.31$_{\pm 3.87}$	56.46$_{\pm 11.03}$	47.17$_{\pm 5.15}$	46.65$_{\pm 1.09}$	21.66$_{\pm 2.70}$
IGAP	68.76$_{\pm 3.99}$	**30.62**$_{\pm 2.42}$	55.24$_{\pm 0.71}$	35.73$_{\pm 3.46}$	32.18$_{\pm 3.05}$	59.73$_{\pm 7.88}$	47.62$_{\pm 5.20}$	49.97$_{\pm 1.32}$	25.14$_{\pm 2.42}$
MTG	67.91$_{\pm 3.62}$	28.84$_{\pm 2.27}$	54.86$_{\pm 1.11}$	36.52$_{\pm 3.38}$	33.57$_{\pm 2.90}$	58.42$_{\pm 7.65}$	43.18$_{\pm 4.56}$	49.54$_{\pm 1.21}$	26.42$_{\pm 2.14}$
SUPT	66.84$_{\pm 3.47}$	27.51$_{\pm 3.18}$	54.13$_{\pm 0.73}$	35.64$_{\pm 3.30}$	32.76$_{\pm 2.79}$	57.06$_{\pm 7.49}$	50.84$_{\pm 5.71}$	50.75$_{\pm 2.26}$	26.71$_{\pm 2.19}$
GAPTUNE	70.15$_{\pm 3.18}$	29.15$_{\pm 2.18}$	55.62$_{\pm 0.63}$	37.88$_{\pm 3.14}$	35.34$_{\pm 2.53}$	60.71$_{\pm 7.05}$	40.95$_{\pm 4.02}$	52.43$_{\pm 1.43}$	27.82$_{\pm 1.98}$
GAPTUNE+	**71.94**$_{\pm 2.95}$	29.88$_{\pm 2.00}$	**56.11**$_{\pm 0.59}$	**39.13**$_{\pm 2.96}$	**36.81**$_{\pm 2.35}$	**62.18**$_{\pm 6.72}$	**38.90**$_{\pm 4.20}$	**54.78**$_{\pm 1.76}$	**28.96**$_{\pm 1.86}$

Cross-dataset transfer. Across the 36 comparisons in Tables 1 and 14, GAPTUNE and GAPTUNE+ exceed the strongest prompting-baseline mean in 29 and 32 cases, respectively. At 5-shot, GAPTUNE+ gains 7.02 points on Photo with ZINC and 3.24 on Chameleon with PubMed; its ToxCast gains are 1.37 and 1.46 ROC-AUC points, respectively. GAPTUNE+ exceeds GAPTUNE in all 36 comparisons and architecture-matched scratch training in all 18 5-shot and 15 of 18 100-shot comparisons. On QM7b with ZINC, its 5-shot MAE is 5.42, versus 5.59 for scratch GCN, but scratch training remains stronger at 100-shot. Thus, access to source graphs does not make pretraining uniformly beneficial. Comparisons remain within checkpoint blocks; Appendix C.9 gives the uncertainty analysis, which does not establish family-wise superiority.

Same-dataset adaptation. The best-observed GAPTUNE+ means exceed the strongest prompting baseline in 17 of 18 comparisons and tie ProNoG on 100-shot QM7b at 4.06 MAE (Tables 2 and 15). Its 5-shot gains are 1.19, 2.40, 1.71, and 2.16 points on Photo, ogbn-arxiv, Airports, and Chameleon, while ToxCast gains are 2.00 and 1.36 ROC-AUC points at 5-shot and 100-shot. On 5-shot QM7b, GAPTUNE+ reduces MAE from ProNoG's 8.40 to 4.60, compared with 5.59 for scratch GCN.

Table 2: Same-dataset 5-shot performances. Bold/underline mark the best/second test means.

Methods	Homophilic graphs: E-commerce **Photo** NC / Acc. ↑	Homophilic graphs: Academic **ogbn-arxiv** NC / Acc. ↑	Homophilic graphs: Academic **DBLP** LP / AUC ↑	Heterophilic graphs: Transport **Airports** NC / Acc. ↑	Heterophilic graphs: Web **Chameleon** NC / Acc. ↑	Heterophilic graphs: Web **Cornell** LP / AUC ↑	Graph-level tasks: Chemistry **QM7b** GR / MAE ↓	Graph-level tasks: Chemistry **ToxCast** GC / AUC ↑	Graph-level tasks: Vision **MNIST** GC / Acc. ↑
Target-supervised controls: training from scratch (no pretraining)									
GCN	$77.08_{\pm 1.52}$	$22.86_{\pm 1.72}$	$54.94_{\pm 0.45}$	$32.51_{\pm 3.89}$	$28.79_{\pm 4.71}$	$58.29_{\pm 8.87}$	$5.59_{\pm 0.28}$	$48.76_{\pm 0.98}$	$21.08_{\pm 0.72}$
GAT	$72.23_{\pm 2.53}$	$19.79_{\pm 1.41}$	$55.01_{\pm 1.13}$	$28.80_{\pm 3.49}$	$27.74_{\pm 3.74}$	$63.72_{\pm 4.61}$	$21.56_{\pm 1.26}$	$48.58_{\pm 1.53}$	$22.77_{\pm 2.40}$
GIN	$71.84_{\pm 1.52}$	$17.86_{\pm 1.31}$	$55.91_{\pm 0.82}$	$35.18_{\pm 3.08}$	$29.01_{\pm 3.20}$	$61.91_{\pm 4.48}$	$41.65_{\pm 5.39}$	$45.97_{\pm 2.36}$	$26.79_{\pm 2.20}$
H2GCN	$76.77_{\pm 1.94}$	$20.25_{\pm 1.34}$	$55.33_{\pm 0.78}$	$25.50_{\pm 3.47}$	$29.80_{\pm 3.80}$	$70.13_{\pm 5.92}$	$6.14_{\pm 0.17}$	$48.83_{\pm 1.31}$	$23.83_{\pm 2.38}$
FAGCN	$75.89_{\pm 1.79}$	$23.60_{\pm 0.84}$	$53.81_{\pm 0.86}$	$28.02_{\pm 2.26}$	$31.36_{\pm 5.31}$	$62.37_{\pm 7.41}$	$6.16_{\pm 0.43}$	$48.22_{\pm 0.80}$	$21.89_{\pm 1.35}$
Transformer	$76.19_{\pm 3.34}$	$22.89_{\pm 1.68}$	$56.95_{\pm 0.52}$	$33.98_{\pm 3.06}$	$28.41_{\pm 3.29}$	$72.42_{\pm 8.03}$	$24.64_{\pm 37.88}$	$48.73_{\pm 0.70}$	$22.79_{\pm 2.93}$
NodeFormer	$79.04_{\pm 2.30}$	$4.43_{\pm 1.98}$	$54.20_{\pm 4.08}$	$33.47_{\pm 3.84}$	$28.06_{\pm 6.79}$	$58.75_{\pm 9.62}$	$52.70_{\pm 47.67}$	$50.51_{\pm 0.75}$	$14.64_{\pm 3.46}$
Same-dataset pretraining + prompting (best-observed summaries)									
All-in-One	$79.45_{\pm 1.29}$	$30.31_{\pm 0.26}$	$55.73_{\pm 0.68}$	$37.64_{\pm 4.45}$	$33.61_{\pm 1.78}$	$77.50_{\pm 4.81}$	$36.08_{\pm 2.00}$	$57.51_{\pm 3.09}$	$26.89_{\pm 1.30}$
EdgePrompt	$71.53_{\pm 5.19}$	$31.51_{\pm 1.42}$	$57.40_{\pm 0.43}$	$38.17_{\pm 6.37}$	$34.71_{\pm 3.01}$	$76.89_{\pm 2.88}$	$36.00_{\pm 1.98}$	$52.39_{\pm 1.93}$	$24.48_{\pm 2.13}$
EdgePrompt+	$70.42_{\pm 3.71}$	$32.45_{\pm 2.50}$	$56.99_{\pm 0.30}$	$38.80_{\pm 5.58}$	$35.39_{\pm 2.10}$	$78.04_{\pm 4.02}$	$35.07_{\pm 1.59}$	$52.46_{\pm 2.22}$	$28.54_{\pm 2.58}$
GPF	$80.88_{\pm 4.46}$	$31.20_{\pm 0.91}$	$57.21_{\pm 0.30}$	$38.67_{\pm 4.85}$	$34.95_{\pm 2.84}$	$78.88_{\pm 3.67}$	$36.77_{\pm 3.24}$	$52.60_{\pm 1.47}$	$26.67_{\pm 2.78}$
GPF+	$81.27_{\pm 3.42}$	$30.34_{\pm 1.75}$	$56.72_{\pm 0.85}$	$37.62_{\pm 4.03}$	$34.40_{\pm 2.46}$	$80.92_{\pm 2.24}$	$36.74_{\pm 1.65}$	$52.35_{\pm 1.69}$	$25.53_{\pm 5.97}$
GPPT	$78.46_{\pm 1.94}$	$28.39_{\pm 4.30}$	$54.41_{\pm 0.61}$	$35.01_{\pm 2.04}$	$33.72_{\pm 2.27}$	$65.06_{\pm 8.45}$	$51.24_{\pm 26.55}$	$51.09_{\pm 1.67}$	$22.35_{\pm 2.61}$
GraphPrompt	$77.56_{\pm 1.63}$	$14.67_{\pm 2.23}$	$55.83_{\pm 0.60}$	$35.40_{\pm 4.13}$	$27.83_{\pm 6.74}$	$72.60_{\pm 2.88}$	$44.47_{\pm 1.01}$	$47.53_{\pm 1.92}$	$28.16_{\pm 2.70}$
GraphPrompt+	$77.22_{\pm 2.58}$	$13.59_{\pm 1.88}$	$56.37_{\pm 0.50}$	$35.50_{\pm 3.45}$	$26.15_{\pm 6.21}$	$64.23_{\pm 10.89}$	$25.02_{\pm 4.18}$	$44.65_{\pm 2.66}$	$24.61_{\pm 1.79}$
ProNoG	$80.56_{\pm 3.53}$	$27.10_{\pm 3.22}$	$57.03_{\pm 0.70}$	$32.03_{\pm 3.68}$	$30.57_{\pm 3.07}$	$70.00_{\pm 5.18}$	$8.40_{\pm 3.46}$	$48.06_{\pm 0.75}$	$27.28_{\pm 0.44}$
IGAP	$80.38_{\pm 4.53}$	$25.19_{\pm 3.96}$	$54.45_{\pm 0.68}$	$39.45_{\pm 5.10}$	$32.63_{\pm 2.35}$	$68.38_{\pm 12.24}$	$37.34_{\pm 1.54}$	$52.42_{\pm 1.45}$	$25.69_{\pm 2.21}$
MTG	$75.40_{\pm 3.21}$	$29.00_{\pm 3.91}$	$56.12_{\pm 3.61}$	$42.39_{\pm 4.76}$	$36.29_{\pm 2.53}$	$70.30_{\pm 14.50}$	$33.31_{\pm 1.53}$	$53.64_{\pm 1.66}$	$27.29_{\pm 1.74}$
SUPT	$81.91_{\pm 2.17}$	$27.87_{\pm 8.01}$	$55.08_{\pm 0.69}$	$39.21_{\pm 4.33}$	$34.73_{\pm 2.16}$	$66.34_{\pm 10.44}$	$35.97_{\pm 2.13}$	$53.74_{\pm 1.51}$	$25.05_{\pm 1.74}$
GAPTUNE+	**83.10**$_{\pm 2.41}$	**34.85**$_{\pm 1.86}$	**59.41**$_{\pm 0.43}$	**44.10**$_{\pm 3.96}$	**38.45**$_{\pm 2.05}$	**82.10**$_{\pm 3.26}$	**4.60**$_{\pm 0.46}$	**59.51**$_{\pm 1.07}$	**30.54**$_{\pm 2.18}$

Several baselines, including GPPT and GraphPrompt, were originally formulated for classification rather than graph regression (Sun et al., 2022; Liu et al., 2023); their task-specific designs may transfer unevenly to QM7b.

4.3 Ablations and Practical Trade-offs

Table 3: Prompt-value ablation on four targets at 5-shot (%).

Values	Photo Acc. ↑	Chameleon Acc. ↑	DBLP AUC ↑	MNIST Acc. ↑
Head only	$64.73_{\pm 4.12}$	$29.24_{\pm 3.17}$	$52.52_{\pm 0.88}$	$21.86_{\pm 2.58}$
Target	$72.44_{\pm 4.06}$	$33.08_{\pm 2.96}$	$53.92_{\pm 0.76}$	$26.53_{\pm 2.23}$
Source	$71.81_{\pm 3.91}$	$32.36_{\pm 3.08}$	$53.49_{\pm 0.74}$	$26.77_{\pm 2.15}$
Paired mean	$73.72_{\pm 3.88}$	$33.95_{\pm 2.90}$	$54.17_{\pm 0.69}$	$27.12_{\pm 2.08}$
Free values	$74.63_{\pm 3.96}$	$34.91_{\pm 2.81}$	$53.93_{\pm 0.72}$	$25.71_{\pm 2.14}$
GAPTUNE+	**77.86**$_{\pm 3.44}$	**36.47**$_{\pm 2.39}$	**55.82**$_{\pm 0.57}$	**27.63**$_{\pm 1.79}$

Prompt values. Table 3 changes prompt values under ZINC/GCN/EdgePred while retaining local descriptors, signed gates, and joint node/message insertion. Gap values achieve the highest mean on all four targets, improving over equally parameterized free values by 3.23, 1.56, 1.89, and 1.92 points on Photo, Chameleon, DBLP, and MNIST, respectively. The gains over paired means are 4.14, 2.52, 1.65, and 0.51 points in the same order. Because paired means retain both source and target conditioning, this comparison tests subtraction against averaging, not merely the presence of source information. Paired means are the strongest non-gap control on DBLP and MNIST, so the smaller MNIST margin also shows why the choice of comparator matters. These mean improvements favor gap-derived values beyond trainable count alone, without requiring equal realized prompt norms; Appendix C.8 reports the corresponding uncertainty.

Insertion locations. Table 4 matches free- and gap-value parameter counts within each insertion pattern. Joint gaps improve over the stronger single-location gap variant by 3.63, 1.49, 0.53, and 1.22 points on Photo, Chameleon, DBLP, and MNIST, respectively. In contrast, joint free values fall below message-only free values by 1.81 points on DBLP and 1.23 on MNIST. On DBLP, free values lead at both single locations but lose the joint comparison, separating the benefit of gap values from the choice of insertion sites. The joint gain is therefore not automatic: it depends on value construction as well as the additional capacity.

Table 4: 5-shot insertion ablations; free/gap parameter counts match within each pattern.

Variant	Photo / Acc. ↑	Chameleon / Acc. ↑	DBLP / AUC ↑	MNIST / Acc. ↑
Head only	$64.73_{\pm 4.12}$	$29.24_{\pm 3.17}$	$52.52_{\pm 0.88}$	$21.86_{\pm 2.58}$
Free values: node only	$71.35_{\pm 4.11}$	$31.73_{\pm 3.07}$	$53.84_{\pm 0.73}$	$25.32_{\pm 2.44}$
Free values: message only	$70.27_{\pm 4.22}$	$34.19_{\pm 2.94}$	$55.74_{\pm 0.75}$	$26.94_{\pm 2.26}$
Free values: node + message	$74.63_{\pm 3.96}$	$34.91_{\pm 2.81}$	$53.93_{\pm 0.72}$	$25.71_{\pm 2.14}$
Gap values: node only	$74.23_{\pm 3.91}$	$32.62_{\pm 3.08}$	$53.66_{\pm 0.73}$	$25.82_{\pm 2.25}$
Gap values: message only	$72.41_{\pm 3.87}$	$34.98_{\pm 2.73}$	$55.29_{\pm 0.66}$	$26.41_{\pm 2.13}$
GAPTUNE+: node + message	$\mathbf{77.86}_{\pm 3.44}$	$\mathbf{36.47}_{\pm 2.39}$	$\mathbf{55.82}_{\pm 0.57}$	$\mathbf{27.63}_{\pm 1.79}$

Table 5: Shared queries and local signed composition; accuracy (%).

Variant	Photo / 5-shot	Photo / 100-shot	Chameleon / 5-shot	Chameleon / 100-shot
Frozen shared queries	$76.98_{\pm 3.64}$	$86.43_{\pm 2.25}$	$35.77_{\pm 2.75}$	$40.71_{\pm 1.54}$
Untied source/target queries	$75.29_{\pm 4.16}$	$\mathbf{87.71}_{\pm 2.26}$	$34.91_{\pm 3.21}$	$\mathbf{41.44}_{\pm 1.61}$
Uniform mixture weights	$73.63_{\pm 3.82}$	$84.08_{\pm 2.33}$	$34.07_{\pm 2.82}$	$39.10_{\pm 1.63}$
Learned global mixture weights	$74.91_{\pm 3.69}$	$85.32_{\pm 2.18}$	$34.62_{\pm 2.84}$	$39.93_{\pm 1.59}$
Nonnegative gates	$75.91_{\pm 3.74}$	$86.84_{\pm 2.15}$	$34.23_{\pm 2.88}$	$40.35_{\pm 1.61}$
GAPTUNE+	$\mathbf{77.86}_{\pm 3.44}$	$87.48_{\pm 2.09}$	$\mathbf{36.47}_{\pm 2.39}$	$41.32_{\pm 1.42}$

Pairing and local composition. In Table 5, learned global mixtures and nonnegative gates reduce accuracy by 1.39–2.95 and 0.64–2.24 points, respectively. Learned shared queries outperform frozen queries throughout, whereas untied queries trail at 5-shot but lead slightly at 100-shot. Thus, local signed use of context differences is more consistently useful than query sharing alone.

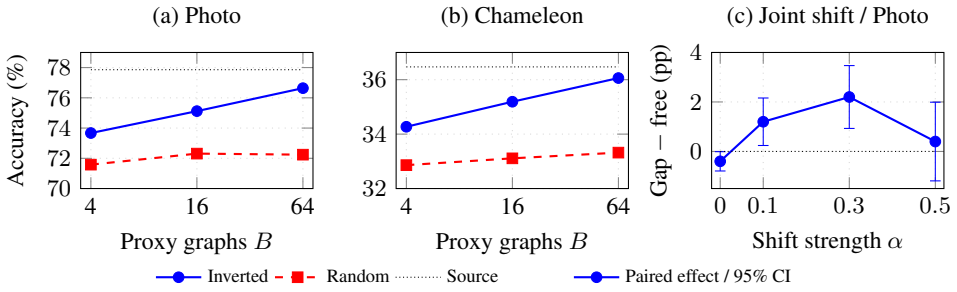

Figure 3: Source construction and controlled-shift evidence. (a,b) ZINC/GCN/EdgePred proxy-budget means at 5-shot; dotted lines use source graphs. (c) Gap-minus-free effects under joint shifts with a pretrained GCN, unchanged feature coordinates, and 10 paired repetitions (Table 9).

Source construction and controlled shifts. Inversion outperforms random proxies in 11 of 12 dataset–budget comparisons, gaining 2.81 points on Photo and 2.08 on Chameleon at $B = 16$ (Figure 3). With a separate Photo/DGI checkpoint and unchanged feature coordinates, the gap-minus-free effect is 2.20 points at joint-shift strength 0.30, with interval $[0.93, 3.47]$, but falls to 0.40 at 0.50. Thus, the benefit is not monotone in shift severity. The fixed-predictor study tests source-context replacement under Proposition 3.3 (Appendix C.6).

Practical trade-offs. The GCN cost study retains 15.125 KiB of source contexts but uses 367.2 MB of adaptation memory and 4.96 ms/batch at inference, versus 224.7 MB and 1.81 ms for full fine-tuning. Compact retained state therefore does not imply lower working memory or latency: inference still needs two target passes and graph-dependent descriptors and prompts.

5 CONCLUDING REMARKS

GAPTUNE adapts frozen GNNs with local, signed combinations of source–target context gaps. Our analysis establishes gap-supported prompt bounds, task-compatible symmetries, and fixed-predictor stability under source-context approximation. Experiments favor joint gap values over free values on four ablation targets, while insertion and controlled-shift studies show that additional prompt locations and stronger graph shifts are not automatically beneficial.

AI USE STATEMENT

Generative AI tools assisted with literature checking, manuscript polishing, coding, and experiment monitoring. The authors are responsible for the final text, mathematical claims, experimental evidence, and disclosure of AI use.

ETHICS STATEMENT

This work studies graph-model adaptation on existing benchmark datasets and does not report prospective deployment or newly recruited human participants. Graph-model inversion should be performed only with authorization to use the pretrained model and its retained information. The absence of source graphs during adaptation is an access restriction, not a privacy guarantee: proxy responses and retained contexts can still disclose information about model training. Applications to social or biomedical data require separate checks for privacy, dataset bias, and the consequences of prediction errors; benchmark performance alone does not establish deployment safety.

REPRODUCIBILITY STATEMENT

Section 3 and Algorithm 1 specify the forward passes, trainable parameters, optimization, and retained inference state. Appendix B states the theoretical assumptions and proofs. Appendices A, C, and D provide the empirical diagnostic, ablations, essential data and evaluation conventions, and architecture-specific results. Our code contains the complete execution settings and method-specific configurations. Our code and data are available at `https://anonymous.4open.science/r/GapTune-915F`.

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A SOURCE–TARGET CONTEXT SHIFTS AND PROMPT TRANSFERABILITY

Figure 1 examines prompt reuse under controlled graph shifts using Photo/GCN/DGI/EdgePrompt+. The context-gap measurements are independent of GAPTUNE's queries and prompt generator.

A.1 EXPERIMENTAL SETTING

Let $G_s = (V, E_s, X_s)$ be the unperturbed Photo graph (Shchur et al., 2018), and let F_Θ be a GCN (Kipf & Welling, 2017) pretrained with DGI (Veličković et al., 2019) without downstream labels. The EdgePrompt+ (Fu et al., 2025a) diagnostic holds this checkpoint and its persistent buffers fixed in evaluation mode, but recomputes normalized propagation for each target adjacency. Source and target are unperturbed and perturbed views in the same feature coordinates, not distinct datasets or label populations. Ten repetitions each use a support $\mathcal{S}_r$ of five training nodes per class, retaining the baseline split, support identities, and evaluation partition across views. Evaluation labels enter neither prompt fitting nor context measurement. Perturbations and optimization randomness vary across repetitions, while the checkpoint and hyperparameters remain fixed and each donor prompt is reused across its target conditions.

A.2 CONTROLLED TARGET VIEWS

The perturbation families are $\mathcal{F} = \{\text{feature}, \text{structure}, \text{joint}\}$, with nonzero strengths $\mathcal{A} = \{0.05, 0.10, 0.20, 0.30\}$. Each repetition contains twelve nonzero conditions and one shared unperturbed control. All views preserve node identities, labels, feature dimensions, and the prediction task, and no perturbation consults labels.

Feature shifts. Let X_s be the feature matrix after the checkpoint's fixed input preprocessing, and let $\sigma_{X,j}$ be the source standard deviation of coordinate j. Feature-perturbed views use

$$X_{r,\alpha} = X_s + \alpha\, \Xi_r\, \mathrm{Diag}(\sigma_X), \qquad (\Xi_r)_{ij} \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0,1). \tag{22}$$

One noise draw is reused across strengths within a repetition, and the joint condition reuses that noise. Zero-variance coordinates receive no added noise. No subsequent clipping, binarization, or target-specific feature renormalization is applied. Feature-only views retain the source adjacency.

Structure shifts. We treat E_s as a simple undirected edge set before adding implementation self-loops. A double-edge swap selects edges $\{u, v\}$ and $\{a, b\}$ with four distinct endpoints and, after random endpoint orientation, replaces them with $\{u, b\}$ and $\{a, v\}$. A swap is accepted only when both new edges are valid, distinct, and absent from the graph. The nominal strength specifies $b_\alpha = \lceil \alpha |E_s|/2 \rceil$ accepted swaps; rejected proposals do not count toward this budget. Increasing strengths use prefixes of the same accepted-swap sequence, and joint views reuse the structure-only adjacency. This preserves every node's degree and the total edge count, but not necessarily connectedness or higher-order graph structure. Because an edge can be modified more than once, the realized changed-edge fraction is distinct from the nominal strength:

$$\eta_{r,\alpha} = \frac{|E_s \triangle E_{r,\alpha}|}{2|E_s|}. \tag{23}$$

Here, $\triangle$ denotes symmetric difference, and $\eta_{r,\alpha}$ need not equal α. Structure-only views retain the source features, while joint views combine the perturbed features and adjacency. Equal numerical strengths are not assumed to represent equal severity across perturbation families.

A.3 PROMPT TRAINING AND MATCHED TARGET-HEAD EVALUATION

In repetition r, train a donor prompt $P_{s,r}$ and temporary linear head on G_s using $\mathcal{S}_r$, then freeze all prompt values and conditioning parameters. For each target view, train a separate prompt $P_{t,r,f,\alpha}$ of the same family from scratch with a temporary linear head and the same support; the unperturbed control receives its own separately initialized target prompt. Donor and target fitting match capacity, initialization distributions, optimizer settings, update budgets, and validation-based checkpoint rules, without updating the pretrained GNN or warm-starting target prompts. Frozen conditional

prompts recompute their outputs on each target view: the transferred object is the learned prompting rule, not cached source activations. Context-gap measurements are not used to choose prompts, hyperparameters, or runs.

Discard the temporary classifiers and optimizer states, and fit two fresh linear heads on the same target support above the frozen donor and target-trained prompts. Their initial weights, optimizer settings, budgets, validation rules, and test nodes are matched. This isolates relative prompt reuse from source-head transfer while holding training labels fixed.

A.4 Independent Context-Gap Measurements

Unprompted observations. Context measurements use the original frozen GNN with prompting disabled and the full permitted graph view before measurement-vector sampling. At layer $\ell \in \{1, \dots, L\}$, $H_s^{(\ell)}$ and $H_{r,f,\alpha}^{(\ell)}$ contain sampled node representations after the layer update and activation. The collections $M_s^{(\ell)}$ and $M_{r,f,\alpha}^{(\ell)}$ contain sampled directed neighbor messages after GCN degree weighting and before summation. Implementation self-loops remain in the GNN forward pass but are excluded from the sampled neighbor-message set; both orientations of an undirected edge are eligible. These diagnostic hidden-state collections differ from GapTune's node-input observation type N, which uses initial states to construct node prompt values. Thus, δ_H is not the norm of a learned node-input gap, and δ_M is not the norm of a learned message prompt.

Sampling and standardization. Let B_H and B_M be fixed node and directed-message sampling budgets. We sample $n_H = \min(B_H, |V|)$ nodes uniformly without replacement and retain the same identities in source and target views within a repetition. We sample $n_M = \min(B_M, 2|E_s|)$ directed messages without replacement from each graph's own edge set. Unchanged edge sets reuse message identities, whereas rewired views are sampled from the complete target edge set rather than only surviving source edges. For representation type $q \in \{H, M\}$ and layer ℓ, source-sample coordinate means $\mu_{q,\ell,j}$ and standard deviations $\sigma_{q,\ell,j}$ define

$$\widetilde{z}_j = \frac{z_j - \mu_{q,\ell,j}}{\max(\sigma_{q,\ell,j}, \varepsilon)}. \tag{24}$$

The numerical floor ε is fixed, and the same source-fitted transformation is applied to target vectors. This standardization affects measurement only, not prompt training inputs or prediction activations.

Kernel discrepancy. For standardized samples $U = \{u_i\}_{i=1}^n$ and $V' = \{v_j\}_{j=1}^m$, the empirical squared maximum mean discrepancy includes diagonal terms (Gretton et al., 2012):

$$\begin{aligned}\widehat{\mathrm{MMD}}_k^2(U, V') = \frac{1}{n^2}\sum_{i=1}^n\sum_{i'=1}^n k(u_i, u_{i'}) + \frac{1}{m^2}\sum_{j=1}^m\sum_{j'=1}^m k(v_j, v_{j'}) \\ - \frac{2}{nm}\sum_{i=1}^n\sum_{j=1}^m k(u_i, v_j).\end{aligned} \tag{25}$$

We use $k_{q,\ell}(u, v) = \exp(-\|u - v\|_2^2/(2\tau_{q,\ell}^2))$. The squared bandwidth $\tau_{q,\ell}^2$ is the median nonzero squared pairwise distance in the standardized source sample, with a positive floor for a degenerate sample. It is fixed across target conditions within the repetition and is independent of transfer scores. The layer-averaged discrepancies are

$$\delta_{H,r,f,\alpha} = \frac{1}{L}\sum_{\ell=1}^L \widehat{\mathrm{MMD}}_{k_{H,\ell}}^2\left(\widetilde{H}_s^{(\ell)}, \widetilde{H}_{r,f,\alpha}^{(\ell)}\right), \tag{26}$$

$$\delta_{M,r,f,\alpha} = \frac{1}{L}\sum_{\ell=1}^L \widehat{\mathrm{MMD}}_{k_{M,\ell}}^2\left(\widetilde{M}_s^{(\ell)}, \widetilde{M}_{r,f,\alpha}^{(\ell)}\right). \tag{27}$$

This squared distance between empirical kernel mean embeddings is nonnegative up to numerical precision and differs from the unbiased U-statistic. Because observations within a graph are dependent, we use these quantities as descriptive discrepancies and do not apply an independent-sample significance test to individual nodes or messages.

A.5 Transfer Loss, Aggregation, and Uncertainty

Let $A^{\mathrm{match}}_{r,f,\alpha}$ and $A^{\mathrm{transfer}}_{r,f,\alpha}$ be target test accuracies in $[0,1]$ after fresh-head fitting for the target-trained and donor prompts. Their signed transfer loss, in percentage points, is

$$R_{r,f,\alpha} = 100\left(A^{\mathrm{match}}_{r,f,\alpha} - A^{\mathrm{transfer}}_{r,f,\alpha}\right). \tag{28}$$

The same-context value $R_{r,0}$ compares the donor and separately trained control prompt on the unperturbed graph under the same evaluation protocol. Excess transfer loss is

$$E_{r,f,\alpha} = R_{r,f,\alpha} - R_{r,0}. \tag{29}$$

Higher E means an additional penalty for source-prompt reuse relative to the same-context comparison. Negative E means a smaller penalty than in that control, not necessarily a transferred prompt that outperforms target-specific prompting. The zero-strength value is zero by definition, even when $R_{r,0}$ is nonzero. Centering removes a repetition-specific offset but does not by itself remove changes in task difficulty or optimization effects.

Each curve point averages $E_{r,f,\alpha}$ over ten repetitions, while each scatter point is one repetition–condition pair. The 120 nonzero scatter points are therefore not 120 independent datasets. For $\mathcal{C} = \mathcal{F} \times \mathcal{A}$ and $q \in \{H, M\}$, we report the average within-repetition correlation

$$\bar{\rho}_q = \frac{1}{10}\sum_{r=1}^{10} \mathrm{Spearman}\left(\{\delta_{q,r,f,\alpha}\}_{(f,\alpha)\in\mathcal{C}}, \{E_{r,f,\alpha}\}_{(f,\alpha)\in\mathcal{C}}\right). \tag{30}$$

Ties receive average ranks; a constant vector has an undefined correlation rather than a value of zero. The shared zero-strength control is excluded from the correlation calculation. Subtracting $R_{r,0}$ preserves within-repetition ranks, so this Spearman statistic is identical for R and E but differs from pooling all 120 observations into one correlation.

The percentile bootstrap resamples ten complete repetitions with replacement, using 2,000 resamples. Every sampled repetition retains its control, twelve conditions, and paired scores. The 2.5th and 97.5th percentiles of recomputed curve means and mean within-repetition correlations give the 95% intervals. Curve intervals are pointwise rather than simultaneous bands. The resampling unit is the repetition, not a node, message, or individual scatter point, and the GNN is not retrained. The resulting uncertainty is conditional on the dataset, checkpoint, and validation/test partition.

A.6 Results and Interpretation

Figure 1 shows a larger relative prompt-reuse penalty under stronger perturbations, with the increase flattening for feature shifts. The mean within-repetition Spearman correlations are $\bar{\rho}_H = 0.76$ and $\bar{\rho}_M = 0.81$, with repetition-bootstrap intervals $[0.69, 0.81]$ and $[0.77, 0.85]$. Pooling the forty observations within each perturbation family gives node/message correlations of $0.519/0.408$ for feature shifts, $0.822/0.848$ for structure shifts, and $0.876/0.899$ for joint shifts. These positive within-family associations show that the combined trend is not explained solely by separation between perturbation families; they are descriptive statistics, not independent-sample tests. All correlations retain variation in perturbation strength and are not adjusted for unprompted target accuracy.

This single-configuration diagnostic motivates comparing source and target contexts, but does not establish causality, the benefit of local composition, or accurate source-free approximation. The measured transfer loss is relative to a target-trained prompt, so a larger penalty need not imply lower absolute accuracy for both systems. The adaptation ablations in Appendix C test whether gap-derived values improve target prediction, and the fixed-predictor experiment separately tests sensitivity to source-context replacement.

B Additional Method Details

This appendix provides proofs, differentiation rules, source-context retention, computational costs, and checkpoint-specific implementations for the method in Section 3.

Algorithm 1 GapTune: source–target context-gap prompt learning

Require: Frozen L-layer GNN F_Θ; labeled target instances $\mathcal{D}_t^{\mathrm{lab}}$, validation data, and permitted graph observations; source graphs $\mathcal{G}_s$, or a compatible inversion routine $\mathcal{I}_\Theta$ with pretrained assets $\mathcal{A}_{\mathrm{pre}}$ and synthesis budget B_{inv}; query counts $\{K_q\}$ and training budget T.
Ensure: Learned $\Phi^\star, \psi^\star$ and retained source contexts $C_s^\star$.

Form task-bearing target subgraphs, retaining focal node or unordered-pair identifiers and graph labels.
Freeze Θ and stored normalization statistics; use deterministic evaluation of the pretrained GNN.
if source graphs are available **then**
    $\mathcal{G}_s^{\mathrm{ctx}} \leftarrow \mathcal{G}_s$.
else
    $\mathcal{G}_s^{\mathrm{ctx}} \leftarrow \mathcal{I}_\Theta(\mathcal{A}_{\mathrm{pre}}; \xi, B_{\mathrm{inv}})$. ▷ Only inversion variables are optimized
end if
Collect and fix $\{\mathcal{Z}_s^q\}$ from unprompted source-side encodings.
Initialize $\Phi = \{Q^q, W^q, \vartheta^q\}_{q\in\mathcal{I}}$ and head g_ψ.
for $t = 1, \dots, T$ **do**
    Sample labeled target instances $\mathcal{B}_t \subseteq \mathcal{D}_t^{\mathrm{lab}}$.
    for each distinct target graph G represented in $\mathcal{B}_t$ **do**
        Run unprompted F_Θ on the permitted graph; detach $\{\mathcal{Z}_t^q(G), \zeta_o^q\}$.
        for each observation type $q \in \mathcal{I} = \{N, M_1, \dots, M_L\}$ **do**
            if $\mathcal{Z}_s^q$ or $\mathcal{Z}_t^q(G)$ is empty **then**
                Set $p_o^q \leftarrow 0$ for all objects of this observation type.
            else
                Pool $c_{s,k}^q, c_{t,k}^q$ using shared Q^q via Equations 8– 9.
                $d_k^q \leftarrow c_{s,k}^q - c_{t,k}^q$ for $k = 1, \dots, K_q$.
                Compute $a_{o,k}^q$ from W^q, ζ_o^q using Equation 11.
                $p_o^q \leftarrow \sum_k a_{o,k}^q \tanh(\vartheta_k^q) d_k^q$.
            end if
        end for
        $\widetilde{h}_v^{(0)} \leftarrow \bar{h}_v^{(0)} + p_v^N$ for all nodes.
        for $\ell = 1, \dots, L$ **do**
            $\widetilde{m}_{u\to v}^{(\ell)} \leftarrow \mathrm{MSG}_\Theta^{(\ell)}(G, \widetilde{H}^{(\ell-1)})_{u\to v} + p_{u\to v}^{M_\ell}$.
            Aggregate $\widetilde{m}^{(\ell)}$ and update $\widetilde{H}^{(\ell)}$ using Equation 16.
        end for
        Predict labeled batch objects using the readout in Equation 17 and g_ψ.
    end for
    Compute $\mathcal{L}_{\mathcal{B}_t}$ on observed training labels only.
    Update $Q^q, W^q, \vartheta^q, \psi$ through the prompted pass and context pooling; leave Θ fixed.
end for
Restore $(\Phi^\star, \psi^\star)$ from the checkpoint selected by the validation monitor.
Recompute $C_s^\star$ from $\{\mathcal{Z}_s^q\}$ using $Q^{q\star}$; retain zero-prompt flags for source-empty observation types.
return $\Phi^\star, \psi^\star, C_s^\star$.

B.1 Notation and Scope

We use the observation types and collections from Equations 4–5, retaining observation multiplicities. A type is active only when both source and target collections are nonempty; inactive types receive zero prompts, and approximation comparisons preserve this active-type pattern. For $\nu(z) = z/\sqrt{\|z\|_2^2 + \varepsilon^2}$ and positive $\varepsilon, \tau_c, \tau_p$, the shared-query pooling in Equations 8–9 uses normalized observations for attention and original responses as values. Let $s_k^q = \tanh(\vartheta_k^q)$ and use the unprompted descriptors, local relevance, and prompts from Equations 10–12. The receiving objects $\mathcal{O}_q(G)$ include all prompted nodes or directed messages, not only labeled objects or observations retained for context pooling. Write $P^q = \{p_o^q : o \in \mathcal{O}_q(G)\}$, $P = \{P^q : q \in \mathcal{I}\}$, and $\|B\|_{\max,2} = \max_o \|B_o\|_2$, with zero for an empty collection. In $f_o(P) = g_\psi(r_o(G; P))$, prompts

are inputs to a fixed prediction map; all other graph and model quantities are held fixed, and $\epsilon_q = 0$ for inactive types.

B.2 Gap Support, Magnitude, and the Zero-Gap Case

Proof of Proposition 3.1. Equation 12 directly gives the span restriction. Because $a^q_{o,k} \geq 0$, $\sum_k a^q_{o,k} = 1$, and $|s^q_k| \leq 1$, the triangle inequality and normalized weights give

$$\|p^q_o\|_2 \leq \sum_k a^q_{o,k} |s^q_k| \, \|d^q_k\|_2 \leq \max_k \|d^q_k\|_2. \tag{31}$$

Each context is a convex combination of its observations, so observation norms bounded by C_q imply $\|c^q_{a,k}\|_2 \leq C_q$. The triangle inequality then gives $\|d^q_k\|_2 \leq \|c^q_{s,k}\|_2 + \|c^q_{t,k}\|_2 \leq 2C_q$. □

Prompt geometry and aggregation. For fixed contexts and gates, p^q_o lies in the convex hull of $\{s^q_k d^q_k\}_{k=1}^{K_q}$, not an unrestricted part of their span. The norm bound is relative to the context gaps; a graph-independent bound additionally requires uniformly bounded observations. For message prompts, the bound applies before aggregation. For example, under sum aggregation,

$$\left\| \sum_{u \in \mathcal{N}(v)} p^{M_\ell}_{u \to v} \right\|_2 \leq |\mathcal{N}(v)| \max_k \|d^{M_\ell}_k\|_2. \tag{32}$$

Bounding each message prompt does not bound its aggregate independently of the node degree.

Proposition B.1 (Identical empirical contexts)**.** *Suppose the empirical probability measures on the original observation vectors coincide for an active type q:*

$$\mu^q_s = \frac{1}{n^q_s} \sum_i \delta_{z^q_{s,i}} = \frac{1}{n^q_t} \sum_i \delta_{z^q_{t,i}} = \mu^q_t, \tag{33}$$

where δ_z is a point mass at z. Then $c^q_{s,k} = c^q_{t,k}$ for every query, and all prompts of that type are zero. If this holds for every active type, the prompted and unprompted encoders coincide.

Proof. For a query vector u, context pooling can be written as

$$c(\mu, u) = \frac{\int z \exp(u^\top \nu(z)/\tau_c) \, d\mu(z)}{\int \exp(u^\top \nu(z)/\tau_c) \, d\mu(z)}. \tag{34}$$

Equal measures give equal numerators and positive denominators. Hence $d^q_k = 0$ and $p^q_o = 0$ for every query and object. If all prompts are zero, the initial node states are unchanged. Induction through the fixed message-passing layers yields $\widetilde{H}^{(\ell)} = \bar{H}^{(\ell)}$ for all ℓ, because native messages, aggregation, and updates coincide in the two passes. □

Observation scope and structural shifts. With graph inputs and observation selection fixed, changing the labeled support does not change the label-free observation collections. Identical source and target collections therefore reduce GapTune to head-only adaptation. Independent subsampling can create differences even on the same graph, but these may reflect sampling rather than distribution shift. Equal pooled contexts for a finite query set do not conversely imply equal observation distributions.

The node-input gaps use initial states, whereas deeper node states enter only their local descriptors. Consequently, topology-only changes produce no node-input prompts when the selected initial-state collections remain unchanged. The message observations and message prompts can still change. This conclusion need not hold for topology-dependent initial states.

B.3 Permutation Consistency and Task-Native Readouts

Proof of Proposition 3.2. σ relabels nodes and graph data consistently; pretrained equivariance gives

$$\bar{h}^{(\ell)}_{\sigma(v)}(\sigma G) = \bar{h}^{(\ell)}_{v}(G), \qquad \bar{m}^{(\ell)}_{\sigma(u)\to\sigma(v)}(\sigma G) = \bar{m}^{(\ell)}_{u\to v}(G). \tag{35}$$

Observation selection that commutes with relabeling preserves the selected collections up to reordering. Both the attention normalization and the weighted sum in Equation 9 are unchanged by reordering. Source and target contexts, and hence their gaps, are invariant. The same argument permits independent relabeling of the source graphs.

Equation 10 transports each descriptor with its node or directional message. The shared relevance map and gates therefore give $a^q_{\sigma(o),k}(\sigma G) = a^q_{o,k}(G)$ and $p^q_{\sigma(o)}(\sigma G) = p^q_o(G)$. Adding node prompts preserves equivariance of the initial states. At each layer, native messages and added prompts transform with their sender and receiver. Permutation-invariant neighborhood aggregation and equivariant updates preserve this property for the next node states. Induction then proves equivariance.

Node selection follows the focal node under relabeling. For a candidate link $\{u, v\}$, both $\widetilde{h}_u+\widetilde{h}_v$ and $\widetilde{h}_u \odot \widetilde{h}_v$ are unchanged under endpoint exchange, so $r_{\{u,v\}}(G) = r_{\{v,u\}}(G)$. Graph mean pooling is invariant to node ordering. Applying the same task head to corresponding readouts preserves these symmetries, for classification logits and regression outputs alike. □

Sampling and scope. The exact statement for randomized selection requires a sampled collection to be transported with the relabeling. An invariant sampling distribution gives equivariance in distribution, not identical predictions under two independent draws. Selection tied to raw node identifiers can violate the assumption. These results establish task-compatible symmetries, not unrestricted expressivity or prediction accuracy. Classification output transformations and coordinate-wise regression outputs preserve the stated graph symmetries.

B.4 Source-Context Approximation and Prediction Stability

Proof of Proposition 3.3. Fix the quantities stated in the proposition and suppose

$$\max_k \|\widehat{c}^q_{s,k} - c^q_{s,k}\|_2 \le \epsilon_q. \tag{36}$$

Target contexts, relevance weights, and signed gates are unchanged. In particular, relevance depends on fixed target descriptors, not source contexts. Thus

$$\begin{aligned} \widehat{p}^q_o - p^q_o &= \sum_k a^q_{o,k} s^q_k (\widehat{c}^q_{s,k} - c^q_{s,k}), \\ \|\widehat{P}^q - P^q\|_{\max,2} &\le \max_o \sum_k a^q_{o,k} |s^q_k| \|\widehat{c}^q_{s,k} - c^q_{s,k}\|_2 \le \epsilon_q. \end{aligned} \tag{37}$$

For the output bound, order the observation types as $q_1, \ldots, q_{L+1}$. Let $P^{[j]}$ use approximated prompts for the first j types and original prompts for the remaining types, so that $P^{[0]} = P$ and $P^{[L+1]} = \widehat{P}$. The separate Lipschitz condition holds along this sequence of type-wise replacements:

$$\|f_o(U) - f_o(V)\|_\infty \le \kappa_{o,q} \|U^q - V^q\|_{\max,2} \tag{38}$$

for collections differing only in type q, throughout a domain containing these intermediate replacements. Applying the triangle inequality across the sequence of type-wise replacements gives

$$\begin{aligned} \|f_o(\widehat{P}) - f_o(P)\|_\infty &\le \sum_{j=1}^{L+1} \|f_o(P^{[j]}) - f_o(P^{[j-1]})\|_\infty \\ &\le \sum_{q\in\mathcal{I}} \kappa_{o,q} \|\widehat{P}^q - P^q\|_{\max,2} \le \sum_{q\in\mathcal{I}} \kappa_{o,q}\epsilon_q =: b_o. \end{aligned} \tag{39}$$

Inactive types contribute zero to the accumulated prompt and output perturbations at every step. □

A layer-wise sufficient condition. Let $\mathcal{T}_\ell(H, U)$ denote the layer-ℓ update on states H and message prompts U. Assume the following bound holds on a domain containing all compared states and all intermediate type-wise replacement trajectories:

$$\|\mathcal{T}_\ell(H, U) - \mathcal{T}_\ell(H', U')\|_{\max,2} \le A_\ell \|H - H'\|_{\max,2} + B_\ell \|U - U'\|_{\max,2}, \tag{40}$$

where $A_\ell, B_\ell \ge 0$ are fixed bounds. Define $\Delta_\ell = \|\widehat{\widetilde{H}}^{(\ell)} - \widetilde{H}^{(\ell)}\|_{\max,2}$. Then $\Delta_0 \le \epsilon_N$ and $\Delta_\ell \le A_\ell \Delta_{\ell-1} + B_\ell \epsilon_{M_\ell}$. Repeated substitution yields

$$\Delta_L \le \left(\prod_{j=1}^{L} A_j\right) \epsilon_N + \sum_{\ell=1}^{L} B_\ell \left(\prod_{j=\ell+1}^{L} A_j\right) \epsilon_{M_\ell}, \tag{41}$$

where every empty product equals one, including the product for the final message layer.

Node selection and graph mean pooling are 1-Lipschitz from the maximum-node Euclidean norm to the Euclidean readout norm. For the symmetric edge readout in Equation 17, suppose all compared endpoint embeddings have coordinate magnitudes at most R_h. Its sum component changes by at most $2\Delta_L$. The identity

$$h_u \odot h_v - \widehat{h}_u \odot \widehat{h}_v = h_u \odot (h_v - \widehat{h}_v) + (h_u - \widehat{h}_u) \odot \widehat{h}_v \tag{42}$$

bounds the product component by $2R_h\Delta_L$. Combining the two components gives readout constant $L_{r,o} = 2\sqrt{1 + R_h^2}$ for the concatenated sum-and-product representation.

For the affine task head, let $C_\psi = \max_j \|(W_\psi)_{j,:}\|_2$. Since $\|f_o(\widehat{P}) - f_o(P)\|_\infty \le C_\psi L_{r,o} \Delta_L$, the following choices satisfy the type-wise Lipschitz bounds:

$$\kappa_{o,N} = C_\psi L_{r,o} \prod_{j=1}^{L} A_j, \qquad \kappa_{o,M_\ell} = C_\psi L_{r,o} B_\ell \prod_{j=\ell+1}^{L} A_j. \tag{43}$$

These constants can depend on graph size, topology, the pretrained GNN, and the fitted head. In particular, prompts added after structural weighting are not automatically averaged during sum aggregation.

Corollary B.2 (Classification and regression consequences)**.** *Under Proposition 3.3, let* $b_o = \sum_q \kappa_{o,q} \epsilon_q$. *For the unique prediction* $c = \arg\max_j f_{o,j}(P)$*, the class decision is unchanged if*

$$f_{o,c}(P) - \max_{j \ne c} f_{o,j}(P) > 2b_o. \tag{44}$$

For binary or multilabel prediction at sigmoid threshold $1/2$*, coordinate* j *retains its decision if* $|f_{o,j}(P)| > b_o$*. For regression with a fixed target value* y_j*,*

$$\Big|\, |f_{o,j}(\widehat{P}) - y_j| - |f_{o,j}(P) - y_j| \,\Big| \le b_o. \tag{45}$$

These conclusions apply to the prescribed node-, edge-, and graph-level readouts.

Proof. Each logit changes by at most b_o, so the original top-class margin can decrease by at most $2b_o$. A logit of magnitude greater than b_o cannot change sign, proving the binary and multilabel statement. For regression, the reverse triangle inequality bounds the absolute-error change by $|f_{o,j}(\widehat{P}) - f_{o,j}(P)| \le b_o$. □

Scope of the stability result. The input errors are differences between source contexts pooled by the same fixed queries. The result does not derive these errors from the proxy-graph size or establish accurate inversion. All learned parameters remain fixed in the comparison; independently retrained source-available and source-free models are not covered. Preserving a decision does not establish its correctness, and these bounds are not population-risk or generalization guarantees.

B.5 End-to-End Differentiation

Unprompted observations and descriptors are fixed inputs to prompt learning. Context pooling, gaps, coefficients, and the prompted pass remain differentiable. For one target graph, let $\mathcal{L}$ be its scalar task loss and let $\eta_o^q = \nabla_{p_o^q} \mathcal{L}$ be the gradient through the prompted GNN and task head. This gradient includes the effect of the inserted prompt on all downstream states and labeled predictions.

Shared-query gradients. Define $J^q_{a,k} = \partial c^q_{a,k}/\partial (q^q_k)^\top$. The attention softmax gives

$$\nabla_{q^q_k} \pi^q_{a,k,i} = \frac{\pi^q_{a,k,i}}{\tau_c} \left(\nu(z^q_{a,i}) - \sum_j \pi^q_{a,k,j} \nu(z^q_{a,j}) \right). \tag{46}$$

Substitution into the derivative of the pooled context yields

$$J^q_{a,k} = \frac{1}{\tau_c} \sum_i \pi^q_{a,k,i} (z^q_{a,i} - c^q_{a,k}) \nu(z^q_{a,i})^\top. \tag{47}$$

Since local relevance and signed gates do not depend on Q^q,

$$\nabla_{q^q_k} \mathcal{L} = (J^q_{s,k} - J^q_{t,k})^\top \sum_{o \in \mathcal{O}_q(G)} a^q_{o,k} s^q_k \eta^q_o. \tag{48}$$

Thus, target supervision updates both source and target context extraction. Detaching either pooled summary removes its contribution to the query gradient; detaching the gap removes both contributions.

Relevance and gate gradients. Differentiating Equation 12 gives

$$\nabla_{w^q_k} \mathcal{L} = \frac{1}{\tau_p} \sum_{o \in \mathcal{O}_q(G)} a^q_{o,k} \langle \eta^q_o, s^q_k d^q_k - p^q_o \rangle \nu(\zeta^q_o), \tag{49}$$

$$\frac{\partial \mathcal{L}}{\partial \vartheta^q_k} = (1 - (s^q_k)^2) \sum_{o \in \mathcal{O}_q(G)} a^q_{o,k} \langle \eta^q_o, d^q_k \rangle. \tag{50}$$

The first identity follows from $\partial p^q_o / \partial (w^q_k)^\top = a^q_{o,k} (s^q_k d^q_k - p^q_o) \nu(\zeta^q_o)^\top / \tau_p$; the second uses the derivative of $\tanh$. Gradients sum across target graphs in a minibatch, with shared source pooling and graph-specific target pooling. The full context Jacobians need not be stored; only their products with upstream gradients are required.

Fixed parameters and initialization. The prompted pass retains derivatives with respect to prompts without updating Θ. Disabling differentiation for the whole pass would also block prompt learning. Stored normalization statistics and the evaluation mode of the pretrained GNN remain fixed.

If all gates of one observation type are initialized to zero, its prompts and initial task-loss gradients to Q^q and W^q are zero, but its gate gradients need not vanish. Under Proposition B.1, both d^q_k and $J^q_{s,k} - J^q_{t,k}$ vanish identically, so all task-loss gradients to that type's prompt parameters are zero. In contrast, a zero gap at one query value need not imply a zero query derivative.

B.6 Context Reuse and Inference

Reuse during training. Raw observations and descriptors can be reused while graph inputs, permitted neighborhoods, preprocessing, selected observations, and pretrained GNN evaluation remain unchanged. Changes to these inputs require recomputation of the affected observations. Pooled contexts must be recomputed with the current queries, retaining their gradient paths. Reusing an old detached source summary while updating Q^q defines a different optimization procedure.

Source pooling can be evaluated once per optimization step and shared across target graphs if gradients from all graphs reach those summaries. Chunked pooling preserves the global softmax; separately normalized chunk averages generally differ.

Proposition B.3 (Exact retention of source contexts)**.** *Fix the selected final parameters $\Phi^\star, \psi^\star$ and source observations. For every q with $n^q_s > 0$, retain*

$$C^\star_s = \left\{ c^{q\star}_{s,k} = c^q_{s,k}(Q^{q\star}; \mathcal{Z}^q_s) : \; n^q_s > 0, \; 1 \le k \le K_q \right\}, \tag{51}$$

and the set of source-empty observation types. Replacing source observations by this state leaves every target prediction unchanged when all other prediction rules are unchanged.

Proof. With fixed queries, source summaries do not depend on the new target graph. All subsequent dependence on source observations is through these summaries and the source-empty rule. Retaining them yields the same gaps, prompts, prompted states, readouts, and predictions. A target-empty collection is checked separately for each new graph. □

Deployment state. Retain summaries for all source-nonempty types, including types that were inactive for a particular training graph because its target collection was empty. Inference uses the pretrained GNN, learned prompt and head parameters, retained summaries, source-empty flags, and the prescribed observation-selection rules. A new target graph supplies its own unprompted observations and descriptors before prompted prediction. No source graphs, proxy graphs, repeated inversion, target labels, or test-time parameter optimization are needed. Summaries must be recomputed if the queries or the source-observation definition change.

B.7 Parameter, Time, and Memory Costs

Trainable parameters. With $e_q = \dim(\zeta_o^q)$, queries, relevance vectors, and gates contain $K_q d_q$, $K_q e_q$, and K_q parameters, respectively. Thus

$$N_{\text{prompt}} = \sum_{q \in \mathcal{I}} K_q(d_q + e_q + 1). \tag{52}$$

An affine head with readout and output dimensions d_r, d_y adds $d_y(d_r + 1)$ parameters. Pretrained weights and stored observations are not trainable prompt parameters, but still incur storage costs.

Prompt-side time. Dense source and target pooling costs $O(K_q(n_s^q + n_t^q)d_q)$. Local relevance and gap combination cost $O(n_o^q K_q e_q)$ and $O(n_o^q K_q d_q)$, respectively, where $n_o^q = |\mathcal{O}_q(G)|$. For distinct target graphs $\mathcal{B}_G$ in a minibatch, sharing source pooling gives

$$O\left(\sum_q K_q n_s^q d_q + \sum_{G \in \mathcal{B}_G} \sum_q \left[K_q n_t^q(G) d_q + n_o^q(G) K_q(e_q + d_q)\right]\right). \tag{53}$$

Backward differentiation through these operations has the same asymptotic order. Retained source contexts remove the first term at inference.

These costs exclude source-observation extraction, unprompted target encoding when not reused, prompted GNN evaluation and its training backward pass, and the task head. Inversion adds a separate preparation cost. Freezing GNN weights removes parameter updates, not the cost of propagating prompt gradients. For message types, n_o^q counts carried messages rather than labeled objects; limiting the context sample does not eliminate message-prompt construction costs.

Memory. Raw source observations require $O(\sum_q n_s^q d_q)$ storage, whereas retained source contexts require $O(\sum_q K_q d_q)$. For one target graph, directly materializing observations, descriptors, attention weights, contexts, and prompts uses prompt-side working memory of order

$$O\left(\sum_q \left[(n_s^q + n_t^q)d_q + n_o^q e_q + K_q(n_s^q + n_t^q + n_o^q) + n_o^q d_q + K_q d_q\right]\right). \tag{54}$$

This estimate excludes model parameters, optimizer states, and prompted-GNN activations. Chunking and recomputation can reduce materialization costs while preserving normalization; few trainable parameters do not imply time or memory independent of graph size.

B.8 Checkpoint-Dependent Source-Free Construction

Available information and attribution. The source-free stage follows the graph-inversion approach of OGMM (Wang et al., 2026b), but uses the EdgePred- or GraphCL-compatible objective below rather than its classifier-conditioned model-merging construction. The frozen checkpoint must retain its pretrained edge scorer or contrastive projection and permit differentiation with respect to proxy inputs; a newly initialized target head cannot replace these components. Appendix D.2 summarizes their use; complete construction settings are provided in our code.

Differentiable proxy graphs. Let B be the graph budget and let proxy b contain n_b nodes with trainable continuous states $X_b \in \mathbb{R}^{n_b \times d_0}$, initialized from independent standard normal entries. These states occupy the encoder's continuous input space, not an unconstrained relaxation of categorical atom identities. An edge network e_ω maps concatenated endpoint states to one logit. For undirected graphs, symmetrize the logits before sampling:

$$\ell_{b,uv} = \tfrac{1}{2}\big(e_\omega([x_{b,u}; x_{b,v}]) + e_\omega([x_{b,v}; x_{b,u}])\big), \qquad u < v. \tag{55}$$

A three-layer edge network can realize this map. For independent $U_{b,uv} \sim \mathrm{Uniform}(0,1)$ and temperature $\tau_A > 0$, a binary relaxation of the sampled adjacency is

$$S_{b,uv} = \mathrm{sigmoid}\left(\frac{\ell_{b,uv} + \log U_{b,uv} - \log(1 - U_{b,uv})}{\tau_A}\right), \qquad S_{b,vu} = S_{b,uv}, \qquad S_{b,uu} = 0. \tag{56}$$

Self-loops, when required, are added by the pretrained operator rather than learned twice. A hard forward pass may use $\mathrm{stopgrad}(\mathbf{1}[S_b \geq 1/2] - S_b) + S_b$, whose backward pass follows the continuous relaxation. All potential edges must remain represented in that backward pass; removing zero-weight entries before propagation can remove their gradients.

EdgePred-compatible extension. A retained edge scorer s_{pre} supplies binary edge logits rather than graph-class probabilities. One explicit extension draws fixed positive and negative conditioning sets $\mathcal{Q}_b^+, \mathcal{Q}_b^-$ of unordered pairs $\{u, v\}$ from a generated random template, with both sets nonempty. These sets remain fixed during inversion and do not use source or target labels. Remove both reciprocal copies of every conditioning pair from the adjacency used to compute the loss. For $t_{b,uv} = s_{\mathrm{pre}}(F_\Theta(S_b^{\setminus \mathcal{Q}_b}, X_b), u, v)$, use the balanced objective

$$\mathcal{L}_{\mathrm{edge}} = -\frac{1}{2B}\sum_b \left[\frac{\sum_{\{u,v\}\in\mathcal{Q}_b^+} \log \sigma(t_{b,uv})}{|\mathcal{Q}_b^+|} + \frac{\sum_{\{u,v\}\in\mathcal{Q}_b^-} \log(1 - \sigma(t_{b,uv}))}{|\mathcal{Q}_b^-|}\right]. \tag{57}$$

For a dot-product checkpoint, the scorer is the original dot product, not an additional trained classifier. The conditioning sets and their binary targets remain fixed, whereas the scorer outputs $t_{b,uv}$ remain differentiable with respect to the proxy inputs. Conditioning pairs are excluded from the message-passing adjacency used to evaluate the inversion loss. This avoids supervising a pair solely from its direct presence in message passing, but does not identify the original source-edge distribution.

GraphCL-compatible extension. When the trained projection g_{pre} is retained, independently augment each proxy twice using a declared, label-free view rule $\mathcal{T}$. Let $z_b^{(r)}$ be the unit-normalized projected graph representation of $\mathcal{T}_r(S_b, X_b)$, and index the resulting $2B$ representations by i with positive counterpart i^+. For $B \geq 2$, an explicit contrastive objective is

$$\mathcal{L}_{\mathrm{con}} = -\frac{1}{2B}\sum_{i=1}^{2B} \log \frac{\exp(z_i^\top z_{i^+}/\tau_{\mathrm{con}})}{\sum_{j\neq i}\exp(z_i^\top z_j/\tau_{\mathrm{con}})}. \tag{58}$$

The encoder, projection, and their normalization states remain fixed. This objective uses positive-pair consistency and cross-proxy negatives, not categorical prediction entropy. This requires the specified projection and view rule; an untrained projection cannot recover pretrained information.

Optimization and use. Both pretext objectives use the following feature and density controls:

$$\mathcal{R}_X = \frac{\sum_b \|X_b\|_F^2}{\sum_b n_b d_0}, \qquad \mathcal{R}_A = B^{-1}\sum_b \left(\frac{\sum_{u\neq v}\sigma(\ell_{b,uv})}{n_b(n_b-1)} - \rho\right)^2. \tag{59}$$

The density ρ is a declared generation prior, not a measured source density. Optimize the selected pretext loss plus $\lambda_X\mathcal{R}_X + \lambda_A\mathcal{R}_A$, projecting each input state onto a radius-R_X ball with $R_X = 10$ in the evaluated construction. The evaluated construction uses pretext supervision without BatchNorm matching, a bounded continuous feature space, and density-constrained final discretization. After the configured updates, freeze the generator, discretize its edge probabilities with the declared rule, and extract unprompted node states and messages from the resulting graphs. Only these observations enter downstream query pooling; the downstream task loss does not update inversion variables. Graph-size and feature priors alone do not replace the retained pretrained scorer or projection. The stability theory conditions on the resulting context error and does not guarantee its size or establish source-distribution recovery.

B.9 From Observation Error to Context Error

The source-context assumption can be related to differences between the observation measures themselves. This comparison concerns responses in the pretrained GNN's coordinates, not recovery of the source graph or an alignment between unrelated feature meanings. For probability measures $\mu, \widehat{\mu}$, let $\mathsf{W}_1(\mu, \widehat{\mu})$ be the infimum of $\mathbb{E}\|Z - \widehat{Z}\|_2$ over couplings with those marginals.

Proposition B.4 (Stability of query-weighted contexts)**.** *Suppose μ and $\widehat{\mu}$ are supported in the radius-C Euclidean ball, the query u is fixed, and $a = \|u\|_2/\tau_c$. For the context map in Equation 34,*

$$\|c(\mu, u) - c(\widehat{\mu}, u)\|_2 \le \min\left\{2C,\ e^{2a}\left(1 + \frac{2Ca}{\varepsilon}\right)\mathsf{W}_1(\mu, \widehat{\mu})\right\}. \tag{60}$$

Proof. The Jacobian of $\nu(z) = z/\sqrt{\|z\|_2^2 + \varepsilon^2}$ has operator norm at most $1/\varepsilon$, and $\|\nu(z)\|_2 \le 1$. Writing $b(z) = \exp(u^\top \nu(z)/\tau_c)$ gives $e^{-a} \le b(z) \le e^a$ and Lipschitz constant at most $e^a a/\varepsilon$. The vector map $v(z) = zb(z)$ is Lipschitz on the ball with constant at most $e^a(1 + Ca/\varepsilon)$. Let $A_\mu = \int v\, d\mu$ and $B_\mu = \int b\, d\mu$, and similarly for $\widehat{\mu}$. A coupling and the triangle inequality bound the numerator difference by $e^a(1 + Ca/\varepsilon)\mathsf{W}_1$ and the denominator difference by $e^a a\mathsf{W}_1/\varepsilon$. Using $B_\mu \ge e^{-a}$ and $\|A_{\widehat{\mu}}\|_2 \le CB_{\widehat{\mu}}$ bounds the difference of normalized weighted contexts:

$$\left\|\frac{A_\mu}{B_\mu} - \frac{A_{\widehat{\mu}}}{B_{\widehat{\mu}}}\right\|_2 \le \frac{\|A_\mu - A_{\widehat{\mu}}\|_2 + C|B_\mu - B_{\widehat{\mu}}|}{B_\mu} \tag{61}$$

$$\le e^{2a}\left(1 + \frac{2Ca}{\varepsilon}\right)\mathsf{W}_1(\mu, \widehat{\mu}). \tag{62}$$

Both contexts belong to the radius-C ball, which also gives the $2C$ bound. □

Consequences and scope. Applying the proposition to each source query supplies a sufficient bound for ϵ_q in Proposition 3.3, including when source and proxy collections have different sizes. The constants depend on response magnitudes, query norms, the attention temperature, and the normalization floor; the bound is not uniformly small without controlling these quantities. It establishes continuity of the stated context map, not that inversion finds a small observation discrepancy or that the bound is tight. The diagnostic MMD in Figure 1 is a different quantity and cannot be substituted for W_1 without an additional argument.

B.10 Architecture-Specific Operator Interfaces

The message formulation separates a native encoder operator from its additive prompt intervention. For a structurally weighted message $m_{u\to v} = a_{vu}v_u$, the convention in Eq. 15 is $a_{vu}v_u + p_{u\to v}$, not $a_{vu}(v_u + p_{u\to v})$. These interventions differ by $(a_{vu} - 1)p_{u\to v}$ and therefore must not be identified by their common use of an edge-prompt tensor. The equations below distinguish the native backbone operators from additive prompt interfaces. The H2GCN and NodeFormer descriptions below specify their encoder operators and additive prompt interfaces.

GCN, GIN, and attention layers. For GCN, the native observation is $m_{u\to v}^{(\ell)} = \widetilde{A}_{vu}W_\ell h_u^{(\ell-1)}$, where $\widetilde{A}$ includes the checkpoint's degree normalization and self-loop convention (Kipf & Welling, 2017). The prompt is added after this multiplication and before summation; the native bias, normalization, activation, and residual operations remain in the update operator. For GIN, the neighbor message is $h_u^{(\ell-1)}$ and the native update applies its MLP to the neighbor sum and $(1+\epsilon_\ell)h_v^{(\ell-1)}$ (Xu et al., 2019). The ego term is kept separate unless the native implementation explicitly represents it as a message. For attention-based layers, the message includes the head-specific attention coefficient and value projection; attention is recomputed from prompted states during the prediction pass (Veličković et al., 2018; Dwivedi & Bresson, 2021). A multi-head message can be represented by concatenating its weighted head channels before prompt insertion and then applying the native head-combination operator. Signed structural coefficients, including those in frequency-adaptive propagation, are part of the native message rather than the learned prompt gate (Bo et al., 2021).

H2GCN. H2GCN indicates the evaluated encoder, which applies two successive neighborhood means and concatenates their outputs. This variant differs from the strict higher-order-neighborhood construction of the original H2GCN (Zhu et al., 2020); its definition is shared by scratch, pretraining, and adaptation experiments. Let S denote its row-normalized, self-loop-augmented propagation matrix and let ϕ_1, ϕ_2 contain the native affine maps, normalization, and activations. Its unprompted operator is

$$H_1 = \phi_1(SX), \qquad H_2 = \phi_2(SH_1), \qquad H_{\text{out}} = W_{\text{out}}[H_1 \| H_2] + b_{\text{out}}. \tag{63}$$

For additive post-weighting prompts, the two observation spaces are $S_{vu}x_u$ and $S_{vu}h_{1,u}$, with dimensions matching the inputs to ϕ_1 and ϕ_2, respectively. The corresponding prompted aggregates are $S\widetilde{X} + \sum_u P^{M_1}_{u\to v}$ and $S\widetilde{H}_1 + \sum_u P^{M_2}_{u\to v}$, followed by the unchanged update and concatenation. The second propagation expands the receptive field; it does not exclude nodes also reached at one hop.

NodeFormer: sparse corrections to native kernel attention. The prompt interface in Appendix D.2 adds prompts to native attention messages on the input graph's directed edges; it does not prompt every all-pair interaction or introduce a relational-bias branch. NodeFormer retains its factorized all-pair attention and any relational-bias branch already present in the checkpoint (Wu et al., 2022). For one graph and one attention head, let $\varphi(q_v), \varphi(k_u) \in \mathbb{R}^r$ be the positive kernel features and v_u the projected value. The native aggregate is

$$u_v = \frac{\varphi(q_v)^\top \sum_u \varphi(k_u) v_u^\top}{\varphi(q_v)^\top \sum_u \varphi(k_u)}. \tag{64}$$

Let E_P contain each directed input edge once, using the supplied graph convention and adding no new self-loops. For $u \to v \in E_P$, compute $\alpha_{vu} = \varphi(q_v)^\top \varphi(k_u) / (\varphi(q_v)^\top \sum_j \varphi(k_j))$ using the same kernel features and denominator as the native operator. The unprompted observation $\bar{m}^{(\ell)}_{u\to v}$ concatenates $\bar{\alpha}_{vu}\bar{v}_u$ across attention heads, so its dimension is the number of heads times their value width. The local descriptor remains the sender state, receiver state, and this weighted message, as in Eq. 10. One K_q-query bank and one relevance map are used per layer across the concatenated head channels, rather than adding an independent bank for each edge or head. In the prediction pass, recompute native attention from prompted states and reshape $p^{M_\ell}_{u\to v}$ into head channels before adding it:

$$\widetilde{a}^{(\ell)}_v = \widetilde{u}^{(\ell)}_v + \widetilde{r}^{(\ell)}_v + \sum_{u:(u\to v)\in E_P} p^{M_\ell}_{u\to v}. \tag{65}$$

Here, $\widetilde{r}^{(\ell)}_v$ is the sum of any native relational-bias contributions evaluated at the prompted states, and is zero when the checkpoint has none. The native output projection, residual, normalization, and update act on $\widetilde{a}^{(\ell)}_v$ without modification. The prompt is added after attention weighting and normalization, is not multiplied again by α_{vu}, and is zero for all interactions outside E_P. The unprompted aggregation still includes those other interactions through Eq. 64; sparse prompting does not sparsify the encoder itself. Thus, a checkpoint with `rb_order=0` remains without relational bias, while a checkpoint with an existing branch retains its frozen coefficients and native edge sets.

For deterministic evaluation, the native random-feature generator is called once per layer with seed $s + 1009\ell$, and its projection is retained for all source, target, and prompted passes of that checkpoint and repetition. The native kernel map, random-feature count, attention temperature, and numerical stabilizers are inherited from the checkpoint; dropout and training-only Gumbel sampling are disabled by evaluation mode. The implementation does not reseed its projection as a function of prompted queries; zero-prompt parity is defined against the native operator supplied with those same retained projections. Both kernel reductions and prompt-context pooling are segmented by graph, and only edges whose endpoints belong to the same graph are accepted. Sparse coefficients require $O(|E_P|Hr)$ work for H heads and r random features per head, and local prompt construction requires $O(|E_P|K_q(d_q + e_q))$ work, in addition to the unchanged native attention. Observation subsampling limits only the pooling bank; every edge in E_P still receives its local prompt, without materializing a dense all-pair prompt tensor.

Implementation checks. Zero-prompt parity requires the prompted wrapper to reproduce the native checkpoint under identical evaluation settings, normalization states, and controlled random features. An active-path check additionally requires nonzero prompt contributions to affect the intended

states and receive task gradients while pretrained parameters remain fixed; query and relevance gradients are checked away from the all-zero-gate initialization.

B.11 When Context Subtraction Is Useful or Harmful

Coordinate compatibility is not semantic correspondence. The same frozen GNN supplies a common numerical response space, but independently fitted feature maps can assign different meanings to its coordinates. For example, let a one-layer identity encoder observe the same semantic state represented by e_1 on the source and by e_2 on the target after an independent change of input basis. With one observation on each side, every query gives the nonzero gap $e_1 - e_2$, although the semantic state is unchanged. Conversely, different semantic states can have equal pooled responses and therefore give a zero gap. Shared queries remove the need for node correspondence; they do not identify an unknown mapping between feature meanings.

Feature preprocessing. SVD coordinates admit sign changes and rotations within repeated singular-value subspaces, so caching each dataset's feature map does not align independently reduced datasets. The cross-dataset results evaluate the fixed preprocessing pipeline, whereas Appendices A and C.7 keep feature coordinates unchanged. Alternative learned projections and value-normalization rules are not evaluated.

Task-directed gate learning. A context discrepancy does not by itself specify a descent direction for the downstream loss. The following result makes this distinction explicit for the actual shared-gate construction rather than allowing an independently chosen sign for each object. Fix a finite collection of training graphs, their observations, queries, relevance maps, and head, and stack all inserted prompt coordinates into a vector p. Let s stack the signed gate values and define the linear map T by $(Ts)^q_o(G) = \sum_k a^q_{o,k}(G) d^q_k(G) s^q_k$. The same coordinate s^q_k is shared across all objects and graphs of type q. Let $\mathcal{L}(p)$ be the resulting empirical task loss with prompts treated as independent inputs.

Proposition B.5 (Task-directed descent with shared gates)**.** *Suppose $\mathcal{L}$ is differentiable and has a β-Lipschitz gradient on the line segment from 0 to $-\eta T T^\top g$, where $g = \nabla\mathcal{L}(0)$, and write $b = T^\top g$. If $b \neq 0$, choose $\eta > 0$ with $\eta\|b\|_\infty < 1$ and $\beta\eta\|T\|_2^2 \leq 1$. The finite gate parameters $\vartheta = \operatorname{arctanh}(-\eta b)$ realize a feasible prompt satisfying*

$$\mathcal{L}\big(T \tanh \vartheta\big) \leq \mathcal{L}(0) - \frac{\eta}{2}\|T^\top g\|_2^2. \tag{66}$$

If $T^\top g = 0$, every feasible gate perturbation has zero first-order loss change at zero gates.

Proof. The inverse hyperbolic tangent is finite because every coordinate of $-\eta b$ lies strictly between -1 and 1. Thus $T \tanh \vartheta = -\eta T b$. The smoothness inequality gives

$$\mathcal{L}(-\eta T b) \leq \mathcal{L}(0) - \eta\langle g, Tb\rangle + \frac{\beta\eta^2}{2}\|Tb\|_2^2 \tag{67}$$

$$\leq \mathcal{L}(0) - \eta\|b\|_2^2 + \frac{\beta\eta^2}{2}\|T\|_2^2\|b\|_2^2 \tag{68}$$

$$\leq \mathcal{L}(0) - \frac{\eta}{2}\|b\|_2^2. \tag{69}$$

When $b = 0$, $\langle g, Tv\rangle = \langle T^\top g, v\rangle = 0$ for every gate direction v. □

At zero gates, the gate gradient is $T^\top g$, consistent with Appendix B.5; the inverse-tanh construction proves existence of a feasible descent step rather than specifying the optimizer's update. Shared gates allow contributions from different objects to cancel, and larger gaps can increase both the gradient signal and the curvature factor $\|T\|_2^2$. Thus, gap magnitude alone does not imply easier optimization or higher accuracy. Learned queries can subsequently change T, and the local smoothness assumption need not hold across arbitrary ReLU activation boundaries. The proposition establishes neither convergence of joint prompt learning nor population-risk improvement.

For fixed-predictor replacement, the sharper factor $\gamma_q = \max_{G,o} \sum_k a^q_{o,k}(G) |\tanh \vartheta^q_k| \leq 1$ yields $\|\widehat{P}^q - P^q\|_{\max,2} \leq \gamma_q \epsilon_q$ by the proof of Proposition 3.3. This bounds sensitivity to source-context errors without certifying semantic correspondence or prediction correctness.

C Ablation Protocols and Detailed Analysis

The value, insertion, composition, proxy-construction, and rotation studies use the ZINC/GCN/EdgePred checkpoint. Photo and Chameleon are node-classification tasks, DBLP is link prediction, and MNIST is graph classification. The value, insertion, proxy, and rotation studies use 5-shot, with DBLP retaining its task-specific link partition; composition also includes 100-shot node classification. Each trained variant uses validation-based checkpoint selection, whereas fixed-predictor interventions do not refit or reselect parameters. Bold and underlined entries denote the best and second distinct displayed means, not statistical significance.

C.1 Which Vectors Should Supply Prompt Values?

Variant definitions. Table 3 keeps the local descriptors, signed gates, and node/message insertion locations fixed while changing the value vectors. The head-only control learns the prediction head without prompts. The target-context, source-context, and paired-mean variants use $c^q_{t,k}$, $c^q_{s,k}$, and $(c^q_{s,k} + c^q_{t,k})/2$, respectively, in place of the gap $d^q_k = c^q_{s,k} - c^q_{t,k}$. The free-value variant learns prompt-value vectors rather than deriving them from paired context differences. All prompting variants use a common response-norm envelope that is nonbinding for the context values and gaps and also constrains free values. This controls the permitted scale but does not make every realized local prompt norm equal across variants.

Comparison scope. The head-only control tests the complete prompting construction, whereas source-only, target-only, and paired-mean values test its information use. Paired means retain both source and target conditioning, making their comparison with gaps a direct test of subtraction against averaging. The means favor gaps over all three context-derived alternatives and free values on every target. The strongest non-gap controls are free values on Photo and Chameleon and paired means on DBLP and MNIST, with gap improvements of 3.23, 1.56, 1.65, and 0.51 points, respectively. Thus, paired source and target information is useful, but using their difference rather than their average further improves the mean in each joint-insertion comparison. Free-value parameters are fixed after training, while their effective values can still depend on the graph through the norm constraint. Paired uncertainty and multiplicity are reported in Appendix C.8; marginal deviations alone do not determine a gap-minus-paired-mean interval.

C.2 Gap Information Versus Insertion Locations

Comparison design. Table 4 compares node-only, message-only, and joint insertion for both free and gap-derived values. Node-only prompts act on initial node states, while message-only prompts act before neighborhood aggregation at the message locations defined in Section 3. The reported free-versus-gap comparisons match trainable-parameter counts within each insertion pattern. The defined gap construction has $K_q(d_q + e_q + 1)$ prompt parameters per active type; a free-value implementation matches this count by replacing the $K_q d_q$ query parameters, rather than retaining a trainable query bank alongside the free values. This equality counts trainable parameters, not fixed observations, source information, or evaluation cost. The counts differ between node-only, message-only, and joint patterns, so improvements from joint insertion cannot be attributed solely to complementary information rather than additional capacity. The head-only and joint-model results are the same comparisons reported in Table 3, not independent repetitions of those experiments.

Interpretation. Joint gap insertion improves on the stronger single-location gap variant on all four targets, whereas joint free values improve on Photo and Chameleon but trail message-only free values by 1.81 points on DBLP and 1.23 on MNIST. On DBLP, gap-minus-free effects change from -0.18 for node-only and -0.45 for message-only insertion to $+1.89$ for joint insertion. On MNIST, the corresponding effects are $+0.50$, -0.53, and $+1.92$ points, so the four-target advantage of joint gap values should not be extended to every insertion pattern. These orderings show that more insertion sites do not by themselves ensure better adaptation; the available value directions and their local use also matter. Joint models have more parameters than single-location models, so the observed gains do not isolate a capacity-independent interaction between the two prompt locations. The diagnostic's deeper node representations are not the initial-state observations used to construct node-input prompt values.

Table 6: Source-context construction under ZINC/GCN/EdgePred transfer in the 5-shot setting. B denotes the number of proxy graphs; accuracy and ROC-AUC are percentages.

Variant	Photo / Acc. ↑	Chameleon / Acc. ↑	DBLP / AUC ↑	MNIST / Acc. ↑
Random proxies ($B = 4$)	$71.58_{\pm 4.02}$	$32.86_{\pm 2.99}$	$54.68_{\pm 0.78}$	$25.68_{\pm 2.24}$
Random proxies ($B = 16$)	$72.31_{\pm 3.87}$	$33.11_{\pm 2.85}$	$54.91_{\pm 0.75}$	$25.94_{\pm 2.11}$
Random proxies ($B = 64$)	$72.24_{\pm 3.69}$	$33.32_{\pm 2.76}$	$54.94_{\pm 0.72}$	$26.21_{\pm 2.07}$
Inverted proxies ($B = 4$)	$73.67_{\pm 3.98}$	$34.27_{\pm 2.94}$	$54.87_{\pm 0.73}$	$25.54_{\pm 2.18}$
GAPTUNE ($B = 16$)	$75.12_{\pm 3.61}$	$35.19_{\pm 2.56}$	$55.15_{\pm 0.62}$	$26.28_{\pm 1.91}$
Inverted proxies ($B = 64$)	$\underline{76.64_{\pm 3.77}}$	$\underline{36.06_{\pm 2.60}}$	$\underline{55.62_{\pm 0.61}}$	$\mathbf{27.84}_{\pm 1.91}$
GAPTUNE+ (source available)	$\mathbf{77.86}_{\pm 3.44}$	$\mathbf{36.47}_{\pm 2.39}$	$\mathbf{55.82}_{\pm 0.57}$	$\underline{27.63_{\pm 1.79}}$

C.3 SHARED QUERIES AND LOCAL SIGNED COMPOSITION

Variant definitions and parameter scope. Each row of Table 5 changes one component of GAPTUNE+. Frozen shared queries keep context-extraction queries fixed rather than learning them from the target task. Untied queries use separate source and target query parameters in place of a shared extraction rule. Uniform mixtures replace local relevance with $a^q_{o,k} = 1/K_q$, while learned global mixtures use trainable weights shared by all target objects of the same observation type. Nonnegative gates restrict each gap's gate to a nonnegative contribution instead of allowing the sign changes in Equation 12. Untied queries increase the trainable parameter count, whereas frozen queries and simpler mixtures reduce it; these are design comparisons rather than equal-parameter comparisons.

Interpretation. Learning shared queries improves on frozen queries in all four settings, but untied queries become slightly stronger at 100-shot. Uniform and learned global mixtures reduce accuracy relative to object-dependent mixtures, and signed gates improve on nonnegative gates throughout. The local signed composition is therefore more consistently beneficial than query sharing alone in this study. Each signed gate remains shared across objects; the experiment does not introduce independently chosen signs for every object–gap pair.

C.4 SOURCE-FREE CONTEXT CONSTRUCTION AND PROXY BUDGET

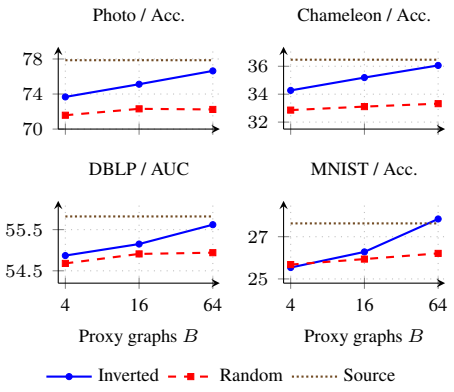

Figure 4: Proxy-budget means at 5-shot; dotted lines denote GAPTUNE+.

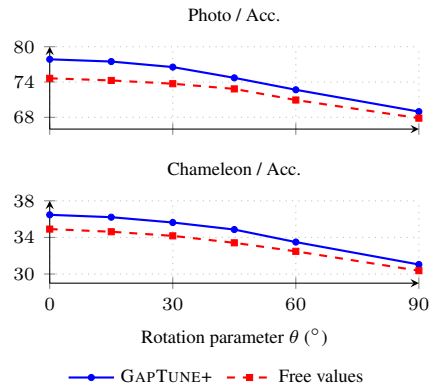

Figure 5: Fixed-predictor accuracy under norm-preserving rotations at 5-shot.

Comparison design. Table 6 compares random and inverted proxy graphs at budgets $B \in \{4, 16, 64\}$, where B counts proxy graphs rather than nodes, messages, or inversion updates. At each budget, the two constructions share initialization and graph-size/feature constraints. Their unprompted responses are used as source observations by the same downstream gap-prompting mechanism. The source-available comparison instead uses the pretraining source graphs. Figure 4 plots the means from this table, while the table retains their accompanying dispersion estimates. At $B = 16$, the Photo, Chameleon, DBLP, and MNIST entries match the source-free ZINC results in Table 1; these correspondences do not specify inversion budgets for other main-table configurations.

Response construction matters beyond graph count. Inversion outperforms random proxies in 11 of the 12 matched comparisons; the exception is MNIST at $B = 4$, where the means are 25.54 and 25.68. At $B = 16$, inversion improves Photo, Chameleon, DBLP, and MNIST by 2.81, 2.08, 0.24, and 0.34 points, respectively. Increasing the random-proxy budget from four to sixty-four graphs changes the four scores by only 0.66, 0.46, 0.26, and 0.53 points. The corresponding changes for inverted proxies are 2.97, 1.79, 0.75, and 2.30 points. The value of additional proxy graphs therefore depends on how their responses are constructed, rather than graph count alone.

Relation to observed source contexts and theory. At $B = 64$, the inverted-proxy means are below the source-available means by 1.22 points on Photo, 0.41 on Chameleon, and 0.20 on DBLP, but above the source-available mean by 0.21 on MNIST. Source availability is therefore a useful comparator, not a guaranteed empirical upper bound. The budget study evaluates independently adapted predictors and does not measure the pooled-context errors in Proposition 3.3. That proposition holds learned parameters fixed and bounds prediction changes conditional on source-context error; it does not establish that larger proxy budgets reduce that error or directly explain differences between retrained models.

C.5 Prompt Direction at Fixed Magnitude

Intervention. After training, an orthogonal transformation $R_q(\theta)$ is applied to every value vector of observation type q, with $R_q(0) = I$. Here, θ parameterizes the transformation; in multiple dimensions it need not equal the angle between every individual vector and its transformed value. The same transformation is used across target graphs within an observation type and repetition. Queries, local relevance coefficients, signed gates, and the prediction head are not refitted. Writing the original values as v_k^q, where $v_k^q = d_k^q$ for gap prompts, linearity gives

$$p_{o,\theta}^q = \sum_k a_{o,k}^q \tanh(\vartheta_k^q) R_q(\theta) v_k^q = R_q(\theta) p_o^q, \qquad \|p_{o,\theta}^q\|_2 = \|p_o^q\|_2. \tag{70}$$

Thus, the intervention preserves each local prompt's Euclidean norm for both gap and free-value models, rather than only preserving the norms of the individual value vectors. The zero-angle scores match the corresponding trained models in Tables 3 and 4.

Results and interpretation. From 0° to 90°, Photo accuracy decreases from 77.86 to 68.97 for gap values and from 74.63 to 67.86 for free values, losses of 8.89 and 6.77 points. On Chameleon, the corresponding losses are 5.43 and 4.55 points. Prompt orientation therefore matters to the trained predictors even when prompt magnitude is unchanged. Both constructions are sensitive, and the gap-value model has the larger absolute drop on each dataset. Consequently, the experiment does not establish that gap prompts are more rotation-robust or that their orientation sensitivity uniquely identifies source–target information. Its role is narrower: it rules out prompt magnitude alone as a complete explanation of the behavior of these fixed predictors.

C.6 Fixed-Predictor Source-Context Replacement

This experiment separates source-context replacement from downstream retraining, using five paired repetitions on Photo and Chameleon under ZINC/GCN/EdgePred. Unlike the independently adapted source-free models in Table 6, each comparison keeps a single fitted predictor fixed and changes only its pooled source contexts.

Predictor and replacement controls. We restore the selected source-available predictor and freeze its GNN, shared queries, local-relevance parameters, signed gates, prediction head, and normalization statistics. The target graphs, unprompted observations, local descriptors, evaluation objects, and original source summaries $C_s^\star$ are unchanged. Inversion-based and random proxy collections use matched budgets $B \in \{4, 16, 64\}$ and the same graph-size, feature, and discretization policies, and are pooled using the frozen queries. Replacing $C_s^\star$ by $\widehat{C}_s^{(B)}$ therefore changes the gap values without refitting the head or local coefficients. Proxy construction excludes target test labels and does not select proxies using their error against the original source contexts. Original contexts are used to measure replacement error after construction; identity replacement reuses them exactly.

Context, prompt, and output measurements. For each active observation type and repetition, we measure

$$\epsilon_q(B) = \max_k \|\widehat{c}_{s,k}^{q,(B)} - c_{s,k}^{q,\star}\|_2, \qquad \delta_{P,q}(B) = \max_{G,o} \|\widehat{p}_o^{q,(B)}(G) - p_o^{q,\star}(G)\|_2. \tag{71}$$

The maximum includes all prompted objects in the evaluation graphs, not only labeled objects. For object o, the output change is $\delta_{f,o} = \|f_o(\widehat{P}) - f_o(P)\|_\infty$, measured on pre-softmax logits with the original prediction rule. We summarize its object-wise mean and maximum within each repetition before averaging over repetitions. Prediction agreement compares original and replaced-context class decisions, while the task change is replacement accuracy minus original accuracy on the same examples. The pointwise 95% interval uses the five paired accuracy differences, as defined in Equation 74. Table 8 reports context and prompt errors by type, and Figure 6 summarizes $E_C = \max_q \epsilon_q$, output change, and agreement.

Table 7: Fixed-predictor source-context replacement over five paired repetitions per target. E_f^{mean} and $E_f^{\max}$ summarize per-object infinity-norm logit changes; agreement and accuracy are percentages. Δ Acc. is replacement minus original accuracy, with a pointwise 95% paired t interval in percentage points. Maxima are computed within each repetition before averaging.

Target	Source contexts	B	E_f^{mean}	$E_f^{\max}$	Agree (%)	Acc. (%)	Δ Acc. [95% CI]
Photo	Original (identity)	–	0.000	0.000	100.00	77.86	0.00 [0.00, 0.00]
Photo	Inversion	4	0.086	0.251	92.94	72.63	−5.23 [−7.24, −3.22]
Photo	Inversion	16	0.048	0.140	96.39	75.21	−2.65 [−3.41, −1.89]
Photo	Inversion	64	0.031	0.083	97.83	76.25	−1.61 [−1.98, −1.24]
Photo	Random	4	0.156	0.458	86.66	67.90	−9.96 [−12.51, −7.40]
Photo	Random	16	0.144	0.402	87.71	68.69	−9.17 [−11.11, −7.22]
Photo	Random	64	0.135	0.393	88.70	69.46	−8.40 [−10.78, −6.02]
Chameleon	Original (identity)	–	0.000	0.000	100.00	36.47	0.00 [0.00, 0.00]
Chameleon	Inversion	4	0.091	0.273	91.51	34.61	−1.86 [−2.16, −1.55]
Chameleon	Inversion	16	0.062	0.176	94.41	35.24	−1.23 [−1.58, −0.88]
Chameleon	Inversion	64	0.038	0.120	96.70	35.73	−0.74 [−0.91, −0.57]
Chameleon	Random	4	0.147	0.438	86.34	33.61	−2.86 [−3.54, −2.19]
Chameleon	Random	16	0.140	0.439	86.98	33.84	−2.63 [−3.25, −2.02]
Chameleon	Random	64	0.136	0.438	86.61	33.70	−2.77 [−3.67, −1.87]

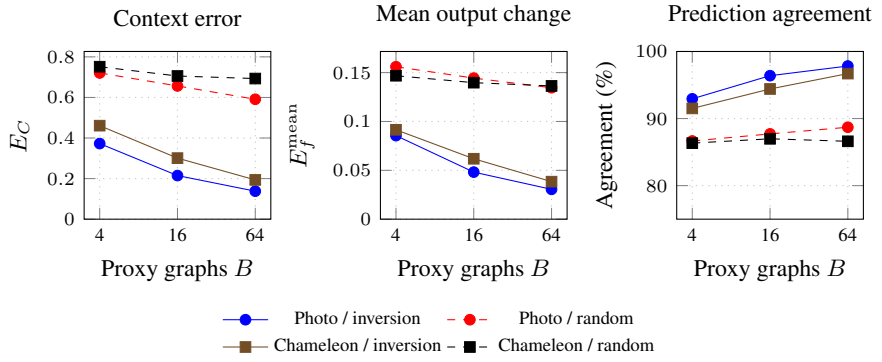

Figure 6: Fixed-predictor replacement over five paired repetitions. Original contexts give zero error and 100% agreement. Inversion-based contexts reduce context error and prediction changes more consistently than random contexts across the tested proxy budgets.

Replacement quality and downstream sensitivity. Increasing the inversion budget from four to sixty-four graphs raises Photo prediction agreement from 92.94% to 97.83% and reduces the mean logit change from 0.086 to 0.031. The corresponding accuracy loss decreases from 5.23 to 1.61 percentage points, but remains nonzero. At $B = 64$, random contexts yield 88.70% agreement and an 8.40-point Photo accuracy loss. Chameleon exhibits the same advantage for inverted contexts: agreement rises from 91.51% to 96.70%, and the accuracy loss decreases from 1.86 to 0.74 points.

Table 8: Type-wise context and prompt errors for fixed-predictor replacement. Each cell reports the mean $\epsilon_q/\delta_{P,q}$ in response units over five repetitions. N denotes initial node states, and M_1, M_2, M_3 denote layer-wise messages.

Target	Source contexts	B	N	M_1	M_2	M_3
Photo	Original (identity)	–	0.000/0.000	0.000/0.000	0.000/0.000	0.000/0.000
Photo	Inversion	4	0.313/0.112	0.347/0.119	0.352/0.140	0.336/0.110
Photo	Inversion	16	0.190/0.068	0.192/0.066	0.212/0.085	0.184/0.060
Photo	Inversion	64	0.107/0.038	0.133/0.046	0.132/0.052	0.125/0.041
Photo	Random	4	0.539/0.190	0.650/0.220	0.706/0.279	0.619/0.202
Photo	Random	16	0.529/0.187	0.572/0.198	0.640/0.256	0.568/0.182
Photo	Random	64	0.488/0.174	0.531/0.180	0.578/0.230	0.525/0.169
Chameleon	Original (identity)	–	0.000/0.000	0.000/0.000	0.000/0.000	0.000/0.000
Chameleon	Inversion	4	0.389/0.143	0.428/0.141	0.452/0.144	0.370/0.133
Chameleon	Inversion	16	0.257/0.096	0.270/0.092	0.294/0.093	0.236/0.084
Chameleon	Inversion	64	0.163/0.059	0.191/0.063	0.182/0.059	0.176/0.062
Chameleon	Random	4	0.543/0.200	0.642/0.208	0.727/0.231	0.643/0.229
Chameleon	Random	16	0.585/0.222	0.622/0.207	0.649/0.206	0.575/0.202
Chameleon	Random	64	0.517/0.189	0.613/0.207	0.659/0.207	0.615/0.219

Random-context Chameleon accuracy is not monotone in budget, with losses of 2.63 and 2.77 points at $B = 16$ and $B = 64$. Thus, improved aggregate context approximation does not guarantee a monotone task-accuracy change.

Connection to conditional stability. Writing A^q for the fixed local-relevance matrix, s^q for the signed gates, and E^q for the source-context differences gives the exact identity

$$\Delta P^q = A^q \operatorname{Diag}(s^q) E^q. \tag{72}$$

Consequently, $\delta_{P,q} \le \epsilon_q$ follows from the normalized nonnegative relevance weights and bounded gates, as in Proposition 3.3. Identity replacement gives zero context, prompt, and output changes and 100% agreement. The reported accuracy changes also obey $|\Delta\mathrm{Acc.}| \le 100 - \mathrm{Agreement}$, because only changed decisions can change correctness. These checks connect the replacement experiment to the fixed-predictor analysis; they do not turn the theorem into a guarantee about inversion quality or independently retrained models.

C.7 Prompt Values Under Controlled Context Shifts

This study compares gap, free, and target-context values as graph context changes, using separate within-dataset DGI-pretrained GCNs for Photo and Chameleon. It extends the perturbations in Appendix A.2 rather than transferring the ZINC/GCN/EdgePred checkpoint used in the preceding ablations. Unlike the prompt-reuse diagnostic in Figure 1, the comparison fits each prompt construction directly on the target support and does not require a source-trained donor prompt.

Matched adaptation. For each dataset, the pretrained checkpoint, input transformation, and baseline data-split convention are shared by all compared methods. Each of ten repetitions uses five labeled training nodes per class from that shared split and retains their identities across perturbed views, without introducing a method-specific support pool. Observable features and connectivity follow the baseline protocol, and evaluation labels do not enter perturbation construction, context extraction, or training. Each method is trained afresh with a common budget of 500 updates, common optimizer settings, and matched head initialization, without warm-starting across conditions. The checkpoint is selected using validation performance within this budget and evaluated on the test partition. The input map is fitted once on the permitted unperturbed features and is not refitted after perturbation.

Value and capacity controls. Head-only adaptation trains the prediction head without prompts. The prompting variants use gaps $c^q_{s,k} - c^q_{t,k}$, target contexts $c^q_{t,k}$, or free vectors v^q_k, with the same descriptors, local relevance, signed gates, node/message insertion locations, and permitted value-norm

envelope. The free-value construction replaces the $K_q d_q$ query parameters by the same number of free-value parameters; the target-context construction retains one query bank but excludes source observations. All three therefore have $\sum_q K_q(d_q + e_q + 1)$ trainable prompt parameters, although their information access and execution costs differ.

Perturbations and zero-gap controls. Feature noise, accepted double-edge swaps, and joint shifts follow Appendix A.2, with strengths $\alpha \in \{0, 0.05, 0.10, 0.20, 0.30, 0.50\}$. The same noise draw and accepted-swap sequence are reused across strengths within a repetition, and joint views reuse the corresponding feature and structure changes. Node identities, labels, feature coordinates, and the degree sequence under structure shifts are preserved, while GCN normalization is recomputed for each target adjacency. Node- and message-context discrepancies are measured independently of learned prompt values using Appendix A.4. Whole-graph source and target context collections use identical selection identities at zero shift, so all gap prompts vanish and the gap model coincides with the unprompted GNN under the same head-training trajectory. Structure-only shifts likewise preserve zero initial-state gaps while allowing message gaps and deeper node descriptors to change. This zero-gap control differs from comparing a pretraining collection with a local prediction subgraph in the adaptation benchmarks.

Paired effects. For comparator $v \in \{\text{free}, \text{target}\}$, the within-repetition effect is

$$D^{(v)}_{r,f,\alpha} = \text{Acc.}^{\text{gap}}_{r,f,\alpha} - \text{Acc.}^{(v)}_{r,f,\alpha}. \tag{73}$$

Figure 7 reports mean gap-minus-free effects and pointwise 95% paired t intervals over ten repetitions. Table 9 also reports absolute accuracy and gap-minus-target effects for selected strengths. The shared zero-strength control is reused across perturbation families and is not counted as additional independent repetitions.

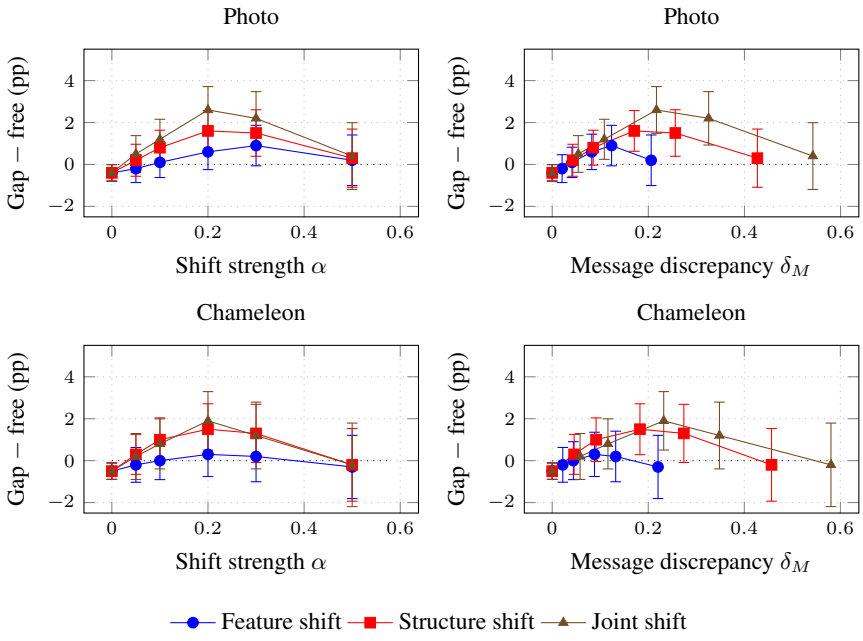

Figure 7: Gap-minus-free accuracy effects under controlled context shifts. Error bars are pointwise 95% paired t intervals over ten repetitions. The shared zero-strength control is reused across families rather than counted as independent observations.

Benefits depend on shift type and strength. For joint shifts on Photo, the mean gap-minus-free effect changes from -0.40 points at zero shift to 2.60 at $\alpha = 0.20$, then decreases to 0.40 at $\alpha = 0.50$. The corresponding Chameleon effects are -0.50, 1.90, and -0.20 points. At $\alpha = 0.30$, the Photo gap-minus-free effects are 0.90, 1.50, and 2.20 points for feature, structure, and joint

Table 9: Prompt-value comparisons under controlled shifts using separate within-dataset DGI-pretrained GCNs. Accuracy is a percentage, and effects are percentage-point differences with pointwise 95% paired t intervals over ten repetitions. At zero shift, gap prompts vanish and the gap and same-head head-only predictions coincide.

Target	Shift	α	Head	Target	Free	Gap	Gap − free [95% CI]	Gap − target [95% CI]
Photo	Control	0.00	78.60	78.80	79.00	78.60	-0.40 $[-0.79, -0.01]$	-0.20 $[-0.59, +0.19]$
Photo	Feature	0.10	76.90	77.20	77.50	77.60	$+0.10$ $[-0.62, +0.82]$	$+0.40$ $[-0.27, +1.07]$
Photo	Feature	0.30	72.50	73.00	73.40	74.30	$+0.90$ $[-0.07, +1.87]$	$+1.30$ $[+0.40, +2.20]$
Photo	Feature	0.50	67.30	68.40	68.80	69.00	$+0.20$ $[-1.01, +1.41]$	$+0.60$ $[-0.52, +1.72]$
Photo	Structure	0.10	74.90	75.10	76.00	76.80	$+0.80$ $[-0.03, +1.63]$	$+1.70$ $[+0.92, +2.48]$
Photo	Structure	0.30	66.90	68.40	69.80	71.30	$+1.50$ $[+0.39, +2.61]$	$+2.90$ $[+1.87, +3.93]$
Photo	Structure	0.50	58.30	60.90	62.20	62.50	$+0.30$ $[-1.09, +1.69]$	$+1.60$ $[+0.31, +2.89]$
Photo	Joint	0.10	73.00	73.90	74.60	75.80	$+1.20$ $[+0.24, +2.16]$	$+1.90$ $[+1.01, +2.79]$
Photo	Joint	0.30	60.60	63.30	64.50	66.70	$+2.20$ $[+0.93, +3.47]$	$+3.40$ $[+2.21, +4.59]$
Photo	Joint	0.50	48.80	52.50	53.10	53.50	$+0.40$ $[-1.19, +1.99]$	$+1.00$ $[-0.48, +2.48]$
Chameleon	Control	0.00	34.90	35.05	35.40	34.90	-0.50 $[-0.89, -0.11]$	-0.15 $[-0.54, +0.24]$
Chameleon	Feature	0.10	33.90	34.00	34.60	34.60	0.00 $[-0.91, +0.91]$	$+0.60$ $[-0.24, +1.44]$
Chameleon	Feature	0.30	30.80	31.50	31.90	32.10	$+0.20$ $[-1.01, +1.41]$	$+0.60$ $[-0.52, +1.72]$
Chameleon	Feature	0.50	27.00	28.00	28.20	27.90	-0.30 $[-1.81, +1.21]$	-0.10 $[-1.50, +1.30]$
Chameleon	Structure	0.10	32.90	33.10	34.00	35.00	$+1.00$ $[-0.04, +2.04]$	$+1.90$ $[+0.93, +2.87]$
Chameleon	Structure	0.30	28.40	29.80	30.80	32.10	$+1.30$ $[-0.09, +2.69]$	$+2.30$ $[+1.01, +3.59]$
Chameleon	Structure	0.50	23.90	26.40	27.00	26.80	-0.20 $[-1.93, +1.53]$	$+0.40$ $[-1.21, +2.01]$
Chameleon	Joint	0.10	31.90	32.80	33.40	34.20	$+0.80$ $[-0.39, +1.99]$	$+1.40$ $[+0.29, +2.51]$
Chameleon	Joint	0.30	25.90	27.90	28.90	30.10	$+1.20$ $[-0.39, +2.79]$	$+2.20$ $[+0.72, +3.68]$
Chameleon	Joint	0.50	21.00	23.90	24.40	24.20	-0.20 $[-2.19, +1.79]$	$+0.30$ $[-1.55, +2.15]$

shifts, respectively. The Chameleon effects at that strength are 0.20, 1.30, and 1.20 points. Gap-derived values are therefore more useful in the tested intermediate structural and joint shifts than in the zero-shift or strongest-shift comparisons. However, absolute accuracy decreases under stronger perturbations, and several pointwise intervals include zero. The results do not support a monotone relation between context discrepancy and prompt benefit, nor does the stability analysis predict an optimal perturbation strength.

C.8 Paired Uncertainty for Prompt Comparisons

Paired comparisons retain the pretrained checkpoint, feature map, graph partition, support identities, evaluation examples, and random-seed policy within each repetition. A repetition, rather than an individual node or graph within a fitted model, is the sampling unit. Let D_s denote the improvement of GapTune+ over a comparator in repetition s, using percentage-point differences for accuracy and ROC-AUC. For MAE, the improvement convention is comparator minus GapTune+ in the original target units; different metrics are not averaged together.

Intervals and win counts. For n paired repetitions, we compute

$$\overline{D} = \frac{1}{n}\sum_{s=1}^{n} D_s, \qquad \mathrm{CI}_{0.95} = \overline{D} \pm t_{0.975,n-1}\frac{s_D}{\sqrt{n}}, \quad s_D^2 = \frac{1}{n-1}\sum_{s=1}^{n}(D_s - \overline{D})^2. \tag{74}$$

The value and source-context comparisons use $n = 5$ with $t_{0.975,4} \approx 2.776$, whereas the controlled-shift study uses ten repetitions and nine degrees of freedom. W/T/L counts the repetitions with positive, zero, and negative differences. These intervals characterize paired effects under the independent-repetition assumption; with small n, their interpretation remains sensitive to the distribution of the differences. They are pointwise intervals rather than a family-wise significance test across all datasets, methods, and conditions.

Results. The Photo gap-minus-free effect is 3.23 points with paired interval $[0.56, 5.90]$ and five wins in five repetitions. Chameleon gains 1.56 points with interval $[-0.77, 3.89]$ and four wins, so a positive mean need not yield an interval excluding zero. The DBLP and MNIST gap-minus-free mean effects are $+1.89$ and $+1.92$ points; their daggered intervals use the marginal-summary

Table 10: Prompt comparisons over five repetitions per target; effects and intervals are in percentage points. $\overline{\Delta}$ is GAPTUNE+ minus the comparator; s_Δ and W/T/L summarize paired differences. Daggered rows use marginal deviations and rounding allowances to bound s_Δ and construct conservative 95% intervals, without inferring paired win counts.

Target	Comparator	$\overline{\Delta}$	s_Δ	95% interval	W/T/L
Photo	Free values	$+3.23$	2.15	$[+0.56, +5.90]$	5/0/0
Photo	Target values	$+5.42$	2.66	$[+2.11, +8.73]$	5/0/0
Photo	GAPTUNE	$+2.74$	1.73	$[+0.59, +4.89]$	5/0/0
Chameleon	Free values	$+1.56$	1.88	$[-0.77, +3.89]$	4/0/1
Chameleon	Target values	$+3.39$	2.14	$[+0.74, +6.04]$	5/0/0
Chameleon	GAPTUNE	$+1.28$	1.32	$[-0.36, +2.92]$	4/0/1
DBLP	Free values	$+1.89$	$\leq 1.30^\dagger$	$[+0.26, +3.52]^\dagger$	—
DBLP	Target values	$+1.90$	0.62	$[+1.13, +2.67]$	5/0/0
DBLP	GAPTUNE	$+0.67$	0.36	$[+0.22, +1.12]$	5/0/0
MNIST	Free values	$+1.92$	$\leq 3.94^\dagger$	$[-2.99, +6.83]^\dagger$	—
MNIST	Target values	$+1.10$	1.63	$[-0.93, +3.13]$	4/0/1
MNIST	GAPTUNE	$+1.35$	1.05	$[+0.04, +2.66]$	4/0/1

construction below rather than paired deviations or win counts. Against target-only values, the effects are positive on all four targets, but the MNIST paired interval includes zero.

Relation to marginal standard deviations. The paired variance depends on covariance,

$$\mathrm{Var}(A - B) = \mathrm{Var}(A) + \mathrm{Var}(B) - 2\,\mathrm{Cov}(A, B), \tag{75}$$

so separate mean±standard-deviation entries do not determine the uncertainty of a difference. An exact paired interval or W/T/L count cannot therefore be recovered from marginal means and deviations alone. For the DBLP and MNIST gap-minus-free comparisons, the deterministic inequality $s_\Delta \leq s_{\mathrm{gap}} + s_{\mathrm{free}}$ instead supplies an upper bound on the paired sample deviation. Allowing 0.01 for mean-difference rounding and 0.01 for the sum of deviation roundings gives $\overline{\Delta} \pm [0.01 + t_{0.975,4}(s_{\mathrm{gap}} + s_{\mathrm{free}} + 0.01)/\sqrt{5}]$. The outward-rounded intervals are $[0.26, 3.52]$ on DBLP and $[-2.99, 6.83]$ on MNIST; only the former excludes zero. These conservative intervals contain the ordinary paired t intervals under the same independent, normally distributed repetition-difference assumption; they are not reconstructed paired estimates.

Multiplicity across the twelve contrasts. For contrasts with paired deviations, Table 11 calculates the two-sided t value from $\overline{\Delta}/(s_\Delta/\sqrt{5})$. For the two daggered contrasts, it replaces the denominator deviation by its marginal upper bound and reduces the absolute mean difference by the 0.01 rounding allowance, producing conservative p-value upper bounds. Holm adjustment is applied to all twelve entries, retaining the original comparison family rather than dropping the two marginal-summary contrasts (Holm, 1979). The conservative adjusted analysis certifies the DBLP gap-minus-target effect below 0.05, but does not resolve multiplicity-adjusted superiority over free values across the four targets. The DBLP gap-minus-free marginal interval excludes zero pointwise, which is distinct from this family-wise conclusion. Exact paired deviations and adjusted tests for the two daggered contrasts require their paired run scores; the displayed bounds do not substitute for those estimates.

C.9 CROSS-DATASET UNCERTAINTY FROM MARGINAL SUMMARIES

The cross-dataset tables provide marginal means and standard deviations, but not the covariance required for ordinary paired intervals. For two methods on the same five repetitions, the sample deviation of their difference satisfies $s_D \leq s_A + s_B$. Under independent and identically normally distributed repetition differences, an enlarged Bonferroni-adjusted paired interval is

$$I_{A,B} = \left[\overline{D} - q_M \frac{s_A + s_B}{\sqrt{5}},\ \overline{D} + q_M \frac{s_A + s_B}{\sqrt{5}}\right], \qquad q_M = t_{1-0.05/(2M),4}. \tag{76}$$

The comparison family contains both gap variants, twelve prompting baselines, and 36 target–checkpoint–shot cells, giving $M = 864$ and $q_M \approx 17.8511$. This family includes selection of

Table 11: Multiplicity-aware analysis of the twelve comparisons in Table 10. Two-sided t calculations use five repetitions and four degrees of freedom; daggered p values are upper bounds from marginal summaries. $p^{\mathrm{bd}}_{\mathrm{Holm}}$ applies Holm adjustment to this complete vector of estimates and bounds, giving conservative adjusted values rather than exact adjusted tests for the two daggered contrasts.

Target	Comparator	$\overline{\Delta}$	s_Δ	p	$p^{\mathrm{bd}}_{\mathrm{Holm}}$
Photo	Free values	$+3.23$	2.15	0.0283	0.2157
Photo	Target values	$+5.42$	2.66	0.0104	0.1141
Photo	GAPTUNE	$+2.74$	1.73	0.0240	0.2157
Chameleon	Free values	$+1.56$	1.88	0.1371	0.4114
Chameleon	Target values	$+3.39$	2.14	0.0240	0.2157
Chameleon	GAPTUNE	$+1.28$	1.32	0.0960	0.3840
DBLP	Free values	$+1.89$	$\leq 1.30^{\dagger}$	$\leq 0.0319^{\dagger}$	0.2157
DBLP	Target values	$+1.90$	0.62	0.0024	0.0285
DBLP	GAPTUNE	$+0.67$	0.36	0.0141	0.1413
MNIST	Free values	$+1.92$	$\leq 3.94^{\dagger}$	$\leq 0.3394^{\dagger}$	0.4116
MNIST	Target values	$+1.10$	1.63	0.2058	0.4116
MNIST	GAPTUNE	$+1.35$	1.05	0.0452	0.2262

the strongest observed baseline within each cell; it does not correct the separate same-dataset configuration search. Using a 0.01 allowance for mean rounding and $s_A + s_B + 0.01$ for deviation rounding, every interval against a strongest observed baseline contains zero. The cross-dataset win counts therefore remain descriptive, not a family-wise statistical superiority result. These model-dependent intervals are conservative because there are only five repetitions and paired covariance is unavailable; they are not distribution-free guarantees. The union bound does not require independence between comparisons, but each paired t calculation requires the stated assumptions across repetitions.

C.10 PARAMETER, TIME, AND MEMORY ACCOUNTING

The cost study uses a bias-enabled three-layer GCN with widths $100 \to 128 \to 128 \to 128$, no additional trainable normalization or embedding modules, and an eight-class affine Photo head. It uses $K_q = 8$ values for each active type, response dimensions $d_q = (100, 128, 128, 128)$, and descriptor dimensions $e_q = (228, 328, 384, 384)$. These counts describe this cost-study configuration rather than every architecture in the benchmark grid.

Trainable parameters and retained contexts. The encoder contains $45{,}952$ parameters and the head contains $1{,}032$. Equation 52 gives $14{,}496$ prompt parameters, yielding $15{,}528$ trainable parameters including the head, compared with $46{,}984$ for full fine-tuning. The matched joint free-value control has the same trainable count because free values replace the query parameters. Node-only and message-only free-value controls contain $3{,}664$ and $12{,}896$ trainable parameters including the head, respectively. The retained source contexts contain $3{,}872$ scalars, or 15.125 KiB in FP32, excluding model parameters and temporary working memory.

Workload and stage definitions. A fixed batch contains 64 disjoint subgraphs with 8,192 nodes and 65,536 directed message instances, including the self-loop convention. All methods use FP32 and the same batch sequence and evaluation calls. Gap and free-value methods use both an unprompted descriptor pass and a prompted prediction pass; head-only adaptation and full fine-tuning need one prediction pass at inference. The accounting does not reuse a cross-update cache of target observations. Source-free preparation uses $B = 16$ proxy graphs with 32 nodes each and 1,000 inversion updates, followed by response extraction. Source-available preparation contains response extraction only. Both gap variants use a budget of 512 source-node observations and 2,048 source-message observations per layer, giving equal post-preparation tensor shapes in this comparison. Adaptation comprises 500 updates and 20 fixed-batch evaluations, and total time additionally includes preparation. The preparation and adaptation stages are sequential, so their all-stage memory peak is their maximum rather than their sum. Timing variability is summarized over five timing blocks, separately from accuracy variability across training repetitions.

Table 12: Parameter and execution costs for the stated GCN workload, including the Photo affine head. Times are mean±sample standard deviation over five timing blocks. Adaptation includes 500 updates and 20 fixed-batch evaluations; preparation is separate. Inference includes all required target passes and excludes inversion.

Method	Trainable (# param.)	Prep. (s)	Update (ms)	Adapt. (s)	Infer. (ms/batch)	Total (s)
Head only	1,032	$0.00_{\pm 0.00}$	$2.74_{\pm 0.04}$	$1.41_{\pm 0.02}$	$1.81_{\pm 0.03}$	$1.41_{\pm 0.02}$
Full fine-tuning	46,984	$0.00_{\pm 0.00}$	$9.64_{\pm 0.24}$	$4.85_{\pm 0.12}$	$1.81_{\pm 0.03}$	$4.85_{\pm 0.12}$
Free: node only	3,664	$0.00_{\pm 0.00}$	$9.19_{\pm 0.10}$	$4.67_{\pm 0.05}$	$3.60_{\pm 0.05}$	$4.67_{\pm 0.05}$
Free: message only	12,896	$0.00_{\pm 0.00}$	$12.29_{\pm 0.30}$	$6.23_{\pm 0.15}$	$4.00_{\pm 0.06}$	$6.23_{\pm 0.15}$
Free: node + message	15,528	$0.00_{\pm 0.00}$	$12.85_{\pm 0.22}$	$6.51_{\pm 0.11}$	$4.17_{\pm 0.09}$	$6.51_{\pm 0.11}$
GAPTUNE	15,528	$41.73_{\pm 1.73}$	$14.96_{\pm 0.29}$	$7.58_{\pm 0.15}$	$4.96_{\pm 0.10}$	$49.31_{\pm 1.72}$
GAPTUNE+	15,528	$2.22_{\pm 0.09}$	$14.96_{\pm 0.29}$	$7.58_{\pm 0.15}$	$4.96_{\pm 0.10}$	$9.80_{\pm 0.22}$

Table 13: Peak working memory (MB) for the cost-study workload, summarized over five timing blocks. Preparation and adaptation are sequential; the all-stage peak is their maximum. Parameter savings do not remove activation, descriptor, or message-prompt storage.

Method	Preparation	Adaptation	All-stage peak
Head only	$0.0_{\pm 0.0}$	$56.2_{\pm 0.4}$	$56.2_{\pm 0.4}$
Full fine-tuning	$0.0_{\pm 0.0}$	$224.7_{\pm 1.5}$	$224.7_{\pm 1.5}$
Free: node only	$0.0_{\pm 0.0}$	$179.9_{\pm 1.3}$	$179.9_{\pm 1.3}$
Free: message only	$0.0_{\pm 0.0}$	$321.2_{\pm 3.6}$	$321.2_{\pm 3.6}$
Free: node + message	$0.0_{\pm 0.0}$	$333.1_{\pm 3.3}$	$333.1_{\pm 3.3}$
GAPTUNE	$126.4_{\pm 0.0}$	$367.2_{\pm 2.0}$	$367.2_{\pm 2.0}$
GAPTUNE+	$83.5_{\pm 0.0}$	$367.2_{\pm 2.0}$	$367.2_{\pm 2.0}$

Performance–cost tradeoff. Joint gap prompting reduces the trainable count by 66.95% relative to full fine-tuning, but its two target passes and local prompt operations increase execution cost in this workload. Adaptation takes 7.58 seconds and inference takes 4.96 milliseconds per batch, compared with 4.85 seconds and 1.81 milliseconds for full fine-tuning. Source-free preparation contributes 41.73 seconds, whereas source-available response preparation contributes 2.22 seconds. Preparation is a first-use cost and is not repeated during deployment, because the final source summaries are retained. The adaptation-memory means are 367.2 MB for joint gap prompting and 224.7 MB for full fine-tuning, reflecting the storage of descriptors, attention weights, and message prompts in addition to model and optimizer state. Parameter efficiency therefore should not be identified with lower latency or lower working memory. These workload-specific comparisons do not establish an ordering for different devices, graph sizes, batching rules, or caching strategies.

Query-count and temperature dependence. For common $K_q = K$ in this workload, the prompt count is $1812K$ and retained source storage is $484K$ FP32 scalars; the reported cost study uses $K = 8$. The forward function depends on Q^q/τ_c and W^q/τ_p, so jointly rescaling a parameter bank and its temperature preserves that function, but not necessarily its optimization trajectory. No query-count or temperature accuracy sweep is reported. With $K_q = 1$, the local mixture is constant and cannot depend on the descriptor; additional queries can increase the gap-bank rank only up to $\min(K_q, d_q)$. Graph-dependent time and memory costs are given in Appendix B.7 and should not be inferred from retained source storage alone.

Adapter comparison scope. Three width-18 residual bottleneck adapters $h \mapsto h + U\sigma(Vh + b) + c$ on 128-dimensional layers, together with the same head, contain $15{,}294$ trainable parameters, compared with $15{,}528$ for the gap model. This is a capacity calculation only; adapter accuracy and runtime are not evaluated.

D EXPERIMENTAL PROTOCOLS AND ADDITIONAL RESULTS

This appendix describes the data-processing and evaluation procedures used in our experiments, the training and configuration-search settings, and the complete architecture–objective results.

D.1 DATASETS, PREPROCESSING, AND METRICS

Datasets and reported metrics. Node classification uses Photo (Shchur et al., 2018), ogbn-arxiv (Hu et al., 2020a), Airports-USA (Ribeiro et al., 2017), and Chameleon (Rozemberczki et al., 2021). Link prediction uses CitationFull/DBLP (Bojchevski & Günnemann, 2018) and Cornell from WebKB (Pei et al., 2020); graph regression uses QM7b (Montavon et al., 2013); graph classification uses ToxCast (Wu et al., 2018) and GNNBenchmarkDataset/MNIST (Dwivedi et al., 2023). NC, LP, GR, and GC denote node classification, link prediction, graph regression, and graph classification. NC and MNIST use accuracy, LP and ToxCast use ROC-AUC, and QM7b uses MAE. Accuracy and ROC-AUC are percentages with higher values better; MAE is an error with lower values better. These task assignments need not coincide with the tasks or partitions of the original dataset publications.

Supervision and shared evaluation settings. Table 16 summarizes the task-specific support budgets and shared data settings used in our experiments. For each task and repetition, all methods use the same support, validation, and test partitions, dataset-level feature transformation, and permitted graph observations. The nominal shot setting specifies the training support; validation labels form a separate supervised partition used for checkpoint selection.

Link-prediction pairs and graph access. We represent each undirected positive pair once as $\{u, v\}$ with $u < v$; this canonical representation does not make the prediction task directional. The training/validation/test fractions are $(0.05, 0.10, 0.10)$ and $(0.10, 0.05, 0.10)$ for the nominal 5-shot and 100-shot same-dataset settings, respectively. We partition the positive-pair set into mutually disjoint message-only, support, validation, and test sets, E_{ctx}, P_{tr}, P_{val}, and P_{te}. Only E_{ctx} supplies message-passing edges at every downstream stage, including evaluation; validation and test positives are never added to this graph. Support positives supply training targets, not additional propagation edges. The model-independent split routine can consult the complete observed positive set when excluding false negatives, but neither the held-out positive list nor the exclusion lookup is an input to the predictor. Negative pairs are sampled without replacement from distinct-node pairs absent from the complete observed positive set, at a fixed 1:1 negative-to-positive ratio for each split. Negative sets are mutually disjoint, sampled once per repetition, and shared across methods. Algorithm 2 summarizes the masking, feature construction, context extraction, and prediction steps used in the LP experiments. Same-dataset pretraining and source-observation extraction use only the message-only graph; an EdgePred pretext additionally removes both orientations of its conditioning pairs before computing any structure-dependent inputs. Independent cross-dataset source checkpoints retain their own source graphs; their target observations still follow the target split restrictions. For every query, we remove both orientations before neighborhood selection, degree features, structural encodings, normalization, and cached-response construction, so an earlier preprocessing step cannot retain the queried link. Evaluation negatives follow exactly the same graph-construction pipeline as evaluation positives. The data pipeline checks canonical-pair disjointness, reciprocal-edge masking, checkpoint graph access, and the graph dependencies of features and caches.

ToxCast support and masked supervision. For each repetition, ToxCast uses disjoint molecule partitions and an assay-specific support-label mask shared by all methods. The effective supervision budget is determined by the selected observed labels, not by multiplying the nominal shot setting by the total number of assays. Let I_{tr}, I_{val}, and I_{te} be disjoint molecule-index sets, let $Y_{it} \in \{0, 1\}$ be an observed assay label, and let M_{it} indicate that the label is observed. A binary support mask $S_{it} \le M_{it}$ selects the training labels on I_{tr}; other observed labels on a selected molecule are used only when included in this mask. Missing entries are excluded by index selection before loss evaluation, not multiplied by zero after evaluating a loss at an undefined label. For GAPTUNE and GAPTUNE+, the multitask training loss averages binary cross-entropy over the selected observed support labels:

$$\mathcal{L}_{\mathrm{ToxCast}} = \frac{1}{|\Omega_{\mathrm{tr}}|} \sum_{(i,t)\in\Omega_{\mathrm{tr}}} \mathrm{BCEWithLogits}(z_{it}, Y_{it}), \qquad \Omega_{\mathrm{tr}} = \{(i,t) : i \in I_{\mathrm{tr}},\ S_{it} = 1\}. \quad (77)$$

Table 14: Cross-dataset adaptation at 100-shot with validation-selected checkpoints; link prediction uses the shared task-specific partitions. Each block repeats the architecture-matched scratch control from Table 15. Bold/underline mark the best/second test means, including scratch.

Methods	Datasets: Homophilic graphs			Heterophilic graphs			Graph-level tasks		
	E-commerce **Photo** NC / Acc. ↑	Academic **ogbn-arxiv** NC / Acc. ↑	Academic **DBLP** LP / AUC ↑	Transport **Airports** NC / Acc. ↑	Web **Chameleon** NC / Acc. ↑	Web **Cornell** LP / AUC ↑	Chemistry **QM7b** GR / MAE ↓	Chemistry **ToxCast** GC / AUC ↑	Vision **MNIST** GC / Acc. ↑
Source dataset: ZINC, GNN: GCN, Pretraining: EdgePred									
GCN (scratch)	87.37$_{\pm 0.78}$	**37.72**$_{\pm 0.68}$	55.60$_{\pm 0.65}$	39.82$_{\pm 3.13}$	34.27$_{\pm 1.32}$	62.78$_{\pm 5.43}$	**5.08**$_{\pm 0.08}$	52.49$_{\pm 1.21}$	24.37$_{\pm 2.61}$
All-in-One	54.12$_{\pm 1.62}$	9.44$_{\pm 0.72}$	52.18$_{\pm 0.77}$	34.02$_{\pm 2.66}$	30.37$_{\pm 1.91}$	56.29$_{\pm 7.16}$	17.82$_{\pm 1.75}$	50.38$_{\pm 1.28}$	21.08$_{\pm 2.10}$
EdgePrompt	65.76$_{\pm 3.64}$	15.98$_{\pm 1.08}$	53.48$_{\pm 0.69}$	35.17$_{\pm 2.82}$	32.29$_{\pm 1.78}$	58.63$_{\pm 7.31}$	12.54$_{\pm 1.11}$	51.94$_{\pm 0.65}$	25.77$_{\pm 2.75}$
EdgePrompt+	71.94$_{\pm 3.22}$	19.85$_{\pm 1.19}$	54.02$_{\pm 0.62}$	37.84$_{\pm 2.74}$	34.43$_{\pm 1.66}$	60.18$_{\pm 7.54}$	10.61$_{\pm 0.92}$	53.17$_{\pm 2.76}$	29.84$_{\pm 1.80}$
GPF	67.31$_{\pm 2.89}$	16.91$_{\pm 1.02}$	52.76$_{\pm 0.64}$	34.84$_{\pm 2.50}$	33.17$_{\pm 1.70}$	57.05$_{\pm 7.04}$	28.72$_{\pm 2.12}$	53.20$_{\pm 1.84}$	23.16$_{\pm 3.18}$
GPF+	73.62$_{\pm 2.74}$	20.54$_{\pm 1.11}$	53.68$_{\pm 0.59}$	36.15$_{\pm 2.36}$	35.02$_{\pm 1.59}$	59.02$_{\pm 6.84}$	24.36$_{\pm 1.42}$	49.11$_{\pm 0.92}$	28.63$_{\pm 2.14}$
GPPT	49.48$_{\pm 2.59}$	8.17$_{\pm 1.13}$	51.51$_{\pm 1.12}$	33.29$_{\pm 2.34}$	29.21$_{\pm 1.85}$	55.38$_{\pm 7.62}$	35.17$_{\pm 5.81}$	50.06$_{\pm 0.32}$	24.07$_{\pm 1.54}$
GraphPrompt	59.66$_{\pm 1.83}$	11.64$_{\pm 0.82}$	52.31$_{\pm 0.68}$	34.41$_{\pm 2.24}$	29.83$_{\pm 2.54}$	57.13$_{\pm 6.51}$	10.34$_{\pm 0.96}$	43.56$_{\pm 1.36}$	29.62$_{\pm 1.18}$
GraphPrompt+	64.58$_{\pm 2.76}$	10.73$_{\pm 0.89}$	53.04$_{\pm 0.71}$	35.06$_{\pm 2.18}$	30.57$_{\pm 2.28}$	58.44$_{\pm 6.93}$	8.72$_{\pm 1.06}$	43.92$_{\pm 1.65}$	28.73$_{\pm 1.10}$
ProNoG	60.63$_{\pm 2.19}$	11.87$_{\pm 0.72}$	52.69$_{\pm 0.71}$	32.84$_{\pm 1.81}$	29.88$_{\pm 1.88}$	58.61$_{\pm 7.30}$	14.16$_{\pm 2.06}$	41.15$_{\pm 2.91}$	28.49$_{\pm 1.46}$
IGAP	71.83$_{\pm 2.62}$	27.94$_{\pm 1.77}$	55.41$_{\pm 0.64}$	40.21$_{\pm 2.31}$	37.62$_{\pm 1.71}$	63.22$_{\pm 7.06}$	8.24$_{\pm 0.72}$	51.94$_{\pm 1.42}$	33.74$_{\pm 1.74}$
MTG	80.14$_{\pm 2.58}$	26.82$_{\pm 1.68}$	55.06$_{\pm 1.21}$	41.67$_{\pm 2.23}$	39.44$_{\pm 1.59}$	61.87$_{\pm 6.77}$	6.92$_{\pm 0.54}$	52.80$_{\pm 0.94}$	35.28$_{\pm 1.61}$
SUPT	78.72$_{\pm 2.34}$	25.61$_{\pm 2.32}$	54.28$_{\pm 0.67}$	40.38$_{\pm 2.18}$	38.13$_{\pm 1.55}$	60.42$_{\pm 6.63}$	9.36$_{\pm 0.83}$	53.09$_{\pm 1.82}$	34.93$_{\pm 1.75}$
GAPTUNE	84.92$_{\pm 2.28}$	28.91$_{\pm 1.66}$	55.91$_{\pm 0.60}$	42.88$_{\pm 2.08}$	40.26$_{\pm 1.51}$	64.31$_{\pm 6.24}$	8.08$_{\pm 0.74}$	55.08$_{\pm 2.04}$	36.22$_{\pm 1.44}$
GAPTUNE+	**87.48**$_{\pm 2.09}$	30.16$_{\pm 1.53}$	**56.38**$_{\pm 0.55}$	**44.21**$_{\pm 1.94}$	**41.32**$_{\pm 1.42}$	**65.56**$_{\pm 5.84}$	7.42$_{\pm 0.68}$	**55.83**$_{\pm 2.00}$	**37.51**$_{\pm 1.33}$
Source dataset: PubMed, GNN: GIN, Pretraining: GraphCL									
GIN (scratch)	87.05$_{\pm 0.63}$	31.82$_{\pm 0.91}$	55.24$_{\pm 1.26}$	40.68$_{\pm 1.53}$	37.59$_{\pm 0.38}$	**69.74**$_{\pm 8.13}$	36.71$_{\pm 2.31}$	51.45$_{\pm 1.86}$	38.59$_{\pm 1.96}$
All-in-One	73.12$_{\pm 1.34}$	34.18$_{\pm 0.31}$	54.01$_{\pm 0.66}$	35.14$_{\pm 1.47}$	33.28$_{\pm 1.20}$	57.04$_{\pm 7.02}$	64.72$_{\pm 7.15}$	56.40$_{\pm 1.79}$	29.84$_{\pm 2.83}$
EdgePrompt	77.85$_{\pm 2.12}$	37.62$_{\pm 0.58}$	54.86$_{\pm 0.72}$	37.08$_{\pm 2.14}$	35.41$_{\pm 1.36}$	59.28$_{\pm 6.92}$	58.36$_{\pm 6.62}$	49.37$_{\pm 0.72}$	31.53$_{\pm 2.61}$
EdgePrompt+	79.73$_{\pm 1.98}$	39.04$_{\pm 0.73}$	55.31$_{\pm 0.65}$	39.26$_{\pm 2.05}$	37.19$_{\pm 1.29}$	60.47$_{\pm 6.71}$	53.42$_{\pm 5.88}$	51.00$_{\pm 2.30}$	34.71$_{\pm 1.72}$
GPF	80.21$_{\pm 1.52}$	38.11$_{\pm 0.65}$	54.58$_{\pm 0.62}$	37.92$_{\pm 2.00}$	36.18$_{\pm 1.31}$	58.26$_{\pm 6.83}$	68.14$_{\pm 6.74}$	50.05$_{\pm 2.06}$	31.07$_{\pm 2.97}$
GPF+	81.02$_{\pm 1.74}$	39.35$_{\pm 0.77}$	55.02$_{\pm 0.60}$	38.47$_{\pm 1.86}$	36.77$_{\pm 1.24}$	59.17$_{\pm 6.55}$	61.83$_{\pm 6.12}$	49.16$_{\pm 0.86}$	33.24$_{\pm 2.11}$
GPPT	59.82$_{\pm 2.88}$	28.73$_{\pm 2.42}$	52.18$_{\pm 0.96}$	35.82$_{\pm 1.77}$	31.54$_{\pm 1.41}$	56.13$_{\pm 7.10}$	87.26$_{\pm 11.62}$	51.46$_{\pm 0.52}$	28.62$_{\pm 1.74}$
GraphPrompt	73.74$_{\pm 2.10}$	23.08$_{\pm 0.94}$	54.22$_{\pm 0.69}$	36.28$_{\pm 2.18}$	31.77$_{\pm 2.16}$	57.62$_{\pm 7.40}$	60.52$_{\pm 6.22}$	45.61$_{\pm 1.65}$	34.82$_{\pm 1.44}$
GraphPrompt+	76.18$_{\pm 2.39}$	21.76$_{\pm 1.03}$	54.71$_{\pm 0.71}$	37.44$_{\pm 2.06}$	32.59$_{\pm 2.03}$	59.14$_{\pm 7.05}$	56.74$_{\pm 5.93}$	44.01$_{\pm 1.77}$	33.53$_{\pm 1.38}$
ProNoG	77.74$_{\pm 1.56}$	32.78$_{\pm 0.90}$	54.96$_{\pm 0.62}$	39.44$_{\pm 2.36}$	34.28$_{\pm 1.86}$	60.96$_{\pm 9.55}$	40.34$_{\pm 3.47}$	45.61$_{\pm 1.45}$	33.36$_{\pm 1.50}$
IGAP	84.26$_{\pm 1.98}$	46.08$_{\pm 1.22}$	56.87$_{\pm 0.65}$	42.12$_{\pm 1.91}$	40.47$_{\pm 1.41}$	66.48$_{\pm 6.49}$	37.84$_{\pm 3.21}$	53.00$_{\pm 1.34}$	36.18$_{\pm 1.73}$
MTG	83.61$_{\pm 1.92}$	**47.22**$_{\pm 1.16}$	56.42$_{\pm 1.14}$	43.05$_{\pm 1.84}$	41.52$_{\pm 1.35}$	63.41$_{\pm 6.32}$	34.26$_{\pm 2.86}$	50.44$_{\pm 0.73}$	37.51$_{\pm 1.61}$
SUPT	82.94$_{\pm 1.77}$	44.63$_{\pm 1.68}$	55.74$_{\pm 0.68}$	42.33$_{\pm 1.79}$	40.84$_{\pm 1.33}$	62.17$_{\pm 6.20}$	40.72$_{\pm 3.45}$	52.02$_{\pm 1.57}$	37.26$_{\pm 1.72}$
GAPTUNE	85.91$_{\pm 1.76}$	45.88$_{\pm 1.18}$	57.08$_{\pm 0.60}$	44.32$_{\pm 1.74}$	42.38$_{\pm 1.31}$	65.11$_{\pm 5.91}$	32.67$_{\pm 2.74}$	55.24$_{\pm 1.68}$	38.12$_{\pm 1.39}$
GAPTUNE+	**87.38**$_{\pm 1.61}$	46.71$_{\pm 1.10}$	**57.62**$_{\pm 0.55}$	**45.48**$_{\pm 1.62}$	**43.26**$_{\pm 1.23}$	65.92$_{\pm 5.62}$	**30.85**$_{\pm 2.55}$	**57.02**$_{\pm 2.21}$	**38.96**$_{\pm 1.29}$

Table 15: Same-dataset 100-shot performances. Bold/underline mark the best/second test means.

Methods	Datasets: Homophilic graphs			Heterophilic graphs			Graph-level tasks		
	E-commerce **Photo** NC / Acc. ↑	Academic **ogbn-arxiv** NC / Acc. ↑	Academic **DBLP** LP / AUC ↑	Transport **Airports** NC / Acc. ↑	Web **Chameleon** NC / Acc. ↑	Web **Cornell** LP / AUC ↑	Chemistry **QM7b** GR / MAE ↓	Chemistry **ToxCast** GC / AUC ↑	Vision **MNIST** GC / Acc. ↑
Target-supervised controls: training from scratch (no pretraining)									
GCN	87.37$_{\pm 0.78}$	37.72$_{\pm 0.68}$	55.60$_{\pm 0.65}$	39.82$_{\pm 3.13}$	34.27$_{\pm 1.32}$	62.78$_{\pm 5.43}$	5.08$_{\pm 0.08}$	52.49$_{\pm 1.21}$	24.37$_{\pm 2.61}$
GAT	86.41$_{\pm 0.57}$	37.84$_{\pm 0.53}$	56.01$_{\pm 0.59}$	35.57$_{\pm 1.87}$	35.26$_{\pm 1.35}$	69.72$_{\pm 9.48}$	21.51$_{\pm 0.59}$	53.17$_{\pm 1.03}$	27.96$_{\pm 0.88}$
GIN	87.05$_{\pm 0.63}$	31.82$_{\pm 0.91}$	55.24$_{\pm 1.26}$	40.68$_{\pm 1.53}$	37.59$_{\pm 0.38}$	69.74$_{\pm 8.13}$	36.71$_{\pm 2.31}$	51.45$_{\pm 1.86}$	38.59$_{\pm 1.96}$
H2GCN	87.01$_{\pm 0.79}$	38.89$_{\pm 1.00}$	55.47$_{\pm 0.73}$	27.14$_{\pm 0.84}$	41.26$_{\pm 1.68}$	73.42$_{\pm 6.76}$	5.64$_{\pm 0.16}$	52.14$_{\pm 1.25}$	33.61$_{\pm 1.15}$
FAGCN	87.21$_{\pm 0.68}$	42.00$_{\pm 0.64}$	54.62$_{\pm 1.33}$	36.51$_{\pm 2.99}$	37.33$_{\pm 1.12}$	62.81$_{\pm 13.20}$	5.47$_{\pm 0.10}$	52.05$_{\pm 0.82}$	23.41$_{\pm 2.00}$
Transformer	88.44$_{\pm 0.36}$	39.24$_{\pm 0.68}$	57.03$_{\pm 0.42}$	41.09$_{\pm 2.15}$	39.64$_{\pm 0.96}$	76.79$_{\pm 7.10}$	10.71$_{\pm 1.28}$	52.74$_{\pm 0.54}$	37.32$_{\pm 1.53}$
NodeFormer	83.94$_{\pm 0.84}$	40.47$_{\pm 2.33}$	53.29$_{\pm 1.73}$	37.42$_{\pm 3.58}$	39.40$_{\pm 1.28}$	62.68$_{\pm 3.99}$	13.71$_{\pm 0.06}$	51.34$_{\pm 0.74}$	14.54$_{\pm 4.72}$
Same-dataset pretraining + prompting (best-observed summaries)									
All-in-One	88.80$_{\pm 0.41}$	45.06$_{\pm 0.14}$	56.30$_{\pm 0.68}$	43.34$_{\pm 0.86}$	39.95$_{\pm 0.43}$	77.53$_{\pm 6.41}$	11.78$_{\pm 0.57}$	60.96$_{\pm 1.64}$	37.50$_{\pm 0.55}$
EdgePrompt	83.10$_{\pm 1.76}$	46.89$_{\pm 0.59}$	57.63$_{\pm 0.92}$	43.04$_{\pm 1.72}$	42.10$_{\pm 0.96}$	75.77$_{\pm 7.66}$	9.22$_{\pm 0.33}$	53.98$_{\pm 0.63}$	33.69$_{\pm 3.79}$
EdgePrompt+	85.07$_{\pm 1.50}$	44.96$_{\pm 1.34}$	57.09$_{\pm 0.54}$	47.67$_{\pm 1.34}$	42.15$_{\pm 1.08}$	76.22$_{\pm 7.85}$	9.26$_{\pm 0.32}$	54.54$_{\pm 3.25}$	39.31$_{\pm 2.50}$
GPF	89.35$_{\pm 0.46}$	46.68$_{\pm 0.80}$	57.36$_{\pm 0.46}$	41.95$_{\pm 1.55}$	41.36$_{\pm 1.30}$	76.89$_{\pm 5.18}$	33.24$_{\pm 1.56}$	53.79$_{\pm 2.33}$	34.22$_{\pm 4.13}$
GPF+	89.23$_{\pm 0.78}$	43.02$_{\pm 0.27}$	56.90$_{\pm 0.48}$	42.86$_{\pm 1.64}$	41.01$_{\pm 1.30}$	76.30$_{\pm 3.92}$	32.62$_{\pm 0.72}$	53.72$_{\pm 0.91}$	35.53$_{\pm 1.48}$
GPPT	88.21$_{\pm 0.67}$	36.06$_{\pm 0.60}$	54.39$_{\pm 1.57}$	42.48$_{\pm 1.21}$	40.25$_{\pm 0.64}$	67.56$_{\pm 8.05}$	43.58$_{\pm 9.14}$	50.82$_{\pm 0.62}$	31.34$_{\pm 1.48}$
GraphPrompt	87.81$_{\pm 0.51}$	24.46$_{\pm 0.65}$	55.76$_{\pm 0.78}$	40.76$_{\pm 1.59}$	32.76$_{\pm 4.18}$	73.44$_{\pm 2.61}$	9.73$_{\pm 0.32}$	47.17$_{\pm 1.26}$	38.30$_{\pm 0.52}$
GraphPrompt+	87.78$_{\pm 0.95}$	22.58$_{\pm 0.48}$	56.64$_{\pm 0.99}$	41.92$_{\pm 0.98}$	33.82$_{\pm 4.14}$	71.58$_{\pm 7.51}$	7.31$_{\pm 1.92}$	46.52$_{\pm 1.64}$	38.11$_{\pm 0.40}$
ProNoG	87.40$_{\pm 0.47}$	41.35$_{\pm 0.68}$	56.44$_{\pm 0.53}$	37.97$_{\pm 1.24}$	37.56$_{\pm 1.46}$	65.97$_{\pm 10.09}$	**4.06**$_{\pm 0.07}$	45.69$_{\pm 1.34}$	31.31$_{\pm 0.75}$
IGAP	89.18$_{\pm 0.63}$	38.29$_{\pm 0.45}$	56.63$_{\pm 2.67}$	43.40$_{\pm 1.10}$	39.67$_{\pm 1.03}$	73.90$_{\pm 8.02}$	34.77$_{\pm 0.82}$	55.55$_{\pm 1.32}$	36.52$_{\pm 2.05}$
MTG	87.81$_{\pm 1.45}$	47.15$_{\pm 0.98}$	57.05$_{\pm 3.17}$	46.25$_{\pm 1.70}$	43.10$_{\pm 1.15}$	70.89$_{\pm 7.41}$	16.32$_{\pm 0.36}$	54.66$_{\pm 0.89}$	38.52$_{\pm 2.69}$
SUPT	89.87$_{\pm 0.63}$	44.19$_{\pm 0.82}$	56.32$_{\pm 0.82}$	44.56$_{\pm 1.45}$	40.76$_{\pm 1.27}$	72.61$_{\pm 9.60}$	32.37$_{\pm 0.76}$	54.77$_{\pm 1.29}$	36.52$_{\pm 3.90}$
GAPTUNE+	**91.35**$_{\pm 0.54}$	**48.89**$_{\pm 0.91}$	**59.63**$_{\pm 0.55}$	**49.67**$_{\pm 1.28}$	**44.40**$_{\pm 0.98}$	**80.57**$_{\pm 5.36}$	**4.06**$_{\pm 0.04}$	**62.32**$_{\pm 1.52}$	**44.46**$_{\pm 1.02}$

A minibatch with no selected observed labels makes no optimizer update, and an empty support mask invalidates the run. The supervision record contains the number of distinct support molecules, $|\Omega_{\mathrm{tr}}|$, the positive and negative label counts for every assay, and the validation/test molecule counts. Graph pooling and target-context extraction remain molecule-specific, with no cross-molecule context pooling.

ToxCast evaluation. For evaluation split I, define $\mathcal{T}_I$ using only its observed ground-truth labels: an assay is eligible exactly when it contains at least one positive and one negative label. We report

Table 16: Task-specific support budgets and shared data settings used in the experiments.

Task	Support convention	Shared data and evaluation settings
NC; MNIST GC	5 or 100 examples per class.	Class set, support/validation/test partitions, permitted unlabeled observations, and accuracy.
QM7b GR	5 or 100 training graphs.	PyG data-processing settings, graph representation, graph splits, fourteen targets, and original-coordinate MAE.
DBLP/Cornell LP	5% or 10% of positive pairs for training.	Canonical positive partitions, fixed 1:1 negatives, message-only graph, query masking, and ROC-AUC.
ToxCast GC	Assay-specific support-label mask.	Molecule partitions, observed-label and support masks, eligible assays, and macro ROC-AUC.

Table 17: Graph access at each stage of the LP experiments.

Stage	Permitted graph and targets
Same-dataset pretraining	Message graph E_{ctx} only; pretext targets exclude downstream held-out pairs.
Same-dataset source contexts	Frozen responses to E_{ctx}; no support, validation, or test positives as extra edges.
Cross-dataset source contexts	The independent source reference or proxy graphs belonging to the fixed source checkpoint.
Target unprompted pass	Query subgraph built after bidirectional query masking from E_{ctx}; no downstream labels.
Target prompted pass	The same sanitized subgraph and feature map; only support labels enter adaptation loss.
Validation and test scoring	Fixed prediction graphs from E_{ctx}; validation selects the within-run checkpoint, while configuration summaries follow Appendix D.2.

the unweighted mean of the eligible assay AUCs:

$$\mathrm{AUC}_I = \frac{100}{|\mathcal{T}_I|} \sum_{t \in \mathcal{T}_I} \mathrm{AUC}_{\mathrm{bin}}(\{(Y_{it}, z_{it}) : i \in I,\ M_{it} = 1\}) \,. \tag{78}$$

Here, $\mathrm{AUC}_{\mathrm{bin}}$ is the binary ROC-AUC on the unit interval. Eligibility is fixed for all methods within a split, independent of their predictions; validation and test may have different eligible task sets, which are both recorded. Non-finite predictions cause an evaluation failure rather than method-specific task deletion; if $\mathcal{T}_I$ is empty, the split has no defined macro-AUC. Within each fixed configuration, validation AUC selects the adaptation checkpoint; test AUC never selects the retained epoch. Across completed same-dataset configurations, the reported summary uses the best observed test mean under Appendix D.2; cross-dataset checkpoints remain separate. The molecule partitions, support-label mask, and eligible task sets are fixed within each repetition and shared across methods.

Feature preprocessing and subgraphs. The transfer checkpoints use 100-dimensional continuous inputs following the SVD-based dimension-unification design of Zhao et al. (2024). For $X = U\Sigma V^\top$ with at least 100 feature columns, the reducer uses $U_{:,:100}\Sigma_{:100,:100}$; narrower representations are right-zero-padded. Degree supplies node features when attributes are absent, followed by padding to the checkpoint width. The dataset-level feature map is fitted once on the permitted features, cached, and shared across methods using the same checkpoint input space; the same map is used in both target passes. Node and edge queries use induced subgraphs; graph-level examples retain complete graphs. Common subgraph defaults are 10–30 nodes with expansion up to five hops and an edge-query cap of 60 nodes, subject to the released method-specific settings. Source contexts pool the pretraining reference, while target contexts use only their current prediction graph, not unrelated graphs in the same minibatch. This local reference comparison need not represent a dataset-level shift, and matching feature width does not establish semantic alignment (Appendix B.11).

QM7b input and target coordinates. We load and process QM7b with PyG (Fey & Lenssen, 2019); all models use the same data-processing settings, graph representation, support/validation/test partitions, and fourteen regression targets. Continuous node inputs follow the shared feature-processing pipeline above, and all methods are evaluated with the same original-coordinate MAE. For targets

Algorithm 2 Link-prediction data construction and evaluation

Require: Observed positive pairs E^+, attributes, repetition seed, positive-pair fractions, and a compatible encoder configuration.

1: Canonicalize pairs, discard self-pairs, and partition E^+ into E_{ctx}, P_{tr}, P_{val}, P_{te}.
2: Assign the floor of each requested positive-pair count to its split; assign the remainder to E_{ctx}.
3: Sample mutually disjoint fixed negatives N_a outside E^+ with $|N_a| = |P_a|$ for each split a.
4: For same-dataset pretraining, train the encoder using E_{ctx} only, with any additional pretext-specific pair masking.
5: Construct source observations from the permitted source reference and retain their graph-access record.
6: **for** each support, validation, or test query $\{u, v\}$ **do**
7: Remove (u, v) and (v, u) from the propagation graph before selecting the query subgraph.
8: Build topology-dependent features, descriptors and caches from that sanitized graph only.
9: Run unprompted context extraction and prompted prediction on the identical sanitized input.
10: **end for**
11: For each fixed configuration, fit on support pairs and select its checkpoint using validation pairs.
12: Evaluate the selected checkpoint on test pairs; aggregate configurations by Appendix D.2.
13: Retain pair partitions, feature and checkpoint identifiers, and cache dependencies with the run records.

and original-coordinate predictions $Y, \widehat{Y} \in \mathbb{R}^{n\times 14}$, the metric is

$$\mathrm{MAE}(\widehat{Y}, Y) = \frac{1}{14n} \sum_{i=1}^{n} \sum_{j=1}^{14} |\widehat{Y}_{ij} - Y_{ij}|. \tag{79}$$

The unweighted average retains the fourteen properties' heterogeneous scales and has no single common physical unit. Method-specific training configurations follow the official implementations; the GAPTUNE/GAPTUNE+ settings are given in Appendix D.2.

D.2 Training, Checkpoint Selection, and Configuration Search

Pretrained configurations and controls. Cross-dataset adaptation keeps ZINC/GCN/EdgePred (Sterling & Irwin, 2015) and PubMed/GIN/GraphCL (Namata et al., 2012) as separate checkpoint blocks at both shot settings. The same-dataset grid contains GCN, GAT, GIN, H2GCN, FAGCN, Transformer, and NodeFormer (Kipf & Welling, 2017; Veličković et al., 2018; Xu et al., 2019; Zhu et al., 2020; Bo et al., 2021; Dwivedi & Bresson, 2021; Wu et al., 2022), and AttrMasking, ContextPred, DGI, EdgePred, GraphCL, and InfoGraph (Hu et al., 2020b; Veličković et al., 2019; You et al., 2020; Sun et al., 2020). The twelve baselines are All-in-One, EdgePrompt, EdgePrompt+, GPF, GPF+, GPPT, GraphPrompt, GraphPrompt+, ProNoG, IGAP, MTG, and SUPT (Sun et al., 2023; Fu et al., 2025a; Fang et al., 2023; Sun et al., 2022; Liu et al., 2023; Yu et al., 2024; 2025; Yan et al., 2024; Chen et al., 2026; Lee et al., 2026). The seven scratch controls have no pretraining; GCN and GIN are repeated beside their transfer blocks without additional runs. Full fine-tuning updates the pretrained encoder, whereas the head-only control freezes it. Cross-dataset results do not include full fine-tuning of the transfer checkpoints; same-dataset fine-tuning and the cost study are separate references. Architecture-specific operators are defined in Appendix B.10, including the evaluated H2GCN variant and the fixed-random-feature NodeFormer interface.

The cross- and same-dataset benchmark results use five repetitions with seeds $[42, 0, 100, 123, 2024]$ and report mean$\pm$sample standard deviation. Within each fixed architecture–objective configuration, validation performance selects the retained checkpoint before test evaluation. For each method and target setting, the same-dataset summary then reports the best observed test mean across completed candidates in the common 7×6 grid, together with that candidate's own sample deviation. This descriptive summary includes configuration selection; it does not select a different architecture for each repetition or quantify uncertainty from the outer search. Ties share a displayed rank, and out-of-memory candidates are excluded rather than assigned scores. All 234 prompting summary entries, comprising 216 baseline and 18 GAPTUNE+ entries, match a best displayed mean and its associated deviation in the detailed grid. Baseline optimization settings follow the official implementations; complete configurations, method-specific budgets, and execution details are provided in our code.

Prompt learning and source construction. GAPTUNE and GAPTUNE+ use $K_q = 8$ queries per active type, zero-initialized signed gates, and an affine task head; only prompt and head parameters are optimized. Source observations are sampled once per checkpoint and repetition with caps of 512 nodes and 2,048 directed messages per layer; target pooling uses eligible observations from its own prediction graph. Unprompted observations and descriptors are detached, while context pooling and prompted propagation retain task gradients. Classification uses cross-entropy or binary cross-entropy as appropriate; QM7b uses support-standardized squared error and original-coordinate MAE for validation and testing. Source-free construction uses 16 proxy graphs with 32 nodes and 64 final unordered edges each, optimized for 1,000 updates with the checkpoint-compatible objective in Appendix B.8. The proxy-budget study changes the graph count, whereas GAPTUNE+ directly uses pretraining graphs; all remaining initialization, optimization, and discretization settings are provided in our code.

Value-norm control. The free-value control uses the graph-specific envelope $C_q(G) = \max_{z \in \mathcal{Z}_s^q} \|z\|_2 + \max_{z \in \mathcal{Z}_t^q(G)} \|z\|_2$. A free vector v is replaced by $v \min\{1, C_q(G)/\max(\|v\|_2, 10^{-12})\}$ at each forward pass; context values and gaps already satisfy this bound and are not rescaled. Free values replace the query parameters and inherit their Gaussian initialization, retaining the same descriptor, gate, and insertion rules without a trainable query bank. The control stores only the source norm scalar for clipping, adds no parameters for this constraint, and does not equate the realized local prompt norms of different variants.

D.3 100-shot Results and Shot-Setting Comparisons

At 100-shot, GAPTUNE and GAPTUNE+ exceed the strongest prompting-baseline mean in 14 and 15 of the 18 target–checkpoint comparisons, respectively (Table 14). For GAPTUNE+, the exceptions are QM7b with ZINC and ogbn-arxiv with PubMed, where MTG leads, and Cornell with PubMed, where IGAP leads. On ToxCast, GAPTUNE+ scores 55.83 with ZINC and 57.02 with PubMed, ex-

ceeding the strongest baseline by 2.63 and 0.62 ROC-AUC points. Source-free GAPTUNE exceeds GPF with ZINC (55.08 versus 53.20) but trails All-in-One with PubMed (55.24 versus 56.40).

Between 5-shot and 100-shot, the same-dataset GAPTUNE+ summary improves from 83.10 to 91.35 on Photo and from 59.51 to 62.32 on ToxCast, while QM7b MAE decreases from 4.60 to 4.06. The selected architecture or objective changes for seven of nine targets; Cornell retains H2GCN/AttrMasking and ToxCast retains GCN/InfoGraph. These differences combine supervision and configuration changes, not only the addition of labels. Fixed-checkpoint transfer comparisons avoid configuration changes but are not nested-support learning curves; link and multitask partitions also differ from single-label per-class sampling.

The joint-model entries reused across value, insertion, source-construction, and rotation studies are shared experimental references, not independent replications. The proxy-budget study retrains the prompt and head for each source collection, whereas the fixed-predictor replacement study alone matches the fixed-parameter comparison of Proposition 3.3.

D.4 SOURCE-FREE COMPARISON SCOPE

Source-free access specifies absence of source examples, not identical pretrained information or target supervision. SFGAR adapts a task-specific source predictor to an unlabeled target with a shared class space using reconstruction and adversarial alignment (Yang et al., 2026). OGMM uses generated graphs to merge multiple pretrained predictors (Wang et al., 2026b), whereas GAPTUNE adapts one frozen encoder with labeled target support and a new task head. Their published scores therefore cannot be inserted into the present tables without matching tasks, retained components, supervision, and partitions.

Our source-construction study compares random and inverted proxies within the same downstream prompt mechanism at $B \in \{4, 16, 64\}$, not different learned generator families. Each proxy has 32 nodes and 64 final unordered edges; increasing B increases work per inversion update and the GraphCL negative pool despite the common 1000-update count. These experiments establish neither superiority over SFGAR or OGMM nor a matched-compute comparison between reconstruction methods. Proxy features occupy the encoder's continuous input space and are not asserted to be chemically valid molecules or recovered source examples. Authorization and privacy limitations are stated in the Ethics Statement.

D.5 ARCHITECTURE-SPECIFIC ADAPTATION GRID

The following tables retain full fine-tuning, all twelve prompting baselines, and GAPTUNE+ on all nine targets at 5-shot and 100-shot. Each block fixes an architecture and pretraining objective; bold and underline indicate its best and second distinct means, including full fine-tuning, with ties sharing a rank. OOM denotes an out-of-memory configuration and is not a numerical score. QM7b uses MAE and ToxCast uses ROC-AUC throughout.

Table 18: 5-shot same-dataset results for GCN across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	76.29±1.77	18.33±8.05	54.79±0.74	32.70±3.78	28.80±4.97	56.56±3.84	69.86±58.95	48.84±0.86	22.72±1.93
All-in-One	75.48±2.56	10.60±2.23	53.79±1.24	37.56±2.58	28.04±5.05	54.26±10.92	106.36±0.49	55.14±2.79	12.29±3.90
EdgePrompt	64.04±4.16	24.04±3.29	54.34±0.80	34.12±4.93	32.38±3.84	55.84±7.43	109.57±0.17	50.89±1.49	19.54±6.46
EdgePrompt+	66.05±5.86	20.00±2.91	53.87±0.69	34.70±6.09	31.88±3.00	52.42±11.00	109.25±0.20	51.68±0.76	24.42±1.50
GPF	76.70±2.18	23.36±2.41	53.76±1.29	31.08±5.22	31.53±1.05	59.85±4.92	110.98±0.26	51.94±0.80	20.42±4.38
GPF+	77.15±2.55	20.41±1.81	53.70±1.08	32.50±4.48	31.30±2.12	58.75±5.10	110.93±0.28	50.31±2.41	23.03±1.96
GPPT	72.48±3.39	17.51±5.27	52.27±1.19	31.64±4.36	27.50±4.80	61.51±6.31	108.52±0.77	49.90±0.87	18.43±1.52
GraphPrompt	68.39±3.65	11.08±2.18	53.50±0.61	31.81±1.43	25.00±5.49	56.05±7.69	99.99±0.20	43.07±2.99	24.64±0.74
GraphPrompt+	45.13±8.54	12.63±2.55	53.90±1.33	35.21±3.95	22.14±2.37	59.36±6.78	83.94±8.25	42.83±2.77	20.04±1.49
ProNoG	72.48±4.64	24.66±3.36	54.12±1.01	28.36±2.87	26.79±2.43	52.50±5.90	**10.13**±4.09	43.23±2.32	23.38±1.05
IGAP	75.23±3.48	19.04±2.19	53.89±0.49	36.42±4.09	30.68±3.05	50.12±7.67	107.45±0.26	51.41±1.34	23.48±1.76
MTG	68.85±5.24	21.82±3.08	53.80±0.60	37.31±5.50	33.54±2.96	50.10±8.44	108.08±0.22	51.08±1.47	23.51±2.58
SUPT	**78.06**±2.13	20.55±2.04	54.07±0.50	30.84±4.87	31.52±2.42	51.36±7.52	110.75±0.22	50.99±1.67	23.68±2.21
GAPTUNE+	76.70±2.00	**24.75**±2.56	**56.51**±0.59	**39.48**±4.46	**35.44**±2.56	**62.66**±5.08	13.08±1.68	**58.06**±1.29	**26.24**±2.08
Pretrain (ContextPred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	76.95±4.53	19.71±10.06	54.20±0.40	30.91±5.89	29.33±4.53	59.59±4.06	**5.78**±0.61	49.65±1.42	22.53±2.85
All-in-One	72.52±1.87	6.62±1.03	54.03±0.62	32.55±2.42	29.86±4.80	53.19±4.64	109.54±0.70	50.08±0.56	18.29±4.34
EdgePrompt	68.26±7.93	29.24±2.51	53.67±0.59	34.43±4.80	31.16±2.51	59.69±6.55	110.51±0.10	50.51±0.68	21.66±0.83
EdgePrompt+	67.70±5.29	25.95±1.70	53.80±0.42	35.95±6.14	31.92±2.94	57.42±3.61	110.27±0.17	50.67±1.65	25.37±1.21
GPF	78.37±3.80	**29.75**±2.29	53.45±0.39	34.12±4.71	31.58±2.61	59.03±5.57	111.08±0.15	50.11±0.98	20.94±3.57
GPF+	78.31±2.82	26.40±1.26	53.51±0.25	34.87±3.87	31.49±2.13	61.58±5.08	111.02±0.12	50.48±1.38	24.54±1.77
GPPT	76.88±2.48	16.81±7.21	52.07±1.78	30.29±4.69	30.13±1.57	60.97±7.70	109.06±0.79	50.36±0.87	20.12±0.63
GraphPrompt	74.80±4.84	10.51±1.28	52.92±0.41	29.42±4.90	23.09±4.43	59.46±6.55	101.18±0.50	47.18±3.69	25.64±1.73
GraphPrompt+	64.50±8.04	8.33±3.20	53.28±0.40	33.28±2.52	22.41±3.57	56.91±8.12	87.03±8.01	42.97±3.00	19.62±3.50
ProNoG	76.78±1.88	22.72±3.23	53.29±0.91	29.98±4.45	27.53±2.75	55.84±8.02	12.16±1.99	45.57±1.87	26.01±1.25
IGAP	78.42±3.31	22.37±1.36	53.24±0.54	39.45±5.10	29.58±2.89	54.28±8.65	107.88±0.20	51.53±1.35	25.09±1.86
MTG	72.05±5.12	28.64±1.78	53.11±0.46	39.27±4.81	32.65±2.85	52.66±10.52	109.34±0.13	50.26±1.00	25.76±1.28
SUPT	**80.49**±2.27	27.36±1.24	52.55±0.62	38.08±4.54	31.49±2.26	45.69±6.56	110.82±0.14	49.92±1.08	25.05±1.74
GAPTUNE+	78.56±2.58	29.46±1.82	**55.80**±0.57	**40.68**±4.74	**34.52**±2.51	**64.45**±4.29	12.67±1.22	**55.57**±0.96	**27.56**±1.75
Pretrain (DGI) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	77.37±2.31	21.77±1.58	54.97±0.67	31.79±4.06	29.53±5.36	60.20±8.51	**5.78**±0.50	46.52±2.48	19.93±5.94
All-in-One	74.79±1.49	17.58±2.20	53.98±0.31	33.68±5.48	30.21±4.22	55.51±9.56	104.46±1.05	46.69±1.00	16.50±4.01
EdgePrompt	68.90±2.33	22.87±3.45	54.22±0.65	32.29±5.15	34.14±3.98	63.57±3.92	108.74±0.38	49.07±0.36	20.05±5.04
EdgePrompt+	66.76±5.24	22.18±1.65	54.24±0.78	33.42±4.82	33.37±3.34	58.52±6.89	108.44±0.13	49.33±0.71	24.37±2.94
GPF	**77.84**±1.94	22.71±1.00	54.07±0.56	26.75±2.42	32.00±3.58	63.72±4.54	110.30±1.18	48.60±0.73	20.76±4.66
GPF+	77.04±2.08	21.67±1.75	54.31±0.74	28.79±4.09	33.29±3.64	64.21±3.36	109.29±0.10	48.71±0.55	23.98±1.89
GPPT	44.63±4.05	17.01±4.40	51.61±1.73	26.34±6.34	21.37±4.67	58.80±7.21	104.90±2.04	50.32±1.57	11.27±1.68
GraphPrompt	74.47±3.97	9.96±2.27	53.46±0.38	31.38±1.49	23.99±4.54	60.56±5.63	87.45±0.76	42.85±3.06	24.23±1.98
GraphPrompt+	70.06±9.35	10.39±2.27	53.97±0.37	30.82±2.30	25.30±6.51	62.78±1.19	63.87±9.30	43.07±2.83	21.13±0.50
ProNoG	74.13±5.42	24.55±3.32	52.33±0.61	27.06±3.29	28.69±2.84	53.34±3.67	17.14±6.97	45.35±1.40	23.17±0.85
IGAP	75.13±2.57	18.83±1.61	53.09±0.57	29.64±3.90	31.62±4.01	55.26±10.51	102.88±0.33	47.08±1.46	24.47±2.12
MTG	71.70±4.47	23.60±2.48	53.67±0.39	32.62±4.32	34.94±3.25	53.75±7.41	107.26±0.17	48.62±0.65	24.77±2.42
SUPT	77.83±1.97	23.00±2.01	53.29±0.36	26.58±3.62	32.87±3.36	49.69±9.67	109.01±0.30	48.50±0.58	23.37±2.38
GAPTUNE+	75.82±2.26	**26.55**±1.80	**56.56**±0.61	**36.00**±5.35	**36.47**±2.59	**67.30**±3.47	10.40±1.50	**53.18**±1.18	**26.45**±2.23
Pretrain (EdgePred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**76.49**±1.88	15.55±9.12	54.72±1.14	30.19±4.24	29.41±5.13	52.76±7.56	**5.60**±0.69	46.66±2.30	19.93±5.94
All-in-One	24.39±2.10	3.06±1.32	54.62±0.75	34.50±3.67	29.80±4.51	52.60±6.73	114.39±0.75	46.67±2.19	13.97±2.99
EdgePrompt	45.40±10.29	10.80±2.40	52.94±0.73	35.15±3.98	24.31±4.56	45.61±11.30	110.51±0.10	50.93±1.20	19.66±4.50
EdgePrompt+	63.60±5.16	23.01±1.67	54.22±1.12	35.06±7.36	30.33±6.92	49.03±7.91	110.27±0.17	50.48±1.19	24.27±1.00
GPF	38.96±5.94	9.03±2.04	53.03±0.69	30.87±6.17	30.01±1.66	50.79±6.01	116.65±0.45	50.74±1.03	13.18±7.45
GPF+	63.61±5.21	12.52±2.47	54.07±1.21	29.74±4.87	31.17±1.89	52.45±6.27	111.02±0.12	49.20±1.65	22.35±1.67
GPPT	16.72±3.99	3.28±1.24	52.48±0.85	33.93±3.29	26.71±2.54	**59.03**±8.87	109.06±0.79	50.08±0.22	20.80±0.83
GraphPrompt	23.01±1.45	4.02±0.66	52.51±0.88	30.17±2.65	24.19±3.24	51.76±7.40	113.85±1.87	45.72±1.79	23.57±1.01
GraphPrompt+	45.89±9.69	2.74±0.92	53.60±0.55	32.21±2.46	25.13±5.83	55.61±7.57	87.03±8.01	42.84±2.71	19.16±1.09
ProNoG	20.78±3.10	5.09±0.55	52.76±0.30	32.03±3.68	27.14±2.07	51.33±8.06	12.16±1.99	42.49±2.71	25.82±0.90
IGAP	51.66±4.26	13.34±1.68	52.68±0.32	34.47±4.50	31.97±3.19	46.52±8.21	111.22±0.53	50.57±1.25	23.03±1.26
MTG	65.64±5.62	20.62±1.68	53.54±0.41	33.34±6.89	31.03±5.41	50.32±10.63	108.98±0.14	51.70±1.44	24.34±1.92
SUPT	62.68±5.48	11.57±2.51	53.10±0.36	32.32±6.12	30.64±1.90	40.99±6.57	111.71±0.21	50.19±1.76	22.57±2.68
GAPTUNE+	61.15±4.19	**23.57**±1.72	**55.72**±0.69	**37.55**±5.49	**33.36**±2.78	57.75±4.90	13.15±1.41	**53.91**±1.36	**26.24**±1.76
Pretrain (GraphCL) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	77.31±3.64	12.17±8.16	55.01±0.76	32.32±3.37	28.84±4.94	52.68±11.99	34.35±13.23	46.43±1.29	21.22±5.40
All-in-One	71.01±3.11	6.54±2.18	52.56±1.00	34.94±3.67	28.13±4.35	52.14±11.25	114.31±0.68	54.89±2.61	20.03±2.76
EdgePrompt	68.43±6.51	22.10±1.67	54.28±0.89	34.79±4.61	30.81±2.31	51.71±11.30	110.34±0.27	47.87±1.82	21.55±1.56
EdgePrompt+	69.36±5.13	23.01±1.67	54.23±0.67	35.20±4.70	30.58±2.56	51.30±7.05	110.00±0.14	47.83±2.01	25.16±1.88
GPF	77.81±1.38	23.22±1.42	53.93±0.63	26.68±3.30	31.51±2.08	54.46±12.55	116.14±0.13	48.26±2.52	22.68±1.16
GPF+	**77.92**±1.33	22.32±1.53	53.65±0.87	27.57±4.50	31.77±2.64	53.75±12.14	116.07±0.13	48.11±2.30	24.28±1.36
GPPT	66.71±1.56	12.27±4.16	51.19±1.77	27.83±3.46	26.23±2.35	55.48±8.64	115.34±0.13	49.16±0.95	19.10±1.83
GraphPrompt	69.52±3.67	10.76±1.27	54.35±0.63	29.85±2.76	22.32±3.47	53.78±9.79	113.67±0.12	44.76±2.37	24.24±1.96
GraphPrompt+	74.01±4.90	11.00±1.44	54.13±0.46	32.24±1.34	24.59±6.20	57.50±7.86	97.09±12.95	42.63±3.21	19.38±2.37
ProNoG	67.47±1.59	18.54±1.36	53.74±0.82	28.85±2.59	26.85±3.00	53.95±8.12	**9.68**±2.42	45.93±1.66	24.26±1.22
IGAP	73.78±2.22	20.97±1.53	53.46±0.43	29.15±4.44	31.34±2.47	47.04±9.57	113.73±0.11	48.39±2.44	24.64±1.86
MTG	74.33±4.33	23.64±1.50	53.25±0.59	34.26±4.96	32.00±2.83	45.27±12.55	109.64±0.15	48.12±1.72	25.20±1.82
SUPT	77.73±1.33	23.01±1.47	53.51±0.39	25.07±4.81	31.30±2.35	43.10±6.59	116.00±0.14	48.07±1.99	24.26±1.45
GAPTUNE+	76.93±1.68	**25.91**±2.01	**56.59**±0.57	**36.72**±4.18	**34.37**±2.41	**59.27**±6.15	14.60±1.67	**56.78**±1.76	**26.90**±2.22
Pretrain (InfoGraph) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**77.58**±1.74	**21.94**±2.16	54.90±0.99	32.26±3.46	28.74±5.10	57.12±7.22	**5.67**±0.67	48.87±0.85	19.93±5.94
All-in-One	46.06±2.64	3.06±1.32	53.19±0.95	34.50±3.67	28.46±4.82	50.89±5.84	114.39±0.75	57.51±3.09	13.97±2.99
EdgePrompt	61.78±5.70	11.40±2.20	54.46±0.42	35.15±3.98	31.40±4.85	51.91±10.30	112.15±0.06	50.93±1.20	19.66±4.50
EdgePrompt+	64.39±7.89	14.63±0.98	53.80±0.90	34.15±5.76	30.87±3.67	56.56±6.39	111.88±0.09	50.48±1.19	24.27±1.00
GPF	70.38±4.68	10.97±1.53	54.22±0.30	27.98±4.51	28.32±1.57	57.17±5.69	116.30±0.05	50.78±1.08	20.23±2.85
GPF+	77.51±3.02	12.17±1.22	53.64±0.84	27.56±3.92	30.99±1.47	57.55±2.35	116.29±0.06	50.51±0.95	23.88±0.92
GPPT	48.07±3.59	4.35±0.51	51.56±1.47	29.11±2.75	29.79±3.05	60.05±8.76	114.89±0.39	50.08±0.22	20.80±0.83
GraphPrompt	44.42±2.94	5.32±0.64	53.23±0.43	30.09±2.17	25.09±5.51	53.75±5.79	112.52±0.06	45.68±1.85	23.25±0.91
GraphPrompt+	63.79±6.28	3.44±1.34	53.91±0.58	32.00±2.15	23.62±3.58	55.43±9.12	96.34±12.56	42.57±2.68	20.94±3.04
ProNoG	52.61±2.75	8.87±0.69	53.09±0.86	28.51±3.59	28.77±2.68	55.38±6.67	12.53±3.09	43.89±2.14	22.98±1.15
IGAP	66.40±3.11	10.50±1.14	53.17±0.40	30.59±3.17	29.88±2.82	51.66±9.13	114.15±0.07	50.34±1.06	23.84±1.00
MTG	68.52±6.70	15.30±1.40	53.16±0.46	33.36±4.69	33.15±3.56	53.25±9.81	111.08±0.08	50.44±0.98	24.49±1.61
SUPT	76.41±3.55	12.11±1.16	53.15±0.28	28.37±4.32	30.06±1.67	43.59±12.16	116.11±0.07	50.67±1.17	24.29±1.23
GAPTUNE+	73.18±2.39	18.27±1.65	**56.64**±0.52	**36.68**±4.28	**34.14**±2.67	**60.93**±3.65	14.98±2.07	**59.51**±1.07	**26.14**±1.57

Table 19: 5-shot same-dataset results for GAT across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	76.45±4.21	26.60±1.53	54.98±0.99	28.82±2.61	28.80±4.19	60.33±9.00	33.13±23.94	50.63±0.71	22.25±2.22
All-in-One	76.71±4.34	15.03±1.60	53.04±0.99	31.76±1.57	24.43±2.91	59.01±7.10	108.70±0.06	55.98±2.50	11.20±1.64
EdgePrompt	59.57±18.75	28.41±1.25	54.34±0.54	22.32±7.46	26.92±2.53	58.83±9.60	111.97±0.21	50.19±0.36	13.45±5.17
EdgePrompt+	69.07±4.88	23.53±2.21	54.22±1.12	31.13±4.31	29.67±4.11	63.70±7.06	111.97±0.23	50.19±0.98	20.39±4.07
GPF	77.65±2.16	28.27±1.51	53.97±1.25	26.27±1.44	27.77±3.12	55.15±3.72	113.13±0.23	50.48±0.18	12.96±4.15
GPF+	78.20±1.15	23.43±1.69	54.04±1.05	23.79±4.49	31.17±3.29	59.01±5.02	113.12±0.18	50.83±0.40	13.56±5.60
GPPT	75.91±6.79	17.36±1.76	53.08±1.27	28.80±3.98	27.81±4.60	60.31±6.43	110.13±0.91	50.27±0.78	19.38±2.29
GraphPrompt	71.79±3.34	11.72±1.01	54.09±0.37	34.03±3.30	24.96±4.88	55.05±6.35	111.51±5.82	42.70±3.00	**27.46**±1.47
GraphPrompt+	61.42±5.15	12.22±1.30	54.18±1.23	**35.18**±3.94	22.32±2.43	57.19±9.46	99.66±6.87	42.94±2.51	24.61±1.79
ProNoG	76.55±5.00	22.80±2.43	54.63±0.47	26.63±1.60	27.59±3.21	50.94±4.46	**13.74**±3.36	42.28±2.62	25.92±1.27
IGAP	76.31±2.64	20.66±2.35	53.47±0.54	27.66±3.74	28.70±4.29	49.52±7.11	111.55±1.40	50.28±0.50	19.57±5.37
MTG	70.91±8.10	26.45±1.64	53.77±0.52	29.93±4.20	31.45±2.85	58.40±9.97	110.58±0.26	50.45±0.78	17.53±4.68
SUPT	**79.58**±1.42	24.53±2.25	53.45±0.56	26.22±3.34	29.03±2.76	47.43±5.79	112.14±0.17	50.80±0.38	13.39±5.38
GAPTUNE+	78.09±1.95	**28.58**±2.00	**56.57**±0.45	34.29±4.75	**33.14**±2.68	**63.84**±4.90	14.29±1.25	**57.81**±1.10	24.26±2.70
Pretrain (ContextPred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**75.50**±3.20	29.02±1.19	55.83±0.62	27.32±2.20	30.29±4.70	59.16±11.19	20.35±0.75	49.58±0.93	25.26±2.54
All-in-One	69.36±3.59	20.00±0.92	54.25±0.17	28.07±3.82	25.12±3.13	49.21±10.67	115.82±0.08	46.74±1.31	22.51±2.40
EdgePrompt	68.58±5.23	**31.38**±0.88	56.01±0.65	36.99±2.41	29.56±1.60	63.34±4.60	115.57±0.10	49.34±0.76	22.20±5.26
EdgePrompt+	68.42±6.28	26.30±0.63	55.51±0.42	37.45±3.03	31.07±3.28	62.55±14.31	115.38±0.07	49.97±1.33	28.54±2.58
GPF	73.93±3.95	31.20±0.91	55.61±0.65	26.87±2.87	28.84±2.22	56.89±10.55	116.56±0.02	49.58±1.46	26.67±2.78
GPF+	74.48±3.02	20.10±11.29	55.01±0.83	27.15±2.61	28.68±3.74	59.16±11.94	116.62±0.13	50.05±0.84	25.53±5.97
GPPT	67.34±2.66	26.80±5.03	50.71±0.91	31.59±2.72	28.22±1.48	62.84±10.53	116.27±0.17	50.04±1.16	22.35±2.61
GraphPrompt	70.24±1.84	12.25±1.09	54.88±0.42	28.17±3.75	23.91±4.30	60.28±13.27	114.58±0.15	42.89±2.64	27.43±2.21
GraphPrompt+	69.02±2.53	11.13±1.57	54.41±0.32	34.50±3.81	22.45±2.24	61.71±11.19	113.57±1.09	42.73±2.77	21.15±2.82
ProNoG	71.75±2.34	25.39±2.42	55.41±0.50	26.60±1.27	28.07±2.66	51.89±11.92	**13.32**±2.16	45.16±1.85	25.59±1.69
IGAP	74.88±3.18	17.71±8.14	52.96±0.52	29.58±2.79	30.35±4.36	49.04±11.68	115.36±0.12	48.74±1.38	25.53±4.45
MTG	71.04±5.55	27.40±2.23	52.77±0.58	36.63±2.50	31.02±3.71	48.41±17.57	114.00±0.09	50.36±1.03	25.52±4.51
SUPT	75.49±2.58	21.01±7.66	53.15±0.55	28.37±2.61	26.95±3.49	54.05±8.65	116.15±0.11	49.01±1.31	24.54±5.59
GAPTUNE+	72.75±2.77	29.48±1.13	**57.64**±0.46	**38.30**±3.45	**33.10**±2.83	**63.59**±5.03	15.79±0.53	**53.15**±1.13	**30.54**±2.18
Pretrain (DGI) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**75.55**±2.05	22.73±1.25	55.89±0.43	28.26±1.93	30.47±5.14	62.78±11.18	31.11±7.76	49.48±1.01	26.08±3.15
All-in-One	59.23±5.81	20.51±0.88	52.88±1.08	28.21±3.58	33.61±1.78	47.32±12.55	111.70±0.12	50.06±0.90	19.87±0.92
EdgePrompt	48.10±2.80	22.15±1.22	55.64±0.53	28.14±4.12	34.58±3.45	54.34±9.33	110.52±0.09	51.36±1.59	18.63±4.05
EdgePrompt+	61.19±5.38	23.09±0.74	56.04±0.56	32.82±3.27	31.20±3.88	58.49±12.19	110.40±0.08	50.78±1.56	21.00±4.07
GPF	53.91±4.12	23.02±2.28	55.50±0.33	25.61±1.07	33.61±2.05	56.76±7.58	115.50±0.05	51.01±0.93	19.65±4.71
GPF+	57.67±3.47	19.22±9.35	55.41±0.82	26.55±2.57	32.09±4.75	59.89±4.34	115.67±0.37	50.05±0.74	20.66±3.07
GPPT	43.14±7.78	13.53±6.11	50.35±0.75	30.96±5.73	29.13±5.80	50.03±14.15	113.86±0.42	50.02±0.16	16.56±2.90
GraphPrompt	49.69±8.13	8.60±1.75	55.23±0.68	29.16±1.95	23.26±3.83	50.20±5.35	111.87±0.12	43.14±3.19	**26.91**±2.06
GraphPrompt+	53.07±7.97	10.22±2.53	54.79±0.86	32.85±6.66	23.77±5.27	57.35±8.48	110.87±0.63	42.95±2.57	21.61±2.51
ProNoG	44.42±8.12	24.46±2.79	54.48±0.45	27.37±2.32	30.47±3.51	44.08±10.84	**14.04**±2.33	42.77±2.60	20.81±1.66
IGAP	56.97±4.63	15.49±6.79	52.89±0.61	28.40±2.46	31.50±4.12	49.11±12.31	113.45±0.37	49.96±0.87	21.89±2.34
MTG	59.68±4.56	24.51±1.95	53.56±0.76	31.99±3.53	34.60±3.95	47.80±9.69	109.91±0.12	49.45±0.85	20.87±3.80
SUPT	58.66±4.42	16.29±7.74	52.82±0.60	26.46±1.86	31.47±4.09	41.91±12.15	115.21±0.29	49.23±0.73	21.22±3.65
GAPTUNE+	59.77±4.14	**26.42**±1.56	**57.47**±0.51	**35.37**±4.97	**36.26**±2.66	**63.29**±5.00	15.06±0.51	**55.18**±1.23	24.20±2.35
Pretrain (EdgePred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**67.75**±6.64	**22.89**±1.70	55.58±0.36	26.82±2.17	27.53±4.45	62.58±8.13	20.65±2.88	46.57±1.73	26.68±1.81
All-in-One	26.01±1.79	5.04±0.61	52.66±0.59	30.60±4.98	25.99±1.53	53.09±8.82	115.82±0.08	45.16±2.05	19.44±5.10
EdgePrompt	28.00±2.49	10.40±1.99	54.62±0.77	24.17±2.28	31.74±2.67	58.60±7.41	115.57±0.10	51.35±2.27	16.52±5.74
EdgePrompt+	56.86±7.73	14.64±1.21	55.19±0.45	29.76±3.65	30.56±5.36	64.49±6.18	115.38±0.07	51.43±1.68	25.23±1.19
GPF	20.24±6.16	9.75±1.08	54.32±0.51	25.56±1.10	28.29±2.93	61.81±6.90	116.56±0.02	52.60±1.47	21.70±1.36
GPF+	32.61±5.46	11.37±1.52	55.00±0.65	25.11±0.04	29.25±2.39	61.35±5.49	116.56±0.02	52.35±1.69	22.34±1.97
GPPT	12.16±5.96	2.40±0.68	50.51±0.39	29.81±3.20	25.19±2.98	64.35±4.79	116.27±0.17	49.81±0.71	15.33±2.38
GraphPrompt	16.96±2.58	3.23±0.36	53.96±0.41	31.21±2.04	24.05±3.56	63.44±7.72	114.58±0.15	42.60±2.84	25.24±1.54
GraphPrompt+	36.22±6.18	3.78±0.88	55.13±0.95	**33.81**±3.34	25.25±2.49	62.09±6.62	113.57±1.09	42.67±2.91	21.79±2.74
ProNoG	14.28±3.62	3.97±0.68	53.70±0.60	25.03±7.24	27.31±1.86	60.26±5.04	**13.32**±2.16	42.74±2.75	24.50±1.51
IGAP	30.25±5.02	10.11±1.12	52.34±0.57	30.01±1.16	29.07±2.65	49.09±5.60	115.46±0.07	49.55±1.36	24.21±1.53
MTG	50.28±5.72	15.40±1.59	52.98±0.44	27.99±2.93	30.62±4.22	55.18±7.61	114.15±0.07	**53.64**±1.66	24.09±2.63
SUPT	30.09±4.85	11.47±1.26	52.62±0.65	25.84±0.27	27.78±2.29	57.76±6.08	116.28±0.02	50.28±1.52	23.08±2.02
GAPTUNE+	39.98±4.86	17.84±1.55	**56.86**±0.54	33.26±4.10	**32.48**±2.63	**65.96**±5.26	16.13±0.49	53.51±1.66	**27.00**±1.80
Pretrain (GraphCL) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	73.68±3.84	23.28±1.58	55.58±0.66	27.37±2.31	30.08±3.03	55.00±14.51	45.35±7.04	48.46±1.10	17.91±1.95
All-in-One	65.18±2.67	18.55±1.29	52.92±0.92	28.60±2.60	26.60±3.80	53.19±14.10	112.93±0.05	48.35±1.59	14.08±2.59
EdgePrompt	69.60±6.19	22.63±2.97	53.34±1.00	35.04±2.69	30.32±2.41	60.89±9.45	111.21±0.25	49.04±0.67	13.52±2.39
EdgePrompt+	69.97±5.37	22.11±0.96	53.71±0.76	36.65±3.56	31.18±2.73	59.18±12.71	111.25±0.22	48.95±0.98	19.32±3.93
GPF	75.10±2.02	22.41±4.01	53.36±0.92	30.36±4.26	30.07±2.56	58.04±12.28	116.65±0.08	49.00±1.12	12.25±2.02
GPF+	**76.61**±2.27	20.52±3.33	53.96±0.93	27.98±2.13	30.46±2.48	56.38±12.46	116.61±0.15	48.93±1.27	11.40±1.25
GPPT	67.83±2.14	15.37±5.46	53.46±0.99	28.29±6.71	25.80±2.21	54.86±11.28	114.86±0.30	49.41±0.95	12.20±0.76
GraphPrompt	66.17±2.60	11.25±1.53	53.70±0.44	28.68±4.84	20.92±3.46	55.23±10.14	112.67±0.09	45.60±2.64	19.94±2.15
GraphPrompt+	71.98±2.32	10.50±1.42	54.10±0.48	31.23±3.99	26.15±6.21	58.19±6.93	110.84±0.41	42.86±3.15	17.73±3.20
ProNoG	64.90±1.41	21.93±3.18	53.46±1.21	28.56±3.75	26.60±2.46	56.51±10.77	**10.44**±1.66	46.82±2.01	14.82±1.22
IGAP	74.67±3.04	18.73±2.66	53.45±0.46	31.51±2.81	27.68±2.01	52.53±4.71	114.54±0.18	48.45±1.07	15.76±1.75
MTG	72.83±5.75	23.27±2.35	53.31±0.44	37.21±2.67	32.97±3.02	50.72±6.20	110.77±0.20	48.10±1.13	18.28±3.49
SUPT	76.20±2.98	21.70±4.19	53.54±0.60	30.26±2.09	30.07±2.80	53.37±3.83	116.50±0.14	47.55±0.93	12.58±1.25
GAPTUNE+	72.73±2.53	**25.03**±2.13	**55.81**±0.67	**38.57**±3.30	**34.32**±2.53	**62.37**±6.01	16.44±0.47	**53.58**±1.28	**21.97**±3.05
Pretrain (InfoGraph) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**73.73**±1.98	**23.14**±1.91	55.80±0.62	29.11±1.87	28.78±3.53	63.67±6.56	43.11±7.43	49.19±1.05	21.96±4.74
All-in-One	29.75±2.30	8.88±1.52	54.28±1.04	28.19±2.67	29.90±3.86	60.36±8.84	114.58±0.09	52.84±1.32	11.97±1.41
EdgePrompt	51.93±7.22	7.77±2.56	55.03±0.69	27.01±4.91	32.35±2.44	66.66±3.86	114.32±0.30	49.69±1.31	14.23±2.64
EdgePrompt+	66.75±5.36	13.69±1.65	54.90±0.91	33.76±2.98	31.82±3.56	65.26±8.10	114.35±0.20	49.59±1.82	17.85±4.51
GPF	43.87±3.98	9.23±1.84	54.89±0.85	25.97±2.41	27.35±1.48	63.62±7.77	116.64±0.03	50.79±1.15	12.61±1.74
GPF+	63.68±4.30	10.46±5.05	54.54±0.84	28.39±2.77	27.82±1.53	64.92±8.16	116.65±0.06	51.36±1.14	11.08±1.75
GPPT	34.86±1.98	3.66±0.27	53.36±2.06	27.59±3.88	29.14±3.00	59.99±7.76	116.41±0.30	49.97±0.17	18.01±2.15
GraphPrompt	29.55±2.17	5.06±0.67	54.04±0.32	29.52±0.99	25.54±6.20	66.15±4.61	116.01±1.18	47.53±1.92	**23.33**±1.33
GraphPrompt+	68.15±4.43	5.91±0.77	54.56±0.52	33.01±1.68	22.66±3.23	55.54±8.53	111.65±0.97	42.68±3.02	22.33±1.28
ProNoG	35.53±0.97	8.60±0.64	53.96±0.60	27.66±2.66	28.35±3.06	64.57±5.62	**9.10**±1.99	43.74±2.14	20.04±1.40
IGAP	56.20±4.05	11.76±3.41	53.23±0.38	30.27±2.02	28.59±2.59	52.90±10.13	115.48±0.27	51.38±0.87	14.57±2.65
MTG	65.93±6.49	14.55±1.78	53.73±0.39	32.38±2.98	32.20±2.53	54.38±8.79	112.92±0.21	51.82±1.27	15.72±4.18
SUPT	60.46±5.45	11.09±4.43	53.29±0.55	29.05±2.32	27.57±1.31	55.13±10.58	116.46±0.04	51.46±1.41	12.45±1.74
GAPTUNE+	61.77±3.36	17.81±1.68	**56.88**±0.60	**35.49**±4.04	**33.43**±2.43	**68.62**±4.29	16.46±0.53	**56.89**±1.21	21.93±2.69

Table 20: 5-shot same-dataset results for GIN across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**75.84**$_{\pm 1.45}$	**27.54**$_{\pm 0.71}$	55.84$_{\pm 0.63}$	33.64$_{\pm 2.66}$	29.67$_{\pm 2.38}$	63.65$_{\pm 6.54}$	41.38$_{\pm 2.62}$	47.99$_{\pm 2.53}$	**28.22**$_{\pm 1.25}$
All-in-One	72.98$_{\pm 3.70}$	10.30$_{\pm 2.10}$	54.04$_{\pm 0.27}$	32.14$_{\pm 2.67}$	27.98$_{\pm 4.92}$	61.86$_{\pm 5.35}$	59.26$_{\pm 1.43}$	53.97$_{\pm 4.02}$	19.82$_{\pm 5.25}$
EdgePrompt	60.45$_{\pm 4.78}$	14.13$_{\pm 1.32}$	57.06$_{\pm 0.35}$	33.21$_{\pm 3.23}$	24.47$_{\pm 4.28}$	57.73$_{\pm 9.19}$	95.57$_{\pm 1.49}$	48.47$_{\pm 1.23}$	22.92$_{\pm 0.97}$
EdgePrompt+	54.49$_{\pm 18.55}$	13.60$_{\pm 1.56}$	56.47$_{\pm 0.76}$	31.90$_{\pm 3.94}$	24.99$_{\pm 4.52}$	60.89$_{\pm 5.38}$	93.85$_{\pm 1.33}$	48.18$_{\pm 0.52}$	25.28$_{\pm 0.98}$
GPF	68.74$_{\pm 4.70}$	16.97$_{\pm 3.68}$	55.92$_{\pm 0.61}$	35.85$_{\pm 4.58}$	23.99$_{\pm 4.10}$	61.86$_{\pm 4.67}$	97.29$_{\pm 1.49}$	49.54$_{\pm 1.94}$	24.95$_{\pm 2.23}$
GPF+	72.10$_{\pm 3.12}$	18.47$_{\pm 2.32}$	55.29$_{\pm 0.99}$	35.78$_{\pm 4.30}$	26.54$_{\pm 4.25}$	59.16$_{\pm 6.33}$	97.07$_{\pm 0.69}$	49.39$_{\pm 1.64}$	24.14$_{\pm 2.88}$
GPPT	51.52$_{\pm 10.79}$	18.60$_{\pm 6.61}$	52.08$_{\pm 1.14}$	32.44$_{\pm 4.46}$	23.68$_{\pm 2.82}$	62.28$_{\pm 8.44}$	75.19$_{\pm 5.35}$	50.05$_{\pm 0.65}$	17.49$_{\pm 2.39}$
GraphPrompt	66.87$_{\pm 4.31}$	13.58$_{\pm 1.97}$	54.69$_{\pm 0.34}$	34.99$_{\pm 3.65}$	24.58$_{\pm 4.56}$	53.34$_{\pm 8.70}$	67.37$_{\pm 33.79}$	44.11$_{\pm 3.34}$	23.70$_{\pm 1.15}$
GraphPrompt+	44.22$_{\pm 7.38}$	8.90$_{\pm 1.83}$	55.16$_{\pm 0.49}$	35.33$_{\pm 4.17}$	22.23$_{\pm 2.29}$	53.95$_{\pm 11.84}$	41.73$_{\pm 1.57}$	42.73$_{\pm 2.79}$	21.36$_{\pm 1.07}$
ProNoG	74.40$_{\pm 5.06}$	25.51$_{\pm 4.74}$	55.17$_{\pm 0.79}$	30.77$_{\pm 4.48}$	25.79$_{\pm 1.81}$	55.38$_{\pm 8.61}$	55.81$_{\pm 41.58}$	42.81$_{\pm 2.67}$	24.03$_{\pm 1.18}$
IGAP	67.62$_{\pm 4.82}$	16.04$_{\pm 2.01}$	53.19$_{\pm 0.67}$	36.01$_{\pm 3.27}$	24.65$_{\pm 4.18}$	45.14$_{\pm 7.61}$	89.13$_{\pm 8.61}$	47.47$_{\pm 1.71}$	25.69$_{\pm 2.21}$
MTG	60.29$_{\pm 10.92}$	16.38$_{\pm 1.85}$	54.47$_{\pm 0.73}$	36.28$_{\pm 4.36}$	28.84$_{\pm 4.64}$	50.06$_{\pm 8.64}$	93.20$_{\pm 1.36}$	48.14$_{\pm 2.47}$	25.13$_{\pm 1.08}$
SUPT	72.14$_{\pm 3.34}$	17.61$_{\pm 2.33}$	52.93$_{\pm 0.61}$	32.79$_{\pm 4.97}$	26.79$_{\pm 4.47}$	40.51$_{\pm 10.78}$	97.01$_{\pm 0.88}$	44.44$_{\pm 3.25}$	25.03$_{\pm 2.63}$
GAPTUNE+	71.48$_{\pm 2.42}$	20.05$_{\pm 2.32}$	**58.44**$_{\pm 0.47}$	**38.42**$_{\pm 3.43}$	**30.86**$_{\pm 4.07}$	**64.49**$_{\pm 4.69}$	**8.69**$_{\pm 0.46}$	**56.56**$_{\pm 1.69}$	26.71$_{\pm 1.50}$
Pretrain (ContextPred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	71.93$_{\pm 2.94}$	**22.44**$_{\pm 1.70}$	56.71$_{\pm 0.52}$	33.91$_{\pm 3.31}$	29.80$_{\pm 3.09}$	58.44$_{\pm 9.09}$	44.29$_{\pm 6.18}$	47.05$_{\pm 1.07}$	**27.14**$_{\pm 1.92}$
All-in-One	67.78$_{\pm 2.00}$	12.93$_{\pm 2.18}$	54.40$_{\pm 0.54}$	32.60$_{\pm 4.09}$	27.80$_{\pm 4.15}$	59.01$_{\pm 5.36}$	36.08$_{\pm 2.00}$	54.01$_{\pm 3.01}$	21.17$_{\pm 7.56}$
EdgePrompt	60.50$_{\pm 1.28}$	4.97$_{\pm 0.66}$	56.95$_{\pm 0.26}$	30.34$_{\pm 3.27}$	26.71$_{\pm 4.45}$	57.12$_{\pm 5.31}$	36.00$_{\pm 1.98}$	52.39$_{\pm 1.93}$	24.27$_{\pm 3.04}$
EdgePrompt+	56.71$_{\pm 3.51}$	6.96$_{\pm 2.10}$	56.70$_{\pm 0.31}$	33.21$_{\pm 1.82}$	26.95$_{\pm 5.39}$	55.48$_{\pm 6.81}$	35.07$_{\pm 1.59}$	52.46$_{\pm 2.22}$	25.09$_{\pm 2.26}$
GPF	69.72$_{\pm 2.51}$	10.82$_{\pm 1.93}$	56.34$_{\pm 0.75}$	36.07$_{\pm 5.10}$	25.65$_{\pm 4.60}$	55.89$_{\pm 7.05}$	36.77$_{\pm 3.24}$	51.05$_{\pm 2.16}$	21.21$_{\pm 6.25}$
GPF+	70.03$_{\pm 4.72}$	10.21$_{\pm 4.18}$	56.28$_{\pm 0.49}$	36.21$_{\pm 4.91}$	30.37$_{\pm 5.85}$	54.08$_{\pm 8.60}$	37.04$_{\pm 1.22}$	49.50$_{\pm 2.52}$	21.76$_{\pm 6.75}$
GPPT	70.08$_{\pm 3.75}$	3.65$_{\pm 1.65}$	50.49$_{\pm 0.48}$	32.55$_{\pm 1.63}$	24.77$_{\pm 4.70}$	60.29$_{\pm 6.19}$	51.24$_{\pm 26.55}$	50.78$_{\pm 1.16}$	22.13$_{\pm 2.10}$
GraphPrompt	71.31$_{\pm 4.37}$	7.11$_{\pm 0.84}$	54.83$_{\pm 0.55}$	31.95$_{\pm 6.42}$	24.05$_{\pm 4.04}$	**66.76**$_{\pm 7.43}$	44.88$_{\pm 2.01}$	44.49$_{\pm 2.07}$	26.52$_{\pm 2.68}$
GraphPrompt+	51.63$_{\pm 13.25}$	3.80$_{\pm 1.93}$	55.20$_{\pm 0.69}$	35.11$_{\pm 4.03}$	22.28$_{\pm 2.17}$	59.57$_{\pm 6.54}$	44.96$_{\pm 1.99}$	43.21$_{\pm 2.30}$	21.79$_{\pm 1.00}$
ProNoG	**73.91**$_{\pm 3.66}$	13.65$_{\pm 3.07}$	55.78$_{\pm 0.50}$	27.56$_{\pm 6.16}$	23.25$_{\pm 2.73}$	54.57$_{\pm 8.97}$	25.85$_{\pm 11.80}$	46.28$_{\pm 1.06}$	24.79$_{\pm 1.25}$
IGAP	72.08$_{\pm 5.06}$	9.06$_{\pm 3.48}$	54.11$_{\pm 1.14}$	35.67$_{\pm 5.54}$	27.83$_{\pm 4.13}$	61.67$_{\pm 8.90}$	37.34$_{\pm 1.54}$	52.14$_{\pm 2.85}$	24.26$_{\pm 5.42}$
MTG	62.01$_{\pm 2.88}$	8.31$_{\pm 2.32}$	54.95$_{\pm 0.84}$	34.12$_{\pm 2.16}$	28.67$_{\pm 4.39}$	53.68$_{\pm 6.10}$	33.31$_{\pm 1.53}$	51.03$_{\pm 2.17}$	25.34$_{\pm 3.06}$
SUPT	72.54$_{\pm 4.01}$	12.12$_{\pm 4.10}$	54.04$_{\pm 0.85}$	34.06$_{\pm 4.98}$	28.73$_{\pm 4.68}$	47.13$_{\pm 9.19}$	36.18$_{\pm 1.39}$	51.83$_{\pm 1.95}$	21.00$_{\pm 5.34}$
GAPTUNE+	70.48$_{\pm 3.68}$	13.46$_{\pm 2.50}$	**58.48**$_{\pm 0.40}$	**38.15**$_{\pm 4.08}$	**30.71**$_{\pm 3.05}$	61.36$_{\pm 6.46}$	**6.24**$_{\pm 0.39}$	**57.67**$_{\pm 1.73}$	27.00$_{\pm 2.19}$
Pretrain (DGI) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**75.87**$_{\pm 5.11}$	17.91$_{\pm 2.13}$	55.96$_{\pm 0.59}$	34.34$_{\pm 3.18}$	31.27$_{\pm 4.41}$	57.32$_{\pm 8.70}$	41.31$_{\pm 4.51}$	46.90$_{\pm 2.46}$	22.33$_{\pm 2.04}$
All-in-One	70.25$_{\pm 3.60}$	5.25$_{\pm 3.19}$	52.90$_{\pm 1.79}$	32.36$_{\pm 3.03}$	29.57$_{\pm 4.17}$	55.87$_{\pm 15.79}$	63.35$_{\pm 1.50}$	53.68$_{\pm 1.61}$	16.72$_{\pm 8.07}$
EdgePrompt	58.65$_{\pm 6.71}$	20.95$_{\pm 3.05}$	57.01$_{\pm 0.40}$	26.75$_{\pm 8.63}$	33.85$_{\pm 4.08}$	45.48$_{\pm 11.14}$	98.26$_{\pm 0.65}$	48.71$_{\pm 2.53}$	18.33$_{\pm 4.27}$
EdgePrompt+	56.97$_{\pm 6.86}$	21.73$_{\pm 1.20}$	56.98$_{\pm 0.45}$	32.91$_{\pm 6.22}$	33.06$_{\pm 5.12}$	55.31$_{\pm 11.93}$	96.91$_{\pm 1.40}$	48.96$_{\pm 2.26}$	22.46$_{\pm 1.77}$
GPF	72.78$_{\pm 6.35}$	13.56$_{\pm 2.81}$	56.34$_{\pm 0.35}$	32.38$_{\pm 5.59}$	31.16$_{\pm 3.44}$	44.16$_{\pm 13.22}$	99.56$_{\pm 1.22}$	49.83$_{\pm 1.96}$	16.19$_{\pm 6.13}$
GPF+	72.34$_{\pm 5.20}$	19.39$_{\pm 5.46}$	56.40$_{\pm 0.29}$	31.50$_{\pm 4.01}$	32.59$_{\pm 3.91}$	53.06$_{\pm 15.58}$	98.82$_{\pm 0.97}$	47.86$_{\pm 0.99}$	19.94$_{\pm 2.30}$
GPPT	23.66$_{\pm 11.54}$	5.03$_{\pm 2.04}$	50.77$_{\pm 0.73}$	29.28$_{\pm 3.57}$	20.02$_{\pm 7.35}$	59.07$_{\pm 9.05}$	79.70$_{\pm 5.45}$	49.54$_{\pm 0.85}$	13.11$_{\pm 0.96}$
GraphPrompt	52.81$_{\pm 5.43}$	11.82$_{\pm 2.50}$	55.83$_{\pm 0.60}$	30.92$_{\pm 3.38}$	21.04$_{\pm 3.31}$	51.47$_{\pm 14.01}$	46.57$_{\pm 2.37}$	44.05$_{\pm 2.01}$	19.64$_{\pm 0.87}$
GraphPrompt+	44.14$_{\pm 16.99}$	5.03$_{\pm 1.13}$	54.52$_{\pm 0.64}$	34.50$_{\pm 5.75}$	23.05$_{\pm 1.92}$	51.81$_{\pm 9.01}$	44.83$_{\pm 1.98}$	43.22$_{\pm 2.79}$	21.84$_{\pm 2.06}$
ProNoG	67.63$_{\pm 6.50}$	21.94$_{\pm 4.95}$	56.57$_{\pm 0.52}$	27.79$_{\pm 2.31}$	28.23$_{\pm 4.19}$	50.84$_{\pm 14.59}$	16.58$_{\pm 9.57}$	43.71$_{\pm 2.65}$	15.43$_{\pm 0.51}$
IGAP	63.97$_{\pm 4.86}$	19.42$_{\pm 4.33}$	53.32$_{\pm 0.55}$	33.28$_{\pm 4.87}$	30.77$_{\pm 3.64}$	54.65$_{\pm 6.18}$	84.92$_{\pm 1.47}$	49.49$_{\pm 1.75}$	20.21$_{\pm 1.59}$
MTG	56.74$_{\pm 7.99}$	22.06$_{\pm 2.13}$	54.02$_{\pm 0.84}$	34.51$_{\pm 5.44}$	35.83$_{\pm 4.28}$	**60.09**$_{\pm 7.77}$	95.77$_{\pm 1.28}$	47.37$_{\pm 2.61}$	21.73$_{\pm 2.85}$
SUPT	71.56$_{\pm 7.08}$	20.89$_{\pm 5.35}$	52.74$_{\pm 0.63}$	30.50$_{\pm 3.87}$	33.20$_{\pm 3.93}$	54.06$_{\pm 4.38}$	98.81$_{\pm 1.12}$	49.51$_{\pm 1.58}$	20.12$_{\pm 3.45}$
GAPTUNE+	68.60$_{\pm 3.89}$	**22.86**$_{\pm 1.82}$	**58.92**$_{\pm 0.45}$	**36.57**$_{\pm 4.02}$	**36.85**$_{\pm 2.44}$	59.49$_{\pm 6.94}$	**7.60**$_{\pm 0.58}$	**56.25**$_{\pm 1.65}$	**24.38**$_{\pm 2.38}$
Pretrain (EdgePred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**65.44**$_{\pm 4.00}$	7.37$_{\pm 1.30}$	55.33$_{\pm 0.87}$	33.69$_{\pm 2.13}$	29.02$_{\pm 3.19}$	56.86$_{\pm 10.00}$	44.29$_{\pm 6.18}$	45.32$_{\pm 2.05}$	27.24$_{\pm 1.80}$
All-in-One	22.49$_{\pm 1.91}$	5.09$_{\pm 1.17}$	53.85$_{\pm 0.48}$	28.68$_{\pm 2.54}$	25.38$_{\pm 3.24}$	55.31$_{\pm 5.64}$	36.08$_{\pm 2.00}$	53.91$_{\pm 5.96}$	24.76$_{\pm 3.33}$
EdgePrompt	50.07$_{\pm 10.53}$	3.95$_{\pm 1.43}$	55.92$_{\pm 0.76}$	33.73$_{\pm 5.49}$	27.05$_{\pm 5.05}$	58.06$_{\pm 8.76}$	36.00$_{\pm 1.98}$	45.07$_{\pm 1.91}$	23.28$_{\pm 2.63}$
EdgePrompt+	48.11$_{\pm 14.93}$	4.01$_{\pm 0.56}$	55.78$_{\pm 0.52}$	31.86$_{\pm 3.03}$	26.86$_{\pm 3.26}$	61.07$_{\pm 9.48}$	35.07$_{\pm 1.59}$	45.22$_{\pm 1.82}$	25.63$_{\pm 0.81}$
GPF	37.56$_{\pm 3.75}$	5.28$_{\pm 1.98}$	55.65$_{\pm 0.77}$	35.44$_{\pm 4.50}$	26.97$_{\pm 5.07}$	54.97$_{\pm 8.22}$	36.77$_{\pm 3.24}$	44.92$_{\pm 2.22}$	19.51$_{\pm 5.84}$
GPF+	48.47$_{\pm 3.53}$	3.61$_{\pm 0.73}$	55.25$_{\pm 1.09}$	32.38$_{\pm 1.99}$	30.37$_{\pm 2.21}$	57.02$_{\pm 7.21}$	36.74$_{\pm 1.65}$	45.45$_{\pm 2.17}$	23.45$_{\pm 2.98}$
GPPT	13.46$_{\pm 9.04}$	3.21$_{\pm 4.28}$	51.70$_{\pm 1.13}$	33.27$_{\pm 2.95}$	26.81$_{\pm 3.06}$	55.96$_{\pm 6.59}$	51.24$_{\pm 26.55}$	51.09$_{\pm 1.67}$	18.33$_{\pm 0.66}$
GraphPrompt	16.21$_{\pm 2.27}$	2.42$_{\pm 0.70}$	54.73$_{\pm 0.32}$	33.09$_{\pm 2.40}$	22.78$_{\pm 3.42}$	61.43$_{\pm 6.57}$	44.88$_{\pm 2.01}$	42.66$_{\pm 3.06}$	22.41$_{\pm 2.16}$
GraphPrompt+	25.92$_{\pm 7.09}$	2.60$_{\pm 0.73}$	54.92$_{\pm 0.49}$	31.76$_{\pm 3.72}$	23.99$_{\pm 5.01}$	61.07$_{\pm 11.71}$	44.96$_{\pm 1.99}$	42.23$_{\pm 2.11}$	23.55$_{\pm 2.48}$
ProNoG	15.35$_{\pm 2.77}$	2.62$_{\pm 0.46}$	54.81$_{\pm 0.54}$	32.02$_{\pm 3.34}$	24.81$_{\pm 1.91}$	59.69$_{\pm 7.11}$	25.85$_{\pm 11.80}$	42.60$_{\pm 2.71}$	20.59$_{\pm 1.70}$
IGAP	41.32$_{\pm 5.42}$	4.30$_{\pm 0.63}$	52.26$_{\pm 0.58}$	33.60$_{\pm 2.43}$	29.11$_{\pm 2.75}$	57.00$_{\pm 15.40}$	37.86$_{\pm 1.59}$	45.13$_{\pm 1.97}$	24.93$_{\pm 2.37}$
MTG	47.15$_{\pm 12.16}$	5.21$_{\pm 0.87}$	52.56$_{\pm 0.85}$	33.44$_{\pm 3.40}$	27.46$_{\pm 3.43}$	53.75$_{\pm 12.77}$	33.39$_{\pm 1.77}$	46.14$_{\pm 1.73}$	26.83$_{\pm 1.66}$
SUPT	48.49$_{\pm 3.96}$	5.16$_{\pm 1.13}$	52.10$_{\pm 0.61}$	34.14$_{\pm 3.03}$	27.46$_{\pm 2.64}$	50.06$_{\pm 14.08}$	35.97$_{\pm 2.13}$	48.41$_{\pm 3.63}$	24.86$_{\pm 3.86}$
GAPTUNE+	49.75$_{\pm 4.09}$	**10.02**$_{\pm 1.35}$	**57.78**$_{\pm 0.49}$	**37.27**$_{\pm 3.86}$	**30.48**$_{\pm 2.83}$	**62.81**$_{\pm 5.09}$	**6.51**$_{\pm 0.55}$	**56.11**$_{\pm 2.51}$	**27.64**$_{\pm 1.72}$
Pretrain (GraphCL) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**61.30**$_{\pm 6.00}$	17.52$_{\pm 1.40}$	55.77$_{\pm 0.65}$	34.63$_{\pm 2.56}$	28.93$_{\pm 3.53}$	54.97$_{\pm 12.68}$	39.88$_{\pm 4.84}$	46.74$_{\pm 1.51}$	26.51$_{\pm 2.06}$
All-in-One	50.02$_{\pm 2.39}$	19.00$_{\pm 0.64}$	54.70$_{\pm 1.51}$	29.74$_{\pm 2.07}$	27.20$_{\pm 2.66}$	55.18$_{\pm 13.23}$	36.18$_{\pm 2.03}$	52.42$_{\pm 3.35}$	22.39$_{\pm 7.37}$
EdgePrompt	59.67$_{\pm 3.13}$	17.05$_{\pm 1.24}$	56.86$_{\pm 0.68}$	32.92$_{\pm 5.26}$	28.97$_{\pm 6.29}$	52.24$_{\pm 12.83}$	41.99$_{\pm 2.30}$	47.65$_{\pm 1.36}$	23.24$_{\pm 2.97}$
EdgePrompt+	57.82$_{\pm 2.83}$	18.19$_{\pm 0.61}$	56.61$_{\pm 0.56}$	33.66$_{\pm 4.51}$	27.24$_{\pm 6.12}$	53.49$_{\pm 10.39}$	40.58$_{\pm 2.80}$	47.82$_{\pm 1.28}$	26.48$_{\pm 1.39}$
GPF	57.34$_{\pm 1.43}$	15.84$_{\pm 1.86}$	56.09$_{\pm 0.54}$	31.38$_{\pm 6.56}$	28.57$_{\pm 5.38}$	46.43$_{\pm 4.97}$	42.43$_{\pm 4.18}$	49.03$_{\pm 1.77}$	20.33$_{\pm 8.16}$
GPF+	56.19$_{\pm 3.49}$	18.27$_{\pm 1.39}$	55.73$_{\pm 0.51}$	29.30$_{\pm 3.77}$	28.93$_{\pm 4.05}$	54.41$_{\pm 11.51}$	41.83$_{\pm 2.97}$	48.99$_{\pm 1.35}$	24.06$_{\pm 2.79}$
GPPT	14.03$_{\pm 5.34}$	11.17$_{\pm 5.25}$	51.70$_{\pm 1.39}$	32.29$_{\pm 2.86}$	20.01$_{\pm 1.90}$	52.09$_{\pm 11.48}$	156.03$_{\pm 224.12}$	49.57$_{\pm 0.96}$	22.09$_{\pm 2.18}$
GraphPrompt	51.11$_{\pm 3.64}$	9.03$_{\pm 1.51}$	54.79$_{\pm 0.57}$	30.70$_{\pm 4.33}$	22.29$_{\pm 3.02}$	47.88$_{\pm 9.93}$	44.86$_{\pm 2.04}$	44.34$_{\pm 2.54}$	27.42$_{\pm 2.72}$
GraphPrompt+	61.25$_{\pm 7.89}$	7.76$_{\pm 1.63}$	56.13$_{\pm 0.69}$	34.51$_{\pm 4.83}$	22.18$_{\pm 3.58}$	56.53$_{\pm 10.85}$	44.97$_{\pm 1.96}$	42.84$_{\pm 2.96}$	21.71$_{\pm 0.78}$
ProNoG	56.27$_{\pm 2.78}$	18.07$_{\pm 2.34}$	57.03$_{\pm 0.70}$	30.91$_{\pm 3.78}$	25.99$_{\pm 3.98}$	49.34$_{\pm 10.99}$	51.79$_{\pm 37.24}$	46.77$_{\pm 1.18}$	26.85$_{\pm 2.38}$
IGAP	55.74$_{\pm 2.77}$	16.04$_{\pm 1.35}$	53.45$_{\pm 0.87}$	33.23$_{\pm 4.38}$	26.59$_{\pm 4.23}$	50.91$_{\pm 9.56}$	41.58$_{\pm 3.53}$	47.93$_{\pm 1.30}$	24.33$_{\pm 2.60}$
MTG	60.84$_{\pm 3.45}$	20.17$_{\pm 0.98}$	53.38$_{\pm 1.02}$	35.19$_{\pm 3.64}$	28.79$_{\pm 6.42}$	46.72$_{\pm 10.72}$	39.46$_{\pm 2.44}$	48.02$_{\pm 1.33}$	27.29$_{\pm 1.74}$
SUPT	57.96$_{\pm 3.23}$	17.54$_{\pm 1.34}$	53.02$_{\pm 0.58}$	29.48$_{\pm 3.95}$	29.96$_{\pm 3.85}$	41.99$_{\pm 7.24}$	40.59$_{\pm 3.21}$	50.46$_{\pm 2.42}$	23.78$_{\pm 4.61}$
GAPTUNE+	58.77$_{\pm 3.52}$	**21.43**$_{\pm 1.14}$	**58.67**$_{\pm 0.60}$	**37.83**$_{\pm 4.53}$	**31.21**$_{\pm 2.89}$	**58.93**$_{\pm 5.43}$	**6.28**$_{\pm 0.40}$	**55.35**$_{\pm 1.59}$	**28.54**$_{\pm 2.08}$
Pretrain (InfoGraph) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	71.65$_{\pm 1.78}$	**14.77**$_{\pm 2.36}$	56.07$_{\pm 0.93}$	33.95$_{\pm 2.52}$	30.04$_{\pm 3.00}$	62.91$_{\pm 7.56}$	36.17$_{\pm 3.05}$	46.36$_{\pm 1.76}$	25.50$_{\pm 1.84}$
All-in-One	59.24$_{\pm 0.96}$	2.69$_{\pm 1.56}$	53.06$_{\pm 0.63}$	29.91$_{\pm 3.49}$	27.38$_{\pm 2.70}$	59.72$_{\pm 2.60}$	110.13$_{\pm 1.01}$	53.90$_{\pm 3.17}$	17.47$_{\pm 5.38}$
EdgePrompt	60.48$_{\pm 4.41}$	2.80$_{\pm 0.50}$	56.92$_{\pm 0.36}$	32.36$_{\pm 4.58}$	24.31$_{\pm 4.56}$	64.67$_{\pm 8.95}$	111.52$_{\pm 0.24}$	46.28$_{\pm 1.43}$	22.23$_{\pm 4.34}$
EdgePrompt+	62.64$_{\pm 4.87}$	5.02$_{\pm 1.11}$	56.47$_{\pm 0.68}$	32.48$_{\pm 3.89}$	23.93$_{\pm 3.76}$	65.61$_{\pm 8.86}$	111.29$_{\pm 0.04}$	47.28$_{\pm 1.38}$	23.77$_{\pm 2.18}$
GPF	71.86$_{\pm 3.63}$	5.92$_{\pm 1.62}$	56.13$_{\pm 0.46}$	32.38$_{\pm 2.66}$	25.39$_{\pm 4.79}$	61.79$_{\pm 6.21}$	113.70$_{\pm 0.21}$	48.86$_{\pm 1.01}$	18.30$_{\pm 6.27}$
GPF+	**73.38**$_{\pm 2.13}$	5.08$_{\pm 1.92}$	56.12$_{\pm 0.80}$	33.93$_{\pm 4.63}$	28.55$_{\pm 5.71}$	63.16$_{\pm 6.46}$	113.66$_{\pm 0.14}$	48.06$_{\pm 1.06}$	22.54$_{\pm 3.40}$
GPPT	61.38$_{\pm 2.15}$	3.43$_{\pm 4.11}$	50.61$_{\pm 0.55}$	32.56$_{\pm 2.69}$	23.80$_{\pm 2.17}$	60.69$_{\pm 6.52}$	112.68$_{\pm 0.58}$	50.23$_{\pm 0.43}$	18.26$_{\pm 1.81}$
GraphPrompt	54.81$_{\pm 2.40}$	3.21$_{\pm 0.83}$	55.24$_{\pm 0.82}$	31.66$_{\pm 1.21}$	22.63$_{\pm 2.71}$	60.59$_{\pm 10.16}$	113.68$_{\pm 3.52}$	44.52$_{\pm 2.18}$	20.76$_{\pm 1.64}$
GraphPrompt+	48.43$_{\pm 11.83}$	5.18$_{\pm 2.05}$	54.90$_{\pm 0.68}$	33.18$_{\pm 5.48}$	24.96$_{\pm 5.69}$	55.94$_{\pm 9.79}$	75.51$_{\pm 9.74}$	43.06$_{\pm 2.80}$	20.60$_{\pm 1.58}$
ProNoG	60.38$_{\pm 2.27}$	3.21$_{\pm 0.46}$	56.21$_{\pm 0.43}$	29.28$_{\pm 3.99}$	24.53$_{\pm 4.16}$	61.81$_{\pm 6.64}$	**11.44**$_{\pm 4.29}$	43.74$_{\pm 2.63}$	20.09$_{\pm 1.46}$
IGAP	68.00$_{\pm 2.48}$	5.18$_{\pm 1.20}$	54.45$_{\pm 0.68}$	34.02$_{\pm 3.91}$	28.06$_{\pm 4.93}$	50.70$_{\pm 6.48}$	112.51$_{\pm 1.00}$	46.78$_{\pm 1.18}$	23.70$_{\pm 2.71}$
MTG	67.28$_{\pm 5.17}$	7.17$_{\pm 1.12}$	53.34$_{\pm 0.84}$	37.31$_{\pm 4.03}$	27.86$_{\pm 4.65}$	51.93$_{\pm 8.95}$	110.27$_{\pm 0.10}$	46.49$_{\pm 1.82}$	24.71$_{\pm 3.30}$
SUPT	73.01$_{\pm 1.96}$	5.26$_{\pm 1.79}$	54.71$_{\pm 0.92}$	35.34$_{\pm 4.11}$	29.02$_{\pm 5.19}$	54.23$_{\pm 10.04}$	113.46$_{\pm 0.17}$	46.52$_{\pm 0.99}$	24.64$_{\pm 5.26}$
GAPTUNE+	69.90$_{\pm 2.52}$	10.86$_{\pm 1.57}$	**58.57**$_{\pm 0.46}$	**39.18**$_{\pm 3.70}$	**30.44**$_{\pm 3.17}$	**67.02**$_{\pm 4.69}$	11.76$_{\pm 1.50}$	**56.47**$_{\pm 1.89}$	**26.06**$_{\pm 2.38}$

Table 21: 5-shot same-dataset results for H2GCN across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**76.95**$_{\pm 1.74}$	28.60$_{\pm 1.45}$	55.31$_{\pm 0.93}$	25.03$_{\pm 3.16}$	29.72$_{\pm 4.74}$	77.96$_{\pm 6.59}$	11.87$_{\pm 0.34}$	50.05$_{\pm 1.75}$	**26.79**$_{\pm 1.28}$
All-in-One	74.69$_{\pm 4.22}$	27.26$_{\pm 3.14}$	54.40$_{\pm 0.70}$	**35.76**$_{\pm 3.93}$	27.90$_{\pm 3.52}$	73.11$_{\pm 3.34}$	105.06$_{\pm 0.65}$	51.40$_{\pm 1.11}$	22.09$_{\pm 2.93}$
EdgePrompt	70.42$_{\pm 2.20}$	31.25$_{\pm 3.26}$	53.80$_{\pm 1.42}$	25.97$_{\pm 2.18}$	31.11$_{\pm 4.13}$	76.89$_{\pm 2.88}$	109.00$_{\pm 0.26}$	50.15$_{\pm 2.33}$	21.01$_{\pm 6.28}$
EdgePrompt+	70.21$_{\pm 4.30}$	26.47$_{\pm 2.80}$	53.69$_{\pm 0.50}$	28.21$_{\pm 5.17}$	30.43$_{\pm 3.80}$	78.04$_{\pm 4.02}$	108.06$_{\pm 0.35}$	49.19$_{\pm 1.20}$	24.62$_{\pm 1.38}$
GPF	75.03$_{\pm 2.21}$	29.19$_{\pm 2.77}$	53.30$_{\pm 0.98}$	25.16$_{\pm 0.78}$	30.22$_{\pm 2.39}$	78.88$_{\pm 3.67}$	110.75$_{\pm 0.21}$	51.68$_{\pm 2.39}$	21.15$_{\pm 1.67}$
GPF+	75.02$_{\pm 3.15}$	21.08$_{\pm 7.62}$	52.89$_{\pm 0.67}$	26.27$_{\pm 1.48}$	31.40$_{\pm 2.90}$	80.92$_{\pm 2.24}$	110.76$_{\pm 0.23}$	51.74$_{\pm 1.21}$	20.86$_{\pm 2.22}$
GPPT	66.56$_{\pm 4.83}$	21.11$_{\pm 3.46}$	52.80$_{\pm 1.57}$	28.14$_{\pm 8.33}$	31.23$_{\pm 3.25}$	60.83$_{\pm 4.47}$	108.56$_{\pm 1.22}$	50.31$_{\pm 0.70}$	18.05$_{\pm 3.91}$
GraphPrompt	67.31$_{\pm 3.97}$	12.05$_{\pm 1.32}$	53.07$_{\pm 0.72}$	34.77$_{\pm 3.24}$	25.05$_{\pm 4.76}$	72.60$_{\pm 2.88}$	99.27$_{\pm 0.82}$	42.60$_{\pm 2.64}$	21.80$_{\pm 2.24}$
GraphPrompt+	54.23$_{\pm 3.17}$	10.61$_{\pm 1.62}$	53.94$_{\pm 1.19}$	35.16$_{\pm 3.93}$	21.82$_{\pm 3.27}$	64.23$_{\pm 10.89}$	58.94$_{\pm 18.31}$	42.93$_{\pm 2.83}$	21.22$_{\pm 1.38}$
ProNoG	71.54$_{\pm 2.25}$	26.98$_{\pm 5.03}$	53.97$_{\pm 0.83}$	26.80$_{\pm 2.67}$	28.52$_{\pm 4.12}$	70.00$_{\pm 5.18}$	16.30$_{\pm 9.25}$	43.10$_{\pm 2.70}$	22.05$_{\pm 3.31}$
IGAP	73.08$_{\pm 2.58}$	19.85$_{\pm 5.89}$	53.24$_{\pm 0.42}$	31.12$_{\pm 3.10}$	31.94$_{\pm 3.46}$	68.38$_{\pm 12.24}$	106.74$_{\pm 0.36}$	48.76$_{\pm 2.20}$	21.90$_{\pm 2.13}$
MTG	75.40$_{\pm 3.21}$	28.84$_{\pm 3.34}$	53.53$_{\pm 0.64}$	29.24$_{\pm 4.76}$	30.07$_{\pm 3.63}$	70.30$_{\pm 14.50}$	107.08$_{\pm 0.40}$	49.23$_{\pm 1.59}$	24.88$_{\pm 2.42}$
SUPT	75.30$_{\pm 2.98}$	22.93$_{\pm 7.46}$	53.37$_{\pm 0.46}$	27.10$_{\pm 1.33}$	**33.32**$_{\pm 3.17}$	66.34$_{\pm 10.44}$	110.50$_{\pm 0.22}$	52.38$_{\pm 1.63}$	22.06$_{\pm 1.94}$
GAPTUNE+	73.85$_{\pm 2.75}$	**31.82**$_{\pm 1.97}$	**56.09**$_{\pm 0.69}$	33.43$_{\pm 4.10}$	33.12$_{\pm 2.71}$	**82.10**$_{\pm 3.26}$	**10.04**$_{\pm 1.64}$	56.10$_{\pm 1.45}$	26.22$_{\pm 2.12}$
Pretrain (ContextPred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	76.93$_{\pm 3.61}$	26.60$_{\pm 1.98}$	54.75$_{\pm 0.74}$	24.80$_{\pm 3.29}$	30.56$_{\pm 3.48}$	**70.66**$_{\pm 7.09}$	**6.43**$_{\pm 0.91}$	48.90$_{\pm 0.85}$	26.71$_{\pm 1.96}$
All-in-One	73.98$_{\pm 3.61}$	22.26$_{\pm 2.03}$	54.12$_{\pm 0.92}$	**35.97**$_{\pm 5.00}$	27.26$_{\pm 3.07}$	64.87$_{\pm 7.31}$	98.75$_{\pm 0.82}$	47.06$_{\pm 1.08}$	26.11$_{\pm 0.61}$
EdgePrompt	67.72$_{\pm 5.34}$	**28.81**$_{\pm 2.52}$	53.58$_{\pm 0.56}$	25.61$_{\pm 0.30}$	29.81$_{\pm 2.77}$	55.28$_{\pm 15.44}$	108.77$_{\pm 0.35}$	51.02$_{\pm 0.71}$	24.48$_{\pm 2.13}$
EdgePrompt+	68.54$_{\pm 3.95}$	24.62$_{\pm 0.81}$	53.89$_{\pm 1.01}$	25.28$_{\pm 0.49}$	31.99$_{\pm 2.80}$	61.61$_{\pm 14.95}$	108.79$_{\pm 0.24}$	50.96$_{\pm 0.65}$	24.64$_{\pm 2.30}$
GPF	76.79$_{\pm 3.86}$	24.07$_{\pm 12.47}$	53.12$_{\pm 0.86}$	25.32$_{\pm 0.72}$	30.32$_{\pm 2.23}$	63.34$_{\pm 7.02}$	108.79$_{\pm 0.25}$	50.47$_{\pm 1.05}$	19.13$_{\pm 3.87}$
GPF+	77.06$_{\pm 3.04}$	23.31$_{\pm 6.14}$	54.03$_{\pm 0.74}$	25.61$_{\pm 1.78}$	30.57$_{\pm 1.83}$	63.14$_{\pm 9.45}$	109.13$_{\pm 0.67}$	50.72$_{\pm 0.54}$	16.28$_{\pm 4.95}$
GPPT	76.04$_{\pm 2.42}$	28.39$_{\pm 4.30}$	52.16$_{\pm 1.49}$	33.83$_{\pm 2.78}$	31.47$_{\pm 1.85}$	63.19$_{\pm 5.24}$	104.39$_{\pm 1.99}$	50.07$_{\pm 0.31}$	22.23$_{\pm 0.83}$
GraphPrompt	76.03$_{\pm 3.39}$	13.80$_{\pm 2.05}$	54.06$_{\pm 0.70}$	34.07$_{\pm 5.20}$	26.79$_{\pm 6.10}$	62.40$_{\pm 8.64}$	97.03$_{\pm 13.10}$	42.98$_{\pm 2.58}$	25.51$_{\pm 1.09}$
GraphPrompt+	72.54$_{\pm 5.04}$	9.72$_{\pm 2.51}$	53.97$_{\pm 0.48}$	35.11$_{\pm 3.94}$	22.63$_{\pm 2.33}$	58.67$_{\pm 10.27}$	69.12$_{\pm 14.13}$	42.45$_{\pm 2.98}$	20.22$_{\pm 2.24}$
ProNoG	**78.92**$_{\pm 2.23}$	25.87$_{\pm 4.28}$	53.35$_{\pm 0.76}$	26.26$_{\pm 1.45}$	28.42$_{\pm 3.31}$	57.37$_{\pm 5.76}$	18.82$_{\pm 10.39}$	43.47$_{\pm 2.58}$	24.14$_{\pm 0.44}$
IGAP	75.68$_{\pm 3.41}$	24.49$_{\pm 4.25}$	54.22$_{\pm 0.44}$	28.55$_{\pm 2.45}$	30.92$_{\pm 2.77}$	58.67$_{\pm 8.80}$	104.75$_{\pm 3.56}$	50.60$_{\pm 0.66}$	21.84$_{\pm 3.54}$
MTG	71.70$_{\pm 3.76}$	27.18$_{\pm 1.75}$	53.87$_{\pm 0.42}$	25.51$_{\pm 0.70}$	32.30$_{\pm 2.65}$	50.33$_{\pm 10.06}$	107.63$_{\pm 0.34}$	50.34$_{\pm 1.10}$	24.21$_{\pm 2.61}$
SUPT	75.80$_{\pm 3.79}$	24.42$_{\pm 6.40}$	53.96$_{\pm 0.42}$	26.15$_{\pm 1.47}$	30.40$_{\pm 2.09}$	58.79$_{\pm 10.93}$	109.08$_{\pm 0.57}$	49.70$_{\pm 0.70}$	18.82$_{\pm 4.13}$
GAPTUNE+	74.48$_{\pm 3.21}$	27.85$_{\pm 1.63}$	**56.04**$_{\pm 0.56}$	32.80$_{\pm 3.34}$	**34.09**$_{\pm 2.19}$	67.88$_{\pm 5.37}$	11.53$_{\pm 1.47}$	**54.30**$_{\pm 0.87}$	**27.16**$_{\pm 2.05}$
Pretrain (DGI) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	76.60$_{\pm 2.59}$	23.31$_{\pm 1.26}$	54.56$_{\pm 1.49}$	27.21$_{\pm 2.81}$	30.88$_{\pm 3.63}$	70.74$_{\pm 3.66}$	9.08$_{\pm 0.82}$	48.86$_{\pm 1.42}$	**25.71**$_{\pm 1.50}$
All-in-One	74.30$_{\pm 2.54}$	18.66$_{\pm 1.88}$	55.39$_{\pm 0.54}$	**32.97**$_{\pm 4.26}$	28.71$_{\pm 3.43}$	**77.50**$_{\pm 4.81}$	103.84$_{\pm 0.28}$	48.74$_{\pm 2.07}$	24.50$_{\pm 1.56}$
EdgePrompt	69.31$_{\pm 4.89}$	22.77$_{\pm 2.28}$	53.86$_{\pm 0.56}$	26.02$_{\pm 2.19}$	30.68$_{\pm 2.23}$	71.48$_{\pm 10.29}$	88.47$_{\pm 2.13}$	50.26$_{\pm 2.01}$	23.45$_{\pm 0.91}$
EdgePrompt+	70.42$_{\pm 3.71}$	22.84$_{\pm 1.35}$	54.24$_{\pm 1.04}$	26.29$_{\pm 2.60}$	30.68$_{\pm 2.44}$	71.94$_{\pm 9.28}$	84.45$_{\pm 1.98}$	51.35$_{\pm 1.85}$	21.31$_{\pm 4.35}$
GPF	77.74$_{\pm 3.28}$	19.38$_{\pm 7.94}$	53.71$_{\pm 0.42}$	26.14$_{\pm 5.63}$	30.56$_{\pm 1.50}$	71.30$_{\pm 8.24}$	111.54$_{\pm 0.21}$	51.53$_{\pm 1.77}$	17.47$_{\pm 5.33}$
GPF+	77.37$_{\pm 2.95}$	17.59$_{\pm 8.06}$	54.15$_{\pm 1.16}$	26.19$_{\pm 1.78}$	30.37$_{\pm 2.98}$	72.81$_{\pm 6.58}$	111.87$_{\pm 0.75}$	51.00$_{\pm 1.14}$	16.13$_{\pm 6.05}$
GPPT	19.86$_{\pm 6.40}$	16.07$_{\pm 5.11}$	51.12$_{\pm 1.88}$	30.29$_{\pm 1.06}$	31.27$_{\pm 2.16}$	55.99$_{\pm 7.58}$	106.25$_{\pm 1.30}$	49.78$_{\pm 0.48}$	13.85$_{\pm 4.18}$
GraphPrompt	70.68$_{\pm 4.03}$	9.35$_{\pm 1.79}$	53.30$_{\pm 0.47}$	31.76$_{\pm 4.07}$	25.99$_{\pm 4.58}$	64.01$_{\pm 9.62}$	98.98$_{\pm 3.47}$	43.06$_{\pm 2.72}$	24.12$_{\pm 1.08}$
GraphPrompt+	62.01$_{\pm 6.59}$	6.19$_{\pm 1.11}$	53.76$_{\pm 0.45}$	31.95$_{\pm 1.70}$	22.08$_{\pm 2.45}$	55.82$_{\pm 10.39}$	48.79$_{\pm 6.48}$	42.24$_{\pm 3.01}$	21.37$_{\pm 2.03}$
ProNoG	72.75$_{\pm 6.90}$	19.85$_{\pm 3.14}$	53.22$_{\pm 0.86}$	27.61$_{\pm 2.59}$	28.88$_{\pm 3.78}$	62.86$_{\pm 6.78}$	42.28$_{\pm 31.30}$	42.87$_{\pm 2.53}$	24.04$_{\pm 1.32}$
IGAP	75.96$_{\pm 3.30}$	17.60$_{\pm 5.66}$	53.20$_{\pm 0.67}$	27.33$_{\pm 2.14}$	31.18$_{\pm 2.52}$	59.74$_{\pm 11.87}$	102.77$_{\pm 1.67}$	51.65$_{\pm 1.36}$	21.33$_{\pm 4.77}$
MTG	73.66$_{\pm 4.03}$	23.56$_{\pm 2.43}$	53.41$_{\pm 0.45}$	26.32$_{\pm 2.31}$	32.32$_{\pm 2.07}$	51.27$_{\pm 9.54}$	86.97$_{\pm 1.60}$	48.31$_{\pm 2.59}$	23.56$_{\pm 3.30}$
SUPT	**78.50**$_{\pm 3.09}$	18.74$_{\pm 7.97}$	53.54$_{\pm 0.51}$	26.99$_{\pm 2.59}$	30.14$_{\pm 2.45}$	52.82$_{\pm 12.29}$	111.66$_{\pm 0.63}$	50.96$_{\pm 1.49}$	15.91$_{\pm 5.87}$
GAPTUNE+	76.08$_{\pm 2.74}$	**24.48**$_{\pm 2.07}$	**56.43**$_{\pm 0.60}$	31.95$_{\pm 3.76}$	**34.63**$_{\pm 2.20}$	74.93$_{\pm 4.51}$	**8.09**$_{\pm 0.91}$	**54.76**$_{\pm 1.19}$	24.57$_{\pm 2.90}$
Pretrain (EdgePred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**74.34**$_{\pm 1.94}$	**19.69**$_{\pm 1.24}$	55.48$_{\pm 0.80}$	25.81$_{\pm 2.70}$	30.27$_{\pm 4.09}$	68.83$_{\pm 7.39}$	**6.43**$_{\pm 0.91}$	48.07$_{\pm 1.01}$	25.65$_{\pm 1.02}$
All-in-One	25.76$_{\pm 5.97}$	2.44$_{\pm 0.88}$	53.43$_{\pm 0.60}$	**37.64**$_{\pm 4.45}$	26.48$_{\pm 4.83}$	65.79$_{\pm 9.65}$	98.75$_{\pm 0.82}$	49.54$_{\pm 1.25}$	24.56$_{\pm 1.98}$
EdgePrompt	50.52$_{\pm 13.18}$	6.20$_{\pm 2.33}$	53.84$_{\pm 0.48}$	25.06$_{\pm 0.16}$	29.11$_{\pm 2.65}$	64.18$_{\pm 6.75}$	108.77$_{\pm 0.35}$	50.21$_{\pm 1.88}$	23.30$_{\pm 1.56}$
EdgePrompt+	65.80$_{\pm 5.49}$	7.33$_{\pm 2.69}$	54.90$_{\pm 0.87}$	25.32$_{\pm 0.18}$	30.23$_{\pm 5.37}$	68.29$_{\pm 8.74}$	108.79$_{\pm 0.24}$	48.83$_{\pm 0.28}$	23.51$_{\pm 1.73}$
GPF	40.44$_{\pm 9.38}$	4.01$_{\pm 1.54}$	52.78$_{\pm 1.39}$	25.06$_{\pm 0.13}$	28.44$_{\pm 3.08}$	65.92$_{\pm 6.35}$	108.79$_{\pm 0.25}$	48.96$_{\pm 0.68}$	20.65$_{\pm 5.20}$
GPF+	56.78$_{\pm 8.79}$	6.25$_{\pm 0.74}$	54.54$_{\pm 1.19}$	25.73$_{\pm 0.72}$	27.91$_{\pm 3.65}$	67.42$_{\pm 4.17}$	110.49$_{\pm 3.71}$	48.92$_{\pm 0.83}$	23.79$_{\pm 0.49}$
GPPT	14.48$_{\pm 5.09}$	2.87$_{\pm 1.70}$	50.75$_{\pm 1.28}$	32.65$_{\pm 2.61}$	22.99$_{\pm 2.74}$	65.06$_{\pm 8.45}$	104.39$_{\pm 1.99}$	50.04$_{\pm 0.17}$	19.00$_{\pm 1.21}$
GraphPrompt	19.38$_{\pm 3.43}$	4.37$_{\pm 0.94}$	52.45$_{\pm 0.53}$	34.38$_{\pm 3.48}$	24.33$_{\pm 2.95}$	63.09$_{\pm 5.79}$	87.42$_{\pm 0.46}$	46.19$_{\pm 2.86}$	23.64$_{\pm 1.43}$
GraphPrompt+	43.80$_{\pm 7.04}$	2.72$_{\pm 0.92}$	53.12$_{\pm 0.44}$	35.28$_{\pm 3.84}$	24.33$_{\pm 3.79}$	60.84$_{\pm 7.86}$	69.12$_{\pm 14.13}$	42.81$_{\pm 2.83}$	19.22$_{\pm 2.76}$
ProNoG	17.81$_{\pm 2.60}$	7.42$_{\pm 0.55}$	52.44$_{\pm 0.63}$	27.16$_{\pm 2.49}$	22.88$_{\pm 2.94}$	59.62$_{\pm 6.56}$	18.82$_{\pm 10.39}$	44.19$_{\pm 2.23}$	21.88$_{\pm 1.23}$
IGAP	46.23$_{\pm 8.26}$	7.24$_{\pm 1.42}$	52.43$_{\pm 0.75}$	29.31$_{\pm 1.36}$	27.76$_{\pm 3.43}$	57.56$_{\pm 10.63}$	103.40$_{\pm 2.56}$	50.05$_{\pm 1.89}$	24.60$_{\pm 0.98}$
MTG	57.29$_{\pm 7.75}$	7.79$_{\pm 2.26}$	52.74$_{\pm 0.40}$	25.94$_{\pm 0.25}$	31.56$_{\pm 5.05}$	62.79$_{\pm 8.59}$	107.35$_{\pm 0.81}$	50.61$_{\pm 0.85}$	24.52$_{\pm 1.68}$
SUPT	54.86$_{\pm 8.28}$	6.24$_{\pm 0.73}$	52.27$_{\pm 0.91}$	26.58$_{\pm 0.53}$	28.18$_{\pm 3.06}$	55.53$_{\pm 11.57}$	108.54$_{\pm 2.28}$	47.81$_{\pm 1.67}$	23.96$_{\pm 1.43}$
GAPTUNE+	55.98$_{\pm 3.97}$	12.43$_{\pm 2.18}$	**56.05**$_{\pm 0.56}$	33.06$_{\pm 3.66}$	**32.49**$_{\pm 3.81}$	**70.83**$_{\pm 3.41}$	10.98$_{\pm 1.68}$	**54.60**$_{\pm 1.05}$	**25.89**$_{\pm 2.04}$
Pretrain (GraphCL) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	77.02$_{\pm 3.00}$	23.28$_{\pm 0.62}$	54.63$_{\pm 0.98}$	26.53$_{\pm 2.73}$	28.62$_{\pm 4.32}$	65.10$_{\pm 14.38}$	**6.97**$_{\pm 0.68}$	49.17$_{\pm 1.42}$	24.54$_{\pm 1.88}$
All-in-One	67.14$_{\pm 2.05}$	22.55$_{\pm 2.42}$	54.59$_{\pm 0.43}$	32.39$_{\pm 5.84}$	27.91$_{\pm 1.61}$	61.99$_{\pm 11.07}$	89.82$_{\pm 1.25}$	49.53$_{\pm 2.70}$	23.03$_{\pm 0.89}$
EdgePrompt	67.51$_{\pm 5.31}$	26.35$_{\pm 1.29}$	53.91$_{\pm 1.11}$	28.15$_{\pm 3.73}$	30.67$_{\pm 2.49}$	64.57$_{\pm 13.98}$	106.09$_{\pm 0.47}$	50.07$_{\pm 0.98}$	21.51$_{\pm 2.11}$
EdgePrompt+	70.21$_{\pm 4.96}$	23.13$_{\pm 1.21}$	53.76$_{\pm 0.64}$	34.00$_{\pm 2.81}$	31.18$_{\pm 2.25}$	66.20$_{\pm 10.41}$	106.10$_{\pm 0.34}$	49.48$_{\pm 0.96}$	23.74$_{\pm 0.57}$
GPF	76.89$_{\pm 1.93}$	24.59$_{\pm 5.13}$	53.40$_{\pm 1.08}$	25.98$_{\pm 2.87}$	30.36$_{\pm 2.45}$	62.60$_{\pm 14.64}$	106.14$_{\pm 0.29}$	49.26$_{\pm 1.68}$	20.30$_{\pm 4.40}$
GPF+	76.70$_{\pm 1.71}$	19.80$_{\pm 6.62}$	53.59$_{\pm 0.99}$	26.63$_{\pm 2.40}$	30.67$_{\pm 2.01}$	61.28$_{\pm 13.88}$	106.73$_{\pm 1.15}$	49.18$_{\pm 1.24}$	19.77$_{\pm 4.29}$
GPPT	66.93$_{\pm 1.84}$	12.12$_{\pm 2.86}$	52.56$_{\pm 1.80}$	30.10$_{\pm 3.92}$	30.12$_{\pm 1.86}$	60.59$_{\pm 10.73}$	99.91$_{\pm 3.12}$	49.43$_{\pm 0.74}$	18.52$_{\pm 2.44}$
GraphPrompt	66.58$_{\pm 3.57}$	10.70$_{\pm 1.53}$	53.67$_{\pm 0.65}$	27.81$_{\pm 4.87}$	26.29$_{\pm 4.81}$	59.03$_{\pm 13.07}$	80.25$_{\pm 17.73}$	44.54$_{\pm 2.51}$	23.38$_{\pm 1.59}$
GraphPrompt+	71.09$_{\pm 2.71}$	11.22$_{\pm 1.76}$	53.93$_{\pm 0.64}$	33.28$_{\pm 3.73}$	26.11$_{\pm 4.36}$	58.39$_{\pm 11.26}$	55.93$_{\pm 22.12}$	42.45$_{\pm 2.91}$	20.48$_{\pm 3.20}$
ProNoG	63.55$_{\pm 2.31}$	18.30$_{\pm 1.73}$	53.39$_{\pm 1.24}$	26.58$_{\pm 3.38}$	29.22$_{\pm 2.55}$	58.88$_{\pm 15.89}$	48.49$_{\pm 49.84}$	46.24$_{\pm 1.69}$	21.94$_{\pm 1.22}$
IGAP	72.28$_{\pm 2.48}$	21.87$_{\pm 4.68}$	53.67$_{\pm 0.36}$	30.21$_{\pm 3.28}$	29.26$_{\pm 2.59}$	57.23$_{\pm 11.85}$	101.22$_{\pm 5.07}$	48.78$_{\pm 1.42}$	21.32$_{\pm 2.65}$
MTG	74.81$_{\pm 4.84}$	25.03$_{\pm 2.05}$	53.61$_{\pm 0.41}$	32.70$_{\pm 2.92}$	33.56$_{\pm 2.03}$	51.42$_{\pm 8.13}$	104.60$_{\pm 0.59}$	50.07$_{\pm 1.69}$	23.86$_{\pm 1.35}$
SUPT	**78.29**$_{\pm 2.10}$	23.53$_{\pm 6.18}$	53.64$_{\pm 0.33}$	26.28$_{\pm 2.13}$	31.71$_{\pm 1.93}$	62.14$_{\pm 9.18}$	106.62$_{\pm 0.87}$	48.54$_{\pm 1.16}$	20.52$_{\pm 3.14}$
GAPTUNE+	75.78$_{\pm 1.90}$	**27.09**$_{\pm 1.87}$	**56.29**$_{\pm 0.66}$	**35.84**$_{\pm 3.58}$	**34.59**$_{\pm 1.97}$	**67.32**$_{\pm 6.39}$	9.66$_{\pm 1.95}$	**54.58**$_{\pm 1.57}$	**25.73**$_{\pm 1.65}$
Pretrain (InfoGraph) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**76.71**$_{\pm 2.53}$	26.42$_{\pm 1.27}$	54.94$_{\pm 0.78}$	25.33$_{\pm 2.99}$	29.80$_{\pm 4.54}$	**68.93**$_{\pm 9.82}$	**7.39**$_{\pm 1.17}$	50.88$_{\pm 1.32}$	**26.40**$_{\pm 0.95}$
All-in-One	62.42$_{\pm 1.40}$	19.45$_{\pm 1.02}$	54.73$_{\pm 0.89}$	**35.90**$_{\pm 4.66}$	29.15$_{\pm 4.47}$	58.72$_{\pm 13.51}$	111.67$_{\pm 0.14}$	52.29$_{\pm 2.72}$	21.94$_{\pm 1.14}$
EdgePrompt	67.53$_{\pm 4.96}$	28.10$_{\pm 2.17}$	53.85$_{\pm 0.55}$	25.01$_{\pm 0.28}$	31.12$_{\pm 2.93}$	54.54$_{\pm 15.76}$	115.17$_{\pm 0.17}$	52.18$_{\pm 0.92}$	20.72$_{\pm 1.89}$
EdgePrompt+	69.73$_{\pm 2.62}$	25.73$_{\pm 0.75}$	53.73$_{\pm 0.87}$	27.42$_{\pm 2.96}$	30.96$_{\pm 4.46}$	58.75$_{\pm 16.84}$	115.13$_{\pm 0.17}$	52.18$_{\pm 1.33}$	24.42$_{\pm 1.45}$
GPF	74.30$_{\pm 2.74}$	26.51$_{\pm 1.72}$	53.90$_{\pm 0.94}$	25.95$_{\pm 1.66}$	31.51$_{\pm 2.59}$	53.98$_{\pm 14.39}$	115.51$_{\pm 0.18}$	50.76$_{\pm 1.68}$	19.16$_{\pm 6.14}$
GPF+	76.29$_{\pm 2.48}$	20.26$_{\pm 7.50}$	54.15$_{\pm 0.79}$	27.03$_{\pm 4.18}$	32.29$_{\pm 2.74}$	61.76$_{\pm 14.18}$	115.55$_{\pm 0.13}$	51.90$_{\pm 0.93}$	22.29$_{\pm 1.74}$
GPPT	65.30$_{\pm 1.47}$	13.92$_{\pm 2.28}$	54.32$_{\pm 0.95}$	27.47$_{\pm 3.06}$	30.75$_{\pm 3.24}$	61.91$_{\pm 10.27}$	113.01$_{\pm 0.73}$	50.04$_{\pm 0.39}$	16.55$_{\pm 3.39}$
GraphPrompt	62.45$_{\pm 2.89}$	8.99$_{\pm 1.38}$	54.58$_{\pm 0.43}$	31.06$_{\pm 4.79}$	25.96$_{\pm 4.87}$	60.31$_{\pm 11.29}$	111.03$_{\pm 0.11}$	44.91$_{\pm 2.45}$	24.84$_{\pm 1.60}$
GraphPrompt+	73.92$_{\pm 4.48}$	6.84$_{\pm 1.28}$	55.01$_{\pm 0.50}$	34.31$_{\pm 4.36}$	23.77$_{\pm 2.59}$	59.90$_{\pm 10.06}$	88.02$_{\pm 15.79}$	42.75$_{\pm 2.96}$	21.86$_{\pm 1.96}$
ProNoG	68.41$_{\pm 0.66}$	23.13$_{\pm 2.41}$	54.91$_{\pm 0.73}$	27.35$_{\pm 2.04}$	28.06$_{\pm 1.73}$	52.93$_{\pm 12.51}$	8.40$_{\pm 3.46}$	44.52$_{\pm 1.94}$	22.28$_{\pm 1.08}$
IGAP	70.54$_{\pm 2.58}$	16.95$_{\pm 5.02}$	53.55$_{\pm 0.49}$	27.42$_{\pm 4.21}$	32.62$_{\pm 3.56}$	60.42$_{\pm 12.06}$	113.73$_{\pm 0.15}$	52.42$_{\pm 1.45}$	24.13$_{\pm 1.43}$
MTG	72.42$_{\pm 3.26}$	27.35$_{\pm 1.85}$	53.51$_{\pm 0.31}$	28.66$_{\pm 2.43}$	30.91$_{\pm 4.57}$	63.08$_{\pm 6.83}$	113.78$_{\pm 0.16}$	51.19$_{\pm 1.32}$	24.16$_{\pm 1.64}$
SUPT	74.84$_{\pm 2.15}$	23.82$_{\pm 6.44}$	53.46$_{\pm 0.55}$	28.27$_{\pm 3.68}$	31.76$_{\pm 2.40}$	58.85$_{\pm 13.53}$	115.27$_{\pm 0.14}$	52.16$_{\pm 1.65}$	20.77$_{\pm 2.95}$
GAPTUNE+	70.46$_{\pm 2.20}$	**28.51**$_{\pm 1.63}$	**56.57**$_{\pm 0.54}$	33.42$_{\pm 3.68}$	**33.67**$_{\pm 2.86}$	66.28$_{\pm 6.41}$	13.50$_{\pm 1.86}$	**56.96**$_{\pm 1.77}$	25.87$_{\pm 2.15}$

Table 22: 5-shot same-dataset results for FAGCN across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	76.57±1.07	27.53±1.09	54.30±1.49	29.28±1.77	**32.49**±2.97	55.41±6.12	6.38±0.63	48.50±0.86	23.80±1.65
All-in-One	76.84±2.32	**29.69**±0.97	53.37±0.90	31.95±2.81	28.35±2.32	48.09±7.23	78.06±0.55	52.13±3.57	22.29±2.47
EdgePrompt	68.55±6.14	24.37±3.15	53.45±0.62	32.32±4.39	24.89±5.02	56.30±9.81	91.73±0.60	49.31±1.50	23.98±1.23
EdgePrompt+	69.09±3.76	24.14±3.95	54.11±0.59	33.68±5.39	25.95±4.61	53.88±10.85	90.65±0.71	48.96±0.71	25.06±1.03
GPF	76.56±1.75	28.82±1.63	53.02±1.17	31.74±5.16	24.97±1.88	55.51±4.34	101.41±1.86	49.93±0.77	20.61±4.74
GPF+	77.63±2.50	20.60±9.03	53.37±1.24	29.42±2.91	25.68±2.08	52.93±8.66	101.28±1.60	49.88±0.56	22.04±1.67
GPPT	43.81±10.53	19.63±6.20	52.77±2.08	34.26±1.91	22.85±4.18	58.80±8.54	86.29±7.90	48.98±0.81	16.77±2.96
GraphPrompt	64.18±4.01	12.05±2.24	53.57±0.46	35.16±3.93	23.24±1.95	58.44±6.74	68.05±33.95	42.70±2.86	24.27±1.54
GraphPrompt+	50.86±3.52	12.87±1.71	53.48±0.45	35.16±3.92	22.01±2.46	51.33±11.86	29.22±5.33	42.83±2.80	21.41±4.02
ProNoG	73.18±3.37	25.75±4.22	54.05±0.47	26.84±2.45	26.55±2.31	49.29±5.14	20.23±2.90	42.93±2.83	24.26±1.18
IGAP	71.65±2.79	21.21±6.18	53.97±0.30	33.34±4.57	26.09±2.27	47.53±6.44	89.17±8.90	50.56±1.34	23.10±1.76
MTG	73.65±5.08	29.00±3.91	54.13±0.35	34.15±5.00	26.03±4.18	51.50±11.02	91.06±0.66	48.83±1.61	25.51±1.01
SUPT	**77.80**±2.06	27.87±8.01	54.04±0.41	31.85±3.51	25.74±1.93	53.14±6.24	101.81±1.59	48.90±0.97	21.37±2.93
GAPTUNE+	77.47±2.23	28.86±2.57	**56.05**±0.58	**37.52**±4.65	29.18±2.65	**59.14**±5.12	**6.23**±0.71	**55.88**±2.01	**27.03**±1.68
Pretrain (ContextPred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	79.93±3.11	**23.77**±1.46	53.96±0.69	28.79±2.12	**31.05**±3.59	58.93±12.83	**6.24**±0.38	48.08±0.93	25.37±0.93
All-in-One	74.81±4.43	18.47±1.98	53.18±0.67	34.21±2.45	28.80±1.38	46.81±5.58	100.97±1.51	42.72±2.96	22.50±1.88
EdgePrompt	71.53±5.19	18.42±3.79	53.64±0.90	34.19±5.67	28.23±3.63	51.38±12.77	107.05±0.53	50.06±1.39	21.97±2.51
EdgePrompt+	69.81±4.66	19.51±1.32	54.59±0.71	35.09±4.99	28.23±6.21	**63.90**±10.53	107.40±0.68	50.03±1.34	24.41±1.62
GPF	80.88±4.46	19.54±1.13	53.09±0.47	32.96±3.11	28.57±3.46	54.62±5.70	108.22±0.99	49.64±1.34	21.03±3.01
GPF+	81.27±3.42	15.34±5.89	53.63±0.84	33.15±3.44	30.08±3.31	59.44±8.02	108.64±1.87	49.23±0.59	20.73±2.55
GPPT	74.46±2.92	14.06±2.03	50.41±0.33	32.21±3.70	28.37±3.19	60.87±5.28	98.75±4.23	50.38±1.20	18.77±2.34
GraphPrompt	75.76±5.33	10.47±2.00	53.53±0.72	31.74±2.92	25.15±5.97	55.97±8.68	73.11±1.46	43.52±2.82	24.69±1.42
GraphPrompt+	75.67±3.84	10.15±2.14	53.65±0.41	34.51±3.32	22.42±2.53	55.89±9.38	63.28±14.33	42.71±3.14	21.74±3.89
ProNoG	80.56±3.53	14.69±3.24	53.43±1.07	28.36±3.21	27.52±2.45	53.70±7.34	15.27±5.49	43.66±2.80	24.87±1.44
IGAP	80.38±4.53	15.10±3.31	53.83±0.36	35.11±4.10	29.21±3.93	52.16±9.78	98.87±1.76	47.25±1.69	23.46±1.67
MTG	73.64±4.07	21.25±2.56	54.08±0.33	34.97±4.77	26.56±4.52	51.85±6.28	106.19±0.87	48.69±2.13	22.67±1.75
SUPT	**81.54**±3.33	14.87±5.22	53.83±0.34	34.91±2.29	29.78±3.04	50.94±8.36	109.18±1.61	47.38±1.21	21.42±2.47
GAPTUNE+	78.77±2.27	21.86±1.96	**56.15**±0.59	**37.99**±4.24	30.45±2.56	63.15±5.21	10.33±1.34	**51.79**±1.32	**26.28**±2.06
Pretrain (DGI) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	76.40±4.64	27.18±1.88	53.49±0.53	30.80±4.58	32.67±3.82	61.53±1.94	**7.68**±1.86	47.71±0.90	23.36±1.42
All-in-One	74.84±5.49	25.28±0.70	54.16±0.42	31.91±0.85	32.30±3.66	56.02±8.70	105.82±1.53	45.37±1.75	21.34±3.44
EdgePrompt	63.47±5.05	29.90±1.82	53.64±0.91	28.89±7.49	34.07±2.93	64.34±9.07	108.19±0.14	50.79±0.41	21.04±1.77
EdgePrompt+	67.43±6.78	29.51±1.33	54.08±0.63	29.62±6.57	34.22±1.42	**66.86**±5.72	108.04±0.62	50.99±0.56	26.23±0.64
GPF	74.44±5.93	28.92±1.11	52.87±0.69	27.42±3.18	31.59±2.34	58.52±4.03	110.40±0.21	48.67±1.10	20.57±3.10
GPF+	76.10±4.66	22.97±10.48	53.24±0.79	27.16±6.98	31.33±0.90	58.27±9.30	110.65±0.65	48.94±1.17	20.76±6.73
GPPT	11.25±0.23	22.77±4.69	50.84±1.57	28.58±6.06	30.37±2.31	58.81±7.08	106.89±1.71	49.97±1.46	19.67±2.16
GraphPrompt	66.59±9.67	8.03±1.80	53.20±0.33	29.54±4.02	23.05±4.63	65.08±8.35	95.45±0.56	43.42±2.63	26.79±0.57
GraphPrompt+	68.25±7.13	9.44±2.03	53.75±0.58	29.50±2.12	24.31±3.65	56.25±10.75	68.06±17.05	43.00±2.87	19.39±2.78
ProNoG	68.56±9.04	26.96±3.12	51.96±0.59	28.46±2.32	28.42±3.04	65.18±11.23	21.26±16.10	46.09±1.41	27.28±0.44
IGAP	73.54±6.64	21.90±7.93	53.13±0.53	31.14±5.43	30.57±1.69	56.82±9.78	105.63±0.61	47.11±1.24	25.20±4.49
MTG	69.64±6.61	28.37±2.46	53.72±0.45	32.59±7.38	35.06±1.82	52.55±9.01	107.48±0.47	50.36±0.92	25.12±1.76
SUPT	**79.28**±4.49	24.42±8.23	53.37±0.45	24.58±6.89	31.84±1.35	59.11±9.20	110.24±0.53	49.77±1.24	20.10±7.45
GAPTUNE+	77.08±3.21	**31.05**±1.51	**56.13**±0.68	**34.99**±5.57	**36.05**±2.08	64.33±6.08	10.70±1.57	**52.77**±0.99	**27.65**±1.21
Pretrain (EdgePred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**75.45**±1.19	**21.32**±0.96	53.48±1.13	31.25±3.14	30.53±2.47	55.99±11.67	**6.24**±0.38	47.05±1.36	23.96±1.59
All-in-One	33.44±2.90	5.33±0.69	51.25±0.71	35.27±2.17	30.91±3.50	54.90±7.46	100.97±1.51	46.92±1.24	20.40±1.79
EdgePrompt	19.05±4.67	4.35±1.15	52.93±0.72	32.26±4.28	25.28±7.45	59.77±9.19	107.05±0.53	47.95±0.97	21.27±1.72
EdgePrompt+	50.13±8.34	5.36±1.15	53.11±0.91	29.13±8.46	29.40±5.61	54.97±10.92	107.40±0.68	48.00±0.67	24.24±2.68
GPF	36.76±6.51	4.74±1.14	52.48±0.58	29.76±4.86	30.31±2.98	54.97±10.84	108.22±0.99	48.78±0.62	22.65±1.52
GPF+	67.73±7.31	10.89±2.25	53.11±0.97	27.54±3.16	26.94±5.15	55.41±12.65	107.94±0.49	48.53±0.73	23.16±1.25
GPPT	35.35±3.15	2.95±0.65	51.14±1.26	30.89±2.04	27.69±5.88	57.76±7.62	98.75±4.23	50.33±0.14	18.65±2.04
GraphPrompt	29.45±3.09	3.73±0.19	51.34±0.75	35.13±3.55	21.17±4.40	53.04±3.91	73.11±1.46	44.83±1.66	26.49±0.91
GraphPrompt+	55.11±3.57	3.87±0.29	54.14±0.93	33.69±3.97	24.29±4.71	52.65±9.66	63.28±14.33	42.84±2.93	18.82±2.52
ProNoG	32.42±2.28	4.43±0.52	51.15±0.63	26.02±4.40	28.77±3.31	52.86±6.46	15.27±5.49	43.62±2.57	23.98±1.51
IGAP	57.59±6.55	9.28±1.54	52.44±0.46	32.28±4.54	26.83±4.44	48.83±4.26	98.63±0.79	48.21±0.95	25.08±1.43
MTG	51.05±10.85	7.03±1.25	52.77±0.33	30.91±5.74	30.92±5.58	49.77±7.71	105.70±0.63	48.30±0.72	24.46±1.81
SUPT	66.18±7.32	9.63±2.27	53.27±0.36	27.29±3.96	27.27±4.99	50.98±4.22	107.81±0.61	48.10±0.68	23.52±1.45
GAPTUNE+	62.76±4.34	12.47±1.91	**55.50**±0.65	**35.68**±4.67	**32.80**±3.18	**60.57**±6.77	10.36±1.73	**52.77**±1.12	**26.71**±2.45
Pretrain (GraphCL) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	77.25±2.30	27.87±1.15	53.09±0.92	29.28±1.74	31.18±2.91	57.27±13.63	**6.16**±0.53	48.64±1.48	20.66±1.13
All-in-One	77.65±1.73	**30.31**±0.26	52.87±1.08	29.08±4.11	28.32±2.25	53.42±9.40	94.09±2.07	55.07±2.91	20.89±2.23
EdgePrompt	64.00±4.96	28.59±2.48	53.07±1.30	36.07±3.43	26.87±2.14	51.02±5.13	102.40±0.28	49.65±1.42	21.33±1.84
EdgePrompt+	64.65±5.19	26.89±3.38	55.10±1.17	34.63±2.84	27.49±2.13	51.71±5.89	102.23±0.39	49.41±1.43	21.27±1.69
GPF	77.65±2.36	30.09±2.36	52.66±1.14	24.89±4.75	27.74±1.48	52.53±10.05	103.01±0.81	49.92±1.66	19.44±1.55
GPF+	78.47±1.45	19.74±8.23	52.98±0.96	30.79±2.85	28.94±1.84	55.38±14.46	103.99±2.55	49.94±1.13	18.25±3.66
GPPT	78.46±1.94	15.22±0.90	54.41±0.61	33.09±1.71	27.95±4.86	51.96±6.66	91.04±6.00	49.11±0.87	13.32±0.74
GraphPrompt	76.46±2.77	14.67±2.23	53.45±0.62	35.08±2.93	24.96±6.86	50.48±7.21	55.96±2.14	45.30±2.25	21.00±2.00
GraphPrompt+	76.99±3.02	13.59±1.88	53.61±0.72	34.89±3.12	23.21±2.92	51.48±11.23	44.72±15.83	43.12±2.63	17.13±2.85
ProNoG	76.99±1.61	27.10±3.22	53.73±0.82	28.27±6.22	26.99±3.13	50.69±8.88	15.91±5.14	45.79±1.84	23.58±1.66
IGAP	77.28±2.45	18.72±6.29	53.56±0.56	32.96±3.06	30.34±3.75	51.53±6.31	92.04±2.25	49.21±1.83	20.01±3.56
MTG	70.23±3.73	28.41±4.08	53.86±0.47	34.80±3.21	30.41±2.06	50.11±6.27	100.96±0.63	52.13±2.30	22.61±2.56
SUPT	**78.88**±1.57	22.02±7.55	53.43±0.63	30.26±2.83	28.70±1.90	54.52±6.50	103.55±2.59	53.74±1.51	19.98±4.23
GAPTUNE+	77.65±1.72	29.05±2.21	**56.00**±0.74	**36.95**±4.04	**32.36**±1.97	**59.84**±7.58	7.87±1.34	**57.12**±1.87	**24.17**±2.36
Pretrain (InfoGraph) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	77.04±1.41	**26.12**±1.78	54.05±1.16	30.36±3.79	31.76±5.33	61.07±7.86	**6.37**±0.73	48.71±1.11	24.08±2.35
All-in-One	75.84±2.48	25.05±0.82	53.24±0.65	**37.42**±4.48	30.75±2.70	60.13±3.34	112.06±0.25	56.80±2.85	16.49±4.67
EdgePrompt	58.86±3.31	20.63±2.43	53.57±0.52	26.73±2.26	34.17±3.41	61.58±3.64	112.23±0.14	48.68±0.56	21.46±1.82
EdgePrompt+	63.23±4.78	18.86±1.45	54.42±0.80	32.48±4.99	33.45±3.62	58.98±7.35	112.11±0.07	48.71±0.36	24.64±2.63
GPF	76.20±3.34	24.28±2.10	53.36±0.41	28.60±5.29	32.47±3.25	57.32±6.13	113.86±0.24	49.95±1.97	21.85±1.81
GPF+	76.64±3.75	18.01±6.75	53.38±0.86	26.80±4.42	31.98±2.74	58.44±11.31	113.90±0.15	50.01±0.58	20.41±2.95
GPPT	73.92±2.80	17.07±2.40	53.74±0.83	32.99±3.01	31.80±3.37	59.54±7.20	111.70±0.34	49.97±0.39	20.67±1.64
GraphPrompt	71.62±4.37	7.05±0.33	53.65±0.61	33.61±3.05	25.06±5.15	57.91±7.46	111.13±1.60	45.09±2.69	**27.69**±0.83
GraphPrompt+	75.42±3.66	12.63±1.37	54.02±0.74	33.93±0.88	24.38±4.02	58.34±11.38	97.41±5.78	42.75±2.78	21.41±2.12
ProNoG	75.89±0.90	25.75±2.11	53.65±0.77	28.02±2.44	29.08±2.94	52.68±8.43	9.66±5.30	43.28±2.66	24.85±1.07
IGAP	75.33±4.31	14.20±4.96	53.92±0.38	27.50±4.26	32.28±3.55	52.12±7.83	112.44±0.62	51.76±0.82	23.60±2.44
MTG	66.48±3.73	20.03±2.67	53.83±0.54	31.42±3.99	32.83±3.53	43.44±5.82	110.66±0.11	49.88±0.92	23.97±2.35
SUPT	**79.15**±3.17	18.37±6.42	53.66±0.43	26.46±4.81	32.09±3.03	50.90±4.53	113.35±0.16	49.76±1.08	20.55±2.72
GAPTUNE+	75.90±2.92	24.30±1.85	**56.26**±0.49	35.39±3.88	**34.69**±3.06	**62.15**±4.84	14.76±1.34	**57.76**±1.23	26.50±2.51

Table 23: 5-shot same-dataset results for Transformer across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	80.32±1.36	26.98±1.49	57.36±0.63	33.38±5.47	29.33±3.77	**68.65**±8.87	15.17±1.60	49.88±1.33	**26.40**±2.51
All-in-One	79.45±1.29	**30.08**±0.92	53.21±0.52	35.90±3.94	30.60±2.74	57.40±13.82	94.59±5.02	48.01±1.50	23.51±2.22
EdgePrompt	67.44±4.94	25.31±2.59	56.94±0.65	34.14±3.47	30.44±3.37	58.90±7.86	107.44±0.28	49.03±0.40	18.02±3.87
EdgePrompt+	68.39±6.42	23.73±2.37	56.46±0.89	34.62±3.34	30.84±3.79	54.54±12.75	106.96±0.40	49.13±0.81	22.55±2.33
GPF	80.81±2.33	23.54±1.59	56.88±0.69	38.10±3.36	30.66±3.36	53.60±10.22	111.34±0.29	49.08±0.60	17.53±4.34
GPF+	80.27±1.70	22.42±1.52	56.72±0.85	37.62±4.03	32.08±2.20	56.91±6.29	111.29±0.26	49.08±0.54	18.88±2.99
GPPT	73.02±10.93	18.80±6.48	51.90±1.37	29.98±4.56	32.50±3.56	57.26±5.71	108.23±1.59	48.95±1.55	12.01±0.75
GraphPrompt	72.76±1.47	12.56±1.72	54.34±0.41	35.40±4.13	27.83±6.74	54.36±8.55	103.93±4.21	44.30±3.65	21.84±1.26
GraphPrompt+	64.06±7.51	11.78±1.38	56.37±0.50	35.23±4.04	22.18±2.35	55.36±11.22	45.22±35.40	42.47±2.86	22.78±1.27
ProNoG	78.39±4.68	25.13±4.00	55.60±0.53	29.23±5.98	28.34±2.53	55.28±9.25	14.45±8.52	42.41±3.26	24.62±1.32
IGAP	78.26±2.65	19.81±1.61	52.66±0.49	38.18±4.07	29.42±3.70	48.45±4.52	108.00±1.26	46.83±1.28	19.72±2.69
MTG	70.90±6.01	25.47±2.23	53.02±0.39	33.56±3.63	32.24±3.28	48.86±6.70	105.95±0.33	45.90±1.80	21.65±2.39
SUPT	81.91±2.17	22.95±1.36	52.83±0.60	38.02±4.20	31.13±2.68	47.44±5.34	110.86±0.25	47.73±1.37	19.51±3.41
GAPTUNE+	**83.10**±2.41	27.77±1.88	**58.46**±0.61	**38.92**±3.60	**34.30**±2.49	61.17±6.60	**7.22**±1.51	**53.61**±1.16	25.07±2.43
Pretrain (ContextPred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	76.70±3.54	**22.98**±1.64	57.16±0.45	33.45±3.28	30.42±2.94	68.72±10.51	**8.79**±2.00	48.76±0.76	**23.86**±1.43
All-in-One	76.09±1.11	21.20±2.31	55.73±0.68	30.19±5.26	31.89±2.10	61.40±9.07	96.94±0.16	42.49±3.37	22.52±1.15
EdgePrompt	69.11±7.34	17.68±1.30	56.96±0.45	38.17±6.37	30.65±4.74	66.07±8.96	107.31±0.19	49.35±1.10	22.15±2.17
EdgePrompt+	69.56±3.97	15.45±2.48	56.09±0.57	38.80±5.58	30.52±3.75	69.21±8.86	107.35±0.13	49.65±0.61	21.31±2.18
GPF	78.85±0.63	19.80±1.72	56.66±0.48	37.88±5.08	29.92±3.43	66.84±12.68	107.31±0.37	49.99±1.16	20.15±2.74
GPF+	78.85±1.18	17.20±2.43	55.83±0.84	37.32±4.45	29.92±3.43	67.02±11.08	107.69±0.93	49.32±1.23	18.28±3.16
GPPT	76.17±1.93	12.01±4.72	51.71±1.83	31.85±2.14	30.18±2.08	62.09±6.84	101.58±3.74	49.52±1.08	15.12±1.21
GraphPrompt	77.56±1.63	9.40±1.64	55.11±0.84	28.48±5.32	25.63±6.32	65.97±12.20	77.86±1.06	42.64±2.90	20.15±1.27
GraphPrompt+	74.01±3.90	7.32±1.84	55.06±0.87	34.36±2.53	23.94±3.79	63.65±7.30	62.37±10.61	42.52±2.92	18.39±2.83
ProNoG	79.42±1.95	15.43±2.76	56.29±0.53	28.80±2.17	28.40±3.03	61.66±11.25	13.12±3.81	42.84±2.52	19.46±1.62
IGAP	77.35±1.52	15.82±1.83	53.94±0.85	36.78±3.61	28.87±3.40	53.80±10.20	99.95±0.90	49.71±1.11	18.11±2.26
MTG	70.35±4.85	19.99±2.11	55.68±1.14	41.12±6.03	33.01±3.75	55.80±12.27	105.89±0.23	47.05±1.19	22.23±3.13
SUPT	**81.09**±0.85	18.46±2.14	55.08±0.69	38.29±4.62	30.97±3.72	48.98±10.82	107.44±0.90	49.49±1.21	17.60±3.11
GAPTUNE+	80.45±1.21	21.54±2.66	**58.84**±0.46	**42.58**±4.69	**34.82**±2.66	**69.35**±6.29	10.02±1.37	**51.49**±1.65	23.85±2.04
Pretrain (DGI) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	79.02±1.72	24.57±1.20	57.41±0.49	32.65±3.28	31.19±4.24	**63.49**±13.49	6.16±0.27	49.94±0.87	**26.24**±1.13
All-in-One	76.22±2.52	22.67±0.68	55.67±1.60	30.99±4.69	32.46±2.01	61.02±7.64	47.88±5.38	52.54±1.16	20.60±4.42
EdgePrompt	71.30±4.02	24.68±0.75	57.40±0.43	33.44±6.06	34.71±3.01	58.06±7.53	97.14±0.73	51.14±1.95	17.19±3.65
EdgePrompt+	70.41±2.58	23.22±0.87	56.90±0.31	32.55±7.02	35.39±2.10	62.09±7.68	97.02±0.73	51.57±2.50	21.39±3.42
GPF	78.12±2.32	24.02±0.93	57.21±0.30	34.41±2.47	34.95±2.84	52.35±13.62	100.32±1.07	51.39±1.16	20.19±1.58
GPF+	79.11±3.03	19.77±9.61	56.66±0.29	33.45±3.48	34.40±2.46	50.48±8.91	101.06±2.04	51.24±0.45	18.93±6.12
GPPT	44.42±11.79	14.15±6.94	51.20±2.08	31.25±2.40	29.29±2.94	58.65±6.76	80.94±4.37	49.19±1.42	18.80±2.40
GraphPrompt	72.20±7.04	7.58±0.94	55.43±0.72	30.34±2.69	23.83±4.18	53.42±11.18	44.47±1.01	42.95±2.87	23.86±1.42
GraphPrompt+	68.32±2.99	9.45±0.85	55.21±0.63	29.01±4.05	23.24±5.61	62.09±13.06	25.02±4.18	42.81±2.33	22.42±1.66
ProNoG	74.11±5.64	25.12±2.70	56.61±0.42	24.41±3.22	30.12±1.69	54.54±8.81	21.97±7.51	42.98±3.09	25.52±1.03
IGAP	76.30±3.80	17.87±7.33	54.06±0.75	31.28±4.01	32.63±2.35	49.67±9.16	84.72±1.75	51.74±0.99	19.83±4.70
MTG	75.09±2.82	24.39±2.51	54.77±0.81	31.62±6.33	36.29±2.53	57.72±7.46	95.69±0.79	52.09±1.27	20.44±4.15
SUPT	**79.53**±3.08	20.49±7.62	54.48±0.92	35.71±3.11	34.73±2.16	48.60±9.99	100.70±2.19	52.13±1.09	20.02±5.59
GAPTUNE+	77.77±2.75	**27.90**±1.96	**59.41**±0.43	**36.01**±5.05	**38.45**±2.05	59.66±6.36	**4.60**±0.46	**56.76**±1.13	24.67±2.30
Pretrain (EdgePred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**64.42**±22.74	**22.87**±1.19	56.93±0.47	33.06±3.33	29.31±3.03	**71.96**±5.16	**7.27**±1.37	48.89±0.89	23.93±2.15
All-in-One	30.46±2.61	7.12±0.97	52.91±1.29	32.91±5.06	29.33±3.21	60.13±7.39	96.94±0.16	48.18±1.55	21.65±2.70
EdgePrompt	38.53±6.09	5.09±2.43	55.39±0.76	38.12±3.98	28.58±1.44	65.23±5.02	109.83±3.84	50.37±0.55	20.85±2.36
EdgePrompt+	53.82±10.12	6.39±1.57	55.67±0.62	38.63±5.32	29.32±1.99	67.78±6.49	107.35±0.13	50.14±0.80	23.98±1.85
GPF	35.39±3.48	6.80±2.49	55.31±0.49	37.71±4.32	28.98±4.22	65.23±6.01	107.31±0.37	50.36±1.17	19.86±3.59
GPF+	54.48±2.35	11.65±2.02	56.29±0.47	37.16±3.62	29.08±3.68	63.72±6.30	107.30±0.12	50.54±0.79	21.39±3.50
GPPT	33.90±1.11	2.28±0.48	51.24±0.90	32.44±1.81	28.58±2.55	59.72±11.49	101.58±3.74	50.00±0.65	17.99±2.28
GraphPrompt	25.28±1.29	3.99±0.80	54.17±0.46	33.13±4.11	25.09±5.28	63.98±7.57	77.86±1.06	44.69±1.91	25.76±0.93
GraphPrompt+	41.25±7.00	3.77±0.96	55.50±0.67	34.65±4.09	25.70±3.95	59.46±7.80	62.37±10.61	42.42±3.02	20.10±2.98
ProNoG	29.26±4.06	5.19±0.63	54.29±0.78	29.27±4.21	28.31±1.85	59.08±10.42	13.12±3.81	43.88±2.41	23.26±1.38
IGAP	45.48±3.15	9.33±1.45	52.12±0.69	38.96±3.45	27.85±3.30	53.20±12.37	99.28±0.35	49.44±1.37	24.08±2.92
MTG	50.70±8.16	9.23±1.84	51.01±0.64	42.39±4.76	30.80±2.03	55.29±9.91	106.69±1.03	48.39±1.01	24.81±2.52
SUPT	51.48±2.90	11.71±2.17	52.09±0.59	38.36±4.03	30.63±3.22	58.86±9.16	106.85±0.15	49.64±1.11	22.20±3.20
GAPTUNE+	53.06±2.62	12.26±1.63	**57.62**±0.56	**44.10**±3.96	**33.14**±2.83	67.18±4.57	9.97±1.26	**54.18**±1.20	**25.94**±2.42
Pretrain (GraphCL) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	75.10±3.59	25.07±1.05	57.01±0.65	33.61±4.20	28.50±2.88	**63.29**±5.47	**7.50**±2.25	48.50±0.91	25.75±0.60
All-in-One	70.74±2.21	24.10±1.55	54.39±0.97	32.24±4.27	29.44±1.65	55.69±10.61	91.21±0.21	52.43±1.16	26.89±1.30
EdgePrompt	68.03±4.96	26.03±0.47	57.22±0.55	35.73±5.43	30.92±2.56	54.49±12.50	109.62±0.12	48.25±2.05	22.68±1.81
EdgePrompt+	68.38±4.80	24.90±1.39	56.99±0.30	34.09±4.47	30.75±2.55	57.35±12.71	109.56±0.09	48.56±1.23	23.75±1.52
GPF	73.69±3.19	27.73±1.12	56.86±0.80	38.67±4.85	29.46±2.19	55.77±8.51	109.83±0.14	48.06±1.96	21.01±2.81
GPF+	73.61±1.84	22.42±5.75	56.43±0.75	37.32±4.72	29.46±2.19	55.00±9.59	109.82±0.10	48.31±1.19	20.88±1.88
GPPT	62.52±3.17	18.26±2.34	51.48±0.62	33.62±2.87	28.75±3.37	56.56±9.88	106.96±2.55	49.72±0.76	19.20±2.37
GraphPrompt	67.13±1.39	12.78±1.43	54.92±0.54	29.03±2.40	23.12±4.22	54.39±6.71	92.81±0.64	43.95±2.66	**28.16**±2.70
GraphPrompt+	**77.22**±2.58	11.86±1.45	55.62±0.66	34.58±4.48	23.98±4.25	53.44±6.41	50.38±18.61	42.67±2.79	20.28±3.22
ProNoG	65.97±1.90	20.70±1.48	57.01±0.60	31.21±4.15	27.83±3.28	52.22±9.46	18.78±24.14	46.45±1.94	25.18±1.66
IGAP	71.50±2.24	25.19±3.96	52.51±0.70	34.93±4.76	28.36±2.13	47.82±8.03	105.26±0.25	49.94±1.38	24.22±1.72
MTG	69.82±4.28	26.33±1.79	53.13±1.10	35.09±5.60	32.08±2.79	52.43±6.56	108.21±0.10	50.21±1.60	24.96±1.95
SUPT	74.52±1.95	23.59±4.73	52.66±0.57	39.21±4.33	28.97±2.34	50.94±8.22	109.41±0.13	48.42±1.43	22.69±1.68
GAPTUNE+	74.23±2.31	**28.54**±1.72	**59.14**±0.39	**39.74**±4.63	**33.89**±2.42	59.81±5.17	9.15±1.62	**55.75**±0.94	26.53±2.28
Pretrain (InfoGraph) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	76.99±3.75	**25.09**±1.34	57.07±0.36	33.20±3.90	29.88±3.57	**70.48**±7.67	**6.38**±0.50	50.22±0.76	21.62±2.50
All-in-One	63.63±6.80	22.26±2.23	54.75±0.94	32.21±2.72	30.64±2.61	57.47±13.67	105.34±0.15	57.03±2.42	11.84±1.71
EdgePrompt	62.26±5.73	18.30±2.00	56.51±0.48	36.85±5.34	31.63±1.77	67.47±5.62	114.05±0.18	51.00±1.34	21.66±2.89
EdgePrompt+	69.15±6.24	18.53±1.83	56.14±0.67	37.83±5.02	32.85±1.21	67.88±7.34	113.68±0.25	51.07±1.17	21.76±2.65
GPF	75.90±2.80	19.33±1.15	56.38±0.60	37.95±3.33	31.00±3.17	67.83±8.99	115.28±0.12	50.46±1.55	13.99±4.67
GPF+	76.62±3.88	19.17±1.27	55.95±0.68	36.91±2.83	32.82±1.01	64.21±10.12	115.23±0.08	49.59±1.00	16.85±4.97
GPPT	62.64±0.94	10.61±2.03	50.64±0.40	32.62±2.12	33.72±2.27	59.07±10.17	111.89±0.94	50.02±0.23	13.40±1.97
GraphPrompt	57.86±2.41	7.12±0.95	55.70±0.63	31.30±1.56	25.22±4.90	63.19±10.83	111.78±2.61	43.75±2.33	18.84±0.74
GraphPrompt+	68.66±4.54	8.67±2.42	55.32±0.65	35.35±4.36	25.22±4.90	58.29±7.88	81.15±21.78	43.16±3.18	22.24±3.28
ProNoG	63.12±1.25	19.94±1.67	56.68±0.54	29.13±2.09	30.57±3.07	59.87±9.97	8.83±3.31	43.81±2.48	14.77±0.60
IGAP	73.00±4.50	17.00±1.42	52.54±1.02	38.05±2.71	31.68±1.53	51.22±9.40	113.21±0.80	52.07±1.04	19.03±3.51
MTG	71.48±5.91	19.85±1.91	54.71±1.28	40.38±3.58	33.50±1.04	51.48±11.19	112.43±0.24	50.83±1.12	21.70±3.01
SUPT	**77.30**±3.14	20.87±1.25	53.51±0.84	36.99±2.76	32.87±1.50	49.00±7.32	115.21±0.09	49.55±2.06	17.43±5.35
GAPTUNE+	76.43±2.75	21.76±1.97	**58.50**±0.45	**41.56**±3.02	**35.54**±1.62	67.90±5.43	11.69±1.83	**58.57**±1.56	**24.01**±2.29

Table 24: 5-shot same-dataset results for NodeFormer across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	75.98±1.41	10.75±2.05	54.77±1.81	30.65±6.57	31.88±1.73	58.85±15.20	109.04±10.15	50.21±0.32	18.86±3.46
All-in-One	72.82±1.58	18.70±4.90	53.26±0.78	32.05±3.37	29.83±3.36	35.61±18.65	107.06±0.19	44.77±2.44	20.52±0.66
EdgePrompt	70.61±6.42	31.51±1.42	56.99±1.01	25.25±0.27	32.04±2.33	57.65±19.41	111.07±0.13	50.71±0.24	21.91±1.28
EdgePrompt+	69.38±6.62	32.45±2.50	56.73±1.06	24.75±0.49	32.28±2.20	58.95±19.93	111.07±0.12	50.66±0.31	22.55±1.37
GPF	76.72±2.89	30.64±1.42	55.55±0.16	26.17±2.15	32.13±2.88	62.73±11.58	111.33±0.31	50.74±0.30	13.99±5.73
GPF+	**76.82**±4.06	30.34±1.75	54.78±1.86	25.09±0.16	**32.80**±3.36	67.22±13.31	111.23±0.26	50.81±0.30	16.33±2.13
GPPT	68.29±8.59	17.00±5.89	52.45±0.70	35.01±2.04	32.60±2.35	61.49±12.37	109.59±0.73	50.20±0.60	16.43±2.67
GraphPrompt	69.29±4.08	13.80±2.02	53.18±1.12	35.13±3.97	26.82±4.95	54.92±10.77	101.97±0.34	42.79±2.70	21.63±1.88
GraphPrompt+	73.41±1.51	11.28±2.34	54.26±1.71	**35.27**±3.85	22.80±3.58	60.92±12.83	86.39±5.27	43.23±3.09	19.02±2.80
ProNoG	72.53±5.52	25.31±3.82	53.51±0.99	30.92±5.63	29.02±3.76	58.32±18.03	**8.78**±3.85	42.93±2.69	24.46±1.36
IGAP	67.32±3.89	4.64±2.02	54.07±3.47	28.78±1.43	21.78±2.35	50.81±21.33	110.60±0.59	46.46±2.04	16.68±4.29
MTG	66.53±4.71	6.23±2.33	56.12±3.61	26.39±0.18	22.90±2.49	53.16±19.21	111.54±0.58	44.42±2.26	15.83±4.29
SUPT	67.13±2.85	5.03±2.51	53.28±1.91	26.35±1.25	21.01±2.42	52.44±19.07	112.70±0.64	49.33±1.05	10.91±3.61
GAPTUNE+	70.45±2.61	**34.85**±1.86	**58.45**±0.70	33.25±3.83	30.18±2.40	**68.29**±5.95	12.72±1.12	**52.72**±1.32	**24.52**±1.74
Pretrain (ContextPred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	77.04±3.25	0.66±0.52	54.17±1.83	34.41±7.76	28.20±4.57	59.23±6.81	107.61±11.80	50.38±0.46	10.41±0.52
All-in-One	72.58±3.91	3.44±3.61	53.73±1.07	32.44±3.69	26.15±4.08	53.39±17.22	109.95±0.28	51.21±2.13	10.92±1.33
EdgePrompt	67.60±4.98	1.37±1.86	56.17±0.89	29.64±4.43	28.17±1.15	52.60±13.05	112.19±0.08	49.29±0.37	10.97±3.05
EdgePrompt+	67.78±4.27	4.81±4.44	56.56±0.62	29.91±5.49	28.92±1.32	55.48±8.52	112.18±0.04	49.34±0.21	10.32±0.56
GPF	75.36±2.38	11.36±6.65	56.02±0.43	33.20±5.51	28.97±2.21	54.36±7.26	112.62±0.10	49.91±0.23	9.74±0.38
GPF+	76.73±2.62	8.50±7.31	54.57±0.87	30.97±6.08	29.35±1.34	54.67±10.13	112.66±0.08	49.97±0.24	9.65±0.58
GPPT	75.52±2.23	1.31±0.99	52.01±1.16	34.99±2.03	26.22±2.79	51.10±7.25	110.57±0.75	49.98±1.31	10.17±0.60
GraphPrompt	74.17±3.58	3.46±0.85	54.39±0.91	35.11±3.97	23.18±4.03	54.36±8.65	108.16±0.13	43.15±2.63	15.87±2.60
GraphPrompt+	66.22±5.09	3.92±0.91	56.13±0.84	**35.30**±3.94	22.05±3.95	54.69±11.07	99.97±0.90	43.00±2.77	16.44±3.20
ProNoG	75.50±0.58	13.45±0.90	56.41±1.14	27.56±7.81	27.11±1.51	43.39±5.76	15.12±1.72	42.77±2.29	**21.59**±0.96
IGAP	79.20±3.03	9.55±4.35	53.51±3.35	28.43±1.90	27.05±3.43	45.82±7.75	111.13±1.60	51.18±0.74	14.20±3.31
MTG	72.81±6.96	6.92±4.66	53.90±4.28	26.01±0.34	29.22±4.11	59.55±11.31	112.54±0.94	48.43±1.54	17.43±3.26
SUPT	**79.51**±2.91	6.89±4.40	51.99±2.32	26.27±0.91	26.75±4.27	57.83±11.95	113.74±1.37	50.55±1.20	13.15±3.41
GAPTUNE+	75.96±2.61	**14.81**±2.73	**58.03**±0.66	34.09±4.02	**31.57**±2.98	**60.35**±6.59	**14.22**±0.57	**55.66**±1.52	17.03±2.21
Pretrain (DGI) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**77.42**±2.40	10.85±9.04	56.45±0.65	25.06±0.23	26.97±5.33	61.76±12.24	109.12±10.30	49.77±0.14	10.44±0.49
All-in-One	58.37±3.54	11.44±2.70	54.79±1.08	33.25±4.52	25.05±2.51	48.65±19.29	106.02±0.47	45.05±2.32	10.36±0.95
EdgePrompt	50.55±4.11	14.37±2.38	56.24±0.37	25.01±0.11	28.73±2.07	64.18±19.96	114.20±0.28	50.79±0.38	9.55±0.45
EdgePrompt+	52.12±5.66	12.99±2.41	56.37±0.38	24.96±0.00	**28.75**±2.48	64.62±20.92	113.35±0.35	50.53±0.92	9.82±0.48
GPF	61.77±4.09	11.41±4.33	53.84±0.79	24.96±0.00	27.82±1.95	64.44±12.26	114.52±0.58	51.32±0.78	9.88±0.52
GPF+	74.98±3.98	13.14±2.85	53.30±2.38	24.96±0.00	25.28±1.33	60.10±17.30	114.43±0.47	51.22±0.65	10.28±0.57
GPPT	57.57±5.58	11.49±3.19	51.03±1.65	30.58±1.22	26.10±4.70	58.81±14.01	105.93±1.37	49.92±1.09	9.75±0.66
GraphPrompt	58.39±3.77	8.20±2.70	55.16±0.85	35.15±4.05	22.99±4.53	**67.37**±12.11	94.21±2.06	42.73±2.79	14.80±2.96
GraphPrompt+	55.98±3.81	5.65±1.08	54.21±0.62	**35.50**±3.45	23.59±4.35	64.13±9.98	83.51±14.54	42.79±2.75	14.89±2.98
ProNoG	59.36±3.49	12.64±3.35	56.01±1.35	24.32±4.51	25.84±3.90	56.28±13.46	15.99±2.06	42.92±2.99	14.16±1.07
IGAP	42.06±10.55	7.76±3.68	52.19±2.13	28.56±3.18	24.19±2.44	53.76±22.34	109.72±0.11	48.59±1.46	10.90±0.65
MTG	43.90±11.76	9.61±5.85	53.08±2.18	26.22±0.64	24.14±3.06	52.08±24.79	110.38±0.12	49.56±1.38	10.97±0.09
SUPT	26.91±12.00	8.95±4.86	52.09±2.28	27.02±2.33	25.18±2.42	51.03±22.99	111.15±0.08	49.43±1.60	10.19±0.18
GAPTUNE+	45.94±5.03	**17.64**±2.24	**58.13**±0.43	32.70±3.07	28.72±2.55	65.15±6.38	**13.03**±1.79	**53.31**±1.19	**15.59**±2.03
Pretrain (EdgePred) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**69.14**±1.64	1.98±2.83	56.19±1.32	**33.45**±3.14	**30.50**±5.41	50.18±16.97	108.82±10.61	49.38±0.86	21.47±2.21
All-in-One	15.97±3.54	2.59±1.36	53.61±0.76	29.66±1.70	29.35±4.83	52.02±28.36	109.97±0.27	54.68±2.01	17.33±1.72
EdgePrompt	11.57±4.27	2.73±2.52	56.10±1.06	32.29±2.90	21.27±4.49	51.35±15.96	112.22±0.08	51.85±0.69	14.04±1.98
EdgePrompt+	28.87±10.61	3.34±2.29	55.77±0.91	32.24±2.69	20.03±3.71	**67.93**±10.28	112.28±0.09	51.99±0.93	20.24±3.12
GPF	10.58±2.53	6.61±1.00	56.15±0.61	32.67±3.73	25.91±2.96	64.57±9.25	112.61±0.06	52.42±1.42	16.34±1.58
GPF+	22.63±2.07	6.77±4.13	55.98±0.98	27.61±5.03	24.95±6.01	53.98±11.75	112.64±0.10	51.92±1.48	19.36±2.94
GPPT	14.23±3.82	4.13±5.55	51.61±0.78	27.37±5.80	19.32±3.51	60.62±7.85	110.60±0.74	50.35±0.74	15.30±2.46
GraphPrompt	20.37±3.27	3.00±0.95	55.10±1.19	29.88±3.76	23.06±2.65	46.99±19.42	108.75±0.67	43.23±2.23	16.51±1.91
GraphPrompt+	25.12±1.16	3.48±0.62	55.96±0.49	32.22±3.56	23.08±4.38	62.45±4.34	102.93±4.44	43.15±2.86	18.36±3.18
ProNoG	18.77±3.05	3.80±0.58	56.98±1.20	28.27±2.78	25.19±2.25	57.91±10.31	15.04±1.74	43.41±2.57	18.81±1.87
IGAP	17.36±4.68	2.43±3.31	51.13±2.40	27.37±1.55	26.32±2.61	43.08±10.48	111.24±0.13	49.75±1.82	12.60±0.87
MTG	13.79±3.77	3.72±1.52	51.13±1.10	26.93±1.25	22.78±1.26	40.35±11.43	111.20±0.15	49.10±1.40	10.33±0.52
SUPT	15.63±6.10	2.88±4.20	50.23±2.72	25.12±1.12	25.14±2.78	52.87±11.20	113.03±0.08	49.09±1.25	10.59±1.31
GAPTUNE+	25.42±3.58	**12.61**±2.48	**58.03**±0.68	33.30±2.90	27.26±2.17	61.68±6.82	**14.19**±1.14	**57.56**±1.55	**22.00**±2.49
Pretrain (GraphCL) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	**71.55**±3.12	14.67±6.67	54.36±2.39	31.98±1.62	28.97±3.36	54.54±7.41	108.70±11.12	49.21±1.39	10.01±0.30
All-in-One	65.72±2.66	15.97±1.14	54.44±1.01	31.35±2.54	25.60±2.64	55.31±9.42	107.03±1.46	52.89±1.86	11.09±1.32
EdgePrompt	63.51±3.10	24.06±1.29	55.84±0.68	**37.97**±4.69	27.45±3.86	54.41±11.20	111.16±0.09	49.77±1.10	9.14±0.83
EdgePrompt+	63.94±3.77	21.47±4.12	55.31±1.20	37.52±4.61	27.13±3.54	52.83±10.67	111.14±0.05	49.79±1.11	9.78±0.43
GPF	68.52±1.41	23.56±0.66	53.34±1.28	31.66±8.39	29.37±2.32	52.55±6.22	111.19±0.09	49.46±1.00	13.15±4.29
GPF+	70.72±0.94	23.13±1.17	53.21±1.29	34.51±3.58	29.17±4.01	51.71±8.49	111.20±0.10	49.81±1.21	11.75±3.28
GPPT	62.61±3.08	19.32±1.94	51.52±0.68	32.77±4.29	26.79±3.84	50.66±11.68	108.29±1.37	49.71±0.66	9.85±0.12
GraphPrompt	68.06±1.18	12.02±1.58	52.60±1.08	31.76±4.04	24.96±3.84	47.60±12.15	103.20±0.35	47.38±1.93	14.97±2.94
GraphPrompt+	70.14±3.36	10.36±1.90	53.75±0.96	31.35±4.22	23.58±3.98	54.97±13.57	93.12±0.23	44.65±2.66	**15.86**±3.40
ProNoG	66.09±2.18	19.12±1.71	53.10±0.56	30.31±6.74	27.06±2.60	48.37±10.58	14.77±1.79	48.06±0.75	13.89±1.77
IGAP	62.42±3.93	10.04±2.28	48.96±4.05	29.59±1.62	26.68±4.68	57.24±14.20	113.27±0.09	51.43±1.47	12.29±1.14
MTG	51.01±6.46	12.25±1.98	50.23±3.95	26.12±0.32	28.62±3.81	50.40±14.96	113.45±0.05	50.77±1.01	11.35±0.37
SUPT	62.41±3.89	12.22±3.40	48.58±3.77	24.95±1.27	26.84±3.81	48.44±11.99	115.13±0.03	49.55±1.25	10.91±0.16
GAPTUNE+	63.64±2.46	**25.78**±1.97	**57.27**±0.62	34.48±3.86	**31.18**±2.96	**57.87**±6.60	**13.76**±0.36	**56.01**±1.32	15.44±1.98
Pretrain (InfoGraph) + Fine-tuning / Prompting 5-shot									
Full fine-tuning	70.60±4.17	8.45±7.29	54.49±2.33	27.78±4.45	**29.98**±5.07	56.05±14.94	107.78±11.63	50.52±0.65	9.82±0.65
All-in-One	46.98±5.35	15.28±1.96	52.56±1.01	**36.60**±2.66	23.01±3.74	49.49±8.25	110.84±0.19	55.36±2.45	11.95±1.51
EdgePrompt	53.37±6.36	16.68±3.47	56.39±0.94	25.03±0.07	25.92±3.54	54.39±10.53	115.10±0.03	50.20±1.18	9.95±1.13
EdgePrompt+	49.47±17.46	15.36±4.33	56.44±0.48	25.49±0.65	25.75±3.27	55.79±11.70	115.10±0.10	50.13±1.21	10.77±0.76
GPF	52.74±1.73	18.47±3.92	53.88±0.88	25.04±0.17	26.15±2.23	51.84±11.54	115.36±0.06	50.30±0.87	10.74±1.22
GPF+	**70.72**±2.27	17.43±2.65	52.37±1.55	25.88±1.68	29.67±3.16	48.39±13.87	115.33±0.05	50.89±1.75	11.10±2.37
GPPT	46.08±5.11	10.11±2.63	51.21±1.00	34.62±2.02	23.64±6.01	53.47±10.98	112.73±1.00	49.98±0.87	9.98±1.00
GraphPrompt	47.75±3.57	9.59±1.36	52.10±1.05	35.27±3.90	22.40±3.66	53.65±8.35	111.43±0.19	43.44±2.72	15.92±2.54
GraphPrompt+	57.84±7.85	6.85±2.10	53.48±0.83	35.15±3.96	22.83±2.81	**59.67**±12.12	103.04±2.19	42.82±2.68	15.18±2.78
ProNoG	48.39±3.19	13.38±2.21	51.35±1.32	29.42±6.46	22.37±3.22	47.50±8.84	**14.70**±1.65	44.34±2.16	14.83±1.39
IGAP	66.59±5.53	5.07±2.56	53.08±1.98	27.94±2.43	24.59±3.09	53.47±10.67	112.56±0.07	49.40±0.91	11.65±1.40
MTG	48.89±9.00	8.02±4.89	51.38±0.78	24.30±0.53	22.43±2.93	49.37±12.01	112.50±0.03	51.73±1.34	11.03±0.59
SUPT	67.30±4.73	4.08±2.37	54.41±2.33	25.45±1.79	22.69±2.45	45.52±17.28	114.07±0.02	49.97±1.36	10.69±0.96
GAPTUNE+	64.34±3.62	**21.35**±2.62	**57.74**±0.61	31.60±3.23	26.67±2.54	56.65±7.41	15.15±0.79	**57.45**±1.62	**16.00**±2.13

Table 25: 100-shot same-dataset results for GCN across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.75±0.63	37.84±0.46	55.49±0.48	40.03±3.77	33.79±1.16	59.01±6.61	40.11±48.15	50.34±1.30	25.61±8.79
All-in-One	87.92±0.57	32.11±3.41	53.43±1.19	39.92±0.51	36.78±1.18	51.73±9.61	88.08±2.16	57.51±1.51	22.97±0.81
EdgePrompt	82.32±0.87	**44.05**±0.73	54.53±0.45	39.34±0.94	39.68±1.17	**59.36**±6.52	80.98±0.22	52.32±0.63	25.20±3.19
EdgePrompt+	84.17±1.17	39.40±0.73	54.37±0.26	45.52±2.13	38.22±1.25	55.94±11.39	80.43±0.86	52.47±0.64	28.78±1.41
GPF	**89.11**±0.33	43.64±0.61	54.38±0.88	39.62±1.91	39.49±0.97	58.47±4.54	104.80±0.57	52.07±0.95	24.05±3.06
GPF+	87.36±0.43	41.38±0.54	54.08±0.42	41.80±2.24	37.88±1.32	55.92±5.39	104.42±0.43	52.53±0.34	27.87±0.53
GPPT	88.21±0.67	25.28±2.97	54.07±0.80	33.06±5.94	33.13±4.04	57.73±9.24	113.64±1.78	50.02±1.92	19.18±1.16
GraphPrompt	81.10±0.31	19.58±0.96	53.98±0.36	38.66±0.99	28.75±0.51	56.20±8.79	20.46±0.37	44.45±1.41	30.47±1.12
GraphPrompt+	85.25±1.30	19.29±0.81	54.29±0.70	37.92±1.09	26.13±1.10	56.45±7.05	18.33±1.33	42.67±1.16	25.51±2.42
ProNoG	86.26±0.30	39.08±0.51	54.62±0.82	32.99±1.92	31.21±1.30	48.70±9.25	**7.92**±2.02	42.85±1.41	26.59±0.42
IGAP	85.38±0.56	36.88±0.76	53.93±0.34	43.37±2.05	36.10±1.33	49.14±8.77	79.08±0.47	54.66±0.52	28.13±0.75
MTG	87.01±0.74	42.79±0.81	53.82±0.39	43.62±2.34	39.65±1.21	50.76±10.75	82.61±0.74	52.78±0.56	29.28±1.37
SUPT	88.49±0.48	42.76±0.50	54.02±0.31	41.55±2.48	37.70±1.28	44.67±7.52	104.33±0.46	53.97±0.75	27.97±0.90
GAPTUNE+	88.85±0.43	41.98±0.85	**57.00**±0.65	**46.52**±1.57	**40.97**±1.18	58.63±7.85	9.04±0.37	**60.06**±1.23	**34.04**±1.39
Pretrain (ContextPred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.57±0.50	37.75±0.48	55.11±0.79	40.71±1.70	35.00±0.86	60.94±5.17	43.34±45.36	52.18±0.84	24.33±7.46
All-in-One	86.01±0.51	16.42±0.70	54.61±0.60	39.97±0.64	37.05±0.79	53.06±6.97	98.92±2.70	50.83±1.41	28.81±0.55
EdgePrompt	81.43±1.78	43.08±0.65	54.28±0.57	40.48±1.39	38.78±1.83	55.69±10.08	93.07±0.43	52.21±0.70	28.11±3.09
EdgePrompt+	83.66±2.43	39.22±1.09	54.06±0.50	**46.94**±2.55	37.63±1.30	56.96±9.88	92.62±0.56	52.30±1.56	30.73±1.11
GPF	**88.33**±0.42	**43.20**±0.94	54.00±0.66	41.59±1.07	38.59±0.94	57.55±8.59	105.54±0.41	52.02±0.71	28.88±0.90
GPF+	86.60±0.41	41.93±0.76	54.13±0.61	41.32±1.78	37.55±0.77	57.55±8.93	105.23±0.35	51.89±1.14	30.46±0.75
GPPT	86.83±0.57	29.30±3.73	52.17±0.82	35.70±1.01	36.26±1.88	57.32±8.11	113.94±1.87	50.25±0.61	20.76±1.20
GraphPrompt	86.12±0.32	20.01±0.62	53.27±0.66	38.10±2.25	29.29±1.50	62.32±7.28	20.60±0.50	47.17±1.26	29.99±0.36
GraphPrompt+	85.62±0.53	18.90±2.23	53.88±0.62	37.95±1.71	28.29±2.27	**64.41**±4.34	19.70±0.19	44.58±1.21	27.20±1.88
ProNoG	85.76±0.70	36.49±0.47	53.49±0.61	35.16±1.26	30.47±2.28	53.60±11.50	10.31±1.91	44.75±1.25	26.28±0.71
IGAP	86.86±0.68	36.87±0.71	53.21±0.48	43.06±1.88	35.62±0.86	51.84±7.20	81.76±0.41	52.49±1.08	29.94±0.80
MTG	85.01±1.85	42.10±1.03	53.79±0.40	44.26±1.99	39.61±1.61	54.15±4.82	93.03±0.61	51.65±1.14	31.40±1.37
SUPT	87.36±0.41	42.86±0.81	53.33±0.56	42.67±1.79	37.42±0.83	48.15±7.71	104.98±0.30	52.00±0.95	30.38±0.78
GAPTUNE+	88.20±0.55	41.79±0.92	**56.43**±0.62	46.64±1.67	**40.48**±1.18	60.80±6.03	**8.69**±0.13	**56.90**±1.32	**35.58**±1.11
Pretrain (DGI) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.67±0.60	33.24±0.45	55.73±0.56	42.28±1.40	35.40±1.16	62.60±4.98	**5.36**±0.20	44.94±2.04	29.26±1.05
All-in-One	86.54±0.39	31.59±2.09	54.64±0.36	40.23±1.17	38.05±0.92	57.65±11.14	80.60±4.12	53.77±0.86	26.91±2.43
EdgePrompt	80.73±2.98	30.50±2.95	54.48±0.71	38.66±0.84	41.06±0.87	59.59±6.79	86.04±0.88	51.04±0.67	25.23±3.45
EdgePrompt+	83.61±1.70	32.85±1.23	54.42±0.64	45.62±1.61	40.43±0.99	**66.30**±4.02	85.22±0.73	51.20±0.51	30.93±1.30
GPF	88.30±0.36	30.63±2.93	54.41±0.68	40.78±2.68	40.14±1.14	60.33±5.83	97.76±0.72	51.02±0.57	25.51±2.80
GPF+	86.60±0.53	30.08±2.71	54.76±0.64	40.00±1.42	38.27±0.57	61.66±7.01	97.16±0.69	51.20±0.61	29.29±1.61
GPPT	84.54±0.78	36.01±0.92	52.03±2.14	34.51±3.83	36.68±0.87	54.95±7.71	104.84±8.45	50.18±1.08	23.22±1.43
GraphPrompt	81.67±0.30	19.03±1.38	53.56±0.44	35.27±1.62	28.49±1.41	59.90±9.95	18.38±0.08	44.37±1.01	31.80±0.56
GraphPrompt+	86.25±0.41	16.37±2.01	54.11±0.34	38.33±2.93	29.66±2.28	61.15±9.62	18.58±0.28	44.86±1.20	27.48±2.88
ProNoG	79.23±0.57	**37.97**±0.35	52.86±0.83	34.66±1.71	31.22±2.70	51.99±8.68	9.63±1.89	45.04±0.72	27.46±0.46
IGAP	85.23±0.66	29.83±2.10	53.61±0.47	41.21±1.39	37.73±0.64	51.95±11.11	75.45±0.50	51.09±0.53	30.88±1.07
MTG	85.75±1.89	34.33±1.78	54.11±0.57	44.61±1.62	41.26±0.86	55.65±12.20	85.69±0.81	52.47±0.67	31.53±2.20
SUPT	88.69±0.45	31.09±2.43	53.51±0.53	41.10±1.54	38.98±0.76	51.19±11.17	97.34±0.79	52.41±0.91	29.22±1.85
GAPTUNE+	**88.78**±0.55	35.75±1.15	**56.85**±0.66	**46.82**±1.51	**42.10**±0.90	63.53±6.88	8.50±0.14	**57.83**±1.16	**36.12**±1.12
Pretrain (EdgePred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**87.17**±0.40	**38.18**±0.78	55.42±0.67	41.62±1.42	35.39±0.93	**59.69**±4.37	**5.39**±0.19	45.94±2.84	29.26±1.05
All-in-One	60.67±0.78	12.22±1.04	55.03±0.80	43.34±0.86	37.52±1.53	54.85±11.40	98.92±2.70	60.96±1.64	24.97±1.76
EdgePrompt	73.82±3.73	28.97±1.33	52.81±0.36	39.67±1.11	37.15±0.73	50.38±11.76	93.07±0.43	52.65±0.89	27.04±2.37
EdgePrompt+	83.56±1.24	32.70±1.34	54.39±0.72	46.96±2.17	38.59±0.79	55.18±8.60	92.62±0.56	52.88±1.01	30.34±1.00
GPF	74.90±2.71	26.77±2.01	52.83±0.51	40.53±1.90	37.48±0.99	50.71±7.81	105.54±0.41	52.29±0.97	23.70±3.66
GPF+	86.29±0.86	29.57±1.91	54.49±0.11	41.57±0.48	38.47±1.46	53.27±5.34	105.23±0.35	50.33±2.36	29.05±0.66
GPPT	32.33±2.73	3.30±0.28	52.84±1.40	35.62±1.76	30.96±1.34	57.55±8.05	113.94±1.87	49.99±0.23	23.22±1.43
GraphPrompt	37.21±1.49	10.73±0.52	52.53±0.61	34.99±1.22	29.27±3.01	51.81±10.36	39.54±42.82	46.17±1.42	31.86±0.39
GraphPrompt+	81.55±1.35	9.64±2.64	53.94±0.37	37.90±2.31	28.46±1.59	59.57±8.94	19.70±0.19	43.33±1.45	23.95±0.66
ProNoG	33.02±0.48	14.54±0.54	52.17±0.86	37.47±1.76	31.23±1.25	50.77±12.47	10.31±1.91	41.53±1.20	26.13±0.66
IGAP	74.66±1.12	26.78±1.22	52.91±0.50	41.49±0.80	36.31±1.21	42.57±5.33	89.98±9.67	51.77±1.26	29.66±0.67
MTG	83.09±1.48	32.85±1.79	53.66±0.51	45.47±1.98	38.49±0.79	51.66±7.27	93.52±0.52	51.09±1.05	30.86±1.23
SUPT	84.90±1.13	29.98±1.82	52.85±0.67	42.92±0.85	37.74±1.28	38.02±6.57	105.27±0.34	51.90±1.14	29.02±1.24
GAPTUNE+	84.43±0.90	33.04±1.21	**55.85**±0.69	**47.89**±1.74	**39.88**±0.85	59.02±8.01	9.28±0.35	**61.24**±1.34	**35.58**±1.22
Pretrain (GraphCL) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.66±0.70	37.30±0.83	55.83±0.19	39.90±1.91	34.80±1.03	57.12±10.40	5.67±0.11	50.82±1.52	29.76±0.49
All-in-One	86.78±0.55	14.33±1.18	53.62±0.82	42.28±1.31	36.43±0.76	49.29±10.70	111.92±1.17	56.66±1.66	28.01±0.73
EdgePrompt	82.92±0.52	**37.89**±2.92	54.81±0.37	39.27±0.67	39.07±0.92	50.18±10.27	69.30±0.53	50.91±0.98	28.10±0.32
EdgePrompt+	84.06±2.19	33.56±1.03	54.37±0.31	46.28±2.27	38.31±1.91	51.51±8.69	63.53±1.01	52.15±1.07	28.76±0.79
GPF	**88.75**±0.50	35.56±1.64	54.74±0.34	41.47±2.44	37.57±1.22	56.07±11.58	114.92±1.24	51.02±1.36	28.01±0.30
GPF+	87.56±0.70	35.36±2.34	54.26±0.67	39.80±1.95	36.78±1.18	55.20±10.97	113.95±0.94	51.22±1.10	29.28±0.44
GPPT	87.82±1.03	29.86±0.64	51.70±1.57	32.84±1.97	37.12±0.79	54.48±10.02	116.83±0.24	50.09±0.28	19.34±0.98
GraphPrompt	84.32±0.50	20.28±0.23	54.18±0.47	36.46±1.48	26.15±1.98	54.69±8.44	102.03±0.35	45.75±2.03	29.10±0.81
GraphPrompt+	87.38±0.60	20.32±0.22	54.62±0.37	37.47±0.66	29.34±1.14	**59.06**±12.07	26.21±9.61	44.92±1.39	27.46±0.65
ProNoG	86.81±0.28	30.46±0.49	54.45±0.78	36.18±2.12	29.17±1.38	51.84±11.29	**5.37**±1.14	43.71±1.36	25.76±0.68
IGAP	86.96±0.94	32.12±1.52	53.52±0.43	42.46±2.21	33.73±1.58	45.26±7.29	103.47±0.73	53.95±1.25	29.49±0.70
MTG	87.81±1.45	35.93±1.63	53.81±0.27	44.42±2.43	40.51±1.21	45.60±7.67	70.46±0.93	51.10±0.84	30.12±0.68
SUPT	86.71±0.60	36.36±2.04	53.58±0.21	40.96±1.91	36.86±1.32	47.28±8.87	114.10±1.01	50.55±0.93	29.14±0.53
GAPTUNE+	88.64±0.68	34.90±1.44	**57.19**±0.49	**46.89**±1.66	**41.15**±1.15	56.81±8.92	11.76±0.77	**59.29**±1.51	**34.53**±1.07
Pretrain (InfoGraph) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.19±0.75	**38.25**±1.11	55.57±0.68	41.09±1.77	34.59±1.22	58.24±3.32	**5.26**±0.07	50.42±1.75	29.32±0.57
All-in-One	74.86±0.55	19.65±8.10	54.02±0.33	43.34±0.86	37.91±0.73	53.27±7.71	112.04±1.15	60.96±1.64	24.97±1.76
EdgePrompt	79.45±1.07	36.47±0.57	54.80±0.54	39.67±1.11	39.74±0.82	48.52±5.31	96.44±1.28	52.65±0.89	27.04±2.37
EdgePrompt+	83.60±1.80	36.33±0.10	54.20±0.53	46.96±2.17	38.87±0.70	54.08±4.17	95.50±0.52	52.88±1.01	30.34±1.00
GPF	87.38±0.27	34.92±0.68	54.52±0.78	39.90±1.09	39.09±0.60	56.71±7.22	115.53±0.86	52.54±0.97	25.84±3.26
GPF+	87.50±0.50	33.72±1.15	54.38±0.50	39.87±1.64	37.82±0.41	54.85±5.90	114.90±0.98	52.77±1.00	30.25±0.62
GPPT	73.22±1.01	5.51±0.34	51.67±1.20	35.62±1.76	36.20±1.01	56.76±9.51	116.78±0.27	49.99±0.23	20.04±0.70
GraphPrompt	74.63±0.75	14.20±1.05	53.28±0.62	36.03±0.69	30.07±2.14	58.44±10.98	99.37±0.56	46.60±2.07	31.97±0.46
GraphPrompt+	85.65±0.86	15.07±2.42	54.39±0.67	36.99±1.39	27.80±1.31	**60.23**±9.69	20.30±1.06	44.15±1.35	30.09±3.23
ProNoG	76.77±1.03	20.33±0.70	53.68±0.63	34.76±1.49	34.39±1.37	50.74±10.10	8.04±1.46	41.86±1.30	27.28±0.45
IGAP	85.13±0.65	30.06±0.91	53.42±0.39	41.32±1.58	37.06±0.98	48.27±6.56	107.27±0.74	53.49±0.79	30.92±0.59
MTG	85.73±1.50	38.11±0.37	53.58±0.46	45.94±1.92	40.34±0.66	51.86±7.26	97.20±0.65	54.11±0.86	31.40±1.27
SUPT	**88.45**±0.43	34.60±1.22	53.27±0.26	41.30±1.32	37.57±0.56	37.55±6.80	114.64±0.76	51.69±0.65	29.98±1.18
GAPTUNE+	88.28±0.43	36.55±0.64	**57.08**±0.62	**48.09**±1.72	**41.28**±0.81	58.60±6.68	10.20±0.30	**62.32**±1.52	**36.00**±0.93

Table 26: 100-shot same-dataset results for GAT across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.29±0.75	39.88±0.64	55.91±0.21	34.84±1.67	36.11±1.05	**63.49**±9.99	24.94±6.90	52.87±1.01	**38.93**±1.24
All-in-One	**87.79**±0.37	34.79±0.99	53.14±0.75	36.86±2.17	32.04±0.92	56.53±13.35	97.19±0.61	57.64±0.56	18.14±8.00
EdgePrompt	75.92±5.10	**44.89**±0.53	54.16±0.44	26.48±1.74	34.30±1.54	61.43±8.98	98.86±0.75	50.69±0.59	18.40±3.79
EdgePrompt+	77.56±3.95	40.84±1.07	55.02±0.60	39.47±1.10	36.80±0.74	60.97±4.33	98.30±0.89	52.22±1.35	33.82±3.02
GPF	87.10±1.30	44.84±0.61	53.84±0.50	28.81±2.34	34.33±0.68	59.90±9.36	109.48±0.43	50.72±0.94	22.65±4.37
GPF+	86.41±1.29	42.64±1.06	54.67±0.44	33.59±0.90	36.70±1.85	59.82±5.80	109.45±0.57	51.12±0.60	23.51±6.44
GPPT	87.74±0.62	24.18±2.39	52.49±1.92	27.67±4.43	33.47±1.92	61.53±5.31	113.77±2.16	49.75±0.71	20.50±2.86
GraphPrompt	83.95±0.76	20.56±0.95	54.41±0.27	38.53±0.86	29.08±1.53	56.73±5.99	24.26±0.52	42.94±1.50	34.40±0.45
GraphPrompt+	84.41±1.07	20.49±1.51	54.98±0.21	37.92±1.09	28.34±2.18	53.29±8.66	23.65±3.69	42.40±1.08	35.46±0.90
ProNoG	87.40±0.47	38.38±0.62	55.08±0.52	30.20±0.99	30.79±1.87	50.51±6.83	11.32±1.69	41.43±1.28	31.31±0.75
IGAP	84.59±1.63	37.59±1.08	53.73±0.20	37.62±0.93	35.39±1.59	47.39±7.75	86.10±0.66	47.94±1.14	29.86±4.60
MTG	81.79±3.18	43.69±1.00	53.62±0.27	37.29±1.10	37.70±1.03	57.34±5.85	98.36±0.74	50.69±1.00	29.47±3.98
SUPT	86.76±1.23	44.19±0.82	53.87±0.21	33.73±1.28	35.59±2.05	44.91±9.15	109.27±0.54	52.98±0.73	22.95±5.42
GAPTUNE+	87.41±0.72	42.78±0.89	**56.91**±0.54	**41.16**±1.28	**38.67**±1.12	62.97±7.55	**10.70**±0.45	**59.52**±1.02	37.08±1.41
Pretrain (ContextPred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**87.76**±0.76	39.36±0.59	56.40±0.26	34.89±2.30	36.20±1.28	63.32±14.02	20.94±1.19	52.56±1.13	35.54±3.52
All-in-One	85.97±0.65	35.07±0.64	54.08±0.47	34.03±1.14	31.04±1.06	49.03±8.94	113.94±0.71	50.40±2.18	35.75±2.58
EdgePrompt	77.43±1.44	43.16±0.77	56.03±0.29	39.39±0.94	32.79±0.80	50.64±12.35	110.30±0.48	51.85±0.82	33.69±3.79
EdgePrompt+	84.31±1.01	39.85±0.67	55.73±0.58	40.00±1.06	36.20±1.39	56.28±16.38	110.13±0.84	52.73±1.14	38.82±1.27
GPF	87.22±0.43	**43.93**±0.60	55.97±0.41	30.84±0.96	32.68±0.43	53.29±13.27	116.00±0.49	51.77±1.21	34.22±4.13
GPF+	86.71±1.14	41.15±2.30	55.58±0.44	32.91±1.97	35.82±0.54	55.08±15.51	116.19±0.53	51.98±0.92	35.07±3.84
GPPT	86.06±0.85	34.53±3.68	50.30±0.42	35.06±1.33	31.52±2.23	**65.40**±7.82	116.95±0.14	49.33±2.95	27.21±0.56
GraphPrompt	82.49±0.82	20.82±0.38	54.36±0.69	37.80±2.05	27.69±1.43	61.91±6.65	108.35±0.41	45.01±1.58	34.84±0.34
GraphPrompt+	84.36±1.39	21.57±0.81	54.81±0.70	38.63±1.16	27.62±2.41	59.95±5.79	105.19±1.39	45.41±1.68	35.55±0.84
ProNoG	82.30±1.14	35.78±0.60	55.35±0.63	26.63±2.45	29.85±0.80	51.56±14.48	**10.54**±0.90	44.25±1.29	30.97±0.24
IGAP	86.43±1.28	37.05±1.65	53.87±0.37	36.71±1.76	34.15±0.94	51.55±12.11	112.86±0.63	51.76±1.36	34.78±2.25
MTG	85.11±1.07	41.94±0.89	53.89±0.39	39.82±1.30	36.58±1.02	49.48±12.03	109.57±0.90	51.28±1.79	37.38±2.60
SUPT	87.18±0.99	42.67±2.22	53.86±0.29	32.47±1.84	35.73±0.57	55.03±10.58	116.06±0.49	51.68±1.54	36.52±3.90
GAPTUNE+	87.27±0.75	40.82±0.79	**57.89**±0.39	**42.24**±1.29	**37.85**±1.16	57.48±5.70	11.91±0.16	**56.13**±1.72	**42.54**±1.31
Pretrain (DGI) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**87.23**±0.96	36.22±0.54	56.46±0.46	32.13±1.86	38.40±0.91	64.67±7.90	27.83±4.37	51.43±1.32	38.82±1.41
All-in-One	82.67±0.88	32.65±2.17	53.34±0.97	34.25±6.58	37.93±1.01	45.36±14.35	107.98±0.46	50.05±1.11	22.30±1.17
EdgePrompt	76.24±1.81	35.20±3.42	56.13±0.45	30.53±6.29	38.62±2.16	55.48±7.92	78.37±0.85	51.37±1.60	25.10±6.77
EdgePrompt+	80.97±2.64	36.17±1.10	56.29±0.64	40.71±0.46	37.75±2.07	**64.80**±5.02	71.91±0.24	50.79±1.64	39.20±1.01
GPF	82.89±3.11	34.12±4.80	55.91±0.30	27.92±3.64	38.65±1.07	58.62±4.85	113.88±1.09	50.89±0.85	29.24±3.69
GPF+	82.20±0.74	32.78±2.71	56.38±0.53	33.57±2.88	39.10±0.94	60.71±4.57	113.91±1.17	50.54±0.25	32.42±2.34
GPPT	69.92±8.95	36.06±0.60	50.95±1.05	32.03±1.50	35.36±2.06	60.03±10.57	116.55±0.47	50.13±0.22	24.92±2.82
GraphPrompt	67.62±0.27	15.49±2.25	55.42±0.15	31.80±0.49	31.11±4.07	58.04±8.12	92.94±0.57	40.37±0.99	38.30±0.52
GraphPrompt+	76.37±2.79	17.59±0.84	55.66±0.64	38.41±3.04	30.73±3.79	54.23±6.64	84.89±2.52	41.02±0.79	38.07±0.60
ProNoG	57.84±1.03	**37.86**±0.51	55.22±0.66	30.41±1.85	34.99±2.42	55.97±10.10	12.79±0.49	40.21±0.98	26.93±1.38
IGAP	78.63±0.81	29.98±2.42	53.68±0.37	36.20±2.16	37.77±1.88	46.09±9.69	101.89±0.79	46.79±0.70	34.84±1.82
MTG	82.69±2.50	36.62±1.89	53.94±0.24	38.49±2.32	38.94±1.92	48.08±10.39	78.38±0.50	51.57±0.70	35.28±2.24
SUPT	82.70±1.16	31.38±3.72	53.38±0.24	32.66±3.29	39.13±1.18	41.46±13.76	113.55±1.24	50.30±0.82	33.49±2.16
GAPTUNE+	83.95±1.18	36.61±1.24	**58.10**±0.56	**41.82**±1.46	**40.57**±1.13	58.42±7.49	**11.67**±0.30	**55.78**±1.58	**42.31**±0.83
Pretrain (EdgePred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**88.27**±0.27	**38.09**±0.66	55.53±0.46	30.33±2.30	37.42±1.19	**64.08**±11.37	20.94±1.29	49.11±2.53	34.58±1.35
All-in-One	55.30±1.92	13.37±1.88	52.79±0.66	33.67±6.96	33.43±2.54	55.54±10.18	113.94±0.71	46.17±1.49	29.10±1.22
EdgePrompt	60.28±7.97	28.00±1.72	54.48±0.82	25.14±0.11	36.20±0.47	55.77±6.47	110.30±0.48	51.07±4.88	22.58±5.98
EdgePrompt+	81.10±0.92	34.76±1.11	55.42±0.77	34.91±3.92	37.70±1.11	62.68±12.47	110.13±0.84	54.54±3.25	33.69±2.27
GPF	61.18±7.30	26.39±1.01	54.32±1.20	25.29±0.62	35.59±1.34	60.79±9.90	116.00±0.49	53.79±2.33	20.76±3.68
GPF+	84.65±1.99	30.28±3.21	55.27±0.29	25.54±0.70	37.38±0.68	57.12±11.46	116.00±0.54	53.33±2.40	25.64±1.85
GPPT	12.45±1.83	3.06±0.54	51.54±1.86	34.94±1.27	29.06±0.75	61.79±9.89	116.95±0.14	50.05±0.48	15.61±2.98
GraphPrompt	23.39±1.55	6.42±0.77	53.41±0.76	35.44±2.23	28.46±2.43	57.07±13.82	108.35±0.41	42.13±2.22	33.91±1.38
GraphPrompt+	76.60±2.60	6.57±1.78	55.18±0.36	**39.39**±0.87	27.74±2.29	62.55±8.22	105.19±1.39	41.50±1.01	32.14±2.48
ProNoG	20.47±1.23	7.98±0.70	53.56±0.84	33.11±1.49	30.19±1.61	56.76±6.43	**10.54**±0.90	40.71±0.99	28.99±0.71
IGAP	69.14±1.48	24.42±2.47	52.58±0.42	30.28±1.49	35.88±1.14	57.59±6.88	112.30±0.57	49.96±3.35	29.43±1.65
MTG	78.61±2.65	35.45±1.63	53.50±0.42	33.46±2.61	38.92±0.93	52.85±7.22	109.52±0.56	49.55±2.94	31.02±2.84
SUPT	80.37±2.79	30.65±3.09	52.90±0.29	24.85±0.82	36.72±0.91	54.73±7.19	115.56±0.49	53.29±4.68	25.31±1.91
GAPTUNE+	79.67±1.32	33.62±1.13	**56.90**±0.58	38.18±2.02	**39.41**±0.91	62.05±8.87	13.91±0.19	**54.78**±2.09	**37.63**±1.49
Pretrain (GraphCL) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.54±0.23	**37.80**±0.69	55.76±0.47	35.09±1.55	36.85±1.54	60.59±12.50	31.11±1.16	52.46±1.33	20.18±2.09
All-in-One	86.13±0.69	35.35±3.11	53.36±1.00	35.27±3.60	28.33±1.13	53.65±15.82	110.30±0.28	53.21±1.84	26.32±0.56
EdgePrompt	83.10±1.76	35.76±1.80	53.55±0.26	38.00±0.43	34.24±0.83	60.36±11.18	84.63±1.06	51.62±0.35	17.07±4.76
EdgePrompt+	84.69±0.93	32.72±1.82	54.07±0.66	41.04±0.48	37.52±1.46	57.70±11.33	80.95±1.07	52.56±1.36	24.82±2.11
GPF	**89.35**±0.46	36.54±1.89	53.84±0.48	34.13±1.28	34.59±0.95	54.80±12.60	116.01±0.49	50.85±0.91	16.77±3.05
GPF+	87.85±0.27	35.08±4.24	54.41±0.38	36.08±0.61	35.49±1.78	58.16±13.60	116.07±0.40	51.03±0.46	12.57±2.67
GPPT	86.58±0.82	31.70±0.91	52.50±1.27	36.81±2.45	34.45±1.41	56.05±10.71	116.76±0.25	49.71±0.73	16.43±2.24
GraphPrompt	84.29±0.23	19.05±0.95	53.90±0.43	33.92±1.07	23.37±0.74	55.69±10.22	102.39±0.84	46.51±0.89	29.92±0.45
GraphPrompt+	85.68±3.01	18.59±0.83	54.55±0.53	39.82±1.03	29.21±1.50	61.07±10.27	93.03±1.43	45.20±1.17	30.07±1.02
ProNoG	84.05±0.82	33.11±0.42	54.51±0.55	33.57±1.41	29.81±1.40	57.09±10.25	**5.08**±0.46	45.21±1.05	24.33±0.28
IGAP	86.99±0.34	31.23±3.05	53.94±0.31	37.54±0.70	33.23±1.33	53.04±10.00	106.86±0.49	50.44±0.82	18.42±1.94
MTG	87.27±0.97	36.14±2.16	53.80±0.22	40.13±0.47	38.25±1.36	52.73±6.52	85.93±1.15	53.36±1.04	22.98±3.32
SUPT	88.35±0.31	35.92±3.73	53.83±0.35	36.75±0.85	36.71±1.78	56.30±9.06	115.83±0.46	49.04±0.87	14.29±2.79
GAPTUNE+	88.02±0.41	34.93±1.49	**56.29**±0.54	**42.68**±0.81	**39.25**±1.21	**61.20**±8.03	12.66±0.20	**57.53**±1.59	**32.30**±1.31
Pretrain (InfoGraph) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**87.63**±0.75	**39.27**±0.80	56.28±0.39	32.76±2.12	38.05±1.19	69.49±9.49	33.41±2.15	53.56±1.56	27.44±3.13
All-in-One	63.43±0.93	24.83±0.98	54.63±0.50	31.39±5.55	36.33±1.53	60.23±6.14	112.10±0.61	56.04±0.87	25.18±0.84
EdgePrompt	77.59±3.56	38.69±1.82	55.18±0.33	26.96±4.61	38.54±0.97	**70.46**±5.32	106.33±0.61	52.09±1.09	11.66±2.99
EdgePrompt+	81.29±2.61	36.14±1.22	55.58±0.38	41.24±1.35	37.96±1.31	68.29±10.31	105.41±0.47	52.97±1.18	22.00±3.37
GPF	83.13±0.95	38.69±1.29	55.32±0.48	25.16±0.50	36.29±2.37	65.05±11.73	116.09±0.43	52.72±1.05	13.97±3.01
GPF+	85.26±1.22	32.81±2.12	55.13±0.46	26.08±1.83	37.48±1.56	62.30±10.43	116.08±0.52	53.72±0.91	12.89±4.11
GPPT	60.12±1.62	5.17±0.54	51.48±1.51	32.84±3.51	34.77±1.48	56.51±9.15	116.98±0.14	49.96±0.35	20.73±0.80
GraphPrompt	55.93±1.41	14.03±0.47	54.08±0.26	36.20±1.68	31.18±1.45	68.04±9.28	108.50±0.89	46.08±1.45	35.03±0.56
GraphPrompt+	84.01±2.79	14.42±1.19	55.10±0.56	38.23±1.63	29.75±2.49	58.24±6.01	87.00±8.59	43.37±1.57	**38.11**±0.40
ProNoG	56.01±2.37	20.15±0.32	54.09±0.51	30.41±0.98	33.27±1.09	65.97±10.09	**4.78**±0.11	41.03±1.03	29.61±0.56
IGAP	78.51±1.32	28.66±1.71	53.43±0.22	32.39±1.63	36.41±1.47	56.80±7.15	112.08±0.73	54.48±1.30	19.94±2.90
MTG	82.35±2.54	37.56±1.26	53.94±0.15	37.57±2.44	39.33±1.15	53.03±9.51	106.00±0.49	53.50±0.69	19.79±3.71
SUPT	86.33±1.20	34.13±2.05	53.64±0.17	26.49±1.58	36.56±1.31	55.79±5.71	116.02±0.41	53.63±1.00	14.83±3.73
GAPTUNE+	85.76±0.66	37.08±1.05	**57.25**±0.44	**42.44**±1.57	**39.95**±1.12	66.87±7.01	11.13±0.35	**59.76**±1.28	31.79±1.44

Table 27: 100-shot same-dataset results for GIN across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.72±0.72	36.95±0.89	56.07±0.67	40.13±2.23	**37.79**±1.27	**66.51**±12.60	37.03±3.68	50.16±2.01	**39.53**±1.10
All-in-One	86.53±0.28	22.95±1.99	54.61±0.40	38.96±2.29	35.75±1.35	60.23±5.84	27.80±0.85	54.87±1.37	26.16±4.38
EdgePrompt	79.97±0.73	39.71±1.10	57.40±0.54	38.23±1.39	34.29±2.36	58.06±5.28	41.59±1.71	51.04±0.76	24.75±6.50
EdgePrompt+	82.59±1.76	38.08±1.23	56.89±0.65	41.75±4.02	34.24±2.22	65.20±3.83	37.08±1.66	52.25±1.27	32.91±1.24
GPF	87.21±0.45	36.95±1.06	56.26±0.60	39.01±0.68	32.85±2.47	61.40±5.50	53.32±2.87	51.74±1.27	31.93±3.05
GPF+	86.92±0.39	36.51±0.53	55.66±0.30	39.92±1.57	32.56±7.21	60.31±6.15	48.00±2.50	51.19±1.39	31.05±1.47
GPPT	87.54±0.78	27.83±3.16	52.14±1.76	36.41±1.55	29.48±4.95	59.17±7.60	43.58±9.14	50.76±1.39	19.13±0.54
GraphPrompt	85.78±0.94	23.16±0.82	54.64±0.42	38.35±0.97	29.51±1.16	53.83±4.67	35.57±4.98	42.18±1.69	31.44±0.37
GraphPrompt+	72.27±14.41	19.27±4.64	55.54±0.48	37.90±1.09	26.08±1.19	55.66±10.98	33.20±1.18	42.69±0.67	29.26±3.05
ProNoG	83.51±1.42	39.73±0.74	55.29±0.50	37.97±1.24	30.79±1.91	54.44±9.99	17.45±9.80	42.00±1.38	25.22±1.25
IGAP	86.39±0.82	33.89±0.57	54.00±0.50	40.79±1.73	32.01±6.08	49.24±12.90	42.73±3.62	48.75±1.30	31.93±1.13
MTG	83.70±1.32	**40.31**±1.16	54.69±0.69	42.03±3.19	34.29±2.63	53.85±7.12	38.63±1.70	53.59±1.16	30.79±2.49
SUPT	**88.38**±0.44	37.04±0.55	53.29±0.81	41.69±1.42	33.89±7.57	43.29±11.13	49.45±1.87	50.13±1.54	32.03±2.18
GAPTUNE+	88.05±0.37	39.00±0.95	**58.98**±0.56	**43.90**±1.74	36.28±2.21	64.55±5.56	**7.50**±0.17	**58.57**±1.57	37.14±1.22
Pretrain (ContextPred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**87.49**±0.63	**34.07**±0.58	56.73±1.00	39.95±1.61	38.28±1.17	64.08±11.46	36.24±1.66	52.22±1.59	**42.46**±0.31
All-in-One	83.43±0.35	24.38±0.84	54.83±0.32	40.03±1.27	36.00±1.22	59.77±8.07	36.04±0.94	54.13±1.40	30.01±4.39
EdgePrompt	75.17±4.30	18.57±1.81	57.02±0.48	40.03±2.13	35.61±1.50	53.88±6.00	32.97±0.77	53.98±0.63	31.87±1.77
EdgePrompt+	82.79±2.91	20.78±2.28	56.91±0.58	44.43±2.43	36.07±0.97	56.58±11.60	33.09±1.58	54.12±1.14	34.43±7.53
GPF	86.61±0.47	30.94±1.75	56.63±0.15	40.25±1.55	37.36±2.00	53.67±11.46	33.24±1.56	53.71±1.96	31.36±3.79
GPF+	86.00±0.38	32.64±1.79	56.49±0.62	40.00±1.81	38.80±1.86	54.64±12.57	32.62±0.72	52.49±2.07	35.53±1.48
GPPT	84.64±0.78	6.21±1.63	50.52±0.85	37.04±3.00	30.41±4.11	54.74±9.78	50.05±21.49	49.46±1.68	27.06±0.80
GraphPrompt	82.94±1.04	9.82±2.23	54.36±0.59	37.67±1.99	28.50±0.60	**64.72**±9.10	45.46±1.72	46.49±1.38	36.24±0.47
GraphPrompt+	74.15±18.49	2.40±0.47	54.77±0.99	37.34±1.14	26.65±1.56	57.60±6.60	45.32±1.51	45.85±1.02	32.80±6.17
ProNoG	83.20±1.04	23.33±2.79	55.03±0.55	35.54±2.08	30.26±2.06	48.72±10.73	13.77±4.69	44.94±1.15	30.12±0.83
IGAP	85.33±0.90	25.90±1.86	54.42±0.52	41.20±1.88	35.60±1.18	55.95±17.24	35.76±1.10	53.14±1.56	36.52±2.05
MTG	82.91±2.84	23.87±1.73	55.52±0.50	44.53±2.45	38.03±1.29	53.90±11.28	31.38±1.21	53.11±1.96	36.26±4.62
SUPT	85.80±0.36	32.40±1.46	54.79±1.00	41.26±1.95	38.23±1.83	58.73±16.38	32.53±0.79	52.30±1.69	34.92±1.60
GAPTUNE+	86.21±0.50	26.82±1.33	**58.69**±0.58	**47.40**±1.61	**39.05**±1.31	62.66±9.76	**6.00**±0.15	**58.96**±1.60	40.25±1.98
Pretrain (DGI) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**88.04**±1.05	32.41±1.02	56.19±0.96	40.68±2.59	39.48±0.98	**67.32**±9.26	37.00±2.73	49.74±2.12	**37.96**±1.08
All-in-One	85.15±1.15	8.22±3.80	53.95±2.03	39.75±0.72	35.91±0.91	58.67±11.08	34.42±0.82	53.72±1.39	19.49±9.47
EdgePrompt	67.88±5.14	23.17±3.70	57.19±0.38	34.94±3.11	37.23±1.35	56.15±7.34	50.69±2.26	52.54±1.49	25.46±1.63
EdgePrompt+	75.04±5.32	27.14±4.56	57.00±0.53	44.86±1.14	37.87±2.02	62.88±12.64	45.75±1.68	52.69±1.60	31.20±2.25
GPF	86.22±1.09	16.61±2.67	56.42±0.33	39.92±1.09	39.45±0.98	60.33±8.29	60.35±2.85	50.13±2.48	27.56±3.24
GPF+	86.09±1.00	22.90±5.41	56.09±0.25	40.94±1.79	39.92±0.99	61.61±8.62	57.08±2.19	48.87±2.35	27.39±2.12
GPPT	39.21±8.62	22.04±6.48	50.90±0.95	38.05±1.73	34.62±0.89	55.38±1.60	49.71±11.97	49.92±0.40	23.53±1.12
GraphPrompt	63.05±4.76	20.77±0.44	55.76±0.78	35.85±4.08	27.33±2.02	56.35±9.62	44.65±1.00	43.47±1.73	32.94±0.39
GraphPrompt+	60.75±23.42	20.01±1.18	54.64±0.84	39.47±2.65	27.64±1.84	55.31±8.92	44.81±1.01	44.30±1.70	30.03±5.33
ProNoG	63.89±1.90	**35.26**±1.11	56.06±0.67	31.11±2.48	30.10±4.00	59.64±7.23	10.17±2.98	41.86±1.09	24.21±0.22
IGAP	77.06±2.55	23.14±3.58	53.43±0.66	41.90±2.26	38.12±1.44	51.78±7.77	52.68±1.46	49.12±1.81	29.50±1.90
MTG	76.67±5.13	28.02±5.20	54.67±0.65	43.08±1.41	39.52±1.78	59.50±6.44	47.36±2.00	49.84±2.10	30.50±2.38
SUPT	86.47±0.94	21.83±4.73	53.03±0.81	42.50±1.76	40.09±0.82	55.98±10.47	57.59±1.97	50.73±2.12	26.60±2.59
GAPTUNE+	85.53±0.71	25.89±2.16	**59.01**±0.48	**45.43**±1.11	**40.88**±1.03	62.42±7.08	**6.77**±0.14	**57.74**±1.79	36.80±1.73
Pretrain (EdgePred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**87.05**±0.66	**27.13**±1.13	55.10±0.93	40.84±1.79	**38.06**±1.07	**66.96**±7.95	36.24±1.66	46.44±4.87	**40.97**±1.87
All-in-One	33.07±0.96	9.01±1.38	54.19±0.63	38.99±1.60	36.07±1.43	57.35±4.94	36.08±0.99	56.94±2.25	30.21±3.44
EdgePrompt	74.63±1.81	12.07±1.29	55.92±0.61	35.85±2.19	33.57±1.59	56.02±11.31	32.97±0.77	46.34±2.08	27.57±3.50
EdgePrompt+	76.44±4.74	16.34±1.85	55.78±0.73	47.24±0.61	34.60±0.70	55.61±4.51	33.09±1.58	47.18±3.64	34.67±4.25
GPF	75.16±2.33	11.49±2.48	55.57±0.72	40.78±1.57	36.22±1.16	56.58±6.72	33.24±1.56	43.80±1.00	30.84±1.86
GPF+	84.47±1.25	18.79±2.08	55.23±1.10	41.06±1.86	37.66±1.54	57.58±4.51	32.62±0.72	45.36±2.73	31.87±3.81
GPPT	19.08±4.82	3.42±3.27	50.91±0.91	39.16±2.42	31.32±1.91	57.07±7.02	50.05±21.49	50.31±0.70	24.42±1.13
GraphPrompt	22.49±0.46	3.14±1.15	54.36±0.98	38.53±2.14	27.30±1.19	58.39±7.57	44.51±0.58	44.26±3.45	34.48±0.84
GraphPrompt+	31.21±3.75	5.99±0.72	54.84±0.52	38.48±1.71	26.03±2.07	55.51±6.79	45.32±1.51	43.73±1.86	32.29±7.29
ProNoG	19.04±0.82	2.39±0.65	54.22±0.60	37.01±2.52	29.21±2.42	54.11±7.88	13.77±4.69	41.62±1.10	29.83±0.56
IGAP	68.56±1.07	15.42±1.94	52.87±0.30	43.24±1.78	34.70±1.27	50.49±13.50	34.77±0.82	45.09±2.72	35.11±3.18
MTG	79.62±4.18	17.34±1.48	54.04±0.53	44.17±1.12	35.55±1.06	53.71±11.60	32.23±1.18	44.80±3.27	32.49±3.56
SUPT	83.96±1.70	17.75±2.08	52.53±0.40	40.78±2.05	37.35±1.32	49.05±15.16	32.37±0.76	45.70±2.31	32.19±3.51
GAPTUNE+	83.07±1.16	18.54±1.32	**57.86**±0.47	**47.99**±0.93	37.46±1.20	61.30±5.20	**5.96**±0.17	**57.69**±2.18	40.11±1.79
Pretrain (GraphCL) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**87.71**±0.90	29.55±1.37	55.95±0.60	40.63±1.06	**38.26**±1.80	**67.83**±8.18	36.20±2.91	51.40±1.93	42.05±1.76
All-in-One	79.64±1.80	24.72±2.43	54.96±0.72	36.89±2.60	34.49±1.63	53.78±11.34	36.17±0.99	53.55±2.17	29.54±4.84
EdgePrompt	79.21±3.19	30.51±2.89	57.18±0.28	34.99±1.16	33.87±3.47	53.85±9.43	35.72±0.76	49.74±1.89	30.38±4.17
EdgePrompt+	82.11±1.85	30.17±3.44	57.09±0.42	45.24±2.21	36.16±1.58	60.00±7.30	35.92±1.44	49.99±1.54	39.31±2.50
GPF	84.98±1.06	23.55±3.29	56.23±0.56	40.96±1.31	36.11±2.06	49.77±5.37	37.19±2.05	51.35±1.72	32.45±0.76
GPF+	84.74±0.75	25.19±2.55	55.86±0.73	42.86±1.64	35.52±1.33	51.02±6.27	35.69±3.48	50.65±1.49	34.80±1.52
GPPT	22.75±2.59	11.63±2.70	51.17±0.61	40.53±1.70	23.46±3.58	54.82±9.47	108.95±94.89	49.99±1.93	31.34±1.48
GraphPrompt	67.70±2.15	15.06±0.61	55.28±0.73	33.04±2.87	22.84±2.15	47.37±8.16	45.73±1.06	44.38±1.75	37.20±0.59
GraphPrompt+	72.14±10.48	11.91±1.51	55.83±0.68	40.41±1.95	25.24±3.13	51.35±11.85	46.29±2.73	45.77±1.53	33.60±6.64
ProNoG	79.05±0.66	**32.73**±0.48	56.33±0.40	33.77±2.09	29.49±1.27	49.34±9.66	29.13±18.92	44.76±1.60	30.28±0.45
IGAP	80.32±1.48	24.93±2.14	52.74±0.64	41.74±2.06	32.36±1.97	48.59±3.76	36.38±2.77	50.34±1.69	35.70±1.23
MTG	83.45±2.05	30.84±3.50	53.87±0.72	43.49±2.08	37.11±1.47	56.40±5.14	34.88±1.64	50.82±1.14	38.52±2.69
SUPT	85.03±0.80	24.11±2.70	52.54±0.67	44.56±1.45	35.22±1.37	50.05±4.66	36.81±3.36	49.46±1.84	35.19±1.53
GAPTUNE+	85.04±0.83	29.94±1.48	**59.07**±0.49	**47.48**±1.92	37.86±1.17	58.61±6.23	**5.89**±0.18	**57.30**±2.10	**44.46**±1.02
Pretrain (InfoGraph) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**88.06**±0.50	**32.98**±1.06	56.21±0.75	40.51±1.98	**38.17**±1.22	**72.58**±3.90	34.91±1.55	51.13±2.52	**40.43**±1.47
All-in-One	78.21±0.74	5.03±2.48	54.05±0.58	39.62±0.65	35.35±1.35	55.59±4.78	102.05±3.11	54.77±2.75	25.12±5.56
EdgePrompt	76.73±5.34	12.92±1.77	57.52±0.35	39.22±2.11	28.20±3.20	64.03±9.70	91.32±2.50	48.23±1.37	28.49±3.23
EdgePrompt+	83.52±1.13	14.81±1.48	56.76±0.55	47.67±1.34	34.06±2.52	60.28±13.69	87.41±1.71	51.30±4.42	33.75±1.94
GPF	86.10±0.28	17.03±4.12	56.50±0.62	39.97±1.05	34.76±1.63	61.40±9.69	111.70±0.60	51.88±2.05	27.60±3.90
GPF+	86.72±0.99	24.35±2.83	56.36±0.44	40.25±1.49	37.97±2.08	62.65±8.88	111.55±0.64	50.93±1.72	30.36±0.54
GPPT	78.11±0.73	2.14±0.38	50.46±0.35	39.01±1.75	32.03±1.11	58.57±7.06	115.53±1.14	50.12±0.11	23.10±0.46
GraphPrompt	72.92±1.50	4.85±2.07	54.49±0.64	40.10±0.86	26.75±0.35	62.32±6.89	81.75±31.52	45.07±1.67	32.19±0.41
GraphPrompt+	68.82±18.27	13.02±2.14	55.06±0.43	41.47±1.55	28.68±1.53	56.15±8.35	43.83±1.06	46.52±1.64	30.17±4.05
ProNoG	71.94±0.52	6.56±1.47	55.20±0.63	36.81±1.62	30.43±0.67	55.89±7.97	**7.59**±1.21	41.57±1.27	28.84±0.44
IGAP	83.51±1.14	18.49±2.31	54.21±0.23	41.69±1.14	34.39±2.00	52.06±8.92	102.62±7.95	51.14±2.90	31.74±0.80
MTG	84.76±1.55	17.42±1.97	54.95±0.25	46.25±1.70	33.80±2.31	54.52±5.91	91.13±1.86	50.37±3.59	33.00±1.87
SUPT	88.00±1.01	22.53±3.55	54.85±0.13	41.86±1.67	37.58±2.03	51.93±9.32	111.26±0.59	50.92±2.59	30.16±1.22
GAPTUNE+	87.24±0.77	20.93±1.35	**59.06**±0.59	**49.67**±1.28	37.22±1.37	62.53±5.95	9.03±0.40	**58.31**±2.49	38.90±1.29

Table 28: 100-shot same-dataset results for H2GCN across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	88.29±0.49	39.48±0.84	55.87±0.47	28.56±4.09	**41.68**±1.48	78.57±6.13	10.69±0.49	51.83±0.66	34.27±2.35
All-in-One	88.45±0.32	44.06±0.44	54.81±0.67	**40.68**±1.08	35.27±0.97	77.53±6.41	82.90±1.99	52.56±0.78	30.60±0.49
EdgePrompt	80.48±2.47	**46.89**±0.59	54.20±0.77	24.89±0.07	37.95±0.80	75.77±7.66	69.09±0.95	51.46±1.92	27.44±1.37
EdgePrompt+	84.41±0.95	43.01±0.63	54.31±0.35	34.94±3.81	39.43±1.44	76.22±7.85	65.57±0.74	52.38±1.48	31.33±1.07
GPF	**88.86**±0.39	46.57±0.45	54.18±0.47	25.80±0.64	39.32±0.97	76.89±5.18	106.73±3.79	52.79±2.93	26.19±0.97
GPF+	87.34±1.06	39.10±11.87	53.66±0.49	35.90±2.27	40.28±0.62	76.30±3.92	103.72±0.74	53.51±0.81	29.26±1.17
GPPT	86.10±3.65	31.99±1.98	52.35±1.64	33.04±4.85	36.03±1.10	63.20±6.05	114.27±3.63	49.74±1.08	20.50±0.62
GraphPrompt	87.16±0.75	22.13±0.76	53.34±0.44	38.35±1.49	32.20±2.57	73.44±2.61	20.21±0.47	44.14±1.68	29.60±0.67
GraphPrompt+	85.09±0.96	20.43±2.02	54.29±0.73	37.92±1.09	28.53±4.49	58.78±8.03	21.74±2.58	43.71±1.07	30.86±0.68
ProNoG	84.21±0.95	41.35±0.68	54.64±0.62	33.77±1.48	36.14±1.25	65.61±6.94	**6.33**±1.34	42.06±1.11	27.74±0.68
IGAP	86.65±1.06	34.57±8.44	53.98±0.45	38.27±2.16	38.58±1.23	73.90±8.02	76.64±0.65	51.62±1.17	29.16±1.14
MTG	85.67±1.72	44.18±2.63	54.08±0.32	34.33±3.10	40.75±1.29	70.89±7.41	70.45±0.64	54.66±0.89	31.04±1.38
SUPT	88.43±1.12	43.08±7.19	53.92±0.38	35.86±2.05	40.61±0.75	72.61±9.60	103.93±1.18	53.22±0.76	29.54±1.21
GAPTUNE+	88.31±0.61	45.62±1.14	**56.80**±0.62	38.16±1.78	41.52±0.98	**80.57**±5.36	9.18±0.39	**57.85**±1.41	**36.47**±1.07
Pretrain (ContextPred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	88.24±0.45	38.75±0.86	55.48±0.63	28.48±3.73	**41.20**±1.18	**73.39**±7.05	**6.08**±0.13	50.70±1.58	38.57±0.75
All-in-One	87.97±0.33	38.59±0.53	54.73±0.30	**40.94**±1.27	30.80±1.40	64.95±6.15	59.96±2.64	48.97±0.75	36.97±0.46
EdgePrompt	81.37±1.41	**41.53**±0.42	54.40±0.44	25.49±0.48	37.02±1.07	56.71±15.08	94.78±1.12	51.29±0.96	30.90±3.30
EdgePrompt+	85.07±1.50	39.24±1.04	54.61±0.51	36.00±0.96	38.29±1.03	62.37±10.29	94.64±0.54	51.34±0.79	35.94±1.58
GPF	88.34±0.49	41.24±0.57	54.02±0.46	26.10±0.27	37.50±0.75	53.42±13.50	96.33±1.58	51.19±0.89	29.14±1.84
GPF+	87.70±0.23	39.98±1.94	54.54±0.40	34.25±1.60	39.00±1.75	65.87±12.22	97.31±3.00	51.18±0.77	29.17±3.18
GPPT	87.34±0.40	30.60±6.04	51.40±1.86	34.35±2.46	32.86±2.88	60.57±8.15	104.76±4.84	50.19±0.63	24.58±0.61
GraphPrompt	86.93±1.28	21.35±0.63	54.15±0.46	38.03±1.19	29.89±1.15	59.06±11.13	19.16±0.19	42.47±1.62	32.68±1.33
GraphPrompt+	87.46±0.78	20.94±1.21	54.51±0.39	37.92±1.09	26.52±1.50	57.22±9.29	19.32±0.22	41.63±1.02	33.83±2.02
ProNoG	86.58±0.43	37.10±0.95	53.99±0.61	28.23±2.46	31.96±1.25	53.60±10.60	12.67±6.09	41.36±0.69	28.52±0.54
IGAP	88.15±0.57	36.48±1.58	53.94±0.32	36.55±1.39	36.67±1.54	63.34±10.50	78.19±1.53	49.43±0.74	29.62±2.89
MTG	86.91±1.43	40.56±0.98	53.92±0.26	34.43±1.03	38.78±1.10	56.40±8.03	93.55±0.86	50.92±1.01	35.39±1.79
SUPT	89.07±0.25	41.08±1.41	53.99±0.24	32.99±1.72	38.15±1.48	60.87±11.45	96.85±2.83	48.80±0.80	31.80±2.22
GAPTUNE+	**89.14**±0.49	39.20±0.84	**56.70**±0.49	40.14±1.06	40.01±1.00	68.97±7.49	9.66±0.13	**55.67**±1.06	**39.92**±1.41
Pretrain (DGI) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.49±0.91	40.15±1.10	56.04±0.25	31.67±4.56	**42.22**±0.91	73.75±5.30	6.55±0.54	50.96±1.00	37.24±2.44
All-in-One	87.10±0.23	34.54±2.12	56.11±1.00	**41.82**±1.75	36.54±1.36	74.77±8.08	78.26±0.33	52.78±1.44	37.20±0.41
EdgePrompt	81.04±1.22	39.16±3.25	54.63±0.76	26.86±0.91	39.37±1.11	68.49±9.99	12.77±3.49	53.08±2.46	31.02±2.20
EdgePrompt+	84.47±1.57	39.49±2.43	54.94±0.96	36.68±2.51	37.97±2.05	70.82±8.47	10.63±1.83	53.10±1.44	34.65±2.72
GPF	87.74±0.36	33.88±4.51	53.89±0.42	27.67±2.52	39.54±1.13	68.34±8.64	104.12±0.12	52.54±2.26	30.67±3.13
GPF+	87.43±0.54	31.10±2.82	54.81±0.44	31.62±3.03	38.83±1.12	70.59±7.60	104.55±1.53	53.24±0.90	26.25±7.40
GPPT	81.09±1.79	35.07±0.50	50.28±0.18	34.66±0.94	35.94±0.57	65.50±7.20	107.60±7.05	50.08±0.23	27.10±1.50
GraphPrompt	79.26±0.78	19.04±1.06	53.16±0.47	34.18±1.99	28.72±0.61	65.71±8.99	17.76±0.49	42.66±1.81	31.61±1.53
GraphPrompt+	82.90±1.64	17.85±2.15	54.31±0.82	36.89±1.01	25.80±1.12	54.39±13.44	11.19±2.82	42.78±1.21	31.64±4.11
ProNoG	73.72±0.72	37.46±0.44	53.61±0.49	31.11±1.74	37.56±1.46	62.35±10.54	12.54±5.09	40.87±1.05	28.97±0.18
IGAP	86.14±0.69	30.07±1.99	53.09±0.36	32.66±2.64	36.36±0.97	53.04±10.90	68.59±1.35	50.97±1.05	29.08±5.02
MTG	86.57±1.13	**40.33**±2.57	53.72±0.16	34.63±2.13	40.34±1.56	59.19±12.11	22.34±1.96	52.95±2.94	33.07±2.97
SUPT	87.21±0.49	32.46±3.07	53.47±0.48	32.37±3.17	38.51±1.04	65.58±10.18	104.49±1.15	52.75±1.53	28.62±5.88
GAPTUNE+	**88.20**±0.56	37.95±1.77	**57.09**±0.67	39.11±1.86	41.35±1.18	**75.54**±6.51	**4.95**±0.28	**58.01**±1.34	**38.98**±1.72
Pretrain (EdgePred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**87.19**±0.60	**38.53**±0.62	**56.40**±0.47	26.94±0.65	**41.17**±1.10	70.41±11.08	**6.08**±0.13	49.32±1.93	34.75±3.30
All-in-One	58.70±0.87	16.74±0.90	53.60±0.57	**40.43**±1.94	36.30±1.67	65.82±9.21	59.96±2.64	54.60±1.24	33.78±0.56
EdgePrompt	74.09±2.72	24.08±2.17	53.92±0.38	25.29±0.19	36.70±0.96	63.16±8.59	94.78±1.12	52.11±0.93	26.01±1.25
EdgePrompt+	82.98±1.84	33.53±1.08	54.88±0.88	27.27±0.11	39.32±1.09	69.97±7.95	94.64±0.54	50.08±1.08	30.09±0.44
GPF	79.06±3.46	15.55±2.81	52.79±0.78	25.42±0.11	36.96±1.04	68.09±4.48	96.33±1.58	50.20±0.88	25.97±1.24
GPF+	86.87±0.66	25.89±2.50	54.99±0.50	26.46±0.98	37.11±4.98	68.27±4.71	95.95±1.23	49.14±0.67	27.73±0.66
GPPT	24.08±4.45	3.74±2.25	50.78±0.74	35.01±0.93	28.51±0.76	60.40±7.46	104.76±4.84	49.97±0.41	20.78±0.53
GraphPrompt	39.68±1.22	8.43±1.04	52.22±0.37	38.76±0.72	25.68±3.65	63.47±9.57	19.15±0.17	43.81±2.05	34.58±1.08
GraphPrompt+	79.39±1.94	5.82±1.05	54.71±0.56	37.87±1.36	29.65±5.12	61.58±8.15	19.32±0.22	41.74±1.40	26.99±0.56
ProNoG	32.20±2.11	16.91±0.47	52.11±0.52	30.66±0.79	26.25±0.95	58.80±11.75	12.67±6.09	41.72±1.09	28.79±0.94
IGAP	74.71±0.93	23.59±1.68	52.45±0.22	30.23±0.76	34.36±4.31	59.75±5.69	76.08±0.74	49.99±1.22	30.71±0.56
MTG	83.65±1.70	31.16±1.56	53.00±0.46	27.89±0.21	38.74±1.58	63.34±6.73	93.40±0.68	50.66±0.99	30.27±0.92
SUPT	87.05±1.02	24.02±2.36	53.07±0.22	26.97±0.85	33.48±4.66	57.51±4.39	95.54±1.29	50.55±0.99	27.81±0.87
GAPTUNE+	86.42±0.61	30.45±1.16	56.39±0.58	35.20±1.10	39.13±1.47	**70.53**±5.56	8.75±0.14	**57.94**±1.17	**36.02**±0.80
Pretrain (GraphCL) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	88.08±1.11	40.12±1.00	55.24±0.46	27.32±1.37	**41.49**±1.69	**69.92**±10.47	**6.08**±0.21	51.88±1.28	32.59±1.44
All-in-One	87.15±0.39	39.07±0.40	54.72±0.50	**42.41**±0.95	34.54±1.97	64.64±12.35	33.99±3.22	53.20±1.20	31.45±0.33
EdgePrompt	80.34±2.21	40.27±0.68	54.19±0.77	26.00±0.70	38.23±0.98	62.93±16.29	84.11±1.74	52.50±0.90	27.35±1.98
EdgePrompt+	84.71±0.23	39.58±0.82	54.37±0.39	36.91±0.98	39.53±0.73	65.03±5.87	83.88±0.86	53.14±1.50	29.26±1.27
GPF	88.62±0.64	38.97±0.58	53.89±0.34	26.20±1.12	37.73±1.14	53.69±17.15	85.70±1.23	51.14±1.25	28.00±2.30
GPF+	87.57±0.37	40.21±0.51	54.34±0.28	34.58±1.07	40.18±1.05	58.01±14.62	85.02±0.58	50.99±0.79	28.41±1.79
GPPT	87.42±0.88	22.06±1.79	52.04±1.34	35.14±2.60	37.15±1.13	58.67±11.78	86.26±7.48	49.73±0.67	21.51±1.10
GraphPrompt	85.54±0.44	19.34±0.48	54.04±0.50	36.58±1.29	27.33±3.67	62.12±15.10	18.98±0.20	45.23±1.60	29.64±0.39
GraphPrompt+	87.78±0.95	18.90±1.01	54.51±0.21	39.37±0.81	30.79±5.44	56.20±9.21	18.97±0.20	45.06±1.66	31.68±1.89
ProNoG	85.12±1.02	33.32±0.38	54.22±0.62	32.38±0.68	36.11±1.32	55.10±17.74	16.31±6.53	44.02±1.72	25.85±0.29
IGAP	87.36±0.46	35.89±0.56	53.81±0.36	36.33±1.25	37.06±1.86	59.43±11.74	67.61±0.57	52.09±1.30	29.50±1.41
MTG	85.81±0.57	**40.91**±0.73	54.02±0.29	33.89±0.69	40.06±0.75	57.39±10.34	82.02±1.05	52.40±1.23	30.30±1.44
SUPT	89.06±0.46	39.88±0.56	53.56±0.38	34.80±1.34	39.34±1.02	51.37±10.88	85.25±0.73	51.58±0.95	29.85±1.95
GAPTUNE+	**89.31**±0.47	39.58±0.83	**56.73**±0.62	40.48±1.22	40.99±0.89	68.15±7.72	8.82±0.14	**58.01**±1.56	**35.98**±1.27
Pretrain (InfoGraph) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.65±0.50	40.02±1.70	55.89±0.52	26.89±0.41	**42.30**±1.70	**72.35**±10.63	5.89±0.11	52.45±1.55	36.74±1.59
All-in-One	86.40±0.92	40.15±0.80	55.06±0.37	**41.82**±0.93	38.17±0.62	62.60±12.61	109.14±0.81	57.42±0.84	33.87±0.45
EdgePrompt	80.38±2.76	44.03±0.60	54.34±0.22	25.06±0.22	38.67±1.27	51.96±18.88	109.92±0.68	52.92±0.86	27.59±2.44
EdgePrompt+	83.30±1.42	40.95±1.10	53.97±0.54	27.72±0.65	40.25±1.17	62.17±8.96	108.72±0.50	53.27±1.13	33.92±1.45
GPF	**88.51**±0.71	**46.68**±0.80	54.37±0.55	24.99±0.11	38.74±0.96	57.42±12.27	113.93±1.01	52.60±1.74	27.07±1.68
GPF+	87.61±0.51	39.08±10.70	54.73±0.50	25.87±0.66	41.01±1.30	64.13±11.85	113.94±1.16	53.22±0.56	29.63±0.87
GPPT	84.91±0.46	22.01±2.64	52.00±1.48	36.58±1.06	38.22±0.47	59.53±11.80	116.20±1.24	50.19±0.22	22.81±1.22
GraphPrompt	83.45±0.44	17.37±2.62	54.65±0.40	38.10±1.07	31.62±2.21	62.35±12.07	78.73±0.58	46.11±1.70	36.78±0.44
GraphPrompt+	85.81±3.40	12.79±1.10	55.31±0.42	38.53±1.48	27.15±0.90	59.08±11.50	19.08±0.22	45.16±1.42	36.11±2.39
ProNoG	83.50±0.75	37.39±1.21	54.97±0.63	31.67±1.30	35.32±1.01	53.47±14.79	**4.81**±0.20	42.26±1.17	28.72±0.40
IGAP	86.02±0.68	35.68±7.27	53.61±0.27	30.59±0.69	39.39±1.61	59.72±4.74	104.02±1.07	55.55±1.32	32.00±0.85
MTG	86.54±1.52	42.78±2.78	53.66±0.35	27.85±0.63	40.03±0.96	57.79±6.37	108.41±0.56	53.33±1.04	32.15±1.57
SUPT	88.39±0.44	43.32±9.84	53.80±0.27	25.66±0.62	40.44±1.40	59.16±5.54	113.38±1.34	54.77±1.29	30.57±1.23
GAPTUNE+	87.59±0.50	42.04±1.12	**57.05**±0.46	34.99±1.12	41.45±1.24	66.61±8.19	9.58±0.14	**60.37**±1.45	**38.48**±1.38

Table 29: 100-shot same-dataset results for FAGCN across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.17±0.90	42.18±0.76	55.00±0.56	34.81±1.45	37.38±1.39	**61.10**±8.39	6.04±0.41	50.79±1.61	31.77±0.89
All-in-One	88.80±0.41	45.06±0.14	54.21±0.39	31.42±4.50	33.28±1.12	48.88±5.65	11.78±0.57	57.26±0.83	28.22±0.83
EdgePrompt	82.09±0.75	45.63±0.70	54.24±0.46	34.33±6.18	38.30±1.07	57.93±11.92	9.22±0.33	51.11±0.67	28.66±0.21
EdgePrompt+	83.08±0.75	44.96±1.34	54.69±0.89	**43.22**±1.79	39.17±1.48	55.26±8.62	9.26±0.32	51.58±0.57	31.96±1.52
GPF	88.88±0.31	45.22±0.38	53.80±1.36	34.35±4.14	32.70±1.10	53.88±2.49	66.49±3.63	51.63±0.39	28.05±0.55
GPF+	88.64±0.47	42.53±0.78	54.20±0.41	31.82±2.42	36.33±1.42	57.86±5.53	63.64±0.76	51.87±0.73	27.81±2.51
GPPT	85.80±1.54	29.10±2.32	54.39±1.57	36.13±0.48	24.24±4.35	55.42±9.24	57.95±6.47	50.69±1.57	16.50±1.45
GraphPrompt	78.80±1.79	20.28±0.42	53.85±0.22	37.92±1.09	28.68±1.09	57.93±3.79	19.60±0.22	43.45±1.39	30.47±0.67
GraphPrompt+	82.03±2.49	20.22±0.37	54.13±0.45	37.92±1.09	25.80±0.94	51.40±9.19	15.45±1.80	42.21±0.58	28.13±2.79
ProNoG	85.20±1.10	39.14±0.67	54.75±0.66	30.25±1.30	27.92±0.35	49.31±10.11	17.06±2.51	41.47±0.95	24.39±0.34
IGAP	86.02±0.88	37.57±0.65	53.82±0.10	35.77±2.24	35.93±1.29	50.61±7.59	43.87±0.64	54.16±0.51	29.30±1.75
MTG	83.87±0.63	47.15±0.98	54.23±0.08	38.55±2.65	40.17±1.31	49.76±10.19	16.32±0.36	53.74±0.61	31.24±1.57
SUPT	**89.14**±0.45	43.92±0.79	53.76±0.08	32.89±2.48	35.73±1.41	47.28±7.84	64.02±1.32	53.20±0.70	28.16±2.11
GAPTUNE+	89.02±0.40	**48.89**±0.91	**56.91**±0.76	42.88±1.69	**40.28**±1.25	56.59±5.49	**5.65**±0.18	**59.50**±1.52	**36.90**±1.24
Pretrain (ContextPred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	88.47±0.52	**41.85**±0.38	54.69±1.25	33.67±1.78	36.36±0.51	55.33±12.11	**5.77**±0.29	48.63±1.38	27.88±0.43
All-in-One	87.14±0.35	35.25±0.35	54.34±0.40	39.32±1.12	34.86±0.98	47.53±8.99	67.47±5.13	51.14±1.72	29.77±0.59
EdgePrompt	81.13±0.43	31.90±0.87	54.05±0.24	36.84±2.59	34.69±0.87	48.39±12.52	79.63±1.00	48.93±0.61	27.51±1.01
EdgePrompt+	83.00±0.79	36.95±1.39	54.90±0.33	40.38±1.02	**40.72**±0.56	56.76±10.40	79.39±0.68	48.65±0.62	31.73±1.41
GPF	88.39±0.16	33.09±0.97	53.85±0.20	33.29±2.53	34.19±1.82	54.21±7.58	87.34±2.01	48.59±0.57	26.12±0.96
GPF+	**88.74**±0.23	31.15±3.35	53.65±0.82	34.66±1.21	35.93±1.46	54.57±9.89	90.14±7.75	48.75±0.55	25.43±1.79
GPPT	87.21±1.06	19.44±5.38	51.09±1.56	35.47±2.88	33.71±1.02	57.31±8.91	82.91±7.15	49.70±0.92	20.63±1.02
GraphPrompt	86.61±0.68	17.26±0.45	53.84±0.48	37.37±1.58	29.95±1.40	58.21±10.00	19.45±0.26	42.25±1.75	31.79±0.84
GraphPrompt+	86.93±0.44	19.05±1.26	54.18±0.42	39.75±1.00	27.91±1.39	55.26±8.41	19.61±0.14	41.76±0.93	33.77±1.22
ProNoG	87.31±0.42	22.83±0.30	53.95±0.48	34.66±0.97	30.78±0.97	51.05±11.19	12.30±4.31	41.44±0.94	24.50±0.56
IGAP	88.70±0.45	29.58±2.52	53.94±0.30	38.02±1.28	35.69±1.25	**63.29**±8.46	72.09±4.35	47.18±0.89	27.59±1.44
MTG	84.91±0.72	37.24±1.75	54.42±0.26	39.47±1.50	39.48±0.69	58.31±8.65	80.05±1.48	50.27±0.98	30.12±1.24
SUPT	88.31±0.22	32.53±3.24	53.70±0.24	34.94±1.33	35.44±1.76	52.74±7.58	87.59±6.20	49.65±0.80	26.93±1.65
GAPTUNE+	88.44±0.32	36.60±1.33	**56.62**±0.47	**42.01**±1.24	40.04±0.77	57.03±8.05	9.34±0.10	**55.86**±1.26	**35.75**±1.34
Pretrain (DGI) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	88.29±0.59	42.23±0.43	53.77±1.01	38.30±3.12	39.47±1.63	57.32±13.68	**5.86**±0.26	50.90±1.06	31.93±2.92
All-in-One	87.65±0.38	42.12±0.69	55.22±0.60	39.39±1.55	38.92±1.11	49.90±8.21	86.50±6.14	51.08±0.92	29.29±2.59
EdgePrompt	79.80±1.55	44.84±0.81	54.44±0.39	29.85±5.39	37.15±1.91	65.27±9.46	55.67±4.09	51.98±0.47	28.45±1.69
EdgePrompt+	81.77±1.00	44.03±1.28	53.90±1.02	**44.25**±2.35	38.86±1.53	**66.79**±7.90	57.63±2.12	52.20±0.56	33.42±1.28
GPF	87.22±0.56	42.94±0.63	53.12±0.62	31.75±3.78	36.66±0.28	58.16±7.92	102.30±0.96	51.29±0.54	25.89±2.08
GPF+	88.15±0.27	41.59±1.53	53.84±0.51	35.72±1.66	37.70±1.16	61.84±9.67	103.21±3.04	51.06±1.13	26.46±4.42
GPPT	72.62±2.63	30.83±5.10	50.00±0.21	32.71±5.02	34.88±1.79	54.82±7.38	111.23±2.61	50.52±2.59	19.92±0.53
GraphPrompt	72.64±2.61	16.36±2.63	53.15±0.39	30.25±4.83	32.76±4.18	60.61±7.66	19.85±6.87	43.86±2.20	31.17±1.44
GraphPrompt+	84.86±1.25	22.10±1.02	53.84±0.24	33.70±2.47	30.58±1.60	56.94±10.20	14.64±0.73	45.01±1.45	27.16±0.64
ProNoG	70.56±4.49	40.95±0.58	52.22±0.75	28.43±2.76	32.57±2.43	65.54±9.01	8.64±4.27	44.68±1.12	27.64±0.43
IGAP	83.98±0.81	36.71±1.50	53.46±0.37	35.94±2.74	38.84±1.93	51.47±6.30	75.35±3.83	50.71±0.84	27.77±3.16
MTG	84.02±0.89	**45.76**±1.21	53.87±0.32	40.50±2.81	39.64±1.60	58.52±5.86	63.12±2.81	52.62±0.56	32.71±1.95
SUPT	**89.62**±0.38	43.18±1.39	53.39±0.24	36.05±2.23	37.68±1.07	57.04±9.29	101.90±2.89	51.13±0.92	26.85±4.17
GAPTUNE+	89.29±0.47	45.38±0.98	**56.66**±0.57	43.44±1.90	**40.20**±1.30	60.11±7.75	6.96±0.32	**56.54**±1.04	**37.60**±1.26
Pretrain (EdgePred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**87.76**±0.51	**42.02**±1.10	54.56±0.19	33.11±1.84	38.85±1.73	**66.66**±9.00	**5.77**±0.29	48.10±1.87	22.40±3.56
All-in-One	57.38±1.05	24.70±0.60	52.34±0.50	38.58±0.62	36.33±0.97	44.31±8.86	67.47±5.13	49.55±0.67	25.91±0.95
EdgePrompt	57.16±3.33	9.04±0.89	53.10±0.79	38.76±2.05	35.37±1.74	48.47±8.65	79.63±1.00	48.98±1.16	25.01±1.07
EdgePrompt+	78.89±1.58	20.37±3.07	53.22±0.83	39.57±2.15	37.95±1.13	49.64±8.60	79.39±0.68	49.41±1.05	30.68±1.22
GPF	75.42±2.34	9.60±0.71	52.80±0.61	28.48±4.87	34.62±1.14	51.91±9.81	87.34±2.01	51.62±0.77	26.84±2.61
GPF+	87.02±0.43	30.06±1.13	53.76±0.39	32.23±2.94	34.80±3.73	52.35±11.50	88.48±4.17	51.43±1.10	23.94±3.39
GPPT	55.72±0.63	3.36±0.46	50.34±0.19	32.68±2.22	32.66±2.05	57.51±9.46	82.91±7.15	49.86±0.23	18.99±1.22
GraphPrompt	49.73±0.74	5.94±0.27	51.18±0.81	36.00±1.44	32.52±3.59	52.47±6.22	19.27±0.11	43.25±1.30	28.58±0.24
GraphPrompt+	85.04±1.35	6.99±0.22	53.98±0.78	37.95±1.00	32.13±4.58	51.38±9.20	19.61±0.14	41.54±1.30	25.36±0.22
ProNoG	47.14±1.19	7.91±0.16	51.72±0.67	36.03±1.93	33.10±0.79	45.69±8.58	12.30±4.31	41.08±1.13	26.33±0.42
IGAP	77.32±0.57	23.81±1.31	52.46±0.51	36.06±2.49	35.24±2.88	52.22±6.53	69.62±2.75	50.05±1.17	26.34±2.25
MTG	76.89±1.48	21.38±2.20	52.74±0.56	38.26±2.45	38.96±1.61	48.90±5.97	79.37±1.20	49.72±1.06	28.85±1.50
SUPT	85.38±0.85	25.91±1.08	53.44±0.24	31.64±3.62	33.29±2.64	49.76±6.18	90.85±3.34	53.18±1.02	25.60±3.60
GAPTUNE+	84.94±0.74	25.09±1.29	**55.83**±0.66	**41.64**±1.79	**39.46**±1.14	53.43±8.15	9.00±0.11	**55.33**±1.16	**35.27**±1.24
Pretrain (GraphCL) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.07±0.69	42.45±1.23	54.30±0.60	35.77±1.83	37.94±1.24	56.99±12.82	**5.96**±0.46	51.77±1.01	26.28±1.07
All-in-One	87.05±0.79	43.51±0.24	53.80±0.35	35.01±2.73	33.92±0.77	51.02±11.57	45.75±6.03	57.09±0.98	23.97±0.19
EdgePrompt	81.80±0.93	44.80±0.25	53.91±0.38	**42.56**±1.66	34.64±0.58	53.67±10.74	65.49±0.48	50.69±1.73	24.26±0.22
EdgePrompt+	82.19±0.57	44.53±0.28	55.61±0.74	38.30±5.84	36.85±1.16	56.07±13.19	65.38±0.74	50.53±1.27	27.79±0.45
GPF	88.53±0.59	44.24±0.61	53.79±0.36	30.51±3.63	33.81±1.03	51.35±11.99	73.46±2.61	52.31±1.69	22.89±1.13
GPF+	87.09±1.00	39.67±7.96	53.88±0.40	34.56±1.68	36.36±0.96	54.44±12.81	75.81±10.29	52.36±1.39	24.84±0.60
GPPT	88.11±0.40	18.57±3.07	51.95±1.84	34.96±1.75	33.90±1.95	51.57±10.34	64.83±3.34	50.17±0.43	17.78±2.20
GraphPrompt	87.81±0.51	24.46±0.65	54.00±0.39	39.57±2.13	30.94±2.50	52.96±9.73	19.37±0.52	45.21±1.85	22.59±1.12
GraphPrompt+	87.64±0.41	20.82±3.29	54.17±0.22	38.10±1.42	28.09±0.76	52.83±10.03	19.50±0.06	45.20±1.51	21.22±1.71
ProNoG	86.46±0.19	39.48±0.68	54.51±0.44	34.33±0.84	31.85±1.64	48.16±11.98	12.66±4.71	43.07±1.62	26.45±0.70
IGAP	87.49±0.83	37.35±4.04	54.15±0.30	37.07±2.07	35.36±1.34	47.89±8.82	60.39±6.71	51.19±1.35	25.02±0.79
MTG	85.43±0.57	**45.78**±1.41	54.00±0.39	38.53±4.33	37.78±0.88	51.50±5.23	64.91±1.89	53.89±1.27	27.51±0.42
SUPT	88.77±0.90	40.67±8.06	53.68±0.24	34.64±2.01	37.08±1.06	51.80±7.87	75.17±9.10	53.78±1.32	24.84±0.83
GAPTUNE+	**89.00**±0.54	43.95±0.85	**56.61**±0.51	40.26±2.18	**38.51**±0.86	**57.36**±9.83	6.57±0.10	**59.24**±1.72	**33.73**±0.85
Pretrain (InfoGraph) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.31±0.43	42.01±0.98	54.48±0.47	36.05±1.85	38.32±1.17	57.47±10.43	6.01±0.39	50.05±0.94	28.23±0.37
All-in-One	87.60±0.35	41.63±0.34	53.71±0.32	42.71±0.83	39.14±1.43	57.22±7.98	109.32±0.75	60.04±0.90	27.09±1.02
EdgePrompt	80.97±1.78	**46.69**±0.24	54.07±0.58	36.51±4.42	39.75±1.04	57.37±8.86	100.21±0.69	50.67±0.68	27.09±1.92
EdgePrompt+	79.97±4.18	43.66±0.74	54.86±0.42	43.59±1.29	40.41±1.26	59.26±10.64	99.78±0.62	51.52±1.33	34.86±1.15
GPF	88.90±0.34	44.74±0.95	54.05±0.61	36.71±3.85	38.91±0.56	56.15±10.76	110.83±0.41	51.29±1.68	23.96±0.80
GPF+	88.18±0.92	43.02±0.27	54.01±0.69	35.62±3.55	37.27±1.30	53.85±10.60	110.75±0.38	51.83±0.47	29.63±1.28
GPPT	87.72±0.70	25.17±1.42	53.42±1.55	36.33±2.34	38.28±0.88	58.62±7.93	115.53±1.47	49.87±0.30	21.22±0.79
GraphPrompt	86.96±0.52	19.21±0.97	53.78±0.66	38.91±1.93	30.76±2.44	**60.71**±11.73	59.11±0.36	45.52±2.38	34.88±0.19
GraphPrompt+	87.66±0.64	19.41±1.23	54.56±0.47	38.89±1.29	28.91±1.05	55.23±9.60	18.95±0.70	44.10±1.24	34.88±0.83
ProNoG	85.99±0.81	38.81±1.03	54.40±0.49	33.87±0.76	36.06±1.24	51.58±11.50	**4.79**±0.20	41.34±1.49	27.70±0.70
IGAP	87.59±1.54	38.29±0.45	53.89±0.24	40.15±3.06	36.07±1.63	55.12±7.07	95.71±0.43	54.85±0.54	31.66±1.05
MTG	82.71±3.97	46.20±0.61	54.33±0.21	42.36±2.00	40.96±1.38	52.72±3.47	100.18±0.56	51.29±0.70	34.25±1.46
SUPT	89.26±0.85	43.66±0.32	54.09±0.23	35.64±3.52	37.28±1.22	52.96±5.79	110.72±0.44	53.70±0.77	29.03±1.22
GAPTUNE+	**89.30**±0.76	46.07±0.75	**56.77**±0.48	**45.17**±1.29	**41.35**±1.33	60.61±7.86	9.61±0.23	**60.62**±1.10	**39.04**±1.18

Table 30: 100-shot same-dataset results for Transformer across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	88.99±0.57	40.54±0.95	57.05±0.54	41.42±2.51	39.83±0.81	**66.81**±14.96	16.45±1.96	51.84±1.75	35.59±1.38
All-in-One	88.32±0.76	43.98±0.27	53.68±0.95	40.33±1.07	38.95±1.06	53.21±16.27	49.04±14.78	52.67±0.65	28.76±1.76
EdgePrompt	63.13±15.86	**46.14**±0.51	56.97±0.65	39.27±1.29	39.14±0.44	61.94±5.65	44.90±0.59	49.33±1.39	25.07±3.01
EdgePrompt+	OOM	42.10±0.70	56.60±0.66	40.08±1.09	40.36±0.59	64.74±7.42	43.96±0.47	51.16±1.29	28.83±1.87
GPF	88.28±0.76	45.29±0.56	56.76±0.53	40.10±1.34	35.33±10.37	53.47±7.70	104.48±0.73	48.69±1.48	24.06±1.54
GPF+	89.23±0.78	42.39±0.43	56.90±0.48	39.57±0.84	38.73±0.56	55.54±8.28	104.39±0.69	50.90±1.43	22.89±1.70
GPPT	87.64±0.96	27.97±2.54	52.01±1.26	35.19±4.50	37.84±1.76	58.14±10.01	112.68±3.02	47.64±1.42	16.12±1.10
GraphPrompt	86.04±0.62	22.67±0.93	54.35±0.47	38.63±1.21	30.40±3.69	53.11±9.49	22.57±0.21	41.72±1.28	**36.98**±0.85
GraphPrompt+	78.17±2.25	22.58±0.48	56.18±0.38	37.95±0.97	26.07±0.98	57.78±12.17	19.59±0.92	41.91±0.80	32.32±2.40
ProNoG	84.25±0.41	40.26±0.56	55.75±0.68	36.63±2.12	34.63±0.79	52.88±11.77	8.00±2.23	40.75±1.09	27.14±0.32
IGAP	89.06±0.69	37.50±0.64	52.94±0.50	40.53±0.93	38.44±1.28	55.32±14.04	74.33±0.47	51.66±0.81	28.57±1.31
MTG	77.25±9.70	44.36±0.56	53.19±0.84	41.77±1.09	41.06±0.50	59.04±11.09	51.97±0.54	51.52±0.90	27.89±2.25
SUPT	89.77±0.71	43.35±0.48	52.80±0.37	41.03±0.79	37.84±3.10	50.61±15.45	104.49±0.88	50.25±1.31	23.08±1.41
GAPTUNE+	**90.29**±0.55	43.71±0.63	**58.54**±0.63	**43.27**±1.14	**41.65**±0.79	60.25±10.53	**6.36**±0.15	**56.74**±1.33	35.61±1.70
Pretrain (ContextPred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	88.76±0.60	**39.71**±0.61	57.08±0.43	41.62±1.36	39.76±0.52	**72.83**±13.50	**8.79**±1.11	51.96±2.10	**34.82**±2.38
All-in-One	88.26±0.30	38.85±0.29	56.30±0.68	40.30±2.48	38.06±0.54	60.03±10.49	54.76±0.50	49.17±1.16	33.91±0.86
EdgePrompt	71.63±17.47	38.20±0.35	56.88±0.77	42.35±1.22	38.13±0.75	65.26±7.70	90.15±0.35	51.23±1.14	26.25±3.09
EdgePrompt+	OOM	32.95±1.22	56.19±0.69	46.00±0.86	39.46±1.39	70.38±6.87	90.27±0.47	51.35±0.98	25.17±1.46
GPF	88.73±0.42	39.67±0.18	56.73±0.62	41.42±0.93	37.68±0.48	64.62±8.29	90.25±1.50	50.99±1.18	28.01±1.69
GPF+	87.72±0.81	35.47±3.00	56.00±0.30	42.08±1.19	38.96±1.24	67.78±11.01	91.63±4.49	50.57±1.09	26.97±2.81
GPPT	87.51±0.90	11.63±3.63	50.85±1.30	38.08±2.43	35.58±1.96	57.63±11.59	90.08±7.13	50.54±0.33	20.40±1.71
GraphPrompt	86.85±0.36	14.89±0.62	54.99±0.78	40.51±1.98	27.93±1.02	68.83±6.25	18.88±0.16	43.06±0.81	28.70±0.68
GraphPrompt+	85.58±3.16	16.44±0.98	54.67±0.87	38.94±1.67	26.91±1.86	60.69±9.14	19.13±0.33	41.85±0.96	29.31±1.15
ProNoG	86.04±0.47	27.37±0.49	55.23±0.30	34.08±2.58	30.37±0.56	60.05±14.08	9.89±1.44	41.06±0.95	23.52±0.71
IGAP	89.18±0.63	30.79±2.38	54.91±0.81	43.40±1.10	37.38±0.99	65.34±10.85	72.79±2.87	49.67±0.81	26.01±2.28
MTG	80.87±10.77	35.54±1.47	56.83±1.00	45.79±0.80	40.35±1.28	61.05±11.80	88.25±1.20	50.62±0.86	27.01±1.79
SUPT	88.14±0.70	37.37±2.70	56.32±0.82	43.26±1.09	38.96±1.24	57.93±14.80	92.55±4.08	50.17±0.84	28.91±2.53
GAPTUNE+	**89.76**±0.40	37.18±1.08	**58.88**±0.70	**47.59**±1.08	**41.54**±1.07	66.40±7.38	9.42±0.16	**55.62**±1.49	32.28±1.04
Pretrain (DGI) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	88.82±0.76	37.92±1.44	57.43±0.46	40.73±1.79	40.41±1.75	**74.90**±6.78	5.89±0.24	52.15±1.01	**32.13**±4.42
All-in-One	87.22±0.68	33.51±2.23	56.03±0.92	33.82±4.59	39.95±0.43	54.31±8.37	14.89±2.88	54.57±0.46	25.74±2.23
EdgePrompt	71.72±12.57	**40.57**±1.48	57.41±0.39	40.46±3.83	39.74±0.96	65.77±6.29	19.81±16.43	52.85±1.73	23.42±2.98
EdgePrompt+	OOM	35.75±3.33	57.09±0.54	45.37±0.92	40.34±0.92	66.25±5.23	11.61±0.57	52.97±0.89	22.56±5.08
GPF	89.00±0.79	33.52±1.55	57.36±0.46	40.25±2.92	40.79±0.38	58.98±10.35	64.01±2.41	52.96±0.59	24.37±1.76
GPF+	87.86±0.48	34.58±2.59	56.82±0.57	39.92±2.32	39.89±2.13	51.66±8.13	66.12±9.76	52.78±0.71	22.20±4.55
GPPT	84.27±2.48	35.37±3.55	52.10±2.48	36.78±1.65	39.43±1.18	60.80±9.06	59.32±17.17	50.43±1.15	22.13±0.83
GraphPrompt	81.06±1.13	12.18±1.53	55.49±0.66	33.04±3.90	27.87±2.56	57.68±7.13	18.81±0.14	43.97±1.20	30.94±0.18
GraphPrompt+	79.18±3.28	17.75±1.26	55.94±0.40	36.48±2.34	29.18±1.88	64.64±12.01	21.00±2.40	44.31±1.80	29.66±1.99
ProNoG	79.58±0.58	38.97±0.43	55.63±0.45	30.94±1.41	31.77±4.53	56.79±11.48	17.96±9.94	41.33±0.95	25.78±1.09
IGAP	85.88±0.74	30.76±2.22	54.44±0.62	40.82±2.55	38.37±2.05	48.76±8.12	45.41±6.54	54.21±0.60	26.24±3.35
MTG	85.02±6.50	38.75±3.65	56.37±0.76	44.48±2.25	42.30±1.16	54.80±10.87	21.44±5.61	53.23±0.80	22.84±3.97
SUPT	89.87±0.63	35.71±2.21	55.12±0.93	41.62±1.92	40.52±2.05	43.81±7.89	65.89±9.53	52.54±0.93	21.89±3.44
GAPTUNE+	**91.35**±0.54	39.58±1.64	**59.03**±0.39	**45.99**±1.44	**43.07**±1.30	61.92±7.13	**4.44**±0.21	**58.76**±0.93	31.17±1.79
Pretrain (EdgePred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**88.82**±0.64	**39.87**±1.24	57.20±0.47	42.51±0.94	39.01±0.76	**73.78**±6.72	**8.21**±1.20	51.89±2.22	34.93±1.10
All-in-One	62.37±0.46	27.31±0.64	53.50±0.60	41.24±1.72	36.70±0.47	58.52±5.65	54.76±0.50	54.21±0.70	31.66±1.16
EdgePrompt	41.14±17.45	24.06±1.08	55.54±0.46	41.97±1.98	35.86±1.02	65.36±11.76	90.15±0.35	51.78±0.93	25.17±1.92
EdgePrompt+	OOM	24.25±1.51	55.62±0.59	45.62±1.58	36.42±0.64	73.55±7.28	90.27±0.47	51.36±0.43	31.22±1.09
GPF	80.82±1.37	31.81±1.03	55.40±0.61	40.53±1.75	39.03±0.81	62.02±9.75	90.25±1.50	51.43±1.19	26.86±0.68
GPF+	87.28±0.62	33.40±0.94	56.50±1.14	40.03±2.48	37.42±5.17	53.09±10.50	90.05±1.34	51.96±0.71	27.13±0.59
GPPT	55.66±0.55	4.00±2.02	50.93±0.86	38.35±1.91	31.66±0.50	63.42±9.10	90.08±7.13	50.05±0.69	18.69±1.41
GraphPrompt	43.81±0.77	6.92±1.44	54.45±0.86	37.24±0.88	27.56±3.62	66.33±12.72	57.92±53.39	44.36±1.15	31.58±0.27
GraphPrompt+	78.39±4.71	11.74±0.98	55.98±0.67	38.38±1.22	27.82±0.96	54.74±7.11	19.13±0.33	41.58±1.02	30.05±2.11
ProNoG	46.25±0.54	11.93±0.53	54.00±0.93	36.00±2.37	31.96±1.28	64.11±10.62	9.89±1.44	41.85±0.92	27.33±0.61
IGAP	74.45±0.62	26.57±1.03	51.76±0.42	40.70±1.65	33.84±5.24	53.99±9.46	81.74±12.19	51.49±0.77	29.50±0.51
MTG	67.00±9.18	26.84±1.30	51.95±1.06	45.24±1.64	37.83±1.30	56.10±12.77	88.85±0.68	52.52±0.65	30.73±1.28
SUPT	86.02±0.76	33.48±1.01	52.77±0.50	41.34±2.10	35.32±3.90	59.19±7.77	89.57±1.47	52.27±1.04	27.86±0.60
GAPTUNE+	84.23±0.64	28.60±0.98	**57.72**±0.56	**46.84**±1.77	**39.29**±1.48	64.64±6.94	8.89±0.14	**58.07**±1.13	**35.89**±1.15
Pretrain (GraphCL) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	88.45±0.38	39.53±0.89	57.27±0.62	41.52±2.31	39.74±0.86	**68.60**±10.83	6.82±0.58	52.69±0.90	34.33±2.28
All-in-One	87.91±0.11	40.34±0.37	55.40±0.78	41.57±1.82	38.62±0.74	58.49±8.83	37.73±0.51	55.70±1.64	37.50±0.55
EdgePrompt	66.19±16.31	40.00±0.48	57.54±0.42	41.34±2.02	37.92±0.84	52.70±10.51	96.19±0.61	51.88±1.07	28.55±2.73
EdgePrompt+	OOM	37.35±0.66	56.86±0.62	43.65±1.56	39.79±0.89	56.84±10.12	96.49±0.41	52.11±1.18	34.92±0.97
GPF	88.17±0.27	40.40±1.12	57.23±0.51	40.53±1.31	37.60±0.53	54.82±4.18	100.57±0.86	50.79±1.09	28.53±0.74
GPF+	88.39±1.29	41.04±0.86	56.87±0.38	40.66±1.08	38.55±1.45	56.73±7.19	100.50±0.74	50.55±0.82	31.43±1.65
GPPT	86.96±0.70	25.16±1.31	52.27±1.80	39.29±1.72	38.96±0.95	57.61±7.47	106.20±2.97	49.27±1.26	21.42±1.32
GraphPrompt	84.04±0.69	20.52±1.19	55.43±0.37	40.18±1.50	25.73±2.90	53.01±9.79	9.73±0.32	46.27±1.54	35.07±0.59
GraphPrompt+	87.49±0.50	21.74±1.11	56.12±0.59	39.06±1.37	29.15±5.22	51.79±11.90	12.67±4.78	44.23±2.13	37.69±0.44
ProNoG	83.92±0.67	33.08±0.28	56.44±0.53	36.48±0.97	33.82±1.90	52.58±11.32	**5.45**±0.65	44.64±1.30	29.42±0.59
IGAP	87.87±1.21	35.87±0.82	53.12±0.43	41.79±1.31	35.88±1.77	53.85±8.97	76.49±0.58	53.91±1.33	33.23±1.23
MTG	77.33±10.98	39.69±0.68	53.79±0.83	42.98±1.92	41.08±1.22	52.25±8.83	95.85±0.39	51.52±0.97	34.54±1.36
SUPT	88.16±1.04	**42.01**±0.89	52.59±0.42	41.80±1.17	37.73±1.37	59.43±8.65	100.32±0.70	52.40±1.39	31.67±1.28
GAPTUNE+	**89.21**±0.73	39.99±0.95	**59.31**±0.42	**45.70**±1.37	**41.70**±1.18	61.89±6.53	6.92±0.36	**58.71**±1.28	**40.14**±1.06
Pretrain (InfoGraph) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**88.91**±0.70	39.06±1.05	57.26±0.66	42.66±2.37	40.42±0.89	**72.63**±10.37	7.07±0.71	52.75±0.60	22.72±1.88
All-in-One	86.79±0.20	41.34±0.30	55.28±0.27	42.51±1.50	39.46±0.76	60.97±7.72	84.43±0.71	59.71±0.56	16.54±2.59
EdgePrompt	55.51±27.19	43.71±0.62	56.73±0.63	42.51±1.31	42.10±0.96	60.84±5.96	105.37±0.42	52.46±1.10	27.50±1.11
EdgePrompt+	OOM	39.53±0.84	55.91±0.64	47.01±1.15	42.15±1.08	64.87±8.53	105.65±0.54	52.66±0.49	25.22±3.24
GPF	87.53±0.29	**44.70**±0.49	56.48±0.61	41.95±1.55	41.36±1.30	66.53±5.70	112.56±1.78	51.81±0.79	12.50±1.49
GPF+	87.49±0.49	42.19±0.75	55.87±0.52	41.52±1.25	40.69±0.97	61.91±6.68	112.54±1.93	52.22±0.81	12.33±1.41
GPPT	82.81±0.48	19.99±1.70	50.94±0.79	40.08±0.97	40.25±0.64	59.63±7.91	115.95±1.02	50.35±0.15	16.58±0.64
GraphPrompt	79.87±0.36	17.83±1.30	55.36±0.49	37.92±2.45	31.09±2.45	66.22±3.61	54.54±0.94	44.73±1.51	27.08±0.39
GraphPrompt+	81.96±5.17	18.11±1.19	54.96±0.26	38.86±1.85	28.54±1.56	57.68±9.52	19.78±5.87	44.35±1.38	29.25±1.46
ProNoG	78.30±1.09	34.27±0.37	55.83±0.30	35.85±1.55	36.92±1.89	58.78±12.56	**4.06**±0.07	41.80±1.33	20.61±0.81
IGAP	86.21±0.52	37.00±1.17	53.60±0.70	42.67±1.39	39.67±1.03	55.39±10.32	96.63±1.57	54.86±0.61	18.00±1.41
MTG	71.97±15.07	42.81±0.96	56.19±1.06	46.00±1.29	43.10±1.15	56.75±9.77	105.01±0.68	52.83±0.59	23.76±2.39
SUPT	87.65±0.48	43.55±0.71	54.34±0.84	42.47±1.39	40.76±1.27	53.83±8.32	112.37±1.56	54.61±0.56	12.08±1.52
GAPTUNE+	88.23±0.48	41.09±0.94	**58.56**±0.55	**47.72**±1.17	**44.40**±0.98	66.03±5.85	8.93±0.41	**61.01**±1.15	**31.67**±1.45

Table 31: 100-shot same-dataset results for NodeFormer across six pretraining objectives.

Methods	Photo NC / Acc. ↑	ogbn-arxiv NC / Acc. ↑	DBLP LP / AUC ↑	Airports NC / Acc. ↑	Chameleon NC / Acc. ↑	Cornell LP / AUC ↑	QM7b GR / MAE ↓	ToxCast GC / AUC ↑	MNIST GC / Acc. ↑
Pretrain (AttrMasking) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	87.34±0.97	**42.16**±1.27	55.59±1.54	36.91±1.52	38.05±0.74	62.96±7.30	**4.89**±0.10	51.58±1.18	26.06±2.79
All-in-One	87.84±0.55	36.13±0.80	54.28±0.60	34.38±3.49	36.06±1.04	43.98±13.38	91.24±0.58	44.41±1.42	25.95±0.50
EdgePrompt	80.55±0.74	42.06±0.36	57.63±0.92	35.65±3.52	36.86±1.26	47.32±6.44	103.21±0.77	50.84±0.08	27.22±1.85
EdgePrompt+	82.53±0.57	41.85±0.26	56.93±1.25	29.09±4.52	37.63±0.64	56.02±9.39	103.20±0.36	50.78±0.22	31.03±0.62
GPF	**87.90**±0.25	40.16±0.64	55.35±1.57	34.51±4.18	37.81±0.49	56.35±20.01	106.35±0.83	50.72±0.19	17.54±4.11
GPF+	87.76±0.67	40.14±0.93	53.55±1.51	36.13±1.23	**38.84**±0.75	**66.81**±12.84	105.53±0.32	50.87±0.24	17.07±3.13
GPPT	82.65±4.49	17.66±2.29	53.21±1.10	34.30±2.49	37.21±0.94	52.45±14.37	113.34±1.67	50.82±0.62	16.71±1.91
GraphPrompt	80.65±0.42	21.80±0.58	54.07±1.44	**37.92**±1.09	31.54±4.59	51.58±7.21	24.22±0.38	40.47±1.21	22.56±2.10
GraphPrompt+	84.47±1.16	21.80±1.15	54.94±1.33	37.90±1.16	33.82±4.14	53.04±8.84	9.37±1.40	40.60±1.32	23.96±1.24
ProNoG	82.84±0.91	36.83±0.67	54.23±0.62	36.76±1.14	30.89±2.68	49.95±11.24	4.94±0.54	40.26±0.90	24.00±0.40
IGAP	79.66±2.61	12.93±4.13	56.63±2.67	32.23±2.30	27.98±3.20	47.72±16.68	84.83±0.97	40.75±1.07	21.57±3.11
MTG	80.76±7.66	17.20±8.45	57.05±3.17	32.38±4.47	31.12±2.95	58.28±19.41	104.23±0.87	44.63±0.82	22.27±1.95
SUPT	83.62±1.95	7.61±6.38	54.41±2.57	27.93±1.26	27.69±3.01	47.44±16.58	106.88±0.45	45.88±0.59	16.50±4.02
GAPTUNE+	85.65±0.82	38.45±1.55	**59.63**±0.55	36.85±2.35	36.09±1.37	55.53±9.16	4.91±0.25	**53.09**±1.35	**34.58**±0.81
Pretrain (ContextPred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	85.05±1.29	**42.50**±0.95	54.49±1.95	38.78±1.99	**39.52**±1.54	55.43±6.22	13.90±0.19	50.89±0.41	23.08±1.41
All-in-One	84.60±0.22	30.02±4.12	54.05±0.35	40.13±1.32	29.88±2.24	44.87±5.73	102.67±1.55	56.20±0.79	19.60±1.59
EdgePrompt	72.53±6.71	11.45±5.47	56.65±0.25	31.16±3.77	28.06±1.12	49.18±8.87	110.39±0.75	49.39±0.05	13.31±3.90
EdgePrompt+	76.47±1.20	7.62±2.64	56.64±0.36	34.05±2.74	27.59±1.41	54.11±6.70	110.27±1.07	49.49±0.15	23.72±3.68
GPF	84.96±0.25	26.48±8.47	55.95±0.47	38.03±0.69	32.76±2.66	53.06±7.19	112.92±0.09	50.67±0.24	19.92±3.87
GPF+	85.97±0.77	30.61±1.17	55.51±0.53	40.08±1.71	35.17±2.54	50.41±10.49	112.74±0.24	50.69±0.35	23.98±0.99
GPPT	82.11±1.86	4.07±6.79	50.75±1.16	35.70±1.32	28.01±2.95	51.25±10.25	115.40±1.16	49.34±1.05	10.38±0.94
GraphPrompt	77.41±0.83	11.17±3.66	54.22±1.36	37.92±1.09	30.33±0.83	**55.79**±7.95	58.64±29.95	40.56±1.19	20.31±0.67
GraphPrompt+	82.10±4.08	17.29±1.19	56.23±0.51	37.97±1.07	30.22±2.83	49.64±8.95	46.13±20.04	42.00±2.12	20.32±0.78
ProNoG	82.84±0.93	31.24±0.70	55.90±0.65	36.99±1.16	28.24±0.85	43.93±3.68	13.57±0.67	40.22±0.85	22.52±0.42
IGAP	82.94±1.67	23.87±1.87	53.36±3.89	28.98±2.03	32.26±2.67	52.85±6.26	93.15±0.11	47.34±0.45	24.35±4.07
MTG	71.84±3.97	14.50±3.01	52.43±4.11	29.57±4.92	31.90±4.62	55.15±9.65	107.14±0.07	46.88±0.56	19.73±3.69
SUPT	**87.46**±0.85	32.89±2.00	51.57±2.00	27.14±1.60	31.74±1.37	53.25±4.39	110.55±0.58	52.35±0.44	19.79±4.14
GAPTUNE+	86.66±0.70	24.38±1.48	**58.56**±0.49	**40.53**±2.10	34.24±1.99	54.34±6.16	**10.34**±0.88	**58.56**±1.08	**30.22**±1.92
Pretrain (DGI) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**85.48**±0.99	**40.89**±1.28	56.18±0.62	34.28±3.38	**38.12**±1.42	66.56±12.19	13.84±0.06	51.24±0.49	**24.45**±1.36
All-in-One	72.38±2.39	18.05±1.81	54.90±1.12	36.61±2.74	33.81±1.23	49.08±17.43	94.32±8.87	54.00±0.57	10.45±1.81
EdgePrompt	59.62±2.98	22.34±2.14	57.09±1.28	24.94±0.00	34.39±0.47	68.93±17.13	105.87±0.44	51.81±0.58	10.22±0.99
EdgePrompt+	67.93±6.75	22.19±1.65	56.80±1.02	24.94±0.00	34.71±1.30	73.01±8.28	107.47±3.27	51.79±0.60	13.47±5.77
GPF	72.78±0.85	21.56±2.04	53.21±1.06	25.04±0.17	32.63±2.03	**75.77**±15.13	110.70±1.25	52.44±0.21	14.15±4.87
GPF+	81.69±1.79	22.48±3.05	53.10±2.16	24.96±0.06	36.00±1.32	64.29±7.94	112.70±2.30	51.87±1.23	18.18±1.87
GPPT	62.16±5.28	14.69±2.60	50.33±1.32	33.22±3.93	32.13±1.99	67.56±8.05	110.98±6.45	50.69±1.60	9.71±0.37
GraphPrompt	56.48±1.28	14.48±1.00	55.12±0.86	**37.92**±1.11	31.15±3.31	70.43±5.01	11.21±12.74	42.26±1.38	16.26±1.25
GraphPrompt+	75.83±1.78	14.72±3.90	54.85±1.22	**37.92**±1.09	28.66±1.20	71.58±7.51	7.31±1.92	43.02±1.45	18.29±0.81
ProNoG	62.37±2.86	18.41±0.77	55.13±1.29	27.87±3.02	30.68±1.17	54.36±12.76	14.30±1.16	40.63±1.08	16.47±0.44
IGAP	61.65±16.47	21.75±1.78	51.04±2.36	29.71±3.57	31.37±2.91	44.81±26.93	85.45±0.12	53.23±0.76	13.00±0.66
MTG	38.55±19.47	11.66±3.99	52.00±3.19	27.49±5.81	31.13±3.66	47.84±27.00	106.05±0.03	48.56±0.97	12.26±0.29
SUPT	60.87±20.88	31.13±2.17	51.74±1.75	26.35±3.54	34.90±3.32	45.53±27.00	107.81±0.02	53.55±0.50	11.30±0.92
GAPTUNE+	69.05±2.78	18.24±1.75	**58.82**±0.86	33.39±1.06	34.24±1.72	63.43±7.15	**4.06**±0.04	**58.28**±0.94	23.00±1.89
Pretrain (EdgePred) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**86.81**±1.06	**31.27**±15.38	56.29±0.79	40.18±3.86	**39.18**±1.16	59.80±11.12	13.90±0.18	52.35±1.07	25.33±2.95
All-in-One	54.01±2.03	23.04±7.79	53.29±0.64	35.90±1.68	35.54±1.37	26.79±14.85	102.72±1.55	56.28±0.38	22.73±1.29
EdgePrompt	44.65±3.84	10.36±2.23	56.29±0.72	35.24±1.40	28.08±1.89	56.53±13.69	110.63±0.74	52.94±0.34	22.15±0.62
EdgePrompt+	67.67±3.46	10.64±2.70	55.95±0.84	33.59±1.98	30.34±3.15	**64.57**±11.33	110.49±1.05	53.10±0.58	23.90±0.92
GPF	48.56±1.98	27.32±1.56	56.21±0.41	38.78±0.43	36.33±1.32	50.61±7.72	112.95±0.09	52.73±0.63	23.32±2.43
GPF+	76.08±9.42	19.05±2.91	55.00±1.65	**40.78**±2.54	35.93±1.63	50.26±14.91	112.74±0.25	52.80±0.61	25.33±0.37
GPPT	21.75±5.56	4.01±6.93	50.64±0.45	33.19±0.87	25.04±2.92	61.89±5.21	115.29±1.24	50.27±0.48	16.38±1.82
GraphPrompt	45.96±2.12	10.22±2.44	55.45±0.57	36.38±0.86	25.97±1.09	56.02±4.69	45.67±0.16	42.76±1.49	21.65±0.29
GraphPrompt+	58.95±13.74	9.06±3.74	56.64±0.99	38.78±1.29	27.33±1.48	56.20±8.31	43.16±13.21	43.69±1.70	23.69±0.53
ProNoG	39.30±0.54	7.42±4.25	56.13±0.72	29.57±2.99	29.71±2.90	61.66±12.23	**13.56**±0.74	41.30±0.97	22.87±0.53
IGAP	21.18±4.95	17.14±4.97	51.15±1.50	31.49±1.31	29.70±2.65	45.64±13.45	98.92±7.78	49.03±0.58	16.46±1.67
MTG	25.60±5.93	7.68±3.79	51.87±1.60	32.96±2.74	27.13±4.01	58.99±15.49	107.36±0.06	49.55±0.86	18.83±2.34
SUPT	28.88±5.55	21.03±7.48	51.45±1.51	27.78±1.34	30.04±1.24	54.77±12.04	110.12±0.55	50.37±0.75	11.51±2.77
GAPTUNE+	50.13±2.02	17.87±2.19	**58.43**±0.68	39.06±1.33	32.62±1.66	49.28±10.71	14.04±0.79	**59.17**±0.99	**29.82**±1.01
Pretrain (GraphCL) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**86.65**±0.62	**40.96**±1.38	55.50±0.81	38.13±3.00	38.51±1.35	55.89±9.16	13.88±0.14	52.42±1.17	25.42±3.09
All-in-One	86.08±0.34	27.25±0.71	54.58±0.90	39.11±2.24	34.60±0.50	45.97±15.17	90.38±4.70	53.59±1.20	11.50±1.74
EdgePrompt	76.43±0.94	35.02±0.86	56.62±0.55	43.04±1.72	35.72±1.01	48.90±9.78	106.98±0.39	51.43±0.80	9.74±0.45
EdgePrompt+	77.38±1.63	35.16±0.92	56.34±0.46	43.32±1.54	35.85±1.26	45.87±10.88	106.89±0.32	51.44±1.02	19.36±8.78
GPF	85.21±0.27	34.41±0.63	53.30±1.49	38.38±5.05	36.77±0.64	53.44±8.44	107.65±0.50	51.44±1.23	20.43±1.46
GPF+	86.56±0.92	36.06±2.39	53.02±0.87	41.67±3.01	38.75±0.94	**56.10**±7.28	107.55±1.04	52.12±0.65	21.11±0.89
GPPT	81.73±1.33	27.74±2.86	51.93±0.48	42.48±1.21	34.33±0.78	47.08±10.33	113.28±2.40	50.49±1.67	10.80±0.65
GraphPrompt	82.62±0.92	20.04±0.50	53.19±0.58	40.76±1.59	28.71±1.53	47.19±12.28	13.02±0.30	45.59±1.46	16.33±0.62
GraphPrompt+	81.11±6.09	20.36±0.92	54.31±0.41	41.92±0.98	27.90±1.37	54.90±11.83	32.47±7.93	45.36±1.32	18.61±0.70
ProNoG	80.55±1.23	30.51±0.36	53.92±0.61	36.56±2.49	31.81±0.66	46.53±12.63	13.55±0.37	45.69±1.34	16.18±0.19
IGAP	68.49±4.96	14.27±1.63	49.38±2.86	30.06±1.28	35.87±2.80	55.88±11.96	104.89±0.60	52.35±1.07	11.91±0.91
MTG	66.35±5.94	20.84±1.12	51.29±3.31	26.00±0.23	37.90±1.30	47.96±12.64	114.45±2.84	51.77±1.12	11.32±0.72
SUPT	69.63±5.01	13.09±1.92	49.51±3.17	27.13±1.20	35.80±2.67	49.45±15.70	112.93±0.06	51.43±1.11	10.35±1.83
GAPTUNE+	78.38±1.18	27.32±0.94	**58.18**±0.56	**45.73**±1.64	**39.05**±1.08	54.74±9.15	**9.52**±0.40	**57.73**±1.38	**26.09**±2.27
Pretrain (InfoGraph) + Fine-tuning / Prompting 100-shot									
Full fine-tuning	**86.42**±0.94	**40.50**±6.13	53.82±1.81	38.58±1.44	**38.12**±0.72	55.36±8.71	13.94±0.10	51.80±1.17	22.26±7.16
All-in-One	71.53±0.95	34.55±1.97	53.41±1.48	**40.10**±0.88	37.73±0.90	60.28±4.66	104.68±0.67	56.55±1.09	15.06±0.48
EdgePrompt	64.94±1.74	27.43±1.36	56.43±0.67	34.33±1.82	28.99±1.72	45.61±12.12	111.85±1.98	51.20±0.97	11.04±0.43
EdgePrompt+	73.68±3.02	27.85±2.42	56.45±0.93	32.66±1.74	30.73±1.57	45.94±9.22	110.89±0.58	51.28±0.99	21.42±5.51
GPF	75.67±0.96	32.27±1.78	54.22±1.12	25.11±0.19	35.00±1.46	45.66±15.35	113.16±1.78	51.80±1.19	20.50±1.80
GPF+	84.75±1.21	34.78±1.75	53.35±1.72	25.65±0.46	37.64±1.25	48.42±6.93	114.00±0.68	52.48±0.96	20.41±0.39
GPPT	60.55±2.12	14.14±2.42	51.64±0.65	34.86±1.83	33.42±1.47	52.44±10.33	116.45±0.39	50.42±0.79	10.27±1.01
GraphPrompt	63.88±1.70	17.53±0.94	52.07±0.59	37.82±1.07	30.58±2.48	56.05±6.25	86.93±0.31	44.03±1.43	18.62±0.47
GraphPrompt+	82.93±2.01	18.54±1.55	53.12±1.68	37.92±1.09	28.04±0.82	59.06±9.17	56.99±19.29	44.33±1.39	19.00±0.61
ProNoG	63.42±1.19	24.29±0.65	52.18±0.53	37.37±1.41	30.29±0.91	43.01±10.96	13.41±0.20	43.17±1.32	17.71±0.41
IGAP	68.17±10.50	4.91±2.66	53.25±0.96	32.45±1.66	33.01±1.81	52.25±6.65	99.47±0.10	47.63±1.33	14.22±3.75
MTG	59.46±4.04	5.71±2.09	52.79±0.30	31.35±1.65	29.56±0.83	50.04±9.76	108.74±0.64	48.51±1.29	13.43±3.05
SUPT	66.26±12.54	5.85±3.61	53.36±0.90	27.24±1.57	32.24±2.25	49.22±6.94	112.18±0.12	49.90±0.90	11.53±3.70
GAPTUNE+	74.48±2.10	25.24±1.29	**58.09**±0.65	37.67±1.30	34.48±1.08	**61.90**±6.52	**11.63**±0.57	**59.14**±1.35	**26.74**±1.97