

## Appendix

### A LLM USAGE

We used LLMs to refine the writing of this paper. All ideas, content, and results are entirely our own; the LLM’s role was limited to enhancing clarity, grammar, style, and LaTeX formatting.

### B COMPUTATIONAL COMPLEXITY OF HYDRA

For a snapshot  $G_t = (V_t, E_t)$  with  $n = |V_t|$  nodes and  $m = |E_t|$  edges, the per-snapshot complexity of Hydra is

$$\mathcal{O}(m \cdot d + n \cdot d^2 + n \cdot \log n + N \cdot m + K \cdot d),$$

where  $d$  is the hidden dimension,  $K$  is the number of task-specific heads, and  $N$  is the number of Chebyshev moments used in the kernel polynomial method approximation of the DOS. The term  $m \cdot d$  arises from spatial message passing, since each edge propagates a  $d$ -dimensional embedding. The term  $n \cdot d^2$  comes from recurrent or attention-based updates. Pooling with top- $k$  selection contributes  $n \cdot \log n$ , reflecting the computation of attention scores for all nodes followed by partial sorting. The spectral DOS module adds  $N \cdot m$ , as each moment requires one sparse matrix–vector multiplication. Finally, the cost of task-specific heads is  $K \cdot d$ . Over  $N$  networks with  $T$  snapshots each, the overall training cost scales as

$$\mathcal{O}(N \cdot T [m \cdot (d + N) + n \cdot d^2 + n \cdot \log n + K \cdot d]).$$

In our implementation, the spatial hidden dimension is fixed to 16, the DOS descriptor dimension is 20, and we train with  $K = 3$  task-specific heads. Substituting these values, the per-snapshot complexity of Hydra becomes

$$\mathcal{O}(16 \cdot m + 256 \cdot n + n \log n + N \cdot m + 108),$$

where  $m = |E_t|$  and  $n = |V_t|$ . The terms correspond to spatial message passing ( $16 \cdot m$ ), recurrent/attention updates ( $256 \cdot n$ ), pooling with top- $k$  selection ( $n \log n$ ), DOS spectral approximation with  $N$  Chebyshev moments ( $N \cdot m$ ), and three task heads on a 36-dimensional joint embedding (108). For each snapshot, the overall training complexity scales as

$$\mathcal{O}(((16 + N)m + 256n + n \log n)).$$

In practice, with hidden size and Chebyshev moment parameters fixed, the per-snapshot complexity of Hydra reduces to  $\mathcal{O}(N \cdot m + n \log n)$ , dominated by sparse matrix–vector multiplications in the DOS module.

### C DATASET

We evaluate Hydra on temporal transaction networks from the MiNT benchmark (Shamsi et al., 2025), the first large-scale dataset designed for training and evaluating temporal graph models across multiple heterogeneous networks. MiNT contains 84 ERC-20 token transaction graphs collected from the Ethereum blockchain between 2017 and 2023, spanning more than six years of activity. The biggest MiNT token network contains 128,159 unique addresses and 554,705 transactions, while the smallest token network has 1,454 nodes. Each network is represented as a sequence of weekly snapshots, where nodes correspond to wallet addresses and edges represent token transfers. Across their full duration, networks range from tens of thousands to over 100K unique nodes and up to several million edges, reflecting the scale of real-world token ecosystems.

A distinctive feature of MiNT is its strong inductiveness: new addresses and transactions appear continuously, making prediction inherently open-world. This reflects the real behavior of blockchain networks, where adoption cycles, liquidity shocks, and market events constantly introduce novel participants and structural patterns. The long temporal duration further amplifies this effect, as networks exhibit bursts of rapid growth, periods of stagnation, and sudden fragmentation or collapse. Such novelty and surprise factors make MiNT particularly challenging, as models must generalize across highly dynamic trajectories rather than stationary or repetitive patterns.

Table 5: All token networks’ statistics.

Token	#Node	#Transaction	#Snapshots (days)	Growth rate	Novelty	Surprise	Token	#Node	#Transaction	#Snapshots (days)	Growth rate	Novelty	Surprise
ARC	11325	70968	606	0.43	0.32	0.88	Metis	52586	343141	907	0.44	0.48	0.89
CELK	65350	235807	1691	0.49	0.56	0.96	eDAI	52753	358050	1437	0.45	0.46	0.9
CMT	86895	205961	309	0.45	0.72	0.92	BITCOIN	34051	347054	178	0.48	0.39	0.63
DRGN	113453	341849	2164	0.44	0.57	0.97	INJ	60472	312822	1113	0.46	0.52	0.98
GHST	35156	180955	1146	0.43	0.51	0.93	MIM	23038	269366	885	0.44	0.4	0.89
INU	8556	66315	154	0.27	0.41	0.59	GLM	53385	234912	1080	0.5	0.53	0.96
IOTX	63079	288469	1993	0.45	0.56	0.99	Mog	14590	240680	107	0.37	0.38	0.55
QSP	117977	299671	2178	0.45	0.67	0.99	DPI	40627	234246	1150	0.49	0.5	0.86
REP	83282	224843	346	0.46	0.69	0.96	LINA	45342	227147	1144	0.45	0.46	0.95
RFD	23208	173695	169	0.3	0.39	0.6	YI-DAI	22466	226875	1158	0.42	0.31	0.87
TNT	88247	316352	1216	0.43	0.55	0.93	BOB	42806	212099	199	0.35	0.48	0.73
TRAC	71667	299181	2110	0.46	0.54	0.97	RGT	35277	211932	1110	0.44	0.46	0.98
RLB	28033	240291	129	0.43	0.49	0.76	TVK	42539	208082	1062	0.41	0.48	0.93
steCRV	19079	211538	1033	0.45	0.53	0.9	RSR	50645	205906	659	0.47	0.62	0.91
ALBT	63042	434881	1152	0.43	0.44	0.89	WOJAK	34341	198653	201	0.37	0.48	0.73
POLS	128159	554705	1132	0.45	0.61	0.94	ANT	36517	200262	1107	0.47	0.46	0.93
SWAP	69230	509769	1213	0.46	0.45	0.79	LADYS	37486	192176	181	0.37	0.52	0.79
SUPER	83299	502030	986	0.47	0.46	0.85	ETH2x-FLI	11008	199088	965	0.47	0.28	0.84
RARI	87186	502960	1207	0.43	0.47	0.91	TURBO	38638	189048	189	0.33	0.48	0.72
KP3R	39323	493258	1102	0.43	0.33	0.88	REPv2	39061	191367	1194	0.48	0.5	0.97
MIR	79984	444998	1066	0.45	0.43	0.92	NOLA	29798	185528	1133	0.46	0.37	0.7
aUSDC	23742	475880	1067	0.46	0.4	0.73	0x0	21531	182430	283	0.51	0.46	0.81
LUSD	25852	430473	943	0.48	0.36	0.87	PSYOP	25450	168896	169	0.32	0.39	0.59
PICKLE	28498	430262	1149	0.48	0.34	0.69	ShibDoge	40023	134697	680	0.43	0.53	0.8
DODO	47046	390443	1131	0.47	0.45	0.91	ADX	14567	123755	1188	0.44	0.4	0.91
YFII	43964	391984	1196	0.44	0.44	0.96	BAG	11860	122634	298	0.31	0.44	0.87
STARL	71590	369913	856	0.46	0.48	0.86	QQM	21757	118292	598	0.46	0.41	0.81
LQTY	34687	374230	943	0.45	0.34	0.91	BEPRO	26521	120261	1132	0.46	0.48	0.87
FEG	118294	367584	1007	0.4	0.62	0.92	AIOZ	29231	119926	947	0.43	0.49	0.89
AUDIO	91218	362685	1108	0.45	0.58	0.95	PRE	40476	118625	1113	0.5	0.55	0.86
OHM	45728	377068	690	0.43	0.46	0.88	CRU	19990	117712	1144	0.5	0.43	0.95
WOOL	16874	351178	716	0.41	0.18	0.41	POOH	27245	111641	193	0.26	0.49	0.69
DERC	24277	111205	824	0.45	0.49	0.83	aDAI	13648	187050	1068	0.45	0.46	0.82
stkAAVE	37355	110924	1128	0.42	0.57	0.71	ORN	44010	239451	1134	0.46	0.47	0.87
BTRFLY	8450	108371	453	0.48	0.34	0.44	DOGE2.0	7664	79047	123	0.45	0.38	0.66
SDEX	9127	104869	240	0.41	0.44	0.75	HOICHI	5075	77361	436	0.36	0.32	0.71
XCN	20085	104185	607	0.46	0.42	0.84	EVERMOON	7552	79868	163	0.24	0.35	0.52
HOP	37004	102650	514	0.41	0.6	0.88	MUTE	12426	82345	977	0.43	0.46	0.95
MAHA	18401	96180	749	0.43	0.47	0.91	crvUSD	2950	88647	174	0.61	0.37	0.73
DINO	15837	94140	358	0.44	0.44	0.74	SLP	6675	95368	1151	0.43	0.36	0.91
bendWETH	1454	96898	593	0.51	0.21	0.51	sILV2	12838	92905	611	0.4	0.34	0.48
PUSH	14501	93103	936	0.46	0.38	0.83	SPONGE	25852	90468	184	0.31	0.66	0.81

We summarize detailed statistics of each token network in MiNT datasets in Table 5. Most networks have more than 10k nodes and over 100k edges. The lifespan of MiNT networks varies from 107 days to 6 years, and there exists at least one transaction each day. As the table shows, the token networks have quite high surprise values with an average of 0.82.

For our experiments, we follow the MiNT protocol and split the dataset into 64 financial networks for training and 20 additional networks for unseen testing. This setup allows Hydra to learn transferable temporal representations from diverse source networks and evaluate zero-shot generalization on new target networks that are only available at inference time.

## D BASELINES

In this section, we give further details about the temporal graph learning models we used as a baseline for our work.

**TGCN** (Zhao et al., 2020) is a combination of GCN and GRU. In particular, GCN is used to learn complex topological structures, while GRU is used to model embedding dynamically to capture temporal dependence.

**HTGN** (Yang et al., 2021) leverages the power of hyperbolic geometry, which is well-suited for capturing hierarchical structures and complex relationships in temporal networks. HTGN maps the temporal graph into hyperbolic space and utilizes hyperbolic graph neural networks and hyperbolic gated recurrent neural networks to model the evolving dynamics. It incorporates two key modules that are hyperbolic temporal contextual self-attention (HTA) and hyperbolic temporal consistency (HTC)-to ensure that temporal dependencies are effectively captured and that the model is both stable and generalizable across various tasks.

**GraphPulse** (Shamsi et al., 2024) addresses the challenge of learning from nodes and edges with different timestamps, which many existing models struggle with. It combines two key techniques: the Mapper method from topological data analysis to extract clustering information from graph nodes and Recurrent Neural Networks (RNNs) for temporal reasoning. This principled approach helps capture both the structure and dynamics of evolving graphs.

**GCLSTM** (Chen et al., 2022a) combines a Graph Convolutional Network (GCN) and Long Short-Term Memory (LSTM) units to handle both the structural and temporal aspects of evolving net-

works. The GCN is used to capture the local structural properties of the network at each snapshot, while the LSTM learns the temporal evolution of these snapshots over time.

**EvolveGCN** (Pareja et al., 2020) is designed to capture the temporal dynamics of graph-structured data. Instead of relying on static node embeddings, EvolveGCN evolves the parameters of a graph convolutional network (GCN) over time. By using a recurrent neural network (RNN) to adapt the GCN parameters, this model is capable of dynamically adjusting during both training and testing, allowing it to handle evolving graphs, even when node sets vary significantly across different time steps.

**ROLAND** (You et al., 2022) is a dynamic graph learning framework that models node representations as hierarchical states, updated recurrently to capture temporal dependencies in evolving graphs. It supports scalable training using techniques like truncated backpropagation through time and meta-learning. In our DTDG setting, we use ROLAND to benchmark its performance and adaptability across diverse temporal networks.

**WinGNN** (Zhu et al., 2023) uses a simple GNN to model topological information from the graph as other models existing in the literature. However, to model temporal dependencies, WinGNN proposes a novel mechanism of random gradient aggregation and meta learning strategy. In particular, WinGNN computes the frame-wise loss of the current snapshot and passes the loss gradient to the next to model graph dynamics without using RNN-based modules. Then it introduces the randomized sliding-window to acquire the window-aware gradient on consecutive snapshots, and the calculated two types of gradient are aggregated to update the GNN modules.

## E TASK FORMALIZATIONS

In this section, we provide detailed definitions for all classification and regression tasks considered in Hydra. Each temporal snapshot corresponds to a 7-day interval, and the property prediction setup follows GraphPulse (Shamsi et al., 2024). We also note that some of these tasks and the corresponding labels were processed specifically for this work, ensuring consistency and comparability across networks.

Setting  $n = 7$ ,  $\delta_1 = 3$ , and  $\delta_2 = 10$  days, we establish a practical graph property with a 7-day prediction window. This choice is particularly relevant in financial contexts, such as Ethereum asset networks, where it can guide investment decisions (Abay et al., 2019).

### E.1 CLASSIFICATION TASKS

**Node Growth/Shrinkage (Node G/S).** Let  $V(t_1, t_n)$  denote the set of unique nodes active between times  $t_1$  and  $t_n$ . The task predicts whether the number of nodes increases in the prediction interval  $[t_{n+\delta_1}, t_{n+\delta_2}]$ :

$$P_{\text{nodes}}(\mathcal{G}, t_1, t_n, \delta_1, \delta_2) = \begin{cases} 1, & \text{if } |V(t_{n+\delta_1}, t_{n+\delta_2})| > |V(t_1, t_n)|, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

**Importance.** Node growth measures adoption, reflecting the entry of new addresses, while shrinkage signals attrition. In token ecosystems, this corresponds to market expansion or decline.

**Edge Growth/Shrinkage (Edge G/S).** Let  $E(t_1, t_n)$  denote the set of transactions in  $[t_1, t_n]$ . The model predicts whether transaction activity grows in the next interval:

$$P_{\text{edges}}(\mathcal{G}, t_1, t_n, \delta_1, \delta_2) = \begin{cases} 1, & \text{if } |E(t_{n+\delta_1}, t_{n+\delta_2})| > |E(t_1, t_n)|, \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

**Importance.** Edge growth captures changes in liquidity and market engagement, with direct implications for trading activity and token valuation.

**Largest Connected Component Growth/Shrinkage (LCC G/S).** Let  $C(t_1, t_n)$  denote the size of the largest connected component during  $[t_1, t_n]$ . The task is to predict whether connectivity expands:

$$P_{\text{LCC}}(\mathcal{G}, t_1, t_n, \delta_1, \delta_2) = \begin{cases} 1, & \text{if } |C(t_{n+\delta_1}, t_{n+\delta_2})| > |C(t_1, t_n)|, \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

**Importance.** LCC growth reflects stronger structural integration, improving liquidity and market stability in blockchain networks.

## E.2 REGRESSION TASKS

**New Node Count.** Let  $V_{\text{new}}(t_{n+\delta_1}, t_{n+\delta_2})$  denote the set of nodes that appear for the first time in the prediction interval. The regression target is:

$$\hat{y}_{\text{new-nodes}}(\mathcal{G}, t_1, t_n, \delta_1, \delta_2) = |V_{\text{new}}(t_{n+\delta_1}, t_{n+\delta_2})|. \quad (4)$$

**Importance.** New node prediction quantifies adoption and user acquisition, a key indicator of ecosystem growth.

**Edge Count.** The task is to predict the number of transactions in the future interval:

$$\hat{y}_{\text{edges}}(\mathcal{G}, t_1, t_n, \delta_1, \delta_2) = |E(t_{n+\delta_1}, t_{n+\delta_2})|. \quad (5)$$

**Importance.** Transaction forecasts provide fine-grained estimates of liquidity and demand surges in decentralized markets.

**Influential Node Count.** Define influential nodes as those with a degree greater than 5 in the prediction interval. Empirically, degree distributions of ERC-20 token graphs are heavy-tailed (Shamsi et al., 2025): most nodes appear only once or twice, and a small fraction appear hundreds or thousands of times. When we plot the cumulative distribution of node degrees, there is usually a sharp drop in frequency after degree 1–2, followed by a long but thinner tail. Setting the threshold at 5 sits just beyond this long tail cutoff, ensuring that only the top 10–20% of nodes in activity are retained as influential. In practice, this excludes wallets that perform only a handful of transfers while capturing the repeat participants who actually shape liquidity and flow.

Let  $V_{\text{inf}}(t_{n+\delta_1}, t_{n+\delta_2}) = \{v \in V : \deg(v) > 5\}$ . The regression target is:

$$\hat{y}_{\text{inf}}(\mathcal{G}, t_1, t_n, \delta_1, \delta_2) = |V_{\text{inf}}(t_{n+\delta_1}, t_{n+\delta_2})|. \quad (6)$$

**Importance.** Influential nodes represent hubs such as active traders, liquidity providers, or contracts, which shape the stability and price dynamics of token ecosystems.

## E.3 IMPORTANCE OF TEMPORAL PROPERTY PREDICTION

Monitoring global structural dynamics in temporal graphs is essential in domains where the evolution of the entire network, rather than individual edges, drives operational decisions. In blockchain transaction networks, most transactions occur only once and do not repeat, so link-level prediction is not informative. Graph properties instead track global indicators such as changes in connectivity, activity, and influential participants, which often serve as early signals of liquidity risk, instability, or ecosystem decline (Abay et al., 2019; Gurcan Akcora et al., 2021). Since thousands of Ethereum-based tokens evolve with their own user bases and activity patterns (Zhu et al., 2024), training a separate temporal model for each network is not practical. A single model that learns from many heterogeneous networks and jointly predicts several graph properties offers a more scalable and informative solution. Similar considerations arise in communication, payment, and social systems, where forecasting network-level behaviors helps detect anomalies, anticipate demand, and understand system health (Kazemi et al., 2020). A multi-task approach is particularly valuable because these properties move together and provide complementary signals, leading to more reliable and actionable predictions than solving each task independently.

## F EVALUATION METRICS

We evaluate models using both performance scores and ranking-based statistics. Below we provide formal definitions of each metric used in the main paper.

**First-Place Count.** For a given task, the *first-place count* measures how often a method achieves the top performance across datasets. Let  $\mathcal{D}$  denote the set of datasets and  $\mathcal{M}$  the set of methods. For dataset  $d \in \mathcal{D}$ , let  $m^*(d) = \arg \max_{m \in \mathcal{M}} \text{Perf}(m, d)$ , where  $\text{Perf}(m, d)$  is the task-specific score (AUC for classification, MAE for regression). Then the first-place count for method  $m$  is  $\text{First}(m) = \sum_{d \in \mathcal{D}} \mathbf{1}[m = m^*(d)]$ .

**Average Rank.** Each method is ranked per dataset according to performance. Let  $\text{rank}(m, d)$  be the rank of method  $m$  on dataset  $d$  (lower is better). The average rank of method  $m$  is  $\text{AvgRank}(m) = \frac{1}{|\mathcal{D}|} \sum_{d \in \mathcal{D}} \text{rank}(m, d)$ .

**Average AUC (Classification).** For binary classification, the Area Under the ROC Curve (AUC) for dataset  $d$  is  $\text{AUC}(d) = \Pr(\hat{y}_i > \hat{y}_j | y_i = 1, y_j = 0)$ , where  $\hat{y}_i$  are predicted scores and  $y_i \in \{0, 1\}$  are ground-truth labels. The average AUC of method  $m$  is  $\text{AvgAUC}(m) = \frac{1}{|\mathcal{D}|} \sum_{d \in \mathcal{D}} \text{AUC}(m, d)$ .

**Average MAE (Regression).** For regression, the Mean Absolute Error (MAE) on dataset  $d$  is  $\text{MAE}(d) = \frac{1}{N_d} \sum_{i=1}^{N_d} |\hat{y}_i - y_i|$ , where  $\hat{y}_i$  are predictions and  $y_i$  ground truth labels. The average MAE of method  $m$  is  $\text{AvgMAE}(m) = \frac{1}{|\mathcal{D}|} \sum_{d \in \mathcal{D}} \text{MAE}(m, d)$ .

**Relative Gain Across Tasks.** Relative gain quantifies Hydra’s improvement over the strongest baseline by comparing the average metric values across all 20 test datasets for each task. For classification (where higher AUC is better), the gain for task  $t$  is defined as

$$\text{Gain}_t = \frac{\overline{\text{AUC}}_{\text{Hydra}}(t) - \max_{m \in \mathcal{B}} \overline{\text{AUC}}_m(t)}{\max_{m \in \mathcal{B}} \overline{\text{AUC}}_m(t)} \times 100\%,$$

where  $\overline{\text{AUC}}_m(t)$  denotes the average AUC of method  $m$  on task  $t$  across all test datasets.

For regression (where lower MAE is better), the gain is

$$\text{Gain}_t = \frac{\min_{m \in \mathcal{B}} \overline{\text{MAE}}_m(t) - \overline{\text{MAE}}_{\text{Hydra}}(t)}{\min_{m \in \mathcal{B}} \overline{\text{MAE}}_m(t)} \times 100\%,$$

where  $\overline{\text{MAE}}_m(t)$  denotes the average MAE of method  $m$  on task  $t$  across all test datasets.

Finally, the overall gain across a group of tasks  $\mathcal{T}$  (e.g., all classification tasks) is computed as the mean of the per-task gains:  $\text{Gain}_{\mathcal{T}} = \frac{1}{|\mathcal{T}|} \sum_{t \in \mathcal{T}} \text{Gain}_t$ .

## G ABLATION STUDIES

To better understand Hydra components, we conduct an ablation study on the edge growth/shrinkage task. The ablations reflect different stages in the model’s incremental development. First, we compare the initial version of Hydra without pooling, evaluating the impact of adding Density of States (DOS) features in the spectral path. Next, we consider models that already include DOS and assess the effect of introducing attention-based pooling in the spatial path. Results are reported in Appendix Tables 6 and 7. Together, these comparisons show that DOS enhances the capture of global spectral structure, while pooling improves the selection of informative subgraphs, confirming their complementary roles in Hydra’s design and performance.

**Impact of DOS.** To assess the contribution of the DOS module, we compare Hydra with and without DOS features (Table 6). This setup isolates the effect of spectral information on predictive performance, holding all other components fixed. The results show that incorporating DOS substantially improves performance on most datasets: Hydra with DOS achieves the best results in 14 out of 20 networks, compared to 6 without DOS. On average, DOS raises AUC from 0.697 to 0.719 and improves the mean rank from 1.70 to 1.30. Gains are particularly large on challenging datasets such as *EVERMOON*, *DOGE2.0*, and *DINO*, where DOS more effectively captures global spectral structure. These findings highlight that DOS provides complementary information to the spatial path, leading to stronger generalization across temporal networks.

**Impact of Attention-based Pooling.** The ablation on the edge growth/shrinkage task (Table 7) shows the contribution of the pooling mechanism within Hydra’s spatial path. When pooling is enabled, the model achieves higher AUC on 17 out of 20 datasets, with the average score improving from 0.719 to 0.753 and the mean rank from 1.85 to 1.15. The improvement is particularly noticeable when pooling helps the spatial path focus on structurally important nodes, resulting in stronger graph-level representations. These findings indicate that pooling is an essential component for producing compact, informative graph-level representations and strengthen Hydra’s ability to capture temporal dynamics.



Table 6: DOS ablation study on task Edge G/S. AUC values are reported. Best results per dataset are in **bold**.

Dataset	Hydra w/o DOS	Hydra w DOS
MIR	<b>0.791 (<math>\pm 0.014</math>)</b>	0.755 ( $\pm 0.013$ )
DOGE2.0	0.500 ( $\pm 0.102$ )	<b>0.732 (<math>\pm 0.044</math>)</b>
MUTE	0.675 ( $\pm 0.030$ )	<b>0.699 (<math>\pm 0.011</math>)</b>
EVERMOON	0.426 ( $\pm 0.129$ )	<b>0.796 (<math>\pm 0.219</math>)</b>
DERC	0.748 ( $\pm 0.029$ )	<b>0.761 (<math>\pm 0.030</math>)</b>
ADX	0.678 ( $\pm 0.019$ )	<b>0.703 (<math>\pm 0.006</math>)</b>
HOICHI	<b>0.792 (<math>\pm 0.052</math>)</b>	0.572 ( $\pm 0.016$ )
SDEX	<b>0.599 (<math>\pm 0.134</math>)</b>	0.261 ( $\pm 0.129$ )
BAG	0.759 ( $\pm 0.294$ )	<b>0.874 (<math>\pm 0.017</math>)</b>
XCN	0.822 ( $\pm 0.073$ )	<b>0.825 (<math>\pm 0.038</math>)</b>
ETH2x-FLI	0.716 ( $\pm 0.020$ )	<b>0.736 (<math>\pm 0.026</math>)</b>
stkAAVE	0.708 ( $\pm 0.021$ )	<b>0.719 (<math>\pm 0.006</math>)</b>
GLM	0.755 ( $\pm 0.194$ )	<b>0.810 (<math>\pm 0.015</math>)</b>
QOM	0.639 ( $\pm 0.015$ )	<b>0.698 (<math>\pm 0.024</math>)</b>
WOJAK	0.548 ( $\pm 0.081$ )	<b>0.633 (<math>\pm 0.081</math>)</b>
DINO	0.672 ( $\pm 0.044$ )	<b>0.843 (<math>\pm 0.031</math>)</b>
Metis	<b>0.785 (<math>\pm 0.050</math>)</b>	0.713 ( $\pm 0.027$ )
REPV2	<b>0.761 (<math>\pm 0.039</math>)</b>	0.736 ( $\pm 0.028$ )
TRAC	<b>0.794 (<math>\pm 0.041</math>)</b>	0.732 ( $\pm 0.007$ )
BEPRO	0.775 ( $\pm 0.022$ )	<b>0.786 (<math>\pm 0.009</math>)</b>
1 <sup>st</sup> -Place Count $\uparrow$	6	<b>14</b>
Avg. Rank $\downarrow$	1.70	<b>1.30</b>
Avg. AUC $\uparrow$	0.697	<b>0.719</b>

Table 7: SAG pooling ablation study on task Edge G/S. AUC values are reported. Best results per dataset are in **bold**.

Dataset	Hydra w/o Pooling	Hydra w Pooling
MIR	0.755 ( $\pm 0.013$ )	<b>0.793 (<math>\pm 0.002</math>)</b>
DOGE2.0	0.732 ( $\pm 0.044$ )	<b>0.897 (<math>\pm 0.089</math>)</b>
MUTE	0.699 ( $\pm 0.011$ )	<b>0.701 (<math>\pm 0.098</math>)</b>
EVERMOON	0.796 ( $\pm 0.219$ )	<b>0.818 (<math>\pm 0.046</math>)</b>
DERC	0.761 ( $\pm 0.030$ )	<b>0.839 (<math>\pm 0.008</math>)</b>
ADX	0.703 ( $\pm 0.006$ )	<b>0.722 (<math>\pm 0.087</math>)</b>
HOICHI	0.572 ( $\pm 0.016$ )	<b>0.591 (<math>\pm 0.103</math>)</b>
SDEX	0.261 ( $\pm 0.129$ )	<b>0.348 (<math>\pm 0.066</math>)</b>
BAG	0.874 ( $\pm 0.017$ )	<b>0.969 (<math>\pm 0.008</math>)</b>
XCN	0.825 ( $\pm 0.038$ )	<b>0.844 (<math>\pm 0.012</math>)</b>
ETH2x-FLI	<b>0.736 (<math>\pm 0.026</math>)</b>	0.712 ( $\pm 0.045$ )
stkAAVE	0.719 ( $\pm 0.006$ )	<b>0.732 (<math>\pm 0.011</math>)</b>
GLM	0.810 ( $\pm 0.015$ )	<b>0.850 (<math>\pm 0.009</math>)</b>
QOM	0.698 ( $\pm 0.024$ )	<b>0.745 (<math>\pm 0.003</math>)</b>
WOJAK	<b>0.633 (<math>\pm 0.081</math>)</b>	0.585 ( $\pm 0.067$ )
DINO	0.843 ( $\pm 0.031$ )	<b>0.895 (<math>\pm 0.003</math>)</b>
Metis	0.713 ( $\pm 0.027$ )	<b>0.733 (<math>\pm 0.004</math>)</b>
REPV2	0.736 ( $\pm 0.028$ )	<b>0.772 (<math>\pm 0.016</math>)</b>
TRAC	<b>0.732 (<math>\pm 0.007</math>)</b>	0.722 ( $\pm 0.001$ )
BEPRO	0.786 ( $\pm 0.009$ )	<b>0.800 (<math>\pm 0.002</math>)</b>
1 <sup>st</sup> -Place Count $\uparrow$	3	<b>17</b>
Avg. Rank $\downarrow$	1.85	<b>1.15</b>
Avg. AUC $\uparrow$	0.719	<b>0.753</b>

## H SCALING BEHAVIOR IN HYDRA

We conducted scaling trend experiments to evaluate Hydra under different training pack sizes systematically. Four model variations were trained using 8, 16, and 32 networks, enabling us to observe how increasing the number of networks in the training loop affects performance. This setup provides a consistent method to study Hydra’s behavior when exposed to varying amounts of training data across multiple tasks. For each task, we present results for all four Hydra variants. These results demonstrate how Hydra scales with the number of training networks and are shown in the following tables. Each table provides a detailed breakdown by task and model variation, offering a comprehensive view of performance under various scaling setups. The detailed results of each Hydra variation trained with different datapacks across all six tasks are reported in Table 8. Subsections (a)–(c) present classification tasks (Node G/S, Edge G/S, LCC G/S), while (d)–(f) correspond to regression tasks (New Node Count, Influential Node Count, Edge Count).

## I EXTENDED NETWORK AND TASK RESULTS

This section reports the full per-network results for all classification and regression tasks, using the same evaluation protocol as in the main text. These tables complement the summary figures by showing the complete distribution of baseline and Hydra performance across datasets.

**Classification.** Extended **classification** results are provided for *Edge-G/S*, *LLC-G/S*, and *Node-G/S* in Table 9, Table 10, and Table 11, respectively.

**Regression.** Extended **regression** results are provided for *Edge Count*, *New Node Count*, and *Influential Node Count* in Table 12, Table 13, and Table 14, respectively.

For **classification**, Hydra achieves the highest AUC on the majority of datasets across Edge-G/S, LLC-G/S, and Node-G/S. For **regression** Hydra consistently delivers the lowest or near-lowest MAE, remaining competitive even on tasks where another baseline occasionally leads. These results confirm that Hydra’s advantages are not limited to averages: the model transfers robustly across heterogeneous temporal networks and maintains strong performance in the zero-shot setting.

Table 8: Performance of Hydra across six tasks as the number of training networks increases from 8 to 32.

(a) Classification : Node G/S				(b) Classification : Edge G/S			
Dataset	Hydra-8	Hydra-16	Hydra-32	Dataset	Hydra-8	Hydra-16	Hydra-32
MIR	<b>0.769 (±0.003)</b>	<b>0.769 (±0.007)</b>	0.764 (±0.001)	MIR	<b>0.800 (±0.007)</b>	0.796 (±0.001)	0.793 (±0.002)
DOGE2.0	0.613 (±0.083)	0.573 (±0.133)	<b>0.633 (±0.064)</b>	DOGE2.0	0.859 (±0.022)	<b>0.897 (±0.089)</b>	<b>0.897 (±0.089)</b>
MUTE	0.755 (±0.016)	<b>0.763 (±0.003)</b>	0.748 (±0.025)	MUTE	0.757 (±0.004)	<b>0.764 (±0.004)</b>	0.701 (±0.098)
EVERMOON	0.624 (±0.005)	0.582 (±0.031)	<b>0.655 (±0.040)</b>	EVERMOON	0.698 (±0.180)	0.750 (±0.024)	<b>0.818 (±0.046)</b>
DERC	0.734 (±0.010)	0.725 (±0.006)	<b>0.742 (±0.004)</b>	DERC	0.823 (±0.018)	0.826 (±0.002)	<b>0.839 (±0.008)</b>
ADX	0.753 (±0.027)	<b>0.767 (±0.004)</b>	0.718 (±0.051)	ADX	0.760 (±0.004)	<b>0.768 (±0.015)</b>	0.722 (±0.087)
HOICHI	<b>0.582 (±0.029)</b>	0.552 (±0.050)	0.558 (±0.047)	HOICHI	0.606 (±0.015)	<b>0.617 (±0.026)</b>	0.591 (±0.103)
SDEX	<b>0.762 (±0.008)</b>	0.748 (±0.068)	0.743 (±0.026)	SDEX	0.288 (±0.023)	0.331 (±0.049)	<b>0.348 (±0.066)</b>
BAG	0.963 (±0.010)	0.952 (±0.021)	<b>0.969 (±0.009)</b>	BAG	<b>0.969 (±0.009)</b>	0.955 (±0.015)	<b>0.969 (±0.008)</b>
XCN	0.862 (±0.017)	0.821 (±0.070)	<b>0.878 (±0.009)</b>	XCN	<b>0.847 (±0.006)</b>	0.845 (±0.010)	0.844 (±0.012)
ETH2x-FLI	<b>0.717 (±0.030)</b>	0.710 (±0.009)	0.678 (±0.031)	ETH2x-FLI	0.735 (±0.006)	<b>0.738 (±0.005)</b>	0.712 (±0.045)
stkAAVE	0.776 (±0.009)	0.776 (±0.003)	<b>0.779 (±0.007)</b>	stkAAVE	<b>0.744 (±0.008)</b>	0.743 (±0.007)	0.732 (±0.011)
GLM	0.750 (±0.011)	0.746 (±0.010)	<b>0.763 (±0.005)</b>	GLM	0.849 (±0.003)	0.841 (±0.015)	<b>0.850 (±0.009)</b>
QOM	0.703 (±0.012)	0.707 (±0.013)	<b>0.719 (±0.012)</b>	QOM	0.755 (±0.015)	<b>0.762 (±0.008)</b>	0.745 (±0.003)
WOJAK	<b>0.502 (±0.103)</b>	0.352 (±0.157)	0.412 (±0.060)	WOJAK	<b>0.627 (±0.014)</b>	0.561 (±0.101)	0.585 (±0.067)
DINO	0.903 (±0.029)	0.905 (±0.021)	<b>0.910 (±0.013)</b>	DINO	0.875 (±0.030)	0.889 (±0.009)	<b>0.895 (±0.003)</b>
Metis	0.685 (±0.002)	0.632 (±0.091)	<b>0.693 (±0.007)</b>	Metis	<b>0.735 (±0.004)</b>	0.697 (±0.062)	0.733 (±0.004)
REPV2	<b>0.728 (±0.022)</b>	0.721 (±0.023)	0.689 (±0.013)	REPV2	0.778 (±0.001)	<b>0.784 (±0.009)</b>	0.772 (±0.016)
TRAC	0.756 (±0.005)	0.745 (±0.014)	<b>0.765 (±0.003)</b>	TRAC	0.713 (±0.010)	0.711 (±0.011)	<b>0.722 (±0.001)</b>
BEPRO	0.858 (±0.023)	0.806 (±0.094)	<b>0.865 (±0.010)</b>	BEPRO	0.783 (±0.009)	0.743 (±0.085)	<b>0.800 (±0.002)</b>
1 <sup>st</sup> -Place Count↑	6	3	12	1 <sup>st</sup> -Place Count↑	6	7	9
Avg. Rank↓	1.85	2.45	1.70	Avg. Rank↓	1.95	1.95	2
Avg. AUC↑	<b>0.740</b>	0.718	0.734	Avg. AUC↑	0.75	0.751	<b>0.753</b>

  

(c) Classification : LCC G/S				(d) Regression : New Node Count			
Dataset	Hydra-8	Hydra-16	Hydra-32	Dataset	Hydra-8	Hydra-16	Hydra-32
MIR	<b>0.819 (±0.004)</b>	0.817 (±0.001)	0.815 (±0.007)	MIR	0.056 (±0.057)	0.040 (±0.042)	<b>0.013 (±0.004)</b>
DOGE2.0	<b>0.762 (±0.010)</b>	0.667 (±0.175)	0.702 (±0.160)	DOGE2.0	0.068 (±0.023)	<b>0.060 (±0.027)</b>	0.092 (±0.008)
MUTE	0.714 (±0.049)	<b>0.756 (±0.006)</b>	0.704 (±0.085)	MUTE	0.073 (±0.036)	0.036 (±0.025)	<b>0.025 (±0.005)</b>
EVERMOON	0.600 (±0.057)	0.639 (±0.029)	<b>0.667 (±0.045)</b>	EVERMOON	0.070 (±0.053)	0.038 (±0.045)	<b>0.012 (±0.005)</b>
DERC	<b>0.819 (±0.003)</b>	0.813 (±0.005)	0.808 (±0.022)	DERC	0.071 (±0.049)	0.038 (±0.040)	<b>0.015 (±0.004)</b>
ADX	0.691 (±0.066)	<b>0.770 (±0.021)</b>	0.727 (±0.093)	ADX	0.069 (±0.047)	0.029 (±0.035)	<b>0.016 (±0.005)</b>
HOICHI	0.610 (±0.044)	<b>0.640 (±0.041)</b>	0.638 (±0.075)	HOICHI	0.064 (±0.038)	0.048 (±0.030)	<b>0.029 (±0.008)</b>
SDEX	0.784 (±0.017)	0.810 (±0.048)	<b>0.816 (±0.025)</b>	SDEX	0.074 (±0.021)	0.072 (±0.011)	<b>0.063 (±0.006)</b>
BAG	0.968 (±0.013)	0.957 (±0.021)	<b>0.976 (±0.006)</b>	BAG	0.072 (±0.023)	0.056 (±0.009)	<b>0.052 (±0.002)</b>
XCN	0.863 (±0.011)	0.863 (±0.029)	<b>0.887 (±0.014)</b>	XCN	0.067 (±0.056)	0.036 (±0.044)	<b>0.009 (±0.002)</b>
ETH2x-FLI	<b>0.708 (±0.011)</b>	0.703 (±0.001)	0.687 (±0.032)	ETH2x-FLI	0.053 (±0.034)	0.032 (±0.023)	<b>0.030 (±0.004)</b>
stkAAVE	0.753 (±0.011)	<b>0.757 (±0.003)</b>	0.748 (±0.012)	stkAAVE	0.085 (±0.037)	<b>0.057 (±0.024)</b>	0.078 (±0.017)
GLM	<b>0.853 (±0.006)</b>	0.844 (±0.020)	0.848 (±0.012)	GLM	0.097 (±0.013)	0.103 (±0.008)	<b>0.094 (±0.007)</b>
QOM	0.725 (±0.009)	<b>0.730 (±0.002)</b>	0.729 (±0.010)	QOM	0.073 (±0.054)	0.034 (±0.040)	<b>0.012 (±0.001)</b>
WOJAK	<b>0.558 (±0.032)</b>	0.458 (±0.142)	0.500 (±0.083)	WOJAK	0.076 (±0.059)	0.034 (±0.042)	<b>0.009 (±0.000)</b>
DINO	0.878 (±0.021)	<b>0.883 (±0.032)</b>	0.818 (±0.049)	DINO	0.065 (±0.053)	0.046 (±0.042)	<b>0.018 (±0.007)</b>
Metis	0.727 (±0.006)	0.669 (±0.100)	<b>0.731 (±0.001)</b>	Metis	0.072 (±0.030)	0.037 (±0.016)	<b>0.034 (±0.010)</b>
REPV2	0.781 (±0.004)	<b>0.785 (±0.009)</b>	0.764 (±0.020)	REPV2	0.083 (±0.024)	0.074 (±0.015)	<b>0.066 (±0.004)</b>
TRAC	0.772 (±0.006)	0.768 (±0.008)	<b>0.781 (±0.004)</b>	TRAC	0.074 (±0.042)	0.029 (±0.026)	<b>0.022 (±0.005)</b>
BEPRO	0.826 (±0.015)	0.800 (±0.058)	<b>0.830 (±0.006)</b>	BEPRO	0.081 (±0.067)	0.034 (±0.046)	<b>0.004 (±0.001)</b>
1 <sup>st</sup> -Place Count↑	6	7	7	1 <sup>st</sup> -Place Count↑	0	2	18
Avg. Rank↓	1.95	2	2	Avg. Rank↓	2.90	1.95	1.15
Avg. AUC↑	<b>0.761</b>	0.756	0.759	Avg. MAE↓	0.072	0.047	<b>0.035</b>

  

(e) Regression : Influential Node Count				(f) Regression : Edge Count			
Dataset	Hydra-8	Hydra-16	Hydra-32	Dataset	Hydra-8	Hydra-16	Hydra-32
MIR	0.080 (±0.059)	0.059 (±0.004)	<b>0.039 (±0.005)</b>	MIR	0.087 (±0.057)	0.035 (±0.027)	<b>0.016 (±0.004)</b>
DOGE2.0	<b>0.065 (±0.034)</b>	0.094 (±0.003)	0.126 (±0.032)	DOGE2.0	<b>0.115 (±0.023)</b>	0.135 (±0.032)	0.187 (±0.008)
MUTE	0.103 (±0.070)	0.078 (±0.034)	<b>0.045 (±0.027)</b>	MUTE	0.092 (±0.036)	0.048 (±0.017)	<b>0.021 (±0.005)</b>
EVERMOON	0.107 (±0.067)	0.072 (±0.018)	<b>0.038 (±0.024)</b>	EVERMOON	0.085 (±0.053)	0.041 (±0.029)	<b>0.017 (±0.005)</b>
DERC	0.063 (±0.065)	0.056 (±0.012)	<b>0.033 (±0.017)</b>	DERC	0.082 (±0.049)	0.033 (±0.024)	<b>0.021 (±0.004)</b>
ADX	0.084 (±0.070)	0.054 (±0.009)	<b>0.030 (±0.001)</b>	ADX	0.082 (±0.047)	0.029 (±0.018)	<b>0.025 (±0.005)</b>
HOICHI	0.115 (±0.066)	0.088 (±0.045)	<b>0.055 (±0.028)</b>	HOICHI	0.090 (±0.038)	0.062 (±0.006)	<b>0.027 (±0.008)</b>
SDEX	0.087 (±0.027)	0.083 (±0.068)	<b>0.042 (±0.019)</b>	SDEX	0.080 (±0.021)	<b>0.077 (±0.018)</b>	0.095 (±0.006)
BAG	0.141 (±0.064)	0.109 (±0.045)	<b>0.075 (±0.027)</b>	BAG	0.099 (±0.023)	0.065 (±0.005)	<b>0.041 (±0.002)</b>
XCN	<b>0.071 (±0.033)</b>	0.096 (±0.008)	0.126 (±0.033)	XCN	0.066 (±0.056)	<b>0.027 (±0.009)</b>	0.062 (±0.002)
ETH2x-FLI	0.066 (±0.059)	0.052 (±0.007)	<b>0.033 (±0.020)</b>	ETH2x-FLI	0.084 (±0.034)	0.035 (±0.019)	<b>0.023 (±0.004)</b>
stkAAVE	0.067 (±0.049)	0.063 (±0.008)	<b>0.042 (±0.013)</b>	stkAAVE	0.065 (±0.037)	<b>0.025 (±0.004)</b>	0.051 (±0.017)
GLM	0.108 (±0.045)	0.088 (±0.014)	<b>0.075 (±0.017)</b>	GLM	0.106 (±0.013)	0.101 (±0.007)	<b>0.087 (±0.007)</b>
QOM	0.066 (±0.055)	0.055 (±0.004)	<b>0.039 (±0.020)</b>	QOM	0.074 (±0.054)	<b>0.032 (±0.019)</b>	0.036 (±0.001)
WOJAK	0.116 (±0.068)	0.074 (±0.006)	<b>0.036 (±0.027)</b>	WOJAK	0.090 (±0.059)	0.034 (±0.035)	<b>0.010 (±0.000)</b>
DINO	0.085 (±0.066)	0.059 (±0.009)	<b>0.034 (±0.002)</b>	DINO	0.085 (±0.053)	0.040 (±0.028)	<b>0.017 (±0.007)</b>
Metis	0.082 (±0.056)	0.072 (±0.022)	<b>0.046 (±0.008)</b>	Metis	0.087 (±0.030)	0.041 (±0.005)	<b>0.034 (±0.010)</b>
REPV2	<b>0.127 (±0.015)</b>	0.130 (±0.004)	0.129 (±0.022)	REPV2	0.127 (±0.024)	<b>0.105 (±0.003)</b>	0.111 (±0.004)
TRAC	0.069 (±0.053)	0.059 (±0.003)	<b>0.043 (±0.023)</b>	TRAC	0.086 (±0.042)	0.029 (±0.020)	<b>0.021 (±0.005)</b>
BEPRO	0.105 (±0.068)	0.064 (±0.005)	<b>0.033 (±0.018)</b>	BEPRO	0.094 (±0.067)	0.037 (±0.036)	<b>0.011 (±0.001)</b>
1 <sup>st</sup> -Place Count↑	3	0	17	1 <sup>st</sup> -Place Count↑	1	5	14
Avg. Rank↓	2.70	2.05	1.25	Avg. Rank↓	2.85	1.75	1.40
Avg. MAE↓	0.090	0.075	<b>0.056</b>	Avg. MAE↓	0.089	0.052	<b>0.046</b>

Table 9: AUC results for the Edge Growth/Shrinkage prediction task ( classification ). Best results are in **bold**, second best are underlined.

Dataset	Single Model on Individual Networks							Transfer Models	
	HTGN	GC-LSTM	EvolveGCN	GraphPulse	ROLAND	TGCN	WinGNN	MiNT	Hydra (Ours)
MIR	0.750 $\pm$ 0.005	0.768 $\pm$ 0.026	0.745 $\pm$ 0.015	0.689 $\pm$ 0.097	0.228 $\pm$ 0.060	0.749 $\pm$ 0.026	0.742 $\pm$ 0.015	<b>0.836 <math>\pm</math>0.016</b>	0.793 $\pm$ 0.026
DOGE2.0	<u>0.590 <math>\pm</math>0.059</u>	0.538 $\pm$ 0.000	0.551 $\pm$ 0.022	0.384 $\pm$ 0.180	0.513 $\pm$ 0.022	0.487 $\pm$ 0.044	0.577 $\pm$ 0.038	0.538 $\pm$ 0.038	<b>0.897 <math>\pm</math>0.044</b>
MUTE	0.649 $\pm$ 0.015	0.593 $\pm$ 0.030	0.617 $\pm$ 0.010	<b>0.779 <math>\pm</math>0.004</b>	0.289 $\pm$ 0.042	0.557 $\pm$ 0.068	0.593 $\pm$ 0.054	0.673 $\pm$ 0.013	0.701 $\pm$ 0.068
EVERMOON	0.512 $\pm$ 0.023	<u>0.562 <math>\pm</math>0.179</u>	0.451 $\pm$ 0.046	0.519 $\pm$ 0.130	0.349 $\pm$ 0.119	0.463 $\pm$ 0.149	0.525 $\pm$ 0.114	0.517 $\pm$ 0.039	<b>0.818 <math>\pm</math>0.149</b>
DERC	0.683 $\pm$ 0.013	0.703 $\pm$ 0.022	0.669 $\pm$ 0.009	<u>0.769 <math>\pm</math>0.040</u>	0.405 $\pm$ 0.357	0.743 $\pm$ 0.077	0.674 $\pm$ 0.044	<u>0.798 <math>\pm</math>0.027</u>	<b>0.839 <math>\pm</math>0.077</b>
ADX	<u>0.769 <math>\pm</math>0.018</u>	0.723 $\pm$ 0.002	0.718 $\pm$ 0.004	<b>0.784 <math>\pm</math>0.002</b>	0.761 $\pm$ 0.011	0.674 $\pm$ 0.034	0.733 $\pm$ 0.023	0.679 $\pm$ 0.024	0.722 $\pm$ 0.034
HOICHI	<u>0.807 <math>\pm</math>0.047</u>	<b>0.857 <math>\pm</math>0.000</b>	0.856 $\pm$ 0.001	0.714 $\pm$ 0.010	0.815 $\pm$ 0.036	0.836 $\pm$ 0.034	0.769 $\pm$ 0.101	0.765 $\pm$ 0.018	0.591 $\pm$ 0.034
SDEX	<b>0.762 <math>\pm</math>0.034</b>	0.720 $\pm$ 0.002	0.733 $\pm$ 0.028	0.436 $\pm$ 0.030	0.483 $\pm$ 0.254	<u>0.759 <math>\pm</math>0.039</u>	0.726 $\pm$ 0.000	0.614 $\pm$ 0.020	0.348 $\pm$ 0.039
BAG	0.673 $\pm$ 0.227	0.196 $\pm$ 0.179	0.329 $\pm$ 0.040	<u>0.934 <math>\pm</math>0.020</u>	0.418 $\pm$ 0.016	0.334 $\pm$ 0.171	0.485 $\pm$ 0.105	0.931 $\pm$ 0.028	<b>0.969 <math>\pm</math>0.171</b>
XCN	0.668 $\pm$ 0.099	0.306 $\pm$ 0.092	0.512 $\pm$ 0.067	0.821 $\pm$ 0.004	0.765 $\pm$ 0.015	0.703 $\pm$ 0.037	0.586 $\pm$ 0.029	<b>0.851 <math>\pm</math>0.043</b>	<u>0.844 <math>\pm</math>0.037</u>
ETH2x-FLI	0.610 $\pm$ 0.059	0.670 $\pm$ 0.009	0.688 $\pm$ 0.010	0.666 $\pm$ 0.047	0.621 $\pm$ 0.023	0.647 $\pm$ 0.020	0.617 $\pm$ 0.056	<b>0.729 <math>\pm</math>0.015</b>	0.712 $\pm$ 0.020
stkAAVE	0.702 $\pm$ 0.042	0.368 $\pm$ 0.011	0.397 $\pm$ 0.022	<b>0.743 <math>\pm</math>0.006</b>	0.591 $\pm$ 0.122	0.577 $\pm$ 0.129	0.572 $\pm$ 0.018	0.709 $\pm$ 0.022	<u>0.732 <math>\pm</math>0.129</u>
GLM	0.830 $\pm$ 0.029	0.451 $\pm$ 0.003	0.501 $\pm$ 0.033	0.769 $\pm$ 0.018	0.559 $\pm$ 0.357	0.531 $\pm$ 0.008	0.530 $\pm$ 0.004	0.831 $\pm$ 0.024	<b>0.850 <math>\pm</math>0.008</b>
QOM	0.633 $\pm$ 0.017	0.612 $\pm$ 0.001	0.618 $\pm$ 0.002	<b>0.775 <math>\pm</math>0.011</b>	0.641 $\pm$ 0.003	0.647 $\pm$ 0.032	0.645 $\pm$ 0.099	0.647 $\pm$ 0.019	<u>0.745 <math>\pm</math>0.032</u>
WOJAK	0.479 $\pm$ 0.005	0.484 $\pm$ 0.000	0.505 $\pm$ 0.023	0.467 $\pm$ 0.030	<u>0.529 <math>\pm</math>0.005</u>	0.516 $\pm$ 0.021	0.511 $\pm$ 0.026	0.524 $\pm$ 0.027	<b>0.585 <math>\pm</math>0.021</b>
DINO	0.730 $\pm$ 0.195	<u>0.874 <math>\pm</math>0.028</u>	0.868 $\pm$ 0.029	0.801 $\pm$ 0.020	0.497 $\pm$ 0.092	0.544 $\pm$ 0.314	0.628 $\pm$ 0.251	0.779 $\pm$ 0.113	<b>0.895 <math>\pm</math>0.314</b>
Metis	0.715 $\pm$ 0.122	0.646 $\pm$ 0.023	0.688 $\pm$ 0.027	<b>0.812 <math>\pm</math>0.011</b>	0.696 $\pm$ 0.108	0.709 $\pm$ 0.033	0.690 $\pm$ 0.039	<u>0.760 <math>\pm</math>0.025</u>	0.733 $\pm$ 0.033
REPv2	0.760 $\pm$ 0.012	0.725 $\pm$ 0.014	0.709 $\pm$ 0.002	<b>0.830 <math>\pm</math>0.001</b>	0.751 $\pm$ 0.003	0.696 $\pm$ 0.035	0.744 $\pm$ 0.026	<u>0.789 <math>\pm</math>0.020</u>	0.772 $\pm$ 0.035
TRAC	0.712 $\pm$ 0.071	0.748 $\pm$ 0.000	0.748 $\pm$ 0.000	<u>0.767 <math>\pm</math>0.001</u>	0.495 $\pm$ 0.223	0.741 $\pm$ 0.012	0.752 $\pm$ 0.007	<b>0.785 <math>\pm</math>0.008</b>	0.722 $\pm$ 0.012
BEPRO	0.655 $\pm$ 0.038	0.632 $\pm$ 0.019	0.610 $\pm$ 0.012	<u>0.783 <math>\pm</math>0.003</u>	0.439 $\pm$ 0.125	0.744 $\pm$ 0.074	0.736 $\pm$ 0.018	0.782 $\pm$ 0.003	<b>0.800 <math>\pm</math>0.074</b>
1 <sup>st</sup> -Place Count $\uparrow$	1	1	0	6	0	0	0	4	8
Avg. Rank $\downarrow$	4.85	5.80	6.10	3.80	6.30	5.60	5.55	3.30	<b>2.80</b>
Avg. AUC $\uparrow$	0.684	0.609	0.626	0.712	0.542	0.633	0.642	0.727	<b>0.753</b>

Table 10: AUC results for the LCC Growth/Shrinkage prediction task ( classification ). Best results are in **bold**, second best are underlined.

Dataset	Single Model on Individual Networks							Transfer Models	
	HTGN	GC-LSTM	EvolveGCN	GraphPulse	ROLAND	TGCN	WinGNN	MiNT	Hydra (Ours)
MIR	0.745 ( $\pm$ 0.023)	0.585 ( $\pm$ 0.128)	0.575 ( $\pm$ 0.146)	0.800 ( $\pm$ 0.008)	0.536 ( $\pm$ 0.275)	0.585 ( $\pm$ 0.055)	0.749 ( $\pm$ 0.020)	<b>0.845 (<math>\pm</math>0.035)</b>	0.815 ( $\pm$ 0.007)
DOGE2.0	0.446 ( $\pm$ 0.164)	0.387 ( $\pm$ 0.294)	0.583 ( $\pm$ 0.115)	0.333 ( $\pm$ 0.042)	0.411 ( $\pm$ 0.232)	0.464 ( $\pm$ 0.182)	0.595 ( $\pm$ 0.176)	0.661 ( $\pm$ 0.047)	<b>0.702 (<math>\pm</math>0.160)</b>
MUTE	0.574 ( $\pm$ 0.022)	0.579 ( $\pm$ 0.022)	0.578 ( $\pm$ 0.033)	<u>0.647 (<math>\pm</math>0.014)</u>	0.624 ( $\pm$ 0.037)	0.567 ( $\pm$ 0.007)	0.641 ( $\pm$ 0.061)	0.582 ( $\pm$ 0.078)	<b>0.704 (<math>\pm</math>0.085)</b>
EVERMOON	0.494 ( $\pm$ 0.127)	0.512 ( $\pm$ 0.112)	0.548 ( $\pm$ 0.152)	0.463 ( $\pm$ 0.034)	0.491 ( $\pm$ 0.157)	<u>0.624 (<math>\pm</math>0.004)</u>	0.603 ( $\pm$ 0.041)	0.527 ( $\pm$ 0.118)	<b>0.667 (<math>\pm</math>0.045)</b>
DERC	0.717 ( $\pm$ 0.035)	0.591 ( $\pm$ 0.010)	0.553 ( $\pm$ 0.044)	<u>0.727 (<math>\pm</math>0.009)</u>	0.481 ( $\pm$ 0.131)	0.523 ( $\pm$ 0.103)	0.582 ( $\pm$ 0.043)	0.689 ( $\pm$ 0.096)	<b>0.808 (<math>\pm</math>0.022)</b>
ADX	<b>0.753 (<math>\pm</math>0.013)</b>	0.599 ( $\pm$ 0.012)	0.604 ( $\pm$ 0.030)	0.661 ( $\pm$ 0.006)	0.606 ( $\pm$ 0.059)	0.621 ( $\pm$ 0.017)	0.611 ( $\pm$ 0.062)	0.587 ( $\pm$ 0.014)	<u>0.727 (<math>\pm</math>0.093)</u>
HOICHI	0.746 ( $\pm$ 0.010)	<u>0.749 (<math>\pm</math>0.001)</u>	0.745 ( $\pm$ 0.003)	0.730 ( $\pm$ 0.017)	0.360 ( $\pm$ 0.121)	<b>0.750 (<math>\pm</math>0.002)</b>	0.635 ( $\pm$ 0.183)	0.722 ( $\pm$ 0.034)	0.638 ( $\pm$ 0.075)
SDEX	<b>0.911 (<math>\pm</math>0.104)</b>	0.721 ( $\pm$ 0.138)	0.601 ( $\pm$ 0.105)	0.808 ( $\pm$ 0.050)	<u>0.825 (<math>\pm</math>0.047)</u>	0.770 ( $\pm$ 0.231)	0.575 ( $\pm$ 0.282)	0.382 ( $\pm$ 0.280)	0.816 ( $\pm$ 0.025)
BAG	0.493 ( $\pm$ 0.043)	0.291 ( $\pm$ 0.180)	0.480 ( $\pm$ 0.052)	0.900 ( $\pm$ 0.010)	0.463 ( $\pm$ 0.019)	0.463 ( $\pm$ 0.141)	0.490 ( $\pm$ 0.080)	0.893 ( $\pm$ 0.074)	<b>0.976 (<math>\pm</math>0.006)</b>
XCN	0.566 ( $\pm$ 0.199)	0.481 ( $\pm$ 0.160)	0.533 ( $\pm$ 0.257)	<u>0.681 (<math>\pm</math>0.005)</u>	0.569 ( $\pm$ 0.204)	0.638 ( $\pm$ 0.045)	0.549 ( $\pm$ 0.133)	0.827 ( $\pm$ 0.025)	<b>0.887 (<math>\pm</math>0.014)</b>
ETH2x-FLI	0.561 ( $\pm$ 0.037)	0.529 ( $\pm$ 0.017)	0.547 ( $\pm$ 0.009)	<u>0.653 (<math>\pm</math>0.047)</u>	0.499 ( $\pm$ 0.135)	0.549 ( $\pm$ 0.019)	0.505 ( $\pm$ 0.090)	0.618 ( $\pm$ 0.025)	<b>0.687 (<math>\pm</math>0.032)</b>
stkAAVE	0.623 ( $\pm$ 0.077)	0.581 ( $\pm$ 0.085)	0.551 ( $\pm$ 0.102)	0.662 ( $\pm$ 0.004)	0.532 ( $\pm$ 0.140)	0.543 ( $\pm$ 0.102)	0.489 ( $\pm$ 0.105)	0.688 ( $\pm$ 0.019)	<b>0.748 (<math>\pm</math>0.012)</b>
GLM	0.761 ( $\pm$ 0.031)	0.481 ( $\pm$ 0.073)	0.636 ( $\pm$ 0.123)	0.749 ( $\pm$ 0.014)	0.802 ( $\pm$ 0.037)	0.425 ( $\pm$ 0.005)	0.489 ( $\pm$ 0.079)	0.818 ( $\pm$ 0.074)	<b>0.848 (<math>\pm</math>0.012)</b>
QOM	0.658 ( $\pm$ 0.150)	0.509 ( $\pm$ 0.100)	0.562 ( $\pm$ 0.022)	<b>0.747 (<math>\pm</math>0.006)</b>	0.627 ( $\pm$ 0.134)	0.419 ( $\pm$ 0.044)	0.546 ( $\pm$ 0.152)	0.645 ( $\pm$ 0.109)	<u>0.729 (<math>\pm</math>0.010)</u>
WOJAK	0.378 ( $\pm$ 0.028)	0.489 ( $\pm$ 0.133)	0.394 ( $\pm$ 0.079)	<b>0.550 (<math>\pm</math>0.036)</b>	0.360 ( $\pm$ 0.005)	0.481 ( $\pm$ 0.092)	0.415 ( $\pm$ 0.017)	0.492 ( $\pm$ 0.107)	<u>0.500 (<math>\pm</math>0.083)</u>
DINO	0.706 ( $\pm$ 0.120)	<u>0.796 (<math>\pm</math>0.023)</u>	0.710 ( $\pm$ 0.034)	0.661 ( $\pm$ 0.026)	0.523 ( $\pm$ 0.238)	0.773 ( $\pm$ 0.043)	0.731 ( $\pm$ 0.037)	0.561 ( $\pm$ 0.006)	<b>0.818 (<math>\pm</math>0.049)</b>
Metis	0.679 ( $\pm$ 0.039)	<u>0.687 (<math>\pm</math>0.018)</u>	0.672 ( $\pm$ 0.016)	<b>0.783 (<math>\pm</math>0.007)</b>	0.672 ( $\pm$ 0.103)	0.657 ( $\pm$ 0.014)	0.634 ( $\pm$ 0.042)	0.780 ( $\pm$ 0.041)	0.731 ( $\pm$ 0.001)
REPv2	0.730 ( $\pm$ 0.007)	0.653 ( $\pm$ 0.015)	0.644 ( $\pm$ 0.027)	<u>0.752 (<math>\pm</math>0.001)</u>	0.658 ( $\pm$ 0.103)	0.646 ( $\pm$ 0.025)	0.683 ( $\pm$ 0.014)	0.742 ( $\pm$ 0.041)	<b>0.764 (<math>\pm</math>0.020)</b>
TRAC	0.733 ( $\pm$ 0.009)	0.629 ( $\pm$ 0.005)	0.623 ( $\pm$ 0.004)	0.686 ( $\pm$ 0.001)	0.606 ( $\pm$ 0.117)	0.620 ( $\pm$ 0.005)	0.599 ( $\pm$ 0.026)	<u>0.762 (<math>\pm</math>0.028)</u>	<b>0.781 (<math>\pm</math>0.004)</b>
BEPRO	0.694 ( $\pm$ 0.009)	0.595 ( $\pm$ 0.008)	0.557 ( $\pm$ 0.058)	<u>0.725 (<math>\pm</math>0.004)</u>	0.482 ( $\pm$ 0.146)	0.536 ( $\pm$ 0.031)	0.582 ( $\pm$ 0.063)	0.628 ( $\pm$ 0.017)	<b>0.830 (<math>\pm</math>0.006)</b>
1 <sup>st</sup> -Place Count $\uparrow$	2	0	0	3	0	1	0	1	13
Avg. Rank $\downarrow$	4.40	6.00	6.30	3.50	6.95	6.10	6.10	3.95	<b>1.70</b>
Avg. AUC $\uparrow$	0.648	0.572	0.585	0.686	0.556	0.583	0.585	0.672	<b>0.759</b>



Table 11: AUC results for the Node Growth/Shrinkage prediction task ( **classification** ). Best results are in **bold**, second best are underlined.

Dataset	Single Model on Individual Networks							Transfer Models	
	HTGN	GC-LSTM	EvolveGCN	GraphPulse	ROLAND	TGCN	WinGNN	MinT	Hydra (Ours)
MIR	0.545 ( $\pm 0.030$ )	0.537 ( $\pm 0.033$ )	0.528 ( $\pm 0.081$ )	0.633 ( $\pm 0.066$ )	0.472 ( $\pm 0.040$ )	0.532 ( $\pm 0.021$ )	0.525 ( $\pm 0.043$ )	0.622 ( $\pm 0.030$ )	<b>0.764</b> ( $\pm 0.001$ )
DOGE2.0	0.427 ( $\pm 0.065$ )	0.633 ( $\pm 0.014$ )	0.400 ( $\pm 0.061$ )	0.403 ( $\pm 0.035$ )	0.260 ( $\pm 0.000$ )	0.627 ( $\pm 0.034$ )	0.693 ( $\pm 0.041$ )	<b>0.750</b> ( $\pm 0.014$ )	0.633 ( $\pm 0.064$ )
MUTE	0.518 ( $\pm 0.023$ )	0.448 ( $\pm 0.008$ )	0.475 ( $\pm 0.051$ )	0.677 ( $\pm 0.008$ )	0.411 ( $\pm 0.053$ )	0.458 ( $\pm 0.009$ )	0.562 ( $\pm 0.015$ )	0.606 ( $\pm 0.056$ )	<b>0.748</b> ( $\pm 0.025$ )
EVERMOON	0.585 ( $\pm 0.059$ )	0.606 ( $\pm 0.021$ )	0.488 ( $\pm 0.088$ )	0.463 ( $\pm 0.002$ )	0.427 ( $\pm 0.137$ )	0.567 ( $\pm 0.030$ )	0.548 ( $\pm 0.116$ )	0.614 ( $\pm 0.071$ )	<b>0.655</b> ( $\pm 0.040$ )
DERC	0.662 ( $\pm 0.051$ )	0.492 ( $\pm 0.069$ )	0.503 ( $\pm 0.084$ )	0.611 ( $\pm 0.049$ )	0.551 ( $\pm 0.013$ )	0.447 ( $\pm 0.003$ )	0.517 ( $\pm 0.034$ )	0.569 ( $\pm 0.004$ )	<b>0.742</b> ( $\pm 0.004$ )
ADX	0.678 ( $\pm 0.017$ )	0.505 ( $\pm 0.043$ )	0.509 ( $\pm 0.022$ )	0.701 ( $\pm 0.003$ )	0.557 ( $\pm 0.082$ )	0.484 ( $\pm 0.048$ )	0.504 ( $\pm 0.018$ )	0.507 ( $\pm 0.037$ )	<b>0.718</b> ( $\pm 0.051$ )
HOICHI	0.687 ( $\pm 0.004$ )	0.718 ( $\pm 0.007$ )	0.685 ( $\pm 0.020$ )	<b>0.745</b> ( $\pm 0.006$ )	0.347 ( $\pm 0.084$ )	0.718 ( $\pm 0.002$ )	0.526 ( $\pm 0.188$ )	0.492 ( $\pm 0.120$ )	0.558 ( $\pm 0.047$ )
SDEX	0.824 ( $\pm 0.106$ )	0.364 ( $\pm 0.148$ )	0.817 ( $\pm 0.032$ )	<b>0.865</b> ( $\pm 0.011$ )	0.779 ( $\pm 0.018$ )	0.755 ( $\pm 0.202$ )	0.757 ( $\pm 0.072$ )	0.861 ( $\pm 0.025$ )	0.743 ( $\pm 0.026$ )
BAG	0.735 ( $\pm 0.075$ )	0.337 ( $\pm 0.089$ )	0.166 ( $\pm 0.066$ )	0.897 ( $\pm 0.016$ )	0.390 ( $\pm 0.088$ )	0.391 ( $\pm 0.219$ )	0.515 ( $\pm 0.008$ )	0.685 ( $\pm 0.038$ )	<b>0.969</b> ( $\pm 0.009$ )
XCN	0.476 ( $\pm 0.012$ )	0.466 ( $\pm 0.012$ )	0.407 ( $\pm 0.176$ )	0.671 ( $\pm 0.020$ )	0.430 ( $\pm 0.144$ )	0.483 ( $\pm 0.036$ )	0.355 ( $\pm 0.017$ )	0.505 ( $\pm 0.002$ )	<b>0.878</b> ( $\pm 0.009$ )
ETH2x-FLI	0.628 ( $\pm 0.022$ )	0.548 ( $\pm 0.001$ )	0.548 ( $\pm 0.002$ )	0.615 ( $\pm 0.020$ )	0.488 ( $\pm 0.063$ )	0.553 ( $\pm 0.036$ )	0.586 ( $\pm 0.098$ )	0.411 ( $\pm 0.066$ )	<b>0.678</b> ( $\pm 0.031$ )
stkAAVE	0.517 ( $\pm 0.093$ )	0.543 ( $\pm 0.043$ )	0.456 ( $\pm 0.069$ )	0.643 ( $\pm 0.005$ )	0.661 ( $\pm 0.037$ )	0.425 ( $\pm 0.029$ )	0.465 ( $\pm 0.036$ )	0.561 ( $\pm 0.007$ )	<b>0.779</b> ( $\pm 0.007$ )
GLM	0.706 ( $\pm 0.014$ )	0.566 ( $\pm 0.001$ )	0.516 ( $\pm 0.105$ )	0.595 ( $\pm 0.003$ )	0.493 ( $\pm 0.149$ )	0.575 ( $\pm 0.019$ )	0.610 ( $\pm 0.024$ )	0.720 ( $\pm 0.045$ )	<b>0.763</b> ( $\pm 0.005$ )
QOM	0.647 ( $\pm 0.094$ )	0.492 ( $\pm 0.003$ )	0.485 ( $\pm 0.001$ )	0.705 ( $\pm 0.002$ )	0.592 ( $\pm 0.080$ )	0.495 ( $\pm 0.004$ )	0.409 ( $\pm 0.051$ )	0.572 ( $\pm 0.017$ )	<b>0.719</b> ( $\pm 0.012$ )
WOJAK	0.417 ( $\pm 0.143$ )	0.338 ( $\pm 0.068$ )	0.357 ( $\pm 0.104$ )	0.500 ( $\pm 0.000$ )	0.202 ( $\pm 0.018$ )	0.488 ( $\pm 0.080$ )	0.314 ( $\pm 0.029$ )	<b>0.618</b> ( $\pm 0.035$ )	0.412 ( $\pm 0.060$ )
DINO	0.845 ( $\pm 0.015$ )	0.323 ( $\pm 0.148$ )	0.444 ( $\pm 0.052$ )	0.686 ( $\pm 0.007$ )	0.330 ( $\pm 0.115$ )	0.615 ( $\pm 0.070$ )	0.600 ( $\pm 0.292$ )	0.735 ( $\pm 0.005$ )	<b>0.910</b> ( $\pm 0.013$ )
Metis	0.589 ( $\pm 0.049$ )	0.483 ( $\pm 0.052$ )	0.566 ( $\pm 0.012$ )	0.652 ( $\pm 0.029$ )	0.574 ( $\pm 0.040$ )	0.549 ( $\pm 0.011$ )	0.510 ( $\pm 0.005$ )	0.616 ( $\pm 0.012$ )	<b>0.693</b> ( $\pm 0.007$ )
REPV2	0.650 ( $\pm 0.004$ )	0.519 ( $\pm 0.023$ )	0.515 ( $\pm 0.019$ )	0.662 ( $\pm 0.008$ )	0.597 ( $\pm 0.028$ )	0.534 ( $\pm 0.029$ )	0.626 ( $\pm 0.058$ )	<b>0.710</b> ( $\pm 0.129$ )	0.689 ( $\pm 0.013$ )
TRAC	0.670 ( $\pm 0.031$ )	0.527 ( $\pm 0.016$ )	0.524 ( $\pm 0.003$ )	0.610 ( $\pm 0.055$ )	0.546 ( $\pm 0.024$ )	0.524 ( $\pm 0.001$ )	0.528 ( $\pm 0.020$ )	0.600 ( $\pm 0.027$ )	<b>0.765</b> ( $\pm 0.003$ )
BEPRO	0.500 ( $\pm 0.055$ )	0.332 ( $\pm 0.010$ )	0.356 ( $\pm 0.015$ )	0.707 ( $\pm 0.005$ )	0.490 ( $\pm 0.016$ )	0.372 ( $\pm 0.100$ )	0.420 ( $\pm 0.018$ )	0.561 ( $\pm 0.022$ )	<b>0.865</b> ( $\pm 0.010$ )
1 <sup>st</sup> -Place Count $\uparrow$	0	0	0	2	0	0	0	3	15
Avg. Rank $\downarrow$	3.65	6.65	7.00	2.95	6.70	6.15	6.20	3.55	1.95
Avg. AUC $\uparrow$	0.615	0.489	0.487	0.652	0.480	0.530	0.528	0.616	0.734

Table 12: MAE results for the Edge Count prediction task ( **regression** ). Best results are in **bold**, second best are underlined.

Dataset	Single Model on Individual Networks							Transfer Models	
	HTGN	TGCN	GCLSTM	ROLAND	EGCN	GraphPulse	WinGNN	Hydra (Ours)	
MIR	0.059 ( $\pm 0.007$ )	0.044 ( $\pm 0.009$ )	0.047 ( $\pm 0.003$ )	0.039 ( $\pm 0.000$ )	0.057 ( $\pm 0.015$ )	0.059 ( $\pm 0.001$ )	0.046 ( $\pm 0.010$ )	<b>0.016</b> ( $\pm 0.005$ )	
DOGE2.0	0.101 ( $\pm 0.035$ )	0.063 ( $\pm 0.017$ )	0.106 ( $\pm 0.029$ )	0.052 ( $\pm 0.003$ )	0.092 ( $\pm 0.031$ )	0.046 ( $\pm 0.000$ )	<b>0.045</b> ( $\pm 0.003$ )	0.187 ( $\pm 0.008$ )	
MUTE	0.025 ( $\pm 0.006$ )	0.038 ( $\pm 0.004$ )	<b>0.017</b> ( $\pm 0.001$ )	0.040 ( $\pm 0.007$ )	0.049 ( $\pm 0.005$ )	0.025 ( $\pm 0.002$ )	0.027 ( $\pm 0.003$ )	0.021 ( $\pm 0.022$ )	
EVERMOON	<b>0.010</b> ( $\pm 0.001$ )	0.021 ( $\pm 0.013$ )	0.025 ( $\pm 0.007$ )	0.016 ( $\pm 0.016$ )	0.030 ( $\pm 0.010$ )	0.235 ( $\pm 0.005$ )	0.025 ( $\pm 0.004$ )	0.017 ( $\pm 0.000$ )	
DERC	0.038 ( $\pm 0.015$ )	0.059 ( $\pm 0.011$ )	<b>0.016</b> ( $\pm 0.005$ )	0.060 ( $\pm 0.008$ )	0.023 ( $\pm 0.007$ )	0.023 ( $\pm 0.003$ )	0.032 ( $\pm 0.001$ )	0.021 ( $\pm 0.003$ )	
ADX	0.017 ( $\pm 0.001$ )	0.018 ( $\pm 0.003$ )	<b>0.016</b> ( $\pm 0.001$ )	0.017 ( $\pm 0.002$ )	0.021 ( $\pm 0.002$ )	0.019 ( $\pm 0.001$ )	<b>0.016</b> ( $\pm 0.000$ )	0.025 ( $\pm 0.008$ )	
HOICHI	0.034 ( $\pm 0.010$ )	<b>0.020</b> ( $\pm 0.001$ )	0.046 ( $\pm 0.013$ )	<b>0.020</b> ( $\pm 0.003$ )	0.034 ( $\pm 0.013$ )	0.044 ( $\pm 0.002$ )	0.028 ( $\pm 0.005$ )	0.027 ( $\pm 0.020$ )	
SDEX	0.080 ( $\pm 0.029$ )	0.128 ( $\pm 0.046$ )	<b>0.058</b> ( $\pm 0.007$ )	0.121 ( $\pm 0.002$ )	0.085 ( $\pm 0.025$ )	0.106 ( $\pm 0.005$ )	0.128 ( $\pm 0.008$ )	0.095 ( $\pm 0.043$ )	
BAG	<b>0.022</b> ( $\pm 0.003$ )	0.023 ( $\pm 0.017$ )	0.025 ( $\pm 0.002$ )	0.030 ( $\pm 0.016$ )	0.027 ( $\pm 0.005$ )	0.063 ( $\pm 0.001$ )	0.260 ( $\pm 0.064$ )	0.041 ( $\pm 0.020$ )	
XCN	0.074 ( $\pm 0.006$ )	0.112 ( $\pm 0.042$ )	0.107 ( $\pm 0.024$ )	0.120 ( $\pm 0.035$ )	0.121 ( $\pm 0.011$ )	0.118 ( $\pm 0.000$ )	0.072 ( $\pm 0.018$ )	<b>0.062</b> ( $\pm 0.015$ )	
ETH2x-FLI	0.055 ( $\pm 0.015$ )	0.079 ( $\pm 0.019$ )	0.177 ( $\pm 0.057$ )	0.040 ( $\pm 0.026$ )	0.066 ( $\pm 0.016$ )	0.144 ( $\pm 0.009$ )	0.030 ( $\pm 0.011$ )	<b>0.023</b> ( $\pm 0.001$ )	
stkAAVE	0.083 ( $\pm 0.008$ )	0.087 ( $\pm 0.005$ )	0.092 ( $\pm 0.017$ )	0.104 ( $\pm 0.012$ )	0.079 ( $\pm 0.010$ )	0.096 ( $\pm 0.006$ )	0.100 ( $\pm 0.004$ )	<b>0.051</b> ( $\pm 0.022$ )	
GLM	0.072 ( $\pm 0.010$ )	0.058 ( $\pm 0.005$ )	0.063 ( $\pm 0.002$ )	0.058 ( $\pm 0.003$ )	0.060 ( $\pm 0.001$ )	0.076 ( $\pm 0.001$ )	<b>0.054</b> ( $\pm 0.003$ )	0.087 ( $\pm 0.008$ )	
QOM	0.042 ( $\pm 0.005$ )	0.085 ( $\pm 0.020$ )	0.053 ( $\pm 0.030$ )	0.057 ( $\pm 0.030$ )	0.069 ( $\pm 0.013$ )	0.055 ( $\pm 0.001$ )	0.046 ( $\pm 0.006$ )	<b>0.036</b> ( $\pm 0.013$ )	
WOJAK	0.009 ( $\pm 0.002$ )	0.012 ( $\pm 0.003$ )	0.013 ( $\pm 0.004$ )	0.016 ( $\pm 0.008$ )	0.013 ( $\pm 0.007$ )	0.057 ( $\pm 0.008$ )	<b>0.006</b> ( $\pm 0.002$ )	0.010 ( $\pm 0.004$ )	
DINO	0.069 ( $\pm 0.020$ )	0.025 ( $\pm 0.009$ )	0.040 ( $\pm 0.019$ )	<b>0.014</b> ( $\pm 0.004$ )	0.039 ( $\pm 0.011$ )	0.087 ( $\pm 0.002$ )	0.021 ( $\pm 0.008$ )	0.017 ( $\pm 0.007$ )	
Metis	0.038 ( $\pm 0.002$ )	0.054 ( $\pm 0.001$ )	0.047 ( $\pm 0.003$ )	0.057 ( $\pm 0.008$ )	0.053 ( $\pm 0.004$ )	0.066 ( $\pm 0.006$ )	0.043 ( $\pm 0.001$ )	<b>0.034</b> ( $\pm 0.010$ )	
REPV2	0.117 ( $\pm 0.013$ )	0.108 ( $\pm 0.004$ )	0.115 ( $\pm 0.004$ )	<b>0.106</b> ( $\pm 0.001$ )	0.128 ( $\pm 0.036$ )	0.119 ( $\pm 0.001$ )	0.118 ( $\pm 0.001$ )	0.111 ( $\pm 0.008$ )	
TRAC	0.026 ( $\pm 0.004$ )	0.036 ( $\pm 0.010$ )	0.061 ( $\pm 0.006$ )	0.023 ( $\pm 0.004$ )	0.036 ( $\pm 0.003$ )	<b>0.017</b> ( $\pm 0.000$ )	0.040 ( $\pm 0.014$ )	0.021 ( $\pm 0.001$ )	
BEPRO	0.009 ( $\pm 0.001$ )	0.009 ( $\pm 0.003$ )	0.009 ( $\pm 0.002$ )	0.015 ( $\pm 0.017$ )	<b>0.007</b> ( $\pm 0.001$ )	<b>0.007</b> ( $\pm 0.000$ )	<b>0.007</b> ( $\pm 0.002$ )	0.011 ( $\pm 0.008$ )	
1 <sup>st</sup> -Place Count $\uparrow$	2	1	4	3	1	2	5	6	
Avg. Rank $\downarrow$	3.95	4.60	4.58	4.58	5.30	5.72	3.93	3.35	
Avg. MAE $\downarrow$	0.049	0.054	0.057	0.050	0.054	0.073	0.057	0.046	

Table 13: MAE results for the New Node Count prediction task ( regression ). Best results are in **bold**, second best are underlined.

	Single Model on Individual Networks							Transfer Models
Dataset	HTGN	TGCN	GCLSTM	ROLAND	EGCN	GraphPulse	WinGNN	Hydra (ours)
MIR	0.031 ( $\pm 0.002$ )	0.028 ( $\pm 0.001$ )	0.039 ( $\pm 0.005$ )	0.025 ( $\pm 0.018$ )	0.030 ( $\pm 0.001$ )	0.025 ( $\pm 0.001$ )	0.037 ( $\pm 0.011$ )	<b>0.013</b> ( $\pm 0.004$ )
DOGE2.0	0.046 ( $\pm 0.009$ )	0.064 ( $\pm 0.021$ )	<b>0.044</b> ( $\pm 0.014$ )	0.073 ( $\pm 0.019$ )	0.051 ( $\pm 0.031$ )	0.157 ( $\pm 0.010$ )	0.098 ( $\pm 0.009$ )	0.092 ( $\pm 0.008$ )
MUTE	<b>0.021</b> ( $\pm 0.003$ )	0.041 ( $\pm 0.005$ )	0.030 ( $\pm 0.003$ )	0.048 ( $\pm 0.002$ )	0.053 ( $\pm 0.003$ )	0.031 ( $\pm 0.001$ )	0.051 ( $\pm 0.015$ )	0.025 ( $\pm 0.005$ )
EVERMOON	<b>0.010</b> ( $\pm 0.004$ )	0.017 ( $\pm 0.008$ )	0.026 ( $\pm 0.009$ )	0.029 ( $\pm 0.019$ )	0.028 ( $\pm 0.017$ )	0.222 ( $\pm 0.005$ )	0.022 ( $\pm 0.002$ )	<u>0.012</u> ( $\pm 0.005$ )
DERC	0.028 ( $\pm 0.009$ )	0.034 ( $\pm 0.018$ )	0.016 ( $\pm 0.024$ )	0.043 ( $\pm 0.024$ )	0.019 ( $\pm 0.004$ )	0.043 ( $\pm 0.011$ )	0.027 ( $\pm 0.003$ )	<b>0.015</b> ( $\pm 0.004$ )
ADX	0.014 ( $\pm 0.001$ )	<b>0.010</b> ( $\pm 0.001$ )	<u>0.011</u> ( $\pm 0.001$ )	0.024 ( $\pm 0.296$ )	0.012 ( $\pm 0.000$ )	0.024 ( $\pm 0.002$ )	0.011 ( $\pm 0.000$ )	0.016 ( $\pm 0.005$ )
HOICHI	0.044 ( $\pm 0.004$ )	0.035 ( $\pm 0.025$ )	0.053 ( $\pm 0.028$ )	0.204 ( $\pm 0.028$ )	0.039 ( $\pm 0.023$ )	0.066 ( $\pm 0.001$ )	<b>0.027</b> ( $\pm 0.004$ )	0.029 ( $\pm 0.008$ )
SDEX	0.075 ( $\pm 0.002$ )	0.093 ( $\pm 0.006$ )	0.069 ( $\pm 0.002$ )	0.088 ( $\pm 0.002$ )	0.077 ( $\pm 0.008$ )	0.087 ( $\pm 0.002$ )	0.090 ( $\pm 0.025$ )	<b>0.063</b> ( $\pm 0.006$ )
BAG	0.023 ( $\pm 0.007$ )	0.031 ( $\pm 0.008$ )	<b>0.019</b> ( $\pm 0.007$ )	0.053 ( $\pm 0.006$ )	0.030 ( $\pm 0.004$ )	0.054 ( $\pm 0.000$ )	0.230 ( $\pm 0.062$ )	0.052 ( $\pm 0.002$ )
XCN	0.014 ( $\pm 0.007$ )	0.015 ( $\pm 0.006$ )	0.017 ( $\pm 0.007$ )	0.012 ( $\pm 0.012$ )	0.017 ( $\pm 0.007$ )	0.040 ( $\pm 0.001$ )	0.015 ( $\pm 0.002$ )	<b>0.009</b> ( $\pm 0.002$ )
ETH2x-FLI	0.031 ( $\pm 0.010$ )	0.041 ( $\pm 0.001$ )	0.069 ( $\pm 0.010$ )	<b>0.020</b> ( $\pm 0.004$ )	0.030 ( $\pm 0.002$ )	0.092 ( $\pm 0.001$ )	0.028 ( $\pm 0.003$ )	0.030 ( $\pm 0.004$ )
stkAAVE	0.128 ( $\pm 0.018$ )	0.136 ( $\pm 0.008$ )	0.128 ( $\pm 0.018$ )	0.154 ( $\pm 0.005$ )	0.124 ( $\pm 0.005$ )	0.151 ( $\pm 0.000$ )	0.147 ( $\pm 0.008$ )	<b>0.078</b> ( $\pm 0.017$ )
GLM	<b>0.066</b> ( $\pm 0.000$ )	0.068 ( $\pm 0.001$ )	0.068 ( $\pm 0.000$ )	0.068 ( $\pm 0.002$ )	<u>0.067</u> ( $\pm 0.002$ )	0.092 ( $\pm 0.000$ )	<b>0.066</b> ( $\pm 0.000$ )	0.094 ( $\pm 0.007$ )
QOM	0.035 ( $\pm 0.006$ )	0.038 ( $\pm 0.010$ )	0.032 ( $\pm 0.020$ )	0.018 ( $\pm 0.010$ )	0.035 ( $\pm 0.020$ )	0.033 ( $\pm 0.004$ )	0.029 ( $\pm 0.007$ )	<b>0.012</b> ( $\pm 0.001$ )
WOJAK	0.008 ( $\pm 0.001$ )	0.009 ( $\pm 0.001$ )	0.015 ( $\pm 0.003$ )	0.029 ( $\pm 0.017$ )	0.014 ( $\pm 0.003$ )	0.067 ( $\pm 0.005$ )	<b>0.007</b> ( $\pm 0.001$ )	0.009 ( $\pm 0.000$ )
DINO	0.061 ( $\pm 0.017$ )	0.024 ( $\pm 0.002$ )	0.028 ( $\pm 0.019$ )	<b>0.013</b> ( $\pm 0.005$ )	0.030 ( $\pm 0.005$ )	0.085 ( $\pm 0.001$ )	0.051 ( $\pm 0.029$ )	0.018 ( $\pm 0.007$ )
Metis	<b>0.034</b> ( $\pm 0.010$ )	0.045 ( $\pm 0.006$ )	0.041 ( $\pm 0.006$ )	0.043 ( $\pm 0.005$ )	0.042 ( $\pm 0.004$ )	0.054 ( $\pm 0.001$ )	<b>0.034</b> ( $\pm 0.002$ )	<b>0.034</b> ( $\pm 0.010$ )
REPy2	0.061 ( $\pm 0.003$ )	0.061 ( $\pm 0.004$ )	0.075 ( $\pm 0.003$ )	<b>0.055</b> ( $\pm 0.002$ )	0.063 ( $\pm 0.004$ )	0.068 ( $\pm 0.000$ )	0.063 ( $\pm 0.000$ )	0.066 ( $\pm 0.004$ )
TRAC	0.043 ( $\pm 0.021$ )	0.030 ( $\pm 0.003$ )	0.071 ( $\pm 0.021$ )	0.021 ( $\pm 0.006$ )	0.025 ( $\pm 0.009$ )	<b>0.018</b> ( $\pm 0.000$ )	0.044 ( $\pm 0.010$ )	0.022 ( $\pm 0.005$ )
BEPRO	0.012 ( $\pm 0.002$ )	0.010 ( $\pm 0.002$ )	0.011 ( $\pm 0.017$ )	0.011 ( $\pm 0.011$ )	0.009 ( $\pm 0.000$ )	0.012 ( $\pm 0.000$ )	0.006 ( $\pm 0.001$ )	<b>0.004</b> ( $\pm 0.001$ )
1 <sup>st</sup> -Place Count $\uparrow$	4	1	2	3	0	1	4	8
Avg. Rank $\downarrow$	3.45	4.10	4.00	4.35	3.90	5.75	4.05	<b>2.50</b>
Avg. MAE $\downarrow$	0.039	0.042	0.043	0.052	0.040	0.071	0.054	<b>0.035</b>

Table 14: MAE results for the Influential Node Count prediction task ( regression ). Best results are in **bold**, second best are underlined.

	Single Model on Individual Networks							Transfer Models
Dataset	HTGN	TGCN	GCLSTM	ROLAND	EGCN	GraphPulse	WinGNN	Hydra (ours)
MIR	0.114 ( $\pm 0.003$ )	0.119 ( $\pm 0.005$ )	0.105 ( $\pm 0.020$ )	0.115 ( $\pm 0.020$ )	0.114 ( $\pm 0.017$ )	0.127 ( $\pm 0.002$ )	<u>0.082</u> ( $\pm 0.007$ )	<b>0.039</b> ( $\pm 0.005$ )
DOGE2.0	0.064 ( $\pm 0.031$ )	0.090 ( $\pm 0.023$ )	<b>0.053</b> ( $\pm 0.021$ )	0.070 ( $\pm 0.015$ )	0.059 ( $\pm 0.021$ )	0.087 ( $\pm 0.004$ )	0.091 ( $\pm 0.009$ )	0.126 ( $\pm 0.032$ )
MUTE	0.028 ( $\pm 0.004$ )	0.042 ( $\pm 0.002$ )	<b>0.018</b> ( $\pm 0.002$ )	0.051 ( $\pm 0.006$ )	0.042 ( $\pm 0.012$ )	0.021 ( $\pm 0.001$ )	0.045 ( $\pm 0.033$ )	0.045 ( $\pm 0.027$ )
EVERMOON	<b>0.011</b> ( $\pm 0.002$ )	0.014 ( $\pm 0.006$ )	0.018 ( $\pm 0.008$ )	0.014 ( $\pm 0.004$ )	0.032 ( $\pm 0.015$ )	0.235 ( $\pm 0.004$ )	0.026 ( $\pm 0.006$ )	0.038 ( $\pm 0.024$ )
DERC	0.069 ( $\pm 0.007$ )	0.084 ( $\pm 0.001$ )	0.053 ( $\pm 0.002$ )	0.104 ( $\pm 0.011$ )	0.058 ( $\pm 0.010$ )	0.048 ( $\pm 0.001$ )	0.077 ( $\pm 0.003$ )	<b>0.033</b> ( $\pm 0.017$ )
ADX	0.016 ( $\pm 0.003$ )	0.015 ( $\pm 0.000$ )	<b>0.012</b> ( $\pm 0.001$ )	0.022 ( $\pm 0.009$ )	0.015 ( $\pm 0.001$ )	0.020 ( $\pm 0.001$ )	0.015 ( $\pm 0.004$ )	0.030 ( $\pm 0.001$ )
HOICHI	0.039 ( $\pm 0.011$ )	<b>0.020</b> ( $\pm 0.007$ )	0.046 ( $\pm 0.017$ )	0.030 ( $\pm 0.015$ )	0.034 ( $\pm 0.016$ )	0.047 ( $\pm 0.009$ )	0.024 ( $\pm 0.016$ )	0.055 ( $\pm 0.028$ )
SDEX	0.037 ( $\pm 0.011$ )	0.049 ( $\pm 0.022$ )	<b>0.031</b> ( $\pm 0.012$ )	0.058 ( $\pm 0.017$ )	0.037 ( $\pm 0.005$ )	0.067 ( $\pm 0.009$ )	0.066 ( $\pm 0.025$ )	0.042 ( $\pm 0.019$ )
BAG	<b>0.009</b> ( $\pm 0.000$ )	0.017 ( $\pm 0.002$ )	0.030 ( $\pm 0.008$ )	0.019 ( $\pm 0.010$ )	0.030 ( $\pm 0.009$ )	0.064 ( $\pm 0.001$ )	0.074 ( $\pm 0.094$ )	0.075 ( $\pm 0.027$ )
XCN	0.061 ( $\pm 0.008$ )	0.155 ( $\pm 0.009$ )	<b>0.055</b> ( $\pm 0.003$ )	0.124 ( $\pm 0.005$ )	0.066 ( $\pm 0.008$ )	0.080 ( $\pm 0.004$ )	0.159 ( $\pm 0.029$ )	0.126 ( $\pm 0.033$ )
ETH2x-FLI	0.050 ( $\pm 0.007$ )	0.053 ( $\pm 0.035$ )	0.100 ( $\pm 0.014$ )	<b>0.023</b> ( $\pm 0.005$ )	0.044 ( $\pm 0.010$ )	0.108 ( $\pm 0.003$ )	0.033 ( $\pm 0.010$ )	0.033 ( $\pm 0.020$ )
stkAAVE	0.062 ( $\pm 0.001$ )	0.080 ( $\pm 0.009$ )	0.062 ( $\pm 0.001$ )	0.057 ( $\pm 0.005$ )	0.061 ( $\pm 0.006$ )	0.108 ( $\pm 0.009$ )	0.066 ( $\pm 0.003$ )	<b>0.042</b> ( $\pm 0.013$ )
GLM	0.066 ( $\pm 0.002$ )	0.057 ( $\pm 0.001$ )	0.067 ( $\pm 0.004$ )	<u>0.057</u> ( $\pm 0.005$ )	0.054 ( $\pm 0.002$ )	0.082 ( $\pm 0.000$ )	<b>0.053</b> ( $\pm 0.002$ )	0.075 ( $\pm 0.017$ )
QOM	0.060 ( $\pm 0.004$ )	0.088 ( $\pm 0.040$ )	0.061 ( $\pm 0.032$ )	0.074 ( $\pm 0.018$ )	0.075 ( $\pm 0.015$ )	0.076 ( $\pm 0.004$ )	0.062 ( $\pm 0.012$ )	<b>0.039</b> ( $\pm 0.020$ )
WOJAK	<b>0.007</b> ( $\pm 0.001$ )	0.008 ( $\pm 0.003$ )	0.012 ( $\pm 0.003$ )	0.027 ( $\pm 0.010$ )	0.011 ( $\pm 0.004$ )	0.066 ( $\pm 0.019$ )	<b>0.007</b> ( $\pm 0.001$ )	0.036 ( $\pm 0.027$ )
DINO	0.078 ( $\pm 0.036$ )	0.024 ( $\pm 0.004$ )	0.068 ( $\pm 0.001$ )	0.024 ( $\pm 0.003$ )	0.036 ( $\pm 0.007$ )	0.087 ( $\pm 0.003$ )	<b>0.022</b> ( $\pm 0.000$ )	0.034 ( $\pm 0.002$ )
Metis	0.056 ( $\pm 0.003$ )	0.078 ( $\pm 0.004$ )	0.068 ( $\pm 0.005$ )	0.085 ( $\pm 0.030$ )	0.073 ( $\pm 0.004$ )	0.071 ( $\pm 0.010$ )	0.063 ( $\pm 0.001$ )	<b>0.046</b> ( $\pm 0.008$ )
REPy2	<b>0.115</b> ( $\pm 0.000$ )	0.118 ( $\pm 0.006$ )	0.119 ( $\pm 0.002$ )	<b>0.115</b> ( $\pm 0.001$ )	0.138 ( $\pm 0.027$ )	0.127 ( $\pm 0.000$ )	0.126 ( $\pm 0.001$ )	0.129 ( $\pm 0.022$ )
TRAC	0.045 ( $\pm 0.005$ )	0.058 ( $\pm 0.002$ )	0.079 ( $\pm 0.002$ )	0.055 ( $\pm 0.009$ )	0.056 ( $\pm 0.005$ )	<b>0.033</b> ( $\pm 0.005$ )	0.074 ( $\pm 0.009$ )	0.043 ( $\pm 0.023$ )
BEPRO	0.016 ( $\pm 0.006$ )	0.014 ( $\pm 0.003$ )	0.012 ( $\pm 0.002$ )	0.013 ( $\pm 0.001$ )	0.012 ( $\pm 0.002$ )	0.012 ( $\pm 0.000$ )	<b>0.010</b> ( $\pm 0.001$ )	0.033 ( $\pm 0.018$ )
1 <sup>st</sup> -Place Count $\uparrow$	4	1	5	2	0	1	4	5
Avg. Rank $\downarrow$	<b>3.52</b>	4.85	3.80	4.55	4.20	5.90	4.28	4.90
Avg. MAE $\downarrow$	<b>0.050</b>	0.059	0.053	0.057	0.052	0.078	0.059	0.056