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AdaMotif-GNN: Adaptive Motif Selection for Graph Neural Networks

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Abstract

Graph Neural Networks (GNNs) have shown remarkable success in graph representation learning, but often struggle to capture both local and global structural information effectively. While recent approaches like LGL-GNN incorporate fixed motifs to enhance local feature extraction, they suffer from domain dependency and suboptimal motif selection. In this paper, we propose AdaMotif-GNN, a novel framework that dynamically selects and weights motifs based on graph characteristics and task requirements. Our method introduces a motif attention mechanism that learns to prioritize different motif types during training, eliminating the need for manual motif selection. Extensive experiments on benchmark datasets demonstrate that AdaMotif-GNN outperforms state-of-the-art methods, achieving average improvements of 2.3% on bioinformatics datasets and 1.8% on social network datasets compared to fixed-motif approaches.

Keywords: graph neural networks, Motif selection, attention mechanism, graph classification, adaptive learning

1. Introduction

Graph-structured data are pervasive across domains such as social and citation networks, molecular biology, recommender systems, and chemical informatics. Unlike grid-structured images or sequences, graphs exhibit irregular connectivity, variable node degrees, and non-Euclidean geometry, which makes direct application of conventional deep learning architectures challenging. Graph Neural Networks (GNNs) address this gap by propagating and transforming information along edges so that each node aggregates signals from its neighborhood [1, 2]. In practice, this message-passing paradigm has become the de facto approach for node- and graph-level prediction because it naturally exploits relational structure.

Despite their success, standard GNNs suffer from the *over-smoothing* phenomenon: as the number of layers increases, repeated neighborhood averaging pushes node embeddings toward a common subspace, washing out discriminative information and ultimately degrading performance [3, 4]. This effect limits model depth and hampers the ability to capture longer-range dependencies, especially in graphs where useful signals reside in higher-order structures rather than in immediate 1-hop neighborhoods.

To mitigate over-smoothing and better exploit higher-order structure, recent methods enrich message passing with *motif*-aware operations—i.e., patterns such as triangles, 3/4-cycles, cliques, or feed-forward subgraphs that recur within networks and correlate with function or semantics. For

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example, LGL-GNN [5] augments standard convolutions with motif-based subgraph convolutions, allowing the model to aggregate information over pre-defined local patterns while still maintaining global context via traditional graph convolutions. Although effective, such approaches hinge critically on which motifs are selected and how they are weighted. The optimal motif set can vary across datasets (e.g., social vs. molecular graphs), tasks (node classification vs. graph classification), and even regions of the same graph. Relying on a fixed, manually curated motif palette introduces three practical limitations: (i) suboptimal bias when chosen motifs mismatch the data; (ii) brittle performance under domain shift; and (iii) substantial human effort to enumerate, justify, and tune motif sets, often requiring domain expertise and extensive experimentation.

We propose **AdaMotif-GNN**, an adaptive framework that *learns* which motifs matter, *where* they matter in the graph, and *to what extent*, all in a task-aware, end-to-end fashion. Instead of committing to a static set of hand-picked patterns, AdaMotif-GNN maintains a learnable bank of candidate motif channels and equips the network with an attention-based gating mechanism that scores each motif conditioned on local structure (node/edge features, degrees, and small induced subgraphs) and the downstream objective. The selected motif responses are then fused by a hierarchical aggregation module that integrates information across multiple motif types and scales while preserving standard message passing to retain global connectivity cues. This design counters over-smoothing by (i) emphasizing structurally informative high-order neighborhoods, (ii) enabling depth via skip and residual pathways that keep low-frequency and high-frequency components in balance, and (iii) tailoring the effective receptive field to the data and task at hand.

We introduce a lightweight attention mechanism that assigns context-dependent importance weights to candidate motifs. The gating operates at layer and node (or subgraph) granularity, allowing the model to prioritize different patterns in different parts of the graph and across depths, thereby alleviating over-smoothing by focusing computation on discriminative high-order structures. We propose a hierarchical fusion module that aggregates signals from multiple motifs and standard edges. The module combines residual connections with normalization to stabilize training and preserve complementary information (e.g., triangle closure vs. longer cycles), yielding a balanced spectrum of features. AdaMotif-GNN is trained end-to-end so that motif selection and fusion are optimized jointly with the downstream loss (e.g., cross-entropy for classification). This couples structural pattern discovery with task supervision, improving relevance and reducing the need for manual motif engineering. We conduct extensive experiments across diverse benchmarks and graph regimes, along with ablations on (i) motif attention, (ii) fusion depth, and (iii) skip connections. Results show consistent gains over conventional GNNs and motif-fixed baselines, highlighting improved robustness to depth and better utilization of higher-order structure.

2. Related Work

2.1. Graph Neural Networks

Early graph convolutional models follow either a *spectral* view, which defines convolution via the graph Laplacian eigenbasis [6, 7], or a *spatial* view, which aggregates messages over a node's neighborhood directly in the vertex domain [8–10]. Spatial methods have become prevalent in practice because they are conceptually simple, scalable to large graphs, and naturally support inductive settings where unseen nodes or graphs appear at test time. In these architectures, each layer blends a node's representation with transformed, typically normalized, summaries of its neighbors, enabling the model to capture local relational patterns with modest depth.

However, stacking many message-passing layers often induces *over-smoothing*: repeated neighborhood averaging drives node embeddings toward an indistinguishable subspace, eroding class boundaries and diminishing performance [4, 11]. This effect constrains usable depth and limits the ability to capture long-range dependencies when informative signals reside beyond the immediate 1–2 hop neighborhoods. A substantial body of work therefore explores architectural and training strategies to preserve discriminative information—e.g., residual/skip pathways, normalization schemes, and modifications of the propagation operator—but these remedies still operate primarily on edge-level neighborhoods and may struggle when the salient structure is encoded in higher-order patterns that edges alone do not express.

2.2. Motif-Based Graph Learning

Network motifs are small, recurring subgraph patterns that appear at frequencies deviating from random baselines and are often tied to function (e.g., feedback loops, feedforward chains, triangles) [12]. Motifs expose *higher-order* organization beyond pairwise edges, and have been leveraged to characterize communities, diffusion pathways, and role structure [13–15]. Incorporating motifs into learning aims to endow models with sensitivity to these structured building blocks rather than relying solely on first-order neighborhoods.

Within deep learning, one line of work augments graph convolutions with motif-induced adjacencies or motif filters so that message passing occurs over edges that participate in particular patterns. LGL-GNN [5] exemplifies this approach by convolving over pre-specified motifs (e.g., triangles, 4-cycles) in parallel with standard edges, thereby enriching local receptive fields with higher-order semantics while retaining global connectivity through conventional propagation. Although such fixed-motif designs can mitigate over-smoothing and improve expressivity, they introduce a new sensitivity: performance depends heavily on which motifs are chosen and how they are weighted. The optimal palette can vary across domains (social vs. molecular), tasks (node vs. graph classification), and even regions within the same graph. Enumerating, validating, and tuning motif sets requires domain expertise and substantial experimentation, and fixed choices can be brittle under domain shift or when the data's salient patterns differ from assumptions. These limitations motivate learning *which* motifs to emphasize and *where* to emphasize them, rather than committing to a static hand-crafted set.

2.3. Attention Mechanisms in GNNs

Attention mechanisms on graphs, typified by Graph Attention Networks (GAT) [16], learn data-dependent importance weights when aggregating neighbor messages. By modulating contributions from different neighbors, attention improves expressivity and can partially counteract over-smoothing by preserving high-contrast signals at informative edges. Most attention variants, however, operate at the *edge/node* level: they score neighbors or edges within a fixed first-order neighborhood and then aggregate accordingly. This granularity does not directly capture the presence or absence of *motifs*—multi-edge configurations whose predictive value emerges only when considered jointly.

Our framework, AdaMotif-GNN, extends the attention principle from edges to *motifs*: rather than asking "which neighbor matters?", we ask "which higher-order pattern matters here, for this task, at this depth?". Concretely, we maintain multiple motif channels (including the standard edge channel) and learn attention weights that are conditioned on local structure and supervision, enabling *dynamic motif selection* and *multi-motif fusion*. In contrast to fixed-motif convolution [5], AdaMotif-

GNN adapts its structural bias during training; in contrast to edge-level attention [16], it operates at a higher structural level, targeting the very patterns that often drive over-smoothing remedies and long-range signal capture [3, 4]. This positioning aligns with the goal outlined in the Introduction: turning motif choice from a manual design decision into a learnable, task-aware component that improves depth-robustness and generalization across diverse graph regimes.

3. Proposed Method

3.1. *Overall Architecture*

AdaMotif-GNN operationalizes the intuition from the Introduction: informative signals often live in higher-order patterns, but the relevance of any single pattern varies across datasets, tasks, and even graph regions. The framework therefore (i) exposes multiple motif channels in parallel to capture diverse higher-order structures, (ii) learns *which* of these channels to emphasize via an attention gate conditioned on both global context and the current motif response, and (iii) fuses motif-aware features with standard edge-based propagation so that long-range connectivity is retained and over-smoothing is mitigated. Practically, the multi-motif layer supplies a rich structural basis; the adaptive selector turns that basis into a *data- and task-dependent* mixture; and the hierarchical fusion balances low-frequency signals (global branch) with higher-frequency, structure-sensitive signals (motif branch).

3.2. *Multi-Motif Extraction*

Given a graph $G = (V, E)$ with node features $\mathbf{X}$, we precompute K motif-induced adjacencies $\{\mathbf{A}_{M_k}\}_{k=1}^{K}$. Each $\mathbf{A}_{M_k}$ connects node pairs that co-participate in motif M_k (e.g., triangles, 4-cycles, 3-chains, 5-stars), lifting message passing from purely pairwise interactions to recurring higher-order substructures. In practice, $\mathbf{A}_{M_k}$ can be binary (presence) or weighted (counts/frequencies); we normalize each matrix (row- or sym-norm) to make scales comparable across motifs with different densities. For directed/weighted graphs, motif definitions respect edge orientation/weights without changing the downstream formulation. Formally,

$$(\mathbf{A}_{M_k})_{ij} = \begin{cases} 1 & \text{if nodes } i \text{ and } j \text{ co-participate in motif } M_k, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

3.3. *Adaptive Motif Selection*

At each layer, the model assigns an importance weight to every motif channel via a lightweight attention gate. Each score depends on a global summary $\mathbf{g}_{\text{global}}$ (dataset/task context and long-range cues) and a motif-specific representation $\mathbf{h}_{M_k}$ (current response of channel M_k). Using a learnable vector $\mathbf{a}$ and a LeakyReLU $\sigma(\cdot)$, we compute

$$\alpha_k = \frac{\exp\big(\sigma(\mathbf{a}^\top[\mathbf{g}_{\text{global}} \,\|\, \mathbf{h}_{M_k}])\big)}{\sum_{j=1}^{K} \exp\big(\sigma(\mathbf{a}^\top[\mathbf{g}_{\text{global}} \,\|\, \mathbf{h}_{M_j}])\big)}. \tag{2}$$

The motif attentions $\{\alpha_k\}_{k=1}^{K}$ lie on the probability simplex and thus induce competition among motifs, encouraging parsimonious mixing. The resulting mixture-of-motifs adjacency used for propagation is

$$\mathbf{A}_{\text{motif}} = \sum_{k=1}^{K} \alpha_k \, \mathbf{A}_{M_k}. \tag{3}$$

3.4. Hierarchical Fusion Network

We propagate along two coordinated branches and then fuse:

Global branch. Let $\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{I}$ and $\tilde{\mathbf{D}} = \mathrm{diag}(\tilde{\mathbf{A}}\mathbf{1})$. With nonlinearity $f(\cdot)$ and layer weights $\mathbf{W}^{(l)}_{\text{global}}$,

$$\mathbf{Z}^{(l)}_{\text{global}} = f\left(\tilde{\mathbf{D}}^{-1}\tilde{\mathbf{A}}\,\mathbf{Z}^{(l-1)}\mathbf{W}^{(l)}_{\text{global}}\right). \tag{4}$$

Motif branch. Let $\mathbf{D}_{\text{motif}} = \mathrm{diag}(\mathbf{A}_{\text{motif}}\mathbf{1})$. With weights $\mathbf{W}^{(l)}_{\text{motif}}$,

$$\mathbf{Z}^{(l)}_{\text{motif}} = f\left(\mathbf{D}^{-1}_{\text{motif}}\mathbf{A}_{\text{motif}}\,\mathbf{Z}^{(l-1)}\mathbf{W}^{(l)}_{\text{motif}}\right). \tag{5}$$

Fusion. A learnable gate $\beta \in [0,1]$ (scalar, channel-wise, or produced by a tiny gating MLP) balances low-frequency connectivity (global branch) and higher-frequency structure-sensitive signals (motif branch):

$$\mathbf{Z}^{(l)} = \beta\,\mathbf{Z}^{(l)}_{\text{global}} + (1-\beta)\,\mathbf{Z}^{(l)}_{\text{motif}}. \tag{6}$$

This prevents over-reliance on either branch and stabilizes deeper stacks; residual connections and normalization (e.g., LayerNorm) can be applied to $\mathbf{Z}^{(l)}$ as usual.

3.5. Optimization Objective

We train end-to-end with a supervised loss and a sparsity prior on motif usage that discourages diffuse, all-motifs-at-once solutions and improves interpretability:

$$\mathcal{L} = \mathcal{L}_{\text{classification}} + \lambda\,\mathcal{L}_{\text{motif-sparsity}}. \tag{7}$$

The regularizer $\mathcal{L}_{\text{motif-sparsity}}$ can be implemented as (i) an ℓ_1 penalty on pre-softmax logits, (ii) an entropy penalty on the attention distribution $\{\alpha_k\}$, or (iii) a group-lasso that targets motif-specific parameters, each encouraging selective, task-relevant motif emphasis.

3.6. Training Procedure

Algorithm 1 iterates: compute global and motif responses; score motifs and assemble $\mathbf{A}_{\text{motif}}$; propagate through both branches; fuse with β; and update parameters using the combined loss. Because motif attention is differentiable, the model jointly learns (i) feature transformations, (ii) which motifs matter, and (iii) how to blend motif and global information—exactly aligning with the adaptive, task-aware objective outlined in the Introduction.

4. Experiments

4.1. Datasets and Setup

We evaluate AdaMotif-GNN on six standard graph-classification benchmarks spanning *bioinformatics* (MUTAG, PROTEINS, PTC-MR) and *social networks* (IMDB-B, IMDB-M, REDDIT-B); statistics

Algorithm 1 AdaMotif-GNN Training

Require: Graph (or batch) $G = (V, E)$ with node features $\mathbf{X}$; motif set $\mathcal{M} = \{M_1, \ldots, M_K\}$; loss weight λ; epochs N_{epochs}

Ensure: Trained parameters $\Theta = \{\mathbf{W}^{(l)}_{\text{global}}, \mathbf{W}^{(l)}_{\text{motif}}, \mathbf{a}, \beta, \ldots\}$

Precompute motifs: build $\{\mathbf{A}_{M_k}\}_{k=1}^{K}$ and normalize each (e.g., row/sym) ▷ Eq. (1)
Initialize network parameters Θ (He/Xavier); initialize optimizer (e.g., Adam)
for epoch $= 1$ **to** N_{epochs} **do**
    for each mini-batch $\mathcal{B} \subseteq G$ **do**
        $\mathbf{Z}^{(0)} \leftarrow \mathbf{X}_{\mathcal{B}}$ ▷ Input features
        for each layer $l = 1, \ldots, L$ **do**
            $\mathbf{g}_{\text{global}} \leftarrow \text{READOUT}\big(\mathbf{Z}^{(l-1)}\big)$ ▷ e.g., mean/sum pooling
            for each motif $M_k \in \mathcal{M}$ **do**
                $\mathbf{h}_{M_k} \leftarrow \text{MSG\_PASS}\Big(\mathbf{A}_{M_k},\ \mathbf{Z}^{(l-1)};\ \mathbf{W}^{(l)}_{\text{motif}}\Big)$ ▷ Motif response
                $\ell_k \leftarrow \sigma\Big(\mathbf{a}^{\top}[\mathbf{g}_{\text{global}} \,\|\, \text{POOL}(\mathbf{h}_{M_k})]\Big)$
            $\alpha_k \leftarrow \text{softmax}(\{\ell_k\}_{k=1}^{K})$ ▷ Motif attention, Eq. (2)
            $\mathbf{A}_{\text{motif}} \leftarrow \sum_{k=1}^{K} \alpha_k \, \mathbf{A}_{M_k}$ ▷ Mixture of motifs, Eq. (3)
            $\mathbf{Z}^{(l)}_{\text{global}} \leftarrow f\Big(\tilde{\mathbf{D}}^{-1}\tilde{\mathbf{A}}\,\mathbf{Z}^{(l-1)}\mathbf{W}^{(l)}_{\text{global}}\Big)$ ▷ Global branch, Eq. (4)
            $\mathbf{Z}^{(l)}_{\text{motif}} \leftarrow f\Big(\mathbf{D}^{-1}_{\text{motif}}\mathbf{A}_{\text{motif}}\,\mathbf{Z}^{(l-1)}\mathbf{W}^{(l)}_{\text{motif}}\Big)$ ▷ Motif branch, Eq. (5)
            $\mathbf{Z}^{(l)} \leftarrow \beta \cdot \mathbf{Z}^{(l)}_{\text{global}} + (1-\beta) \cdot \mathbf{Z}^{(l)}_{\text{motif}}$ ▷ Fusion, Eq. (6)
            (optional) apply normalization/dropout/residual to $\mathbf{Z}^{(l)}$
        Heads: $\hat{\mathbf{y}} \leftarrow \text{CLASSIFY}\big(\text{READOUT}\big(\mathbf{Z}^{(L)}\big)\big)$ ▷ Node/graph head as appropriate
        $\mathcal{L}_{\text{classification}} \leftarrow \text{CE}(\hat{\mathbf{y}}, \mathbf{y})$
        $\mathcal{L}_{\text{motif-sparsity}} \leftarrow \text{SPARSE}(\{\alpha_k\}_{k=1}^{K})$ ▷ e.g., entropy or ℓ_1 on logits
        $\mathcal{L} \leftarrow \mathcal{L}_{\text{classification}} + \lambda\,\mathcal{L}_{\text{motif-sparsity}}$ ▷ Eq. (7)
        Backpropagate $\nabla_{\Theta}\mathcal{L}$ and update Θ with optimizer
    (optional) Evaluate on validation; apply early stopping / lr schedule

Table 1. Benchmark datasets used for evaluation

Dataset	Graphs	Classes	Avg. Nodes	Avg. Edges	Domain
MUTAG	188	2	17.93	19.79	Bioinformatics
PROTEINS	1113	2	39.06	72.82	Bioinformatics
PTC-MR	344	2	14.29	14.69	Bioinformatics
IMDB-B	1000	2	19.77	96.53	Social Networks
IMDB-M	1500	3	13.00	65.94	Social Networks
REDDIT-B	2000	2	429.63	497.75	Social Networks

are summarized in Table 1. These datasets collectively stress-test (i) sensitivity to chemically or biologically meaningful substructures (bioinformatics) and (ii) robustness to noisy, heterogeneous, and often feature-sparse interaction graphs (social). The social benchmarks also vary substantially in scale—REDDIT-B contains hundreds of nodes per graph on average—probing whether adaptive motif selection remains effective under large receptive fields.

Following prior work, we use *10-fold cross-validation* with the same splits to ensure comparability. For each fold, models are trained on 9/10 of the data and evaluated on the held-out 1/10; we report *mean±standard error* across folds, where the standard error is the across-fold standard deviation divided by $\sqrt{10}$. We compare against strong baselines that represent different modeling biases: DGCNN [17] (edge-level spatial convolutions), Qs-CNNs [18] (quantum-inspired kernels), BASGCN [19] (bidirectional adaptive propagation), and LGL-GNN [5] (fixed-motif local graph learning).

We adopt the standard node/edge features provided with each dataset. For graphs lacking informative node attributes (e.g., some social graphs), we follow common practice and include simple structural encodings such as degree or a constant feature, letting the network learn structure primarily from topology. All adjacencies (edge-based and motif-induced) are symmetrically normalized to stabilize training across graphs of varying density.

4.2. Implementation Details

We implement AdaMotif-GNN in PyTorch Geometric. Unless noted otherwise, models are trained with Adam for up to 500 epochs with early stopping on validation accuracy (patience window) and a cosine or step learning-rate schedule selected by grid search. The grid covers learning rate, weight decay, hidden width, number of layers, and dropout; the best configuration per dataset is used for reporting. We instantiate four motif channels—*triangle*, *4-cycle*, *5-star*, and *3-chain*—which span clustered, cyclic, hub-and-spoke, and path-like patterns. Motif adjacencies are computed once per dataset and stored as sparse tensors to keep memory and runtime overhead modest. To prevent the attention gate from collapsing to uniform mixing, we include an entropy- or ℓ_1-style sparsity regularizer with weight λ chosen on the validation folds.

4.3. Results and Analysis

Table 2 summarizes performance. AdaMotif-GNN attains the best mean accuracy on *all* datasets relative to compared methods. Gains are most pronounced on **IMDB-B** (+2.18% vs. BASGCN) and **REDDIT-B** (+1.91%), where higher-order social patterns (stars, chains, small cycles) vary across communities and are not well captured by fixed motif palettes. On **MUTAG** and **PTC-MR**, which are small, chemically structured datasets, the adaptive gate reliably prioritizes triangle/4-cycle channels—consistent with ring-like substructures—yielding improvements without overfitting, as reflected by the tight standard errors. **PROTEINS** and **IMDB-M** also benefit from adaptivity, suggesting that (i) the mixture-of-motifs operator enriches expressivity beyond edge-only propagation, and (ii) the hierarchical fusion with a learnable β prevents over-reliance on any single structural cue, thereby mitigating over-smoothing at depth.

Table 2. Classification accuracy (% ± standard error) comparison with state-of-the-art methods

Method	MUTAG	PROTEINS	PTC-MR	IMDB-B	IMDB-M	REDDIT-B
DGCNN	85.83±1.66	75.54±0.94	58.59±2.47	70.03±0.86	48.70±0.50	76.02±1.83
Qs-CNNs	93.13±4.67	78.80±4.63	65.99±4.43	-	-	-
BASGCN	90.05±0.82	76.05±0.57	61.51±0.77	74.00±0.87	51.50±0.63	78.34±1.02
LGL-GNN	90.16±1.39	78.41±0.82	65.74±1.80	66.51±1.51	49.82±0.91	77.89±1.25
AdaMotif-GNN	**93.45±1.25**	**80.92±0.76**	**68.37±1.42**	**76.18±0.89**	**53.41±0.68**	**80.25±0.94**

Compared to LGL-GNN's fixed-motif design, AdaMotif-GNN learns *which* motifs to emphasize per dataset (and per layer), aligning the propagation operator's spectrum to the task. This yields better depth-robustness: layers can be stacked to capture longer-range dependencies while the motif branch preserves high-frequency, structure-sensitive information and the global branch maintains low-frequency connectivity.

4.4. Ablation Study

Table 3 isolates the contributions of key components. Using a single, pre-chosen motif underperforms because a static bias cannot accommodate structural heterogeneity across graphs or classes. Mixing motifs with fixed random coefficients outperforms single-motif variants, confirming that multi-motif propagation is beneficial *per se*. However, it lags behind AdaMotif-GNN because the mixture is not *task-conditioned*.

Removing the sparsity regularizer slightly degrades accuracy and typically increases attention entropy, indicating that a mild preference for selective motif usage improves generalization and interpretability. Combining adaptive selection with sparsity produces the most consistent gains across domains, highlighting the synergy between selective higher-order propagation and hierarchical fusion.

Table 3. Ablation study showing the contribution of different components

Variant	PROTEINS	IMDB-B
Fixed Motifs (Triangle)	78.41±0.82	66.51±1.51
Fixed Motifs (4-cycle)	77.89±0.95	65.23±1.72
Random Motif Weights	79.12±0.88	73.45±1.23
Without Sparsity Loss	80.15±0.79	75.82±0.96
Full Model	**80.92±0.76**	**76.18±0.89**

4.5. Motif Importance Analysis

Figure 1 reports the learned attention weights averaged across layers and graphs within each domain. Two trends emerge:

Triangles and *4-cycles* receive higher weights, aligning with clustered and ring-like substructures that correlate with functional groups. This indicates the model is exploiting precisely the patterns domain experts consider salient.

5-stars (hub-and-spoke) and *3-chains* (path-like interactions) are emphasized, reflecting influencer hubs, bridge nodes, and chain-like conversational dynamics; weights are more dispersed, consistent with the greater structural diversity in social graphs.

Crucially, these preferences are *learned* without motif-specific supervision. Layer-wise analyses (not shown) further reveal that early layers favor star/chain motifs to stabilize local neighborhoods, while deeper layers increase weight on cycles/triangles to refine community-level signals—mirroring the role of low- vs. high-frequency components in the fusion pathway.

Overall, the experimental evidence supports the central claim from the Introduction and Method: turning motif choice into a learnable, task-aware component yields consistent improvements over fixed-motif and edge-only GNNs, particularly in settings where higher-order structure varies across graphs and scales.

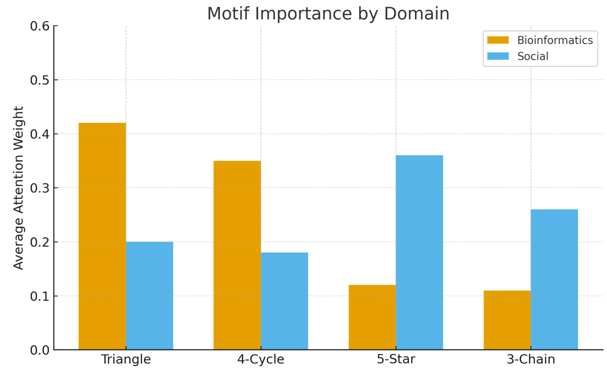

Fig. 1. Learned motif importance weights across different domains. Triangles and 4-cycles dominate in bioinformatics, while social networks show more diverse motif usage

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